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Final Report:

Scaling and Classifying Delinquent Careers:
The Criminal Career-Line Approach

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ABSTRACT

Despite several criminological theories that imply specialization in criminal careers, empirical studies have failed to find many specialized careers. These empirical works have been based primarily on a typological approach to the classification of offenders. This approach has several shortcomings that may be circumvented by conceptualizing the offense history as a criminal career-line. A scaling method known as Variance Centroid Scaling is used to derive four dimensions of delinquency on a sample of 1047 New Jersey delinquents. The career-lines of 913 chronic delinquents (those with six or more arrests) are depicted as regression lines and classified on the basis of their fit to these underlying dimensions of crime. Both stable and developmental specialization is found. It is concluded that there may be more specialization in criminal careers than previous empirical study has shown. General implications are drawn for etiological criminological theory, as well as for the criminal justice system.

EXECUTIVE SUMMARY

Criminologists have been interested in the extent to which criminals specialize in certain types of offenses, such as burglary, robbery, and drug offenses. Various typologies have been developed in an attempt to classify the offense histories of criminals, but it is generally recognized that they fail to identify unambiguously very many offenders as specialists (Gibbons, 1975). An apparent diversity of offenses in the careers of criminals has made the traditional typological approach difficult to apply (Chaiken and Chaiken, 1982). This diversity contradicts several widely-held theories that argue for varying degrees of specialization. These persectives include differential opportunity, differential association, social control, deterrence, and labeling theories. All these theories lead one to expect some degree of specialization for criminals over time.

The official arrest histories of a sample of highly delinquent offenders (N=1005) who were incarcerated in correctional facilities in New Jersey in 1977-78 (see Chapter Two), are analysed to develop an alternative to the traditional typological approach. Dimensions of crime, analogous to a "seriousness" dimension of crime, are uncovered using a scaling program called Variance Centroid Scaling (VCS). This technique is used rather than factor analysis or multidimensional scaling techniques for reasons described in detail in Appendix A. Four dimensions of delinquency are identified by VCS. For example, dimension one is characterized by serious crimes against the person on one end of the dimension and property crimes such as burglary and auto theft on the other end of the dimension. The four dimensions (described in full in Chapter Three) tell us how crimes co-occur in the delinquent careers.

We introduce the idea of a criminal career-line in Chapter Four. A criminal career-line consists of a line drawn through the points of a plot in which the horizontal axis represents the sequence number of the offense in the delinquent career in chronological order with "1" assigned to the first crime of the career and "n" to the nth crime. The vertical axis consists of a dimension of crime in which each crime type has a scale value. For example, the career-line of an offender who only commits burglary would be a straight line passing through all the points and horizontal to the crime sequence number axis of the plot. Since most criminals commit a variety of crime types, variation around the criminal career-line must be allowed. We use simple bivariate regression for each individual in the sample in which the scale value in a dimension is regressed on the offense sequence number.

We focus on 913 chronic offenders (those with six or more arrests), thus 3652 bivariate regressions are examined (four for each person). Criteria are established for identifying delinquent career-lines as <u>stable</u> (low slope and variation), <u>developmental</u> (career-line end and beginning points substantively distant), or <u>diverse</u> (excessive variation around the career-line). Nine types of stable and developmental career-lines occur frequently, accounting for 66.3% of the chronic delinquents. These common career-line patterns are:

1. Burglary/Auto Theft to general delinquency
2. General delinquency to serious persons with burglary
3. General delinquency to serious persons
4. Serious persons offenses to general delinquency
5. Stable general delinquency career
6. Status offenses to general delinquency
7. Stable general delinquency career -- auto theft
8. General delinquency to property/petty crimes
9. Property/petty crimes to general delinquency

The validity of the delinquent career-lines classifications is tested using adult record information that was collected on the sample until they reached an average age of 23. The occurrence of adult robbery, burglary, and auto theft crimes were predicted successfully using the nine-fold delinquent career-line classification, providing support for the value of the delinquent career-line classificatory schema.

Support is found for each of the theoretical orientations that led us to expect specialization. Also, the value of the criminal "career" concept itself is reinforced by the findings, countering the arguments of some of its critics (see Gottfredson and Hirschi, 1986). It is concluded that the conceptualization of a criminal career as a line is a valuable one, that it leads to the identification of many systematic careers forms, and suggests that many etiological and criminal justice theories should try to take this into account. Further research is necessary, however, particularly on methodological issues of the implementation of the career-line approach, including validation of our findings on another sample of offenders.

Chapter One: Offender Classification and The Career-Line Approach

Introduction

Criminals are perceived popularly as murderers, robbers, burglars, embezzlers, drug-dealers, arsonists, prostitutes, etc., -- specialists in their criminal roles. This conception of a "division of labor" among offenders has been reinforced by criminologists who define these activities as "roles" and focus on the learning process by which potential offenders acquire the techniques and motivations necessary for specific criminal behaviors. The time and motivation invested in learning to be a burglar, for example, curtails the learning of new criminal trades -- much like specialization in conventional careers constrains one's occupational options. The plausibility of this conception of criminals has been strongly tested, however, by several studies that have shown that criminals are remarkably diverse in their criminal activities (Wolfgang et al., 1972; Smith and Smith, 1984; Bursik, 1980; Hood and Sparks, 1970; Hartjen and Gibbons, 1969; Gibbons, 1975). In general these studies have found that there are relatively few offenders who specialize in one type of crime over the course of their careers.

Despite these studies, various researchers continue to find offense specialization important to their research goals, and they continue to develop and apply typologies of offenders. On the surface, there are a number of reasons why typologies continue to be used. For one, there is no consensus that the empirical issue of specialization is settled -- there may be subgroups of yet unidentified offenders who _do_ specialize (See Chaiken and Chaiken, 1982). Second, there is no consensus as to whether to define specialization in a narrow or a broad sense. In a _narrow_ sense specialization could be defined as the exclusive repetition of the same offense throughout the career. In a broad sense, specialization may be defined as a tendency to commit crimes that are similar according to some abstract property, e.g., a criminal who illegally and repetitively takes property is a "property offender." Lacking clear conceptions of specialization results in inconsistent claims in the classification literature. Thus, Chaiken and Chaiken (1982), using relatively liberal criteria, classify all the offenders in their sample as "specialists," while Hartjen and Gibbons (1967), using a more conservative standard, find that only twenty-two percent were classified using a modified version of Gibbons' (1968) classification system. In addition to these empirical and conceptual issues, the criminal justice system frequently purports to use such systems in the adjudication and treatment of offenders. Thus, there are policy reasons as well as unsettled empirical and conceptual questions that perpetuate traditional offender typologies.

Theoretical Considerations: The Structure of Crime and Criminal Careers

The search for offender typologies may be misdirected, however, unless there are theoretical justifications for expecting that specialization exists in the first place. We argue that there are at least five theories that imply specialization. Most explicit is the differential opportunity perspective of Cloward and Ohlin (1960), who describe how delinquents are likely to participate in one of three delinquent subcultures: criminal, conflict, or retreatist. Juveniles specialize in property, persons, and drug offenses, depending on the subculture with which they affiliate. Thus differential opportunity theory suggests specialization in a broad sense.

A second theoretical justification for expecting specialization is that of Edwin Sutherland, who argued that criminal behavior is a learning process in which techniques (sometimes very complicated ones) and specific motivations are learned through interaction and communication with family, friends, and peers. Differential association theory implies a division of labor in that presumably not every delinquent or criminal associates with all types of criminals nor with individuals who are proficient in all types of crime.

A third perspective -- social control theory -- posits that there is variation in the normative seriousness of crimes, as there is variation in stakes in conformity to conventional lines of action, which limit criminal or delinquent participation (Hirschi, 1969; Toby, 1974). Although one's stake in conformity, for example, may be adequate to keep one from committing a robbery, it may not be sufficient to keep one from shoplifting. Assuming further that stake in conformity does not shift drastically over short time periods, i.e., on a day-to-day basis, it would seem to follow that some structuring or progression in crime along a seriousness dimension would be expected.

Two ways in which this could come about are as follows: the juvenile may "progress" toward increasingly serious crimes as his/her stake in conformity decreases; or the diversity of the offenses in the career could increase with the seriousness of the offense. That is, specialization may be a function of the individual's stake in conformity. Low stake in conformity individuals would be expected to commit a variety of types of crimes while high stake in conformity individuals would be limited to relatively less serious crimes. Hence, a robber would also commit shoplifting, but a shoplifter would not rob. The implication here is that some form of specialization is more likley to be seen among the less serious crimes.

A fourth perspective argues that punitive intervention by the criminal justice system will deter criminals from commiting the more serious crimes, but not the less serious crimes. A robber who serves time in a correctional facility may be deterred from committing future robberies, yet be willing to take the risks of lesser offenses, such as shoplifting, because he/she knows the penalty is not likely to be reincarceration.

Finally, although primary deviance may consist of diverse forms of behavior, labeling theory posits that once the individual is caught and labeled by social control agents, he or she is stigmatized by the label and begins to develop an identity in accordance with the label (Lemert, 1951). This suggests that labeling burglars tends to produce individuals who define themselves as such and who are likely, therefore, to engage in secondary deviance as burglars. This perspective suggests that specialists "converge" upon particular crimes as their criminal behavior becomes more consistent with their label.

In summary, five different theoretical orientations -- subcultural, differential association, social control, deterrence, and labeling theories -- all lead one to expect some degree of specialization or structuring in criminal career histories. The specialization implied varies, however, across theories. Cloward and Ohlin's work, as well as Sutherland's, seem to suggest repetition of types of acts over the course of the career, whereas social control, deterrence, and labeling theory imply development or change in the course of criminal careers as individuals lose stake in conformity, are deterred by punitive intervention, or become stigmatized.

The specific form criminal careers take remains unaddressed by all the perspectives except, perhaps, Cloward and Ohlin's. Empirical studies of differential opportunity theory, however, produced little evidence of the three-part specialization in delinquency that they predict (Short et. al. 1965). A similar argument can be made against learning theory applications.

Gibbons, for example, defines specialization as a "role-career" in which a "type" of offender may commit several kinds of crime. For example, a "predatory gang delinquent" of Gibbons's delinquency typology, may commit serious thefts, burglary, vandalism, automobile theft, and sexual delinquency (Gibbons, 1965:70). Yet there is no empirical verification of the existence of this combination (Gibbons, 1975).

The other three theoretical perspectives are more suggestive of the forms of specialized careers than they are of explicit patterns. We know of no social control theorist who has advanced the hypothesis that criminal careers are specialized as a function of stake in conformity. In fact, social control theorists such as Travis Hirschi and Michael Gottfredson have claimed that "career" conceptions of criminal behavior are misdirected (Gottfredson and Hirschi, 1986). The argument is that individuals are tempted to commit numerous kinds of delinquent acts, some do not because they have too great a degree of commitment to conventional institutions or are too attached to conventional others to risk delinquency. Diversity of behavior is expected where these controls are weak because of the (assumed) diversity of temptations. Hence, any attmept to find different etiological theories for different types of offenders will fail (Hirschi, 1969). Hirschi may be right, but we argue here that it is equally plausible to expect specialization to be positively correlated with commitment and/or attachment to conventional others. We think that the empirical evidence for diversity of offense histories is in part an artifact of inadequate methods, as will be elaborated below.

Deterrence theorists have not, to our knowledge, explicitly derived the hypothesis that the seriousness of the offense behavior decreases with punitive intervention. Instead, they have focussed on whether or not an individual recidivates, or on how sanctions are perceived (Tittle, 1982), or on the rate of offense behavior before and after intervention (Murray and Cox, 1979). Similarly, for labeling theory there are only suggestive remarks that the delinquent label narrows the field of possible behaviors (Lemert, 1951). Thus, there is theoretical ambiguity as to what specific forms of specialization to expect in delinquent careers. Nevertheless, the expectation that some structuring exists is derivable from all five perspectives and further exploration is warranted into why it is that empirical approaches have failed to find it.

Assumptions of Offense Classifications

Several methodological implications are involved in typical implementations of classification schema and these may account for the failure of past research to find specialized careers. In general two steps are involved in implementing an offender typology: one, determining what crimes are similar; and two, making rules as to what constitutes specialization or diversity -- rules by which to make classification decisions on the empirically varied offenses in a career.

As for the first step, researchers have used both an *a priori* approach and an *a posteriori* approach to arrive at judgments of similar offenses. With an *a priori* approach, the researcher usually draws upon broad theoretical guidelines in order to legitimate the grouping of offenses. Larceny, possession of stolen property, and burglary, for example, may be deemed similar because they involve the theft of property. Individuals with a high proportion of such similar crimes in their careers might be called "property offenders." Crimes may be considered similar for a variety of reasons:

motivations to commit the act, the self-concept of individuals who commit these crimes, degree of group support, similarity in societal response to the behaviors, similar offense seriousness, similar interactional settings where the offenses take place, and so on (Clinard and Quinney, 1970). These theoretical considerations guide the researcher in making judgments on the similarity of offenses.

The second general approach to grouping crimes is to let the empirical co-occurrence of crimes in criminal careers define what crimes are similar. This method is _a posteriori_ in that crimes are assumed to be similar by the fact of their empirical co-occurence in careers. Crime groupings frequently are based on an empirical data-reduction technique such as factor analysis or multidimensional scaling (e.g., Nye and Short, 1957). Theory explicitly enters the process after crimes are grouped, and the dimensions of crime are identified or "labeled" by the researcher. This approach rests on the assumption that the criminal career itself, as it consists of crimes that co-occur, is important in defining what crimes are similar.

Assumptions of Offender Classifications

Once the crimes are grouped, either by an _a priori_ or an _a posteriori_ approach, the researcher still faces the second step in classifying offenders -- deciding on _rules_ by which to handle offense diversity in the careers of individuals. Several decisions must be made in order to implement a behavioral typology of _individuals_. The problem with such research efforts is that very few offense histories consist solely of the same offense repeated (few are even repetitions of a general class of offenses). The Chaikens, for example, found 256 different combinations of eight self-reported offense types in the criminal careers of 2058 inmates. How can these different combinations of offense histories be reduced? In the literature three general strategies are employed: impose a selective hierarchy on the offenses, use an offense "window" (segment of a criminal career), and simply assume stability over the course of a criminal career.

Selective Hierarchy. In order to classify a large proportion of offenders according to their criminal histories, it is frequently assumed that some crimes are more relevant or important than others to the classification, and that less relevant crimes can be ignored. That is, a hierarchy of relevance or importance is imposed by the researcher to differentiate "allowable exceptions" from crimes that are essential to the definition of the classification system. For example, if someone's offense history consists of murder, burglary, and larceny, he or she may be classified as a murderer if murder is considered the more significant offense. The basis for the imposed selective hierarchy is often offense seriousness (the more serious the offense, the greater its status in the hierarchy), or chronicity (e.g., drug users are more likely to be persistent offenders), or some other specific characteristic, such as the predatory nature of the offense (e.g., robbery may be given priority over assault).

Offense Windows. A second methodological decision on the part of researchers implementing typologies is the use of offense history "windows." On the surface it may seem to be a convenient mechanism to eliminate potential diversity from a career by simply ignoring crimes not within a narrow time period. Offense windows, however, are usually employed for the practical reason that it is difficult -- if not impossible -- to collect the complete offense histories of individuals from birth to death. One finds, however, variation in the length of time in the window period. Some studies with relatively wide window periods focus on juvenile delinquency (Wolfgang et al., 1972), or on adult offenses (Blumstein and Cohen, 1979). Others employ relatively narrow -- two, three, or four-year windows of self-reported offense histories (Petersilia and Greenwood, 1977; Greenwood, 1982; Chaiken and Chaiken, 1982).

Even if narrow windows are used, they are long enough for many combinations of crimes to occur. Yet, by artificially truncating the careers by using windows, some diversity can be eliminated or offense consistency missed. Further, developmental patterns such as those suggested by social control or labeling theory are less likely to be observed. More problematic is a more extreme version of the windows -- that which defines offenders according to the most recent or instant offense (Miller et al., 1982). Obviously, in this case the career of the offender is largely ignored.

Career Stability. Both the imposition of selective hierarchy and the use of narrow study windows are often used in conjunction with a further assumption: stability in the type of criminal acts committed over a career. Relatively few studies have focussed on the dynamic aspects of criminal careers (e.g., Bursik, 1980; Wolfgang, et al., 1972; Smith and Smith, 1984). Within the typological approach, the tendency has been to assume that the offender repeats the same type of offense over the criminally active years (Godfrey and Schulman, 1972; Roebuck, 1963; Irwin, 1970; Gibbons, 1975). That is, time is effectively ignored.

There are numerous examples of criminal behavior typologies in the literature which employ the three assumptions discussed above to varying degrees. Some broadly classify offenders into categories such as status, misdemeanor, and felony (Erickson, 1979; Thomas, 1976) or victimless, property, and personal crimes (Cernkovich, 1978) or theft, nonindex, damage, assault, and a combination of index offenses (Wolfgang et al., 1972). Don

Gibbons proposed 15 adult types and 9 juvenile types (1968). Some of Gibbons's categories for juveniles include three types of gang delinquents (predatory, conflict, and casual), as well as casual delinquent, auto thief, drug user, etc.. Other typologies vary in content from theorist to theorist (Clinard and Quinney, 1967; Roebuck, 1963). In recent research conducted by the Rand Corporation, various typologies were employed. For example, the Chaikens (1982) arrived at ten varieties of criminal behavior: violent predators, robber-assaulters, robber-dealers, low-level robbers, mere assaulters, burglar-dealers, low-level burglars, property and drug offenders, low-level property offenders, and drug dealers.

The traditional typological approach has been useful. It has identified reasons for differentiating some criminal career patterns from others, helped us understand why individuals commit crime, and clarified how motivations differ from one type of crime to another. Unfortunately, the typological approach raises many questions about the possibility of unambiguous classification of high proportions of offenders -- a point acknowledged by Gibbons (1975). In the categorization used by the Chaikens, for example, robbers may or may not also commit burglary and theft; what they call "burglar-dealers" can commit assault (although most do not). Furthermore, the Chaikens point out certain exceptions: criminals who are involved with drugs do a broad range of crimes, robbers frequently steal autos but are not likely to commit forgery or credit card crimes. The extent to which such exceptions cause analytic or empirical problems in these analyses is unknown. We argue that the three assumptions above rule out the possibility of empirically considering the whole (i.e., all known arrests) criminal career in classifying offenders, despite the fact that the concept of a criminal career suggests such a consideration. Below we propose a method that attempts to classify the whole criminal career.

In summary, there are three problematic aspects to typological approaches: (1) criminal careers seem to be highly diverse, even for adult criminals (Hood and Sparks, 1966), leading to the imposition of a selective hierarchy on the offenses; (2) offense windows are frequently used to facilitate the classification of offenders -- particularly short windows where self-reported data are used (Chaiken and Chaiken, 1982; (3) most offender classifications ignore the <u>dynamic</u> or diachronic component of classification and focus on the <u>static</u>, e.g., behavioral classifications in which the offender's entire career is classified as a "burglar" or "robber" (Clements, 1981:23). Each of these assumptions may be avoided using the method proposed below -- the career-line approach -- which we believe will lead ultimately to more systematic offender classification.

The Career-Line Approach

As an alternative to the traditional typological approaches, consider plotting the temporally ordered crimes of an individual's career according to some underlying dimension of crime (e.g., seriousness, Sellin and Wolfgang, 1964). The entire career can then be viewed as a career-line, a sequence of points along the dimension of crime. The nature of the career-line can then be conveniently operationalized through the apparatus of bivariate regression. Further, individuals can then be classified according to the characteristics of their career-line (e.g., the slope, intercept and variance around the line). Note that conceptualizing a criminal career in this manner allows for the simultaneous consideration of all the offenses of the career <u>and</u> the dynamic aspects of the career.

Dimensions of crime have been utilized previously in the literature. One of the more widely-used dimensions of crime is that of offense seriousness

(Sellin and Wolfgang, 1964; Wolfgang et al., 1972; Rossi et al., 1974). Others include "violence" (Miller et al., 1982); and "juvenile delinquency" (Shannon, 1968; Nye and Short, 1957); seven clusters of delinquency (Hindelang and Weis, 1972); and Guttman scales of crime seriousness (Wanderer, 1984; Shannon, 1968).

While a number of studies have used these dimensions to scale criminal offenses, surprisingly few have developed classification schema of individuals based on the groupings of crimes in the scaling technique. The career-line approach offers such an opportunity. For purposes of illustration, consider Figure 1.1 where the crimes of a hypothetical career are plotted, in the order in which they occur, against the seriousness of each offense. In this simplified career, the grouping of crimes by the dimension of seriousness clearly organizes the criminal behavior of the offender. At the onset of the career, the seriousness of the offenses is low and increases with the number of offenses. The entire career can thus be summarized by the bivariate regression of the seriousness of the offenses on the position of the crime in the career (its temporal order): the regression line serves to operationalize the career-line. Once the characteristics of the career-line are known, the offender can be classified, in this case as one whose career "develops" into serious offenses.

Several aspects of the career-line approach are noteworthy. First, the determination of the line uses all of the offenses of the career. A selective hierarchy is not imposed, nor is the identification of the career-line limited through the use of an offense window. Second, the temporal nature of the career is built into the definition of the career-line. Stability of the career need not be assumed. Indeed, the dynamic form of the career is an integral component of the career-line. Third, the actual crimes observed are

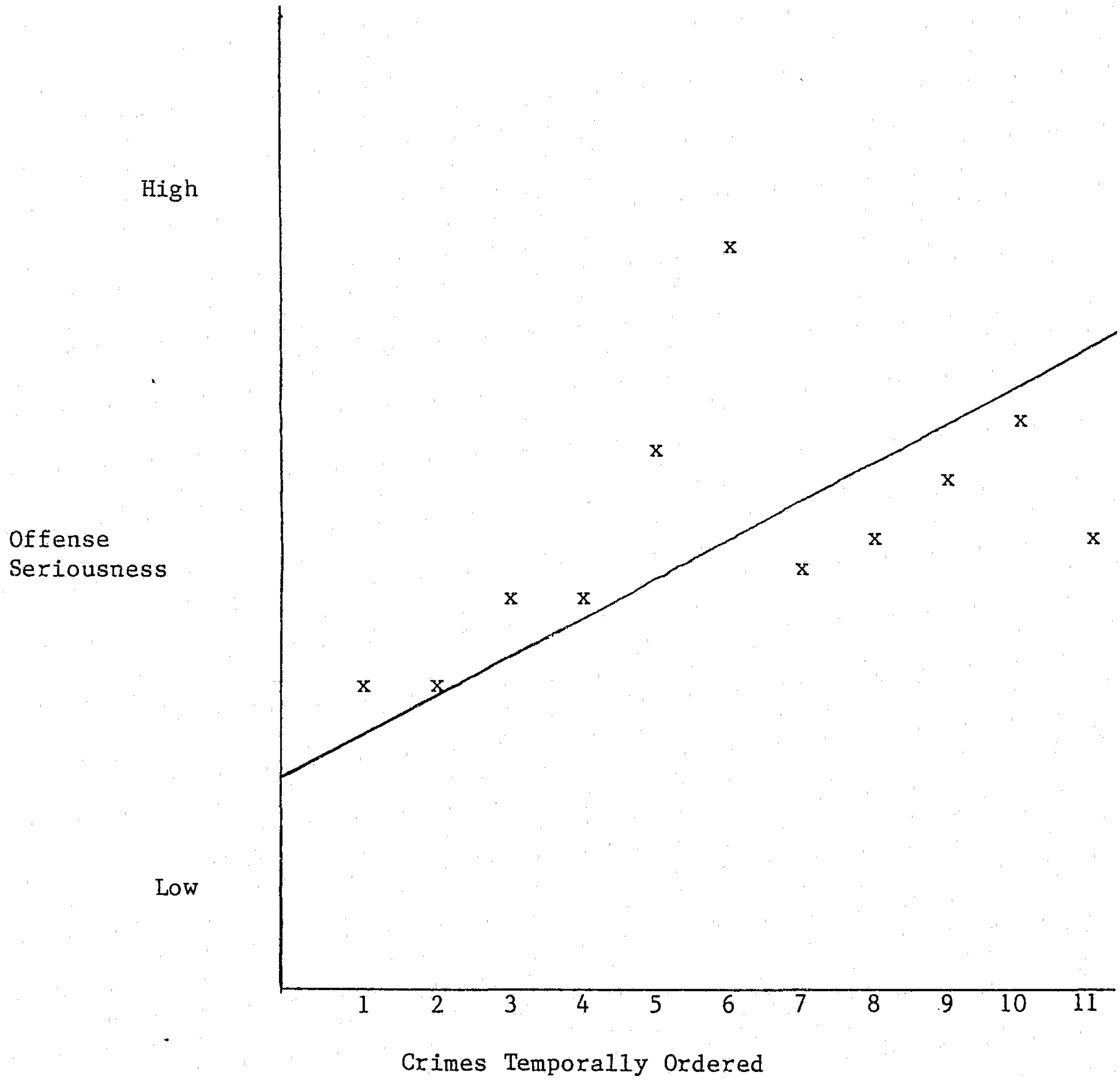


Figure 1.1: A Hypothetical Criminal Career Expressed As a Career-Line

treated as imperfect realizations of the offender's true career: the career-line operationalizes a latent form of the offender's career. Offenses that do not "fit" neatly into a classificatory scheme (e.g., the sixth crime of the hypothetical career in Figure 1.1) can then be seen as random deviations from the underlying true career-line. Consequently, some degree of diversity in career is to be expected in the form of crimes varying around the career-line organizing the career.

Finally, the reconceptualization of offense histories in terms of career-lines shifts the focus of offender classifications from the groupings of crimes to the grouping of career-lines. Instead of sorting offenders by the types of crimes they commit, offenders are to be sorted by the form and content of their individual career lines. The typology to be developed is one of career patterns, not one based per se upon finding certain kinds of crimes (e.g., robbery or burglary) in an offense history.

A necessary prerequisite for the study of career-lines is the identification of the dimensions that organize criminal careers. The dimension of offense seriousness, used in the hypothetical example, is not necessarily appropriate as offenders do not empirically show marked tendencies toward increasingly serious crimes (Wolfgang, et al., 1972). The literature on the scaling of crimes provides an alternative. We contend that in part the results from the scaling techniques have often resulted in too many factors or groupings of crimes to be useful in theoretical or practical applications (see Klein, 1984). In Appendix A we review some of the implications resulting from using factor analysis and multidimensional scaling techniques. We conclude that these techniques have proved inadequate because the properties of criminal histories are at variance with the strong assumptions made by these data-reduction techniques -- particularly the assumption that the data are complete. We propose to use an alternative method, called Variance Centroid Scaling (VCS), which we argue is better suited to the kind of data arrest records represent -- one characterized by a high degree of missing data. Data is missing both in that offenses are committed that go undetected by the criminal justice system and, even if an arrest is made, the information may be missing from the official records due to clerical errors, arrests cleared before a court hearing, etc. Readers interested in a more technical discussion as well as in a additional theoretical justification for the choice of VCS should see Appendix A.

In general our analysis consists of two parts: determining the dimensions of crime and, given these dimensions, classifying the career-lines of specific individuals. First, we propose that a more appropriate data reduction technique than those commonly used (e.g., factor analysis or multidimensional scaling) be employed to arrive at dimensions of crime. Second, rather than use the dimensions of crime to group crimes in a typology, we propose to characterize an individual's offense career as a sequence of crimes along these dimensions and then to classify the individuals' histories in accordance with their "fit" to the underlying dimensions of crime. Before turning to that, it is necessary to describe the sample we will utilize in our analyses.

Chapter Two: The Sample

The Data Base

The data base that we use in the analysis below consists of all juveniles incarcerated in the state of New Jersey between April, 1977 and December, 1978, plus inmates who were currently in these facilities at the time of a cross-sectional interview in 1978. The original data base is from previous studies (Smith et al., 1982).

The nature of the data base is somewhat complex and is diagrammed in Figure 2.1. The top line of the figure represents the left and right censoring dates of the arrest records for the sample studied. The earliest arrest for any of the juveniles was September, 1962 and the last arrest was August, 1984. It must be kept in mind that the offenders in the sample are of varying ages, such that relatively few offenders have arrest records extending back in time to 1962. Data on the arrest histories are available for 1047 individuals. Data for the arrests of the juvenile years are taken from the Family Courts of each county of the state of New Jersey. Adult arrest records are taken from the state police arrest "rap" sheets — the SAC date base (New Jersey State Prison Systems and Communication File.) Data from the juvenile courts were collected by our staff from the file folders or cards available at each court. The SAC arrest records were provided by the New Jersey State Police in printout form, from which the arrest records were coded.

The definition of the sample is somewhat complicated by the fact that a previous study served as a basis for the current study. Originally, data were collected to evaluate the effects of various juvenile correctional

Figure 2.1 -- Time Frame for Data Collection

Time 9/62 / / 8/84 >

Intake Interview 4/77 12/78 (N=796)

Cross-Section Interview 3/78 12/78 (N=658)

Exit Interview 3/78 9/79 (N=451)

Wave 3 Followup 11/78 4/80 (N=371)

Wave 4 Followup 12/83 8/84 (N=148)

Arrest Histories 9/62 / / 8/84 (N=1047)

institutions on the offenders placed there. Interviews of 796 juvenile were conducted in their first week at the institution. (See the second line from the top of Figure 2.1.) The interviews began in April, 1977 and ended in December, 1978. Questions concerning the juveniles past involvements in crime and arrests, as well as questions concerning his/her attitude toward the institution, staff, him/herself, etc. were asked during this "intake" interview.

Subsequent to the intake interview, a second interview was conducted in an attempt to get at characteristics of the correctional "unit" in which the juvenile was placed. A "unit" could consist of a dormitory floor or a wing of a prison-like facility, or a "cottage," (a separate, relatively small building), or what is known as a "fields" unit -- a unit of usually less than 30 youths often in a home-like setting, usually removed from traditional institutional grounds. When the second interview was conducted, an attempt was made to interview everyone in the unit, regardless of how long they had been there. Thus, 658 offenders were interviewed in what we call the "cross-section" interview -- not all of them were juveniles since some of the units had some young adults on them as well as juveniles. Note also that not all of the juveniles who were interviewed originally in the intake interview area were in the cross-section interview -- often they had left the units before the cross-section interview was conducted. Together, the intake and cross-section interviews constitute the individuals who make-up the 1047 individuals of the current analysis.

Although in the analysis below we do not make use of any additional waves of data that were collected (but see Appendix B), it should be noted that three more interviews of some subjects were carried out over several years following the initial interviews. An exit interview was conducted with each of the offenders who had a successfully completed an intake interview. Due to the complex movement of juveniles within the correctional system, not all juveniles could be interviewed at exit; only 451 exit interviews were completed. The last exit interview was conducted in September, 1979. Approximately a year later, a telephone follow-up interview was conducted with those juveniles who had completed an intake and exit interview and who could be located (N=371). Similarly, about three years later, beginning in December, 1983 and ending in August, 1984, a fourth panel of offenders was interviewed (Again see Figure 2.1.) Again, we tried to interview all those we could find who had been successfully interviewed on the previous three occasions.

Around the time of the fourth wave, the decision was made to get the complete juvenile and adult arrest records for the entire sample, whether or not they were interviewed successfully. Thus, there are arrest records for the entire juvenile careers and the adult arrest histories up to August 1984 for all 1047 individuals. The availability of career data is not related to the presence or absence of information in one of the waves of data collection. However, much of what is known about the characteristics and opinions of these offenders is constrained by the wave in which data were collected.

Results from those interviewed at the intake wave or the cross-section wave allow for a characterization of the composite sample. Individuals in the sample began their criminal careers at an early age -- on the average age 13 (Table 2.1). The average age at first interview, or of inclusion into the sample, was 16.9. The average number of prior arrests was 6.9 and the average number of months of incarceration prior to the first interview was 5.9. The incarceration that brought them into the sample did not stop their "misbehaving" in that the average number of disciplinary infraction in the facilities was 5.1.

More offenders are black than any other racial or ethnic group (Table 2.2). Whereas 45.7% of the sample is black, only 39.1% is white, and 11.6% Hispanic. Over 31% are Catholic, 28% Protestant, and 15% Muslim (Table 2.3). The educational achievement level of the sample as a whole was rather low for the age group. Although the average age at first interview was 16.9, only about a third of the sample had reached the 10th grade (See Table 2.4). About another third was at the 8th grade level or below. Information on parents educational level was often missing (in 29.5% of the cases it was missing for the mother and 40.7% for the father), but where it was available, just over half of the parents had graduated from high school (Table 2.5).

The youth were generally optimistic when interviewed about their prospects for staying out of prison in the future -- only about 2% thought that the chances of reincarceration were "good" to "definite" (Table 2.6). Even fewer thought that they had "no chance" or only "some" chance of "going straight" upon release. Prior to the incarceration that placed them in our sample, only 21.9% said they did not make any money from crime -- perhaps indicative of the extent to which they were involved in criminal activities at that time.

Overall these individuals have the general characteristics one might have expected of a sample of incarcerated juveniles. Onset of criminal behavior was at an early age and sufficient trouble with the law had accumulated to warrant institutional custody. Minorities constitute a high proportion of the sample and the evidence on offender education and parental background are suggestive of disadvantaged youth. The limited information supplied by the attitudinal measures and the disciplinary problems during incarceration point to a group of chronic delinquents, but not hard-core criminals.

Table 2.1 -- Descriptive Statistics for Criminal Activity of the Sample up to First Interview

Variable	Mean	Std. Dev.	Minimum	Maximum	N
Age at First Arrest	13.13	2.42	6	21	915
Age at Interview	16.86	1.56	12	26	929
Arrests Prior to Interview	6.92	5.16	0	47	924
Months Served Prior Incarcerations	5.89	10.84	0	82	942
Disciplinary Infractions during 1977 Incarceration	5.11	11.02	0	108	776

Table 2.2 -- Race of the Sample

Race	Frequency	Percent
Black	478	45.7%
White	409	39.1%
Hispanic	121	11.6%
Other	4	.4%
Missing	35	3.3%
Total	1047	100.1%

Table 2.3 -- Religion of the Sample

Race	Frequency	Percent
None	183	17.5%
Catholic	332	31.7%
Protestant	297	28.4%
Muslim	165	15.8%
Jewish	6	.6%
Other	27	2.6%
Missing	37	3.5%
Total	1047	100.1%

Table 2.4 -- Educational Attainment of Sample at Time of First Interview

Highest Grade Completed	Frequency	Percent
Third	5	.5%
Fourth	3	.3%
Fifth	8	.8%
Sixth	29	2.8%
Seventh	79	7.5%
Eighth	205	19.6%
Ninth	270	25.8%
Tenth	225	21.5%
Eleventh	88	8.4%
Twelfth	34	3.2%
Missing	101	9.6%
Total	1047	100.0%

Table 2.5 -- Parental Education for the Sample (N in Parentheses)

Highest Grade Completed	Father		Mother	
None	.4%	(4)	.5%	(5)
First	.0%	(-)	.1%	(1)
Second	.1%	(1)	.2%	(2)
Third	.5%	(5)	.3%	(3)
Fourth	.6%	(6)	.8%	(8)
Fifth	.7%	(7)	.5%	(5)
Sixth	1.5%	(16)	1.2%	(13)
Seventh	1.5%	(16)	.9%	(9)
Eighth	4.5%	(47)	3.7%	(39)
Ninth	3.7%	(39)	4.8%	(50)
Tenth	5.2%	(54)	6.6%	(69)
Eleventh	4.9%	(51)	8.4%	(88)
Twelfth	29.9%	(313)	34.8%	(364)
College	5.3%	(55)	7.1%	(74)
Graduate/ Professional	.7%	(7)	.8%	(8)
Missing	40.7%	(426)	29.5%	(309)
Total	100.0%	(1047)	100.0%	(1047)

Table 2.6 -- Other Characteristics of the Sample

2.6.a

Perceived Chance of Future Incarceration

Chance	No Chance	Some	50-50	Good	Definite	Missing
Frequency	706	120	93	19	8	101
Percentage	67.4%	11.5%	8.9%	1.8%	.8%	9.6%

2.6.b

Perceived Chance of Being Straight Upon Release

Chance	No Chance	Some	50-50	Good	Definite	Missing
Frequency	4	2	52	193	197	599
Percentage	.4%	.2%	5.0%	18.4%	18.8%	57.2%

2.6.c

Money From Crime Before Incarceration

Amount	None	Some	Half	Most	All	Missing
Frequency	229	369	140	148	60	101
Percent	21.9%	35.2%	13.4%	14.1%	5.7%	9.6%

The Offenses

One of the essential features of this sample of delinquents is the extent of their criminal activity. Table 2.7 summarizes the arrests of the offenders as juveniles (all their arrests for delinquent acts) and as adults. Here the percentages are presented as percent of all the offenses in the sample. Thus, we find that there were 24,134 crimes resulting in arrest for the 1047 individuals in the sample, for an average of 23.09. Although most of these crimes occurred during the juvenile years (an average of 15.69), the offenders averaged 7.41 offenses as adults by August, 1984, when their average age was about 23. At the first interview, the average number of offenses was 6.92. (Those researchers interested in incapacitation may note that roughly 17,000 offenses (minimally) would have been prevented by an incapacitative stay of approximately seven years (from 1977 to 1984) for the 1047 individuals in the sample.)

Property crimes dominate the arrest histories. Together the 1047 individuals in the sample accounted for 2280 breaking and entering and 1853 "breaking and entry with larceny" offenses. Larcency alone accounted for 14.2 percent of all the offenses (3,429 offenses). Robbery accounted for 1,224, and assault and battery 1,355 of the offenses. As for even more serious persons offenses, there were 54 homicides and 563 attrocious assaults among the 24,134 offenses.

In short, the sample represents an approriate one for the study of criminal careers. It excludes, for the most part, individuals who have short criminal careers or careers consisting mainly of trivial offenses. This is in part because the sample is defined as juveniles who were incarcerated, and usually juvenile incarceration is symptomatic of having committed serious offenses or of having severe dispositional or attitudinal problems

Table 2.7 -- Distribution of Offenses in the Sample

	Total Career		Arrests as a Junvenile		Arrests as an Adult	
	N	%	N	%	N	%
NONINDEX CRIMES						
Selling Narcotics	17	.1	6	.0	11	.1
Selling Synthetic Drugs	6	.0	5	.0	1	.0
Selling Marijuana	18	.1	10	.1	8	.1
Possession of Narcotics	125	.5	15	.1	110	1.4
Possession of Synthetics Drugs	32	.1	13	.1	19	.2
Possession of Marijuana	647	2.7	244	1.5	403	5.2
Glue Sniffing	50	.2	49	.3	1	.0
Possession of Alcohol	105	.4	98	.6	7	.1
Possession of Drug Paraphanalia	93	.4	19	.1	74	1.0
Under Influence of Drugs	42	.2	21	.1	21	.3
Malicious Mischief	171	.7	161	.1	10	.1
Prostitution	7	.0	6	.0	1	.0
Fornication	42	.2	36	.2	6	.1
Drunk or Drinking	18	.1	16	.1	2	.0
Drunk and Disorderly	42	.2	40	.2	2	.0
Driving without a License	296	1.2	281	1.7	15	.2
Conspiracy	57	.2	40	.2	17	.2
Contempt of Court	30	.1	7	.0	23	.3
Escape	392	1.6	320	2.0	72	.9
False Information to Police	143	.6	69	.4	74	1.0
Disorderly Person	756	3.1	551	3.4	205	2.6
Loitering	128	.5	123	.8	5	.1
Violation of Parole	92	.4	39	.2	53	.7
Violation of Probation	789	3.3	691	4.2	98	1.3
Juvenile Delinquency	2	.0	2	.0	-	-
Incorrigible	483	2.0	483	2.9	-	-
Runaway	366	1.5	363	2.2	3	.0
Truancy	272	1.1	272	1.7	-	-
Trespassing	489	2.0	426	2.6	63	.8
Eluding Police	114	.5	94	.6	20	.3
Impairing the Morals of a Minor	27	.1	21	.1	6	.1
Contributing to the Delinquency of Minor	29	.1	2	.0	27	.3

Table 2.7 -- Distribution of Offenses in the Sample
(Continued)

	Total Career		Arrests as a Junvenile		Arrests as an Adult	
	N	%	N	%	N	%
NONINDEX CRIMES (Continued)						
Possession of Drugs to Distribute	147	.6	29	.2	118	1.5
Possession of Dangerous Drugs	309	1.3	149	.9	160	2.1
Juvenile in Need of Supervision	7	.0	7	.0	-	-
Impersonating a Policeman	3	.0	2	.0	1	.0
Hitchhiking	3	.0	3	.0	-	-
Failure to Pay Fine	1	.0	-	-	1	.0
Failure to Appear in Court	36	.1	-	-	36	.5
Smuggling	4	.0	-	-	4	.1
Nonsupport	1	.0	-	-	1	.0
Gambling	5	.0	3	.0	2	.0
Bribery	2	.0	1	.0	1	.0
Family Offense	1	.0	-	-	1	.0
Immoral Conduct	28	.1	28	.2	-	-
Attempted Suicide	2	.0	2	.0	-	-
PROPERTY CRIMES						
Arson	111	.5	98	.6	13	.2
Attempted Arson	9	.0	6	.0	3	.0
Setting Explosives	11	.0	11	.1	-	-
Breaking and Entering	2280	9.4	1124	6.9	1156	14.9
Attempted Breaking and Entering	273	1.1	181	1.1	92	1.2
Breaking, Entering and Larceny	1853	7.7	1755	10.7	98	1.3
Attempted Breaking Entering, Larceny	366	1.5	342	2.1	24	.3
Larceny	3429	14.2	2162	13.2	1267	16.4
Attempted Larceny	188	.8	147	.9	41	.5
Extortion	21	.1	13	.1	8	.1
Forgery	125	.5	48	.3	77	1.0
Auto Theft	1100	4.6	829	5.1	271	3.5
Possession of Motor Vehicle	235	1.0	184	1.1	51	.7
Attempted Auto Theft	46	.2	34	.2	12	.2

Table 2.7 -- Distribution of Offenses in the Sample (Continued)

	Total Career		Arrests as a Junvenile		Arrests as an Adult	
	N	%	N	%	N	%
PROPERTY CRIMES (Continued)						
Fraud/Illegal Use of Credit Card	147	.6	22	.1	125	1.6
Attempted Fraud	13	.1	4	.0	9	.1
Embezzlement	2	.0	2	.0	-	-
Possession of Stolen Property	1295	5.4	775	4.7	520	6.7
Possession of Burglary Tools	296	1.2	130	.8	166	2.1
Other Property Offenses	1	.0	-	-	1	.0
DAMAGE CRIMES						
Malicious Damage	781	3.2	609	3.7	172	2.2
Vandlism	39	.2	38	.2	1	.0
Other Damage	1	.0	1	.0	-	-
ROBBERY						
Armed Robbery	296	1.2	133	.8	163	2.1
Attempted Armed Robbery	23	.1	19	.1	4	.1
Robbery	788	3.3	407	2.5	381	4.9
Attempted Robbery	117	.5	90	.5	27	.3
INJURY CRIMES						
Threaten to Kill	86	.4	74	.5	12	.2
Kidnapping	34	.1	10	.1	24	.3
Rape	72	.3	32	.2	40	.5
Attempted Rape	24	.1	19	.1	5	.1
Forcible Sex	65	.3	33	.2	32	.4
Attempted Forcible Sex	10	.0	9	.1	1	.0
Unlawful Imprison-ment	1	.0	-	-	1	.0
Assault with a Weapon	101	.4	92	.6	9	.1
Attrocious Assault	563	2.3	238	1.5	325	4.2
Assault and Battery	1355	5.6	1117	6.8	238	3.1
Threaten with Weapon	28	.1	25	.2	3	.0

Table 2.7 -- Distribution of Offenses in the Sample (Continued)

	Total Career		Arrests as a Junvenile		Arrests as an Adult	
	N	%	N	%	N	%
INJURY CRIMES (Continued)						
Threaten without Weapon	181	.7	106	.6	75	1.0
Weapons Possession	751	3.1	370	2.3	381	4.9
Resisting Arrest	250	1.0	89	.5	161	2.1
Intent to use Weapon	4	.0	2	.0	2	.0
Homicide	54	.2	24	.1	30	.4
Attempted Homicide	11	.0	4	.0	7	.1
Manslaughter	10	.0	9	.1	1	.0
MISSING OFFENSES						
Unknown number or kinds of offenses	70	.3	53	.3	17	.2
Out-of-State record unavailable	189	.8	176	1.1	13	.2
TOTAL	24134	100.0	16393	100.0	7741	100.0
Average Arrests Per Individual	23.09		15.69		7.41	

(incorrigible) as a youth. Thus, in that distinctive patterns of criminal careers are found, it is more likely to involve offenses that are considered serious by the public — robbery, burglary, drugs, and assault. Thus, the current sample can be distinguished from studies of birth cohorts (Wolfgang et al., 1972; Shannon, 1981) in which all offenders are often the object of interest relative to issues in criminal careers, or a subsample defined solely by chronicity of arrests (e.g., 6 or more). In a sense, the current sample may be preferable to others in that the offender's "badness" had to be judged by criminal justice authorities on an individual basis. Cohort studies have tended to rely on an arbitrary number of arrests.

