NYC 311 Service Requests

Predicting the number of calls in the next week

Pranav Karnani

Executive Summary

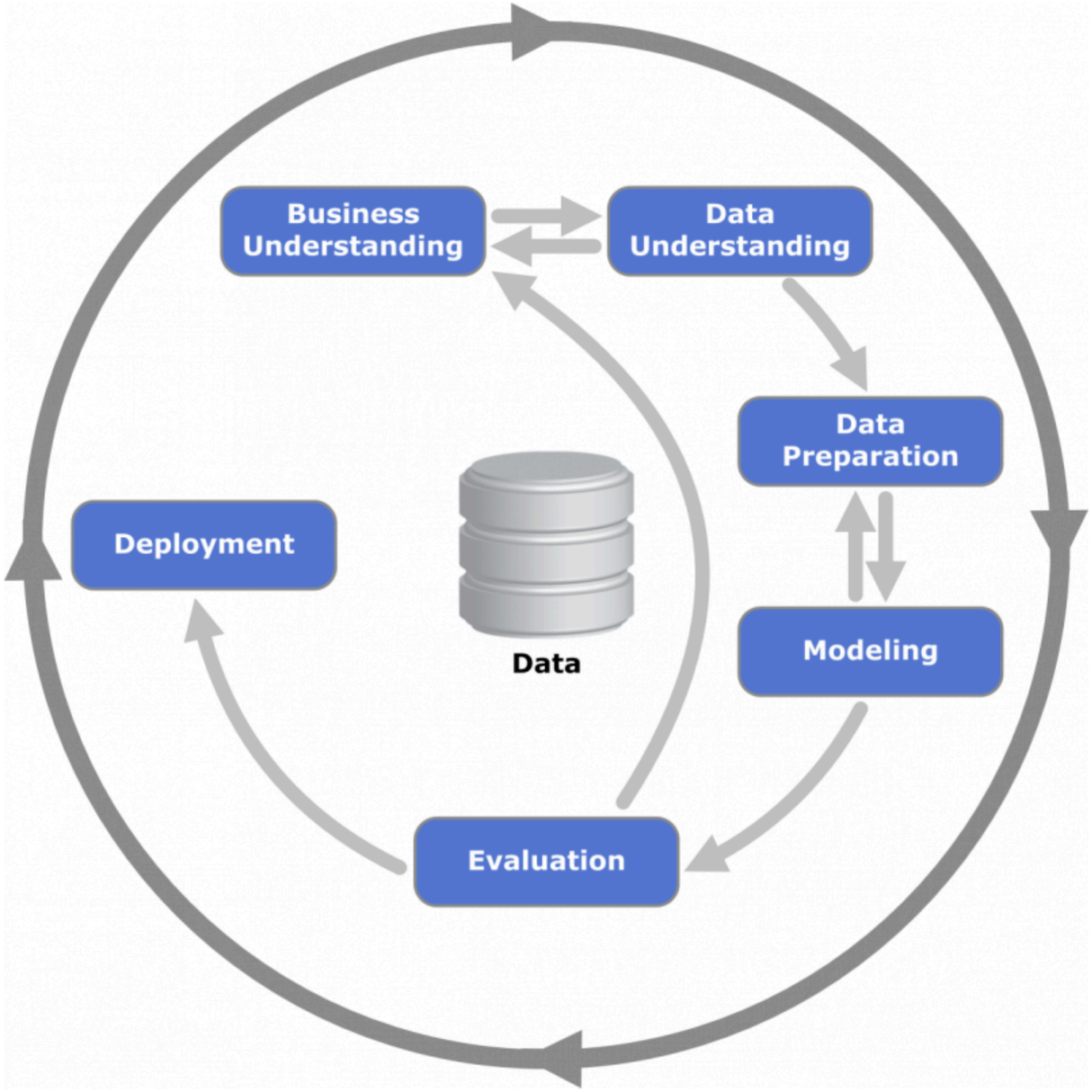
Problem Statement: Predict the number of 311 Service Request calls in the next week.

Deliverables	Method	Performance
A detailed analysis of the different types of requests based on historical data, ranging from location, complaint type etc	Simulation Plots, Distribution Plots, Word Clouds	
A time series model which predicts the temperature and other weather attributes	ARIMA	**RMSE:** 123.93 **MAPE:** 0.15
Causal tests to check for the causal effect of temperature and other weather attributes on the number of service requests raised.	Panel OLS	**p-Value:** 0.0464
A time series model, which uses weather as an exogenous variable to predict the number of calls in the upcoming week	SARIMA, Random Forest	**RMSE:** 120.30 **MAPE:** 0.17

Methodology

CRISP-DM Framework

- Business Understanding
- Data Understanding
- Data Preparation
- Modeling
- Evaluation
- Deployment



How to deal with such a large dataset ?

Removed features with:

- More than **80% null** values
- Exhibiting **1-1 correspondence** (Agency Name, Agency)
- More than **99% values** as Unspecified (Park Facility Name)
- With very **granular** information (Address, Street Name)
- Records where Closed Date is **before** the Created Date

- Subsetted the data on **Phone / Mobile** channels using Channel Type

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- Subsetted the data on **Phone / Mobile** channels using Channel Type

Reduced dataset size by 70%

Data Understanding

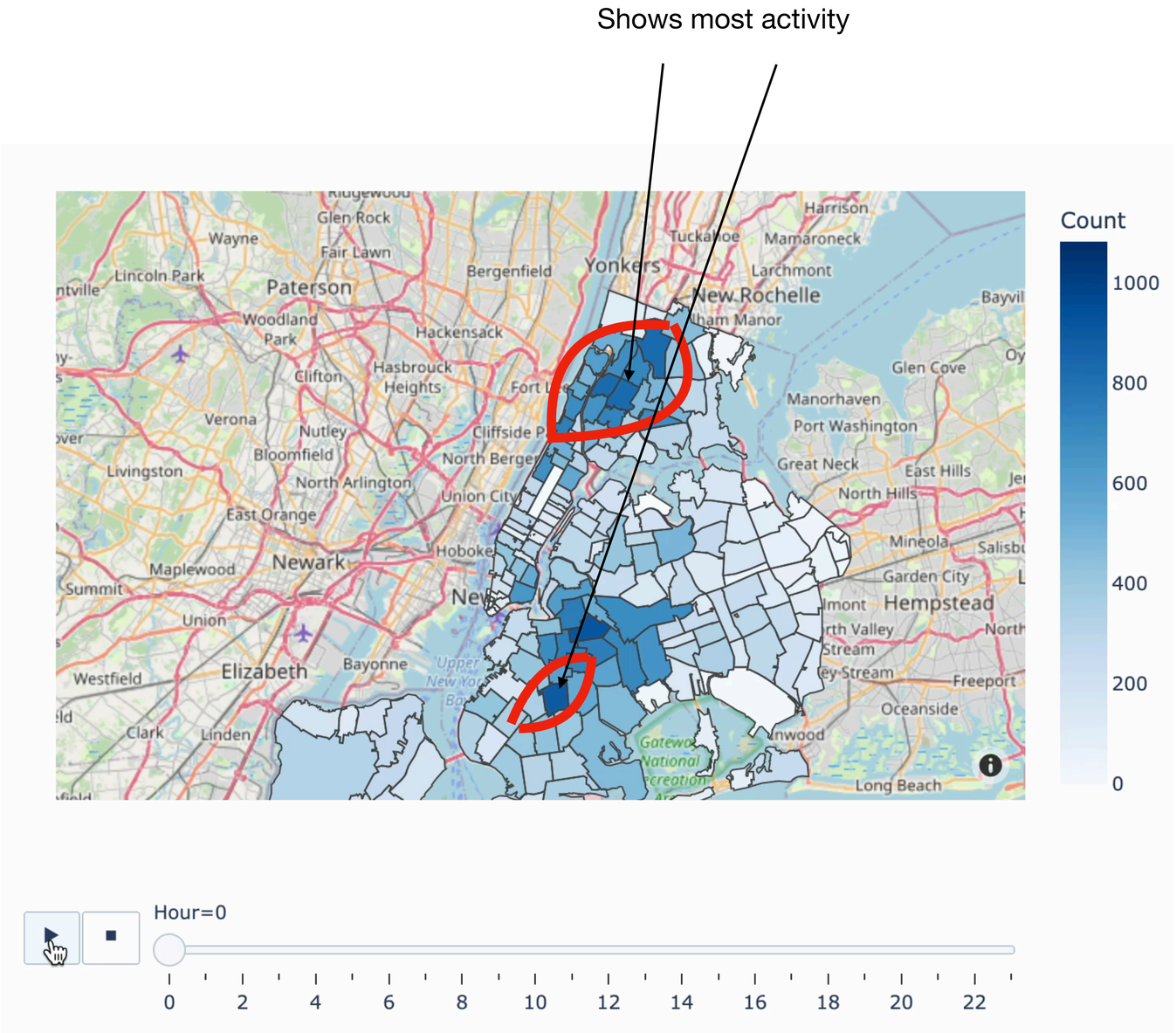
What we have ?

