Learning Where to Inspect: Location Learning for Crime Prediction

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***Abstract*— Crime studies conclude that crime does not occur evenly across urban landscapes but concentrates in certain areas. Spatial crime analysis, primarily focuses on *crime hotspots*, areas with disproportionally higher crime density. Using CRIMETRACER, a personalized random walk based approach to spatial crime analysis and crime location prediction outside of hotspots, we propose here a probabilistic model of spatial behavior of known offenders within their *activity space.* Crime Pattern Theory states that offenders, rather than venture into unknown territory, frequently commit opportunistic crimes by taking advantage of opportunities they encounter in places they are most familiar with as part of their activity space. Our experiments on a large crime dataset show that CRIMETRACER outperforms all other methods used for location recommendation we evaluate here.**

***Keywords*-Predictive policing; Spatial crime analysis; Random walk model; Activity space; Co-offending networks**

I. INTRODUCTION

The spatial analysis of crime is re-emerging in importance [2], [8], [7], [13]. Studies find that crime does not occur uniformly or randomly across the urban landscapes [8], [13]. Crime *hotspots*, areas with high crime intensity, generate a larger percentage of criminal events [8]. Hotspot analysis enables law enforcement to better prioritize their use of resources for crime reduction and prevention. Likewise, better understanding of areas with lower concentration of criminal events, referred here as *coldspots*, is of value because these areas account for approximately half of all urban crimes [13].

Coldspots cover a much wider area than hotspots. Targeted policing, a.k.a. hotspot policing, is not feasible for crime reduction or prevention in coldspot areas. Development of intervention strategies requires better understanding the spatial distribution of crime incidents in coldspots. Hotspot analysis focuses on modeling the emergence, evolution and stability of hotspots and is often based on aggregate crime patterns. Coldspot analysis, as is explored here, requires modeling of individual offender spatial behavior. This calls for models that are flexible and can be personalized.

Our model focuses on individualized offending and decision making with different decision rules for the occasional offender and the frequent repeat offender and repeat co-offender. The model is derived from Crime Pattern Theory [2] based on the assumption that offenders, rather than venture into unknown territory, frequently commit crimes in places they are most familiar with as part of their *activity space* [2].

An activity space is a subset of an awareness space. Activity spaces and awareness spaces change over time with movement to new home locations, new employment, the development of new shopping and entertainment areas and the development of new mass transit and roads. But, fortunately, crime is relatively rare, and acceptable targets of crime or victims are likely to be found easily within an awareness space. Outside an activity or awareness space, an offender will have to consciously hunt for criminological opportunities and likely face higher uncertain or unforeseeable risks. *Crime occurrence space* is more likely a part of an activity space that intersects with the location of suitable targets preferred by an offender.

We present here CRIMETRACER, an extended random walk model for generating the activity space of offenders living in an urban area. The focus is on crimes that are linked to individual offenders in non-hotspot urban areas. It uses random walk to model how offenders encounter criminal opportunities at a local level near anchor locations in an activity space [9]. In [9], the authors propose a random walk based model for capturing the dynamics of hotspot formation (See [9] for a Levy Flight model). In CRIMETRACER, the random walk process is personalized to uncover the spatial behavior of all individual offenders. The work presented here extends and improves our earlier work [10], adding a discussion on offender mobility, improving the CRIMETRACER performance using a new movement directionality approach, advancing the experimental evaluation, and discussing the new results.

For the urban layout we assume a small-scale (detailed) road network on which an offender moves about in an urban area. By doing so, we gradually compute an approximation of the offenders activity space by reflecting the probability of visiting (and possibly committing crime) for each road segment of the urban area. This result is then used for predicting crime locations for individual offenders, something not addressed in crime spatial analysis to the best of our knowledge. Based on our experimental evaluation, personalization is successful for detecting crime locations in coldspots.

The following sections of the article address related work, details of the CRIMETRACER model, our experimental model evaluation and the results.

II. RELATED WORK

Several studies have explored the activity space of offenders. Rossmo [7] has developed a widely recognized method of inferring the activity space of an offender to determine the likely home location based on the person's crime locations.

