Course: CIVIL 293A
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Final Report

- SPATIAL AND TEMPORAL ANALYSIS: LINKING 911 CALLS TO SOCIO-ECONOMIC CONTEXTS IN STOCKTON, CA-

Introduction:

Emergency dispatch systems require rapid, accurate resource allocation based on incoming 911 calls. In Stockton, California, the Stockton Police Department manages over 2.5 million emergency calls (2019–2023) across neighborhoods with vastly different socio-economic characteristics. Understanding spatial and temporal distribution of these calls, and their relationship to neighborhood conditions, is essential for optimizing resource allocation and improving public safety. Geographic Information Systems (GIS) have become core tools for emergency management, enabling spatial analysis of incident patterns and integration with census and infrastructure data (Abdalla, 2016).

Research consistently shows that neighborhoods with lower median incomes, higher unemployment, and lower educational attainment experience elevated rates of crime and emergency service demand (Sampson et al., 1997; Schreck et al., 2009). GIS-based crime studies have used choropleth mapping and regression analysis to link socio-economic variables-income, education, employment, age-to spatial patterns of crime and disorder (Mitchell, 2011). However, multicity analyses of 911 systems reveal that a large proportion of calls are noncriminal: welfare checks, disputes, and complaints. Call patterns vary substantially across neighborhoods and demographic areas (Neusteter et al., 2020). This suggests that 911 demand can reflect both underlying crime/disorder and broader social service needs, distributed unevenly across urban space.

The emergency response system faces significant operational challenges rooted in how 911 calls are initially processed. One of them is inconsistent and error-prone classification**.** Emergency dispatchers must rapidly classify incoming calls with limited, real-time information. This challenge creates substantial opportunities for misclassification-such as sending the wrong type or number of responders-which results in resource inefficiency and potentially suboptimal outcomes. Multi-city studies confirm systematic variation in how different dispatchers and jurisdictions categorize and resolve calls (Neusteter et al., 2020; Wang et al., 2023). Another challenge is mismanaged demand patterns: while emergency call demand exhibits clear daily, weekly, and seasonal rhythms (peaking during business hours and mid-week), many jurisdictions fail to fully characterize or act on these predictable patterns. The incomplete understanding of these temporal structures (Sirenko et al., 2025) often leads to inefficient staffing models that are misaligned with actual demand peaks.

This study applies GIS-based spatial analysis, statistical correlation, temporal characterization, and machine learning to address three key questions: (1) How do socio-economic factors explain variation in 911 call volume and type across Stockton's neighborhoods? (2) What temporal patterns characterize call demand across hours, days, and seasons? (3) Can machine learning models reduce dispatcher misclassification errors? By integrating quantitative frameworks, this analysis generates both scientific insights and operational improvements relevant to Stockton and other urban jurisdictions.

Research Question, Goals and Deliverables:

The main goal of this study is to answer the following**:** How do neighborhood-level socio-economic factors explain spatial variation in 911 call volume and call type distribution across Stockton, California, and can machine learning models improve the accuracy of emergency call classification compared to initial dispatcher assessments? This can be answered by solving the following: (1) What geographic disparities exist in emergency call distribution, and do they correlate with neighborhood characteristics? (2) How do temporal patterns (hourly, daily, seasonal) vary by call volume? (3) What is the magnitude of discrepancy between dispatcher-assigned and final call types, and what factors contribute? (4) Can a machine learning model trained on location, time, dispatch code, and call notes reduce classification errors while maintaining acceptable precision and recall?

Analysis of 2.5 million 911 calls across Stockton city limits (2019–2023), examined at police district and census block group scales. Socio-economic analysis focuses on three variables: median household income, educational attainment, and household composition. Machine learning model evaluation uses held-out test data. The deliverables, including various forms of visualizations and maps are:

(1) Three choropleth maps of socio-economic factors by block group.

(2) Heat map of 911 call spatial clustering.

(3) Ranked frequency table of call types by police district.

(4) Temporal analysis visualizations (hourly, day-of-week, monthly).

(5) Correlation analysis with Pearson coefficients and scatter plots.

(6) Dispatcher accuracy assessment and misclassification rates.

(7) Trained XGBoost model with precision, recall, and F1 metrics.

Methodology/Data Collection:

Emergency dispatch records: The dataset comprises 2.5 million 911 calls from Stockton Police Department Open Data (2019–2023), including timestamp, dispatcher-assigned radio code, final call type, geocoded location, and narrative call notes. This structure mirrors multicity 911 analyses that examine both metadata and narrative text to characterize call processing and outcomes (Neusteter et al., 2020).

Geographic and socio-economic data: City boundary, police district shapefiles, and census block group boundaries and 2019–2023 American Community Survey estimates (median household income, educational attainment, household composition) were obtained from the U.S. Census Bureau. Socio-economic attributes were spatially joined to calls through block group identifiers.

Call type consolidation: Over 200 police radio codes were consolidated into 16 analytical categories (Violent Crime, Property Crime, Vehicle-Related, Disturbances, Suspicious Activity, Welfare/Mental Check, Medical & Fire Aid, Alarm-Related, Public Service/Administrative, Animal-Related, Weapons, Drug/Vice Related, Sexual Offenses, Missing/Found/Welfare, Special Operations/Hazard, Administrative/Other) using Stockton Police Department documentation, California Penal Code, and external reference databases.

