SEA600 Machine Learning Assignment 1

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Project Github Link

Problem & Data Description

Objective

The objective of this machine learning project is to build a price prediction model for NYC FHV (For-Hire Vehicle).

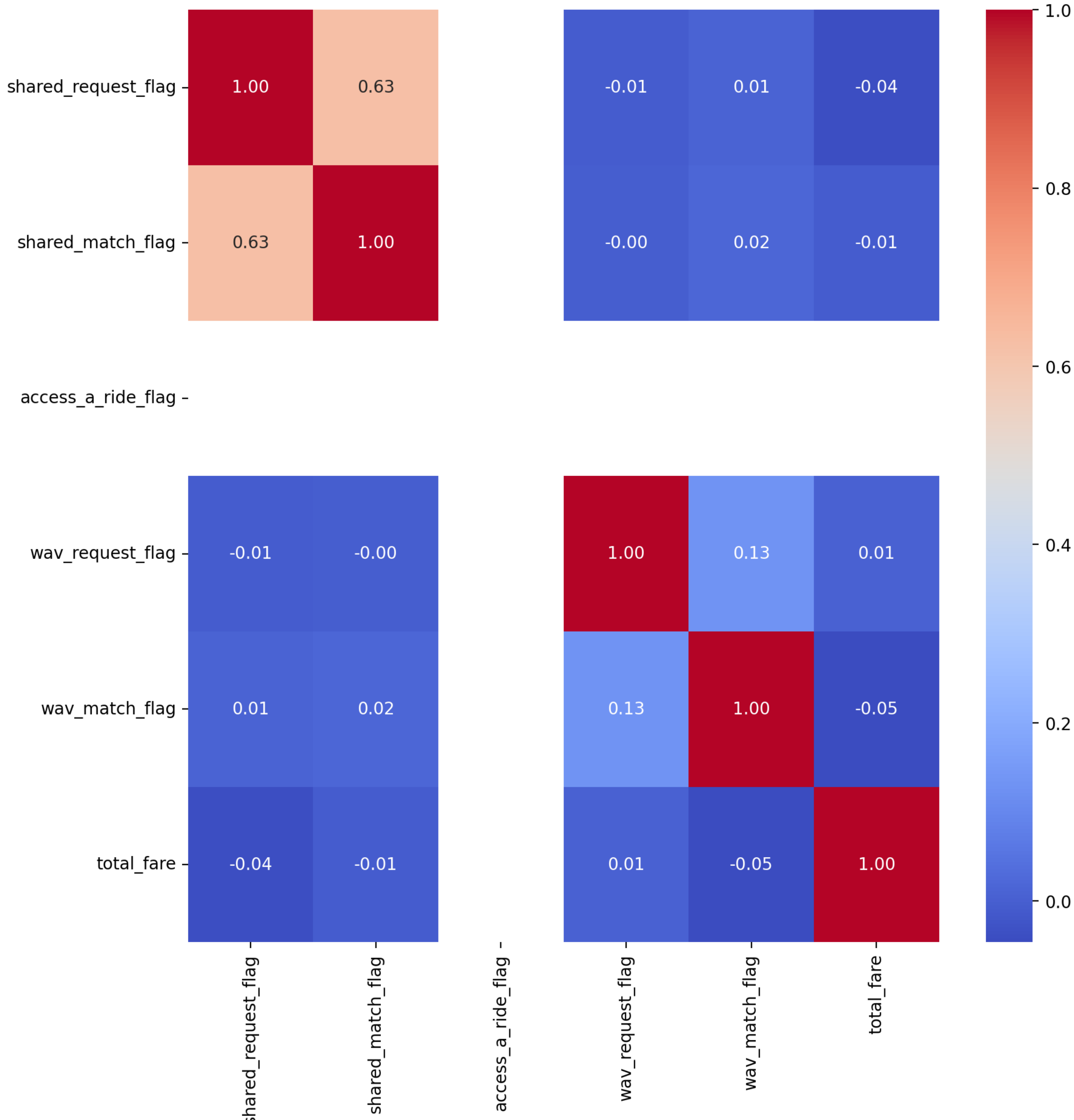
Introduction

The goal of this project is to build a price model that predicts ride fares for FHV in New York City. A regression model or a neural net model that can provide an expected output based on feature inputs will fit into this problem. The dataset used in this project can be found on the New York City government website. The size of the entire dataset is large, and we will use the latest subset (from November, 2022) for this project. Even though it's a subset, it still contains more than 18 million rows of data with 24 features. Thus, we will choose samples randomly from this dataset for training and testing. Due to the number of rows, models such as high degree (>3) regression, and non-linear SVR will not be explored as these models have high time complexity. Regarding societal, economic, health and safety, and regulatory factors that might affect the design, there's no edvidence that shows these factors would affect the design decision.

Preliminary Data Exploration and Preparation

This dataset contains 24 features (See ***Appendix I: Feature Data Dictionary***) and not all of them are useful, such as *Hvfhs_license_num*, *Dispatching_base_num* and *originating_base_num*, they only contain the information about the vehicle, which is irrelevant to the objective of this project.

Feature Selection Based on the correlation heatmap, we decided to drop these features: *shared_request_flag, shared_match_flag, access_a_ride_flag, wav_request_flag, wav_match_flag*.



In addition, features such as *driver_pay, tips, tolls, bcf, sales_tax, request_datetim, on_scene_datetime* are not useful nor relevant to the project objective. *Tolls* usually depend on the route chosen and *bcf* (black car fee) is random, thus, we excluded these fees in our model.

After cleaning up the columns, the new dataset will look like this:

index	pickup_datetime	dropoff_datetime	PULocationID	DOLocationID	trip_miles	trip_time	base_passenger_fare	congestion_surcharge	airport_fee
12201792	2022-11-20 11:02:45	2022-11-20 11:19:49	41	48	5.28	1024	25.21	2.75	0.0
5140632	2022-11-09 18:19:42	2022-11-09 18:26:37	157	82	1.39	415	10.64	0.00	0.0
13040156	2022-11-21 19:13:41	2022-11-21 19:33:56	163	125	4.79	1215	42.57	2.75	0.0

index	pickup_datetime	dropoff_datetime	PULocationID	DOLocationID	trip_miles	trip_time	base_passenger_fare	congestion_surcharge	airport_fee
2107754	2022-11-04 17:47:21	2022-11-04 18:03:00	10	130	2.21	939	14.28	0.00	0.0
17227919	2022-11-29 15:29:02	2022-11-29 15:33:30	210	210	0.63	268	7.51	0.00	0.0

Data Visualization (See ***Appendix II: Data Visualization***)

After data visualization, we can clearly see a linear relationship between trip miles and base fare, trip time and base fare.

Regarding the airport fee and congestion surcharge, we see that most trips have 0 fee for both and nearly 40% of the trips were charged with a congestion fee of 2.75.

Statistic

Statistic	pickup_datetime	dropoff_datetime	PULocationID	DOLocationID	trip_miles	trip_time	base_passenger_fare	congestion_surcharge	airport_fee
count	100000	100000	100000.00000	100000.00000	100000.000	100000.00	100000.00000	100000.00000	100000.0000
mean	2022-11-15 19:57:13.143010	2022-11-15 20:17:03.214390	139.92574	143.09041	5.04131	1191.8698	23.806279	1.140580	0.215383
min	2022-11-01 00:00:43	2022-11-01 00:09:03	3.00000	1.00000	**0.00000**	**1.00000**	**-33.250000**	0.000000	0.000000
25%	2022-11-08 15:01:34.750000	2022-11-08 15:21:22.250000	76.00000	76.00000	1.59000	609.00000	11.430000	0.000000	0.000000
50%	2022-11-15 19:52:28.500000	2022-11-15 20:10:41	141.00000	142.00000	3.00350	972.00000	18.030000	0.000000	0.000000
75%	2022-11-22 19:08:38	2022-11-22 19:32:05.750000	211.00000	219.00000	6.25500	1524.0000	29.240000	2.750000	0.000000
max	2022-11-30 23:59:30	2022-12-01 00:38:28	265.00000	265.00000	186.54000	14994.000	**551.620000**	5.500000	5.000000
std	NaN	NaN	74.690144	77.634162	5.86778	850.07404	19.883770	1.351592	0.703936

Given the statistic above, we see that data cleaning is required: there's negative *base_passenger_fare*, zero *trip_miles* and one-second *trip_time*.

In this case, we will only keep rows with *base_passenger_fare* greater than 5 dollars, *trip_miles* greater than 1 and *trip_time* greater than 5 mins and less than 2 hours.

Feature Engineering

Fare, Airport Trip and Congestion Since the dataset only contains a base fare column called *base_passenger_fare*, we will construct a new column called ***total_fare*** which is the sum of the base fare, congestion surcharge and airport fee.

Although the *airport_fee* and *congestion_surcharge* are numerical, given the data visualization result earlier, these features shall be treated as categorical features. Therefore, we will construct new features to represent these original features to reduce the cardinality.

For *airport_fee*, we will construct a new feature called ***is_airport_trip*** which will contain 1s and 0s indicating whether there's an *airport_fee*.

