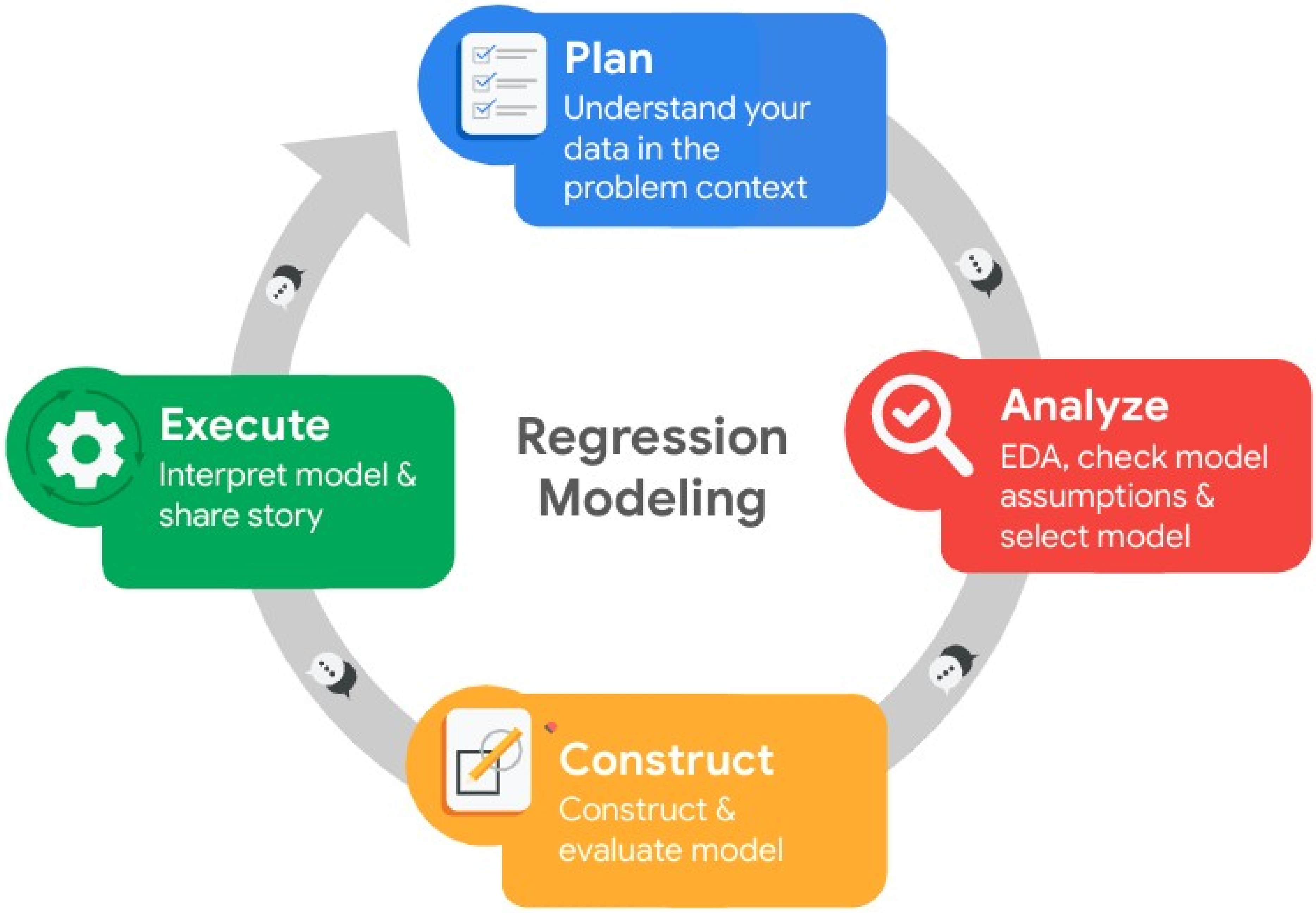
PACE Stages: The Project Framework



Pace: Plan Stage

Estimating Taxi Fares for Riders in advance:

1. **Project goal:**

In this fictional scenario, the New York City Taxi and Limousine Commission (TLC) has approached the data consulting firm Automatidata to develop an app that enables TLC riders to estimate the taxi fares in advance of their ride.

1. **Background:**

Since 1971, TLC has been regulating and overseeing the licensing of New York City's taxi cabs, for-hire vehicles, commuter vans, and paratransit vehicles.

1. **Scenario:**

New York City TLC stakeholders have been impressed with the data analytical work completed by the Automatidata team in this project. As a result, they have reached out once again for assistance in creating a machine learning model that can help predict the taxi fares for riders in advance.

Step 1. Imports & Loading Dataset

```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

from scipy import stats

# For displaying all of the columns in dataframes
pd.set_option('display.max_columns', None)

import warnings
warnings.filterwarnings('ignore')

from datetime import date, datetime, timedelta

from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

```python
import sklearn.metrics as metrics

from xgboost import XGBRegressor, plot_importance
from sklearn.ensemble import RandomForestRegressor

df = pd.read_csv(r"D:\Google Advanced Data Analytics\Go Beyond the Numbers\Automatidata_EDA_Project\
2017_Yellow_Taxi_Trip_Data.csv")
df.head(5)
```

```
   Unnamed: 0  VendorID     tpep_pickup_datetime    tpep_dropoff_datetime  \
0    24870114         2   03/25/2017 8:55:43 AM   03/25/2017 9:09:47 AM
1    35634249         1        04/11/2017 14:53        04/11/2017 15:19
2   106203690         1   12/15/2017 7:26:56 AM   12/15/2017 7:34:08 AM
3    38942136         2        05/07/2017 13:17        05/07/2017 13:48
4    30841670         2  04/15/2017 11:32:20 PM  04/15/2017 11:49:03 PM

   passenger_count  trip_distance  RatecodeID store_and_fwd_flag  \
0                6           3.34           1                  N
1                1           1.80           1                  N
2                1           1.00           1                  N
3                1           3.70           1                  N
4                1           4.37           1                  N

   PULocationID  DOLocationID  payment_type  fare_amount  extra  mta_tax  \
0           100           231             1         13.0    0.0      0.5
1           186            43             1         16.0    0.0      0.5
2           262           236             1          6.5    0.0      0.5
3           188            97             1         20.5    0.0      0.5
4             4           112             2         16.5    0.5      0.5

   tip_amount  tolls_amount  improvement_surcharge  total_amount
0        2.76           0.0                    0.3         16.56
1        4.00           0.0                    0.3         20.80
2        1.45           0.0                    0.3          8.75
3        6.39           0.0                    0.3         27.69
4        0.00           0.0                    0.3         17.80
```

Step 2. Data Exploration (Initial EDA and data cleaning)

Gather basic information about the data

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 18 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Unnamed: 0             22699 non-null  int64
 1   VendorID               22699 non-null  int64
 2   tpep_pickup_datetime   22699 non-null  object
 3   tpep_dropoff_datetime  22699 non-null  object
 4   passenger_count        22699 non-null  int64
 5   trip_distance          22699 non-null  float64
 6   RatecodeID             22699 non-null  int64
 7   store_and_fwd_flag     22699 non-null  object
 8   PULocationID           22699 non-null  int64
 9   DOLocationID           22699 non-null  int64
 10  payment_type           22699 non-null  int64
 11  fare_amount            22699 non-null  float64
 12  extra                  22699 non-null  float64
 13  mta_tax                22699 non-null  float64
 14  tip_amount             22699 non-null  float64
 15  tolls_amount           22699 non-null  float64
 16  improvement_surcharge  22699 non-null  float64
 17  total_amount           22699 non-null  float64
dtypes: float64(8), int64(7), object(3)
memory usage: 3.1+ MB
```

Gather descriptive statistics about the data

```python
df.describe(include= "all").T
```

```
                         count unique               top   freq  \
Unnamed: 0             22699.0    NaN               NaN    NaN
VendorID               22699.0    NaN               NaN    NaN
tpep_pickup_datetime     22699  22435  02/01/2017 21:08      3
tpep_dropoff_datetime    22699  22451  11/08/2017 22:34      3
passenger_count        22699.0    NaN               NaN    NaN
trip_distance          22699.0    NaN               NaN    NaN
RatecodeID             22699.0    NaN               NaN    NaN
store_and_fwd_flag       22699      2                 N  22600
PULocationID           22699.0    NaN               NaN    NaN
DOLocationID           22699.0    NaN               NaN    NaN
payment_type           22699.0    NaN               NaN    NaN
fare_amount            22699.0    NaN               NaN    NaN
extra                  22699.0    NaN               NaN    NaN
```

```
mta_tax               22699.0    NaN                NaN    NaN
tip_amount            22699.0    NaN                NaN    NaN
tolls_amount          22699.0    NaN                NaN    NaN
improvement_surcharge 22699.0    NaN                NaN    NaN
total_amount          22699.0    NaN                NaN    NaN

                              mean           std      min         25%  \
Unnamed: 0            56758486.171285  32744929.492148  12127.0  28520556.0
VendorID                     1.556236         0.496838      1.0         1.0
tpep_pickup_datetime              NaN              NaN      NaN         NaN
tpep_dropoff_datetime             NaN              NaN      NaN         NaN
passenger_count              1.642319         1.285231      0.0         1.0
trip_distance                2.913313         3.653171      0.0        0.99
RatecodeID                   1.043394         0.708391      1.0         1.0
store_and_fwd_flag                NaN              NaN      NaN         NaN
PULocationID               162.412353        66.633373      1.0       114.0
DOLocationID               161.527997        70.139691      1.0       112.0
payment_type                 1.336887         0.496211      1.0         1.0
fare_amount                 13.026629        13.243791   -120.0         6.5
extra                        0.333275         0.463097     -1.0         0.0
mta_tax                      0.497445         0.039465     -0.5         0.5
tip_amount                   1.835781         2.800626      0.0         0.0
tolls_amount                 0.312542         1.399212      0.0         0.0
improvement_surcharge        0.299551         0.015673     -0.3         0.3
total_amount                16.310502        16.097295   -120.3        8.75

                             50%         75%          max
Unnamed: 0            56731504.0  85374524.0  113486300.0
VendorID                     2.0         2.0          2.0
tpep_pickup_datetime         NaN         NaN          NaN
tpep_dropoff_datetime        NaN         NaN          NaN
passenger_count              1.0         2.0          6.0
trip_distance               1.61        3.06        33.96
RatecodeID                   1.0         1.0         99.0
store_and_fwd_flag           NaN         NaN          NaN
PULocationID               162.0       233.0        265.0
DOLocationID               162.0       233.0        265.0
payment_type                 1.0         2.0          4.0
fare_amount                  9.5        14.5       999.99
extra                        0.0         0.5          4.5
mta_tax                      0.5         0.5          0.5
tip_amount                  1.35        2.45        200.0
tolls_amount                 0.0         0.0         19.1
improvement_surcharge        0.3         0.3          0.3
total_amount                11.8        17.8      1200.29
```

Check missing values

```
df.isna().sum()
```

```
Unnamed: 0               0
VendorID                 0
tpep_pickup_datetime     0
tpep_dropoff_datetime    0
passenger_count          0
trip_distance            0
RatecodeID               0
store_and_fwd_flag       0
PULocationID             0
DOLocationID             0
payment_type             0
fare_amount              0
extra                    0
mta_tax                  0
tip_amount               0
tolls_amount             0
improvement_surcharge    0
total_amount             0
dtype: int64
```

Check duplicates

```
df.duplicated().sum()
```

```
0
```

pAce: Analyze Stage

Step 3. Data Exploration (Continue EDA)

Convert pickup & dropoff columns to datetime

```
df[["tpep_pickup_datetime", "tpep_dropoff_datetime"]].dtypes
```

```
tpep_pickup_datetime     object
tpep_dropoff_datetime    object
dtype: object
```

```
df["tpep_pickup_datetime"] = pd.to_datetime(df["tpep_pickup_datetime"], format= 'mixed')
df["tpep_dropoff_datetime"] = pd.to_datetime(df["tpep_dropoff_datetime"], format= 'mixed')
```

```
df[["tpep_pickup_datetime", "tpep_dropoff_datetime"]].dtypes
```

```
tpep_pickup_datetime     datetime64[ns]
tpep_dropoff_datetime    datetime64[ns]
dtype: object
```

Create duration column

```
df["trip_duration"] = (df["tpep_dropoff_datetime"] - df["tpep_pickup_datetime"]) / np.timedelta64(1, "m")
df["trip_duration"].describe()
```

```
count    22699.000000
mean        17.010830
std         61.996458
min        -17.000000
25%          6.750000
50%         11.000000
75%         18.258333
max       1440.000000
Name: trip_duration, dtype: float64
```

Check outliers

```
round(df.describe(include= [np.number], percentiles= [.5]).T, 1)
```

```
                         count        mean         std      min         50%  \
Unnamed: 0             22699.0  56758486.2  32744929.5  12127.0  56731504.0
VendorID               22699.0         1.6         0.5      1.0         2.0
passenger_count        22699.0         1.6         1.3      0.0         1.0
trip_distance          22699.0         2.9         3.7      0.0         1.6
RatecodeID             22699.0         1.0         0.7      1.0         1.0
PULocationID           22699.0       162.4        66.6      1.0       162.0
DOLocationID           22699.0       161.5        70.1      1.0       162.0
payment_type           22699.0         1.3         0.5      1.0         1.0
fare_amount            22699.0        13.0        13.2   -120.0         9.5
extra                  22699.0         0.3         0.5     -1.0         0.0
mta_tax                22699.0         0.5         0.0     -0.5         0.5
tip_amount             22699.0         1.8         2.8      0.0         1.4
tolls_amount           22699.0         0.3         1.4      0.0         0.0
improvement_surcharge  22699.0         0.3         0.0     -0.3         0.3
total_amount           22699.0        16.3        16.1   -120.3        11.8
trip_duration          22699.0        17.0        62.0    -17.0        11.0

                               max
Unnamed: 0             113486300.0
VendorID                       2.0
passenger_count                6.0
trip_distance                 34.0
RatecodeID                    99.0
PULocationID                 265.0
DOLocationID                 265.0
payment_type                   4.0
fare_amount                 1000.0
extra                          4.5
mta_tax                        0.5
tip_amount                   200.0
tolls_amount                  19.1
improvement_surcharge          0.3
total_amount                1200.3
trip_duration               1440.0
```

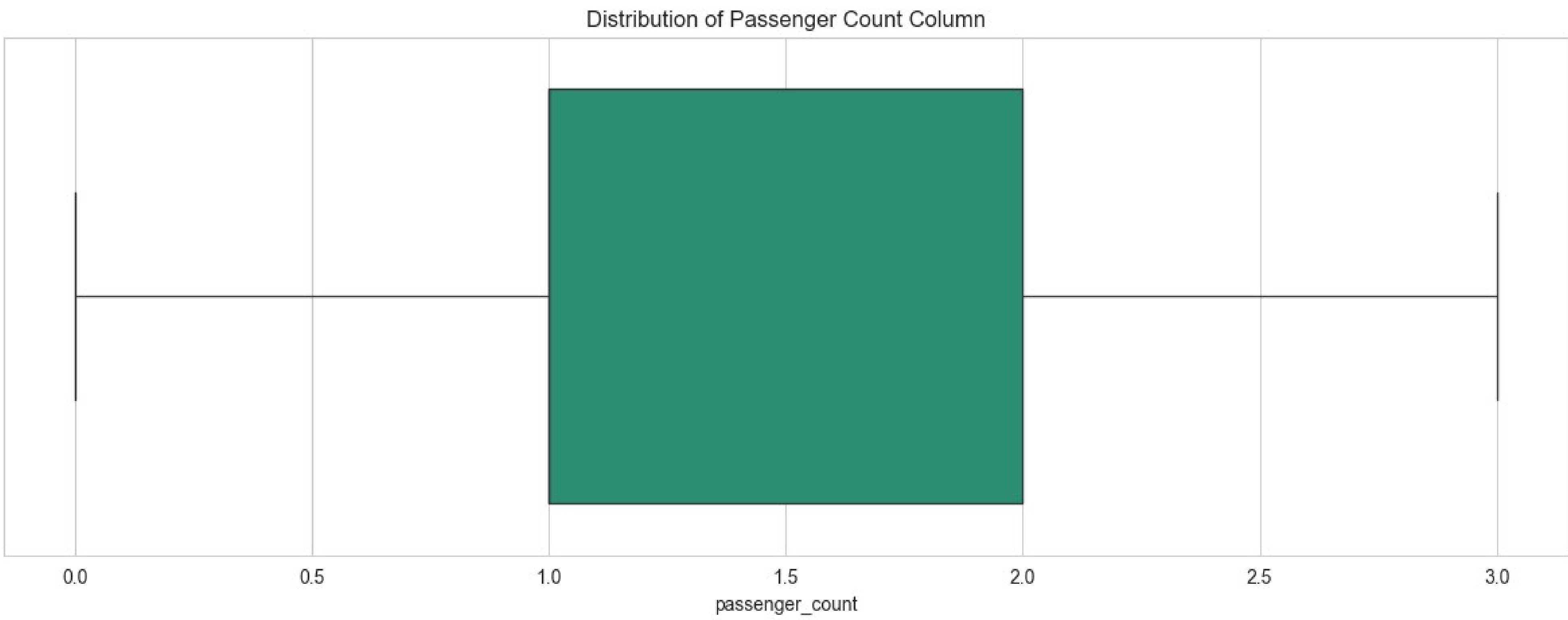
From above description for numerical variables, we could observe outliers in:

