Police Incident Patterns and Response Time Modeling in Montgomery County, MD

The Washington Post [1]

Introduction and Motivation

As a long-time resident of Montgomery County since my sophomore year of high school, I have often wondered about police activity in my neighborhood. Every day, police dispatch centers in Montgomery County, MD, receive hundreds of varying calls, from petty disturbances to life-threatening emergencies. The time it takes to dispatch officers and their arrival on the scene can make a significant difference between resolving the incident and a critical situation. This project aims to understand police response times and the final disposition of calls. With the various dispatch data available, including location, call type, priority, time, etc., I hope to identify patterns that will help determine optimal staffing and resource allocation for a public safety initiative.

Project Significance and Goals

In this project, I will evaluate the **Police Dispatched Incidents**[2] dataset from Montgomery County, Maryland. The police dispatch incidents dataset contains a lot of time based information about each incident call in Montgomery County, including timestamp, geocoded address, call type, priority, response time, and description. With response time as a continuous variable, low and high priority as binary variables, and disposition code as a multi-class variable, I would be able to analyze police incident patterns and build a model of response time to support future emergency response planning.

Project Goals:

1. **Data Collection** – Fetch October 2025 incident records from the Montgomery County open data API.
2. **Data Cleaning** – Parse numeric fields, handle missing values, handle duplicate values, etc.
3. **Exploratory Data Analysis** – Create visualizations to understand the distribution of different call type, priority, timing, and geography.
4. **Unsupervised Learning** – Apply feature selection to the data and apply clustering algorithms to group police incidents.
5. **Supervised Learning** – Define targets for regression, binary classification, and multi-class classification.
6. **Reporting and Storytelling** – Summarize exploratory data analysis findings and modeling to create a report for non-technical audiences.

Research Questions

1. **What are some factors that drive dispatch-to-arrival time?**
   What are the combinations of original call type, priority, location, and time of day that are correlated the strongest with response times?
2. **How do response times vary by time during the day or days in a week?**
   Are there specific displays of dispatch and arrival times for specific call types, and do we observe a pattern on a day of the week?
3. **Are there distinct spatial clusters of incident types and response times?**
   Are there specific areas within Montgomery County that consistently have similar comments, priorities, and response times?
4. **Can we predict whether a call will be classified as high priority?**
   Is it possible to predict a call's priority level based on other information, such as the original call type, location, and timing metrics?
5. **How accurately can we forecast the final disposition of an incident?**
   Is it possible to predict the final call disposition based on the original call type, priority, location, and response times?

Literature Review

1. The literature review section identifies what previous researchers have done and examines the data, methods, and findings of their work. To speed up the literature review, LLM tools are used in this section to better understand the following papers[1].

Predictors of Police Response Time — A Scoping Review[2]

Objectives:
The research document uses empirical studies about police response duration to study response time variables through spatial analysis of police response duration. The authors combine response time elements to establish relevant variables that impact response time while identifying the unclear factors that make response time evaluation challenging. The authors combine new research with outdated and insufficient data to establish specific variables for response-time assessment by organizing existing knowledge.

Data and Methods:
The authors examine 39 empirical studies written in English that detail how response time varies with certain predictors. Given the large volume and diversity, the authors decided to use a narrative synthesis approach tailored to areas with large, complex bodies of literature where straightforward qualitative reviews are inappropriate, and meta-analyses cannot be applied. The authors report 630 statistical relationships involving 122 different predictors, which they systematically classified into different levels of a hierarchy. The authors detail their process and have uploaded all predictor datasets to GitHub to facilitate further validation of their results.

Key Findings:
This review particularly underscores factors relating to police response time and emphasizes them as among the oldest, most limited in scope, and least well documented; therefore, no causal conclusions can be drawn. Instead of estimating causal impacts, the authors take this as an opportunity to draw a lesson. They encourage more precise work in the future on the underlying mechanisms of the delays, on differentiating the precise elements of reporting, response, and travel time to construct a meaningfully formulated response, and on the use of systemic terminology for the variables and outcomes of interest. They note the reporting phase as a weakness in the literature as well and have called for greater attention to this gap. The review attempts to provide, in the literature, a first-pass account of what could be understood causally, while being clear that this is merely observational; therefore, they have approached the predictor variables in a somewhat mythical sense.

The Effect of Police Response Time on Crime Clearance Rates[3]

Objectives:
This paper challenges the popular belief that police response time relies heavily on crime clearance outcomes. The authors of this paper aim to quantify how much a response time delay shifts an offender's probability of apprehension or of a crime being solved, to inform understanding of the operational significance of response time in policing.

Data and Methods:
The study uses a detailed dataset obtained from the Greater Manchester Police that records responses to crime incidents. To identify causal effects, the authors employ a boundary-discontinuity approach that leverages abrupt changes in distance to police-division boundaries—adjacent neighborhoods served by different divisions with systematically different response times. This experimental design provides variation in response times, allowing the authors to estimate how a 10% increase in response time affects the likelihood that a crime is cleared.

Key Findings:
The outcomes show that the longer the response time, the less likely it is to clear the crime. The authors show that with

each additional 10% of response time, the likelihood of clearing the crime lessens by 4.7%. This negative effect is especially pronounced for theft offenses; however, it is still noteworthy for all other offenses. More rapid response times also increase the chances of on-the-spot arrests, and the odds are raised that the victim and/or witnesses will be able to name the perpetrator.

What Conditions Affect Police Response Time? Examining Situational and Neighborhood Factors[4]

Objectives:
The aim of this analysis is to examine individual call attributes and the more integrated features of the adjoining areas. The goal of the authors is to assess whether the quicker or slower police officer response is due to specific characteristics of the call (i.e., the presence of a weapon, day and time of calls, or complainants' characteristics) and/or is due to a community-level correlate, such as socioeconomic disadvantage or residential instability. This inquiry goes beyond the response-time norm and seeks to determine whether response time is due to call or community attributes.

Data and Methods:
The authors examine neighborhood effects at census-tract levels by analyzing domestic dispute calls to a large police department in Texas. To appropriately handle the nested structure of calls by neighborhood, the authors apply multilevel (or hierarchical) modeling to adjust for call prioritization, neighborhood, and situation variables simultaneously. This focuses on the complainant's race and weaponization, response time, and other situational characteristics, as well as the variables of concentrated disadvantage, immigration density, and residential turnover.

Key Findings:
This research shows that several factors affect police response time, including whether a weapon is present, the time and day, and the ethnicity of the complainants. Response times are fastest for Hispanic complainants. Geographic factors like clustered disadvantage, immigration saturation, and residential turnover suggest that social structure is important for understanding response times. However, call volume and population diversity do not seem to predict response time. The data also shows a lot of variation between census tracts, so it is important to consider both incident-specific and contextual factors when measuring police effectiveness.

After conducting several literature reviews, I did not find any academic studies that focus on police incident patterns and response time modeling. Accordingly, I have decided to proceed with my own research on police incident patterns and response-time modeling in Montgomery County, MD.

Audience

This site is my DSAN 5000 final project for the Data Science and Analytics Program at Georgetown University, and it also targets data professionals, academics, and public policy professionals interested in the public-safety analytics sphere in Montgomery County, MD, and the surrounding areas. It combines the concepts of exploratory data analysis, predictive modeling, and data storytelling to demonstrate the value of data-science methodologies and how they can substantially improve our insights into the workings of the police, including the decisions made and the processes employed.

About Me

I am currently pursuing a Master's in Data Science and Analytics at Georgetown University with a concentration in Artificial Intelligence, building on my experience in HR analytics, business intelligence, and AI solutions at

Mercedes-Benz, Farfetch, and Forbes. I am passionate about using data, analytics, and AI to drive innovation, efficiency, and strategic impact in industries such as automotive, enterprise transformation, and advanced analytics. If you'd like to learn more about my background and experiences, please visit my full bio HERE.

References

1. ChatGPT, version-5.1, OpenAI, NOV-2025, chat.openai.com.
2. Verlaan, T. & Ruiter, S. Predictors of police response time: A scoping review. *Crime Science* **12**, 1–23 (2023).
3. Blanes i Vidal, J. & Kirchmaier, T. The effect of police response time on crime clearance rates. *Review of Economic Studies* (2017).
4. Lee, J.-S., Lee, J. & Hoover, L. T. What conditions affect police response time? Examining situational and neighborhood factors. *Police Quarterly* **20**, 1–26 (2016).

Footnotes

1. The Washington Post: Montgomery Co. police data collection is 'woefully inadequate,' audit says ↩
2. Montgomery County Open Data Portal – Police Dispatched Incidents ↩

DSAN 5000 - Incident Response Modeling (MCMD)

Police Incident Patterns and Response Time Modeling in Montgomery County, MD

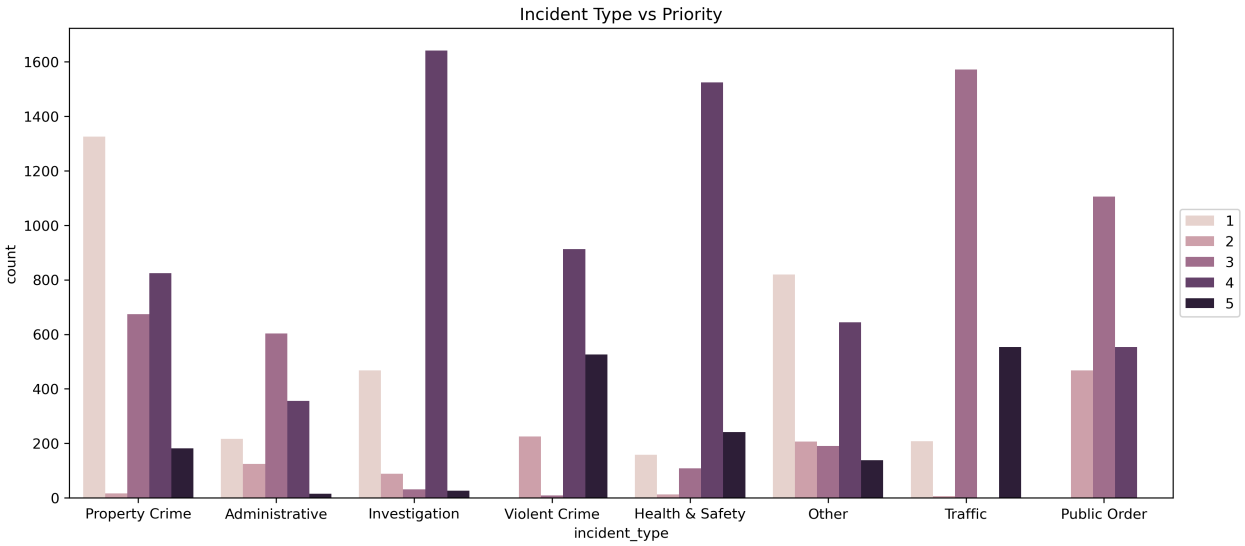
Introduction

Every day, in Montgomery County, the police dispatch center receives various incident calls from minor disturbances, such as traffic-related incidents, to life-threatening emergencies such as violent crimes. As a Montgomery County resident, it is natural to wonder how quickly police officers arrive on the scene and how responses differ by neighborhood, time of week, and incident type. The time between a call and officers' arrival at the scene can change the outcome of an event, especially in serious cases.

WUSA9 [1]

In this project, I will study police-dispatched incident records from Montgomery County, Maryland. The focus of this research is on patterns in response time and on the final outcome of incident calls. The police incident dataset contains detailed information, including location, call type, priority level, various timestamps, and police district, that describes the flow of incident calls from initial contact with dispatch centers to incident closure. By examining these variables, this project provide a clearer picture of how local police respond across different locations in Montgomery County and at different times. More importantly, how those responses can inform public safety planning.

Prior research on police response time has looked at factors such as call characteristics, neighborhood conditions, and distance to patrol units. Recent reviews show that many studies rely on limited data and often cannot draw strong causal conclusions. At the same time, evidence from specific cities suggests that longer response times are linked with lower chances of solving crimes and making arrests. There is still a need for detailed case studies that connect incident-level data with day-to-day operations. In this project, I will evaluate this gap for Montgomery County, Maryland.

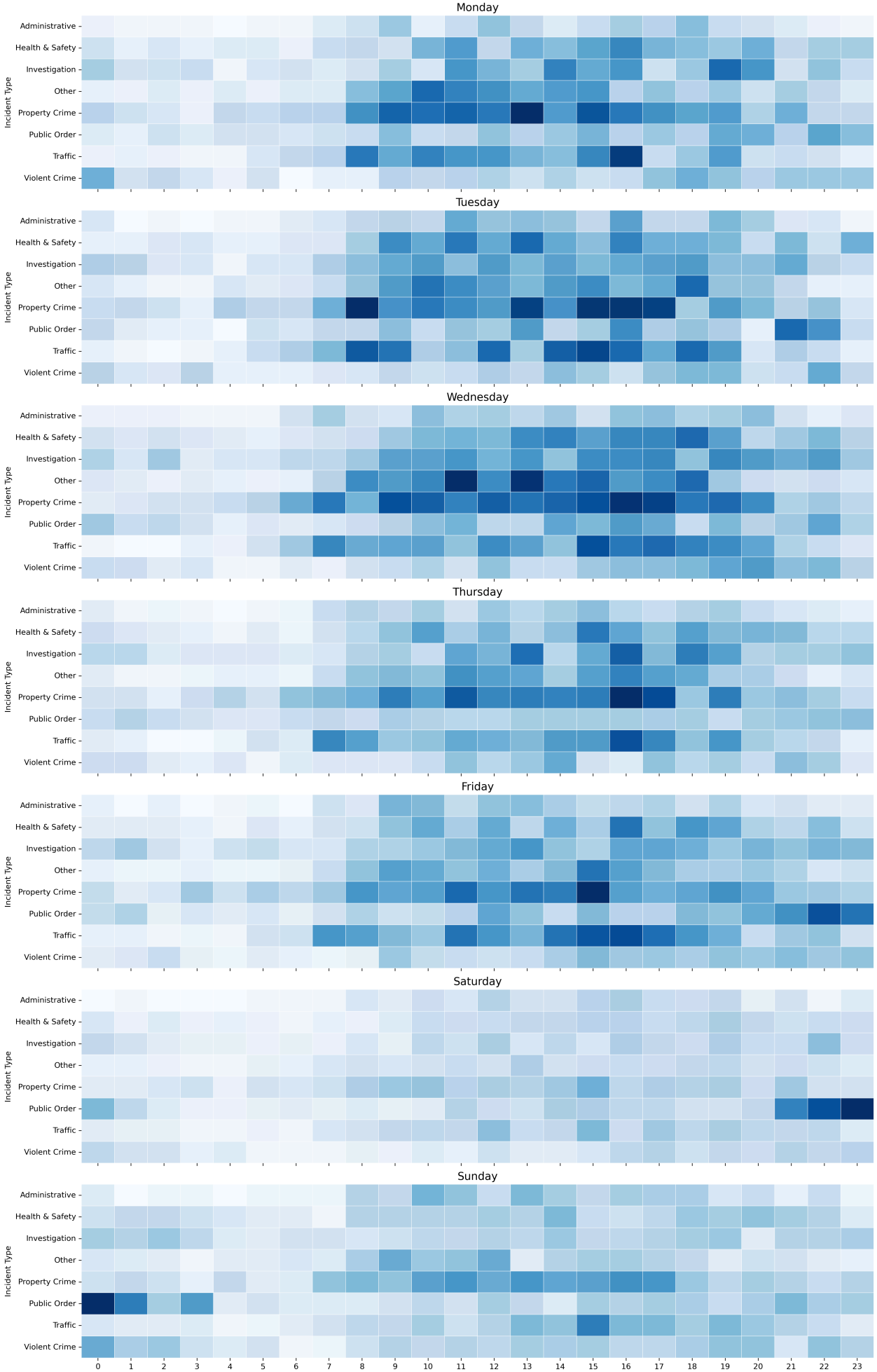


Incident Type by Priority Level

Objective

The main goal of this project is to understand how police incident characteristics relate to response time and call outcomes in Montgomery County. Using the Police Dispatched Incidents dataset, the project examines both patterns in the data and the potential of basic predictive models to support future emergency response planning.

More specifically, we will first examine which combinations of incident call type, priority, location, and time of day are most strongly associated with dispatch-to-arrival time. We will then investigate how response times vary by hour of day and day of week. With this topic, we will check if there are any distinct temporal patterns. Next, we will explore whether the incidents form natural spatial or temporal clusters based on their features. Finally, we will test whether simple models can predict high-priority calls, forecast final dispositions, and estimate response time based on the available variables.

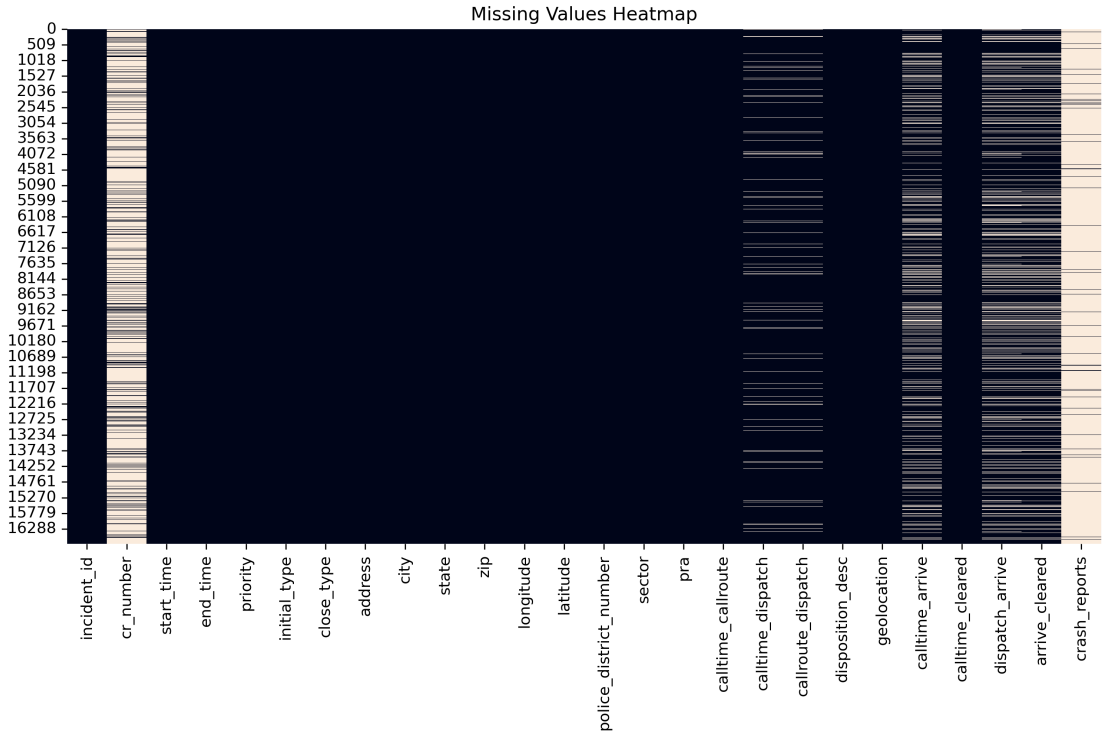

Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Incident Type
Administrative
Health & Safety
Investigation
Other
Property Crime
Public Order
Traffic
Violent Crime
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23

Incident Type by Hour of Day and Day of Week

Methodology Overview

Data Collection

In this analysis, I will use Montgomery County's Police Dispatched Incidents dataset from the county's open data portal. The extracted police incident data for October 2025 contains 16,782 records, each with 26 variables. These variables contain unique incident identifiers, multiple timestamps, initial and final classifications of the call, priority level, address, police district, and derived timing intervals, including call-to-dispatch time and dispatch-to-arrival time. In the police incident calls dataset, columns including incident ID, start time, and initial type are fully populated, while other columns, such as crime report numbers and several time interval fields, contain substantial missing values.



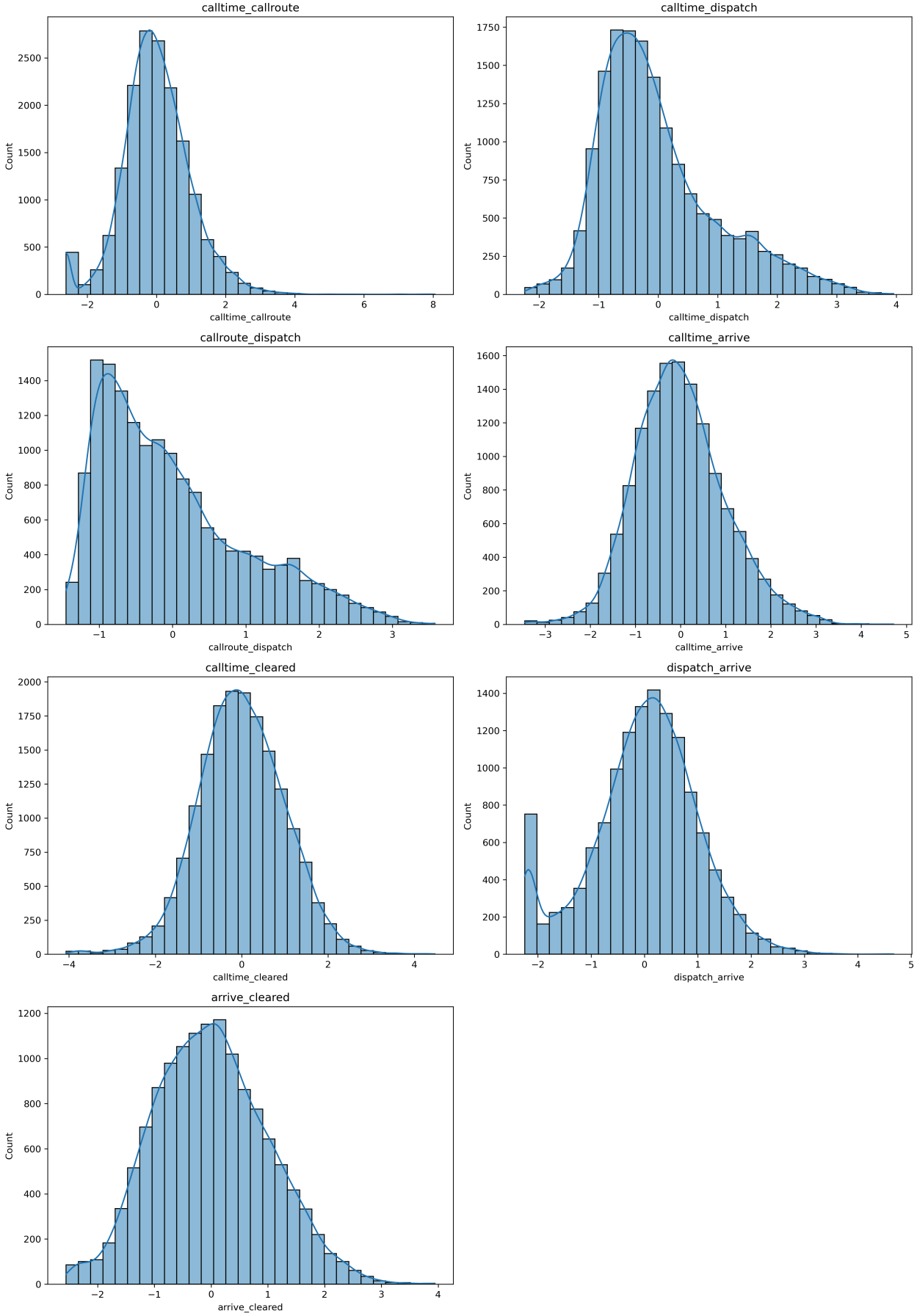
Police Incident Calls Dataset Missing Value Heatmap

Data Cleaning

The raw police incident call data are being cleaned into two main datasets during the data cleaning stage. The first is a cleaned dataset specifically for exploratory data analysis. In this step, timestamps are cleaned into proper dates, numeric fields are corrected, missing values are handled, and irrelevant columns are removed. Categorical variables, such as initial and closing types, are rephrased to improve readability. In the first step, I still kept the original structure and ranges, specifically for exploratory data analysis.

The second dataset is cleaned specifically for machine learning, including supervised and unsupervised learning. This step begins with the cleaned exploratory dataset and applies additional steps. In this process, numeric columns are z-score normalized, and categorical variables are encoded into numbers. Any remaining missing

values are removed so that models can train without errors. However, a major challenge in the data-cleaning stage is the large number of missing coordinates. To support spatial analysis, missing longitude and latitude values have to be filled. Luckily, the specific address of each incident is recorded in the data, so I was able to use the Google Geocoding API to obtain accurate longitudes and latitudes.



Distribution of Normalized Data

Exploratory Data Analysis

The exploratory data analysis examines both single variables and relationships between variables. For numeric features, summary statistics and histograms indicate that time-related measures, including call-to-dispatch or dispatch-to-arrival, are highly skewed to the right and exhibit long right tails. Most of the incidents are handled within a short period of time, while a small number take much longer, resulting in extreme values in the distribution.

The categorical variables, including incident call type, priority, and police district, are examined through frequency tables and bar charts. Crosstab tables and grouped bar plots are then used to study how incident types vary by time of day, weekday, and district. Correlation analysis of the standardized time intervals helps to reveal how different stages of the response process move together.

Unsupervised Learning

In the unsupervised learning stage, I focus on feature selection, dimensionality reduction, and clustering. Dimensionality reduction methods, including principal component analysis and t-distributed stochastic neighbor embedding, project the data into two dimensions, which makes it easier to visualize relationships among different types of incidents. Clustering algorithms such as the K-means, density-based clustering, and hierarchical clustering are then applied to these representations with different parameter settings and distance functions. The goal of this is to determine whether the incidents form natural groups based on features such as timing and priority.

Supervised Learning

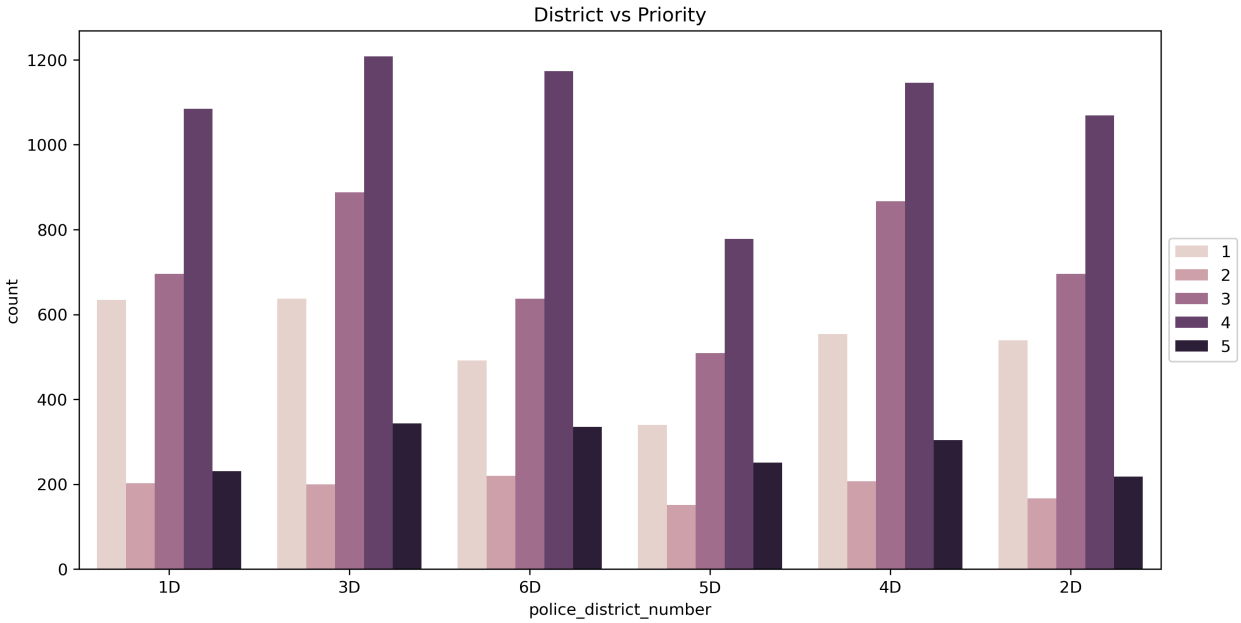
The supervised learning stage builds models with three different targets. The first is a binary classification method that predicts whether an incident is high or low priority. The second is a multi-class classification model that predicts the final disposition code of an incident. The last one is a linear regression that predicts the dispatch-to-arrival time as a continuous outcome. For the regression analysis, it starts by predicting the mean standardized response time. It is then compared to more complex models such as random forests and gradient boosting regressors. The input features used in this process include timing intervals, incident type, priority, and district, and the model performance is evaluated using classification accuracy value, recall value, and error measures.

Key Findings

Patterns in Incidents and Response Times

The exploratory analysis shows that the time related variables are all positively correlated. Incidents with long times in one stage of the process, such as call to dispatch, also tend to have long times in later stages, such as dispatch to arrival and arrival to clearance. This suggests that delays accumulate across the workflow rather than occurring in isolation.

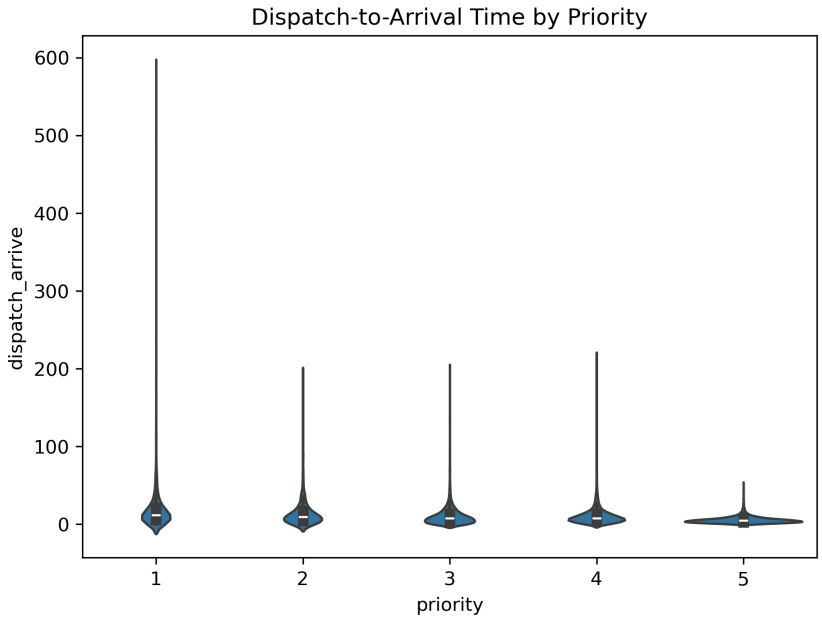
Looking at the different incident types, property crime is the incident type that occurred the most. Property crime is also prominent among high-priority calls, along with violent crime, health and safety, and traffic incidents. On the other hand, some low-priority calls tend to involve less urgent issues. The grouped bar chart of incident types by police district below shows that certain districts, such as the Silver Spring (3D) area, have particularly high counts of property incidents, which points to local variation in workload.



District Police Incidents by Priority

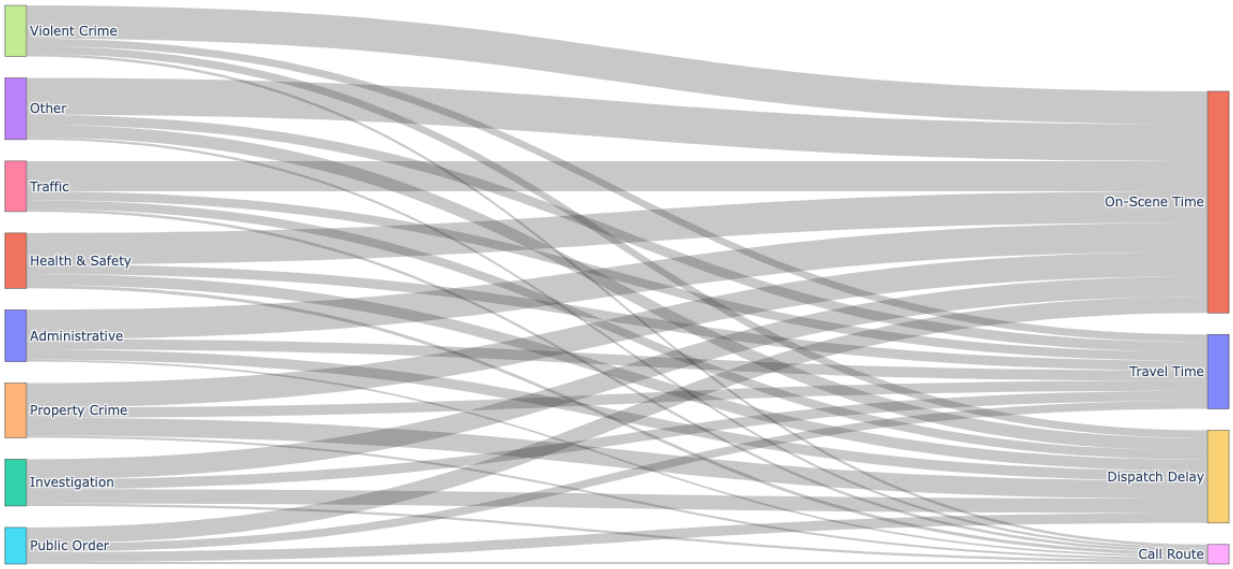
Temporal patterns are also pretty obvious. When incidents are grouped by hour of the day and incident type, most types peak around four o'clock in the afternoon. Public order incidents are an exception, with peaks late at night and especially on weekend evenings. Traffic incidents are more common on workdays. When grouped by weekday, total incident counts tend to be higher in the middle of the week, from Wednesday through Friday.

However, response time differs across these dimensions. Incidents that occur at night often have shorter dispatch-to-arrival times on average than daytime incidents, but the total number of incidents that occur is lower at night. Also, high-priority calls tend to have shorter response times and fewer extreme delays than the low-priority category. Intermediate priority levels show similar distributions and share some extreme outliers. Across districts, median response times are broadly similar, though a few have more very long dispatch-to-arrival times than others.



Dispatch-to-Arrival Time by Priority

The Sankey diagram below highlights the time it spends in the call process, dispatch delay, and on-scene as key components of the total duration from call to clearance for police incidents. From the results, we can tell that the dispatch delay contributes a lot to long total handling times, given that police dispatch delay should normally be pretty short. Also, some incidents remain open for a very long period after officers arrive on the scene. These visualizations support the view that operational delays can occur at multiple stages, not just during travel to the scene.

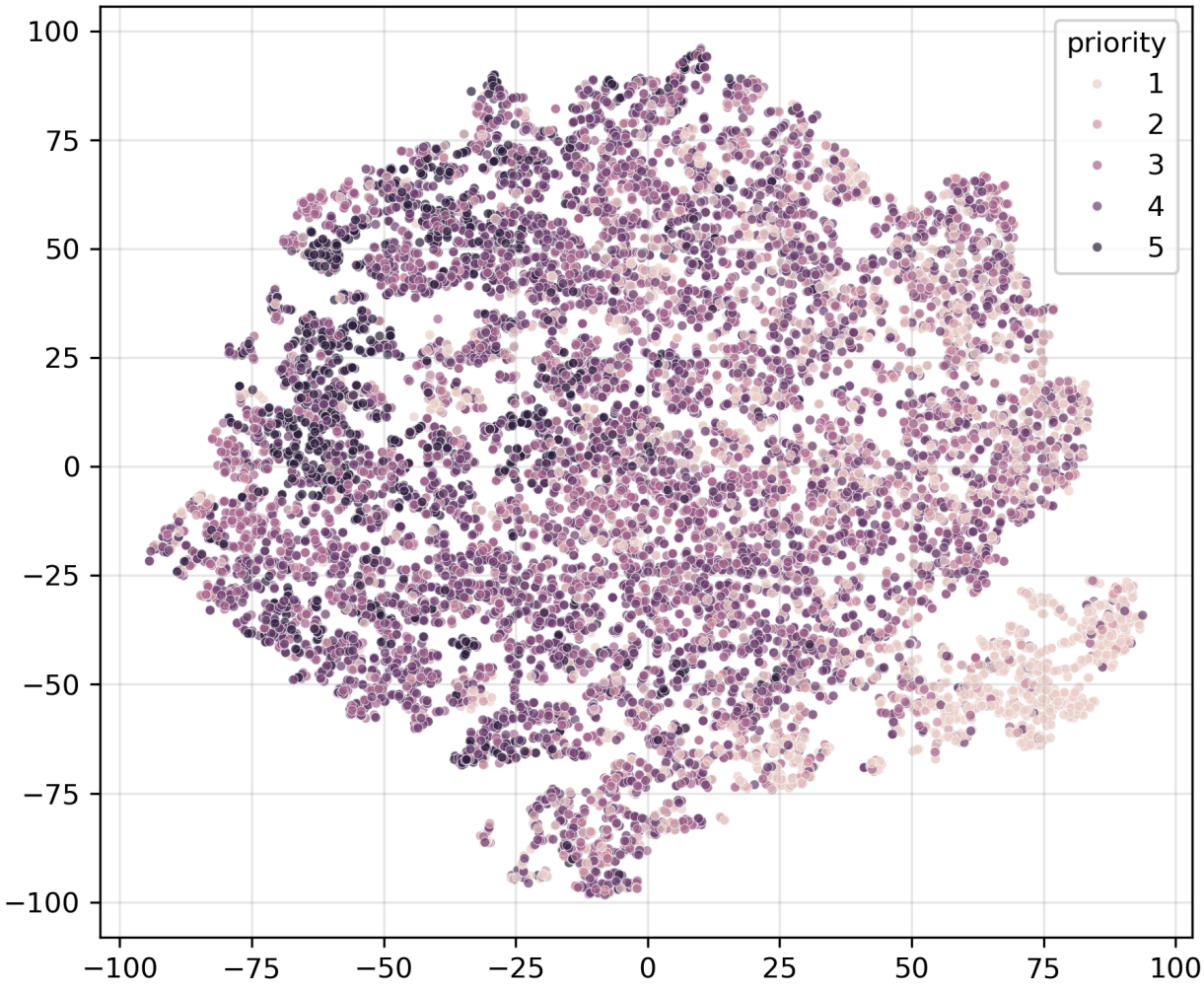


Sankey Diagram of Call Route, Dispatch, Arrival, and Clearance Stages

Unsupervised Learning Results

The dimensionality reduction plots show that all police incidents form a single and dense cloud with smooth transitions between types and priorities. The different clusters are not well separated groups when looking at the two main components. Clustering algorithms struggle to find distinct, interpretable, and stable clusters. Instead, the data form a continuous spectrum. Incidents that are close in the reduced space do not always share the same type, priority, or outcome.

The attempts to cluster on different subsets of features and with different distance measures leads to a similar conclusion. While algorithms can force a partition of the data, the boundaries between clusters do not reflect sharp differences in police operations. Instead, they often cut across incident types or split regions of the cloud without a clear operational meaning.



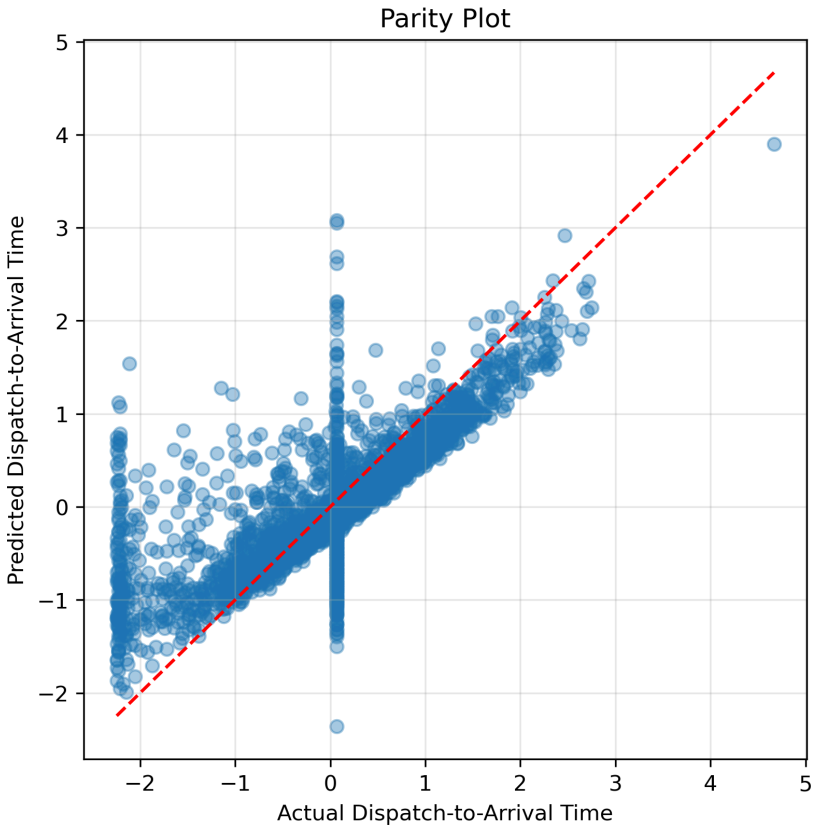
t-Distributed Stochastic Neighbor Embedding Result

Supervised Learning Results

For the binary priority classification method, models such as logistic regression and random forest reach reasonable accuracy and recall for high-priority incidents. These models show that priority can be predicted using incident details and call time features. However, many calls lie near the decision boundary, and many high-priority calls look similar to low-priority ones based on the features used.