Based on criminological theories, several studies propose mathematical models of spatial and temporal characteristics of crime to predict future crimes. However, these models do not predict individual offender behavior. For instance in [5], the authors use a point-pattern-based transition density model for crime space-event prediction. This model computes the likelihood of a criminal incident occurring at a specified location based on previous incidents. In [9], the authors model the emergence and dynamics of crime hotspots. This work uses a two-dimensional lattice model for residential burglary, where each location is assigned a dynamic attractiveness value, and the behavior of each offender is modeled with a random walk process. The authors study the impact of the model parameters on hotspot formation using a computer simulation.

Note that all of the above-mentioned methods solve related but different problems to which the experiments presented here can not be compared. However, we compare CRIMETRACER to different *Collaborative Filtering* methods which are used for location recommendation in location-based social networks [12]. Collaborating filtering (CF) infers the user's implicit preference form the explicit opinions of similar users based on the idea that users with similar behavior in the past will have similar behavior in the future.

III. CRIMETRACER MODEL

In this section we present CRIMETRACER, our crime spatial analysis model, starting with the problem characterization.

Given a crime dataset $\mathcal{C}$, an offender u_i and road network $R(L, Q)$ associated with $\mathcal{C}$, the goal is to learn the *activity space distribution* F for u_i on R. That is, for each road $l_j \in L$, $F(i, j)$ states the probability that l_j is part of the activity space of u_i, and thus the likelihood for offender u_i committing a crime at road l_j is

$$F(i,j) \longrightarrow [0,1] \text{ with } \sum_{j=1}^{|L|} F(i,j) = 1 \tag{1}$$

By learning the activity space distribution of individual offenders, we obtain a probabilistic model of offender activity space that can be used for personalized prediction of future crime locations of the offender. The assumption is that the richer and more detailed the offender profile is, the more accurate is the probabilistic activity space model, and also the prediction of future crime locations. This probabilistic view of activity space means that there is no sharp boundary between activity space and awareness space, reflecting the intuitive understanding of the concept of activity space in criminology.

A *random walk* over a graph is a stochastic process starting in a given initial state. The next state is chosen using a transition probability matrix that identifies the probability of moving from one node to a next node. Under certain conditions the random walk process converges to a stationary distribution [4] assigning an importance value to each node of the graph.

The random walk method satisfies the locality aspect of crimes, which states that offenders do not attempt to move far from their anchor locations. But it has some shortcomings that we aim to address in the CRIMETRACER model.

A. Random Walk Process

For each offender, we perform a series of random walks on the road network $R(L, Q)$. In each random walk the offender starts his exploration from one of his anchor locations, traversing the road network to locate a criminal opportunity.

For offender u_i, the random walk process starts from one of his anchor locations with predefined probabilities (see Section III-B). At each step k of the random walk, the offender is at a certain road l_j and makes one of two possible decisions:

- with probability α he decides to return to an anchor location and not look for a criminal opportunity this time, choosing an anchor location in one of two ways: 1. with probability β he decides to return to a *main anchor location* $l \in \mathcal{L}_i$. 2. with probability $1 - \beta$ he returns to an *intermediate anchor location* $l \in \mathcal{I}_i$. The way we distinguish main and intermediate anchor locations is discussed in the next section.
- with probability $1 - \alpha$ he continues looking for a crime opportunity.

If he continues his random walk then he has two options:

- with probability $\theta(u_i, l_j, k)$ stop the random walk, which means the offender commits a crime at road l_j.
- with probability $1 - \theta(u_i, l_j, k)$ continue the random walk, moving to another road which is a direct neighbor of l_j.

To continue the random walk at road l_j, we select a direct neighbor road from Π_{l_j}. The probability of selecting road segment l_k in the next step is defined as

$$P(l_j \to l_k) = \frac{\phi_{\bar{w}}(l_k)}{\sum\limits_{l_p \in \pi_{l_j}} \phi_{\bar{w}}(l_p)} \tag{2}$$

The random walks terminate when $||F^{m+1}|| - ||F^m|| \leq \epsilon$, where $F^m = \begin{pmatrix} F(u_i, l_1) \\ \vdots \\ F(u_i, l_{|L|}) \end{pmatrix}$ is the results for u_i after m walks. For some offenders the random walks do not converge, in which case we terminate the overall process at $m > 10,000$.

