In [264…
```
%%html

<h1>List of chapters in this book:<h1>
<h2>Chapter 7 - Data Cleaning and Preparation</h2>
<h2>Chapter 8 - Data wrangling: Join, Combine, and Reshape</h2>
```

List of chapters in this book:

Chapter 7 - Data Cleaning and Preparation

Chapter 8 - Data wrangling: Join, Combine, and Reshape

In [3]:
```
%%html
<h2>Chapter 7 - Data Cleaning and Preparation</h2>
Code examples are taken from <a href="https://github.com/wesm/pydata-book/blob/3rd-edition/ch07.ipynb">https://gith
```

Chapter 7 - Data Cleaning and Preparation

Code examples are taken from https://github.com/wesm/pydata-book/blob/3rd-edition/ch07.ipynb

In [6]:
```
import pandas as pd
import numpy as np
```

In [8]:
```
%%html
<h3>Handling Missing Data</h3>
```

Handling Missing Data

In [9]:
```
float_data = pd.Series([1.2, -3.5, np.nan, 0])
float_data
```

Out[9]:
```
0    1.2
1   -3.5
2    NaN
3    0.0
dtype: float64
```

In [10]:
```
float_data.isna()
```

Out[10]:
```
0    False
1    False
2     True
3    False
dtype: bool
```

In [11]:
```
data = pd.Series([1, np.nan, 3.5, np.nan, 7])
data
```

Out[11]:
```
0    1.0
1    NaN
2    3.5
3    NaN
4    7.0
dtype: float64
```

In [16]:
```
data.dropna()
```

Out[16]:
```
0    1.0
2    3.5
4    7.0
dtype: float64
```

In [19]:
```
data = pd.DataFrame([[1., 6.5, 3.], [1., np.nan, np.nan],
                     [np.nan, np.nan, np.nan], [np.nan, 6.5, 3.]])
data
data.dropna()
```

Out[19]:

	0	1	2
0	1.0	6.5	3.0

In [20]:
```
# It will drop only rows that are all NaN
data.dropna(how="all")
```

Out[20]:

	0	1	2
0	1.0	6.5	3.0
1	1.0	NaN	NaN
3	NaN	6.5	3.0

In [23]:
```
data[4] = np.nan
data
```

Out[23]:

	0	1	2	4
0	1.0	6.5	3.0	NaN
1	1.0	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN
3	NaN	6.5	3.0	NaN

In [24]:
```
data.dropna(axis="columns", how="all")
```

Out[24]:

	0	1	2
0	1.0	6.5	3.0
1	1.0	NaN	NaN
2	NaN	NaN	NaN
3	NaN	6.5	3.0

In [25]:
```
%%html
<h3>Filling Missing Data</h3>
```

Filling Missing Data

In [26]:
```
data
```

Out[26]:

	0	1	2	4
0	1.0	6.5	3.0	NaN
1	1.0	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN
3	NaN	6.5	3.0	NaN

In [27]:
```
data.fillna(0.)
```

Out[27]:

	0	1	2	4
0	1.0	6.5	3.0	0.0
1	1.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0
3	0.0	6.5	3.0	0.0

In [29]:
```
data
```

Out[29]:

	0	1	2	4
0	1.0	6.5	3.0	NaN
1	1.0	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN
3	NaN	6.5	3.0	NaN

In [31]:
```
data.fillna(method="ffill")
```

```
/tmp/ipykernel_11050/2321864255.py:1: FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in
a future version. Use obj.ffill() or obj.bfill() instead.
  data.fillna(method="ffill")
```

Out[31]:

	0	1	2	4
0	1.0	6.5	3.0	NaN
1	1.0	6.5	3.0	NaN
2	1.0	6.5	3.0	NaN
3	1.0	6.5	3.0	NaN

In [50]:
```
%%html
<h3>Data Transformation</h3>
<h4>Removing the duplicates</h4>
```

Data Transformation

Removing the duplicates

In [38]:
```
data = pd.DataFrame({"k1": ["one", "two"] * 3 + ["two"],
                     "k2": [1, 1, 2, 3, 3, 4, 4]})

print(data)
data.duplicated()
data.drop_duplicates()
# It removed the last row where both columns values of the row is same as 5th index row
```

```
    k1  k2
0  one   1
1  two   1
2  one   2
3  two   3
4  one   3
5  two   4
6  two   4
```

Out[38]:

	k1	k2
0	one	1
1	two	1
2	one	2
3	two	3
4	one	3
5	two	4

In [49]:

```
# We can check for the subset of columns for the duplicates
data["v1"] = range(7)
print(data)
print("")
print("After one column in the subset attribute")
print("")
print(data.drop_duplicates(subset=["k1"]))
print("")
print("After two columns in the subset attribute")
print("")
print(data.drop_duplicates(subset=["k1","k2"]))
```

```
    k1  k2  v1
0  one   1   0
1  two   1   1
2  one   2   2
3  two   3   3
4  one   3   4
5  two   4   5
6  two   4   6

After one column in the subset attribute

    k1  k2  v1
0  one   1   0
1  two   1   1

After two columns in the subset attribute

    k1  k2  v1
0  one   1   0
1  two   1   1
2  one   2   2
3  two   3   3
4  one   3   4
5  two   4   5
```

In [51]:
```
%%html
<h4>Transforming data using a function or mapping</h4>
```

Transforming data using a function or mapping

In [52]:
```
data = pd.DataFrame({"food": ["bacon", "pulled pork", "bacon",
                              "pastrami", "corned beef", "bacon",
                              "pastrami", "honey ham", "nova lox"],
                     "ounces": [4, 3, 12, 6, 7.5, 8, 3, 5, 6]})
data
```

Out[52]:

	food	ounces
0	bacon	4.0
1	pulled pork	3.0
2	bacon	12.0
3	pastrami	6.0
4	corned beef	7.5
5	bacon	8.0
6	pastrami	3.0
7	honey ham	5.0
8	nova lox	6.0

In [59]:

```
food_to_animal = {
  "bacon": "pig",
  "pulled pork": "pig",
  "pastrami": "cow",
  "corned beef": "cow",
  "honey ham": "pig",
  "nova lox": "salmon"
}

def get_animal(x):
    return food_to_animal[x]

data['animal'] = data['food'].map(get_animal)
data
```

Out[59]:

	food	ounces	animal
0	bacon	4.0	pig
1	pulled pork	3.0	pig
2	bacon	12.0	pig
3	pastrami	6.0	cow
4	corned beef	7.5	cow
5	bacon	8.0	pig
6	pastrami	3.0	cow
7	honey ham	5.0	pig
8	nova lox	6.0	salmon

In [60]:
```
%%html
<h4>Renaming axis indexes</h4>
```

Renaming axis indexes

In [62]:
```
data = pd.DataFrame(np.arange(12).reshape((3, 4)),
                    index=["Ohio", "Colorado", "New York"],
                    columns=["one", "two", "three", "four"])
data
```

Out[62]:

	one	two	three	four
Ohio	0	1	2	3
Colorado	4	5	6	7
New York	8	9	10	11

In [67]:
```
def mapping(x):
    return x[:4].upper()

print(data.index.map(mapping))
```

```
data.index = data.index.map(mapping)
data
```

```
Index(['OHIO', 'COLO', 'NEW '], dtype='object')
```

Out[67]:

	one	two	three	four
OHIO	0	1	2	3
COLO	4	5	6	7
NEW	8	9	10	11

In [68]:
```
%%html
<h4>Discretization & binning</h4>
```

Discretization & binning

In [ ]:
```
ages = [20, 22, 25, 27, 21, 23, 37, 31, 61, 45, 41, 32]
bins = [18, 25, 35, 60, 100]
# it converts the ages into bins: 18 to 25, 255 to 35, 60 to 100
age_categories = pd.cut(ages, bins)
age_categories
```

In [72]:
```
age_categories.categories
```

Out[72]:
```
IntervalIndex([(18, 25], (25, 35], (35, 60], (60, 100]], dtype='interval[int64, right]')
```

In [74]:
```
pd.value_counts(age_categories)
```

```
/tmp/ipykernel_11050/3010498523.py:1: FutureWarning: pandas.value_counts is deprecated and will be removed in a futu
re version. Use pd.Series(obj).value_counts() instead.
  pd.value_counts(age_categories)
```

Out[74]:
```
(18, 25]     5
(25, 35]     3
(35, 60]     3
(60, 100]    1
Name: count, dtype: int64
```

In [78]:
```
# If we pass an integer instead of a list in bin attributes, it will dvidedthe data specified integer no. of bins

data = np.random.uniform(size=21)
data
pd.cut(data, 4)
```

Out[78]:
```
array([0.1079196 , 0.65967945, 0.4119345 , 0.13176666, 0.60006722,
       0.68983366, 0.01658643, 0.5010701 , 0.17507584, 0.3512456 ,
       0.39140835, 0.35190866, 0.32518611, 0.10655427, 0.04213229,
       0.25048114, 0.07727767, 0.8057591 , 0.20699889, 0.88114253,
       0.00606917])
```

In [87]:
```
# Creating quartile: 4 => qcut creates the each bin with same number of data points where as cut wont'do that
data = np.random.standard_normal(1000)
quartile = pd.qcut(data, 4, precision=2)
test_with_cut = pd.cut(data, 4, precision=2)
```

In [85]:
```
pd.value_counts(quartile)
```

```
/tmp/ipykernel_11050/4228863495.py:1: FutureWarning: pandas.value_counts is deprecated and will be removed in a futu
re version. Use pd.Series(obj).value_counts() instead.
  pd.value_counts(quartile)
```

Out[85]:
```
(-3.61, -0.72]      250
(-0.72, -0.0028]    250
(-0.0028, 0.66]     250
(0.66, 3.02]        250
Name: count, dtype: int64
```

In [88]:
```
pd.value_counts(test_with_cut)
```

```
/tmp/ipykernel_11050/1120107730.py:1: FutureWarning: pandas.value_counts is deprecated and will be removed in a futu
re version. Use pd.Series(obj).value_counts() instead.
  pd.value_counts(test_with_cut)
```

Out[88]:
```
(0.0065, 1.47]     439
(-1.46, 0.0065]    427
(-2.93, -1.46]      67
(1.47, 2.94]        67
Name: count, dtype: int64
```

In [89]:
```
%%html
<h4>Detecting and filtering outliers</h4>
```

Detecting and filtering outliers

In [91]:
```
data = pd.DataFrame(np.random.standard_normal((1000, 4)))
data.describe()
```

Out[91]:

	0	1	2	3
count	1000.000000	1000.000000	1000.000000	1000.000000
mean	0.032673	-0.028110	-0.024413	0.024666
std	1.007846	0.993278	1.024149	1.006475
min	-3.357931	-3.009217	-3.035152	-3.130328
25%	-0.626578	-0.701481	-0.704032	-0.700567
50%	0.055235	-0.035837	-0.033858	-0.011936
75%	0.676512	0.661261	0.676005	0.703756
max	3.042454	3.173949	2.972772	4.055141

In [94]:
```
col = data[2]
col
```

Out[94]:
```
0     -0.981120
1      2.140322
2      0.830040
3      0.808377
4      0.487802
         ...
995   -1.622898
996   -1.962332
997   -0.868515
998    1.079087
999   -0.940871
Name: 2, Length: 1000, dtype: float64
```

In [93]:
```
col[col.abs() > 3]
```

Out[93]:
```
598   -3.035152
Name: 2, dtype: float64
```

In [95]:
```
%%html
<h4>Permutation and random sampling</h4>
```

Permutation and random sampling

In [100…
```
df = pd.DataFrame(np.arange(5 * 7).reshape(5, 7))
df
```

Out[100…

	0	1	2	3	4	5	6
0	0	1	2	3	4	5	6
1	7	8	9	10	11	12	13
2	14	15	16	17	18	19	20
3	21	22	23	24	25	26	27
4	28	29	30	31	32	33	34

In [105…
```
sampler = np.random.permutation(5)
sampler
```

Out[105…
```
array([2, 0, 1, 3, 4])
```

In [106…
```
df.iloc[sampler]
```

Out[106…

	0	1	2	3	4	5	6
2	14	15	16	17	18	19	20
0	0	1	2	3	4	5	6
1	7	8	9	10	11	12	13
3	21	22	23	24	25	26	27
4	28	29	30	31	32	33	34

In [107…

```
# We can do the same on columns
df[sampler]
```

Out[107…

	2	0	1	3	4
0	2	0	1	3	4
1	9	7	8	10	11
2	16	14	15	17	18
3	23	21	22	24	25
4	30	28	29	31	32

In [108…

```
%%html
<h4>Computing Indicator/Dummy Variables</h4>
```

Computing Indicator/Dummy Variables

In [109…

```
df = pd.DataFrame({"key": ["b", "b", "a", "c", "a", "b"],
                   "data1": range(6)})
df
```

Out[109…

	key	data1
0	b	0
1	b	1
2	a	2
3	c	3
4	a	4
5	b	5

In [113…

```
dummies = pd.get_dummies(df["key"])
```

In [117…

```
df = df.drop(["key"], axis=1)
df.join(dummies)
```

Out[117…

	data1	a	b	c
0	0	False	True	False
1	1	False	True	False
2	2	True	False	False
3	3	False	False	True
4	4	True	False	False
5	5	False	True	False

In [118…

```
# to make example repeatable
np.random.seed(12345)
```

In [120…

```
%%html
<h3>String manipulation</h3>
<h4>String function in pandas</h4>
```

String manipulation

String function in pandas

In [121…
```
data = {"Dave": "dave@google.com", "Steve": "steve@gmail.com",
        "Rob": "rob@gmail.com", "Wes": np.nan}
data = pd.Series(data)
data
```

Out[121…
```
Dave     dave@google.com
Steve    steve@gmail.com
Rob        rob@gmail.com
Wes                  NaN
dtype: object
```

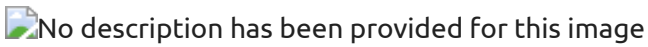
In [123…
```
data.str.contains("gmail")
```

Out[123…
```
Dave     False
Steve     True
Rob       True
Wes        NaN
dtype: object
```

In [124…
```
%%html

Partial listing of series string methods
<img src="images/series_string.png"width=400/>
```

Partial listing of series string methods


No description has been provided for this image

In [125…
```
data.str.count("gmail")
```

Out[125…
```
Dave     0.0
Steve    1.0
Rob      1.0
Wes      NaN
dtype: float64
```

In [131…
```
%%html
<h2>Chapter 8 - Data wrangling: Join, Combine, and Reshape</h2>
Code examples are taken from <a href="https://github.com/wesm/pydata-book/blob/3rd-edition/ch08.ipynb">https://gith
```

Chapter 8 - Data wrangling: Join, Combine, and Reshape

Code examples are taken from https://github.com/wesm/pydata-book/blob/3rd-edition/ch08.ipynb

In [167…
```
%%html

<h3>Heirarchial Indexing</h3>

It's an important feature in pandas which enables the multiple index levels on an axis.
This is the way pandas can be used to represent higher dimensional data in tabular format
```

Heirarchial Indexing

It's an important feature in pandas which enables the multiple index levels on an axis. This is the way pandas can be used to represent higher dimensional data in tabular format

In [136…
```
data = pd.Series(np.random.uniform(size=9),
                 index=[["a", "a", "a", "b", "b", "c", "c", "d", "d"],
                        [1, 2, 3, 1, 3, 1, 2, 2, 3]])
data
```

Out[136…
```
a  1    0.929616
   2    0.316376
   3    0.183919
b  1    0.204560
   3    0.567725
c  1    0.595545
   2    0.964515
d  2    0.653177
   3    0.748907
dtype: float64
```

In [137…
```
data.index
```

Out[137…
```
MultiIndex([('a', 1),
            ('a', 2),
            ('a', 3),
            ('b', 1),
            ('b', 3),
            ('c', 1),
            ('c', 2),
            ('d', 2),
            ('d', 3)],
           )
```

In [138…
```
data["b"]
```

Out[138…
```
1    0.204560
3    0.567725
dtype: float64
```

In [139…
```
data.unstack()
```

Out[139…

	1	2	3
a	0.929616	0.316376	0.183919
b	0.204560	NaN	0.567725
c	0.595545	0.964515	NaN
d	NaN	0.653177	0.748907

In [143…
```
frame = pd.DataFrame(np.arange(12).reshape((4, 3)),
                     index=[["a", "a", "b", "b"], [1, 3, 1, 2]],
                     columns=[["Ohio", "Ohio", "Colorado"],
                              ["Green", "Red", "Green"]])
frame
```

Out[143…

		Ohio		Colorado
		Green	Red	Green
a	1	0	1	2
	3	3	4	5
b	1	6	7	8
	2	9	10	11

In [147…

```
frame.index.names = ["key1", "key2"]
frame.columns.names = ["state", "colour"]
frame
```

Out[147…

	state		Ohio	Colorado
	colour	Green	Red	Green
key1	key2			
a	1	0	1	2
	3	3	4	5
b	1	6	7	8
	2	9	10	11

In [151…

```
frame["Ohio"]
```

Out[151…

	colour	Green	Red
key1	key2		
a	1	0	1
	3	3	4
b	1	6	7
	2	9	10

In [155…
```
frame.loc["a":"a","Ohio"]
```

Out[155…

	colour	Green	Red
key1	key2		
a	1	0	1
	3	3	4

In [165…
```
# we can use set_index function to create heirachial df from the normal df.
frame = pd.DataFrame({"a": range(7), "b": range(7, 0, -1),
                      "c": ["one", "one", "one", "two", "two",
                            "two", "two"],
                      "d": [0, 1, 2, 0, 1, 2, 3]})
frame
```

Out[165…

```
0  a      0
   b      7
   c    one
   d      0
1  a      1
   b      6
   c    one
   d      1
2  a      2
   b      5
   c    one
   d      2
3  a      3
   b      4
   c    two
   d      0
4  a      4
   b      3
   c    two
   d      1
5  a      5
   b      2
   c    two
   d      2
6  a      6
   b      1
   c    two
   d      3
dtype: object
```

In [160…

```
frame = frame.set_index(["c","d"])
frame
```

Out[160…

		a	b
c	**d**		
one	**0**	0	7
	1	1	6
	2	2	5
two	**0**	3	4
	1	4	3
	2	5	2
	3	6	1

In [166…

```
# reset index to go back to previous indeing
frame.reset_index()
```

Out[166…

	index	a	b	c	d
0	0	0	7	one	0
1	1	1	6	one	1
2	2	2	5	one	2
3	3	3	4	two	0
4	4	4	3	two	1
5	5	5	2	two	2
6	6	6	1	two	3

In [164…

Out[164…
```
c    d
one  0  a    0
        b    7
     1  a    1
        b    6
     2  a    2
        b    5
two  0  a    3
        b    4
     1  a    4
        b    3
     2  a    5
        b    2
     3  a    6
        b    1
dtype: int64
```

In [168…
```
%%html

<h3>Combining and Merging Datasets</h3>
```

Combining and Merging Datasets

In [173…
```
df1 = pd.DataFrame({"key": ["b", "b", "a", "c", "a", "a", "b"],
                    "data1": pd.Series(range(7), dtype="Int64")})
df2 = pd.DataFrame({"key": ["a", "b", "d"],
                    "data2": pd.Series(range(3), dtype="Int64")})
print(df1)
df2
```

```
  key  data1
0   b      0
1   b      1
2   a      2
3   c      3
4   a      4
5   a      5
6   b      6
```

Out[173…

	key	data2
0	a	0
1	b	1
2	d	2

In [172…

```
pd.merge(df1,df2)
# It does the inner join. We haven't specified which coumn to match the inner join.
# In this case key is the common and it automatically joined the dfs using key column.
# Here, a & b are common and they are merged, but cfrom df1 and d from df2 is removed from the result as they are n
# we can also perform the merge operation like this df1.merge(df2)
```

Out[172…

	key	data1	data2
0	b	0	1
1	b	1	1
2	a	2	0
3	a	4	0
4	a	5	0
5	b	6	1

In [175…

```
# we can specify different types of join using how attribute: inner, left,right, outer =>inner is bydefault
pd.merge(df1,df2, how="left") # in this case they merge all the items in df1 with common items in df2
```

Out[175…

	key	data1	data2
0	b	0	1
1	b	1	1
2	a	2	0
3	c	3	<NA>
4	a	4	0
5	a	5	0
6	b	6	1

In [178…

```
# if there are multiple columns have the same in both dfs. We can specify which columns needs to be matched using o
pd.merge(df1,df2, on="key", how="outer")
```

Out[178…

	key	data1	data2
0	a	2	0
1	a	4	0
2	a	5	0
3	b	0	1
4	b	1	1
5	b	6	1
6	c	3	<NA>
7	d	<NA>	2

In [185…

```
# In the below example we do not have common columns and in that case, we have to specify which of theses columns n
df3 = pd.DataFrame({"lkey": ["b", "b", "a", "c", "a", "a", "b"],
                    "data1": pd.Series(range(7), dtype="Int64")})
df4 = pd.DataFrame({"rkey": ["a", "b", "d"],
                    "data2": pd.Series(range(3), dtype="Int64")})
pd.merge(df3,df4,left_on="lkey",right_on="rkey")
```

Out[185…

	lkey	data1	rkey	data2
0	b	0	b	1
1	b	1	b	1
2	a	2	a	0
3	a	4	a	0
4	a	5	a	0
5	b	6	b	1

In [186…

```
# we can merge with multiple keys
left = pd.DataFrame({"key1": ["foo", "foo", "bar"],
                     "key2": ["one", "two", "one"],
                     "lval": pd.Series([1, 2, 3], dtype='Int64')})
right = pd.DataFrame({"key1": ["foo", "foo", "bar", "bar"],
                      "key2": ["one", "one", "one", "two"],
                      "rval": pd.Series([4, 5, 6, 7], dtype='Int64')})
pd.merge(left, right, on=["key1", "key2"], how="outer")
```

Out[186…

	key1	key2	lval	rval
0	bar	one	3	6
1	bar	two	<NA>	7
2	foo	one	1	4
3	foo	one	1	5
4	foo	two	2	<NA>

In [189…

```
# we use index as the merge key sing left_index=True and/or right_index=True

left1 = pd.DataFrame({"key": ["a", "b", "a", "a", "b", "c"],
                      "value": pd.Series(range(6), dtype="Int64")})
right1 = pd.DataFrame({"group_val": [3.5, 7]}, index=["a", "b"])
left1
```

```
right1
pd.merge(left1, right1, left_on="key", right_index=True)
```

Out[189…

	key	value	group_val
0	a	0	3.5
1	b	1	7.0
2	a	2	3.5
3	a	3	3.5
4	b	4	7.0

In [192…

```
# There is a join method that simplify the merging by index
left2 = pd.DataFrame([[1., 2.], [3., 4.], [5., 6.]],
                     index=["a", "c", "e"],
                     columns=["Ohio", "Nevada"]).astype("Int64")
right2 = pd.DataFrame([[7., 8.], [9., 10.], [11., 12.], [13, 14]],
                      index=["b", "c", "d", "e"],
                      columns=["Missouri", "Alabama"]).astype("Int64")

left2.join(right2, how="outer")
```

Out[192…

	Ohio	Nevada	Missouri	Alabama
a	1	2	<NA>	<NA>
b	<NA>	<NA>	7	8
c	3	4	9	10
d	<NA>	<NA>	11	12
e	5	6	13	14

In [213…

```
%%html

<h3>Concatening along an axis</h3>
Pandas.concat function argument
<img src="images/concat.png"width=400/>
```

Concatening along an axis

Pandas.concat function argument

 No description has been provided for this image

In [197…
```
s1 = pd.Series([0, 1], index=["a", "b"], dtype="Int64")
s2 = pd.Series([2, 3, 4], index=["c", "d", "e"], dtype="Int64")
s3 = pd.Series([5, 6], index=["f", "g"], dtype="Int64")
pd.concat([s1,s2,s3])
```

Out[197…
```
a    0
b    1
c    2
d    3
e    4
f    5
g    6
dtype: Int64
```

In [198…
```
pd.concat([s1,s2,s3],axis=1)
```

Out[198…

	0	1	2
a	0	<NA>	<NA>
b	1	<NA>	<NA>
c	<NA>	2	<NA>
d	<NA>	3	<NA>
e	<NA>	4	<NA>
f	<NA>	<NA>	5
g	<NA>	<NA>	6

In [ ]:
```
# we can do the join as welll
```

In [200…
```
s4 = pd.concat([s1, s3])
pd.concat([s1,s4],axis=1, join="inner")
```

Out[200…

	0	1
a	0	0
b	1	1

In [202…
```
df1 = pd.DataFrame(np.arange(6).reshape(3, 2), index=["a", "b", "c"],
                   columns=["one", "two"])
df2 = pd.DataFrame(5 + np.arange(4).reshape(2, 2), index=["a", "c"],
                   columns=["three", "four"])

pd.concat([df1, df2], axis="columns")
```

Out[202…

	one	two	three	four
a	0	1	5.0	6.0
b	2	3	NaN	NaN
c	4	5	7.0	8.0

In [207…
```
test_df = pd.concat([df1, df2], axis="columns", keys=["level1", "level2"])
test_df
```

Out[207…

	level1		level2	
	one	**two**	**three**	**four**
a	0	1	5.0	6.0
b	2	3	NaN	NaN
c	4	5	7.0	8.0

In [206…
```
test_df["level1"]
```

Out[206…

	one	two
a	0	1
b	2	3
c	4	5

In [208…

```
pd.concat([df1, df2],keys=["level1", "level2"])
```

Out[208…

		one	two	three	four
level1	**a**	0.0	1.0	NaN	NaN
	b	2.0	3.0	NaN	NaN
	c	4.0	5.0	NaN	NaN
level2	**a**	NaN	NaN	5.0	6.0
	c	NaN	NaN	7.0	8.0

In [212…

```
pd.concat([df1, df2],keys=["level1", "level2"], join="inner")
```

Out[212…

level1	**a**
	b
	c
level2	**a**
	c

In [214…

```
%%html

<h3>Combining data with overlap</h3>
```

Combining data with overlap

In [215…
```
a = pd.Series([np.nan, 2.5, 0.0, 3.5, 4.5, np.nan],
              index=["f", "e", "d", "c", "b", "a"])
b = pd.Series([0., np.nan, 2., np.nan, np.nan, 5.],
              index=["a", "b", "c", "d", "e", "f"])

np.where(pd.isna(a), b, a)
```

Out[215…
```
array([0. , 2.5, 0. , 3.5, 4.5, 5. ])
```

In [217…
```
np.where(pd.isna(b), a, b)
```

Out[217…
```
array([0. , 2.5, 2. , 3.5, 4.5, 5. ])
```

In [218…
```
a.combine_first(b)
```

Out[218…
```
a    0.0
b    4.5
c    3.5
d    0.0
e    2.5
f    5.0
dtype: float64
```

In [220…
```
%%html

<h3>Reshaping & pivoting</h3>
<h4>Reshaping with heirarchial indexing</h4>
```

Reshaping & pivoting

Reshaping with heirarchial indexing

In [222…
```
# stack rotates or pivots from the columns in the data to the rows.
# unstack pivots from the rows into the columns.

data = pd.DataFrame(np.arange(6).reshape((2, 3)),
                    index=pd.Index(["Ohio", "Colorado"], name="state"),
                    columns=pd.Index(["one", "two", "three"],
```

```
                    name="number"))
data
```

Out[222…

number	one	two	three
state			
Ohio	0	1	2
Colorado	3	4	5

In [228…

```
result = data.stack()
result
```

Out[228…

```
state     number
Ohio      one       0
          two       1
          three     2
Colorado  one       3
          two       4
          three     5
dtype: int64
```

In [227…

```
result.unstack()
```

Out[227…

number	one	two	three
state			
Ohio	0	1	2
Colorado	3	4	5

In [229…

```
# We can specify the levels as during the unstack & stack
df = pd.DataFrame({"left": result, "right": result + 5},
                  columns=pd.Index(["left", "right"], name="side"))
df
```

Out[229…

	side	left	right
state	number		
Ohio	one	0	5
	two	1	6
	three	2	7
Colorado	one	3	8
	two	4	9
	three	5	10

In [230…
```
df.index
```

Out[230…
```
MultiIndex([(    'Ohio',   'one'),
            (    'Ohio',   'two'),
            (    'Ohio', 'three'),
            ('Colorado',   'one'),
            ('Colorado',   'two'),
            ('Colorado', 'three')],
           names=['state', 'number'])
```

In [234…
```
# from rows to column
df.unstack(level="state")
```

Out[234…

side	left		right	
state	Ohio	Colorado	Ohio	Colorado
number				
one	0	3	5	8
two	1	4	6	9
three	2	5	7	10

In [235…
```
df.unstack(level="number")
```

Out[235…

side			left			right
number	one	two	three	one	two	three
state						
Ohio	0	1	2	5	6	7
Colorado	3	4	5	8	9	10

In [237…

```
#From column to rows
df
```

Out[237…

	side	left	right
state	number		
Ohio	one	0	5
	two	1	6
	three	2	7
Colorado	one	3	8
	two	4	9
	three	5	10

In [238…

```
df.stack(level="side")
```

Out[238…
```
state     number  side
Ohio      one     left      0
                  right     5
          two     left      1
                  right     6
          three   left      2
                  right     7
Colorado  one     left      3
                  right     8
          two     left      4
                  right     9
          three   left      5
                  right    10
dtype: int64
```

In [239…
```
%%html

<h3>Pivoting long to wide format</h3>
```

Pivoting long to wide format

In [247…
```
# Pivoting from long to wide format

data = pd.read_csv("examples/macrodata.csv")
data = data.loc[:, ["year", "quarter", "realgdp", "infl", "unemp"]]
data.head()
```

Out[247…

	year	quarter	realgdp	infl	unemp
0	1959	1	2710.349	0.00	5.8
1	1959	2	2778.801	2.34	5.1
2	1959	3	2775.488	2.74	5.3
3	1959	4	2785.204	0.27	5.6
4	1960	1	2847.699	2.31	5.2

In [248…
```
periods = pd.PeriodIndex(year=data.pop("year"),
                         quarter=data.pop("quarter"),
                         name="date")
periods
data.index = periods.to_timestamp("D")
data.head()
```

```
/tmp/ipykernel_11050/539240372.py:1: FutureWarning: Constructing PeriodIndex from fields is deprecated. Use PeriodIn
dex.from_fields instead.
  periods = pd.PeriodIndex(year=data.pop("year"),
```

Out[248…

date	realgdp	infl	unemp
1959-01-01	2710.349	0.00	5.8
1959-04-01	2778.801	2.34	5.1
1959-07-01	2775.488	2.74	5.3
1959-10-01	2785.204	0.27	5.6
1960-01-01	2847.699	2.31	5.2

In [249…
```
data = data.reindex(columns=["realgdp", "infl", "unemp"])
data.columns.name = "item"
data.head()
```

Out[249…

item date	realgdp	infl	unemp
1959-01-01	2710.349	0.00	5.8
1959-04-01	2778.801	2.34	5.1
1959-07-01	2775.488	2.74	5.3
1959-10-01	2785.204	0.27	5.6
1960-01-01	2847.699	2.31	5.2

In [253…
```
long_data = (data.stack()
             .reset_index()
             .rename(columns={0: "value"}))
long_data
# Normally this would be the way the data is stored in the database.
# We can transform or pivot this result in such a way it can be much easier to process
```

Out[253…

	date	item	value
0	1959-01-01	realgdp	2710.349
1	1959-01-01	infl	0.000
2	1959-01-01	unemp	5.800
3	1959-04-01	realgdp	2778.801
4	1959-04-01	infl	2.340
…	…	…	…
604	2009-04-01	infl	3.370
605	2009-04-01	unemp	9.200
606	2009-07-01	realgdp	12990.341
607	2009-07-01	infl	3.560
608	2009-07-01	unemp	9.600

609 rows × 3 columns

In [252…
```
long_data.pivot(index="date", columns="item", values="value")
```

Out[252…

item	infl	realgdp	unemp
date			
1959-01-01	0.00	2710.349	5.8
1959-04-01	2.34	2778.801	5.1
1959-07-01	2.74	2775.488	5.3
1959-10-01	0.27	2785.204	5.6
1960-01-01	2.31	2847.699	5.2
…	…	…	…
2008-07-01	-3.16	13324.600	6.0
2008-10-01	-8.79	13141.920	6.9
2009-01-01	0.94	12925.410	8.1
2009-04-01	3.37	12901.504	9.2
2009-07-01	3.56	12990.341	9.6

203 rows × 3 columns

In [254…

```
long_data["value2"] = np.random.standard_normal(len(long_data))
long_data[:10]
```

Out[254…

	date	item	value	value2
0	1959-01-01	realgdp	2710.349	1.248804
1	1959-01-01	infl	0.000	0.774191
2	1959-01-01	unemp	5.800	-0.319657
3	1959-04-01	realgdp	2778.801	-0.624964
4	1959-04-01	infl	2.340	1.078814
5	1959-04-01	unemp	5.100	0.544647
6	1959-07-01	realgdp	2775.488	0.855588
7	1959-07-01	infl	2.740	1.343268
8	1959-07-01	unemp	5.300	-0.267175
9	1959-10-01	realgdp	2785.204	1.793095

In [257…

```
# if we omit the last argument(values), then we get df with hierarchical columns
pivoted = long_data.pivot(index="date", columns="item")
pivoted.head()
```

Out[257…

	value			value2		
item	**infl**	**realgdp**	**unemp**	**infl**	**realgdp**	**unemp**
date						
1959-01-01	0.00	2710.349	5.8	0.774191	1.248804	-0.319657
1959-04-01	2.34	2778.801	5.1	1.078814	-0.624964	0.544647
1959-07-01	2.74	2775.488	5.3	1.343268	0.855588	-0.267175
1959-10-01	0.27	2785.204	5.6	-0.652929	1.793095	-1.886837
1960-01-01	2.31	2847.699	5.2	0.644448	1.059626	-0.007799

In [258…

```
pivoted["value"]
```

Out[258…

item	infl	realgdp	unemp
date			
1959-01-01	0.00	2710.349	5.8
1959-04-01	2.34	2778.801	5.1
1959-07-01	2.74	2775.488	5.3
1959-10-01	0.27	2785.204	5.6
1960-01-01	2.31	2847.699	5.2
…	…	…	…
2008-07-01	-3.16	13324.600	6.0
2008-10-01	-8.79	13141.920	6.9
2009-01-01	0.94	12925.410	8.1
2009-04-01	3.37	12901.504	9.2
2009-07-01	3.56	12990.341	9.6

203 rows × 3 columns

In [259…

```
pivoted["value"]["infl"]
```

Out[259…

```
date
1959-01-01    0.00
1959-04-01    2.34
1959-07-01    2.74
1959-10-01    0.27
1960-01-01    2.31
              ...
2008-07-01   -3.16
2008-10-01   -8.79
2009-01-01    0.94
2009-04-01    3.37
2009-07-01    3.56
Name: infl, Length: 203, dtype: float64
```

In [260…
```
# Pivoting from wide to long format
```

In [261…
```
df = pd.DataFrame({"key": ["foo", "bar", "baz"],
                   "A": [1, 2, 3],
                   "B": [4, 5, 6],
                   "C": [7, 8, 9]})
df
```

Out[261…

	key	A	B	C
0	foo	1	4	7
1	bar	2	5	8
2	baz	3	6	9

In [262…
```
melted = pd.melt(df, id_vars="key")
melted
```

Out[262…

	key	variable	value
0	foo	A	1
1	bar	A	2
2	baz	A	3
3	foo	B	4
4	bar	B	5
5	baz	B	6
6	foo	C	7
7	bar	C	8
8	baz	C	9

In [263…
```
reshaped = melted.pivot(index="key", columns="variable",
                        values="value")
reshaped
```

Out[263…

variable	A	B	C
key			
bar	2	5	8
baz	3	6	9
foo	1	4	7

In [ ]: