Yet Another Mathematical Approach to Geographic Profiling

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Abstract

Geographic profiling is a mathematical technique to derive information about a serial crime spree given the locations and times of previous crimes in a given crime series. We have created a crime prediction model by using the *anchor-distance-decay* and *hot-spotting* geographic profiling techniques. Based on the observation that the anchor-distance-decay model tends to predict a large area while hot-spotting provides a narrow, but not necessarily compherensive area, we devised a heuristic scheme to combine the results of the two techniques. We then tested the combined model relative to both the *anchor-distance-decay* and *hot-spotting* profiling techniques on a data set generated for this purpose. We found that using a specific combination of the two results in an effective search area for law enforcement.

The *anchor-distance-decay* geographic profiling assumes that an offender chooses future crime targets dependent on distance from an "anchor point" (such as a home or workplace) and the targets' desirability based on data from other crimes. The geographic profile yields a probability distribution indicating the likelihood of an anchor point at a particular location accounting for geographical factors and historical crime data. From a generated anchor point distribution, we compute the predictive distribution of possible future locations of the next crime. The other prediction scheme is *hot-spotting*, in which we generate a probability distribution of likely locations of future crimes by assuming that their geographic location is close to that of the offender's prior crimes, especially crimes commited most recently. Our combined model is a combination of the two that optimizes their relative performance.

Due to the difficulty of obtaining sets of crime data, we generated a data set on which to test all three models. We believe that the generated data is representative of data that would be used by law enforcement agencies using these models.

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1 Introduction

Geographic profiling is the process of aggregating and generalizing geographic data about a series of crimes. This process has many uses for law-enforcement as it allows predictins such things as the criminal's home or workplace, or the location of the next crime.

Geographic profiling of criminals is a relatively new field, started by K. Rossmo around 1987, but only very recently made mathematically rigorous by M. O'Leary. However, geographic profiling of crime locations has existed for a long time in the form of hot-spotting, whereby police presense is increased in areas of high crime frequency.

In our model, most geographic profiling techniques are a result of work by M. O'Leary due to his careful and thorough work on the field. M. O'Leary's analysis can be found in [4].

2 Background

2.1 Key Terms and Definition

For our paper we clarify the following definitions

- A **serial offender** an individual who has committed a serial crime.
- A **serial crime** a crime in a series of 3 or more crimes committed at different times and locations.
- An **anchor-point** is the location from where a serial criminal is operating such as a home or workplace. It is assumed that the offender operates from one location and does not move his starting location in between the crimes.
- **Geographic profiling** is the process by which geographic information about an event or individual can be determined. Geographic profiling of the offender establishes the offender's home base. Geographic profiling of the crime series establishes the areas where the crimes are likely to occur, and thus provides a prediction for the location of the next crime.

2.2 Cluster analysis and hotspot prediction

A class of attempts to use software to aid in crime prevention rely on forecasting crime "hotspots", that is, areas where crimes are more likely to occur. The hotspots allow police to redirect resources to those areas. The hotspots are based on the compilation of geographic data from recent crimes. For example, Bowers, Johnson, & Pease [1] attempt to decrease the size of clusters to make the prediction more effective at the expense of failing to cover outlying crimes. Other studies, such as Liu & Brown [3] evaluate the likelihood of crimes occurring at certain locations based on favorable factors, such as annual income and homeowner age. Most of these studies are observation-based and not mathematically rigorous.

2.3 Rossmo and Geographic Profiling

In 1991, while travelling on a bullet train in Japan, Dr. Kim Rossmo began to realize a new approach to using software to help solve crimes. Rossmo was interested in using past crime data to generate a geographical profile of the criminal, that is, the likely area from whree the offender operates. Rossmo's model was the following:

- The offender is more likely to target areas that are closer to his home or workplace than areas which are farther away.
- The offender does not target areas that are too close for psychological fear of being detected.

Based on this model, he came up with the formula

$$p_x = N \sum_n \left[\frac{\phi}{(d(x, x_n))^f} + \frac{(1-\phi)B^{g-f}}{(2B - d(x, x_n))^g} \right]$$

Where N is the normalization constant and f, g are empirically determined. $d(x_1, x_2)$ is the metric-dependent distance function. Rossmo used the Manhattan metric,

$$d((x_1, x_2), (y_1, y_2)) = |x_2 - x_1| + |y_2 - y_1|$$

To produce what is known today as Rossmo's Formula.