Software and tools: Python (Pandas, GeoPandas) was used for data cleaning, transformation, and spatial joins. QGIS 3.x and Matplotlib produced choropleth maps of socio-economic variables and kernel density heat maps. Python SciPy and Statsmodels libraries computed Pearson correlations and multiple regression models. XGBoost implemented gradient boosting classification, with text features generated using Word2Vec vectorization of call notes.

Methodology justification: Analysis at both police district (operational) and block group (socio-economic) scales aligns with recommendations from emergency management and crime mapping literature to combine operational units with fine-grained census data (Abdalla, 2016;

Mitchell, 2011). Multi-scale temporal analysis (hourly, daily, monthly) reflects documented temporal structure in emergency demand (Wang et al., 2023; Sirenko et al., 2025). Regression-based modeling of socio-economic predictors follows precedent from Pittsburgh crime analysis, where economic indicators explained substantial but incomplete variation in spatial patterns (Mitchell, 2011). Examining dispatcher assignment versus final call type is motivated by 911 process evaluations that trace calls from intake through resolution and identify systematic coding variation (Neusteter et al., 2020).

Results/Spatial/Temporal Mapping:

a. **Socio-Economic Context.** Understanding the socio-economic landscape of Stockton is essential for interpreting the geographic patterns of 911 call demand. Three key neighborhood-level variables-median household income, educational attainment, and household composition-reveal substantial spatial disparities across the city. These factors serve as baseline contextual data against which to examine call distribution patterns.

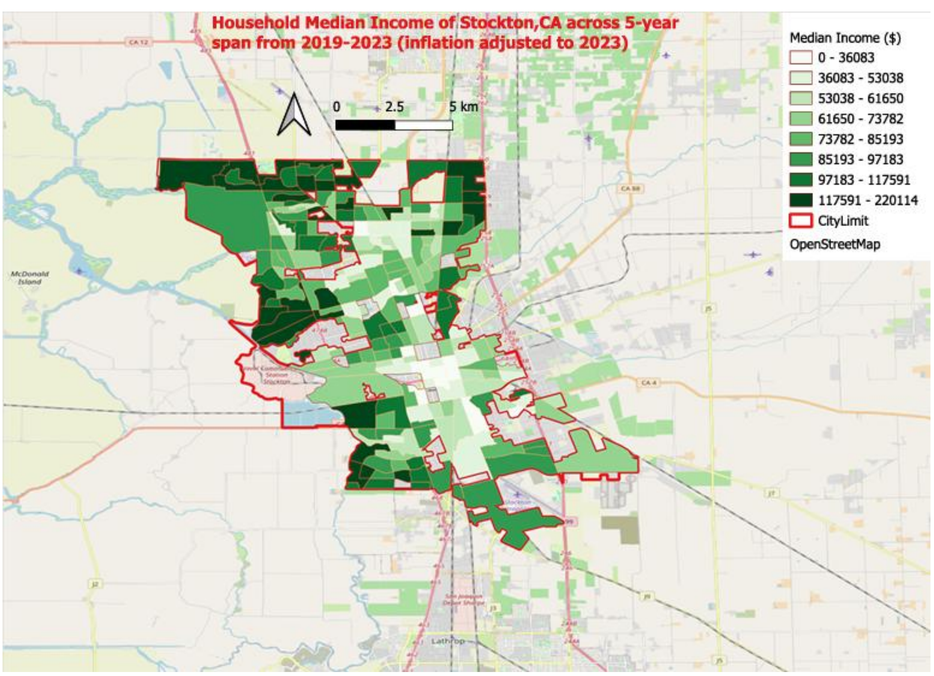

Figure 1. Median household income ($) by census block group, 2019–2023 ACS estimate. Downtown and civic areas show concentrations of low income brackets; peripheral neighborhoods range in the high-end.

