Aiding Strategic Decision-Making Among Police Departments Using An Artificial-Intelligence Software Tool

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ABSTRACT

More police departments than ever before are utilizing information technology for solving and combating crime. However, most of these uses are for operational or tactical purposes. This paper presents an Artificial Intelligence (AI) software, 'Crime X-Windows Similarity (CXS)' that helps police departments in having a strategic viewpoint toward decision-making. CXS utilizes socioeconomic, crime and enforcement profiles to generate a list of cities that are best candidates to cooperate and share experiences. By providing a list of relevant similar communities from whom past experience and learnings can be shared, this tool enables proactive decision-making in police departments. This software provides a user-friendly, front-end interface enabling easy usage by police department personnel. In an effort to better serve their communities and reduce crime, police departments of the cities of Camden, NJ and Philadelphia, PA have been partners in this development effort. Feedback from these two police departments has validated exciting possibilities this software offers for co-operation and information sharing among police departments nationwide. Evaluation of the system using human subjects showed that the software provided significantly better support than a conventional database tool for quality and speed of decision making. With an Internet interface effort already under way, this application will soon be accessible to a much wider audience across the United States.

1 INTRODUCTION

"Probably the single greatest technical limitation on the criminal justice system's ability to make decisions wisely and fairly is that people in the system often are required to decide issues without information" (Katzenbach et al., 1967). Information technology for law enforcement has improved significantly since those words were written. Now police managers regularly retrieve and use information on crime patterns, responses to calls for service, vehicle locations, personnel, finances, and various aspects of departmental performance (Northrop, Kraemer, King, 1995). Emerging technologies in data collection and usage have opened possibilities for police departments to develop and test new problem-solving techniques (Block, Dabdoub, Fregly, 1993). However many of these policing trends, such as rapid-response to 911-calls, are reactive instead of being proactive in problem solving (Sparrow 1993).

Recent emphasis on community policing and problem-oriented policing shows a definite shift in policing philosophy toward better resource management. Scarcity of resources and increased public attention to crime reduction has put additional pressure on police departments to improve their performance. Police departments need to be able to sort through the clutter of approaches and controversies to find tactics and initiatives that really work. Therefore, there is a growing effort among law enforcement departments, local government agencies and academics toward institutionalizing the process of 'learning' in police departments so that they can better serve and strengthen their communities (Geller 1997).

This project provides a technical platform for police departments to make more informed decisions via dialog with cities having similar conditions and problems. The application software developed here utilizes case-based reasoning (CBR) (Kolodner, 1993), an artificial intelligence technique, and the power of computers to compare cities along multiple dimensions - demographic, crime and enforcement. The software retrieves ‘matches’ that would have been otherwise difficult to generate due to limits in human cognitive abilities, particularly in short term memory (Miller 1956).

2 RELATED WORK

For years, computers have been used for law enforcement applications. Systems included those that keep track of arrests, crimes and their types, criminal history, and missing persons. Recently, more advanced systems have helped police respond to crime - Automated Fingerprint Identification (VanDuyn 1991) and Computer-aided Dispatch (CAD) systems, particularly tied to 9-1-1 systems (Sparrow 1993). While these systems can also help an officer by providing much information in preparing to respond to a call (Rubin 1991), they tend to be geared to fast response.

Other systems include those that allow sharing of information among agencies (Stratton 1993) (e.g. FBI’s National Crime Information Center, NCIC). They provide cross checking capability for firearms and child care checks, speed dispatch through use of global positioning systems (GPS) for automated vehicle location (AVL) (Pilant 1995), and enhance communication by putting terminals in police cars (Nunn 1993). Still these are geared toward day-to-day, and minute-to-minute tactical needs of police. Many innovations are ways of “managing the environment, rather than changing it” (Manning 1992).

A recent emphasis on Geographic Information Systems (GIS) allows mapping of information to help crime analysis and problem detection (NIJ 1995, Block, Dabdoub, and Fregly 1993, McEwen & Taxman 1995). These systems can be used to map crime patterns within a city where various kinds of data can be overlaid over the maps to facilitate visualization of “hot spots” of crime or trends. This kind of application can aid in planning and problem-solving, a valuable asset for community policing (Rewers and Green 1993, Stallo 1993, Hicks and Wilson 1993, Block 1993, Lewin and Morison 1993).

The software developed in this project, however, provides an additional dimension for policing. It promotes a wider view, a longer range perspective, encouraging greater communication between agencies and among community groups, creating opportunities for cooperation. It facilitates the dissemination and use of the more useful and successful of the above kinds of systems and strategies.

Technologically, the proposed project has some commonality with some previously developed software. The FBI developed an automated crime profiling expert system (Icove 1986, Reboussin 1990, Reboussin and Tafoya 1990) which found previous incidents of crime for solving current crime incidents. The similarities were judged using “rules” that were developed by experts in criminal justice profiling. The differences from the current project are both in technology and in use - rules were used instead of general similarity measurement techniques and crime investigation was the focus instead of communication and strategic planning. Constructing rules is a painstaking process, and is only possible if genuine experts exist. It is for these reasons that the popularity of expert systems has waned. In the current project, using rule-based AI technology would not be desirable due to a scarcity of experts for an intrinsically difficult task.

The technique used here, CBR, has been an active research area in computer science for almost 15 years (Kolodner and Simpson 1984) and has been successfully employed for numerous purposes (Kolodner 1993). Some of the applications include automobile diagnosis (Redmond 1992), medical diagnosis (Turner 1989, Hunter 1989), banquet planning (Hinrichs 1991), and architectural design. More recently, this technique has received much attention due to its use for commercial purposes. For instance, Dell Computers reports great success using CBR for its customer support services (http://www.dell.com). Other commercial uses include matching the colors of plastics by General Electric (Cheetham 1997) and detecting rail defects by Dutch Railways (Jarmulak 1997). However, it has not been used for any law enforcement tasks. Thus, the proposed project is both a new use of the technology and a new capability for those involved in law enforcement.

The next section discusses the modeling framework, followed by a section on software development and evaluation. Section 5 presents examples to illustrate potential uses of the application. The last section presents future enhancements and some concluding remarks.

3 MODELING FRAMEWORK

Conceptually this model seeks to generate a list of matching cities which will enable the 'cue' city to satisfy one of the following broad goals - (a) crime reduction, (b) reducing expenditure while maintaining same level of service, (c) making a case for getting additional funding, and (d) increasing cooperation among departments (for instance, departments facing similar problems may request joint funding from government agencies). Note that the model presents a process and opportunity for achieving goals instead of specifying a mechanism for satisfying them. We let the computer do what it does best – handle a large volume of data and calculations - and let humans do what the computer does not do best, communicating with people, and distilling lessons from somebody else's experience.

In order to achieve the goals, the software requires a process of matching communities appropriately based on input data. Our approach considers each community or city a “case” to be used as an example for problem solving. In the context of our application, the socioeconomic, law enforcement, and crime factors are all considered part of the case problem description and are inputs to the model. A *factor* is similar in spirit to the term “attribute” in a database, or “feature” in CBR, or “field” in data processing - representing a piece of data available for a collection of related instances. Based on the problem description, the decision-making application, ‘Crime X-Windows Similarity (CXS)’, then retrieves communities that have relevant similarity, allowing the law enforcement user to contact representatives of the retrieved communities for discussions enabling dialog, discussion and learning.

