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An Optimal Police Patrol Planning Strategy for Smart City Safety

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Abstract— **The safety of citizens is an integral part of any smart city project. Police patrol provides an effective way to detect suspects and possible crimes. However, policing is a limited resource just like any other service that a Smart City provides. In order to efficiently consume this resource, the city has several aspects that can be controlled to make efficient use of Police patrolling: where (area), what (number), when (hour). In this paper, we utilize the LA County Sheriff's open crime dataset to study the police patrol planning problem. We propose a novel approach to build a network of clusters to efficiently assign patrols based on informational entropy. This minimizes Police time-to-arrival and lowers the overall numbers of police on patrol. Our algorithm relies upon the categories of crimes, and the locations of crimes. Since we use real-time traffic analysis to join crime clusters, our solution is extensible enough to be applied to any metropolitan area.**

Keywords— Smart cities; city safety; police patrol; smart planning; resource optimization.

I. INTRODUCTION

The concept of Smart City as a means to enhance the life quality of citizens has been gaining increasing importance in the agenda of policy makers [9]. Most recently, 10 cities in the United States were selected to participate in the Smart Cities Initiative [10], including Los Angeles, Dallas, and eight other cities. The involved projects deal with smart transit/parking, Internet of Things, micro-grids, streetlights and smart poles, integrated smart city systems and more [11].

A smart city must be a secure city first. While many smart-city projects will increase well-being or quality of life, the safety of the citizens should be an integral part of any city project. With advancement of civilization, day-to-day human life is safer today than ever before. However, in view of new threats of terrorism, organized crimes, gang violence and gun crimes, securing cities remains an equally important and a big challenge that smart city initiatives could provide unique solutions to.

Routine activities theory posits that crimes, both individual and serial, occur when a motivated offender encounters a suitable target in a time and place where there is an absence of capable guardianship [12]. Police patrol provides an effective way to detect suspects and possible crimes, thereby deterring offenders from committing crimes. For example, *suspect-oriented patrol* occurs when a suspect matches the description of an offender in a series, and *directed patrol* involves instructing officers to visit certain locations at certain times. The current practice of police patrol is either based on officers' experience or neighborhood crime statistics, that is, if an area has more crimes in the near past, more officers will patrol in that area.

Motorized and foot police patrols have been utilized as a crime deterrent method for many years. Studies have been done on this method to discover whether or not it is effective in eliminating crime, or whether crime just moves away from the areas patrols have increased. An experiment [16] conducted in Philadelphia of more than 200 foot patrol officers in the summer of 2009 found that police foot patrols raised the public's perception of the police in the communities, reducing their fear of crime. They studied police effectiveness over 60 violent crime problem areas. In 12 weeks, there was a significant reduction in the amount of crimes in the targeted areas, exceeding the control site numbers by 23% with 53 violent crimes prevented. These findings show that police patrols in targeted areas where violent crime occurs can have a significant impact on violent crime rates at a microspatial level.

Patrol placement is a critical process used to maximize the effectiveness of the police department in its activities. However, police are limited in supply. To be effective at policing, officers must be qualified, formally trained, and developed. For example, officers in the City of Los Angeles Police Department (LAPD) must be 21 years of age, and have

TABLE I. INFORMATION ABOUT LOS ANGELES COUNTY AND BUDGET/ EQUIPMENT OF LAPD.

Policing coverage & equipment	Quantity
LA area	~12,300 km^2
LA population	3.8 million residents
Police budget	$1.4 billion
Number of police stations	21
Number of police officers	~10,000
Officers per 10k residents	~25.6
Number of patrol cars	Unknown
Number of police boats	2
Number of police helicopters	26
Number of police fixed-wing	3
Number of mounted (horses)	21
Number of K-9 units (canine)	22

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TABLE II. SELECTED ATTRIBUTES OF LA COUNTY CRIME DATA.

Attribute	Explanation
Incident Date	Date a crime incident occurred
Category	Incident crime category
Statistical Code	A three digit number to identify the primary crime category for an incident
Statistical Code Description	The definition of the statistical code number
Full Address	The street number, street name, state and zip where the incident occurred
Street Address	The street number and street name where the incident occurred
City	The city where the incident occurred
X Geocode	Used to map the general location of the incident
Y Geocode	Used to map the general location of the incident

TABLE III. SAMPLE OF CRIME CATEGORIES

Category	Count	Weight	Reasoning
Arson	4337	0	Investigation occurs after the fact in coordination with the Fire Services Investigator. Officer must be present to cordon off the scene.
Commitments	14	1	Drunk/Drug tank; officer must be present to take suspect into custody.
Criminal Homicide	1689	5	Most heinous crime which requires immediate Police response.
Forgery	16531	0	Not time-sensitive.
Fraud/NSF Checks	44681	0	Not time-sensitive or critical.
Traffic Accidents	14402	4	First responders are needed to direct traffic and resource other assets.
Warrants	2326	0	Served on an as-needed basis.

completed a six-month training course before beginning their year-long probationary period [6]. These constraints mean that the number of officers, like many other city resources, is inelastic. Further, the limited availability of resources in comparison to the city's large population and size makes it more difficult to patrol the entire city of Los Angeles. Limited budget implies limited number of patrols cars which can pose a problem to availability of back up officers present at crime scenes or in the pursuit of criminals. The limited police personnel and budget makes patrol planning a challenging task. A smart placement strategy is needed to assure the safety of smart cities.