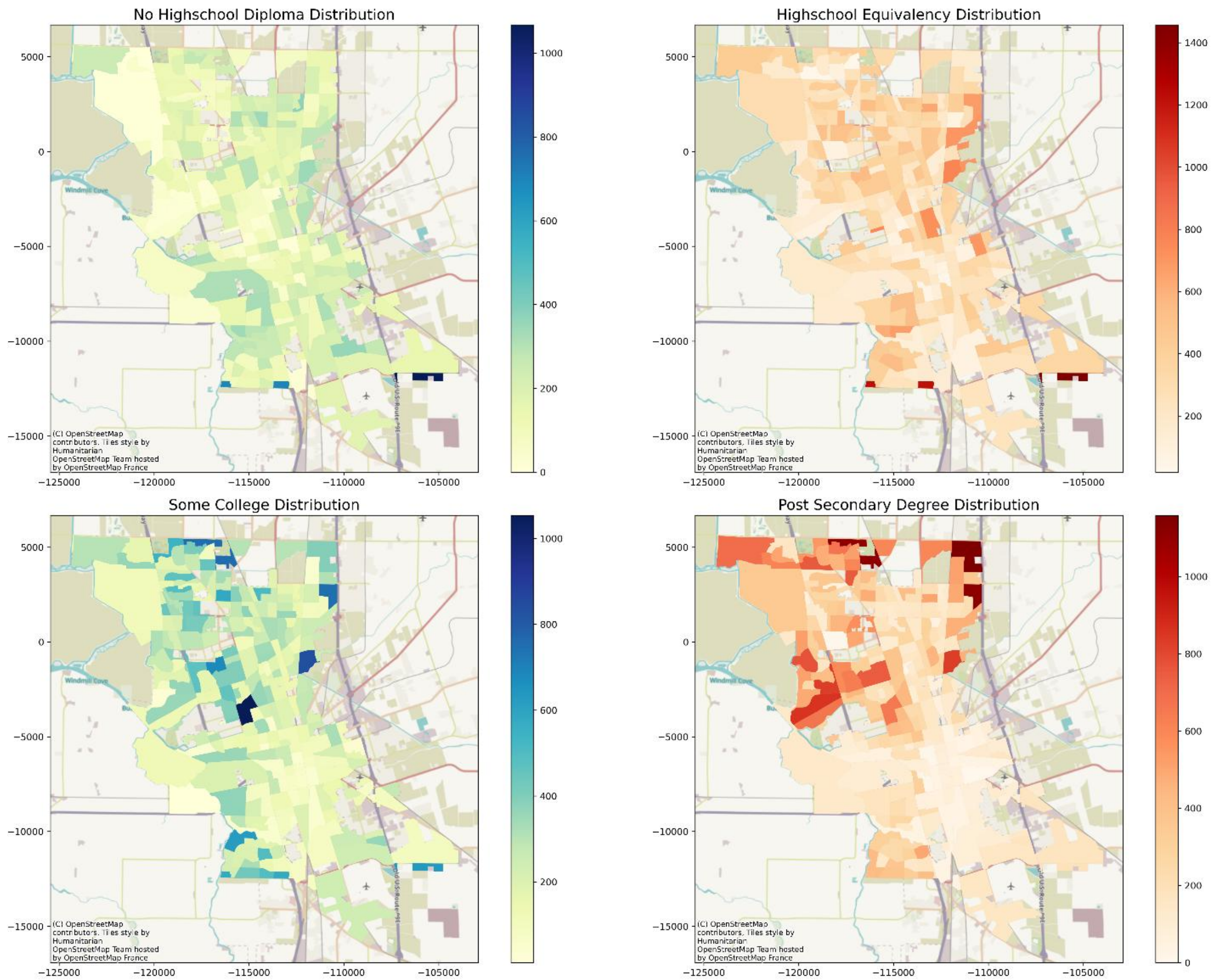

Figure 2. Percentage of population with various level of education attainment, no highschool, highschool, college, and post-secondary by census block group.

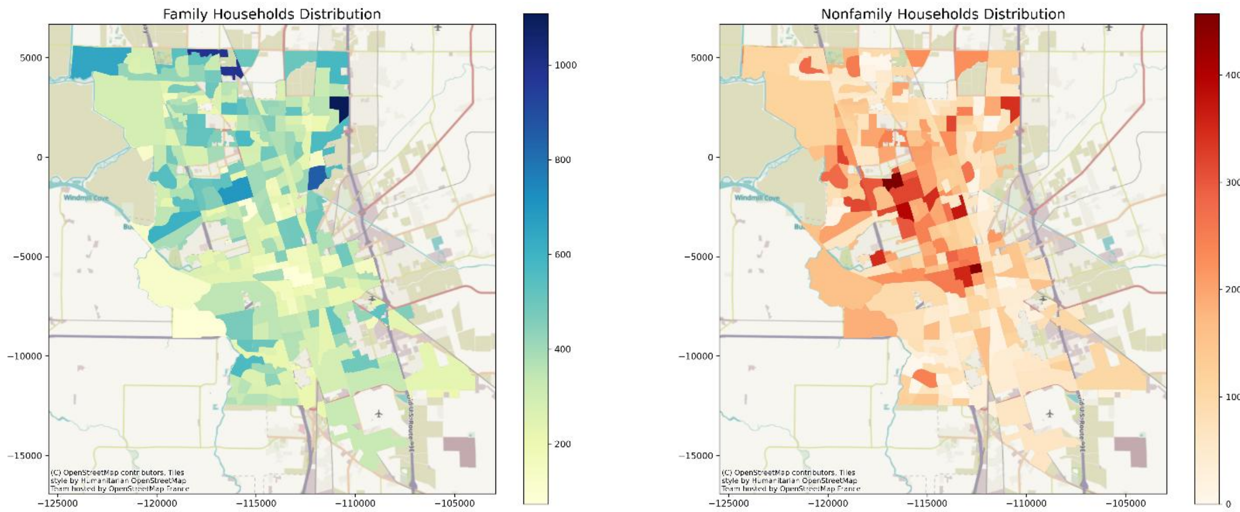

Figure 3. Percentage of family and nonfamily households by census block group. Downtown/central: 35–50% family households; peripheral areas: 70–85%, reflecting residential versus mixed commercial/transient patterns.

