

# Chapter 6

## Data Manipulation with Pandas



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# About Authors



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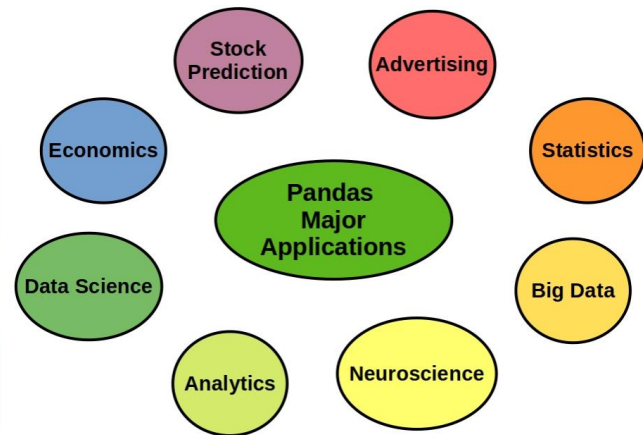
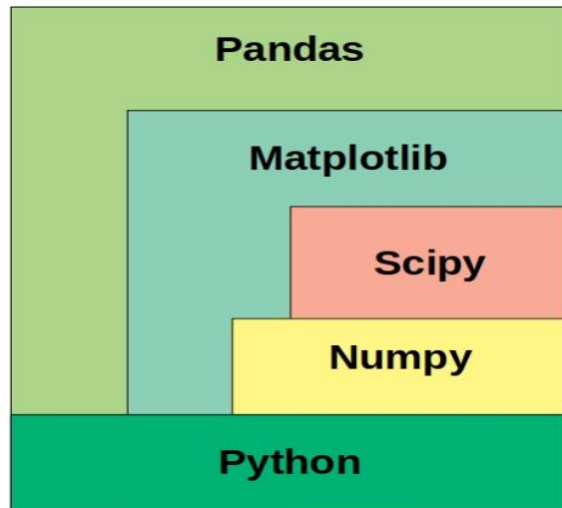
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- Introduction
- Pandas Getting Started With
- Pandas vs SQL
- Pandas Features
- Pandas Data Structure
- Operations on Pandas
- Working with text data
- Working with time series data

→ **Pandas** is an essential tool to data analysis and manipulation.



# Pandas Getting Started



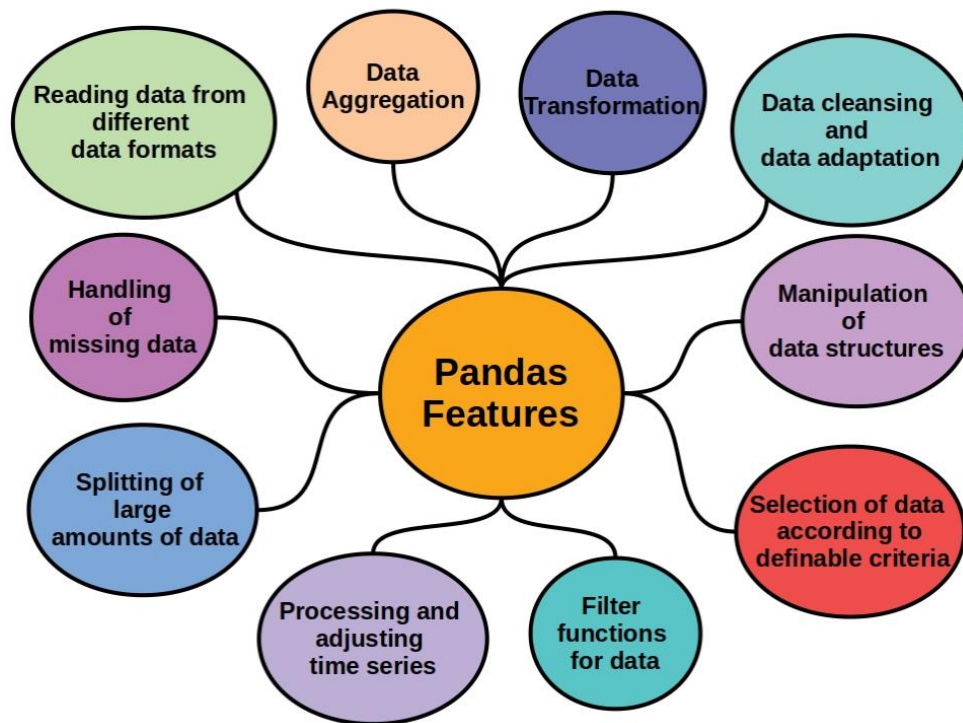
- Installing Numpy: `pip install pandas`
- Import Numpy: `import pandas`
- Alias of Numpy: `import pandas as pd`
- Check Numpy version: `pd.__version__`

