# Point process modeling with spatiotemporal covariates for predicting crime

Alex Reinhart, Joel Greenhouse and Xizhen Cai

Carnegie Mellon University

August 3, 2016

# Crime modeling goals

- Police departments need to target resources, and have lots of data
- Hard to answer crime questions: do crimes lead to others? do they repeat? where is crime most likely?

# Crime modeling goals

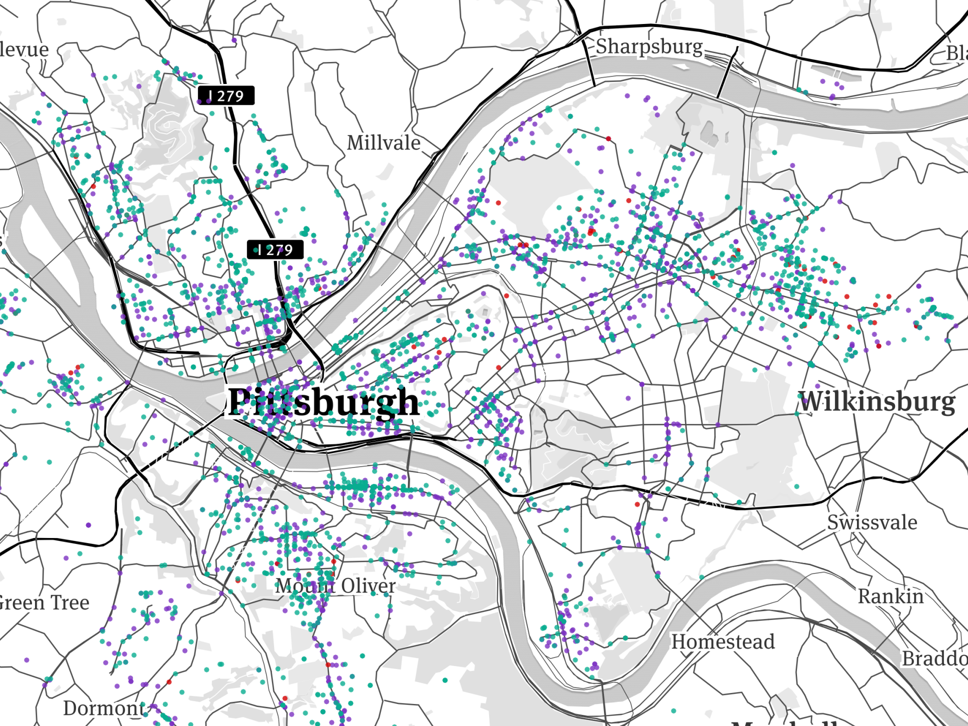
- Police departments need to target resources, and have lots of data
- Hard to answer crime questions: do crimes lead to others? do they repeat? where is crime most likely?

We'd like a model to:

- Accurately predict where crime is most likely
- Understand spatial factors leading to crime
- Analyze crime dynamics (near-repeats, leading indicators)

# Pittsburgh crime data

- Over a million incident reports from 2008 to 2015
- Selected and geocoded 136,573 violent crimes
  - Homicide
  - Assault
  - Robbery
  - Theft
  - Burglary
  - Shots fired and drug 911 calls
  - Drug dealing
- Includes date, time, address of each incident


levue
I 279
Sharpsburg
Bla
Millvale
I 279
Pittsburgh
Wilkinsburg
Swissvale
Mount Oliver
Rankin
Green Tree
Homestead
Braddo
Dormont

# Current state of crime modeling

- Three main approaches:
  - Hotspot models, using previous crime data
  - Regression using spatial factors or leading indicators
  - Near-repeat phenomena

# Current state of crime modeling

- Three main approaches:
  - Hotspot models, using previous crime data
  - Regression using spatial factors or leading indicators
  - Near-repeat phenomena
- No easy way to combine crime data, spatial factors, near-repeat effects
- Limited tools to assess model fit or do variable selection

# Self-exciting point process model

- Developed by Mohler (2014) to use leading indicators and near-repeats
- Crime is caused by two components:
  - A static background $\mu(x, y)$
  - Local increases in risk caused by recent crimes

  Both components are weighted kernel densities, and are fit as a mixture model with EM.

# Self-exciting point process model

- Developed by Mohler (2014) to use leading indicators and near-repeats
- Crime is caused by two components:
  - A static background $\mu(x, y)$
  - Local increases in risk caused by recent crimes

Both components are weighted kernel densities, and are fit as a mixture model with EM.

$$\lambda(x, y, t) = \mu(x, y) + \sum_{\substack{\text{all events } i \\ \text{before time } t}} g(x - x_i, y - y_i, t - t_i, M_i),$$

where $M_i$ indicates the *type* of crime $i$ and $g$ is a kernel.

