

Python For Data Analysis

By: Ani Anisyah, M.T.
Universitas Pendidikan Indonesia

Content

- Overview of Python
 Libraries for Data
 Scientists
- 2. Reading Data
- 3. Plotting Data
- 4. Descriptive Statistics
- 5. Assignment



Python Libraries for Data Science

Many popular Python Libraries such as:

- 1. Numpy
- 2. SciPy
- 3. Pandas
- 4. Scikit-Learn
- 5. Matplotlib
- 6. Seaborn
- 7. And Many More

Numpy



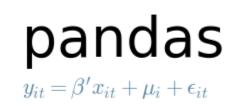
- Numpy is a module which provides the basic data structures, implementing multi-dimensional
 arrays and matrices. Besides that the module supplies the necessary functionalities to create
 and manipulate these data structures as well as functions that allow to easily perform advanced
 mathematical and statistical operations on those objects.
- Provides vectorization of mathematical operations on arrays and matrices which significantly improves the performance.
- Link: https://numpy.org/

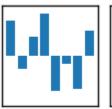
SciPy

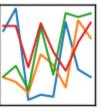


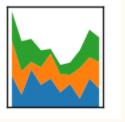
- SciPy is based on top of Numpy, i.e. it uses the data structures provided by NumPy. It extends the capabilities of NumPy with further useful functions for minimization, regression, Fouriertransformation and many others.
- SciPy have Collection of algorithms for linear algebra, differential equations, numerical integration, optimization, statistics and more.
- Link: https://scipy.org/

Pandas









- Pandas provides tools for data manipulation: reshaping, merging, sorting, slicing, aggregation etc. it provides add data structures and tools designed to work with table-like data (similar to Series and Data Frames in R). Besides that, it allows handling missing data.
- The special focus of Pandas consists in offering data structures and operations for manipulating numerical tables and time series.
- Link: http://pandas.pydata.org/

Scikit-Learn



- Scikit-learn provides simple and efficient tools for data mining and data analysis and is accessible to everyone and reusable in various contexts.
- Scikit-learn is known for its user-friendly interface, comprehensive documentation, and wide range of algorithms. It provides machine learning algorithms such as classification, regression, clustering, model validation, etc.
- Scikit-learn is a popular machine learning library for Python, built on NumPy, SciPy, and matplotlib
- Link: http://scikit-learn.org/

Matplotlib



- Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python. It is widely used for generating plots, histograms, power spectra, bar charts, error charts, scatterplots, etc.,
- Python 2D plotting library which produces publication quality figures in a variety of hardcopy formats
- Having relatively low-level; some effort needed to create advanced visualization
- Link: http://matplotlib.org/

Seaborn

- Seaborn is a Python visualization library based on Matplotlib that provides a high-level interface for drawing attractive and informative statistical graphics. It simplifies the process of creating complex visualizations and enhances the visual appeal of Matplotlib plots.
- Similar (in style) to the popular ggplot2 library in R
- Link: https://seaborn.pydata.org/



