SAN FRANCISCO Crime Prediction

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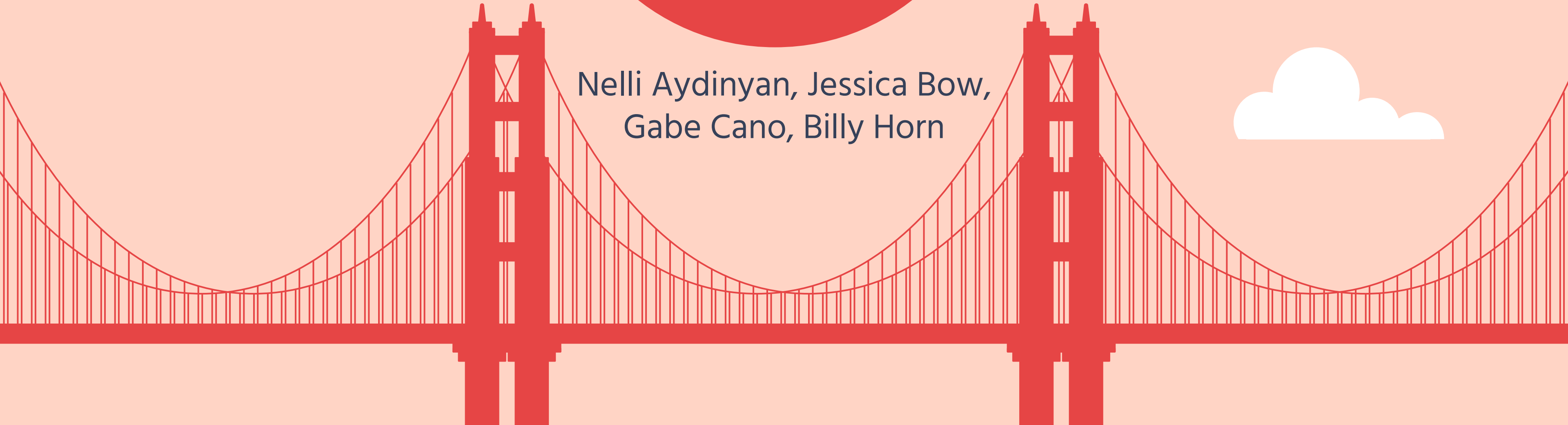

Overview

Problem Statement

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Problem Statement

As part of the public outcry to defund the police and dismantle and restructure law enforcement as a whole, there has been a call to provide funding for new and existing services to step in where applicable.

Based on the specific features of a crime, we endeavor to predict which type of intervention is needed for a particular crime.

Methodology for Crime Categorization

Police (Emergency)

Any crime that can be considered an immediate danger to human life or public safety

Police (Non-Urgent)

Serious crimes that don’t pose an immediate threat to human lives

Specialty

Crimes where other services may be a more qualified first response, including mental illness, substance abuse, sex crimes, domestic crimes, etc.

