CoGrammar

Welcome to this session:

Task Walkthrough - Tasks 11 - 12

The session will start shortly...

Questions? Drop them in the chat. We'll have dedicated moderators answering questions.

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- The use of disrespectful language is prohibited in the questions, this is a supportive, learning environment for all - please engage accordingly. **(Fundamental British Values: Mutual Respect and Tolerance)**
- 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 Academic Sessions. You can submit these questions here: **Questions**

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- For all **non-academic questions**, please submit a query: ***www.hyperiondev.com/support***
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- We would love your feedback on lectures: ***Feedback on Lectures***
- If you are hearing impaired, please kindly use your computer's function through Google chrome to enable captions.

Learning Outcomes

- **Load and explore datasets using pandas** to understand their structure and contents.
- **Perform basic data manipulations** on DataFrames, such as filtering, sorting, and summarizing data.
- **Create visualizations using matplotlib and seaborn** to identify trends, patterns, and relationships in data.
- **Combine DataFrame operations with visualizations** to generate comprehensive data analysis reports.

Task Walkthrough

For today's task you're a data scientist analyzing movie data for a streaming platform.

Your task is to:

- Load and explore a dataset containing information about movies (e.g., title, genre, rating, revenue).

- Perform basic manipulations to answer key questions like:
  - Which genre has the highest average rating?
  - Which movie had the highest revenue?
  - How many movies were released each year?

Task Walkthrough

- Visualize trends and insights using matplotlib and seaborn, such as:
  - A bar chart of average ratings by genre.
  - A line graph showing the number of movies released per year.
  - A scatter plot of revenue vs. rating to identify correlations.

- Create advanced visualizations with seaborn to gain deeper insights, including:
  - Heatmaps to explore correlations between numerical variables (e.g., rating and revenue).
  - Box plots to visualize the distribution of ratings by genre.
  - Violin plots to compare revenue distributions for different genres.
  - Pair plots to explore relationships between multiple variables.

Which pandas method is used to calculate the average of a column grouped by another column?

A. groupby() and mean()
B. value_counts()
C. filter()
D. pivot_table()

What is the purpose of a scatter plot?

A. To compare categories
B. To show trends over time
C. To display relationships between two numerical variables
D. To count occurrences of data points

Pandas DataFrame

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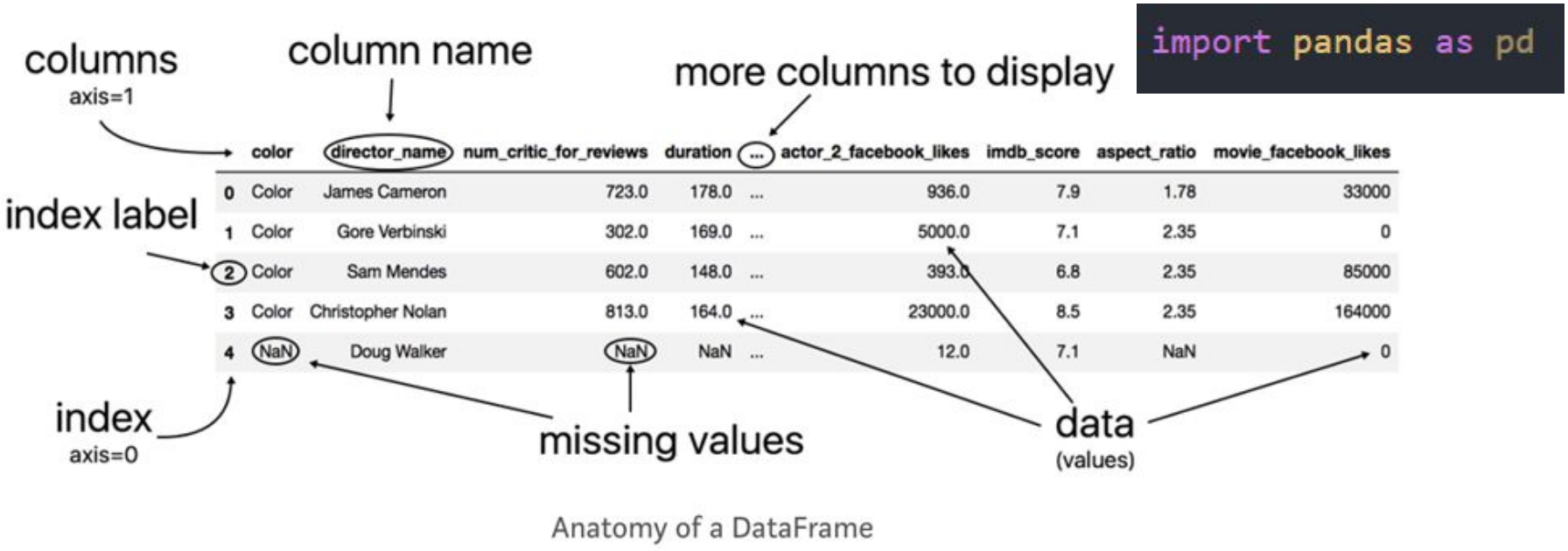
Pandas DataFrame

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



	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(), pd.read_sql()**, to bring your data directly into your coding environment as DataFrames.

- This is where you start turning your raw data into something easily workable.

```
import pandas as pd
```

```
# 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

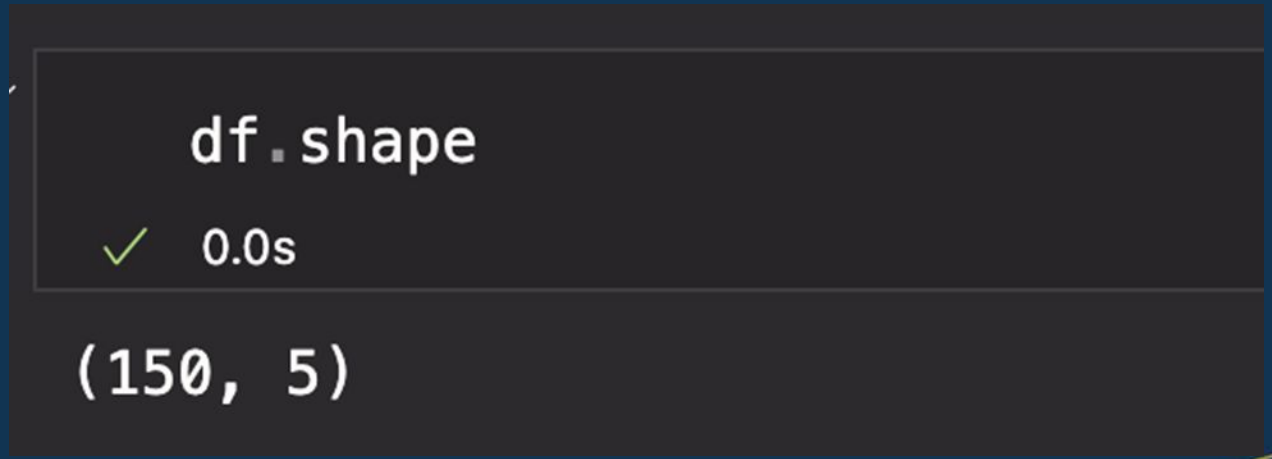
```
df.tail()
```

✓ 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.



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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
```

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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

Manipulating Data

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Manipulating Data

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

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Manipulating Data

- **Filtering Rows:** Focus on specific subsets meeting certain conditions, e.g., df[df['species'] == 'setosa']

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

✓ 0.0s

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Manipulating Data

- **Creating New Columns:** Derived features, e.g., calculating area from length and width.