For the multi-class disposition prediction, the models did better on common disposition codes. Random forest and gradient boosting capture part of the variation in final outcomes but leave a great number of misclassifications, especially for infrequent codes. This result reflects the unbalanced nature of the data and suggests that a richer context, such as narrative fields or neighborhood-level variables, would be needed to improve performance.

The regression models for dispatch-to-arrival time provide a similar story. A simple baseline that predicts the average standardized response time already achieves moderate accuracy. More complicated models, including random forest and gradient boosting, reduce errors but still leave a large amount of unexplained variation. They are better at capturing broad patterns than predicting the exact response time for each individual incident.



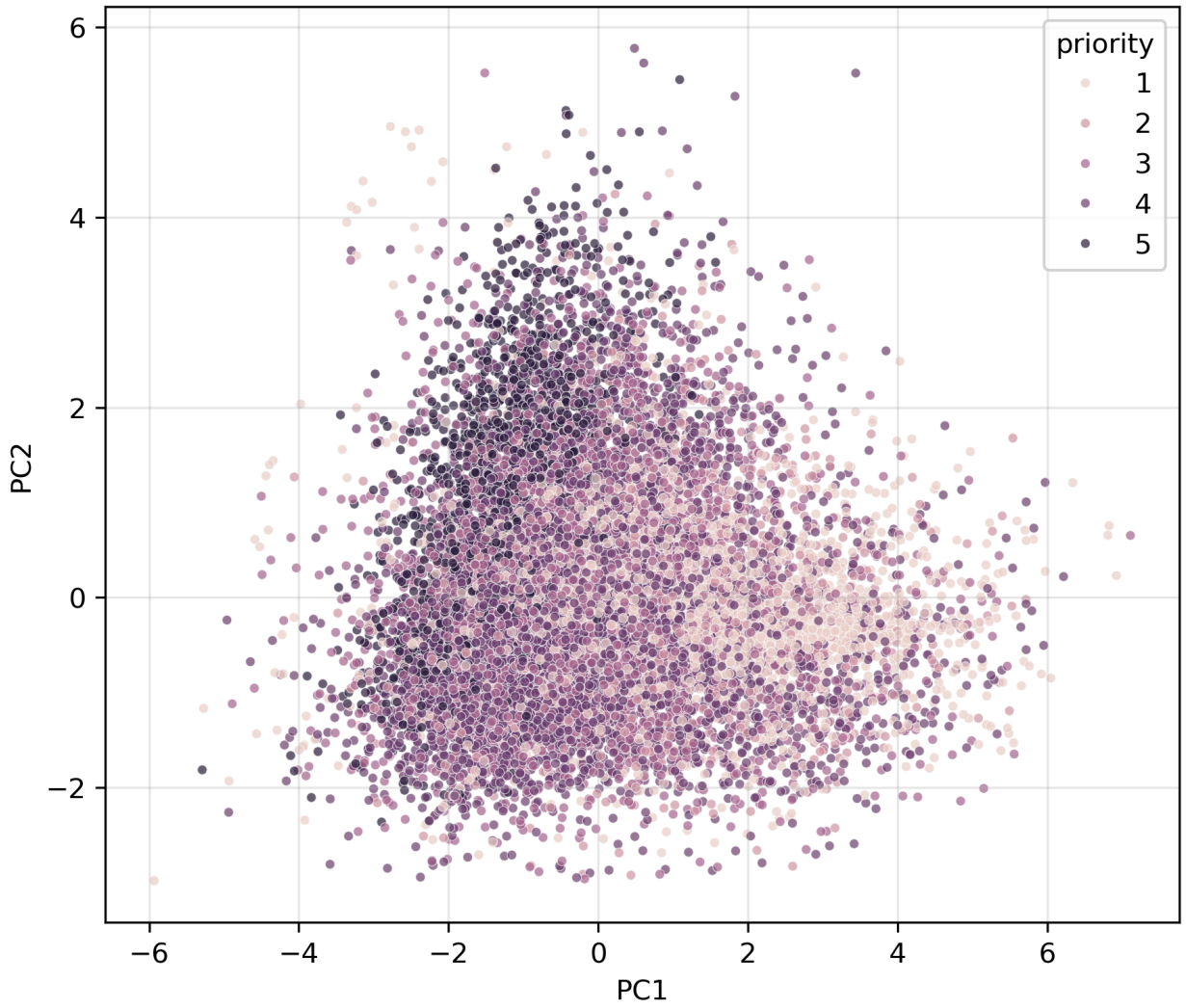
Predicted versus Actual Standardized Dispatch-to-Arrival Time

Societal Implications

In this research, we've looked at the distribution of police incidents by incident type, call time, and different areas of the county. We've identified areas with high counts of property crime, peaks in incident volume during late afternoons, and high volumes of public order incidents on weekends. The findings above could help adjust the police staffing levels and patrol areas to better align with the observed patterns.

In most incident calls, police officers arrive in a very short time, which is also why the data visualizations of all different call times are skewed to the right. However, on the other hand, we observed data with very long delays. We've concluded that this might be driven by dispatch delays. Understanding when and where these delays occur in the process can help to reduce them, improving safety outcomes.

In the next part, several clustering results all concluded that the police incident call times don't have clearly separate groups. It is very likely that the response times are driven by specific factors unique to each incident, which previous research has also concluded.



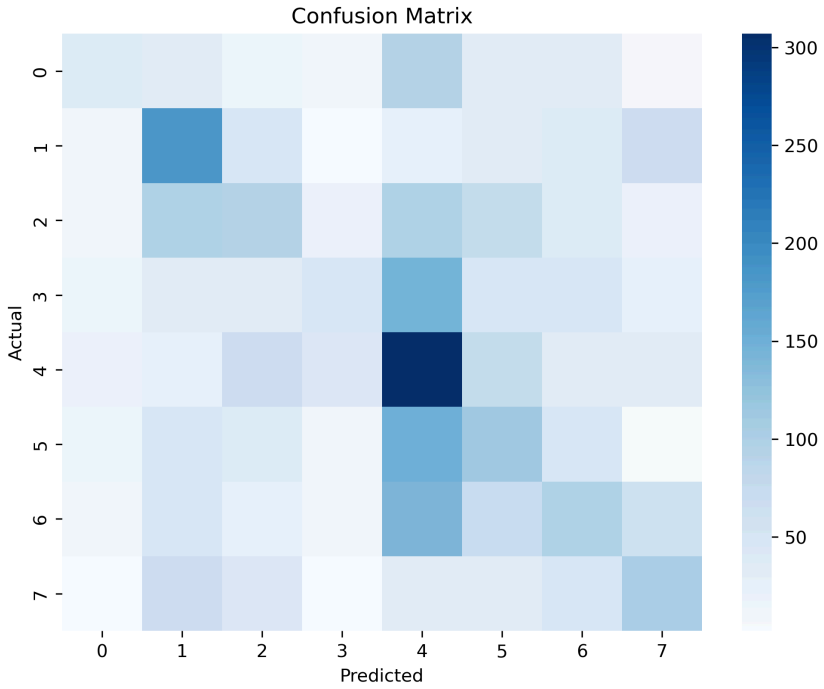
Principal Component Analysis

At the same time, the supervised models demonstrate that some aspects of police work can be supported by predictive tools, but also that these tools should not be treated as decision makers on their own. They are most useful for summarizing trends and highlighting potential high risk calls rather than for replacing human judgment.

Call to Action

Police managers and data analysts in Montgomery County can take several steps based on this project. Regular checks of incident patterns by hour of day, day of week type, and district can help match staffing and deployment to real demand. Areas with steady levels of property crime or traffic incidents may need to be focused on for patrols. Time periods with many incidents and slow response times may show that shift schedules or dispatch procedures should be adjusted.

Focusing on stages where delays build up can guide more targeted actions to reduce dispatch-to-clearance time. These stages include dispatch queues and long on-scene times. Looking closely at call routing rules and the handling of complicated incidents may help uncover the sources of slowdowns. Small changes in these parts of the process can create clear improvements in the overall response time.



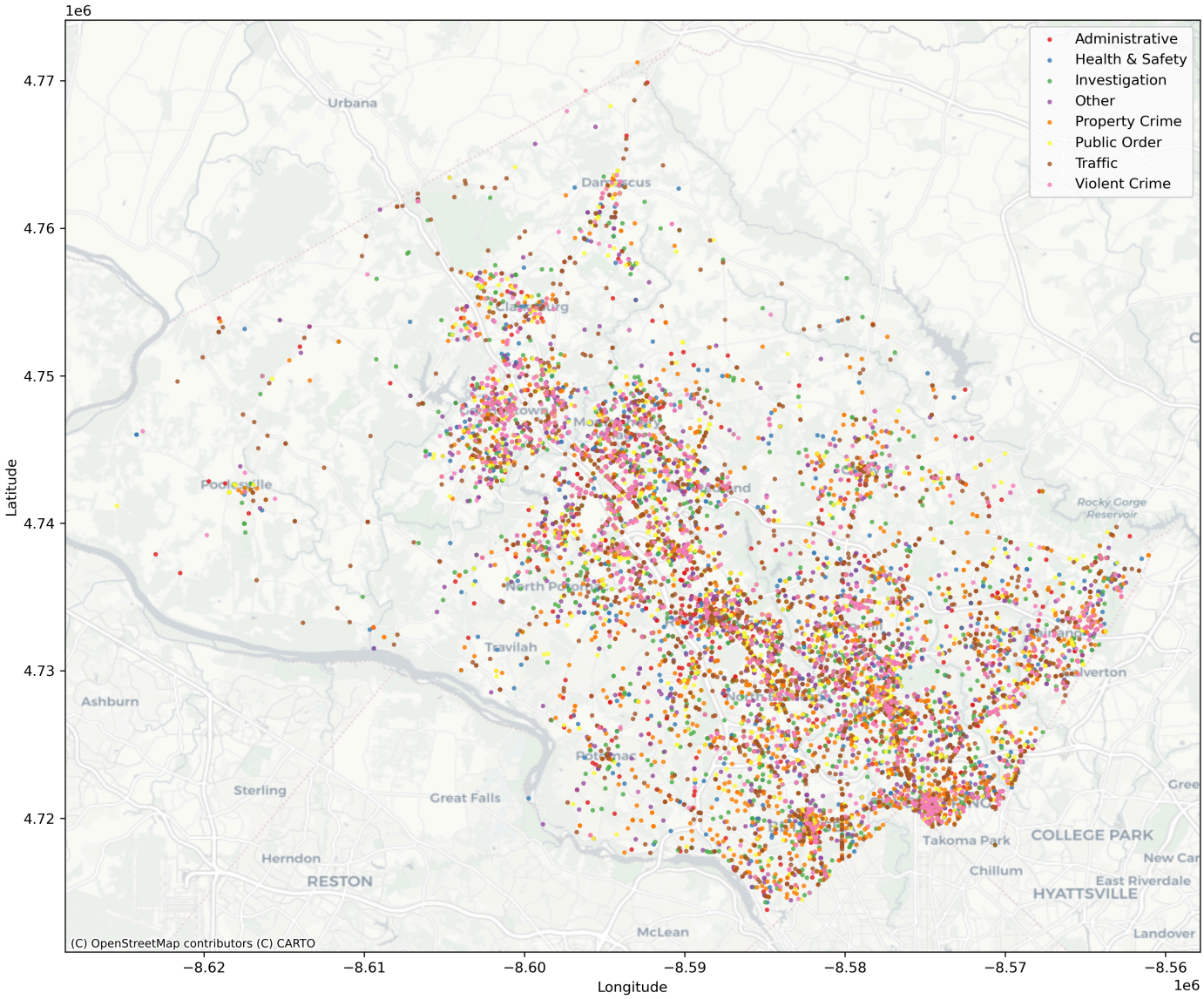
Multiclass Logistic Regression Confusion Matrix

For data teams and policymakers, this research demonstrates the importance of detailed police incident data. The models' limitations emphasize the need for richer features, such as several text fields and neighborhood markers. Future work can link the current incident data to census records to build a deeper understanding of how police response times behave.

Conclusion

This project brings together the full data science process from data collection to data cleaning to exploratory data analysis to unsupervised learning to supervised learning. The goal is to study police incident call patterns in Montgomery County Maryland. The work starts with a large dataset and turns it into forms that are ready for analysis. It is then prepared for machine learning and used in statistical and machine learning methods to answer questions about police incident calls.

Incident patterns and response times change by type of incident time of day and location. Property crime and traffic incidents make up a large part of the workload and there are strong peaks by hour and weekday. At the same time the county does not break into simple groups based on incident features or response times. Predictive models can offer helpful signals for priority and response time yet they cannot capture the full complexity of real world policing and should be viewed as tools that support decisions rather than final decision makers.



Overall, this research shows that detailed data work combined with exploration and modeling can improve our understanding of public safety systems. By refining the data, adding missing context, and trying new models, future work can build on these results and support the design of more effective and fair emergency response strategies in Montgomery County.

Footnotes

1. Montgomery County sheriff's deputy will not be charged in shooting death of man who struck him with a large piece of wood, authorities say ↩

DSAN 5000 - Incident Response Modeling (MCMD)

Data Collection

Overview

The following section explains how I will collect incident-level records from the Police Dispatched Incidents dataset using Montgomery County's open data API. In a data scientist's workflow, reliable raw data is the foundation of everything, as all following steps, including data wrangling, analysis, and modeling, depend on the quality of the raw data. In the details below, I will outline how I will set up and run the API query, organize and save raw files, check the schema, and record counts.

Methods

Data Source Information

Information utilized in this project is from the Montgomery County, Maryland Open Data Portal, specifically the dataset "Police Dispatched Incidents[1]" (dataset ID 98cc-bc7d). This dataset consists of about 1.76 million records of police dispatch calls, containing their timestamps, locations, nature of the calls, and duration of responses. This dataset is publicly available and can be downloaded from the Open Data Portal and from the Socrata API in the JSON format. Since I won't be needing all 1.76 million records, I will be only using data from October 2025.

Data Collection Methods

To collect data, I used the Socrata Open Data API to query the dataset, from the API endpoint: `https://data.montgomerycountymd.gov/resource/98cc-bc7d.json`. To get only records of October 2025, I added a SoQL `where` clause to filter the `start_time` field for that month. I also added a `limit` clause and set it to a large limit to ensure I receive all data of October 2025. By using the `requests` library, I sent an HTTP GET request to the endpoint mentioned above and parsed the JSON response into a Pandas DataFrame.

> **What is the Socrata Open Data API (SODA)?**[1]
>
> The **Socrata Open Data API (SODA)** is a standardized web API used by governments to publish and share open data in machine-readable formats such as JSON, CSV, and OData. It enables analysts, developers, and researchers to query public datasets directly—filtering, aggregating, and retrieving only the records they need.
>
> SODA is widely adopted across U.S. federal, state, and local governments, including major cities (New York City, Chicago, Los Angeles), states (Maryland, Utah, Washington), and several federal agencies. Its broad adoption makes it one of the most common and reliable ways to access public-sector data programmatically.

Data Structure and Format

The dataset comprises a sequential table wherein every unit is an individual incident reported and dispatched by police. Each unit tray records a variety of data, including but not limited to, identifiers, timestamps, dispositions, and location data along with different types of response time data. The data is updated 4 times per day. A complete list of all columns, including their field names and data types is provided in the table below.

Column Name	Description	API Field Name	Data Type
Incident_ID	CAD Incident Number	incident_id	Text
Crime Reports	Crime reports written for the event.	cr_number	Text
Crash Reports	Crash reports written for the event.	crash_reports	Text
Start Time	Incident call pickup date/time	start_time	Floating Timestamp
End Time	Last unit cleared date/time	end_time	Floating Timestamp
Priority	0 thru 4, with 0 as the highest priority	priority	Text
Initial Type	159 different codes for initial call type.	initial_type	Text
Close Type	Incident call type could change by the end of the call.	close_type	Text
Address	GIS process to geocode the actual address from police to the 100-block level address.	address	Text
City	City (mailing address value, not jurisdiction/municipality).	city	Text
State	State	state	Text
Zip	Zip Code	zip	Text
Longitude	Longitude for actual address, geocoded to 100-block level.	longitude	Number
Latitude	Latitude for actual address, geocoded to 100-block level.	latitude	Number
Police District	Incident location.	police_district_number	Text

Column Name	Description	API Field Name	Data Type
Number			
Beat	Incident location.	sector	Text
PRA	Incident location.	pra	Text
CallTime CallRoute	Seconds from call pickup to data entry start.	calltime_callroute	Number
Calltime Dispatch	Seconds from call pickup to first unit dispatched.	calltime_dispatch	Number
Calltime Arrive	Seconds from call pickup to first unit arriving on scene.	calltime_arrive	Number
Calltime Cleared	Seconds from call pickup to last unit cleared.	calltime_cleared	Number
CallRoute Dispatch	Seconds from data entry start to first unit dispatched.	callroute_dispatch	Number
Dispatch Arrive	Seconds from first unit dispatched to first unit arriving on scene.	dispatch_arrive	Number
Arrive Cleared	Seconds from first unit arriving on scene to last unit cleared.	arrive_cleared	Number
Disposition Desc	Final call disposition from last unit cleared.	disposition_desc	Text
Location	Geospatial point (latitude/longitude) of the incident.	geolocation	Point

The table above is directly based on the table from Montgomery County Open Data.

Linking to Data

Dataset Portal Page:

Police Dispatched Incidents – Montgomery County Open Data

API Endpoint (JSON):

```
https://data.montgomerycountymd.gov/resource/98cc-bc7d.json
```

Filtered Endpoint for October 2025:

https://data.montgomerycountymd.gov/resource/98cc-bc7d.json?$where=start_time%20between%20'2025-10-01T00:00:00'%20and%20'2025-10-31T23:59:59'

Code

The code block below fetches police dispatch data from Montgomery County's open-data API using API requests, converts the returned JSON into a pandas DataFrame, and saves it as a CSV file for future use.

```
import requests
import pandas as pd

# Step 1: Define the API endpoint for October 2025 data with a limit of 50000 records
url = ("https://data.montgomerycountymd.gov/resource/98cc-bc7d.json"
       "?$where=start_time between '2025-10-01T00:00:00' and '2025-10-31T23:59:59'"
       "&$limit=50000")

# Step 2: Send a GET request to the API endpoint above and parse the JSON response
data = requests.get(url).json()

# Step 3: Convert the JSON data into a pandas DataFrame
police_incident = pd.DataFrame(data)

# Step 4: Save the DataFrame to a CSV file
police_incident.to_csv("../../data/raw-data/police_incident.csv", index=False)

# Step 5: Display the DataFrame info
print(police_incident.describe())
```

```
        incident_id             cr_number               start_time  \
count         16782                  3056                    16782
unique        16782                  3056                    16714
top     P2500322473  250048786, 250050052  2025-10-09T16:14:56.000
freq              1                     1                        2

                      end_time priority                    initial_type  \
count                    16782    16782                           16782
unique                   16720        5                             161
top     2025-10-08T10:53:27.000        1  TRAFFIC/TRANSPORTATION INCIDENT
freq                         2     6459                            1394

                           close_type                  address  \
count                           16782                    16767
unique                            160                     6976
top     TRAFFIC/TRANSPORTATION INCIDENT  11100 BLK  VEIRS MILL RD
freq                              1392                      141

                city  state  ... calltime_callroute calltime_dispatch  \
count          16781  16781  ...              16782             15811
unique            32      1  ...                752              3104
```

```
top     SILVER SPRING     MD  ...                  0                204
freq             5528  16781  ...                442                 47

       callroute_dispatch    disposition_desc  \
count               15811               16782
unique               2937                 272
top                     0  OTHERMISCELLANEOUS
freq                  183                2960

                                    geolocation calltime_arrive  \
count                                     16782           13532
unique                                     5412            3628
top     {'type': 'Point', 'coordinates': [0, 0]}             613
freq                                       2406              20

       calltime_cleared dispatch_arrive arrive_cleared crash_reports
count             16779           13200          13531           664
unique             6780            2292           4592           664
top                1294               2            289     250048974
freq                 14             193             20             1

[4 rows x 26 columns]
```

```
print(police_incident.head())
```

```
   incident_id             cr_number               start_time  \
0  P2500322473  250048786, 250050052  2025-10-30T16:33:10.000
1  P2500324177             250048984  2025-10-31T23:30:25.000
2  P2500323992             250048964  2025-10-31T20:33:57.000
3  P2500323724                   NaN  2025-10-31T16:07:23.000
4  P2500324147             250048985  2025-10-31T22:50:14.000

                 end_time priority  \
0  2025-11-07T14:57:06.000        4
1  2025-11-01T02:45:49.000        2
2  2025-11-01T02:25:52.000        2
3  2025-11-01T01:37:13.000        4
4  2025-11-01T01:36:36.000        4

                                      initial_type  \
0  VANDALISM, DAMAGE, MISCHIEF-TRS - TELEPHONE RE...
1                              ASSIST OTHER AGENCY
2                              ASSIST OTHER AGENCY
3  FRAUDT-TRS FRAUD / DECEPTION - TELEPHONE REPOR...
4  STLVEHT - TRS STOLEN VEHICLE - TELEPHONE REPOR...

                                        close_type  \
0  VANDALISM, DAMAGE, MISCHIEF-TRS - TELEPHONE RE...
1                              ASSIST OTHER AGENCY
2                              ASSIST OTHER AGENCY
```

```
3  FRAUDT–TRS FRAUD / DECEPTION – TELEPHONE REPOR...
4  STLVEHT – TRS STOLEN VEHICLE – TELEPHONE REPOR...

                    address           city state  ... calltime_callroute  \
0     19900 BLK  WOOTTON AVE    POOLESVILLE    MD  ...                123
1      8200 BLK  GEORGIA AVE  SILVER SPRING    MD  ...                  0
2     1  BLK  TURTLE DOVE CT   GAITHERSBURG    MD  ...                  0
3  15200 BLK  SIESTA KEY WAY      ROCKVILLE    MD  ...                183
4      8000 BLK  EASTERN AVE  SILVER SPRING    MD  ...                412

  calltime_dispatch callroute_dispatch       disposition_desc  \
0              6804               6681     VANDALISM–DWELLING
1               137                137        MENTALTRANSPORT
2               NaN                NaN          CDS–USEDRUGOD
3              2329               2145   FORGERY/CNTRFT–ALLOTH
4              3191               2779  AUTOTHEFT–PASSENGERVEH

                                      geolocation calltime_arrive  \
0          {'type': 'Point', 'coordinates': [0, 0]}            NaN
1  {'type': 'Point', 'coordinates': [–77.0266, 38...            190
2  {'type': 'Point', 'coordinates': [–77.1873, 39...            217
3  {'type': 'Point', 'coordinates': [–77.1946, 39...            NaN
4  {'type': 'Point', 'coordinates': [–77.031, 38....            NaN

  calltime_cleared dispatch_arrive arrive_cleared crash_reports
0              NaN             NaN            NaN           NaN
1            11723              53          11532           NaN
2            21115             NaN          20898           NaN
3            34189             NaN            NaN           NaN
4             9982             NaN            NaN           NaN

[5 rows x 26 columns]
```

Conclusion

Among all the future steps in the data workflow, the data collection stage is the simplest, with only a single task, which is obtaining Montgomery County's police dispatch incident records from the county's open-data portal. The data extracted included a total of 16,782 records about police dispatch incidents. Each of the records contains 26 attributes, including unique identifiers, timestamps, initial and closing call classifications, priority, address, police district, and derived timing intervals. The `incident_id`, `start_time` and `initial_type` columns are fully populated, but some other columns such as `cr_number`, `calltime_arrive` and `crash_reports` contain null values. As a result, data cleaning steps like imputing or dropping missing data will be necessary.

Challenges

The only technical difficulty occured during the initial data acquisition stage is that the data.gov[2] CKAN API delivers only metadata, so the workflow had to pivot to the Montgomery County Socrata Open Data API to fetch the actual records.

References

1. ChatGPT, version-5.1, OpenAI, NOV-2025, chat.openai.com.

Footnotes

1. Montgomery County Police Dispatched Incident Dataset ↩
2. DATA.GOV, Police Dispatched Incidents, Montgomery County of Maryland ↩

DSAN 5000 - Incident Response Modeling (MCMD)

Data Cleaning

Overview

During data cleaning, I will transform the raw Police Dispatched Incidents data into a usable dataset. If this step is not performed well, misleading values or categories can lead to misleading results later on. I will convert timestamps to date and time, ensure that numeric fields are correct, fix missing values, and add features such as priority flags or indicators. More specifically, I will first parse fields like `start_time`, `end_time`, `latitude`, `longitude`, and various call-time durations, standardize columns like `initial_type`, `close_type`, and `disposition_desc`, and handle missing and duplicate values. For each of the code blocks below, I will document each step with notes and explanations. I will include a visualization of the data before and after cleaning. Also, the process of data cleaning might need to be revisited as the project evolves and analysis goals change.

Methods and Codes (EDA)

In this section, I will mainly focuse on preparing the dataset for exploratory data analysis (EDA). This includes handling missing values, visualizing missing data patterns, converting units, generate missing longitude and latitudes based on addresses, generate new columns, and ensuring the dataset is clean and ready for analysis.

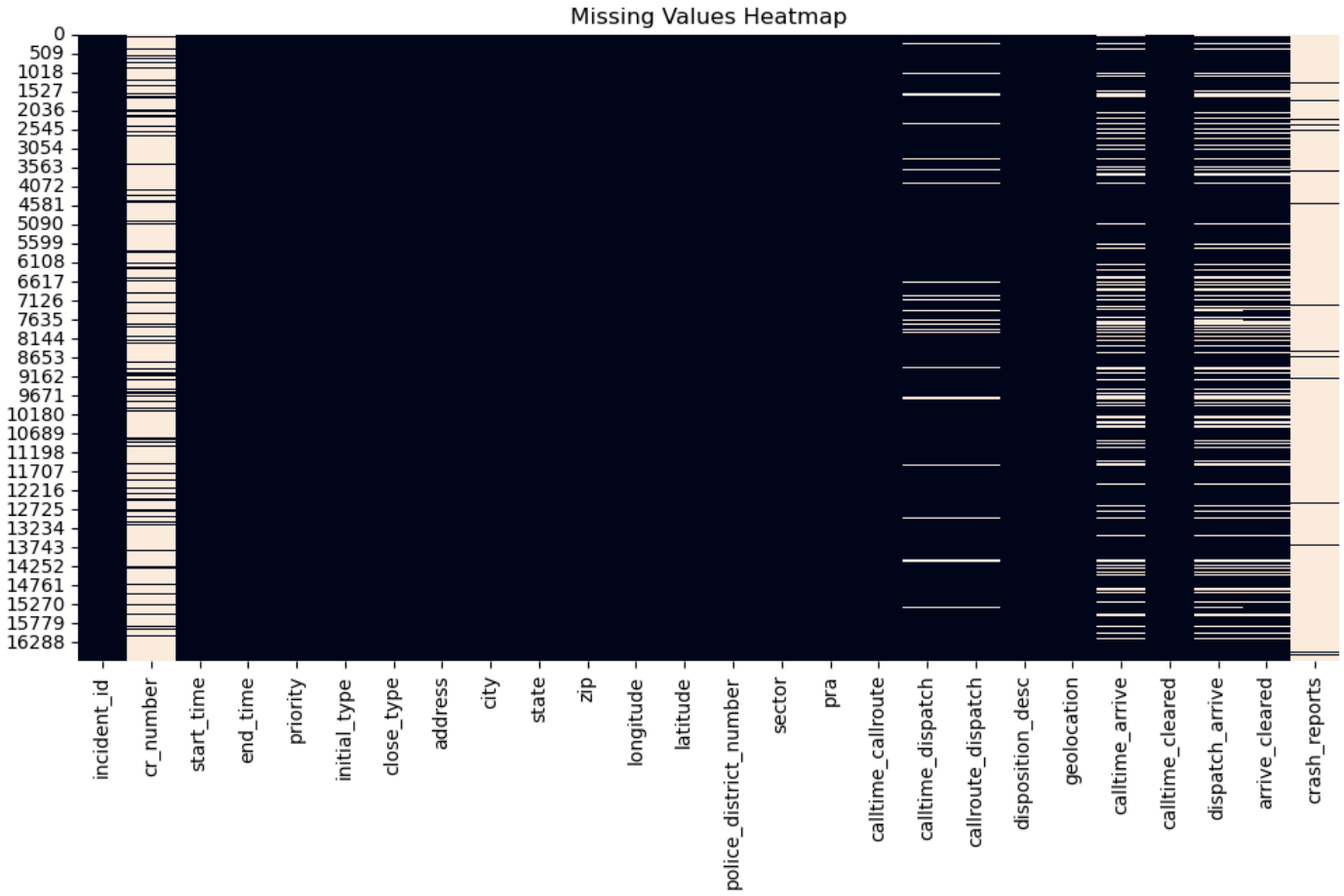
Visualize Missing Data

In this step, I will create a heatmap to show the distribution of missing values in the dataset. This helps to identify patterns of missingness and informs decisions on how to handle them. Also, I can remove columns with excessive missing values based on the visualization.

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# Load the police incident dataset
police_incident = pd.read_csv("../../data/raw-data/police_incident.csv")

# Visualize missing data using a heatmap
plt.figure(figsize=(12,6))
sns.heatmap(police_incident.isna(), cbar=False)
plt.title("Missing Values Heatmap")
plt.savefig("../../report/visual3.png", dpi=300, bbox_inches="tight")
plt.show()
```



Handling Columns with Large Amounts of Missing Data

From the visualization above, we can identify two columns with significant missing data: `cr_number` and `crash_reports`. Since these columns have substantial missing data, they are not helpful to our analysis, so I will remove these columns to improve the dataset's quality and ensure that subsequent analyses are not biased by this information. I will also provide a summary of data tyoes, nulls and zeros of the remaining columns.

```
# Remove columns with large amounts of missing data
police_incident = police_incident.drop("cr_number", axis=1)
police_incident = police_incident.drop("crash_reports", axis=1)

# Summary of nulls, zeros, and data types for each column
pd.DataFrame({
    'null_count': police_incident.isnull().sum(),
    'zero_count': (police_incident == 0).sum(),
    'dtype': police_incident.dtypes
})
```

	null_count	zero_count	dtype
incident_id	0	0	object

	null_count	zero_count	dtype
start_time	0	0	object
end_time	0	0	object
priority	0	1682	int64
initial_type	0	0	object
close_type	0	0	object
address	15	0	object
city	1	0	object
state	1	0	object
zip	1	0	float64
longitude	0	2406	float64
latitude	0	2406	float64
police_district_number	0	0	object
sector	1	0	object
pra	1	0	float64
calltime_callroute	0	442	int64
calltime_dispatch	971	0	float64
callroute_dispatch	971	183	float64
disposition_desc	0	0	object
geolocation	0	0	object
calltime_arrive	3250	0	float64
calltime_cleared	3	0	float64
dispatch_arrive	3582	0	float64
arrive_cleared	3251	0	float64

Data Type Correction

By reviewing the table above, I will review the data types of each column to ensure they are appropriate for analysis. I converted `start_time` and `end_time` into datetime objects. The `zip` column was cast to a string. Several descriptive fields, including `priority`, `initial_type`, `close_type`, `city`, `state`, `sector`, and `disposition_desc`, were converted to categorical types. Finally, all response-time metrics, including `calltime_callroute`, `calltime_dispatch`, `callroute_dispatch`, `calltime_arrive`, `calltime_cleared`, `dispatch_arrive`, and `arrive_cleared`, were converted to numeric values.

```
# Data Type Correction
police_incident['start_time'] = pd.to_datetime(police_incident['start_time'])
police_incident['end_time'] = pd.to_datetime(police_incident['end_time'])
```

```
police_incident['zip'] = police_incident['zip'].astype('Int64').astype('string')

police_incident['priority'] = police_incident['priority'].astype('category')
police_incident['initial_type'] = police_incident['initial_type'].astype('category')
police_incident['close_type'] = police_incident['close_type'].astype('category')
police_incident['city'] = police_incident['city'].astype('category')
police_incident['state'] = police_incident['state'].astype('category')
police_incident['sector'] = police_incident['sector'].astype('category')
police_incident['disposition_desc'] = police_incident['disposition_desc'].astype('categor

police_incident['calltime_callroute'] = pd.to_numeric(police_incident['calltime_callroute
police_incident['calltime_dispatch'] = pd.to_numeric(police_incident['calltime_dispatch']
police_incident['callroute_dispatch'] = pd.to_numeric(police_incident['callroute_dispatch
police_incident['calltime_arrive'] = pd.to_numeric(police_incident['calltime_arrive'], er
police_incident['calltime_cleared'] = pd.to_numeric(police_incident['calltime_cleared'],
police_incident['dispatch_arrive'] = pd.to_numeric(police_incident['dispatch_arrive'], er
police_incident['arrive_cleared'] = pd.to_numeric(police_incident['arrive_cleared'], erro

# Summary of nulls, zeros, and data types for each column
pd.DataFrame({
    'null_count': police_incident.isnull().sum(),
    'zero_count': (police_incident == 0).sum(),
    'dtype': police_incident.dtypes
})
```

	null_count	zero_count	dtype
incident_id	0	0	object
start_time	0	0	datetime64[ns]
end_time	0	0	datetime64[ns]
priority	0	1682	category
initial_type	0	0	category
close_type	0	0	category
address	15	0	object
city	1	0	category
state	1	0	category
zip	1	0	string[python]
longitude	0	2406	float64
latitude	0	2406	float64
police_district_number	0	0	object
sector	1	0	category
pra	1	0	float64
calltime_callroute	0	442	int64

	null_count	zero_count	dtype
calltime_dispatch	971	0	float64
callroute_dispatch	971	183	float64
disposition_desc	0	0	category
geolocation	0	0	object
calltime_arrive	3250	0	float64
calltime_cleared	3	0	float64
dispatch_arrive	3582	0	float64
arrive_cleared	3251	0	float64

Handle Missing Longitude and Latitude

Since the longitude and latitude columns are essential for generating maps and spatial analysis, I will fill in the missing values using the Google Geocoding API, since I have the address information for each incident. This approach ensures that we have complete geographical data for all incidents, which is crucial for accurate spatial analysis and visualization.

```
import requests
import numpy as np
import time
from dotenv import load_dotenv
import os

# Load the API key from environment variables
load_dotenv("../../apikey.env")
API_KEY = os.getenv("GOOGLE_API_KEY")
GEOCODE_URL = "https://maps.googleapis.com/maps/api/geocode/json"

# Define the geocoding function
def geocode(address):
    req = requests.get(GEOCODE_URL, params={"address": address, "key": API_KEY}).json()
    if req.get("status") == "OK":
        loc = req["results"][0]["geometry"]["location"]
        return loc["lng"], loc["lat"]
    return np.nan, np.nan

# Identify rows with missing latitude or longitude
missing = police_incident[(police_incident["longitude"] == 0) | (police_incident["latitud

# Iterate over missing rows and update longitude and latitude
count = 0

for idx, row in missing.iterrows():
    address = f"{row['address']}, {row['city']}, {row['state']} {row['zip']}"
    lon, lat = geocode(address)
```

```
    police_incident.loc[idx, "longitude"] = lon
    police_incident.loc[idx, "latitude"] = lat
    count += 1
    print(f"[{count}/{len(missing)}] Index {idx}: {lon}, {lat}")

# To avoid too many api requests for my google api key
police_incident.to_csv("../../data/processed-data/police_incident_longitude&latitude.csv"
print("Saved")
```

```
[1/2406] Index 0: -77.41542679999999, 39.1434676
[2/2406] Index 13: -77.2742373, 39.1467753
[3/2406] Index 21: -77.2160456, 39.0097548
[4/2406] Index 25: -77.1564864, 38.9909745
[5/2406] Index 33: -77.13367579999999, 38.9778763
[6/2406] Index 37: -76.9414044, 39.0842899
[7/2406] Index 50: -77.2747315, 39.2144536
[8/2406] Index 56: -77.1102449, 38.9782397
[9/2406] Index 58: -77.2707555, 39.0555524
[10/2406] Index 60: -77.20849450000001, 39.2872181
[11/2406] Index 67: -77.261729, 39.187493
[12/2406] Index 74: -77.0507011, 39.0369934
[13/2406] Index 84: -77.1928255, 39.1442494
[14/2406] Index 115: -77.1972425, 39.1836612
[15/2406] Index 120: -77.19296560000001, 39.1474639
[16/2406] Index 128: -77.0923952, 39.0501657
[17/2406] Index 133: -76.9879646, 39.1473132
[18/2406] Index 137: -76.9844652, 39.0184131
[19/2406] Index 146: -77.11292259999999, 39.0213603
[20/2406] Index 150: -77.0218648, 38.9971837
[21/2406] Index 152: -77.4090434, 39.14368750000001
[22/2406] Index 165: -77.05541989999999, 39.0556524
[23/2406] Index 167: -77.0503559, 39.058254
[24/2406] Index 188: -77.17634819999999, 38.9962098
[25/2406] Index 189: -76.9472612, 39.0827914
[26/2406] Index 194: -77.0046161, 39.0696777
[27/2406] Index 197: -77.2039928, 39.2508087
[28/2406] Index 202: -76.9898226, 38.9991051
[29/2406] Index 213: -77.0482408, 39.0413702
[30/2406] Index 217: -77.087991, 39.1411867
[31/2406] Index 219: -77.0804689, 39.0901267
[32/2406] Index 233: -76.96803369999999, 39.0565845
[33/2406] Index 234: -77.1394384, 39.0792326
[34/2406] Index 235: -77.056175, 38.9941413
[35/2406] Index 238: -77.0218648, 38.9971837
[36/2406] Index 240: -77.0169196, 38.9879087
[37/2406] Index 259: -77.1004896, 39.0907042
[38/2406] Index 276: -77.07751449999999, 39.0760398
[39/2406] Index 278: -77.2095056, 39.0186509
[40/2406] Index 316: -77.2056459, 39.01591
[41/2406] Index 320: -77.0503559, 39.058254
```

```
[42/2406] Index 328: -77.2586498, 39.2317476
[43/2406] Index 336: -76.9788651, 39.09785110000001
[44/2406] Index 338: -76.97203809999999, 39.1008533
[45/2406] Index 339: -77.096732, 38.9911745
[46/2406] Index 351: -77.0503559, 39.058254
[47/2406] Index 354: -77.0304429, 38.9947772
[48/2406] Index 356: -77.0531, 39.061364
[49/2406] Index 376: -77.22719649999999, 39.0392587
[50/2406] Index 387: -77.10145729999999, 38.9632952
[51/2406] Index 394: -77.0513692, 39.0603083
[52/2406] Index 402: -77.10197699999999, 39.0931164
[53/2406] Index 413: -77.0477767, 39.045273
[54/2406] Index 418: -77.137371, 39.0917302
[55/2406] Index 420: -77.18687419999999, 39.1739128
[56/2406] Index 423: -77.0521418, 39.0418728
[57/2406] Index 425: -77.04706279999999, 38.9956155
[58/2406] Index 434: -77.1332048, 39.0014769
[59/2406] Index 440: -77.05341059999999, 39.0478294
[60/2406] Index 448: -77.2118407, 39.2813446
[61/2406] Index 454: -77.096732, 38.9911745
[62/2406] Index 470: -77.17634819999999, 38.9962098
[63/2406] Index 476: -77.2325831, 39.1153651
[64/2406] Index 504: -77.4206647, 39.1425355
[65/2406] Index 507: -77.071968, 39.1516646
[66/2406] Index 508: -77.20279239999999, 39.0760616
[67/2406] Index 510: -77.0321359, 38.9974075
[68/2406] Index 514: -76.9472612, 39.0827914
[69/2406] Index 517: -77.01672649999999, 39.0412122
[70/2406] Index 519: -77.0454558, 39.0365977
[71/2406] Index 524: -77.096732, 38.9911745
[72/2406] Index 525: -77.2855295, 39.2218699
[73/2406] Index 536: -77.0754709, 39.030936
[74/2406] Index 541: -77.00316140000001, 39.0330374
[75/2406] Index 546: -77.1364919, 39.0535941
[76/2406] Index 553: -77.1100027, 39.0509191
[77/2406] Index 565: -77.0284697, 38.9942096
[78/2406] Index 566: -77.2614478, 39.1846433
[79/2406] Index 575: -77.0284697, 38.9942096
[80/2406] Index 577: -77.2055748, 39.2906426
[81/2406] Index 579: -77.0321359, 38.9974075
[82/2406] Index 584: -77.0531484, 39.1455341
[83/2406] Index 590: -77.0304429, 38.9947772
[84/2406] Index 591: -77.1895389, 39.0185405
[85/2406] Index 603: -76.9403895, 39.0870183
[86/2406] Index 616: -76.9472612, 39.0827914
[87/2406] Index 624: -77.1191525, 39.0729866
[88/2406] Index 628: -77.0704485, 39.0770626
[89/2406] Index 640: -77.0704485, 39.0770626
[90/2406] Index 651: -77.19418329999999, 39.1450142
[91/2406] Index 657: -77.0320065, 38.9960781
[92/2406] Index 660: -77.1944214, 39.1887816
```

```
[93/2406] Index 674: -77.17495989999999, 39.1529136
[94/2406] Index 678: -77.0521418, 39.0418728
[95/2406] Index 680: -77.17634819999999, 38.9962098
[96/2406] Index 681: -77.1972425, 39.1836612
[97/2406] Index 695: -76.9677966, 39.0540986
[98/2406] Index 700: -77.0704485, 39.0770626
[99/2406] Index 704: -77.096732, 38.9911745
[100/2406] Index 713: -77.1394384, 39.0792326
[101/2406] Index 720: -77.153899, 39.1798986
[102/2406] Index 725: -77.0218648, 38.9971837
[103/2406] Index 728: -77.1218317, 39.0848457
[104/2406] Index 742: -77.0218648, 38.9971837
[105/2406] Index 746: -77.1218317, 39.0848457
[106/2406] Index 750: -77.071489, 39.07236109999999
[107/2406] Index 767: -77.0357279, 39.0260298
[108/2406] Index 776: -76.97423549999999, 39.0921702
[109/2406] Index 779: -77.0503559, 39.058254
[110/2406] Index 789: -77.0304429, 38.9947772
[111/2406] Index 790: -77.0570594, 39.0808601
[112/2406] Index 802: -77.10026839999999, 38.9907397
[113/2406] Index 810: -77.0503559, 39.058254
[114/2406] Index 818: -77.037466, 38.9958963
[115/2406] Index 829: -77.0521418, 39.0418728
[116/2406] Index 845: -77.2601712, 39.2452183
[117/2406] Index 846: -77.01437419999999, 39.0034711
[118/2406] Index 852: -77.10273579999999, 39.00523039999999
[119/2406] Index 854: -77.0513359, 39.0387866
[120/2406] Index 859: -77.1009826, 39.00844319999999
[121/2406] Index 862: -77.2637907, 39.182903
[122/2406] Index 881: -77.0516921, 39.0506864
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[2390/2406] Index 16590: -77.0513359, 39.0387866
[2391/2406] Index 16591: -77.1167706, 39.0504708
[2392/2406] Index 16612: -77.1234697, 39.0125086
[2393/2406] Index 16613: -77.1048279, 38.9622969
[2394/2406] Index 16627: -76.95688659999999, 39.0493731
[2395/2406] Index 16646: -77.0503559, 39.058254
[2396/2406] Index 16669: -76.9399071, 39.0900694
[2397/2406] Index 16670: -77.1301427, 39.0059686
[2398/2406] Index 16674: -77.1772737, 39.1733025
[2399/2406] Index 16677: -77.16569779999999, 38.99494929999999
[2400/2406] Index 16683: -77.0693411, 39.0659336
[2401/2406] Index 16686: -77.2049452, 39.2920299
[2402/2406] Index 16689: -77.137371, 39.0917302
[2403/2406] Index 16701: -77.2414349, 39.20007440000001
[2404/2406] Index 16707: -77.20432819999999, 39.0466638
[2405/2406] Index 16742: -77.0513935, 39.0923639
[2406/2406] Index 16781: -77.22087479999999, 39.109296
Saved
```

Removing Unwanted Columns and Rows

After using Google API to fill in missing longitude and latitude values, I will remove the address-related columns, including `address`, `city`, `state`, `zip`, `pra` and `geolocation`, since the `longitude` and `latitude` columns are enough for spatial analysis and visualization. Also, I notice there are null values in the `longitude` and `latitude` columns after geocoding. I will take a look at the value first. After identifying below that this data point has an invalid address and is outside the county, I will remove this row from the dataset to ensure data integrity. Also, there are several columns that are not useful for my EDA analysis or modeling, such as `incident_id`. I will remove these unique identifier columns to focus on relevant information.

