In [1]:
```python
#Package for numerics and dataframe
import pandas as pd
import numpy as np

#package for visualization
import seaborn as sns
import matplotlib.pyplot as plt

#package for date conversion
from datetime import datetime
from datetime import date
from datetime import timedelta

#package for OLS, MLR, Confusion matrix
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

import warnings

# Use the warnings module to filter out specific warnings
warnings.filterwarnings("ignore")

# Make sure to disable the scroll bar
%matplotlib inline

# Set the context to control the plot size
sns.set_context("notebook")
```

In [2]:
```
df = pd.read_csv(r"C:\Users\mani ganesh\Downloads\taxi data\2017_Yellow_Tax
df
```

Out[2]:

	Unnamed: 0	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count
0	24870114	2	03/25/2017 8:55:43 AM	03/25/2017 9:09:47 AM	6
1	35634249	1	04/11/2017 2:53:28 PM	04/11/2017 3:19:58 PM	1
2	106203690	1	12/15/2017 7:26:56 AM	12/15/2017 7:34:08 AM	1
3	38942136	2	05/07/2017 1:17:59 PM	05/07/2017 1:48:14 PM	1
4	30841670	2	04/15/2017 11:32:20 PM	04/15/2017 11:49:03 PM	1
...	...	...	...	...	...
22694	14873857	2	02/24/2017 5:37:23 PM	02/24/2017 5:40:39 PM	3
22695	66632549	2	08/06/2017 4:43:59 PM	08/06/2017 5:24:47 PM	1
22696	74239933	2	09/04/2017 2:54:14 PM	09/04/2017 2:58:22 PM	1
22697	60217333	2	07/15/2017 12:56:30 PM	07/15/2017 1:08:26 PM	1
22698	17208911	1	03/02/2017 1:02:49 PM	03/02/2017 1:16:09 PM	1

22699 rows × 18 columns

In [4]:
```
df.size
```

Out[4]:
```
408582
```

In [5]:
```
df.describe()
```

Out[5]:

	Unnamed: 0	VendorID	passenger_count	trip_distance	RatecodeID	PULocatio
count	2.269900e+04	22699.000000	22699.000000	22699.000000	22699.000000	22699.000
mean	5.675849e+07	1.556236	1.642319	2.913313	1.043394	162.412
std	3.274493e+07	0.496838	1.285231	3.653171	0.708391	66.633
min	1.212700e+04	1.000000	0.000000	0.000000	1.000000	1.000
25%	2.852056e+07	1.000000	1.000000	0.990000	1.000000	114.000
50%	5.673150e+07	2.000000	1.000000	1.610000	1.000000	162.000
75%	8.537452e+07	2.000000	2.000000	3.060000	1.000000	233.000
max	1.134863e+08	2.000000	6.000000	33.960000	99.000000	265.000

In [6]:
```
df.info()
```

```
 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
```

In [7]:
```
df.nunique()
```

Out[7]:
```
Unnamed: 0               22699
VendorID                     2
tpep_pickup_datetime     22687
tpep_dropoff_datetime    22688
passenger_count              7
trip_distance             1545
RatecodeID                   6
store_and_fwd_flag           2
PULocationID               152
DOLocationID               216
payment_type                 4
fare_amount                185
extra                        6
mta_tax                      3
tip_amount                 742
tolls_amount                38
improvement_surcharge        3
total_amount              1369
dtype: int64
```

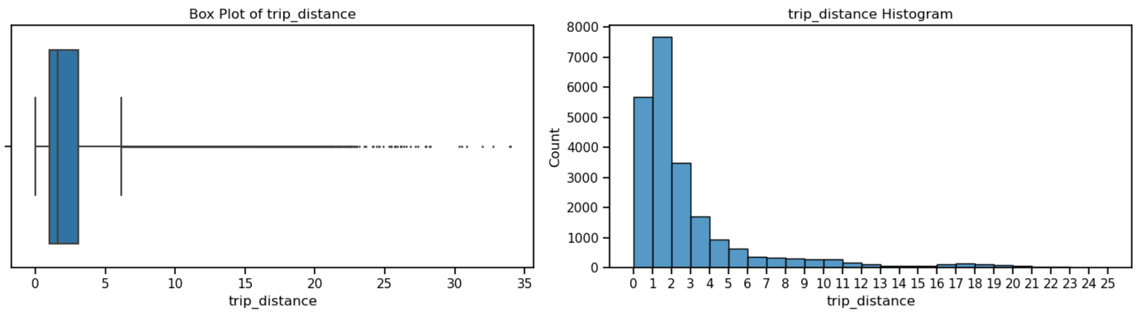
In [8]:
```
#converting data columns to datetime
df['tpep_pickup_datetime'] = pd.to_datetime(df['tpep_pickup_datetime'])
df['tpep_dropoff_datetime'] = pd.to_datetime(df['tpep_dropoff_datetime'])
```

In [9]:
```python
# Create a figure with two subplots
fig, axes = plt.subplots(1, 2, figsize=(14, 4))

# Box plot of trip distance
sns.boxplot(x=df['trip_distance'], fliersize=1, ax=axes[0])
axes[0].set_title('Box Plot of trip_distance')

# Histogram of trip distance
ax = sns.histplot(df['trip_distance'], bins=range(0, 26, 1), ax=axes[1])
ax.set_xticks(range(0, 26, 1))
ax.set_xticklabels(range(0, 26, 1))
axes[1].set_title('trip_distance Histogram')

# Adjust spacing between subplots
plt.tight_layout()
```



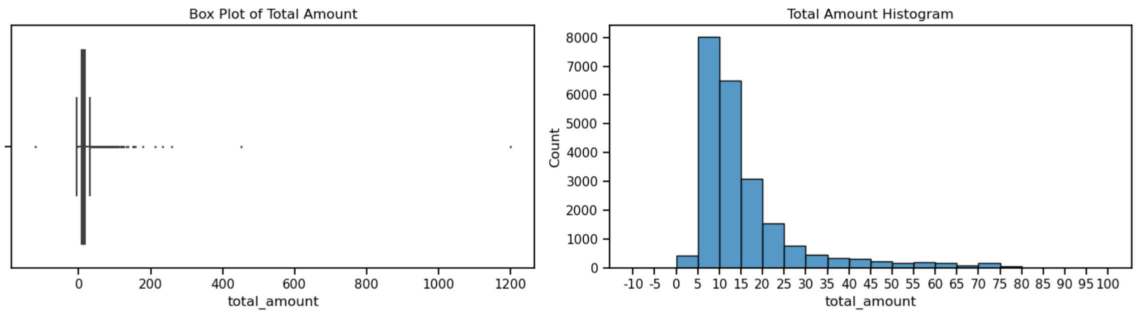
The majority of trips were journeys of less than two miles. The number of trips falls away steeply as the distance traveled increases beyond two miles

In [10]:
```python
# Create a figure with two subplots
fig, axes = plt.subplots(1, 2, figsize=(14, 4))

# Box plot of total_amount
sns.boxplot(x=df['total_amount'], fliersize=1, ax=axes[0])
axes[0].set_title('Box Plot of Total Amount')

# Histogram of total_amount
ax = sns.histplot(df['total_amount'], bins=range(-10, 101, 5), ax=axes[1])
ax.set_xticks(range(-10, 101, 5))
ax.set_xticklabels(range(-10, 101, 5))
axes[1].set_title('Total Amount Histogram')

# Adjust spacing between subplots
plt.tight_layout()
```



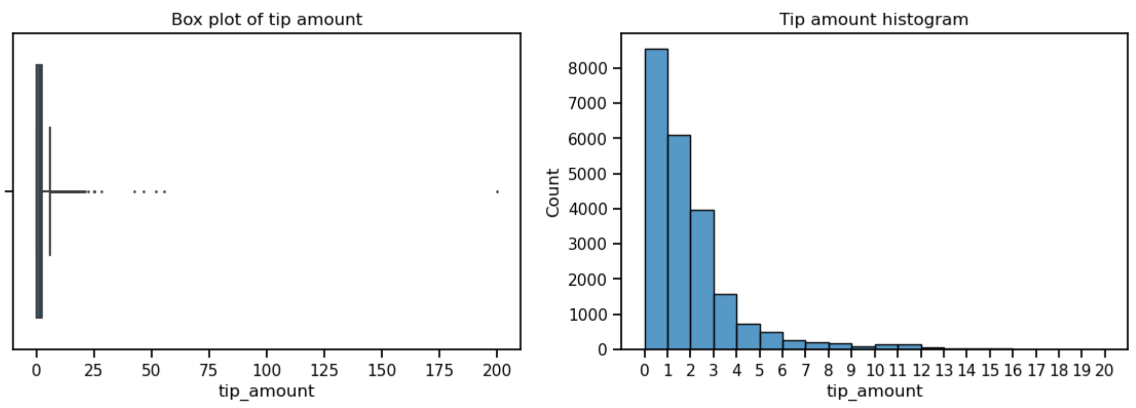
The total cost of each trip also has a distribution that skews right, with most costs falling in the $5-15 range.