In this paper, we propose a data-driven, smart decision making approach to place police officers for the optimal patrol. Our goal is to maximize the responsiveness of police departments in their activities while having limited police officers and resources. Our proposed approach leverages an entropic metric in selecting patrol locations and in searching for the cluster locations that maximize the total entropy in the Patrol Police Network (PPN), relating maximal entropy with maximal clusters coverage. We use Los Angeles Open Data (LAOD) [13], especially the crime related datasets, and evaluate the performance of our proposed patrol planning strategy. The experimental results show that response-time can be reduced and police can cover more crimes through our entropy-based approach. We want to emphasize that this is not a crime-prevention strategy, as crime factors are complex and numerous. Instead we will treat crime like a resource that should be monitored, with patrols as the sensors that do the monitoring.

The rest of the paper is organized as follows. We describe the crime datasets from LAOD and a classification of crime types in Section II and Section III. The methodology and patrol planning design are presented in Section IV. The implementation and detailed evaluation results are reported in Section V and Section VI. We introduce the related work in Section VII and conclude this paper and discuss possible future work in Section VIII.

II. CITY SAFETY DATASET

We explore the Los Angeles County Sheriff's Department Jurisdiction Data available from Los Angeles County GIS Data Portal [14] in this study. Los Angeles County was chosen because of three main reasons:

- Weather stability
- Land size
- Dataset size & crime variation

The historical average temperature in LA County varies from a December low of 8.6 °C, to an August high of 23.5 °C [20]. Month by month, this results in a mean daily temperature variation of only 10.8 °C, with a standard deviation of 0.54. For comparison, Chicago, which is similar in population size, has a daily average low of -10.8 °C in January to an average high of 28.6 in July. This results in a mean of 11.6 °C with a standard deviation of 1.63. With regards to rain and snow, LA receives an average 379.2 mm of rainfall each year, while Chicago receives 936.2 mm of precipitation. LA County has no average snow or ice. Compared to Chicago, LA has more stable weather and this stability should produce more

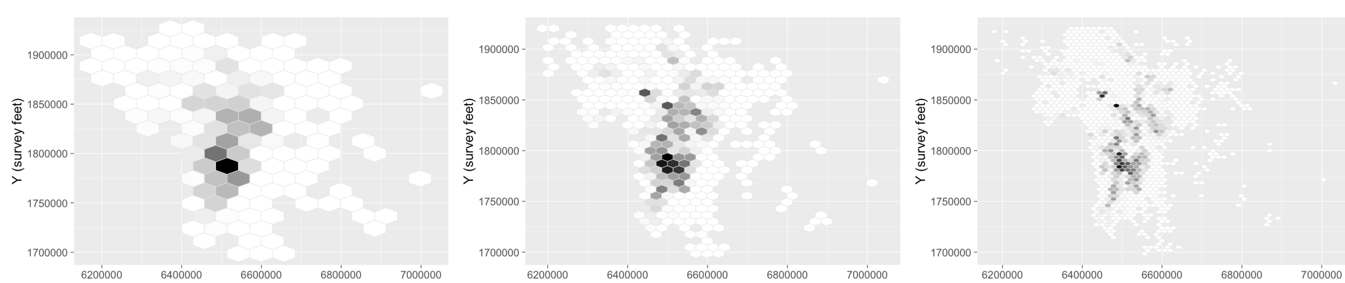

Fig. 1. Hexbin clustering of crimes based on X and Y coordinates in survey feet. (a) Bin size 15. (b) Bin size 30. (c) Bin size 50.

consistent crime data that isn't affected by seasonal patterns.

Since we utilize the drive-time between clusters for our calculations, it makes sense to have a dataset that is geographically distributed. Once again, compared to Cook County (Chicago), LA county is much larger at 12,300 km² versus 4,235 km². Ideally this would produce geographically distributed clusters of crime which would show the effectiveness of the strategy.

The dataset consists of 2,130,504 crimes from 2005 to 2015 (11 years). Each year is formatted as a CSV file, and there are 18 data fields for each record. Selected attributes are listed in TABLE II. The variations in crime is discussed in Section III below.