3 Known Prediction Schemes

3.1 O'Leary's New Mathematical Approach to Criminal Profiling

O'Leary [4] approaches the geographic profiling problem by developing a rigorous and explicit mathematical framework. O'Leary's framework takes into account geographic features for both anchor point prediction and crime site selection, and returns a distribution of offender's home base location. This location distribution and the same model can then be used to forecast future crimes.

Let $\boldsymbol{x} \in \mathbb{R}$, with $\boldsymbol{x} = (x^{(1)}, x^{(2)})$, be a point on a 2-D spatial grid. Let $\boldsymbol{z} \in \mathbb{R}$, with $\boldsymbol{z} = (\boldsymbol{z}^{(1)}, \boldsymbol{z}^{(2)})$ be the anchor point of the offender. Let $\alpha \in \mathbb{R}$ be the offender's average offense distance. Let P be the probability density function. P represents our knowledge of the behavior of the offender.

3.1.1 Bayesian Analysis of Single Crime

For the simplest case, suppose the offender has committed only one crime at location $\boldsymbol{x}$. Then we compute an estimate for the probability distribution for the anchor point $\boldsymbol{z}$ using Bayes' Theorem,

$$P(\boldsymbol{z}, \alpha|\boldsymbol{x}) = \frac{P(\boldsymbol{x}|\boldsymbol{z}, \alpha)\pi(\boldsymbol{z}, \alpha)}{P(\boldsymbol{x})}$$

where

- $P(\boldsymbol{z}, \alpha|\boldsymbol{x})$ is the *posterior distribution*; the probability density that the offender anchor point $\boldsymbol{z}$ and average offense distance α given offender has committed a crime at the location $\boldsymbol{x}$.
- $P(x)$ is the *marginal distribution*, which must be independent of $\boldsymbol{z}$ and α to retain equality (rather than proportionality).
- $\pi(\boldsymbol{z}, \alpha)$ is the *prior distribution*; our knowledge of the probability density that offender has anchor point $\boldsymbol{z}$ and average offense distance α before considering crime series.

With the assumption that $\boldsymbol{z}$ is independent of the average offense distance α we can factor to obtain

$$\pi(\boldsymbol{z}, \alpha) = H(\boldsymbol{z})\pi(\alpha)$$

where

- $H(\boldsymbol{z})$ is the prior probability density function for the distribution of anchor points before incorporating crime series.
- $\pi(\alpha)$ is the probability density function for the prior distribution of the offender's average offense distance before incorporating crime series.

Hence we have

$$P(\boldsymbol{z},\alpha|\boldsymbol{x}) \propto P(\boldsymbol{x}|\boldsymbol{z},\alpha)\pi(\boldsymbol{z},\alpha),$$

for the probability distribution of the anchor point given a single crime.

3.1.2 Bayesian Analysis of Crime Series

For the typical case, to estimate probability density for the anchor point $\boldsymbol{z}$ given crime series $\boldsymbol{x}_1,\dots,\boldsymbol{x}_n$, Bayes' Theorem implies

$$P(\boldsymbol{z},\alpha|\boldsymbol{x}_1,\dots,\boldsymbol{x}_n) = \frac{P(\boldsymbol{x}_1,\dots,\boldsymbol{x}_n|\boldsymbol{z},\alpha)\pi(\boldsymbol{z},\alpha)}{P(\boldsymbol{x}_1,\dots,\boldsymbol{x}_n)}.$$

Again

- $P(\boldsymbol{z},\alpha|\boldsymbol{x}_1,\dots,\boldsymbol{x}_n)$ is the *posterior distribution* giving the probability density that the offender has anchor point $\boldsymbol{z}$ and average offense distance α given offender has committed offenses at $\boldsymbol{x}_1,\dots,\boldsymbol{x}_n$.
- $P(\boldsymbol{x}_1,\dots,\boldsymbol{x}_n)$ is the *marginal distribution*, since it is independent of $\boldsymbol{z}$ and $\boldsymbol{x}$ it can be ignored.
- $\pi(\boldsymbol{z},\boldsymbol{x})$ can be factored again into $\pi(\boldsymbol{z},\boldsymbol{x}) = H(\boldsymbol{z})\pi(\alpha)$ with same definitions for H and π made above.