Another useful feature of the current sample is that it captures the offenders during their most criminally active years -- juvenile and young adult years (Blumstein, et al., 1986:23). This may have important consequences for the study of the transition from juvenile to young adult criminality in that this is one of the few data sets we know of that has both juvenile and adult arrest histories available for the same individuals (see Cohen, 1986). It may be possible to show, for example, that certain patterns of juvenile arrest histories are predictive of adult criminal behavior and serve possibly as a useful tool in the early identification of juvenile offenders who are likely to become adult robbers, burglars, auto thieves, and so on.

In the previous chapter we argued that the appropriate concern of classification is the entire criminal career, from onset to termination. However, the present sample offers the unique opportunity to compare juvenile delinquency to adult criminality. We therefore differentiate between the juvenile career, defined as onset to last arrest before age 18 and the adult career, defined as all arrests after turning age 18. We focus on the _juvenile_ years for the classification component of our analysis and thus derive classifications of the juvenile career-lines. The results of this classification may then be compared to adult arrests.

In addition to restricting the classification scheme to be developed to juvenile career-lines only, two other important data management decisions were made. First, only the arrest histories of males will be analysed. Of the 1047 individuals in the sample, only 42 (3.9%) are female offenders. This percentage of female juveniles was thought to be too low to justify separate analyses by sex, and, to the extent to which the criminal careers of female delinquents differs from males, it is unwise to combine these careers in the same analysis. Therefore, the scaling and classification results are based on the careers of 1005 male offenders.

Second, some coding decisions had to be made in the treatment of the crimes in the juvenile careers of these 1005 offenders. These careers vary considerably in both length and content. The number of arrests in the juvenile career ranges from 3 to 125. The length of the career is not problematic, however, as the scaling technique treats each career as a unit (see Appendix A). The variability of types of crimes within and between careers (their content) is considerable. It is this variability that necessitated special attention.

As can be seen in Table 2.7, the coding of the offense within these juvenile arrest histories used 84 different types of crimes. Many occurred infrequently across arrest histories. For example, of the 16,393 arrests as juveniles, only one was for bribery, nine were for homicide, two were for juvenile delinquency and so forth. In the identification of the dimensions underlying delinquent careers (Chapter 3), infrequent crimes are troublesome in that they contribute little to the derivation of the dimensions. The

Table 2.8

Offense Groups Used in the Analysis

	Label	Description
1	SMARIJ	Selling marijuana
2	PNARC	Possession of narcotics
3	PMARIJ	Possession of marijuana
4	GLUE	Glue Sniffing
5	PALCH	Possession of alcohol
6	PPARA	Possession of drug paraphanalia
7	UNDINF	Under the influence of drugs
8	MALMIS	Malicious mischief, including impersonating an officer
9	IMMORAL	Immoral conduct, including prostitution
10	FORN	Fornication
11	DWI	Driving while intoxicated
12	D&D	Drunk and disorderly
13	DWOL	Driving without a license
14	CONSPIR	Conspiracy
15	DISORD	Disorderly, including contempt of court, gambling and attempted suicide
16	ESCAPE	Escape
17	FALSINF	Poviding false information to police
18	LOITER	Loitering, including hitchhiking
19	VOPAR	Violation of parole
20	VOPROB	Violation of probation
21	INCORR	Incorrigible, including juvenile delinquency and juvenile in need of supervision
22	RUNAWAY	Runaway
23	TRUANT	Truancy
24	TRESPASS	Trespassing
25	ELUDE	Eluding police
26	IMPAIR	Impairing the moras of a minor, including contributing to the delinquency of a minor
27	PDRUGS	Possession of synthetic drugs
28	FRAUD	Fraud, including attempted fraud, embezzlement and bribery
29	SETEXP	Setting exposives
30	B&E	Breaking and entering
31	ATTB&E	Attempted breaking and entering
32	BE&L	Breaking, entering and larceny
33	ATTBE&L	Attempted breaking, entering and larceny
34	LARC	Larceny
35	ATTLARC	Attempted larceny
36	EXTORT	Extortion
37	FORGE	Forgery
38	CARTHFT	Auto theft
39	POSSMV	Possession of a stolen motor vehicle
40	ATTCAR	Attempted auto theft
41	PPROP	Possession of stolen property
42	PBURG	Possession of burglary tools

Table 2.8
(continued)

Offense Groups Used in the Analysis

	Label	Description
43	MALDAM	Malicious damage
44	VANDAL	Vandalism, including other damage
45	ARMROB	Armed robbery
46	ATTARM	Attempted armed robbery
47	ROB	Robbery
48	ATTROB	Attempted robbery
49	TKILL	Threaten to kill, including kidnapping
50	RAPE	Rape
51	ATTRAPE	Attempted Rape
52	FORSEX	Forcible sex, including attempted forcible sex
53	ASSWEAP	Assault with a weapon
54	ATTROC	Attrocious assault
55	A&B	Assault and battery
56	TWEAP	Threaten with a weapon
57	ATTASS	Attempted assault, including threaten without weapon
58	PWEAP	Weapons possession, including intent to use weapon
59	RESIST	Resisting arrest

Variance Centroid Scaling algorithm used in the present research is particularly sensitive to infrequent offenses (Smith et al., 1984; Appendix A). In order to avoid results that were highly dependent upon the existence of relatively rare crimes, the original 84 offense types were further collapsed into comparable, more inclusive groupings.

When deciding to group crimes, we were guided by the similarity between criminal acts. For example, murder, homicide, and attempted murder were placed together as they are all representative of serious violent crimes against the person. Similarly, kidnapping and unlawful imprisonment were combined. In general, we attempted to yield sufficient numbers of occurrences within groupings of offenses and this was often achieved by blurring the distinction between an attempted crime and its actual completion. For instance, attempted fraud and fraud were grouped as simply "fraud." The original 84 distinct crime types were thus reduced to 62 offense groups for the initial analysis.

The preliminary results using these 62 crime groups identified a further variant of problems due to infrequent crimes. Three categories of offenses differentiated themselves from the other 59 by becoming, in essence, their own "dimension" or unique cluster of criminal behavior. The three groups, arson (including attempted arson), murder (including attempted murder and homicide), and other drug crimes (a residual category of drug offenses not grouped elsewhere), are important in their own right. However, as these three groups are empirically distinct clusters, they are less useful in determining the general dimensions of crime that may organize career-lines. Consequently, the three offense groups were deleted from the analysis. Note that it is the offenses that were removed and not the individuals who committed them. The arrest histories containing arson, murder, or other drug crimes were retained and used in the full analysis. This was achieved through setting any arrests for arson, etc., to missing and analyzing the remaining career as if no arrest for the crimes deleted had occurred.

The final analysis is thus based on collapsing the crimes in the juvenile arrest histories into 59 distinct groups of offenses. These groups, as well as a pneumonic used in the presentation of the scaling results of the next chapter, are given in Table 2.8. The definition of the 59 groups, when combined with those deleted from consideration, allow for a mapping of the original 84 categories of Table 2.7 into those of Table 2.8.

In summary, the derivation of the dimensions of crime to be used in the classification of career lines is to be based on the juvenile arrests histories of a sample of 1005 male, chronic delinquents. The crimes of the arrest histories differentiate between 59 distinct groups of offenses. After the dimensions of crime have been identified, the 1005 offenders will be classified into "types" and the resulting classification scheme compared to the arrests found in the adult arrest histories of these offenders.

Chapter Three: Variance Centroid Scaling Results

Choice of a Scaling Technique

To demonstrate how a classification system that is based on the career-line metaphor may be implemented it is first necessary to determine meaningful dimensions of crime. In general we proceed in accordance with the *a posteriori* approach and allow the co-occurrence of crimes to help define what crimes are similar. It has been argued elsewhere that choice of a scaling technique may be important in this endeavor (Smith et al., 1984, and Appendix A). Official arrest records, as well as self-reported crimes, represent a special form of data -- "pick-any" data -- where an individual's choice to commit an offense is made from a subject-specific set of alternatives. For example, if an individual is asked to select a beverage or person he or she likes, or an organization he or she to join, he or she may not consider all the possible alternatives before making a choice. Since the alternatives considered by each person will vary from individual to individual, the researcher cannot tell if a nonchosen object was rejected (considered but not chosen) or simply not considered.

Crime data are analogous to "pick-any" data in several respects. When an individual commits an illegal act, it represents a choice from among all possible illegal acts. Of course, we do not know which other possible acts were considered at the time. For example, when a person commits a robbery, we do not know if the decision was made not to use a weapon (i.e., armed robbery was rejected) any more than we know if the person considered breaking and entering instead. Therefore, a robbery expresses a form of "preference" and tells us nothing about the rejection of other possible alternatives. Indeed, situational or opportunity theories of crime (e.g., Briar and Piliavin, 1965) argue strongly that few alternative offenses are considered at the time of the crime. This, coupled with the fact that the careers of criminals display considerable diversity (demonstrating an ability to "choose" many possible acts), suggests that the appearance of a charge on an official record or the admission of an illegal act says nothing about the rejection of other possible offenses. In summary, those acts committed should be analysed; those acts not, ignored.

The analogy between crime and "pick-any" data can be extended to official record data. Those offenses that result in contact with the authorities represent a subset of crimes that are "picked" from among all illegal behaviors. Thus, while the appearance of a crime on an official record may be taken as an indication that the act was committed, the absence of a charge on a record cannot be used as an indication that the individual did not engage in the behavior. The statistical implication of the pick-any assumption is that zeroes on an arrest record (no arrests for a particular type or class of crimes) should be ignored rather than assumed to signify that an offense did not occur. Because of these considerations, we chose a "pick-any" scaling method, variance centroid scaling or VCS (Levine, 1979; Noma, 1982; Smith and Noma, 1985), to arrive at dimensions of crime in the analysis discussed below. (See Appendix A for a more detailed discussion of the reasons for choosing VCS.)

Results of VCS

As with most multidimensional analytic procedures, VCS yields as many dimensions as there are items being scaled. By definition, the first dimension places all items (crimes) at the same point and thus is substantively uninteresting. We shall thus refer to the first nontrivial dimension as dimension "one." The remaining dimensions must be interpreted in much the same fashion as the results of an exploratory factor analysis. Decisions must be made as to how many factors are retained and those retained must be interpreted.

One guide in the retention of VCS dimensions is the eigenvalue associated with each dimension. The eigenvalues associated with dimensions one through nine are .251, .222, .199, .193, .177, .167, .156, .149, and .146 respectively. An eigenvalue at or near the maximum of 1.00 is indicative of separation of crimes into disjoint clusters. Were this the case, some careers would have crimes that were not contained in any other careers, and thus those offenses would cluster together as distinct subsets on a dimension with a corresponding eigenvalue near 1.00. It is clear from the distribution of eigenvalues that this is not the case, and thus specialization in the narrow sense is not to be found in this sample of juvenile delinquents. The point bears repeating. The eigenstructure of the VCS dimensions indicates that strict specialization in these careers is not to be found. (The lack of specialization in the narrow sense does not, however, preclude the existance of specialization in the broad sense. The extent to which these dimensions allow for the identification of more broadly defined specialization is the empirical question that is addressed in the next chapter.)

The gradual tapering off in the distribution of eigenvalues is not particularly instructive for deciding which dimensions should be retained for the subsequent analysis. No large drops are seen between adjacent eigenvalues (the equivalent of the scree test used in factor analysis). Furthermore, the separation of crimes produced by these nine dimensions is statistically significant according to the appropriate chi-square test

(Nishisato, 1980). (Indeed, the eigenvalues associated with dimensions one through forty eight are statistically significant.) As a consequence, purely statistical criteria are not helpful in determining which dimensions to retain.

Using the criterion of substantive interpretability, choosing which of the dimensions to retain is easier. Dimensions 1 through 4 of the variance centroid scaling results yield highly interpretable dimensions of crime. The scale values for each of the four dimensions are presented in Table 3.1. The actual scale values have been multiplied by 10,000 for presentational purposes. These values represent ordinal spacings of crimes as determined by their co-occurrence within the same criminal histories. As the difference in scale values increases, crimes may be said to be more "distant" from one another and thus less likely to be found together in a delinquent career. Thus "armed robbery" is distant from "runaway" on dimension two, suggesting that careers containing the crime of armed robbery are less likely to include arrests for running away. Taken together, the four dimensions of crime may be thought of as the "latent structure" of crime. (Readers interested in a more technical discussion of the interpretation of the scale values, should see Appendix A.)

The reader may gain a better intuitive understanding of the VCS crime dimensions by contrasting them with a "seriousness" dimension of crime. Crimes may be ranked on a seriousness scale and given a scale value representing the degree to which the crime is a serious violation of societal norms. Seriousness thus identifies sets of offenses as being more or less alike. Instead of "seriousness" constituting the ranking of crimes, VCS uses the co-occurrence of the crimes themselves to produce a latent structure of crime. The underlying structure is determined not by the magnitude of

TABLE 3.1
VARIANCE CENTROID SCALING RESULTS:
SCALE VALUES (X10,000) FOR FIRST FOUR DIMENSIONS

Dimension One		Dimension Two		Dimension Three		Dimension Four	
-205	ATTRAPE	-132	ATTRAPE	-206	SMARIJ	-137	FORSEX
-161	ARMROB	-94	ARMROB	-157	FORSEX	-99	GLUE
-161	FORSEX	-78	ROB	-130	RUNAWAY	-62	VANDAL
-151	ATTARM	-77	PWEAP	-93	PNARC	-45	LARC
-127	ASSWEAP	-72	BE&L	-77	UNDINF	-42	ATTLARC
-124	RAPE	-67	ATTROC	-75	D&D	-41	FALSINF
-115	ATTROC	-60	RAPE	-66	INCORR	-40	B&E
-114	ROB	-56	TWEAP	-64	FORN	-37	FORN
-112	ATTROB	-55	ATTROB	-57	FRAUD	-35	PBURG
-102	PWEAP	-55	VANDAL	-57	BE&L	-32	MALMIS
-100	TWEAP	-55	ATTB&E	-57	DWI	-31	ATTB&E
-92	TKILL	-44	B&E	-52	IMPAIR	-30	INCORR
-75	A&B	-39	ASSWEAP	-50	PALCH	-22	IMMORAL
-68	ATTASS	-28	ATTLARC	-50	IMMORAL	-19	ROB
-63	EXTORT	-27	ATTARM	-39	PDRUGS	-19	ATTBE&L
-61	D&D	-26	ATTBE&L	-38	LOITER	-18	A&B
-48	IMMORAL	-25	CONSPIR	-38	PMARIJ	-15	ESCAPE
-47	IMPAIR	-22	TKILL	-31	RESIST	-14	VOPROB
-35	INCORR	-16	LARC	-30	VOPROB	-12	TRESPASS
-26	DISORD	-10	PPROP	-23	DISORD	-10	DISORD
-26	RUNAWAY	-7	MALDAM	-23	ATTBE&L	-10	ATTROB
-25	FORN	-7	UNDINF	-22	TRUANT	-7	RUNAWAY
-23	CONSPIR	-2	EXTORT	-20	TWEAP	-7	ATTASS
-18	ATTLARC	-1	TRESPASS	-19	MALMIS	-6	PPROP
-15	RESIST	2	VOPAR	-16	MALDAM	-2	TRUANT
-11	TRESPASS	4	SETEXP	-15	VANDAL	-1	CARTHFT
-8	VOPROB	5	FORSEX	-13	A&B	2	ATTCAR
-5	LOITER	5	PBURG	-6	TRESPASS	3	IMPAIR
-3	SMARIJ	10	IMPAIR	-4	B&E	4	MALDAM
1	MALMIS	11	ATTASS	1	LARC	5	RAPE
2	TRUANT	12	A&B	8	ATTASS	10	VOPAR
2	LARC	12	ATTCAR	8	ATTB&E	14	POSSMV
3	PMARIJ	15	MALMIS	12	ESCAPE	17	EXTORT
4	ESCAPE	17	PDRUGS	12	PPARA	17	PDRUGS
8	PNARC	17	RESIST	19	VOPAR	19	LOITER
8	PDRUGS	23	PMARIJ	20	CONSPIR	19	RESIST
11	FALSINF	26	PPARA	23	ATTARM	21	TKILL
13	FRAUD	27	IMMORAL	29	ATTLARC	31	ATTARM
13	PALCH	29	DISORD	29	TKILL	32	BE&L
17	GLUE	34	LOITER	30	ATTROC	34	ATTRAPE
18	DWI	35	PNARC	31	FORGE	36	ATTROC
20	MALDAM	36	TRUANT	31	ATTROB	50	ELUDE
21	PPROP	45	PALCH	32	PPROP	51	UNDINF
28	VANDAL	52	GLUE	41	SETEXP	53	DWI
28	VOPAR	55	FALSINF	45	ASSWEAP	55	PALCH
35	ATTCAR	60	VOPROB	46	EXTORT	60	FRAUD
38	UNDINF	60	POSSMV	49	ARMROB	67	PWEAP
39	B&E	62	CARTHFT	49	ROB	74	SETEXP
43	PBURG	63	ESCAPE	49	FALSINF	85	TWEAP
43	PPARA	68	ELUDE	56	PWEAP	85	PPARA
48	CARTHFT	75	FORN	60	ATTRAPE	95	DWOL
49	ATTBE&L	85	DWOL	68	POSSMV	96	CONSPIR
54	POSSMV	100	D&D	71	RAPE	116	ASSWEAP
56	ATTB&E	106	INCORR	95	PBURG	136	D&D
57	ELUDE	109	FORGE	119	ELUDE	154	ARMROB
61	FORGE	111	DWI	127	GLUE	166	FORGE
77	BE&L	123	FRAUD	131	DWOL	205	PMARIJ
78	DWOL	161	RUNAWAY	137	CARTHFT	570	PNARC
82	SETEXP	184	SMARIJ	222	ATTCAR	1015	SMARIJ

violation of societal norms, but by how frequently the crimes are found together in the careers of offenders. (In this regard, the dimensions of crime generated by VCS are similar to the dimensions of crime that a factor analysis might produce.)

The structure identified by the VCS analysis is substantively different from seriousness: Offense seriousness does not correlate highly with any of the dimensions. This can be inferred by looking at the scaled offenses in Table 3.1. Although there is a tendency for more serious offenses to be found at the negative poles of dimensions of one and two, the same cannot be said of dimensions three and four. In an earlier analysis (Smith et al., 1984), we found the correlations of similar dimensions with a seriousness scale to be quite low, never exceeding a value of .40.

Below we will characterize the dimensions by the nature of the crimes that appear together on the dimensions. For example, dimension one has "serious crimes against person" on the negative end of the scale, while breaking and entry and auto theft appear on the positive end of the scale. These crimes or crime types can be used to substantively characterize the first dimension. While the discussion and interpretation is in terms of how the <u>crimes</u> are arrayed in a dimension, it will be remembered that one distinguishing feature of VCS is that these dimensions are derived throguh the analysis of <u>careers</u>. Therefore, crimes are near one another precisely because they are likely to be found together in the careers of offenders.

The graphs of the scale values of the dimensions are also instructive of the nature of the dimensions. A graphic representation of dimension one scale values against dimension two scale values and a second graph of dimension three scale values against dimension four scale values are presented in Figure 3.1 and Figure 3.2. In Figure 3.1, it can be seen that serious crimes against

Figure 3.1 -- Dimension One (Vertical) By Dimension Two (Horizontal) -- Variance Centroid Scaling Results

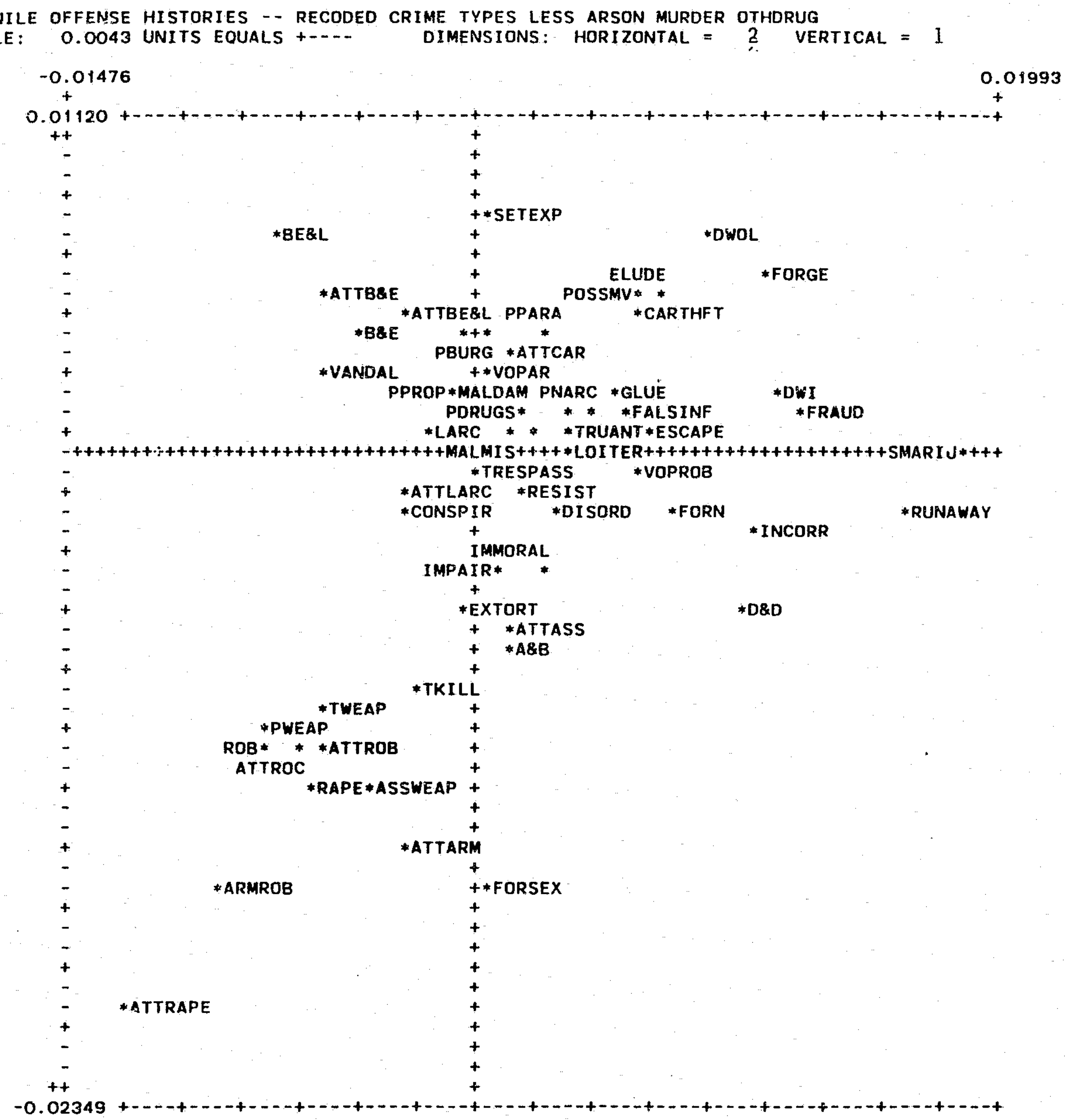


Figure 3.2-- Dimension Three (Vertical) By Dimension Four (Horizontal) -- Variance Centroid Scaling Results

```
JUVENILE OFFENSE HISTORIES -- RECODED CRIME TYPES LESS ARSON MURDER OTHDRUG
 SCALE:   0.0159 UNITS EQUALS +----      DIMENSIONS:  HORIZONTAL =  4   VERTICAL =    3

        -0.01950                                                                        0.10730
           +                                                                                +
      0.06418 +----+----+----+----+----+----+----+----+----+----+----+----+----+----+----+
          ++            +
           -            +
           -            +
           +            +
           -            +
           -            +
           +            +
           -            +
           -            +
           +            +
           -            +
           -            +
           +            +
           -            +
           -            +
           +            +
           -            *ATTCAR
           -            +
           +      CARTHFT  DWOL
           -     *GLUE *     *
           -            +  *ELUDE
           +     BURG* +PWEAPARMROB
           -   FALSINF*****  *    *
           -   ATTLARC* **** *  *  *FORGE
           ++++++LARC*********+*ASSWEAP++++++++++++++++++++++++++++++++++++++++++++++++++++++++
           -  VANDAL* *****DWI*TWEAP
           -    IMMORAL**** *FRAUD   *PMARIJ
           +      FORN*BE&L *    *D&D
           -     INCORR UNDINF                                  *PNARC
           -            *RUNAWAY
           +    *FORSEX +
           -            +
           -            +                                                      SMARIJ*
           +            +
           -            +
           -            +
           +            +
           -            +
           -            +
           +            +
           -            +
           -            +
           +            +
           -            +
           -            +
           +            +
           -            +
           -            +
          ++            +
     -0.06263 +----+----+----+----+----+----+----+----+----+----+----+----+----+----+----+
```

person constitute the low negative values of both dimensions one and two (attempted rape, armed robbery, robbery, attrocious assault, etc.). We refer to this phenomenon as "pivoting." That is, certain offenses pivot off of the other crimes as we move from dimension to dimension. Thus, serious persons crimes seem to "pivot" off burglary in the first dimension, but pivot off status offenses in dimension two.

Second, in addition to the pivoting phenomenon, there is a pattern of movement of crimes across dimensions -- we call this "internal differentiation" by which we mean that a particular crime or subset of crimes is differentiated from other crimes of its group across dimensions. Thus we find that breaking and entering is with auto theft on dimension one, but not on dimension two -- it is opposite auto theft and in the company of serious person offenses.

We note also from Figures 3.1 and 3.2 that very frequent offenses such as larceny are unlikely to appear near the ends or poles of the dimensions. This suggests that larceny is one of the most shared crimes, and dimensions of criminal careers cannot be distinguished by this offense. In general, the absence of narrow specialization, alluded to by the eigenvalues associated with these dimensions, suggests that the more frequently a particular offense occurs, the more likely it is to be found in many careers. Offenses common to many careers thus are near all other types of crimes. Consequently, larceny is near the center of each of the four dimensions.

We characterize the dimensions in terms of the crimes occuring at the end or poles of the dimensions. The first dimension in Table 3.1 contrasts burglary and auto theft on one pole against serious persons crimes on the other; the second contrasts serious persons crime with status offenses, including auto theft. In the third dimension, status offenses are differentiated against auto theft offenses. Finally, the fourth dimension provides a comparison of drug possession and armed robbery against property and juvenile delinquency offenses. While the identification of these dimensions in terms of the crimes on the poles is important, we call attention to the differing orderings of the other offenses in each dimension. The orderings of all offenses in each dimension, as well as the differentiation of poles of the dimension, forms the basis for the classification scheme developed below.

It is interesting that crimes at the poles are substantively similar on each of the four dimensions (though not necessarily similar across dimensions). Crimes between the poles seem to have no "face-value" ordering, but rather seem to constitute a mix of offenses. Allowing for this interpretational "residual" category of crimes (the mid-section of each dimension), one can characterize each dimension as having three qualitative categories -- the <u>two pole areas</u> and <u>the heterogeneous midsection</u>. This trichotomy will be used to interpret the results below concerning stability and change in careers over time.

The trichotomy of interpretable sections in a dimension can be identified with reference to the scale values themselves (see Table 3.1). Breaking these four dimensions at particular cut-off points yields substantively similar offenses. These cut-off points are: -62, +35 for dimension one; -21, +40 for dimension two; -35, +50 for dimension three; and -21, +50 for dimension four. Thus, the crimes below -62 on dimension one constitute substantively similar crimes, as do the crimes above 35 on dimension one. The cut-off points for the four dimension are discussed further in Chapter Four, where they are given a statistical basis to supplement their substantive interpretation.

The substantive significance of the poles of these dimensions is supported by a correspondence with some of the classification categories found here and in the existing literature. The semi-professional property role-career offender (Gibbons, 1968:258), who commits robbery, burglary and strong-arm robbery, corresponds to the negative pole of the second dimension. The automobile-thief "joyrider" (Gibbons, 1968:199) may correspond with the positive pole of the second dimension. The violent sex offender role-career (Gibbons, 1968:390) seems similar to the negative end of dimension one or alternatively the positive end of dimension three, although auto theft is not mentioned by Gibbons as part of this role-career. The opiate-addict role career (Gibbons, 1968:421) may correspond to the positive pole of dimension four. Property/juvenile delinquent offenses seem to correspond to Gibbons's general discussion of juvenile delinquents (1968:221).

Additionally, several poles of the four dimensions are similar to classes of offenders defined by Chaiken and Chaiken (1982). Violent predators (1982:29) seem similar to the negative pole of dimension two, with robber-assaulters similar to the negative pole of dimension one (1982:29). Robber-dealers (1982:29) seem to correspond to the positive pole of dimension four; burglar-dealers seem similar to the negative pole of dimension 3, but so do property-drug offenders. Low-level burglars, defined as having burglary, and for some offenders auto theft, robbery, and other theft (1982:29) seem similar to the positive pole of dimension one. (It should be remembered that, since the Chaikens were classifying adults, and we are looking at dimensions of delinquent behavior, a close correspondence should not be expected.)

Thus, all the poles of each dimension bear some plausibility as meaningful categories of delinquent behavior in that other researchers have either found similar groupings of offenses or argue from theoretically-driven criteria for such groupings. There are other classification systems that could be used to establish the face-validity of the dimensions discussed here, but our interest is only to demonstrate that the groupings of behavior the VCS technique uncovers are plausible within the criminological literature.

It should be noted that although we have described the dimensions of crime in terms of their poles and midsection, we only do so to attach substantive meaning to the dimensions of crime. Considering the discrete aspects of these dimensions aids in their interpretation, but the dimensions themselves represent continuous orderings of crimes. In the next chapter we focus on the fit of each individual's criminal career-line to the underlying dimension.

Finally, we there is one other inference that can be made from the VCS results. Often, discrete, highly interpretable, clusters of crimes appear only when two dimensions are considered simultaneously. This is most easily seen in Figure 3.1 where dimension one in conjuction with dimension two produces a clear cluster of serious persons crimes (i.e., robbery, atrocious assault, rape, attempted robbery, assault with a weapon, and so forth). An additional cluster of auto-related crimes (driving without a license, auto theft, eluding police, attempted car theft, possession of a stolen motor vehicle) is found when dimension one is plotted against dimension three (not shown here). Similarly, in Figure 3.1, a cluster of breaking and entering, attempted breaking and entering, BE&L and attempted BE&L is seen when dimension one is considered along with dimension two.

Such clusters of crimes correspond closely to categories of common typologies. However, empirically, these crime clusters are not the result of a single dimension of crime. This can be seen in dimension two, where the crimes of the breaking and entering cluster are interspersed with those of the serious persons cluster. What produces the familiar categories of offenders, as in Figure 3.1, is the pivoting phenomenon. The implication is that extant typologies have produced their classifications through forcing the multiple dimensions of crime into the single dimension represented by the taxonomy. In fact, as our results show, there are actually multiple dimensions of crime rather than the single 'dimension' assumed by traditional typologies.

Chapter Four: Classifying Criminal Career-Lines

From Dimensions of Crime To Criminal Career-Lines

In the previous chapter, four dimensions of crime were found using the VCS technique. Although these four dimensions are of interest in that they tell us something about how crimes co-occur, they do not tell us about a specific individual's offense history. How would we characterize an individual's offense history relative to the dimensions of crime that we discovered? Take a hypothetical case of an individual who is a specialist (in the strict sense), committing only burglary. Suppose that we assign a number -- 1, 2, 3, . . . n -- to each crime in chronological sequence, i.e., with "1" for the first offense, "2" for the second, and so on, for the n offenses of the career. Since the scale value for "breaking and entering" on dimension one, is +39, we can plot these burglary crimes on the vertical axis at that value and on the horizontal axis by the offense sequence number. The result would be a series of points, through which we could draw a straight line, parallel to the horizontal axis. We refer to this line as a criminal career-line. This line could then be characterized as representing a stable career of burglary. We might also project the career-line into the future, predicting that this individual will continue to commit burglaries.

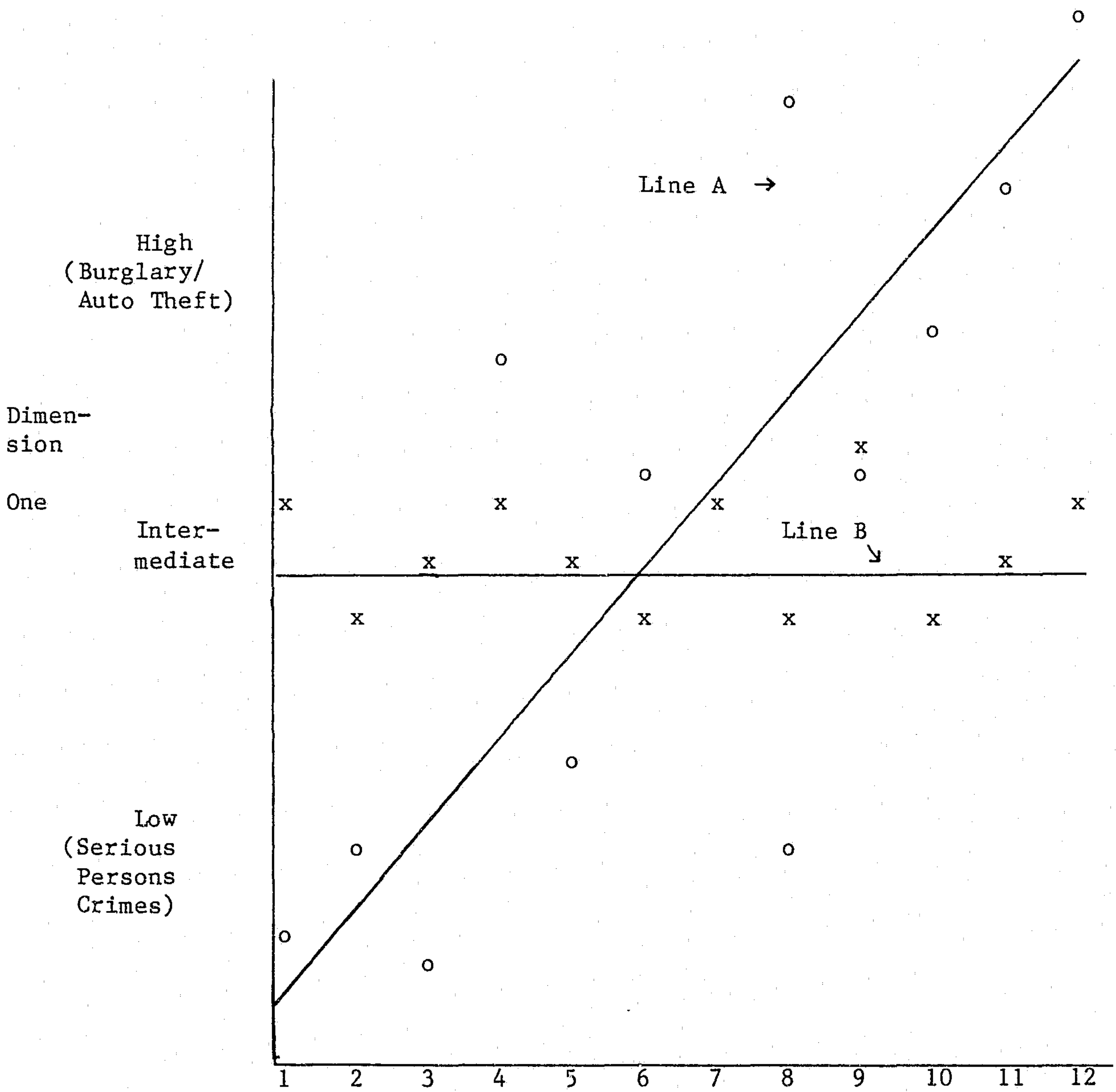
Unfortunately, there are no such highly specialized careers in our sample, (nor are there very many in others either; Cohen, 1986). Instead, individuals have commited several types of crimes over the course of their careers and it is not possible to draw a straight line <u>through</u> the crime points on the plot such that all points fall on the line. Fortunately, the situation is conveniently dealt with by simple bivariate regression: project a line through the points such that the line minimizes the variation around the line. Take the equation:

$$Y' = a + bX$$

in which Y′ is the estimated dimension one values, a is the intercept value, b is the slope of the estimated regression line, and X is the sequence number of the offense. By utilizing simple bivariate regression, each individual's crime history can be depicted as a regression line. The characteristics of these regression lines (e.g., slope, intercept, etc.) may be useful in identifying and classifying types of criminal careers on each of the four dimensions of crime. In addition to the parameters in the equation above, we can also examine the differences between the predicted values and the observed values to see if they tend to be close for far apart.

For a more intuitive grasp of the advantage of conceptualizing the careers in this fashion, see Figure 4.1. Here two hypothetical careers are represented as two regression lines on dimension one. Line A is a career that begins near the negative pole of dimension one and ends near the positive pole of that dimension. Line B begins in the midsection of dimension one and remains in the midsection. The observed crimes lie both above and below the estimated regression lines. We could reasonably refer to Line A as one that involves development or change from one pole to the other. Line B, on the other hand, might be referred to as a stable career-line. We could also imagine a career-line that begins at the positive pole and ends near the negative pole, or another that begins at the positive pole and ends in the midsection area of the dimension. Given that there are three discrete substantive ranges of dimension one -- burglary/auto theft on the positive pole, undifferentiated or general delinquent behavior in the midsection, and serious persons crimes at the negative pole -- and thus three possible

Figure 4.1 Hypothetical Stable and Developmental Career-Line*



*Xs are observed cases of Line B.
Circles are observed cases of Line A.

"substantive" beginning or ending points for each of the types of career lines, there are thus nine logically possible classifications for dimension one (see Table 4.1 below). Individual criminal histories can then be classified according to these nine types of criminal career-lines.

In summary, the trajectory of the line in a given dimension can form the basis for developing a classification. It is conveniently operationalized through a bivariate regression in which the crime's scale value in a dimension is regressed on its location in the career (i.e., the arrest sequence number). In the analysis below, four regressions were run for each individual studied here. Scale values (the values of Table 3.1 divided by 100) on each of the four dimensions were regressed on the sequence number of the offense. Each of these regression lines serves as a career-line with a specific trajectory in each dimension.