For *congestion_surcharge*, we will construct a new feature called ***congestion_lvl*** based on the congestion surcharge:

surcharge	congestion level	description
0	0	no congestion
less than 2	1	low congestion
less than 3	2	medium congestion
greater or equal than 3	3	high congestion

Trip Time The statistic shows that the *trip_time* column needs attention. Instead of using the original feature, we will construct a new feature *trip_time_real* deriving from the *dropoff_datatime* and *pickup_datetime*.

DateTime More information can be extracted from the *dropoff_datetime* and *pickup_datetime* features such as year, month, day of week, hour etc.

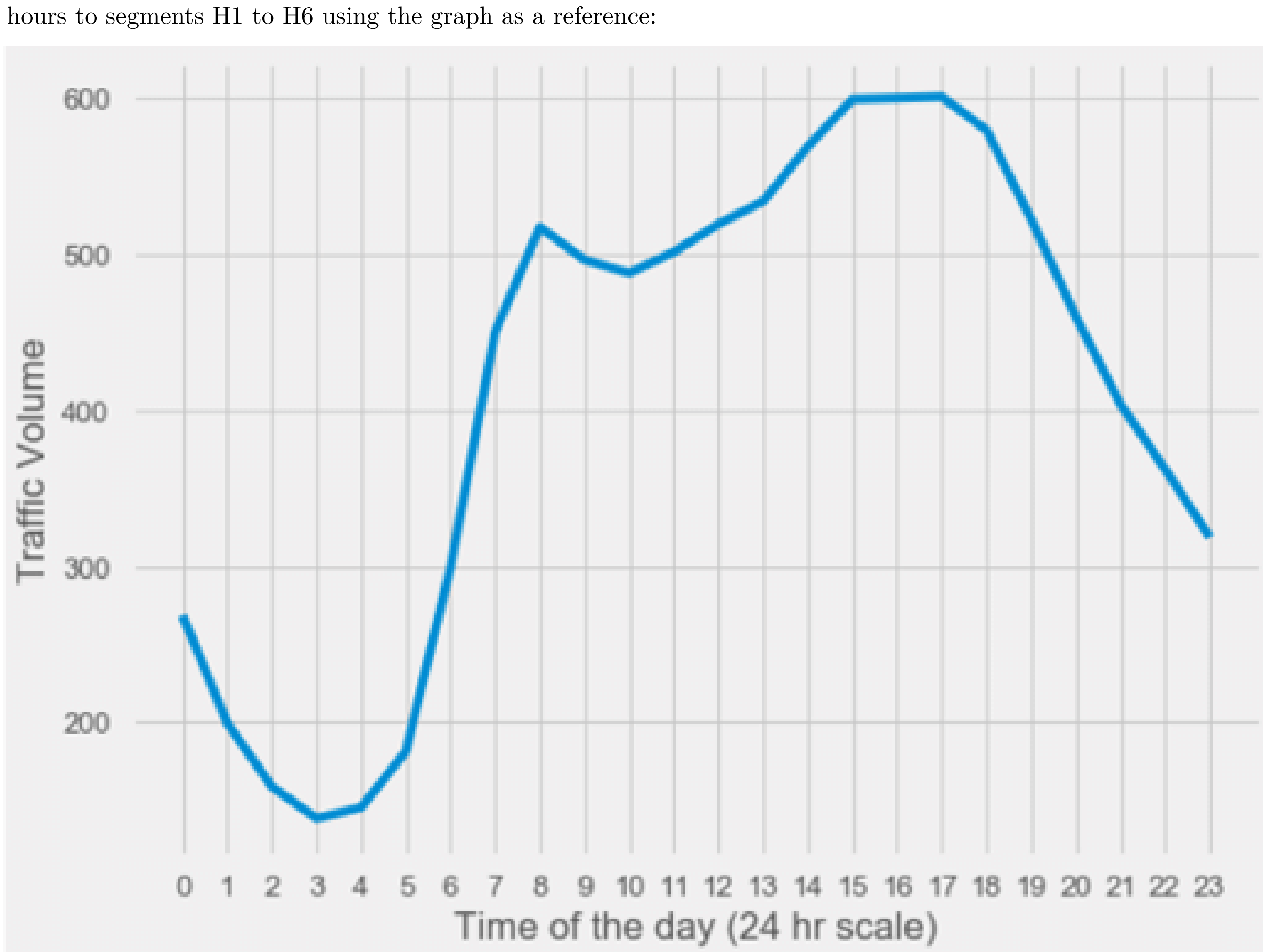
Given the data is collected in the same month, in this case, we will only consider the day of the week and hour, thus, two features we can generate are ***pickup_day_no*** which contains values from 0 to 6 mapping Monday to Sunday and ***pickup_hour*** containing hour value from 0 to 23.

Location *PULocationID* and *DOLocationID* are categorical features, which contain 262 possible values each. Using one-hot encoding is not feasible. We will discuss more about these features later in this report.

Encoding The ***pickup_hour*** feature has 24 possible values and ***pickup_day_no*** has 7. Using One-Hot Encoding will increase the dimension by 31. Other encoding methods are not really applicable to these features. Thus, we have decided to divide these features into segments.

For ***pickup_day_no***, we simply reduce the categories to weekday and weekend.

For ***pickup_hour***, we map the hours to segments H1 to H6 using the graph as a reference:



Source: A Paradigmatic Approach to Exploratory Data Analysis Utilising New York's Road Traffic to Derive Coherent Inferences

H1 will map hours with traffic volume under 200, H2 is between 200 to 300, . . . , H6 is greater than 600.

Other Considerations and Exploration Done

Consideration 1: Target Encoding for *PULocationID* and *DOLocationID* We considered encoding *PULocationID* and *DOLocationID* because we thought these might be useful features. However, One-Hot Encoding will increase the dimension of features by more than 500. Therefore, we considered Target Encoding, which makes the most sense and is more relevant among other encoding methods.

Thoughts: The fare amount will depend on the *DOLocationID*, if we do feature-cross before encoding, the new feature might not be very helpful since it will just be the average fare between two locations.

Consideration 2: Feature Crossing *pickup_day_no* and *pickup_hour* The fare amount at 5:00 a.m. Monday will be very different from the fare amount at 5:00 p.m. Friday. Each hour on a different day can be considered as a 'category' itself. If we do feature cross, by simply appending the values, for instance, Monday at 5 a.m. would be '05' and Friday at 5 p.m. would be 617, we will have 168 categories. With a high-cardinal feature, we may apply Target Encoding.

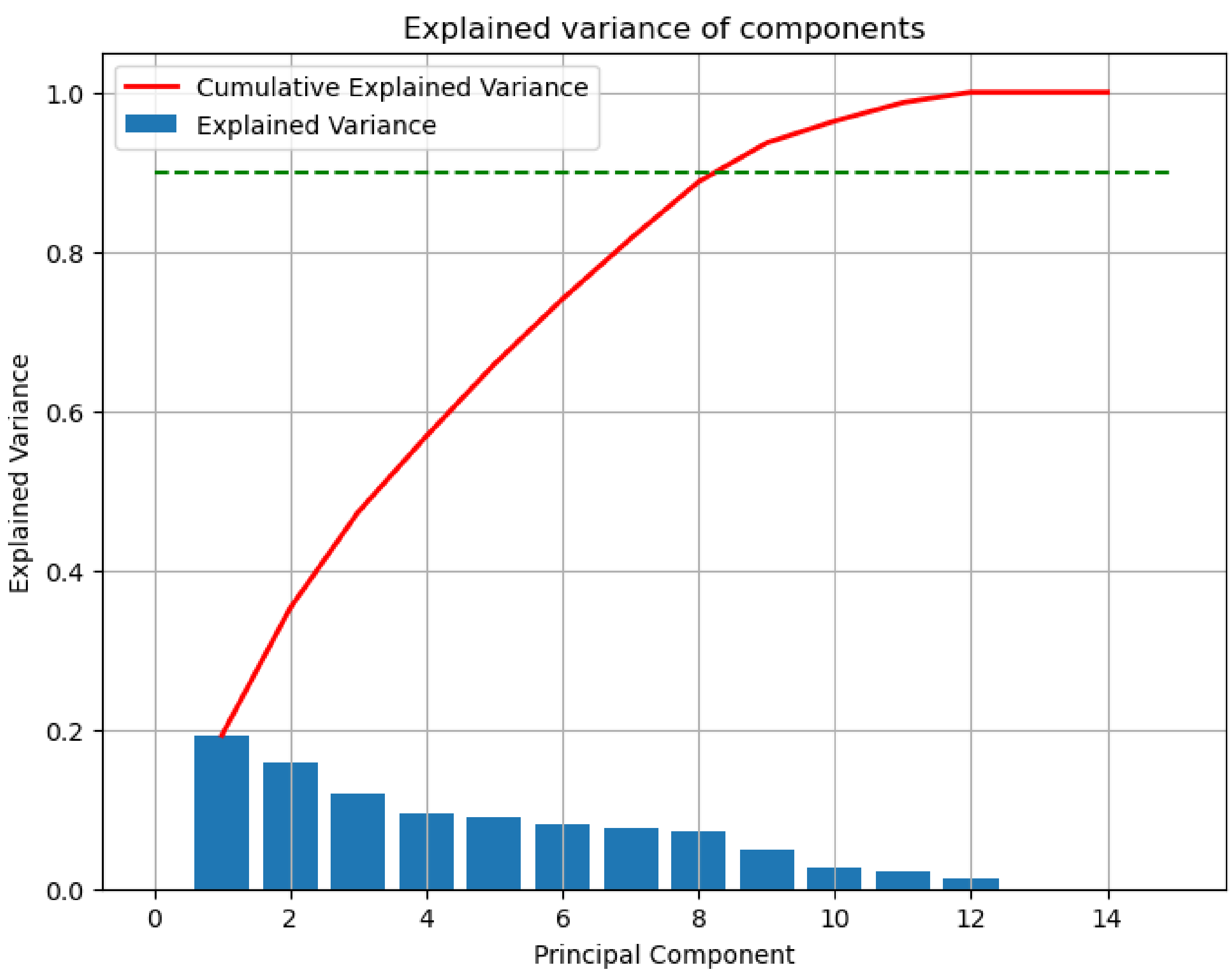
Thoughts: Feature cross is possible but target encoding can be problematic since the total fare largely depends on the distance travelled. If we use *total fare* as the target, it will create inaccurate encoding. If we create a new feature called *fare_per_mile*, it will be more accurate.