B. Starting Probabilities

CRIMETRACER distinguishes two types of starting nodes:

a) Main anchor locations are all anchor locations of a single offender and his co-offenders: $\mathcal{L}_i = L_i \cup \{l_j : l_j \in L_v, v \in \Gamma_u\}$. Co-offending links are the reason for many spatial effects related to crime. It is concluded that offenders who are socially close, are spatially close too [11]. The rational is that offenders who have collaborated in the past likely may have shared information in their activity space, an aspect that possibly affects their choice of future crime locations. In computing the starting probability of each anchor location, the two primary factors are the frequency and the last time an offender visited an anchor location. The probability that offender u_i starts his random walk from l_j thus is

$$S(i,j) = \frac{f_{i,j} \times e^{\frac{-(t-t_{i,j})}{\rho}}}{\sum\limits_{l_k \in \mathcal{L}_i} f_{i,k} \times e^{\frac{-(t-t_{i,k})}{\rho}}} \tag{3}$$

where t is the current time, and ρ is the parameter controlling the effect of the timing.

b) Intermediate anchor locations are the closest locations to main anchor locations. Human mobility models use Gaussian distribution to analyze human movement around a particular point such as home or work location [3]. We assume that offender movement around his main anchor locations follows a Gaussian distribution. Each main anchor location of offender u_i is used as the center, and the probability of u_i being located in a road is modeled with a Gaussian distribution. Given road l the probability of u_i residing at l is computed as follows:

$$S(i,l) = \sum_{l_j \in \mathcal{L}_i} \frac{f_{i,j}}{\sum\limits_{l_k \in \mathcal{L}_i} f_{i,k}} \frac{\mathcal{N}(l|\mu_{l_j}, \Sigma_{l_j})}{\sum\limits_{l_k \in \mathcal{L}_i} \mathcal{N}(l|\mu_{l_k}, \Sigma_{l_k})} \tag{4}$$

Here l is a road which does not belong to the set of main anchor locations. $\mathcal{N}(l|\mu_{l_j}, \Sigma_{l_j})$ is a Gaussian distribution for visiting a road when u_i is at anchor location l_j, with μ_{l_j} and Σ_{l_j} as mean and covariance. We consider the normalized activity frequency of u_i at l_j, meaning that a main anchor location with higher activity frequency has higher importance. For offender u_i, the roads with the highest probability of being an intermediate anchor location are added to the set $\mathcal{I}_i$ as additional starting nodes besides the main anchor locations.

C. Movement Directionality

Directionality of offender movement plays an important role in activity space formation. We propose here two approaches to determining movement directionality. The first approach learns the weights of the features that determine the probability of selecting a road among all neighbor roads in a random walk process. The second approach leads an offender in the direction that gets him closer to the crime hotspots.

1) Hotspots Influence: In this approach the transition probability is computed based on proximity of a road to the crime hotspots and the importance of each crime hotspot, which is proportional to the number of crimes committed there. The function $\phi(l_k)$ is used in computing the transition probability (refer to Section III-A) of moving offender u_i from l_j to l_k:

$$\phi(l_k) = \sum_{n=1}^{|\Delta|} D_{j,n} \times f_n \tag{5}$$

where $D_{j,n}$ is the distance of l_j from hotspot $l_n \in \Delta$, that is the length of the shortest path between the roads on the road network. f_n is the number of crimes committed at l_n.

2) Learning Road Feature Weights: Road feature weights $\bar{w}$ are used to compute the transition probabilities. The function $\phi_{\bar{w}}(l_j)$ is computed based on the road features

$$\phi_{\bar{w}}(l_j) = \sum_{k=1}^{m+1} w_k \times y_{j,k} \tag{6}$$

where $\bar{y}_{j,k}$ is the value of kth feature of the road l_j, and w_k is the corresponding weight of the feature k.

We use the same idea used in the supervised random walks method [1] for link prediction in social networks. This method guides the random walk toward the preferred target nodes by utilizing node and edge attributes.

Each offender in a random walk staring from his home location reaches a crime location. In the training data for each offender we have a series of crime journeys, meaning that for a source node s we have a set of destination nodes $D = \{d_1, d_2, \ldots, d_n\}$, and a set of non-destination nodes $Z = \{z_1, z_2, \ldots, z_m\}$. The probability of visiting a node p_d is influenced by the road transition probabilities. And the transition probabilities are dependent on the road features weight. Now, we sway an offender starting from node s so as to visit destination nodes $d_i \in D$ more often than non-destination nodes $z_i \in Z$ by formulating the following optimization problem:

$$\min_{\bar{w}} F(\bar{w}) = \|\bar{w}\|^2 + \lambda \sum_{d \in D, z \in Z} loss(p_z - p_d) \tag{7}$$

where λ is the regularization parameter, and $loss$ is a predefined loss function for penalizing the cases in which the stationary probability of a non-destination node p_z is higher than the stationary probability of a destination node p_d.