These three socio-economic maps establish clear geographic disparities across Stockton, with downtown and central neighborhoods consistently showing lower income, lower educational attainment, and lower proportions of family households compared to peripheral areas. These gradients form the spatial baseline for subsequent analysis of emergency call distribution.

b. Spatial Distribution of 911 Calls

The spatial distribution of 911 calls reveals pronounced geographic clustering that closely aligns with the socio-economic disparities documented above. The concentration of emergency demand in specific neighborhoods has direct implications for resource allocation and operational planning.

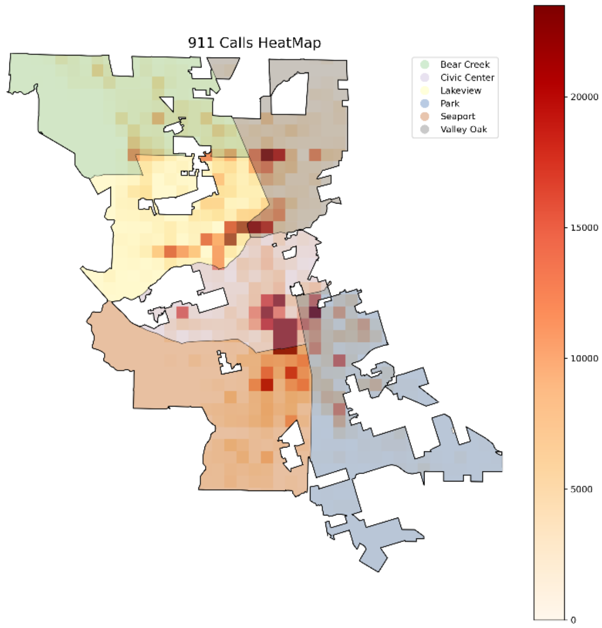

Figure 4. Heat map showing spatial concentration of 911 calls from all five years. Highest density (dark red) concentrates in downtown Stockton and portions of Civic district; density decreases toward city periphery. District boundaries overlaid in black.

Call density is highly concentrated in downtown Stockton and extends into portions of the Civic district. Density declines progressively toward the city periphery. This clustering persists even when normalized visually by area, indicating that emergency call demand is spatially uneven and concentrated in a limited number of neighborhoods.

c. Call Type Distribution by Police District

Beyond total call volume, the types of emergency calls vary meaningfully across the six police districts. Ranking the top 15 call categories within each district reveals both common patterns and notable district-specific variations. This ranking provides operational insight into the relative demand for different response types across Stockton's patrol divisions.

Table 1: Ranking of top 15 call categories by frequency within each police district (1 = highest frequency, 15 = lowest). Disturbances rank first across five of six districts, second in Civic. Vehicle-Related and Medical & Fire Aid consistently rank 2–4, indicating broad dispatch demand for non-criminal service calls.

Call Category	**Bear Creek**	**Civic**	**Lakeview**	**Park**	**Seaport**	**Valley Oak**
Disturbances	1	2	1	1	1	1
Vehicle-Related	2	5	3	2	2	3
Medical & Fire Aid	3	4	4	4	3	2
Administrative / Other	4	3	2	3	4	4
Public Service/ Admin.	5	1	5	5	5	5
Welfare & Mental Health	6	6	8	7	7	8
Violent Crime	7	7	7	6	6	6
Property Crime	8	8	6	8	8	7
Suspicious Activity	9	9	9	9	9	9
Special Operations / Hazard	10	11	11	11	10	11
Alarm-Related	11	10	10	10	11	10
Weapons	12	12	12	12	12	12
Animal-Related	13	13	13	13	13	13
Sexual Offenses	14	14	14	15	15	15
Drug / Vice Related	15	15	15	14	14	14

d. Temporal Patterns in 911 Call Demand

Emergency call volume exhibits strong temporal structure across multiple time scales. Analyzing patterns by hour of day, day of week, and month reveals systematic variation in when emergency demand peaks and how demand varies by call category. These temporal patterns reflect underlying human activity cycles and offer opportunities for demand-responsive resource scheduling.