The effort involved identification of the data, development of a method of determining similarity and using the similarity matching to meet different user goals. Therefore, three major aspects defining the modeling framework for CXS are (i) the input factors, (ii) the matching process which forms the intelligence core of the software, and (iii) the user goals. Below we discuss each of these components.

3.1 Input Factors

To arrive at the input factors to the model, extensive discussions were held with top law enforcement officials from the partner police departments in the cities of Camden, NJ and Philadelphia, PA. In addition, discussions were held with academics from relevant disciplines of criminal justice, geography and public policy. Multiple interviews were held including brainstorming sessions to identify and prioritize the inputs. Questions were posed in semi-formal format, ensuring focus, yet allowing flexibility for the end-users to raise relevant issues not considered by the authors. Sample printouts of data were provided to the officials to assist them in the discussions. Subsequently a tentative list of relevant factors was developed, which was then fine-tuned via follow-up interviews.

While the software could easily deal with hundreds of factors, it was our goal to limit the number of factors to a manageable number. In particular, when a similarity match is returned, a user may want to see how the community matches up. Presenting the user with numerous pieces of data for their community and the retrieved community is more likely to be overwhelming than useful. Therefore, it was a major goal of our interviews to come up with the best *small* set of factors.

After identification, these factors were aggregated into three *dimensions*: environment, enforcement and crime, where a dimension is an aggregation of factors describing one aspect of a community. The environment dimension deals mainly with the socioeconomic conditions of the community, factors that are closely linked with crime. Note that this model does not assume any causality but merely recognizes the correlation between crime and these factors. The factors incorporated in this dimension are shown in Table 1. These factors were taken directly from the U.S. Census data where available, while others were generated from multiple raw factors. For instance, population density was calculated from population and land area, and percent of adults over 25 without a high school diploma was calculated from numbers of adults in each educational category.

The enforcement dimension measures resources available for law enforcement, demand for service on the resources, and deployment of these resources toward fighting crime. The factors chosen are shown in Table 1.

The enforcement factors were either obtained directly from the Law Enforcement Management and Administrative Statistics (LEMAS) survey or were calculated by a simple combination with the Census data. However, the racial match factor, which was developed to measure the sensitivity of deployment to ethnic and minority groups (a key factor for garnering community help in community policing) involved a more complex calculation. This calculation is illustrated in the Appendix.

Table 1 - Factors Used in Environment, Enforcement and Crime Dimensions

ENVIRONMENT	Population density Median household income percent of households receiving public assistance percent of population between age 16 and 24 percent of adults who haven't completed high school percent of households that are owner occupied
ENFORCEMENT	Number of police officers Police officers per 100,000 population Number of requests for police service per officer Police operating budget per 100,000 population Percent of officers on patrol Whether the police had a special gang unit The percent of police officers assigned to special drug units The racial match of the police force to the community
CRIME	Total violent crime rate Murder rate Drug arrest rate Total non-violent crime rate

The crime dimension quantifies the prevalence of crime in a community, and each factor incorporated in this dimension has been normalized per 100,000 population to ease comparison.

The factors chosen (Table 1) and were obtained from the Federal Bureau of Investigation's (FBI) Uniform Crime Reports. Note that while murder, violent and non-violent crime data describe *occurrences* of crime, the drug arrest is only a surrogate measure of drug-related offenses.

3.2 Intelligence Core of the Software Model

The main objective of this software application is to facilitate strategic decision making via learning from similar problems. As mentioned above, we utilize a technique from the field of Artificial intelligence, Case-Based Reasoning (CBR). CBR's intelligence lies in its 'memory' of a successful case of problem solving, used to solve new instances of similar problem, without having a complete model or knowledge of the task. The central step in any Case-Based Reasoning system is the *retrieval* of appropriately similar previous cases (Redmond 1990, Kolodner 1993). CBR's inherent strength in targeted retrievals makes it desirable for use in our application. One popular form of case-based retrieval is nearest neighbor retrieval (Cost and Salzberg 1993), in which all factors are combined to derive similarity between cases. The core of CXS uses three nearest neighbor retrievals, one for each of the three dimensions. In section 6 we discuss how this retrieval process can incorporate learning in response to user feedback. Next we explain the Nearest-Neighbor Retrieval approach.

3.2.1 Nearest Neighbor Approach

In a nearest-neighbor retrieval, cases in 'memory' are compared to the given (or "cue") case on all relevant problem-description factors. For each factor, the difference between the cue and the stored cases is calculated. The resulting differences are combined using one of several potential metrics. The 'Manhattan' metric adds the absolute value of the weighted differences together. The Euclidean metric adds the squares of the weighted differences, favoring cases that have no large differences. Regardless of the metric, the case in memory with the smallest result is retrieved as the ‘closest’ case i.e., it is the “least distance away”. Our CXS application uses the weighted Manhattan distance metric (see Equation 1) as it allows many similar factors not to be overruled by a single significantly different factor. As typical of most uses of nearest neighbor approach, each factor is weighted so that some factors have more impact than others.

$$\text{Distance}_j = w_1|c_1 - m_{i1}| + w_2|c_2 - m_{i2}| + \ldots w_n\,|c_n - m_{ij}| \quad (1)$$

Where,

c_n is the value for the nth attribute for the cue community,

m_{ij} is the value for the ith attribute for the jth community in memory,

w_n is the weight for the nth attribute.

This nearest-neighbor approach takes advantage of the computer’s capability to consider all factors put together, whereas a person asked to judge similarity, would have to focus on only a few relevant factors due to short-term memory limitations (Glass and Holyoak 1986). The software program has the additional advantage of being able to keep hundreds or thousands of cases efficiently, in its memory.

In CXS, the nearest-neighbor retrievals are limited by city population. Our users indicated that cities of drastically different populations would not be useful matches even if many attributes were similar, since law enforcement issues are qualitatively different. Accordingly we chose to perform distance measurement only on comparable cities - those with a similar population to the cue city. Utilizing FBI's standard categorization of cities into groups by population, CXS's nearest-neighbor retrieval only considers cities in the same or adjoining population categories as the cue city.