Challenge One main challenge that target encoding poses is that we cannot use cross-validation on the training set since the features are engineered using the training target value. And the complexity of constructing an actual pipeline is high. Thus, we will create a dedicated validation set in the custom pipeline.

In the pipeline, we take extra samples from the dataset, then we use Train-Test Split to split the data into training and test sets, and then we split the test set again into validation set and test set.

Other explorations: We tried crossing *day*, *time* and *locations*, making a *wait_time* feature using *pickuptime - onscene_time* , making time related features such as *is_morning*, *is_afternoon* and no evidence shows that they have considerable impact on the model.

PCA PCA in this case was not helpful. We could use PCA to reduce the dimension of the data but we get increased error. Based on the result, only a couple of features can be reduced without really affecting the accuracy. Therefore, we decided not to use PCA.



Processed Dataset

After cleaning up the dataset and feature crossing and encoding, this is how the dataset looks like.

trip_miles	is_airport_trip	congestion_lvl	trip_time_real	hourly_segments_H1	. . .	hourly_segments_H6	day_segments_WD	day_segments_WK	total_fare	enc_day_x_time	enc_PUxDOL
1.660	0	2	12.667	0	. . .	0	1	0	17.91	5.371463	22.811771
4.240	0	0	15.583	1	. . .	0	0	1	16.91	5.977721	25.739411
2.690	0	0	11.050	0	. . .	0	0	1	12.50	4.534792	24.736056
1.867	0	0	8.033	0	. . .	0	1	0	11.53	5.753829	23.149589
4.380	0	0	15.067	0	. . .	0	1	0	15.10	6.306063	24.531976

Model Training (with 20000 samples)

From previous experiments and observations, we decided to train and evaluate these models:

- Linear Regressor: the data visualization shows a linear relationship
- Polynomial Regressor: other features such as the engineered features might have a non-linear relationship with the target
- Ridge Regressor: ridge regressor can filter out useless features
- KNN Regressor: given the data points are sparse, KNN might be more accurate

Linear Regressor

Simple Linear Regressor will act as our baseline model. In the project, we did simple regression with datasets with and without the encoded features. In addition, we did validation and cross-validation.

MSE	With E-features	Without E-features
Validation	88.032151	89.146471
Cross Validation	66.030708	70.319246

The result indicates that the model with E-features performs slightly better.

E-featuers: *enc_day_x_time and enc_PUxDOL*

Validation: *using the validation set from the pipeline.*

Cross Validation: *using the training set from the pipeline, the E-features are engineered using target encoding, which might affect the result if we use the dataset with E-features*

Polynomial Features - Linear Regressor

Which Degree? Due to limited computational power, we were only able to try out degrees 2, 3 and 4 with cross-validation. Results indicated that degree 2 will best fit the dataset.

degree	mean MSE with E-features	mean MSE without E-feature
2	55.596956258167644	69.7306410526892
3	68.49016039277582	80.10497379604051
4	3645844246931548.0	1008693765148216.1

Degree 2 Poly Regressor MSE

MSE	With E-features	Without E-features
Validation	122.386827	79.897460
Cross Validation	62.504570	74.498702

Ridge Regressor

Parameters:

```
ridge = Ridge(alpha=3, solver='sag', fit_intercept=True)
```

MSE Result:

MSE	With E-features	Without E-features
Validation	88.044958	89.148403
Cross Validation	66.046759	70.313172

Poly Ridge: With the Polynomial feature of degree 2, the Ridge Regressor performs the same as the Linear Regressor with the polynomial feature degree 2 based on the grid search result.

```
Best parameters: {'alpha': 9, 'fit_intercept': True, 'solver': 'lsqr'}
Best score: -55.55625956334685
```

KNN Regressor

Parameters:

```
knn = KNeighborsRegressor(n_neighbors=5)
```

MSE Result:

MSE	With E-features	Without E-features
Validation	95.597957	105.013722
Cross Validation	67.921930	83.407372

Resource Utilization (With E-features)

Time: (ms)

	Linear	Poly_Linear_2	Ridge	KNN
Overall	27.1	207	40.3	153
Fitting	5.98	73.6	24.2	5.28
Predicting	3.72	0.842	1.52	95.9

Memory: (peak memory in MiB, Increment in Mib)

	Linear	Poly_Linear_2	Ridge	KNN
Overall	259.47, 4.66	296.00, 36.5	281.42, 1.93	283.22, 1.80
Fitting	253.58, 0.00	284.34, 33.92	288.03, 3.69	290.20, 2.17
Predicting	235.84, -7.23	240.25, 0.41	242.75, 0.03	243.50, 0.50 MiB

Final Model

To choose the final model, we will consider the model with the lowest value when:

- Single validation is used when there are E-features
- Cross-validation is used when there are no E-features

In addition, the resource usage of this model is acceptable.

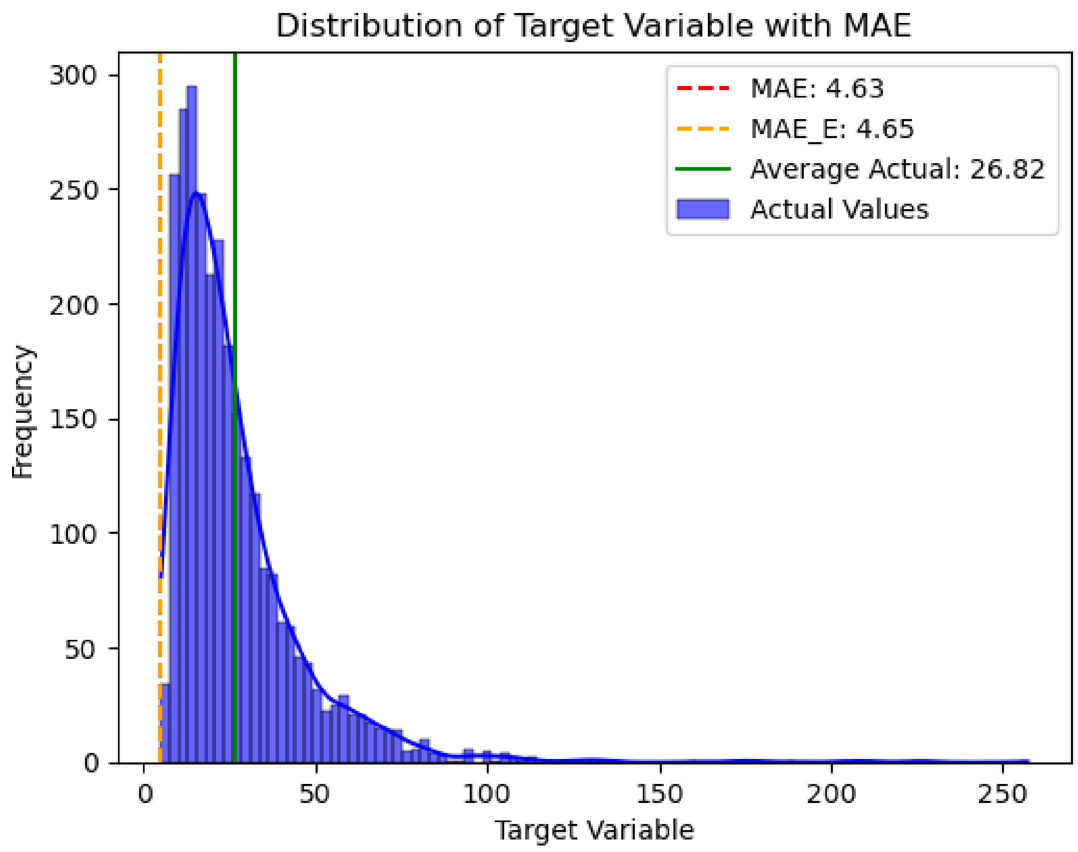
These parameters are used based on the grid search result:

```
Best parameters: {'alpha': 3, 'fit_intercept': True, 'solver': 'sag'}
Best score: -66.02571857571097
```

