Table of Contents

1. Objectives

The report describes dataset, preparation and modeling done to predict taxi demands for Manhattan and the airports.

2. Data

The dataset used in yellow taxi trip dataset for January 2015. Due to huge size that cannot be processed by current computational power, I opt for smaller dataset as a sample to represent the whole 2015 dataset.

The data is checked for missing values and duplicates. I had taken out 6 regions from the Jan 2015 dataset that concentrate these areas which the client requested.

I have analysed by grouping into dates according to each zone to explore duration, fare amount and passenger counts.

I have dropped unwanted features that are useless, created new features like duration, is Holiday, Day of Pickup and Demand as target.

Statistical tests ANOVA and Chi-Square tests are performed to find out the p-values.

As for correlation, total amount is highly correlates with fare amount and tip amount.

Test train split is performed with 80% training and 20% testing.

Modeling

The model will be multi-classification model since there are demand results are Low, Medium and High.

Two scenarios created:

1. Baseline Model

2. Tweaked Model to reduce false negatives in Low Demand

I used Logistic Regression and XGBoost for creating models in this project. Hyperparameter tuning is done for XGBoost. There is no balancing of target feature done for demand. Crossvalidation is also done to ensure accuracy as a whole.

Metrics used are accuracy, recall, precision and F1-score.

Conclusion

Both models gave perfect score for classifying taxi demand, hence logistic regression model is recommended for simplicity.

Appendix: Code Section

Modeling Tasks

Good work so far preparing the data to classify taxi demand and evaluating predictors. Now you can get started with the modeling! There are a couple scenarios to address below. As usual for classification modeling, you'll need to report at least the following for each of your best/final models:

- Accuracy
- Confusion matrix
- cMetrics output (or equivalent)

Scenario 1:

Start off with a baseline model that emphasizes overall accuracy. Use your test data set to verify your modeling results. This model will be useful for analysis and comparison later. It may be also a good way to investigate model types and hyperparameters, class imbalance, and which features are most useful.

Scenario 2 Main Points:

- Emphasize reducing false negatives for Low demand, especially Low demand classified as High demand.
- Also, try to reduce false positives for Low, especially missed High.
- Some increase in false positives for Low demand is an acceptable trade-off to reduce false negatives for Low demand.
- Medium/High demand misclassification is not a priority to reduce.
- Use reasonable modifications to the cost matrix to achieve your goals. You'll need to include a discussion of your customizations in your report.
- Use your test data set to verify your modeling results.

Import Libraries

In [1]:

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

import xgboost as xgb
from xgboost import XGBClassifier, XGBRegressor
from xgboost import to_graphviz, plot_importance

from sklearn.linear_model import ElasticNet, Lasso, LinearRegression, LogisticRegression, Ridge
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor, ExtraTreeClassifier, ExtraTreeRegres
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor, GradientBoostingClassifier, Grad
from sklearn.svm import SVC, SVR, LinearSVC, LinearSVR

%matplotlib inline
sns.set_style('dark')
sns.set(font_scale=1.2)

from sklearn.pipeline import Pipeline
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.feature_selection import RFE, RFECV, SelectKBest, f_classif, f_regression, chi2

from sklearn.inspection import permutation_importance
from sklearn.model_selection import cross_val_score, train_test_split, GridSearchCV, RandomizedSearchCV
from sklearn.preprocessing import LabelEncoder, StandardScaler, MinMaxScaler, OneHotEncoder
from sklearn.pipeline import Pipeline
from sklearn.metrics import confusion_matrix, classification_report, mean_absolute_error, mean_squared_error
from sklearn.metrics import plot_confusion_matrix, plot_precision_recall_curve, plot_roc_curve, accuracy_sco
from sklearn.metrics import auc, f1_score, precision_score, recall_score, roc_auc_score


from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import RandomOverSampler
from imblearn.over_sampling import SMOTE

import warnings
warnings.filterwarnings('ignore')

import pickle
from pickle import dump, load

np.random.seed(0)

from pycaret.classification import *

pd.set_option('display.max_columns',100)
#pd.set_option('display.max_rows',100)
pd.set_option('display.width', 1000)
np.set_printoptions(suppress=True)
```

Data Exploration and Analysis

In [2]:

```
df = pd.read_csv("finaltrain2.csv")
```

In [3]:

```
df
```

Out[3]:

	passenger_count	trip_distance	pickup_location	fare_amount	extra	tip_amount	total_amount	duration	pickupday	demand	ishol
0	2	12.74	JFK Airport	47.5	0.5	9.60	58.40	24.0	29	low	
1	1	17.50	JFK Airport	52.0	0.0	7.00	65.13	32.0	1	low	
2	2	18.50	JFK Airport	51.0	0.5	0.00	57.63	30.0	18	low	
3	1	14.80	JFK Airport	41.0	0.0	0.00	41.80	29.0	13	low	
4	1	14.30	JFK Airport	39.5	0.5	0.00	40.80	22.0	29	low	
...	...	...	...	...	...	...	...	...	...	...	
68563	1	1.69	Upper East Side	8.0	0.0	0.00	8.80	8.0	10	low	
68564	1	1.80	Upper East Side	12.5	0.0	2.00	15.30	18.0	3	low	
68565	5	1.54	Upper East Side	7.5	1.0	1.70	11.00	7.0	15	high	
68566	1	0.78	Upper East Side	5.5	1.0	1.25	8.55	5.0	15	low	
68567	1	1.01	Upper East Side	7.0	1.0	1.60	10.40	8.0	15	low	

68568 rows × 12 columns

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 68568 entries, 0 to 68567
Data columns (total 12 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   passenger_count  68568 non-null  int64  
 1   trip_distance    68568 non-null  float64
 2   pickup_location  68568 non-null  object 
 3   fare_amount      68568 non-null  float64
 4   extra            68568 non-null  float64
 5   tip_amount       68568 non-null  float64
 6   total_amount     68568 non-null  float64
 7   duration         68568 non-null  float64
 8   pickupday        68568 non-null  int64  
 9   demand           68568 non-null  object 
 10  isholiday        68568 non-null  int64  
 11  label            68568 non-null  int64  
dtypes: float64(6), int64(4), object(2)
memory usage: 6.3+ MB
```

In [5]:

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

Out[5]:

	passenger_count	trip_distance	pickup_location	fare_amount	extra	tip_amount	total_amount	duration	pickupda
count	68568.000000	6.856800e+04	68568	68568.000000	68568.000000	68568.000000	68568.000000	68568.000000	68568.00000
unique	NaN	NaN	5	NaN	NaN	NaN	NaN	NaN	Na
top	NaN	NaN	Midtown	NaN	NaN	NaN	NaN	NaN	Na
freq	NaN	NaN	39799	NaN	NaN	NaN	NaN	NaN	Na
mean	1.690424	5.194054e+01	NaN	13.839213	0.285746	1.760108	17.174227	14.549921	15.83800
std	1.346843	1.267113e+04	NaN	13.059612	0.365959	2.775889	16.001486	36.983077	8.71698
min	0.000000	0.000000e+00	NaN	-52.000000	-1.000000	0.000000	-52.800000	0.000000	1.00000
25%	1.000000	1.000000e+00	NaN	6.500000	0.000000	0.000000	8.160000	6.000000	8.00000
50%	1.000000	1.700000e+00	NaN	9.000000	0.000000	1.000000	11.300000	10.000000	15.00000
75%	2.000000	3.400000e+00	NaN	14.500000	0.500000	2.160000	17.800000	17.000000	23.00000
max	6.000000	3.318000e+06	NaN	570.080000	1.000000	94.510000	590.380000	1440.000000	31.00000

