Introduction to Pandas: Data Analysis Made Easy

a powerful Python library for data manipulation and analysis.

Why Use Pandas?

Pandas is well suited for:

- Tabular data with heterogeneously-typed columns, as in an SQL table or Excel spreadsheet
- Ordered and unordered (not necessarily fixed-frequency) time series data.
- Arbitrary matrix data (homogeneously typed or heterogeneous) with row and column labels
- Any other form of observational / statistical data sets. The data actually need not be labeled at all to be placed into a pandas data structure

Key features:

- Easy handling of **missing data**
- **Size mutability**: columns can be inserted and deleted from DataFrame and higher dimensional objects
- Automatic and explicit **data alignment**: objects can be explicitly aligned to a set of labels, or the data can be aligned automatically
- Powerful, flexible **group by functionality** to perform split-apply-combine operations on data sets
- Intelligent label-based **slicing, fancy indexing, and subsetting** of large data sets
- Intuitive **merging and joining** data sets
- Flexible **reshaping and pivoting** of data sets
- **Hierarchical labeling** of axes
- Robust **IO tools** for loading data from flat files, Excel files, databases, and HDF5
- **Time series functionality**: date range generation and frequency conversion, moving window statistics, moving window linear regressions, date shifting and lagging, etc.

Series: One-Dimensional Labeled Data

- Definition of Series: a one-dimensional labeled array capable of holding any data type.

- Show syntax:

```
import pandas as pd
data = pd.Series([data], index=[])
```

```
bacteria = pd.Series([632, 1638, 569, 115], index =['Firmicutes', 'Proteobacteria', 'Actinobacteria', 'Bacteroidetes'])

bacteria
```

```
Firmicutes         632
Proteobacteria    1638
Actinobacteria     569
Bacteroidetes      115
dtype: int64
```

DataFrame: Two-Dimensional Tabular Data

- Definition of DataFrame: a 2D labeled data structure with columns that can hold different data types.

- Show syntax:

```
import pandas as pd
data = pd.DataFrame(data, columns=columns)
```

A DataFrame has a second index, representing the columns:

```
data = pd.DataFrame({'value':[632, 1638, 569, 115, 433, 1130, 754, 555],
                     'patient':[1, 1, 1, 1, 2, 2, 2, 2],
                     'classification':['Firmicutes', 'Proteobacteria', 'Actinobacteria',
    'Bacteroidetes', 'Firmicutes', 'Proteobacteria', 'Actinobacteria', 'Bacteroidetes']})
data
```

	value	patient	classification
0	632	1	Firmicutes
1	1638	1	Proteobacteria
2	569	1	Actinobacteria
3	115	1	Bacteroidetes
4	433	2	Firmicutes
5	1130	2	Proteobacteria
6	754	2	Actinobacteria
7	555	2	Bacteroidetes

- Operations on DataFrames
    - selecting columns
    - filtering rows
    - basic statistics (transpose a matrix)
    - creates a separate copy of Dataframe
    - Add new columns
    - Remove columns

Loading Data into Pandas

- from CSV
  - Select rows
  - check NA

```
mb = pd.read_csv("data/microbiome.csv")
mb.head()
```

	Taxon	Patient	Tissue	Stool
0	Firmicutes	1	632	305
1	Firmicutes	2	136	4182
2	Firmicutes	3	1174	703
3	Firmicutes	4	408	3946
4	Firmicutes	5	831	8605

Loading Data into Pandas

- from Excel
  - Choose sheet

```
mb_file = pd.ExcelFile('data/microbiome/MID1.xls')
mb_file
```

```
<pandas.io.excel._base.ExcelFile at 0x7fa83800e460>
```

```
mb1 = mb_file.parse("Sheet 1", header=None)
mb1.columns = ["Taxon", "Count"]
mb1.head()
```

	Taxon	Count
0	Archaea "Crenarchaeota" Thermoprotei Desulfuro...	7
1	Archaea "Crenarchaeota" Thermoprotei Desulfuro...	2
2	Archaea "Crenarchaeota" Thermoprotei Sulfoloba...	3
3	Archaea "Crenarchaeota" Thermoprotei Thermopro...	3
4	Archaea "Euryarchaeota" "Methanomicrobia" Meth...	7

Manipulating indices

- It refers to the process of altering the index (or row labels) of a data structure, such as a Series or DataFrame, to match a new set of labels or indices. This operation is useful when you need to realign data or fill in missing values based on a new index.