1. passenger_count
2. trip_distance
3. RatecodeID
4. fare_amount
5. extra
6. mta_tax
7. tip_amount
8. improvement_surcharge
9. total_amount
10. trip_duration

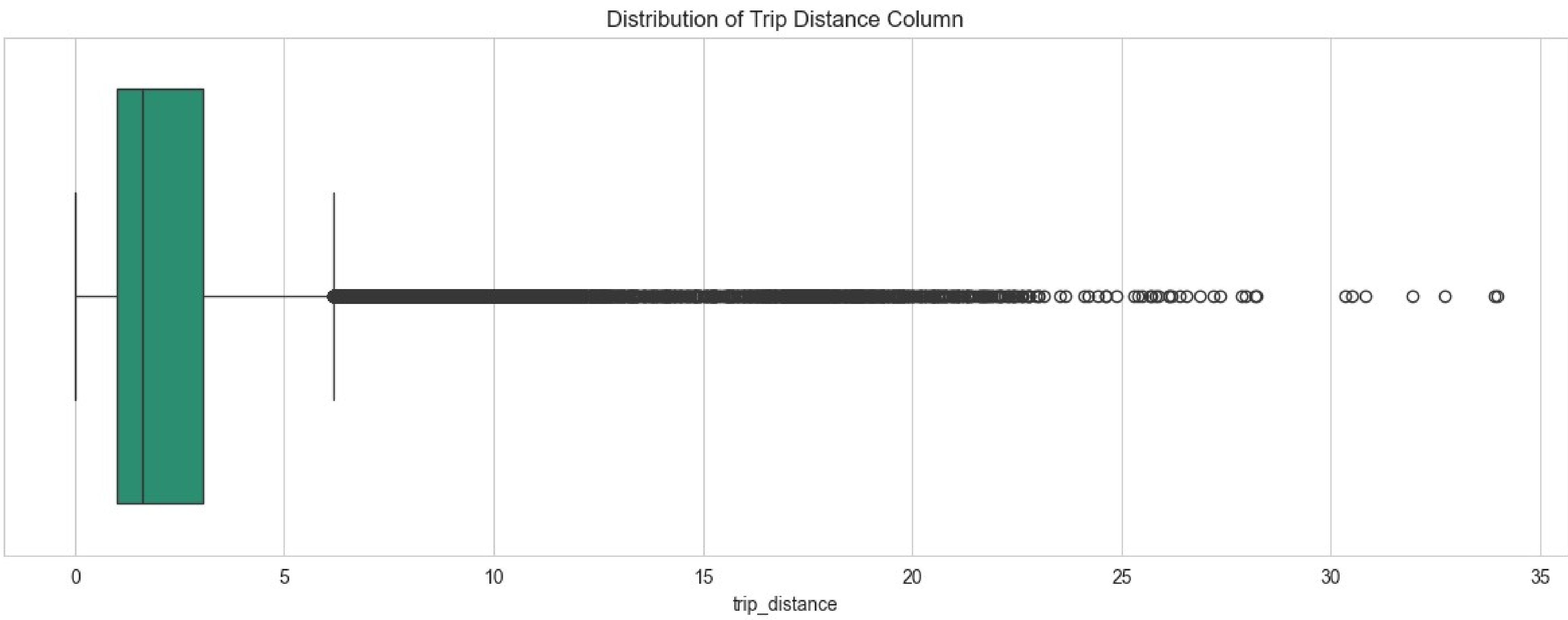
Box Plots

```
sns.set_style("whitegrid")
sns.set_palette("Dark2")
```

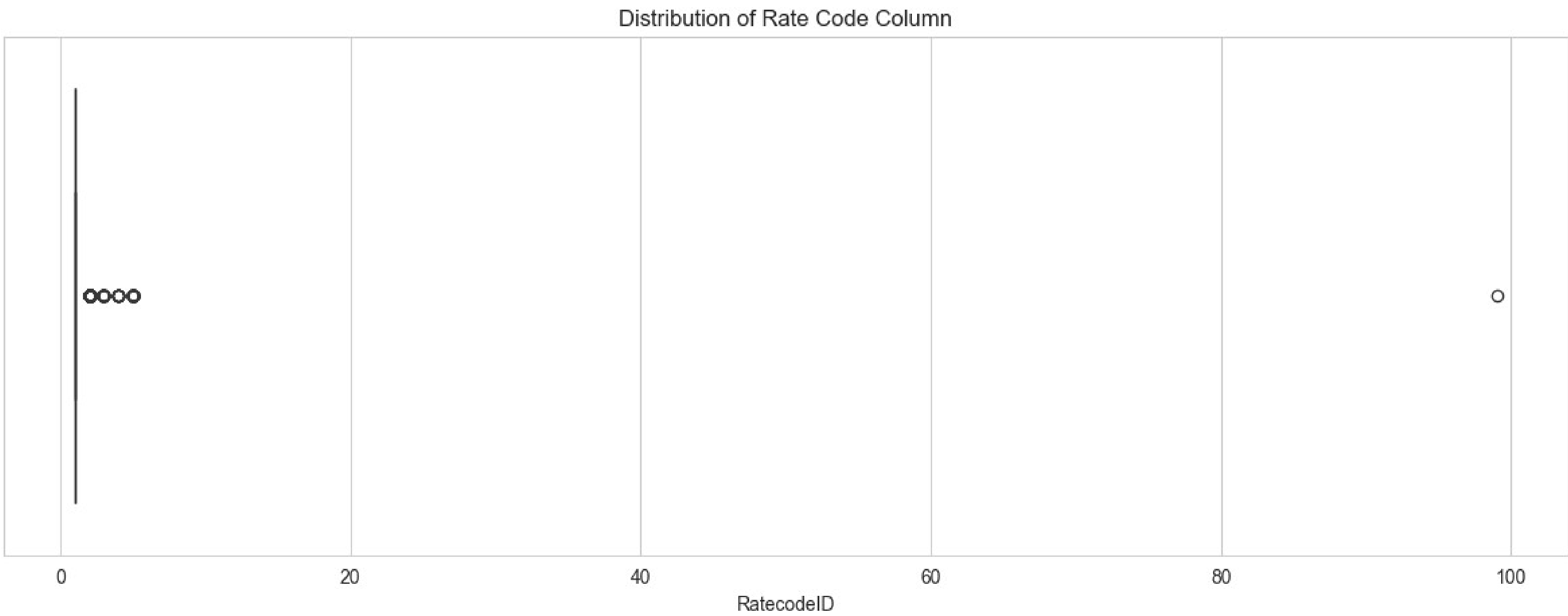
```
plt.figure(figsize = (15, 5))
sns.boxplot(data= df, x= "passenger_count", showfliers= False)
plt.title("Distribution of Passenger Count Column")
plt.show()
```



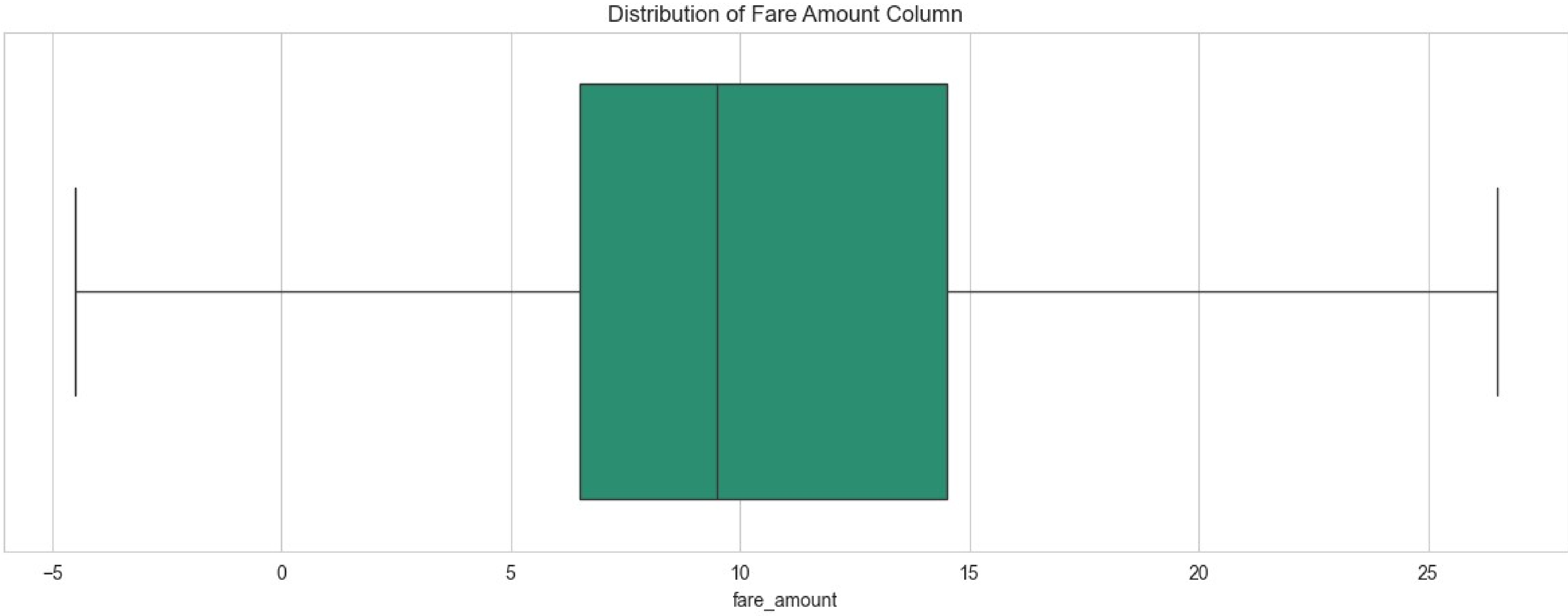

```
plt.figure(figsize = (15, 5))
sns.boxplot(data= df, x= "trip_distance", showfliers= True)
plt.title("Distribution of Trip Distance Column")
plt.show()
```



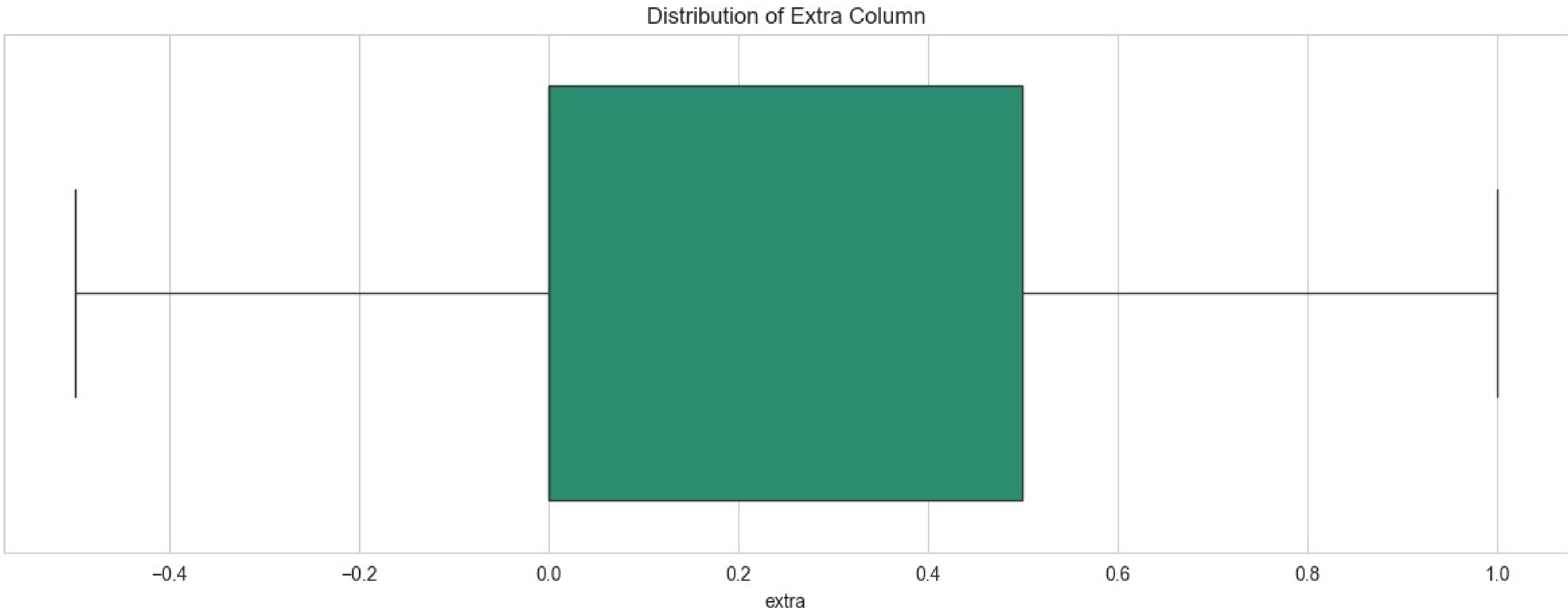

```
plt.figure(figsize = (15, 5))
sns.boxplot(data= df, x= "RatecodeID", showfliers= True)
plt.title("Distribution of Rate Code Column")
plt.show()
```



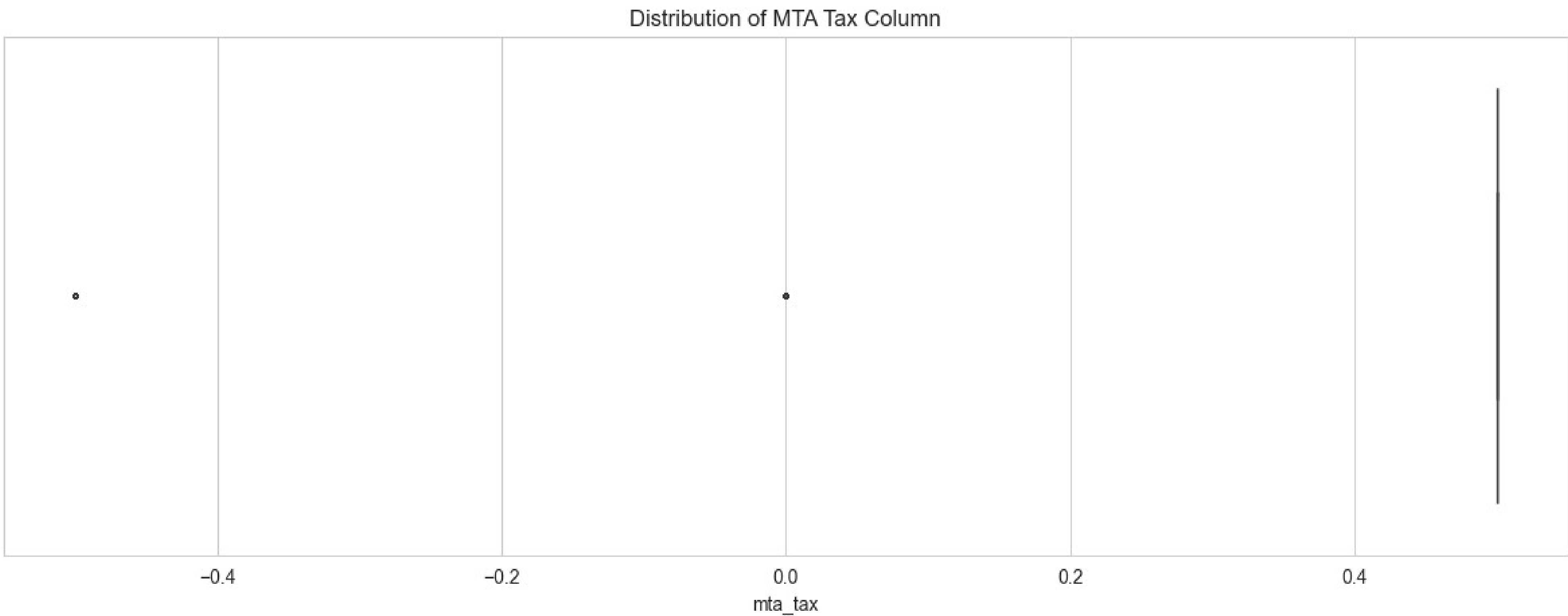

```
plt.figure(figsize = (15, 5))
sns.boxplot(data= df, x= "fare_amount", showfliers= False)
plt.title("Distribution of Fare Amount Column")
plt.show()
```



