Elements Of Data Science - F2020

Week 3: Pandas, Data Exploration and Visualization

9/28/2020

TODOs

- **Read** Practical Statistics for Data Scientists, Chapter 3 EBSCO
- (Optional) Data Science From Scratch, Chapter 5,6,7 EBSCO
- (Optional) Seaborn Tutorial https://seaborn.pydata.org/tutorial.html

- Complete Week 3 Quiz

- HW1 next week, after Hypothesis Testing

Questions?

TODAY

- Pandas
- Data Exploration
- Visualization in Python

Intro to Pandas

Pandas is an open source, BSD-licensed library providing:

- **high-performance, easy-to-use data structures** and
- **data analysis tools**

In [2]:
```python
# usually imported as pd
import pandas as pd
```

- **Series**: 1D array with a flexible index
- **Dataframe**: 2D matrix with flexible index and column names

Pandas Series

- 1D array of data (any numpy datatype) plus an associated **index** array

In [3]:
```
s = pd.Series(np.random.rand(4))
s
```

Out[3]:
```
0    0.045003
1    0.500485
2    0.502491
3    0.577879
dtype: float64
```

In [4]:
```
# return the values of the series
s.values
```

Out[4]:
```
array([0.04500301, 0.50048463, 0.50249066, 0.57787909])
```

In [5]:
```
# return the index of the series
s.index
```

Out[5]:
```
RangeIndex(start=0, stop=4, step=1)
```

Pandas Series Cont.

- index is flexible, can be anything hashable (integers, strings, ...)

In [6]:
```
# create Series from array and set index
s = pd.Series(np.random.rand(3),index=['a','b','c'])
s
```

Out[6]:
```
a    0.783338
b    0.634322
c    0.739958
dtype: float64
```

In [7]:
```
s['a']
```

Out[7]:
```
0.7833376791406063
```

In [8]:
```
s[['b','c']]
```

Out[8]:
```
b    0.634322
c    0.739958
dtype: float64
```

Pandas Series Cont.

In [9]:
```
# Can create series with index from a dictionary
s = pd.Series({'a':1,'b':2,'c':3,'d':4})
s
```

Out[9]:
```
a    1
b    2
c    3
d    4
dtype: int64
```

In [10]:
```
s[s.index[-2:]]
```

Out[10]:
```
c    3
d    4
dtype: int64
```

Pandas DataFrame

- tabular datastructure
- each column a single datatype
- contains both row and column indices
- single column == Series

Pandas DataFrame Cont.

In [11]:
```
df = pd.DataFrame({'Year':[2017,2018,2018,2019],
                   'Class_Name':['A','A','B','A'],
                   'Measure1':[2.1,3.0,2.4,1.9]
                  })
```

In [12]:
```
df
```

Out[12]:

	Year	Class_Name	Measure1
0	2017	A	2.1
1	2018	A	3.0
2	2018	B	2.4
3	2019	A	1.9

In [13]:
```
print(df)
```

```
   Year Class_Name  Measure1
0  2017          A       2.1
1  2018          A       3.0
2  2018          B       2.4
3  2019          A       1.9
```

In [14]:
```
display(df)
```

	Year	Class_Name	Measure1
0	2017	A	2.1
1	2018	A	3.0
2	2018	B	2.4
3	2019	A	1.9

Pandas DataFrame Cont.

In [15]:
```
data = [[2017,'A',2.1],
        [2018,'A',3.0],
        [2018,'B',2.4],
        [2019,'A',1.9]]
```

In [16]:
```
df = pd.DataFrame(data,
                  columns=['Year','Class_Name','Measure1'],
                  index=['001','002','003','004'])
df.shape
```

Out[16]: (4, 3)

In [17]:
```
df
```

Out[17]:

	Year	Class_Name	Measure1
001	2017	A	2.1
002	2018	A	3.0
003	2018	B	2.4
004	2019	A	1.9

Pandas Attributes

- Get shape of DataFrame : `shape`

In [18]:
```
df.shape # rows, columns
```
Out[18]:
```
(4, 3)
```

- Get index values : `index`

In [19]:
```
df.index
```
Out[19]:
```
Index(['001', '002', '003', '004'], dtype='object')
```

- Get column values : `columns`

In [20]:
```
df.columns
```
Out[20]:
```
Index(['Year', 'Class_Name', 'Measure1'], dtype='object')
```

Pandas Indexing/Selection

Select by label:

- `.loc[]`

In [21]:
```
df.loc['001']
```

Out[21]:
```
Year            2017
Class_Name         A
Measure1         2.1
Name: 001, dtype: object
```

In [22]:
```
df.loc['001','Measure1']
```

Out[22]:
```
2.1
```

Pandas Indexing/Selection Cont.

Select by position:

- `.iloc[]`

In [23]:
```
df.iloc[0]
```

Out[23]:
```
Year           2017
Class_Name        A
Measure1        2.1
Name: 001, dtype: object
```

In [24]:
```
df.iloc[0,2]
```

Out[24]:
```
2.1
```

Pandas Indexing/Selection Cont.

Selecting multiple rows/columns: use list (fancy indexing)

In [25]:
```
df.loc[['002','004']]
```

Out[25]:

	Year	Class_Name	Measure1
002	2018	A	3.0
004	2019	A	1.9

In [26]:
```
df.loc[['002','004'],['Year','Measure1']]
```

Out[26]:

	Year	Measure1
002	2018	3.0
004	2019	1.9

Pandas Slicing

In [27]:
```
# Get last two rows
df.iloc[-2:]
```

Out[27]:

	Year	Class_Name	Measure1
003	2018	B	2.4
004	2019	A	1.9

In [28]:
```
# Get first two rows and first two columns
df.iloc[:2,:2]
```

Out[28]:

	Year	Class_Name
001	2017	A
002	2018	A

NOTE: `.iloc` is **exclusive** (start:end+1)

Pandas Slicing Cont.

Can also slice using labels:

In [29]:
```
df.loc['002':'004']
```

Out[29]:

	Year	Class_Name	Measure1
002	2018	A	3.0
003	2018	B	2.4
004	2019	A	1.9

In [30]:
```
df.loc['002':'004',:'Class_Name']
```

Out[30]:

	Year	Class_Name
002	2018	A
003	2018	B
004	2019	A

NOTE: `.loc` is **inclusive**

Pandas Slicing Cont.

How to indicate all rows or all columns? `:`

In [31]:
```
df.loc[:,'Measure1']
```

Out[31]:
```
001    2.1
002    3.0
003    2.4
004    1.9
Name: Measure1, dtype: float64
```

In [32]:
```
df.iloc[2:,:]
```

Out[32]:

	Year	Class_Name	Measure1
003	2018	B	2.4
004	2019	A	1.9

Pandas Indexing Cont.

Shortcut for indexing:

In [33]:
```python
df['Class_Name']
```

Out[33]:
```
001    A
002    A
003    B
004    A
Name: Class_Name, dtype: object
```

In [34]:
```python
# can use dot notation if there is no space in label
df.Class_Name
```

Out[34]:
```
001    A
002    A
003    B
004    A
Name: Class_Name, dtype: object
```

Panda Selection Chaining

Get 'Year' and 'Measure1' for first 3 rows:

In [35]:
```
df.iloc[:3].loc[:,['Year','Measure1']]
```

Out[35]:

	Year	Measure1
001	2017	2.1
002	2018	3.0
003	2018	2.4

For records '001' and '003' get last two columns

In [36]:
```
df.loc[['001','003']].iloc[:,-2:]
```

Out[36]:

	Class_Name	Measure1
001	A	2.1
003	B	2.4

Panda Selection Chaining Cont.

For record '001' get last two columns?:

In [37]:
```
%xmode minimal
df.loc['001'].iloc[:,-2:] # row with label '001', then all rows, last two columns?
```

```
Exception reporting mode: Minimal

IndexingError: Too many indexers
```

In [38]:
```
df.loc['001']
```

Out[38]:
```
Year            2017
Class_Name         A
Measure1         2.1
Name: 001, dtype: object
```

In [39]:
```
df.loc['001'].iloc[-2:] # row with label '001', last two elements of Series
```

Out[39]:
```
Class_Name      A
Measure1      2.1
Name: 001, dtype: object
```

Pandas `head` and `tail`

Get a quick view of the first or last rows in a DataFrame

In [40]:
```
df.head() # first 5 rows by default
```

Out[40]:

	Year	Class_Name	Measure1
001	2017	A	2.1
002	2018	A	3.0
003	2018	B	2.4
004	2019	A	1.9

In [41]:
```
df.tail(2) # only print 2 rows
```

Out[41]:

	Year	Class_Name	Measure1
003	2018	B	2.4
004	2019	A	1.9

Pandas Boolean Mask

In [42]:
```
# Which rows have Class_Name of 'A'?
df.Class_Name == 'A'
```

Out[42]:
```
001     True
002     True
003    False
004     True
Name: Class_Name, dtype: bool
```

In [43]:
```
# Get all data for rows with with Class_Name 'A'
df.loc[df.Class_Name == 'A']
```

Out[43]:

	Year	Class_Name	Measure1
001	2017	A	2.1
002	2018	A	3.0
004	2019	A	1.9

In [44]:
```
# Get Measure1 for all records for Class_Name 'A'
df.loc[df.Class_Name == 'A','Measure1']
```

Out[44]:
```
001    2.1
002    3.0
004    1.9
Name: Measure1, dtype: float64
```

Pandas Boolean Mask Cont.

Get all records for class 'A' before 2019

In [45]:
```
df.loc[(df.Class_Name == 'A') & (df.Year < 2019)]
```

Out[45]:

	Year	Class_Name	Measure1
001	2017	A	2.1
002	2018	A	3.0

Get all records in a set of years:

In [46]:
```
df.loc[df.Year.isin([2017,2019])]
```

Out[46]:

	Year	Class_Name	Measure1
001	2017	A	2.1
004	2019	A	1.9

Pandas Selection Review

- `.loc[]`
- `.iloc[]`
- Fancy Indexing
- Slicing
- Chaining
- `head` and `tail`
- Boolean Mask

Pandas Sorting

In [47]:
```
df.sort_values(by=['Measure1']).head(3)
```

Out[47]:

	Year	Class_Name	Measure1
004	2019	A	1.9
001	2017	A	2.1
003	2018	B	2.4

In [48]:
```
df.sort_values(by=['Measure1'],ascending=False).head(3)
```

Out[48]:

	Year	Class_Name	Measure1
002	2018	A	3.0
003	2018	B	2.4
001	2017	A	2.1

In [49]:
```
df.sort_values(by=['Year','Measure1']).head(3)
```

Out[49]:

	Year	Class_Name	Measure1
001	2017	A	2.1
003	2018	B	2.4
002	2018	A	3.0

Questions?

Data Exploration and Visualization

For a new set of data, would like to know:

- amount of data (rows, columns)
- range (min, max)
- counts of discrete values
- central tendencies (mean, median)
- dispersion or spread (variance, IQR)
- skew
- covariance and correlation ...

Yellowcab Dataset

- Records of Yellowcab Taxi trips from January 2017
- more info: https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page

Loading Datasets from CSV (Comma Separated Values)

- columns separated by delimiter, eg. comma, tab (\t), pipe (|)
- one row per record, observation
- often, strings quoted
- often, first row contains column headings
- often, comment rows starting with #

In [50]:
```
!head ../data/yellowcab_demo.csv
```

```
pickup_datetime,dropoff_datetime,trip_distance,fare_amount,tip_amount,payment_type
2017-01-05 14:49:04,2017-01-05 14:53:53,0.89,5.5,1.26,Credit card
2017-01-15 01:07:22,2017-01-15 01:26:47,2.7,14.0,0.0,Cash
2017-01-29 09:55:00,2017-01-29 10:04:43,1.41,8.0,0.0,Cash
2017-01-10 05:40:12,2017-01-10 05:42:22,0.4,4.0,0.0,Cash
2017-01-06 17:02:48,2017-01-06 17:16:10,2.3,11.0,0.0,Cash
2017-01-14 19:03:14,2017-01-14 19:08:41,0.8,5.5,,Credit card
2017-01-06 18:51:52,2017-01-06 18:55:45,0.2,4.5,0.0,Cash
2017-01-04 20:47:30,2017-01-04 21:01:24,2.68,11.5,,Credit card
2017-01-21 09:44:28,2017-01-21 09:48:13,0.6,4.5,0.0,Cash
```

Loading Datasets with Pandas

In [51]:

```
import pandas as pd
df = pd.read_csv('../data/yellowcab_demo.csv',
                 sep=',',
                 header=0,
                 parse_dates=['pickup_datetime','dropoff_datetime'])
```

In [52]:

```
# display first 5 rows
df.head(5)
```

Out[52]:

	pickup_datetime	dropoff_datetime	trip_distance	fare_amount	tip_amount	payment_type
0	2017-01-05 14:49:04	2017-01-05 14:53:53	0.89	5.5	1.26	Credit card
1	2017-01-15 01:07:22	2017-01-15 01:26:47	2.70	14.0	0.00	Cash
2	2017-01-29 09:55:00	2017-01-29 10:04:43	1.41	8.0	0.00	Cash
3	2017-01-10 05:40:12	2017-01-10 05:42:22	0.40	4.0	0.00	Cash
4	2017-01-06 17:02:48	2017-01-06 17:16:10	2.30	11.0	0.00	Cash

Get Size of Dataset

In [53]:
```
df.shape
```

Out[53]:
```
(1000, 6)
```

In [54]:
```
# rows
f'{df.shape[0]} rows'
'1000 rows'
```

Out[54]:
```
'1000 rows'
```

In [55]:
```
f'{df.shape[1]} columns'
'6 columns'
```

Out[55]:
```
'6 columns'
```

In [56]:
```
'number of rows: {}, number of columns: {}'.format(*df.shape)
```

Out[56]:
```
'number of rows: 1000, number of columns: 6'
```

What are the column names?

In [57]:
```
df.columns
```

Out[57]:
```
Index(['pickup_datetime', 'dropoff_datetime', 'trip_distance', 'fare_amount',
       'tip_amount', 'payment_type'],
      dtype='object')
```

In [58]:
```
df.columns.values
```

Out[58]:
```
array(['pickup_datetime', 'dropoff_datetime', 'trip_distance',
       'fare_amount', 'tip_amount', 'payment_type'], dtype=object)
```

In [59]:
```
df.columns.tolist()
```

Out[59]:
```
['pickup_datetime',
 'dropoff_datetime',
 'trip_distance',
 'fare_amount',
 'tip_amount',
 'payment_type']
```

What are the column datatypes?

In [60]:
```
df.dtypes
```

Out[60]:
```
pickup_datetime     datetime64[ns]
dropoff_datetime    datetime64[ns]
trip_distance              float64
fare_amount                float64
tip_amount                 float64
payment_type                object
dtype: object
```

In [61]:
```
type(df.dtypes)
```

Out[61]:
```
pandas.core.series.Series
```

Get Summary Info for DataFrame

In [62]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 6 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   pickup_datetime   1000 non-null   datetime64[ns]
 1   dropoff_datetime  1000 non-null   datetime64[ns]
 2   trip_distance     1000 non-null   float64
 3   fare_amount       1000 non-null   float64
 4   tip_amount        910 non-null    float64
 5   payment_type      1000 non-null   object
dtypes: datetime64[ns](2), float64(3), object(1)
memory usage: 47.0+ KB
```

- number of rows
- number of columns
- column names, number of filled values, datatypes
- number of each datatype seen
- size of dataset in memory

Variable (Observation) Types

- **Numeric** (eg. weight, temperature)
    - usually has a zero value
    - describes magnitude

- **Categorical** (eg. class, variety)
    - usually a finite set
    - no order

- **Ordinal** (eg. Likert scale, education level, etc.)
    - usually a finite set
    - has order
    - usually missing zero
    - difference between levels may not be the same

Numeric: Data Ranges

In [63]:
```
df.trip_distance.min()
```
Out[63]:
```
0.0
```
In [64]:
```
df.trip_distance.max()
```
Out[64]:
```
32.77
```
In [65]:
```
df.min(numeric_only=True)
```
Out[65]:
```
trip_distance    0.0
fare_amount      2.5
tip_amount       0.0
dtype: float64
```
In [66]:
```
df.max(numeric_only=True)
```
Out[66]:
```
trip_distance    32.77
fare_amount      88.00
tip_amount       22.70
dtype: float64
```

Numeric: Central Tendency with Mean

- Sample Mean

$$\bar{x} = \frac{1}{n} \sum x_i$$

```
In [67]: df.fare_amount.mean()
Out[67]: 12.4426
```

```
In [68]: print(f'{df.fare_amount.mean()=:0.2f}')
df.fare_amount.mean()=12.44
```

- Mean is sensitive to *outliers*
- **Outlier:** a data point that differs significantly from other observations
    - data error
    - effect of heavy tailed distribution?

Numeric: Central Tendency with Median

- Median
    - Divides sorted dataset into two equal sizes
    - 50% of the data is less than or equal to the median

In [69]:
```
df.fare_amount.median()
```
Out[69]:
```
9.0
```

- Median is *robust* to outliers
- **Robust:** Not affected by outliers

Numeric: Quantiles/Percentiles

- **Quantile:**: cut point for splitting distribution
- **Percentile:** x% of data is less than or equal to the xth percentile

In [70]:
```
df.fare_amount.quantile(.95) # 95% of the data is less than or equal to x?
```

Out[70]:
```
33.5
```

In [71]:
```
df.fare_amount.quantile([.05,.95]) # 90% of the data is between 4 and 33.5
```

Out[71]:
```
0.05     4.0
0.95    33.5
Name: fare_amount, dtype: float64
```

In [72]:
```
df.fare_amount.quantile([0,.25,.5,.75,1]) # Quartiles: 25% of data is between each pair
```

Out[72]:
```
0.00     2.5
0.25     6.5
0.50     9.0
0.75    14.0
1.00    88.0
Name: fare_amount, dtype: float64
```

Numeric: Spread with Variance

- Sample Variance

$$s^2 = \frac{\sum(x - \bar{x})^2}{n-1}$$

In [73]:
```
df.fare_amount.var()
```

Out[73]:
```
116.80859383383383
```

but this is in dollars^2 !

Numeric: Spread with Standard Deviation

- Sample Standard Deviation

$$s = \sqrt{\frac{\sum(x-\bar{x})^2}{n-1}}$$

In [74]:
```
df.fare_amount.std()
```

Out[74]:
```
10.807802451647321
```

- Back in original scale of dollars
- Sensitive to outliers

Numeric: Exploring Spread with IQR

- Quartiles
  - ~25% of data is ≤ first quartile, 25th percentile
  - ~50% of data is ≤ second quartile, 50th percentile (Median)
  - ~75% of data is ≤ third quartile, 75th percentile

- Can find quartiles with: pandas quantile or numpy percentile

- **Interquartile Range (IQR)**
  - (third quartile - first quartile) or (75th percentile - 25th percentile)

```
In [75]: df.fare_amount.quantile(.75) - df.fare_amount.quantile(.25)

Out[75]: 7.5
```

- IQR is robust to outliers

Numeric Summary Stats with `.describe`

In [76]:
```
df.describe()
```

Out[76]:

	trip_distance	fare_amount	tip_amount
count	1000.000000	1000.000000	910.000000
mean	2.880010	12.442600	1.766275
std	3.678534	10.807802	2.315507
min	0.000000	2.500000	0.000000
25%	0.950000	6.500000	0.000000
50%	1.565000	9.000000	1.350000
75%	3.100000	14.000000	2.460000
max	32.770000	88.000000	22.700000

Numeric: Exploring Distribution with Skew

- **Skewness**
  - measures assymetry of distribution around mean
  - indicates tail to left (neg) or right (pos)
  - skew will lead to difference between median and mean

In [77]:
```
df.fare_amount.skew()
```
Out[77]:
```
2.882730031010152
```

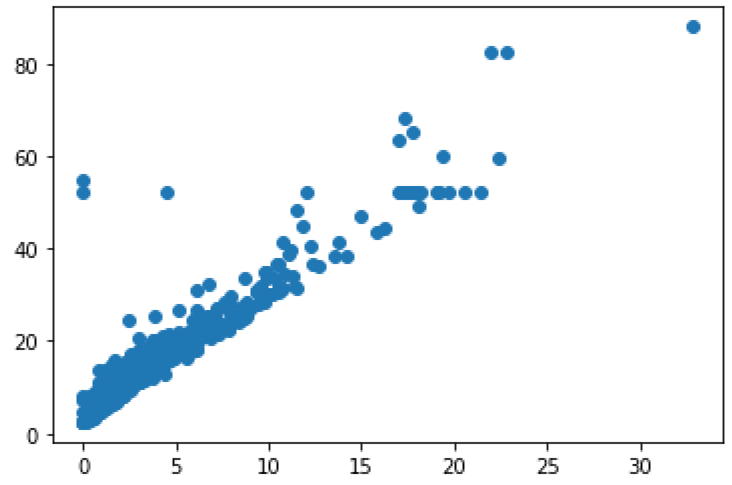
Easier to understand with a plot...

Matplotlib.pyplot

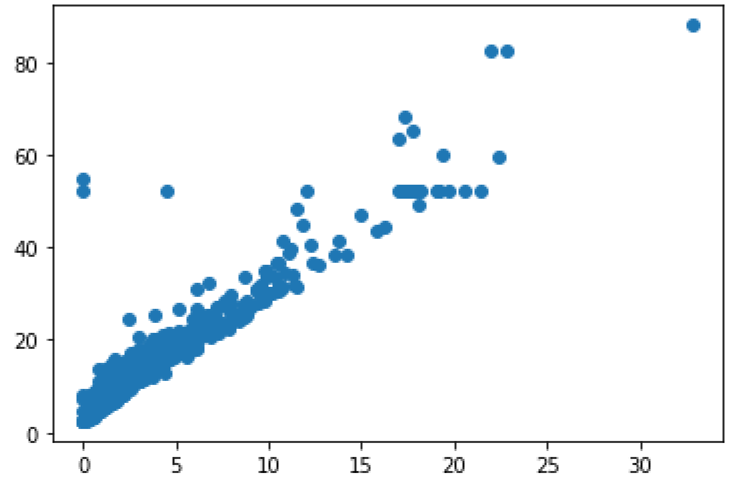
In [78]:
```
import matplotlib.pyplot as plt

%matplotlib inline
```

In [79]:
```
plt.scatter(df.trip_distance,df.fare_amount)
```

Out[79]: <matplotlib.collections.PathCollection at 0x7f1df5b0bf40>



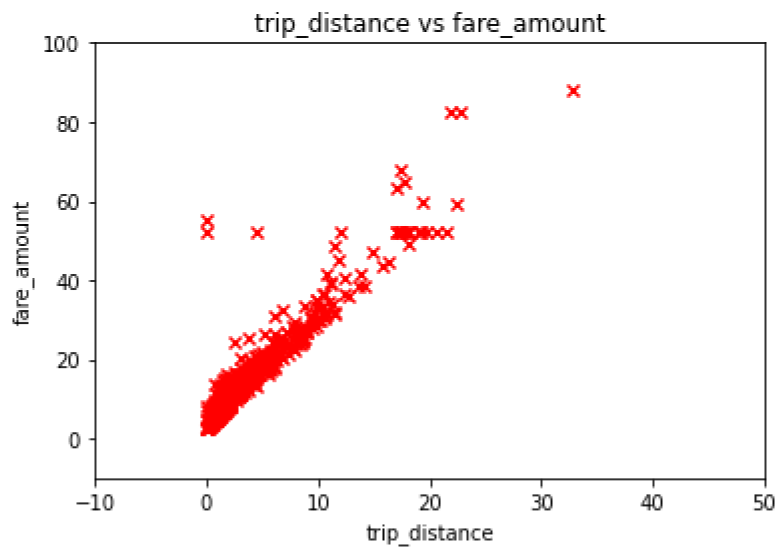
In [80]:
```
plt.scatter(df.trip_distance,df.fare_amount);
```



Matplotlib Axes

Matplotlib Axes

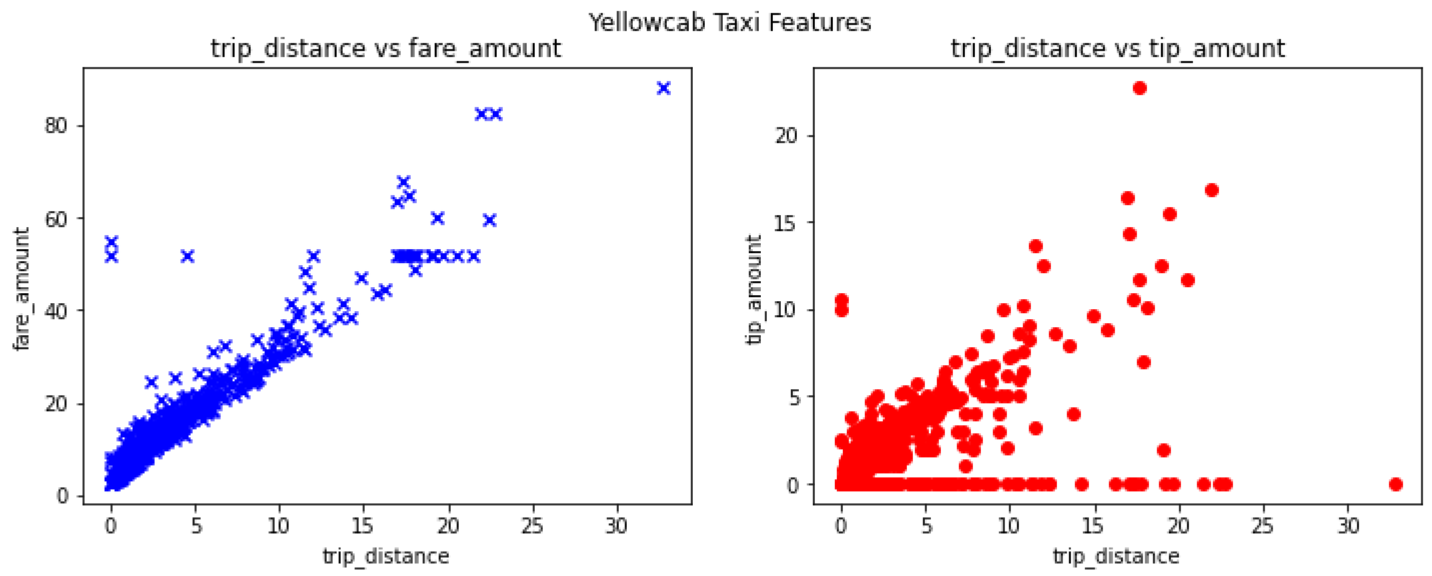
In [81]:
```
fig = plt.figure(figsize=(6,4))

ax = fig.gca()

ax.scatter(x=df.trip_distance,
           y=df.fare_amount,
           marker='x',
           color='red'
          )

ax.set_xlabel('trip_distance')
ax.set_ylabel('fare_amount')

ax.set_xlim([-10,50])
ax.set_ylim([-10,100])

ax.set_title('trip_distance vs fare_amount');
```



Matplotlib: Subplots, Figure and Axis

Matplotlib: Subplots, Figure and Axis

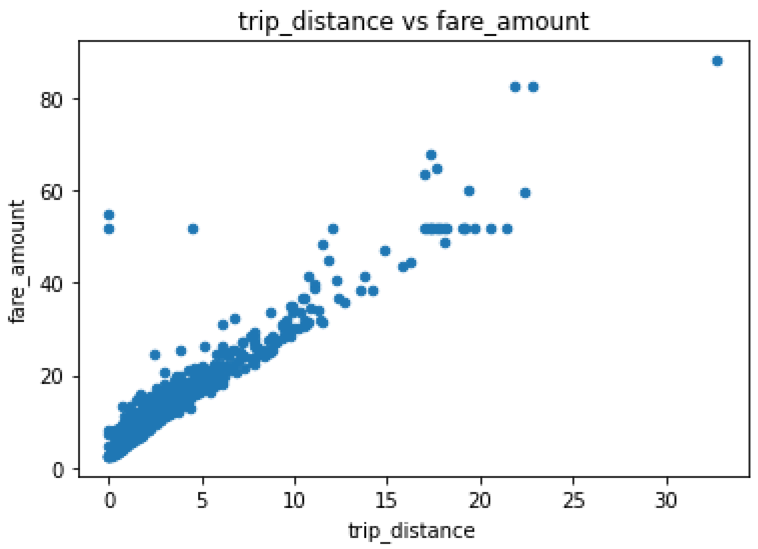
In [82]:
```
fig,ax = plt.subplots(1,2,figsize=(12,4))

ax[0].scatter(df.trip_distance,df.fare_amount,marker='x',color='blue')
ax[1].scatter(df.trip_distance,df.tip_amount,color='red');

ax[0].set_xlabel('trip_distance')
ax[1].set_xlabel('trip_distance')

ax[0].set_ylabel('fare_amount'), ax[1].set_ylabel('tip_amount')

ax[0].set_title('trip_distance vs fare_amount')
ax[1].set_title('trip_distance vs tip_amount')

fig.suptitle('Yellowcab Taxi Features');
```



Plotting via Pandas

Plotting via Pandas

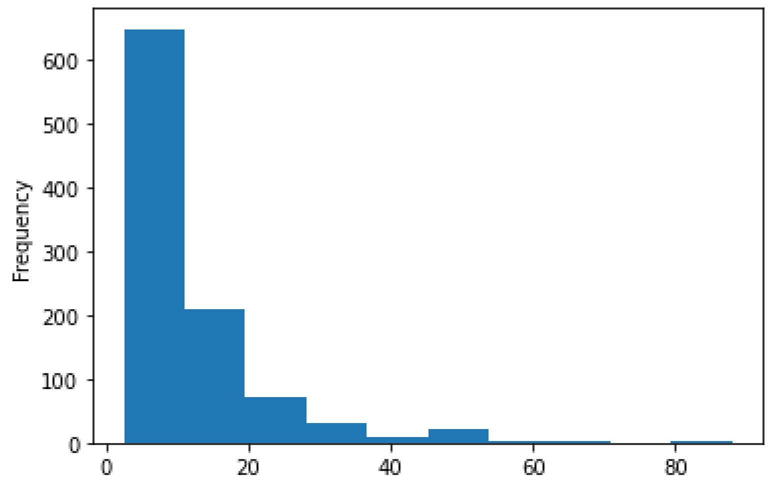
In [83]:
```python
ax = df.plot.scatter(x='trip_distance',y='fare_amount');
ax.set_title('trip_distance vs fare_amount');
```



Univariate Distribution: Histogram

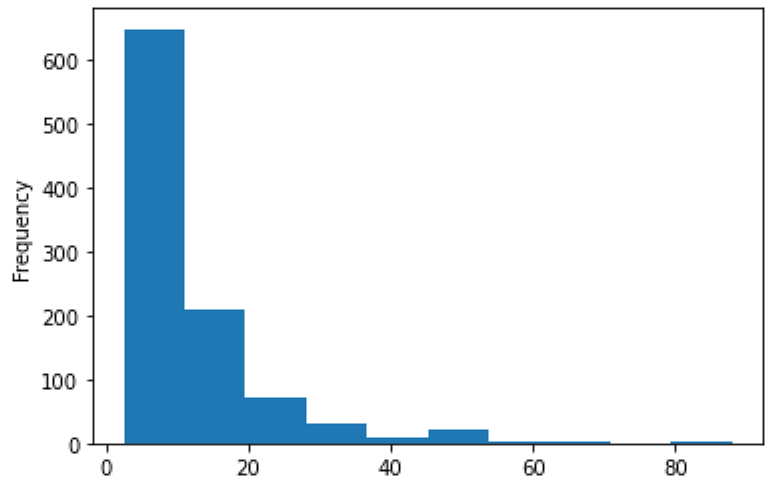
Univariate Distribution: Histogram

In [84]:
```
df.fare_amount.plot.hist();
```

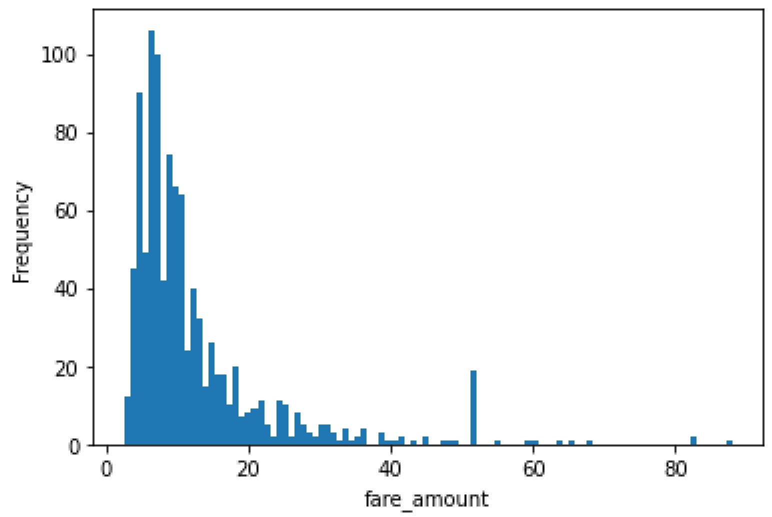


Univariate Distribution: Histogram

In [84]:
```
df.fare_amount.plot.hist();
```



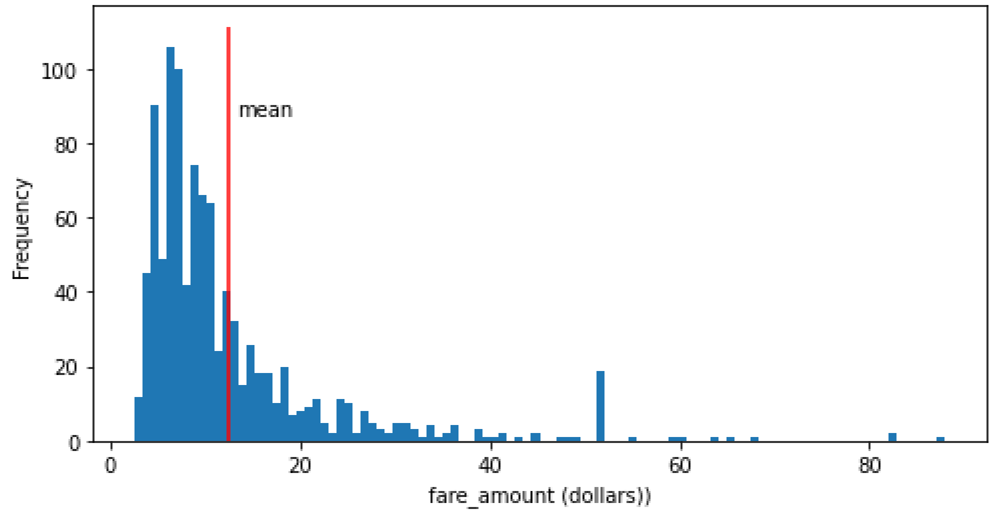
In [85]:
```
ax = df.fare_amount.plot.hist(bins=100)
ax.set_xlabel('fare_amount');
```



Univariate Distribution: Histogram

Univariate Distribution: Histogram

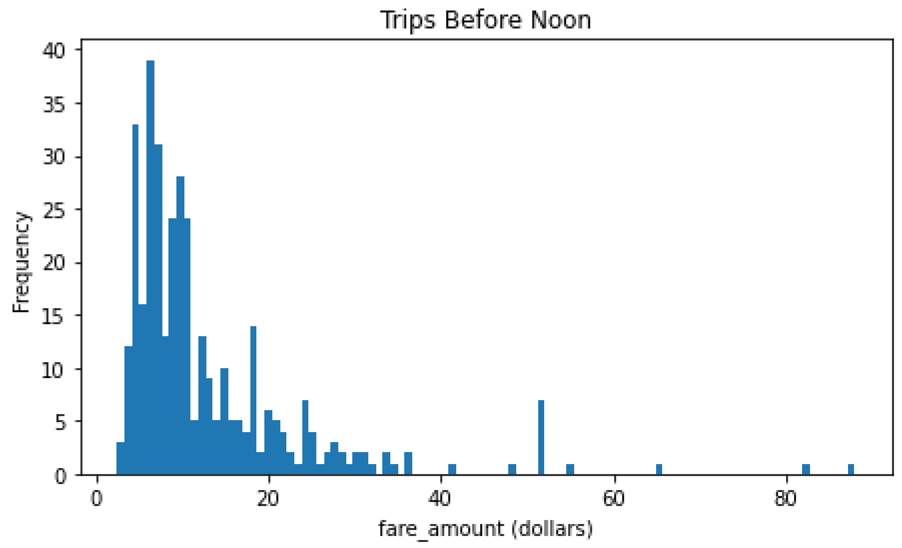
In [86]:
```
fig,ax = plt.subplots(1,1,figsize=(8,4));

df.fare_amount.plot.hist(bins=100, ax=ax);
ax.set_xlabel('fare_amount (dollars))');

# add a vertical line
ax.vlines(df.fare_amount.mean(),*ax.get_ylim(),color='r');

# add some text
ax.text(df.fare_amount.mean()+1,ax.get_ylim()[1]*.75,'mean');
```

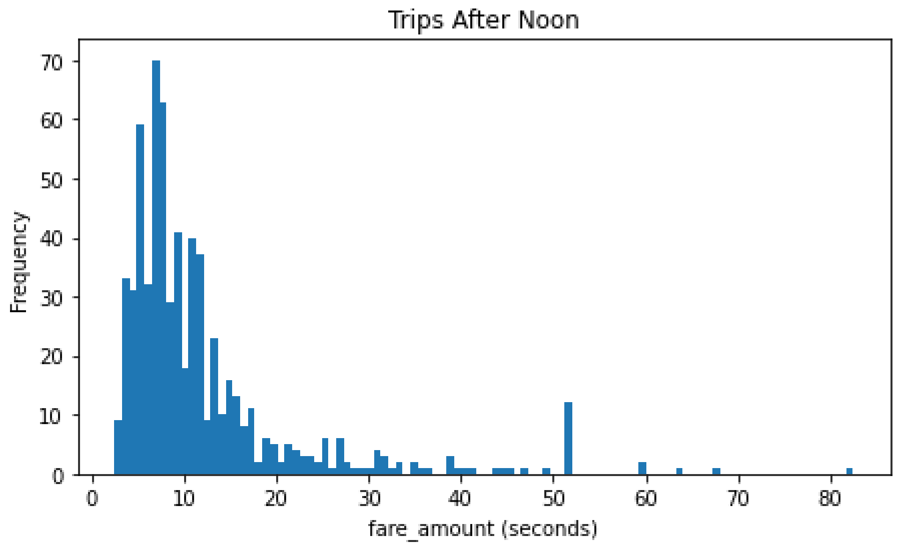


Subplots with Pandas

Subplots with Pandas

In [87]:
```
fig,ax = plt.subplots(1,2,figsize=(16,4))
df[df.pickup_datetime.dt.hour < 12].fare_amount.plot.hist(bins=100,ax=ax[0]);
ax[0].set_xlabel('fare_amount (dollars)');
ax[0].set_title('Trips Before Noon');
df[df.pickup_datetime.dt.hour >= 12].fare_amount.plot.hist(bins=100,ax=ax[1]);
ax[1].set_xlabel('fare_amount (seconds)');
ax[1].set_title('Trips After Noon');
```

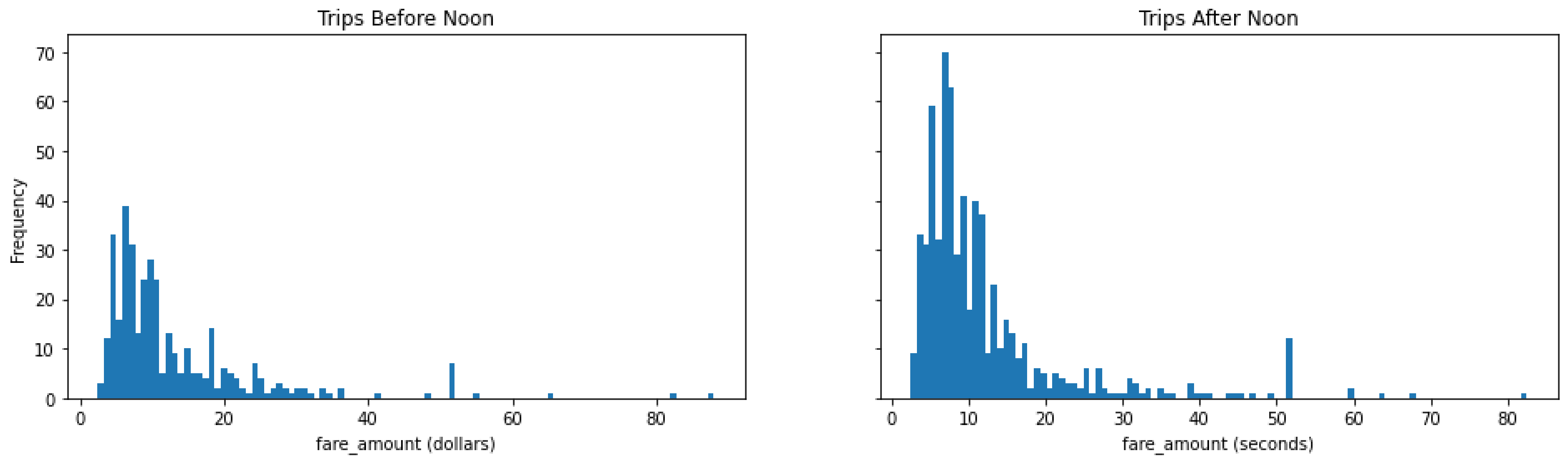




Sharing Axes

Sharing Axes

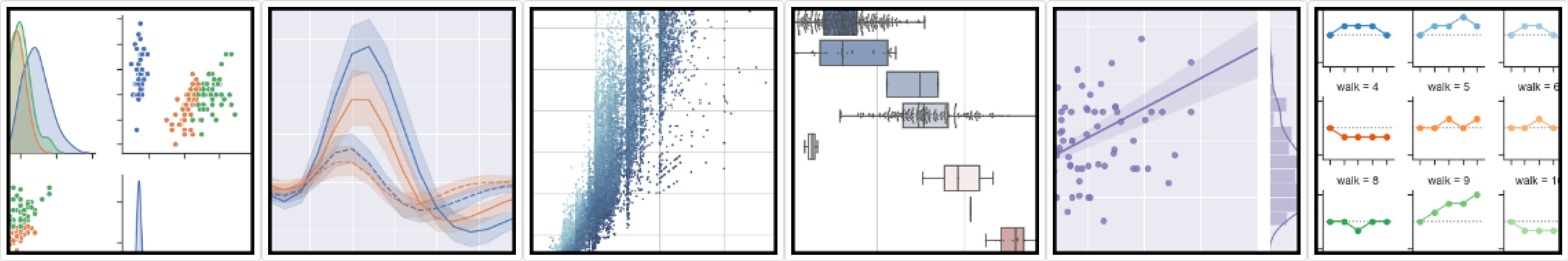
In [88]:
```
fig,ax = plt.subplots(1,2,figsize=(16,4), sharey=True)