In [6]:

```
df.shape
```

Out[6]:

```
(68568, 12)
```

In [7]:

```
df.columns
```

Out[7]:

```
Index(['passenger_count', 'trip_distance', 'pickup_location', 'fare_amount', 'extra', 'tip_amount', 'total_a
mount', 'duration', 'pickupday', 'demand', 'isholiday', 'label'], dtype='object')
```

In [8]:

```
dfpickup = pd.get_dummies(data=df.pickup_location, drop_first=True)
```

In [9]:

```
dfpickup
```

Out[9]:

	LaGuardia Airport	Lower Manhattan	Midtown	Upper East Side
0	0	0	0	0
1	0	0	0	0

2	0	0	0	0
3	0	0	0	0
4	0	0	0	0
...	...	...	...	...
68563	0	0	0	1
68564	0	0	0	1
68565	0	0	0	1
68566	0	0	0	1
68567	0	0	0	1

68568 rows × 4 columns

```
In [10]: df2 = pd.concat([df,dfpickup],axis=1)
```

```
In [11]: df2
```

Out[11]:

	passenger_count	trip_distance	pickup_location	fare_amount	extra	tip_amount	total_amount	duration	pickupday	demand	ishol
0	2	12.74	JFK Airport	47.5	0.5	9.60	58.40	24.0	29	low	
1	1	17.50	JFK Airport	52.0	0.0	7.00	65.13	32.0	1	low	
2	2	18.50	JFK Airport	51.0	0.5	0.00	57.63	30.0	18	low	
3	1	14.80	JFK Airport	41.0	0.0	0.00	41.80	29.0	13	low	
4	1	14.30	JFK Airport	39.5	0.5	0.00	40.80	22.0	29	low	
...	...	...	...	...	...	...	...	...	...	...	
68563	1	1.69	Upper East Side	8.0	0.0	0.00	8.80	8.0	10	low	
68564	1	1.80	Upper East Side	12.5	0.0	2.00	15.30	18.0	3	low	
68565	5	1.54	Upper East Side	7.5	1.0	1.70	11.00	7.0	15	high	
68566	1	0.78	Upper East Side	5.5	1.0	1.25	8.55	5.0	15	low	
68567	1	1.01	Upper East Side	7.0	1.0	1.60	10.40	8.0	15	low	

68568 rows × 16 columns

```
In [12]: df2.columns
```

```
Out[12]: Index(['passenger_count', 'trip_distance', 'pickup_location', 'fare_amount', 'extra', 'tip_amount', 'total_a
mount', 'duration', 'pickupday', 'demand', 'isholiday', 'label', 'LaGuardia Airport', 'Lower Manhattan', 'Mi
dtown', 'Upper East Side'], dtype='object')
```

```
In [13]: df2.drop(['pickup_location','label'],axis=1,inplace=True)
```

```
In [14]: df2.head()
```

Out[14]:

	passenger_count	trip_distance	fare_amount	extra	tip_amount	total_amount	duration	pickupday	demand	isholiday	LaGuardia Airport	Man
0	2	12.74	47.5	0.5	9.6	58.40	24.0	29	low	0	0	
1	1	17.50	52.0	0.0	7.0	65.13	32.0	1	low	1	0	
2	2	18.50	51.0	0.5	0.0	57.63	30.0	18	low	0	0	
3	1	14.80	41.0	0.0	0.0	41.80	29.0	13	low	0	0	
4	1	14.30	39.5	0.5	0.0	40.80	22.0	29	low	0	0	

```
In [15]: df2.columns
```

```
Out[15]: Index(['passenger_count', 'trip_distance', 'fare_amount', 'extra', 'tip_amount', 'total_amount', 'duration',
'pickupday', 'demand', 'isholiday', 'LaGuardia Airport', 'Lower Manhattan', 'Midtown', 'Upper East Side'], d
type='object')
```

```
In [16]: df2 = df2[['passenger_count', 'trip_distance', 'fare_amount', 'extra', 'tip_amount',
                    'total_amount', 'duration', 'pickupday', 'isholiday', 'LaGuardia Airport',
                    'Lower Manhattan', 'Midtown', 'Upper East Side', 'demand' ]]
```

```
In [17]: df2.head()
```

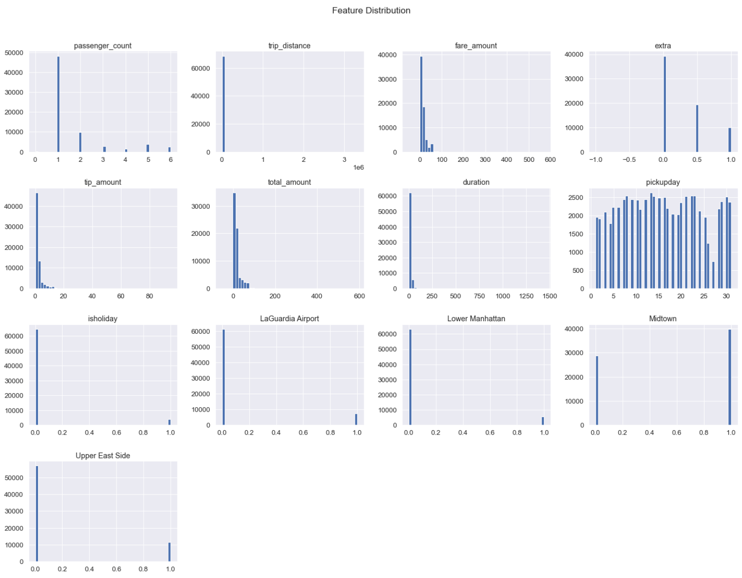
Out[17]:

	passenger_count	trip_distance	fare_amount	extra	tip_amount	total_amount	duration	pickupday	isholiday	LaGuardia Airport	Lower Manhattan	M
0	2	12.74	47.5	0.5	9.6	58.40	24.0	29	0	0	0	
1	1	17.50	52.0	0.0	7.0	65.13	32.0	1	1	0	0	
2	2	18.50	51.0	0.5	0.0	57.63	30.0	18	0	0	0	
3	1	14.80	41.0	0.0	0.0	41.80	29.0	13	0	0	0	
4	1	14.30	39.5	0.5	0.0	40.80	22.0	29	0	0	0	