A simple use of `reindex` is to alter the order of the rows:

Slide Type Fragment

```
baseball.reindex(baseball.index[::-1]).head() # reverse the order of the rows in the baseball DataFrame
```

id	player	year	stint	team	lg	g	ab	r	h	X2b	...	rbi	sb	cs	bb	so	ibb	hbp	sh	sf	gidp
89534	alomasa02	2007	1	NYN	NL	8	22	1	3	1	...	0.0	0.0	0.0	0	3.0	0.0	0.0	0.0	0.0	0.0
89533	aloumo01	2007	1	NYN	NL	87	328	51	112	19	...	49.0	3.0	0.0	27	30.0	5.0	2.0	0.0	3.0	13.0
89530	ausmubr01	2007	1	HOU	NL	117	349	38	82	16	...	25.0	6.0	1.0	37	74.0	3.0	6.0	4.0	1.0	11.0
89526	benitar01	2007	1	SFN	NL	19	0	0	0	0	...	0.0	0.0	0.0	0	0.0	0.0	0.0	0.0	0.0	0.0
89525	benitar01	2007	2	FLO	NL	34	0	0	0	0	...	0.0	0.0	0.0	0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 22 columns

- Reindex in Series

```python
import pandas as pd

# Create a Series with initial index
data = pd.Series([1, 2, 3], index=['a', 'b', 'c'])

# Reindexing with a new index
new_index = ['a', 'b', 'c', 'd']
reindexed_series = data.reindex(new_index)

print(reindexed_series)
```

In this example, the reindex operation creates a new Series with the provided new_index.
Since 'd' is not present in the original index, Pandas fills it with a NaN (missing value).

- Reindex in DataFrame

```python
import pandas as pd

# Create a DataFrame with initial index and columns
data = {'A': [1, 2, 3], 'B': [4, 5, 6]}
df = pd.DataFrame(data, index=['a', 'b', 'c'])

# Reindexing with new index and columns
new_index = ['a', 'b', 'c', 'd']
new_columns = ['A', 'B', 'C']
reindexed_df = df.reindex(index=new_index, columns=new_columns)

print(reindexed_df)
```

In this DataFrame example, reindex is used to change both the index and the columns.
As with Series, missing elements are filled with NaN.

Indexing and Selection

- **Indexing** involves accessing a specific element or subset of elements within a data structure using its index or label. In Pandas, indexing can be performed using various methods:

Position-based Indexing:

```
# Numpy-style indexing
hits[:3]
```

```
womacto01CHN2006     14
schilcu01BOS2006      1
myersmi01NYA2006      0
Name: h, dtype: int64
```

Label-based Indexing:

```
# Indexing by label
hits[['womacto01CHN2006','schilcu01BOS2006']]
```

```
womacto01CHN2006     14
schilcu01BOS2006      1
Name: h, dtype: int64
```

- **Selection** involves extracting specific portions of data from a data structure. It's closely related to indexing but often involves retrieving more than just a single element. Selection can be performed using methods like slicing and boolean indexing:
  - Slicing extracts a subset of elements using a range of indices. It works for both Series and DataFrames. For example:

```
subset = series[start_index:end_index]
subset = dataframe[start_row:end_row, start_column:end_column]
```

In a `DataFrame` we can slice along either or both axes:

```
baseball_newind[['h','ab']]  # select two specific columns, 'h' and 'ab'
```

	h	ab
womacto01CHN2006	5	50
schilcu01BOS2006	5	2
myersmi01NYA2006	5	0
helliri01MIL2006	5	3
johnsra05NYA2006	5	6
...	...	...
benitar01FLO2007	0	0
benitar01SFN2007	0	0
ausmubr01HOU2007	82	349
aloumo01NYN2007	112	328
alomasa02NYN2007	3	22