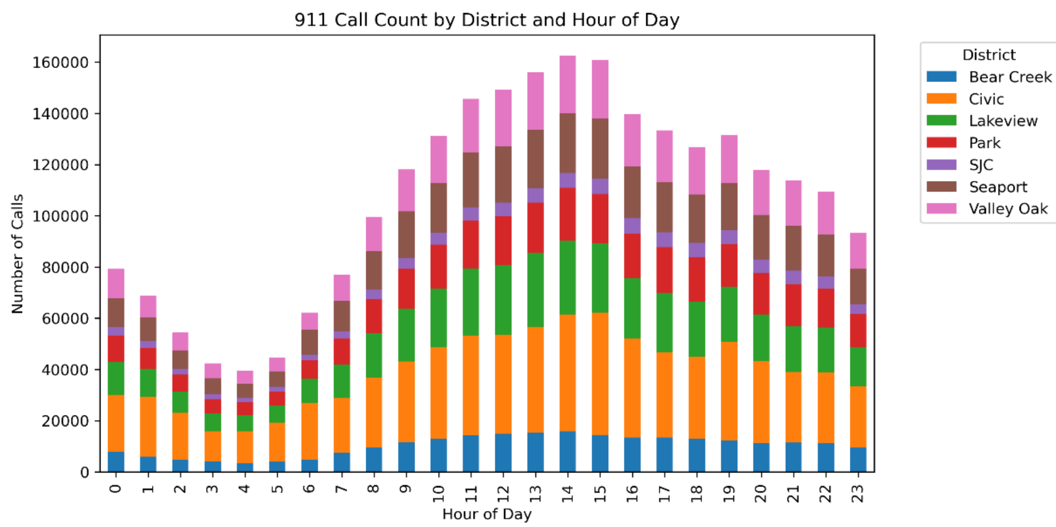

Figure 5. Call volume by hour of day (0–23), aggregated across five years. Peak volume 10 AM–4 PM; minimum volume midnight–6 AM. Pronounced diurnal sinusoid reflects circadian rhythm in human activity.

The diurnal pattern shows a pronounced peak during mid-day hours (approximately 10:00 AM to 4:00 PM), where call volumes reach their maximum, and pronounced troughs during overnight hours (midnight to 6:00 AM), where call volumes drop substantially. This pattern directly reflects circadian rhythms in human activity: peak dispatch demand aligns with periods of maximum human activity, occupational work, traffic congestion, and daytime hazard exposure. Overnight minima reflect periods when most of the population is sleeping and activity-based incident occurrence is naturally lower.

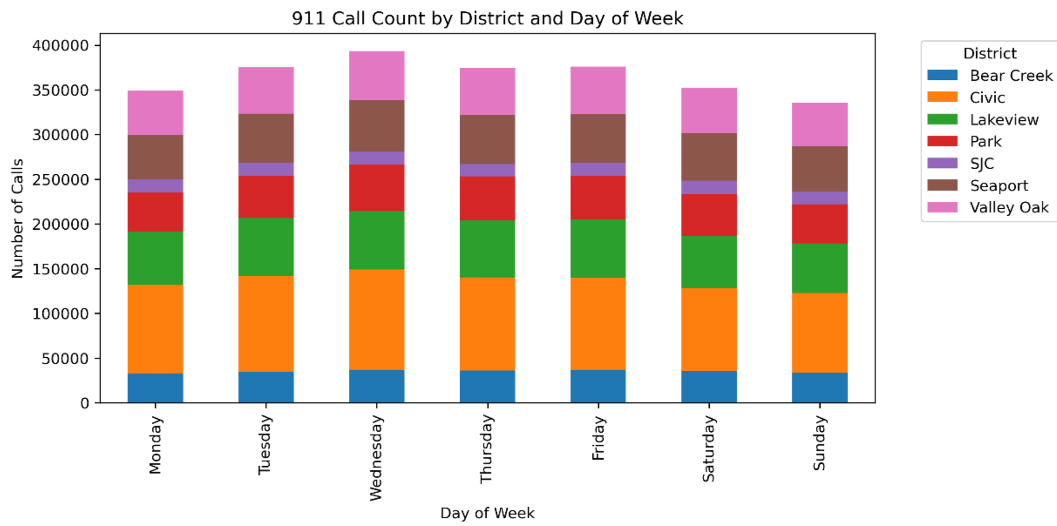

Figure 6 Mean daily call volume by day of week. Wednesday–Thursday peaks (~5–7% above weekly average); weekend days slightly lower. Mid-week elevation suggests employment and school activity patterns drive call volume.

Call volume exhibits a subtle but consistent weekly pattern, with Wednesday and Thursday showing the highest average daily volumes, while weekends (Saturday and Sunday) show slightly lower volumes. This approximately 5–7% elevation during mid-week compared to weekends suggests that 911 demand responds to weekday routine activities including employment, school, and traffic patterns. The weekend reduction likely reflects behavioral shifts as people's routine activities change on weekends, potentially resulting in fewer incidents or differences in reporting patterns.

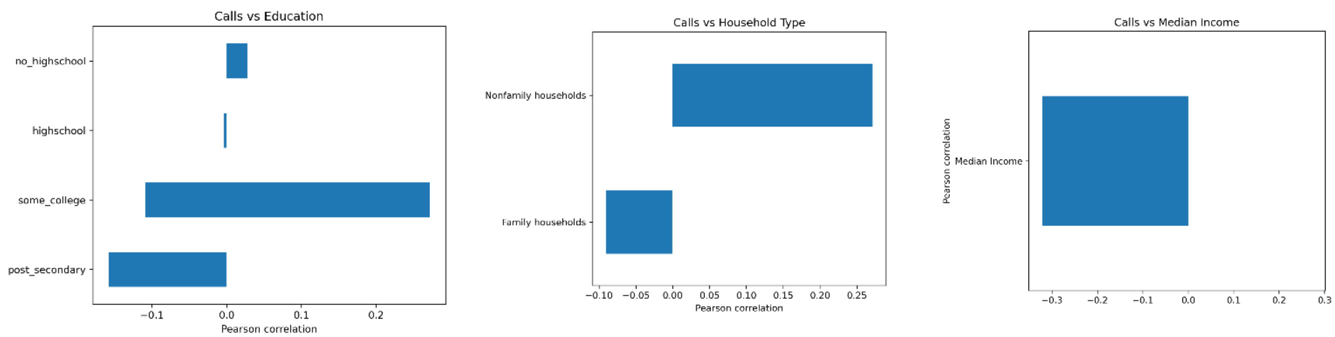

Figure 8. Pearson correlation coefficients between socio-economic variables and 911 call volume at the census block group level.

