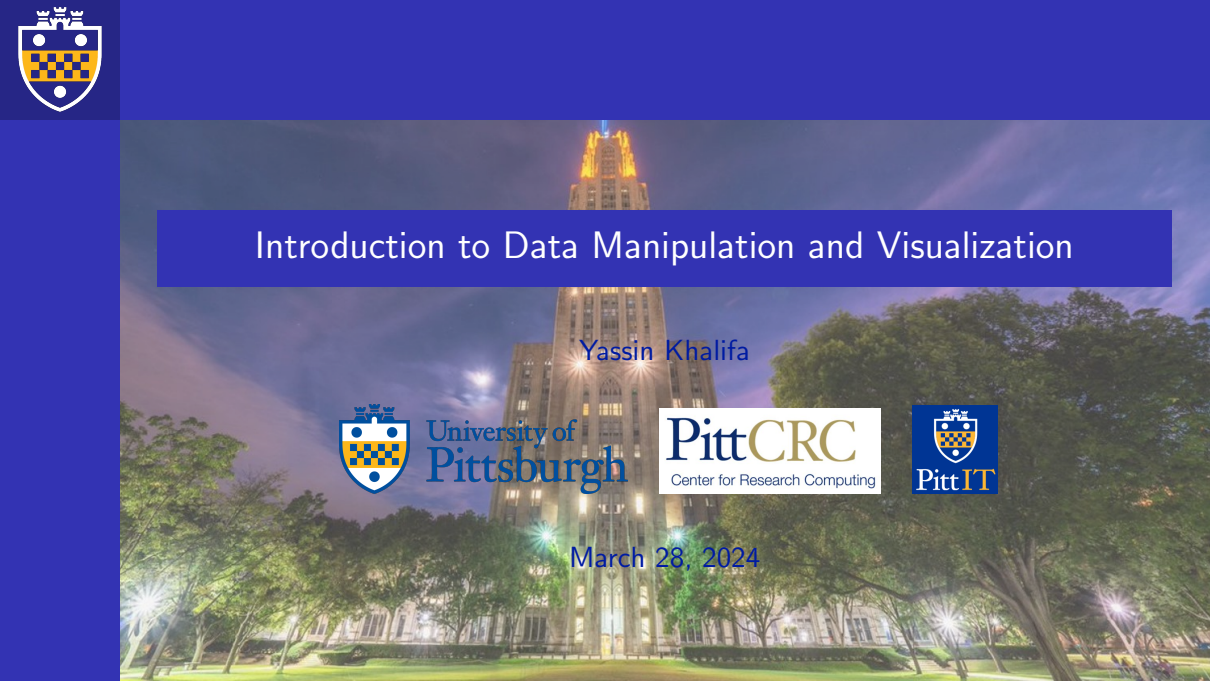

Introduction to Data Manipulation and Visualization

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Data structures in Python

List	Dictionary
List is a collection of index-values pairs as that of array in c++.	Dictionary is a hashed structure of key-value pairs.
List is created by placing elements in [ ] separated by commas “, “	Dictionary is created by placing elements in { } as "key": "value", each key value pair is separated by commas ","
The indices of list are integers starting from 0.	The keys of dictionary can be of any data type.
The elements are accessed via indices.	The elements are accessed via keys.
The order of the elements entered are maintained.	There is no guarantee for maintaining order.

What is missing:

- Data structures with more flexible indexing for accessibility using both keys and numeric indices.
- Built-in methods that allow for data manipulation within the data structure.

Series

Series is a "dict-like" one-dimensional labeled array capable of holding any data type (integers, strings, floating point numbers, Python objects, etc.). The axis labels are collectively referred to as the index.

```
# import libraries
>>> import pandas as pd
>>> import numpy as np

# the basic method to create a series is to call
>>> s = pd.Series(data, index=index)
```

---

data can be many different things:

- a Python dict
- an ndarray
- a scalar value

index is a list of axis labels

Series: Create

```
>>> s = pd.Series(np.random.randn(5), index=["a", "b", "c", "d", "e"])
>>> s
a    0.469112
b   -0.282863
c   -1.509059
d   -1.135632
e    1.212112
dtype: float64
>>> s.index
Index(['a', 'b', 'c', 'd', 'e'], dtype='object')
>>> d = {"x": 0.0, "y": 1.0, "z": 2.0}
>>> pd.Series(d)
x    0.0
y    1.0
z    2.0
dtype: float64
```

Series: Indexing and data operations

```
>>> s['a']
0.469112
>>> s[['a', 'c']]
a    0.469112
c   -1.509059
dtype: float64
>>> s[0]
0.469112
>>> s[2:]
c   -1.509059
d   -1.135632
e    1.212112
dtype: float64
>>> s[s < 0]
b   -0.282863
c   -1.509059
d   -1.135632
dtype: float64
```

```
>>> np.power(s, 4)
a    0.000009
b    0.060818
c    0.015160
d    1.335574
e    6.791131
dtype: float64
>>> s.to_numpy()
array([ 0.4691, -0.2829, -1.5091,
 ↪  -1.1356,  1.2121])
>>> s = pd.Series(np.random.randn(5),
 ↪  name="something")
0   -0.390516
1    0.644527
2    1.315244
3    0.142816
4   -0.445948
Name: something, dtype: float64
```

DataFrame

DataFrame is a 2-dimensional labeled data structure with columns of potentially different types. You can think of it like a spreadsheet or SQL table, or a dict of Series objects. It is generally the most commonly used pandas object.

```
# the basic method to create a dataframe is to call
>>> s = pd.DataFrame(data)
```

Like Series, DataFrame accepts many different kinds of input:

- Dict of 1D ndarrays, lists, dicts, or Series
- 2-D numpy.ndarray
- Structured or record ndarray
- A Series
- Another DataFrame

DataFrame: Create

```
>>> d = {"one": pd.Series([1.0, 2.0,
↪  3.0], index=["a", "b", "c"]), "two":
↪  pd.Series([1.0, 2.0, 3.0, 4.0],
↪  index=["a", "b", "c", "d"])}
>>> df = pd.DataFrame(d)
>>> df
   one  two
a  1.0  1.0
b  2.0  2.0
c  3.0  3.0
d  NaN  4.0
>>> pd.DataFrame(d, index=["d", "a",
↪  "c"])
   one  two
d  NaN  4.0
a  1.0  1.0
c  3.0  3.0
>>> pd.DataFrame(d, index=["d", "a"],
↪  columns=["two", "three"])
   two three
d  4.0   NaN
a  1.0   NaN
>>> d = {"one": [1.0, 2.0, 3.0], "two":
↪  [3.0, 2.0, 1.0]}
>>> pd.DataFrame(d)
   one  two
0  1.0  3.0
1  2.0  2.0
2  3.0  1.0
>>> pd.DataFrame(d, index=["a", "b",
↪  "c"])
   one  two
a  1.0  3.0
b  2.0  2.0
c  3.0  1.0
>>> d = {"one": pd.Series([1.0, 2.0,
↪  3.0], index=["a", "b", "c"]), "two":
↪  pd.Series([1.0, 2.0, 3.0, 4.0],
↪  index=["a", "b", "c", "d"])}
```

DataFrame: Indexing and selection

```
>>> df = pd.DataFrame(d)
>>> df
   one  two
a  1.0  1.0
b  2.0  2.0
c  3.0  3.0
d  NaN  4.0
>>> df["one"]
a    1.0
b    2.0
c    3.0
d    NaN
Name: one, dtype: float64
>>> df["three"] = df["one"] * df["two"]
>>> df["flag"] = df["one"] > 2
   one  two  three   flag
a  1.0  1.0    1.0  False
b  2.0  2.0    4.0  False
c  3.0  3.0    9.0   True
d  NaN  4.0    NaN  False
```

```
>>> del df["two"]
   one  three   flag
a  1.0    1.0  False
b  2.0    4.0  False
c  3.0    9.0   True
d  NaN    NaN  False
>>> df["newcol"] = "Python"
   one  three   flag  newcol
a  1.0    1.0  False  Python
b  2.0    4.0  False  Python
c  3.0    9.0   True  Python
d  NaN    NaN  False  Python
>>> df.insert(1, "bar", df["one"])
   one  bar  three   flag  newcol
a  1.0  1.0    1.0  False  Python
b  2.0  2.0    4.0  False  Python
c  3.0  3.0    9.0   True  Python
d  NaN  NaN    NaN  False  Python
>>> df.assign(newcol2 =
↪  np.power(df['one'], 2))
```

DataFrame: Indexing and selection

Operation	**Syntax**	**Result**
Select column	$df[col]$	Series
Select row by label	$df.loc[label]$	Series
Select row by integer location	$df.iloc[loc]$	Series
Slice rows	$df[5:10]$	DataFrame
Select rows by boolean vector	$df[bool\_vec]$	DataFrame

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The pandas I/O API functions

Data Description	Reader	Writer
CSV	*read_csv*	*to_csv*
JSON	*read_json*	*to_json*
XML	*read_xml*	*to_xml*
MS Excel	*read_excel*	*to_excel*
HDF5 Format	*read_hdf*	*to_hdf*
Python Pickle Format	*read_pickle*	*to_pickle*
SQL	*read_sql*	*to_sql*
Google BigQuery	*read_gbq*	*to_gbq*

Load data into dataframes

```
>>> dailyActivity = pd.read_csv('./data/dailyActivity_merged.csv')
>>> dailyCalories = pd.read_csv('./data/dailyCalories_merged.csv')
>>> dailyIntensities = pd.read_csv('./data/dailyIntensities_merged.csv')
>>> dailySteps = pd.read_csv('./data/dailySteps_merged.csv')
>>> sleepDay = pd.read_csv('./data/sleepDay_merged.csv')
>>> weightLogInfo = pd.read_csv('./data/weightLogInfo_merged.csv')
>>> sleepDay.head()
```

	Id	SleepDay	TotalSleepRecords	TotalMinutesAsleep	TotalTimeInBed
0	1503960366	4/12/2016 12:00:00 AM	1	327	346
1	1503960366	4/13/2016 12:00:00 AM	2	384	407
2	1503960366	4/15/2016 12:00:00 AM	1	412	442
3	1503960366	4/16/2016 12:00:00 AM	2	340	367
4	1503960366	4/17/2016 12:00:00 AM	1	700	712

Explore the data


```
>>> dailyActivity.head(3)
           Id ActivityDate  TotalSteps  ...  Calories
0  1503960366    4/12/2016       13162  ...      1985
1  1503960366    4/13/2016       10735  ...      1797
2  1503960366    4/14/2016       10460  ...      1776

[3 rows x 15 columns]
>>> dailyActivity.tail(3)
            Id ActivityDate  TotalSteps  ...  Calories
937  8877689391    5/10/2016       10733  ...      2832
938  8877689391    5/11/2016       21420  ...      3832
939  8877689391    5/12/2016        8064  ...      1849

[3 rows x 15 columns]
```

Explore the data

```
>>> dailyActivity.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 940 entries, 0 to 939
Data columns (total 15 columns):
#   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
0   Id                         940 non-null    int64
1   ActivityDate               940 non-null    object
2   TotalSteps                 940 non-null    int64
3   TotalDistance              940 non-null    float64
4   TrackerDistance            940 non-null    float64
5   LoggedActivitiesDistance   940 non-null    float64
6   VeryActiveDistance         940 non-null    float64
7   ModeratelyActiveDistance   940 non-null    float64
8   LightActiveDistance        940 non-null    float64
9   SedentaryActiveDistance    940 non-null    float64
10  VeryActiveMinutes          940 non-null    int64
11  FairlyActiveMinutes        940 non-null    int64
12  LightlyActiveMinutes       940 non-null    int64
13  SedentaryMinutes           940 non-null    int64
14  Calories                   940 non-null    int64
dtypes: float64(7), int64(7), object(1)
memory usage: 110.3+ KB
```

Explore the data

```
>>> dailyActivity.shape
(940, 16)
>>> dailyActivity.describe()
                 Id    TotalSteps  TotalDistance  ...     Calories
count  9.400000e+02    940.000000     940.000000  ...   940.000000
mean   4.855407e+09   7637.910638       5.489702  ...  2303.609574
std    2.424805e+09   5087.150742       3.924606  ...   718.166862
min    1.503960e+09      0.000000       0.000000  ...     0.000000
25%    2.320127e+09   3789.750000       2.620000  ...  1828.500000
50%    4.445115e+09   7405.500000       5.245000  ...  2134.000000
75%    6.962181e+09  10727.000000       7.712500  ...  2793.250000
max    8.877689e+09  36019.000000      28.030001  ...  4900.000000

[8 rows x 14 columns]
```

Explore the data


```
>>> dailyActivity.describe(percentiles=[0.2, 0.4, 0.6, 0.8])
                 Id    TotalSteps  TotalDistance  ...     Calories
count  9.400000e+02    940.000000     940.000000  ...   940.000000
mean   4.855407e+09   7637.910638       5.489702  ...  2303.609574
std    2.424805e+09   5087.150742       3.924606  ...   718.166862
min    1.503960e+09      0.000000       0.000000  ...     0.000000
20%    2.026352e+09   2991.800000       2.056000  ...  1725.000000
40%    4.020333e+09   6116.600000       4.266000  ...  2010.000000
50%    4.445115e+09   7405.500000       5.245000  ...  2134.000000
60%    5.553957e+09   8865.400000       6.260000  ...  2364.600000
80%    7.086362e+09  11599.000000       8.256000  ...  2899.600000
max    8.877689e+09  36019.000000      28.030001  ...  4900.000000

[10 rows x 14 columns]
```

Explore the data

```
>>> penguins = sns.load_dataset("penguins")
>>> penguins.head(4)
species     island  bill_length_mm  bill_depth_mm  flipper_length_mm  body_mass_g     sex
0  Adelie  Torgersen            39.1           18.7              181.0       3750.0    Male
1  Adelie  Torgersen            39.5           17.4              186.0       3800.0  Female
2  Adelie  Torgersen            40.3           18.0              195.0       3250.0  Female
3  Adelie  Torgersen             NaN            NaN                NaN          NaN     NaN
>>> penguins.sum()
species              AdelieAdelieAdelieAdelieAdelieAdelieAdelieAdel...
island               TorgersenTorgersenTorgersenTorgersenTorgersenT...
bill_length_mm                                                15021.3
bill_depth_mm                                                  5865.7
flipper_length_mm                                             68713.0
body_mass_g                                                 1437000.0
>>> penguins.count()
penguins.count()
species              344
island               344
bill_length_mm       342
bill_depth_mm        342
flipper_length_mm    342
body_mass_g          342
sex                  333
```

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Converting from object to date


```
>>> dailyActivity['ActivityDate'] = pd.to_datetime(dailyActivity['ActivityDate'])
>>> dailyActivity.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 940 entries, 0 to 939
Data columns (total 15 columns):
#   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
0   Id                         940 non-null    int64
1   ActivityDate               940 non-null    datetime64[ns]
2   TotalSteps                 940 non-null    int64
3   TotalDistance              940 non-null    float64
4   TrackerDistance            940 non-null    float64
5   LoggedActivitiesDistance   940 non-null    float64
6   VeryActiveDistance         940 non-null    float64
7   ModeratelyActiveDistance   940 non-null    float64
8   LightActiveDistance        940 non-null    float64
9   SedentaryActiveDistance    940 non-null    float64
10  VeryActiveMinutes          940 non-null    int64
11  FairlyActiveMinutes        940 non-null    int64
12  LightlyActiveMinutes       940 non-null    int64
13  SedentaryMinutes           940 non-null    int64
14  Calories                   940 non-null    int64
dtypes: datetime64[ns](1), float64(7), int64(7)
memory usage: 110.3 KB
```

Create date/time fields in dataframes

```
>>> dti = pd.date_range("2020-01-01", periods=4, freq="2H")
>>> dti
DatetimeIndex(['2020-01-01 00:00:00', '2020-01-01 02:00:00', '2020-01-01 04:00:00',
 ↪  '2020-01-01 06:00:00'], dtype='datetime64[ns]', freq='2H')
>>> d = {"one": pd.Series([1.0, 2.0, 3.0], index=["a", "b", "c"]), "two": pd.Series([1.0,
 ↪  2.0, 3.0, 4.0], index=["a", "b", "c", "d"]), "date":dti}
>>> df=pd.DataFrame(d)
>>> df.info()
<class 'pandas.core.frame.DataFrame'>
Index: 4 entries, a to d
Data columns (total 3 columns):
#   Column  Non-Null Count  Dtype
---  ------  --------------  -----
0   one     3 non-null      float64
1   two     4 non-null      float64
2   date    4 non-null      datetime64[ns]
dtypes: datetime64[ns](1), float64(2)
memory usage: 128.0+ bytes
```

Create date/time fields in dataframes

```
>>> df['date'] = df['date'] + pd.Timedelta("2 hours")
   one  two                date
a  1.0  1.0 2020-01-01 02:00:00
b  2.0  2.0 2020-01-01 04:00:00
c  3.0  3.0 2020-01-01 06:00:00
d  NaN  4.0 2020-01-01 08:00:00
>>> df['date'] = df['date'] + pd.Timedelta("2 days")
   one  two                date
a  1.0  1.0 2020-01-03 02:00:00
b  2.0  2.0 2020-01-03 04:00:00
c  3.0  3.0 2020-01-03 06:00:00
d  NaN  4.0 2020-01-03 08:00:00
>>> df['dateDoW'] = df['date'].dt.day_name()
   one  two                date dateDoW
a  1.0  1.0 2020-01-03 02:00:00  Friday
b  2.0  2.0 2020-01-03 04:00:00  Friday
c  3.0  3.0 2020-01-03 06:00:00  Friday
d  NaN  4.0 2020-01-03 08:00:00  Friday
```

Outline

Indexing by boolean vectors


```
>>> dailyActivity['ActivityDoW'] = dailyActivity['ActivityDate'].dt.day_name()
>>> dailyActivity.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 940 entries, 0 to 939
Data columns (total 16 columns):
#   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
0   Id                         940 non-null    int64
1   ActivityDate               940 non-null    datetime64[ns]
2   TotalSteps                 940 non-null    int64
3   TotalDistance              940 non-null    float64
4   TrackerDistance            940 non-null    float64
5   LoggedActivitiesDistance   940 non-null    float64
6   VeryActiveDistance         940 non-null    float64
7   ModeratelyActiveDistance   940 non-null    float64
8   LightActiveDistance        940 non-null    float64
9   SedentaryActiveDistance    940 non-null    float64
10  VeryActiveMinutes          940 non-null    int64
11  FairlyActiveMinutes        940 non-null    int64
12  LightlyActiveMinutes       940 non-null    int64
13  SedentaryMinutes           940 non-null    int64
14  Calories                   940 non-null    int64
15  ActivityDoW                940 non-null    object
dtypes: datetime64[ns](1), float64(7), int64(7), object(1)
memory usage: 117.6+ KB
```

Indexing by boolean vectors


```
>>> dailyActivity['ActivityDoW']=='Saturday'
0      False
1      False
...
939    False
Name: ActivityDoW, Length: 940, dtype: bool
>>> sat_activity = dailyActivity[dailyActivity['ActivityDoW']=='Saturday']
>>> sat_activity.head(3)
Id ActivityDate  TotalSteps  TotalDistance ... Calories  ActivityDoW
4   1503960366   2016-04-16       12669           8.16   ...    1863     Saturday
11  1503960366   2016-04-23       14371           9.04   ...    1949     Saturday
18  1503960366   2016-04-30       14673           9.25   ...    1947     Saturday
[3 rows x 16 columns]
>>> we_activity = dailyActivity[(dailyActivity['ActivityDoW']=='Saturday') | (dailyActivity['ActivityDoW']=='Sunday')]
>>> we_activity.head(3)
Id ActivityDate  TotalSteps  TotalDistance ... Calories  ActivityDoW
4   1503960366   2016-04-16       12669           8.16   ...    1863     Saturday
5   1503960366   2016-04-17        9705           6.48   ...    1728       Sunday
11  1503960366   2016-04-23       14371           9.04   ...    1949     Saturday
[3 rows x 16 columns]
>>> we_activity = dailyActivity[dailyActivity['ActivityDoW'].isin(['Saturday', 'Sunday'])]
>>> we_activity.head(3)
Id ActivityDate  TotalSteps  TotalDistance ... Calories  ActivityDoW
4   1503960366   2016-04-16       12669           8.16   ...    1863     Saturday
5   1503960366   2016-04-17        9705           6.48   ...    1728       Sunday
11  1503960366   2016-04-23       14371           9.04   ...    1949     Saturday
[3 rows x 16 columns]
```

Indexing by integer location


```
>>> dailyActivity.iloc[100,:]
Id                          1844505072
ActivityDate       2016-04-20 00:00:00
TotalSteps                           8
TotalDistance                     0.01
TrackerDistance                   0.01
LoggedActivitiesDistance           0.0
VeryActiveDistance                 0.0
ModeratelyActiveDistance           0.0
LightActiveDistance               0.01
SedentaryActiveDistance            0.0
VeryActiveMinutes                    0
FairlyActiveMinutes                  0
LightlyActiveMinutes                 1
SedentaryMinutes                  1439
Calories                          1349
ActivityDoW                  Wednesday
Name: 100, dtype: object
```

```
>>> dailyActivity.iloc[100, [2, 3, 4]]
TotalSteps            8
TotalDistance      0.01
TrackerDistance    0.01
Name: 100, dtype: object
>>> dailyActivity.iloc[100:103, [2, 4]]
     TotalSteps  TrackerDistance
100           8             0.01
101        8054             5.32
102        5372             3.55
```

Indexing by label


```
>>> dailyActivity.loc[100,:]
Id                                1844505072
ActivityDate         2016-04-20 00:00:00
TotalSteps                              8
TotalDistance                        0.01
TrackerDistance                      0.01
LoggedActivitiesDistance              0.0
VeryActiveDistance                    0.0
ModeratelyActiveDistance              0.0
LightActiveDistance                  0.01
SedentaryActiveDistance               0.0
VeryActiveMinutes                       0
FairlyActiveMinutes                     0
LightlyActiveMinutes                    1
SedentaryMinutes                     1439
Calories                             1349
ActivityDoW                     Wednesday
Name: 100, dtype: object
```

```
>>> dailyActivity.set_index('l' +
↪  dailyActivity.index.astype(str),
↪  inplace=True)
>>> dailyActivity.loc['l100',
↪  ['TotalSteps', 'Calories',
↪  'ActivityDate']]
TotalSteps                        8
Calories                       1349
ActivityDate    2016-04-20 00:00:00
Name: l100, dtype: object
>>> dailyActivity.loc[['l100', 'l101',
↪  'l102'], ['TotalSteps', 'Calories',
↪  'ActivityDate']]
TotalSteps  TrackerDistance
      TotalSteps  Calories ActivityDate
l100           8      1349   2016-04-20
l101        8054      2062   2016-04-21
l102        5372      1827   2016-04-22
```

Indexing by column label and row slicing

```
>>> dailyActivity[['ActivityDate', 'TotalSteps']]
      ActivityDate  TotalSteps
110     2016-04-12       13162
...            ...         ...
1939    2016-05-12        8064
[940 rows x 2 columns]
>>> dailyActivity[dailyActivity.columns[[1,2]]]
      ActivityDate  TotalSteps
110     2016-04-12       13162
...            ...         ...
1939    2016-05-12        8064
[940 rows x 2 columns]
>>> dailyActivity[10:15]
            Id ActivityDate  TotalSteps  TotalDistance  Calories  ActivityDoW
110  1503960366   2016-04-22       12764           8.13      1827       Friday
111  1503960366   2016-04-23       14371           9.04      1949     Saturday
112  1503960366   2016-04-24       10039           6.41      1788       Sunday
113  1503960366   2016-04-25       15355           9.80      2013       Monday
114  1503960366   2016-04-26       13755           8.79      1970      Tuesday
[5 rows x 16 columns]
>>> dailyActivity[10:15][['TotalSteps', 'TotalDistance']]
     TotalSteps  TotalDistance
110       12764           8.13
111       14371           9.04
112       10039           6.41
113       15355           9.80
114       13755           8.79
```

Row slicing by label

```
>>> dailyActivity.loc['1100':'1103'][['Id', 'TotalSteps']]
             Id  TotalSteps
1100  1844505072           8
1101  1844505072        8054
1102  1844505072        5372
1103  1844505072        3570
>>> dailyActivity.loc['1100':'1103', 'Id':'TotalSteps']
             Id ActivityDate  TotalSteps
1100  1844505072    4/20/2016           8
1101  1844505072    4/21/2016        8054
1102  1844505072    4/22/2016        5372
1103  1844505072    4/23/2016        3570
>>> dailyActivity.loc['1100':'1103', 'Id'] = 0
      Id ActivityDate  TotalSteps
1100   0    4/20/2016           8
1101   0    4/21/2016        8054
1102   0    4/22/2016        5372
1103   0    4/23/2016        3570
>>> dailyActivity.iloc[100:103, dailyActivity.columns.get_loc('Id'):dailyActivity.columns.get_loc('TotalSteps')]
          Id ActivityDate
1100   0    4/20/2016
1101   0    4/21/2016
1102   0    4/22/2016
```

Random sample selection

```
>>> dailyActivity.sample(n=4)[['Id', 'TotalSteps', 'TotalDistance']]
                          Id  TotalSteps  TotalDistance
1414  4388161847        8863          6.82
1298  3372868164        8844          6.03
1550  5553957443       11886          7.76
1359  4020332650           0          0.00
>>> dailyActivity.sample(n=4, weights=np.random.rand(len(dailyActivity)))[['Id', 'TotalSteps', 'TotalDistance']]
                          Id  TotalSteps  TotalDistance
1407  4319703577        3672          2.46
1168  2022484408       10119          7.19
1929  8877689391        4790          3.64
1465  4445114986        2923          1.96
>>> dailyActivity.sample(n=4, weights=np.random.rand(len(dailyActivity)), replace=True)[['Id', 'TotalSteps',
↪  'TotalDistance']]
                          Id  TotalSteps  TotalDistance
1819  8378563200       12386          9.82
1717  7007744171       14816         10.98
1723  7007744171       11085          7.42
1574  5577150313       12574          9.42
>>> dailyActivity.sample(frac=0.003, replace=True)[['Id', 'TotalSteps', 'TotalDistance']]
                          Id  TotalSteps  TotalDistance
1258  2347167796       16901         11.37
1502  4558609924        6435          4.25
1696  6962181067       12627          8.35
```

Misc data selection functionality

```
>>> dailyActivity.where(dailyActivity['TotalSteps']>11100)
                Id ActivityDate  TotalSteps  TotalDistance ... Calories
10    1.503960e+09    4/12/2016     13162.0       8.500000  ...  1985.0
11             NaN           NaN         NaN            NaN  ...     NaN
...            ...           ...         ...            ...  ...     ...
1939           NaN           NaN         NaN            NaN  ...     NaN
[940 rows x 15 columns]
>>> dailyActivity.mask(dailyActivity['TotalSteps']>11100)
                Id ActivityDate  TotalSteps  TotalDistance ... Calories
10             NaN           NaN         NaN            NaN  ...     NaN
11    1.503960e+09    4/13/2016     10735.0           6.97  ...  1797.0
...            ...           ...         ...            ...  ...     ...
1939  8.877689e+09    5/12/2016      8064.0           6.12  ...  1849.0
[940 rows x 15 columns]
>>> dailyActivity2 = dailyActivity
>>> dailyActivity2.loc['1120':'1122', 'Id'] = 0
>>> dailyActivity.loc['1120':'1122', 'Id']
1120    0
1121    0
1122    0
Name: Id, dtype: int64
>>> dailyActivity3 = dailyActivity.copy(deep=False)
Shallow Copy: Changes reflect into the orignal dataframe iff you change the existing data but reflect into the copy
↪  only if you add more data that is not available in the original dataframe.
>>> dailyActivity4 = dailyActivity.copy(deep=True)
Deep Copy: This is a completely independent dataframe with its own data and index and no matter what modifications were
↪  done, they will reflect into the original dataframe.
```

Misc data selection functionality

```
>>> penguins = sns.load_dataset("penguins")
>>> penguins.head(4)
species     island  bill_length_mm  bill_depth_mm  flipper_length_mm  body_mass_g     sex
0  Adelie  Torgersen            39.1           18.7              181.0       3750.0    Male
1  Adelie  Torgersen            39.5           17.4              186.0       3800.0  Female
2  Adelie  Torgersen            40.3           18.0              195.0       3250.0  Female
3  Adelie  Torgersen             NaN            NaN                NaN          NaN     NaN
>>> penguins == penguins
species  island  bill_length_mm  bill_depth_mm  flipper_length_mm  body_mass_g   sex
0       True    True            True           True               True         True  True
1       True    True            True           True               True         True  True
2       True    True            True           True               True         True  True
3       True    True           False          False              False        False  False
>>> np.all(penguins == penguins)
False
>>> penguins.equals(penguins)
True
```

Dataframe index change

```
>>>  sat_activity = dailyActivity[dailyActivity['ActivityDoW']=='Saturday'][['Id', 'TotalSteps', 'TotalDistance',
↪  'Calories']]
>>> sat_activity.head(3)
            Id  TotalSteps  TotalDistance  Calories
14   1503960366       12669           8.16      1863
111  1503960366       14371           9.04      1949
118  1503960366       14673           9.25      1947
>>> sat_activity.loc['10',:]
"KeyError"
>>> sat_activity = dailyActivity[dailyActivity['ActivityDoW']=='Saturday'][['Id', 'TotalSteps', 'TotalDistance',
↪  'Calories']].reset_index()
   index          Id  TotalSteps  TotalDistance  Calories
0     14  1503960366       12669       8.160000      1863
1    111  1503960366       14371       9.040000      1949
2    118  1503960366       14673       9.250000      1947
>>> sat_activity = dailyActivity[dailyActivity['ActivityDoW']=='Saturday'][['Id', 'TotalSteps', 'TotalDistance',
↪  'Calories']].reset_index(drop=True)
            Id  TotalSteps  TotalDistance  Calories
0   1503960366       12669       8.160000      1863
1   1503960366       14371       9.040000      1949
2   1503960366       14673       9.250000      1947
>>> sat_activity.set_index('Id', inplace=True)
            TotalSteps  TotalDistance  Calories
Id
1503960366       12669           8.16      1863
1503960366       14371           9.04      1949
1503960366       14673           9.25      1947
```

Editing/dropping dataframe columns


```
>>> dailyActivity['TotalSteps'] = pd.cut(dailyActivity['TotalSteps'], bins=3, labels=('low', 'medium', 'high'))
           Id ActivityDate TotalSteps ... Calories  ActivityDoW
10  1503960366   2016-04-12     medium   ...    1985      Tuesday
11  1503960366   2016-04-13        low   ...    1797    Wednesday
12  1503960366   2016-04-14        low   ...    1776     Thursday
[3 rows x 16 columns]
>>> categories = {'low':0, 'medium':1, 'high':2}
>>> dailyActivity['TotalSteps'] = dailyActivity['TotalSteps'].map(categories)
           Id ActivityDate TotalSteps ... Calories  ActivityDoW
10  1503960366   2016-04-12          1   ...    1985      Tuesday
11  1503960366   2016-04-13          0   ...    1797    Wednesday
12  1503960366   2016-04-14          0   ...    1776     Thursday
[3 rows x 16 columns]
>>> sat_activity.drop(['TotalSteps', 'Calories'], axis=1, inplace=True)
>>> sat_activity.head(3)
                    TotalDistance
Id
1503960366               8.16
1503960366               9.04
1503960366               9.25
>>> sat_activity.rename(columns={'TotalDistance':'dist'}, inplace=True)
>>> sat_activity.head(3)
                                dist
Id
1503960366               8.16
1503960366               9.04
1503960366               9.25
```

Hierarchical indexing (Multiindexing)

Hierarchical indexing in pandas, is a multi-level indexing that extends indices to lists of tuples (each of which is unique) and allows for working with high dimensional data.

```
>>> arrays = [["bar", "bar", "baz", "baz", "foo",
↪  "foo", "qux", "qux"],["one", "two", "one", "two",
↪  "one", "two", "one", "two"]]
>>> tuples = list(zip(*arrays))
[('bar', 'one'),
('bar', 'two'),
('baz', 'one'),
('baz', 'two'),
('foo', 'one'),
('foo', 'two'),
('qux', 'one'),
('qux', 'two')]
>>> index = pd.MultiIndex.from_tuples(tuples,
↪  names=["first", "second"])
MultiIndex([('bar', 'one'),
            ('bar', 'two'),
            ('baz', 'one'),
            ('baz', 'two'),
            ('foo', 'one'),
            ('foo', 'two'),
            ('qux', 'one'),
            ('qux', 'two')],
           names=['first', 'second'])
```

```
>>> s = pd.Series(np.random.randn(8), index=index)
first  second
bar    one       0.469112
       two      -0.282863
baz    one      -1.509059
       two      -1.135632
foo    one       1.212112
       two      -0.173215
qux    one       0.119209
       two      -1.044236
dtype: float64
>>> iterables = [["bar", "baz", "foo"], ["one",
↪  "two"]]
>>> pd.MultiIndex.from_product(iterables,
↪  names=["first", "second"])
MultiIndex([('bar', 'one'),
            ('bar', 'two'),
            ('baz', 'one'),
            ('baz', 'two'),
            ('foo', 'one'),
            ('foo', 'two')],
           names=['first', 'second'])
```

Slicing in hierarchical indexing

Hierarchical indexing in pandas, is a multi-level indexing that extends indices to lists of tuples (each of which is unique) and allows for working with high dimensional data.

```
>>> df = pd.DataFrame(np.random.randn(8,4),
↪  index=index)
                     0         1         2         3
first second
bar   one      0.672494 -1.640724  1.081894  0.692540
      two      0.548721  1.768512  0.455014 -0.852776
baz   one      0.709193 -0.465862  0.664963 -1.694255
      two      0.167234 -1.334412  1.192999  0.328606
foo   one      0.821292  0.492201  1.499802  1.564745
      two     -0.979484  1.051543  0.734119 -0.478086
qux   one     -0.332113  0.380919  1.105194  0.852695
      two      0.572332 -1.063268  0.409088 -1.229017
>>> df.loc[('bar', 'two'),:]
0    0.548721
1    1.768512
2    0.455014
3   -0.852776
Name: (bar, two), dtype: float64
>>> df.loc[[('bar', 'two'), ('foo', 'one')],:]
                     0         1         2         3
first second
bar   two      0.548721  1.768512  0.455014 -0.852776
foo   one      0.821292  0.492201  1.499802  1.564745
```

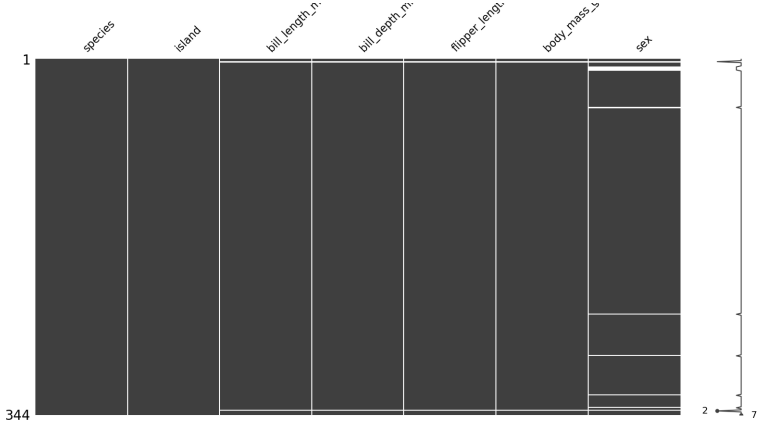
```
>>> df.loc[('bar', 'two'):('foo', 'two'),:]
first second
bar   two      0.548721  1.768512  0.455014 -0.852776
baz   one      0.709193 -0.465862  0.664963 -1.694255
      two      0.167234 -1.334412  1.192999  0.328606
foo   one      0.821292  0.492201  1.499802  1.564745
      two     -0.979484  1.051543  0.734119 -0.478086
>>> df.iloc[2, :]
0    0.709193
1   -0.465862
2    0.664963
3   -1.694255
Name: (baz, one), dtype: float64
>>> df.iloc[2:5, :]
                     0         1         2         3
first second
baz   one      0.709193 -0.465862  0.664963 -1.694255
      two      0.167234 -1.334412  1.192999  0.328606
foo   one      0.821292  0.492201  1.499802  1.564745
```

Handling missing data

```
>>> import seaborn as sns
>>> penguins = sns.load_dataset("penguins")
>>> penguins.head(4)
  species     island  bill_length_mm  bill_depth_mm  flipper_length_mm  body_mass_g     sex
0  Adelie  Torgersen            39.1           18.7              181.0       3750.0    Male
1  Adelie  Torgersen            39.5           17.4              186.0       3800.0  Female
2  Adelie  Torgersen            40.3           18.0              195.0       3250.0  Female
3  Adelie  Torgersen             NaN            NaN                NaN          NaN     NaN
>>> penguins.isna().head(4)
   species  island  bill_length_mm  bill_depth_mm  flipper_length_mm  body_mass_g    sex
0    False   False           False          False              False        False  False
1    False   False           False          False              False        False  False
2    False   False           False          False              False        False  False
3    False   False            True           True               True         True   True
>>> np.any(penguins['sex'].isna())
True
>>> np.any(penguins.isna(), axis=0)
species              False
island               False
bill_length_mm        True
bill_depth_mm         True
flipper_length_mm     True
body_mass_g           True
sex                   True
dtype: bool
```

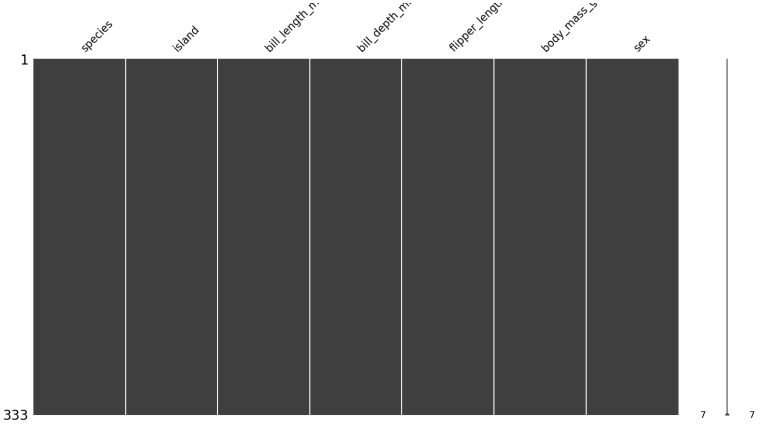
Handling missing data

```
>>> import missingno as msn
>>> msn.matrix(penguins)
>>> plt.show()
```



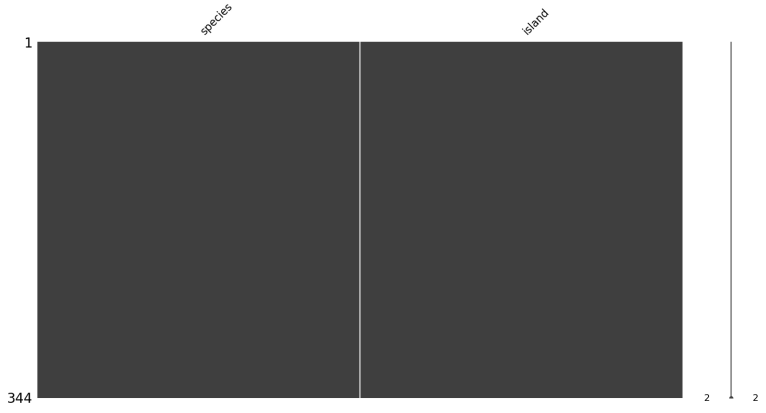
Handling missing data


```
>>> penguins.dropna(how='any', inplace=True)
>>> msn.matrix(penguins)
>>> plt.show()
```



Handling missing data

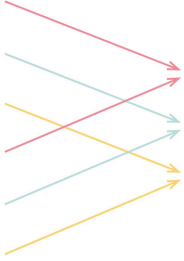
```
>>> penguins.dropna(how='any', axis=1, inplace=True)
>>> msn.matrix(penguins)
>>> plt.show()
```



Outline

Group by field/column

title	genre	qty
book 1	adventure	4
book 2	fantasy	5
book 3	romance	2
book 4	adventure	3
book 5	fantasy	3
book 6	romance	1



genre	total
adventure	7
fantasy	8
romance	3

```
SELECT genre, SUM(qty) AS total
FROM Books
GROUP BY genre
```

Group by field/column

```
>>> unique_users = dailyActivity['Id'].unique()
>>> print('Number of unique users in the database is: {}'.format(len(unique_users)))
Number of unique users in the database is: 33
>>> dailyActivity.groupby('Id')['Calories'].mean().head(5)
Id
1.503960e+09    1816.419355
1.624580e+09    1483.354839
1.644430e+09    2811.300000
1.844505e+09    1573.483871
1.927972e+09    2172.806452
Name: Calories, dtype: float64
>>> dailyActivity.groupby('Id', sort=True)[['Calories', 'TotalDistance']].mean().head()
              Calories  TotalDistance
Id
1503960366  1816.419355       7.809677
1624580081  1483.354839       3.914839
1644430081  2811.300000       5.295333
1844505072  1605.666667       1.735417
>>> dailyActivity.groupby('Id', sort=True).agg({'Calories':'mean', 'TotalDistance':'sum'}).head()
              Calories  TotalDistance
Id
0           1557.750000      11.710000
1503960366  1816.419355     242.099999
1624580081  1483.354839     121.360001
1644430081  2811.300000     158.860001
1844505072  1605.666667      41.650000
```

Common aggregation functions

Function	Description
mean()	Compute mean of groups
sum()	Compute sum of group values
size()	Compute group sizes
count()	Compute count of group
std()	Standard deviation of groups
var()	Compute variance of groups
sem()	Standard error of the mean of groups
describe()	Generates descriptive statistics
first()	Compute first of group values
last()	Compute last of group values
nth()	Take nth value, or a subset if n is a list
min()	Compute min of group values
max()	Compute max of group values

Group by field/column


```
>>> dailyActivity.groupby('Id', sort=True).agg({'Calories':'mean', 'TotalDistance': lambda x:x.max()-x.mean()}).head()
            Calories  TotalDistance
Id
1503960366  1816.419355       4.400323
1624580081  1483.354839      24.115162
1644430081  2811.300000       7.944666
1844505072  1605.666667       3.514583
>>> dailyActivity.groupby('Id', sort=True)[['Calories', 'TotalDistance']].agg([np.sum, np.mean, np.std]).head(5)
           Calories                          TotalDistance
                sum         mean         std           sum      mean       std
Id
1624580081    45984  1483.354839  256.582871    121.360001  3.914839  4.796242
1644430081    84339  2811.300000  507.488349    158.860001  5.295333  3.143581
1844505072    38536  1605.666667  258.297379     41.650000  1.735417  1.719575
>>> dailyActivity.groupby('Id', sort=True)[['Calories', 'TotalDistance']].agg([np.sum, np.mean,
↪  np.std]).rename(columns={"sum": "x", "mean": "y", "std": "z"}).head(5)
                 Calories                      TotalDistance
                        x            y           z            x         y         z
Id
0                   12462  1557.750000  493.147544    11.710000  1.463750  2.054785
1503960366          56309  1816.419355  352.574793   242.099999  7.809677  1.984180
1624580081          45984  1483.354839  256.582871   121.360001  3.914839  4.796242
1644430081          84339  2811.300000  507.488349   158.860001  5.295333  3.143581
1844505072          38536  1605.666667  258.297379    41.650000  1.735417  1.719575
```

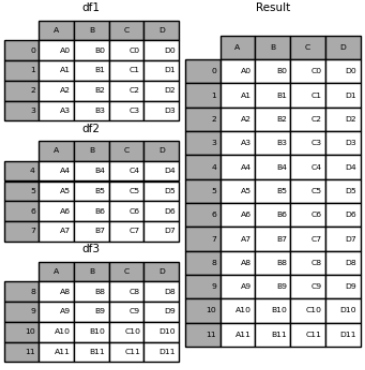
Group by field/column


```
>>> dailyActivity.groupby('Id', sort=True).agg(avg_cal=('Calories', 'mean'), max_dist=('TotalDistance', 'max')).head(5)
                            avg_cal   max_dist
Id
1503960366  1816.419355  12.210000
1624580081  1483.354839  28.030001
1644430081  2811.300000  13.240000
>>> dailyActivity.groupby('Id', sort=True).agg(**{'avg>cal':('Calories', 'mean'), 'max$dist':('TotalDistance',
↪  'max')}).head(5)
               avg>cal   max$dist
Id
0           1557.750000   5.320000
1503960366  1816.419355  12.210000
1624580081  1483.354839  28.030001
1644430081  2811.300000  13.240000
1844505072  1605.666667   5.250000
```

Outline

Concatenation (row stacking)

```
>>> df1 = pd.DataFrame({"A": ["A0",
 ↪  "A1", "A2", "A3"], "B": ["B0", "B1",
 ↪  "B2", "B3"], "C": ["C0", "C1", "C2",
 ↪  "C3"], "D": ["D0", "D1", "D2",
 ↪  "D3"]}, index=[0, 1, 2, 3])
>>> df2 = pd.DataFrame({"A": ["A4",
 ↪  "A5", "A6", "A7"], "B": ["B4", "B5",
 ↪  "B6", "B7"], "C": ["C4", "C5", "C6",
 ↪  "C7"], "D": ["D4", "D5", "D6",
 ↪  "D7"]}, index=[4, 5, 6, 7])
>>> df3 = pd.DataFrame({"A": ["A8",
 ↪  "A9", "A10", "A11"], "B": ["B8",
 ↪  "B9", "B10", "B11"], "C": ["C8",
 ↪  "C9", "C10", "C11"], "D": ["D8",
 ↪  "D9", "D10", "D11"]}, index=[8, 9,
 ↪  10, 11])
>>> result = pd.concat([df1, df2, df3],
 ↪  axis=0)
```



Concatenate dataframe with series

```
>>> df1 = pd.DataFrame({"A": ["A0", "A1", "A2", "A3"], "B": ["B0", "B1", "B2", "B3"],
 ↪  "C": ["C0", "C1", "C2", "C3"], "D": ["D0", "D1", "D2", "D3"]}, index=[0, 1, 2, 3])
>>> df4 = pd.DataFrame({"B": ["B2", "B3", "B6", "B7"], "D": ["D2", "D3", "D6", "D7"],
 ↪  "F": ["F2", "F3", "F6", "F7"]}, index=[2, 3, 6, 7])
>>> s1 = pd.Series(["X0", "X1", "X2", "X3"], name="X")

>>> result = pd.concat([df1, s1], axis=1)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

s1

	X
0	X0
1	X1
2	X2
3	X3

Result

	A	B	C	D	X
0	A0	B0	C0	D0	X0
1	A1	B1	C1	D1	X1
2	A2	B2	C2	D2	X2
3	A3	B3	C3	D3	X3

Concatenation with group keys

```
>>> df1 = pd.DataFrame({"A": ["A0",
↪   "A1", "A2", "A3"], "B": ["B0", "B1",
↪   "B2", "B3"], "C": ["C0", "C1", "C2",
↪   "C3"], "D": ["D0", "D1", "D2",
↪   "D3"]}, index=[0, 1, 2, 3])
>>> df2 = pd.DataFrame({"A": ["A4",
↪   "A5", "A6", "A7"], "B": ["B4", "B5",
↪   "B6", "B7"], "C": ["C4", "C5", "C6",
↪   "C7"], "D": ["D4", "D5", "D6",
↪   "D7"]}, index=[4, 5, 6, 7])
>>> df3 = pd.DataFrame({"A": ["A8",
↪   "A9", "A10", "A11"], "B": ["B8",
↪   "B9", "B10", "B11"], "C": ["C8",
↪   "C9", "C10", "C11"], "D": ["D8",
↪   "D9", "D10", "D11"]}, index=[8, 9,
↪   10, 11])
>>> result = pd.concat([df1, df2, df3],
↪   keys=["x", "y", "z"])
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df2

	A	B	C	D
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7

df3

	A	B	C	D
8	A8	B8	C8	D8
9	A9	B9	C9	D9
10	A10	B10	C10	D10
11	A11	B11	C11	D11

Result

		A	B	C	D
x	0	A0	B0	C0	D0
x	1	A1	B1	C1	D1
x	2	A2	B2	C2	D2
x	3	A3	B3	C3	D3
y	4	A4	B4	C4	D4
y	5	A5	B5	C5	D5
y	6	A6	B6	C6	D6
y	7	A7	B7	C7	D7
z	8	A8	B8	C8	D8
z	9	A9	B9	C9	D9
z	10	A10	B10	C10	D10
z	11	A11	B11	C11	D11

Concatenation with group keys


```
>>> df1 = pd.DataFrame({"A": ["A0",
↪   "A1", "A2", "A3"], "B": ["B0", "B1",
↪   "B2", "B3"], "C": ["C0", "C1", "C2",
↪   "C3"], "D": ["D0", "D1", "D2",
↪   "D3"]}, index=[0, 1, 2, 3])
>>> df2 = pd.DataFrame({"A": ["A4",
↪   "A5", "A6", "A7"], "B": ["B4", "B5",
↪   "B6", "B7"], "C": ["C4", "C5", "C6",
↪   "C7"], "D": ["D4", "D5", "D6",
↪   "D7"]}, index=[4, 5, 6, 7])
>>> df3 = pd.DataFrame({"A": ["A8",
↪   "A9", "A10", "A11"], "B": ["B8",
↪   "B9", "B10", "B11"], "C": ["C8",
↪   "C9", "C10", "C11"], "D": ["D8",
↪   "D9", "D10", "D11"]}, index=[8, 9,
↪   10, 11])
>>> result = pd.concat({"x": df1, "y":
↪   df2, "z": df3})
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df2

	A	B	C	D
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7

df3

	A	B	C	D
8	A8	B8	C8	D8
9	A9	B9	C9	D9
10	A10	B10	C10	D10
11	A11	B11	C11	D11

Result

		A	B	C	D
x	0	A0	B0	C0	D0
x	1	A1	B1	C1	D1
x	2	A2	B2	C2	D2
x	3	A3	B3	C3	D3
y	4	A4	B4	C4	D4
y	5	A5	B5	C5	D5
y	6	A6	B6	C6	D6
y	7	A7	B7	C7	D7
z	8	A8	B8	C8	D8
z	9	A9	B9	C9	D9
z	10	A10	B10	C10	D10
z	11	A11	B11	C11	D11

"Column" join types

Table 1

1	
2	

Table 2

1	
3	
4	

Outer Join

1		
2		
3		
4		

Inner Join

1		

Left Join

1		
2		

Cross Join

1		1	
1		3	
1		4	
2		1	
2		3	
2		4	

Full outer join with concatenate

```
>>> >>> df1 = pd.DataFrame({"A": ["A0", "A1", "A2", "A3"], "B": ["B0", "B1", "B2", "B3"],
↪  "C": ["C0", "C1", "C2", "C3"], "D": ["D0", "D1", "D2", "D3"]}, index=[0, 1, 2, 3])
>>> df4 = pd.DataFrame({"B": ["B2", "B3", "B6", "B7"], "D": ["D2", "D3", "D6", "D7"],
↪  "F": ["F2", "F3", "F6", "F7"]}, index=[2, 3, 6, 7])
>>> result = pd.concat([df1, df4], axis=1, join='outer') #default
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

	A	B	C	D	B	D	F
0	A0	B0	C0	D0	NaN	NaN	NaN
1	A1	B1	C1	D1	NaN	NaN	NaN
2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	B3	D3	F3
6	NaN	NaN	NaN	NaN	B6	D6	F6
7	NaN	NaN	NaN	NaN	B7	D7	F7

Inner join with concatenate

```
>>> df1 = pd.DataFrame({"A": ["A0", "A1", "A2", "A3"], "B": ["B0", "B1", "B2", "B3"],
↪   "C": ["C0", "C1", "C2", "C3"], "D": ["D0", "D1", "D2", "D3"]}, index=[0, 1, 2, 3])
>>> df4 = pd.DataFrame({"B": ["B2", "B3", "B6", "B7"], "D": ["D2", "D3", "D6", "D7"],
↪   "F": ["F2", "F3", "F6", "F7"]}, index=[2, 3, 6, 7])
>>> result = pd.concat([df1, df4], axis=1, join='inner')
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

	A	B	C	D	B	D	F
2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	B3	D3	F3

Database-style left join

```
>>> left = pd.DataFrame({"key1": ["K0", "K0", "K1", "K2"], "key2": ["K0", "K1", "K0",
↪  "K1"], "A": ["A0", "A1", "A2", "A3"], "B": ["B0", "B1", "B2", "B3"]})
>>> right = pd.DataFrame({"key1": ["K0", "K1", "K1", "K2"], "key2": ["K0", "K0", "K0",
↪  "K0"], "C": ["C0", "C1", "C2", "C3"], "D": ["D0", "D1", "D2", "D3"]})
>>> result = pd.merge(left, right, how="left", on=["key1", "key2"])
```

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K0	K1	A1	B1	NaN	NaN
2	K1	K0	A2	B2	C1	D1
3	K1	K0	A2	B2	C2	D2
4	K2	K1	A3	B3	NaN	NaN

Database-style right join

```
>>> left = pd.DataFrame({"key1": ["K0", "K0", "K1", "K2"], "key2": ["K0", "K1", "K0",
↪   "K1"], "A": ["A0", "A1", "A2", "A3"], "B": ["B0", "B1", "B2", "B3"]})
>>> right = pd.DataFrame({"key1": ["K0", "K1", "K1", "K2"], "key2": ["K0", "K0", "K0",
↪   "K0"], "C": ["C0", "C1", "C2", "C3"], "D": ["D0", "D1", "D2", "D3"]})
>>> result = pd.merge(left, right, how="right", on=["key1", "key2"])
```

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	C2	D2
3	K2	K0	NaN	NaN	C3	D3

Database-style outer join

```
>>> left = pd.DataFrame({"key1": ["K0", "K0", "K1", "K2"], "key2": ["K0", "K1", "K0",
↪  "K1"], "A": ["A0", "A1", "A2", "A3"], "B": ["B0", "B1", "B2", "B3"]})
>>> right = pd.DataFrame({"key1": ["K0", "K1", "K1", "K2"], "key2": ["K0", "K0", "K0",
↪  "K0"], "C": ["C0", "C1", "C2", "C3"], "D": ["D0", "D1", "D2", "D3"]})
>>> result = pd.merge(left, right, how="outer", on=["key1", "key2"])
```

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K0	K1	A1	B1	NaN	NaN
2	K1	K0	A2	B2	C1	D1
3	K1	K0	A2	B2	C2	D2
4	K2	K1	A3	B3	NaN	NaN
5	K2	K0	NaN	NaN	C3	D3

Database-style inner join

```
>>> left = pd.DataFrame({"key1": ["K0", "K0", "K1", "K2"], "key2": ["K0", "K1", "K0",
↪   "K1"], "A": ["A0", "A1", "A2", "A3"], "B": ["B0", "B1", "B2", "B3"]})
>>> right = pd.DataFrame({"key1": ["K0", "K1", "K1", "K2"], "key2": ["K0", "K0", "K0",
↪   "K0"], "C": ["C0", "C1", "C2", "C3"], "D": ["D0", "D1", "D2", "D3"]})
>>> result = pd.merge(left, right, how="inner", on=["key1", "key2"])
```

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	C2	D2

Database-style cross join

```
>>> left = pd.DataFrame({"key1": ["K0", "K0", "K1", "K2"], "key2": ["K0", "K1", "K0",
↪  "K1"], "A": ["A0", "A1", "A2", "A3"], "B": ["B0", "B1", "B2", "B3"]})
>>> right = pd.DataFrame({"key1": ["K0", "K1", "K1", "K2"], "key2": ["K0", "K0", "K0",
↪  "K0"], "C": ["C0", "C1", "C2", "C3"], "D": ["D0", "D1", "D2", "D3"]})
>>> result = pd.merge(left, right, how="cross")
```

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

	key1_x	key2_x	A	B	key1_y	key2_y	C	D
0	K0	K0	A0	B0	K0	K0	C0	D0
1	K0	K0	A0	B0	K1	K0	C1	D1
2	K0	K0	A0	B0	K1	K0	C2	D2
3	K0	K0	A0	B0	K2	K0	C3	D3
4	K0	K1	A1	B1	K0	K0	C0	D0
5	K0	K1	A1	B1	K1	K0	C1	D1
6	K0	K1	A1	B1	K1	K0	C2	D2
7	K0	K1	A1	B1	K2	K0	C3	D3
8	K1	K0	A2	B2	K0	K0	C0	D0
9	K1	K0	A2	B2	K1	K0	C1	D1
10	K1	K0	A2	B2	K1	K0	C2	D2
11	K1	K0	A2	B2	K2	K0	C3	D3
12	K2	K1	A3	B3	K0	K0	C0	D0
13	K2	K1	A3	B3	K1	K0	C1	D1
14	K2	K1	A3	B3	K1	K0	C2	D2
15	K2	K1	A3	B3	K2	K0	C3	D3

Outline

Reshaping by melting

```
>>> df = pd.DataFrame({"first": ["John", "Mary"], "last": ["Doe", "Bo"], "height": [5.5, 6.0], "weight": [130, 150]})
>>> df.melt(id_vars=["first", "last"])
  first last variable  value
0  John  Doe   height    5.5
1  Mary   Bo   height    6.0
2  John  Doe   weight  130.0
3  Mary   Bo   weight  150.0
>>> df.melt(id_vars=["first", "last"], var_name="quantity")
  first last quantity  value
0  John  Doe   height    5.5
1  Mary   Bo   height    6.0
2  John  Doe   weight  130.0
3  Mary   Bo   weight  150.0
```

	first	last	height	weight
0	John	Doe	5.5	130
1	Mary	Bo	6.0	150

	first	last	variable	value
0	John	Doe	height	5.5
1	Mary	Bo	height	6.0
2	John	Doe	weight	130
3	Mary	Bo	weight	150

Reshaping by pivoting


```
>>> df = pd.DataFrame({"foo": ["one", "one", "one", "two", "two", "two"], "bar": ["A", "B", "C", "A", "B", "C"], "baz":
↪  [1, 2, 3, 4, 5, 6], "zoo": ["x", "y", "z", "q", "w", "t"]})
>>> df.pivot(index = 'foo', columns='bar', values='baz')
bar  A  B  C
foo
one  1  2  3
two  4  5  6
>>> df.pivot(index = 'foo', columns=['bar','zoo'], values='baz')
bar    A    B    C    A    B    C
zoo    x    y    z    q    w    t
foo
one  1.0  2.0  3.0  NaN  NaN  NaN
two  NaN  NaN  NaN  4.0  5.0  6.0
```

	foo	bar	baz	zoo
0	one	A	1	x
1	one	B	2	y
2	one	C	3	z
3	two	A	4	q
4	two	B	5	w
5	two	C	6	t

bar	A	B	C
foo			
one	1	2	3
two	4	5	6

Reshaping by stacking

```
>>> tuples = list(zip(*[["bar", "bar", "baz", "baz"], ["one", "two", "one", "two"]]))
>>> index = pd.MultiIndex.from_tuples(tuples, names=["first", "second"])
>>> df = pd.DataFrame({'A': [1, 3, 5, 7], 'B': [2, 4, 6, 8]}, index=index)
>>> df.stack()
first  second
bar    one     A    1
               B    2
       two     A    3
               B    4
baz    one     A    5
               B    6
       two     A    7
               B    8
```

		A	B
first	second		
bar	one	1	2
	two	3	4
baz	one	5	6
	two	7	8

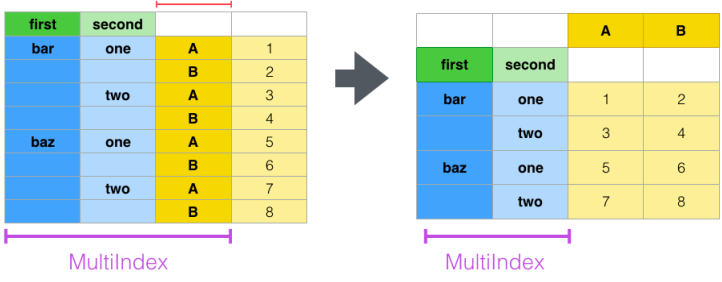
MultiIndex

first	second		
bar	one	A	1
		B	2
	two	A	3
		B	4
baz	one	A	5
		B	6
	two	A	7
		B	8

MultiIndex

Reshaping by unstacking

```
>>> df2=df.stack()
>>> df2.unstack()
                A  B
first second
  bar    one    1  2
         two    3  4
  baz    one    5  6
         two    7  8
```



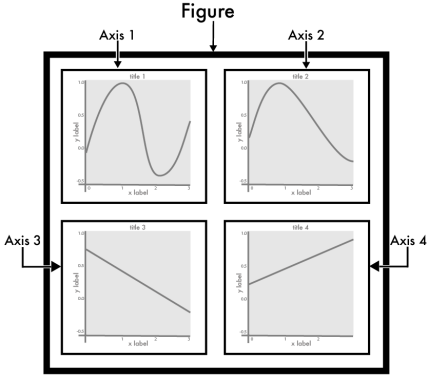
Outline

Matplotlib vs Seaborn

Mainly deployed for basic plotting (line, bar, pie, scatter charts)	Offers variety of visualization patterns (e.g. advanced statistical plots) and uses easier (fewer) syntax
A graphics package for data visualization in Python, well integrated with NumPy and pandas with the pyplot module closely mirrors the MATLAB plotting commands	Extends Matplotlib for integration with dataframes and more straightforward set of commands.
Doesn't include methods to handle categorical variables in certain plot types	Has methods to plot/handle categorical variables in boxplots and violin plots
Widely used in general, with less documentation	Better documentation and widely used for plotting regression analysis

Anatomy of figure


```
>>> import matplotlib.pyplot as plt
>>> import seaborn as sns
>>> fig, (ax1, ax2, ax3, ax4) = plt.subplots(2, 2, figsize=(10, 10))
```

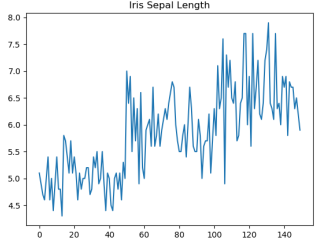


Outline

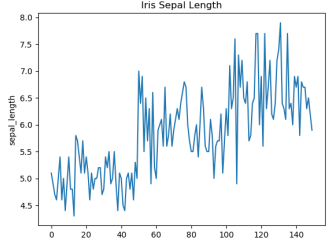
Simple line plots for the iris dataset

```
>>> iris = sns.load_dataset("iris")
>>> iris.head(3)
   sepal_length  sepal_width  petal_length  petal_width species
0           5.1          3.5           1.4          0.2  setosa
1           4.9          3.0           1.4          0.2  setosa
2           4.7          3.2           1.3          0.2  setosa
```

```
# create figure and axis
>>> fig, ax = plt.subplots()
>>> ax.plot(iris.index.to_list(),
↪  iris["sepal_length"])
>>> ax.set_title("Iris Sepal Length")
>>> plt.show()
```

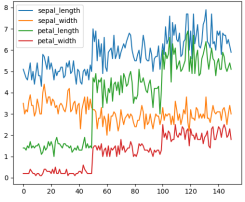



```
# create figure and axis
>>> fig, ax = plt.subplots()
>>> sns.lineplot(x=iris.index.to_list(),
↪  y=iris["sepal_length"])
>>> ax.set_title("Iris Sepal Length")
>>> plt.show()
```

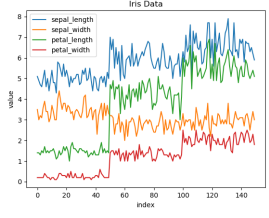


Overlaid line plots for the iris dataset

```
>>> iris.drop("species", axis=1).head()
   sepal_length  sepal_width  petal_length
0           5.1          3.5           1.4
1           4.9          3.0           1.4
2           4.7          3.2           1.3
3           4.6          3.1           1.5
>>> fig, ax = plt.subplots()
>>> for column in iris.columns.drop("species"):
...     ax.plot(iris.index.to_list(), iris[column])
>>> ax.set_title("Iris Data")
>>> ax.legend(labels=iris.columns.drop("species"),
↪  loc='upper left')
>>> plt.show()
```




```
>>> new_iris = iris.reset_index().drop("species",
↪  axis=1).melt(id_vars='index',
↪  var_name='property')
       index      property  value
0          0  sepal_length    5.1
1          1  sepal_length    4.9
2          2  sepal_length    4.7
>>> fig, ax = plt.subplots()
>>> sns.lineplot(x='index', y='value',
↪  hue='property', data=new_iris)
>>> ax.set_title("Iris Data")
>>> ax.legend(loc='upper left')
>>> plt.show()
```

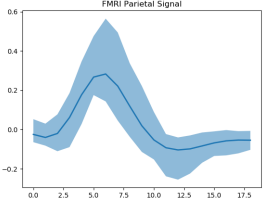


Line plots with error bands

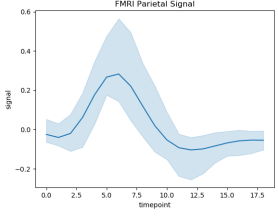
```
>>> fmri = sns.load_dataset("fmri")
>>> fmri.head(3)
  subject  timepoint event    region    signal
0     s13         18  stim  parietal -0.017552
1      s5         14  stim  parietal -0.080883
2     s12         18  stim  parietal -0.081033
>>> new_fmri = fmri[(fmri['event']=='stim')&(fmri['region']=='parietal')]
    subject  timepoint event    region    signal
0       s13         18  stim  parietal -0.017552
1        s5         14  stim  parietal -0.080883
2       s12         18  stim  parietal -0.081033
```

Line plots with error bands

```
>>> fmri_gb_timep =
↪  new_fmri.groupby('timepoint')['signal'].agg([np.max,
↪  np.mean, np.min])
              amax      mean      amin
timepoint
0         0.052619 -0.024995 -0.064454
1         0.029822 -0.040460 -0.082174
>>> fig, ax = plt.subplots()
>>> ax.fill_between(fmri_gb_timep.index.to_list(),
↪  fmri_gb_timep['amin'], fmri_gb_timep['amax'],
↪  alpha=.5, linewidth=0)
>>> ax.plot(fmri_gb_timep.index.to_list(),
↪  fmri_gb_timep['mean'], linewidth=2)
>>> ax.set_title("FMRI Parietal Signal")
>>> plt.show()
```




```
>>> new_fmri = fmri[(fmri['event']=='stim') &
↪  (fmri['region']=='parietal')]
    subject  timepoint event    region    signal
0       s13         18  stim  parietal -0.017552
1        s5         14  stim  parietal -0.080883
2       s12         18  stim  parietal -0.081033
>>> fig, ax = plt.subplots()
>>> sns.lineplot(x='timepoint', y='signal',
↪  errorbar=lambda x:(x.min(), x.max()),
↪  data=new_fmri)
>>> ax.set_title("FMRI Parietal Signal")
>>> plt.show()
>>>
>>>
>>>
```



Outline

Data Handling and Manipulation
Data Structures in pandas
IO Tools and Essential Functionality
Time Series and Date Functionality
Indexing and Data Selection
Grouping and Aggregation
Merge, join and concatenate
Reshaping and Pivoting
Data Visualization
Line Plots
Scatter Plots
Bar and Distribution Plots
Box and Violin Plots
Stacking Plots
Regression Plots

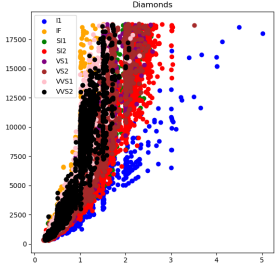
Simple scatter plots


```
>>> diamonds = sns.load_dataset("diamonds")
```

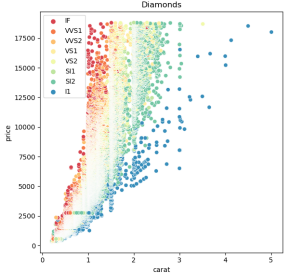
	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
3	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75

Simple scatter plots

```
>>> colors = {'I1':'blue', 'IF':'orange',
↪  'SI1':'green', 'SI2':'red', 'VS1':'purple',
↪  'VS2':'brown', 'VVS1':'pink', 'VVS2':'black'}
>>> fig, ax = plt.subplots(figsize=(6.5, 6.5))
>>> for key in colors.keys():
...     data = diamonds[diamonds['clarity'] == key]
...     ax.scatter(data["carat"], data["price"],
↪  label=key, c=colors[key])
>>> ax.set_title("Diamonds")
>>> ax.legend()
>>> plt.show()
```



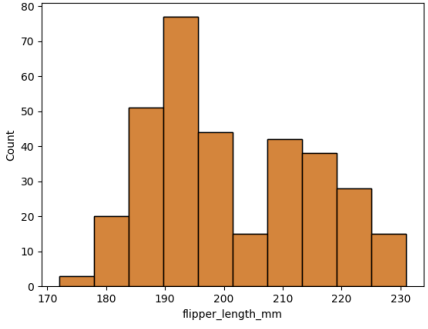

```
>>> fig, ax = plt.subplots(figsize=(6.5, 6.5))
>>> sns.scatterplot(x="carat", y="price",
↪  hue="clarity",
↪  palette=sns.color_palette("Spectral", 8),
↪  data=diamonds, ax=ax)
>>> ax.set_title("Diamonds")
>>> ax.legend()
>>> plt.show()
>>>
>>>
>>>
```



Outline

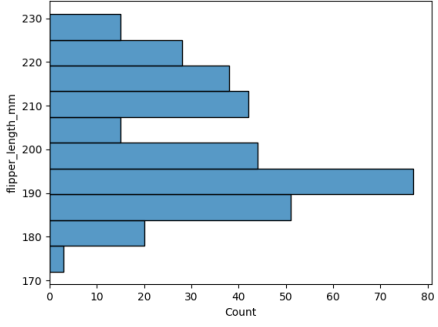
Histograms


```
>>>
>>> sns.histplot(x="flipper_length_mm", data=penguins)
>>> plt.show()
```



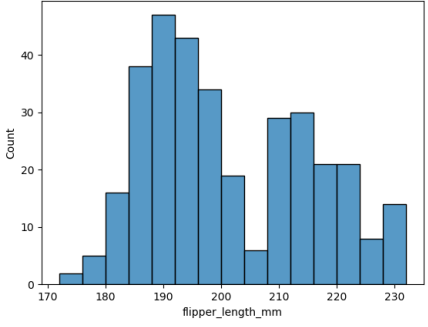
Histograms (horizontal)

```
>>>
>>> sns.histplot(y="flipper_length_mm", data=penguins)
>>> plt.show()
```



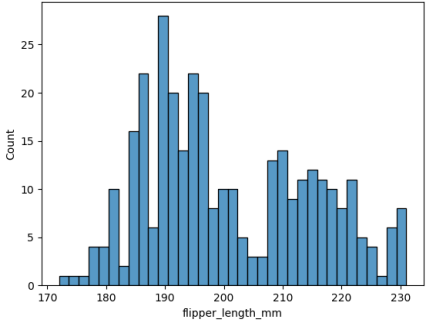
Histograms (change bin width)

```
>>>
>>> sns.histplot(x="flipper_length_mm", data=penguins, binwidth=4)
>>> plt.show()
```



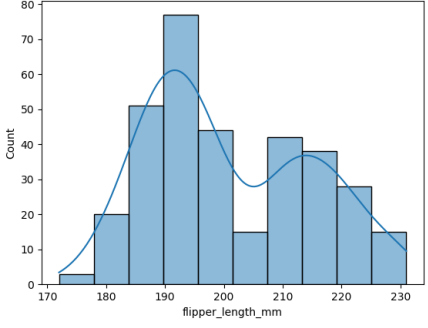
Histograms (change bin number)

```
>>>
>>> sns.histplot(x="flipper_length_mm", data=penguins, bins=35)
>>> plt.show()
```



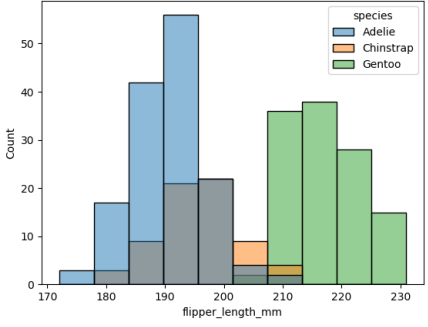
Histograms (include pdf)


```
>>>
>>> sns.histplot(x="flipper_length_mm", data=penguins, kde=True)
>>> plt.show()
```



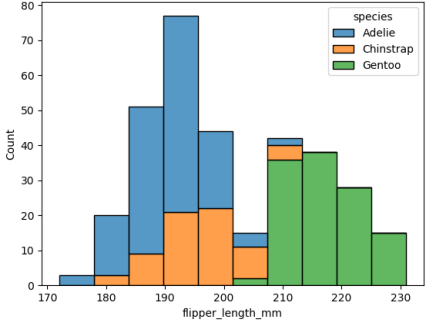
Histograms (layering)

```
>>>
>>> sns.histplot(x="flipper_length_mm", hue="species", data=penguins)
>>> plt.show()
```



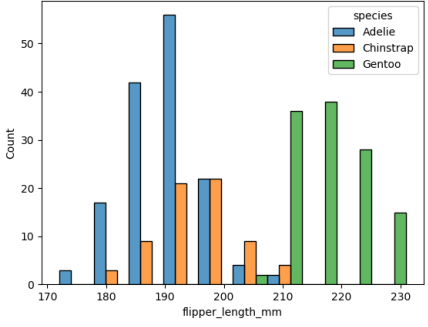
Histograms (stacking)

```
>>>
>>> sns.histplot(x="flipper_length_mm", hue="species", multiple="stack", data=penguins)
>>> plt.show()
```



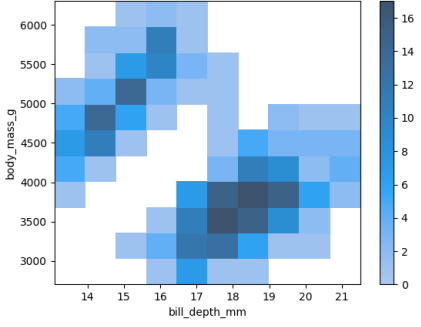
Histograms (dodge)

```
>>>
>>> sns.histplot(x="flipper_length_mm", hue="species", multiple="dodge", data=penguins)
>>> plt.show()
```



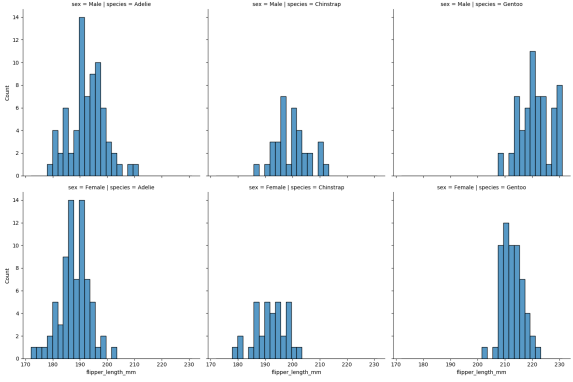
Histograms (bi-variate)

```
>>>
>>> sns.histplot(x="flipper_length_mm", y="body_mass_g", cbar=True, data=penguins)
>>> plt.show()
```



Histograms (facets)

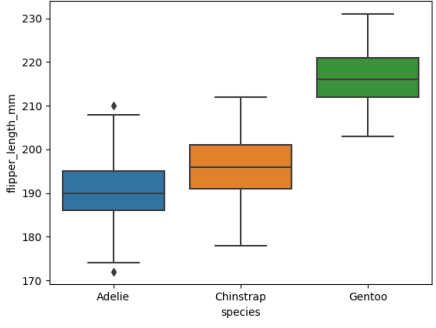
```
>>>
>>> sns.displot(x="flipper_length_mm", col="species", row="sex", bins=30, data=penguins)
>>> plt.show()
```



Outline

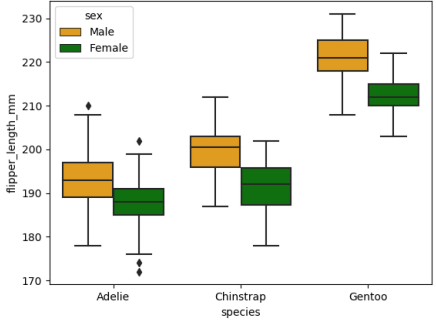
Box plots

```
>>>
>>> sns.boxplot(x="species", y="flipper_length_mm", data=penguins)
>>> plt.show()
```



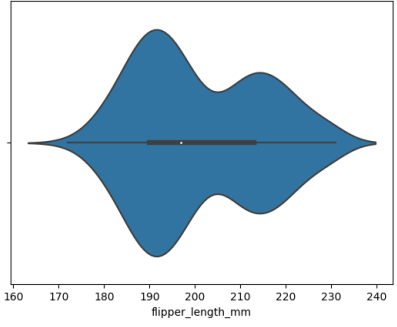
Box plots (grouped)

```
>>>
>>> sns.boxplot(x="species", y="flipper_length_mm", hue="sex", palette=["orange","green"], data=penguins)
>>> plt.show()
```



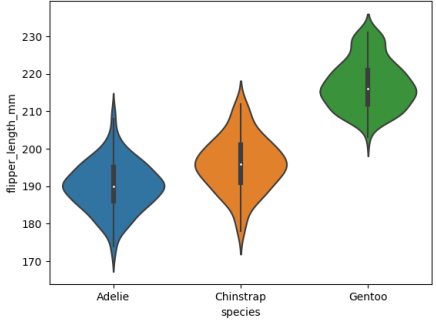
Violin plots

```
>>>
>>> sns.violinplot(x="flipper_length_mm", data=penguins)
>>> plt.show()
```



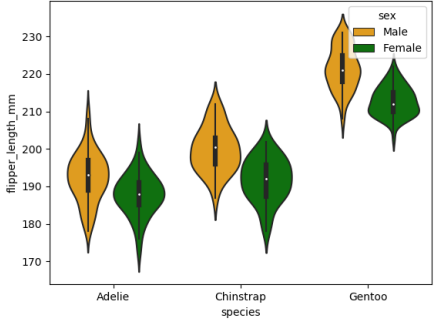
Violin plots

```
>>>
>>> sns.violinplot(x="species", y="flipper_length_mm", data=penguins)
>>> plt.show()
```



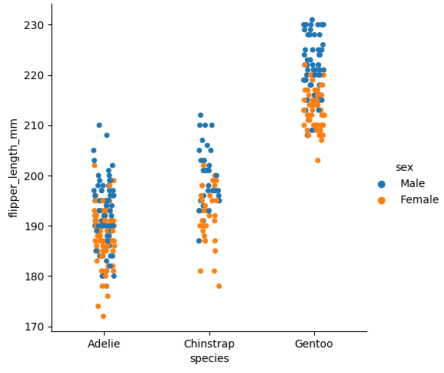
Violin plot (grouped)

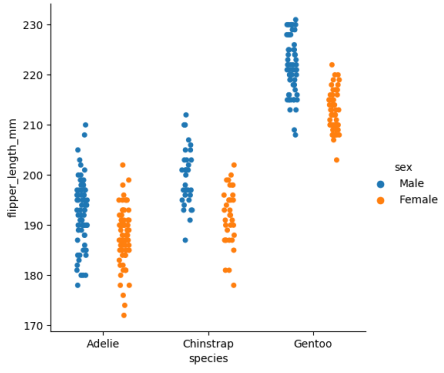
```
>>>
>>> sns.violinplot(x="species", y="flipper_length_mm", hue="sex", palette=["orange","green"], data=penguins)
>>> plt.show()
```



Categorical plots (scatter)

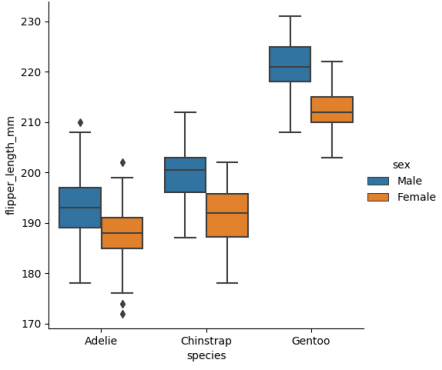
```
>>>
>>> sns.catplot(x="species", y="flipper_length_mm", hue="sex", data=penguins) #use dodge=True to separate
>>> plt.show()
```





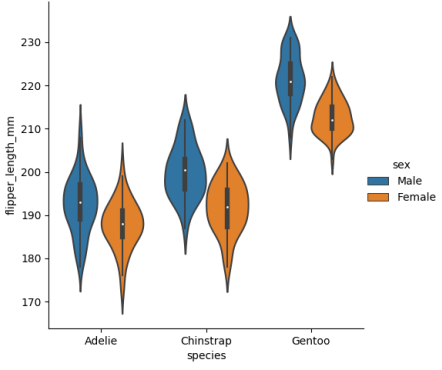
Categorical plots (box)

```
>>>
>>> sns.catplot(x="species", y="flipper_length_mm", hue="sex", kind="box", data=penguins)
>>> plt.show()
```



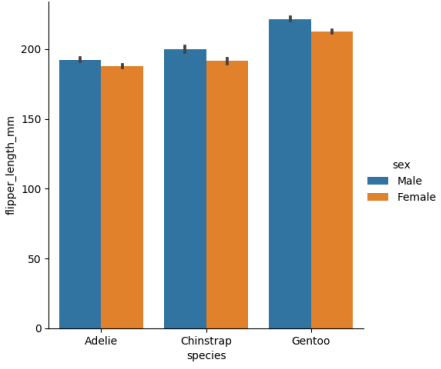
Categorical plots (violin)

```
>>>
>>> sns.catplot(x="species", y="flipper_length_mm", hue="sex", kind="violin", data=penguins)
>>> plt.show()
```



Categorical plots (bar)

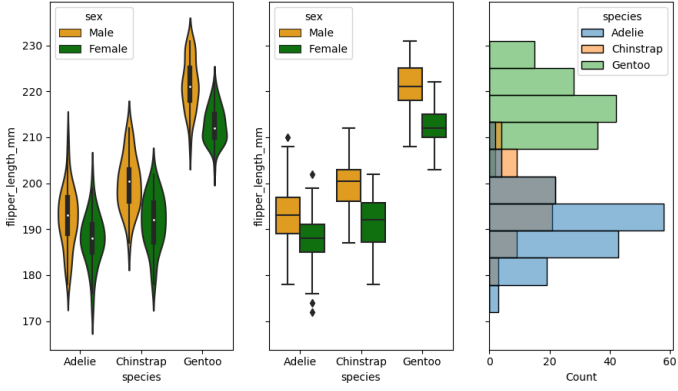
```
>>>
>>> sns.catplot(x="species", y="flipper_length_mm", hue="sex", kind="bar", data=penguins)
>>> plt.show()
```



Outline

Stacking plots

```
>>> f, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(5, 7), sharey=True)
>>> sns.violinplot(x="species", y="flipper_length_mm", hue="sex", palette=["orange","green"], data=penguins, ax=ax1)
>>> sns.boxplot(x="species", y="flipper_length_mm", hue="sex", palette=["orange","green"], data=penguins, ax=ax2)
>>> sns.histplot(y="flipper_length_mm", hue="species", data=penguins, ax=ax3)
>>> plt.show()
```

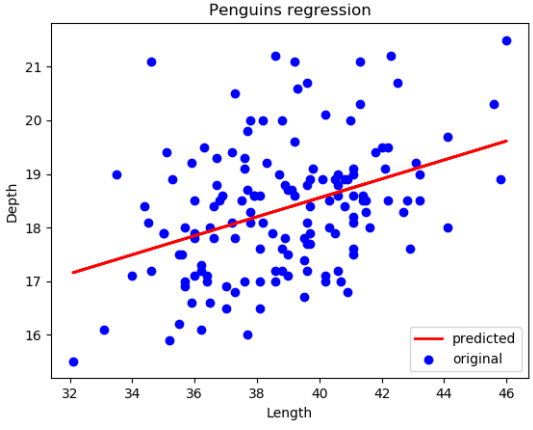


Outline

Linear regression plots (matplotlib)

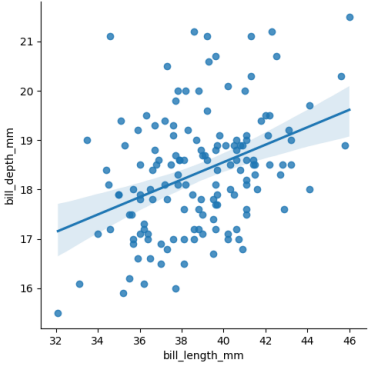

```
>>> from sklearn.linear_model import LinearRegression
>>> penguins = sns.load_dataset("penguins")
>>> penguins.dropna(how='any', inplace=True)
species     island  bill_length_mm  bill_depth_mm  flipper_length_mm  body_mass_g     sex
0  Adelie  Torgersen            39.1           18.7              181.0       3750.0    Male
1  Adelie  Torgersen            39.5           17.4              186.0       3800.0  Female
2  Adelie  Torgersen            40.3           18.0              195.0       3250.0  Female
>>>
>>> new_penguins = penguins[penguins['species']=='Adelie']
>>>
>>> lm = LinearRegression()
>>>
>>> lm.fit(new_penguins['bill_length_mm'].values.reshape(-1,1), new_penguins['bill_depth_mm'].values.reshape(-1,1))
>>>
>>> pred_depth = lm.predict(new_penguins['bill_length_mm'].values.reshape(-1,1))
>>> fig, ax = plt.subplots()
>>> ax.scatter(new_penguins['bill_length_mm'].values.reshape(-1,1), new_penguins['bill_depth_mm'].values.reshape(-1,1),
↪  color="blue", label='original')
>>> ax.plot(new_penguins['bill_length_mm'].values.reshape(-1,1), pred_depth, color="red", linewidth=2,
↪  label='predicted')
>>> ax.set_title("Penguins regression")
>>> ax.set_xlabel("Length")
>>> ax.set_ylabel("Depth")
>>> ax.legend()
>>> plt.show()
```

Linear regression plots (matplotlib)



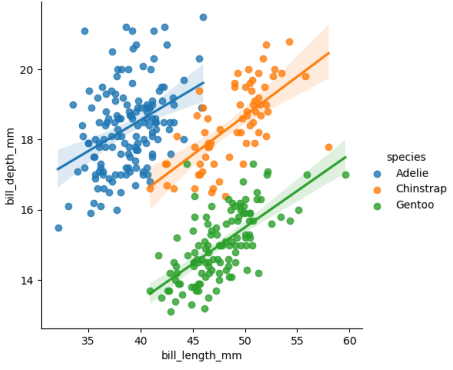
Linear regression plots (seaborn)


```
>>> new_penguins = penguins[penguins['species']=='Adelie']
>>> sns.lmplot(x="bill_length_mm", y="bill_depth_mm", data=new_penguins)
>>> plt.show()
```



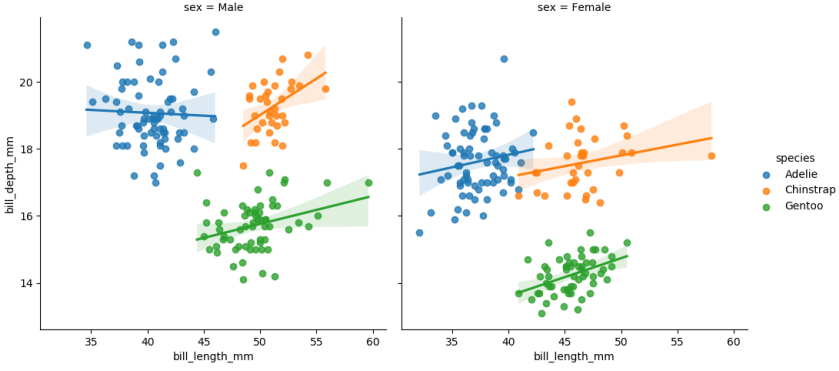
Linear regression plots (seaborn)

```
>>>
>>> sns.lmplot(x="bill_length_mm", y="bill_depth_mm", hue="species", data=penguins)
>>> plt.show()
```



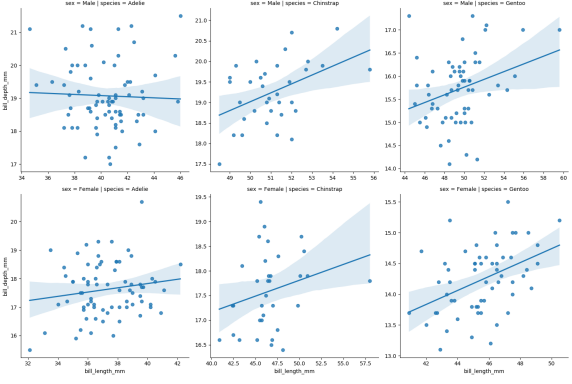
Linear regression plots (seaborn)

```
>>>
>>> sns.lmplot(x="bill_length_mm", y="bill_depth_mm", hue="species", col="sex", data=penguins)
>>> plt.show()
```



Linear regression plots (seaborn)

```
>>>
>>> sns.lmplot(x="bill_length_mm", y="bill_depth_mm", col="species", row="sex", facet_kws=dict(sharex=False,
↪   sharey=False), data=penguins)
>>> plt.show()
```



THANK YOU!