



CoGrammar

Datasets and DataFrames



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Data Science Lecture Housekeeping

- The use of disrespectful language is prohibited in the questions, this is a supportive, learning environment for all - please engage accordingly.
(FBV: Mutual Respect.)
- No question is daft or silly - **ask them!**
- There are **Q&A sessions** midway and at the end of the session, should you wish to ask any follow-up questions. Moderators are going to be answering questions as the session progresses as well.
- If you have any questions outside of this lecture, or that are not answered during this lecture, please do submit these for upcoming Open Classes.
You can submit these questions here: [Open Class Questions](#)

Data Science Lecture Housekeeping cont.

- For all **non-academic questions**, please submit a query: www.hyperiondev.com/support
- Report a **safeguarding** incident: www.hyperiondev.com/safeguardreporting
- We would love your **feedback** on lectures: [Feedback on Lectures](#)

Lecture Objectives

- Learn how to **read and manipulate data** with **Pandas**

Datasets

- ★ A dataset is a **structured collection of information relevant to a specific investigation or project**
- ★ In data science, they provide the raw material for analysis and modeling. Understanding different dataset formats ensures you can work with data from various sources (databases, online repositories, etc.).
- ★ With the help of pandas DataFrames, we can effortlessly manipulate data to suit our needs.

DataFrames

- ★ A DataFrame is the way the Pandas library in Python **represents tabular data. It's like a powerful spreadsheet within your code.**
- ★ **Rows:** Each row represents a **single observation** or data point (e.g., a person, a product, a transaction).
- ★ **Columns:** Each column represents a **variable or feature** (e.g., height, price, date). Data within a column usually shares the **same data type** (numbers, text, etc.).

Jupyter Notebook

- ★ An **interactive environment** perfect for **data science work**. They let you **combine code, the results of the code (output), and explanatory text (like in a scientific report)**.
- ★ This fosters **clear data exploration and storytelling**, all in one place

Pandas DataFrame

- ★ The pandas' library documentation defines a DataFrame as a **“two-dimensional, size-mutable, with labelled rows and columns.”**

columns axis=1

column name

more columns to display

index label

index axis=0

missing values

data (values)

| | color | director_name | num_critic_for_reviews | duration | actor_2_facebook_likes | imdb_score | aspect_ratio | movie_facebook_likes |
|---|-------|-------------------|------------------------|-----------|------------------------|------------|--------------|----------------------|
| 0 | Color | James Cameron | 723.0 | 178.0 ... | 936.0 | 7.9 | 1.78 | 33000 |
| 1 | Color | Gore Verbinski | 302.0 | 169.0 ... | 5000.0 | 7.1 | 2.35 | 0 |
| 2 | Color | Sam Mendes | 602.0 | 148.0 ... | 393.0 | 6.8 | 2.35 | 85000 |
| 3 | Color | Christopher Nolan | 813.0 | 164.0 ... | 23000.0 | 8.5 | 2.35 | 164000 |
| 4 | NaN | Doug Walker | NaN | NaN ... | 12.0 | 7.1 | NaN | 0 |

Anatomy of a DataFrame

Pandas DataFrame

- ★ Pandas provides functions like **pd.read_csv()**, **pd.read_excel()**, etc., to bring your data directly into your coding environment as DataFrames.
- ★ This is where you start turning your raw data into something easily workable.

```
# url = 'https://raw.githubusercontent.com/mwaskom/seaborn-data/master/iris.csv'  
# df = pd.read_csv(url)  
  
iris = datasets.load_iris()  
df = pd.DataFrame(iris.data, columns=iris.feature_names)
```

Exploring Datasets

- ★ **df.head(), df.tail():** Peek at the **top** and **bottom** rows for initial understanding.

```
df.head()
```

✓ 0.0s

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | species |
|---|-------------------|------------------|-------------------|------------------|---------|
| 0 | 5.1 | 3.5 | 1.4 | 0.2 | 0 |
| 1 | 4.9 | 3.0 | 1.4 | 0.2 | 0 |
| 2 | 4.7 | 3.2 | 1.3 | 0.2 | 0 |
| 3 | 4.6 | 3.1 | 1.5 | 0.2 | 0 |
| 4 | 5.0 | 3.6 | 1.4 | 0.2 | 0 |

Exploring Datasets

- ★ **df.head(), df.tail():** Peek at the **top** and **bottom** rows for initial understanding.

```
df.tail()
```

✓ 0.0s

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | species |
|-----|-------------------|------------------|-------------------|------------------|---------|
| 145 | 6.7 | 3.0 | 5.2 | 2.3 | 2 |
| 146 | 6.3 | 2.5 | 5.0 | 1.9 | 2 |
| 147 | 6.5 | 3.0 | 5.2 | 2.0 | 2 |
| 148 | 6.2 | 3.4 | 5.4 | 2.3 | 2 |
| 149 | 5.9 | 3.0 | 5.1 | 1.8 | 2 |

Exploring Datasets

- ★ **df.shape**: Tells you the **dimensions (rows, columns)** of your data.

```
df.shape
```

```
✓ 0.0s
```

```
(150, 5)
```

Exploring Datasets

- ★ **df.info()**: Gives the **data types** of each column, and if columns have missing values.

```
df.info()
✓ 0.0s

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
#   Column                Non-Null Count  Dtype
---  -
0   sepal length (cm)      150 non-null   float64
1   sepal width (cm)       150 non-null   float64
2   petal length (cm)      150 non-null   float64
3   petal width (cm)       150 non-null   float64
4   species                150 non-null   int64
dtypes: float64(4), int64(1)
memory usage: 6.0 KB
```

Exploring Datasets

- ★ **df.describe():** Quick **summary statistics** for **numerical columns**.

```
df.describe()
```

✓ 0.0s

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | species |
|-------|-------------------|------------------|-------------------|------------------|------------|
| count | 150.000000 | 150.000000 | 150.000000 | 150.000000 | 150.000000 |
| mean | 5.843333 | 3.057333 | 3.758000 | 1.199333 | 1.000000 |
| std | 0.828066 | 0.435866 | 1.765298 | 0.762238 | 0.819232 |
| min | 4.300000 | 2.000000 | 1.000000 | 0.100000 | 0.000000 |
| 25% | 5.100000 | 2.800000 | 1.600000 | 0.300000 | 0.000000 |
| 50% | 5.800000 | 3.000000 | 4.350000 | 1.300000 | 1.000000 |
| 75% | 6.400000 | 3.300000 | 5.100000 | 1.800000 | 2.000000 |
| max | 7.900000 | 4.400000 | 6.900000 | 2.500000 | 2.000000 |

Exploring Datasets

- ★ All the previous methods **let you quickly grasp the size and structure of your data, helping you plan analysis steps.**

Manipulating Data

- ★ **Selecting Columns:** You often work with a **subset of features**. Using `df[['column1', 'column2']]` gets you only specified columns.

```
df.columns
```

```
✓ 0.0s
```

```
Index(['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)',  
      'petal width (cm)', 'species'],  
      dtype='object')
```

```
# Select specific columns
```

```
df_selected = df[['species', 'petal length (cm)', 'petal width (cm)']]
```

```
✓ 0.0s
```


Manipulating Data

- ★ **Filtering Rows:** Focus on specific subsets meeting certain conditions, e.g., `df[df['age'] > 30]`.

```
# Filter by flower species  
df_setosa = df[df['species'] == 'setosa']  
✓ 0.0s
```

Manipulating Data

- ★ **Creating New Columns:** Derived features, e.g., calculating BMI from height and weight.

```
# Create a new calculated column  
df['petal area (cm^2)'] = df['petal length (cm)'] * df['petal width (cm)']  
✓ 0.0s
```

Manipulating Data

- ★ **Renaming/Dropping:** Improve clarity or get rid of unneeded data.

```
# Rename a column  
df = df.rename(columns={'sepal length (cm)': 'sepal_len'})  
✓ 0.0s
```

- ★ Data manipulation gives you a **highly customized DataFrame focused on your exact analysis needs.**

Built-in Methods

- ★ Pandas offers a toolbox of functions for calculations:
 - **mean()** - Computes the mean for each column.
 - **min()** - Computes the minimum for each column.
 - **max()** - Computes the maximum for each column.
 - **std()** - Computes the standard deviation for each column.
 - **var()** - Computes the variance for each column.
 - **nunique()** - Computes the number of unique values in each column.

- ★ This is the start of understanding the characteristics of your data.

Grouping and Aggregation

- ★ **df.groupby():** Divide your data **based on categories** in a column (e.g., group by country).

```
print(df['petal area (cm^2)'].mean())
print(df['species'].nunique())
print(df.groupby('species')['petal length (cm)'].std())
✓ 0.0s

5.794066666666667
3
species
0    0.173664
1    0.469911
2    0.551895
Name: petal length (cm), dtype: float64
```

Grouping and Aggregation

- ★ **.agg()**: Apply calculations within each group (e.g., average salary per country).

```
df.groupby('species').agg(  
    mean_petal_length=('petal length (cm)', 'mean'),  
    max_sepal_width=('sepal width (cm)', 'max')  
)
```

✓ 0.0s

| | mean_petal_length | max_sepal_width |
|---------|-------------------|-----------------|
| species | | |
| 0 | 1.462 | 4.4 |
| 1 | 4.260 | 3.4 |
| 2 | 5.552 | 3.8 |

Data Visualization

- ★ There is a whole lecture dedicated to this, but libraries like **Matplotlib** and **Seaborn** make visually exploring data easy. **Plots (scatter plots, histograms, etc.) rapidly uncover relationships and distributions that are less clear from tables of numbers.**
- ★ Some good examples are in the [Seaborn Gallery](#).

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Q & A SECTION

**Please use this time to ask
any questions relating to the
topic, should you have any.**



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Thank you for joining!