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Crime Analysis Geographic Information Systems Services: Advanced Tools Report

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Completed for Environmental Systems Research Institute (ESRI)
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National Institute of Justice Crime Data Project
Final Summary Report

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EXECUTIVE SUMMARY AND INTRODUCTION

This final report consists of an executive summary and introduction, a specified summary of seven research reports already submitted to ESRI highlighting algorithms and issues of implementation as covered in the reports, recommendations, and appendices containing the original reports, flowcharts and GUIs (Appendix 1; Appendix 2).

This introduction is divided into two parts: findings and recommendations, and a brief history of the project.

The findings are based upon a double random survey of one thousand police departments and a major effort to do an exhaustive literature survey of crime mapping. The police survey showed in prioritized order of importance:
1) Most police departments are PC-based and use Windows 95/98.
2) Most police departments prefer "off the shelf" solutions to "customized software" solutions.
3) GIS sophistication and use generally correlates with size of police department.
4) The demand for and more sophisticated use of GIS by police departments is increasing at a very rapid rate.
5) Map-Info is losing market share to ArcView.

The literature survey showed:
1). There exists a considerable crime mapping literature.
2) The vast majority of it is "gray literature" consisting of unpublished documents, web sites, list-servers, and internal documents.
3) It is difficult to access and most police departments are not aware of its existence.

There are three types of recommendations in the executive summary: major recommendations regarding overall advanced tool creation and implementation, specific tool by tool recommendations, and implementation recommendations. These are detailed in the Recommendations section of this final report.

Brief Project History:

The history of the advanced tool kit project is a positive and successful joint effort by the public sector (NIJ and partner police departments), the private sector (ESRI), and the education sector (University at Buffalo). The original proposal to NIJ was to develop a crime mapping tool kit for police departments with standard and advanced crime-mapping tools. The design was to be generalized and fulfill the needs of most police departments. It was to use ArcView as a base platform and to have both standard and advanced tools.

The first project goal for the University at Buffalo was to determine the state of the art of advanced tools for crime mapping. In order to do so, the advanced tool kit project team undertook:
1) *a random survey of police departments* to determine what crime mapping software was being used and their capability to used advanced tools.
2) *an exhaustive survey of the literature* to determine what had previously been developed and was available.
3) *a structured set of interactions, meetings, and interviews with project police partners and other police departments to* determine their present needs and future desires.

The second project goal for the University of Buffalo was to create a set of advanced tools in crime mapping. In order to do so, the advanced tool kit project team undertook:
4) *to determine which tools* were most important in prioritized order on the basis of the police and literature surveys and consultation with the partner police departments, ESRI, and NIJ.
5) *to create new tools.*
6) *to find, use, modify or create appropriate statistics, spatial analytic techniques and algorithms.*
7) *to flow chart* the processes for each algorithm.
8) *to design GUIs* for each tool.
9) *to report on* each tool to ESRI.
10) *to test and validate* each tool programmed by ESRI using data provided by the police departments.

The first eight of the nine goals were accomplished by the end of 1998 according to schedule and within budget. At the beginning of January 1999, the contractor (ESRI) asked the advanced tool project team to stop all research and development by the contractor due to exigencies. We complied.

The personnel on the advanced tool project and their responsibilities were:

Ezra Zubrow (administration and overall design)
Rajan Batta (precinct and beat design).
Monika Bolino (editing, writing, administration)
Christopher Brunnelli (police survey and literature review)
Hugh Calkins (chloropleth design)
Patrick Daly (police survey and literature review)
Michael Frachetti (police survey and literature review)
Kristie Lockwood (GUI design)
Philip Mitchell (systems administration and pattern analysis)
Peter Rogerson (hotspot analysis)
Christopher Rump (precinct and beat design)
Shoou-Jiun Wang (cluster analysis and neural networks)
Joseph Woefel (neural networks)

It was a pleasure to work with NIJ and ESRI and we look forward to doing so again in the near future.

RESULTS

The content and results of the project reports are summarized below. Original full-text reports are included in Appendix 1.

Report: Cluster Analysis -- Classify Subjects or Variables
Author: Shoou-Jiun Wang

This report is comprised of five sections. Section one summarizes cluster analysis, and includes a review of hierarchical and nonhierarchical methods and algorithms. Cluster analysis, also known as classification, pattern recognition, numerical taxonomy, or morphometrics, is used to identify natural groupings of data set individuals or variables. Three main types of data set clustering are described: d-dimensional, proximity matrix, and sorting data.

Section two discusses similarity coefficients; in order to perform a cluster analysis, clustering data must first be placed in a similarity matrix. The size of the matrix is one of the major limiting factors. Pairs of items are compared for presence or absence of certain characteristics. This section of the report provides several algorithms for calculating coefficients for individuals or pairs.

A comparison of hierarchical and nonhierarchical clustering methods is examined in the next two sections of the report. Hierarchical methods can be further categorized as agglomerative or divisive. Agglomerative hierarchies are formed by grouping individual objects by similarity, forming subgroups. Part of the agglomerative algorithm includes establishing distances between analyzed clusters and the rest of the clusters.

These linkage methods are defined as single linkage, complete linkage, or average linkage. In single linkage, groups are merged with the nearest neighbor. While single linkage methods cannot detect poorly separated clusters, they are one of the few methods able to delineate nonellipsoidal clusters. Complete linkage functions the same as single linkage except that similarity between objects is reckoned via the longest distance between members, resulting in compact clusters. A disadvantage of this linkage scheme is that there is a tendency toward poor concordance with true clusters, and a poor separation capability. The third type of linkage is average linkage, in which the distance between two clusters is regarded as the average distance between all pairs of items where one member of a pair belongs to each cluster. Average linkage is more conservative in its reckoning, and features the least distortion.

Other hierarchical methods are outlined including Ward's Algorithm, the Centroid method, and Divisive hierarchical methods. Ward's Algorithm, a favorite method, uses ANOVA regression principles. A disadvantage is that the method does not guarantee optimal partitioning of objects into clusters. Moreover, due to the nature of clustering, the minimum value of E is contingent on previously formed clusters, somewhat biasing the results. Despite these disadvantages, Ward's Algorithm remains one of the most satisfactory solutions. Ward's method offers a reduction in the computations. In

addition, clusters are usually equal in size and dense, and have small intracluster variance. In centroid clustering, the similarity between clusters is reckoned from a central point. The Centroid method is not a common approach. Results can be difficult to interpret and data is subject to "reversals." Alternatives to these agglomerative methods include divisive approaches. In divisive methods, objects are divided into subgroups until all objects stand alone in their own subgroup. An example of nonhierarchical methods is represented by an explanation of the K-means Method.

Deciding which cluster analysis strategy to use is contingent on the specific problem. Crime data, which uses many variables and objects, seems most compatible with a hierarchical analytical method. Ward's Algorithm in particular is recommended as a starting option though users may prefer to choose from other cluster analysis strategies.

Report: Detecting Hotspots
Author: Peter Rogerson

Clusters of criminal activity, or "hotspots," were examined by Peter Rogerson in preparation for hotspot detection tool development. This type of analysis is a form of point pattern analysis, a statistical application often overlooked in crime detection. According to Berg and Newell (1991), this strategy addresses three primary tests: general tests, which determine overall map patterns via point locations; tests for clusters which focus around a single prespecified event or small number of events; and tests for determining cluster size and location when cluster activity is not known beforehand.

All tests can be grouped into those that use local statistics or those that use global statistics. The former searches for deviations from a random or normal pattern. Local statistics, in contrast, examine clusters around specific events and are oriented toward hypothesis suggestion rather than confirmation. Furthermore, local statistics can determine if the study area is homogeneous, or if local outliers contribute to the global model.

This report devotes a large section to summaries of the following global and local statistics applications and formulas:

Global Statistics:

Nearest neighbor
Quadrat analysis
Moran's I.
Oden's I pop Statistic
Tango's Cg Statistic
Rogerson's R Statistic

Local Statistics

Local Moran Statistic
Tango's Cf Statistic
Rogerson's R1 Statistic
Getis' Gi Statistic
Openshaw's (1987) Geographical Analysis Machine (GAM)
Besag and Newall's Test for the Detection of Clusters
Fotheringham and Zhan's (1996) Method
Cluster Evaluation Permutation Procedure
Spatial Scan Statistic with Variable Window Size
Openshaw's Space-Time-Attribute Machine (STAM)

Most of the formulas employed in the development of the hotspot detection tool evolved from formulas first used in other fields, particularly natural history disciplines; they are just starting to be employed in crime analysis. Rogerson briefly discusses three notable packages which do rely on point pattern analysis models, including the Illinois Criminal Justice Information Authority's STAC (Spatial and Temporal Analysis of Crime), the Montgomery County Spatial Crime Analysis System, and CrimeStat, a package presently under development.

The report concludes with an outlined list of suggestions for the design of hotspot analyzers and recommends different statistics for different levels of users. Level One is appropriate for all crime mapping programs. Level Two should be used in most crime mapping packages for crime analysts who need to do routine hotspot analysis. Level Three is best suited for crime analysts who need to very accurately determine the type and exact character of each hotspot. Most likely, Level Three will be appropriate for only crime analysts in larger metropolitan areas.

Report: Chloropleth Mapping
Author: Hugh Calkins

In this introductory report, Hugh Calkins discusses points to consider when preparing chloropleth maps. Calkins identifies five issues: disparate sizes between units; classification methods used to determine map ranges; normalization of the data; color selection; and the number of displayed variables. Three specific options are recommended. First, a single button option should be implemented; in this option, users would select data sets from drop-down lists, and are afforded more control over the program's color schemes. The second option is similar to the first but allows even more user control over classification and color selection. Finally, histogram and rank order array functionality for the selection of classes are incorporated in a third option.

Report: Artificial Neural Networks (ANN)
Author: Shoou-Jiun Wang and Joseph D. Woelfel

This report explores the use of artificial neural networks (ANN) in criminal analysis, as well as the development and theoretical applications of chaotic cellular forecasting (CCF).

The randomness, non-linear nature, and seeming chaos of criminal activity often makes it difficult to employ traditional prediction tools such as geographic information systems (GIS). In contrast, artificial neural networks are better equipped to address the inherently unpredictable nature of criminal events. ANNs are flexible and self-adaptive with randomly initialized parameters, factors that make them particularly appropriate for criminal activity forecasting. In addition, artificial neural networks are able to discern patterns and associations within noisy or incomplete information frameworks such as criminal activity data. In case studies, ANN-based algorithms have proven superior to traditional regression models.

When ANNs and cellular automata are combined with GIS-based data, this fusion of methodologies is known as chaotic cellular forecasting (CCF), a type of analytical tool grounded in chaos theory. The report details the characteristics of the three primary ANN models. The most common is the supervised model, which requires target, or correct, outputs in order to adjust connection weights between neurons. In contrast, the self-organizing model adjusts itself to current input patterns, superceding the need for target outputs. A final type is the hybrid model, which operates in a mixed environment and borrows from both supervised and self-organizing networks.

One drawback of backpropagation networks is their need for very large numbers of observations for training. The use of geographic information systems may facilitate this requirement. A second obstacle encountered with such networks is their tendency for overfitting. This problem was solved by adding direct input to output connections, as well as averaging spatially lagged variables. A final drawback to backpropagation networks is their inability to render results as an equation with perimeters; delineating dependent and independent variables may overcome this limitation.

A key advantage of neural networks is their flexibility. ANN transfer functions are nonlinear and multilayer in structure, ensuring a good fitting for all functional forms. Moreover, neural networks find the functional form automatically without further data input from the analyst.

The report concludes with three recommendations for further study. First, patrol beats should replace grid cells as neutrons, with the incorporation of fuzzy logic to monitor neighborhood relationships. Second, backpropagation networks should be altered to induce quicker problem solving; one strategy might be to employ genetic algorithms. Finally, development of ANN should include the implementation of hidden layers to accommodate the nonlinear nature of input and output neurons. The report concludes with a brief outline discussing the design of Chaotic Cellular Forecasting (CCF).

Report: Pattern Analyses, Pattern Recognition
Author: Phillip C. Mitchell

This report discusses the significance of disruptions in patterns using two examples from the crime data set; the first uses data regarding licensing violations associated with bars, taverns and night clubs, while the second focuses on violation records maintained by the licensing agency and includes other vendors such as grocery stores and restaurants.

Disruptions to the data sets may be classified as spatial or temporal. For example, two objects considered nearest neighbors based on spatial proximity may in fact be disassociated due to a major highway separating them. Temporal variability may include the time of day or season; schools and businesses exhibit different tempos, albeit many are predictable. Moreover, data may be static, with long intervals between updates, or dynamic, such as in-house data sets which are updated daily or weekly.

The report also notes the problematic nature of the large data pool characteristic of crime data sets. Quantitative and qualitative aspects have created a data overload; comparing data sets becomes an even more formidable challenge. For instance, data may be organized by grid, point, or polygon templates, with each type more likely to produce a given pattern. Locally, individual "cognitive maps" impact pattern constructions as people have different expectations due to their mode of transportation (subway riders versus automobile drivers) or location (schoolyard versus park). Fringe areas further complicate pattern construction; such areas are defined as the interface of different spatial, demographic, and political areas that do not have inherent associations.

Another issue concerning crime data processing is the varying needs of the diverse end user pool. This report discusses the three main groups of users and their specific priorities. Users include administration, who require district-level analysis, best obtained via a polygon scheme; police, who need localized, specific data via point and cluster analysis; and investigators, who typically employ specific data in comparisons with other regions.

The report concludes with discussion and algorithms of specific cluster analysis strategies, including CSR or scattered quadrates, two dimensions of the nearest neighbor scheme, the polygon technique and the cluster process model.

Report: Patrol Car Allocation Tool (PCAT)
Author: Christopher M. Rump

The Patrol Car Allocation Tool (PCAT) is described in this report, which consists of programmer notes and instructions for implementing the tool. The PCAT uses notations to stand for ten possible objects including the number of call priority classes, geographic jurisdictions, time blocks, and weekly patrol car hours as well as the size of geographic jurisdiction and average response velocity. Other objects combine multiple components of these elements (the effective number of patrol cars allocated to jurisdiction during a given time period, for example). This algorithm key is also used in the Precinct Optimization Tool.

The PCAT employs three formulas for determining patrol car allocation: Hazard, Workload, and Queueing. These may be characterized as elementary, intermediate, and advanced strategies based on the amount of data required for each formula. The Hazard Formula determines patrol car allocation by calls for service (CFS), while the intermediate Workload Formula calculates allocation based on travel and on-scene service times as well as the CFS rate. The most advanced strategy is the Queueing Formula, which determines allocation according to CFS rates, service time, and response velocities. This report includes step-by-step instructions for each strategy, as well as a fourth option, the Greedy Algorithm.

Report: Precinct Design Optimization Tool (PDOT)
Author: Christopher M. Rump

The Precinct Design Optimization Tool (PDOT) tracks information for a given precinct. Notations represent ten possible objects including the number of call priority classes, geographic jurisdictions, time blocks, and weekly patrol car hours as well as the size of geographic jurisdiction and average response velocity. Other objects combine multiple components of these elements (the effective number of patrol cars allocated to jurisdiction during a given time period, for example). These codes are also used in the implementation of a complementary tool, the Patrol Car Allocation Tool (PCAT).

This report provides explicit step-by-step instructions for calculating beat optimization, as well as a flowchart illustrating the process.

RECOMMENDATIONS

This section provides general recommendations as well as tool-specific suggestions.

The three major recommendations are as follows:
1) There is a need for advanced crime mapping tools.
2) These tools should consist of advanced statistics being coupled to advanced spatial analysis.
3) Advanced crime mapping tools should consist of linked attribute analysis and spatial analysis algorithms. They should make the attribute (statistical)- spatial (geographic) boundary transparent to the user. (For example, cluster analysis of attribute data should automatically direct appropriate algorithms for hotspot analysis and vice versa. If one is aware of a cluster of attributes on a particular day, then automatically a hot spot analysis is used to see if there is any spatial coherence or vice versa – if one sees a hot spot, one automatically is provided with the cluster of attributes that is determining it).

The specific tool by tool recommendations are:
1) The clustering tool should minimally use hierarchical clustering methods with Ward's algorithm.
2) The hotspot tools should minimally have pinmaps, density maps, standard deviational ellipses, globally "nearest neighbor" and "Moran's I" algorithms and locally "geographical analysis machine" and "local Moran" algorithms.
3) Chloropleth mapping should incorporate histogram and rank order classification systems providing the user with increased flexibility in classification categories.
4) Neural networks have high potential for an advanced tool kit but need more research at this time.
5) There is an important need for a spatial, temporal and attribute predictor. This would best be served by a multivariate linear and non-linear regression predictor that operates independently on attribute data, independently on spatial data, and jointly on both.
6) A pattern recognition tool should be created minimally using nearest neighbor analysis and Thiessen polygons. It should have both an interactive and automatic button. The interactive button allows the user to select points and run a pattern analysis test. The user then selects more points and finds out if the new selection is more patterned than the previous selection. The automatic button does the same process recursively for all possible points and finds the most patterned set of points given user specified minima.
7) PCAT is an adequate patrol car allocation tool if one provides a choice of patrol allocation by CFS, workload formula, and queueing formula.
8) PDOT is an adequate precinct design optimization tool using beat optimization, workload formula and queueing formula.

In addition, there are four implementation recommendations:
1) The advanced tool kit was designed to consist of modular tools. Thus it may be used as an entire package, it may be used as single tools, or it may be cannibalized and used for parts in other products.
2) The advanced tool kit was intended to be part of the ESRI Crime Mapping Product for NIJ and both the algorithm and GUI architecture was designed for easy insertion.
3) The advanced tool kit may be added in part or whole to CrimeView with changes to GUI design.
4) The advanced tool kit may exist as a stand-alone product. This is the least desirable.

Appendix 1:

Full-Text Reports

Cluster Analysis: Classify Subjects or Variables

Author: Shoou-Jiun Wang

1. Introduction

The basic objective in cluster analysis is to discover natural groupings of the individuals or variables. It should be noted that cluster analysis goes under a number of names, including classification, pattern recognition (with "unsupervised learning"), numerical taxonomy, and morphometrics (Seber 1984). To perform a cluster analysis, important considerations include the nature of the variables (discrete, continuous, binary) or scales of measurement (nominal, ordinal, interval, ratio) and subject matter knowledge. In turns we must first develop a quantitative scale on which to measure the similarity between objects to run a cluster analysis.