- **311 Service Requests from 2016 to 2018 (~7M+ records)**
    - Complaint Type (Noise, Heat, etc.)
    - Borough (Manhattan, Brooklyn etc.)
    - Location (Sidewalk, Residential etc.)
- **Weather Data collected from stations across the NY state from 2010 to 2018**
    - Snow and Precipitation
    - Temperature
    - Wind / Gust

Data Understanding
Call Patterns

- Simulation plots which help get a better picture of **high activity zip-codes.**

- Plot on the right is a heat map of how calls on an **hourly basis.**

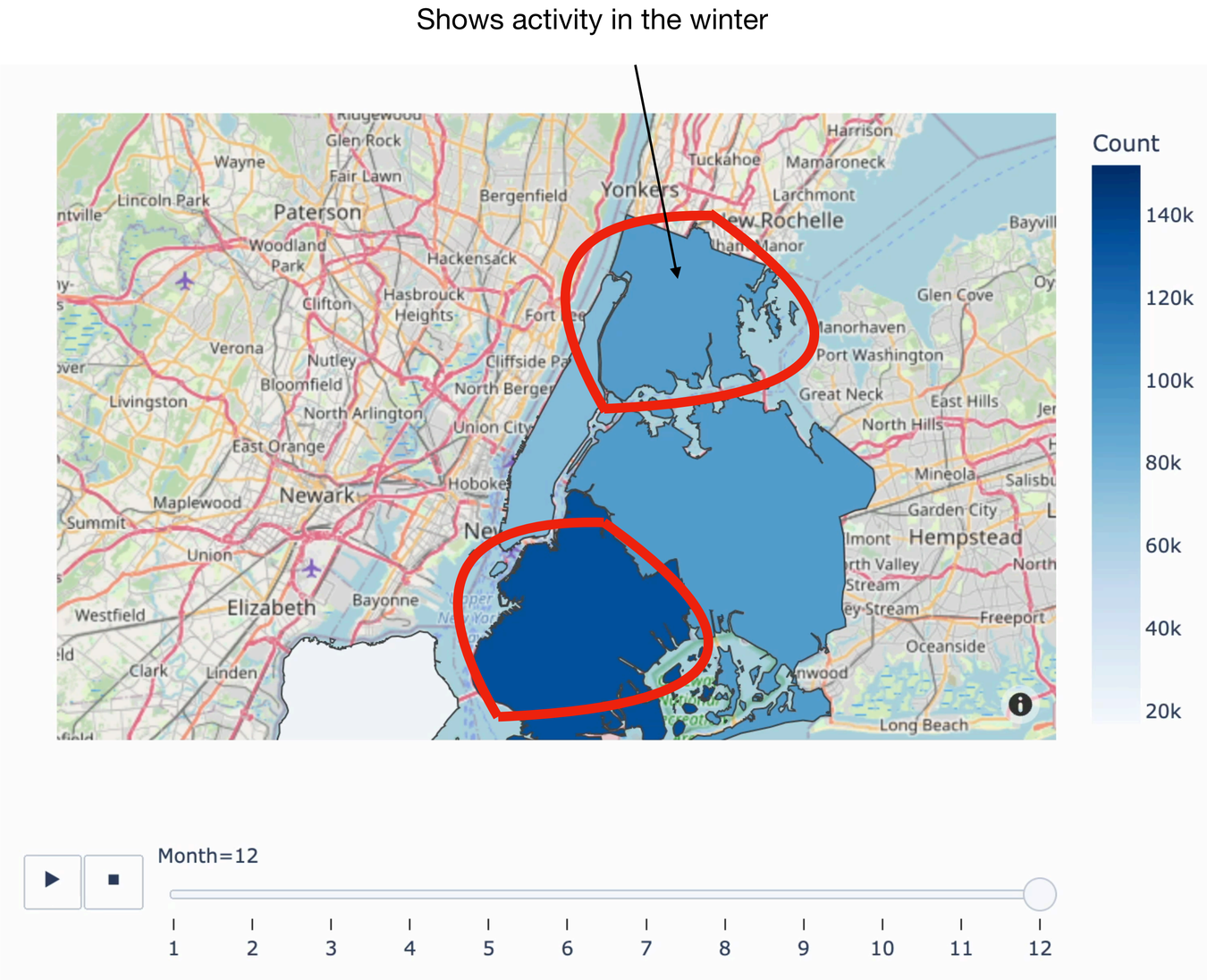


Data Understanding
Call Patterns

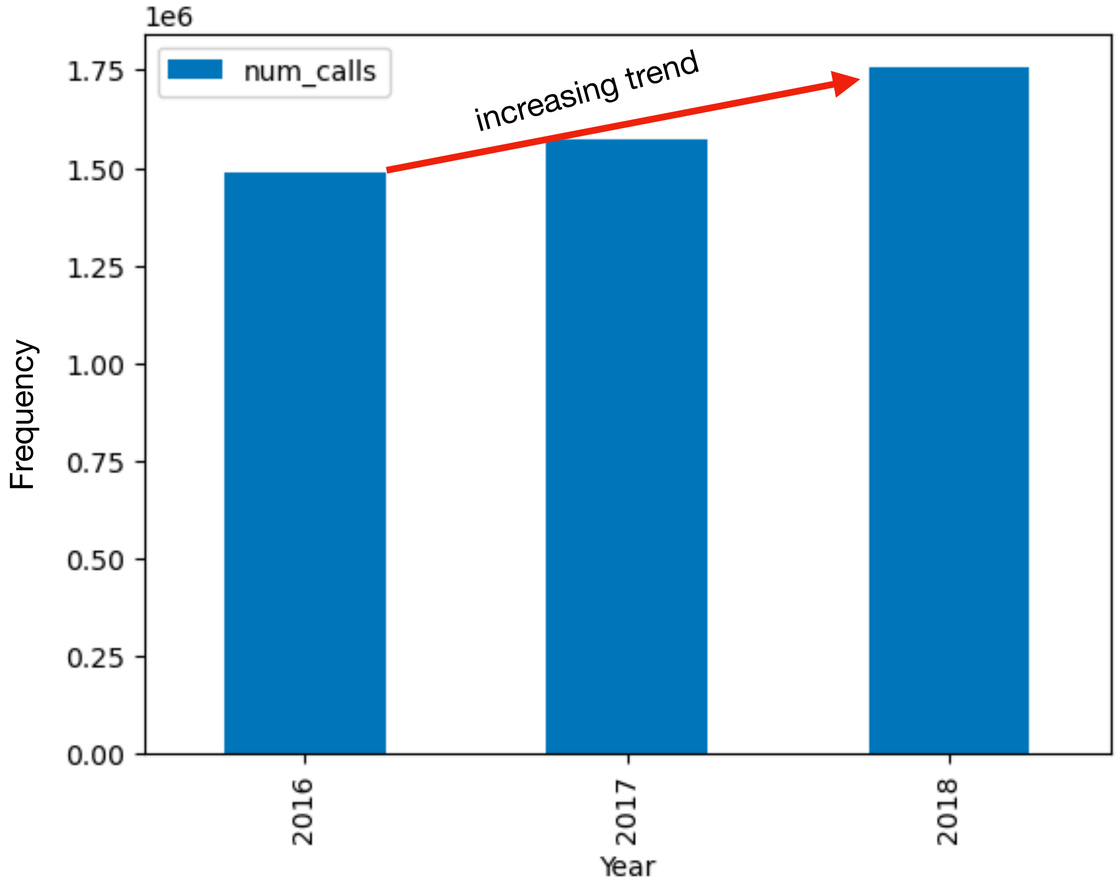
- Simulation plots which help get a better picture of **high activity boroughs.**

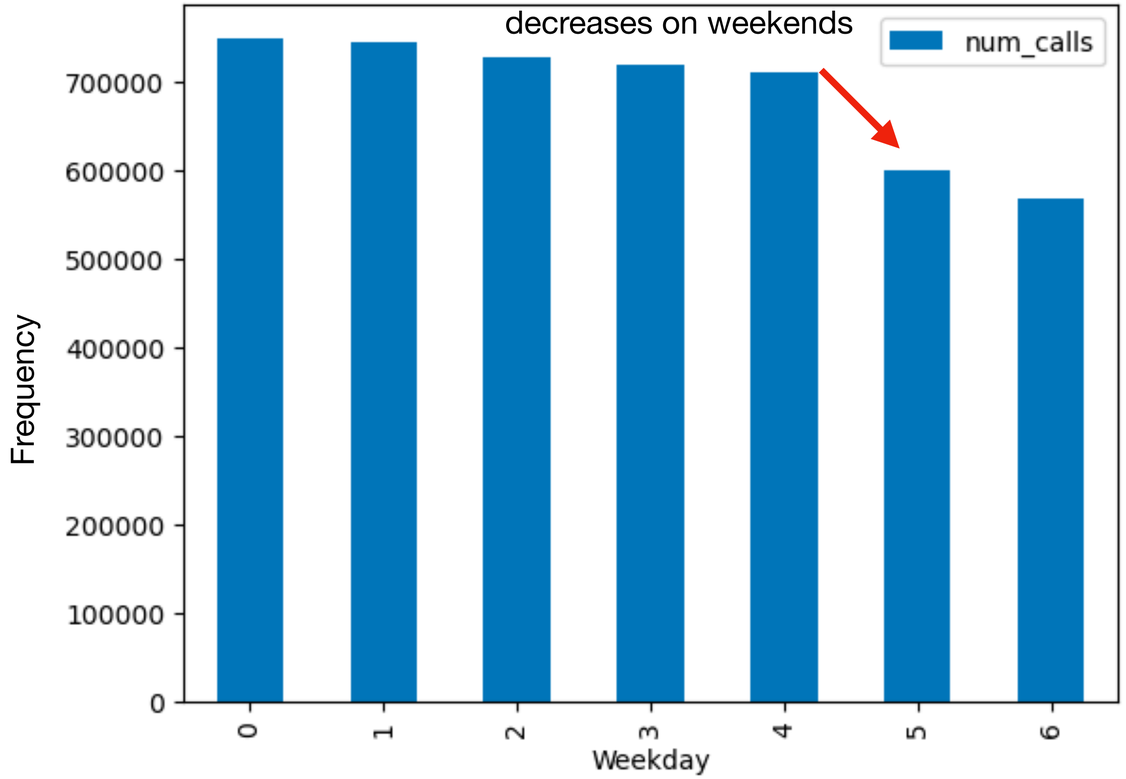
- Plot on the right is a heat map of how calls on a **monthly basis.**

- Performed a similar analysis:
  - For select agencies
  - Complaint types
  - Varying level of granularity (weekdays / hourly / monthly)



Data Understanding
Call Patterns

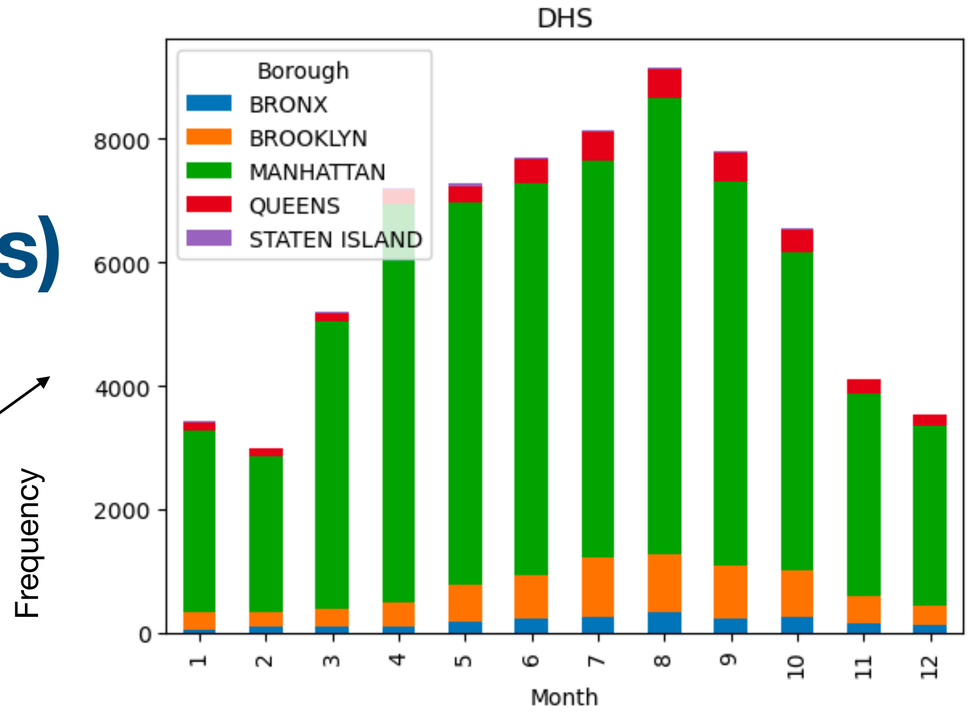


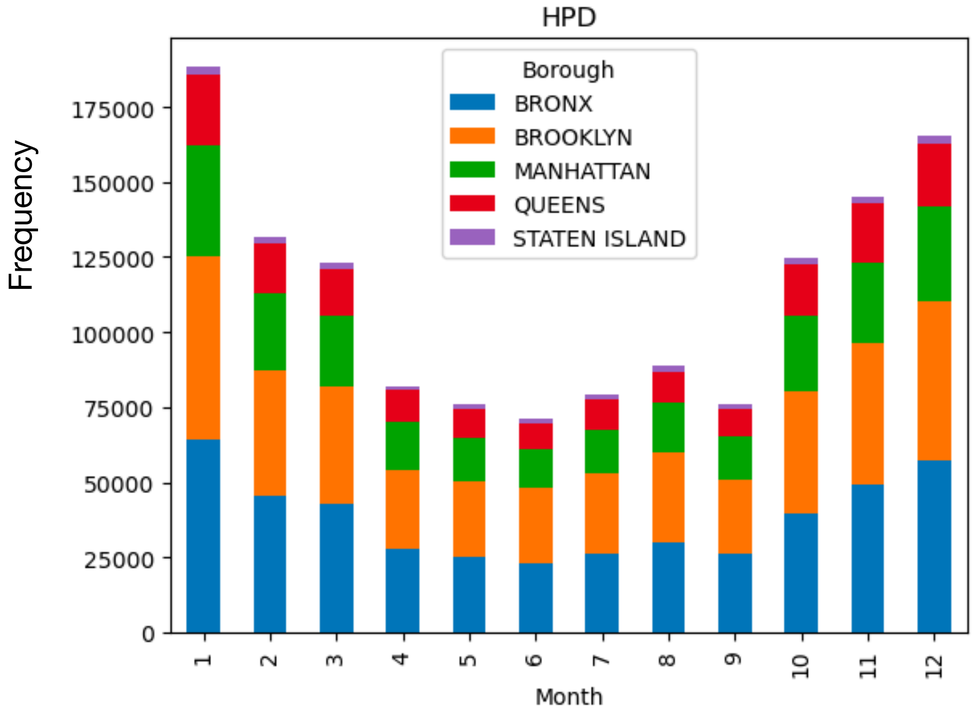


Data Understanding
Call Patterns - Agency (over Months)

- **DHS service requests mainly originate from Manhattan and is mostly dominant in the summer months**

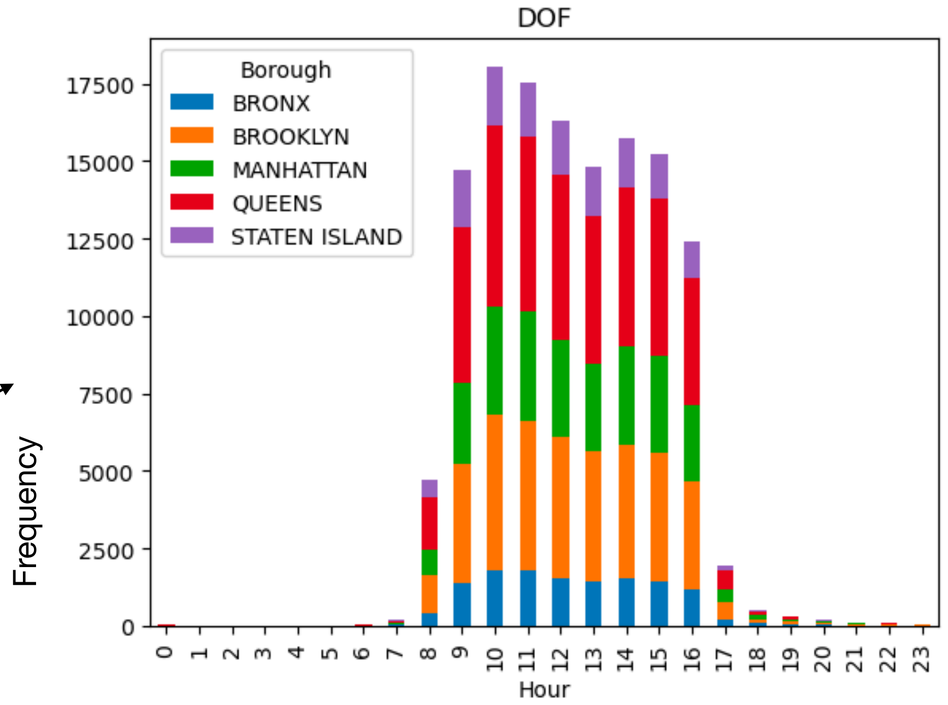
- **HPD which receives the 2nd most number of calls, after NYPD is mostly witnessing requests in the winter.**



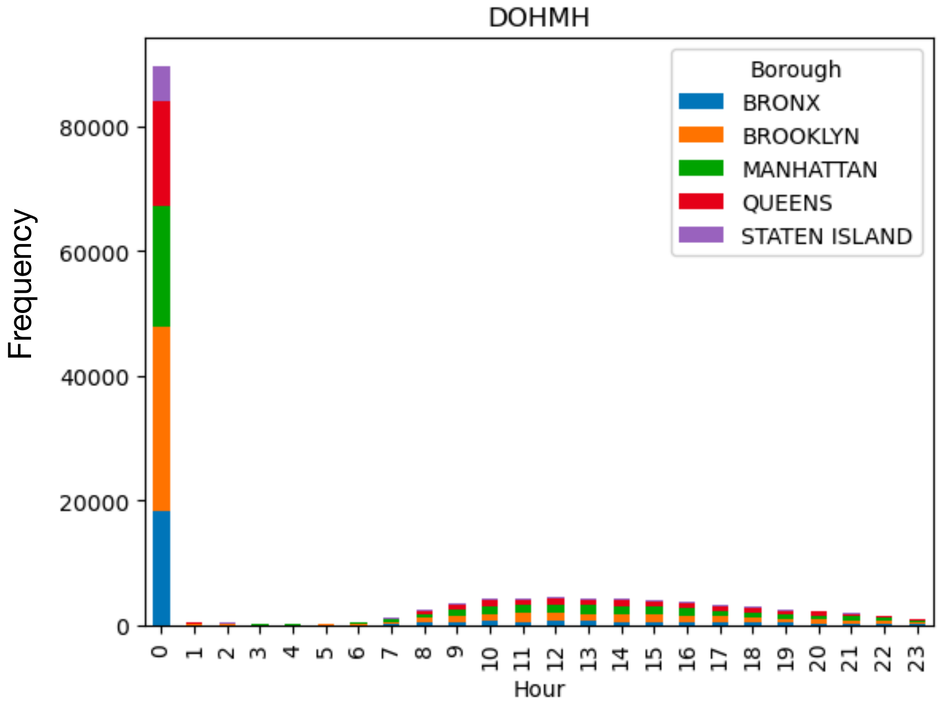


Data Understanding
Call Patterns - Agency (over Hours)

- **DOF** receives a high number of service requests from **9AM - 4PM.**



- **DOMHH**, receives the most number of calls **at midnight.**

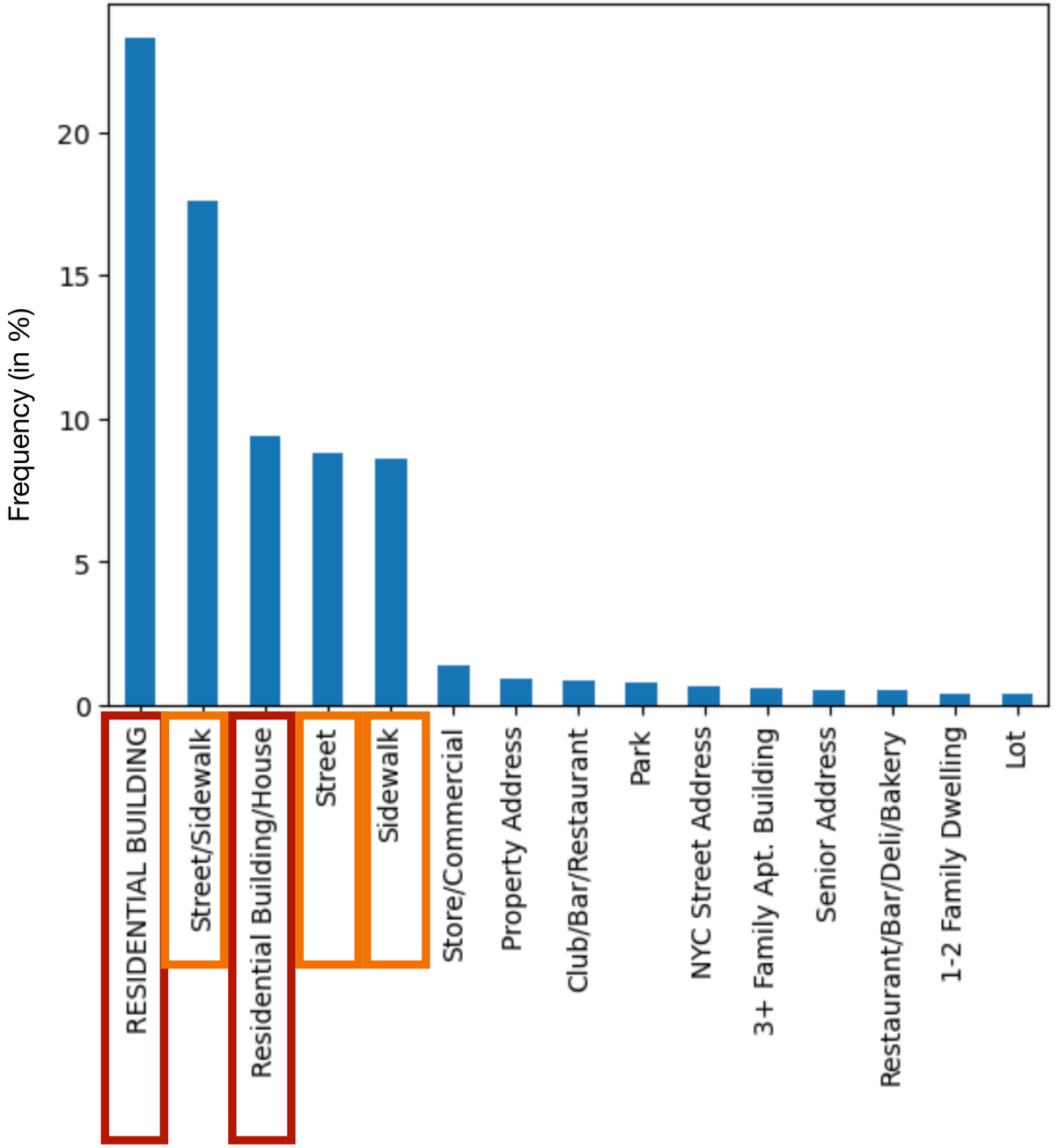


Data Understanding

- Data grouping / categorization is **inconsistent**

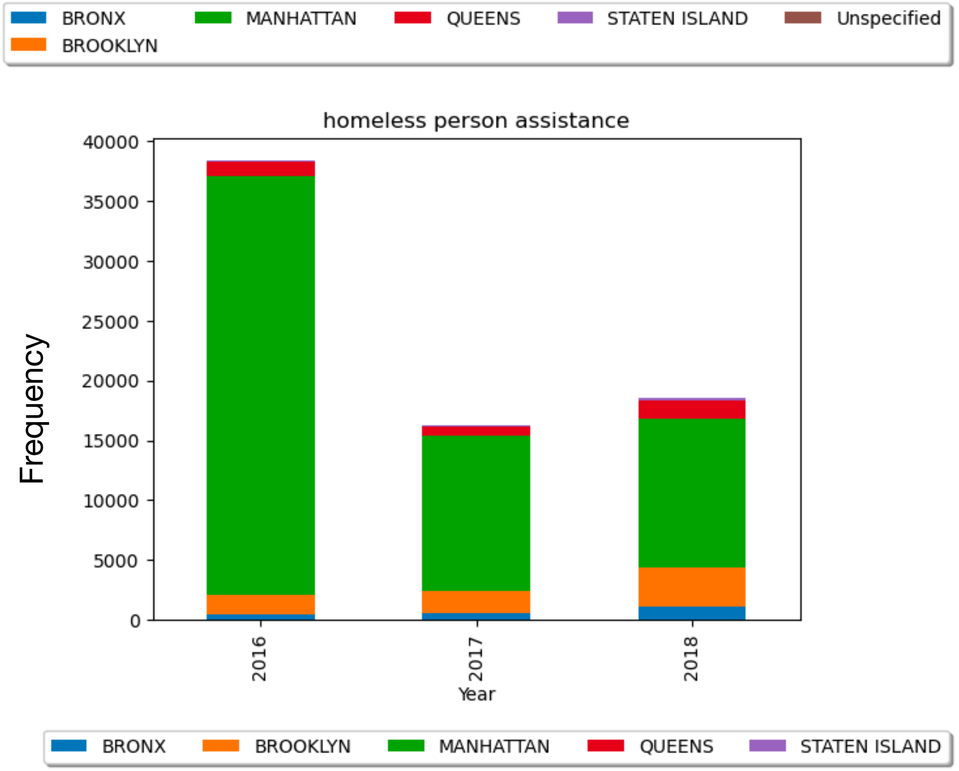
- Used a string matching library: (fuzzy_wuzzy) to make more **robust categories**

- Found similar issues with:
  - **Location Type**
  - **Complaint Type**

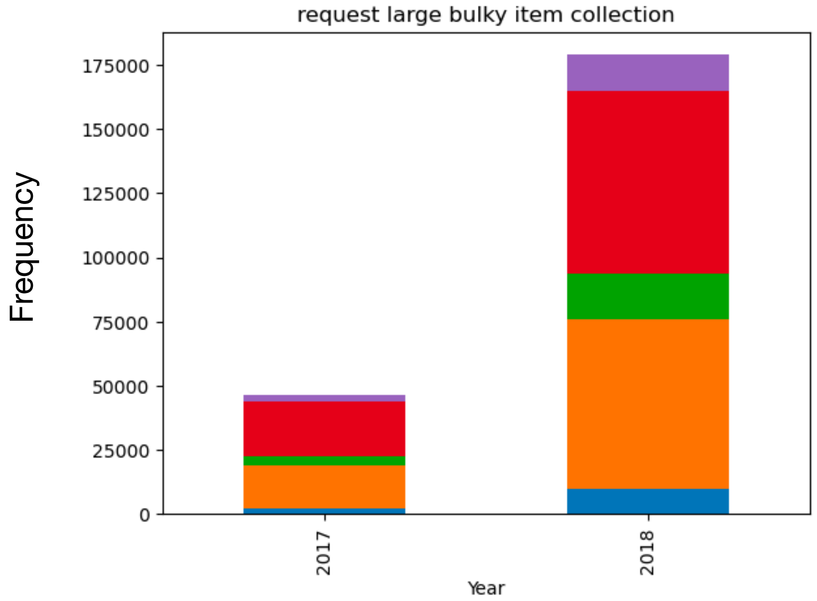


Data Understanding
Call Patterns - Agency (over Hours)

- **Homeless person assistance** requests have decreased over the years, but is most dominant in **Manhattan.**

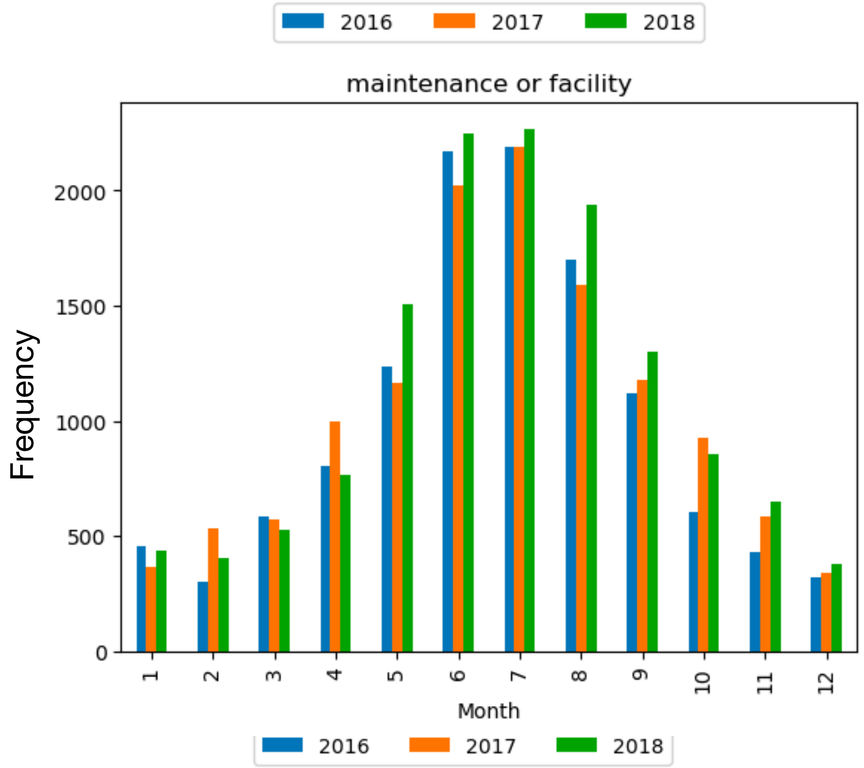


- **Request large bulky item collection** have increased exponentially from 2017. It also **did not exist** in 2016.

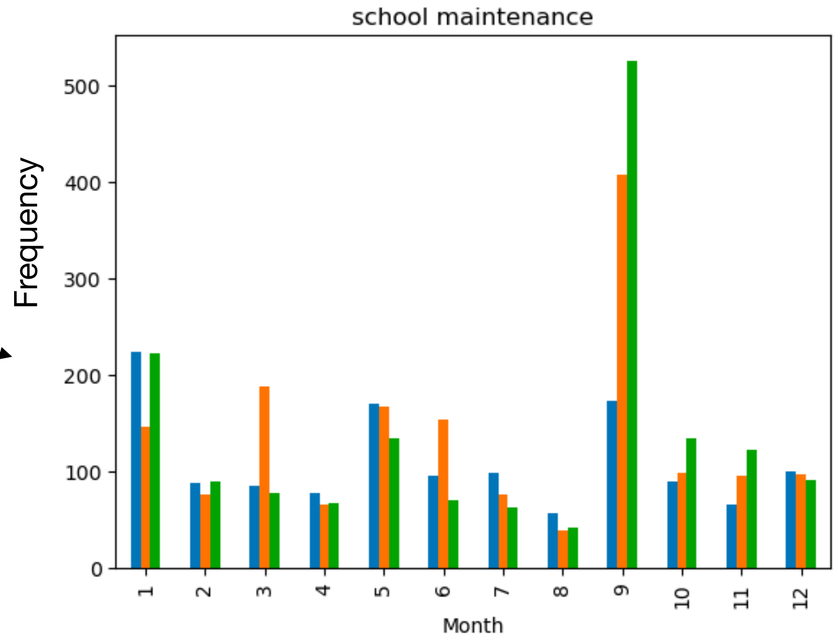


Data Understanding
Call Patterns

- **Maintenance or facility** service requests increase until July and then decrease consistently.

