Ethics & Biases of Big Data-Decision Making: Predictive Policing

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What is Big Data Decision-Making?

- Examples:
  - Using a FitBit
  - Deciding whom to date
  - Deciding what colleges are worth attending*
  - Deciding whether a convicted criminal is likely to re-offend*

* Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy, Cathy O'Neil

Ethics for Big Data Decision-Making:

When is it “ethical” to use big data to inform decision making?*

1. Is the model **interpretable** and **transparent** to those involved and affected?
2. Can the model be **scaled** outside of its intended application?
3. Does this model have the potential of **creating damage**?

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Biases of Big Data Decision-Making

What are potential fallibilities of using a machine learning model to inform decisions?

- Flaws in the data
- Flaws in the algorithm
- Flaws in interpretation

Predictive Policing Case Study

Based on the **PredPol** software company and **existing research** in the field

Predictive Policing

- Using police record data to understand crime patterns
- PredPol, LASER, Azavea, KeyStats
- L.A., N.Y.C., Chicago, + more

*Predictive Policing Explained, Tim Lau (Brennan Center for Justice)

Ethics of Predictive Policing

- Transparency?
- Scalability?
- Damage?

*Predictive Policing Explained, Tim Lau (Brennan Center for Justice

Biases of Predictive Policing

- Does predictive policing software avoid problematic biases?
  - Training Data bias
  - Algorithmic Focus bias
  - Interpretation bias
  - Feedback loop bias
- How can we conceptualize how these biases could play a role?

Creating a Predictive Policing Algorithm

Based on ***To Predict and Serve?*** and ***Randomized Controlled Field Tests of Predictive Policing***

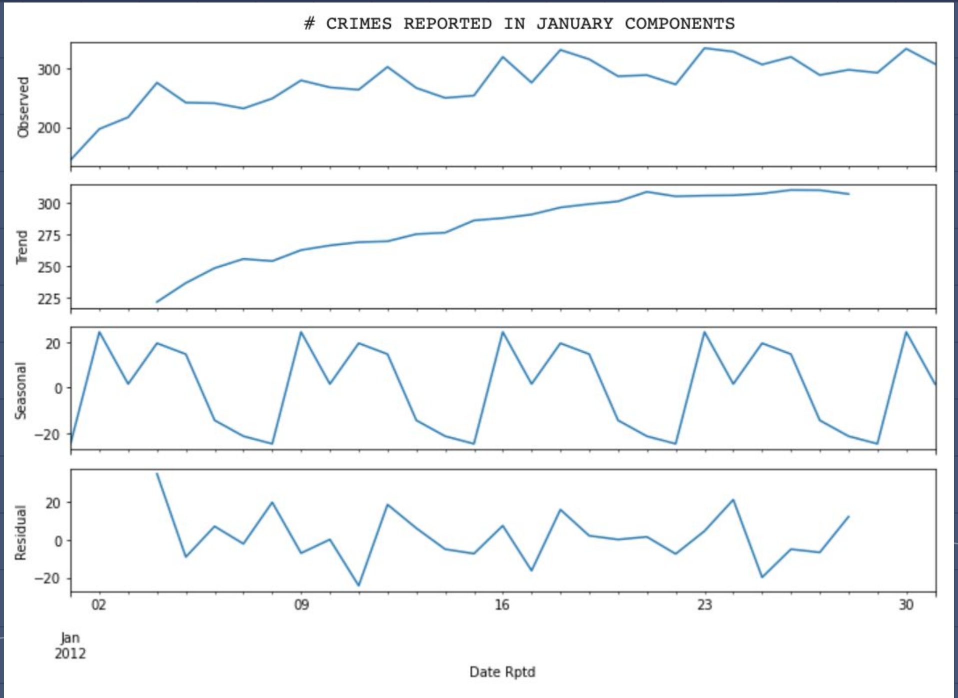
Data

- L.A. crime data for January, 2012 (from police reports)
- From L.A.'s Open Data initiative*
- Excludes crimes not tagged with locations

*https://data.lacity.org/

Predictive Model

- Holt-Winters exponential smoothing model
  - Positive trend
  - Seasonal component (week)
  - Weighs recent data more
- Applied on a *rolling basis*



Training Data/Reporting Bias

- Is police reporting data representative?
  - Rates of report vary across demographics[1]
  - Trust in police correlated with likelihood of report[1]
  - Example:
    - Center for Public Integrity identified major discrepancy between # of sexual assaults reported by universities across U.S. and # of sexual assaults reflected by victim-support groups/resources on campus[2]

