# Data Manipulation and Cleaning with Python

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## Data Cleaning

Data cleaning is the process that removes data that does not belong in your dataset.

Data transformation is the process of converting data from one format or structure into another. Transformation processes can also be referred to as data wrangling, or data munging, transforming and mapping data from one "raw" data form into another format for warehousing and analyzing.

A data set (or dataset) is **a collection of data**. In the case of tabular data, a data set corresponds to one or more database tables, where every column of a table represents a particular variable, and each row corresponds to a given record of the data set in question

## Why Cleaning?

- Before data can be used **it needs to be cleaned**. This arduous process includes everything from removing duplicate values to missing outlier data. The more accurate your cleaning stage, the easier it will be to derive value from **datasets** in the data manipulation, algorithm learning, and modeling stages.
- In fact, the bulk of any data science-based project first requires effective data cleaning and manipulation.

## What is Data Manipulation/Cleaning?

- As a data scientist, upon beginning a project, you will need to start by gathering a variety of data sets, either by extracting them yourself from external websites, or by receiving them from different internal sources, depending on your requirements.
- Not all of the data you acquire will be relevant to your cause. In order to separate the relevant data from the irrelevant, you will need to cleanse the collected data sets. In other words, you may need to remove or modify columns, remove duplicate values, deal with missing values and outlier data, and so on. You may also need to normalize and scale your data in order for it to fit within a certain range.
- Data cleaning also includes the process of visualizing the data through the use of graphs and statistical functions in order to find the 'underlying data', also known as the 'mean', 'median', 'range', 'distribution', etc.

## Why is Data Manipulation/Cleansing Important to Data Scientists?

Before any data scientist can focus on modeling, they will need to master data cleaning. Depending on how effectively you can clean your data will determine how complicated your modeling will be. The more organized your data sets are in the cleansing stage, the simpler your learning algorithms will need to be in the modeling stage. The structure of your data will also have a direct impact on the precision of your projections.

In short, data cleansing is just as crucial as building the algorithms themselves. Once you have mastered data cleansing you can expect:

- Lower processing times
- More precise projections
- Simplified algorithm functionality
- Increased model learning

## Why Python?

**Python** is becoming the favored coding language in data science for many reasons. For one, it provides a variety of computation libraries that can be used for data science projects, including data manipulation and cleansing. In this article, we will be using the *Pandas* Python library.

## How do you clean data?

While the techniques used for data cleaning may vary according to the types of data your company stores, you can follow these basic steps to map out a framework for your organization.

Step 1: Remove duplicate or irrelevant observations

Remove unwanted observations from your dataset, including duplicate observations or irrelevant observations. Duplicate observations will happen most often during data collection. When you combine data sets from multiple places, scrape data, or receive data from clients or multiple departments, there are opportunities to create duplicate data. De-duplication is one of the largest areas to be considered in this process. Irrelevant observations are when you notice observations that do not fit into the specific problem you are trying to analyze.

- For example, if you want to analyze data regarding millennial customers, but your dataset includes older generations, you might remove those irrelevant observations. This can make analysis more efficient and minimize distraction from your primary target—as well as creating a more manageable and more performant dataset.

## Step 2: Fix structural errors

Structural errors are when you measure or transfer data and notice strange naming conventions, typos, or incorrect capitalization. These inconsistencies can cause mislabeled categories or classes. For example, you may find "N/A" and "Not Applicable" both appear, but they should be analyzed as the same category.

## Step 3: Filter unwanted outliers

Often, there will be one-off observations where, at a glance, they do not appear to fit within the data you are analyzing. If you have a legitimate reason to remove an outlier, like improper data-entry, doing so will help the performance of the data you are working with. However, sometimes it is the appearance of an outlier that will prove a theory you are working on. Remember: just because an outlier exists, doesn't mean it is incorrect. This step is needed to determine the validity of that number. If an outlier proves to be irrelevant for analysis or is a mistake, consider removing it.

## Step 4: Handle missing data

You can’t ignore missing data because many algorithms will not accept missing values. There are a couple of ways to deal with missing data. Neither is optimal, but both can be considered.

- As a first option, you can drop observations that have missing values, but doing this will drop or lose information, so be mindful of this before you remove it.
- As a second option, you can input missing values based on other observations; again, there is an opportunity to lose integrity of the data because you may be operating from assumptions and not actual observations.
- As a third option, you might alter the way the data is used to effectively navigate null values.

## Step 5: Validate and QA

At the end of the data cleaning process, you should be able to answer these questions as a part of basic validation:

- Does the data make sense?
- Does the data follow the appropriate rules for its field?
- Does it prove or disprove your working theory, or bring any insight to light?
- Can you find trends in the data to help you form your next theory?
- If not, is that because of a data quality issue?

