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:
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)
- Agent based crime forecasting (Malleson and Birkin 2012)
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)
  - Agent based crime forecasting (Malleson and Birkin 2012)

• **Many implementations**
Literature

- **Many methods**
  - Spatial kernel density smoothing (Johnson et al. 2009; Gorr and Lee 2015)
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- **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:**

<table>
<thead>
<tr>
<th>Category</th>
<th>Date</th>
<th>Latitude</th>
<th>Longitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Burglary</td>
<td>4/5/2017</td>
<td>45.538723</td>
<td>-122.477039</td>
</tr>
</tbody>
</table>

Burglaries April 2017
1. Simple Counts

- **Split geography into grids,** \( g \in G \)
- **\( G \) chosen as 600ft x 600ft grids**
  - Literature
  - Realistic policing requirements
- \( C_g = \sum_i \text{crime}_{i,g} \)

- **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**

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

- **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 $\lambda$ process.

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

- $\mu_s$: Background rate $\rightarrow$ structural difference across grids
- $g(t) = \sum_{t_i < t} \alpha_s e^{-\beta_s(t-t_i)}$: Triggering function $\rightarrow$ 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 $\Rightarrow$ 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 $\rightarrow$ stationary component (intrinsic differences across “grids”)
- $g(\cdot)$: Triggering function $\rightarrow$ 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: \(\omega\) determines the timescale
- Gaussian in space: \(\sigma\) 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
Forecast Approach

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Forecast Approach

- 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 (≈ 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 (≈ 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

- \( PAI = \frac{n}{N \times 0.01} \)
Graphical Results

PAI - 15% Coverage

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

## 1% Coverage

<table>
<thead>
<tr>
<th>Crime Type</th>
<th>PAI</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Street Crime</td>
<td>Simple Counts</td>
<td>0.063</td>
<td>0.239</td>
</tr>
<tr>
<td></td>
<td>SEM</td>
<td>14.178</td>
<td>8.377</td>
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<tr>
<td></td>
<td>Hawkes</td>
<td>20.370</td>
<td>4.552</td>
</tr>
<tr>
<td></td>
<td>Mohler</td>
<td>19.749</td>
<td>4.653</td>
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</table>

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<th>SD</th>
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</thead>
<tbody>
<tr>
<td>Burglary</td>
<td>Simple Counts</td>
<td>0.004</td>
<td>0.016</td>
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<tr>
<td></td>
<td>SEM</td>
<td>3.030</td>
<td>1.631</td>
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<tr>
<td></td>
<td>Hawkes</td>
<td>4.407</td>
<td>0.317</td>
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<tr>
<td></td>
<td>Mohler</td>
<td>4.456</td>
<td>0.293</td>
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## 15% Coverage

<table>
<thead>
<tr>
<th>Crime Type</th>
<th>PAI</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Street Crime</td>
<td>Simple Counts</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>SEM</td>
<td>10.900</td>
<td>24.006</td>
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<td></td>
<td>Hawkes</td>
<td>1.975</td>
<td>5.717</td>
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<tr>
<td></td>
<td>Mohler</td>
<td>6.377</td>
<td>14.977</td>
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<tr>
<td>Burglary</td>
<td>Simple Counts</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>SEM</td>
<td>3.299</td>
<td>2.197</td>
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<tr>
<td></td>
<td>Hawkes</td>
<td>0.132</td>
<td>0.381</td>
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<tr>
<td></td>
<td>Mohler</td>
<td>2.461</td>
<td>1.960</td>
</tr>
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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.
  
  \[ W = \sum_{t=1}^{T} \text{sgn}(y_{2,t} - y_{1,t}) \cdot R_t \]

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

<table>
<thead>
<tr>
<th>Crime Type</th>
<th></th>
<th>1% Coverage</th>
<th></th>
<th>15% Coverage</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Method</td>
<td>&gt; Simple Count</td>
<td>&gt; Mohler</td>
<td>&gt; Simple Count</td>
<td>&gt; Mohler</td>
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<td>Street Crime</td>
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<tr>
<td>Simple Counts</td>
<td>-</td>
<td>NS</td>
<td>-</td>
<td>NS</td>
<td></td>
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<tr>
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<td>***</td>
<td>NS</td>
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</table>

* 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)