# Towards Simulating Criminal Offender Movement Based on Insights from Human Dynamics and Location-Based Social Networks

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**Abstract.** Interest in data-driven crime simulations has been growing in recent years, confirming its potential to advance crime prevention and prediction. Especially, the use of new data sources in crime simulation models can contribute towards safer and smarter cities. Previous work on agent-based models for crime simulations have intended to simulate offender behavior in a geographical environment, relying exclusively on a small sample of offender homes and crime locations. The complex dynamics of crime and the lack of information on criminal offender's movement patterns challenge the design of offender movement in simulations. At the same time, the availability of big, GPS-based user data samples (mobile data, social media data, etc.) already allowed researchers to determine the laws governing human mobility patterns, which, we argue, could inform offender movement. In this paper, we explore: (1) the use of location-based venue data from Foursquare in New York City (NYC), and (2) human dynamics insights from previous studies to simulate offender movement. We study 9 offender mobility designs in an agent-based model, combining search distances strategies (static, uniform distributed, and Lévy-flight approximation) and target selection algorithms (random intersection, random Foursquare venues, and popular Foursquare venues). The offender behavior performance is measured using the ratio of crime locations passed vs average distance traveled by each offender. Our initial results show that agents moving between POI perform best, while the performance of the three search distance strategies is similar. This work provides a step forward towards more realistic crime simulations.

**Keywords:** Crime · Simulation · ABM · LSBN · Offender mobility · Human mobility patterns

## 1 Introduction and Related Work

Public safety has been a topic of concern for cities worldwide for many years. Recent technological developments and in particular the availability of novel data sources has shown potential towards addressing this problem by advancing crime prevention and this contributing to the safety of cities. As an approach, crime simulations can be applied to crime prevention to test the performance of various scenarios and derive


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strategies for intervention at a very low cost [1]. In addition, these methods can be used to inform police forces about future crime events and thus support effective deployment of their patrols. Researchers investigating at the intersection between criminology and computational social science are building agent-based models (ABM) simulating crime with different purposes e.g. testing crime theories [2, 3], analyzing the performance of prevention strategies [4–6], and forecasting crime developments [7–9]. One of the main issues faced when building such models is not only related to the complexity of the phenomena itself, but to the lack of detailed information about offender movement in space [10]. There is no data tracking offender movement, which would provide insights into daily patterns and criminal target search strategies. A reason for the lack of such data is ethical, e.g. mobile user-data is not available for offenders but only for anonymized general population. Due to this limitation, in the field of criminology, attention has been paid mostly to the demographic characteristics of offenders (age, gender, ethnicity, etc.) and to their possible motivations for committing crimes, while research on movement patterns is still rather scarce. Previous crime simulation models include criminal agents who derive their movement behavior from Routine Activity Theory (RAT) [11], which describes certain aspects of offender behavior. According to RAT, offenders are believed to engage in criminal activities along their usual movement path (e.g. along their path to leisure activities), thus limiting the offender's movement between fixed points. Such activity areas, identified as attracting locations are disproportionally often located near areas with elevated criminal activity [12], confirming that the offenders' target selection strategy is largely influenced by the offenders' *awareness space*[1]. Following RAT, related work has simulated offender movement, based on offenders with known home and crime locations, to derive their possible trajectories [6, 8, 9]. The offender's travel-paths are then built between the fixed home location and other points, representing a reduced number of offenders and not being generalizable for the larger phenomena of crime.

In the current era, where large amounts of location-based user data are available providing detailed insights into human mobility patterns [13, 14], it seems natural, that gained knowledge could inform criminal offender's movement. Human mobility patterns have recently been studied using GPS-based user data [14, 15], and location-based social networks data e.g. gained from Twitter [16] and Foursquare[2] [17]. In this paper, we explore the use of (1) human dynamics insights from literature and (2) location-based social networks (LSBN), to inform offender mobility in an agent-based model. We hypothesize, that offender agents follow similar patterns to those of the general population. The contribution of our paper is twofold. First, we compare three approaches for step size calculation informed by human dynamic insights, i.e. a static, a uniform and a Lévy-flight distance trajectory, with the goal of determining the optimal strategy for calculation of the search area radius. Second, we leverage user-generated content from Foursquare (i.e. venues and check-ins) to inform offenders target selection. The aim of this comparison is to assess if unknown offenders can be realistically modeled in such a

[1] Area between usual activity nodes.

[2] Foursquare is a mobile application offering location-search-and-discovery for its users: https://foursquare.com/.

manner. In short, we study offender mobility using insights in human mobility patterns, historical crime data and Foursquare data for New York City (NYC), resulting in the design and implementation of 9 offender behaviors and the performance assessment of each behavior.

## 2 Offender Mobility

In this work, we study how to model offender mobility based on general human mobility patterns.

