



# Uber Trip Analysis

Internship Project Report

## 📌 Section 1: Project Overview

Project Title:

Uber Trip Analysis

Project Type:

Data Analysis & Machine Learning

Technologies Used:

- ✓ Python (Data Processing, Machine Learning, Web App)
- ✓ Flask (Web Application Development)
- ✓ Pandas & NumPy (Data Manipulation)
- ✓ Scikit-Learn (Machine Learning)
- ✓ Matplotlib, Seaborn (Data Visualization)
- ✓ Joblib (Model Saving & Deployment)

Project Difficulty Level:

## Advanced

### **Section 2: Project Objective & Need**

#### **Objective**

The aim of this project is to predict Uber trip demand based on historical ride-hailing data using machine learning models. This system helps:

-  Estimate demand for Uber trips at different times of the day
-  Analyze ride-hailing trends using advanced data visualizations
-  Assist businesses & drivers in making data-driven decisions on fleet distribution

#### **Why is This Project Needed?**

-  The demand for ride-hailing services fluctuates throughout the day.
-  Accurate trip demand prediction helps Uber optimize its fleet for better efficiency.

-  Prevents surge pricing & availability issues by forecasting peak ride demand.
-  Helps city planners analyze urban mobility patterns for better infrastructure.

### **Section 3: Dataset Information**

#### **Dataset Source:**

The dataset is obtained from Uber FOIL (January-February) trip records.

#### **Dataset Features (Columns Used for Prediction):**

**Feature Name      Description**

Active Vehicles      Number of Uber vehicles available at a given time.

Hour      The hour of the day (0-23).

Day of the Week      The weekday (Monday-Sunday).

Month      The month of the year.

Weekend Flag      Indicates if the day is a weekend (1) or weekday (0).

#### **Target Variable (What We Predict):**

 **Number of Uber Trips**

## Section 4: Project Execution - Steps & Implementation

### Step 1: Data Collection

- ✓ Load the dataset using Pandas.
- ✓ Check for missing values, duplicates, and data types.

### Step 2: Data Preprocessing

- ✓ Convert date column to datetime format.
- ✓ Extract hour, day of the week, and month from timestamps.
- ✓ Create a weekend flag (1 for weekends, 0 for weekdays).
- ✓ Handle missing values and normalize numerical features using StandardScaler.

### Step 3: Exploratory Data Analysis (EDA)

- ✓ Trips per hour of the day (Bar Graph)
- ✓ Trips per day of the week (Grouped Bar Chart)
- ✓ Trips vs Active Vehicles (Scatter Plot)

- ✓ Hourly Trip Demand Heatmap

## Step 4: Feature Engineering

- ✓ Select relevant features:

Active Vehicles

Hour

Day of the Week

Month

Weekend Flag

- ✓ Scale numerical features using StandardScaler for better ML performance.

## Step 5: Model Building

- ✓ Train a Linear Regression model for trip prediction.
- ✓ Train a Random Forest model for better accuracy.
- ✓ Use GridSearchCV for hyperparameter tuning.

## Step 6: Model Evaluation

- ✓ Use Mean Absolute Error (MAE), Mean Squared Error (MSE), and R<sup>2</sup> Score to measure accuracy.

- ✓ Compare actual vs. predicted values using a scatter plot.

## Step 7: Data Visualization

- ✓ Pie Chart → Distribution of trips vs active vehicles.
- ✓ Bar Graph → Comparison of predicted trips & active vehicles.
- ✓ Line Chart → Trend analysis of trips over 24 hours.
- ✓ Scatter Plot → Relationship between active vehicles & trip demand.
- ✓ Heatmap → Visualizing hourly trip demand patterns.

## Step 8: Flask Web Application

- ✓ Built a Flask web app for users to input date, time, and active vehicles.
- ✓ Predicts trip demand dynamically based on user input.
- ✓ Displays related visualizations (bar charts, pie charts, line charts, heatmaps).
- ✓ Fully responsive & modern UI (Dark Theme with Gold Accents).

## Section 5: Results & Conclusion

### Key Achievements

- ◆ Successfully built a machine learning model to predict Uber trip demand.
- ◆ Integrated real-time interactive visualizations (pie charts, bar graphs, line charts).
- ◆ Developed a Flask-powered web app for seamless user interaction.
- ◆ Created a modern, responsive UI/UX with dark mode & gold accents.

### Future Enhancements

- ✓ Improve accuracy using XGBoost & Deep Learning models.
- ✓ Add real-time Uber API integration for dynamic trip predictions.
- ✓ Deploy on Cloud (AWS, Heroku, or Streamlit) for public access.

# Uber-Trip-Analysis

```
# Import necessary libraries
import pandas as pd # For data handling
import numpy as np # For numerical operations
import matplotlib.pyplot as plt # For visualization
import seaborn as sns # For better plots
from datetime import datetime # For date-time processing

# Load the dataset
file_path = "Uber-Jan-Feb-FOIL.csv" # Replace with actual file path
df = pd.read_csv(file_path)

# Display the first few rows
print("First 5 rows of dataset:")
print(df.head())

# Display dataset info
print("\nDataset Information:")
print(df.info())

# Check for missing values
print("\nMissing values in each column:")
print(df.isnull().sum())

First 5 rows of dataset:
   dispatching_base_number      date  active_vehicles  trips
0                  B02512  1/1/2015              190    1132
1                  B02765  1/1/2015              225    1765
2                  B02764  1/1/2015             3427  29421
3                  B02682  1/1/2015              945    7679
4                  B02617  1/1/2015             1228   9537

Dataset Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 354 entries, 0 to 353
Data columns (total 4 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   dispatching_base_number  354 non-null   object 
 1   date                 354 non-null   object 
 2   active_vehicles       354 non-null   int64  
 3   trips                354 non-null   int64  
dtypes: int64(2), object(2)
memory usage: 11.2+ KB
None

Missing values in each column:
```

```
dispatching_base_number      0
date                          0
active_vehicles                0
trips                         0
dtype: int64

print(df.columns)

Index(['dispatching_base_number', 'date', 'active_vehicles', 'trips'],
      dtype='object')

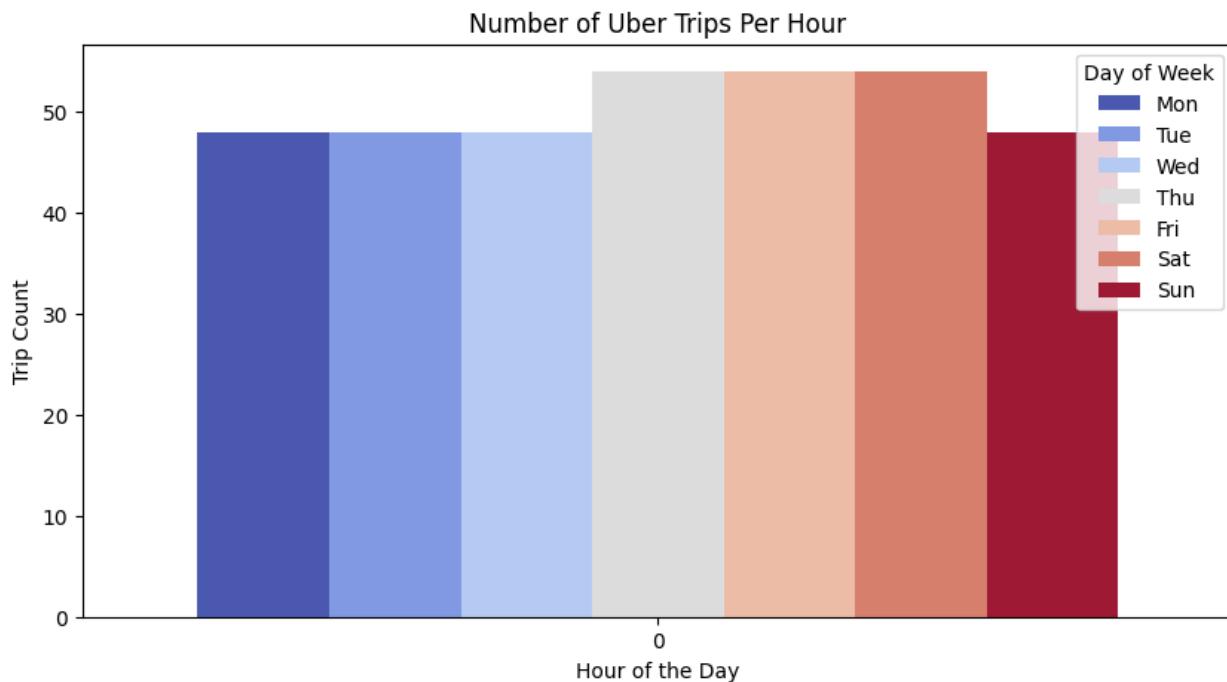
df['date'] = pd.to_datetime(df['date'])
print(df.info()) # Verify the new format

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 354 entries, 0 to 353
Data columns (total 4 columns):
 #   Column           Non-Null Count  Dtype  
 --- 
  0   dispatching_base_number    354 non-null   object  
  1   date                  354 non-null   datetime64[ns] 
  2   active_vehicles        354 non-null   int64   
  3   trips                 354 non-null   int64   
dtypes: datetime64[ns](1), int64(2), object(1)
memory usage: 11.2+ KB
None

df['Hour'] = df['date'].dt.hour
df['Day'] = df['date'].dt.day
df['DayOfWeek'] = df['date'].dt.dayofweek # 0 = Monday, 6 = Sunday
df['Month'] = df['date'].dt.month
```

Plot number of trips per hour, colored by day of the week

```
plt.figure(figsize=(10, 5))
sns.countplot(x=df['Hour'], hue=df['DayOfWeek'], palette="coolwarm")
plt.title("Number of Uber Trips Per Hour")
plt.xlabel("Hour of the Day")
plt.ylabel("Trip Count")
plt.legend(title="Day of Week", labels=["Mon", "Tue", "Wed", "Thu",
"Fri", "Sat", "Sun"])
plt.show()
```