In [11]:
```python
#create a figure with two subplots
fig, axes = plt.subplots(1,2, figsize = (14,4))

#box plot of tip amount
sns.boxplot(x=df['tip_amount'],fliersize=1, ax= axes[0])
axes[0].set_title('Box plot of tip amount')

#histogram of tip amount
ax = sns.histplot(df['tip_amount'], bins = range(0,21,1))
ax.set_xticks(range(0,21,1))
ax.set_xticklabels(range(0,21,1))
axes[1].set_title('Tip amount histogram')
```

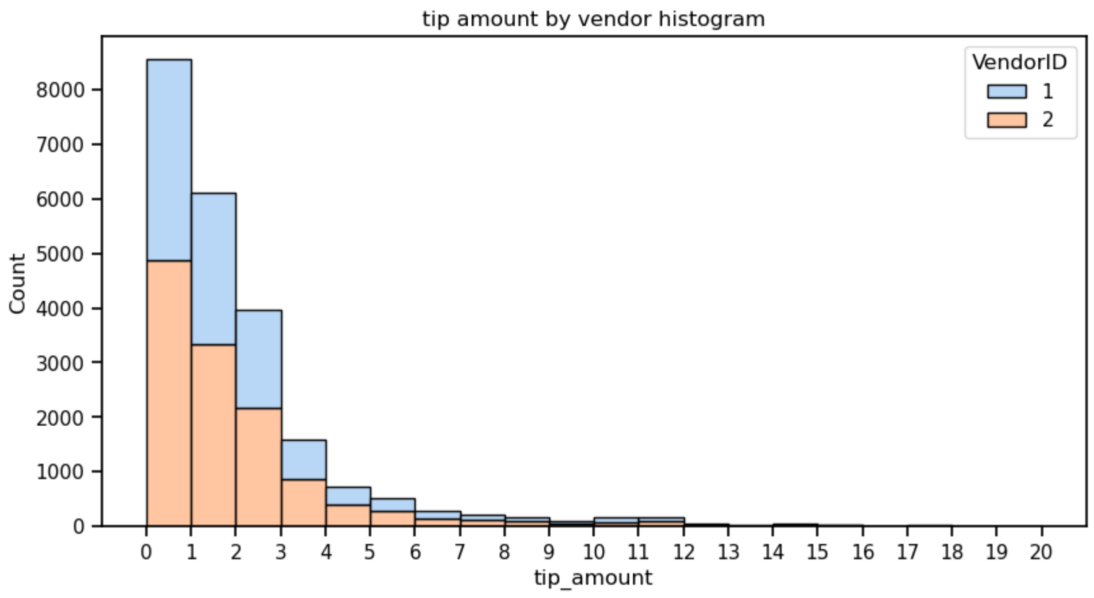
Out[11]:
```
Text(0.5, 1.0, 'Tip amount histogram')
```



The distribution for tip amount is right-skewed, with nearly all the tips in the $0-3 range

In [12]:
```
#histogram of tip_amount by vendor
plt.figure(figsize = (10,5))
ax = sns.histplot(data = df, x = 'tip_amount', bins=range(0,21,1),
                  hue='VendorID',
                  multiple='stack',
                  palette='pastel')
ax.set_xticks(range(0,21,1))
ax.set_xticklabels(range(0,21,1))
plt.title('tip amount by vendor histogram')
```

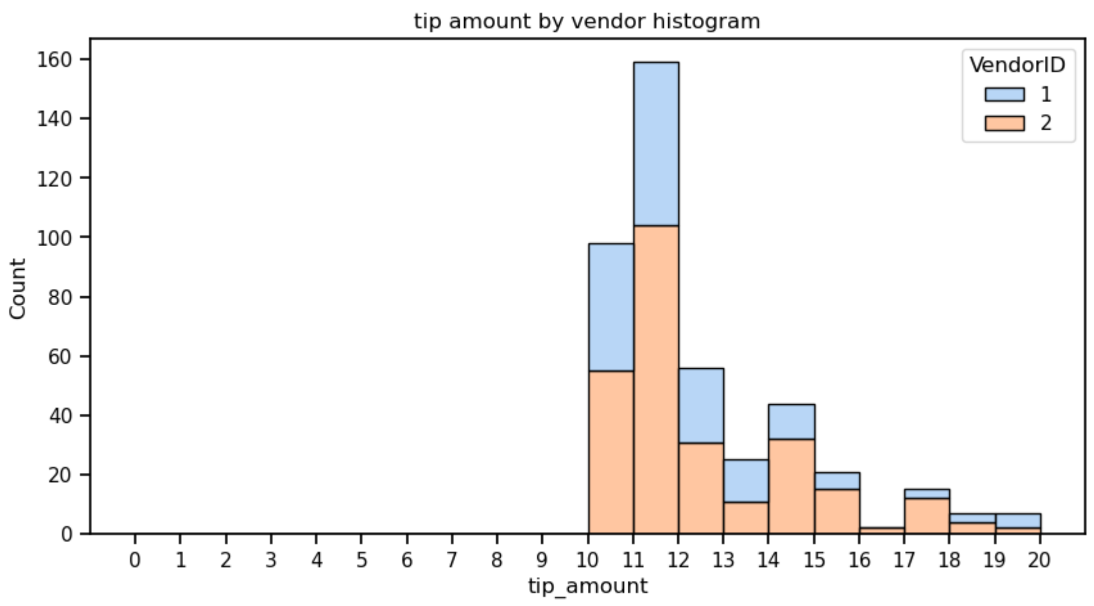
Out[12]:
```
Text(0.5, 1.0, 'tip amount by vendor histogram')
```



There are no noticeable aberrations in the distribution of tips between the two vendors in the dataset. Vendor two has a slightly higher share of the rides, and this proportion is approximately maintained for all tip amounts.

In [13]:
```
#histogram of tip_amount by vendor for ips > 10
tips_over_ten = df[df['tip_amount'] > 10]
plt.figure(figsize = (10,5))
ax = sns.histplot(data = tips_over_ten, x = 'tip_amount', bins=range(0,21,1
                  hue='VendorID',
                  multiple='stack',
                  palette='pastel')
ax.set_xticks(range(0,21,1))
ax.set_xticklabels(range(0,21,1))
plt.title('tip amount by vendor histogram')
```

Out[13]:
```
Text(0.5, 1.0, 'tip amount by vendor histogram')
```



The proportions are maintained even at these higher tip amounts, with the exception being at highest extremity.

In [14]:
```
#unique values in the passenger count
df['passenger_count'].value_counts()
```

Out[14]:
```
1    16117
2     3305
5     1143
3      953
6      693
4      455
0       33
Name: passenger_count, dtype: int64
```

Nearly two thirds of the rides were single occupancy, though there were still nearly 700 rides with as many as six passengers. Also, there are 33 rides with an occupancy count of zero, which doesn’t make sense. These would likely be dropped

In [15]:
```python
# Calculate mean tips by passenger_count
mean_tips_by_passenger_count = df.groupby(['passenger_count']).mean(numeric
mean_tips_by_passenger_count
```

Out[15]:

	tip_amount
passenger_count	
0	2.135758
1	1.848920
2	1.856378
3	1.716768
4	1.530264
5	1.873185
6	1.720260

In [16]:
```python
mean_tips_by_passenger_count.tip_amount.mean()
```

Out[16]:
```
1.8116474806258194
```

Mean tip amount varies very little by passenger count. Although it does drop noticeably for four-passenger rides, it’s expected that there would be a higher degree of fluctuation because rides with four passengers were the least plentiful in the dataset (aside from rides with zero passengers).

