



## Digital Skills Training for Student Central Computer Center, KUET



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Machine Learning with Python (ML-1)

# Session 9: Pandas DataFrame



# Contents

## Session 9: Pandas DataFrame

- Introduction Pandas DataFrame
- Creating DataFrame and read\_csv()
- DataFrame attributes and methods
- Dataframe Math Methods
- Selecting cols and rows from dataframe
- Filtering a Dataframe
- Adding new columns
- Dataframe function – astype()

# Pandas

Pandas is a Python library used for working with data sets.

It has functions for analyzing, cleaning, exploring, and manipulating data.

The name "Pandas" has a reference to both "Panel Data", and "Python Data Analysis" and was created by Wes McKinney in 2008.



Install it using this command:

```
C:\Users\Your Name>pip install pandas
```

```
import pandas
import pandas as pd
print(pd.__version__)
```

<https://pandas.pydata.org/>

<https://github.com/pandas-dev/pandas>



# Pandas Series

A Pandas Series is like a column in a table.

It is a one-dimensional array holding data of any type.

```
import pandas as pd  
a = [1, 7, 2]  
myvar = pd.Series(a)  
print(myvar)
```

If nothing else is specified, the values are labeled with their index number.

```
print(myvar[0])
```



# Pandas DataFrames

Data sets in Pandas are usually multi-dimensional tables, called DataFrames.

Series is like a column, a DataFrame is the whole table.

```
data = {  
    "calories": [420, 380, 390],  
    "duration": [50, 40, 45]  
}  
df = pd.DataFrame(data)  
  
print(df)
```



# Pandas DataFrames

Pandas use the **loc** attribute to return one or more specified row(s)

#refer to the row index:

```
print(df.loc[0])
```

 [This example returns a Pandas **Series.**]

```
print(df.loc[[0, 1]])
```

 [When using [ ], the result is a Pandas DataFrame]

```
df = pd.DataFrame(data, index = ["day1", "day2", "day3"])  
print(df)
```

#refer to the named index:

```
print(df.loc["day2"])
```



# Pandas Read CSV

A simple way to store big data sets is to use CSV files (comma separated files).

CSV files contains plain text and is a well know format that can be read by everyone including Pandas.

```
import pandas as pd
df = pd.read_csv('/content/drive/MyDrive/EDGE
Training/Pandas/data.csv')
print(df.to_string()) [to print the entire DataFrame.]
print(df) [will only return the first 5 rows, and the last 5 rows]
df
print(pd.options.display.max_rows)
pd.options.display.max_rows = 9999
print(df)
```

# Pandas Read JSON



Big data sets are often stored, or extracted as JSON. [**JSON = Python Dictionary**]

JSON is plain text, but has the format of an object, and is well known in the world of programming, including Pandas.

```
import pandas as pd
df = pd.read_json('/content/drive/MyDrive/data.js')
print(df.to_string())
print(df)
```





# Selecting cols and rows from dataframe

```
Pulse = df["Pulse"] [select specific columns from a DataFrame]  
print(Pulse)
```

```
Pulse_MaxPulse = df[["Pulse", "Maxpulse"]]  
print(Pulse_MaxPulse)
```

```
above_100 = df[df["Pulse"] > 100] [filter specific rows]  
print(above_100)
```

```
p_max = df.loc[df["Pulse"] > 35, "Maxpulse"]  
print(p_max) [specific rows and columns]
```

```
df.iloc[9:25, 2:5]
```



# Selecting cols and rows from dataframe

## REMEMBER

- When selecting subsets of data, square brackets [] are used.
- Inside these brackets, you can use a single column/row label, a list of column/row labels, a slice of labels, a conditional expression or a colon.
- Select specific rows and/or columns using loc when using the row and column names.
- Select specific rows and/or columns using iloc when using the positions in the table.
- You can assign new values to a selection based on loc/iloc.



# DataFrame attributes and methods

- Attributes provide direct information about the DataFrame (its structure, size, or column names).
- Methods perform actions on the DataFrame, like modifying or analyzing the data.

Attribute	Method
<ul style="list-style-type: none"><li>• Stores metadata</li></ul>	<ul style="list-style-type: none"><li>• Performs operations or calculations</li></ul>
<ul style="list-style-type: none"><li>• No parentheses required</li></ul>	<ul style="list-style-type: none"><li>• Requires parentheses</li></ul>
<ul style="list-style-type: none"><li>• Cannot take arguments</li></ul>	<ul style="list-style-type: none"><li>• Can take arguments to customize behavior</li></ul>
<ul style="list-style-type: none"><li>• Often returns static info (e.g., columns, shape, dtypes)</li></ul>	<ul style="list-style-type: none"><li>• Often modifies, summarizes, or transforms the data</li></ul>
<ul style="list-style-type: none"><li>• Example: <code>df.shape</code></li></ul>	<ul style="list-style-type: none"><li>• Example: <code>df.drop()</code></li></ul>

# Analyzing DataFrames



## #Viewing the Data

```
print(df.head(10))
```

[Return the first  $n$  rows.]

```
print(df.head(-100))
```

[Returns all rows except the last  $/n/$  rows]

```
print(df.tail(5))
```

[Return the last  $n$  rows.]

```
print(df.tail(-5))
```

[Returns all rows except the first  $/n/$  rows]

```
print(df.info())
```

```
print(df.index)
```

```
print(df.index)
```

```
print(df.index)
```

```
df.select_dtypes(include=['float64'], exclude=['int64'])
```

# Analyzing DataFrames



## #Viewing the Data

<code>print(df.values)</code>	[Return a Numpy representation of the DataFrame.]
<code>print(df.axes)</code>	[Return a list representing the axes of the DataFrame.]
<code>df.ndim</code>	[Return 1 if Series. Otherwise return 2 if DataFrame.]
<code>df.size</code>	[Return an int representing the number of elements in this object.]
<code>df.shape</code>	[Return a tuple representing the dimensionality of the DataFrame.]
<code>df.memory_usage(index=False, deep=True)</code>	[Return the memory usage of each column in bytes.]
<code>df.empty</code>	[Indicator whether Series/DataFrame is empty.]

# Analyzing DataFrames



```
df.astype(dtype, copy=None, errors='raise')
```

[ Cast a pandas object to a specified dtype ]

**Dtype :** *str, data type, Series or Mapping of column name -> data type*

**Copy :** *bool, default True*

**Errors :** *{'raise', 'ignore'}, default 'raise'*

```
df.dtypes
```

```
df.astype('int32').dtypes
```

```
df.astype({'Pulse': 'int32'}).dtypes
```

```
print(df.describe())
```

# Analyzing DataFrames



```
df.convert_dtypes(infer_objects=True, convert_string=True,  
convert_integer=True, convert_boolean=True,  
convert_floating=True, dtype_backend='numpy_nullable')
```

[Convert columns to the best possible dtypes using dtypes supporting pd.NA.]

**infer\_objects** : *bool, default True*

**convert\_string** : *bool, default True*

**convert\_integer** : *bool, default True*

**convert\_Boolean** : *bool, defaults True*

**convert\_floating** : *bool, defaults True*

**dtype\_backend** : *{'numpy\_nullable', 'pyarrow'}, default 'numpy\_nullable'*



# Adding new columns

```
df["2xPulse"] = df["Pulse"] * 2
df_renamed = df.rename(
    columns={
        "name1": "name2",
        "col1": "col2",
    }
)
```

## REMEMBER

- Create a new column by assigning the output to the DataFrame with a new column name in between the [].
- Operations are element-wise, no need to loop over rows.
- Use rename with a dictionary or function to rename row labels or column names.





# Cleaning Data

Data cleaning means fixing bad data in your data set.

Bad data could be:

- Empty cells
- Data in wrong format
- Wrong data
- Duplicates

## data.csv

- contains some empty cells ("Date" in row 22, and "Calories" in row 18 and 28).
- contains wrong format ("Date" in row 26).
- contains wrong data ("Duration" in row 7).
- contains duplicates (row 11 and 12).



# Cleaning Data

## Empty Cells

Empty cells can potentially give you a wrong result when you analyze data.

### 1. Remove Rows

- One way to deal with empty cells is to remove rows that contain empty cells.
- This is usually OK, since data sets can be very big, and removing a few rows will not have a big impact on the result.

```
new_df = df.dropna()  
print(new_df.to_string())
```

[By default, the `dropna()` method returns a new DataFrame, and will not change the original]

```
df.dropna(inplace = True)
```



# Cleaning Data

## 2. Replace Empty Values

- This way you do not have to delete entire rows just because of some empty cells.

```
df.fillna(130) [insert a new value instead.]
```

```
df["Calories"].fillna(130) [Replace Only For Specified Columns]
```

```
x = df["Calories"].mean()  
df["Calories"].fillna(x, inplace = True)
```

```
x = df["Calories"].median()  
df["Calories"].fillna(x, inplace = True)
```

```
x = df["Calories"].mode()[0]  
df["Calories"].fillna(x, inplace = True)
```



# Cleaning Data

## Data of Wrong Format

- Cells with data of wrong format can make it difficult, or even impossible, to analyze data.
- To fix it, you have two options: remove the rows, or convert all cells in the columns into the same format.

### 1. Convert Into a Correct Format

```
df['Date'] = pd.to_datetime(df['Date'])  
print(df.to_string())
```

### 2. Removing Rows

```
df.dropna(subset=['Date'], inplace = True)
```



# Cleaning Data

## Wrong Data

"Wrong data" does not have to be "empty cells" or "wrong format", it can just be wrong, like if someone registered "199" instead of "1.99".

### 1. Replacing Values

```
df.loc[7, 'Duration'] = 45
```

To replace wrong data for larger data sets you can create some rules

```
for x in df.index:  
    if df.loc[x, "Duration"] > 120:  
        df.loc[x, "Duration"] = 120
```

### 2. Removing Rows

```
for x in df.index:  
    if df.loc[x, "Duration"] > 120:  
        df.drop(x, inplace = True)
```



# Cleaning Data

## Duplicates

Duplicate rows are rows that have been registered more than one time.

```
print(df.duplicated())
```

## Removing Duplicates

```
df.drop_duplicates(inplace = True)
```



# Data Correlations

## Finding Relationships

A great aspect of the Pandas module is the `corr()` method.

The `corr()` method calculates the relationship between each column in your data set.

`df.corr()` [The `corr()` method ignores "not numeric" columns.]

Perfect Correlation: **1.000000**

Good Correlation: **0.922721**

Bad Correlation: **0.009403**

	Duration	Pulse	Maxpulse	Calories
Duration	1.000000	-0.155408	0.009403	0.922721
Pulse	-0.155408	1.000000	0.786535	0.025120
Maxpulse	0.009403	0.786535	1.000000	0.203814
Calories	0.922721	0.025120	0.203814	1.000000



# Filtering a Dataframe

```
DataFrame.filter(items=None, like=None, regex=None,  
axis=None)
```

[Subset the dataframe rows or columns according to the specified index labels.]

Items - *list-like*

Like - *str*

Regex - *str (regular expression)*

Axis - *{0 or 'index', 1 or 'columns', None}, default None*





# pandas.DataFrame.groupby

```
DataFrame.groupby(by=None, axis=<no_default>,  
level=None, as_index=True, sort=True,  
group_keys=True, observed=<no_default>,  
dropna=True)
```

Group DataFrame using a mapper or by a Series of columns.

```
grouped_data =  
df.groupby('Gender')['Salary'].mean()  
print(grouped_data  
)
```

# Apply a Function to a Column



```
# Define a function to increase salary by 10%
def increase_salary(salary):
    return salary * 1.10

# Apply the function to the 'Salary' column
df['Salary'] = df['Salary'].apply(increase_salary)
print(df.head())
```



# Practice Problem

Load nba.csv and perform following tasks:

1. Display a summary of the dataset
2. Handle Missing Values
3. Filter Data Based on Conditions
4. Group the data by a categorical column and calculate the mean of another column.
5. Identify and remove duplicate rows from the dataset.
6. Sort the DataFrame based on one or more columns.
7. Create a new column based on existing data.
8. Apply a custom function to modify values in a column.
9. Merge two DataFrames.
10. Create a histogram of a numeric column (e.g., "Age") and a bar plot of categorical data (e.g., "Gender").



# Practice Problem

Load nba.csv and perform following tasks:

1. Detect and remove outliers based on a numerical column.
2. Create a pivot table summarizing data.
3. Filter the data based on a date range (if time series data exists).
4. Analyze correlations between numerical columns.
5. Perform multi-level grouping and aggregation.
6. Normalize a numeric column using Min-Max Scaling.
7. Create a new column based on multiple conditions.
8. Count the number of unique values in a categorical column.
9. Fill missing values with group-specific averages.
10. Calculate a rolling average for a numeric column.
11. Resample data if the dataset contains time-series data.
12. Calculate the percentage change in a numeric column over time.



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# Thank You!