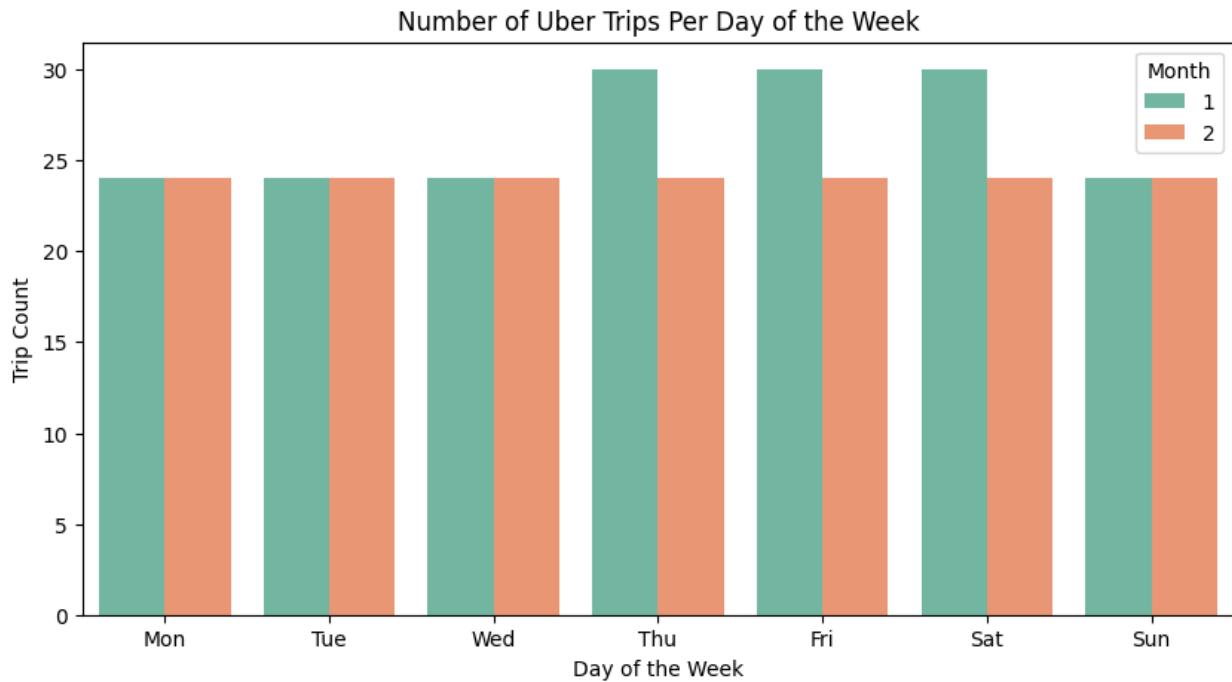


```
# Check the column names in the dataset
print(df.columns)

Index(['dispatching_base_number', 'date', 'active_vehicles', 'trips',
       'Hour',
       'Day', 'DayOfWeek', 'Month'],
      dtype='object')
```

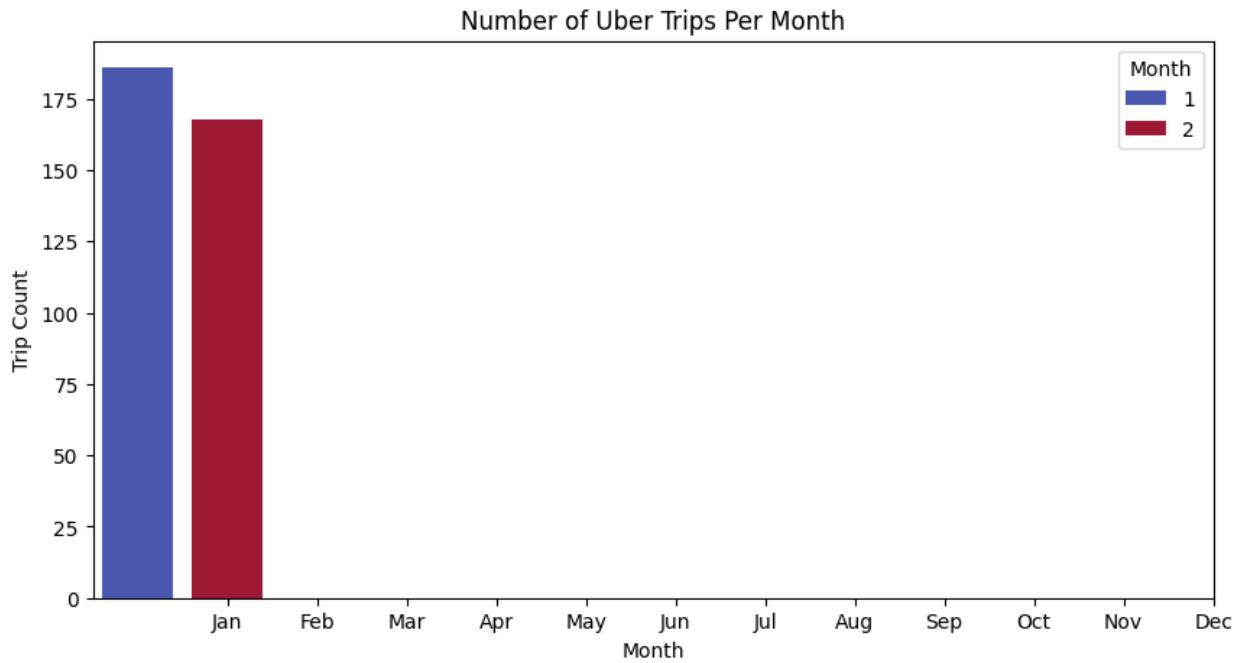
Plot number of trips per day of the week, colored by Month (for example)

```
plt.figure(figsize=(10, 5))
sns.countplot(x=df['DayOfWeek'], hue=df['Month'], palette="Set2")
plt.title("Number of Uber Trips Per Day of the Week")
plt.xlabel("Day of the Week")
plt.ylabel("Trip Count")
plt.xticks(ticks=np.arange(7), labels=["Mon", "Tue", "Wed", "Thu",
"Fri", "Sat", "Sun"])
plt.show()
```



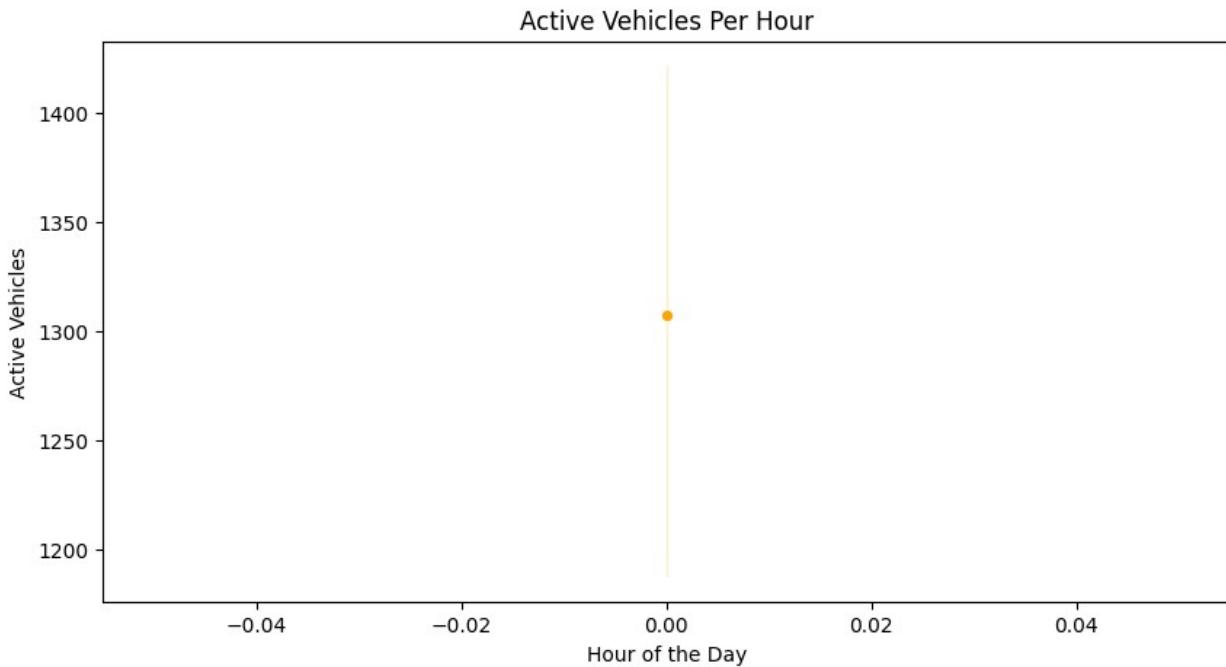
Plot number of trips per month with hue for coloring (if you want categories)

```
plt.figure(figsize=(10, 5))
sns.countplot(x=df['Month'], hue=df['Month'], palette="coolwarm")
plt.title("Number of Uber Trips Per Month")
plt.xlabel("Month")
plt.ylabel("Trip Count")
plt.xticks(ticks=np.arange(1, 13), labels=["Jan", "Feb", "Mar", "Apr",
"May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"])
plt.show()
```



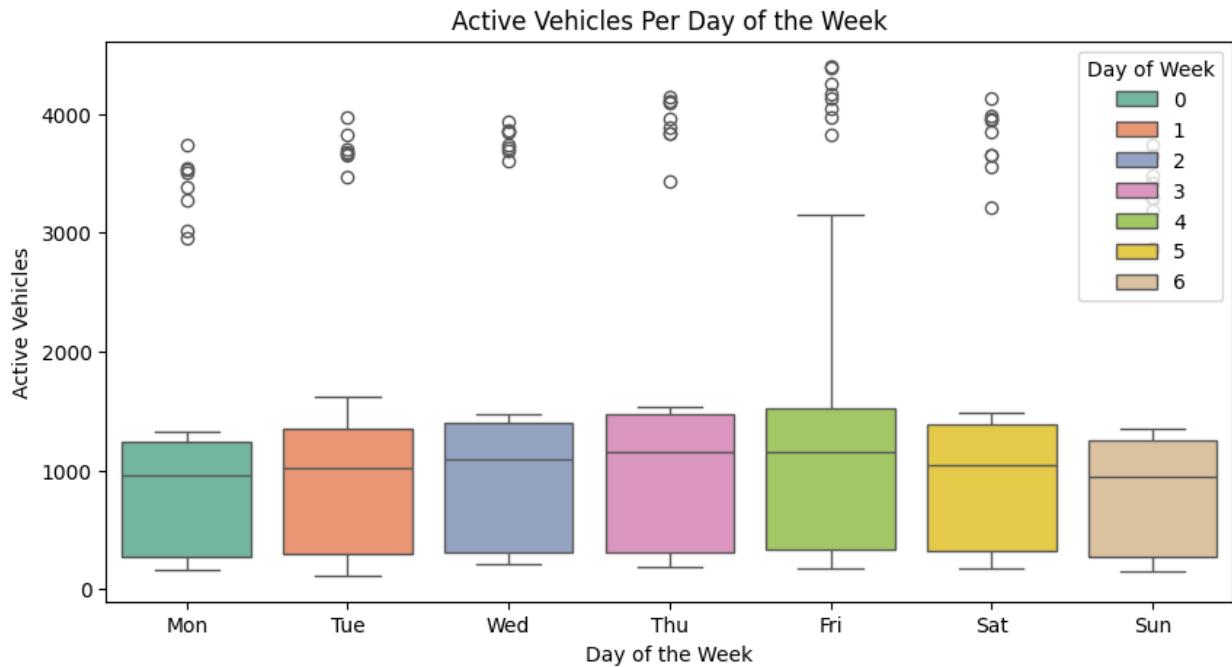
## Plot active vehicles per hour

```
plt.figure(figsize=(10, 5))
sns.lineplot(x=df['Hour'], y=df['active_vehicles'], marker='o',
color='orange')
plt.title("Active Vehicles Per Hour")
plt.xlabel("Hour of the Day")
plt.ylabel("Active Vehicles")
plt.show()
```



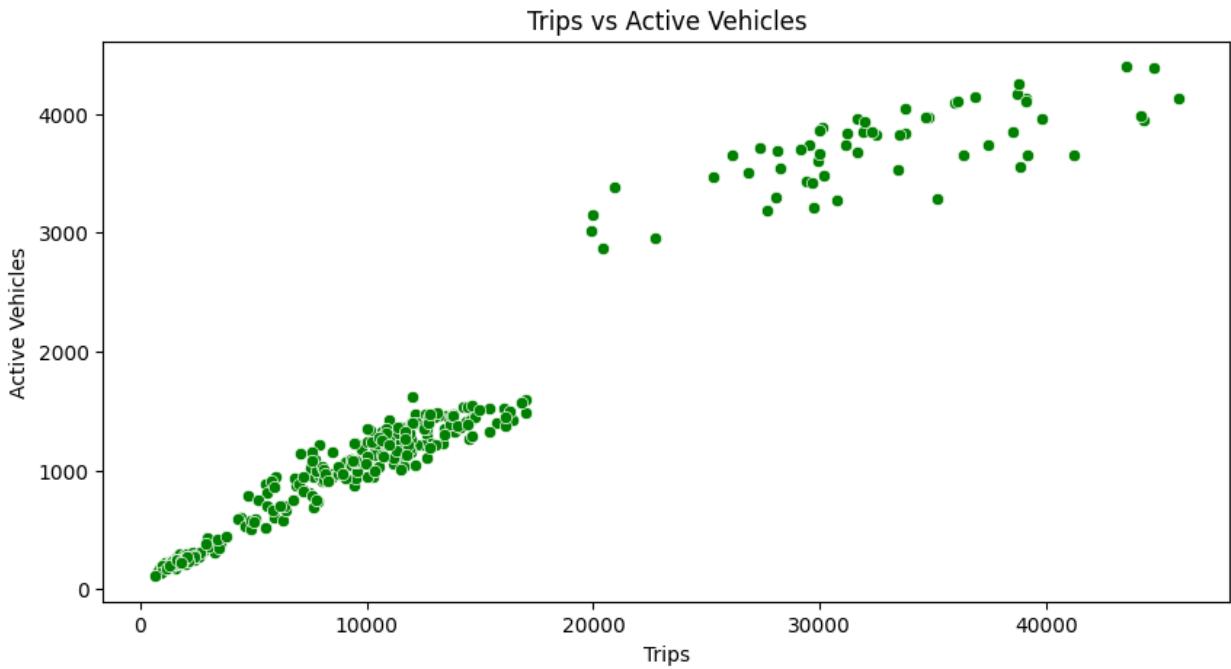
Plot active vehicles per day of the week with hue for coloring

```
plt.figure(figsize=(10, 5))
sns.boxplot(x=df['DayOfWeek'], y=df['active_vehicles'],
hue=df['DayOfWeek'], palette="Set2")
plt.title("Active Vehicles Per Day of the Week")
plt.xlabel("Day of the Week")
plt.ylabel("Active Vehicles")
plt.xticks(ticks=np.arange(7), labels=["Mon", "Tue", "Wed", "Thu",
"Fri", "Sat", "Sun"])
plt.legend(title="Day of Week")
plt.show()
```



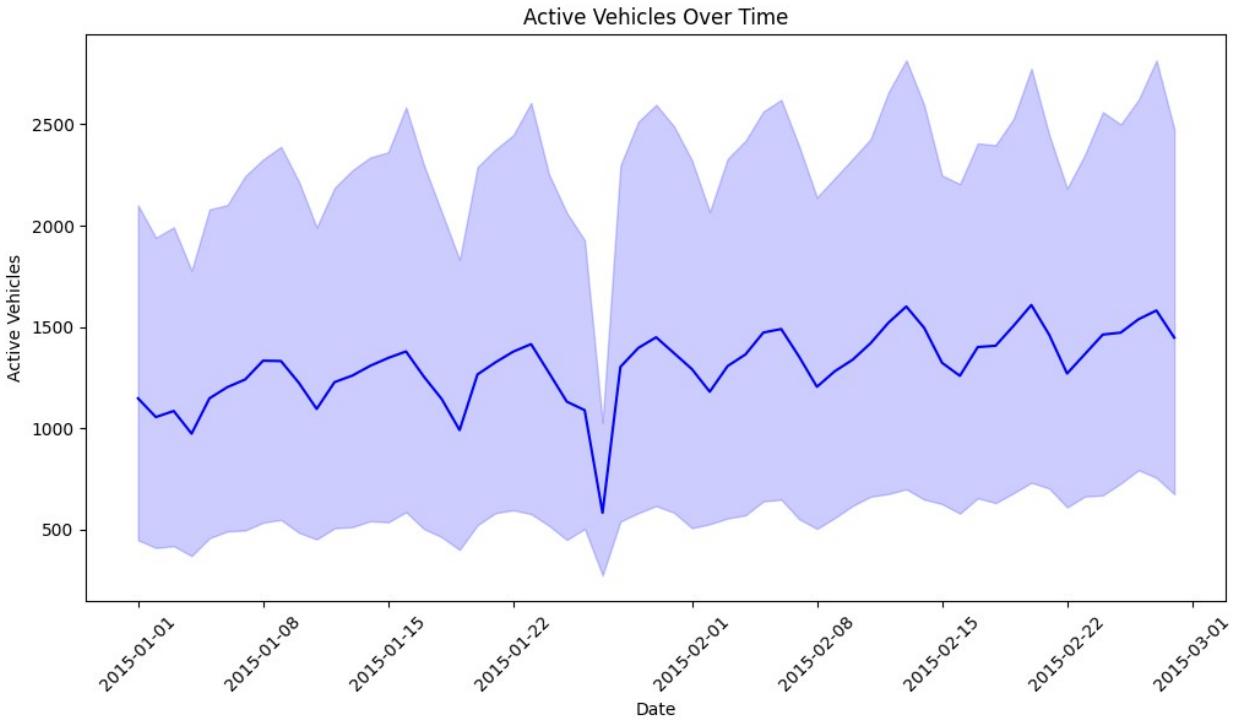
## Plot trips vs active vehicles

```
plt.figure(figsize=(10, 5))
sns.scatterplot(x=df['trips'], y=df['active_vehicles'], color='green')
plt.title("Trips vs Active Vehicles")
plt.xlabel("Trips")
plt.ylabel("Active Vehicles")
plt.show()
```



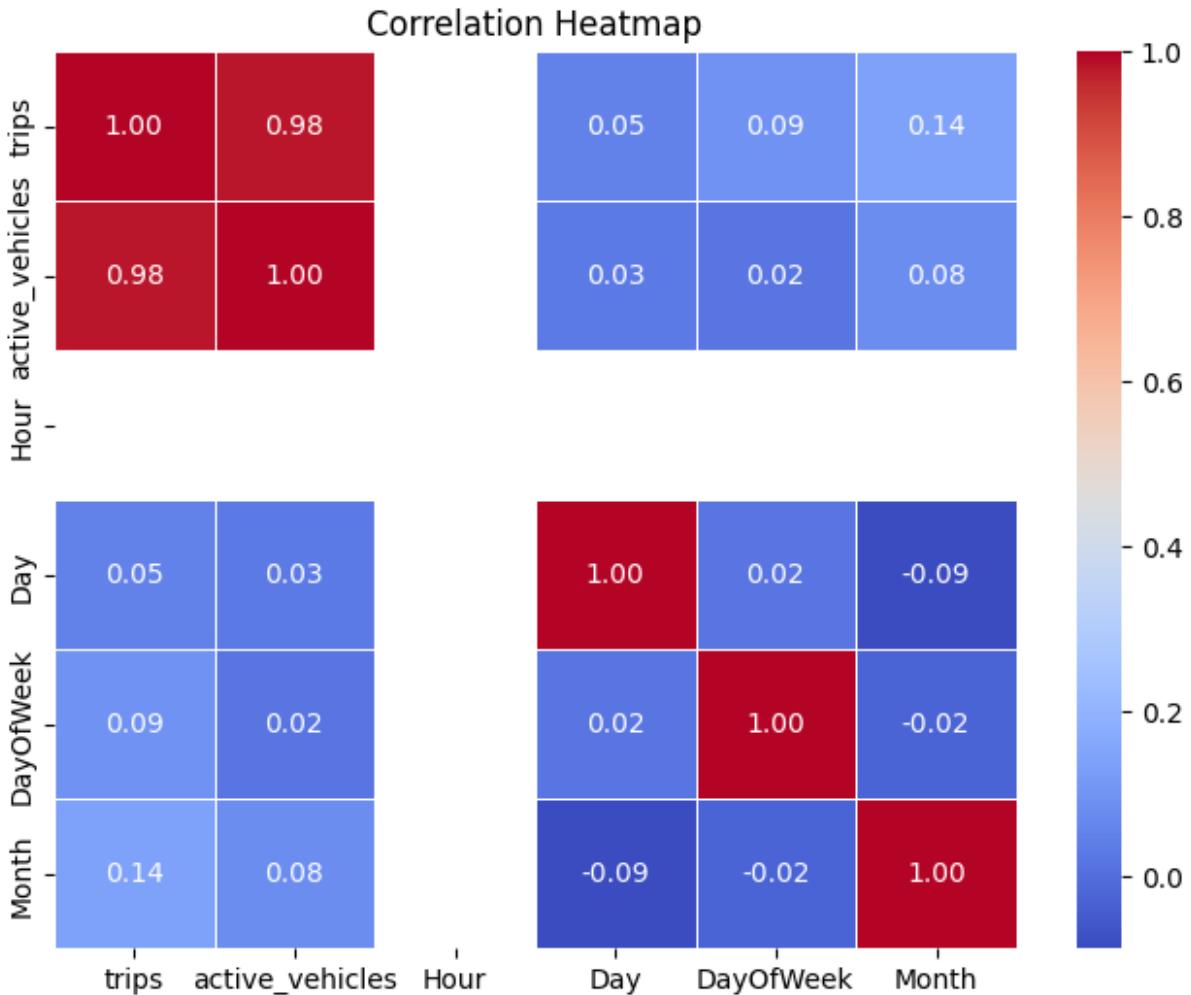
Plot active vehicles trend over time (by date)

```
plt.figure(figsize=(12, 6))
sns.lineplot(x=df['date'], y=df['active_vehicles'], color='blue')
plt.title("Active Vehicles Over Time")
plt.xlabel("Date")
plt.ylabel("Active Vehicles")
plt.xticks(rotation=45)
plt.show()
```



```
# Compute correlations between numerical features
correlation_matrix = df[['trips', 'active_vehicles', 'Hour', 'Day',
'DayOfWeek', 'Month']].corr()

# Plot the heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm",
fmt=".2f", linewidths=0.5)
plt.title("Correlation Heatmap")
plt.show()
```



```
# Add weekday name
df['Weekday'] = df['date'].dt.strftime('%A') # Converts DayOfWeek to
# full weekday name (e.g., Monday, Tuesday)

# Add Weekend flag (1 for weekend, 0 for weekday)
df['Weekend'] = df['DayOfWeek'].apply(lambda x: 1 if x >= 5 else 0)

# Display the first few rows to verify
print(df[['DayOfWeek', 'Weekday', 'Weekend']].head())

      DayOfWeek Weekday Weekend
0            3 Thursday      0
1            3 Thursday      0
2            3 Thursday      0
3            3 Thursday      0
4            3 Thursday      0

from sklearn.preprocessing import StandardScaler
```

```

# Initialize the scaler
scaler = StandardScaler()

# Scale the 'trips' and 'active_vehicles' columns
df['scaled_trips'] = scaler.fit_transform(df[['trips']])
df['scaled_active_vehicles'] =
scaler.fit_transform(df[['active_vehicles']])

# Display the first few rows to verify
print(df[['trips', 'scaled_trips', 'active_vehicles',
'scaled_active_vehicles']].head())

      trips  scaled_trips  active_vehicles  scaled_active_vehicles
0    1132       -0.990791           190            -0.962586
1    1765       -0.931261           225            -0.932436
2   29421        1.669641          3427             1.825846
3    7679       -0.375080           945            -0.312211
4    9537       -0.200345          1228            -0.068427

```

## Predictive Modeling

```

from sklearn.model_selection import train_test_split

# Select features and target
X = df[['active_vehicles', 'Hour', 'DayOfWeek', 'Month', 'Weekend']]
# Features
y = df['trips'] # Target (number of trips)

# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Display the shape of training and testing sets
print(f"Training Set Size: {X_train.shape[0]}")
print(f"Testing Set Size: {X_test.shape[0]}")

Training Set Size: 283
Testing Set Size: 71

from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score

# Initialize the model
model = LinearRegression()

# Train the model
model.fit(X_train, y_train)

```

```

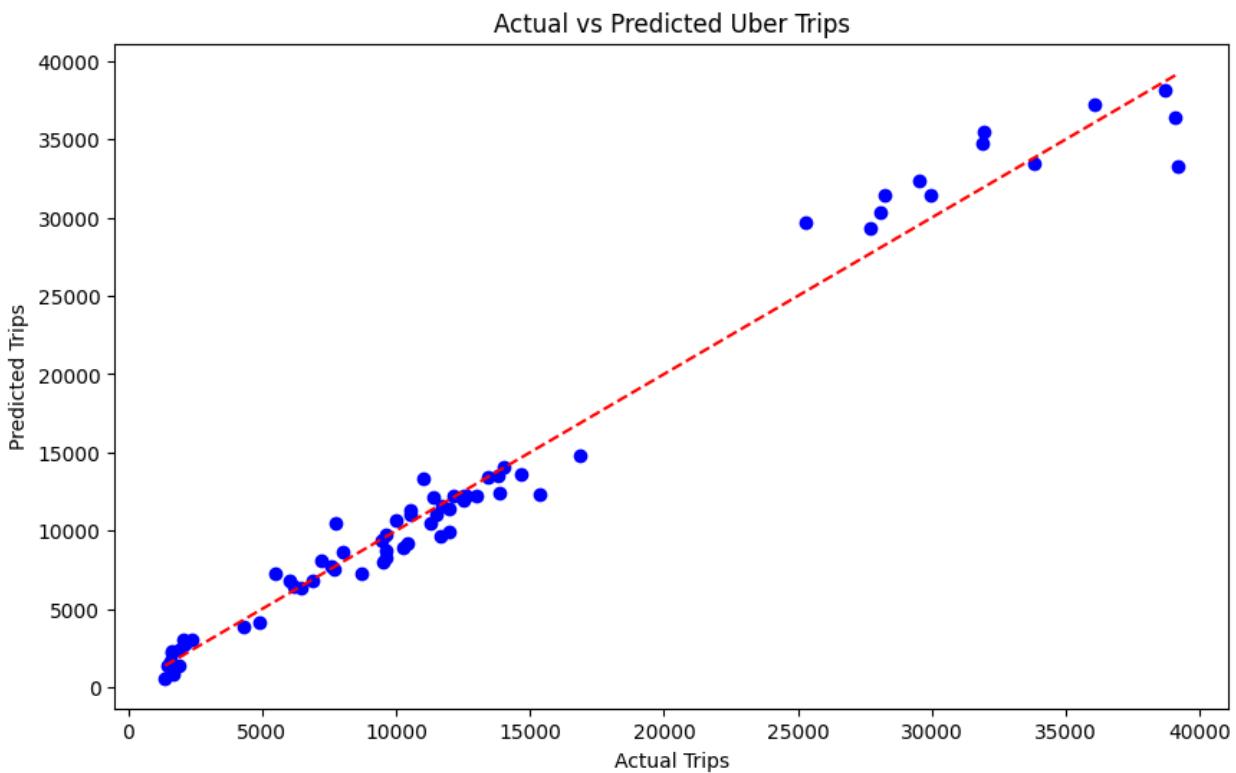
# Predict on the test set
y_pred = model.predict(X_test)

# Display the model's performance metrics
print("Model Performance:")
print(f"Mean Absolute Error (MAE): {mean_absolute_error(y_test, y_pred)}")
print(f"Mean Squared Error (MSE): {mean_squared_error(y_test, y_pred)}")
print(f"R-squared: {r2_score(y_test, y_pred)}")

Model Performance:
Mean Absolute Error (MAE): 1111.8851978507662
Mean Squared Error (MSE): 2487470.123943445
R-squared: 0.9769314775935857

# Plot actual vs predicted trips
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linestyle='--') # 45-degree line
plt.title("Actual vs Predicted Uber Trips")
plt.xlabel("Actual Trips")
plt.ylabel("Predicted Trips")
plt.show()

```



```

from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV

# Initialize the model
rf_model = RandomForestRegressor(random_state=42)

# Define hyperparameters for tuning
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 20, None],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2],
}

# Initialize GridSearchCV
grid_search = GridSearchCV(estimator=rf_model, param_grid=param_grid,
cv=5, scoring='neg_mean_absolute_error', n_jobs=-1, verbose=2)

# Fit the model
grid_search.fit(X_train, y_train)

# Best hyperparameters
print("Best hyperparameters:", grid_search.best_params_)

# Predict on the test set using the best model
best_rf_model = grid_search.best_estimator_
y_pred_rf = best_rf_model.predict(X_test)

# Evaluate the model
print("Random Forest Model Performance:")
print(f"MAE: {mean_absolute_error(y_test, y_pred_rf)}")
print(f"MSE: {mean_squared_error(y_test, y_pred_rf)}")
print(f"R-squared: {r2_score(y_test, y_pred_rf)}")

Fitting 5 folds for each of 36 candidates, totalling 180 fits
Best hyperparameters: {'max_depth': 10, 'min_samples_leaf': 1,
'min_samples_split': 2, 'n_estimators': 300}
Random Forest Model Performance:
MAE: 925.6039423517923
MSE: 1762135.0763385603
R-squared: 0.9836581544838008

from sklearn.model_selection import cross_val_score

# Evaluate model using cross-validation
cv_scores = cross_val_score(model, X, y, cv=5,
scoring='neg_mean_absolute_error')
print(f"Mean MAE from cross-validation: {-cv_scores.mean()}")

Mean MAE from cross-validation: 1243.8186067973807

```

```

from statsmodels.tsa.arima.model import ARIMA
import matplotlib.pyplot as plt

# Prepare time series data (using 'date' as the index)
df.set_index('date', inplace=True)

# Fit ARIMA model (adjust parameters based on your data)
arima_model = ARIMA(df['trips'], order=(1,1,1)) # (p,d,q) parameters
arima_model_fit = arima_model.fit()

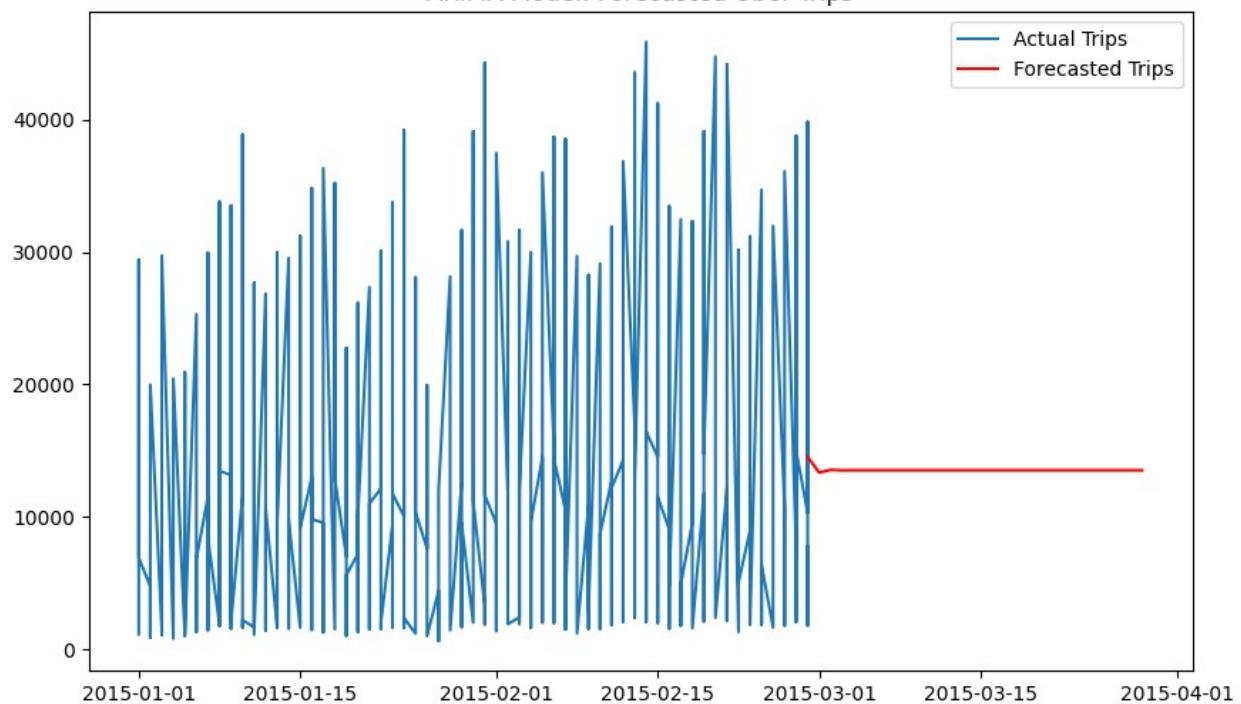
# Make predictions
forecast = arima_model_fit.forecast(steps=30) # Forecast the next 30 days

# Plot the forecasted trips
plt.figure(figsize=(10,6))
plt.plot(df.index, df['trips'], label='Actual Trips')
plt.plot(pd.date_range(df.index[-1], periods=30, freq='D'), forecast,
label='Forecasted Trips', color='red')
plt.legend()
plt.title('ARIMA Model: Forecasted Uber Trips')
plt.show()

C:\Users\91834\AppData\Local\Programs\Python\Python310\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: A date
index has been provided, but it has no associated frequency
information and so will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
C:\Users\91834\AppData\Local\Programs\Python\Python310\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: A date
index has been provided, but it has no associated frequency
information and so will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
C:\Users\91834\AppData\Local\Programs\Python\Python310\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: A date
index has been provided, but it has no associated frequency
information and so will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
C:\Users\91834\AppData\Local\Programs\Python\Python310\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:837: ValueWarning: No
supported index is available. Prediction results will be given with an
integer index beginning at `start`.
    return get_prediction_index()
C:\Users\91834\AppData\Local\Programs\Python\Python310\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:837: FutureWarning: No
supported index is available. In the next version, calling this method
in a model without a supported index will result in an exception.
    return get_prediction_index()

