Importing libraries

In [56]: import numpy as np import pandas as pd import matplotlib.pyplot as plt import seaborn as sns sns.set() from sklearn.pipeline import Pipeline from sklearn.compose import ColumnTransformer from sklearn.model_selection import train_test_split from sklearn.ensemble import RandomForestRegressor from sklearn.metrics import mean_squared_error, r2_score **Data Preprocessing**

data=pd.read_csv('uber_data (1).csv') VendorID pickup_latitude RatecodeID store_and_fwd_flag tpep_pickup_datetime tpep_dropoff_datetime passenger_count trip_distance pickup_longitude dropof

2.50 0 2016-03-01 00:00:00 2016-03-01 00:07:55 -73.976746 Ν 40.765152

2016-03-01 00:11:06 2016-03-01 00:00:00 2.90 -73.983482 40.767925

In [4]: data Out[4]: 2 2016-03-01 00:00:00 2016-03-01 00:31:06 2 19.98 Ν -73.782021 40.644810

2016-03-01 00:00:00 2016-03-01 00:00:00 10.78 -73.863419 40.769814 40.792183 4 2016-03-01 00:00:00 2016-03-01 00:00:00 30.43 -73.971741 3 99995 2016-03-01 06:17:10 2016-03-01 06:22:15 1 0.50 -73.990898 40.750519 Ν 99996 2016-03-01 06:17:10 2016-03-01 06:32:41 3.40 -74.014488 40.718296

99997 2016-03-01 06:17:10 2016-03-01 06:37:23 9.70 -73.963379 40.774097 99998 2016-03-01 06:17:10 2016-03-01 06:22:09 0.92 -73.984901 40.763111 99999 1.00 Ν 2016-03-01 06:17:11 2016-03-01 06:22:00 -73.990685 40.750473 100000 rows × 19 columns data.head()

VendorID tpep_pickup_datetime tpep_dropoff_datetime passenger_count trip_distance pickup_longitude pickup_latitude RatecodeID store_and_fwd_flag 0 2016-03-01 00:00:00 2016-03-01 00:07:55 1 2.50 -73.976746 40.765152 Ν

2016-03-01 00:00:00 2016-03-01 00:11:06 2.90 -73.983482 40.767925 2 2 2 2016-03-01 00:00:00 2016-03-01 00:31:06 19.98 -73.782021 Ν 40.644810 2 2016-03-01 00:00:00 2016-03-01 00:00:00

-74.00 -74.00 -73.97 2 2016-03-01 00:00:00 2016-03-01 00:00:00 30.43 -73.971741 -74.17 40.792183 In [6]: data.describe(include='all') VendorID tpep_pickup_datetime tpep_dropoff_datetime passenger_count trip_distance pickup_longitude pickup_latitude RatecodeID store_and_fwd_

count 100000.00000 100000 100000 100000.000000 100000.000000 100000.000000 100000.000000 100000.000000 100 38332 39981 unique NaN NaN NaN NaN NaN NaN 2016-03-10 09:35:06 top NaN 2016-03-11 00:00:00 NaN NaN NaN NaN NaN freq NaN 14 18 NaN NaN NaN NaN NaN 99 3.034270 1.88327 NaN NaN 1.929170 -73.288983 40.375220 1.040120 mean 0.284238 0.32110 NaN 1.589408 3.846951 7.089652 3.901413 std NaN

1.00000 NaN NaN 0.000000 0.000000 -121.933327 0.000000 1.000000 min 25% 2.00000 NaN NaN 1.000000 0.990000 -73.990959 40.738891 1.000000 50% 2.00000 NaN NaN 1.000000 1.670000 -73.980202 40.755299 1.000000 75% 2.00000 NaN 2.000000 3.200000 -73.964203 40.769021 1.000000 NaN 2.00000 NaN NaN 6.000000 184.400000 0.000000 41.204548 6.000000 max In [7]: data.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 100000 entries, 0 to 99999 Data columns (total 19 columns): # Column Non-Null Count Dtype _____ VendorID 100000 non-null int64 tpep_pickup_datetime 100000 non-null object tpep_dropoff_datetime 100000 non-null object passenger_count 100000 non-null int64 100000 non-null float64 4 trip_distance 5 pickup_longitude 100000 non-null float64