In addition to the crime data, we also collect the information of equipment and resources of Los Angeles Police Department (LAPD). Our goal is to effectively allocate these resources for optimal police patrolling to respond to and suppress crimes. For now, we will focus on just allocating patrol cars, as specialized assets require specific use cases for deployment. Information and selected resources of the LAPD are shown in TABLE I.

III. Crime Prioritization and Statistical Analsysis

In the LA county crime dataset, a total of 42 major crime categories are specified. Due to the limited police personnel and resources, we prioritize these crime types by assigning higher priorities to those types that need more immediate police response. To this end, we have consulted with a domain expert in Criminal Justice to help us better understand the datasets we use. Since some crimes are more critical than other crimes, i.e. rape vs. larceny, we weight each crime on a scale of zero to five. A weighting of five is the most important, whereas a 1 is of the lowest importance. A weighting of zero means we do not include this crime in our algorithm. Each crime belongs to a "Category" and we can exploit this field to base our weighting. There are a total of 42 major crime categories and 369 sub-categories. The domain expert finds many of these categories are not time-sensitive. A sample of some of the categories, the count in our dataset, the weighting and our reasoning is presented in 0 Due to space limitations, we have only listed some of the crime categories. Fig. 2 shows the number of crime records at each of the five priority levels.

Each crime record contains an X and a Y coordinate that locate the crime within LA County. Although each complete crime also includes the full address, we would have to geocode each address through an API, severely limiting our throughput. The X and Y coordinates are in the State Plane Coordinate System (SPS) format, specifically California Zone V (5). We remove those records that do not contain X or Y coordinates. A histogram plot of these records results in a spike from coordinates X[6200000:7000000] and Y[1700000:1900000]. Some of the outliers are as far away as Colorado, and include bad negative coordinates that are not even possible with the SPCS. The LA crime dataset of 2015 does not include the time for each crime. This skews our hourly results towards midnight, since every crime occurs at 00:00 in that dataset.

After pre-processing we end up with 1,486,678 crimes, i.e., about 70% of the original data. We use *hexagonal binning* to check if the crime distribution is uniform across coordinates. Sample sizes for 15, 30 and 50 bins are show in Fig. 1. The clusters are not uniform and the figures show the centroids begin to dissipate at bin size 30.

We further analyze the distribution of crimes by hours of the day and days of the week using both the overall layout of the crimes and the density of the crimes. These are shown in Fig. 3 and Fig. 4. From the figures, we can see that the distributions for hourly and daily crimes are not uniform. More crimes happen during 16:00-01:00 and on Fridays than other times and days. Meanwhile, 03:00-06:00 and Sundays have the least number of crimes. These uneven crime distributions suggest that we should differentiate police allocation to achieve better cost-effective patrolling. To minimize the affect of time, we will group the crime data into hours for this paper. More specialized implementation can be performed on a per-day basis. Holidays and other city events were not selected as attributes, but could be used for further study since they also affect crime patterns.

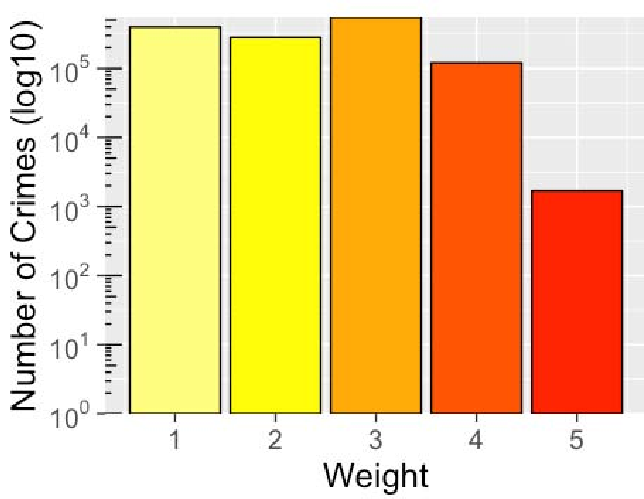

Fig. 2. Distribution of crimes based by weight/priority.

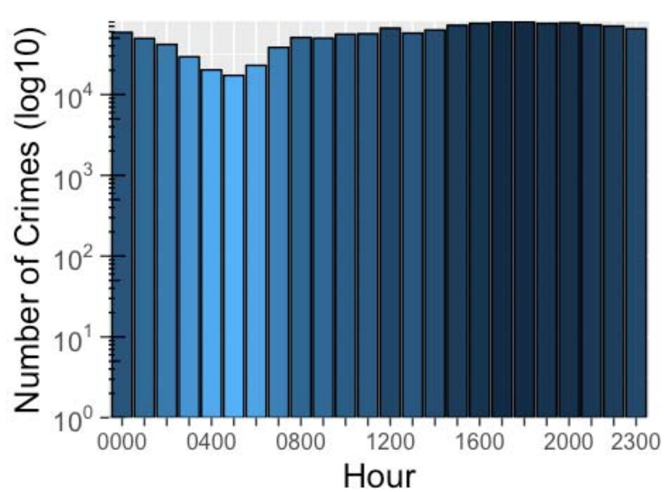

Fig. 3. Distribution of crimes by hour.

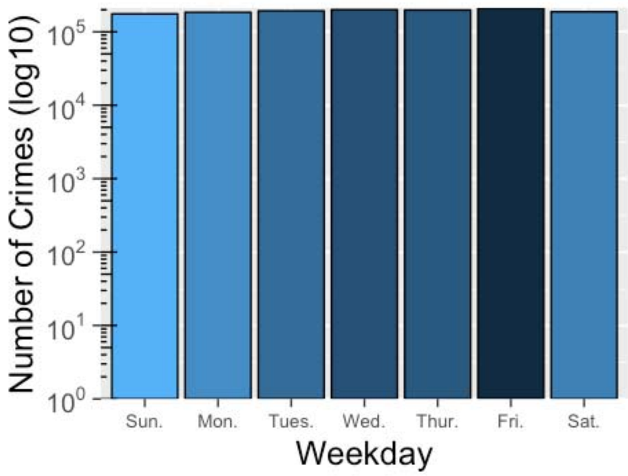

Fig. 4. Distribution of crimes by day.

Since we use data clustering methods for our patrol planning algorithm, we need for further pre-processing of the data. We filter the crime data set, first by removing all zero-weight crimes, and further restricting the X geo-coordinate to between 6270000 and 6680000 survey feet. This leaves us with 1,351,527 crime records. Since data clustering methods do not use weighting, we replicate each of the weight lines the number of its respective weight. This results in a total count of 3,101,851 crime records.

IV. Optimal Police Patrolling Strategy

The patrol planning problem can be informally described as follows. For an area in question (such as a city or a county), given its historical crime data and available police resources, find the best officer placement for patrol that can maximally suppress possible crimes. This is a challenging problem as it involves geolocations of many streets in the area and unevenly distributed crime occurrences at those locations under the constraint of limited police resources.

A. Design of Police Patrolling Strategy

To address these challenges and make the best patrol planning, we formalize the preceding problem as an *entropy maximization problem in a police placement network* and derive the optimal solution. Before presenting the details of our police patrolling strategy, we briefly describe entropy and equivocation.

Entropy [15] quantifies the smoothness with which a transformation occurs and of the disorder and the amount of wasted energy during the transformation from one state to another. Mathematically, entropy can be expressed as $H_a = \sum p_a \ln(1/p_a)$, where p_a is the probability mass function of variable a. The entropy of two variables can be calculated as

$$H(A,B) = H(A \mid B) + H(B \mid A) + I(A,B), \qquad (1)$$

where *I(A,B)* is the mutual information between *A* and *B*, which is determined by

$$I(A,B) = \sum_{a\in A, b\in B} p(a,b)\ln\left(\frac{p(a,b)}{p(a)p(b)}\right). \qquad (2)$$

H(A|B) in Equation (1) is the entropy of A conditional on B, which is called equivocation. Equivocation is computed as follows.

$$H(A \mid B) = \sum_{a\in A, b\in B} p(a,b)\ln\left(\frac{p(b)}{p(a,b)}\right). \qquad (3)$$

For a system with n variables, entropy $H(p1,...,pn)$ is a

measure of a system's order and stability. Its value is maximized when the system is at an equiprobability state. A greater value of entropy indicates a more balanced system in terms of the measured information.

The police patrol planning problem can be restated as one in which patrol locations are sought so that the system entropy is maximized. We define the probability term p_a in terms of a statistical measure of the ratio of an officer's patrolling radius (r) with regard to the quickest path to other locations over the length of the network. It also includes the effect of historical crime data in terms of the crime weight (w, defined in Section III). That is

$$H_{c1} = -p(c_1)\ln p(c_1), \quad p(c_1) = \left(\frac{r_{c1}}{r_{sys}} + \frac{w_{c1}}{w_{sys}}\right)\Big/ 2 \; . \qquad (4)$$

That is, the entropy is a combination of the weight of a crime centroid (w_{c1}), generated from crime clustering, over the total system weight (w_{sys}), added to the quickest path from the centroid to any other centroid (r_{c1}), over the quickest path in the entire system (r_{sys}). This balances the need for multiple patrols to cover a larger area that has few short paths between centroids. The value of r_{sys} can be determined by the length of