1 Predictive Policing: Bias in, Bias Out, Kristian Lum
2 The Mismeasure of Crime, Clayton Mosher, Terance Miethe, and Timothy Hart

Interpretation Bias

- What is a predictive policing model predicting?
  - Training data for model is police reports
  - Model is predicting **where crime is likely to be reported**
  - Model's output interpreted as **where crime is likely to occur**

Algorithmic Focus Bias

- What crimes does predictive policing aim to “catch”?
- Part 1 vs. Part 2 crimes highly correlated, but Part 2 crimes often endemic to low-income neighborhoods*
- Part 2 crimes easier to predict*

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CORRELATION FOR # PART 1 and # PART 2 CRIMES REPORTED:
________________________________________________________________________
Correlation Coefficient btw # PART 1 and # PART 2 CRIMES REPORTED: 0.9375599920574694
P-Value for Correlation btw # PART 1 and # PART 2 CRIMES REPORTED: 3.344385327092054e-76
Correlation btw # PART 1 and # PART 2 CRIMES REPORTED: Very high significant
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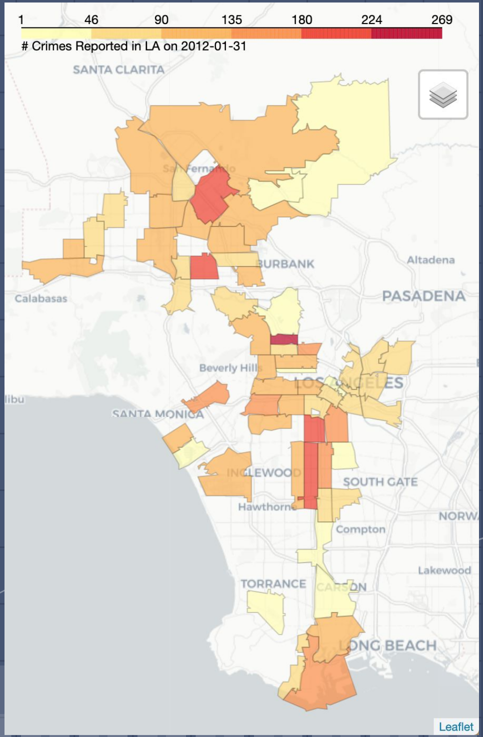
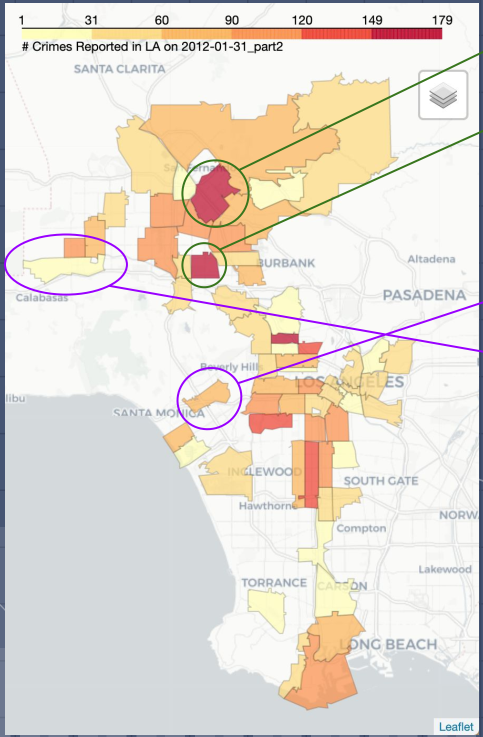
Running the Model on Part 1 vs. Part 2 Crimes:

ONLY PART 1



ONLY PART 2



<u>LOW PART 1, HIGH PART 2:</u>

91401: Median income: $46,420
46% Black, 43% Latinx

91331: Median income: $51,477
88% Latinx

<u>HIGH PART 1, LOW PART 2:</u>

90064: Median income: $84,578
61% white

91367: Median income: $76,548
68% white

Support for the theory that location-based technique still reinforces racial/socioeconomic bias