### 2.1 Problem Description

Our research is guided by the main hypothesis, that criminal offenders follow human mobility patterns identified for the general population (H1). This is derived from the notion, that crime is linked to a legal definition and does not provide information on, or define group behavior [18]. Traveling distances of humans have been identified in related work as following a scale-free random walk referred to as Lévy-flight [13, 14]. Thus, the distances traveled by humans follows a power-law distribution. Humans have a high probability to travel short distances and a low probability to travel long distances. This behavior is described in Eq. 1, where $\mathrm{P}(\Delta r)$ is the distribution of displacement and $\beta < 2$ is the displacement exponent.

$$\mathrm{P}(\Delta r) \sim \Delta r^{-(1+\beta)} \tag{1}$$

Furthermore, we hypothesize, that offenders move between Points of Interest (POI), meaning that the target of a movement path is a POI (H2), this is in line with general human attractors [19] as well as with research on the influence of POI for shaping offenders' awareness space [12, 20]. The path taken by offenders to any location, in this case POI builds up the space known by the offender (awareness space), increasing the probability for a crime to be committed in the same area, which is in line with RAT. In the same direction, we hypothesize, that offenders are strongly drawn to more popular POI (H3), following the general population patterns.

Formally, there is a set of Offenders O each traveling to a location $\ell \in \mathcal{L}$ within distance $r \in \mathbb{R}$ in the area $a \in \mathrm{A}$ Our goal is to identify the right strategy for selecting $\ell$ and $r$ to maximize the number of crime locations $\mathrm{c} \in \mathrm{C}$ on the actual travelled path.

To test the defined hypotheses, we design 3 distance selection strategies and 3 target selection algorithms, which combined make up 9 offender behaviors instantiated in our model. The distance selection strategies defines the search radius (H1), within which an offender selects a target. The search radius is optimized against the actual travelled distances, informed by human dynamics research (see Sect. 2.2 for more details). The first distance selection strategy uses a static search radius $r \in \mathbb{R}$. The second strategy, chooses its search radius from a continuous uniform distributed random variable, described by $R \sim U(0, 2r)$ so that $\mathbb{E}[\mathrm{R}] = r$. For the third strategy we use Lévy-flight to determine the search radius $r$ (see Eq. 1). We transformed the formula (see Eq. 2) to produce random radius $r \in \mathbb{R}$ following a power-law distribution within a probability range adapted to the area of study.

$$\mathrm{P}(r) \sim r^{-(1+\beta)} \rightarrow r \sim \frac{1}{P(r)} \cdot \mathrm{e}^{\frac{1}{1+\beta}} \tag{2}$$

In turn, the target selection algorithm defines the type of location $\ell$ an offender can select as a destination within $r$. The first $\ell$ type is any intersection, the second is a random POI and the third is a POI based on its popularity. The popularity of the venues is determined by the number of check-ins, influencing the probability to be chosen as a target POI, where the probability for choosing the target is given by Eq. (3).

$$\mathrm{P}[\ell] = \frac{check - in}{check - ins\, total\, within\, r} \tag{3}$$

The performance of the 9 offender behaviors is assessed by an adaption of Predictive Accuracy Index (PAI), a standard measure developed for crime prediction models [21], which divides the hit rate by the area of study (see Eq. 4). For the purpose of this study, we adapt PAI to the simulation by dividing the hit-rate-crimes-passed by the total crimes in the study area. The larger the result, the better the performance of the index.

$$PAI = \frac{\left(\frac{c\, assed}{c\, otal}\right)}{\left(\frac{a\, traveled}{a\, total}\right)} \tag{4}$$

## 2.2 Dataset

We constructed a set of data to simulate the described problem. The simulation builds on the road network for NYC including 117,321 street segments collected from NYC open data portal[3]. Crime data was also obtained from the NYC open data portal, and includes anonymized felony crimes at street segment level (projected to the center) and intersection level, projected to the road network of the simulation. The crime data includes additional information such as type of crime, date, time, etc. The dataset includes the following types of crime: grand larceny, grand larceny of motor vehicle, robbery, burglary, and felony assault. For simulation purpose, we use crime data for 1 year (2015), to obtain an up-to-date overview of crime patterns for that period, resulting in 69,731 crime incidents mapped. Furthermore, we collected Foursquare data to gain information on popular venues attracting larger crowds of people, as proxy for human target preferences. The data was collected from the Foursquare API (in May and June 2016), including information about venues in the area of NYC: venue name, location, check-in count (cumulated over time), associated categories, etc. The set is composed of 273,149 venues in the proximity of every incident from the crime data set with over 122 million check-ins associated and categories ranging from Arts and Entertainment, College and University, Events, Food, Nightlife Spot to Shop and Service, etc.

[3] https://opendata.cityofnewyork.us/.