Data Background

300K+ crimes in San Francisco

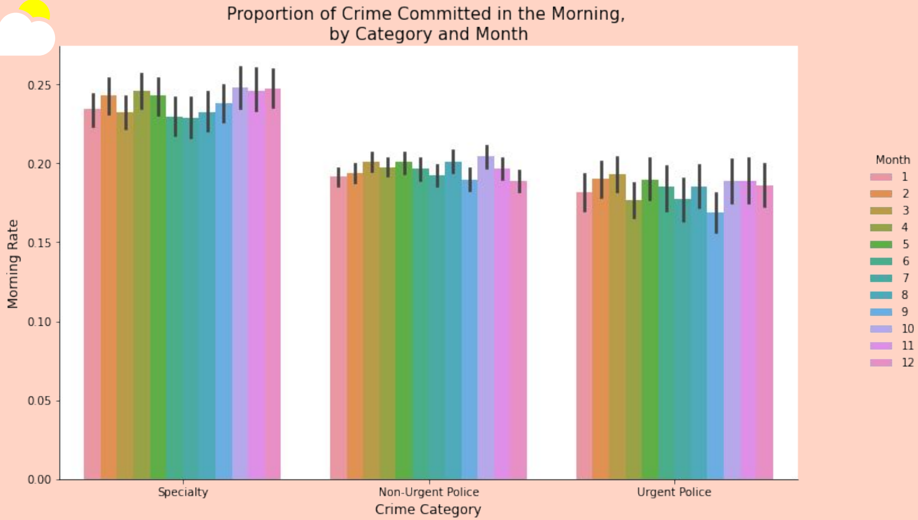
Ranges from 2016 - 2018

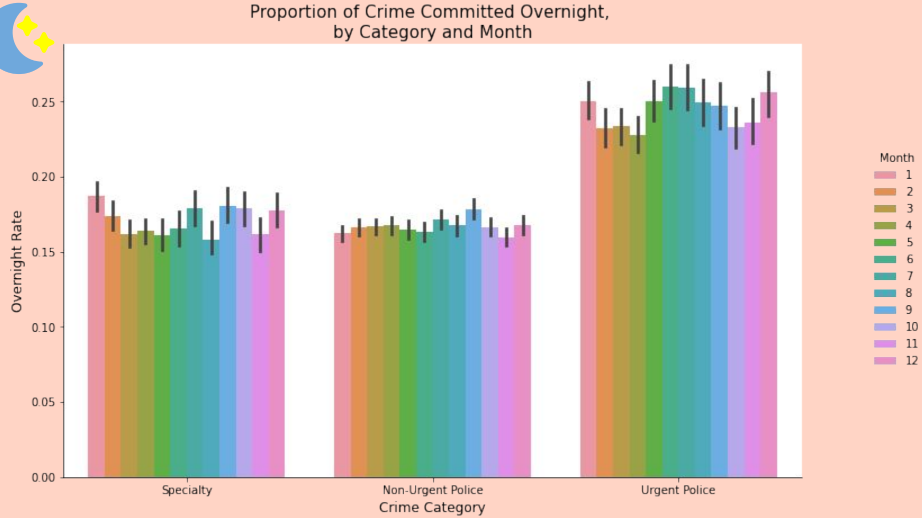
Includes:

- Geospatial data
- Crime category
- Crime description

Crimes: Morning vs. Night

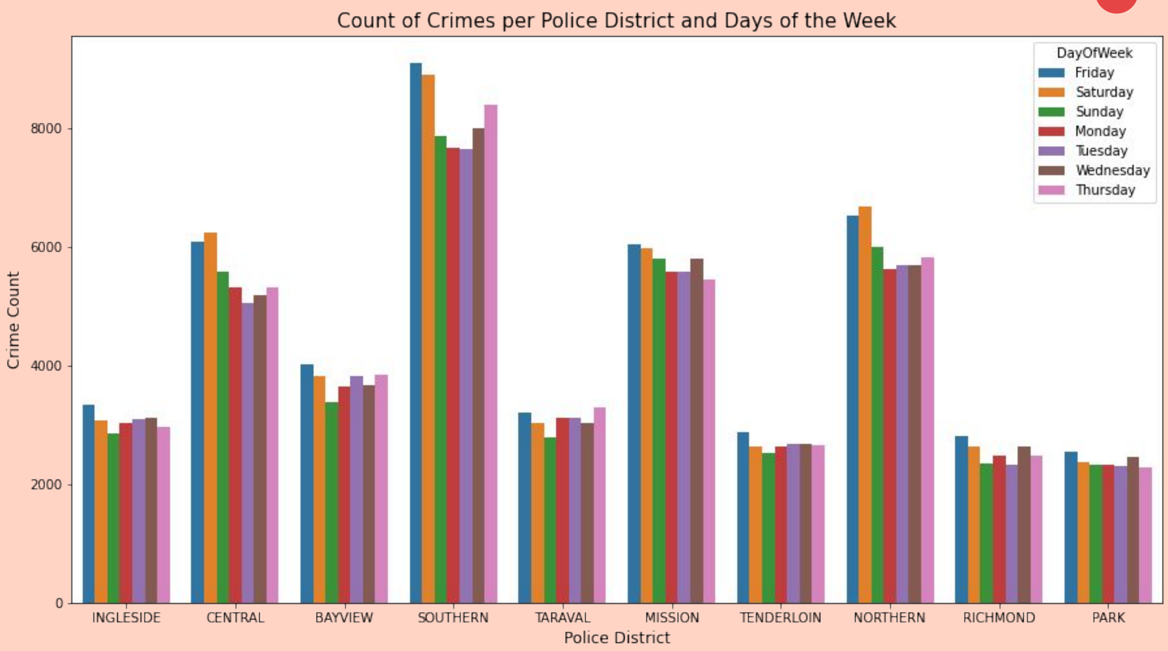
- Specialty crimes are highest in the morning
- Morning crimes are much higher in winter months
- Crimes requiring police intervention are highest at night
- Urgent crimes are highest in summer