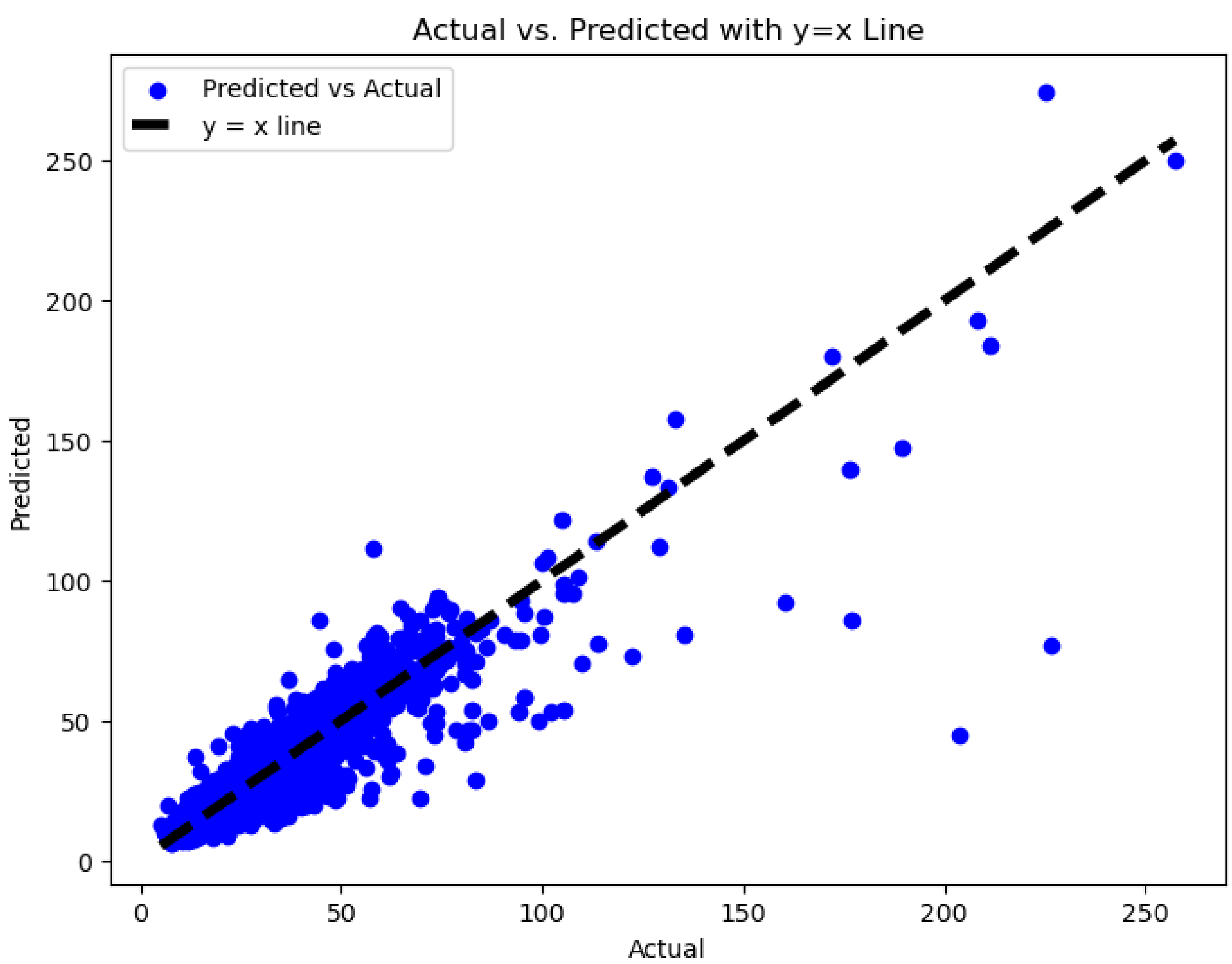
We trained 2 models with and without the E-features and in this case, the results are pretty similar:

	With E-features	Without E-features
MAE	4.6459	4.6256

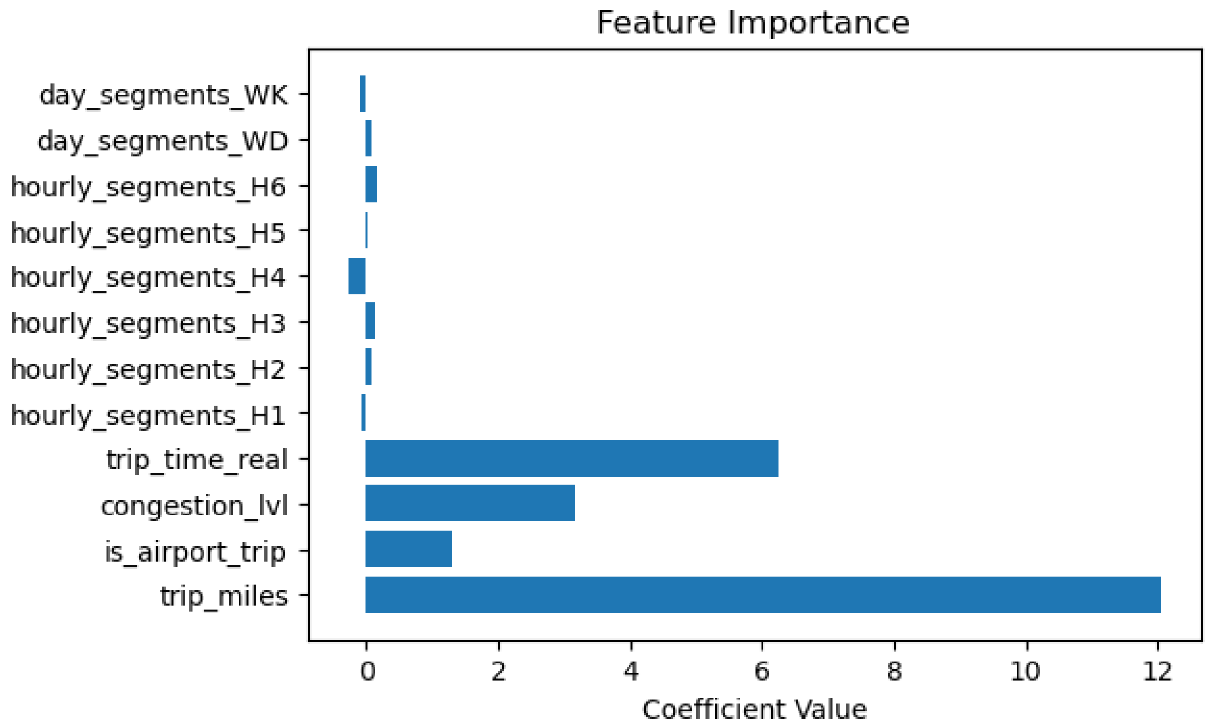
Compared to the range of 25 to 75 percentile, the **MAE% is 25.09%**.



Below is the scatter plot of Actual vs Predicted Value.



Below is the feature importance:



We use the traffic volume chart as a reference to divide the hour segments. H6 is the rush hour, 3 - 5 p.m. and the model was able to capture this information. In addition, the fare is higher if it's a weekday and lower at weekends. However, the date and time information does not contribute largely to the fare. The fare mainly depends on the trip miles and trip time.

Summary & Reflection

This project was a simple linear regression project, however, it's not simple to come up with an accurate model. The challenges we faced was the resources. The dataset contains 18 million rows, the amount of data was simply too much for data exploration and experiment purposes. Therefore, we only sampled a subset of it for experiment and model training. In addition, the results changes as the number of sample changes as well.

The majority of the effort was spent on feature engineering as we were trying to make use of the pickup and drop-off locations, and the day and time. However, these features have high cardinality, and PCA was not a good solution, we had to find other ways to keep the useful information provided by these features yet keep the dimension as low as possible. Target encoding was a good way to encode features with high cardinality but it poses challenges mentioned earlier in this report. The final result also shows that feature crossing and encoding did not significantly improve the regression model. However, it might be useful for a neural network model if we add an embedding layer after feature crossing to address the high cardinality. In addition, a pipeline is needed for this project since it involves feature selection and engineering. To reduce the complexity of the experiment, a custom pipeline was built for data processing. For details, please see ***Appendix III: Custom Pipeline***

We also spent some time exploring different models such as LinearSVR, Stacking Regressor, ElasticNet, Lasso, RandomForest etc. These models came up with similar or event worse results and some of them requires additional resources. Thus, they were not used in the final code and report.