In [17]:
```python
#Create a month and day column

df['month'] = df ['tpep_pickup_datetime'].dt.month_name()

df['day'] = df ['tpep_pickup_datetime'].dt.day_name()
```

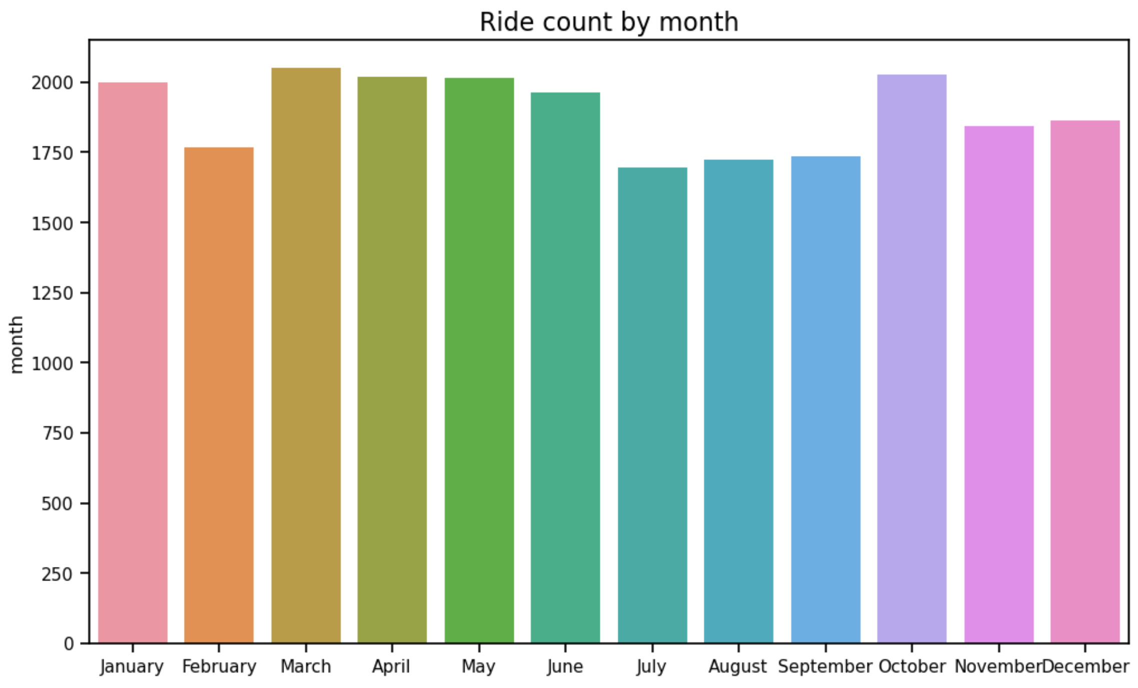
In [18]:
```python
#total number of rides for each month
monthly_rides = df['month'].value_counts()
monthly_rides
```

Out[18]:
```
March        2049
October      2027
April        2019
May          2013
January      1997
June         1964
December     1863
November     1843
February     1769
September    1734
August       1724
July         1697
Name: month, dtype: int64
```

```
In [19]: #reordering the months
         month_order = ['January', 'February', 'March', 'April', 'May', 'June',
                        'July','August', 'September', 'October', 'November', 'Decemb
         monthly_rides = monthly_rides.reindex(index=month_order)
         monthly_rides
```

```
Out[19]: January      1997
         February     1769
         March        2049
         April        2019
         May          2013
         June         1964
         July         1697
         August       1724
         September    1734
         October      2027
         November     1843
         December     1863
         Name: month, dtype: int64
```

```
In [20]: #bar plot of total rides per month
         plt.figure(figsize=(12,7))
         ax = sns.barplot(x=monthly_rides.index, y=monthly_rides)
         ax.set_xticklabels(month_order)
         plt.title('Ride count by month', fontsize=16);
```

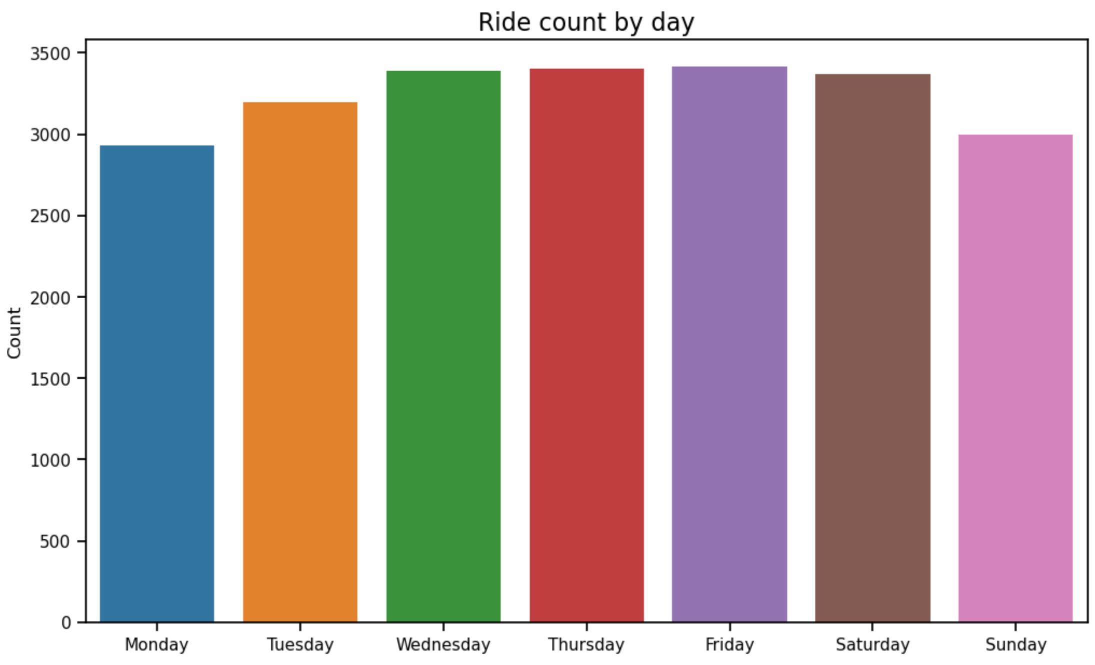


Monthly rides are fairly consistent, with notable dips in July, August, and September, and also in February.

In [21]:
```
# Rides by day
daily_rides = df['day'].value_counts()
day_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday','Saturd
daily_rides = daily_rides.reindex(index=day_order)
daily_rides
```

Out[21]:
```
Monday       2931
Tuesday      3198
Wednesday    3390
Thursday     3402
Friday       3413
Saturday     3367
Sunday       2998
Name: day, dtype: int64
```

In [22]:
```
#bar plot for ride count by day
plt.figure(figsize=(12,7))
ax = sns.barplot(x=daily_rides.index, y=daily_rides)
ax.set_xticklabels(day_order)
ax.set_ylabel('Count')
plt.title('Ride count by day', fontsize=16);
```



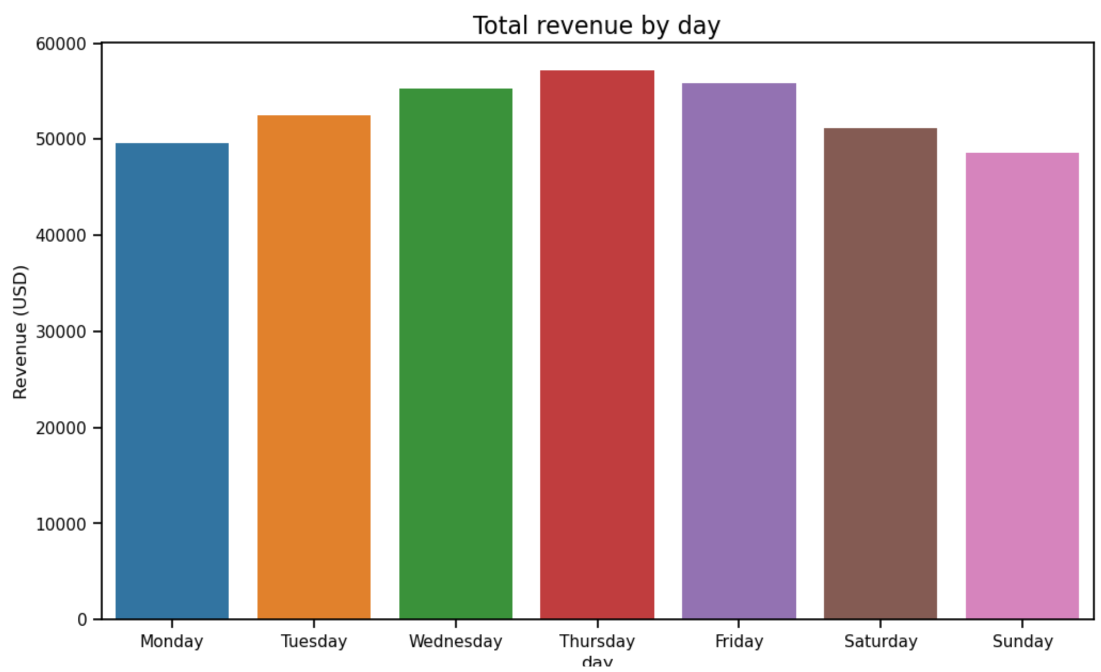
Wednesday through Saturday had the highest number of daily rides, while Sunday and Monday had the least.