```

ARIMA Model: Forecasted Uber Trips



```
import joblib

# Save the trained Random Forest model (or any model)
joblib.dump(best_rf_model, 'uber_trip_predictor_model.pkl')

['uber_trip_predictor_model.pkl']
```

# Flask App.py

```
from flask import Flask, render_template, request
import pandas as pd
import joblib
import matplotlib.pyplot as plt
import seaborn as sns
import io
import base64
import numpy as np
from datetime import datetime

# Initialize Flask app
app = Flask(__name__)

# Load the trained model
model = joblib.load("uber_trip_predictor_model.pkl")

def preprocess_input(date_time, active_vehicles):
    """Extracts features from date and time input."""
    date_time = pd.to_datetime(date_time)
    hour = date_time.hour
    day_of_week = date_time.weekday()
    month = date_time.month
    weekend = 1 if day_of_week >= 5 else 0 # 1 for weekend, 0 for weekdays
    return [active_vehicles, hour, day_of_week, month, weekend]

def generate_visualizations(active_vehicles, prediction, date_time):
    """Generate multiple visualizations including pie chart, bar graph, line chart, scatter plot, and heatmap."""
    img_pie, img_bar, img_line, img_scatter, img_heatmap =
    io.BytesIO(), io.BytesIO(), io.BytesIO(), io.BytesIO(), io.BytesIO()

    # Pie chart
    labels = ['Predicted Trips', 'Remaining Capacity']
    sizes = [prediction, max(0, active_vehicles - prediction)]
    colors = ['#ff9999', '#66b3ff']
    plt.figure(figsize=(5, 5))
    plt.pie(sizes, labels=labels, autopct='%1.1f%%', colors=colors,
    startangle=90)
    plt.axis('equal')
    plt.savefig(img_pie, format='png')
    img_pie.seek(0)
    pie_url = base64.b64encode(img_pie.getvalue()).decode('utf8')

    # Bar graph
    plt.figure(figsize=(6, 4))
```

```

    sns.barplot(x=['Predicted Trips', 'Active Vehicles'],
y=[prediction, active_vehicles], palette=['#ff9999', '#66b3ff'])
    plt.ylabel('Count')
    plt.title('Trips vs Active Vehicles')
    plt.savefig(img_bar, format='png')
    img_bar.seek(0)
    bar_url = base64.b64encode(img_bar.getvalue()).decode('utf8')

    # Line Chart (Trip Trends Over Time)
    hours = np.arange(24)
    trip_predictions = [model.predict([[active_vehicles, h,
date_time.weekday(), date_time.month, 1 if date_time.weekday() >= 5
else 0]])[0] for h in hours]
    plt.figure(figsize=(6, 4))
    plt.plot(hours, trip_predictions, marker='o', linestyle='--',
color='#FFA500')
    plt.xlabel('Hour of the Day')
    plt.ylabel('Predicted Trips')
    plt.title('Predicted Trip Trend Over 24 Hours')
    plt.savefig(img_line, format='png')
    img_line.seek(0)
    line_url = base64.b64encode(img_line.getvalue()).decode('utf8')

    # Scatter Plot (Active Vehicles vs. Predicted Trips)
    plt.figure(figsize=(6, 4))
    sns.scatterplot(x=[active_vehicles]*24, y=trip_predictions,
color='#FF4500')
    plt.xlabel('Active Vehicles')
    plt.ylabel('Predicted Trips')
    plt.title('Active Vehicles vs. Predicted Trips')
    plt.savefig(img_scatter, format='png')
    img_scatter.seek(0)
    scatter_url =
base64.b64encode(img_scatter.getvalue()).decode('utf8')

    # Heatmap (Hourly Trip Distribution)
    data = np.array(trip_predictions).reshape(1, -1)
    plt.figure(figsize=(8, 2))
    sns.heatmap(data, annot=True, fmt='.0f', cmap='coolwarm',
xticklabels=hours, yticklabels=['Predicted Trips'])
    plt.xlabel('Hour of the Day')
    plt.title('Heatmap of Predicted Trips')
    plt.savefig(img_heatmap, format='png')
    img_heatmap.seek(0)
    heatmap_url =
base64.b64encode(img_heatmap.getvalue()).decode('utf8')

    return pie_url, bar_url, line_url, scatter_url, heatmap_url

```

```

@app.route("/", methods=["GET", "POST"])
def index():
    if request.method == "POST":
        date_time = request.form["date_time"]
        active_vehicles = request.form.get("active_vehicles", 1000) # Default value

        try:
            active_vehicles = int(active_vehicles)
        except ValueError:
            active_vehicles = 1000

        # Convert input to model-ready format
        input_features = preprocess_input(date_time, active_vehicles)
        prediction = model.predict(input_features)[0]

        # Generate visualizations
        pie_chart, bar_chart, line_chart, scatter_plot, heatmap =
        generate_visualizations(active_vehicles, int(prediction),
        pd.to_datetime(date_time))

        return render_template("result.html", date_time=date_time,
        active_vehicles=active_vehicles, prediction=int(prediction),
        pie_chart=pie_chart, bar_chart=bar_chart, line_chart=line_chart,
        scatter_plot=scatter_plot, heatmap=heatmap)

    return render_template("index.html")

if __name__ == "__main__":
    app.run(debug=True, host="0.0.0.0", port=8080, use_reloader=False)

* Serving Flask app '__main__'
* Debug mode: on

WARNING: This is a development server. Do not use it in a production
deployment. Use a production WSGI server instead.
* Running on all addresses (0.0.0.0)
* Running on http://127.0.0.1:8080
* Running on http://192.168.1.6:8080
Press CTRL+C to quit
192.168.1.6 - - [05/Feb/2025 21:41:18] "GET / HTTP/1.1" 200 -
192.168.1.6 - - [05/Feb/2025 21:41:20] "GET /favicon.ico HTTP/1.1" 404
-
C:\Users\91834\AppData\Local\Programs\Python\Python310\lib\site-
packages\sklearn\base.py:493: UserWarning: X does not have valid
feature names, but RandomForestRegressor was fitted with feature names
    warnings.warn(
C:\Users\91834\AppData\Local\Temp\ipykernel_10968\3605251356.py:43:
FutureWarning:

```

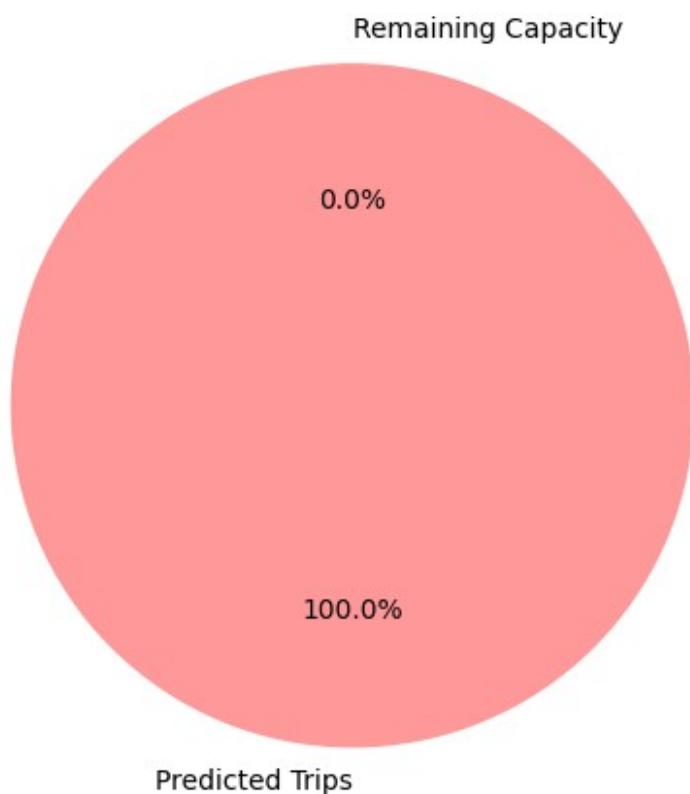
Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.