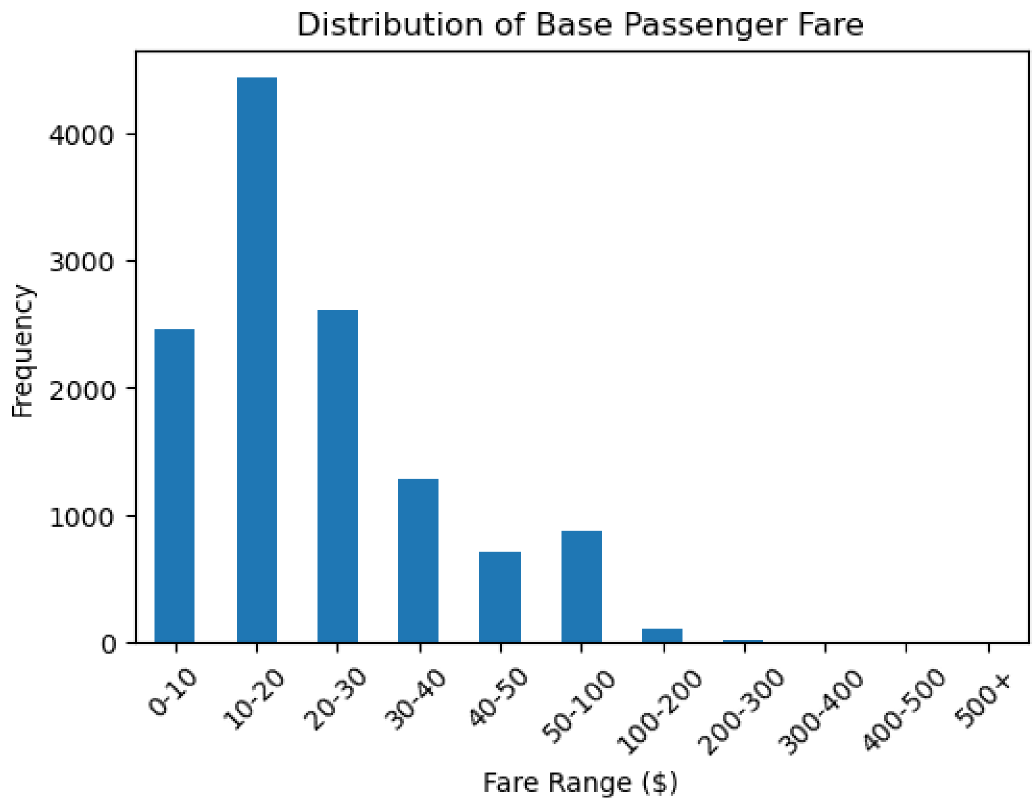
Conclusion: based on the experiments, using feature engineering and differnt models result in similar error: around 4.5. We consider the model acceptable given the data itself is sparse, i.e. the prices of the same trip can vary. To make this model more accurate, we could consider other factors such as weather, and include more data samples and data from other month and year. Other model such as neural network might be used instead to improve the accuracy.

Appendix I: Feature Data Dictionary

Field Name	Description
Hvfhs_license_num	The TLC license number of the HVFHS base or business. HVFHS licensees include Juno (HV0002), Uber (HV0003), Via (HV0004), Lyft (HV0005).
Dispatching_base_num	The TLC Base License Number of the base that dispatched the trip
Pickup_datetime	The date and time of the trip pick-up
DropOff_datetime	The date and time of the trip drop-off
PULocationID	TLC Taxi Zone in which the trip began
DOLocationID	TLC Taxi Zone in which the trip ended
originating_base_num	Base number of the base that received the original trip request
request_datetime	Date/time when passenger requested to be picked up
on_scene_datetime	Date/time when driver arrived at the pick-up location (Accessible Vehicles-only)
trip_miles	Total miles for passenger trip
trip_time	Total time in seconds for passenger trip
base_passenger_fare	Base passenger fare before tolls, tips, taxes, and fees
tolls	Total amount of all tolls paid in trip
bcf	Total amount collected in trip for Black Car Fund
sales_tax	Total amount collected in trip for NYS sales tax
congestion_surcharge	Total amount collected in trip for NYS congestion surcharge
airport_fee	$2.50 for both drop off and pick up at LaGuardia, Newark, and John F. Kennedy airports
tips	Total amount of tips received from passenger
driver_pay	Total driver pay (not including tolls or tips and net of commission, surcharges, or taxes)
shared_request_flag	Did the passenger agree to a shared/pooled ride, regardless of whether they were matched? (Y/N)
shared_match_flag	Did the passenger share the vehicle with another passenger who booked separately at any point during the trip? (Y/N)
access_a_ride_flag	Was the trip administered on behalf of the Metropolitan Transportation Authority (MTA)? (Y/N)
wav_request_flag	Did the passenger request a wheelchair-accessible vehicle (WAV)? (Y/N)
wav_match_flag	Did the trip occur in a wheelchair-accessible vehicle (WAV)? (Y/N)

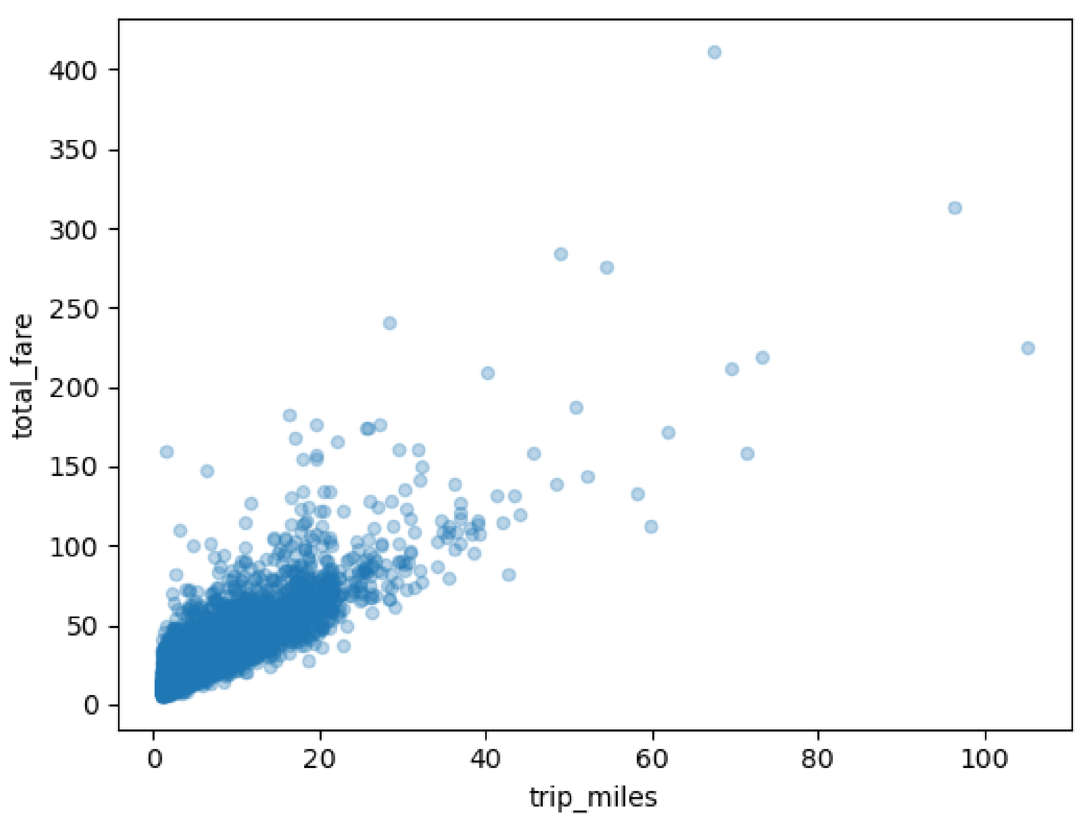
Appendix II: Data Visualization

Base Fare Distribution

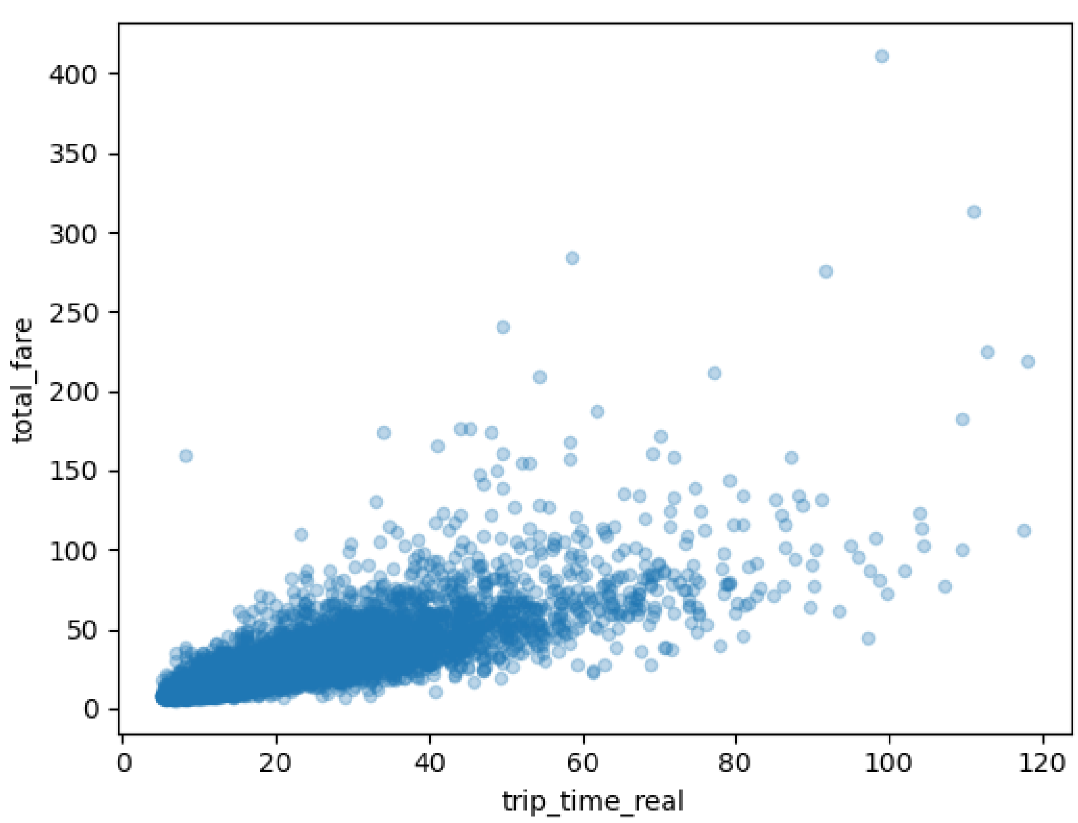


As shown in the graph, the majority of the data are in range of 0 to 30.

