Part 3: Machine Learning – Predictive Modeling

Objective

Build predictive models to forecast demand and identify high-tipping scenarios.

Tasks & Models

1. **Weekly Trip Demand Forecasting**
   Goal: Predict number of trips per week using historical trip counts and seasonal patterns.

2. **High-Tip Prediction Model**
   Goal: Predict if a trip will have a tip_amount above the average using trip_distance, boroughs, and time-based features.

3. **Route-Based Revenue Forecasting (Optional)**
   Goal: Forecast total_amount for a specific pickup_borough–dropoff_borough pair in future months.

```
# Basic imports
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score,
classification_report
from sklearn.ensemble import RandomForestRegressor,
RandomForestClassifier

import pandas as pd
import glob

# folder
folder_path = r"C:/Users/parth/OneDrive/Desktop/Trips/"

# Load  CSV
all_files = glob.glob(folder_path + "*.csv")

# Show  files
print("Files found:", all_files)

# Read and combine
df_list = []
for file in all_files:
    print("Loading:", file)
    temp_df = pd.read_csv(file)
    df_list.append(temp_df)

# Combine all years
df = pd.concat(df_list, ignore_index=True)

# Show preview
df.head(), df.shape
```

```
Files found: ['C:/Users/parth/OneDrive/Desktop/Trips\\
2017_trimmed.csv', 'C:/Users/parth/OneDrive/Desktop/Trips\\
2018_trimmed.csv', 'C:/Users/parth/OneDrive/Desktop/Trips\\
2019_trimmed.csv', 'C:/Users/parth/OneDrive/Desktop/Trips\\
2020_trimmed.csv']
Loading: C:/Users/parth/OneDrive/Desktop/Trips\2017_trimmed.csv
Loading: C:/Users/parth/OneDrive/Desktop/Trips\2018_trimmed.csv
Loading: C:/Users/parth/OneDrive/Desktop/Trips\2019_trimmed.csv
Loading: C:/Users/parth/OneDrive/Desktop/Trips\2020_trimmed.csv

(   VendorID     lpep_pickup_datetime    lpep_dropoff_datetime  \
 0       2.0  2017-01-04 18:03:23.000  2017-01-04 18:10:41.000
 1       2.0  2017-02-21 14:36:40.000  2017-02-21 14:44:06.000
 2       2.0  2017-03-09 08:53:53.000  2017-03-09 08:59:02.000
 3       2.0  2017-12-05 20:15:50.000  2017-12-05 20:18:26.000
 4       2.0  2017-07-12 14:45:33.000  2017-07-12 14:50:52.000

   store_and_fwd_flag  RatecodeID  PULocationID  DOLocationID
passenger_count  \
 0                  N         1.0            33            52
1.0
 1                  N         1.0            25            97
1.0
 2                  N         1.0            41           166
1.0
 3                  N         1.0           260           260
5.0
 4                  N         1.0            17            17
1.0

    trip_distance  fare_amount  extra  mta_tax  tip_amount
tolls_amount  \
 0           0.96          6.5    1.0      0.5        1.66
0.0
 1           1.12          6.5    0.0      0.5        2.19
0.0
 2           0.95          6.0    0.0      0.5        1.36
0.0
 3           0.55          4.0    0.5      0.5        1.00
0.0
 4           0.63          5.5    0.0      0.5        0.00
0.0

   improvement_surcharge  total_amount  payment_type  trip_type  \
 0                    0.3          9.96           1.0        1.0
 1                    0.3          9.49           1.0        1.0
 2                    0.3          8.16           1.0        1.0
 3                    0.3          6.30           1.0        1.0
 4                    0.3          6.30           2.0        1.0

   congestion_surcharge
 0                  NaN
 1                  NaN
 2                  NaN
 3                  NaN
 4                  NaN  ,
 (400000, 19))
```

```
# Ensure datetime column is in datetime format
df["lpep_pickup_datetime"] =
pd.to_datetime(df["lpep_pickup_datetime"])

# Create a week start date column
df["week_start"] =
df["lpep_pickup_datetime"].dt.to_period("W").apply(lambda r:
r.start_time)

weekly = (
    df.groupby("week_start")
      .size()
      .reset_index(name="trip_count")
      .sort_values("week_start")
)

weekly.head(), weekly.tail()
```

```
(  week_start  trip_count
 0 2008-12-29           8
 1 2010-09-20           3
 2 2016-12-26         318
 3 2017-01-02        1956
 4 2017-01-09        2170,
     week_start  trip_count
 207 2020-11-30        1193
 208 2020-12-07        1249
 209 2020-12-14        1053
 210 2020-12-21         980
 211 2020-12-28         642)
```

```
# Create lag features: previous 1, 2, 3 weeks' trip counts
for lag in [1, 2, 3]:
    weekly[f"lag_{lag}"] = weekly["trip_count"].shift(lag)

# Drop first few rows with NaNs from lagging
weekly_ml = weekly.dropna().reset_index(drop=True)

X = weekly_ml[["lag_1", "lag_2", "lag_3"]]
y = weekly_ml["trip_count"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, shuffle=False
)

model_weekly = RandomForestRegressor(random_state=42)
model_weekly.fit(X_train, y_train)

y_pred = model_weekly.predict(X_test)

print("Weekly demand forecasting RMSE:", mean_squared_error(y_test,
y_pred, squared=False))
print("R²:", r2_score(y_test, y_pred))

# Plot actual vs predicted
plt.figure()
plt.plot(y_test.values, label="Actual")
plt.plot(y_pred, label="Predicted")
plt.title("Weekly Trip Demand – Actual vs Predicted")
plt.xlabel("Test Weeks")
plt.ylabel("Trips")
plt.legend()
plt.show()

----------------------------------------------------------------------
-----
KeyError                                  Traceback (most recent call
last)
File ~\AppData\Local\Programs\Python\Python313\Lib\site-packages\
pandas\core\indexes\base.py:3812, in Index.get_loc(self, key)
   3811 try:
-> 3812     return self._engine.get_loc(casted_key)
   3813 except KeyError as err:

File pandas/_libs/index.pyx:167, in
pandas._libs.index.IndexEngine.get_loc()

File pandas/_libs/index.pyx:175, in
pandas._libs.index.IndexEngine.get_loc()

File pandas/_libs/index_class_helper.pxi:245, in
pandas._libs.index.MaskedUInt32Engine._check_type()

KeyError: 'trip_count'
```

```
The above exception was the direct cause of the following exception:

KeyError                                  Traceback (most recent call
last)
Cell In[56], line 3
      1 # Create lag features: previous 1, 2, 3 weeks' trip counts
      2 for lag in [1, 2, 3]:
----> 3     weekly[f"lag_{lag}"] = weekly["trip_count"].shift(lag)
      5 # Drop first few rows with NaNs from lagging
      6 weekly_ml = weekly.dropna().reset_index(drop=True)

File ~\AppData\Local\Programs\Python\Python313\Lib\site-packages\
pandas\core\series.py:1130, in Series.__getitem__(self, key)
   1127     return self._values[key]
   1129 elif key_is_scalar:
-> 1130     return self._get_value(key)
   1132 # Convert generator to list before going through hashable part
   1133 # (We will iterate through the generator there to check for
slices)
   1134 if is_iterator(key):

File ~\AppData\Local\Programs\Python\Python313\Lib\site-packages\
pandas\core\series.py:1246, in Series._get_value(self, label,
takeable)
   1243     return self._values[label]
   1245 # Similar to Index.get_value, but we do not fall back to
positional
-> 1246 loc = self.index.get_loc(label)
   1248 if is_integer(loc):
   1249     return self._values[loc]

File ~\AppData\Local\Programs\Python\Python313\Lib\site-packages\
pandas\core\indexes\base.py:3819, in Index.get_loc(self, key)
   3814     if isinstance(casted_key, slice) or (
   3815         isinstance(casted_key, abc.Iterable)
   3816         and any(isinstance(x, slice) for x in casted_key)
   3817     ):
   3818         raise InvalidIndexError(key)
-> 3819     raise KeyError(key) from err
   3820 except TypeError:
   3821     # If we have a listlike key, _check_indexing_error will
raise
   3822     #  InvalidIndexError. Otherwise we fall through and re-
raise
   3823     #  the TypeError.
   3824     self._check_indexing_error(key)

KeyError: 'trip_count'
```

```
# ================================
# ▯ Weekly Aggregation (using previous approach)
# ================================
df['lpep_pickup_datetime'] =
pd.to_datetime(df['lpep_pickup_datetime'])

df['week_start'] =
df['lpep_pickup_datetime'].dt.to_period("W").apply(lambda r:
r.start_time)

weekly = (
    df.groupby('week_start')
      .size()
      .reset_index(name='trip_count')
      .sort_values('week_start')
)

print("Weekly data:")
weekly.head()
```

```
Weekly data:
```

```
  week_start  trip_count
0 2008-12-29           8
1 2010-09-20           3
2 2016-12-26         318
3 2017-01-02        1956
4 2017-01-09        2170
```

```
# xyz
# Create lag features
# xyz
for lag in [1, 2, 3]:
    weekly[f'lag_{lag}'] = weekly['trip_count'].shift(lag)

weekly_ml = weekly.dropna().reset_index(drop=True)

X = weekly_ml[['lag_1', 'lag_2', 'lag_3']]
y = weekly_ml['trip_count']

print(weekly_ml.head())
```

```
  week_start  trip_count   lag_1   lag_2   lag_3
0 2017-01-02        1956   318.0     3.0     8.0
1 2017-01-09        2170  1956.0   318.0     3.0
2 2017-01-16        2006  2170.0  1956.0   318.0
3 2017-01-23        2211  2006.0  2170.0  1956.0
4 2017-01-30        2262  2211.0  2006.0  2170.0
```