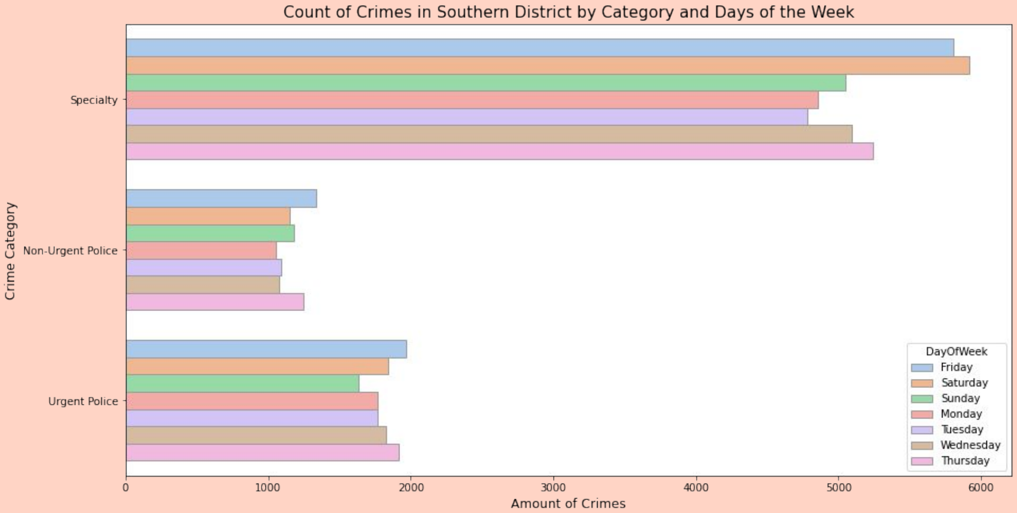
Crime Count: Police District and Days of the Week

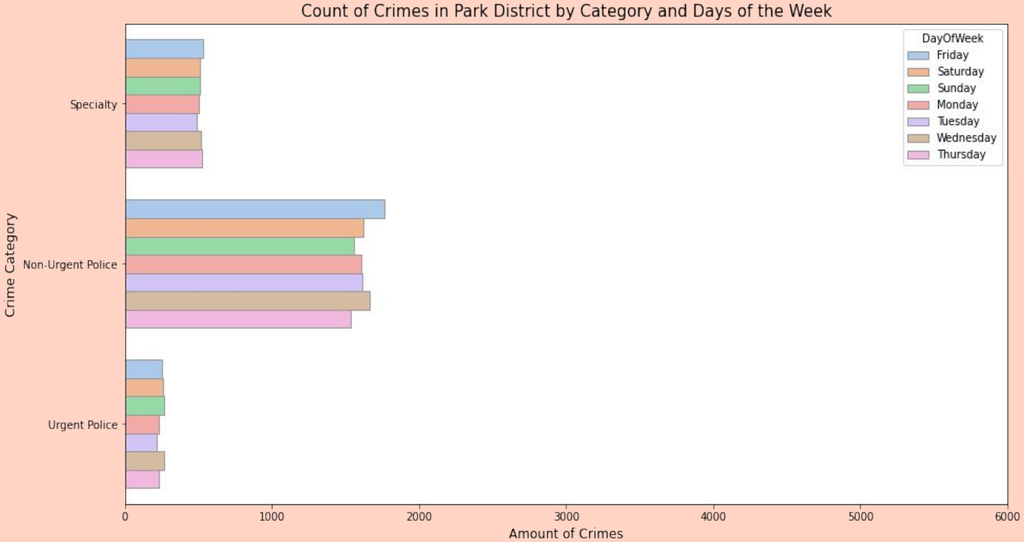
- Across districts, crimes tend to happen most often on Fridays and Saturdays
- Southern is the police district that's had the most reported crime
- Tuesdays and Sundays are safest days of the week.