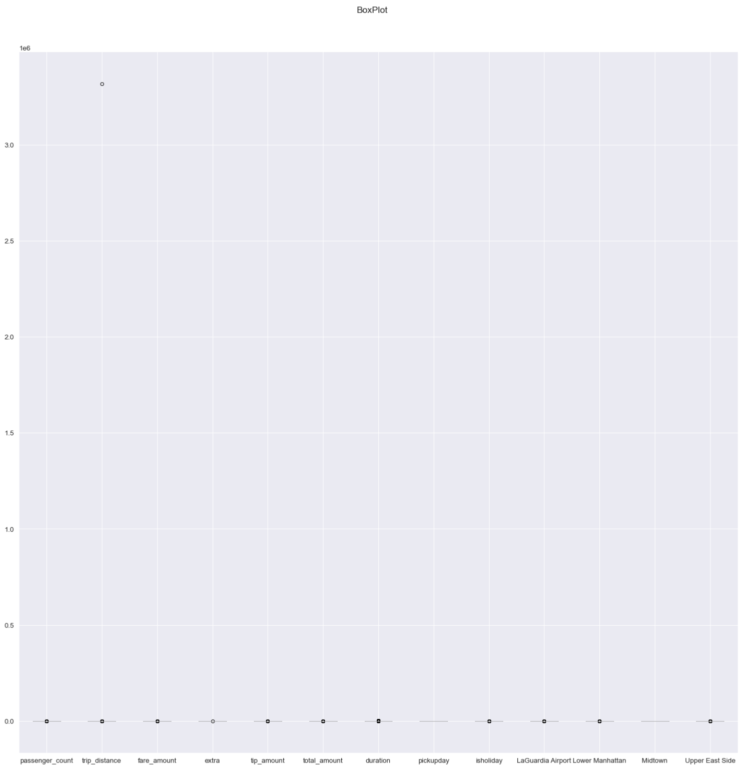
Data Visualization

Univariate Data Exploration

```
In [18]: df2.hist(bins=50, figsize=(20,15))
         plt.suptitle('Feature Distribution', x=0.5, y=1.02, ha='center', fontsize='large')
         plt.tight_layout()
         plt.show()
```



```
In [19]: df2.boxplot(figsize=(20,20))
         plt.suptitle('BoxPlot', x=0.5, y=1.02, ha='center', fontsize='large')
         plt.tight_layout()
         plt.show()
```



Correlation

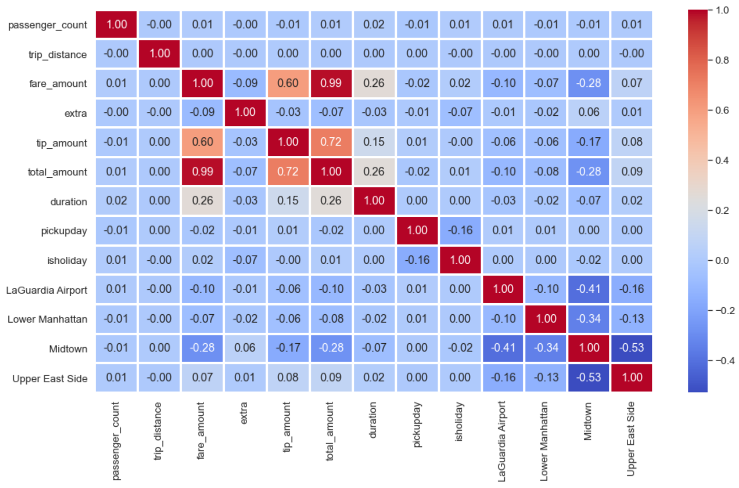
```
In [20]: df2.corr()
```

Out[20]:

	passenger_count	trip_distance	fare_amount	extra	tip_amount	total_amount	duration	pickupday	isholiday	LaGua Airp
passenger_count	1.000000	-0.001952	0.013251	-0.004897	-0.009516	0.010623	0.015734	-0.012447	0.009499	0.005
trip_distance	-0.001952	1.000000	0.000253	-0.003012	0.002720	0.000517	0.000451	0.003563	-0.000938	-0.001
fare_amount	0.013251	0.000253	1.000000	-0.091227	0.604967	0.985443	0.261480	-0.021277	0.018778	-0.100
extra	-0.004897	-0.003012	-0.091227	1.000000	-0.034286	-0.066663	-0.026354	-0.005520	-0.069695	-0.008
tip_amount	-0.009516	0.002720	0.604967	-0.034286	1.000000	0.715987	0.149022	0.014505	-0.000159	-0.058
total_amount	0.010623	0.000517	0.985443	-0.066663	0.715987	1.000000	0.255307	-0.016650	0.014982	-0.100
duration	0.015734	0.000451	0.261480	-0.026354	0.149022	0.255307	1.000000	0.004476	0.004844	-0.028
pickupday	-0.012447	0.003563	-0.021277	-0.005520	0.014505	-0.016650	0.004476	1.000000	-0.161067	0.012
isholiday	0.009499	-0.000938	0.018778	-0.069695	-0.000159	0.014982	0.004844	-0.161067	1.000000	0.002
LaGuardia Airport	0.005835	-0.001355	-0.100120	-0.008645	-0.058870	-0.100853	-0.028464	0.012614	0.002639	1.000
Lower Manhattan	-0.006575	-0.001139	-0.073609	-0.016675	-0.060522	-0.077941	-0.017849	0.007767	0.001484	-0.100

Midtown	-0.007640	0.003133	-0.279646	0.057144	-0.170010	-0.277848	-0.073539	0.004426	-0.015934	-0.405
Upper East Side	0.005656	-0.001693	0.071621	0.007416	0.078581	0.088905	0.023480	0.000890	0.004641	-0.155

In [21]:
```
plt.figure(figsize=(16,9))
sns.heatmap(df2.corr(),cmap="coolwarm",annot=True,fmt='.2f',linewidths=2)
plt.show()
```



Treat Missing Values

In [22]:
```
df2.isnull().sum()
```

Out[22]:
```
passenger_count      0
trip_distance        0
fare_amount          0
extra                0
tip_amount           0
total_amount         0
duration             0
pickupday            0
isholiday            0
LaGuardia Airport    0
Lower Manhattan      0
Midtown              0
Upper East Side      0
demand               0
dtype: int64
```

Treat Duplicate Values

In [23]:
```
df2.duplicated(keep='first').sum()
```

Out[23]:
```
1128
```

In [24]:
```
df2[df2.duplicated(keep=False)] #Check duplicate values
```

Out[24]:

	passenger_count	trip_distance	fare_amount	extra	tip_amount	total_amount	duration	pickupday	isholiday	LaGuardia Airport	Lowe Manhatta
722	1	0.0	2.5	0.0	0.0	3.30	0.0	18	0	0	
820	1	0.0	2.5	0.0	0.0	3.30	0.0	18	0	0	
823	1	18.7	52.0	0.0	0.0	58.13	52.0	12	0	0	
3831	1	18.7	52.0	0.0	0.0	58.13	52.0	12	0	0	
3887	1	0.0	2.5	0.0	0.0	3.30	0.0	18	0	0	
...	...	...	...	...	...	...	...	...	...	...	
68185	1	1.4	6.5	0.0	1.0	8.30	5.0	15	0	0	
68297	3	1.1	6.5	0.0	0.0	7.30	6.0	10	0	0	
68449	1	1.1	5.5	0.5	0.0	6.80	4.0	4	0	0	
68459	1	1.2	6.0	0.5	0.0	7.30	5.0	24	0	0	
68532	1	0.8	5.0	0.0	0.0	5.80	4.0	31	0	0	