Trip Miles vs Fare

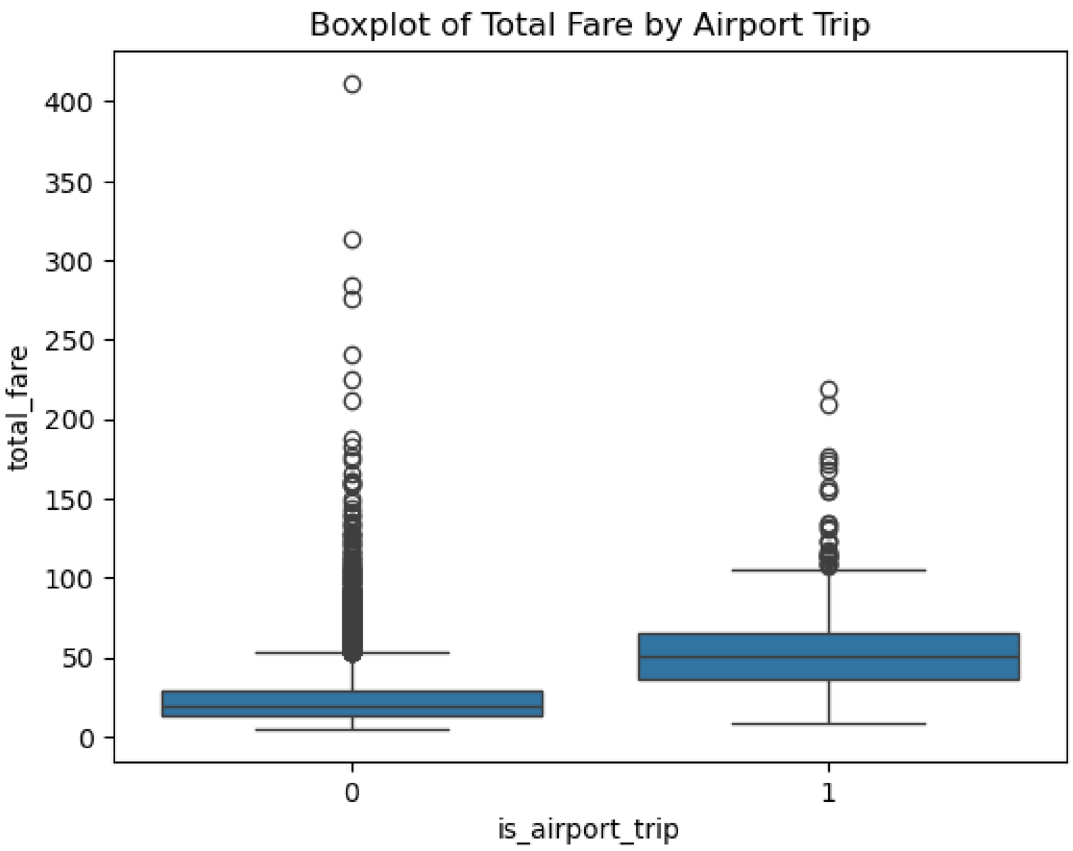


Trip Time vs Fare



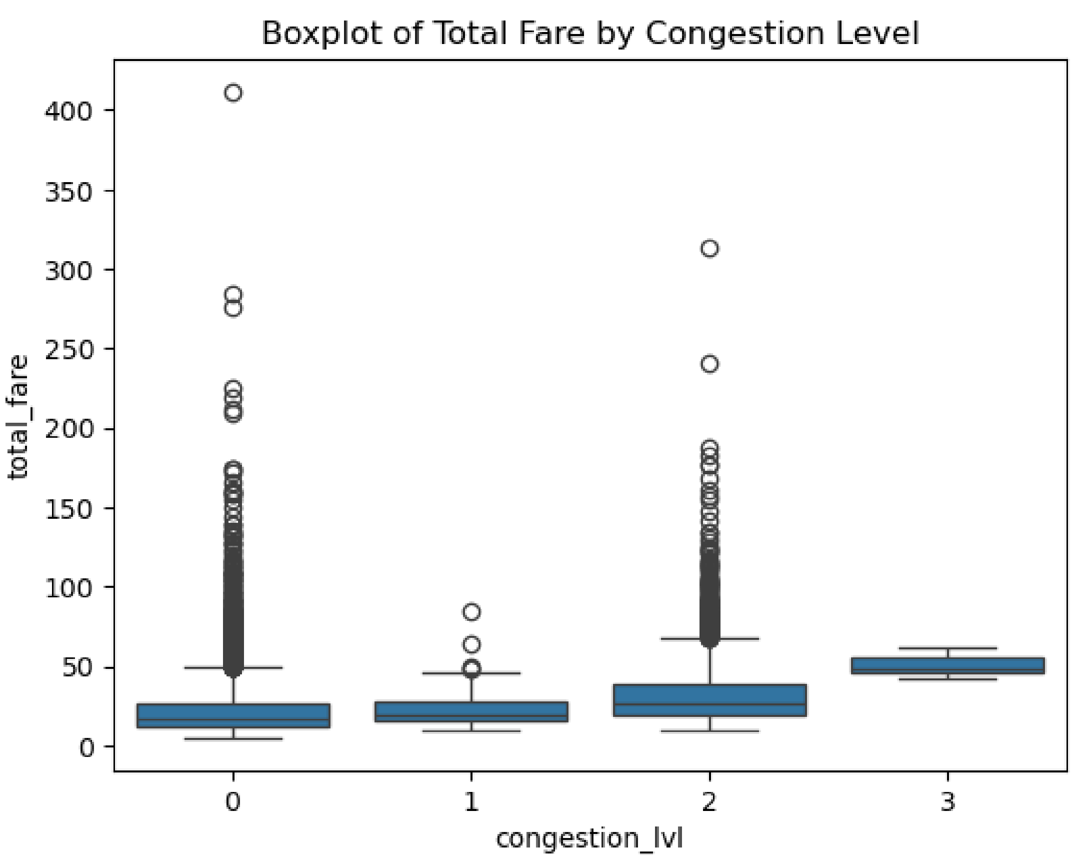
These graphs show linear relationship between miles, trip time and total.

Airport Trip vs Fare

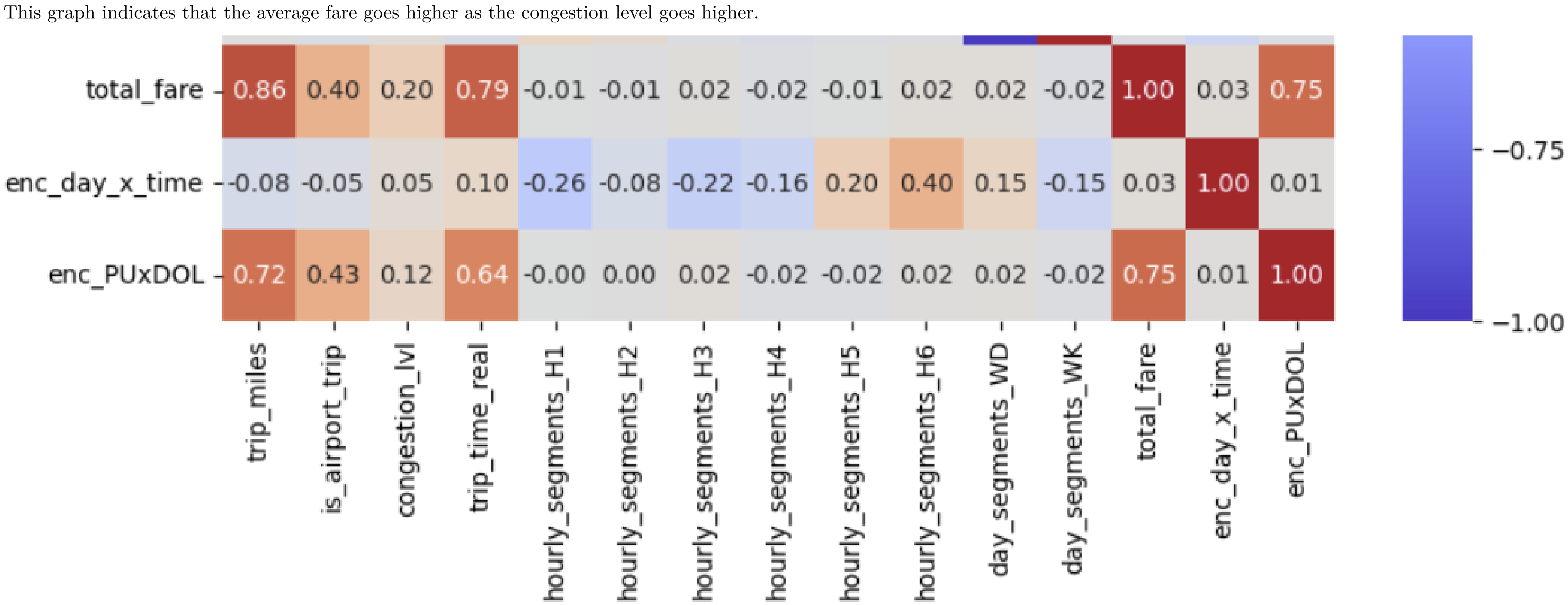


This graph indicates that the average fare of an airport trip is higher than non-airport trip.

