Crime Analysis and Predictions from historical Crime and Transportation Data*

Valerii Klymchuk† and Candacey Primo‡
Saint Peter's University
2641 John F. Kennedy Boulevard, Jersey City, NJ 07306

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Law enforcement agencies across the globe are employing a range of predictive policing methods. Smart, effective, and proactive policing is clearly preferable to simply reacting to criminal acts.

This paper proposes a novel approach to model, visualize, and predict crime risk levels for continuous geographic domain based on demographic, historical and transportation data. The main contribution of this approach lays in using passenger counts from major transportation hubs to tackle a crime prediction problem.

While previous research efforts have used either background historical knowledge or offender's profiling, our findings show that aggregated data captured from Public Transit Infrastructure, in combination with basic demographic information, and historical crime records can be used to predict crime.

In our experimental results with real crime data from Bogota we obtained a set of statistics that describe seasonality in crime patterns, which can accompany predictive machine learning models assessing the risks of crime. Moreover, this work provides a discussion on implementation, design and final findings, suggesting a prototype for cloud based crime analytics dashboard.

I. INTRODUCTION

The ability to predict the locations of future crime events can serve as a valuable source of knowledge for law enforcement, both from tactical and strategic perspectives. Predictive mapping holds a big promise for identification of areas in which to focus interventions, but it also may improve the way those interventions are implemented, if one can examine both distributions of past crimes and predictions of future concentrations[1].

The objective of this study was to develop a prototype to illustrate the benefits of easy to use and, web-delivered digital solution for visualization, analysis and exploration of criminal activity data in space and time. A new prototype was created as a web-based analytic dashboard to illustrate the potential benefits of new interactive tools for studying crime and transportation data provided by city of Bogota.

This work primarily makes an attempt to investigate the predictive power of people dynamics derived from transportation data in combination with historical crime records within a place-centric and data driven paradigm. While retrospective mapping efforts are useful, the true promise of crime mapping for police lies in its ability to identify early warning signs across time and space, and inform a proactive problem solving and crime prevention[1].

The current paper suggests a design for an interactive prototype of Tableau analytic dashboard panel hosted on a cloud computer server, equipped with an interactive map and a set of filtering controls, which support linear and composite view, interactive temporal legends, and a set of informative interactive map layers.

We believe that that proposed solution can assist crime analysts it identifying new insights about spatio-temporal crime patterns within urban city environment. Preliminary finding can accompany further predictive modeling efforts in crime prediction.

II. PROBLEM UNDERSTANDING AND RELATED WORK

The use of statistical and geo-spatial analyses to forecast crime levels has been around for decades. GIS outputs can be used to visually identify concentrations and patterns and to communicate those findings. GIS has been widely used to produce maps depicting crime "hot spots" as well as to conduct spatial analyses that suggest relationships between crime and characteristics of the social and physical environments in which crime concentrations occur[1].

In recent years, however, there has been a surge of interest in analytical tools that draw on very large data sets to make predictions in support of crime prevention[2]. Police agencies often use computer analysis of information about past crimes, the local environment, and other intelligence to "predict" and prevent crime. Predictive methods allow police to work more proactively with limited amount of resources. Improved situational awareness at the tactical and strategic levels results, for example, in more efficient and effective policing, capable to prevent criminal activity by repeat offenders against repeat victims.

Conventional approaches often apply human judgement and start with mapping crime locations and de-

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† Also at Computer and Information Sciences Department, Saint Peter's University.

‡ cprimo@mail.saintpeters.edu

termining where crimes are concentrated (”hot spots”). Such methods identify individuals at high risk of offending in the future and relate to assessing individuals risk [2]. The most common method of ”forecasting” crime in police departments is simply to assume that the hot spots of yesterday are the hotspots of tomorrow

Meanwhile our approach relies rather on a new technique that adds up the number of various risk factors to create an overall risk score. The objective of such data driven technique is to forecast places and times with an increased risk of crime in order to develop effective strategies for police to prevent crime more proactively or make investigation efforts more effective.

A. Why Crime is Predictable. Criminological Justification for Predictive Policing

A notion that crime is predictable is supported by major theories of criminal behavior, such as routine activity theory, rational choice theory, and crime pattern theory[2]. These theories can be consolidated into a blended theory:

a. Criminals and victims follow common life patterns; overlaps in those patterns indicate an increased likelihood of crime.

b. Geographic and temporal features influence the where and when of those patterns.

c. As they move within those patterns, criminals make ”rational” decisions about whether to commit crimes, taking into account such factors as the area, the target’s suitability, and the risk of getting caught.

The blended theory best fits ”stranger offenses”, such as robberies, burglaries, and thefts. It is less applicable to vice and relationship violence, both of which involve human connections that both extend beyond limited geographic boundaries and lead to decisions that do not fit into traditional ”criminal rational choice” frameworks[2].

It is more manageable for police agencies to allocate resources to places that are most attractive to motivated offenders and to where crime is most likely to occur given certain characteristics of the environment.

