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Splunking Crime Part II — Analyzing Bias in Police Actions

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Who are We?

NCC Group is a security consultancy and advisory business helping to solve complex security challenges day in and day out.

Our Ninjas are based worldwide and passionate about making the internet safer and revolutionizing the way in which organizations think about cyber security.

- United Kingdom
- Manchester (HQ)
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- Cambridge
- Edinburgh
- Glasgow
- Leatherhead
- Leeds
- Milton Keynes
- Reading

- Europe
- Denmark
- Germany
- Lithuania
- Spain
- Switzerland
- Netherlands (Amsterdam)
- Netherlands (Delft)
- Netherlands(The Hague)

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- Austin, TX
- Boston, MA
- Campbell, CA
- Chicago, IL
- New York, NY
- San Francisco, CA
- Seattle, WA
- Sunnyvale, CA
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- Asia Pacific
- Sydney
- Singapore
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What are We Talking About Today?

Data

Challenges

Digital Technology Applications

Machine Learning

Bias

Analyse Bias

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Data

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Data

Data

- Truth
- Improves Things
- Predicts Future

Crime Data

- What crimes are
- How many crimes are committed
- How the police service works

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Challenges

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Challenges

- Budget Cuts
- Increase in Numbers
- Advanced Adversaries
- Reduced Priority

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Digital Applications

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Digital Applications

- Real world experience
- Advanced analytics
- Automation
- Feedback loops

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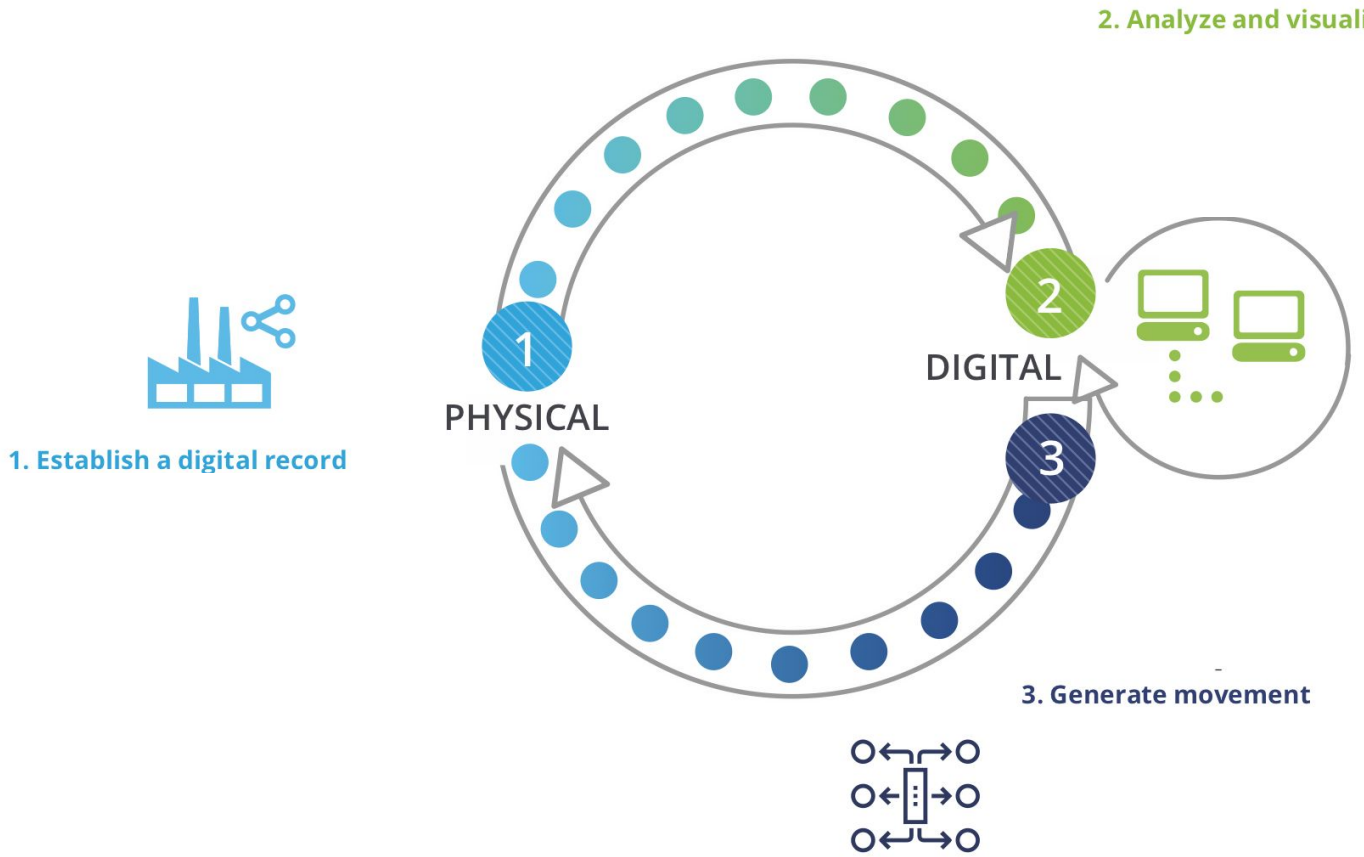
Physical to Digital to Physical Loop



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Bias

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What is Bias and Why Should we Worry?

- Prejudice
- Disparity
- Unbalanced outcomes
- Responsibility to know the Effect

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How Bias is Introduced

- Data Collection
- Feature Engineering
- Algorithm Function
- Decision Making

Machine Learning Bias in Big Data

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- IT Ops
- Security
- Business

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Other Industries Impacted by ML Bias

- Banking
- Insurance
- Employment
- Fraud
- Government
- Finance

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Machine Learning for the Police

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Machine Learning & Policing

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- Pattern Recognition
- Logical Evolution
- Police Intervention & Crime Prevention
- Unstructured Data

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Effect of Biased Predictive Models

- Negative Feedback Loop
- Incomplete Features
- Human Discretion

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Creating a Machine Learning Model in Splunk

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What Data Sources Did we Use?

Crime Data

https://data.police.uk/

Office for National Statistics

Census Data

https://www.ons.gov.uk

LONDON DATASTORE

Various London Datasets

https://data.london.gov.uk

Trust for London
Tackling poverty and inequality

London Poverty Data

https://www.trustforlondon.org.uk/data/child-poverty-borough/

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How We Build ML in Splunk

Building the Dataset

- Crime per LSOA
- Census for different age groups
- School Absences
- Child Poverty
- Income

Analyse Data in Splunk

- kmeans
- analyzefields
- anomalousvalue

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How to Use Splunk ML Toolkit to Create a Predictive Model

Pre-Processing

- Transform your machine data
- 5 options
- We have used Field Selector

Algorithm Selection

- 7 algorithms
- We have used 4 of them

Predictive Model

- Highest “R Squared”
- Minimum RMSE (Root Mean Square Error)

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Measuring Bias in ML Models

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Measuring Bias in Machine Learning Models

- Predictive Numeric fields
- Variance
- Binary Outcome Field
- Chosen Metrics
- Metrics Value

Representation Bias

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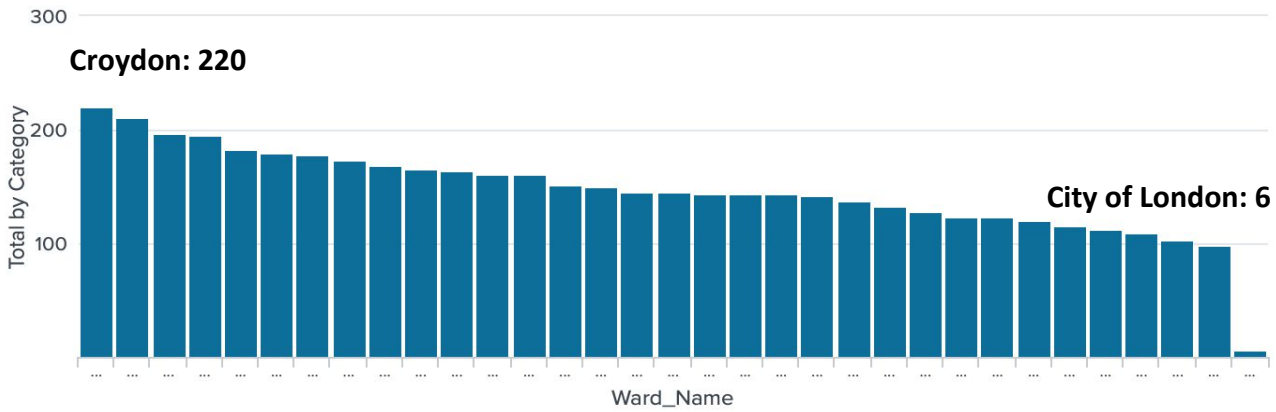
Difference in Number of Data Points compared to Croydon