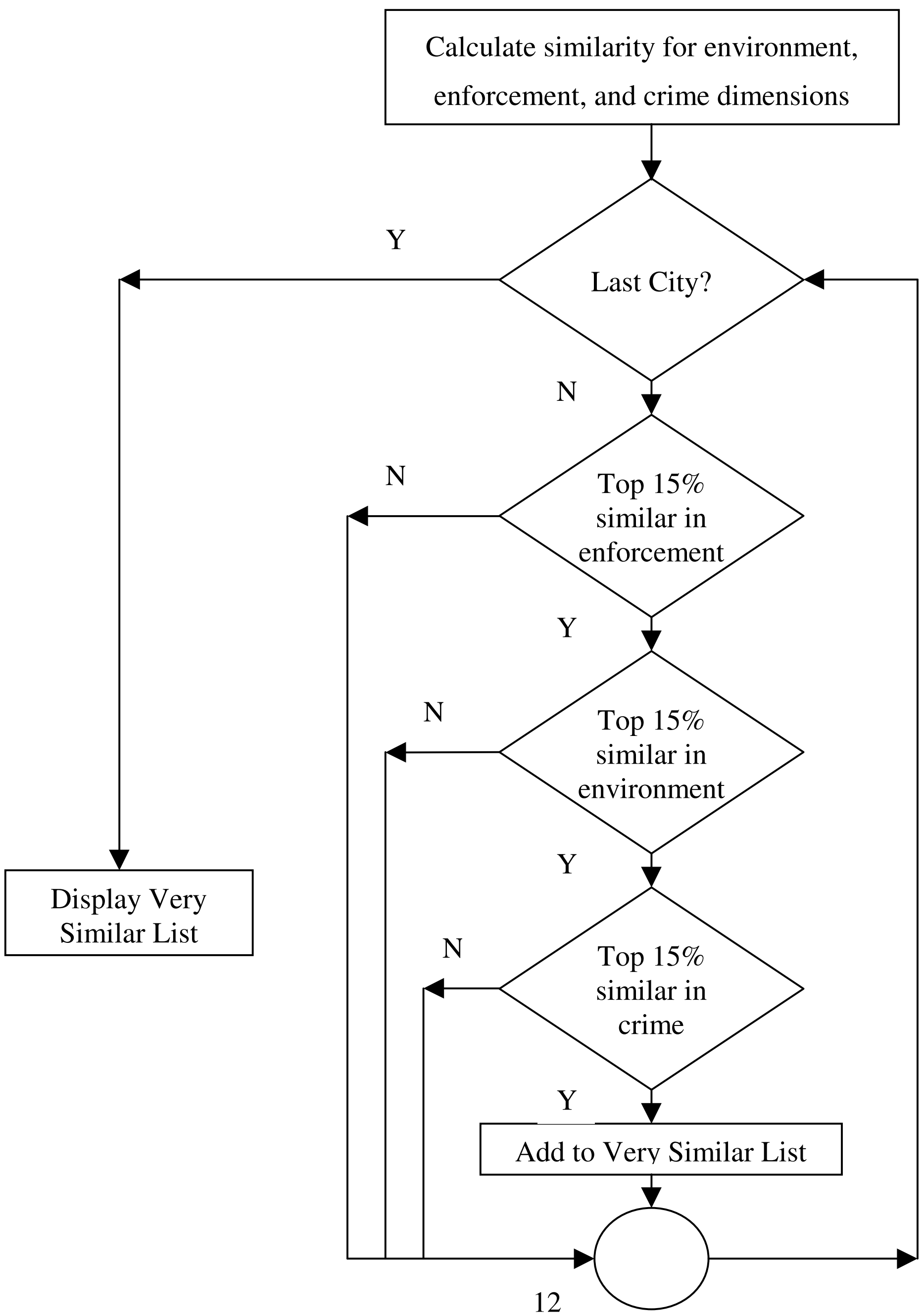
This computational approach of judging similarity also provides several advantages over human-assisted database retrieval. A person performing database retrievals still must choose a criterion to use, which requires picking a small set of factors and determining cut-off for each factor. In such a database retrieval, using a very small set of factors could lead to inaccuracies if some important factors are left out. On the other hand, using a large number of factors would be tedious for the user. Additionally, the user may have to do experimentation for selecting most appropriate cut-offs, and wrong choices may lead to too few or too many retrievals. In contrast the nearest- neighbor approach weighs all the factors appropriately in finding the best 'partial' match where no perfect match for a particular factor is required. See evaluation in Section 4.6 for an empirical comparison between use of CXS and a database to search for similar communities. With the possibility of having a built-in learning feature, this nearest neighbor approach can change the weights based on feedback from users over time, and thus provide closer targeted matches.

3.2.2 Assigning Weights

The process of finding the appropriate factor weights required multiple interviews with the experts over a period of one year. As discussed above, the experts were first asked to suggest possible factors and to respond to factors that had been identified based on prior consultations. Next they were asked to place the factors for a dimension into 2 lists - list A consisting of the factors perceived more important and list B consisting of the relatively less important ones. They were then asked to assign a cumulative percent weight on the factors in list A. After assigning a cumulative weight on each list, they ranked the factors in each list. The experts were then asked to further split each list into two smaller sub-lists and repeat the above procedure if necessary until they felt "comfortable" to assign a numerical weight on *each* factor.

Instead of numerically combining the weight assignment of various experts, we used them to enrich our viewpoint. While consensus helped consolidate a certain weight, disagreement helped uncover avenues for discussions and deliberations until convergence.

Figure 1: Similar Communities Goal Flowchart



In the second stage the experts were shown the impacts of the weights via results and were given the opportunity to revise their assignments. Even though this stage was tedious (for it required looking at a myriad of data), its impact on the quality of the model solution was invaluable. Fine-tuning of the weights was an on-going process through all the stages of this project.