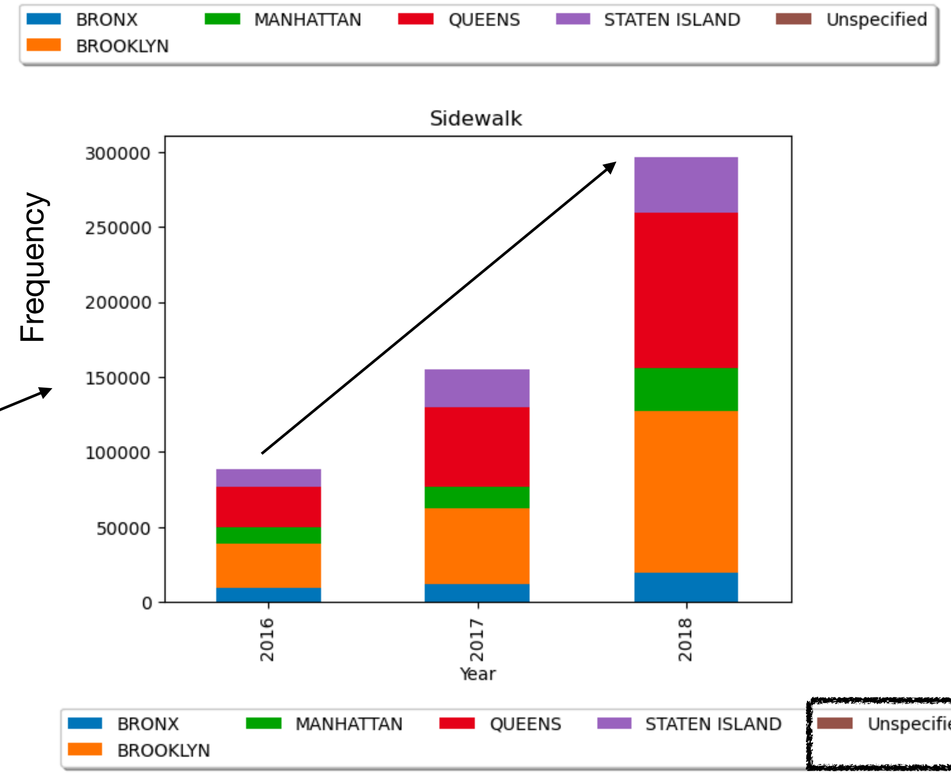


- **School maintenance** peak in the month of **September.**

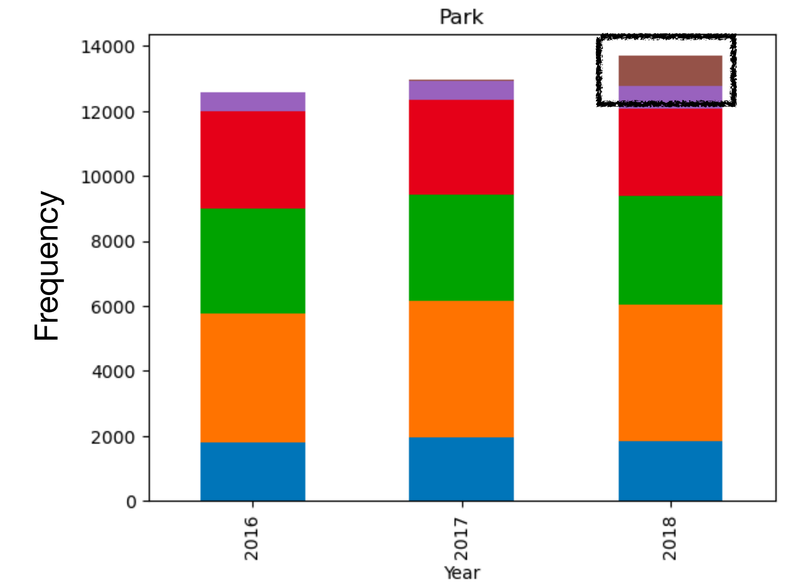


Data Understanding
Call Patterns

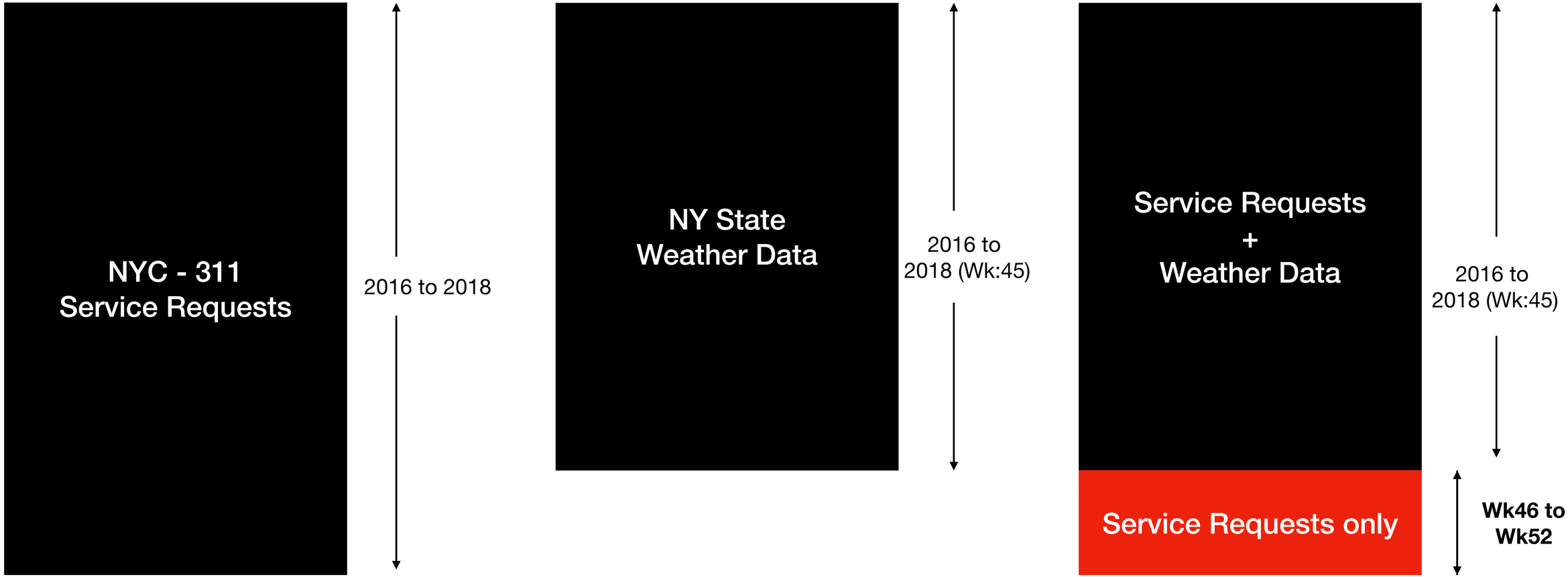
- **Sidewalks** service requests have increased exponentially from 2016.



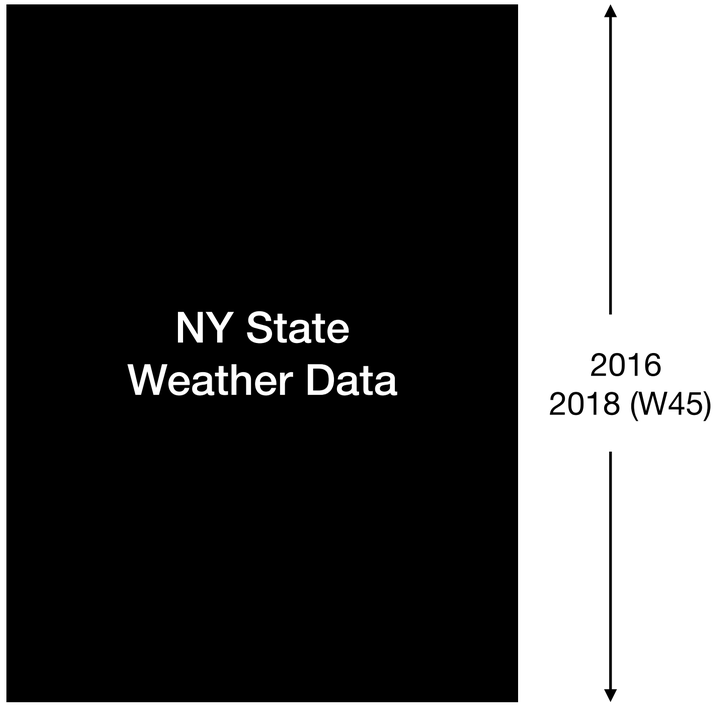
- In 2018, approximately 12.5% of the service requests at **parks** do not belong to a borough