D. Stopping Criteria

The probability of stopping the random walk for an offender at a given road corresponds to the probability of this offender committing a crime in that road segment. Two factors influence the stopping probability of offender u_i in the road l_j. The first one relates to the similarity of the crime trend of offender u_i and the criminal attractiveness of road l_j, where higher similarity means a higher chance that u_i's random walk stops at l_j. The second factor is the distance of l_j from the starting point measured in the number of steps from the starting point. To satisfy the locality aspect of crimes, the probability of continuing the random walk should decrease while getting farther from the starting point:

$$\theta(u_i, l_j, k) = Sim(i,j) \times \frac{1}{1 + e^{\frac{-k}{2}}} \tag{8}$$

where Sim(i,j) denotes the cosine similarity of crime trend of u_i and the road attractiveness of the road l_j. The stopping probability is inversely proportional to the step number k:

$$Sim(i,j) = \frac{\bar{x}_i.\bar{a}_j}{|\bar{x}_i||\bar{a}_j|} \tag{9}$$

IV. Experimental Evaluation

This section describes the used dataset for this study, our experimental design, the comparison partners, and the results.

A. Dataset

For a time period of five years (2001-2006), the BC police arrest dataset amounts to approx. 4.4 million crime records. This includes all persons associated with a crime, but in our experiments we consider all subjects in four main categories: *charged, chargeable, charge recommended or suspect*. Being in one of these categories means that the police were serious enough about a subjects involvement in a crime as to warrant calling them 'offenders'. For the study presented here, we concentrate on the crimes in Metro Vancouver, where different regions are connected through a road network composed of 64,108 road segments with an average length $0.2\,km$. Table 1 shows the statistics of the used crime dataset.

B. Experimental Design

For each offender we order his crime events chronologically based on their time. Then we split these events into a training set and a test set. The first 80% of the crimes are used for training the model which predicts the offender activity space. The remaining 20% of crimes are used for testing the model.

TABLE I: Statistical properties of the dataset used in this study

Property	Value
No. of crimes	125,927
No. of offenders	189,675
No. of offenders with more than one crime	25,162
No. of co-offending links	68,577
No. of co-offenders in co-offending network	17,181

We note that the training data used for learning road features as described in Section III-C2 is not included in the evaluation to prevent biasing CRIMETRACER.

After learning the offender activity space in the training phase, the trained model is applied in the test phase to predict future crime locations. To do so, the top-N roads with the highest probability are suggested as the most probable places for an offender to commit future crimes. As discussed above, the focus of this work is modeling offenders' spatial behavior in the coldspots. Thus, in our experiments we exclude the top 100 roads with the highest crime numbers, the hotspots.

To evaluate the accuracy of activity space prediction, we measure the number of crimes committed by an offender in his testing dataset among the top-N predicted locations. If a crime location in an offender's test set is also among the top-N predicted locations, that crime location is considered to be correctly *predicted*. As evaluation measures we use two well-known accuracy measures, *precision*, *recall*. We also use *utility* which computes the percentage of offenders with at least one correctly predicted crime location. Recall and precision are averaged across all offenders to determine the overall performance for different values of N.

C. Comparison Partners

In this section we introduce different versions of CRIMETRACER and the comparison partners methods used in our evaluation. For evaluating the CRIMETRACER performance, we test the two different movement directionality approaches and the following types of locations in the activity space of offenders. For every offender locations are categorized into three groups: a) *Known locations* that includes home and crime locations of the offender. b) *Derived locations* which are locations shared with co-offenders and intermediate anchor locations. These locations are derived from observed information in the crime dataset. c) *Unknown locations* that includes any location which is not a known or derived location.

For a deeper understanding of CRIMETRACER performance and the role of each of above-mentioned location types, we consider three approaches : $1-$ In the first approach (denoted by U) we include only unknown locations in the activity space of an offender and consequently in the crime location prediction. $2-$ In the second approach (denoted by D) we include only unknown and derived locations in the activity space of an offender. $3-$ In the last approach (denoted by A) all locations are considered.

