# Accident Analysis: Predicting Traffic Accident Duration


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# Introduction

## What specific factors significantly influenced the duration of traffic accidents across various cities?

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CHASE HERTEL

# Dataset

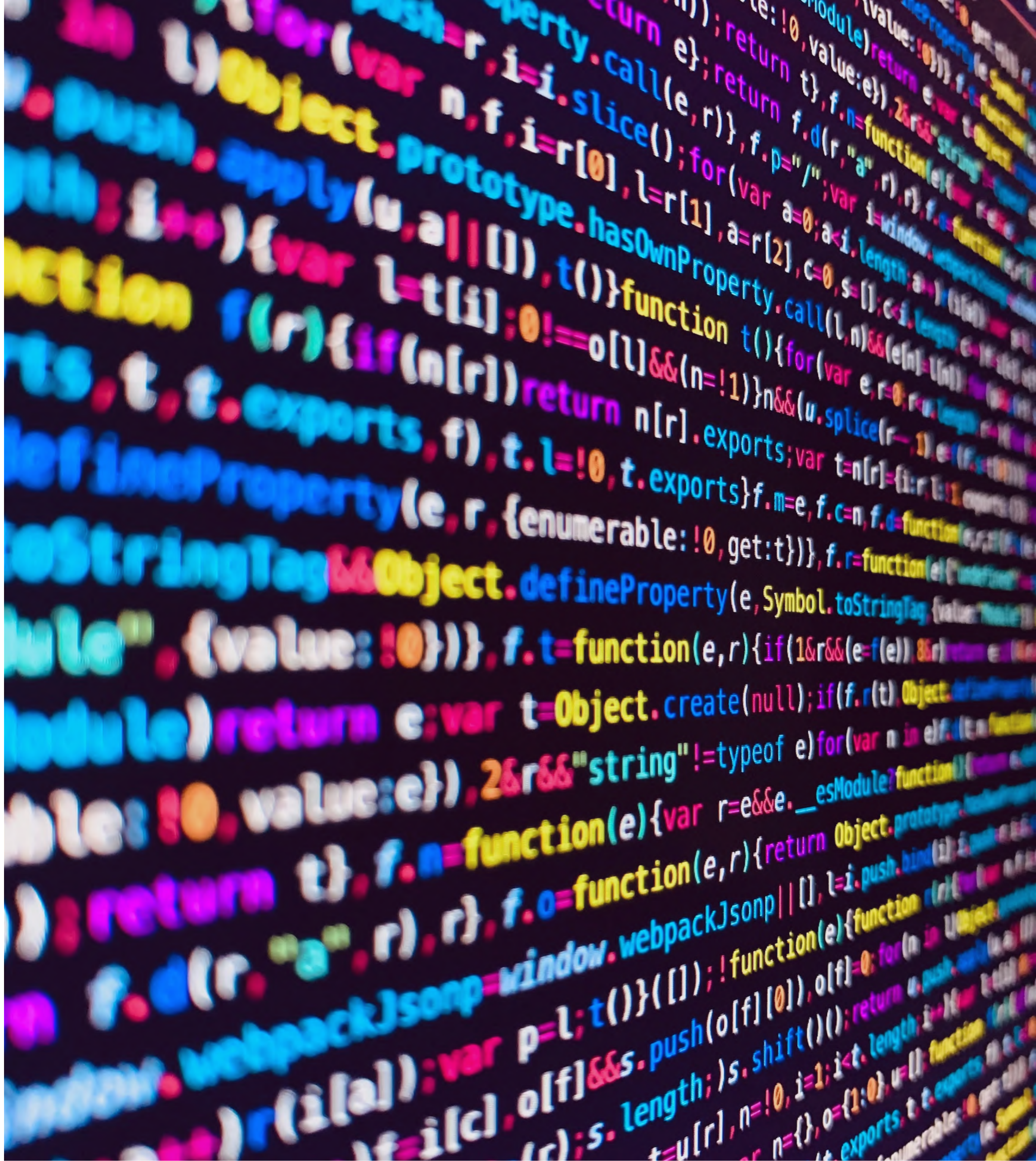
US Accidents (2016 - 2023): A Countrywide Traffic Accident Dataset from Kaggle

Contains car accident information from across 49 U.S. states, The data originates from sources such as traffic cameras, sensors, and government agencies, offering a comprehensive overview of approximately 7.7 million recorded accidents. These incidents were gathered through multiple APIs that stream real-time traffic event data.

Weather, time, and location-based features are some of the most important attributes and make up some of total 46 columns







# Accident Patterns and Duration Analysis

**Insights**

**Methods**

**Recommendations**

# Houston

Worst traffic in Texas, and ranked 2nd in the US for worst traffic

Home of one of the largest interchanges in the world

**Dataset**
Trained on historical logged accidents data in Houston, TX

**Prediction**
Predict accident duration in seconds using logged data

**Insight**
Predict accident duration as soon as accident data is initially logged for city and public usage

# Houston

## Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
best_dt = DecisionTreeClassifier(
    criterion='entropy',
    max_depth=40,
    max_features='log2',
    min_samples_leaf=12,
    min_samples_split=7
)
best_dt.fit(X_train, y_train)
```

Score: 0.24

Accuracy: 0.36

## Random Forest

```
from sklearn.ensemble import RandomForestClassifier
best_rf = RandomForestClassifier(
    max_depth=30,
    max_features='sqrt',
    min_samples_leaf=1,
    min_samples_split=13,
    n_estimators=67
)
best_rf.fit(X_train, y_train)
```

Score: 0.27

Accuracy: 0.55

## MLP

