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An Assessment of Crime Forecasting Models

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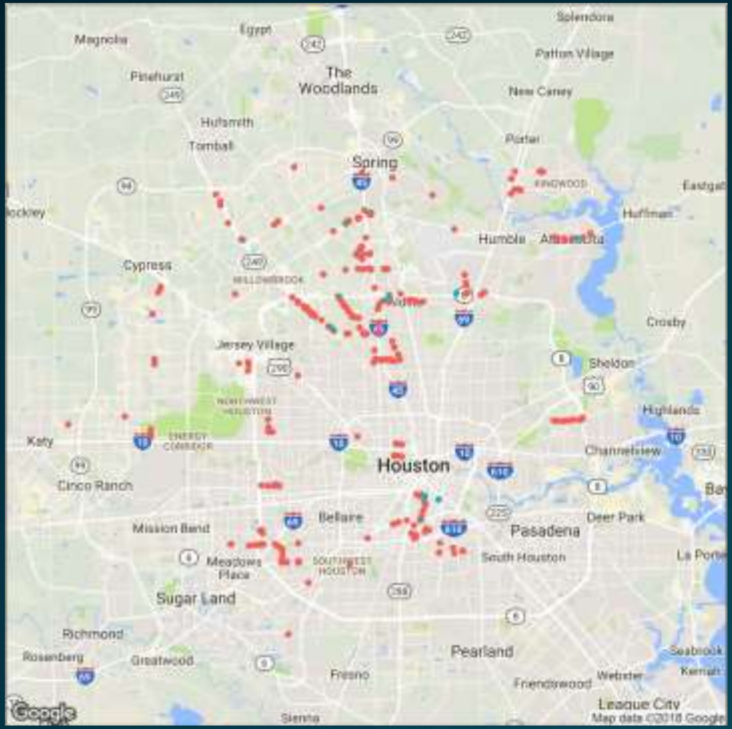
Introduction to Predictive Policing

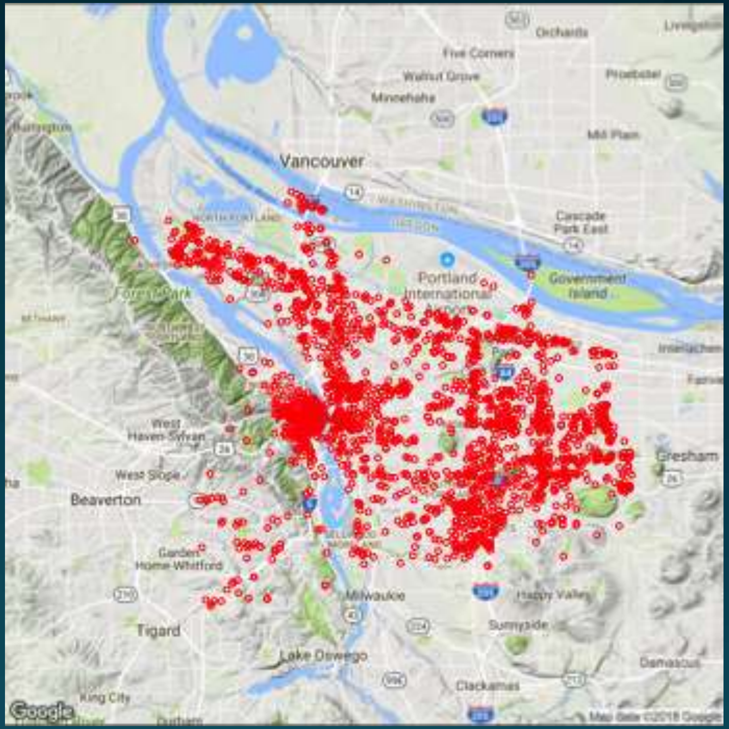
- **Crime is highly clustered - in time and space** (Sherman et al. 1989; Budd 2001; Clark and Eck 2005)
  - **⇒ Random police patrolling is ineffective**
  - **⇒ modern policing concentrates resources in high-risk "hotspots"**
- **Law-enforcement demand + More datasets + Methods/comp. advances**

  = Extremely active development of predictive policing techniques
- **Predictive policing: the application of analytical techniques to identify promising geographical targets for police intervention.**

Introduction to Predictive Policing

- **Applications**
  - **Optimal Inspection Regimes**
  - **Reactive vs Preventative**
- **Clustering:**





Literature

- Many methods
  - Spatial kernel density smoothing (Johnson et al. 2009; Gorr and Lee 2015)
  - Risk-terrain modelling (Caplan et al. 2010)
  - Natural language processing (Wang et al. 2012)
  - Self-exciting point processes (Mohler et al. 2011; Rosser and Cheng 2016)
  - Marked Point Process (Mohler 2014)
  - Deep neural networks (Kang and Kang 2017, Duan et al. 2017)
  - Agent-based crime forecasting (Malleson and Birkin (2012)

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  - Agent-based crime forecasting (Malleson and Birkin (2012)
- **Many implementations**

PREDPOL The Predictive Policing Company

HunchLab

CIVICSCAPE

Literature

- **Many methods**
  - **Spatial kernel density smoothing (Johnson et al. 2009; Gorr and Lee 2015)**
  - **Risk-terrain modelling (Caplan et al. 2010)**
  - **Natural language processing (Wang et al. 2012)**
  - **Self-exciting point processes (Mohler et al. 2011; Rosser and Cheng 2016)**
  - **Marked Point Process (Mohler 2014)**
  - **Deep neural networks (Kang and Kang 2017, Duan et al. 2017)**
  - **Agent-based crime forecasting (Malleson and Birkin (2012)**
- **Few evaluations**

  "there is little consensus in academic circles on how best to assess and compare a new method and systematic evaluation is virtually absent in operational environments" – Adepeju et al. (2016)

Today

- Describe 4 (event-based) crime forecasting techniques
  - State-of-the-art spatio-temporal marked point process method (Mohler 2014)
  - 3 simplified versions – Simple Crime Counts, Hawkes Process, Spatial Model
- Train models on crime data from Portland, Oregon for April-May 2017
- Predict daily crime (calls) to inform daily operations.
- Evaluate comparative performance across multiple days and crimes