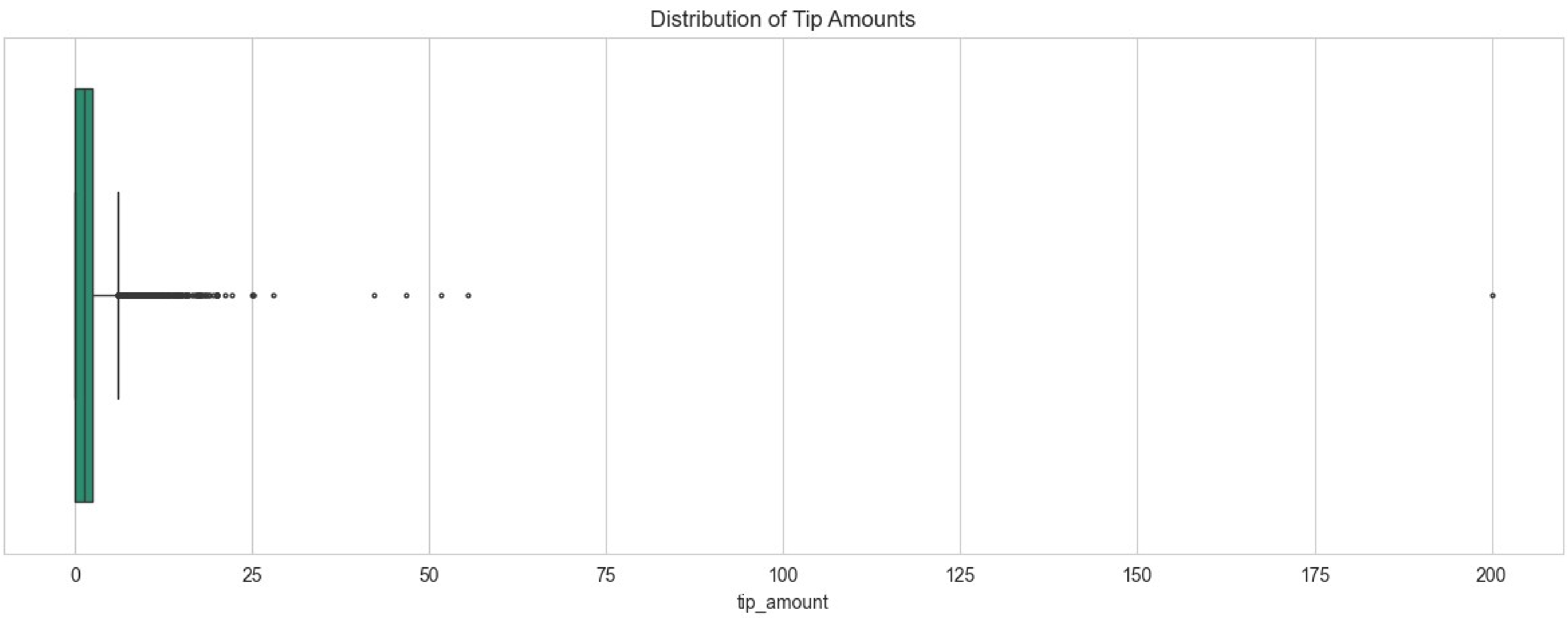

```
plt.figure(figsize = (15, 5))
sns.boxplot(data= df, x= "extra", showfliers= False)
plt.title("Distribution of Extra Column")
plt.show()
```



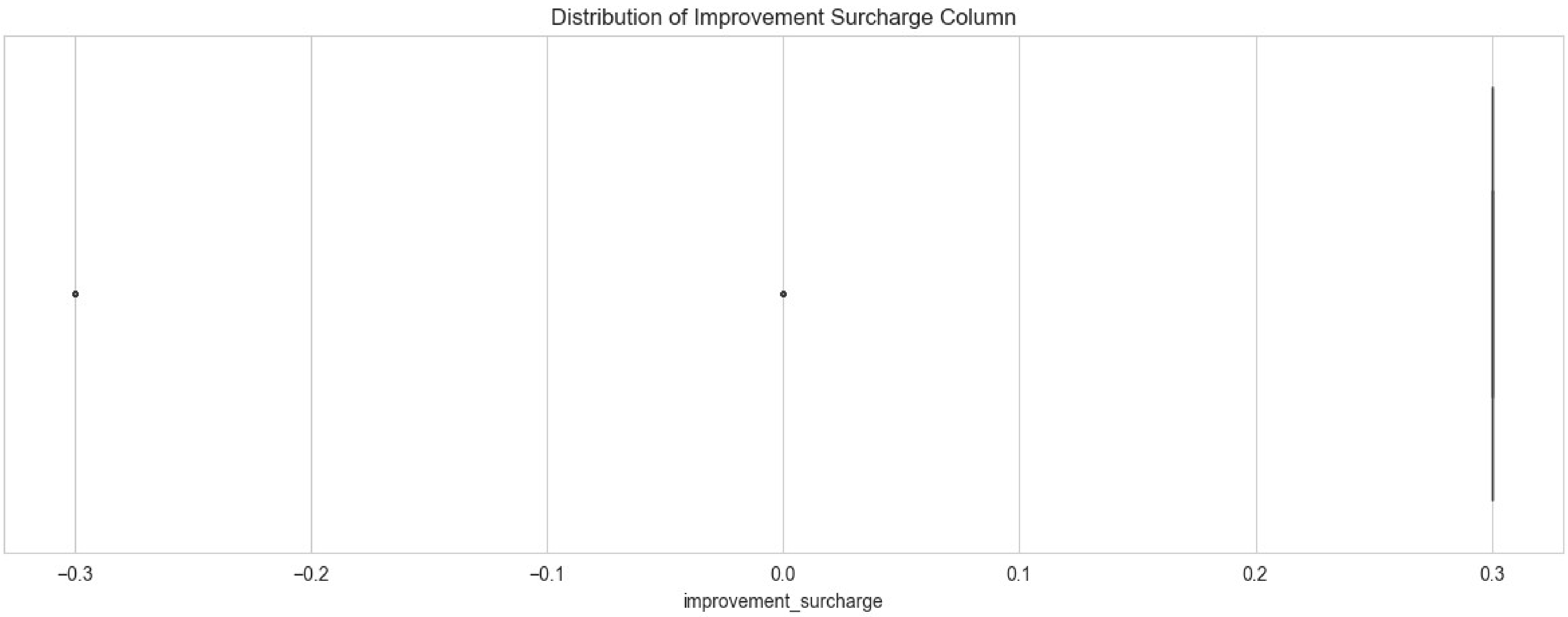

```
plt.figure(figsize = (15, 5))
sns.boxplot(data= df, x= "mta_tax", showfliers= True, fliersize= 2)
plt.title("Distribution of MTA Tax Column")
plt.show()
```



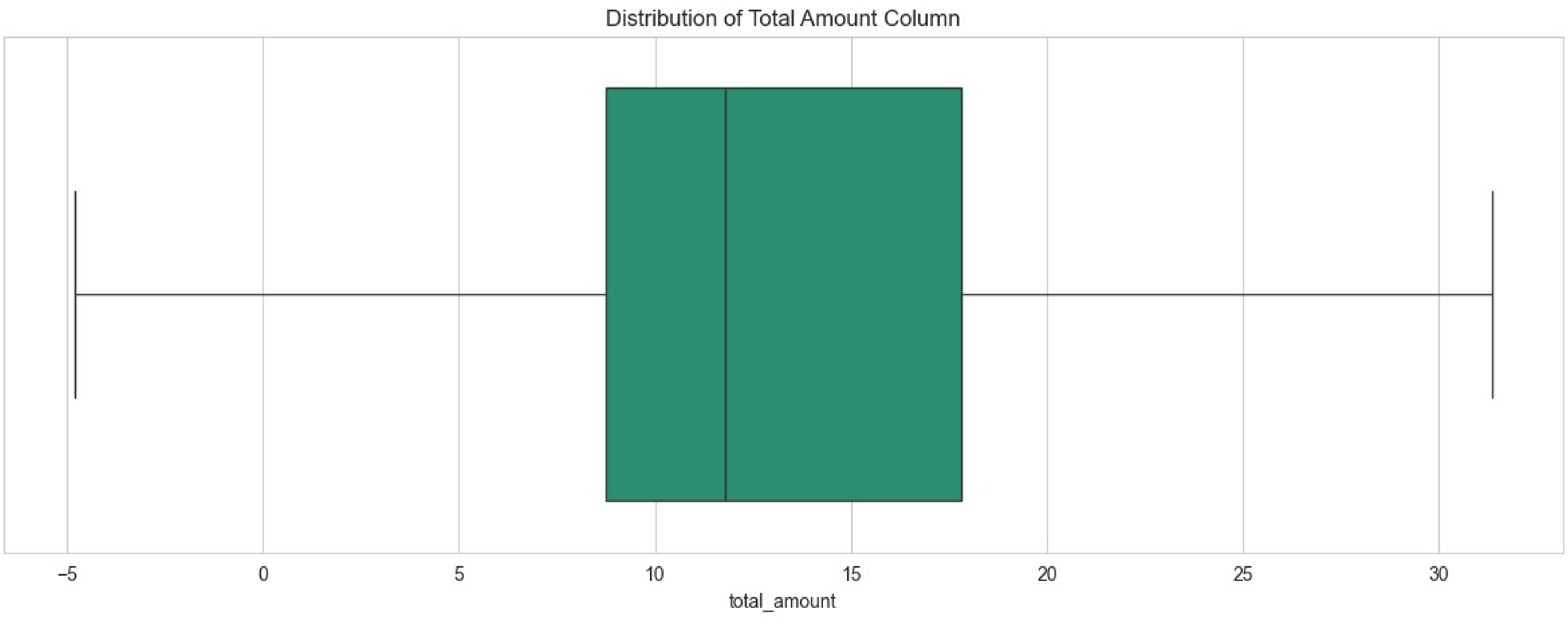

```
plt.figure(figsize = (15, 5))
sns.boxplot(data= df, x= "tip_amount", showfliers= True, fliersize= 2)
plt.title("Distribution of Tip Amounts")
plt.show()
```



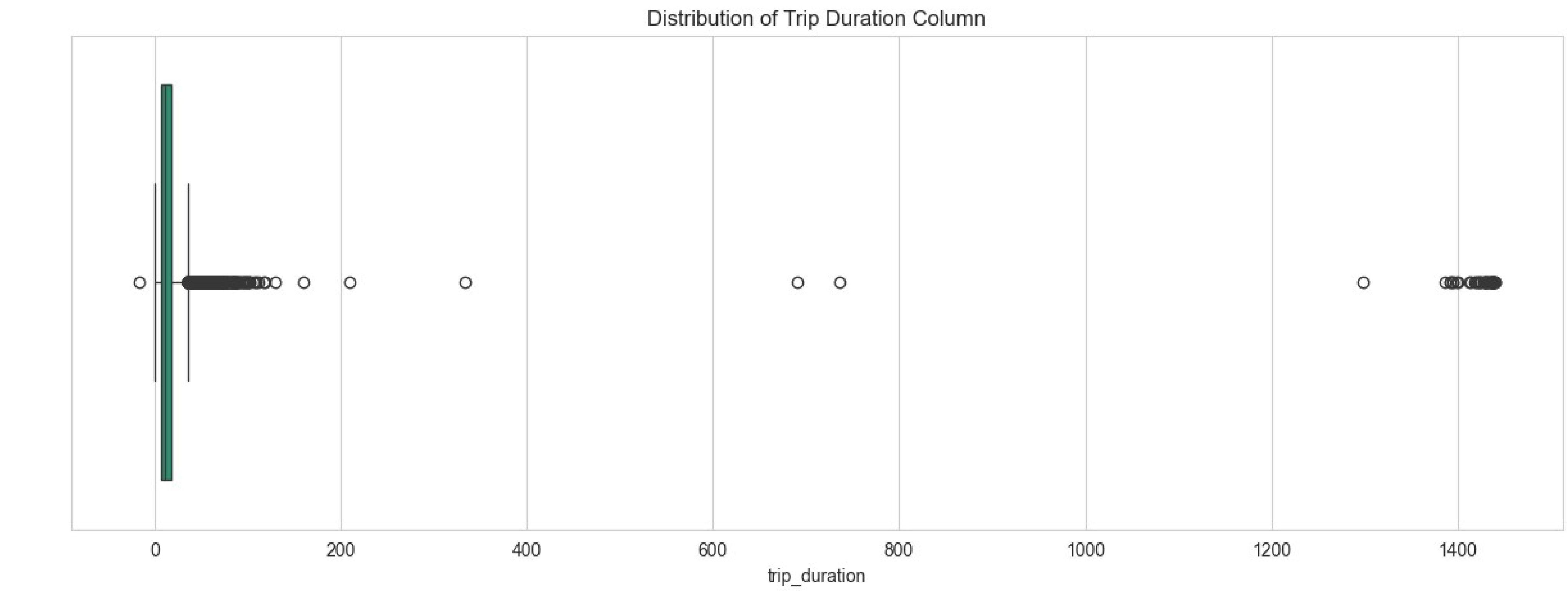

```
plt.figure(figsize = (15, 5))
sns.boxplot(data= df, x= "improvement_surcharge", showfliers= True, fliersize= 2)
plt.title("Distribution of Improvement Surcharge Column")
plt.show()
```




```
plt.figure(figsize = (15, 5))
sns.boxplot(data= df, x= "total_amount", showfliers= False)
plt.title("Distribution of Total Amount Column")
plt.show()
```




```
plt.figure(figsize = (15, 5))
sns.boxplot(data= df, x= "trip_duration", showfliers= True)
plt.title("Distribution of Trip Duration Column")
plt.show()
```



Imputations

`passenger_count` imputation

```
df[["passenger_count"]].value_counts()
```

```
passenger_count
1                  16117
2                   3305
5                   1143
3                    953
6                    693
4                    455
0                     33
Name: count, dtype: int64
```

```
df.loc[df["passenger_count"] == 0, "passenger_count"] = 1
```

`RatecodeID` imputation

```
df[["RatecodeID"]].value_counts()
```

```
RatecodeID
1             22070
2               513
5                68
3                39
4                 8
99                1
Name: count, dtype: int64
```

```
df.loc[df["RatecodeID"] == 99, "RatecodeID"] = 3
```

`extra` imputation

```
df.loc[df["extra"] < 0, "extra"].count()
```

```
9
```

```
df.loc[df["extra"] < 0, "extra"] = 0
```

`mta_tax` imputation

```
df.loc[df["mta_tax"] < 0, "mta_tax"].count()
```

```
13
```

```
df.loc[df["mta_tax"] < 0, "mta_tax"] = 0
```

`tip_amount` imputation

```
df["tip_amount"].sort_values(ascending= False).head(5)
```

```
8476     200.00
6064      55.50
13861     51.64
12511     46.69
984       42.29
Name: tip_amount, dtype: float64
```

```
df.loc[df["tip_amount"] == 200, "tip_amount"] = 55.50
```

`improvement_surcharge` imputation

```
df.loc[df["improvement_surcharge"] < 0, "improvement_surcharge"].count()
```

```python
df.loc[df["improvement_surcharge"] < 0, "improvement_surcharge"] = 0
```

```python
def impute_outliers(column_list, iqr_factor):
    '''
    Impute upper-limit values in specified columns based on their interquartile range.

    Arguments:
        column_list: A list of columns to iterate over
        iqr_factor: A number representing x in the formula:
                    Q3 + (x * IQR). Used to determine maximum threshold,
                    beyond which a point is considered an outlier.

    The IQR is computed for each column in column_list and values exceeding
    the upper threshold for each column are imputed with the upper threshold value.
    '''
    for column in column_list:
        # Reassign minimum to zero
        df.loc[df[column] < 0, column] = 0

        # Calculate upper threshold
        Q3 = df[column].quantile(.75)
        Q1 = df[column].quantile(.25)
        iqr = Q3 - Q1
        upper_limit = Q3 + (iqr_factor * iqr)
        print(column)
        print("Q3:", round(Q3, 3))
        print("Upper threshold:", round(upper_limit, 3))

        # Reassign values > threshold to threshold
        df.loc[df[column] > upper_limit, column] = upper_limit
```

`trip_distance` imputation

```python
impute_outliers(["trip_distance"], 9)
```

```
trip_distance
Q3: 3.06
Upper threshold: 21.69
```

```python
df["trip_distance"].describe()
```

```
count    22699.000000
mean         2.904191
std          3.598010
min          0.000000
25%          0.990000
50%          1.610000
75%          3.060000
max         21.690000
Name: trip_distance, dtype: float64
```

`trip_duration` imputation

```python
impute_outliers(["trip_duration"], 9)
```

```
trip_duration
Q3: 18.258
Upper threshold: 121.833
```

```python
df["trip_duration"].describe()
```

```
count    22699.000000
mean        14.538892
std         12.546985
min          0.000000
25%          6.750000
50%         11.000000
75%         18.258333
max        121.833333
Name: trip_duration, dtype: float64
```

`fare_amount` imputation

```python
impute_outliers(["fare_amount"], 9)
```

```
fare_amount
Q3: 14.5
Upper threshold: 86.5
```

```python
df["fare_amount"].describe()
```

```
count    22699.000000
mean        12.944139
std         10.795620
min          0.000000
25%          6.500000
```

```
50%          9.500000
75%         14.500000
max         86.500000
Name: fare_amount, dtype: float64
```

`total_amount` imputation

```python
impute_outliers(["total_amount"], 9)
```

```
total_amount
Q3: 17.8
Upper threshold: 99.25
```

```python
df["total_amount"].describe()
```

```
count    22699.000000
mean        16.210212
std         13.337089
min          0.000000
25%          8.750000
50%         11.800000
75%         17.800000
max         99.250000
Name: total_amount, dtype: float64
```

Feature Engineering

```python
# Create `pickup_dropoff` column
df["pickup_dropoff"] = df["PULocationID"].astype("str") + " >> " + df["DOLocationID"].astype("str")
df["pickup_dropoff"].head(5)
```

```
0    100 >> 231
1     186 >> 43
2    262 >> 236
3     188 >> 97
4      4 >> 112
Name: pickup_dropoff, dtype: object
```

```python
df["pickup_dropoff"].describe()
```

```
count          22699
unique          4172
top       264 >> 264
freq             277
Name: pickup_dropoff, dtype: object
```

When deployed, the model will not know the duration of a trip until after the trip occurs, so you cannot train a model that uses this feature. However, you can use the statistics of trips you *do* know to generalize about ones you do not know.