Educational attainment (percent with college degree or higher) is similarly neutral. Percent non-family households shows a mild positive correlation with call volume. Median household income shows a moderate negative correlation with call volume. These correlations mildly suggest that block groups with lower income, lower educational attainment, and nonfamily residential generate higher emergency call volumes.

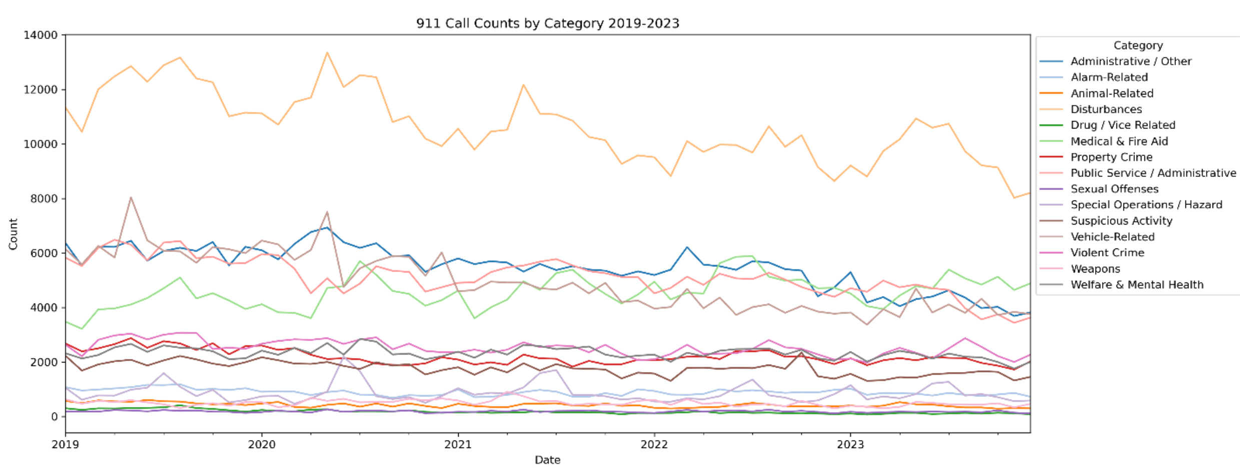

Figure 9 Caption: Total call volume by month across five-year period. Seasonal variation: modest peaks in summer (June–August), slightly lower winter. Notable 15–20% decline during 2020 (COVID-19 lockdowns); recovery by 2021.

The five-year time series reveals seasonal variation in call volume, with modest peaks during summer and early fall months (June–August) and slightly lower volumes during winter months (January–February). This seasonal pattern is consistent with research documenting summer peaks in crime-related calls and general emergency demand in many urban areas. The most dramatic feature of the time series is the pronounced decline in call volumes, coinciding with COVID-19 pandemic lockdowns.

e. Xgboost Predictive Modeling

A critical operational challenge in emergency dispatch is the discrepancy between the call type assigned by dispatchers and the final call type determined by responding officers. This mismatch creates inefficiencies: calls routed with incorrect initial classifications may receive inappropriate response levels, unit types, or resource allocations. Analysis of dispatcher versus final call type across all 2.5 million calls reveals a 10.94% overall misclassification rate.

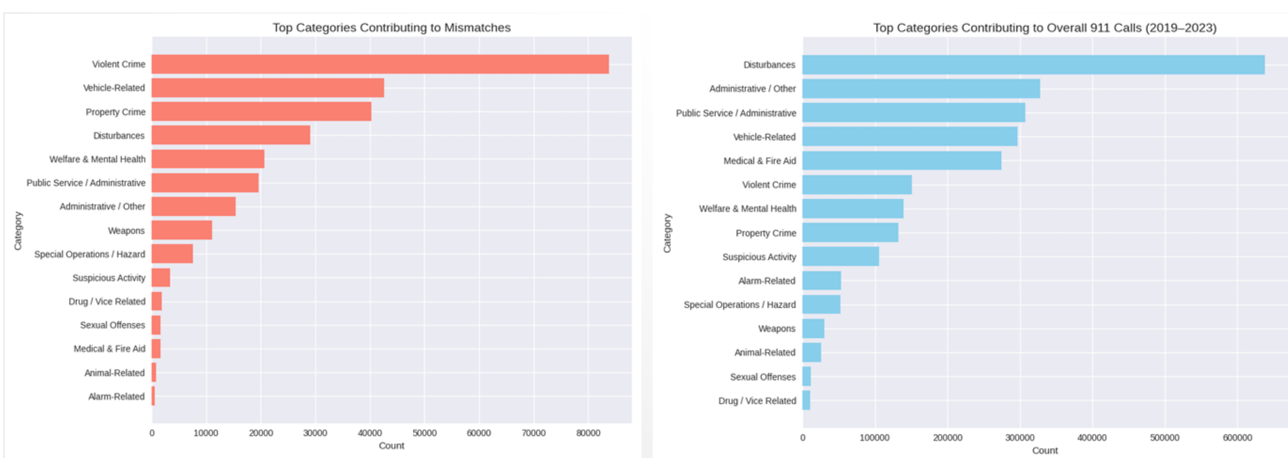

Figure 10. Top categories contributing to the call discrepancies from 2019-2023.

