Mining 911 Calls in New York City: Temporal Patterns, Detection and Forecasting

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Abstract

Objective

- Improve emergency response strategies through advanced data analytics.

Methods

- Pattern Identification: Analyze 911 call data to recognize trends over time.
- Predictive Modeling: Forecast future call volumes to anticipate resource needs.
- Anomaly Detection: Identify unusual incidents to improve readiness.

Benefits

- Informed decisions on resource allocation.
- Effective deployment across various precincts.

Strategy

- Utilize comprehensive data analysis for smarter resource distribution as part of a broader NYPD strategy.

Introduction

- New approaches to help NYPD precinct commanders better allocate patrol cars each week.

The paper introduces three new methods using emergency call data and other urban data sets:

- 1. Identifying Patterns:
    - Analyzing when and where emergency calls happen to understand local patterns over different times and places. This gives a clearer picture than just using broad crime statistics.
- 2. Predicting Future Needs:
    - Developing models that predict where and when police resources will be needed, based on various factors that might influence crime. This reduces the need for commanders to rely solely on their judgment.
- 3. Spotting Unusual Events:
    - Detecting emergency calls that are out of the ordinary, allowing commanders to respond quickly to unexpected or extreme situations.

- These methods are meant to improve how resources are allocated weekly, making decisions more data-driven and responsive to actual needs.

Data

Analyzed two years of 911 call data from New York City's dispatch systems to improve police response

- Main Data Sources
  - SPRINT System: Older system with 6.3 million calls analyzed.
  - ICAD System: Newer system providing detailed call data, 2.7 million calls analyzed.
  - 311 Calls: Non-emergency citizen complaints categorized into groups (Noise, Street Conditions, Building Issues, Sanitation), totaling 6.7 million records.
- Additional Data
  - Weather data and PLUTO land use information incorporated to predict and understand call patterns more effectively.

Table 1: Datasets

Dataset	Date Range	Size
911: ICAD	6/2013–12/2013	2.7 million
911: SPRINT	2/2012–5/2013	6.3 million
311 Complaints	2/2003–5/2014	7.4 million