Today

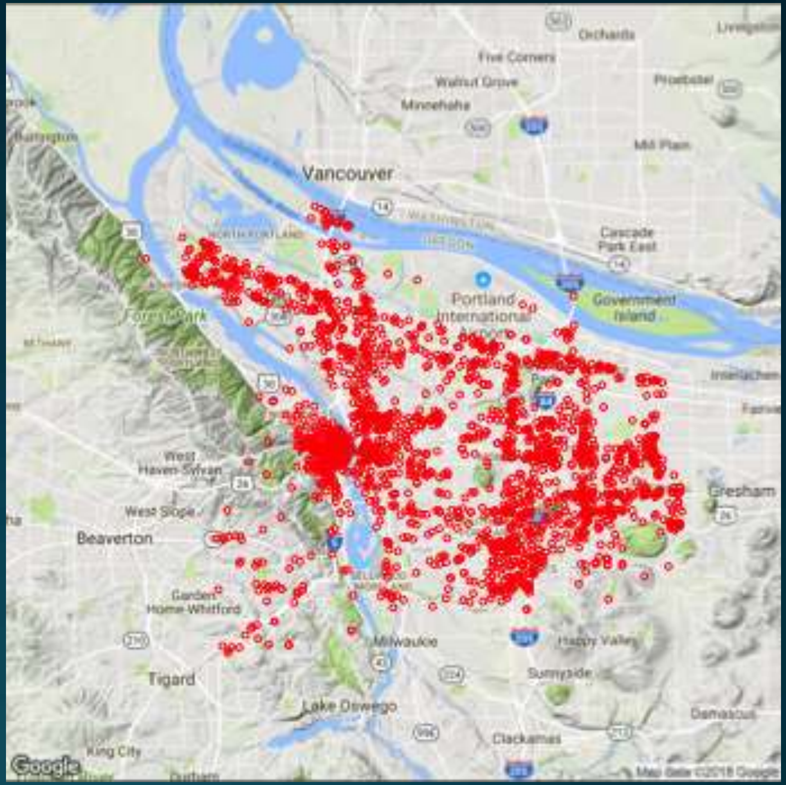
- Describe 4 (event-based) crime forecasting techniques
  - State-of-the-art spatio-temporal self-exciting point process method (Mohler 2014)
  - 3 simplified versions – Simple Crime Counts, Hawkes Process, Spatial Model
- Train models on crime data from Portland, Oregon for April-May 2017
- Predict crime
- Evaluate comparative performance across multiple days and crimes
- Not evaluating:
  - Techniques identifying individuals at risk of offending
  - Methods predicting perpetrators' identities
  - Algorithms predicting victims of crimes
  - Performance against other important criteria like racial bias

Data

- Public data of reported crime occurrences in Portland, OR for April-May 2017
- Provided by the National Institute of Justice for Crime Forecasting Competition
- Example Dataset:

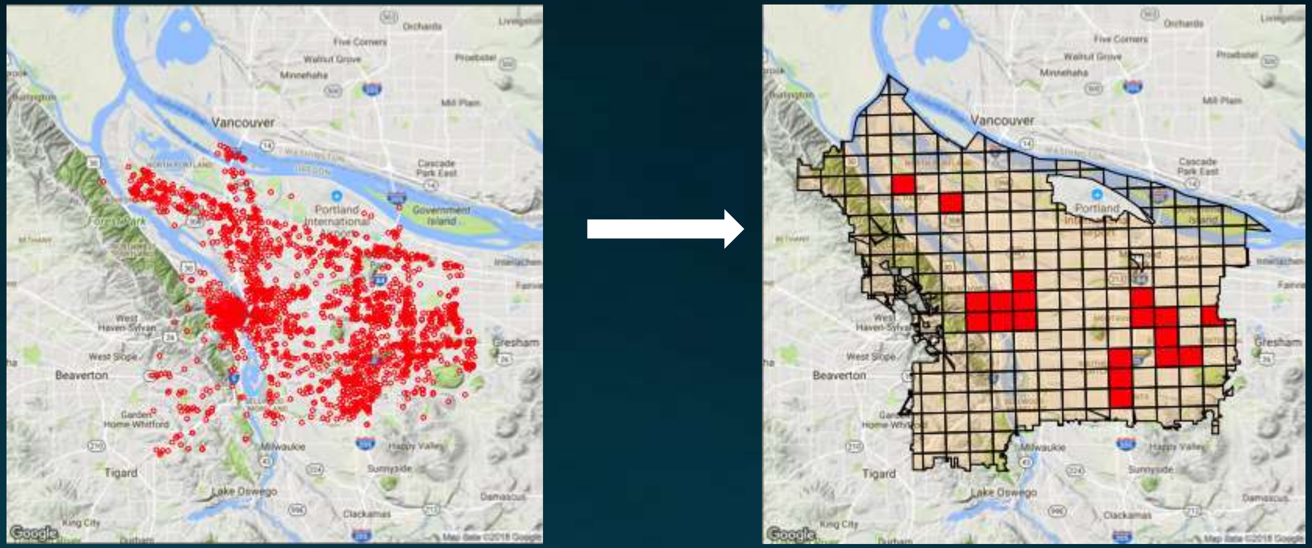
Category	Date	Latitude	Longitude
Burglary	4/5/2017	45.538723	-122.477039

Burglaries April 2017



1. Simple Counts

- **Split geography into grids, $g \in G$**
- G chosen as 600ft x 600ft grids
  - Literature
  - Realistic policing requirements
- $C_g = \sum_i crime_{i,g}$



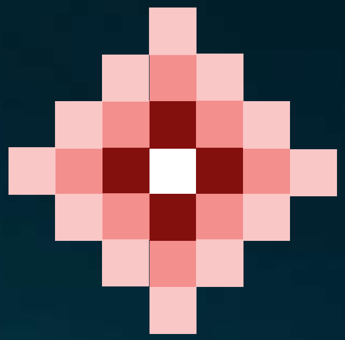
- **Pros:** Simple
  - What (most) PD do; used as benchmark here
- **Cons:** Does not account for spatial or temporal dimension and different crime types