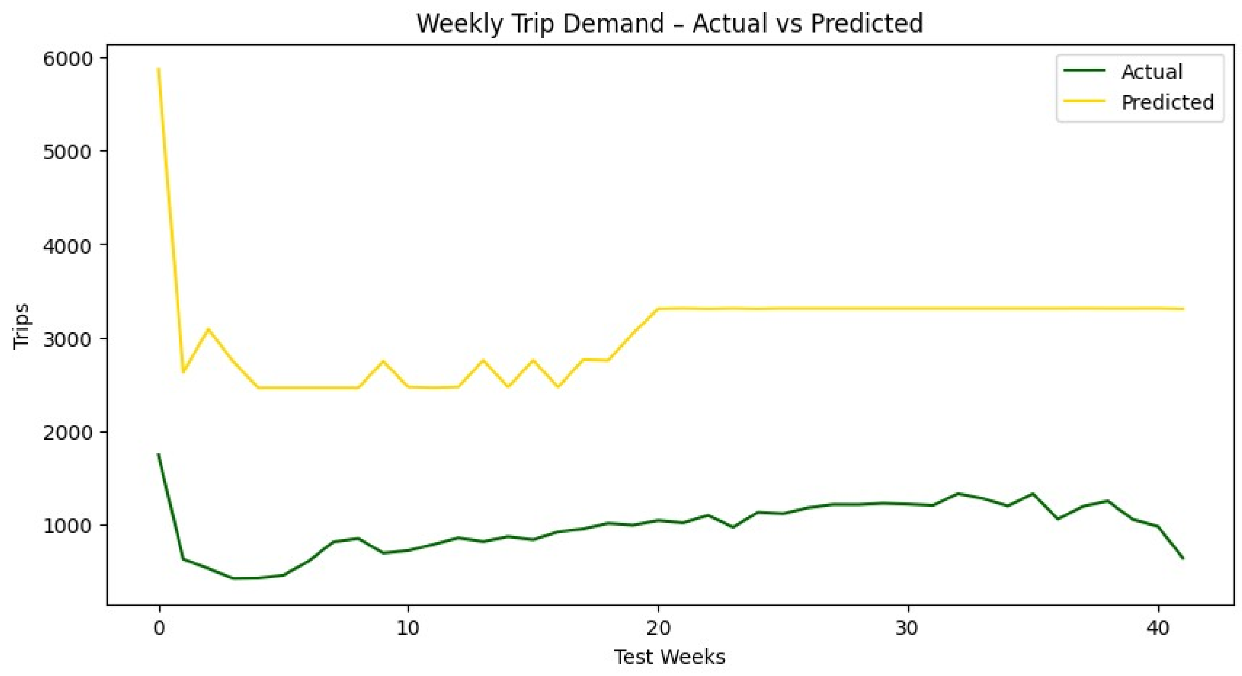
```
# xyz
#Train RandomForest model (previous code style)
```

```
# xyz
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, shuffle=False
)

model_weekly = RandomForestRegressor(random_state=42)
model_weekly.fit(X_train, y_train)

y_pred = model_weekly.predict(X_test)

rmse = mean_squared_error(y_test, y_pred) ** 0.5   # works for all
sklearn versions
print("Weekly demand forecasting RMSE:", rmse)
print("R²:", r2_score(y_test, y_pred))
```

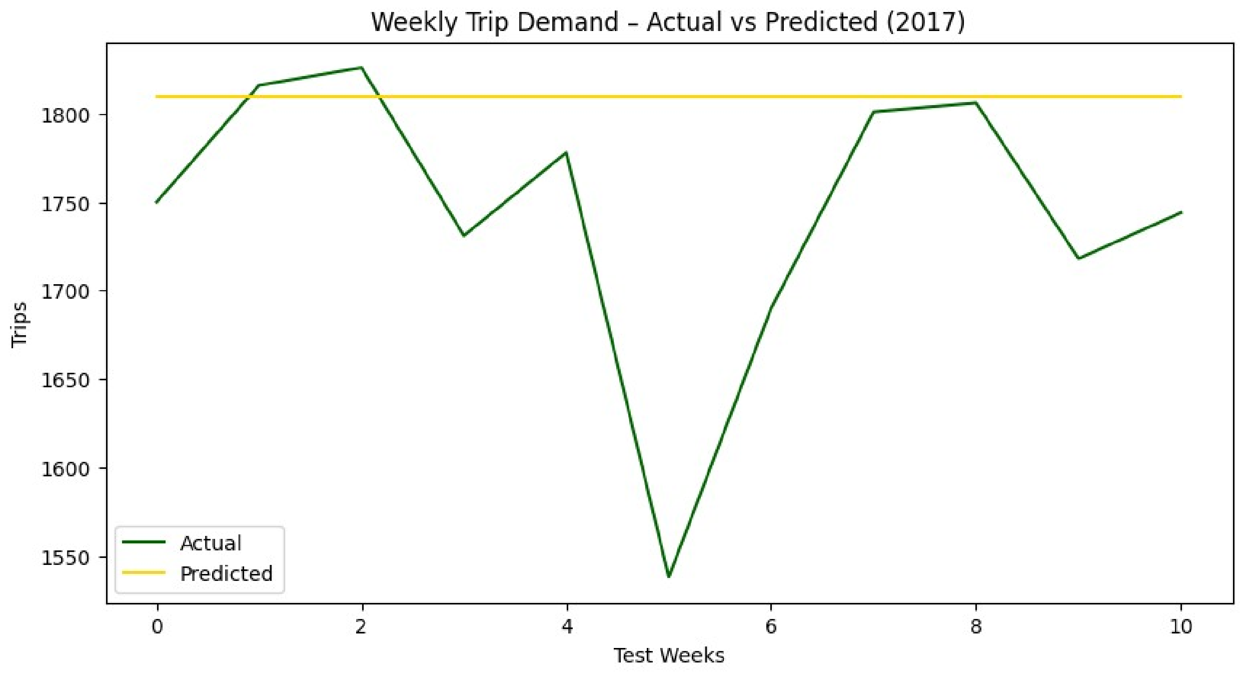
```
Weekly demand forecasting RMSE: 2129.342294309051
R²: -57.46218052500757
```