2144 rows × 14 columns

In [25]:
```
df2.drop_duplicates(ignore_index=True, inplace=True)
```

In [26]:
```
df2.duplicated(keep='first').sum()
```

Out[26]:
```
0
```

In [27]:
```
df2.shape
```

Out[27]:
```
(67440, 14)
```

Treat Outliers

In [28]:
```
df2.describe()
```

Out[28]:

	passenger_count	trip_distance	fare_amount	extra	tip_amount	total_amount	duration	pickupday	isholiday
count	67440.000000	6.744000e+04	67440.000000	67440.000000	67440.000000	67440.000000	67440.000000	67440.000000	67440.000000
mean	1.700964	5.279263e+01	13.966014	0.287745	1.784418	17.335439	14.686907	15.836225	0.058170
std	1.354785	1.277665e+04	13.127648	0.366618	2.791333	16.081857	37.273105	8.718419	0.234067
min	0.000000	0.000000e+00	-52.000000	-1.000000	0.000000	-52.800000	0.000000	1.000000	0.000000
25%	1.000000	1.000000e+00	6.500000	0.000000	0.000000	8.300000	6.000000	8.000000	0.000000
50%	1.000000	1.720000e+00	9.000000	0.000000	1.000000	11.400000	10.000000	15.000000	0.000000
75%	2.000000	3.420000e+00	15.000000	0.500000	2.200000	17.800000	17.000000	23.000000	0.000000
max	6.000000	3.318000e+06	570.080000	1.000000	94.510000	590.380000	1440.000000	31.000000	1.000000

Treat Data Types

In [29]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 67440 entries, 0 to 67439
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   passenger_count    67440 non-null  int64  
 1   trip_distance      67440 non-null  float64
 2   fare_amount        67440 non-null  float64
 3   extra              67440 non-null  float64
 4   tip_amount         67440 non-null  float64
 5   total_amount       67440 non-null  float64
 6   duration           67440 non-null  float64
 7   pickupday          67440 non-null  int64  
 8   isholiday          67440 non-null  int64  
 9   LaGuardia Airport  67440 non-null  uint8  
 10  Lower Manhattan    67440 non-null  uint8  
 11  Midtown            67440 non-null  uint8  
 12  Upper East Side    67440 non-null  uint8  
 13  demand             67440 non-null  object 
dtypes: float64(6), int64(3), object(1), uint8(4)
memory usage: 5.4+ MB
```

Create and save processed dataset

In [30]:
```
#df2.to_csv("finaltrain3.csv",index=False)
```

Train Test Split

In [31]:
```
df = pd.read_csv("finaltrain3.csv")
```

In [32]:
```
df.shape
```

Out[32]:
```
(67440, 14)
```

In [33]:
```
df.head()
```

Out[33]:

	passenger_count	trip_distance	fare_amount	extra	tip_amount	total_amount	duration	pickupday	isholiday	LaGuardia Airport	Lower Manhattan	M
0	2	12.74	47.5	0.5	9.6	58.40	24.0	29	0	0	0	
1	1	17.50	52.0	0.0	7.0	65.13	32.0	1	1	0	0	
2	2	18.50	51.0	0.5	0.0	57.63	30.0	18	0	0	0	
3	1	14.80	41.0	0.0	0.0	41.80	29.0	13	0	0	0	
4	1	14.30	39.5	0.5	0.0	40.80	22.0	29	0	0	0	

In [34]:
```
df["demand"].value_counts()
```

Out[34]:
```
low       56917
high       6304
medium     4219
Name: demand, dtype: int64
```

In [35]:
```
le = LabelEncoder()
```

In [36]:
```
df["demand"] = le.fit_transform(df["demand"])
```

In [37]:
```
df.head()
```

Out[37]:

	passenger_count	trip_distance	fare_amount	extra	tip_amount	total_amount	duration	pickupday	isholiday	LaGuardia Airport	Lower Manhattan	M
0	2	12.74	47.5	0.5	9.6	58.40	24.0	29	0	0	0	
1	1	17.50	52.0	0.0	7.0	65.13	32.0	1	1	0	0	
2	2	18.50	51.0	0.5	0.0	57.63	30.0	18	0	0	0	
3	1	14.80	41.0	0.0	0.0	41.80	29.0	13	0	0	0	
4	1	14.30	39.5	0.5	0.0	40.80	22.0	29	0	0	0	

In [38]:
```
df["demand"].value_counts()  # Low = 1; Medium = 2, High = 0
```

Out[38]:
```
1    56917
0     6304
2     4219
Name: demand, dtype: int64
```

In [39]:
```
#df.to_csv("finaltrain4.csv",index=False)
```

In [40]:
```
X = df.iloc[:,0:13]
y = df.iloc[:,13]
```

In [41]:
```
X.values, y.values
```

Out[41]:
```
(array([[ 2.  , 12.74, 47.5 , ...,  0.  ,  0.  ,  0.  ],
        [ 1.  , 17.5 , 52.  , ...,  0.  ,  0.  ,  0.  ],
        [ 2.  , 18.5 , 51.  , ...,  0.  ,  0.  ,  0.  ],
        ...,
        [ 5.  ,  1.54,  7.5 , ...,  0.  ,  0.  ,  1.  ],
        [ 1.  ,  0.78,  5.5 , ...,  0.  ,  0.  ,  1.  ],
        [ 1.  ,  1.01,  7.  , ...,  0.  ,  0.  ,  1.  ]]),
 array([1, 1, 1, ..., 0, 1, 1]))
```

In [42]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
```

```
In [43]:  X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
Out[43]:  ((53952, 13), (13488, 13), (53952,), (13488,))
```

Feature Scaling

```
In [44]:  X_train
```

Out[44]:

	passenger_count	trip_distance	fare_amount	extra	tip_amount	total_amount	duration	pickupday	isholiday	LaGuardia Airport	Lowe Manhatta
66137	1	9.79	30.0	0.0	8.83	44.96	24.0	13	0	0	
41743	1	1.28	6.5	1.0	0.00	8.30	6.0	20	0	0	
12199	1	0.80	5.0	1.0	1.35	8.15	5.0	21	0	0	
9707	1	4.12	18.5	0.0	2.00	21.30	25.0	31	0	1	
22540	1	0.55	4.5	0.5	1.50	7.30	4.0	5	0	0	
...	...	...	...	...	...	...	...	...	...	...	
41993	1	1.49	8.5	0.0	2.79	12.09	11.0	30	0	0	
21243	1	3.53	13.5	0.0	2.00	16.30	17.0	28	0	0	
45891	2	0.50	5.5	0.0	1.25	7.55	6.0	10	0	0	
42613	1	4.00	14.0	0.5	0.00	15.30	10.0	21	0	0	
43567	1	2.50	12.0	0.0	3.80	16.60	14.0	25	0	0	