```
from sklearn.neural_network import MLPClassifier
best_mlp = MLPClassifier(
    hidden_layer_sizes=(50,),
    activation='tanh',
    solver='adam',
    verbose=1
)
best_mlp.fit(X_train, y_train)
```

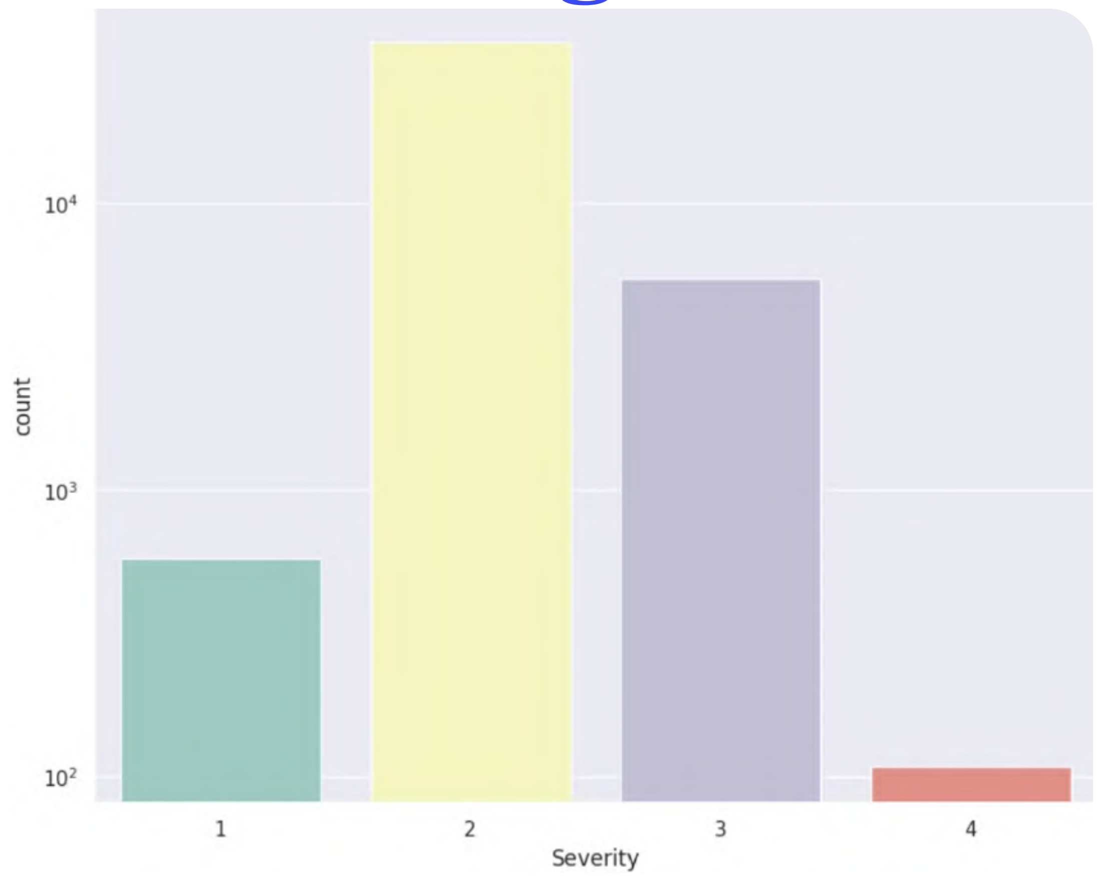
Score: 0.26

Accuracy: 0.36

# Houston

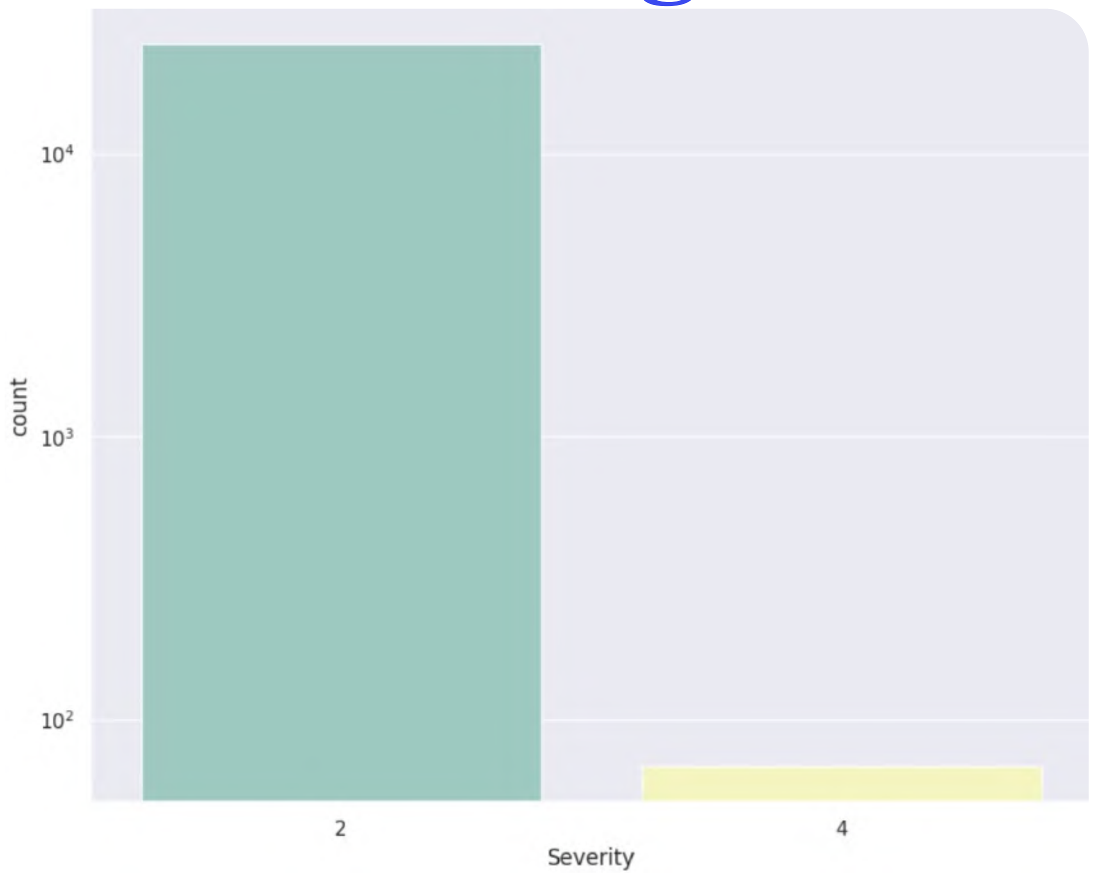
## Severity of Accidents

### Missing Data




Missing end longitude and latitude, however those are key features in predicting accident duration

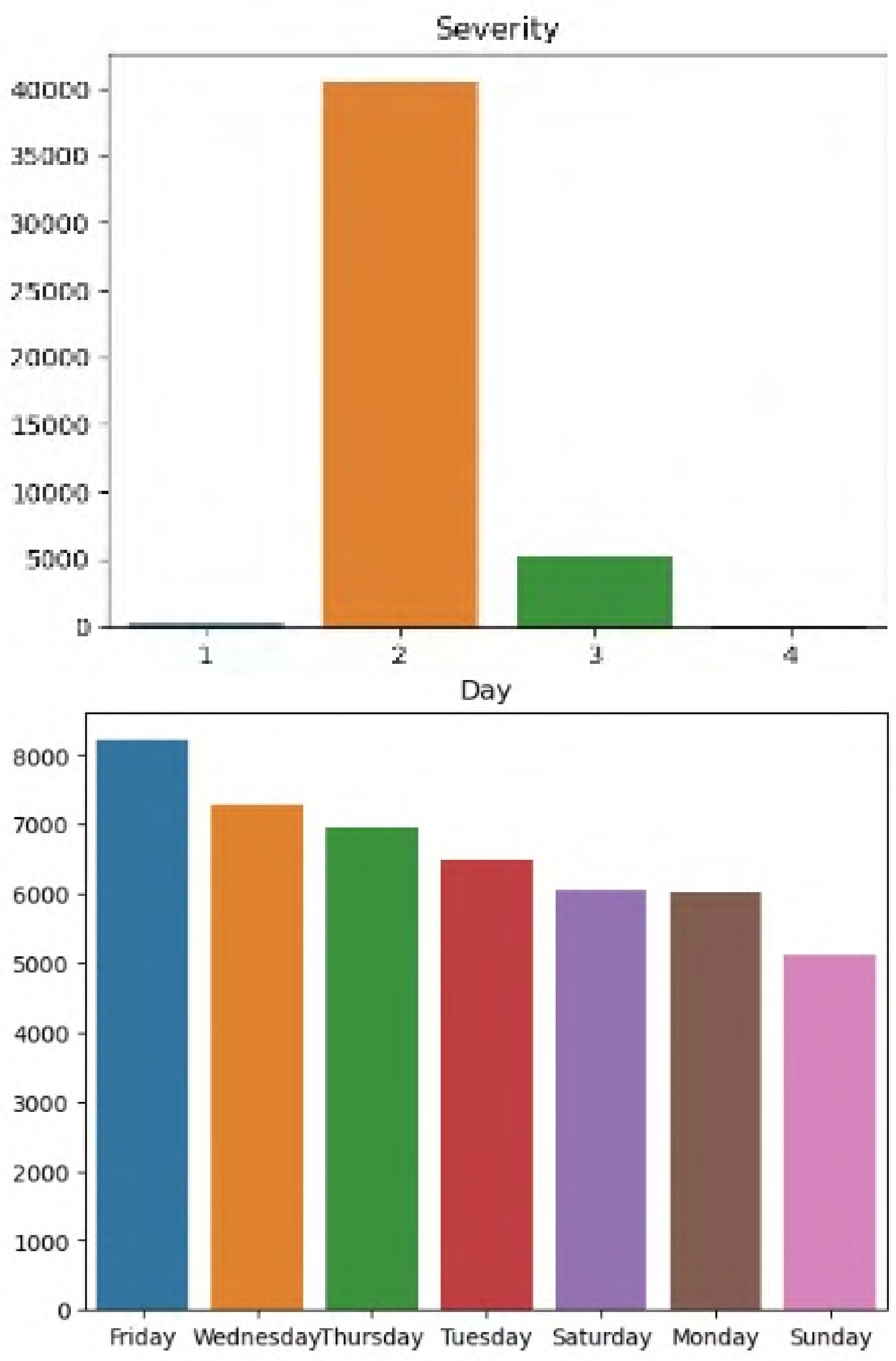
### No Missing Data

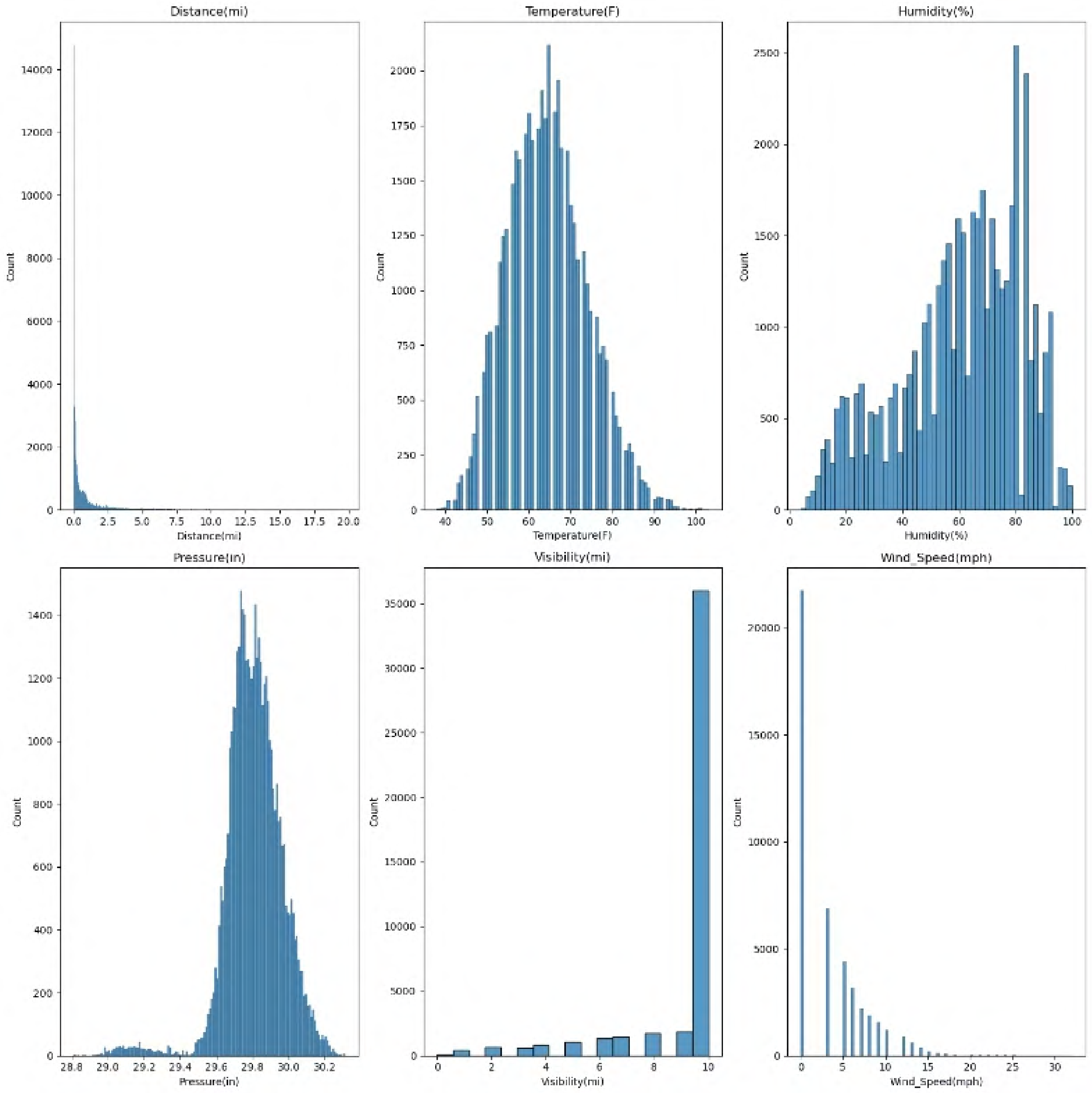


