Pandas

Kittikun Jitpairod

Introduction to Pandas

PPandas is a powerful Python library used for data manipulation and analysis. It provides data structures for efficiently storing large datasets and tools for working with them. The two primary data structures in pandas are:

Series: A one-dimensional labeled array

DataFrame: A two-dimensional labeled data structure with columns of potentially different types

Before we begin, make sure Pandas is installed:

```
pip install pandas
```

For Excel support, we also need:

```
pip install openpyxl
```

Let's start by importing Pandas:

```python
import pandas as pd
```

Creating DataFrames

From a dictionary

When creating a DataFrame from a dictionary, the keys become column names, and the values become the data in those columns.

```python
data = {
    'Name': ['John', 'Anna', 'Peter', 'Linda'],
    'Age': [28, 34, 29, 32],
    'City': ['New York', 'Paris', 'Berlin', 'London']
}

df = pd.DataFrame(data)

print(df)
display(df)
```

```
    Name  Age      City
0   John   28  New York
1   Anna   34     Paris
2  Peter   29    Berlin
3  Linda   32    London
```

	Name	Age	City
0	John	28	New York
1	Anna	34	Paris
2	Peter	29	Berlin
3	Linda	32	London

From a list of dictionaries

Sometimes, your data might be in the form of a list of dictionaries, where each dictionary represents a row of data. This method allows for more flexibility in the data structure, as each dictionary (row) doesn't necessarily need to have the same keys (columns).

```python
data = [
    {'Name': 'John', 'Age': 28, 'City': 'New York'},
    {'Name': 'Anna', 'Age': 34, 'City': 'Paris'},
    {'Name': 'Peter', 'Age': 29, 'City': 'Berlin'},
    {'Name': 'Linda', 'Age': 32, 'City': 'London'}
]

df = pd.DataFrame(data)
print(df)
```

```
    Name  Age      City
0   John   28  New York
1   Anna   34     Paris
2  Peter   29    Berlin
3  Linda   32    London
```

From a NumPy array

NumPy arrays are efficient for numerical computations. When you have data in a NumPy array, you can easily convert it to a DataFrame for further analysis.

```
import numpy as np

arr = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]])

df = pd.DataFrame(arr, columns=['A', 'B', 'C'])

print(df)
```

```
   A  B  C
0  1  2  3
1  4  5  6
2  7  8  9
```

Note that when creating a DataFrame from a NumPy array, **you need to specify column names separately**, as arrays don't have built-in column labels.

From a CSV file

CSV (Comma-Separated Values) files are one of the most common formats for storing tabular data. Pandas makes it easy to read these files into DataFrames.

```
df = pd.read_csv('ex_csv.csv')
print(df.head())
```

```
  Serie  Value 1  Value 2  Value 3
0     A        9       96        2
1     B       61       71       28
2     C       36       87       38
3     D       54       77       60
4     E       18       32       99
```

From an Excel Files

Pandas uses the `read_excel()` function for reading Excel files.

You may need to install additional library.

```
pip install openpyxl
```

```
# Basic reading
df = pd.read_excel('ex_excel.xlsx')
print('Basic reading')
print(df.head())

# Reading a specific sheet
df = pd.read_excel('ex_excel.xlsx', sheet_name='Sheet2')
print('\nSheet2')
print(df.head())

# Reading multiple sheets
xlsx = pd.ExcelFile('ex_excel.xlsx')
df1 = pd.read_excel(xlsx, 'Sheet1')
df2 = pd.read_excel(xlsx, 'Sheet2')
```

```
Basic reading
  Serie  Value 1  Value 2  Value 3
0     A        9       96        2
1     B       61       71       28
2     C       36       87       38
3     D       54       77       60
4     E       18       32       99

Sheet2
  Serie  Value 4  Value 5  Value 6
0     K       46       98       99
1     L       71       68       13
2     M       55       45       77
3     N       59        0       15
4     O        5       32       96
```

Export DataFrame

Writing DataFrames to CSV files

Writing DataFrames to CSV files is just as straightforward with the `to_csv()` method.

```
# Basic writing
df.to_csv('output.csv')

# Writing with specific options
df.to_csv('output.csv',
```

```python
          index=False,  # Don't write index
          columns=['Name', 'Age'],  # Only write specific columns
          sep=';',  # Use semicolon as separator
          encoding='utf-8')  # Specify encoding

# Writing without header
df.to_csv('output.csv', header=False)
```