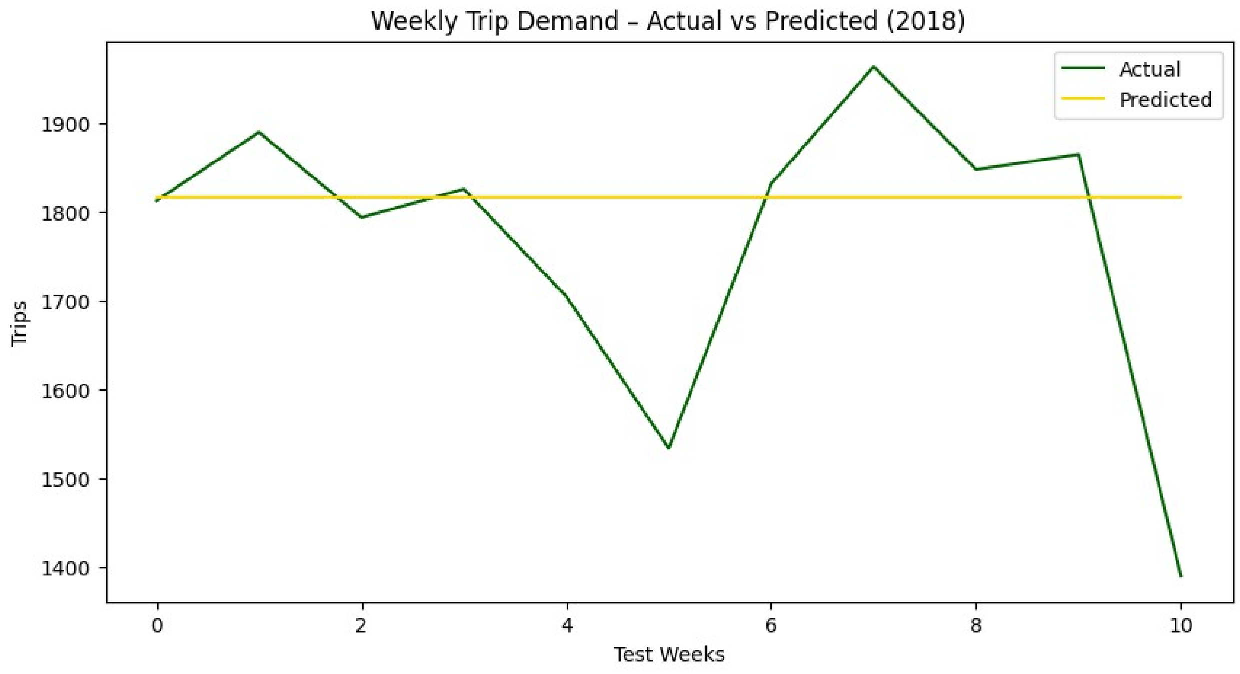
```
# ================================
# □ Plot Actual vs Predicted
# ================================
plt.figure()
plt.figure(figsize=(10,5))
plt.plot(y_test.values, color="#006400", label="Actual")      # Dark
Green
plt.plot(y_pred, color="#FFD700", label="Predicted")          # Dark
Yellow (Gold)
plt.title("Weekly Trip Demand – Actual vs Predicted")
plt.xlabel("Test Weeks")
plt.ylabel("Trips")
plt.legend()
plt.show()
```

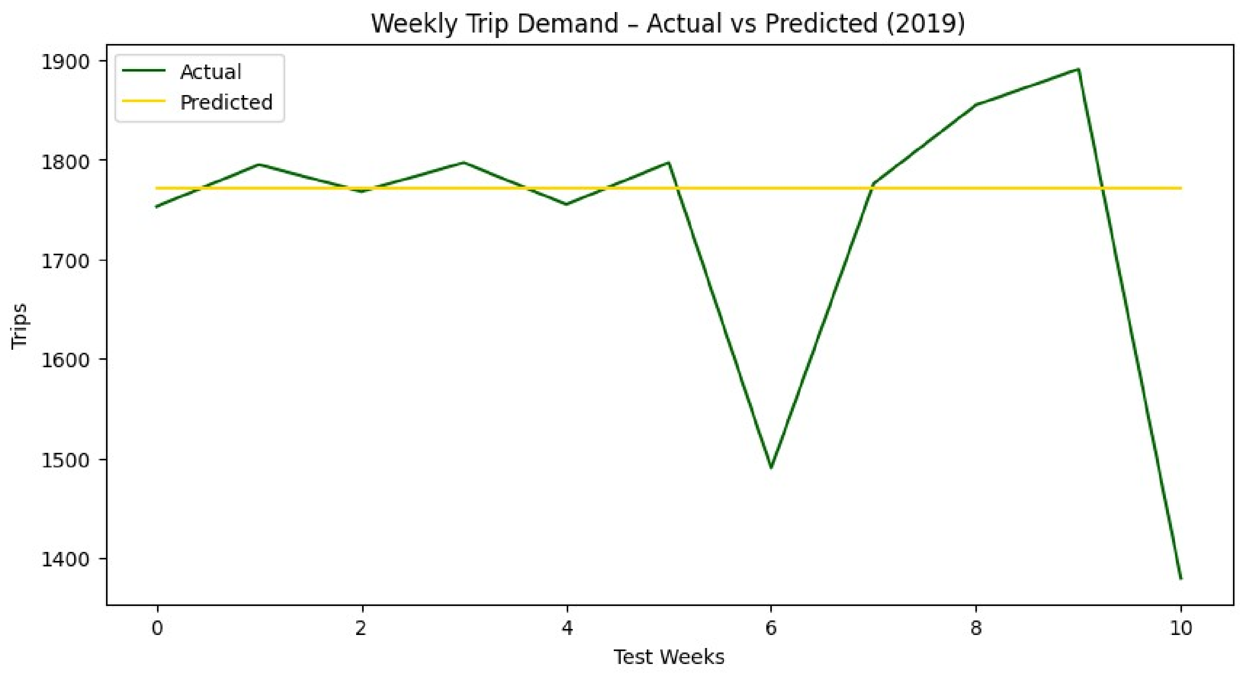
```
<Figure size 640x480 with 0 Axes>
```