B. Place centric crime paradigm

Studies suggest that individuals are at greater risk to commit crime at the presence of criminogenic opportunities[3]. Places and environments have characteristics that encourage or discourage the occurrence of crime and, therefore, raise or lower criminogenic risk.

In 2008 criminologist David Weinberg proposed switch to switch from popular people-centric to place-centric paradigm [4].

In contrast to previous research on the spatial distribution of crime, in which explanations were sought in the social, demographic, and economic characteristics of the resident population, this study is mainly concerned with examining block-to-block variations in land use.

One related study shows that the size of the resident population, the racial and ethnic composition of the block, and the poverty level in the block group do have additional effects beyond those of land use, but also suggest that the effects of crime attractors, generators and offender anchor points are general and apply independently of whether they are located in residential blocks and independently of the specific characteristics of the people who live in the block [5]. Other spatially corre-

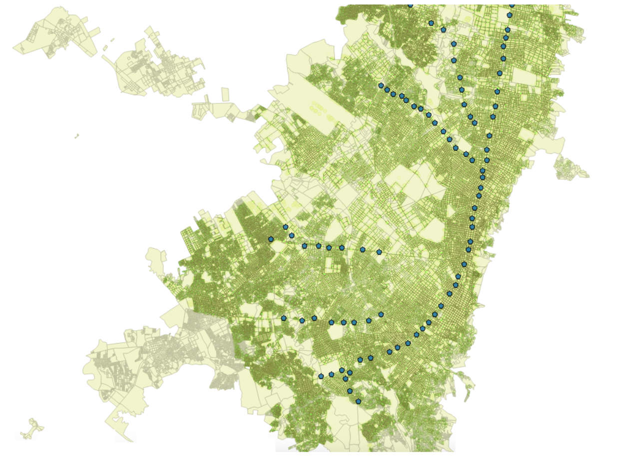

Figure 1. Subway stations depicted atop of crime intensity base map of Bogota. Darker colors depict higher total crime counts based on 2007 and 2013 data.

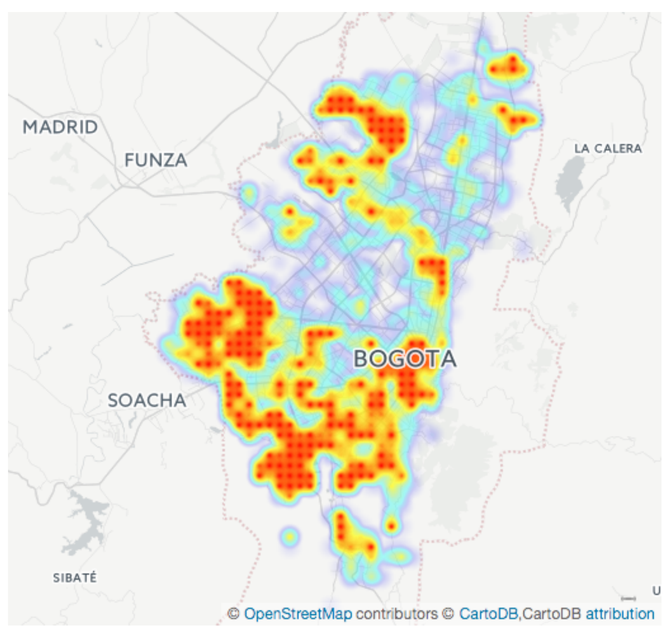

Figure 2. Homicide heat-map with hot-spots of predominantly concentrated in southern and some northern parts of Bogota city.

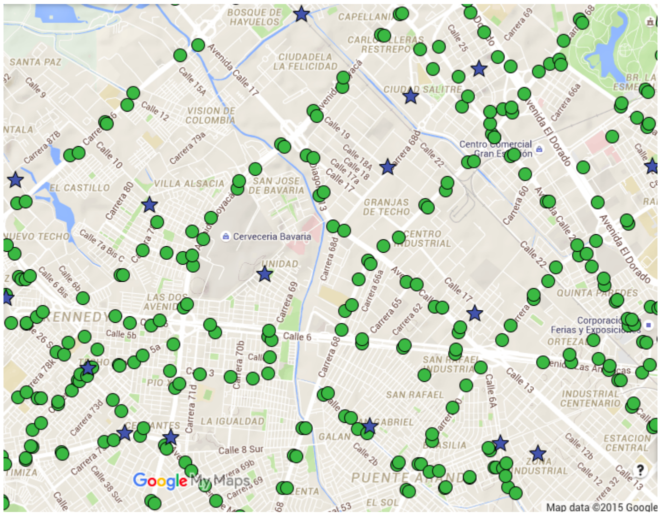

Figure 3. Bus stops and police stations in parts of Bogota city atop of street network base map.

lated factors also drive the distribution of crime incidents at block level. The settings and times for which some factors become most relevant should also be considered by predictive model.

The risk of crime at places that have criminogenic attributes is sought to be higher than at other places because these locations attract motivated offenders (are more likely to concentrate them in close proximity) and create a backcloth for certain events to occur. Attractors are those specific features that attract offenders to places in which they commit crime. Generators can be seen as greater opportunities for crime that burgeon from increased volume of interaction occurring at these areas, resulting in greater risk and likelihood of crime.