Ward_Name	Total by Category	Representation Difference
City of London	6	-97.27%
Kingston upon Thames	98	-55.45%
Kensington and Chelsea	103	-53.18%
Barking and Dagenham	110	-50.00%
Hammersmith and Fulham	113	-48.64%
Richmond upon Thames	115	-47.73%
Sutton	121	-45.00%
Islington	123	-44.09%
Merton	124	-43.64%
Westminster	128	-41.82%



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Accuracy Bias

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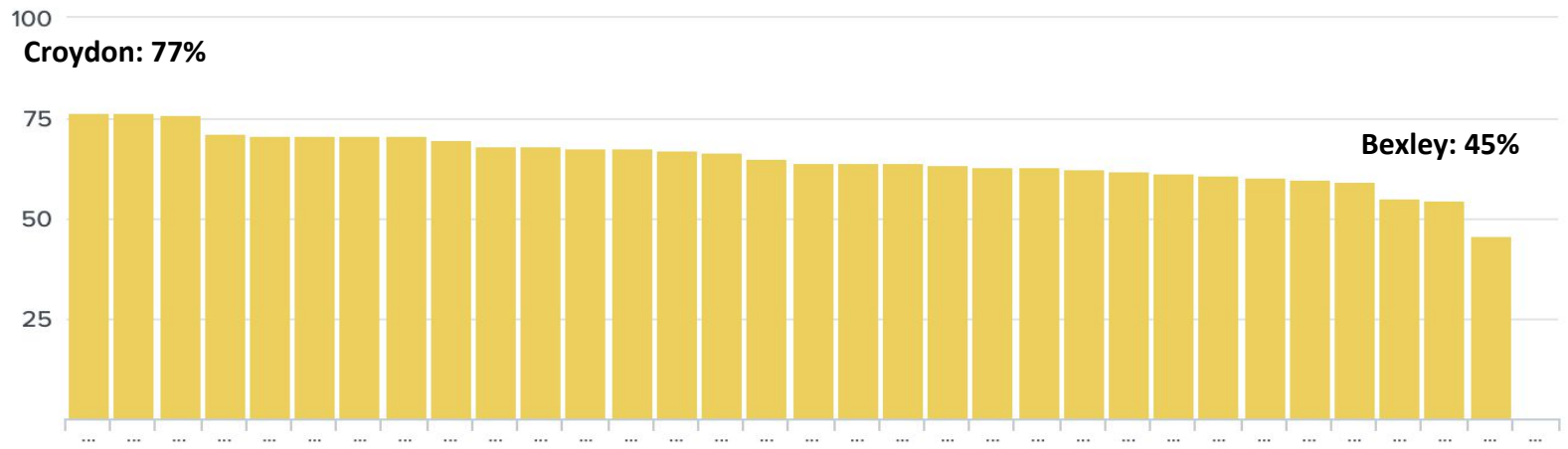
Difference in Precision rate compared to Croydon

Bexley	-35.28%
Sutton	-23.08%
Greenwich	-22.48%
Westminster	-16.27%
Hackney	-15.78%
Harrow	-14.56%
Brent	-14.41%
Barnet	-13.11%
Richmond upon Thames	-12.93%
Tower Hamlets	-11.86%
Newham	-11.43%
Merton	-11.29%
Haringey	-10.52%



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Analyze Police Data for Bias

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Looking at the data

Ingest and analyse the police stop & search data to analyse Data and Feature Bias