# The static crime background

The background is a kernel density estimate of all crime:

$$\mu(x, y) = \sum_i \frac{\alpha_{M_i}}{2\pi\eta^2 T} \exp\left(-\frac{(x - x_i)^2 + (y - y_i)^2}{2\eta^2}\right)$$

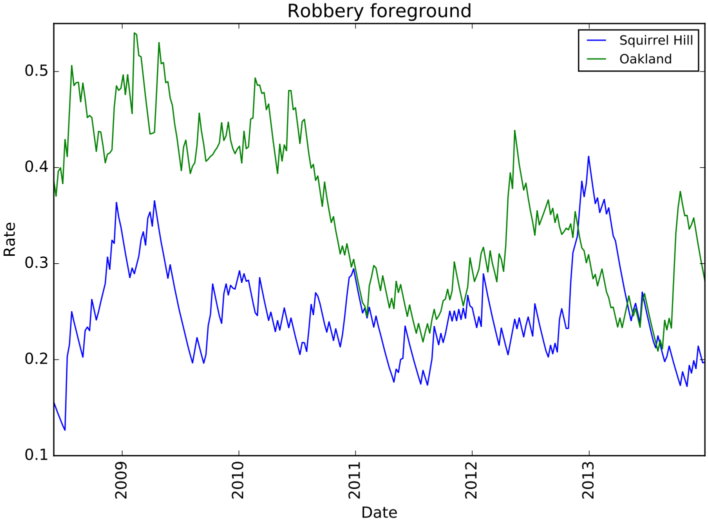
$\alpha$ determines the contribution of each crime type to the target.

# The local crime kernel

$$g(x, y, t, M) = \frac{\theta_M \omega}{2\pi\sigma^2} \exp(-\omega t) \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

$\theta$ determines how each crime type increases the risk of the target. This decays at a rate $\omega$.

# Video




Foreground of robbery in Squirrel Hill and Oakland, week by week

# New model features

- Inference (via asymptotic normality)
- Fixed features: bus stops, bars, liquor stores...
- Model diagnostics and residuals:

$$R(C) = \int_C N(\mathrm{d}t \times \mathrm{d}x \times \mathrm{d}y) - \lambda(x, y, t)\,\mathrm{d}t\,\mathrm{d}x\,\mathrm{d}y$$

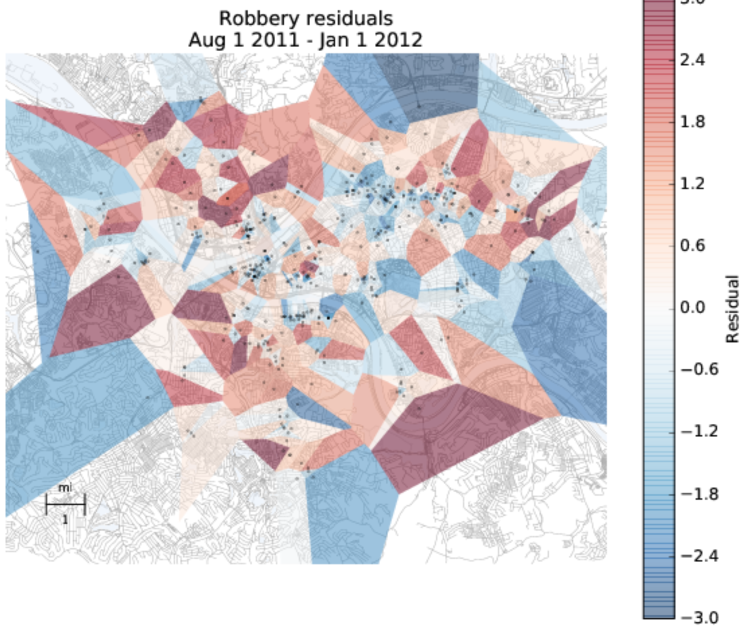
over a space-time cell $C$.

# Example fit parameters

Predicting robbery:

| Parameter | Value | CI |
|---|---|---|
| Time decay | 123 days | [105, 149] |
| Foreground decay | 180 meters | [167, 191] |
| Background decay | 9.2 meters | [8.9, 9.4] |

| Crime | N | Foreground | Background |
|---|---|---|---|
| Robbery | 4756 | 0.19 | 0.18 |
| 911 drugs/shots fired | 19702 | 0.01 | 0.06 |
| Assault | 12521 | 0.02 | 0.05 |
| Firearms offense | 2006 | 0.00 | 0.02 |
| Bus stops | 4048 | - | 0.18 |


Robbery residuals
Aug 1 2011 - Jan 1 2012
mi
1
3.0
2.4
1.8
1.2
0.6
0.0
−0.6
−1.2
−1.8
−2.4
−3.0
Residual

# In-progress extensions

- Covariates on each crime
- Covariates affect how likely each crime is to cause others:

$$\lambda(x, y, t) = \mu(x, y; \xi) + \sum_{\substack{\text{all events } i \\ \text{before time } t}} e^{Z_i \beta} g(x - x_i, y - y_i, t - t_i, M_i)$$

- With parameter inference, allows testing of many criminological hypotheses

# Thanks

- To Pittsburgh Bureau of Police for providing data and expertise
- To the National Institute of Justice for financial support