POLITECNICO
DI TORINO

Data Science Lab

Pandas

DataBase and Data Mining Group

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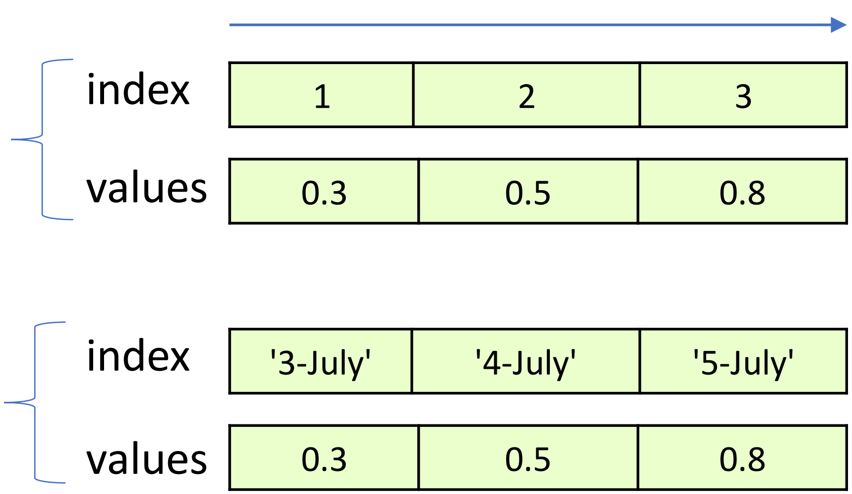
- Pandas
  - Provides useful data structures (Series and DataFrames) and data analysis tools
  - Based on **Numpy** arrays

  - Tools:
    - Managing **tables** and **series**
      - data selection
      - grouping, pivoting
    - Managing **missing data**
    - **Statistics** on data

Pandas Series

- **Series**: 1-Dimensional sequence of homogeneous elements
- Elements are associated to an explicit **index**
  - index elements can be either strings or integers
- Examples:



Pandas Series

- **Creation** from list
  - When not specified, index is set automatically with a progressive number

In [1]:

```
import pandas as pd
s1 = pd.Series([2.0, 3.1, 4.5])
print(s1)
```

Out[1]:

```
0    2.0
1    3.1
2    4.5
```

Pandas Series

- **Creation** from list, specifying index

In [1]:
```
pd.Series([2.0, 3.1, 4.5], index=['mon', 'tue', 'wed'])
```

Out[1]:
```
'mon'    2.0
'tue'    3.1
'wed'    4.5
```

Pandas Series

- **Creation** from dictionary
  - keys define the index

In [1]:
```
pd.Series({'c':2.0, 'b':3.1, 'a':4.5})
```

Out[1]:
```
'c'    2.0
'b'    3.1
'a'    4.5
```

- Obtaining **values** and **index** from a Series

In [1]:
```
s1 = pd.Series([2.0, 3.1, 4.5], index=['mon', 'tue', 'wed'])
print(s1.values)   # Numpy array
print(s1.index)
```

Out[1]:
```
[2.0, 3.1, 4.5]
Index(['mon', 'tue', 'wed'], dtype='object')
```

- **Index** is a custom Python object defined in Pandas

- Accessing Series elements
- **Access by Index**
  - **Explicit:** the one specified while creating a Series
    - Use the Series.**loc** attribute
  - **Implicit:** number associated to the element order (similarly to Numpy arrays)
    - Use the Series.**iloc** attribute

- Accessing Series elements

In [1]:

```
s1 = pd.Series([2.0, 3.1, 4.5], index=['a', 'b', 'c'])
print(s1.loc['a'])           # With explicit index
print(s1.iloc[0])            # With implicit index
s1.loc['b'] = 10             # Allows editing values
print(f"Series:\n{s1}")
```

Out[1]:

```
2.0
2.0
Series:
'a'    2.0
'b'    10
'c'    4.5
```

- Accessing Series elements: **slicing**

In [1]:

```
s1 = pd.Series([2.0, 3.1, 4.5], index=['a', 'b', 'c'])
print(s1.loc['b':'c']) # explicit index (stop element included)
print(s1.iloc[1:3])    # implicit index (stop element excluded)
```

Out[1]:

```
b 3.1
c 4.5


b 3.1
c 4.5
```

- Accessing Series elements: **masking**

In [1]:

```
s1 = pd.Series([2.0, 3.1, 4.5], index=['a', 'b', 'c'])
print(s1[(s1>2) & (s1<10)])
```

Out[1]:

```
b 3.1
c 4.5
```

Pandas Series

- Accessing Series elements: **fancy indexing**

In [1]:

```
s1 = pd.Series([2.0, 3.1, 4.5], index=['a', 'b', 'c'])
print(s1.loc[['a', 'c']])
```

Out[1]:

```
a 2.0
c 4.5
```

- **DataFrame**: 2-Dimensional array
  - Can be thought as a table where **columns are Series** objects that share the **same index**
    - Each column has a **name**

- Example:

Index	'Price'	'Quantity'	'Liters'
'Water'	1.0	5	1.5
'Beer'	1.4	10	0.3
'Wine'	5.0	8	1

- **Creation** from Series
  - Use a **dictionary** to set column names

In [1]:
```
price = pd.Series([1.0, 1.4, 5], index=['a', 'b', 'c'])
quantity = pd.Series([5, 10, 8], index=['a', 'b', 'c'])
liters = pd.Series([1.5, 0.3, 1], index=['a', 'b', 'c'])
df = pd.DataFrame({'Price':price, 'Quantity':quantity,
                   'Liters':liters})
print(df)
```

Out[1]:
```
   Price  Quantity  Liters
a    1.0         5     1.5
b    1.4        10     0.3
c    5.0         8     1.0
```

Pandas DataFrame

- **Creation** from list of dictionaries
  - **Each dictionary** is associated to a **row**
  - **Index** is automatically set to a progressive number
- Example:

In [1]:
```
dic_list = [{'c1':i, 'c2':2*i} for i in range(3)]
df = pd.DataFrame(dic_list)
print(df)
```

Out[1]:
```
    c1     c2
0    0      0
1    1      2
2    2      4
```

- **Creation** from 2D Numpy array
- Example:

In [1]:
```
arr = np.arange(6).reshape((3,2))
df = pd.DataFrame(arr, columns=['c1', 'c2'],
                       index=['a', 'b', 'c'])
print(df)
```

Out[1]:
```
    c1    c2
a    0     1
b    2     3
c    4     5
```

- Load DataFrame from **csv** file
  - Allows specifying the column **delimiter (sep)**
  - Automatically read **header** from first line of the file (after **skipping** the specified number of rows)
  - Column data types are inferred

```
df = pd.read_csv('./mycsv.csv', sep=',', skiprows=1)
```

mycsv.csv

```
MyTitle
c1,c2,c3
0,1,2
3,4,5
6,7,8
```

→

	c1	c2	c3
0	0	1	2
1	3	4	5
2	6	7	8

- Load DataFrame from **csv** file
  - If it contains **null** values, you can specify how to recognize them
  - The string 'NaN' is automatically recognized

```
df = pd.read_csv('./mycsv.csv', sep=',',
                 na_values=['no info', 'x'])
```

mycsv.csv

```
c1,c2,c3
0,no info,2
3,4,5
6,x,NaN
```

→

	c1	c2	c3
0	0	NaN	2
1	3	4	5
2	6	NaN	NaN

- **Save** DataFrame to csv

```
df.to_csv('./savedcsv.csv', sep=',')
```

	c1	c2	c3
0	0	NaN	2
1	3	4	5
2	6	NaN	NaN

savedcsv.csv

```
 c1,c2,c3
0,0,,2
1,3,4,5
2,6,,
```

- Use **index=False** to avoid writing the index

```
df.to_csv('./savedcsv.csv', sep=',', index=False)
```

- Load DataFrame from **json** file

```
df = pd.read_json('./myjson.json')
```

myjson.csv

```
{"c1":{"0":0, "1":3, "2":6},
"c2":{"0":null, "1":4, "2":null},
"c3":{"0":2, "1":5, "2":null}}
```

→

	c1	c2	c3
0	0	NaN	2
1	3	4	5
2	6	NaN	NaN

- Use **pd.to_json(path)** to save a DataFrame in json format

DataFrames and I/O

- Many other data types are supported
  - Excel, HTML, HDF5, SAS, …
- Check the pandas documentation
  - https://pandas.pydata.org/pandas-docs/stable/user_guide/io.html

- Obtaining **column names** and **index** from a DataFrame

Index	Price	Quantity	Liters
a	1.0	5	1.5
b	1.4	10	0.3
c	5.0	8	1

In [2]:

```
print(df.columns)  # Index object with column names
print(df.index)    # Index object
```

Out[2]:

```
Index(['Price', 'Quantity', 'Liters'], dtype='object')
Index(['a', 'b', 'c'], dtype='object')
```

- **Accessing** DataFrame data
  - Get a 2D Numpy array

Index	Price	Quantity	Liters
a	1.0	5	1.5
b	1.4	10	0.3
c	5.0	8	1

In [2]:
```
print(df.values)   # Numpy array with data
```

Out[2]:
```
array([[1.0, 5.0, 1.5],
       [1.4, 10.0, 0.3],
       [5.0, 8.0, 1.0]])
```

- **Accessing** DataFrames
  - Access a DataFrame column
  - Access rows and columns with indexing
    - **df.loc**
      - **Explicit** index
      - Slicing, masking, fancy indexing
    - **df.iloc**
      - **Implicit** index
- Whether a **copy** or **view** will be returned it depends on the context
  - Usually it is difficult to make assumptions

- **Accessing** DataFrame columns
  - Returns a **Series** with column data

Index	Price	Quantity	Liters
a	1.0	5	1.5
b	1.4	10	0.3
c	5.0	8	1

In [1]:

```
df['Quantity']
```

Out[1]:

```
a     5
b    10
c     8
```

Pandas DataFrame

- **Accessing** single DataFrame **row** by index
  - **loc** (explicit), **iloc** (implicit)
  - Return a **Series** with an element for each column

In [1]:

```
print(df.loc['a'])          # Get the first row (explicit)
print(df.iloc[0])           # Get the first row
```

Out[1]:

```
Price    1.0
Quantity 5.0
Liters   1.5


Price    1.0
Quantity 5.0
Liters   1.5
```

- **Accessing** DataFrames with **slicing**
  - Allows selecting rows and columns

In [1]:

```
print(df.loc['b':'c', 'Quantity':'Liters'])
```

Out[1]:

```
     Quantity   Liters
b          10      0.3
c           8        1
```

Pandas DataFrame

- **Accessing** DataFrames with **masking**
  - Select rows based on a condition

Index	Price	Quantity	Liters
a	1.0	**5**	**1.5**
b	1.4	10	0.3
c	5.0	8	1

In [1]:

```
mask = (df['Quantity']<10) & (df['Liters']>1)
df.loc[mask, 'Quantity':]   # Use mask and slicing
```

Out[1]:

```
     Quantity   Liters
a           5      1.5
```

- **Accessing** DataFrames with **fancy indexing**
  - To select **columns**…

Index	Price	Quantity	Liters
a	**1.0**	5	**1.5**
b	1.4	10	0.3
c	5.0	8	1

In [1]:
```
mask = (df['Quantity']<10) & (df['Liters']>1)
df.loc[mask, ['Price','Liters']]   # Use mask and fancy
```

Out[1]:
```
     Price       Liters
a      1.0          1.5
```

- **Accessing** DataFrames with **fancy indexing**
  - To select **rows** and **columns**…

Index	**Price**	Quantity	**Liters**
a	**1.0**	5	**1.5**
b	1.4	10	0.3
c	**5.0**	8	**1**

In [1]:

```
df.loc[['a', 'c'], ['Price','Liters']]
```

Out[1]:

```
     Price       Liters
a        1.0         1.5
c        5.0         1.0
```

- **Assign value** to selected items

In [1]:
```
df.loc[['a', 'c'], ['Price','Liters']] = 0
```

Index	Price	Quantity	Liters
a	**0.0**	5	**0.0**
b	1.4	10	0.3
c	**0.0**	8	**0.0**

- **Add new column** to DataFrame
  - DataFrame is modified **inplace**

Index	Price	Quantity	Liters
a	**0.0**	5	**0.0**
b	1.4	10	0.3
c	**0.0**	8	**0.0**

→

Index	Price	Quantity	Liters	Available
a	1.0	5	1.5	True
b	1.4	10	0.3	False
c	5.0	8	1	True

In [1]:
```
df['Available'] = pd.Series([True, False, True],
                            index=['a', 'b', 'c'])
```

  - If the DataFrame already has a column with the specified name, then this is **replaced**

- **Add new column** to DataFrame
  - It is also possible to assign directly a **list**

Index	Price	Quantity	Liters
a	**0.0**	5	**0.0**
b	1.4	10	0.3
c	**0.0**	8	**0.0**

→

Index	Price	Quantity	Liters	Available
a	1.0	5	1.5	True
b	1.4	10	0.3	False
c	5.0	8	1	True

In [1]:
```
df['Available'] = [True, False, True]
```

Drop column(s)

- Returns a **copy** of the updated DataFrame

Index	Price	Quantity	Liters	Available
a	1.0	5	1.5	True
b	1.4	10	0.3	False
c	5.0	8	1	True

In [1]:

```
df = df.drop(columns=['Quantity', 'Liters'])
```

Rename column(s)

- Use a **dictionary** which maps old names with new names
- Returns a **copy** of the updated DataFrame

Index	Price	Quantity	Liters	Available
a	1.0	5	1.5	True
b	1.4	10	0.3	False
c	5.0	8	1	True

→

Index	Price	**nItems**	**[L]**	Available
a	1.0	5	1.5	True
b	1.4	10	0.3	False
c	5.0	8	1	True

In [1]:
```
df = df.rename(columns={'Quantity': 'nItems',
                        'Liters': '[L]'})
```

- Unary operations on Series and DataFrames
  - exponentiation, logarithms, …
- Operations between Series and DataFrames
  - Operations are performed **element-wise**, being aware of their **indices**
- Aggregations (min, max, std, …)

Computation with Pandas

- Unary operations on Series and DataFrames
  - They work with any **Numpy** ufunc
  - The operation is applied to each element of the Series/DataFrame
- Examples:
  - res = my_series/4 + 1
  - res = np.abs(my_series)
  - res = np.exp(my_dataframe)
  - res = np.sin(my_series/4)
  - ...

- Operations between Series (+,-,*,/)
  - Applied element-wise after **aligning indices**
    - Index elements which do not match are set to **NaN** (Not a Number)
  - Example:
    - res = my_series1 + my_series2

After index alignment index in the result is **sorted**

my_series1

Index	
b	3
a	1
c	**10**

my_series2

Index	
a	1
b	3
d	**30**

res

Index	
a	2
b	6
c	**NaN**
d	**NaN**

Computation with Pandas

- Operations between DataFrames
  - Applied element-wise after **aligning indices** and **columns**
  - Example (align **index**):
    - res = my_dataframe1 + my_dataframe2

Index in the result is **sorted**

Index	Total	Quantity
b	3	4
a	1	2
c	**10**	**20**

my_dataframe1

Index	Total	Quantity
a	1	2
b	3	4
d	**30**	**40**

my_dataframe2

Index	Total	Quantity
a	2	4
b	6	8
c	**NaN**	**NaN**
d	**NaN**	**NaN**

res

- Operations between DataFrames
  - Example (align **columns**)
    - res = my_dataframe1 + my_dataframe2

Columns in the result are **sorted**

Index	Total	Quantity
a	1	**2**
b	3	**4**
c	5	**6**

my_dataframe1

Index	Total	Price
a	1	**2**
b	3	**4**
c	5	**6**

my_dataframe2

Index	Price	Quantity	Total
a	**NaN**	**NaN**	2
b	**NaN**	**NaN**	6
c	**NaN**	**NaN**	10

res

- Operations between DataFrames and Series
  - The operation is applied between the Series and each **row** of the DataFrame
    - Follows **broadcasting** rules
  - Example:
    - res = my_dataframe1 + my_series1

Index	Total	Quantity
a	1	2
b	3	4
c	5	6

my_dataframe1

Index	
Total	1
Quantity	2

my_series1

Index	Total	Quantity
a	2	4
b	4	6
c	6	8

res

- Pandas Series and DataFrames allow performing aggregations
  - mean, std, min, max, sum
- Examples

In [1]:
```
my_series.mean()   # Return the mean of Series elements
```

  - For DataFrames, aggregate functions are applied **column-wise** and return a Series

In [1]:
```
my_df.mean()       # Return a Series
```

- Example of **aggregations** with DataFrames: z-score normalization

In [1]:
```
mean_series = df.mean()
std_series = df.std()
df_norm = (df-mean_series)/std_series
```

Index	Total	Quantity
a	1	2
b	3	4
c	5	6

my_dataframe1

Index	
Total	3.0
Quantity	4.0

mean_series

Index	
Total	2.0
Quantity	2.0

std_series

Missing values

- Represented with **sentinel** value
  - **None**: Python null value
  - **np.nan**: Numpy Not A Number
- None is a Python **object**:
  - np.array([4, None, 5]) has dtype=Object
- np.NaN is a **Floating point** number
  - np.array([4, np.nan, 5]) has dtype=Float

- Using **nan** achieves better **performances** when performing numerical computations

Missing values

- Pandas supports both **None** and **NaN**, and automatically converts between them when appropriate
- Example:

In [1]:
```
pd.Series([4, None, 5, np.nan])
```

Out[1]:
```
0    4.0
1    NaN
2    5.0
3    NaN
dtype=float64
```

Missing values

- Operating on missing values (for Series and DataFrames)
  - isnull()
    - Return a boolean mask indicating null values
  - notnull()
    - Return a boolean mask indicating not null values
  - dropna()
    - Return filtered data containing null values
  - fillna()
    - Return new data with filled or input missing values

Missing values

- Operating on missing values: **isnull, notnull**
  - Return a new Series/DataFrame with the same shape as the input

In [1]:

```
s1 = pd.Series([4, None, 5, np.nan])
s1.isnull()
```

Out[1]:

```
0     False
1     True
2     False
3     True
dtype=bool
```

Missing values

- Operating on missing values: **dropna**
  - For Series it removes null elements

In [1]:
```
s1 = pd.Series([4, None, 5, np.nan])
s1.dropna()
```

Out[1]:
```
0     4.0
2     5.0
dtype=float64
```

Missing values

- Operating on missing values: **dropna**
  - For DataFrames it removes **rows** that contain at least a missing value (default behaviour)

Index	Total	Quantity
a	1	2
b	3	NaN
c	5	6

→

Index	Total	Quantity
a	1	2
c	5	6

  - Alternatively, it is possible to remove columns

```
dropped_df = df.dropna(axis='columns')
```

Missing values

- Operating on missing values: **fillna**
  - Fill null fields with a specified value (for both Series and DataFrames)

In [1]:

```
s1 = pd.Series([4, None, 5, np.nan])
s1.fillna(0)
```

Out[1]:

```
0    4.0
1    0.0
2    5.0
3    0.0
dtype=float64
```

- Operating on missing values: **fillna**
  - The parameter **method** allows specifying different filling techniques
    - **ffill**: propagate last valid observation forward
    - **bfill**: use next valid observation to fill gap

In [1]:
```
s1 = pd.Series([4, None, 5, np.nan])
s1.fillna(method='ffill')
```

Out[1]:
```
0    4.0
1    4.0
2    5.0
3    5.0
```

Notebook Examples

- **3-Pandas Examples.ipynb**
  - **1. Accessing DataFrames and Series**

Combining Pandas objects

- Pandas provides 2 methods for combining Series and DataFrames
  - concat()
    - Concatenate a sequence of Series/DataFrames
  - append()
    - Append a Series/DataFrame to the specified object

- Concatenating 2 Series
  - Index is preserved, even if **duplicated**

In [1]:

```
s1 = pd.Series(['a', 'b'], index=[1,2])
s2 = pd.Series(['c', 'd'], index=[1,2])
pd.concat((s1, s2))
```

Out[1]:

```
1    a
2    b
1    c
2    d
dtype=object
```

- Concatenating 2 Series
  - To avoid duplicates use **ignore_index**

In [1]:
```
s1 = pd.Series(['a', 'b'], index=[1,2])
s2 = pd.Series(['c', 'd'], index=[1,2])
pd.concat((s1, s2), ignore_index=True)
```

Out[1]:
```
0    a
1    b
2    c
3    d
dtype=object
```

Combining Pandas objects

- Concatenating 2 DataFrames
  - Concatenate **vertically** by default

In [1]:
```
pd.concat((df1, df2))
```

Index	Total	Quantity
a	1	2
b	3	4

Index	Total	Quantity
c	5	6
d	7	8

→

Index	Total	Quantity
a	1	2
b	3	4
c	5	6
d	7	8

Combining Pandas objects

- Concatenating 2 DataFrames
  - Missing columns are filled with NaN

In [1]:
```
pd.concat((df1, df2))
```

Index	Total	Quantity
a	1	2
b	3	4

Index	Total	Quantity	Liters
c	5	6	1
d	7	8	2

→

Index	Total	Quantity	Liters
a	1	2	**NaN**
b	3	4	**NaN**
c	5	6	1
d	7	8	2

Combining Pandas objects

- The **append**() method is a shortcut for concatenating DataFrames
  - Returns the result of the concatenation

In [1]:
```
df_concat = df1.append(df2)
```

is equivalent to:

In [1]:
```
df_concat = pd.concat((df1, df2))
```

Combining Pandas objects

- Joining DataFrames with relational algebra: **merge**()
  - Column(s) with the same name in the two DataFrames are used as key
  - Depending on the DataFrames, a **one-to-one**, **many-to-one** or **many-to-many** join can be performed
  - Indices of the input DataFrames are **discarded**

In [1]:

```
joined_df = pd.merge(df1, df2)
```

Examples

one-to-one

Index	**k1**	c2
i1	0	a
i2	1	b

Index	**k1**	c3
i1	1	b1
i2	0	a1

→

Index	**k1**	c2	c3
0	0	a	a1
1	1	b	b1

many-to-one

Index	**k1**	c2
i1	0	a
i2	1	b
i3	0	c
i4	1	d

Index	**k1**	c3
i1	1	b1
i2	0	a1

→

Index	**k1**	c2	c3
0	0	a	a1
1	0	c	a1
2	1	b	b1
3	1	d	b1

Grouping data

- Pandas provides the equivalent of the SQL group by statement
- It allows the following operations:
  - **Iterating** on groups
  - **Aggregating** the values of each group (mean, min, max, …)
  - **Filtering** groups according to a condition

- **Applying** group by
  - Specify the column where you want to group (**key**)
  - Obtain a DataFrameGroupBy object

```
df = pd.DataFrame({'k' : ['a','b','a','b'],
                   'c1': [2,10,3,15], 'c2' : [4,20,5,30]})
grouped_df = df.groupby('k')   # 2 groups: 'a' and 'b'
```

Index	k	c1	c2
0	a	2	4
1	b	10	20
2	a	3	5
3	b	15	30

→

Index	k	c1	c2
0	a	2	4
2	a	3	5
1	**b**	**10**	**20**
3	**b**	**15**	**30**

- **Iterating** on groups
  - Each group is a subset of the original DataFrame

In [1]:

```
for key, group_df in grouped_df:
    print(key)
    print(group_df)
```

Out[1]:

```
a
    k1  c1   c2
0   a    2    4
2   a    3    5
b
    k1  c1   c2
1   b   10   20
3   b   15   30
```

Index	k1	c1	c2
0	a	2	4
2	a	3	5

Index	k1	c1	c2
1	b	10	20
3	b	15	30

Grouping data

- **Aggregating** by group (min, max, mean, std)
  - The output is a DataFrame with the result of the aggregation for each group

In [1]:
```python
grouped_df.mean()  # Mean, separately for each group
```

Out[1]:

k	c1	c2
a	2.5	4.5
b	12.5	25.0

Index	k1	c1	c2
0	a	2	4
2	a	3	5

Index	k1	c1	c2
1	b	10	20
3	b	15	30

The index of the result is the key of each group

- **Aggregating** a single column by group
  - The output is a Series with the result of the aggregation for each group

In [1]:

```
grouped_df['c1'].mean()
```

Out[1]:

```
k
a     2.5
b    12.5
Name: c1, dtype=float64
```

Index	k1	c1	c2
0	a	**2**	4
2	a	**3**	5

Index	k1	c1	c2
1	b	**10**	20
3	b	**15**	30

- **Filtering** data by group
  - The filter is expressed with a lambda function working with each group DataFrame (x)

In [1]:
```python
# Keep groups for which column c1 has a mean > 5
grouped_df.filter(lambda x: x['c1'].mean()>5)
```

Out[1]:

	k	c1	c2
1	b	10	20
3	b	15	30

Index	k1	c1	c2
0	a	**2**	4
2	a	**3**	5

mean = 2.5
x: filtered out

Index	k1	c1	c2
1	b	**10**	20
3	b	**15**	30

mean = 12.5
x: kept in the result

Pivoting

- Pivoting allows inspecting relationships within a dataset
- Suppose to have the following dataset:

```
df = pd.DataFrame({'type':['a','b','b','a','b','a','b','a'],
                   'class':[3,2,3,3,2,1,1,2],
                   'fail':[1,1,1,0,1,0,0,0]})
```

Index	type	class	fail
0	a	3	1
1	b	2	1
2	b	3	1
3	a	3	0
4	b	2	1
5	a	1	0
6	b	1	0
7	a	2	0

- that shows **failures** for sensors of a given type and class during some test

Pivoting

In [1]:
```
df.pivot_table('fail', index='type',
               columns='class', aggfunc='sum')
```

- Shows the number of **failures** for all the combinations of **type** and **class**

Out[1]:
```
class   1  2  3
type
a       0  0  1
b       0  2  1
```

2 sensors of type b and class 2 had some failure

Index	type	class	fail
0	a	3	1
1	**b**	**2**	**1**
2	b	3	1
3	a	3	0
4	**b**	**2**	**1**
5	a	1	0
6	b	1	0
7	a	2	0

Pivoting

In [1]:
```
df.pivot_table('fail', index='type',
               columns='class', aggfunc='mean')
```

- Shows the percentage of **failures** for all the combinations of **type** and **class**

Out[1]:
```
class     1    2    3
type
a       0.0  0.0  0.5
b       0.0  1.0  1.0
```

50% of sensors of type a and class 3 had some failure

Index	type	class	fail
0	**a**	**3**	**1**
1	b	2	1
2	b	3	1
3	**a**	**3**	**0**
4	b	2	1
5	a	1	0
6	b	1	0
7	a	2	0

Multi-Index

- **Multi-Index** allows specifying an index hierarchy for
  - Series
  - DataFrames
- Example: index a Series by city and year

index	city	Rome	Rome	Turin	Turin
	year	2018	2019	2018	2019
values		10	13	7	9

Multi-Index

- Building a **multi-indexed Series**

In [1]:

```
ix = [['Rome', 'Rome', 'Turin', 'Turin'],
      ['2018', '2019', '2018', '2019']]
s1 = pd.Series([10,13,7,9], index=ix)
s1 = s1.sort_index()  # Multi-Index must be sorted
                      # if you want to use slicing
print(s1)
```

Out[1]:

```
Rome    2018    10
        2019    13
Turin   2018     7
        2019     9
```

- **Naming** index levels

In [1]:
```
s1.index.names=['city', 'year']
print(s1)
```

Out[1]:
```
city   year
Rome   2018    10
       2019    13
Turin  2018     7
       2019     9
```

- **Accessing index levels**
  - **Slicing** and **simple indexing** are allowed
  - Slicing on index levels follows Numpy rules

In [1]:
```
print(s1.loc['Rome'])       # Outer index level
print(s1.loc[:,'2018'])    # All cities, only 2018
```

Out[1]:
```
year
2018     10
2019     13

city
Rome      10
Turin      7
```

Rome	Rome	Turin	Turin
2018	2019	2018	2019
10	13	7	9

Accessing index levels (Examples)

In [1]:

```
print(s1.loc['Turin', '2018':'2019'])
print(s1[s1>10])     # Masking
```

Out[1]:

```
city    year
Turin   2018     7
        2019     9

city   year
Rome   2019     13
```

Rome	Rome	Turin	Turin
2018	2019	2018	2019
10	13	7	9

- **Multi-indexed DataFrame**
  - Specify a multi-index for **rows**
  - **Columns** can be multi-indexed as well

		Humidity		**Temperature**	
		max	min	max	min
Turin	2018	33	48	6	33
	2019	35	45	5	35
Rome	2018	40	59	2	33
	2019	41	57	3	34

- **Multi-indexed DataFrame: creation**

In [1]:

```
ix = [['Rome', 'Rome', 'Turin', 'Turin'],
      ['2018', '2019', '2018', '2019']]
cols = [['c1','c1','c2','c2'],['a','b','a','b']]
data = np.arange(16).reshape((4,4))
df = pd.DataFrame(data, index=ix, columns=cols)
print(df)
```

Out[1]:

```
            c1      c2
            a   b   a   b
Rome  2018  0   1   2   3
      2019  4   5   6   7
Turin 2018  8   9   10  11
      2019  12  13  14  15
```

- **Multi-indexed DataFrame:** access with **outer** index level

In [1]:

```
print(df['c1'])                 # Access by column
print(df.loc['Rome', 'c1']) # Access rows and cols
```

Out[1]:

```
            a   b
Rome  2018  0   1
      2019  4   5
Turin 2018  8   9
      2019  12  13

      a  b
2018  0  1
2019  4  5
```

		c1		c2	
		a	b	a	b
Rome	2018	0	1	2	3
	2019	4	5	6	7
Turin	2018	8	9	10	11
	2019	12	13	14	15

- **Multi-indexed DataFrame:** access with **outer** and **inner** index levels

In [1]:
```
df['c1', 'a']                # Access by column
```

Out[1]:
```
Rome   2018    0
       2019    4
Turin  2018    8
       2019   12
```

		c1		c2	
		a	b	a	b
Rome	**2018**	**0**	1	2	3
	2019	**4**	5	6	7
Turin	**2018**	**8**	9	10	11
	2019	**12**	13	14	15

- **Multi-indexed DataFrame:** access with **outer** and **inner** index levels

In [1]:

```
ix = pd.IndexSlice
df.loc[ix['Rome', '2018'], ix['c1':'c2', 'a']]
```

Out[1]:

```
c1  a    0
c2  a    2
```

		c1		c2	
		a	b	a	b
Rome	**2018**	**0**	1	**2**	3
	2019	4	5	6	7
Turin	2018	8	9	10	11
	2019	12	13	14	15

- **Reset Index:** transform index to DataFrame columns

In [1]:

```
df.index.names = ['city', 'year']
df_reset = df.reset_index()
print(df_reset)
```

Out[1]:

	city	year	c1		c2	
			a	b	a	b
0	Rome	2018	0	1	2	3
1	Rome	2019	4	5	6	7
2	Turin	2018	8	9	10	11
3	Turin	2019	12	13	14	15

- **Set Index:** transform columns to Multi-Index
  - Inverse function of reset_index()

In [1]:
```
df_reset.set_index(['city', 'year'])
```

	city	year	c1		c2	
			a	b	a	b
0	Rome	2018	0	1	2	3
1	Rome	2019	4	5	6	7
2	Turin	2018	8	9	10	11
3	Turin	2019	12	13	14	15

→

city	year	c1		c2	
		a	b	a	b
Rome	2018	0	1	2	3
	2019	4	5	6	7
Turin	2018	8	9	10	11
	2019	12	13	14	15

- **Unstack:** transform multi-indexed Series to a Dataframe

```
myseries.unstack()
```

city	year	
Rome	2018	0
	2019	4
Turin	2018	8
	2019	12

→

	2018	2019
Rome	0	4
Turin	8	12

Multi-Index

- **Stack:** inverse function of unstack
  - From DataFrame to multi-indexed Series

```
mydataframe.stack()
```

	2018	2019
Rome	0	4
Turin	8	12

→

city	year	
Rome	2018	0
	2019	4
Turin	2018	8
	2019	12

PoliTo DBMG

Aggregates on multi-indices

- Allowed by passing the **level** parameter
- Level specifies the **row granularity** at which the result is computed

```
my_dataframe.max(level='city')
```

city	year	c1		c2	
		a	b	a	b
Rome	2018	0	1	2	3
	2019	4	5	6	7
Turin	2018	8	9	10	11
	2019	12	13	14	15

→

city	c1		c2	
	a	b	a	b
Rome	4	5	6	7
Turin	12	13	14	15

- **Aggregates on multi-indices**

```
my_dataframe.max(level='year')
```

city	year	c1		c2	
		a	b	a	b
Rome	2018	0	1	2	3
	2019	4	5	6	7
Turin	2018	8	9	10	11
	2019	12	13	14	15

→

year	c1		c2	
	a	b	a	b
2018	8	9	10	11
2019	12	13	14	15

Aggregates on multi-indices

- Can also aggregate columns
  - Specify axis=1

```
my_dataframe.max(axis=1, level=0)
```

city	year	c1		c2	
		a	b	a	b
Rome	2018	0	1	2	3
	2019	4	5	6	7
Turin	2018	8	9	10	11
	2019	12	13	14	15

→

city	year	c1	c2
Rome	2018	1	3
Rome	2019	5	7
Turin	2018	9	11
Turin	2019	13	15