# Why uses Pandas?



- one of the most widely used data science libraries in the world.
- capable of handling huge sets of data.
- Useful for data analysis and machine learning
- Working with data in a new way
- *“to master data science, you must be skillful in Pandas”*

# Pandas Features

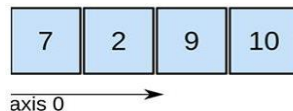


# Pandas Data Structure

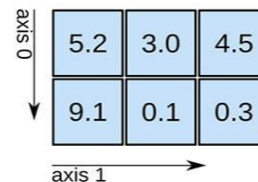


Data Structure	Dimension	Description
Series	1	<ul style="list-style-type: none"> <li>1Dimentional</li> <li>Size Immutable</li> <li>Value of Data Mutable</li> </ul>
Data-Frame	2	<ul style="list-style-type: none"> <li>2Dimentional</li> <li>Size Mutable</li> <li>Heterogeneous columns typed</li> </ul>
Panel	3	<ul style="list-style-type: none"> <li>3Dimentional</li> <li>Size Mutable</li> </ul>

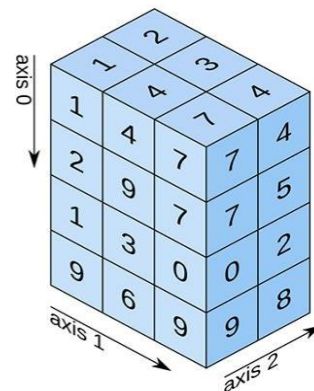
**SERIES**



**DATA FRAME**



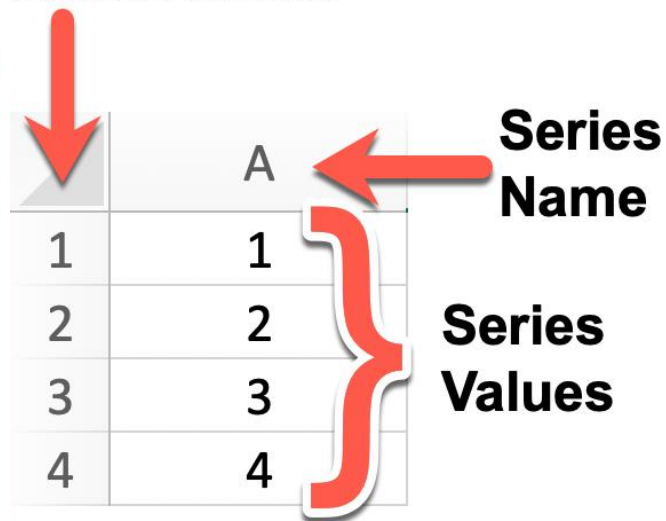
**PANEL**





→ a one-dimensional labeled array capable of holding any data type

## Series Index



	A
1	1
2	2
3	3
4	4

**Series Name**

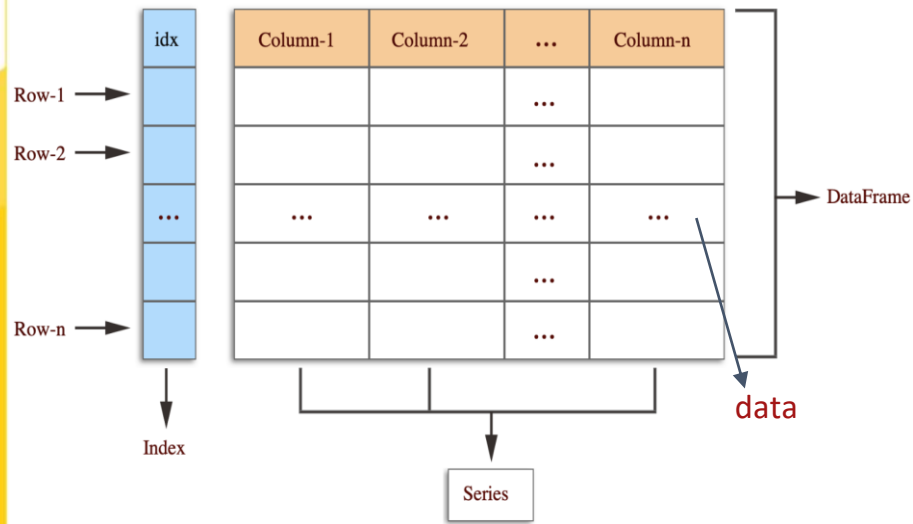
**Series Values**

```
s = pd.Series(np.random.randn(5), index=["a", "b", "c", "d", "e"])
s
```

```
a    0.115188
b    0.893129
c    0.659912
d    2.502990
e   -0.956800
dtype: float64
```