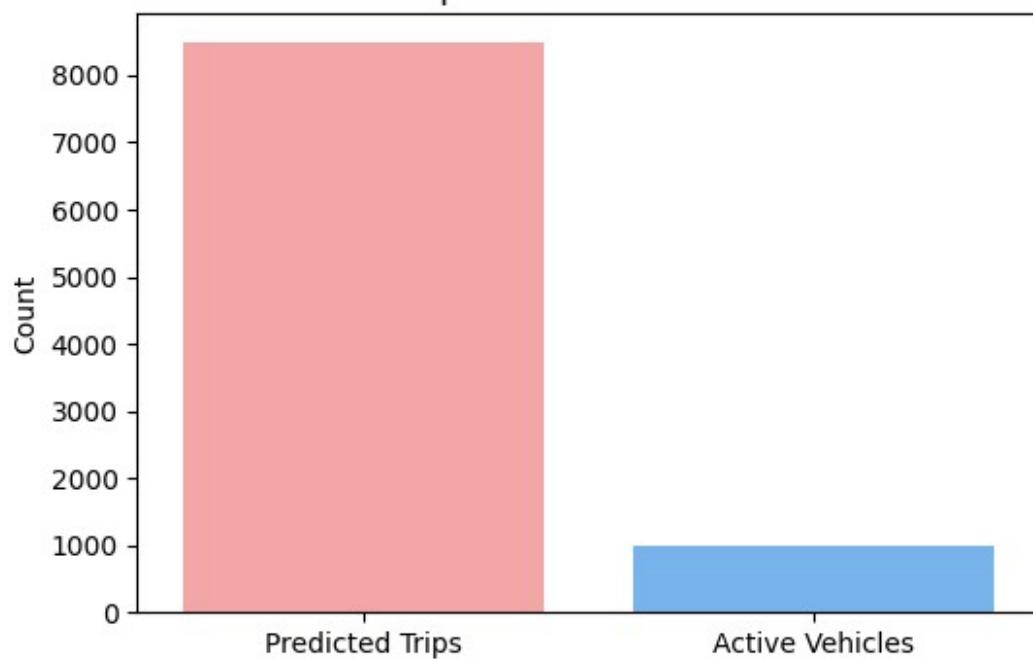




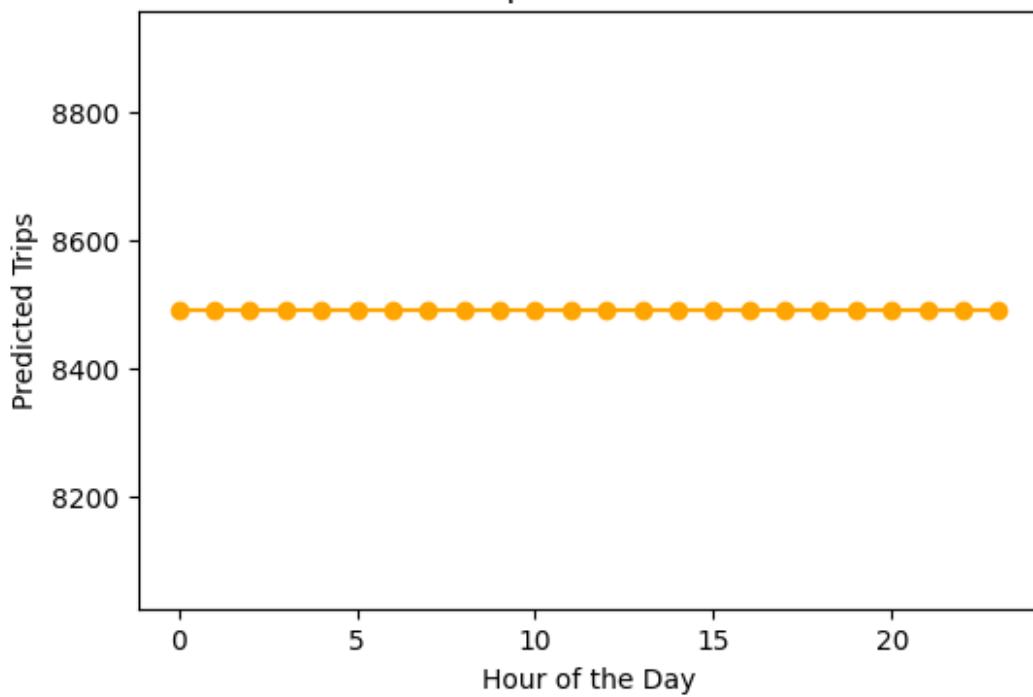
```
    warnings.warn(  
C:\Users\91834\AppData\Local\Programs\Python\Python310\lib\site-  
packages\sklearn\base.py:493: UserWarning: X does not have valid  
feature names, but RandomForestRegressor was fitted with feature names  
    warnings.warn(  
C:\Users\91834\AppData\Local\Programs\Python\Python310\lib\site-  
packages\sklearn\base.py:493: UserWarning: X does not have valid  
feature names, but RandomForestRegressor was fitted with feature names  
    warnings.warn(  
C:\Users\91834\AppData\Local\Programs\Python\Python310\lib\site-  
packages\sklearn\base.py:493: UserWarning: X does not have valid  
feature names, but RandomForestRegressor was fitted with feature names  
    warnings.warn(  
C:\Users\91834\AppData\Local\Programs\Python\Python310\lib\site-  
packages\sklearn\base.py:493: UserWarning: X does not have valid  
feature names, but RandomForestRegressor was fitted with feature names  
    warnings.warn(  
192.168.1.6 - - [05/Feb/2025 21:42:19] "POST / HTTP/1.1" 200 -
```