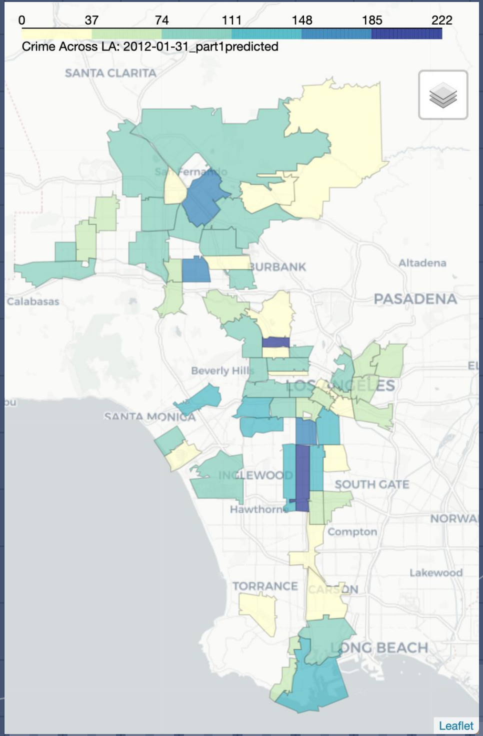
*https://www.unitedstateszipcodes.org/
*http://www.laalmanac.com/population/po24la_zip.php

Runaway Feedback Loops

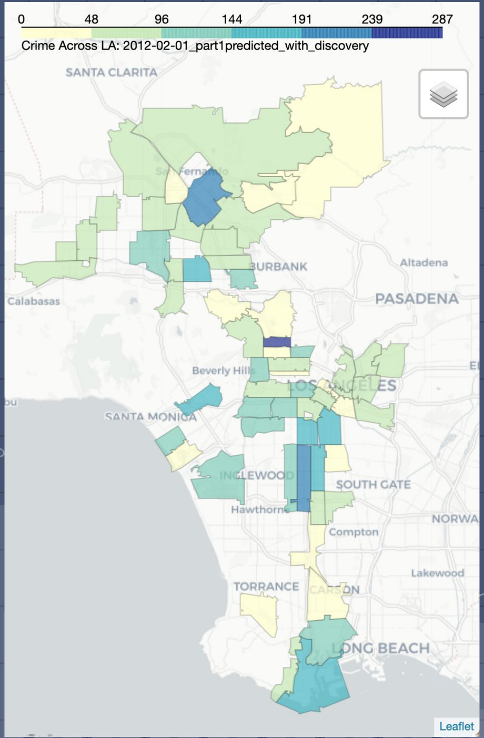
- For each day, assume that the algorithm sends L.A.P.D. to the ZIP codes predicted to have the most crime from previous day’s data
- Because L.A.P.D. is in particular ZIP codes, they are more likely to *discover* crime there
- Re-run model and increase number of crimes reported in highly-predicted ZIP codes by 20% for each day

Running the Model after adding "Discovered" Crimes

WITHOUT DISCOVERY

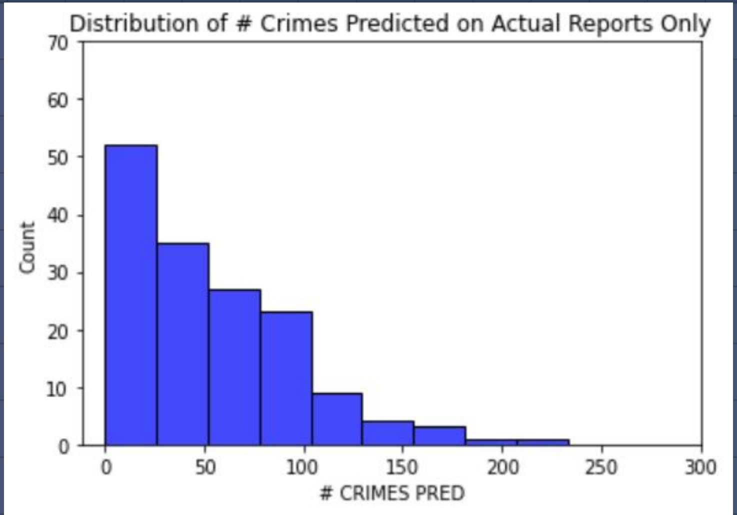


WITH DISCOVERY



Analyzing Including Discovered Crimes

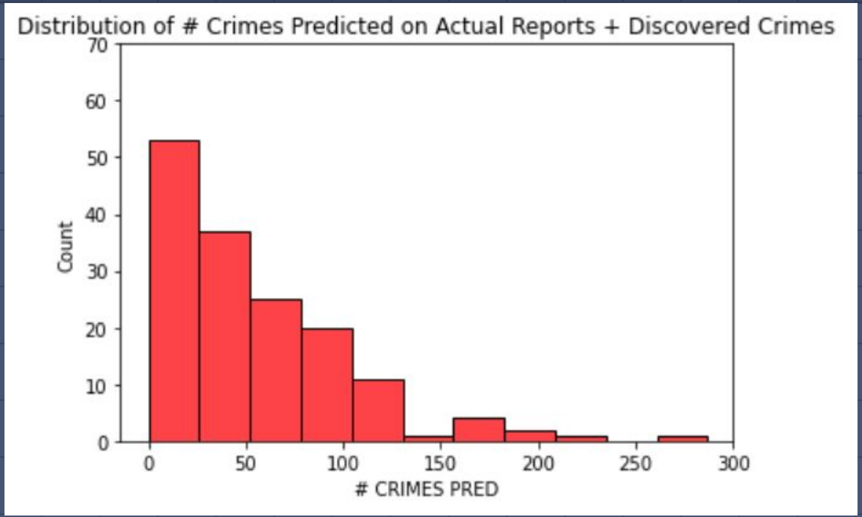
WITHOUT DISCOVERY



Stats for Crimes Predicted Across Zipcodes Based Only on Actual Reports:

Mean: 49.303225806451614
Range: 0.0, 233.0
Standard Deviation: 46.7903180215941
Variance: 2189.333860561914

WITH DISCOVERY



Stats for Crimes Predicted Across Zipcodes Based on Actual Reports and "Discovered" Crimes:

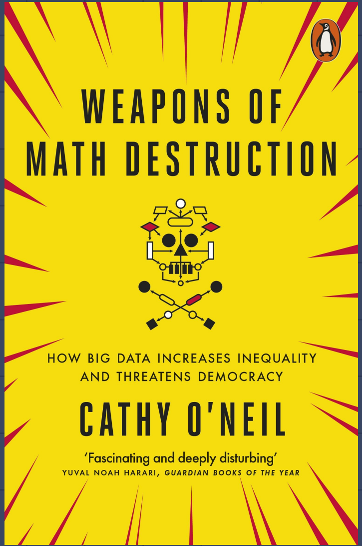
Mean: 49.883870967741935
Range: 0.0, 287.0
Standard Deviation: 50.251747501465985
Variance: 2525.238126951093

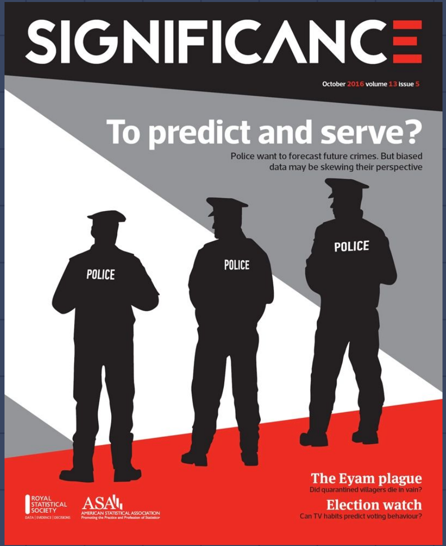
Effects of including discovered crimes: higher average crime prediction, greater spread across ZIP codes, top ZIP codes have much higher # crimes predicted

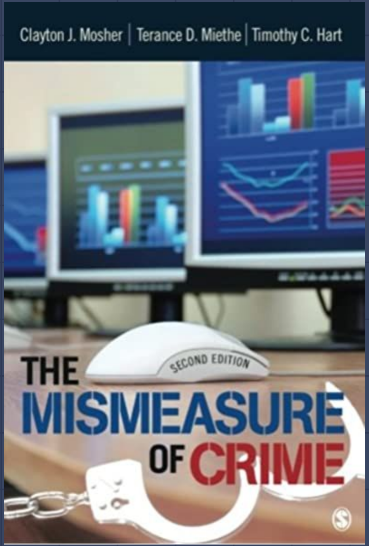
Findings & Limitations:

- Predictive policing models could be construed as unethical
- Predictive policing models susceptible to training data, interpretation, algorithmic focus, and feedback loop bias which could significantly affect the results and outcome of this tech
- Model is same category as most predictive policing algorithms but a simple version
- L.A. data has been digitized from handwritten police reports, so potential errors in this process may influence the result
- Next steps: different models, different cities, different times

Resources







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