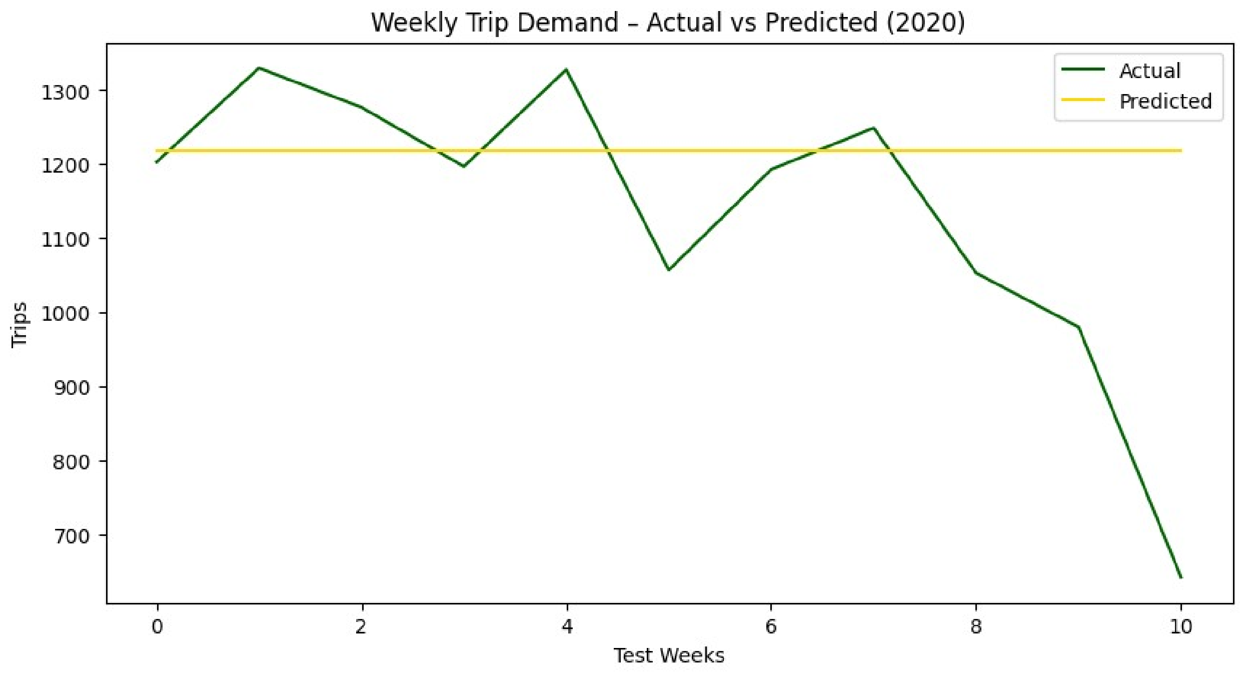


```
# Add year column if not already added
df['year'] = df['lpep_pickup_datetime'].dt.year

unique_years = sorted(df['year'].unique())

for yr in unique_years:
    df_year = df[df['year'] == yr]

    # Recreate weekly grouping for each year
    weekly =
df_year.groupby(df_year['lpep_pickup_datetime'].dt.isocalendar().week)
.size()

    # Split into train-test for each year
    X = weekly.index.values.reshape(-1, 1)
    y = weekly.values

    from sklearn.model_selection import train_test_split
    X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, shuffle=False)

    # Fit model
    from sklearn.ensemble import RandomForestRegressor
    model = RandomForestRegressor()
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    # Plot
    plt.figure(figsize=(10,5))
    plt.plot(y_test, color="#006400", label="Actual")    # Dark green
    plt.plot(y_pred, color="#FFD700", label="Predicted") # Gold
    plt.title(f"Weekly Trip Demand – Actual vs Predicted ({yr})")
    plt.xlabel("Test Weeks")
    plt.ylabel("Trips")
    plt.legend()
    plt.show()
```









```
# ================================
# 🎯 Create High-Tip Target
# ================================
df2 = df.copy()
df2 = df2[df2['tip_amount'] >= 0]  # remove invalid values

avg_tip = df2['tip_amount'].mean()
print("Average tip amount:", avg_tip)
```

```
df2['high_tip'] = (df2['tip_amount'] > avg_tip).astype(int)

Average tip amount: 1.1060786931477258

# ====================
#  Create Model Features
# xyz
df2['hour'] = df2['lpep_pickup_datetime'].dt.hour
df2['day_of_week'] = df2['lpep_pickup_datetime'].dt.dayofweek  #
Monday = 0
df2['month'] = df2['lpep_pickup_datetime'].dt.month

# Columns that must exist:
# trip_distance, pickup_borough, dropoff_borough

df2.columns.tolist()

['VendorID',
 'lpep_pickup_datetime',
 'lpep_dropoff_datetime',
 'store_and_fwd_flag',
 'RatecodeID',
 'PULocationID',
 'DOLocationID',
 'passenger_count',
 'trip_distance',
 'fare_amount',
 'extra',
 'mta_tax',
 'tip_amount',
 'tolls_amount',
 'improvement_surcharge',
 'total_amount',
 'payment_type',
 'trip_type',
 'congestion_surcharge',
 'week_start',
 'high_tip',
 'hour',
 'day_of_week',
 'month']

   # ================================
# □ Select Columns for Model (using existing columns)
# xyz
cat_cols = ['PULocationID', 'DOLocationID']      # categorical
features
num_cols = ['trip_distance', 'passenger_count',
            'hour', 'day_of_week', 'month']      # numeric / time
features
```

```
# Build modeling dataframe
df_model = pd.get_dummies(
    df2[cat_cols + num_cols + ['high_tip']],
    columns=cat_cols,
    drop_first=True
)

X = df_model.drop("high_tip", axis=1)
y = df_model["high_tip"]

print("Model feature shape:", X.shape)
X.head()
```

```
Model feature shape: (399984, 520)

   trip_distance  passenger_count  hour  day_of_week  month
PULocationID_3  \
0           0.96              1.0    18            2      1
False
1           1.12              1.0    14            1      2
False
2           0.95              1.0     8            3      3
False
3           0.55              5.0    20            1     12
False
4           0.63              1.0    14            2      7
False

   PULocationID_4  PULocationID_5  PULocationID_6  PULocationID_7  ...
\
0           False           False           False           False  ...

1           False           False           False           False  ...

2           False           False           False           False  ...

3           False           False           False           False  ...

4           False           False           False           False  ...


   DOLocationID_256  DOLocationID_257  DOLocationID_258
DOLocationID_259  \
0             False             False             False
False
1             False             False             False
False
2             False             False             False
False
3             False             False             False
```

```
False
4              False              False              False
False

   DOLocationID_260  DOLocationID_261  DOLocationID_262
DOLocationID_263  \
0              False              False              False
False
1              False              False              False
False
2              False              False              False
False
3               True              False              False
False
4              False              False              False
False

   DOLocationID_264  DOLocationID_265
0              False              False
1              False              False
2              False              False
3              False              False
4              False              False

[5 rows x 520 columns]
```