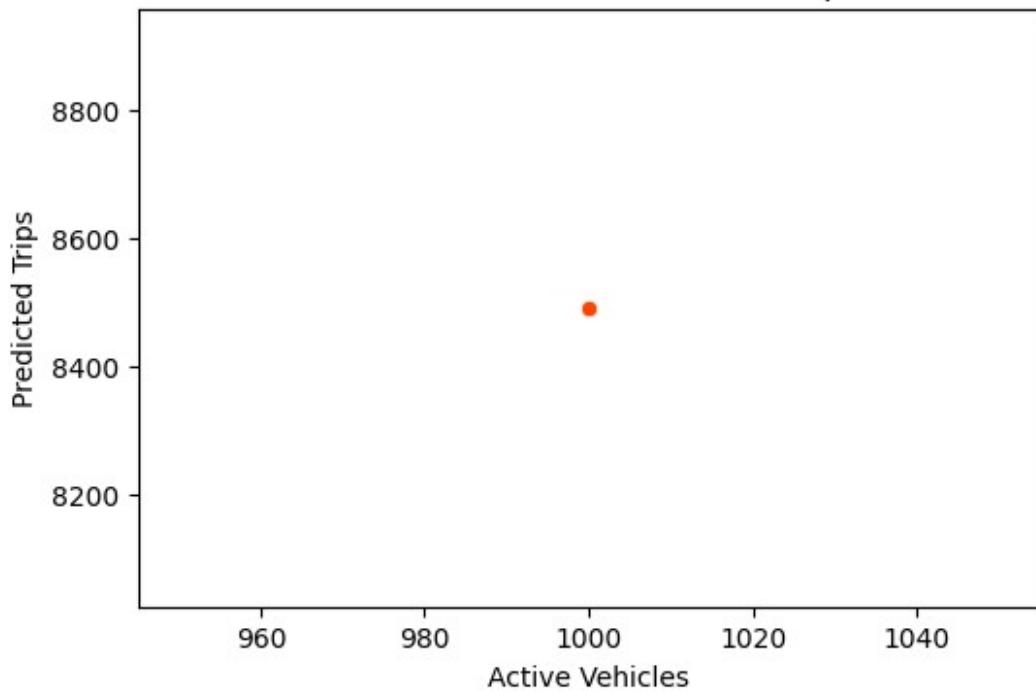
### Trips vs Active Vehicles



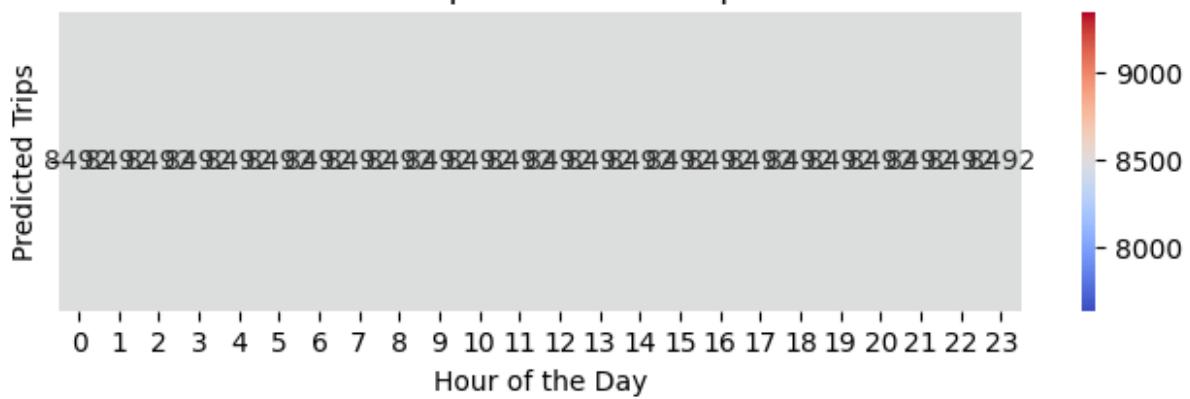
### Predicted Trip Trend Over 24 Hours

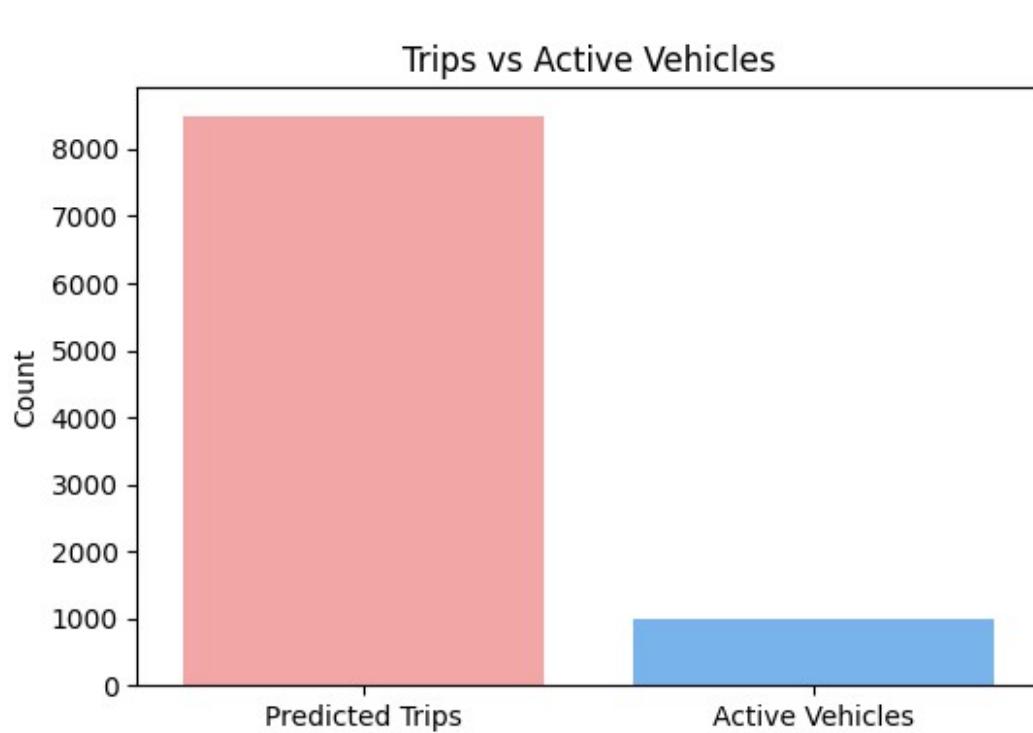
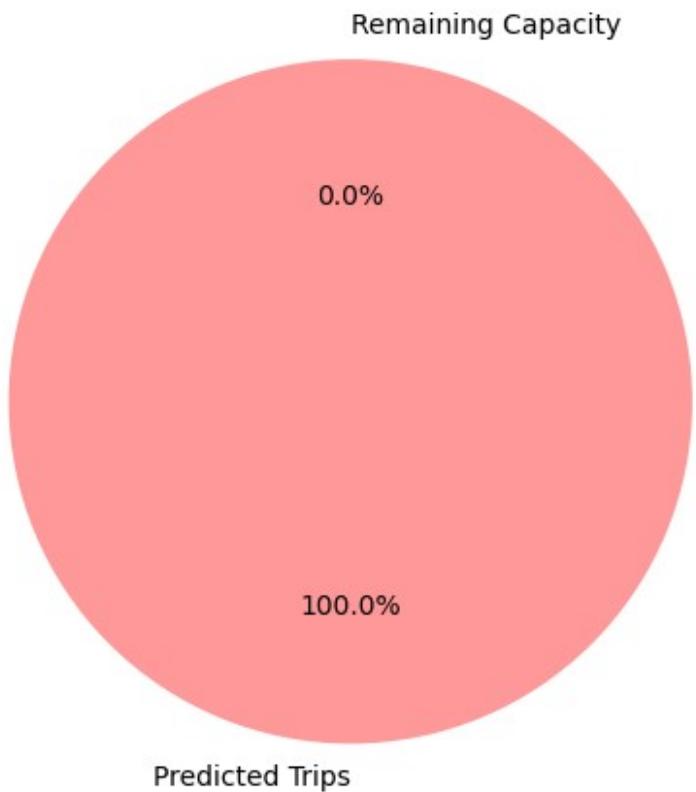


Active Vehicles vs. Predicted Trips

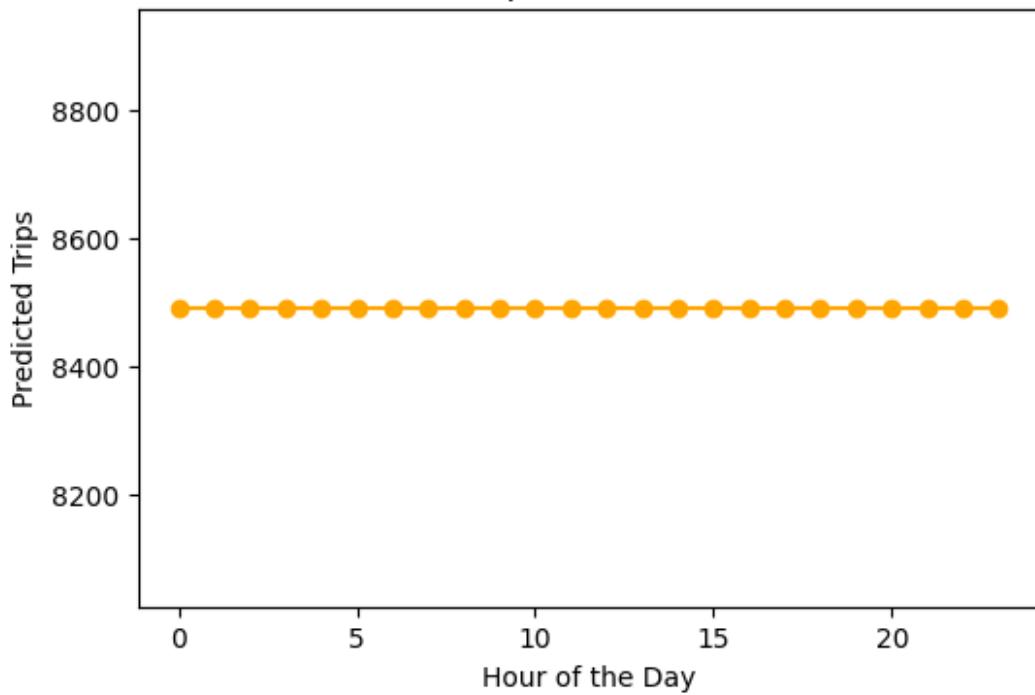


Heatmap of Predicted Trips

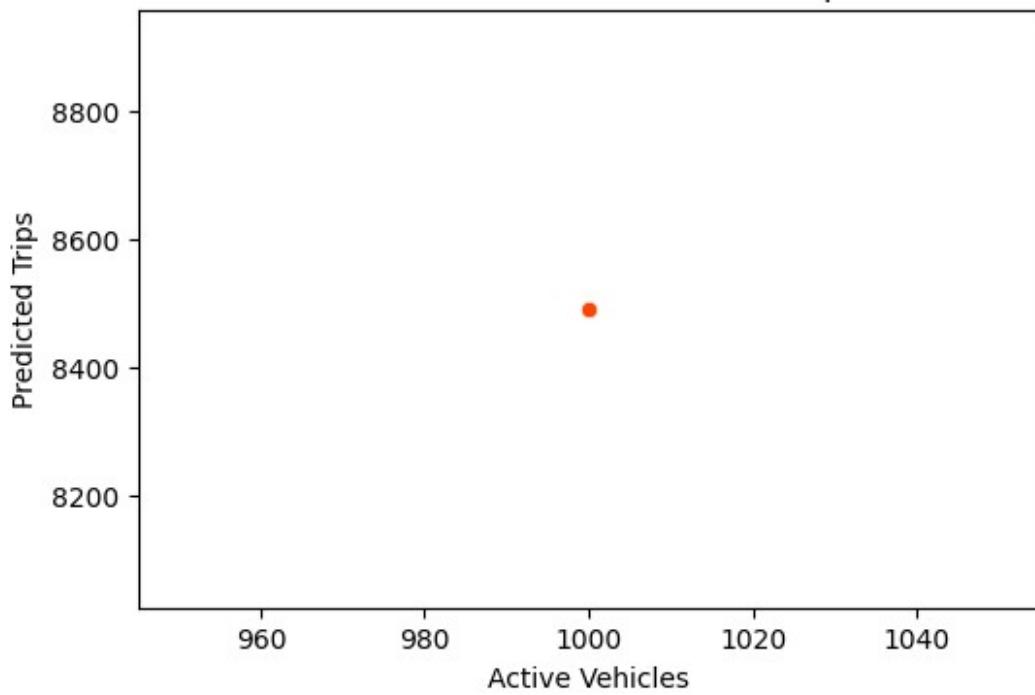




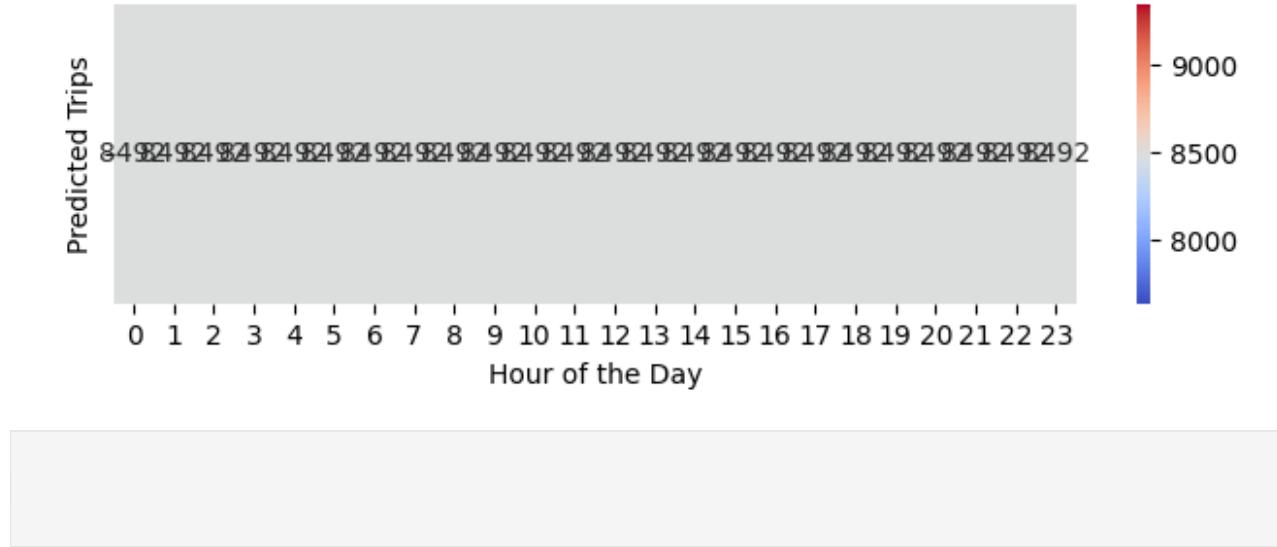
Predicted Trip Trend Over 24 Hours



Active Vehicles vs. Predicted Trips



### Heatmap of Predicted Trips



# Uber Trip Demand Prediction

Select Date & Time:

15-05-2023 15:18



Active Vehicles (Optional):

