Exemplar_ Course 5 Automatidata project lab

October 1, 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 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 building 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?

Exemplar responses: Find the answers to those questions later in the notebook.

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 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 sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
```

```
import sklearn.metrics as metrics # For confusion matrix
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]:
```
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?

Exemplar response:

1. Outliers and extreme data values can significantly impact linear regression equations. After visualizing data, make a plan for addressing outliers by dropping rows, substituting extreme data with average data, and/or removing data values greater than 3 standard deviations.
2. EDA activities also include identifying missing data to help the analyst make decisions on their exclusion or inclusion by substituting values with data set means, medians, and other similar methods.
3. It's important to check for things like multicollinearity between predictor variables, as well to understand their distributions, as this will help you decide what statistical inferences can be made from the model and which ones cannot.
4. Additionally, it can be useful to engineer new features by multiplying variables together or taking the difference from one variable to another. For example, in this dataset you can create a `duration` variable by subtracting `tpep_dropoff` from `tpep_pickup time`.

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]:
```
# Start with `.shape` and `.info()`

# Keep `df0` as the original dataframe and create a copy (df) where changes␣
↪will go
# Can revert `df` to `df0` if needed down the line
df = df0.copy()

# Display the dataset's shape
```

```python
print(df.shape)

# Display basic info about the dataset
df.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()`.

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

# Check for duplicates
print('Shape of dataframe:', df.shape)
print('Shape of dataframe with duplicates dropped:', df.drop_duplicates().shape)

# Check for missing values in dataframe
print('Total count of missing values:', df.isna().sum().sum())

# Display missing values per column in dataframe
print('Missing values per column:')
df.isna().sum()
```

```
Shape of dataframe: (22699, 18)
Shape of dataframe with duplicates dropped: (22699, 18)
Total count of missing values: 0
Missing values per column:
```

[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
```

Exemplar note: There are no duplicates or missing values in the data.

Use `.describe()`.

[5]:
```python
# Display descriptive stats about the data
df.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
```

Exemplar note: Some things stand out from this table of summary statistics. For instance, there are clearly some outliers in several variables, like `tip_amount` ($200) and `total_amount` ($1,200). Also, a number of the variables, such as `mta_tax`, seem to be almost constant throughout the data, which would imply that they would not be expected to be very predictive.

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

[6]:
```python
# Check the format of the data
df['tpep_dropoff_datetime'][0]
```

[6]:
```
'03/25/2017 9:09:47 AM'
```

[7]:
```python
# Convert datetime columns to datetime
# Display data types of `tpep_pickup_datetime`, `tpep_dropoff_datetime`
print('Data type of tpep_pickup_datetime:', df['tpep_pickup_datetime'].dtype)
print('Data type of tpep_dropoff_datetime:', df['tpep_dropoff_datetime'].dtype)

# Convert `tpep_pickup_datetime` to datetime format
df['tpep_pickup_datetime'] = pd.to_datetime(df['tpep_pickup_datetime'],␣
 ↪format='%m/%d/%Y %I:%M:%S %p')

# Convert `tpep_dropoff_datetime` to datetime format
```

```python
df['tpep_dropoff_datetime'] = pd.to_datetime(df['tpep_dropoff_datetime'],␣
↪format='%m/%d/%Y %I:%M:%S %p')

# Display data types of `tpep_pickup_datetime`, `tpep_dropoff_datetime`
print('Data type of tpep_pickup_datetime:', df['tpep_pickup_datetime'].dtype)
print('Data type of tpep_dropoff_datetime:', df['tpep_dropoff_datetime'].dtype)

df.head(3)
```

```
Data type of tpep_pickup_datetime: object
Data type of tpep_dropoff_datetime: object
Data type of tpep_pickup_datetime: datetime64[ns]
Data type of tpep_dropoff_datetime: datetime64[ns]
```

[7]:
```
   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

   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

   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

   tip_amount  tolls_amount  improvement_surcharge  total_amount
0        2.76           0.0                    0.3         16.56
1        4.00           0.0                    0.3         20.80
2        1.45           0.0                    0.3          8.75
```

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.

[8]:
```python
# Create `duration` column
df['duration'] = (df['tpep_dropoff_datetime'] - df['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.

[9]:
```
df.info()
```

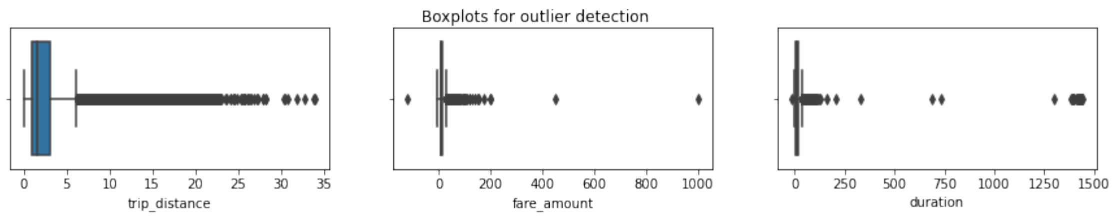
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 19 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Unnamed: 0             22699 non-null  int64
 1   VendorID               22699 non-null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

[10]:
```
fig, axes = plt.subplots(1, 3, figsize=(15, 2))
fig.suptitle('Boxplots for outlier detection')
sns.boxplot(ax=axes[0], x=df['trip_distance'])
sns.boxplot(ax=axes[1], x=df['fare_amount'])
sns.boxplot(ax=axes[2], x=df['duration'])
plt.show();
```



Exemplar response: 1. All three variables contain outliers. Some are extreme, but others not so much.

2. It's 30 miles from the southern tip of Staten Island to the northern end of Manhattan and that's in a straight line. With this knowledge and the distribution of the values in this column, it's reasonable to leave these values alone and not alter them. However, the values for `fare_amount` and `duration` definitely seem to have problematic outliers on the higher end.

3. Probably not for the latter two, but for `trip_distance` it might be okay.

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?

[11]:
```python
# Are trip distances of 0 bad data or very short trips rounded down?
sorted(set(df['trip_distance']))[:10]
```

[11]:
```
[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.