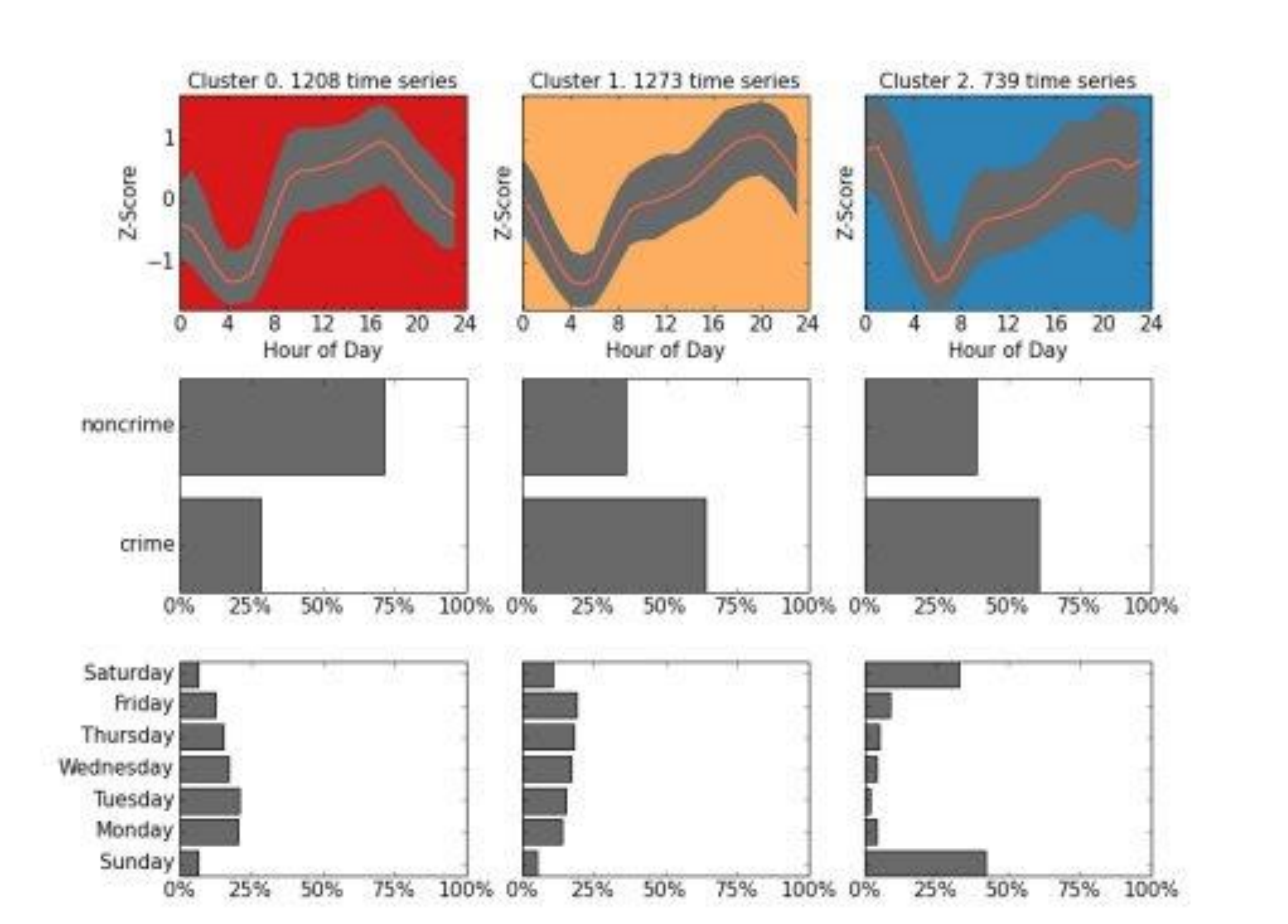
Table 2: 311 Complaint Type Groupings

Groupings	Complaint Types
Noise	Noise
Street Condition	Street Condition, Blocked Driveway, Traffic Signal Condition, Illegal Parking
Building	Sewer, Water System, Building/Use, General Construction/Plumbing
Dirty Conditions	Dirty Conditions, Rodent, Sanitation Condition, Missed Collection, Damaged Tree, Derelict Vehicle

Temporal Call Behavior

Initial step sought to understand typical temporal behavioral patterns for calls

- The visual analysis presents three distinct behavioral patterns for emergency call times throughout the day and week, based on **k-means clustering:**
- Cluster 0: This group shows a higher volume of non-crime related calls during workday hours, which typically peak in the middle of the day.
- Cluster 1: This pattern has a peak of crime-related calls in the evening hours on weekdays.
- Cluster 2: Here, there's a peak in crime calls late at night on weekends, which aligns with what NYPD officers have noted anecdotally.
- These clusters were formed by analyzing emergency call data, both crime and non-crime, across different days of the week and times, and then **standardizing the data (z-normalizing)**. The goal was to minimize the difference between the calls in a cluster and the average pattern of calls within that cluster.



Cluster 0. 1208 time series
Cluster 1. 1273 time series
Cluster 2. 739 time series
Z-Score
Hour of Day
noncrime
crime
Saturday
Friday
Thursday
Wednesday
Tuesday
Monday
Sunday
0%
25%
50%
75%
100%

Predictive Model

- Forecasts the demand for police calls within each sector of the city. This model is designed to help precinct commanders plan and distribute patrol units, which work in eight-hour shifts, more efficiently by predicting where crime-related calls are most likely to occur.
- The predictive model uses **supervised learning**, a type of machine learning where the system is trained on a labeled dataset.

Building a Predictive Model: Feature Extraction Process

- Historical Call Data: Mean and median of 911 and 311 call volumes over periods from 1 hour to 8 weeks.
- Time-Specific Patterns: Statistics matched to corresponding days and times for weekly trends.
- Comprehensive Call Metrics: Data encompassing all call types and outcomes.
- Incorporated Datasets:
  - Weather: Impact of temperature, humidity, solar radiation, precipitation.
  - PLUTO: Built environment characteristics, e.g., building types, values.
  - Contextual Variables: Day of the week, time slots, call classifications from clustering.
- Data Structure: Crime call counts per sector for 8-hour shifts paired with the feature set.
- Feature Optimization: Refined from ~2,600 to 300+ features, focusing on historical 911 data for model efficacy.

Rolling Forecast Method

Rolling Forecast Method:

- Initial Data & Continuous Learning:
  - Starts with 90 eight-hour periods of data.
  - Continuously learns from new data to improve accuracy.
- Model Types Tested:
  - Random Forest Regression:
    - Handles complex data with 100 decision trees.
  - Poisson Regression:
    - Suitable for predicting event counts within fixed intervals.
- Localized Models:
  - City-wide model in use; exploring smaller area-specific models.