Congestion Level vs Fare



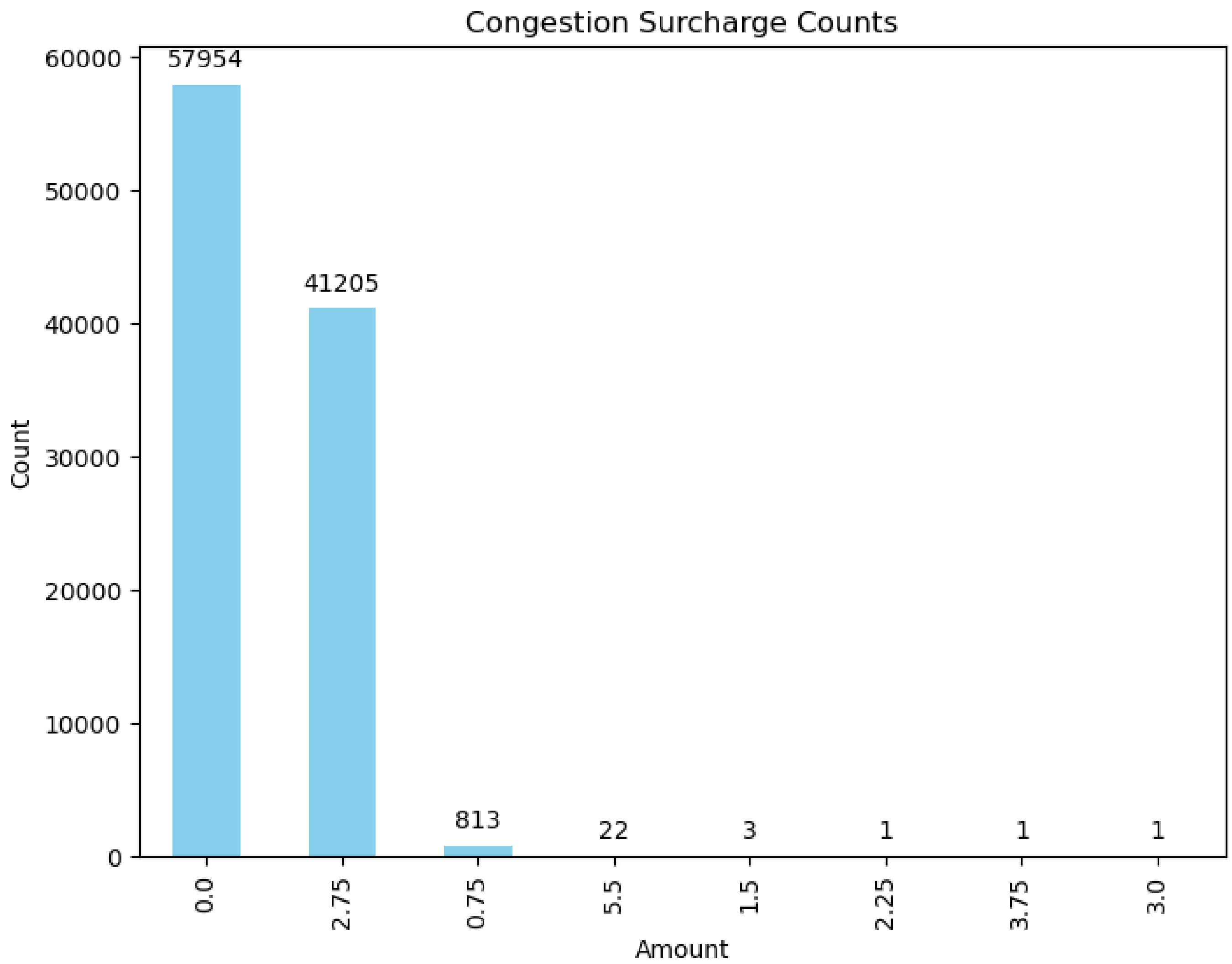
This graph indicates that the average fare goes higher as the congestion level goes higher.

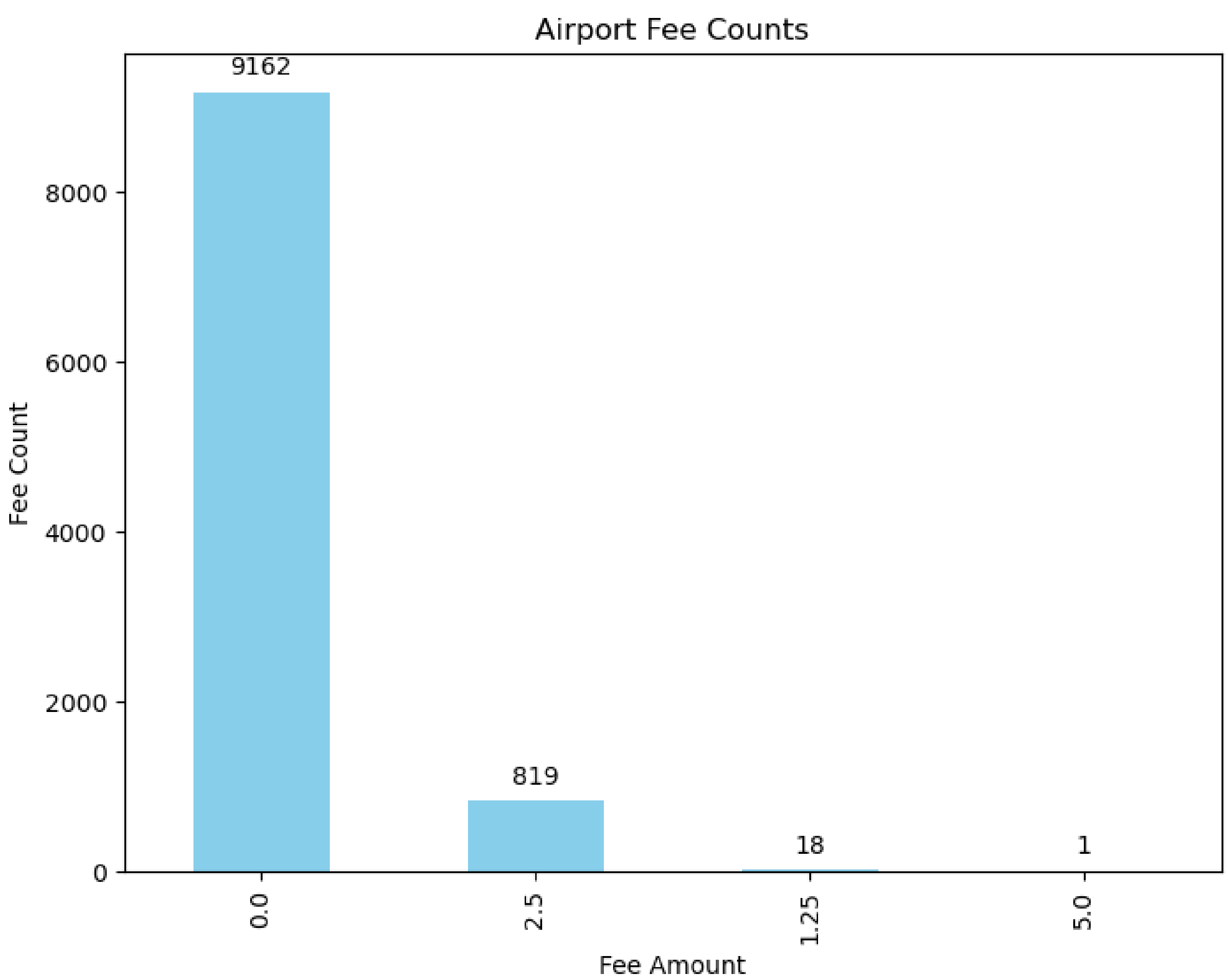


This heatmap indicates strong correlations between the target and trip miles, time, is airport trip, and congestion level.

