



MANIPULATING DATAFRAMES WITH PANDAS

Manipulating DataFrames with pandas



What you will learn

- Extracting, filtering, and transforming data from DataFrames
- Advanced indexing with multiple levels
- Tidying, rearranging and restructuring your data
- Pivoting, melting, and stacking DataFrames
- Identifying and splitting DataFrames by groups



MANIPULATING DATAFRAMES WITH PANDAS

**See you in
the course!**



MANIPULATING DATAFRAMES WITH PANDAS

Indexing DataFrames



A simple DataFrame

```
In [1]: import pandas as pd
```

```
In [2]: df = pd.read_csv('sales.csv', index_col='month')
```

```
In [3]: df
```

```
Out[3]:
```

	eggs	salt	spam
month			
Jan	47	12.0	17
Feb	110	50.0	31
Mar	221	89.0	72
Apr	77	87.0	20
May	132	NaN	52
Jun	205	60.0	55



Indexing using square brackets

```
In [4]: df
```

```
Out[4]:
```

	eggs	salt	spam
month			
Jan	47	12.0	17
Feb	110	50.0	31
Mar	221	89.0	72
Apr	77	87.0	20
May	132	NaN	52
Jun	205	60.0	55

```
In [5]: df['salt']['Jan']
```

```
Out[5]: 12.0
```



Using column attribute and row label

```
In [6]: df
```

```
Out[6]:
```

	eggs	salt	spam
month			
Jan	47	12.0	17
Feb	110	50.0	31
Mar	221	89.0	72
Apr	77	87.0	20
May	132	NaN	52
Jun	205	60.0	55

```
In [7]: df.eggs['Mar']
```

```
Out[7]: 221
```



Using the .loc accessor

```
In [8]: df
```

```
Out[8]:
```

	eggs	salt	spam
month			
Jan	47	12.0	17
Feb	110	50.0	31
Mar	221	89.0	72
Apr	77	87.0	20
May	132	NaN	52
Jun	205	60.0	55

```
In [9]: df.loc['May', 'spam']
```

```
Out[9]: 52.0
```




Using the .iloc accessor

```
In [10]: df
```

```
Out[10]:
```

	eggs	salt	spam
month			
Jan	47	12.0	17
Feb	110	50.0	31
Mar	221	89.0	72
Apr	77	87.0	20
May	132	NaN	52
Jun	205	60.0	55

```
In [11]: df.iloc[4, 2]
```

```
Out[11]: 52.0
```



Selecting only some columns

```
In [12]: df_new = df[['salt', 'eggs']]
```

```
In [13]: df_new
```

```
Out[13]:
```

	salt	eggs
month		
Jan	12.0	47
Feb	50.0	110
Mar	89.0	221
Apr	87.0	77
May	NaN	132
Jun	60.0	205



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Slicing DataFrames



sales DataFrame

```
In [1]: df
```

```
Out[1]:
```

	eggs	salt	spam
month			
Jan	47	12.0	17
Feb	110	50.0	31
Mar	221	89.0	72
Apr	77	87.0	20
May	132	NaN	52
Jun	205	60.0	55



Selecting a column (i.e., Series)

```
In [2]: df['eggs']
```

```
Out[2]:
```

```
month
```

```
Jan      47
```

```
Feb     110
```

```
Mar     221
```

```
Apr      77
```

```
May     132
```

```
Jun     205
```

```
Name: eggs, dtype: int64
```

```
In [3]: type(df['eggs'])
```

```
Out[3]: pandas.core.series.Series
```



Slicing and indexing a Series

```
In [4]: df['eggs'][1:4] # Part of the eggs column
```

```
Out[4]:
```

```
month
```

```
Feb      110
```

```
Mar      221
```

```
Apr       77
```

```
Name: eggs, dtype: int64
```

```
In [5]: df['eggs'][4] # The value associated with May
```

```
Out[5]: 132
```



Using .loc[] (1)

```
In [6]: df.loc[:, 'eggs':'salt'] # All rows, some columns
```

```
Out[6]:
```

	eggs	salt
month		
Jan	47	12.0
Feb	110	50.0
Mar	221	89.0
Apr	77	87.0
May	132	NaN
Jun	205	60.0



Using .loc[] (2)

```
In [7]: df.loc['Jan':'Apr',:] # Some rows, all columns
```

```
Out[7]:
```

	eggs	salt	spam
month			
Jan	47	12.0	17
Feb	110	50.0	31
Mar	221	89.0	72
Apr	77	87.0	20



Using .loc[] (3)

```
In [8]: df.loc['Mar': 'May', 'salt': 'spam']
```

```
Out[8]:
```

	salt	spam
month		
Mar	89.0	72
Apr	87.0	20
May	NaN	52



Using .iloc[]

```
In [9]: df.iloc[2:5, 1:] # A block from middle of the DataFrame  
Out[9]:
```

	salt	spam
month		
Mar	89.0	72
Apr	87.0	20
May	NaN	52



Using lists rather than slices (1)

```
In [10]: df.loc['Jan': 'May', ['eggs', 'spam']]
```

```
Out[10]:
```

	eggs	spam
month		
Jan	47	17
Feb	110	31
Mar	221	72
Apr	77	20
May	132	52



Using lists rather than slices (2)

```
In [11]: df.iloc[[0,4,5], 0:2]
```

```
Out[11]:
```

	eggs	salt
month		
Jan	47	12.0
May	132	NaN
Jun	205	60.0



Series versus 1-column DataFrame

```
# A Series by column name
```

```
In [13]: df['eggs']
```

```
Out[13]:
```

```
month
```

```
Jan      47
```

```
Feb     110
```

```
Mar     221
```

```
Apr      77
```

```
May     132
```

```
Jun     205
```

```
Name: eggs, dtype: int64
```

```
In [14]: type(df['eggs'])
```

```
Out[14]:
```

```
pandas.core.series.Series
```

```
# A DataFrame w/ single column
```

```
In [15]: df[['eggs']]
```

```
Out[15]:
```

```
eggs
```

```
month
```

```
Jan      47
```

```
Feb     110
```

```
Mar     221
```

```
Apr      77
```

```
May     132
```

```
Jun     205
```

```
In [16]: type(df[['eggs']])
```

```
Out[16]:
```

```
pandas.core.frame.DataFrame
```



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Filtering DataFrames



Creating a Boolean Series

```
In [1]: df.salt > 60
Out[1]:
month
Jan    False
Feb    False
Mar     True
Apr     True
May    False
Jun    False
Name: salt, dtype: bool
```



Filtering with a Boolean Series

```
In [2]: df[df.salt > 60]
```

```
Out[2]:
```

	eggs	salt	spam
month			
Mar	221	89.0	72
Apr	77	87.0	20

```
In [3]: enough_salt_sold = df.salt > 60
```

```
In [4]: df[enough_salt_sold]
```

```
Out[4]:
```

	eggs	salt	spam
month			
Mar	221	89.0	72
Apr	77	87.0	20



Combining filters

```
In [5]: df[(df.salt >= 50) & (df.eggs < 200)] # Both conditions
Out[5]:
```

	eggs	salt	spam
month			
Feb	110	50.0	31
Apr	77	87.0	20

```
In [6]: df[(df.salt >= 50) | (df.eggs < 200)] # Either condition
Out[6]:
```

	eggs	salt	spam
month			
Jan	47	12.0	17
Feb	110	50.0	31
Mar	221	89.0	72
Apr	77	87.0	20
May	132	NaN	52
Jun	205	60.0	55



DataFrames with zeros and NaNs

```
In [7]: df2 = df.copy()
```

```
In [8]: df2['bacon'] = [0, 0, 50, 60, 70, 80]
```

```
In [9]: df2
```

```
Out[9]:
```

	eggs	salt	spam	bacon
month				
Jan	47	12.0	17	0
Feb	110	50.0	31	0
Mar	221	89.0	72	50
Apr	77	87.0	20	60
May	132	NaN	52	70
Jun	205	60.0	55	80



Select columns with all nonzeros

```
In [10]: df2.loc[:, df2.all()]
```

```
Out[10]:
```

	eggs	salt	spam
month			
Jan	47	12.0	17
Feb	110	50.0	31
Mar	221	89.0	72
Apr	77	87.0	20
May	132	NaN	52
Jun	205	60.0	55



Select columns with any nonzeros

```
In [11]: df2.loc[:, df2.any()]
```

```
Out[11]:
```

	eggs	salt	spam	bacon
month				
Jan	47	12.0	17	0
Feb	110	50.0	31	0
Mar	221	89.0	72	50
Apr	77	87.0	20	60
May	132	NaN	52	70
Jun	205	60.0	55	80



Select columns with any NaNs

```
In [12]: df.loc[:, df.isnull().any()]
```

```
Out[12]:
```

	salt
month	
Jan	12.0
Feb	50.0
Mar	89.0
Apr	87.0
May	NaN
Jun	60.0



Select columns without NaNs

```
In [13]: df.loc[:, df.notnull().all()]
```

```
Out[13]:
```

	eggs	spam
month		
Jan	47	17
Feb	110	31
Mar	221	72
Apr	77	20
May	132	52
Jun	205	55



Drop rows with any NaNs

```
In [14]: df.dropna(how='any')
```

```
Out[14]:
```

	eggs	salt	spam
month			
Jan	47	12.0	17
Feb	110	50.0	31
Mar	221	89.0	72
Apr	77	87.0	20
Jun	205	60.0	55



Filtering a column based on another

```
In [15]: df.eggs[df.salt > 55]
Out[15]:
month
Mar      221
Apr       77
Jun     205
Name: eggs, dtype: int64
```



Modifying a column based on another

```
In [16]: df.eggs[df.salt > 55] += 5
```

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

```
Out[17]:
```

	eggs	salt	spam
month			
Jan	47	12.0	17
Feb	110	50.0	31
Mar	226	89.0	72
Apr	82	87.0	20
May	132	NaN	52
Jun	210	60.0	55



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Transforming DataFrames



DataFrame vectorized methods

```
In [1]: df.floordiv(12) # Convert to dozens unit
```

```
Out[1]:
```

	eggs	salt	spam
month			
Jan	3	1.0	1
Feb	9	4.0	2
Mar	18	7.0	6
Apr	6	7.0	1
May	11	NaN	4
Jun	17	5.0	4



NumPy vectorized functions

```
In [2]: import numpy as np
```

```
In [3]: np.floor_divide(df, 12) # Convert to dozens unit
```

```
Out[3]:
```

	eggs	salt	spam
month			
Jan	3.0	1.0	1.0
Feb	9.0	4.0	2.0
Mar	18.0	7.0	6.0
Apr	6.0	7.0	1.0
May	11.0	NaN	4.0
Jun	17.0	5.0	4.0



Plain Python functions (1)

```
In [4]: def dozens(n):  
.....:     return n//12
```

```
In [5]: df.apply(dozens) # Convert to dozens unit
```

```
Out[5]:
```

	eggs	salt	spam
month			
Jan	3	1.0	1
Feb	9	4.0	2
Mar	18	7.0	6
Apr	6	7.0	1
May	11	NaN	4
Jun	17	5.0	4



Plain Python functions (2)

```
In [6]: df.apply(lambda n: n//12)
```

```
Out[6]:
```

	eggs	salt	spam
month			
Jan	3	1.0	1
Feb	9	4.0	2
Mar	18	7.0	6
Apr	6	7.0	1
May	11	NaN	4
Jun	17	5.0	4



Storing a transformation

```
In [7]: df['dozens_of_eggs'] = df.eggs.floordiv(12)
```

```
In [8]: df
```

```
Out[8]:
```

	eggs	salt	spam	dozens_of_eggs
month				
Jan	47	12.0	17	3
Feb	110	50.0	31	9
Mar	221	89.0	72	18
Apr	77	87.0	20	6
May	132	NaN	52	11
Jun	205	60.0	55	17



The DataFrame index

```
In [9]: df
```

```
Out[9]:
```

	eggs	salt	spam	dozens_of_eggs
month				
Jan	47	12.0	17	3
Feb	110	50.0	31	9
Mar	221	89.0	72	18
Apr	77	87.0	20	6
May	132	NaN	52	11
Jun	205	60.0	55	17

```
In [10]: df.index
```

```
Out[10]: Index(['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun'],  
dtype='object', name='month')
```



Working with string values (1)

```
In [11]: df.index = df.index.str.upper()
```

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

```
Out[12]:
```

	eggs	salt	spam	dozens_of_eggs
month				
JAN	47	12.0	17	3
FEB	110	50.0	31	9
MAR	221	89.0	72	18
APR	77	87.0	20	6
MAY	132	NaN	52	11
JUN	205	60.0	55	17



Working with string values (2)

```
In [13]: df.index = df.index.map(str.lower)
```

```
In [14]: df
```

```
Out[14]:
```

	eggs	salt	spam	dozens_of_eggs
jan	47	12.0	17	3
feb	110	50.0	31	9
mar	221	89.0	72	18
apr	77	87.0	20	6
may	132	NaN	52	11
jun	205	60.0	55	17



Defining columns using other columns

```
In [15]: df['salty_eggs'] = df.salt + df.dozens_of_eggs
```

```
In [16]: df
```

```
Out[16]:
```

	eggs	salt	spam	dozens_of_eggs	salty_eggs
jan	47	12.0	17	3	15.0
feb	110	50.0	31	9	59.0
mar	221	89.0	72	18	107.0
apr	77	87.0	20	6	93.0
may	132	NaN	52	11	NaN
jun	205	60.0	55	17	77.0



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Index objects and labeled data



pandas Data Structures

- Key building blocks
 - Indexes: Sequence of labels
 - Series: 1D array with Index
 - DataFrames: 2D array with Series as columns
- Indexes
 - Immutable (Like dictionary keys)
 - Homogenous in data type (Like NumPy arrays)



Creating a Series

```
In [1]: import pandas as pd
```

```
In [2]: prices = [10.70, 10.86, 10.74, 10.71, 10.79]
```

```
In [3]: shares = pd.Series(prices)
```

```
In [4]: print(shares)
```

```
0    10.70
```

```
1    10.86
```

```
2    10.74
```

```
3    10.71
```

```
4    10.79
```

```
dtype: float64
```



Creating an index

```
In [5]: days = ['Mon', 'Tue', 'Wed', 'Thur', 'Fri']
```

```
In [6]: shares = pd.Series(prices, index=days)
```

```
In [7]: print(shares)
```

```
Mon    10.70  
Tue    10.86  
Wed    10.74  
Thur    10.71  
Fri    10.79  
dtype: float64
```



Examining an index

```
In [8]: print(shares.index)
Index(['Mon', 'Tue', 'Wed', 'Thur', 'Fri'], dtype='object')
```

```
In [9]: print(shares.index[2])
Wed
```

```
In [10]: print(shares.index[:2])
Index(['Mon', 'Tue'], dtype='object')
```

```
In [11]: print(shares.index[-2:])
Index(['Thur', 'Fri'], dtype='object')
```

```
In [12]: print(shares.index.name)
None
```



Modifying index name

```
In [13]: shares.index.name = 'weekday'
```

```
In [14]: print(shares)
```

```
weekday
```

```
Monday      10.70
```

```
Tuesday     10.86
```

```
Wednesday   10.74
```

```
Thursday    10.71
```

```
Friday      10.79
```

```
dtype: float64
```



Modifying index entries

```
In [15]: shares.index[2] = 'Wednesday'
```

```
TypeError: Index does not support mutable operations
```

```
In [16]: shares.index[:4] = ['Monday', 'Tuesday',  
    ....:                    'Wednesday', 'Thursday']
```

```
TypeError: Index does not support mutable operations
```



Modifying all index entries

```
In [17]: shares.index = ['Monday', 'Tuesday', 'Wednesday',  
.....:                  'Thursday', 'Friday']
```

```
In [18]: print(shares)
```

Monday	10.70
Tuesday	10.86
Wednesday	10.74
Thursday	10.71
Friday	10.79

dtype: float64



Unemployment data

```
In [19]: unemployment = pd.read_csv('Unemployment.csv')
```

```
In [20]: unemployment.head()
```

```
Out[20]:
```

	Zip	unemployment	participants
0	1001	0.06	13801
1	1002	0.09	24551
2	1003	0.17	11477
3	1005	0.10	4086
4	1007	0.05	11362



Unemployment data

```
In [21]: unemployment.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 33120 entries, 0 to 33119
Data columns (total 3 columns):
Zip                33120 non-null int64
unemployment       32556 non-null float64
participants       33120 non-null int64
dtypes: float64(1), int64(2)
memory usage: 776.3 KB
```



Assigning the index

```
In [22]: unemployment.index = unemployment['Zip']
```

```
In [23]: unemployment.head()
```

```
Out[23]:
```

	Zip	unemployment	participants
Zip			
1001	1001	0.06	13801
1002	1002	0.09	24551
1003	1003	0.17	11477
1005	1005	0.10	4086
1007	1007	0.05	11362



Removing extra column

```
In [24]: unemployment.head(3)
```

```
Out[24]:
```

	Zip	unemployment	participants
Zip			
1001	1001	0.06	13801
1002	1002	0.09	24551
1003	1003	0.17	11477

```
In [25]: del unemployment['Zip']
```

```
In [26]: unemployment.head(3)
```

```
Out[26]:
```

	unemployment	participants
Zip		
1001	0.06	13801
1002	0.09	24551
1003	0.17	11477



Examining index & columns

```
In [27]: print(unemployment.index)
Int64Index([1001, 1002, 1003, 1005, 1007, 1008, 1009, 1010, 1011, 1012,
...
          966, 968, 969, 971, 976, 979, 982, 983, 985, 987],
dtype='int64', name='Zip', length=33120)
```

```
In [28]: print(unemployment.index.name)
Zip
```

```
In [29]: print(type(unemployment.index))
<class 'pandas.indexes.numeric.Int64Index'>
```

```
In [30]: print(unemployment.columns)
Index(['unemployment', 'participants'], dtype='object')
```



read_csv() with index_col

```
In [31]: unemployment = pd.read_csv('Unemployment.csv',  
    ....:                             index_col='Zip')
```

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

```
Out[32]:
```

	unemployment	participants
Zip		
1001	0.06	13801
1002	0.09	24551
1003	0.17	11477
1005	0.10	4086
1007	0.05	11362



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Hierarchical Indexing



Stock data

```
In [1]: import pandas as pd
```

```
In [2]: stocks = pd.read_csv('datasets/stocks.csv')
```

```
In [3]: print(stocks)
```

	Date	Close	Volume	Symbol
0	2016-10-03	31.50	14070500	CSCO
1	2016-10-03	112.52	21701800	AAPL
2	2016-10-03	57.42	19189500	MSFT
3	2016-10-04	113.00	29736800	AAPL
4	2016-10-04	57.24	20085900	MSFT
5	2016-10-04	31.35	18460400	CSCO
6	2016-10-05	57.64	16726400	MSFT
7	2016-10-05	31.59	11808600	CSCO
8	2016-10-05	113.05	21453100	AAPL

Repeated
values

Repeated
values



Setting index

```
In [4]: stocks = stocks.set_index(['Symbol', 'Date'])
```

```
In [5]: print(stocks)
```

		Close	Volume
Symbol	Date		
CSCO	2016-10-03	31.50	14070500
AAPL	2016-10-03	112.52	21701800
MSFT	2016-10-03	57.42	19189500
AAPL	2016-10-04	113.00	29736800
MSFT	2016-10-04	57.24	20085900
CSCO	2016-10-04	31.35	18460400
MSFT	2016-10-05	57.64	16726400
CSCO	2016-10-05	31.59	11808600
AAPL	2016-10-05	113.05	21453100



MultiIndex on DataFrame

```
In [6]: print(stocks.index)
MultiIndex(levels=[['AAPL', 'CSCO', 'MSFT'], ['2016-10-03',
'2016-10-04', '2016-10-05']], labels=[[1, 0, 2, 0, 2, 1, 2, 1, 0],
[0, 0, 0, 1, 1, 1, 2, 2, 2]], names=['Symbol', 'Date'])
```

```
In [7]: print(stocks.index.name)
None
```

```
In [8]: print(stocks.index.names)
['Symbol', 'Date']
```



Sorting index

```
In [9]: stocks = stocks.sort_index()
```

```
In [10]: print(stocks)
```

		Close	Volume
AAPL	2016-10-03	112.52	21701800
	2016-10-04	113.00	29736800
	2016-10-05	113.05	21453100
CSCO	2016-10-03	31.50	14070500
	2016-10-04	31.35	18460400
	2016-10-05	31.59	11808600
MSFT	2016-10-03	57.42	19189500
	2016-10-04	57.24	20085900
	2016-10-05	57.64	16726400



Indexing (individual row)

```
In [11]: stocks.loc[('CSCO', '2016-10-04')]
```

```
Out[11]:
```

```
Close          31.35
```

```
Volume      18460400.00
```

```
Name: (CSCO, 2016-10-04), dtype: float64
```

```
In [12]: stocks.loc[('CSCO', '2016-10-04'), 'Volume']
```

```
Out[12]: 18460400.0
```



Slicing (outermost index)

```
In [13]: stocks.loc['AAPL']
```

```
Out[13]:
```

	Close	Volume
Date		
2016-10-03	112.52	21701800
2016-10-04	113.00	29736800
2016-10-05	113.05	21453100



Slicing (outermost index)

```
In [14]: stocks.loc['CSCO':'MSFT']
```

```
Out[14]:
```

		Close	Volume
CSCO	2016-10-03	31.50	14070500
	2016-10-04	31.35	18460400
	2016-10-05	31.59	11808600
MSFT	2016-10-03	57.42	19189500
	2016-10-04	57.24	20085900
	2016-10-05	57.64	16726400



Fancy indexing (outermost index)

```
In [15]: stocks.loc(['AAPL', 'MSFT'], '2016-10-05'), :]
```

```
Out[15]:
```

		Close	Volume
Symbol	Date		
AAPL	2016-10-05	113.05	21453100
MSFT	2016-10-05	57.64	16726400

```
In [16]: stocks.loc(['AAPL', 'MSFT'], '2016-10-05'), 'Close']
```

```
Out[16]:
```

Symbol	Date	
AAPL	2016-10-05	113.05
MSFT	2016-10-05	57.64

Name: Close, dtype: float64



Fancy indexing (innermost index)

```
In [17]: stocks.loc[('CSCO', ['2016-10-05', '2016-10-03']), :]  
Out[17]:
```

		Close	Volume
Symbol	Date		
CSCO	2016-10-03	31.50	14070500
	2016-10-05	31.59	11808600



Slicing (both indexes)

```
In [18]: stocks.loc[(slice(None), slice('2016-10-03', '2016-10-04')), :]  
Out[18]:
```

		Close	Volume
Symbol	Date		
AAPL	2016-10-03	112.52	21701800
	2016-10-04	113.00	29736800
CSCO	2016-10-03	31.50	14070500
	2016-10-04	31.35	18460400
MSFT	2016-10-03	57.42	19189500
	2016-10-04	57.24	20085900



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Pivoting DataFrames



Clinical trials data

```
In [1]: import pandas as pd
```

```
In [2]: trials = pd.read_csv('trials_01.csv')
```

```
In [3]: print(trials)
```

	id	treatment	gender	response
0	1	A	F	5
1	2	A	M	3
2	3	B	F	8
3	4	B	M	9



Reshaping by pivoting

```
In [4]: trials.pivot(index='treatment',  
....:                 columns='gender',  
....:                 values='response')
```

Out[4]:

gender	F	M
treatment		
A	5	3
B	8	9



Pivoting multiple columns

```
In [5]: trials.pivot(index='treatment', columns='gender')  
Out[5]:
```

	id		response	
	F	M	F	M
treatment				
A	1	2	5	3
B	3	4	8	9



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Stacking & unstacking DataFrames



Creating a multi-level index

```
In [1]: print(trials)
      id treatment gender  response
0     1           A      F         5
1     2           A      M         3
2     3           B      F         8
3     4           B      M         9
```

```
In [2]: trials = trials.set_index(['treatment', 'gender'])
```

```
In [3]: print(trials)
      treatment gender  id  response
A           F      1     5
           M      2     3
B           F      3     8
           M      4     9
```



Unstacking a multi-index (1)

```
In [4]: print(trials)
```

		id	response
A	gender		
	F	1	5
B	M	2	3
	F	3	8
	M	4	9

```
In [5]: trials.unstack(level='gender')
```

```
Out[5]:
```

	id		response	
gender	F	M	F	M
treatment				
A	1	2	5	3
B	3	4	8	9



Unstacking a multi-index (2)

```
In [6]: print(trials)
```

		id	response
A	gender		
	F	1	5
	M	2	3
B	F	3	8
	M	4	9

```
In [7]: trials.unstack(level=1)
```

```
Out[7]:
```

	id		response	
gender	F	M	F	M
treatment				
A	1	2	5	3
B	3	4	8	9



Stacking DataFrames

```
In [8]: trials_by_gender = trials.unstack(level='gender')
```

```
In [9]: trials_by_gender
```

```
Out[9]:
```

	id		response	
gender	F	M	F	M
treatment				
A	1	2	5	3
B	3	4	8	9

```
In [10]: trials_by_gender.stack(level='gender')
```

```
Out[10]:
```

		id	response
treatment	gender		
	A		
	F	1	5
	M	2	3
B	F	3	8
	M	4	9



Stacking DataFrames

```
In [11]: stacked = trials_by_gender.stack(level='gender')
```

```
In [12]: stacked
```

```
Out[12]:
```

		id	response
treatment	gender		
A	F	1	5
	M	2	3
B	F	3	8
	M	4	9



Swapping levels

```
In [13]: swapped = stacked.swaplevel(0, 1)
```

```
In [14]: print(swapped)
```

		id	response
gender	treatment		
F	A	1	5
M	A	2	3
F	B	3	8
M	B	4	9



Sorting rows

```
In [15]: sorted_trials = swapped.sort_index()
```

```
In [16]: print(sorted_trials)
```

		id	response
gender	treatment		
F	A	1	5
	B	3	8
M	A	2	3
	B	4	9



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Melting DataFrames



Clinical trials data

```
In [1]: import pandas as pd
```

```
In [2]: trials = pd.read_csv('trials_01.csv')
```

```
In [3]: print(trials)
```

	id	treatment	gender	response
0	1	A	F	5
1	2	A	M	3
2	3	B	F	8
3	4	B	M	9



Clinical trials after pivoting

```
In [4]: trials.pivot(index='treatment',  
...:                  columns='gender',  
...:                  values='response')
```

```
Out[4]:
```

gender	F	M
treatment		
A	5	3
B	8	9



Clinical trials data

```
In [5]: new_trials = pd.read_csv('trials_02.csv')
```

```
In [6]: print(new_trials)
```

	treatment	F	M
0	A	5	3
1	B	8	9



Melting DataFrame

```
In [7]: pd.melt(new_trials)
```

```
Out[7]:
```

	variable	value
0	treatment	A
1	treatment	B
2	F	5
3	F	8
4	M	3
5	M	9



Specifying id_vars

```
In [8]: pd.melt(new_trials, id_vars=['treatment'])
```

```
Out[8]:
```

	treatment	variable	value
0	A	F	5
1	B	F	8
2	A	M	3
3	B	M	9



Specifying value_vars

```
In [9]: pd.melt(new_trials, id_vars=['treatment'],  
....:          value_vars=['F', 'M'])
```

Out[9]:

	treatment	variable	value
0	A	F	5
1	B	F	8
2	A	M	3
3	B	M	9



Specifying value_name

```
In [10]: pd.melt(new_trials, id_vars=['treatment'],  
....:           var_name='gender', value_name='response')
```

```
Out[10]:
```

	treatment	gender	response
0	A	F	5
1	B	F	8
2	A	M	3
3	B	M	9



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Pivot tables



More clinical trials data

```
In [1]: import pandas as pd
```

```
In [2]: more_trials = pd.read_csv('trials_03.csv')
```

```
In [3]: print(more_trials)
```

	id	treatment	gender	response
0	1	A	F	5
1	2	A	M	3
2	3	A	M	8
3	4	A	F	9
4	5	B	F	1
5	6	B	M	8
6	7	B	F	4
7	8	B	F	6



Rearranging by pivoting

```
In [4]: more_trials.pivot(index='treatment',  
    ...:                   columns='gender',  
    ...:                   values='response')
```

ValueError: Index contains duplicate entries, cannot reshape



Pivot table

```
In [5]: more_trials.pivot_table(index='treatment',  
    ....:                        columns='gender',  
    ....:                        values='response')
```

```
Out[5]:
```

gender	F	M
treatment		
A	7.000000	5.5
B	3.666667	8.0



Other aggregations

```
In [6]: more_trials.pivot_table(index='treatment',  
    ....:                        columns='gender',  
    ....:                        values='response',  
    ....:                        aggfunc='count')
```

Out[6]:

gender	F	M
treatment		
A	2	2
B	3	1



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Categoricals and groupby



Sales data

```
In [1]: sales = pd.DataFrame(  
    ...: {  
    ...:     'weekday': ['Sun', 'Sun', 'Mon', 'Mon'],  
    ...:     'city': ['Austin', 'Dallas', 'Austin', 'Dallas'],  
    ...:     'bread': [139, 237, 326, 456],  
    ...:     'butter': [20, 45, 70, 98]  
    ...: }  
    ...: )
```

```
In [2]: sales
```

```
Out[2]:
```

	bread	butter	city	weekday
0	139	20	Austin	Sun
1	237	45	Dallas	Sun
2	326	70	Austin	Mon
3	456	98	Dallas	Mon



Boolean filter and count

```
In [3]: sales.loc[sales['weekday'] == 'Sun'].count()
Out[3]:
bread      2
butter     2
city       2
weekday    2
dtype: int64
```



Groupby and count

```
In [4]: sales.groupby('weekday').count()
```

```
Out[4]:
```

	bread	butter	city
weekday			
Mon	2	2	2
Sun	2	2	2



Split-apply-combine

- `sales.groupby('weekday').count()`
 - split by 'weekday'
 - apply `count()` function on each group
 - combine counts per group

Aggregation/Reduction

- Some reducing functions
 - `mean()`
 - `std()`
 - `sum()`
 - `first()`, `last()`
 - `min()`, `max()`



Groupby and sum

```
In [5]: sales.groupby('weekday')['bread'].sum()  
Out[5]:  
weekday  
Mon      782  
Sun      376  
Name: bread, dtype: int64
```



Groupby and sum: multiple columns

```
In [6]: sales.groupby('weekday')[['bread', 'butter']].sum()  
Out[6]:
```

	bread	butter
weekday		
Mon	782	168
Sun	376	65



Groupby and mean: multi-level index

```
In [7]: sales.groupby(['city', 'weekday']).mean()  
Out[7]:
```

		bread	butter
city	weekday		
Austin	Mon	326	70
	Sun	139	20
Dallas	Mon	456	98
	Sun	237	45



Customers

```
In [8]: customers = pd.Series(['Dave', 'Alice', 'Bob', 'Alice'])
```

```
In [9]: customers
```

```
Out[9]:
```

```
0      Dave
```

```
1     Alice
```

```
2       Bob
```

```
3     Alice
```

```
dtype: object
```



Groupby and sum: by series

```
In [10]: sales.groupby(customers)['bread'].sum()
```

```
Out[10]:
```

```
Alice      693
```

```
Bob        326
```

```
Dave       139
```

```
Name: bread, dtype: int64
```



Categorical data

```
In [11]: sales['weekday'].unique()
```

```
Out[11]: array(['Sun', 'Mon'], dtype=object)
```

```
In [12]: sales['weekday'] = sales['weekday'].astype('category')
```

```
In [13]: sales['weekday']
```

```
Out[13]:
```

```
0      Sun
```

```
1      Sun
```

```
2      Mon
```

```
3      Mon
```

```
Name: weekday, dtype: category
```

```
Categories (2, object): [Mon, Sun]
```



Categorical data

- Advantages
 - Uses less memory
 - Speeds up operations like `groupby()`



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Groupby and aggregation



Sales data

```
In [1]: sales = pd.DataFrame(  
    ...: {  
    ...:     'weekday': ['Sun', 'Sun', 'Mon', 'Mon'],  
    ...:     'city': ['Austin', 'Dallas', 'Austin', 'Dallas'],  
    ...:     'bread': [139, 237, 326, 456],  
    ...:     'butter': [20, 45, 70, 98]  
    ...: }  
    ...: )
```

```
In [2]: sales
```

```
Out[2]:
```

	bread	butter	city	weekday
0	139	20	Austin	Sun
1	237	45	Dallas	Sun
2	326	70	Austin	Mon
3	456	98	Dallas	Mon



Review: groupby

```
In [3]: sales.groupby('city')[['bread', 'butter']].max()
```

```
Out[3]:
```

	bread	butter
city		
Austin	326	70
Dallas	456	98



Multiple aggregations

```
In [4]: sales.groupby('city')[['bread', 'butter']].agg(['max', 'sum'])
```

```
Out[4]:
```

	bread		butter	
	max	sum	max	sum
city				
Austin	326	465	70	90
Dallas	456	693	98	143

Aggregation functions

- string names
 - 'sum'
 - 'mean'
 - 'count'



Custom aggregation

```
In [5]: def data_range(series):  
        ....:     return series.max() - series.min()
```



Custom aggregation

```
In [6]: sales.groupby('weekday')[['bread', 'butter']].agg(data_range)
```

```
Out[6]:
```

	bread	butter
weekday		
Mon	130	28
Sun	98	25



Custom aggregation: dictionaries

```
In [7]: sales.groupby(customers)[['bread', 'butter']]  
....:      .agg({'bread': 'sum', 'butter': data_range})
```

```
Out[7]:
```

	butter	bread
Alice	53	693
Bob	0	326
Dave	0	139



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Groupby and transformation



The z-score

```
In [1]: def zscore(series):  
...:     return (series - series.mean()) / series.std()
```




The automobile dataset

```
In [2]: auto = pd.read_csv('auto-mpg.csv')
```

```
In [3]: auto.head()
```

```
Out[3]:
```

	mpg	cyl	displ	hp	weight	accel	yr	origin	name
0	18.0	8	307.0	130	3504	12.0	70	US	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	US	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	US	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	US	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	US	ford torino



MPG z-score

```
In [4]: zscore(auto['mpg']).head()
```

```
Out[4]:
```

	mpg
0	-0.697747
1	-1.082115
2	-0.697747
3	-0.953992
4	-0.825870



MPG z-score by year

```
In [5]: auto.groupby('yr')['mpg'].transform(zscore).head()
```

```
Out[5]:
```

	mpg
0	0.058125
1	-0.503753
2	0.058125
3	-0.316460
4	-0.129168



Apply transformation and aggregation

```
In [6]: def zscore_with_year_and_name(group):  
...:     df = pd.DataFrame(  
...:         {'mpg': zscore(group['mpg']),  
...:          'year': group['yr'],  
...:          'name': group['name']})  
...:     return df
```



Apply transformation and aggregation

```
In [7]: auto.groupby('yr').apply(zscore_with_year_and_name).head()  
Out[7]:
```

	mpg		name	year
0	0.058125	chevrolet	chevelle malibu	70
1	-0.503753		buick skylark 320	70
2	0.058125		plymouth satellite	70
3	-0.316460		amc rebel sst	70
4	-0.129168		ford torino	70



Apply transformation and aggregation

```
In [8]: def zscore_with_year_and_name(group):  
...:     df = pd.DataFrame(  
...:         {'mpg': zscore(group['mpg']),  
...:         'year': group['yr'],  
...:         'name': group['name']})  
...:     return df
```

```
In [9]: auto.groupby('yr').apply(zscore_with_year_and_name).head()
```

```
Out[9]:
```

	mpg		name	year
0	0.058125	chevrolet	chevelle malibu	70
1	-0.503753		buick skylark 320	70
2	0.058125		plymouth satellite	70
3	-0.316460		amc rebel sst	70
4	-0.129168		ford torino	70



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Groupby and filtering



The automobile dataset

```
In [1]: auto = pd.read_csv('auto-mpg.csv')
```

```
In [2]: auto.head()
```

```
Out[2]:
```

	mpg	cyl	displ	hp	weight	accel	yr	origin	name
0	18.0	8	307.0	130	3504	12.0	70	US	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	US	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	US	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	US	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	US	ford torino



Mean MPG by year

```
In [3]: auto.groupby('yr')['mpg'].mean()
```

```
Out[3]:
```

```
yr
```

```
70    17.689655
```

```
71    21.111111
```

```
72    18.714286
```

```
73    17.100000
```

```
74    22.769231
```

```
75    20.266667
```

```
76    21.573529
```

```
77    23.375000
```

```
78    24.061111
```

```
79    25.093103
```

```
80    33.803704
```

```
81    30.185714
```

```
82    32.000000
```

```
Name: mpg, dtype: float64
```



groupby object

```
In [4]: splitting = auto.groupby('yr')
```

```
In [4]: type(splitting)
```

```
Out[4]: pandas.core.groupby.DataFrameGroupBy
```

```
In [5]: type(splitting.groups)
```

```
Out[5]: dict
```

```
In [6]: print(splitting.groups.keys())
```

```
Out[6]: dict_keys([70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82])
```



groupby object: iteration

```
In [7]: for group_name, group in splitting:
....:     avg = group['mpg'].mean()
....:     print(group_name, avg)
```

```
Out[7]:
```

```
70 17.6896551724
71 21.1111111111
72 18.7142857143
73 17.1
74 22.7692307692
75 20.2666666667
76 21.5735294118
77 23.375
78 24.0611111111
79 25.0931034483
80 33.8037037037
81 30.1857142857
82 32.0
```



groupby object: iteration and filtering

```
In [8]: for group_name, group in splitting:
...:     avg = group.loc[group['name'].str.contains('chevrolet'), 'mpg'].mean()
...:     print(group_name, avg)
```

Out[8]:

```
70 15.6666666667
71 20.25
72 15.3333333333
73 14.8333333333
74 18.6666666667
75 17.6666666667
76 23.25
77 20.25
78 23.2333333333
79 21.6666666667
80 30.05
81 23.5
82 29.0
```



groupby object: comprehension

```
In [9]: chevy_means = {year:group.loc[group['name'].str.contains('chevrolet'),'mpg'].mean()  
....:                      for year,group in splitting}
```

```
In [10]: pd.Series(chevy_means)
```

```
Out[10]:
```

```
70    15.666667  
71    20.250000  
72    15.333333  
73    14.833333  
74    18.666667  
75    17.666667  
76    23.250000  
77    20.250000  
78    23.233333  
79    21.666667  
80    30.050000  
81    23.500000  
82    29.000000
```

```
dtype: float64
```



Boolean groupby

```
In [11]: chevy = auto['name'].str.contains('chevrolet')
```

```
In [12]: auto.groupby(['yr', chevy])['mpg'].mean()
```

```
Out[12]:
```

yr	name	
70	False	17.923077
	True	15.666667
71	False	21.260870
	True	20.250000
72	False	19.120000
	True	15.333333
73	False	17.500000
	True	14.833333
74	False	23.304348
	True	18.666667
75	False	20.555556
	True	17.666667
76	False	21.350000
	True	23.250000



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Case Study: Olympic Medals



Olympic medals dataset

	City	Edition	Sport	Discipline	Athlete	NOC	Gender	Event	Event_gender	Medal
0	Athens	1896	Aquatics	Swimming	HAJOS, Alfred	HUN	Men	100m freestyle	M	Gold
1	Athens	1896	Aquatics	Swimming	HERSCHMANN, Otto	AUT	Men	100m freestyle	M	Silver
2	Athens	1896	Aquatics	Swimming	DRIVAS, Dimitrios	GRE	Men	100m freestyle for sailors	M	Bronze
3	Athens	1896	Aquatics	Swimming	MALOKINIS, Ioannis	GRE	Men	100m freestyle for sailors	M	Gold
4	Athens	1896	Aquatics	Swimming	CHASAPIS, Spiridon	GRE	Men	100m freestyle for sailors	M	Silver
5	Athens	1896	Aquatics	Swimming	CHOROPHAS, Efstathios	GRE	Men	1200m freestyle	M	Bronze
6	Athens	1896	Aquatics	Swimming	HAJOS, Alfred	HUN	Men	1200m freestyle	M	Gold
7	Athens	1896	Aquatics	Swimming	ANDREOU, Joannis	GRE	Men	1200m freestyle	M	Silver
8	Athens	1896	Aquatics	Swimming	CHOROPHAS, Efstathios	GRE	Men	400m freestyle	M	Bronze
9	Athens	1896	Aquatics	Swimming	NEUMANN, Paul	AUT	Men	400m freestyle	M	Gold



Reminder: indexing & pivoting

- Filtering and indexing
 - One-level indexing
 - Multi-level indexing
- Reshaping DataFrames with `pivot()`
- `pivot_table()`



Reminder: groupby

- Useful DataFrame methods
 - `unique()`
 - `value_counts()`
- Aggregations, transformations, filtering



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Understanding the column labels



“Gender” and “Event_gender”

	NOC	Gender	Event	Event_gender	Medal
145	GRE	Men	heavyweight - two hand lift	M	Bronze
146	DEN	Men	heavyweight - two hand lift	M	Gold
147	GBR	Men	heavyweight - two hand lift	M	Silver
148	GRE	Men	open event	M	Bronze
149	GER	Men	open event	M	Gold
150	GRE	Men	open event	M	Silver
151	HUN	Men	1500m freestyle	M	Bronze
152	GBR	Men	1500m freestyle	M	Gold
153	AUT	Men	1500m freestyle	M	Silver
154	NED	Men	200m backstroke	M	Bronze



Reminder: slicing & filtering

- Indexing and slicing
 - `.loc[]` and `.iloc[]` accessors
- Filtering
 - Selecting by Boolean Series
 - Filtering null/non-null and zero/non-zero values



Reminder: Handling categorical data

- Useful DataFrame methods for handling categorical data:
 - `value_counts()`
 - `unique()`
 - `groupby()`
- `groupby()` aggregations:
 - `mean()`, `std()`, `count()`



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Constructing alternative country rankings



Counting distinct events

```
In [1]: medals['Sport'].unique() # 42 distinct events
```

```
Out[1]:
```

```
array(['Aquatics', 'Athletics', 'Cycling', 'Fencing', 'Gymnastics',  
      'Shooting', 'Tennis', 'Weightlifting', 'Wrestling', 'Archery',  
      'Basque Pelota', 'Cricket', 'Croquet', 'Equestrian', 'Football',  
      'Golf', 'Polo', 'Rowing', 'Rugby', 'Sailing', 'Tug of War',  
      'Boxing', 'Lacrosse', 'Roque', 'Hockey', 'Jeu de paume', 'Rackets',  
      'Skating', 'Water Motorsports', 'Modern Pentathlon', 'Ice Hockey',  
      'Basketball', 'Canoe / Kayak', 'Handball', 'Judo', 'Volleyball',  
      'Table Tennis', 'Badminton', 'Baseball', 'Softball', 'Taekwondo',  
      'Triathlon'], dtype=object)
```



Ranking of distinct events

- Top five countries that have won medals in the most sports
- Compare medal counts of USA and USSR from 1952 to 1988



Two new DataFrame methods

- `idxmax()`: Row or column label where maximum value is located
- `idxmin()`: Row or column label where minimum value is located



idxmax() Example

```
In [2]: weather = pd.read_csv('monthly_mean_temperature.csv',  
....:                        index_col='Month')
```

```
In [3]: weather # DataFrame with single column
```

```
Out[3]:
```

	Mean TemperatureF
Month	
Apr	53.100000
Aug	70.000000
Dec	34.935484
Feb	28.714286
Jan	32.354839
Jul	72.870968
Jun	70.133333
Mar	35.000000
May	62.612903
Nov	39.800000
Oct	55.451613
Sep	63.766667



Using idxmax()

```
In [4]: weather.idxmax() # Returns month of highest temperature
Out[4]:
Mean TemperatureF    Jul
dtype: object
```




Using `idxmax()` along columns

```
In [5]: weather.T # Returns DataFrame with single row, 12 columns
```

```
Out[5]:
```

Month	Apr	Aug	Dec	Feb	Jan	Jul	\
Mean TemperatureF	53.1	70.0	34.935484	28.714286	32.354839	72.870968	

Month	Jun	Mar	May	Nov	Oct	Sep
Mean TemperatureF	70.133333	35.0	62.612903	39.8	55.451613	63.766667

```
In [6]: weather.T.idxmax(axis='columns')
```

```
Out[6]:
```

```
Mean TemperatureF    Jul
dtype: object
```



Using idxmin()

```
In [7]: weather.T.idxmin(axis='columns')  
Out[7]:  
Mean TemperatureF    Feb  
dtype: object
```



MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Reshaping DataFrames for visualization



Reminder: plotting DataFrames

```
In [1]: all_medals = medals.groupby('Edition')['Athlete'].count()
```

```
In [2]: all_medals.head(6) # Series for all medals, all years
```

```
Out[2]:
```

```
Edition
```

1896	151
1900	512
1904	470
1908	804
1912	885
1920	1298

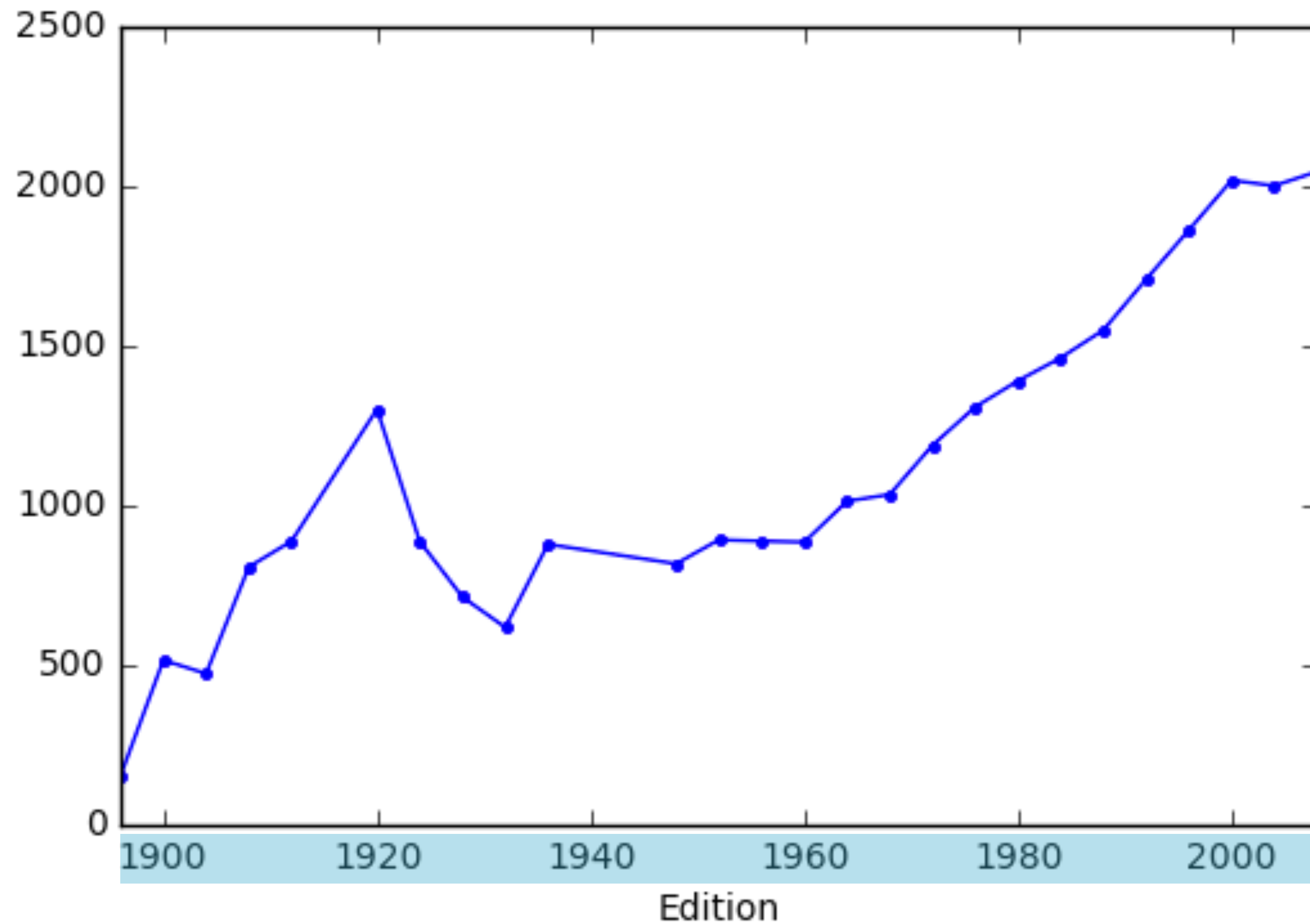
```
Name: Athlete, dtype: int64
```

```
In [3]: all_medals.plot(kind='line', marker='.')
```

```
In [4]: plt.show()
```



Plotting DataFrames





Grouping the data

```
In [5]: france = medals.NOC == 'FRA' # Boolean Series for France
```

```
In [6]: france_grps = medals[france].groupby(['Edition', 'Medal'])
```

```
In [7]: france_grps['Athlete'].count().head(10)
```

```
Out[7]:
```

Edition	Medal	
1896	Bronze	2
	Gold	5
	Silver	4
1900	Bronze	53
	Gold	46
	Silver	86
1908	Bronze	21
	Gold	9
	Silver	5
1912	Bronze	5

```
Name: Athlete, dtype: int64
```



Reshaping the data

```
In [8]: france_medals = france_grps['Athlete'].count().unstack()
```

```
In [9]: france_medals.head(12)    # Single level index
```

```
Out[9]:
```

Medal Edition	Bronze	Gold	Silver
1896	2.0	5.0	4.0
1900	53.0	46.0	86.0
1908	21.0	9.0	5.0
1912	5.0	10.0	10.0
1920	55.0	13.0	73.0
1924	20.0	39.0	63.0
1928	13.0	7.0	16.0
1932	6.0	23.0	8.0
1936	18.0	12.0	13.0
1948	21.0	25.0	22.0
1952	16.0	14.0	9.0
1956	13.0	6.0	13.0



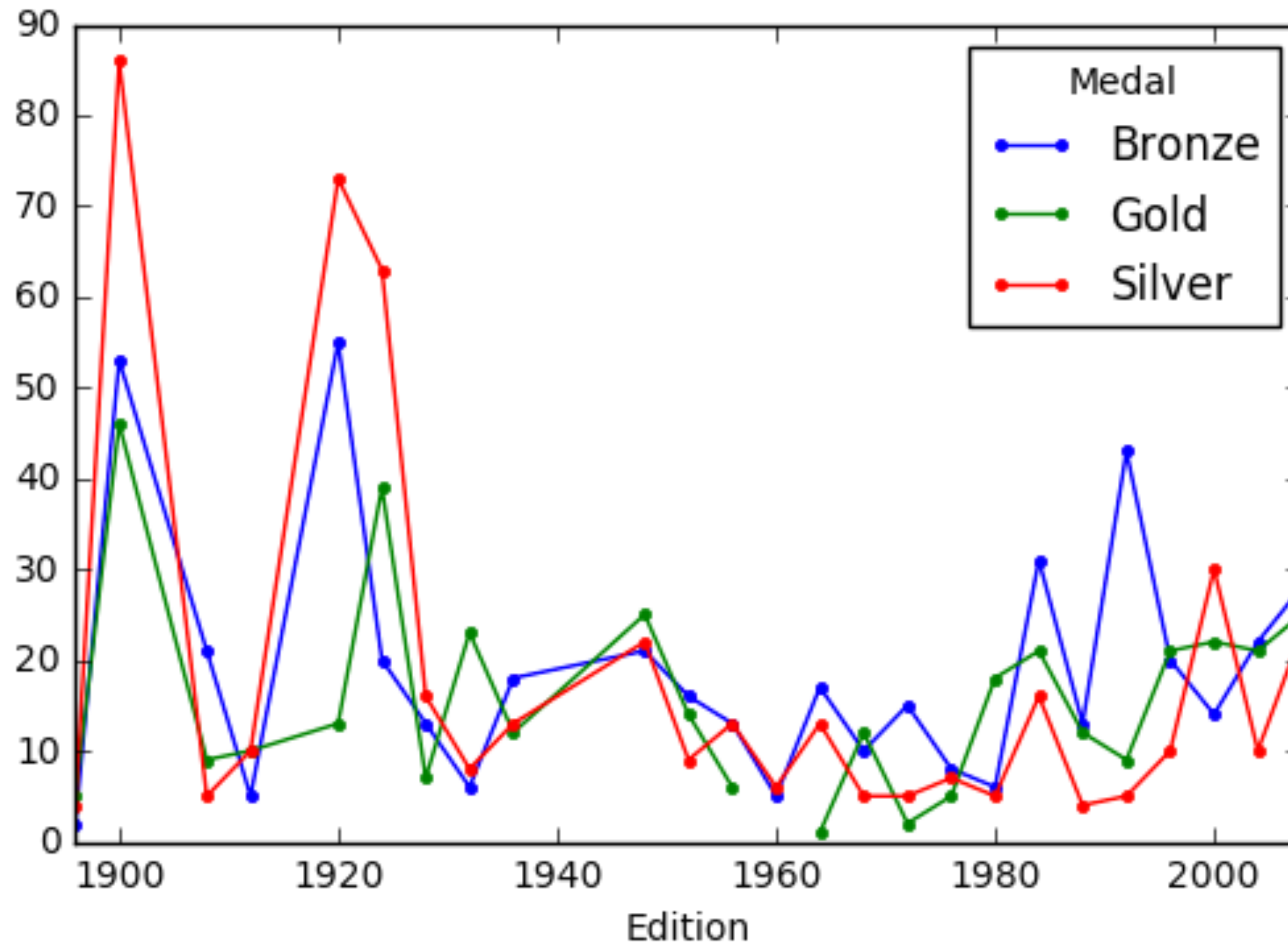
Plotting the result

```
In [10]: france_medals.plot(kind='line', marker='.')
```

```
In [11]: plt.show()
```



Plotting the result





MANIPULATING DATAFRAMES WITH PANDAS

Let's practice!



MANIPULATING DATAFRAMES WITH PANDAS

Final thoughts

You can now...

- Transform, extract, and filter data from DataFrames
- Work with pandas indexes and hierarchical indexes
- Reshape and restructure your data
- Split your data into groups and categories



MANIPULATING DATAFRAMES WITH PANDAS

**See you in the
next course!**