Algorithm 1 Rolling Forecast Prediction Model

for $s = 1$ **to** S **do**
  for $t = 0$ **to** T **by** Δt **do**
    for τ in $\boldsymbol{\tau}$ **do**
      $\mathbf{C}^{911}_{t-\tau} = \{\bar{c}^{911}_{t-\tau}, \mathrm{var}(c^{911}_{t-\tau}), \tilde{c}^{911}_{t-\tau}\}$
      $\mathbf{C}^{311}_{t-\tau} = \{\bar{c}^{311}_{t-\tau}, \mathrm{var}(c^{311}_{t-\tau}), \tilde{c}^{311}_{t-\tau}\}$
    end for
  end for
  $\mathbf{x}_{s,t} = \mathbf{C}\,^{911}_{s,t}, \mathbf{C}\,^{311}_{s,t}, C\,^{\text{PLUTO}}_{s}, C\,^{\text{Weather}}_{t}, C\,^{\text{Contextual}}_{t}$
end for
Input: $\{\mathbf{x}_{s,t}, c_{s,t}\}_{n=1}^{N}$
for $n = n_{\text{boundary}}$ **to** N **do**
  fit $\{\hat{c}_{s,t}\}_{n=1}^{n-1}$ = f($\{\mathbf{x}_{s,t}\}_{n=1}^{n-1}$, w)
  predict $c^{n*}_{s,t}$ = f($\mathbf{x}^{n}_{s,t}$, ŵ)
end for
Output: $\{c_{s,t}\}_{n=n_{\text{boundary}}}^{N}$

Performance

- Initial Random Forest Model:
  - Predicted daily call counts.
  - R2 = .7 ρ=0.83 – Good at detecting patterns.
- Shift-Specific Predictions:
  - Adapted for 8-hour shifts.
  - Lower accuracy: R2≈0.5, ρ=0.7.
  - Overestimates low and underestimates high call counts.
- Feature Analysis:
  - Short-term features lack immediate context.
  - Long-term historical data more stable and predictive.

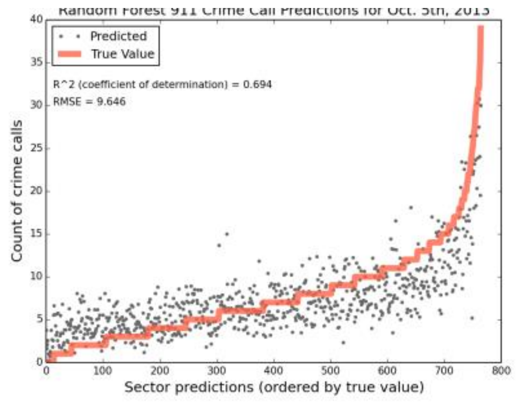


Figure 5: Random forest model predictions for the 24-hour period of October 5th, 2013. Sectors are ordered by actual target count along the x-axis. The red line indicates the target count of the sector on this date; each dot represents the

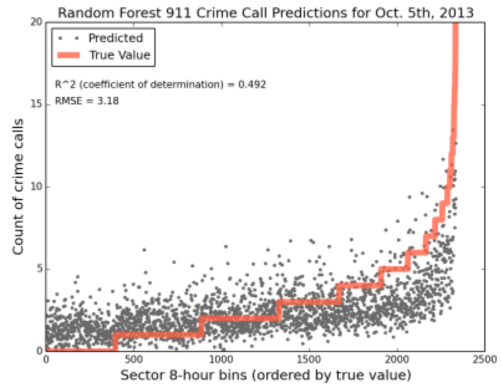


Figure 6: Random forest model predictions for the 8-hour officer shifts on October 5th, 2013. Similar to Figure 5, but predicting on a finer timescale.