2. Spatial Model (Arraiz et al. 2010)

- Seemingly Unrelated Regression among 4 categories with Spatial Weight

$$y_t^x = \alpha^x + \tau y_{t-1}^x + \rho W y_t^x + \sum_{z \in \{b,m,s,o\},\ z \neq x} \beta^z y_t^z + \varepsilon_t^x, \qquad x \in \{b, m, s, o\}$$

- Weight matrix: k nearest neighbors (k = 24)
- IV: y_{t-1}^c for y_t^c , $c \in \{b, m, s, o\}$
- Split data in 2 equal-sized windows (15-day) to estimate parameters
- Flag hotspots based on $(\hat{y}_t^b, \hat{y}_t^m, \hat{y}_t^s, \hat{y}_t^o)$
- Pros: spatial and (some) temporal dimension and different crime types
- Cons: temporal dimension in a restrictive way (one-period lag) and linear specification



3. Hawkes (1971) Process

- **Extension of simple Poisson λ process.**

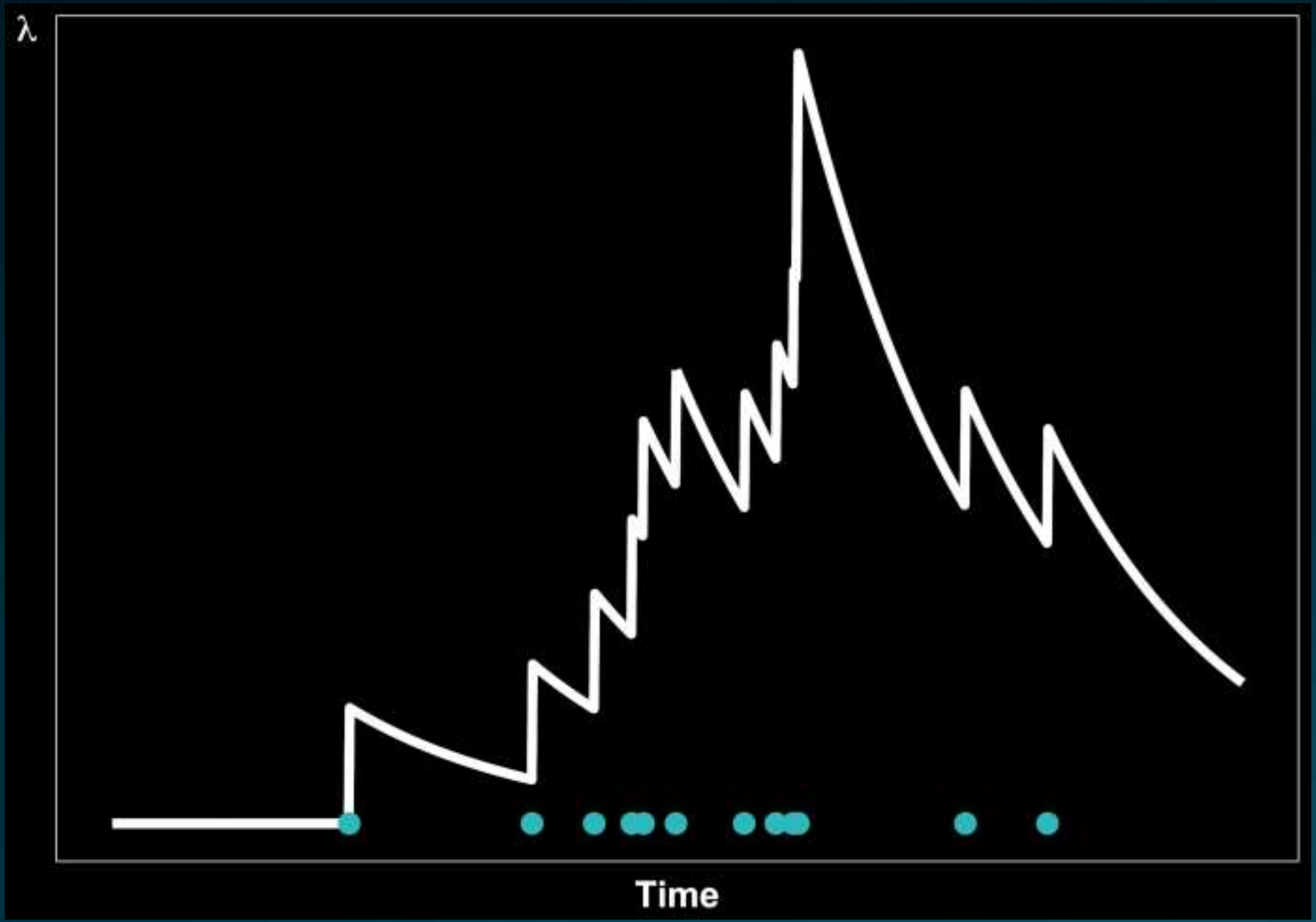
$$\lambda_s(t) = \mu_s + g_s(t)$$

- μ_s: **Background rate → structural difference across grids**
- $g(\cdot) = \sum_{t_i<t} \alpha_s e^{-\beta_s(t-t_i)}$: **Triggering function → near-repeat time effects**

- **Pros: reflects criminology crime clustering explanations like "broken window" theory**
- **Cons: ignores spatial dimension**

3. Hawkes (1971) Process

- **Self-exciting process ⇒ Clustering**



4. Mohler (2014)

- **Marked Point Process**
  - Spatial and temporal dimension
  - Developed for earthquake modeling (Daley and Vere-Jones 1988)
  - Also, different crime types $M = 1, 2, \ldots, N_c$

- **Crime intensity modeled as:**

$$\lambda(x, y, t) = \mu(x, y) + \sum_{t > t_i} g(x - x_i, y - y_i, t - t_i, M_i)$$

  - $\mu(\cdot)$: Background rate → stationary component (intrinsic differences across "grids")
  - $g(\cdot)$: Triggering function → near-repeat effects (space, time, and crime types)

4. Mohler (2014)

- **Triggering function:**

$$g(x, y, t, M) = \theta(M)\omega exp(-\omega t) \times \frac{1}{2\pi\sigma^2} exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