The enc_PUxDOL variable here can be redundant. It's the pickup location cross drop-off action and encoded using the target variable, information that this variable provides shall be captured by the trip miles already.

Congestion and Airport Fee Counts





The above graphs show that there are only a few possible values for congestion surcharge and airport fees. Thus, these can be treated as categorical features.

Appendix III: Custom Pipeline

The FHVProcessPipeline takes an FHV dataset file and returns a training set, validation set, test set and the original dataset without unuseful columns.

Following are the steps in the pipeline:

Step 1. Dropping Columns:

Irrelevant columns are dropped in this step:

`['hvfhs_license_num', 'dispatching_base_num', 'originating_base_num', 'shared_request_flag', 'shared_match_flag', 'access_a_ride_flag', 'wav_request_flag', 'wav_match_`

In addition, the returned original dataset is the result of step 1.

Step 2. Feature Engineering

In this step, new features are engineered:

- is_airport_trip: 1 if air_port fee is not zero and 0 otherwise.
- congestion_lvl: map the congestion surcharge to the congestion level from 0 to 3. (No congestion to high congestion)
- trip_time_real: dropoff_datetime - pickup_datetime
- total_fare: sum of base_passenger_fare, airport_fee and congestion_surcharge
- pickup_day_no: day of the week in numerical format, ranging from 0 - 6 (Mon - Sun)
- pickup_hour: hour of the day, ranging from 0 to 23
- hourly_segments: maps the hour of day into different segments using hourly traffic volume as a reference
- day_segments: maps the day of the week to weekday or weekend

Step 3. Dropping Outliers

In this step, outliers are dropped:

- base_passenger_fare less than 5
- real trip time of less than 5 minutes or greater than 2 hours
- trip_miles less than 1

Step 4. Feature Crossing

In this step, features pickup_day_no and pickup_hour are crossed to generate a new categorical feature called day_x_time.

The same applies to PULocationID and DOLocationID, the new feature is called PUxDOL

Step 5. Train Test Split

The data will be split into a training set and a test set since the next step involves encoding using the target variable.

Step 6A. Encoding

The step encodes the features day_x_time and PUxDOL using a derived target feature fare_per_mile and the target variable total_fare.

The encoded variables are called enc_day_x_time and enc_PUxDOL

Step 6B. Encoding Test Set

The encoders were fit using the training data and is used to transform the test set in this step.

Step 7. Dropping Columns

The columns that will not be used for prediction will be dropped:

`['pickup_datetime', 'dropoff_datetime','PULocationID','DOLocationID', 'trip_time', 'base_passenger_fare', 'congestion_surcharge', 'airport_fee', 'pickup_day_no', 'picku`

Step 8. Generate Validation Set

This step will take part of the data in the test set as a validation set.

Full Code

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import metrics
import category_encoders as ce
from sklearn.model_selection import train_test_split

class FHVProcessPipeline():

    '''
    creates a dataset, and samples it
    '''
    def __init__(self, data_path, samples=100000, random_state=42):

        self.data=pd.read_parquet(data_path)
        self.data = self.data.sample(n=samples + int(samples * 0.25), random_state=random_state)
        self.original_data = self.data.copy()
        self.test_data = None

    def drop_columns(self, cols):
        self.data.drop(columns=cols, inplace=True)
        if self.test_data is not None:
            self.test_data.drop(columns=cols, inplace=True)


    def feature_engineering(self):
        self.data['is_airport_trip'] = np.where(self.data['airport_fee'] > 0, 1, 0)
        self.data['congestion_lvl'] = self.data['congestion_surcharge'].apply(self.calcular_congestion_surcharge)
```

```
        self.data['trip_time_real'] = round((self.data['dropoff_datetime'] - self.data['pickup_datetime']).dt.total_seconds() / 60.0,3)
        self.data["total_fare"] = self.data["base_passenger_fare"] + self.data["congestion_surcharge"] + self.data["airport_fee"]
        self.data['pickup_datetime']=pd.to_datetime(self.data['pickup_datetime'])
        self.data['pickup_day_no']=self.data['pickup_datetime'].dt.weekday # monday 0 - sunday 6
        self.data['pickup_hour']=self.data['pickup_datetime'].dt.hour
        self.data['hourly_segments'] = self.data.pickup_hour.map({0:'H2',1:'H1',2:'H1',3:'H1',4:'H1',5:'H2',6:'H3',7:'H4',8:'H5',
                                     9:'H4',10:'H4',11:'H5',12:'H5',13:'H5',14:'H5',15:'H6',16:'H6',
                                     17:'H6',18:'H5',19:'H4',20:'H4',21:'H3',22:'H3',23:'H3'})

        self.data['day_segments'] = self.data.pickup_day_no.map({0:'WD',1:'WD',2:'WD',3:'WD',4:'WD',5:'WK',6:'WK'})
        self.data = pd.get_dummies(self.data, columns=['hourly_segments', 'day_segments'])
        bool_cols = [
                    'hourly_segments_H1', 'hourly_segments_H2', 'hourly_segments_H3',
                    'hourly_segments_H4', 'hourly_segments_H5', 'hourly_segments_H6',
                    'day_segments_WD', 'day_segments_WK']

        # https://www.kaggle.com/code/yasserh/uber-fare-prediction-comparing-best-ml-models
        for c in bool_cols:
            self.data[c] = self.data[c].astype(int)

    def drop_outliers(self):
        self.data = self.data[(self.data['base_passenger_fare'] > 5)]
        # Only consider trip time greater than 5 mins and less than 2 hours and trip mile greater than 1
        self.data = self.data[(self.data['trip_time_real'] > 5) & (self.data['trip_time_real'] < 120) & (self.data['trip_miles'] > 1)]

    def split_data(self, test_size):
        X = self.data.drop('total_fare', axis=1)  # Assuming 'total_fare' is the target
        y = self.data['total_fare']
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_size, random_state=42)
        self.data = pd.concat([X_train, y_train], axis=1)
        self.test_data = pd.concat([X_test, y_test], axis=1)

    def split_val_test(self):
        X = self.test_data.drop('total_fare', axis=1)  # Assuming 'total_fare' is the target
        y = self.test_data['total_fare']
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5, random_state=42)
        self.validate_data = pd.concat([X_train, y_train], axis=1)
        self.test_data = pd.concat([X_test, y_test], axis=1)


    def process_data(self, test_size=0.25):
        # step 1: drop unecessary columns
        cols_to_drop = ['hvfhs_license_num', 'dispatching_base_num', 'originating_base_num', 'shared_request_flag', 'shared_match_flag', 'access_a_ride_flag', 'wav_requ

        self.drop_columns(cols_to_drop)

        self.original_data.drop(columns=cols_to_drop, inplace=True)

        # step 2: make new feature
        self.feature_engineering()

        # step 3: drop outliers
        self.drop_outliers()

        # step 4: feature cross
        self.ft_cross()

        # step 5: split data into training and test set
        self.split_data(test_size)

        # step 6: encode training and testset
        self.target_encode()
        self.target_encode_test()

        # clean up columns
        self.drop_columns(['day_x_time', 'PUxDOL'])

        # step 7: clear out columns
        self.drop_columns(['pickup_datetime', 'dropoff_datetime','PULocationID','DOLocationID', 'trip_time', 'base_passenger_fare', 'congestion_surcharge', 'airport_fe

        # step 8: spit test set into validation and test set
        self.split_val_test()

        return self.data, self.validate_data, self.test_data, self.original_data

    def ft_cross(self):
        self.data['day_x_time'] = self.data['pickup_day_no'].astype(str) + self.data['pickup_hour'].astype(str).str.zfill(2)
        self.data['PUxDOL'] = self.data['PULocationID'].astype(str) + self.data['DOLocationID'].astype(str)

    def target_encode(self):
        self.dt_encoder = ce.TargetEncoder()
        self.data["fare_per_mile"] = (self.data["total_fare"] / self.data["trip_miles"]).round(2)
        self.data['enc_day_x_time'] = self.dt_encoder.fit_transform(self.data['day_x_time'], self.data['fare_per_mile'])
        self.data.drop(columns=['fare_per_mile'], inplace= True)
        self.loc_encoder = ce.TargetEncoder()
        self.data['enc_PUxDOL'] = self.loc_encoder.fit_transform( self.data['PUxDOL'],  self.data['total_fare'])

    def target_encode_test(self):
        self.test_data['enc_day_x_time'] = self.dt_encoder.transform(self.test_data['day_x_time'])
        self.test_data['enc_PUxDOL'] = self.loc_encoder.transform(self.test_data['PUxDOL'])

    def calcular_congestion_surcharge(self,congestion_surcharge):
```

```python
if congestion_surcharge == 0:
    return 0        # no congestion
elif congestion_surcharge > 0 and congestion_surcharge < 2:
    return 1        # low
elif congestion_surcharge >= 2 and congestion_surcharge < 3:
    return 2        # medium
else:
    return 3        # high
```

Reference

Uber Fare Prediction - (Comparing Best ML Models)

NY_Trip_Datexland_Price_Model

A Paradigmatic Approach to Exploratory Data Analysis Utilising New York's Road Traffic to Derive Coherent Inferences

Machine Learning Design Patterns