The misclassification trend does not align with the distribution of overall 911 calls. Heavy crime like violence, vehicle-related, and property are top of the list. This variation reflects the inherent challenge of rapid, real-time classification based on subjective caller descriptions and limited information.

To address dispatcher misclassification, an XGBoost gradient boosting classifier was trained to predict the final call type classification using information available to dispatchers at call intake. The model uses combinations of geographic (district, block group, xy coordinates), temporal (hour, day of week, month), dispatcher radio code, and vectorized call notes. The dataset was split into 80% training and 20% held-out test set. The test set was used exclusively for model evaluation, ensuring unbiased assessment of generalization performance.

On the held-out test set, the model achieved a macro-averaged precision of 0.71, recall of 0.68, and F1-score of 0.69. Effective misclassification rate drops from 10.94% to 7.32%, representing a 33% relative reduction in classification error. Different operational scenarios prioritize precision (minimizing false positives) versus recall (minimizing missed cases) differently. The confusion matrix analysis reveals that misclassifications typically occur between conceptually related categories-for example, confusing "Disorderly Conduct" with "Domestic Dispute" (both disturbance-type incidents)-rather than across dramatically different incident types.

However, high-consequence misclassifications do occur: calls initially classified as Vehicle-Related that actually involve Violent Crime, or calls classified as Suspicious Activity that resolve as Weapons violations. For these high-consequence errors, recall (detecting the true incident type) is operationally critical to ensure adequate police response. The model achieves reasonable recall on violent and weapons categories, though with lower precision, suggesting the model tends toward some over-classification of serious incidents - a bias that prioritizes not missing serious crimes over avoiding false alarms.

This precision-recall profile aligns with operational priorities in emergency dispatch: missing a violent crime call is operationally worse than flagging a call that turns out to be lower-severity, since under-response to serious incidents can result in officer safety issues or victim harm.

Discussion/Implication of Results:

Being a non-family with lower household income and lower educational attainment generates more call volumes. However, these findings should not be interpreted as evidence that disadvantaged neighborhoods are inherently more criminal. The call-type distribution shows that violent and property crimes rank consistently below service-oriented categories like disturbances and administrative requests. In other words, the idea is "socio-economic disadvantage is linked to greater interaction with emergency services overall, rather than exclusively to serious criminal activity". In neighborhoods with fewer private resources, limited access to social services, and higher residential turnover, residents may rely more heavily on 911 as a point of access for conflict resolution, welfare concerns, and public assistance.

The spatial concentration of 911 calls in downtown Stockton and the Civic district closely mirrors the socio-economic gradients observed in the census block group analysis. Downtown and Civic districts combine higher population density, mixed residential–commercial zoning, transient populations, and transportation hubs. These features increase the likelihood of observable incidents and third-party reporting, independent of underlying crime rates. The spatial analysis therefore highlights the need to interpret call density as a composite signal reflecting socio-economic conditions, land use, and reporting behavior, rather than as a direct indication of criminality alone.

Across all police districts, non-criminal and service-oriented calls dominate dispatch demand. Disturbances rank among the most frequent call types citywide, followed closely by vehicle-related incidents and medical and fire aid. Violent crime and property crime consistently rank in the middle of the distribution rather than at the top. This uniformity suggests that differences in total call volume are driven more by frequency of everyday service needs than by differences in crime mix. This finding has important implications for staffing, training, and interagency coordination. Dispatchers and responding officers must be equipped not only for enforcement tasks but also for de-escalation, welfare checks, and coordination with medical and social service providers. High-demand districts may benefit from specialized response units or alternative response models that divert appropriate calls away from traditional law enforcement when feasible, thereby reducing system strain without compromising public safety.

Temporal analysis reveals that emergency call demand follows highly predictable daily, weekly, and seasonal rhythms. The pronounced mid-day peak and overnight trough observed in hourly call volume reflect routine human activity cycles, including work schedules, traffic flow, commercial activity, and social interaction. These patterns indicate that emergency demand is largely exposure-driven: incidents occur when people are active, mobile, and interacting in shared spaces. Weekly patterns further reinforce this interpretation. Elevated call volumes on Wednesdays and Thursdays, relative to weekends, suggest that institutional schedules - such as employment and school routines - play a stronger role in shaping demand than leisure-oriented activities. Seasonal variation, while more modest, shows higher volumes during summer months, consistent with increased outdoor activity and travel.