Create `mean_distance` column

```python
grouped_pickup_dropoff = round(df.groupby(["pickup_dropoff"])[["trip_distance"]].mean(), 2)
grouped_pickup_dropoff.head(5)
```

```
                trip_distance
pickup_dropoff
1 >> 1                   2.43
10 >> 148               15.70
100 >> 1                16.89
100 >> 100               0.25
100 >> 107               1.18
```

```python
# 1. Convert `grouped` to a dictionary
grouped_dict = grouped_pickup_dropoff.to_dict()

# 2. Reassign to only contain the inner dictionary
grouped_dict = grouped_dict["trip_distance"]

# 1. Create a mean_distance column that is a copy of the pickup_dropoff helper column
df["mean_distance"] = df["pickup_dropoff"]

# 2. Map `grouped_dict` to the `mean_distance` column
df["mean_distance"] = df["mean_distance"].map(grouped_dict)

# Confirm that it worked
df["mean_distance"].head(5)
```

```
0    3.52
1    3.11
2    0.88
3    3.70
4    4.44
Name: mean_distance, dtype: float64
```

Create `mean_duration` column

```python
grouped_pickup_dropoff = round(df.groupby(["pickup_dropoff"])[["trip_duration"]].mean(), 2)
grouped_pickup_dropoff.head(5)
```

```
                trip_duration
pickup_dropoff
1 >> 1                   0.00
10 >> 148               69.00
100 >> 1                48.00
100 >> 100              3.12
100 >> 107              11.37
```

```
# 1. Convert `grouped` to a dictionary
grouped_dict = grouped_pickup_dropoff.to_dict()

# 2. Reassign to only contain the inner dictionary
grouped_dict = grouped_dict["trip_duration"]
```

```
# 1. Create a mean_duration column that is a copy of the pickup_dropoff helper column
df["mean_duration"] = df["pickup_dropoff"]

# 2. Map `grouped_dict` to the `mean_duration` column
df["mean_duration"] = df["mean_duration"].map(grouped_dict)

# Confirm that it worked
df["mean_duration"].head(5)
```

```
0    22.88
1    24.29
2     7.26
3    31.00
4    14.36
Name: mean_duration, dtype: float64
```

Create day & month columns

```
# Create 'day' col
df["day"] = df["tpep_pickup_datetime"].dt.day_name().str.lower()

# Create 'month' col
df["month"] = df["tpep_pickup_datetime"].dt.month_name().str.lower()
```

Create rush_hour column

Define rush hour as:

- Any weekday (not Saturday or Sunday) AND
- Either from 06:00–10:00 or from 16:00–20:00

Create a binary `rush_hour` column that contains a 1 if the ride was during rush hour and a 0 if it was not.

```
# Create 'rush_hour' col
df["rush_hour"] = df["tpep_pickup_datetime"].dt.hour

# If day is Saturday or Sunday, impute 0 in `rush_hour` column
df.loc[df["day"].isin(["saturday", "sunday"]), "rush_hour"] = 0

df["rush_hour"].head(5)
```

```
0     0
1    14
2     7
3     0
4     0
Name: rush_hour, dtype: int32
```

```
def rush_hourizer(hour):
    if 6 <= hour <= 10:
        val = 1
    elif 16 <= hour <= 20:
        val = 1
    else:
        val = 0
    return val
```

```
df["rush_hour"] = df["rush_hour"].apply(rush_hourizer)
df["rush_hour"].head(5)
```

```
0    0
1    0
2    1
3    0
4    0
Name: rush_hour, dtype: int64
```

Ordering columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 25 columns):
 #   Column                 Non-Null Count  Dtype
```

```
---  ------                 --------------  -----
 0   Unnamed: 0             22699 non-null  int64
 1   VendorID               22699 non-null  int64
 2   tpep_pickup_datetime   22699 non-null  datetime64[ns]
 3   tpep_dropoff_datetime  22699 non-null  datetime64[ns]
 4   passenger_count        22699 non-null  int64
 5   trip_distance          22699 non-null  float64
 6   RatecodeID             22699 non-null  int64
 7   store_and_fwd_flag     22699 non-null  object
 8   PULocationID           22699 non-null  int64
 9   DOLocationID           22699 non-null  int64
 10  payment_type           22699 non-null  int64
 11  fare_amount            22699 non-null  float64
 12  extra                  22699 non-null  float64
 13  mta_tax                22699 non-null  float64
 14  tip_amount             22699 non-null  float64
 15  tolls_amount           22699 non-null  float64
 16  improvement_surcharge  22699 non-null  float64
 17  total_amount           22699 non-null  float64
 18  trip_duration          22699 non-null  float64
 19  pickup_dropoff         22699 non-null  object
 20  mean_distance          22699 non-null  float64
 21  mean_duration          22699 non-null  float64
 22  day                    22699 non-null  object
 23  month                  22699 non-null  object
 24  rush_hour              22699 non-null  int64
dtypes: datetime64[ns](2), float64(11), int64(8), object(4)
memory usage: 4.3+ MB
```

```
df1 = df[["VendorID", "tpep_pickup_datetime", "tpep_dropoff_datetime", "day", "month", "rush_hour",\
           "passenger_count", "trip_distance", "trip_duration","RatecodeID", "store_and_fwd_flag",\
           "PULocationID", "DOLocationID", "pickup_dropoff", "mean_distance", "mean_duration", "payment_type",\
           "fare_amount", "extra", "mta_tax", "tip_amount", "tolls_amount", "improvement_surcharge",
"total_amount"]]
df1.shape
```

```
(22699, 24)
```

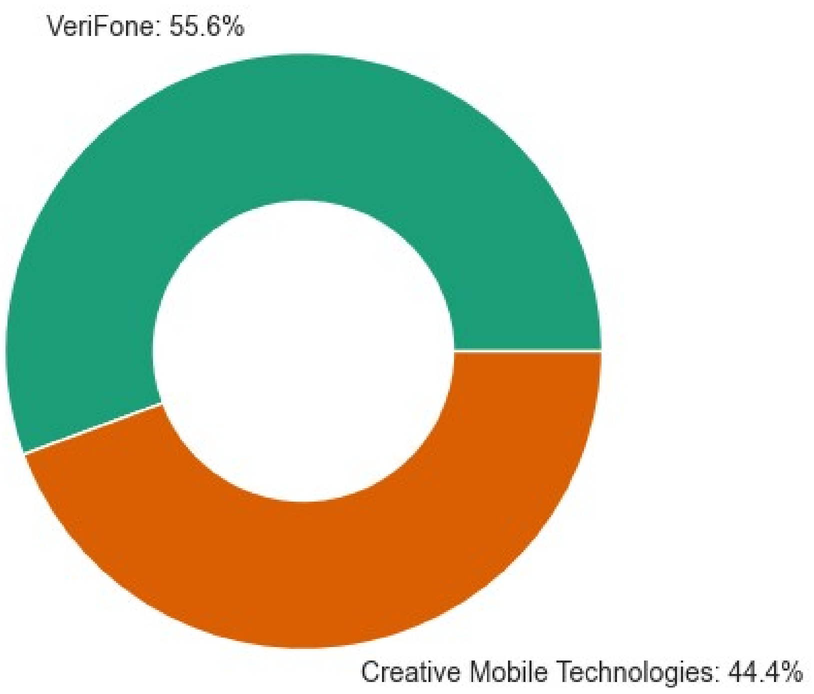
Data visualizations for `tip_amount`

Tips by Vendor

```
df1["VendorID"].value_counts(normalize= True)
```

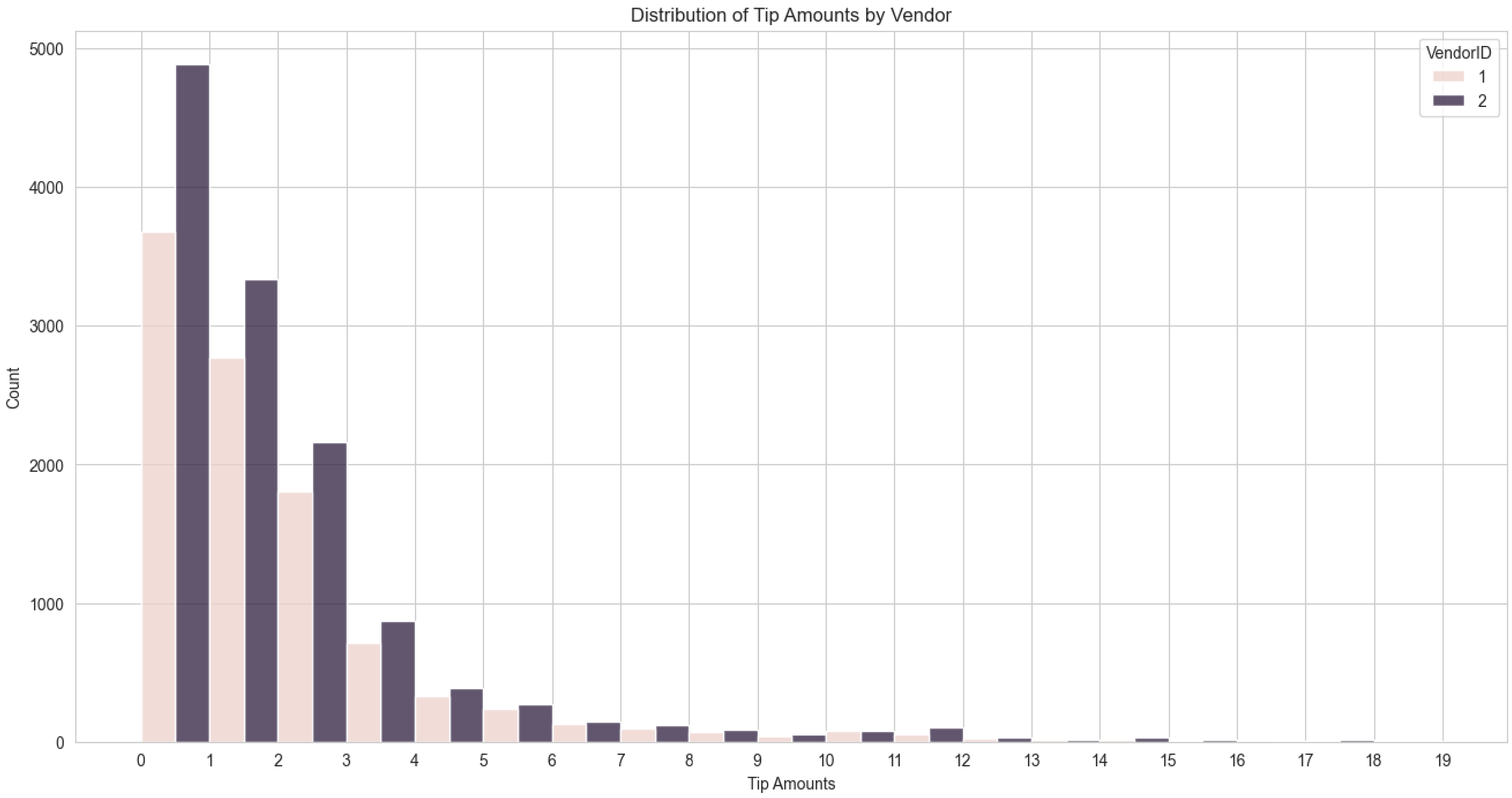
```
VendorID
2    0.556236
1    0.443764
Name: proportion, dtype: float64
```

```
plt.figure(figsize= (15, 5))
plt.pie(df1["VendorID"].value_counts(), labels= ["VeriFone: 55.6%", "Creative Mobile Technologies: 44.4%"])

my_circle = plt.Circle( (0,0), 0.5, color= 'white')
p= plt.gcf()
p.gca().add_artist(my_circle)
plt.show()
```




```
plt.figure(figsize = (16, 8))
ax= sns.histplot(data= df1, x= "tip_amount", bins= range(0, 20, 1), hue= "VendorID", multiple= "dodge")

ax.set_xticks(range(0, 20, 1))
ax.set_xticklabels(range(0, 20, 1))
plt.xlabel("Tip Amounts")
```

```
plt.title("Distribution of Tip Amounts by Vendor")
plt.show()
```




```
df_vendor = df1.groupby(["VendorID"])[["tip_amount", "total_amount"]].agg({"sum", "mean"})
df_vendor
```

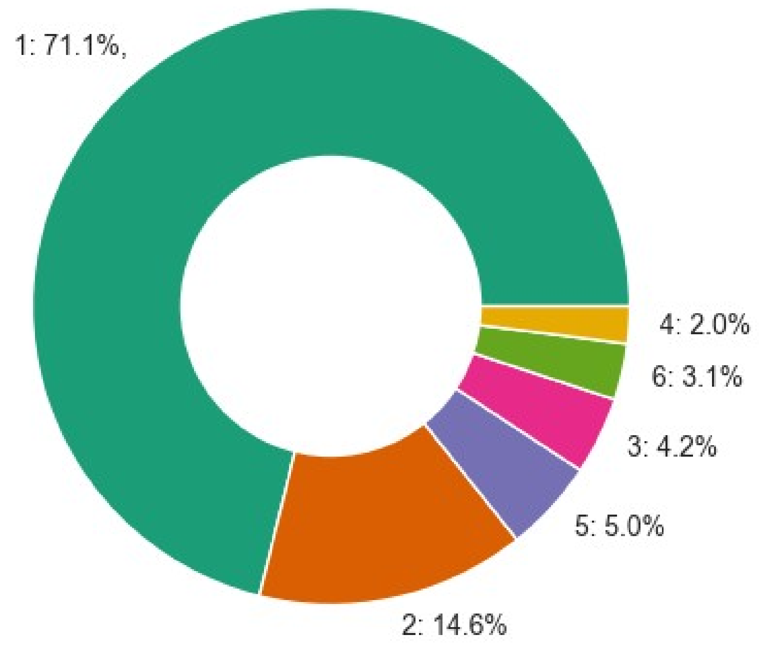
```
         tip_amount           total_amount
                sum      mean          sum       mean
VendorID
1          18362.12  1.822905    162838.95  16.165884
2          23163.78  1.834610    205116.65  16.245577
```

Tips by Passenger Count

```
round(df1["passenger_count"].value_counts(normalize= True), 3) * 100
```

```
passenger_count
1    71.1
2    14.6
5     5.0
3     4.2
6     3.1
4     2.0
Name: proportion, dtype: float64
```

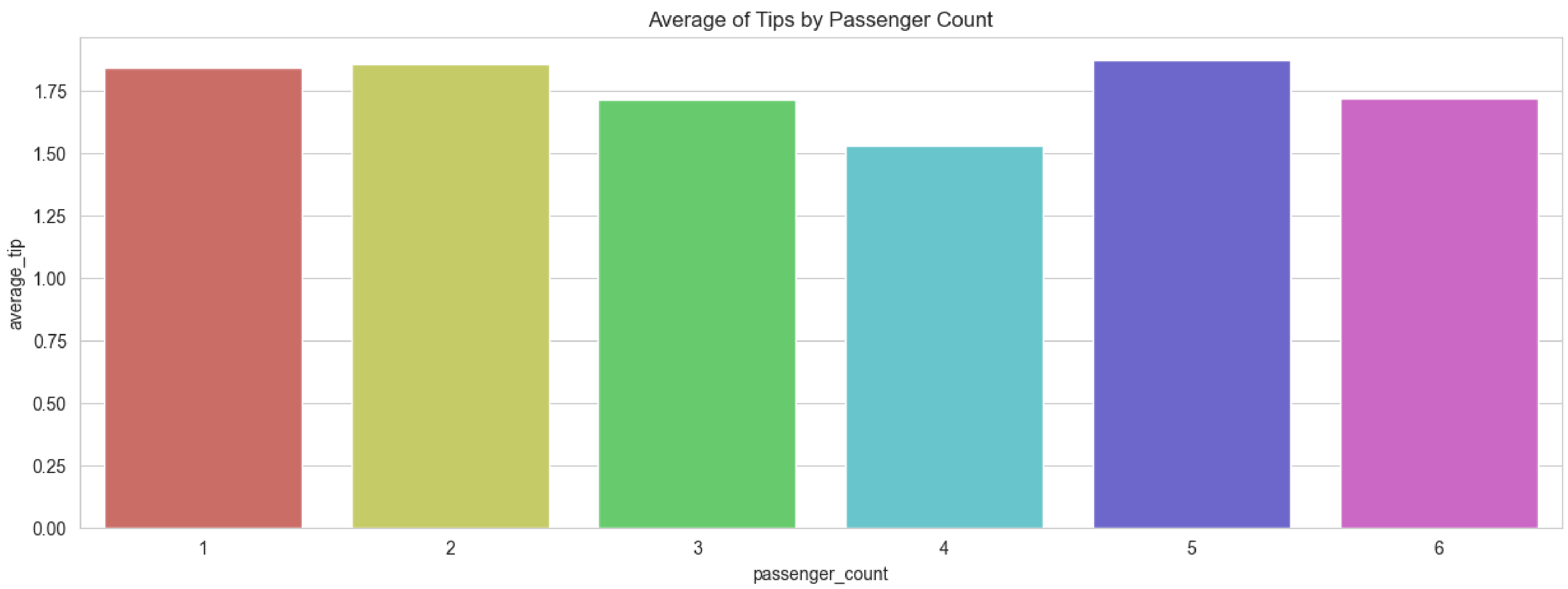
```
plt.figure(figsize= (15, 5))
plt.pie(df1["passenger_count"].value_counts(), labels= ["1: 71.1%,", "2: 14.6%", "5: 5.0%", "3: 4.2%", "6: 
3.1%", "4: 2.0%"])

my_circle = plt.Circle( (0,0), 0.5, color= 'white')
p= plt.gcf()
p.gca().add_artist(my_circle)
plt.show()
```




```
mean_tips_by_pass = df1.groupby(["passenger_count"])[["tip_amount"]].mean().reset_index().rename(columns=
{"tip_amount": "average_tip"})
mean_tips_by_pass
```

	passenger_count	average_tip
0	1	1.840559
1	2	1.856378
2	3	1.716768
3	4	1.530264
4	5	1.873185
5	6	1.720260

```
plt.figure(figsize = (15, 5))
sns.barplot(data= mean_tips_by_pass, x= "passenger_count", y= "average_tip", palette= "hls")
plt.title("Average of Tips by Passenger Count")
plt.show()
```

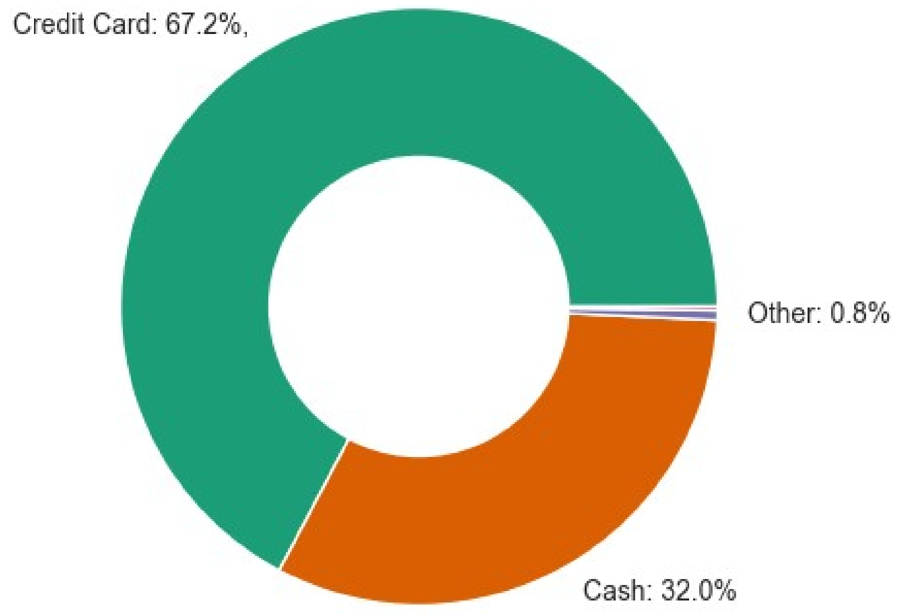


Tips by Payment Types

```
round(df1["payment_type"].value_counts(normalize= True), 3) * 100
```

```
payment_type
1    67.2
2    32.0
3     0.5
4     0.2
Name: proportion, dtype: float64
```

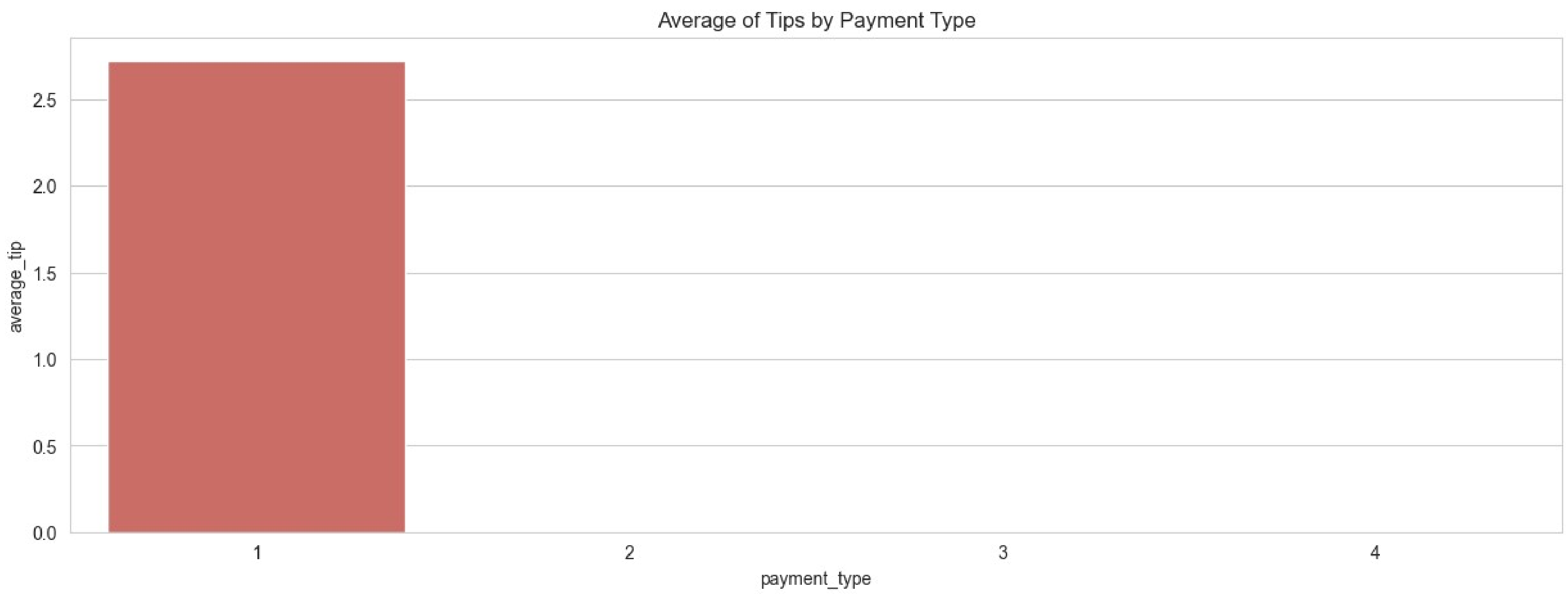
```
plt.figure(figsize= (15, 5))
plt.pie(df1["payment_type"].value_counts(), labels= ["Credit Card: 67.2%,", "Cash: 32.0%", "Other: 0.8%", ""])

my_circle = plt.Circle( (0,0), 0.5, color= 'white')
p= plt.gcf()
p.gca().add_artist(my_circle)
plt.show()
```




```
mean_tips_by_pay = df1.groupby(["payment_type"])[["tip_amount"]].mean().reset_index().rename(columns=
{"tip_amount": "average_tip"})
mean_tips_by_pay
```

```
   payment_type  average_tip
0             1     2.720334
1             2     0.000000
2             3     0.000000
3             4     0.000000
```

```
plt.figure(figsize = (15, 5))
sns.barplot(data= mean_tips_by_pay, x= "payment_type", y= "average_tip", palette= "hls")
plt.title("Average of Tips by Payment Type")
plt.show()
```



Conduct an A/B Test with a two-sample t-test

```
df1.groupby(["payment_type"])["fare_amount"].agg({"mean", "median"})
```

```
                   mean  median
payment_type
1             13.330766     9.5
2             12.141302     9.0
3             12.367934     7.0
4             12.989130     8.5
```

Based on the averages shown, it appears that customers who pay in credit card tend to pay a larger fare amount than customers who pay in cash. However, this difference might arise from rando sampling, rather than being a true difference in fare amount. To assess whether the difference s statistically significanwe'llyou conduct a hypothesis test.

```
credit_card = df1[df1["payment_type"] == 1]["fare_amount"]
cash = df1[df1["payment_type"] == 2]["fare_amount"]
print(len(credit_card))
print(len(cash))
```

```
15265
7267
```

Considering our hypotheses for this project as listed below:

1. H0: There is no difference in the average fare amount between customers who use credit cards and customers who use cash.

2. HA: There is a difference in the average fare amount between customers who use credit cards and customers who use cash.

We choose 5% as the significance level and proceed with a two-sample t-test.

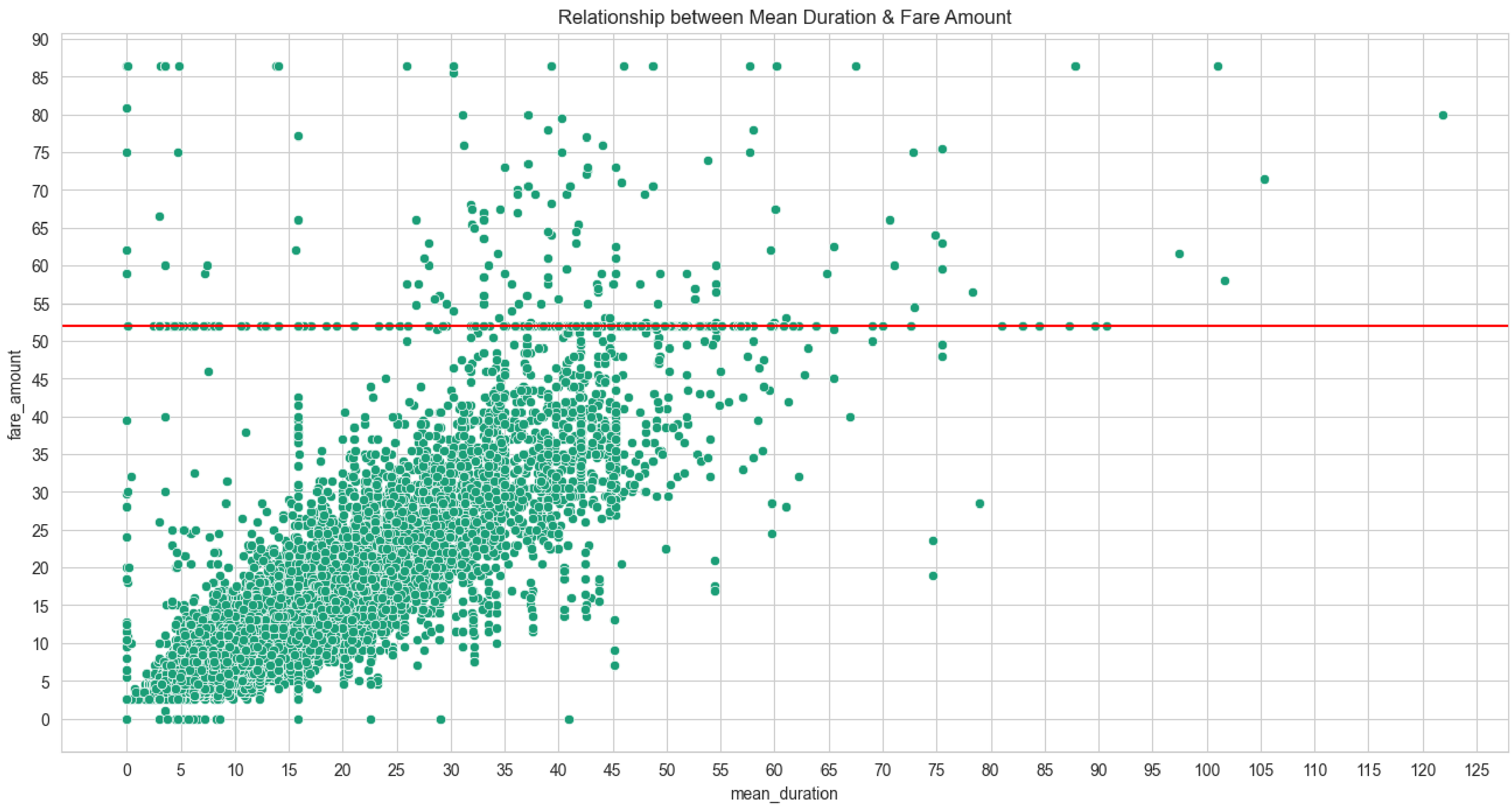
```
stats.ttest_ind(a= credit_card, b= cash, equal_var= False)
```

```
TtestResult(statistic=7.928029528935512, pvalue=2.381707989138683e-15, df=15078.192451526904)
```

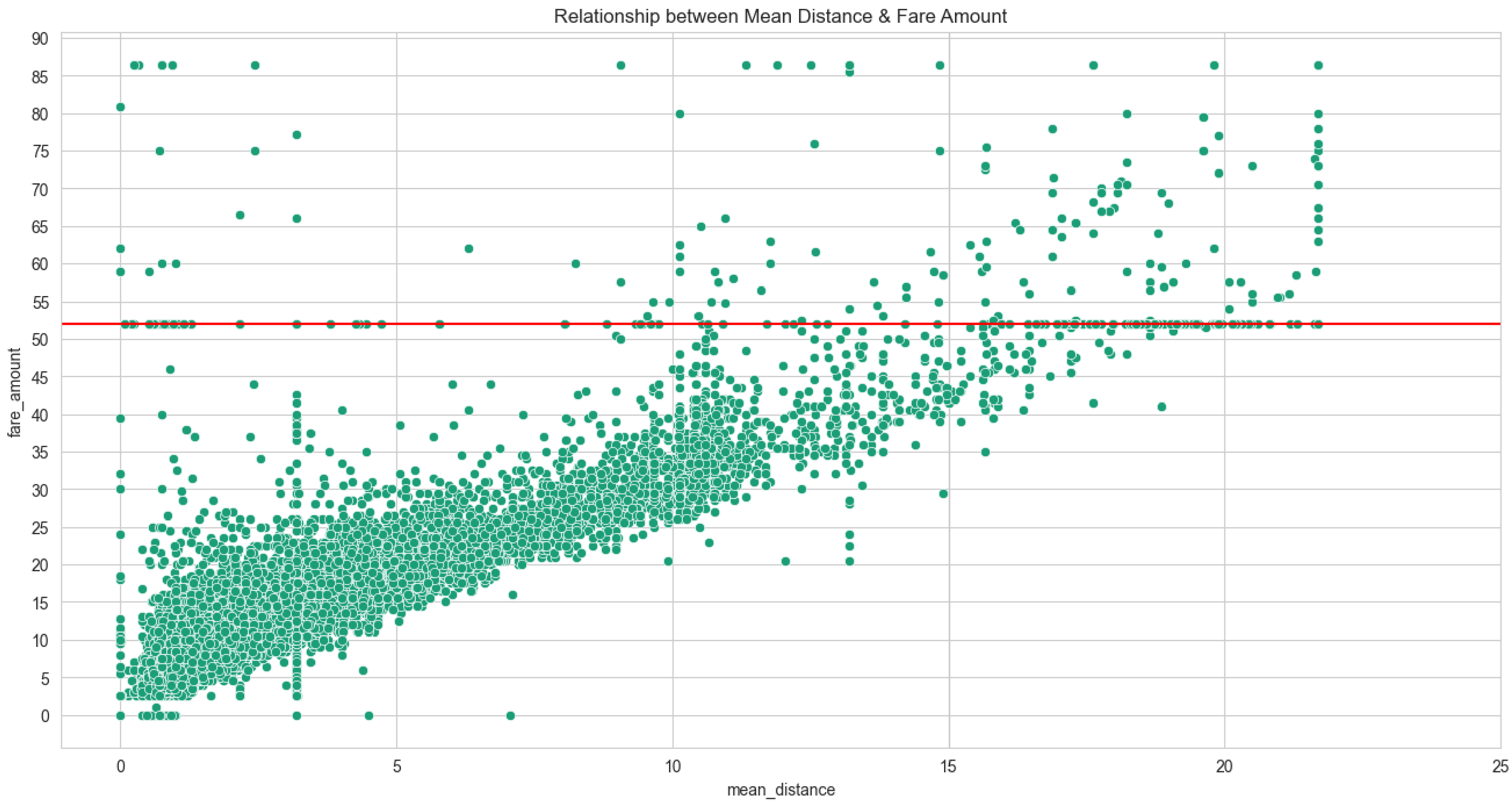
Since the p-value < significance level, then we reject the null hypothesis and accept the alternative hypothesis stating that there is a statistically significant difference in the average fare amount between customers who use credit cards and customers who use cash.

Scatter plots

```
plt.figure(figsize= (16, 8))
sns.scatterplot(data= df1, x= "mean_duration", y= "fare_amount")
plt.axhline(52, color= "red")

plt.xticks(range(0, 126, 5))
plt.yticks(range(0, 91, 5))
plt.title("Relationship between Mean Duration & Fare Amount")
plt.show()
```




```
plt.figure(figsize= (16, 8))
sns.scatterplot(data= df1, x= "mean_distance", y= "fare_amount")
plt.axhline(52, color= "red")

plt.xticks(range(0, 26, 5))
plt.yticks(range(0, 91, 5))
plt.title("Relationship between Mean Distance & Fare Amount")
plt.show()
```



The mean_duration variable correlates with the target variable. But what are the horizontal line around fare amount of 52 dollars?

```
df1[df1["fare_amount"] > 50]["fare_amount"].value_counts().head(3)
```

```
fare_amount
52.0    514
86.5     23
50.5      9
Name: count, dtype: int64
```

```
# Set pandas to display all columns
pd.set_option("display.max_columns", None)
df1[df1["fare_amount"] == 52].head(10)
```

```
     VendorID tpep_pickup_datetime tpep_dropoff_datetime        day  \
11          2  2017-03-05 19:15:00   2017-03-05 19:52:00     sunday
110         1  2017-06-03 14:24:00   2017-06-03 15:31:00   saturday
161         2  2017-11-11 20:16:00   2017-11-11 20:17:00   saturday
247         2  2017-12-06 23:37:00   2017-12-07 00:06:00  wednesday
379         2  2017-09-24 23:45:45   2017-09-25 00:15:14     sunday
388         1  2017-02-28 18:30:05   2017-02-28 19:09:55    tuesday
406         2  2017-06-05 12:51:00   2017-06-05 13:07:00     monday
449         2  2017-08-03 22:47:00   2017-08-03 23:32:00   thursday
468         2  2017-09-26 13:48:26   2017-09-26 14:31:17    tuesday
520         2  2017-04-23 21:34:48   2017-04-23 22:46:23     sunday

         month  rush_hour  passenger_count  trip_distance  trip_duration  \
11       march          0                2          18.90      37.000000
110       june          0                1          18.00      67.000000
161   november          0                1           0.23       1.000000
247   december          0                1          18.93      29.000000
379  september          0                1          17.99      29.483333
388   february          1                1          18.40      39.833333
406       june          0                1           4.73      16.000000
449     august          0                2          18.21      45.000000
468  september          0                1          17.27      42.850000
520      april          0                6          18.34      71.583333

     RatecodeID store_and_fwd_flag  PULocationID  DOLocationID pickup_dropoff  \
11            2                  N           236           132     236 >> 132
110           2                  N           132           163     132 >> 163
161           2                  N           132           132     132 >> 132
247           2                  N           132            79      132 >> 79
379           2                  N           132           234     132 >> 234
388           2                  N           132            48      132 >> 48
406           2                  N           228            88      228 >> 88
449           2                  N           132            48      132 >> 48
468           2                  N           186           132     186 >> 132
520           2                  N           132           148     132 >> 148

     mean_distance  mean_duration  payment_type  fare_amount  extra  mta_tax  \
11           19.21          46.10             1         52.0    0.0      0.5
110          19.13          53.07             1         52.0    0.0      0.5
161           2.16           3.02             2         52.0    0.0      0.5
```

```
247          19.43          47.16             2          52.0    0.0      0.5
379          17.65          49.78             1          52.0    0.0      0.5
388          18.52          59.85             2          52.0    4.5      0.5
406           4.73          16.00             2          52.0    0.0      0.5
449          18.52          59.85             2          52.0    0.0      0.5
468          17.10          42.79             2          52.0    0.0      0.5
520          17.99          46.37             1          52.0    0.0      0.5

     tip_amount  tolls_amount  improvement_surcharge  total_amount
11        14.58          5.54                    0.3         72.92
110        0.00          0.00                    0.3         52.80
161        0.00          0.00                    0.3         52.80
247        0.00          0.00                    0.3         52.80
379       14.64          5.76                    0.3         73.20
388        0.00          5.54                    0.3         62.84
406        0.00          5.76                    0.3         58.56
449        0.00          5.76                    0.3         58.56
468        0.00          5.76                    0.3         58.56
520        5.00          0.00                    0.3         57.80
```

It seems that almost all of the trips in the first 30 rows where the fare amount was $52 either begin or end at location 132, and all of them have a `RatecodeID` of 2.

There is no readily apparent reason why PULocation 132 should have so many fares of 52 dollars. They seem to occur on all different days, at different times, with both vendors, in all months. However, there are many toll amounts of $5.76 and \$5.54. This would seem to indicate that location 132 is in an area that frequently requires tolls to get to and from. It's likely this is an airport.

Isolate modelling variables

```
df1.info()
```

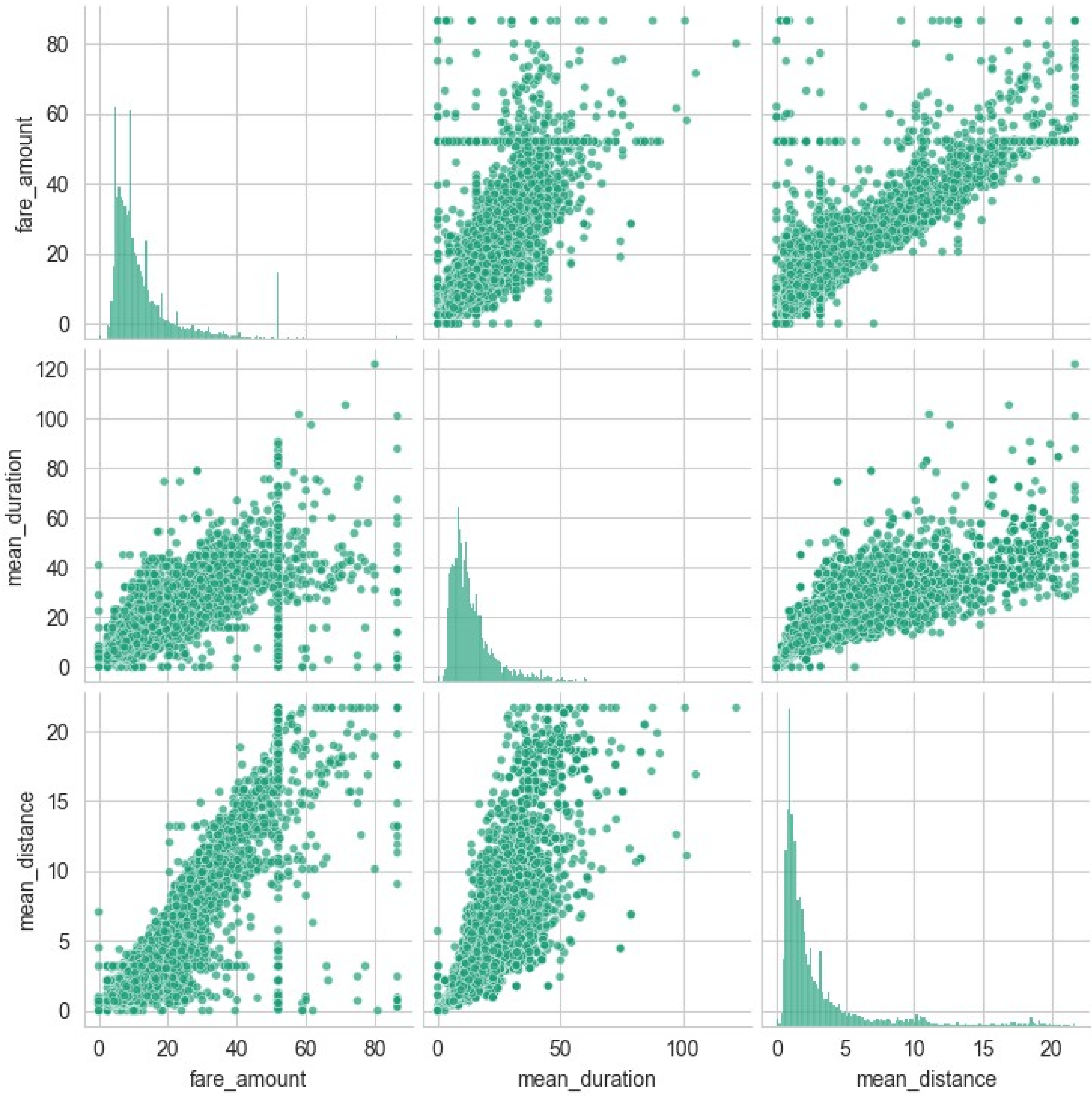
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 24 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   VendorID               22699 non-null  int64
 1   tpep_pickup_datetime   22699 non-null  datetime64[ns]
 2   tpep_dropoff_datetime  22699 non-null  datetime64[ns]
 3   day                    22699 non-null  object
 4   month                  22699 non-null  object
 5   rush_hour              22699 non-null  int64
 6   passenger_count        22699 non-null  int64
 7   trip_distance          22699 non-null  float64
 8   trip_duration          22699 non-null  float64
 9   RatecodeID             22699 non-null  int64
 10  store_and_fwd_flag     22699 non-null  object
 11  PULocationID           22699 non-null  int64
 12  DOLocationID           22699 non-null  int64
 13  pickup_dropoff         22699 non-null  object
 14  mean_distance          22699 non-null  float64
 15  mean_duration          22699 non-null  float64
 16  payment_type           22699 non-null  int64
 17  fare_amount            22699 non-null  float64
 18  extra                  22699 non-null  float64
 19  mta_tax                22699 non-null  float64
 20  tip_amount             22699 non-null  float64
 21  tolls_amount           22699 non-null  float64
 22  improvement_surcharge  22699 non-null  float64
 23  total_amount           22699 non-null  float64
dtypes: datetime64[ns](2), float64(11), int64(7), object(4)
memory usage: 4.2+ MB
```

```
df2 = df1.copy()

df2 = df2.drop(["tpep_pickup_datetime", "tpep_dropoff_datetime", "day", "month", "trip_distance", 
"trip_duration",\
                "store_and_fwd_flag", "PULocationID", "DOLocationID", "pickup_dropoff", "payment_type", 
"RatecodeID",\
                "extra", "mta_tax", "tip_amount", "tolls_amount", "improvement_surcharge", "total_amount"], 
axis= 1)
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   VendorID         22699 non-null  int64
 1   rush_hour        22699 non-null  int64
 2   passenger_count  22699 non-null  int64
 3   mean_distance    22699 non-null  float64
 4   mean_duration    22699 non-null  float64
 5   fare_amount      22699 non-null  float64
dtypes: float64(3), int64(3)
memory usage: 1.0 MB
```

Pair plot

```
sns.pairplot(data= df2[["fare_amount", "mean_duration", "mean_distance"]], plot_kws= {"alpha": 0.7, "size":
0.7})
plt.show()
```

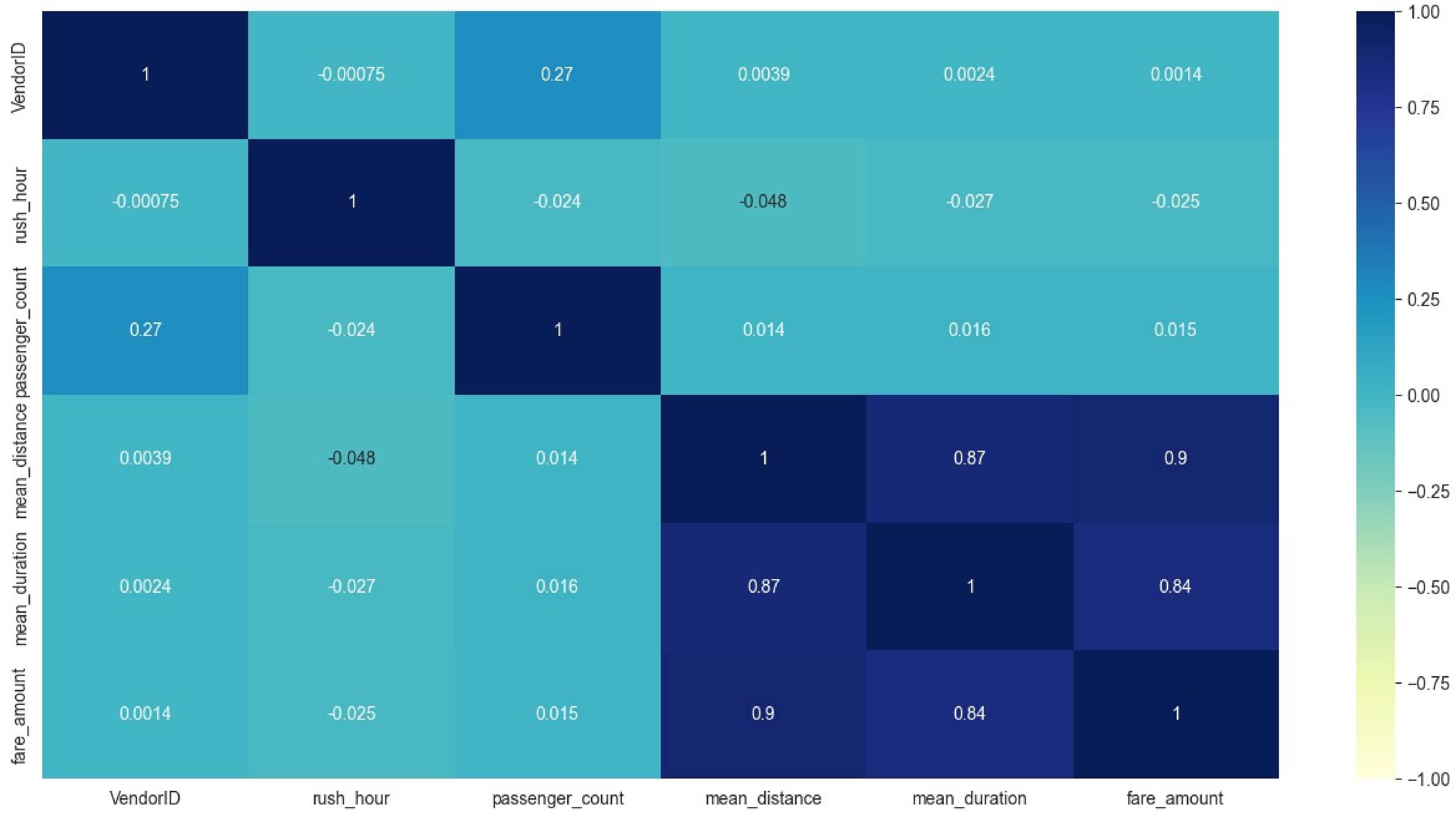


Identify correlations

```
# Correlation matrix to help determine most correlated variables
df2.corr(method= "pearson")
```

```
                 VendorID  rush_hour  passenger_count  mean_distance  \
VendorID         1.000000  -0.000752         0.265464       0.003876
rush_hour       -0.000752   1.000000        -0.024259      -0.047741
passenger_count  0.265464  -0.024259         1.000000       0.013635
mean_distance    0.003876  -0.047741         0.013635       1.000000
mean_duration    0.002441  -0.026922         0.015732       0.869964
fare_amount      0.001379  -0.025329         0.015012       0.902685

                 mean_duration  fare_amount
VendorID              0.002441     0.001379
rush_hour            -0.026922    -0.025329
passenger_count       0.015732     0.015012
mean_distance         0.869964     0.902685
mean_duration         1.000000     0.840942
fare_amount           0.840942     1.000000
```

```
# Create correlation heatmap
plt.figure(figsize= (16, 8))
sns.heatmap(data= df2.corr(method= "pearson"), vmin= -1, vmax= 1, annot= True, cmap= "YlGnBu")
plt.show()
```



paCe: Construct Stage

Step 4. Model Building

Split data into outcome variable and features

```
# Remove the target column from the features
X = df2.drop(columns='fare_amount')

# Set y variable
y = df2[["fare_amount"]]

# Display first few rows
X.head(3)
```

```
   VendorID  rush_hour  passenger_count  mean_distance  mean_duration
0         2          0                6           3.52          22.88
1         1          0                1           3.11          24.29
2         1          1                1           0.88           7.26
```

Dummy encode categorical vendorID

```
# Convert VendorID to string
X["VendorID"] = X["VendorID"].astype("str")

# Get dummies
X = pd.get_dummies(X, drop_first= False)
X.head(3)
```

```
   rush_hour  passenger_count  mean_distance  mean_duration  VendorID_1  \
0          0                6           3.52          22.88       False
1          0                1           3.11          24.29        True
2          1                1           0.88           7.26        True

   VendorID_2
0        True
1       False
2       False
```

Split data into training and testing sets

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size= 0.2, random_state= 0)
```

Modelling Approach [A]: Multiple Linear Regression

Standardize the data

```
# Standardize the X variables
scaler = StandardScaler().fit(X_train)
X_train_scaled = scaler.transform(X_train)
print("X_train_scaled:\n", X_train_scaled)
```

```
X_train_scaled:
 [[-0.77153979 -0.50468931  0.88394718  0.16609516 -0.89286563  0.89286563]
```

```
 [ 1.29610943 -0.50468931 -0.60457634 -0.70337029 -0.89286563  0.89286563]
 [-0.77153979  0.27243722 -0.48265917 -0.57192814  1.11998936 -1.11998936]
 ...
 [-0.77153979 -0.50468931 -0.45430634 -0.66637176  1.11998936 -1.11998936]
 [ 1.29610943 -0.50468931 -0.59607049 -0.84844347  1.11998936 -1.11998936]
 [-0.77153979  1.82669027  0.84992379  1.11734684 -0.89286563  0.89286563]]
```

Fit the model

```python
# Fit your model to the training data
mlr = LinearRegression(n_jobs= -1)
mlr.fit(X_train_scaled, y_train)
```

```
LinearRegression(n_jobs=-1)
```

Evaluate the model

```python
def evaluate_regressor(actual, predicted):
    print(f"R^2: {round(r2_score(actual, predicted), 2)}")
    print(f"MAE: {round(mean_absolute_error(actual, predicted), 2)}")
    print(f"MSE: {round(mean_squared_error(actual, predicted), 2)}")
    print(f"RMSE: {round(np.sqrt(mean_squared_error(actual, predicted)), 2)}")
```

```python
y_pred_train_mlr = mlr.predict(X_train_scaled)
```

```python
evaluate_regressor(y_train, y_pred_train_mlr)
```

```
R^2: 0.82
MAE: 2.25
MSE: 20.95
RMSE: 4.58
```

```python
X_test_scaled = scaler.transform(X_test)
```

```python
y_pred_test_mlr = mlr.predict(X_test_scaled)
```

```python
evaluate_regressor(y_test, y_pred_test_mlr)
```

```
R^2: 0.85
MAE: 2.19
MSE: 16.56
RMSE: 4.07
```

Coefficients for multiple linear regression

```python
print("Coefficients:\n", mlr.coef_)
```

```
Coefficients:
 [[ 1.40972853e-01  2.84896083e-02  7.59366967e+00  2.46856907e+00
  -2.19545604e+13 -2.19545604e+13]]
```

```python
coefficients = round(pd.DataFrame(data= mlr.coef_, columns= X.columns) * 100, 4)
coefficients
```

```
   rush_hour  passenger_count  mean_distance  mean_duration    VendorID_1  \
0    14.0973            2.849        759.367       246.8569 -2.195456e+15   

     VendorID_2  
0 -2.195456e+15  
```

These coefficients represent the relative increase in fare_amount for every unit increased in standard deviation of these variables. To simplify the interpretation, let's calculate the standard deviation of the most effective variables:

```python
print(X_train['mean_distance'].std())
```

```python
print(7.5937 / X_train['mean_distance'].std())
```

```
3.52708203496952
2.15296948716012
```

Now you can make a more intuitive interpretation: for every 3.53 miles traveled, the fare increased by a mean of \$7.59. Or, for every 1 mile traveled, the fare increased by a mean of \$2.15.

```python
print(X_train['mean_duration'].std())
```

```python
print(2.4686 / X_train['mean_duration'].std())
```

```
10.270961194893056
0.24034751501421708
```

For every 10.27 minutes traveled, the fare increased by a mean of \$2.47. Or, for every 1 minute traveled, the fare increased by a mean of \$0.24.

Modelling Approach [B]: Random Forest Regressor

```python
ranfor_reg = RandomForestRegressor(random_state= 17)
```

```python
cv_params = {"max_depth": [4, 6, 8, 10], "min_samples_leaf": [1, 2, 3, 4], "n_estimators": [100, 150, 200, 
250]}
```

```python
scoring = ["explained_variance", "neg_mean_absolute_error", "neg_mean_squared_error", 
"neg_root_mean_squared_error"]
```

```
ranfor_cv = GridSearchCV(estimator= ranfor_reg, param_grid= cv_params, scoring= scoring, cv= 5, refit=
"explained_variance", n_jobs= -1, verbose= 2)
```

```
%%time
```

```
ranfor_cv.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 64 candidates, totalling 320 fits
CPU times: total: 4.48 s
Wall time: 3min 7s
```

```
GridSearchCV(cv=5, estimator=RandomForestRegressor(random_state=17), n_jobs=-1,
             param_grid={'max_depth': [4, 6, 8, 10],
                         'min_samples_leaf': [1, 2, 3, 4],
                         'n_estimators': [100, 150, 200, 250]},
             refit='explained_variance',
             scoring=['explained_variance', 'neg_mean_absolute_error',
                      'neg_mean_squared_error', 'neg_root_mean_squared_error'],
             verbose=2)
```

```
ranfor_cv.best_params_
```

```
{'max_depth': 8, 'min_samples_leaf': 1, 'n_estimators': 200}
```

```
ranfor_cv.best_score_
```

```
0.8391621789484782
```

Fit the model

```
ranfor_reg = RandomForestRegressor(n_estimators= 200, criterion= 'squared_error', max_depth= 8,
min_samples_leaf= 1, n_jobs= -1, verbose= 1, random_state= 17)
ranfor_reg.fit(X_train, y_train)
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    0.0s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:    0.5s
[Parallel(n_jobs=-1)]: Done 200 out of 200 | elapsed:    0.6s finished
```

```
RandomForestRegressor(max_depth=8, n_estimators=200, n_jobs=-1, random_state=17,
                      verbose=1)
```

Evaluate the model

```
# Evaluate the model performance on the training data
y_pred_train_ranfor = ranfor_reg.predict(X_train)
```

```
evaluate_regressor(y_train, y_pred_train_ranfor)
```

```
R^2: 0.88
MAE: 2.05
MSE: 14.45
RMSE: 3.8
```

```
[Parallel(n_jobs=8)]: Using backend ThreadingBackend with 8 concurrent workers.
[Parallel(n_jobs=8)]: Done  34 tasks      | elapsed:    0.0s
[Parallel(n_jobs=8)]: Done 184 tasks      | elapsed:    0.0s
[Parallel(n_jobs=8)]: Done 200 out of 200 | elapsed:    0.0s finished
```

```
# Evaluate the model performance on the testing data
y_pred_test_ranfor = ranfor_reg.predict(X_test)
```

```
evaluate_regressor(y_test, y_pred_test_ranfor)
```

```
R^2: 0.86
MAE: 2.13
MSE: 15.41
RMSE: 3.93
```

```
[Parallel(n_jobs=8)]: Using backend ThreadingBackend with 8 concurrent workers.
[Parallel(n_jobs=8)]: Done  34 tasks      | elapsed:    0.0s
[Parallel(n_jobs=8)]: Done 184 tasks      | elapsed:    0.0s
[Parallel(n_jobs=8)]: Done 200 out of 200 | elapsed:    0.0s finished
```

Modelling Approach [C]: Extreme Gradient Boost Regressor

```
xgboost_reg = XGBRegressor(objective= 'reg:squarederror', random_state= 17)
```

```
cv_params = {"max_depth": [4, 6, 8, 10], "min_child_weight": [1, 2, 3, 4], "n_estimators": [100, 150, 200,
250], "learning_rate": [0.05, 0.1, 0.2]}
```

```
scoring = ["explained_variance", "neg_mean_absolute_error", "neg_mean_squared_error",
"neg_root_mean_squared_error"]
```

```
xgboost_cv = GridSearchCV(estimator= xgboost_reg, param_grid= cv_params, scoring= scoring, cv= 5, refit=
"explained_variance", n_jobs= -1, verbose= 2)
```

```
%%time

xgboost_cv.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 192 candidates, totalling 960 fits
CPU times: total: 8.98 s
Wall time: 1min 31s

GridSearchCV(cv=5,
             estimator=XGBRegressor(base_score=None, booster=None,
                                    callbacks=None, colsample_bylevel=None,
                                    colsample_bynode=None,
                                    colsample_bytree=None, device=None,
                                    early_stopping_rounds=None,
                                    enable_categorical=False, eval_metric=None,
                                    feature_types=None, gamma=None,
                                    grow_policy=None, importance_type=None,
                                    interaction_constraints=None,
                                    learning_rate=None, m...
                                    multi_strategy=None, n_estimators=None,
                                    n_jobs=None, num_parallel_tree=None,
                                    random_state=17, ...),
             n_jobs=-1,
             param_grid={'learning_rate': [0.05, 0.1, 0.2],
                         'max_depth': [4, 6, 8, 10],
                         'min_child_weight': [1, 2, 3, 4],
                         'n_estimators': [100, 150, 200, 250]},
             refit='explained_variance',
             scoring=['explained_variance', 'neg_mean_absolute_error',
                      'neg_mean_squared_error', 'neg_root_mean_squared_error'],
             verbose=2)
```

```
xgboost_cv.best_params_
```

```
{'learning_rate': 0.05,
 'max_depth': 4,
 'min_child_weight': 3,
 'n_estimators': 250}
```

```
xgboost_cv.best_score_
```

```
0.8364500917599068
```

Fit the model

```
xgboost_reg = XGBRegressor(n_estimators= 250, learning_rate= 0.05, max_depth= 4, min_child_weight= 3, n_jobs= -
1, verbose= 1, random_state= 17)
xgboost_reg.fit(X_train, y_train)
```

```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.05, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=4, max_leaves=None,
             min_child_weight=3, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=250, n_jobs=-1,
             num_parallel_tree=None, random_state=17, ...)
```

Evaluate the model

```
# Evaluate the model performance on the training data
y_pred_train_xgb = xgboost_reg.predict(X_train)

evaluate_regressor(y_train, y_pred_train_xgb)
```

```
R^2: 0.86
MAE: 2.12
MSE: 16.2
RMSE: 4.03
```

```
# Evaluate the model performance on the testing data
y_pred_test_xgb = xgboost_reg.predict(X_test)

evaluate_regressor(y_test, y_pred_test_xgb)
```

```
R^2: 0.86
MAE: 2.12
MSE: 15.55
RMSE: 3.94
```

pacE: Execute Stage

Step 5. Results and Evaluation

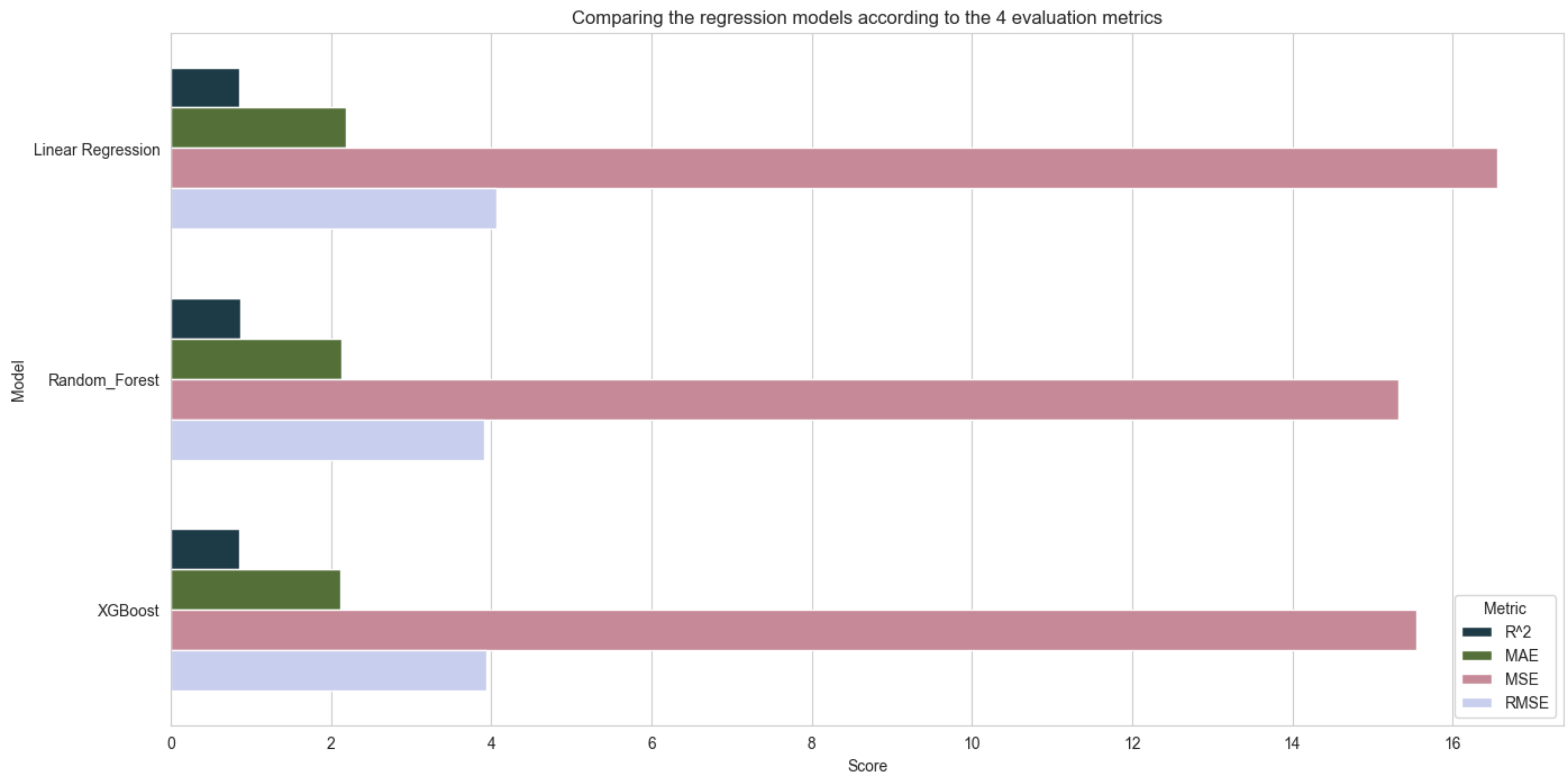
Comparing models

```
data = {"Model": ["Linear Regression", "Linear Regression", "Linear Regression", "Linear Regression",
"Random_Forest", "Random_Forest", "Random_Forest", "Random_Forest", "XGBoost", "XGBoost", "XGBoost",
"XGBoost"],\
       "Metric": ["R^2", "MAE", "MSE", "RMSE", "R^2", "MAE", "MSE", "RMSE", "R^2", "MAE", "MSE", "RMSE"],\
       "Score": [0.85, 2.19, 16.56, 4.07, 0.87, 2.13, 15.32, 3.91, 0.86, 2.12, 15.55, 3.94]}
```

```
comparing_models_ = pd.DataFrame(data)
comparing_models_
```

```
                Model Metric  Score
0   Linear Regression    R^2   0.85
1   Linear Regression    MAE   2.19
2   Linear Regression    MSE  16.56
3   Linear Regression   RMSE   4.07
4       Random_Forest    R^2   0.87
5       Random_Forest    MAE   2.13
6       Random_Forest    MSE  15.32
7       Random_Forest   RMSE   3.91
8             XGBoost    R^2   0.86
9             XGBoost    MAE   2.12
10            XGBoost    MSE  15.55
11            XGBoost   RMSE   3.94
```

```
plt.figure( figsize= (16, 8))
fig = sns.barplot(data= comparing_models_, x= "Score", y= "Model", orient= "horizontal", hue= "Metric",
palette= "cubehelix", width= 0.7, dodge= True)
fig.set_title("Comparing the regression models according to the 4 evaluation metrics")
plt.show()
```



We could observe that the Random Forest Model performs the best based on the all metrics except for the mean absolute error.

Random forest model results

```
# Create a `results` dataframe
results = pd.DataFrame(data= {"actual": y_test["fare_amount"], "predicted": y_pred_test_ranfor.ravel()})
results.head(5)
```

```
       actual  predicted
5818     14.0  12.107306
18134    28.0  16.999474
4655      5.5   6.541329
7378     15.5  15.847178
13914     9.5  10.174875
```

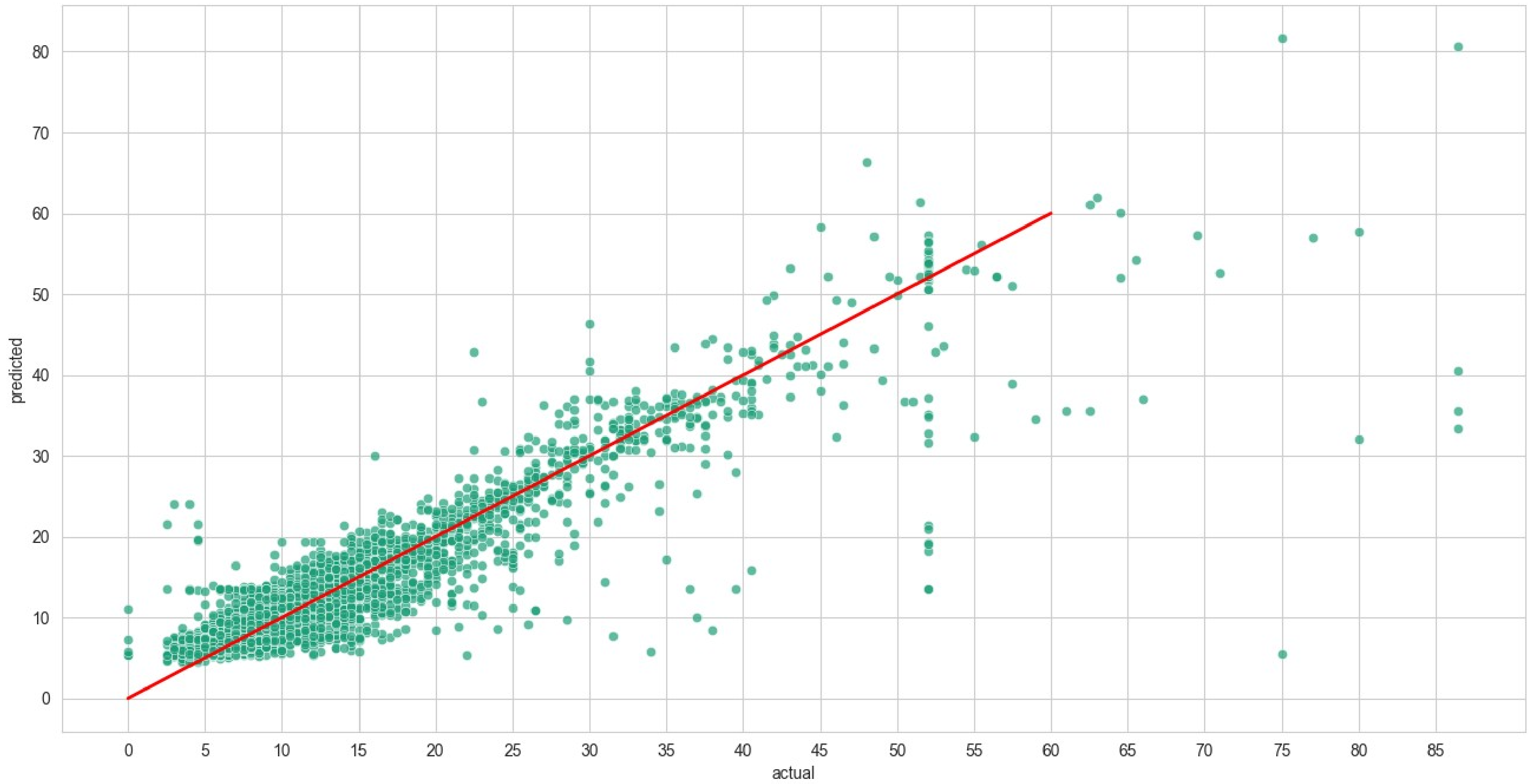
```
results["residual"] = results["actual"] - results["predicted"]
results.head(5)
```

```
       actual  predicted   residual
5818     14.0  12.107306   1.892694
18134    28.0  16.999474  11.000526
4655      5.5   6.541329  -1.041329
```

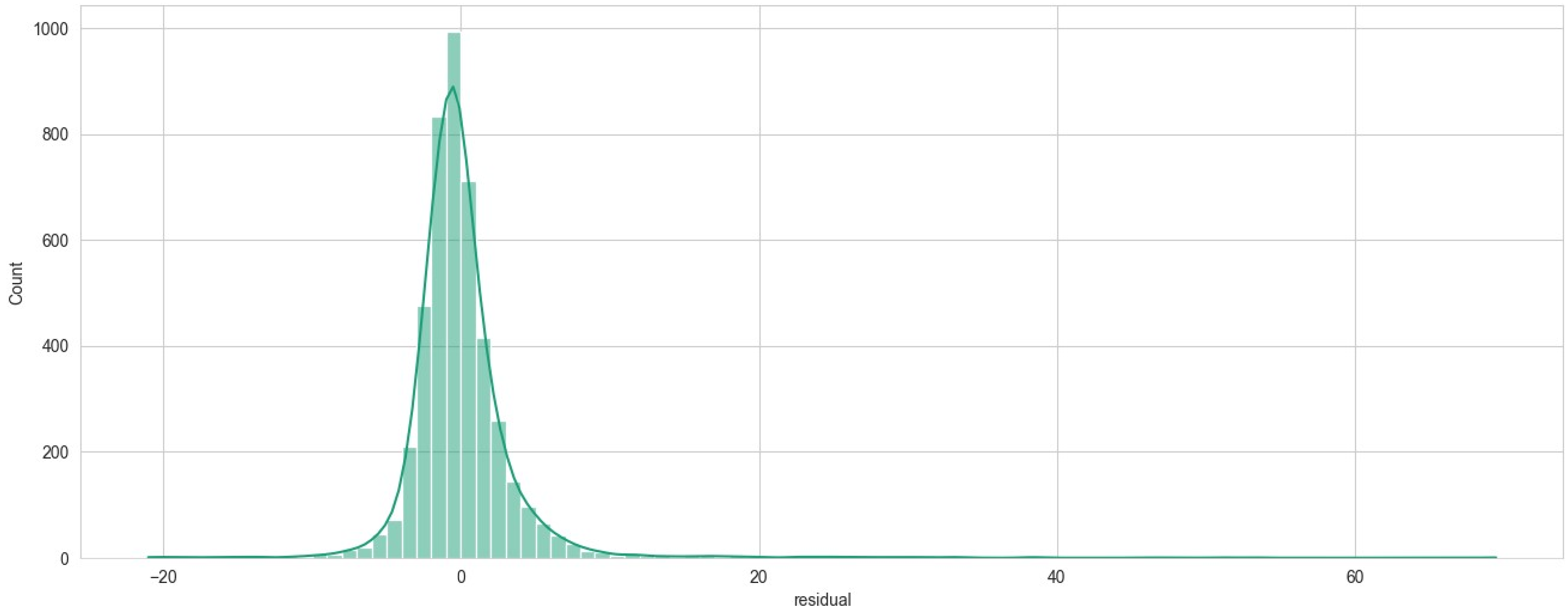
```
7378     15.5  15.847178  -0.347178
13914     9.5  10.174875  -0.674875
```

Visualize random forest model results

```python
# Create a scatterplot to visualize `predicted` over `actual`
plt.figure(figsize= (16, 8))
sns.scatterplot(data= results, x= "actual", y= "predicted", alpha= 0.7)
plt.plot([0, 60], [0, 60], c= "red", linewidth= "2")
plt.xticks(range(0, 86, 5))
plt.show()
```



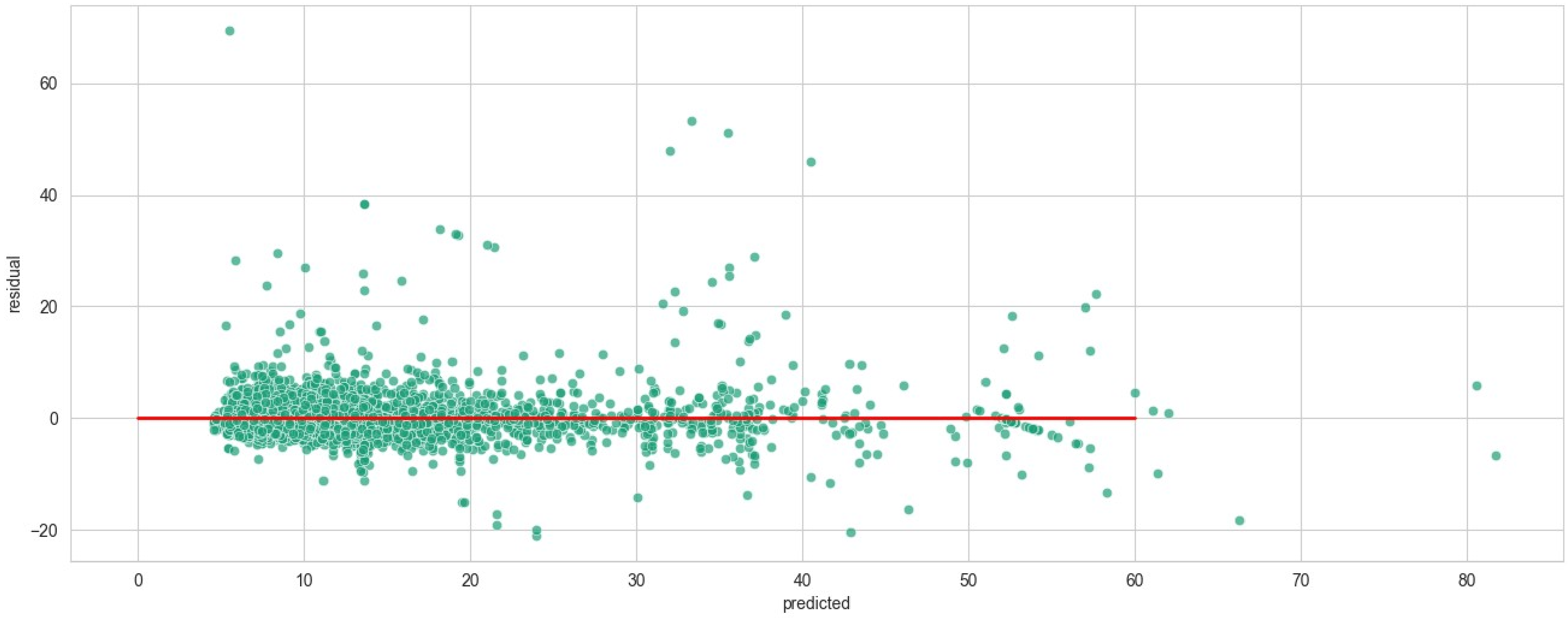

```python
# Visualize the distribution of the `residuals`
plt.figure(figsize= (16, 6))
sns.histplot(data= results, x= "residual", kde= True, bins= np.arange(-20, 20, 1))
plt.show()
```




```python
# Calculate residual mean
print("Residual Mean =", round(results["residual"].mean(), 4))
```

```
Residual Mean = 0.0253
```

```python
# Create a scatterplot of `residuals` over `predicted`
plt.figure(figsize= (16, 6))
sns.scatterplot(data= results, x= "predicted", y= "residual", alpha= 0.7)
plt.plot([0, 60], [0, 0], c= "red", linewidth= "2")
plt.show()
```



Feature importance

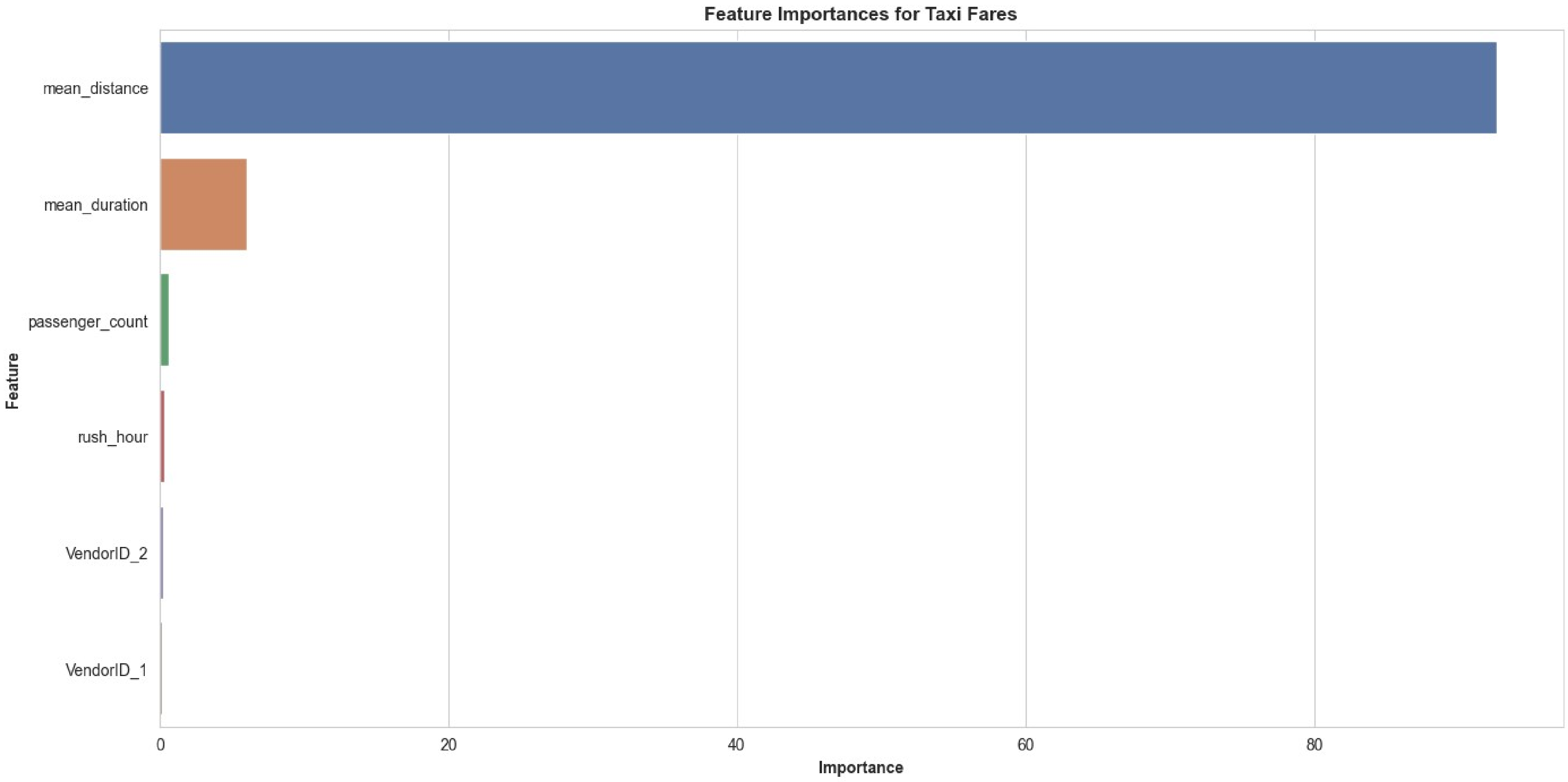
```
feature_importances = ranfor_reg.feature_importances_
feature_importances
```

```
array([0.00325539, 0.00609513, 0.92578617, 0.06039367, 0.00206913,
       0.00240051])
```

```
forest_importances = pd.DataFrame(list(X.columns), columns= ["feature"])
forest_importances["importance"] = feature_importances * 100
forest_importances = forest_importances.sort_values(by="importance", ascending= False)
forest_importances
```

	feature	importance
2	mean_distance	92.578617
3	mean_duration	6.039367
1	passenger_count	0.609513
0	rush_hour	0.325539
5	VendorID_2	0.240051
4	VendorID_1	0.206913

```
plt.figure(figsize= (16, 8))
sns.barplot(data= forest_importances, x= "importance", y= "feature", palette= "deep", orient= "h")
plt.title("Feature Importances for Taxi Fares", fontweight= "bold")
plt.ylabel("Feature", fontweight= "bold")
plt.xlabel("Importance", fontweight= "bold")
plt.show()
```



From the above graph, we observe that the mean distance of the trip is the most influential factor in estimating the taxi fares in advance with relative importance of 92.58%. In the future, adding more information on a rider's past behavior may also be beneficial in helping the stakeholder address their business problem.