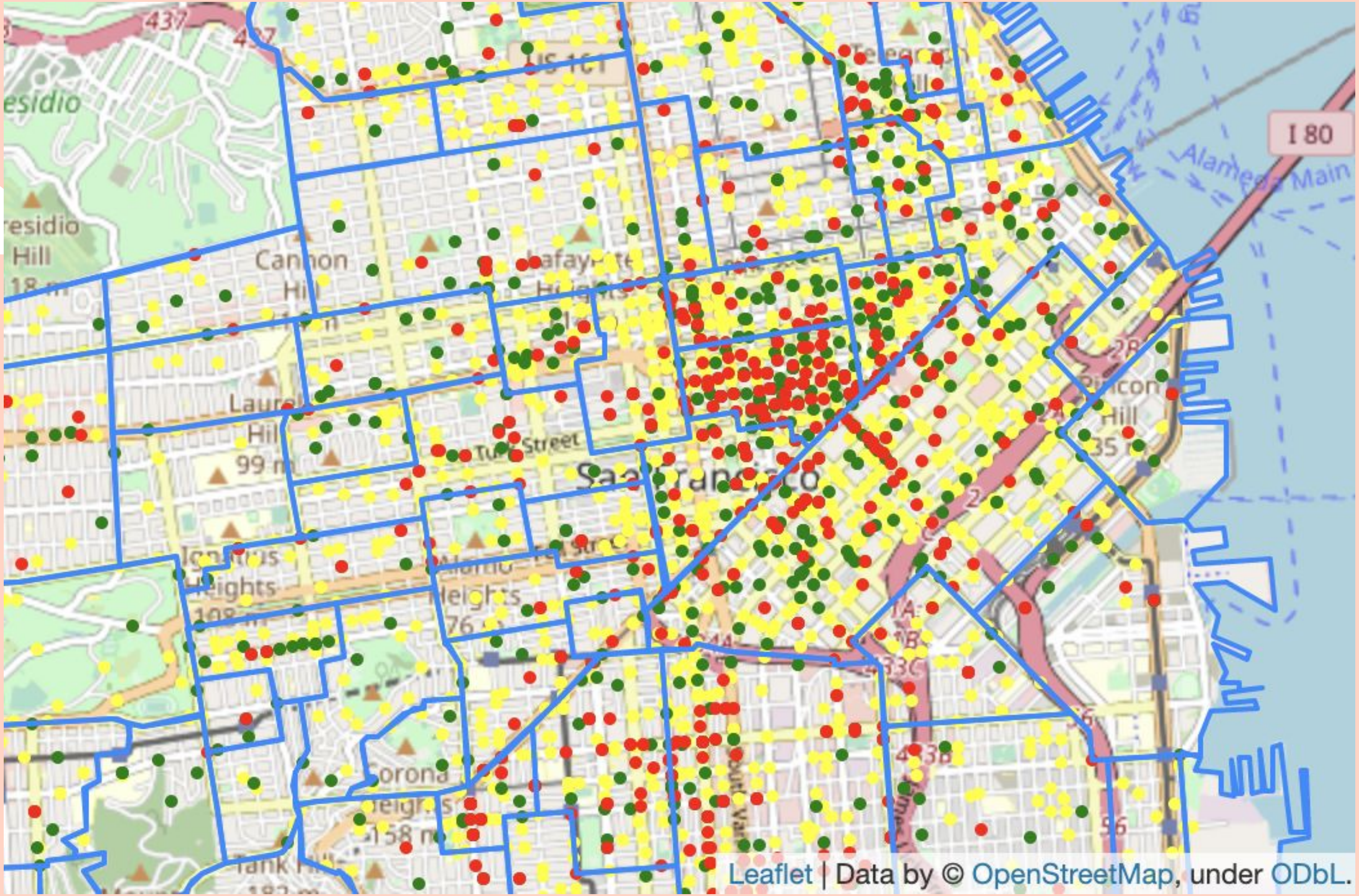


Highest vs. Lowest Crime Districts

- Most crimes in Park District are non-urgent
- Southern has around 3x amount of crime overall and 10x amount of urgent crimes
- Almost 10x the amount of urgent crimes