Various potentially relevant crime attractors and crime generators may include, for example, bus stops, parking places, supermarkets, warehouses, bookstores, clothing stores, and pharmacies, as well such characteristics as signs of physical deterioration and the lack of collective efficacy [6]. Another study outlines the following key factors related to urban residential burglary[7]: social disorganization, proximity to pawn shops, proximity to bus stops, time of the day, day of the week, proximity to police stations, fire stations and hospitals.

Crime analytic dashboard was developed to identify and communicate environmental attractors of crime. The dashboard and an interactive map can be used to anticipate places most suitable for illegal behavior, identify where new crime incidents can emerge and/or cluster. All environmental factors that determine specific vulnerabilities are weighted by the model according to their relative spatial influence on the outcome event, and final map articulates the vulnerability in relative risk values as for any given geographic location across the terrain.

1. Units of analysis

A common thread among opportunity theorists is that the unit of analysis for "opportunity" is a place, and that the dynamic nature of that place constitutes opportunities for crime. The way in which features of a landscape affect places throughout the landscape is referred to as the concept of spatial influence. Effective predictive models need to incorporate small areas as units of analysis, which more accurately reflect "micro-places", such as city blocks, street segments, and intersections.

Not all census blocks in Bogota are on a perfect grid. Some streets are diagonals and blocks along these streets are triangles. Furthermore, census blocks are not only bounded by streets but also by railways and natural barriers such as rivers and lakes and the mountains. Therefore using more detailed geographic features than census block boundaries could provide a deeper understanding of how spatial patterns of crime are influenced by the geography and land use. Also a face block, the two sides of a street between two junctions, is a natural spatial unit, not only because it is smaller than a block but also because it is characterized by inter-visibility [8].

To model a continuous crime opportunity surface in a geographic information system, we use a grid of equally sized cells that comprise entire jurisdiction. Each cell represents a micro place throughout the landscape, while the cell size is selected as a function of street segment/block length, so that environmental backcloth is constructed in a manner that reflects unique landscape of each jurisdiction and its street network on which people travel and to which crimes are geo-coded. Half the mean block length guided the choice of cell size in a micro cellular grid, which is more consistent with expectations about the continuous nature of criminogenic risk[3].

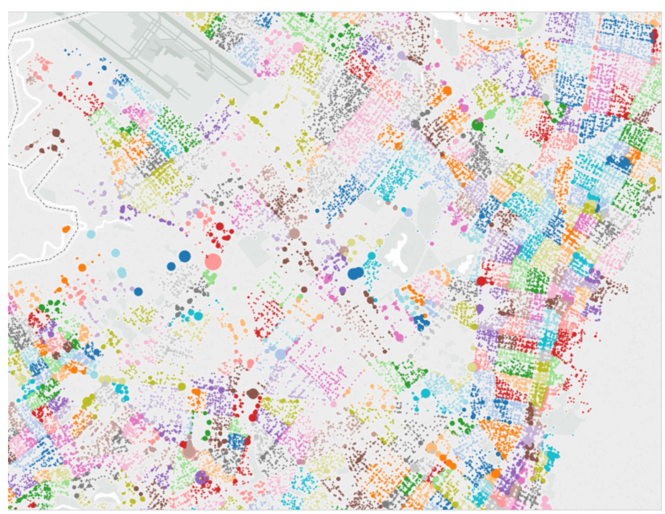

Figure 4. Spatial view of the city divided into city blocks, coded with color.

2. *Target variable*

Choice of variables is critical to the success of the model and must be informed by theory. Theory-based modeling enables to identify which factors influence crime target selection, and thus inform crime prevention efforts. Risk of crime in this study is seen as a function of vulnerability within the context of other factors that carry different weights relative one to another, therefore in the absence of motivated offenders, the existent risk of crime can be relatively low.

Analyzing risk terrains along with event-dependent assessments is useful for generating a more complete understanding of crime problems. The study of spatial concentrations of crime relies upon evidence-based methods, and do not rely on the physical or social characteristics of individuals who enter and leave these locations, only on the geographic factors that make these places risky.

Crime risk can be modeled as a dichotomous variable, which is rarely or never zero. The risk posed by each criminogenic feature is located at one or more places on a landscape; their confluence at the same place contributes to a risk value that, when raised a set amount, increases the likelihood of crime.

Risk terrain modeling produces a metric for place-based opportunity, as measured by the spatial influences of place-based risk factors to be used for measuring vulnerable places. Opportunity can be measured in degrees and changes over space and time as our perceptions about the environments evolve; as new crimes occur; as police intervene; or as motivated offenders and suitable targets travel. Hotspots can be used as a proxy measure of places where the dynamic interactions of underlying criminogenic factors exist or persist over time[3]. The risk values serve as a measure of the clustering of the risk factors, and forecast whether crime will occur or possibly cluster.