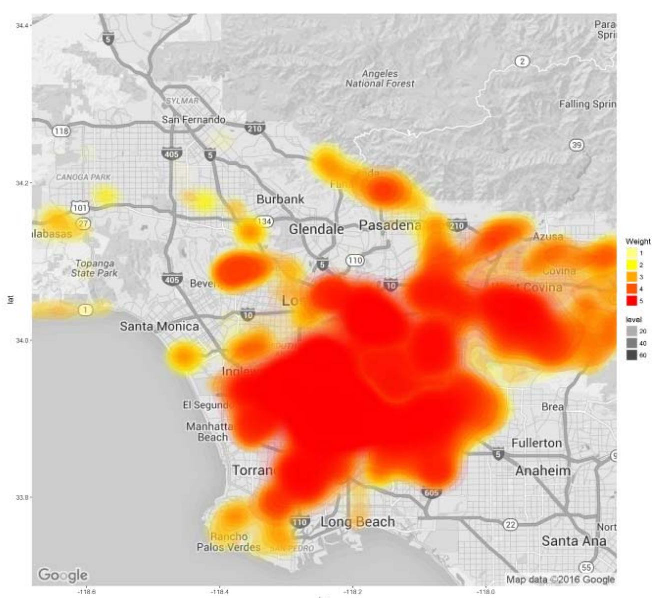

Fig. 5. *stat_density2d* plot of all crimes by weight, size=1, bins=128.

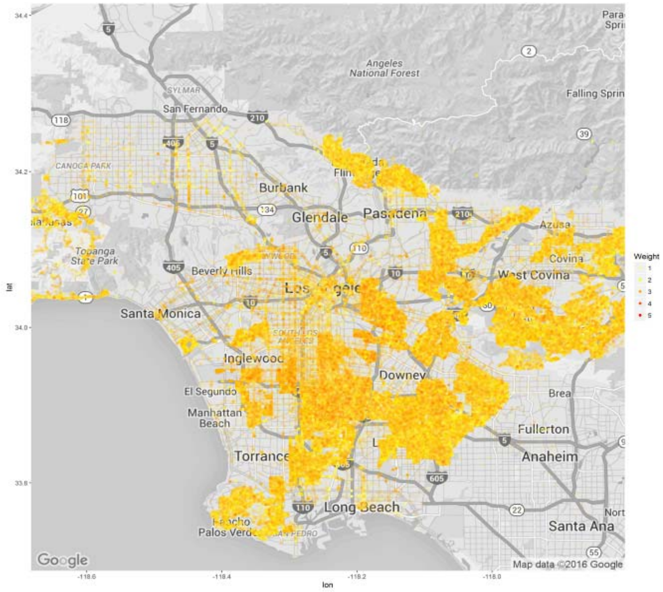

Fig. 6. *geom_point* plot of all crimes by weight, alpha=1/10.

an area's all paths being patrolled.

The total system entropy can be computed by summing up the entropy values for each path. That is $H_{System} = \sum_{ci} H_{ci}$. The goal, therefore, is to maximize the system entropy subject to the allowable maximum number of officers and patrolling resources, or equivalently to maximize the entropy while minimizing the number of officers and resources used.

The entropy maximization approach works as follows. It starts with the nodal entropy values from the all officer configuration as the calculation base, and assumes that the entropy contributions to the total system entropy from the patrolling officers are not subject to the equivocation property. After ranking the nodal entropies in descending order, the method selects the node that contributes the maximum to the system entropy and places an officer at that node. After assigning an officer to a node, the entropy values of the connected nodes are adjusted, considering equivocation and entropy maximization approach. The nodal entropies are re-calculated and the node with the highest entropy is selected for patrol placement. The process is repeated until the entire area is covered or the number of available officers is reached.

B. Implementation of Police Patrolling Strategy

To ensure that the geospatial distribution is fairly uniform, we plot the crimes against a map of LA County using the library *ggmap* [1]. A 2d density plot of the crimes is shown in Fig. 5 and a plot of the all the crimes shaded by crime weight is shown in Fig. 6. Both figures were generated using the R [21] library *ggplot2* [22].

We use Google Maps as the base layer for *ggmap* to present crime clusters and police patrol placement. We convert each crime record from the State Plane Coordinate System (SPS) format to the actual latitude/ longitude since that is the only format Google Maps API will allow. The correct State Plane projection for California V is European Petroleum Survey Group (EPSG) 2229 [2]. To get the correct latitude/longitude we use the *rgdal* [3] library in R to convert each X/Y pair to EPSG 4326, which is the EPSG identifier for World Geodetic System (WGS) 84.