53952 rows × 13 columns

```
In [45]:  minmax = MinMaxScaler()
```

```
In [46]:  X_train_scaled = minmax.fit_transform(X_train)
```

```
In [47]:  X_test_scaled = minmax.transform(X_test)
```

```
In [48]:  X_train_scaled
```

```
Out[48]: array([[0.16666667, 0.00000295, 0.13181584, ..., 0.        , 0.        ,
                 1.        ],
                [0.16666667, 0.00000039, 0.09403935, ..., 0.        , 1.        ,
                 0.        ],
                [0.16666667, 0.00000024, 0.09162809, ..., 1.        , 0.        ,
                 0.        ],
                ...,
                [0.33333333, 0.00000015, 0.09243184, ..., 0.        , 1.        ,
                 0.        ],
                [0.16666667, 0.00000121, 0.10609568, ..., 0.        , 1.        ,
                 0.        ],
                [0.16666667, 0.00000075, 0.10288066, ..., 0.        , 1.        ,
                 0.        ]])
```

```
In [49]:  X_test_scaled
```

```
Out[49]: array([[0.5       , 0.00000579, 0.16718107, ..., 0.        , 0.        ,
                 0.        ],
                [0.16666667, 0.00000036, 0.0932356 , ..., 0.        , 1.        ,
                 0.        ],
                [0.33333333, 0.00000058, 0.09805813, ..., 0.        , 1.        ,
                 0.        ],
                ...,
                [0.16666667, 0.00000527, 0.16718107, ..., 0.        , 0.        ,
                 0.        ],
                [0.16666667, 0.00000043, 0.09484311, ..., 0.        , 1.        ,
                 0.        ],
                [0.16666667, 0.00000096, 0.10689943, ..., 0.        , 0.        ,
                 0.        ]])
```

Model Training

Using PyCaret

```
In [50]:  exp = setup(data = df, target = 'demand', session_id=0, normalize=True,
                      train_size= 0.8,normalize_method='minmax',
                      categorical_features=['LaGuardia Airport','Lower Manhattan','Midtown','Upper East Side'],
                      numeric_features=['passenger_count']
                     )
```

	Description	Value
0	session_id	0
1	Target	demand
2	Target Type	Multiclass
3	Label Encoded	None
4	Original Data	(67440, 14)
5	Missing Values	False
6	Numeric Features	8
7	Categorical Features	5
8	Ordinal Features	False
9	High Cardinality Features	False
10	High Cardinality Method	None
11	Transformed Train Set	(53952, 13)
12	Transformed Test Set	(13488, 13)
13	Shuffle Train-Test	True
14	Stratify Train-Test	False
15	Fold Generator	StratifiedKFold
16	Fold Number	10
17	CPU Jobs	-1
18	Use GPU	False
19	Log Experiment	False
20	Experiment Name	clf-default-name
21	USI	b8b2
22	Imputation Type	simple
23	Iterative Imputation Iteration	None
24	Numeric Imputer	mean
25	Iterative Imputation Numeric Model	None
26	Categorical Imputer	constant
27	Iterative Imputation Categorical Model	None
28	Unknown Categoricals Handling	least_frequent
29	Normalize	True
30	Normalize Method	minmax
31	Transformation	False
32	Transformation Method	None
33	PCA	False
34	PCA Method	None
35	PCA Components	None
36	Ignore Low Variance	False
37	Combine Rare Levels	False
38	Rare Level Threshold	None
39	Numeric Binning	False
40	Remove Outliers	False
41	Outliers Threshold	None
42	Remove Multicollinearity	False
43	Multicollinearity Threshold	None
44	Clustering	False
45	Clustering Iteration	None
46	Polynomial Features	False

47	Polynomial Degree	None
48	Trignometry Features	False
49	Polynomial Threshold	None
50	Group Features	False
51	Feature Selection	False
52	Features Selection Threshold	None
53	Feature Interaction	False
54	Feature Ratio	False
55	Interaction Threshold	None
56	Fix Imbalance	False
57	Fix Imbalance Method	SMOTE

In [51]:
```
models()
```

Out[51]:

ID	Name	Reference	Turbo
lr	Logistic Regression	sklearn.linear_model._logistic.LogisticRegression	True
knn	K Neighbors Classifier	sklearn.neighbors._classification.KNeighborsCl...	True
nb	Naive Bayes	sklearn.naive_bayes.GaussianNB	True
dt	Decision Tree Classifier	sklearn.tree._classes.DecisionTreeClassifier	True
svm	SVM - Linear Kernel	sklearn.linear_model._stochastic_gradient.SGDC...	True
rbfsvm	SVM - Radial Kernel	sklearn.svm._classes.SVC	False
gpc	Gaussian Process Classifier	sklearn.gaussian_process._gpc.GaussianProcessC...	False
mlp	MLP Classifier	pycaret.internal.tunable.TunableMLPClassifier	False
ridge	Ridge Classifier	sklearn.linear_model._ridge.RidgeClassifier	True
rf	Random Forest Classifier	sklearn.ensemble._forest.RandomForestClassifier	True
qda	Quadratic Discriminant Analysis	sklearn.discriminant_analysis.QuadraticDiscrim...	True
ada	Ada Boost Classifier	sklearn.ensemble._weight_boosting.AdaBoostClas...	True
gbc	Gradient Boosting Classifier	sklearn.ensemble._gb.GradientBoostingClassifier	True
lda	Linear Discriminant Analysis	sklearn.discriminant_analysis.LinearDiscrimina...	True
et	Extra Trees Classifier	sklearn.ensemble._forest.ExtraTreesClassifier	True
xgboost	Extreme Gradient Boosting	xgboost.sklearn.XGBClassifier	True
lightgbm	Light Gradient Boosting Machine	lightgbm.sklearn.LGBMClassifier	True
catboost	CatBoost Classifier	catboost.core.CatBoostClassifier	True

In [52]:
```
compare_models(exclude=['catboost','lightgbm','lda','qda','mlp','nb','ridge'],fold=5)
```

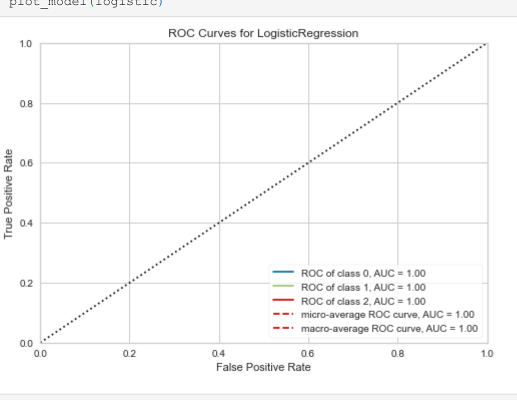
	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
lr	Logistic Regression	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	2.0980
dt	Decision Tree Classifier	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.0800
rf	Random Forest Classifier	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0880
ada	Ada Boost Classifier	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9680
gbc	Gradient Boosting Classifier	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	8.0040
et	Extra Trees Classifier	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9800
xgboost	Extreme Gradient Boosting	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	2.0520
knn	K Neighbors Classifier	0.9990	0.9999	0.9947	0.9990	0.9990	0.9963	0.9963	3.4880
svm	SVM - Linear Kernel	0.9729	0.0000	0.8556	0.9751	0.9629	0.8896	0.8962	0.1840

