Activity_ Course 5 Automatidata project lab

May 3, 2024

1 Automatidata project

Course 5 - Regression Analysis: Simplify complex data relationships

The data consulting firm Automatidata has recently hired you as the newest member of their data analytics team. Their newest client, the NYC Taxi and Limousine Commission (New York City TLC), wants the Automatidata team to build a multiple linear regression model to predict taxi fares using existing data that was collected over the course of a year. The team is getting closer to completing the project, having completed an initial plan of action, initial Python coding work, EDA, and A/B testing.

The Automatidata team has reviewed the results of the A/B testing. Now it's time to work on predicting the taxi fare amounts. You've impressed your Automatidata colleagues with your hard work and attention to detail. The data team believes that you are ready to build the regression model and update the client New York City TLC about your progress.

A notebook was structured and prepared to help you in this project. Please complete the following questions.

2 Course 5 End-of-course project: Build a multiple linear regression model

In this activity, you will build a multiple linear regression model. As you've learned, multiple linear regression helps you estimate the linear relationship between one continuous dependent variable and two or more independent variables. For data science professionals, this is a useful skill because it allows you to consider more than one variable against the variable you're measuring against. This opens the door for much more thorough and flexible analysis to be completed.

Completing this activity will help you practice planning out and buidling a multiple linear regression model based on a specific business need. The structure of this activity is designed to emulate the proposals you will likely be assigned in your career as a data professional. Completing this activity will help prepare you for those career moments.

The purpose of this project is to demostrate knowledge of EDA and a multiple linear regression model

The goal is to build a multiple linear regression model and evaluate the model *This activity has three parts:*

Part 1: EDA & Checking Model Assumptions * What are some purposes of EDA before constructing a multiple linear regression model?

Part 2: Model Building and evaluation * What resources do you find yourself using as you complete this stage?

Part 3: Interpreting Model Results

- What key insights emerged from your model(s)?
- What business recommendations do you propose based on the models built?

3 Build a multiple linear regression model

4 PACE stages

Throughout these project notebooks, you'll see references to the problem-solving framework PACE. The following notebook components are labeled with the respective PACE stage: Plan, Analyze, Construct, and Execute.

4.1 PACE: Plan

Consider the questions in your PACE Strategy Document to reflect on the Plan stage.

4.1.1 Task 1. Imports and loading

Import the packages that you've learned are needed for building linear regression models.

[1]:
```
# Imports
# Packages for numerics + dataframes
import numpy as np

# Packages for visualization
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt

# Packages for date conversions for calculating trip durations
import datetime as dt

# Packages for OLS, MLR, confusion matrix
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from statsmodels.formula.api import ols
import sklearn.metrics as metrics
from sklearn.linear_model import LinearRegression
```

```python
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
```

Note: `Pandas` is used to load the NYC TLC dataset. As shown in this cell, the dataset has been automatically loaded in for you. You do not need to download the .csv file, or provide more code, in order to access the dataset and proceed with this lab. Please continue with this activity by completing the following instructions.

[2]:
```python
# Load dataset into dataframe
df0=pd.read_csv("2017_Yellow_Taxi_Trip_Data.csv")
```

4.2 PACE: Analyze

In this stage, consider the following question where applicable to complete your code response:

- What are some purposes of EDA before constructing a multiple linear regression model?

==> ENTER YOUR RESPONSE HERE

4.2.1 Task 2a. Explore data with EDA

Analyze and discover data, looking for correlations, missing data, outliers, and duplicates.

Start with `.shape` and `.info()`.

[3]:
```python
# Start with `.shape` and `.info()`
df0.info()
df0.shape
```

```
<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
```

[3]:
```
(22699, 18)
```

Check for missing data and duplicates using `.isna()` and `.drop_duplicates()`.

[4]:
```python
# Check for missing data and duplicates using .isna() and .drop_duplicates()

# Check for Duplicates
print("Dataframe Shape:", df0.shape)
print("Shape of Dataframe with Duplicates Dropped:", df0.drop_duplicates().
 ↪shape)

# Check for Missing Values
print("Total Count of Missing Values:", df0.isna().sum().sum())

# Display Missing Values per Column
df0.isna().sum()
```

```
Dataframe Shape: (22699, 18)
Shape of Dataframe with Duplicates Dropped: (22699, 18)
Total Count of Missing Values: 0
```

[4]:
```
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
```

Use `.describe()`.

[5]:
```python
# Use .describe()
df0.describe()
```

[5]:
```
         Unnamed: 0      VendorID  passenger_count  trip_distance  \
count  2.269900e+04  22699.000000     22699.000000   22699.000000
mean   5.675849e+07      1.556236         1.642319       2.913313
std    3.274493e+07      0.496838         1.285231       3.653171
min    1.212700e+04      1.000000         0.000000       0.000000
25%    2.852056e+07      1.000000         1.000000       0.990000
50%    5.673150e+07      2.000000         1.000000       1.610000
75%    8.537452e+07      2.000000         2.000000       3.060000
max    1.134863e+08      2.000000         6.000000      33.960000

         RatecodeID  PULocationID  DOLocationID  payment_type   fare_amount  \
count  22699.000000  22699.000000  22699.000000  22699.000000  22699.000000
mean       1.043394    162.412353    161.527997      1.336887     13.026629
std        0.708391     66.633373     70.139691      0.496211     13.243791
min        1.000000      1.000000      1.000000      1.000000   -120.000000
25%        1.000000    114.000000    112.000000      1.000000      6.500000
50%        1.000000    162.000000    162.000000      1.000000      9.500000
75%        1.000000    233.000000    233.000000      2.000000     14.500000
max       99.000000    265.000000    265.000000      4.000000    999.990000

              extra       mta_tax    tip_amount  tolls_amount  \
count  22699.000000  22699.000000  22699.000000  22699.000000
mean       0.333275      0.497445      1.835781      0.312542
std        0.463097      0.039465      2.800626      1.399212
min       -1.000000     -0.500000      0.000000      0.000000
25%        0.000000      0.500000      0.000000      0.000000
50%        0.000000      0.500000      1.350000      0.000000
75%        0.500000      0.500000      2.450000      0.000000
max        4.500000      0.500000    200.000000     19.100000

       improvement_surcharge  total_amount
count           22699.000000  22699.000000
mean                0.299551     16.310502
std                 0.015673     16.097295
min                -0.300000   -120.300000
25%                 0.300000      8.750000
50%                 0.300000     11.800000
75%                 0.300000     17.800000
max                 0.300000   1200.290000
```

4.2.2 Task 2b. Convert pickup & dropoff columns to datetime

[6]:
```
# Check the format of the data
df0.dtypes
```

[6]:
```
Unnamed: 0                 int64
VendorID                   int64
tpep_pickup_datetime      object
tpep_dropoff_datetime     object
passenger_count            int64
trip_distance            float64
RatecodeID                 int64
store_and_fwd_flag        object
PULocationID               int64
DOLocationID               int64
payment_type               int64
fare_amount              float64
extra                    float64
mta_tax                  float64
tip_amount               float64
tolls_amount             float64
improvement_surcharge    float64
total_amount             float64
dtype: object
```

[7]:
```
# Convert datetime columns to datetime
df0['tpep_pickup_datetime'] = pd.to_datetime(df0['tpep_pickup_datetime'])
df0['tpep_dropoff_datetime'] = pd.to_datetime(df0['tpep_dropoff_datetime'])
```

[8]:
```
df0.dtypes
```

[8]:
```
Unnamed: 0                        int64
VendorID                          int64
tpep_pickup_datetime     datetime64[ns]
tpep_dropoff_datetime    datetime64[ns]
passenger_count                   int64
trip_distance                   float64
RatecodeID                        int64
store_and_fwd_flag               object
PULocationID                      int64
DOLocationID                      int64
payment_type                      int64
fare_amount                     float64
extra                           float64
mta_tax                         float64
tip_amount                      float64
tolls_amount                    float64
```

```
improvement_surcharge          float64
total_amount                   float64
dtype: object
```

4.2.3 Task 2c. Create duration column

Create a new column called `duration` that represents the total number of minutes that each taxi ride took.

[9]:
```python
# Create `duration` column
df0['duration'] = (df0['tpep_dropoff_datetime'] - df0['tpep_pickup_datetime']) /
 ↪ pd.Timedelta(minutes=1)
df0['duration'] = df0['duration'].round()
```

4.2.4 Outliers

Call `df.info()` to inspect the columns and decide which ones to check for outliers.

[10]:
```python
df0.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 19 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  duration               22699 non-null  float64
dtypes: datetime64[ns](2), float64(9), int64(7), object(1)
memory usage: 3.3+ MB
```

Keeping in mind that many of the features will not be used to fit your model, the most important columns to check for outliers are likely to be: * `trip_distance` * `fare_amount` * `duration`

4.2.5 Task 2d. Box plots

Plot a box plot for each feature: `trip_distance`, `fare_amount`, `duration`.

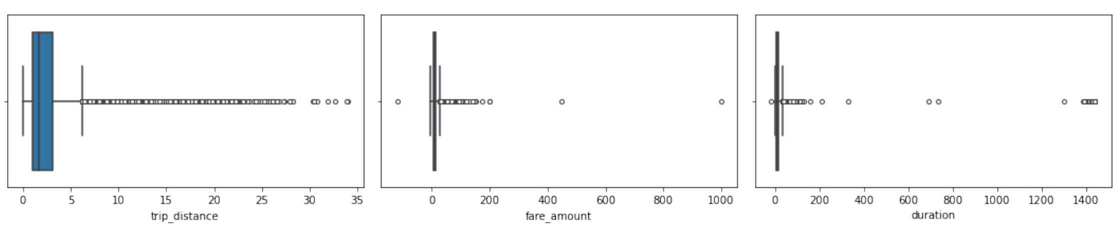
[12]:
```
# Create a figure with 3 subplots in a row
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(15, 3))

# Customize outlier properties
flier_kws = dict(marker='o', markerfacecolor='white', markersize=4, linestyle='none')

# Plot each boxplot with the modified outlier size
sns.boxplot(x="trip_distance", data=df0, ax=axes[0], flierprops=flier_kws)
sns.boxplot(x="fare_amount", data=df0, ax=axes[1], flierprops=flier_kws)
sns.boxplot(x="duration", data=df0, ax=axes[2], flierprops=flier_kws)

# Adjust spacing and labels (optional)
fig.tight_layout()

plt.show()
```



Questions: 1. Which variable(s) contains outliers?

2. Are the values in the `trip_distance` column unbelievable?

3. What about the lower end? Do distances, fares, and durations of 0 (or negative values) make sense?

1. Outliers are present in all three variables.

2. While most cab trips are short (around 2 miles), there are outliers extending up to 6 miles. Trips exceeding 20 miles are significantly less common.

3. Fare amounts of 0 likely indicate data errors and should be addressed or excluded from the analysis.

4.2.6 Task 2e. Imputations

`trip_distance` outliers You know from the summary statistics that there are trip distances of 0. Are these reflective of erroneous data, or are they very short trips that get rounded down?

To check, sort the column values, eliminate duplicates, and inspect the least 10 values. Are they rounded values or precise values?

[13]:
```
# Are trip distances of 0 bad data or very short trips rounded down?
sorted(set(df0['trip_distance']))[:10]
```

[13]:
```
[0.0, 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09]
```

The distances are captured with a high degree of precision. However, it might be possible for trips to have distances of zero if a passenger summoned a taxi and then changed their mind. Besides, are there enough zero values in the data to pose a problem?

Calculate the count of rides where the `trip_distance` is zero.

[15]:
```
count_zero_distance_trips = (df0["trip_distance"] == 0.0).sum()
```

[16]:
```
count_zero_distance_trips
```

[16]:
```
148
```

`fare_amount` outliers

[17]:
```
df0["fare_amount"].describe()
```

[17]:
```
count    22699.000000
mean        13.026629
std         13.243791
min       -120.000000
25%          6.500000
50%          9.500000
75%         14.500000
max        999.990000
Name: fare_amount, dtype: float64
```

Question: What do you notice about the values in the `fare_amount` column?

- The 'fare_amount' column contains negative values, indicating likely data errors. Zero fares are plausible (representing cancelled trips). However, extremely high fares (reaching 1000) seem unrealistic. We can address these outliers by capping them with a calculated threshold, such as using the Q3 + (X * IQR) formula.

Impute values less than $0 with `0`.

[18]:
```
# Impute values less than $0 with 0
df0['fare_amount'] = df0['fare_amount'].where(df0['fare_amount'] >= 0, 0)
```

Now impute the maximum value as Q3 + (6 * IQR).

[19]:
```
'''
    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.
    '''

def impute_with_outlier_limit(df, columns):
    for col in columns:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        outlier_limit = Q3 + (6 * IQR)
        df[col] = np.where(df[col] > outlier_limit, outlier_limit, df[col])

    return df

# Specify the columns to process
columns_to_impute = ['trip_distance','fare_amount', 'total_amount','tip_amount']

# Impute values using the function
df0 = impute_with_outlier_limit(df0, columns_to_impute)
```

[20]:
```
df0.describe()
```

[20]:
```
         Unnamed: 0      VendorID  passenger_count  trip_distance  \
count  2.269900e+04  22699.000000     22699.000000   22699.000000
mean   5.675849e+07      1.556236         1.642319       2.823424
std    3.274493e+07      0.496838         1.285231       3.252029
min    1.212700e+04      1.000000         0.000000       0.000000
25%    2.852056e+07      1.000000         1.000000       0.990000
50%    5.673150e+07      2.000000         1.000000       1.610000
75%    8.537452e+07      2.000000         2.000000       3.060000
max    1.134863e+08      2.000000         6.000000      15.480000

         RatecodeID  PULocationID  DOLocationID  payment_type   fare_amount  \
count  22699.000000  22699.000000  22699.000000  22699.000000  22699.000000
```

```
mean       1.043394    162.412353    161.527997       1.336887      12.897913
std        0.708391     66.633373     70.139691       0.496211      10.541137
min        1.000000      1.000000      1.000000       1.000000       0.000000
25%        1.000000    114.000000    112.000000       1.000000       6.500000
50%        1.000000    162.000000    162.000000       1.000000       9.500000
75%        1.000000    233.000000    233.000000       2.000000      14.500000
max       99.000000    265.000000    265.000000       4.000000      62.500000

              extra       mta_tax    tip_amount  tolls_amount  \
count  22699.000000  22699.000000  22699.000000  22699.000000
mean       0.333275      0.497445      1.818543      0.312542
std        0.463097      0.039465      2.374812      1.399212
min       -1.000000     -0.500000      0.000000      0.000000
25%        0.000000      0.500000      0.000000      0.000000
50%        0.000000      0.500000      1.350000      0.000000
75%        0.500000      0.500000      2.450000      0.000000
max        4.500000      0.500000     17.150000     19.100000

       improvement_surcharge  total_amount      duration
count           22699.000000  22699.000000  22699.000000
mean                0.299551     16.116802     17.012952
std                 0.015673     12.940043     61.998403
min                -0.300000   -120.300000    -17.000000
25%                 0.300000      8.750000      7.000000
50%                 0.300000     11.800000     11.000000
75%                 0.300000     17.800000     18.000000
max                 0.300000     72.100000   1440.000000
```

duration outliers

[21]:

```python
# Call .describe() for duration outliers
df0['duration'].describe()
```

[21]:

```
count    22699.000000
mean        17.012952
std         61.998403
min        -17.000000
25%          7.000000
50%         11.000000
75%         18.000000
max       1440.000000
Name: duration, dtype: float64
```

The `duration` column has problematic values at both the lower and upper extremities.

- **Low values:** There should be no values that represent negative time. Impute all negative durations with `0`.

- **High values:** Impute high values the same way you imputed the high-end outliers for fares: `Q3 + (6 * IQR)`.

[22]:
```
# Impute a 0 for any negative values
df0['duration'] = df0['duration'].where(df0['duration'] >= 0, 0)
```

[23]:
```
df0['duration'].describe()
```

[23]:
```
count    22699.000000
mean        17.013701
std         61.998094
min          0.000000
25%          7.000000
50%         11.000000
75%         18.000000
max       1440.000000
Name: duration, dtype: float64
```

[24]:
```
# Impute the high outliers

def impute_with_outlier_limit(df, col):
    """ Imputes missing values or extreme outliers with an outlier limit """

    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1

    outlier_limit = Q3 + (6 * IQR)  # Adjust '6' for a more or less strict limit
    df[col] = np.where(df[col] > outlier_limit, outlier_limit, df[col])

    return df

# Impute values using the function
df0 = impute_with_outlier_limit(df0, 'duration')
```

[25]:
```
df0['duration'].describe()
```

[25]:
```
count    22699.000000
mean        14.443368
std         11.854509
min          0.000000
25%          7.000000
50%         11.000000
75%         18.000000
max         84.000000
Name: duration, dtype: float64
```

4.2.7 Task 3a. Feature engineering

Create `mean_distance` column 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.

In this step, create a column called `mean_distance` that captures the mean distance for each group of trips that share pickup and dropoff points.

For example, if your data were:

|Trip|Start|End|Distance| |–: |:—:|:-:| | | 1 | A | B | 1 | | 2 | C | D | 2 | | 3 | A | B |1.5 | | 4 | D | C | 3 |

The results should be:

```
A -> B: 1.25 miles
C -> D: 2 miles
D -> C: 3 miles
```

Notice that C -> D is not the same as D -> C. All trips that share a unique pair of start and end points get grouped and averaged.

Then, a new column `mean_distance` will be added where the value at each row is the average for all trips with those pickup and dropoff locations:

Trip	Start	End	Distance	mean_distance
1	A	B	1	1.25
2	C	D	2	2
3	A	B	1.5	1.25
4	D	C	3	3

Begin by creating a helper column called `pickup_dropoff`, which contains the unique combination of pickup and dropoff location IDs for each row.

One way to do this is to convert the pickup and dropoff location IDs to strings and join them, separated by a space. The space is to ensure that, for example, a trip with pickup/dropoff points of 12 & 151 gets encoded differently than a trip with points 121 & 51.

So, the new column would look like this:

Trip	Start	End	pickup_dropoff
1	A	B	‘A B’
2	C	D	‘C D’
3	A	B	‘A B’
4	D	C	‘D C’

[26]:
```
# Create `pickup_dropoff` column
```

```python
df0['pickup_dropoff'] = df0['PULocationID'].astype(str) + ' ' +␣
↪df0['DOLocationID'].astype(str)
```

[27]:
```python
df0.head()
```

[27]:
```
   Unnamed: 0  VendorID tpep_pickup_datetime tpep_dropoff_datetime  \
0    24870114         2  2017-03-25 08:55:43   2017-03-25 09:09:47
1    35634249         1  2017-04-11 14:53:28   2017-04-11 15:19:58
2   106203690         1  2017-12-15 07:26:56   2017-12-15 07:34:08
3    38942136         2  2017-05-07 13:17:59   2017-05-07 13:48:14
4    30841670         2  2017-04-15 23:32:20   2017-04-15 23:49:03

   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  duration  \
0        2.76           0.0                    0.3         16.56      14.0
1        4.00           0.0                    0.3         20.80      26.0
2        1.45           0.0                    0.3          8.75       7.0
3        6.39           0.0                    0.3         27.69      30.0
4        0.00           0.0                    0.3         17.80      17.0

  pickup_dropoff
0        100 231
1         186 43
2        262 236
3         188 97
4          4 112
```

Now, use a `groupby()` statement to group each row by the new `pickup_dropoff` column, compute the mean, and capture the values only in the `trip_distance` column. Assign the results to a variable named `grouped`.

[28]:
```python
grouped = df0.groupby('pickup_dropoff').
↪mean(numeric_only=True)[['trip_distance']]
```

[29]:
```
grouped[:5]
```

[29]:
```
                 trip_distance
pickup_dropoff
1 1                   2.433333
10 148               15.480000
100 1                15.480000
100 100               0.253333
100 107               1.180000
```

`grouped` is an object of the `DataFrame` class.

1. Convert it to a dictionary using the `to_dict()` method. Assign the results to a variable called `grouped_dict`. This will result in a dictionary with a key of `trip_distance` whose values are another dictionary. The inner dictionary's keys are pickup/dropoff points and its values are mean distances. This is the information you want.

```
Example:
grouped_dict = {'trip_distance': {'A B': 1.25, 'C D': 2, 'D C': 3}
```

2. Reassign the `grouped_dict` dictionary so it contains only the inner dictionary. In other words, get rid of `trip_distance` as a key, so:

```
Example:
grouped_dict = {'A B': 1.25, 'C D': 2, 'D C': 3}
```

[30]:
```
# 1. Convert `grouped` to a dictionary
grouped_dict = grouped.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.

2. Use the `map()` method on the `mean_distance` series. Pass `grouped_dict` as its argument. Reassign the result back to the `mean_distance` series. When you pass a dictionary to the `Series.map()` method, it will replace the data in the series where that data matches the dictionary's keys. The values that get imputed are the values of the dictionary.

```
Example:
df['mean_distance']
```

mean_distance
'A B'
'C D'
'A B'
'D C'
'E F'

```
grouped_dict = {'A B': 1.25, 'C D': 2, 'D C': 3}
```

```
df['mean_distance`] = df['mean_distance'].map(grouped_dict)
df['mean_distance']
```

mean_distance
1.25
2
1.25
3
NaN

When used this way, the `map()` `Series` method is very similar to `replace()`, however, note that `map()` will impute `NaN` for any values in the series that do not have a corresponding key in the mapping dictionary, so be careful.

[31]:
```
# 1. Create a mean_distance column that is a copy of the pickup_dropoff helper␣
↪column
df0['mean_distance'] = df0['pickup_dropoff']

# 2. Map `grouped_dict` to the `mean_distance` column
df0['mean_distance'] = df0['mean_distance'].map(grouped_dict)
```

[32]:
```
# Confirm that it worked
df0.head()
```

[32]:
```
   Unnamed: 0  VendorID tpep_pickup_datetime tpep_dropoff_datetime  \
0    24870114         2  2017-03-25 08:55:43   2017-03-25 09:09:47
1    35634249         1  2017-04-11 14:53:28   2017-04-11 15:19:58
2   106203690         1  2017-12-15 07:26:56   2017-12-15 07:34:08
3    38942136         2  2017-05-07 13:17:59   2017-05-07 13:48:14
4    30841670         2  2017-04-15 23:32:20   2017-04-15 23:49:03

   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  …  fare_amount  extra  mta_tax  tip_amount  \
0           100           231  …         13.0    0.0      0.5        2.76
1           186            43  …         16.0    0.0      0.5        4.00
2           262           236  …          6.5    0.0      0.5        1.45
3           188            97  …         20.5    0.0      0.5        6.39
4             4           112  …         16.5    0.5      0.5        0.00

   tolls_amount  improvement_surcharge  total_amount  duration  \
```

```
0          0.0                       0.3         16.56      14.0
1          0.0                       0.3         20.80      26.0
2          0.0                       0.3          8.75       7.0
3          0.0                       0.3         27.69      30.0
4          0.0                       0.3         17.80      17.0

   pickup_dropoff mean_distance
0         100 231      3.521667
1          186 43      3.108889
2         262 236      0.881429
3          188 97      3.700000
4           4 112      4.435000

[5 rows x 21 columns]
```

Create `mean_duration` column Repeat the process used to create the `mean_distance` column to create a `mean_duration` column.

[34]:
```python
grouped = df0.groupby('pickup_dropoff').mean(numeric_only=True)[['duration']]

# Create a dictionary where keys are unique pickup_dropoffs and values are
# mean trip duration for all trips with those pickup_dropoff combos

grouped_dict = grouped.to_dict()
grouped_dict = grouped_dict['duration']

df0['mean_duration'] = df0['pickup_dropoff']
df0['mean_duration'] = df0['mean_duration'].map(grouped_dict)
```

[35]:
```python
# Confirm that it worked
df0.head()
grouped[:5]
```

[35]:
```
                 duration
pickup_dropoff
1 1              0.333333
10 148          69.000000
100 1           48.000000
100 100          3.166667
100 107         11.333333
```

Create `day` and `month` columns Create two new columns, `day` (name of day) and `month` (name of month) by extracting the relevant information from the `tpep_pickup_datetime` column.

[37]:
```python
# Create 'day' col
df0['day'] = df0['tpep_pickup_datetime'].dt.day

# Create 'month' col
df0['month'] = df0['tpep_pickup_datetime'].dt.month
```

[38]:
```python
df0.head()
```

[38]:
```
   Unnamed: 0  VendorID tpep_pickup_datetime tpep_dropoff_datetime  \
0    24870114         2  2017-03-25 08:55:43   2017-03-25 09:09:47
1    35634249         1  2017-04-11 14:53:28   2017-04-11 15:19:58
2   106203690         1  2017-12-15 07:26:56   2017-12-15 07:34:08
3    38942136         2  2017-05-07 13:17:59   2017-05-07 13:48:14
4    30841670         2  2017-04-15 23:32:20   2017-04-15 23:49:03

   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  …  tip_amount  tolls_amount  \
0           100           231  …        2.76           0.0
1           186            43  …        4.00           0.0
2           262           236  …        1.45           0.0
3           188            97  …        6.39           0.0
4             4           112  …        0.00           0.0

   improvement_surcharge  total_amount  duration  pickup_dropoff  \
0                    0.3         16.56      14.0         100 231
1                    0.3         20.80      26.0          186 43
2                    0.3          8.75       7.0         262 236
3                    0.3         27.69      30.0          188 97
4                    0.3         17.80      17.0           4 112

   mean_distance  mean_duration  day  month
0       3.521667      23.000000   25      3
1       3.108889      24.444444   11      4
2       0.881429       7.257143   15     12
3       3.700000      30.000000    7      5
4       4.435000      15.000000   15      4