# Los Angeles


1. One of the largest cities in the states(high population density)
2. Very car-dependent (city is structured around cars)
3. Attracts lots of people (e.g. tourism)
4. Poor road infrastructure (due to rapid growth)

# EDA


Severity
40000
35000
30000
25000
20000
15000
10000
5000
0
1
2
3
4
Day
8000
7000
6000
5000
4000
3000
2000
1000
0
Friday
Wednesday
Thursday
Tuesday
Saturday
Monday
Sunday


Distance(mi)
Temperature(F)
Humidity(%)
Pressure(in)
Visibility(mi)
Wind_Speed(mph)
Count

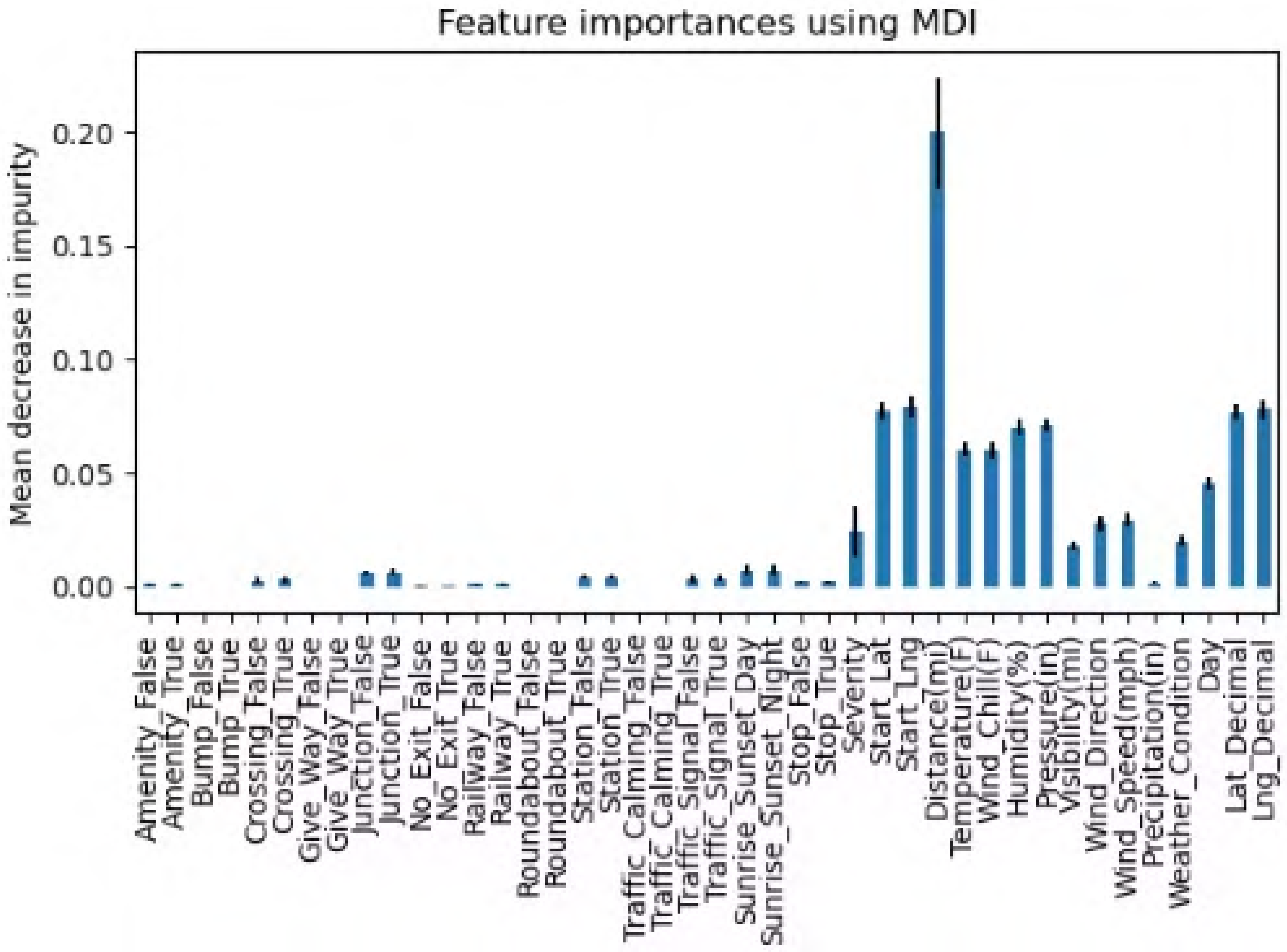
# Feature Engineering

