Activity_ Course 5 Automatidata project lab

December 6, 2023

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 pandas as pd
import numpy as np

# Packages for visualization
import matplotlib.pyplot as plt
import statsmodels.api as sm
import seaborn as sns
# Packages for date conversions for calculating trip durations
from datetime import datetime
from datetime import date
from datetime import timedelta
# Packages for OLS, MLR, confusion matrix
from statsmodels.formula.api import ols
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
import sklearn.metrics as metrics
```

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error,r2_score,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]:
```
# 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()`.

[79]:
```
# Start with `.shape` and `.info()`
print(df0.shape)
df0.info()
```

```
(22699, 18)
<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
```

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

[3]:
```
# Check for missing data and duplicates using .isna() and .drop_duplicates()
df0.isna().any(axis=0).sum()
```

[3]:
```
0
```

Use .describe().

[81]:
```
# Use .describe()
df0.describe()
```

[81]:
```
         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

[4]:
```python
# Check the format of the data
df0['tpep_pickup_datetime'][0]
```

[4]:
```
'03/25/2017 8:55:43 AM'
```

[5]:
```python
# 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'])



df0.dtypes
```

[5]:
```
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.

[6]:
```
# Create `duration` column
df0['duration'] = (df0['tpep_dropoff_datetime'] - df0['tpep_pickup_datetime'])/
↪np.timedelta64(1,'m')
```

4.2.4 Outliers

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

[86]:
```
### YOUR CODE HERE ###

df0.info()
```

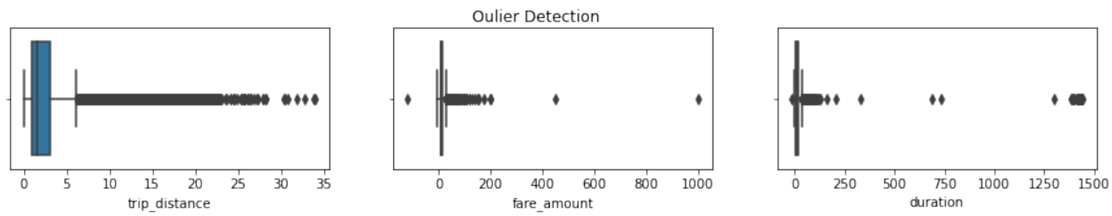
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 19 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Unnamed: 0             22699 non-null  int64
 1   VendorID               22699 non-null  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`.

[87]:
```
fig, axes = plt.subplots(1, 3, figsize=(15, 2))
fig.suptitle('Oulier Detection')
sns.boxplot(ax=axes[0], x=df0['trip_distance'])
sns.boxplot(ax=axes[1], x=df0['fare_amount'])
sns.boxplot(ax=axes[2], x=df0['duration'])
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?

All variables contain outliers but fare amount and duration have extreme outliers.

The distance does seem believable, a maximum of 35 miles does not seem unreasonable.

It does not make sense for 0 or negative values to be present unless it is within fare amount (like possible refunds)

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?

[50]:
```
# Are trip distances of 0 bad data or very short trips rounded down?
sorted(set(df0['trip_distance']))[:10]
```

[50]:
```
[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.

[51]:
```
sum(df0['trip_distance']==0)
```

[51]:
```
148
```

fare_amount outliers

[52]:
```
df0['fare_amount'].describe()
```

[52]:
```
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?

There is a minimum of -120 and a maximum of 999.99

Impute values less than $0 with `0`.

[7]:
```
# Impute values less than $0 with 0
df0.loc[df0['fare_amount'] < 0, 'fare_amount'] = 0
df0['fare_amount'].min()
```

[7]:
```
0.0
```

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

[8]:
```
def outlier_imputer(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 col in column_list:
        # Reassign minimum to zero
        df0.loc[df0[col] < 0, col] = 0

        # Calculate upper threshold
        q1 = df0[col].quantile(0.25)
        q3 = df0[col].quantile(0.75)
        iqr = q3 - q1
        upper_threshold = q3 + (iqr_factor * iqr)
        print(col)
        print('q3:', q3)
        print('upper_threshold:', upper_threshold)

        # Reassign values > threshold to threshold
        df0.loc[df0[col] > upper_threshold, col] = upper_threshold
        print(df0[col].describe())
        print()
```

[10]:
```
outlier_imputer(['fare_amount'], 6)
```

```
fare_amount
q3: 14.5
upper_threshold: 62.5
count    22699.000000
mean        12.897913
std         10.541137
min          0.000000
25%          6.500000
50%          9.500000
75%         14.500000
max         62.500000
Name: fare_amount, dtype: float64
```

duration outliers

[106]:
```
# Call .describe() for duration outliers
df0['duration'].describe()
```

[106]:
```
count    22699.000000
mean        17.013777
std         61.996482
min        -16.983333
25%          6.650000
50%         11.183333
75%         18.383333
```

```
max        1439.550000
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)`.

[8]:
```python
# Impute a 0 for any negative values
df0.loc[df0['duration'] < 0, 'duration'] = 0
df0['duration'].min()
```

[8]:
```
0.0
```

[13]:
```python
# Impute the high outliers
outlier_imputer(['duration'], 6)
```

```
duration
q3: 18.383333333333333
upper_threshold: 88.78333333333333
count    22699.000000
mean        14.460555
std         11.947043
min          0.000000
25%          6.650000
50%         11.183333
75%         18.383333
max         88.783333
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'

[9]:
```
# Create `pickup_dropoff` column
df0['pickup_dropoff'] = df0['PULocationID'].astype(str) + ' ' +␣
↪df0['DOLocationID'].astype(str)
df0['pickup_dropoff'].head(2)
```

[9]:
```
0    100 231
1     186 43
Name: pickup_dropoff, dtype: object
```

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`.

[10]:
```
grouped = df0.groupby('pickup_dropoff').␣
↪mean(numeric_only=True)[['trip_distance']]
grouped[:5]
```

[10]:
```
                  trip_distance
pickup_dropoff
1 1                    2.433333
10 148                15.700000
100 1                 16.890000
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}
```

[11]:
```
# 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.

[12]:
```python
# 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)

# Confirm that it worked
df0[(df0['PULocationID']==100) & (df0['DOLocationID']==231)][['mean_distance']]
```

[12]:
```
       mean_distance
0           3.521667
4909        3.521667
16636       3.521667
18134       3.521667
19761       3.521667
20581       3.521667
```

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

[13]:
```python
grouped = df0.groupby('pickup_dropoff').mean(numeric_only=True)[['duration']]
grouped

# 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)

# Confirm that it worked
df0[(df0['PULocationID']==100) & (df0['DOLocationID']==231)][['mean_duration']]
```

[13]:
```
       mean_duration
0          22.847222
4909       22.847222
16636      22.847222
18134      22.847222
19761      22.847222
20581      22.847222
```

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.

[14]:
```
# Create 'day' col
df0['day'] = df0['tpep_pickup_datetime'].dt.day_name().str.lower()

# Create 'month' col
df0['month'] = df0['tpep_pickup_datetime'].dt.strftime('%b').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.

[15]:
```
# Create 'rush_hour' col
df0['rush_hour'] = df0['tpep_pickup_datetime'].dt.hour

# If day is Saturday or Sunday, impute 0 in `rush_hour` column
df0.loc[df0['day'].isin(['saturday', 'sunday']), 'rush_hour'] = 0
```

[16]:
```
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
```

[17]:
```
# 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)
df0.head()
```

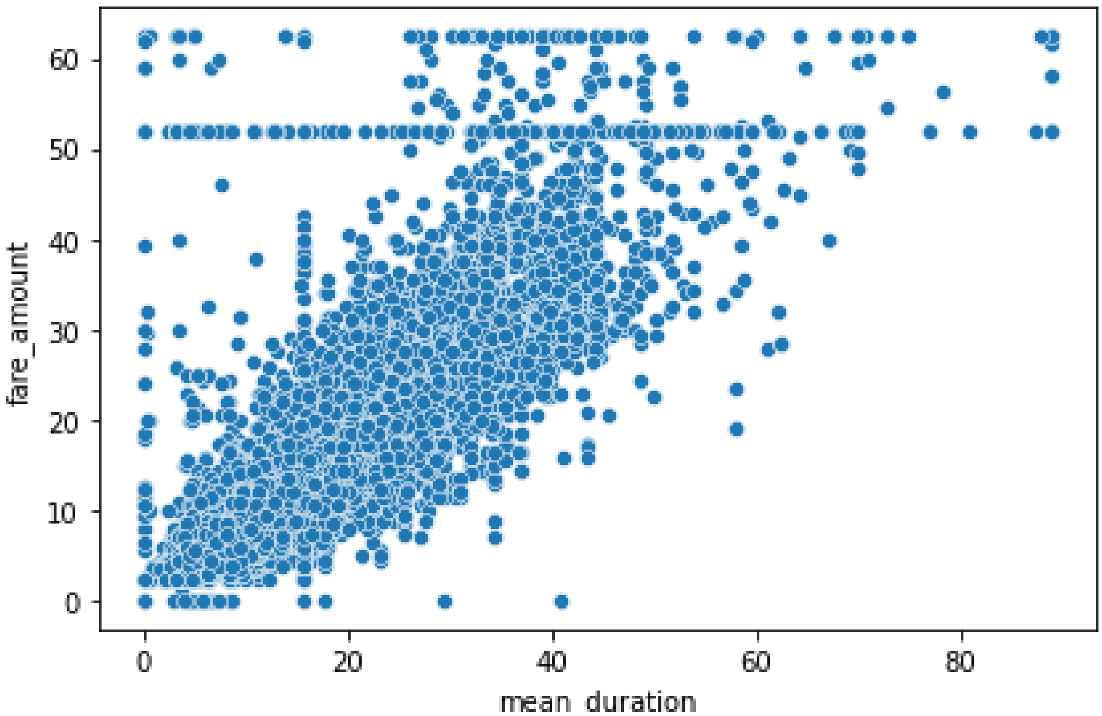
[17]:
```
   Unnamed: 0  VendorID tpep_pickup_datetime tpep_dropoff_datetime  \
0    24870114         2  2017-03-25 08:55:43   2017-03-25 09:09:47
1    35634249         1  2017-04-11 14:53:28   2017-04-11 15:19:58
```

```
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  \
0         16.56  14.066667         100 231       3.521667      22.847222
1         20.80  26.500000          186 43       3.108889      24.470370
2          8.75   7.200000         262 236       0.881429       7.250000
3         27.69  30.250000          188 97       3.700000      30.250000
4         17.80  16.716667           4 112       4.435000      14.616667

        day  month rush_hour
0  saturday    mar         0
1   tuesday    apr         0
2    friday    dec         1
3    sunday    may         0
4  saturday    apr         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`.

[38]:
```
# Create a scatterplot to visualize the relationship between variables of␣
↪interest
sns.scatterplot(x = df0['mean_duration'], y = df0['fare_amount'])

plt.tight_layout()
```



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.

[18]:
```
df0[df0['fare_amount'] > 50]['fare_amount'].value_counts().head()
```

[18]:
```
52.0    514
59.0      9
50.5      9
57.5      8
51.0      7
Name: fare_amount, dtype: int64
```

Examine the first 30 of these trips.

[19]:
```
# Set pandas to display all columns
pd.set_option('display.max_columns', None)
df0[df0['fare_amount']==52].head(30)
```

[19]:

	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	
161	95729204	2	2017-11-11 20:16:16	2017-11-11 20:17:14	
247	103404868	2	2017-12-06 23:37:08	2017-12-07 00:06:19	
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	
1097	68882036	2	2017-08-14 23:01:15	2017-08-14 23:03:35	
1110	74720333	1	2017-09-06 10:46:17	2017-09-06 11:44:41	
1179	51937907	2	2017-06-19 06:23:13	2017-06-19 07:03:53	

	passenger_count	trip_distance	RatecodeID	store_and_fwd_flag	\
11	2	18.90	2	N	
110	1	18.00	2	N	
161	1	0.23	2	N	
247	1	18.93	2	N	
379	1	17.99	2	N	
388	1	18.40	2	N	
406	1	4.73	2	N	
449	2	18.21	2	N	
468	1	17.27	2	N	
520	6	18.34	2	N	
569	1	18.65	2	N	
572	1	0.00	2	N	
586	1	17.76	2	N	
692	2	16.97	2	N	

717	1	20.80	2	N
719	1	21.60	2	N
782	2	18.81	2	N
816	5	16.94	2	N
818	1	17.77	2	N
835	1	18.57	2	N
840	1	22.43	2	N
861	2	17.80	2	N
881	6	18.23	2	N
958	1	21.80	2	N
970	1	19.57	2	N
984	1	16.70	2	N
1082	1	1.09	2	N
1097	5	2.12	2	N
1110	1	19.10	2	N
1179	6	19.77	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	
161	132	132	2	52.0	0.0	0.5	
247	132	79	2	52.0	0.0	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	
1097	265	265	2	52.0	0.0	0.5	
1110	239	132	1	52.0	0.0	0.5	

1179	238	132	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	
569	10.56	0.00	0.3	63.36	
572	11.71	5.76	0.3	70.27	
586	11.71	5.76	0.3	70.27	
692	11.71	5.76	0.3	70.27	
717	5.85	5.76	0.3	64.41	
719	12.60	5.76	0.3	75.66	
782	13.20	0.00	0.3	66.00	
816	2.00	5.54	0.3	60.34	
818	11.71	5.76	0.3	70.27	
835	13.20	0.00	0.3	66.00	
840	0.00	5.76	0.3	58.56	
861	6.00	5.76	0.3	64.56	
881	0.00	0.00	0.3	52.80	
958	0.00	0.00	0.3	52.80	
970	11.67	5.54	0.3	70.01	
984	42.29	0.00	0.3	99.59	
1082	0.00	5.54	0.3	62.84	
1097	0.00	0.00	0.3	52.80	
1110	15.80	0.00	0.3	68.60	
1179	17.57	5.76	0.3	76.13	

	duration	pickup_dropoff	mean_distance	mean_duration	day	\
11	36.800000	236 132	19.211667	265.147222	sunday	
110	66.850000	132 163	19.229000	52.941667	saturday	
161	0.966667	132 132	2.255862	3.021839	saturday	
247	29.183333	132 79	19.431667	47.275000	wednesday	
379	29.483333	132 234	17.654000	49.833333	sunday	
388	39.833333	132 48	18.761905	61.604762	tuesday	
406	15.616667	228 88	4.730000	15.616667	monday	
449	45.450000	132 48	18.761905	61.604762	thursday	
468	42.850000	186 132	17.096000	42.920000	tuesday	
520	71.583333	132 148	17.994286	46.340476	sunday	
569	28.883333	132 144	18.537500	37.000000	wednesday	
572	0.216667	230 161	0.685484	7.965591	tuesday	

586	55.700000	211 132	16.580000	61.691667	monday
692	30.533333	132 170	17.203000	37.113333	tuesday
717	34.033333	132 239	20.901250	44.862500	wednesday
719	57.366667	264 264	3.191516	25.329964	friday
782	52.750000	163 132	17.275833	164.759722	friday
816	48.600000	132 170	17.203000	37.113333	tuesday
818	129.316667	132 246	18.515000	86.583333	tuesday
835	36.983333	132 48	18.761905	61.604762	tuesday
840	45.066667	132 163	19.229000	52.941667	friday
861	28.000000	75 132	18.442500	36.204167	saturday
881	36.000000	68 132	18.785000	63.737500	saturday
958	35.166667	132 261	22.115000	51.493750	sunday
970	33.783333	132 140	19.293333	36.791667	friday
984	55.050000	132 230	18.571200	60.800000	wednesday
1082	14.366667	170 48	1.265789	14.135965	tuesday
1097	2.333333	265 265	0.753077	3.411538	monday
1110	58.400000	239 132	19.795000	50.562500	wednesday
1179	40.666667	238 132	19.470000	53.861111	monday

	month	rush_hour
11	mar	0
110	jun	0
161	nov	0
247	dec	0
379	sep	0
388	feb	1
406	jun	0
449	aug	0
468	sep	0
520	apr	0
569	nov	0
572	jul	0
586	jun	0
692	nov	0
717	dec	0
719	aug	1
782	jun	1
816	feb	1
818	jun	1
835	jan	0
840	oct	0
861	dec	0
881	dec	0
958	oct	0
970	feb	0
984	aug	1
1082	feb	1

```
1097    aug         0
1110    sep         0
1179    jun         1
```

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

Nearly all of the rides with fare amounts of $52 have location 132 in common. And every one has a ratecode of 2. Also all of the pickup times seem to be very late at night or very early morning, there is only a few that have mid-after times.

4.2.9 Task 5. Isolate modeling variables

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

[42]:
```
df0.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  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
```

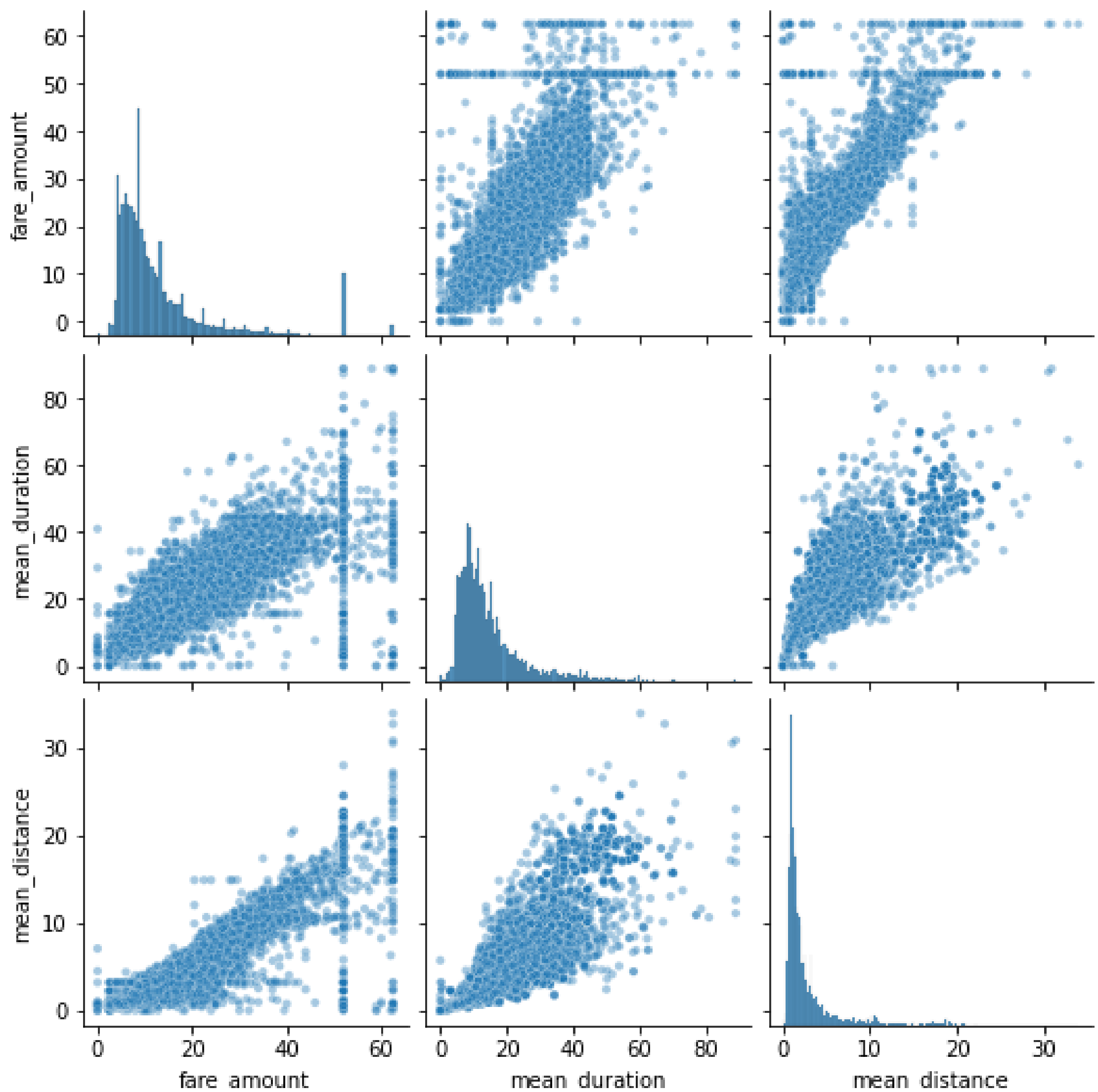
[20]:
```
df1 = df0.copy()

df1 = df1.drop(['Unnamed: 0', 'tpep_dropoff_datetime', 'tpep_pickup_datetime',
'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
'PULocationID', 'DOLocationID',
'payment_type', 'extra', 'mta_tax', 'tip_amount',
'tolls_amount', 'improvement_surcharge',
'total_amount', 'tpep_dropoff_datetime', 'tpep_pickup_datetime',
'duration',
'pickup_dropoff', 'day', 'month'
], axis=1)

df1.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
```

4.2.10 Task 6. Pair plot

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

[44]:
```
# Create a pairplot to visualize pairwise relationships between variables in
↪the data
sns.pairplot(df1[['fare_amount', 'mean_duration', 'mean_distance']],
             plot_kws={'alpha':0.4, 'size':5},
             );
```



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.

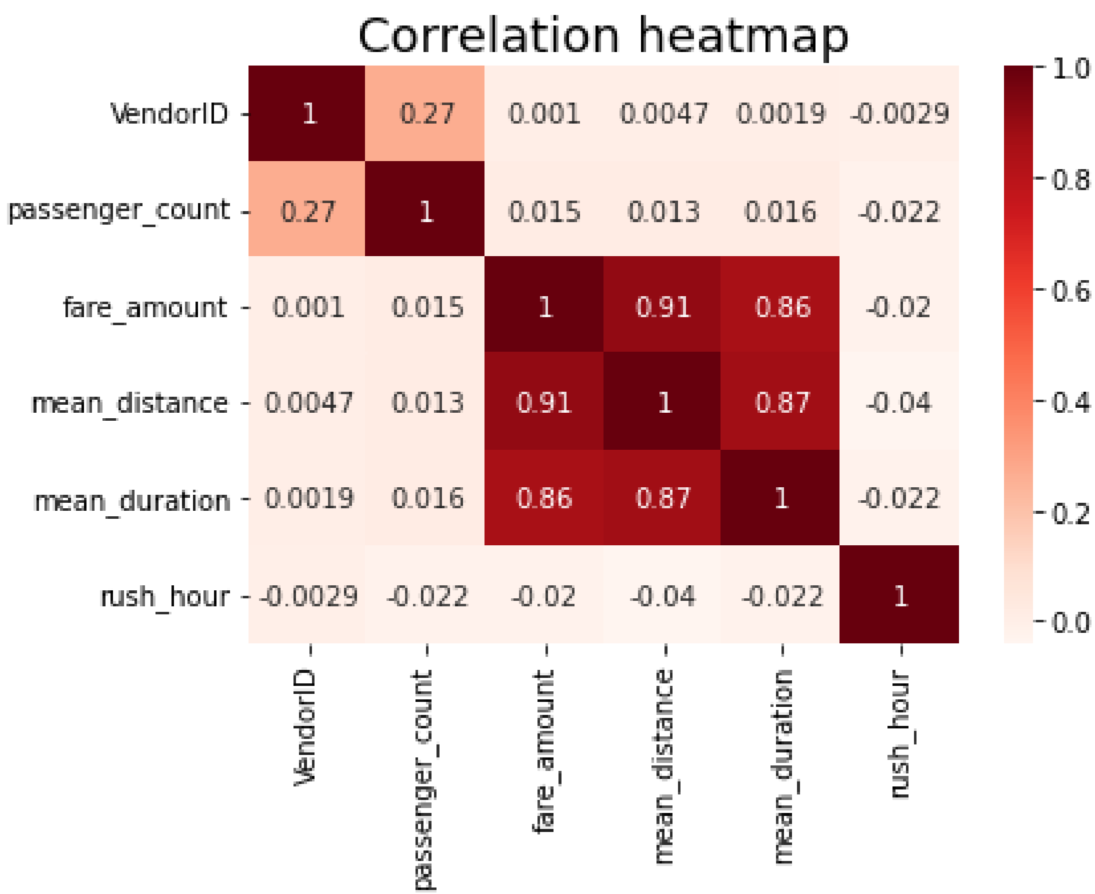
[45]:
```
# Correlation matrix to help determine most correlated variables
df1.corr(method='pearson')
```

[45]:
```
                 VendorID  passenger_count  fare_amount  mean_distance  \
VendorID         1.000000         0.266463     0.001045       0.004741
passenger_count  0.266463         1.000000     0.014942       0.013428
fare_amount      0.001045         0.014942     1.000000       0.910185
```

```
mean_distance     0.004741          0.013428      0.910185        1.000000
mean_duration     0.001876          0.015852      0.859105        0.874864
rush_hour        -0.002874         -0.022035     -0.020075       -0.039725

                 mean_duration  rush_hour
VendorID              0.001876  -0.002874
passenger_count       0.015852  -0.022035
fare_amount           0.859105  -0.020075
mean_distance         0.874864  -0.039725
mean_duration         1.000000  -0.021583
rush_hour            -0.021583   1.000000
```

Visualize a correlation heatmap of the data.

[46]:
```python
# Create correlation heatmap
plt.figure(figsize=(6,4))
sns.heatmap(df1.corr(method='pearson'), annot=True, cmap='Reds')
plt.title('Correlation heatmap',
fontsize=18)
plt.show()
```



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

mean_druation and fare_amount are highly correlated with fare_amount.

Try modeling with both variables even though they are correlated.

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

[47]:
```
df1.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.

[21]:
```
# Remove the target column from the features
# X = df2.drop(columns='fare_amount')
X = df1.drop(columns=['fare_amount'])

# Set y variable
y = df1[['fare_amount']]

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

[21]:

	VendorID	passenger_count	mean_distance	mean_duration	rush_hour
0	2	6	3.521667	22.847222	0
1	1	1	3.108889	24.470370	0
2	1	1	0.881429	7.250000	1
3	2	1	3.700000	30.250000	0

4	2	1	4.435000	14.616667	0

4.3.2 Task 8b. Pre-process data

Dummy encode categorical variables

[22]:
```
# Convert VendorID to string
X['VendorID'] = X['VendorID'].astype(str)

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

[22]:

	passenger_count	mean_distance	mean_duration	rush_hour	VendorID_2
0	6	3.521667	22.847222	0	1
1	1	3.108889	24.470370	0	0
2	1	0.881429	7.250000	1	0
3	1	3.700000	30.250000	0	1
4	1	4.435000	14.616667	0	1

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`.

[23]:
```
# Create training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=0)
```

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`.

[27]:
```
# Standardize the X variables
scaler = StandardScaler().fit(X_train)
X_train_scaled = scaler.transform(X_train)
print('X_train scaled: ' , X_train_scaled)
```

```
X_train scaled:  [[-0.50301524  0.8694684  -0.03115262 -0.64893329  0.89286563]
 [-0.50301524 -0.60011281 -0.39523923  1.54099045  0.89286563]
 [ 0.27331093 -0.47829156 -0.34307963 -0.64893329 -1.11998936]
 …
 [-0.50301524 -0.45121122 -0.3871602  -0.64893329 -1.11998936]
```

```
 [-0.50301524 -0.58944763 -0.46149795  1.54099045 -1.11998936]
 [ 1.82596329  0.83673851  0.36686348 -0.64893329  0.89286563]]
```

4.3.5 Fit the model

Instantiate your model and fit it to the training data.

[29]:
```
# Fit your model to the training data
lr=LinearRegression()
lr.fit(X_train_scaled, y_train)
```

[29]:
```
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.

[41]:
```
# Evaluate the model performance on the training data
r_sq = lr.score(X_train_scaled, y_train)
print('Coefficient of determination:', r_sq)
y_pred_train = lr.predict(X_train_scaled)
print('R^2:', r2_score(y_train, y_pred_train))
print('MAE:', mean_absolute_error(y_train, y_pred_train))
print('MSE:', mean_squared_error(y_train, y_pred_train))
print('RMSE:',np.sqrt(mean_squared_error(y_train, y_pred_train)))
```

```
Coefficient of determination: 0.5079996278862282
R^2: 0.5079996278862282
MAE: 2.6717170977886697
MSE: 92.88372147478809
RMSE: 9.637620114674997
```

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`.

[31]:
```
# Scale the X_test data
X_test_scaled = scaler.transform(X_test)
```

```
[32]: # Evaluate the model performance on the testing data
r_sq_test = lr.score(X_test_scaled, y_test)
print('Coefficient of determination:', r_sq_test)
y_pred_test = lr.predict(X_test_scaled)
print('R^2:', r2_score(y_test, y_pred_test))
print('MAE:', mean_absolute_error(y_test,y_pred_test))
print('MSE:', mean_squared_error(y_test, y_pred_test))
print('RMSE:',np.sqrt(mean_squared_error(y_test, y_pred_test)))
```

```
Coefficient of determination: 0.8261127809154183
R^2: 0.8261127809154183
MAE: 2.5028493495005453
MSE: 20.458845782372048
RMSE: 4.523145562810471
```

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.

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

[33]:

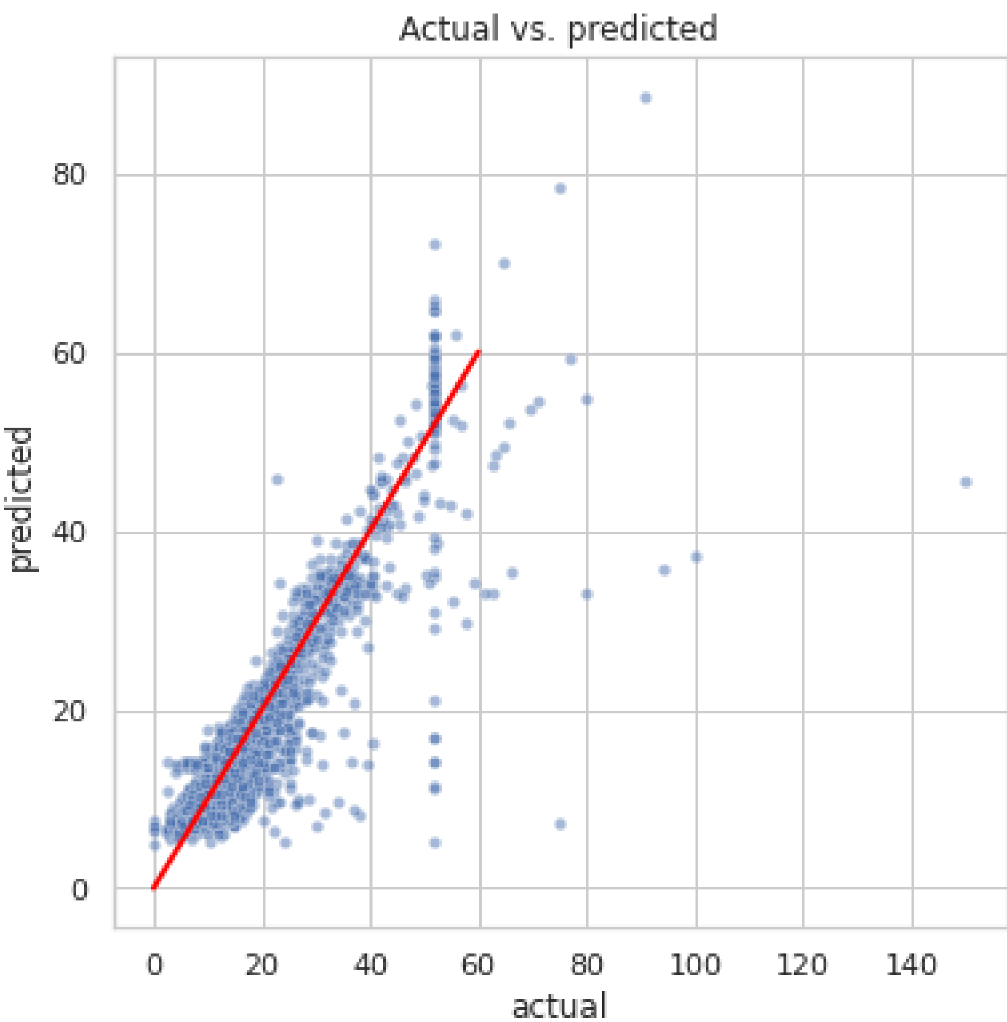
	actual	predicted	residual
5818	14.0	12.711169	1.288831
18134	28.0	14.592348	13.407652
4655	5.5	7.269140	-1.769140
7378	15.5	17.270201	-1.770201
13914	9.5	10.445021	-0.945021

4.4.2 Task 9b. Visualize model results

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

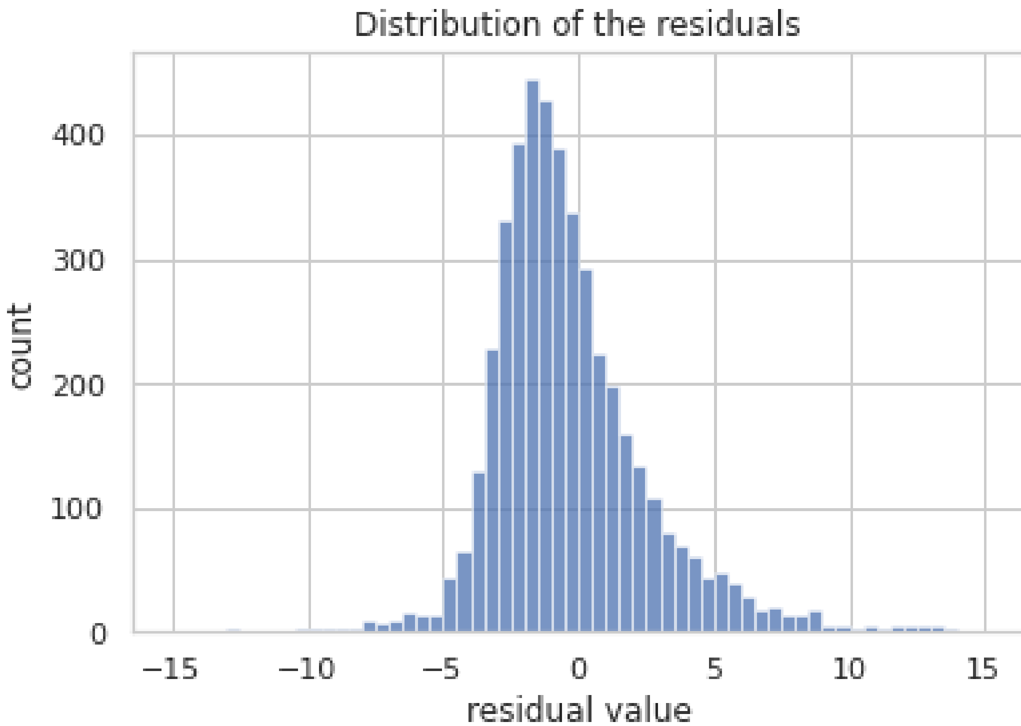
```
[36]: # Create a scatterplot to visualize `predicted` over `actual`
fig, ax = plt.subplots(figsize=(6, 6))
sns.set(style='whitegrid')
sns.scatterplot(x='actual',
                y='predicted',
```

```
                data=results,
                s=20,
                alpha=0.5,
                ax=ax)

plt.plot([0,60], [0,60], c='red', linewidth=2)
plt.title('Actual vs. predicted');
```



Visualize the distribution of the `residuals` using a histogram.

[37]:
```
# Visualize the distribution of the `residuals`
sns.histplot(results['residual'], bins=np.arange(-15,15.5,0.5))
plt.title('Distribution of the residuals')
plt.xlabel('residual value')
plt.ylabel('count');
```

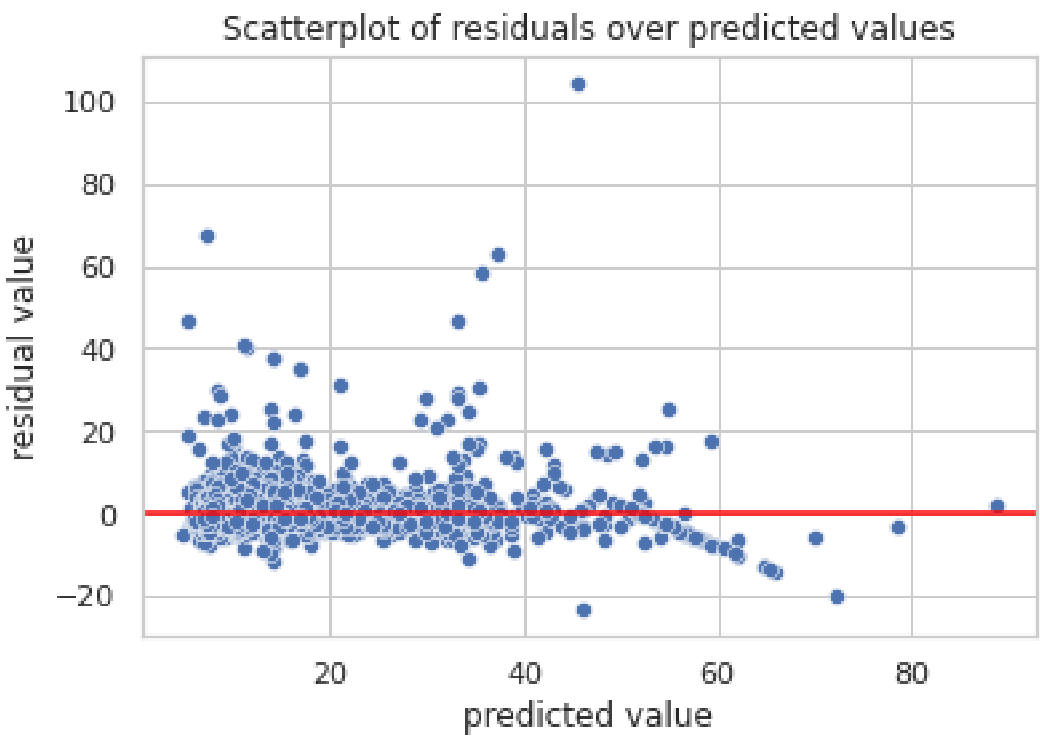


[38]:
```
# Calculate residual mean
results['residual'].mean()
```

[38]: -0.08253077178091318

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

[39]:
```
# Create a scatterplot of `residuals` over `predicted`
sns.scatterplot(x='predicted', y='residual', data=results)
plt.axhline(0, c='red')
plt.title('Scatterplot of residuals over predicted values')
plt.xlabel('predicted value')
plt.ylabel('residual value')
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?

[40]:
```
coefficients = pd.DataFrame(lr.coef_, columns=X.columns)
coefficients
```

[40]:

	passenger_count	mean_distance	mean_duration	rush_hour	VendorID_2
0	0.014424	9.686934	0.279576	0.151489	-0.076263

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

The coeffecients here show that mean_distance is what makes the biggest impact on fare_amount. With that being said the way to interpret this is for each +1 in standard deviation the fare amount increases $9.68.

4.4.4 Task 9d. Conclusion

1. What are the key takeaways from this notebook? Regression models take a lot of trial and error to produce information that is accurate and helpful, but once implemented correctly the results can be extremely helpful.

2. What results can be presented from this notebook? Results from this section is that the data follows multiple linear regression and the scores from the model can be presented.

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.