In this research, the foursquare venues are used as proxies for Points of Interest (POI), and the check-in and user-counts are used as proxies for human activity. All geographic data has been projected to NAD83/New York Long Island (ftUS) allowing measurement in foot for NYC area. Concrete human mobility pattern insights were gained from previous research and include the average trip length traveled by the New York State (NY) population [22].

## 3 Offender Simulation

The simulation model for offender mobility is implemented in the Java-based platform REPAST. The agent-based model is built on a geographic environment consisting of the road network for NYC (represented as a network graph, mapping roads to edges with information on crimes and intersections to nodes) and venue points from Foursquare (including venue type, check-in, and user-count information). The simulated criminal offenders travel on the road network from a random start point on an intersection to the most likely attractor (target), selecting the shortest path, weighted by road length. Thus, the agents perceive the geographic environment, select a radius to determine the travel distance, and move to a target within that distance. The model is set up in different scenarios, each running a different instantiation of offender behavior, to assess the best performing offender mobility design. The different offender behaviors are inspired by the hypotheses mentioned in Sect. 2.1. Grounded by findings in human mobility and criminology, the simulation scenarios have been shaped combining the following two behavior characteristics: (1) search space selection defines the search space radius in which the agent selects a target destination for its current movement. The average trip length for the simulation has been calibrated against the average trip length of 39,600 feet (average trip length for NY population) after completion of the 50 steps of the simulation. The optimal parameters for each search strategy are depicted in Table 1, while we have used the optimal parameter for Lévy-flight as described in previous research [13], we have adapted the probability interval to the size of NYC; and (2) target selection algorithm, defines the offenders' strategy to choose a target for its movement within the distance selected in the previous behavior and has been implemented as described in Sect. 2.1. The three target selection algorithms include: (a) random target selection, offering a choice of road intersections, (b) venue target selection, offering a choice of venues, and (c) priority venue target selection, offering a choice of venues, weighted by popularity.

**Table 1.** Search space selection strategy parameters

| Static search | Uniform distributed search | Lévy-flight search |
|---|---|---|
| $r = 40{,}000$ feet[1] | $r = 80{,}000$ feet | $\beta = 0.6$ |

[1]The Lévy-flight (Eq. 2) is defined for km in literature, we transformed the output distance in feet in line with the projection of our data.

The model is run for 50 steps with 25 offender agents for each offender behavior, as an analogue to previous crime simulations [3]. This number of agents allows us to diffuse the impact of the starting location and therefore reduce the effects of path dependencies.

## 4 Simulation Results

The simulation model described in the previous section was used to generate various simulation scenarios, aiming to compare the performance of each offender implementation. In Table 2 we show the performance measure (see Eq. 4 in Sect. 2.1) for each agent type. In comparison, the search space selection strategies perform very similarly (the uniform strategy performs slightly better), while the target selection algorithm selecting POI as movement target performs best. Combined, the uniform distance selection strategy selecting POI as targets performs best, followed by the algorithm selecting popular POI. This confirms H2 and partly H3, stating that offenders travel to POI and popular POI, but does not confirm that offenders' movement distances follow a Lévy-flight (H1). In contrast, the uniform distribution seems to better capture offender mobility.

**Table 2.** Performance measurement, PAI

| | Static strat. | Uniform strat. | Lévy strat. |
|---|---|---|---|
| Road al. | 0.324 | 0.382 | 0.267 |
| POI alg. | **0.439** | **0.519** | **0.425** |
| Popular POI alg. | 0.347 | **0.523** | 0.283 |

## 5 Discussion and Implications

In summary, we have proposed designed and compared criminal offender movement behavior, distinguishing between search space and target selection. Our work has theoretical and practical implications.

On the theoretical side, we have shown that, offenders move similar to the general human population in some manner. The simulated target selection algorithm has shown, that offenders can be modeled traveling between POI's. In turn, the distance selection strategy did not show clear results. This could be due to the relatively small distances that agents can travel in NYC. Combined, these findings corroborate that offender behavior can be modeled using certain human mobility pattern insights, while these should still be further adapted to offenders.

On the practical side, our results especially show the potential of crowdsourced data (POI's and check-in information) for modeling offender behavior in crime simulations and can set a basis for modeling offender mobility in future crime simulations.

The main weakness of the model used in this study, is the limited amount of data used for the offenders target selection strategy. Ideally, the environment would hold additional information about attracting features.

In the future we plan to: (i) exploit additional types of data and compose new features to refine the target selection algorithm e.g. metro venues with user counts [20]; (ii) study other routing mechanisms; (iii) evaluate the performance of the offenders with additional metrics e.g. Euclidean and block distance of the traveled path to crime locations [12], and; (iv) study the performance of the implementation for different crimes types.

