Elements Of Data Science - F2025

Week 8: Data Cleaning and Feature Engineering

11/11/2025

Homework 3 due on 11/25/2025 @ 11:59 pm

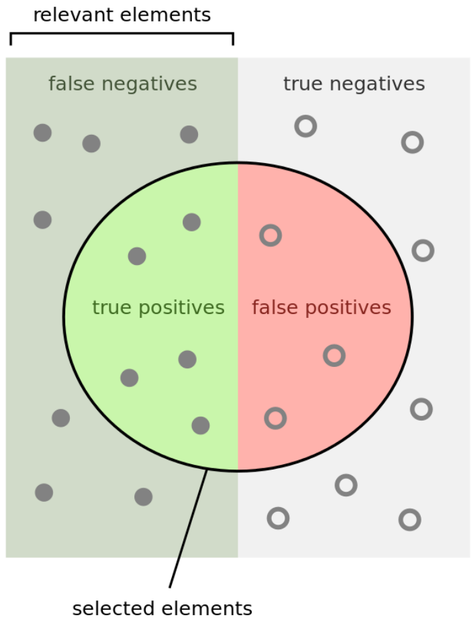
Weekly Quiz due on Nov 18 @ 11:59 pm

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/)

Precision & Recall and ROC visualizations

Precision & Recall



How many selected items are relevant?

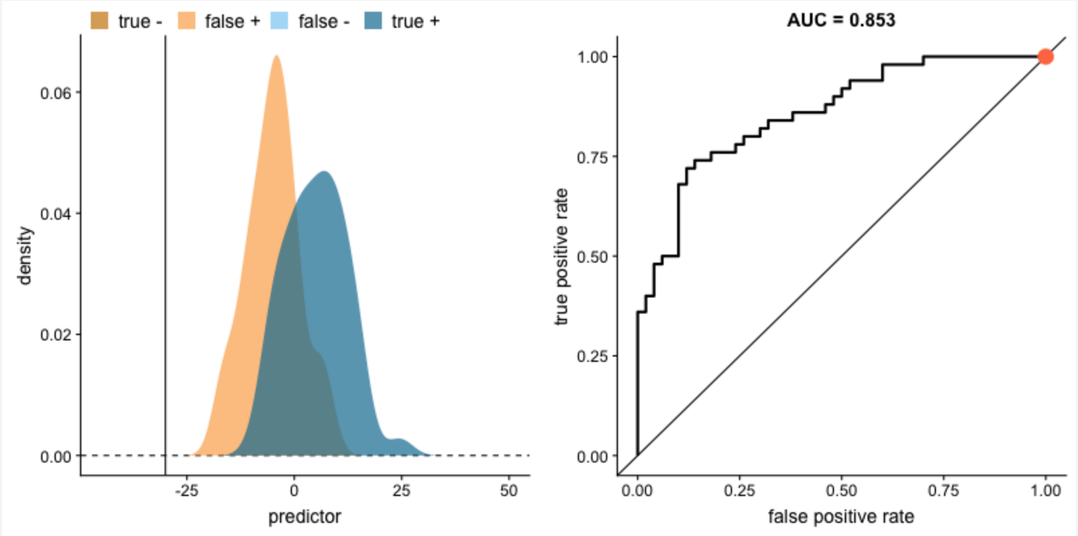
$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

How many relevant items are selected?

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

https://www.wikiwand.com/en/Precision_and_recall

ROC

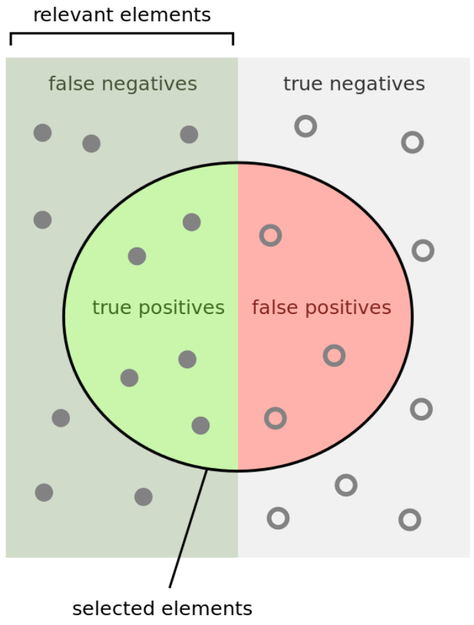


This and more at https://github.com/dariyasydykova/open_projects/tree/master/ROC_animation

Also see the interactive viz at http://www.navan.name/roc/

Precision & Recall and ROC visualizations

Precision & Recall



How many selected items are relevant?

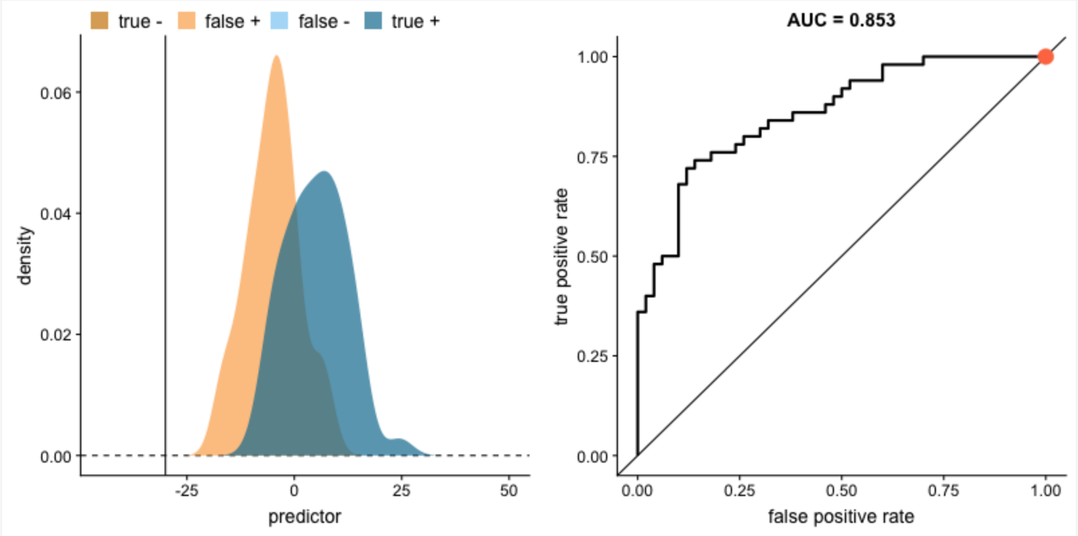
$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

How many relevant items are selected?