Two different movement directionality methods are introduced in Section III-C: hotspot influence (denoted by H) and learning road feature weights (denoted by F). For each of these CRIMETRACER versions we consider the three above-mentioned evaluation approaches. For instance CRIMETRACER-HU denotes CRIMETRACER using the hotspot influence method (H) for movement directionality that includes only unknown locations (U) in the predicted locations.

As discussed in Section II, there is no related work that solves the problem of personalized crime location prediction. However we use the following methods which are equivalent to state-of-the-art methods for location recommendation [12]:

Random Walk. This is the standard random walk with restart method (RWR).

Hotspots. Using the basic hotspot approach (HS), roads are ranked based on the number of crimes in that road.

Proximity. In the proximity approach (DS) we rank the roads based on their distance from the offender's anchor locations. Here distance denotes the length of the shortest path between two roads on the road network.

Offender-based CF. The intuition behind the offender-based CF approach (OCF) is that offenders who had similar behavior in the past will have similar behavior in the future. Let $b_{ij} = 1$ if $l_j \in \mathcal{L}_i$, and $b_{ij} = 0$ if $l_j \notin \mathcal{L}_i$. Now $F(i, j)$ is the probability of a crime committed in road l_j by u_i:

$$F(i,j) = \frac{\sum\limits_{u_k \in V \wedge k \neq i} Sim(i,k).b_{k,j}}{\sum\limits_{u_k \in V \wedge k \neq i} Sim(i,k)} \tag{10}$$

where $Sim(i, k)$ denotes the cosine similarity measure between offenders u_i and u_k:

$$Sim(i,k) = \frac{\sum\limits_{l_j \in L} b_{i,j}.b_{k,j}}{\sqrt{\sum\limits_{l_j \in L} b_{i,j}^2}\sqrt{\sum\limits_{l_j \in L} b_{k,j}^2}} \tag{11}$$

Location-based CF. In location-based CF (LCF) we consider the similarity of locations instead of the similarity of offenders:

$$F(i,j) = \frac{\sum\limits_{l_k \in L \wedge k \neq j} Sim(j,k).b_{i,k}}{\sum\limits_{l_k \in L \wedge k \neq j} Sim(j,k)} \tag{12}$$

where $Sim(j, k)$ is the cosine similarity measure between roads l_j and l_k:

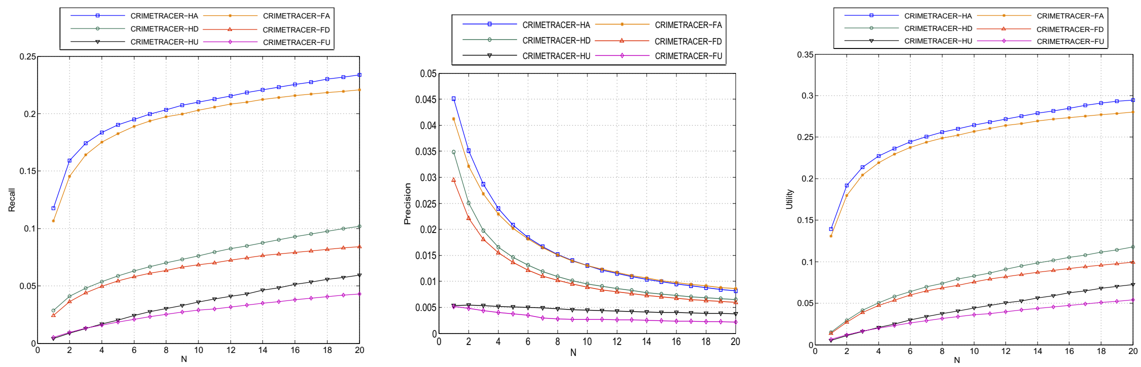
$$Sim(j,k) = \frac{\sum\limits_{u_i \in V} b_{i,j}.b_{i,k}}{\sqrt{\sum\limits_{u_i \in V} b_{i,j}^2}\sqrt{\sum\limits_{u_i \in V} b_{i,k}^2}} \tag{13}$$

Co-offending-based CF. Co-offenders can share their information about criminal opportunities and take advantage of this information in committing a new crime. Co-offending-based CF (SCF) computes the probability of a crime being committed in road l_j by u_i as follows:

$$F(i,j) = \frac{\sum\limits_{u_k \in \Gamma_i} Sim(i,k).b_{k,j}}{\sum\limits_{u_k \in \Gamma_i} Sim(i,k)} \tag{14}$$

$Sim(i, k)$ denotes the geo-social influence between u_i and u_k:

$$Sim(i,k) = \frac{|\Gamma_i \cap \Gamma_k|}{|\Gamma_i \cup \Gamma_k|} + \frac{|\mathcal{L}_i \cap \mathcal{L}_k|}{|\mathcal{L}_i \cup \mathcal{L}_k|} \tag{15}$$



(a) Recall

(b) Precision

(c) Utility

Fig. 1: Performance of different versions of CRIMETRACER for different values of N

D. Results

CRIMETRACER Scenarios. Figures 1a, 1b and 1c show performance of six different versions of CRIMETRACER including CRIMETRACER-HU CRIMETRACER-HD, CRIMETRACER-HA, CRIMETRACER-FU, CRIMETRACER-FD and CRIMETRACER-FA in terms of recall, precision and utility measures. With regard to the type of locations included in the prediction process, as expected CRIMETRACER-HA and CRIMETRACER-FA have the best performance, and CRIMETRACER-HU and CRIMETRACER-FU have the worst performance. The recall of CRIMETRACER-HA, CRIMETRACER-HD and CRIMETRACER-HU for $N = 20$ is 23.4%, 10.2% and 5.9%, respectively. Derived and known locations increase the recall by 4.3% and 13.1%, respectively. We observe a similar result when comparing the performance of CRIMETRACER-FA, CRIMETRACER-FD and CRIMETRACER-FU.

An important question is which of these scenarios should be used in a real-world application of CRIMETRACER. According to criminological theories such as exact-repeat / near repeat event and broken window theory, known locations of offenders are always likely places to commit a new crime. The results presented in this section also support this idea. In a real-world application known locations may be included in the predicted locations automatically. One may conclude that CRIMETRACER-HD and CRIMETRACER-FD are more appropriate versions of CRIMETRACER for a real-world application.

Considering the two movement directionality approaches, both versions of CRIMETRACER achieve higher performance compared to the standard random walk. CRIMETRACER-HD compared to CRIMETRACER-FD and CRIMETRACER-HU compared to CRIMETRACER-FU have higher recall, precision and utility. CRIMETRACER-HA compared to CRIMETRACER-FA has higher recall and utility for all values of N, but their precision values are almost identical for $N >= 6$. We conclude that the hotspot influence outperforms the other method, showing the great impact of crime attractors and generators in committing a new crime by an offender.

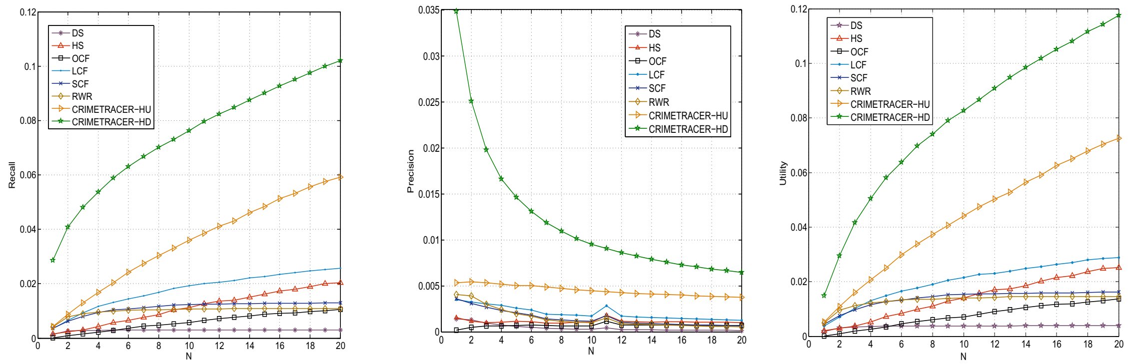
Comparison Partners. Figures 2a, 2b and 2c show the overall performance of the different evaluated methods in terms of recall, precision and utility.

To compare CRIMETRACER against the baseline methods, we use only the best performing versions CRIMETRACER-HD and CRIMETRACER-HU. Both of these methods consistently outperform all baseline methods for all values of N with regard to all evaluation metrics. The baseline methods use the same experimental design as CRIMETRACER-HD, but we also test CRIMETRACER-HU in the comparison to show that even in this case of a more restricted scenario, CRIMETRACER still outperforms the baseline methods.

DS obtains the lowest precision and recall values. Despite the well-studied theory of the relationship between crime commitment and distance from anchor locations, this result shows that this approach is not effective for personalized crime prediction. Among the CF-based approaches, OCF has the poorest performance. LCF achieves better recall, but SCF achieves higher precision. It is interesting to observe that location similarity contributes more to the accuracy of crime location prediction than offender similarity. One can conclude that SCF uses more reliable but limited information for predicting the offenders activity space. The recall of HS improves with increasing N, but this method naturally is strong in predicting crimes in hotspots and not in coldspots.

Predicting even one crime location of each offender is very important for the critical task of crime prevention. As for the other two evaluation metrics, both versions of CRIMETRACER outperform the baseline methods in terms of utility. The utility of CRIMETRACER-HU and CRIMETRACER-HD is 1.3% and 1.5%, respectively larger than their recall ($N = 20$), making no significant difference. One reason for this effect is that half of the offenders committed only two crimes, and we can predict only one crime location for them, meaning that for these offenders the recall and utility values are the same.

CRIMETRACER Elements. We studied the contribution of different components of CRIMETRACER to its performance. Compared to the standard random walk with restart, CRIMETRACER incorporates additional anchor locations(co-offending information and intermediate anchor locations), movement directionality and stopping criteria. We added these components separately to RWR to determine their individual contribution. Table 2 shows the results. The strongest compo-



(a) Recall (b) Precision (c) Utility

Fig. 2: Performance for different values of N

TABLE II: Contribution of different elements of CRIMETRACER to its performance ($N = 20$)

Method	Recall	Precision	Utility
RWR	0.011	0.004	0.014
RWR + Road features weight	0.013	0.003	0.017
RWR + Hotspot influence	0.015	0.003	0.016
RWR + Additional anchor locations	0.019	0.001	0.024
RWR + Stopping criteria	0.036	0.003	0.045
CRIMETRACER-HU	0.059	0.006	0.073
CRIMETRACER-FU	0.043	0.004	0.054
CRIMETRACER-HD	0.102	0.007	0.118
CRIMETRACER-FD	0.084	0.006	0.010
CRIMETRACER-HA	0.23	0.008	0.30
CRIMETRACER-FA	0.22	0.008	0.28

nent is the stopping criteria and the weakest is the learning of road feature weights. The main idea behind the stopping criteria is to stop the random walk of an offender in a road where the crime history is similar to the offender crime trend. However combining all components in CRIMETRACER-HD achieves the best result and improves the performance of RWR significantly in terms of all evaluation metrics. We include the performance of other versions of CRIMETRACER in Table 2 to be able to compare the performance of different versions of CRIMETRACER more exactly.

We note that the overall performance of CRIMETRACER is comparable to that of state-of-the-art methods for location recommendation [12], where the information about spatial patterns of users is much denser than the available information about offenders. One may criticize that, while location recommendation methods predict the exact locations, CRIMETRACER predicts offender activity space as road segments. However, as discussed in [6], roads are the natural domain for many policing activities, and a more realistic urban element for predicting a crime than the exact latitude and longitude. In addition, the road network we use in our study is in the micro scale with an average road segment length of 0.2 km.

V. CONCLUSIONS

Although crime hotspot detection and hotspot policing have received much attention, few researches have analyzed spatial distribution in coldspots. To address this problem, we propose CRIMETRACER, a random walk based approach to model offender activity space. CRIMETRACER uses a personalized random walk to derive a *probabilistic activity space* model for known offenders based on facts from their criminal history as documented in an offender profile. We evaluate our algorithm by data mining operational police records from crimes in Metro Vancouver within a 5-year time period. We are not aware of any similar work for modeling offender activity space and, hence, compare the proposed approach with location recommendation methods. CRIMETRACER outperforms all other evaluated methods tested here. It boosts the prediction performance of the repeat offenders, compared to the non-repeat offenders, by using co-offending information.

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