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

✓ 0.0s

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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.

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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.
  - **unique()** - Computes the number of unique values in each column.

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

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Grouping and Aggregation

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

```
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
```

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Grouping and Aggregation

- **.agg()**: Apply calculations within each group (e.g., average length, maximum width).

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

✓ 0.0s

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

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Matplotlib

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Matplotlib

Installation

```
pip install matplotlib
```

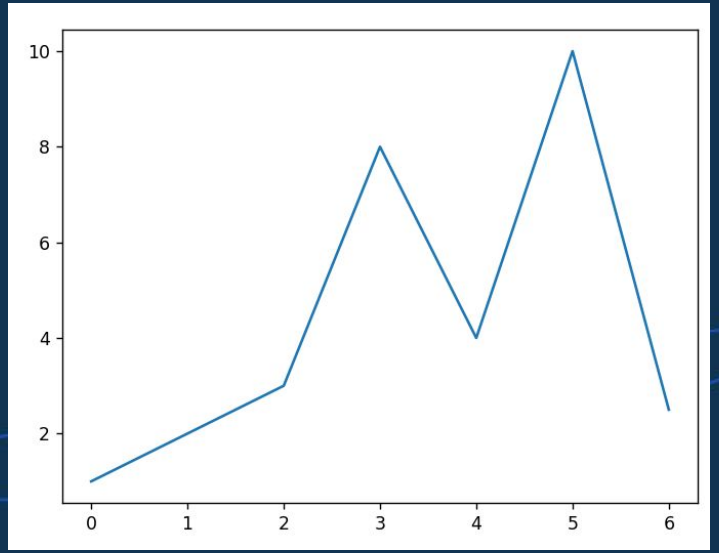
Importing

```
import matplotlib.pyplot as plt
```

```
import matplotlib.pyplot as plt
import numpy as np

ypoints = np.array([1, 2, 3, 8, 4, 10, 2.5])

plt.plot(ypoints)
plt.show()
```



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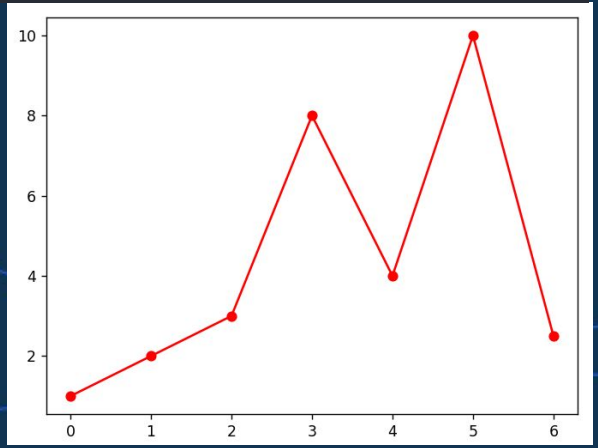
Matplotlib

```
import matplotlib.pyplot as plt
import numpy as np

ypoints = np.array([1, 2, 3, 8, 4, 10, 2.5])

plt.plot(ypoints, 'o-r')

plt.show()
```



Markers
o = Circle, * = Star,
. = Point, x = Cross,
s = Square, d = diamond

Linestyle ls
- Solid line
: Dotted line
-- Dashed line
-. Dashed/dotted line

Colour ***List of colours***
b = Blue, r = Red, g = Green,
c = Cyan, m = Magenta, y = Yellow, k = Black, w = White

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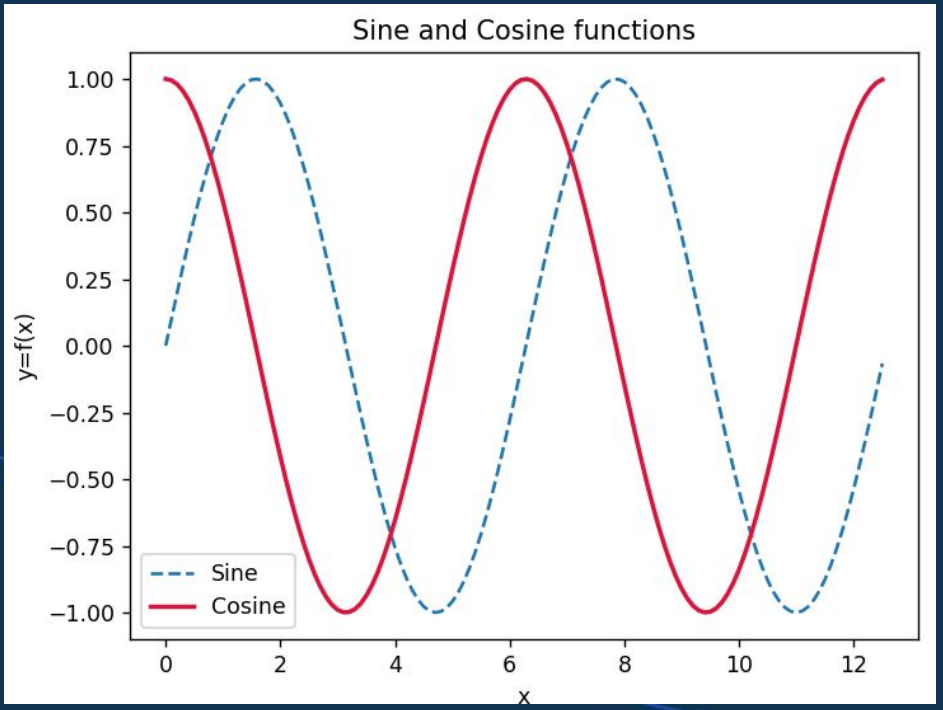
Matplotlib




```python
import matplotlib.pyplot as plt
import numpy as np

pi = np.pi
# Creating x axis with range
#and y axis with sine/cosine
x = np.arange(0, 4*pi, 0.1)
y1 = np.sin(x)
y2 = np.cos(x)

#Plotting sine/cosine on the same plot
plt.plot(x,y1, label='Sine', ls='--')
plt.plot(x,y2, label='Cosine', lw=2, c='crimson')

#x-axis, y-axis label, and plot title
plt.xlabel('x')
plt.ylabel('y=f(x)')
plt.title('Sine and Cosine functions')

#Legend for the two curves
plt.legend()
plt.show() #plt.savefig('sine.png')
```