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

https://www.wikiwand.com/en/Precision_and_recall

ROC



This and more at https://github.com/dariyasydykova/open_projects/tree/master/ROC_animation

Also see the interactive viz at http://www.navan.name/roc/

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 [99]:

```
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?

- **To remove duplicates** Want one row per observation
- **To remove/fill missing** Most models cannot handle missing data
- **To engineer features** Most models require fixed length feature vectors

- 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

Example Data

Example Data

In [100]:

```python
# 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

Duplicated Data

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

In [101]:
```
1 df_shop.duplicated().iloc[-3:] # are any of the last 3 rows duplicates?
```

Out[101]:
```
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 [101]:
```
1 df_shop.duplicated().iloc[-3:] # are any of the last 3 rows duplicates?
```

Out[101]:
```
998     False
999     False
1000     True
dtype: bool
```

In [102]:
```
1 df_shop[df_shop.duplicated(keep='first')] # default: keep 'first' duplicated row
```

Out[102]:

	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 [101]:
```
1 df_shop.duplicated().iloc[-3:] # are any of the last 3 rows duplicates?
```

Out[101]:
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998     False
999     False
1000     True
dtype: bool
```

In [102]:
```
1 df_shop[df_shop.duplicated(keep='first')] # default: keep 'first' duplicated row
```

Out[102]:

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

In [103]:
```
1 df_shop[df_shop.duplicated(keep=False)] # keep=False to show all duplicated rows
```

Out[103]:

	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 [110]:
```
# if it's important that a subset of columns is not duplicated
(
    df_shop
    .sort_values(by='purchase_id')
    .loc[df_shop.duplicated(subset=['purchase_id'], keep =False)]

)
```

Out[110]:

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

In [107]:
```
df_shop.loc[df_shop.duplicated(subset=['purchase_id']),:]
```

Out[107]:

	purchase_id	lastname	purchase_date	stars	price	favorite_flower
101	1101	BURKE	2017-08-16	4	18.56	daffodil
1000	1010	FERGUSON	2017-05-04	2	21.02	daffodil

Duplicated Data for Subset of Columns

In [110]:
```
# if it's important that a subset of columns is not duplicated
(
    df_shop
    .sort_values(by='purchase_id')
    .loc[df_shop.duplicated(subset=['purchase_id'], keep =False)]

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Out[110]:

	purchase_id	lastname	purchase_date	stars	price	favorite_flower
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10	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

In [107]:
```
df_shop.loc[df_shop.duplicated(subset=['purchase_id']),:]
```

Out[107]:

	purchase_id	lastname	purchase_date	stars	price	favorite_flower
101	1101	BURKE	2017-08-16	4	18.56	daffodil
1000	1010	FERGUSON	2017-05-04	2	21.02	daffodil

In [105]:
```
# could also use the indexing shortcut
df_shop[df_shop.duplicated(subset=['purchase_id'],keep='first')].sort_values(by='purchase_id')
```

Out[105]:

	purchase_id	lastname	purchase_date	stars	price	favorite_flower
1000	1010	FERGUSON	2017-05-04	2	21.02	daffodil
101	1101	BURKE	2017-08-16	4	18.56	daffodil

Dropping Duplicates

Dropping Duplicates

In [9]:

```
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 [9]:
```
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 [10]:
```
# 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 [9]:
```
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 [10]:
```
# 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 [11]:
```
# 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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    - 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

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

In [12]:
```
# Earlier, we saw missing values in the dataframe summary
# df_shop.info()
```

Missing Data in Pandas: `np.nan`

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

In [12]:
```
# Earlier, we saw missing values in the dataframe summary
# df_shop.info()
```

In [13]:
```
# can we check for NaN using "x == np.nan"? No!
np.nan == np.nan

```

Out[13]:
```
False
```

Missing Data in Pandas: `np.nan`

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

In [12]:
```
# Earlier, we saw missing values in the dataframe summary
# df_shop.info()
```

In [13]:
```
# can we check for NaN using "x == np.nan"? No!
np.nan == np.nan

```

Out[13]: False

`==` operator compares the values of both the operands and checks for value equality. `is` *operator*, on the other hand, checks whether both the operands refer to the same object or not.

IEEE 754 Standard: The standard specifically dictates that NaN should not be equal to anything, including itself. This design choice is based on the idea that if you have two unknown or invalid values, you cannot definitively say they are the same.

Missing Data in Pandas: `np.nan`

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

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In [13]:
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# can we check for NaN using "x == np.nan"? No!
np.nan == np.nan

```

Out[13]:
```
False
```

`==` operator compares the values of both the operands and checks for value equality. `is` *operator*, on the other hand, checks whether both the operands refer to the same object or not.

IEEE 754 Standard: The standard specifically dictates that NaN should not be equal to anything, including itself. This design choice is based on the idea that if you have two unknown or invalid values, you cannot definitively say they are the same.

In [14]:
```
# however
np.nan is np.nan
```

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

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

In [18]:
```
# some missing data
df_shop.loc[20:21,'price']
```

Out[18]:
```
20      NaN
21    10.53
Name: price, dtype: float64
```

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

In [18]:
```
# some missing data
df_shop.loc[20:21,'price']
```

Out[18]:
```
20      NaN
21    10.53
Name: price, dtype: float64
```

In [19]:
```
# .isna() returns True where data is missing, False otherwise
df_shop.loc[20:21,'price'].isna()
```

Out[19]:
```
20     True
21    False
Name: price, dtype: bool
```

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

In [18]:
```
# some missing data
df_shop.loc[20:21,'price']
```

Out[18]:
```
20      NaN
21    10.53
Name: price, dtype: float64
```

In [19]:
```
# .isna() returns True where data is missing, False otherwise
df_shop.loc[20:21,'price'].isna()
```

Out[19]:
```
20     True
21    False
Name: price, dtype: bool
```

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

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

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

In [18]:
```
# some missing data
df_shop.loc[20:21,'price']
```

Out[18]:
```
20      NaN
21    10.53
Name: price, dtype: float64
```

In [19]:
```
# .isna() returns True where data is missing, False otherwise
df_shop.loc[20:21,'price'].isna()
```

Out[19]:
```
20     True
21    False
Name: price, dtype: bool
```

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

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

In [21]:
```
# find rows where price is missing
df_shop[df_shop.price.isna()].head()
```

Out[21]:

	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 [22]:
```
# How many nan's in a single column?
df_shop.price.isna().sum()
```

Out[22]: 22

Counting NaNs

In [22]:
```
# How many nan's in a single column?
df_shop.price.isna().sum()
```

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

In [23]:
```
# How many nan's per column?
df_shop.isna().sum()
```

Out[23]:
```
purchase_id          0
lastname             0
purchase_date        0
stars                0
price               22
favorite_flower    178
dtype: int64
```

Counting NaNs

In [22]:
```
# How many nan's in a single column?
df_shop.price.isna().sum()
```

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

In [23]:
```
# How many nan's per column?
df_shop.isna().sum()
```

Out[23]:
```
purchase_id          0
lastname             0
purchase_date        0
stars                0
price               22
favorite_flower    178
dtype: int64
```

In [24]:
```
# How many total nan's?
df_shop.isna().sum().sum()
```

Out[24]:
```
200
```

Missing Data: Drop Rows

Missing Data: Drop Rows

In [25]:
```
1 df_shop.shape
```

Out[25]:
```
(999, 6)
```

Missing Data: Drop Rows

In [25]:
```
1 df_shop.shape
```

Out[25]: (999, 6)

In [26]:
```
1 # drop rows with nan in any column
2 df_shop.dropna().shape
```

Out[26]: (801, 6)

Missing Data: Drop Rows

In [25]:
```
1 df_shop.shape
```

Out[25]: (999, 6)

In [26]:
```
1 # drop rows with nan in any column
2 df_shop.dropna().shape
```

Out[26]: (801, 6)

In [27]:
```
1 # drop only rows with nan in price using subset
2 df_shop.dropna(subset=['price']).shape
```

Out[27]: (977, 6)

Missing Data: Drop Rows

In [25]:
```
df_shop.shape
```

Out[25]: (999, 6)

In [26]:
```
# drop rows with nan in any column
df_shop.dropna().shape
```

Out[26]: (801, 6)

In [27]:
```
# drop only rows with nan in price using subset
df_shop.dropna(subset=['price']).shape
```

Out[27]: (977, 6)

In [28]:
```
# drop only rows with nans in all columns (a row of all nans)
df_shop.dropna(how='all').shape
```

Out[28]: (999, 6)

Missing Data: Drop Rows Cont.

Missing Data: Drop Rows Cont.

In [29]:
```
# save a new dataframe with dropped rows
df_shop = df_shop_raw.dropna().copy()
df_shop.shape
```

Out[29]:
```
(803, 6)
```

Missing Data: Drop Rows Cont.

In [29]:
```
# save a new dataframe with dropped rows
df_shop = df_shop_raw.dropna().copy()
df_shop.shape
```

Out[29]: (803, 6)

In [30]:
```
# drop rows in current dataframe with inplace
df_shop = df_shop_raw.copy()

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

Out[30]: (803, 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 [31]:
```
1 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 [31]:
```
df_shop = df_shop_raw.drop_duplicates().copy() # make a new copy of the data
```

In [32]:
```
df_shop.price[20:22]
```

Out[32]:
```
20      NaN
21    10.53
Name: price, dtype: float64
```

Missing Data: Fill with Constant

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

In [31]:
```
1 df_shop = df_shop_raw.drop_duplicates().copy() # make a new copy of the data
```

In [32]:
```
1 df_shop.price[20:22]
```

Out[32]:
```
20      NaN
21    10.53
Name: price, dtype: float64
```

In [33]:
```
1 df_shop.price[20:22].fillna(0)
```

Out[33]:
```
20     0.00
21    10.53
Name: price, dtype: float64
```

Missing Data: Fill with Constant

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

In [31]:
```
df_shop = df_shop_raw.drop_duplicates().copy() # make a new copy of the data
```

In [32]:
```
df_shop.price[20:22]
```

Out[32]:
```
20      NaN
21    10.53
Name: price, dtype: float64
```

In [33]:
```
df_shop.price[20:22].fillna(0)
```

Out[33]:
```
20     0.00
21    10.53
Name: price, dtype: float64
```

In [34]:
```
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 [35]:
```
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 [35]:
```
print(df_shop.price.mean().round(2))
print(df_shop.price.fillna(df_shop.price.mean()).mean().round(2))
```

```
23.4
23.4
```

In [36]:
```
# make a copy to keep our original df
df_shop_impute = df_shop.copy()
```

Missing Data: Impute

In [35]:
```
print(df_shop.price.mean().round(2))
print(df_shop.price.fillna(df_shop.price.mean()).mean().round(2))
```

```
23.4
23.4
```

In [36]:
```
# make a copy to keep our original df
df_shop_impute = df_shop.copy()
```

In [37]:
```
# fill missing price with mean of price
df_shop_impute['price'] = df_shop.price.fillna(df_shop.price.mean())
```

Missing Data: Impute

In [35]:
```
print(df_shop.price.mean().round(2))
print(df_shop.price.fillna(df_shop.price.mean()).mean().round(2))
```

```
23.4
23.4
```

In [36]:
```
# make a copy to keep our original df
df_shop_impute = df_shop.copy()
```

In [37]:
```
# fill missing price with mean of price
df_shop_impute['price'] = df_shop.price.fillna(df_shop.price.mean())
```

In [38]:
```
# 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 [112]:
```
assert df_shop.price.std() > df_shop_impute.price.std()
```

Missing Data: Impute

In [35]:
```
print(df_shop.price.mean().round(2))
print(df_shop.price.fillna(df_shop.price.mean()).mean().round(2))
```

```
23.4
23.4
```

In [36]:
```
# make a copy to keep our original df
df_shop_impute = df_shop.copy()
```

In [37]:
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# also, that our mean hasn't changed
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```

In [112]:
```
assert df_shop.price.std() > df_shop_impute.price.std()
```

In [39]:
```
# inplace works here as well
df_shop_impute.price.fillna(df_shop_impute.price.mean(),inplace=True)
```

Missing Data: Impute Cont.

if data is cathegorical?

Missing Data: Impute Cont.

if data is cathegorical?

In [40]:
```
1 df_shop.favorite_flower.mode() # may be more than 1!
```

Out[40]:
```
0    lilac
Name: favorite_flower, dtype: object
```

Missing Data: Impute Cont.

if data is cathegorical?

In [40]:
```
df_shop.favorite_flower.mode() # may be more than 1!
```

Out[40]:
```
0    lilac
Name: favorite_flower, dtype: object
```

In [41]:
```
# 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: 87.0+ KB
```

Missing Data: Impute Cont. Using SimpleImputer

Missing Data: Impute Cont. Using SimpleImputer

In [42]:
```
1 df_shop[['price','stars']].loc[20:22]
```

Out[42]:

	price	stars
20	NaN	3
21	10.53	2
22	19.77	1

Missing Data: Impute Cont. Using SimpleImputer

In [42]:
```
1 df_shop[['price','stars']].loc[20:22]
```

Out[42]:

	price	stars
20	NaN	3
21	10.53	2
22	19.77	1

In [43]:
```
1 from sklearn.impute import SimpleImputer
2
3 imp = SimpleImputer(strategy='mean').fit(df_shop[['price','stars']])
4 print(f'fill values = {imp.statistics_.round(2)}')
5 imp.transform(df_shop.loc[20:22,['price','stars']]).round(2)
```

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

Out[43]:
```
array([[23.4 ,  3.  ],
       [10.53,  2.  ],
       [19.77,  1.  ]])
```

Missing Data: Impute Cont. Using SimpleImputer

In [42]:
```
df_shop[['price','stars']].loc[20:22]
```

Out[42]:

	price	stars
20	NaN	3
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```

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

Out[43]:
```
array([[23.4 ,  3.  ],
       [10.53,  2.  ],
       [19.77,  1.  ]])
```

In [44]:
```
df_shop.favorite_flower[:3]
```

Out[44]:
```
0         iris
1          NaN
2    carnation
Name: favorite_flower, dtype: object
```

Missing Data: Impute Cont. Using SimpleImputer

In [42]:
```
df_shop[['price','stars']].loc[20:22]
```

Out[42]:

	price	stars
20	NaN	3
21	10.53	2
22	19.77	1

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```

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

Out[43]:
```
array([[23.4 ,  3.  ],
       [10.53,  2.  ],
       [19.77,  1.  ]])
```

In [44]:
```
df_shop.favorite_flower[:3]
```

Out[44]:
```
0         iris
1          NaN
2    carnation
Name: favorite_flower, dtype: object
```

In [45]:
```
imp = SimpleImputer(strategy='most_frequent').fit(df_shop[['favorite_flower']])
imp.transform(df_shop.loc[:2,['favorite_flower']])
```

Out[45]:
```
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

Missing Data: Infer

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

In [46]:

```
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: Infer

- Pros:
    - better estimate (based on other data)
- Cons:
    - have to train another model
    - colinear features!

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**)

Missing Data: Adjacent Data

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- Use when there is reason to believe data not i.i.d. (eg: **timeseries**)

```
In [47]: 1 df_shop.price.loc[19:21]

Out[47]: 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 [47]:
```
1 df_shop.price.loc[19:21]
```

Out[47]:
```
19    20.45
20      NaN
21    10.53
Name: price, dtype: float64
```

In [48]:
```
1 df_shop.price.fillna(method='ffill').loc[19:21]
```

Out[48]:
```
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 [49]:

```
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 [50]:
```
# finding where data was missing
np.where(df_shop.price_missing == 1)
```

Out[50]:
```
(array([ 20,  41,  54,  63, 145, 186, 194, 203, 212, 360, 367, 382, 429,
        469, 522, 570, 595, 726, 792, 821, 974, 978]),)
```

Missing Data: Add a Dummy Column First

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        469, 522, 570, 595, 726, 792, 821, 974, 978]),)
```

In [51]:
```
df_shop[['price','price_missing']].iloc[20:23]
```

Out[51]:

	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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- Methods of rescaling
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    - others...

In [52]:

```
# 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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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 [53]:

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

Out[53]:

	trip_duration	tip_amount
mean	765.03	2.41
std	496.83	1.55
min	2.00	0.01

Rescaling: Standardization

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

Rescaling: Standardization

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    - X_scaled = (X - X.mean()) / X.std()

In [54]:
```
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[54]:
```
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()

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

Out[54]:
```
array([[-0.5 , -0.48],
       [-0.17, -0.91]])
```

In [55]:
```
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[55]:

	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

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- X_scaled = (X - X.min()) / (X.max() - X.min())
- removes negative values

In [56]:
```
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[56]:

	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

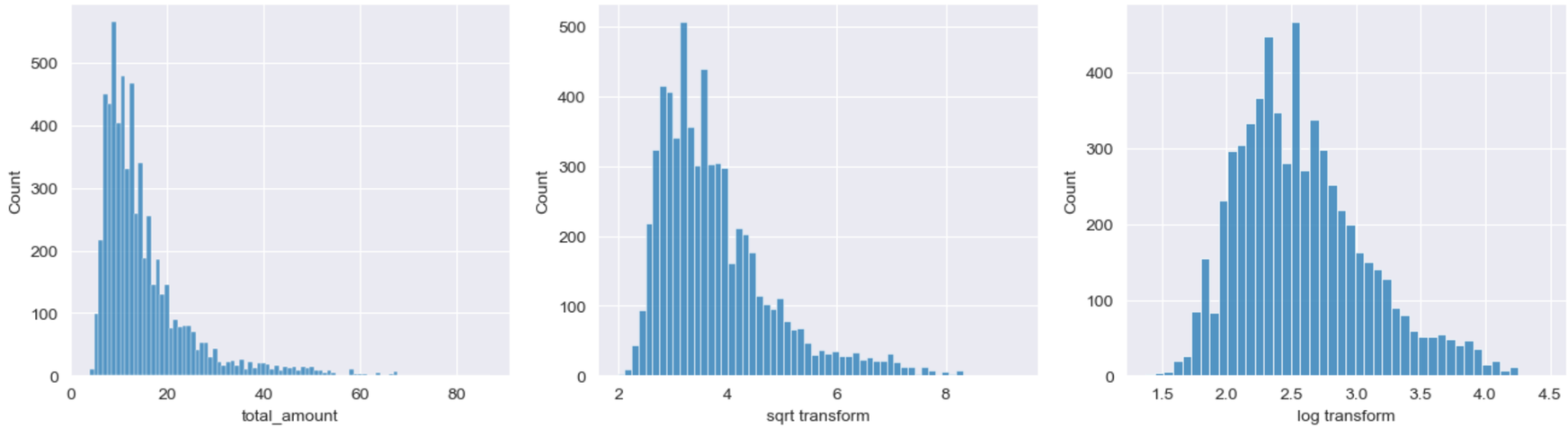
Dealing with Skew

- 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

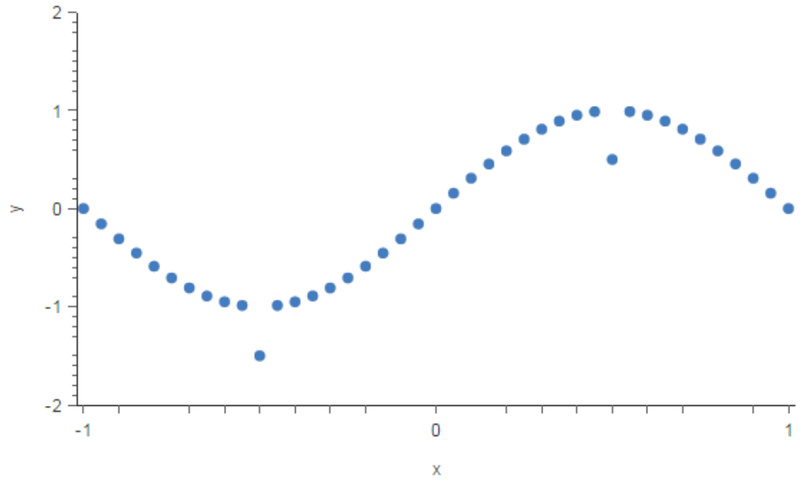
- Many models expect "normal", symmetric data (ex: linear models)
- Highly skewed: tail has larger effect on model (outliers?)
- Transform with `log` or `sqrt`