6 pickup_latitude 100000 non-null float64 7 RatecodeID 100000 non-null int64 RatecodeID 100000 non-null int64 store_and_fwd_flag 100000 non-null object dropoff_longitude 100000 non-null float64 10 dropoff_latitude 100000 non-null float64 11 payment_type 100000 non-null int64 12 fare_amount 100000 non-null float64 100000 non-null float64 13 extra 14 mta_tax 100000 non-null float64 15 tip_amount 100000 non-null float64 100000 non-null float64 16 tolls_amount 17 improvement_surcharge 100000 non-null float64 18 total_amount 100000 non-null float64 dtypes: float64(12), int64(4), object(3) memory usage: 14.5+ MB In [8]: data['tpep_pickup_datetime']=pd.to_datetime(data['tpep_pickup_datetime']) data['tpep_dropoff_datetime'] = pd.to_datetime(data['tpep_dropoff_datetime']) In [9]: data.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 100000 entries, 0 to 99999 Data columns (total 19 columns): Non-Null Count Dtype # Column VendorID 100000 non-null int64 tpep_pickup_datetime 100000 non-null datetime64[ns] tpep_dropoff_datetime 100000 non-null datetime64[ns] 3 passenger_count 100000 non-null int64
4 trip_distance 100000 non-null float64
5 pickup_longitude 100000 non-null float64
6 pickup_latitude 100000 non-null float64
7 RatecodeID 100000 non-null int64

 7
 RatecodeID
 100000 non-null int64

 8
 store_and_fwd_flag
 100000 non-null object

 9
 dropoff_longitude
 100000 non-null float64

 10
 dropoff_latitude
 100000 non-null float64

 11
 payment_type
 100000 non-null float64

 12
 fare_amount
 100000 non-null float64

 13
 extra
 100000 non-null float64

 14
 mta_tax
 100000 non-null float64

 15
 tip_amount
 100000 non-null float64

 16
 tolls_amount
 100000 non-null float64

 17
 improvement surcharge
 100000 non-null float64

17 improvement_surcharge 100000 non-null float64 18 total_amount 100000 non-null float64

memory usage: 14.5+ MB

0

2

4000

2000

0

10000

0

Feature Engineering

data_with_dummies.head()

2016-03-01

2016-03-01

2016-03-01

2016-03-01

2016-03-01

In [38]: # Drop columns not used as features columns_to_exclude = [

5 rows × 31 columns

X.shape, y.shape

Out[38]: ((100000, 24), (100000,))

y = data[target]

In [60]: features = [

0

2

3

In [27]: # Create dummy variables for categorical features

Display the first few rows of the modified dataframe

2016-03-01 00:07:55

2016-03-01 00:11:06

2016-03-01 00:31:06

2016-03-01 00:00:00

2016-03-01 00:00:00

'tpep_pickup_datetime', 'tpep_dropoff_datetime',

X = data_with_dummies.drop(columns=columns_to_exclude)

Define features and target variable

'VendorID', 'passenger_count', 'trip_distance', 'pickup_longitude',

numeric_features = list(set(features) - set(categorical_features))

('num', 'passthrough', numeric_features),

'pickup_latitude', 'RatecodeID', 'store_and_fwd_flag', 'dropoff_longitude',

categorical_features = ['VendorID', 'RatecodeID', 'store_and_fwd_flag', 'payment_type']

('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features)

('regressor', RandomForestRegressor(n_estimators=100, random_state=42))

'pickup_longitude', 'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude',

'total_amount' # Target variable

Define features (X) and target (y)

y = data_with_dummies['total_amount']

Display the shapes of features and target

categorical_cols = ['VendorID', 'RatecodeID', 'store_and_fwd_flag', 'payment_type'] data_with_dummies = pd.get_dummies(data, columns=categorical_cols, drop_first=True)

In [19]: # Map numeric day to day name

1

2

In [18]: # Extract day of the week from pickup datetime (0=Monday, 6=Sunday)

data['pickup_day_of_week'] = data['tpep_pickup_datetime'].dt.dayofweek

day_name_map = {0: 'Monday', 1: 'Tuesday', 2: 'Wednesday', 3: 'Thursday',

In [10]: # Extract hour, day, weekday name, and month

In [11]: # Display the first few rows with the new columns

2016-03-01

2016-03-01

2016-03-01

2016-03-01

2016-03-01

dtypes: datetime64[ns](2), float64(12), int64(4), object(1)

data['pickup_hour'] = data['tpep_pickup_datetime'].dt.hour data['pickup_day'] = data['tpep_pickup_datetime'].dt.day

data['pickup_month'] = data['tpep_pickup_datetime'].dt.month

0

0

data['pickup_weekday'] = data['tpep_pickup_datetime'].dt.day_name()

tpep_pickup_datetime pickup_hour pickup_day pickup_weekday pickup_month

1

data[['tpep_pickup_datetime', 'pickup_hour', 'pickup_day', 'pickup_weekday', 'pickup_month']].head()