# Pandas DataFrame

→ is a 2 dimensional data structure with mutable size and potentially heterogeneous tabular data.



```
import pandas as pd
#create a simple dataframe of people
df = pd.DataFrame([["Anna", "New York", 20], ["Peter", "Paris", 15], ["John", "London", 18]],
                  columns=['Name', 'Location', 'Age'])
display(df)
```

	Name	Location	Age
0	Anna	New York	20
1	Peter	Paris	15
2	John	London	18

→ `pandas.DataFrame([data, index, columns, dtype, copy])`

- ◆ data – the data from which the dataframe will be made
- ◆ index – states the index from dataframe
- ◆ columns – states the column label
- ◆ dtype – the datatype for the dataframe
- ◆ copy – any copied data taken from inputs (**True/False**)

→ Create an empty DataFrame

```
import pandas as pd  
df = pd.DataFrame()
```

→ Create a DataFrame from the inputs like *dictionaries, ndarrays, Series, Lists*.

- a 3-dimensional container of data
- its origins in econometrics
- partially responsible for the name of the library pandas: panel datas.

# Pandas Panel Creation

- `pandas.Panel(data, items, major_axis, minor_axis, dtype, copy)`
- ◆ `data`: the data will be represented by the panel.
  - ◆ `items`: can represent and compare to a `DataFrame`.
  - ◆ `major-axis`: rows of a `DataFrame`.
  - ◆ `minor-axis`: columns of a `DataFrame`.
  - ◆ `copy`: Boolean value to denote whether data will be copied from inputs.
  - ◆ `dtype`: specifies a data type.

- Retrieving Data from **csv** file
- Handling of missing data
- Data Extraction/Filter
- Data Addition/Deletion
- Concatenation DataFrame
- Merging /Joining DataFrame
- Data Grouping

# Retrieving Data from CSV



- **CSV (*comma-separated value*)** files are a common file format for transferring and storing data.
- Using `read_csv()` function to retrieve data from CSV file , where the delimiter is a comma character.
- Demo

# Handling of missing data

	ID	Name	Age	Address	Qualification
0	I0	John	27	Chicago	Btech
1	I1	Jim	24	NaN	NaN
2	I2	Jackson	22	Texas	B.A
3	I3	Amy	32	New York	Bcom

## Missing data

- a very big problem in a real-life scenarios
- it exists and was not collected or it never existed
- represented for None and NaN (Not a Number) indicating missing or null values

- Checking for missing values using `isnull()` and `notnull()`
- Filling missing values using `fillna()`, `replace()` and `interpolate()`
- Dropping missing values using `dropna()`



# Data Extraction

→ Extract a column data of DataFrame by calling it by the column name.

```
df[['Location']]
```

	Name	Location	Age
0	Anna	New York	20
1	Peter	Paris	15
2	John	London	18

Location	
Anna	New York
Peter	Paris
John	London

Location Age		Name
Anna	New York	20
Peter	Paris	15
John	London	18

→ Extract a row data of DataFrame by using method `loc()` and `iloc()`.

```
df.loc['Peter']
df.iloc[1]
```

```
Location    Paris
Age         15
Name: Peter, dtype: object
```

# Data Filter

→ Using `filter()` method

`DataFrame.filter(items, like, regex, axis)`

- **item** – Takes list of axis labels that need to filter.
- **like** – Takes axis string label that need to filter
- **regex** – regular expression
- **axis** – {0 or 'index', 1 or 'columns', None}, default None. When not specified it used columns.