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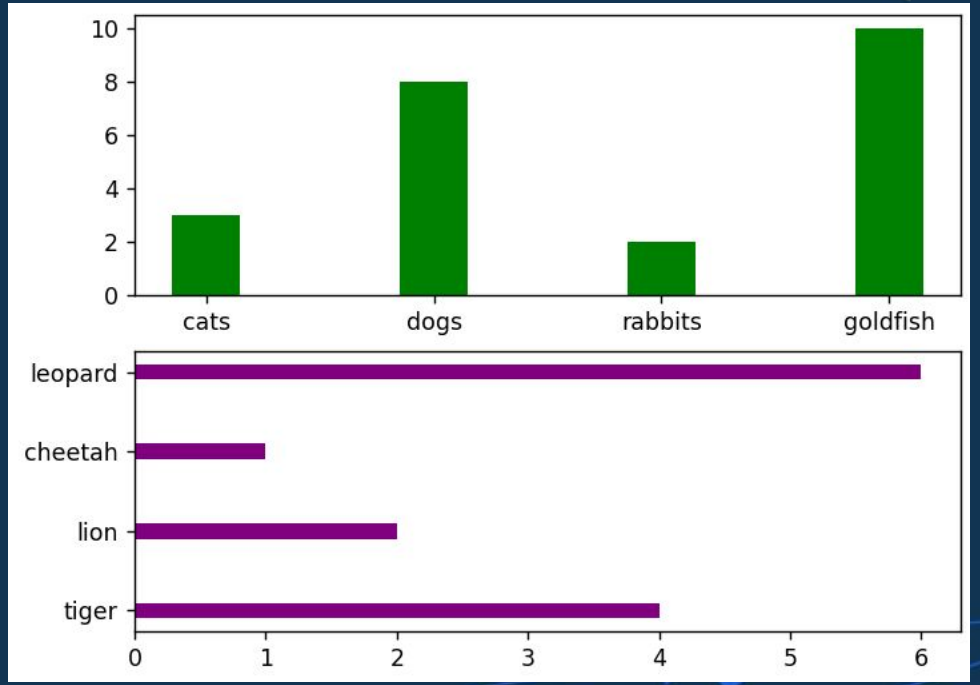
Matplotlib: Barplot

```
import matplotlib.pyplot as plt
import numpy as np

#x,y for 1st and 2nd barplots
x1 = np.array(["cats", "dogs", "rabbits", "goldfish"])
y1 = np.array([3, 8, 2, 10])
x2 = np.array(["tiger", "lion", "cheetah", "leopard"])
y2 = np.array([4, 2, 1, 6])

#Subplot, parameters(rows, columns, index of current plot)
plt.subplot(2,1,1)
plt.bar(x1, y1, color = 'g', width=0.3)
plt.subplot(2,1,2)
plt.barh(x2, y2, color = '#800080', height=0.2)
plt.show()
```



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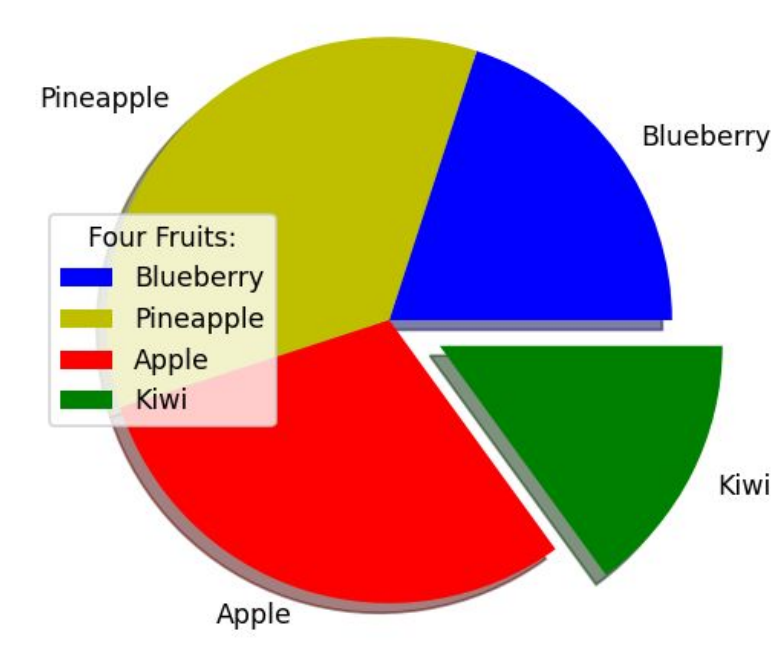
Matplotlib: Pie chart




```python
import matplotlib.pyplot as plt
import numpy as np

y = np.array([20, 35, 30, 15])
mylabels = ['Blueberry', 'Pineapple','Apple', 'Kiwi']
mycolors = ['b', 'y', 'r', 'g']
myexplode = [0, 0, 0, 0.2]

plt.pie(y, labels = mylabels, colors = mycolors,
        explode = myexplode, shadow = True)
plt.legend(loc='center left',title = "Four Fruits:")
plt.show()
```

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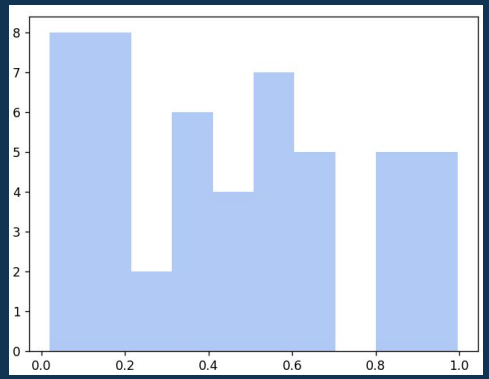
Histograms & Scatterplots

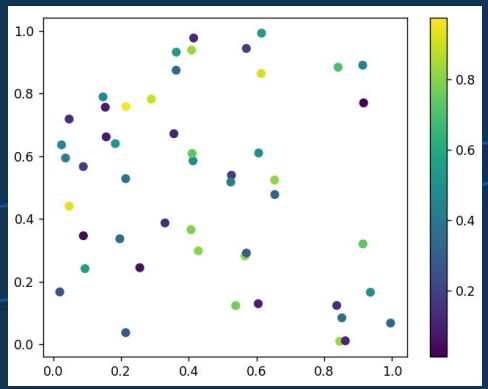
A graph showing frequency distributions, the number of observations within each given interval.

```
N = 50
x = np.random.rand(N)
y = np.random.rand(N)
colors = np.random.rand(N)

plt.hist(x, color='cornflowerblue', alpha=0.5)
plt.show()

plt.scatter(x, y, c=colors)
plt.colorbar()
plt.show()
```





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Seaborn

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Seaborn

- **Matplotlib** is a low-level plotting library, create highly customizable visualizations.

- **Seaborn**, built on top of Matplotlib, is a high-level interface for creating statistical graphics, with a range of built-in statistical functions for complex statistical analyses with the visualizations.

- Designed to work with **Pandas** dataframes

Seaborn

Installation `pip install seaborn`

Importing `import seaborn as sns`

```python
# Import seaborn, matplotlib
import seaborn as sns
import matplotlib.pyplot as plt

#Check available datasets
print(sns.get_dataset_names())

# Load an example dataset
peng_df = sns.load_dataset("penguins")
#Check the dataset
peng_df.info()
```

- load_dataset() is like pd.read_csv()

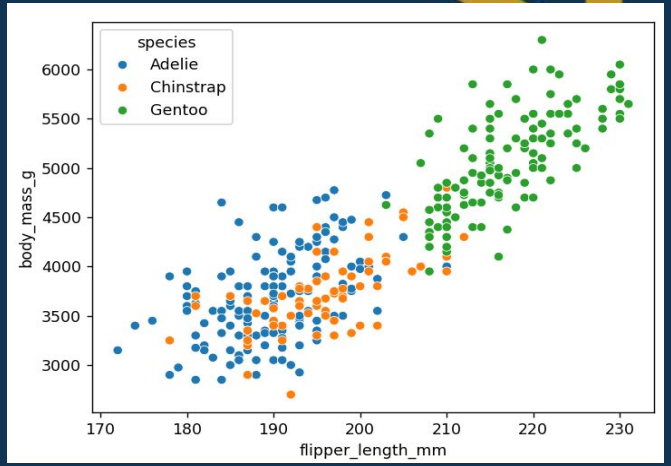
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 344 entries, 0 to 343
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   species            344 non-null    object
 1   island             344 non-null    object
 2   bill_length_mm     342 non-null    float64
 3   bill_depth_mm      342 non-null    float64
 4   flipper_length_mm  342 non-null    float64
 5   body_mass_g        342 non-null    float64
 6   sex                333 non-null    object
```

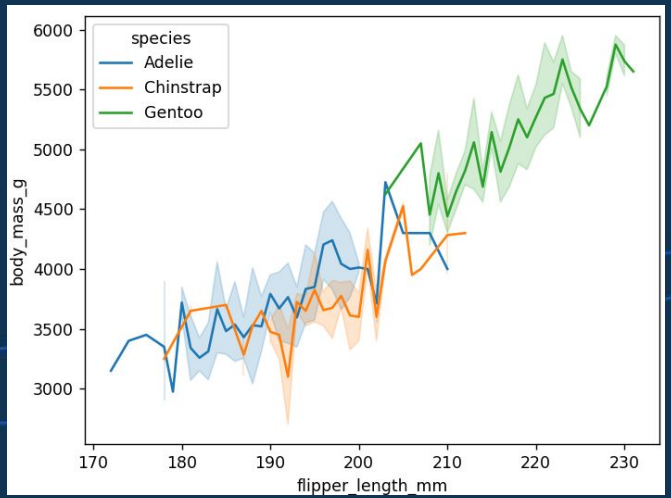
Seaborn plots

Scatter and Line plots

```
#Scatterplot
sns.scatterplot(x="flipper_length_mm", y="body_mass_g",
                data=peng_df, hue="species")
plt.show()

#Lineplot
sns.lineplot(x="flipper_length_mm", y="body_mass_g",
             data=peng_df, hue="species")
plt.show()
```





- If not in Jupyter or IPython notebook, explicitly call matplotlib.pyplot for displaying the plot

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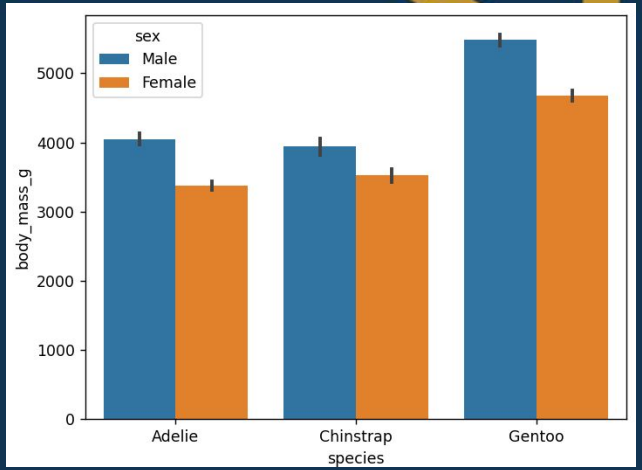
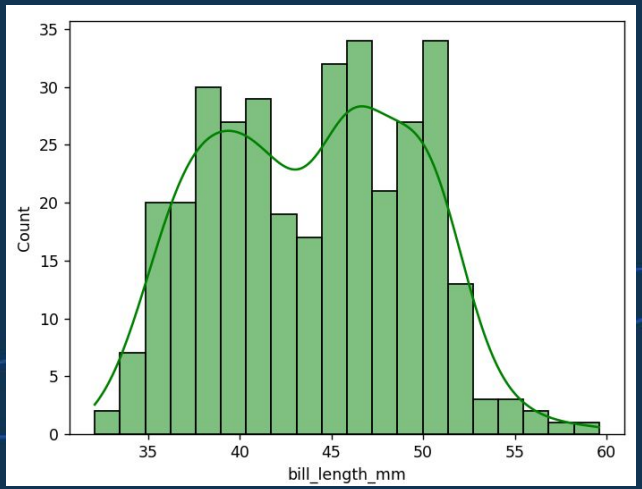
Seaborn plots

Bar plots and histogram

```
#Barplot
sns.barplot(x="species", y="body_mass_g",
            hue="sex", data=peng_df)
plt.show()