[12]:
```python
sum(df['trip_distance']==0)
```

[12]:
```
148
```

Exemplar note: 148 out of ~23,000 rides is relatively insignificant. You could impute it with a value of 0.01, but it's unlikely to have much of an effect on the model. Therefore, the `trip_distance` column will remain untouched with regard to outliers.

`fare_amount` outliers

[13]:
```
df['fare_amount'].describe()
```

[13]:
```
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
```

Exemplar response:

The range of values in the `fare_amount` column is large and the extremes don't make much sense.

- **Low values:** Negative values are problematic. Values of zero could be legitimate if the taxi logged a trip that was immediately canceled.
- **High values:** The maximum fare amount in this dataset is nearly \$1,000, which seems very unlikely. High values for this feature can be capped based on intuition and statistics. The interquartile range (IQR) is \$8. The standard formula of `Q3 + (1.5 * IQR)` yields $26.50. That doesn't seem appropriate for the maximum fare cap. In this case, we'll use a factor of `6`, which results in a cap of $62.50.

Impute values less than $0 with `0`.

[14]:
```
# Impute values less than $0 with 0
df.loc[df['fare_amount'] < 0, 'fare_amount'] = 0
df['fare_amount'].min()
```

[14]:
```
0.0
```

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

[15]:
```
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
        df.loc[df[col] < 0, col] = 0

        # Calculate upper threshold
        q1 = df[col].quantile(0.25)
        q3 = df[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
        df.loc[df[col] > upper_threshold, col] = upper_threshold
        print(df[col].describe())
        print()
```

[16]:
```
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

[17]:
```
df['duration'].describe()
```

[17]:
```
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)`.

[18]:
```python
# Impute a 0 for any negative values
df.loc[df['duration'] < 0, 'duration'] = 0
df['duration'].min()
```

[18]:
```
0.0
```

[19]:
```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'

[20]:
```python
# Create `pickup_dropoff` column
df['pickup_dropoff'] = df['PULocationID'].astype(str) + ' ' +␣
↪df['DOLocationID'].astype(str)
df['pickup_dropoff'].head(2)
```

[20]:
```
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`.

[21]:
```python
grouped = df.groupby('pickup_dropoff').
↪mean(numeric_only=True)[['trip_distance']]
grouped[:5]
```

[21]:
```
                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}
```

[22]:
```
# 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.

[23]:
```
# 1. Create a mean_distance column that is a copy of the pickup_dropoff helper␣
↪column
df['mean_distance'] = df['pickup_dropoff']

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

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

[23]:
```
       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.

[24]:
```
grouped = df.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']

df['mean_duration'] = df['pickup_dropoff']
df['mean_duration'] = df['mean_duration'].map(grouped_dict)

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

[24]:
```
       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.

[25]:
```python
# Create 'day' col
df['day'] = df['tpep_pickup_datetime'].dt.day_name().str.lower()

# Create 'month' col
df['month'] = df['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.

[26]:
```python
# Create 'rush_hour' col
df['rush_hour'] = df['tpep_pickup_datetime'].dt.hour

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

[27]:
```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
```

[28]:
```python
# Apply the `rush_hourizer()` function to the new column
df.loc[(df.day != 'saturday') & (df.day != 'sunday'), 'rush_hour'] = df.
↪apply(rush_hourizer, axis=1)
df.head()
```

[28]:
```
   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
```

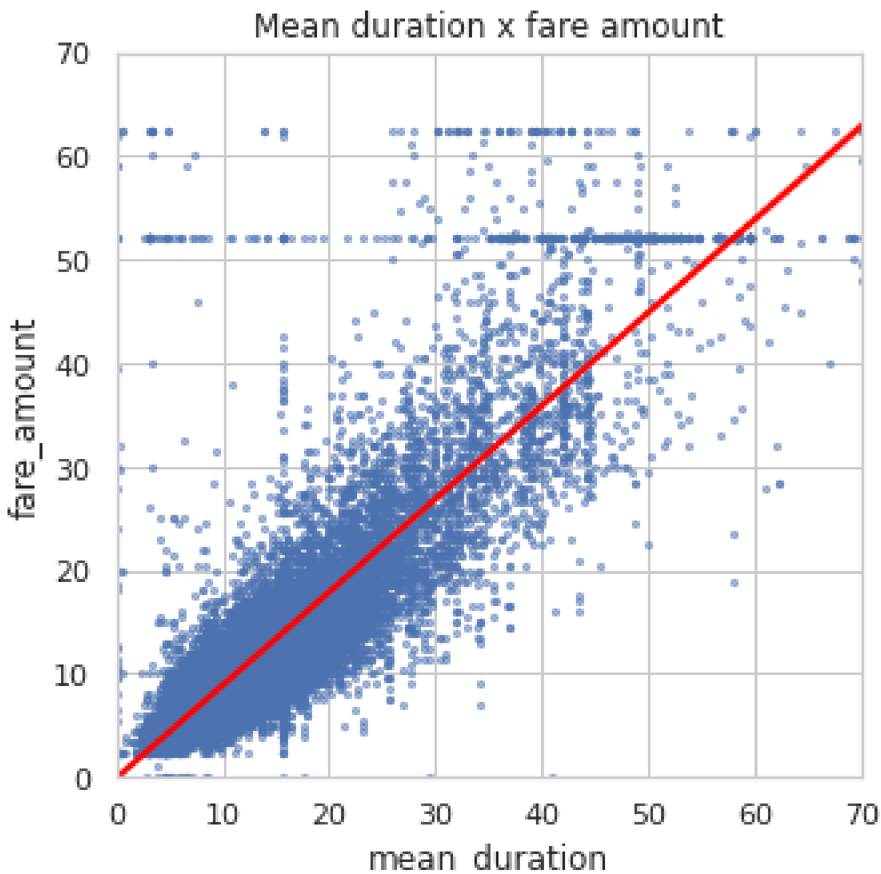
```
2   106203690         1  2017-12-15 07:26:56   2017-12-15 07:34:08
3    38942136         2  2017-05-07 13:17:59   2017-05-07 13:48:14
4    30841670         2  2017-04-15 23:32:20   2017-04-15 23:49:03