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

clf = RandomForestClassifier(
    n_estimators=150,
    max_depth=None,
    random_state=42,
    n_jobs=-1
)

clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n")
print(classification_report(y_test, y_pred))
```

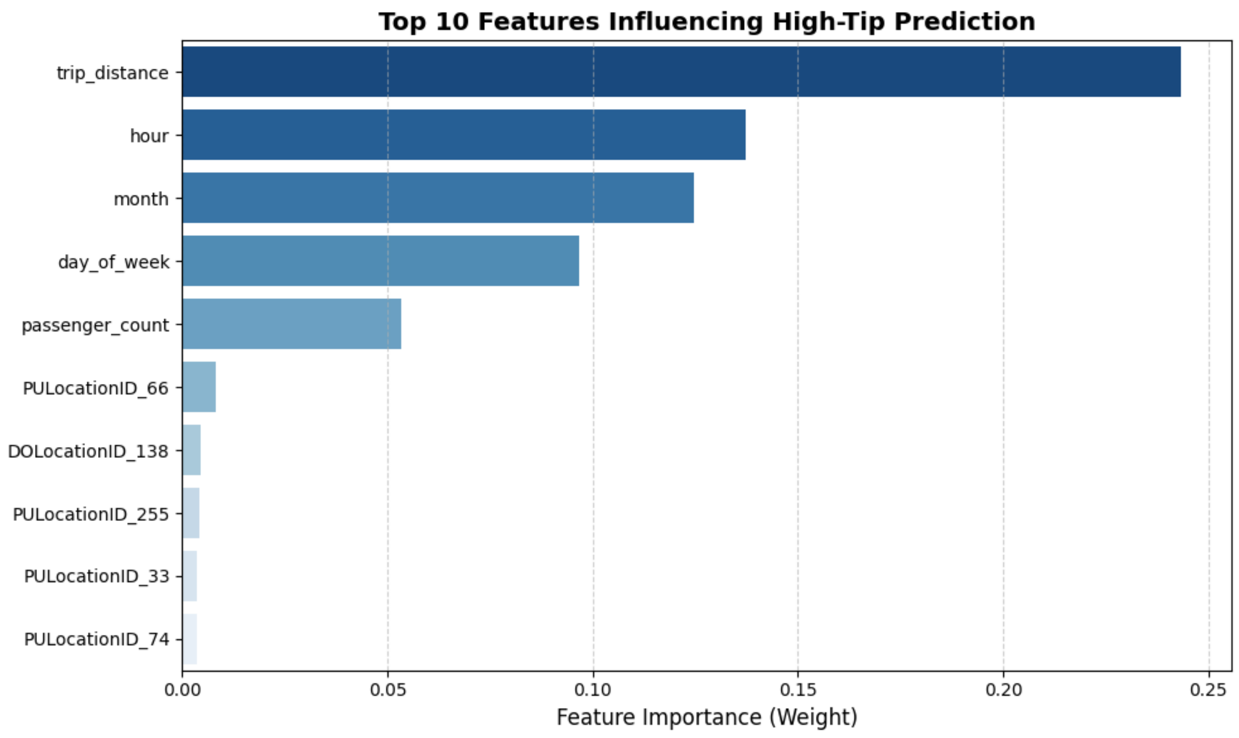
```
Accuracy: 0.7094766053727015

Classification Report:

              precision    recall  f1-score   support

           0       0.75      0.83      0.79     51808
           1       0.61      0.49      0.54     28189

    accuracy                           0.71     79997
   macro avg       0.68      0.66      0.67     79997
weighted avg       0.70      0.71      0.70     79997


# ================================
# Train RandomForest Classifier
# xyz
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

clf = RandomForestClassifier(
    n_estimators=150,
    max_depth=None,
    random_state=42,
    n_jobs=-1
)

clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)

# ================================
#  Model Evaluation
# xyz
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n")
print(classification_report(y_test, y_pred))

Accuracy: 0.7094766053727015

Classification Report:

              precision    recall  f1-score   support

           0       0.75      0.83      0.79     51808
           1       0.61      0.49      0.54     28189

    accuracy                           0.71     79997
   macro avg       0.68      0.66      0.67     79997
weighted avg       0.70      0.71      0.70     79997


!pip install seaborn
```

```
Requirement already satisfied: seaborn in c:\users\parth\appdata\
local\programs\python\python313\lib\site-packages (0.13.2)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in c:\users\parth\
appdata\local\programs\python\python313\lib\site-packages (from
seaborn) (2.3.2)
Requirement already satisfied: pandas>=1.2 in c:\users\parth\appdata\
local\programs\python\python313\lib\site-packages (from seaborn)
(2.3.1)
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in c:\users\
parth\appdata\local\programs\python\python313\lib\site-packages (from
seaborn) (3.10.6)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\parth\
appdata\local\programs\python\python313\lib\site-packages (from
matplotlib!=3.6.1,>=3.4->seaborn) (1.3.3)
Requirement already satisfied: cycler>=0.10 in c:\users\parth\appdata\
local\programs\python\python313\lib\site-packages (from matplotlib!
=3.6.1,>=3.4->seaborn) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\parth\
appdata\local\programs\python\python313\lib\site-packages (from
matplotlib!=3.6.1,>=3.4->seaborn) (4.59.2)
Requirement already satisfied: kiwisolver>=1.3.1 in c:\users\parth\
appdata\local\programs\python\python313\lib\site-packages (from
matplotlib!=3.6.1,>=3.4->seaborn) (1.4.9)
Requirement already satisfied: packaging>=20.0 in c:\users\parth\
appdata\local\programs\python\python313\lib\site-packages (from
matplotlib!=3.6.1,>=3.4->seaborn) (25.0)
Requirement already satisfied: pillow>=8 in c:\users\parth\appdata\
local\programs\python\python313\lib\site-packages (from matplotlib!
=3.6.1,>=3.4->seaborn) (11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\parth\
appdata\local\programs\python\python313\lib\site-packages (from
matplotlib!=3.6.1,>=3.4->seaborn) (3.2.3)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\parth\
appdata\local\programs\python\python313\lib\site-packages (from
matplotlib!=3.6.1,>=3.4->seaborn) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in c:\users\parth\appdata\
local\programs\python\python313\lib\site-packages (from pandas>=1.2-
>seaborn) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in c:\users\parth\
appdata\local\programs\python\python313\lib\site-packages (from
pandas>=1.2->seaborn) (2025.2)
Requirement already satisfied: six>=1.5 in c:\users\parth\appdata\
local\programs\python\python313\lib\site-packages (from python-
dateutil>=2.7->matplotlib!=3.6.1,>=3.4->seaborn) (1.17.0)

WARNING: Ignoring invalid distribution ~treamlit (C:\Users\parth\
AppData\Local\Programs\Python\Python313\Lib\site-packages)
WARNING: Ignoring invalid distribution ~treamlit (C:\Users\parth\
AppData\Local\Programs\Python\Python313\Lib\site-packages)
WARNING: Ignoring invalid distribution ~treamlit (C:\Users\parth\
AppData\Local\Programs\Python\Python313\Lib\site-packages)

[notice] A new release of pip is available: 25.2 -> 25.3
[notice] To update, run: python.exe -m pip install --upgrade pip
```

```python
# Feature Importance
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Use your trained RandomForestClassifier
importances = clf.feature_importances_
indices = np.argsort(importances)[::-1]   # sort descending
features_list = X.columns

feat_imp_df = pd.DataFrame({
    'Feature': features_list[indices],
    'Importance': importances[indices]
})

feat_imp_df.head(10)
```

```
            Feature  Importance
0     trip_distance    0.243412
1              hour    0.137212
2             month    0.124673
3       day_of_week    0.096598
4   passenger_count    0.053187
5    PULocationID_66    0.008116
6  DOLocationID_138    0.004482
7  PULocationID_255    0.004215
8    PULocationID_33    0.003505
9    PULocationID_74    0.003426
```