Data Preparation
Merging the two datasets

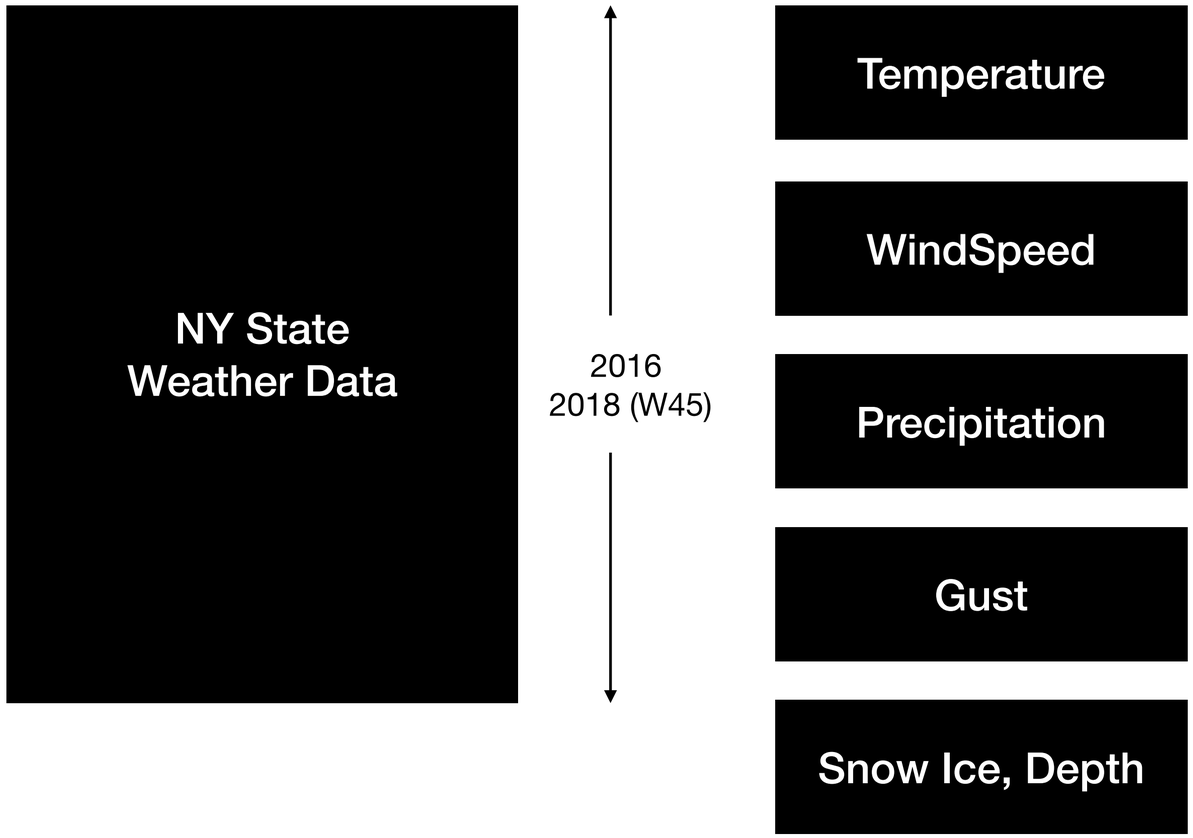


Data Preparation
Understanding the Weather Data



- Average distance between stations: **~200kms**
- We find the **max, min and mean (north, south and centre)** Latitude and Longitude for each borough in the dataset to get an idea of its bounds
- We use the geodesic distance to find the **5 nearest stations** to each borough and remove others

Data Preparation
Understanding the Weather Data



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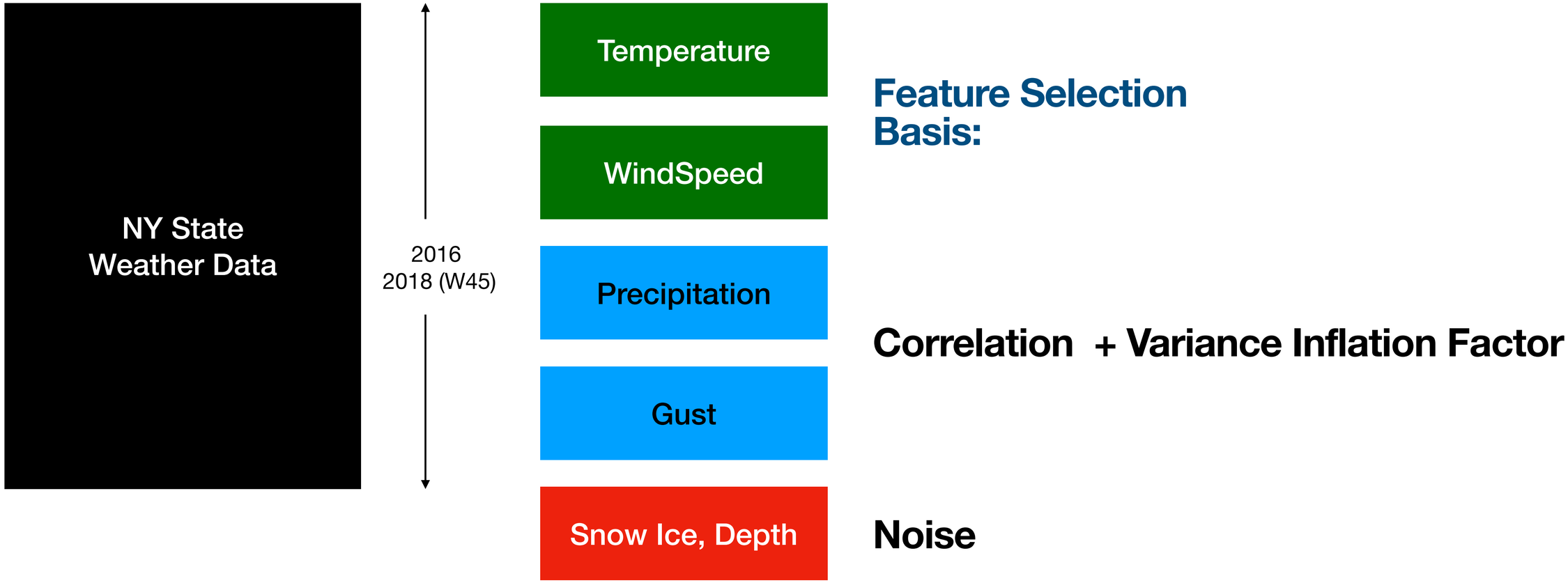
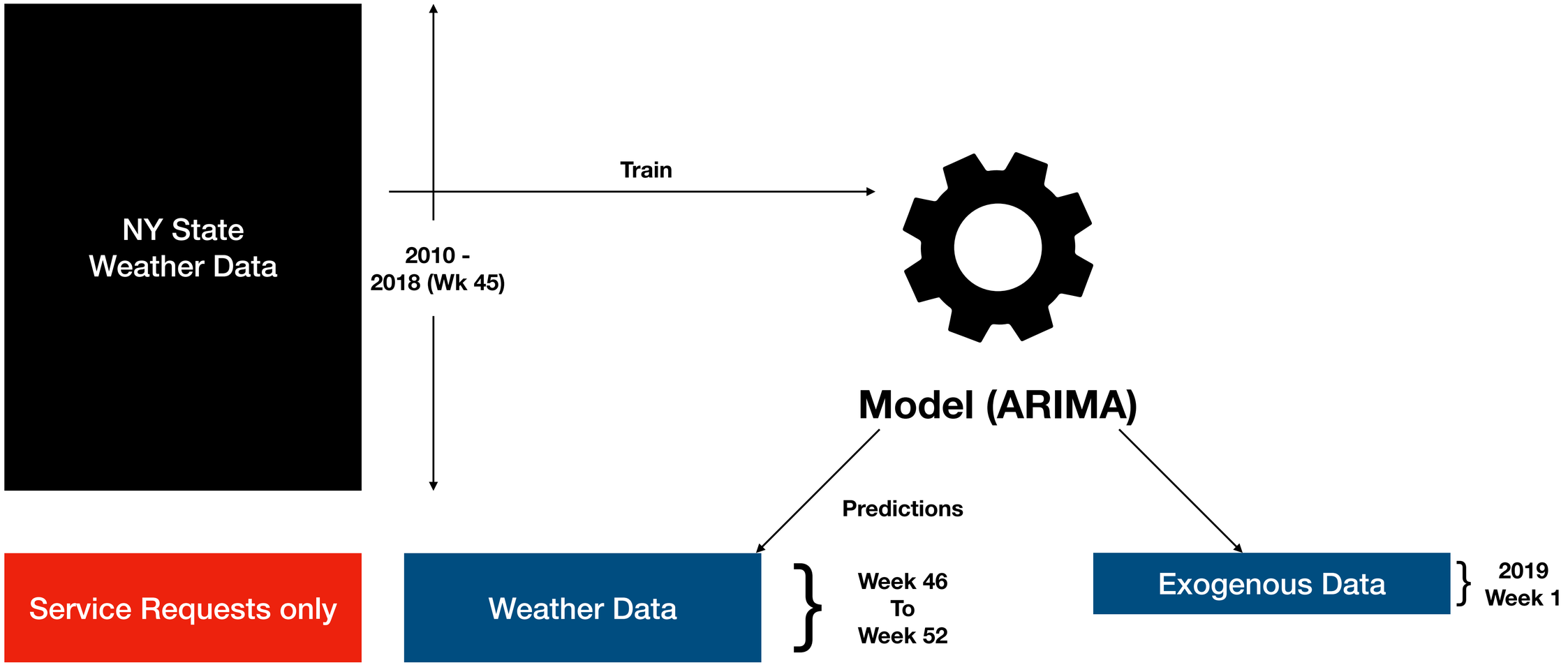
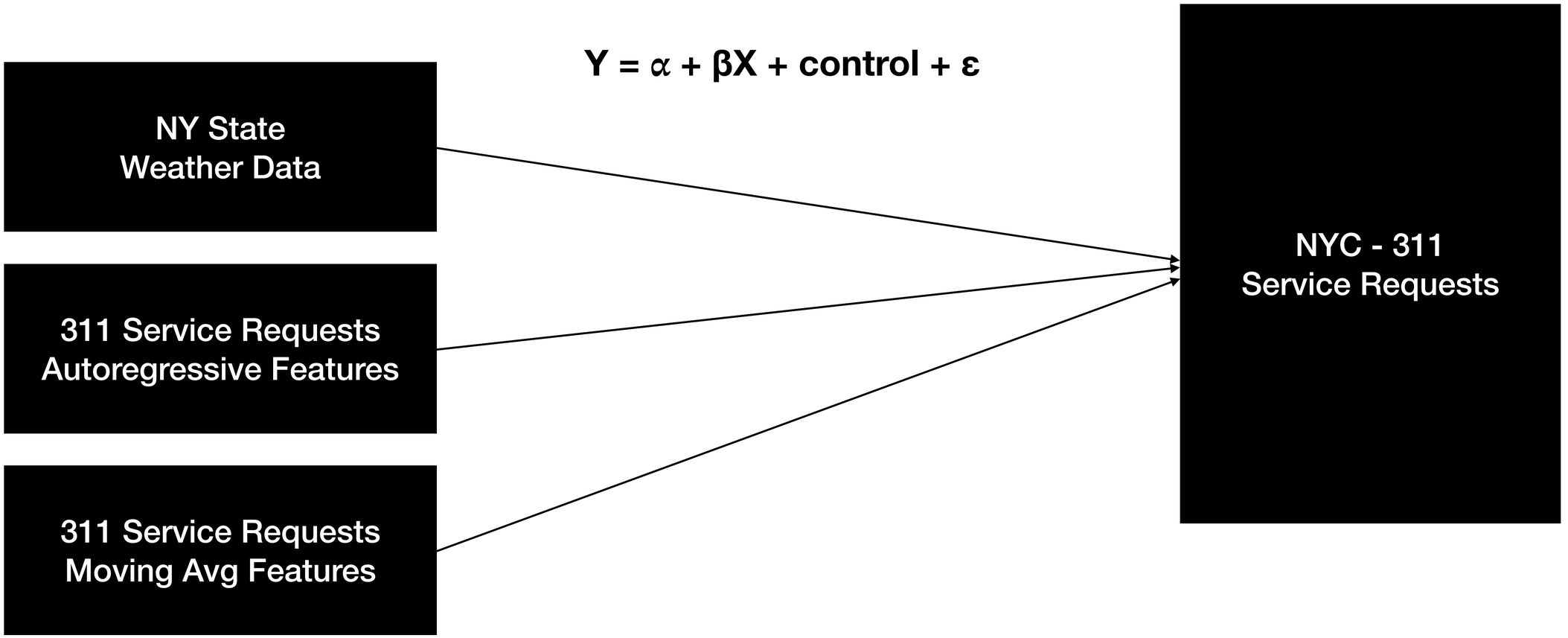