100 rows × 2 columns

- **Boolean Indexing:** involves using conditional statements to filter and extract elements that satisfy specific conditions. For example:

```
subset = series[series > threshold]
subset = dataframe[dataframe['column'] > threshold]
```

Slic

```
baseball_newind[baseball_newind.ab>500]
```

	player	year	stint	team	lg	g	ab	r	h	X2b	...	rbi	sb	cs	bb	so	ibb	hbp	sh	sf	gidp
gonzalu01ARI2006	gonzalu01	2006	1	ARI	NL	153	586	93	5	52	...	73.0	0.0	1.0	69	58.0	10.0	7.0	0.0	6.0	14.0
vizquom01SFN2007	vizquom01	2007	1	SFN	NL	145	513	54	126	18	...	51.0	14.0	6.0	44	48.0	6.0	1.0	14.0	3.0	14.0
thomafr04TOR2007	thomafr04	2007	1	TOR	AL	155	531	63	147	30	...	95.0	0.0	0.0	81	94.0	3.0	7.0	0.0	5.0	14.0
rodriiv01DET2007	rodriiv01	2007	1	DET	AL	129	502	50	141	31	...	63.0	2.0	2.0	9	96.0	1.0	1.0	1.0	2.0	16.0
griffke02CIN2007	griffke02	2007	1	CIN	NL	144	528	78	146	24	...	93.0	6.0	1.0	85	99.0	14.0	1.0	0.0	9.0	14.0
delgaca01NYN2007	delgaca01	2007	1	NYN	NL	139	538	71	139	30	...	87.0	4.0	0.0	52	118.0	8.0	11.0	0.0	6.0	12.0
biggicr01HOU2007	biggicr01	2007	1	HOU	NL	141	517	68	130	31	...	50.0	4.0	3.0	23	112.0	0.0	3.0	7.0	5.0	5.0

7 rows × 22 columns

Indexing and Selection

- **Selection:** The indexing field loc allows us to select subsets of rows and columns in an intuitive way:

```
import pandas as pd

# Create a sample Series
data = pd.Series([10, 20, 30, 40], index=['A', 'B', 'C', 'D'])

# Using .loc to select a single element
value = data.loc['B']
print(value)  # Output: 20

# Using .loc to select a subset of elements
subset = data.loc[['A', 'C', 'D']]
print(subset)
```

```python
import pandas as pd

# Create a sample DataFrame
data = {
    'A': [1, 2, 3],
    'B': [4, 5, 6],
    'C': [7, 8, 9]
}
df = pd.DataFrame(data, index=['X', 'Y', 'Z'])

# Using .loc to select a single element
value = df.loc['Y', 'B']
print(value)  # Output: 5

# Using .loc to select a row or rows
row_subset = df.loc['Y']
print(row_subset)

# Using .loc to select specific rows and columns
subset = df.loc[['X', 'Z'], ['A', 'C']]
print(subset)
```

When using .loc with a DataFrame, you provide two arguments separated by a comma:

.loc[row_label(s), column_label(s)]

Similarly, the cross-section method `xs` (not a field) extracts a single column or row *by label* and returns it as a `Series`:

```
baseball_newind.xs('myersmi01NYA2006')
```

```
player    myersmi01
year           2006
stint             1
team            NYA
lg               AL
g                62
ab                0
r                 0
h                 5
X2b               0
X3b               0
hr                0
rbi             0.0
sb              0.0
cs              0.0
bb                0
so              0.0
ibb             0.0
hbp             0.0
sh              0.0
sf              0.0
gidp            0.0
Name: myersmi01NYA2006, dtype: object
```

Sorting and Ranking

- .sort_index():