In [23]:
```
# total revenue by day
day_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday','Saturd
total_amount_day = df.groupby('day').sum(numeric_only = True)[['total_amoun
total_amount_day = total_amount_day.reindex(index=day_order)
total_amount_day
```

Out[23]:

	total_amount
day	
Monday	49574.37
Tuesday	52527.14
Wednesday	55310.47
Thursday	57181.91
Friday	55818.74
Saturday	51195.40
Sunday	48624.06

In [24]:
```
# bar plot of total revenue by day
plt.figure(figsize=(12,7))
ax = sns.barplot(x=total_amount_day.index, y=total_amount_day['total_amount
ax.set_xticklabels(day_order)
ax.set_ylabel('Revenue (USD)')
plt.title('Total revenue by day', fontsize=16);
```



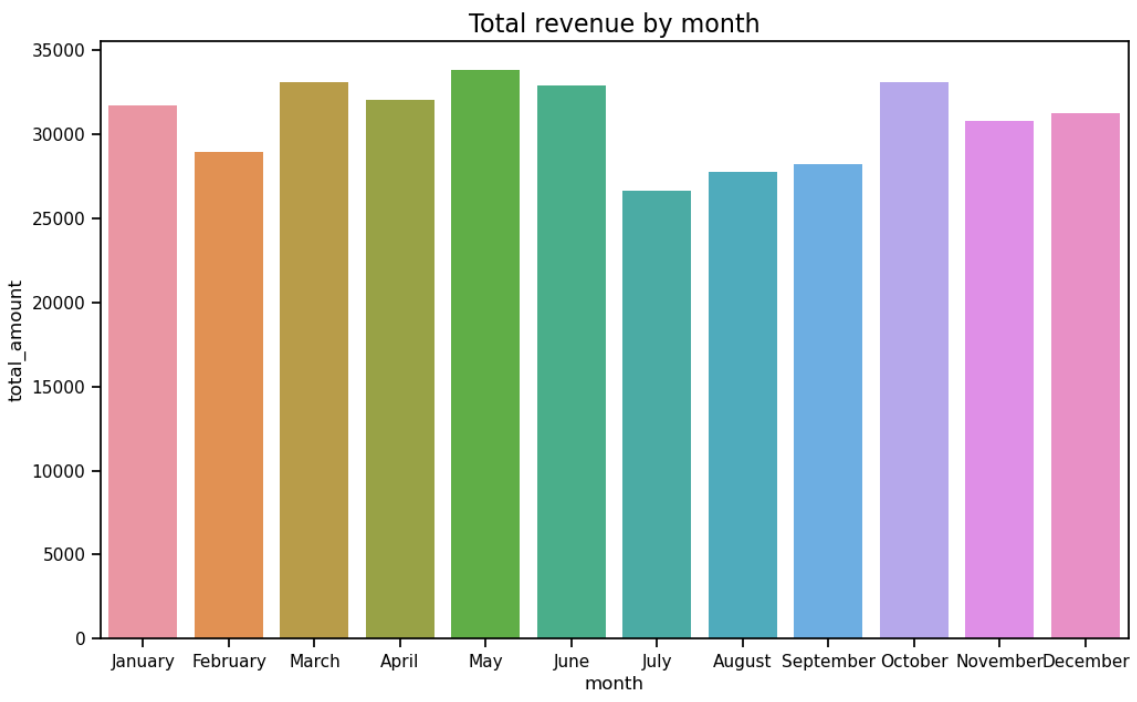
Thursday had the highest gross revenue of all days, and Sunday and Monday had the least. Interestingly, although Saturday had only 35 fewer rides than Thursday, its gross revenue was ~$6,000 less than Thursday's—more than a 10% drop.

In [25]:
```
#total revenue by month
total_amount_month = df.groupby('month').sum(numeric_only = True)[['total_a
total_amount_month = total_amount_month.reindex(index=month_order)
total_amount_month
```

Out[25]:

	total_amount
month	
January	31735.25
February	28937.89
March	33085.89
April	32012.54
May	33828.58
June	32920.52
July	26617.64
August	27759.56
September	28206.38
October	33065.83

In [26]:
```
#bar plot of total revenue by month
plt.figure(figsize=(12,7))
ax = sns.barplot(x=total_amount_month.index,y=total_amount_month['total_amo
plt.title('Total revenue by month', fontsize=16);
```



Monthly revenue generally follows the pattern of monthly rides, with noticeable dips in July, August, and September, and also one in February.

In [27]:
```
#number unique location drop_off id's
df['DOLocationID'].nunique()
```

Out[27]:
```
216
```

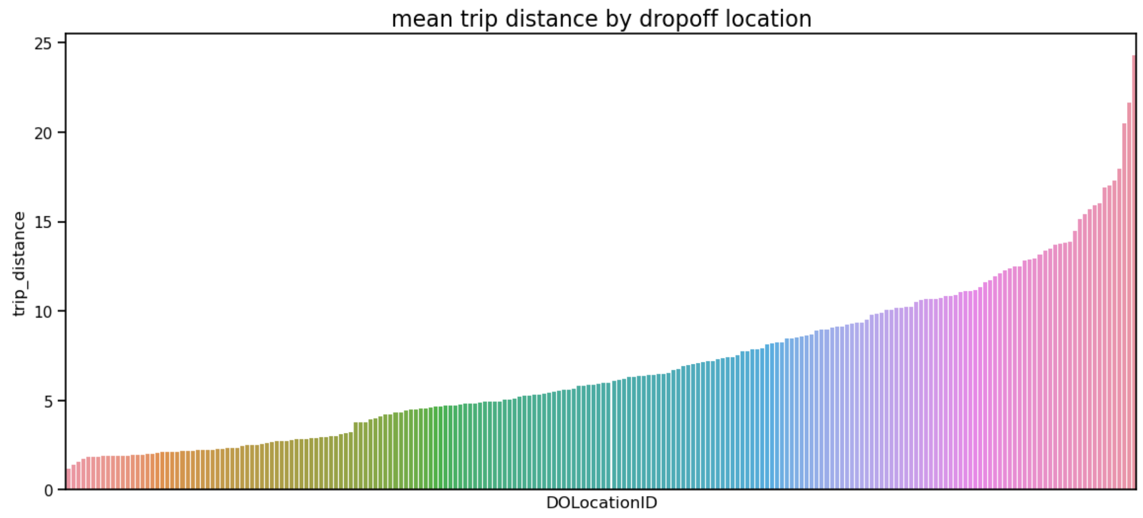
In [28]:
```
# Calculate the mean trip distance for each drop-off location
distance_by_dropoff = df.groupby('DOLocationID').mean()[['trip_distance']]

# Sort the results in descending order by mean trip distance
distance_by_dropoff = distance_by_dropoff.sort_values(by='trip_distance')
distance_by_dropoff
```

Out[28]:

	trip_distance
DOLocationID	
207	1.200000
193	1.390556
237	1.555494
234	1.727806
137	1.818852
...	...
51	17.310000
11	17.945000
210	20.500000
29	21.650000

In [29]:
```python
#Bar plot of mean trip distances by drop-off location
plt.figure(figsize=(14,6))
ax= sns.barplot(x=distance_by_dropoff.index,
               y=distance_by_dropoff['trip_distance'],
               order=distance_by_dropoff.index)
ax.set_xticklabels([])
ax.set_xticks([])
plt.title('mean trip distance by dropoff location', fontsize = 16);
```



the drop-off points are relatively evenly distributed over the terrain

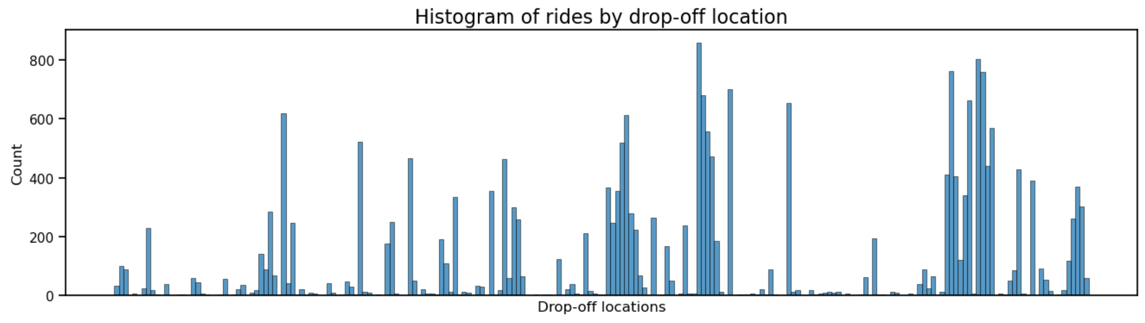
In [30]:
```python
#drop off locations are consecutively numbered
df['DOLocationID'].max()-len(set(df['DOLocationID']))
```

Out[30]:
```
49
```

There are 49 numbers that do not represent a drop-off location.

