Abstract:

This paper discusses the NYPD's efforts to improve how they respond to emergencies by using advanced data analysis techniques. It explores methods to better understand the patterns of 911 calls, including identifying trends over time, predicting future call volumes, and spotting unusual incidents. These methods help the NYPD make more informed decisions about where and how to allocate resources effectively across different police precincts. This approach is part of a broader strategy to use data for smarter resource distribution.

Introduction:

The paper achieves three primary objectives through the utilization of emergency, call data, and other urban datasets:

1. Identifying Patterns:** This involves analyzing the frequency and locations of emergency calls to discern local patterns across different temporal and spatial contexts. This approach offers a more nuanced understanding compared to relying solely on broad crime statistics.
2. Predicting Future Needs:** By developing predictive models, the paper aims to forecast the areas and times where police resources will likely be required, considering various factors that influence criminal activity. This method mitigates the reliance on subjective judgments of commanders.
3. Spotting Unusual Events:** The paper also focuses on detecting emergency calls that deviate from typical patterns, enabling swift responses from commanders to unexpected or extreme situations.

Data:

The research entails analyzing two years' worth of 911 call data from New York City's dispatch systems to enhance police response strategies. They utilized data from both an older system called SPRINT and a newer one named ICAD, with ICAD offering more comprehensive details about each call. The analysis encompassed over 2.7 million calls logged by ICAD and 6.3 million by SPRINT.

Furthermore, data from 311 calls were incorporated to aid in predicting 911 call patterns. These 311 calls were categorized into groups such as noise complaints, street conditions, building issues, and sanitation problems, totaling 6.7 million records. Additionally, the study incorporated other public datasets such as weather and land use information to enrich the prediction and comprehension of police call demand across various city sectors.

Temporal Call Behavior:

To achieve the first objective of identifying patterns in the 911 dataset, the researchers employed a behavioral method to discern call patterns. Initially, they utilized K-means clustering to categorize non-emergency calls into three distinct behavioral patterns throughout the day and week.

- Cluster 0: This group exhibits a higher volume of non-crime-related calls during workday hours, with a peak typically occurring in the middle of the day.
- Cluster 1: This pattern displays a peak of crime-related calls in the evening hours on weekdays.
- Cluster 2: Here, there's a peak in crime-related calls late at night on weekends, corroborating anecdotal observations noted by NYPD officers.

These clusters were derived from the analysis of the 911 dataset and both criminal and non-criminal data across different days of the week and times. Subsequently, the data underwent standardization via Z normalization. This normalization aimed to minimize the disparity between the calls and their respective clusters, and the average pattern of calls within each cluster.

Predictive Model

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 $\{\hat{c}_{s,t}\}_{n=1}^{n-1} = \mathrm{f}(\{\mathbf{x}_{s,t}\}_{n=1}^{n-1}, \mathrm{w})$
    predict $c^{n*}_{s,t} = \mathrm{f}(\mathbf{x}^{n}_{s,t}, \hat{\mathrm{w}})$
end for
Output: $\{c_{s,t}\}_{n=n_{\text{boundary}}}^{N}$

To accomplish the second objective of predicting future needs, researchers developed a predictive model employing supervised learning. This model is designed to assist first responders in planning and distributing patrol units effectively by predicting the likelihood of crime-related calls in different areas. To ensure the model's efficacy, researchers adopted the rolling forecast method.

Within the rolling forecast method, two critical aspects need to be understood. Initially, the model is trained using a rolling window of historical data, specifically 98 hours, to establish a foundation for initial predictions. Subsequently, the model undergoes continuous learning, where each prediction is refined using the corresponding actual data, allowing the model to continuously improve and adapt over time.

To evaluate this model, random forest regression was utilized alongside Poisson and regression methods. Both model types incorporated features such as historical 911 and 311 call data, weather data, PLUTO building information, and other contextual factors. These features enable the model to capture both the autoregressive nature of calls, based on past data, and the influence of environmental and contextual variables.

Performance

The paper evaluates the performance of the predictive models used for forecasting NYPD 911 call counts. Here are the key takeaways regarding the performance assessment:

- Model Comparison Over Time:
    - The rolling forecast model, which updates with new data daily, outperformed an "extended" forecast model that was only trained once with a month’s data.
    - The Poisson model underperformed compared to the random forest, largely due to overdispersion in the data.
- Top Predictive Features:
    - The top 10 features for the random forest model were mostly historical aggregates related to the time of day, underscoring the importance of understanding the temporal patterns in crime calls.

- Ongoing Work:
    - Future research is exploring localized Poisson and Negative Binomial models that could better handle or avoid the issues of overdispersion.

The analysis indicates that while the random forest model is effective at identifying patterns in call data, there are still improvements to be made, especially in terms of incorporating real-time data and addressing overdispersion in the modeling process.

Spatial cluster detection:

Algorithm 2 Expectation Based Poisson Scan Statistic

Input: $\mathbf{C}\,^{911}_{s,t}$, 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^*

To fulfill the third objective of event detection, the researchers employed spatial cluster detection to identify regions with significantly higher 911 crime call counts than expected based on historical data. Specifically, they utilized an adaptation of Kulldorff's population-based Poisson scan statistic, a method commonly used for detecting disease outbreaks.

This model operates on a uniform two-dimensional grid, systematically evaluating rectangular regions to pinpoint areas with unusually high call counts. It assumes that the counts within these regions follow a Poisson distribution, where the call rate is unknown but the expected historical call count is known. The technique seeks regions that maximize a Poisson likelihood ratio, comparing observed data under two hypotheses: H0 - a uniform call rate across all areas, and H1 (S) - an elevated call rate in specific regions.

To ascertain the statistical significance of detected regions, randomization testing is employed. This involves calculating p-values by comparing the score of the most significant region against scores obtained from replica grids.

Discussion/Conclusion:

The discussion and conclusion of the paper outline ongoing efforts and future plans aimed at refining the predictive model for police resource allocation. The current focus includes:

- Refining Predictive Features:Efforts are directed towards improving predictive features extracted from 311 calls, PLUTO data, and weather information. This refinement aims to enhance the accuracy of the model's predictions.
- Development of Localized Models: Plans involve developing localized models tailored for specific sectors. These sector-specific models can then be integrated for broader application, thereby improving the precision of resource allocation strategies.
- Incorporation of Long-term and Short-term Data:To capture seasonal trends effectively, both long-term historical data and dynamic short-term data are being incorporated into the predictive model. This approach ensures a more comprehensive understanding of temporal patterns in emergency situations.
- Expansion of Training Datasets:Efforts are underway to compile more comprehensive training datasets, including social network data. By incorporating a wider range of variables, these datasets aim to better account for the variability observed in emergency situations.
- Improvements in Event Detection:The paper discusses transitioning to a Bayesian scan statistic method for more efficient and detailed monitoring of multiple event types simultaneously. This new approach will replace older statistical methods and integrate the predictive model's outputs to enhance anomaly detection at a finer spatial resolution.

Overall, these developments aim to establish a sophisticated system for optimizing police resource allocation in New York City, thereby improving emergency response and public safety.