#Histogram
sns.histplot(x="bill_length_mm", data=peng_df,
             bins=20, kde=True, color="green")
plt.show()
```





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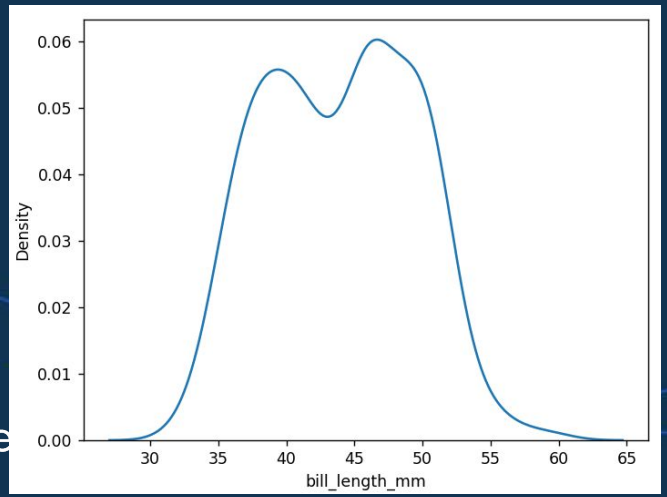
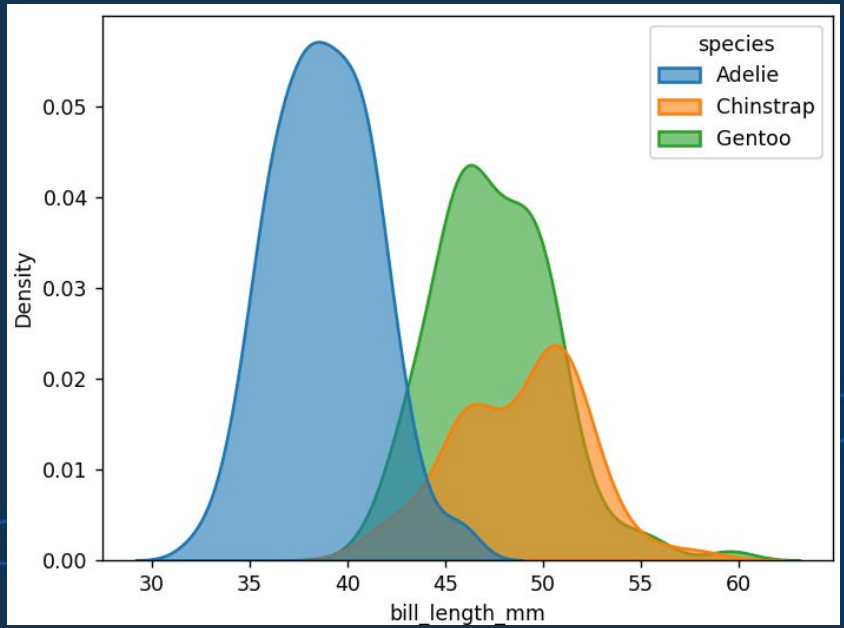
Seaborn plots

```
#Kernel density plot
sns.kdeplot(data=peng_df, x="bill_length_mm")
plt.show()
sns.kdeplot(data=peng_df, x="bill_length_mm",
            hue="species", fill=True, alpha=0.6,
            linewidth=1.5)
plt.show()
```

Kernel density plots:

Smooth curves representing density of data points, great for comparing distributions of several groups.





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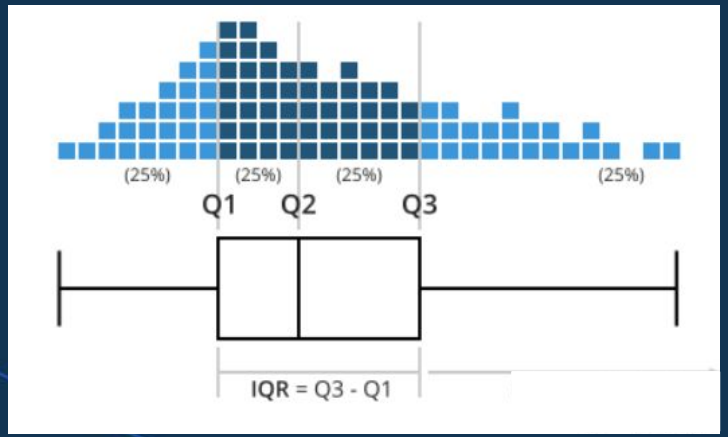
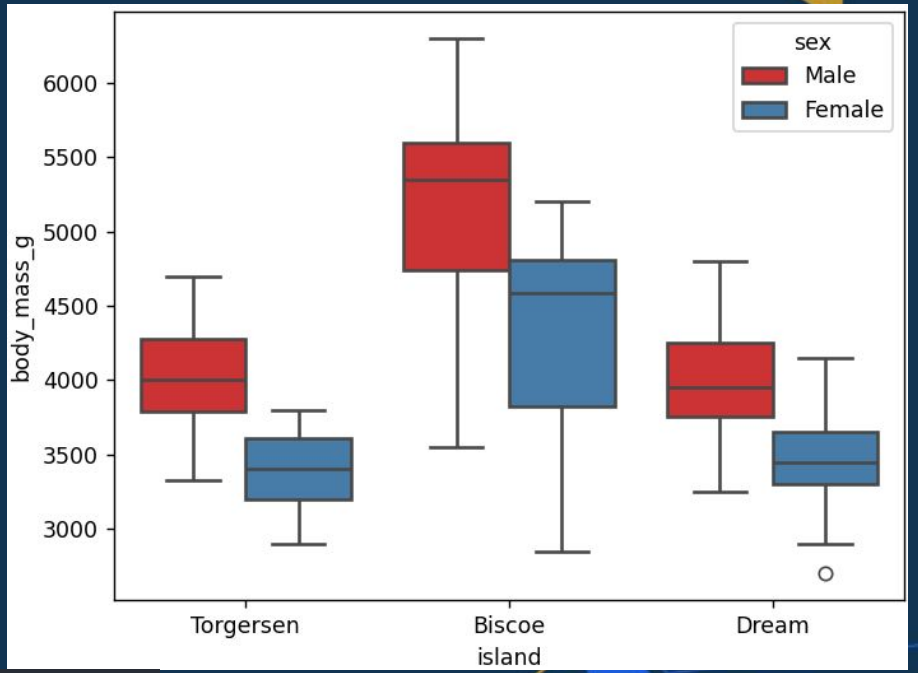
Seaborn plots

Box plot



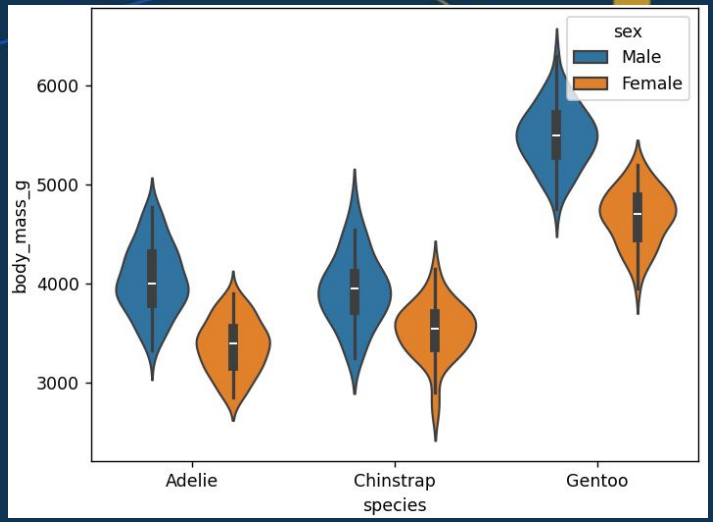



```
#Boxplot
sns.boxplot(x="island", y="body_mass_g", hue="sex",
            data=peng_df, palette="Set1", linewidth=1.5)
plt.show()
```

Seaborn plots

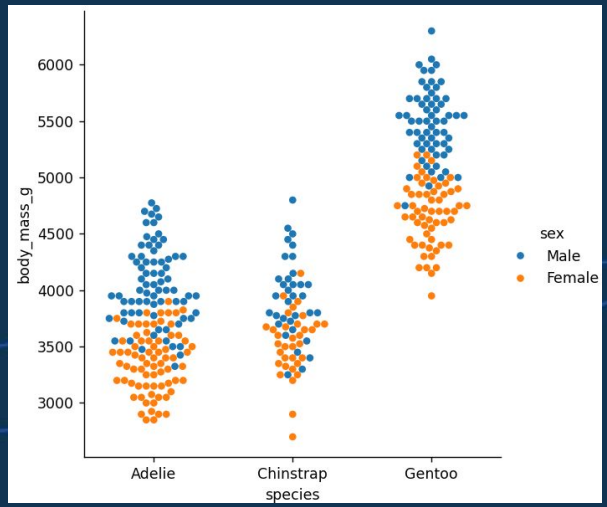
Violin plot: Combine aspects of KDEs and boxplots, ideal for showing density alongside summary statistics.