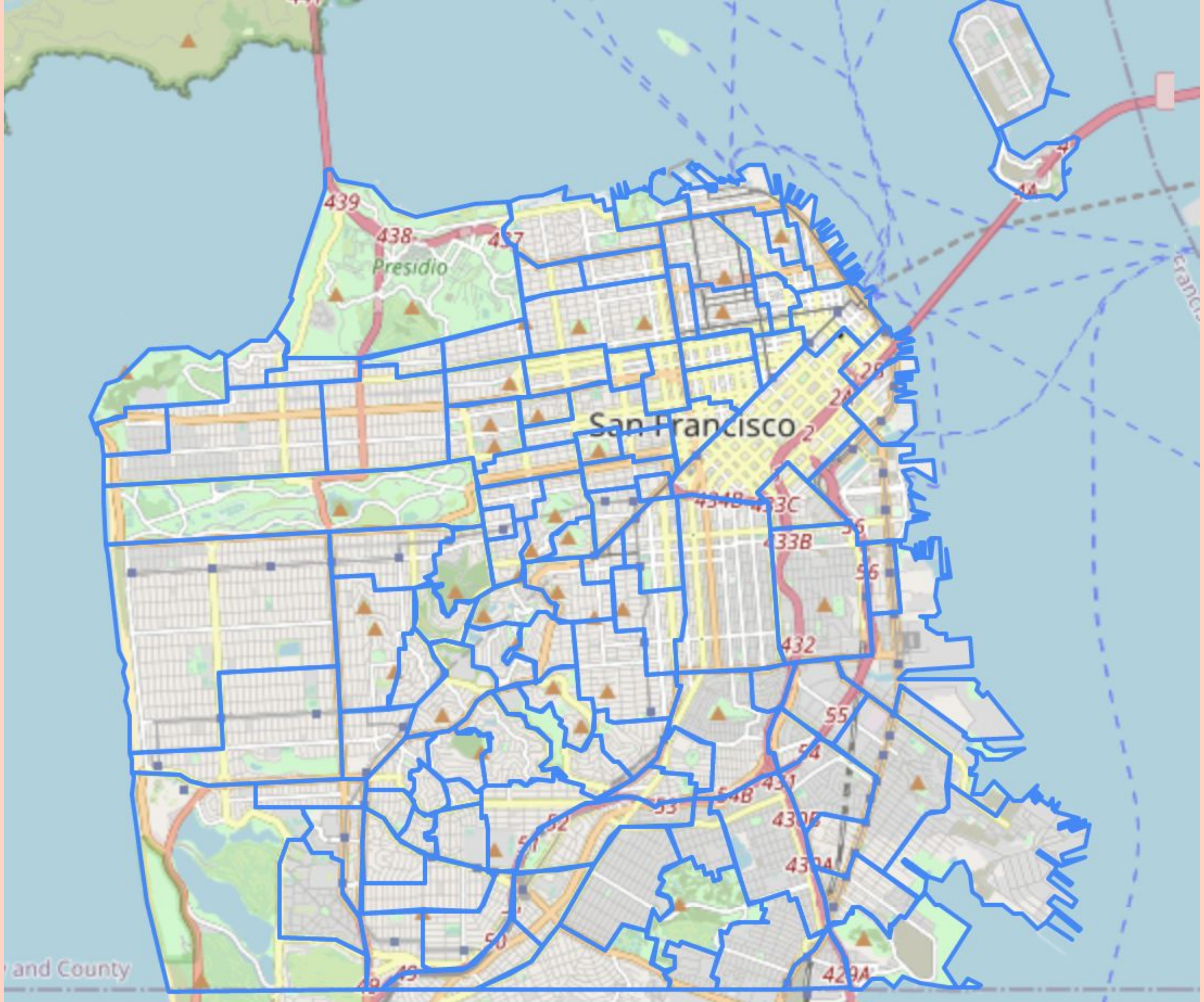


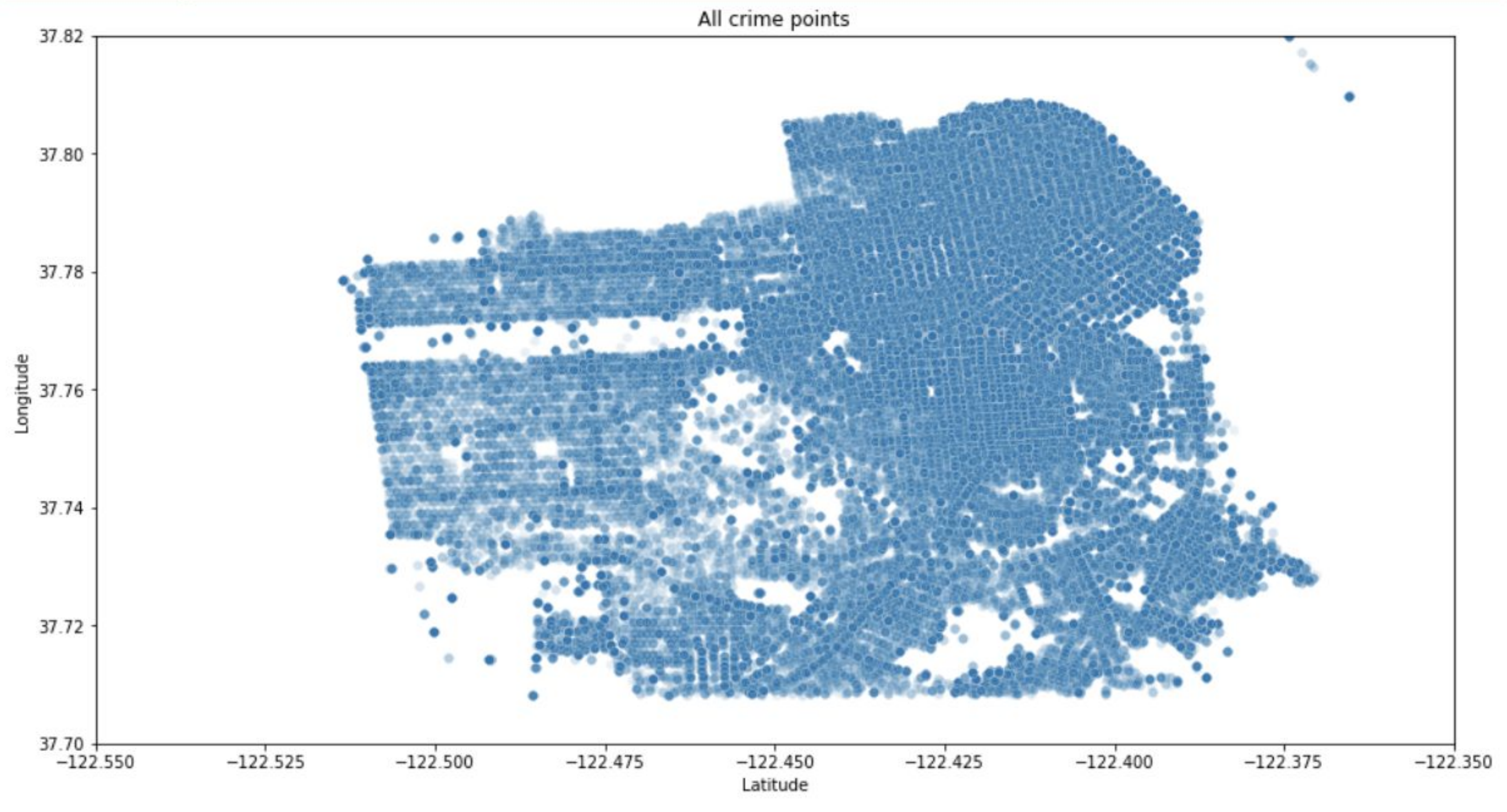




Crime between 11pm-6am for Saturdays in 2018

- Police
- Non Urgent PD
- Specialty Services


San Francisco
Presidio
and County


All crime points
Longitude
Latitude
37.82
37.80
37.78
37.76
37.74
37.72
37.70
−122.550
−122.525
−122.500
−122.475
−122.450
−122.425
−122.400
−122.375
−122.350

Shapely Example

```
geom = [Point(xy) for xy in zip(crime_df['X'], crime_df['Y'])]
```

```
for i in range(len(neighb_geo)):
    crime_geo.loc[crime_geo.intersects(neighb_geo.loc[i, 'geometry']), 'neighbourhood'] = neighb_geo['name'].loc[i]
```

Folium Example

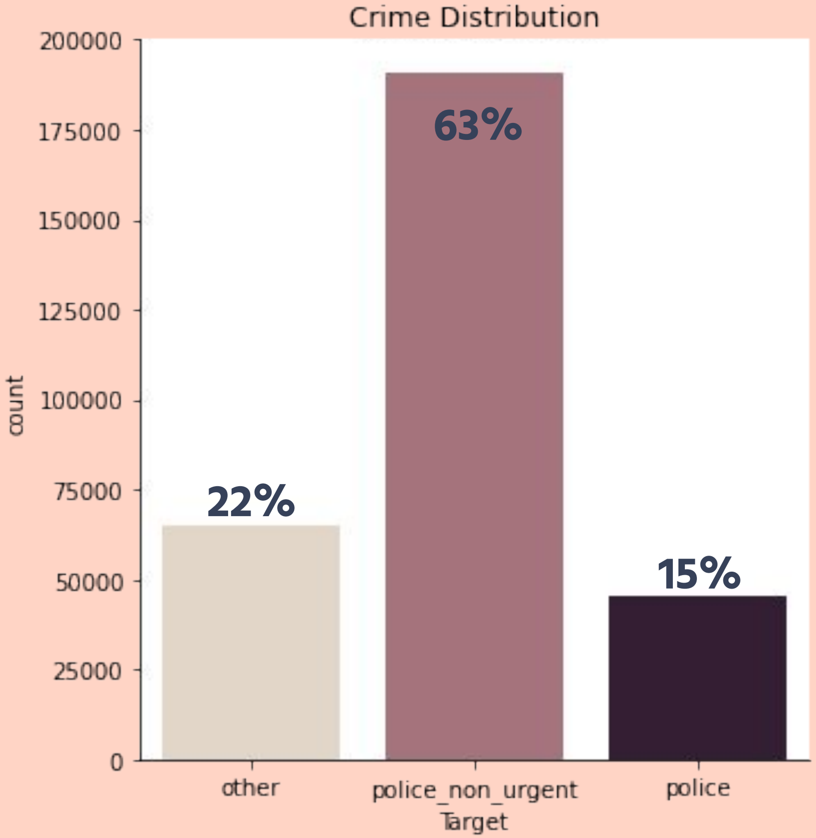
```
sf_map_1 = folium.Map(location=[37.8, -122.5])

pnu.apply(lambda row:folium.CircleMarker(location=[row['Y'], row['X']], radius=1, color='yellow').add_to(sf_map_1), axis=1)
sp_sup.apply(lambda row:folium.CircleMarker(location=[row['Y'], row['X']], radius=1, color='green').add_to(sf_map_1), axis=1)
pol.apply(lambda row:folium.CircleMarker(location=[row['Y'], row['X']], radius=1, color='red').add_to(sf_map_1), axis=1)

neighb_geo.apply(lambda row:folium.Polygon(locations=[row['lon_lat']], weight=2).add_to(sf_map_1), axis=1)

sf_map_1
```

Greatly Unbalanced Target Class



Model Results Summary

	TRAIN	TEST
Logistic	53%	53%
Bagging	88%	68%
Random Forest	89%	69%
AdaBoost	48%	47%
XGBoost	55%	54%

Modeling

- Over 10,000 model combinations
- Baseline Accuracy: 33%
- Best Model Accuracy: 55%,

  +24% over baseline
- XGBoost

Model Feature Weights

Weight	Feature
0.0163	neighbourhood_South of Market
0.0138	neighbourhood_Downtown / Union Square
0.0129	neighbourhood_Fishermans Wharf
0.0127	neighbourhood_Eureka Valley
0.0122	neighbourhood_Central Waterfront
0.0122	neighbourhood_Chinatown
0.0122	neighbourhood_Sunnyside
0.0120	neighbourhood_Mint Hill
0.0119	neighbourhood_Upper Market
0.0003	DayOfWeek_Saturday
0.0003	DayOfWeek_Tuesday
0.0003	DayOfWeek_Wednesday
0.0003	DayOfWeek_Monday
0.0002	Month
0.0002	Day
0.0002	DayOfWeek_Sunday
0.0002	Year_2018
0	neighbourhood_Candlestick Point SRA
0	neighbourhood_Sherwood Forest
0	neighbourhood_Treasure Island
0	neighbourhood_Westwood Highlands

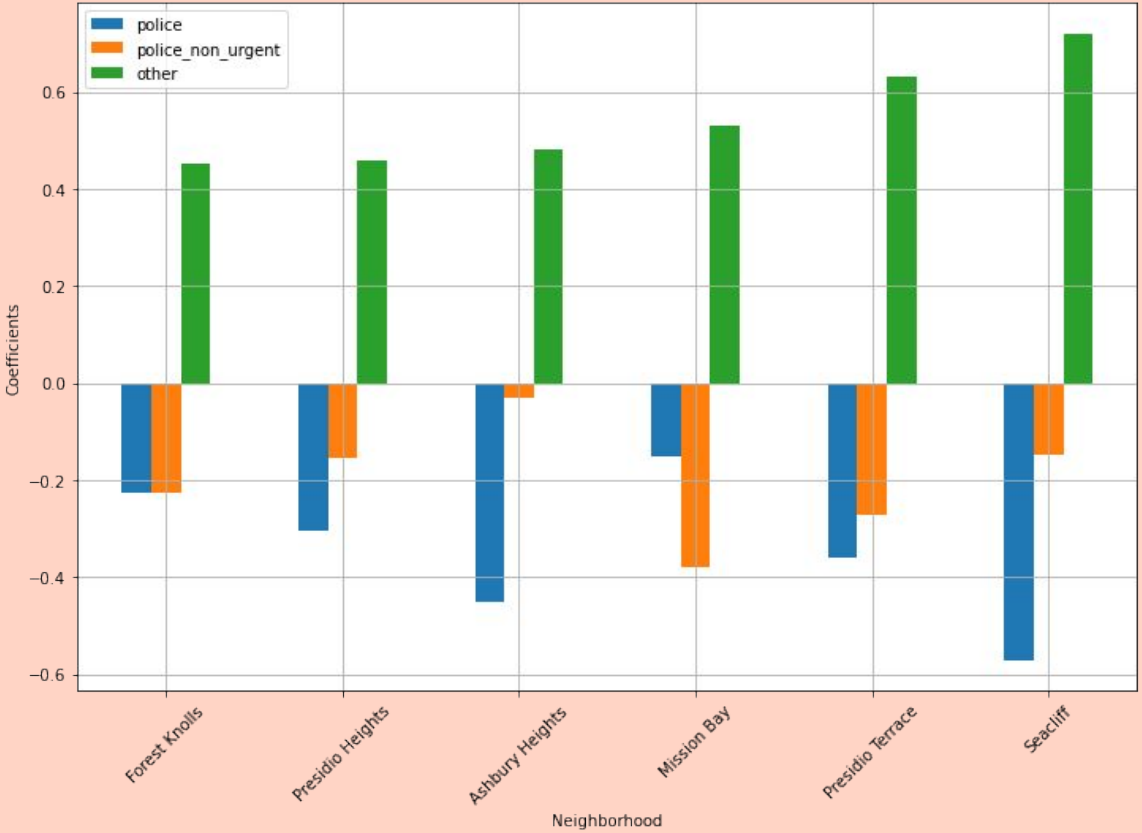
S. of Market Crimes:

- Total: 43,016
- Police: 33,832
- Specialty: 9,184

Treasure Island Crimes:

- Total: 25
- Police: 21
- Specialty: 4

Model Coefficients



Predictive Power:

- Can provide log odds of crime category by neighborhood

Conclusions/Future Considerations

- More robust feature engineering
- Refining target categories
- More NLP on crime description column
- Investigate crime resolution vs neighborhood demographics

Thank You!
Questions?

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