III. DATASETS

For our study we exploit datasets provided by the city of Bogota, Colombia. Throughout the project we have working access to the following data:

1. Crime dataset contains historical crime records for the city of Bogota. Among other fields this dataset contains geographic coordinates (X, Y) for over 100k of crimes commited between January, 2007 - March, 2013 and include such fields, as: types of crime, street address for each of the crime scenes, along with $ObjectId$ (ZIP - like Code, presumably - police district, or city block) in Bogota. Each $ObjectId$ has its own Coordinates specified as longitude and latitude.

2. Transportation dataset in *.cvs* format contains coordinates for subway stations in Bogota, together with counts of passengers entering each station every 15 minutes over the span of 2-3 years.

3. Bus Transit dataset lists dates, bus route numbers with corresponding Destination (names of final stops) to which each bus is heading, with counts of passengers.

4. Publicly accessible datasets in *.csv* format with coordinates for Bus stops, Police Stations, Schools, Hospitals, Churches in Bogota, etc.

5. Demographic dataset for the city of Bogota in *.shp* format. A set of Bogota borough profiles related to homelessness, households, residential property sales, housing market and societal well-being. Borough profiles datasets contain area codes, area names, metrics about the population of a particular geographic area, such as statistics about the population, households, demographics, migrant population, ethnicity, employment, earnings, house prices, indices of multiple deprivation, etc.

A. Data understanding

Rank ordered statistics is the most well known way of looking at data. Figure 5 shows a frequency summaries for 8 types of crime in descending order based on number of counts. We see personal theft and personal injury as being predominant types of crime in the dataset, with over 55 and 36 thousand incidents accordingly between years 2007 and 2013. Those are followed by burglaries, commercial theft, vehicle and motorcycle theft. Also homicide corresponds to over 5 thousand records in our data. Type of crime is recorded as categorical variable Delito, with 8 distinct levels, corresponding to each distinct type of crime.

Parallel coordinate plot in figure 7 represents seasonal variability of crime counts for each year. In this chart years are color-coded and each line represents yearly pattern in total number of cases per month. Chart in figure7 demonstrates an evident deviation from regular pattern in the years 2008 and 2012. Those two years compared to others had most uncommon pattern due to some fac-

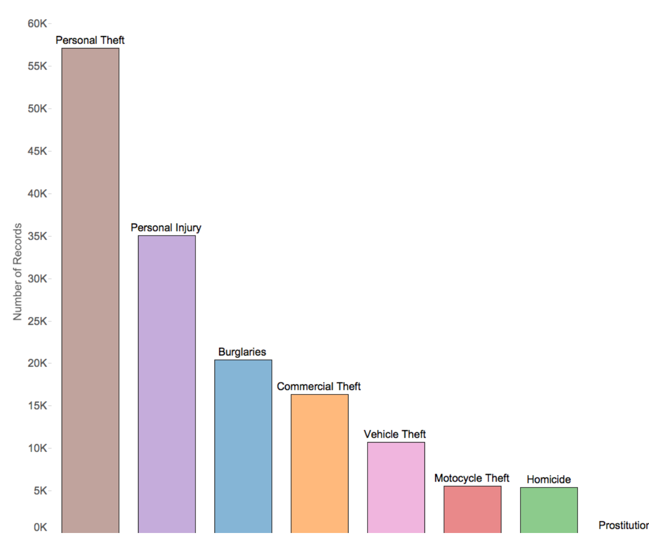

Figure 5. Types of crime, ordered in decreasing order based on total counts over the period of observation.

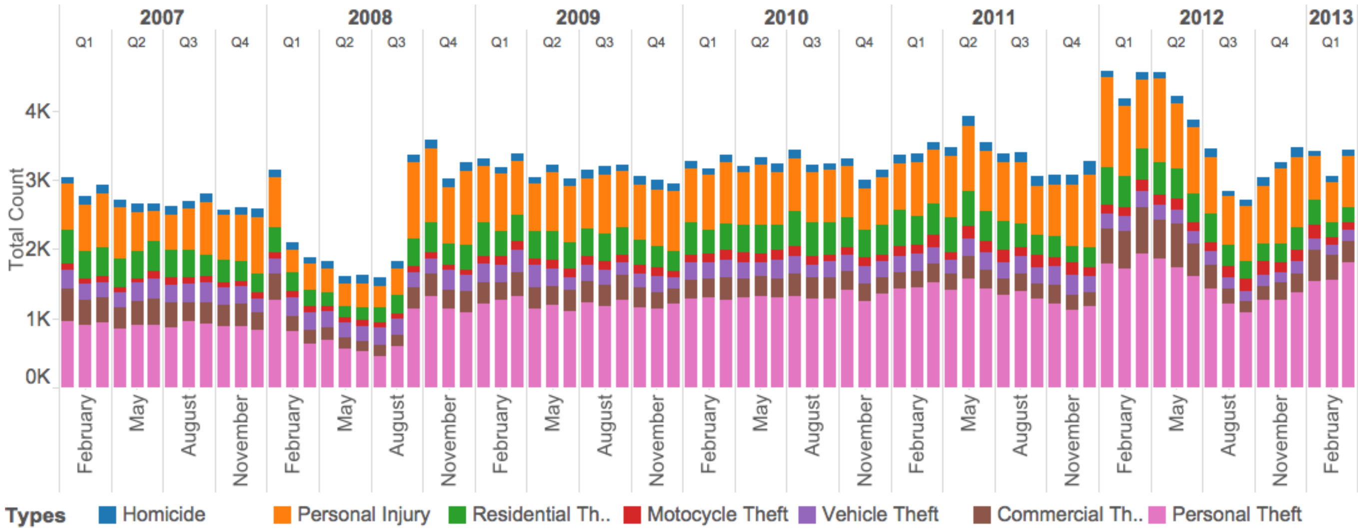

Figure 6. Seasonal variability of crime counts.

tors, which could have influenced crime counts in specified time-frame. Considering, that presidential elections in Colombia follow 4 year cycle, it might be safe to assume that those patterns could have been influenced partially or at large by the election campaigns taking place.

Time series chart in figure 6 provides a view of crime counts variability over time. Stacked columns in this chart represent monthly totals split and color-coded by crime type. This chart exhibits a significant dip in crime during first and second quarters of 2008, followed by spike in third quarter; crime counts also dipped even faster between second and third quarters of 2012, and risen again in forth quarter. Such facts indicate presence of a long term pattern within a span of 4 years of data. Notice, that this could support the hypothesis about correlation with 4 year election cycles, mentioned before.

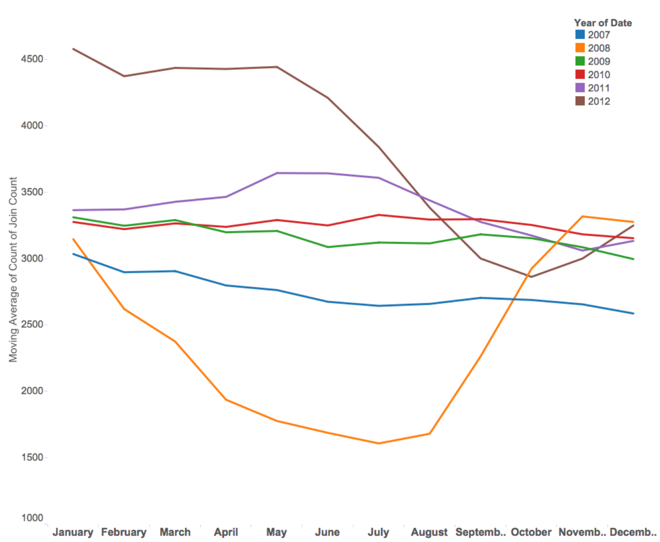

Figure 7. Yearly seasonalities for different types of crime. Each line represents a year of data.

1. Data preparation

Following preprocessing steps were performed on data:

1. Referencing all geo-tagged data to the cells.

2. The features: for each of the variables related to the cell the mathematical functions were computed to characterize the distributions and properties of such variables, e.g. mean, median, standard deviation, min and max values, and Shannon entropy.

3. Bogota demographic profile feature has to be aggregated to each of the cells.

Correlation measures the numerical relationship of one variable to another and are good for identifying variables which are related to each other. Pairs of highly correlated variables indicate redundancy in the data which should be considered, since redundant variables dont provide new information to help with prediction, and some algorithms can be harmed numerically by variables that are highly correlated one to another. For high correlation values (greater than 0.95) a rule of thumb was applied: variables were considered identical, and treated as redundant variables by the model.

The final results can be very sensitive to the input data. Thus, if there are seasonal effects in the data, such sensitivity can lead to spurious patterns or trends, which can make results difficult to reproduce. However, correlations are linear measures, which are affected severely by outliers and skewness. Visualization is a good idea to verify that high correlation is real. Using parallel line chart we can see immediately which pairs of variables are highly correlated all in one plot.

Chart in figure 8 displays weekly patterns for different types of crime in the dataset. Each line represents a total number of cases for each type of crime, based on the day of the week. Notice, how pattern for personal theft is different from pattern of personal injury, for example. While personal theft counts clime up on weekdays, personal injury counts decrease; and spike on weekends for personal injuries corresponds to decline in personal theft. Such observations can indicate that weekly work/home cycles largely affect individual's vulnerability for some types of crime.

2. *Outliers and skew*

Positive skew in variables results in mean values no longer representing a typical value for the variable. Home values, for example are reported using the median rather than mean; because the mean gets inflated by the large values to the right of the distribution[9]. For positively skewed data *log* scale can be effective in changing the data to see the data resolution and pattern better. Once *log* transform is applied, data will be in log units instead of original units. The first indication of positive skew is when the mean is larger than the median. An additional indicator is when the mode is less than the median, which is also less than the mean.

Unsupervised learning technique - clustering was used to identify multidimensional outlier. Clusters with relatively few values in them are indicative of unusual groups of data, and therefore may represent multidimensional outliers. Dummy variables were created by the model to indicate whether the interaction is an outlier, as a membership in a cluster of multidimensional outliers.

The assumption is that the outliers can distort the model so much that they harm more than help. Therefore we must remove outliers for linear regression, k-nearest neighbor, K-Means clustering, and PCA. It is also possible to separate the outliers and create separate models just for outliers by relaxing the definition of an outlier from 3 standard deviations from the mean down to 2 standard deviations from the mean. In some cases we want to leave the outliers in the data without modification purposely allowing model to be biased. Decision trees, for example, are not affected by outliers[9].

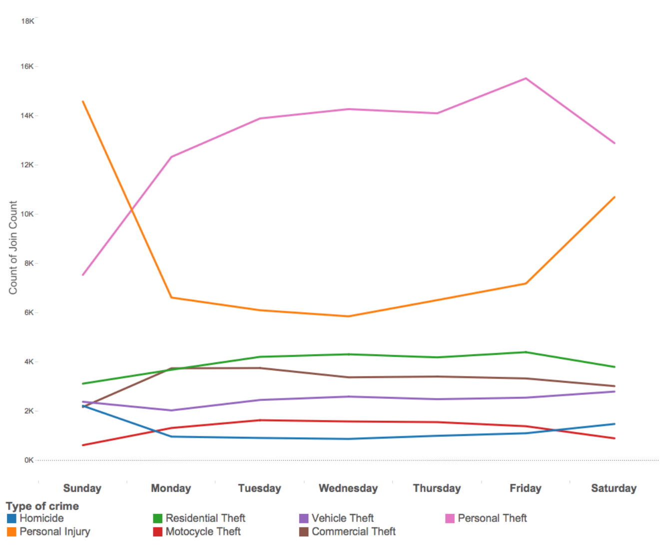

Figure 8. Weekly patterns of crime vary for different type of crime, and should be considered by the predictive model.

Good features can make the patterns between inputs and the target variable far more transparent. In this work we generated a separate column dummy variable to indicate that the value is an outlier. We also transform the outliers so that they are no longer outliers by binning the data; and convert the numeric variables to categorical to mitigate the numeric affect on the algorithms.

Finally, new additional features were added to the data as new variables created from one or more existing variables already in the data. Significant improvement in model performance metrics can be achieved by introducing refined second order features, to allow capturing inter-temporal dependencies of the problem and to make the feature space more compact.

IV. METHODOLOGY

Analyzing risk terrains along with event-dependent assessments is useful for generating a more complete understanding of crime. Empirical research demonstrates that including a measure of environmental risk yields a better model of future crime locations compared to predictions made with past crime incidents alone[3]. Assuming that every new crime incident is a potential instigator for near repeats, priority can be given to new crimes that occur at high risk places with other high risk places in close proximity.

Defining vulnerable places, therefore, is a function of the combined spatial influence of criminogenic features throughout a landscape that contribute to crime by attracting and concentrating illegal behavior. Extra spatial factors, such as knowledge about potential victims or offenders can also be considered. The steps in this work were taken along the following road map:

1. Linking all information to the corresponding cells.

2. Data-set are randomly split into training (80% of data) and testing (20% of data) sets. Each dimension of the feature vector was normalized.

3. Pearson correlation analysis yields a large subset of features with strong mutual correlations and a subset of uncorrelated features.

4. Pipeline variable selection approach, based on feature ranking and feature subset selection is performed using only data from the training set. Top variables-predictors of crime are being identified by our model, sorted by the mean reduction in accuracy.

Given the high skewness of the distribution and based on previous research and ground-truth data about counts

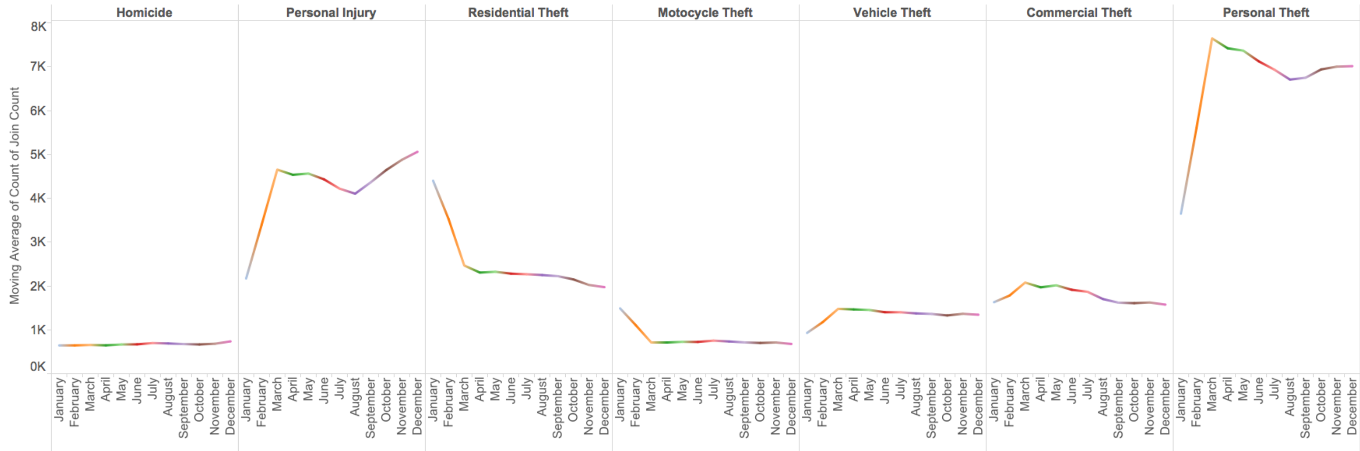

Figure 9. Monthlly patterns for different types of crime reveal the nature of change in the total counts.

of crimes in each given sell, we split the criminal dataset with respect to it's median into these seven classes:

a) "class -3": $\text{median} - 3\sigma \leq N \leq \text{median} - 2\sigma$;
b) "class -2": $\text{median} - 2\sigma \leq N \leq \text{median} - \sigma$;
c) "class -1": $\text{median} - \sigma \ \leq N \leq \text{median}$;
d) "class $+1$": $\text{median} \leq N \leq \text{median} + \sigma$;
e) "class $+2$": $\text{median} + \sigma \ \leq N \leq \text{median} + 2\sigma$;
f) "class $+3$": $\text{median} + 2\sigma \leq N \leq \text{median} + 3\sigma$;
g) "class $\ 0$ ": $\text{median} + 3\sigma \leq N \leq \text{median} - 3\sigma$.

Algorithms automate most steps of risk terrain modeling. Clustering groups data records into similar groups, and classification techniques assign data records to categories (commonly referred to as classes). The algorithm tests a variety of spatial influences for every risk factor input to identify the most grounded spatial associations with known crime incident locations and considers only the most appropriate risk factors with their spatial influences to produce risk terrain surface.

The exposure to personal crime in an area normally includes both the resident and the transient population (Andresen 2006), those who live in the area and those who visit the area. Note that the transient population size is not measured directly but is presumed to be incorporated in the effect of the other variables[10]. In other words, crime generators generate crime by drawing an enlarged transient population into the block. Shannon entropy reflects the predictable structure of a place in terms of the types of people present over the day[11].

Clustering algorithms are commonly used as part of data exploration in order to find commonalities across crimes [2]. For example, clustering was applied on a data set of burglaries to find those exhibiting similar tactics. These can be evidence of a serial burglar, or could suggest interventions against some of the clusters. As a specific example, Adderley and Musgrove had clustered perpetrators of serious sexual assaults using self-organizing maps [12]. SOM cluster observations with similar traits into related groups to identify crimes committed by the same individual because of such similarities.

The information could be fed into the hot spot models to identify the perpetrators next target, or it could be used for geographic profiling methods to identify the perpetrators home base. Unsupervised learning techniques can project high dimensional data onto two dimensions. Multidimensional scaling (MDS) algorithms, such as the Sammon Projection, try to retain the relative distance of data points in the 2D projection as found in higher dimensional space could be another option. A simpler way is to use color, size, and shape.

The metric for feature ranking can be the mean decrease in the Gini coefficient of inequality. The feature with maximum mean decrease in Gini coefficient is expected to have the maximum influence in minimizing the out-of-the-bag error. Minimizing the out-of-the-bag error results in maximizing common performance metrics used to evaluate models.

When there is considerable overdispersion in the data (alpha value of 1.24), the negative binomial models might fit the data better than a Poisson model. Therefore the-

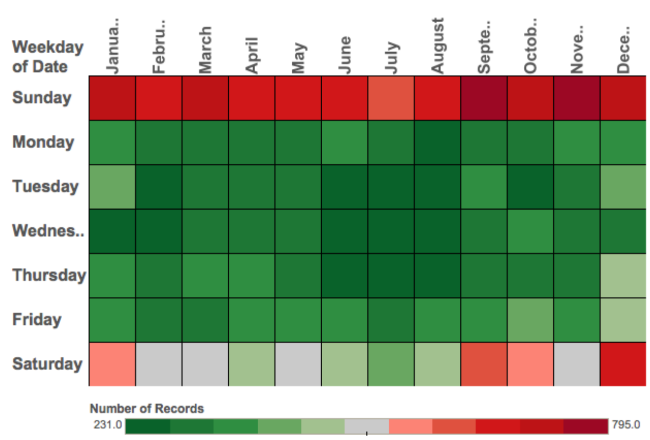

Figure 10. Personal injury patterns by month and day of the week sgow, that Sunday is the likeliest day for this crime.

oretical arguments were put forward to use (negative binomial) regression models with lagged independent variables rather than spatial error or spatial lag regression models [5].

V. RESULTS AND EVALUATION

Place-based risk assessment with risk terrain modeling permits real-time evaluation of the propensity for a new crime to become an instigator for near repeats.

Some activities in adjacent blocks are correlated (i.e., spatial autocorrelation in the independent variable) and are the effects of activities in adjacent focal block according to the model's interpretation. Thus, for example, the presence of a gas station in the block increases robberies in the block, but so does the presence of a gas station in an adjacent block. Thus, the land uses that attract crime have similar crime-attracting repercussions on the adjacent blocks.

Some recent studies support the hypotheses that crime generators, crime attractors, and offender anchor points increase the number of robberies. For example, adding a liquor store to the block may increase the expected number of robberies by 67 percent, and the blocks with a gas station have more than 4 times as many robberies as similar blocks without a gas station.

Heatmap in figure 12 depicts clustering of personal theft along south-east to central-north direction, which is reminiscent with subway line path in figure 1. Another cluster of personal injuries lays in south-west part of Bogota, where other carcinogenic features might be strong. Notice, that density of overlapping records is plotted in figure1 to see darker colors for more common patterns and lighter for less common ones.

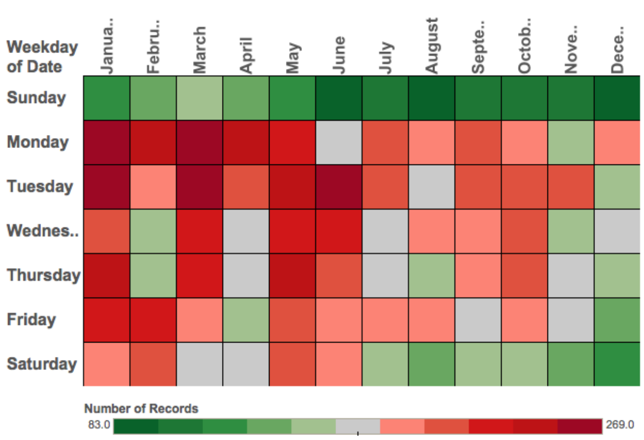

Figure 11. Seasonality of commercial theft counts by month and day of the week Sunday is the least likely day for such.

Figure 12. Interactive map view depicting concentraton of near repeat incidents in central part of Bogota.

VI. DISCUSSION

In urban crime analytics domain, an important issue is the development of collaborative crime information systems that integrate historical crime data, geographical data with dynamics of people flow. Such systems can be of great interest for many applications related to monitoring and analysis of crime dynamics, where people flow as well as network properties are changing in fast and almost continuous mode. This work aims to introduce a framework consisting of crime analytics dashboard, GIS and several specialized applications to support predictive policing effort in real time with lack of resources.

All predictive techniques depend on data. Both the volume and the quality of these data will determine the usefulness of any approach. The saying garbage in, garbage out strongly applies to these analyses. Efforts should be made to ensure that data are accurate and complete, though some techniques are less sensitive to small errors than others [2].

Ideally GIS software should have a data creation ETL-tool and/or wizard that simplifies data creation steps. Crime analysts work in tactical environments where they work with data in real time leaving little room for cumbersome multi-step processes [13]. Occasionally analysts need to create new, unique data layers. Comprehensive GIS software needs to include geoprocessing tools for extracting and clipping features from larger collections, merging map layers, editing spatial and attribute features of map layers.

It is recommended that the most efficient and useful way to make use of RTM in investigating the risk of urban residential burglary based on the surrounding environmental context is by conducting an analysis at a citylevel [7]. It is believed that at this level of spatial analysis, the identification of crime correlates and temporal features will produce information that is not only insightful but also practical.

VII. IMPLICATIONS AND LIMITATIONS

Hotspot maps, for instance, show the concentration of crime but offer little in the sense of context. By articulating the environmental context of crime incident locations, risk terrain modeling helps to identify and prioritize specific areas and features of the landscape to be addressed by a targeted intervention.

Strategies to address crime problems, therefore, must incorporate both the spatial and temporal patterns of recent known crime incidents and the environmental risks of micro places if they are to yield the most efficient and actionable information for police resource allocation. Looking ahead, it could be useful to move beyond predictions towards offering explicit decision support for resource allocation and other decisions. To be useful in law enforcement, predictive policing methods must be a part of a comprehensive crime prevention strategy.

The speed at which analytic dashboard operates depends heavily on the processing capabilities of the computer on which it is installed. Therefore, it is highly recommended that you install and operate this software on a cloud computer or server with abundant memory.

Finally, the most important measure of a crime forecasting is whether it aids in crime control and prevention, and how the outputs of models translate into practice [1]. In thinking about these needs, it is important that the value of predictive policing tools is in their ability to provide situational awareness of risks and the information needed to act on those risks and prevent crime [2].

VIII. CONCLUSION

In conclusion many analysts and investigators have a professional interest in how these approaches improve their work and make it more useful; police chiefs are eager to find new techniques to reduce crime without adding to their workforce; and the private sector sees potential funding from research grants, consulting, and software development. Policing methods, including predictive analyses, could be useful for peacekeeping applications as well.

Large agencies with large volumes of incident and intelligence data that need to be analyzed and shared will want to consider more advanced and, therefore, more effective systems. It is helpful to think of these as enterprise information technology systems [2]. Such systems make sense of large datasets to provide situational awareness to decision makers and to the public. These systems help agencies understand the where, when, of crime and identify the specific problems that drive crime in order to take action against them. The predictive policing systems provide the shared situational awareness needed to make decisions about where and how to take action. Designing intervention programs that take these attributes into account, in combination with solid predictive analytics, can go a long way ensuring that predicted crime risks do not become real crimes.

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