Tuesday

Tuesday

Tuesday

Tuesday

Tuesday

3

3

3

In [13]: import matplotlib.pyplot as plt In [14]: # Convert pickup datetime column to datetime type data['tpep_pickup_datetime'] = pd.to_datetime(data['tpep_pickup_datetime']) In [15]: # Extract hour from pickup datetime data['pickup_hour'] = data['tpep_pickup_datetime'].dt.hour In [16]: # Count number of trips per hour trips_per_hour = data['pickup_hour'].value_counts().sort_index() In [17]: # Plotting plt.figure(figsize=(12, 6)) trips_per_hour.plot(kind='bar', color='skyblue') plt.title('Number of Trips per Hour') plt.xlabel('Hour of Day') plt.ylabel('Number of Trips') plt.xticks(rotation=0) plt.grid(axis='y', linestyle='--', alpha=0.7) plt.tight_layout() plt.show() Number of Trips per Hour 12000 10000 8000 Number of Trips 6000

4: 'Friday', 5: 'Saturday', 6: 'Sunday'} data['pickup_day_name'] = data['pickup_day_of_week'].map(day_name_map) In [20]: # Count number of trips per day of the week trips_per_day = data['pickup_day_name'].value_counts().reindex(['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday'] In [21]: # Plotting plt.figure(figsize=(12, 6)) trips_per_day.plot(kind='bar', color='lightgreen') plt.title('Number of Trips per Day of the Week') plt.xlabel('Day of the Week') plt.ylabel('Number of Trips') plt.xticks(rotation=45) plt.grid(axis='y', linestyle='--', alpha=0.7) plt.tight_layout() plt.show() Number of Trips per Day of the Week 80000 70000 60000 50000 ber of Trips 40000 30000 20000

Day of the Week

tpep_pickup_datetime tpep_dropoff_datetime passenger_count trip_distance pickup_longitude pickup_latitude dropoff_longitude dropoff_latitude fare_amount extra

2.50

2.90

19.98

10.78

30.43

2

5

-73.976746

-73.983482

-73.782021

-73.863419

-73.971741

-74.004265

-74.005943

-73.974541

-73.969650

-74.177170

40.746128

40.733166

40.675770

40.757767

40.695053

0.5

0.5

0.5

0.0

0.0

9.0

54.5

98.0

40.765152

40.767925

40.644810

40.769814

40.792183

7

Hour of Day

9

10

11

12

13

14

'dropoff_latitude', 'payment_type', 'fare_amount', 'extra', 'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge' target = 'total_amount' X = data[features]

In [64]: from sklearn.preprocessing import OneHotEncoder

In [66]: # Preprocessing: encode categorical features

preprocessor = ColumnTransformer(

('preprocessor', preprocessor),

transformers=[

In [68]: # Create the model pipeline

])

model = Pipeline(steps=[

num

▶ passthrough

In [73]: # Predictions and evaluation

In [76]: # Plotting true vs predicted values plt.figure(figsize=(10, 6))

> plt.grid(True) plt.tight_layout()

plt.show()

250

200

150

100

50

0

Predicted Total Amount

plt.xlabel('Actual Total Amount') plt.ylabel('Predicted Total Amount')

Pipeline

► RandomForestRegressor

Predict on the test set

preprocessor: ColumnTransformer (

cat

▶ OneHotEncoder

Split the data into training and testing sets
<pre># Split data X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)</pre>
Train a Random Forest Regressor
<pre># Train the model model.fit(X_train, y_train)</pre>

<pre>y_pred = model.predict(X_test) mse = mean_squared_error(y_test, y_pred) r2 = r2_score(y_test, y_pred)</pre>
mse, r2
(0.28509262500602883, 0.998591839653688)
Visualization of Predictions

plt.scatter(y_test, y_pred, alpha=0.3, color='blue', edgecolor='k')

plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2)

300

plt.title('Actual vs Predicted Total Amount')

50 100 150 200 250 300 Actual Total Amount conclusion

Actual vs Predicted Total Amount

1.(datetime.date(2016, 3, 10), 76780) is the busiest day 2.Late evenings are the popular pickup times. 3.Mean Squared Error (MSE): ~0.107 R² Score: ~0.999 This indicates the model predicts base fares with high accuracy.