```python
#  Top 10 Most Important Features
# xyz
plt.figure(figsize=(10,6))

sns.barplot(
    data = feat_imp_df.head(10),
    x = 'Importance',
    y = 'Feature',
    palette = 'Blues_r',
    dodge = False
)

plt.title("Top 10 Features Influencing High-Tip Prediction",
          fontsize=14, weight='bold')

plt.xlabel("Feature Importance (Weight)", fontsize=12)
plt.ylabel("")
plt.grid(axis='x', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()

C:\Users\parth\AppData\Local\Temp\ipykernel_15004\2225236825.py:6:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(
```



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

# Feature Importance Calculation
# xyz
import numpy as np
import pandas as pd

importances = clf.feature_importances_      # <-- IMPORTANT
indices = np.argsort(importances)[::-1]
features_list = X.columns
```

```python
feat_imp_df = pd.DataFrame({
    'Feature': features_list[indices],
    'Importance': importances[indices]
})

feat_imp_df.head()
```

```
           Feature  Importance
0    trip_distance    0.243412
1             hour    0.137212
2            month    0.124673
3      day_of_week    0.096598
4  passenger_count    0.053187
```

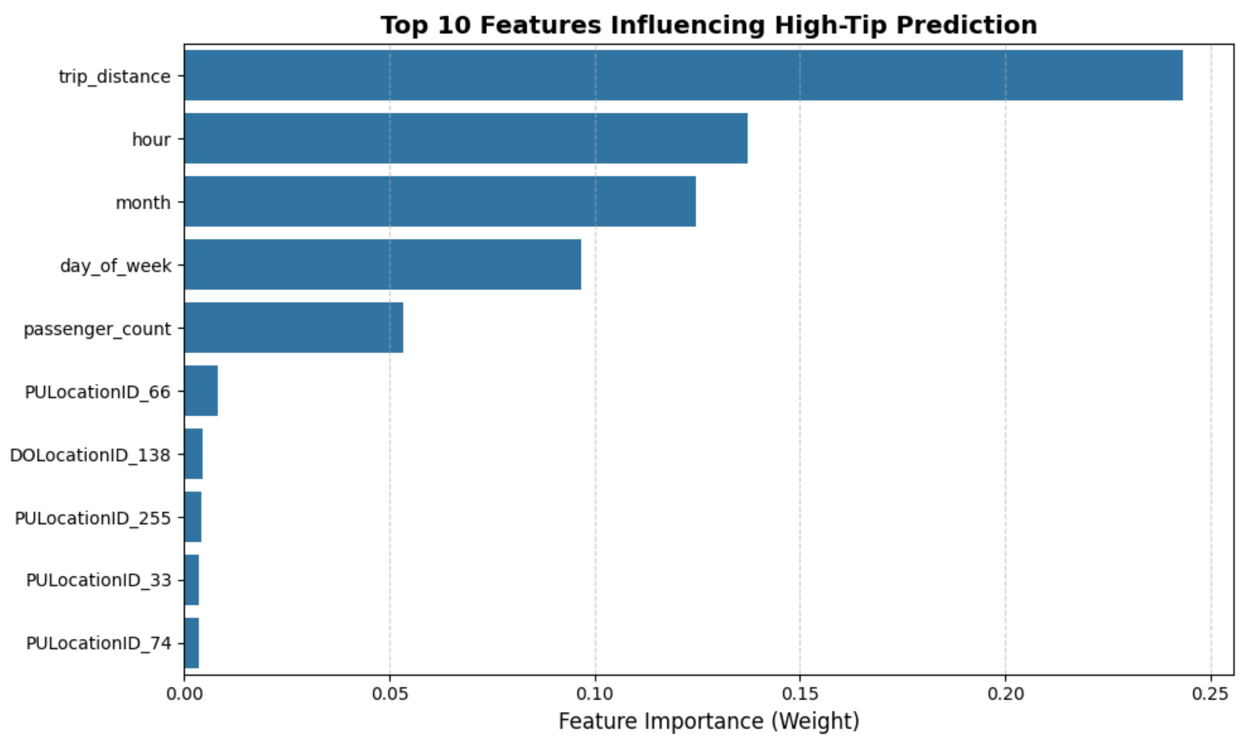
```python
cat_cols = ['PULocationID', 'DOLocationID']
num_cols = ['trip_distance', 'passenger_count', 'hour', 'day_of_week',
'month']

df_model = pd.get_dummies(
    df2[cat_cols + num_cols + ['high_tip']],
    columns=cat_cols,
    drop_first=True
)

X = df_model.drop("high_tip", axis=1)
y = df_model["high_tip"]

print(X.shape, y.shape)
```

```
(399984, 520) (399984,)
```

```python
# High-Tip Prediction Model + Top 10 Feature Importance
# xyz

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

from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report

# 1 Build feature matrix X and target y
cat_cols = ['PULocationID', 'DOLocationID']   # categorical
num_cols = ['trip_distance', 'passenger_count',
            'hour', 'day_of_week', 'month']   # numeric / time

df_model = pd.get_dummies(
    df2[cat_cols + num_cols + ['high_tip']],
    columns=cat_cols,
    drop_first=True
)

X = df_model.drop('high_tip', axis=1)
y = df_model['high_tip']

print("Feature matrix shape:", X.shape)
print("Target distribution:\n", y.value_counts(normalize=True))

# 2 Train / Test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# 3 Train RandomForest classifier
clf = RandomForestClassifier(
    n_estimators=150,
    max_depth=None,
    random_state=42,
    n_jobs=-1
)

clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)

# 4 Evaluation
print("\nAccuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n")
print(classification_report(y_test, y_pred))

# 5 Feature importance calculation
importances = clf.feature_importances_
indices = np.argsort(importances)[::-1]
features_list = X.columns

feat_imp_df = pd.DataFrame({
    'Feature': features_list[indices],
    'Importance': importances[indices]
})

print("\nTop 10 features by importance:\n", feat_imp_df.head(10))

# 6 Plot Top 10 Most Important Features
plt.figure(figsize=(10, 6))
sns.barplot(
    data=feat_imp_df.head(10),
    x='Importance',
    y='Feature',
    dodge=False
```

```
)

plt.title("Top 10 Features Influencing High-Tip Prediction",
          fontsize=14, weight='bold')
plt.xlabel("Feature Importance (Weight)", fontsize=12)
plt.ylabel("")
plt.grid(axis='x', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
```

```
Feature matrix shape: (399984, 520)
Target distribution:
 high_tip
0    0.647626
1    0.352374
Name: proportion, dtype: float64

Accuracy: 0.7094641049039339

Classification Report:

              precision    recall  f1-score   support

           0       0.75      0.83      0.79     51808
           1       0.61      0.49      0.54     28189

    accuracy                           0.71     79997
   macro avg       0.68      0.66      0.67     79997
weighted avg       0.70      0.71      0.70     79997


Top 10 features by importance:
             Feature  Importance
0      trip_distance    0.243412
1               hour    0.137212
2              month    0.124673
3        day_of_week    0.096598
4    passenger_count    0.053187
5    PULocationID_66    0.008116
6   DOLocationID_138    0.004482
7   PULocationID_255    0.004215
8    PULocationID_33    0.003505
9    PULocationID_74    0.003426
```