Assuming that the offense sites are independent we can reduce

$$P(\boldsymbol{x}_1,\dots,\boldsymbol{x}_n|\boldsymbol{z},\alpha) = P(\boldsymbol{x}_1|\boldsymbol{z},\alpha)\cdots P(\boldsymbol{x}_n|\boldsymbol{z},\alpha).$$

Substituting we get that

$$P(\boldsymbol{z},\alpha|\boldsymbol{x}_1,\dots,\boldsymbol{x}_n) \propto P(\boldsymbol{x}_1|\boldsymbol{z},\alpha)\cdots P(\boldsymbol{x}_n|\boldsymbol{z},\alpha)H(\boldsymbol{z})\pi(\alpha).$$

Finally we can since we are only interested in $\boldsymbol{z}$ we take the *conditional distribution* to obtain

$$P(\boldsymbol{z}|\boldsymbol{x}_1,\ldots,\boldsymbol{x}_n) \propto \int_0^\infty P(\boldsymbol{x}_1|\boldsymbol{z},\alpha)\cdots P(\boldsymbol{x}_n|\boldsymbol{z},\alpha)H(\boldsymbol{z})\pi(\alpha)d\alpha.$$

where $P(\boldsymbol{z}|\boldsymbol{x}_1,\ldots,\boldsymbol{x}_n)$ gives the probability density that the offender has anchor point $\boldsymbol{z}$ given offenses at locations $\boldsymbol{x}_1,\ldots,\boldsymbol{x}_n$. This is a general framework for geographic profiling that allowing for many possible choices of $P(\boldsymbol{x}|\boldsymbol{z},\alpha)$. This also allows us to easily add additional parameters or remove parameter α without significantly altering the mathematics.

In construction of this framework two fundamental assumptions were made

- z is *independent* of α; average distance the offender is willing travel is independent of offender's anchor point.
- offender's choice of crime sites are pairwise independent.

Both assumptions are reasonable (other sources? maybe he uses in paper pg. 19) and necessary for some factorization. What remains is deciding a model for Offender Behavior $P(\boldsymbol{x}|\boldsymbol{z},\alpha)$.

3.1.3 Simple Models for Offender Behavior

The simple model for offender behavior is the encompasses most models in the current literature. The following models make the assumption that all offenders have the same average offense distance α known in advance.

If we assume that an offender chooses a target location based only on the Euclidean distance from offense location to offender's anchor point, then we result in a (normal) *bivariate distribution*

$$P(\boldsymbol{x}|\boldsymbol{z},\alpha) = \frac{1}{4\alpha^2}\exp\left(-\frac{\pi}{4\alpha^2}|\boldsymbol{x}-\boldsymbol{z}|^2\right).$$

Assuming that all offenders have the same average offense distance α obtain a *product of normal distributions*

$$P(\boldsymbol{z}|\boldsymbol{x}_1,\ldots,\boldsymbol{x}_n) = \left(\frac{1}{4\alpha^2}\right)^n \exp\left(-\frac{\pi}{4\alpha^2}\sum_{n=i}^{n}|\boldsymbol{x}_i-\boldsymbol{z}|^2\right).$$

Another model of offender behavior is the *maximum likelihood estimate* for the anchor point as the mean center of the crime site locations. This is the *centrography* mentioned in Rossmo's Thesis [5] and basis of Rossmo's Formula; this is also the mode of the posterior anchor point probability distribution $P(\boldsymbol{z}|\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n)$.

Another behavior model is that the offender choose a target location based only on the Euclidean distance from the offense location to the offender's anchor point, but as a (bivariate) *negative exponential* so that

$$P(\boldsymbol{x}|\boldsymbol{z}, \alpha) = \frac{2}{\pi\alpha^2} \exp\left(-\frac{2}{\alpha}|\boldsymbol{x} - \boldsymbol{z}|\right).$$

and by making the assumption that all offenders have same average offense distances and all anchor points are equally likely, then

$$P(\boldsymbol{z}|\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n) = \left(\frac{2}{\pi\alpha^2}\right)^n \exp\left(-\frac{2}{\alpha}\sum_{i=1}^{n}|\boldsymbol{x}_i - \boldsymbol{z}|\right).$$

And the maximum likelihood estimate for the offender's anchor point is simply the center of minimum distance for the crime series locations.

And finally we have the hit-score method popular in current methods by constructing hit-score function

$$S(\boldsymbol{y}) = \sum_{i=1}^{n} f(d(\boldsymbol{x}_i, \boldsymbol{y})$$

with suitable distance metric d and decay function f. Regions with high hit-score are more likely to contain offender's anchor point and likewise the converse. Hence $S(\boldsymbol{z}) = \ln P(\boldsymbol{z}|\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n)$ is a similar hit-score type.

3.1.4 O'Leary's General Model for Offender Behavior

The general framework of O'Leary's model allows for a realistic geographic profiling by allowing a simple way to incorporate geographical features into the model. We suppose the *probability density distribution* is in the form

$$P(\boldsymbol{x}|\boldsymbol{z}, \alpha) = D(d(\boldsymbol{x}, \boldsymbol{z}), \alpha)G(\boldsymbol{x})N(\boldsymbol{z}, \alpha)$$

where

- $D(d, \alpha)$ is a factor accounting for *distance decay effect*.
- $d(\boldsymbol{x}, \boldsymbol{z})$ is a suitable *distance metric* used in D.
- $G(\boldsymbol{x})$ accounts for local geographic features that influence the selection of offense site.
- $N(\boldsymbol{z}, \alpha)$ is a normalization factor independent of $\boldsymbol{x}$.

Like we have seen before, the distance decay function D can take many forms and any desired distance metric d. But, the main factor of interest is the geographical influence on target weighting, $G(\boldsymbol{x})$.

3.1.5 Jurisdiction Boundaries – Characteristic Function

A simple variant on $G(\boldsymbol{x})$ is a characteristic function approach, that is

$$G(\boldsymbol{x}) = \chi_J(\boldsymbol{x}) = \begin{cases} 1 & \text{if } \boldsymbol{x} \in J \\ 0 & \text{if } \boldsymbol{x} \notin J \end{cases}.$$

This accounts for a region J corresponding to one or more regions of jurisdiction, i.e. area where crimes are known. Crimes can occur outside of J, but these are presumed to be unknown to profiler. Also the anchor point may lie outside of J. Fortunately the model treats areas outside of J as having no information about crimes.

3.1.6 Incorporating Available Geographic and Demographic Data

Making the assumption that historical crime rates are reasonable predictors of likelihood that a particular region will be the site of an offense, we can factor in historical data to a estimate the target density function $G(\boldsymbol{x})$. Given a representative list of crimes $\boldsymbol{c}_1, \ldots, \boldsymbol{c}_n$ using a kernel density function $K(\boldsymbol{y}|\lambda)$ with bandwidth data, we compute local target attractiveness by

$$G(\boldsymbol{x}) = \sum_{i=1}^{N} K(\boldsymbol{x} - \boldsymbol{c}_i|\lambda).$$

As in the software code, a typical choice for λ is the *mean nearest neighbor distance* between historical crimesites $\boldsymbol{c}_i$ and for K a simple normal/bivariate distribution.

Now the prior probability density for offender anchor points $H(\boldsymbol{z})$ incorporates knowledge of offender's anchor points before using information from the crime series. If nothing is known $H(\boldsymbol{z}) = 1$. Otherwise, like software, assuming that the anchor pint is the offender's home and the distribution of anchor points follows population density we can incorporate U.S. census data, which is given at the block level. Using more kernel density parameter estimation, we calculate $H(\boldsymbol{z})$ by

$$H(\boldsymbol{z}) = \sum_{i=1}^{N_{\text{blocks}}} = p_i K(\boldsymbol{z} - \boldsymbol{q}_i | \sqrt{A_i}).$$

where a block has population p_i, center q_i, and a chosen bandwidth equal to the side lenth of a square with area A_i of the block. With available data, $H(\boldsymbol{z})$ can also be calculated by starting with similar anchor points of similar crime sprees and calculate H like G.

The final element is the estimation of the prior distribution of average distance to crime $\pi(\alpha)$ which is distribution of the average offense distances across offenders. The software uses a complicated approach of *Tikhonov regularization* and *L-curve method* to compute π.

3.1.7 Future Offense Prediction

Posed mathematically, to estimate the location of the serial offender's next target, given a series of crimes at $\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n$ committed by a single serial offender, we wish to estimate $P(\boldsymbol{x}_{\text{next}} | \boldsymbol{x}_1, \ldots, \boldsymbol{x}_n)$ where $\boldsymbol{x}_{\text{x}}$ is the location of the next offense. The simple Bayesian approach is to calculate the *posterior predictive distribution*

$$\begin{aligned} P(\boldsymbol{x}_{\text{next}} | \boldsymbol{x}_1, \ldots, \boldsymbol{x}_n) &= \iiint P(\boldsymbol{x}_{\text{next}} | \boldsymbol{z}, \alpha) P(\boldsymbol{z}, \alpha | \boldsymbol{x}_1, \ldots, \boldsymbol{x}_n) dz^{(1)} dz^{(2)} d\alpha \\ &\propto \iiint P(\boldsymbol{x}_{\text{next}} | \boldsymbol{z}, \alpha) P(\boldsymbol{z}, \alpha | \boldsymbol{x}_1) \cdots P(\boldsymbol{z}, \alpha | \boldsymbol{x}_n) H(\boldsymbol{z}) \pi(\alpha) dz^{(1)} dz^{(2)} d\alpha. \end{aligned}$$

Where we used the factoring methods used earlier by making the same independence assumptions.

3.2 Estimation based on prior offenses

Our second scheme to predict future crime locations is a time-dependent geographic proximity model. The fundamental assumptions of this model are:

- The offender prefers to target areas that he has experience with, that is, areas that he has previously targeted
- The offender prefers to reoffend in the same area

Based on these assumptions, we directly determine a probability distribution of the next offense as follows:

1. For each past crime scene $(\boldsymbol{x}, t)$, we define a *kernel density function* $K(\boldsymbol{x}, \lambda) = N(\boldsymbol{x}, \sqrt{\lambda})$ as a bivariate normal distribution centered at $\boldsymbol{x}$ and with variance λ where λ is the mean *nearest neighbor distance* over all crime scenes using the Euclidean metric. The bivariate normal distribution has the form
$$N(\boldsymbol{x}, \alpha) = \frac{1}{4\alpha^2} \exp\left(-\frac{\pi}{4\alpha^2}|\boldsymbol{x} - \boldsymbol{z}|^2\right).$$
2. We define a temporal decay function $\tau(t)$ where t is the time elapsed since the crime. For simplicity, we define τ to be linear in time with $\tau(t_0) = 0.5$ for the first crime and $\tau(t_n) = 1$ for the last crime.
3. The search area is the sum
$$P(\boldsymbol{x}_{\text{next}}|\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n) = \sum_{i=1}^{n} K(\boldsymbol{x}_i, \lambda)\tau(t_i)$$

This procedure is a variation of the one used in O'Leary's model [4] to generate a possible target density function provided a list of historical crime data. Our model instead generates a target density function specific to the offender and includes time-dependse whereas O'Leary's model does not.

4 Combined Model

Let P_1 be the result from using O'Leary's method, and P_2 be the result from the second profiling scheme. Our heuristic combined estimate is

$$P = \chi P_1 + (1 - \chi)P_2$$

To find a "good enough" value for χ, we consider the effect of the two models on generating a useful prediction. While an anchor-distance-decay model can provide a very good estimate of the offender's home location, it is not very useful in predicting the location of the next crime. Practically, predicting based on the home base location yields a large watch area "centered" at the home base and encompassing all prior crimes. This area is too big to search for all practical purposes. However, it provides us with a practical upper bound on the area where the next crime could occur.

On the contrary, the second scheme effectively finds clusters in crimes and generates a much smaller watch area. Doing so increases the possibility of missing the next crime, but the area is large enough so that it catches most crimes. Thus the proximity-based model is more important to law enforcement than the anchor-distance-decay model.

Lacking more precise comparative evaluation of the two models, we assume

$$\chi = 0.25$$

5 Example

To test our combined model relative to the anchor-distance-decay and hot-spotting models, we generated data to represent a series of residential burglaries. We also generated a set of prior crime and home base location data. Figure 1 shows the generated historical data from two crimes, plotted in Google Earth. We believe that these generated data are representative of actual crimes.

5.1 Anchor-Distance Decay

We ran O'Leary's geographic profiling model using U.S. Census data. The relevant part of the Census data is shown in Figure 2, The model generated a home base distribution, shown in Figure 3. The distribution was then used to generate a prediction for the next crime location, shown in Figure 4.

5.2 Hot-spotting model

We then tested the crime data with the hot-spotting model. Results are shown in Figure 5.

5.3 Combined Model

We then tested the crime data with our combined model. Results are shown in Figure 6.

6 Conclusion

The example demonstrates that the combined model is effective at both predicting the most likely crime locations. It is effective to law enforcement agencies by outputing both a most likely watch area, and a general large area where crimes can occur. In contrast, anchor-distance-decay alone, while effective for determining home base location, outputs a very large search area, and hot-spotting alone outputs a narrow search area but may miss crimes that occur outside of the hotspots, such as the two outlying crimes in Figure 5. Thus the combined model is more useful than either anchor-distance-decay and hot-spotting alone.

References

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A Executive Summary

Geographic profiling is a mathematical technique to derive information about a serial crime spree given the locations and times of previous crimes in a given crime series. We have created a crime prediction model by using the *anchor-distance-decay* and *hot-spotting* geographic profiling techniques. Based on the observation that the anchor-distance-decay model tends to predict a large area while hot-spotting provides a narrow, but not necessarily comprehensive area, we devised a heuristic scheme to combine the results of the two techniques. We then tested the combined model relative to both the *anchor-distance-decay* and *hot-spotting* profiling techniques on a data set generated for this purpose.

To use our model the user will need the Windows environment and download:

- Google Earth
- The most recent version of Michael O'Leary's open-source geographical profiling software: `http://pages.towson.edu/moleary/Profiler.html`.
- Our software patch with our modifications for next crime prediction, as well as the time-dependent hot-spotting prediction and the combined prediction that we explain in our paper.

The user will need to provide a series of crime events for the serial crime, a series of previous crime incidences of solved cases (used in O'Leary's profiler) as well as locations of the homes or workplaces of the criminals from where they operated. The program also requires U.S. Census data for the counties being profiled (links to download these are included in O'Leary's software). The crime data should be in the text format described by O'Leary, or converted from a Google Earth KML file using a script included in our patch.

The *anchor-distance-decay* geographic profiling assumes that an offender chooses future crime targets dependent on distance from an "anchor point" (such as a home or workplace) and the targets' desirability based on data from other crimes. The software is best used for criminals operating from a single anchor point. The geographic profile yields a probability distribution indicating the likelihood of an anchor point at a particular location accounting for geographical factors and historical crime data. Law enforcement agencies should begin the search for the criminal at the highest points of the distribution, indicated by the red areas. In addition, the program will output

the predictive distribution of possible future locations of the next crime, this is the area police authorities should most closely monitor for new crimes. This area is likely big, so *anchor-distance-decay* should be used in conjunction with *hot-spotting*, in which a probability distribution of likely locations of future crimes is generated by assuming that their geographic location is close to that of the offender's prior crimes, especially crimes committed most recently.

We recommend that law enforcement agencies use our combined method, as it combines *hot-spotting*, providing authorities with the most likely locations of next crimes, and *anchor-distance-decay*, providing authorities with a broad area encompassing probable crimes that do not lie in the hot spots. However, both models are made available to be used by authorities, should they deem it appropriate.

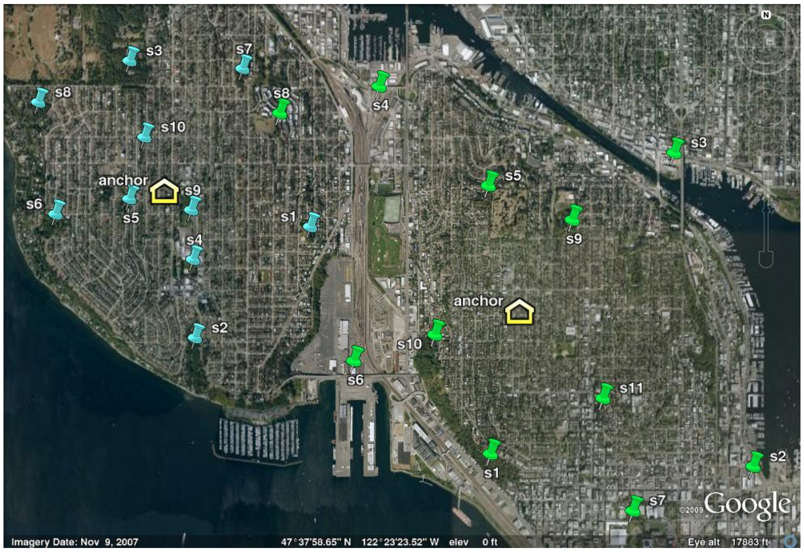

Figure 1: Generated historical crime data

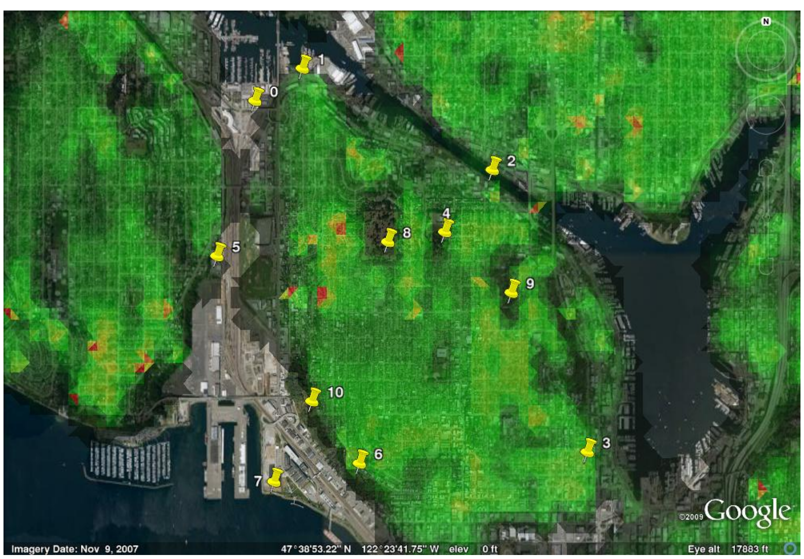

Figure 2: Population density based on U.S. Census data

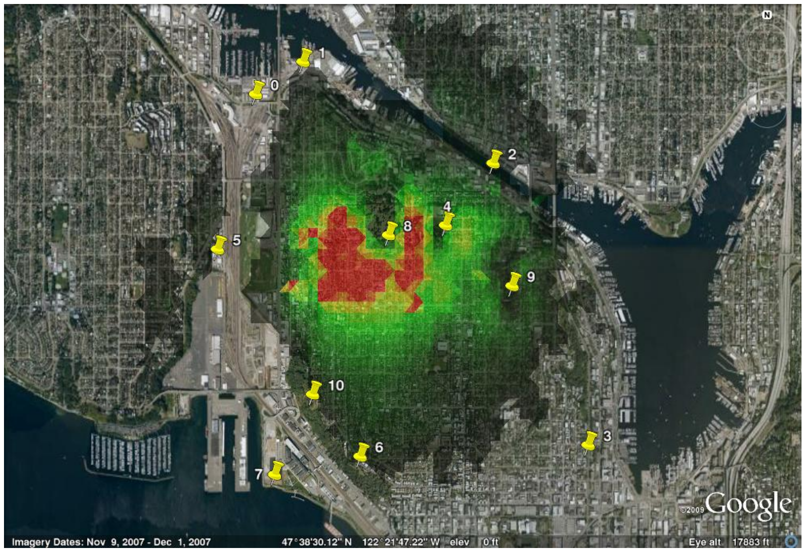

Figure 3: Prediction of home base location, demonstrating O'Leary's model of geographic profiling