```
#Violinplot
sns.violinplot(x="species", y="body_mass_g",
               hue="sex", data=peng_df)
plt.show()
```



Categorical plot

```
#Categorical plot
sns.catplot(data=peng_df, kind="swarm",
            x="species", y="body_mass_g", hue="sex")
plt.show()
```



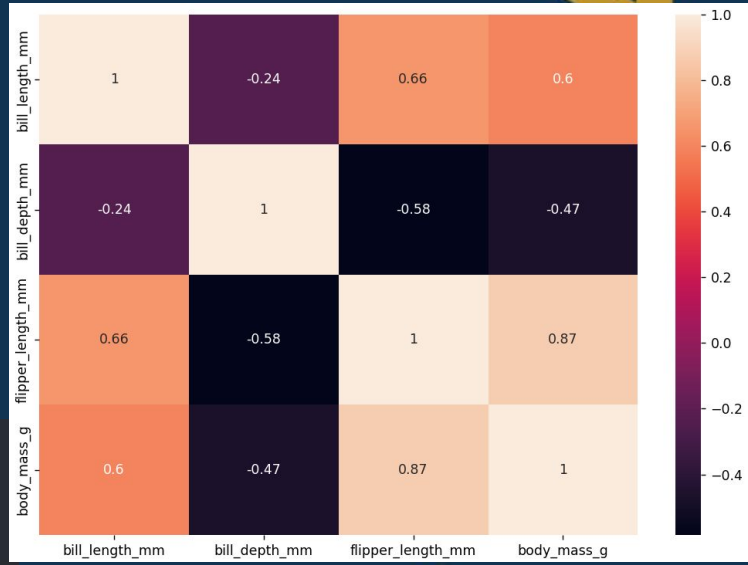
Seaborn plots

Heatmap

Color-coded matrices excellent for **revealing structure, highlighting correlations, and identifying clusters**.

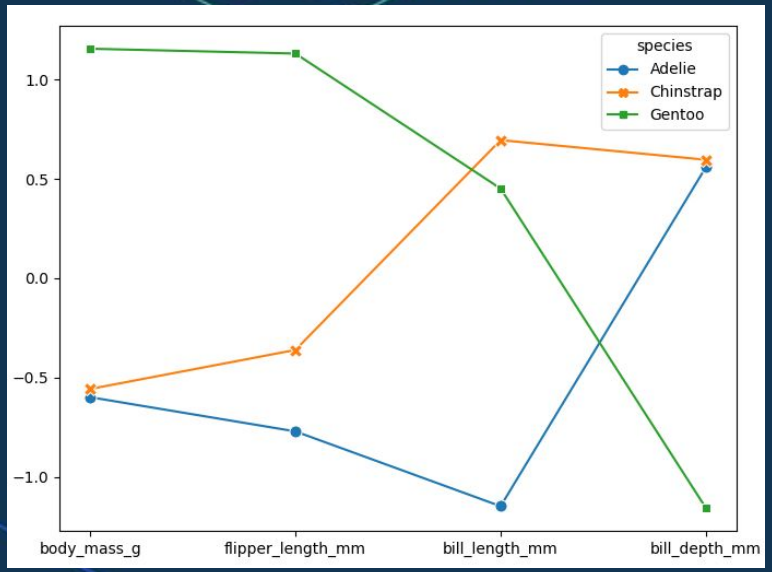
```
#Heatmap
# Create correlation between variables (floats only)
print(peng_df.dtypes)
peng_float = peng_df.select_dtypes(include=[np.float64])
corr = peng_float.corr()

#Plot
plt.figure(figsize=(10,7))
sns.heatmap(corr, annot=True)
plt.show()
```



Customization in heatmaps is key for optimal interpretation.

Parallel coordinates



- Show many dimensions on the same plot
- Each feature has a vertical axis, data points become lines crossing them.
- Ideal when you have many interrelated variables and need to spot outliers or group characteristics.

```python
#Parallel coordinates
# Calculate the average values for each continent
average_data = peng_df.groupby('species')[['body_mass_g', 'flipper_length_mm',
                                           'bill_length_mm','bill_depth_mm']].mean()

# Normalize the data for better visualization
normalized_data = (average_data - average_data.mean()) / average_data.std()