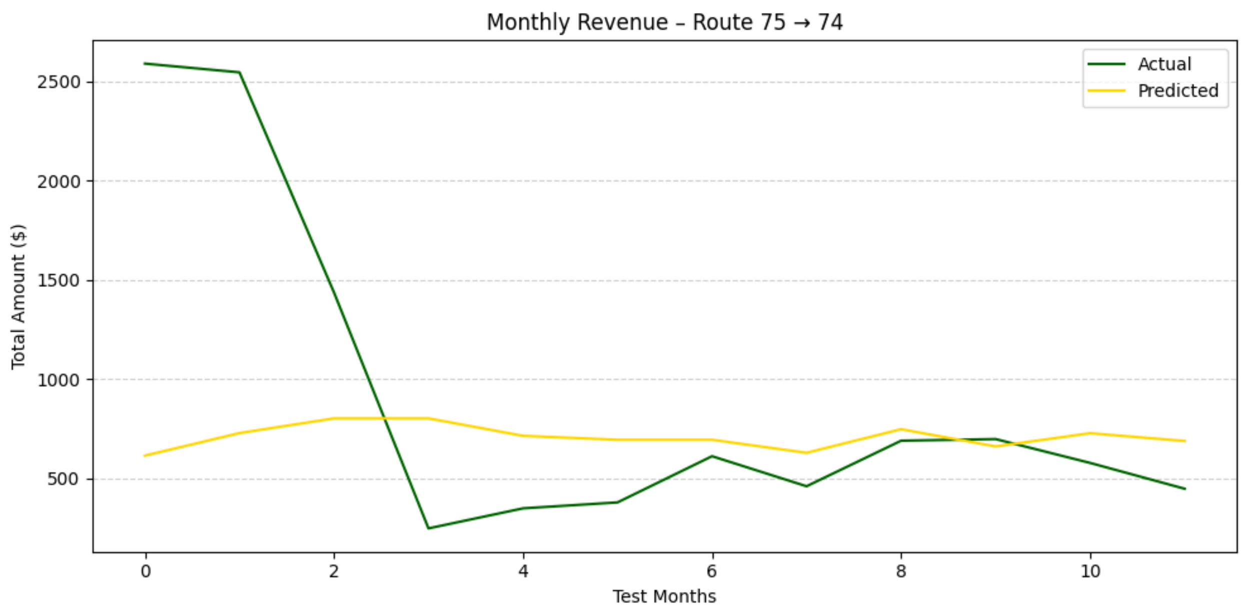
```
# Route-Based Monthly Revenue Forecasting


import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# 1 Ensure correct datetime format
df['lpep_pickup_datetime'] =
pd.to_datetime(df['lpep_pickup_datetime'], errors='coerce')

# 2 Identify top route (highest trip count)
route_counts = (
    df.groupby(['PULocationID', 'DOLocationID'])
      .size()
      .reset_index(name='trip_count')
      .sort_values('trip_count', ascending=False)
)

print("Top 10 busiest routes:")
display(route_counts.head(10))

# Automatically pick the most frequent route
```

```python
top_route = route_counts.iloc[0]
pu_id = int(top_route['PULocationID'])
do_id = int(top_route['DOLocationID'])

print(f"\nUsing Route: PULocationID={pu_id} → DOLocationID={do_id}")

# 3 Filter data for selected route
route_df = df[(df['PULocationID'] == pu_id) &
              (df['DOLocationID'] == do_id)].copy()

print("Total records for selected route:", len(route_df))

# 4 Create monthly revenue
route_df['year_month'] =
route_df['lpep_pickup_datetime'].dt.to_period('M').dt.to_timestamp()

monthly_rev = (
    route_df.groupby('year_month')['total_amount']
            .sum()
            .reset_index(name='monthly_revenue')
            .sort_values('year_month')
)

print("\nMonthly revenue preview:")
display(monthly_rev.head())

# 5 Create lag features
monthly_rev['lag_1'] = monthly_rev['monthly_revenue'].shift(1)
monthly_rev['lag_2'] = monthly_rev['monthly_revenue'].shift(2)

# Drop NaNs
monthly_ml = monthly_rev.dropna().reset_index(drop=True)

X = monthly_ml[['lag_1', 'lag_2']]
y = monthly_ml['monthly_revenue']

# 6 Train / Test Split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.25, shuffle=False  # keep time order
)

# 7 Train RandomForestRegressor
model = RandomForestRegressor(
    n_estimators=150,
    random_state=42
)

model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

```
# 8 Performance Metrics
rmse = mean_squared_error(y_test, y_pred) ** 0.5
r2 = r2_score(y_test, y_pred)

print("\n□ Route Revenue Forecasting Results")
print("RMSE:", rmse)
print("R² Score:", r2)

# 9 Plot Actual vs Predicted
plt.figure(figsize=(10,5))
plt.plot(y_test.values, label="Actual", color="#006400")       # Dark
green
plt.plot(y_pred, label="Predicted", color="#FFD700")          # Dark
yellow
plt.title(f"Monthly Revenue – Route {pu_id} → {do_id}")
plt.xlabel("Test Months")
plt.ylabel("Total Amount ($)")
plt.legend()
plt.grid(axis='y', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
```

```
Top 10 busiest routes:

      PULocationID  DOLocationID  trip_count
7029            75            74        4594
130              7             7        4545
6822            74            75        3830
3473            41            42        3789
9340            95            95        3358
6821            74            74        3056
8039            82           129        3012
3672            42            42        3001
3472            41            41        2934
3496            41            74        2809


Using Route: PULocationID=75 → DOLocationID=74
Total records for selected route: 4594

Monthly revenue preview:

  year_month  monthly_revenue
0 2017-01-01           706.56
1 2017-02-01           716.12
2 2017-03-01           815.45
3 2017-04-01           655.81
4 2017-05-01           736.07


□ Route Revenue Forecasting Results
```

```
RMSE: 829.7019772888709
R² Score: -0.09976580535236113
```



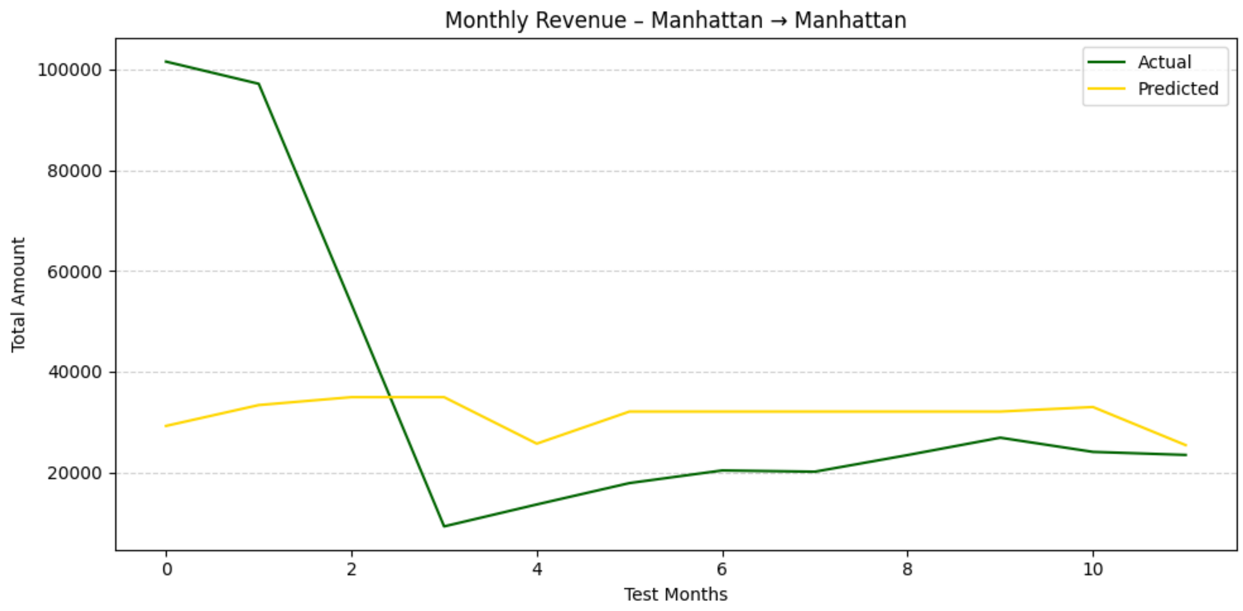
```
taxi_zones = pd.read_csv(
    "C:/Users/parth/OneDrive/Desktop/Trips 2/taxi_zones.csv")