df[df.pickup_datetime.dt.hour < 12].fare_amount.plot.hist(bins=100,ax=ax[0]);
ax[0].set_xlabel('fare_amount (dollars)');
ax[0].set_title('Trips Before Noon');
df[df.pickup_datetime.dt.hour >= 12].fare_amount.plot.hist(bins=100,ax=ax[1]);
ax[1].set_xlabel('fare_amount (seconds)');
ax[1].set_title('Trips After Noon');
```



Plotting with Seaborn

Plotting with Seaborn

- Python data visualization library
- Based on matplotlib.
- It provides a high-level interface for drawing attractive and informative statistical graphics.



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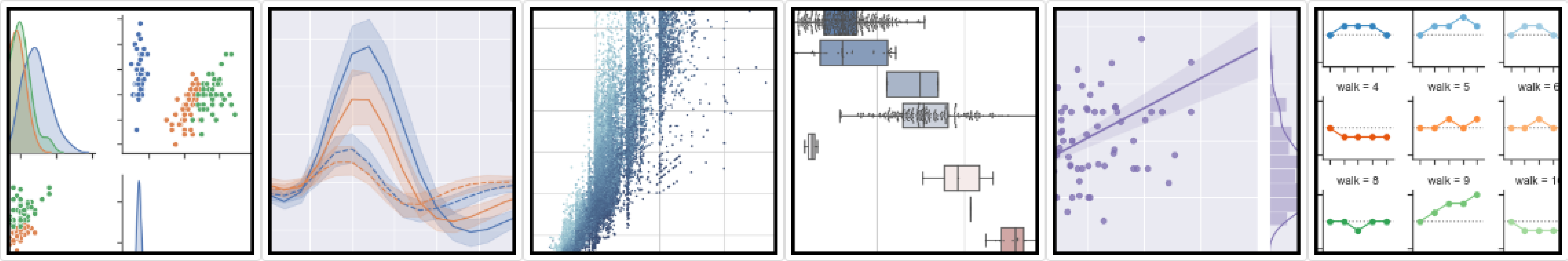
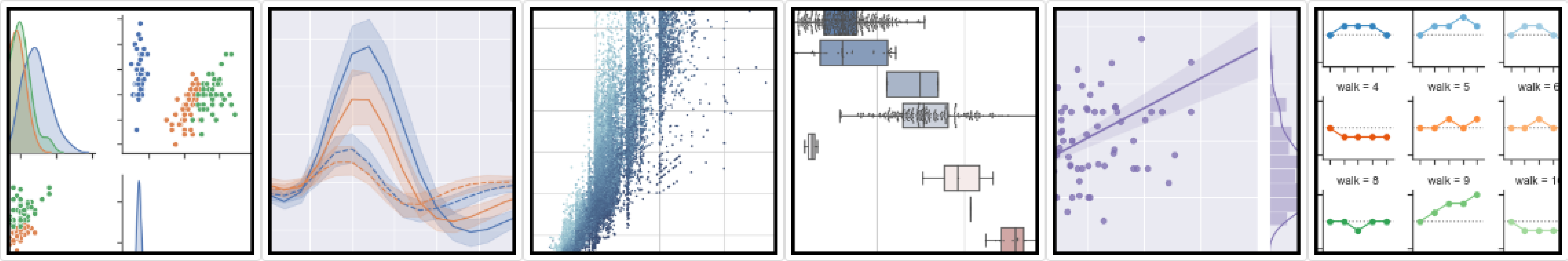


NOTE!!: Upgrade to 0.11 as of September 2020

```
$ conda install -n eods-f20 seaborn
```

Plotting with Seaborn

- Python data visualization library
- Based on matplotlib.
- It provides a high-level interface for drawing attractive and informative statistical graphics.



NOTE!!: Upgrade to 0.11 as of September 2020

```
$ conda install -n eods-f20 seaborn
```

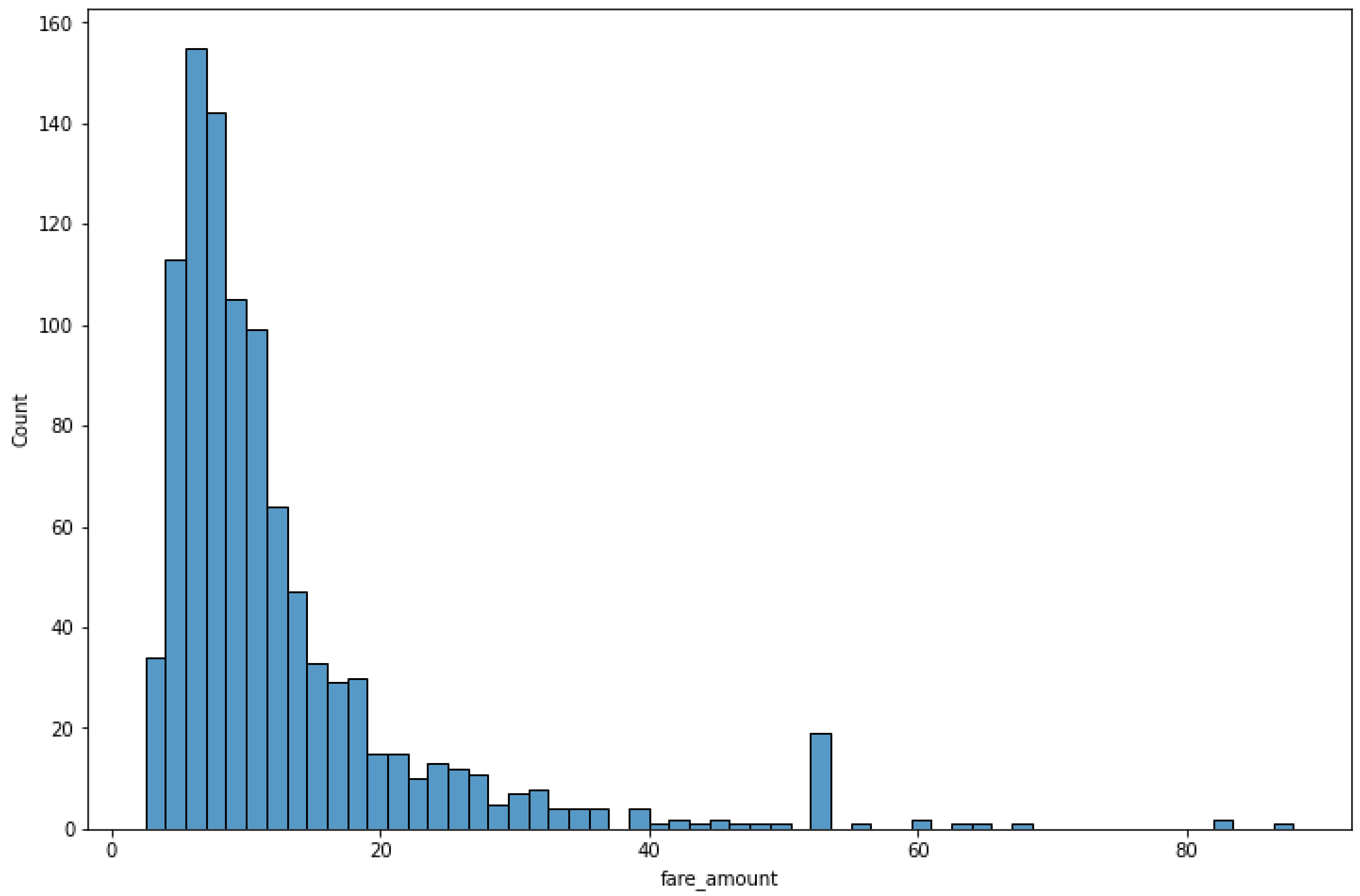
In [89]:
```
import seaborn as sns
sns.__version__
```

Out[89]: '0.11.0'

Univariate Distribution with Seaborn Histplot

Univariate Distribution with Seaborn Histplot

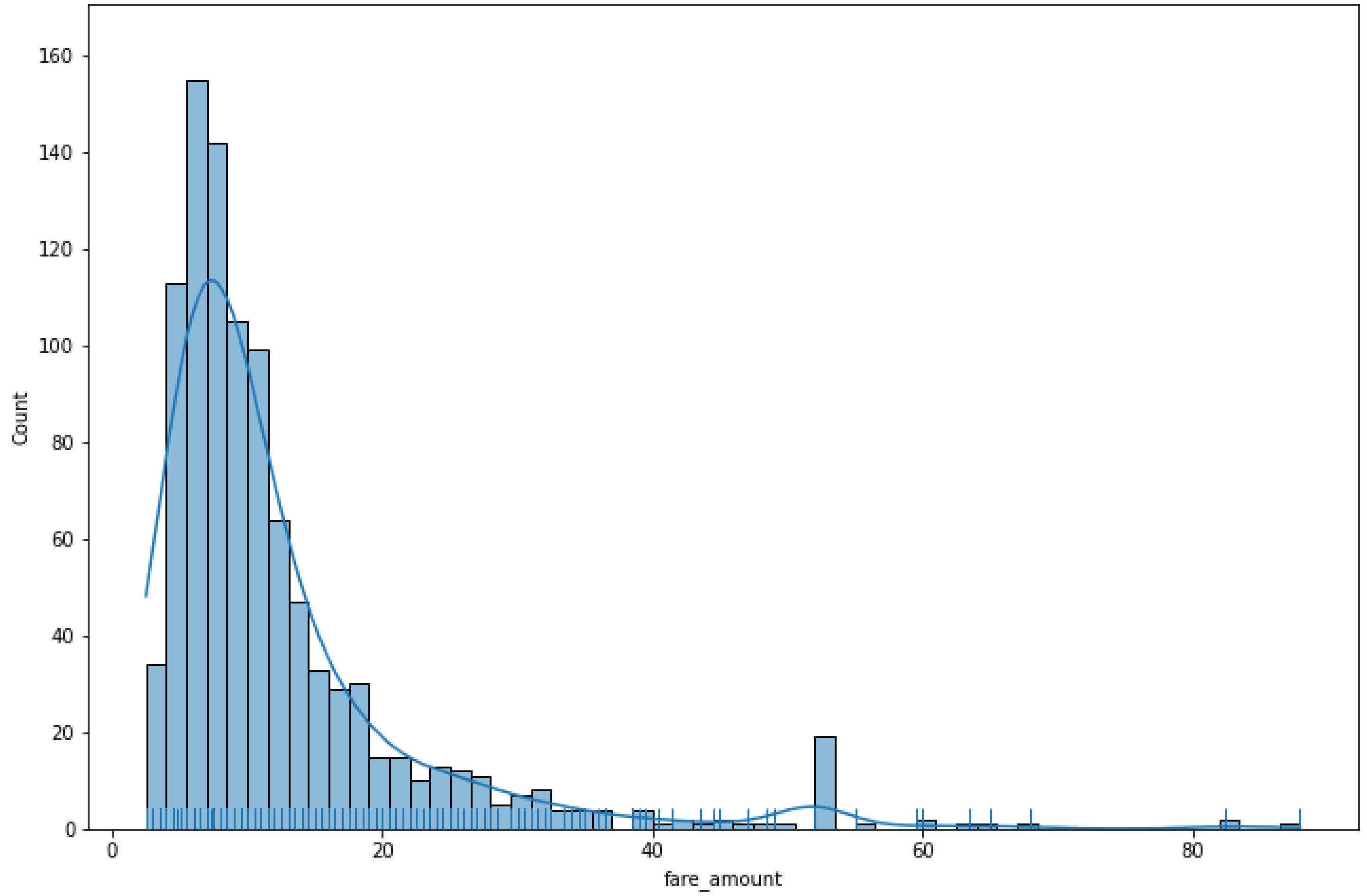
In [90]:
```
fig,ax = plt.subplots(1,1,figsize=(12,8))

sns.histplot(df.fare_amount,ax=ax);
```



Univariate Distribution: Histogram with KDE and Rugplot

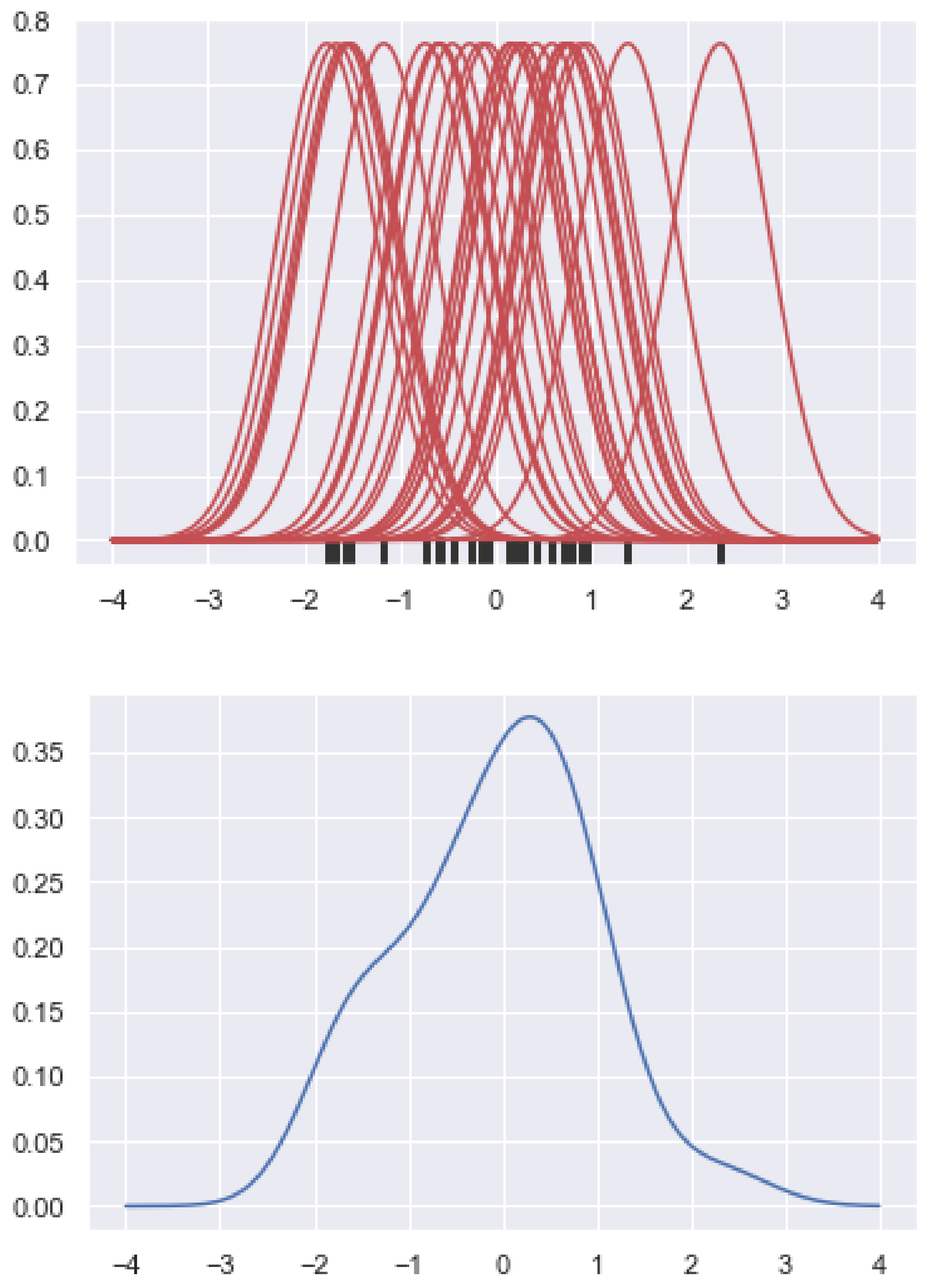
Univariate Distribution: Histogram with KDE and Rugplot

In [91]:
```
fig,ax = plt.subplots(1,1,figsize=(12,8))