```
import pandas as pd

# Load the updated police incident dataset with geocoded longitude and latitude
police_incident = pd.read_csv("../../data/processed-data/police_incident_longitude&latitu

# Summary of nulls, zeros, and data types for each column
pd.DataFrame({
    'null_count': police_incident.isnull().sum(),
    'zero_count': (police_incident == 0).sum(),
    'dtype': police_incident.dtypes
})
```

	null_count	zero_count	dtype
incident_id	0	0	object
start_time	0	0	object

	null_count	zero_count	dtype
end_time	0	0	object
priority	0	1682	int64
initial_type	0	0	object
close_type	0	0	object
address	15	0	object
city	1	0	object
state	1	0	object
zip	1	0	float64
longitude	1	0	float64
latitude	1	0	float64
police_district_number	0	0	object
sector	1	0	object
pra	1	0	float64
calltime_callroute	0	442	int64
calltime_dispatch	971	0	float64
callroute_dispatch	971	183	float64
disposition_desc	0	0	object
geolocation	0	0	object
calltime_arrive	3250	0	float64
calltime_cleared	3	0	float64
dispatch_arrive	3582	0	float64
arrive_cleared	3251	0	float64

```
# Check the row with missing longitude and latitude
police_incident[police_incident['longitude'].isna()]
```

	incident_id	start_time	end_time	priority	initial_type	close_type	address	city	state	zip	...	pra	calltime_c
12153	P2500299963	2025-10-09 16:21:04	2025-10-09 16:53:28	4	OC - OUT OF COUNTY	OC - OUT OF COUNTY	NaN	NaN	NaN	NaN	...	NaN	25

1 rows × 24 columns

```
# Remove rows with missing longitude and latitude and unwanted columns related to address
police_incident = police_incident.dropna(subset=['longitude', 'latitude'])
police_incident = police_incident.drop(columns=['address', 'city', 'state', 'zip', 'geolo
```

```
# Remove unique identifier columns & unwanted columns
police_incident = police_incident.drop(columns=['disposition_desc', 'incident_id'])

# Summary of nulls, zeros, and data types for each column
pd.DataFrame({
    'null_count': police_incident.isnull().sum(),
    'zero_count': (police_incident == 0).sum(),
    'dtype': police_incident.dtypes
})
```

	null_count	zero_count	dtype
start_time	0	0	object
end_time	0	0	object
priority	0	1682	int64
initial_type	0	0	object
close_type	0	0	object
longitude	0	0	float64
latitude	0	0	float64
police_district_number	0	0	object
sector	0	0	object
calltime_callroute	0	442	int64
calltime_dispatch	971	0	float64
callroute_dispatch	971	183	float64
calltime_arrive	3250	0	float64
calltime_cleared	3	0	float64
dispatch_arrive	3582	0	float64
arrive_cleared	3251	0	float64

To reduce data size and improve processing efficiency, I will review the initial_type and close_type columns. It turns out that only 447 cases have different initial and close types out of all the records. I've decided to drop the `initial_type` column since `close_type` is the "ground truth" after investigation. This column will be enough for the EDA and modeling. I will rename `close_type` to `incident_type` for clarity.

```
# Compare initial vs close types
different = police_incident[police_incident['initial_type'] != police_incident['close_typ
print(f"Total incidents: {len(police_incident)}")
print(f"Difference: {len(different)} ({len(different)/len(police_incident)*100:.2f}%)")

# Remove rename close_type to incident_type
police_incident = police_incident.rename(columns={'close_type': 'incident_type'})
police_incident = police_incident.drop(columns=['initial_type'])
```

```
Total incidents: 16781
Difference: 447 (2.66%)
```

Modify Data for Better Intepretation

To enhance the interpretability of my dataset, I will modify several columns, including priority and incident types. Originally, the `priority` column ranges from 0 to 4, with 0 being the highest priority. To make it more intuitive, I will modify this scale so that 1 is the lowest priority and 5 is the highest priority. Also, for the incident types columns, I will group around 180 columns into several broader categories based on incident type, which will be better for exploratory data analysis and modeling. The new categories include 'Violent Crime', 'Property Crime', 'Public Order', 'Health & Safety', 'Investigation', 'Assistance & Administrative', and 'Other'. I will also convert all numeric columns from a unit of seconds to unit of minutes.

Modify Scale of Priority

```
police_incident['priority'] = 5 - police_incident['priority']

# Summary of nulls, zeros, and data types for each column
pd.DataFrame({
    'null_count': police_incident.isnull().sum(),
    'zero_count': (police_incident == 0).sum(),
    'dtype': police_incident.dtypes
})
```

	null_count	zero_count	dtype
start_time	0	0	object
end_time	0	0	object
priority	0	0	int64
incident_type	0	0	object
longitude	0	0	float64
latitude	0	0	float64
police_district_number	0	0	object
sector	0	0	object
calltime_callroute	0	442	int64
calltime_dispatch	971	0	float64
callroute_dispatch	971	183	float64
calltime_arrive	3250	0	float64
calltime_cleared	3	0	float64
dispatch_arrive	3582	0	float64
arrive_cleared	3251	0	float64

Group Incident Types into Broad Categories

```
# Check catagories in initial_type and close_type
pd.set_option('display.max_rows', None)
print(sorted(police_incident['incident_type'].unique()))
```

```
['ABDUCTION (KIDNAPPING) – CUSTODIAL ABDUCTION, HOSTAGE SITUAT', 'ABDUCTION (KIDNAPPING)
– CUSTODIAL ABDUCTION, HOSTAGE SITUAT – OCCURRED EARLIER', 'ABUSE, ABANDONMENT, NEGLECT',
'ABUSE, ABANDONMENT, NEGLECT – OCCURRED EARLIER', 'ABUSEOS', 'ADMINISTRATIVE (DOCUMENT,
LOST OR FOUND PROP, MESSAGES – OCCURRED EARLIER', 'ADMINISTRATIVE (DOCUMENT, LOST OR
FOUND PROPERTY, MESSAGES,', 'ADMINISTRATIVE (DOCUMENT, LOST OR FOUND PROPERTY, MESSAGES,
– OCCURRED EARLIER', 'ALARMBB – BANK BURGLARY/INTRUSION', 'ALARMBH – BANK
HOLDUP/DURESS/PANIC', 'ALARMRB – ALARM COMMERCIAL BURGLARY/INTRUSION', 'ALARMRB –
COMMERCIAL HOLDUP/DURESS/PANIC', 'ALARMRB – RESIDENTIAL BURGLARY/INTRUSION', 'ALARMRB –
RESIDENTIAL HOLDUP/DURESS/PANIC', 'ALARMU – ALARM OTHER/UNKNOWN', 'ALARMV – ALARM
VEHICLE', 'ANI – ANIMAL COMPL ON PATROL', 'ANIMAL ABUSE', 'ANIMAL ABUSE – OCCURRED
EARLIER', 'ANIMAL COMPL', 'ANIMAL MISC', 'ANIMAL RESCUE', 'ANIMAL VICIOUS', 'ANIMAL
VICIOUS – OCCURRED EARLIER', 'ANIMALVJ – ANIMAL VICIOUS JUST OCCURRED', 'ASLTA',
'ASLTJA', 'ASLTOS', 'ASSAULT', 'ASSAULT – OCCURRED EARLIER', 'ASSAULT JUST OCCURRED –
ROUTINE', 'ASSAULT–TRS – TELEPHONE REPORTING UNIT', 'ASSIST OTHER AGENCY',
'ASSIST/STANDBY', 'BOMB DEVICE FOUND, SUSP PACKAGE, CONTAMINATION', 'BOMB THREAT, CBRN,
CONTAMINATION', 'BOX ALARM – VIA FRS', 'BURGLARY', 'BURGLARY – OCCURRED EARLIER',
'BURGLARY JUST OCCURRED', 'BURGOS', 'CAR JACKING', 'CDS', 'CDS – OCCURRED EARLIER',
'CHECK WELFARE', 'CRYWOLF INTERFACE INCIDENT TYPE', 'DECEASED PERSON', 'DISPJ', 'DISPOS',
'DISTURBANCE/NUISANCE', 'DISTURBANCE/NUISANCE – OCCURRED EARLIER', 'DOMDOS', 'DOMESTIC
DISPUTE', 'DOMESTIC DISTURBANCE/VIOLENCE', 'DOMESTIC DISTURBANCE/VIOLENCE – OCCURRED
EARLIER', 'DOMESTIC DISTURBANCE/VIOLENCE OCCURRED EARLIER', 'DOMESTIC VIOLENCE', 'DOMVA',
'DOMVJA', 'DOMVOS', 'DRIVING UNDER THE INFLUENCE', 'DT – DETAIL', 'E911 DISCONNECT',
'EVALUATION BY MCOT', 'FOLLOW UP/SUPPLEMENTAL INFORMATION', 'FOLLOW UP/SUPPLEMENTAL
INFORMATION – OCCURRED EARLIER', 'FOLLOWT–TRS / SUPPLEMENTAL INFORMATION – TELEPHONE
REPORTING UNIT', 'FRAUD/DECEPTION', 'FRAUD/DECEPTION – OCCURRED EARLIER', 'FRAUDJ',
'FRAUDT–TRS FRAUD / DECEPTION – TELEPHONE REPORTING UNIT', 'HARASSMENT, STALKING,
THREATS', 'HARASSMENT, STALKING, THREATS – OCCURRED EARLIER', 'HARASSMENT, STLAKING,
THREATS', 'HARASSOS', 'HARASST–TRS HARASSMENT, STALKING, THREATS – TELEPHONE REPORTING
UNIT', 'HAZARDOUS MATERIAL – VIA FRS', 'HUNT – HUNTING – ILLEGAL', 'INDECENCY/LEWDNESS',
'INDECENCY/LEWDNESS – OCCURRED EARLIER', 'INV – POLICE INVESTIGATION', 'LOCK OUT/IN',
'LOSTT–TRS ADMIN (DOCUMENT, LOST OR FOUND PROP, MESSAGES – TELEPHONE REPORTING UNIT',
'MENTAL DISORDER', 'MENTAL DISORDER – VIA FRS', 'MIS – MISC ON PATROL', 'MISC–ADMIN
(DOCUMENT, LOST OR FOUND PROPERTY, MESSAGES,', 'MISSARDD', 'MISSING, RUNAWAY, FOUND
PERSON', 'NEGLECTOS', 'NOISE – NOISE – OTHER COMPLAINTS', 'NON–PRIORITY RESPONSE
TRANSPORT', 'ORDNANCE – FOUND UNEXPLODED', 'OVERDOSE – VIA FRS', 'PARKING OFFENSE',
'PEDESTRIAN STRUCK', 'PEDESTRIAN STRUCK – OCCURRED EARLIER', 'PRIORITY RESPONSE
TRANSPORT', 'PROSTITUTION', 'RAPE', 'RAPEO – OCCURRED EARLIER', 'RAPEOS', 'RESCUE WITH
FRS', 'ROBBERY', 'ROBBERY – OCCURRED EARLIER', 'ROBBERY JUST OCCURRED', 'ROBOS', 'SEX
ASSAULT', 'SEXASLTJA', 'SEXASLTOS', 'SEXUAL ASSAULT', 'SEXUAL ASSAULT – OCCURRED
EARLIER', 'SHOOT – SHOOTING', 'SHOOTING', 'SHOOTO – SHOOTING – OCCURRED EARLIER',
'SHOTSOS', 'STAB – STABBING', 'STABBING', 'STABO – STABBING – OCCURRED EARLIER',
'STALKOS', 'STATION RESPONSE', 'STLVEHT – TRS STOLEN VEHICLE – TELEPHONE REPORTING UNIT',
'SUICIDAL PERSON/ATTEMPTED SUICIDE', 'SUICIDAL PERSON/ATTEMPTED SUICIDE – OCCURRED
EARLIER', 'SUSICIOUS CIRCUMSTANCE, PERSON, VEHICLE – OCCURRED EARLIER', 'SUSPICIOUS CIRC,
```

```
PERSONS, VEHICLE', 'TD – TRAFFIC DETAIL', 'THEFT/LARCENY', 'THEFT/LARCENY – HOLDING
SUSPECT', 'THEFT/LARCENY – OCCURRED EARLIER', 'THEFT/LARCENY FROM AUTO', 'THEFT/LARCENY
FROM AUTO – OCCURRED EARLIER', 'THEFTT – TRS THEFT/LARCENY – TELEPHONE REPORTING UNIT',
'THREATOS', 'THREATT – TRS HARASSMENT, STALKING, THREATS – TELEPHONE REPORTING UNIT',
'TRAFFIC ASSIST FOR FRS', 'TRAFFIC VIOLATION', 'TRAFFIC VIOLATION – OCCURRED EARLIER',
'TRAFFIC/TRANSPORTATION  INCIDENT – OCCURRED EARLIER', 'TRAFFIC/TRANSPORTATION INCIDENT',
'TRAFFIC/TRANSPORTATION INCIDENT – OCCURRED EARLIER', 'TRAIN COLLISION – VIA FRS', 'TRE –
TRESP ON PATROL', 'TRESPASSING/UNWANTED', 'TRESPASSING/UNWANTED – OCCURRED EARLIER',
'TRESPJ', 'TRESPOS', 'URGENT ASSIST', 'VANDALISM, DAMAGE, MISCHIEF', 'VANDALISM, DAMAGE,
MISCHIEF – OCCURRED EARLIER', 'VANDALISM, DAMAGE, MISCHIEF–TRS – TELEPHONE REPORTING
UNIT', 'WANTED PERSON, VEHICLE', 'WEAPJ', 'WEAPONS/FIREARMS', 'WEAPONS/FIREARMS –
OCCURRED EARLIER', 'WEAPOS', 'WEAPSUR', 'WORKING CODE', 'WS – WARRANT SERVICE']
```

To improve efficiency, the following code block us generated by Claude to group 180+ incident types into broader categories.[1]

```
# Group incident types into broader categories (Claude Sonnet4.5 Generated)
def group_type(incident_type):
    incident_type = str(incident_type).upper()

    if any(x in incident_type for x in ['ASSAULT', 'ASLT', 'SHOOT', 'STAB', 'DOMESTIC', '
        return 'Violent Crime'
    elif any(x in incident_type for x in ['THEFT', 'LARCENY', 'BURGLARY', 'BURG', 'ROBBER
        return 'Property Crime'
    elif 'TRAFFIC' in incident_type or 'PEDESTRIAN STRUCK' in incident_type or 'DUI' in i
        return 'Traffic'
    elif any(x in incident_type for x in ['DISTURBANCE', 'NUISANCE', 'NOISE', 'TRESPASS',
        return 'Public Order'
    elif any(x in incident_type for x in ['WELFARE', 'MENTAL', 'SUICID', 'OVERDOSE', 'MIS
        return 'Health & Safety'
    elif any(x in incident_type for x in ['SUSPICIOUS', 'ALARM', 'FRAUD', 'HARASSMENT', '
        return 'Investigation'
    elif any(x in incident_type for x in ['ASSIST', 'ADMINISTRATIVE', 'FOLLOW UP', 'STATI
        return 'Administrative'
    else:
        return 'Other'

police_incident['incident_type'] = police_incident['incident_type'].apply(group_type)
```

```
# Verify the new incident types
print(sorted(police_incident['incident_type'].unique()))
```

```
['Administrative', 'Health & Safety', 'Investigation', 'Other', 'Property Crime', 'Public
Order', 'Traffic', 'Violent Crime']
```

Convert Time Columns from Seconds to Minutes

```
# Convert time-related columns from seconds to minutes
calltime_cols = ['calltime_callroute', 'calltime_dispatch', 'callroute_dispatch', 'callti
```

```
for col in calltime_cols:
    police_incident[col] = police_incident[col] / 60
```

Generate Day of Week and Hour Column

```
# Correct start_time to data type
police_incident['start_time'] = pd.to_datetime(police_incident['start_time'], errors='coe

# Extract hour and weekday from start_time
police_incident['hour'] = police_incident['start_time'].dt.hour

# Extract weekday number
police_incident['weekday'] = police_incident['start_time'].dt.dayofweek + 1
```

```
# Verify the data after all previous modifications
print(police_incident.describe())

# Summary of nulls, zeros, and data types for each column
pd.DataFrame({
    'null_count': police_incident.isnull().sum(),
    'zero_count': (police_incident == 0).sum(),
    'dtype': police_incident.dtypes
})
```

```
                      start_time      priority     longitude  \
count                      16781  16781.000000  16781.000000
mean   2025-10-16 14:41:22.890054144      3.135749    -77.119698
min              2025-10-01 00:01:37      1.000000    -77.483699
25%              2025-10-08 18:16:50      2.000000    -77.196409
50%              2025-10-16 16:04:51      3.000000    -77.116200
75%              2025-10-24 10:34:18      4.000000    -77.048500
max              2025-10-31 23:59:04      5.000000    -76.905300
std                              NaN      1.264269      0.093557

           latitude  calltime_callroute  calltime_dispatch  \
count  16781.000000        16781.000000       15810.000000
mean      39.083999            2.896116          14.518516
min       38.945130            0.000000           0.133333
25%       39.031930            1.600000           3.633333
50%       39.077568            2.366667           6.183333
75%       39.141840            3.533333          12.933333
max       39.345283          154.366667        2854.433333
std        0.069480            3.043298          32.897465

       callroute_dispatch  calltime_arrive  calltime_cleared  dispatch_arrive  \
count        15810.000000     13531.000000      16778.000000     13199.000000
mean            11.608343        23.708330         56.591461        11.553745
min              0.000000         0.300000          0.333333         0.016667
```

```
25%              1.133333         9.583333        22.037500         3.783333
50%              3.083333        15.766667        38.041667         7.533333
75%              9.300000        26.891667        68.312500        13.566667
max           2852.316667      4433.150000      4549.766667      4410.633333
std             32.706549        50.818737        85.391884        46.686458
```

```
       arrive_cleared          hour       weekday
count    13530.000000  16781.000000  16781.000000
mean        32.711503     13.387343      4.026578
min          0.016667      0.000000      1.000000
25%          6.866667      9.000000      3.000000
50%         15.750000     14.000000      4.000000
75%         35.437500     18.000000      6.000000
max       4541.316667     23.000000      7.000000
std         68.250035      5.929021      1.904611
```

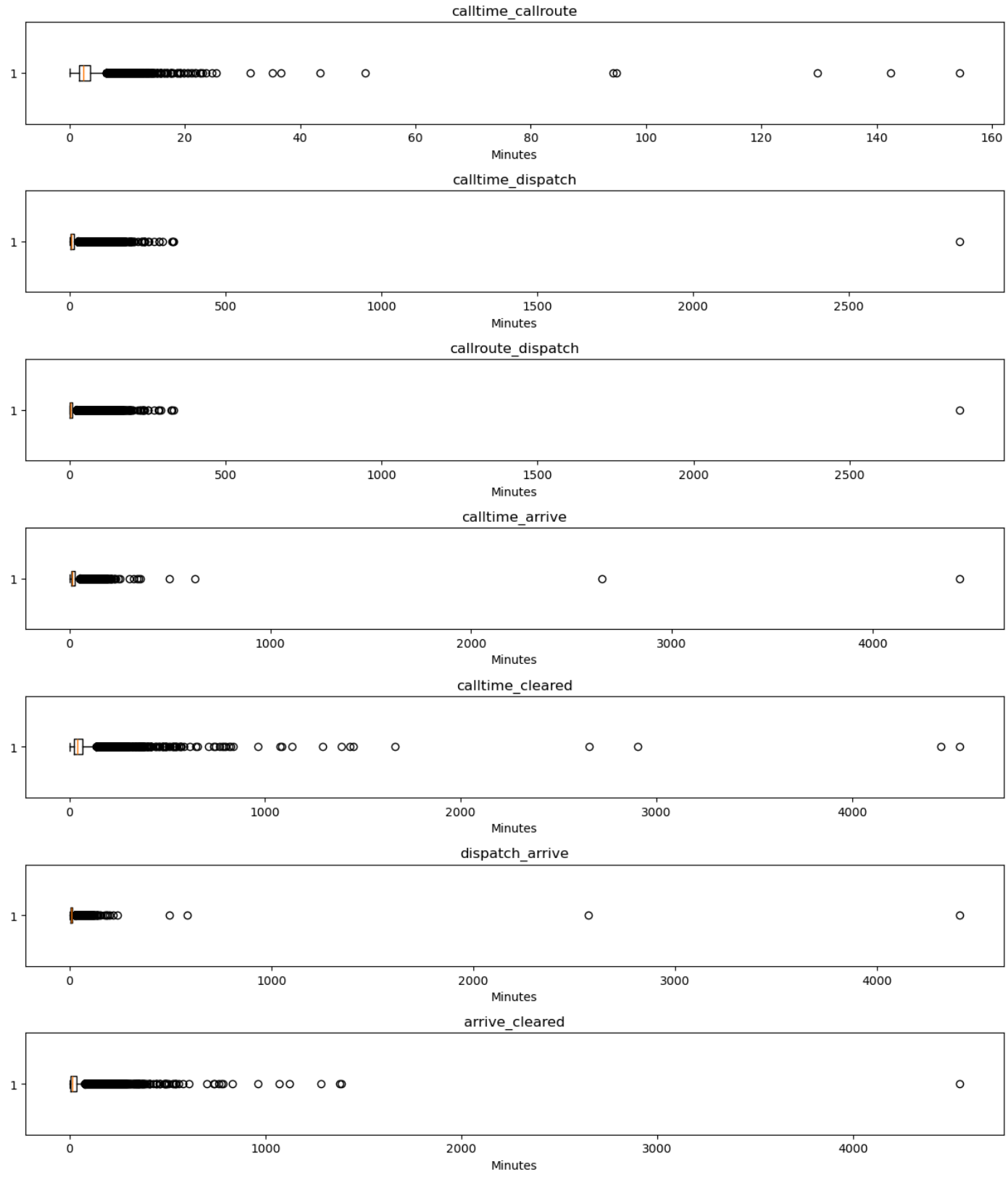
	null_count	zero_count	dtype
start_time	0	0	datetime64[ns]
end_time	0	0	object
priority	0	0	int64
incident_type	0	0	object
longitude	0	0	float64
latitude	0	0	float64
police_district_number	0	0	object
sector	0	0	object
calltime_callroute	0	442	float64
calltime_dispatch	971	0	float64
callroute_dispatch	971	183	float64
calltime_arrive	3250	0	float64
calltime_cleared	3	0	float64
dispatch_arrive	3582	0	float64
arrive_cleared	3251	0	float64
hour	0	465	int32
weekday	0	0	int32

Outlier Detection and Treatment

In this step, I will visualize and check for any extreme outliers that might seems like its an error using IQR fencing. After this step, the data is ready for exploratory data analysis. I will export a cleaned version of the dataset for EDA and proceed with normalization for future data modeling. I will not remove outliers that is not an error, since these

outliers might be important for the analysis. Some police incidents might take longer time to respond due to various reasons.

```
import matplotlib.pyplot as plt

# Visualize outliers in time-related columns using boxplots
fig, axes = plt.subplots(len(calltime_cols), 1, figsize=(12, len(calltime_cols)*2))
for i, col in enumerate(calltime_cols):
    axes[i].boxplot(police_incident[col].dropna(), vert=False)
    axes[i].set_title(col)
    axes[i].set_xlabel('Minutes')
plt.tight_layout()
plt.show()
```




```
# Check for any rows with values of 1000 or more minutes in any time column
pd.set_option('display.max_columns', None)
print(police_incident[(police_incident[calltime_cols] > 1000).any(axis=1)])
```

```
             start_time             end_time  priority    incident_type  \
853   2025-10-28 20:49:25  2025-10-30 17:06:22         1    Investigation
```

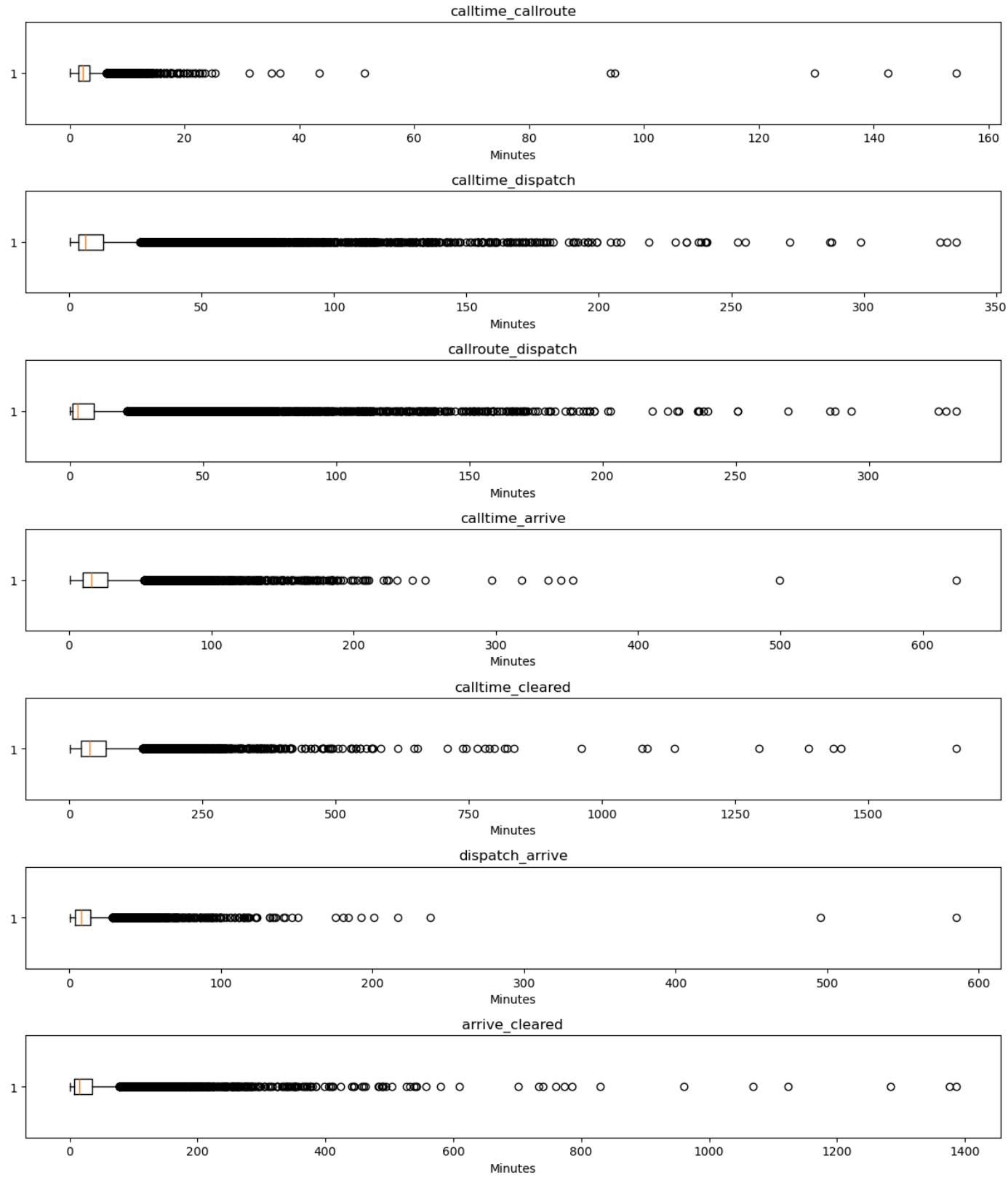
```
1508  2025-10-26 09:31:00  2025-10-29 13:20:46         1   Property Crime
2614  2025-10-26 15:59:53  2025-10-27 10:04:58         5            Other
3067  2025-10-25 12:35:26  2025-10-26 11:44:03         4            Other
4470  2025-10-23 00:02:29  2025-10-23 18:59:20         4    Violent Crime
7331  2025-10-17 22:01:01  2025-10-18 15:57:17         1   Property Crime
9191  2025-10-14 06:04:59  2025-10-15 09:50:49         1   Property Crime
9197  2025-10-14 09:17:10  2025-10-15 09:26:55         4    Violent Crime
10994 2025-10-08 18:20:13  2025-10-11 20:33:34         1   Property Crime
11150 2025-10-10 15:49:03  2025-10-11 15:43:35         1    Investigation
12284 2025-10-07 12:07:11  2025-10-09 12:34:03         3          Traffic
16104 2025-10-01 13:47:35  2025-10-02 11:22:23         4  Health & Safety

       longitude   latitude police_district_number sector  calltime_callroute  \
853   -77.073700  39.046920                     4D     L1            2.000000
1508  -77.152781  39.083999                     1D     A3            1.716667
2614  -77.287525  39.230198                     5D     N3            2.466667
3067  -77.091700  39.040480                     2D     D1            2.300000
4470  -77.068900  39.098150                     4D     K1            1.850000
7331  -77.050285  39.039970                     4D     L2            4.766667
9191  -77.248900  39.229450                     5D     M3            2.733333
9197  -77.247300  39.164670                     5D     N1            9.016667
10994 -77.170900  39.032870                     1D     B1            3.800000
11150 -77.210886  39.095812                     1D     B2            1.316667
12284 -77.094200  38.984660                     2D     D2            2.100000
16104 -77.174960  39.152914                     6D     P3            1.150000

       calltime_dispatch  callroute_dispatch  calltime_arrive  \
853            78.950000           76.933333      2651.500000
1508            2.983333            1.266667         8.433333
2614            3.383333            0.900000        16.650000
3067            8.366667            6.066667        12.500000
4470            2.433333            0.583333        12.933333
7331           14.216667            9.433333              NaN
9191           60.800000           58.066667              NaN
9197           10.283333            1.250000        63.316667
10994          22.500000           18.700000      4433.150000
11150         132.400000          131.083333              NaN
12284        2854.433333         2852.316667              NaN
16104           2.066667            0.916667        11.633333

       calltime_cleared  dispatch_arrive  arrive_cleared  hour  weekday
853         2656.933333      2572.550000        5.416667    20        2
1508        4549.766667         5.433333     4541.316667     9        7
2614        1085.066667        13.250000     1068.416667    15        7
3067        1388.600000         4.116667     1376.100000    12        6
4470        1136.833333        10.483333     1123.900000     0        4
7331        1076.266667              NaN             NaN    22        5
9191        1665.833333              NaN             NaN     6        2
9197        1449.750000        53.033333     1386.416667     9        2
10994       4453.333333      4410.633333       20.183333    18        3
11150       1434.516667              NaN             NaN    15        5
```

```
12284        2906.866667              NaN              NaN     12         2
16104        1294.783333         9.550000      1283.133333     13         3
```

For the indices of `853`, `1508`, `10994`, and `12284`, I will remove them from the dataset since these extreme outliers are likely due to data entry errors. It is unusual for `dispatch_arrive`, `calltime_dispatch`, and `calltime_arrive` to have such high values.

```
# Remove extreme outliers by their indices
police_incident = police_incident.drop([853, 1508, 10994, 12284])
```

```
# Visualize updated box plots
fig, axes = plt.subplots(len(calltime_cols), 1, figsize=(12, len(calltime_cols)*2))
for i, col in enumerate(calltime_cols):
    axes[i].boxplot(police_incident[col].dropna(), vert=False)
    axes[i].set_title(col)
    axes[i].set_xlabel('Minutes')
plt.tight_layout()
plt.show()
```




```
police_incident.describe(include='all')
```

	start_time	end_time	priority	incident_type	longitude	latitude	police_district_number	se
count	16777	16777	16777.000000	16777	16777.000000	16777.000000	16777	16

	start_time	end_time	priority	incident_type	longitude	latitude	police_district_number	se
unique	NaN	16715	NaN	8	NaN	NaN	6	3
top	NaN	2025-10-19 13:06:03	NaN	Property Crime	NaN	NaN	3D	G
freq	NaN	2	NaN	3022	NaN	NaN	3276	1(
mean	2025-10-16 14:40:56.703165184	NaN	3.136139	NaN	-77.119697	39.084010	NaN	N
min	2025-10-01 00:01:37	NaN	1.000000	NaN	-77.483699	38.945130	NaN	N
25%	2025-10-08 18:16:50	NaN	2.000000	NaN	-77.196409	39.031930	NaN	N
50%	2025-10-16 16:04:51	NaN	3.000000	NaN	-77.116200	39.077570	NaN	N
75%	2025-10-24 10:34:00	NaN	4.000000	NaN	-77.048500	39.141840	NaN	N
max	2025-10-31 23:59:04	NaN	5.000000	NaN	-76.905300	39.345283	NaN	N
std	NaN	NaN	1.264097	NaN	0.093566	0.069482	NaN	N

```
police_incident.to_csv("../../data/processed-data/police_incident_eda.csv",index=False)
print("Saved")
```

```
Saved
```

Methods and Codes (ML)

In this section, I will focus on preparing the dataset for machine learning modeling. I will continue from the cleaned dataset used for EDA, and perform steps such as normalization, make sure catagorical data are encoded, perform log transformation and z-score transformation to ensure the data is suitable for later supervised or unsupervised modeling.

Check Skewness and Kurtosis

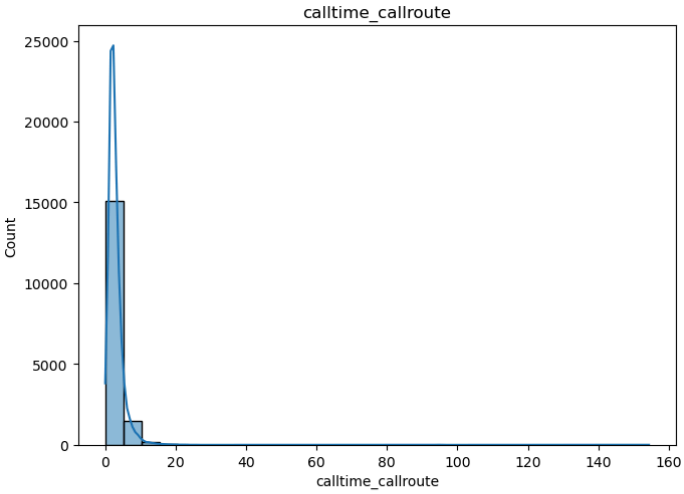
Before normalization, I will first check the skewness and kurtosis of each numeric column to understand their distribution. This helps to identify any columns that may require transformation to meet the assumptions of certain machine learning algorithms.

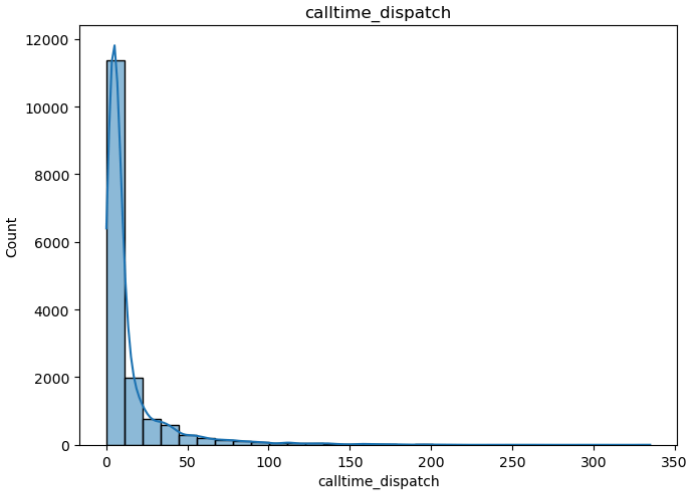
```
import pandas as pd
import numpy as np

# Import the cleaned police incident dataset
police_incident = pd.read_csv("../../data/processed-data/police_incident_eda.csv")
```

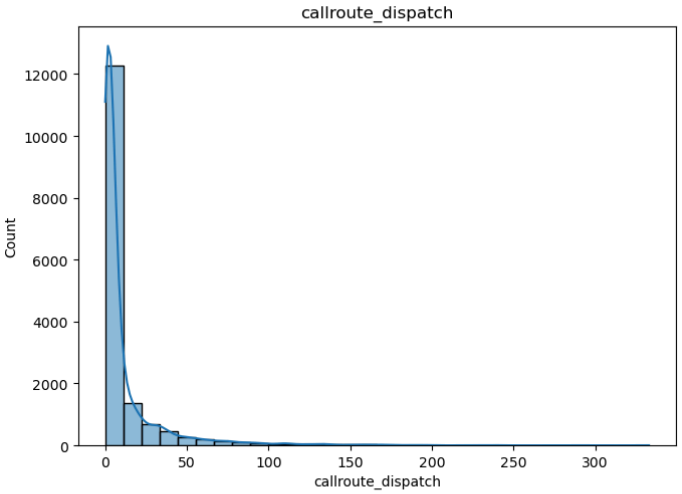
```
# Define time-related columns
cols = ['calltime_callroute','calltime_dispatch','callroute_dispatch','calltime_arrive','

# Check skewness and kurtosis of time-related columns
police_incident[cols].agg(['skew', 'kurt'])
```

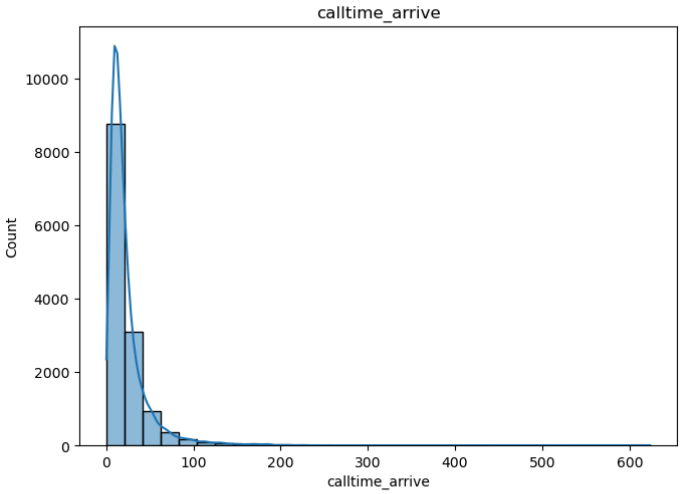
	calltime_callroute	calltime_dispatch	callroute_dispatch	calltime_arrive	calltime_cleared	dispatch_arrive	arrive_
skew	22.104397	4.483037	4.568264	4.865430	6.963982	10.595679	7.8982
kurt	915.915062	28.585118	29.562967	52.672626	104.300570	290.717513	119.03

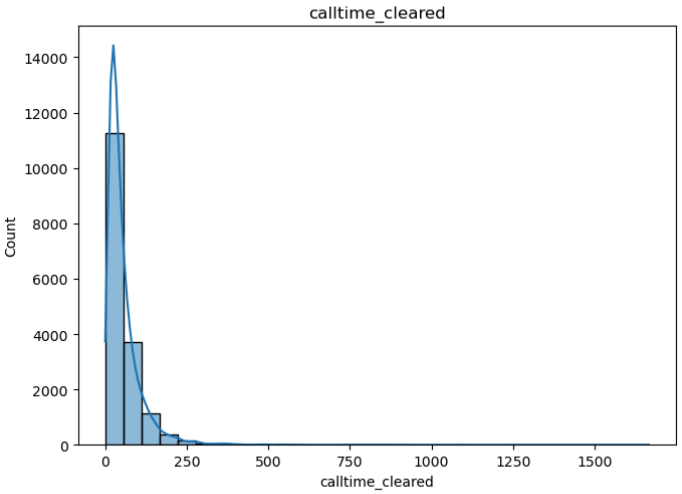
```
import matplotlib.pyplot as plt
import seaborn as sns