   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`.

[29]:
```python
# Create a scatter plot of duration and trip_distance, with a line of best fit
sns.set(style='whitegrid')
f = plt.figure()
f.set_figwidth(5)
f.set_figheight(5)
sns.regplot(x=df['mean_duration'], y=df['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.

[30]:
```
df[df['fare_amount'] > 50]['fare_amount'].value_counts().head()
```

[30]:
```
52.0    514
62.5     84
59.0      9
50.5      9
```

```
57.5      8
Name: fare_amount, dtype: int64
```

Exemplar note: There are 514 trips whose fares were $52.

Examine the first 30 of these trips.

[31]:
```python
# Set pandas to display all columns
pd.set_option('display.max_columns', None)
df[df['fare_amount']==52].head(30)
```

[31]:
```
      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 month  \
11    36.800000        236 132      19.211667      40.500000     sunday   mar
110   66.850000        132 163      19.229000      52.941667   saturday   jun
```

161	0.966667	132 132	2.255862	3.021839	saturday	nov
247	29.183333	132 79	19.431667	47.275000	wednesday	dec
379	29.483333	132 234	17.654000	49.833333	sunday	sep
388	39.833333	132 48	18.761905	58.246032	tuesday	feb
406	15.616667	228 88	4.730000	15.616667	monday	jun
449	45.450000	132 48	18.761905	58.246032	thursday	aug
468	42.850000	186 132	17.096000	42.920000	tuesday	sep
520	71.583333	132 148	17.994286	46.340476	sunday	apr
569	28.883333	132 144	18.537500	37.000000	wednesday	nov
572	0.216667	230 161	0.685484	7.965591	tuesday	jul
586	55.700000	211 132	16.580000	61.691667	monday	jun
692	30.533333	132 170	17.203000	37.113333	tuesday	nov
717	34.033333	132 239	20.901250	44.862500	wednesday	dec
719	57.366667	264 264	3.191516	15.618773	friday	aug
782	52.750000	163 132	17.275833	52.338889	friday	jun
816	48.600000	132 170	17.203000	37.113333	tuesday	feb
818	88.783333	132 246	18.515000	66.316667	tuesday	jun
835	36.983333	132 48	18.761905	58.246032	tuesday	jan
840	45.066667	132 163	19.229000	52.941667	friday	oct
861	28.000000	75 132	18.442500	36.204167	saturday	dec
881	36.000000	68 132	18.785000	58.041667	saturday	dec
958	35.166667	132 261	22.115000	51.493750	sunday	oct
970	33.783333	132 140	19.293333	36.791667	friday	feb
984	55.050000	132 230	18.571200	59.598000	wednesday	aug
1082	14.366667	170 48	1.265789	14.135965	tuesday	feb
1097	2.333333	265 265	0.753077	3.411538	monday	aug
1110	58.400000	239 132	19.795000	50.562500	wednesday	sep
1179	40.666667	238 132	19.470000	53.861111	monday	jun

	rush_hour
11	0
110	0
161	0
247	0
379	0
388	1
406	0
449	0
468	0
520	0
569	0
572	0
586	0
692	0
717	0
719	1
782	1

```
816             1
818             1
835             0
840             0
861             0
881             0
958             0
970             0
984             1
1082            1
1097            0
1110            0
1179            1
```

Exemplar response:

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

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

The data dictionary says that `RatecodeID` of 2 indicates trips for JFK, which is John F. Kennedy International Airport. A quick Google search for "new york city taxi flat rate $52" indicates that in 2017 (the year that this data was collected) there was indeed a flat fare for taxi trips between JFK airport (in Queens) and Manhattan.

Because `RatecodeID` is known from the data dictionary, the values for this rate code can be imputed back into the data after the model makes its predictions. This way you know that those data points will always be correct.

4.2.9 Task 5. Isolate modeling variables

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

[32]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 25 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Unnamed: 0             22699 non-null  int64
 1   VendorID               22699 non-null  int64
 2   tpep_pickup_datetime   22699 non-null  datetime64[ns]
 3   tpep_dropoff_datetime  22699 non-null  datetime64[ns]
```

```
 4   passenger_count        22699 non-null  int64
 5   trip_distance          22699 non-null  float64
 6   RatecodeID             22699 non-null  int64
 7   store_and_fwd_flag     22699 non-null  object
 8   PULocationID           22699 non-null  int64
 9   DOLocationID           22699 non-null  int64
 10  payment_type           22699 non-null  int64
 11  fare_amount            22699 non-null  float64
 12  extra                  22699 non-null  float64
 13  mta_tax                22699 non-null  float64
 14  tip_amount             22699 non-null  float64
 15  tolls_amount           22699 non-null  float64
 16  improvement_surcharge  22699 non-null  float64
 17  total_amount           22699 non-null  float64
 18  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
```