df = df.merge(
    taxi_zones[['LocationID', 'Borough']],
    left_on='PULocationID',
    right_on='LocationID',
    how='left'
)

df = df.rename(columns={'Borough': 'pickup_borough'})
df = df.drop(columns=['LocationID'])

df = df.merge(
    taxi_zones[['LocationID', 'Borough']],
    left_on='DOLocationID',
    right_on='LocationID',
    how='left'
)

df = df.rename(columns={'Borough': 'dropoff_borough'})
df = df.drop(columns=['LocationID'])

df.columns.tolist()

['VendorID',
 'lpep_pickup_datetime',
 'lpep_dropoff_datetime',
 'store_and_fwd_flag',
 'RatecodeID',
 'PULocationID',
 'DOLocationID',
 'passenger_count',
 'trip_distance',
 'fare_amount',
 'extra',
 'mta_tax',
 'tip_amount',
 'tolls_amount',
 'improvement_surcharge',
 'total_amount',
 'payment_type',
 'trip_type',
 'congestion_surcharge',
 'week_start',
 'pickup_borough',
 'dropoff_borough',
 'dropoff_borough',
 'dropoff_borough',
 'pickup_borough',
 'dropoff_borough']

# Keep only first occurrence of each column name
df = df.loc[:, ~df.columns.duplicated()]

df.columns.tolist()   # just to check, you should now see each name
only once

['VendorID',
 'lpep_pickup_datetime',
 'lpep_dropoff_datetime',
 'store_and_fwd_flag',
 'RatecodeID',
 'PULocationID',
 'DOLocationID',
 'passenger_count',
 'trip_distance',
 'fare_amount',
 'extra',
 'mta_tax',
 'tip_amount',
 'tolls_amount',
 'improvement_surcharge',
 'total_amount',
 'payment_type',
 'trip_type',
 'congestion_surcharge',
 'week_start',
 'pickup_borough',
 'dropoff_borough']

df['route'] = df['pickup_borough'] + " → " + df['dropoff_borough']
df[['pickup_borough', 'dropoff_borough', 'route']].head()

C:\Users\parth\AppData\Local\Temp\ipykernel_15004\3927191911.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df['route'] = df['pickup_borough'] + " → " + df['dropoff_borough']

  pickup_borough dropoff_borough                  route
0       Brooklyn        Brooklyn    Brooklyn → Brooklyn
1       Brooklyn        Brooklyn    Brooklyn → Brooklyn
2      Manhattan       Manhattan  Manhattan → Manhattan
3         Queens          Queens        Queens → Queens
4       Brooklyn        Brooklyn    Brooklyn → Brooklyn

df.loc[:, 'route'] = df['pickup_borough'] + " → " +
df['dropoff_borough']

# 1. Filter to years 2017–2020  (if not already done)

df['lpep_pickup_datetime'] =
pd.to_datetime(df['lpep_pickup_datetime'], errors='coerce')
df = df[(df['lpep_pickup_datetime'].dt.year >= 2017) &
        (df['lpep_pickup_datetime'].dt.year <= 2020)]

# 2. Check top borough→borough routes

print("Top 10 borough routes by trip count:")
print(df['route'].value_counts().head(10))

# Pick one route to forecast (you can change this string)
target_route = df['route'].value_counts().index[0]   # or e.g.
"Manhattan → Brooklyn"
print("\nUsing route:", target_route)

route_df = df[df['route'] == target_route].copy()

# =======================================================
# 3. Build monthly revenue series for that route
# =======================================================
route_df['year_month'] =
route_df['lpep_pickup_datetime'].dt.to_period('M').dt.to_timestamp()
```

```python
monthly_rev = (route_df
               .groupby('year_month')['total_amount']
               .sum()
               .reset_index(name='monthly_revenue')
               .sort_values('year_month'))

print("\nMonthly revenue preview:")
print(monthly_rev.head())


# 4. Create lag features

monthly_rev['lag_1'] = monthly_rev['monthly_revenue'].shift(1)
monthly_rev['lag_2'] = monthly_rev['monthly_revenue'].shift(2)

# Drop first rows with NaN lags
monthly_ml = monthly_rev.dropna().reset_index(drop=True)

X = monthly_ml[['lag_1', 'lag_2']]
y = monthly_ml['monthly_revenue']


# 5. Train / test split
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.25, shuffle=False
)

model = RandomForestRegressor(
    n_estimators=150,
    random_state=42
)

model.fit(X_train, y_train)
y_pred = model.predict(X_test)

rmse = mean_squared_error(y_test, y_pred) ** 0.5
r2 = r2_score(y_test, y_pred)

print("\n Route Revenue Forecasting Results (borough based)")
print("Route:", target_route)
print("RMSE:", rmse)
print("R²:", r2)


# 6. Plot Actual vs Predicted monthly revenue
```

```
plt.figure(figsize=(10,5))
plt.plot(y_test.values, label="Actual", color="#006400")      # dark 
green
plt.plot(y_pred, label="Predicted", color="#FFD700")         # dark 
yellow
plt.title(f"Monthly Revenue – {target_route}")
plt.xlabel("Test Months")
plt.ylabel("Total Amount")
plt.legend()
plt.grid(axis='y', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
```

```
C:\Users\parth\AppData\Local\Temp\ipykernel_15004\2662573679.py:4: 
SettingWithCopyWarning: 
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: 
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df['lpep_pickup_datetime'] = 
pd.to_datetime(df['lpep_pickup_datetime'], errors='coerce')

Top 10 borough routes by trip count:
route
Manhattan → Manhattan    119029
Queens → Queens           97614
Brooklyn → Brooklyn       97315
Bronx → Bronx             19023
Brooklyn → Manhattan      17506
Manhattan → Bronx         11054
Queens → Manhattan         7588
Brooklyn → Queens          6708
Bronx → Manhattan          6047
Queens → Brooklyn          5205
Name: count, dtype: int64

Using route: Manhattan → Manhattan

Monthly revenue preview:
  year_month  monthly_revenue
0 2017-01-01         29748.80
1 2017-02-01         29763.81
2 2017-03-01         31136.45
3 2017-04-01         29900.01
4 2017-05-01         30307.12

 Route Revenue Forecasting Results (borough based)
Route: Manhattan → Manhattan
```

```
RMSE: 30430.07166554574
R²: -0.017662602963947505
```


Monthly Revenue – Manhattan → Manhattan
Actual
Predicted
Total Amount
Test Months