sns.histplot(df.fare_amount,kde=True,ax=ax);
sns.rugplot(df.fare_amount);
```



Aside: KDE

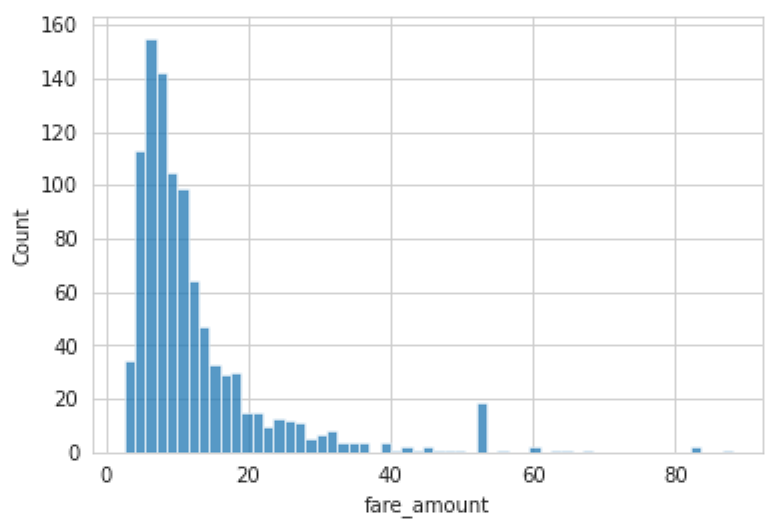
Aside: KDE


0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
−4
−3
−2
−1
0
1
2
3
4
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−4
−3
−2
−1
0
1
2
3
4

Seaborn Styles

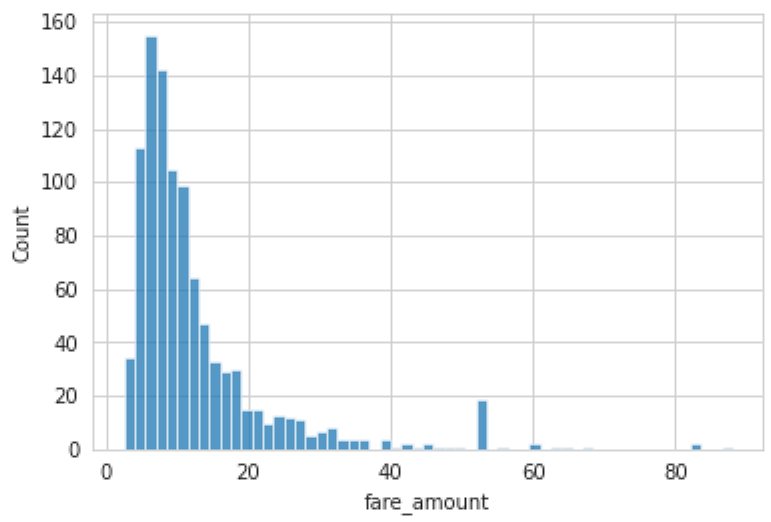
Seaborn Styles

In [92]:
```
# for a single plot using a context
with sns.axes_style('whitegrid'):
    sns.histplot(df.fare_amount);
```



Seaborn Styles

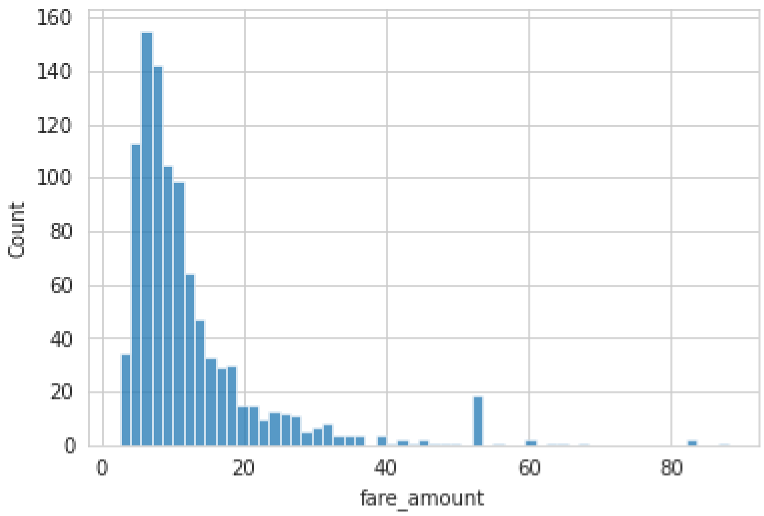
In [92]:
```
# for a single plot using a context
with sns.axes_style('whitegrid'):
    sns.histplot(df.fare_amount);
```



In [93]:
```
# set style globally
sns.set_style('darkgrid')
```

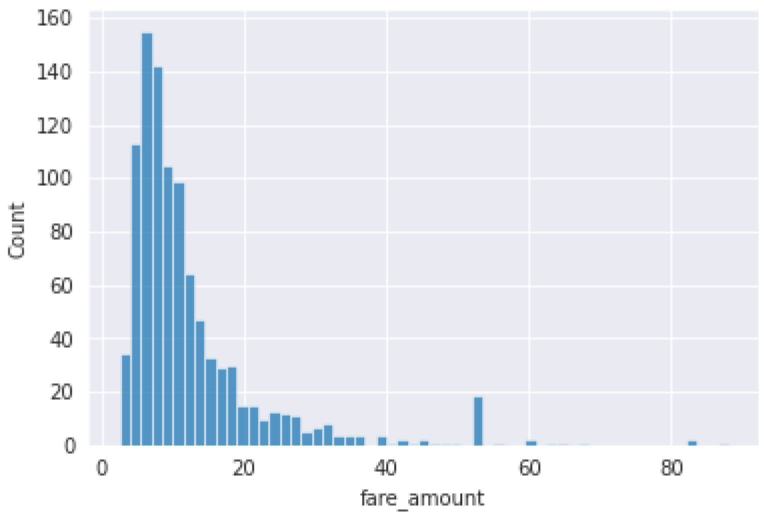
Seaborn Styles

In [92]:
```python
# for a single plot using a context
with sns.axes_style('whitegrid'):
    sns.histplot(df.fare_amount);
```



In [93]:
```python
# set style globally
sns.set_style('darkgrid')
```

In [94]:
```python
sns.histplot(x=df.fare_amount);
```

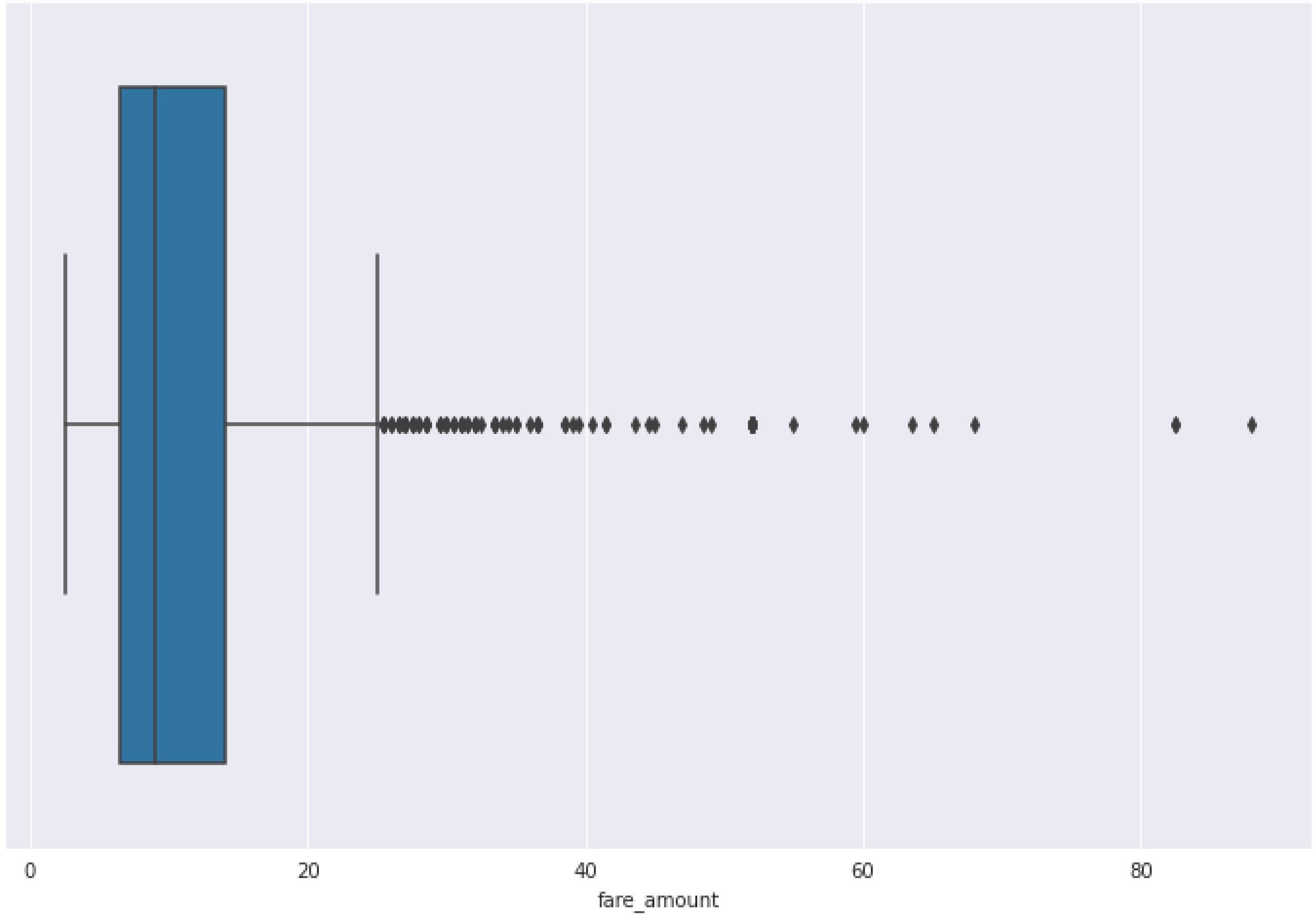


Univariate Distributions: Boxplot

Univariate Distributions: Boxplot

In [95]:

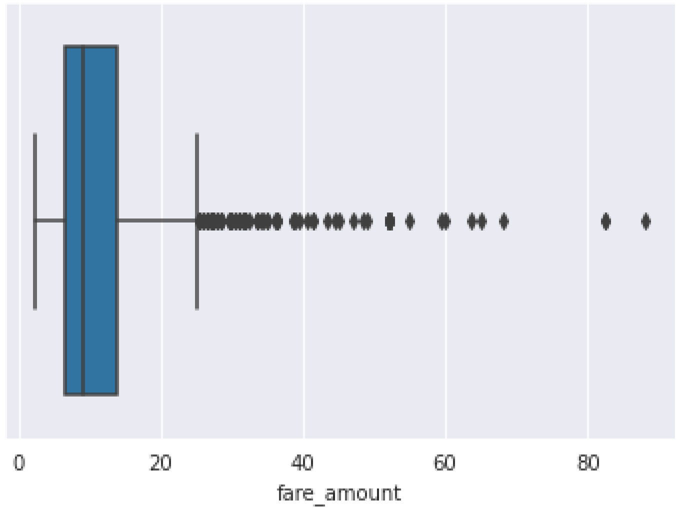
```
fig,ax = plt.subplots(1,1,figsize=(12,8))

sns.boxplot(x=df.fare_amount,ax=ax);
```



Univariate Distributions: Boxplot

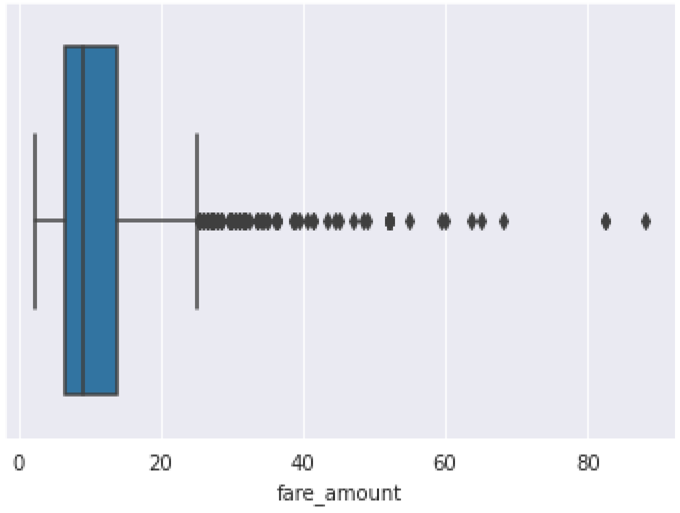
Univariate Distributions: Boxplot

In [96]:
```
fig,ax = plt.subplots(1,1,figsize=(6,4))

sns.boxplot(x=df.fare_amount,ax=ax);
```



Univariate Distributions: Boxplot

In [96]:
```
fig,ax = plt.subplots(1,1,figsize=(6,4))

sns.boxplot(x=df.fare_amount,ax=ax);
```

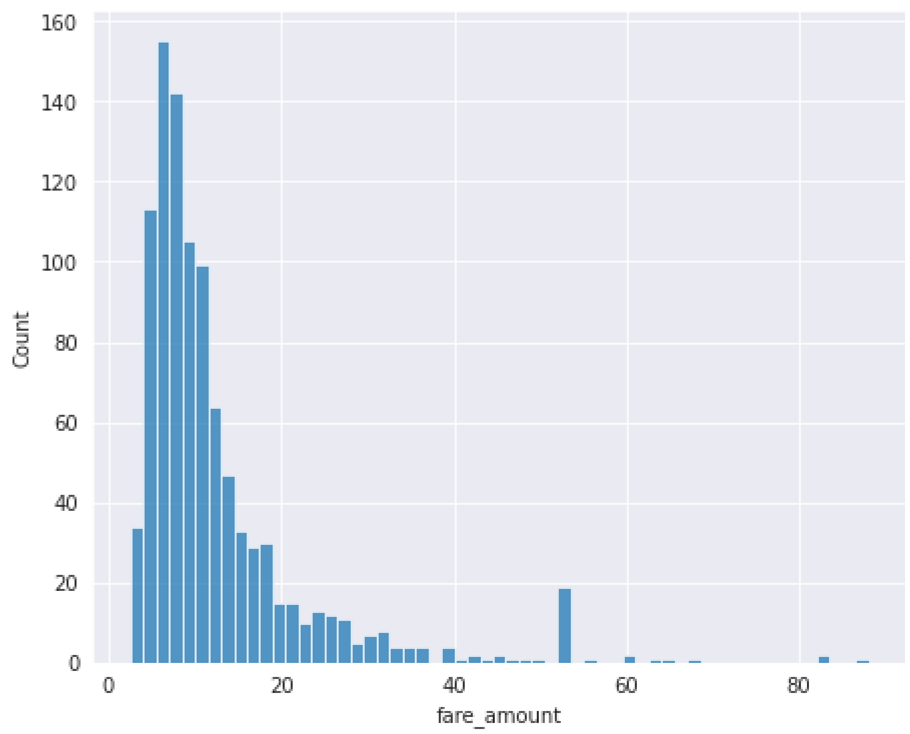


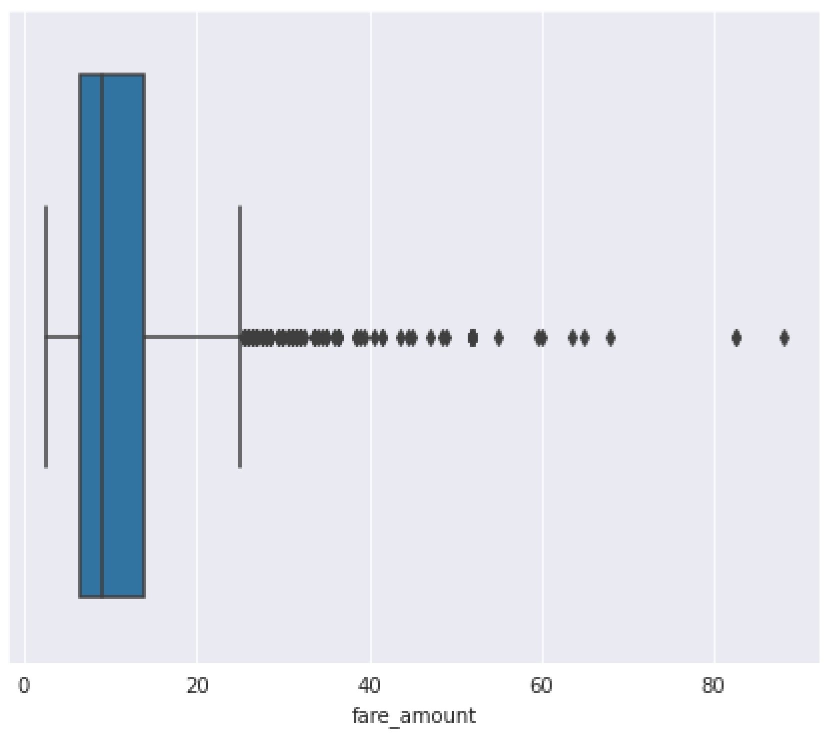
- first quartile
- second quartile (Median)
- third quartile
- whiskers (usually 1.5*IQR)
- outliers

Combining Plots with Subplots

Combining Plots with Subplots

In [97]:
```
fig,ax = plt.subplots(1,2,figsize=(16,6))

sns.histplot(x=df.fare_amount, ax=ax[0]);
sns.boxplot(x=df.fare_amount, ax=ax[1]);
```



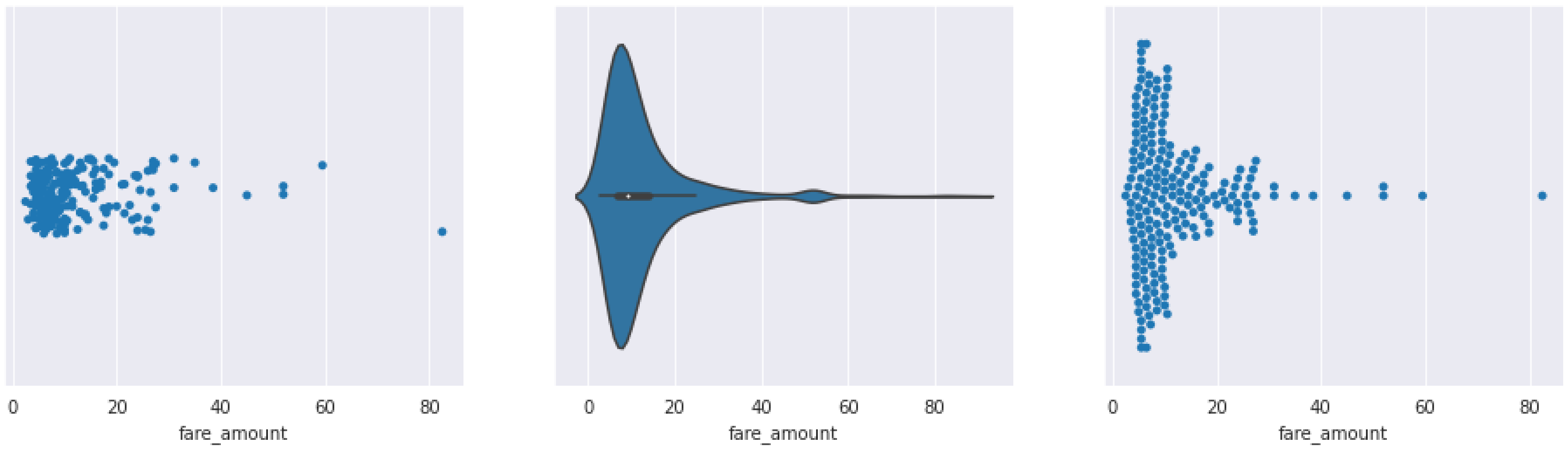


Other Univariate Distribution Visualizations

Other Univariate Distribution Visualizations

In [98]:

```
fig,ax = plt.subplots(1,3,figsize=(16,4))

sns.stripplot(x='fare_amount',data=df[:200],ax=ax[0])
sns.violinplot(x='fare_amount',data=df,ax=ax[1])
sns.swarmplot(x='fare_amount',data=df[:200],ax=ax[2]);
```



Bivariate: Evaluating Correlation

Bivariate: Evaluating Correlation

- **Correlation:** the degree to which two variables are linearly related

- Pearson Correlation Coefficient: $\rho_{XY} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}$

- Sample Correlation: $r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{(n-1)s_x s_y}$

- Takes values between:
  - -1 (highly negatively correlated)
  - 0 (not correlated)
  - 1 (highly positively correlated)

Bivariate: Evaluating Correlation

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- Takes values between:
  - -1 (highly negatively correlated)
  - 0 (not correlated)
  - 1 (highly positively correlated)

In [99]:
```
df.trip_distance.corr(df.fare_amount)
```

Bivariate: Evaluating Correlation

- **Correlation:** the degree to which two variables are linearly related

- Pearson Correlation Coefficient: $\rho_{XY} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}$

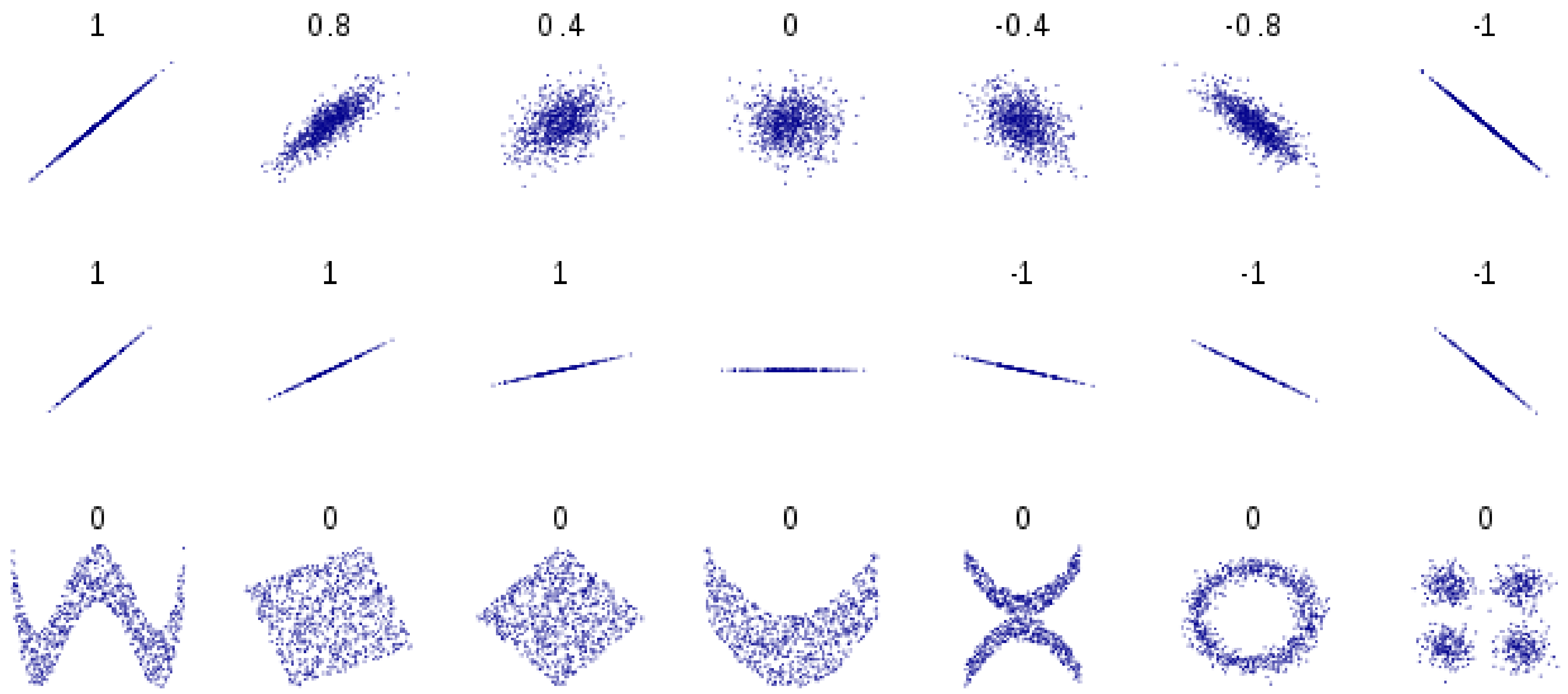
- Sample Correlation: $r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{(n-1)s_x s_y}$

- Takes values between:
  - -1 (highly negatively correlated)
  - 0 (not correlated)
  - 1 (highly positively correlated)

```
In [99]: df.trip_distance.corr(df.fare_amount)
```

Pearson Correlation

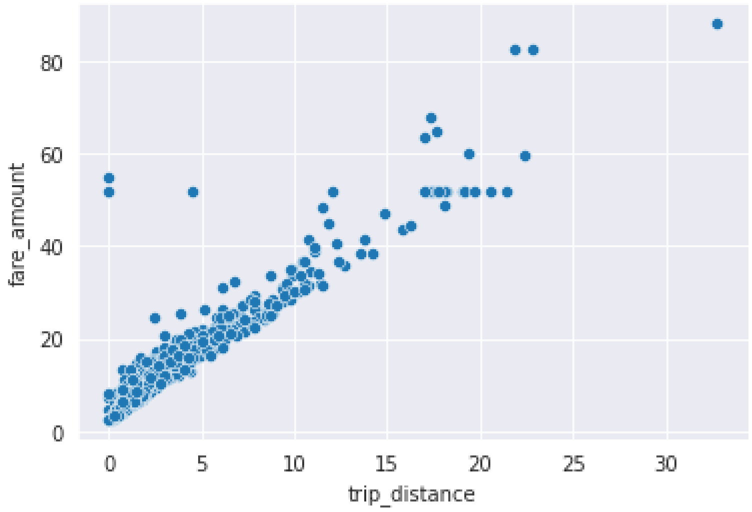
Pearson Correlation



Bivariate: Scatterplot

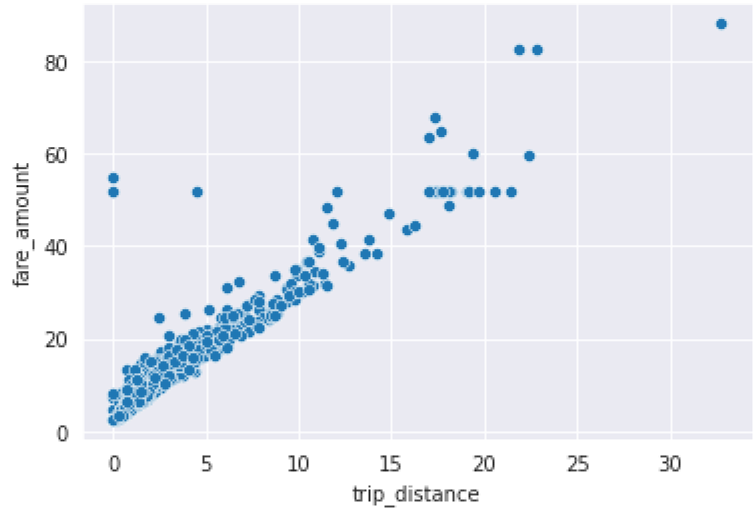
Bivariate: Scatterplot

In [101]:
```
sns.scatterplot(x='trip_distance',y='fare_amount',data=df);
```

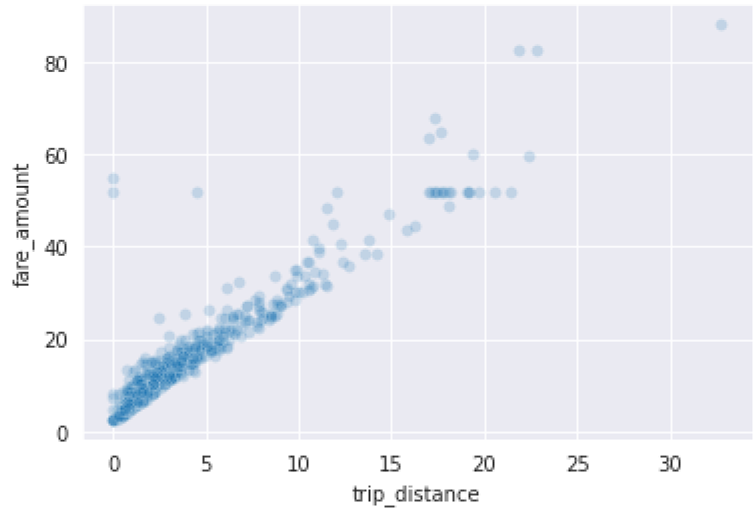


Bivariate: Scatterplot

In [101]:
```
sns.scatterplot(x='trip_distance',y='fare_amount',data=df);
```



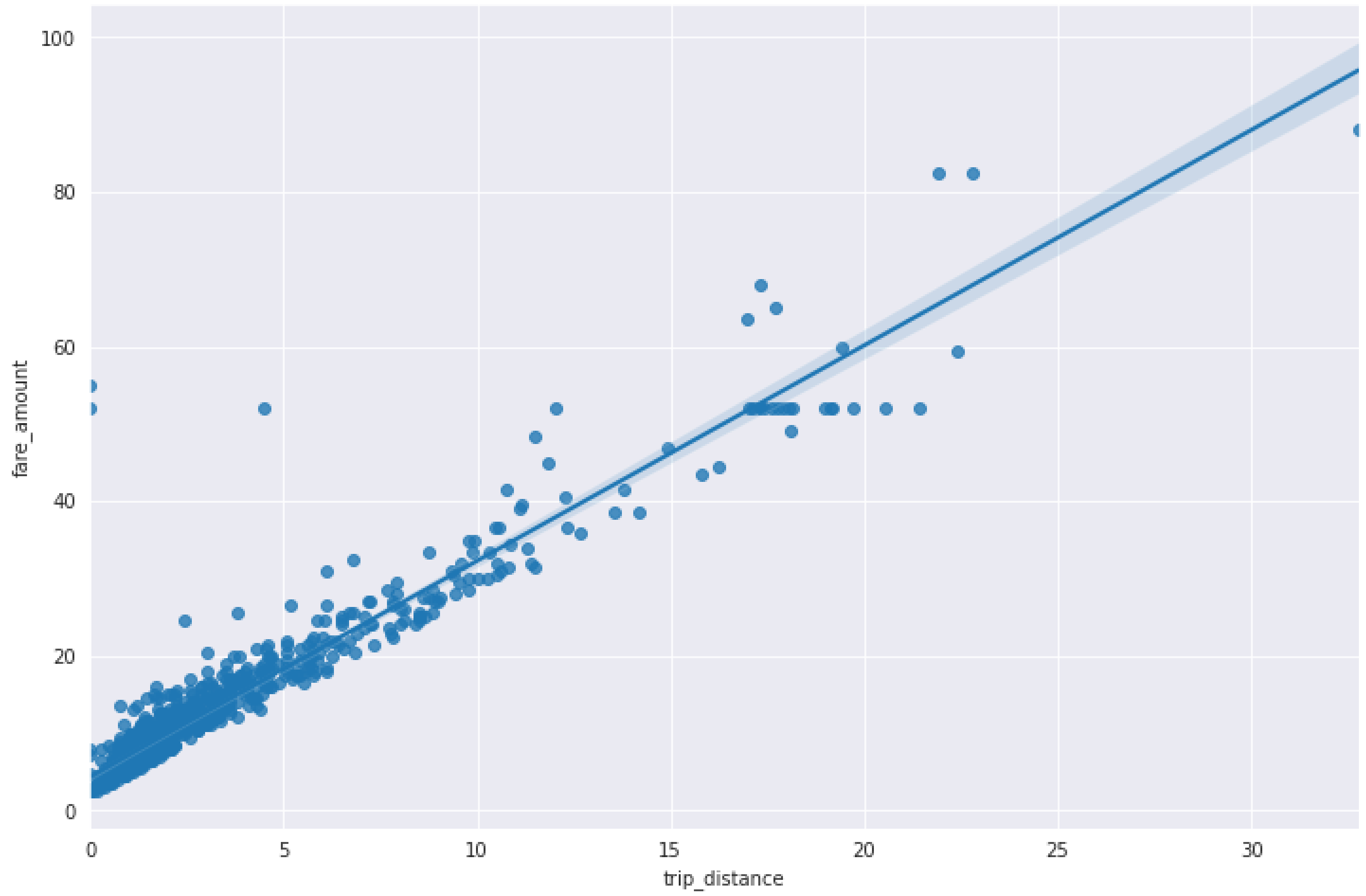
In [102]:
```
sns.scatterplot(x='trip_distance',y='fare_amount',data=df,alpha=0.2);
```



Bivariate: Add Regression Line

Bivariate: Add Regression Line

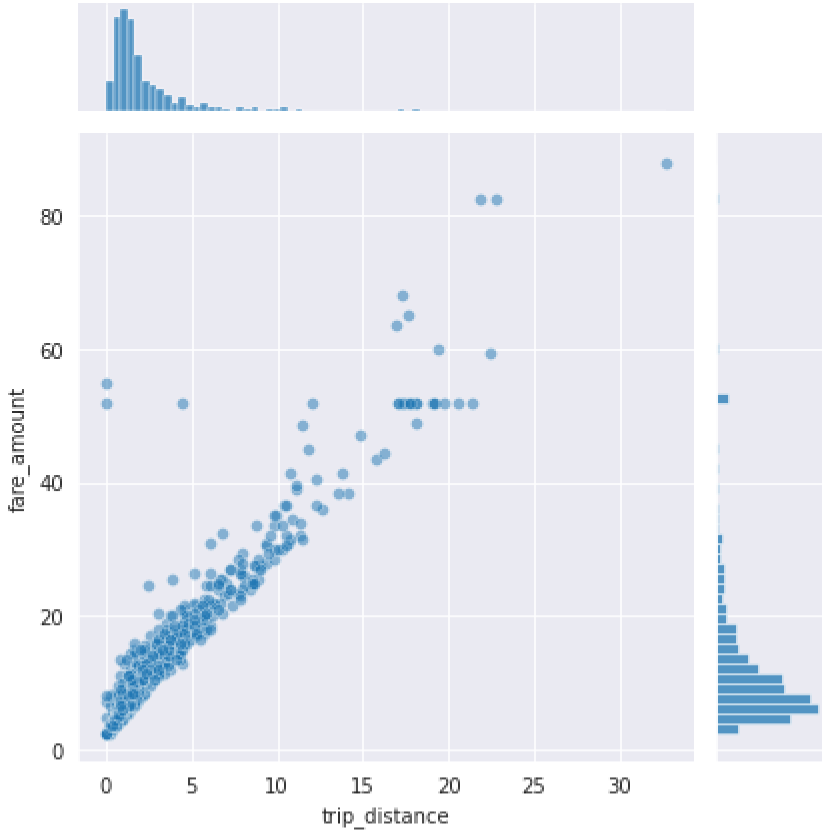
In [103]:
```
fig,ax = plt.subplots(1,1,figsize=(12,8))