Writing Excel Files with Pandas

Writing to Excel files is done using the `to_excel()` method.

```python
# Basic writing
df.to_excel('output.xlsx', sheet_name='Sheet1')

# Writing multiple DataFrames to different sheets
with pd.ExcelWriter('output.xlsx') as writer:
    df1.to_excel(writer, sheet_name='Sheet1')
    df2.to_excel(writer, sheet_name='Sheet2')
```

Basic DataFrame Operations

Once you have a DataFrame, there are numerous operations you can perform to explore and manipulate your data:

Viewing Data

These methods allow you to quickly inspect your DataFrame:

```python
data = {
    'Name': ['John', 'Anna', 'Peter', 'Linda'],
    'Age': [28, 34, 29, 32],
    'City': ['New York', 'Paris', 'Berlin', 'London']
}
df = pd.DataFrame(data)
```

```python
print(df.head(3))  # First 3 rows
```

```
    Name  Age      City
0   John   28  New York
1   Anna   34     Paris
2  Peter   29    Berlin
```

```python
print(df.tail(3))  # Last 3 rows
```

```
    Name  Age    City
1   Anna   34   Paris
2  Peter   29  Berlin
3  Linda   32  London
```

DataFrame info, including column types and non-null counts

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4 entries, 0 to 3
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Name    4 non-null      object
 1   Age     4 non-null      int64
 2   City    4 non-null      object
dtypes: int64(1), object(2)
memory usage: 228.0+ bytes
None
```

Statistical summary of numerical columns

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

```
             Age
count   4.000000
mean   30.750000
std     2.753785
min    28.000000
25%    28.750000
50%    30.500000
75%    32.500000
max    34.000000
```

These operations are crucial for getting a quick overview of your data, understanding its structure, and identifying potential issues or patterns.

Accessing Data

Accessing a single column

```
print(df['Name'])
```

```
0     John
1     Anna
2    Peter
3    Linda
Name: Name, dtype: object
```

Accessing multiple columns

```
print(df[['Name', 'Age']])
```

```
    Name  Age
0   John   28
1   Anna   34
2  Peter   29
3  Linda   32
```

Accessing a row by label

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

```
Name        John
Age           28
City    New York
Name: 0, dtype: object
```

Accessing a row by integer index

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

```
Name        John
Age           28
City    New York
Name: 0, dtype: object
```

Accessing a specific value

```
print(df.loc[0, 'Name'])
```

```
John
```

Adding and Deleting Columns

DataFrames are mutable, allowing you to add or remove columns as needed:

Adding a new column

```
df['Salary'] = [50000,60000,55000,65000]
print(df)
```

```
    Name  Age      City  Salary
0   John   28  New York   50000
1   Anna   34     Paris   60000
2  Peter   29    Berlin   55000
3  Linda   32    London   65000
```

Deleting a column

```
df = df.drop('Salary', axis=1)
print(df)
```

```
    Name  Age      City
0   John   28  New York
1   Anna   34     Paris
2  Peter   29    Berlin
3  Linda   32    London
```

Filtering row

Filtering allows you to focus on specific subsets of your data:

```
print(df[df['Age'] > 30])
```

```
    Name  Age    City
1   Anna   34   Paris
3  Linda   32  London
```

```
print(df[df['Age'] > 30]['City'])
```

```
1     Paris
3    London
Name: City, dtype: object
```

```
print(df[(df['Age'] > 30) & (df['City'] == 'London')])  # AND condition
```

```
    Name  Age    City
3  Linda   32  London
```

```
print(df[(df['Age'] > 30) | (df['City'] == 'New York')])  # OR condition
```

```
    Name  Age      City
0   John   28  New York
1   Anna   34     Paris
3  Linda   32    London
```

Filtering row (using `.loc()`)

Filtering allows you to focus on specific subsets of your data:

```
print(df.loc[df['Age'] > 30])
```

```
    Name  Age    City
1   Anna   34   Paris
3  Linda   32  London
```

```
print(df.loc[df['Age'] > 30, 'City'])
```

```
1     Paris
3    London
Name: City, dtype: object
```

```
print(df.loc[(df['Age'] > 30) & (df['City'] == 'London')])  # AND condition
```

```
    Name  Age    City
3  Linda   32  London
```

```python
print(df.loc[(df['Age'] > 30) | (df['City'] == 'New York')])  # OR condition
```

```
    Name  Age      City
0   John   28  New York
1   Anna   34     Paris
3  Linda   32    London
```

Data Manipulation

Data manipulation is at the heart of data analysis. Pandas provides powerful tools for sorting, grouping, aggregating, and transforming data:

Sorting

Sorting allows you to order your data based on one or more columns:

```python
print(df.sort_values('Age', ascending=False))  # Sort descending
```

```
    Name  Age      City
1   Anna   34     Paris
3  Linda   32    London
2  Peter   29    Berlin
0   John   28  New York
```

```python
print(df.sort_values(['City', 'Age']))  # Sort by multiple columns
```

```
    Name  Age      City
2  Peter   29    Berlin
3  Linda   32    London
0   John   28  New York
1   Anna   34     Paris
```

Grouping and Aggregation

Grouping allows you to split your data into groups based on some criteria and then perform calculations on each group:

```python
print(df.groupby('City')['Age'].mean())  # Mean age by city
```

```
City
Berlin      29.0
London      32.0
New York    28.0
Paris       34.0
Name: Age, dtype: float64
```

```
print(df.groupby('City').agg({'Age': 'mean', 'Name': 'count'}))  # Multiple aggregations
```

```
           Age  Name
City
Berlin    29.0     1
London    32.0     1
New York  28.0     1
Paris     34.0     1
```

Pandas provides a wide range of aggregation functions. Here are some commonly used ones:

1. `count()`: Count of non-null values
2. `sum()`: Sum of values
3. `mean()`: Arithmetic mean of values
4. `median()`: Median of values
5. `min()`, `max()`: Minimum and maximum values
6. `std()`, `var()`: Standard deviation and variance
7. `first()`, `last()`: First and last non-null values
8. `nunique()`: Number of unique values
9. `quantile()`: Quantile of values
10. `agg()`: Allows applying multiple aggregation functions at once

Applying Functions

You can apply custom functions to your data using the `apply` method:

```
df['Name_Length'] = df['Name'].apply(len)  # Apply a function to a column
print(df)
```

```
    Name  Age      City  Name_Length
0   John   28  New York            4
1   Anna   34     Paris            4
2  Peter   29    Berlin            5
3  Linda   32    London            5
```

This allows for complex transformations and feature engineering.

Merging

Combining data from different sources is a common task in data analysis:

```
df2 = pd.DataFrame({
    'City': ['New York', 'Paris', 'Berlin', 'London'],
    'Country': ['USA', 'France', 'Germany', 'UK']
})
merged_df = pd.merge(df, df2, on='City')
print(merged_df)
```

```
    Name  Age      City  Name_Length  Country
0   John   28  New York            4      USA
1   Anna   34     Paris            4   France
2  Peter   29    Berlin            5  Germany
3  Linda   32    London            5       UK
```

Merging allows you to combine data from different sources **based on common columns or indices**.

Mapping DataFrames

Mapping allows you to replace values in a DataFrame based on a dictionary:

```
data = {
    'Name': ['John', 'Anna', 'Peter', 'Linda'],
    'Age': [28, 34, 29, 32],
    'City': ['New York', 'Paris', 'Berlin', 'London']
}
df = pd.DataFrame(data)

# Create a mapping dictionary
city_country = {
    'New York': 'USA',
    'Paris': 'France',
    'Berlin': 'Germany',
    'London': 'UK'
}

# Apply the mapping to create a new column
df['Country'] = df['City'].map(city_country)
print(df)
```

```
    Name  Age      City  Country
0   John   28  New York      USA
1   Anna   34     Paris   France
2  Peter   29    Berlin  Germany
3  Linda   32    London       UK
```

Mapping is useful for categorizing data, replacing codes with meaningful labels, or performing lookups based on a dictionary.

Concatenating DataFrames

Concatenation allows you to combine DataFrames along a particular axis:

```
df1 = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
                    'B': ['B0', 'B1', 'B2']},
                    index=['K0', 'K1', 'K2'])

df2 = pd.DataFrame({'C': ['C0', 'C1', 'C2'],
                    'D': ['D0', 'D1', 'D2']},
                    index=['K0', 'K1', 'K2'])
```

Concatenate along columns (axis=1)

```
result = pd.concat([df1, df2], axis=1)
print(result)
```

```
    A   B   C   D
K0  A0  B0  C0  D0
K1  A1  B1  C1  D1
K2  A2  B2  C2  D2
```

Concatenate along rows (axis=0)

```
df3 = pd.DataFrame({'A': ['A3', 'A4'],
                      'B': ['B3', 'B4']},
                      index=['K3', 'K4'])

result = pd.concat([df1, df3])
print(result)
```

```
      A   B
K0   A0  B0
K1   A1  B1
K2   A2  B2
K3   A3  B3
K4   A4  B4
```

Concatenate with different indexes

```
df4 = pd.DataFrame({'A': ['A5', 'A6'],
                    'C': ['C5', 'C6']},
                    index=['K1', 'K6'])

result = pd.concat([df1, df4])
print(result)
```

```
      A    B    C
K0   A0   B0  NaN
K1   A1   B1  NaN
K2   A2   B2  NaN
K1   A5  NaN   C5
K6   A6  NaN   C6
```

```
result = pd.concat([df1, df4], ignore_index=True)
print(result)
```

```
     A    B    C
0   A0   B0  NaN
1   A1   B1  NaN
2   A2   B2  NaN
3   A5  NaN   C5
4   A6  NaN   C6
```

```
result = pd.concat([df1, df4]).reset_index() # reset index of DataFrame
print(result)
```

```
  index   A    B    C
0    K0  A0   B0  NaN
1    K1  A1   B1  NaN
2    K2  A2   B2  NaN
3    K1  A5  NaN   C5
4    K6  A6  NaN   C6
```

Handling Missing Data

Missing data is common in real-world datasets. Let's see how to handle it:

```
df = pd.DataFrame({
    'A': [1, np.nan, 4],
    'B': [5, np.nan, np.nan],
    'C': [9, 10, 11]})
```

Check for missing values

```
print(df.isnull())
```

```
       A      B      C
0  False  False  False
1   True   True  False
2  False   True  False
```

Drop rows with missing values

```
print(df.dropna())
```

```
     A    B  C
0  1.0  5.0  9
```

Fill missing values with 0

```
print(df.fillna(0))
```

```
     A    B   C
0  1.0  5.0   9
1  0.0  0.0  10
2  4.0  0.0  11
```

Fill missing values with mean

```
df['B'] = df['B'].fillna(df['B'].mean())
print(df)
```

```
     A    B   C
0  1.0  5.0   9
1  NaN  5.0  10
2  4.0  5.0  11
```

Reshaping Data

In data analysis, we often need to reshape our data. Two common operations for this are pivot and unpivot, which transform data between "wide" and "long" formats.

Wide vs. Long Tables

Wide Format (or Wide Table):

- Each subject's repeated responses are in a single row.
- Each response is in a separate column.
- Usually easier for humans to read.

Long Format (or Long Table):

- Each row is a single subject-response combination.
- Usually easier for machines to process and for certain types of analysis.

Let's look at an example:

Wide format data

```python
wide_data = pd.DataFrame({
    'Name': ['Alice', 'Bob'],
    'Math': [90, 70],
    'Science': [85, 80]
})

print("Wide Format:")
print(wide_data)
```

```
Wide Format:
    Name  Math  Science
0  Alice    90       85
1    Bob    70       80
```

Long format data

```python
long_data = pd.DataFrame({
    'Name': ['Alice', 'Alice', 'Bob', 'Bob'],
    'Subject': ['Math', 'Science', 'Math', 'Science'],
    'Score': [90, 85, 70, 80]
})

print("Long Format:")
print(long_data)
```

```
Long Format:
    Name  Subject  Score
0  Alice     Math     90
1  Alice  Science     85
2    Bob     Math     70
3    Bob  Science     80
```

Unpivot (Wide to Long)

Unpivot (also known as “melt” in Pandas) is the opposite operation, transforming data from wide format to long format.

- It turns columns into rows.
- In Pandas, we use the `melt()` function for this operation.

```python
# Unpivot operation (Wide to Long)
melted = wide_data.melt(id_vars=['Name'], var_name='Subject', value_name='Score')

print("After Melt (Wide to Long):")
print(melted)
```

```
After Melt (Wide to Long):
    Name  Subject  Score
0  Alice     Math     90
1    Bob     Math     70
2  Alice  Science     85
3    Bob  Science     80
```

Pivot (Long to Wide)

Pivot is an operation that transforms data from long format to wide format.

- It typically uses one column to create new columns.
- Values from another column fill these new columns.

```python
# Pivot operation (Long to Wide)
pivoted = long_data.pivot(index='Name', columns='Subject', values='Score')

print("After Pivot (Long to Wide):")
print(pivoted)
```

```
After Pivot (Long to Wide):
Subject  Math  Science
Name
Alice      90       85
Bob        70       80
```

When to Use Each Format

1. Use Long Format when:
    - Performing statistical analyses that assume each observation is a row.
    - Creating certain types of visualizations (e.g., with libraries like Seaborn).
    - Working with time-series data.
2. Use Wide Format when:
    - Creating summary tables for reports.
    - Performing operations that require values to be in the same row.