The use of a career-line's trajectory allows us to identify the degree and history of specialization by characteristics of the career-line. Four parameters that are derived from the regressions are of interest for this characterization: the slope, the beginning point of the career-line, the end point, and the standard error of the estimate -- the variance around the career-line. Nonzero slopes are associated with developmental careers in which the individual moves to qualitatively different types of crimes as more offenses are committed. Slopes of zero (or near zero) indicate less systematic movement over a career than nonzero slopes.

It is important for the substantive interpretation of a career-line to know where in a dimension a career in crime began. Thus, the slope value must be used in conjunction with a second criterion: the intercept or beginning point of a career-line. That is, it is important to classify the individual

Table 4.1 Logically Possible Types of Delinquent Career-Lines for Dimension One.

Description of Criminal Career-Line	Beginning Point	End Point
Stable Burglary/Auto Theft	+	+
Burglary/Auto Theft to Midsection	+	0
Burglary/Auto theft to Serious Persons	+	-
Stable Midsection (General Delinquency)	0	0
Midsection to Burglary/Auto Theft	0	+
Midsection to Serious Persons	0	-
Stable Serious Persons	-	-
Serious Persons to Midsection	-	0
Serious Persons to Burglary/Auto Theft	-	+

in accordance with the point of origin of his criminal career in each dimension of crime. Did the individual begin his/her criminal career near the serious persons pole of dimension one or somewhere else?

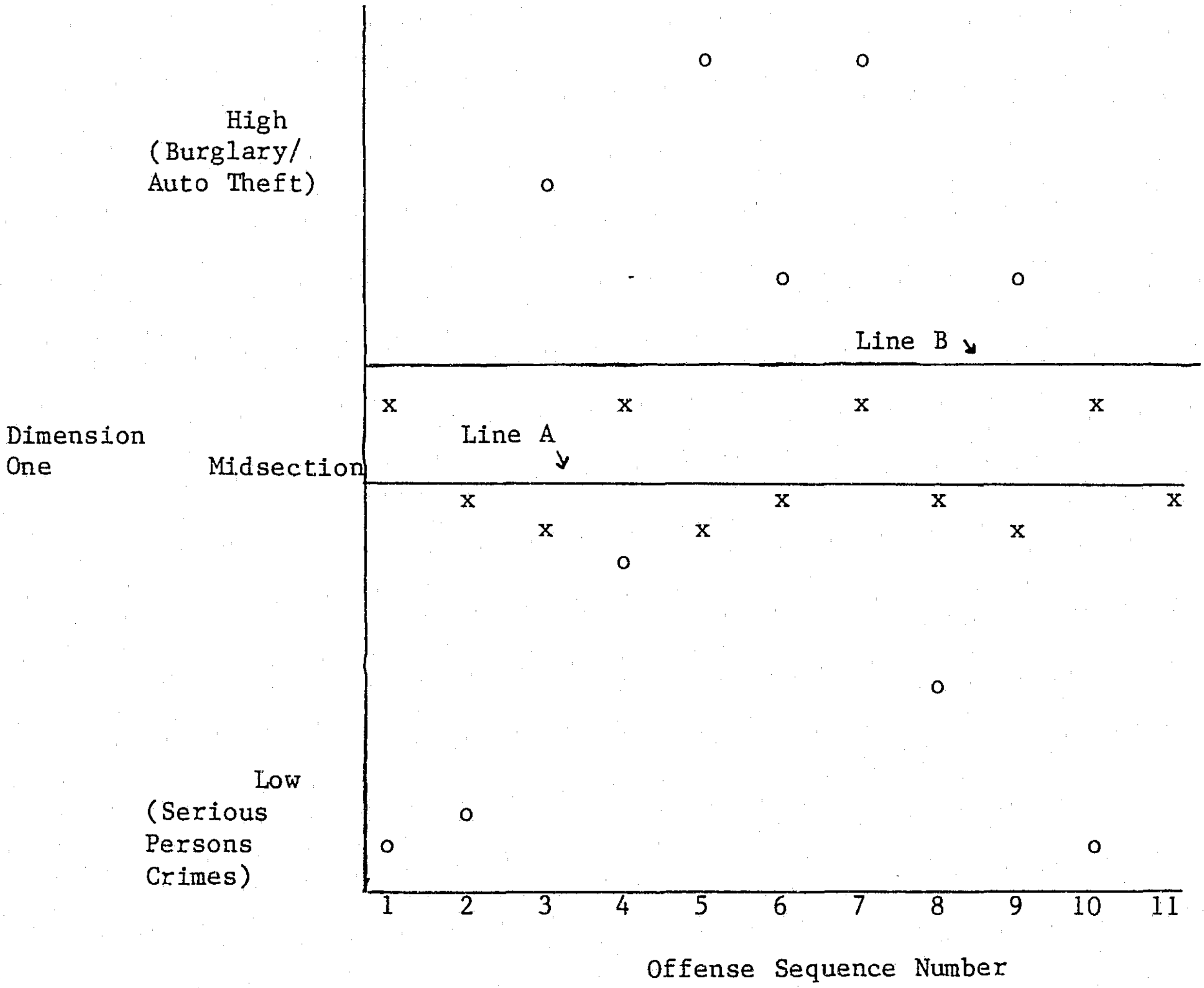
The third characteristic of interest is the end-point of the career-line. That is, where did the individual end his/her career-line? The end-point can by operationalized as the predicted value of the last crime in the sequence. That is, rather than use the actual final juvenile arrest, the value on the line at the last juvenile crime can represent the end-point of the career.

Finally, the variability of the offenses around the estimated line is important. The greater the variability of crimes around the career-line, the less the career is either specialized or developmental (i.e., the more diverse it is). By specification of the slope, variation, intercept, and end point, it is possible to characterize a criminal career regression line as stable, developmental, or diverse.

Criteria for Classification

Stable, developmental, and diverse careers must be operationally defined. For example, in Figure 4.2 Line A and Line B (ficticious cases) might both be considered stable career-lines, but clearly Line B's variation around the regression line is excessive -- many points fall in the pole sectors -- and one would not want to characterize that career line as stable. Line A, on the other hand, has variation around the regression line, but all data points fall within the bounds of the midsection of Dimension one. Thus, we might classify Line A as a stable career-line, and Line B as a diverse career-line. Given low variability around the career-line, there are the nine logically possible career patterns. These are listed in Table 4.1. A tenth -- diverse

Figure 4.2. Hypothetical Criminal Career-Lines*



*Xs are observed cases of Line B.
Circles are observed cases of Line A.

careers, or careers that show no systematic patterning — is needed to yield an exhaustive set of logically possible career-line trajectories.

For each offender, career-lines were operationalized in each of the four dimensions described in Chapter Three. In all, three thousand six hundred fifty-two bivariate regressions were computed. Each career-line was then characterized by the parameters of the intercept, slope, and standard error of the estimate (variability) for a particular dimension. Summary statistics, by dimension, of these career-line parameters are given in Table 4.2.

These summary statistics allow for the characterization of average career-lines. The average career-line in dimension one starts between possession of narcotics and escape (see Table 3.1). With each additional offense, the line moves toward the negative pole of the dimension. At the twentieth crime of the career, for example, the line is near "resisting arrest" in dimension one. Note, however, that the variability of this "average" career-line is such that any crime could be within 46.6 scale points of the line, using the values of Table 3.1. Consequently, the average career-line is expected to contain offenses in the undifferentiated midsection in dimension one.

The classification of career-lines as either stable or developmental must consider slope, beginning and end points, and variation around the regression line. If these parameters of the career-lines were distributed in such a way that there would be natural "breaks" in the distributions, it would be plausible to argue that that these natural breaks provide grounds for empirically establishing cut-off points to define how much slope is too much. For example, at what point does the career qualify as a stable career, or how much variation around the regression-line is too much to qualify as a stable career. Visual inspection of the cumulative distributions for the variables

Table 4.2 Descriptive Statistics on Parameters of the Career-Lines (N=913)

	Dimension 1	Dimension 2	Dimension 3	Dimension 4
Mean Intercept	.054	.050	-.123	.083
Standard Deviation	.434	.439	.488	.363
Skewness	-.226	-.678	-5.151	2.150
Kurtosis	5.089	10.390	91.100	13.984
Mean Slope	-.010	-.006	.014	.013
Standard Deviation	.061	.056	.053	.066
Skewness	-.903	-.314	.860	4.695
Kurtosis	7.837	5.429	7.928	49.475
Mean Standard Error of the Estimate	.466	.483	.474	.425
Standard Deviation	.156	.149	.189	.371
Skewness	.435	.470	.377	5.837
Kurtosis	.844	.786	.050	47.165

summarized in Table 4.2 found no natural breaks. Empirically, the career-line parameters are normally distributed in this sample. Therefore, we must use other means to arrive at operational definitions of what is too much slope or too much variation.

Consider the definition of a stable career-line. The standard error of the estimate or the average variation of the observed crimes from the estimated regression line is a convenient indicator of the degree of variation in a criminal career-line. Yet, how much variation can we tolerate before we reject the hypothesis that a career-line is stable? We argue that a standard error of the estimate (s.e.e.) of .26 or greater is too much variation to classify a career as stable. Why .26? Take an ideal type; for example a case with a slope of zero and an intercept value of zero in dimension one. If the s.e.e. is .25 or less, then the average variation of the residuals is still within the range of values of the midsection of dimension one (-.61 to .35). Some points may fall outside the range, but generally they will fall within the mid-section. But why .25 rather than .30 or .35?

The average value across dimensions for one standard deviation below the mean standard error is .25. That is, .25 is the average point across the four dimensions that lies one standard deviation below the average or "grand mean" of the standard error of the estimates. Thus, while .25 is somewhat arbitrary, it represents variation considerably below the average variation around the regression lines of any dimension. Another way to view the .25 value is shown in Table 4.2. The average standard error of the estimate for the 3652 regressions -- 913 regressions for each dimension -- is between .425 and .483, for an approximate average of .46. Thus our .25 cut-off value is a little more than half the average standard error across dimensions. (It should be noted that our objective at this point is to identify specialized careers according to statistical definitions -- we will address validity issues further below).

In addition to placing a restriction on the degree of variation around the regression line, the stable career line must not be allowed to slope too much in one direction or another, otherwise the claim could be made that it is a developmental career. How much slope is too much? We argue that an absolute value for the slope of .025 is a good cut-off point for trajectories of a stable career because the average career is about 16 offenses (See Table 2.7). If a hypothetical career-line had an intercept of zero and average career length, then it would take a slope of greater than .025 for that career-line to end outside the substantive range of the midsection of the dimensions. (Across the four dimensions, the average range for the midsections is plus or minus .40 and 16 x .025 = .40). That is, slopes of greater than .025 will tend to produce average careers that begin with one set of offenses but end at a substantively different location in a dimension. Another way to think of the slope value of .025 is that it is a little less than half of the standard deviation of the slope (see Table 4.2). Empirically, slopes of less than .025 are near average, while slopes with an absolute value greater than .025 are not.

Of course, these criteria make more sense the closer the intercept value is to zero -- if the beginning point is zero, relatively few offenses are likely to fall outside of the midsection range. Yet the criteria for stable careers are strict in another, less obvious, sense. The standard error is likely to be greater the further the intercept is from zero, consequently careers with intercept values far from zero are likely to be rejected as stable careers for having too high a standard error. We realize that this is a weakness in our criteria for defining stable career-lines (see below), resulting in a failure to find a substantial number of stable careers at the ends of the poles of any of the dimensions. But it must be remembered that our primary purpose here is to demonstrate the usefuless of the proposed approach in identifying "specialized" careers, not to yield an infallible implementation or to identify all possible "specialized" careers.

In summary stable delinquent careers are defined by the following criteria: the slope of the career-line must be less than or equal to .025 and the s.e.e. must be less than or equal to .25. If these criteria are met, the career line is classified as one of three logically possible types of stable careers in any dimension. These three are: stable at the negative pole, the midsection, or the positive pole of a dimension.

The operational definition of developmental careers proceeds differently. We argue that the standard error of the estimate criteria are useful, for establishing statistically significant differences between the crimes that begin and end the career. That is, if the beginning point of a career line is in a pole region or midsection of a dimension and is substantially distant from the end point of the career-line, then the career should be considered developmental. We define "substantially" as 1.98 times the standard error of the estimate (s.e.e.) or outside the 95% range of the estimated beginning point of the career. To implement the classification we begin by coding all criminal career-lines' end points and beginning points as +, -, or zero, depending on whether or not they end or begin in the positive, negative, or midsection regions of a dimension. For example, if the end point of an individual's career-line on dimension one is in the range of negative values less than -.62 (i.e., within the range that defines the negative pole of dimension one), its end point is coded as -1. If the beginning point is greater than .35, then the beginning point is coded +1.

Assume that an individual's career-line has an average s.e.e. (.466, see Table 4.2). If the end point category (-1) is less than the beginning point category (+1) minus the quantity "1.98 x .466" (or 1 - .922 = .078), it can be considered a negative developmental career. That is, the career-line moves significantly from a positive pole to a negative pole over time. As the movement is from a negative pole to a positive pole value, this negative developmental career can be designated as a dimension one "+/-" career-line. Other negative developmental career-lines may start in the mid-section and move to the positive pole. If the end point is less than the midsection value of zero minus the quantity "1.98 x the s.e.e," the career-line is also considered a negative developmental career, but of the "0/-" variety. If a career-line goes from the positive pole to the midsection of the dimension, it is labeled a "+/0" negative developmental career-line.

The converse of these criteria applies in defining the positive developmental career-lines. Here, if the end point (again coded as +1, 0, -1) is greater than or equal to the quantity "beginning point plus 1.98 s.e.e.," then the career-line is considered positive developmental. If positive developmental career lines begin in the midsection and end in the positive range of the pole values of a dimension, it is considered a "0/+" type. If it begins in the negative range of the pole and ends in the midsection, then it is a "-/0" type; and if it is a "-/+" type if the career line involves beginning and end points at the two poles of a dimension.

In summary, developmental career-lines are defined by two criteria: first, the career-line must begin and end in different substantive portions of a dimension. Second, the end point of the career-line must be signficantly higher (or lower) than the beginning point. Statistically significant differences are determined using 1.98 times the s.e.e. for a given career. Therefore, significant changes in the substantive content of career is determined for each individual. The three types of positive developmental careers are: from the negative pole to the positive pole, from the negative pole to the midsection, and from the midsection to the positive pole. The three resulting types of negative developmental careers are: from the positive pole to the negative pole, from the positive pole to the midsection, and from the midsection to the negative pole.

Method of Classification

Using the above criteria, we classified the career-lines of all individuals with more than six offenses. The choice of six offenses allows us to focus on the more chronic delinquents as well as to stabilize the regression coefficients. This definition of chronic delinquents is in agreement with previous definitions (Wolfgang et al., 1972). The restriction of six or more arrests in the career resulted in the retention of 913 of the original 1005 male offenders.

Careers fall into three general discrete types: stable careers, developing careers, and indeterminate (diverse) careers. In _stable_ careers, the delinquent starts with one group of crimes and continues to commit them. Translated to the career-line metaphor, the individual has relatively constant values in a dimension over the course of his career, and thus low variability in the scale values of his crimes. _Developing_ careers are those that begin within one substantive range of a dimension and end in another. An _indeterminate_ or diverse delinquent career is defined simply as one that does not qualify for inclusion in the above two categories, that is, it may not be classified as either stable or developmental.

We characterize the ranges at the poles of the dimensions (+,-) according to the substantive character of the more commonly occurring crimes found there (see Chapter Three). For example, on the positive end of dimension one, we find "eluding police" and "setting explosives." Rather than characterize this pole by these crimes, we refer instead to the more common "breaking and entry" and auto theft related crimes. Since the midsection of all the dimensions (coded 0 in Table 4.2) have a mix of offense types, we refer to this section as "general delinquency" for all four of the dimensions (See Table 4.3). Thus, we have ten logically possible categories of classification for each of the four dimensions, or 40 possible categories when all dimensions are considered.

Classification Results

Each individual has criminal career-lines to be classified. In Table 4.3 the results of the classifications, using the operational definitions of stable, developmental, and diverse, are presented. Some dimensions allow for the classification of more specialists than other dimensions. Classifications of stable and developmental careers on dimension three, for example, results in the classification of only 25% of the delinquents. Stable and developmental careers derived from dimension four, on the other hand result in almost half of the careers being classified as "specialists" (47%). Furthermore, certain dimensions have frequently occurring developmental career-lines, while others have both developmental and stable career-lines. For example, dimension one has 74 negative developmental career-lines of the "+/0" type and 67 positive developmental career-lines of the "0/+" type, but only 3 stable +/+ and 1 stable -/- type. Dimension three and four have 54 and 72 career-lines, respectively, of the stable "0/0" type.

Table 4.3. Classification of Delinquents' Career-Lines by Type of Career

Stable, Developmental or Diverse Career	Dimension 1		Dimension 2		Dimension 3		Dimension 4	
	Cases	%	Cases	%	Cases	%	Cases	%
Stable +/+	3	.3	0	0	1	.1	0	0
NegDev +/0	74	8.1	22	2.4	3	.3	4	.4
NegDev +/-	21	2.3	39	4.3	4	.3	6	.7
PosDev 0/+	67	7.3	28	3.1	10	1.1	5	.5
Stable 0/0	33	3.6	13	1.4	54	5.9	72	7.9
NegDev 0/-	28	3.1	142	15.6	35	3.8	82	9.0
PosDev -/+	2	.2	31	3.4	26	2.8	33	3.6
PosDev -/0	12	1.3	75	8.2	90	9.9	210	23.0
Stable -/-	1	.1	7	.8	2	.2	19	2.1
Diverse	672	73.6	556	60.9	688	75.4	485	53.1

Stable +/+ = career-line began at positive pole and ended at positive pole
NegDev +/0 = career-line began at positive pole and ended at midsection
NegDev +/- = career-line began at positive pole and ended at negative pole
PosDev 0/+ = career-line began at mid-section and ended at positive pole
Stable 0/0 = career-line began at mid-section and ended at midsection
NegDev 0/- = career-line began at mid-section and ended at negative pole
PosDev -/+ = career-line began at negative pole and ended at positive pole
PosDev -/0 = career-line began at negative pole and ended at midsection
Stable -/- = career-line began at negative pole and ended at negative pole

Since some of the classes represent very few career-lines, we will focus on those classes with the more frequently occurring career-lines. We arbitrarily define frequent as those with 50 or more cases, or approximately 5 percent or more of the entire sample. We select these because if a classification is to have any value, empirical cases of it should occur frequently enough to warrant our attention.

When we applied the classification criteria described above, 66.3 percent of the sample were be classified into nine of the 40 logically possible classifications in Table 4.3. These nine categories are listed in Table 4.4. In the first dimension, two frequently occurring patterns were found: career-lines beginning with burglary/auto theft and developing into a general delinquency pattern and those going in the opposite direction (8.1 and 7.3 percent, respectively.) A somewhat similar pattern is found in dimension two where 15.6% are found moving from general delinquency to serious persons offenses. An additional 8.2% are found developing from serious person crimes to general delinquency. In dimension three, two frequent types of career-lines were found. One involves movement from status offenses to general delinquency (9.9%), and another involves those stable on the general delinquency mid-section (5.9%). Another stable career pattern occurs on dimension four, again across the midsection of the dimension (7.9%). Additionally, from dimension four, we observe general delinquency development to a property/petty crime pattern for 9.0% of the sample. A rather large proportion (23.0 percent) of the sample moved from property/petty crimes to general delinquency in that dimension.

While these nine types of career-lines appear to have face validity, since earlier researchers did not focus on the development of types of careers that change over time, it is impossible to evaluate the validity of our results

Table 4.4 Frequently Occurring Types of Career-Lines

Description	Dimension	Percent
1. Burglary/Auto Theft to general delinquency	1	8.1
2. General delinquency to serious persons	1	7.3
3. General delinquency to serious persons	2	15.6
4. Serious persons offenses to general delinquency	2	8.2
5. Stable general delinquency career	3	5.9
6. Status offenses to general delinquency	3	9.9
7. Stable general delinquency career	4	7.9
8. General delinquency to property/petty crimes	4	9.0
9. Property/petty crimes to general delinquency	4	23.0

relative to theirs. Also, it is interesting to note that only 14 percent of the 605 individuals who were classified in the nine categories of Table 4.4 had stable careers. This is somewhat low in that others (Hartjen and Gibbons, 1969) were able to unambiguously identify 22% of a sample of probationers using an _a priori_ traditional typological approach. One of the reasons why we may be finding so few stable careers is that our criteria for stable careers are too strict for stable careers, especially at the poles of the dimensions. A stable career of serious persons crimes is unlikely in dimension one or two, because the scale values for such a career would have to be high in almost all cases. Only one or two crimes from the middle or opposite end of these poles would make the slope or standard error too high for the stable career criteria. In summary, a remarkably high percentage of career-lines were found to exhibit systematic patterning -- some in the form of _stable_ career-lines and many more in the form of _developmental_ career-lines. Although the traditional typological approach identified more stable careers than we found here (Hartjen and Gibbons, 1969), we know of no similar successful classification of developmental careers using the typological approach. Careers not classified as either stable or developmental in Tables 4.3 and 4.4 are deemed _indeterminate_ and account for 33.7% of the career-lines. Thus, we are able to classify as stable or developmental (or both -- see below) 66.7% of the sample. Overall, the regression results presented in the tables above indicate that the career-line analysis is useful for classifying individuals in two basic ways: (1) according to the progression of criminal activities over time (a nonzero slope and low variation) and (2) classification of stable career patterns (flat slopes and low variation).

Career-Line Multidimensionality

The classifications in Table 4.3 and 4.4 are not mutually exclusive. In fact the 605 individuals classified into the nine categories of Table 4.4, account for 911 classifications, or an average of about one and a half classifications per individual: career-lines may display systematic patterning in more than one dimension. Table 4.5 breaks down the multiple classifications for the nine frequently occurring career-lines. Here the diagonal represents career-lines uniquely classified. Thus, 389 of the 605 individuals classified here (or 64%) are uniquely classified. The off-diagonal values represent career-lines classified on other dimensions. Thus, 31 dimension one developmental career-lines (+/0, or burglary/auto crimes to general delinquency careers) are also dimension two career lines (0/-, or general delinquency to serious persons careers). Thus some individuals may go in seemingly different directions in different dimensions. This latter fact may be due to the frequency of serious persons offenses occurring in the latter phases of the careers. Certain types of career-lines, such as developmental ones from larceny/petty crimes to general delinquency (on dimension four) are co-classified with many other types of career-lines (see the column for dimension four, -/0 pattern).

At first glance, the fact that a delinquent's career-line is classified in multiple ways may be disturbing. It may suggest that our criteria for evaluating stable, developmental or diverse careers are too liberal. Yet, over 23 percent (210) of the 913 classifications on Table 4.5 can be accounted for by the dimension four (-/0) pattern -- larceny/petty delinquency to general delinquency -- a pattern that is not only common, but rules out few crime patterns relative to others by the substantive nature of the pattern.

Table 4.5 Multiple Classifications of Chronic Delinquent
(Proportion of Offenders Uniquely Identified in Parenthesis)

	Dimension I		Dimension II		Dimension III		Dimension IV			Number of Career Lines
	+/0	0/+	0/–	–/0	0/+	–/0	0/–	0/0	–/0	
Dim I +/0	21 (.268)		31		3	16	2	13	6	97
Dim I 0/+		27 (.346)		21	1	5	4	2	18	78
Dim II 0/–			52 (.347)		7	7	4	7	42	150
Dim II –/0				27 (.346)	3	1	1	11	14	78
Dim III 0/+					18 (.333)		6	4	12	54
Dim III –/0						41 (.456)	6	6	8	90
Dim IV 0/–							49 (.681)			72
Dim IV 0/0								39 (.476)		82
Dim IV –/0									110 (.524)	210

That is, larceny/petty delinquency to general delinquency may represent more of an "average" or undistinguished career than the other career types, and thus we expect some overlap with the other classifications. Other patterns with overlap can be accounted for by the substantive similarity of the dimensions. For example, the 21 individuals shared by classification dimension one (0/+), general delinquency to burglary/auto theft offenses, and by dimension two (-/0), serious persons offenses to general delinquency, may represent substantively similar careers in that both are moving away from serious persons offenses. Thus, the fact that all individuals cannot be uniquely identified is not necessarily of concern.

In fact, the non-unique classifications point toward one of the strengths of the current classification -- the fact that multiple classifications provide the researcher with options in characterizing an individual's history of crimes. Various a priori hierarchies of importance may be utilized in examining criminal career-lines. For example, if the same individual is classified on dimension one as moving from burglary/auto theft to general delinquency, and at the same time classified as moving from general delinquency to serious crimes against the person in dimension two, the latter classification may be given preference because of the relative importance of identifying individuals with careers in crime heading toward serious person offenses. Thus, the multidimensional and non-unique classifications that result allow for flexibility in their applications.

The re-occurrence of the same crimes on the poles of different dimensions led us to expect frequent multiple classifications. Serious persons crimes, for example, comprise the negative poles of both dimension one and Dimension two. The patterns of offenses leading to a classification of negative development on one of the first two dimensions might be expected to lead to a similar classification in the other. The relatively high degree of multiple classifications across Dimensions One and Two suggest just that. However, there are also many individuals' career-lines whose classifications do not overlap, suggesting that these dimensions are not the same and that the orderings of crimes in each dimension is tapping substantively <u>different</u> patterns of behavior. That is, more than one sequence of offenses leads to the sets of crimes on the poles of these dimensions: there are distinct "paths" of offenses leading to serious persons crimes. Furthermore, these paths (or the clusters of offenses leading to a classification of a stable career) may not be obvious under one dimension of crime, but become apparent when other dimensions are considered. Thus, in addition to the ability to classify more behavior, a multidimensional approach can tell us about the content of the career path.

Viewing crimes as multidimensional also allows for checks on inaccuracies of any one classification. If the criteria for defining developmental careers are criticized, for example, because a career-line marginally crosses over the cut-off point into one of the pole ranges of a dimension, then it may be demonstrated that the career-line can be classified more appropriately on another dimension. The multidimensional character of crime offers us a high degree of flexibility in identifying the most appropriate career-line classification.

Predicting Adult Offenses

Thus far, the validity of the classification has been advanced on the basis of mainly statistical criteria pertaining to slope, beginning and end points, and variation. The validity of the classifications can be further developed by determining if they are useful in predicting subsequent criminality. Since we have classified the entire juvenile arrest records as one type or another of career-line, the subsequent criminal activity is that of the adult years. Although there may be reason to believe that juveniles make fundamental changes in their lives as they age into adulthood (often making transitions from school to work, single to married status), it is less clear that their crimes change qualitatively at the same time. Assuming a trajectory of juvenile delinquent offenses into adult criminal offenses, we would assume that the classification system will allow us to predict specific adult criminal involvements. That is, if there is continuity from juvenile to adult years, the classifications of juveniles should be useful in predicting adult criminal involvements.

To test the validity of the delinquent classifications, arrests for five types of adult crimes are predicted using each of the nine frequently occurring patterns of offenses described above. The five adult crimes are: robbery, burglary, drug usage, auto theft, and aggravated assault. These crimes are chosen because they represent commonly occurring adult offenses, they are often distinguished from one another, and all are of a serious nature. Particular patterns of juvenile career-lines should be more likely to be followed by specific kinds of adult arrests. For example, juvenile careers moving in the direction of serious persons crimes would be more likely to have robbery arrests as adults. Those with delinquent careers moving toward auto theft as juveniles are more likely to have auto thefts as adults. Tables 4.6a-d show some support for these hypotheses, and hence support for the validity of the nine-fold classification scheme discussed above.

In Table 4.6a, the two common dimension one juvenile classifications are used to predict whether or not these career-lines are more or less likely than other forms of juvenile career-lines to lead to arrests for robbery, burglary,

Table 4.6a. Dimension One Frequent Juvenile Career-Lines and Adult Arrests for Crime Types (frequency, column proportions, and adjusted standardized residuals)

Arrested as Adult For:	Burglary/Auto to General Delinquency	General Delinquency to Burglary/Auto	Row Marginal
Robbery	23 .311 .4	11 .164 -2.4	.291
Burglary	40 .450 1.4	30 .448 -.2	.462
Drugs	33 .446 1.8	20 .299 -1.0	.353
Auto	22 .297 2.3	13 .194 0	.194
Aggravated Assault	16 .216 .2	13 .194 -.3	.207
Total	74	67	

Table 4.6b. Dimension Two Frequent Juvenile Career-Lines and Adult Arrest for Crime Types (frequency, column proportions, and adjusted standardized residuals)

Arrested As Adult For:	General Delinquency To Serious Persons/ Burglary	Serious Persons/Burglary to General Delinquency	Row Marginal
Robbery	52 .366 2.1	19 .253 -.8	.291
Burglary	58 .408 -1.4	40 .533 1.3	.462
Drugs	52 .366 .4	24 .320 -.6	.353
Auto	25 .176 -.6	15 .200 .1	.194
Aggravated Assault	26 .183 -.8	14 .187 -.5	.207
Total	142	75	

Table 4.6c. Dimension Three Frequent Juvenile Career-Lines and Adult Arrests for Crime Types (frequency, column proportions, and adjusted standardized residuals)

Arrested As Adult for:	Stable General Delinquency	Status Offense to General Delinquency	Row Marginal
Robbery	14 .259 -.5	19 .211 -1.8	.291
Burglary	28 .519 .9	42 .467 .1	.462
Drugs	13 .241 -1.8	31 .344 -.2	.353
Auto Theft	5 .093 -1.9	10 .111 -2.1	.194
Aggravated Assault	13 .241 .6	15 .167 -1.0	.207
Total	54	90	

Table 4.6d. Dimension Four Frequent Juvenile Career Lines and Adult Arrest for Crime Types (frequency, column proportions, and adjusted standardized residuals)

Arrested As Adult For:	Stable General Delinquency	General Delinquency to Larceny/Petty Crimes	Larceny/Petty Crimes to General Delinquency	Row Marginal
Robbery	24 .333 .8	22 .268 -.5	67 .319 1.0	.292
Burglary	39 .542 1.4	37 .451 -.2	88 .419 -1.4	.462
Drugs	26 .361 .2	23 .280 -1.4	72 .343 -.3	.353
Auto Theft	23 .319 2.8	12 .146 -1.1	38 .181 -.5	.194
Aggravated Assault	20 .278 1.5	14 .171 -.8	39 .186 -.9	.207
Total	72	82	210	

drug usage, auto theft and aggravated assault as an adult. Each of the ten logically possible career-line forms in a given dimension (Table 4.3), were classified against a variable representing whether or not an arrest occurred for a particular crime as an adult. Only the results for the commonly found career-lines in a dimension are shown. Thus, for example, in Table 4.6a, the results for robbery arrests as an adult are, in reality, two cells of the full two (arrested or not for robbery as an adult) by 10 (dimension one career-line forms) cross-classification. The adjusted standardized residual tells us how far above or below the row marginals the observed cell values are relative to the other logically possible classifications (not shown).

Thus, we see that those juveniles who had developmental careers going from general delinquency to burglary/auto theft crimes, are significantly less likely than would be expected under the model to have robbery offenses as an adult -- providing support for the notion that these offenders were moving away from the serious persons crimes that characterize the negative pole of dimension one. That is, only 11 of 64 of those in this developmental career category, or 16.4%, committed robbery as an adult, compared with 29.1% of the rest of the delinquents (yielding an adjusted standardized residual of -2.4). At the same time, however, it must be pointed out that those moving from burglary/auto theft toward general delinquency are <u>not</u> more likely to be arrested for robbery as adults -- suggesting that their delinquent career-line trajectory does not extend to more serious persons crimes as adults. Rather, these individuals are more likely to engage in auto theft as adults, as evidenced by an adjusted standardized residual of 2.3. Thus, their movement as juveniles away from burglary/auto-theft, seems to have resulted in a movement <u>back</u> to auto-theft, and to some extent burglary and drugs (adjusted standardized residuals of 1.4 and 1.8, respectively) as <u>adults</u> -- a finding we did not expect, yet one that is plausible. Because we did not predict it, however, it is ambiguous as to whether it provides validation of the two dimension one career-line forms.

Validation is found for the dimension two juvenile classifications because juveniles moving from general delinquency toward serious persons offenses are relatively more likely than other trajectories to lead to arrests as an adult for robbery (adjusted standardized residual of 2.1). These same individuals may also have a tendency to not be arrested for burglary (although the adjusted standardized residual is only -1.4.) Those who are moving away from serious person crimes toward general delinquency may have a tendency not to commit robberies, and to commit burglaries, but the adjusted standardized residuals are only about -1.0 and 1.1, respectively. Again there seems to be some support for the validity of the juvenile classifications, but the evidence is not overwhelming.

There are two juvenile classifications from dimension three. One seems to capture individuals who are not likely to be arrested for auto theft as adults. Those stable on dimension three as juveniles show a tendency to stay away from drugs and auto theft as adults. Those whose juvenile careers are moving from status offenses to general delinquency have a tendency not be be arrested as robbers, and a strong tendency not be be arrested as auto thieves as adults (adjusted standardized residuals of -1.5 and -2.9, respectively). Again, there is some support for the classification system, but not all of it could be predicted.

Auto theft as an adult is likely for the stable dimension four career-lines. (Auto theft and attempted auto theft are around the zero point of dimension four.) Stable dimension four delinquents are more likely to be arrested as adults for auto theft (adjusted standardized residual of 2.8).

They also seem to have a tendency to commit burglary and aggravated assault as adults. Those moving away from the midsection of the fourth dimension seem to have a tendency to avoid auto theft and drug offenses as adults. Those who move toward the midsection and away from larceny and petty crimes seem to have a tendency for robbery, and not burglary, as adults -- again the adjusted standardized residuals are small, 1.0 and -1.4, respectively. Thus, the results are somewhat ambiguous as to strong support for the validity of the delinquent classifications.

In summary, the attempt to validate the results of the juvenile classifications based on the VCS dimensions provides some support for the validity of these classifications in that some types of adult arrests seem to be predictable or at least in harmony with expectations. Since not all the findings could be anticipated, however, it should be noted that further research needs to be done to determine how valid these classifications are. It should also be noted that this validation assumes continuity between the juvenile and adult years, an assumption that may not hold true for all individuals. In general, however, we are encouraged by the findings and think that the classification attempt made here has been fruitful. Not only have meaningful groupings of offenses been identified, but some of the classifications of individuals resulting from these groupings of crimes have been found to be predictive of subsequent criminal behavior.

Chapter Five: Conclusions and Implications

Theoretical Implications

We argue that there is support, in varying degrees, for the five theoretical perspectives outlined in Chapter One. These perspectives lead us to expect specialization in delinquent or criminal careers, and we have found it. The existence of the nine frequent patterns of juvenile offenses, and the ability to classify 66.3% of the juvenile careers, suggests that a high degree of specialization is occurring. The form of that specialization is quite complex, however, in that most of the patterns involve change or development in the criminal careers over time.

Some support for Cloward and Ohlin is found in that juvenile offenders specialize in property or serious persons offenses (but not many in drug offenses). However, these juveniles do not seem to simply pursue these activities over the course of their delinquent careers, but move into and out of these patterns over time -- a finding not predicted by Cloward and Ohlin's differential opportunity perspective (yet not necessarily contradictory to it).

Differential association theory is supported by our finding that specialization occurs at points in juvenile careers, particularly burglary, serious person crimes, and auto theft. It may be that these crimes involve certain technical skills, physical abilities, or familiarity with means of disposing of the auto that are relatively specialized skills/knowledge. Again, differential association theory did not anticipate the dynamic aspects of career development. The expectation was that more stable careers would be discovered. Yet, the methodological difficulties associated with our failure to find very many stable careers at the poles of the dimensions may account for the limited number of stable careers. That is, refining our criteria for operationalizing what constitutes a stable career may result in more such classificatons at the poles of the dimensions.

Social control theory led us to hypothesize that offense seriousness would be a positive function of specialization. We have not fully explored the implications of this hypothesis, but there is some evidence that careers do advance in the direction of increasingly serious crimes -- perhaps associated with decreasing stake in conformity. For example, in dimension two 15.6% of the sample moves from general delinquency toward serious persons crimes, or in dimension three 9.9% of the sample moves from status offenses to general delinquency. These patterns are plausibly supportive of social control predictions.

In support of deterrence theory, there is some evidence of movement from serious offenses to less serious offenses, as in dimension two classifications where juveniles move from serious persons offenses to general delinquency. We have not yet explored whether or not these individuals experienced punitive incarcerations at the appropriate moments in their careers to account for these shifts.

There is little specific evidence that is relevant to labeling theory, but since stable career-patterns were found, there is some basis for the idea of a delinquent identity being acquired and resulting in similar behavior being repeated in secondary deviant behavior. It is also possible that the inherent dynamic aspects of the findings support the idea of a process by which deviant identities are acquired. Thus, a juvenile may "experiment" with larceny/petty crimes before moving on to more serious crimes as they acquire an identity as a "delinquent."

What we have observed then, are patterns of delinquent career-lines that are consistent with expectations from each of the five theoretical perspectives. No one perspective has received more empirical support than the others, nor have we found career-line forms that are unexpected from at least one perspective. This suggests that it may be possible to arrive at a theoretical synthesis of the varying perspectives. Perhaps opportunity, learning, social control, deterrence, and labeling processes are all involved in the emergence of the types of juvenile and adult criminal involvements discovered in our analysis. No attempt at such a synthesis will be made here.

Aside from these theoretical considerations, the results address critics of attempts to establish that there is specialization or even "criminal careers" for significant proportions of the juvenile delinquent population. Our findings provide a foundation for further examination of the nature and extent of such criminal careers. It should be noted, however, that while many of the approaches to the study of criminal careers have focussed on the quantitative aspects of those careers (lambda or mu rates, i.e., rates of crime or of arrests per time period, -- see Blumstein et al., 1986), the current study has focussed on the qualitative aspects of criminal careers. We have returned to pursuing the interests of those associated with the traditional typological perspective. We believe that an adequate understanding of criminal careers must involve both the quantitative and qualitative aspects of career dynamics and hope to contribute to such an understanding through future work.

Methodological Considerations

The present analyses and findings are preliminary. While we have established the utility of the career-line approach for developing offender classifications, additional research is needed on how career-lines are to be operationalized. In particular, four lines of inquiry need to be followed before a complete career-line classification system can be implemented. These are 1) the functional form of the career-line trajectory, 2) the derivation of appropriate cut-off points in the dimensions of crime, 3) simultaneous consideration of multiple dimensions of career-line trajectories; and, 4) the crime space in which career-lines are measured. Each is discussed in turn.

Our analysis has stressed the linear form taken by the career-line trajectory. This has been useful in that it has allowed for the detection of movement into substantively different sets of crimes over the course of the juvenile career (the developmental careers of Chapter Four). There is no a priori reason, however, that career-lines must be linear. Additional functional forms of career-lines, for example exponential or logistic curves, may provide more accurate representations of the trajectories taken in the dimensions of crime.

Of particular interest are non-linear trajectories that will yield an understanding of the convergence of criminal behavior into limited groups of crime. For example, labeling theory suggests that an offender initially experiments with diverse behaviors, and then specializes in certain types of crimes as his/her behavior becomes more consistent with the label resulting from contact with the criminal justice system. The imagery here is that the offenses of the career are initially quite diverse, displaying greater variability around the underlying career-line. It is only later in the criminal career that crimes become more "specialized" with offenses nearer to the trajectory of the career.

Our preliminary classification scheme is insensitive to non-linear career-line forms and changes in variation associated with increasing career length. The apparatus needed to operationalize non-linear trajectories is readily available in the form of curve-fitting models, and statistics are also available to check for decreasing (or increasing) error around the fitted line. (Simple tests for homoscedastistic error would be appropriate for assessing changes in the variablility of crimes over time around the career-line.) The suspicion is that many of the career-lines we were unable to classify in the present analysis (the "diverse" careers) would be classifiable if nonlinear forms of career-lines were used and greater attention was paid to the temporal variability of offenses around the career-line.

A second focus for future research should be in the choice of cutting-points to be used when classifying offenders. In some respects, the career-line approach has redirected the set of problems found with the typological approach. All classification systems face ambiguous cases and the ambiguities must be reconciled for classification to proceed. Other standard typologies have this problem with offenders who do not "fit" clearly into one of the categories of the typology being used. These ambiguous cases must be addressed on a case-by-case basis.

With the career-line approach, there is much less uncertainty about classifying a given career-line, once the cutting points for a dimension have been determined. However, determining appropriate cutting points creates new problems for classification research. These new problems may be summarized as: 1) potentially arbitrary cut-off points as to what are stable, developmental, or indeterminate careers and 2) too liberal a criterion for classifying offense specialization by allowing too much variation in a career. The entire classification system developed here rests on the choice of cutting points for the four career-line parameters of starting point, ending point, slope, and career variability around the line. Once these parameters have been suitably categorized, classification proceeds quickly, but clearly the efficacy of the resulting classifications is heavily dependent upon the values selected as cutting points for each parameter.

The criteria we used to determine appropriate cutting points in each dimension were not selected haphazardly. The choice of positive, negative, and middle ranges in each dimension was guided by the substantive content of the crimes of the dimension. Other parameters were empirically derived. For example, the ending point of the career-line had to be significantly different from the intercept before a career could be considered "developmental." While there are sound reasons for selecting the cutting points we have used, their import for the ultimate manner in which career-lines are classified is too great to consider the matter settled. Further research is needed to investigate the consequences of how the four career-line parameters are used to define stable, developmental, and indeterminant careers.