sns.regplot(x='trip_distance',y='fare_amount',data=df,ax=ax);
```



Bivariate: Joint Plot

Bivariate: Joint Plot

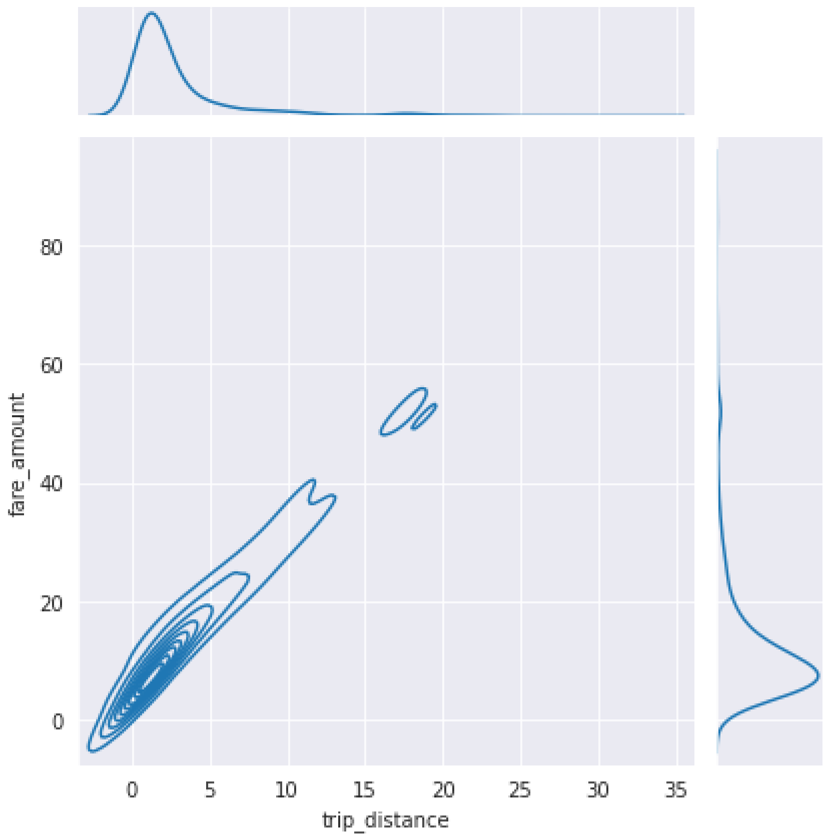
In [104]:
```
sns.jointplot(x='trip_distance',y='fare_amount',data=df,alpha=0.5);
```



Bivariate: Joint Plot with KDE

Bivariate: Joint Plot with KDE

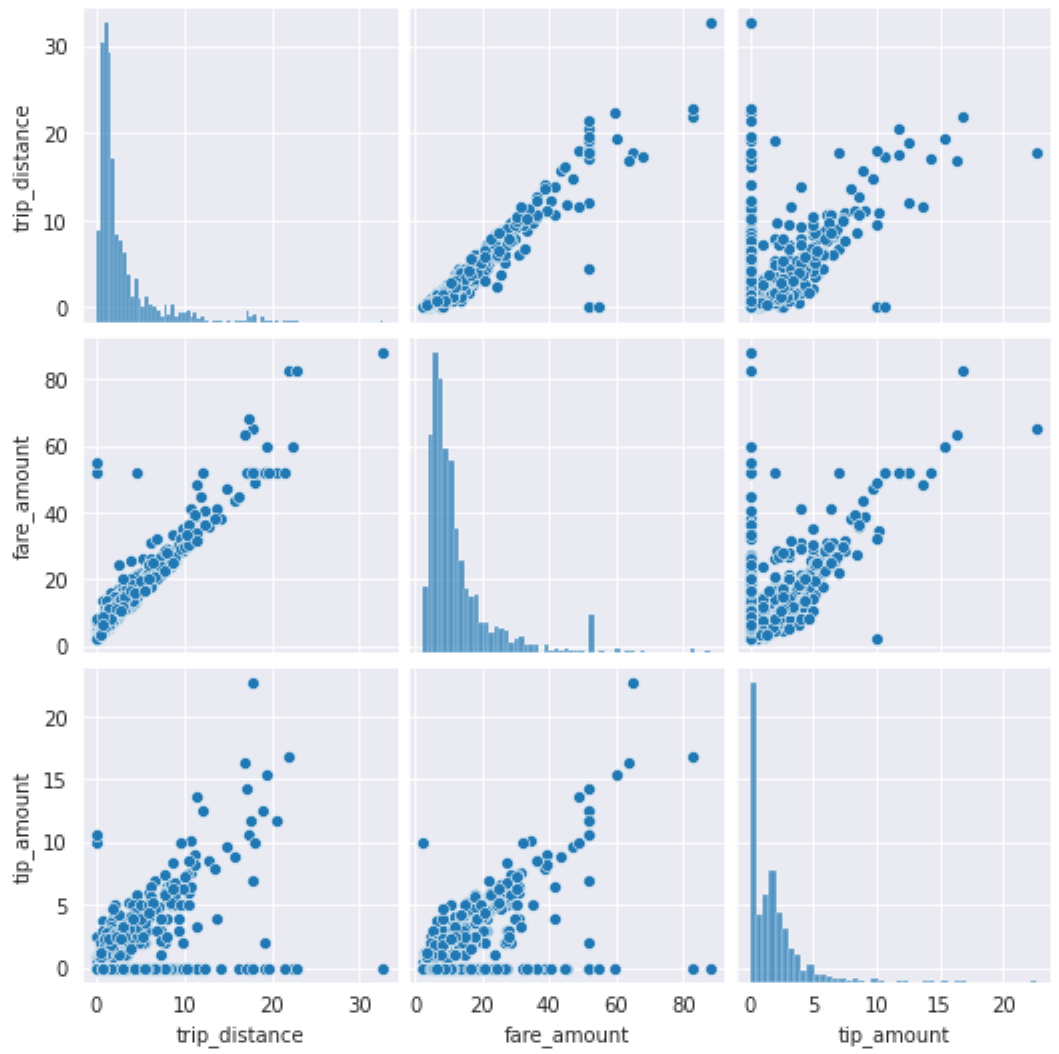
In [105]:
```
sns.jointplot(x='trip_distance', y='fare_amount',
              data=df,
              kind='kde');
```



Comparing Multiple Variables with `pairplot`

Comparing Multiple Variables with `pairplot`

In [106]:
```
sns.pairplot(df[['trip_distance','fare_amount','tip_amount']]);
```



Categorical Variables: Frequency

Categorical Variables: Frequency

In [107]:
```
df.payment_type.value_counts()
```

Out[107]:
```
Credit card    663
Cash           335
No charge        2
Name: payment_type, dtype: int64
```

Categorical Variables: Frequency

In [107]:
```
df.payment_type.value_counts()
```

Out[107]:
```
Credit card    663
Cash           335
No charge        2
Name: payment_type, dtype: int64
```

In [108]:
```
df.payment_type.value_counts(normalize=True)
```

Out[108]:
```
Credit card    0.663
Cash           0.335
No charge      0.002
Name: payment_type, dtype: float64
```

Categorical Variables: Frequency

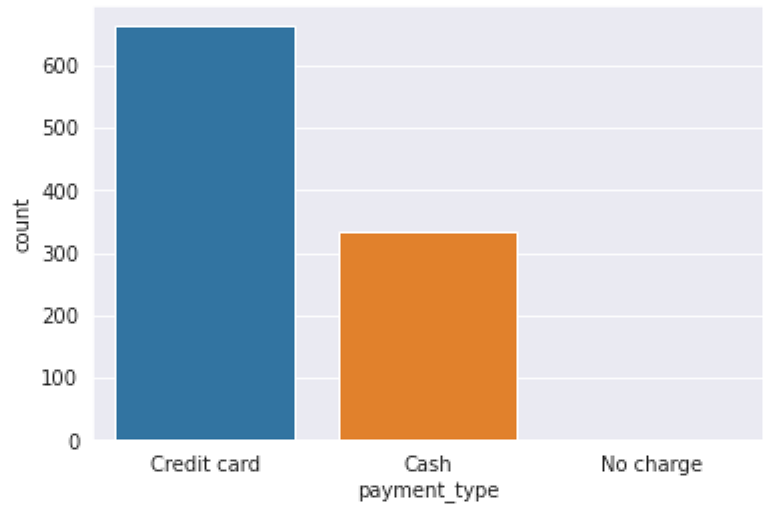
In [107]:
```
df.payment_type.value_counts()
```

Out[107]:
```
Credit card    663
Cash           335
No charge        2
Name: payment_type, dtype: int64
```

In [108]:
```
df.payment_type.value_counts(normalize=True)
```

Out[108]:
```
Credit card    0.663
Cash           0.335
No charge      0.002
Name: payment_type, dtype: float64
```

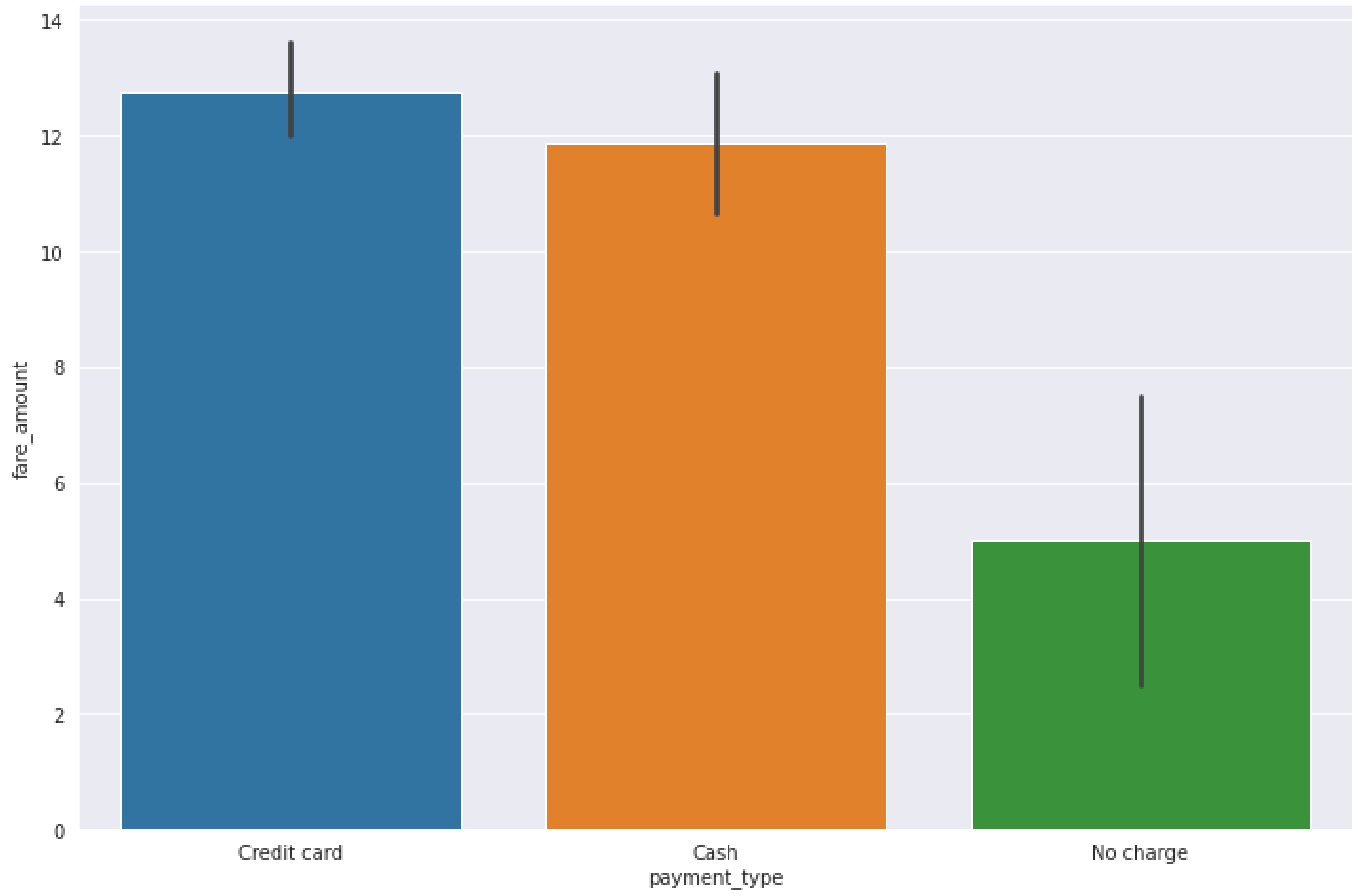
In [109]:
```
sns.countplot(x=df.payment_type);
```



Plotting Numeric and Categorical

Plotting Numeric and Categorical

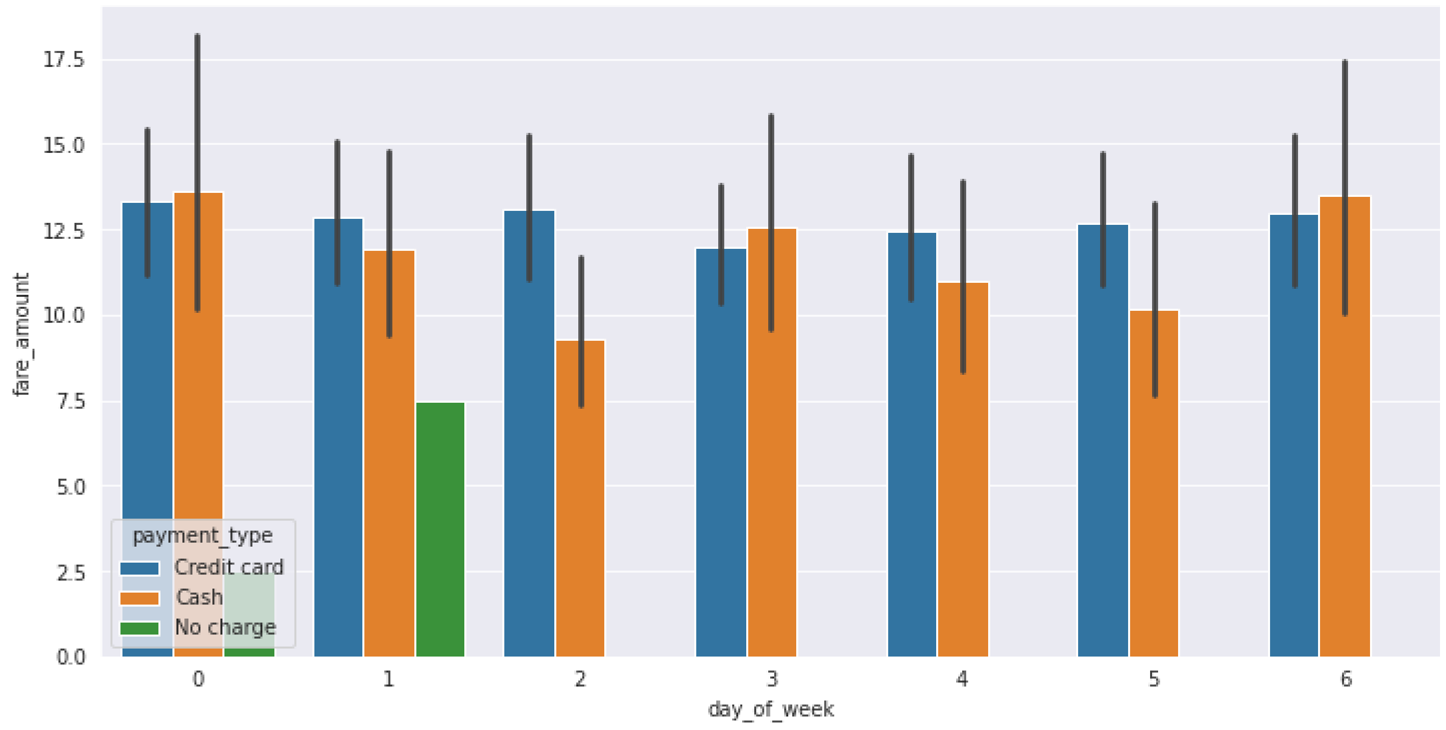
In [110]:
```
fig,ax = plt.subplots(1,1,figsize=(12,8))

sns.barplot(x='payment_type',y='fare_amount',data=df);
```



Plotting with Hue

Plotting with Hue

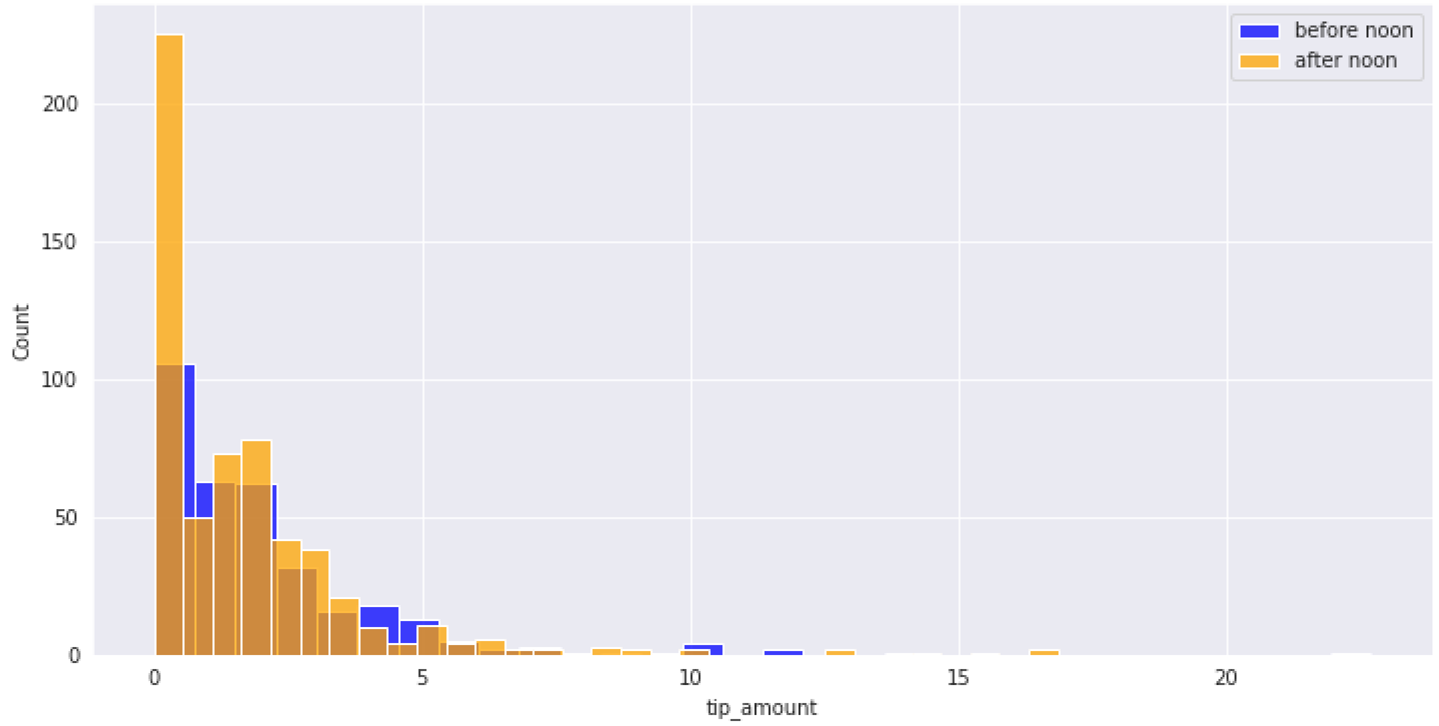
In [111]:
```
# Adding Another Categorical
df['day_of_week'] = df.pickup_datetime.dt.dayofweek

fig,ax = plt.subplots(1,1,figsize=(12,6))

sns.barplot(x='day_of_week',
            y='fare_amount',
            hue='payment_type',
            data=df);
```



Same Axis, Multiple Plots with Seaborn

Same Axis, Multiple Plots with Seaborn

In [112]:
```
fig,ax = plt.subplots(1,1,figsize=(12,6))
sns.histplot(df[df.pickup_datetime.dt.hour < 12].tip_amount, label='before noon',color='blue',ax=ax);
sns.histplot(df[df.pickup_datetime.dt.hour >= 12].tip_amount, label='after noon',color='orange',ax=ax);
plt.legend(loc='best');
```



Data Exploration and Viz Review

- central tendencies: mean, median
- spread: variance, std deviation, IQR
- correlation: pearson correlation coefficient
- plotting real valued variables: histogram, scatter, regplot
- plotting categorical variables: count, bar
- plotting interactions: jointplot, pairplot

Questions?