```
# Converting Duration to categorys

# 15 mins or less = 0
# 15 - 30mins = 1
# 30 mins - 1hr = 2
# 1 - 3hr = 3
# 3hr - 6hr = 4
# rest of day = 5

la['ETA'] = 0
la.loc[la['Accident_Duration'] <= 900, 'ETA'] = 0
la.loc[(la['Accident_Duration'] <= 1800) & (la['Accident_Duration'] > 900), 'ETA'] = 1
la.loc[(la['Accident_Duration'] <= 3600) & (la['Accident_Duration'] > 1800), 'ETA'] = 2
la.loc[(la['Accident_Duration'] <= 10800) & (la['Accident_Duration'] > 3600), 'ETA'] = 3
la.loc[(la['Accident_Duration'] <= 21600) & (la['Accident_Duration'] > 10800), 'ETA'] = 4
la.loc[la['Accident_Duration'] > 21600, 'ETA'] = 5
```

```
# Get the decimal points of latitude and longtitude so it can be more sensitive to the model for location
la['Lat_Decimal'] = la.Start_Lat.astype(str).str.extract('\.(.*)').astype(int)
la['Lng_Decimal'] = la.Start_Lng.astype(str).str.extract('\.(.*)').astype(int)
```

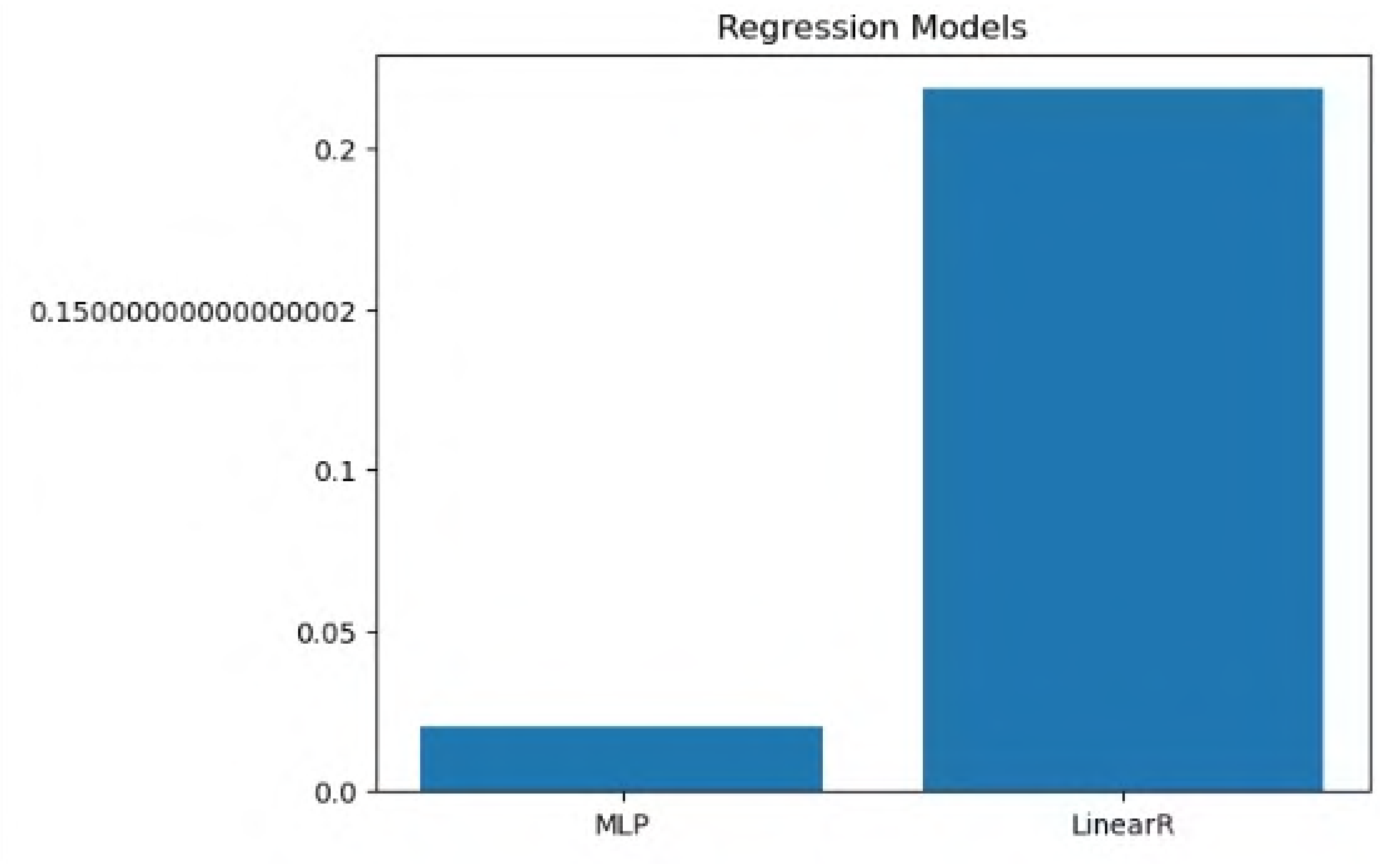
| Lat_Decimal | Lng_Decimal |
|---|---|
| 98748 | 137558 |
| 928959000000006 | 368271 |
| 989342 | 256462 |
| 4945 | 270073 |
| 30895 | 217926 |

# Feature Importance

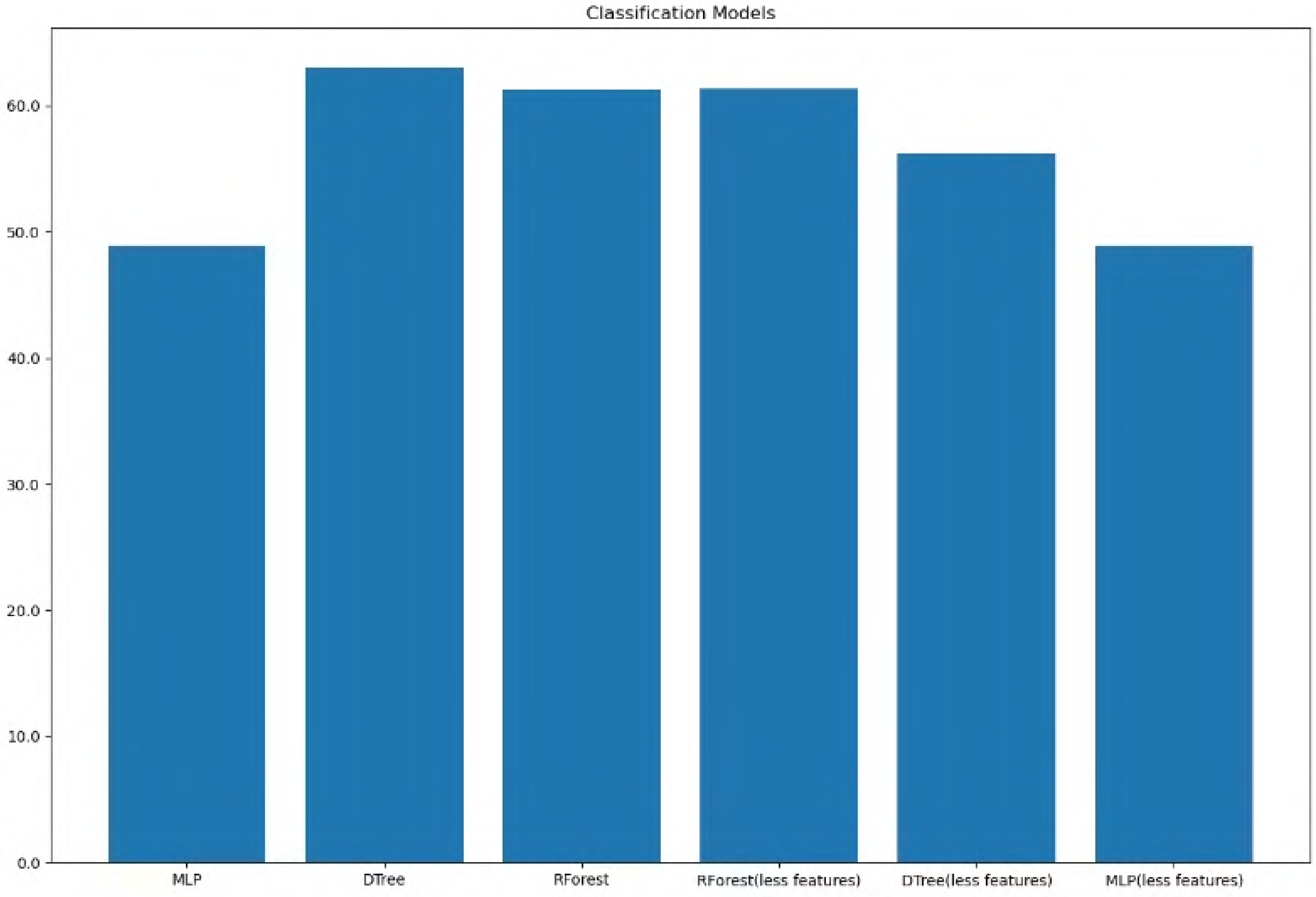



- Distance plays a large role in predicting accident duration
- Latitude, Longitude, Temperature, Wind Chill, Humidity, and Pressure plays a relatively significant role as well.