Out[52]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=1000,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=0, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

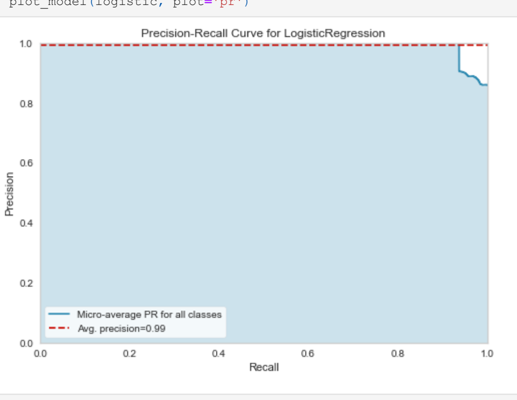
In [53]:
```
logistic = create_model('lr', fold=5)
```

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
4	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Mean	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
SD	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

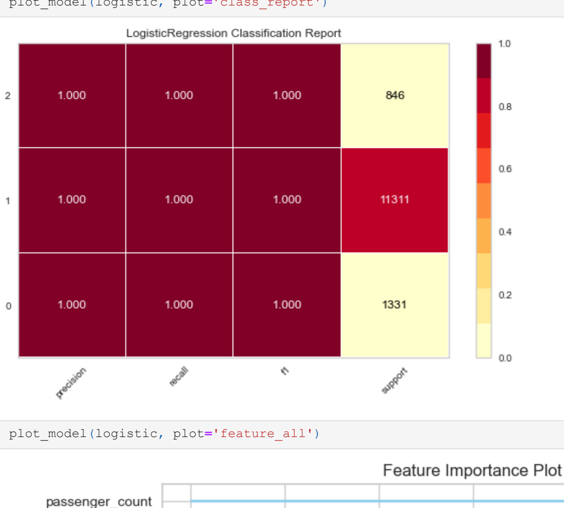
In [54]:
```
plot_model(logistic)
```

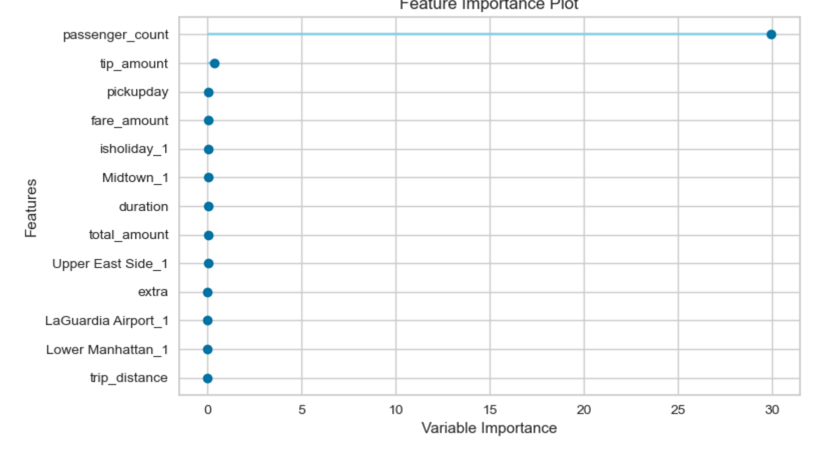


In [55]:
```
plot_model(logistic, plot='pr')
```



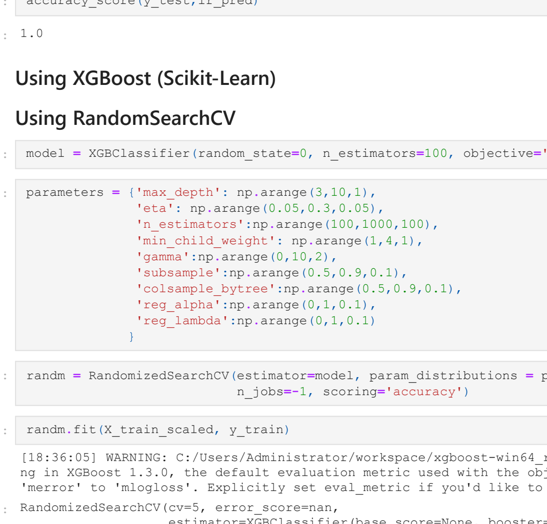
In [56]:
```
plot_model(logistic, plot='confusion_matrix')
```





Using Classification Models (Model 1)

Model Evaluation



In [65]:
```
print(classification_report(y_test,lr_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1331
           1       1.00      1.00      1.00     11311
           2       1.00      1.00      1.00       846

    accuracy                           1.00     13488
   macro avg       1.00      1.00      1.00     13488
weighted avg       1.00      1.00      1.00     13488
```

In [66]:
```
accuracy_score(y_test,lr_pred)
```

Out[66]: 1.0

Using XGBoost (Scikit-Learn)

Using RandomSearchCV

In [67]:
```
model = XGBClassifier(random_state=0, n_estimators=100, objective='softmax:multi')
```

In [68]:
```
parameters = {'max_depth': np.arange(3,10,1),
              'eta': np.arange(0.05,0.3,0.05),
              'n_estimators':np.arange(100,1000,100),
              'min_child_weight': np.arange(1,4,1),
              'gamma':np.arange(0,10,2),
              'subsample':np.arange(0.5,0.9,0.1),
              'colsample_bytree':np.arange(0.5,0.9,0.1),
              'reg_alpha':np.arange(0,1,0.1),
              'reg_lambda':np.arange(0,1,0.1)
             }
```

In [69]:
```
randm = RandomizedSearchCV(estimator=model, param_distributions = parameters, cv = 5, n_iter = 10,
                           n_jobs=-1, scoring='accuracy')
```

In [70]:
```
randm.fit(X_train_scaled, y_train)
```

```
[18:36:05] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was changed from
'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

Out[70]:
```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=XGBClassifier(base_score=None, booster=None,
                                           colsample_bylevel=None,
                                           colsample_bynode=None,
                                           colsample_bytree=None, gamma=None,
                                           gpu_id=None, importance_type='gain',
                                           interaction_constraints=None,
                                           learning_rate=None,
                                           max_delta_step=None, max_depth=None,
                                           min_child_weight=None, missing=nan,
                                           monotone_constraints=None,
                                           n...
                                        'min_child_weight': array([1, 2, 3]),
                                        'n_estimators': array([100, 200, 300, 400, 500, 600, 700, 800, 90
0]),
                                        'reg_alpha': array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.
9]),
                                        'reg_lambda': array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.
9]),
                                        'subsample': array([0.5, 0.6, 0.7, 0.8])},
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score=False, scoring='accuracy', verbose=0)
```

In [71]:
```
randm.best_estimator_
```

Out[71]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.7, eta=0.1, gamma=8,
              gpu_id=-1, importance_type='gain', interaction_constraints='',
              learning_rate=0.100000001, max_delta_step=0, max_depth=6,
              min_child_weight=3, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=4, num_parallel_tree=1,
              objective='multi:softprob', random_state=0, reg_alpha=0.0,
              reg_lambda=0.30000000000000004, scale_pos_weight=None,
              subsample=0.7999999999999999, tree_method='exact',
              use_label_encoder=True, validate_parameters=1, verbosity=None)
```