  - Exponential decay in time: ω determines the timescale
  - Gaussian in space: σ controls the length scale

- **Background rate:**

$$\mu(x, y) = \sum_{t>t_i} \frac{\alpha(M)}{T} \frac{1}{2\pi\eta^2} \times exp\left(-((x - x_i)^2 + (y - y_i)^2)/2\eta^2\right)$$

4. Mohler (2014)

- **11 Parameters to estimate:** $(\omega, \sigma, \eta, \theta^b, \ldots, \theta^o, \alpha^b, \ldots, \alpha^o)$

- **Expectation-Maximization (EM) algorithm:**
  - Each crime generated by one of the mixture kernels (with certain probabilities)
  - Convergence: probabilities are proportional to the value of the kernel at the crime space-time location relative to the sum of all kernels at the crime location
  - E-step: determine the probabilities that event i trigger crime j
  - M-step: given probabilities from E-step, updates parameters
  - For a given initial guess, EM algorithm updates the probabilities and the parameters until convergence

4. Mohler (2014)

- Pros:
  - Spatial and temporal dimension and different crime types
  - Models clustering

- Cons:
  - Complex ➔ functional form assumptions and computational costs

Model Hierarchy

Spatial

SEM:
$\mu(s) + g(s - s_i)$

Mohler:
$\mu(s) + g(t - t_i, s - s_i)$

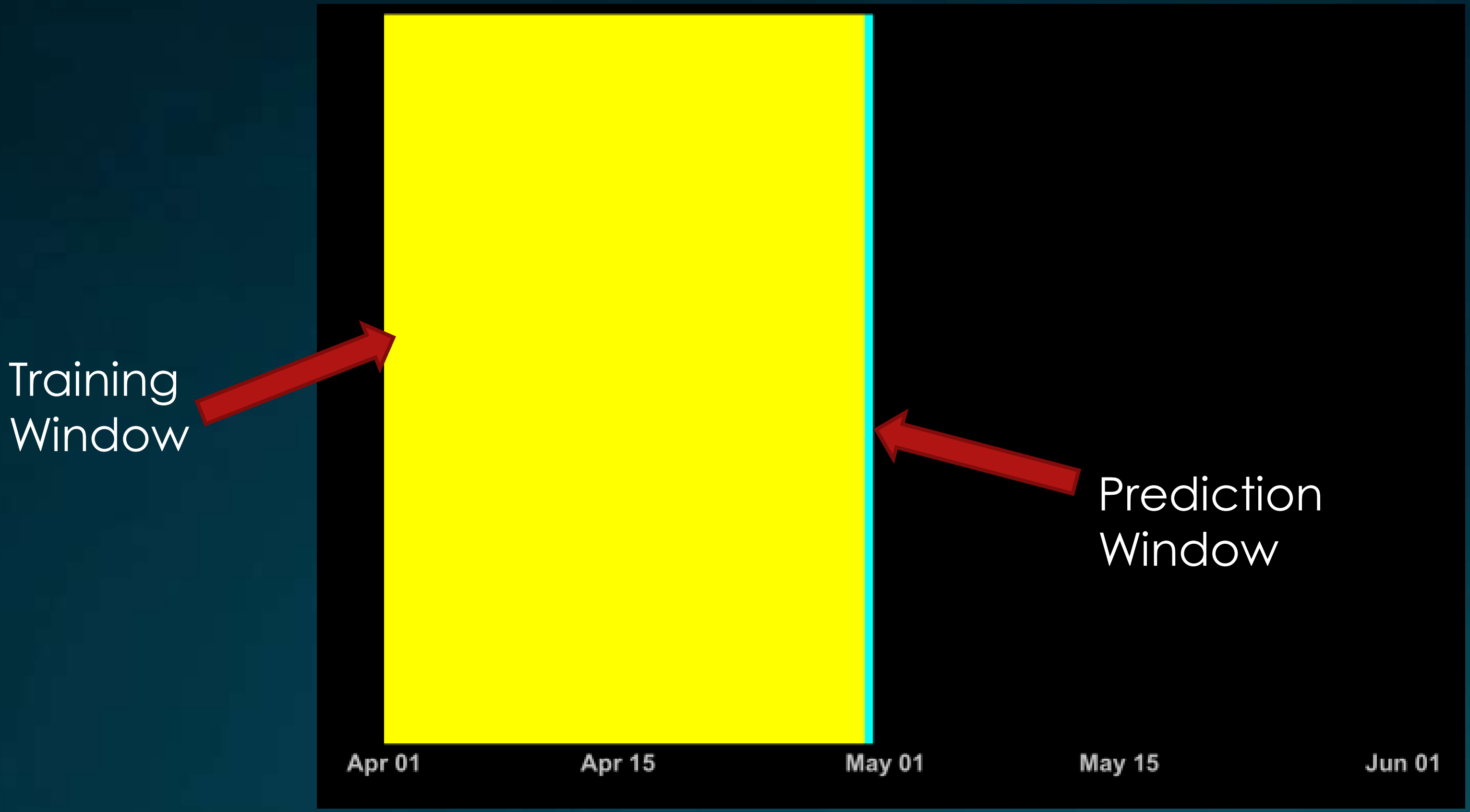
Simple Counts:
$\mu(s)$

Hawkes Process:
$\mu(s) + g(t - t_i)$

Temporal

Forecast Approach

- **1 day prediction window (consistent with police practice) through May 2017**
- **30-day rolling training window**