The presented simulation model can be refined and further developed to include criminal behavior. This would provide a fuller crime simulations to test prevention strategies and the opportunity to predict future crime.

## References

1. Gerritsen, C., Elffers, H.: Investigating prevention by simulation methods. In: LeClerc, B., Savona, E.U. (eds.) Crime Prevention in the 21st Century. Insightful Approaches for Crime Prevention Initiatives. Springer, Cham, Switzerland (2017)
2. Brantingham, P.J., Tita, G.: Offender mobility and crime pattern formation from first principles. In: Liu, L., Eck, J. (eds.) Artificial Crime Analysis Systems. Using Computer Simulations and Geographic Information Systems, Information Science Reference, Hershey, N.Y., London (2008)
3. Birks, D.J., Townsley, M., Stewart, A.: Emergent regularities of interpersonal victimization. an agent-based investigation. J. Res. Crime Delinquency **51**(1), 119–140 (2014)
4. Dray, A., Mazerolle, L., Perez, P., Ritter, A.: Policing Australia's 'heroin drought'. using an agent-based model to simulate alternative outcomes. J. Experimental Criminol. **4**(3), 267–287 (2008)
5. Devia, N., Weber, R.: Generating crime data using agent-based simulation. Comput. Environ. Urban Syst. **42**, 26–41 (2013)
6. Hayslett-McCall, K.L., Qiu, F., Curtin, K.M., Chastain, B., Schubert, J., Carver, V.: The simulation of the journey to residential burglary. In: Liu, L., Eck, J. (eds.) Artificial Crime Analysis Systems. Using Computer Simulations and Geographic Information Systems. Information Science Reference, Hershey, N.Y., London, pp. 281–299 (2008)
7. Gunderson, L., Brown, D.: Using a multi-agent model to predict both physical and cyber criminal activity. In: Proceedings of the IEEE International Conference on Systems, Man and Cybernetics. Cybernetics Evolving to Systems, Humans, Organizations, and their Complex Interactions, vol. 4, Piscataway, pp. 2338–2343 (2000)
8. Peng, C., Kurland, J.: The agent-based spatial simulation to the burglary in Beijing. In: Hutchison, D. et al. (eds.) Computational Science and Its Applications – ICCSA 2014. Lecture Notes in Computer Science, LNCS. Springer, Cham, pp. 31–43 (2014)
9. Malleson, N., Evans, A., Jenkins, T.: An agent-based model of burglary. Environ. Planning B Planning Des. **36**(6), 1103–1123 (2009)
10. Malleson, N., See, L., Evans, A., Heppenstall, A.: Implementing comprehensive offender behaviour in a realistic agent-based model of burglary. Simulation **88**(1), 50–71 (2012)
11. Cohen, L.E., Felson, M.: Social change and crime rate trends: a routine activity approach. Am. Sociol. Rev. **44**(4), 588–608 (1979)
12. Reid, A.A., Frank, R., Iwanski, N., Dabbaghian, V., Brantingham, P.: Uncovering the spatial patterning of crimes. a criminal movement model (CriMM). J. Res. Crime Delinquency **51** (2), 230–255 (2014)

13. Brockmann, D., Hufnagel, L., Geisel, T.: The scaling laws of human travel. Nature **439** (7075), 462–465 (2006)
14. Gonzalez, M.C., Hidalgo, C.A., Barabasi, A.-L.: Understanding individual human mobility patterns. Nature **453**(7196), 779–782 (2008)
15. Song, C., Qu, Z., Blumm, N., Barabasi, A.-L.: Limits of predictability in human mobility. Science (New York, N.Y.) **327**(5968), 1018–1021 (2010)
16. Jurdak, R., Zhao, K., Liu, J., AbouJaoude, M., Cameron, M., Newth, D.: Understanding human mobility from Twitter. PLoS ONE **10**(7), e0131469 (2015)
17. Noulas, A., Scellato, S., Lambiotte, R., Pontil, M., Mascolo, C.: A tale of many cities: universal patterns in human urban mobility. PLoS ONE **7**(5), e37027 (2012)
18. Tappan, P.W.: Who is the Criminal? Am. Sociol. Rev. **12**(1), 96–102 (1947)
19. Calabrese, F., Di Lorenzo, G., Ratti, C.: Human mobility prediction based on individual and collective geographical preferences. In: 2010 13th International IEEE Conference on Intelligent Transportation Systems - (ITSC 2010), pp. 312–317 (2010)
20. Kadar, C., Iria, J., Pletikosa Cvijikj, I.: Exploring Foursquare-derived features for crime prediction in New York City (2016)
21. Chainey, S., Tompson, L., Uhlig, S.: The utility of hotspot mapping for predicting spatial patterns of crime. Secur. J. **21**(1–2), 4–28 (2008)
22. New York State Department of Transportation. A Transportation Profile Of New York State (2012)