After the coordinates are converted, we cluster consecutive sets of data for different hours of a day and different days of a week. We use a simple data clustering method, i.e., K-Means clustering, with a size of 50 based on the hexbin plots shown in Fig. 1. Since K-Means clustering does not implement a weight feature, we replicate each row times its weight for clustering. For the optimum clustering, Mclust or DBSCAN should be used and data should not have to be replicated. The resulting cluster centroids are aggregated with their sum weights and

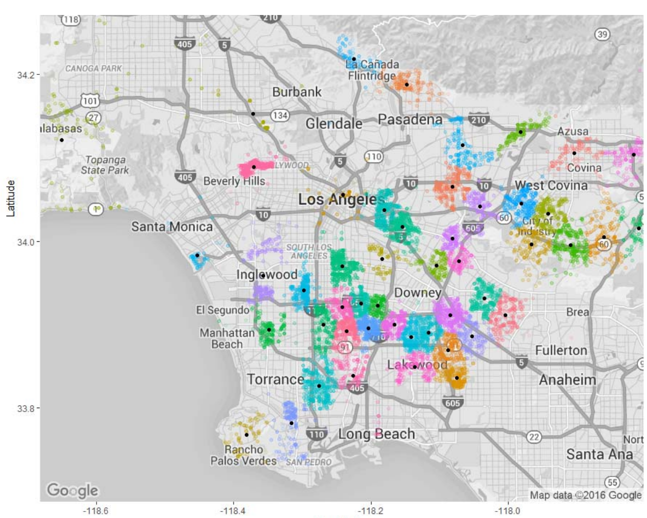

Fig. 7. Crime clusters generated by K-means for Monday at 0000 hours. Black dots represent each cluster's center (centroid).

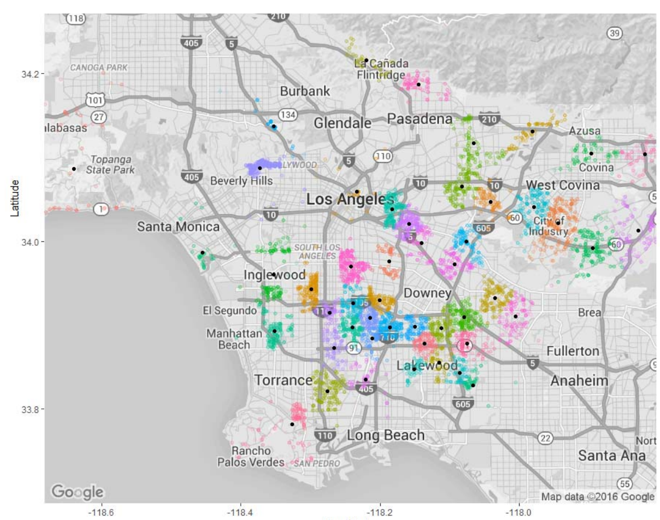

Fig. 8. Crime clusters generated by K-means for Monday at 0100 hours. Black dots represent each cluster's center (centroid).

saved.

We use real-time traffic analysis as the basis for our "pipes" between clusters. The Google Maps Distance Matrix API [5] provides traffic-time between points, and can be used to predict traffic at future dates/times. Using the Google Maps Distance Matrix API, the distance between each pair of the centroids is the drive-time calculated to each other. For cluster i and cluster j we use the first drive-time calculation, i.e. from i to j. A more robust solution would be to calculate bi-directional travel-times for each centroid in the fully-connected graph. Since the free-limit for the API is 2500/per day, we find that the bi-directional aspect would not affect our experimental data.

As we collect all the traffic data, our algorithm connects the cluster centroids using this traffic-time. Using this network, we then place patrols within the centroids. Patrols are placed according to the entropy calculation using Equation (4) for each edge in the connected centroid graph.

We place a fraction (denoted by f) of the number of centroids as patrols (denoted by n), such as 50%. This is a fair number of patrols to emphasize our approach, although this number would obviously be adjusted for real cities. This is a small number for such a large area, but our algorithm is generalized enough that any area and cluster combination is calculable. The only restriction is the drive-time between clusters using the Google API, since for a robust algorithm, the number of edges is ${}_nP_2$ permutation of the number of centroids.

After each edge entropy is calculated, the $f*n$ patrols are placed according to the most information gained from the entropy calculation. All preprocessing, filtering, and feature selection is done using the Go programming language for speed and concurrency, and then the data are exported to CSV for visualization in R.

V. Experimental Results

Fig. 7 and Fig. 8 show the results of crime groups by using K-Means clustering approach. One is for Monday at 0000 hours and another is for Monday at 0100 hours.

Using our entropy calculation to place patrols, we emphasize the long drive time needed between crime clusters and the actual amount and severity of crime in a given area. There are several outliers located in the south-east corner of LA County, which means that the entropy formula must be balanced between the aggregate weighting and drive-time. These plots are available in Fig. 9 and Fig. 10.

Larger area cities might need to assign a higher weight to drive-time during entropy calculation, whereas smaller cities could emphasize crime aggregates and disregard drive-time.