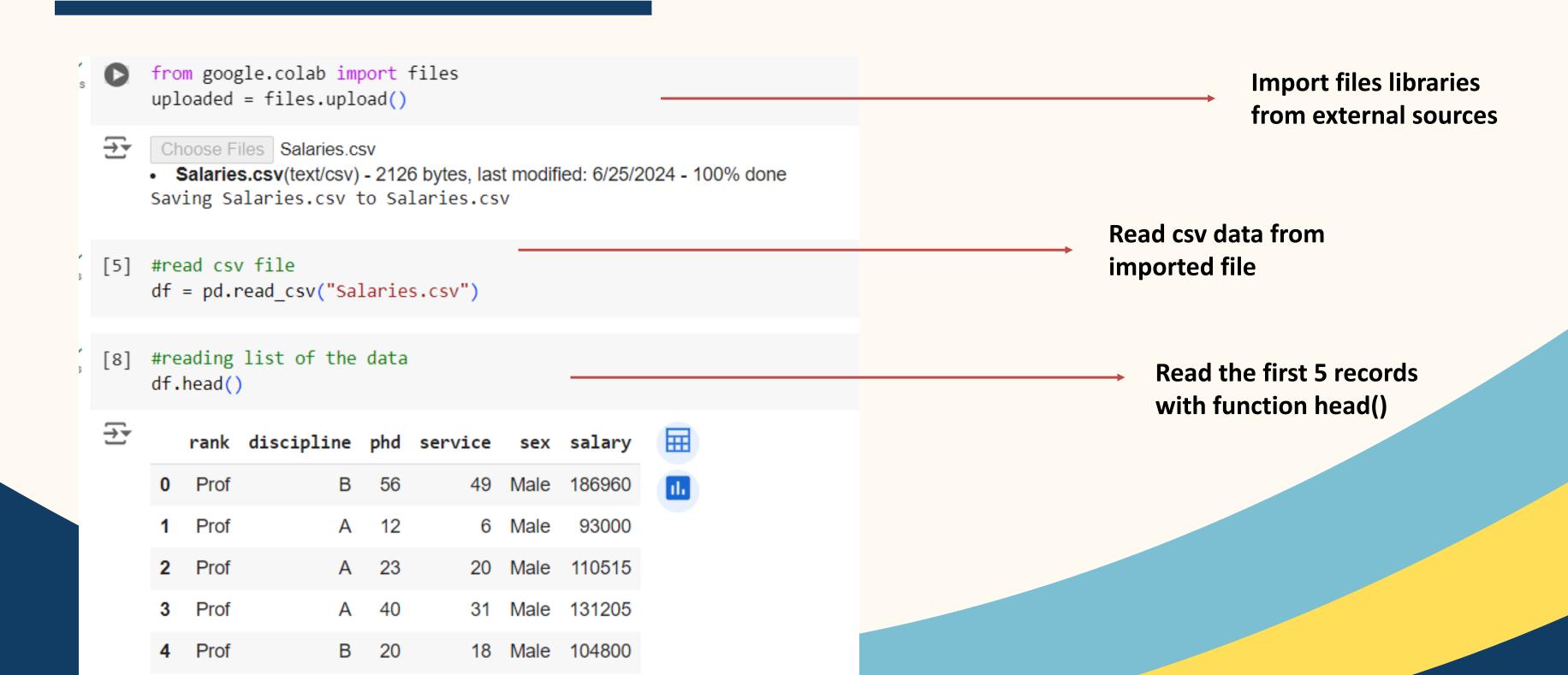
Reading Data with Python Libraries

Selecting and Filtering the Data; Data manipulation, sorting, grouping, rearranging

Loading Python Libraries

```
#import python libraries
import numpy as np
import scipy as sp
import pandas as pd
import matplotlib as mpl
import seaborn as sns
```

Reading data Using Pandas Libraries



Data Frame

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 <u>datetime</u> module in Python's standard library)	Values meant to hold time data. Look into these for time series experiments.

Data Frame Data Types

```
#check a particular column type
     df['salary'].dtype
→ dtype('int64')
[10] #check types for all columns
     df.dtypes
                   object
     rank
     discipline
                   object
     phd
                   int64
     service
                  int64
                   object
     sex
     salary
                    int64
```

Data Frame Attributes

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

Data Frame Method

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

Data Frame Method

Give the max of salary of the first 5 records in the dataset

```
#get max values of the first 5 records
df['salary'].head(5).max()
```

186960

Data Frame with 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

```
data = pd.read_csv("Salaries (2).csv")
#make dataframe from data
df_data = pd.DataFrame(data)

#group data using sex
df_sex = df_data.groupby('sex')

#calculate mean value for each numeric column per each group
df_sex['salary'].mean()

sex
Female 101002.410256
Male 115045.153846
Name: salary, dtype: float64
[] Start coding or generate with AI.
```

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 \$150K:

0	<pre>#find salary more than \$150K df_sub = df[df['salary'] > 150000] df_sub</pre>						
_		rank	discipline	phd	service	sex	salary
	0	Prof	В	56	49	Male	186960
	13	Prof	В	35	33	Male	162200
	14	Prof	В	25	19	Male	153750
	15	Prof	В	17	3	Male	150480
	19	Prof	Α	29	27	Male	150500
	27	Prof	Α	45	43	Male	155865
	31	Prof	В	22	21	Male	155750
	44	Prof	В	23	19	Female	151768
	72	Prof	В	24	15	Female	161101

Any logical operator can be used:

Symbol	Description
>	Greater
<	Less
==	Equal
>=	Greater or equal
<=	Less or equal
!=	Not equal

Data Frame: Filtering

Any logical operator can be used:

Symbol	Description
>	Greater
<	Less
==	Equal
>=	Greater or equal
<=	Less or equal
!=	Not equal

```
#Select only those rows that contain female professors:
    df_f = df[ df['sex'] == 'Female' ]
    df f
₹
            rank discipline phd service
                                             sex salary
             Prof
                                       18 Female 129000
             Prof
                              39
                                       36 Female 137000
     41 AssocProf
                          A 13
                                        8 Female
                                                  74830
          AsstProf
                                        2 Female
                                                   80225
                                                   77000
          AsstProf
                                        0 Female
                                       19 Female 151768
             Prof
     44
     45
             Prof
                                       25 Female 140096
          AsstProf
                                        3 Female
                                                  74692
```

Data Frame: Slicing

There are number of ways to subset the data frame:

- 1. One or more columns
- 2. One or more rows
- 3. A subset of rows and columns

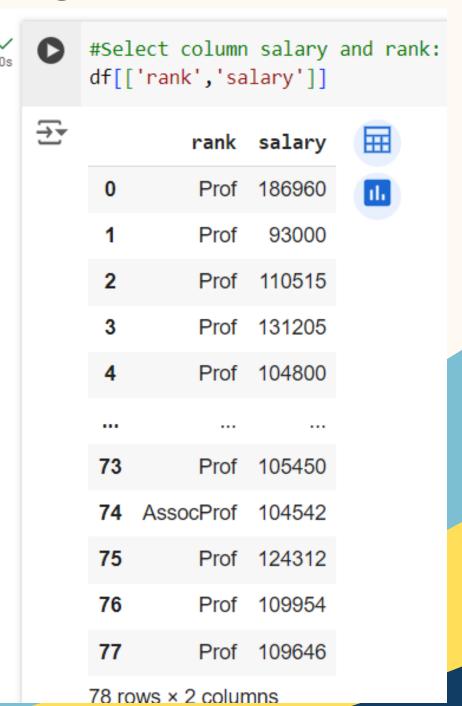
Data Frame: Slicing

Example: selecting one column

```
#select column salary
     df['salary']
\overline{\mathbf{T}}
            186960
             93000
           110515
            131205
            104800
            105450
            104542
     74
           124312
     76
            109954
     77
            109646
     Name: salary, Length: 78, dtype: int64
```

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

Example: selecting more than one column



Data Frame: Selecting Rows

Example: selecting rows by their position



Data Frame: method iloc

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

use method iloc

	df.1loc[10:20,[0, 3, 4, 5]]				
₹		rank	service	sex	salary
	10	Prof	33	Male	128250
	11	Prof	23	Male	134778
	12	AsstProf	0	Male	88000
	13	Prof	33	Male	162200
	14	Prof	19	Male	153750
	15	Prof	3	Male	150480
	16	AsstProf	3	Male	75044
	17	AsstProf	0	Male	92000
	18	Prof	7	Male	107300
	19	Prof	27	Male	150500

#Select rows by their labels:

Data Frame: method iloc

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

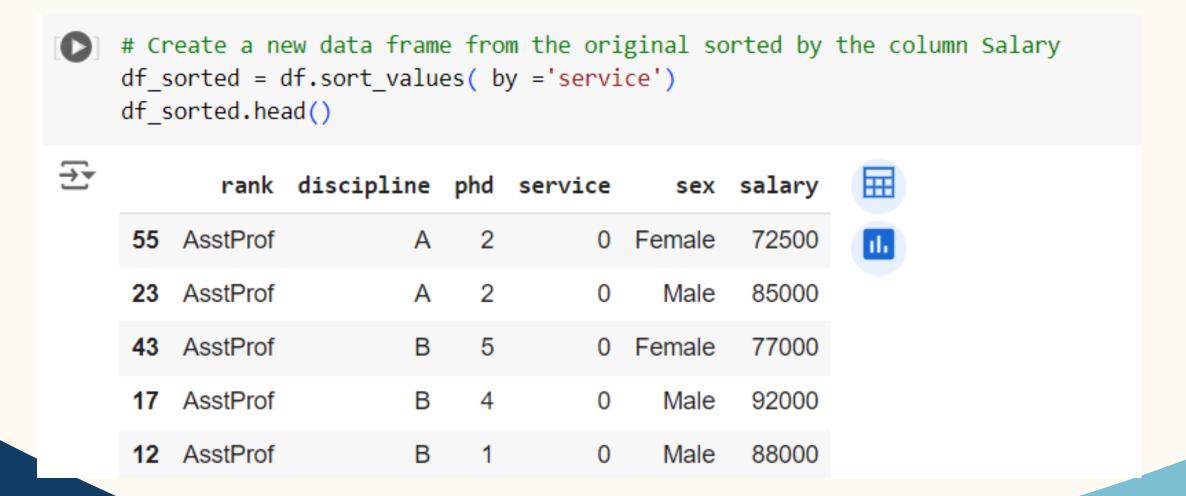
df.iloc[:, 0] # First column
df.iloc[:, -1] # Last column

df.iloc[:, -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 Frame: 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.



Data Frame: sorting

Example: sorting using 2 or more columns

```
[79] df_sorted = df.sort_values( by =['service', 'salary'], ascending = [True, False])
     df_sorted.head(10)
₹
            rank discipline phd service
                                              sex salary
     52
             Prof
                           A 12
                                        0 Female
                                                   105000
     17 AsstProf
                                                    92000
                                             Male
     12 AsstProf
                                             Male
                                                    88000
     23 AsstProf
                                             Male
                                                    85000
     43 AsstProf
                                        0 Female
                                                    77000
      55 AsstProf
                                        0 Female
                                                    72500
      57 AsstProf
                                                    72500
                                        1 Female
      28 AsstProf
                                             Male
                                                    91300
      42 AsstProf
                                                    80225
                                        2 Female
      68 AsstProf
                                                    77500
                                        2 Female
```

Plotting Data

Missing Value

- Missing values are marked as NaN
- 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 Value

- 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)

Descriptive Analysis

Aggregation Function in Pandas

In pandas, aggregation functions are used to perform operations on data, typically after grouping it. Common aggregation functions include sum, mean, median, min, max, count, and others. Here's how you can use them with pandas DataFrames:

1. Grouping data using groupby:

•The groupby method is used to split the data into groups based on some criteria.

2.Applying aggregation functions:

•Once the data is grouped, you can apply aggregation functions using methods like agg, sum, mean, etc.

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

Aggregation Function in Pandas

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

```
os df['salary'].agg(['min', 'max', 'mean'])

min 57800.0000000
max 186960.0000000
mean 108023.782051
Name: salary, dtype: float64
```

Graphic to explore the data

Visualize the data with matplotlib library

```
import matplotlib.pyplot as plt
    class_averages = data.groupby('rank')['salary'].mean()
    # Membuat grafik bar untuk data rata-rata
    plt.figure(figsize=(10,6))
    class_averages.plot(kind='bar')
    plt.xlabel('Rank')
    plt.ylabel('Salary')
    plt.title('Salary per Rank')
    # Menunjukan grafik bar
    plt.show()
\overline{z}
                                                          Salary per Rank
        120000
        100000
         80000
         40000
         20000
                                                                 Rank
```

Assignment

About Data

This dataset is having the 50000 sales orders data that consist of columns as following:

- 1. Order ID
- 2. Quantity
- 3. Product Id
- 4. Seller Id
- 5. Freight Value
- 6. Customer Id
- 7. Order Status
- 8. Purchase Status
- 9. Payment Type
- 10. Product Category Name
- 11. Product Weight in gram

Objectives

- Conduct exploratory Data Analysis (EDA): Perform EDA to understand the distribution and relationships between variables from the data
- Analyzing Sales Dataset is to identify salles patterns from order data that resonate with consumers and propel them to purchase.
- Translate insights into actionable recommendations that optimize product development, inform marketing strategies, and boost competitive edge.

Description Task

Exploring the data Sales involves a step-by-step process:

- 1. Check and prepare data to clean and handling missing values and ensuring consistency.
- 2. Summaries the data with statistical analysis: Use descriptive statistics with aggregation function (i.e sum, count, average, min, max) for searching meaningful information such as: top product sales, total amount, average amount, etc
- 3. Use Statistical methods to identify significant correlation/comparative/ distribution/trending between variables from the data
- 4. Visualize the data with charts and graphs to see patterns and relationships (min. 3 graph)
- 5. Use related python library to handle all of tasks
- 6. Upload your source code with python extension file such as .py or .ipynb and file .rawgraphs (if you used visualize data using rawgraphs)
- 7. Tomorrow some of you will present the result of your assignment

Python Libraries

- We will use the following libraries:
 - 1. Pandas: Data manipulation and analysis
 - 2. Numpy: Numerical operations and calculations
 - 3. Matplotlib: Data visualization and plotting
 - 4. Seaborn: Enhanced data visualization and statistical graphics
 - 5. Scipy: Scientific computing and advanced mathematical operations
 - 6. RawGraph: A free and open source tool for data visualization (https://www.rawgraphs.io/)



"Summer Course 2024"

Thank You

Any Question?