Elements Of Data Science - F2022

# Week 8: Data Cleaning and Feature Engineering

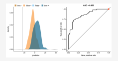
10/26/2022

# TODOs

- Readings:
  - PML Ch4.5 : Selecting Meaningful Features
  - PML Ch5.1 : Unsupervised dimensionality reduction via principal component analysis
  - [Recommended] Pandas: Merge, join, concatenate and compare
  - [Additional] PDSH 5.9 : PCA
  - [Optional] : Nice ROC visualization (http://www.navan.name/roc/)

- **Quiz 8**, due **Tuesday Nov 1st, 11:59pm ET**
- HW2 Due Nov 4th

# Precision & Recall and ROC visualizations

| | |
|---|---|
| Precision & Recall<br><br>https://www.wikiwand.com/en/Precision_and_recall | ROC<br><br><br>This and more at https://github.com/dariyasydykova/open_projects/tree/master/ROC_animation<br><br>Also see the interactive viz at http://www.navan.name/roc/ |

# Homework 2 Notes

- new homework submission points
    - (1pt) The homework should be spread over multiple pdf pages, not one single pdf page
    - (1pt) When submitting, assign each question to the pdf page where the solution is printed. If there is no print statement for a question, assign the question to the first pdf page where the code for the question is visible.
- string formatting vs. `round()` instead for setting precision

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- string formatting vs. `round()` instead for setting precision

In [1]:
```
import numpy as np

x  = 0.5555
print(f"x                   : {x}")
print(f"using str formatting: {x:0.3f}")
print(f"using round()       : {round(x,3)}")
print(f"using numpy .round(): {np.float64(x).round(3)}") # Use numpy for floats!
```

```
x                   : 0.5555
using str formatting: 0.555
using round()       : 0.555
using numpy .round(): 0.556
```

# Homework 2 Notes Continued

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- creating a dataframe from a dictionary of string:list pairs

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- creating a dataframe from a dictionary of string:list pairs

In [2]:
```
import pandas as pd

levels = [2,4,6,8]
vals1 = [0.1,0.2,0.3,0.4]
vals2 = [0.1,0.2,0.2,0.1]
df_tmp = pd.DataFrame({'column1':vals1,'column2':vals2},
                      index=levels
                     )
df_tmp.round(2)
```

Out[2]:

| | column1 | column2 |
|---|---|---|
| **2** | 0.1 | 0.1 |
| **4** | 0.2 | 0.2 |
| **6** | 0.3 | 0.2 |
| **8** | 0.4 | 0.1 |

# Homework 2 Notes Continued

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- Plotting line plots from a dataframe with numeric columns

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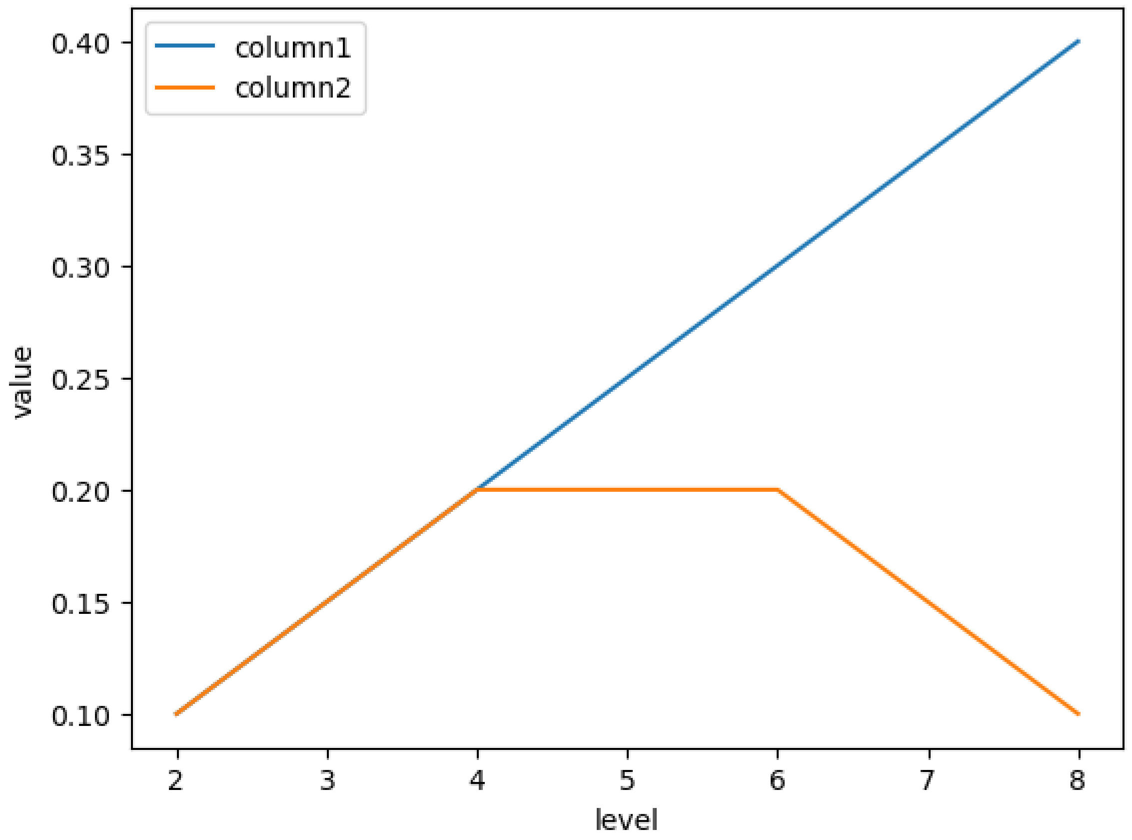
- Plotting line plots from a dataframe with numeric columns

```
In [3]: display(df_tmp.round(2))
        ax = df_tmp.plot();
        ax.set_xlabel('level');
        ax.set_ylabel('value');
```

| | column1 | column2 |
|---|---|---|
| **2** | 0.1 | 0.1 |
| **4** | 0.2 | 0.2 |
| **6** | 0.3 | 0.2 |
| **8** | 0.4 | 0.1 |



# Notes from Quiz 7

- LinearRegression (regression) vs LogisticRegression (classification)
- using a model "with default settings"

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- LinearRegression (regression) vs LogisticRegression (classification)
- using a model "with default settings"

In [6]:
```
from sklearn.ensemble import GradientBoostingClassifier

gbc = GradientBoostingClassifier()
```

# Today

- **Data Cleaning**
    - Duplicates
    - Missing Data
    - Dummy Variables
    - Rescaling
    - Dealing With Skew
    - Removing Outliers
- **Feature Engineering**
    - Binning
    - One-Hot encoding
    - Derived
        - string functions
        - datetime functions

# Questions?

# Environment Setup

# Environment Setup

In [7]:
```
import numpy
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from mlxtend.plotting import plot_decision_regions

sns.set_style('darkgrid')

%matplotlib inline
```

# Data Cleaning

Why do we need clean data?

- Want one row per observation (need to remove duplicates)
- Most models cannot handle missing data (need to remove/fill missing)
- Most models require fixed length feature vectors (need to engineer features)

- Different models require different types of data (transformation)
    - Linear models: real valued features with similar scale
    - Distance based: real valued features with similar scale
    - Tree based: can handle unscaled real and categorical (sklearn requires real)

# Example Data

# Example Data

In [8]:

```
# read in example data
df_shop_raw = pd.read_csv('../data/flowershop_data_with_dups_week8.csv',
                          header=0,
                          delimiter=',')
df_shop_raw['purchase_date'] = pd.to_datetime(df_shop_raw.purchase_date)

# make a copy for editing
df_shop = df_shop_raw.copy()

df_shop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1001 entries, 0 to 1000
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   purchase_id      1001 non-null   int64
 1   lastname         1001 non-null   object
 2   purchase_date    1001 non-null   datetime64[ns]
 3   stars            1001 non-null   int64
 4   price            979 non-null    float64
 5   favorite_flower  823 non-null    object
dtypes: datetime64[ns](1), float64(1), int64(2), object(2)
memory usage: 47.0+ KB
```

# Duplicated Data

- Only drop duplicates if you know data should be unique
    - Example: if there is a unique id per row

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- Only drop duplicates if you know data should be unique
    - Example: if there is a unique id per row

In [9]:
```
df_shop.duplicated().iloc[-3:] # are any of the last 3 rows duplicates?
```

Out[9]:
```
998     False
999     False
1000     True
dtype: bool
```

# Duplicated Data

- Only drop duplicates if you know data should be unique
    - Example: if there is a unique id per row

In [9]:
```
df_shop.duplicated().iloc[-3:] # are any of the last 3 rows duplicates?
```

Out[9]:
```
998     False
999     False
1000     True
dtype: bool
```

In [10]:
```
df_shop[df_shop.duplicated(keep='first')] # default: keep 'first' duplicated row
```

Out[10]:

| | purchase_id | lastname | purchase_date | stars | price | favorite_flower |
|---|---|---|---|---|---|---|
| **1000** | 1010 | FERGUSON | 2017-05-04 | 2 | 21.02 | daffodil |

# Duplicated Data

- Only drop duplicates if you know data should be unique
  - Example: if there is a unique id per row

In [9]:
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999      False
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In [10]:
```
df_shop[df_shop.duplicated(keep='first')] # default: keep 'first' duplicated row
```

Out[10]:

| | purchase_id | lastname | purchase_date | stars | price | favorite_flower |
|---|---|---|---|---|---|---|
| **1000** | 1010 | FERGUSON | 2017-05-04 | 2 | 21.02 | daffodil |

In [11]:
```
df_shop[df_shop.duplicated(keep=False)] # keep=False to show all duplicated rows
```

Out[11]:

| | purchase_id | lastname | purchase_date | stars | price | favorite_flower |
|---|---|---|---|---|---|---|
| **10** | 1010 | FERGUSON | 2017-05-04 | 2 | 21.02 | daffodil |
| **1000** | 1010 | FERGUSON | 2017-05-04 | 2 | 21.02 | daffodil |

# Duplicated Data for Subset of Columns

# Duplicated Data for Subset of Columns

In [12]:

```
# if it's important that a subset of columns is not duplicated
(
    df_shop
    .loc[df_shop.duplicated(subset=['purchase_id'],keep=False)]
    .sort_values(by='purchase_id')
)
```

Out[12]:

| | purchase_id | lastname | purchase_date | stars | price | favorite_flower |
|---|---|---|---|---|---|---|
| **10** | 1010 | FERGUSON | 2017-05-04 | 2 | 21.02 | daffodil |
| **1000** | 1010 | FERGUSON | 2017-05-04 | 2 | 21.02 | daffodil |
| **100** | 1101 | WEBB | 2017-07-13 | 2 | 8.00 | iris |
| **101** | 1101 | BURKE | 2017-08-16 | 4 | 18.56 | daffodil |

# Duplicated Data for Subset of Columns

In [12]:
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(
    df_shop
    .loc[df_shop.duplicated(subset=['purchase_id'],keep=False)]
    .sort_values(by='purchase_id')
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```

Out[12]:

| | purchase_id | lastname | purchase_date | stars | price | favorite_flower |
|---|---|---|---|---|---|---|
| **10** | 1010 | FERGUSON | 2017-05-04 | 2 | 21.02 | daffodil |
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In [13]:
```python
# could also use the indexing shortcut
df_shop[df_shop.duplicated(subset=['purchase_id'],keep=False)].sort_values(by='purchase_id')
```

Out[13]:

| | purchase_id | lastname | purchase_date | stars | price | favorite_flower |
|---|---|---|---|---|---|---|
| **10** | 1010 | FERGUSON | 2017-05-04 | 2 | 21.02 | daffodil |
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# Dropping Duplicates

# Dropping Duplicates

In [14]:
```
df_shop = df_shop.drop_duplicates(subset=None,    # consider all columns
                                  keep='first',   # or 'last' or False)
                                  inplace=False   # default, return a modified dataframe
                                 )
```

# Dropping Duplicates

In [14]:
```
df_shop = df_shop.drop_duplicates(subset=None,    # consider all columns
                                  keep='first',   # or 'last' or False)
                                  inplace=False   # default, return a modified dataframe
                                 )
```

In [15]:
```
# or can use inplace to change the original dataframe
df_shop.drop_duplicates(subset=None,
                        keep='first',
                        inplace=True # change the dataframe in place
                       )
```

# Dropping Duplicates

In [14]:
```
df_shop = df_shop.drop_duplicates(subset=None,    # consider all columns
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In [15]:
```
# or can use inplace to change the original dataframe
df_shop.drop_duplicates(subset=None,
                        keep='first',
                        inplace=True # change the dataframe in place
                       )
```

In [16]:
```
# can also drop rows with duplicates considering only a subset of columns
df_shop = df_shop.drop_duplicates(subset=['purchase_id'])
```

# Missing Data

- Reasons for missing data
  - Sensor error (random?)
  - Data entry error (random?)
  - Survey-subject decisions (non-random?)
  - etc.

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- Reasons for missing data
    - Sensor error (random?)
    - Data entry error (random?)
    - Survey-subject decisions (non-random?)
    - etc.

- Dealing with missing data
    - Drop rows
    - Impute from data in the same column
    - Infer from other features
    - Fill with adjacent data

# Missing Data in Pandas: `np.nan`

- Missing values represented by `np.nan` : Not A Number

# Missing Data in Pandas: `np.nan`

- Missing values represented by `np.nan` : Not A Number

In [17]:
```
# Earlier, we saw missing values in the dataframe summary
df_shop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 999 entries, 0 to 999
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   purchase_id      999 non-null    int64
 1   lastname         999 non-null    object
 2   purchase_date    999 non-null    datetime64[ns]
 3   stars            999 non-null    int64
 4   price            977 non-null    float64
 5   favorite_flower  821 non-null    object
dtypes: datetime64[ns](1), float64(1), int64(2), object(2)
memory usage: 54.6+ KB
```

# Missing Data in Pandas: `np.nan`

- Missing values represented by `np.nan` : Not A Number

In [17]:
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# Earlier, we saw missing values in the dataframe summary
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 5   favorite_flower  821 non-null    object
dtypes: datetime64[ns](1), float64(1), int64(2), object(2)
memory usage: 54.6+ KB
```

In [18]:
```
# can we check for NaN using "x == np.nan"? No!
np.nan == np.nan
```

Out[18]:
```
False
```

# Missing Data in Pandas: `np.nan`

- Missing values represented by `np.nan` : Not A Number

In [17]:
```
# Earlier, we saw missing values in the dataframe summary
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 5   favorite_flower  821 non-null    object
dtypes: datetime64[ns](1), float64(1), int64(2), object(2)
memory usage: 54.6+ KB
```

In [18]:
```
# can we check for NaN using "x == np.nan"? No!
np.nan == np.nan
```

Out[18]:
```
False
```

In [19]:
```
# however
np.nan is np.nan
```

Out[19]:
```
True
```

# How to check for NaN: `.isna()` and `.notna()`

# How to check for NaN: `.isna()` and `.notna()`

In [20]:
```
# some missing data
df_shop.loc[20:21,'price']
```

Out[20]:
```
20      NaN
21    10.53
Name: price, dtype: float64
```

# How to check for NaN: `.isna()` and `.notna()`

In [20]:
```
# some missing data
df_shop.loc[20:21,'price']
```

Out[20]:
```
20      NaN
21    10.53
Name: price, dtype: float64
```

In [21]:
```
# .isna() returns True where data is missing, False otherwise
df_shop.loc[20:21,'price'].isna()
```

Out[21]:
```
20     True
21    False
Name: price, dtype: bool
```

# How to check for NaN: `.isna()` and `.notna()`

In [20]:
```
# some missing data
df_shop.loc[20:21,'price']
```

Out[20]:
```
20      NaN
21    10.53
Name: price, dtype: float64
```

In [21]:
```
# .isna() returns True where data is missing, False otherwise
df_shop.loc[20:21,'price'].isna()
```

Out[21]:
```
20     True
21    False
Name: price, dtype: bool
```

In [22]:
```
# .notna() returns True where data is NOT missing, False otherwise
df_shop.loc[20:21,'price'].notna()
```

Out[22]:
```
20    False
21     True
Name: price, dtype: bool
```

# How to check for NaN: `.isna()` and `.notna()`

In [20]:
```
# some missing data
df_shop.loc[20:21,'price']
```

Out[20]:
```
20      NaN
21    10.53
Name: price, dtype: float64
```

In [21]:
```
# .isna() returns True where data is missing, False otherwise
df_shop.loc[20:21,'price'].isna()
```

Out[21]:
```
20     True
21    False
Name: price, dtype: bool
```

In [22]:
```
# .notna() returns True where data is NOT missing, False otherwise
df_shop.loc[20:21,'price'].notna()
```

Out[22]:
```
20    False
21     True
Name: price, dtype: bool
```

In [23]:
```
# find rows where price is missing
df_shop[df_shop.price.isna()].head()
```

Out[23]:

| | purchase_id | lastname | purchase_date | stars | price | favorite_flower |
|---|---|---|---|---|---|---|
| **20** | 1020 | CLARK | 2017-01-05 | 3 | NaN | NaN |
| **41** | 1041 | PETERS | 2017-02-01 | 4 | NaN | orchid |
| **54** | 1054 | GREEN | 2017-02-13 | 5 | NaN | daffodil |
| **63** | 1063 | BARNETT | 2017-08-27 | 4 | NaN | gardenia |
| **145** | 1145 | CARROLL | 2017-07-29 | 3 | NaN | tulip |

# Counting NaNs

# Counting NaNs

In [24]:
```
# How many nan's in a single column?
df_shop.price.isna().sum()
```

Out[24]:
```
22
```

# Counting NaNs

In [24]:
```
# How many nan's in a single column?
df_shop.price.isna().sum()
```

Out[24]:
```
22
```

In [25]:
```
# How many nan's per column?
df_shop.isna().sum()
```

Out[25]:
```
purchase_id          0
lastname             0
purchase_date        0
stars                0
price               22
favorite_flower    178
dtype: int64
```

# Counting NaNs

In [24]:
```
# How many nan's in a single column?
df_shop.price.isna().sum()
```

Out[24]:
```
22
```

In [25]:
```
# How many nan's per column?
df_shop.isna().sum()
```

Out[25]:
```
purchase_id          0
lastname             0
purchase_date        0
stars                0
price               22
favorite_flower    178
dtype: int64
```

In [26]:
```
# How many total nan's?
df_shop.isna().sum().sum()
```

Out[26]:
```
200
```

# Missing Data: Drop Rows

# Missing Data: Drop Rows

In [27]:
```
df_shop.shape
```

Out[27]:
```
(999, 6)
```

# Missing Data: Drop Rows

In [27]:
```
df_shop.shape
```

Out[27]:
```
(999, 6)
```

In [28]:
```
# drop rows with nan in any column
df_shop.dropna().shape
```

Out[28]:
```
(801, 6)
```

# Missing Data: Drop Rows

In [27]:
```
df_shop.shape
```

Out[27]: (999, 6)

In [28]:
```
# drop rows with nan in any column
df_shop.dropna().shape
```

Out[28]: (801, 6)

In [29]:
```
# drop only rows with nan in price using subset
df_shop.dropna(subset=['price']).shape
```

Out[29]: (977, 6)

# Missing Data: Drop Rows

In [27]:
```
df_shop.shape
```

Out[27]: (999, 6)

In [28]:
```
# drop rows with nan in any column
df_shop.dropna().shape
```

Out[28]: (801, 6)

In [29]:
```
# drop only rows with nan in price using subset
df_shop.dropna(subset=['price']).shape
```

Out[29]: (977, 6)

In [30]:
```
# drop only rows with nans in all columns (a row of all nans)
df_shop.dropna(how='all').shape
```

Out[30]: (999, 6)

# Missing Data: Drop Rows Cont.

# Missing Data: Drop Rows Cont.

In [31]:
```
# save a new dataframe with dropped rows
df_shop = df_shop.dropna()
df_shop.shape
```

Out[31]:
```
(801, 6)
```

# Missing Data: Drop Rows Cont.

In [31]:
```python
# save a new dataframe with dropped rows
df_shop = df_shop.dropna()
df_shop.shape
```

Out[31]: (801, 6)

In [32]:
```python
# drop rows in current dataframe
df_shop = df_shop_raw.drop_duplicates().copy()

df_shop.dropna(inplace=True)
df_shop.shape
```

Out[32]: (802, 6)

# Missing Data: Drop Rows

- Pros:
  - easy to do
  - simple to understand
- Cons:
  - potentially large data loss

# Missing Data: Fill with Constant

- Use .fillna()
- Common filler: 0, -1

In [33]:
```
df_shop = df_shop_raw.drop_duplicates().copy() # make a new copy of the data
```

# Missing Data: Fill with Constant

- Use .fillna()
- Common filler: 0, -1

In [33]:
```
df_shop = df_shop_raw.drop_duplicates().copy() # make a new copy of the data
```

In [34]:
```
df_shop.price[20:22]
```

Out[34]:
```
20      NaN
21    10.53
Name: price, dtype: float64
```

# Missing Data: Fill with Constant

- Use .fillna()
- Common filler: 0, -1

In [33]:
```
df_shop = df_shop_raw.drop_duplicates().copy() # make a new copy of the data
```

In [34]:
```
df_shop.price[20:22]
```

Out[34]:
```
20      NaN
21    10.53
Name: price, dtype: float64
```

In [35]:
```
df_shop.price[20:22].fillna(0)
```

Out[35]:
```
20     0.00
21    10.53
Name: price, dtype: float64
```

# Missing Data: Fill with Constant

- Use .fillna()
- Common filler: 0, -1

In [33]:
```
df_shop = df_shop_raw.drop_duplicates().copy() # make a new copy of the data
```

In [34]:
```
df_shop.price[20:22]
```

Out[34]:
```
20      NaN
21    10.53
Name: price, dtype: float64
```

In [35]:
```
df_shop.price[20:22].fillna(0)
```

Out[35]:
```
20     0.00
21    10.53
Name: price, dtype: float64
```

In [36]:
```
print(df_shop.price.mean().round(2))
print(df_shop.price.fillna(0).mean().round(2))
```

```
23.4
22.89
```

# Missing Data: Fill with Constant

Pros:

- easy to do
- simple to understand

Cons:

- values may not be realistic

# Missing Data: Impute

- Impute: fill with value infered from existing values in that column
- Use .fillna() or sklearn methods
- Common filler values:
    - mean
    - median
    - "most frequent" aka mode

# Missing Data: Impute

# Missing Data: Impute

In [37]:
```
print(df_shop.price.mean().round(2))
print(df_shop.price.fillna(df_shop.price.mean()).mean().round(2))
```

```
23.4
23.4
```

# Missing Data: Impute

In [37]:
```
print(df_shop.price.mean().round(2))
print(df_shop.price.fillna(df_shop.price.mean()).mean().round(2))
```

```
23.4
23.4
```

In [38]:
```
# make a copy to keep our original df
df_shop_impute = df_shop.copy()
```

# Missing Data: Impute

In [37]:
```
print(df_shop.price.mean().round(2))
print(df_shop.price.fillna(df_shop.price.mean()).mean().round(2))
```

```
23.4
23.4
```

In [38]:
```
# make a copy to keep our original df
df_shop_impute = df_shop.copy()
```

In [39]:
```
# fill missing price with mean of price
df_shop_impute['price'] = df_shop.price.fillna(df_shop.price.mean())
```

# Missing Data: Impute

In [37]:
```
print(df_shop.price.mean().round(2))
print(df_shop.price.fillna(df_shop.price.mean()).mean().round(2))
```

```
23.4
23.4
```

In [38]:
```
# make a copy to keep our original df
df_shop_impute = df_shop.copy()
```

In [39]:
```
# fill missing price with mean of price
df_shop_impute['price'] = df_shop.price.fillna(df_shop.price.mean())
```

In [40]:
```
# check to make sure all nulls filled
assert df_shop_impute.price.isna().sum() == 0
assert df_shop_impute.price.notna().all()

# also, that our mean hasn't changed
assert df_shop.price.mean() == df_shop_impute.price.mean()
```

# Missing Data: Impute

In [37]:
```
print(df_shop.price.mean().round(2))
print(df_shop.price.fillna(df_shop.price.mean()).mean().round(2))
```

```
23.4
23.4
```

In [38]:
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# make a copy to keep our original df
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df_shop_impute['price'] = df_shop.price.fillna(df_shop.price.mean())
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# check to make sure all nulls filled
assert df_shop_impute.price.isna().sum() == 0
assert df_shop_impute.price.notna().all()

# also, that our mean hasn't changed
assert df_shop.price.mean() == df_shop_impute.price.mean()
```

In [41]:
```
# inplace works here as well
df_shop_impute.price.fillna(df_shop_impute.price.mean(),inplace=True)
```

# Missing Data: Impute Cont.

# Missing Data: Impute Cont.

In [42]:
```
df_shop.favorite_flower.mode() # may be more than 1!
```

Out[42]:
```
0    lilac
Name: favorite_flower, dtype: object
```

# Missing Data: Impute Cont.

In [42]:
```
df_shop.favorite_flower.mode() # may be more than 1!
```

Out[42]:
```
0    lilac
Name: favorite_flower, dtype: object
```

In [43]:
```
# Note that we have to index into the DataFrame returned by mode to get a value
df_shop_impute.favorite_flower.fillna(df_shop_impute.favorite_flower.mode().iloc[0],inplace=True)

df_shop_impute.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000 entries, 0 to 999
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   purchase_id      1000 non-null   int64
 1   lastname         1000 non-null   object
 2   purchase_date    1000 non-null   datetime64[ns]
 3   stars            1000 non-null   int64
 4   price            1000 non-null   float64
 5   favorite_flower  1000 non-null   object
dtypes: datetime64[ns](1), float64(1), int64(2), object(2)
memory usage: 54.7+ KB
```

# Missing Data: Impute Cont. Using SimpleImputer

# Missing Data: Impute Cont. Using SimpleImputer

```
In [44]: df_shop[['price','stars']].loc[20:22]
```

Out[44]:

| | price | stars |
|---|---|---|
| **20** | NaN | 3 |
| **21** | 10.53 | 2 |
| **22** | 19.77 | 1 |

# Missing Data: Impute Cont. Using SimpleImputer

In [44]:
```
df_shop[['price','stars']].loc[20:22]
```

Out[44]:

| | price | stars |
|---|---|---|
| **20** | NaN | 3 |
| **21** | 10.53 | 2 |
| **22** | 19.77 | 1 |

In [45]:
```
from sklearn.impute import SimpleImputer

imp = SimpleImputer(strategy='mean').fit(df_shop[['price','stars']])
print(f'fill values = {imp.statistics_.round(2)}')
imp.transform(df_shop.loc[20:22,['price','stars']]).round(2)
```

```
fill values = [23.4  3.6]
```

Out[45]:
```
array([[23.4 ,  3.  ],
       [10.53,  2.  ],
       [19.77,  1.  ]])
```

# Missing Data: Impute Cont. Using SimpleImputer

In [44]:
```
df_shop[['price','stars']].loc[20:22]
```

Out[44]:

| | price | stars |
|---|---|---|
| **20** | NaN | 3 |
| **21** | 10.53 | 2 |
| **22** | 19.77 | 1 |

In [45]:
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```

```
fill values = [23.4  3.6]
```

Out[45]:
```
array([[23.4 ,  3.  ],
       [10.53,  2.  ],
       [19.77,  1.  ]])
```

In [46]:
```
df_shop.favorite_flower[:3]
```

Out[46]:
```
0         iris
1          NaN
2    carnation
Name: favorite_flower, dtype: object
```

# Missing Data: Impute Cont. Using SimpleImputer

In [44]:
```
df_shop[['price','stars']].loc[20:22]
```

Out[44]:

| | price | stars |
|---|---|---|
| 20 | NaN | 3 |
| 21 | 10.53 | 2 |
| 22 | 19.77 | 1 |

In [45]:
```
from sklearn.impute import SimpleImputer

imp = SimpleImputer(strategy='mean').fit(df_shop[['price','stars']])
print(f'fill values = {imp.statistics_.round(2)}')
imp.transform(df_shop.loc[20:22,['price','stars']]).round(2)
```

```
fill values = [23.4  3.6]
```

Out[45]:
```
array([[23.4 ,  3.  ],
       [10.53,  2.  ],
       [19.77,  1.  ]])
```

In [46]:
```
df_shop.favorite_flower[:3]
```

Out[46]:
```
0         iris
1          NaN
2    carnation
Name: favorite_flower, dtype: object
```

In [47]:
```
imp = SimpleImputer(strategy='most_frequent').fit(df_shop[['favorite_flower']])
imp.transform(df_shop.loc[:2,['favorite_flower']])
```

Out[47]:
```
array([['iris'],
       ['lilac'],
       ['carnation']], dtype=object)
```

# Missing Data: Impute

- Pros:
  - easy to do
  - simple to understand
- Cons:
  - may missing feature interactions

# Missing Data: Infer

- Predict values of missing features using a model
- Ex: Can we predict price based on any of the other features?
- Additional feature engineering may be needed prior to this

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- Predict values of missing features using a model
- Ex: Can we predict price based on any of the other features?
- Additional feature engineering may be needed prior to this

In [48]:
```
from sklearn.linear_model import LinearRegression

df_shop_infer = df_shop.copy()

not_missing = df_shop_infer.price.notna()
missing     = df_shop_infer.price.isna()

lr = LinearRegression().fit(df_shop_infer.loc[not_missing,['stars']],
                            df_shop_infer.loc[not_missing,'price'])

df_shop_infer.loc[missing,'price'] = lr.predict(df_shop_infer.loc[missing,['stars']])
```

# Missing Data: Impute

# Missing Data: Adjacent Data

- Use `.fillna()` with method:
  - ffill: propagate last valid observation forward to next valid
  - bfill: use next valid observation to fill gap backwards
- Use when there is reason to believe data not i.i.d. (eg: timeseries)

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  - bfill: use next valid observation to fill gap backwards
- Use when there is reason to believe data not i.i.d. (eg: timeseries)

In [49]:
```
df_shop.price.loc[19:21]
```

Out[49]:
```
19    20.45
20      NaN
21    10.53
Name: price, dtype: float64
```

# Missing Data: Adjacent Data

- Use `.fillna()` with method:
    - ffill: propagate last valid observation forward to next valid
    - bfill: use next valid observation to fill gap backwards
- Use when there is reason to believe data not i.i.d. (eg: timeseries)

In [49]:
```
df_shop.price.loc[19:21]
```

Out[49]:
```
19    20.45
20      NaN
21    10.53
Name: price, dtype: float64
```

In [50]:
```
df_shop.price.fillna(method='ffill').loc[19:21]
```

Out[50]:
```
19    20.45
20    20.45
21    10.53
Name: price, dtype: float64
```

# Missing Data: Add a Dummy Column First

- Data may be missing for a reason!
- Capture "missing" before filling

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In [51]:
```
df_shop = df_shop_raw.drop_duplicates().copy()

# storing a column of 1:missing, 0:not-missing
df_shop['price_missing'] = df_shop.price.isna().astype(int)

# can now fill missing values
df_shop['price'] = df_shop.price.fillna(df_shop.price.mean())
```

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# can now fill missing values
df_shop['price'] = df_shop.price.fillna(df_shop.price.mean())
```

In [52]:
```
# finding where data was missing
np.where(df_shop.price_missing == 1)
```

Out[52]:
```
(array([ 20,  41,  54,  63, 145, 186, 194, 203, 212, 360, 367, 382, 429,
        469, 522, 570, 595, 726, 792, 821, 974, 978]),)
```

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(array([ 20,  41,  54,  63, 145, 186, 194, 203, 212, 360, 367, 382, 429,
        469, 522, 570, 595, 726, 792, 821, 974, 978]),)
```

In [53]:
```
df_shop[['price','price_missing']].iloc[20:23]
```

Out[53]:

| | price | price_missing |
|---|---|---|
| **20** | 23.403384 | 1 |
| **21** | 10.530000 | 0 |
| **22** | 19.770000 | 0 |

# Rescaling

- Often need features to be in the same scale
- Methods of rescaling
    - Standardization (z-score)
    - Min-Max rescaling
    - others...

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- Often need features to be in the same scale
- Methods of rescaling
    - Standardization (z-score)
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    - others...

In [54]:
```
# load taxi data
df_taxi_raw = pd.read_csv('../data/yellowcab_tripdata_2017-01_subset10000rows.csv',
                          parse_dates=['tpep_pickup_datetime','tpep_dropoff_datetime'])
# create trip_duration
df_taxi_raw['trip_duration'] = (df_taxi_raw.tpep_dropoff_datetime - df_taxi_raw.tpep_pickup_datetime).dt.seconds

# select subset
df_taxi_raw = df_taxi_raw[df_taxi_raw.trip_duration.lt(3600) &
                          df_taxi_raw.tip_amount.between(0,10,inclusive='neither')]

df_taxi = df_taxi_raw.copy()
```

# Rescaling

- Often need features to be in the same scale
- Methods of rescaling
    - Standardization (z-score)
    - Min-Max rescaling
    - others...

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                          parse_dates=['tpep_pickup_datetime','tpep_dropoff_datetime'])
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# select subset
df_taxi_raw = df_taxi_raw[df_taxi_raw.trip_duration.lt(3600) &
                          df_taxi_raw.tip_amount.between(0,10,inclusive='neither')]

df_taxi = df_taxi_raw.copy()
```

In [55]:
```
df_taxi[['trip_duration','tip_amount']].agg(['mean','std','min','max'],axis=0).round(2)
```

Out[55]:

| | trip_duration | tip_amount |
|---|---|---|
| **mean** | 765.03 | 2.41 |
| **std** | 496.83 | 1.55 |

# Rescaling: Standardization

- rescale to 0 mean, standard deviation of 1
  - X_scaled = (X - X.mean()) / X.std()

# Rescaling: Standardization

- rescale to 0 mean, standard deviation of 1
  - X_scaled = (X - X.mean()) / X.std()

In [56]:
```
from sklearn.preprocessing import StandardScaler

# instantiate
ss = StandardScaler(with_mean=True, with_std=True) # default is center and scale

# fit to the data
ss.fit(df_taxi[['trip_duration','tip_amount']])

# transform the data
X_ss = ss.transform(df_taxi[['trip_duration','tip_amount']])
X_ss[:2].round(2)
```

Out[56]:
```
array([[-0.5 , -0.48],
       [-0.17, -0.91]])
```

# Rescaling: Standardization

- rescale to 0 mean, standard deviation of 1
    - X_scaled = (X - X.mean()) / X.std()

In [56]:
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# fit to the data
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# transform the data
X_ss = ss.transform(df_taxi[['trip_duration','tip_amount']])
X_ss[:2].round(2)
```

Out[56]:
```
array([[-0.5 , -0.48],
       [-0.17, -0.91]])
```

In [57]:
```
df_taxi_ss = pd.DataFrame(X_ss,columns=['trip_duration_scaled','tip_amount_scaled'])
df_taxi_ss.agg(['mean','std','min','max'],axis=0).round(2)
```

Out[57]:

| | trip_duration_scaled | tip_amount_scaled |
|---|---|---|
| **mean** | 0.00 | -0.00 |
| **std** | 1.00 | 1.00 |
| **min** | -1.54 | -1.54 |
| **max** | 5.62 | 4.88 |

# Rescaling: Min-Max

- rescale values between 0 and 1
- X_scaled = (X - X.min()) / (X.max() - X.min())
- removes negative values

# Rescaling: Min-Max

- rescale values between 0 and 1
- X_scaled = (X - X.min()) / (X.max() - X.min())
- removes negative values

In [58]:
```
from sklearn.preprocessing import MinMaxScaler

X_mms = MinMaxScaler(feature_range=(0,1) # default is to rescale between 0 and 1
                    ).fit_transform(df_taxi[['trip_duration','tip_amount']])

df_taxi_mms = pd.DataFrame(X_mms,columns=['trip_duration_scaled','tip_amount_scaled'])
df_taxi_mms.agg(['mean','std','min','max']).round(2)
```

Out[58]:

| | trip_duration_scaled | tip_amount_scaled |
|---|---|---|
| **mean** | 0.21 | 0.24 |
| **std** | 0.14 | 0.16 |
| **min** | 0.00 | 0.00 |
| **max** | 1.00 | 1.00 |

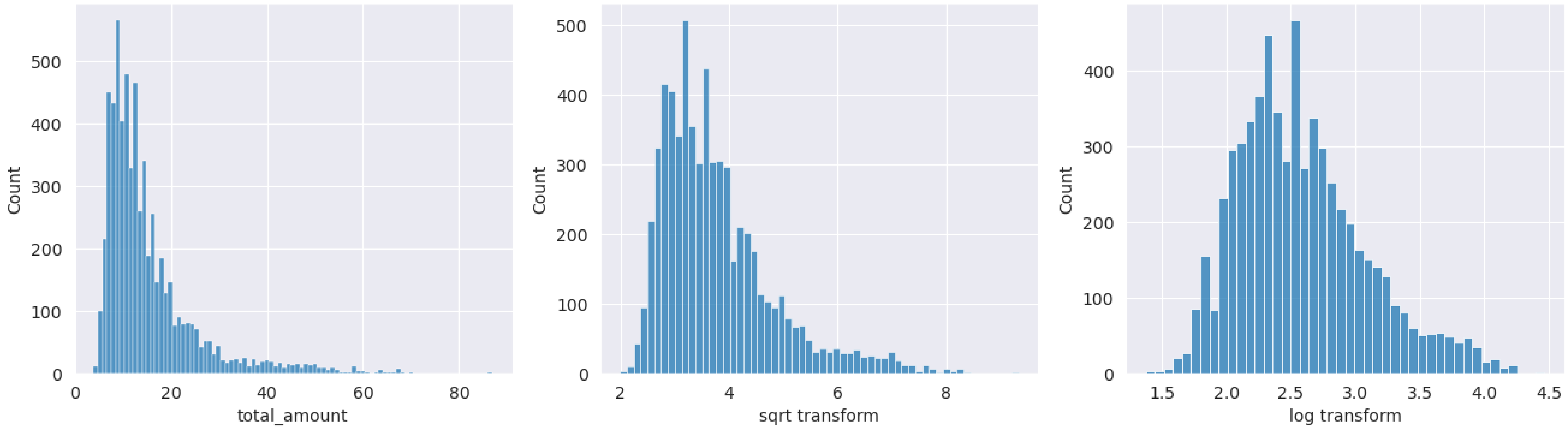
# Dealing with Skew

- Many models expect "normal", symmetric data (ex: linear models)
- Highly skewed: tail has larger effect on model (outliers?)
- Transform with `log` or `sqrt`

# Dealing with Skew

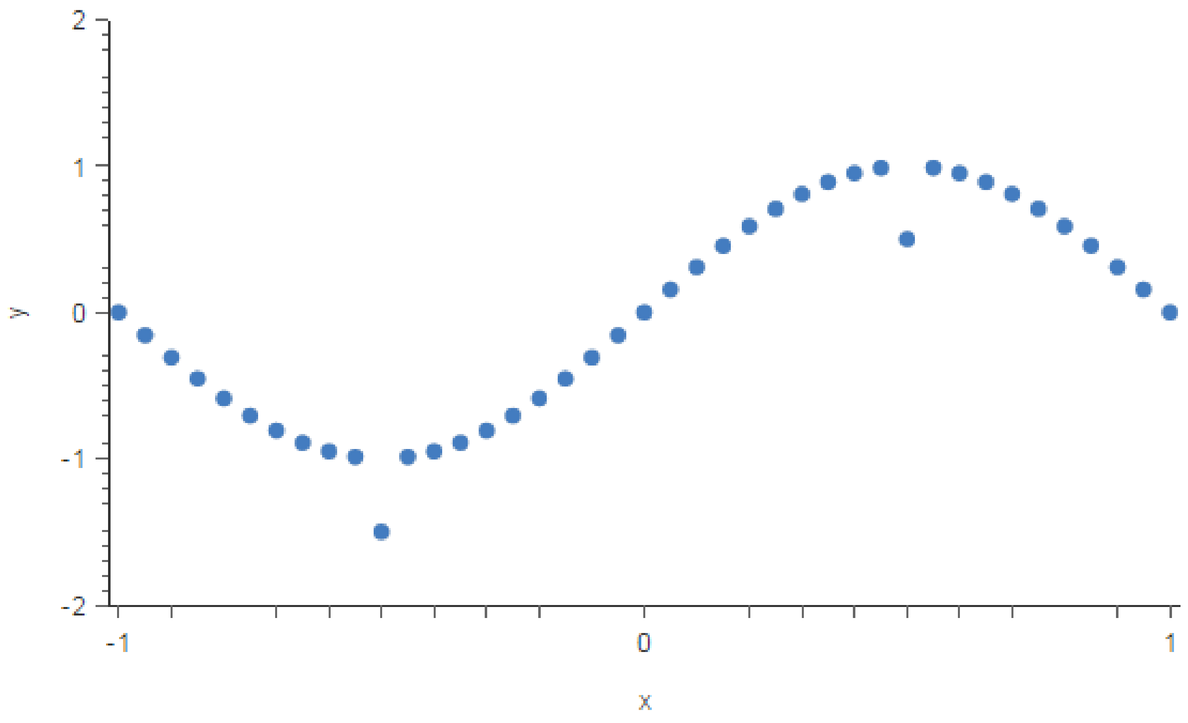
- Many models expect "normal", symmetric data (ex: linear models)
- Highly skewed: tail has larger effect on model (outliers?)
- Transform with `log` or `sqrt`

In [59]:
```
fig,ax = plt.subplots(1,3,figsize=(16,4))
sns.histplot(x=df_taxi.total_amount, ax=ax[0]);
sns.histplot(x=df_taxi.total_amount.apply(np.sqrt), ax=ax[1]); ax[1].set_xlabel('sqrt transform');
sns.histplot(x=df_taxi.total_amount.apply(np.log),  ax=ax[2]); ax[2].set_xlabel('log transform');
```



# Outliers

- Similar to missing data:
  - human data entry error
  - instrument measurement errors
  - data processing errors
  - natural deviations



# Outliers

- Why worry about them?
    - can give misleading results
    - can indicate issues in data/measurement

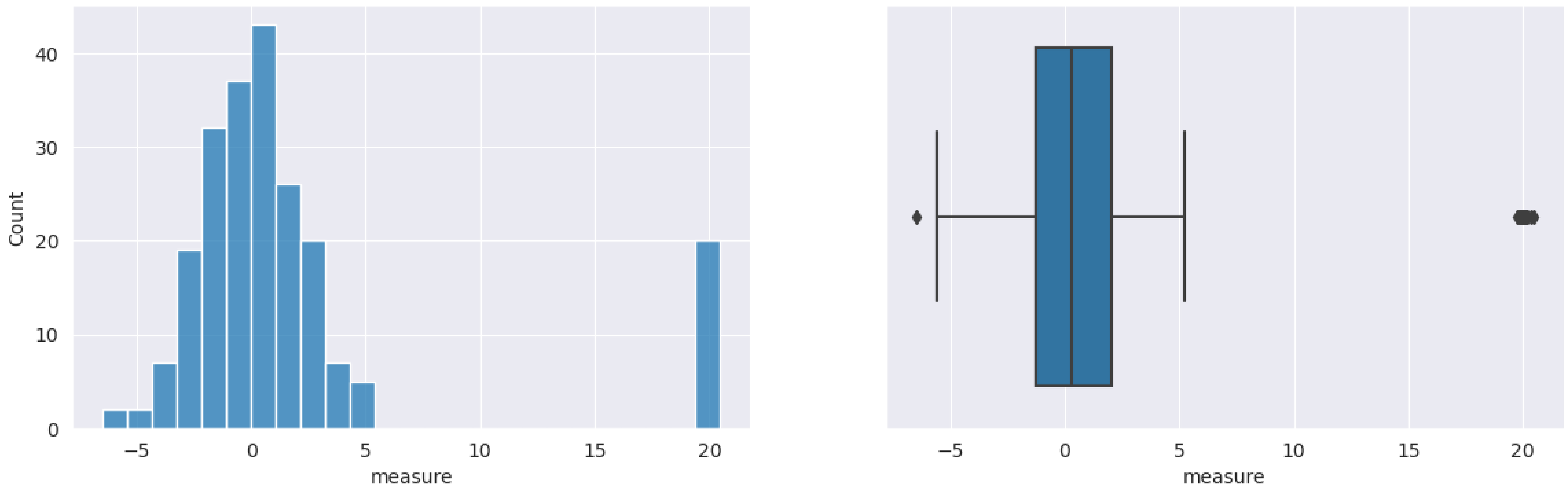
- Detecting Outliers
    - understand your data!
    - visualizations
    - 1.5*IQR
    - z-scores
    - etc..

# Detecting Outliers

# Detecting Outliers

In [60]:
```
np.random.seed(123)
data_rand = np.concatenate([np.random.normal(0,2,200),np.random.normal(20,.2,20)])
df_rand = pd.DataFrame({'measure':data_rand})

fig,ax = plt.subplots(1,2, figsize=(14,4))
sns.histplot(x=df_rand.measure,ax=ax[0]);sns.boxplot(x=df_rand.measure,ax=ax[1]);
```



# Detecting Outliers

In [60]:
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data_rand = np.concatenate([np.random.normal(0,2,200),np.random.normal(20,.2,20)])
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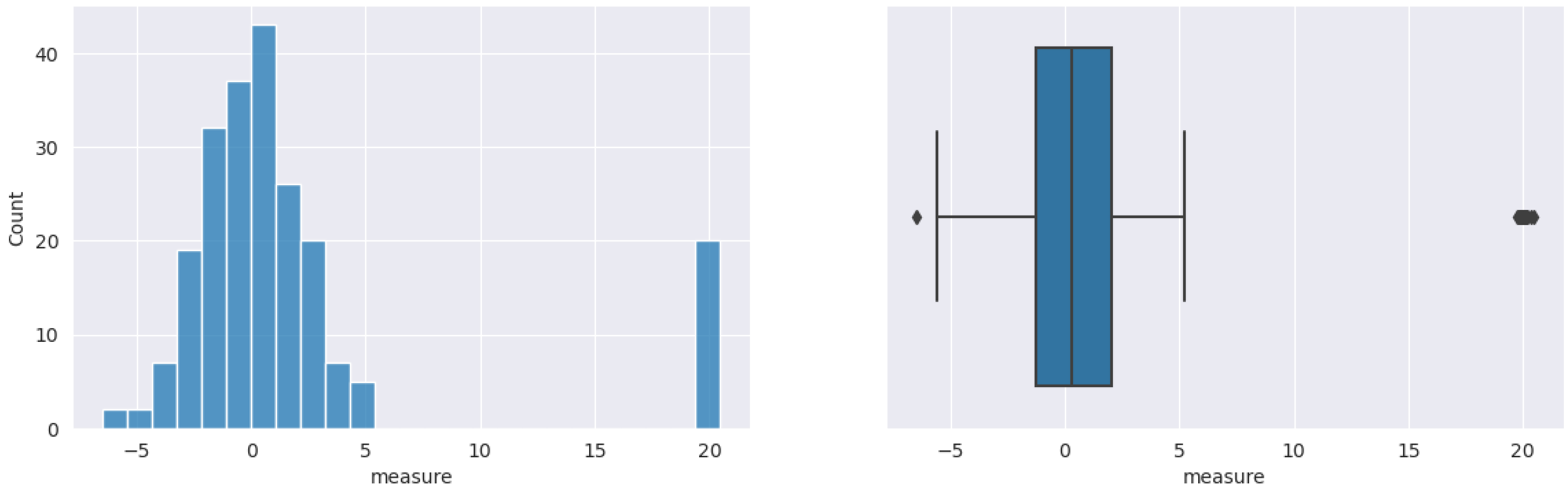
sns.histplot(x=df_rand.measure,ax=ax[0]);sns.boxplot(x=df_rand.measure,ax=ax[1]);
```




In [61]:
```
# Calculating IQR
p25,p75 = df_rand.measure.quantile([.25,.75])
iqr = p75 - p25
round(iqr,2)
```

Out[61]: 3.3

# Detecting Outliers

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```
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data_rand = np.concatenate([np.random.normal(0,2,200),np.random.normal(20,.2,20)])
df_rand = pd.DataFrame({'measure':data_rand})

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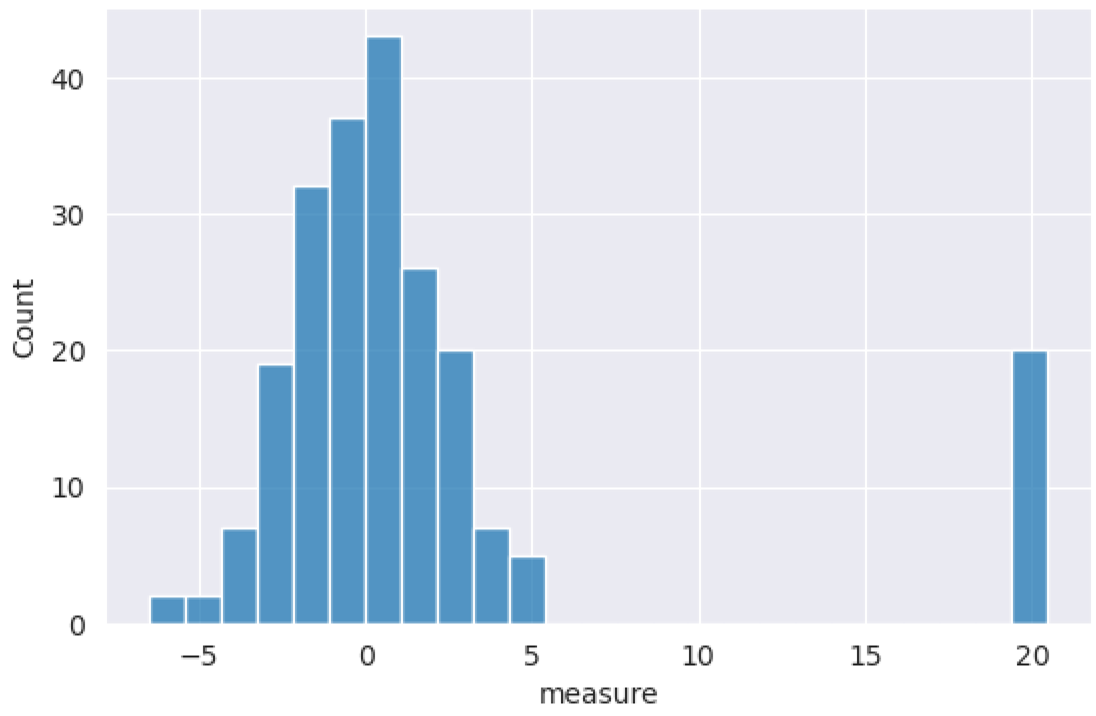
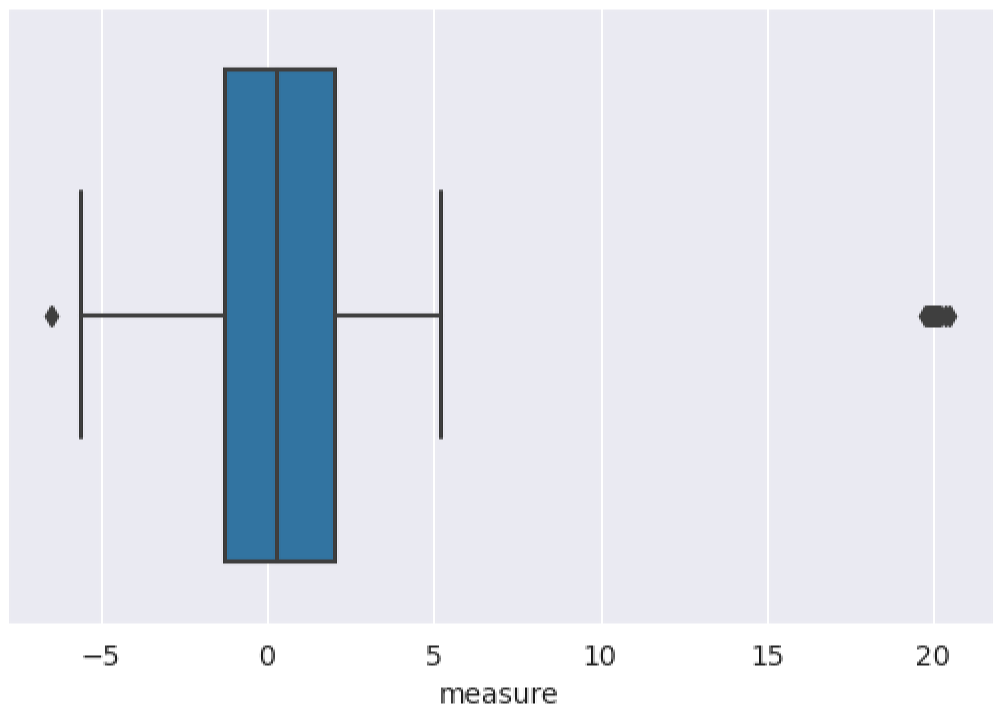



In [61]:
```
# Calculating IQR
p25,p75 = df_rand.measure.quantile([.25,.75])
iqr = p75 - p25
round(iqr,2)
```

Out[61]: 3.3

In [62]:
```
# Finding outliers with IQR (first two examples found)
df_rand.measure[(df_rand.measure > p75+(1.5*iqr)) | (df_rand.measure < p25-(1.5*iqr))].sort_values().head(2).round(2)
```

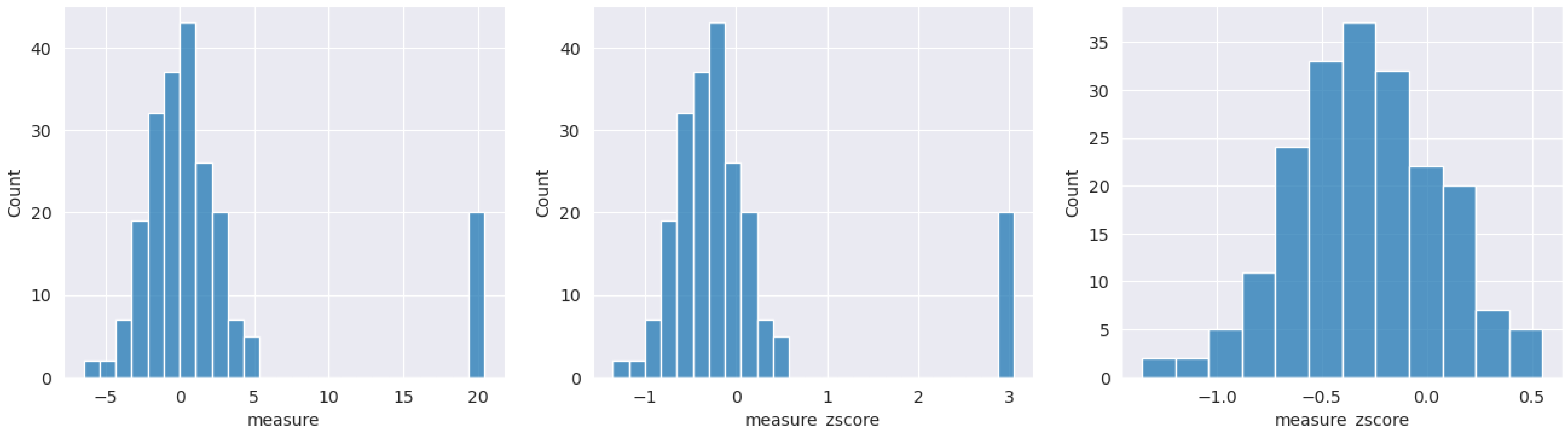
# Detecting Outliers with z-score

# Detecting Outliers with z-score

In [63]:
```
# zscore
df_rand['measure_zscore'] = (df_rand.measure - df_rand.measure.mean()) / df_rand.measure.std()

fig, ax = plt.subplots(1,3,figsize=(16,4))
sns.histplot(x=df_rand.measure,ax=ax[0]);
sns.histplot(x=df_rand.measure_zscore, ax=ax[1]);

keep_idx = np.abs(df_rand.measure_zscore) < 2
sns.histplot(x=df_rand[keep_idx].measure_zscore, ax=ax[2]);

# sample of points getting dropped
df_rand[np.abs(df_rand.measure_zscore) >= 2].sort_values(by='measure').head(3).round(2)
```

Out[63]:

| | measure | measure_zscore |
|---|---|---|
| **213** | 19.72 | 2.93 |
| **207** | 19.82 | 2.94 |
| **218** | 19.85 | 2.95 |



# Other Outlier Detection Methods

- Many more parametric and non-parametric methods
    - Standardized Residuals
    - DBScan
    - ElipticEnvelope
    - IsolationForest
    - other Anomoly Detection techniques
    - See sklearn docs on Outlier Detection for more details

# Dealing with Outliers

- How to deal with outliers?
  - drop data
  - treat as missing
  - encode with dummy variable first

# Putting It All Together: Different Styles

# Putting It All Together: Different Styles

In [64]:
```
df_shop1 = pd.read_csv('../data/flowershop_data_with_dups_week8.csv')
df_shop1 = df_shop1.drop_duplicates()
df_shop1['purchase_date']           = pd.to_datetime(df_shop1.purchase_date)
df_shop1['price_missing']           = df_shop1.price.isna().astype(int)
df_shop1['price']                   = df_shop1.price.fillna(df_shop1.price.mean())
df_shop1['price_scaled']            = StandardScaler().fit_transform(df_shop1[['price']])
df_shop1['favorite_flower_missing'] = df_shop1.favorite_flower.isna().astype(int)
df_shop1['favorite_flower']         = SimpleImputer(strategy='most_frequent').fit(df_shop1[['favorite_flower']])
```

# Putting It All Together: Different Styles

In [64]:
```
df_shop1 = pd.read_csv('../data/flowershop_data_with_dups_week8.csv')
df_shop1 = df_shop1.drop_duplicates()
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df_shop1['price_missing']           = df_shop1.price.isna().astype(int)
df_shop1['price']                   = df_shop1.price.fillna(df_shop1.price.mean())
df_shop1['price_scaled']            = StandardScaler().fit_transform(df_shop1[['price']])
df_shop1['favorite_flower_missing'] = df_shop1.favorite_flower.isna().astype(int)
df_shop1['favorite_flower']         = SimpleImputer(strategy='most_frequent').fit(df_shop1[['favorite_flower']])
```

In [65]:
```
df_shop2 = (
    pd.read_csv('../data/flowershop_data_with_dups_week8.csv')
    .drop_duplicates()
    .assign(
        purchase_date           = lambda df_ : pd.to_datetime(df_.purchase_date),
        price_missing           = lambda df_ : df_.price.isna().astype(int),
        price                   = lambda df_ : df_.price.fillna(df_.price.mean()),
        price_scaled            = lambda df_ : StandardScaler().fit_transform(df_[['price']]),
        favorite_flower_missing = lambda df_ : df_.favorite_flower.isna().astype(int),
        favorite_flower         = lambda df_ : (SimpleImputer(strategy='most_frequent')
                                                 .fit_transform(df_shop1[['favorite_flower']])
                                                )
    )
)
```

# Putting It All Together: Different Styles

In [64]:
```
df_shop1 = pd.read_csv('../data/flowershop_data_with_dups_week8.csv')
df_shop1 = df_shop1.drop_duplicates()
df_shop1['purchase_date']           = pd.to_datetime(df_shop1.purchase_date)
df_shop1['price_missing']           = df_shop1.price.isna().astype(int)
df_shop1['price']                   = df_shop1.price.fillna(df_shop1.price.mean())
df_shop1['price_scaled']            = StandardScaler().fit_transform(df_shop1[['price']])
df_shop1['favorite_flower_missing'] = df_shop1.favorite_flower.isna().astype(int)
df_shop1['favorite_flower']         = SimpleImputer(strategy='most_frequent').fit(df_shop1[['favorite_flower']])
```

In [65]:
```
df_shop2 = (
    pd.read_csv('../data/flowershop_data_with_dups_week8.csv')
    .drop_duplicates()
    .assign(
        purchase_date           = lambda df_ : pd.to_datetime(df_.purchase_date),
        price_missing           = lambda df_ : df_.price.isna().astype(int),
        price                   = lambda df_ : df_.price.fillna(df_.price.mean()),
        price_scaled            = lambda df_ : StandardScaler().fit_transform(df_[['price']]),
        favorite_flower_missing = lambda df_ : df_.favorite_flower.isna().astype(int),
        favorite_flower         = lambda df_ : (SimpleImputer(strategy='most_frequent')
                                                 .fit_transform(df_shop1[['favorite_flower']])
                                                )
    )
)
```

In [66]:
```
pd.testing.assert_frame_equal(df_shop1,df_shop2) # throws an exeption when data frames are not the same
```

# Data Cleaning Review

- duplicate data
- missing data
- rescaling
- dealing with skew
- outlier detection

# Feature Engineering

- Binning
- One-Hot encoding
- Derived Features

# Binning

- Transform continuous features to categorical
- Use:
    - pd.cut
    - sklearn.preprocessing.KBinsDiscretizer (combined binning and one-hot-encoding)

# Binning

- Transform continuous features to categorical
- Use:
    - pd.cut
    - sklearn.preprocessing.KBinsDiscretizer (combined binning and one-hot-encoding)

In [67]:
```
trip_duration_bins = [df_taxi.trip_duration.min(),
                      df_taxi.trip_duration.median(),
                      df_taxi.trip_duration.quantile(0.75),
                      df_taxi.trip_duration.max(),]
```

# Binning

- Transform continuous features to categorical
- Use:
    - pd.cut
    - sklearn.preprocessing.KBinsDiscretizer (combined binning and one-hot-encoding)

In [67]:
```
trip_duration_bins = [df_taxi.trip_duration.min(),
                      df_taxi.trip_duration.median(),
                      df_taxi.trip_duration.quantile(0.75),
                      df_taxi.trip_duration.max(),]
```

In [68]:
```
df_taxi_bin = df_taxi_raw.copy()
df_taxi_bin['trip_duration_binned'] = pd.cut(df_taxi_bin.trip_duration,
                                             bins=trip_duration_bins,          # can pass bin edges or number of bins
                                             labels=['short','medium','long'],
                                             right=True,                      # all bins right-inclusive
                                             include_lowest=True              # first interval left-inclusive
                                            )
df_taxi_bin[['trip_duration','trip_duration_binned']].iloc[:3]
```

Out[68]:

| | trip_duration | trip_duration_binned |
|---|---|---|
| 1 | 516 | short |
| 2 | 683 | medium |
| 7 | 834 | medium |

# One-Hot Encoding

- Encode categorical features for models that can't handle categorical (eg. Linear)
- One column per category, '1' in only one column per row
- Use `pd.get_dummies()` or `sklearn.preprocessing.OneHotEncoder`

# One-Hot Encoding

- Encode categorical features for models that can't handle categorical (eg. Linear)
- One column per category, '1' in only one column per row
- Use `pd.get_dummies()` or `sklearn.preprocessing.OneHotEncoder`

In [69]:
```
pd.get_dummies(df_taxi_bin.trip_duration_binned, prefix='trip_duration').iloc[:2]
```

Out[69]:

| | trip_duration_short | trip_duration_medium | trip_duration_long |
|---|---|---|---|
| **1** | 1 | 0 | 0 |
| **2** | 0 | 1 | 0 |

# One-Hot Encoding

- Encode categorical features for models that can't handle categorical (eg. Linear)
- One column per category, '1' in only one column per row
- Use `pd.get_dummies()` or `sklearn.preprocessing.OneHotEncoder`

In [69]:
```
pd.get_dummies(df_taxi_bin.trip_duration_binned, prefix='trip_duration').iloc[:2]
```

Out[69]:

| | trip_duration_short | trip_duration_medium | trip_duration_long |
|---|---|---|---|
| **1** | 1 | 0 | 0 |
| **2** | 0 | 1 | 0 |

In [70]:
```
# to add back to dataframe, use join (will discuss .join() next time)
df_taxi_bin.join(pd.get_dummies(df_taxi_bin.trip_duration_binned, prefix='trip_duration')).iloc[:2,-6:] # not saved
```

Out[70]:

| | total_amount | trip_duration | trip_duration_binned | trip_duration_short | trip_duration_medium | trip_duration_long |
|---|---|---|---|---|---|---|
| **1** | 9.96 | 516 | short | 1 | 0 | 0 |
| **2** | 10.30 | 683 | medium | 0 | 1 | 0 |

# One-Hot Encoding

- Encode categorical features for models that can't handle categorical (eg. Linear)
- One column per category, '1' in only one column per row
- Use `pd.get_dummies()` or `sklearn.preprocessing.OneHotEncoder`

In [69]:
```
pd.get_dummies(df_taxi_bin.trip_duration_binned, prefix='trip_duration').iloc[:2]
```

Out[69]:

| | trip_duration_short | trip_duration_medium | trip_duration_long |
|---|---|---|---|
| **1** | 1 | 0 | 0 |
| **2** | 0 | 1 | 0 |

In [70]:
```
# to add back to dataframe, use join (will discuss .join() next time)
df_taxi_bin.join(pd.get_dummies(df_taxi_bin.trip_duration_binned, prefix='trip_duration')).iloc[:2,-6:] # not saved
```

Out[70]:

| | total_amount | trip_duration | trip_duration_binned | trip_duration_short | trip_duration_medium | trip_duration_long |
|---|---|---|---|---|---|---|
| **1** | 9.96 | 516 | short | 1 | 0 | 0 |
| **2** | 10.30 | 683 | medium | 0 | 1 | 0 |

In [71]:
```
# or let pandas determine which columns to one-hot
pd.get_dummies(df_taxi_bin).iloc[:2,-6:] # not being saved
```

Out[71]:

| | trip_duration | store_and_fwd_flag_N | store_and_fwd_flag_Y | trip_duration_binned_short | trip_duration_binned_medium | trip_duration_binned_long |
|---|---|---|---|---|---|---|
| **1** | 516 | 1 | 0 | 1 | 0 | 0 |
| **2** | 683 | 1 | 0 | 0 | 1 | 0 |

# One-Hot Encoding with sklearn

# One-Hot Encoding with sklearn

In [72]:
```
from sklearn.preprocessing import OneHotEncoder

ohe = OneHotEncoder(categories=[['short','medium','long']],  # or leave as 'auto'
                    sparse=True,
                    handle_unknown='ignore')                 # will raise error otherwise

ohe.fit(df_taxi_bin[['trip_duration_binned']])
ohe.categories_
```

Out[72]:
```
[array(['short', 'medium', 'long'], dtype=object)]
```

# One-Hot Encoding with sklearn

In [72]:
```
from sklearn.preprocessing import OneHotEncoder

ohe = OneHotEncoder(categories=[['short','medium','long']],  # or leave as 'auto'
                    sparse=True,
                    handle_unknown='ignore')                 # will raise error otherwise

ohe.fit(df_taxi_bin[['trip_duration_binned']])
ohe.categories_
```

Out[72]:
```
[array(['short', 'medium', 'long'], dtype=object)]
```

In [73]:
```
ohe.transform(df_taxi_bin[['trip_duration_binned']])[:3] # returns a sparse matrix!
```

Out[73]:
```
<3x3 sparse matrix of type '<class 'numpy.float64'>'
        with 3 stored elements in Compressed Sparse Row format>
```

# One-Hot Encoding with sklearn

In [72]:
```
from sklearn.preprocessing import OneHotEncoder

ohe = OneHotEncoder(categories=[['short','medium','long']],  # or leave as 'auto'
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                    handle_unknown='ignore')                  # will raise error otherwise

ohe.fit(df_taxi_bin[['trip_duration_binned']])
ohe.categories_
```

Out[72]:
```
[array(['short', 'medium', 'long'], dtype=object)]
```

In [73]:
```
ohe.transform(df_taxi_bin[['trip_duration_binned']])[:3] # returns a sparse matrix!
```

Out[73]:
```
<3x3 sparse matrix of type '<class 'numpy.float64'>'
	with 3 stored elements in Compressed Sparse Row format>
```

In [74]:
```
ohe.transform(df_taxi_bin[['trip_duration_binned']])[:3].todense() # use .todense() to convert sparse to dense
```

Out[74]:
```
matrix([[1., 0., 0.],
        [0., 1., 0.],
        [0., 1., 0.]])
```

# Bin and One-Hot Encode with sklearn

# Bin and One-Hot Encode with sklearn

In [75]:
```python
from sklearn.preprocessing import KBinsDiscretizer

# NOTE: We're not setting the bin edges explicitly
#       For control over bin edges, use Binarizer
kbd = KBinsDiscretizer(n_bins=3,
                       encode="onehot",     # or onehot (sparse), ordinal
                       strategy="quantile", # or uniform or kmeans (clustering)
                      ).fit(df_taxi[['trip_duration']])
print(kbd.bin_edges_)
print(kbd.bin_edges_[0].astype(int))
```

```
[array([2.000e+00, 4.780e+02, 8.700e+02, 3.556e+03])]
[   2  478  870 3556]
```

# Bin and One-Hot Encode with sklearn

In [75]:
```
from sklearn.preprocessing import KBinsDiscretizer

# NOTE: We're not setting the bin edges explicitly
#       For control over bin edges, use Binarizer
kbd = KBinsDiscretizer(n_bins=3,
                       encode="onehot",     # or onehot (sparse), ordinal
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                      ).fit(df_taxi[['trip_duration']])
print(kbd.bin_edges_)
print(kbd.bin_edges_[0].astype(int))
```

```
[array([2.000e+00, 4.780e+02, 8.700e+02, 3.556e+03])]
[   2  478  870 3556]
```

In [76]:
```
df_taxi[['trip_duration']].tail(3)
```

Out[76]:

| | trip_duration |
|---|---|
| **9994** | 905 |
| **9995** | 296 |
| **9997** | 2089 |

# Bin and One-Hot Encode with sklearn

In [75]:
```
from sklearn.preprocessing import KBinsDiscretizer

# NOTE: We're not setting the bin edges explicitly
#       For control over bin edges, use Binarizer
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                       encode="onehot",     # or onehot (sparse), ordinal
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                      ).fit(df_taxi[['trip_duration']])
print(kbd.bin_edges_)
print(kbd.bin_edges_[0].astype(int))
```

```
[array([2.000e+00, 4.780e+02, 8.700e+02, 3.556e+03])]
[   2  478  870 3556]
```

In [76]:
```
df_taxi[['trip_duration']].tail(3)
```

Out[76]:

| | trip_duration |
|---|---|
| **9994** | 905 |
| **9995** | 296 |
| **9997** | 2089 |

In [77]:
```
kbd.transform(df_taxi[['trip_duration']])[-3:]
```

Out[77]:
```
<3x3 sparse matrix of type '<class 'numpy.float64'>'
	with 3 stored elements in Compressed Sparse Row format>
```

# Bin and One-Hot Encode with sklearn

In [75]:
```
from sklearn.preprocessing import KBinsDiscretizer

# NOTE: We're not setting the bin edges explicitly
#       For control over bin edges, use Binarizer
kbd = KBinsDiscretizer(n_bins=3,
                       encode="onehot",      # or onehot (sparse), ordinal
                       strategy="quantile", # or uniform or kmeans (clustering)
                      ).fit(df_taxi[['trip_duration']])
print(kbd.bin_edges_)
print(kbd.bin_edges_[0].astype(int))
```

```
[array([2.000e+00, 4.780e+02, 8.700e+02, 3.556e+03])]
[   2  478  870 3556]
```

In [76]:
```
df_taxi[['trip_duration']].tail(3)
```

Out[76]:

| | trip_duration |
|---|---|
| **9994** | 905 |
| **9995** | 296 |
| **9997** | 2089 |

In [77]:
```
kbd.transform(df_taxi[['trip_duration']])[-3:]
```

Out[77]:
```
<3x3 sparse matrix of type '<class 'numpy.float64'>'
	with 3 stored elements in Compressed Sparse Row format>
```

In [78]:
```
kbd.transform(df_taxi[['trip_duration']])[-3].todense()
```

Out[78]:
```
matrix([[0., 0., 1.]])
```

# Dealing with Ordinal Variables

# Dealing with Ordinal Variables

In [79]:
```
df_pml = pd.DataFrame([['green','M',10.1,'class2'],
                       ['red','L',13.5,'class1'],
                       ['blue','XL',15.3,'class2']],
                      columns=['color','size','price','classlabel'])
df_pml
```

Out[79]:

| | color | size | price | classlabel |
|---|---|---|---|---|
| **0** | green | M | 10.1 | class2 |
| **1** | red | L | 13.5 | class1 |
| **2** | blue | XL | 15.3 | class2 |

# Dealing with Ordinal Variables

In [79]:

```
df_pml = pd.DataFrame([['green','M',10.1,'class2'],
                       ['red','L',13.5,'class1'],
                       ['blue','XL',15.3,'class2']],
                      columns=['color','size','price','classlabel'])
df_pml
```

Out[79]:

| | color | size | price | classlabel |
|---|---|---|---|---|
| **0** | green | M | 10.1 | class2 |
| **1** | red | L | 13.5 | class1 |
| **2** | blue | XL | 15.3 | class2 |

In [80]:

```
# if we know the numerical difference between ordinal values
# eg XL = L+1 = M+2

size_mapping = {'XL':3,
                'L':2,
                'M':1}

df_pml_features = pd.DataFrame()

df_pml_features['size'] = df_pml['size'].map(size_mapping)
df_pml_features
```

Out[80]:

| | size |
|---|---|
| **0** | 1 |
| **1** | 2 |
| **2** | 3 |

# Dealing with Ordinal Variables Cont.

# Dealing with Ordinal Variables Cont.

In [81]:
```
df_pml
```

Out[81]:

| | color | size | price | classlabel |
|---|---|---|---|---|
| **0** | green | M | 10.1 | class2 |
| **1** | red | L | 13.5 | class1 |
| **2** | blue | XL | 15.3 | class2 |

# Dealing with Ordinal Variables Cont.

In [81]:
```
df_pml
```

Out[81]:

| | color | size | price | classlabel |
|---|---|---|---|---|
| **0** | green | M | 10.1 | class2 |
| **1** | red | L | 13.5 | class1 |
| **2** | blue | XL | 15.3 | class2 |

In [82]:
```
# if we don't know the numerical difference between ordinal values
# generate threshold features
df_pml_features = pd.DataFrame()
df_pml_features['x > M'] = df_pml['size'].apply(lambda x: 1 if x in ['L','XL'] else 0)
df_pml_features['x > L'] = df_pml['size'].apply(lambda x: 1 if x == 'XL' else 0)
df_pml_features
```

Out[82]:

| | x > M | x > L |
|---|---|---|
| **0** | 0 | 0 |
| **1** | 1 | 0 |
| **2** | 1 | 1 |

# Derived Features

- Anything that is a transformation of our data
- This is where the money is!
- Examples:
    - "is a high demand pickup location"
    - "is a problem house sale"
    - "high-performing job candidate"

# Polynomial Features

# Polynomial Features

In [83]:

```
from sklearn.preprocessing import PolynomialFeatures

pf = PolynomialFeatures(degree=2,
                        include_bias=False)
X_new = pf.fit_transform(df_taxi[['passenger_count','trip_duration']])

new_columns = ['passenger_count','trip_duration','passenger_count^2','passenger_count*trip_duration','trip_duration^2']
pd.DataFrame(X_new[3:5],columns=new_columns)
```

Out[83]:

| | passenger_count | trip_duration | passenger_count^2 | passenger_count*trip_duration | trip_duration^2 |
|---|---|---|---|---|---|
| **0** | 3.0 | 298.0 | 9.0 | 894.0 | 88804.0 |
| **1** | 1.0 | 396.0 | 1.0 | 396.0 | 156816.0 |

# Python String Functions

# Python String Functions

In [84]:
```
doc = "D.S. is great!"
doc
```

Out[84]:
```
'D.S. is great!'
```

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In [84]:
```
doc = "D.S. is great!"
doc
```

Out[84]:
```
'D.S. is great!'
```

In [85]:
```
doc.lower(),doc.upper()       # change capitalization
```

Out[85]:
```
('d.s. is great!', 'D.S. IS GREAT!')
```

# Python String Functions

In [84]:
```
doc = "D.S. is great!"
doc
```
Out[84]:
```
'D.S. is great!'
```
In [85]:
```
doc.lower(),doc.upper()       # change capitalization
```
Out[85]:
```
('d.s. is great!', 'D.S. IS GREAT!')
```
In [86]:
```
doc.split() , doc.split('.')  # split a string into parts (default is whitespace)
```
Out[86]:
```
(['D.S.', 'is', 'great!'], ['D', 'S', ' is great!'])
```

# Python String Functions

In [84]:
```
doc = "D.S. is great!"
doc
```

Out[84]:
```
'D.S. is great!'
```

In [85]:
```
doc.lower(),doc.upper()       # change capitalization
```

Out[85]:
```
('d.s. is great!', 'D.S. IS GREAT!')
```

In [86]:
```
doc.split() , doc.split('.')  # split a string into parts (default is whitespace)
```

Out[86]:
```
(['D.S.', 'is', 'great!'], ['D', 'S', ' is great!'])
```

In [87]:
```
'|'.join(['ab','c','d'])      # join items in a list together
```

Out[87]:
```
'ab|c|d'
```

# Python String Functions

In [84]:
```
doc = "D.S. is great!"
doc
```
Out[84]: 'D.S. is great!'

In [85]:
```
doc.lower(),doc.upper()       # change capitalization
```
Out[85]: ('d.s. is great!', 'D.S. IS GREAT!')

In [86]:
```
doc.split() , doc.split('.')  # split a string into parts (default is whitespace)
```
Out[86]: (['D.S.', 'is', 'great!'], ['D', 'S', ' is great!'])

In [87]:
```
'|'.join(['ab','c','d'])      # join items in a list together
```
Out[87]: 'ab|c|d'

In [88]:
```
'|'.join(doc[:5])             # a string itself is treated like a list of characters
```
Out[88]: 'D|.|S|.| '

# Python String Functions

```
In [84]: doc = "D.S. is great!"
         doc
Out[84]: 'D.S. is great!'

In [85]: doc.lower(),doc.upper()       # change capitalization
Out[85]: ('d.s. is great!', 'D.S. IS GREAT!')

In [86]: doc.split() , doc.split('.')  # split a string into parts (default is whitespace)
Out[86]: (['D.S.', 'is', 'great!'], ['D', 'S', ' is great!'])

In [87]: '|'.join(['ab','c','d'])      # join items in a list together
Out[87]: 'ab|c|d'

In [88]: '|'.join(doc[:5])             # a string itself is treated like a list of characters
Out[88]: 'D|.|S|.| '

In [89]: '  test   '.strip()           # remove whitespace from the beginning and end of a string
Out[89]: 'test'
```

# Python String Functions

```
In [84]: doc = "D.S. is great!"
         doc

Out[84]: 'D.S. is great!'

In [85]: doc.lower(),doc.upper()       # change capitalization

Out[85]: ('d.s. is great!', 'D.S. IS GREAT!')

In [86]: doc.split() , doc.split('.')  # split a string into parts (default is whitespace)

Out[86]: (['D.S.', 'is', 'great!'], ['D', 'S', ' is great!'])

In [87]: '|'.join(['ab','c','d'])      # join items in a list together

Out[87]: 'ab|c|d'

In [88]: '|'.join(doc[:5])             # a string itself is treated like a list of characters

Out[88]: 'D|.|S|.| '

In [89]: '  test   '.strip()           # remove whitespace from the beginning and end of a string

Out[89]: 'test'
```

and more, see https://docs.python.org/3.8/library/string.html

# String Functions in Pandas

# String Functions in Pandas

```
In [90]: df_shop.iloc[:2].loc[:,'lastname']

Out[90]: 0     PERKINS
         1    ROBINSON
         Name: lastname, dtype: object
```

# String Functions in Pandas

In [90]:
```
df_shop.iloc[:2].loc[:,'lastname']
```

Out[90]:
```
0     PERKINS
1    ROBINSON
Name: lastname, dtype: object
```

In [91]:
```
df_shop.loc[:,'lastname'].iloc[:2].str.lower()
```

Out[91]:
```
0     perkins
1    robinson
Name: lastname, dtype: object
```

# String Functions in Pandas

In [90]:
```
df_shop.iloc[:2].loc[:,'lastname']
```

Out[90]:
```
0     PERKINS
1    ROBINSON
Name: lastname, dtype: object
```

In [91]:
```
df_shop.loc[:,'lastname'].iloc[:2].str.lower()
```

Out[91]:
```
0     perkins
1    robinson
Name: lastname, dtype: object
```

In [92]:
```
df_shop.lastname[:2].str.capitalize()
```

Out[92]:
```
0     Perkins
1    Robinson
Name: lastname, dtype: object
```

# String Functions in Pandas

In [90]:
```
df_shop.iloc[:2].loc[:,'lastname']
```

Out[90]:
```
0     PERKINS
1    ROBINSON
Name: lastname, dtype: object
```

In [91]:
```
df_shop.loc[:,'lastname'].iloc[:2].str.lower()
```

Out[91]:
```
0     perkins
1    robinson
Name: lastname, dtype: object
```

In [92]:
```
df_shop.lastname[:2].str.capitalize()
```

Out[92]:
```
0     Perkins
1    Robinson
Name: lastname, dtype: object
```

In [93]:
```
df_shop.lastname[:2].str.startswith('ROB') # .endswith() , .contains()
```

Out[93]:
```
0    False
1     True
Name: lastname, dtype: bool
```

# String Functions in Pandas

In [90]:
```
df_shop.iloc[:2].loc[:,'lastname']
```

Out[90]:
```
0     PERKINS
1    ROBINSON
Name: lastname, dtype: object
```

In [91]:
```
df_shop.loc[:,'lastname'].iloc[:2].str.lower()
```

Out[91]:
```
0     perkins
1    robinson
Name: lastname, dtype: object
```

In [92]:
```
df_shop.lastname[:2].str.capitalize()
```

Out[92]:
```
0     Perkins
1    Robinson
Name: lastname, dtype: object
```

In [93]:
```
df_shop.lastname[:2].str.startswith('ROB') # .endswith() , .contains()
```

Out[93]:
```
0    False
1     True
Name: lastname, dtype: bool
```

In [94]:
```
df_shop.lastname[:2].str.replace('R','^')
```

Out[94]:
```
0     PE^KINS
1    ^OBINSON
Name: lastname, dtype: object
```

# String Functions in Pandas

In [90]:
```
df_shop.iloc[:2].loc[:,'lastname']
```

Out[90]:
```
0     PERKINS
1    ROBINSON
Name: lastname, dtype: object
```

In [91]:
```
df_shop.loc[:,'lastname'].iloc[:2].str.lower()
```

Out[91]:
```
0     perkins
1    robinson
Name: lastname, dtype: object
```

In [92]:
```
df_shop.lastname[:2].str.capitalize()
```

Out[92]:
```
0     Perkins
1    Robinson
Name: lastname, dtype: object
```

In [93]:
```
df_shop.lastname[:2].str.startswith('ROB') # .endswith() , .contains()
```

Out[93]:
```
0    False
1     True
Name: lastname, dtype: bool
```

In [94]:
```
df_shop.lastname[:2].str.replace('R','^')
```

Out[94]:
```
0     PE^KINS
1    ^OBINSON
Name: lastname, dtype: object
```

# Pandas datetime functions

# Pandas datetime functions

In [95]:
```
df_taxi.iloc[:2].tpep_pickup_datetime
```

Out[95]:
```
1   2017-01-05 15:14:52
2   2017-01-11 14:47:52
Name: tpep_pickup_datetime, dtype: datetime64[ns]
```

# Pandas datetime functions

In [95]:
```
df_taxi.iloc[:2].tpep_pickup_datetime
```

Out[95]:
```
1   2017-01-05 15:14:52
2   2017-01-11 14:47:52
Name: tpep_pickup_datetime, dtype: datetime64[ns]
```

In [96]:
```
df_taxi.iloc[:2].tpep_pickup_datetime.dt.day
```

Out[96]:
```
1     5
2    11
Name: tpep_pickup_datetime, dtype: int64
```

# Pandas datetime functions

In [95]:
```
df_taxi.iloc[:2].tpep_pickup_datetime
```

Out[95]:
```
1   2017-01-05 15:14:52
2   2017-01-11 14:47:52
Name: tpep_pickup_datetime, dtype: datetime64[ns]
```

In [96]:
```
df_taxi.iloc[:2].tpep_pickup_datetime.dt.day
```

Out[96]:
```
1     5
2    11
Name: tpep_pickup_datetime, dtype: int64
```

In [97]:
```
df_taxi.iloc[:2].tpep_pickup_datetime.dt.day_of_week
```

Out[97]:
```
1    3
2    2
Name: tpep_pickup_datetime, dtype: int64
```

# Pandas datetime functions

In [95]:
```
df_taxi.iloc[:2].tpep_pickup_datetime
```

Out[95]:
```
1   2017-01-05 15:14:52
2   2017-01-11 14:47:52
Name: tpep_pickup_datetime, dtype: datetime64[ns]
```

In [96]:
```
df_taxi.iloc[:2].tpep_pickup_datetime.dt.day
```

Out[96]:
```
1     5
2    11
Name: tpep_pickup_datetime, dtype: int64
```

In [97]:
```
df_taxi.iloc[:2].tpep_pickup_datetime.dt.day_of_week
```

Out[97]:
```
1    3
2    2
Name: tpep_pickup_datetime, dtype: int64
```

In [98]:
```
(df_taxi.tpep_dropoff_datetime - df_taxi.tpep_pickup_datetime).dt.seconds.iloc[:2]
```

Out[98]:
```
1    516
2    683
dtype: int64
```

# Pandas datetime functions

In [95]:
```
df_taxi.iloc[:2].tpep_pickup_datetime
```

Out[95]:
```
1   2017-01-05 15:14:52
2   2017-01-11 14:47:52
Name: tpep_pickup_datetime, dtype: datetime64[ns]
```

In [96]:
```
df_taxi.iloc[:2].tpep_pickup_datetime.dt.day
```

Out[96]:
```
1     5
2    11
Name: tpep_pickup_datetime, dtype: int64
```

In [97]:
```
df_taxi.iloc[:2].tpep_pickup_datetime.dt.day_of_week
```

Out[97]:
```
1    3
2    2
Name: tpep_pickup_datetime, dtype: int64
```

In [98]:
```
(df_taxi.tpep_dropoff_datetime - df_taxi.tpep_pickup_datetime).dt.seconds.iloc[:2]
```

Out[98]:
```
1    516
2    683
dtype: int64
```

In [99]:
```
(pd.to_datetime('today') - df_taxi.tpep_dropoff_datetime).dt.days.div(365).iloc[:2].round(2)
```

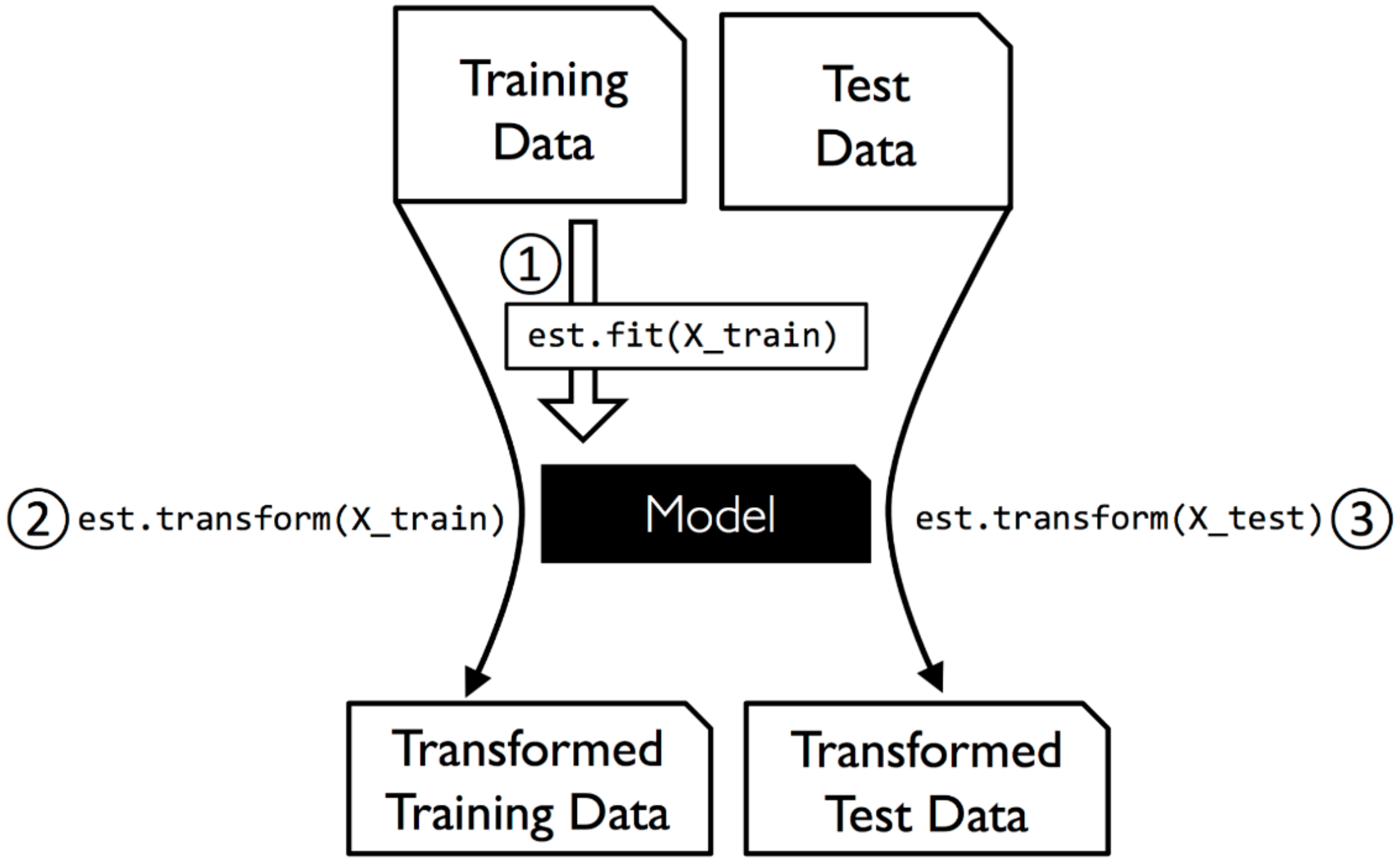
Out[99]:
```
1    5.81
2    5.79
Name: tpep_dropoff_datetime, dtype: float64
```

# Pandas datetime functions

```
In [95]: df_taxi.iloc[:2].tpep_pickup_datetime

Out[95]: 1   2017-01-05 15:14:52
         2   2017-01-11 14:47:52
         Name: tpep_pickup_datetime, dtype: datetime64[ns]

In [96]: df_taxi.iloc[:2].tpep_pickup_datetime.dt.day

Out[96]: 1     5
         2    11
         Name: tpep_pickup_datetime, dtype: int64

In [97]: df_taxi.iloc[:2].tpep_pickup_datetime.dt.day_of_week

Out[97]: 1    3
         2    2
         Name: tpep_pickup_datetime, dtype: int64

In [98]: (df_taxi.tpep_dropoff_datetime - df_taxi.tpep_pickup_datetime).dt.seconds.iloc[:2]

Out[98]: 1    516
         2    683
         dtype: int64

In [99]: (pd.to_datetime('today') - df_taxi.tpep_dropoff_datetime).dt.days.div(365).iloc[:2].round(2)

Out[99]: 1    5.81
         2    5.79
         Name: tpep_dropoff_datetime, dtype: float64
```

# Transforming with Train/Test Split

- When performing data transformation



# Next Time

- Dimensionality Reduction
  - Feature Selection
  - Feature Extraction

# Questions?