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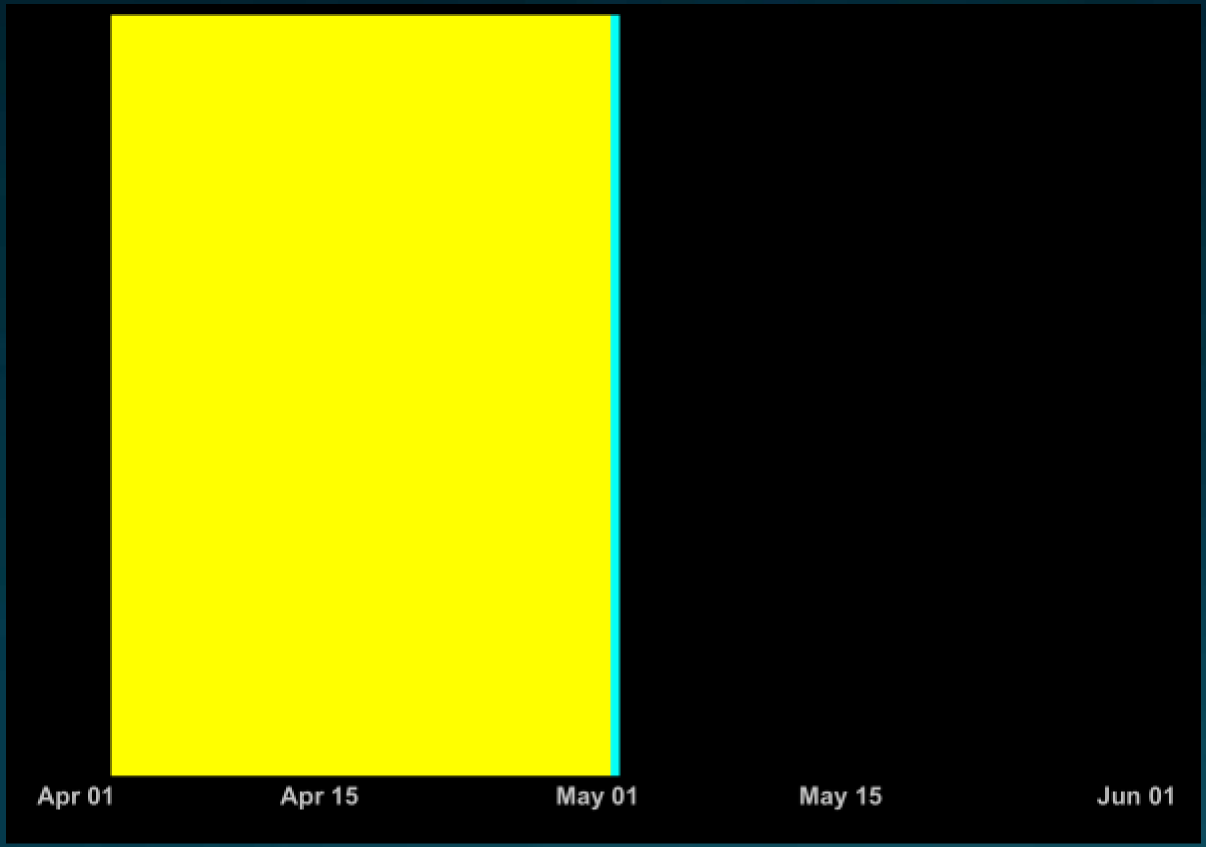

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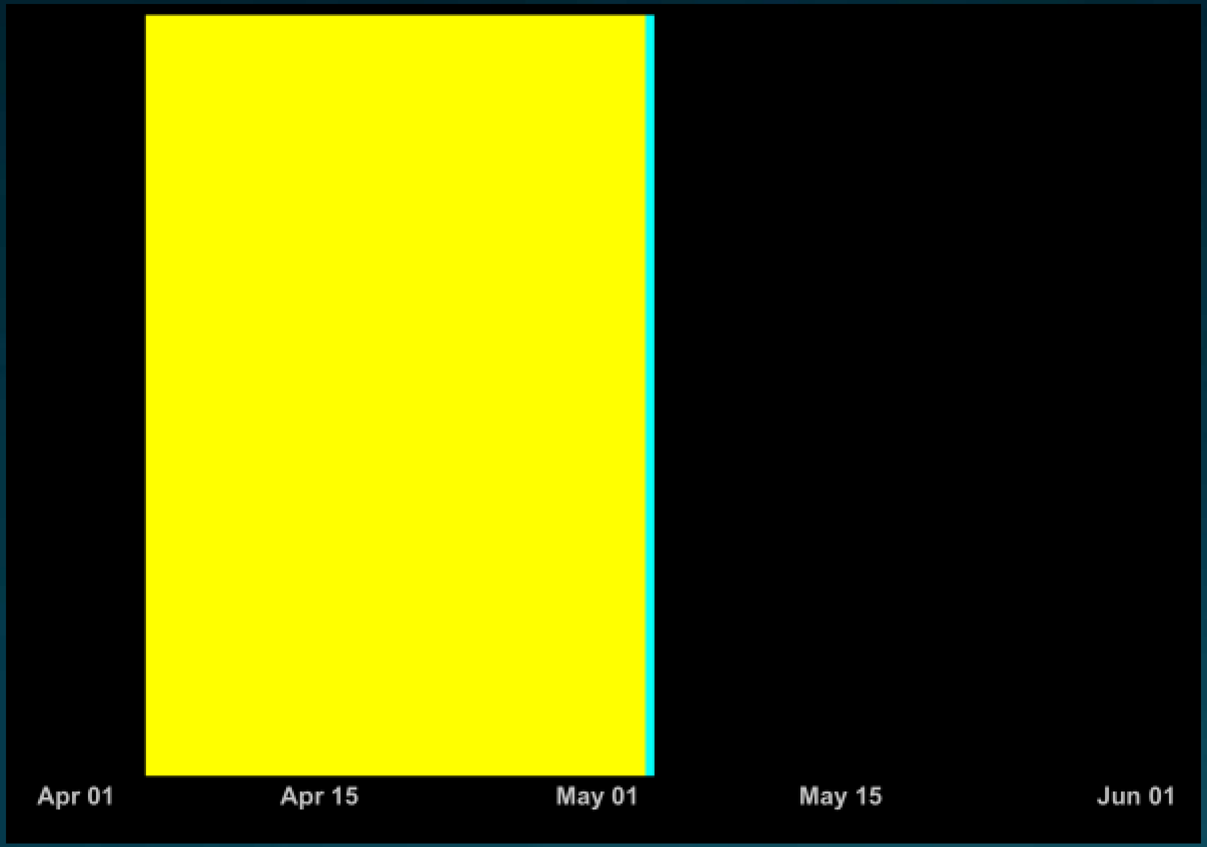

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- 1 day prediction window through May 2017
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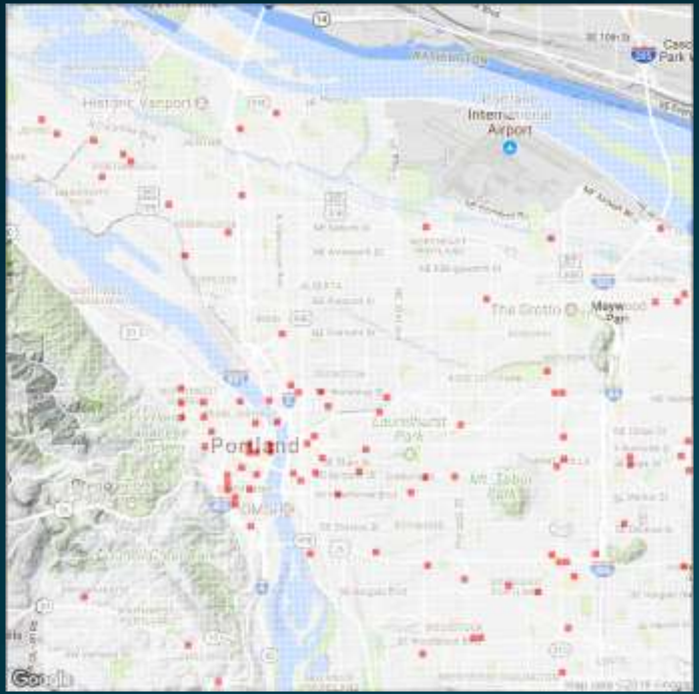
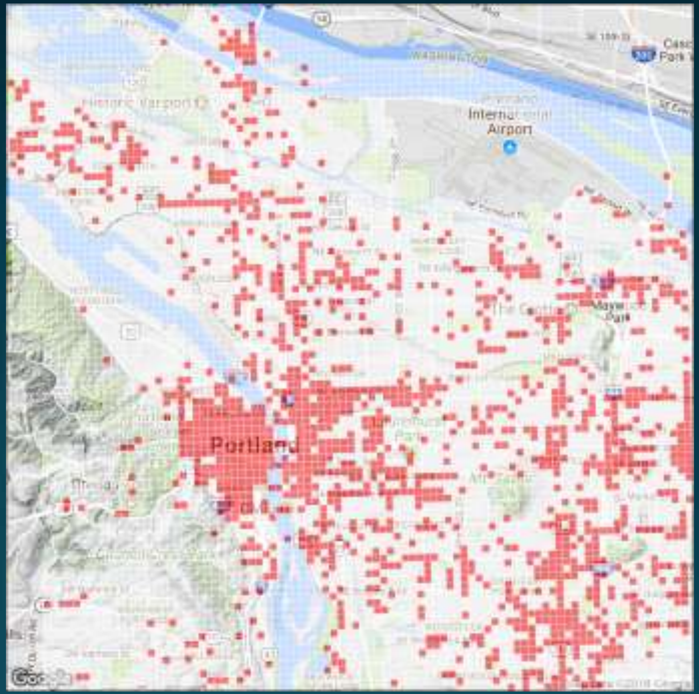
- 600ft x 600ft grids ($\approx 12,000$ grids)

Forecast Approach

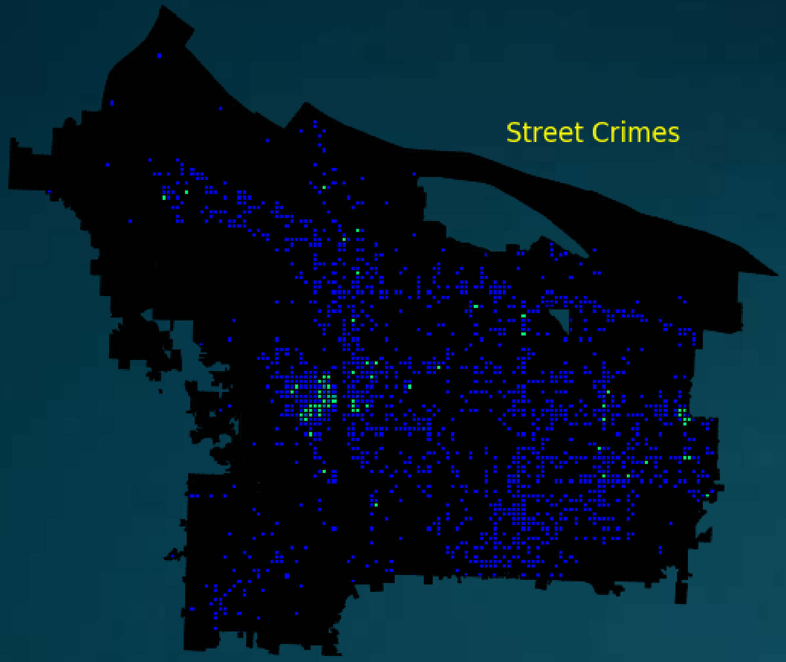
- 1 day prediction window through May 2017
- 30-day rolling training window
- 600ft x 600ft grids ($\approx 12,000$ grids)
- 2 coverage areas: 1% (≈ 120 hotspots) and 15% (≈1,800 hotspots)

