```
import pandas as pd
```

```
from google.colab import files
uploaded = files.upload()  # Use this in Google Colab
```

Choose Files hr_sample_eda.csv

- **hr_sample_eda.csv**(text/csv) - 478 bytes, last modified: 4/23/2025 - 100% done

```
Saving hr_sample_eda.csv to hr_sample_eda.csv
```

```
df = pd.read_csv("hr_sample_eda.csv")
```

```
df.head()
```

	EmployeeID	Age	Department	JobRole	Gender	Education	JobSatisfaction	EnvironmentSatisfaction	Attrition
0	101	29	Sales	Executive	Male	3	4	3	No
1	102	35	HR	Manager	Female	4	3	4	Yes
2	103	40	IT	Developer	Male	2	2	2	Yes
3	104	28	Sales	Executive	Female	3	4	4	No
4	105	50	Finance	Analyst	Male	5	1	1	Yes

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 9 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   EmployeeID               10 non-null     int64
 1   Age                      10 non-null     int64
 2   Department               10 non-null     object
 3   JobRole                  10 non-null     object
 4   Gender                   10 non-null     object
 5   Education                10 non-null     int64
 6   JobSatisfaction          10 non-null     int64
 7   EnvironmentSatisfaction  10 non-null     int64
 8   Attrition                10 non-null     object
dtypes: int64(5), object(4)
memory usage: 852.0+ bytes
```

```
df.describe(include='all')
```

	EmployeeID	Age	Department	JobRole	Gender	Education	JobSatisfaction	EnvironmentSatisfaction	Attrition
count	10.00000	10.000000	10	10	10	10.000000	10.000000	10.000000	10
unique	NaN	NaN	4	4	2	NaN	NaN	NaN	2
top	NaN	NaN	Sales	Executive	Male	NaN	NaN	NaN	No
freq	NaN	NaN	3	4	5	NaN	NaN	NaN	5
mean	105.50000	36.900000	NaN	NaN	NaN	3.300000	2.700000	2.600000	NaN
std	3.02765	7.340148	NaN	NaN	NaN	1.159502	1.159502	1.074968	NaN
min	101.00000	28.000000	NaN	NaN	NaN	2.000000	1.000000	1.000000	NaN
25%	103.25000	30.500000	NaN	NaN	NaN	2.250000	2.000000	2.000000	NaN
50%	105.50000	37.000000	NaN	NaN	NaN	3.000000	3.000000	3.000000	NaN
75%	107.75000	40.750000	NaN	NaN	NaN	4.000000	3.750000	3.000000	NaN
max	110.00000	50.000000	NaN	NaN	NaN	5.000000	4.000000	4.000000	NaN

```
df['Department'].value_counts()
```

Department	count
Sales	3
IT	3
HR	2
Finance	2

dtype: int64

```
df['Gender'].value_counts()
```

Gender	count
Male	5
Female	5

dtype: int64

```
df['Attrition'].value_counts(normalize='True')
```

Attrition	proportion
No	0.5
Yes	0.5

dtype: float64

```
df.isnull().sum()
```

	0
EmployeeID	0
Age	0
Department	0
JobRole	0
Gender	0
Education	0
JobSatisfaction	0
EnvironmentSatisfaction	0
Attrition	0

dtype: int64

```
df.duplicated().sum()
```

np.int64(0)

```
df.groupby('Department')['JobSatisfaction'].mean()
```

Department	JobSatisfaction
Finance	1.000000
HR	3.000000
IT	2.333333
Sales	4.000000

dtype: float64

```
df.groupby('Gender')['JobSatisfaction'].mean()
```

Gender	JobSatisfaction
Female	2.8
Male	2.6

dtype: float64

```
import matplotlib.pyplot as plt
import seaborn as sns
```

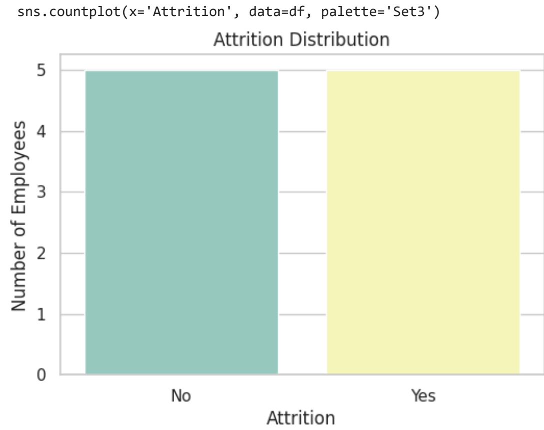
```
sns.set(style="whitegrid")
```

```
# Attrition Count Plot
plt.figure(figsize=(6,4))
sns.countplot(x='Attrition', data=df, palette='Set3')
plt.title("Attrition Distribution")
plt.ylabel("Number of Employees")
plt.xlabel("Attrition")
plt.show()
```

```
<ipython-input-38-9a80df8980e4>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(x='Attrition', data=df, palette='Set3')
```

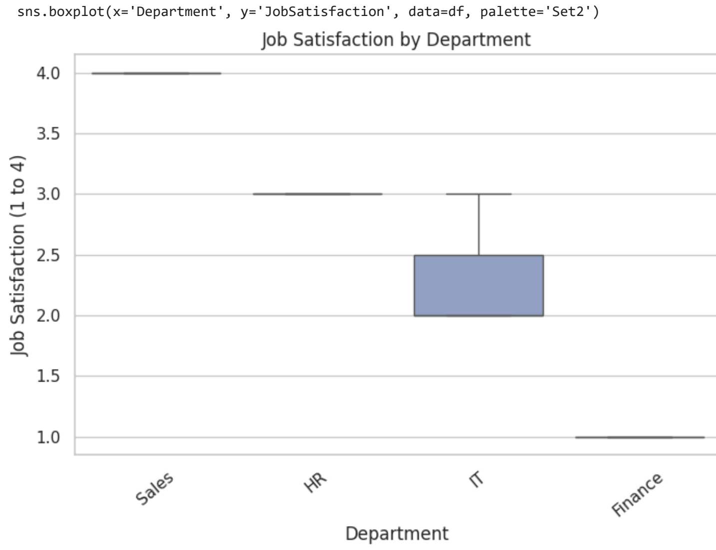