# Create parallel plot
plt.figure(figsize=(8, 6))
parallel_plot = sns.lineplot(data=normalized_data.transpose(),
                             dashes=False,
                             markers=True,
                             markersize=8)
plt.show()
```

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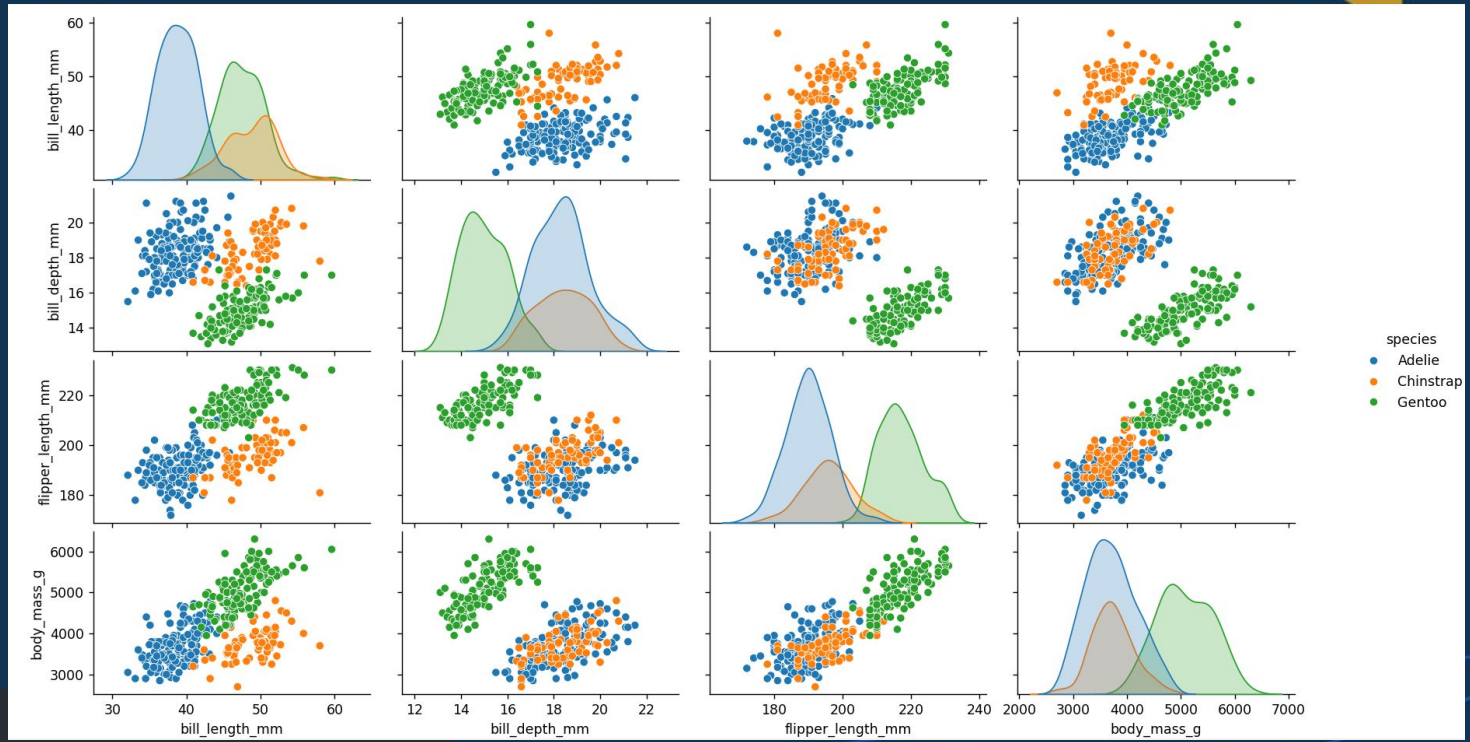
Seaborn plots

Pairplot



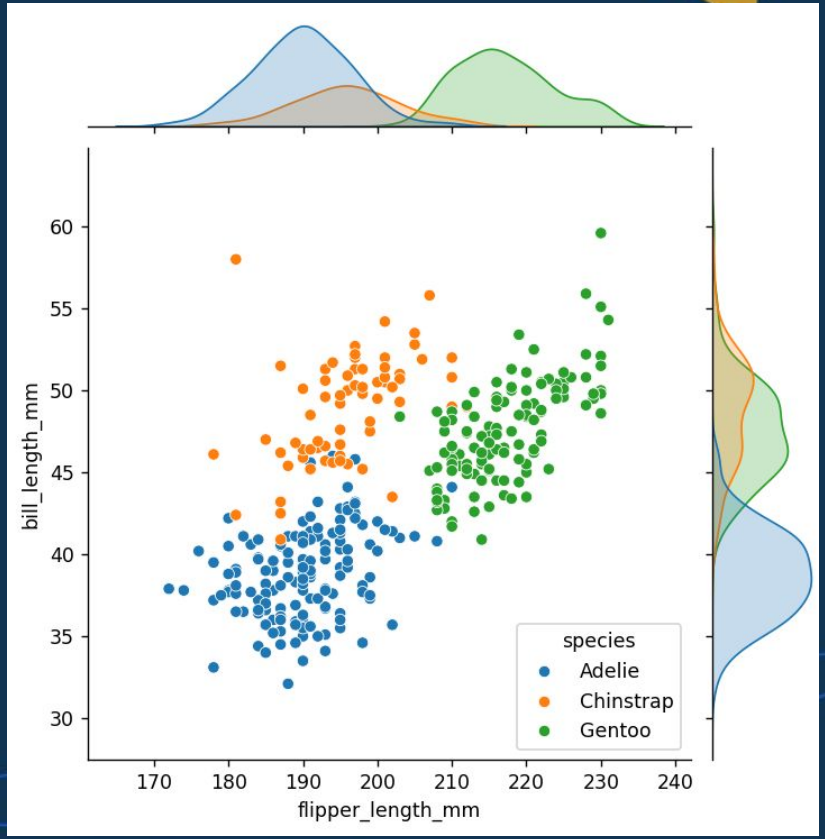

```
#Pairplot
sns.pairplot(peng_df, hue="species")
plt.show()
```

Compact way to depict pairwise relationships between several variables simultaneously.

Seaborn plots

Jointplot