The choice of 25 patrols is used as the number of cluster nodes. For real-world use, the entire entropy of the system could be calculated over hundreds of nodes. Then patrols would be placed on the highest-entropy nodes, and the entropy of the system minus that node would be recalculated. Patrols would be placed until there is no change in entropy, or there is no more "information" gained by covering any other nodes. This is much easier if hundreds of clusters have been generated since patrols will be able to overlap closely (drive-time) related nodes.

Another solution to the closely clustered centroids is described below, which is to collapse clusters that are "clustered" together inside some predetermined constant. Neither solution addresses the aggregate weighting of crimes at nodes, merely the presence of police at a given node. In higher weighted nodes, more physical police presence should be emplaced, while in lower weighted nodes lower-profile solutions could be used instead of police officers. These lower-profile solutions could include community-organized watch or

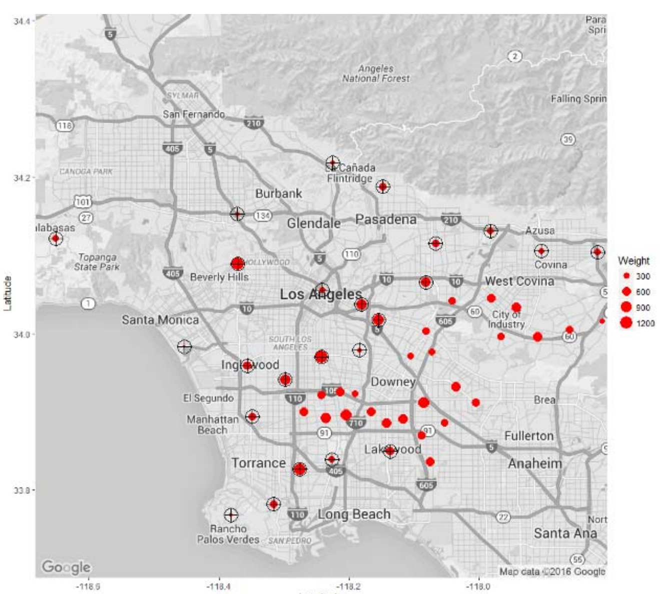

Fig. 9. 50 crime clusters for Monday at 0000 hours with 25 patrols placed. Black cross-hairs show placed patrols.

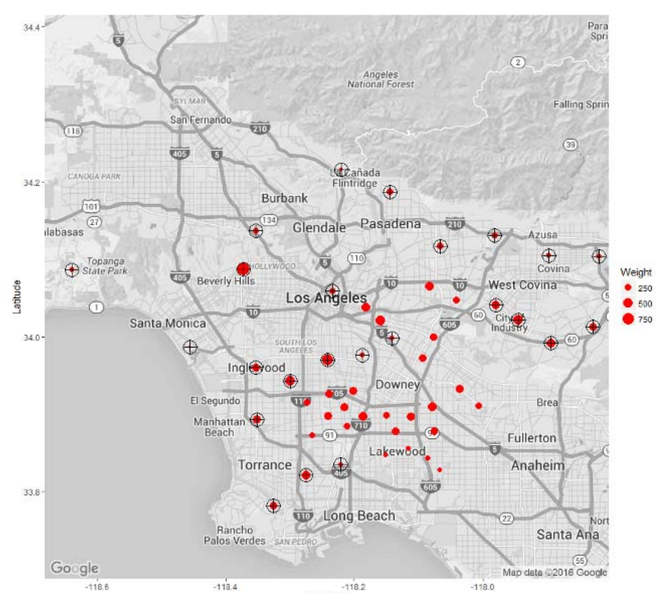

Fig. 10. 50 crime clusters for Monday at 0100 hours with 25 patrols placed. Black cross-hairs show placed patrols.

at-risk youth programs.

While the results follow the information theory of entropy, there is unfortunately no way to determine if the calculated patrols can reduce crime. It would be up to the LAPD to change patrol areas and implement new strategies. Therefore, the impact of this strategy in real-world applications is uncertain.

VI. Discussion

In our experiments, we need to remove about 37% of the original dataset because of incorrect X/Y coordinates or incomplete data. There is a possibility that the crime densities would not be uniform across weightings or hours due to these records. Since our algorithm can work at a more granular level, i.e., by day and hour, this should not affect our performance.

There are many external threats to validity. While police patrols can be varied and changed, police officers are not a resource that can be turned on or off each shift. If officers are not out on patrol, they will be at their station on administrative duty. In addition, while our algorithm balances car patrols among the higher crime areas, criminologists agree that Police presence in communities is one of the main deterrents to crimes being committed. Adding random car or foot patrols to lightly surveilled areas could counteract those criminals.

We do not partition our data into hourly chunks, but for actual implementation, each hour could be treated as its own maximization problem, with carry-over between centroids that cross hourly barriers. In addition, we do not take into consideration the aggregate size of each centroid. Patrol sizes should be adjusted to account for both the aggregate weighting of the centroid and the numbers of crimes within a predefined area of time around the centroid. Statistically we can determine how many crimes will occur in this centroid per hour and adjust the patrol count to adequately cover most crimes within the entire cluster, but this would be up to police management and budget constraints.

There are numerous problems with the crime dataset, from missing time, to blank coordinates, and locations that are not even in the state of California. For future study, completing the dataset and mapping crimes with correct coordinates will improve the results for effective patrol planning.

Regarding the weighting system, since each police force categorizes and prioritizes crime differently, this would be adjusted by city-policy. For Los Angeles, we felt five levels were sufficient, but for other cities that number would be adjusted up or down. In addition, the crime weighting system could be improved by adding a sliding time scale so that more recent crimes are favored over older crimes. The window used in the experiment by Ratcliffe et al. [16] weighted crimes committed each year half as much as the next year, e.g. 2008=1.0, 2007=0.5, 2006=0.25. Since crime hotspots usually have a long-term crime trajectory, weighing each crime's date with an exponential decay may be better suited to robust crime data than spans many years.

VII. Related Work

There has been a recent explosion in Smart City research. The novelty of the field lends itself to vastly different topics and solutions, while still under the "umbrella" of Smart City issues. Many safety-related Smart City research has been focused on mass surveillance and big data analysis, and not predictive/preemptive policing strategies. While many cities have heavily invested in surveillance networks, without combining this technology with "smarter" strategies, it provides both challenges and opportunities for smart city planning.

Predictive Policing. R. van Brakel and P. De Hert surveyed some of the work in predictive policing in their 2013 paper [17]. Their goals were to both determine the latest developments and technology in use for policing, namely the huge increase in surveillance and the viewpoint that using such technology can predict crime. Additionally, they sought to discover the inadvertent consequences that came about because of these "preemptive policing" programs.

Starting in July 2011 [18], the Santa Cruz police implemented the first law-enforcement predictive policing program in the United States. The program processed burglary hotspots within the city, and published a "Top 10" list each day for units to patrol. While the goal was to prevent crime, not to increase arrests, 13 arrests were made during the program. Although in six months they only showed a 4% reduction in burglaries over the same time-period the previous year, the program was innovative in the way it profiled the city for crime-prediction.

One of the main problems with both predictive and proactive policing strategies is how to measure "success". Since overall crime has been statistically on the decline in the United States, it is hard to empirically say a certain policing strategy has had a positive or even negative effect.

Entropy-based resource consumption. In addition to the work on smarter water-distribution [7], many other researchers have explored resource planning based on entropy. Since 100% coverage of resource utilization is infeasible due to both environmental and monetary factors, information-gain systems are a popular way to find optimal solutions.

J. H. Lee describes and entropy-based system for placing water-quality sensors in sewer systems [4]. After gathering data from monitoring points, a genetic algorithm was used to select from 80 points based on information gain. These 80 points represented a real sewer network in a small-subsection of Seoul, South Korea.

D. Xiaoting, C. Rongsi, and X. Bing used a similar technique [19] in Fujian province, China, to timely and accurately classify electric power marketing. Their results showed that using their entropy-based method was a better predictor of usage than the current system in place.

The requirements and results of entropy systems should be very attractive to smart city ventures. For city-planners, entropy systems have basic inputs that are easy to understand, and notably these inputs may already be available for collection. For policy-makers, entropy-based algorithms show a clear and reasonable path to their outcomes, as opposed to the complex neural networks of "deep learning."

VIII. Conclusion

In this paper, we study the police patrol planning problem for the safety of citizens in cities. We formalize the problem as an entropy maximization process in a police placement network and derive the optimal solution. Our algorithm shows that using entropy composed of both the drive-time between cluster centroids and the actual severity and aggregate of the centroid is effective in placing police patrols. These patrols are placed according to the resource maximization of available patrols, and police time is not spent driving between hot-spots of crime within the city. Since our approach is generalizable, any city utilizing smart crime collection can benefit from our work, provided they defined their crime weight and reporting system.

In our study, the main categories are a good estimate for our algorithm, but for future work we will focus on broader datasets and be more pragmatic in filtering records that do not meet a timeliness threshold, i.e., "Exploitation of Child via internet" should not necessitate an immediate police response. For cities with multiple types of police response, e.g., car, foot, and bicycle, the Google API can provide a drive-time for each type of patrol, further benefiting the overall patrol coverage. Lastly, we plan to define a response time and collapse all the clusters that are within that time window into one super-cluster with the aggregate weighting of all sub-clusters before the entropy of the system is calculated.

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