- Day and Severity doesn't contribute as much as I thought (expecting more congestion and delays due to certain days and severity of accidents)
- Try including these features only?

# Results




- Best score is 63% from DecisionTreeClassifier.
- Potential future algorithm to consider is LSTM or RNN for Regression




Accuracy(%): 48.9 63.0 61.3 61.4 56.2 48.9

# Charlotte, North Carolina

One of the top 5 cities with most accidents in the US

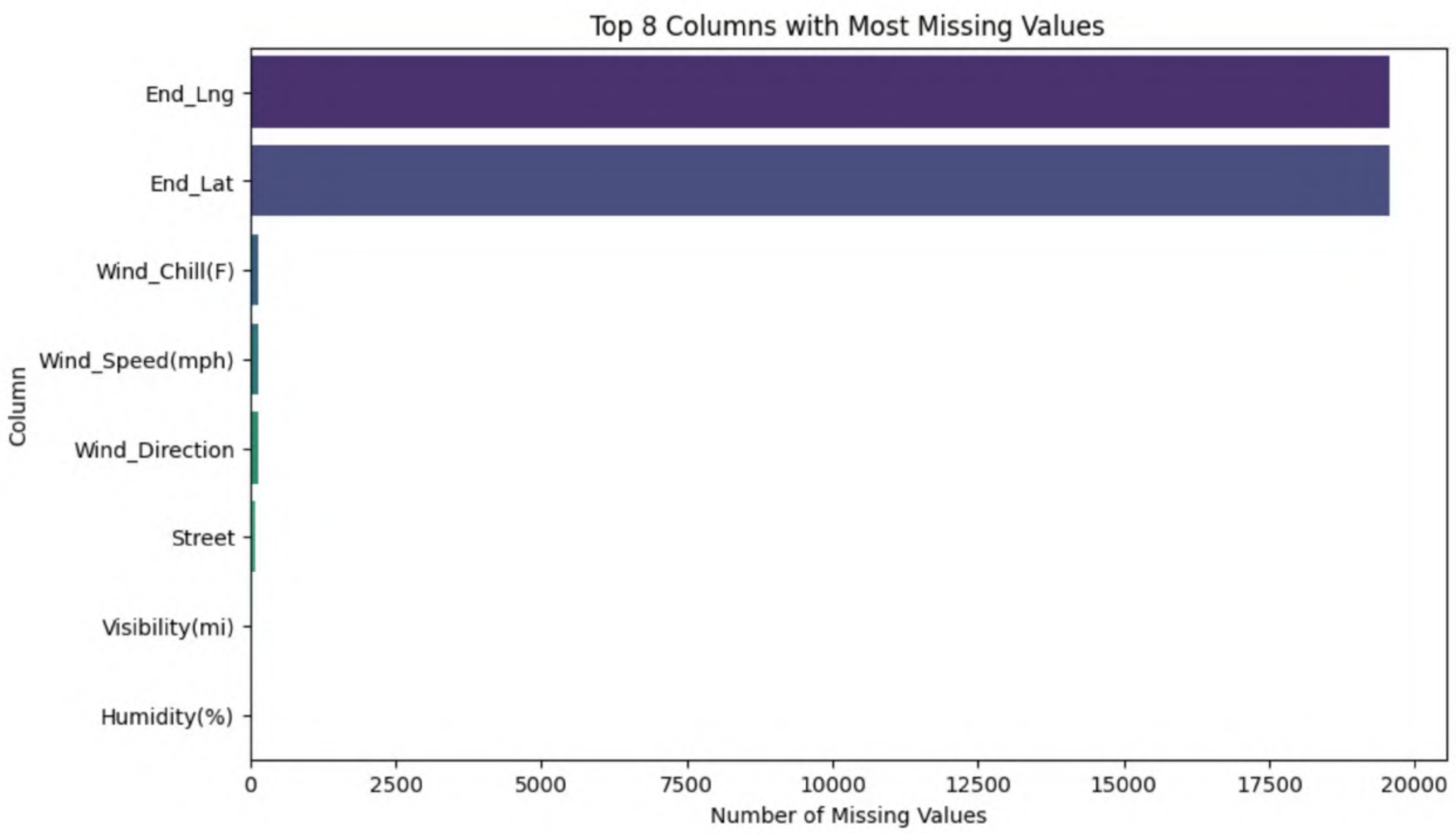
Past 2 years have seen 39000+ reported traffic accidents

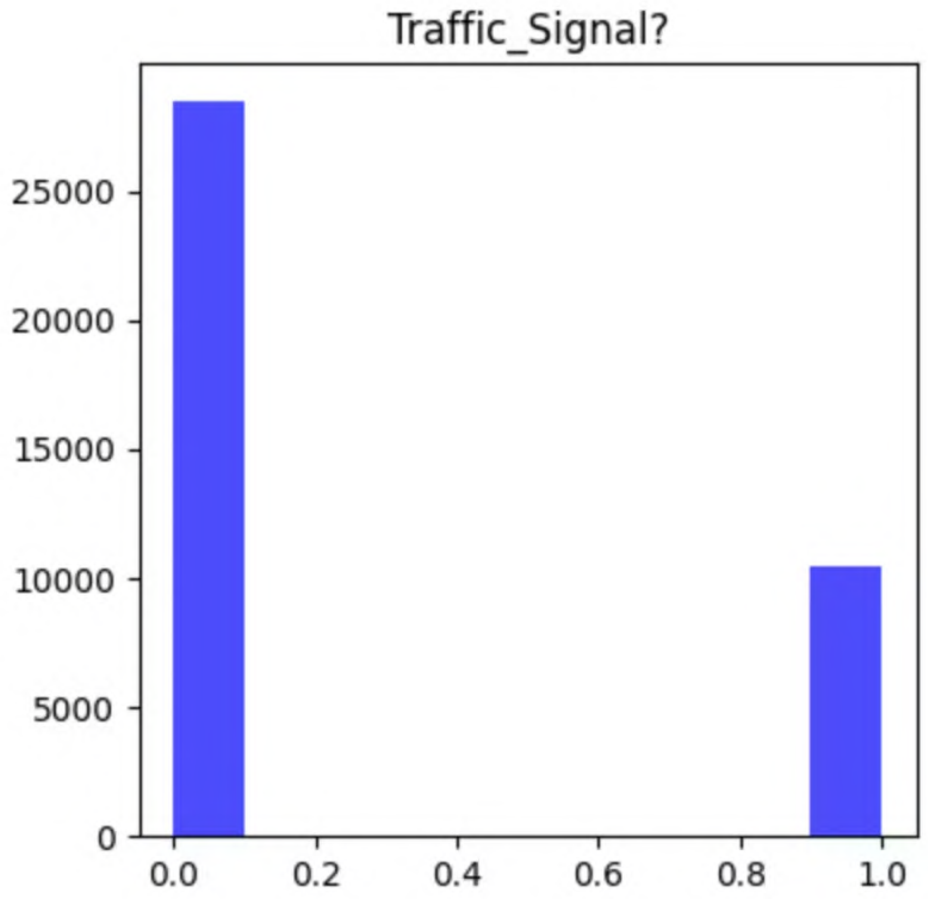
Above average rush-hour traffic travel times

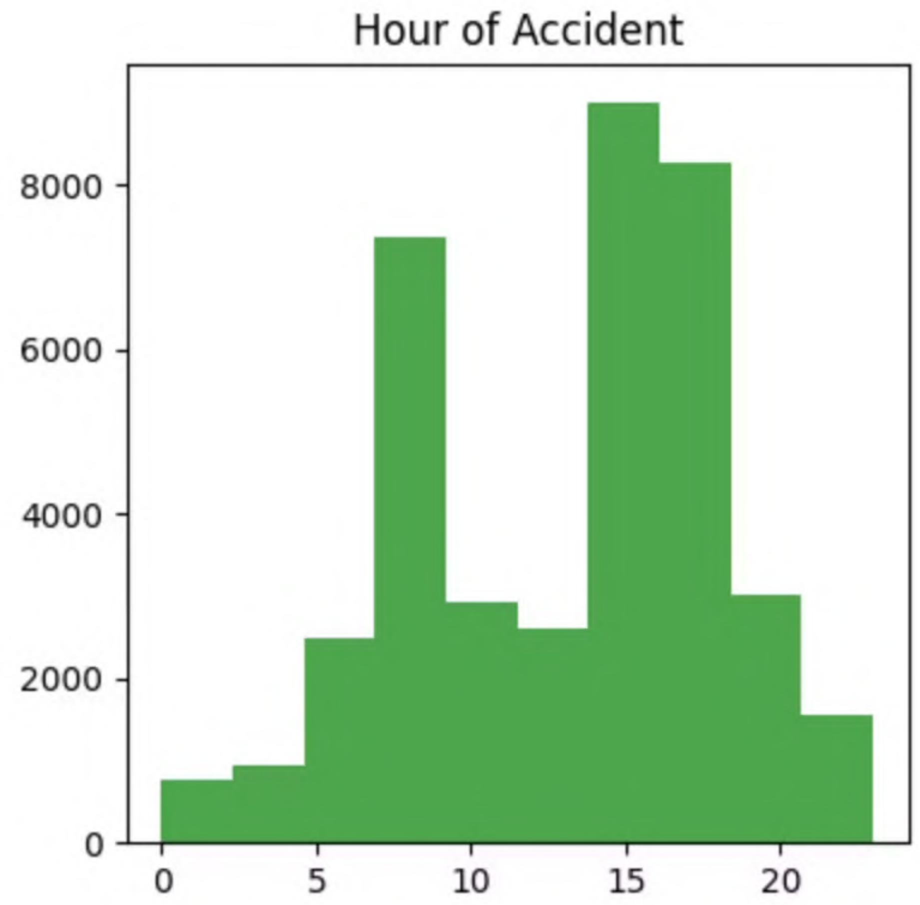
According to surveys, Charlotte ranks in top 10 worst public transportation systems

# EDA and Data Cleaning

Accidents in dataset: 39150



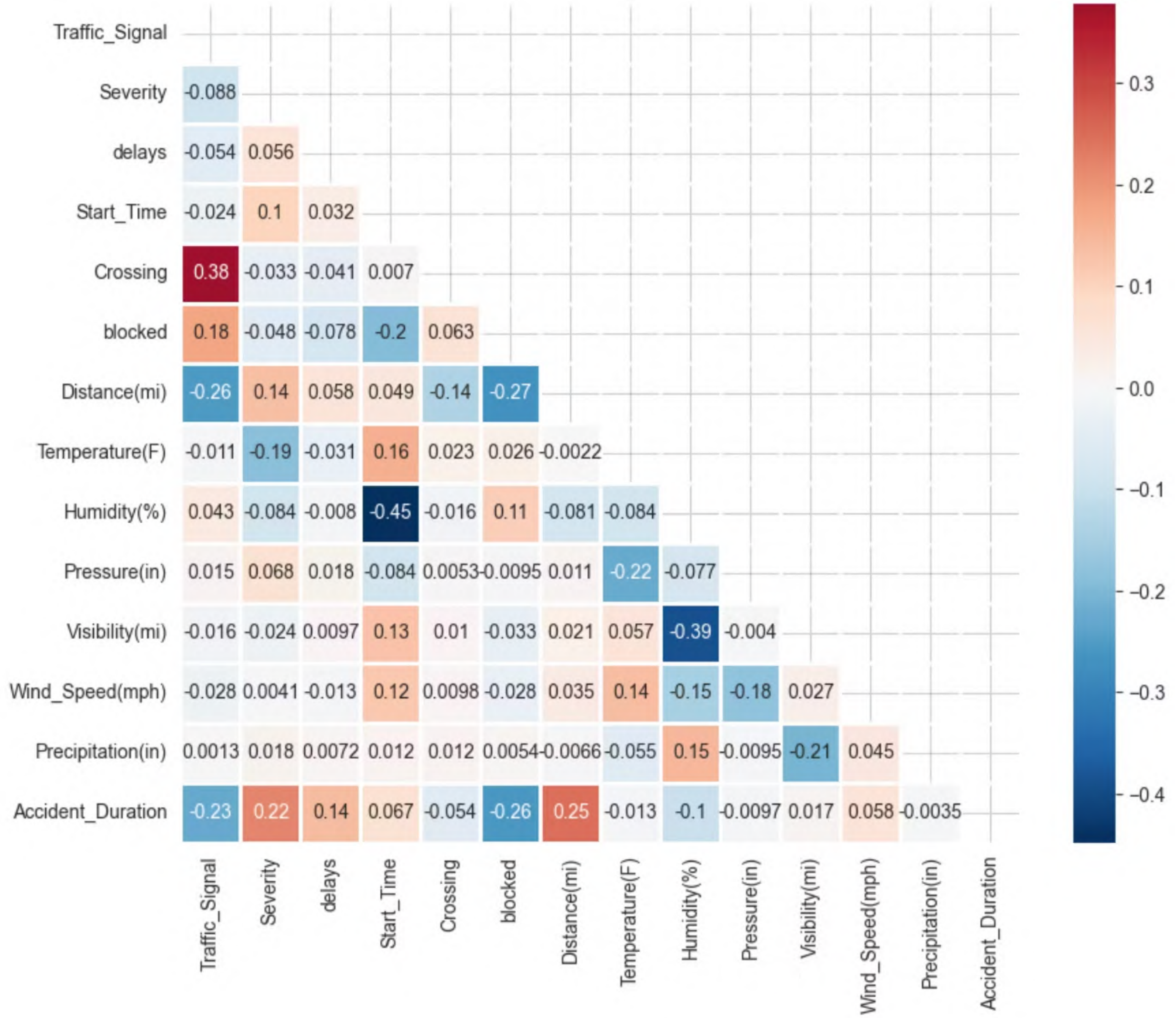



# Feature Engineering

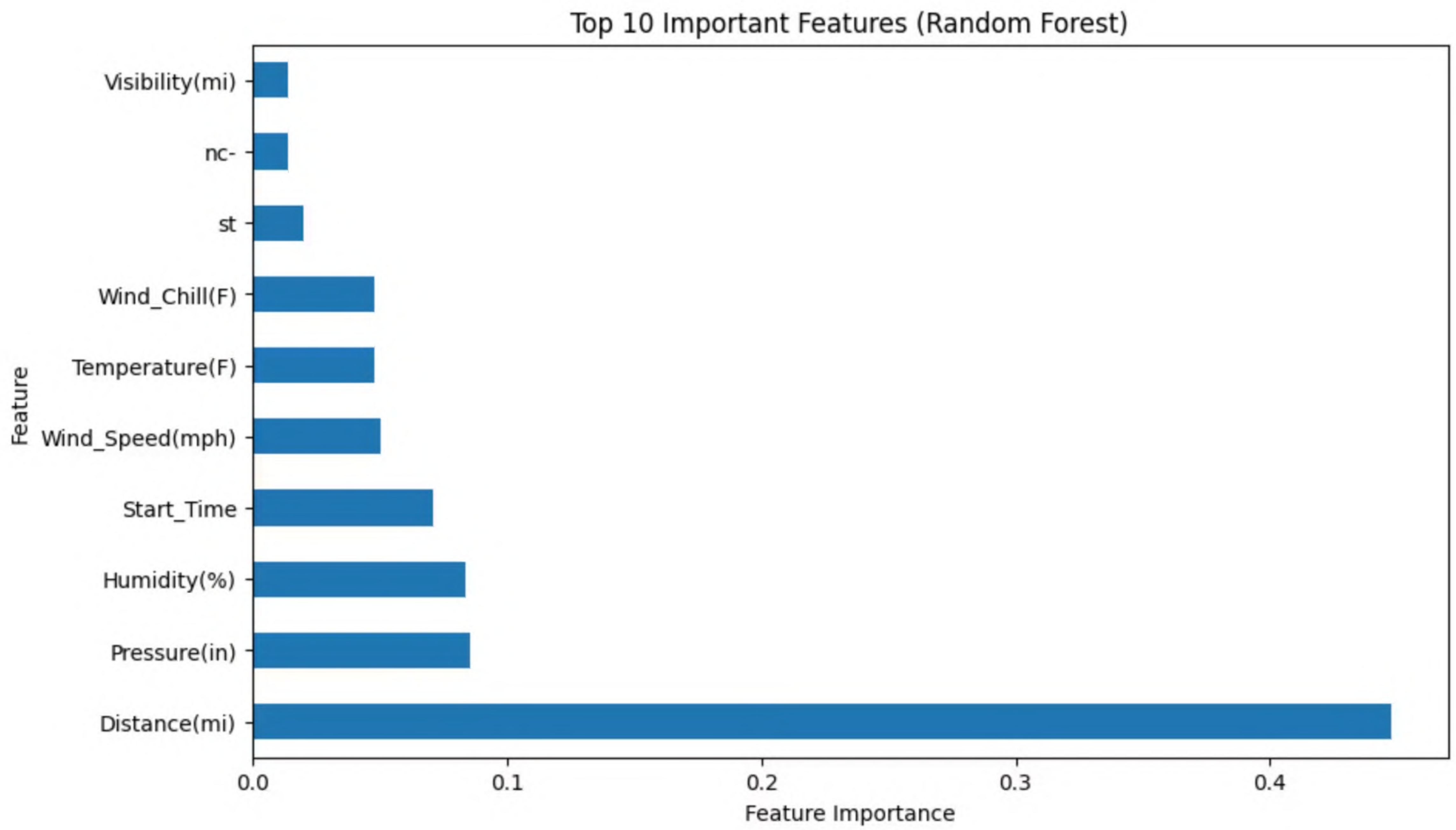
```python
target_column = 'Accident_Duration'
numeric_columns = df.select_dtypes(include=['number'])
correlation_matrix = numeric_columns.corr()
correlations = correlation_matrix[target_column].drop(target_column)
sorted_features = correlations.abs().sort_values(ascending=False)
print(sorted_features)
```

```
blocked              0.254254
Distance(mi)         0.243359
Traffic_Signal       0.223407
Severity             0.221620
delays               0.145592
Humidity(%)          0.096498
Start_Time           0.066515
Crossing             0.065914
Wind_Speed(mph)      0.059779
```

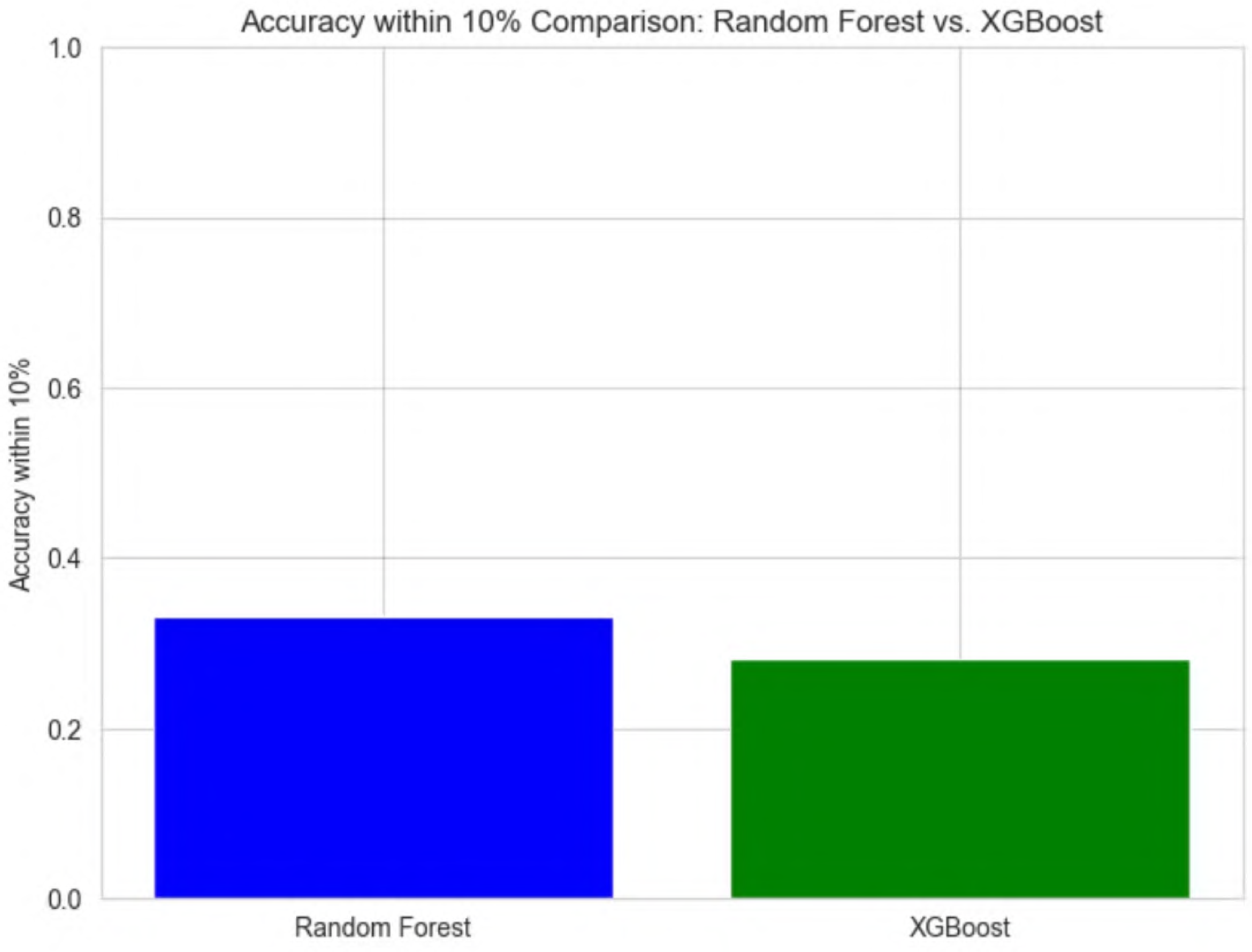



Features that I chose = ['Junction', 'blocked', 'Distance(mi)', 'Temperature(F)', 'Traffic_Signal', 'delays', 'Start_Time', 'Humidity(%)', 'Pressure(in)', 'Crossing', 'Wind_Speed(mph)']

# Feature Engineering

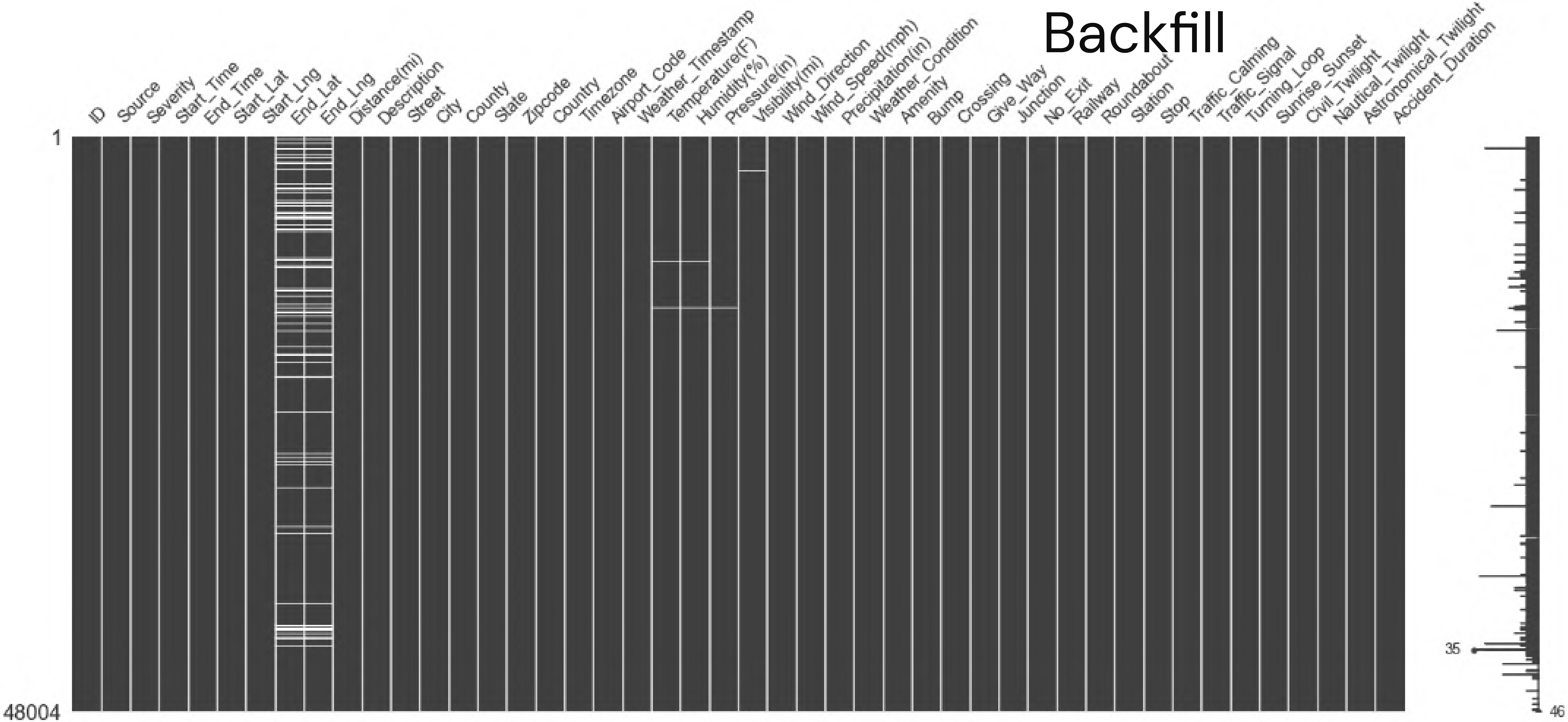


# Model Performance



# Orlando

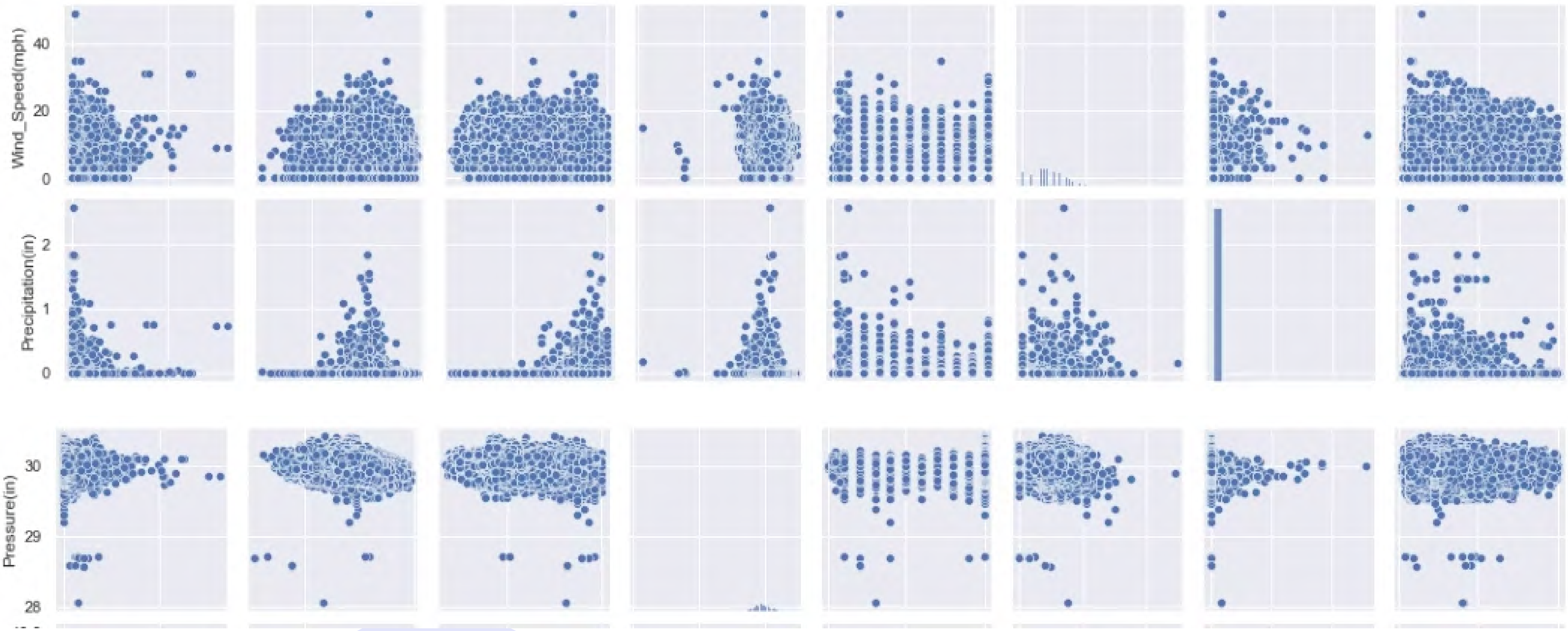
Backfill



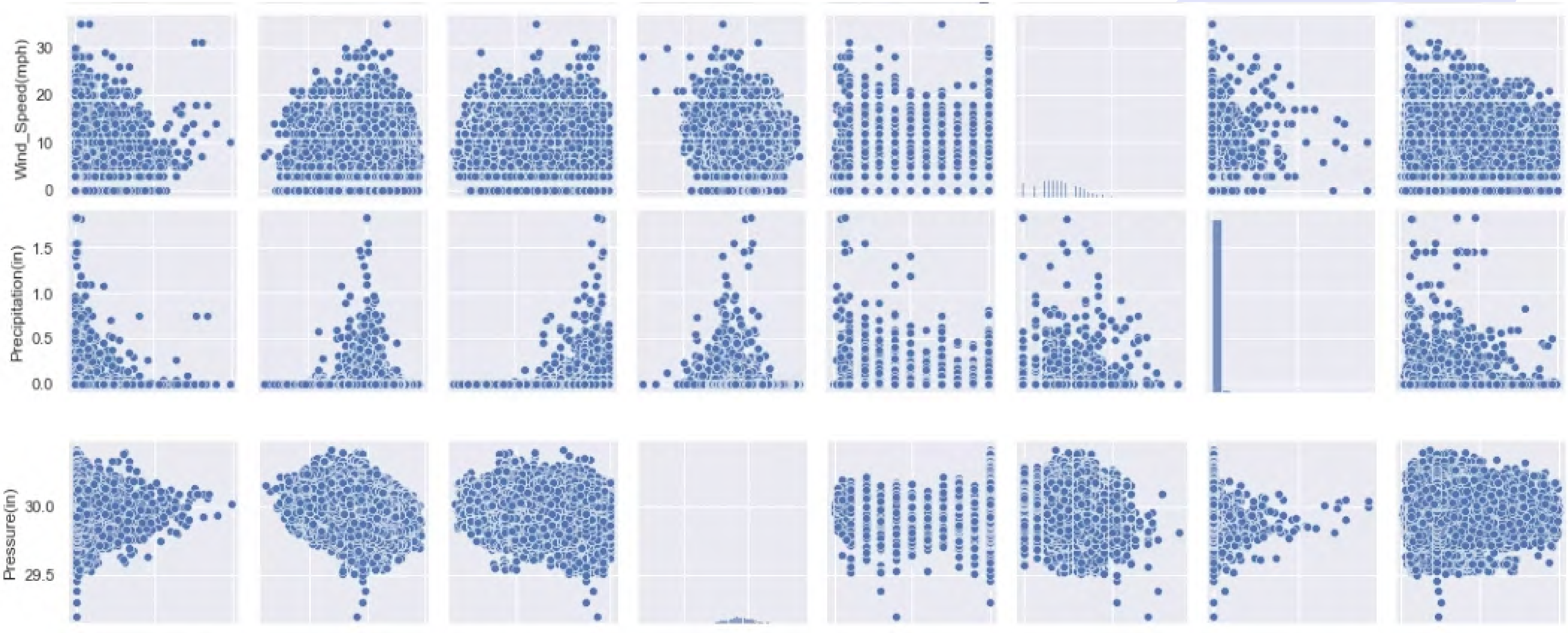

Try Pitch

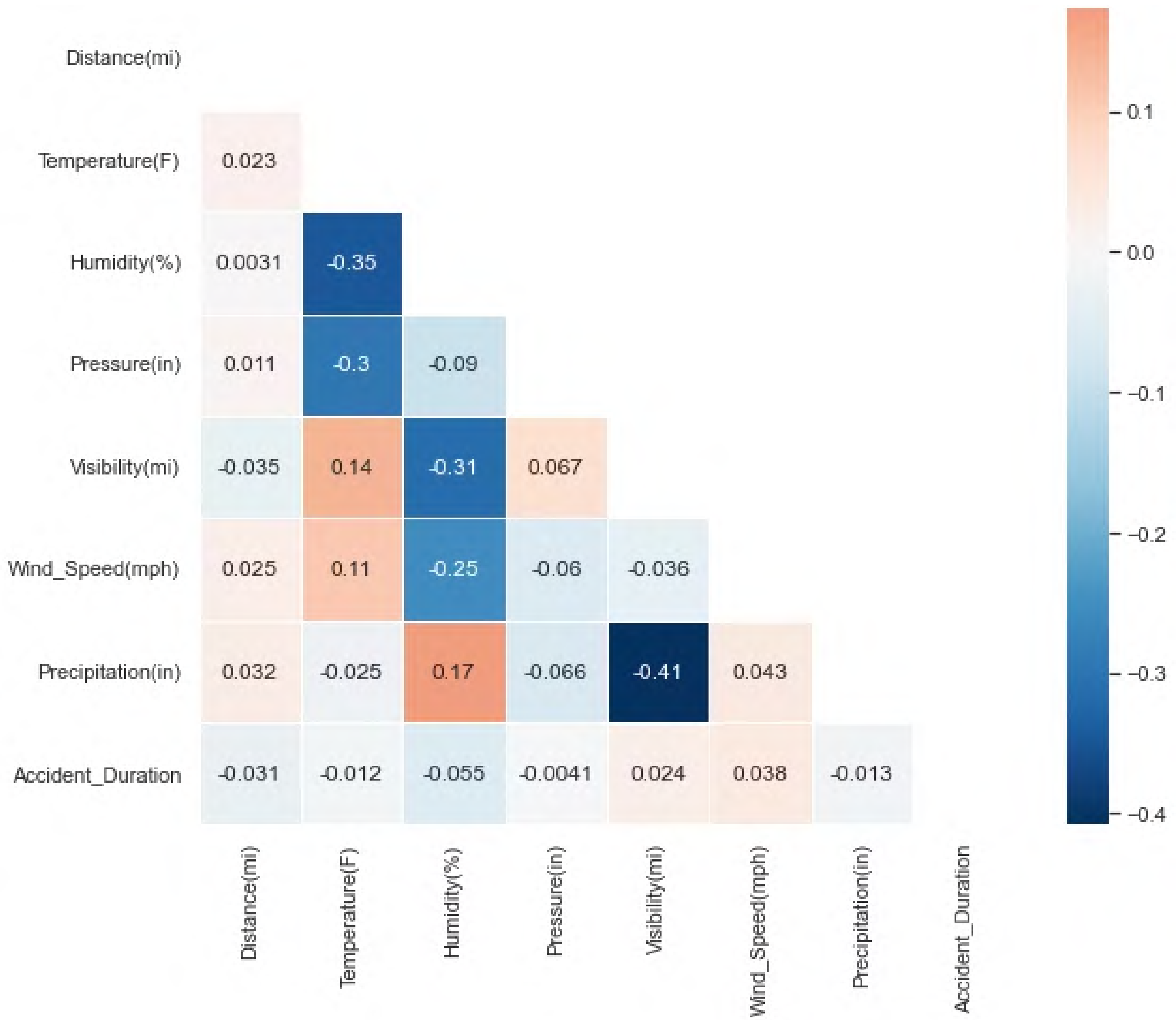
# Drop Outliers

```
df = df.drop(df[df["Distance(mi)"]>10].index)
df = df.drop(df[df["Pressure(in)"]<29].index)
df = df.drop(df[df["Wind_Speed(mph)"]>40].index)
df = df.drop(df[df["Precipitation(in)"]>2].index)
```




Try Pitch


Wind_Speed(mph)
Precipitation(in)
Pressure(in)



Distance(mi)
Temperature(F)
Humidity(%)
Pressure(in)
Visibility(mi)
Wind_Speed(mph)
Precipitation(in)
Accident_Duration
0.023
0.0031
-0.35
0.011
-0.3
-0.09
-0.035
0.14
-0.31
0.067
0.025
0.11
-0.25
-0.06
-0.036
0.032
-0.025
0.17
-0.066
-0.41
0.043
-0.031
-0.012
-0.055
-0.0041
0.024
0.038
-0.013
0.1
0.0
−0.1
−0.2
−0.3
−0.4

# Random Forest

```
rf_params = {'max_depth': randint(1,20), 'min_samples_split'
rf = RandomForestRegressor()
rf_random = RandomizedSearchCV(estimator=rf, param_distribut
rf_random.fit(X_train_std,y_train)
best_params = rf_random.best_params_
best_rf = RandomForestRegressor(**best_params)
best_rf.fit(X_train_std, y_train)
```

rmse: 2661.35

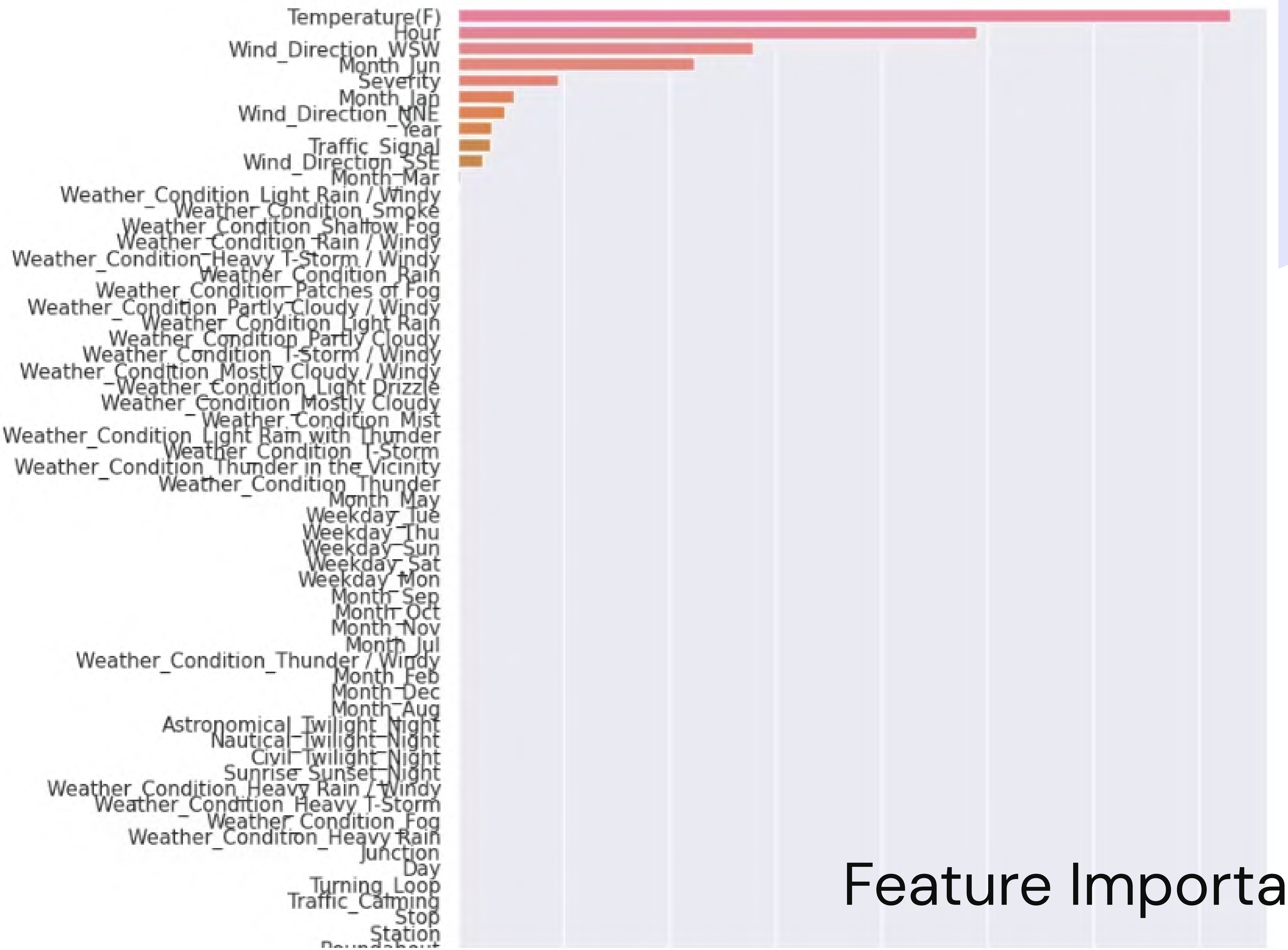
r2: 0.34

# Neural Network

```
def build_nn_model():
    model = Sequential()
    model.add(Dense(128, activation='relu', input_shape=(X_train_std.shape[1],)))
    model.add(Dense(64, activation='relu'))
    model.add(Dense(1))
    model.compile(optimizer='adam', loss='mean_squared_error')
    return model
```

rmse: 2731.53

r2: 0.30




# Feature Importance

# Miami,Florida

Most traffic accidents out of any city in the US

Past 2 years have seen 85,000+ reported traffic accidents

High tourism

Lots of congestion at peak hours

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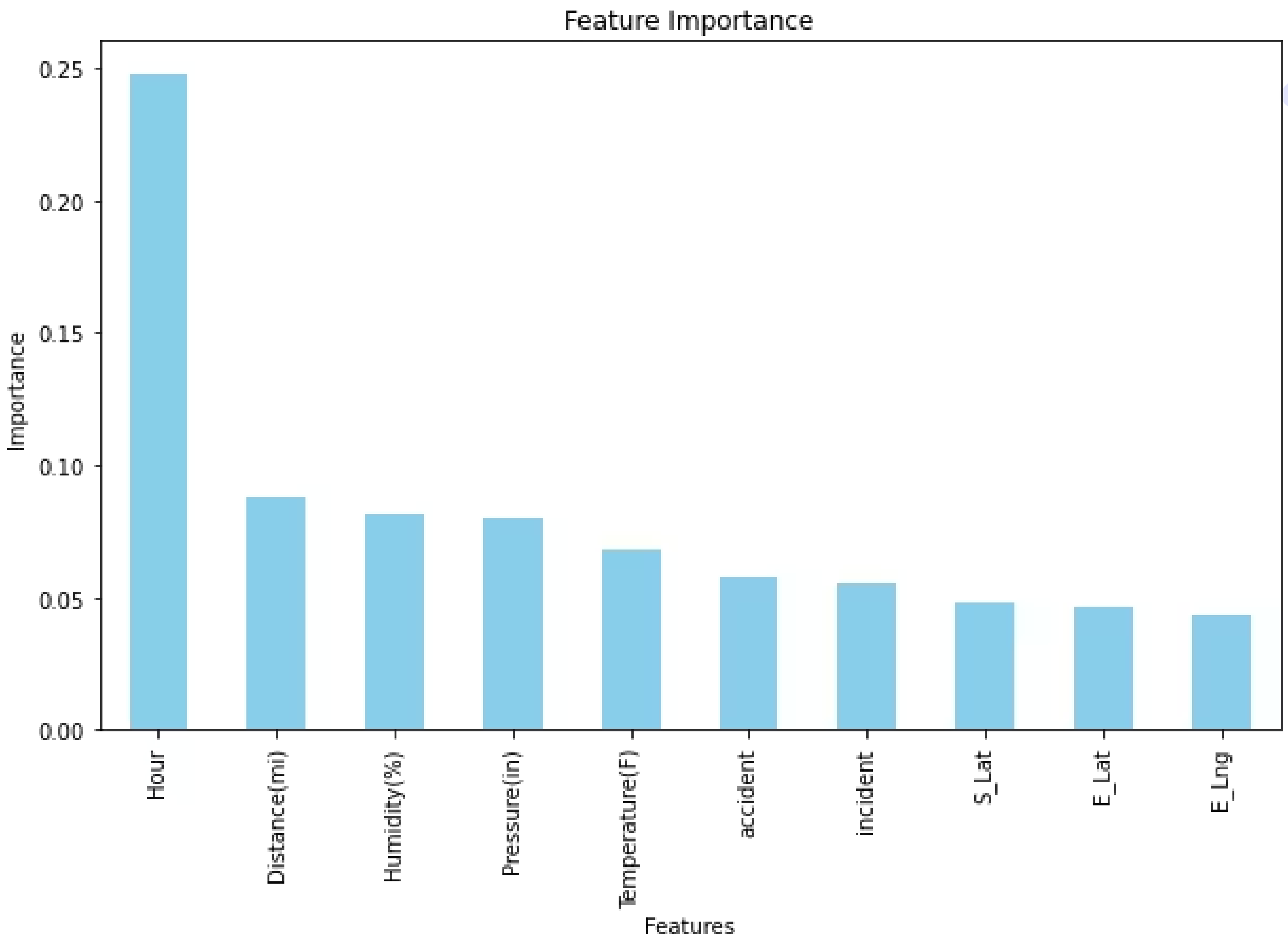
# Workflow

| Procedure | Details |
|---|---|
| 1. Exploratory Data Analysis | Understanding data, distributions, correlation coefficients with target variable |
| 2. Wrangling/Cleaning | Removing NAs, nonsensical data, replacing outliers with 3+ z-score |
| 3. Feature Engineering | Creating features from description text (Regex), discretization, creating day of week/hour features, one hot/binary encoding of non-numeric data, Lasso Regression and Decision Tree Regressors to identify salient variables/relative feature importance |
| 4. Model Testing | Baseline linear regression, random forest, XGBoost, MLP regressor (neural network), mse, r square score, accuracy within 10% |

# Feature Importance

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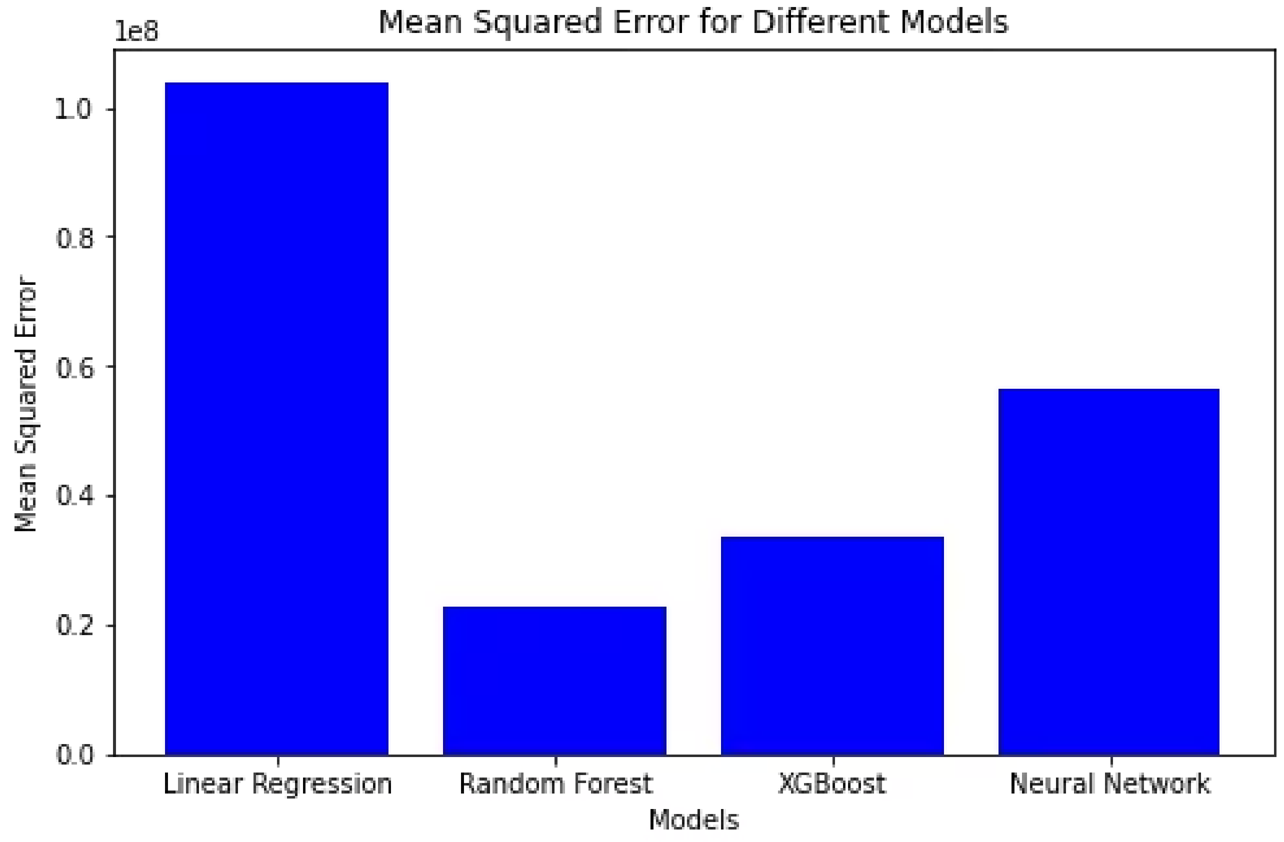
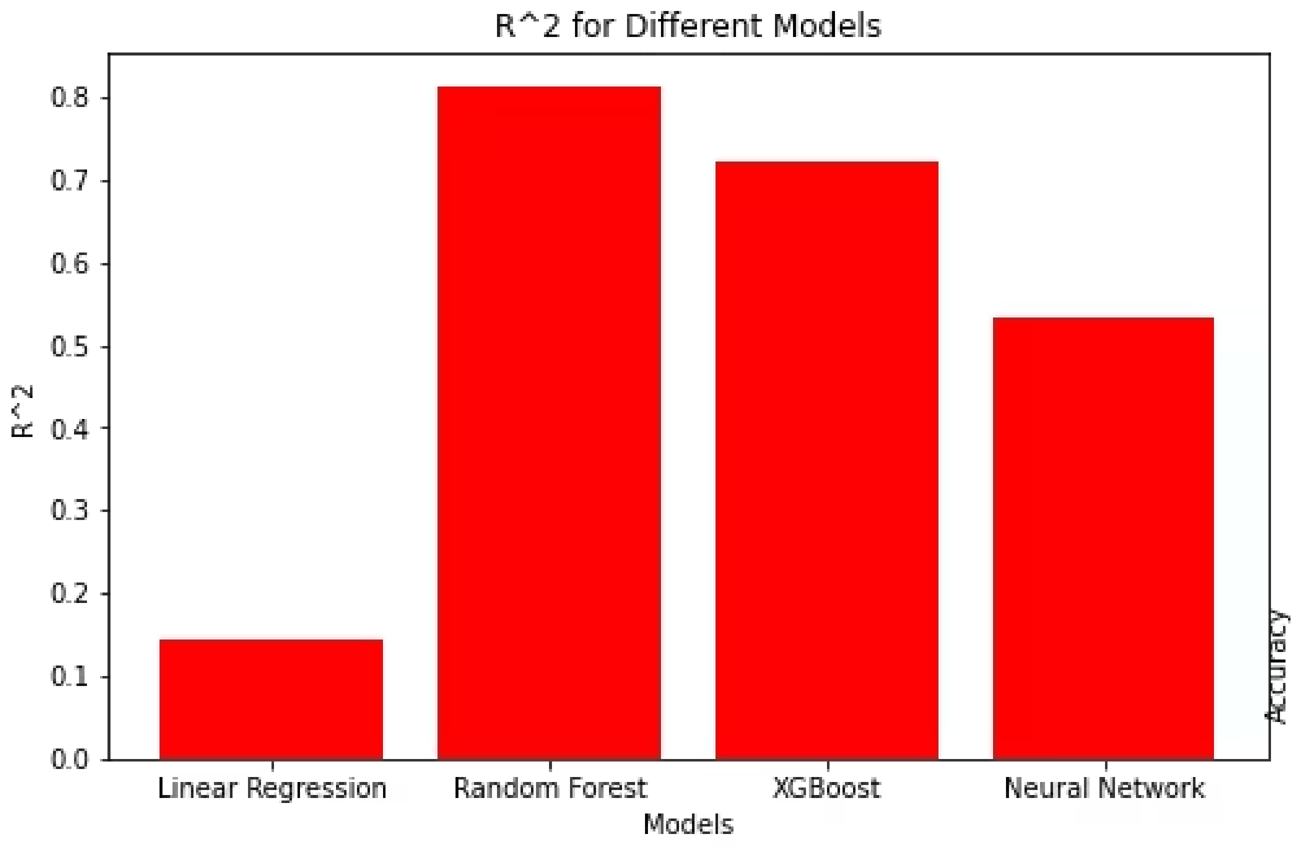
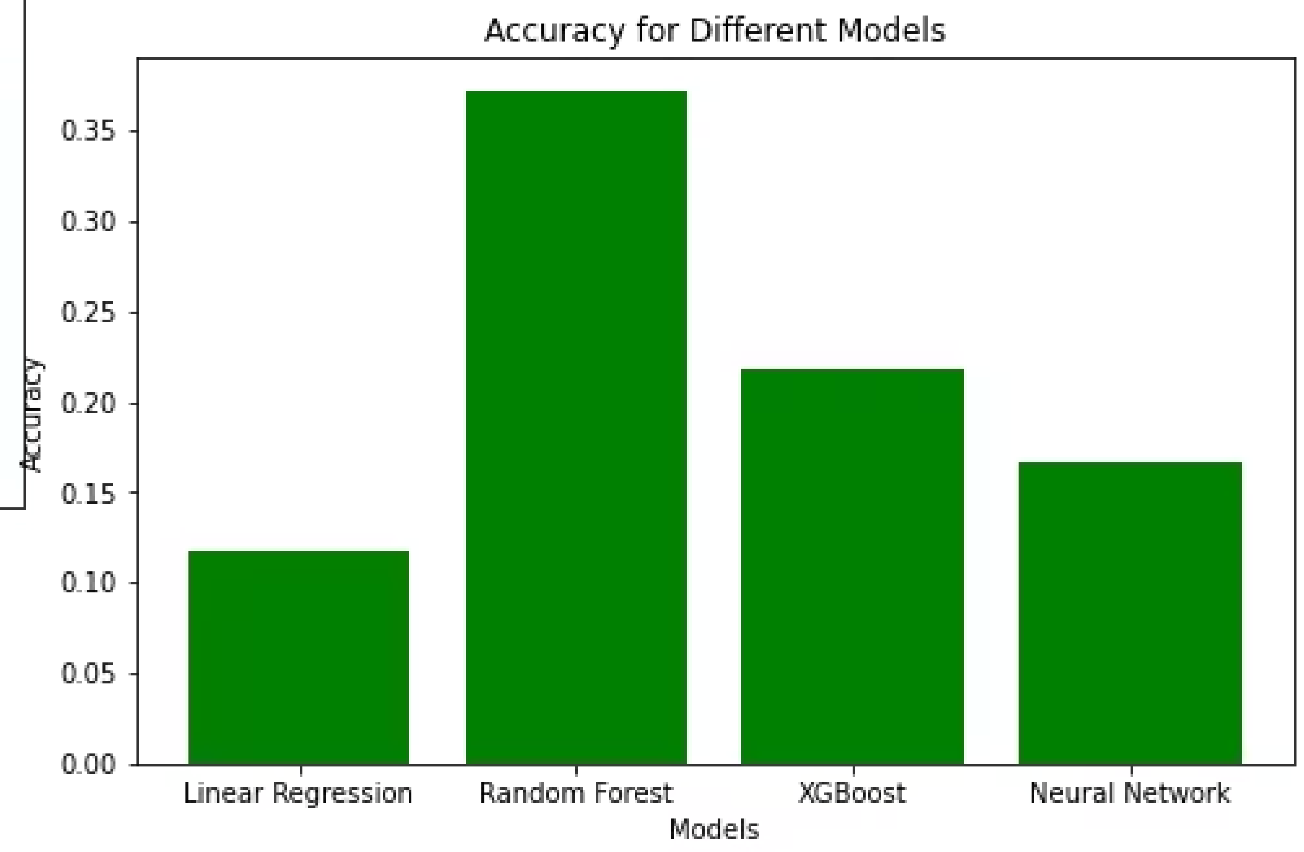
# Model Performance

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# Real World Application of Models

- Using our models raw estimates of accident durations could be computed for different cities
- Useful for web mapping service creators such as Google and Apple to increase accuracy of arrival time
- Emergency Service organizations would be able to analyze whether certain areas have accident durations that are longer than expected
- Drivers, commuters, etc can be notified of accidents and projected accident duration to plan accordingly

# General Limitations of Models

- Less than ideal model performance can be adjusted by training on a greater sample size of accidents
- Training/testing and hyperparameter tuning on more data would require much greater computational power and time which can be accomplished using distributed computing
- For most of the feature importance tables for Random Forests the distance feature dominated
- This can be adjusted by finding datasets with more detailed information geographic and driver information to add other important features

Pitch

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