It is arguable that we have been too liberal in our definitions by allowing excessive variation around the career-lines that are condsidered stable. However, it is also true that the career-line approach allows for ease in measuring the extent of diversity. The typological approach must account for diversity with a series of statements that qualify what are "allowable exceptions" to the offenses considered integral to the definition of a type of offender or criminal history. By "quantifying" the measurement of deviation, it is easier to make comparative statements across classification studies, and to measure the form of exceptions: What is or isn't allowable as an exception is given a strict numerical value.

A third general area for future study involves the multiple representation of one career-line. We have found that one career-line can be classified in several ways depending upon which dimension is used to yield the career-line's trajectory. Conversely, some career-lines are classifiable as stable or developmental in one dimension only, appearing indeterminant in the other dimensions. Maintaining distinct dimensions, as we have done here, is fruitful as we have been able to isolate different paths that juveniles take to arrive at certain clusters of offenses (e.g., serious persons crimes). However, each offender has only one criminal career and the ideal situation is to have only one classification of that career's trajectory.

This can be achieved through development of a classification system that considers several dimensions simultaneously. As was discussed in Chapter Three, the results of the VCS analysis of juvenile careers suggest that certain clusters of crimes (e.g., auto-related offenses) appear only when two dimensions are considered jointly. That is, when a two dimensional "space" of crime is considered, some offenses are found in a distinct subportion of this space. Existing typologies implicitly assume a multidimensional space in that the separate crime clusters are used as one category of the typology.

It is also possible to operationalize career-line trajectories as moving through a multidimensional space. Rather than deriving the career-line using a single dimension, the career-line could be placed in, say, two dimensions such as those shown in Figure 3.1. At the operational level this implies the use of vector calculus and an associated increase in the difficulty of calculating the trajectory of the career-line. The potential payoff, however, is that each individual's career-line can then be uniquely classified.

Finally, future research should address the inherent distinctions between adult crimes and juvenile crimes. From the career-line perspective, this means that greater attention needs to be given to the "crime space" in which career-lines are imbedded. In particular, status offenses exist for juvenile offenders only, with no comparable crimes for adults. Chronic delinquents are likely to have status offenses interspersed throughout their careers, a fact borne out by the distribution of offenses given in Chapter Two. This has several consequences for the study of career-lines and their classification.

Status offenses influence the nature of the crime space derived using VCS (or any other multidimensional analytic technique). Offenses such as juvenile delinquency, truancy, and juvenile in need of supervision link other crimes (e.g., robbery, breaking and entering) because they co-occur in the careers of delinquents. Therefore, the location of acts that are crimes for both juveniles and adults is influenced by the location of acts that are crimes for juveniles only. That is, where a crime, for example assault and battery, is found in plots such as those in Figure 3.1, is in part dependent upon where other crimes (e.g., truancy, running away) are found. There are no assurances that if status offenses were removed from the analysis, the "crime space" uncovered would be similar to that found in the present study.

The legal definitions of acts, therefore, result in a crime space for juveniles that is _a priori_ different from that for adults. Career-line research must take these legal distinctions into account. When juvenile career-line classifications are compared to adult crimes, as we have done here, the comparison is confounded by the fact that juveniles careers are embedded in a differing crime space. Trajectories of juvenile career-lines could easily, and substantively, change when placed in the dimensions of adult crimes.

Two suggestions are offered for investigating the effect of legal definitions on career-line classifications. The juvenile crime space could be derived after deleting all status offenses from the career, yielding a multidimensional representation for only acts that are crimes for both juvenile and adult offenders. The resulting dimensions could then be used to operationalize juvenile career-line trajectories. Conversely, the crime space could be measured using the criminal careers of a sample of adult offenders. Juvenile career-lines could then be placed in this space, again ignoring any status offenses in the juvenile career. Until the inherent differences between the crime spaces for juveniles and adults are reconciled, the comparison between juvenile career-lines and adult crimes and career-lines will be confounded by the legal definitions of acts.

Conclusions

Use of the traditional typological approach has led researchers to impose unnecessary assumptions in the analysis of criminal careers. The career-line approach, on the other hand, conceptualizes the offense diversity as unexplained variation and allows for systematic study of the extent to which criminal careers are diverse.

The use of VCS dimensions is particularly valuable because it allows us to analyze the sequence of the delinquent career-lines. By plotting each career as a regression line, we discovered several patterns of both developmental and stable careers. Several of the types of career-lines found are substantively important relative to the public interest in identifying serious persons offenders. Other types of career patterns are significant in that they support the idea that juveniles may be classified as progressing toward committing burglary, auto theft, status offenses, and larceny/petty crimes. All of these developmental patterns support the contention that some careers progress in the direction of increasing seriousness, or away from serious person crimes. These patterns would not necessarily have been discovered, however, using a unidimensional measure of seriousness or any other unidimensional scale for offenses. Moreover, the frequent tracks of developmental and stable career-lines we have identified would not have been found in a one-dimensional conceptualization of crime.

While the results of our analysis must be viewed as heuristic, they are suggestive of large-scale classifications of offenders based on their behavior -- both in terms of stable and developing career-lines. Future research must address the problem that mutually exclusive classifications may not always be made: some developing careers on one dimension can be classified as developing on another dimension. Similary, the methodological issues raised in the previous section deserve further study. Nevertheless, the results are encouraging for additional explorations of classifications involving multidimensional formulations of crime.

Relative to the traditional typological approach, the career-line approach does not impose the assumptions of selective offense hierarchy, narrow offense windows, or career stability. All the crimes of a career may be considered in the classification of an offender. Relative to the typological approaches' use of "windows" of crimes, the career-line method could be used to classify the entire career -- from onset to termination. Finally, no a priori decision had to be made that all careers are stable. In fact, the frequent occurrence of development over time is one of the more interesting empirical findings of this research.

In addition to these advantages, the approach proposed here may be beneficial in two other areas: etiological theory and correctional treatment. Considerable discussion has centered on the implications of different etiological processes for different types of offenders. The classification scheme described here should allow for meaningful classification into criminal career types and, it is hoped, lead to further research identifying these processes. This is important in light of criticisms of the predominant criminological perspectives -- that although they identify social structural factors correlated with crime, many of these variables cannot be easily manipulated for policy development. Specifically, if we find that other samples have a high percentage of individuals who develop from property offenders to serious persons offenders, we think it reasonable to suggest that future research attempt to identify the factors influencing such career development and perhaps alter its course.

In conclusion, by more precisely delineating the measurement of the dependent variables (illegal behavior) through a multidimensional classification typology, existing explanatory models of delinquent behavior may be refined and more accurate predictions about delinquent behavior may be made. Interventionist resources may then be better allocated in accordance with a behavior-based classification system.

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APPENDIX A

A Comparison of Techniques for Scaling Delinquent Careers

The classification scheme developed in the body of the report rests on the multidimensional scaling results using Variance Centroid Scaling. In principle, <u>any</u> scaling technique could be used to generate the scale values used in the regressions that lead to the classification of career-lines. All that is needed is some numeric value to be given to each of the crime types that are contained in the careers of the sample. However, choice of the scaling technique should not be made haphazardly.

In this appendix (written with E. Noma), we argue that arrest histories represent a special form of data that do not lend themselves to standard multidimensional analyses. An examination of the different theoretical assumptions of Factor Analysis, Multidimensional Scaling, and Variance Centroid Scaling (a form of correspondence analysis) finds marked differences in what is being uncovered by the analysis. These claims are supported by an application of each technique to the arrest histories for 767 chronic juvenile delinquents.

The sample used for the analysis in this appendix is a subset of that used in the body of the report. Only arrest histories for the longitudinal sample (see Chapter 2) are analyzed. The arrest histories for the cross-sectional sample have been deleted. This difference in the number of careers analyzed accounts for the differences in the scaling solutions shown in this appendix and those given in Chapter 3. A slightly revised version of this appendix appeared in the <u>Journal of Quantitative Criminology</u>, Volume 2, pages 329-353.

INTRODUCTION

Attempts to classify offenders are as old as the discipline of modern criminology itself. Lombroso, writing in the latter half of the nineteenth century, classified inmates into categories such as "criminaloids", atavistic, and insane criminals. Whereas Lombroso's categories may seem arcane and his methodology discredited, the search for meaningful classification systems of offenders has persisted throughout the history of criminology. In recent decades a substantial body of literature focuses on issues of classifying offenders in two general ways: according to psychological characteristics, frequently measured using personality inventories (Megargee and Bohn, 1979; Warren, 1971) or according to behavioral characteristics (for example, Gibbons, 1977; Chaiken and Chaiken, 1982; Petersilia and Greenwood, 1977). The latter approach to classifying individuals has been touted as the more promising of these two generic approaches to classification primarily because behavior (e.g., prior offenses) predicts behavior (e.g., subsequent crimes) better than psychological characteristics predict behavior (Monahan et al., 1982) -- and the criminal justice system is more interested in predicting behavior than subsequent psychological states or characteristics.

The attempts to devise an adequate behavioral typology of offenders, however, have encountered a serious problem: there is considerable evidence that the criminal activities of individuals are highly diverse (Hood and Sparks, 1970; Petersilia, 1980; Greenwood, 1982; Gibbons, 1975; Miller et al., 1982), and diverse careers seem to defy straightforward classification. In recognition of the available empirical evidence of diversity, Gibbons, a long-time advocate of criminal typologies, has concluded that the search for a meaningful typology of criminals has largely failed (Gibbons, 1975). We argue that this conclusion may be premature, however, in that the literature on criminal typologies has been limited by the methods used to group offenses. Lacking an adequate method to group offenses, researchers may have prematurely concluded that offender careers are diverse and therefore difficult to classify.

The problem posed by behavioral diversity can be simply stated: judging the diversity of an individual's criminal career depends on both the classification of the illegal acts committed and the coder's tolerance of anomolous crimes. An individual who is convicted of robbery and possession of stolen property, for example, is classified as a specialist only if the typology groups these crimes. Conversely, he or she is judged to have a diverse career if the typology does not group these crimes. For crimes not in the specialty, an individual's degree of specialization depends on what constitutes "acceptable" exceptions. Thus, for example, Chaiken and Chaiken (1982) define "robber-assaulters" as individuals who commit robbery and assault, but they may or may not also commit burglary. Burglary is an acceptable exception.

The difficulty faced by researchers who attempt to classify criminals or delinquents is how to group crimes and thereby know when an offense is an anomaly or not. There are two general approaches to grouping crimes. Apriori typologies are based on a theory or theories developed on a previous group of offenders or as a result of a review of the literature on types of criminals. For example, since some of the literature differentiates burglars from robbers, a typology of criminals might reflect such a differentiation. Classification might proceed as follows: an offender who commits mostly burglaries might be classified a burglar, and an offender who commits mostly robberies a robber. This seemingly straightforward approach has encountered some problems. An examination of the existing typologies reveals little consensus among researchers as to what the types of criminals are. Furthermore, relatively few offenders seem to fit into existing classification schemas. Thus, Hartjen and Gibbons (1969) found that less than 25% of probationers could be classified unambiguously using the typology of Gibbons' Changing The Lawbreaker (plus two categories devised by probation officers).

Whereas some researchers posit theoreticaly-based typologies, others distinguish dimensions of delinquent or criminal behavior aposteriori through commonly used data-reduction techniques such as factor analysis (FA) and multidimensional scaling (MDS) (see, for example, Hindelang and Weis, 1972; Nutch and Bloombaum, 1968; Short et al., 1963; Shohan et al., 1970). Such techniques allow for empirical grouping of crimes (crimes are close to each other or distant according to their co-occurrence in criminal careers). Unfortunately, the aposteriori approach has resulted in different typologies from one study to another -- possibly a reflection of the different samples, or of the different data-reduction techniques that have been used.

The present appendix follows in the aposteriori tradition. We argue that the choice of data-reduction technique is crucial to the grouping of crimes. Two data-reduction techniques, which have been commonly used in crime applications -- factor analysis (FA), multidimensional scaling (MDS) -- and one that has not previously been used -- a version of correspondence analysis called variance centroid scaling (VCS) -- are compared for their ability to develop classifications of crimes. All three techniques assume that crimes may be grouped according to their co-occurrence in criminal histories or careers of individual offenders. That is, certain crimes are similar to other crimes by the fact of their occurring with other crimes in the careers of criminals. However, these techniques differ in the way in which crime groupings are derived. Two general criteria are emphasized: (1) treating crime data as a type of "pick-any" data (Levine, 1979) and; (2) deriving the dimensions of crime from the entire career of the individual rather than on the basis of pair-wise co-occurance of crimes.

CRIME AS 'PICK-ANY' DATA

"Pick-any" data are a common form of social science data where individuals select (pick) preferred objects or actions from an "unconstrained, subject-specific set of alternatives", e.g., what beverages he likes, persons he dislikes, and organizations to which he belongs (Coombs, 1964; Levine, 1979:85). The alternatives from which these objects are selected are presumed to vary from individual to individual, thus making such data difficult to analyze. This is due to a "built-in ambiguity" -- similar subjects may or may not generate similar data choices depending upon the alternatives considered when the choice is made. With "pick-any" data we cannot tell if a nonchosen object was rejected (considered but not chosen) or simply not considered at the moment of choice. This calls into question the strong rejection assumption behind most scaling techniques where a nonchosen alternative is taken as evidence that the alternative has been rejected.

Criminal career history data are analogous to "pick-any" data in two respects. First, when an individual commits an illegal act, it represents a choice from the universe of all possible crimes. However, it would seem desirable to make no assertions about the individual's evaluation of other crimes. Thus, for example, when a juvenile steals an automobile it is doubtful that other possible offenses (breaking and entering, robbery, etc.) were considered and rejected in favor of auto theft. Second, if official crime data are used as the indicator of illegal activities, a "zero" (i.e., no official arrest for the particular crime type) cannot be assumed to be a crime not committed since only a small percentage of illegal acts result in arrest (Elliot and Voss, 1974). Thus, official arrest data represent a form of double "pick-any" data. Of the many crimes that a person may commit, those resulting in an arrest are selected twice as it were -- once at the level of acts committed versus those not committed, <u>and</u> again at the level of acts which result in an arrest (inclusion on a record) versus those that do not.

The treatment of crime data as "pick any" information is to be contrasted with the "strong rejection" assumption in which a "non-chosen" crime (a crime not appearing on an official record) is assumed to be a crime not committed. On the other hand, a crime that does appear on an official record can more safely be assumed to be an act committed. Therefore, the symmetry breaks down between an "accepted" alternative (a crime resulting in arrest) and a "non-accepted" alternative (a crime not appearing on an individual's record). The symmetry of reported-nonreported offenses is implicitly assumed in computing the correlation matrix and is generally assumed in the construction of a true scale (Coombs, 1953). The "pick-any" model is differentiated from more traditional methods in that it utilizes chosen alternatives without reference to non-choices. Variance Centroid Scaling is a pick-any method, whereas FA and MDS, in that they rely on a correlation matrix to measure association or distance between crimes, are not.

THE CAREER AS THE UNIT OF ANALYSIS

The coding decisions faced by users of <u>apriori</u> typologies point to the basic distinction between the classification of <u>crimes</u> and the classification of <u>careers</u>. When we look at only pairs of crimes we find some degree of correspondence between certain types of offenses (e.g., the "robber-assaulters" of Chaiken and Chaiken, 1982). Yet, when we try to classify individuals by the set of crimes in their careers, systematic relationships are much less apparent since most careers seem to be diverse.

The discussion above leads us to a more general assumption about scaling crime data: if the ultimate goal is to classify individuals, then the career should be the starting point for the analysis. Given that offenders have "careers" of crimes, the crimes common to an individual's career can be used to group or distinquish him from offender's with similar/different sets of crimes. In this sense we contend that the whole (the offender's entire history of crimes) gives meaning to the part (each offense of an individual's career.) In general the apriori approach advocated by Gibbons has shared in this conceptualization of the importance of the crimes of the whole career. This is why he and his associates have attempted to classify whole careers according to the general principle that a high proportion of the crimes in a career must be of a similar type in order to classify that individual as a certain type of offender.

Contrast this with a second approach frequently used within the theoretically-based schemes: certain crimes are given priority over other crimes (e.g., serious persons crimes such as robbery and aggravated assault are given priority over property crimes such as burglary and larceny -- see Chaiken and Chaiken, 1982). The offenses with lower priority are "allowable exceptions". If one insists upon the repetition of a single type of offense over the course of a career, few offenders can be classified into any one type since such specialization is rare. If one assumes a hierarchy among the crimes, than classification of more careers is possible, but at the expense of departing from the whole career as the bases of the analysis. The empirical method proposed here -- VCS -- allows the whole career to determine which crimes are similar to other crimes and allows for all the crimes to receive a scale value on the dimensions of crime. Thus, the whole career is given emphasis in the VCS approach.

The entire career may appear to be the unit of analysis of any data-reduction method. Most multidimensional techniques rest on the use of some measure of similarity or proximity between the items being scaled. Often this takes the form of the standard Pearson correlation. The analysis then proceeds by simultaneously considering all pairwise relationships. When applied to crime data, such an approach loses sight of the whole career that initially links the crimes. The VCS approach, on the other hand, depicts the crimes in a career and the people who commit crimes as having a centroid such that crimes are near the centroid of the person who commits them, and the person is near the centroid of the crimes committed. As described in a more technical discussion below, VCS simultaneously tries to find the coordinates of both centroids. Emphasis is shifted away from crimes that are commonly found together in pairs and toward groups of crimes that are commonly found together in careers. Another way of looking at this problem is to argue that each career represents a form of "specialization", and crimes can be grouped to accentuate individual specialization. In this method, the crimes are grouped, but so are the people with similar specialization patterns.

VCS -- SOME TECHNICAL CONSIDERATIONS

Factor analysis and multidimensional scaling are widely available in standard analysis packages. In addition, accessible introductory and advanced treatments of these techniques can be found. (See, for example, Kim and Mueller, 1978a,b and Harman, 1976 on factor analysis; Kruskal and Wish, 1978; Green and Rao, 1972; and Baird and Noma, 1978, on multidimensional scaling.) However, "pick-any" techniques are relatively new to criminologists. We therefore briefly describe the computational approach of VCS.

VCS (Nishisato, 1980) has two properties that are relevant for the "pick-any" analysis of delinquent careers. First, VCS is based upon the treatment of the career as the unit of analysis so each juvenile makes a unit contribution to the solution regardless of the number of crimes he has committed: for example, the contribution to the solution is the same for the person who commits ten crimes as the one who commits two.

Second, VCS assumes a grouping by career 'types'. If one assumes that there is specialization, then it seems reasonable to conceive of each individual's career as representing a "specialized" case. The method assumes this in that each juvenile's delinquent career is characterized by a central tendency. Scale values then are derived to minimize the variance of a given individual's career. Mathematically, if individual k commits crimes i and j, his central tendency becomes the mean of the derived scaled, x_i and x_j:[1]

$$\bar{x}_k = (x_i + x_j)/2 \tag{1}$$

The "pick-any" assumption requires that only the offenses contained in a given career should be considered in its analysis. VCS meets this objective by assigning values to only those crimes in the career; values that minimize the spread of these crimes around a career's central tendency. In symbols, the scaling minimizes V_k where:

$$V_k = \sum_{i \epsilon Ck} (x_i - \bar{x}_k)^2 \tag{2}$$

where C_k is the set of offenses in the career.

An alternative way of conceptualizing this is more convenient for the computation of the VCS dimensions. Consider a matrix W in which each row corresponds to an individual and each column corresponds to a crime. A "one" means that the row individual has committed the column crime only once -- numbers greater than one indicate the frequency with which the column crime was committed. A zero indicates that the row individual did not commit the column offense. Continuing the above example, the k'th row has $W_{ki}=1$, $W_{kj}=1$, and all other $W_{km}=0$. The within-offender variance in offenses, V_k, can be expressed as:

$$V_k = \sum_i W_{ki} (x_i - \bar{x}_k)^2 \qquad (3)$$

where

$$\bar{x}_k = \frac{\sum_i W_{ki} x_i}{\sum_i W_{ki}}$$

In order to simultaneously account for all juveniles and their careers, VCS minimizes the sum of the contribution from each offense history:

$$V = \sum_k V_k = \sum_{ki}\sum W_{ki} (x_i - \bar{x}_k)^2 \qquad (4)$$

To yield interesting and interpretable so tions (i.e., not all on a single point), it is necesssary to standardize the scale values for each dimension. The value to be minimized is the sum of the variances within individuals, so VCS standardizes by the variance around a grand mean career value for all juveniles:

$$G = \sum_{ki}\sum W_{ki} (x_i - \bar{\bar{x}}_k)^2 \qquad (5)$$

where

$$\bar{\bar{x}} = \frac{\sum_{ki}\sum W_{ki} x_i}{\sum_{ki}\sum W_{ki}}$$

There are many possible computational methods to determine scale values to minimize (4) and satisfy constraint (5). Elsewhere (Smith et al., 1983) it has been shown how a computational method similar to that used in factor analysis may be applied to career data to yield scale values. In particular, Variance Centroid Scaling may be described as an eigenvalue-eigenvector procedure that takes the information in a crime matrix and represents it as points in an n-dimensional space.

Note that the minimization of V in equation 4 incorporates only the scale values of the crimes committed by each individual. This makes VCS appropriate for "pick-any" data as crimes not committed are ignored in the computation of the solution. Therefore, the addition of crimes not committed by a juvenile will not change the scaling results. Also, all dimensions (save the trivial first dimension) have a unique zero point. This allows for partitioning of crimes according to their positive or negative scores on a particular dimension, and for a comparison of scale values across dimensions -- a feature useful in classifying careers into "types".

As with all multidimensional techniques, VCS provides a measure indicating the goodness-of-fit for the derived solution. There are as many dimensions as the rank of the matrix being scaled. The first of these dimensions has an eigenvalue equal to 1.0. This corresponds to a trivial solution where all crimes are located at a single point in the space. The remaining dimensions may be ordered by the magnitude of their associated eigenvalues. Dimensions with eigenvalues equal to 1.0 identify totally disjoint sets of crimes with such distinct groups suggesting natural typologies for classifying offenders. The existence of only one dimension with an eigenvalue equal to 1.0 indicates that there is only one totally disjoint crime set: the total set of crimes. Dimensions with eigenvalues near 1.0 suggest that there is a good separation of crimes into widely separated clusters, even though there may be some careers that cross clusters. We note that these eigenvalues can serve to show, empirically, how much offense specialization exists: if specialization is present, it will be indicated by relatively high eigenvalues.

A COMPARISON OF VCS, FA, AND MDS

Understanding the advantages of VCS can be furthered through a conceptual (and relatively non-technical) comparison of VCS with FA and MDS. Our comparison centers around four major points: what is being grouped by the analysis; the preparation of the data prior to the analysis; the criteria used to place crimes relative to each other in the identified space; and the determinancy of the results. (Readers interested in further details of comparison should see Levine, 1979; Noma, 1982; Smith and Noma, 1985). We limit the treatment of MDS to one form (Euclidean distances) for this is commonly used and adequately represents the many variants of MDS (Shepard, 1972).[2]

The desire to create typologies of careers suggests that crimes should be grouped to answer two basic questions: which individuals have similar criminal careers? and which sets of crimes are common to these criminal histories? In other words, two criteria should be simultaneously considered in placing crimes in space: (1) similarities of individual's criminal careers (an N-by-N matrix relating each individual career with those of others) and (2) co-occurrence of crimes across all individuals (crime-by-crime matrix relating offenses). Both FA and MDS process either an individual-by-individual or crime-by-crime correlation matrix. This allows for a multidimensional analysis of either the similarity of individuals or the similarity of crimes, but not both simultaneously. As a result, crimes may not be placed in the individual space identified nor can individuals be placed in the crime space identified: there is no model relating crimes to individuals so it is not possible to place them in a common space. In contrast VCS yields a multidimensional solution in which both the individuals and their crimes may be placed.

On the second general criterion of comparison -- the preparation of the data --for both FA and MDS it is standard practice to use correlations as input for scaling. Thus, information supplied to the method is reduced as evidenced by the fact that many different individual-by-crime matrices can produce the same crime-by-crime correlation matrix (Noma, 1984). In addition, correlation coefficients impose certain assumptions on the analysis, implicitly treating crimes not committed as "rejections" despite the reasons for viewing crime histories as "pick-any" data. VCS avoids these difficulties by directly analyzing an individual-by-crime matrix and modeling only those crimes committed by an individual while treating those offenses not in the career as missing data.

Thirdly, all three methods differ according to how the underlying space is operationalized. FA represents each crime as a linear combination of the underlying factors with the correlation between two crimes mirrored in the angular separation of their vectors in the space. MDS represents each crime as a point in the space with crimes having high intercorrelations placed proximal in the space. For both these methods, the unit of analysis is the individual offense. VCS, using the entire career as the unit of analysis, places individuals near the crimes they commit and crimes near the individuals who commit them. This means that the location of crimes in the multidimensional space is determined directly from individuals' criminal behaviors and not indirectly through the tendency for offenses to co-occur across criminal histories.

The final point of comparison pertains to the determinancy of the dimensions derived. To classify individuals with reference to their location on more than one dimension, one must be able to compare locations across dimensions. This is difficult using MDS, for the zero point on each axis is not fixed. In addition, without further assumptions, Euclidean MDS has no fixed axes. In contrast, both "classical" FA and VCS yield dimensions with fixed zero-points that allow for an unambiguous determination of where a point (crime) falls on a given dimension such that comparisons can be made across dimensions. In "classical" FA, (which has the advantage of fixed zero points) the relative locations of each point on a dimension are subject to the manner in which the solution is rotated: the ordering of the points along a dimension can change after the axes are rotated. Thus, the practice of rotation in FA, while highly desirable for producing "clean" factors, can also produce an indeterminant ordering of crimes in a dimension with the relative locations dependent upon the degree and type of rotation. VCS, like principal components FA, identifies a multidimensional space with fixed axes (as well as a fixed zero point) in which the derived solution is the preferred rotation. Therefore, crimes are unambiguously ordered along each dimension of the VCS solution. It should be pointed out that the determinancy of the dimensions may not seem like a serious problem per se in that practitioners who use factor analysis and multidimensional scaling techniques tend to ignore this issue and are content that the dimensions have face validity or predictive validity relative to a particular research need. We are only arguing that comparisons across dimensions are only possible if the zero-points are fixed.

Table A.1 summarizes the various similarities and differences between FA, MDS, and VCS. All techniques share the ability to isolate clusters of offenses, and all provide some index measuring the fit of the solution. Additionally, all assume ratio level data for standard applications such as that given below.[3]

The major differences center around the unit of analysis, the asymmetry of offenses in the career and the availability of a fixed zero point and a preferred rotation (the determinacy of the solution). We next try to determine if these differences influence the multidimensional representation of criminal behavior.

Table A.1

A Comparision of Factor Analysis, Multidimensional Scaling, and Variance Centroid Scaling

	Method			
	FA		MDS	VCS
Feature	"Classical"	Principal Components		
1. Ability to Isolate Clusters of Offenses	Yes	Yes	Yes	Yes
2. Goodness of Fit Indicator	Eigenvalues/ Communalities	Eigenvalues/ Communalities	Stress Coefficient	Eigenvalues
3. Level of Measurement	Ratio	Ratio	Ratio	Ratio
4. Unit of Analysis	Crime or Individual	Crime or Individual	Crime or Individual	Career
5. Asymmetry between present and absent crimes	No	No	No	Yes
6. Fixed Zero Point On Axes	Yes	Yes	No	Yes
7. Preferred Rotation	No	Yes	No	Yes

THE DATA

The data used in the current analysis consist of juvenile delinquency offense histories, taken from official court records, for 767 juvenile males who were incarcerated between September 1977 and October 1978 in the state of New Jersey. These data were originally collected for a different purpose (an evaluation of juvenile correctional facilities), but were chosen because they were ideal for the analytic purposes here: almost all individuals in this data set are highly delinquent. If systematic patterning (e.g., specialization) in delinquent careers is to be found among any group of juveniles, it is more likely to be observed in the most delinquent juveniles, rather than in a birth cohort sample.

It is important to note, first of all, that for convenience sake we refer at times to delinquent acts as crimes or offenses and the delinquent career as a criminal career. Usually these latter terms are reserved for adults. Secondly, we are aware of the fact that there are numerous problems with the use of official data as a source of information about the crimes that people commit. Official crime data not only underestimate the extent of crime, but also underestimate some types of crime more than others (Blumstein and Cohen, 1979). Elsewhere (Smith and Smith, 1985) this problem is discussed in detail. We argue here that official data should not be dismissed outright, and furthermore, that there are payoffs to be gained from the analysis of official data -- particularly because of the fact that sequences of crimes may be systematically studied with official data.[4]

Together these 767 juveniles were arrested for 9,000 crimes with an average career having 11.73 offenses per juvenile. Their ages at the time of incarceration varied from 13 to 18. About 72.2% of the sample were arrested at least once by age 15. Approximately 58% of the sample is non-white (46% black, 12% Hispanic).

Up to thirty offenses were coded for each individual with thirty-six crime categories used in the coding. These crimes, and their mnemonic labels used in the presentation of the results, are listed in Table A.2. Some rare offenses (defined as 2% or less of the sample having arrests for them) were excluded from the analysis and considered as missing data because (a) these rare crimes are substantively difficult to interpret in the context of crimes more commonly committed by juveniles and (b) VCS is somewhat sensitive to the presence of rare categories of offenses. Of the crimes excluded, two -- homicide and drug sales -- are crimes considered important components of delinquency by many researchers. However, such crimes are infrequent in the criminal careers of this sample, and these crimes were deleted. However, these careers, with their remaining offenses, were retained in the analysis.

The arrest histories of the juveniles were arrayed in a 767 (individuals) by 36 (crimes) matrix -- the W matrix refered to earlier. This matrix was input directly into the VCS program. The columns of the W matrix were also correlated to obtain a crime-by-crime matrix of correlations. This matrix of intercorrelations (the measures of co-occurring crimes) was input into factor analyses (PA2 and principal components in the SPSS package) and a multidimensional scaling (ALSCAL in the SAS package).

FACTOR ANALYSIS RESULTS

The results from the factor analysis of the crime correlation matrix are presented in Table A.3. Little was achieved by way of data reduction in the orthogonal rotation shown in the top half of Table A.3 (oblique rotations were also performed allowing for varying degrees of correlation between factors -- with almost identical results). Only 16 of the 36 crimes had factor loadings above .30 on the first ten factors. Each of the factors is identifiable by

Table A.2
Percentage of the Delinquents with at Least One Arrest
For the 36 Offenses (N=767)
and Communalities of Offenses in a Ten-Factor Classical Factor Analysis

Offense	Label	Percent	Ten Factor Commun-ality
1. Breaking and entering, including attempted	B&E	71.8%	.365
2. Larceny, including attempted	LARC	70.0%	.239
3. Assault and battery, including attempted	A&B	47.5%	.213
4. Violation of probation	PROBAT	37.8%	.082
5. Auto theft, including attempted	AUTO	33.4%	.998
6. Robbery, including attempted	ROB	31.6%	.435
7. Possession of stolen property	PROP	30.4%	.069
8. Disorderly conduct	DISORD	28.3%	.229
9. Malicious damage	MALDAM	26.3%	.096
10. Incorrigible person	INCOR	26.2%	.353
11. Trespassing	TRES	21.0%	.042
12. Runaway	RUN	18.3%	.261
13. Truancy	TRUAN	16.8%	.095
14. Possession of a weapon	WEAP-P	14.9%	.172
15. Possession of marijuana	MARJ-P	12.8%	.092
16. Escape	ESCAP	11.2%	.163
17. Attrocious assault	ATTROC	10.2%	.274
18. Driving without a license	DWOL	8.3%	.178
19. Resisting arrest	RESIS	7.0%	.605
20. Malicious mischief	MALMIS	7.0%	.062
21. Loitering	LOIT	6.5%	.331
22. Possession of burglary tools	BURGT-P	6.4%	.072
23. Possession of synthetic drugs	SYN-P	6.3%	.120
24. Arson, including attempted	ARSON	5.7%	.064
25. Contempt of court	CONTM	4.6%	.077
26. Threaten to kill	TKILL	4.4%	.572
27. Drunken person	DRUNK	4.3%	.115
28. Possession of alcohol	ALCH-P	3.3%	.178
29. Rape, including attempted	RAPE	3.0%	.091
30. Drunk and disorderly	D&D	3.0%	.098
31. Forcible sex	FORSEX	2.8%	.036
32. Conspiracy	CONSPR	2.7%	.129
33. Carrying a concealed weapon	WEAP-C	2.3%	.152
34. Sniffing glue	GLUE	2.3%	.014
35. Sex crimes other than rape and forcible	OTHSEX	2.2%	.176
36. Possession of narcotics	NARC-P	.7%	.045

Table A.3

Results from the Orthogonal Factor Analyses: Loadings for the First Five Factors and First Five Principal Components*

Factors

Offenses	1 Auto Theft	2 Status	3 Threat to Kill	4 Robbery	5 Resist Arrest
TKILL			.744		
ROB				.638	
B&E				-.329	
AUTO	.979				
WEAP-C					.371
DWOL	.350				
CONSPR			.316		
RESIS					.724
INCOR		.522			
RUN		.494			

Principal Components

Offenses	1 Auto Theft	2 Persons	3 Status	4 Resist Arrest	5 Threat to Kill
TKILL		.456			.555
ROB		.426			
B&E		-.362			
AUTO	.891		-.303		
WEAP-P		.357			
DWOL	.380				
RESIS	-.393		.455		
INCOR			.422		
RUNAWAY			.300		

*Offenses with loadings between -.30 and .30 on any factor or principal component are omitted. (See Table A.2 for a complete listing of the variables and their communalities in a ten factor solution.)

only one or two crimes that load highly, relative to all other offenses. Indeed, the vast majority of the loadings not shown in the table are below .10. These first ten factors might be named as follows: 1. Auto Theft, 2. Status Offenses, 3. Threaten Life, 4. Robbery, 5. Resisting Arrest, 6. Disorderly Conduct, 7. Burglary and Larceny, 8. Alcohol Violations, 9. Loitering, and 10. Attrocious Assault.

The factor analysis is unsuccessful in reducing the 36 original crimes to a smaller, more parsimonious set of factors. Also, the communalities from the ten-factor solution (see Table A.2) reveal that only 7 variables of the original 36 had communalities greater than .40, and only three of these were above .50. Thus, considerable variation in each variable remains unique. In addition, the eigenvalues for the factors were above 1.0 for only the first two factors. Thus, much of the variance in each of the crimes is not explained by the first ten factors. With the notable exception of auto theft, there is little variance in the occurrence of a crime that is shared with other offenses. The low communalities are suggestive of the fact that crimes do not form parsimonious underlying dimensions of delinquency.

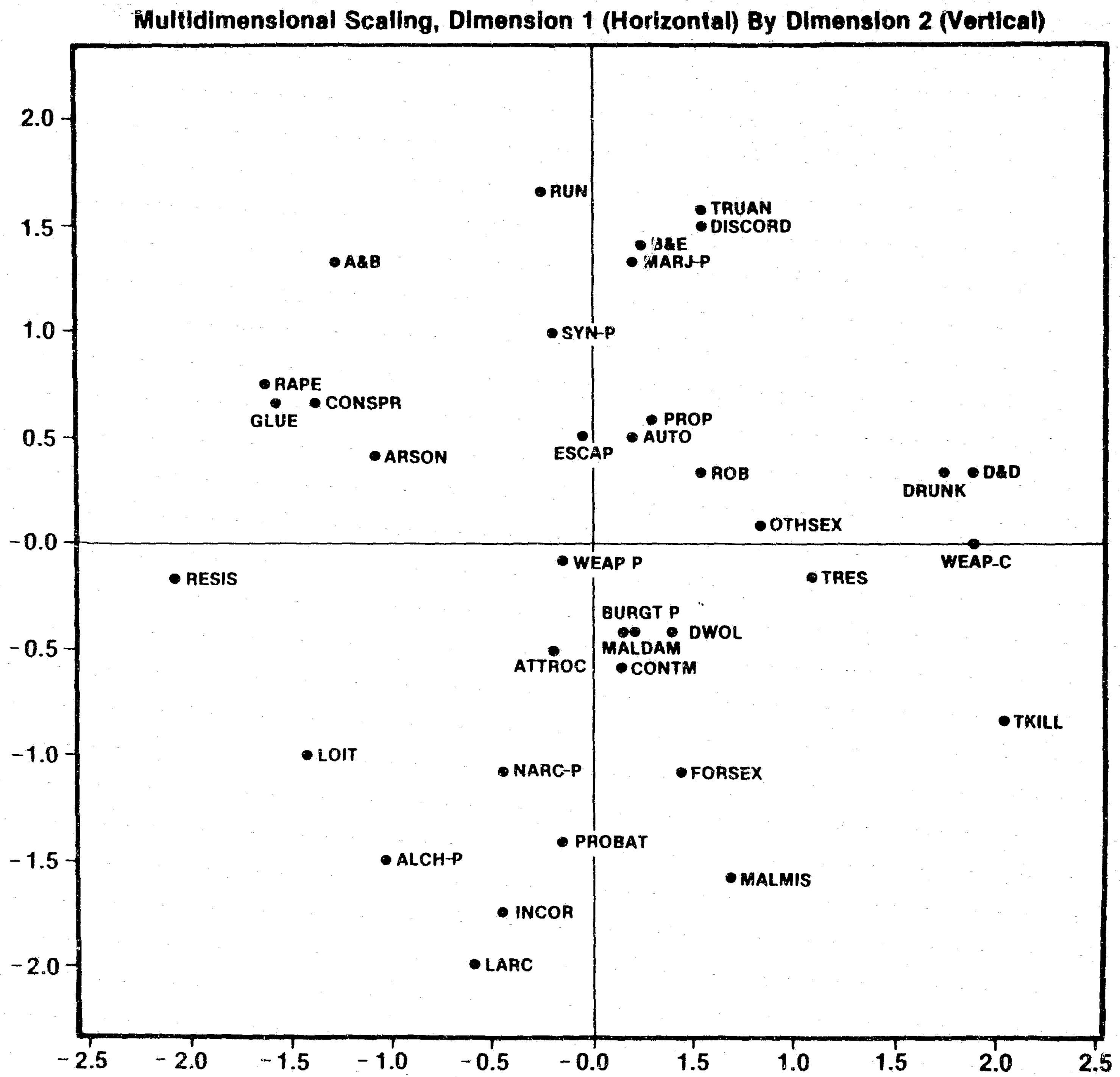
A principal components analysis was also performed on the correlation matrix. The first five principal components (PCs) are presented in the bottom half of Table A.3. The results are quite similar to those of the orthogonally-rotated factor analysis (as would be expected). Again, however, the analysis failed to yield a parsimonious data reduction. The PCs are similar to the factors from the FA, but with a few important differences -- burglary loads negatively on the "serious persons crime" PC (number two) and auto theft loads negatively on the incorrigibility PC (number three). We mention these results because VCS uncovers dimensions somewhat similar to those found on the first three PCs.[5]

MULTIDIMENSIONAL SCALING RESULTS

For the MDS analysis four dimensions of crime were requested, using the default model which produces a Euclidean distance between the points in the space. Plots of MDS dimensions One versus Two, and Three versus Four are shown in Figures A.1 and A.2, respectively.

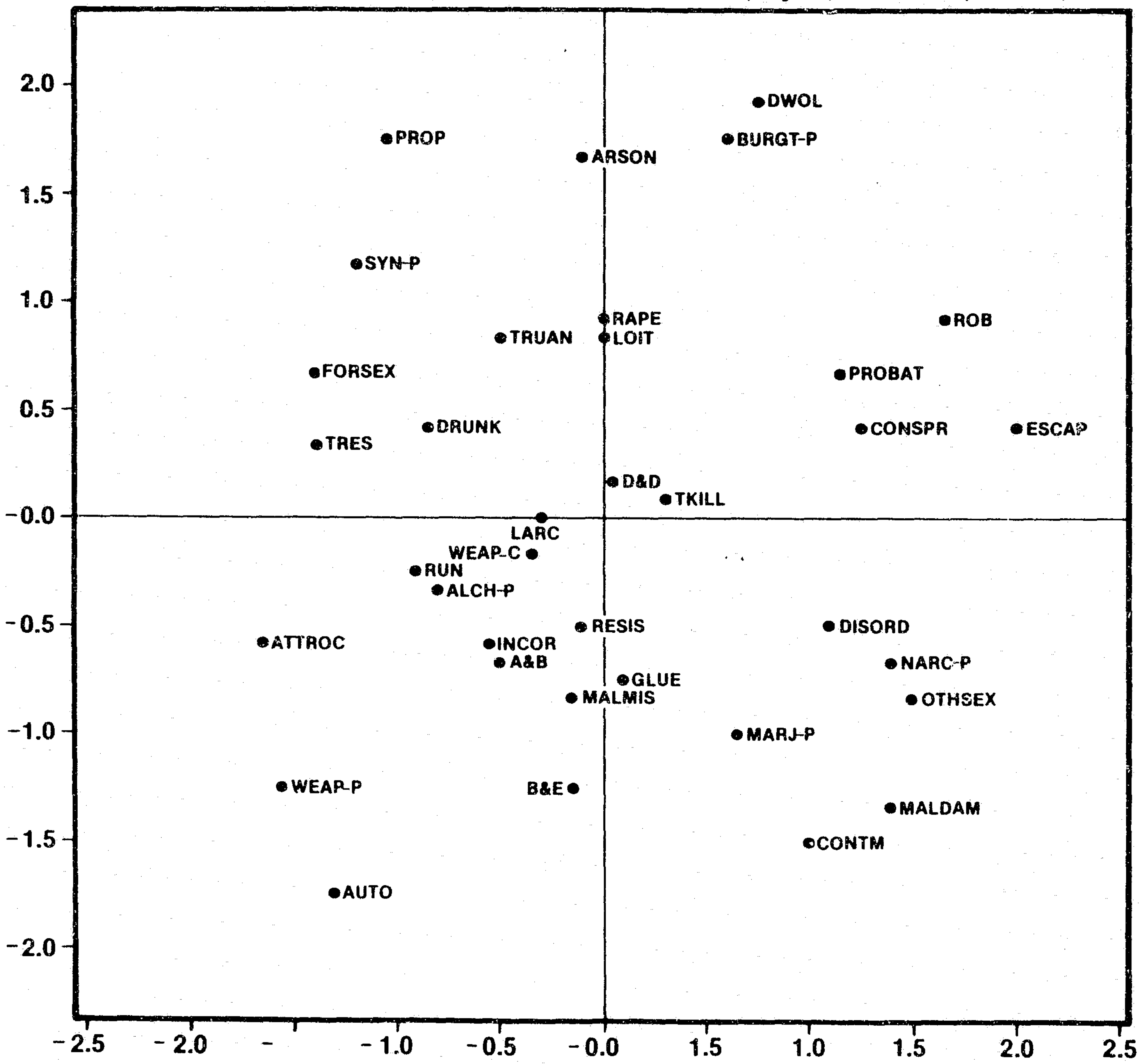
The general configurations in these figures -- circles of offenses -- are indicative of an attempt to place all crimes equidistant, thereby making the identification of meaningful dimensions difficult. Dimension Two, for example, groups running away from home, truancy, burglary, disorderly conduct, assault and battery and marijuana possession at one end of the continuum, and larceny, incorrigibility, alcohol violations, malicious mischief, probation violation, and forced sex on the other end of the same dimension. The remaining three dimensions consist of similar chaotic combinations of offenses. No consistent ordering of offenses seems identifiable. Applications of such dimensions would be difficult to interpret, or even to formulate. The stress coefficient -- which indicates how well the solution reproduces the distances between crimes implied in the correlation matrix -- is .247, evidence of a relatively poor fit. This further suggests that there are not clear groupings of crimes.

These attempts at data reduction have not been very successful. On the one hand, FA gives us clearly interpretable factors, but at the expense of parsimony. On the other hand, the MDS solution yields four uninterpretable dimensions. We contend that these results are due, in part, to the measurement assumptions made by these techniques; assumptions that are not in accord with what we know about reported crimes. In particular, these results arise from the failure to consider crime as "pick-any" data. We now turn to the VCS findings.



Multidimensional Scaling, Dimension 1 (Horizontal) By Dimension 2 (Vertical)
RUN
TRUAN
DISCORD
B&E
MARJ-P
A&B
SYN-P
RAPE
CONSPR
GLUE
PROP
AUTO
ESCAP
ARSON
ROB
D&D
DRUNK
OTHSEX
WEAP-C
WEAP P
RESIS
TRES
BURGT P
DWOL
MALDAM
ATTROC
CONTM
TKILL
LOIT
NARC-P
FORSEX
PROBAT
ALCH-P
MALMIS
INCOR
LARC
2.0
1.5
1.0
0.5
-0.0
-0.5
-1.0
-1.5
-2.0
-2.5
0.0
2.5

Figure A.2
Multidimensional Scaling, Dimension 3 (Horizontal) By Dimension 4 (Vertical)



VARIANCE CENTROID SCALING RESULTS

The results from the VCS are presented in Table A.4. Plots comparable to those of the MDS analysis are shown in Figures A.3 and A.4. Four dimensions (excluding the trivial dimension)[6] are presented as these were the most substantively informative dimensions. Since the analysis gives each crime a positive or negative scale value on each dimension, we choose to identify dimensions according to the crimes with high positive or high negative scale values. (This is analogous to the labeling of factors in a factor analysis.)

Dimension One -- Burglary vs. Serious Persons Crimes. The first non-trivial dimension is characterized by burglary and arson as distinct on the negative end of the scale (see Figure A.3). Forced sex, weapons possession, rape, robbery, attrocious assault, attempt to kill, assault and battery, and carrying a concealed weapon appear on the positive end of the scale. This group seems to be qualitatively different from the next, lower, positively-scaled crimes of incorrigibility, escape from prison, other sex crimes and so forth. This dimension measures property versus serious persons crimes, but property offenses are limited here to burglary and arson (the latter is potentially a persons crime as well).

Dimension Two -- Status Offenses (with Auto Theft) vs. Serious Persons Crimes. The second dimension bears some similarity to the first in that high positively-scaled crimes are serious persons crimes — rape, robbery, attrocious assault, weapons possession, and forced sex. On the negative end of the scale, however, are offenses traditionally considered to be status offenses -- running away from home and driving without a license. It may also be noted that breaking and entering and larceny tend toward the positive end of dimension Two, suggesting that there are two different types of serious persons careers, one inclusive of property offenses and one excluding them.

Table A.4

Variance Centroid Scaling Results:
Scale Values (x1000) and Eigenvalues for First Four Dimensions

Dimension One		Dimension Two		Dimension Three		Dimension Four	
SCALE	ITEM	SCALE	ITEM	SCALE	ITEM	SCALE	ITEM
-107	B&E	-216	RUN	-188	RUN	-699	NARC-P
-097	ARSON	-211	DWOL	-154	LOIT	-247	SYN-P
-032	CONTM	-135	ESCAP	-135	ALCH-P	-211	WEAP-P
-030	MALDAM	-134	AUTO	-125	FORSEX	-172	ATTROC
-028	BURGT-P	-128	DRUNK	-117	SYN-P	-165	MARJ-P
-028	DWOL	-111	NARC-P	-099	INCOR	-119	RUN
-024	ALCH-P	-109	RESIS	-095	DRUNK	-086	ROB
-018	PROP	-107	INCOR	-091	D&D	-048	ESCAP
-018	TRUAN	-097	CONTM	-070	TRUAN	-041	PROBAT
-017	LARC	-066	PROBAT	-055	DISORD	-040	INCOR
-015	AUTO	-065	ALCH-P	-054	MALMIS	-039	B&E
-007	GLUE	-052	OTHSEX	-052	MARJ-P	-033	OTHSEX
-003	LOIT	-038	LOIT	-048	PROBAT	-026	CONSPR
000	SYN-P	-024	TRUAN	-025	OTHSEX	-022	CONTM
003	D&D	-022	WEAP-C	-021	A&B	-017	TKILL
004	RESIS	-020	GLUE	-018	TRES	-017	PROP
015	TRES	-017	CONSPR	-016	MALDAM	-015	BURGT-P
020	NARC-P	-016	MARJ-P	-008	LARC	-008	DRUNK
026	DRUNK	-009	DISORD	-008	B&E	006	LOIT
028	PROBAT	-003	PROP	008	NARC-P	015	MALDAM
032	MALMIS	-001	SYN-P	019	CONTM	023	AUTO
036	CONSPR	003	BURGT-P	024	ESCAP	029	RAPE
043	MARJ-P	010	TRES	029	ARSON	043	LARC
045	RUN	010	TKILL	036	WEAP-C	047	DWOL
046	DISORD	011	MALMIS	055	PROP	053	TRES
047	OTHSEX	025	ARSON	064	ATTROC	062	RESIS
050	ESCAP	032	MALDAM	068	TKILL	071	GLUE
067	INCOR	038	A&B	071	ROB	084	TRUAN
080	WEAP-C	038	LARC	074	RAPE	095	WEAP-C
111	A&B	046	B&E	086	BURGT-P	098	D&D
114	TKILL	050	D&D	092	CONSPIR	103	A&B
152	ATTROC	052	FORSEX	104	GLUE	104	ALCH-P
162	ROB	107	WEAP-P	107	RESIS	116	DISORD
167	RAPE	115	ATTROC	125	WEAP-P	139	ARSON
169	WEAP-P	130	ROB	190	AUTO	179	MALMIS
180	FORSEX	169	RAPE	232	DWOL	217	FORSEX
Eigenvalues							
.2878		.2593		.2282		.2043	

Figure A.3
Plot of VCS Dimension One (Vertical) versus Dimension Two (Horizontal)

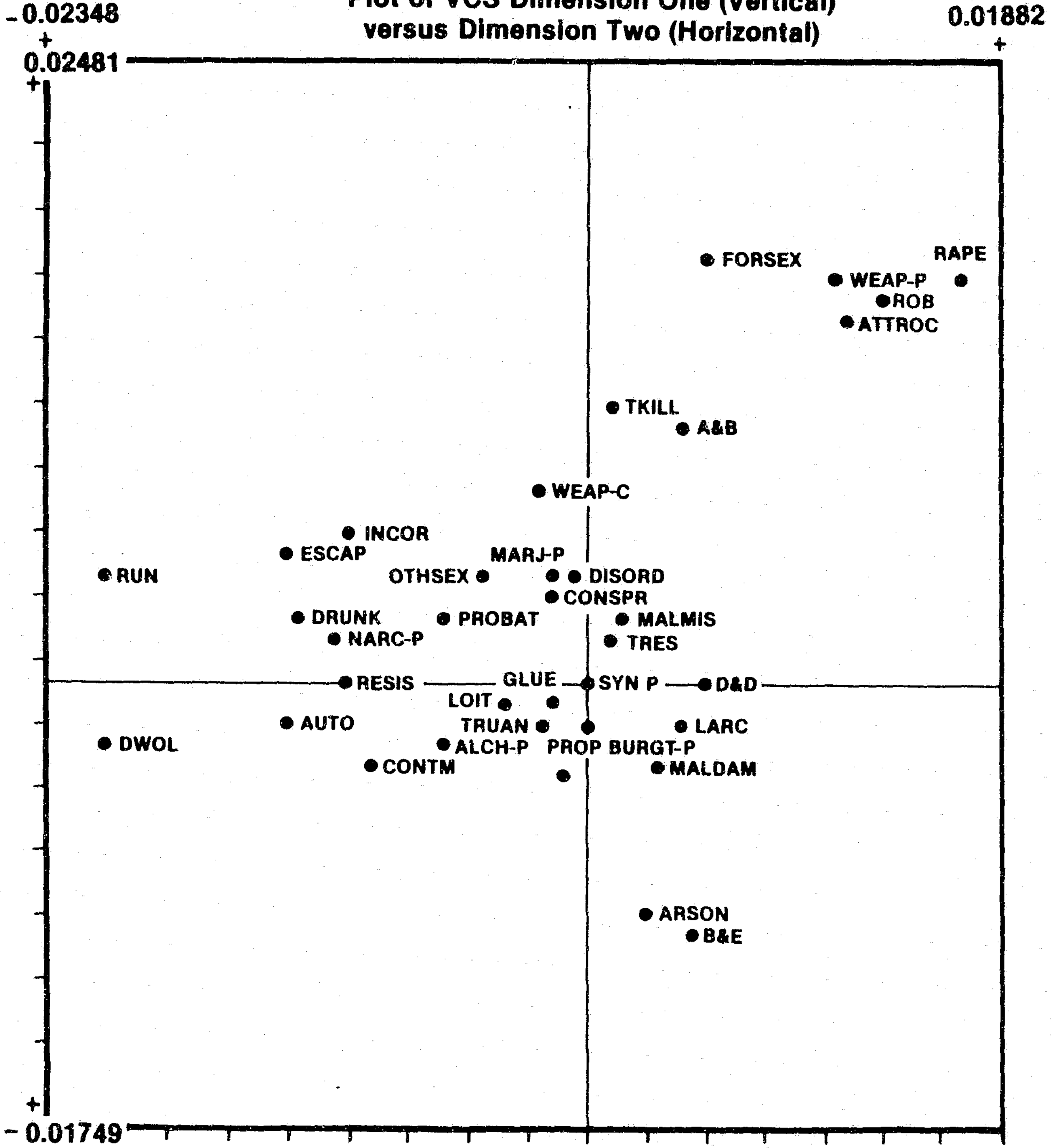
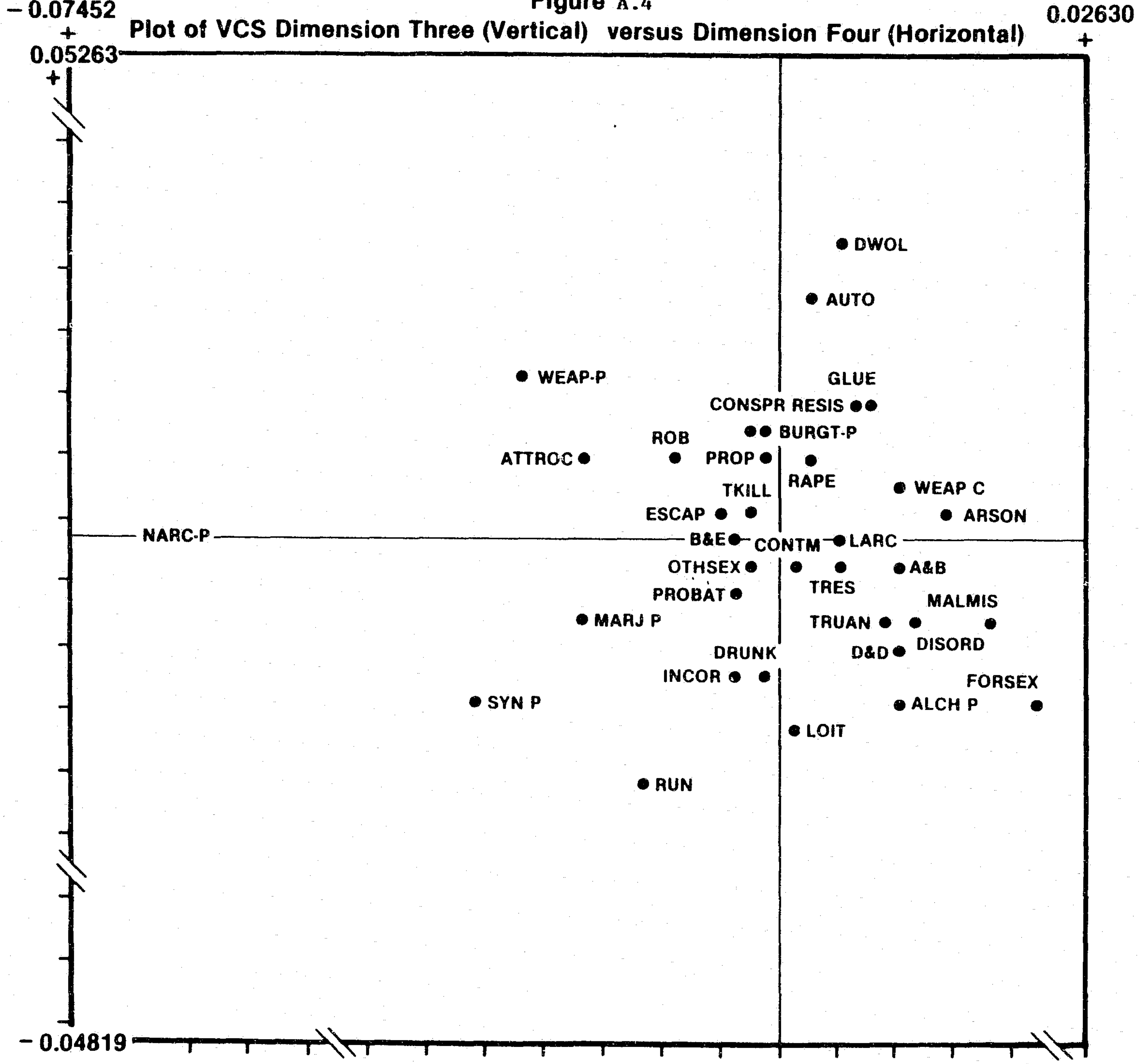


Figure A.4
Plot of VCS Dimension Three (Vertical) versus Dimension Four (Horizontal)



<u>Dimension Three -- Status Offenses vs. Auto Theft</u>. Running away home and loitering characterize the negative pole of dimension Three, while driving without a license and auto theft score highly on the positive end of the dimension. Thus, the third dimension places auto theft on the opposite end of the continuum, away from runaway, while dimension Two places these particular offenses near each other. Again there is the suggestion of two qualitatively different types of careers: status offenses with and without auto theft.

<u>Dimension Four -- Drug Possession and Assault vs. Other Offenses</u>. The fourth dimension clearly differentiates possession of narcotics from all other crimes. (In part this is due to the infrequent occurrence of this offense in the sample. Yet it also suggests that those arrested for narcotics possession do not commit crimes similar to other types of juveniles.) After narcotics possession is a series of drug-related crimes; possession of synthetic drugs, marijuana possession, weapons possession and assault. Thus, the negative pole of this dimension is characterized by a tendency for drug offenses to cluster.

There are several additional interesting aspects of the VCS results that warrant attention in the interpretation of the results. First, certain groups of crimes "surface" more than once at ends of dimensions. We refer to this phenomenon as "pivoting". That is, certain offenses "pivot" off of other crimes as we move from dimension to dimension. Thus, serious persons crimes appear to pivot off burglary in the first dimension and status-auto offenses in the second dimension. This phenomenon is in part a reflection of the algorithm which tries to define dimensions that are orthogonal to each other in the crime space in conjunction with items (crimes) which are not very distinct from each other empirically (see the next section). As a result, the latent structure of crime identified is intrinsically based on related groupings of crimes that distinguished themselves from each other by <u>contrasts</u>

with other groups of crimes. Thus, dimension One consists of serious persons crimes and crimes "opposite" to it (burglary) on this dimension, while the second dimension consists of serious persons crimes and offenses "opposite" to them (status offenses and auto theft).

Second, in addition to the pivoting phenomenon, there is a pattern involving movement across dimensions. This pattern can be seen in the case of auto theft, where there is an internal differentiation occurring between the second and third dimensions. By "internal differentiation" we refer to the case in which a particular crime or subset of crimes is differentiated from the other crimes of its group across dimensions. Thus, we find that auto theft is grouped with status offenses on dimension Two, but is opposite from status offenses on dimension Three.

Third, certain commonly-committed crimes (see Table A.2) do not appear at the extreme ends of the dimensions. Larceny, for example, which is the most frequently found arrest in the sample, is near the center of all four dimensions we have presented. This suggests that it is the most "shared" of crimes in that criminal careers cannot be distinguished by this offense.

Finally, the bottom of Table A.4 shows the eigenvalues for the first four non-trivial dimensions of the VCS solution. None of the eigenvalues approaches 1.0. In fact none is above .300. Given that other "pick-any" analyses in different substantive areas usually result in higher eigenvalues for most dimensions (see Levine, 1979; Noma, 1982; Smith and Noma, 1985), this indicates a relatively poor fit in which distinct subgroups of crimes are not found. This conclusion is similar to that arrived at through either FA or MDS.

THE VALUE OF THE VCS RESULTS

It is difficult to evaluate fully the VCS results relative to FA and MDS. We have compared the three techniques on one sample of delinquents -- other samples should also be studied. Nevertheless, several points can be made about the VCS results that are encouraging as to its ultimate payoff. First, the dimensions seem on the surface to be meaningful. Names can be attached to the dimensions, and the dimensions correspond to some previously conceptualized categories of crimes, e.g., serious persons crimes or status offenses. FA also had interpretable dimensions, but at the expense of parsimony; MDS results were less interpretable. Second, the four dimensions presented in Table A.4 also could be used to classify a large number of delinquent acts that represent a large proportion of juvenile crimes in general. That is, serious persons crimes, burglary, status offenses, auto theft and drug possession crimes are common offenses (though not exhaustive of all crimes), and these categories have been the object of specialized concern. Thus, one finds discussions of status offenders, serious violent offenders, burglars, joy riders, and so forth, are prevalent in the literature (Hamparian et al., 1978; Holzman, 1979; Gibbons, 1965). The FA results could also be used to classify a large number of persons, but only if the existence of a large number of factors is assumed. MDS is less useful -- again because of the difficulty in interpreting its results.

Finally, the fact that reasonable groupings of crimes were found for a small number of dimensions suggests that it should be possible to use the VCS dimensions as a base-line against which to measure an individual's criminal career. That is, the VCS dimensions lend themselves to the study of the dynamic components of criminal careers. The contrasting of status offenses with other crimes, or burglary with serious persons crimes, for example, is consistent with commonly held notions of patterns of development over the course of a criminal career (e.g., from less serious to more serious offenses). The use of VCS dimensions to plot temporal changes in the kinds of crimes in a criminal career would seem more conducive to the study of career development than use of the FA or MDS results found here.

DISCUSSION AND CONCLUSIONS

Criminal careers often contain a diversity of crimes. This diversity creates difficulties when classifying individuals by specialty (Hartjen and Gibbons, 1969) and argues in favor of multidimensional data reduction techniques. Yet, the application of data-reduction techniques must consider the special characteristics of crime data. Crime data, we have argued, may not be optimally suited to some techniques, especially when a correlation matrix of crime is used in the analysis. Computing correlation matrices on data from juvenile delinquent careers for FA and MDS resulted in a non-parsimonious solution in the case of FA and confusing dimensions in the case of MDS. While we have not systematically explored the extent to which our findings may be attributed directly to the different assumptions made by VCS, FA and MDS, our discussion and analysis above suggest that these assumptions make a difference in the results. In particular, the failure to treat arrest histories as "pick any" data and to treat the criminal career holistically can produce dimensions where crimes are seen as more distinct than they should be (the nonparsimonious FA dimensions) or more equally-spaced than they really are (the circular patterns of the MDS solution): exactly how the co-occurance of crimes is studied <u>can</u> influence the results. We have contended that there are methodological and substantive reasons for assuming that the technique of VCS is better suited for uncovering the dimensions of delinquency than are the other two methods.

With some limitations, the use of VCS seems fruitful. A parsimonious and meaningful set of dimensions emerged from the VCS analysis, dimensions that can be used to organize the contents of delinquent careers. If these dimensions provide a meaningful clustering of crimes, individual delinquent careers may be characterized in accordance with these clusterings. Thus the dimensions of crimes may be used to classify individual delinquent careers in a parsimonious, metric-based system rather than in a potentially ad hoc manner.

Over twenty years ago Short et al. observed: "Resolution of theoretical differences, between the past and the present and among currently competing theories requires greater precision, theoretically and empirically, in the delineation of the dependent variables" (1963:41). It is a statement that holds true today. If we wish to test theories that postulate different etiological processes or intervention tactics for types of delinquent behaviors or categories of delinquents, a necessary prerequisite is the ability to classify the delinquent behavior. By giving serious attention to the assumptions of our data analytic techniques, we may be better able to "delineate the dependent variables" which the various competing theories of crime have tried to explain. Failure to consider the nature of delinquent arrest data and the assumptions behind analytic techniques can lead us astray in that endeavor.

Footnotes -- Appendix A

1. The discussion is limited to the one dimensional case with the understanding that the equations generalize to the multidimensional solution.

2. There are many variants of the basic MDS solution. We do not make claims on all of them. Rather, we choose to exemplify the limitations of one MDS solution in which the correlation matrix is the proximity measure and the Euclidean metric is the distance measure.

3. FA and MDS assume that the correlations input to the routines are ratio level data. VCS assumes that the counts of offenses in the W matrix represent ratio level data. Nonmetric factor analysis and multidimensional scaling routines are available, as are nonmetric correspondence analysis solutions. These are not employed in the present analysis.

4. Self-reported data on sequences of crime are difficult to collect with a high degree of accuracy, and we know of no systematic use of self-report data for the purpose of studying crime sequence. Ultimately, it is the sequence of offenses that can lead to the classification of careers as developing, stable, or diverse.

5. Dimensions One and Three in the VCS results discussed below are similar to PCs Two and Three from the Principal Components analysis.

6. Technically, the first dimension of VCS places all offenses at one point with an equivalent scale value for this is the easiest way to minimize the variability of values in the career. We will not consider this as a dimension in the discussion to follow.

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APPENDIX B

A Comparison of the Scaling Solutions Obtained from Self-Reports and Official Arrests

The classification scheme developed in this report uses official arrest histories. However, a long-standing debate centers around the advantages and disadvantages of using self-reported crimes and official arrest records in the study of criminal behavior. In essence, self-reported crimes provide better indicators of the offense rate and types of crimes actually commited by an individual while official records provide more accurate information on the sequence of crimes in the career. In the present study we compare these sources of data on their ability to tell us how the crimes in a careers are organized. Self-reported offenses, self-reported arrests, and official arrest histories for a sample of 148 individuals are scaled using the "pick-any" data reduction technique of Variance Centroid Scaling. The similarities and differences in the scaling solutions are used to suggest how these three sources of data differ in their ability to shed light on the form of criminal careers. This appendix is a revised version of a paper presented at the 37th annual meeting of the American Society of Criminology, San Diego, California, November, 1985.

For many years criminologists have debated the utility of self-reports versus official records for the understanding of criminal behavior. Traditionally the two sources of data have yielded different information: Most often this takes the form of self-reported crime showing little or no differences in criminal behavior across racial groups, social classes and the sexes (e.g., Gould, 1969; Short and Nye, 1957). Conversely, official data (i.e., police arrest records or court records) show much stronger associations between crime and race, sex and social class (e.g., Wolfgang et al., 1972).

As Elliot and Ageton (1980) note, two approaches have dominated in the attempt to account for the observed self-report and official record differences. One is to question the existence of class (and less often racial) differences in official data. The contention is that the relationships found in official records are not as strong as previously thought (Tittle et al., 1978). If this is indeed true, then similar substantive conclusions are reached using either self-report or official data.

The other approach focuses on the methodological problems inherent with self-reported delinquent behavior. A variety of issues are raised dealing with errors in recall, data collection techniques, problematic samples, and poor measures. Thus, for example, it is argued that respondents are not able to accurately remember the offenses committed over long periods of time. (This is especially serious if we wish to study the sequence of offenses over the length of a delinquent or criminal career.) Research into the effects of administration procedures on self-reports has centered on the influence of anonymity (or the lack thereof) and format (questionnaire or interview) on the levels and types of acts reported. While neither anonymity nor format appear to effect the quality of self-reports (Elliot and Ageton, 1980; Krohn et al., 1975), baises due to interviewer effects have been found (Krohn et al., 1975).

The most compelling criticisms of self-reported delinquent behavior concern the domains of crimes tapped by such reports. In the attempt to measure delinquent behavior, self-report measures have focussed frequently on trivial offenses (Gold, 1966). For example, offenses such as running away from home, truancy, and theft of items worth less than $50 occupy a prominant place in most self-report measures. Lacking are many crimes considered serious by the general public and the authorities. This makes a comparison of official records with standard self-report measures an "apples and oranges" affair. Hindelang et al. (1979) demonstrate that these differences in domains are sufficient to account for the discrepancies in results between self-report and official record data.

A standard contention in the literature has been that self-report items measure criminal behavior, while arrest records are more indicative of the actions (and potential biases) of officials. While this argument may indeed explain differences in the correlates of official and self-report data, it masks another important aspect of the problem -- what is being reported: crimes or arrests. Differences between self-reported offenses and self-reported arrests are another source of information to be examined. Some self-report instruments obtain a measure of frequency of involvement in the listed offenses (e.g., Williams and Gold, 1972; Elliot and Ageton, 1980). Others ask for reports of only those offenses resulting in police contact (e.g., Hardt and Peterson-Hardt, 1977). Here too differing domains of behavior are tapped by the self-report data. Yet these differences are seldom studied.

An almost seperate concern in the literature has evolved around the differing levels of offending tapped by self-reports and official records. Given that official records hide a considerable amount of illegal activities

(Elliot and Voss, 1974), that the probability of reporting a crime to the authorities is relatively low (Sourcebook, 1985), and the the probability of arrest given the commission of a crime is also low (Blumstein and Cohen, 1979), more accurate pictures of criminal behavior and offender rates can usually be obtained from well-constructed, inclusive, self-report measures. Exemplary of this approach to the self-report versus official data debate is the work of Greenwood (1982), Chaiken and Chaiken (1982) and Petersilia and Greenwood (1977), where self-reported crimes are used to generate estimates of levels of offending.

Research into self-report and official arrest data thus has centered around three problems: explanations for the differing correlates of the two types of information, methodological aspects of the self-report data, and differences in offender rates evidenced by the two forms of data. The present study attempts to bridge many of these concerns. In essence we investigate the correlates of offenses vis-a-vis each other -- the intercorrelations in the different levels of crime frequency. The question asked departs from those usually found in the self-report versus official data literature, yet one that is more basic to an understanding of the two types of information. Do self-report and official data yield differing <u>structures</u> of crime?

The search for different structures of crime follows in the intellectual tradition of researchers who have tried to identify typologies of crimes based on criminal behavior (Gibbons, 1972). Some researchers have tried to accomplish this by examining offense histories and classifying together all those appearing to be similar according to various criteria. Other researchers have use more sophisticated data reduction techniques such as factor analysis or smallest space analysis to arrive at an underlying structure of crime (Nutch and Bloombaum, 1968; Shannon, 1968; Nye and Short, 1957). Our choice is to pursue the classification of crimes following generally in the latter tradition. Specifically, in the present research we explore the implications of utilizing three sources of crime data using a technique of data reduction probably unfamiliar to most criminologists and yet one that involves assumptions which we argue are more appropriate to the nature of crime data then factor analysis or multidimensional scaling techniques.

A SIMILARITY BETWEEN SELF-REPORT AND OFFICIAL DATA

The self-report versus official record literature has tended to focus on the differences inherent in the two forms of information. Differences in results, the domains of behavior measured and the rates of behavior evidenced by the two types of data are central to the debate. Yet in one crucial respect the two sources of information are similar. Crime data (i.e., frequencies of commission), be they self-report or from official records, are a form of "pick-any" information. "Pick-any" data, and the techniques for analyzing them, are common in other social science disciplines. The basic assumption is that when an individual makes a choice it is often from an unconstrained or unknown set of alternatives (Levine, 1979). For example, when buying cookies at the store, the individual makes a selection, but we do not know which of the many other brands were considered at the time of the selection. Contrast this with the situation where the individual is given a list of alternatives and asked to rank them in order of preference. Here, not only are the available alternatives known to the analyst, but the alternatives are the same for all individuals being studied.

Crime data are analogous to "pick-any" data in several respects. When an individual commits an illegal act, it represents a choice from among the population of all possible illegal acts. Of course, we do not know which other possible acts were considered at the time. For example, when a person commits a robbery, we do not know is the decision was made not to use a weapon (i.e., armed robbery was rejected) anymore than we know if the person considered doing a breaking and entering instead. The fact that the person commits the act (thus expressing a form of "preference") tells us nothing about the rejection of other possible alternatives. Indeed, situational theories of crime (e.g., Briar and Piliavin, 1965) argue strongly that few alternative offenses are considered at the time of the crime. This, coupled with the fact that the careers of criminals display considerable diversity (demonstrating an ability to "choose" many possible acts), suggests that the appearance of a charge on an official record or the admission of an illegal act says nothing about the rejection of other possible offenses. Those acts committed should be analyzed; those acts not, ignored.

The above applies to both data obtained from self-reports and from official records. The analogy between crime and "pick-any" data can be extended, however, in the case of official record data. First, there is the extension of the fact that self-reports and official records tap different levels of criminal behavior. This recognition that official records contain only a small portion of acts committed (Elliot and Voss, 1974) clearly supports the "pick-any" treatment of official data. Those offenses that result in contact with the authorities represent a subset of crimes that are "picked" from among all illegal behaviors. Thus, while the appearance of a crime on official records may be taken as an indication that the act was committed, the absence of a charge on a record cannot be used as an indication that the individual did not engage in the behavior.

The second reason for viewing official data as a form of "pick-any" information comes from another common contention of the self-report versus official record literature. To the extent that arrests are indicative of the behaviors or biases of the authorities, official data contain some 'filtering' of criminal behavior. A selection is made both in terms of the decision whether or not to charge an individual and, if a charge is to be made, the actual crime charged. From an analytic viewpoint, this too means that arrest histories contain data that have been selected from among unknown alternatives: we do not know which offenses were available for charging nor do we know which possible charges were considered at the time.

Thus, while it is reasonable to stress the differences in self-report and official data, it must be done with the recognition that at a more basic level they are similar. Both are forms of "pick-any" data. The generating behavior underlying the two types of data (criminal activity) may be seen as a selection from an unconstrained set of alternatives. This is especially true for official arrest data where the information available for analysis has resulted from several stages of selection, each from a potentially different set of unknown alternatives. The importance of this recognition is that it leads to a particular method of analyzing self-report and official data.

THE MULTIDIMENSIONAL SCALING OF CRIME DATA

Various forms of scaling have been successfully applied to crime data. These techniques have been used to model the form of delinquent or criminal careers (e.g., the Gutmann scaling of Nye and Short, 1957), to effect data reduction (e.g., the factor analysis of Berger and Simon, 1974) and in general to understand the structure of crime and offense patterns (e.g., the Multidimensional Scalogram analysis of Shoham et al., 1970). Further, these techniques have been applied to both self-reported criminal behavior (in addition to Berger and Simon, see Hindelang and Weis, 1972; Arnold, 1965; and Scott, 1959) and official data (in addition to Shoham et al., see Shannon, 1968; Smith et al., 1984). Multidimensional analyses of observer reports of deviant behavior have also been presented (Short et al., 1963; Nutch and Bloombaum, 1968)

The recognition self-report and official data information result from a "pick-any" process requires that an appropriate analytic model be used. "Pick-any" analytic techniques differ from more standard multidimensional analytic techniques in that choices are analyzed (the preferences) without reference to non-choices (the unknown alternatives). While many familiar statistics (e.g., eigenvalues for measuring goodness-of-fit, scale values for ordering items on each dimension, plots of the solution) are generated by "pick-any" methods, how these results are obtained is fundamentally different. Standard multidimensional methods (e.g. factor analysis and multidimensional scaling) treat the absence of a choice as a rejection of that alternative, thus placing non-selected alternatives further from thoses chosen when determining the solution. This runs counter to the basic "pick-any" assumption, where no assertions should be made about the unchosen alternatives. Thus, given the task of analyzing "pick-any" data, only those alternatives selected should be considered in the analysis; non-chosen options should be treated as "missing" data.

"Pick-any" methods come from the general field of correspondance analysis (Levine, 1979; Nishisato, 1980). We employ one form, Variance Centroid Scaling. Space limitations prevent a detailed exposition of the method. Elsewhere, we derive the technique (Smith et al., 1983) and in Appendix A compare it with more standard multidimensional methods. Here we provide only a brief discussion.

Variance Centroid Scaling (VCS) is based on a model that views the criminal career as the factor that organizes the relationships among offenses. To this end, each individual's career (set of offenses) provides the same contribution to the final solution. In addition, the substantive model of offense specialization is taken as the baseline model. That is, VCS scales crimes so as to minimize the variance of scale values in crimes across all individuals' careers. In the course of this minimization, VCS also minimizes the sum of the contribution from each individual. This simultaneously accounts for all persons in the analysis. Finally, the solution is standardized by the variance around a grand mean computed across the scaled values of all individuals. This allows for the comparability of the derived scales across individuals and across the dimensions of the solution.

These aspects of VCS and the general requirements of "pick-any" data can be shown to be met by an eigenvalue-eigenvector procedure based on the number of times each individual reports (is arrested for) the crime types under analysis (Smith et al., 1983). As an eigenvalue-eignvector procedure, VCS is quite similar to factor analysis. Therefore, the results presented below can be interpreted in the same fashion one would interpret factor analysis results. That is, large eigenvalues are indicative of a separation of crimes into distinct clusters of offenses. (In the case of VCS, the largest possible eigenvalue is 1.0. Therefore eigenvalues close to 1.0 are desirable.) Further, VCS organizes crimes in a multidimensional space, resulting in an ordering of offense types along each dimension similar to the factors in a factor analysis.

While the use of multidimensional techniques and the goals of these applications are well established in the literature, they have not to our knowledge been applied with an eye toward differences in self-report and official data. This we do below. However, the generation of hypotheses based on previous findings proves difficult. In part this is due to the lack of cummulative results from the scaling of crime literature: too many different methods have been used on vastly different data sets, precluding expectations for how scalings of self-reported crimes might compare to those of official records. Similarly, the problems of differing domains that has plagued the self-report versus official record studies also appears in the scaling of crimes literature -- differing domains in a multidimensional analysis yield differing clusters as the solution is specific to the system of variables used.

Despite these difficulties, some hypotheses can be offered. We have at our disposal comparable domains of crime types from self-reported offenses, self-reported arrests, and arrests appearing on official records. The simplist expectation for the scaling results of each of these forms of data is that they will be approximately the same. That is, the manner in which crimes are organized by careers (the clusters or factors that emerge) is independent of the way in which the data are collected. This hypothesis rests on the fact that the underlying behavior generating the data, (the activities of delinquents and criminals), is the same for all forms of data. Note too that if this hypothesis is supported, it would imply that while self-reports and official data yield differing <u>levels</u> of offending, the underlying <u>structures</u> would be the same. (Statistically, this would imply different means but similar covariances across the types of data.)

A second hypothesis centers on substantive differences between crimes that result in arrest and crimes that do not. Here the expectation is that self-reported arrests and official arrests will yield similar structures of crime, but this will be different from that found for self-reported offenses. Given that the probability of arrest varies by type of crime (Blumstein and

Cohen, 1979), it is possible that certain kinds of offenses will be more likely to co-occur in the official careers of offenders, thus leading to a distinct structure of crime in arrest data. Similarly, what organizes the crimes resulting in arrest may be more the actions of the authorities than the behaviors of offenders. If this is so, then arrests, either self-reported or recorded, will be structured differently from the actual illegal behavior leading to arrest.

A third hypothesis is that the cognitive organization of crimes reflected in the self-reports is different from the structure evidenced in official data. The contention is that the process of reporting (either crimes leading to an arrest or all offenses committed) produces an organization of crime that is different in some fashion from the process that leads to an official arrest. That is, self-reports yield data structured by the memory of the respondents and limited by selective recall. This filtering makes it more likely for crimes to cluster cleanly.

Finally, to the extent that the justifications for the above hypotheses are valid, there is the possibility that the scaling solutions for each form of data will be different.

THE DATA

The data for the present analysis come from a longitudinal study of a population of incarcerated juveniles (Smith et al., 1982). Originally, all junveniles incarcerated in one of New Jersey's detention facilities between October 1977 and December 1978 were included in the sample. In-person interviews were conducted upon intake into the institution and again upon release. On average, the exit interview occurred six months after the intake interview. A follow-up telephone interview was conducted six months after release (the third wave of data collection). The final wave of data collection was a two-year follow-up phone interview. The results reported here are based on the data collected in the last wave. See Chapter 2 of this report.)

Unfortunately, sample attrition has taken its toll. The first wave contained information from 796 juveniles. At the end of the third wave, 371 individuals had complete data at all three time periods. These were the individuals who were selected for the two year followup. Of the 371 selected, 148 were contacted and agreed to participate in the interview. The present analysis is thus based on a sample size of 148.

Mortality, while nonrandom, does not appear to be overly problematic. A comparision between those remaining in through the <u>third</u> wave sample and those dropping out shows that there are no significant differences on education, parental background, prior arrests, prior incarcertions, the seriousness of the crimes in the career, age of first arrest or total number of arrests (Smith et al., 1982). In short, there appear to be no identifiable differences on major demographic variables or delinquent career variables between those for whom complete data are available and the attrition subgroup. Furthermore, our analysis rests on a comparison of self-reported data to official data <u>within</u> the sample of 148. This comparison is no more limited or generalizable than if data were available for the entire sample.

Table B.1 gives basic descriptive information for both the subsample and the original sample. As can be seen from Table B.1, there are a few differences between the two. Mortality has resulted in a subsample with a higher proportion of white respondents at the expense of a lower percentage of Hispanic respondents. However, there are negligible differences in the demographic background of the sample and subsample as evidenced by the measure

TABLE B.1

Selected Characteristics of the Sample
(Standard Deviations in Parentheses)

		Subsample	Entire Sample
Race	Black	45.3%	45.7%
	White	45.9%	39.1%
	Hispanic	7.4%	11.6%
Educational Attainment at time of First Interview		9.03 years (1.31)	8.95 years (1.47)
Father's Education		10.95 years (2.29)	11.05 years (2.74)
Months Incarcerated Prior to First Interview		2.77 months (7.36)	5.89 months (10.84)
Total Arrests in Career		23.30 arrests (12.04)	23.05 arrests (13.49)
Times Incarcerated in Total Career		2.41 times (1.35)	2.29 times (1.41)
Months Incarcerated in Total Career		17.02 months (12.22)	16.52 months (13.28)

of educational attainment for the respondents and their fathers. The measures of criminal behavior taken from the intake interview and official records (see below) show one major difference. Those respondents in the follow-up telephone interview were less likely to have spent time in a correctional facility before entry into the sample. However, upon exit from the institution the subsample's criminal activity appears similar to that of the entire sample. Average numbers of official arrests are the same, as are numbers of incarcerations and average months incarcerated during the career. Indeed, the subsample appears to have become slightly more criminal than the entire sample after its release.

Self-reported criminal activity was obtained during a telephone interview approximately two years after release from the institution that marked entry into the sample. About half-way through the interview, the respondent was asked "Which of the following have you done since you left [original facility] whether or not you were arrested for them?" A list of nineteen offenses (see Table B.2) was then read to the respondent. If any offense on the list was admitted, the interviewer then probed, asking "How many times?" After the list was completed, the interviewer inquired about other offenses not on the list.

Self-reported arrests were obtained later in the interview. The repondent was told "Now I'm going to ask you some questions about your involvement with the law since you left [original facility]" and then asked "How many times were you arrested and for what?" The same list of offenses covered in the self-reported crimes was then read and an inquiry was made about arrests for any crimes not appearing on the list.

Information on official arrests comes from two sources. While all individuals were legally adults at the time of the follow-up phone interview, some were still juveniles at the time of release from the correctional institution. Arrests as juveniles were obtained from a search of county court records. All charges and subsequent dispositions were coded from these records. Adult arrests were taken from the computerized (and centralized) records maintained by the State of New Jersey. These two sources of official data provide us with the arrest histories for the sample up to early 1984. Furthermore, given the dates accompanying each arrest, it was possible to identify only those arrests occurring during the period bounded by the individual's release from the institution and the date of the follow-up phone interview. Thus, official data was obtained for exactly the same time frame covered by the self-reports.

Table B.2 shows the nineteen offenses covered by the self-reports. (While additional crimes and arrests were identified by the "other" category of self-reports, these proved to be quite infrequent and diverse. We have dropped those offenses from the present analysis.) As can be seen from Table B.2, the domain of offenses avoids many of the problems identified in previous self-report measures. Over half of the offense types are index crimes. A range of seriousness is covered, including crimes considered not serious (e.g., disorderly conduct) and those receiving high scores on most seriousness scales (e.g., rape, homicide, attrocious assault and battery).

Also shown in Table B.2 are the recodes used to make the offenses in the official records comparable to those of the self-reports. The detail contained in official data (e.g., robbery versus attempted robbery) was not possible in the context of a telephone interview. We therefore elected to collapse the detail of the official record data to the common denominator of the broad categories of the self-reports. Often this involved including arrests for attempted crimes with arrests for completed crimes. More liberal

TABLE B.2
Crime Types Used in the Present Analysis

Self-Reported Offenses	Self-Reported Arrests	Official Records
1. Drunk and Disorderly	Drunk and Disorderly	Drunk and Disorderly
2. Drug Possession	Drug Possession	Narcotics Possession
		Synthetic Drug Poss.
		Marijuana Possession
		Poss. to Distribute
		Poss Dangerous Drugs
		Glue Sniffing
		Poss. of Alcohol
		Under Dg. Influence
3. Drug Sales	Drug Sales	Selling Narcotics
		Sell. Synth. Drugs
		Selling Marijuana
4. Armed Robbery	Armed Robbery	Armed Robbery
		Attempted Armed Rob.
5. Robbery	Robbery	Robbery
		Attempted Robbery
6. Breaking and Entering	Breaking and Entering	B&E/Burglary B&E
		Attempted B&E
		BE&Larceny
		Attempted BE&1
7. Larceny	Larceny	Larceny
		Attempted Larceny
8. Disorderly Conduct	Disorderly Conduct	Disorder Person/ Disturbing Peace
9. Arson	Arson	Arson
		Attempted Arson
10. Attrocious Assault and Battery	Attrocious Assault and Battery	Attrocious Assault and Battery
11. Assault and Battery	Assault and Battery	Assault and Battery
		Attempted Assault
12. Vandalism	Vandalism	Malicious Damage
		Vandalism
13. Auto Theft	Auto Theft	Car Theft
		Attempted Car Theft
		Poss. Vehicle w/o Consent
14. Possession of Stolen Property	Possession of Stolen Property	Poss./Receive Stolen Property
15. Weapons Possession	Weapons Possession	Conceal/Poss. Weapon
16. Homicide	Homicide	Homicide
		Attempted Homicide
17. Manslaughter	Manslaughter	Manslaughter
		Attempted Mans.
18. Rape	Rape	Rape
		Attempted Rape
		Forcible Sex
		Att. Forcible Sex
19. Violation of Parole	Violation of Parole	Violation of Parole
		Viol. of Probation

decisions were made involving drug possession, breaking and entering, and auto theft.

One problematic aspect of the self-reported offenses concerns the indicated levels for certain types of crimes. Some respondents could not provide a numerical value for frequency, but rather answered "all the time" or "a lot of the time." This occured most often for weapons possession and violation of parole. That these two crimes should yield such responses is reasonable. The parolee who carries a knife whenever he leaves the house is indeed violating these two statutes on a daily basis. Originally, the responses of "all the time" and "a lot" were coded 98 and 97 respectively. We have arbitraily reset these values to 50. This means that the levels of reporting given below will be underestimates for some crimes. However, this decision appears to have no noticable influence on the results from the VCS analysis. We have scaled the self-reported crimes data using both the 98 and 97 codes and the recoded value of 50 and found similar multidimensional structures. Only the recoded data are presented below.

Within the constraints imposed by the non-numeric responses and the decisions made to make the official and self-reported crimes comparable, we feel a high quality data set has been constructed. The time period of approximately two years provides an adequate period to gauge both official and unofficial illegal activities. Yet, the self-reports avoid the common problem of telescoping over a vague time period. The beginning point for the self-reports is the release from a correctional institution, presumably a salient point in the lives of these individuals. The domain of crimes avoids an overemphasis on trivial offenses. Finally, both the self-reports and the official records cover the exact same time period for each individual.

RESULTS FOR LEVELS OF OFFENDING

In Table B.3 the mean number of self-reported crimes, self-reported arrests and official arrests are reported for each of the 19 types of crimes. In general one finds that (a) individuals report committing many more crimes than they report being arrested for (obviously an expected result); (b) individuals report approximately the same number of arrests as appear in the official records; and (c) where there are large discrepencies between self-reported arrests and official arrests, self-reported arrests are underreported for all offense types except drunk and disorderly, drug sales and manslaughter. Two of these may be overreported relative to official records for the following reasons: the low probability of a drunk and disorderly offense getting into the official record data base used here; reporting manslaughter instead of homicide as a "denial of responsibility" neutralization technique (Matza, 1964).

What is of interest in these results relative to our subsequent analysis is that the levels of self-reported arrests are much closer to the levels of official arrests than to the levels of self-reported offenses. Although this finding is hardly surprising to anyone, it does lead one to expect that there may be some similarity in the underlying structure of crime in the self-reported arrests and official arrests. It would seem likely that, if the level of self-reported arrests is similar to the level of official arrests, that the underlying structure of crimes should be similar also. However, we find that this is unlikely to be the case. For example, the Pearson correlations presented in Table B.3 between each of the modes of crime reporting studied here are generally lower between self-reported arrests and official arrests than between self-reported arrests and self-reported crimes. Only five of the nineteen crime types show a higher correlation between

TABLE B.3

Levels of Reporting, Arrests and Intercorrelations
for 19 Crime Types
(N=148; Standard Deviations in Parentheses)

Crime Type	Self-Reports (a) Offenses	Self-Reports (b) Arrests	Official (c) Arrests		Intercorrelations b)	Intercorrelations c)
Drunk and Disorderly	3.89 (12.07)	.33 (1.33)	.00 (0.00)	a) b)	.272	-- --
Drug Possession	13.58 (24.45)	.33 (.90)	.91 (1.59)	a) b)	.271	.057 .403
Drug Sales	8.78 (20.42)	.11 (.84)	.01 (.08)	a) b)	.182	-.036 -.011
Armed Robbery	.60 (2.28)	.13 (.44)	.18 (.53)	a) b)	.436	.064 .339
Robbery	2.13 (9.60)	.32 (1.09)	.42 (.99)	a) b)	.143	.075 .169
Breaking and Entering	4.90 (13.60)	.96 (4.38)	1.77 (2.79)	a) b)	.092	.228 .145
Larceny	3.11 (10.48)	.53 (2.22)	1.41 (2.10)	a) b)	.210	.305 .294
Disorderly Conduct	2.95 (9.45)	.36 (1.13)	.37 (.76)	a) b)	.308	.078 .039
Arson	.04 (.23)	.02 (.14)	.01 (.08)	a) b)	.603	.346 .573
Attrocious Assault	.89 (3.75)	.26 (1.49)	.39 (.84)	a) b)	.930	.267 .197
Assault and Battery	1.16 (3.79)	.26 (.59)	.63 (1.11)	a) b)	.186	.045 .172
Vandalism	.29 (1.29)	.05 (.43)	.36 (.97)	a) b)	.605	.063 .213
Auto Theft	1.37 (5.13)	.17 (.63)	.43 (.88)	a) b)	.085	.163 .344
Possession of Stolen Property	3.99 (13.23)	.27 (.85)	.49 (.78)	a) b)	.399	-.034 .130
Weapons Possession	7.21 (18.89)	.22 (.63)	.47 (.84)	a) b)	.186	-.079 .232

TABLE B.3
(Continued)

Levels of Reporting, Arrests and Intercorrelations
for 19 Crime Types
(N=148; Standard Deviations in Parentheses)

Crime Type	Self-Reports (a) Offenses	Self-Reports (b) Arrests	Official (c) Arrests		Intercorrelations b)	Intercorrelations c)
Homicide	.04	.03	.03	a)	.720	.659
	(.20)	(.18)	(.20)	b)		.724
Manslaughter	.02	.01	.00	a)	.894	--
	(.18)	(.16)	(0.00)	b)		--
Rape	.04	.01	.09	a)	.628	-.032
	(.37)	(.12)	(.31)	b)		.158
Violation of Parole	1.72	.24	.24	a)	.206	-.040
	(8.97)	(.70)	(.54)	b)		.190

self-reported arrests and official arrests than between self-reported arrests and self-reported acts (drug possession, robbery, auto theft, weapon possession, and homicide). Two crime types (larceny and breaking and entry) show higher correlations between self-reported crimes and official arrests than between the other two possible correlations. Ten correlations of the 19 sets of comparable correlations are highest between self-reported acts and self-reported arrests (the offenses of drunk and disorderly and manslaughter did not occur in the official arrest data so that correlations were not defined). Thus, contrary to our expectation that the similarity of the levels of self-reported arrests and official arrests would result in a higher correlation between these two modes of crime reporting, we found that self-reported arrests and self-reported acts were generally more highly correlated.

This finding may be in part explained by the fact that the self-reported measures were obtained from the same interview, whereas the official record data were taken from police arrest records. The implication of this may be that interviewees who self-report an offense in an interview will have this offense fresh in their memory when subsequently asked about what they were arrested for. Some of the crimes and arrests remembered by those interviewed may not have been included in the police reports, but more likely self-reported crimes and arrests were forgotten or not reported for other reasons (e.g., trying to deceive the interviewer, unwillingness to admit serious criminal acts to the interviewer, etc.)

THE DIMENSIONS OF CRIME BY TYPE OF DATA

Figures B.1 through B.3 show some of the results from the Variance Centroid Scaling (VCS) analyses of the self-reported crimes, self-reported

SELF-REPORTED ARRESTS -- WAVE 4 SUBSAMPLE -- RECODING 98+97
SCALE: 0.0237 UNITS EQUALS +----   DIMENSIONS: HORIZONTAL =   3, VERTICAL =   2

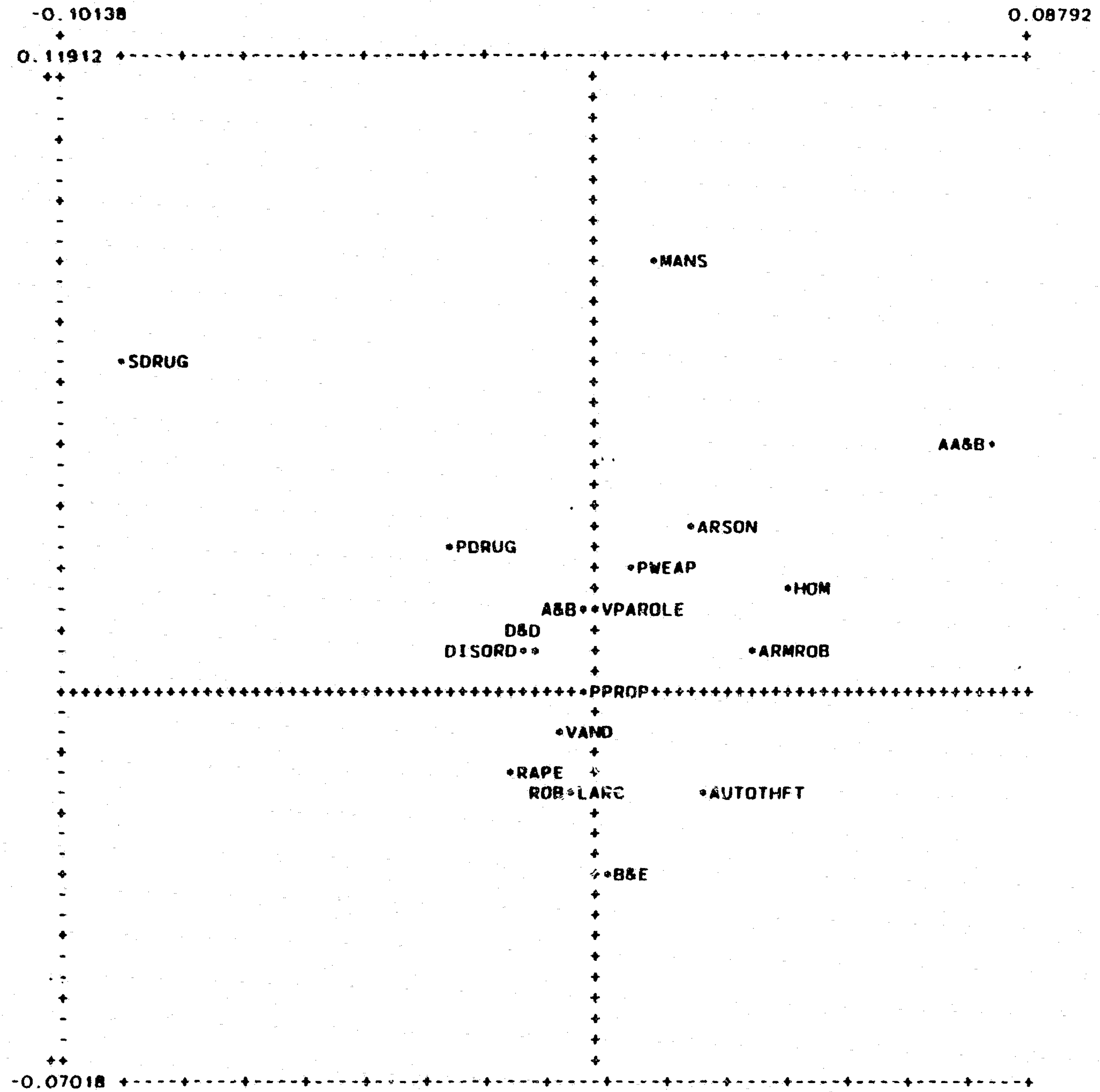

FIGURE B.1

PLOT OF DIMENSIONS TWO AND THREE FOR THE SELF-REPORTED ARREST SOLUTION

PARTIAL ARREST HISTORIES -- WAVE 4 SUBSAMPLE -- ARR RECODES
SCALE: 0.0382 UNITS EQUALS +---- DIMENSIONS: HORIZONTAL = 3. VERTICAL = 2

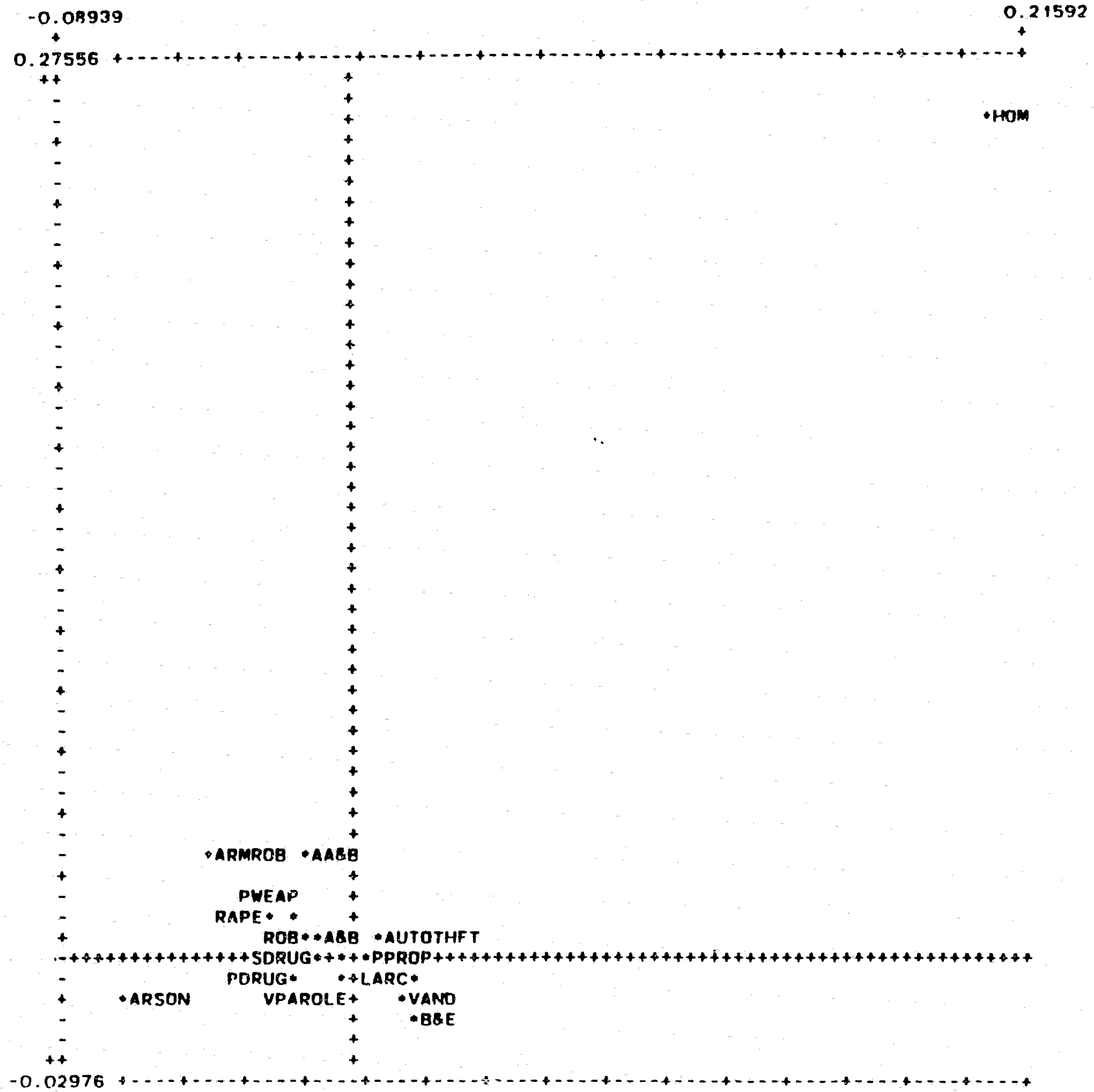

FIGURE B.2

PLOT OF DIMENSIONS TWO AND THREE FOR THE OFFICIAL ARREST SOLUTION

SELF-REPORT CRIMES -- WAVE 4 SUBSAMPLE -- RECODING 98+97
SCALE: 0.0040 UNITS EQUALS +---- DIMENSIONS: HORIZONTAL = 3, VERTICAL = 2

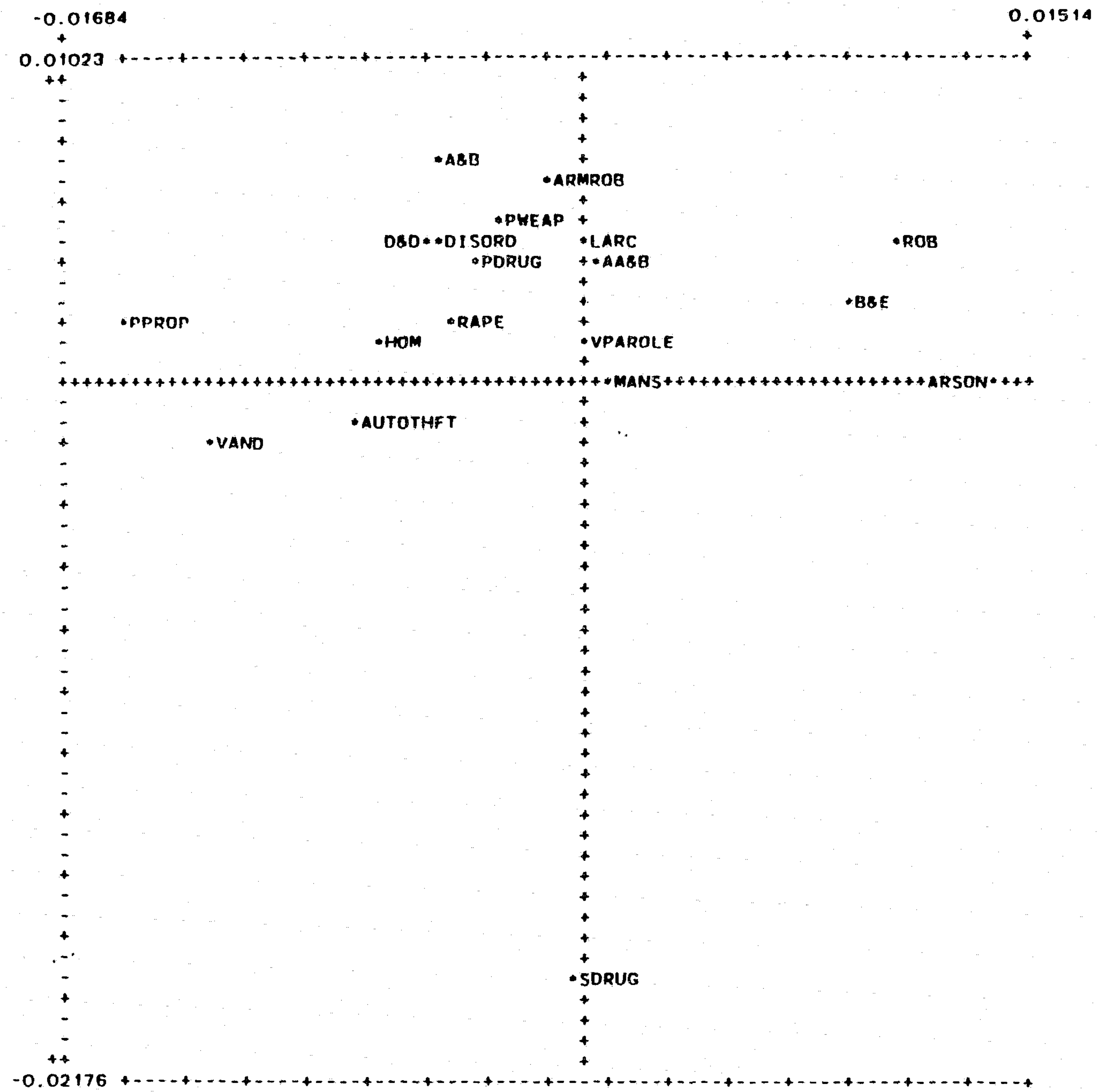

FIGURE B.3

PLOT OF DIMENSIONS TWO AND THREE FOR THE SELF-REPORTED CRIMES SOLUTIONS _arrests_ and _official_ arrests, respectively. In Figure B.1, two dimensions of self-reported crime are shown. There seems to be some correspondence between these results and the classification of offenders (inmates in California, Texas and Michigan) presented by Chaiken and Chaiken (1982:27). The vertical dimension in Figure B.1 shows "sale of drugs" as standing at the negative end of the dimension, quite apart from the other offenses. This may correspond to the "drug dealers" identified by these researchers. The "drug dealers" which they identify do not admit committing other types of crimes such as burglary, robbery, assault, theft, fraud or forgery. Our results (which are of _crimes_, not criminals) also show the uniqueness or separateness of drug sales. At the positive end of the vertical dimension of Figure 1 are robbery-assault crimes, which may correspond to the Chaikens' "robber-assaulters" category. This type of offender may or may not commit burglary and other property crimes, according to the Chaikens. In our analysis crimes such as larceny, drunk and disorderly, and larceny are frequently associated with assault and robbery crimes.

The horizontal dimension in Figure B.1 places burglary, robbery and arson together on the positive end of the dimension, and possession of stolen property, vandalism, and auto theft on the negative end. The latter crimes are similar to the "low-level property offenders" of the Chaikens, whereas the former crimes do not seem to fit neatly into any one of their categories.

By comparison, Figure B.2 shows the dimension for self-reported _arrests_. The vertical dimension has manslaughter, sale of drugs and aggravated assault and battery on the positive end of the dimension and breaking and entry, robbery, larceny, and auto theft at the negative end. On the horizontal dimension, one finds drug sales and possession, rape, and disorderly conduct on one end of the scale and aggravated assault and battery, homicide, armed robbery, arson, auto theft, on the other end of the horizontal dimension. Thus, self-report arrest data yield somewhat different dimensions of crime that do the self-reported crime data. There is also less correspondence with the Chaiken typology. They do not identify a "assault-dealer" group or a "burglar-robber-auto-theft" group, yet these crimes cluster together on the vertical dimension of Figure B.2. The horizontal dimension does appear to be similar to two types of offenders identifyed by the Chaikens — drug dealers and either what they call "mere assaulters", (meaning assault "specialists"), or their "robber-assaulters". It may be that these types of criminals are reflected in the horizontal dimension of crimes shown in Figure B.2. Overall, there seems to be some similarity between the results of the two plots based on a cursory examination of Figures B.1 and B.2 -- serious persons crimes cluster together (robbery and assault) and drug offenses cluster together for self-reported crimes and self-reported arrests.

Figure B.3 shows the results from the official arrest data. Once again the Chaikens' "robber-assaulters" may be identified at one end of a dimension (along with homicide). Burglary, arson, vandalism, and violation of parole are on the other end -- somewhat similar to the results of the self-reported crimes in Figure B.1, except that robbery is associated with the self-reported crimes and vandalism was not. The horizontal dimension also places homicide on the positive end of the scale — this time burglary, larceny, auto theft, possession of stolen property, and vandalism are closest to homicide on the dimension. On the opposite end is arson, armed robbery, rape, drug sale and possession -- crimes again somewhat similar to the Chaikens' "robber-drug dealer" group or what we might call in our case "assaulter-drug dealer-robber-arsonist". Unfortunately, the results for the official arrest histories are not as distinct as for the self-reported crimes or the self-reported arrests. Thus, it is more difficult to see the clustering of crimes. Also, the two dimensions are rather highly correlated (r=.865), making comparisons of their substantive character somewhat redundant.

In addition to examining similarities or differences across the dimensions of the scaling results, one can learn about the structuring of crims from the eigenvalues of the solutions for each of the data sources studied here. Table B.4 shows the eigenvalue (maximum value of 1.0) for eight dimensions for each method of crime reporting. In general the eigenvalues for self-reported arrests are higher that those of the other two, suggesting that the dimensions arrived at using the self-report arrests show relatively clear and separate dimensions of crime -- a result that we generally would consider desirable in attempting to arrive at dimensions of crime. Various factors may explain this result. It could be that an arrest is more readily remembered than a crime. Also, arrests are probably more likely to occur for some of the more serious crimes. The official records may be missing what the interviewee defined as as "arrest", i.e., someone picked up by the police and released without an indictment.

Similarities and differences in the dimension may be difficult to assess by examining Figures B.1, B.2 and B.3. The reader may impose a different structure on the appearance of these crimes that we do. Some of the correlations between the scale values of the offenses for the 19 offense types are presented in Table B.5. This allows for the assessment of how similar the ordering of offenses are across solutions. Here we see that the correlations between the official arrest dimensions and the self-report dimensions of arrests and crimes are generally low. Self-reported arrest Dimension 2 is moderately correlated with self-reported crime Dimension 2 (-.387). (It should be noted that the sign of the correlations are irrelevant to the

TABLE B.4

Eigenvalues for the Centroid Solutions

	Solution		
	Self-Reports		Official
Dimension	Offenses	Arrests	Records
2	.606	.621	.398
3	.476	.594	.363
4	.367	.525	.337
5	.345	.497	.246
6	.293	.452	.217
7	.217	.393	.195
8	.150	.378	.171

substantive interpretation since any dimension may be inverted.) Self-reported crime Dimension 2 is also correlated with self-reported arrest Dimension 3 (.580). Official arrest Dimension 3 is correlated -.338 with self-reported crime Dimension 3 as well as with official arrest Dimension 2 (.865). In summary, then, one might conclude that on the surface there is only partial similarity among the dimensions across the different types of data sources, with official arrest dimensions seemingly dissimilar to the other two types of crime data.

This conclusion of a general lack of correspondence may be premature, however, in that other dimensions (not shown) with lower eigenvalues (see Table B.4) should be examined in order to rule out similarities at these lower levels. An examination of correlations at these lower levels revealed similarities between the fourth dimension of all three data sources (self-reported crimes, self-reported arrests and official arrests) with self-reported arrest Dimension 2 (but less highly with one another -- see bottom half of Table B.6). The nature of these dimensions may allow us to get a glimpse at a single "grand" underlying dimension of crime. By examining the crimes of these dimensions we found that there seems to be an underlying persons crimes dimension in what may be called "amateur" property crimes (robbery, breaking and entry, larceny) on the one end of dimension while the other end consists of "professional" hard-core, persons crimes (rape, armed robbery, and drug sales or possession). This designation may not seem self-evident, but we argue following Holzman (1979) that robbery is not a "sophisticated" crime but that armed robbery involves more "commitment" to robbery (getting a gun, being "serious" enough to use a weapon). Drug sales, and armed robbery (as well as rape) may characterized a "heavy" criminal role-pattern (Gibbons, 1977). Unfortunately, even here, the correlations are

TABLE B.5

Correlations Among Dimensions for Self-Reported (S-R) Crimes, Self-Reported Arrests, and Official Arrests

	S-R Arrests Dimension 2	Official Arrests Dimension 2
S-R Crimes Dimension 2	-.387*	.040
S-R Arrests Dimension 2		.154

	S-R Arrests Dimension 3	Official Arrests Dimension 3
S-R Crimes Dimension 3	.078	-.338
S-R Arrests Dimension 3		.192

	S-R Crimes Dimension 2	S-R Arrest Dimension 2	Official Arrests Dimension 2
S-R Crimes Dimension 3	.012	.060	-.204
S-R Crimes Dimension 3	.580*	-.036	.373
Official Arrest Dimension 3	-.045	-.089	.865*

* Significant at .05 level.

TABLE B.6

Correlations Between Dimensions For Self-Reported Arrests, Self-Reported Crimes, and Official Arrests -- Dimensions Two By Four

	S-R Crimes Dimension 2	S-R Arrests Dimension 2	Official Arrests Dimension 2
S-R Crimes Dimension 4	.134	-.427*	-.040
S-R Arrests Dimension 4	-.008	-.509*	-.079
Official Arrest Dimension 4	.206	-.419*	-.227

	S-R Arrest Dimension 4	Official Arrest Dimension 4
S-R Crimes Dimension 4	-.019	.362
S-R Arrests Dimension 4		-.255

of a scale of magnitude of .42 to .51 with self-reported arrest Dimension 2. Also, detailed examination of these dimensions reveals that there are some substantial differences across the dimensions, accounting for their relatively low correlations. For example, armed robbery appears with robbery on official arrest Dimension 4 and self-reported arrest Dimension 4, while they are quite separate on self-reported crime Dimension 2. This may be a result of arrest data being a reflection of plea bargaining arrangements in which weapon possession was dropped as a charge (and is self-reported as such).

DISCUSSION AND CONCLUSION

The analysis presented here has been disappointing on a number of counts. Our previous research on the comparative advantage of a "pick-any" approach -- such as Variance Centroid Scaling -- over factor analysis or multi-dimensional scaling (Appendix A) had led us to be hopeful as to the usefulness of the "pick-any" technique in allowing us to arrive at a parsimonious, interpretable set of dimensions of crime. Whereas the technique seemed to be quite useful in this regard when analyzing official record data with approximately 36 crime types, it seems to be less useful when one is forced by limitations of the data to focus on only 19 crime types. The foremost consequence of this limitation seems to be that the dimensions arrived at -- whether it be self-reported crimes, self-reported arrests, or official arrests — do not possess a high degree of face validity as to the clustering of crimes, as did our earlier analysis of 36 crime types from official arrests (Smith et al., 1984).

A second disappointment relates to the expectation of patterning in the dimensions across the three data sources studied here. In general each data source results in a somewhat different picture of the underlying structure of crime. Thus, the expectation of a correspondance between data sources in an underlying dimension or dimensions of crime remains unrealized. Some similarities were found, however, among the dimensions. Robbery and assault crimes tended to appear together across the data sources. An examination of the correlation coefficients among lower order dimensions revealed that there may be an underlying "grand" dimension of amateur versus professional crime, but here too a closer inspection of the crimes on the dimensions reveals that a few important crimes have quite different positions on the scales.

Our examination of the plots of crime in Figure B.1, B.2, and B.3 led us to see some clustering of crimes which we identified as somewhat similar to the clustering of crimes in the criminal careers of inmates studied by the Chaikens (1982). The extent to which we "imposed" this structure may be seen perhaps in the relatively low correlations among the dimensions across the three types of data studied here. This leads us to conclusions which generally reflect the disparity among the results obtained from the three data sources.

Relative to the hypotheses which we advanced early in the paper, it would seem that most empirical support goes to the expectation that the results differ according to the data source employed -- although there is some support for there being a clustering of robbery and assault offenses across all three data sources. This is not as exciting a result as one might have hoped, and suggests to us that further study be done to examine the nature of the differences between the varying data sources and the structure of crime.

In that this initial foray into comparative multidimensional analysis on self-reported arrests, self-reported crimes and official arrests is not too discouraging, further analysis would be called for along the following lines. Further "sensitivity" analysis of the scaling results are needed to determine more fuily the extent of the consequences of relatively infrequent behaviors. In other analysis using VCS it was found that the results are often "driven" by these infrequent occurring crimes (Appendix A). Second, applications of VCS on other crime data files -- hopefully ones with more categories of self-reported acts and with a larger sample of individuals -- may be helpful in sorting out the complexities of the results. A third alternative is also available -- using other scaling techniques (factor analysis and multidimensional scaling) not based on the "pick-any" approach. Our preliminary work in that direction, however, suggests to us that such approaches will not be fruitful because of more basic problems such as lack of parsimony of the factor analysis results (too many dimensions or too little data reduction) or lack of any face validity of the derived dimensions.

Another alternative for further analysis is to weight the official arrest data according to the inverse of the likelihood of arrest as estimated from the self-reported crimes. This may yield results that are more comparable to the self-reported crime data in that the frequencies distributions will be more similar. Yet another line of inquiry might focus on the inadequacies of the self-reported data. As discussed above, the self-reported arrests were generally underreported. This suggests that the quality of the self-reported data may be suspect due to memory failure, deception, etc. (Gottfredson and Gottfredson, 1984). In that we can learn more of who is likely to misreport offense behavior, we may be better able to utilize self-report data.

Our initial goal of trying to arrive at dimensions of crime by examining three different data sources may have been overly optimistic as to an underlying similarity. As a result our attempt to compare them may be like trying to compare apples, oranges and pears -- there are some similarities among them, yet what is most obvious are their many differences. As such our results are not unlike those studies which have found that it makes a difference whether one uses self-reported or official arrests as a data source. Whereas those studies look on crime as a dependent variable, potentially explainable by relationships with independent variables, we have focused on the interrelationships among the crimes themselves using the self-report and official data sources and found that it seems to make a difference.

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APPENDIX C

Centroid Scaling Documentation and Source Code

The final product of this research is the Fortran programming necessary to conduct a variance centroid scaling on criminal career data. This appendix, written with E. Noma, provides the minimal documentation needed for data entry into the Centroid program. This documentation is contained on pages C2 to C4. Starting on page C5, the source code for the Centroid program is listed.

The source program is available on an unlabeled, 1600 b.p.i. tape in either uncompiled form (the listing given below) or compiled form for a VAX 11/780 running Fortran 77 under VMS 4.5. Requests for the program tape or inquiries concerning the operation of the program should be sent to:

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CENTROID - correspondence analysis documentation
E. Noma 15-May-1985

***** square on-diagonal matrices (model 2) *****

The following are two sample data files for square on-diagonal matrices (model 2). The first is the full matrix and the second is the same matrix in the form of a sparse matrix:

```
1 TEST RUN OUTPUT FOR CENTROID - MODEL 2
  5
(5F4.0)
  10   5   0   3   2
   9  15   0   2   1
   0   0   0   0   0
   3   4   0  25  20
   4   5   0  18  19
  -1
ONE
TWO
XXX
THREE
FOUR
```

```
1 TEST RUN OUTPUT FOR CENTROID - MODEL 2
  5S
(I3,10(I2,F4.0))
 10
  1 1 10. 2  5. 4  3. 5  2.
  2 1  9. 2 15. 4  2. 5  1.
  4 1  3. 2  4. 4 25. 5 20.
  5 1  4. 2  5. 4 18. 5 19.

ONE
TWO
XXX
THREE
FOUR
```

The format of the full matrix is:

card #1: title
card #2: number of objects (I3 format)
card #3: format of data
card #4:... data
card #9: -1 indicating end of data
card #10:... name of each object (one name per card)

The format of the sparse matrix is:

card #1: title
card #2: number of objects (I3 format) with an S in column 4
card #3: format of data - row number followed by pairs of
numbers indicating column and value in that column

card #4: maximum number of pairs as specified in format in
card #3 (I3 format)
card #5:... the data
card #9: blank card indicating end of data
card #10:... name of each object (one name per card)

Full and sparse matrices produce identical outputs.

CENTROID requires 4 device numbers
- 5 = input of commands (see below)
- 6 = prompts for commands
- 7 = data file
- 8 = output file

After assigning the device numbers, and initiating the program run, you will be prompted on device 6 for three pieces of information, the model (in this case type a 2), the first dimension to plot (usually enter 0 for the default), and the number of dimensions to plot. Responses to these queries are read from device 5.

****** off-diagonal matrix (model 1) *****

The following are two sample data files for off-diagonal rectangular matrices (model 1) for which CENTROID computes scale values for the columns. The first is the full matrix and the second is the same matrix in the form of a sparse matrix:

```
1TEST RUN OUTPUT FOR CENTROID - MODEL 1 WITH ZERO COLUMNS
  5
(A3,5F4.0)
AAA  10   5   0   3   2
BBB   9  15   0   2   1
CCC   3   4   0  25  20
DDD   4   5   0  18  19
     -1
ONE
TWO
XXX
THREE
FOUR
```

```
1TEST RUN OUTPUT FOR CENTROID - MODEL 1 WITH ZERO COLUMNS
  5S
(A3,I3,10(I2,F4.0))
 10
AAA  1 1 10. 2  5. 4  3. 5  2.
BBB  2 1  9. 2 15. 4  2. 5  1.
CCC  3 1  3. 2  4. 4 25. 5 20.
DDD  4 1  4. 2  5. 4 18. 5 19.

ONE
TWO
XXX
THREE
FOUR
```

The format of the full matrix is:

card #1: title
card #2: number of column objects (I3 format)
card #3: format of data - name for row object followed by data
card #4:... data
card #9: -1 indicating end of data
card #10:... name of each column object (one name per card)

The format of the sparse matrix is:

card #1: title
card #2: number of column objects (I3) with an S in column 4
card #3: format of data - row name and number followed by pairs of numbers indicating column and value in that column
card #4: maximum number of pairs as specified in format in card #3 (I3 format)
card #5:... the data
card #9: blank card indicating end of data
card #10:... name of each column object (one name per card)

Full and sparse matrices produce identical outputs.

CENTROID requires 4 device numbers

5 = input of commands (see below)
6 = prompts for commands
7 = data file
8 = output file

After assigning the device numbers, and initiating the program run, you will be prompted on device 6 for three pieces of information, the model (in this case type a 1), the first dimension to plot (usually enter 0 for the default), and the number of dimensions to plot. Responses to these queries are read from device 5.

All routines are written in FORTRAN77 and have been successfully run on a VAX11/780 under the VMS operating system and on a PRIME 400.
There is also a version of these routines that is written in FORTRAN IV.

```
C
C     ***** CENTROID SCALING *****
C
C      WRITTEN BY H. ORLICK , E. NOMA, AND D.R. SMITH
C
C     READS SPARSE OR FULL MATRIX
C     PRODUCES SCALE VALUES FOR EACH ITEM
C     PRINTS SCALE VALUES
C     PLOTS OBJECTS IN 2 DIMENSIONAL SLICES OF THE SPACE
C
C     NOMA,E.THE SIMULTANEOUS SCALING OF CITED AND CITING DOCUMENTS
C       IN A COMMON SPACE, SCIENTOMETRICS, 1982, 4, 205-231.
C
C     NOMA,E. UNTANGLING CITATION NETWORKS, INFORMATION PROCESSING
C       AND MANAGEMENT, 1982, 18, 43-54.
C
      INTEGER*4  NOBJS/0/,NEIGEN,M
      REAL*4     NLINKS
      INTEGER*4  COMIN/5/,COMOUT/6/
      INTEGER*4  INDATA/7/,INNAME/7/,PR/8/,DS/0/,NC/10/
      INTEGER*4  NDIMS,LOWDIM,HIDIM,RDDIM
C
C     MODIFY DIMENSIONS IN FOLLOWING 6 LINES TO SET MAXIMUM NUMBER
C     OF OBJECTS(MAXN) THAT MAY BE SCALED
C
      INTEGER*4  MAXN/450/
      INTEGER*4  TITLE(20)
      REAL*4     ROWVS(450)
      INTEGER*4  NAMES(12,450),LLOC(4,450),NAMEL(450)
C      REAL*8     B(450,450)/202500*0.0/,A(450,450)
      REAL*8     B(450,450),A(450,450),ROWSUM(450)
      REAL*8     DIAG(450), SDIAG(450)
C
      WRITE (COMOUT,1000)
      READ  (COMIN,2000) MODEL
C
      WRITE (COMOUT,1005)
      READ  (COMIN,2000) RDDIM
C
      WRITE (COMOUT,1010)
      READ  (COMIN,2000) NDIMS
C
C  READ LINKAGE MATRIX
C
      IF (MODEL .EQ. 1 .OR. MODEL .EQ. 3) CALL RDMOD1
     1   (INDATA,MAXN,A,B,ROWVS,NOBJS,M,NLINKS,TITLE,PR,INNAME,NAMES)
      IF (MODEL .EQ. 2) CALL RDMOD2
     1   (INDATA,MAXN,A,B,ROWVS,NOBJS,M,NLINKS,TITLE,PR,INNAME,NAMES)
      CALL PMATRX(A,1,NOBJS,1,NOBJS,MAXN,
     1   NC,0,PR,TITLE,' INPUT TO EIGENROUTINE  ',6)
C
C  COMPUTE CENTROID SOLUTION
C
      NEIGEN=NOBJS
```

```
      CALL GETSUM(MAXN,NOBJS,A,B,ROWSUM)
      CALL SCALES(MAXN,NOBJS,NEIGEN,B,DIAG,SDIAG,ROWSUM)
C
C  OUTPUT SCALING RESULTS
C
      CALL DIMRNG(DIAG,NEIGEN,LOWDIM,HIDIM)
      HIDIM = MINO(HIDIM,LOWDIM+NDIMS-1)
      IF (RDDIM .NE. 0) LOWDIM=RDDIM
      IF (RDDIM .NE. 0) HIDIM=NOBJS
C
C     WRITE OUT EIGENVALUES
C
      CALL PEVALS(DIAG,NOBJS,M,NLINKS,NEIGEN,DS,PR,TITLE)
C
      CALL PMATRX
     1(B,1,NOBJS,NEIGEN,1,MAXN,NC,DS,PR,TITLE,' OBJECT SCALES  ',4)

      CALL PLOT(MAXN,B,NOBJS,TITLE,
     1   NEIGEN,DIAG,NC,DS,PR,NAMES,NAMEL,LLOC,LOWDIM,HIDIM)

      IF (MODEL .NE. 2) GOTO 25
        DO 20 K1=LOWDIM,HIDIM
   20     CALL REMAT(K1,B(1,NEIGEN-K1+1),MAXN,NOBJS,NAMES,ROWSUM,PR,A,
     1       TITLE,20)
        GOTO 28
   25 DO 26 K1=LOWDIM,HIDIM
   26   CALL RESTIM(K1,B(1,NEIGEN-K1+1),MAXN,NOBJS,NAMES,ROWSUM,PR,A,
     1     TITLE,20)

   28  DO 30 K1=LOWDIM,HIDIM
   30    CALL LAMBDA(A,B(1,NEIGEN-K1+1),K1,NOBJS,MAXN,TITLE,NAMES,PR)
      STOP
C
 1000 FORMAT ('$ENTER MODEL NUMBER (1,2, OR 3) >')
 1005 FORMAT ('$ENTER FIRST DIMENSION TO BE PRINTED (O FOR DEFAULT) >')
 1010 FORMAT ('$ENTER NUMBER OF DIMENSIONS TO DISPLAY >')
 2000 FORMAT (I10)
      END
      SUBROUTINE RDMOD1
     1   (INDATA,MAXN,A,B,ROWVS,NOBJS,M,NLINKS,TITLE,PR,
     2    INNAME,NAMES)
C
C     *******************************************
C     *     READ MODEL 1 MATRIX AND LABELS      *
C     *******************************************
C
C  PASS TO THIS SUBROUTINE:
C     INDATA,INNAME = DEVICE ADDRESSES OF DATA AND NAME FILES
C     MAXN    = MAX NUMBER OF OBJECTS PERMITTED
C     ROWVS   = TEMPORARY STORAGE OF ROW CONTENTS
C     PR      = DEVICE ADDRESS OF PRINTER(OUTPUT OF ERROR MESSAGES)
C
C  RETURN:
C     A       = SYMMETRIC MATRIX TO BE PASSED TO EIGENROUTINE
```

```
C     NOBJS  = NUMBER OF OBJECTS (NUMBER OF COLUMNS IN INPUT MATRIX)
C     M      = NUMBER OF ROWS IN INPUT MATRIX
C     NLINKS = NUMBER OF LINKS IN INPUT MATRIX
C     TITLE  = TITLE FOR PRINTOUT
C     NAMES  = NAME FOR EACH ITEM
C
      INTEGER*4  MAXN,NOBJS,M,TITLE(20)
      REAL*4     NLINKS
      INTEGER*4  NAMES(12,MAXN)
      REAL*4     ROWVS(MAXN)
      INTEGER*4  INDATA,INNAME,PR
      INTEGER*4  HOLD(450)
      REAL*8     A(MAXN,MAXN),B(MAXN,MAXN)
C
      CALL RD1MAT
     1   (INDATA,MAXN,B,ROWVS,NOBJS,M,NLINKS,TITLE,PR,&30)
      CALL RNAMES(INNAME,NOBJS,NAMES)
      CALL CLEAN(B,NOBJS,NAMES,MAXN,PR,HOLD)
      CALL CONDNS(PR,MAXN,NOBJS,HOLD,B,A,NAMES)
C
      RETURN
   30 STOP
      END
      SUBROUTINE RD1MAT
     1   (INDATA,MAXN,B,ROWVS,NOBJS,M,NLINKS,TITLE,PR,*)
C
C     ******************************
C     *     READ MODEL 1 MATRIX    *
C     ******************************
C
C  PASS TO THIS SUBROUTINE:
C     INDATA = DEVICE ADDRESS OF DATA FILE
C     MAXN   = MAX NUMBER OF OBJECTS PERMITTED
C     ROWVS  = TEMPORARY STORAGE OF ROW CONTENTS
C     PR     = DEVICE ADDRESS OF PRINTER(OUTPUT OF ERROR MESSAGES)
C
C  RETURN:
C     B      = SYMMETRIC MATRIX TO BE CLEANED BEFORE PASSING TO EIGENROUTINE
C     NOBJS  = NUMBER OF OBJECTS (NUMBER OF COLUMNS IN INPUT MATRIX)
C     M      = NUMBER OF ROWS IN INPUT MATRIX
C     NLINKS = NUMBER OF LINKS IN INPUT MATRIX
C
      INTEGER*4  ENDFLG
      INTEGER*4  MAXN,NOBJS,M,TITLE(20)
      REAL*4     NLINKS
      INTEGER*4  ROW
      REAL*4     ROWVS(MAXN)
      INTEGER*4  INDATA,PR
      REAL*8     B(MAXN,MAXN)
      INTEGER    MATTYP
C
      M = 0
      NLINKS = 0
   10 CALL RDROW
```

```
     1   (INDATA,ENDFLG,ROWVS,ROW,MAXN,NOBJS,TITLE,PR,MATTYP,&100)
      IF (ENDFLG .EQ. 1) GOTO 40
         RSUM = 0
         DO 15 K1=1,NOBJS
   15       RSUM = RSUM + ROWVS(K1)
         IF (RSUM .LT. 0) GOTO 40
         IF (RSUM .EQ. 0) GOTO 10
            M = M + 1
            NLINKS = NLINKS + RSUM
            DO 25 K1=1,NOBJS
               IF (ROWVS(K1) .EQ. 0) GOTO 25
                  V2 = ROWVS(K1)/RSUM
                  DO 20 K2=1,K1
   20                B(K1,K2)=B(K1,K2)+ROWVS(K2)*V2
   25          CONTINUE
            GOTO 10
C
   40 DO 50 K1=2,NOBJS
         K1M1=K1-1
         DO 50 K2=1,K1M1
   50       B(K2,K1)=B(K1,K2)
      RETURN
C
  100 RETURN 1
      END
      SUBROUTINE RDMOD2
     1   (INDATA,MAXN,A,B,ROWVS,NOBJS,M,NLINKS,TITLE,PR,INNAME,NAMES)
C
C     ************************************************************
C     *     SETUP MODEL 2 MATRIX AND LABELS FOR EIGENANALYSIS    *
C     ************************************************************
C
C  PASS TO THIS SUBROUTINE:
C     INDATA,INNAME = DEVICE ADDRESSES OF DATA AND NAME FILES
C     MAXN   = MAX NUMBER OF OBJECTS PERMITTED
C     ROWVS  = TEMPORARY STORAGE OF ROW CONTENTS
C     PR     = DEVICE ADDRESS OF PRINTER(OUTPUT OF ERROR MESSAGES)
C
C  RETURN:
C     A      = SYMMETRIC MATRIX TO BE PASSED TO EIGENROUTINE
C     NOBJS  = NUMBER OF OBJECTS (NUMBER OF COLUMNS IN INPUT MATRIX)
C     M      = NUMBER OF ROWS IN INPUT MATRIX
C     NLINKS = NUMBER OF LINKS IN INPUT MATRIX
C     TITLE  = TITLE FOR PRINTOUT
C     NAMES  = NAME FOR EACH ITEM
C
      INTEGER*4  MAXN,NOBJS,M,TITLE(20)
      REAL*4     NLINKS
      INTEGER*4  NAMES(12,MAXN)
      REAL*4     ROWVS(MAXN)
      INTEGER*4  INDATA,INNAME,PR,HOLD(450)
      REAL*8  A(MAXN,MAXN),B(MAXN,MAXN)
C
      CALL RD2MAT
```

```
     1   (INDATA,MAXN,B,ROWVS,NOBJS,NLINKS,TITLE,PR,&30)
      M = NOBJS
      CALL RNAMES(INNAME,NOBJS,NAMES)
      CALL CLEAN(B,NOBJS,NAMES,MAXN,PR,HOLD)
      CALL CONDNS(PR,MAXN,NOBJS,HOLD,B,A,NAMES)
C
      RETURN
   30 STOP
      END
      SUBROUTINE RD2MAT
     1   (INDATA,MAXN,B,ROWVS,NOBJS,NLINKS,TITLE,PR,*)
C
C     *******************************
C     *     READ MODEL 2 MATRIX     *
C     *******************************
C
C  PASS TO THIS SUBROUTINE:
C     INDATA = DEVICE ADDRESS OF DATA FILE
C     MAXN   = MAX NUMBER OF OBJECTS PERMITTED
C     ROWVS  = TEMPORARY STORAGE OF ROW CONTENTS
C     PR     = DEVICE ADDRESS OF PRINTER(OUTPUT OF ERROR MESSAGES)
C
C  RETURN:
C     B      = SYMMETRIC MATRIX TO BE CLEANED BEFORE PASSING TO EIGENROUTINE
C     NOBJS  = NUMBER OF OBJECTS (NUMBER OF COLUMNS IN INPUT MATRIX)
C     NLINKS = NUMBER OF LINKS IN INPUT MATRIX
C
      INTEGER*4  ENDFLG
      INTEGER*4  MAXN,NOBJS,TITLE(20)
      REAL*4     NLINKS
      INTEGER*4  ROW
      REAL*4     ROWVS(MAXN)
      INTEGER*4  INDATA,PR
      REAL*8     B(MAXN,MAXN)
      INTEGER    MATTYP
C
      NLINKS = 0
      KO=1
      ROW=0
   10 CALL RDROW
     1      (INDATA,ENDFLG,ROWVS,ROW,MAXN,NOBJS,TITLE,PR,MATTYP,&30)
      IF (ENDFLG .EQ. 1 .OR. KO .GT. NOBJS) RETURN
         DO 15 K1=1,NOBJS
            NLINKS = NLINKS + ROWVS(K1)
   15       B(ROW,K1)=B(ROW,K1)+ROWVS(K1)
         KO=KO+1
         GOTO 10
C
   30 RETURN 1
      END
      SUBROUTINE RDROW
     1   (INDATA,ENDFLG,ROWVS,ROW,MAXN,NOBJS,TITLE,PR,MATTYP,*)
C
C     ***********************************
```

```
C     *     READ NEXT ROW IN MATRIX     *
C     **********************************
C
C  PASS TO THIS SUBROUTINE:
C     MAXN   = MAX NUMBER OF OBJECTS PERMITTED
C     PR     = DEVICE ADDRESS OF PRINTER(FOR ERROR MESSAGES)
C
C  RETURN:
C     ENDFLG = LAST ROW PROCESSED
C     ROW    = NUMBER OF CURRENT ROW
C     ROWVS  = VECTOR OF VALUES FOR THIS ROW
C
C     FORMAT FOR FULL MATRIX INPUT:
C     CARD#1:TITLE FOR PRINTOUT
C     CARD#2:NUMBER OF OBJECTS IN I3 FORMAT
C     CARD#3:FORMAT FOR INPUT MATRIX - MATRIX IS A RECTANGULAR
C            WITH EACH ROW CORRESPONDING TO A CARD. TO READ IN
C            A 20 COLUMN MATRIX WITH 4 COLUMNS PER CELL ENTRY USE
C            (20F4.0)
C     CARD#4:THE DATA...
C     CARD#X:END THE DATA WITH A BLANK CARD
C     CARD#X+1:ITEM NAMES, ONE NAME PER CARD
C
C     FORMAT FOR SPARSE MATRIX INPUT:
C     CARD#1:TITLE FOR PRINTOUT
C     CARD#2:NUMBER OF OBJECTS IN I3 FORMAT FOLLOWED BY AN 'S' IN COLUMN 4
C     CARD#3:FORMAT FOR INPUT MATRIX - ROW NUMBER FOLLOWED BY
C           COLUMN NUMBER AND VALUE IN THAT CELL OF THE MATRIX
C           E.G. (I2,15(I2,F1.0))
C           ROW NUMBER STARTS THE CARD AND IS IN FIRST TWO COLUMNS
C           COLUMN NUMBER AND VALUE FOR THAT ROW-COLUMN LOCATION
C           FOLLOW IN PAIRS, TWO COLUMNS FOR EACH COLUMN AND ONE
C           COLUMN FOR EACH CELL VALUE, UP TO 15 PAIRS
C     CARD#4:MAXIMUM NUMBER OF PAIRS IN EACH CARD(15 IN THE EXAMPLE)
C          IN I3 FORMAT
C     CARD#5:THE DATA...
C     CARD#X:END THE DATA WITH A BLANK CARD
C     CARD#X+1:ITEM NAMES, ONE NAME PER CARD
C
      INTEGER*4  MAXN,NOBJS,TITLE(20)
      INTEGER*4  ENDFLG,ROW
      REAL*4     ROWVS(MAXN)
      INTEGER*4  FMT(20),NROWS,CRDLEN,SUBNMB
      INTEGER*4  PR
      INTEGER    MATTYP
C
      DO 20 K1=1,MAXN
   20    ROWVS(K1)=0
      IF (ROW .EQ. 0) READ(INDATA,60,END=170) TITLE,NOBJS,MATTYP,FMT
C
      IF (MATTYP .NE. 'S') GOTO 100
C
      IF (ROW .EQ. 0) READ (INDATA,70,END=170) CRDLEN
      CALL RDSROW(INDATA,FMT,ENDFLG,ROWVS,ROW,MAXN,NOBJS,CRDLEN,PR,&200)
```

```
C WRITE (6,'(12H SPARSE READ,2I5)')NOBJS,ROW
      RETURN
C
  100 IF (MATTYP .NE. 'C') GOTO 150
C
      CALL RDCROW(INDATA,FMT,ENDFLG,ROWVS,ROW,MAXN,NOBJS,PR,SUBNMB)
      RETURN
C
  150 CALL RDFROW(INDATA,FMT,ENDFLG,ROWVS,ROW,MAXN,NOBJS,PR)
C WRITE (6,'(10H FULL READ,2I5)')NOBJS,ROW
      RETURN
C
  170 WRITE(PR,180)
  200 RETURN 1
C
   60 FORMAT (20A4/I3,A1/20A4)
   70 FORMAT (I3)
  180 FORMAT (' *** NO DATA READ ***')
      END
      SUBROUTINE RDFROW(INDATA,FMT,ENDFLG,ROWVS,ROW,MAXN,NOBJS,PR)
C
C     ***************************************
C     *      READ NEXT ROW IN FULL MATRIX     *
C     ***************************************
C
C  PASS TO THIS SUBROUTINE:
C     FMT    = FORMAT OF DATA IN FILE
C     MAXN   = MAX NUMBER OF OBJECTS PERMITTED
C     PR     = DEVICE ADDRESS OF PRINTER(FOR ERROR MESSAGES)
C
C  RETURN:
C     ENDFLG = 1 IF END OF FILE OR ERROR
C     ROW    = NUMBER OF CURRENT ROW
C     ROWVS  = VECTOR OF VALUES FOR THIS ROW
C
      INTEGER*4  MAXN,NOBJS
      INTEGER*4  ENDFLG,ROW
      REAL*4     ROWVS(MAXN)
      INTEGER*4  FMT(20),NROWS
      INTEGER*4  PR
C
      DO 20 K1=1,NOBJS
   20    ROWVS(K1)=0
      READ(INDATA,FMT,ERR=50,END=50) (ROWVS(K1),K1=1,NOBJS)
      ROW = ROW + 1
      ENDFLG=0
      RETURN
C
   50 ENDFLG=1
      RETURN
      END
      SUBROUTINE RDSROW
     1   (INDATA,FMT,ENDFLG,ROWVS,ROW,MAXN,NOBJS,CRDLEN,PR,*)
C
```

```
C     ****************************************
C     *     READ NEXT ROW IN SPARSE MATRIX    *
C     ****************************************
C
C  PASS TO THIS SUBROUTINE:
C     FMT     = FORMAT OF DATA IN FILE
C     MAXN    = MAX NUMBER OF OBJECTS PERMITTED
C     PR      = DEVICE ADDRESS OF PRINTER(FOR ERROR MESSAGES)
C
C  RETURN:
C     ENDFLG = 1 IF END OF FILE, ERROR, OR ROW NUMBER=0
C     ROW     = NUMBER OF CURRENT ROW
C     ROWVS   = VECTOR OF VALUES FOR THIS ROW
C
      INTEGER*4   MAXN,NOBJS,TITLE(20)
      INTEGER*4   ENDFLG,ROW
      REAL*4      ROWVS(MAXN),VALS(450)
      INTEGER*4   NROW,COLS(450),FMT(20),CRDLEN
      INTEGER*4   PR
C
      DO 20 K1=1,MAXN
   20    ROWVS(K1)=0
      IF (ROW .GT. 0) GOTO 30
         CALL RDSNXT(INDATA,FMT,CRDLEN,ROW,COLS,VALS,ENDFLG)
         IF (ENDFLG.EQ.1) GOTO 170
         GOTO 40
C
   30 CALL RDSNXT(INDATA,FMT,CRDLEN,ROW,COLS,VALS,ENDFLG)
      IF (ENDFLG .EQ. 1) RETURN
   40 K1 = 0
   50 K1 = K1 + 1
      IF (COLS(K1) .EQ. 0) RETURN
         ROWVS(COLS(K1))=VALS(K1)
         GOTO 50
C
  170 WRITE(PR,180)
  180 FORMAT(' *** NO DATA READ ***')
      RETURN 1
      END
      SUBROUTINE RDSNXT(INDATA,FMT,CRDLEN,ROW,COLS,VALS,ENDFLG)
C
C     *****************************************************************
C     *     READ NEXT CARD OF CELL VALUES IN ROW (SPARSE MATRIX)      *
C     *****************************************************************
C
C  RETURN:
C     ROW     = ROW NUMBER
C     COLS    = LIST OF COLUMN NUMBERS
C     VALS    = LIST OF VALUES FOR COLUMNS IN ROW
C     ENDFLG = 1 IF END OF FILE, ERROR, OR ROW NUMBER=0
C
      INTEGER*4   ENDFLG,ROW,COLS(1),FMT(20),CRDLEN
      REAL*4      VALS(1)
C
```

```
      READ(INDATA,FMT,ERR=20,END=20) ROW,(COLS(K1),VALS(K1),K1=1,CRDLEN)
      IF (ROW.LE.0) GOTO 20
      ENDFLG=0
      RETURN
C
   20 ENDFLG=1
      RETURN
      END
      SUBROUTINE RDCROW
     1   (INDATA,FMT,ENDFLG,ROWVS,ROW,MAXN,NOBJS,PR,SUBNMB)
C
C     ******************************************
C     *     READ NEXT ROW IN CLUSTER MATRIX    *
C     ******************************************
C
C  PASS TO THIS SUBROUTINE:
C     FMT    = FORMAT OF DATA IN FILE
C     MAXN   = MAX NUMBER OF OBJECTS PERMITTED
C     PR     = DEVICE ADDRESS OF PRINTER(FOR ERROR MESSAGES)
C
C  RETURN:
C     ENDFLG = 1 IF END OF FILE OR ERROR
C     ROW    = NUMBER OF CURRENT ROW
C     ROWVS  = VECTOR OF VALUES FOR THIS ROW
C     SUBNMB = SUBJECT NUMBER (ACTUAL ROW IN INPUT MATRIX)
C
      INTEGER*4  MAXN,NOBJS,SUBNMB
      INTEGER*4  ENDFLG,ROW,ALPHAR(450),CLUSID
      REAL*4     ROWVS(MAXN)
      INTEGER*4  FMT(20),NROWS,SPACE/'    '/
      INTEGER*4  PR
C
      DO 20 K1=1,NOBJS
   20    ROWVS(K1)=0
      SUBNMB = 0
      IF (ROW .NE. 0) GOTO 300
  200    IF (SUBNMB .EQ. 1) GOTO 700
         READ (INDATA,FMT,ERR=700,END=700)(ALPHAR(K1),K1=1,NOBJS)
         SUBNMB = SUBNMB + 1
C
  300 CLUSID = 0
      DO 500 K1=1,NOBJS
         IF (ALPHAR(K1) .EQ. SPACE) GOTO 500
            IF (CLUSID .EQ. 0) CLUSID = ALPHAR(K1)
            IF (CLUSID .NE. ALPHAR(K1)) GOTO 500
               ROWVS(K1) = 1
               ALPHAR(K1) = SPACE
  500    CONTINUE
      IF (CLUSID .EQ. 0) GOTO 200
      ENDFLG = 0
      ROW = ROW + 1
      RETURN
C
  700 ENDFLG = 1
```

```
      RETURN
      END
      SUBROUTINE CLEAN (B,NOBJS,NAMES,MAXN,PR,HOLD)
C
C    **************************
C    *   CLEAN INPUT MATRIX   *
C    **************************
C
C     PASS TO THIS SUBROUTINE:
C        PR    = OUTPUT DEVICE NUMBER
C        B     = MATRIX READ
C        NAMES = NAMES READ
C        MAXN  = MAXIMUM NUMBER OF OBJECTS
C        NOJBS = NUMBER OF OBJECTS
C
C     RETURN:
C        HOLD  = OBJECTS TO BE RETAINED
C        NOBJS = NUMBER OF OBJECTS TO BE RETAINED
C
      INTEGER   PR
      INTEGER*4 NOBJS,NAMES(12,NOBJS)
      INTEGER*4 MAXN,SIZE,HOLD(1),TOSS
      REAL*8    B(MAXN,MAXN)
C
      SIZE=NOBJS
      TOSS = 0
C
C       FIND NODES TO BE REMOVED
C
      NOBJS=0
      DO 200 K1=1,SIZE
         DO 60 K2=1,SIZE
   60       IF (K1 .NE. K2 .AND.
     1         (B(K1,K2) .NE. 0.0 .OR. B(K2,K1) .NE. 0.0)) GOTO 100
            IF (TOSS .EQ. 0) WRITE (PR,50)
            TOSS = 1
            WRITE(PR,75) K1,(NAMES(K3,K1),K3=1,12),B(K1,K1)
            GOTO 200
  100    NOBJS=NOBJS+1
         HOLD(NOBJS)=K1
  200    CONTINUE
C
   50 FORMAT('1',6X,'THE FOLLOWING POINTS HAVE ALL OFF-DIAGONAL ZEROS '
     1       'AND HAVE BEEN REMOVED'/
     2       7X,'NUMBER',4X,'NAME',40X,'DIAGONAL VALUE'/)
   75       FORMAT(I10,3X,12A4,F10.3)
      RETURN
      END
      SUBROUTINE CONDNS(PR,MAXN,NOBJS,HOLD,B,A,NAMES)
C
C     ***************************************************************
C     *     DO ACTUAL CONDENSING TO ELIMINATE TRIVIAL SOLUTIONS     *
C     ***************************************************************
C
```

```
C  PASS TO THIS SUBROUTINE:
C      PR     = OUTPUT DEVICE NUMBER
C      MAXN   = MAXIMUM NUMBER OF OBJECTS
C      NOBJS  = NUMBER OF OBJECTS
C      B      = INPUT MATRIX
C      NAMES  = OBJECT NAMES
C      HOLD   = LIST OF OBJECTS TO BE RETAINED
C
C  RETURN:
C      A      = CONDENSED INPUT MATRIX
C      NAMES  = CONDENSED NAME LIST
C
       INTEGER*4  PR,MAXN,NOBJS,HOLD(1)
       INTEGER*4  NAMES(12,1)
       REAL*8     A(MAXN,MAXN),B(MAXN,MAXN)
C
C      DO THE ACTUAL CONDENSING
C
       DO 250 K1=1,NOBJS
           DO 225 K2=1,12
  225         NAMES(K2,K1)=NAMES(K2,HOLD(K1))
           DO 250 K2=1,NOBJS
             A(K1,K2)=B(HOLD(K1),HOLD(K2))
  250        B(K1,K2)=A(K1,K2)
C
       WRITE(PR,400) (K1,(NAMES(K2,K1),K2=1,12),K1=1,NOBJS)
  400  FORMAT('1',10X,'NAMES OF POINTS'/(I10,3X,12A4))
       RETURN
       END
       SUBROUTINE RNAMES(INNAME,NOBJS,NAMES)
C
C      *********************************
C      *      READ NAMES OF OBJECTS    *
C      *********************************
C
C  PASS TO THIS SUBROUTINE:
C      INNAME = DEVICE NUMBER OF FILE CONTAINING NAMES
C      NOBJS  = NUMBER OF OBJECTS
C
C  RETURN:
C      NAMES  = LIST OF NAMES(UP TO 48 CHARACTERS LONG)
C
       INTEGER*4  INNAME,NOBJS,NAMES(12,NOBJS)
C
       READ(INNAME,10) ((NAMES(K1,K2),K1=1,12),K2=1,NOBJS)
   10  FORMAT(12A4)
C
       RETURN
       END
       SUBROUTINE GETSUM(MAXN,NOBJS,A,B,ROWSUM)
C
C      *************************************************
C      *      COMPUTE ROW SUM AND SYMMETRIZE MATRIX     *
C      *************************************************
```

```
C
C  PASS TO THIS SUBROUTINE:
C     A       = MATRIX TO BE NORMALIZED
C     NOBJS   = NUMBER OF OBJECTS TO BE SCALED
C     MAXN    = MAXIMUM NUMBER OF OBJECTS PERMITTED
C
C  RETURN:
C     B       = SYMMETRIC MATRIX
C     ROWSUM = ROW SUMS FOR CENTROID NORMALIZATION
C
      REAL*8      ROWSUM(MAXN)
      REAL*8      A(MAXN,MAXN),B(MAXN,MAXN)
C
      DO 10 K1=1,NOBJS
   10    ROWSUM(K1)=-2*A(K1,K1)
C
      DO 20 K1=1,NOBJS
         DO 20 K2=K1,NOBJS
            B(K1,K2)=A(K1,K2)+A(K2,K1)
            ROWSUM(K1)=ROWSUM(K1)+B(K1,K2)
   20       ROWSUM(K2)=ROWSUM(K2)+B(K1,K2)
C
      RETURN
      END
      SUBROUTINE SCALES(MAXN,NOBJS,NEIGEN,B,DIAG,SDIAG,ROWSUM)
C
C     *************************************
C     *     COMPUTE CENTROID SOLUTION     *
C     *************************************
C
C  PASS TO THIS SUBROUTINE:
C     MAXN    = MAX NUMBER OF OBJECTS PERMITTED
C     NOBJS   = NUMBER OF OBJECTS
C     NEIGEN = NUMBER OF EIGENVECTORS TO COMPUTE
C     B       = INPUT MATRIX - RETURNS EIGENVECTORS
C     ROWSUM = ROW SUM USED FOR COMPUTATIONAL OF CENTROID SOLUTION
C
C  RETURN:
C     DIAG    = VECTORS OF EIGENVALUES
C     SDIAG   = USED BY ROUTINE
C
      INTEGER*4  MAXN,NOBJS,NEIGEN
      REAL*8      B(MAXN,MAXN),DIAG(1),SDIAG(1),ROWSUM(1)
C
      CALL NORMAL(B,ROWSUM,NOBJS,MAXN)
      CALL TRED2(MAXN,NOBJS,B,DIAG,SDIAG,B)
      CALL TQL2(MAXN,NOBJS,DIAG,SDIAG,B,IERR)
      CALL TCOORD(B,ROWSUM,NOBJS,NEIGEN,MAXN)
      RETURN
      END
      SUBROUTINE NORMAL (B,ROWSUM,NOBJS,MAXN)
C
C     ***********************************************************
C     *     NORMALIZE ELEMENTS OF MATRIX FOR EIGENANALYSIS      *
```

```
C     *********************************************************
C
C  PASS TO THIS SUBROUTINE:
C     B       = MATRIX TO BE NORMALIZED
C     NOBJS   = NUMBER OF OBJECTS TO BE SCALED
C     MAXN    = MAXIMUM NUMBER OF OBJECTS PERMITTED
C
C  RETURN:
C     B       = SYMMETRIC MATRIX FOR EIGENANALYSIS
C     ROWSUM = ROW SUMS

      REAL*8      ROWSUM(NOBJS)
      REAL*8      B(MAXN,MAXN)
C
      DO 40 K1=1,NOBJS
         IF(ROWSUM(K1) .EQ. 0)GOTO 40
         DO 30 K2=K1,NOBJS
            IF(ROWSUM(K2) .EQ. 0)GOTO 30
            B(K1,K2)=B(K1,K2)/DSQRT(ROWSUM(K1)*ROWSUM(K2))
            B(K2,K1)=B(K1,K2)
   30       CONTINUE
   40    CONTINUE
C
      RETURN
      END
      SUBROUTINE TCOORD(B,ROWSUM,NOBJS,NEIGEN,MAXN)
C
C     ***************************************************************
C     *      CONVERT EIGENVECTORS BACK TO TRUE COORDINATE SYSTEM     *
C     ***************************************************************
C
C  PASS TO THIS SUBROUTINE:
C     ROWSUM = NUMBER OF LINKS TO ROW OBJECT
C     MAXN    = MAXIMUM NUMBER OF OBJECTS PERMITTED
C     NOBJS   = NUMBER OF OBJECTS
C     NEIGEN = NUMBER OF EIGENVECTORS
C
C  RETURN:
C     B       = MATRIX OF OBJECTS BY SCALE VALUES FOR EACH EIGENVECTOR
C
      REAL*8      ROWSUM(NOBJS)
      REAL*8      B(MAXN,NOBJS),D
C
      DO 20 K1=1,NOBJS
        IF (ROWSUM(K1) .EQ. 0) GOTO 20
         D=1.0D0/DSQRT(ROWSUM(K1))
         DO 10 K2=1,NEIGEN
   10       B(K1,K2)=B(K1,K2) * D
   20  CONTINUE
      RETURN
      END
      SUBROUTINE TRED2(NM,N,A,D,E,Z)
C
      INTEGER I,J,K,L,N,II,NM,JP1
```

```
      REAL*8 A(NM,N),D(N),E(N),Z(NM,N)
      REAL*8 F,G,H,HH,SCALE
      REAL*8 DSQRT,DABS,DSIGN
C
C     THIS SUBROUTINE IS A TRANSLATION OF THE ALGOL PROCEDURE TRED2,
C     NUM. MATH.  11, 181-195(1969) BY MARTIN, REINSCH, AND WILKINSON.
C     HANDBOOK FOR AUTO. COMP.,  VOL.II-LINEAR ALGEBRA, 212-226(1971).
C
C     THIS SUBROUTINE REDUCES A REAL SYMMETRIC MATRIX TO A
C     SYMMETRIC TRIDIAGONAL MATRIX USING AND ACCUMULATING
C     ORTHOGONAL SIMILARITY TRANSFORMATIONS.
C
C     ON INPUT:
C
C        NM MUST BE SET TO THE RCW DIMENSION OF TWO-DIMENSIONAL
C           ARRAY PARAMETERS AS DECLARED IN THE CALLING PROGRAM
C           DIMENSION STATEMENT;
C
C        N  IS THE ORDER OF THE MATRIX;
C
C        A  CONTAINS THE REAL SYMMETRIC INPUT MATRIX.  ONLY THE
C           LOWER TRIANGLE OF THE MATRIX NEED BY SUPPLIED.
C
C     ON OUTPUT:
C
C        D  CONTAINS THE DIAGONAL ELEMENTS OF THE TRIDIAGONAL MATRIX;
C
C        E  CONTAINS THE SUBDIAGONAL ELEMENTS OF THE TRIDIAGONAL
C           MATRIX IN ITS LAST N-1 POSITIONS.  E(1) IS SET TO ZERO;
C
C        Z  CONTAINS THE ORTHOGONAL TRANSFORMATION MATRIX
C           PRODUCED IN THE REDUCTION;
C
C        A AND Z MAY COINCIDE.  IF DISTINCT, A IS UNALTERED.
C
C     QUESTIONS AND COMMENTS SHOULD BE DIRECTED TO B. S. GARBOW,
C     APPLIED MATHEMATICS DIVISION, ARGONNE NATIONAL LABORATORY
C
C     ------------------------------------------------------------------
C
      DO 100 I = 1, N
C
         DO 100 J = 1, I
            Z(I,J) = A(I,J)
  100 CONTINUE
C
      IF (N .EQ. 1) GO TO 320
C     :::::::::: FOR I=N STEP -1 UNTIL 2 DO -- ::::::::::
      DO 300 II = 2, N
         I = N + 2 - II
         L = I - 1
         H = 0.0D0
         SCALE = 0.0D0
         IF (L .LT. 2) GO TO 130
```

```
C     :::::::::: SCALE ROW (ALGOL TOL THEN NOT NEEDED) ::::::::::
      DO 120 K = 1, L
  120 SCALE = SCALE + DABS(Z(I,K))
C
      IF (SCALE .NE. 0.0D0) GO TO 140
  130 E(I) = Z(I,L)
      GO TO 290
C
  140 DO 150 K = 1, L
         Z(I,K) = Z(I,K) / SCALE
         H = H + Z(I,K) * Z(I,K)
  150 CONTINUE
C
      F = Z(I,L)
      G = -DSIGN(DSQRT(H),F)
      E(I) = SCALE * G
      H = H - F * G
      Z(I,L) = F - G
      F = 0.0D0
C
      DO 240 J = 1, L
         Z(J,I) = Z(I,J) / H
         G = 0.0D0
C :::::::::: FORM ELEMENT OF A*U ::::::::::
         DO 180 K = 1, J
  180    G = G + Z(J,K) * Z(I,K)
C
         JP1 = J + 1
         IF (L .LT. JP1) GO TO 220
C
         DO 200 K = JP1, L
  200    G = G + Z(K,J) * Z(I,K)
C  :::::::::: FORM ELEMENT OF P ::::::::::
  220    E(J) = G / H
         F = F + E(J) * Z(I,J)
  240 CONTINUE
C
      HH = F / (H + H)
C  :::::::::: FORM REDUCED A ::::::::::
      DO 260 J = 1, L
         F = Z(I,J)
         G = E(J) - HH * F
         E(J) = G
C
         DO 260 K = 1, J
            Z(J,K) = Z(J,K) - F * E(K) - G * Z(I,K)
  260 CONTINUE
C
  290 D(I) = H
  300 CONTINUE
C
  320 D(1) = 0.0D0
      E(1) = 0.0D0
C     :::::::::: ACCUMULATION OF TRANSFORMATION MATRICES ::::::::::
```

```
      DO 500 I = 1, N
         L = I - 1
         IF (D(I) .EQ. 0.0D0) GO TO 380
C
         DO 360 J = 1, L
         G = 0.0D0
C
         DO 340 K = 1, L
  340    G = G + Z(I,K) * Z(K,J)
C
         DO 360 K = 1, L
            Z(K,J) = Z(K,J) - G * Z(K,I)
  360    CONTINUE
C
  380 D(I) = Z(I,I)
      Z(I,I) = 1.0D0
      IF (L .LT. 1) GO TO 500
C
      DO 400 J = 1, L
         Z(I,J) = 0.0D0
         Z(J,I) = 0.0D0
  400 CONTINUE
C
  500 CONTINUE
C
      RETURN
C     :::::::::: LAST CARD OF TRED2 ::::::::::
      END
      SUBROUTINE TQL2(NM,N,D,E,Z,IERR)
C
      INTEGER I,J,K,L,M,N,II,L1,NM,MML,IERR
      REAL*8 D(N),E(N),Z(NM,N)
      REAL*8 B,C,F,G,H,P,R,S,MACHEP
      REAL*8 DSQRT,DABS,DSIGN
C
C     THIS SUBROUTINE IS A TRANSLATION OF THE ALGOL PROCEDURE TQL2,
C     NUM. MATH.  11, 293-306(1968) BY BOWDLER, MARTIN, REINSCH, AND
C     WILKINSON.
C     HANDBOOK FOR AUTO. COMP., VOL.II-LINEAR ALGEBRA, 227-240(1971).
C
C     THIS SUBROUTINE FINDS THE EIGENVALUES AND EIGENVECTORS
C     OF A SYMMETRIC TRIDIAGONAL MATRIX BY THE QL METHOD.
C     THE EIGENVECTORS OF A FULL SYMMETRIC MATRIX CAN ALSO
C     BE FOUND IF TRED2 HAS BEEN USED TO REDUCE THIS
C     FULL MATRIX TO TRIDIAGONAL FORM.
C
C     ON INPUT:
C
C        NM  MUST BE SET TO THE ROW DIMENSION OF TWO-DIMENSIONAL
C            ARRAY PARAMETERS AS DECLARED IN THE CALLING PROGRAM
C            DIMENSION STATEMENT;
C
C        N   IS THE ORDER OF THE MATRIX;
C
```

```
C        D   CONTAINS THE DIAGONAL ELEMENTS OF THE INPUT MATRIX;
C
C        E   CONTAINS THE SUBDIAGONAL ELEMENTS OF THE INPUT MATRIX
C            IN ITS LAST N-1 POSITIONS.  E(1) IS ARBITRARY;
C
C        Z   CONTAINS THE TRANSFORMATION MATRIX PRODUCED IN THE
C            REDUCTION BY TRED2, IF PERFORMED.  IF THE EIGENVECTORS
C            OF THE TRIDIAGONAL MATRIX ARE DESIRED, Z MUST CONTAIN
C            THE IDENTITY MATRIX.
C
C     ON OUPUT:
C
C        D  CONTAINS THE EIGENVALUES IN ASCENDING ORDER.  IF AN
C           ERROR EXIT IS MADE, THE EIGENVALUES ARE CORRECT BUT
C           UNORDERED FOR INDICES 1,2,...,IERR-1;
C
C        E  HAS BEEN DESTROYED;
C
C        Z  CONTAINS ORTHONORMAL EIGENVECTORS OF THE SYMMETRIC
C           TRIDIAGONAL (OR FULL) MATRIX.  IF AN ERROR EXIT IS MADE,
C           Z CONTAINS THE EIGENVECTORS ASSOCIATED WITH THE STORED
C           EIGENVALUES;
C
C       IERR IS SET TO
C         ZERO       FOR NORMAL RETURN,
C         J          IF THE J-TH EIGENVALUE HAS NOT BEEN
C                    DETERMINED AFTER 30 ITERATIONS.
C
C     QUESTIONS AND COMMENTS SHOULD BE DIRECTED TO B. S. GARBOW.
C     APPLIED MATHEMATICS DIVISION, ARGONNE NATIONAL LABORATORY
C
C     ------------------------------------------------------------------
C
C     :::::::::: MACHEP IS A MACHINE DEPENDENT PARAMETER SPECIFYING
C                THE RELATIVE PRECISION OF FLOATING POINT ARITHMETIC.
C                MACHEP = 16.0D0**(-13) FOR LONG FORM ARITHMETIC
C                CN S360 ::::::::::
      DATA MACHEP/Z3410000000000000/
C      IF USING A VAX COMPUTER, COMMENT THE ABOVE CARD AND REMOVE COMMENT FROM
C      CARD BELOW
C     MACHEP=1.0D-14
C
      IERR = 0
      IF (N .EQ. 1) GO TO 1001
C
      DO 100 I = 2, N
  100 E(I-1) = E(I)
C
      F = 0.0D0
      B = 0.0D0
      E(N) = 0.0D0
C
      DO 240 L = 1, N
         J = 0
```

```
          H = MACHEP * (DABS(D(L)) + DABS(E(L)))
          IF (B .LT. H) B = H
C     :::::::::: LOOK FOR SMALL SUB-DIAGONAL ELEMENT ::::::::::
          DO 110 M = L, N
             IF (DABS(E(M)) .LE. B) GO TO 120
C     :::::::::: E(N) IS ALWAYS ZERO, SO THERE IS NO EXIT
C                THROUGH THE BOTTOM OF THE LOOP ::::::::::
  110     CONTINUE
C
  120     IF (M .EQ. L) GO TO 220
  130     IF (J .EQ. 30) GO TO 1000
          J = J + 1
C     :::::::::: FORM SHIFT ::::::::::
          L1 = L + 1
          G = D(L)
          P = (D(L1) - G) / (2.0D0 * E(L))
          R = DSQRT(P*P+1.0D0)
          D(L) = E(L) / (P + DSIGN(R,P))
          H = G - D(L)
C
          DO 140 I = L1, N
  140     D(I) = D(I) - H
C
          F = F + H
C     :::::::::: QL TRANSFORMATION ::::::::::
          P = D(M)
          C = 1.0D0
          S = 0.0D0
          MML = M - L
C     :::::::::: FOR I=M-1 STEP -1 UNTIL L DO -- ::::::::::
          DO 200 II = 1, MML
             I = M - II
             G = C * E(I)
             H = C * P
             IF (DABS(P) .LT. DABS(E(I))) GO TO 150
             C = E(I) / P
             R = DSQRT(C*C+1.0D0)
             E(I+1) = S * P * R
             S = C / R
             C = 1.0D0 / R
             GO TO 160
  150        C = P / E(I)
             R = DSQRT(C*C+1.0D0)
             E(I+1) = S * E(I) * R
             S = 1.0D0 / R
             C = C * S
  160        P = C * D(I) - S * G
             D(I+1) = H + S * (C * G + S * D(I))
C     :::::::::: FORM VECTOR ::::::::::
             DO 180 K = 1, N
                H = Z(K,I+1)
                Z(K,I+1) = S * Z(K,I) + C * H
                Z(K,I) = C * Z(K,I) - S * H
  180        CONTINUE
```

```
C
  200     CONTINUE
C
          E(L) = S * P
          D(L) = C * P
          IF (DABS(E(L)) .GT. B) GO TO 130
  220     D(L) = D(L) + F
  240 CONTINUE
C     :::::::::: ORDER EIGENVALUES AND EIGENVECTORS ::::::::::
      DO 300 II = 2, N
          I = II - 1
          K = I
          P = D(I)
C
          DO 260 J = II, N
             IF (D(J) .GE. P) GO TO 260
             K = J
             P = D(J)
  260     CONTINUE
C
          IF (K .EQ. I) GO TO 300
          D(K) = D(I)
          D(I) = P
C
          DO 280 J = 1, N
             P = Z(J,I)
             Z(J,I) =Z(J,K)
             Z(J,K) = P
  280     CONTINUE
C
  300 CONTINUE
C
      GO TO 1001
C     :::::::::: SET ERROR -- NO CONVERGENCE TO AN
C                EIGENVALUE AFTER 30 ITERATIONS ::::::::::
 1000 IERR = L
 1001 RETURN
C     :::::::::: LAST CARD OF TQL2 ::::::::::
      END
      SUBROUTINE PMATRX
     1    (B,BGNROW,ENDROW,BGNCOL,ENDCOL,MAX,NC,DS,PR,TITLE,PHEAD,LPHEAD)
C
C     *******************************************
C     *     WRITE MATRIX TO TAPE AND PRINTER     *
C     *******************************************
C
C  PASS TO THIS SUBROUTINE:
C     B          = MATRIX TO BE PRINTED(COLUMNS IN REVERSE ORDER)
C     BGNROW,ENDROW = BEGINNING AND ENDING ROWS TO BE PRINTED
C     BGNCOL,ENDCOL = BEGINNING AND ENDING COLUMSS TO BE PRINTED
C     MAX        = MAXIMUM NUMBER OF ROWS PERMITTED
C     NC         = MAXIMUM NUMBER OF COLUMNS PRINTED PER LINE
C     DS,PR      = DEVICE ADDRESSES OF DISK AND PRINTER
C     TITLE      = PAGE TITLE
```

```
C      PHEAD,LPHEAD = HEADER AND LENGTH OF HEADER(#WORDS IN A4 FORMAT)
C
       REAL*8       B(MAX,1)
       INTEGER*4    BGNROW,ENDROW,BGNCOL,ENDCOL
       INTEGER*4    NROWS,FSTCOL,LSTCOL,LOWCOL,HICOL,LOWROW,HIROW
       INTEGER*4    TITLE(20),PHEAD(1),LPHEAD
       INTEGER*4    DS,PR,NC
C
       LOWROW = MIN0(BGNROW,ENDROW)
       HIROW  = MAX0(BGNROW,ENDROW)
       LOWCOL = MIN0(BGNCOL,ENDCOL)
       HICOL  = MAX0(BGNCOL,ENDCOL)
C
C      WRITE TO DISK
C
       IF (DS.EQ.0) GOTO 15
          DO 5 I=LOWROW,HIROW
             DO 5 J=LOWCOL,HICOL
    5           WRITE(DS,10) B(I,J)
   10           FORMAT(F11.6)
C
C      PRINT MATRIX IN BLOCKS OF 15 COLUMNS
C
   15  NROWS = HIROW - LOWROW + 1
       WRITE(PR,100) TITLE,NROWS,(PHEAD(K1),K1=1,LPHEAD)
C
       FSTCOL=LOWCOL
       GOTO 40
   30  IF (FSTCOL.GT.HICOL) RETURN
          WRITE(PR,110) TITLE
   40     LSTCOL=MIN0(FSTCOL+NC-1,HICOL)
          WRITE(PR,120) (K2,K2=FSTCOL,LSTCOL)
          DO 50 K1=LOWROW,HIROW
             L1=K1
             IF (BGNROW .GT. ENDROW) L1=HIROW-K1+LOWROW
             IF (BGNCOL .LE. ENDCOL)
     1          WRITE(PR,130) K1,(B(L1,K2),K2=FSTCOL,LSTCOL)
   50        IF (BGNCOL .GT. ENDCOL) WRITE(PR,130)
     1          K1,(B(L1,BGNCOL-K2+ENDCOL),K2=FSTCOL,LSTCOL)
          FSTCOL=LSTCOL+1
          GOTO 30
C
  100  FORMAT (20A4/I7,20A4/)
  110  FORMAT (20A4/)
  120  FORMAT (4X,15I11)
  130  FORMAT (I7,15F11.6)
       END
       SUBROUTINE PLOT(MAXN,B,NOBJS,TITLE,
     1    NEIGEN,DIAG,NC,DS,PR,NAMES,NAMEL,LLOC,LOWDIM,HIDIM)
C
C      *********************************************
C      *     PRINT AND PLOT SCALES FOR OBJECTS     *
C      *********************************************
C
```

```
C  PASS TO THIS SUBROUTINE:
C     MAXN   = MAX NUMBER OF OBJECTS PERMITTED
C     B      = MATRIX OF SCALE VALUES FOR OBJECTS
C     NOBJS  = NUMBER OF OBJECTS SCALED
C     NEIGEN = NUMBER OF EIGENVECTORS(SETS OF SCALE VALUES) COMPUTED
C     DIAG   = LIST OF EIGENVALUES(ONE FOR EACH EIGENVECTOR)
C     NC     = NUMBER OF COLUMNS TO PRINT WHEN DISPLAYING SCALE VALUES
C     DS,PR  = DEVICE ADDRESSES OF DISK AND PRINTER
C     NAMEL,LLOC = VECTORS USED BY PLOT SUBROUTINE
C     LOWDIM,HIDIM = MINIMUM AND MAXIMUM DIMENSION TO BE PRINTED
C
      INTEGER*4  MAXN,NOBJS,TITLE(20),NEIGEN
      INTEGER*4  NAMEL(MAXN),LLOC(4,MAXN),NAMES(12,MAXN)
      INTEGER*4  PR,DS,NC,NS
      INTEGER*4  LOWDIM,LOWDP1,HIDIM
      REAL*8     B(MAXN,MAXN),DIAG(MAXN)
      REAL*8     XL,XH,XS,XA,YL,YH,YS,YA
C
C     PLOT TWO-DIMENSIONAL SLICES(NS=#OF SEGMENTS PER PLOT)
C
      IF (LOWDIM .GE. HIDIM) RETURN
      LOWDP1 = LOWDIM + 1
      NS=1
C
      DO 50 K1=LOWDP1,HIDIM
         K1P=NEIGEN-K1+1
         K1M1=K1-1
         DO 50 K2=LOWDIM,K1M1
            K2P=NEIGEN-K2+1
            CALL PSIZE(NOBJS,B(1,K1P),B(1,K2P),XL,XH,YL,YH)
            XS=(XH-XL)/NS
            YS=(YH-YL)/NS
            XA=XH
            DO 30 KX=1,NS
               YA=YH
               DO 20 KY=1,NS
               CALL PLOT2D(TITLE,K1,K2,B(1,K1P),B(1,K2P),NOBJS
     1         ,NEIGEN,NAMES,NAMEL,LLOC,XA-XS,XA,YA-YS,YA)
   20             YA=YA-YS
   30          XA=XA-XS
            XS=(YH-YL)/12
C   50       CALL PLOT2D(TITLE,K1,K2,B(1,K1P),B(1,K2P),NOBJS
C     1          ,NEIGEN,NAMES,NAMEL,LLOC,-XS,XS,-XS,XS)
   50       CONTINUE
      RETURN
      END
      SUBROUTINE PEVALS
     1   (EVALS,N,M,NLINKS,NEVALS,DS,PR,TITLE)
C
C     *******************************************
C     *     WRITE MATRIX TO TAPE AND PRINTER    *
C     *******************************************
C
C  PASS TO THIS SUBROUTINE:
```

```
C     EVALS   = VECTOR OF EIGENVALUES
C     NEVALS  = NUMBER OF EIGENVALUES
C     N       = NUMBER OF OBJECTS (NUMBER OF COLUMNS IN INPUT MATRIX)
C     M       = NUMBER OF ROWS IN INPUT MATRIX
C     NLINKS  = NUMBER OF LINKS IN INPUT MATRIX
C     DS,PR   = DEVICE ADDRESSES OF DISK AND PRINTER
C     TITLE   = PAGE TITLE
C
      REAL*8      EVALS(1),EIGSUM,X2,PROB
      INTEGER*4   N,M,NEVALS,DF
      REAL*4      NLINKS
      INTEGER*4   TITLE(20)
      INTEGER*4   DS,PR
C
C     WRITE TO DISK
C
      IF (DS.EQ.0) GOTO 15
         DO 5 I=1,NEVALS
    5          WRITE(DS,10) EVALS(I)
   10          FORMAT(F11.6)
C
C     PRINT EIGENVALUES, ONE PER ROW WITH OTHER STATISTICS
C
   15 WRITE(PR,100) TITLE,NEVALS
C
      EIGSUM = 0.0
      DO 50 K1P = 1,NEVALS
         K1 = NEVALS + 1 - K1P
         EIGSUM = EIGSUM + EVALS(K1)
         IF (EVALS(K1) .GE. 1.0D0 .OR. EVALS(K1).LT. 0.0D0) GOTO 40
            X2 = -(NLINKS-1-(N+M-1)/2.0)*DLOG(1.0-EVALS(K1))
            DF = N+M+1-2*K1P
            WRITE (PR,130) K1P,EVALS(K1),EIGSUM,X2,DF
            GOTO 50
   40    WRITE (PR,140) K1P,EVALS(K1),EIGSUM
   50    CONTINUE
C
      RETURN
C
  100 FORMAT (20A4//I7,' EIGENVALUES CUMULATIVE',7X,'X2',11X,'DF'/)
  130 FORMAT (I7,2F11.6,F11.3,I11,F11.6)
  140 FORMAT (I7,2F11.6,F11.3)
      END
      SUBROUTINE DIMRNG(DIAG,NEIGEN,LOWDIM,HIDIM)
C
C     *******************************************
C     *     GET RANGE OF PLOTABLE DIMENSIONS    *
C     *******************************************
C
      INTEGER*4   NEIGEN,LOWDIM,HIDIM
      REAL*8      DIAG(1)
C
      DO 100 LOWDIM=2,NEIGEN
  100    IF (DIAG(NEIGEN-LOWDIM+1) .LT. 0.99999D0) GOTO 200
```

```
      LOWDIM = NEIGEN
C
  200 DO 300 HIDIM=LOWDIM,NEIGEN
  300    IF (DIAG(NEIGEN-HIDIM+1) .LE. 0.0D0) GOTO 400
      HIDIM = NEIGEN
      RETURN
C
  400 HIDIM = HIDIM - 1
      RETURN
      END
      SUBROUTINE PSIZE(N,X,Y,X1,X2,Y1,Y2)
C
C     ***********************************
C     *     RANGE OF X AND Y VALUES     *
C     ***********************************
C
      REAL*8    X(1),Y(1),X1,X2,Y1,Y2,Y3
C
      Y1=Y(1)
      Y2=Y(1)
      X1=X(1)
      X2=X(1)
      DO 10 K1=2,N
         Y2=DMAX1(Y2,Y(K1))
         Y1=DMIN1(Y1,Y(K1))
         X2=DMAX1(X2,X(K1))
   10    X1=DMIN1(X1,X(K1))
C
      Y3=1.1*DMAX1(X2-X1,Y2-Y1)
      X1=(X2+X1)/2-Y3/2
      X2=X1+Y3
      Y1=(Y1+Y2)/2-Y3/2
      Y2=Y1+Y3
      RETURN
      END
      SUBROUTINE PLOT2D
     1   (TITLE,DIM1,DIM2,X,Y,N,T,NAME,NAMEL,LLOC,X1,X2,Y1,Y2)
C
C     ************************************************
C     *      2-DIMENSIONAL PLOT OF *'S AND LABELS    *
C     ************************************************
C
C  PASS TO THIS SUBROUTINE:
C     DIM1, DIM2 = NUMBERS OF HORIZONTAL & VERTICAL DIMENSIONS
C     X, Y  = COORDINATES ALONG HORIZONTAL & VERTICAL DIMENSIONS
C     N     = NUMBER OF POINTS TO BE PLOTTED
C     T     = TOTAL NUMBER OF DIMENSIONS IN ENTIRE SPACE
C     NAME  = 12 X N MATRIX OF N NAMES IN A4 FORMAT
C     X1,X2,Y1,Y2 = RANGES OF X AND Y VALUES TO BE PLOTTED
C
C  USED BY THIS SUBROUTINE:
C     NAMEL = N VECTOR THAT WILL CONTAIN THE NUMBER OF CHARS IN LABEL
C     LLOC  = 4 X N MATRIX USED TO STORE THE PRINT LOCATIONS OF LABELS
C
```

```
      COMMON /IO/ OUT
C
      COMMON /SYMB/ SPACE, STAR, PLUS, DASH, DOT, DIGITS
     1   /PRI/ HMARG,VMARG,PRIBUF
C
      INTEGER    HMARG,N,T,VMARG,VMARP1,HZERO,VZERO
     1   ,PRIBUF(132),OUT
     2   ,NAME(12,1),NAMEL(1),LLOC(4,1),UPNAME(48)
      INTEGER*4 SPACE,STAR,PLUS,DASH,DOT,DIGITS(10)
      INTEGER*4 TITLE(20),DIM1,DIM2
      INTEGER    PRI1(21)/'(','T','5',1H,,'F','1','2','.','5',1H,
     1   ,'T',3*' ',1H,,'F','1','2','.','5',')'/,PRI1A(21)
     2   ,PRI2(18)/'(','T','1','1',1H,,1H','+',1H',1H,,'T'
     3   ,3*' ',1H,,1H','+',1H',')'/,PRI2A(18)
      REAL*8     X(1),X1,X2,X3,Y(1),Y1,Y2,Y3
C
C     SET MARGINS
C
      MARGIN=100
      HMARG=5*((MARGIN-20)/5)
      VMARG=HMARG*6/10
C
C     GET LENGTH OF LABELS(NAMEL)
C
      DO 15 K1=1,N
         CALL CONVRT(NAME(1,K1),UPNAME,NAMEL(K1))
   15    CONTINUE
C
C  SET SCALE AND MARGINS
C
      Y3=Y2-Y1
      IF (Y3 .EQ. 0.0D0) RETURN
      X3=HMARG/Y3
      Y3=VMARG/Y3
C
C  SET UP INITIAL POSITION OF *'S AND LABELS
C
C       *   LOCATED AT X=LLOC(1,K)  Y=LLOC(2,K)
C     LABEL LOCATED AT X=LLOC(3,K)  Y=LLOC(4,K)
C
      DO 20 K=1,N
         IF(X(K).LT.X1 .OR. X(K).GT.X2 .OR.
     1      Y(K).LT.Y1 .OR. Y(K).GT.Y2) GOTO 17
         LLOC(1,K)=(X(K)-X1)*X3+1.5
         LLOC(2,K)=(Y2-Y(K))*Y3+1.5
         LLOC(3,K)=LLOC(1,K)+1
         LLOC(4,K)=LLOC(2,K)
         GOTO 20
   17    LLOC(1,K)=-1
   20    CONTINUE
C
      CALL LABFIT(N,NAMEL,LLOC)
C
C     *******************************
```

```
C     *      DO THE ACTUAL PRINT     *
C     ******************************
C
      HZERO=-X1*X3+1.5
      VZERO=Y2*Y3+1.5
C
C     PRINT TOP LINE
C
   90 CALL ERASE
      X3INV=10/X3
      WRITE(OUT,110) TITLE,X3INV,DIM1,DIM2
  110 FORMAT(20A4/' SCALE: ',F8.4,' UNITS EQUALS +---- ',
     15X,'DIMENSIONS:  HORIZONTAL =',I5,', VERTICAL =',I5/)
      IF (T .EQ. 1) GOTO 120
C
         CALL NTOSTR(PRI1(12),5+HMARG,3)
         CALL NTOSTR(PRI2(11),11+HMARG,3)
         CALL A1TOA4(PRI1,21,PRI1A)
         CALL A1TOA4(PRI2,18,PRI2A)
C
         X4=X1+HMARG/X3
         WRITE(OUT,PRI1A) X1,X4
         WRITE(OUT,PRI2A)
  120 CALL AXIS(Y2)
      CALL PRINTS(9,1,PLUS)
C
C  PRINT AXIS
C
      VMARP1=VMARG+1
      DO 140 K1=1,VMARP1
         IF(K1.NE.VZERO) GOTO 125
            DO 122 K2=1,HMARG
  122       CALL PRINTS(K2+10,1,PLUS)
  125    IF (K1 .EQ. VMARG+1) CALL PRINTS(9,1,PLUS)
         CALL PRINTS(10,1,DASH)
         IF (MOD(K1,3) .EQ. 1) CALL PRINTS(10,1,PLUS)
         CALL PRINTS(HZERO+10,1,PLUS)
C
C     PRINT REST OF LINE
C
         DO 130 K2=1,N
            IF (LLOC(1,K2).EQ.-1) GOTO 130
            IF (K1 .EQ. LLOC(2,K2))
     1         CALL PRINTS(LLOC(1,K2)+10,1,STAR)
            IF (K1 .NE. LLOC(4,K2)) GOTO 130
               CALL CONVRT(NAME(1,K2),UPNAME,NAMEL(K2))
               CALL PRINTS(LLOC(3,K2)+10,NAMEL(K2),UPNAME)
  130       CONTINUE
         CALL FLUSH
  140    CONTINUE
C
C     PRINT BOTTOM LINE
C
      CALL AXIS(Y2-VMARG/Y3)
```

```
      RETURN
      END
      SUBROUTINE LABFIT(N,NAMEL,LLOC)
C
C     ********************************************************
C     *     ATTEMPT TO FIT ALL *'S AND LABELS IN PICTURE     *
C     ********************************************************
C
C  PASS TO THIS SUBROUTINE:
C     N     = NUMBER OF POINTS TO BE PLOTTED
C     NAMEL = N VECTOR CONTAINING LENGTHS OF EACH LABEL
C
C  RETURN:
C     LLOC  = 4 X N MATRIX OF X,Y PRINT COORDINATES FOR LABELS
C
      INTEGER FO,N,SO,XO,YO
      INTEGER*4 NAMEL(1),LLOC(4,1)
C
C  MAKE 10 ATTEMPTS TO GET LABELS SO THEY DON'T OVERLAP
C
      DO 80 K9=1,10
C  NO CHANGES SO FAR
      SO=0
C
C  CHECK LABELS ONE AT A TIME
C
      DO 70 K=1,N
      IF (LLOC(1,K).EQ.-1) GOTO 70
C
C  FIRST CHECK IF CURRENT POSITION IS OKAY
C
      FO=-1
      XO=LLOC(3,K)
      YO=LLOC(4,K)
      CALL OLAP(XO,YO,K,FO,N,NAMEL,LLOC)
      IF (FO .EQ. 0) GOTO 70
C
C  IF CONFLICT, TRY TO MOVE THE LABEL
C
      SO=1
      FO=-1
C
C  FIRST TRY POSITIONS TO RIGHT AND LEFT OF *
C
   30   XO=LLOC(1,K)+1
        YO=LLOC(2,K)
        CALL OLAP(XO,YO,K,FO,N,NAMEL,LLOC)
        IF (FO .EQ. 0) GOTO 60
        XO=LLOC(1,K)-NAMEL(K)
        YO=LLOC(2,K)
        CALL OLAP(XO,YO,K,FO,N,NAMEL,LLOC)
        IF (FO .EQ. 0) GOTO 60
C
C  NEXT TRY POSITIONS ON ROWS ABOVE AND BELOW *
```

```
C
      DO 40 K1=1,3,2
         Y0=LLOC(2,K)+K1-2
         LB=MAX0(LLOC(1,K)-NAMEL(K)+1,1)
         LE=LLOC(1,K)
         DO 40 X0=LB,LE
            CALL OLAP(X0,Y0,K,F0,N,NAMEL,LLOC)
         IF (F0 .EQ. 0) GOTO 60
  40     CONTINUE
C
C IF ALL ELSE FAILS, ELIMINATE ANOTHER LABEL FOR NOW
C AND WRITE THIS ONE OUT
C
      IF (F0 .LT. 0) GOTO 50
         LLOC(4,F0)=0
         GO TO 30
C
C IF ELIMINATING ANOTHER LABEL IS NO HELP, GIVE UP FOR NOW
C
  50  LLOC(4,K)=0
      GO TO 70
C
C KEEP NEW POSITION OF LABEL
C
  60  LLOC(3,K)=X0
      LLOC(4,K)=Y0
C
C ALL DONE WITH THIS LABEL
C
  70  CONTINUE
C
C IF NO CONFLICTS, PRINT
C
    IF (S0 .EQ. 0) GOTO 90
  80  CONTINUE
  90 RETURN
    END
    SUBROUTINE AXIS(X)
C
C   *********************************
C   *     PRINT HORIZONTAL AXIS     *
C   *********************************
C
C PASS TO THIS SUBROUTINE:
C   X     = VALUE ALONG VERTICAL AXIS AT THIS POINT
C
    COMMON /IO/ OUT
C
    INTEGER OUT,HMARG,HMARD5,VMARG,PRIBUF(132)
   1,SPACE,STAR,PLUS,DASH,DOT,DIGITS(10)
C
    COMMON /SYMB/ SPACE,STAR,PLUS,DASH,DOT,DIGITS
   1/PRI/ HMARG,VMARG,PRIBUF
C
```

```
      HMARD5=HMARG/5-1
C
      WRITE(OUT,10) X,(DASH,K=1,HMARD5)
   10 FORMAT(F14.5,T16,'+',30(1A1,'---+'))
      RETURN
      END
      SUBROUTINE OLAP(FIRST,Y0,K,F0,N,NAMEL,LLOC)
C
C     ******************************************************
C     *     CHECK IF LABEL K OVERLAPS WITH ANY * OR LABEL     *
C     ******************************************************
C
C     LABEL K TAKES UP LOCATIONS (FIRST,Y0) TO (LAST,Y0)
C
C     RETURNS F0=0 IF NO OVERLAP WITH * OR OTHER LABELS
C               =N .GT. 0 IF OVERLAP, N=NUMBER OF OVERLAPPED LABEL
C
C               F0 IS UNCHANGED IN THE CASE OF MULTIPLE OVERLAPS
C                  OR IF LABEL IS OUTSIDE PLOT BOUNDARIES
C
      INTEGER F0,F9,FIRST,K,LAST,Y0
     1   ,LLOC(4,1),N,NAMEL(1)
     2   ,HMARG,VMARG,PRIBUF(132)
C
      COMMON /PRI/ HMARG,VMARG,PRIBUF
C
C  CHECK IF THE LABEL IS OUTSIDE PLOT BOUNDARIES
C
      LAST=FIRST+NAMEL(K)-1
      IF (FIRST .LT. 1 .OR.
     1   LAST .GT. HMARG .OR.
     2   Y0 .GT. VMARG .OR.
     3   Y0 .LT. 1) RETURN
C
C  CHECK IF THE LABEL OVERLAPS A *
C
          DO 10 K0=1,N
             IF (LLOC(1,K0) .EQ. -1) GOTO 10
             IF (K .NE. K0 .AND.
     1          LLOC(2,K0) .EQ. Y0 .AND.
     2          LAST .GE. LLOC(1,K0) .AND.
     3          FIRST .LE. LLOC(1,K0)) RETURN
   10        CONTINUE
C
C  CHECK IF THE LABEL OVERLAPS ANOTHER LABEL
C
          F9=0
          DO 20 K0=1,N
             IF (LLOC(1,K0) .EQ. -1) GOTO 20
             IF (K .EQ. K0 .OR.
     1          LLOC(4,K0) .NE. Y0 .OR.
     2          LAST .LT. LLOC(3,K0) .OR.
     3          FIRST .GT. LLOC(3,K0)+NAMEL(K0)) GOTO 20
             IF (F9 .GT. 0) RETURN
```

```
            F9=K0
20          CONTINUE
         F0=F9
      RETURN
      END
      SUBROUTINE ERASE
C
C     *****************************
C     *      ERASE PRINT BUFFER     *
C     *****************************
C
      INTEGER HMARG,VMARG,PRIBUF(132),RM
     1,SPACE,STAR,PLUS,DASH,DOT,DIGITS(10)
C
      COMMON /PRI/ HMARG,VMARG,PRIBUF
     1/SYMB/ SPACE,STAR,PLUS,DASH,DOT,DIGITS
C
      RM=HMARG+15
      DO 10 K=1,RM
10       PRIBUF(K)=SPACE
      RETURN
      END
      SUBROUTINE FLUSH
C
C     *********************************************
C     *      PRINT LINE AND ERASE PRINT BUFFER     *
C     *********************************************
C
      COMMON /IO/ OUT
C
      INTEGER OUT,HMARG,VMARG,PRIBUF(132),RM
     1,SPACE,STAR,PLUS,DASH,DOT,DIGITS(10)
C
      COMMON /SYMB/ SPACE,STAR,PLUS,DASH,DOT,DIGITS
     1/PRI/ HMARG,VMARG,PRIBUF
C
      RM=HMARG+15
      DO 10 NK=1,RM
         K=RM+1-NK
         IF (PRIBUF(K) .NE. SPACE) GOTO 20
10       CONTINUE
      GOTO 40
20    WRITE(OUT,30) (PRIBUF(KK),KK=1,K)
30    FORMAT(1H ,132A1)
C
C     ERASE AND RETURN
C
40    CALL ERASE
      RETURN
      END
      SUBROUTINE PRINTS(TAB,LEN,STR)
C
C     ***************************************
C     *      PLACE LABEL IN PRINT BUFFER     *
```

```
C     ***************************************
C
      INTEGER HMARG,VMARG,PRIBUF(132)
     1,LEN,STR(1),TAB
C
      COMMON /PRI/ HMARG,VMARG,PRIBUF
C
      DO 10 K=1,LEN
   10    PRIBUF(K+TAB-1)=STR(K)
      RETURN
      END
      SUBROUTINE INSSTR(STR,INS,LENGTH)
C
C     *************************************
C     *      INSERT STRING INTO STRING     *
C     *************************************
C
      INTEGER LENGTH
      INTEGER*4 STR(1),INS(1)
C
      DO 10 K=1,LENGTH
   10    STR(K)=INS(K)
      RETURN
      END
      LOGICAL FUNCTION STRTON(R,STR,LENGTH)
C
C     ****************************************
C     *      CONVERT STRING TO REAL NUMBER     *
C     ****************************************
C
C     DECODE STR() ASSUMMING F FORMAT
C
      INTEGER*4 STR(1)
      INTEGER   LENGTH,DECLOC,SGN,START
      INTEGER*4 SPACE,STAR,PLUS,DASH,DOT,DIGITS(10)
      REAL*8    R
      DOUBLE PRECISION DR
C
      COMMON /SYMB/SPACE,STAR,PLUS,DASH,DOT,DIGITS
C
      STRTON=.FALSE.
      START=1
      SGN=1
      IF (STR(1) .NE. DASH) GOTO 10
         SGN=-1
         START=2
   10 IF (LENGTH .LT. START) RETURN
      DR=0.0
      DECLOC=LENGTH
      DO 40 K1=START,LENGTH
         DO 20 K2=1,10
            IF (STR(K1) .EQ. DIGITS(K2)) GOTO 30
   20       CONTINUE
         IF (STR(K1) .NE. DOT .OR. DECLOC .NE. LENGTH) RETURN
```

```
         DECLOC=K1
         GOTO 40
   30    DR=10*DR+K2-1
   40    CONTINUE
      R=SGN*DR*10**(DECLOC-LENGTH)
      STRTON=.TRUE.
      RETURN
      END
      SUBROUTINE NTOSTR(STR,N,LENGTH)
C
C     ***************************************************
C     *      CONVERT INTEGER INTO A STRING OF DIGITS    *
C     ***************************************************
C
      INTEGER*4 STR(1)
      INTEGER   N,LENGTH,NN,NN10,NK,K
      INTEGER*4 SPACE,STAR,PLUS,DASH,DOT,DIGITS(10)
C
      COMMON /SYMB/ SPACE,STAR,PLUS,DASH,DOT,DIGITS
C
      NN=N
      DO 10 K=1,LENGTH
   10    STR(K)=SPACE
      DO 20 NK=1,LENGTH
         K=LENGTH-NK+1
         NN10=NN/10
         STR(K)=DIGITS(NN-10*NN10+1)
         IF (NN10 .EQ. 0) RETURN
   20    NN=NN10
      RETURN
      END
      SUBROUTINE CONVRT (CHARS,UPNAME,NAMEL)
C
C     *********************************************
C     *      PUT LABELS IN A1 FORMAT - NAME YR    *
C     *********************************************
C
C  PASS TO THIS SUBROUTINE:
C     CHARS  = 48 CHAR VECTOR CONTAINING LABEL IN A4 FORMAT
C
C  RETURN:
C     UPNAME = 12 CHARACTER VECTOR CONTAINING LABEL IN A1 FORMAT
C     NAMEL  = NUMBER OF CHARACTERS IN A1-FORMAT LABEL
C
      INTEGER*4 UPNAMT,NAMEL
      INTEGER*4 BLNK/'    '/
      LOGICAL*1 CHARS(48),UPCHRS(4),UPNAME(192)
      EQUIVALENCE (UPNAMT,UPCHRS(1))
C
      DO 10 K1=1,48
         UPNAMET=BLNK
         UPCHRS(1)=CHARS(K1)
   10    IF (UPNAMT.NE.BLNK) GOTO 15
C
```

```
   15 DO 20 K2=K1,48
         NAMEL=48+K1-K2
         UPNAMT=BLNK
         UPCHRS(1)=CHARS(NAMEL)
         IF (UPNAMT.NE.BLNK) GOTO 30
   20    CONTINUE
C
   30 DO 40 K2=K1,NAMEL
   40    UPNAME(4*(K2-K1)+1)=CHARS(K2)
      NAMEL=NAMEL-K1+1
      RETURN
      END
      SUBROUTINE A1TOA4(A1CHAR,LEN,A4CHAR)
C
C     ******************************************************
C     *     CONVERT STRING IN A1 FORMAT INTO A4 FORMAT     *
C     ******************************************************
C
      INTEGER*4 LEN
      LOGICAL*1 A1CHAR(1),A4CHAR(1)
C
      DO 10 K1=1,LEN
   10    A4CHAR(K1)=A1CHAR(4*K1-3)
      RETURN
      END
      SUBROUTINE SORT(ISW,VALS,LENGTH,INDEX,ASCEND)
C
C            **********************
C            *     SHELL SORT     *
C            **********************
C
C     ASCEND = T   SORT POINTERS IN INCREASING ORDER
C     ASCEND = F   DECREASING ORDER
C
      REAL*8  VALS(1)
      INTEGER LENGTH,INDEX(1),LD2,INDX,LMKPF
      LOGICAL ASCEND,ISW
C
      IF (ISW) GOTO 20
         DO 10 K=1,LENGTH
   10       INDEX(K)=K
   20 M=LENGTH
   30 M=M/2
      IF (M .EQ. 0) GOTO 80
         KK=LENGTH-M
         J=1
   40    I=J
   50    IPM=I+M
         IF (VALS(INDEX(I)) .LT. VALS(INDEX(IPM))) GOTO 70
   60       J=J+1
            IF (J .GT. KK) GOTO 30
               GOTO 40
   70    LL=INDEX(I)
         INDEX(I)=INDEX(IPM)
```

```
         INDEX(IPM)=LL
         I=I-M
         IF (I .LT. 1) GOTO 60
            GOTO 50
C
   80 IF (.NOT. ASCEND) RETURN
         LD2=LENGTH/2
         DO 90 K=1,LD2
            LMKPF=LENGTH-K+1
            INDX=INDEX(K)
            INDEX(K)=INDEX(LMKPF)
   90       INDEX(LMKPF)=INDX
      RETURN
      END
      BLOCK DATA
      COMMON /IO/ OUT
      COMMON /SYMB/ SPACE,STAR,PLUS,DASH,DOT,DIGITS
C
C  SET I/O DEVICE NUMBERS
C
      INTEGER OUT/8/
      INTEGER*4 SPACE/' '/,STAR/'*'/,PLUS/'+'/
     1   ,DASH/'-'/,DOT/'.'/
     2   ,DIGITS(10)/'0','1','2','3','4','5','6','7','8','9'/
      END
      SUBROUTINE REMAT(DIM,B,MAXN,NOBJS,NAMES,M1,PR,A,TITLE,TITLEL)
C
C     ****************************************************
C     *      PRINT MATRIX WITH ROWS AND COLUMNS SPACED   *
C     *              BY SCALE VALUES                     *
C     ****************************************************
C
C  PASS TO THIS SUBROUTINE:
C     B    = SCALE VALUES
C     NOBJS= NUMBER OF OBJECTS
C     MAXN = MAXIMUM NUMBER OF OBJECTS
C     NAMES= LIST OF NAMES FOR EACH OBJECT
C     PR   = DEVICE NUMBER FOR PRINTER
C     A    = INPUT MATRIX
C     M1   = USED BY ROUTINE FOR SORTING VALUES IN B( )
C
      INTEGER*4 MAXN,NOBJS,PR,NAMES(12,NOBJS),DIM
      INTEGER*4 M1(NOBJS),TITLE(1),TITLEL
      INTEGER   NLINES,HMARG,HMARD5,CURPTR,CUROBJ,PRIBUF(132),GROUP
      INTEGER*4 PLUS/'+'/
      INTEGER   PRICHR(21)/'    ','1   ','2   ','3   ','4   ','5   '
     1   ,'6   ','7   ','8   ','9   ','A   ','B   ','C   ','D   '
     2   ,'E   ','F   ','G   ','H   ','I   ','J   ','K   '/
      INTEGER   MAXCAT/21/
      REAL*8    FIRST,LAST,HSTEP,VSTEP,LVAL
      REAL*8    B(NOBJS),A(MAXN,MAXN)
C
C     SET SOME PAGE PARAMETERS
C
```

```
      NLINES=50
      HMARG=NLINES
      HMARD5=(HMARG+4)/5
C
C     SORT OBJECTS IN ASCENDING SCALE-VALUE ORDER
C
      CALL SORT(.FALSE.,B,NOBJS,M1,.TRUE.)
C
C     SET PARAMETERS TO FIT MATRIX ONTO PAGE
C
      FIRST=B(M1(1))
      LAST=B(M1(NOBJS))
      VSTEP=(LAST-FIRST)/(NLINES-1)
      HSTEP=(HMARG-1)/(LAST-FIRST)
C
C     WRITE TITLE FOR SORTED OUTPUT
C
      WRITE (PR,80)(TITLE(K1),K1=1,TITLEL)
   80 FORMAT (33A4)
      WRITE (PR,90) DIM,(PLUS,K1=1,HMARD5)
   90 FORMAT (' MATRIX REORDERED BY DIMENSION   ',I3//10X,'+',
     1 30('----',1A1))
C
C     ASSEMBLE EACH LINE OF RE-ORDERED MATRIX
C
      CURPTR=1
      DO 500 K1=1,NLINES
         LVAL=(K1)*VSTEP+FIRST
         DO 100 K2=1,HMARG
  100       PRIBUF(K2)=1
C
  150    IF (CURPTR.GT.NOBJS) GOTO 400
            CUROBJ=M1(CURPTR)
            IF (B(CUROBJ).GE.LVAL) GOTO 400
               DO 200 K2=1,NOBJS
                  IF (A(CUROBJ,K2).EQ.0) GOTO 200
                     HLOC=(B(K2)-FIRST)*HSTEP+1
                     PRIBUF(HLOC)=PRIBUF(HLOC)+A(CUROBJ,K2)
  200                CONTINUE
               CURPTR=CURPTR+1
               GOTO 150
C
C     PRINT LINE
C
  400    DO 450 K2=1,HMARG
  450       PRIBUF(K2)=PRICHR(MINO(MAXCAT,PRIBUF(K2)))
C
         IF(MOD(K1,10) .NE. 1 .AND. K1 .NE. NLINES) GOTO 470
             WRITE (PR,460) LVAL,(PRIBUF(K2),K2=1,HMARG)
  460        FORMAT(F7.3,'  +',132A1)
             GOTO 500
  470    IF (MOD(K1,5) .NE. 1) GOTO 490
             WRITE (PR,480) (PRIBUF(K2),K2=1,HMARG)
  480        FORMAT(9X,'+',132A1)
```

```
          GOTO 500
490    WRITE (PR,495) (PRIBUF(K2),K2=1,HMARG)
495         FORMAT(9X,'-',132A1)
500    CONTINUE
C          WRITE OUT KEY FOR REORDERING
       WRITE(PR,590)
590  FORMAT('1',3X,'OBJECT LOCATIONS IN RESCALED MATRIX '/
     1  '  SCALE      GROUP   ITEM')
       DO 600 K1=1,NOBJS
         GROUP=(B(M1(K1))-FIRST)/VSTEP+1
600    WRITE(PR,605)
     1  B(M1(K1)),GROUP,(NAMES(K2,M1(K1)),K2=1,12)
605  FORMAT(F10.4,3X,I4,3X,12A4)
       RETURN
       END
       SUBROUTINE RESTIM(DIM,B,MAXN,NOBJS,NAMES,M1,PR,A,TITLE,TITLEL)
C
C      ****************************************************
C      *      PRINT MATRIX WITH ROWS AND COLUMNS SPACED      *
C      *               BY SCALE VALUES                      *
C      ****************************************************
C
C  PASS TO THIS SUBROUTINE:
C      B    = SCALE VALUES
C      NOBJS= NUMBER OF OBJECTS
C      MAXN = MAXIMUM NUMBER OF OBJECTS
C      NAMES= LIST OF NAMES FOR EACH OBJECT
C      PR   = DEVICE NUMBER FOR PRINTER
C      A    = INPUT MATRIX
C      M1   = USED BY ROUTINE FOR SORTING VALUES IN B( )
C
       INTEGER*4 MAXN,NOBJS,PR,NAMES(12,NOBJS),DIM
       INTEGER*4 M1(NOBJS),TITLE(1),TITLEL
       REAL*8    B(NOBJS),A(MAXN,MAXN)
C
C      SORT OBJECTS IN ASCENDING SCALE-VALUE ORDER
C
       CALL SORT(.FALSE.,B,NOBJS,M1,.TRUE.)
C
C      WRITE TITLE FOR SORTED OUTPUT
C
       WRITE (PR,80)(TITLE(K1),K1=1,TITLEL)
  80 FORMAT (33A4)
       WRITE (PR,90) DIM
  90 FORMAT (' STIMULI REORDERED BY DIMENSION   ',I3//
     1  '  SCALE        ITEM')
       DO 600 K1=1,NOBJS
600    WRITE(PR,605) B(M1(K1)),(NAMES(K2,M1(K1)),K2=1,12)
605  FORMAT(F10.4,3X,12A4)
       RETURN
       END
       SUBROUTINE LAMBDA(A,B,EIGENN,NOBJS,MAXN,TITLE,NAMES,PR)
C
C      ****************************************************
```

```
C     *      PRINT CONTRIBUTION OF EACH ITEM TO LAMBDA     *
C     *****************************************************
C
C  PASS TO THIS SUBROUTINE:
C     B      = SCALE VALUES
C     A      = INPUT MATRIX
C     EIGENN = THIS IS EIGENVALUE NUMBER
C     NOBJS  = NUMBER OF OBJECTS SCALED
C     MAXN   = MAXIMUM NUMBER OF ITEMS
C     TITLE  = TITLE OF PRINTOUT
C     PR     = DEVICE ADDRESS OF OUTPUT DEVICE
C
      INTEGER*4 EIGENN,NOBJS,MAXN,TITLE(20),PR,NAMES(12,NOBJS)
      REAL*8    NUM,DEN,RATIO,A(MAXN,MAXN),B(NOBJS)
C
      WRITE(PR,50) TITLE,EIGENN
   50 FORMAT(20A4/
     1   ' CONTRIBUTIONS MADE BY EACH ITEM, EIGEN =',I3/
     2   23X,'NUMERATOR DENOMINATOR  RATIO N/D'/)
C
      DO 200 K1=1,NOBJS
         NUM=0.0
         DEN=0.0
         DO 100 K2=1,NOBJS
            NUM=NUM+A(K1,K2)*(B(K1)-B(K2))**2
  100       DEN=DEN+A(K1,K2)+A(K2,K1)
         DEN=B(K1)**2*DEN
         RATIO=0
         IF (5.0E5*DEN .GT. NUM)RATIO=NUM/DEN
  200    WRITE(PR,250) (NAMES(K3,K1),K3=1,5),NUM,DEN,RATIO
  250    FORMAT(1X,5A4,2F10.5,F15.5)
C
      RETURN
      END
```