[33]:
```
df2 = df.copy()

df2 = df2.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)

df2.info()
```

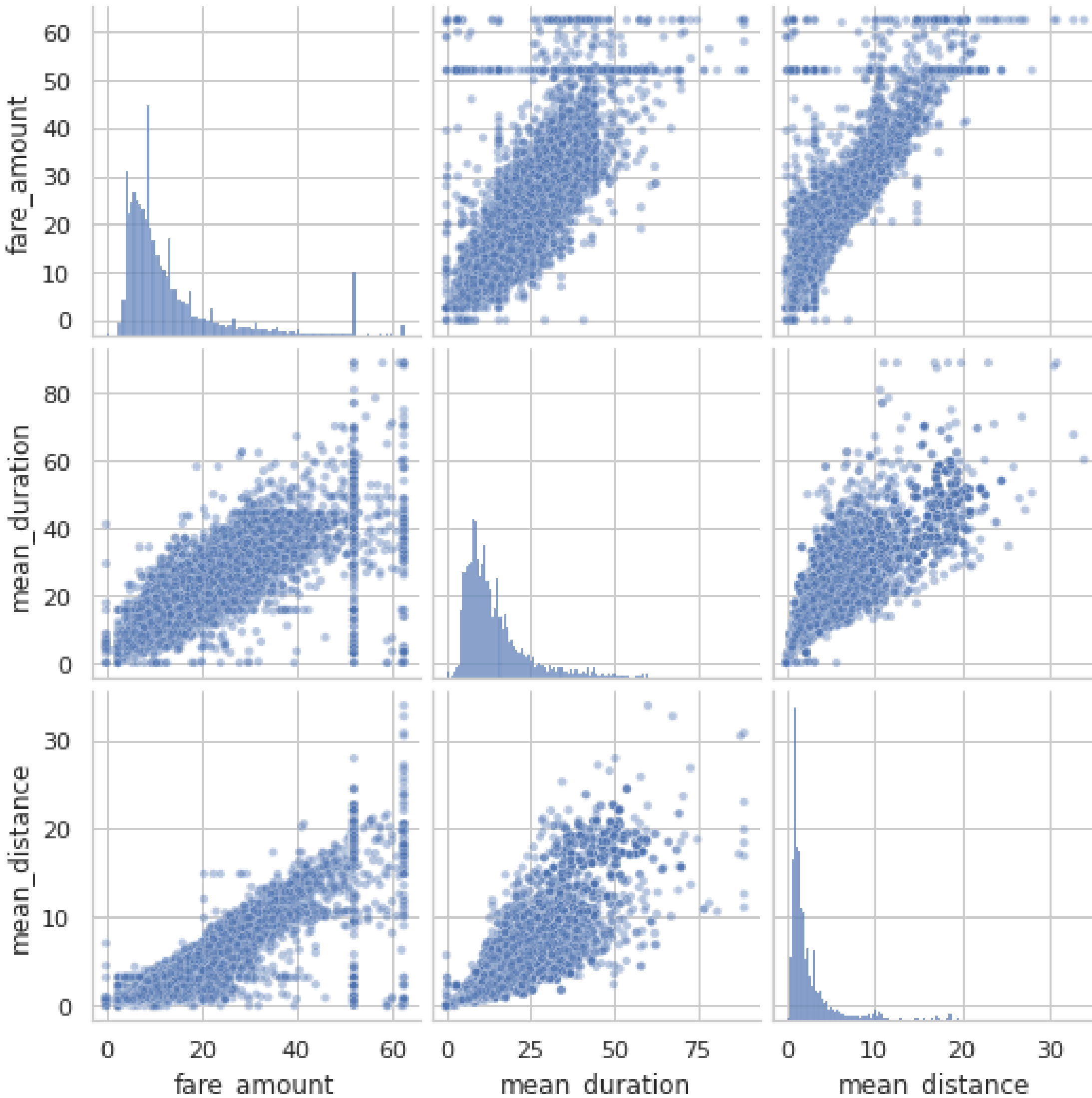
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   VendorID         22699 non-null  int64
 1   passenger_count  22699 non-null  int64
 2   fare_amount      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`.