Performance of Predictive Model

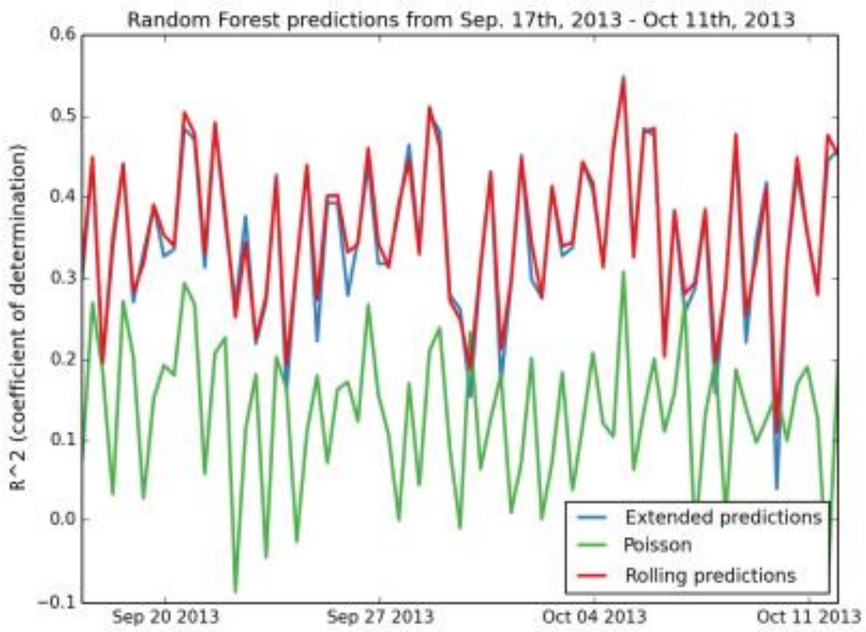


Figure 7: r^2 metrics for three different model types (random forest rolling forecast, random forest extended forecast, and poisson regression) over more than three weeks.

- Model Comparisons:
  - Rolling forecast model outperforms extended forecast.
  - Poisson model struggles with overdispersion.
- Top Features & Future Research:
  - Top features: Time-of-day historical aggregates.
  - Exploring localized models for better handling of data variability.
- Conclusion:
  - Random forest model identifies patterns effectively; improvements needed for dynamic real-time data integration and overdispersion.

Event Detection

Purpose: To identify areas with an unusual number of emergency calls, signaling the need for potential adjustment in police deployment.

Technique: Spatial cluster detection identifies regions where 911 crime call counts are significantly higher than what's typically expected, based on historical data.

Detecting Anomalous Spatial Clusters in 911 Call Data Using Neill's Model

Background and Methodology:

- Adapts Kulldorff's Poisson scan statistic from epidemiology.
- Analyzes rectangular regions on a uniform two-dimensional grid.
- Assesses areas with call counts following a Poisson distribution.

Detection Process:

- Searches for regions with the highest Poisson likelihood ratio.

Compares two hypotheses:

- H0 : Uniform call rate across all areas.
- H1 (S): Elevated call rate in specific regions.

Statistical Significance:

- Uses randomization testing to confirm significance of detected regions.
- Calculates p-values by comparing the score of the most significant region against scores from replica grids.

Outcome:

- Enables precise identification of high-risk areas, optimizing NYPD's response and resource allocation.

Algorithm 2 Expectation Based Poisson Scan Statistic

Input: C $^{911}_{s,t}$, G
for $s = 0$ **to** S **do**
  Likelihood Ratio Statistic: With grid G, calculate F(S) based on H_1(S) and H_0 for each region. **s**
  Max Region: S^* = $\arg\max_S F(S)$ of grid G
  Max Score: F^* = $F(S^*)$
end for
Input: S^*, F^*
for $r = 0$ **to** R **do**
  for $s = 0$ **to** S **do**
    calculate: Likelihood Ratio Statistic, Max Region and Max Score for replica region. **s**
    if: Max Score $> F^*$, R_{beat} += 1
  end for
end for
calculate: ρ_{S^*}
Output: ρ_{S^*}, S^*

Figure 8: Most significant spatial region cluster identified on July 4th, 2012 in Manhattan

Figure 9: Most significant spatial region cluster identified (in red) on July 6th, 2012 in Staten Island

Discussion

- Model Refinement:
  - Data Sources: Enhancing features from 311 calls, PLUTO data, and weather information.
  - Localized Models: Developing sector-specific models for integration into the broader system.
  - Data Integration: Including both long-term historical and dynamic short-term data for seasonal accuracy.
  - Training Datasets: Expanding datasets to include social network data for better emergency situation variability.
- Event Detection Improvements:
  - Bayesian Scan Statistics: Transitioning to more efficient methods for detailed, simultaneous event monitoring.
  - Integration: Merging outputs from the predictive model to improve anomaly detection at finer spatial resolutions.

Connecting back to Our Project

Reference

- Chohlas-Wood, A., Merali, A., Reed, W., & Damoulas, T. (2015, April). Mining 911 calls in New York City: Temporal patterns, detection, and forecasting. In Workshops at the Twenty-Ninth AAAI Conference on Artificial Intelligence.