# Define figure size for plots
plt.figure(figsize=(14,20))

# Iterate over time-related columns to plot histograms
for i, c in enumerate(cols, 1):
    plt.subplot(4,2,i)
    sns.histplot(police_incident[c], kde=True, bins=30)
    plt.title(f"{c}")
    plt.tight_layout()

plt.show()
```

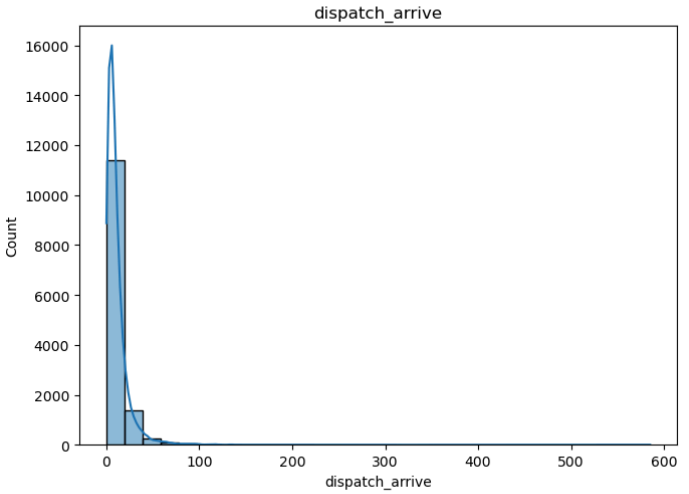

calltime_callroute
Count
calltime_callroute

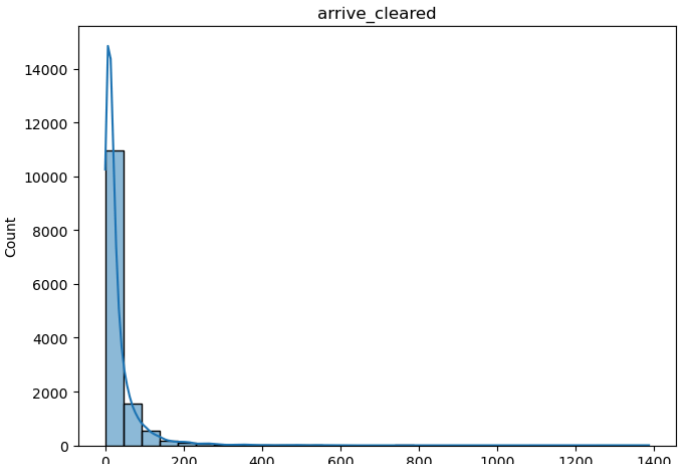

calltime_dispatch
Count
calltime_dispatch


callroute_dispatch
Count
callroute_dispatch


calltime_arrive
Count
calltime_arrive


calltime_cleared
Count
calltime_cleared


dispatch_arrive
Count
dispatch_arrive


arrive_cleared
Count

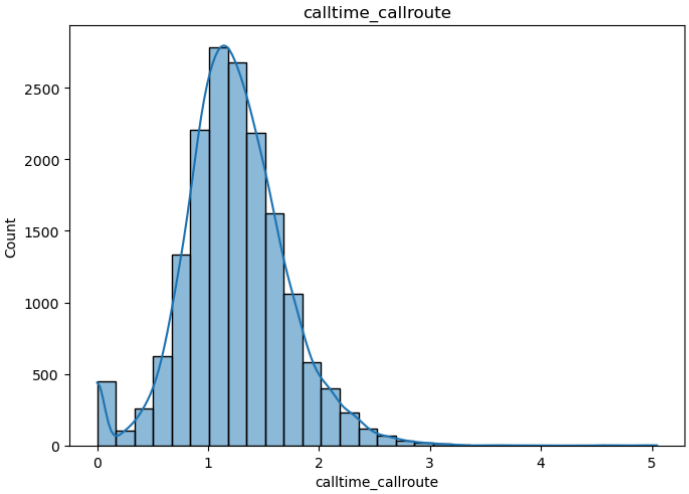
arrive_cleared

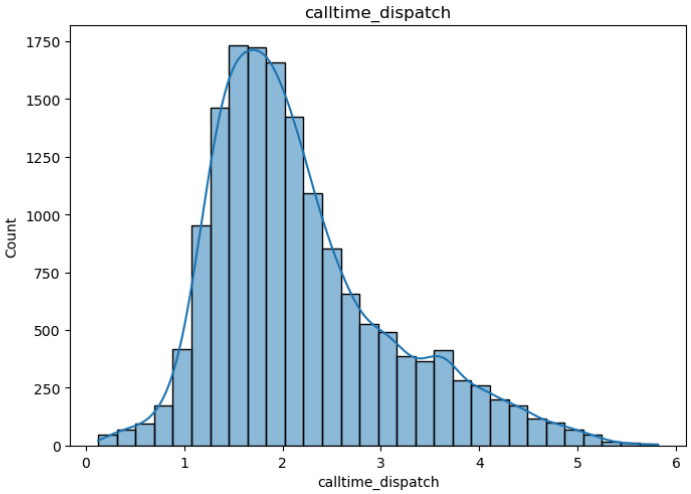
Log Transformation

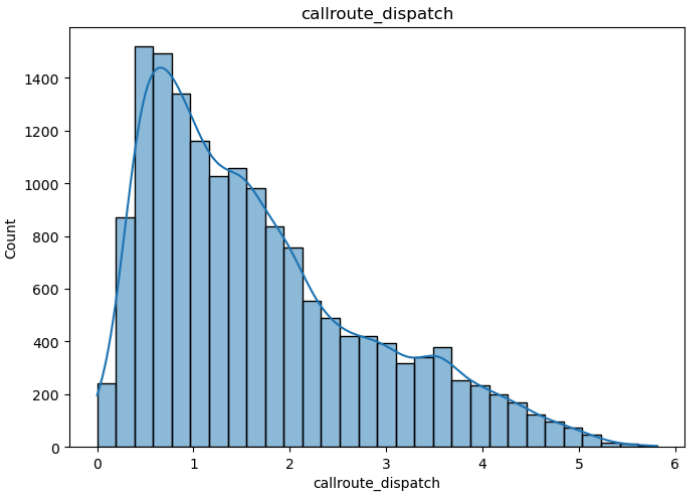
After reviewing the skewness, kurtosis values, and the distributions of each numeric column, I will apply a log transformation to all the numeric columns, because each of the columns shows high skewness. By doing a log transformation, it helps to reduce skewness, stabilize variance, and make the data more normally distributed.

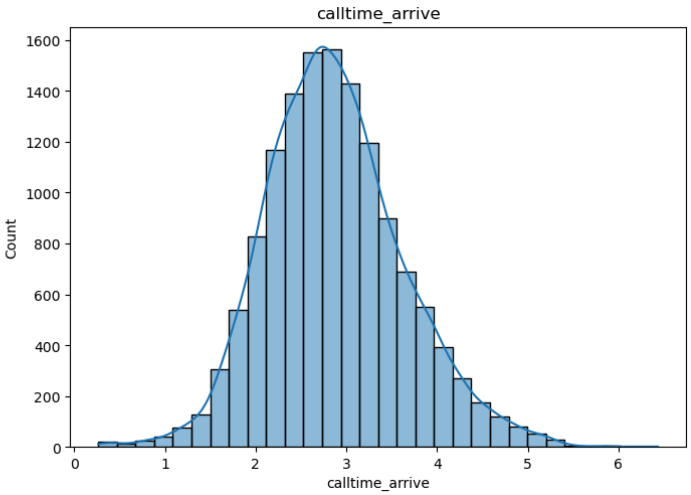
```
# Apply log transformation to time-related columns to reduce skewness
police_incident['calltime_callroute'] = np.log1p(police_incident['calltime_callroute'])
police_incident['calltime_dispatch'] = np.log1p(police_incident['calltime_dispatch'])
police_incident['callroute_dispatch'] = np.log1p(police_incident['callroute_dispatch'])
police_incident['calltime_arrive'] = np.log1p(police_incident['calltime_arrive'])
police_incident['calltime_cleared'] = np.log1p(police_incident['calltime_cleared'])
police_incident['dispatch_arrive'] = np.log1p(police_incident['dispatch_arrive'])
police_incident['arrive_cleared'] = np.log1p(police_incident['arrive_cleared'])
```

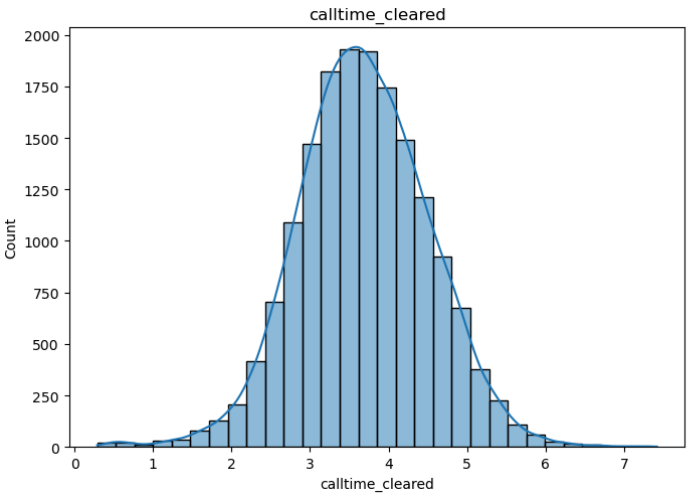
```
import matplotlib.pyplot as plt
import seaborn as sns

# Define figure size for plots
plt.figure(figsize=(14,20))

# Iterate over time-related columns to plot histograms
for i, c in enumerate(cols, 1):
    plt.subplot(4,2,i)
    sns.histplot(police_incident[c], kde=True, bins=30)
    plt.title(f"{c}")
    plt.tight_layout()

plt.show()
```

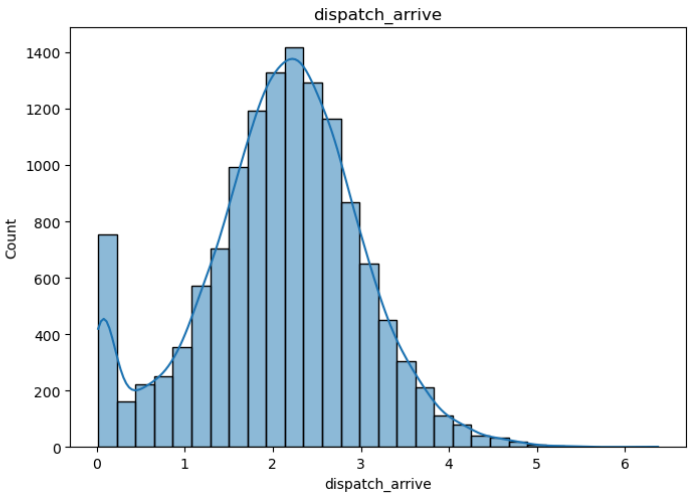

calltime_callroute
Count
calltime_callroute

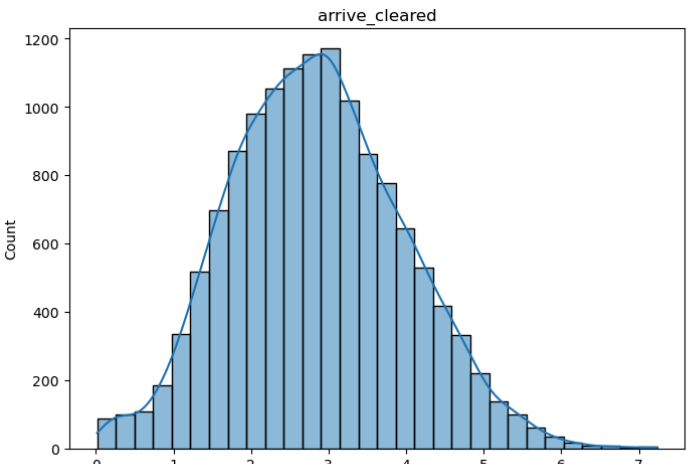

calltime_dispatch
Count
calltime_dispatch


callroute_dispatch
Count
callroute_dispatch


calltime_arrive
Count
calltime_arrive


calltime_cleared
Count
calltime_cleared


dispatch_arrive
Count
dispatch_arrive


arrive_cleared
Count

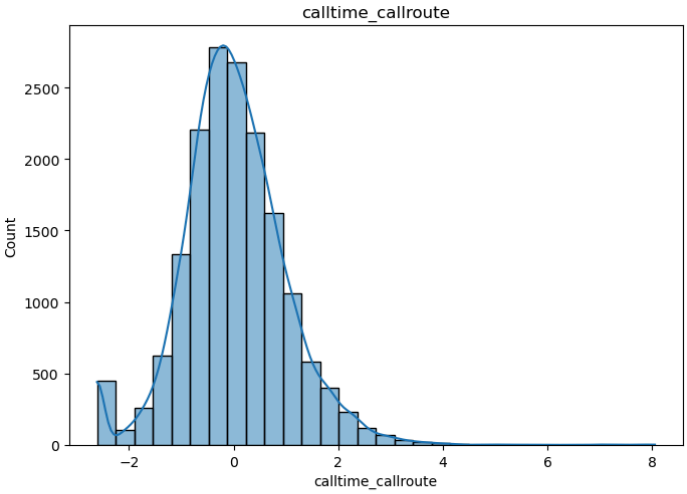
arrive_cleared

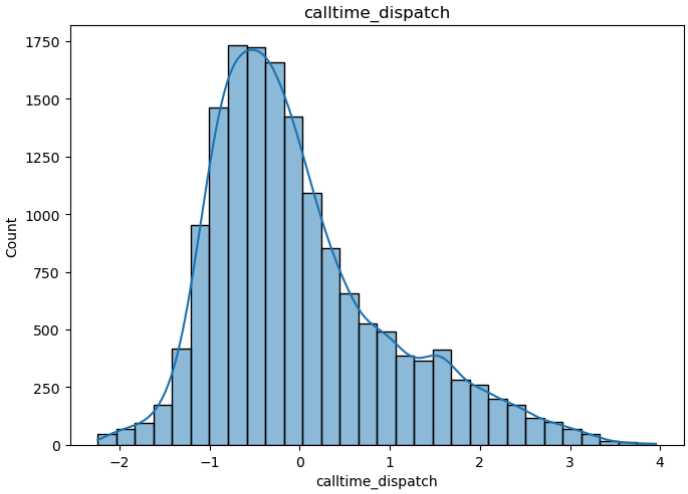
Z-Score Normalization

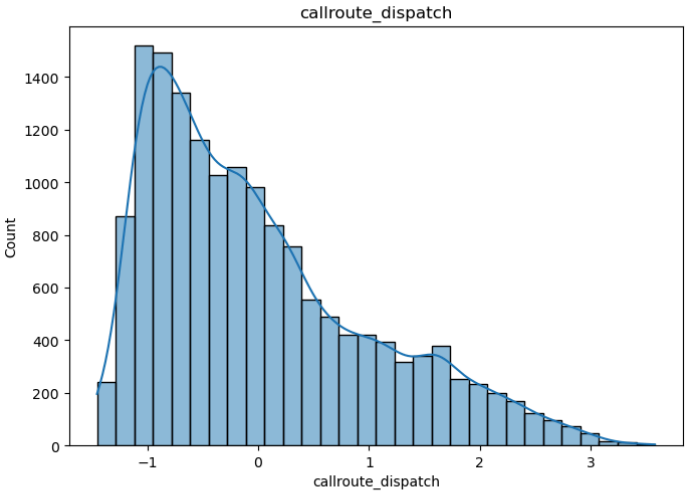
In this step, I will apply z-score normalization to all numeric columns in the dataset. Z-score normalization standardizes the data by subtracting the mean and dividing by the standard deviation, resulting in a distribution with a mean around 0. Z-Score normalization is essential for machine learning algorithms.

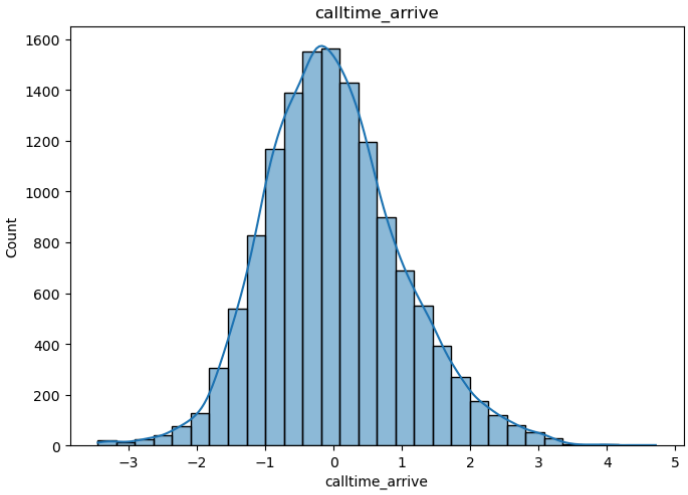
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
police_incident[cols] = pd.DataFrame(scaler.fit_transform(police_incident[cols]), columns
```

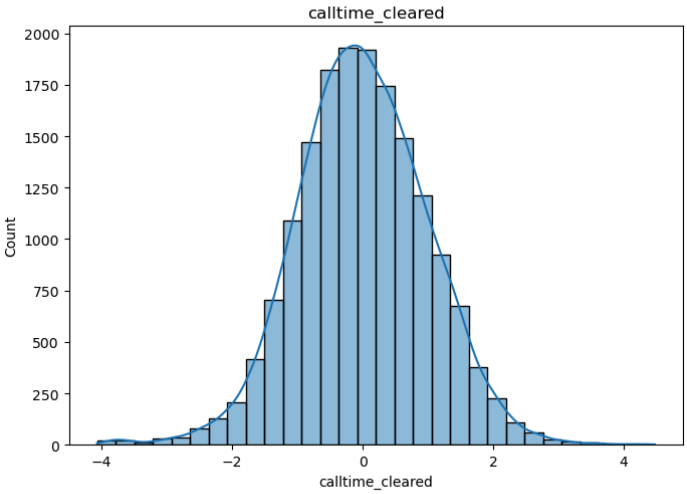
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(14,20))

# Iterate over time-related columns to plot histograms
for i, c in enumerate(cols, 1):
    plt.subplot(4,2,i)
    sns.histplot(police_incident[c], kde=True, bins=30)
    plt.title(f"{c}")
    plt.tight_layout()
plt.savefig("../../report/visual4.png", dpi=300, bbox_inches="tight")
plt.show()
```

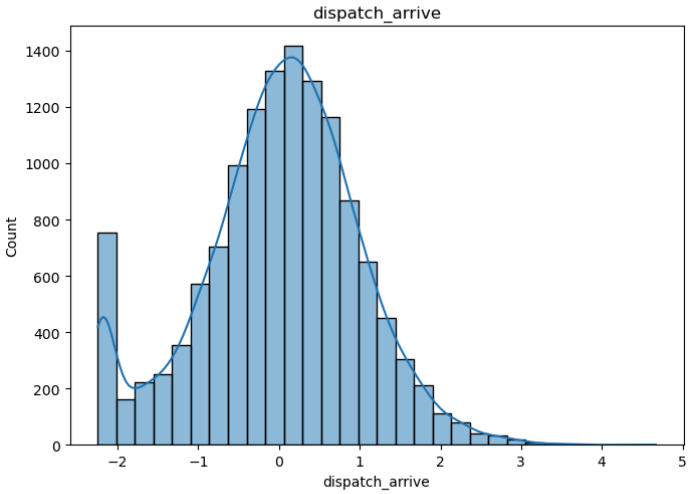

calltime_callroute
Count
calltime_callroute

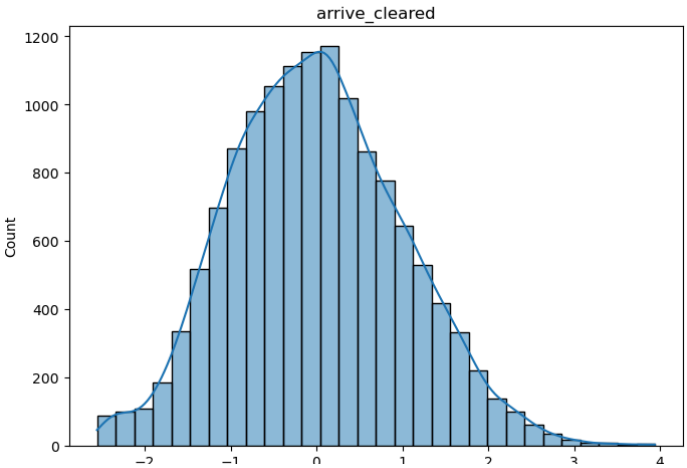

calltime_dispatch
Count
calltime_dispatch


callroute_dispatch
Count
callroute_dispatch


calltime_arrive
Count
calltime_arrive


calltime_cleared
Count
calltime_cleared


dispatch_arrive
Count
dispatch_arrive


arrive_cleared
Count

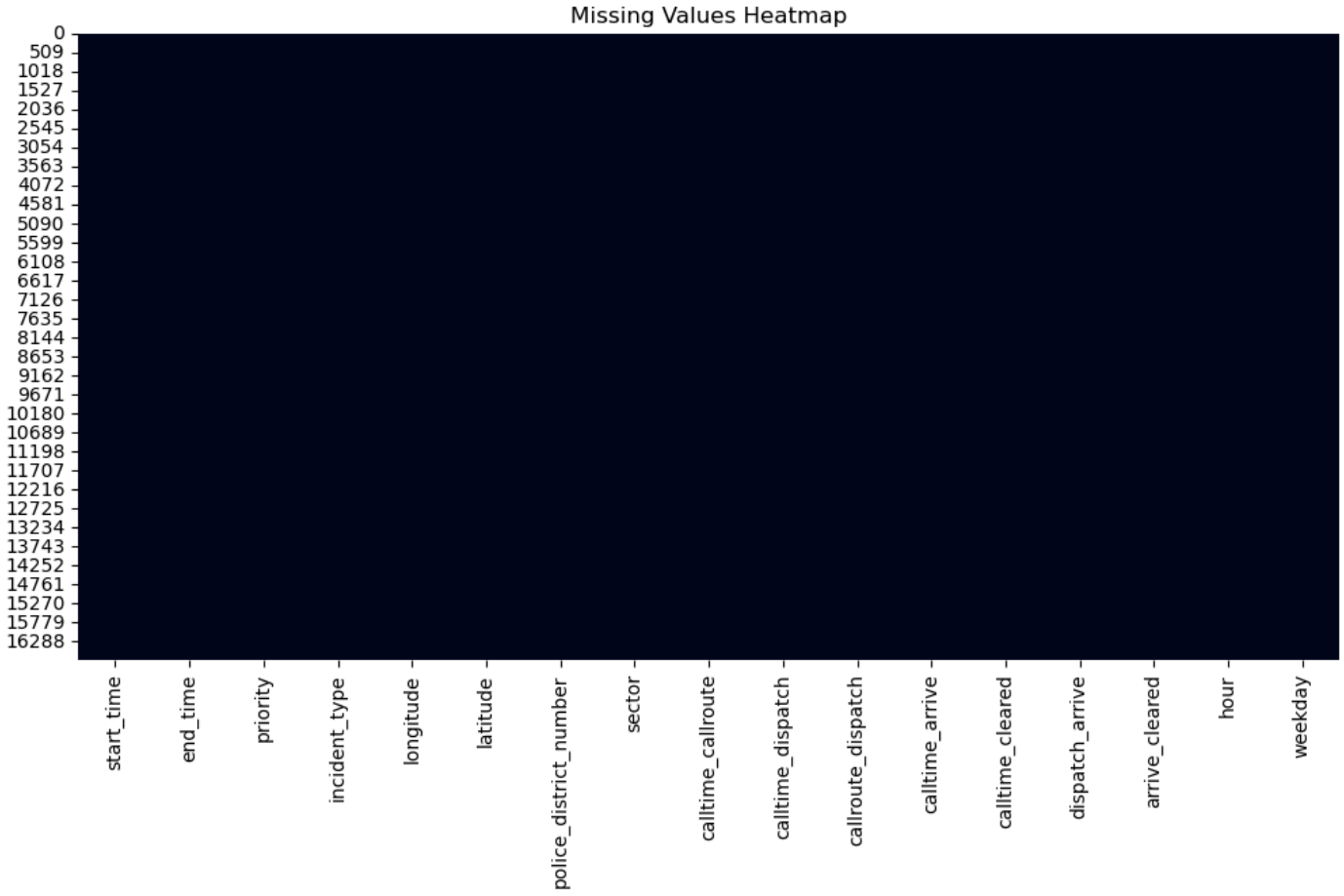
arrive_cleared

Handling Missing Value for Machine Learning

Since some machine learning algorithms cannot handle missing values, I will fill in any remaining missing values using the median of each column, because my columns and skewed even after log transformation. Using the median helps to reduce the impact of outliers and skewness.

```
# Impute missing numeric values with median
numeric_cols = police_incident.select_dtypes(include=['float64','int64']).columns
police_incident[numeric_cols] = police_incident[numeric_cols].fillna(police_incident[nume
```

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt


# Visualize missing data using a heatmap
plt.figure(figsize=(12,6))
sns.heatmap(police_incident.isna(), cbar=False)
plt.title("Missing Values Heatmap")
plt.show()
```



```
# Verify no missing values remain
police_incident.isna().sum()
```

```
start_time                0
end_time                  0
priority                  0
incident_type             0
longitude                 0
latitude                  0
police_district_number    0
sector                    0
calltime_callroute        0
calltime_dispatch         0
callroute_dispatch        0
calltime_arrive           0
calltime_cleared          0
dispatch_arrive           0
arrive_cleared            0
hour                      0
weekday                   0
dtype: int64
```

Remove Unnecessary Columns for Machine Learning

Since the following data will be purely used for machine learning modeling and I already generated new columns s `day_of_week` and `hour`, I will remove the `start_time` and `end_time` columns to avoid redundancy. Also, I will remove the sector column since it has too many catagories, which is not suitable for machine learning.

```
police_incident = police_incident.drop(['start_time', 'end_time', 'sector'], axis=1)

# Summary of nulls, zeros, and data types for each column
pd.DataFrame({
    'null_count': police_incident.isnull().sum(),
    'zero_count': (police_incident == 0).sum(),
    'dtype': police_incident.dtypes
})
```

	null_count	zero_count	dtype
priority	0	0	int64
incident_type	0	0	object
longitude	0	0	float64
latitude	0	0	float64
police_district_number	0	0	object
calltime_callroute	0	0	float64

	null_count	zero_count	dtype
calltime_dispatch	0	0	float64
callroute_dispatch	0	0	float64
calltime_arrive	0	0	float64
calltime_cleared	0	0	float64
dispatch_arrive	0	0	float64
arrive_cleared	0	0	float64
hour	0	465	int64
weekday	0	0	int64

Label Encoding for Categorical Columns

In this step, I will apply label encoding to categorical columns `incident_type` and `police_district_number`. Label encoding converts categorical variables into a number that can be provided to machine learning algorithms to improve predictions.

```
from sklearn.preprocessing import LabelEncoder

# Initialize Label Encoder
le = LabelEncoder()

# Define columns to be label encoded
encode = ['incident_type', 'police_district_number']

# Identify categorical columns to encode
for col in encode:
    police_incident[col] = le.fit_transform(police_incident[col])
    print(dict(zip(le.classes_, le.transform(le.classes_))))
```

```
{'Administrative': 0, 'Health & Safety': 1, 'Investigation': 2, 'Other': 3, 'Property
Crime': 4, 'Public Order': 5, 'Traffic': 6, 'Violent Crime': 7}
{'1D': 0, '2D': 1, '3D': 2, '4D': 3, '5D': 4, '6D': 5}
```

```
# Verify the final dataset
print(police_incident.describe(include='all'))

# Save dataset for machine learning
police_incident.to_csv("../../data/processed-data/police_incident_ml.csv",index=False)
print("Saved")
```

```
           priority  incident_type     longitude      latitude  \
count  16777.000000   16777.000000  16777.000000  16777.000000
mean       3.136139       3.638314    -77.119697     39.084010
std        1.264097       2.111452      0.093566      0.069482
```

```
min        1.000000       0.000000    -77.483699     38.945130
25%        2.000000       2.000000    -77.196409     39.031930
50%        3.000000       4.000000    -77.116200     39.077570
75%        4.000000       5.000000    -77.048500     39.141840
max        5.000000       7.000000    -76.905300     39.345283

       police_district_number  calltime_callroute  calltime_dispatch  \
count            16777.000000        1.677700e+04       16777.000000
mean                 2.436431       -6.717058e-16          -0.013467
std                  1.687856        1.000030e+00           0.972179
min                  0.000000       -2.612978e+00          -2.242074
25%                  1.000000       -5.937044e-01          -0.682764
50%                  2.000000       -4.760530e-02          -0.232681
75%                  4.000000        5.811714e-01           0.421137
max                  5.000000        8.050240e+00           3.951448

       callroute_dispatch  calltime_arrive  calltime_cleared  dispatch_arrive  \
count        16777.000000     16777.000000      16777.000000     16777.000000
mean            -0.013588        -0.013745         -0.000004         0.014537
std              0.972206         0.898430          0.999940         0.887344
min             -1.452536        -3.451517         -4.068133        -2.245511
25%             -0.770082        -0.523680         -0.654916        -0.361219
50%             -0.234774        -0.070976         -0.023295         0.068107
75%              0.485387         0.412183          0.664607         0.473064
max              3.576855         4.713377          4.474310         4.667700

       arrive_cleared          hour       weekday
count    16777.000000  16777.000000  16777.000000
mean        -0.006527     13.387018      4.026703
std          0.898058      5.929295      1.904554
min         -2.555425      0.000000      1.000000
25%         -0.539374      9.000000      3.000000
50%         -0.033692     14.000000      4.000000
75%          0.464969     18.000000      6.000000
max          3.941508     23.000000      7.000000
Saved
```

Conclusion

During the data cleaning phase, I transformed the raw Police Dispatched Incidents data into two dataset. I frist created a cleaned dataset suitable for exploratory data analysis by handling missing values, correcting data types, removing irrelevant columns, and modifying data for better interpretation. Then, I further processed the cleaned eda dataset to prepare it for machine learning modeling by normalizing numeric columns, encoding categorical variables, and ensuring no missing values remain.

Challenges

One of the main challenges I faced during the data cleaning process was handling missing longitude and latitude values. At first, almost 2500 of the longitude and latitude values were missing, but luckily, the columns associated with the actual address were filled. Since these columns are crucial for spatial analysis, I used the Google Geocoding API to fill in missing longitude and latitude values based on address information. Another challenge I faced was having to revisit the data cleaning section after completing half of the exploratory data analysis. I had to make several modifications to different columns, which was pretty time-consuming and repetitive.

References

1. Claude, version-4.5, anthropic, NOV-2025, claude.ai.

DSAN 5000 - Incident Response Modeling (MCMD)

Exploratory Data Analysis

Overview

In this section, I will demonstrate the methods and codes used for exploratory data analysis on the dataset. I will first create univariate analysis for numerical variables, displaying their mean, median, and standard deviation. I will also include histograms to visualize this information. I will then conduct categorical variables analysis by using bar charts and highlight any notable trends observed. Then, I will perform multivariate analysis including correlation analysis, crosstabulations, and feature pairings by including heatmaps, scatterplots, and boxplots. Lastly, I will analyze the skewness and Kurtosis of the data. After defining what steps are needed for normalization, I will head back to the machine learing trasformation portion of the previous stage, data cleaning, to apply transformations, and introduce normalization techniques.

Methods and Codes

Univariate Analysis

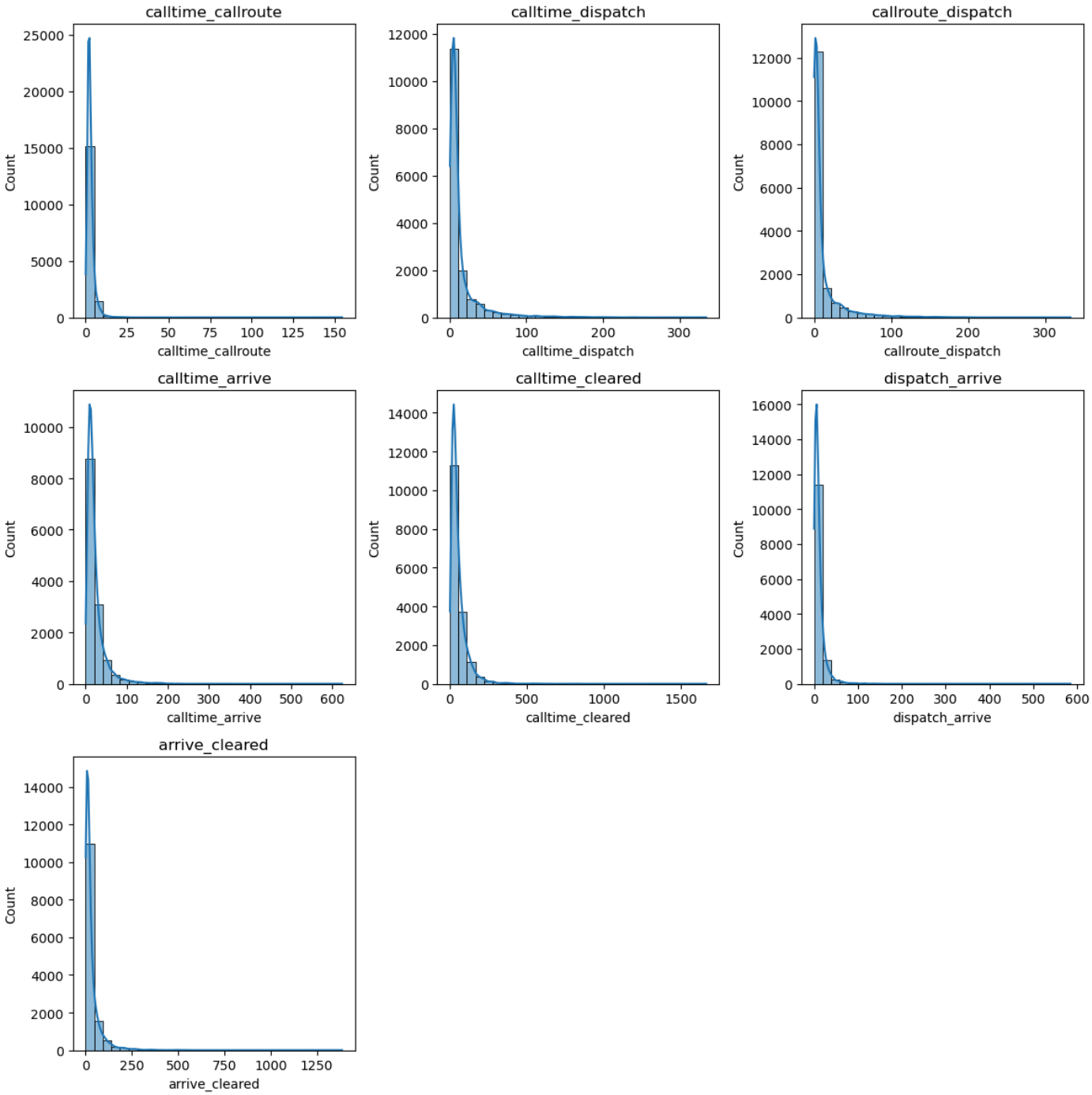
In the following sections, I will explore the distribution of individual numerical variables in the dataset, exploring its mean, median, standard deviation, and visualizing the distribution using histograms. Then, I will analyze categorical variables by examining their frequency counts and visualizing them using bar plots.