1000



Predict

# **Uber Trip Prediction Result**

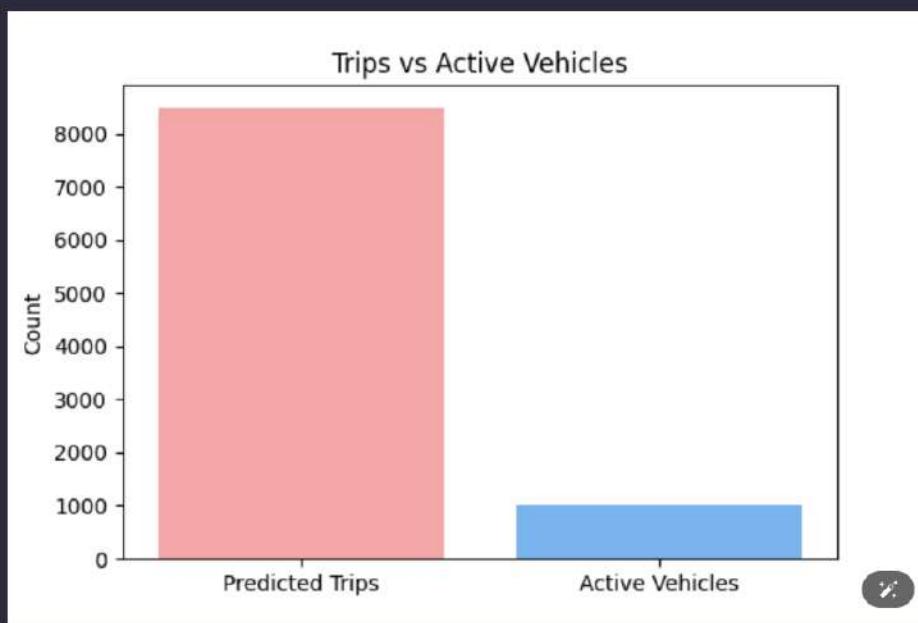
**Predicted Uber Trips: 8491**

## **Trip Details**

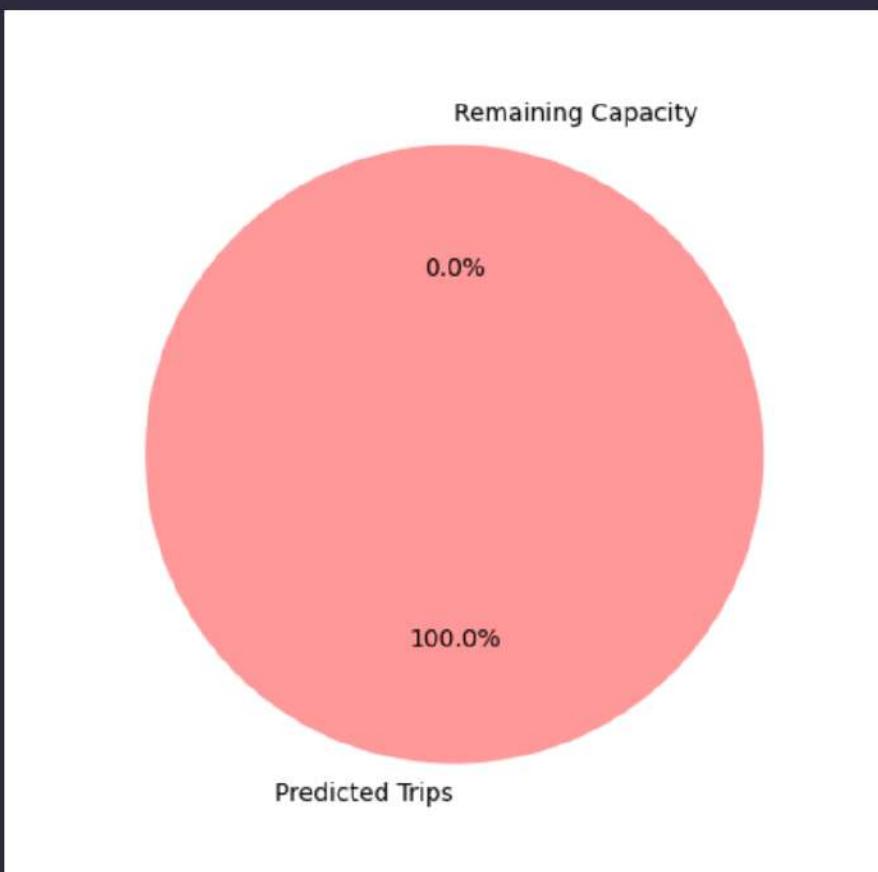
**Date & Time: 2023-05-15T15:18**

**Active Vehicles: 1000**

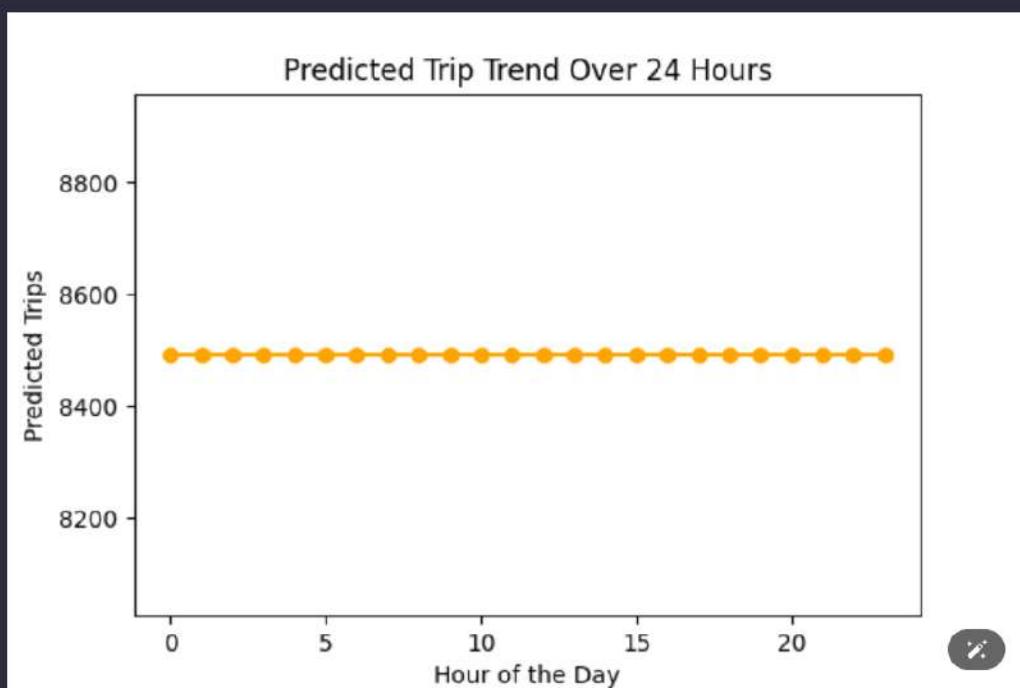
## Trips vs Active Vehicles



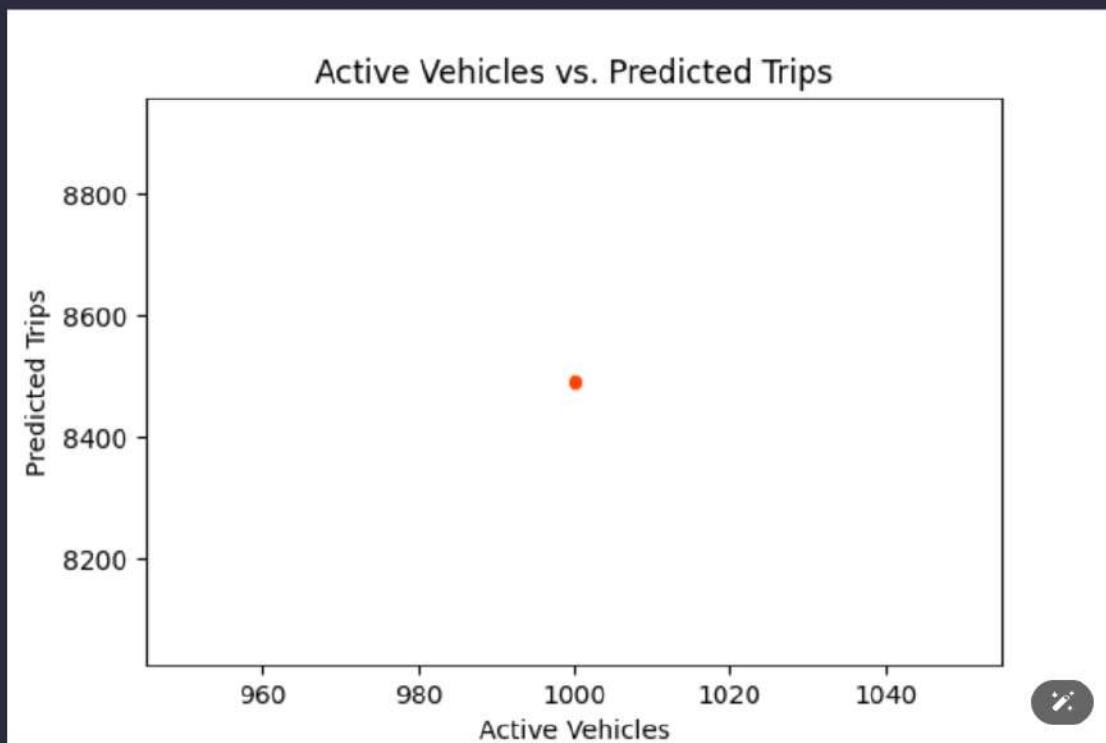
## Trip Distribution



## Trips Trend (Line Chart)

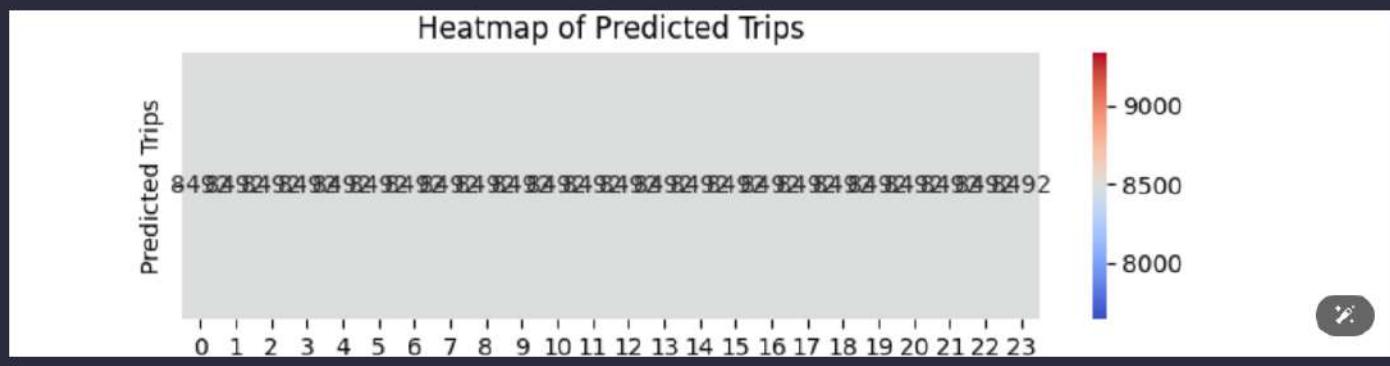


## Scatter Plot (Trips vs Vehicles)



960      980      1000      1020      1040  
Active Vehicles

## Heatmap of Trips



Go Back