3.3 User Goals

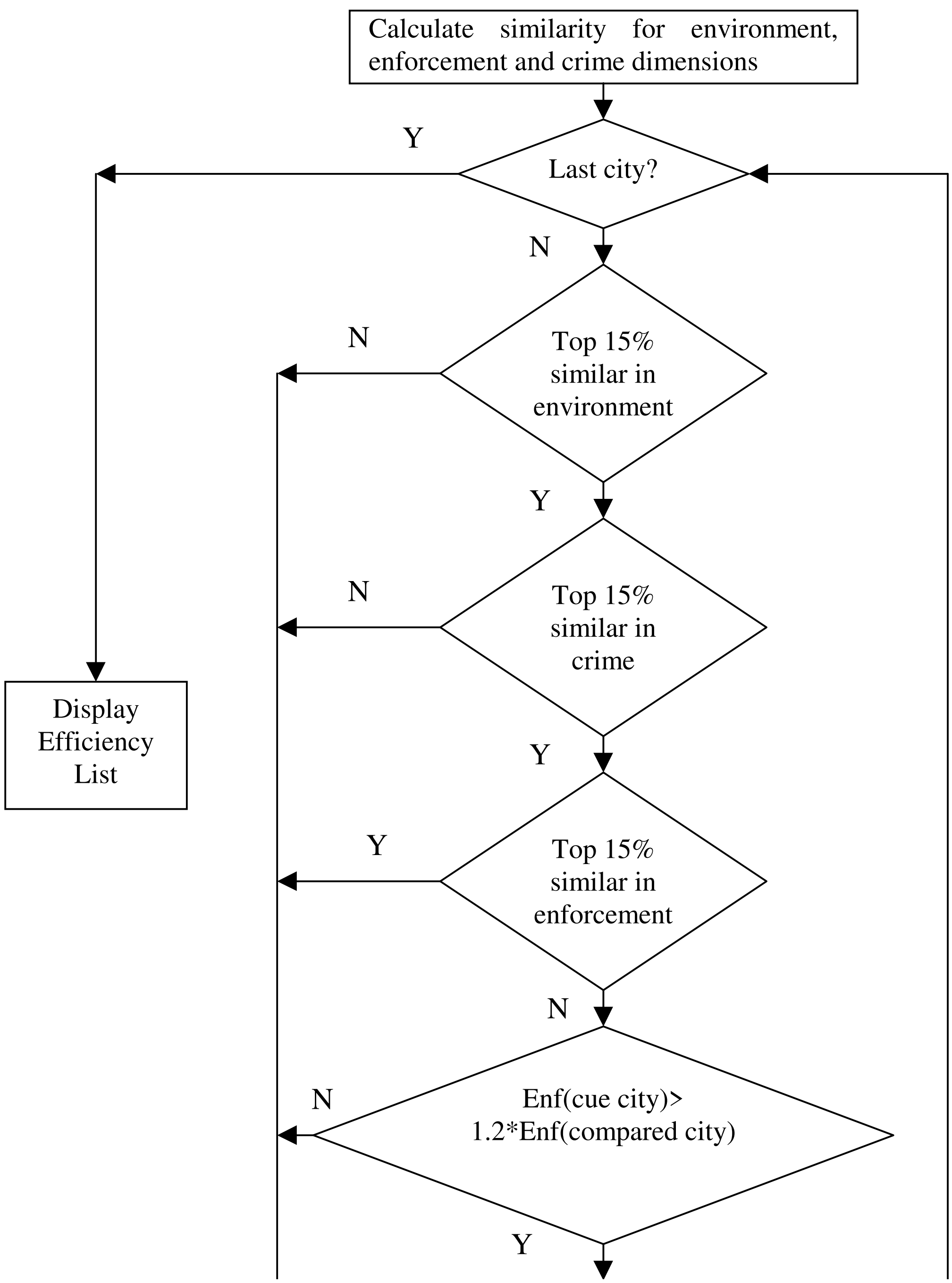
Our initial discussions with our partners, Philadelphia and Camden police departments, focused on the question, "How can the software aid strategic planning and decision making?" While many possibilities were considered, we finally converged to the following four broad goals: (a) find very similar, (b) find more efficient, (c) find more effective, and (d) find funding argument matches. For each of these user goals, CXS performs three nearest neighbor retrievals, one for each of the dimensions. Depending on the user's goal, these individual retrievals are then combined to produce a final result.

The "*find very similar*" goal is targeted to yield communities that are similar to the cue city on all three dimensions - enforcement, environment and crime (see Figure 1). If the software outputs a "very similar" match, it implies that the match was among the top 15% in similarity on all three dimensions. A top 15% cut-off in similarity was implemented since it yielded reasonable results.

In identifying these "very similar" communities, the hope is that it will help develop channels of communication for sharing their experiences and learning from each other. Such a dialog could lead to the identification of strategies that have worked in similar situations elsewhere or warning against pitfalls of other strategies that failed thereby enabling a more informed decision making process. Based on the feedback from our partners, we feel that this communication holds exciting possibilities in making the policing efforts to be proactive and strategic in their outlook.

For the "*find more efficient*" goal, the application displays communities that are similar to the cue community (top 15%) on environment and crime, but significantly lower in enforcement (at least 20% lower, see Figure 2). The possible implication of the match is that the matching communities *could* be using their resources more efficiently, offering a possibility of learning. Such a learning opportunity holds possibilities for aiding decisions on how to reduce spending or

Figure 2: Efficiency Goal Flowchart



in re-deployment of officers. Note that we are not arguing that such a match for any of the above goals is *necessarily* going to be fruitful, but that the potential is worthy of further exploration by the police officials.

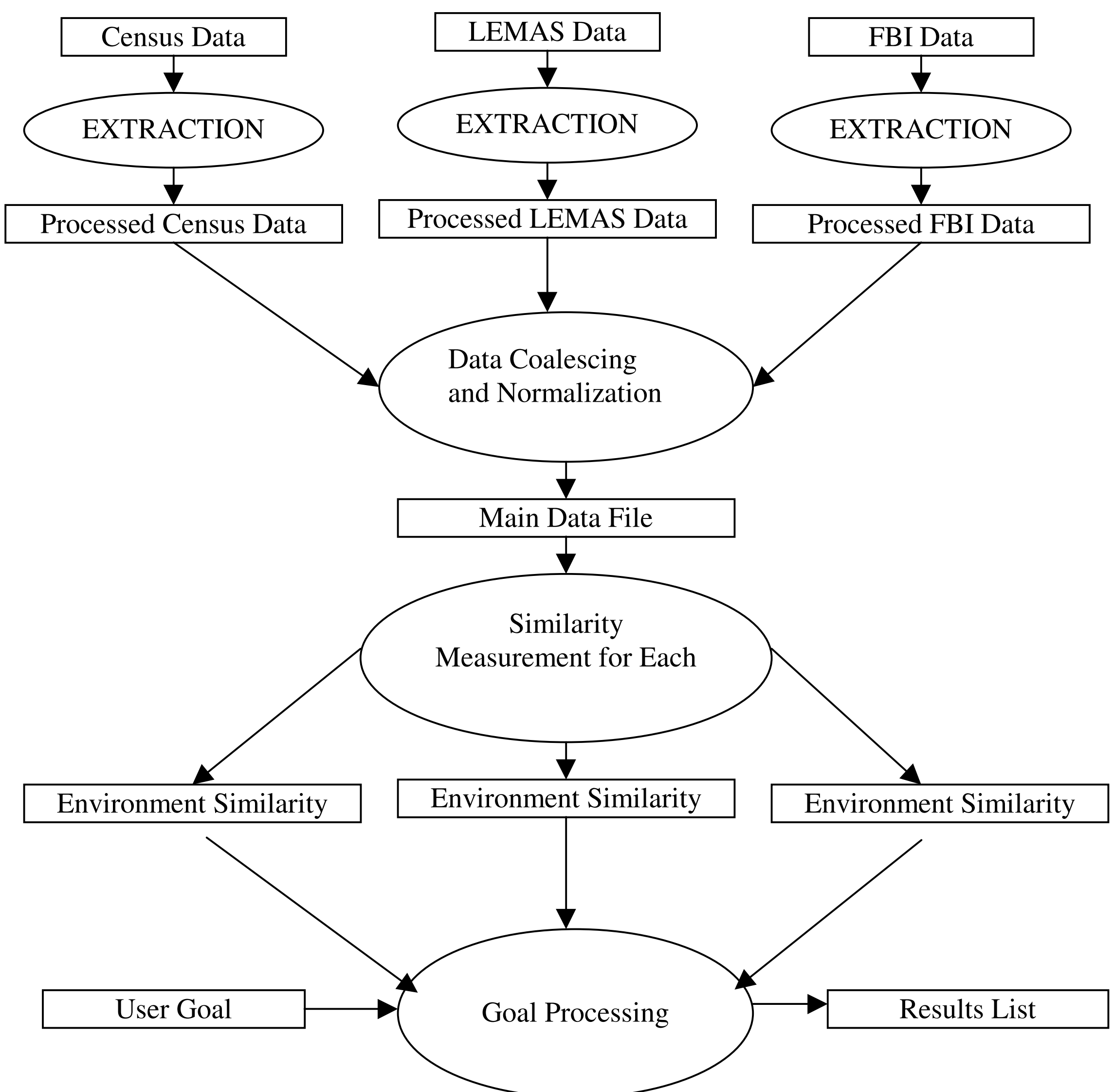
The third goal of "*find more effective*" outputs communities that are similar to the cue community (top 15%) in the environment and enforcement dimension, but are significantly lower in crime (at least 20% lower). A link with such communities could result in decisions to initiate similar programs, which utilize resources more effectively. Consultations could also lead to development of beneficial strategies for both police departments.