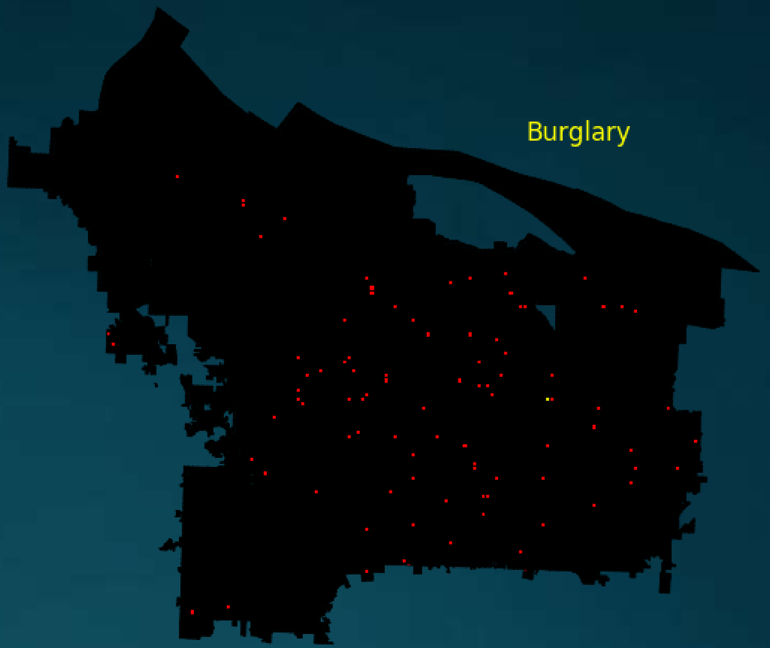




Forecast Approach

- 1 day prediction window through May 2017
- 30-day rolling training window
- 600ft x 600ft grids ($\approx 11,000$ grids)
- Two crime types: Street Crime, Burglary





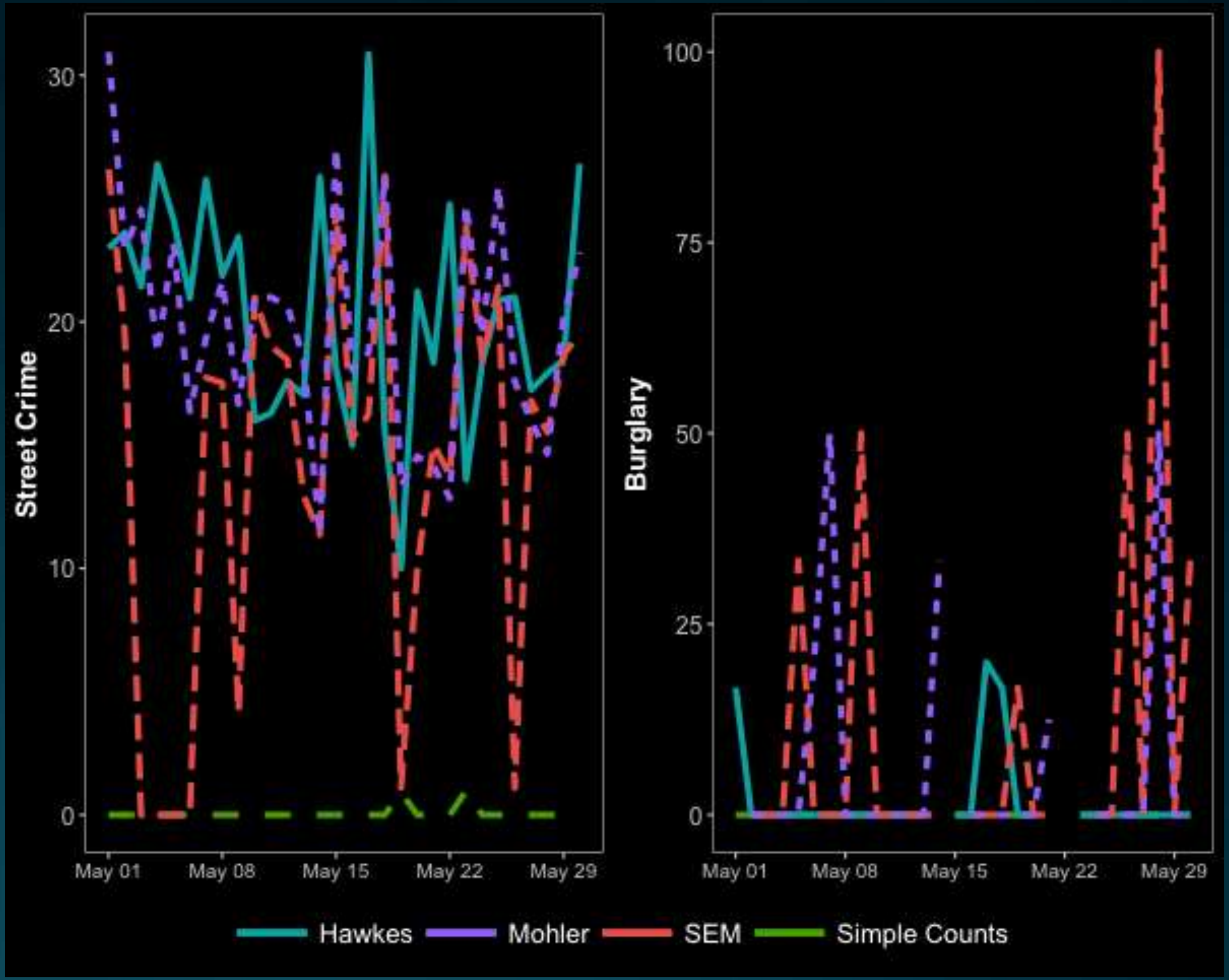
Forecast Metrics

- **Traditional Forecast/Prediction Evaluation Methods: MAE, RMSE**
  - Evaluate entire space and time domain ⇒ unsuitable for sparse (many-zero) crime data
- **Hit Rate:** $HR = \frac{n}{N}$
  - Simple, intuitive. Can be artificially inflated by increasing hotspot size, limited practical use for policing.
- **Predictive Accuracy Index:** $PAI = \left(\frac{n}{N}\right) / \left(\frac{a}{A}\right)$
  - Crime density in hotspots / crime density over the whole region. Hit Rate that accounts for coverage area
- **Prediction Efficiency Index:** $PEI = \frac{n}{n^*}$
  - Performance of forecast compared to optimal (ex-post) solution
  - n^*: maximum number of crimes that can be captured within k grids, where k is the number of hotspots.

Graphical Results

PAI - 1% Coverage

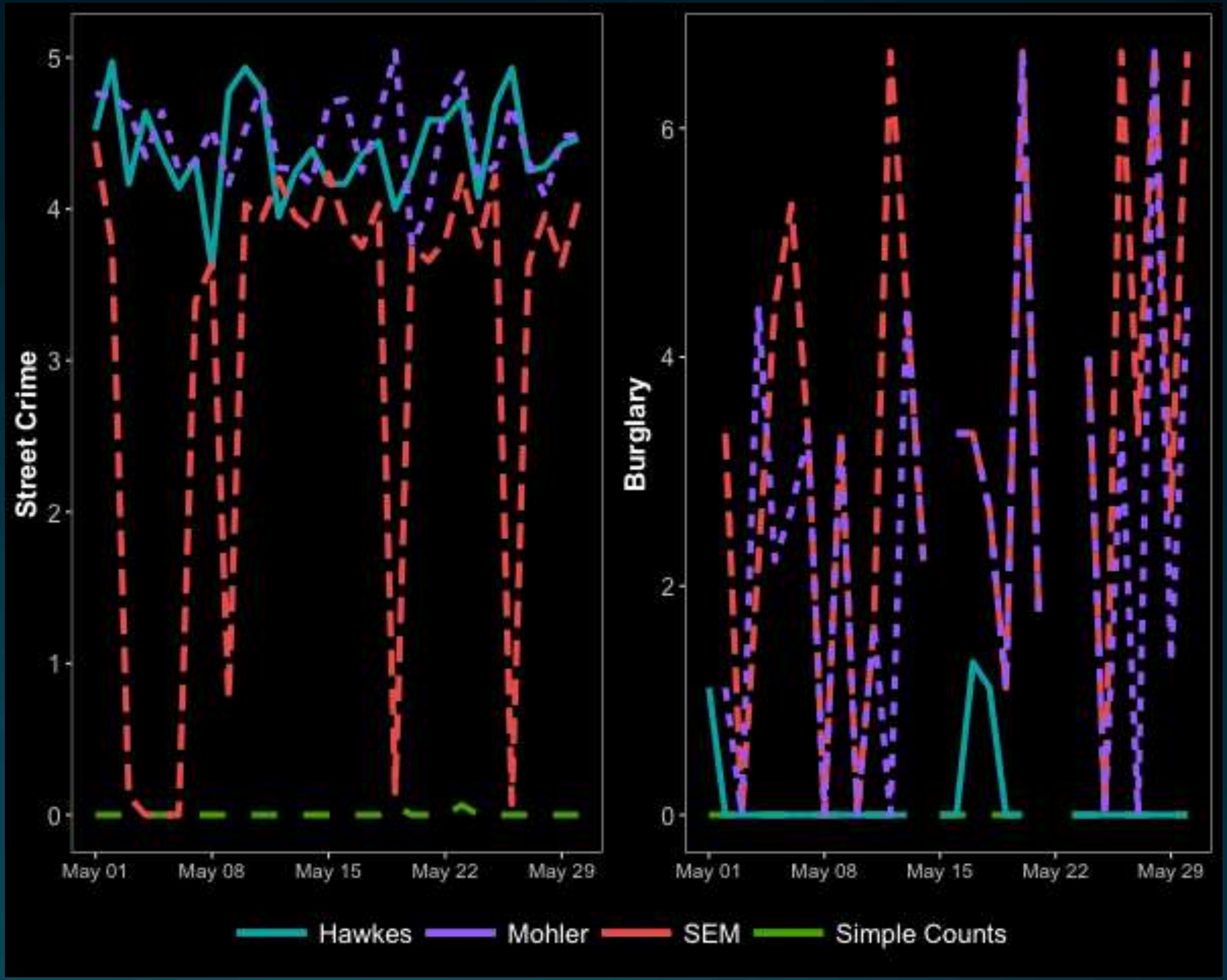
- $PAI = \frac{n}{N}\frac{1}{0.01}$



Graphical Results

PAI - 15% Coverage

- $PAI = \frac{n}{N}\frac{1}{0.15}$
- Smaller magnitude than 1% coverage
- Conjecture:
  - "Emotional" crimes better predicted by temporal models
  - "Planned" crimes better predicted by spatial models.



Analytical Results

1% Coverage

		PAI	
Crime Type		Mean	SD
Street Crime	Simple Counts	0.063	0.239
	SEM	14.178	8.377
	Hawkes	**20.370**	**4.552**
	Mohler	19.749	4.653
Burglary	Simple Counts	0.000	0.000
	SEM	**10.900**	**24.006**
	Hawkes	1.975	5.717
	Mohler	6.377	14.977

15% Coverage

		PAI	
Crime Type		Mean	SD
Street Crime	Simple Counts	0.004	0.016
	SEM	3.030	1.631
	Hawkes	4.407	0.317
	Mohler	**4.456**	**0.293**
Burglary	Simple Counts	0.000	0.000
	SEM	**3.299**	**2.197**
	Hawkes	0.132	0.381
	Mohler	2.461	1.960

Sign Test

- Comparing mean values hides inherent variability in results, especially with techniques designed to improve upon averaging methods.
- **Wilcoxon signed-rank test**
  - **Consider values as time series**
  - **Assumption: Difference in predictive accuracy between methods is independent of underlying crime rate ⇒ time series of differences are i.i.d.**

$$W = \sum_{t=1}^{T} sgn\left(y_{2,t} - y_{1,t}\right) \cdot R_t$$

- $T = 30$, $y_{i,t}$ = relevant accuracy measure (HR, PAI, or PEI) of method i for day t, R_t = rank of the difference and $sgn(\cdot)$ is the sign function

Formal Results

		1% Coverage		15% Coverage	
Crime Type	Method	> Simple Count	> Mohler	> Simple Count	> Mohler
Street Crime	Simple Counts	-	NS	-	NS
	SEM	***	NS	***	NS
	Hawkes	***	NS	***	NS
	Mohler	***	-	***	-
Burglary	Simple Counts	-	NS	-	NS
	SEM	*	NS	***	*****
	Hawkes	*	NS	*	NS
	Mohler	*	-	***	-

* = statistical significance at 10% level and 1% level, respectively.
NS = Not statistically significant

Conclusion/Extensions

- **Formalize model connections**
- **Expand list of models**
- **Extend training windows (perhaps with HPC)**
- **Formally train (rather than estimate) model parameters**
- **Extension of Mohler (2014):**
  - **Moving away from Gaussian assumption for triggering function**
  - **Distributions that allow for rare events (i.e., fat tails)**