```
#Jointplot
sns.jointplot(data=peng_df, x="flipper_length_mm",
              y="bill_length_mm", hue="species")
plt.show()
```



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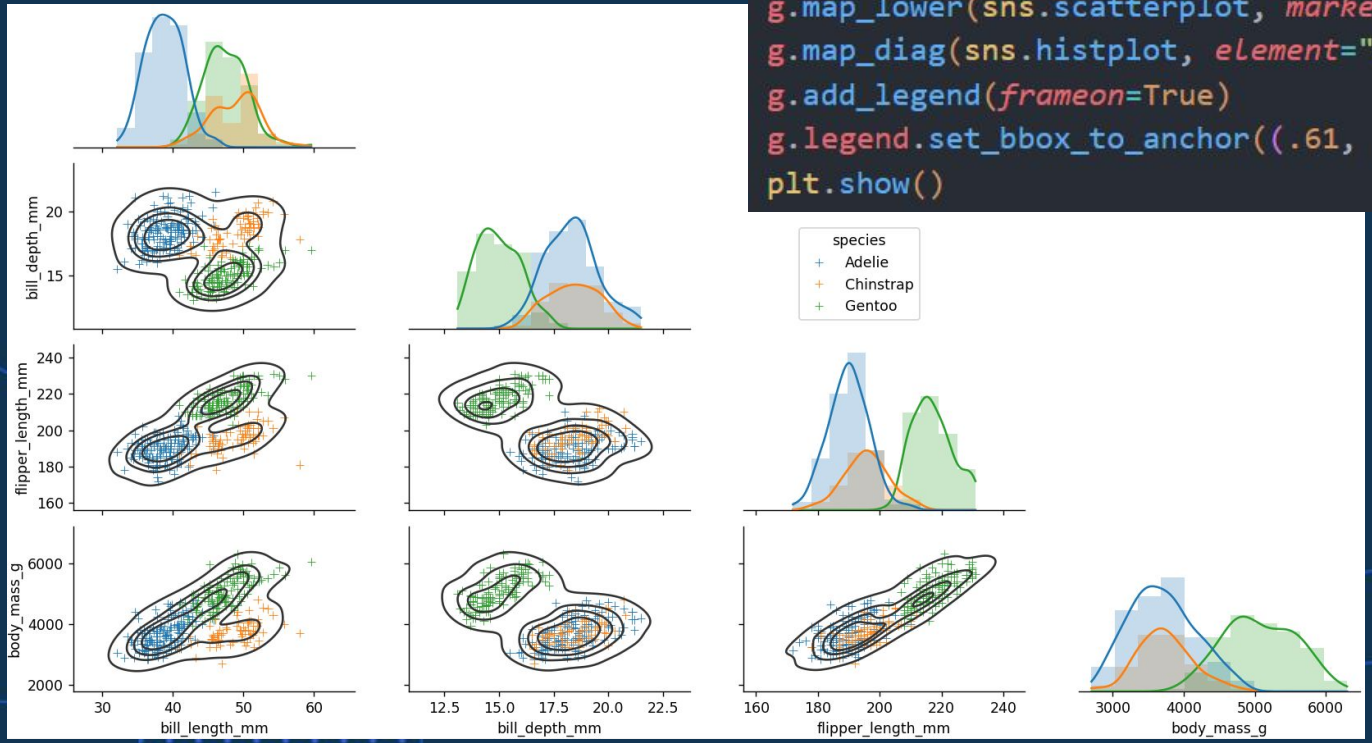
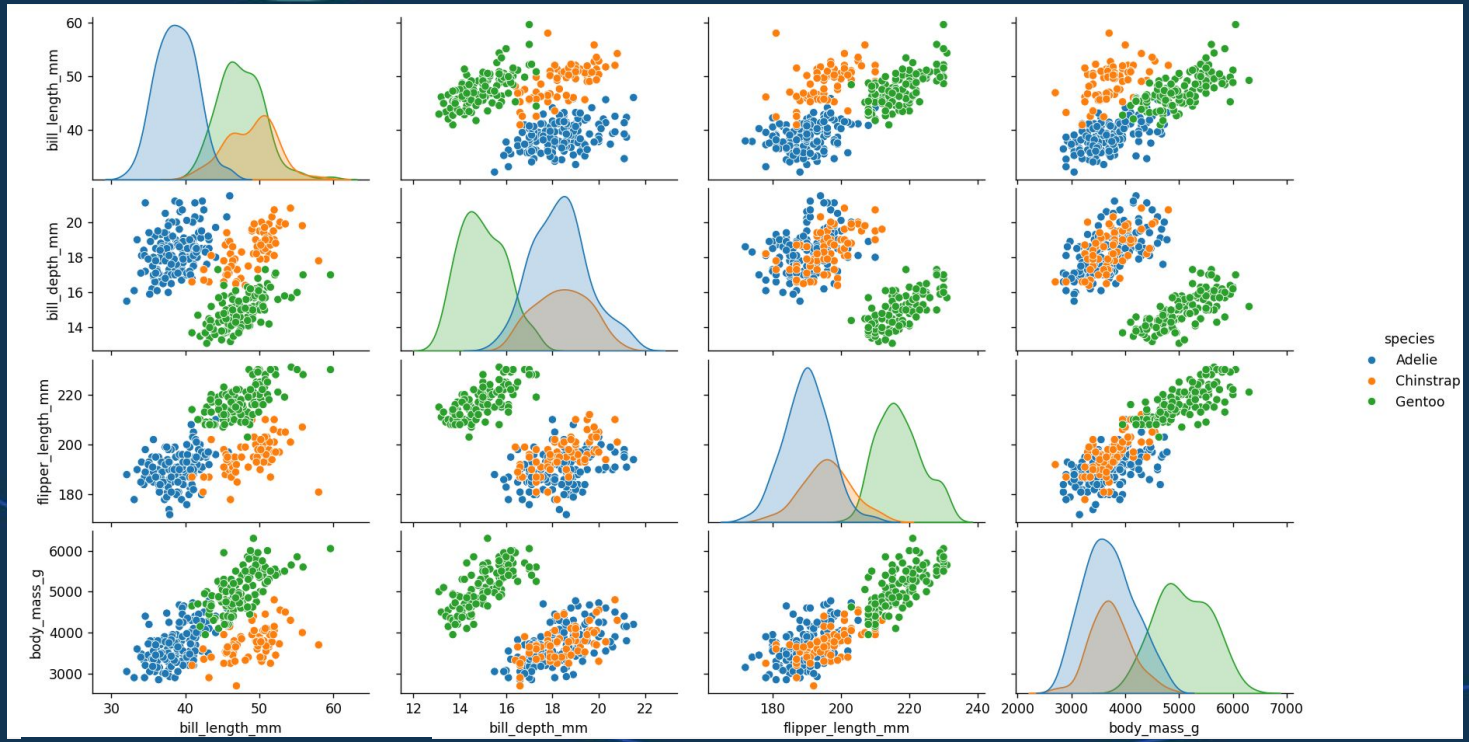
Combination plots

```python
#Combination plots
g = sns.PairGrid(peng_df, hue="species", corner=True)
g.map_lower(sns.kdeplot, hue=None, levels=5, color=".2")
g.map_lower(sns.scatterplot, marker="+")
g.map_diag(sns.histplot, element="step", linewidth=0, kde=True)
g.add_legend(frameon=True)
g.legend.set_bbox_to_anchor((.61, .6))
plt.show()
```



Visualisation analysis



Gentoo, on average

- Higher body mass, flipper length
- Lower bill depth

Adelie has lower bill length on an average

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Task Walkthrough

For today's task you're a data scientist analyzing movie data for a streaming platform.

Your task is to:

- Load and explore a dataset containing information about movies (e.g., title, genre, rating, revenue).

- Perform basic manipulations to answer key questions like:
  - Which genre has the highest average rating?
  - Which movie had the highest revenue?
  - How many movies were released each year?

Task Walkthrough

- Visualize trends and insights using matplotlib and seaborn, such as:
  - A bar chart of average ratings by genre.
  - A line graph showing the number of movies released per year.
  - A scatter plot of revenue vs. rating to identify correlations.

- Create advanced visualizations with seaborn to gain deeper insights, including:
  - Heatmaps to explore correlations between numerical variables (e.g., rating and revenue).
  - Box plots to visualize the distribution of ratings by genre.
  - Violin plots to compare revenue distributions for different genres.
  - Pair plots to explore relationships between multiple variables.

What does the seaborn heatmap() function typically visualize?

A. Relationships between two numerical variables
B. Trends over time
C. Distribution of a single variable
D. Correlation between multiple numerical variables

Which pandas method would you use to display the first few rows of a dataset?

A. describe()
B. head()
C. info()
D. value_counts()

Summary

- **Datasets and DataFrames:**
  Loading and exploring datasets with pandas.
  Summarizing data using .info(), .describe(), and grouping.

- **Data Manipulations**:
  Filtering, grouping, and sorting data.
  Aggregating data to calculate metrics like averages and counts.

- **Data Visualizations:**
  Creating bar charts, line graphs, and scatter plots.
  Using matplotlib for basic plots and seaborn for advanced, aesthetically pleasing visualizations.

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Q & A SECTION

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

Thank you for attending

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