This method sorts the DataFrame's index in ascending order by default. If the index consists of labels, they will be sorted accordingly.

```
baseball_newind.sort_index().head()
```

	player	year	stint	team	lg	g	ab	r	h	X2b	...	rbi	sb	cs	bb	so	ibb	hbp	sh	sf	gidp
alomasa02NYN2007	alomasa02	2007	1	NYN	NL	8	22	1	3	1	...	0.0	0.0	0.0	0	3.0	0.0	0.0	0.0	0.0	0.0
aloumo01NYN2007	aloumo01	2007	1	NYN	NL	87	328	51	112	19	...	49.0	3.0	0.0	27	30.0	5.0	2.0	0.0	3.0	13.0
ausmubr01HOU2007	ausmubr01	2007	1	HOU	NL	117	349	38	82	16	...	25.0	6.0	1.0	37	74.0	3.0	6.0	4.0	1.0	11.0
benitar01FLO2007	benitar01	2007	2	FLO	NL	34	0	0	0	0	...	0.0	0.0	0.0	0	0.0	0.0	0.0	0.0	0.0	0.0
benitar01SFN2007	benitar01	2007	1	SFN	NL	19	0	0	0	0	...	0.0	0.0	0.0	0	0.0	0.0	0.0	0.0	0.0	0.0

- .sort_index(ascending=False):

This method sorts the DataFrame's index in descending order. The ascending=False argument specifies that you want to sort the index in reverse order, meaning that higher index values will appear first.

```
baseball_newind.sort_index(ascending=False).head()
```

	player	year	stint	team	lg	g	ab	r	h	X2b	...	rbi	sb	cs	bb	so	ibb	hbp	sh	sf	gidp
zaungr01TOR2007	zaungr01	2007	1	TOR	AL	110	331	43	80	24	...	52.0	0.0	0.0	51	55.0	8.0	2.0	1.0	6.0	9.0
womacto01CHN2006	womacto01	2006	2	CHN	NL	19	50	6	5	1	...	2.0	1.0	1.0	4	4.0	0.0	0.0	3.0	0.0	0.0
witasja01TBA2007	witasja01	2007	1	TBA	AL	3	0	0	0	0	...	0.0	0.0	0.0	0	0.0	0.0	0.0	0.0	0.0	0.0
williwo02HOU2007	williwo02	2007	1	HOU	NL	33	59	3	6	0	...	2.0	0.0	0.0	0	25.0	0.0	0.0	5.0	0.0	1.0
wickmbo01ATL2007	wickmbo01	2007	1	ATL	NL	47	0	0	0	0	...	0.0	0.0	0.0	0	0.0	0.0	0.0	0.0	0.0	0.0

- We can also sort by value, rather than label.
  - See more examples in github code.
- Ranking: does not re-arrange data, but instead returns an index that ranks each value relative to others in the Series.
  - .rank()
  - See more examples in github code

Missing Values/Data

- NA
- NaN
- None
-
- ?
- -
- -99999

Detecting Missing Values:

•isna() / isnull():
Returns a DataFrame of the same shape as the original, with True where missing values are present.
•notna() / notnull():
Returns a DataFrame with True where values are not missing.

Missing Values/Data

- **Removing Missing Values:**

```
df.dropna()  # Drops rows with any missing values
df.dropna(axis=1)  # Drops columns with any missing values
```

- **Filling Missing Values:**

```
df.fillna(value)  # Fills missing values with a specific value
```

Missing Values/Data

- interpolate(): Performs linear interpolation to fill missing values.

```
df.interpolate()  # Performs linear interpolation along columns
```

- **Replacing Missing Values:**

```
df.replace(to_replace=np.nan, value=0)  # Replaces NaN with 0
```

- **Imputation** involves estimating missing values based on existing data. Methods include mean, median, or machine learning techniques.

Data Summation

- .sum()

  calculates the sum of values along a specified axis in a DataFrame or Series.

- .mean()

  is valuable for understanding the average value of data and its distribution.

- .describe()
  - provides a quick statistical summary of a DataFrame, including various descriptive statistics for each column.
  - is applicable only to numeric columns. If you want to include non-numeric columns in the summary, you can use the include parameter like this: df.describe(include='all').

Writing data to files

- **Writing to CSV:**

```
# Write DataFrame to a CSV file
df.to_csv('data.csv', index=False)
```

- **Writing to Excel:**

```
# Write DataFrame to an Excel file
df.to_excel('data.xlsx', index=False)
```

index=False prevents writing row numbers as an extra column

Data Wrangling with Pandas

What is data wrangling?

- Data wrangling, also known as data munging or data preprocessing, refers to the process of cleaning, transforming, and organizing raw data into a more structured and usable format for analysis.
- In the context of Pandas, data wrangling involves using various techniques and methods to handle and prepare data in a way that makes it suitable for analysis, modeling, visualization, and other data-related tasks.

Handling Date and Time Data:

- Parsing and formatting date and time data (e.g., using .to_datetime()).
- Extracting components of date and time (e.g., using .dt accessor).
- Resampling and time-based aggregation.

The `datetime` built-in library handles temporal information down to the nanosecond.

```
from datetime import datetime
```

```
now = datetime.now()
now
```

```
datetime.datetime(2023, 8, 30, 22, 26, 47, 512750)
```

```
now.day
```

```
30
```

```
now.weekday()
```

```
2
```

Data Transformation:

- Changing data types (e.g., using .astype()).
- Applying functions or operations to columns (e.g., using .apply() or .map()).
- Aggregating and summarizing data (e.g., using .groupby() and aggregation functions).
- Merging, joining, and concatenating DataFrames (e.g., using .merge() or .concat()).

• Merging and Joining DataFrame objects

In Pandas, we can combine tables according to the value of one or more ***keys*** that are used to identify rows, much like an index. Using a trivial example:

```
df1 = pd.DataFrame(dict(id=range(4), age=np.random.randint(18, 31, size=4)))
df2 = pd.DataFrame(dict(id=list(range(3)) + list(range(3)), score=np.random.random(size=6)))

print (df1)
print ("\n")
print (df2)
```

```
   id  age
0   0   24
1   1   23
2   2   18
3   3   26


   id     score
0   0  0.789056
1   1  0.567427
2   2  0.193432
3   0  0.277328
4   1  0.317467
5   2  0.353191
```

- Inner join

Let's say you have two tables:

Table A with columns: ID, Name, Age

Table B with columns: ID, Occupation

You want to combine data from both tables based on the common "ID" column.

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

	id	age	score
0	0	24	0.789056
1	0	24	0.277328
2	1	23	0.567427
3	1	23	0.317467
4	2	18	0.193432
5	2	18	0.353191

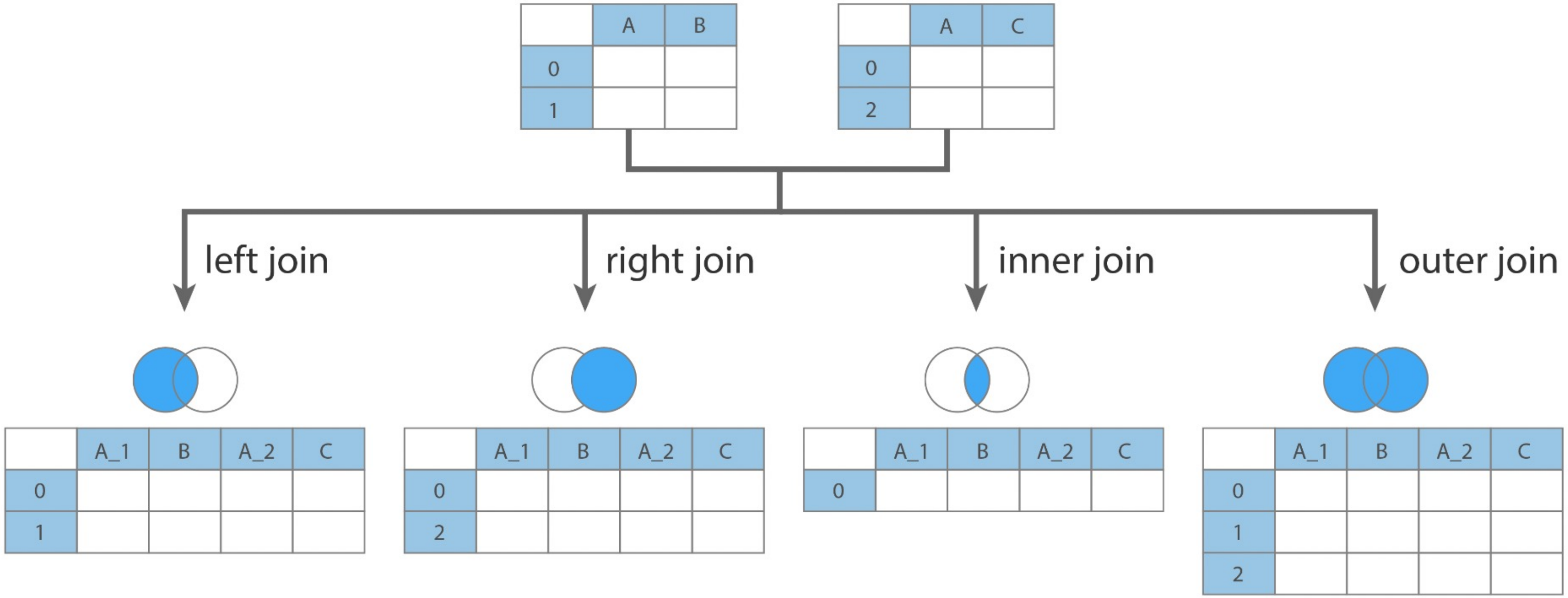
- Outer join

An outer join is a type of database operation used to combine data from two or more tables based on a common key or column. Unlike an inner join, which includes only the rows with matching values in the specified columns, an outer join includes all rows from both tables, filling in missing values with NaN (or other specified values) for non-matching rows.

```
pd.merge(df1, df2, how='outer')
```

	id	age	score
0	0	24	0.789056
1	0	24	0.277328
2	1	23	0.567427
3	1	23	0.317467
4	2	18	0.193432
5	2	18	0.353191
6	3	26	NaN

Joins



See more example codes in github for different ways of join.

- Concatenation

A common data manipulation is appending rows or columns to a dataset that already conform to the dimensions of the exsiting rows or colums, respectively. In NumPy, this is done either with concatenate or the convenience functions c_ and r_:

```
np.concatenate([np.random.random(5), np.random.random(5)])
```

```
array([0.55627575, 0.33710572, 0.66255833, 0.71689758, 0.67439145,
       0.83783671, 0.51672834, 0.36357064, 0.15608224, 0.53061771])
```

```
np.r_[np.random.random(5), np.random.random(5)]
```

```
array([0.7101207 , 0.95955382, 0.01601188, 0.35911948, 0.87334783,
       0.13092789, 0.33191177, 0.35616117, 0.17734696, 0.26362765])
```

concatenate arrays along the first axis, stacking arrays vertically to form rows in the resulting array.

```
np.c_[np.random.random(5), np.random.random(5)]
```

```
array([[0.96997383, 0.54221631],
       [0.66499924, 0.22282137],
       [0.5768224 , 0.8373148 ],
       [0.8814404 , 0.39929759],
       [0.37281569, 0.72967276]])
```

concatenate arrays along the second axis, which is typically the column axis.

Data Transformation:

- Changing data types (e.g., using .astype()).
- Applying functions or operations to columns (e.g., using .apply() or .map()).
- Aggregating and summarizing data (e.g., using .groupby() and aggregation functions).
- Merging, joining, and concatenating DataFrames (e.g., using .merge() or .concat()).

- The .groupby() function in Pandas is used to group rows of a DataFrame based on the values in one or more columns. It's a powerful tool for performing operations on groups of data and aggregating information based on specific criteria.

```python
import pandas as pd

data = {'Category': ['A', 'B', 'A', 'B', 'A'],
        'Value': [10, 20, 15, 25, 30]}

df = pd.DataFrame(data)

# Grouping by the 'Category' column
grouped = df.groupby('Category')

# Calculating the sum of 'Value' for each group
sum_by_category = grouped['Value'].sum()

print(sum_by_category)
```

```
Category
A    55
B    45
Name: Value, dtype: int64
```

- Aggregation in Pandas refers to the process of combining multiple data points into a single summary value. It involves performing a computation on a group of data elements and summarizing the results. Aggregation is often used in combination with the .groupby() function to analyze and summarize data based on specific categories or groups.

  - **Sum**: Calculates the sum of values in a group.
  - **Mean**: Computes the average of values in a group.
  - **Median**: Computes the middle value of values in a group.
  - **Max**: Finds the maximum value in a group.
  - **Min**: Finds the minimum value in a group.
  - **Count**: Counts the number of non-null values in a group.
  - **Size**: Counts the total number of values in a group (including null values).
  - **Std**: Computes the standard deviation of values in a group.
  - **Var**: Computes the variance of values in a group.
  - **Apply**: Applies a custom function to a group.

```python
import pandas as pd

data = {'Category': ['A', 'B', 'A', 'B', 'A'],
        'Value': [10, 20, 15, 25, 30]}

df = pd.DataFrame(data)

# Grouping by the 'Category' column and calculating aggregations
aggregated = df.groupby('Category').agg({
    'Value': ['sum', 'mean', 'max']
})

print(aggregated)
```

```
         Value
           sum       mean max
Category
A           55  18.333333  30
B           45  22.500000  25
```

Data Reshaping:

- Pivoting data from long to wide format (e.g., using .pivot()).
- Melting data from wide to long format (e.g., using .melt()).
- Transposing data (e.g., using .T).

- The .stack() method in Pandas is used to transform or reshape a DataFrame from a wide format to a long format by "stacking" the columns into a single column, resulting in a MultiIndex Series or DataFrame.

```
stacked = cdystonia.stack()
stacked
```

```
0    patient        1
     obs            1
     week           0
     site           1
     id             1
                 ...
630  id            11
     treat      5000U
     age           57
     sex            M
     twstrs        51
Length: 5679, dtype: object
```

To complement this, `unstack` pivots from rows back to columns.

```
stacked.unstack().head()
```

	patient	obs	week	site	id	treat	age	sex	twstrs
0	1	1	0	1	1	5000U	65	F	32
1	1	2	2	1	1	5000U	65	F	30
2	1	3	4	1	1	5000U	65	F	24
3	1	4	8	1	1	5000U	65	F	37
4	1	5	12	1	1	5000U	65	F	39

Data Cleaning:

- Handling missing values (e.g., using .dropna() or .fillna()).
- Removing duplicate rows (e.g., using .drop_duplicates()).
- Correcting inconsistent or erroneous data.

Creating New Features:

- Deriving new columns based on existing ones.
- Using conditional statements to create categorical features.

- Using Basic Arithmetic Operations:

```
import pandas as pd

data = {'A': [10, 20, 30],
        'B': [5, 15, 25]}

df = pd.DataFrame(data)

# Derive a new column 'C' as the sum of columns 'A' and 'B'
df['C'] = df['A'] + df['B']
```

- use built-in functions or user-defined functions to calculate new column values.

```
# Define a function to calculate the square of a number
def square(x):
    return x ** 2

# Derive a new column 'A_squared' using the 'square' function
df['A_squared'] = df['A'].apply(square)
```

- Using Conditional Statements:

```
# Derive a new column 'D' with values based on a condition
df['D'] = df['A'].apply(lambda x: 'High' if x > 20 else 'Low')
```

- Combining Multiple Columns:

```
# Derive a new column 'F' using a combination of columns 'A' and 'B'
df['F'] = df['A'].astype(str) + '_' + df['B'].astype(str')
```

Handling Outliers and Anomalies:

- Identifying and handling outliers using statistical techniques.

Scaling and Normalization:

- Standardizing or normalizing numeric data.