The analysis identifies dispatcher misclassification as a meaningful source of operational inefficiency. An overall discrepancy rate of 10.94% means approximately 1 in 9 calls is initially categorized inaccurately. Misclassification rates are highest for categories with urgent and serious tendency - such as violent, vehicle-related, and property crime – followed by interpretive categories that rely heavily on caller description, including disturbances, suspicious activity, and welfare checks. This aligns with prior research documenting variability and ambiguity in call intake processes. Importantly, the observed misclassification should not be attributed to individual dispatcher performance alone. Instead, it reflects constraints inherent in rapid decision-making under uncertainty.

The XGBoost model results demonstrate that data-driven decision support can meaningfully reduce classification errors when integrated thoughtfully into dispatch workflows. The model achieves balanced performance while exhibiting higher recall for high-severity categories such as violent crime and weapons-related incidents. This recall-heavy profile reflects a conservative bias that prioritizes identifying potentially serious incidents, even at the cost of some false positives. Combined with flagging of predictions can reduce effective misclassification rates by approximately one-third. This approach preserves human judgment while providing an additional layer of situational awareness. Rather than replacing dispatchers, predictive models function most effectively as tools that highlight uncertainty and support more informed decision-making.

Limitations:

The results suggest that improving emergency response efficiency requires both operational adjustments and broader social investment. While staffing and dispatch optimization can mitigate inefficiencies, underlying geographic and socio-economic disparities continue to generate disproportionate demand in certain neighborhoods. Addressing these causes are beyond the scope of policing alone but remains central to long-term reductions in emergency service burden. Furthermore, the analysis is confined to Stockton limits and does not extend to other San Joaquin County jurisdictions, limiting generalizability. Socio-economic analysis incorporates only three variables (income, education, household composition) from the U.S. Census Bureau; unemployment, poverty rate, racial/ethnic composition, and age structure were not included. The dataset spans 2019–2023 and is not the most recent.

Future Work/Conclusions:

Emergency dispatch demand in Stockton concentrates in economically disadvantaged neighborhoods, exhibits temporal clustering, and suffers 10.94% dispatcher misclassification. Socio-economic and geographic factors explain some of call volume variation, indicating social and economic conditions drive emergency service demand. A machine learning model reduces classification errors by 33%. For Stockton leadership: (1) adjust district staffing to demand (e.g., elevated Civic district); (2) invest in social policy addressing root causes (job training, youth services, substance abuse treatment); (3) integrate ML decision support into dispatch to flag misclassifications; (4) enhance call documentation protocols (text features help in model performance); (5) optimize staffing during predictable peaks (10 AM–4 PM, Wednesday–Thursday); (6) develop category-specific response strategies.

Future works may include category-specific and socio-economic regression to identify differential drivers of serious crime and geographic expansion to test generalizability across San Joaquin County. In addition, integration of health, unemployment, and treatment availability data may help improve and further explore patterns in 911 calls. Overall, this study demonstrates that integrating GIS-based spatial analysis, statistical correlation, temporal characterization, and machine learning can produce actionable insights for emergency management practices in a resource-constrained urban environment.

References:

Abdalla, R. (2016). Evaluation of spatial analysis application for urban emergency management. *SpringerPlus, 5*(1), 2081. https://doi.org/10.1186/s40064-016-3778-1

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. https://doi.org/10.1145/2939672.2939785

Mitchell, S. E. (2011). Using GIS to explore the relationship between socioeconomic status and demographic variables and crime in Pittsburgh, Pennsylvania. *Papers in Resource Analysis, 13*(1), 1–11.

National Highway Traffic Safety Administration. (2022). *Current status of 911 geographic information systems technologies*. U.S. Department of Transportation. https://www.911.gov/assets/NHTSA_GIS_Project_Current_Status_of_911_GIS_Technologies_31MAY2022_Final.pdf

Neusteter, S. R., O'Toole, M., Khogali, M., Rad, A., Wunschel, F., Scaffidi, S., & Pineda, H. (2020). *Understanding police enforcement: A multicity 911 analysis*. Vera Institute of Justice.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research, 12*, 2825–2830.

Roman, M. (2024). *Policing socio-geographic boundaries and inequality*. Retrieved from https://www.marcelroman.com/pdfs/pubs/boundaries_fc.pdf

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science, 277*(5328), 918–924. https://doi.org/10.1126/science.277.5328.918

Schreck, C. J., McGloin, J. M., & Kirk, D. S. (2009). On the origins of the violent neighborhood: A study of the nature and predictors of crime-type differentiation across Chicago neighborhoods. *Justice Quarterly*, *26*(4), 771-794.

Sirenko, M., Comes, T., & Verbraeck, A. (2025). The rhythm of risk: Exploring spatio-temporal patterns of urban vulnerability with ambulance calls data. *Environment and Planning B: Urban Analytics and City Science*, *52*(4), 863-881.

Stockton Police Department. (2023). *Stockton Police Department open data: 911 calls for service*. City of Stockton. Retrieved from https://data.stocktonca.gov/

Wang, H., Ng, Q. X., Arulanandam, S., Tan, C., Ong, M. E., & Feng, M. (2023). Building a machine Learning-based ambulance dispatch triage model for emergency medical services. *Health Data Science*, *3*, 0008.