In [72]:
```
randm.best_score_
```

Out[72]: 1.0

In [73]:
```
randm.best_params_
```

Out[73]:
```
{'subsample': 0.7999999999999999,
 'reg_lambda': 0.30000000000000004,
 'reg_alpha': 0.0,
 'n_estimators': 100,
 'min_child_weight': 3,
 'max_depth': 6,
 'gamma': 8,
 'eta': 0.1,
 'colsample_bytree': 0.7}
```

Final Model (Model 2)

In [74]:
```
xgbmodel = XGBClassifier(random_state=0, n_estimators=100, objective='softmax:multi',
                         subsample=0.8,reg_lambda =0.3, reg_alpha = 0.0, min_child_weight = 3,
                         max_depth = 6, gamma = 8, eta = 0.1, colsample_bytree = 0.7)
```

In [75]:
```
xgbmodel.fit(X_train_scaled,y_train,eval_set=[(X_test_scaled,y_test)],eval_metric='mlogloss',early_stopping_
```

```
[0]	validation_0-mlogloss:0.96692
[1]	validation_0-mlogloss:0.85754
[2]	validation_0-mlogloss:0.76518
[3]	validation_0-mlogloss:0.67478
[4]	validation_0-mlogloss:0.59729
[5]	validation_0-mlogloss:0.53932
[6]	validation_0-mlogloss:0.48857
[7]	validation_0-mlogloss:0.44392
[8]	validation_0-mlogloss:0.40212
[9]	validation_0-mlogloss:0.37274
[10]	validation_0-mlogloss:0.33342
[11]	validation_0-mlogloss:0.29865
[12]	validation_0-mlogloss:0.27235
[13]	validation_0-mlogloss:0.24439
[14]	validation_0-mlogloss:0.22382
[15]	validation_0-mlogloss:0.20116
[16]	validation_0-mlogloss:0.18785
[17]	validation_0-mlogloss:0.17263
[18]	validation_0-mlogloss:0.15822
[19]	validation_0-mlogloss:0.14247
[20]	validation_0-mlogloss:0.13378
[21]	validation_0-mlogloss:0.12055
[22]	validation_0-mlogloss:0.11107
[23]	validation_0-mlogloss:0.10015
[24]	validation_0-mlogloss:0.09034
[25]	validation_0-mlogloss:0.08348
[26]	validation_0-mlogloss:0.07864
[27]	validation_0-mlogloss:0.07098
[28]	validation_0-mlogloss:0.06408
[29]	validation_0-mlogloss:0.05909
[30]	validation_0-mlogloss:0.05336
[31]	validation_0-mlogloss:0.04934
[32]	validation_0-mlogloss:0.04574
[33]	validation_0-mlogloss:0.04133
[34]	validation_0-mlogloss:0.03735
[35]	validation_0-mlogloss:0.03468
[36]	validation_0-mlogloss:0.03224
[37]	validation_0-mlogloss:0.03144
[38]	validation_0-mlogloss:0.02982
[39]	validation_0-mlogloss:0.02695
[40]	validation_0-mlogloss:0.02437
[41]	validation_0-mlogloss:0.02203
[42]	validation_0-mlogloss:0.02039
[43]	validation_0-mlogloss:0.01844
[44]	validation_0-mlogloss:0.01667
[45]	validation_0-mlogloss:0.01508
[46]	validation_0-mlogloss:0.01364
[47]	validation_0-mlogloss:0.01264
[48]	validation_0-mlogloss:0.01172
[49]	validation_0-mlogloss:0.01060
[50]	validation_0-mlogloss:0.00984
[51]	validation_0-mlogloss:0.00919
[52]	validation_0-mlogloss:0.00854
[53]	validation_0-mlogloss:0.00795
[54]	validation_0-mlogloss:0.00739
[55]	validation_0-mlogloss:0.00692
[56]	validation_0-mlogloss:0.00641
[57]	validation_0-mlogloss:0.00597
[58]	validation_0-mlogloss:0.00556
[59]	validation_0-mlogloss:0.00534
[60]	validation_0-mlogloss:0.00500
[61]	validation_0-mlogloss:0.00469
[62]	validation_0-mlogloss:0.00435
[63]	validation_0-mlogloss:0.00394
[64]	validation_0-mlogloss:0.00365
[65]	validation_0-mlogloss:0.00341
[66]	validation_0-mlogloss:0.00318
[67]	validation_0-mlogloss:0.00296
[68]	validation_0-mlogloss:0.00284
[69]	validation_0-mlogloss:0.00275
[70]	validation_0-mlogloss:0.00258
[71]	validation_0-mlogloss:0.00234
[72]	validation_0-mlogloss:0.00220
[73]	validation_0-mlogloss:0.00205
[74]	validation_0-mlogloss:0.00193
[75]	validation_0-mlogloss:0.00181
[76]	validation_0-mlogloss:0.00164
[77]	validation_0-mlogloss:0.00158
[78]	validation_0-mlogloss:0.00147
[79]	validation_0-mlogloss:0.00138
[80]	validation_0-mlogloss:0.00129
[81]	validation_0-mlogloss:0.00121
[82]	validation_0-mlogloss:0.00114
[83]	validation_0-mlogloss:0.00111
[84]	validation_0-mlogloss:0.00102
[85]	validation_0-mlogloss:0.00098
[86]	validation_0-mlogloss:0.00092
[87]	validation_0-mlogloss:0.00090
[88]	validation_0-mlogloss:0.00084
[89]	validation_0-mlogloss:0.00082
[90]	validation_0-mlogloss:0.00079
[91]	validation_0-mlogloss:0.00076
[92]	validation_0-mlogloss:0.00073
[93]	validation_0-mlogloss:0.00071
[94]	validation_0-mlogloss:0.00068
[95]	validation_0-mlogloss:0.00068
[96]	validation_0-mlogloss:0.00068
[97]	validation_0-mlogloss:0.00065
[98]	validation_0-mlogloss:0.00063
[99]	validation_0-mlogloss:0.00061
```