In [57]:
```
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..

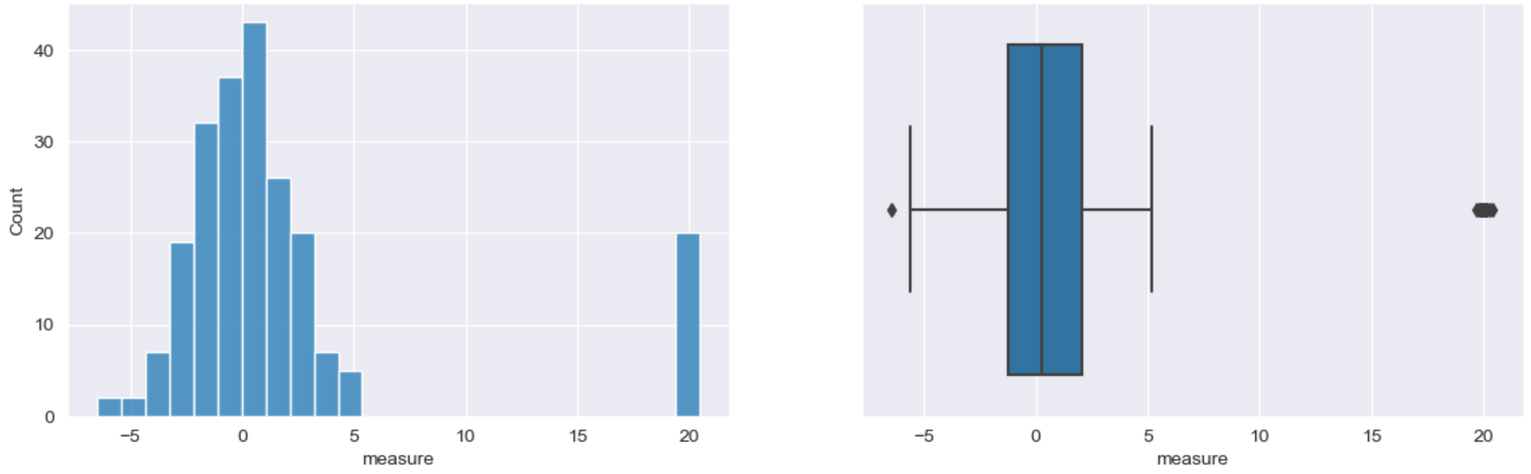
Detecting Outliers

Detecting Outliers

In [58]:

```
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

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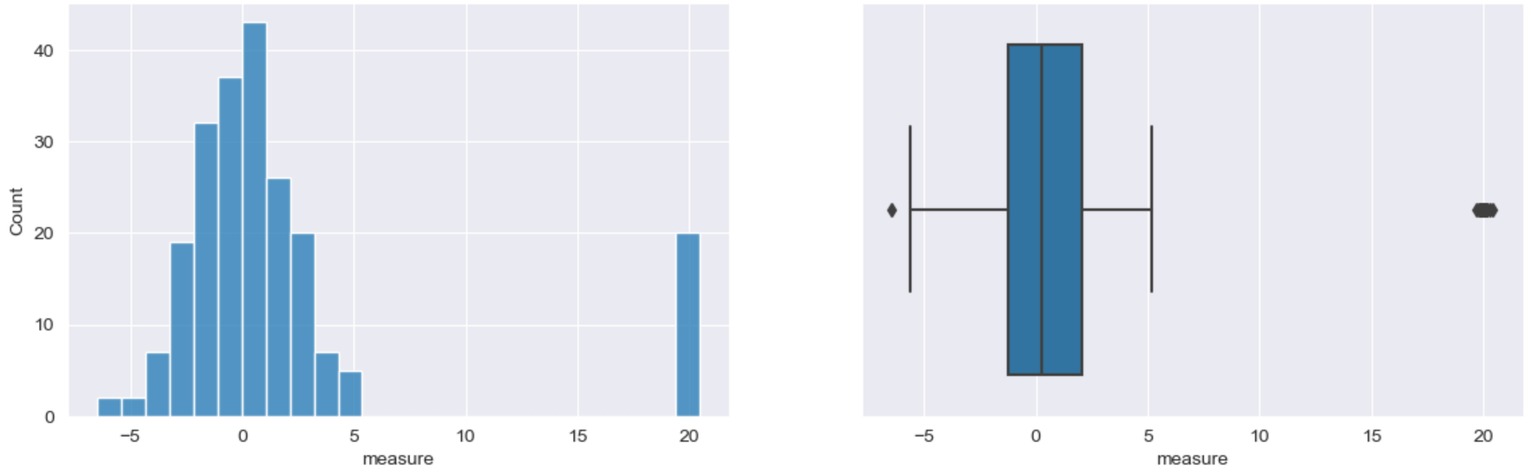
```



In [59]:
```
# Calculating IQR
p25,p75 = df_rand.measure.quantile([.25,.75])
iqr = p75 - p25
round(iqr,2)
```

Out[59]: 3.3

Detecting Outliers

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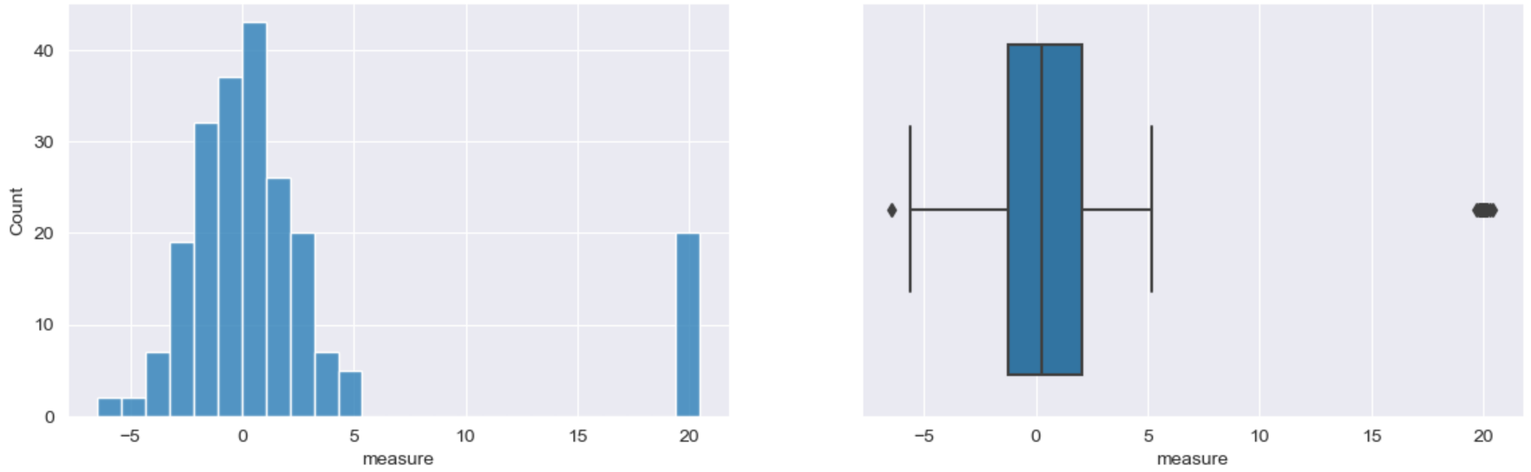
```



In [59]:
```
# Calculating IQR
p25,p75 = df_rand.measure.quantile([.25,.75])
iqr = p75 - p25
round(iqr,2)
```

Out[59]: 3.3

In [60]:
```
# 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 [61]:

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

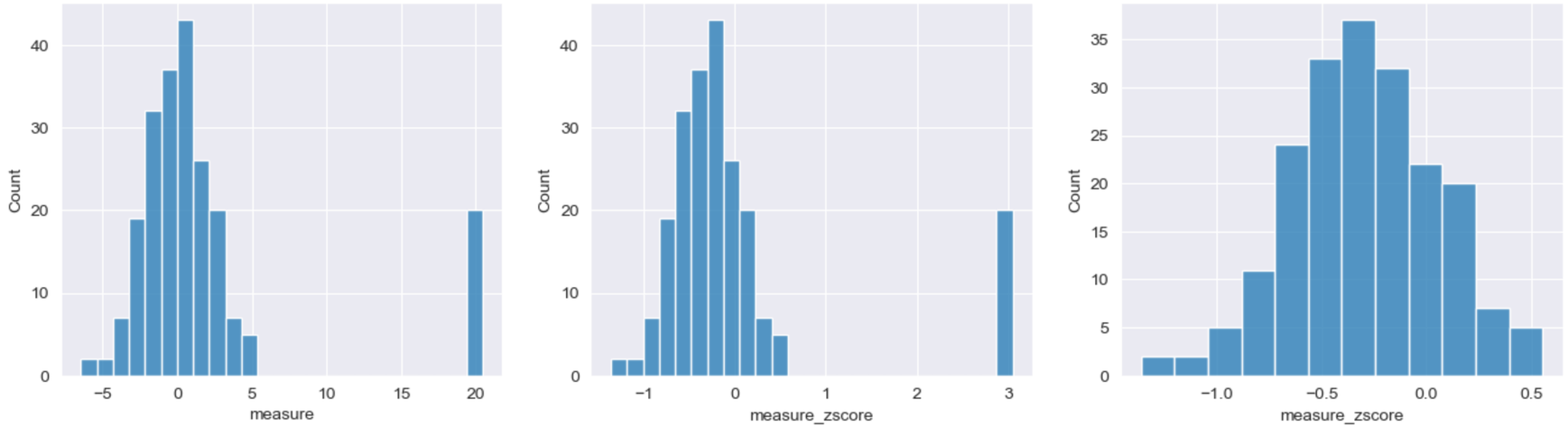
fig, ax = plt.subplots(1,3,figsize=(16,4))
sns.histplot(x=df_rand.measure,ax=ax[0]);
sns.histplot(x=df_rand.measure_zscore, ax=ax[1]);

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[61]:

	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 [62]:

```
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

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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 [63]:
```
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

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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']                   = df_shop1.price.fillna(df_shop1.price.mean())
df_shop1['price_scaled']            = StandardScaler().fit_transform(df_shop1[['price']])
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df_shop1['favorite_flower']         = SimpleImputer(strategy='most_frequent').fit(df_shop1[['favorite_flower']])
```

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        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 [64]:
```
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 [65]:

```
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 [65]:
```
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 [66]:
```
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[:10]

```

Out[66]:

	trip_duration	trip_duration_binned
1	516	short
2	683	medium
7	834	medium
8	298	short

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 [67]:
```
1 pd.get_dummies(df_taxi_bin.trip_duration_binned, prefix='trip_duration').iloc[:2]
```

Out[67]:

	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 [67]:
```
pd.get_dummies(df_taxi_bin.trip_duration_binned, prefix='trip_duration').iloc[:2]
```

Out[67]:

	trip_duration_short	trip_duration_medium	trip_duration_long
1	1	0	0
2	0	1	0

In [68]:
```
# 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[68]:

	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 [67]:
```
1 pd.get_dummies(df_taxi_bin.trip_duration_binned, prefix='trip_duration').iloc[:2]
```

Out[67]:

	trip_duration_short	trip_duration_medium	trip_duration_long
1	1	0	0
2	0	1	0

In [68]:
```
1 # to add back to dataframe, use join (will discuss .join() next time)
2 df_taxi_bin.join(pd.get_dummies(df_taxi_bin.trip_duration_binned, prefix='trip_duration')).iloc[:2,-6:] # not saved
```

Out[68]:

	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 [69]:
```
1 # or let pandas determine which columns to one-hot
2 pd.get_dummies(df_taxi_bin).iloc[:2,-6:] # not being saved
```

Out[69]:

	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 [70]:
```
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[70]:
```
[array(['short', 'medium', 'long'], dtype=object)]
```

One-Hot Encoding with sklearn

In [70]:
```
from sklearn.preprocessing import OneHotEncoder

ohe = OneHotEncoder(categories=[['short','medium','long']],  # or leave as 'auto'
                    sparse=True,
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ohe.fit(df_taxi_bin[['trip_duration_binned']])
ohe.categories_
```

Out[70]:
```
[array(['short', 'medium', 'long'], dtype=object)]
```

In [71]:
```
ohe.transform(df_taxi_bin[['trip_duration_binned']])[:3] # returns a sparse matrix!
```

Out[71]:
```
<3x3 sparse matrix of type '<class 'numpy.float64'>'
        with 3 stored elements in Compressed Sparse Row format>
```

One-Hot Encoding with sklearn

In [70]:
```
from sklearn.preprocessing import OneHotEncoder

ohe = OneHotEncoder(categories=[['short','medium','long']],  # or leave as 'auto'
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ohe.fit(df_taxi_bin[['trip_duration_binned']])
ohe.categories_
```

Out[70]:
```
[array(['short', 'medium', 'long'], dtype=object)]
```

In [71]:
```
ohe.transform(df_taxi_bin[['trip_duration_binned']])[:3] # returns a sparse matrix!
```

Out[71]:
```
<3x3 sparse matrix of type '<class 'numpy.float64'>'
        with 3 stored elements in Compressed Sparse Row format>
```

In [72]:
```
ohe.transform(df_taxi_bin[['trip_duration_binned']])[:3].todense() # use .todense() to convert sparse to dense
```

Out[72]:
```
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 [73]:

```
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 [73]:
```
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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                      ).fit(df_taxi[['trip_duration']])
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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 [74]:
```
df_taxi[['trip_duration']].tail(3)
```

Out[74]:

	trip_duration
9994	905
9995	296
9997	2089

Bin and One-Hot Encode with sklearn

In [73]:
```
from sklearn.preprocessing import KBinsDiscretizer

# NOTE: We're not setting the bin edges explicitly
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kbd = KBinsDiscretizer(n_bins=3,
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print(kbd.bin_edges_)
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```
[array([2.000e+00, 4.780e+02, 8.700e+02, 3.556e+03])]
[   2  478  870 3556]
```

In [74]:
```
df_taxi[['trip_duration']].tail(3)
```

Out[74]:

	trip_duration
9994	905
9995	296
9997	2089

In [75]:
```
kbd.transform(df_taxi[['trip_duration']])[-3:]
```

Out[75]:
```
<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 [73]:
```
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 [74]:
```
df_taxi[['trip_duration']].tail(3)
```

Out[74]:

	trip_duration
9994	905
9995	296
9997	2089

In [75]:
```
kbd.transform(df_taxi[['trip_duration']])[-3:]
```

Out[75]:
```
<3x3 sparse matrix of type '<class 'numpy.float64'>'
        with 3 stored elements in Compressed Sparse Row format>
```

In [76]:
```
kbd.transform(df_taxi[['trip_duration']])[-5:].todense()
```

Out[76]:
```
matrix([[0., 0., 1.],
        [0., 0., 1.],
        [0., 0., 1.],
        [1., 0., 0.],
```

Dealing with Ordinal Variables

Dealing with Ordinal Variables

In [77]:
```
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[77]:

	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 [77]:
```
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[77]:

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

In [78]:
```
# 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[78]:

	size
0	1
1	2
2	3

Dealing with Ordinal Variables Cont.

Dealing with Ordinal Variables Cont.

In [79]:
```
1 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 Cont.

In [79]:
```
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 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[80]:

	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 [117]:
```
from sklearn.preprocessing import PolynomialFeatures

pf = PolynomialFeatures(degree=3,
                        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)
```

In [118]:
```
X_new.shape
```

Out[118]:
```
(6225, 9)
```

Python String Functions

Python String Functions

In [82]:
```
1 doc = "D.S. is good!"
2 doc
```

Out[82]:
```
'D.S. is good!'
```

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1 doc = "D.S. is good!"
2 doc
```

Out[82]:
```
'D.S. is good!'
```

In [83]:
```
1 doc.lower(),doc.upper()       # change capitalization
```

Out[83]:
```
('d.s. is good!', 'D.S. IS GOOD!')
```

Python String Functions

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2 doc
```

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'D.S. is good!'
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```
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```

Out[83]:
```
('d.s. is good!', 'D.S. IS GOOD!')
```

In [84]:
```
1 doc.split() , doc.split('.')  # split a string into parts (default is whitespace)
```

Out[84]:
```
(['D.S.', 'is', 'good!'], ['D', 'S', ' is good!'])
```

Python String Functions

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```
1 doc = "D.S. is good!"
2 doc
```

Out[82]:
```
'D.S. is good!'
```

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```

In [85]:
```
1 '|'.join(['ab','c','d'])      # join items in a list together
```

Out[85]:
```
'ab|c|d'
```

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```

Out[85]:
```
'ab|c|d'
```

In [86]:
```
1 '|'.join(doc[:5])             # a string itself is treated like a list of characters
```

Out[86]:
```
'D|.|S|.| '
```

Python String Functions

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2 doc
```

Out[82]:
```
'D.S. is good!'
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```
'ab|c|d'
```

In [86]:
```
1 '|'.join(doc[:5])             # a string itself is treated like a list of characters
```

Out[86]:
```
'D|.|S|.| '
```

In [87]:
```
1 '  test   '.strip()           # remove whitespace from the beginning and end of a string
```

Out[87]:
```
'test'
```

Python String Functions

In [82]:
```
1 doc = "D.S. is good!"
2 doc
```

Out[82]:
```
'D.S. is good!'
```

In [83]:
```
1 doc.lower(),doc.upper()       # change capitalization
```

Out[83]:
```
('d.s. is good!', 'D.S. IS GOOD!')
```

In [84]:
```
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```

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```

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```
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Out[85]:
```
'ab|c|d'
```

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```
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Out[86]:
```
'D|.|S|.| '
```

In [87]:
```
1 '  test   '.strip()           # remove whitespace from the beginning and end of a string
```

Out[87]:
```
'test'
```

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

String Functions in Pandas

String Functions in Pandas

In [88]:
```
1 df_shop.iloc[:2].loc[:,'lastname']
```

Out[88]:
```
0     PERKINS
1    ROBINSON
Name: lastname, dtype: object
```

String Functions in Pandas

In [88]:
```
1 df_shop.iloc[:2].loc[:,'lastname']
```

Out[88]:
```
0     PERKINS
1    ROBINSON
Name: lastname, dtype: object
```

In [89]:
```
1 df_shop.loc[:,'lastname'].iloc[:2].str.lower()
```

Out[89]:
```
0     perkins
1    robinson
Name: lastname, dtype: object
```

String Functions in Pandas

In [88]:
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df_shop.iloc[:2].loc[:,'lastname']
```

Out[88]:
```
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1    ROBINSON
Name: lastname, dtype: object
```

In [89]:
```
df_shop.loc[:,'lastname'].iloc[:2].str.lower()
```

Out[89]:
```
0     perkins
1    robinson
Name: lastname, dtype: object
```

In [90]:
```
df_shop.lastname[:2].str.capitalize()
```

Out[90]:
```
0     Perkins
1    Robinson
Name: lastname, dtype: object
```

String Functions in Pandas

In [88]:
```
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```

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Name: lastname, dtype: object
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In [89]:
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1 df_shop.loc[:,'lastname'].iloc[:2].str.lower()
```

Out[89]:
```
0     perkins
1    robinson
Name: lastname, dtype: object
```

In [90]:
```
1 df_shop.lastname[:2].str.capitalize()
```

Out[90]:
```
0     Perkins
1    Robinson
Name: lastname, dtype: object
```

In [91]:
```
1 df_shop.lastname[:2].str.startswith('ROB') # .endswith() , .contains()
```

Out[91]:
```
0    False
1     True
Name: lastname, dtype: bool
```

String Functions in Pandas

In [88]:
```
1 df_shop.iloc[:2].loc[:,'lastname']
```

Out[88]:
```
0     PERKINS
1    ROBINSON
Name: lastname, dtype: object
```

In [89]:
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```

Out[89]:
```
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1    robinson
Name: lastname, dtype: object
```

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

Out[90]:
```
0     Perkins
1    Robinson
Name: lastname, dtype: object
```

In [91]:
```
1 df_shop.lastname[:2].str.startswith('ROB') # .endswith() , .contains()
```

Out[91]:
```
0    False
1     True
Name: lastname, dtype: bool
```

In [92]:
```
1 df_shop.lastname[:2].str.replace('P','*')
```

Out[92]:
```
0     *ERKINS
1    ROBINSON
Name: lastname, dtype: object
```

String Functions in Pandas

In [88]:
```
df_shop.iloc[:2].loc[:,'lastname']
```

Out[88]:
```
0     PERKINS
1    ROBINSON
Name: lastname, dtype: object
```

In [89]:
```
df_shop.loc[:,'lastname'].iloc[:2].str.lower()
```

Out[89]:
```
0     perkins
1    robinson
Name: lastname, dtype: object
```

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

Out[90]:
```
0     Perkins
1    Robinson
Name: lastname, dtype: object
```

In [91]:
```
df_shop.lastname[:2].str.startswith('ROB') # .endswith() , .contains()
```

Out[91]:
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0    False
1     True
Name: lastname, dtype: bool
```

In [92]:
```
df_shop.lastname[:2].str.replace('P','*')
```

Out[92]:
```
0     *ERKINS
1    ROBINSON
Name: lastname, dtype: object
```

and more: https://pandas.pydata.org/pandas-docs/stable/user_guide/text.html#method-summary

Pandas datetime functions

Pandas datetime functions

In [93]:
```
1 df_taxi.iloc[:2].tpep_pickup_datetime
```

Out[93]:
```
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 [93]:
```
1 df_taxi.iloc[:2].tpep_pickup_datetime
```

Out[93]:
```
1   2017-01-05 15:14:52
2   2017-01-11 14:47:52
Name: tpep_pickup_datetime, dtype: datetime64[ns]
```

In [94]:
```
1 df_taxi.iloc[:2].tpep_pickup_datetime.dt.day
```

Out[94]:
```
1     5
2    11
Name: tpep_pickup_datetime, dtype: int64
```

Pandas datetime functions

In [93]:
```
1 df_taxi.iloc[:2].tpep_pickup_datetime
```

Out[93]:
```
1   2017-01-05 15:14:52
2   2017-01-11 14:47:52
Name: tpep_pickup_datetime, dtype: datetime64[ns]
```

In [94]:
```
1 df_taxi.iloc[:2].tpep_pickup_datetime.dt.day
```

Out[94]:
```
1     5
2    11
Name: tpep_pickup_datetime, dtype: int64
```

In [95]:
```
1 df_taxi.iloc[:2].tpep_pickup_datetime.dt.day_of_week
```

Out[95]:
```
1    3
2    2
Name: tpep_pickup_datetime, dtype: int64
```

Pandas datetime functions

In [93]:
```
1 df_taxi.iloc[:2].tpep_pickup_datetime
```

Out[93]:
```
1   2017-01-05 15:14:52
2   2017-01-11 14:47:52
Name: tpep_pickup_datetime, dtype: datetime64[ns]
```

In [94]:
```
1 df_taxi.iloc[:2].tpep_pickup_datetime.dt.day
```

Out[94]:
```
1     5
2    11
Name: tpep_pickup_datetime, dtype: int64
```

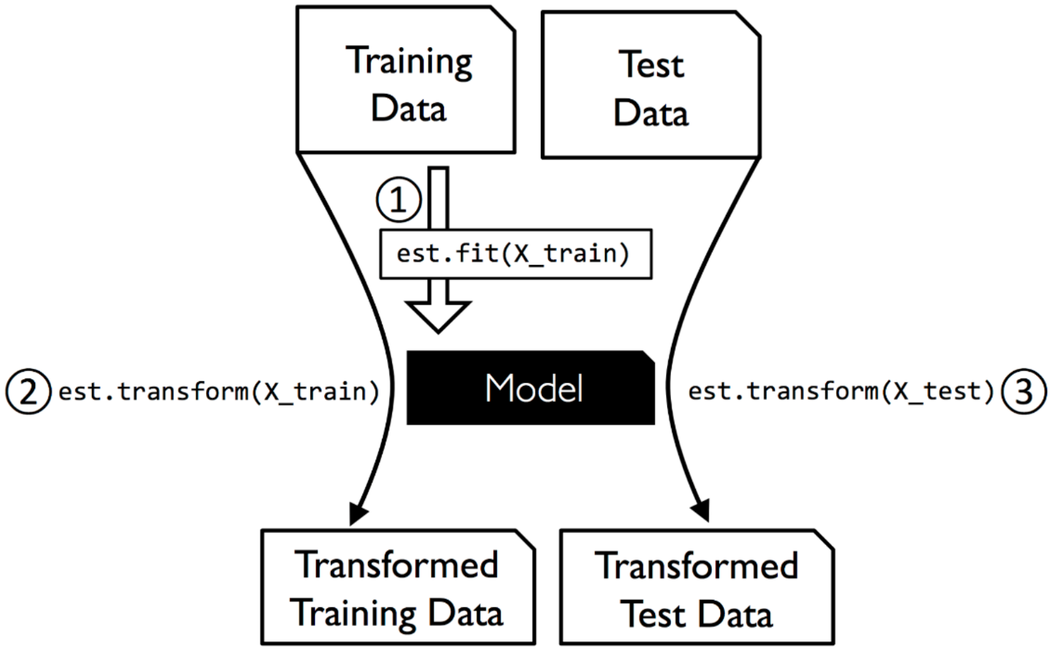
In [95]:
```
1 df_taxi.iloc[:2].tpep_pickup_datetime.dt.day_of_week
```

Out[95]:
```
1    3
2    2
Name: tpep_pickup_datetime, dtype: int64
```

and more: https://pandas.pydata.org/pandas-docs/stable/user_guide/timeseries.html#time-date-components

Transforming with Train/Test Split

- When performing data transformation



Next Time

- Dimensionality Reduction
    - Feature Selection
    - Feature Extraction

Questions?