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))
Many methods

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

- **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>
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**

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

- **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

- $g(\cdot) = \sum_{t_i < t} \alpha_s e^{-\beta_s(t-t_i)}$: 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:**
  \[
  \mu(x, y) = \sum_{t>t_i} \frac{\alpha(M)}{T} \frac{1}{2\pi\eta^2} \times \exp\left(-\frac{(x-x_i)^2+(y-y_i)^2}{2\eta^2}\right)
  \]
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

Simple Counts:
\[ \mu(s) \]

SEM:
\[ \mu(s) + g(s - s_i) \]

Hawkes Process:
\[ \mu(s) + g(t - t_i, s - s_i) \]

Mohler:
\[ \mu(s) + g(t - t_i, s - s_i) \]
Forecast Approach

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

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- 600ft x 600ft grids (≈ 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 ($\approx 11,000$ 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

\[ PAI = \frac{n \cdot 1}{N \cdot 0.01} \]
Graphical Results

PAI - 15% Coverage

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

<table>
<thead>
<tr>
<th>Crime Type</th>
<th>PAI</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Street Crime</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Simple Counts</td>
<td>Mean</td>
<td>0.063</td>
<td>0.239</td>
</tr>
<tr>
<td>SEM</td>
<td>SD</td>
<td>14.178</td>
<td>8.377</td>
</tr>
<tr>
<td><strong>Hawkes</strong></td>
<td></td>
<td>20.370</td>
<td>4.552</td>
</tr>
<tr>
<td>Mohler</td>
<td></td>
<td>19.749</td>
<td>4.653</td>
</tr>
<tr>
<td><strong>Burglary</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Simple Counts</td>
<td>Mean</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>SEM</td>
<td>SD</td>
<td>10.900</td>
<td>24.006</td>
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<tr>
<td><strong>Hawkes</strong></td>
<td></td>
<td>1.975</td>
<td>5.717</td>
</tr>
<tr>
<td>Mohler</td>
<td></td>
<td>6.377</td>
<td>14.977</td>
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<tr>
<td><strong>Street Crime</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Simple Counts</td>
<td>Mean</td>
<td>0.004</td>
<td>0.016</td>
</tr>
<tr>
<td>SEM</td>
<td>SD</td>
<td>3.030</td>
<td>1.631</td>
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<tr>
<td><strong>Hawkes</strong></td>
<td></td>
<td>4.407</td>
<td>0.317</td>
</tr>
<tr>
<td>Mohler</td>
<td></td>
<td>4.456</td>
<td>0.293</td>
</tr>
<tr>
<td><strong>Burglary</strong></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Simple Counts</td>
<td>Mean</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>SEM</td>
<td>SD</td>
<td>3.299</td>
<td>2.197</td>
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<tr>
<td><strong>Hawkes</strong></td>
<td></td>
<td>0.132</td>
<td>0.381</td>
</tr>
<tr>
<td>Mohler</td>
<td></td>
<td>2.461</td>
<td>1.960</td>
</tr>
</tbody>
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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.

\[
W = \sum_{t=1}^{T} sgn(y_{2,t} - y_{1,t}) \cdot R_t
\]

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

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