[5 rows x 24 columns]
```

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.

[39]:
```
# Create 'rush_hour' col
df0['rush_hour'] = df0['tpep_pickup_datetime'].dt.hour
```

[40]:
```
df0.head()
```

[40]:
```
   Unnamed: 0  VendorID tpep_pickup_datetime tpep_dropoff_datetime  \
0    24870114         2  2017-03-25 08:55:43   2017-03-25 09:09:47
1    35634249         1  2017-04-11 14:53:28   2017-04-11 15:19:58
2   106203690         1  2017-12-15 07:26:56   2017-12-15 07:34:08
3    38942136         2  2017-05-07 13:17:59   2017-05-07 13:48:14
4    30841670         2  2017-04-15 23:32:20   2017-04-15 23:49:03

   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  …  tolls_amount  improvement_surcharge  \
0           100           231  …           0.0                    0.3
1           186            43  …           0.0                    0.3
2           262           236  …           0.0                    0.3
3           188            97  …           0.0                    0.3
4             4           112  …           0.0                    0.3

   total_amount  duration  pickup_dropoff  mean_distance  mean_duration  day  \
0         16.56      14.0         100 231       3.521667      23.000000   25
1         20.80      26.0          186 43       3.108889      24.444444   11
2          8.75       7.0         262 236       0.881429       7.257143   15
3         27.69      30.0          188 97       3.700000      30.000000    7
4         17.80      17.0           4 112       4.435000      15.000000   15

   month  rush_hour
0      3          8
1      4         14
2     12          7
3      5         13
4      4         23

[5 rows x 25 columns]
```

[41]:
```python
def rush_hourizer(hour):
    if 6 <= hour['rush_hour'] < 10:
        val = 1
    elif 16 <= hour['rush_hour'] < 20:
        val = 1
    else:
        val = 0
    return val
```

[42]:
```python
# Apply the `rush_hourizer()` function to the new column
df0.loc[(df0.day != 'saturday') & (df0.day != 'sunday'), 'rush_hour'] = df0.
↪apply(rush_hourizer, axis=1)
```

[43]:
```python
df0.head()
```

[43]:
```
   Unnamed: 0  VendorID tpep_pickup_datetime tpep_dropoff_datetime  \
0    24870114         2  2017-03-25 08:55:43   2017-03-25 09:09:47
1    35634249         1  2017-04-11 14:53:28   2017-04-11 15:19:58
2   106203690         1  2017-12-15 07:26:56   2017-12-15 07:34:08
3    38942136         2  2017-05-07 13:17:59   2017-05-07 13:48:14
4    30841670         2  2017-04-15 23:32:20   2017-04-15 23:49:03

   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  …  tolls_amount  improvement_surcharge  \
0           100           231  …           0.0                    0.3
1           186            43  …           0.0                    0.3
2           262           236  …           0.0                    0.3
3           188            97  …           0.0                    0.3
4             4           112  …           0.0                    0.3

   total_amount  duration  pickup_dropoff  mean_distance  mean_duration  day  \
0         16.56      14.0         100 231       3.521667      23.000000   25
1         20.80      26.0          186 43       3.108889      24.444444   11
2          8.75       7.0         262 236       0.881429       7.257143   15
3         27.69      30.0          188 97       3.700000      30.000000    7
4         17.80      17.0           4 112       4.435000      15.000000   15

   month rush_hour
0      3         1
1      4         0
2     12         1
```

```
3       5           0
4       4           0

[5 rows x 25 columns]
```

4.2.8 Task 4. Scatter plot

Create a scatterplot to visualize the relationship between `mean_duration` and `fare_amount`.

[44]:
```
# Create a scatterplot to visualize the relationship between variables of␣
↪interest
sns.set(style="whitegrid")
p=plt.figure()
p.set_figwidth(5)
p.set_figheight(5)
sns.regplot(x=df0['mean_duration'], y=df0['fare_amount'],
            scatter_kws={'alpha':0.5, 's':5},
            line_kws={'color':'red'})

plt.ylim(0,70)
plt.xlim(0,70)
plt.title("Mean Duration x Fare Amount")
plt.show()
```

The `mean_duration` variable correlates with the target variable. But what are the horizontal lines around fare amounts of 52 dollars and 63 dollars? What are the values and how many are there?

You know what one of the lines represents. 62 dollars and 50 cents is the maximum that was imputed for outliers, so all former outliers will now have fare amounts of $62.50. What is the other line?

Check the value of the rides in the second horizontal line in the scatter plot.

[45]:
```
ride_values = df0[(df0['fare_amount'] >= 51) & (df0['fare_amount'] <= 53)]
```

Examine the first 30 of these trips.

[46]:
```
# Set pandas to display all columns
pd.set_option('display.max_columns', None)
ride_values.head(30)
```

[46]:
```
     Unnamed: 0  VendorID tpep_pickup_datetime tpep_dropoff_datetime  \
11     18600059         2  2017-03-05 19:15:30   2017-03-05 19:52:18
110    47959795         1  2017-06-03 14:24:57   2017-06-03 15:31:48
156   104881101         1  2017-12-11 10:21:18   2017-12-11 11:14:57
```

```
161      95729204         2  2017-11-11 20:16:16   2017-11-11 20:17:14
242      67332929         2  2017-08-09 08:32:09   2017-08-09 09:31:11
247     103404868         2  2017-12-06 23:37:08   2017-12-07 00:06:19
356     108458749         2  2017-12-21 21:31:12   2017-12-21 22:11:58
379      80479432         2  2017-09-24 23:45:45   2017-09-25 00:15:14
388      16226157         1  2017-02-28 18:30:05   2017-02-28 19:09:55
406      55253442         2  2017-06-05 12:51:58   2017-06-05 13:07:35
449      65900029         2  2017-08-03 22:47:14   2017-08-03 23:32:41
468      80904240         2  2017-09-26 13:48:26   2017-09-26 14:31:17
520      33706214         2  2017-04-23 21:34:48   2017-04-23 22:46:23
569      99259872         2  2017-11-22 21:31:32   2017-11-22 22:00:25
572      61050418         2  2017-07-18 13:29:06   2017-07-18 13:29:19
586      54444647         2  2017-06-26 13:39:12   2017-06-26 14:34:54
692      94424289         2  2017-11-07 22:15:00   2017-11-07 22:45:32
717     103094220         1  2017-12-06 05:19:50   2017-12-06 05:53:52
719      66115834         1  2017-08-04 17:53:34   2017-08-04 18:50:56
782      55934137         2  2017-06-09 09:31:25   2017-06-09 10:24:10
816      13731926         2  2017-02-21 06:11:03   2017-02-21 06:59:39
818      52277743         2  2017-06-20 08:15:18   2017-06-20 10:24:37
835       2684305         2  2017-01-10 22:29:47   2017-01-10 23:06:46
840      90860814         2  2017-10-27 21:50:00   2017-10-27 22:35:04
861     106575186         1  2017-12-16 06:39:59   2017-12-16 07:07:59
881     110495611         2  2017-12-30 05:25:29   2017-12-30 06:01:29
958      87017503         1  2017-10-15 22:39:12   2017-10-15 23:14:22
970      12762608         2  2017-02-17 20:39:42   2017-02-17 21:13:29
984      71264442         1  2017-08-23 18:23:26   2017-08-23 19:18:29
1082     11006300         2  2017-02-07 17:20:19   2017-02-07 17:34:41

      passenger_count  trip_distance  RatecodeID store_and_fwd_flag  \
11                  2          15.48           2                  N
110                 1          15.48           2                  N
156                 1          15.48           1                  N
161                 1           0.23           2                  N
242                 1          15.48           1                  N
247                 1          15.48           2                  N
356                 6          15.48           1                  N
379                 1          15.48           2                  N
388                 1          15.48           2                  N
406                 1           4.73           2                  N
449                 2          15.48           2                  N
468                 1          15.48           2                  N
520                 6          15.48           2                  N
569                 1          15.48           2                  N
572                 1           0.00           2                  N
586                 1          15.48           2                  N
692                 2          15.48           2                  N
717                 1          15.48           2                  N
```

719	1	15.48	2	N
782	2	15.48	2	N
816	5	15.48	2	N
818	1	15.48	2	N
835	1	15.48	2	N
840	1	15.48	2	N
861	2	15.48	2	N
881	6	15.48	2	N
958	1	15.48	2	N
970	1	15.48	2	N
984	1	15.48	2	N
1082	1	1.09	2	N

	PULocationID	DOLocationID	payment_type	fare_amount	extra	mta_tax \
11	236	132	1	52.0	0.0	0.5
110	132	163	1	52.0	0.0	0.5
156	138	88	1	51.5	0.0	0.5
161	132	132	2	52.0	0.0	0.5
242	138	87	1	53.0	0.0	0.5
247	132	79	2	52.0	0.0	0.5
356	132	145	1	51.5	0.5	0.5
379	132	234	1	52.0	0.0	0.5
388	132	48	2	52.0	4.5	0.5
406	228	88	2	52.0	0.0	0.5
449	132	48	2	52.0	0.0	0.5
468	186	132	2	52.0	0.0	0.5
520	132	148	1	52.0	0.0	0.5
569	132	144	1	52.0	0.0	0.5
572	230	161	1	52.0	0.0	0.5
586	211	132	1	52.0	0.0	0.5
692	132	170	1	52.0	0.0	0.5
717	132	239	1	52.0	0.0	0.5
719	264	264	1	52.0	4.5	0.5
782	163	132	1	52.0	0.0	0.5
816	132	170	1	52.0	0.0	0.5
818	132	246	1	52.0	0.0	0.5
835	132	48	1	52.0	0.0	0.5
840	132	163	2	52.0	0.0	0.5
861	75	132	1	52.0	0.0	0.5
881	68	132	2	52.0	0.0	0.5
958	132	261	2	52.0	0.0	0.5
970	132	140	1	52.0	0.0	0.5
984	132	230	1	52.0	4.5	0.5
1082	170	48	2	52.0	4.5	0.5

	tip_amount	tolls_amount	improvement_surcharge	total_amount	duration \
11	14.58	5.54	0.3	72.10	37.0

110	0.00	0.00	0.3	52.80	67.0
156	11.60	5.76	0.3	69.66	54.0
161	0.00	0.00	0.3	52.80	1.0
242	10.00	5.76	0.3	69.56	59.0
247	0.00	0.00	0.3	52.80	29.0
356	0.00	0.00	0.3	52.80	41.0
379	14.64	5.76	0.3	72.10	29.0
388	0.00	5.54	0.3	62.84	40.0
406	0.00	5.76	0.3	58.56	16.0
449	0.00	5.76	0.3	58.56	45.0
468	0.00	5.76	0.3	58.56	43.0
520	5.00	0.00	0.3	57.80	72.0
569	10.56	0.00	0.3	63.36	29.0
572	11.71	5.76	0.3	70.27	0.0
586	11.71	5.76	0.3	70.27	56.0
692	11.71	5.76	0.3	70.27	31.0
717	5.85	5.76	0.3	64.41	34.0
719	12.60	5.76	0.3	72.10	57.0
782	13.20	0.00	0.3	66.00	53.0
816	2.00	5.54	0.3	60.34	49.0
818	11.71	5.76	0.3	70.27	84.0
835	13.20	0.00	0.3	66.00	37.0
840	0.00	5.76	0.3	58.56	45.0
861	6.00	5.76	0.3	64.56	28.0
881	0.00	0.00	0.3	52.80	36.0
958	0.00	0.00	0.3	52.80	35.0
970	11.67	5.54	0.3	70.01	34.0
984	17.15	0.00	0.3	72.10	55.0
1082	0.00	5.54	0.3	62.84	14.0

	pickup_dropoff	mean_distance	mean_duration	day	month	rush_hour
11	236 132	15.480000	39.666667	5	3	1
110	132 163	15.480000	53.100000	3	6	0
156	138 88	15.353333	63.000000	11	12	0
161	132 132	1.941034	2.931034	11	11	0
242	138 87	13.710833	44.333333	9	8	1
247	132 79	15.480000	47.333333	6	12	0
356	132 145	15.267143	40.857143	21	12	0
379	132 234	15.480000	50.000000	24	9	0
388	132 48	15.480000	58.095238	28	2	1
406	228 88	4.730000	16.000000	5	6	0
449	132 48	15.480000	58.095238	3	8	0
468	186 132	15.480000	43.000000	26	9	0
520	132 148	15.480000	46.428571	23	4	0
569	132 144	15.480000	37.000000	22	11	0
572	230 161	0.685484	7.967742	18	7	0
586	211 132	15.440000	62.000000	26	6	0

```
692          132 170    15.480000    37.200000   7    11          0
717          132 239    15.480000    44.875000   6    12          0
719          264 264     3.018845    15.555957   4     8          1
782          163 132    15.449167    52.000000   9     6          1
816          132 170    15.480000    37.200000  21     2          1
818          132 246    15.480000    64.000000  20     6          1
835           132 48    15.480000    58.095238  10     1          0
840          132 163    15.480000    53.100000  27    10          0
861           75 132    15.480000    36.250000  16    12          1
881           68 132    15.480000    56.750000  30    12          0
958          132 261    15.480000    51.500000  15    10          0
970          132 140    15.480000    36.833333  17     2          0
984          132 230    15.480000    59.000000  23     8          1
1082          170 48     1.265789    14.210526   7     2          1
```

Question: What do you notice about the first 30 trips?

A concentration of trips priced at \$52 with a PULocationID of 132 suggests a potential flat-fare structure. These trips share a RateCodeID of 2, which corresponds to John F. Kennedy International Airport (JFK). Research confirms that a flat fare between JFK and Manhattan was established in 2017.

4.2.9 Task 5. Isolate modeling variables

Drop features that are redundant, irrelevant, or that will not be available in a deployed environment.

[47]:
```python
df02 = df0.copy()

keep_columns =␣
↪['VendorID','passenger_count','fare_amount','mean_distance','mean_duration','rush_hour']
```

[48]:
```python
df02 = df02.loc[:, keep_columns]
```

[49]:
```python
df02.head()
```

[49]:
```
   VendorID  passenger_count  fare_amount  mean_distance  mean_duration  \
0         2                6         13.0       3.521667      23.000000
1         1                1         16.0       3.108889      24.444444
2         1                1          6.5       0.881429       7.257143
3         2                1         20.5       3.700000      30.000000
4         2                1         16.5       4.435000      15.000000

   rush_hour
0          1
1          0
2          1
3          0
```

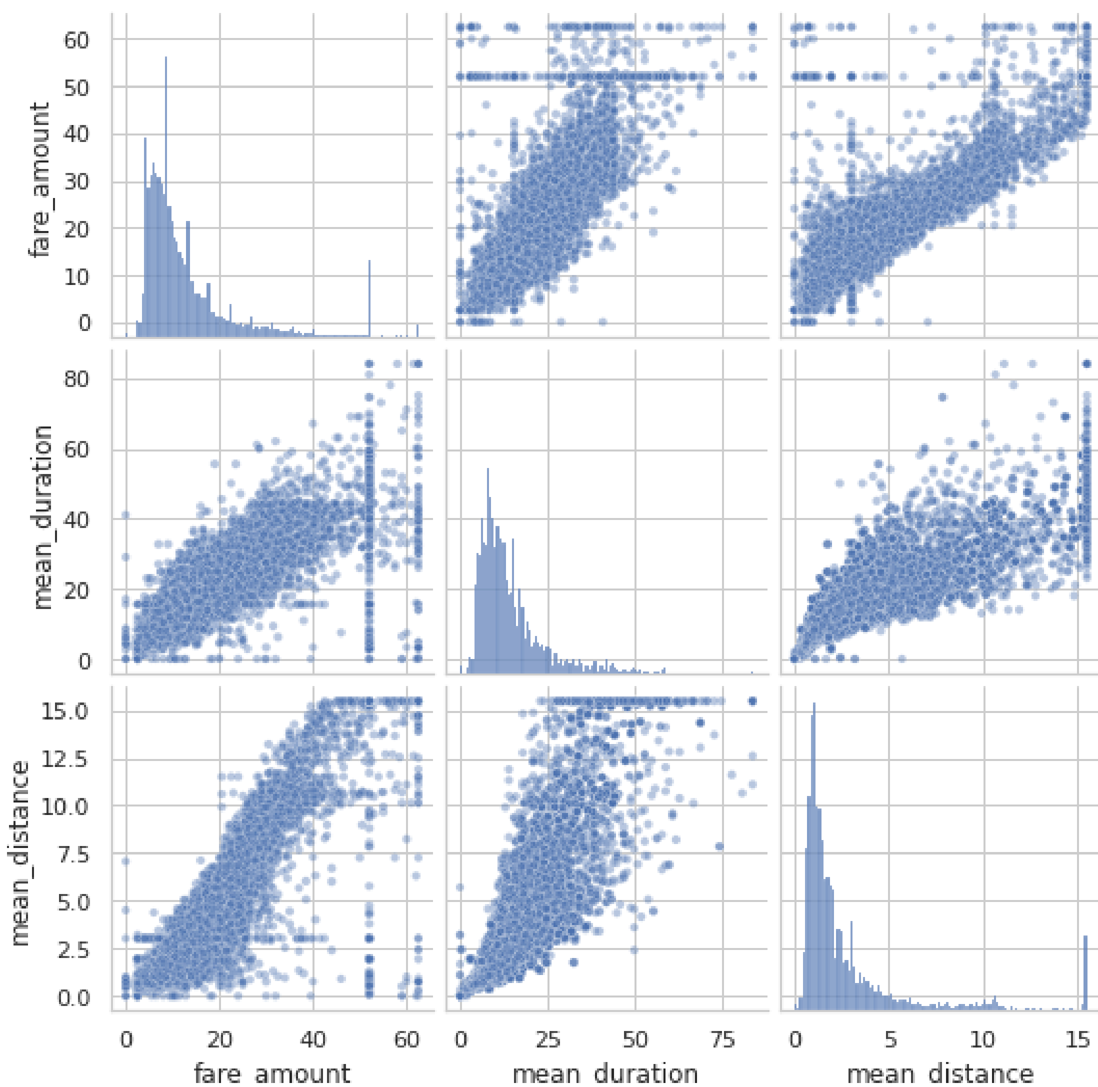
```
4           0
```

4.2.10 Task 6. Pair plot

Create a pairplot to visualize pairwise relationships between `fare_amount`, `mean_duration`, and `mean_distance`.

[50]:
```
# Create a pairplot to visualize pairwise relationships between variables in␣
↪the data
sns.pairplot(df02[["fare_amount","mean_duration","mean_distance"]],␣
↪plot_kws={"alpha":0.4,"size":5})
```

[50]:
```
<seaborn.axisgrid.PairGrid at 0x7b44218a4ad0>
```



These variables all show linear correlation with each other. Investigate this further.

4.2.11 Task 7. Identify correlations

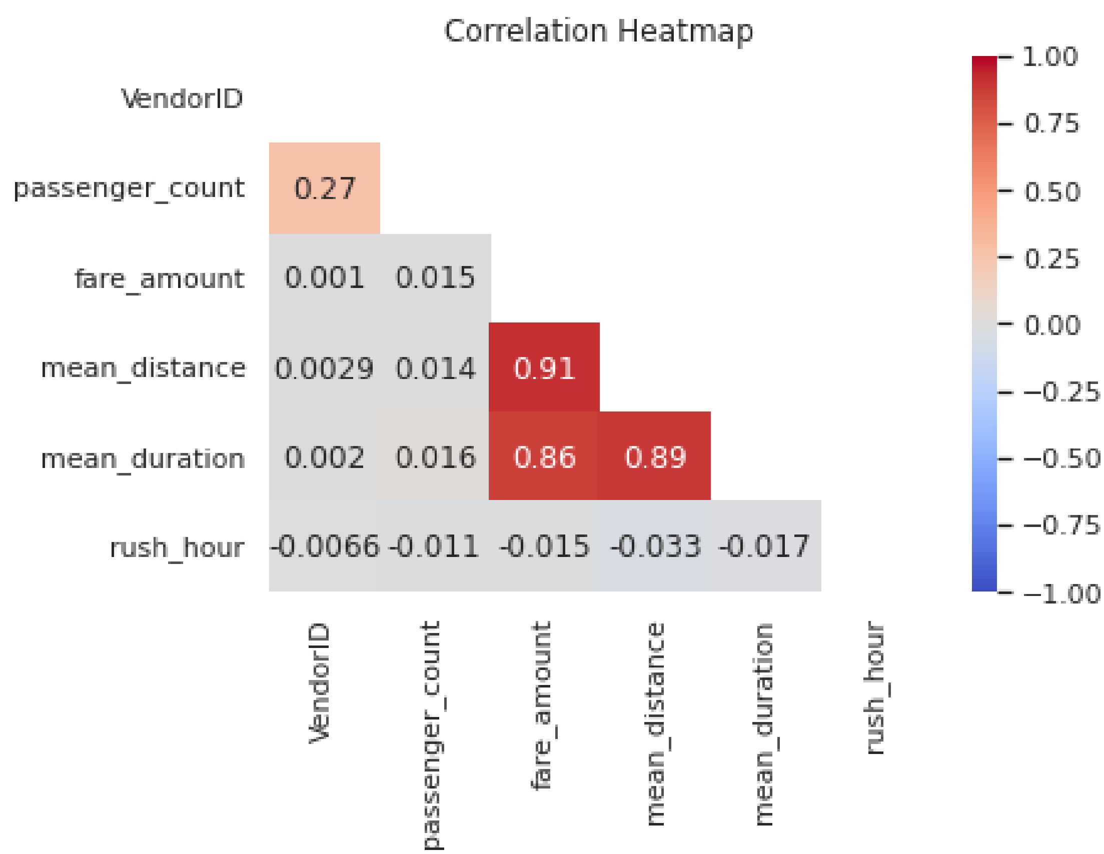
Next, code a correlation matrix to help determine most correlated variables.

[51]:
```
# Correlation matrix to help determine most correlated variables
corr_matrix = df02.corr()
```

Visualize a correlation heatmap of the data.

[52]:
```
# Create correlation heatmap
mask = np.triu(np.ones_like(corr_matrix, dtype=bool))

sns.heatmap(corr_matrix, mask=mask, annot=True, cmap='coolwarm', vmin=-1,␣
↪vmax=1)
plt.title("Correlation Heatmap")
plt.show()
```



Question: Which variable(s) are correlated with the target variable of `fare_amount`?

Try modeling with both variables even though they are correlated.

The variables 'mean_distance' and 'mean_duration' exhibit strong correlations with the target variable, 'fare_amount'. Nevertheless, their high correlation with each other introduces potential multicollinearity issues for linear regression models.

While multicollinearity can complicate the interpretation of individual feature coefficients, it doesn't necessarily hinder predictive performance. If your primary goal is accurate prediction, you may still successfully utilize these correlated variables.

4.3 PACE: Construct

After analysis and deriving variables with close relationships, it is time to begin constructing the model. Consider the questions in your PACE Strategy Document to reflect on the Construct stage.

4.3.1 Task 8a. Split data into outcome variable and features

[53]:
```
df02.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   passenger_count  22699 non-null  int64
 2   fare_amount      22699 non-null  float64
 3   mean_distance    22699 non-null  float64
 4   mean_duration    22699 non-null  float64
 5   rush_hour        22699 non-null  int64
dtypes: float64(3), int64(3)
memory usage: 1.0 MB
```

Set your X and y variables. X represents the features and y represents the outcome (target) variable.

[54]:
```
# Remove the target column from the features
X = df02.drop(columns='fare_amount')

# Set y variable
y = df02[['fare_amount']]

# Display first few rows
print(X.head())
print(y.head())
```

```
   VendorID  passenger_count  mean_distance  mean_duration  rush_hour
0         2                6       3.521667      23.000000          1
1         1                1       3.108889      24.444444          0
```

```
2          1                 1       0.881429       7.257143           1
3          2                 1       3.700000      30.000000           0
4          2                 1       4.435000      15.000000           0
   fare_amount
0          13.0
1          16.0
2           6.5
3          20.5
4          16.5
```

4.3.2 Task 8b. Pre-process data

Dummy encode categorical variables

[55]:
```python
# Convert VendorID to string

# Create dummy variables
dummies = pd.get_dummies(df02['VendorID'])

# Get dummies
df02 = pd.concat([df02, dummies], axis=1)
```

[135]:
```python
df02
```

[135]:
```
       VendorID  passenger_count  fare_amount  mean_distance  mean_duration  \
0             2                6         13.0       3.521667      23.000000
1             1                1         16.0       3.108889      24.444444
2             1                1          6.5       0.881429       7.257143
3             2                1         20.5       3.700000      30.000000
4             2                1         16.5       4.435000      15.000000
…           …               …           …             …              …
22694         2                3          4.0       1.098214       8.607143
22695         2                1         52.0      15.480000      59.250000
22696         2                1          4.5       0.684242       6.606061
22697         2                1         10.5       2.077500      16.750000
22698         1                1         11.0       1.476970       9.424242

       rush_hour  1  2
0              1  0  1
1              0  1  0
2              1  1  0
3              0  0  1
4              0  0  1
…            … .. ..
22694          1  0  1
22695          1  0  1
22696          0  0  1
```

```
22697           0   0   1
22698           0   1   0

[22699 rows x 8 columns]
```

4.3.3 Split data into training and test sets

Create training and testing sets. The test set should contain 20% of the total samples. Set `random_state=0`.

[56]:
```python
# Create training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20,␣
↪random_state=42)
```

4.3.4 Standardize the data

Use `StandardScaler()`, `fit()`, and `transform()` to standardize the `X_train` variables. Assign the results to a variable called `X_train_scaled`.

[57]:
```python
# Standardize the X variables
scaler = StandardScaler().fit(X_train)
X_train_scaled = scaler.transform(X_train)
```

[58]:
```python
print("X_train_scaled:", X_train_scaled)
```

```
X_train_scaled: [[ 0.89575785 -0.49880314 -0.01260334  0.00247249 -0.79866399]
 [ 0.89575785 -0.49880314  0.54126973 -0.05492101  1.25209101]
 [ 0.89575785  0.28284738 -0.45175539  0.01452995 -0.79866399]
 …
 [ 0.89575785  0.28284738 -0.54843653 -0.50996946  1.25209101]
 [ 0.89575785  0.28284738 -0.23043207  0.38404465 -0.79866399]
 [ 0.89575785 -0.49880314  2.07339186  0.73218983 -0.79866399]]
```

4.3.5 Fit the model

Instantiate your model and fit it to the training data.

[59]:
```python
# Fit your model to the training data
lr=LinearRegression()
lr.fit(X_train_scaled, y_train)
```

[59]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

4.3.6 Task 8c. Evaluate model

4.3.7 Train data

Evaluate your model performance by calculating the residual sum of squares and the explained variance score (R^2). Calculate the Mean Absolute Error, Mean Squared Error, and the Root Mean Squared Error.

[99]:
```python
# Evaluate the model performance on the training data
rss = lr.score(X_train_scaled, y_train)

y_pred_train = lr.predict(X_train_scaled)

r2 = r2_score(y_train, y_pred_train)
mae = mean_absolute_error(y_train, y_pred_train)
mse = mean_squared_error(y_train, y_pred_train)
rmse = np.sqrt(mse)

print('Residual Sum of Squares (RSS):', rss)
print('R-squared (R2):', r2)
print('Mean Absolute Error (MAE):', mae)
print('Mean Squared Error (MSE):', mse)
print('Root Mean Squared Error (RMSE):', rmse)
```

```
Residual Sum of Squares (RSS): 0.8497662002020118
R-squared (R2): 0.8497662002020118
Mean Absolute Error (MAE): 2.1843758160626408
Mean Squared Error (MSE): 16.979311620473283
Root Mean Squared Error (RMSE): 4.120596027333095
```

4.3.8 Test data

Calculate the same metrics on the test data. Remember to scale the `X_test` data using the scaler that was fit to the training data. Do not refit the scaler to the testing data, just transform it. Call the results `X_test_scaled`.

[61]:
```python
# Scale the X_test data
X_test_scaled = scaler.transform(X_test)
```

[62]:
```python
# Evaluate the model performance on the testing data

rss_test = lr.score(X_test_scaled, y_test)

y_pred_test = lr.predict(X_test_scaled)

r2 = r2_score(y_test, y_pred_test)
mae = mean_absolute_error(y_test, y_pred_test)
```

```
mse = mean_squared_error(y_test, y_pred_test)
rmse = np.sqrt(mse)

print('Residual Sum of Squares (RSS):', rss)
print('R-squared (R2):', r2)
print('Mean Absolute Error (MAE):', mae)
print('Mean Squared Error (MSE):', mse)
print('Root Mean Squared Error (RMSE):', rmse)
```

```
Residual Sum of Squares (RSS): 0.8497662002020118
R-squared (R2): 0.8304992808151036
Mean Absolute Error (MAE): 2.1491971216895225
Mean Squared Error (MSE): 17.51964670874552
Root Mean Squared Error (RMSE): 4.185647704805735
```

4.4 PACE: Execute

Consider the questions in your PACE Strategy Document to reflect on the Execute stage.

4.4.1 Task 9a. Results

Use the code cell below to get `actual`,`predicted`, and `residual` for the testing set, and store them as columns in a `results` dataframe.

[63]:
```
# Create a `results` dataframe
results = pd.DataFrame(data={'actual': y_test['fare_amount'],
                             'predicted': y_pred_test.ravel()})

results['residual'] = results['actual'] - results['predicted']
```

[64]:
```
results.head()
```

[64]:

	actual	predicted	residual
9199	12.5	9.368783	3.131217
4955	6.0	8.363455	-2.363455
16833	12.0	8.795485	3.204515
13244	20.5	21.595312	-1.095312
1063	14.0	16.158509	-2.158509

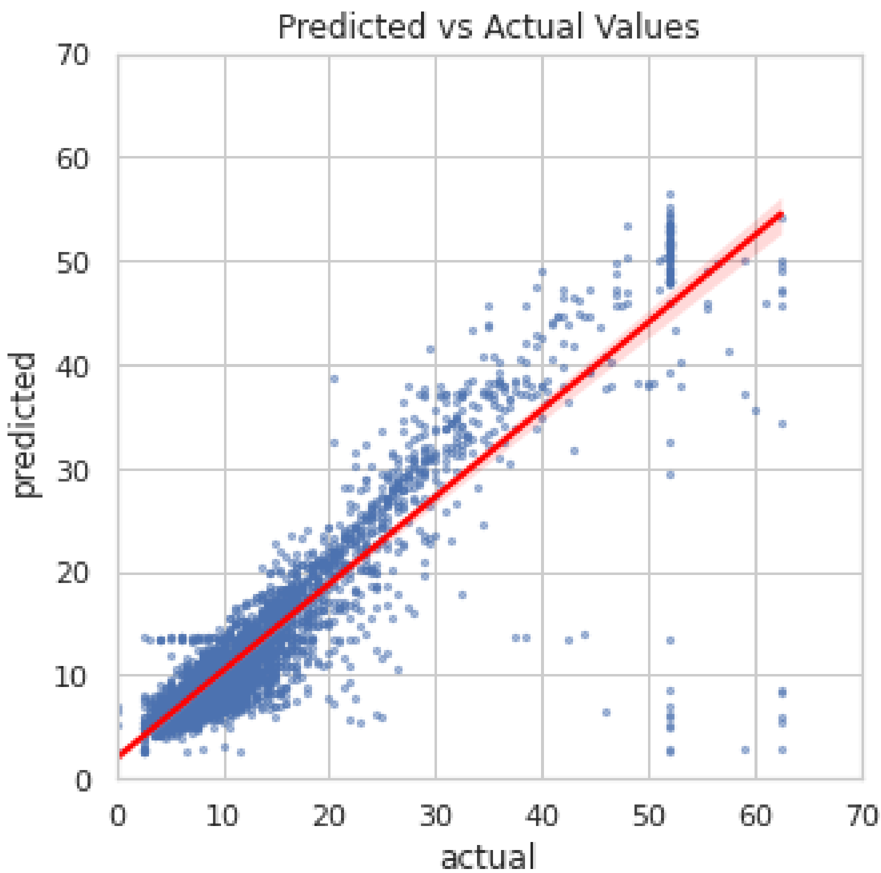
4.4.2 Task 9b. Visualize model results

Create a scatterplot to visualize `actual` vs. `predicted`.

[65]:
```
# Create a scatterplot to visualize `predicted` over `actual`
```

```
sns.set(style="whitegrid")
p=plt.figure()
p.set_figwidth(5)
p.set_figheight(5)
sns.regplot(x=results['actual'], y=results['predicted'],
            scatter_kws={'alpha':0.5, 's':5},
            line_kws={'color':'red'})

plt.ylim(0,70)
plt.xlim(0,70)
plt.title("Predicted vs Actual Values")
plt.show()
```

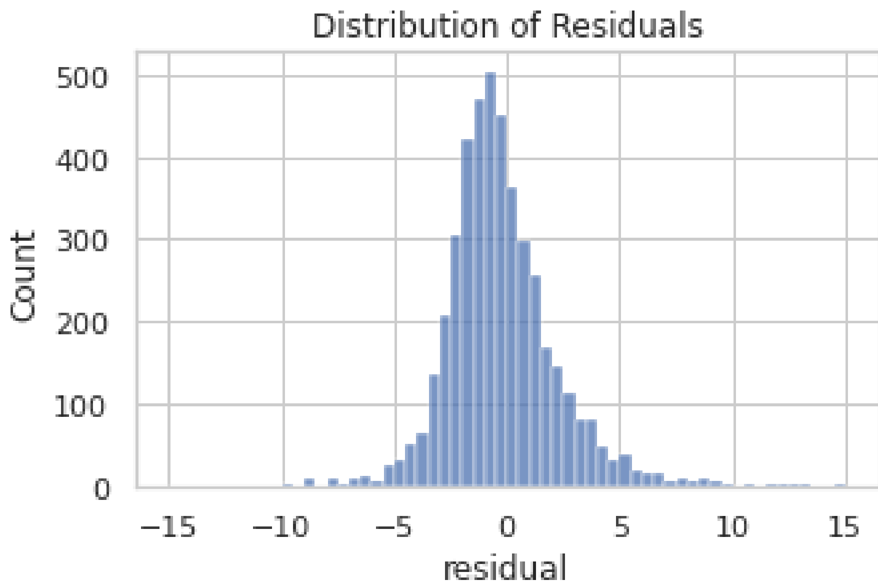


Visualize the distribution of the **residuals** using a histogram

[66]:
```
sns.set(style="whitegrid")
p=plt.figure()
p.set_figwidth(5)
p.set_figheight(3)
```

```
sns.histplot(data=results['residual'],  bins=np.arange(-15,15.5,0.5))

plt.title("Distribution of Residuals")
plt.show()
```



[67]:

```
# Calculate residual mean
results['residual'].mean()
```

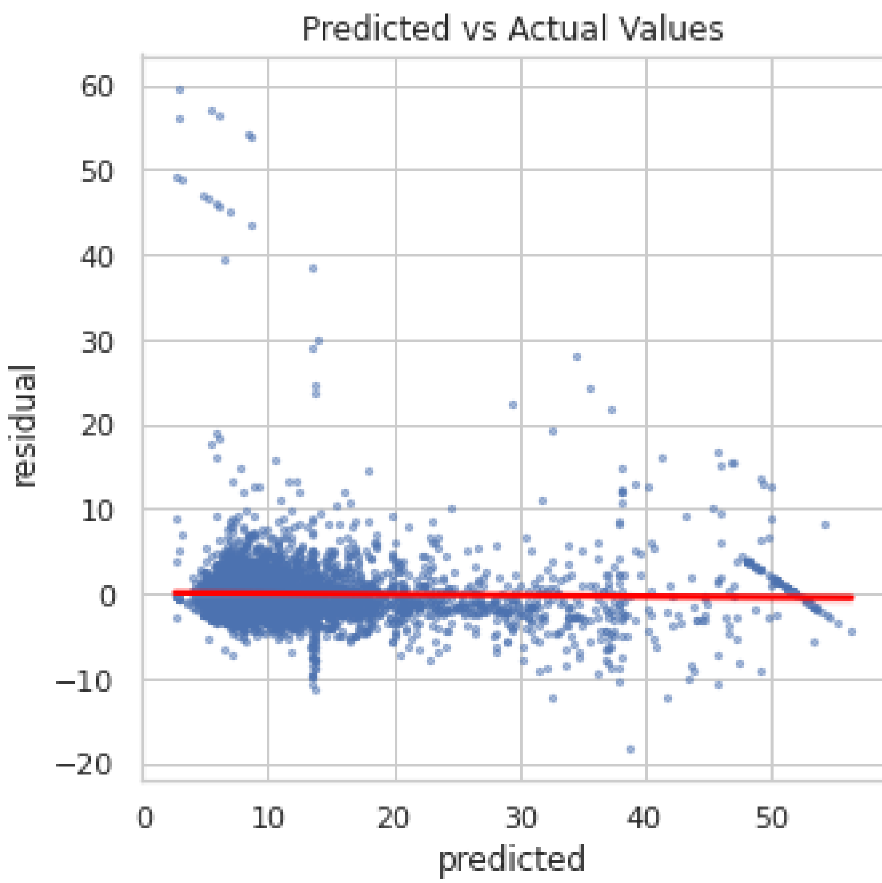
[67]: 0.022724208110295203

Create a scatterplot of `residuals` over `predicted`.

[70]:

```
# Create a scatterplot of `residuals` over `predicted`
sns.set(style="whitegrid")
p=plt.figure()
p.set_figwidth(5)
p.set_figheight(5)
sns.regplot(x=results['predicted'], y=results['residual'],
            scatter_kws={'alpha':0.5, 's':5},
            line_kws={'color':'red'})

plt.title("Predicted vs Actual Values")
plt.show()
```



4.4.3 Task 9c. Coefficients

Use the `coef_` attribute to get the model's coefficients. The coefficients are output in the order of the features that were used to train the model. Which feature had the greatest effect on trip fare?

[74]:
```
coefficients = pd.DataFrame(lr.coef_, columns=X.columns)
coefficients
```

[74]:

	VendorID	passenger_count	mean_distance	mean_duration	rush_hour
0	-0.012848	0.00068	7.533617	2.484461	0.123625

[76]:
```
print(X_train['mean_distance'].std())
print(7.533617 / X_train['mean_distance'].std())
```

```
3.2047936057177266
2.3507339089041945
```

What do these coefficients mean? How should they be interpreted?

Mean distance is the strongest predictor of fare amount, followed by mean duration. Since the features were scaled, a one-unit increase in mean distance corresponds to a $7.53 increase in fare amount, holding other variables constant.

By unscaling the data, we can make a more intuitive prediction: For every 3.2 miles traveled, the average fare increases by $7.53.

4.4.4 Task 9d. Conclusion

1. What are the key takeaways from this notebook?
2. What results can be presented from this notebook?

1.

- Multiple Linear Regression is a powerful tool to estimate a dependent variable based on multiple continuous independent variables.
- Even though you may have multiple independent variables that are highly correlated, the model can still be used to make effective, accurate predictions. However, if you're using the model to learn about your data, this can pose significant issues.
- EDA is crucial for correct feature selection, handling duplicates, missing values and feature engineering.
- Building a multiple linear regression model often involves experimentation to determine the most important features. Techniques like backward elimination and forward selection can be helpful for this process.

2.

- You can present that the variables with the most predictive power are mean_distance and mean_duration. The outcome of evaluating the model performance against the test data indicates, by looking at the R-Squared value, that 83% of the variation in the dependent variable (fare_amount) is explained by the independent variables.

Congratulations! You've completed this lab. However, you may not notice a green check mark next to this item on Coursera's platform. Please continue your progress regardless of the check mark. Just click on the "save" icon at the top of this notebook to ensure your work has been logged.

4.4.5 1. Predict on full dataset

[82]:
```
X_scaled = scaler.transform(X)
y_preds_full = lr.predict(X_scaled)
```

4.4.6 2. Impute ratecode 2 fare

[103]:
```
# Create a new df containing the RatecodeID col.
final_preds = df0[['RatecodeID']].copy()

# Add column containing all predictions
final_preds['y_preds_full'] = y_preds_full
```

```
# Impute a prediction of 52 at all rows where RatecodeID == 52
final_preds.loc[final_preds['RatecodeID']==2, 'y_preds_full'] = 52

# Check
final_preds[final_preds['RatecodeID']==2].head()
```

[103]:

	RatecodeID	y_preds_full
11	2	52.0
110	2	52.0
161	2	52.0
247	2	52.0
379	2	52.0

4.4.7 Check performance on full dataset

[104]:
```
final_preds = final_preds['y_preds_full']

r2 = r2_score(y, final_preds)
mae = mean_absolute_error(y, final_preds)
mse = mean_squared_error(y, final_preds)
rmse = np.sqrt(mse)

print('R-squared (R2):', r2)
print('Mean Absolute Error (MAE):', mae)
print('Mean Squared Error (MSE):', mse)
print('Root Mean Squared Error (RMSE):', rmse)
```

```
R-squared (R2): 0.8893227339544223
Mean Absolute Error (MAE): 2.0276882166328973
Mean Squared Error (MSE): 12.297426290781862
Root Mean Squared Error (RMSE): 3.506768639471652
```

4.4.8 Save final predictions with mean_duration and mean_distance columns

[106]:
```
# Combine means column with predictions column
nyc_preds_means = df0[['mean_duration','mean_distance']].copy()
nyc_preds_means['predicted_fare'] = final_preds

nyc_preds_means.head()
```

[106]:

	mean_duration	mean_distance	predicted_fare
0	23.000000	3.521667	16.773171
1	24.444444	3.108889	15.925566
2	7.257143	0.881429	6.741461

3	30.000000	3.700000	18.647316
4	15.000000	4.435000	16.708504