Numerical Variables

By looking at the summary statistics of numerical variables below, we can tell that all of the numerical data are skewed to the right, and all of them have an extremely long tail on the right side of the distribution. This is possibly because most police incidents are dispatched, arrived, and cleared within a short period of time, while only a small portion of them take a very long time.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load the processed police incident data
police_incident = pd.read_csv("../../data/processed-data/police_incident_eda.csv")

# Define all time or numeric related columns
cols = ['calltime_callroute','calltime_dispatch','callroute_dispatch','calltime_arrive','
```

```
# Set up the matplotlib figure
plt.figure(figsize=(12, 12))

# Create histograms for each time-related column
for i, c in enumerate(cols, start=1):
    plt.subplot(3, 3, i)
    sns.histplot(police_incident[c], bins=30, kde=True)
    plt.title(f"{c}")
plt.tight_layout()
plt.show()
```



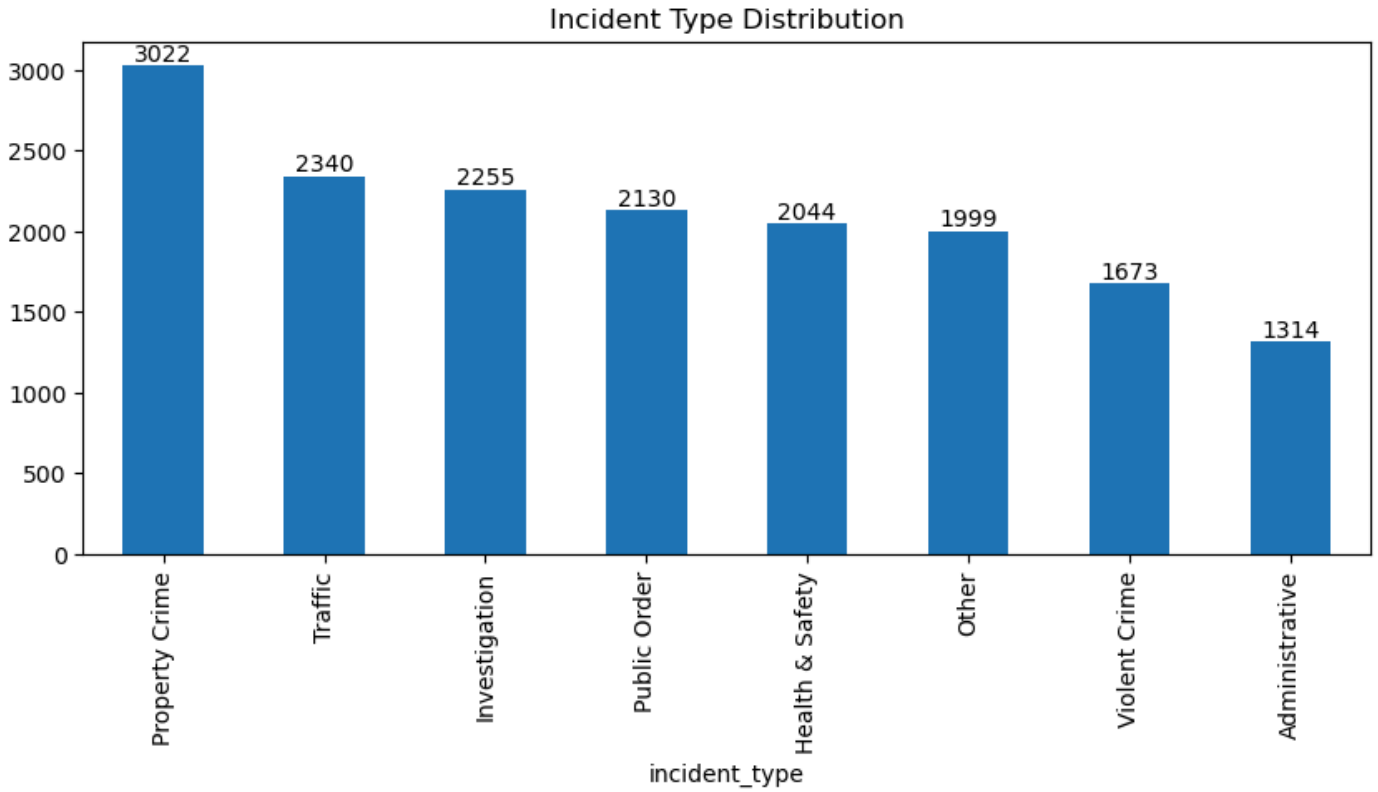
```
# Generate descriptive statistics for the numeric columns
police_incident[cols].describe()
```

	calltime_callroute	calltime_dispatch	callroute_dispatch	calltime_arrive	calltime_cleared	dispatch_arrive	arrive
count	16777.000000	15806.000000	15806.000000	13528.000000	16774.000000	13196.000000	13527.
mean	2.896233	14.334991	11.424692	23.189262	55.736535	11.026771	32.381
std	3.043625	23.914837	23.645323	25.198960	63.632757	14.702792	56.178
min	0.000000	0.133333	0.000000	0.300000	0.333333	0.016667	0.0166
25%	1.600000	3.633333	1.133333	9.583333	22.033333	3.783333	6.8666
50%	2.366667	6.183333	3.083333	15.758333	38.025000	7.533333	15.750
75%	3.533333	12.929167	9.283333	26.870833	68.300000	13.566667	35.425
max	154.366667	334.933333	332.816667	623.566667	1665.833333	585.083333	1386.4

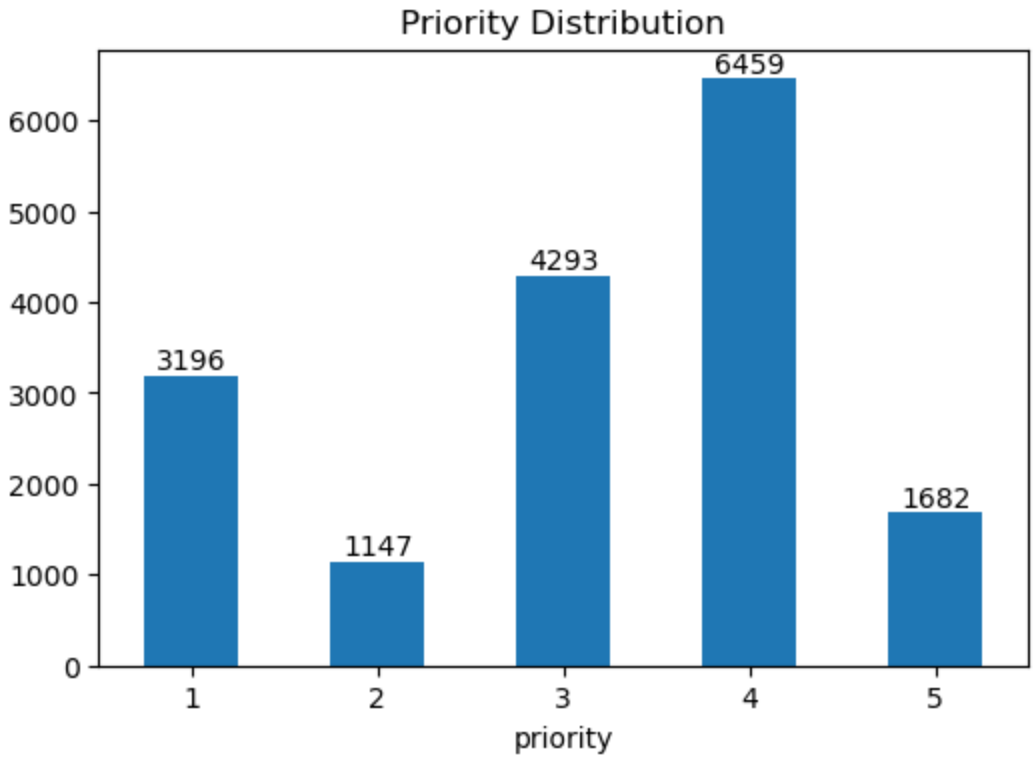
Catagorical Variables

In the following graphs, I will create bar charts for each of the categorical variables, including `incident_type`, `priority`, `police_district_number`, `sector`, and `weekday`. Based on the frequency counts below, the sector contains too many unique values. In the future, I will only be using `police_district_number` for my analysis.

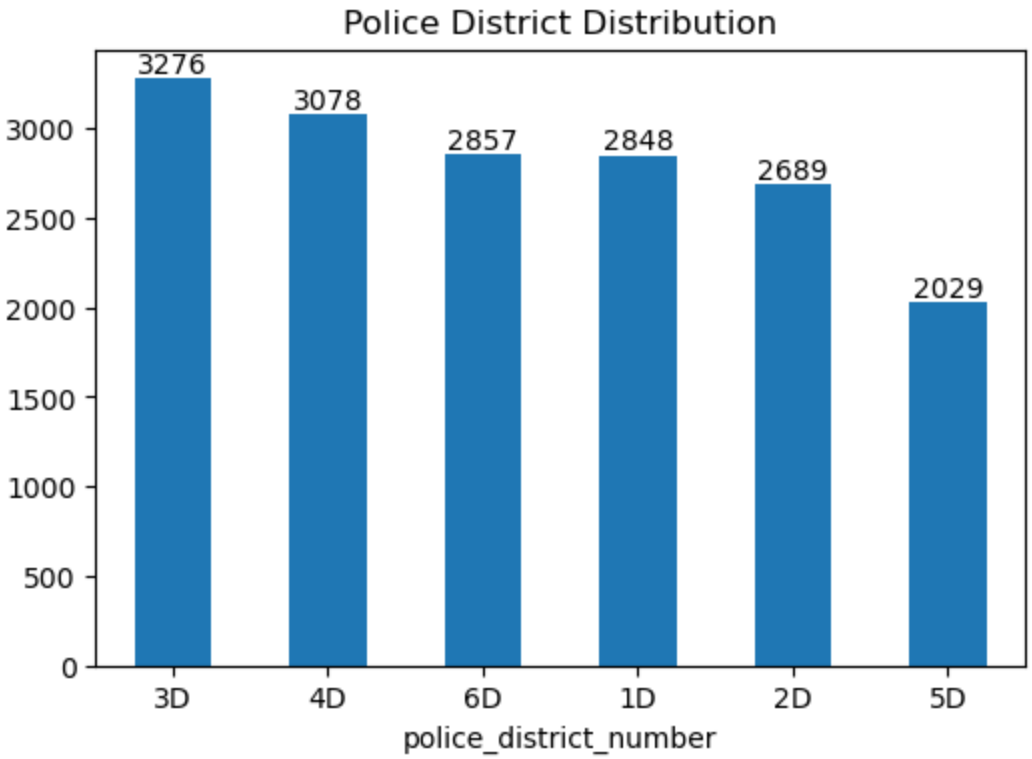
```
# Plot the distribution of incident types
plt.figure(figsize=(10,4))

ax = police_incident['incident_type'].value_counts().plot(kind='bar')
ax.bar_label(ax.containers[0])
plt.title("Incident Type Distribution")
plt.show()
```



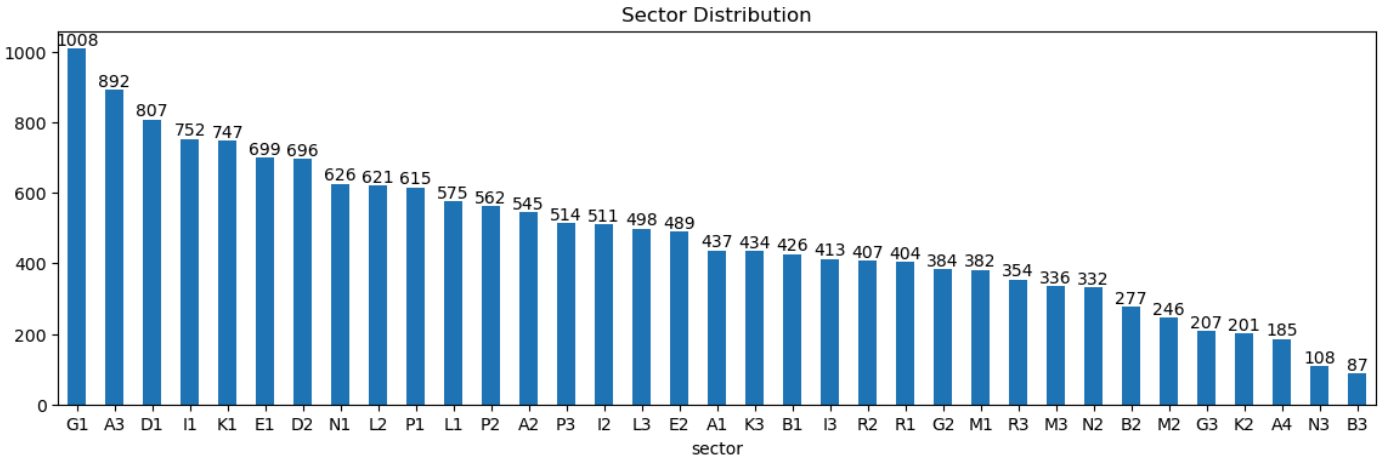

```
# # Plot the distribution of priorities
plt.figure(figsize=(6,4))

ax = police_incident['priority'].value_counts().sort_index().plot(kind='bar')
ax.bar_label(ax.containers[0])
plt.title("Priority Distribution")
plt.xticks(rotation=0)
plt.show()
```




```
# Plot the distribution of police districts
plt.figure(figsize=(6,4))

ax = police_incident['police_district_number'].value_counts().plot(kind='bar')
ax.bar_label(ax.containers[0])
plt.title("Police District Distribution")
plt.xticks(rotation=0)
plt.show()
```

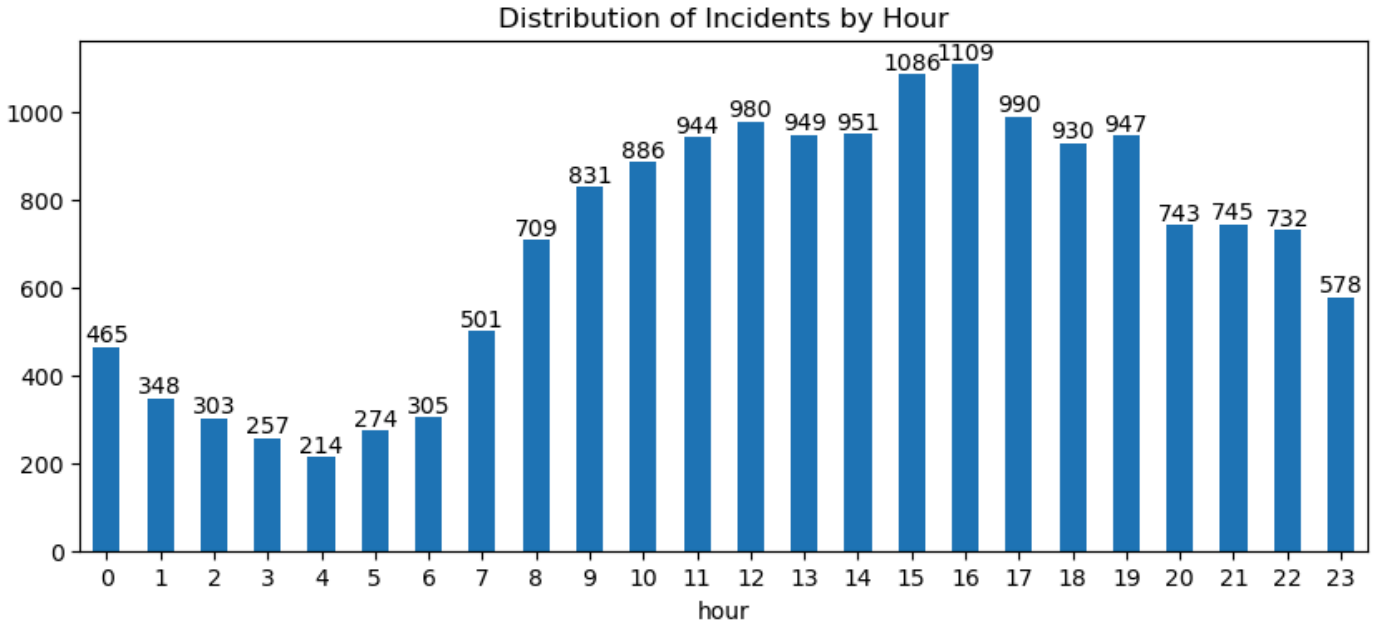



```
# Plot the distribution of sectors
plt.figure(figsize=(14,4))

ax = police_incident['sector'].value_counts().plot(kind='bar')
ax.bar_label(ax.containers[0])
plt.title("Sector Distribution")
plt.xticks(rotation=0)
plt.show()
```

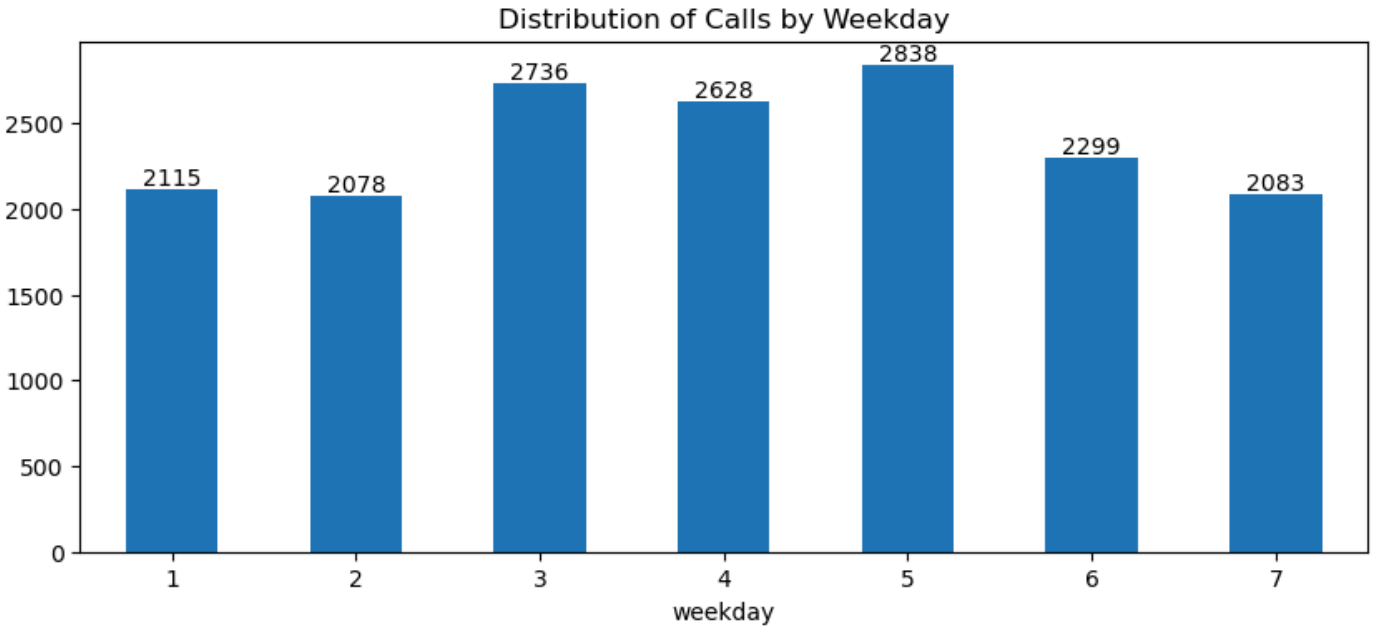



```
# Plot the distribution of incidents by hour
plt.figure(figsize=(10,4))

ax = police_incident['hour'].value_counts().sort_index().plot(kind='bar')
```

```
ax.bar_label(ax.containers[0])
plt.title("Distribution of Incidents by Hour")
plt.xticks(rotation=0)
plt.show()
```




```
# Plot the distribution of incidents by weekday
plt.figure(figsize=(10,4))

ax = police_incident['weekday'].value_counts().sort_index().plot(kind='bar')
ax.bar_label(ax.containers[0])
plt.title("Distribution of Calls by Weekday")
plt.xticks(rotation=0)
plt.show()
```



Key Insights

For all numerical variables, just as I mentioned earlier, we can tell that all of the numerical data including `calltime_callroute`, `calltime_dispatch`, `callroute_dispatch`, `calltime_arrive`, `calltime_cleared`, `dispatch_arrive`, `arrive_cleared`, are skewed to the right, and all of these numeric columns have an extremely long tail on the right side of the distribution, possibly because most police incidents are dispatched, arrived, and cleared within a short period of time, while only a small portion of them take a very long time. For the categorical variable bar charts, we can tell that the order of the incident type occurring is in property crime, traffic, investigation, public order, health & safety, other, violent crime, and administrative. police district 3D has the most incidents occurring, followed by 4D, 6D, 1D, 2D, and 5D, which are in the order of Silver Spring, Wheaton, Gaithersburg, Rockville, Bethesda, and Germantown. Incidents are more likely to occur between noon and midnight, peaking around 4 PM. Incidents are more likely to occur on Wednesdays, Thursdays, and Fridays.

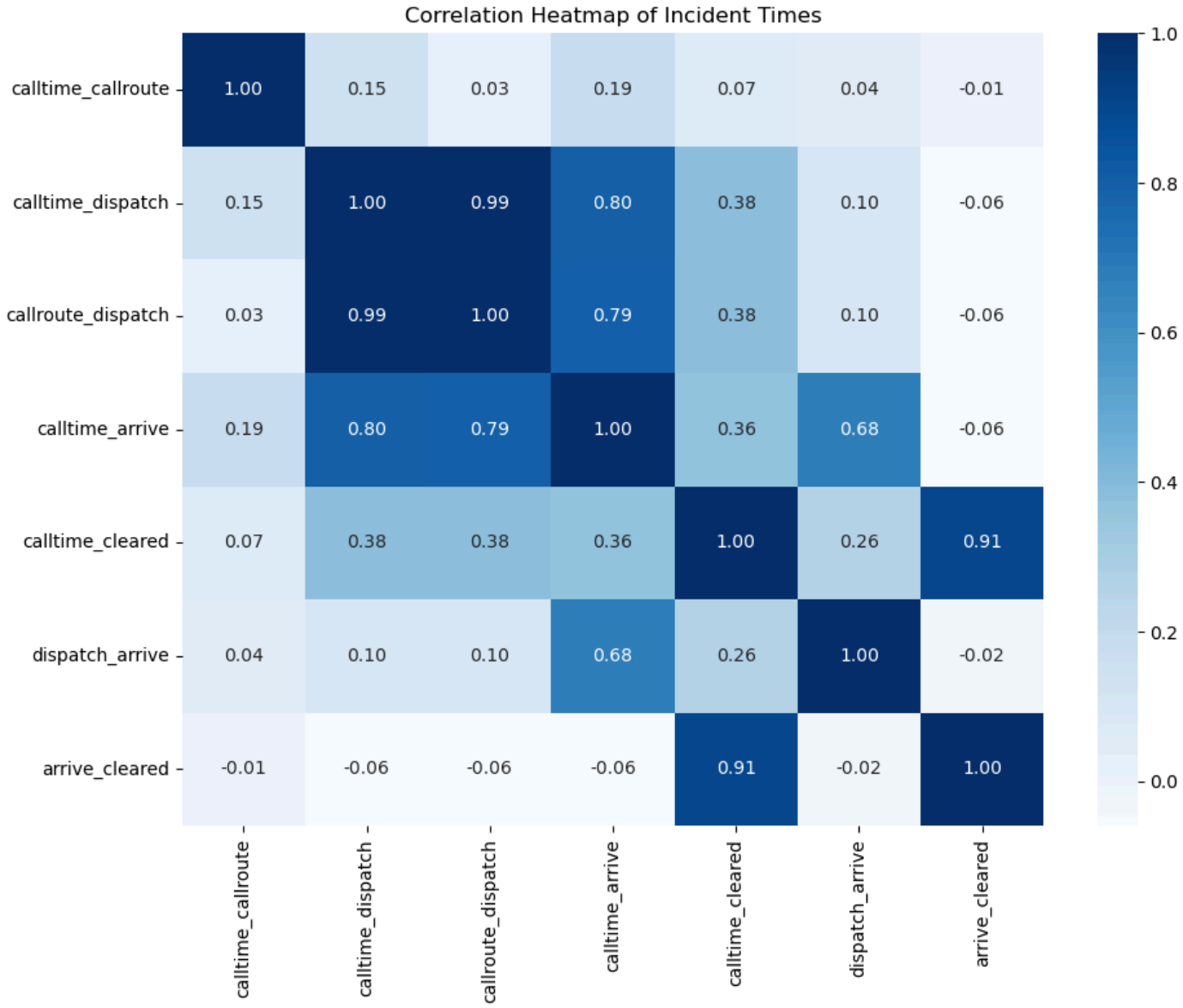
Bivariate and Multivariate Analysis

In the following sections, I will explore relationships between pairs of variables in the dataset, conducting bivariate and multivariate analysis. I will use heatmaps to visualize relationships between numerical variables and violin plots to examine interactions between categorical and numerical variables.

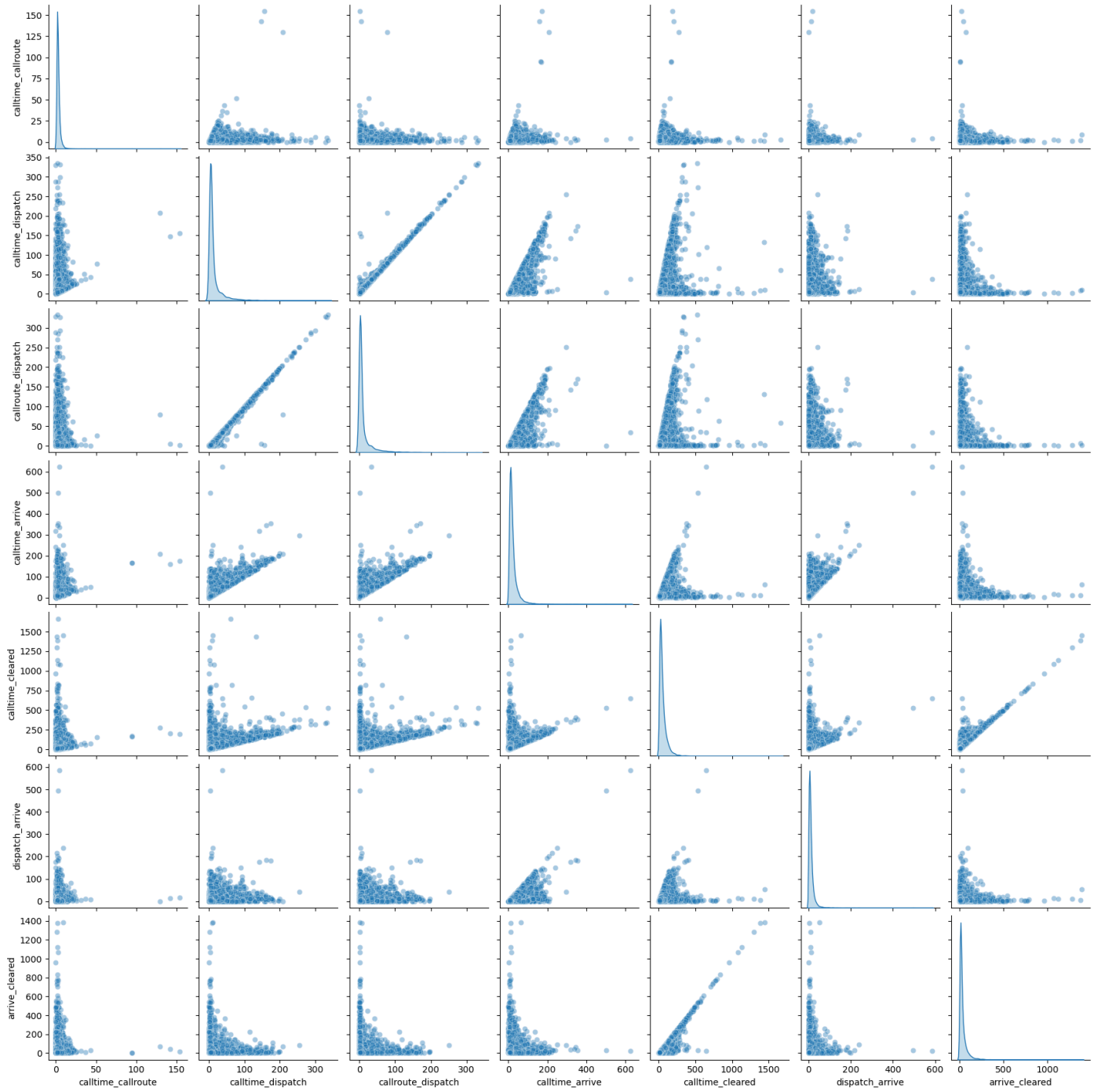
Correlation Analysis

In this part, I will analyze relationships between numerical variables using a correlation matrix, and a heat map. I will explore if any strong correlation exists between numerical variables of different call time variables.

```
# Correlation heatmap of time-related columns
plt.figure(figsize=(10,8))

sns.heatmap(police_incident[cols].corr(), annot=True, cmap='Blues', fmt=".2f")
plt.title("Correlation Heatmap of Incident Times")
plt.tight_layout()
plt.show()
```




```
# Pairplot of time-related columns
sns.pairplot(police_incident[cols], diag_kind="kde", plot_kws={'alpha':0.4})
plt.show()
```

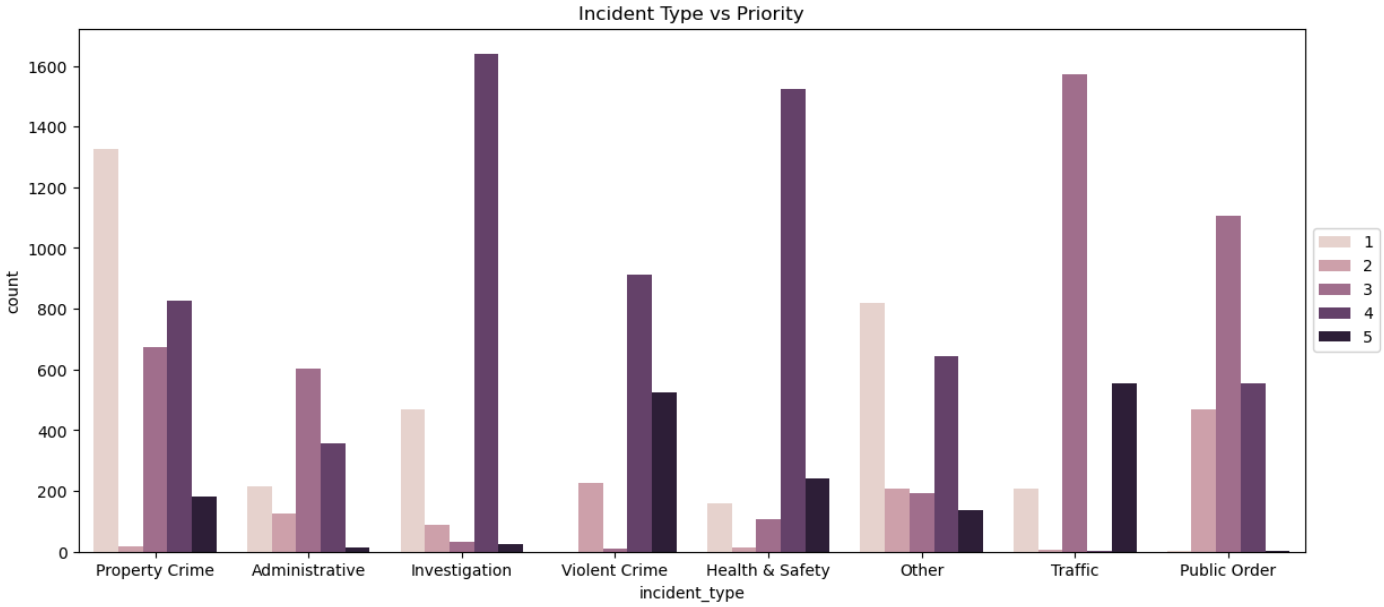


Crosstabulations

For this following section about categorical variables, I will use crosstabulations to explore the relationships and visualize them with grouped bar plots.

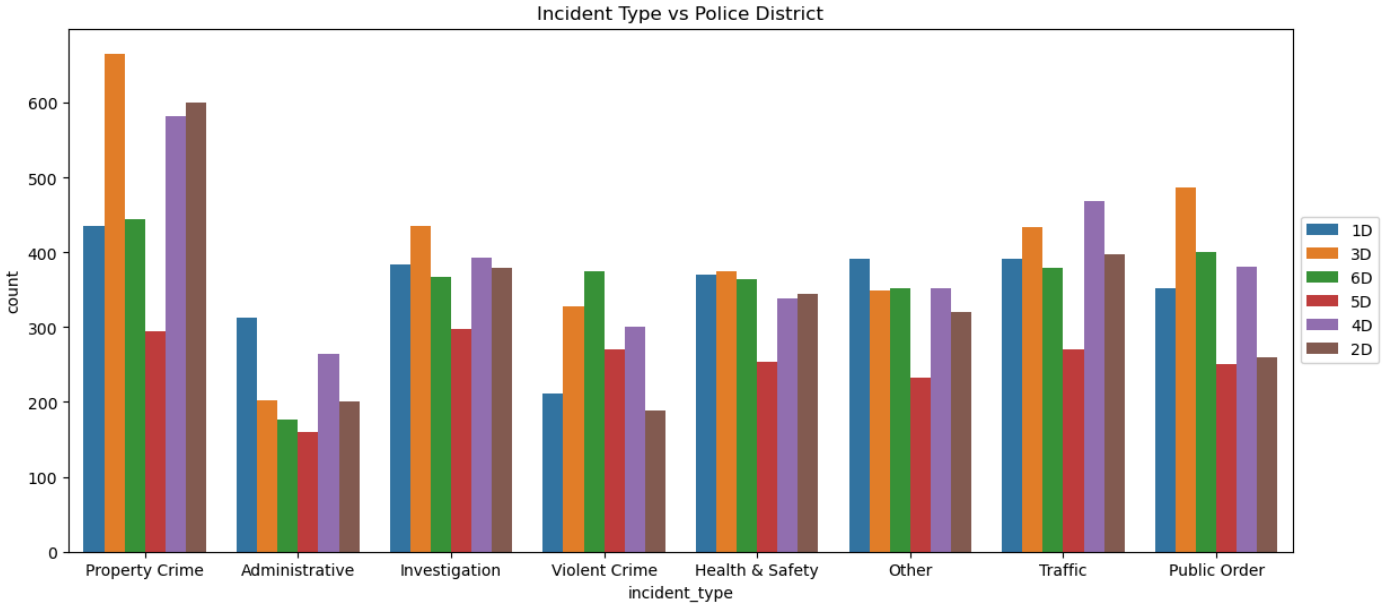
```
# Grouped bar plot of incident type vs priority
plt.figure(figsize=(14,6))
sns.countplot(data=police_incident, x='incident_type', hue='priority')
plt.title("Incident Type vs Priority")
plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
plt.savefig("../../report/visual1.png", dpi=300, bbox_inches="tight")
plt.show()
```

```
# Crosstab of incident type and priority
print(pd.crosstab(police_incident['incident_type'], police_incident['priority']))
```



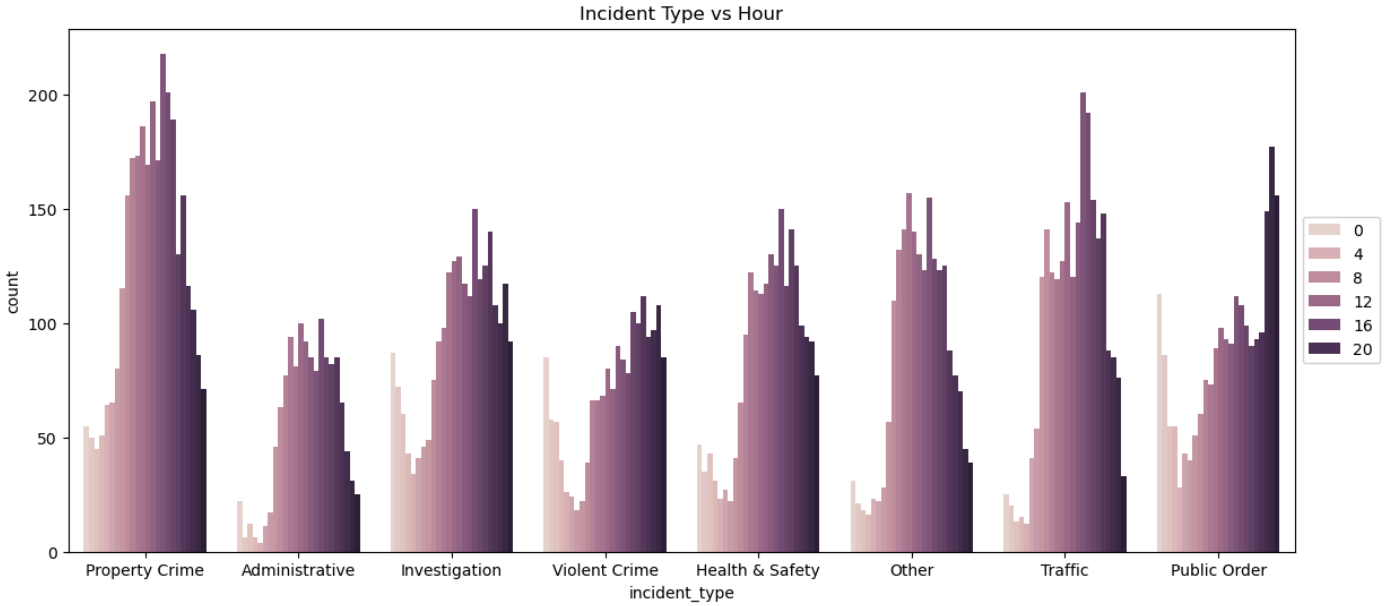
priority	1	2	3	4	5
incident_type					
Administrative	216	124	603	356	15
Health & Safety	158	13	108	1524	241
Investigation	468	89	31	1641	26
Other	820	206	191	644	138
Property Crime	1325	16	674	825	182
Public Order	1	468	1106	554	1
Traffic	208	6	1571	2	553
Violent Crime	0	225	9	913	526

```
# Grouped bar plot of incident type vs police district
plt.figure(figsize=(14,6))
sns.countplot(data=police_incident, x='incident_type', hue='police_district_number')
plt.title("Incident Type vs Police District")
plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
plt.show()

# Crosstab of incident type and police district
print(pd.crosstab(police_incident['incident_type'], police_incident['police_district_numb
```



police_district_number	1D	2D	3D	4D	5D	6D
incident_type						
Administrative	312	200	202	264	160	176
Health & Safety	370	344	375	338	253	364
Investigation	384	379	435	393	297	367
Other	392	321	349	352	233	352
Property Crime	435	600	666	582	295	444
Public Order	352	260	487	381	250	400
Traffic	391	397	434	468	270	380
Violent Crime	212	188	328	300	271	374

```
# Grouped bar plot of incident type vs hour
plt.figure(figsize=(14,6))
sns.countplot(data=police_incident, x='incident_type', hue='hour')
plt.title("Incident Type vs Hour")
plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
plt.show()

# Crosstab of incident type and hour
print(pd.crosstab(police_incident['incident_type'], police_incident['hour']))
```

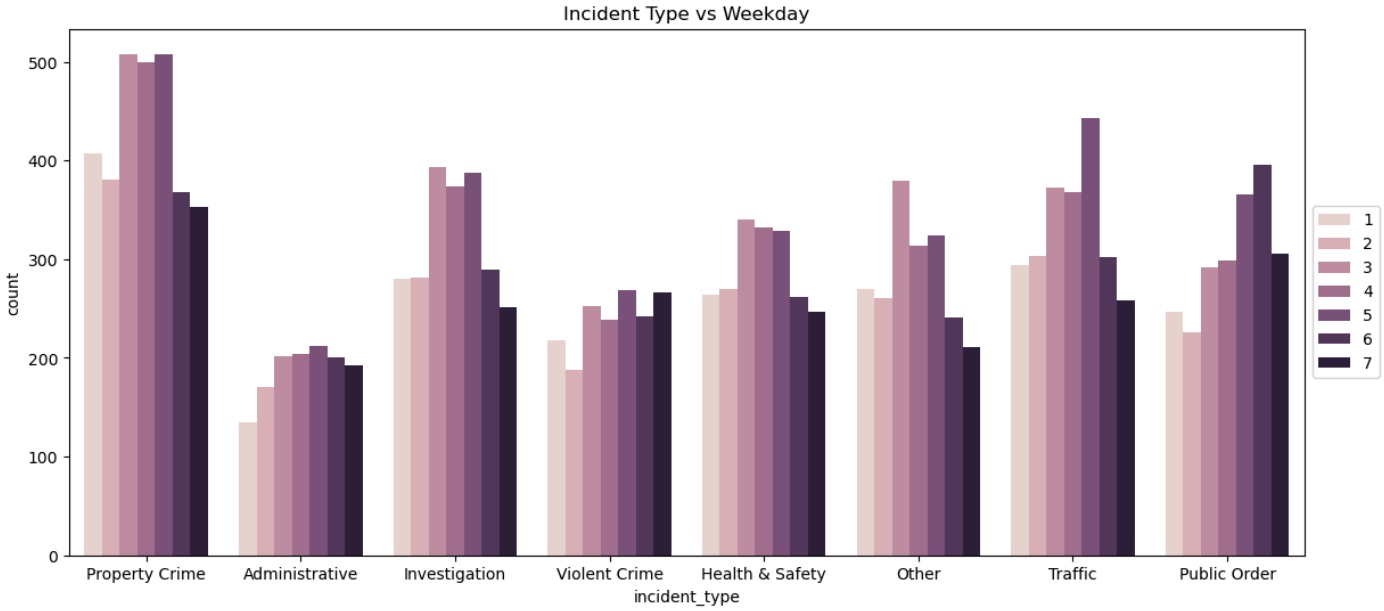


hour	0	1	2	3	4	5	6	7	8	9	...	14	15	\
incident_type											...			
Administrative	22	6	12	6	4	11	17	46	63	77	...	85	79	
Health & Safety	47	35	43	31	23	27	22	41	65	95	...	130	125	
Investigation	87	72	60	43	34	41	46	49	75	92	...	117	112	
Other	31	21	18	16	23	22	28	57	110	132	...	123	155	
Property Crime	55	50	45	51	64	65	80	115	156	172	...	171	218	
Public Order	113	86	55	55	28	43	40	51	60	75	...	91	112	
Traffic	25	20	13	15	12	41	54	120	141	122	...	144	201	
Violent Crime	85	58	57	40	26	24	18	22	39	66	...	90	84	

hour	16	17	18	19	20	21	22	23
incident_type								
Administrative	102	85	82	85	65	44	31	25
Health & Safety	150	116	141	125	99	94	92	77
Investigation	150	119	125	140	108	100	117	92
Other	128	123	125	88	77	70	45	39
Property Crime	201	189	130	156	116	106	86	71
Public Order	108	99	90	93	96	149	177	156
Traffic	192	154	137	148	88	85	76	33
Violent Crime	78	105	100	112	94	97	108	85

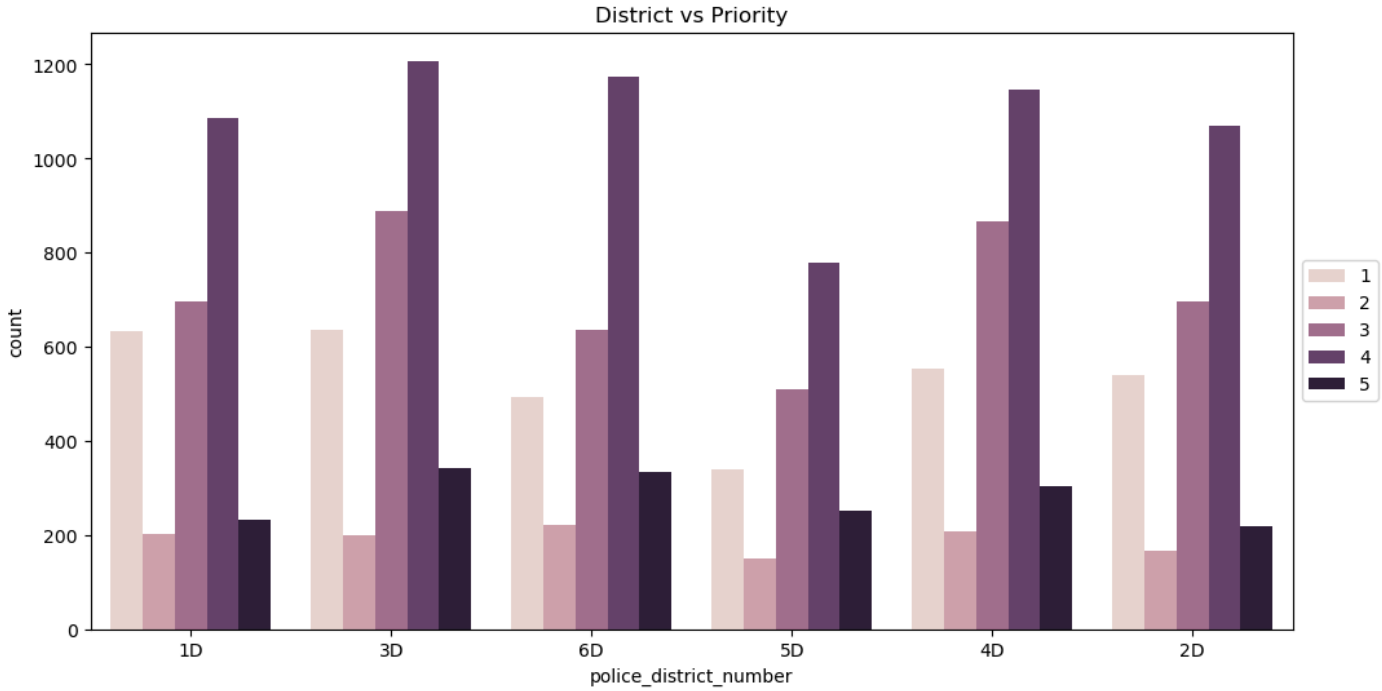
[8 rows x 24 columns]

```
# Grouped bar plot of incident type vs weekday
plt.figure(figsize=(14,6))
sns.countplot(data=police_incident, x='incident_type', hue='weekday')
plt.title("Incident Type vs Weekday")
plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
plt.show()