Ignoring the outcome

- Count by gender
- By age group
- By ethnicity
- By location
- Object of search
- Ethnicity
- Removal of clothing
- By time of year

Outcome – ignoring location

- Count by gender
- By age group
- By ethnicity
- Object of search
- legislation

Outcome – by location

- Count by gender
- By age group
- By ethnicity
- Object of search
- Legislation

Analyse Bias in the Stop & Search Data

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Population of Britain

Total: 62 Million

White: 86%

Black: 3%

Asian: 7%

Other/Mixed: 4%

Stop & Search Data

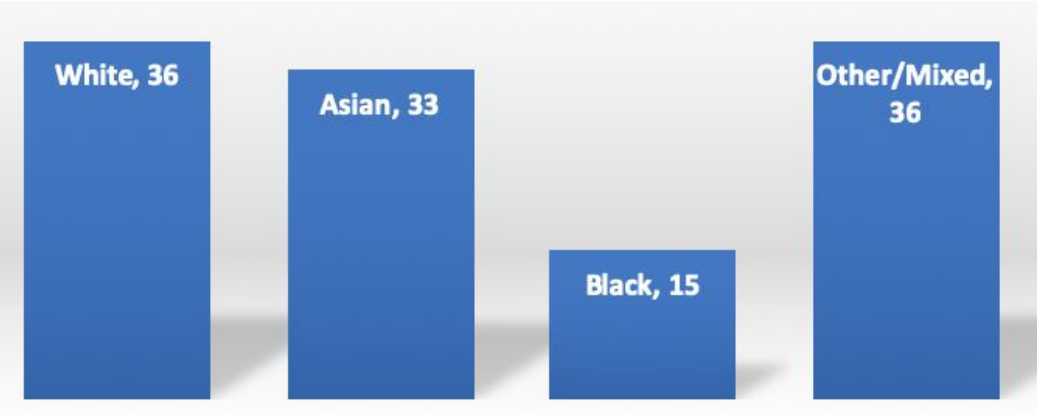
Total Events: 991,038

White: 53%

Black: 25%

Asian: 12%

Other/Mixed: 10%



Ethnicity of People Arrested after Stop and Search

- White: 36%
- Black: 15%
- Asian: 33%
- Other/Mixed: 36%
- Average: 30%

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‘Stop and Search’ Data Bias

- Population % v/s Stop & Search %
- Arrest Probability
- Biased Algorithm

Create Model for Predicting Arrests

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- Stop and search leading to an arrest
- Binary Outcome
- Predict Categorical Fields

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Confusion Matrix

Predicted actual	Predicted 0		Predicted 1	
0	True Positive	95782 (49.3%)	False Negative	98657 (50.7%)
1	False Positive	28257 (33.8%)	True Negative	55270 (66.2%)

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Algorithm Performance Measures

Characteristics of Logistic Regression Algorithm based on Stop & Search data

Precision	Recall	Accuracy	F1
0.65	0.54	0.54	0.59

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Algorithm Bias

- False Negative rate: 50%
- False Positive rate: 33%
- Precision: 0.65
- Recall: 0.54
- Accuracy: 54%

So the algorithm based on just the stop & search dataset from the police is not a very good measure of predictive policing and should not be used in isolation.

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Best Practices for Machine Learning Models

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What steps to follow when creating ML Models

- **Inputs v/s Outputs**
- **Fairness metrics**
- **Diverse team**
- **Data Source**
- **Fair**

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Key Takeaways

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Why is Analysing Bias important

- **Misbehaving Artificial Agents**
- **Accountability**
- **Opacity**

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How to reduce bias in Machine Learning Models

- **Right Learning Model**
- **Representative Training Data**
- **Monitor Performance**
- **Biasness v/s Accuracy**

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What to do after the session?

- **Think hard about the Data, Algorithm and the Output before creating any ML Model.**

Further Reading:

- **https://medium.com/datadriveninvestor/what-is-machine-learning-and-why-is-it-important-6779898227c1**
- **https://www.technologyreview.com/s/612957/predictive-policing-algorithms-ai-crime-dirty-data/**
- **https://statetechmagazine.com/article/2019/05/how-pattern-recognition-and-machine-learning-helps-public-safety-departments-perfcon**

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