False conclusions because of incorrect or “dirty” data can inform poor business strategy and decision-making. False conclusions can lead to an embarrassing moment in a reporting meeting when you realize your data doesn’t stand up to scrutiny. Before you get there, it is important to create a culture of quality data in your organization. To do this, you should document the tools you might use to create this culture and what data quality means to you.

## 5 characteristics of quality data

- **Validity.** The degree to which your data conforms to defined business rules or constraints.
- **Accuracy.** Ensure your data is close to the true values.
- **Completeness.** The degree to which all required data is known.
- **Consistency.** Ensure your data is consistent within the same dataset and/or across multiple data sets.
- **Uniformity.** The degree to which the data is specified using the same unit of measure.

## Benefits of data cleaning

Having clean data will ultimately increase overall productivity and allow for the highest quality information in your decision-making. Benefits include:

- Removal of errors when multiple sources of data are at play.
- Fewer errors make for happier clients and less-frustrated employees.
- Ability to map the different functions and what your data is intended to do.
- Monitoring errors and better reporting to see where errors are coming from, making it easier to fix incorrect or corrupt data for future applications.
- Using tools for data cleaning will make for more efficient business practices and quicker decision-making.

## Content

- Overview of Python Libraries for Data Scientists
- Reading Data; Selecting and Filtering the Data; Data manipulation, sorting, grouping, rearranging
- Plotting the data
- Descriptive statistics
- Inferential statistics

## Python Libraries for Data Science

Many popular Python toolboxes/libraries:

- NumPy
- SciPy
- Pandas
- SciKit-Learn

*All these libraries are installed on the SCC*

Visualization libraries

- matplotlib
- Seaborn

and many more …

## Python Libraries for Data Science

*NumPy:*

- introduces objects for multidimensional arrays and matrices, as well as functions that allow to easily perform advanced mathematical and statistical operations on those objects

- provides vectorization of mathematical operations on arrays and matrices which significantly improves the performance

- many other python libraries are built on NumPy

**Link:** http://www.numpy.org/

# Python Libraries for Data Science

*SciPy:*

- collection of algorithms for linear algebra, differential equations, numerical integration, optimization, statistics and more

- part of SciPy Stack

- built on NumPy

**Link:** https://www.scipy.org/scipylib/

# Python Libraries for Data Science

*Pandas:*

- adds data structures and tools designed to work with table-like data (similar to Series and Data Frames in R)
- provides tools for data manipulation: reshaping, merging, sorting, slicing, aggregation etc.
- allows handling missing data

**Link:** http://pandas.pydata.org/

# Python Libraries for Data Science

*SciKit-Learn:*

- provides machine learning algorithms: classification, regression, clustering, model validation etc.

- built on NumPy, SciPy and matplotlib

**Link:** http://scikit-learn.org/

# Python Libraries for Data Science

*matplotlib:*

- python 2D plotting library which produces publication quality figures in a variety of hardcopy formats
- a set of functionalities similar to those of MATLAB
- line plots, scatter plots, barcharts, histograms, pie charts etc.
- relatively low-level; some effort needed to create advanced visualization

**Link:** https://matplotlib.org/

matplotlib

# Python Libraries for Data Science

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**Link:** https://matplotlib.org/

# Python Libraries for Data Science

*Seaborn:*

- based on matplotlib
- provides high level interface for drawing attractive statistical graphics
- Similar (in style) to the popular ggplot2 library in R

**Link:** https://seaborn.pydata.org/

## Login to the Shared Computing Cluster

- Use your SCC login information if you have SCC account
- If you are using tutorial accounts see info on the blackboard