Data Preparation
Prediction of Service Requests

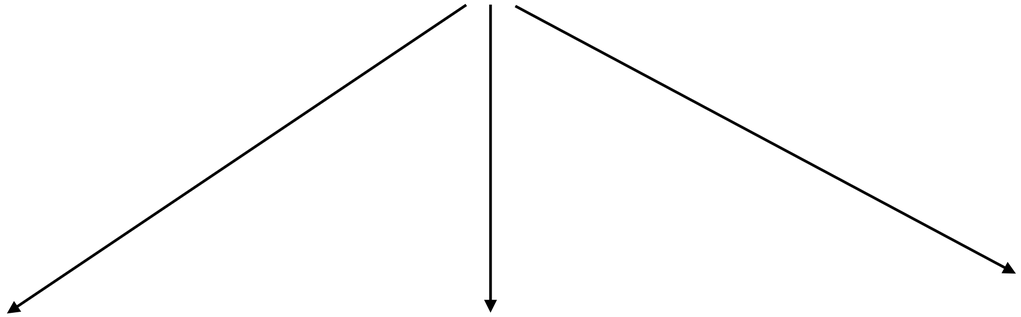


Data Validation
Check for Causality



Data Validation
Check for Causality

$$Y = \alpha + \beta X + control + \varepsilon$$

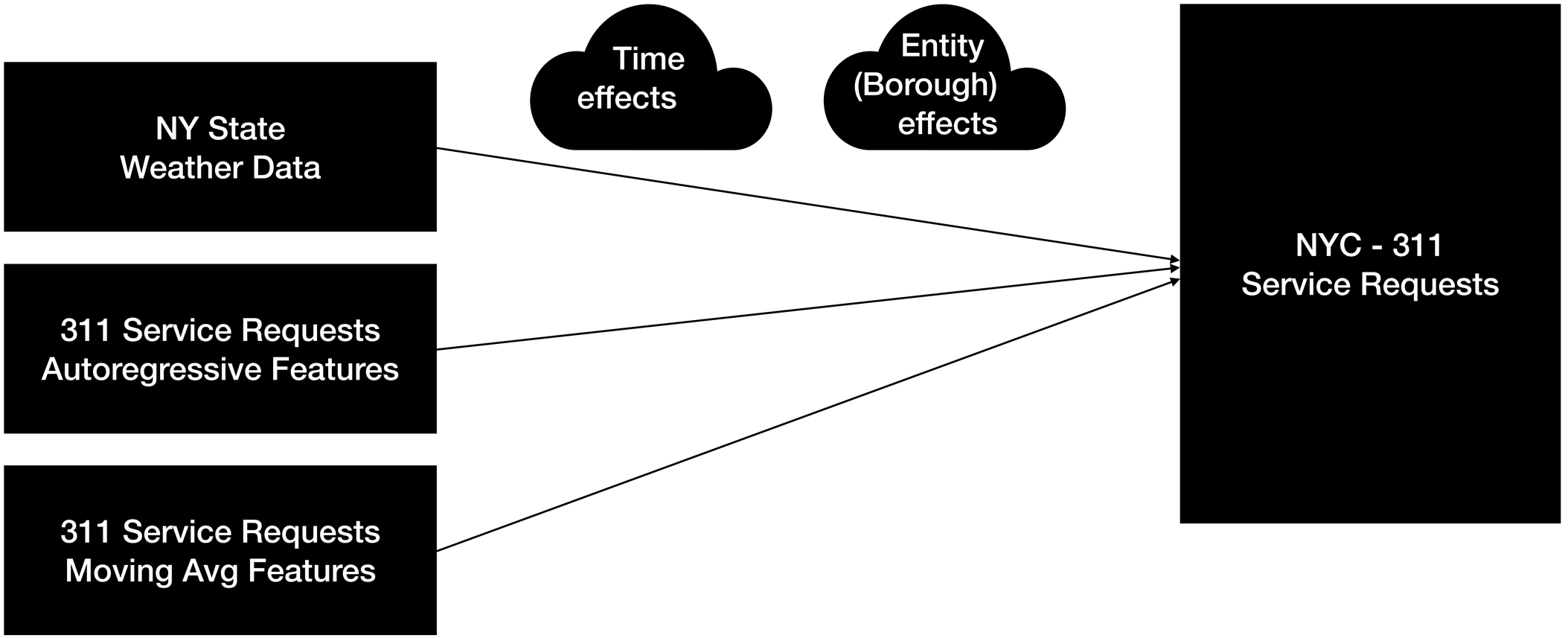


Effects that change differently for different borough with time

Effects that change uniformly for all boroughs with time

Residual error

Data Validation
Check for Causality - Panel OLS



p-Value for Temperature = 0.04

Modelling
Predicting the number of Service Requests

Tests Run:

1. **Augmented Dickey Fuller Test (to check for stationarity)**
2. **Absence of Multi-collinearity**
3. **Data should be homo-skedastic**

NYC 311
Service Requests

+

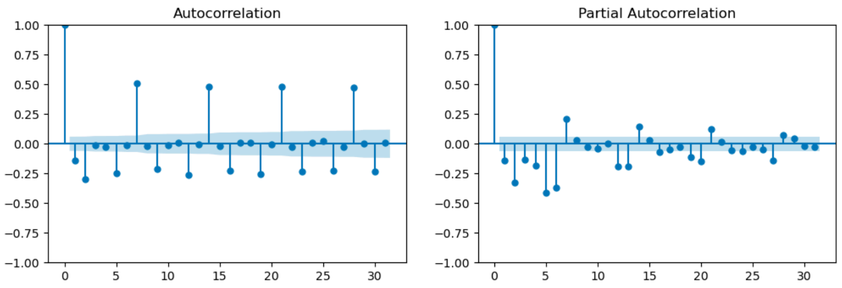
Weather Data

Train

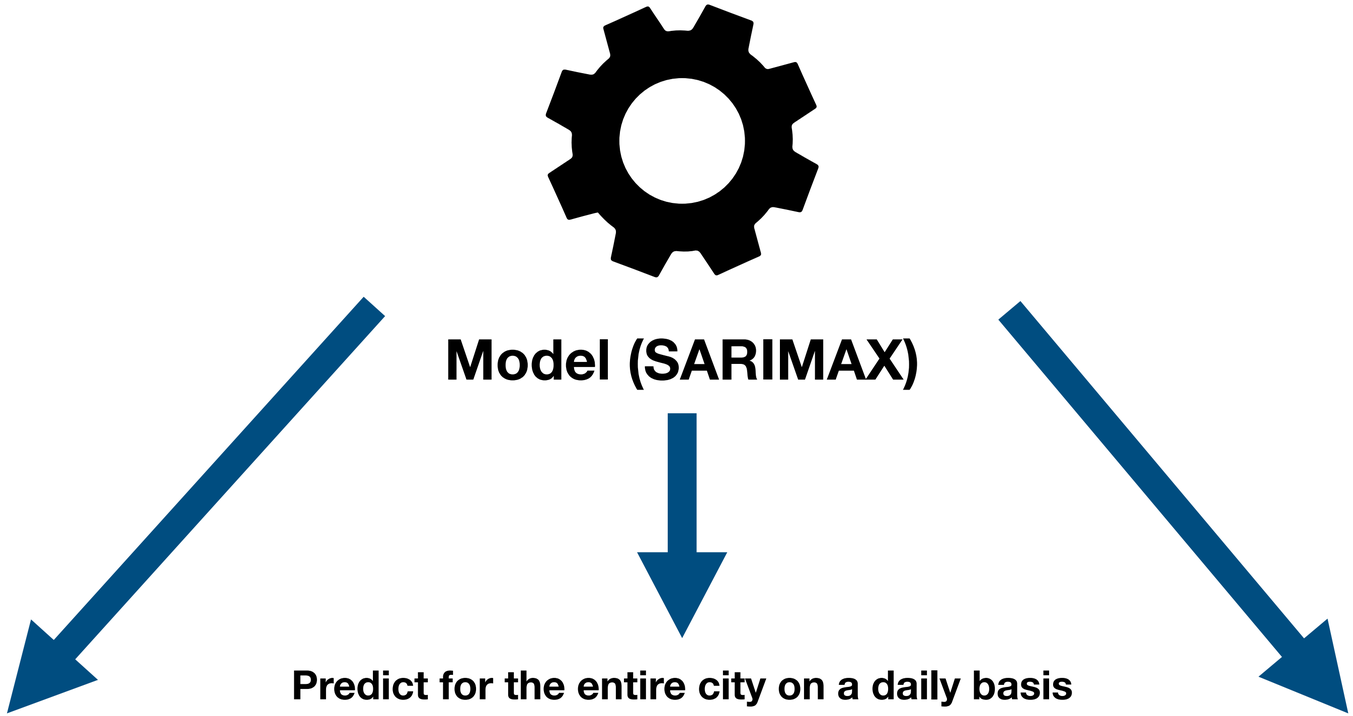
Predictions

Next Week
Predictions

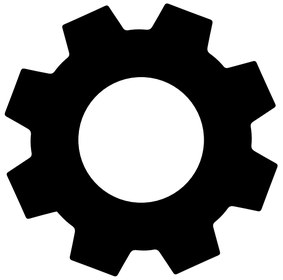
Model (SARIMAX)



Modelling Approaches (Experimented)
Predicting the number of Service Requests



Modeling Approaches (Experimented)
Predicting the number of Service Requests



Model (SARIMAX)