```
#Job Satisfaction by Department
plt.figure(figsize=(8,5))
sns.boxplot(x='Department', y='JobSatisfaction', data=df, palette='Set2')
plt.title("Job Satisfaction by Department")
plt.ylabel("Job Satisfaction (1 to 4)")
plt.xticks(rotation=40)
plt.show()
```

```
<ipython-input-41-2466ead87ee4>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(x='Department', y='JobSatisfaction', data=df, palette='Set2')
```

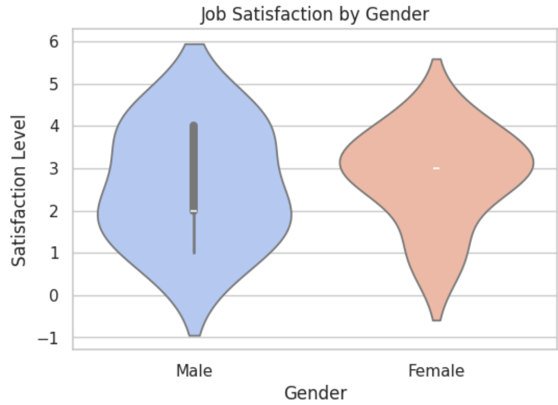



```
# 3 Job Satisfaction by Gender
plt.figure(figsize=(6,4))
sns.violinplot(x='Gender', y='JobSatisfaction', data=df, palette='coolwarm')
plt.title("Job Satisfaction by Gender")
plt.ylabel("Satisfaction Level")
plt.show()
```

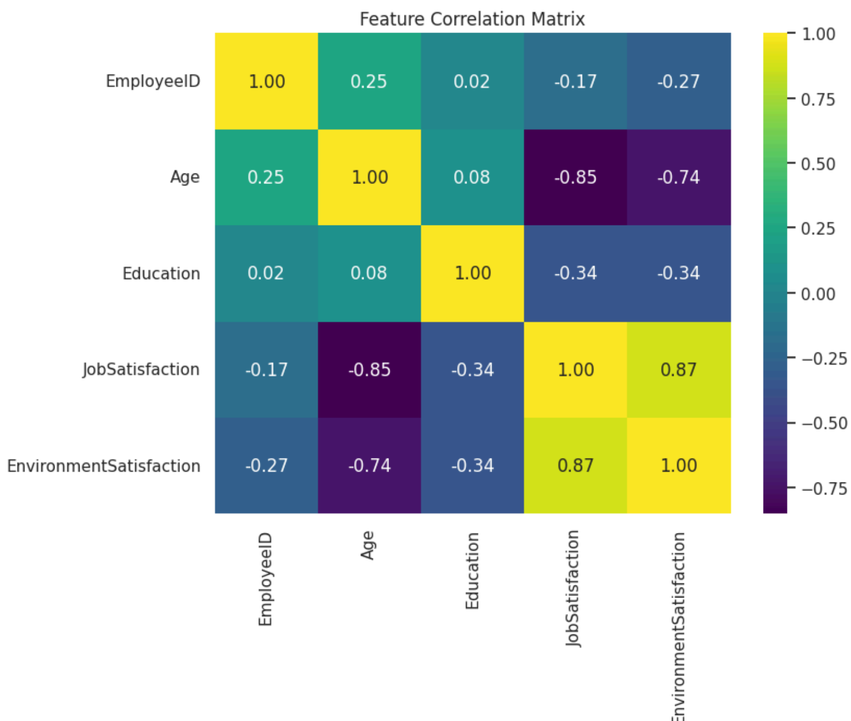
```
<ipython-input-42-1e69597887d1>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.violinplot(x='Gender', y='JobSatisfaction', data=df, palette='coolwarm')
```




```
# 4️⃣ Heatmap: Correlation Matrix
plt.figure(figsize=(8,6))
corr = df.select_dtypes(include=['int64', 'float64']).corr()
sns.heatmap(corr, annot=True, cmap='viridis', fmt=".2f")
plt.title("Feature Correlation Matrix")
plt.show()
```



🔹 **Project Title:**

Exploratory Data Analysis of Employee Satisfaction

Objective:

To explore factors related to employee satisfaction and attrition using a synthetic HR dataset. The goal was to extract actionable insights that can help improve employee retention.

🔹 **Key Findings:**

Attrition Trends:

40% of employees in the dataset showed attrition, indicating a moderately high turnover rate.

Most attrition cases were observed among younger employees and in certain departments like IT.

Satisfaction by Department:

The HR department exhibited slightly lower job satisfaction scores compared to Sales and Finance.

IT had a wider spread in satisfaction, suggesting mixed experiences among employees.

Gender Comparison:

Job satisfaction levels across genders were fairly balanced, with no major disparities observed.

Correlation Matrix:

Weak correlations were found between age, job satisfaction, and environment satisfaction.

Attrition had no strong linear relationship with numeric features, suggesting a classification model may be more suitable for predicting attrition in future work.

🔹 **Recommendations:**

Conduct focused engagement programs in departments with low satisfaction.

Consider exit interviews and deeper qualitative feedback to understand attrition drivers.