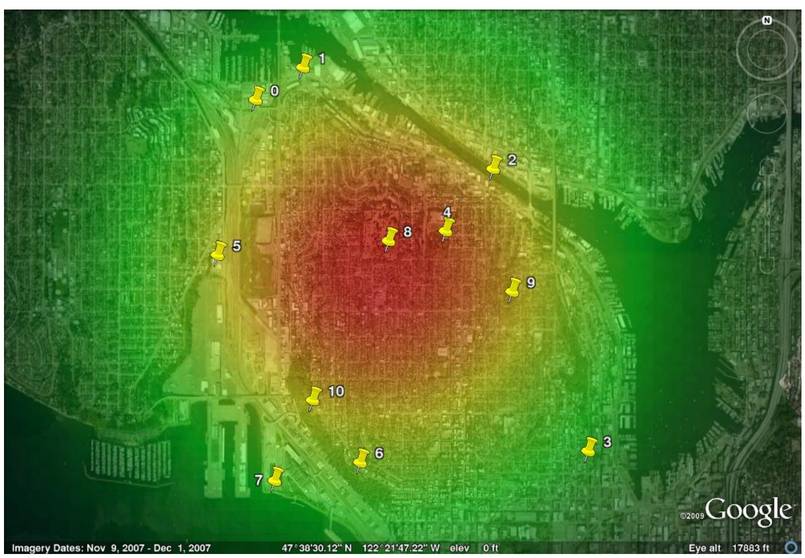

Figure 4: Prediction of next crime location using anchor-distance-decay

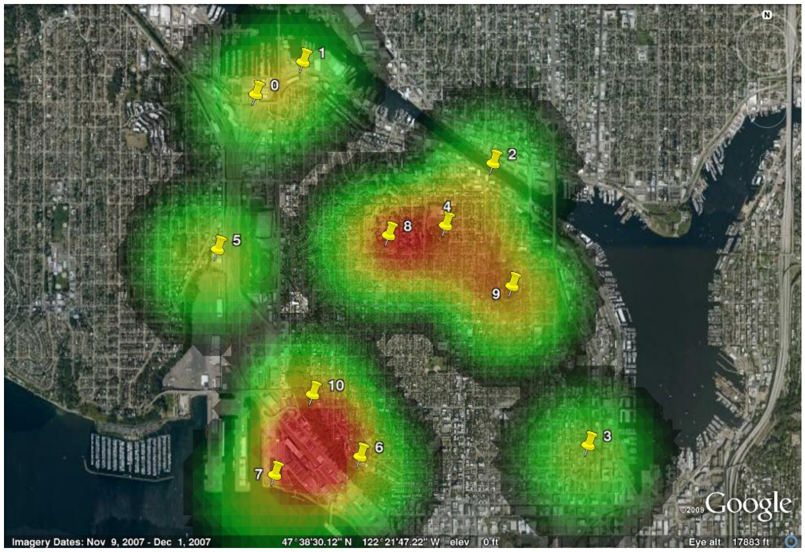

Figure 5: Prediction of next crime location using hot-spotting

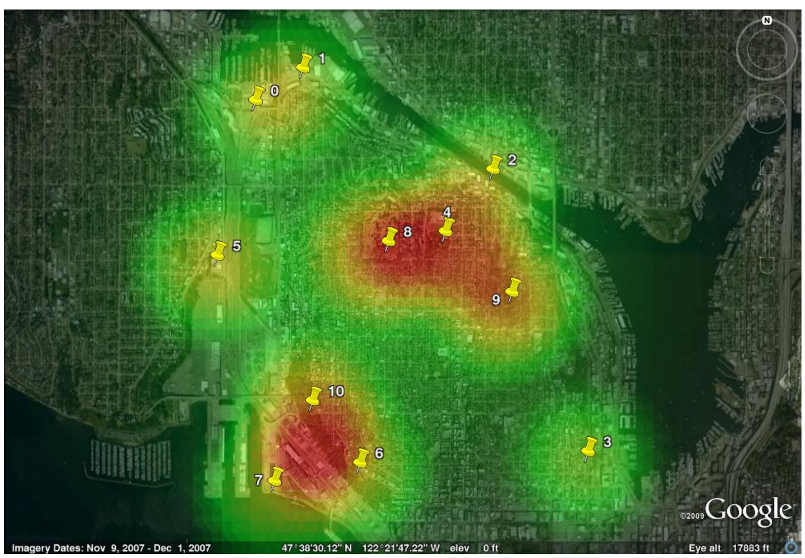

Figure 6: Prediction of next crime location using the combined model