It may be argued that since enforcement and crime are correlated, looking at a community with similar enforcement and lower crime than the cue city is an exception or a statistical "outlier" and therefore should be ignored. For our application however, these exceptions are potentially *very interesting* and could be a function of unusual efforts of the community in reducing crime. Knowledge of such efforts would then enable other communities to make better strategic decisions in their own efforts to reduce crime.

The "*find funding argument*" search yields communities that are similar to the cue community on environment (top 15%), but significantly higher in enforcement and significantly lower on crime. Using such communities as benchmark, the user police department could take a decision to explore opportunities for additional resources from state and federal agencies hoping to bring down their crime (as for the matching community), given that both have a similar environment.

While these were the four goals implemented in the current version of the CXS application, additional goals could be supported within the current modeling framework, some of which are further discussed in Section 5. Next we present the details for the development of the software application.

Figure 3: Process Flow Diagram for CXS



4 SOFTWARE APPLICATION PROTOTYPE DEVELOPMENT

Developing the CXS software was a complex, time-intensive process spanning two calendar years. Multiple data sources with differing formats had to be combined, resulting in additional difficulty. In this section we will discuss the various sources of data, extraction of items from the parent source, coalescing of data from different sources into one dataset, normalization of the data, development of a graphical user interface, and system evaluation of the software. Figure 3 provides an overview of the process of turning raw data into useful retrieval.

4.1 Data Sources

Data for the various socioeconomic factors was obtained from the U.S. Census data, available through CD-ROMs (U.S. Department of Commerce 1992). The data had to be loaded in phases due to the large size of the files, and relevant fields were extracted from each file in turn. The current version of CXS utilizes data from all 50 states and the District of Columbia.

Crime data was obtained from two sources: (a) the non drug-offenses data for the "index crime" obtained from the Uniform Crime Report on the FTP server at the University of Alaska's Criminal Justice Center, and (b) The drug arrest data on tapes purchased directly from the FBI.

The enforcement profile data was obtained from the Law Enforcement Management and Administrative Statistics (LEMAS) Survey of police departments nationwide (U.S. Department of Justice 1992), available through the Inter-University Consortium for Political and Social Research's (ICPSR) WWW site at the University of Michigan-Ann Arbor.

4.2 Data Extraction

Most of the data sets were not “ready-to use” for our purposes, requiring programs to be written for extracting relevant information. For instance, drug arrest data from the FBI dataset provided for every city, monthly arrest data for each offense further branched by each age/race/sex combination. Since our model did not require breakdown by time, age, race, or gender, aggregation was performed to obtain total annual drug arrests for each city. This summary data extraction involved writing a 1200-line program in Pascal.

Similarly the LEMAS data had records on the state police, special agencies and the local police, each with hundreds of fields. Again, a special purpose Pascal program was written to extract only the useful data.

Extraction from the compressed Census data was done using a SAS program. Only the relevant fields and records were extracted and stored in a computer file which was then further processed to get into a useful form.

The UCR data required very little processing as it was already in an acceptable format, providing the annual total for each of the 8 index crimes for each community. In the next section we discuss how these different datasets were combined.

4.3 Data Coalescence

This step involved matching different datasets from multiple sources. The complications included (i) the city names were not unique, and (ii) different sources used different formats for the names (e.g. all capital letters versus mixed case etc.). The data coalescence was achieved using a Pascal program that converted the most “readable” community names, from the census, to each of the other forms (e.g. removing all blank spaces, converting all lower case letters to uppercase, stripping words like “borough”, etc.) and then matched across datasets. Additionally, since city names were not unique, the matching involved checking the state and the county as well.

Along with this coalescence, this program also did some pre-processing of data. For example, the Census data provided raw data on several educational levels of residents, which were converted to percentages during pre-processing.

The result from the above three steps - data collection, extraction and coalescence - was a “master” file to be used as input to the CXS main program (see Figure 3). Currently this master file contains data for 326 communities from 50 states and D.C., each having 21 fields of data, spanning the 3 dimensions.

4.4 Data Normalization

The successful use of a nearest neighbor approach depends on the "normalization" of data - putting all data into the same relative scale. This becomes necessary to ensure that a small difference on one factor (e.g. $10,000 difference in police budget) does not override a very important difference on another factor (e.g. difference of 500 in number of police officers).

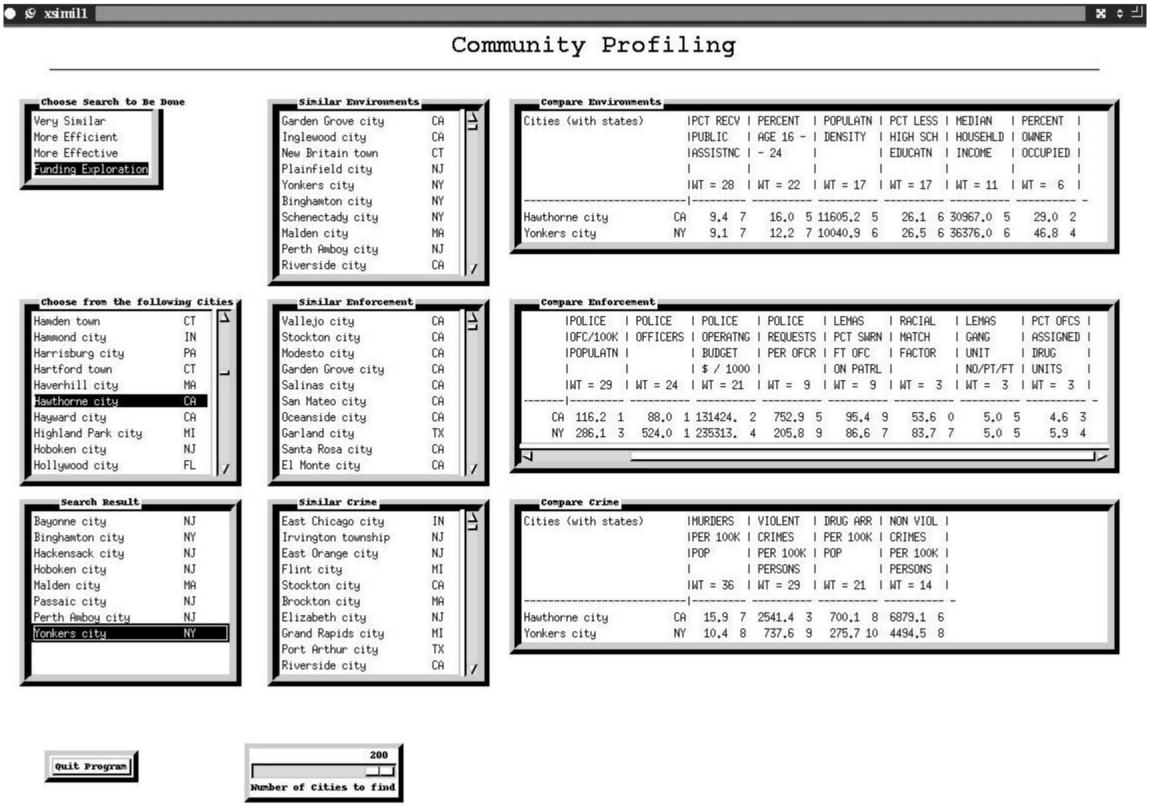
Normalization of data was done by first calculating the standard deviation for each factor. All values at three standard deviations above or below the mean were set aside and, among the rest, the largest and smallest values were found. The largest value (and anything above it) was set to a normalized value 10, while the smallest number (and anything below it) was set to a normalized value of 0. The range between the smallest and the largest values was then divided into 9 equal size ranges numbered 1-9. Raw data falling in each sub-range was assigned the corresponding normalized value. Then, in order to have a consistent meaning for high and low normalized scores, for any factor in which a high number would be considered ‘undesirable’ for a community, the normalized values were then reversed (0→10, 1→9, 2→8, etc.).

This above "discrete categories" normalization approach was chosen over others to enable future comparison of the CBR approach with another AI technique - the prototype method. The three standard deviation cut-offs ensures that 'unusual' data does not force all other values to fall on one side of the scale. Intuitively, the 'equally spaced' interval normalization process captures the mental model that magnitudes of difference between data is the key indicator of similarity, and should be preserved. Thus, for instance, it was not desirable to use z-scores, which tends to provide fine distinctions among data points that are close together but which are separated by many other data points. Our normalization scheme on the other hand preserves the clustering of data.

4.5 Core Software and the Graphical User Interface

As discussed in Section 2, the CXS decision-aid application utilizes a Case-Based Reasoning approach. The software code for this component was written in the "C" programming language and is portable to multiple computer platforms.

Figure 4: A Sample Screen Capture from the Interface of CXS Software



For the CXS application to be used easily and effectively by police officials, development of a good graphical user interface (GUI) was imperative. This front-end of the software was developed for the X-Windows environment using an application development toolkit. This GUI is setup via "function calls" using the toolkit functions. When the user selects choices, the appropriate core algorithm is invoked. The GUI (see Figure 4) allows the user to specify their desired goal, using user-friendly point-and-click technology. To specify the goal, or choose the cue community, the user double-clicks on the appropriate choice in the list box. The user can control the number of retrievals displayed using a sliding scale. Based on feedback from our partner police departments, we now make it possible for users to view the data comparison between the cue city and any city (chosen by the user) in the retrieval list. The layout and functionality of the software have been continually updated based on our ongoing interactions with the police officials. Efforts are underway for developing a WWW interface, offering CXS accessibility to a wider audience.

4.6 System Evaluation

Initially, routine unit and system testing were done to ensure accurate processing, followed by the police departments' officials checking for the reasonableness of the retrievals based on their knowledge and experience. Detailed factor-by-factor calculations of similarity were then presented to officials to show them the underlying process, which often resulted in adjustment of the weights for different factors in the nearest-neighbor algorithm.

Next, the users were asked for feedback on the usability of the program. It was at this stage that the need for displaying the underlying data was identified. Displaying data comparisons enables on-line exploration and analysis of the similarity measurement. Besides helping the users to evaluate the "goodness" of the match, this capability generates user confidence in the reliability of the software.

To evaluate the system's performance in a comprehensive manner, an experiment was conducted using twenty human subjects - all graduate students. The experiment required the subject to retrieve cities similar to the cue cities, Camden, NJ and Cincinnati, OH, using the CXS software and Microsoft Access database software. Subjects had no prior experience in using either software and were given training before the experiment. An average of 10 minutes of training was given on Access followed by a practice exercise on a similar, scaled-down task which lasted approximately 5 mins. On the other hand, each subjects was trained on CXS for about 1 min with no practice exercise. For all subjects, the time spent and their retrievals for both tasks were recorded. In addition, a follow up questionnaire was given to quantify their experience of using each software.

While time was used as a performance measure directly, the retrievals had to be translated into a measure that represented quality. If the reader would recall, closeness to the cue city represents desirable retrieval for this task and hence an indicator of quality. This closeness of retrievals of each subject (representing quality) was calculated by first ranking all the communities in the

$$Q_{ij} = \sum_{s \in S_i} \sum_{k=1}^{18} (R_{sk} - R_{jk}) \quad \text{for i} = 1...20,\ \text{j} = 1,2 \tag{2}$$

where

$\mathrm{i} = \text{subject i}$

$\mathrm{j} = \text{cue cities; } 1 = \text{Camden, } 2 = \text{Cincinnati}$

$\mathrm{k} = \text{input factors}$

$\mathrm{S_i} = \text{set of retrieved cities for subject i}$

$\mathrm{R_{lm}} = \text{Rank of city l on input factor m}$

$\mathrm{Q_{ij}} = \text{Quality of retrievals obtained by subject i for cue city j.}$

database on each of the input factors. Then the difference of ranks between the cue and retrieved city on all input factors was summed up to get a closeness measure for that particular retrieval for each subject. Finally all the these closeness measures were summed for all the retrievals obtained by the subject. Equation (2) summarizes this calculation. Therefore, a lower difference rank sum represents a closer match to the cue city and in effect good quality.

In our initial pilot run we observed some learning effect i.e., time taken by subjects for second city was less than the first one, for both CXS and Access, thus the experiment was designed to counter-balance the ordering of software and city searches. Table 2 shows the average time taken for completing the task for each software and city.

Table 2 : Average Retrieval Time (in seconds)

Software	CXS		ACCESS	
City	Camden	Cincinnati	Camden	Cincinnati
1st City	27.7	27.3	1003.7	1200.2
2nd City	16.6	12.6	681.1	494.8

For instance, using Access, it took an average of 1003.7 seconds for subjects to find matching cities for Camden when done first and 681.1 seconds they had done the retrieval for Cincinnati *before* doing Camden. Since second row values are less than the corresponding values in the first row, the learning effect is apparent. To accommodate this learning effect, a crossover analysis of variance design was employed using a nested, three factor model. The statistical analysis showed that CXS did significantly better than Access ($p<0.001$) on the time measure.

Table 3 summarizes the calculated, average quality measurement for each software and cue city. Since crossover learning effect was not found to be significant, aggregate measurements are provided. An analysis of variance showed CXS better than Access on the quality measurement as well ($p< 0.01$).

Table 3: Average Quality Measurement (Low is good)

Software	CXS		ACCESS	
City	Camden	Cincinnati	Camden	Cincinnati
Quality of Retrievals	1283.17	1393.13	1530.3	1511.7

Finally, the post-experiment questionnaire showed that the users clearly favored CXS over Access on both efficiency and quickness of search, and ease of use. Results are summarized in Table 4.

Table 4: Post – Experiment Questionnaire Results

(on scale 1-5 where 5 is good and 1 is bad)

Software	**CXS**	**ACCESS**
Searching for Matches	4.95	2.63
Ease of use	5.00	3.42

It is important to note that ideally we would have liked police administrators and decision makers to have been subjects in this evaluation experiment. However, that was not possible due to the extensive time commitment required from a large group of senior officials. Regardless of this limitation, this experiment does demonstrate the effectiveness of the CXS software in performing well with a population group not well versed in the task at hand.

Next we illustrate sample uses of the software application.

5 EXAMPLES

In this section we illustrate how the CXS software can be used to achieve three of the supported user goals - "Find Most Similar", "Find More Effective" and "Funding Exploration". As "Find

More Efficient" is very similar in spirit to the "Find More Effective" goal, it is not discussed here.

5.1 Find Most Similar

The most direct search supported by the CXS decision-aid, is finding cities that have similar characteristics to the cue city on all 3 dimensions. Such cities are good candidates for cooperation due to their intrinsic similarity in socioeconomic, enforcement and crime profiles. In the example, we choose the city of Beaumont, TX as the cue city, which yields Grand Rapids, MI as the top candidate on the 'similarity' goal. Tables 5, 6, and 7 show the difference calculations performed by the software for environment, enforcement and crime dimensions, respectively.

Table 5 - Calculations for Environment Dimension (Find Similar)

ENVIRONMENT	% People Receiving Public Assistance	% age 16-24	Population Density	% People Less High School Education	Median Household Income	% House Owner Occupied
Beaumont	7	6	10	7	3	6
Grand Rapids	7	5	9	7	4	6
Difference	0	1	1	0	1	0
Weight	28	22	17	17	11	6
WeightedDifference	0	22	17	0	11	0

Total Weighted Difference: 50

From Table 5, we see that each of the environment factors for Beaumont and Grand Rapids are very similar in their normalized scores, leading to a very small weighted difference of 50 units (differences can range from 0 on the low end to 1000 on the high end). Similarly their differences are 34 (Table 6) and 49 (Table 7) in the enforcement and crime dimensions. This makes Grand Rapids the 7th, 3rd and 4th most similar city to Beaumont on the environment, enforcement and crime dimensions respectively - clearly within the top 15% retrieval cutoff. Given the geographical distance between these two cities, it is unlikely that such a match could be easily uncovered by the cities without using this decision-aid.

Table 6 - Calculations for Enforcement Dimension (Find Similar)

ENFORCE MENT	Police officers	Police officers /100K population	Police operating budget $/1000	Police requests per officer	% officers sworn on patrol	Racial match factor	Gang units	% police officers assigned to drug units
Beaumont	2	1	2	6	7	3	10	2
Grand Rapids	2	1	2	7	7	7	10	10
Difference	0	0	0	1	0	4	0	8
Weight	29	29	21	9	9	3	3	3
Weighted Difference	0	0	0	9	0	1	0	24

Total Weighted Difference: 34

Table 7 - Calculations for Crime Dimension (Find Similar)

CRIME	Murders/100K population	Violent Crimes/100K population	Drug Arrests/100K population	Non Violent Crime/100K population
Beaumont	7	7	6	4
Grand Rapids	7	7	7	6
Difference	0	0	1	2
Weight	36	29	21	14
Weighted Difference	0	0	21	28

Total Weighted Difference: 49

Strategic decision making can be aided by exploring both the similarities and differences between the communities. For instance, similarity in factors could be used to discuss and develop new strategies collaboratively. The two cities could share and explore different strategies for revitalizing neighborhoods, coping with new crime trends or training of their police force. Indeed, a close link among similar cities could be the roadway to opportunities for synergistic alliances for participative decision making.

On a closer look, it is apparent that while the cities have a similar environment, there are differences - Grand Rapids has a better racial match between the community and the police than Beaumont. This may indicate that Grand Rapids is either already initiating community-oriented policing or is better positioned to undertake such efforts. Beaumont can decide to investigate this difference to determine if something useful can be learned from Grand Rapids' experiences with regard to this factor.

5.2 'Find More Effective'

The 'Find More Effective' feature of the software helps the user in finding cities that are similar to the cue community in the environment and enforcement dimensions, but significantly lower in crime. A run of the software for finding a more effective city using Harrisburg, PA as the cue city yields the city of New Bedford, MA as a match. The weighted differences of 51 and 60 shown in tables 8 and 9 show that the two cities are quite similar in the environment and enforcement dimensions respectively.

The CXS software then investigates the crime dimension (Table 10) indicating a significant difference of 314 between the two cities (recall, a higher normalized score implies a lower crime level). In fact, New Bedford is only the 70^{th} most similar community to Harrisburg on the crime dimension. Further, New Bedford's level of 801 is 61% better than Harrisburg's 487 level.

Having established similarity in environment and enforcement, and a significant dissimilarity on the crime dimension, New Bedford *seems* be more effective than Harrisburg in its law enforcement efforts. Harrisburg *may* be able to gain valuable information and learn new strategies from New Bedford police department that could help them in reducing the crime level in Harrisburg.

Table 8 - Calculations for the Environment Dimension (Find More Effective)

ENVIRONMENT	% People Receiving Public Assistance	% age 16-24	Population Density	% People Less High School Education	Median Household Income	% House Owner Occupied
Harrisburg	4	6	8	5	3	4
New Bedford	4	6	8	2	3	4
Difference	0	0	0	3	0	0
Weight	28	22	17	17	11	6
Weighted Difference	0	0	0	51	0	0

Total Weighted Difference: 51

Table 9 - Calculations for the Enforcement Dimension (Find More Effective)

ENFORCEMENT	Police officers	Police officers /100K population	Police operating budget $/1000	Police requests per officer	% officers sworn on patrol	Racial match factor	Gang units	% police officers assigned to drug units
Harrisburg	3	1	2	7	7	5	10	3
New Bedford	3	1	2	6	8	8	0	4
Difference	0	0	0	1	1	3	10	1
Weight	29	29	21	9	9	3	3	3
Weighted Difference	0	0	0	9	9	9	30	3

Total Weighted Difference: 60

For instance the difference in drug related arrests could be a point worthy of further exploration. If New Bedford has some specialized drug-related tactics which are contributing to a lower crime level, Harrisburg can decide to implement similar programs.

Table 10 - Calculations for Crime Dimension (Find More Effective)

CRIME	Murders/100K population	Violent Crimes/100K population	Drug Arrests/100K population	Non Violent Crime/100K population
Harrisburg	6	5	2	6
New Bedford	10	7	6	8
Difference	4	2	4	2
Weight	36	29	21	14
Weighted Difference	144	58	84	28

Total Weighted Difference: 314

Weighted Level for Harrisburg: 487

Weighted Level for New Bedford: 801

5.3 'Funding Exploration'

The CXS system can also be used to support an argument for requesting additional funding. The argument would take the form "city X has a similar environment to ours, but has more enforcement resources and has lower crime". If city of Hawthorne, CA Police Department decides to use the funding exploration goal in the software, CXS then considers cities such as Yonkers, NY, which are similar to Hawthorne in the environment dimension (comparison is shown in Table 11).