Predict for the entire city on a daily basis

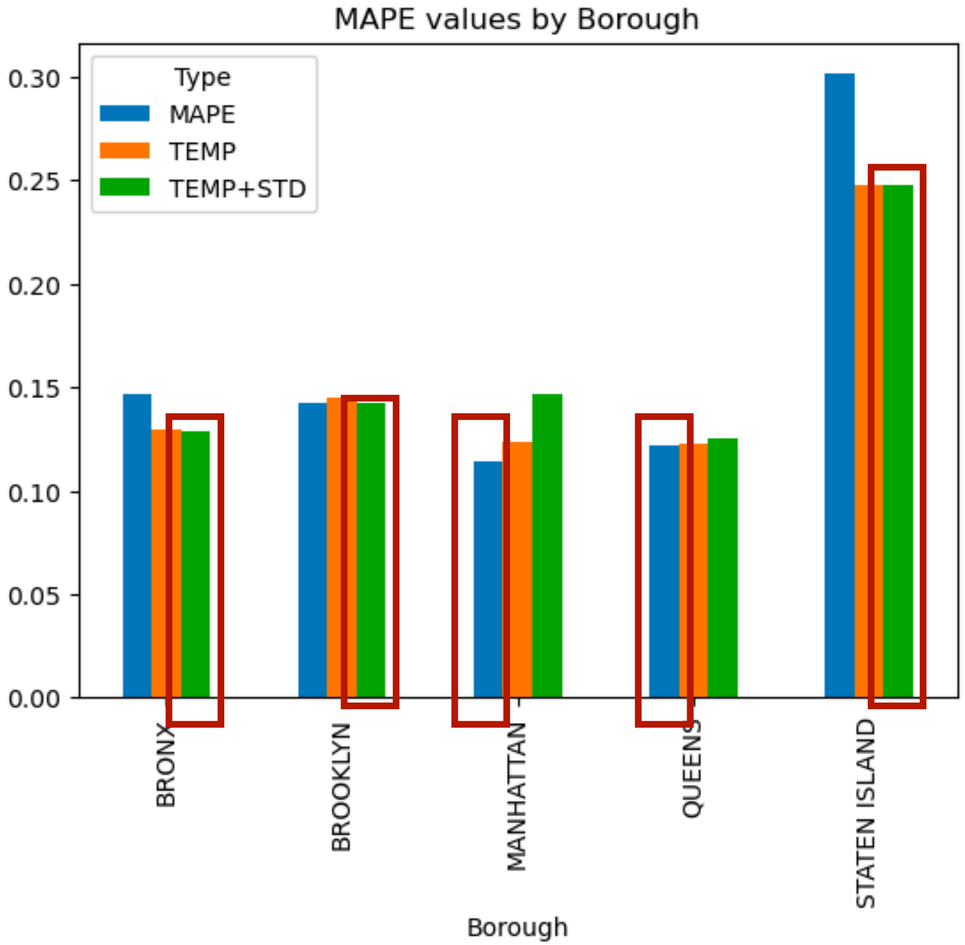
Predict for the entire week as a whole
Infer daily #call records from EDA

Predict for each borough on a daily basis
(Could be tuned further)

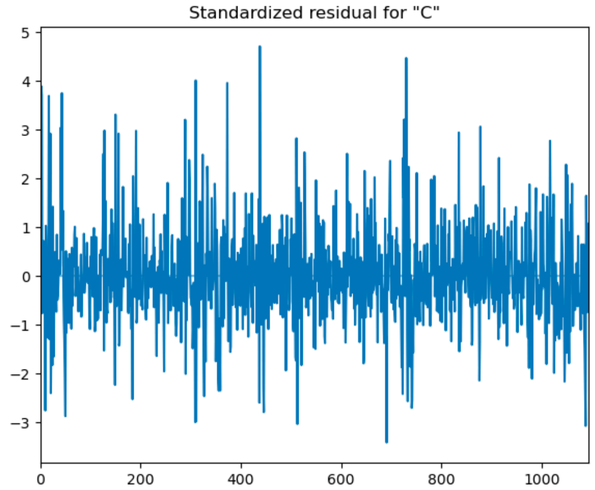
Modeling Approach 1
Predicting the number of Service Requests

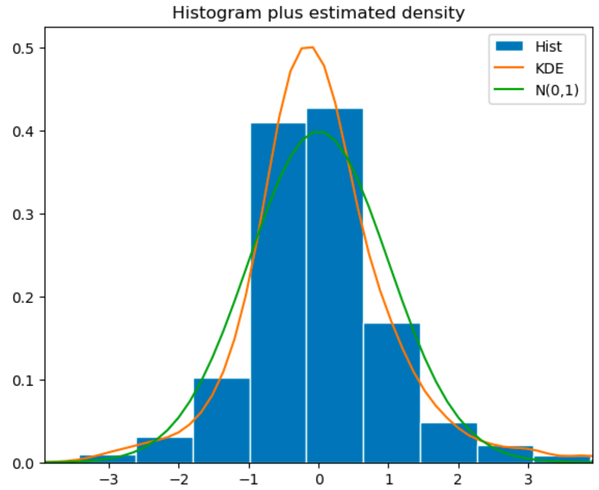
Predict for each borough on a daily basis

- MAPE: **Normal** ARIMA model (with no exogenous variables) — ***MANHATTAN, QUEENS***
- TEMP: **SARIMAX** model (with mean temperature as exogenous variable)
- TEMP + STD: **SARIMAX** model (with mean temperature and standard deviation as exogenous variable) — ***ALL OTHERS***

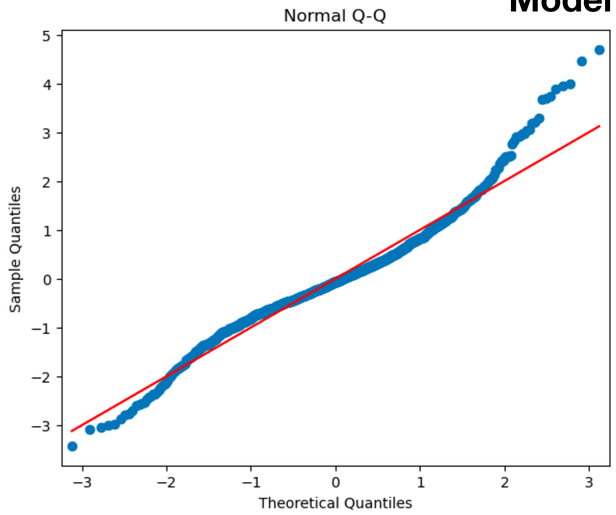


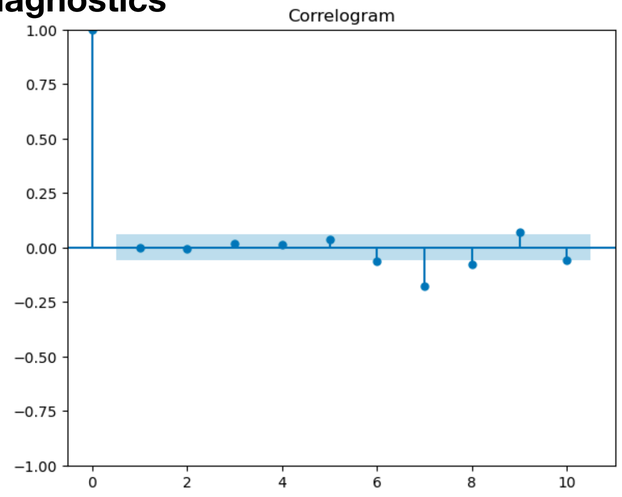
Modeling
Analyzing the Model Performance



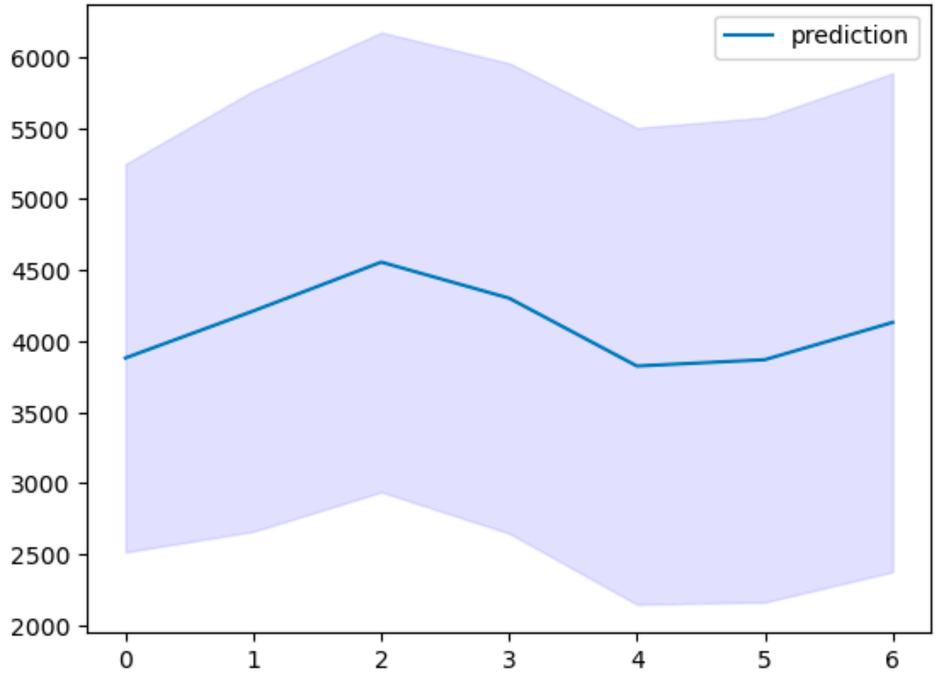


Model Diagnostics





Predictions



Deployment
Model Deployment

- Check for model drift and data drift.
- Use of data versioning tools to understand
- Develop data wrangling pipelines

- Performance drift across each borough’s model with time
- Changes in the implied data distribution (service requests from boroughs)

Future Scope

- Alternative Datasets including:
  - Infrastructure Development / Spending
  - Crime Datasets

- Causality
  - Check for **heterogenous effects** across boroughs

- Other Models:
  - Prophet, Linear Regression with Exponential Smoothening
  - With Explainability measured using **SHAP and LIME**

Future Scope

- Modeling Approaches
    - Develop models for each borough and find exogenous variables that dominate in said boroughs. (Using **cross correlation**).
    - Use **intermittent models** to predict for particular seasons such as **iMAPA** and **Croston-TSB** to measure muted effects.

Thank You