# Examples

```
df.filter(items=['Location'])
```

Location	
Anna	New York
Peter	Paris
John	London

```
df.filter(regex='e$', axis=1)
```

Age	
Anna	20
Peter	15
John	18

	Location	Age
Anna	New York	20
Peter	Paris	15
John	London	18

```
df.filter(like='er', axis=0)
```

	Location	Age
Peter	Paris	15

→ Adding a new column data: declare a new list as a column data and add to a existing Dataframe

```
# Declare a list that is to be converted into a column
height = [1.6, 1.8, 1.5]
#Using 'Height' as the column name and equating it to the list
df['Height'] = height
```

	Location	Age	Height
<b>Anna</b>	New York	20	1.6
<b>Peter</b>	Paris	15	1.8
<b>John</b>	London	18	1.5

→ Adding a new row data: concat the old dataframe with new one

```
#create a new row
new_row = pd.DataFrame({'Name':['Hoa'], 'Location':['Vietnam'], 'Age':[16], 'Height':[1.55]}, index=[0])
#concatenating the new row with the old dataframe
df=pd.concat([new_row,df]).reset_index(drop=True)
```

	Name	Location	Age	Height
<b>0</b>	Hoa	Vietnam	16	1.55
<b>1</b>	Anna	New York	20	1.60
<b>2</b>	Peter	Paris	15	1.80
<b>3</b>	John	London	18	1.50

→ Using the `drop()` method

→ Delete a column:

```
#Dropping columns with column names
df.drop(["Location"],axis=1, inplace = True)
```

	Name	Age	Height
0	Hoa	16	1.55
1	Anna	20	1.60
2	Peter	15	1.80
3	John	18	1.50

→ Deleting a new row: concat the old dataframe with new one

```
#Dropping row with index labels
df.drop([3], inplace = True)
```

	Name	Age	Height
0	Hoa	16	1.55
1	Anna	20	1.60
2	Peter	15	1.80

# Concatenating DataFrame

→ Using `concat()` method to combine DataFrames across axes

- axis=0 (rows)

	Column 0	Column 1	Column 2
0			
1			
2			

	Column 0	Column 1	Column 2
0			
1			
2			



	Column 0	Column 1	Column 2
0			
1			
2			
0			
1			
2			

- axis=1 (columns)

	Column 0	Column 1	Column 2
0			
1			
2			

	Column A	Column B	Column C
0			
1			
2			



	Column 0	Column 1	Column 2	Column A	Column B	Column C
0						
1						
2						

# Concatenating DataFrame



- ◆ With setting different logic on axes
  - Taking the union of them all with the argument join='outer' (default)
  - Taking the intersection with the argument join='inner'
- ◆ With ignoring indexes with the argument ignore\_index=True
- ◆ With group keys with the argument keys

# Examples

	Name	Location	Age
0	Anna	New York	20
1	Peter	Paris	15
2	John	London	18

	Name	Location	Age
3	Jim	Hensiki	21
2	John	London	29

```
# concating dataframe with axes and join='outer'
res2 = pd.concat([df, df2], axis=1, sort=False)
```

	Name	Location	Age	Name	Location	Age
0	Anna	New York	20.0	NaN	NaN	NaN
1	Peter	Paris	15.0	NaN	NaN	NaN
2	John	London	18.0	John	London	29.0
3	NaN	NaN	NaN	Jim	Hensiki	21.0

```
# concating dataframe
res=pd.concat([df,df2])
```

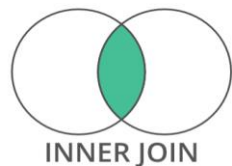
	Name	Location	Age
0	Anna	New York	20
1	Peter	Paris	15
2	John	London	18
3	Jim	Hensiki	21
2	John	London	18

```
# concating dataframe with axes and join='inner'
res=pd.concat([df,df2], axis=1,join='inner')
```

	Name	Location	Age	Name	Location	Age
2	John	London	18	John	London	29

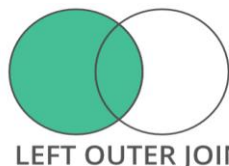


- Using `merge()` method to combine data on common columns or indices.
- Using `join()` method to combine the columns of two differently-indexed DataFrames into a single result DataFrame based on a key column or an index.



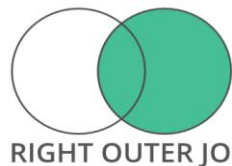
INNER JOIN

how= 'inner'



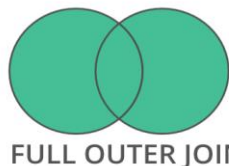
LEFT OUTER JOIN

how= 'left'



RIGHT OUTER JOIN

how= 'right'



FULL OUTER JOIN

how= 'outer'

- with one unique key combination  
on = [key]
- using multiple join keys  
on= [key1, key2, ...]

# Joining Examples

	Name	Age
I0	John	27
I1	Jim	24
I2	Jackson	22
I3	Amy	32

	Address	Qualification
I0	Chicago	Btech
I2	Texas	B.A
I3	New York	Bcom
I4	Florida	B.hons

```
# using join method to join dataframes (based on index)
res2 = df.join(df1)
```

	Name	Age	Address	Qualification
I0	John	27	Chicago	Btech
I1	Jim	24	NaN	NaN
I2	Jackson	22	Texas	B.A
I3	Amy	32	New York	Bcom

```
# getting union
res1 = df.join(df1, how='outer')
```

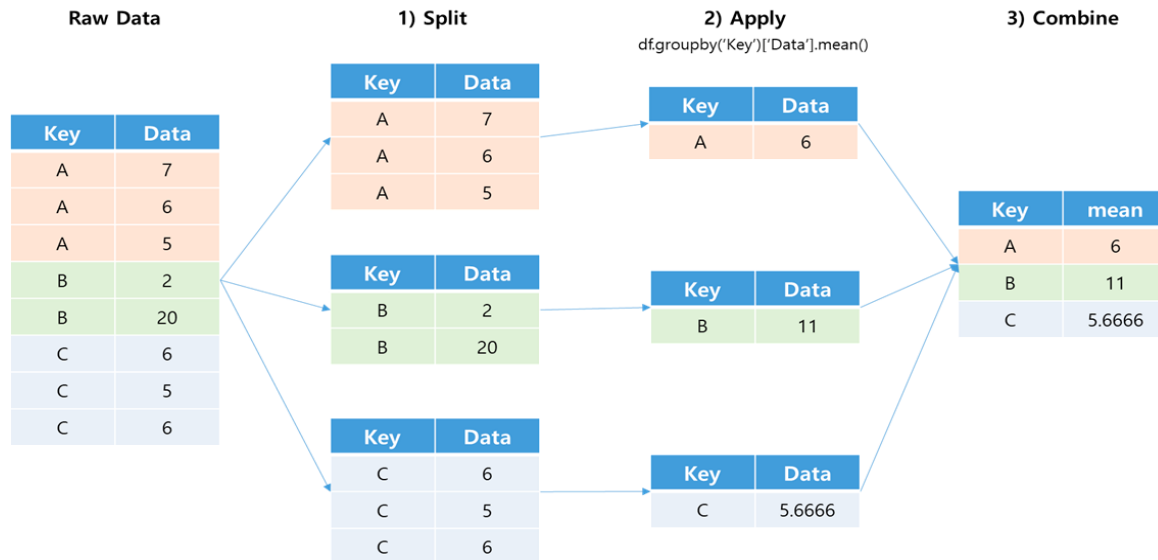
	Name	Age	Address	Qualification
I0	John	27.0	Chicago	Btech
I1	Jim	24.0	NaN	NaN
I2	Jackson	22.0	Texas	B.A
I3	Amy	32.0	New York	Bcom
I4	NaN	NaN	Florida	B.hons

# Data Grouping

→ grouping the data according to the categories and apply a function to the categories.

→ often involves 3 operations:

- *Splitting the Data Object*
- *Applying a function*
- *Combining the results*



# Examples of Splitting Data Objects



Using `groupby()` for splitting the dataframe over some criteria into data subsets.

- `groupby('key')`

```
df.groupby('Key').groups
{'A': [0, 1, 2], 'B': [3, 4], 'C': [5, 6, 7]}
```

- `groupby(['key1', 'key2'])`

```
df.groupby(['Key', 'Data']).groups
{('A', 5): [2], ('A', 6): [1], ('A', 7): [0], ('B', 2): [3], ('B', 20): [4], ('C', 5): [6], ('C', 6): [5, 7]}
```

	Key	Data
0	A	7
1	A	6
2	A	5
3	B	2
4	B	20
5	C	6
6	C	5
7	C	6

→ computing a summary statistic

<code>sum()</code>	Compute sum of column values	<code>first()</code>	Compute first of group values
<code>min()</code>	Compute min of column values	<code>last()</code>	Compute last of group values
<code>max()</code>	Compute max of column values	<code>count()</code>	Compute count of column values
<code>mean()</code>	Compute mean of column	<code>std()</code>	Standard deviation of column
<code>size()</code>	Compute column sizes	<code>var()</code>	Compute variance of column
<code>describe()</code>	Generates descriptive statistics	<code>sem()</code>	Standard error of the mean of column

→ Returns a self-produced dataframe with transformed values after applying the function specified in its parameter.

- ◆ `apply()`
- ◆ `applymap()`
- ◆ `melt()`
- ◆ `transform()`

# apply () function



→ Used to apply a function along an axis of the DataFrame.

`DataFrame.apply( func, axis, raw, reduce=None, result_type, args=(), **kws)`

- **func**: Function to apply to each column or row.
- **axis**: Axis along which the function is applied: 0 or 'index': apply function to each column; 1 or 'columns': apply function to each row.
- **raw**: **False** - passes each row or column as a Series to the function ; **True** - the passed function will receive ndarray objects instead.
- **result\_type**: only act when axis=1 (columns): 'expand' : list-like results will be turned into columns; 'reduce' : returns a Series if possible rather than expanding list-like results; 'broadcast' : results will be broadcast to the original shape of the DataFrame, the original index and columns will be retained.
- **arg()**: Positional arguments to pass to func in addition to the array/series.

<http://vk> **\*\*kws**: Additional keyword arguments to pass as keywords arguments to func.

# Examples



	P	Q
0	3.0	5.0
1	3.0	5.0
2	3.0	5.0

```
df.apply(np.sum, axis=1)
```

```
0    34
1    34
2    34
dtype: int64
```

```
df.apply(lambda x: [1, 2], axis=1)
```

```
0    [1, 2]
1    [1, 2]
2    [1, 2]
dtype: object
```

```
df.apply(lambda x: [1, 2], axis=1, result_type='expand')
```

	0	1
0	1	2
1	1	2
2	1	2

```
df.apply(lambda x: [1, 2], axis=1, result_type='broadcast')
```

	P	Q
0	1	2
1	1	2
2	1	2



# applymap () function



→ Used to apply a function to a Dataframe elementwise.

`DataFrame.apply( func)`

- **func**: Python function, returns a single value from a single value.

	0	1
0	2.000	3.120
1	4.356	5.567

```
df.applymap(lambda x: len(str(x)))
```

	0	1
0	3	4
1	5	5

```
df.applymap(lambda x: x**2)
```

	0	1
0	4.000000	9.734400
1	18.974736	30.991489

# `melt()` function



→ used to unpivot a given DataFrame from wide format to long format

`DataFrame.melt([id_vars], [value_vars], var_name, value_name, [col_level])`

- `[id_vars]`: column(s) to use as identifier variables.
- `[value_vars]`: column(s) to unpivot. If not specified, uses all columns that are not set as `id_vars`.
- `var_name`: name to use for the 'variable' column. If None it uses `frame.columns.name` or 'variable'.
- `value_name`: name to use for the 'value' column.
- `[col_level]`: if columns are a MultiIndex then use this level to melt.

# Examples

	P	Q	R
0	p	1	2
1	q	3	4
2	r	5	6

```
df.melt(id_vars=['P'], value_vars=['Q'])
```

	P	variable	value
0	p	Q	1
1	q	Q	3
2	r	Q	5

```
df.melt(id_vars=['P'], value_vars=['Q', 'R'])
```

	P	variable	value
0	p	Q	1
1	q	Q	3
2	r	Q	5
3	p	R	2
4	q	R	4
5	r	R	6

```
df.melt(id_vars=['P'], value_vars=['Q'],
        var_name='myVarname', value_name='myValname')
```

	P	myVarname	myValname
0	p	Q	1
1	q	Q	3
2	r	Q	5

```
df.melt(col_level=0, id_vars=['P'], value_vars=['Q'])
```

	P	variable	value
0	p	Q	1
1	q	Q	3
2	r	Q	5

# transform() function



→ used to call function (func) on self producing a DataFrame with transformed values and that has the same axis length as self.

```
DataFrame.transform(func, axis, *args, **kwargs)
```

- **func**: Function to use for transforming the data
- **axis**: 0 or 'index': apply function to each column; 1 or 'columns': apply function to each row.
- **\*args**: Positional arguments to pass to func.
- **\*\*kwargs**: Keyword arguments to pass to func.

# Examples

X	Y
0	0 2
1	1 3
2	2 4
3	3 5

```
df.transform(lambda x: x + 1)
```

X	Y
0	1 3
1	2 4
2	3 5
3	4 6

```
df.transform([np.sqrt, np.exp])
```

	X		Y	
	sqrt	exp	sqrt	exp
0	0.000000	1.000000	1.414214	7.389056
1	1.000000	2.718282	1.732051	20.085537
2	1.414214	7.389056	2.000000	54.598150
3	1.732051	20.085537	2.236068	148.413159

- a pandas data type corresponding to categorical variables in statistics, e.g. gender, social class, blood type,....
- Using the standard pandas `Categorical` constructor to create categorical object

`pandas.Categorical(values, categories, ordered)`

```
cat = pd.Categorical(['a', 'b', 'c', 'a', 'b', 'c'], categories=["b","a","c"], ordered=True)
cat
```

```
['a', 'b', 'c', 'a', 'b', 'c']
Categories (3, object): ['b' < 'a' < 'c']
```

- A **time series** is any data set where the values are measured at different points in time.
  - ◆ uniformly spaced. Eg. *hourly weather measurements, daily counts of web site visits, or monthly sales totals.*
  - ◆ irregularly spaced. Eg. *timestamped data in a computer system's event log, a history of 115 emergency calls*
- Pandas provides useful objects in working with time series data:
  - ◆ **Timestamp** Object
  - ◆ **Period** Object
  - ◆ **Timedelta** Object

→ **Period** object represents an interval in time used to check if a specific event occurs within a certain period such as when monitoring the number of flights taking off or the average stock price during a period.

```
# Create time period
p1 = pd.Period('2020-12-25')
# Create time stamp
t1 = pd.Timestamp('2020-12-25 18:12')
# Test Time interval
p1.start_time < t1 < p1.end_time
```



# The function `to_period()`



→ Used to convert a `DatetimeIndex` object to a `PeriodIndex`

```
period _daily= dates.to_period('D')  
# output  
PeriodIndex(['2020-12-25', '2020-07-04', '2018-10-06', '2017-07-07',  
            '2020-05-08', '2020-04-22'],  
            dtype='period[D]', freq='D')
```

```
period _daily= dates.to_period('M')  
# output  
PeriodIndex(['2020-12', '2020-07', '2018-10', '2017-07',  
            '2020-05', '2020-04'],  
            dtype='period[M]', freq='M')
```

→ represents the temporal difference between two `datetime` objects used to calculate the difference between two dates.

```
# Subtract a specific date from dates
dates - pd.to_datetime('2020-05-15')
TimedeltaIndex(['224 days 00:00:00', '50 days 00:00:00',
                '-587 days +00:00:00', '-1043 days +00:00:00',
                '-7 days +00:00:00', '-23 days +20:34:48'],
                dtype='timedelta64[ns]', freq=None)
```

# Date Range and Frequency



- Regular date sequences can be created using functions:
- ◆ The function `date_range()` for *timestamp*
  - ◆ The function `period_range()` for *periods*
  - ◆ The function `timedelta_range()` for *time deltas*

# Working with textual data



<b>lower()</b>	Converts strings in the Series/Index to lower case.
<b>upper()</b>	Converts strings in the Series/Index to upper case.
<b>len()</b>	Computes String length().
<b>strip()</b>	Helps strip whitespace(including newline) from each string in the Series/index from both the sides.
<b>split(' ')</b>	Splits each string with the given pattern.
<b>cat(sep=' ')</b>	Concatenates the series/index elements with given separator.
<b>get_dummies()</b>	Returns the DataFrame with One-Hot Encoded values.
<b>contains(pattern)</b>	Returns a Boolean value True for each element if the substring contains in the element, else False.
<b>replace(a,b)</b>	Replaces the value a with the value b.