# Crosstab of incident type and weekday
print(pd.crosstab(police_incident['incident_type'], police_incident['weekday']))
```



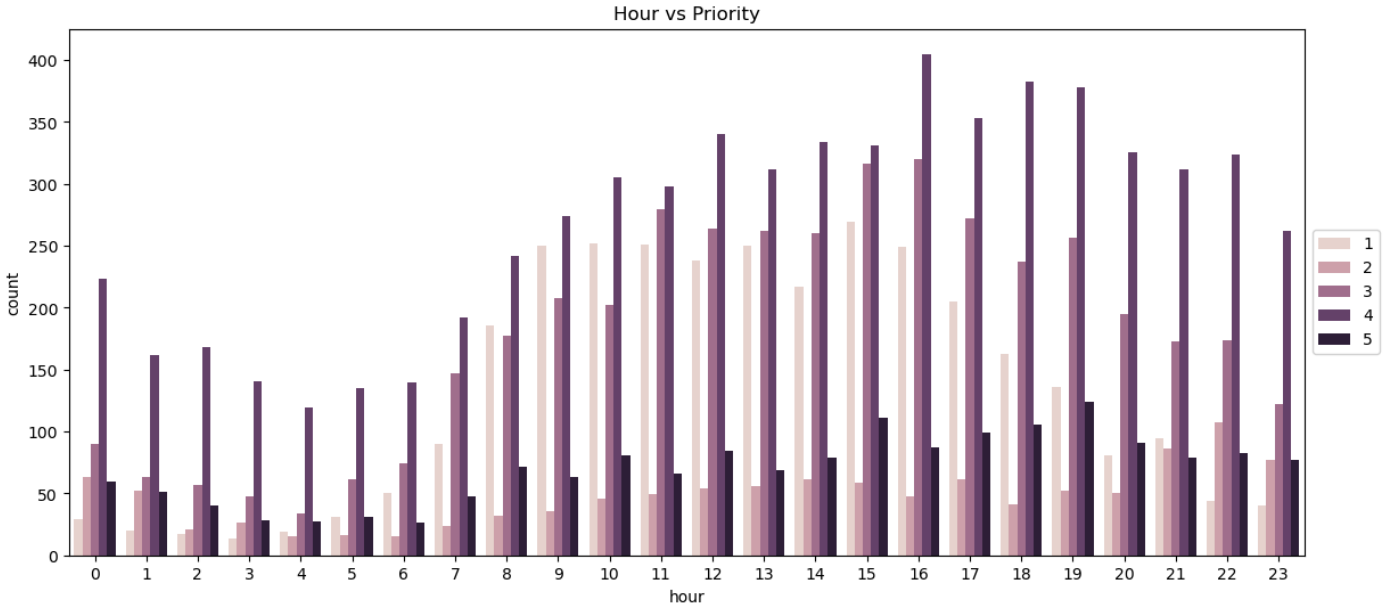
weekday	1	2	3	4	5	6	7
incident_type							
Administrative	135	170	201	204	212	200	192
Health & Safety	264	270	340	332	329	262	247
Investigation	280	281	393	374	387	289	251
Other	270	260	379	314	324	241	211
Property Crime	407	380	507	499	508	368	353
Public Order	247	226	292	299	366	395	305
Traffic	294	303	372	368	443	302	258
Violent Crime	218	188	252	238	269	242	266

```
# Grouped bar plot of district vs priority
plt.figure(figsize=(12,6))
sns.countplot(data=police_incident, x='police_district_number', hue='priority')
plt.title("District vs Priority")
plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
plt.savefig("../../report/visual5.png", dpi=300, bbox_inches="tight")
plt.show()

# Crosstab of police district and priority
print(pd.crosstab(police_incident['police_district_number'], police_incident['priority']))
```



priority	1	2	3	4	5
police_district_number					
1D	634	202	696	1085	231
2D	539	167	696	1069	218
3D	637	200	888	1208	343
4D	554	207	867	1146	304
5D	340	151	509	778	251
6D	492	220	637	1173	335

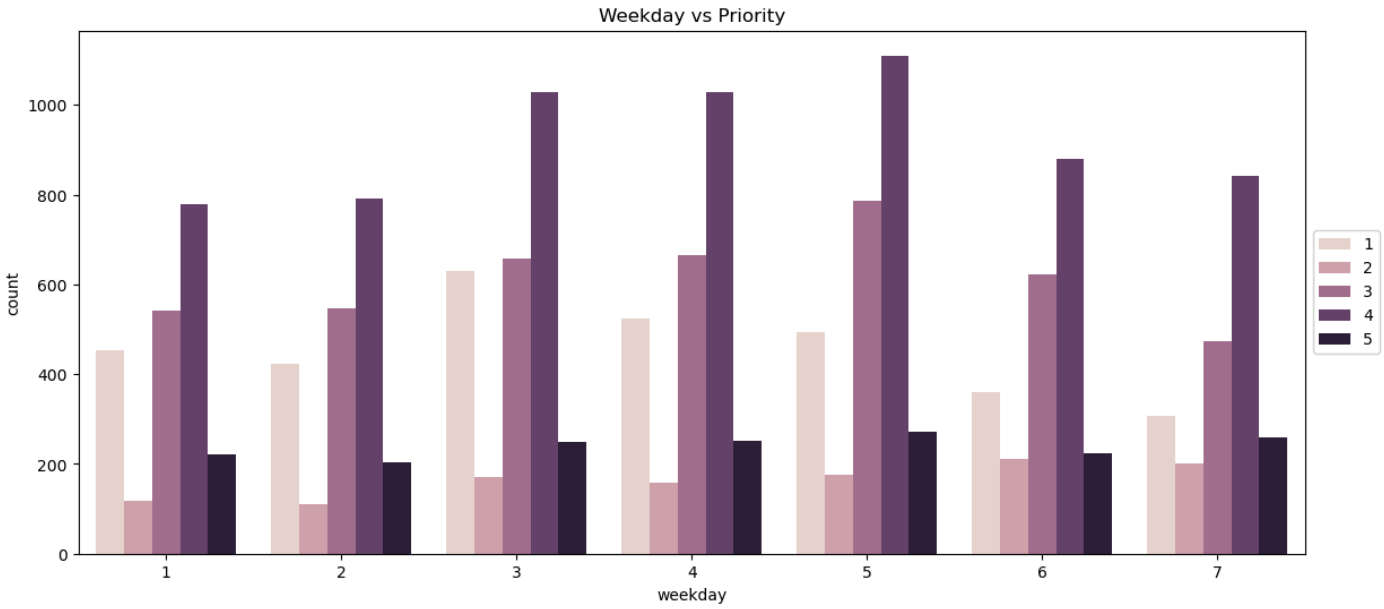
```
# Grouped bar plot of hour vs priority
plt.figure(figsize=(14,6))
sns.countplot(data=police_incident, x='hour', hue='priority')
plt.title("Hour vs Priority")
plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
plt.show()

# Crosstab of hour and priority
print(pd.crosstab(police_incident['hour'], police_incident['priority']))
```



priority	1	2	3	4	5
hour					
0	29	63	90	223	60
1	20	52	63	162	51
2	17	21	57	168	40
3	14	26	48	141	28
4	19	15	34	119	27
5	31	16	61	135	31
6	50	15	74	140	26
7	90	24	147	192	48
8	186	32	177	242	72
9	250	36	208	274	63
10	252	46	202	305	81
11	251	49	280	298	66
12	238	54	264	340	84
13	250	56	262	312	69
14	217	61	260	334	79
15	269	59	316	331	111
16	249	48	320	405	87
17	205	61	272	353	99
18	163	41	237	383	106
19	136	52	257	378	124
20	81	50	195	326	91
21	95	86	173	312	79
22	44	107	174	324	83
23	40	77	122	262	77

```
# Grouped bar plot of weekday vs priority
plt.figure(figsize=(14,6))
sns.countplot(data=police_incident, x='weekday', hue='priority')
plt.title("Weekday vs Priority")
plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
plt.show()
```

```
# Crosstab of weekday and priority
print(pd.crosstab(police_incident['weekday'], police_incident['priority']))
```

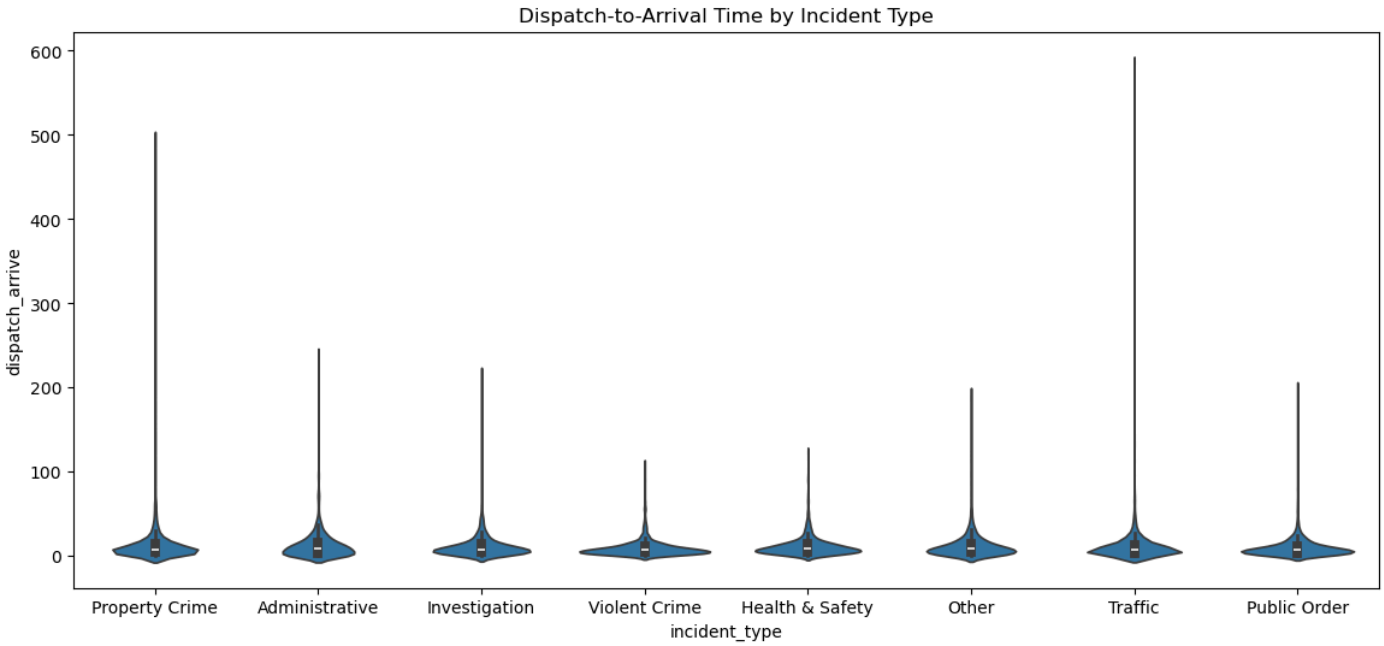


priority	1	2	3	4	5
weekday					
1	453	119	542	779	222
2	424	111	547	792	204
3	631	170	657	1029	249
4	524	159	665	1028	252
5	495	175	786	1110	272
6	361	212	623	879	224
7	308	201	473	842	259

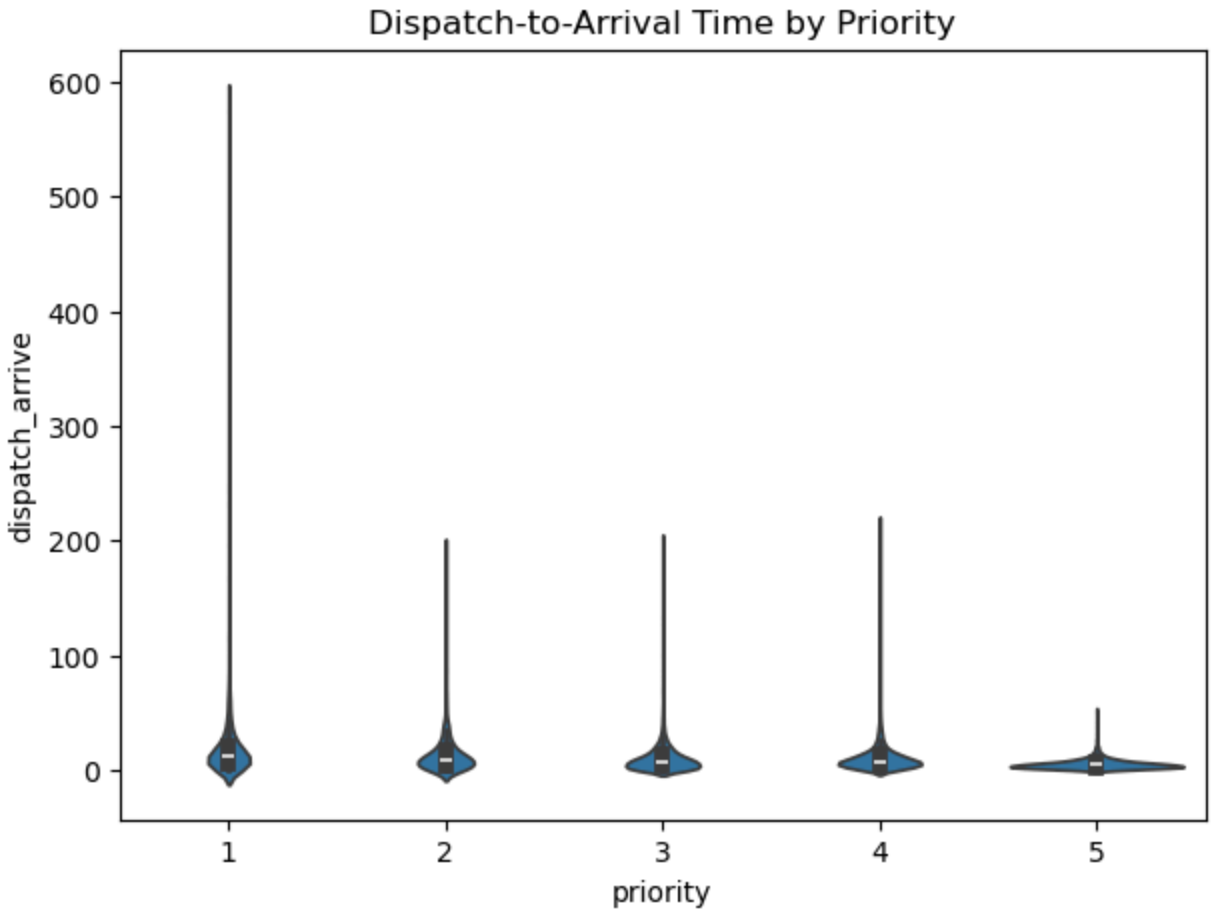
Feature Pairings

In this section, I will analyze relationships between key variables using violin plots. I will explore how different variables interact with each other, such as how incident types vary across dispatch-to-arrival time and how dispatch-to-arrival times differ by priority.

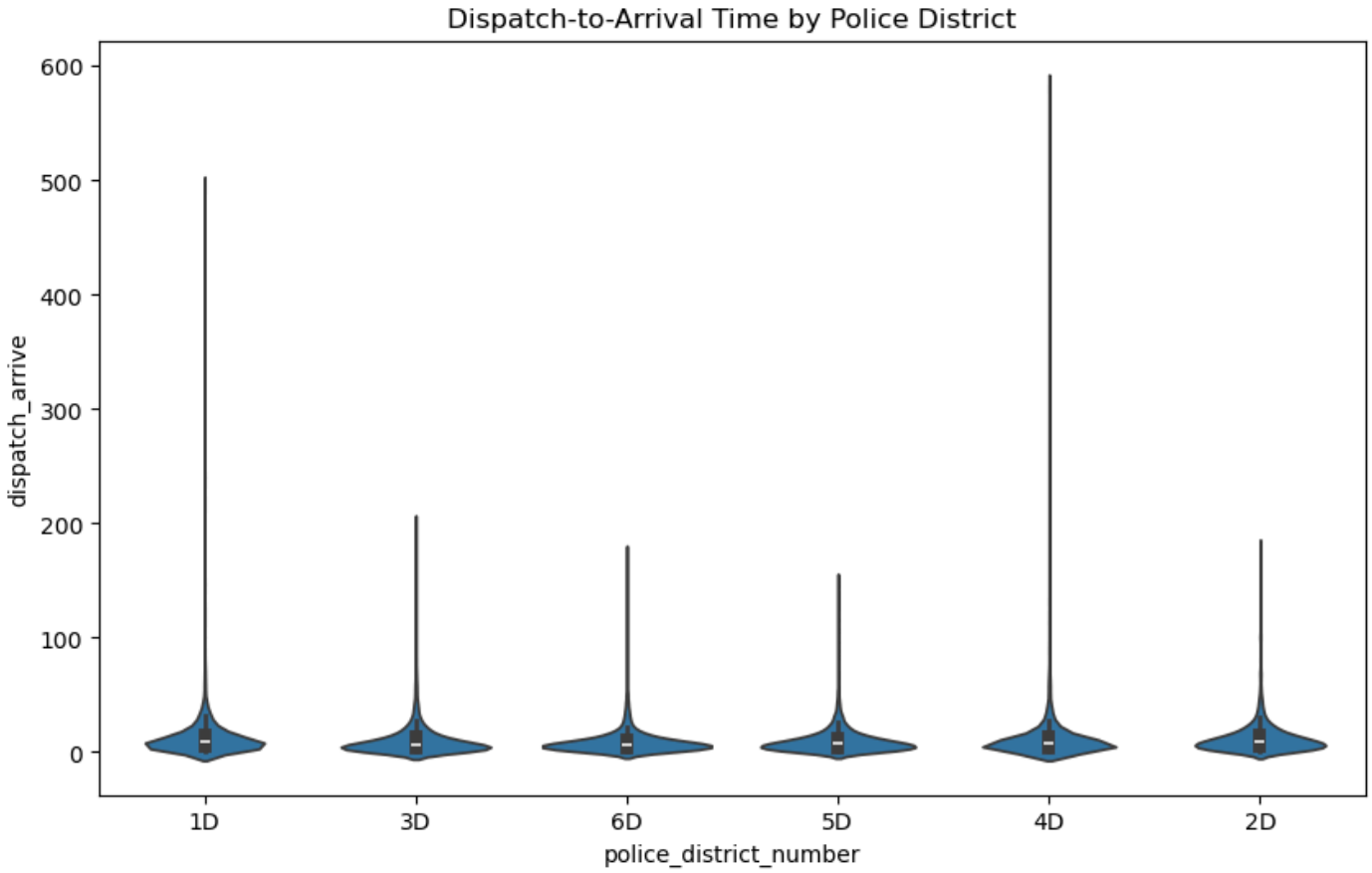
```
# Violin plot of dispatch to arrival time by incident type
plt.figure(figsize=(14,6))
sns.violinplot(data=police_incident, x='incident_type', y='dispatch_arrive')
plt.title("Dispatch-to-Arrival Time by Incident Type")
plt.show()
```



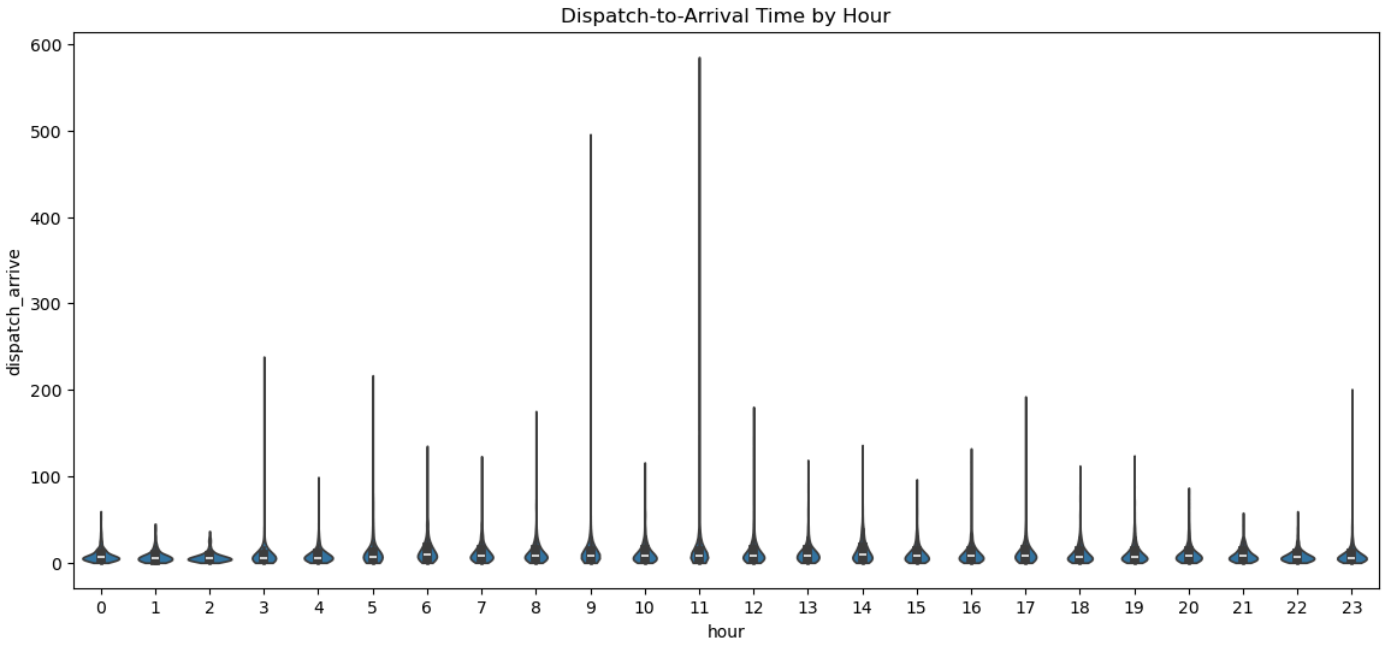

```
# Violin plot of dispatch to arrival time by priority
plt.figure(figsize=(7,5))
sns.violinplot(data=police_incident, x='priority', y='dispatch_arrive')
plt.title("Dispatch-to-Arrival Time by Priority")
plt.savefig("../../report/visual6.png", dpi=300, bbox_inches="tight")
plt.show()
```



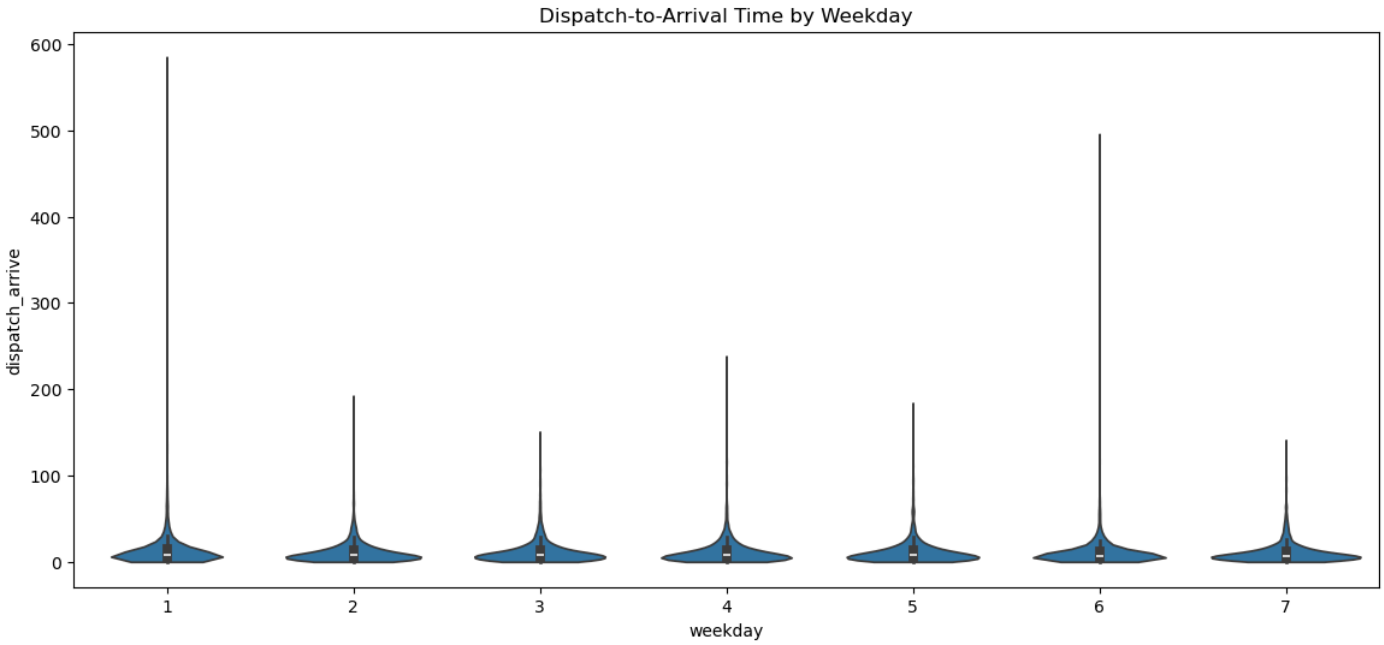

```
# Violin plot of dispatch to arrival time by police district
plt.figure(figsize=(10,6))
sns.violinplot(data=police_incident, x='police_district_number', y='dispatch_arrive')
plt.title("Dispatch-to-Arrival Time by Police District")
plt.show()
```



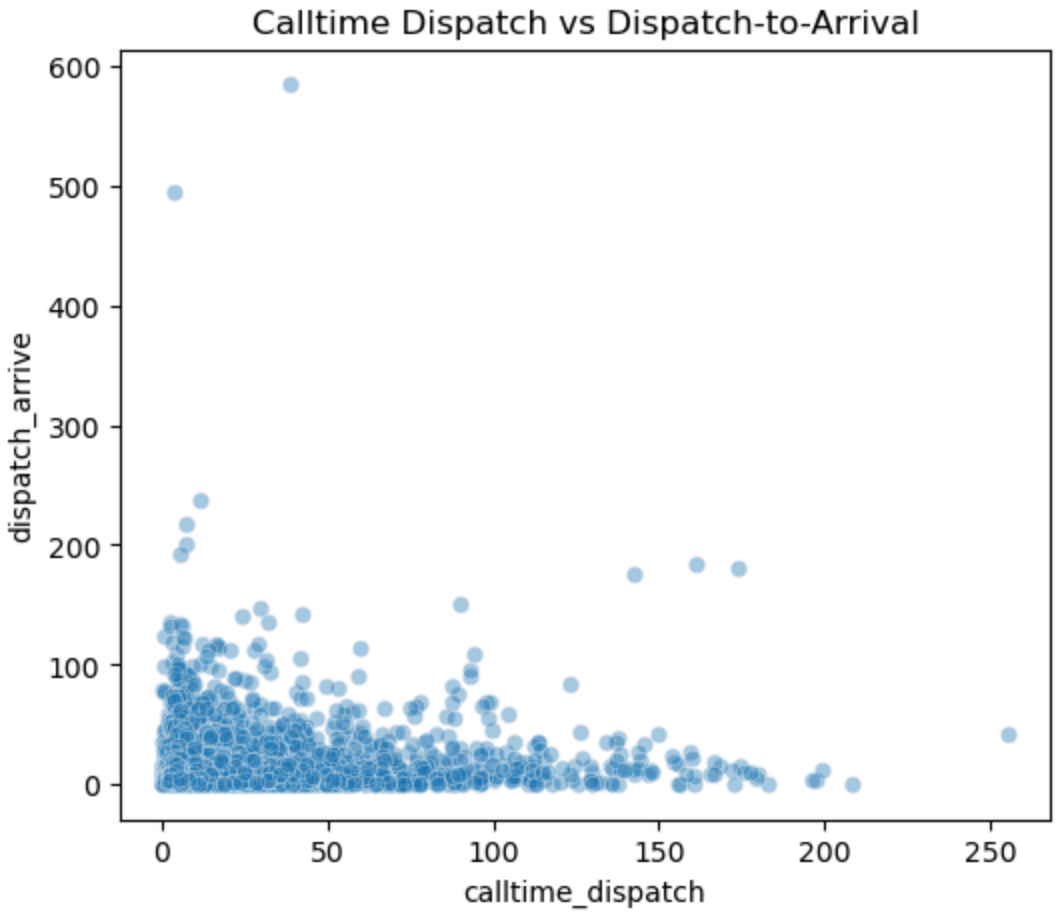

```
# Violin plot of dispatch to arrival time by hour
plt.figure(figsize=(14,6))
sns.violinplot(data=police_incident, x='hour', y='dispatch_arrive', cut=0)
plt.title("Dispatch-to-Arrival Time by Hour")
plt.show()
```



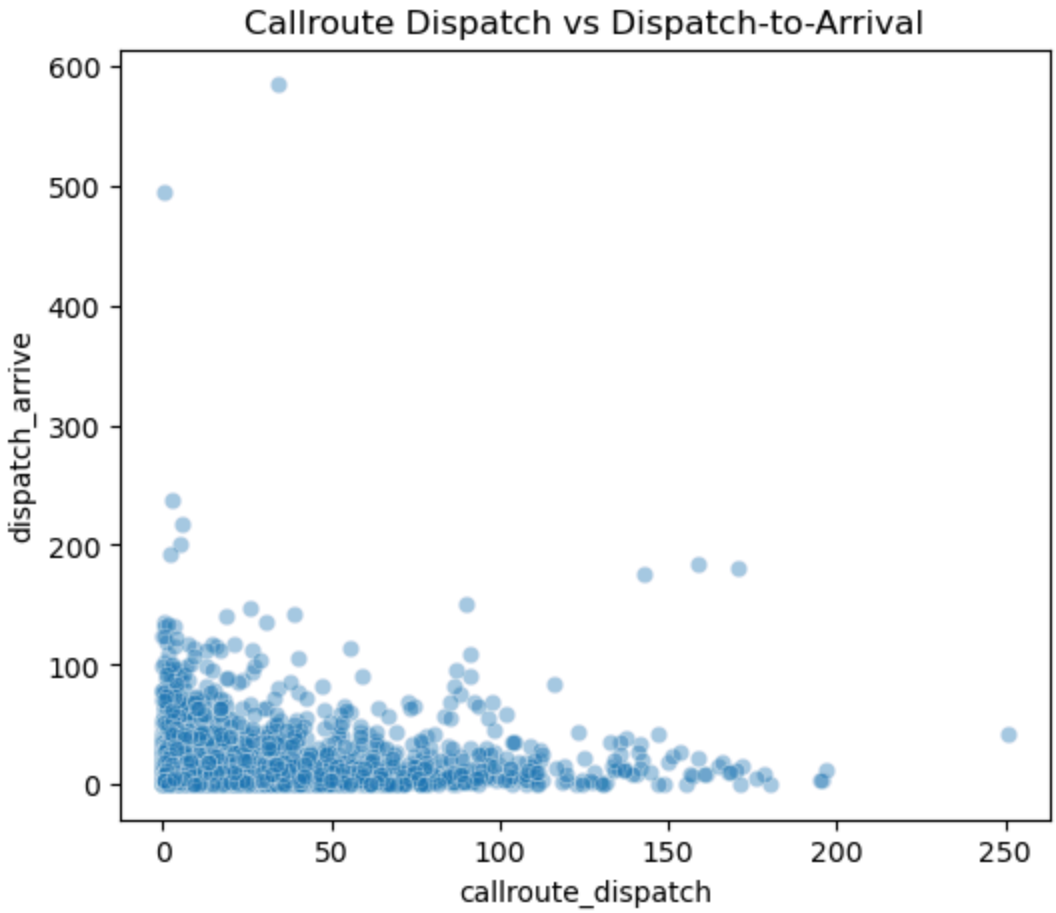
```
# Violin plot of dispatch to arrival time by weekday
plt.figure(figsize=(14,6))
sns.violinplot(data=police_incident, x='weekday', y='dispatch_arrive', cut=0)
plt.title("Dispatch-to-Arrival Time by Weekday")
plt.show()
```




```
# Scatter plot of calltime_dispatch vs dispatch_arrive
plt.figure(figsize=(6,5))
sns.scatterplot(data=police_incident, x='calltime_dispatch', y='dispatch_arrive', alpha=0
plt.title("Calltime Dispatch vs Dispatch-to-Arrival")
plt.show()
```




```
# Scatter plot of callroute_dispatch vs dispatch_arrive
plt.figure(figsize=(6,5))
sns.scatterplot(data=police_incident, x='callroute_dispatch', y='dispatch_arrive', alpha=
plt.title("Callroute Dispatch vs Dispatch-to-Arrival")
plt.show()
```



Key Insights

In this bivariate and multivariate analysis section, I found that there is no strong correlation between most of the numeric variables, except for `callroute_dispatch` and `calltime_dispatch`, `calltime_arrive` and `calltime_dispatch`, `calltime_arrive` and `callroute_dispatch`, `arrive_cleared` and `calltime_cleared`, which all have a moderate to strong positive correlation, which makes sense because these variables are related to each other in terms of time intervals. In the crosstabulation section, several interesting patterns were discovered. For the highest incident priority level (5), the most common incident types were property crime, violent crime, health & safety, and traffic-related incidents. What is interesting is that property crime is also the type with the most incidents, and it is associated with the lowest priority level. In the `incident_type` vs `police_district_number` grouped bar chart, all crime types were distributed relatively evenly, except for property crime in district 3D (Silver Spring), which had a significantly higher count than in other districts. In the `incident_type` vs. `hour` graph, all incident types peaked around 4pm except public order. Public order included the incident type of noise complaints, which peaked late at night. Except for public order incidents, all other incident types showed a similar distribution throughout the day. In the `incident_type` vs. `weekday` graph, nearly all incident types peaked on Wednesday, Thursday, and Friday, which is pretty consistent with the univariate analysis. From the `police_district_number` vs. `priority` graph, nothing stood out; all districts had a similar distribution of incident priority levels. For the `hour` vs. `priority` graph, all priority levels peaked between 3pm and 7pm. Same for the `weekday` vs `priority` graph: all priority levels peaked on Wednesday, Thursday, and Friday.

Now let's look at the difference feature pairing graphs. In the `dispatch_arrive` time by `incident_type` graph, the dispatch to arrival times are distributed similarly across all incident types. However, for property crime and traffic-related incidents, there are some outliers with extremely high dispatch to arrival times. In the `dispatch_arrive` by `priority` graph, we can see that priority level 1 has the highest dispatch to arrival time, while priority level 5 has the lowest, with no outliers or extreme cases. Priority levels 2, 3, and 4 are all relatively similar. `dispatch_arrive` distribution by `police_district_number`: all districts show a similar distribution, with some extreme outliers in 1D and 4D. In the `dispatch_arrive` by `hour` graph, we can see that incidents occurring at night arrive significantly faster than those during the day. `dispatch_arrive` by `weekday` graph: all weekdays show a similar distribution, with no significant difference, but Monday and Thursday have extreme outliers with very high dispatch to arrival times. For the two numerical variable pairings, `calltime_dispatch` vs `dispatch_arrive` and `callroute_dispatch` vs `dispatch_arrive`, no clear patterns were observed.

Data Distribution and Normalization

For Skewness and Kurtosis, and the Normalization section of the EDA, please see the data cleaning section Codes and Method (Machine Learning).

Statistical Insights

In this section, I will conduct several basic statistical tests, including T-tests, ANOVA, and chi-square tests, to explore relationships among variables. I will also summarize the statistical results and their implications for my analysis.

T-Test

Research Question: Do high-priority calls have significantly different dispatch to arrival times than low-priority calls?

Null Hypothesis: The mean dispatch to arrival time for high-priority calls is equal to that of low-priority calls.

Alternative Hypothesis: The mean dispatch to arrival time for high-priority calls is different to that of low-priority calls.

```
import scipy.stats as stats
import pandas as pd

# Load the processed police incident data
police_incident = pd.read_csv("../../data/processed-data/police_incident_eda.csv")

# Define high and low priority groups
low = police_incident[police_incident['priority'] <= 3]['dispatch_arrive']
high  = police_incident[police_incident['priority'] >= 4]['dispatch_arrive']

# Drop NaN values
high = high.dropna()
low = low.dropna()
```

```
# Perform t-test
t_stat, p_val = stats.ttest_ind(high, low, equal_var=False)
print("T-statistic:", t_stat)
print("P-value:", p_val)
```

```
T-statistic: -11.911813620480993
P-value: 1.7549529290249306e-32
```

Since the p-value of the t-test above is less than 0.05, we will reject the null hypothesis. The mean dispatch to arrival time for high-priority calls is significantly different from that of low-priority calls. Also, since the t-stat is negative, we can tall that the dispatch to arrival time for high-priority calls is significantly lower than that of low-priority calls.

ANOVA

Research Question: Do different incident types have significantly different arrival to cleared times?

Null Hypothesis: The mean arrival to cleared time is the same across all incident types.

Alternative Hypothesis: At least on incident type has a mean arrival to cleared time different than other incident types.

```
import scipy.stats as stats

# Perform ANOVA for arrive_cleared time across different incident types
groups = police_incident.groupby('incident_type')['arrive_cleared'].apply(lambda x: x.dro
f_stat, p_val = stats.f_oneway(*groups)
print("F-statistic:", f_stat)
print("P-value:", p_val)
```

```
F-statistic: 35.70717979864037
P-value: 8.496045230736917e-50
```

Since the p-value is less than 0.05, we reject the null hypothesis. There is a very strong statistical evidence prooving that at least one incident type has a mean arrival to cleared time different than other incident types.

Chi-Square Test of Independence

Research Question: Is incident type associated with priority level?

Null Hypothesis: Incident type and priority level are independent. There is no association between incident type and priority level.

Alternative Hypothesis: Incident type and priority level are not independent. There is an association between incident type and priority level.

```
import scipy.stats as stats
import pandas as pd
```

```
# Crosstab of incident type and priority
ct = pd.crosstab(police_incident['incident_type'], police_incident['priority'])

# Chi-square test
chi2, p_val, dof, expected = stats.chi2_contingency(ct)
print("Chi-square statistic:", chi2)
print("Degrees of freedom:", dof)
print("P-value:", p_val)
```

```
Chi-square statistic: 12050.397407578494
Degrees of freedom: 28
P-value: 0.0
```

Since the p-value of the Chi-Square test above is less than 0.05, we will reject the null hypothesis. The is strong evidence proving that incident type and priority level are not independent. There is an association between incident type and priority level.

Data Visualization and Storytelling

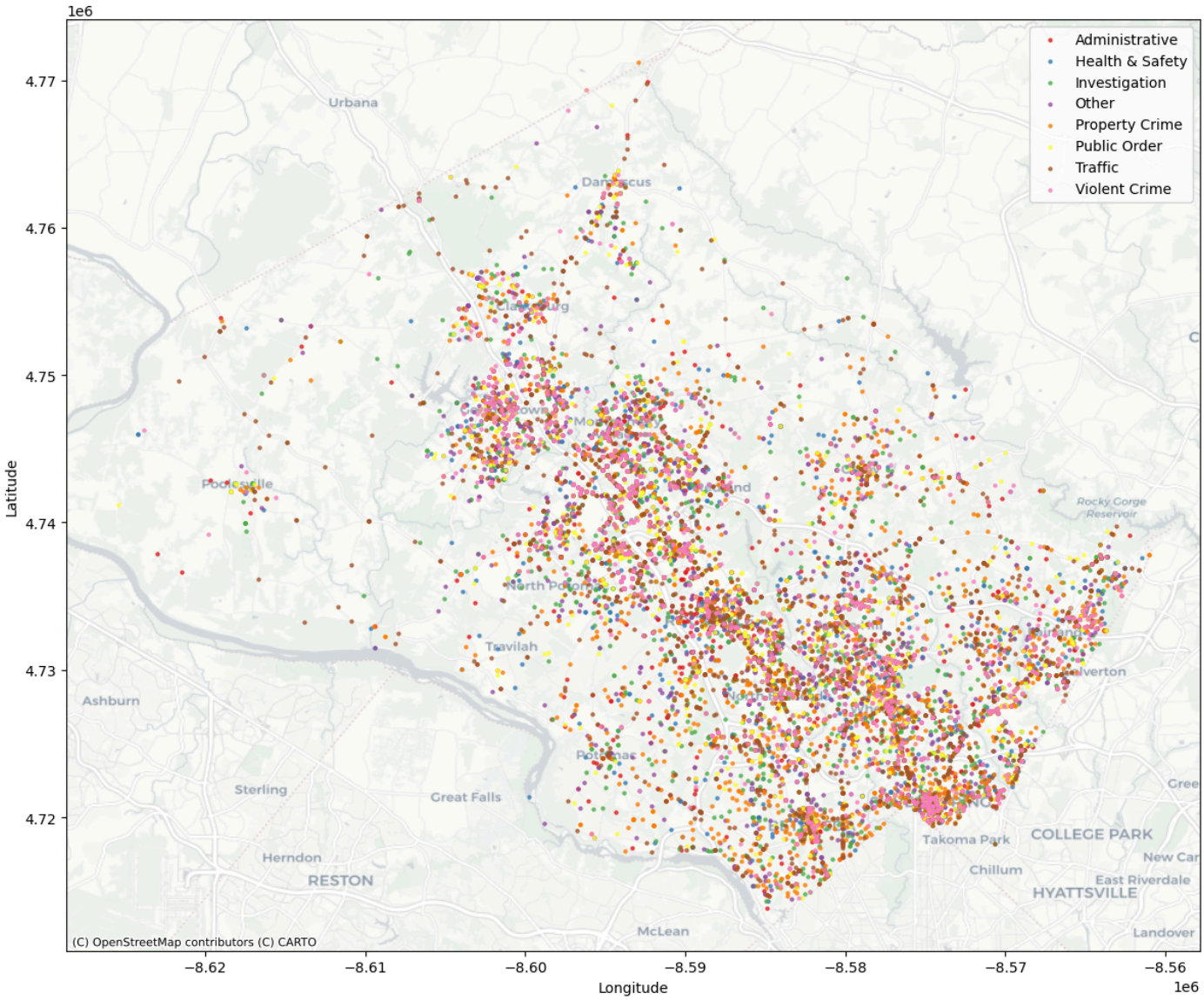
In the following section, I will present several key insights using charts and visualizations, primarily with the Matplotlib and Geopandas packages. I will include interesting graphs that are not in the above sections, and unrelated to machine learning, just for a fun interpretation of the data.

Incident Location by Incident Type

The following visual is a map of Montgomery County that plots each incident occurrence location on top of its true location and distinguishes them by incident type. The following Python codes are partially generated by ChatGPT 5.1[1].

```
import geopandas as gpd
import matplotlib.pyplot as plt
import contextily as ctx
import pandas as pd

# Load processed data
police_incident = pd.read_csv("../../data/processed-data/police_incident_eda.csv")

# Define incident types (sorted for consistent color ordering)
incident_types = sorted(police_incident['incident_type'].unique())

colors = [
    "#e41a1c", "#377eb8", "#4daf4a", "#984ea3",
    "#ff7f00", "#ffff33", "#a65628", "#f781bf"
]

type_to_color = {itype: colors[i] for i, itype in enumerate(incident_types)}

# Create GeoDataFrame
gdf = gpd.GeoDataFrame(
```

```
    police_incident,
    geometry=gpd.points_from_xy(police_incident['longitude'], police_incident['latitude']
    crs="EPSG:4326"
).to_crs(epsg=3857)

fig, ax = plt.subplots(figsize=(12,10))
for incident_type in incident_types:
    subset = gdf[gdf['incident_type'] == incident_type]
    ax.scatter(
        subset.geometry.x,
        subset.geometry.y,
        s=5,
        color=type_to_color[incident_type],
        label=incident_type,
        alpha=0.7
    )

ctx.add_basemap(ax, source=ctx.providers.CartoDB.Positron)
plt.legend(loc='upper right')
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.tight_layout()
plt.savefig("../../report/visual12.png", dpi=300, bbox_inches="tight")
plt.show()
```



From the graph above, we can see that more populated areas have a much higher chance of incidents, which makes sense. Of the above areas, Silver Spring has the most incidents. Along with North Bethesda, around Bethesda Row. We can also see that many incidents occurred along Rockville Pike. As a Montgomery County resident, Rockville Pike is like the main vein of Montgomery County. Nearly all commercial areas, including restaurants, movie theaters, and shopping centers, are built this way. So it is not surprising that there are many incidents.

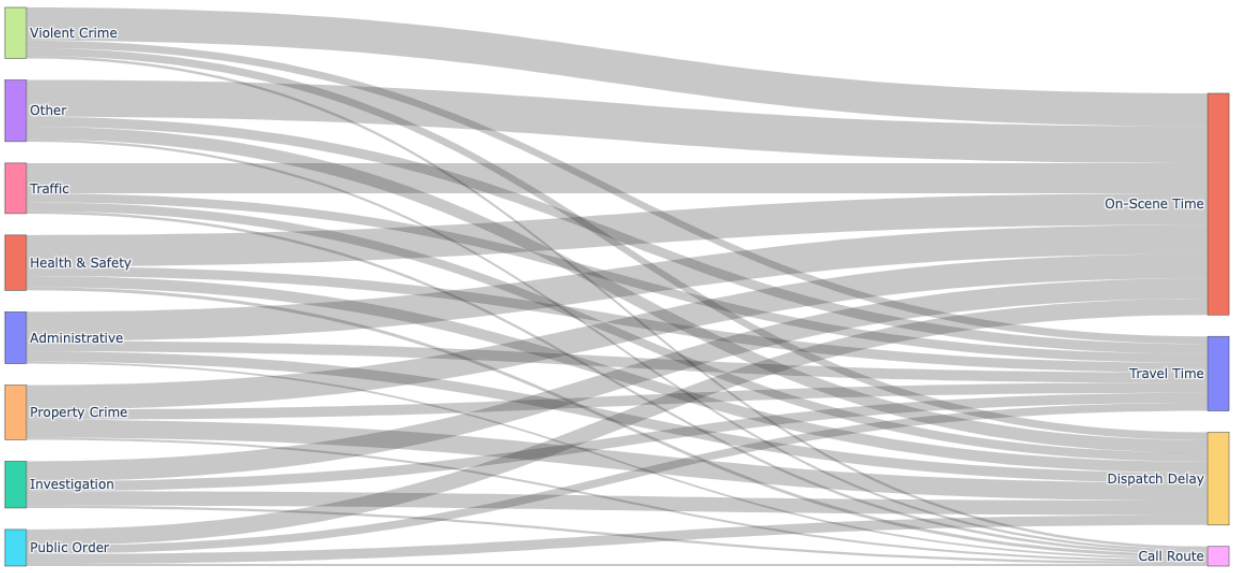
Operational Delay Bottlenecks Sankey Diagram

The following visual shows how time is wasted through the 911 response pipeline, from the initial call to final clearance. It highlights where key operational delays occur and shows which incident types contribute most to bottlenecks. Due to the complexity of the codes, the following codes are partially generated by ChatGPT 5.1[1].

```
import plotly.graph_objects as go
import pandas as pd

incident_types = police_incident['incident_type'].unique()
```

```
avg_times = police_incident.groupby('incident_type')[['calltime_callroute', 'calltime_dis

left_labels = list(avg_times.index)
right_labels = ["Call Route", "Dispatch Delay", "Travel Time", "On-Scene Time"]
labels = left_labels + right_labels

label_to_index = {label: i for i, label in enumerate(labels)}

sources = []
targets = []
values  = []

for inc in avg_times.index:
    for i, stage in enumerate(right_labels):
        sources.append(label_to_index[inc])
        targets.append(label_to_index[stage])
        values.append(avg_times.loc[inc].iloc[i])

fig = go.Figure(data=[go.Sankey(
    node=dict(pad=20, thickness=20, label=labels),
    link=dict(source=sources, target=targets, value=values)
)])

fig.update_layout(font_size=12, height=700, width=1300)
fig.show()
```

```
Unable to display output for mime type(s): application/vnd.plotly.v1+json
```



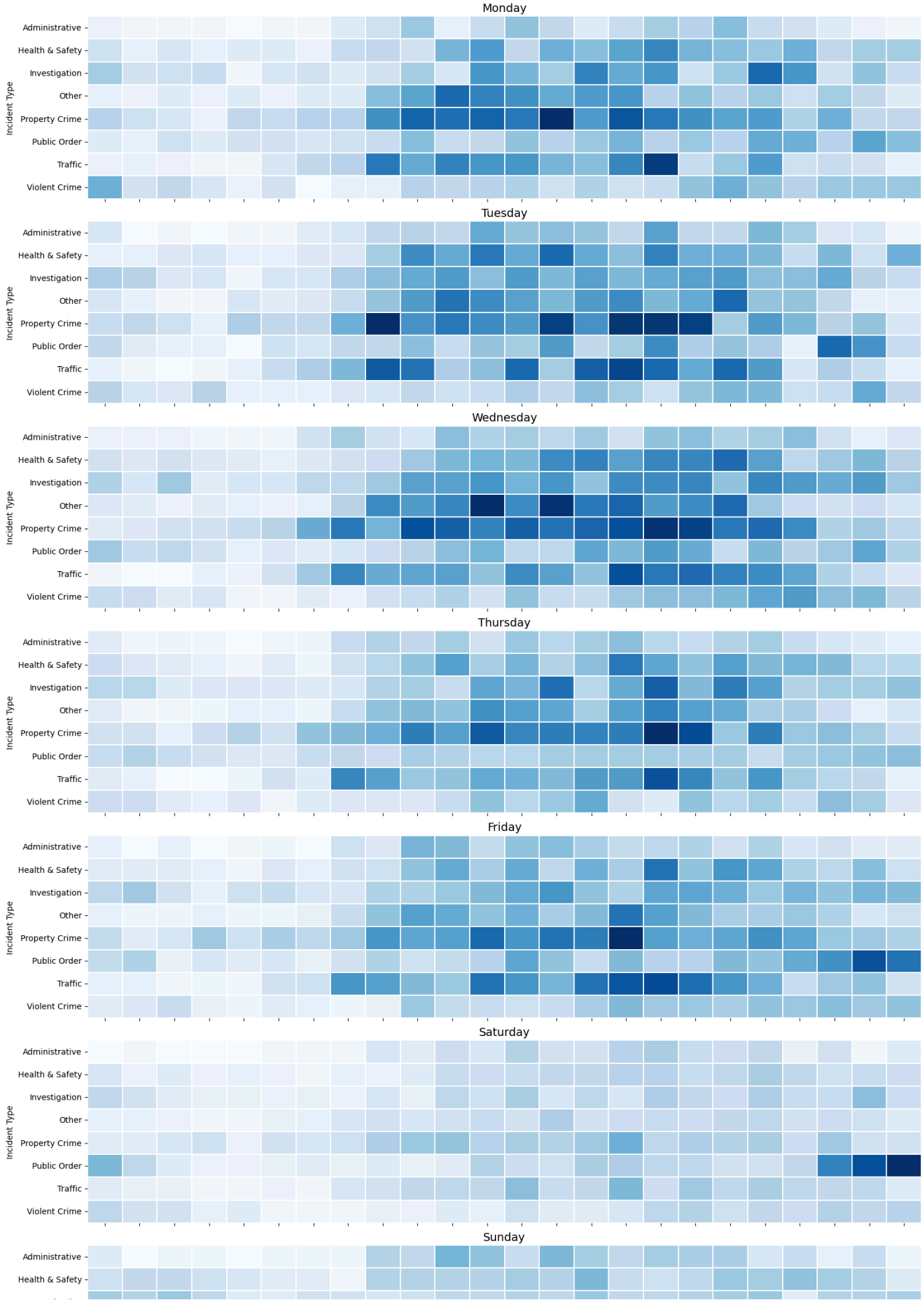
Above plot is shown as image because Plotly version could not be rendered by Quarto due to renderer compatibility issues.

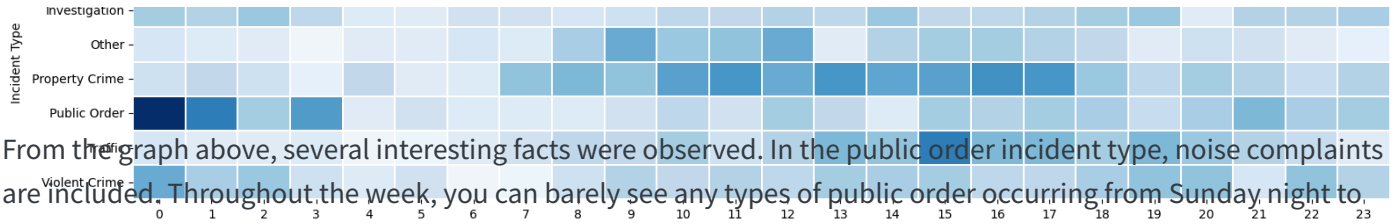
To better understand the graph above, on-scene time is the time it takes the officer to clear the incident, starting from arrival. Travel time is the time it takes from the officer's dispatch to their arrival on scene. Dispatch delay is when the call details are ready, and officers are officially dispatched. The call route is the time it takes 911 to redirect the call to the correct department. From the graph, we can clearly see that the true bottleneck in this whole system is the dispatch-to-delay time. Besides, on-scene time is the longest, which makes sense. Dispatch delay is taking the longest, even longer than travel time.

Incident Type Frequency by Hour and Weekday

The following graph is relatively complex, containing three data fields: `weekday`, `hour`, and `incident_type`. The following graphs display the frequency of incidents occurring by incident type and hours, and are split into weekdays. Due to the complexity of the code, part of the following code is generated by ChatGPT 5.1[1].

```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

weekday_map = {1:"Monday", 2:"Tuesday", 3:"Wednesday", 4:"Thursday", 5:"Friday", 6:"Satur
police_incident['weekday_name'] = police_incident['weekday'].map(weekday_map)

week_order = ["Monday","Tuesday","Wednesday","Thursday","Friday","Saturday","Sunday"]

fig, axes = plt.subplots(7, 1, figsize=(16, 25), sharex=True)

for ax, day in zip(axes, week_order):
    df_day = police_incident[police_incident['weekday_name'] == day]

    ct = pd.crosstab(df_day['incident_type'], df_day['hour'])

    sns.heatmap(
        ct,
        cmap="Blues",
        linewidths=0.1,
        ax=ax,
        cbar=False
    )

    ax.set_title(f"{day}", fontsize=14)
    ax.set_xlabel("")
    ax.set_ylabel("Incident Type")

plt.tight_layout()
plt.savefig("../../report/visual2.png", dpi=300, bbox_inches="tight")
plt.show()
```


Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Incident Type
Administrative
Health & Safety
Investigation
Other
Property Crime
Public Order
Traffic
Violent Crime



From the graph above, several interesting facts were observed. In the public order incident type, noise complaints are included. Throughout the week, you can barely see any types of public order occurring from Sunday night to Thursday night. However, Friday nights and Saturday nights have a whole different story. You can clearly see that the frequency of public order incidents is extremely high, extending into the early AM of the next day. In general, the frequency table shows that all incidents are more likely to occur during the daytime, especially in the afternoon, except for public order incidents. Another interesting point is that traffic incidents are more likely to occur during workdays; they rarely occur on weekends.

Conclusion

In this EDA section, I first conducted univariate analyses of numerical and categorical variables. Then I've conducted bivariate and multivariate analysis, including correlation analysis, crosstabulation tables, and feature pairings. I then visualized the skewness and kurtosis of all variables, and returned to the data cleaning section to resolve skewness by applying log transformations. I then normalized the data using z-score normalization. I also conducted a t-test, a chi-square test of independence, and an ANOVA test. Lastly, I've created three complex graphs to see how this police incident data tells a story. After doing all those visualizations and tests, I now have a better sense of the data, and I will continue to work on my data in the following supervised and unsupervised learning sections.

Challenges

One of the major challenges was that I originally had only the `start_time` and `end_time` fields, which were time-related. Although these specific columns contain the original exact time. But as I move forward in the EDA section, I realized it's kinda hard to process this data as categorical; for example, if I wanted to analyze by day of week or time of day. I had to revisit the data cleaning section halfway through. It is very true that about 70% of the time in a data workflow is spent on data cleaning.

References

1. ChatGPT, version-5.1, OpenAI, NOV-2025, chat.openai.com.

DSAN 5000 - Incident Response Modeling (MCMD)

Unsupervised Learning

Overview

In this section, I will perform several unsupervised learning techniques to explore whether distinct clusters of incident types and response times exist in the police-incident data. The unsupervised learning techniques include dimensionality reduction methods such as PCA and t-SNE, as well as clustering methods such as K-Means, DBSCAN, and hierarchical clustering. After completing the PCA and t-SNE, I will evaluate the effectiveness of these methods and compare their visualization capabilities. In the clustering methods section, I will also discuss the results of each clustering analysis and compare them.

Methods and Codes

Dimensionality Reduction

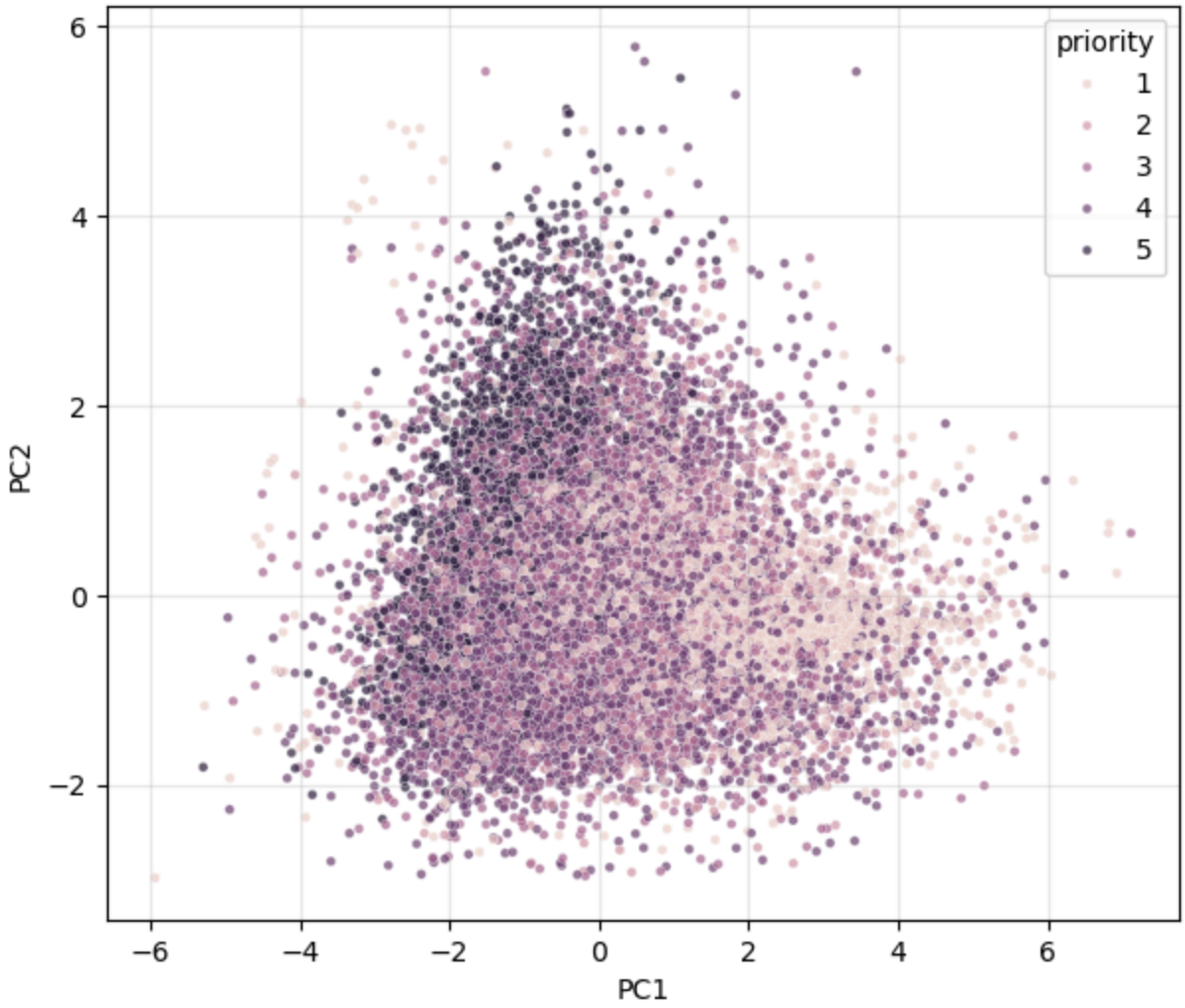
The objective of this section is to explore and demonstrate the effectiveness of PCA and t-SNE in reducing the dimensionality of complex data while preserving essential information and improving visualization.

PCA (Principal Component Analysis)

> **Principal Component Analysis (PCA)**[1]
>
> **Principal Component Analysis (PCA)** is a dimensionality-reduction method that transforms high-dimensional data into a smaller set of uncorrelated variables called principal components. PC1 captures the most variance, PC2 captures the next most while remaining orthogonal, and so on. By focusing on directions of greatest variation, PCA simplifies complex data and makes patterns easier to visualize.

```
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Load the processed police incident data
police_incident = pd.read_csv("../../data/processed-data/police_incident_ml.csv")

# Define features for PCA
cols = ['longitude', 'latitude', 'calltime_callroute', 'calltime_dispatch', 'callroute_di
X = police_incident[cols].values
```

```
# Perform PCA
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)

# Create a DataFrame for PCA results
pca_df = pd.DataFrame({
    'PC1': X_pca[:, 0],
    'PC2': X_pca[:, 1],
    'priority': police_incident['priority']
})

# Plot the PCA results
plt.figure(figsize=(7,6))
sns.scatterplot(
    data=pca_df,
    x='PC1', y='PC2',
    hue='priority',
    s=12,
    alpha=0.7
)
plt.grid(alpha=0.3)
plt.savefig("../../report/visual10.png", dpi=300, bbox_inches="tight")
plt.show()
```



The PCA results above show that the features form a smooth cloud of points, indicating that police dispatch behavior varies gradually rather than forming distinct linear clusters. To better understand the features, I embedded the colors by priority. I discovered that higher-priority calls tend to shift towards one side of PC1, while lower-priority calls shift to the opposite side. This might suggest that priority level is associated with systematic differences in dispatch timing, even though the categories overlap. As a result, we can conclude that dispatch operations exhibit a continuous, correlated structure without sharp boundaries, making them an effective tool for summarizing global variance but not for identifying discrete groups.

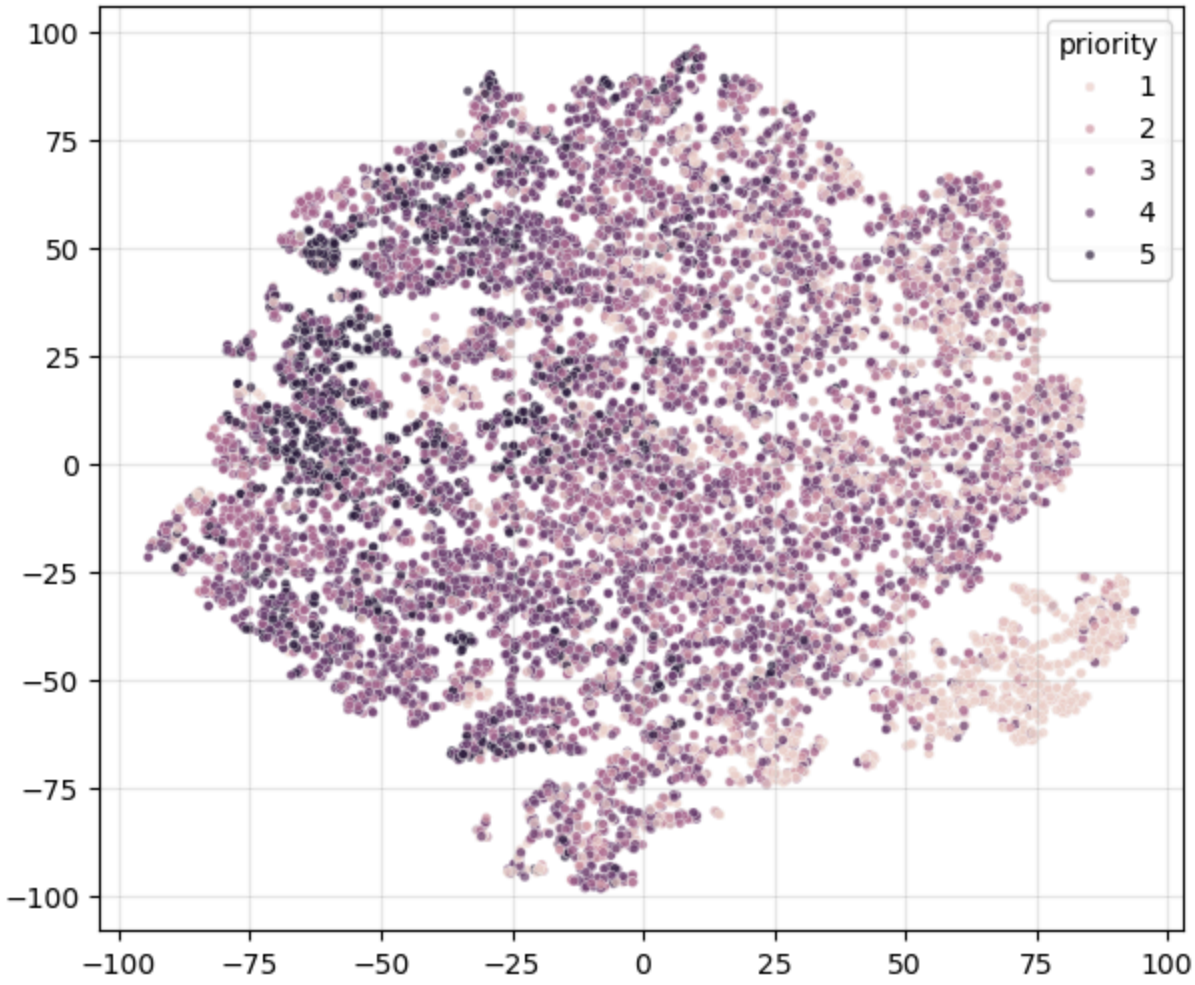
t-SNE (t-distributed Stochastic Neighbor Embedding)

t-Distributed Stochastic Neighbor Embedding (t-SNE)[1]

t-Distributed Stochastic Neighbor Embedding (t-SNE) t-SNE is a nonlinear dimensionality-reduction method that maps high-dimensional data into a low-dimensional space by preserving local neighborhood structure. It converts distances between points into probabilities and finds an embedding that keeps similar points close together while pushing dissimilar points apart, making it especially useful for visualizing patterns or clusters.

```
from sklearn.preprocessing import StandardScaler
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt
```

```
import seaborn as sns

# Standardize the features
X_scaled = StandardScaler().fit_transform(X)

# Perform t-SNE
tsne_res = TSNE(
    n_components=2,
    perplexity=30,
    learning_rate='auto',
    init='pca',
    random_state=42
).fit_transform(X_scaled)

# Plot the t-SNE results
plt.figure(figsize=(7,6))
sns.scatterplot(
    x=tsne_res[:, 0],
    y=tsne_res[:, 1],
    hue=police_incident['priority'],
    s=12,
    alpha=0.7
)
plt.grid(alpha=0.3)
plt.savefig("../../report/visual8.png", dpi=300, bbox_inches="tight")
plt.show()
```



Evaluation and Comparison

As I've mentioned, the PCA provides a basic overview of how the data is distributed. It shows a general pattern and how the main features relate to each other. In the case above, the PCA shows one large cloud with slight differences based on priority, but nothing that forms clear groups. The t-SNE takes a different approach, aiming to place similar points closer together. After testing perplexity values from 5 to 50, the results are similar to those of PCA. The t-SNE formed a large, diffuse cloud with no strong clusters. However, the t-SNE shows a small shift, with different priority levels appearing in different areas, but the overlap is still very large. In comparison, PCA is easier to understand and faster to run, while t-SNE is more detailed but does not reveal anything very different for this dataset. Both methods suggest that the data changes gradually and does not break into clear groups.

Clustering Methods

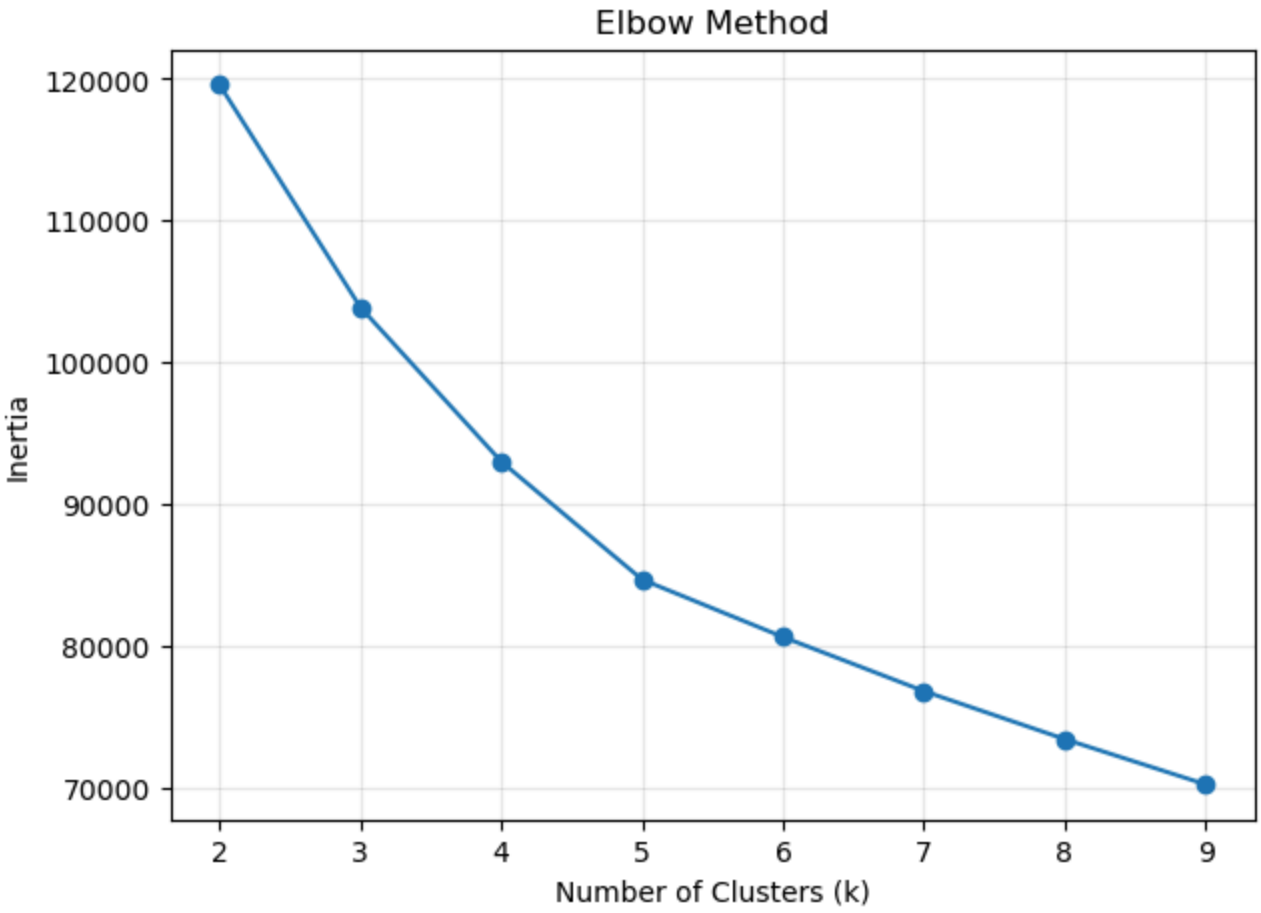
The objective of this section is to apply clustering techniques, including K-Means, DBSCAN, and Hierarchical clustering, to the police incident calls dataset. I will explain how each method works and compare their performance.

K-Means

K-Means[1]

K-Means is a clustering method that groups data into *k* clusters based on similarity. It works by placing *k* centers in the data space, assigning each point to the nearest center, and then adjusting the centers until the assignments stop changing. K-Means is simple, fast, and works best when clusters are roughly round and similar in size.

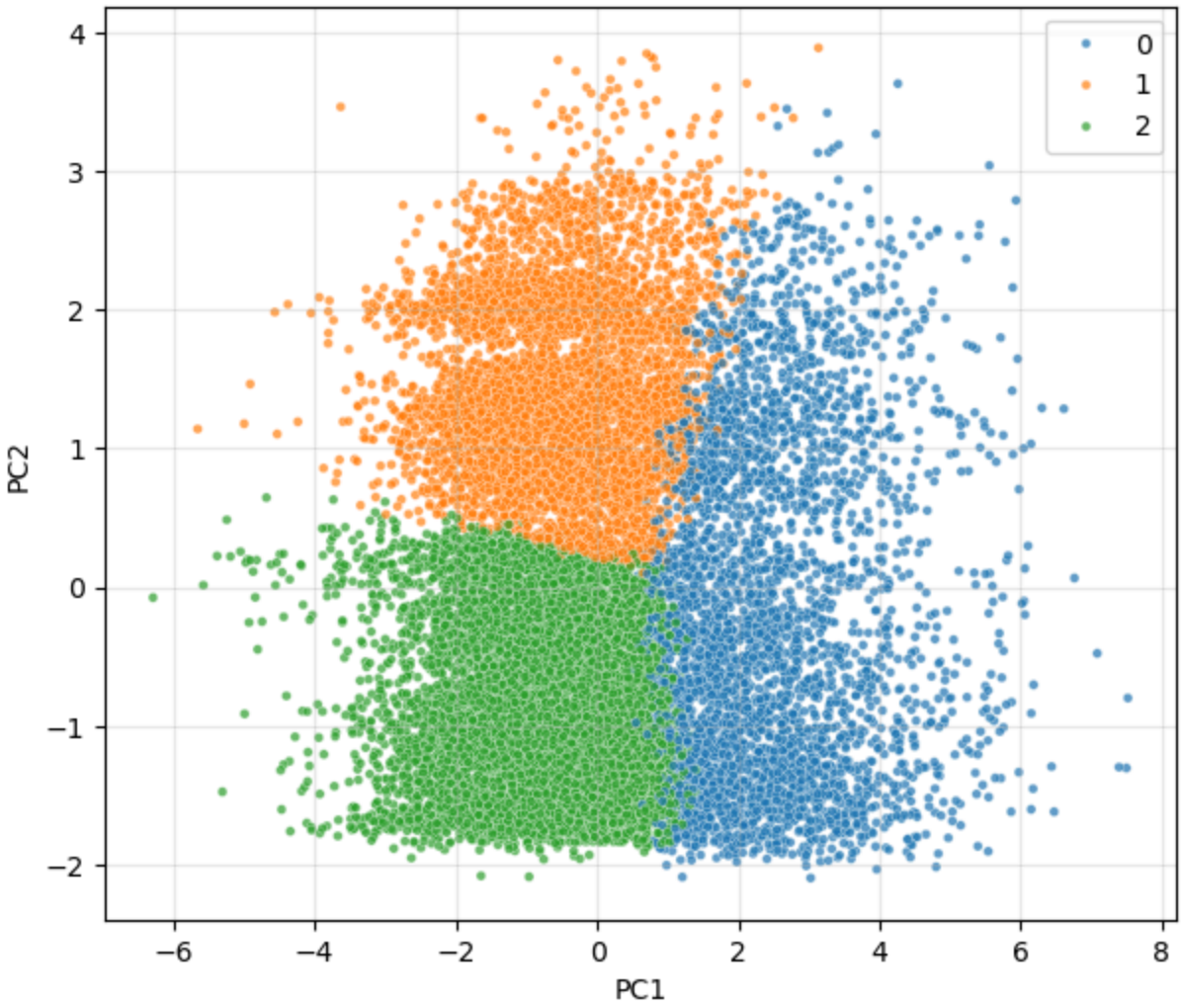
```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Determine the optimal number of clusters using the Elbow Method
inertia_values = []
k_values = range(2, 10)

for k in k_values:
    km = KMeans(n_clusters=k, random_state=42)
    km.fit(X_scaled)
    inertia_values.append(km.inertia_)

# Plot the Elbow Method results
plt.figure(figsize=(7,5))
plt.plot(k_values, inertia_values, marker='o')
plt.title("Elbow Method")
plt.xlabel("Number of Clusters (k)")
plt.ylabel("Inertia")
plt.grid(alpha=0.3)
plt.show()
```



The Elbow plot above shows how inertia decreases as more clusters are added. The inertia dropped by over 50% from k = 2 to k = 4. After k=4, the decrease slows slightly. In this case, no elbow turning point is observed, which indicates that the data does not split into clear clusters. In this case, adding more clusters will only reduce inertia slightly because the data forms a single and smooth shape. Since there is no clear best value of k, I will be using k = 3 in the following k-means clustering to show the overall pattern.

```
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns

# Apply K-Means clustering
kmeans = KMeans(n_clusters=3, random_state=42)
kmeans_labels = kmeans.fit_predict(X_scaled)

# Plot K-Means clustering results
plt.figure(figsize=(7,6))
sns.scatterplot(
    x=X_pca[:,0], y=X_pca[:,1],
    hue=kmeans_labels, palette="tab10",
    s=12, alpha=0.7
)
plt.xlabel("PC1")
plt.ylabel("PC2")
```

```
plt.grid(alpha=0.3)
plt.show()
```



In this clustering method, I used k-means to look for patterns in the police calltime features of the police incident data. Since this data contains spatial information, I decided to use the two PCA dimensions to create my k-means analysis, PC1 and PC2. I first scaled all features using StandardScaler, which, in theory, makes the patterns easier to see.

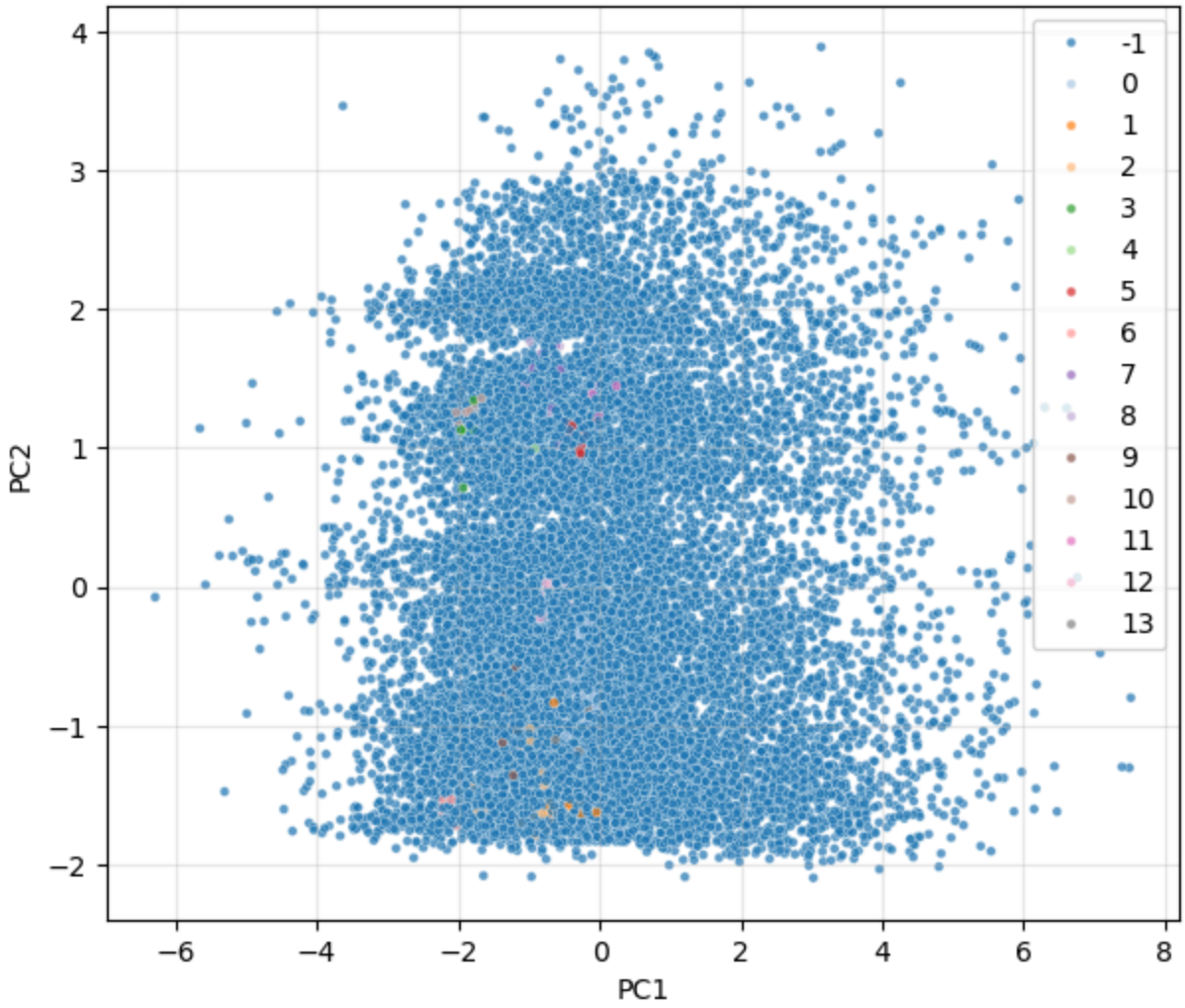
Once the data were scaled and reduced, I ran K-Means with k = 3, based on the previous elbow plot. The above k-means plot shows how the data cloud splits into three main groups, labeled 0, 1, and 2. Since the three groups overlap significantly and there are no clear boundaries, we were unable to define any clusters. Although no clusters were found, the k-means analysis still helps us summarize the general behavior of the timing features, suggesting that police response times change smoothly from one incident to another.

DBSCAN

DBSCAN[1]

> **DBSCAN** is a clustering method that groups points based on how close they are to many neighbors. It forms clusters from dense areas in the data and marks isolated points as noise. Because it looks for dense regions, DBSCAN can find clusters of many different shapes without needing to choose the number of clusters ahead of time.

```
from sklearn.cluster import DBSCAN
import matplotlib.pyplot as plt
import seaborn as sns

# Apply DBSCAN clustering
db = DBSCAN(eps=0.5, min_samples=10)
db_labels = db.fit_predict(X_scaled)

# Plot DBSCAN clustering results
plt.figure(figsize=(7,6))
sns.scatterplot(
    x=X_pca[:,0], y=X_pca[:,1],
    hue=db_labels,
    palette="tab20",
    s=12, alpha=0.7
)
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.grid(alpha=0.3)
plt.show()
```



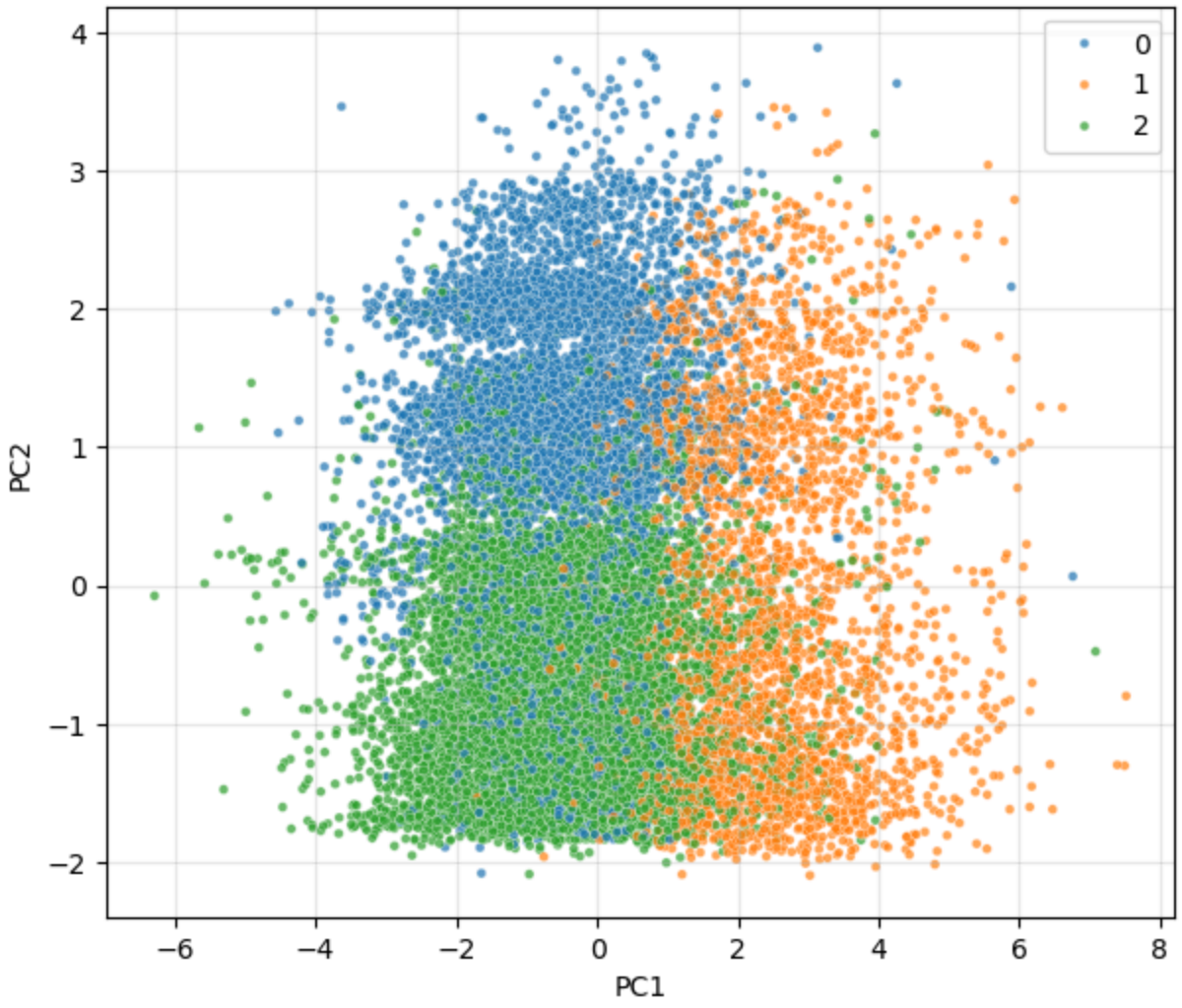
As I mentioned in the definition of DBSCAN above, it is a clustering method that identifies areas where points are densely packed. Instead of using distance to a center, it checks how many neighbors a point has within a set radius. When I ran DBSCAN on the scaled police incident call features, no strong clusters were found. Almost every single point was labeled as having a noise of -1, and the other few clusters that did appear were extremely small. Although no clear clusters were found, this result matches those of PCA and t-SNE, which indicated that the data form a single cloud without clear clusters. Since DBSCAN relies on detecting density differences, it cannot separate the data when the density is nearly uniform everywhere.

Hierarchical Clustering

> **Hierarchical Clustering**[1]
>
> **Hierarchical Clustering** builds clusters step by step by joining the closest points or clusters at each stage. The process creates a tree-like diagram called a dendrogram, which shows how groups form at different levels. This method is useful for exploring structure in the data because you can choose the number of clusters by “cutting” the tree at different heights.

```
from sklearn.cluster import AgglomerativeClustering
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Apply Hierarchical Clustering
hclust = AgglomerativeClustering(n_clusters=3)
h_labels = hclust.fit_predict(X_scaled)

# Plot Hierarchical Clustering results
plt.figure(figsize=(7,6))
sns.scatterplot(
    x=X_pca[:,0], y=X_pca[:,1],
    hue=h_labels,
    palette="tab10",
    s=12, alpha=0.7
)
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.grid(alpha=0.3)
plt.show()
```



In the above definition, Hierarchical clustering works by joining the closest points or clusters repeatedly until everything forms a single structure. In this part, I used the agglomerative clustering method, meaning that each incident starts as its own cluster. It then merges the most similar clusters in steps. When I plotted the results using the two PCA dimensions, the clusters looked very similar to the K-Means output. The data formed a single large

cloud, with overlap among all three groups. This suggests that the data lacks a strong hierarchical structure that would yield clear and separate branches. Instead, the method divides the data based on small, gradual changes along the PCA. In the end, hierarchical clustering reaches the same conclusion as the methods above. The police incident call features shift smoothly across incidents, so the dataset lacks well-defined clusters.

Evaluation and Comparison

Across all three methods above, the results point to the same conclusion. The data form a single, continuous cloud with no breaks or natural groupings between. K-Means produced broad clusters that overlap heavily. DBSCAN finds almost no dense regions, marking most points as noise. Hierarchical clustering also produced groups with no clear boundaries. Together, these results indicate that the police incident call features change gradually across incidents and do not form clusters.

Conclusion

Both the graphs of dimensionality reduction methods and the clustering methods point to the same result. The police incident call data forms a single large cloud with no cluster boundaries. Dimensionality reduction methods, PCA and t-SNE, show gradual changes rather than sharp groups. Clustering methods such as k-means produce heavily overlapping clusters, DBSCAN finds no dense regions, and hierarchical clustering forms groups that blend together.

Challenges

One of the challenges I faced in this step was that my data showed basically no clusters. All methods, including PCA, t-SNE, k-means, DBSCAN, and hierarchical clustering, failed to produce clear clusters. Throughout the semester, when completing homework or lab assignments, we've always used data that show clear clusters. So, during my project, I thought I had done something wrong. Is it because of data cleaning, a problem with my data transformation, or a problem with z-score normalization? As a result, it was really time-consuming for me to verify my data over and over again, and by conducting research, I am confident in my data.

References

1. ChatGPT, version-5.1, OpenAI, NOV-2025, chat.openai.com.

DSAN 5000 - Incident Response Modeling (MCMD)

Supervised Learning

Overview

In the supervised learning stage, we will first preprocess the raw data to prepare it for training. As this step has already been completed in the data cleaning stage, please refer to that stage for details. Techniques used include z-score normalization, log transformation, and categorical variable encoding, among others. I will use a binary classification method to predict whether an incident is high or low priority, a multiclass classification method to predict the final disposition of each call, and regression models to forecast dispatch-to-arrival times based on the prepared police-incident dataset.

Methods and Codes

Data Preprocessing

In the data processing step, I will perform normalization and standardization, encode categorical variables, apply log and z-score transformations, and select relevant features to ensure the data is suitable for supervised learning. For details, please see the Codes and Method (Machine Learning) section.

Binary Classification

Model Rationale

For binary classification, I decided to predict whether a police incident is high-priority, with priority levels of 4 or 5, or low-priority, with priority levels of 1, 2, or 3. This would allow us to look at how emergency dispatch systems often distinguish between routine calls and those that require an immediate response. This analysis can reveal whether the underlying call characteristics and call times align with the urgency level assigned by the control centers. It can also help identify potential mismatches between actual call times and assigned priority levels.

Overview of Algorithms

For this task, I've decided to use logistic regression to model the binary priority classification. Logistic regression works by combining the input features into a simple linear combination. This combination then passes through a sigmoid function, which turns it into a probability between 0 and 1. The model learns by minimizing a loss that compares its predicted probabilities to the true labels. This causes the model to adjust until the predictions stabilize. With this method, I can see which features push an incident towards high priority. This also scales well to my current police incident call dataset and gives stable probability estimates that I can evaluate using ROC curves.

Binary Logistic Regression

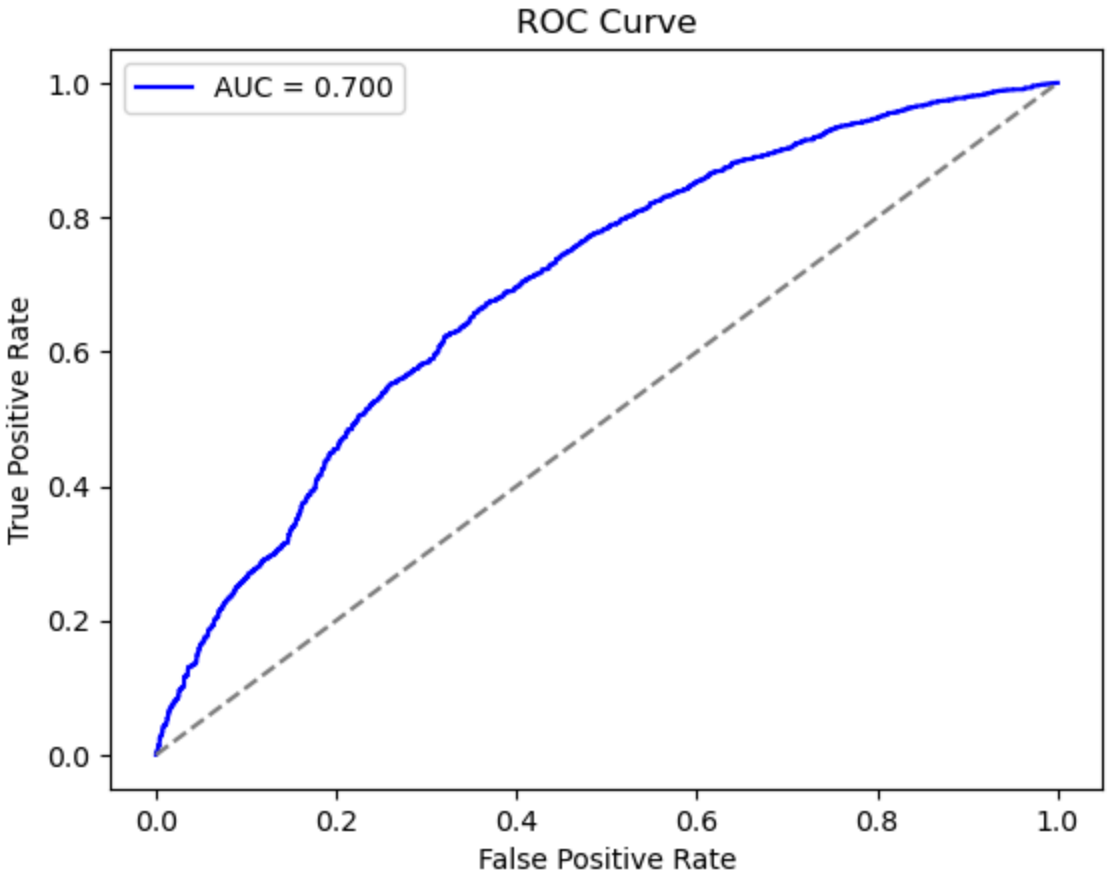
Binary Logistic Regression[1]

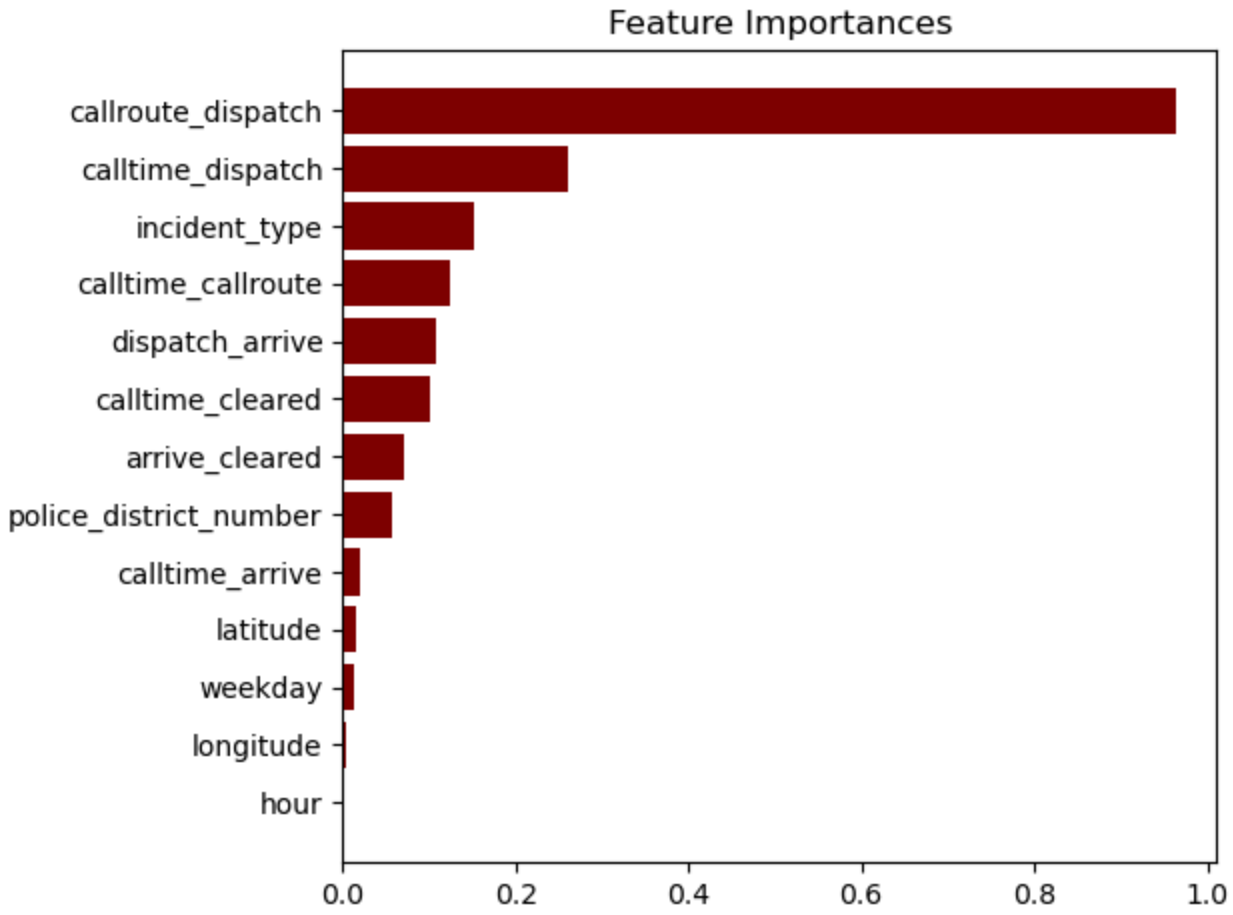
Binary Logistic Regression is a generalized linear classification method used when the target variable has two possible outcomes. The model learns a weighted combination of the input features and converts that result into a probability between 0 and 1 using the logistic transformation. These probabilities describe how likely an observation belongs to the positive class. The model parameters are estimated by finding the values that best match the observed labels, typically by maximizing the likelihood of the data. Once trained, the model assigns a class by applying a probability threshold, making logistic regression both interpretable and effective for many real-world binary prediction tasks, including your priority classification problem.

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (accuracy_score, precision_score, recall_score, f1_score, roc
import numpy as np

# Import police incident data
df = pd.read_csv("../../data/processed-data/police_incident_ml.csv")

# Modify priority to binary classification
df["priority_binary"] = (df["priority"] >= 4).astype(int)

# Remove unnecessary columns
X = df.drop(columns=["priority_binary", "priority"])
y = df["priority_binary"]

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42

# Train logistic regression model
model = LogisticRegression(max_iter=5000)
model.fit(X_train, y_train)

# Evaluate model
y_pred = model.predict(X_test)
y_proba = model.predict_proba(X_test)[:, 1]

print("Accuracy:", accuracy_score(y_test, y_pred))
print("Precision:", precision_score(y_test, y_pred))
print("Recall:", recall_score(y_test, y_pred))
print("F1 Score:", f1_score(y_test, y_pred))

# Plot ROC curve
fpr, tpr, _ = roc_curve(y_test, y_proba)
roc_auc = auc(fpr, tpr)

plt.plot(fpr, tpr, label=f"AUC = {roc_auc:.3f}", color="blue")
```

```
plt.plot([0,1], [0,1], linestyle="--", color="gray")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.show()

# Plot feature importances
coef = model.coef_[0]
feature_names = X.columns

top_idx = np.argsort(np.abs(coef))[-15:]

plt.barh(feature_names[top_idx], np.abs(coef[top_idx]), color="maroon")
plt.title("Feature Importances")
plt.tight_layout()
plt.show()
```

```
Accuracy: 0.6477949940405244
Precision: 0.6251402918069585
Recall: 0.6842751842751843
F1 Score: 0.6533724340175953
```





Model Performance & Insights

From the results, we are able to tell that the binary logistic regression performed pretty well, since the accuracy, precision, recall, and F1 score all falls in the same range. This indicates that the model is producing balanced decisions, meaning that it is not favoring one class. From the results, the recall score is slightly higher than the precision score, indicating that the model is better at identifying high-priority calls. From the ROC curve below, we can see that the AUC is about 0.70, meaning that the model can separate high and low priority calls better than chance and captures real patterns in the data. Although the separation is not perfect, it is sufficient for early screening. Also, the predicted probabilities show a steady improvement over random guessing. In the graph below, the feature importance plot highlights which inputs influence the model the most, with the strongest being `callroute_distach`, followed by `calltime_dispatch`, `incident_type`, `calltime_callroute`, `dispatch_arrive`, `calltime_cleared`, `arrive_cleared`, `police_district_number`, `calltime_arrive`, `latitude`, `longitude`, `weekday`, and `hour`.

Multiclass Classification

Model Rationale

For the multiclass classification problem, I will predict the original police call incident type with the other variables. The result of this would allow us to check how all the other variables in the dataset could separate the eight different categories of police incident call types. I will use a multiclass logistic regression model and a KNN

classifier as a comparison model. With the result of these modes, we will be able to see how much structure actually exists in the incident call type labels and whether the engineered features capture enough signal to distinguish them.

Overview of Algorithms

The multiclass logistic regression uses the softmax function, which transforms a set of raw model scores into probabilities for each class by exponentiating the scores and normalizing so they sum to one. The model picks the class with the highest probability. This gives a simple linear decision surface across all classes. The second model I will use, KNN, looks at the nearest neighbors in the feature space and assigns the class that is most common among them. This makes KNN very sensitive to distances in the data. These two algorithms behave very differently, so using both helped reveal whether linear patterns or local neighborhood patterns existed in the data.

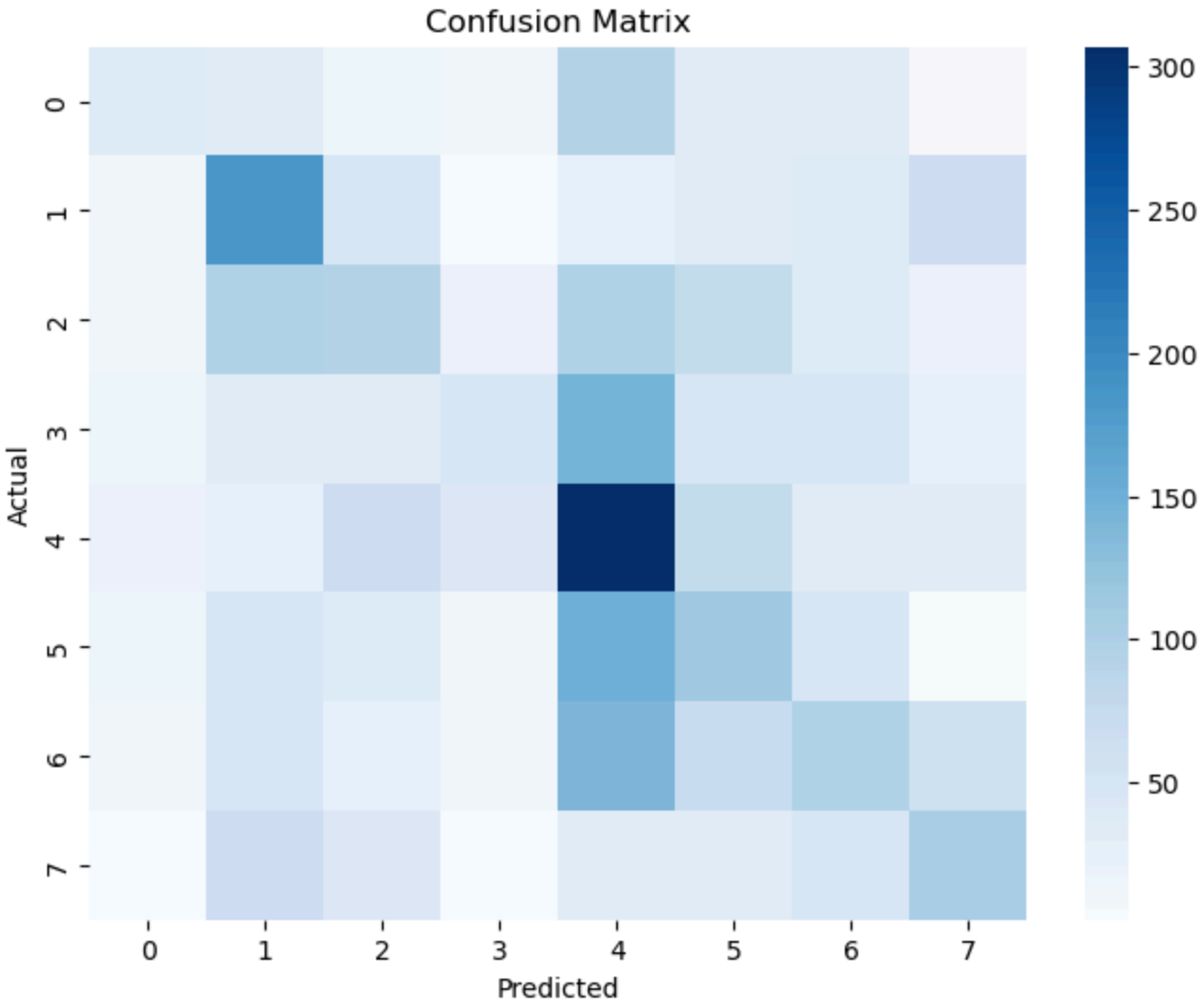
Multiclass Logistic Regression

> **Multiclass Logistic Regression**[1]
>
> **Multiclass Logistic Regression** is a generalized linear classification model used when the response variable contains more than two categories. The model assigns each class a linear score and converts these scores into probabilities using the softmax function, ensuring they sum to one. Parameter estimation is performed by maximizing the multinomial likelihood or minimizing categorical cross-entropy through gradient-based optimization. The predicted class is the one with the highest estimated probability, making this method the direct extension of binary logistic regression to multi-class settings.

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# Load machine learning police incident data
df = pd.read_csv("../../data/processed-data/police_incident_ml.csv")

# Drop unnecessary columns
X = df.drop(columns=["incident_type"])
y = df["incident_type"]

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42

# Multi-class logistic regression
log_model = LogisticRegression(max_iter=5000, multi_class="multinomial")
log_model.fit(X_train, y_train)

y_pred_log = log_model.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred_log))
print(classification_report(y_test, y_pred_log))
```

```
# Confusion Matrix
cm_log = confusion_matrix(y_test, y_pred_log)
plt.figure(figsize=(8,6))
sns.heatmap(cm_log, annot=False, cmap="Blues")
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.savefig("../../report/visual11.png", dpi=300, bbox_inches="tight")
plt.show()
```

```
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_logistic.py:1247:
FutureWarning: 'multi_class' was deprecated in version 1.5 and will be removed in 1.7.
From then on, it will always use 'multinomial'. Leave it to its default value to avoid
this warning.
  warnings.warn(

Accuracy: 0.2938021454112038
              precision    recall  f1-score   support

           0       0.34      0.16      0.21       263
           1       0.35      0.45      0.39       409
           2       0.25      0.21      0.23       451
           3       0.33      0.12      0.18       400
           4       0.31      0.51      0.38       604
           5       0.23      0.26      0.24       426
           6       0.26      0.21      0.23       468
           7       0.32      0.31      0.31       335

    accuracy                           0.29      3356
   macro avg       0.30      0.28      0.27      3356
weighted avg       0.29      0.29      0.28      3356
```



K-Nearest Neighbors (KNN)

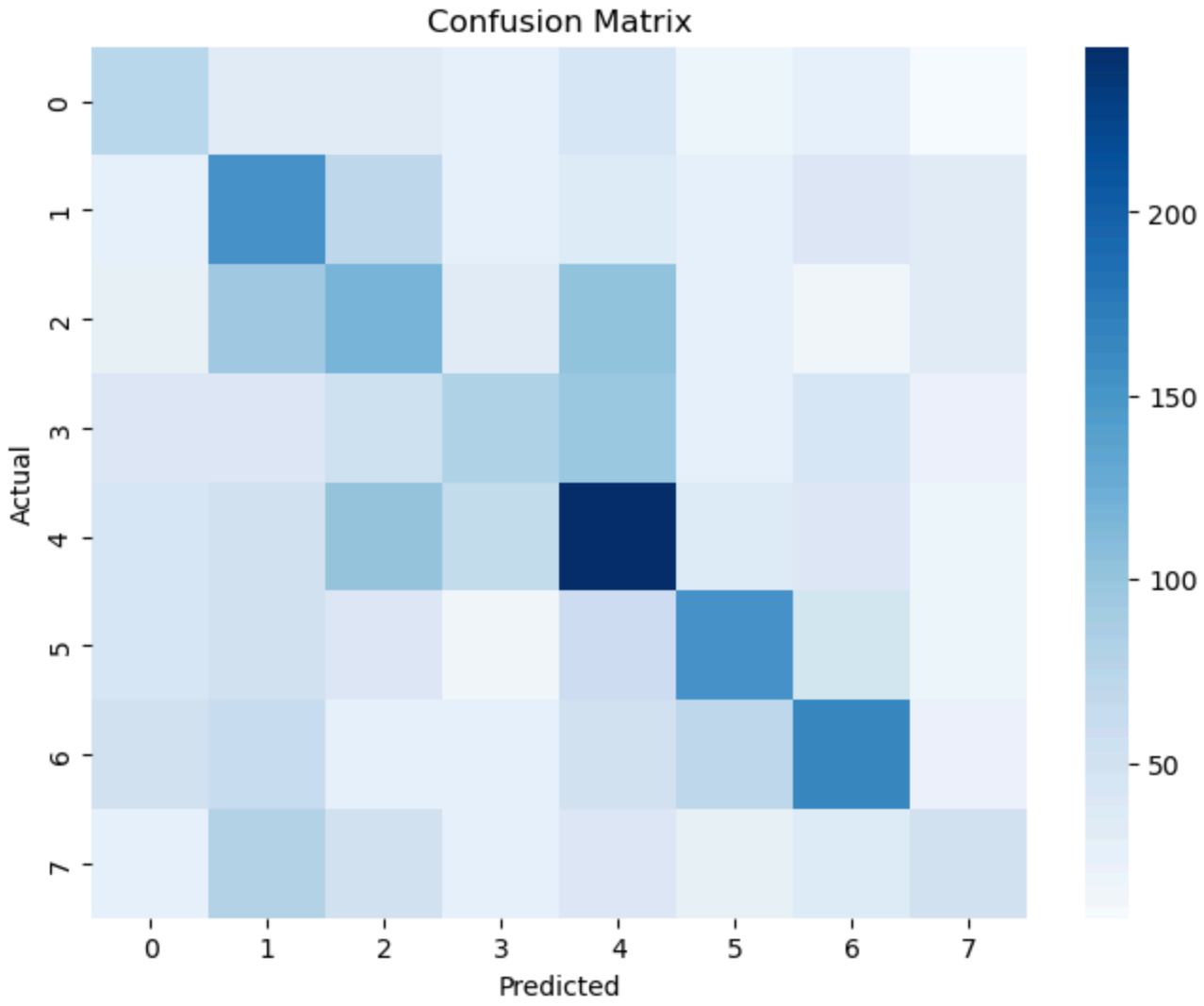
K-Nearest Neighbors (KNN)[1]

K-Nearest Neighbors is a non-parametric classification method that predicts a label based on the classes of the closest observations in the feature space. Instead of learning model parameters, KNN stores the training data and makes decisions by measuring the distance between a new point and existing points. The model identifies the k most similar neighbors and assigns the class most common among them. Because it relies directly on distances, KNN is sensitive to feature scaling and works best when similar cases naturally cluster together in the data.

```
# K-Nearest Neighbors Classifier
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)

y_pred_knn = knn.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred_knn))
print(classification_report(y_test, y_pred_knn))
```

```
# Confusion Matrix for KNN
cm_knn = confusion_matrix(y_test, y_pred_knn)
plt.figure(figsize=(8,6))
sns.heatmap(cm_knn, annot=False, cmap="Blues")
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

```
Accuracy: 0.31078665077473183
              precision    recall  f1-score   support

           0       0.23      0.29      0.25       263
           1       0.28      0.37      0.32       409
           2       0.24      0.26      0.25       451
           3       0.28      0.20      0.23       400
           4       0.36      0.41      0.38       604
           5       0.39      0.36      0.38       426
           6       0.40      0.35      0.38       468
           7       0.25      0.15      0.19       335

    accuracy                           0.31      3356
   macro avg       0.30      0.30      0.30      3356
weighted avg       0.31      0.31      0.31      3356
```



Model Performance & Insights

In the multiclass classification models, both the multiclass logistic regression and the KNN model struggle with predicting police incident types, which is consistent with previous unsupervised learning results from PCA and clustering. The result was that the incident types overlap heavily, meaning that the numerical features do not have a clean boundary between different classes or police incident types. Logistic regression reached an accuracy of about 29%, and the KNN achieved an accuracy rate of 31%. Although the accuracy is low, these values still exceeded the accuracy of random guessing, but it is still low for eight classes. Both the macro and weighted F1 scores is around the 0.18–0.4 range for both models, indicating that both models did not capture strong class-specific patterns, which can also be visualized in the confusion matrices.

Regression

Model Rationale

For this part, I will focus on predicting the dispatch-to-arrival time for each incident using a linear regression. This variable, dispatch_arrive, reflects how long it takes for police officers to reach the scene after they are dispatched, which is the most important operational measure in police emergency response. Modeling this outcome could

help reveal whether features such as location or incident type contain enough signal to explain variations in how quickly units arrive.

Overview of Algorithms

As I mentioned above, I will be using a standard linear regression model for the following analysis. Linear regression attempts to uncover straight-line relationships between the predictors and the continuous target. The model estimates a set of coefficients that minimize the overall prediction error, making it one of the simplest and most interpretable methods for low-dimensional regression and optimization.

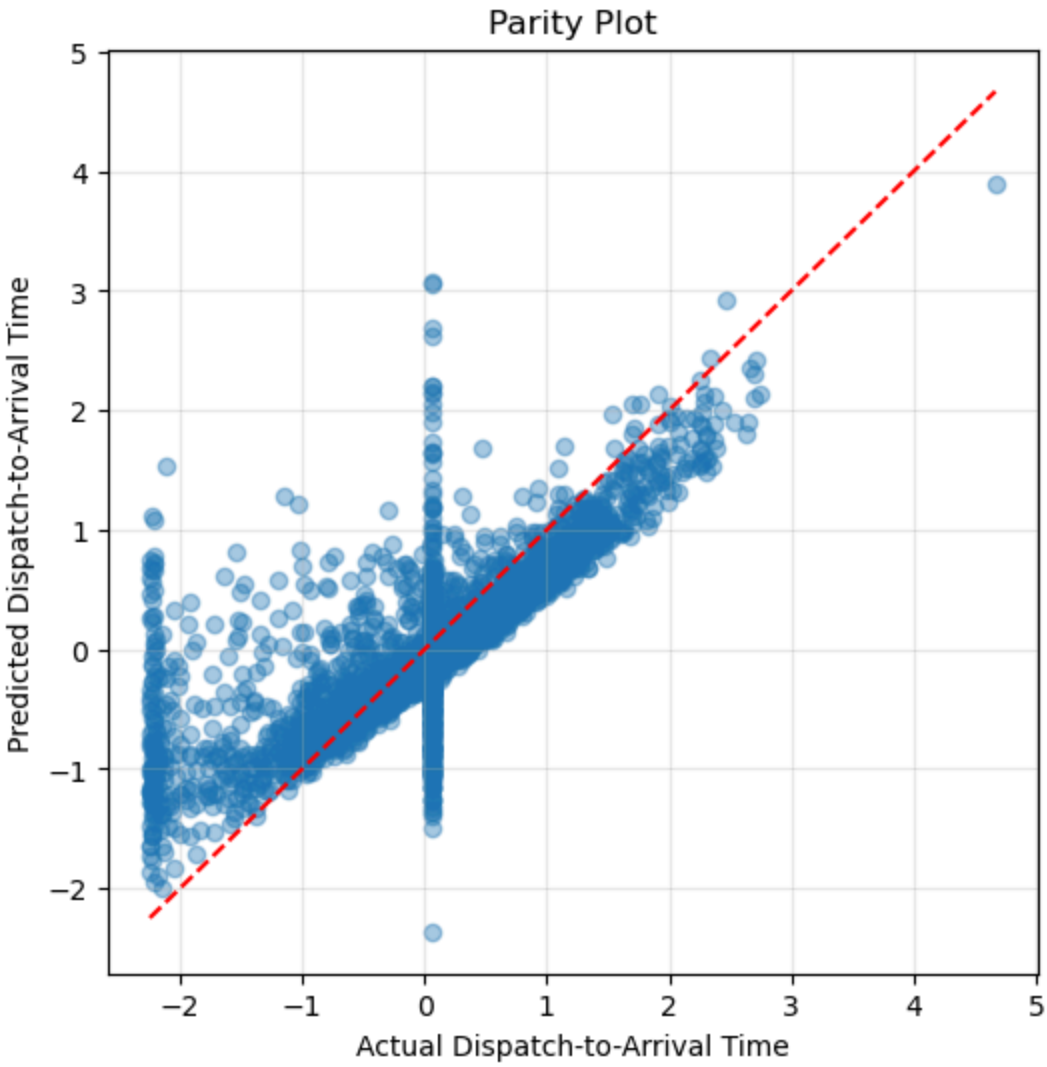
Linear Regression

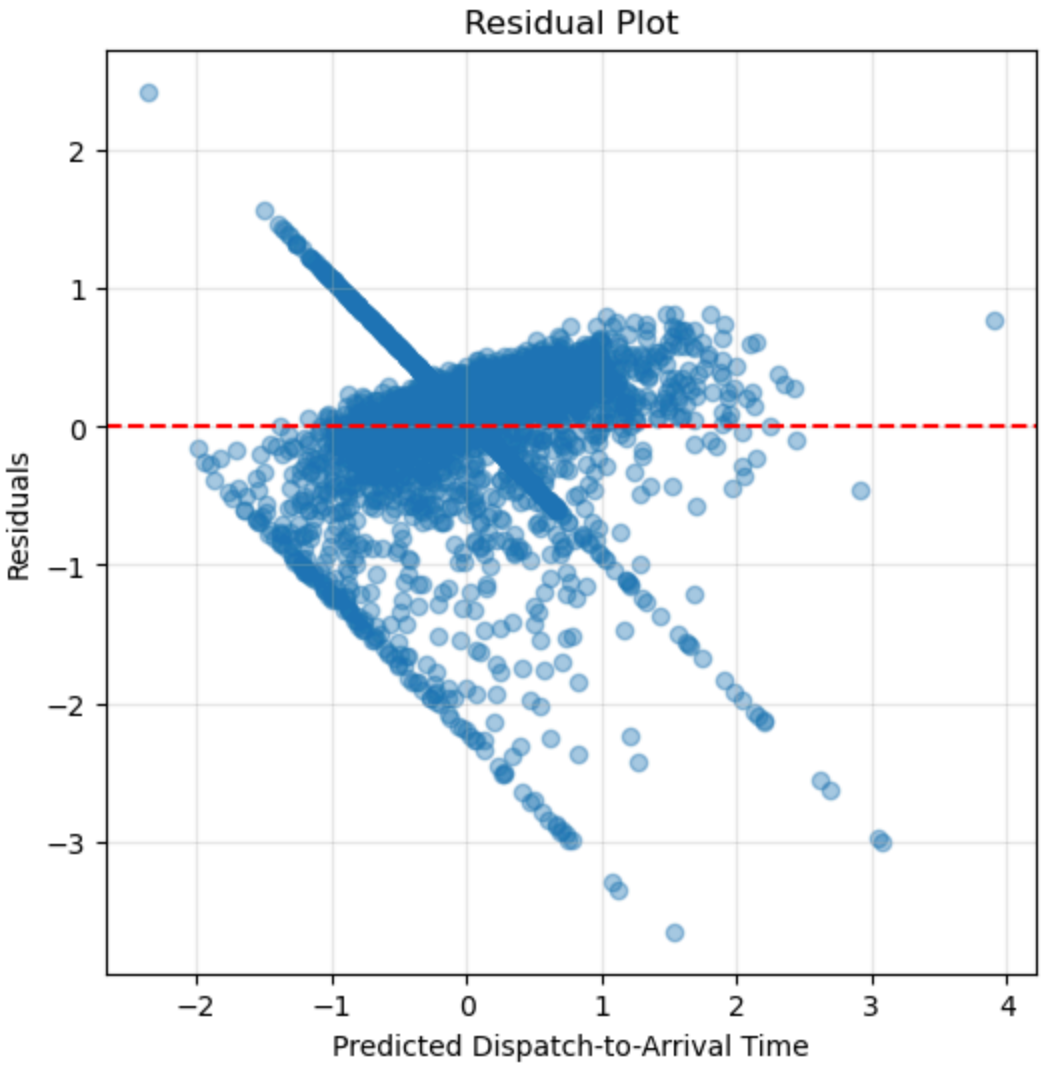
> **Linear Regression**[1]
>
> **Linear Regression** is a supervised learning method used to predict a continuous outcome by estimating a straight-line relationship between the input features and the target variable. The model finds a set of weights that best explain the variation in the data by minimizing prediction error. Because it is simple, fast, and easy to interpret, linear regression is often used as a baseline approach for understanding how different factors influence a numerical response.

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import numpy as np

# Import police incident data
df = pd.read_csv("../../data/processed-data/police_incident_ml.csv")
y = df["dispatch_arrive"]

# Drop unnecessary columns
X = df.drop(columns=["dispatch_arrive"])

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train linear regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Evaluate model
y_pred = model.predict(X_test)

mae  = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2   = r2_score(y_test, y_pred)

print("MAE:", mae)
print("RMSE:", rmse)
```

```
print("R²:", r2)

# Plot Parity Plot
plt.figure(figsize=(6,6))
plt.scatter(y_test, y_pred, alpha=0.4)
plt.plot([y_test.min(), y_test.max()],
         [y_test.min(), y_test.max()],
         "--", color="red")
plt.xlabel("Actual Dispatch-to-Arrival Time")
plt.ylabel("Predicted Dispatch-to-Arrival Time")
plt.title("Parity Plot")
plt.grid(alpha=0.3)
plt.savefig("../../report/visual9.png", dpi=300, bbox_inches="tight")
plt.show()

# Plot Residuals
residuals = y_test - y_pred
plt.figure(figsize=(6,6))
plt.scatter(y_pred, residuals, alpha=0.4)
plt.axhline(0, linestyle="--", color="red")
plt.xlabel("Predicted Dispatch-to-Arrival Time")
plt.ylabel("Residuals")
plt.title("Residual Plot")
plt.grid(alpha=0.3)
plt.show()
```

```
MAE: 0.38191615721899286
RMSE: 0.572601099206643
R²: 0.5876219624467904
```


Parity Plot
Predicted Dispatch-to-Arrival Time
Actual Dispatch-to-Arrival Time
5
4
3
2
1
0
−1
−2
−2
−1
0
1
2
3
4
5



Model Performance & Insights

From the results above, we conclude that the linear regression model achieved moderate predictive performance. The MAE and RMSE values indicate that the average errors are below 1 standardized unit. With an R^2 of about 0.59, the model explains a meaningful portion of the variation in dispatch-to-arrival time. The parity plot above shows a general diagonal trend, indicating that the model is capturing the broad structure of the data. Also, in the plot, there exists an obvious straight line. The straight vertical lines appear due to a huge number of incidents that have the exact same recorded dispatch to arrival time. However, this pattern is normal for this kind of data due to the limitations of the linear model when working with partially discretized features. The residual plot is also reflecting the huge amount of the same dispatch to arrival times. In the residual plot, most residuals fall close to zero, indicating that the model captures the broad pattern. However, there are clear pockets where the spread widens. These results together highlight where the data carries a meaningful signal.

Conclusion

The different models in the supervised learning section show that different predictions reveal different kinds of structure in the police incident call dataset. The binary classification model performed best, indicating that the

features of the data have enough signal to separate high-priority calls from low-priority calls. On the other hand, the multiclass classification model struggled due to heavy overlap among the incident types. The regression model fell somewhere in between the previous two, capturing broad trends in dispatch-to-arrival time but leaving much of the variation unexplained due to factors not represented in the data. In conclusion, the above findings show that some of the models made good predictions, while others remain challenging.

References

1. ChatGPT, version-5.1, OpenAI, NOV-2025, chat.openai.com.