*Note: Your password will not be displayed while you enter it.*

## Selecting Python Version on the SCC

# view available python versions on the SCC

```
[scc1 ~] module avail python
```

# load python 3 version

```
[scc1 ~] module load python/3.6.2
```

## Download tutorial notebook

# On the Shared Computing Cluster

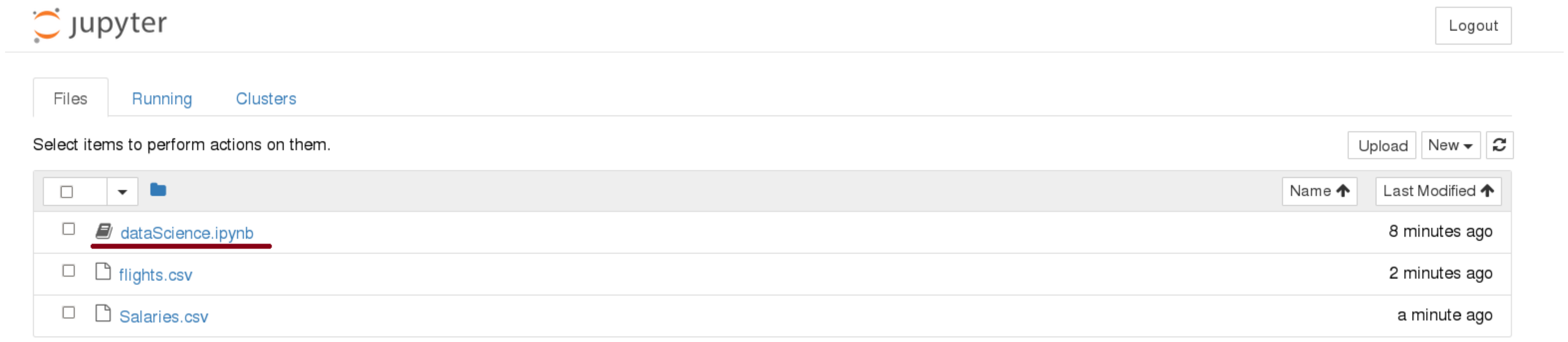
```
[scc1 ~] cp /project/scv/examples/python/data_analysis/dataScience.ipynb .
```

# On a local computer save the link:

http://rcs.bu.edu/examples/python/data_analysis/dataScience.ipynb

# Start Jupyter nootebook

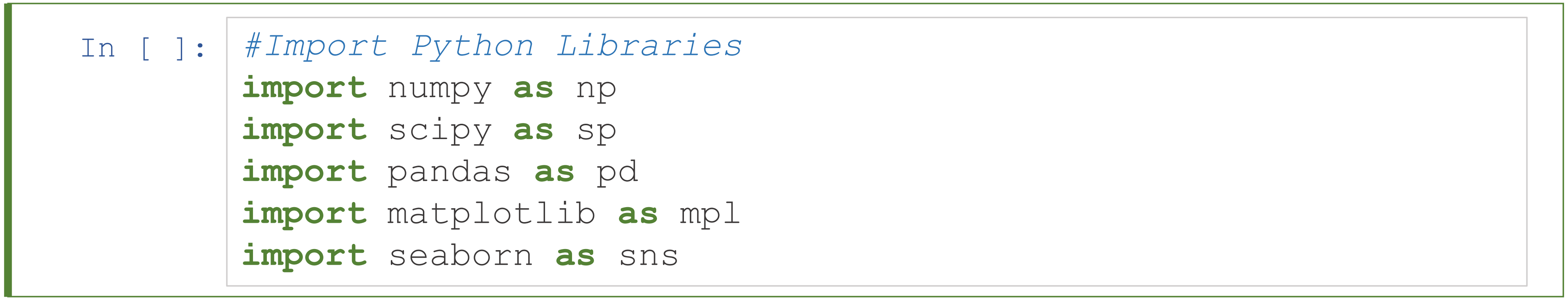
```
# On the Shared Computing Cluster
[scc1 ~] jupyter notebook
```



Select items to perform actions on them.

```
dataScience.ipynb    8 minutes ago
flights.csv          2 minutes ago
Salaries.csv         a minute ago
```

## Loading Python Libraries



```
In [ ]:  #Import Python Libraries
         import numpy as np
         import scipy as sp
         import pandas as pd
         import matplotlib as mpl
         import seaborn as sns
```

Press `Shift+Enter` to execute the *jupyter* cell

## Reading data using pandas

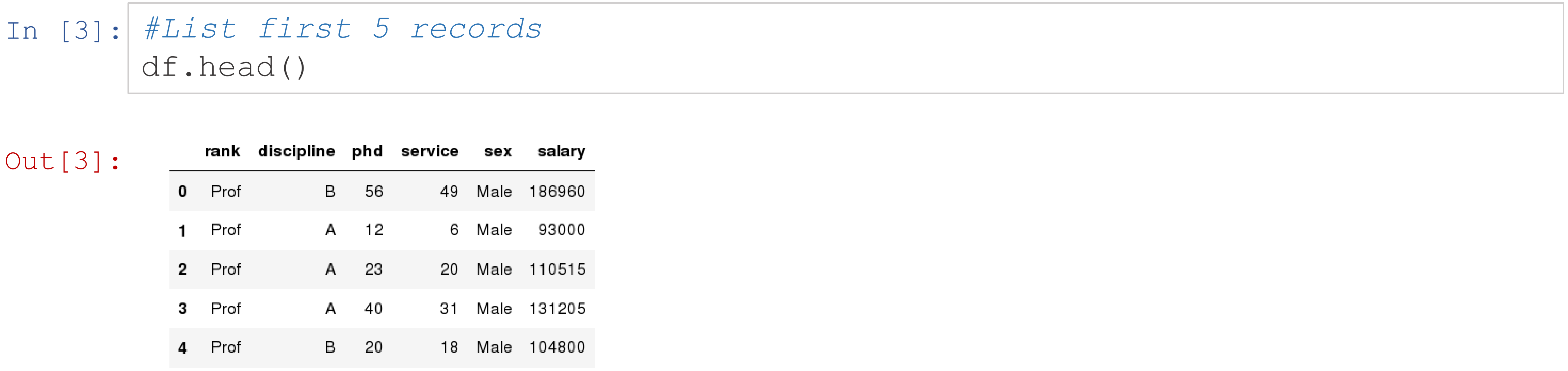
```
In [ ]: #Read csv file
        df = pd.read_csv("http://rcs.bu.edu/examples/python/data_analysis/Salaries.csv")
```

***Note:*** The above command has many optional arguments to fine-tune the data import process.

There is a number of pandas commands to read other data formats:

```
pd.read_excel('myfile.xlsx',sheet_name='Sheet1', index_col=None, na_values=['NA'])
pd.read_stata('myfile.dta')
pd.read_sas('myfile.sas7bdat')
pd.read_hdf('myfile.h5','df')
```

# Exploring data frames



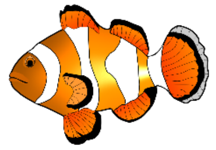
```
In [3]: #List first 5 records
        df.head()
```

```
Out[3]:
     rank  discipline  phd  service   sex   salary
  0  Prof           B   56       49  Male   186960
  1  Prof           A   12        6  Male    93000
  2  Prof           A   23       20  Male   110515
  3  Prof           A   40       31  Male   131205
  4  Prof           B   20       18  Male   104800
```

## Hands-on exercises

- ✓ Try to read the first 10, 20, 50 records;
- ✓ Can you guess how to view the last few records;

*Hint:*



# Data Frame data types

| Pandas Type | Native Python Type | Description |
|---|---|---|
| object | string | The most general dtype. Will be assigned to your column if column has mixed types (numbers and strings). |
| int64 | int | Numeric characters. 64 refers to the memory allocated to hold this character. |
| float64 | float | Numeric characters with decimals. If a column contains numbers and NaNs(see below), pandas will default to float64, in case your missing value has a decimal. |
| datetime64, timedelta[ns] | N/A (but see the datetime module in Python's standard library) | Values meant to hold time data. Look into these for time series experiments. |

## Data Frame data types

```
In [4]: #Check a particular column type
        df['salary'].dtype

Out[4]: dtype('int64')
```

```
In [5]: #Check types for all the columns
        df.dtypes

Out[4]: rank          object
        discipline    object
        phd           int64
        service       int64
        sex           object
        salary        int64
        dtype: object
```

## Data Frames attributes

Python objects have *attributes* and *methods*.

| df.attribute | description |
|---|---|
| dtypes | list the types of the columns |
| columns | list the column names |
| axes | list the row labels and column names |
| ndim | number of dimensions |
| size | number of elements |
| shape | return a tuple representing the dimensionality |
| values | numpy representation of the data |

## Hands-on exercises

- ✓ Find how many records this data frame has;
- ✓ How many elements are there?
- ✓ What are the column names?
- ✓ What types of columns we have in this data frame?

# Data Frames methods

Unlike attributes, python methods have *parenthesis.*
All attributes and methods can be listed with a *dir()* function: `dir(df)`

| df.method() | description |
|---|---|
| head( [n] ), tail( [n] ) | first/last n rows |
| describe() | generate descriptive statistics (for numeric columns only) |
| max(), min() | return max/min values for all numeric columns |
| mean(), median() | return mean/median values for all numeric columns |
| std() | standard deviation |
| sample([n]) | returns a random sample of the data frame |
| dropna() | drop all the records with missing values |

## Hands-on exercises

- ✓ Give the summary for the numeric columns in the dataset
- ✓ Calculate standard deviation for all numeric columns;
- ✓ What are the mean values of the first 50 records in the dataset? ***Hint:*** use head() method to subset the first 50 records and then calculate the mean

## Selecting a column in a Data Frame

*Method 1:* Subset the data frame using column name:

```
df['sex']
```

*Method 2*: Use the column name as an attribute:

```
df.sex
```

*Note:* there is an attribute *rank* for pandas data frames, so to select a column with a name "rank" we should use method 1.

## Hands-on exercises

- ✓ Calculate the basic statistics for the *salary* column;
- ✓ Find how many values in the *salary* column (use *count* method);
- ✓ Calculate the average salary;

## Data Frames *groupby* method

Using "group by" method we can:

- Split the data into groups based on some criteria
- Calculate statistics (or apply a function) to each group
- Similar to dplyr() function in R

```
In [ ]: #Group data using rank
        df_rank = df.groupby(['rank'])
```

```
In [ ]: #Calculate mean value for each numeric column per each group
        df_rank.mean()
```

|  | phd | service | salary |
|---|---|---|---|
| **rank** |  |  |  |
| **AssocProf** | 15.076923 | 11.307692 | 91786.230769 |
| **AsstProf** | 5.052632 | 2.210526 | 81362.789474 |
| **Prof** | 27.065217 | 21.413043 | 123624.804348 |

# Data Frames *groupby* method

Once groupby object is create we can calculate various statistics for each group:

```
In [ ]: #Calculate mean salary for each professor rank:
        df.groupby('rank')[['salary']].mean()
```

```
                 salary
rank
AssocProf  91786.230769
 AsstProf  81362.789474
     Prof 123624.804348
```

*Note:* If single brackets are used to specify the column (e.g. salary), then the output is Pandas Series object. When double brackets are used the output is a Data Frame

## Data Frames *groupby* method

*groupby* performance notes:

- no grouping/splitting occurs until it's needed. Creating the *groupby* object only verifies that you have passed a valid mapping
- by default the group keys are sorted during the *groupby* operation. You may want to pass sort=False for potential speedup:

```
In [ ]: #Calculate mean salary for each professor rank:
        df.groupby(['rank'], sort=False)[['salary']].mean()
```

## Data Frame: filtering

To subset the data we can apply Boolean indexing. This indexing is commonly known as a filter.  For example if we want to subset the rows in which the salary value is greater than $120K:

```
In [ ]: #Calculate mean salary for each professor rank:
        df_sub = df[ df['salary'] > 120000 ]
```

Any Boolean operator can be used to subset the data:

```
>   greater;     >= greater or equal;
<   less;        <= less or equal;
== equal;        != not equal;
```

```
In [ ]: #Select only those rows that contain female professors:
        df_f = df[ df['sex'] == 'Female' ]
```

## Data Frames: Slicing

There are a number of ways to subset the Data Frame:

- one or more columns
- one or more rows
- a subset of rows and columns

Rows and columns can be selected by their position or label

## Data Frames: Slicing

When selecting one column, it is possible to use single set of brackets, but the resulting object will be  a Series (not a DataFrame):

```
In [ ]: #Select column salary:
        df['salary']
```

When we need to select more than one column and/or make the output to be a DataFrame, we should use double brackets:

```
In [ ]: #Select column salary:
        df[['rank','salary']]
```

# Data Frames: Selecting rows

If we need to select a range of rows, we can specify the range using ":"

```
In [ ]: #Select rows by their position:
        df[10:20]
```

Notice that the first row has a position 0, and the last value in the range is omitted: So for 0:10 range the first 10 rows are returned with the positions starting with 0 and ending with 9

## Data Frames: method loc

If we need to select a range of rows, using their labels we can use method loc:

```
In [ ]: #Select rows by their labels:
        df_sub.loc[10:20,['rank','sex','salary']]
```

Out[ ]:

| | rank | sex | salary |
|---|---|---|---|
| **10** | Prof | Male | 128250 |
| **11** | Prof | Male | 134778 |
| **13** | Prof | Male | 162200 |
| **14** | Prof | Male | 153750 |
| **15** | Prof | Male | 150480 |
| **19** | Prof | Male | 150500 |

# Data Frames: method iloc

If we need to select a range of rows and/or columns, using their positions we can use method iloc:

```
In [ ]: #Select rows by their labels:
        df_sub.iloc[10:20,[0, 3, 4, 5]]
```

Out[ ]:

|  | rank | service | sex | salary |
|---|---|---|---|---|
| **26** | Prof | 19 | Male | 148750 |
| **27** | Prof | 43 | Male | 155865 |
| **29** | Prof | 20 | Male | 123683 |
| **31** | Prof | 21 | Male | 155750 |
| **35** | Prof | 23 | Male | 126933 |
| **36** | Prof | 45 | Male | 146856 |
| **39** | Prof | 18 | Female | 129000 |
| **40** | Prof | 36 | Female | 137000 |
| **44** | Prof | 19 | Female | 151768 |
| **45** | Prof | 25 | Female | 140096 |

# Data Frames: method iloc (summary)

```
df.iloc[0]  # First row of a data frame
df.iloc[i]  #(i+1)th row
df.iloc[-1] # Last row
```

```
df.iloc[:, 0]  # First column
df.iloc[:, -1] # Last column
```

```
df.iloc[0:7]        #First 7 rows
df.iloc[:, 0:2]     #First 2 columns
df.iloc[1:3, 0:2]   #Second through third rows and first 2 columns
df.iloc[[0,5], [1,3]]  #1st and 6th rows and 2nd and 4th columns
```

# Data Frames: Sorting

We can sort the data by a value in the column. By default the sorting will occur in ascending order and a new data frame is return.

```
In [ ]: # Create a new data frame from the original sorted by the column Salary
        df_sorted = df.sort_values( by ='service')
        df_sorted.head()
```

Out[ ]:

| | rank | discipline | phd | service | sex | salary |
|---|---|---|---|---|---|---|
| **55** | AsstProf | A | 2 | 0 | Female | 72500 |
| **23** | AsstProf | A | 2 | 0 | Male | 85000 |
| **43** | AsstProf | B | 5 | 0 | Female | 77000 |
| **17** | AsstProf | B | 4 | 0 | Male | 92000 |
| **12** | AsstProf | B | 1 | 0 | Male | 88000 |

# Data Frames: Sorting

We can sort the data using 2 or more columns:

```
In [ ]: df_sorted = df.sort_values( by =['service', 'salary'], ascending = [True, False])
        df_sorted.head(10)
```

Out[ ]:

| | rank | discipline | phd | service | sex | salary |
|---|---|---|---|---|---|---|
| **52** | Prof | A | 12 | 0 | Female | 105000 |
| **17** | AsstProf | B | 4 | 0 | Male | 92000 |
| **12** | AsstProf | B | 1 | 0 | Male | 88000 |
| **23** | AsstProf | A | 2 | 0 | Male | 85000 |
| **43** | AsstProf | B | 5 | 0 | Female | 77000 |
| **55** | AsstProf | A | 2 | 0 | Female | 72500 |
| **57** | AsstProf | A | 3 | 1 | Female | 72500 |
| **28** | AsstProf | B | 7 | 2 | Male | 91300 |
| **42** | AsstProf | B | 4 | 2 | Female | 80225 |
| **68** | AsstProf | A | 4 | 2 | Female | 77500 |

## Missing Values

Missing values are marked as NaN

```
In [ ]: # Read a dataset with missing values
        flights = pd.read_csv("http://rcs.bu.edu/examples/python/data_analysis/flights.csv")
```

```
In [ ]: # Select the rows that have at least one missing value
        flights[flights.isnull().any(axis=1)].head()
```

Out[ ]:

| | year | month | day | dep_time | dep_delay | arr_time | arr_delay | carrier | tailnum | flight | origin | dest | air_time | distance | hour | minute |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **330** | 2013 | 1 | 1 | 1807.0 | 29.0 | 2251.0 | NaN | UA | N31412 | 1228 | EWR | SAN | NaN | 2425 | 18.0 | 7.0 |
| **403** | 2013 | 1 | 1 | NaN | NaN | NaN | NaN | AA | N3EHAA | 791 | LGA | DFW | NaN | 1389 | NaN | NaN |
| **404** | 2013 | 1 | 1 | NaN | NaN | NaN | NaN | AA | N3EVAA | 1925 | LGA | MIA | NaN | 1096 | NaN | NaN |
| **855** | 2013 | 1 | 2 | 2145.0 | 16.0 | NaN | NaN | UA | N12221 | 1299 | EWR | RSW | NaN | 1068 | 21.0 | 45.0 |
| **858** | 2013 | 1 | 2 | NaN | NaN | NaN | NaN | AA | NaN | 133 | JFK | LAX | NaN | 2475 | NaN | NaN |

## Missing Values

There are a number of methods to deal with missing values in the data frame:

| df.method() | description |
|---|---|
| dropna() | Drop missing observations |
| dropna(how='all') | Drop observations where all cells is NA |
| dropna(axis=1, how='all') | Drop column if all the values are missing |
| dropna(thresh = 5) | Drop rows that contain less than 5 non-missing values |
| fillna(0) | Replace missing values with zeros |
| isnull() | returns True if the value is missing |
| notnull() | Returns True for non-missing values |

## Missing Values

- When summing the data, missing values will be treated as zero
- If all values are missing, the sum will be equal to NaN
- cumsum() and cumprod() methods ignore missing values but preserve them in the resulting arrays
- Missing values in GroupBy method are excluded (just like in R)
- Many descriptive statistics methods have *skipna* option to control if missing data should be excluded . This value is set to *True* by default (unlike R)

# Aggregation Functions in Pandas

Aggregation - computing a summary statistic about each group, i.e.

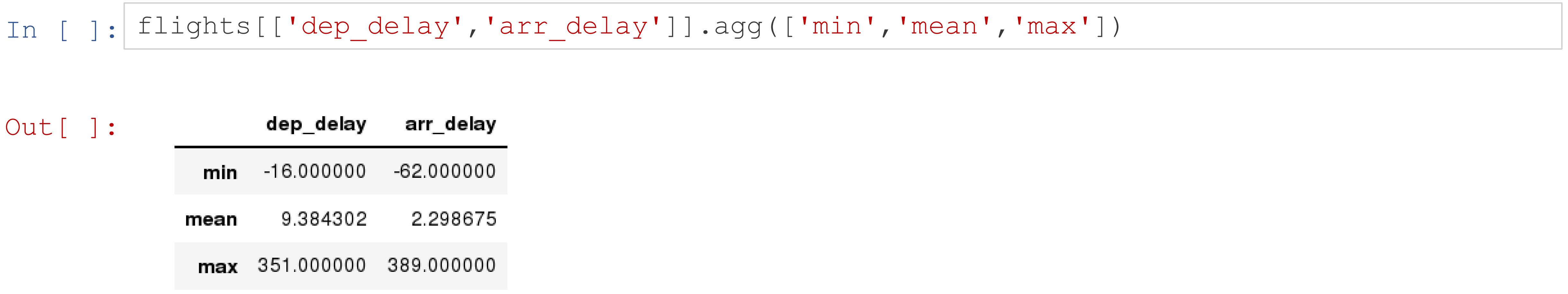
- compute group sums or means
- compute group sizes/counts

Common aggregation functions:

min, max
count, sum, prod
mean, median, mode, mad
std, var

# Aggregation Functions in Pandas

agg() method are useful when multiple statistics are computed per column:



```
In [ ]: flights[['dep_delay','arr_delay']].agg(['min','mean','max'])
```

Out[ ]:

|  | dep_delay | arr_delay |
|---|---|---|
| **min** | -16.000000 | -62.000000 |
| **mean** | 9.384302 | 2.298675 |
| **max** | 351.000000 | 389.000000 |

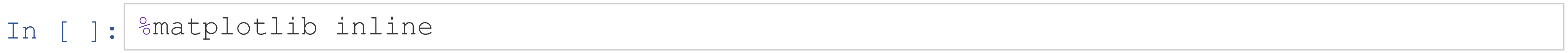
## Basic Descriptive Statistics

| df.method() | description |
|---|---|
| describe | Basic statistics (count, mean, std, min, quantiles, max) |
| min, max | Minimum and maximum values |
| mean, median, mode | Arithmetic average, median and mode |
| var, std | Variance and standard deviation |
| sem | Standard error of mean |
| skew | Sample skewness |
| kurt | kurtosis |

# Graphics to explore the data

Seaborn package is built on matplotlib but provides high level interface for drawing attractive statistical graphics, similar to ggplot2 library in R. It specifically targets statistical data visualization

To show graphs within Python notebook include inline directive:



```
In [ ]: %matplotlib inline
```

## Graphics

| | description |
|---|---|
| distplot | histogram |
| barplot | estimate of central tendency for a numeric variable |
| violinplot | similar to boxplot, also shows the probability density of the data |
| jointplot | Scatterplot |
| regplot | Regression plot |
| pairplot | Pairplot |
| boxplot | boxplot |
| swarmplot | categorical scatterplot |
| factorplot | General categorical plot |

## Basic statistical Analysis

statsmodel and scikit-learn - both have a number of function for statistical analysis

The first one is mostly used for regular analysis using R style formulas, while   scikit-learn is more tailored for Machine Learning.

statsmodels:

- linear regressions
- ANOVA tests
- hypothesis testings
- many more ...

scikit-learn:

- kmeans
- support vector machines
- random forests
- many more ...

See examples in the Tutorial Notebook

## 6 Steps to Manipulate and Cleanse Data with Python

#1: Implementing missing values imputation – This is a standard statistical imputing constant, using KNN imputation.

Outlier/Anomaly Detection is carried out using: Isolation Forest, One Class SVM, Local Outlier Factor, and/or outlier detection algorithms.

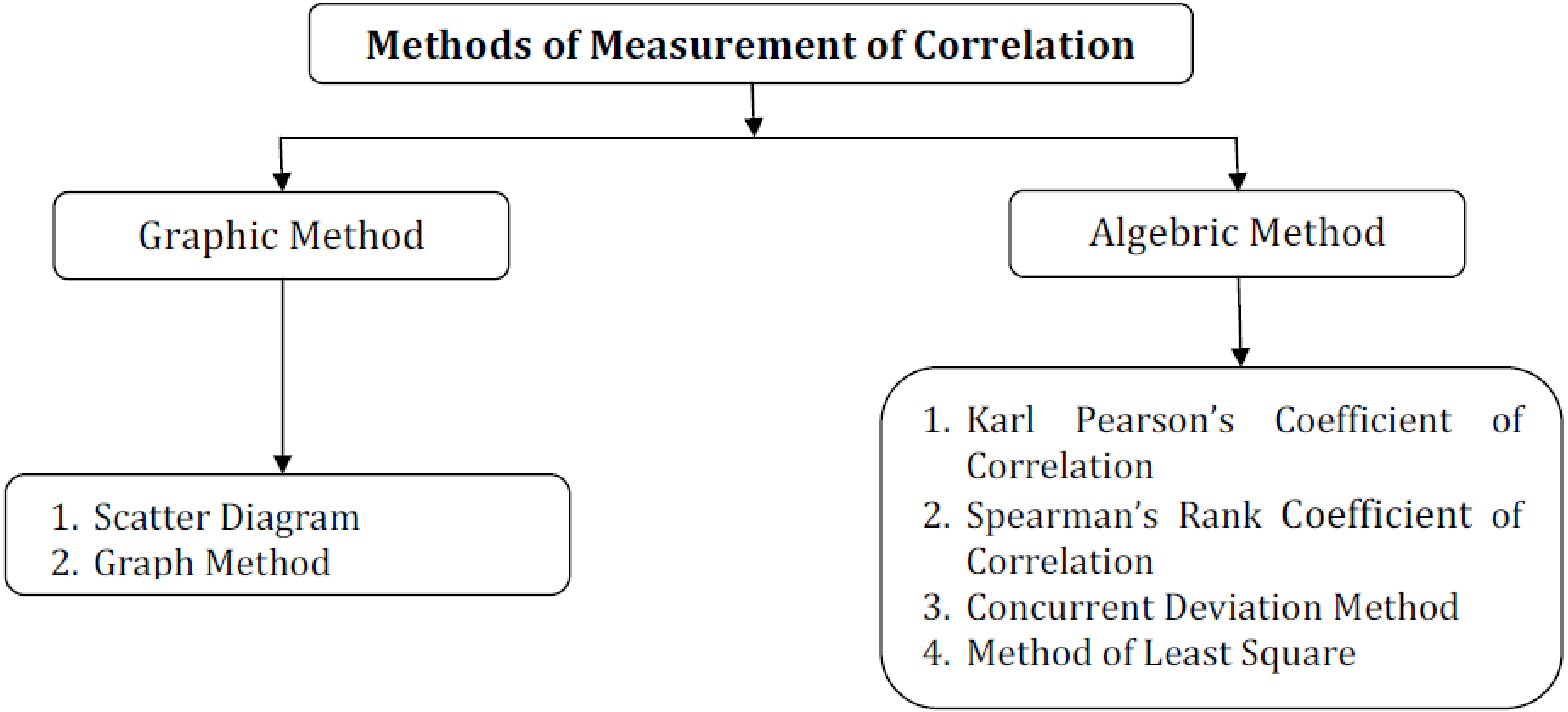
#2: Carrying out outlier/anomaly detection- You can accomplish this by using Isolation Forest, One-Class SVM, and/or Local Outlier Factor outlier detection algorithms.

#3: Utilizing cleaning techniques from the X-Variable family- In this instance, you want to apply custom functions, remove duplicates, as well as replace crucial values.

#4: Using Cleaning Techniques of the Y-Variable sort – Here it is important to do label encoding, one-hot encoding, as well as dictionary mapping.

#5:'DataFrames' need to be merged- This step includes concatenating, merging, and joining.

#6: The last step consists of 'parsing dates'- Here you need to use auto-format detecting strings to accomplish 'DateTime' converting, including changing 'DateTime' objects to numbers.


Methods of Measurement of Correlation
Graphic Method
Algebric Method
1. Scatter Diagram
2. Graph Method
1. Karl Pearson's Coefficient of Correlation
2. Spearman's Rank Coefficient of Correlation
3. Concurrent Deviation Method
4. Method of Least Square

Among these methods we will discuss only the following methods:

1. Scatter Diagram
2. Karl Pearson's Coefficient of Correlation
3. Spearman's Rank Coefficient of Correlation