In [31]:
```
plt.figure(figsize=(16,4))
# DOLocationID column is numeric, so sort in ascending order
sorted_dropoffs = df['DOLocationID'].sort_values()
# Convert to string
sorted_dropoffs = sorted_dropoffs.astype('str')

sns.histplot(sorted_dropoffs, bins=range(0, df['DOLocationID'].max()+1, 1))
plt.xticks([])
plt.xlabel('Drop-off locations')
plt.title('Histogram of rides by drop-off location', fontsize=16);
```



Out of the 200+ drop-off locations, a disproportionate number of locations receive the majority of the traffic, while all the rest get relatively few trips. It’s likely that these high-traffic locations are near popular tourist attractions.

In [32]:
```
df.head()
```

Out[32]:

	Unnamed: 0	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	trip_
0	24870114	2	2017-03-25 08:55:43	2017-03-25 09:09:47	6	
1	35634249	1	2017-04-11 14:53:28	2017-04-11 15:19:58	1	
2	106203690	1	2017-12-15 07:26:56	2017-12-15 07:34:08	1	
3	38942136	2	2017-05-07 13:17:59	2017-05-07 13:48:14	1	
4	30841670	2	2017-04-15 23:32:20	2017-04-15 23:49:03	1	

Relationship between fare amount and payment type

In [33]:
```
from scipy import stats
```

```
In [34]: df.describe(include='all')
```

Out[34]:

	Unnamed: 0	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passen
count	2.269900e+04	22699.000000	22699	22699	226
unique	NaN	NaN	22687	22688	
top	NaN	NaN	2017-07-03 15:45:19	2017-10-18 20:07:45	
freq	NaN	NaN	2	2	
first	NaN	NaN	2017-01-01 00:08:25	2017-01-01 00:17:20	
last	NaN	NaN	2017-12-31 23:45:30	2017-12-31 23:49:24	
mean	5.675849e+07	1.556236	NaN	NaN	
std	3.274493e+07	0.496838	NaN	NaN	
min	1.212700e+04	1.000000	NaN	NaN	
25%	2.852056e+07	1.000000	NaN	NaN	
50%	5.673150e+07	2.000000	NaN	NaN	

In the dataset, payment_type is encoded in integers:

- 1: Credit card
- 2: Cash
- 3: No charge
- 4: Dispute

```
In [35]: df.groupby('payment_type')['fare_amount'].mean()
```

```
Out[35]: payment_type
         1    13.429748
         2    12.213546
         3    12.186116
         4     9.913043
         Name: fare_amount, dtype: float64
```

Hypothesis Testing

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

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

```
In [36]: #hypothesis test
         credit_card = df[df['payment_type']==1]['fare_amount']
         cash = df[df['payment_type']==2]['fare_amount']
         stats.ttest_ind(a=credit_card, b=cash, equal_var=False)
```

```
Out[36]: Ttest_indResult(statistic=6.866800855655372, pvalue=6.797387473030518e-12)
```

In a t-test, one of the assumptions is that the variances of the two groups being compared are equal. This is known as the assumption of homogeneity of variances or homoscedasticity. However, in some cases, it may not be reasonable to assume that the variances of the two groups are equal. When you have reason to believe that the variances are not equal, you can set equal_var=False to perform a t-test that does not assume equal variances.

Choose 5% as the significance level

Since the p-value is significantly smaller than the significance level of 5%, you reject the null hypothesis

Conclusion - that there is a statistically significant difference in the average fare amount between customers who use credit cards and customers who use cash

Build a multiple linear regression model to predict taxi fares using existing data that was collected over the course of a year.

In [37]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 20 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  month                  22699 non-null  object        
 19  day                    22699 non-null  object        
dtypes: datetime64[ns](2), float64(8), int64(7), object(3)
memory usage: 3.5+ MB
```

In [38]:
```
df.shape
```

Out[38]:
```
(22699, 20)
```

In [39]:
```
df.drop_duplicates().shape
```

Out[39]:
```
(22699, 20)
```

```
In [40]: df.isna().sum()
```

```
Out[40]: 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
         month                    0
         day                      0
         dtype: int64
```

```
In [41]: # Check the format of the data
         df['tpep_dropoff_datetime'][0]
```

```
Out[41]: Timestamp('2017-03-25 09:09:47')
```

```
In [42]: # Convert pickup and dropoff to datetime format
         df['tpep_pickup_datetime'] = pd.to_datetime(df['tpep_pickup_datetime'],
                                                      format='%m/%d/%Y %I:%M:%S %p')
         df['tpep_dropoff_datetime'] = pd.to_datetime(df['tpep_dropoff_datetime'],
                                                       format='%m/%d/%Y %I:%M:%S %p')
```

```
In [43]: #new duration column
         df['duration'] = (df['tpep_dropoff_datetime']- df['tpep_pickup_datetime'])/
```

In [44]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 21 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
```

In [45]:
```
#fare amount outliers
df['fare_amount'].describe()
```

Out[45]:
```
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
```

In [46]:
```
df[df['fare_amount'] > 100]
```

6064	49894023	2	2017-06-13 12:30:22	2017-06-13 13:37:51
8476	11157412	1	2017-02-06 05:50:10	2017-02-06 05:51:08
9280	51810714	2	2017-06-18 23:33:25	2017-06-19 00:12:38
10291	76319330	2	2017-09-11 11:41:04	2017-09-11 12:18:58
11269	51920669	1	2017-06-19 00:51:17	2017-06-19 00:52:12
12511	107108848	2	2017-12-17 18:24:24	2017-12-17 18:24:42
13621	93330154	1	2017-11-04 13:32:14	2017-11-04 14:18:50
13861	40523668	2	2017-05-19 08:20:21	2017-05-19 09:20:30
15474	55538852	2	2017-06-06 20:55:01	2017-06-06 20:55:06
16379	101198443	2	2017-11-30 10:41:11	2017-11-30 11:31:45
20312	107558404	2	2017-12-19 09:40:46	2017-12-19 09:40:55

13 rows × 21 columns

In [47]:
```
df['trip_distance'].describe()
```

Out[47]:
```
count    22699.000000
mean         2.913313
std          3.653171
min          0.000000
25%          0.990000
50%          1.610000
75%          3.060000
max         33.960000
Name: trip_distance, dtype: float64
```

In [48]:
```
df[(df['fare_amount'] > 100) & (df['trip_distance'] < 2.9)].head(10)
```

Out[48]:

	Unnamed: 0	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count
8476	11157412	1	2017-02-06 05:50:10	2017-02-06 05:51:08	1
11269	51920669	1	2017-06-19 00:51:17	2017-06-19 00:52:12	2
12511	107108848	2	2017-12-17 18:24:24	2017-12-17 18:24:42	1
15474	55538852	2	2017-06-06 20:55:01	2017-06-06 20:55:06	1
20312	107558404	2	2017-12-19 09:40:46	2017-12-19 09:40:55	2

5 rows × 21 columns

This data filter the fare amount which is greater than 100 and trip distance less than the mean value(2.9) as it not seems to be correct value this are the outliers

In [49]:
```
df = df[~((df['fare_amount'] > 100) & (df['trip_distance'] < 2.9))]
df
```

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
...	...	...	...	...
22694	14873857	2	2017-02-24 17:37:23	2017-02-24 17:40:39
22695	66632549	2	2017-08-06 16:43:59	2017-08-06 17:24:47
22696	74239933	2	2017-09-04 14:54:14	2017-09-04 14:58:22
22697	60217333	2	2017-07-15 12:56:30	2017-07-15 13:08:26
22698	17208911	1	2017-03-02 13:02:49	2017-03-02 13:16:09

```
In [50]: df[df['fare_amount'] < 0]
```

5448	28459983	2	2017-04-06 12:50:26	2017-04-06 12:52:39
5758	833948	2	2017-01-03 20:15:23	2017-01-03 20:15:39
8204	91187947	2	2017-10-28 20:39:36	2017-10-28 20:41:59
10281	55302347	2	2017-06-05 17:34:25	2017-06-05 17:36:29
11204	58395501	2	2017-07-09 07:20:59	2017-07-09 07:23:50
12944	29059760	2	2017-04-08 00:00:16	2017-04-08 23:15:57
14714	109276092	2	2017-12-24 22:37:58	2017-12-24 22:41:08
17602	24690146	2	2017-03-24 19:31:13	2017-03-24 19:34:49
18565	43859760	2	2017-05-22 15:51:20	2017-05-22 15:52:22
20317	75926915	2	2017-09-09 22:59:51	2017-09-09 23:02:06
20698	14668209	2	2017-02-24 00:38:17	2017-02-24 00:42:05

```
In [51]: #remove the outliers when fare amount < 0
         df = df[~(df['fare_amount'] < 0)]
         df
```

Out[51]:

	Unnamed: 0	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_cou
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	
...	...	...	...	...	
22694	14873857	2	2017-02-24 17:37:23	2017-02-24 17:40:39	
22695	66632549	2	2017-08-06 16:43:59	2017-08-06 17:24:47	
22696	74239933	2	2017-09-04 14:54:14	2017-09-04 14:58:22	
22697	60217333	2	2017-07-15 12:56:30	2017-07-15 13:08:26	

```
In [52]: df['duration'].describe()

Out[52]: count    22680.000000
         mean        16.965236
         std         61.341513
         min        -16.983333
         25%          6.666667
         50%         11.183333
         75%         18.383333
         max       1439.550000
         Name: duration, dtype: float64
```

```
In [53]: df[df['duration'] < 0]
```

Out[53]:

	Unnamed: 0	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	tı
9356	93542707	1	2017-11-05 01:23:08	2017-11-05 01:06:09	1	

1 rows × 21 columns

```
In [54]: #remove the outliers when duartion < 0
         df = df[~(df['duration'] < 0)]
         df
```

Out[54]:

	Unnamed: 0	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count
0	24870114	2	2017-03-25 08:55:43	2017-03-25 09:09:47	6
1	35634249	1	2017-04-11 14:53:28	2017-04-11 15:19:58	1
2	106203690	1	2017-12-15 07:26:56	2017-12-15 07:34:08	1
3	38942136	2	2017-05-07 13:17:59	2017-05-07 13:48:14	1
4	30841670	2	2017-04-15 23:32:20	2017-04-15 23:49:03	1
...	...	...	...	...	...
22694	14873857	2	2017-02-24 17:37:23	2017-02-24 17:40:39	3
22695	66632549	2	2017-08-06 16:43:59	2017-08-06 17:24:47	1
22696	74239933	2	2017-09-04 14:54:14	2017-09-04 14:58:22	1
22697	60217333	2	2017-07-15 12:56:30	2017-07-15 13:08:26	1
22698	17208911	1	2017-03-02 13:02:49	2017-03-02 13:16:09	1

22679 rows × 21 columns

Feature Engineering

```
In [55]: # Create `pickup_dropoff` column
         df['pickup_dropoff'] = df['PULocationID'].astype(str) + ' ' +df['DOLocation
         df['pickup_dropoff'].head(2)
```

```
Out[55]: 0    100 231
         1     186 43
         Name: pickup_dropoff, dtype: object
```

Trip distance is not same even if the pickup and dropoff point is same For example:

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.

In [56]:
```
grouped = df.groupby('pickup_dropoff').mean(numeric_only=True)[['trip_dista
grouped[:5]
```

Out[56]:

	trip_distance
pickup_dropoff	
1 1	2.433333
10 148	15.700000
100 1	16.890000
100 100	0.253333
100 107	1.180000

In [57]:
```
# 1. Converting `grouped` to a dictionary
grouped_dict = grouped.to_dict()
# 2. Reassign to only contain the inner dictionary
grouped_dict = grouped_dict['trip_distance']
```

In [58]:
```
# 1. Create a mean_distance column that is a copy of the pickup_dropoff hel
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']
```

Out[58]:

	mean_distance
0	3.521667
4909	3.521667
16636	3.521667
18134	3.521667
19761	3.521667
20581	3.521667

In [59]:
```
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']]
```

Out[59]:

	mean_duration
0	22.847222
4909	22.847222
16636	22.847222
18134	22.847222
19761	22.847222
20581	22.847222

In [60]:
```
# creating month and day column
df['day'] = df['tpep_pickup_datetime'].dt.day_name()

df['month'] = df['tpep_pickup_datetime'].dt.strftime('%b')
```

In [61]:
```
#create rush hour column
df['rush_hour'] = df['tpep_pickup_datetime'].dt.hour

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

In [62]:
```
#create a function
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
```

```
In [63]:  # Apply the `rush_hourizer()` function to the new column
          df.loc[(df.day != 'saturday') & (df.day != 'sunday'), 'rush_hour'] = df.app
          df.head()
```

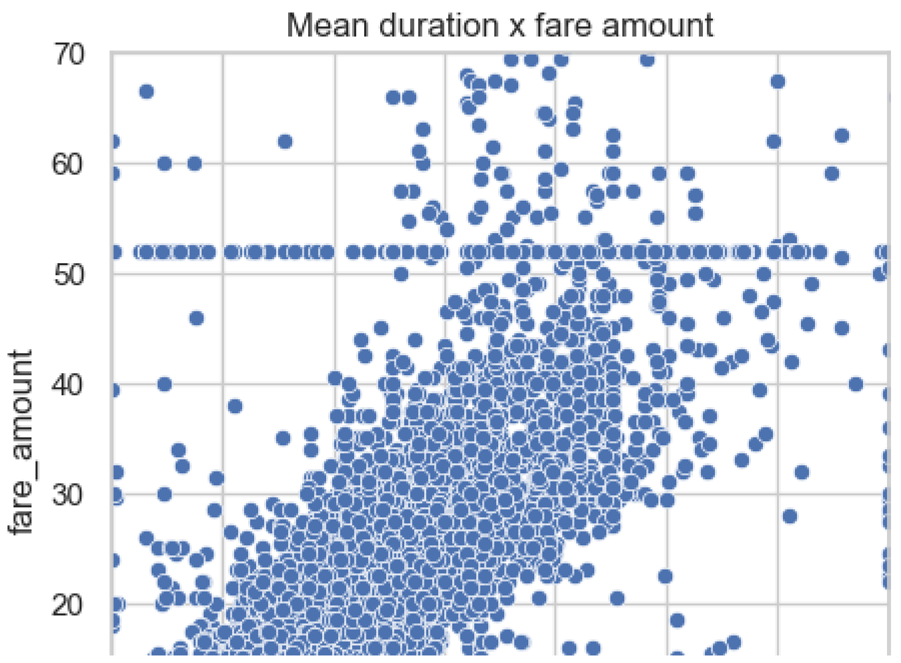
Out[63]:

	Unnamed: 0	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	trip_
0	24870114	2	2017-03-25 08:55:43	2017-03-25 09:09:47	6	
1	35634249	1	2017-04-11 14:53:28	2017-04-11 15:19:58	1	
2	106203690	1	2017-12-15 07:26:56	2017-12-15 07:34:08	1	
3	38942136	2	2017-05-07 13:17:59	2017-05-07 13:48:14	1	
4	30841670	2	2017-04-15 23:32:20	2017-04-15 23:49:03	1	

5 rows × 25 columns

```
In [ ]:
```

```
In [64]: # Create a scatter plot of duration and trip_distance, with a line of best _
         sns.set(style='whitegrid')
         f = plt.figure()
         f.set_figwidth(5)
         f.set_figheight(5)
         sns.scatterplot(x=df['mean_duration'], y=df['fare_amount'])
         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? What are the values and how many are there?

In [65]:
```
df[df['fare_amount'] > 50]['fare_amount'].value_counts().head()
```
Out[65]:
```
52.0    514
59.0      9
50.5      9
57.5      8
51.0      7
Name: fare_amount, dtype: int64
```

In [66]:
```
df[df['fare_amount']==52].head(30)
```
Out[66]:

	Unnamed: 0	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_coun
11	18600059	2	2017-03-05 19:15:30	2017-03-05 19:52:18	2
110	47959795	1	2017-06-03 14:24:57	2017-06-03 15:31:48	1
161	95729204	2	2017-11-11 20:16:16	2017-11-11 20:17:14	1
247	103404868	2	2017-12-06 23:37:08	2017-12-07 00:06:19	1
379	80479432	2	2017-09-24 23:45:45	2017-09-25 00:15:14	1
388	16226157	1	2017-02-28 18:30:05	2017-02-28 19:09:55	1
406	55253442	2	2017-06-05 12:51:58	2017-06-05 13:07:35	1
449	65900029	2	2017-08-03 22:47:14	2017-08-03 23:32:41	2
468	80904240	2	2017-09-26 13:48:26	2017-09-26 14:31:17	1
520	33706214	2	2017-04-23 21:34:48	2017-04-23 22:46:23	[illegible]

In [67]:
```
len(df[df['fare_amount'] == 52])
```
Out[67]:
```
514
```

In [68]:
```
len(df[(df['fare_amount'] == 52) & (df['pickup_dropoff'].str.contains("132"
```
Out[68]:
```
459
```

It seems that almost all of the trips in the 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 $5.76and$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.

Isolating model varibles

In [69]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 22679 entries, 0 to 22698
Data columns (total 25 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Unnamed: 0             22679 non-null  int64
 1   VendorID               22679 non-null  int64
 2   tpep_pickup_datetime   22679 non-null  datetime64[ns]
 3   tpep_dropoff_datetime  22679 non-null  datetime64[ns]
 4   passenger_count        22679 non-null  int64
 5   trip_distance          22679 non-null  float64
 6   RatecodeID             22679 non-null  int64
 7   store_and_fwd_flag     22679 non-null  object
 8   PULocationID           22679 non-null  int64
 9   DOLocationID           22679 non-null  int64
 10  payment_type           22679 non-null  int64
 11  fare_amount            22679 non-null  float64
 12  extra                  22679 non-null  float64
 13  mta_tax                22679 non-null  float64
 14  tip_amount             22679 non-null  float64
 15  tolls_amount           22679 non-null  float64
 16  improvement_surcharge  22679 non-null  float64
 17  total_amount           22679 non-null  float64
 18  month                  22679 non-null  object
 19  day                    22679 non-null  object
 20  duration               22679 non-null  float64
 21  pickup_dropoff         22679 non-null  object
 22  mean_distance          22679 non-null  float64
 23  mean_duration          22679 non-null  float64
 24  rush_hour              22679 non-null  int64
dtypes: datetime64[ns](2), float64(11), int64(8), object(4)
memory usage: 4.5+ MB
```

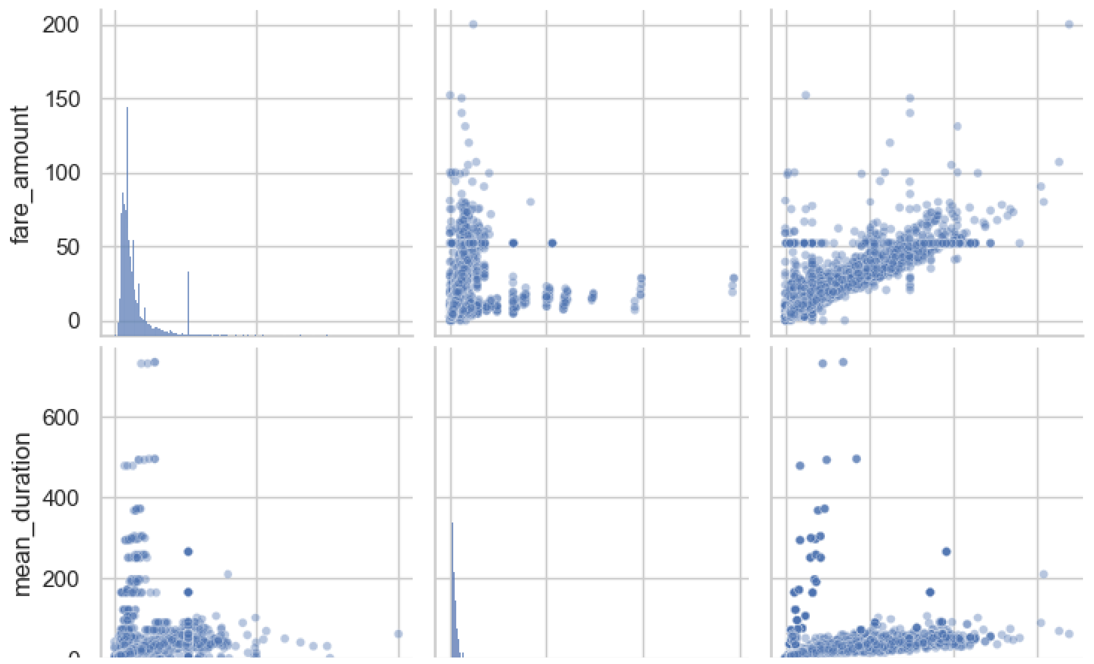
In [70]:
```
#create a copy of the data
df2 = df.copy()

columns_to_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'
]

df2 = df2.drop(columns=columns_to_drop, axis=1)
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 22679 entries, 0 to 22698
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   VendorID         22679 non-null  int64  
 1   passenger_count  22679 non-null  int64  
 2   fare_amount      22679 non-null  float64
 3   mean_distance    22679 non-null  float64
 4   mean_duration    22679 non-null  float64
 5   rush_hour        22679 non-null  int64  
dtypes: float64(3), int64(3)
memory usage: 1.2 MB
```

In [71]:
```
# pair plot
sns.pairplot(df2[['fare_amount', 'mean_duration', 'mean_distance']],
             plot_kws={'alpha':0.4, 'size':5},);
```



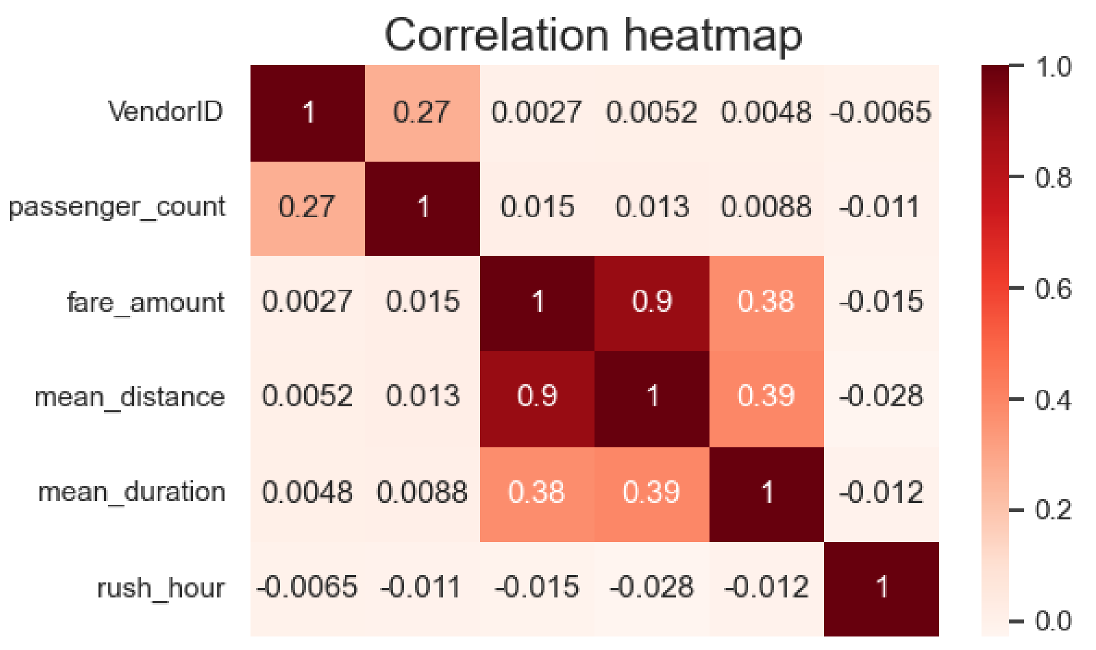
Target variable(fare amount) show correlation with mean distance

In [72]:
```python
# Create correlation matrix containing pairwise correlation of columns, usi
df2.corr(method='pearson')
```

Out[72]:

	VendorID	passenger_count	fare_amount	mean_distance	mean_duration
VendorID	1.000000	0.266626	0.002687	0.005156	0.004833
passenger_count	0.266626	1.000000	0.014810	0.013467	0.008827
fare_amount	0.002687	0.014810	1.000000	0.899184	0.375611
mean_distance	0.005156	0.013467	0.899184	1.000000	0.390750
mean_duration	0.004833	0.008827	0.375611	0.390750	1.000000
rush_hour	-0.006547	-0.010996	-0.015204	-0.028370	-0.011593

In [73]:
```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()
```



mean_distance are highly correlated with the target variable of fare_amount

```
In [74]: # remove the target column from the feature
         x = df2.drop(columns = ['fare_amount'])

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

         x.head()
```

Out[74]:

	VendorID	passenger_count	mean_distance	mean_duration	rush_hour
0	2	6	3.521667	22.847222	1
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

```
In [75]: # covert vendorID to string
         x['VendorID'] = x['VendorID'].astype(str)

         #get dummies
         x = pd.get_dummies(x, drop_first=True)
         x.head()
```

Out[75]:

	passenger_count	mean_distance	mean_duration	rush_hour	VendorID_2
0	6	3.521667	22.847222	1	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

```
In [76]: #split data into training and test sets

         x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2,
```

```
In [77]: # 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: [[-0.49723976 -0.44772554 -0.35315792  1.26418629  0.89477
11 ]
 [-0.49723976  0.46067779  0.38692279 -0.79102266  0.8947711 ]
 [ 1.06640024 -0.54020474 -0.45125412  1.26418629  0.8947711 ]
 ...
 [-0.49723976  0.07479824  0.34486522 -0.79102266 -1.11760427]
 [-0.49723976 -0.29433263 -0.04409188 -0.79102266  0.8947711 ]
 [ 1.06640024 -0.48519689 -0.44861368  1.26418629 -1.11760427]]
```

```
In [78]: # Fit your model to the training data
         lr=LinearRegression()
         lr.fit(x_train_scaled, y_train)
```

```
Out[78]: ▾ LinearRegression

         LinearRegression()
```

```
In [79]: # 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: 0.81596631432855
R^2: 0.81596631432855
MAE: 2.523614093894087
MSE: 21.602410338264765
RMSE: 4.647839319325138
```

```
In [80]: # Scale the X_test data
         X_test_scaled = scaler.transform(x_test)
```

```
In [81]: # 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: 0.7852353529450777
R^2: 0.7852353529450777
MAE: 2.5457664086133907
MSE: 28.037369551992427
RMSE: 5.295032535498949
```

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.

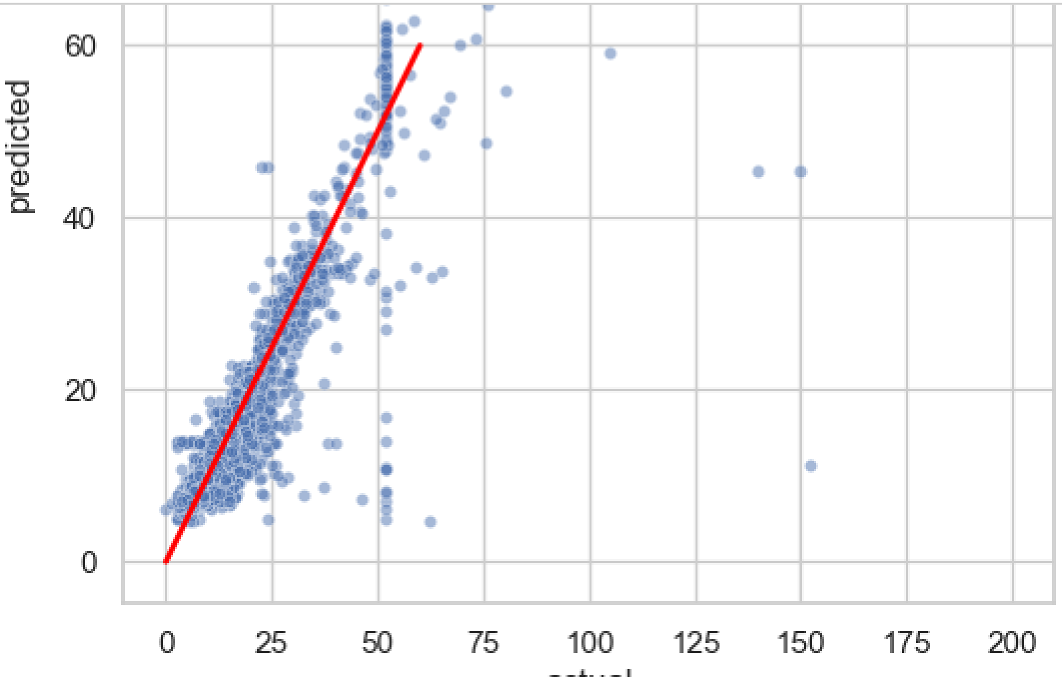
For the test data, an R2 of 0.785 means that 78.5% of the variance in the fare_amount variable is described by the model.

In [82]:
```
# 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()
```

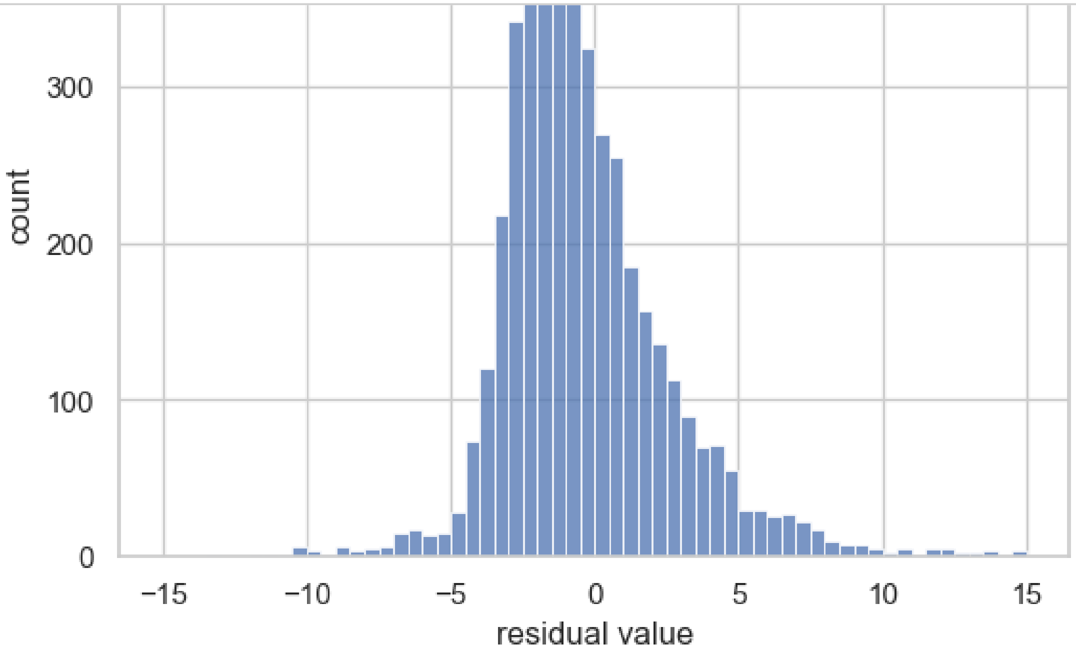
Out[82]:

	actual	predicted	residual
16783	8.0	7.300283	0.699717
517	4.0	7.176523	-3.176523
5011	8.0	7.504668	0.495332
16431	16.5	17.432023	-0.932023
7288	23.5	23.943179	-0.443179

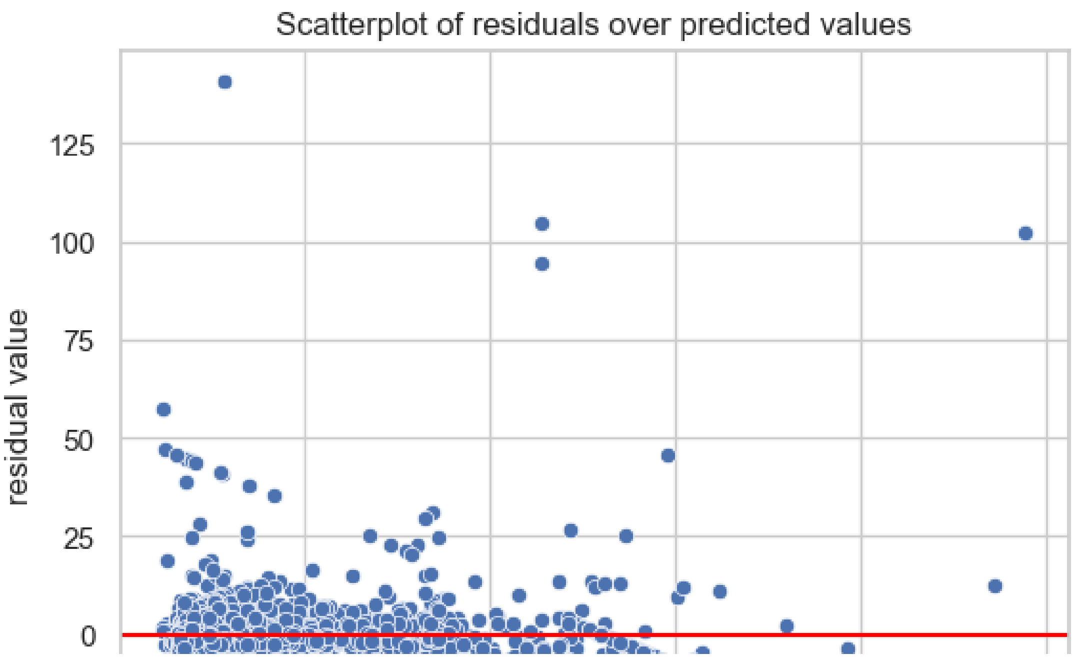
In [83]:
```
# Create a scatterplot to visualize `predicted` over `actual`
fig, ax = plt.subplots(figsize=(6, 6))
sns.set(style='whitegrid')
sns.scatterplot(x='actual',
y='predicted',
data=results,
s=20,
alpha=0.5,
ax=ax
)
# Draw an x=y line to show what the results would be if the model were perf
plt.plot([0,60], [0,60], c='red', linewidth=2)
plt.title('Actual vs. predicted');
```



```
In [84]: # 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');
```



```
In [85]:  # 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()
```



In [86]:
```
# Get model coefficients
coefficients = pd.DataFrame(lr.coef_, columns=x.columns)
coefficients
```

Out[86]:

	passenger_count	mean_distance	mean_duration	rush_hour	VendorID_2
0	0.031938	9.644951	0.354993	0.133789	-0.036598

In [87]:
```
 # 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(9.644951 / x_train['mean_distance'].std())
```

```
3.5594568310004817
2.7096693281960738
```

Now you can make a more intuitive interpretation: for every 3.55 miles traveled, the fare increased by a mean of $9.64 .

Or, reduced: for every 1 mile traveled, the fare increased by a mean of $2.7.