[34]:
```
# Create a pairplot to visualize pairwise relationships between variables in
 ↪the data
### YOUR CODE HERE ###

sns.pairplot(df2[['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.

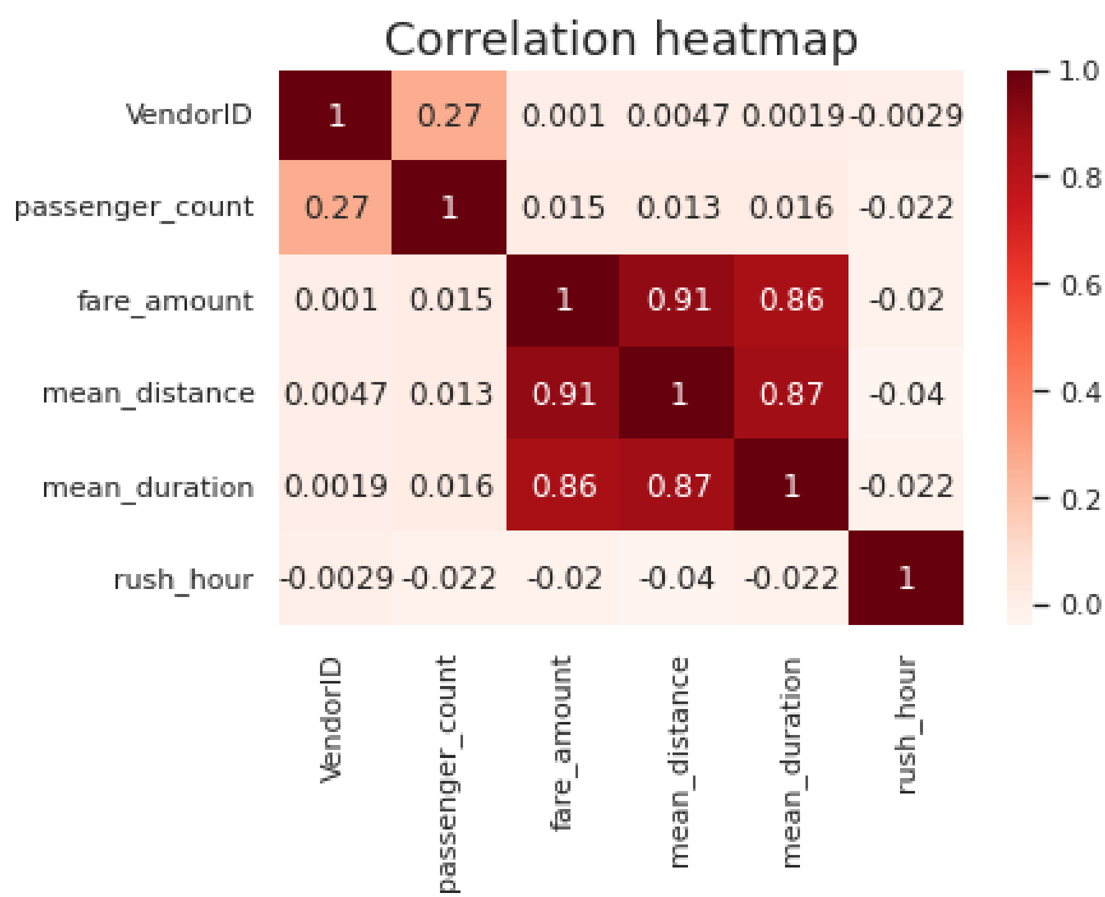
[35]:
```
# Create correlation matrix containing pairwise correlation of columns, using
↪pearson correlation coefficient
df2.corr(method='pearson')
```

[35]:
```
                 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.

[36]:
```python
# Create correlation heatmap

plt.figure(figsize=(6,4))
sns.heatmap(df2.corr(method='pearson'), annot=True, cmap='Reds')
plt.title('Correlation heatmap',
          fontsize=18)
plt.show()
```



Exemplar response: `mean_duration` and `mean_distance` are both highly correlated with the target variable of `fare_amount` They're also both correlated with each other, with a Pearson correlation of 0.87.

Recall that highly correlated predictor variables can be bad for linear regression models when you want to be able to draw statistical inferences about the data from the model. However, correlated predictor variables can still be used to create an accurate predictor if the prediction itself is more important than using the model as a tool to learn about your data.

This model will predict `fare_amount`, which will be used as a predictor variable in machine learning models. Therefore, 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

[37]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   VendorID         22699 non-null  int64
 1   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.

[38]:
```
# Remove the target column from the features
X = df2.drop(columns=['fare_amount'])

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

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

[38]:

	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

[39]:
```
# Convert VendorID to string
X['VendorID'] = X['VendorID'].astype(str)

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

[39]:

	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`.

[40]:
```
# 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`.

[41]:
```
# 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   0.17616665 -0.64893329  0.89286563]
 [-0.50301524 -0.60011281 -0.69829589  1.54099045  0.89286563]
 [ 0.27331093 -0.47829156 -0.57301906 -0.64893329 -1.11998936]
 …
 [-0.50301524 -0.45121122 -0.6788917  -0.64893329 -1.11998936]
 [-0.50301524 -0.58944763 -0.85743597  1.54099045 -1.11998936]
 [ 1.82596329  0.83673851  1.13212101 -0.64893329  0.89286563]]
```

4.3.5 Fit the model

Instantiate your model and fit it to the training data.

[42]:
```
# Fit your model to the training data
lr=LinearRegression()
lr.fit(X_train_scaled, y_train)
```

[42]:
```
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.

[43]:
```
# 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: 0.8398434585044773
R^2: 0.8398434585044773
MAE: 2.186666416775414
MSE: 17.88973296349268
RMSE: 4.229625629236313
```

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`.

[44]:
```python
# Scale the X_test data
X_test_scaled = scaler.transform(X_test)
```

[45]:
```python
# 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: 0.8682583641795454
R^2: 0.8682583641795454
MAE: 2.1336549840593864
MSE: 14.326454156998944
RMSE: 3.785030271609323
```

Exemplar note: The model performance is high on both training and test sets, suggesting that there is little bias in the model and that the model is not overfit. In fact, the test scores were even better than the training scores.