Then the software checks to see if the matched city (Yonkers, NY) has a higher enforcement rate than the cue city. We note that this difference 178 is indeed significant because (a) Yonkers has 58% higher enforcement, above the 20% threshold set in CXS software, and (b) the enforcement levels for Yonkers and Hawthorne were ranked far apart at 32 and 199, respectively. Finally, the software establishes that Yonkers city has a lower crime rate than Hawthorne city (Table 13 shows these calculations).

Table 11- Calculations for the Environment Dimension (Funding Exploration)

ENVIRONMENT	% People Receiving Public Assistance	% age 16-24	Population Density	% People Less High School Education	Median Household Income	% House Owner Occupied
Hawthorne	7	5	5	6	5	2
Yonkers	7	7	6	6	6	4
Difference	0	2	1	0	1	2
Weight	28	22	17	17	11	6
Weighted difference	0	44	17	0	11	12

Total Weighted Difference: 84

Table 12 - Calculations for Enforcement Dimension (Funding Exploration)

ENFORCE MENT	Police officers	Police officers /100K population	Police operating budget $/1000	Police requests per officer	% officers sworn on patrol	Racial match factor	Gang units	% police officers assigned to drug units
Hawthorne	1	1	2	5	9	0	5	3
Yonkers	3	1	4	9	7	7	5	4
Difference	2	0	2	4	2	7	0	1
Weight	29	24	21	9	9	3	3	3
Weighted Difference	58	0	42	36	18	21	0	3

Total Weighted Difference: 178

Weighted Level for Hawthorne: 245

Weighted Level for Yonkers: 387

Table 13- Calculations for Crime Dimension (Funding Exploration)

CRIME	Murders/100K population	Violent Crimes/100K population	Drug Arrests/100K population	Non Violent Crime/100K population
Hawthorne	7	3	8	6
Yonkers	8	9	10	8
Difference	1	6	2	2
Weight	36	29	21	14
Weighted Difference	36	174	42	28

Weighted Level for Hawthorne: 591

Weighted Level for Yonkers: 871

Total Weighted Difference: 280

Based on this documentation, Hawthorne Police Department can make a case for additional law-enforcement funding, citing Yonkers' (which has a similar environment profile) example.

6 CONCLUDING REMARKS

"*An African proverb goes, 'No one tests the depth of a river with both feet'. Yet, thoughtful police sometimes wonder if their department is an exception to this rule. They watch bewildered and despairing as their organization leaps from one tactic and program to another, rarely bothering to conduct a meaningful feasibility study or figure out what did not work and under what conditions the last time a similar problem was tackled"* (Geller 1997). The CXS software developed here is geared toward helping departments go *beyond* learning from their *own* experiences, to learning from other departments' experiences as well. Important strategic decisions can be made having access to this relevant information. The richness of shared relevant experiences holds immense possibilities for cooperation and innovation due to group efforts of police departments.

The software was developed for police officials as primary users. However, it also has the potential of being useful to community groups. The cities with similar environments are good candidates to discuss community-related policing and coordinated revitalization efforts. The software offers strong value addition because it can trade-off many factors and compares many cities. The software is especially useful in finding cities geographically distant, which would not have otherwise been identified by officials. However, even if law enforcement officials know of a similar community, by displaying data comparison the software provides avenues for co-operation at a glance.

A planned enhancement, suggested by the Philadelphia Police representatives, would be a feature in which a city can target to reach a certain reduced crime level. The software will analyze the goal's feasibility and will display cities that have similar environment to the cue city and are closest in crime rate to the target. Using this potential functionality of the software, police managers can make future plans to reach the specified crime level reduction target *utilizing* the experiences of the retrieved cities. This feature could be especially useful in helping communities to revitalize by emulating other communities.

A future functionality in the software would enable a city to find cities that are similar in environment and enforcement but with higher crime rates, for the purpose of determining new trends in crime. This would not only alert a community of future dangers but also enable taking measures for preventing or minimizing occurrence of such trends.

We believe that this modeling framework can support other purposes beyond law enforcement. It could be a useful tool for community revitalization and business relocation efforts. For instance, communities can lure new businesses by showing lowering trends in crime in their neighborhood vis-à-vis other competing communities. Then a community can attempt to attract businesses from other targeted communities - communities that are similar, but whose environment or crime situations have declined over the preceding years. This could be achieved by incorporating a time series feature in the software.

While an extensive effort went into development of the modeling framework and software application, CXS is certainly not a "foolproof" tool. Since its inception, CXS was meant to be an Artificial Intelligence tool that learns from experience enhancing its capability to provide better matches. A future improvement would add a feature allowing the software to incorporate feedback for better matching. On coming across a non-useful match, a user can provide useful input allowing the software to 'learn' and adjust the weight used in the nearest neighbor retrieval.

In contrast to the AI approach used here of finding similar cases and generating matches, alternate paradigms such as Linear Programming based Data Envelopment Analysis (DEA) could be utilized. A DEA analysis could generate relative efficiency lists and find weight assignments enabling comparison. However our CBR approach has two significant advantages over the DEA approach. First, our application provides only those efficient communities that are similar to the cue community. In other words, CXS will not give a retrieval of an efficient community which is significantly different from the cue community in crime, thereby increasing the probability of usefulness of the match. Second, unlike the DEA methodology, our approach is able to distinguish two separate kind of efficiencies – (a) higher inputs (via the find more efficient goal), and (b) not as good outputs (via the find more effective goal).

CXS is an effort toward bringing a strategic, co-operative, learning and proactive viewpoint among police departments. The software's usefulness lies in its easy usage, displaying only relevant information while saving the user from the tedious task of calculations and uncovering relevant factors. However, it is a decision-making tool which is geared to *assist* and not *replace* the decision-maker. With an Internet application interface effort under exploration, its usage could be nationwide offering possibilities and innovations we have not yet envisaged. We feel that exciting possibility of learning and sharing among communities is valuable in and of itself.

APPENDIX

Here we show calculation of the racial-match factor which is one of the factors in the enforcement dimension of the CXS. Consider the data shown in Table 14.

Table 14 – Illustrating the Racial Match Index Calculation

Racial Group	Column 1 % Community	Column 2 % Police Force	Minimum (of Column 1 and 2)
White	55.0	87.7	55.0
Black	41.3	10.5	10.5
Asian	1.7	0	0
		Racial Match Index =	65.5

First the percent of the police force in each racial group is calculated along with the percent of community population in each group. Next, for each racial group, the smaller of the two percentages (community and police) for each racial group is determined. Then, these minimum values are added together to get the racial match index. If there is a perfect match between the percentages in the community and the police force, the index will be 100. Any under-represented racial group leads to a lower index value. In the above example, a mismatch in percent of blacks in the community (41.3%) and percent of blacks in the police force (10.5%) lowered the racial match index. A significantly lower index value than 100 would indicate a poor match.

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