There are three main types of data set in clustering (Kruskal 1977). The first is *d*-dimensional vector data $x_1, x_2,...,x_n$ arising from measuring or observing *d* characteristics on each of *n* objects or individuals. The characteristics or variables should be either quantitative (discrete or continuous) or qualitative (ordinal or nominal). It is usual to treat present-absent (dichotomous) qualitative variables separately. Although such variables are simply two-state qualitative variables, the presence of a given character can be of much greater significance than its absence. No matter which method used for coding the qualitative variables, the aim of cluster analysis is to device a classification scheme for grouping the x_i or variables into clusters (groups, types, classes, etc.). We might want to cluster the variables in some cases.

A second data type for clustering consists of an N*N proximity matrix $[d_{ik}]$, where d_{ik} is a measure of similarity (dissimilarity) between *i*th and *k*th objects. A d_{ik} is called a proximity and the data is referred to as proximity data.

A third data type is called sorting data which is already in a cluster format. For example, each of several subjects may be asked to sort *n* items or stimuli into a number of similar, possibly overlapping groups.

All three types of data can be converted into proximity data and Cormack (1971) lists 10 proximity measures. Once we have the proximity matrix, we can then proceed to form clusters of objects that are similar or close to one another.

This article consists of five sections including this introduction. Section 2

reviews how researchers design similarity coefficients for pair of objects or pair of variables. Section 3 introduces the most commonly used clustering method, hierarchical clustering. Section 4 delineates K-mean method, one of nonhierarchical clustering methods. Section 5 provides a rule of thumb, a small conclusion. Section 6 recommends a way to develop cluster analysis software.

2. Similarity coefficients: to build a similarity matrix

A cluster analysis starts from the similarity matrix. This section reviews some commonly used methodology to decide the similarity coefficients in the matrix.

Similarity coefficients for pairs of individuals

Similarity coefficients for two p-dimensional observations $\boldsymbol{x} = [x_1, x_2,...,x_p]'$ and $\boldsymbol{y} = [y_1, y_2,...,y_p]'$ can be defined as their "distance". Several commonly used distances are listed as follows:

- The Euclidean distance between two observations

$$d(\boldsymbol{x}, \boldsymbol{y}) = [(x_1-y_1)^2 + (x_2-y_2)^2 + ...+(x_p-y_p)^2]^{1/2}.$$

- The statistical distance between two observations

$$d(\boldsymbol{x}, \boldsymbol{y}) = [(\boldsymbol{x}-\boldsymbol{y})'\mathbf{A}(\boldsymbol{x}-\boldsymbol{y})]^{1/2}.$$

  where the entries of $\mathbf{A}^{-1}$ are sample variances and covariances.

- The Minkowski metric between two observations

$$d(\boldsymbol{x}, \boldsymbol{y}) = [\sum_{i=1}^{p} |x_i - y_i|^m]^{1/m}.$$

When objects cannot be represented by meaningful p-dimensional measurements, for example ordinal or nominal data, pairs of items are often compared on the basis of the presence or absence of certain characteristics. The presence or absence of a characteristic can be described mathematically by introducing a binary variable, which assumes value 1 if the characteristics present and value 0 if not.

In some cases a 1-1 match is a stronger indication of similarity than a 0-0 match. For instance, when grouping people, the evidence that two persons both ever commit crimes (1-1) is stronger evidence of similarity than the absence of this record (0-0). To adjust the weighting of 1-1 and 0-0 matches, several schemes for defining similarity coefficients have been suggested.

Similarity Coefficients for Clustering

Coefficient	Description
1. $\frac{a+d}{a+b+c+d}$	Only 1-1 and 0-0 matches are important, and equally.
2. $\frac{p(a+d)}{p(a+d)+b+c}$	Only 1-1 and 0-0 matches are important, and equally. Also, matches are weighted more heavily than are mismatches; p>1.
3. $\frac{a+d}{a+d+p(b+c)}$	Only 1-1 and 0-0 matches are important, and equally. Also, matches are weighted less heavily than are mismatches; p>1.
4. $\frac{a}{a+d+b+c}$	Only 1-1 matches are important.
5. $\frac{a}{a+b+c}$	Only 1-1 matches are important while 0-0 matches are unimportant.
6. $\frac{pa}{pa+b+c}$	Only 1-1 matches are important while 0-0 matches are unimportant. Also, 1-1 matches are weighted more heavily; p>1.
7. $\frac{a}{a+p(b+c)}$	Only 1-1 matches are important while 0-0 matches are unimportant. Also, 1-1 matches are weighted less heavily; p>1.
8. $\frac{a}{b+c}$	Only 1-1 matches are important while 0-0 matches are unimportant.

a: the frequency of 1-1 matches; b: the frequency of 1-0 matches;
c: the frequency of 0-1 matches; d: the frequency of 0-0 matches.

Similarity coefficients for pairs of variables

The correlation coefficient applied to the binary variables in a contingency table gives

$$r = \frac{ad - bc}{[(a+b)(c+d)(a+c)(b+d)]^{\frac{1}{2}}}$$

This number can be taken as a measure of the similarity between two variables. The correlation coefficient is related to the chi-square statistic for testing independence of

two categorical variables. After building up the similarity matrix, we can start clustering. The following section introduces some available hierarchical cluster methods.

3. Hierarchical Clustering Methods

Agglomerative hierarchical methods

The algorithm starts with the individual objects. Thus there are initially as many as clusters as objects. Most similar objects are first grouped, and these initial groups are merged according to their similarity. Eventually, as the similarity decreases, all subgroups are fused into a single cluster.

The following are the steps in the agglomerative hierarchical clustering algorithm for grouping N objects (subjects or variables):

1. Start with N clusters, each containing a single entity and an N*N symmetric matrix of distances (or similarities) $\mathbf{D} = \{d_{it}\}$.
2. Search the distance matrix for the nearest (most similar) pair of clusters. Let the distance between "most similar" clusters U and V be d_{UV}.
3. Merge clusters U and V. Label the newly formed cluster (UV). Update the entries in the distance matrix by (a) deleting the rows and columns corresponding to clusters U and V and (b) adding a row and column giving the distances between cluster UV and the remaining clusters.
4. Repeat steps 2 and 3 a total of N-1 times. Record the identity of clusters that are merged and the levels at which the mergers take place.

In Step 3(b), there are several ways, called linkage methods, to give the distances between cluster UV and the remaining clusters. We shall discuss, in turn, single linkage (minimum distance or nearest neighbor), complete linkage (maximum distance of farthest neighbor), and average linkage (average distance).

Single Linkage:

$$d_{(UV)W} = \min\{d_{UW}, d_{VW}\}.$$

The input to a single linkage algorithm can be distances or similarities between pairs of objects. Groups are formed from the individual entities by merging nearest neighbors, where the term nearest neighbor connotes smallest distance or largest similarity. Since single linkage joins clusters by the shortest link between them the technique cannot discern poorly separated clusters. On the other hand, single linkage is one of the few clustering methods that can delineate nonellipsoidal clusters. The tendency of single linkage to produce compacted trees and pick out long stringlike items known as chaining. Chaining can be misleading if items at opposite ends of the chain are, in fact, quite dissimilar.

Complete Linkage:

$$d_{(UV)W} = \max\{d_{UW}, d_{VW}\}.$$

Complete linkage clustering proceeds in much the same manner as single linkage, with one important exception. At each stage, the distance (similarity) between clusters is determined by the distance (similarity) between the two elements, one from each cluster, that are most distant. Thus complete linkage tends to produce extended trees and ensures that all units in a cluster are within some maximum distance (or minimum similarity) of each other. A well-known advantage of the complete linkage algorithm is that it creates relatively compact clusters. This renders density indices whose variation is in keeping with what one would expect to obtain strictly from changing coterminous surface partitioning. A well-known disadvantage of complete linkage solutions is that they tend to have poor concordance with the true clusters. This algorithm also displays a poor separation capability.

Average Linkage:

$$d_{(UV)W} = (\Sigma_i \Sigma_k d_{ik}) / N_{(UV)} N_W.$$

Average linkage treats the distance between two clusters as the average distance between all pairs of items where one member of a pair belongs to each cluster. This method tends to produce trees intermediate between two extremes, compact trees and extended trees. For researchers, extremes connote risk. To them average linkage is a safer choice compared with single linkage and complete linkage. It turns out that a

theoretical reason supports this intuition. Farris (1969) shows average linkage method tends to give higher values of cophenetic correlation coefficient. It means that average linkage method produces less distortion in transforming the similarities between objects into a tree.

There are many agglomerative hierarchical clustering procedures besides single linkage, complete linkage, and average linkage. For a particular problem, it is good idea to try several clustering methods and, within a given method, a couple different ways of assigning distances (similarities). If the outcomes from the several methods are (roughly) consistent with one another, perhaps a case for "natural" grouping can be advanced. (Johnson and Wichern, 1982). The other two aggolmerative hierarchical methods are introduced in the following.

Ward's Algorithm:

Ward's minimum variance clustering method is the most often used agglomerative hierarchical method based upon ANOVA regression principles. At each step it makes whichever merger of two clusters that will result in the smallest increase in the value of an index E, called the sum-of-squares index, or variance. This means that at each step we have to calculate the value of E for all possible mergers of two clusters, and select that one whose value of E is the smallest. E is computed as follows.

1. Calculate the mean of each cluster.
2. Compute the differences between each object in a given cluster and its cluster mean.
3. For each cluster, square each of the differences which have computed above. Add these for each cluster, giving a sum-of-square for each cluster.
4. Compute the value of E by adding the sum-of-squares values for each cluster.

One point to note about Ward's method is that Ward's method does not guarantee an optimal partitioning of objects into clusters. That is, there may be other partitions that give a value of E that is less than the one obtained by using this method. Because the objects merged at any step are never unmerged at subsequent steps, the finding of the minimum value of E at each step is conditioned on the set of clusters already formed at

prior clustering steps. But using the less-than-optimal solution offered by Ward's method greatly reduces toe computations required by an optimal method, and it usually gives a near-optimal solution that is good enough for most purposes (Romesburg, 1984).

Acknowledged advantages of clusters generated by Ward's algorithm is that they tend to be relatively equal in size, to have relatively small within cluster variances, and to be relatively dense. Ward's algorithm also is recognized as outperforming most other clustering algorithms in terms of separation. A noteworthy disadvantage is that the created clusters tend to display an ordered profile.

Centroid Method:

In centroid method, similarity between two clusters is defined to be the similarity between their centroids, where a cluster's centroid is its center of mass (cluster mean). Each unit is assigned to that cluster having the nearest centroid.

While intuitively appealing, the centroid clustering method is not used much in practice, partly owing to its tendency to produce trees with reversals. Reversals occur when the values at which clusters merge do not increase from one clustering step to the next, but decrease instead. Thus, the tree can collapse onto itself and be difficult to interpret.

An evaluation of those clustering algorithms often can be very instructive, especially prior to an exhaustive analysis of some data set. A researcher should avoid obtaining results of data analysis that principally are attributable to the algorithm employed.

Divisive hierarchical methods

Besides agglomerative hierarchical methods, the other clustering approach is known as divisive hierarchical method. It works in reverse of the agglomerative hierarchical method. In divisive hierarchical methods, a single group of objects is divided into two subgroups such that the objects in one group is dissimilar with the ones in the other. The subgroups are then further divided in the same way until there are as many subgroups as objects.

4. Nonhierarchical Clustering Methods

K-means Method

K-means method assigns each item to the cluster having the nearest centroid (mean). The process is composed of following steps.

1. Partition the items into K initial clusters randomly.
2. Proceed through the list of items, assign an item to the cluster whose centroid (mean) is nearest. Recalculate the centroid for the cluster receiving the new item and for the cluster losing the item.
3. Repeat Step 2 until no more reassignments take place.
4. Once clusters are determined, rearranging the list of items so that those in the first cluster appear first, those in the second cluster appear next, and so forth.

Rather than starting with a partition of all items into K preliminary groups in Step 1, we could specify K initial centroids (seed points) and then proceed to Step 2. The final assignment to clusters will be dependent upon the initial partition or the initial selection of seed points. Experience suggests that most major changes in assignment occur with the first reallocation step. To check the stability of the clustering, it is desirable to rerun the algorithm with different initial partitions.

5. Rule of Thumb

If there is no single overriding desirable property for resulting clusters to exhibit, Ward's algorithm should be selected because it tends to produce the most appealing overall results. Of compact clusters are of primary concern, the complete linkage should be used. If outliers present a serious concern, then the centroid algorithm should be used. In most cases, the single linkage algorithm should be avoided (Griffith and Amrhein, 1997). If we know how many clusters supposed to be in advanced, K-mean method is applicable.

If case of missing valves, current commonly used statistics software, e.g. SPSS, excludes the subjects or variables with missing values. However, in our crime data type with extremely large numbers of subjects and variables and unavoidable some missing

values, excluding the subjects or variables because of a missing value is trivially impractical. We propose to replace the missing values by the average of the corresponding variable.

6. Recommendation for development of a cluster analysis software

Level 1

- Use all the variables and points
- Apply Ward's algorithm
- Plot dendogram and scree plot (help users determine number of clusters)
- Display results visibly, i.e. light up the clusters by gradually coloring.

Level 2

- Users choose interested variables and points
- Apply Ward's algorithm
- Plot dendogram and scree plot (help users determine number of clusters)
- Display results visibly, i.e. light up the clusters by gradually coloring.

Level 3

- Users choose interested variables and points
- Users choose cluster algorithms among Ward's, single linkage, complete linkage, average linkage, centroid method, or K-means method.
- Plot dendogram and scree plot (help users determine number of clusters)
- Display results visibly, i.e. light up the clusters by gradually coloring.

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Crime Analysis: Detecting Hotspots

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1. Introduction

An important activity in the analysis of crime data is the detection of hotspots or clusters of criminal activity. Hotspot detection may be important at several different scales of analysis. At the level of the police beat, patrol officers wish to know where activity has recently occurred in their area. At larger geographical scales, crime analysts look for patterns to decide how to allocate and deploy resources effectively.

Several methods and software packages have been developed explicitly for finding clusters in data represented by point locations. Although some of these methods have been developed within the context of research on crime analysis, many relevant approaches have been developed recently in the field of epidemiology.

Besag and Newell (1991) classify objectives and methods into three primary areas. First are "general" tests, designed to provide a single measure of overall pattern for a map consisting of point locations. These general tests are intended to provide a test of the null hypothesis that there is no underlying pattern, or deviation from randomness, among the set of points. In other situations, the researcher wishes to know whether there is a cluster of events around a single or small number of prespecified foci. For example, we may wish to know whether disease clusters around a toxic waster site, or we may wish to know whether crime clusters around a set of liquor establishments. Finally, Besag and Newell describe "tests for the detection of clustering". Here there is no *a priori* idea of where the clusters may be; the methods are aimed at searching the data and uncovering the size and location of any possible clusters.

General tests are carried out with what are called "global" statistics; again, a single summary value characterizes any deviation from a random pattern. "Local" statistics are used to evaluate whether clustering occurs around particular points, and hence are employed for both focused tests and tests for the detection of clustering. Local statistics have been used in both a confirmatory manner, to test hypotheses, and in an exploratory manner, where the intent is more to suggest, rather than confirm, hypotheses.

This document is structured as follows. Section 2 provides a brief summary of the use of point pattern methods in crime analysis. Section 3 summarizes several prominent global statistics used for general tests of clustering. Section 4 reviews local statistics, and their use both in focused tests and in detecting clusters where there is no prior knowledge of where clusters may be. The final section provides some recommendations for the development of hotspot detection software.

2. Point Pattern Methods Used in Crime Analysis

There has been relatively little effort aimed at incorporating established methods of point pattern analysis within the crime analysis literature and within software tailored for the analysis of crime. The *Spatial and Temporal Analysis of Crime* (STAC), developed by the Illinois Criminal Justice Information Authority, is one exception. STAC searches the study area for areas with the highest incidence density, and then calculates standard deviational ellipses. The most recent version also includes nearest neighbor analysis.

The Montgomery County, MD Spatial Crime Analysis System is similar to STAC, in the sense that it contains procedures for identifying areas of high incident density, and then one can create standard deviational ellipses to portray the orientation and extent of the hotspot areas.

A number of promising packages are currently under development. *CrimeStat* (Levine and Canter 1998) will include nearest neighbor analysis (including a generalization to *k*-order nearest neighbors), Moran's *I*, local Moran statistics, standard deviational ellipses, and a host of other methods for both point pattern and other types of analysis.

3. Global Statistics

3.1 *Nearest neighbor analysis*

Clark and Evans (1954) developed nearest neighbor analysis to analyze the spatial distribution of plant species. They developed a method for comparing the observed average distance between points and their nearest neighbors with the distance that would be expected between nearest neighbors in a random pattern. The nearest neighbor statistic, R, is defined as the ratio between the observed and expected values:

$$R = \frac{R_0}{R_e} = \frac{\bar{x}}{1/(2\sqrt{\lambda})},$$

where $\bar{x}$ is the mean of the distances of points from their nearest neighbors, and λ is the number of points per unit area. R varies from 0 (a value obtained when all points are in one location, and the distance from each point to its nearest neighbor is zero), and a theoretical maximum of about 2.14, for a perfectly uniform or systematic pattern of points spread out on an infinitely large two-dimensional plane. A value of R=1 indicates a random pattern, since the observed mean distance between neighbors is equal to that expected in a random pattern.

To test the null hypothesis of no deviation from randomness, a z-test is employed:

$$z = 3.826(R_0 - R_e)(\sqrt{\lambda n}),$$

where n is the number of points. The quantity z has a normal distribution with mean 0 and variance 1, and hence tables of the standard normal distribution may be used to assess significance. A value of z>1.96 implies that the pattern has significant uniformity, and a value of z<1.96 implies that there is a significant tendency toward clustering.

The strength of this approach lies in the ease of calculation and comprehension. Several cautions should be noted in the interpretation of the statistic. The statistic, and its associated test of significance, may be affected by the shape of the region. Long, narrow, rectangular shapes may have relatively low values of R simply because of the constraints imposed by the region's shape. Points in long, narrow rectangles are *necessarily* close to one another. Boundaries can also make a difference in the analysis. It is therefore recommended that a buffer area be placed around the study area; points inside of the study area may have nearest neighbors that fall into the buffer area, and these distances (rather than distances to those points that are nearest within the study area) should be used in the analysis. Since only nearest neighbor distances are used, clustering is only detected on a relatively small spatial scale. Others have described how the approach may be extended to second- and higher-order nearest neighbors.
Finally, it is often of interest to ask not only whether clustering exists, but whether clustering exists over and above some background factor (such as population). Nearest neighbor methods are not particularly useful in these situations.

3.2 *Quadrat analysis*

Quadrat analysis was also developed by ecologists, during the 1920s through the 1950s. In quadrat analysis, a grid of square cells of equal size is used as an overlay, on top of a map of incidents. One then counts the number of incidents in each cell. In a random pattern, the mean number of points per cell will be roughly equal to the variance of the number of points per cell.

If there is a large amount of variability in the number of points from cell to cell (some cells have many points; some have none, etc.), this implies a tendency toward clustering. If there is very little variability in the number of points from cell to cell, this implies tendency toward a systematic pattern (where the number of points per cell would be the same). The statistical test makes use of a chi-square statistic involving the variance-mean ratio:

$$\chi^2 = \frac{(m-1)\sigma^2}{\bar{x}},$$

where m is the number of quadrats, and $\bar{x}$ and σ^2 are the mean and variance of the number of points per quadrat, respectively. This value is then compared with a critical value from a chi-square table, with m-1 degrees of freedom.

Like nearest neighbor analysis, quadrat analysis is easy to employ, and it has been a mainstay in the spatial analyst's toolkit of pattern detectors over several decades. One important issue is the size of the quadrat; if the cell size is too small, there will be many empty cells, and if clustering exists on all but the smallest spatial scales, it will be missed. If the cell size is too large, one may miss patterns that occur *within* cells.
One may find patterns on some spatial scales and not at others, and thus the choice of quadrat size can seriously influence the results. Curtiss and McIntosh (1950) suggest an "optimal" quadrat size of two points per quadrat. Bailey and Gatrell (1995) suggest that the mean number of points per quadrat should be about 1.6.

3.3 *Moran's I*

Sometimes, point locations are not available, and data are given for areas only. Moran's *I* statistic (1954) is one of the classic ways of measuring the degree of pattern (or, spatial autocorrelation) in areal data. Moran's *I* is calculated as follows:

$$I = \frac{n\sum_i^n \sum_j^n w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{(\sum_i^n \sum_j^n w_{ij}) \sum_i^n (y_i - \bar{y})^2},$$

where there are n regions and w_{ij} is a measure of the spatial proximity between regions i and j. It is interpreted much like a correlation coefficient. Values near +1 indicate a strong spatial pattern (high values tend to be located near one another, and low values tend to be located near one another). Values near -1 indicate strong negative spatial autocorrelation; high values tend to be located near low values. (Spatial patterns with negative autocorrelation are either extremely rare or nonexistent!) Finally, values near 0 indicate an absence of spatial pattern.

In addition to this descriptive interpretation, there is a statistical framework that allows one to decide whether any given pattern deviates significantly from a random pattern. One approximate test of significance is to assume that *I* has a normal distribution with mean and variance equal to

$$E[I] = \frac{-1}{n-1}$$

$$V[I] = \frac{n^2(n-1)S_1 - n(n-1)S_2 - 2S_0^2}{(n+1)(n-1)^2 S_0},$$

where

$$S_0 = \sum_i^n \sum_{j \neq i}^n w_{ij}$$

$$S_1 = 0.5 \sum_i^n \sum_{j \neq i}^n (w_{ij} + w_{ji})^2$$

$$S_2 = \sum_k^n (\sum_j^n w_{kj} + \sum_i^n w_{ik})^2$$

Computation is not complicated, but it is tedious enough to not want to do it by hand! Unfortunately, few software packages that calculate the coefficient and its significance is available. An exception is Anselin's (1992) *SpaceStat*.

The use of the normal distribution to test the null hypothesis of randomness relies upon one of two assumptions:

1. Randomization: each permutation (rearrangement) of the observed regional values is equally likely.
2. Normality: the observed values are taken as arising from normal distributions having identical means and variances

3.4 *Oden's I_{pop} statistic*

One of the characteristics of Moran's *I* is that within-region variations can undermine the validity of the randomization or normality assumptions. For example, regions with small populations may be expected to exhibit more variability. Oden accounts for this within region variation explicitly by modifying *I* as follows:

$$I_{\text{pop}} = \frac{n^2 \sum_i^m \sum_j^m w_{ij}(r_i - p_i)(r_j - p_j) - n(1-2\bar{b}) \sum_i^m w_{ii} r_i - n\bar{b} \sum_i^m w_{ii} p_i}{S_0 \bar{b}(1-\bar{b})},$$

where r_i and p_i are the observed and expected proportion of all cases falling in region *i*, respectively. Furthermore, there are m regions, n incidents, and a total base population of x. The overall prevalence rate is $\bar{b}$ =n/x. Also,

$$S_0 = x^2 A - xB,$$

where

$$A = \sum_i^m \sum_j^m p_i p_j w_{ij}$$

$$B = \sum_i p_i w_{ii}$$

Oden suggests that statistical significance be evaluated via a normal distribution, with mean and variance

$$E[I_{\text{pop}}] = \frac{-1}{x-1}$$

$$V[I_{\text{pop}}] \approx \frac{2A^2 + C/2 - E}{A^2 x^2},$$

where A is defined as above, and

$$C = \sum_i^m \sum_j^m p_i p_j (w_{ij} + w_{ji})^2$$

$$E = \sum_i^m p_i [\sum_j^m p_j (w_{ij} + w_{ji})]^2$$

3.5 *Tango's C_G statistic*

Tango (1995) has recently suggested the following global statistic to detect clusters:

$$C_G = \sum_i^m \sum_j^m w_{ij}(r_i - p_i)(r_j - p_j)$$

In matrix form,

$$C_G = (\mathbf{r} - \mathbf{p})' \mathbf{A} (\mathbf{r} - \mathbf{p}),$$

where **r** and **p** are *m*x1 vectors with elements containing the observed and expected proportion of cases in each region. To test the null hypothesis that the incident pattern is random, Tango first gives the expected value and variance of the statistic as

$$E[C_G] = \frac{1}{N} Tr(\mathbf{AV}_p)$$

$$V[C_G] = \frac{2}{N^2} Tr(\mathbf{AV}_p)^2$$

where

$$\mathbf{V}_p = \Delta\mathbf{p} - \mathbf{pp'}$$

with $\Delta\mathbf{p}$ defined as a *mxm* diagonal matrix containing the elements of **p** on the diagonal. Tango then finds that the test statistic

$$\nu + \frac{C_G - E[C_G]}{\sqrt{V[C_G]}}\sqrt{2\nu}$$

has an approximate chi-square distribution with ν degrees of freedom, where

$$\nu = \left(\frac{Tr(\mathbf{AV}_p^2)^{1.5}}{Tr(\mathbf{AV}_p^3)}\right)^2$$

Tango's statistic is a weighted average of the covariations of all pairs of points.

3.6 *Rogerson's R statistic*

Rogerson (1998) developed and evaluated a spatial chi-square statistic that can be used as a global test of clustering. The statistic is:

$$R = \sum_i^m \sum_j^m \frac{w_{ij}(r_i - p_i)(r_j - p_j)}{\sqrt{p_i p_j}}.$$

Note that this may be written as a combination of a chi-square goodness-of-fit statistic and a Moran-type statistic:

$$R = \sum_i^m \frac{w_{ii}(r_i - p_i)^2}{p_i} + \sum_i^m \sum_{j \neq i}^m \frac{w_{ij}(r_i - p_i)(r_j - p_j)}{\sqrt{p_i p_j}}$$

The statistic *R* will be large when either there are large deviations between observed and expected values within regions, or when nearby pairs of regions have similar deviations. Like Tango's statistic, *R* combines the features of quadrat analysis, which focuses upon what goes on within cells, and Moran's *I*, which focuses upon what the joint variation of pairs of nearby cells. *R* is actually a special case of Tango's C_G, where Tango's weights are modified by dividing by $\sqrt{p_i p_j}$. Thus the distribution theory discussed for Tango's statistic may be adapted when using *R* to test the null hypothesis of randomness.

4. Local Statistics

4.1 *Introduction*

As indicated in the first section, local statistics may be used to detect clusters either when the location is prespecified (focused tests) or when there is no *a priori* idea of cluster location. When a global test finds no significant deviation from randomness, local tests may be useful in uncovering isolated hotspots of increased incidence. When a global test does indicate a significant degree of clustering, local statistics can be useful in deciding whether (a) the study area is relatively homogeneous in the sense that local statistics are quite similar throughout the area, or (b) there are local outliers that contribute to a significant global statistic. Anselin (1995) discusses local tests in more detail.

4.2 *Local Moran statistic*

The local Moran statistic is

$$I_i = \frac{n(y_i - \bar{y})}{\sum_i (y_i - \bar{y})^2} \sum_j w_{ij}(y_j - \bar{y})$$

The sum of local Moran's is equal to the global Moran; i.e., $\sum I_i = I$. Anselin gives the expected value and variance of I_i, and assesses the adequacy of the assumption that the test statistic has a normal distribution under the null hypothesis.

4.3 *Tango's C_F statistic*

Tango uses a modified score statistic to test for clusters around prespecified foci. His statistic is

$$C_F = \mathbf{c}'\mathbf{W}(\mathbf{r} - \mathbf{p}),$$

where **c** is a mx1 vector containing elements c_i=1 if i is one of the prespecified foci, and 0 otherwise. The variance of C_F is

$$V[C_F] = \mathbf{c}'\mathbf{W}\mathbf{V}_p\mathbf{W}\mathbf{c},$$

and under the null hypothesis of no pattern, the quantity $C_F^2 / V[C_F]$ has a chi-square distribution with one degree of freedom. This statistic has the advantage of allowing more than one focal point to be specified beforehand, and it also has been found to be quite powerful in rejecting false null hypotheses, especially when the number of prespecified foci is small.

4.4 *Rogerson's R_i statistic*

The local version of R is

$$R_i = \frac{r_i - p_i}{\sqrt{p_i}} \sum_j \frac{w_{ij}(r_j - p_j)}{\sqrt{p_j}}$$

As with Moran's I, the local statistics sum to the global statistic. The expected value of R_i is

$$E[R_i] = \frac{w_{ii}(1-p_i) - \sqrt{p_i}\sum_j w_{ij}\sqrt{p_j}}{N}$$

The quantity R_i / $E[R_i]$ has, approximately, a chi-square distribution with one degree of freedom.

4.5 *Getis' G_i statistic*

Getis and Ord have used the statistic

$$G_i^* = \frac{\sum_j w_{ij}(d)x_j - W_i^*\bar{x}}{s\{[nS_{1i}^* - W_i^{*2}]/(n-1)\}^{1/2}},$$

where

$$W_i^* = \sum_j w_{ij}(d)$$

$$S_{1i}^* = \sum_j w_{ij}^2$$

and $w_{ij}(d)$ is equal to one if region j is within a distance of d from region I, and 0 otherwise. Also, s is the sample standard deviation. Ord and Getis note that when the underlying variable has a normal distribution, so does the test statistic. Furthermore, the distribution is asymptotically normal when the underlying distribution is not normal, and the distance d becomes large. Since the statistic is written in standardized form, it can be taken as a standard normal random variable, with mean 0 and variance 1.

4.6 *Openshaw's (1987) Geographical Analysis Machine (GAM)*

With Openshaw's exploratory method for detecting clusters, a grid of points is constructed over the area of study. At each grid point, circles of various sizes are constructed. The number of incidents in each circle is counted and is compared with the number of incidents that would be expected if the pattern was random. Although Openshaw originally suggested Monte Carlo testing at this stage, as Besag and Newell note, this is unnecessary, and a Poisson test could be used instead. If the actual number significantly exceeds the expected number, the circle is drawn on the map. The result is a map with a set of circles, where each circle has passed a test of significance.
Because many tests are carried out, it is difficult to correct adequately for multiple tests. If a conservative correction is used, it will be difficult to find any clusters. If, on the other

hand, the degree of correction is not sufficient, clusters may be produced by chance. Openshaw uses a significance level of 0.002, but this is quite arbitrary. The significance level used will dictate the number of circles plotted.

4.7 *Besag and Newell's Test for the Detection of Clusters*

Cases or incidents occur within zones. A critical number of cases, k, is decided upon a priori. For a given case, i, neighboring zones are ordered in terms of increasing distance away from i. The statistic, M, is the minimum number of nearest zones around case i that are needed to accumulate at least k cases. If M is small, that is indicative of a cluster around the zone containing case i. Besag and Newell use Poisson probabilities to find the likelihood that an even smaller number of zones could contain k cases, if the distribution of cases throughout the population was homogeneous. Besag and Newell use their method for detecting clusters of rare diseases.

4.8 *Fotheringham and Zhan's (1996) method*

This method is similar to Openshaw's Geographical Analysis Machine. A circle with a radius chosen randomly within a prespecified range is drawn with its center at a location chosen at random within the study region. The circle is drawn on the map if the number of incidents inside of the circle is sufficiently great that it is unlikely to have occurred by chance. Fotheringham and Zhan compare their method with those of Besag and Newell and Openshaw, and find "the Besag and Newell method appears to be particularly good at not identifying false positives, although the Fotheringham and Zhan method is easier to apply and is not dependent on a definition of minimum cluster size.

4.9 *Cluster Evaluation Permutation Procedure*

Turnbull et al. (1990) suggest a method where the study region is first divided into a large number of regions. For each region, the region is combined with the nearest surrounding regions to form a "ball" of a predefined, fixed number of persons. For each "ball", one counts the number of incidents that are inside. Then the analysts determines whether the ball with the maximum number of incidents has a number that exceeds the number of incidents one would expect if incidents were randomly distributed. If a significant cluster is found, one can then go on to determine whether the ball with the second highest number of incidents has a number that exceeds the no. of incidents one would expect if incidents occurred at random.

4.10 *Spatial scan statistic with variable window size*

Kulldorf and Nagarwalla (1994) use either a regular lattice of points (a la Openshaw) or an irregular lattice of, e.g., area centroids (a la Turnbull et al.) and consider circles of all sizes centered on lattice points. They use a likelihood ratio statistic, and then find the maximum of all these ratios. To assess statistical significance, they compare

the maximum among the likelihood ratios with the maximum obtained from a Monte Carlo simulation.

4.11 *Openshaw's Space-Time-Attribute Machine (STAM)*

Openshaw's STAM begins by defining a study area across space, time, and attributes. The next step is to choose an observed data record. Then the size of geographic, temporal, and attribute search regions are chosen and one determines how many records lie within this tri-space region. Significance is assessed by using a Monte Carlo approach to determine the probability of observing that many records under the null hypothesis of no pattern. If the probability is sufficiently small, one saves the record. The idea is to examine all combinations of geographic, temporal, and attributes; those "search creatures" which do well reproduce, while those that do not find clusters die out. Thus an evolutionary element is embedded to speed up the search for interesting clusters.

5. Some Recommendations for the Design of Hotspot Analyzers

Level 1

- Descriptives
- Pinmap
- Standard deviational ellipse
- Density map of criminal activity

Level 2

- Descriptives
- Pinmap
- Standard deviational ellipses
- Density map of criminal activity
- Global statistics for map pattern
  - Nearest neighbor statistic
  - Moran's *I*
- Local statistics for cluster location
  - Local Moran
  - Geographical Analysis Machine

Level 3

- Descriptives
- Pinmap
- Standard deviational ellipses
- Density map of criminal activity
- Global statistics for general clustering
  - Nearest neighbor
  - Quadrat Analysis
  - Moran's I
  - Tango's C_G
  - Oden's I_{pop}
  - Rogerson's R
- Tests of raised incidence around prespecified points
  - Tango's C_F
  - Local Moran
  - Getis' G_i
  - Rogerson's R_i
- Finding potential clusters
  - Spatial scan statistic
  - Local statistic with multiplicity adjustment
  - Openshaw's exploratory GAM

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28 April 1998

MEMORANDUM

TO: Ezra Zubrow
Lee Hunt

FROM: Hugh Calkins

SUBJECT: Report and Recommendations on Choropleth mapping

Choropleth (or thematic) mapping is a basic tool for representing summary information by small geographic area. The main issues in preparing such maps are:

1. The selection of the geographic unit and a concern for substantial size differences between units - a large unit will give a biased appearance due to the size alone - San Bernardino County is a good example. However for our purposes, this may not be too much of a problem as police beats, blocks, and other urban units don't vary that much.
2. The classification methods used to determine the ranges for mapping - default methods such as those in Arcview assume a normal (or near normal) distribution for the data. Much of the urban data we will use will not have such a distribution. The defaults in Arcview are quintiles, equal interval, standard deviation and equal area. I suggest we add to this a capability to display the data in histogram form and as a rank ordered array so users can see the pattern, and then provide a method to "point-and-click" on the histogram or array to specify the classifications ranges. These selections could then be automatically loaded into the legend editor. (see sample attached).
3. Normalization of the data - on the basis of area, per capita or per household) - these options probably should be button driven.
4. Color selection - we should design special color ramps for our purposes and give the user a little ore control over individual colors. There should be a small number of default color schemes for most users. Currently Arcview has too many choices of color ramp.
5. Number of variables - we should allow for two variables to be displayed - one by color and the second by black pattern overlay.

I would recommend three basic options for choropleth mapping:

1. The single button option
   From drop-down lists be able to select dataset (FI, Call-for-service,crime arrest or a socio-economic variable) and the spatial unit (beat, block, precinct, or census unit).

   Defaults for color and classification (probably 5 classes, equal interval)

Display and label street centerlines and other significant features

2. Same as above but with greater user control over classification scheme and color - this will be much like the current version of AV.

3. An advanced capability incorporating the histogram and rank order array functionality for the selection of classes.

Artificial Neural Networks in Forecasting Crime Emergence

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1. Crime Literature Review

Criminal activity is a space-time phenomenon which often doesn't match basic assumptions of modern statistical theory. For example, its spatio-temporal distributions appear to be chaotic or almost random and are usually non-linear and discontinuous across space and time. Geographers and regional scientists have long realized that local context and spatial heterogeneity are extremely important when forecasting space-time phenomena (see for example Anselin, 1988), and have consequently devised a number of ways in which to do so (see for example Cliff et al, 1975). Although with varying degree of success, only few examples build successful models that employ spatio-temporal forecasting techniques to crime patterns.

Geographic information systems have ability to plot the locations and frequencies of the number of criminal activities. This ability produces high quality spatio-temporal data sets and has resulted in tracking criminal activities successfully. Some police agencies, for example, the Pittsburgh Bureau of Police, have begun to integrate geographic information system with other sources of data such as 911 calls and police records management systems.

Olligschlaeger (1997) introduces an early worming system that incorporates a geographic information system previously developed to track criminal activity and a relatively new technology, artificial neural networks, to predict the emergence of drug hot spot areas. Artificial neural networks have many features which make them attractive for spatio-temporal forecasting. First, they have a flexible and self-adaptive form which is specific suitable to handle the nonlinear relationship between dependent and independent variables. Second, ANNs do not require that parameters be initialized with regression estimates, rather, the parameters are initialized randomly. To the best of our knowledge, Olligschlaeger's research is the only artificial neutral network based spatio-temporal forecasting models has been developed to date. Applying the algorithm to the data from the Pittsburgh Bureau of Police, artificial neural network technique is shown to perform better than traditional regression models do.

This new spatio-temporal forecasting methodology which combines artificial neural networks and cellular automata with GIS-based data is referred as chaotic cellular forecasting (CCF). One of the fundamental tenets of chaos theory is that although chaotic systems seem to display totally random and unpredictable behavior they actually follow strict mathematical rules which can be derive and studied (Pickover, 1990). This character particularly fits our complicated crime activities. CCF uses a gradient descent method to find the optimal neutron connection weights of artificial neural networks. Most importantly, CCF has a nonlinear functional form commonly used in neural set modeling, allowing for increased pattern recognition and accommodation of spatio-temporal heterogeneity. The focus of this article is to describe how CCF was developed and to explain the underlying theory behind neutral network. Next section is a literature review on neural networks. Section three describes the two types of CFF algorithms, one with temporally and spatially constant weights and the other with temporally constant but spatially varying weights from input to hidden neutron, in detail. In section four, advantages and disadvantages of neural networks are discussed and some possible further studies are proposed. The final section provides some recommendations for the development of chaotic cellular forecasting software.

2. Neural Networks Literature Review

Most commonly, there are three fundamental types of artificial neural networks: supervised models, unsupervised or self-organizing models, and hybrid models. Supervised models are by far most commonly applied. The spatially and temporally constant weight type of CCF introduced in section 3 is a supervised model. Supervised models, as we will see later, need target (correct) outputs as a criteria to adjust connection weights between neutrons. In self-organizing model, there is no such need. Instead, the network changes its internal connection strengths to recognize current patterns of inputs. ANNs are also found in mixed environments which employ other technologies in addition to neural models. The temporally constant but spatially varying type of CCF in section 3 is a hybrid model.

Most important among artificial neural networks' properties are ANN's ability to learn to identify complex patterns of information and to associate them with other

patterns. Furthermore, ANNs can recognize and recall these patterns and associations in spite of noisy, incomplete, or otherwise defective information inputs. ANNs can also generalize information learned about one or more patterns to other related patterns. As a result, ANNs have already found extensive use in areas once reserved for multivariate statistical programs such as regression and multiple classification analysis (Woelfel, 1993).

The difference is that regression uses direct linear models whereas multi-layer feedforward networks use indirect nonlinear models. The coefficients to be determined in regression are like the weights to be determined in artificial neural networks. In regression model, the coefficients are decided based on least squared rules. However, in artificial neural network model, the weights are estimated using the generalized delta rule derived by Rumelhart et al (1988) from the Perceptron convergence procedure due to Minsky and Papert (1969), which in turn is a variation of the delta rule proposed by Widrow and Hoff (1960). The goal is to continually update the weights until the sum of all error signal, defined by the difference between the output of the network and the target mapping, is minimized. The generalized delta can be summarized in three parts. For convenience, Azoff (1994) introduces the notation for neural network structure in the backpropagation derivation as follows:

Network Structure	Neuron Label	Output State
	i	o_i^u
W_{ij}		
	j	v_j^u
W_{jk}		
	k	x_k^u
Input μ		

1. The weight change should be proportional to the product of the error signal sent to a receiving neutron along a connection and the activation of the sending neutron. More formally,

$$\Delta W_{qp} = \eta \delta_q v_p$$

$$W_{qp}^{new} = W_{qp}^{old} + \Delta W_{qp}$$

where ΔW_{qp} is the weight change from preceding neutron p to end neutron q, η is the learning rate, δ_q is the error signal sent to q, and V_p is the preceding layer neutron's output (activation).

2. For output neutrons using a logistic activation function, the error signal is defined as

$$\delta_i = (t_i - o_i)o_i(1\text{-}o_i)$$

where t_i and o_i are the target activation and observed layer neuron value for the

output neutron respectively.

$$\delta_j = v_j(1-v_j)\sum_i \delta_i W_{ij}$$

3. For hidden neutron, the error signal is given by

This feedforward artificial neural network with backpropagation lends itself best to complex problems. First, backpropagation networks have been used successfully elsewhere for time series forecasting (see White, 1988; Poli and Jones, 1994). Second, backpropagation networks are capable of estimating extremely complex functions (input to output mappings) without the necessity of specifying a priori the functional form. Finally, the gradient decent method used to minimize the total sum of squared errors is not prone to converging to local minima on the error surface (Weiss and Kulikowski, 1991). Note that learning rates that are too large can lead to oscillations between local minima, whereas small learning rates can require hundreds of thousands of iterations to converge. One way to detect and avoid convergence is to local optimal is to train the network several times with different random initializations of the weights and to compare the results (Rumelhart et at, 1988).

In batch processing, weight changes are summed over all input patterns (observations and time periods), rather than adjusting the weights after each input pattern. After all observations have been processed, the sum of changes is divided by the number of observations multiplied by the number of time periods (i.e. the number of input to output mappings) to arrive at a "smoothed" weight change for each connection.

Experimentation has shown that updating weights in this matter yields better results to faster convergence (Rumelhart et at, 1988).

3. Flowchart of the Algorithm

A key determinant of cellular automata rules is how each cell is influenced by neighboring cells (or connection weights between neutrons). Chaotic cellular forecasting is essentially a cellular automata machine that attempts to learn the rules and then forecast the future through current available data sets. CCF method is derived from cellular automata which act on discrete space or grids rather than a continuous surface and a multilayer feedforward network with backpropagation. This type of ANN is a nonlinear extension of Minsky and Papert's (1969) Perceptrons and the same type of network used by White (1988) in temporal forecasting.

This section describes how Olligschlaeger develops the early warming system by applying chaotic cellular forecasting. First, the data for the early warning system were obtained by superimposing a grid on the data of the city of Pittsburgh and aggregating data for each grid cell and time period. In selecting the size of the cells it was important not to make them too small because otherwise only few cells would have more than one or two calls for service. Too large cells would have resulted in too few data points for neural net modeling. Calls for service data were obtained by counting the number of calls per month within each cell. An example of a data point might be the number of burglary arrests per time period in a grid cell. Since backpropagation networks require a signal from the input neutrons in order for weight adjustment to occur, all variables with a value of zero were adjusted to 0.1. This ensured that connection weights were not adjusted only in the case of non-zero inputs. The learning rate and number of hidden neutrons should be arrived via experimentation on the data. Different learning rates and a different number of hidden neutrons may be optimal for different data sets. The connection weights are randomly assigned in the range [-0.1, +0.1]. The neighborhood used to produce one-step-ahead forecasts in CCF consists of the current observation (cell) and the eight surrounding. There are multiple connections to each grid cell because of multiple signals (independent variables) are processed. This produces spatially and, because the network produced one-step-ahead forecasts, also temporally lagged data points.

The spatial CCF model can be written in algebraic terms:

$$Y_i(t+1) = \sum_{k=1}^{R} W_{ik} I_{ikt} + \sum_{j=1}^{h} W_{ij} \frac{1}{1+e^{net_{jt}}}$$

where Y_i is the target output of the network for observation i, t is the time period, h is the number of hidden neutrons, R is the number of input neutrons (including the averaged spatially lagged variables, this is analogous to the number of independent variables), W_{ik} is the weight along the direct input to output neutron connection between input neutron, k and the output neutron, i, I_{ikt} is the input of neutron k for observation i at time t, W_{ij} is the weight along the connection between the output neutron, i and hidden neutron, j, and net_{jt} is the net input for hidden neutron j at time t which is calculated as follows:

$$net_{jt} = \sum_{k=1}^{R} W_{jkm} I_{jkt} + \theta_j; \quad m \in C$$

where R is the number of input neutrons per cell in the neighborhood plus the number of averaged spatially lagged variables, I_{jkt} is the input from neutron k at time t for hidden neutron j, W_{jkm} is the weight along the connection between hidden neutron j and the kth input neutron, and θ_j is the bias for hidden neutron j, and m is an index in C, the context of spatial weight variation. We will further discuss the spatially constant weight model as well as the spatially varying weight model later. In Olligschlaeger's research, the independent variables are suggested to be related calls of drugs, weapons, robberies, assaults, proportion of residential and commercial properties, and seasonal phenomenon.

For both models, the weights are the parameters to be estimated.

The algorithm for training the CCF network using spatially and temporally constant weights for all connections and a single hidden layer is therefore as follows:

1. Randomly initialize W_{jk} and W_{ij} for each i, j, and k.
2. Set ΔW_{jk} and ΔW_{ij} to zero for each i, j, and k.
3. For each t and j, calculate

   net input : $net_{jt} = \sum_k W_{jk} \mu_{kt}$; hidden neutron activation: $v_{jt} = f(net_{jt})$;
4. For each t and for each i, calculate the output of the network, i.e. the estimated forecast: $o_{it} = \sum_j W_{ij} v_{jt}$.
5. Calculate the forecast error: $e_{it} = t_{it} - o_{it}$.

6. For each connection (input to hidden and hidden to output) calculate the weight change and add it to the sum of weight changes,ΔW, for that connection over all forecasts.
7. Calculate the square forecast error and add to the sum of square forecast errors $e^2 = \sum_i \sum_t e^2_{it}$.
8. $W_{jk}^{new} = W_{jk}^{old} + \Delta W/(N*T)$, where N is the number of observations.
9. $W_{ij}^{new} = W_{ij}^{old} + \Delta W/(G*T)$, where G is the number of grid cells.
10. If the total sum of squared forecast errors in the current iteration is greater than or equal to that of the previous iteration, stop. Otherwise, go to 3.

A second CCF algorithm relaxed the spatially constant weight assumption in that each observation has its own unique set of input neutron connections and associated weights for each cell in the neighborhood. However, the hidden to output neutron weights are spatially constant. This produces a hybrid model that has the advantage of some spatial variation in the weight structure but not too much to cause overfitting. The algorithm for this hybrid CCF model, which assumes temporally constant but spatially varying input to hidden neutron weights and a single layer of hidden neutrons is therefor:

1. Randomly initialize W_{jkn} and W_{ij} for each i, j, k and n.
2. Set ΔW_{jkn} and ΔW_{ij} to zero for each i, j, and k.
3. For each t and j, calculate net input : $net_{jt} = \sum_k W_{jkn}\mu_{ktn}$; hidden neutron activation: $v_{jt} = f(net_{jt})$;
4. For each t and for each i, calculate the output of the network, i.e. the estimated forecast: $o_{it} = \sum_j W_{ij}v_{jt}$.
5. Calculate the forecast error: $e_{it} = t_{it} - o_{it}$.
6. For each connection (input to hidden and hidden to output) calculate the weight change and add it to the sum of weight changes,ΔW, for that connection and grid cell n over all forecasts.
7. Calculate the square forecast error and add to the sum of square forecast errors $e^2 = \sum_i \sum_t e^2_{it}$.
8. $W_{jkn}^{new} = W_{jkn}^{old} + \Delta W/T$.

9. $W_{ij}^{new} = W_{ij}^{old} + \Delta W/(N*T)$, where N is the number of observations.
10. If the total sum of squared forecast errors in the current iteration is greater than or equal to that of the previous iteration, stop. Otherwise, go to 3.

When calculating the input values of the neighborhood, a boundary problem arises. Since backpropagation networks require that all input to output mappings have the same number of input neutrons, CCF tackles this problem by assigning "imaginary" neighbors to border cells. The inputs of the imaginary cells are set to zero.

4. Conclusion

A drawback of backpropagation networks is that they require a very large number of observations for training. This problem is analogous to having too many parameters in regression, resulting in not degrees of freedom. One solution to this problem is to increase the number of observations using the capabilities of geographic information systems.

Further experimentation revealed that adding direct input to output connections to the network architecture kept overfitting in check, i.e., the network would generalize better. In addition, it was found that averaging spatially lagged variables from the neighborhood of an observation rather than connecting each independent variable in each neighboring grid to each hidden neutron reduced the number of connections and the amount of overfitting. In other words, instead of nine sets of inputs, one from each observation in the neighborhood, the architecture only had two sets: one from the current observation, and one for the average spatially lagged independent variables of the eight neighbors. In the Pittsburgh example, this adjustment speeds up the convergence four times faster.

Another drawback of artificial neutral networks is the model is unable to represent the results as an equation with parameters. Usually representing the relationship between dependent and independent variables can be helpful in parameter sensitivity analysis.

An advantage of neural networks is the nonlinearity of transfer functions of the neutrons and the multilayer structure of the network can ensure a good fitting for any

functional form whatever. The other most advantage is no need for the analyst to stipulate the functional form prior analysis, the ANN will find it automatically.

Three recommendations for further studies are made to conclude this section.

1. In Olligschlaeger's research, the spatial concern of an observation takes account on its eight neighbors. If, in stead of using grid cells as neutrons, using police patrol beats as neutrons, then the neighbors of the observation may not have equal size. In this case, should we take the beats which connect to the observation as spatially lagged variables? Or, should we define a neighborhood by a certain size and take account all the beats within this neighborhood? A proposed suggestion is introducing fussy logic in this point to decide the relationship between the observation and its neighbors.
2. There are many ways in which backpropagation networks can be modified so that they converge more quickly to a solution. An additional improvement would be to employ genetic algorithms to develop self-optimizing architectures.
3. The number of hidden layers is a critical issue. For very complex input to output mapping, two or more layers must be more appropriate to capture the nonlinear relationship between input and output neturons.

5. Some Recommendations for the Design of Chaotic Cellular Forecasting

Level 1

- Supervised model (spatially and temporally constant weights)
- Use grid cells as neutrons
- One hidden layer
- Users choose number of hidden neutrons

Level 2

- Supervised model (spatially and temporally constant weights)
- Users choose grid cells or police patrol beats as neutrons
- Users choose number of hidden layers
- Users choose number of hidden neutrons

Level 3

- Users choose supervised model (spatially and temporally constant weights) or hybrid model (temporally constant but spatially varying weights)
- Users choose grid cells or police patrol beats as neutrons
- Users choose number of hidden layers
- Users choose number of hidden neutrons

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Pattern Analyses: Pattern Recognition
Philip Mitchell

Pattern recognition, simply, is the attempt to isolate formalized pattern sets that are of interest or have similar associations. In the case of my research with patterns in crime data there are multitudes of associations that can be incorporated. As an increased number of data sets are added to support these associations the data set size starts to grow exponentially. When several data sets from different agencies are combined there are several conditions that disrupt or alter patterns. The most obvious is the use of differing basic indicators. If two data sets are used, each with a different identifier (Block 54) a matching pattern will be greatly understated.

To illustrate the above I will refer to the example Block used. Two data sets are used to evaluate violations associated with licensed liqueur establishments. The first data set is compiled from police reports where police consider liqueur establishments to mean bars, taverns and nightclubs. The second data set is compiled by the licensing agency, which includes all establishments that have a liqueur license to include grocery stores and restaurants. The correlation between the results of run one and two is only about 60%. The difference between the two sets is the definition of liqueur establishments. Even correcting for this difference in data sets may only raise the relationship up to 95%. The error difference between them has been greatly reduced.

Considerations must also be applied to spatial anomalies within the geographic region that, although have associative coordinates are disassociate due to a physical barrier. An example is a depicted pattern area that is disassociated by a major highway running through the middle. If access between the subsets is restrictive the pattern is not associated as nearest neighbor. The pattern must therefore not have developed from spatial association but by some other association.

The degree to which a data set is organized and how spatial information is represented will effect the matching patterns. Layering data that is point specific, and clustered data represented as polygons will effect comparative associations. Examples of clustered precincts, demographic, socio-economic, ethnic orientation, gang, religious etc, compared to point specific violations is going to have effects on the resulting pattern.

Individuals within a region will have cognitive maps that will effect their activities. Individuals will develop cognitive maps based on their mode of transportation. The activities and daily patterns of those using the metro system will differ greatly from those with privately owned vehicles. The degree to which these cognitive maps are similar will effect regional activities. Differing demographic groups within a region will have varying cognitive maps that will be anchored to varying locations and time. An example of this is school students whose activities during school will be associated geographically with the school. In the evening the same individuals may be associated with a park or another hangout.

Fringe pattern analyses must also be considered. The interface of different spatial, demographic and political areas are bound to have effects due to their spatial associations. An example is the schoolyard where, for political (legal) implications, penalties for certain violations are maximized. This may result in an increase in criminal activities on the fringe area due not to the fringe area but as a result of the association.

Patterns within the data set are of primary concern to predicting criminal activity. There are several variables that hinder start forward ML pattern matching, such as spatial and temporal parameters within which the data exists. Further difficulties arise when considering geographically adjacent points that are not functionally adjacent.

Space should not be separated from time in the search for patterns. If the data is viewed only on the bases of space then change is not easily perceived. Consider crime in the city of

Buffalo over the past 200 years. Areas that have just recently experienced a plethora of crime will not greatly effect the 200 years of comparison. The same condition existed within the time frame of a day. A neighborhood that is, typically, crime free has a rash of petty crimes as the local school lets out. If this neighborhood's crime is viewed within the time frame of the day it will still appear as a low crime area. Viewed within the time frame of an hour after school lets out it is a high crime area. Two dipolar conclusions.

Pattern recognition is also hindered by temporal variability. Patterns may be isolated temporally, occurring within a time frame such as day, evening and night. Seasons and weather will also have a patterning effect. In this case patterns develop within a short predictable period. Other non-obvious conditions such as school districts, places of employment, etc. can also act as an anchoring point for associative patterns to develop around.

Temporal patterns exist within a particular day within a year. Typically there is a correlation between Christmas Eve and Christmas with certain crimes (domestic disputes). It would be of greater use to compare the crime statistics for the last 5 years on Christmas Eve and Christmas then to look at the 5 days prior to Christmas. It might also be useful to compare Christmas Holiday incidents with its associated year's crime to other Christmas holidays and their yearly statistics.

Patterns for individuals can also be enhanced. If it were known that a suspect was within the city of Buffalo during known dates than to be able to quickly isolate those dates from the data set would also be useful.

Patterns can also develop in association to night and day. Although crime statistics might change in relation to the time of day they may fit within the temporal pattern set by sunset.

Conclusion

Patterns must be searched for which have various cognitive temporal associations. Space and time are not a continual to which criminals feel obliged to adhere.

The complete spatial randomness (CSR) after Diggle (1983) exists if the points that were generated are subject to the following two rules:

1. each location in the study area has an equal chance of receiving a point (uniformity); and
2. the selection of a location for a point is in no way influenced by the selection or location of any other point, (independence).

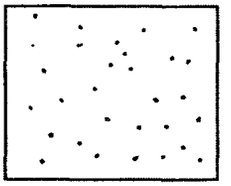

Fig. 1 CSR

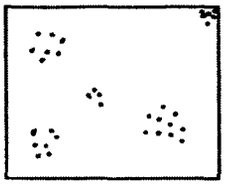

Fig. 2 Clustered Pattern

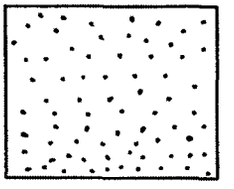

Fig. 3 Regular Pattern

CSR Model - Scattered Quadrates

This model was originally designed by plant ecologist that wanted to test the pattern developed by individual plants within a region. The models require regular as oppose to irregular study areas (Fig. 4). Quadrate centers can be defined by laying a grid randomly over the test area and selecting the (x,y) coordinates where the grid intersects.

We construct a table that shows the points within the quadrate (table 1)

x Number of points per quadrate
O_i Observed Frequency
E_i Expected Frequency

Table 1

x	O_i	Probability of a Quadrate with x Points	E_i	$(O_i - E_i)^2 / E_i$
0	3	0.0743	2.23	0.509
1	3	0.1931	5.79	
2	8	0.2510	7.53	0.029
3	10	0.2176	6.53	1.844
4	4	0.1414	4.24	
5	1	0.0735	2.21	
6	0	0.0319	0.96	0.465
7	0	0.0118	0.35	
8	1	0.0039	0.12	
>8	0	0.0015	0.04	
Total	30	1.0000	30	2.847

The first step to understanding a pattern is to first test to see if the null hypothesis, H□, is true. For both clusters and point patterns the H□ will be rejected. We determine what the frequencies would look like if the H□ was correct. The probability is given by the Poisson probability distribution, which is

$$\rho(x) = (e^{-\lambda} \lambda^x / x! \qquad \text{for x = 0, 1, 2, ...} \qquad [1]$$

where:

λ is the expected number of points per sample area. This value may be estimated by the mean number of points per quadrate. E is the mathematical constant 2.718282.

If we have 30 quadrates and 78 points so we can estimate λ as 78/30+2.6. Thus to obtain the probability p(x) when x=0 (an empty quadrate) in a CSR pattern we substitute x=0 and λ=2.6 into equation 1 noting that 0!=1, so that

$$\rho(x) = e^{-2.6} \cdot (2.6)^0 / 0!$$
$$= e^{-2.6}$$

$$=0.0743$$

For x=1

$$\rho(x) = [e^{-2.6}(2.6)^1]/1!$$

$$= e^{-2.6}2.6$$

$$= 0.1931$$

For x=2

$$\rho(x) = [e^{-2.6}(2.6)^2]/2!$$

$$=0.2510$$

Since the probability must sum to one the value of p(x>8) can be calculated from equation 2.

$$\rho(x > 8) = 1 - \sum_{x=0}^{8} \rho(x) \qquad [2]$$

The test of the H□ is accomplished by comparing the expected frequency against the obtained frequency.

$$X^2 = \sum_{i=1}^{k} (O_i - E_i)^2 / E_i \qquad [3]$$

Where:

O_i Observed Frequency in the ith category

E_i Expected Frequency in the ith category

K is the number of categories

The minimum value of k is an argued point but it should not be less then 5 per category.

Column 5 of table 2 is the values as calculated by equation 3.

Points can be examined under two different views: the dispersion of points in and area or the arrangement of points in relation to each other.

In the above example we tested the H_0. In the event that we found the H🗁 to be true we would not be able to tell whether the pattern was a cluster or regular. Using the information from the table we can run a test of the H_0 to delineate between the two.

$$V = \frac{\sum_x (x-\lambda)^2 f(x)}{n} \qquad [4]$$

n is the number of quadrates
fx is the observed frequency of x

In a Poisson probability distribution the value of λ and V are expected to be equal. If λ is greater then V. If V is less then λ it indicates that each quadrate has an equal number of points. If there is clustering then V is greater then λ.

An alternative equation is to use the chi-square test.

$$t = \frac{(v-\lambda)}{[2/(n-1)]^{1/2}} \qquad [5]$$

Nearest Neighbor Analyses in 2 dimensions

$$\sum_{i=1}^{n} d_i$$

and obtaining the mean nearest neighbor distance

$$\bar{d} = \sum_{i=1}^{n} d_i / n$$

where n is the number of sampled points.

Clark and Evans (1954) equation shows the expected mean average of nearest neighbor distance, $E(d_i)$, for a random sample of points from a CSR pattern is approximated by the equation

$$E(d_i) = 0.5\sqrt{A/N} \qquad [6]$$

A is the area
N points in the pattern

If A = 52.17 sq. miles and N = 132 equation 6 gives $E(d_i) = 0.31$ miles

The observed and the expected distances can be compared using a normally distributed z statistic of the form

$$z = \frac{[d - E(d_i)]}{\sqrt{\text{var}(d)}} \qquad [7]$$

where

$$\text{var}(d) = 0.0683 \frac{A}{N^2} \qquad [8]$$

Equation 7 gives var(d) = 0.000205; substituting this into equation 6 yields

$$z = \frac{(0.22 - 0.31)}{\sqrt{0.000205}} = -6.58$$

The value of z from tables of the normal distribution for a $\alpha = 0.05$ is 1.96. Since the absolute calculated z value from above is 6.58 and therefor greater then 1.96, we would have to reject the H_0 and except the H_0.

Polygon Technique

Point pattern analyses in two dimensions

Points are used to construct a set of Thiessen polygons. This is done by associating areas of a study area that are closer to one point than any other point. Locations that are equal distance from 2 points will lie on the boundary of two adjacent polygons. Locations that are equidistant from 3 or more points in a pattern will form the vertices of adjacent polygons resulting in the creation of a tessellation of contiguous, space-exhaustive polygons.

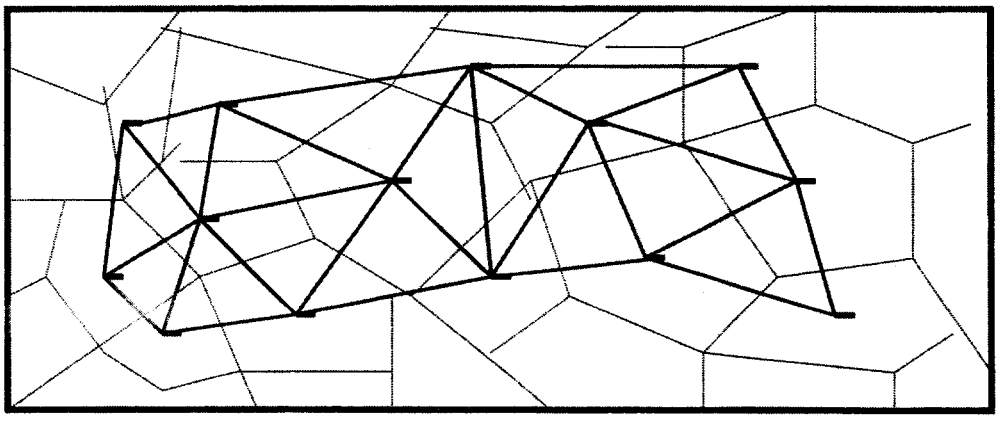

Fig 5

Using the Thiessen polygons for orientation another contiguous, space-exhaustive tessellation is produced known as the Delaunay triangulation. This is accomplished by joining points which share the Thiessen polygon edges.

Although there are several properties of these triangles that can be evaluated the most obvious is the size of the angles. The smallest angle can be quickly determined, which of course can not be greater then 60 degrees. Mardia et al (77) have developed probabilities for obtaining minimum angles less then or equal to some value of x, for Delaunay triangulation's associated with a CSR pattern. This probability, P(x), is given by

$$P(x) = 1 + \tfrac{1}{2}\pi[(6x - 2\pi)\cos 2x - \sin 2x - \sin 4x] \qquad [8]$$

Values in one degree increments of P(x) for equation 8 can be compared to table 4.3

The test involves generating the Delaunay triangulation & identifying the minimum angles in the pattern at a specified interval of x. To avoid edge effect we restrict triangles that are produced by boundaries. The observed frequencies are cumulated and F(x) is calculated by dividing each of the observed cumulative frequencies by the sum of the frequencies.

P(x) for a CSR pattern can be obtained from column 3 of table 4.3 and shown in column 5 of table 4.4.

The absolute difference between values of F(x) and P(x) can be compared using a one-sample Kolmogorov-Smirnov (K-S) test.

The largest number in column 6 of table 4.4 determines the test statistic, Dmax, which is compared with the appropriate value from statistical tables of critical values. If the patterns Dmax is 0.0680, whereas the critical value is 0.2178 we can't reject the H_0 of the CSR pattern.

If the H_0 is rejected the triangle angles can still be evaluated tentatively. A pattern that is arranged perfectly regularly will result in Thiessen polygons that are all regular hexagons. All of the angles within the pattern will measure 60 degrees. In the real world if a large number of minimum angles are approximately 60 degrees a regular pattern exists. Similarly, if a grid pattern exists a large percentage of the minimum angles will be approximately 45 degrees.

Table 4.3 Probability that the Minimum Angle of a Triangle in a Deaunay Triangulation for a Random Point Pattern is Less then or Equal to a Given Value of x.

Cluster Process Model quoted from Ripley's Spatial Statistics p164-165

A Poisson cluster process is defined by taking a Poisson process of intensity α of parent points and centering on each parent an independent daughter process of object. The observed process may be either parents plus daughters of just all daughter objects. We will assume the latter. Another way to view this mechanism is to have an infinite set of independent identically

distributed processes, to use a Poisson process to select a translation for each, and then to add up the objects in all the translated processes. This suggests a modification in which we choose a Poisson process of rigid motion, thereby giving each daughter process an independent uniformly distributed rotation. We will assume that each daughter process contains a finite number of objects. The cluster process will always be homogeneous, but will only be isotropic if the daughter process is isotropic or if the daughters are given an additional rotation The most useful subclass of Poisson cluster processes is Neyman-Scott processes, for which each daughter object is independently distributed around the parent. Then if n is the (random) number of objects in the daughter process,

$$K(t) = \pi t^2 \propto E(n(n-1))f(t)/\lambda^2 \qquad [8.16]$$

$$p(t) = 1 - \exp\{-\propto \int [1 - E\{g(x,t)^n\}]dx\} \qquad [8.17]$$

where all expectations are over n, f is the cumulative distribution function of the distance between two daughters with the same parent, and g(x,t) is the probability that a daughter point does not fall within distance t of x.

Equation (8.16) can be derived from interpretation (1) of K(t). The pairs of points can come either from different clusters giving the first term by the independence of clusters, or from the same cluster. If there are n objects in that cluster, the expected number of pairs not more then t apart is n(n-1)f(t), from which is derived the second term. Note that K(t) -πt is an increase function and that we can infer an estimate of f(t), and hence the cluster size, from ☺(t). Formula (8.17) is a special case of (9.10). Consider the N parent points within a bounded set D. For large D of area A.

1-p(t)≈P(no daughter with parent in D is within t of the origin)

$$= \sum e^{-\propto A}(\propto A)^n \qquad \{\text{no daughter within t / parent in D)}\}^N / N!$$

$$= \exp -\propto A\{1 - P(\text{no daughter within t / parent in D})\}$$

$$= \exp -\propto A\{1 - \int_D E(g(x,t)^n d(x)/A\}$$

using the independence of the daughters and the uniform distribution of parent in D. Letting D increase gives (8.17).

Of course the parent process need not be Poisson; it could itself be a cluster process, giving rise to processes with a (finite) hierarchy of clusters. Another possibility is to take a regular process of parents to avoid the overlapping of clusters.

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Patrol Car Allocation Tool (PCAT)

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Note: *Programmer notes appear in italics.*

Notation:

K = *number of call priority classes*
J = *number of geographic jurisdictions in the allocation*
T = *number of time blocks (hours, shifts, days, etc.) in the week*
R = *number of patrol car hours to be allocated each week*
A_j = *size (square miles) of geographic jurisdiction j, j=1,…,J*
v_jt = *average response velocity (miles per hour) in geographic jurisdiction j during time block t; j=1,…,J, t=1,…,T*
λ_kjt = *calls for service (CFS) arrival rate (calls received per hour) for priority class k in jurisdiction j during time block t; k=1,…,K, j=1,…,J, t=1,…,T*
μ_kjt = *service rate for priority class k in jurisdiction j during time block t = 1/(average service time – dispatch until close – in hours)*
r_jt = *number of patrol cars to allocate to jurisdiction j during time block t*
s_jt = *effective number of patrol cars allocated to jurisdiction j during time block t (after accounting for time spent unavailable for calls)*

1 Choose method for patrol car allocation:

- **Hazard Formula** – allocation by call-for-service (CFS) rates *(default)*
  Data required: CFS rates
  User level: elementary

- **Workload Formula** – allocation by officer utilization
  Data required: CFS rates, service (travel + on-scene) times
  User level: intermediate

- **Queueing Formula** – allocation based on response times, probability of queueing, queue size, etc.
  Data required: CFS rates, service (travel + on-scene) times, response velocities
  User level: advanced

2 How many weekly patrol-car hours are available for allocation? (= R)
(Calculate from data or via user input?: e.g., for 2-man cars, car hours = man hours/2,

*e.g., # cars fielded * shifts per week * hours per shift, etc.)*

3 On what geographic scale is allocation to be performed?
(Data may need to be aggregated or proportionally split to match desired geographic scale.)

- Beats/Sectors
  - How many? ____ *(=J)*
- Precincts/Districts *(default)*
  - How many? ____ *(=J)*
- Other
  - How many? ____ *(=J)*

4 On what time scale is allocation to be performed?
(Data set must be averaged over the chosen weekly time block, e.g., if hourly allocation is desired, data must appear as hourly averages for all 168 hours in the week.)

- Hourly *(default)* *(T=168)*
- Shifts
  - How many shifts per day? ____ *(T=7*(# shifts))*
- Daily *(T=7)*
- Weekly *(T=1)*

5 How many (non-preemptable) priority classes for calls for service? ____ *(=K)*
(Data must be segregated by priority; if not, default to 1 priority class.)

Hazard Formula

6 *(If K>1):*
Assign critical weights from 1-10 for each priority class. *(=w_k , k=1,…,K)*

(1=least critical, 10=most critical)

7 *Perform weighted allocation by assigning*

$$r_{jt} = \left[R \times \sum_{k=1}^{K} \left(w_k \lambda_{kjt} \Big/ \sum_{j=1}^{J} \sum_{t=1}^{T} \lambda_{kjt} \right) \Big/ \sum_{k=1}^{K} w_k \right]$$

resources to jurisdiction j during time block t; j=1,…, J, t=1,…,T.
Note: brackets [ ] denote rounded values.

Workload Formula

8 *Perform weighted allocation by assigning*

$$r_{jt} = \left[R \times \sum_{k=1}^{K} \left(\lambda_{kjt} / \mu_{kjt} \right) \Big/ \sum_{k-1}^{K} \sum_{j=1}^{J} \sum_{t=1}^{T} \left(\lambda_{kjt} / \mu_{kjt} \right) \right]$$

resources to jurisdiction j during time block t; j=1,..., J, t=1,...,T.
Note: brackets [ ] denote rounded values.

Queueing Formula

9 What allocation criterion do you wish to minimize? (Choose one.)

- Fraction of calls delayed in queue *(Compute in 15)*

- Average time that calls are delayed in queue
  - Minimize the average queue time for which calls?
    - Priority 1 *(Compute in 16, k=1)*
    - Priorities 1 & 2 *(if K>1)* *(Compute in 17, m=2)*
    - Priorities 1, 2 & 3 *(if K>2)* *(Compute in 17, m=3)*
    - All Priorities *(default)* *(Compute in 17, m=K)*

- Average response time (queue time + travel time) *(default)*
  - Minimize the average response time for which calls?
    - Priority 1 *(Compute in 18, k=1)*
    - Priorities 1 & 2 *(if K>1)* *(Compute in 19, m=2)*
    - Priorities 1, 2 & 3 *(if K>2)* *(Compute in 19, m=3)*
    - All Priorities *(default)* *(Compute in 19, m=K)*

10 What allocation constraints do you wish to impose? *(Check all that apply)*

- Keep workload (% of time responding to calls) below _____% *(default 100%=1)*
- Keep fraction of calls delayed in queue below _____% *(default 100%=1)*
- Keep queueing delay for non-priority-1 calls below __minutes *(default 120)*
- Keep average travel time below _____ minutes *(default 120)*
- Keep response time for non-priority-1 calls below ____ minutes *(default 120)*

11 What fraction of time are patrol officers on patrol or answering calls for service (as opposed to time spent on paperwork, on break, etc.)? _____% *(=z; default z=0.6 (60%))*

12 Choose approach for computing average travel time:

- Square-Root Method *(default)* *(Compute in 13)*
  Computation time: short
  Data required: response velocities

- Actual Data Averaging
  (Compute average of actual travel times, T_jt, for each jurisdiction j & time t)
  Computation time: intermediate
  Data required: travel times

- Average Shortest Path Method
  (Compute E{T_jt} by averaging the shortest time path between every pair of incident locations in jurisdiction j during time t. **Note:** *n incidents yield n(n-1)/2 pairs.)*
  Computation time: long
  Data required: CFS locations

13 *The expected travel time (in minutes), E[T_jt], in jurisdiction j under an effective allocation of s_jt patrol cars during time block t; j=1,..., J, t=1,...,T, is*

$$E[T_{jt}] = \begin{cases} \dfrac{42.66}{v_{jt}} \times \dfrac{\sqrt{A_j}}{\sqrt{s_{jt} - \lambda_{jt}/\mu_{jt}}}, & \ldots\ldots\ldots\ldots\ldots\ldots s_{jt} - \lambda_{jt}/\mu_{jt} \geq 2 \\ \dfrac{60}{v_{jt}} \times \sqrt{A_j}\left(0.08 + \dfrac{0.598}{s_{jt} - \lambda_{jt}/\mu_{jt}}\right), & \ldots 1 < s_{jt} - \lambda_{jt}/\mu_{jt} < 2 \\ \dfrac{40.68}{v_{jt}} \times \sqrt{A_j}, & \ldots\ldots\ldots\ldots\ldots\ldots s_{jt} - \lambda_{jt}/\mu_{jt} \leq 1 \end{cases}$$

14 *The expected workload, E[W_jt], in jurisdiction j under an effective allocation of s_jt patrol cars during time block t; j=1,..., J, t=1,...,T, is*

$$E[W_{jt}] = \frac{\lambda_{jt}}{s_{jt}\mu_{jt}}$$

15 *The fraction of calls delayed in queue, p_jt, in jurisdiction j under an effective allocation of s_jt patrol cars during time block t; j=1,..., J, t=1,...,T, is*

$$p_{jt} = \left[1 + s_{jt}!\left(1 - \frac{\lambda_{jt}}{s_{jt}\mu_{jt}}\right)\sum_{i=0}^{s_{jt}-1} \frac{1}{\left(\lambda_{jt}/\mu_{jt}\right)^{s_{jt}-i} i!}\right]^{-1}$$

16 *The expected queueing time (in minutes), E[Q_kjt], for a priority k call in jurisdiction j under an effective allocation of s_jt patrol cars during time block t; k=1,…,K, j=1,…, J, t=1,…,T, is*

$$E[Q_{kjt}] = \frac{60}{B_{k-1,jt} B_{kjt} C_{jt}}$$

where

$$B_0 = 1$$

$$B_k = 1 - \sum_{i=1}^{k} \lambda_{ijt} \Big/ \left(s_{jt}\mu_{jt}\right)$$

$$C_{jt} = s_{jt}! \frac{s_{jt}\mu_{jt} - \lambda_{jt}}{\left(\lambda_{jt}/\mu_{jt}\right)^{s_{jt}}} \sum_{i=0}^{s_{jt}} \frac{\left(\lambda_{jt}/\mu_{jt}\right)^{i}}{i!} + s_{jt}\mu_{jt}$$

17 *The expected queueing time (in minutes), E[Q_jt^m], for all calls of priority <=m in jurisdiction j under an effective allocation of s_jt patrol cars during time block t; m=1,…,K, j=1,…, J, t=1,…,T, is*

$$E[Q_{jt}^{m}] = \sum_{k=1}^{m} E[Q_{kjt}] \cdot \left(\lambda_{kjt}/\lambda_{jt}\right)$$

18 *E[D_kjt], the expected response time – time from call received until car arrives on scene – for priority k calls in jurisdiction j under an effective allocation of s_jt patrol cars during time block t; k=1,…,K, j=1,…, J, t=1,…,T, is*

$$E[D_{kjt}] = E[T_{jt}] + E[Q_{kjt}]$$

19 *E[D_jt^m], the expected response time – time from call received until car arrives on scene – for all calls of priority <=m in jurisdiction j under an effective allocation of s_jt patrol cars during time block t; m=1,…,K, j=1,…, J, t=1,…,T, is*

$$E[D_{jt}^{m}] = E[T_{jt}] + E[Q_{jt}^{m}]$$

20 *Greedy Algorithm*

Define

$$\lambda_{jt} = \sum_{k=1}^{K} \lambda_{kjt}$$

$$\mu_{jt} = \sum_{k=1}^{K} \left(\lambda_{kjt} / \lambda_{jt} \right) \mu_{kjt}$$

$$s_{jt} = \lfloor z \times r_{jt} \rfloor$$

Note: brackets in computation of s_jt represent rounding down to nearest integer.

Step 1: *Start with allocation of r_jt = 0 for all j=1,..., J, t=1,...,T.*

Step 2: (Feasibility check)

Note*: if resources run out during this step, then go back to 10 and prompt user to relax constraints.*

- **a)** *For each j and t, increase the allocation r_jt one car at a time until expected workload (computed in 14) falls below constrained value set in 10.*
- **b)** *For those j and t for which the fraction of calls delayed in queue (computed in 15) falls above constrained value set in 10, increase the allocation r_jt until constraint is satisfied. (**Note**: Having completed step 2 a) these fractions will all be no larger than 1. Thus, this step must only be performed if the constraint in 10 has been set below the default of 1.)*
- **c)** *For those j and t for which the queue time for priority k=K calls (computed in 16) falls above constrained value set in 10, increase the allocation r_jt until constraint is satisfied. (**Note**: If K=1 then this step can be skipped.)*
- **d)** *For those j and t for which the travel time (chosen in 12) falls above constrained value set in 10, increase the allocation r_jt until constraint is satisfied.*
- **e)** *For those j and t for which the response time for priority k=K calls (computed in 18) falls above constrained value set in 10, increase the allocation r_jt until constraint is satisfied. (**Note**: If K=1 then this step can be skipped.)*

Step 3: (Optimization)

Using the objective set in 9, increase the allocation r_jt for the j and t combination with the worst (largest) objective value. Reduce the remaining car hours by the amount allocated to this time block. Repeat until all car hour resources are depleted.

Precinct Design Optimization Tool (PDOT)

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Note: *Programmer notes appear in italics.*

Notation:

K = *number of call priority classes*
J = *number of geographic jurisdictions*
T = *number of time blocks (hours, shifts, days, etc.) in the week*
R = *number of patrol car hours to be allocated each week*
A_j = *size (square miles) of geographic jurisdiction j, j=1,…,J*
v_jt = *average response velocity (miles per hour) in jurisdiction j during time block t; j=1,…,J, t=1,…,T*
λ_kjt = *calls for service (CFS) arrival rate (calls received per hour) for priority class k in jurisdiction j during time block t; k=1,…,K, j=1,…,J, t=1,…,T*
μ_kjt = *service rate for priority class k in jurisdiction j during time block t = 1/(average service time – dispatch until close – in hours)*
r_jt = *number of patrol cars to allocate to jurisdiction j during time block t*
s_jt = *effective number of patrol cars allocated to jurisdiction j during time block t (after accounting for time spent unavailable for calls)*

Beat Optimization

1) *Prompt user for allocation criteria (PCAT items 2-5 & 9-12)*
2) *As in Autobounds GIS product, prompt user to define initial partition of city into jurisdictions (beats) by grouping together atoms (Rdistricts) with mouse.*
3) *Prompt user for partition feasibility criteria (see below)*
4) *Prompt user for desired number of iterations (n)*
5) *Set initial temperature, t_0, equal to 1 if user objective is "Fraction of Calls Delayed"; otherwise default to 100.*
6) *Perform Simulated Annealing algorithm. (See Flow Chart below)*
7) *Report optimal objective value of final current solution (or best saved solution).*

A neighboring partition is identical to the current partition except that one (1) atom (Rdistrict) on the border between jurisdictions has been switched to the neighboring jurisdiction. A neighborhood of the current partition consists of all such neighbors. Feasible neighbors are those that satisfy the following feasibility requirements:

- *Response Time – The average response time in each jurisdiction j during all time blocks t in the week should be less than maximum value defined by user.**
- *Travel Time – The average travel time in each jurisdiction j during all time blocks t in the week should be less than maximum value defined by user.**
- *Relative Size – The ratio of the largest district and smallest district should not exceed maximum value defined by user.**
- *Compactness – The ratio of the longest Euclidean length to the square root of the area should not exceed maximum value defined by user.**
- *Convexity – The atom added should not create a protrusion out of the new district, and the atom removed should not create an indentation in the old district. To prevent this, do not allow a switch that places an atom into a new jurisdiction in which it is adjacent to only one atom in that jurisdiction.*
- *Contiguity – The two altered commands should remain contiguous.*

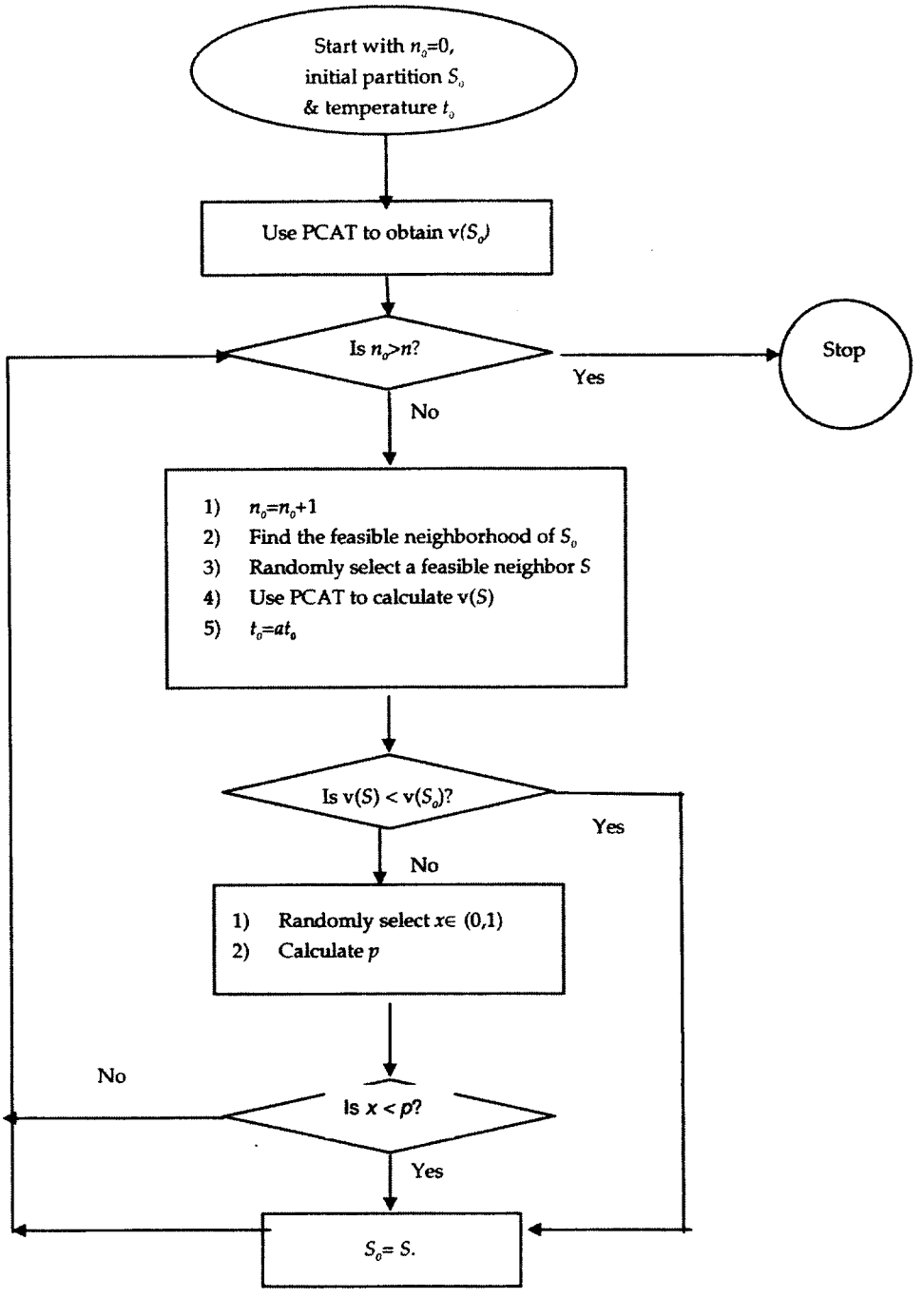
**Prompt user to either enter a value or have calculated from initial partition.*

The probability of inferior solution acceptance, p, at each iteration n of the simulated annealing algorithm is given by

$$p = exp\left(-\frac{v(S) - v(S_0)}{t}\right)$$

where $v(S)$ = objective value of a prospective solution, S
$v(S_0)$ = objective value of the current solution, S_0
t = temperature

This acceptance probability grows smaller over time as the temperature decreases according to the temperature reduction function a t, where a=10^{-4/n}.



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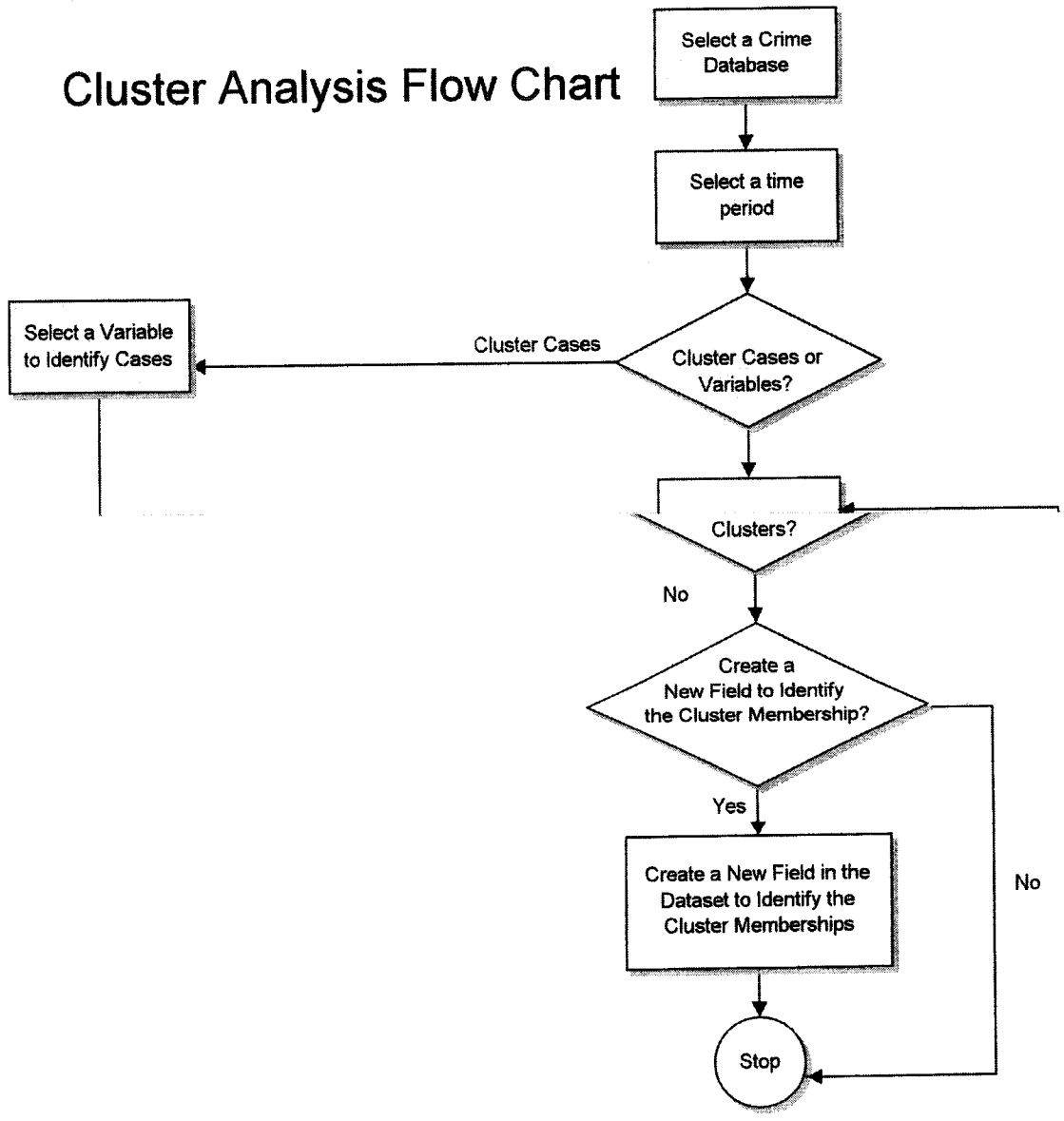
Appendix 2:

Flow Charts and GUIs



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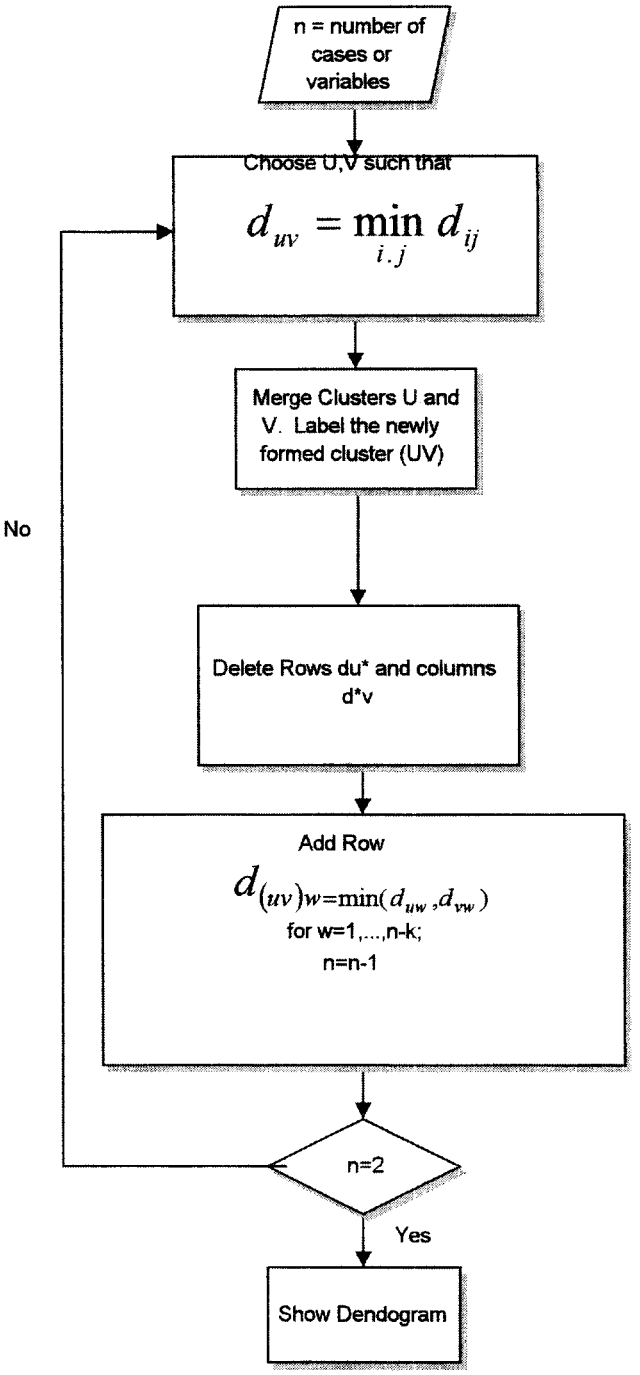

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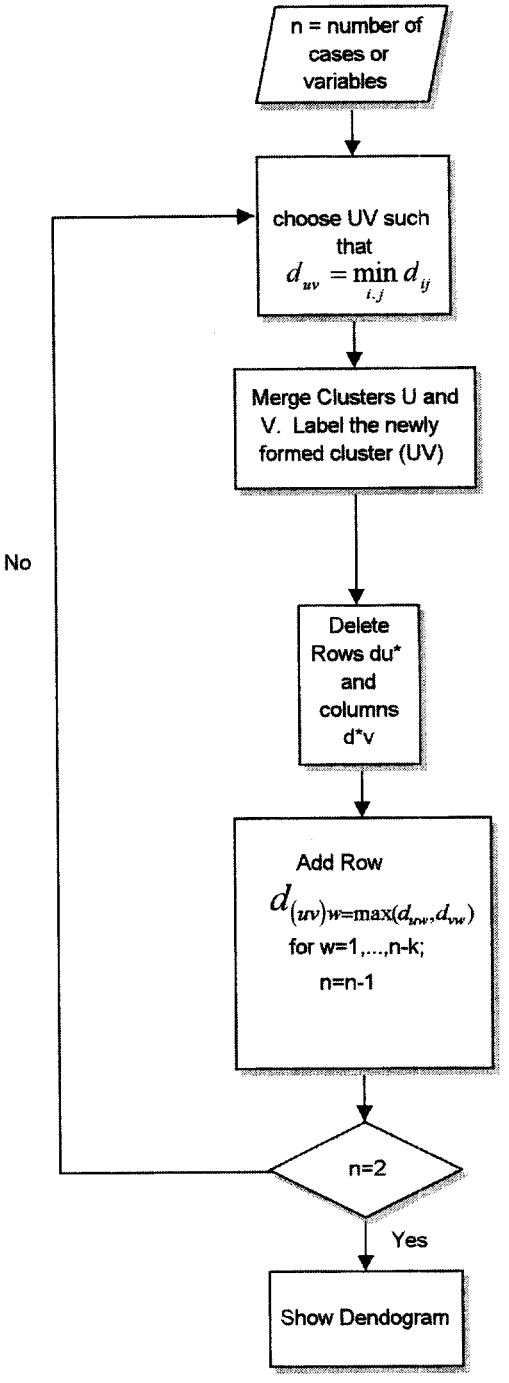
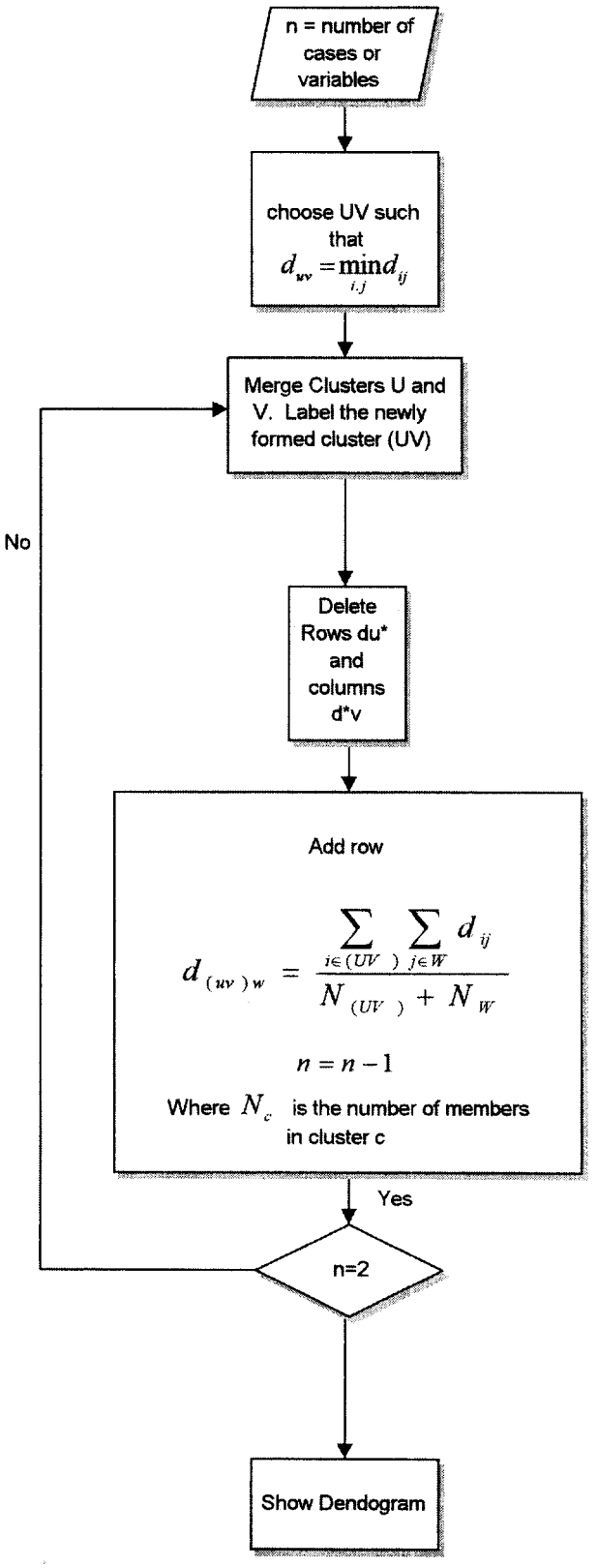
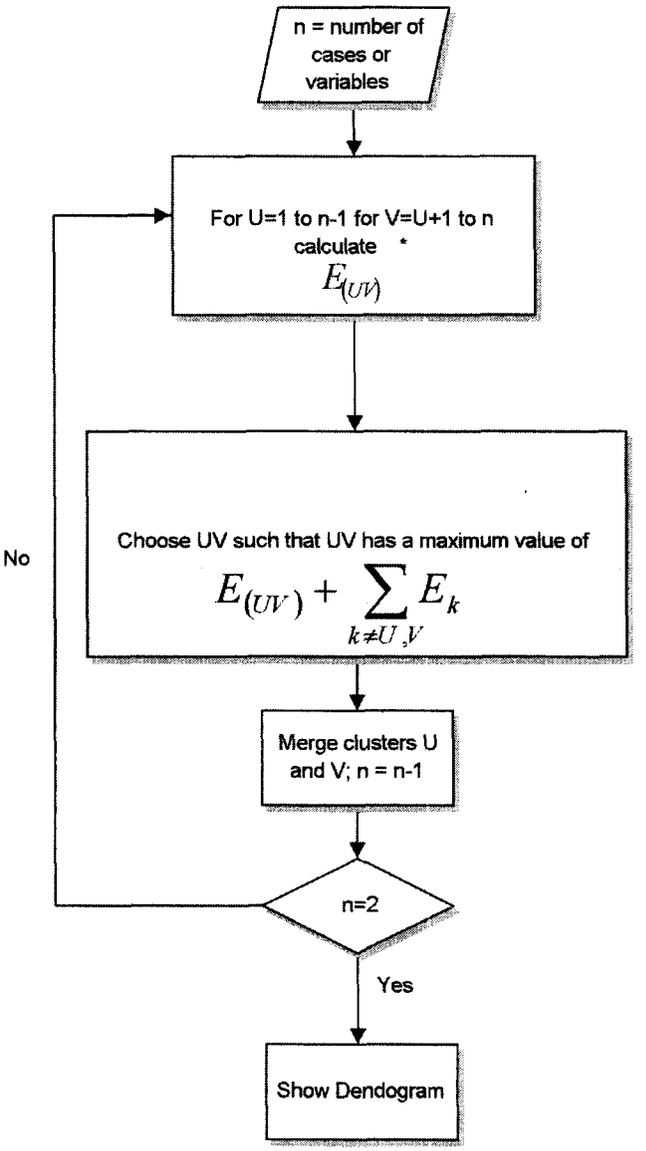


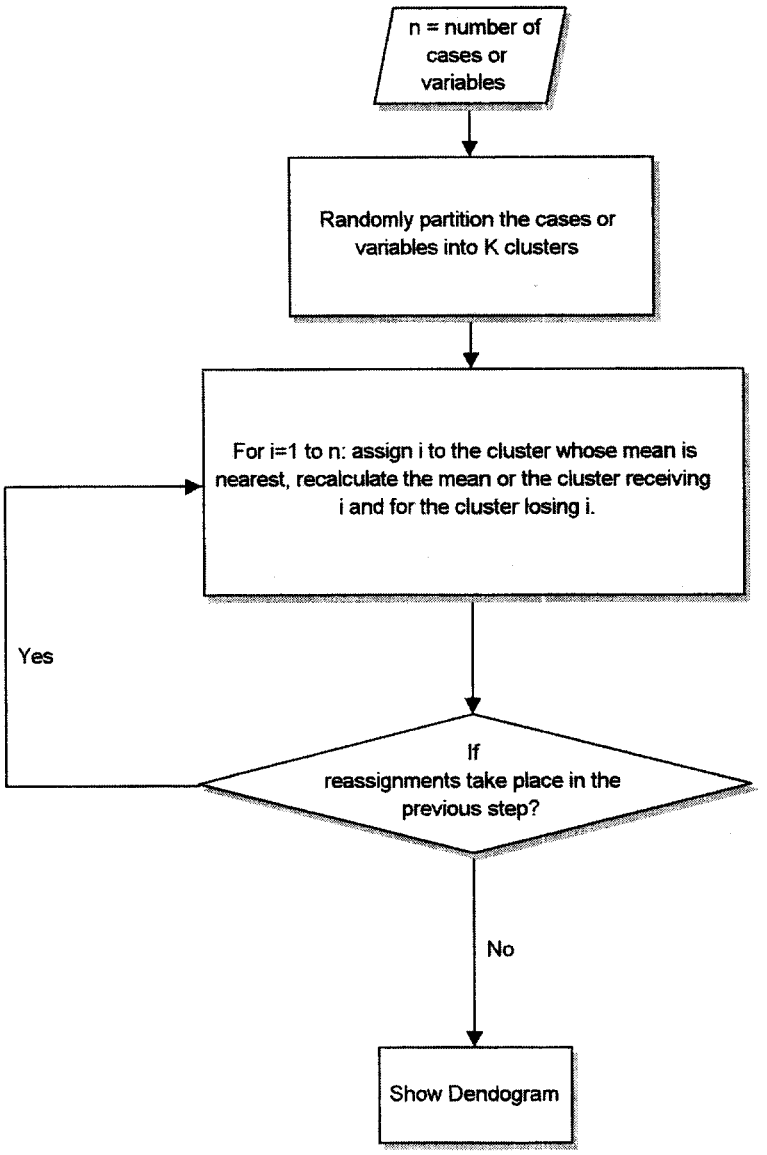
Apply Average Linkage



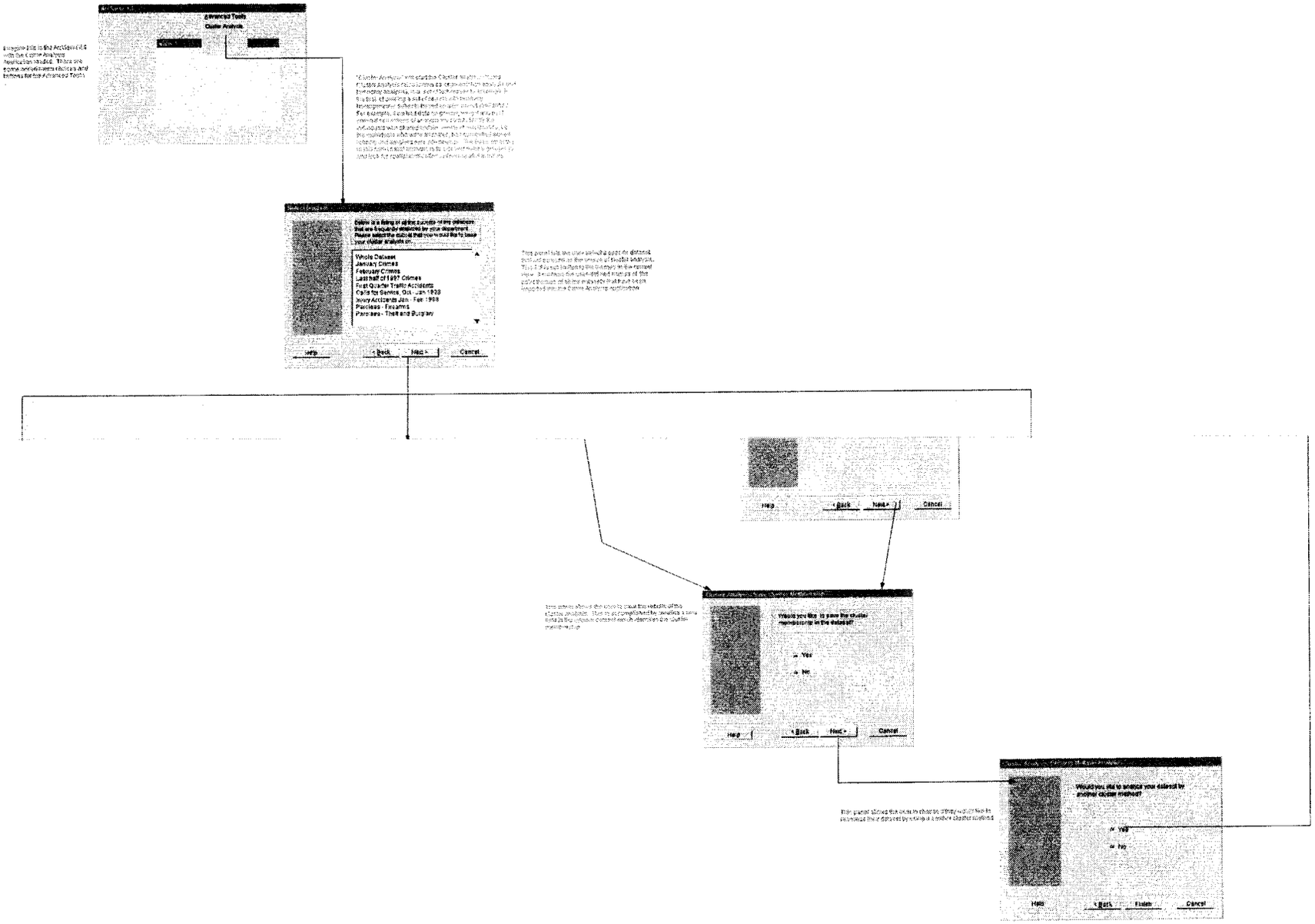
Apply Ward's Algorithm



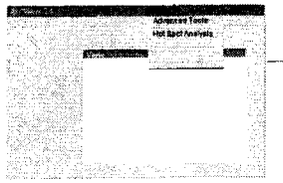
Apply K-Mean Algorithm

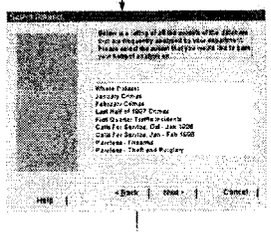


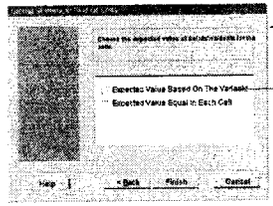
Non-Spatial Cluster Analysis Tool

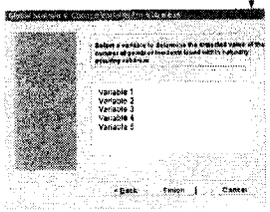


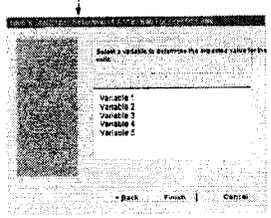
Hot Spot Analysis











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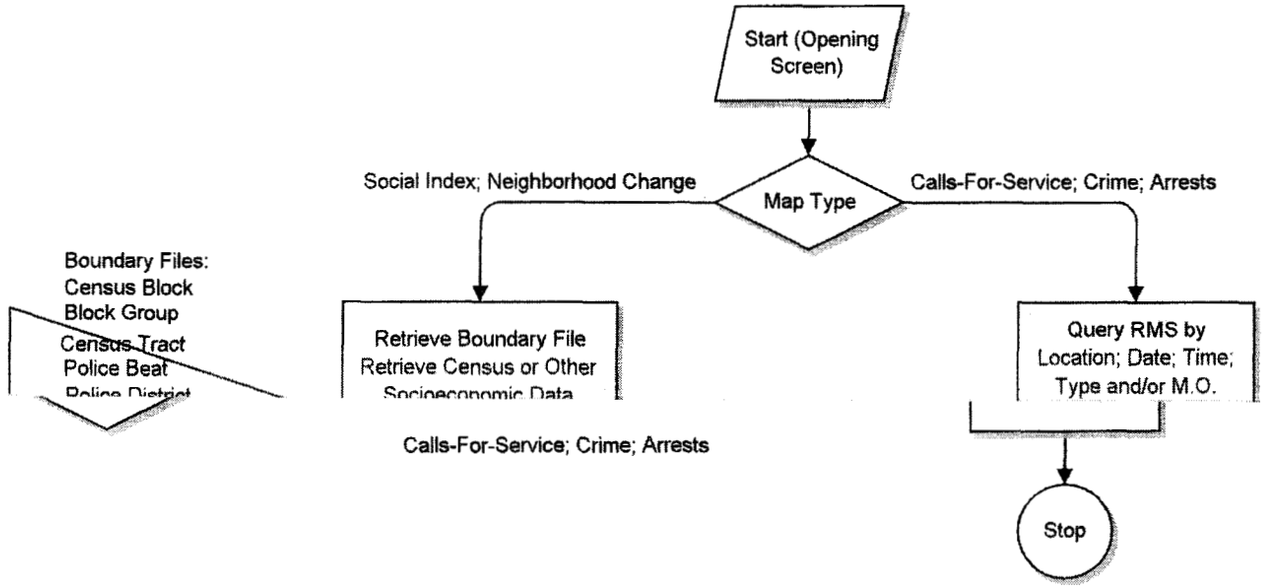
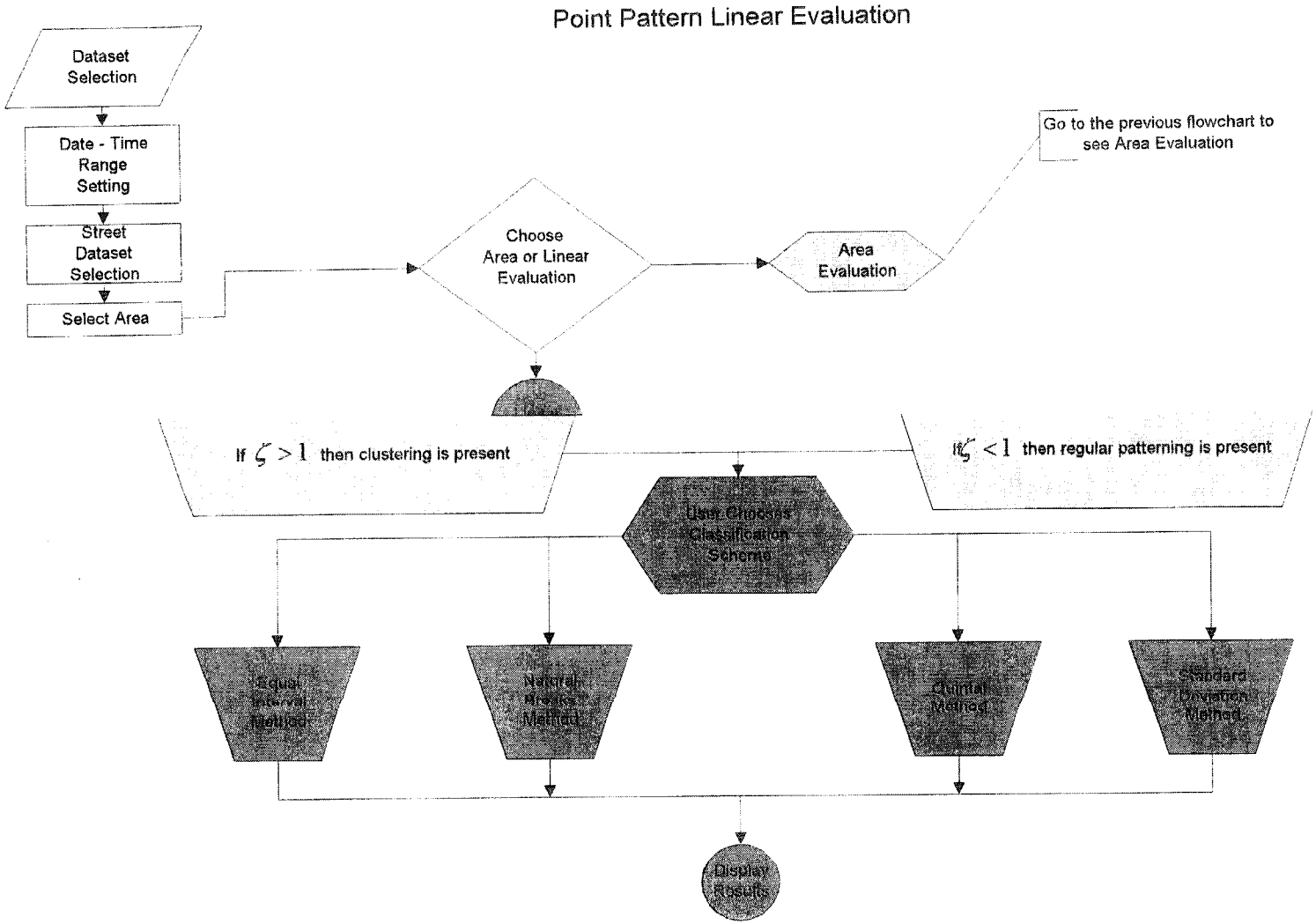
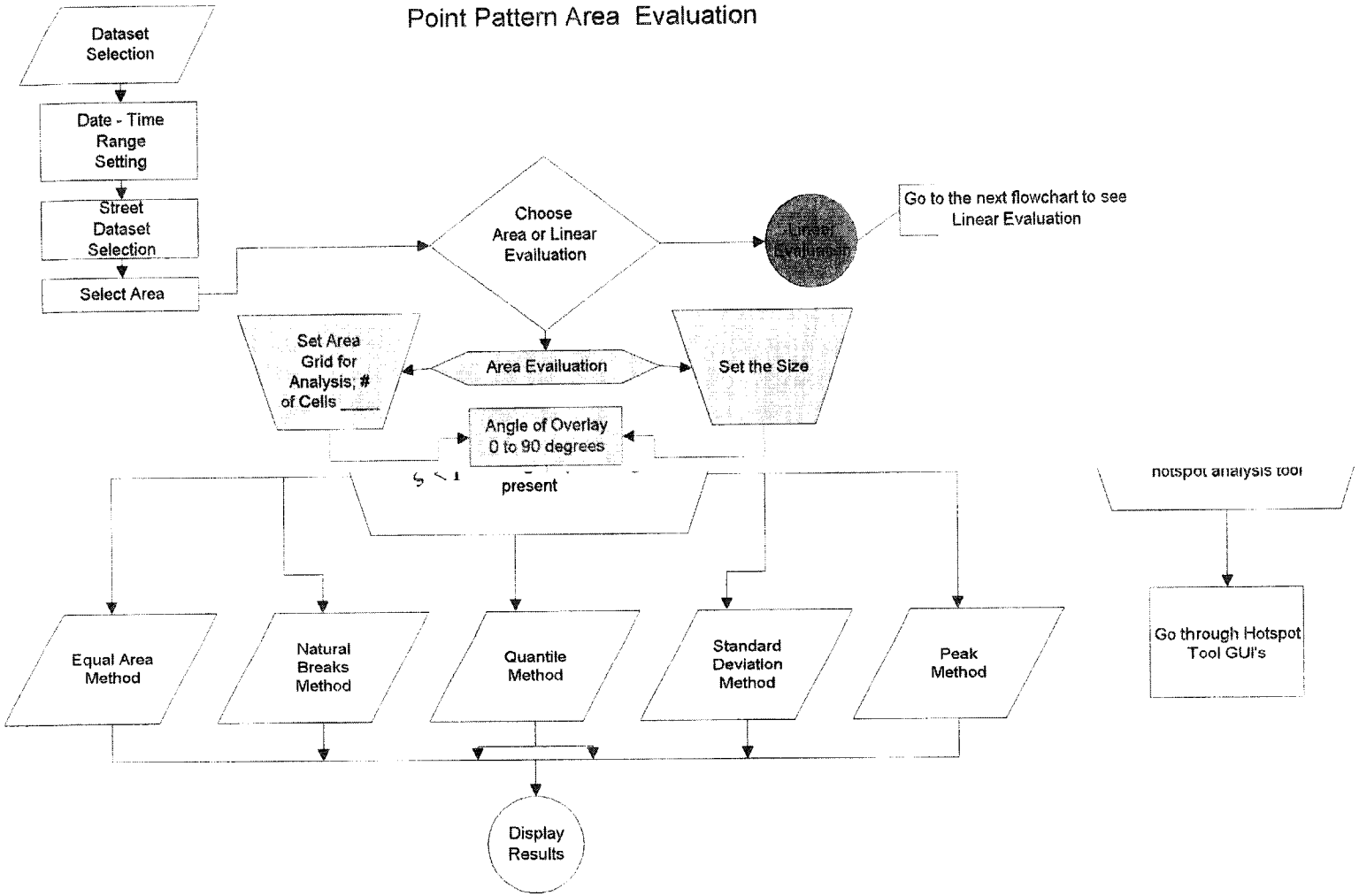
Spatial Chloropleth Flow Chart

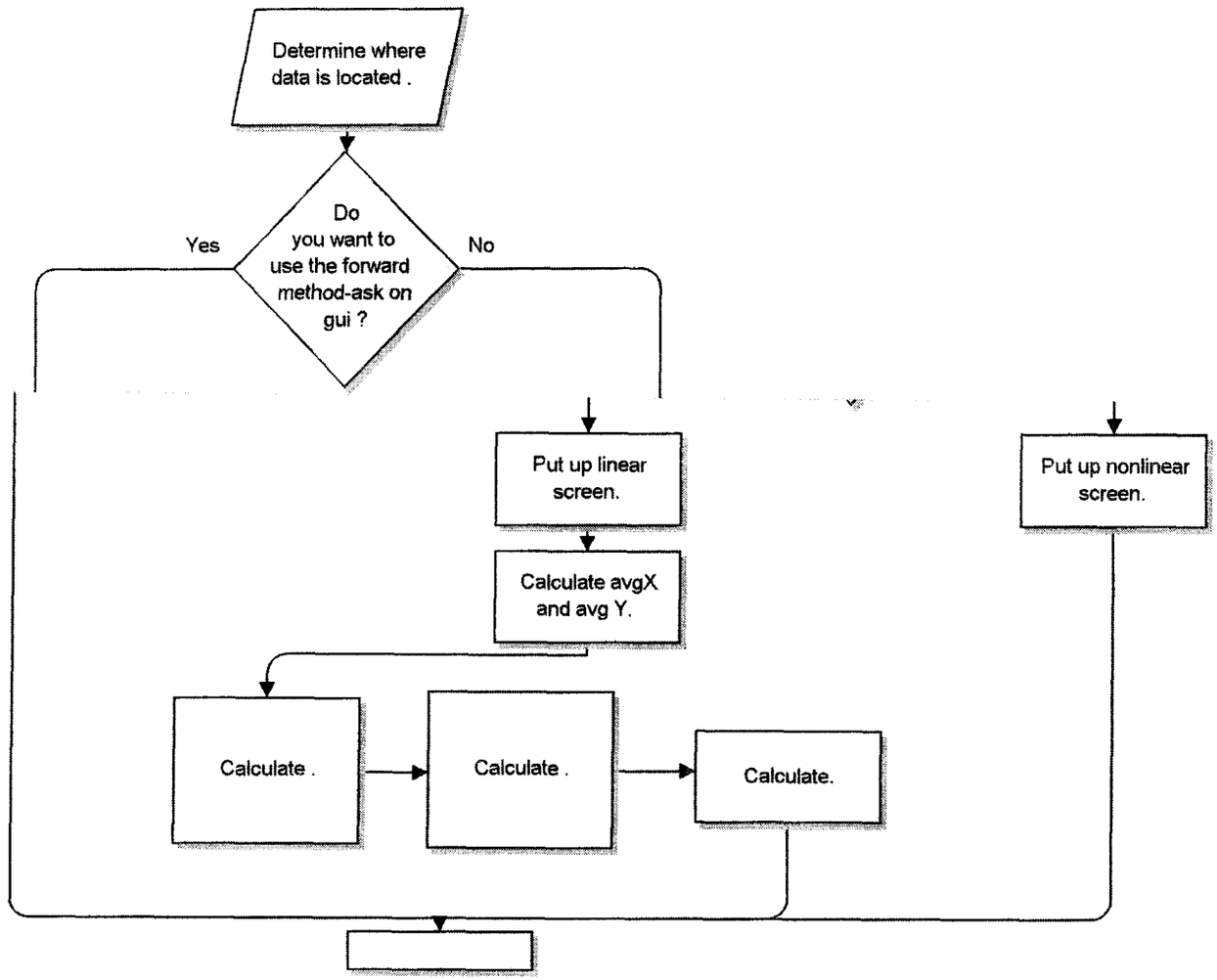


UserName	CompanyName	Wednesday, July 28, 1999, 11:00:46

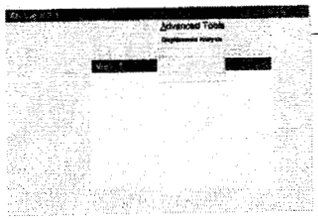




Regression



Displacement Analysis Tool



Displacement Analysis is a tool to measure the connection between the place where criminals reside and the places where they commit crimes. A crime is said to be displaced if the offender commits a crime in a given zone while residing in another. Crime controls programs within a police precinct or beat may deter crime within that precinct or beat. Simultaneously, however, such programs may have the effect of causing criminals to choose to commit their crimes in other police beats or precincts. We can call this crime displacement.

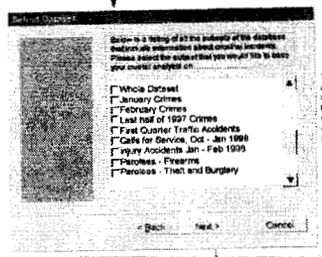
"I should go through the prerequisites of the model, (1) what are needed to perform this model (2) what the procedures are, (3) what information the user can get from the tool."

Displacement analysis creates a "Resistance Matrix". This resistance matrix consists of resistance values which measure the degree of difficulty for a criminal to commit a crime in different geographical areas based on where the criminal resides.

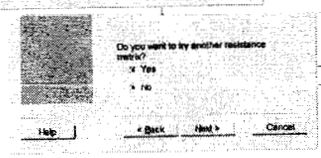
"Need to be fixed". This resistance matrix will be used to forecast the number of crimes moving from where the criminals reside to where they commit crimes by giving the number of crimes in each geographical area before and after a period of time.

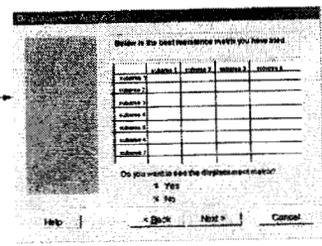
"Need to be fixed". Before determining what variables are significant factors for the displacement model

As numbers in the resistance matrix have positive values and we used ground look for the entries, in the matrix, that have the highest and lowest values. High values mean that it will be more difficult for a criminal to commit a crime in that particular suburbs (tract or precincts) given the criminal's place of residence. Conversely, low values mean that it will be easier for a criminal to commit a crime in that particular suburbs given that the criminal's place of residence.

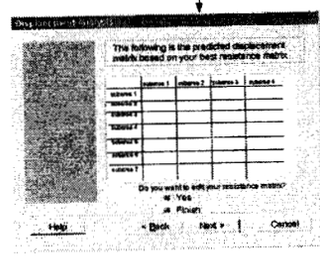


This panel lets the user select a specific dataset or datasets that will be used as the source of displacement analysis. The list is not limited to the themes in the current view. It contains the user-defined names of the crime incident datasets (polulations) of all the datasets that have been imported into the Crime Analysis Application.

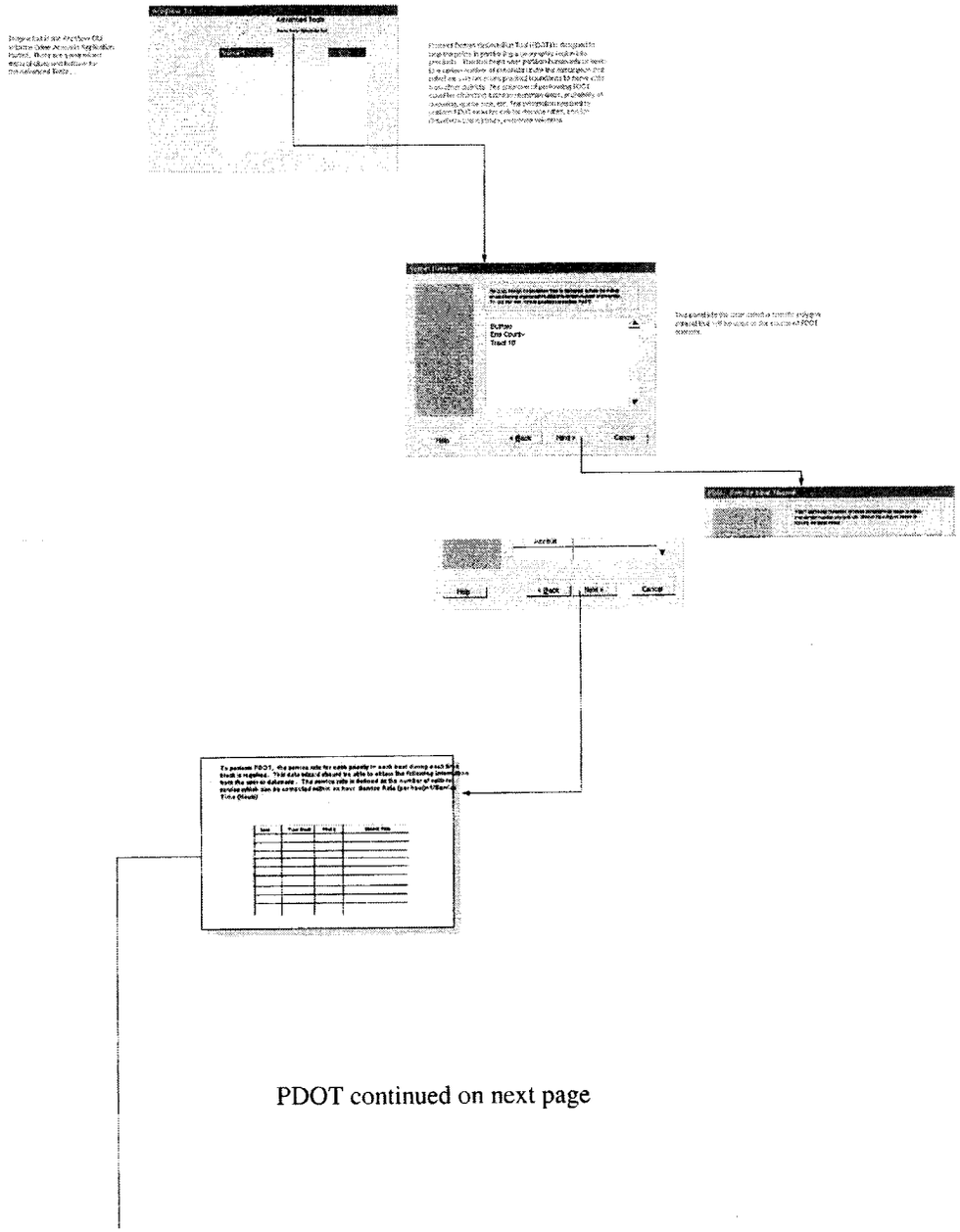




This panel shows the best resistance matrix which has been used by the user.



Precinct Design Optimization Tool



PDOT continued on next page

PDOT continued from previous page