For the test data, an R2 of 0.868 means that 86.8% of the variance in the `fare_amount` variable is described by the model.

The mean absolute error is informative here because, for the purposes of the model, an error of two is not more than twice as bad as an error of one.

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.

[46]:
```python
# 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()
```

[46]:

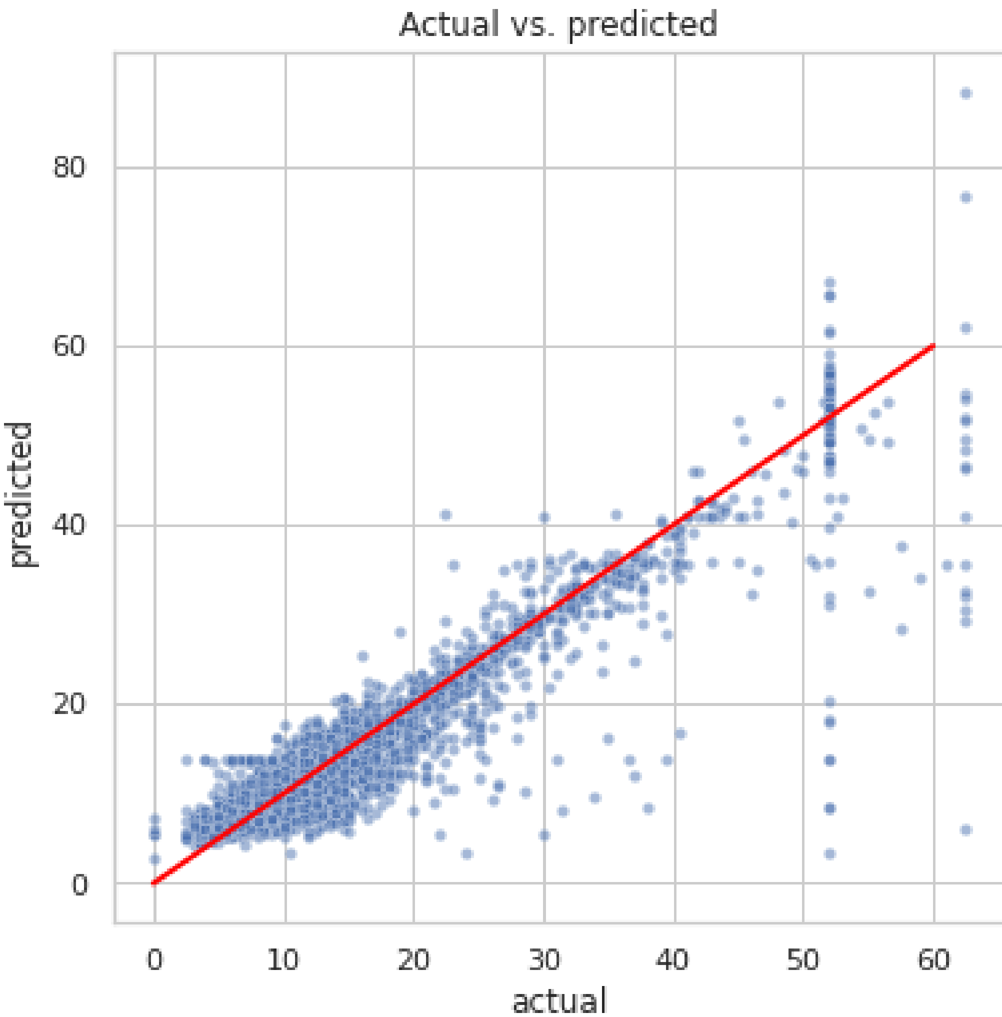
	actual	predicted	residual
5818	14.0	12.356503	1.643497
18134	28.0	16.314595	11.685405
4655	5.5	6.726789	-1.226789
7378	15.5	16.227206	-0.727206

```
13914     9.5  10.536408  -1.036408
```

4.4.2 Task 9b. Visualize model results

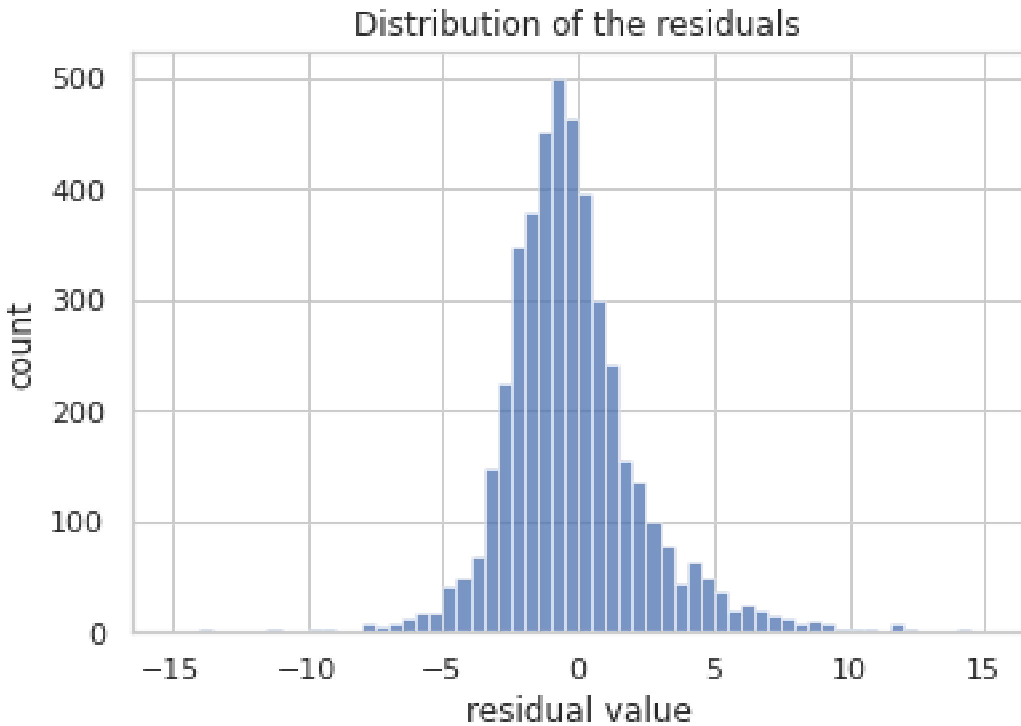
Create a scatterplot to visualize `actual` vs. `predicted`.

[47]:
```python
# 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
)
# Draw an x=y line to show what the results would be if the model were perfect
plt.plot([0,60], [0,60], c='red', linewidth=2)
plt.title('Actual vs. predicted');
```



Visualize the distribution of the `residuals` using a histogram

[48]:
```
# 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');
```



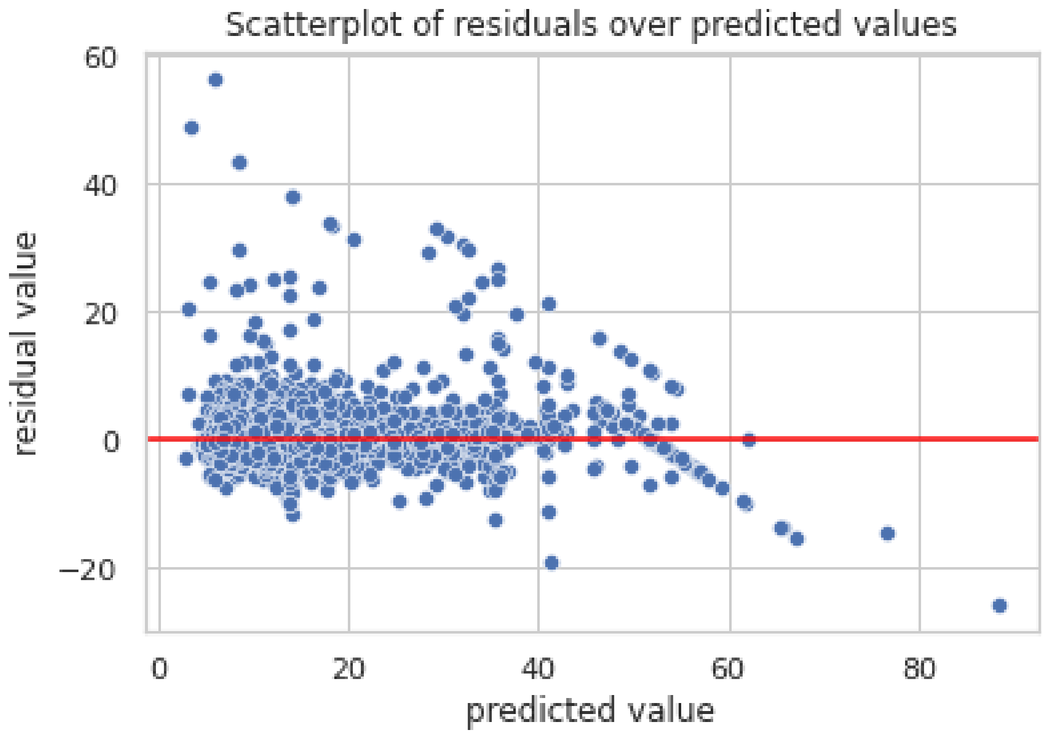
[49]:
```
results['residual'].mean()
```

[49]: -0.01544262152868053

Exemplar note: The distribution of the residuals is approximately normal and has a mean of -0.015. The residuals represent the variance in the outcome variable that is not explained by the model. A normal distribution around zero is good, as it demonstrates that the model's errors are evenly distributed and unbiased.

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

[50]:
```
# 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()
```



Exemplar note: The model's residuals are evenly distributed above and below zero, with the exception of the sloping lines from the upper-left corner to the lower-right corner, which you know are the imputed maximum of \$62.50 and the flat rate of \$52 for JFK airport trips.

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.

[51]:
```
# Get model coefficients
coefficients = pd.DataFrame(lr.coef_, columns=X.columns)
coefficients
```

[51]:

	passenger_count	mean_distance	mean_duration	rush_hour	VendorID_2
0	0.030825	7.133867	2.812115	0.110233	-0.054373

The coefficients reveal that `mean_distance` was the feature with the greatest weight in the model's final prediction. Be careful here! A common misinterpretation is that for every mile traveled, the fare amount increases by a mean of \$7.13. This is incorrect. Remember, the data used to train the model was standardized with `StandardScaler()`. As such, the units are no longer miles. In other words, you cannot say "for every mile traveled…", as stated above. The correct interpretation of this coefficient is: controlling for other variables, *for every +1 change in standard deviation*, the fare amount increases by a mean of \$7.13.

Note also that because some highly correlated features were not removed, the confidence interval of this assessment is wider.

So, translate this back to miles instead of standard deviation (i.e., unscale the data).

1. Calculate the standard deviation of `mean_distance` in the `X_train` data.
2. Divide the coefficient (7.133867) by the result to yield a more intuitive interpretation.

[52]:
```
# 1. Calculate SD of `mean_distance` in X_train data
print(X_train['mean_distance'].std())

# 2. Divide the model coefficient by the standard deviation
print(7.133867 / X_train['mean_distance'].std())
```

```
3.574812975256415
1.9955916713344426
```

Now you can make a more intuitive interpretation: for every 3.57 miles traveled, the fare increased by a mean of \$7.13. Or, reduced: for every 1 mile traveled, the fare increased by a mean of \$2.00.

4.4.4 Task 9d. Conclusion

Exemplar responses: What are the key takeaways from this notebook?

- Multiple linear regression is a powerful tool to estimate a dependent continous variable from several independent variables.
- Exploratory data analysis is useful for selecting both numeric and categorical features for multiple linear regression.
- Fitting multiple linear regression models may require trial and error to select variables that fit an accurate model while maintaining model assumptions (or not, depending on your use case).

What results can be presented from this notebook?

- You can discuss meeting linear regression assumptions, and you can present the MAE and RMSE scores obtained from the model.

5 BONUS CONTENT

More work must be done to prepare the predictions to be used as inputs into the model for the upcoming course. This work will be broken into the following steps:

1. Get the model's predictions on the full dataset.
2. Impute the constant fare rate of \$52 for all trips with rate codes of `2`.
3. Check the model's performance on the full dataset.
4. Save the final predictions and `mean_duration` and `mean_distance` columns for downstream use.

5.0.1 1. Predict on full dataset

[53]:
```
X_scaled = scaler.transform(X)
y_preds_full = lr.predict(X_scaled)
```

5.0.2 2. Impute ratecode 2 fare

The data dictionary says that the `RatecodeID` column captures the following information:

1 = standard rate
2 = JFK (airport)
3 = Newark (airport)
4 = Nassau or Westchester
5 = Negotiated fare
6 = Group ride

This means that some fares don't need to be predicted. They can simply be imputed based on their rate code. Specifically, all rate codes of `2` can be imputed with $52, as this is a flat rate for JFK airport.

The other rate codes have some variation (not shown here, but feel free to check for yourself). They are not a fixed rate, so these fares will remain untouched.

Impute `52` at all predictions where `RatecodeID` is `2`.

[54]:
```
# Create a new df containing just the RatecodeID col from the whole dataset
final_preds = df[['RatecodeID']].copy()

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

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

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

[54]:

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

5.0.3 Check performance on full dataset

[55]:
```
final_preds = final_preds['y_preds_full']
print('R^2:', r2_score(y, final_preds))
print('MAE:', mean_absolute_error(y, final_preds))
print('MSE:', mean_squared_error(y, final_preds))
print('RMSE:',np.sqrt(mean_squared_error(y, final_preds)))
```

```
R^2: 0.8910853978683975
MAE: 1.992506252269974
MSE: 12.101575504689935
RMSE: 3.4787318816905013
```

5.0.4 Save final predictions with `mean_duration` and `mean_distance` columns

[56]:
```
# Combine means columns with predictions column
nyc_preds_means = df[['mean_duration', 'mean_distance']].copy()
nyc_preds_means['predicted_fare'] = final_preds

nyc_preds_means.head()
```

[56]:

	mean_duration	mean_distance	predicted_fare
0	22.847222	3.521667	16.434245
1	24.470370	3.108889	16.052218
2	7.250000	0.881429	7.053706
3	30.250000	3.700000	18.731650
4	14.616667	4.435000	15.845642

Save as a csv file

6 NOTES

This notebook was designed for teaching purposes. As such, there are some things to note that differ from best practice or from how tasks are typically performed.

1. When the `mean_distance` and `mean_duration` columns were computed, the means were calculated from the entire dataset. These same columns were then used to train a model that was used to predict on a test set. A test set is supposed to represent entirely new data that the model has not seen before, but in this case, some of its predictor variables were derived using data that *was* in the test set. This is known as **data leakage**. Data leakage is when information from your training data contaminates the test data. If your model has unexpectedly high scores, there is a good chance that there was some data leakage. To avoid data leakage in this modeling process, it would be best to compute the means using only the training set and then copy those into the test set, thus preventing values from the test set from being included in the computation of the means. This would have created some problems because it's very likely that some combinations of pickup-dropoff locations would

only appear in the test data (not the train data). This means that there would be NaNs in the test data, and further steps would be required to address this. In this case, the data leakage improved the R2 score by ~0.03.

2. Imputing the fare amount for `RatecodeID 2` after training the model and then calculating model performance metrics on the post-imputed data is not best practice. It would be better to separate the rides that did *not* have rate codes of 2, train the model on that data specifically, and then add the `RatecodeID 2` data (and its imputed rates) *after*. This would prevent training the model on data that you don't need a model for, and would likely result in a better final model. However, the steps were combined for simplicity.
3. Models that predict values to be used in another downstream model are common in data science workflows. When models are deployed, the data cleaning, imputations, splits, predictions, etc. are done using modeling pipelines. Pandas was used here to granularize and explain the concepts of certain steps, but this process would be streamlined by machine learning engineers. The ideas are the same, but the implementation would differ. Once a modeling workflow has been validated, the entire process can be automated, often with no need for pandas and no need to examine outputs at each step. This entire process would be reduced to a page of code.

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.