Out[75]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.7, eta=0.1, gamma=8,
              gpu_id=-1, importance_type='gain', interaction_constraints='',
              learning_rate=0.100000001, max_delta_step=0, max_depth=6,
              min_child_weight=3, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=4, num_parallel_tree=1,
              objective='multi:softprob', random_state=0, reg_alpha=0.0,
              reg_lambda=0.3, scale_pos_weight=None, subsample=0.8,
              tree_method='exact', use_label_encoder=True,
              validate_parameters=1, verbosity=None)
```

In [76]:
```
y_pred = xgbmodel.predict(X_test_scaled)
```

In [77]:
```
y_pred
```

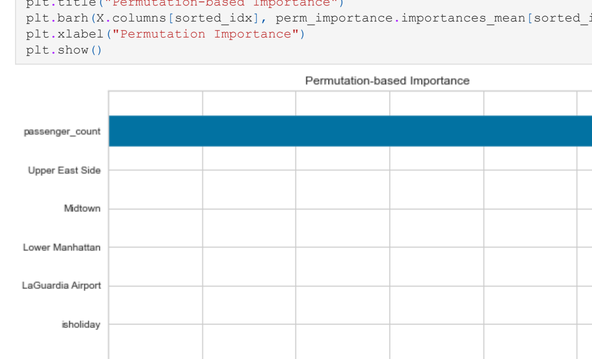
Out[77]: array([2, 1, 1, ..., 1, 1, 1])

Model Evaluation

In [78]:
```
cm = confusion_matrix(y_test,y_pred)
cm
```

Out[78]:
```
array([[ 1331,     0,     0],
       [    0, 11311,     0],
       [    0,     0,   846]], dtype=int64)
```

In [79]:
```
fig , ax = plt.subplots(figsize=(10,5))
sns.heatmap(cm, annot=True,fmt='d',linewidths=2, cmap='viridis')
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()
```



In [80]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1331
           1       1.00      1.00      1.00     11311
           2       1.00      1.00      1.00       846

    accuracy                           1.00     13488
   macro avg       1.00      1.00      1.00     13488
weighted avg       1.00      1.00      1.00     13488
```

The permutation based importance

In [81]:
```
perm_importance = permutation_importance(xgbmodel,X_test_scaled,y_test, random_state=0, scoring='accuracy')
```

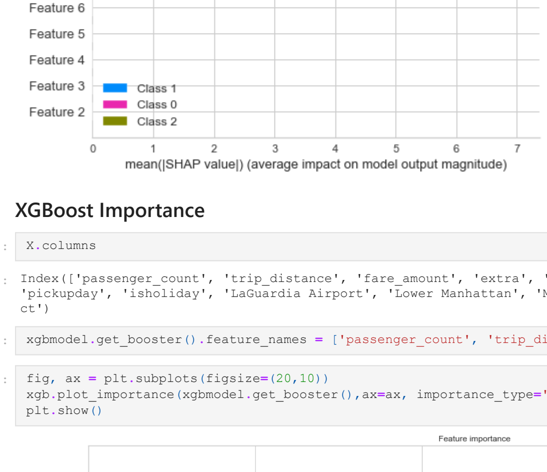
In [82]:
```
sorted_idx = perm_importance.importances_mean.argsort()
plt.figure(figsize=(10,10))
plt.title("Permutation-based Importance")
plt.barh(X.columns[sorted_idx], perm_importance.importances_mean[sorted_idx])
plt.xlabel("Permutation Importance")
plt.show()
```

Compute Importance from SHAP Values

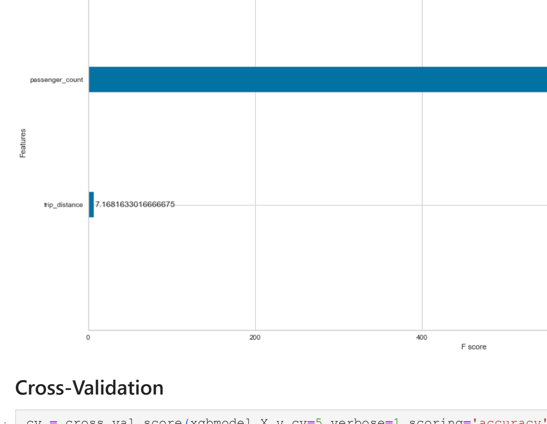
In [83]:
```
explainer = shap.TreeExplainer(xgbmodel)
```

In [84]:
```
shap_values = explainer.shap_values(X_test_scaled)
```

In [85]:
```
shap.summary_plot(shap_values, X_test_scaled, plot_type="bar")
```



In [86]:
```
shap.summary_plot(shap_values, X_test_scaled)
```



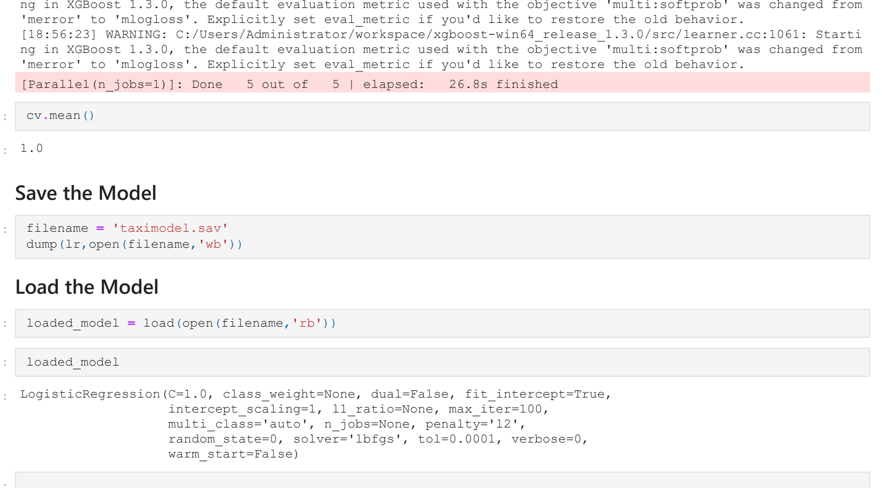
XGBoost Importance

In [87]:
```
X.columns
```

Out[87]:
```
Index(['passenger_count', 'trip_distance', 'fare_amount', 'extra', 'tip_amount', 'total_amount', 'duration',
'pickupday', 'isholiday', 'LaGuardia Airport', 'Lower Manhattan', 'Midtown', 'Upper East Side'], dtype='obje
ct')
```

In [88]:
```
xgbmodel.get_booster().feature_names = ['passenger_count', 'trip_distance', 'fare_amount', 'extra', 'tip_amo
```

In [91]:
```
fig, ax = plt.subplots(figsize=(20,10))
xgb.plot_importance(xgbmodel.get_booster(),ax=ax, importance_type='gain')
plt.show()
```



Cross-Validation

In [92]:
```
cv = cross_val_score(xgbmodel,X,y,cv=5,verbose=1,scoring='accuracy')
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[18:56:02] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was changed from
'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[18:56:07] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was changed from
'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[18:56:12] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was changed from
'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[18:56:18] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was changed from
'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[18:56:23] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was changed from
'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:   26.8s finished
```

In [93]:
```
cv.mean()
```

Out[93]: 1.0

Save the Model

In [94]:
```
filename = 'taximodel.sav'
dump(lr,open(filename,'wb'))
```

Load the Model

In [95]:
```
loaded_model = load(open(filename,'rb'))
```

In [96]:
```
loaded_model
```

Out[96]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=0, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [ ]: