```
from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving HR-Employee-Attrition.csv to HR-Employee-Attrition.csv
```

```
import pandas as pd

df = pd.read_csv("HR-Employee-Attrition.csv")  # Use the exact uploaded filename

# Basic info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 35 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Age                       1470 non-null   int64
 1   Attrition                 1470 non-null   object
 2   BusinessTravel            1470 non-null   object
 3   DailyRate                 1470 non-null   int64
 4   Department                1470 non-null   object
 5   DistanceFromHome          1470 non-null   int64
 6   Education                 1470 non-null   int64
 7   EducationField            1470 non-null   object
 8   EmployeeCount             1470 non-null   int64
 9   EmployeeNumber            1470 non-null   int64
 10  EnvironmentSatisfaction   1470 non-null   int64
 11  Gender                    1470 non-null   object
 12  HourlyRate                1470 non-null   int64
 13  JobInvolvement            1470 non-null   int64
 14  JobLevel                  1470 non-null   int64
 15  JobRole                   1470 non-null   object
 16  JobSatisfaction           1470 non-null   int64
 17  MaritalStatus             1470 non-null   object
 18  MonthlyIncome             1470 non-null   int64
 19  MonthlyRate               1470 non-null   int64
 20  NumCompaniesWorked        1470 non-null   int64
 21  Over18                    1470 non-null   object
 22  OverTime                  1470 non-null   object
 23  PercentSalaryHike         1470 non-null   int64
 24  PerformanceRating         1470 non-null   int64
 25  RelationshipSatisfaction  1470 non-null   int64
 26  StandardHours             1470 non-null   int64
 27  StockOptionLevel          1470 non-null   int64
 28  TotalWorkingYears         1470 non-null   int64
 29  TrainingTimesLastYear     1470 non-null   int64
 30  WorkLifeBalance           1470 non-null   int64
 31  YearsAtCompany            1470 non-null   int64
 32  YearsInCurrentRole        1470 non-null   int64
 33  YearsSinceLastPromotion   1470 non-null   int64
 34  YearsWithCurrManager      1470 non-null   int64
dtypes: int64(26), object(9)
memory usage: 402.1+ KB
```

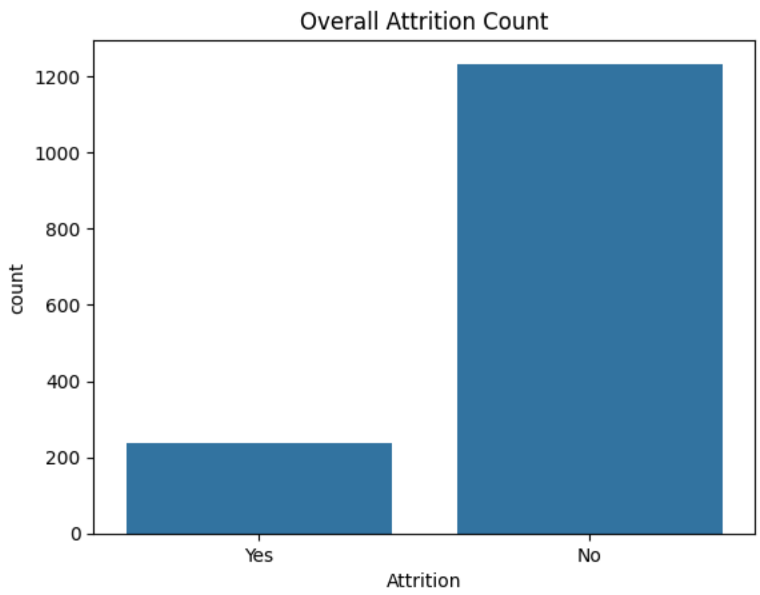
```
df.head()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumbe
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	

5 rows × 35 columns

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

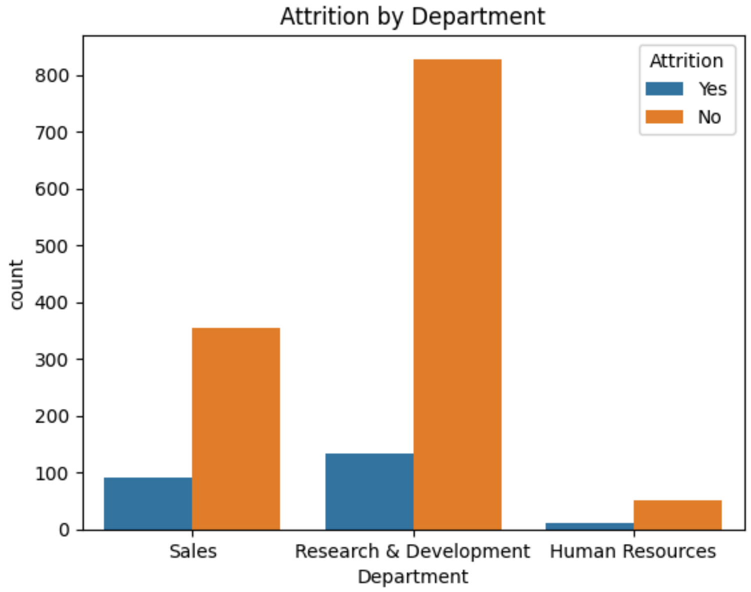
```
# Attrition Count
sns.countplot(x='Attrition', data=df)
plt.title('Overall Attrition Count')
plt.show()
```

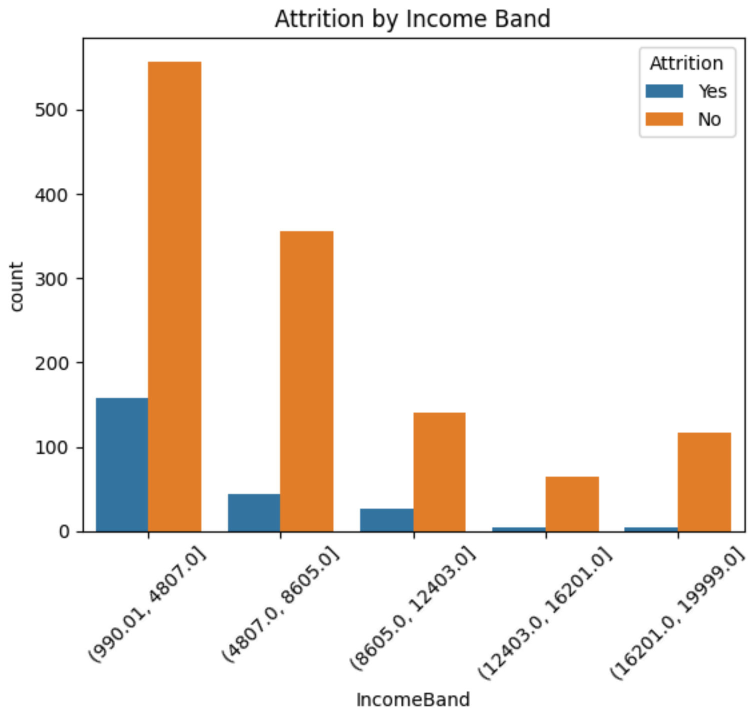



```
# Attrition by Department
sns.countplot(x='Department', hue='Attrition', data=df)
plt.title('Attrition by Department')
plt.show()

# Income Bands
df['IncomeBand'] = pd.cut(df['MonthlyIncome'], bins=5)
sns.countplot(x='IncomeBand', hue='Attrition', data=df)
plt.xticks(rotation=45)
plt.title('Attrition by Income Band')
plt.show()

# Promotion vs Attrition
sns.countplot(x='YearsSinceLastPromotion', hue='Attrition', data=df)
plt.title('Attrition vs. Years Since Last Promotion')
plt.show()
```






```
# Create a copy for modeling
df_model = df.copy()

# Drop the 'IncomeBand' column if it exists
if 'IncomeBand' in df_model.columns:
    df_model.drop('IncomeBand', axis=1, inplace=True)

# Label encode categorical features
le = LabelEncoder()
for col in df_model.select_dtypes(include='object'):
    df_model[col] = le.fit_transform(df_model[col])

# Split features and target
X = df_model.drop(['Attrition'], axis=1)
y = df_model['Attrition']

# Train-test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train model
from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier()
model.fit(X_train, y_train)

# Evaluate model
from sklearn.metrics import classification_report, confusion_matrix
y_pred = model.predict(X_test)
```

```
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[219  36]
 [ 30   9]]

Classification Report:
               precision    recall  f1-score   support

           0       0.88      0.86      0.87       255
           1       0.20      0.23      0.21        39

    accuracy                           0.78       294
   macro avg       0.54      0.54      0.54       294
weighted avg       0.79      0.78      0.78       294
```

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

	count
Attrition	
No	1233
Yes	237

dtype: int64

```
from imblearn.over_sampling import SMOTE

smote = SMOTE(random_state=42)
X_sm, y_sm = smote.fit_resample(X, y)

# New shape after balancing
print(y_sm.value_counts())
```

```
Attrition
1    1233
0    1233
Name: count, dtype: int64
```

```
X_train, X_test, y_train, y_test = train_test_split(X_sm, y_sm, test_size=0.2, random_state=42)

model = DecisionTreeClassifier()
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[181  69]
 [ 38 206]]

Classification Report:
               precision    recall  f1-score   support

           0       0.83      0.72      0.77       250
           1       0.75      0.84      0.79       244

    accuracy                           0.78       494
   macro avg       0.79      0.78      0.78       494
weighted avg       0.79      0.78      0.78       494
```

```
from sklearn.linear_model import LogisticRegression

log_model = LogisticRegression(max_iter=2000)
log_model.fit(X_train, y_train)

y_pred_log = log_model.predict(X_test)
print("Logistic Regression Report:\n", classification_report(y_test, y_pred_log))
```

```
Logistic Regression Report:
               precision    recall  f1-score   support
```

```
           0       0.91      0.98      0.94       255
           1       0.68      0.33      0.45        39

    accuracy                           0.89       294
   macro avg       0.79      0.65      0.69       294
weighted avg       0.88      0.89      0.87       294
```

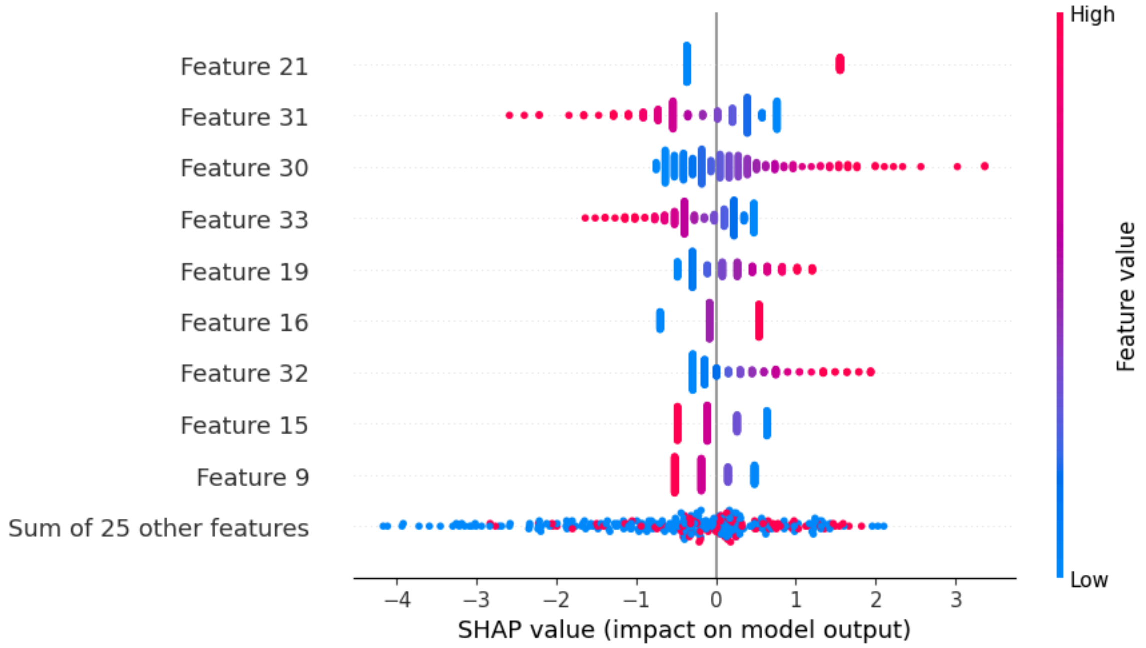
```
!pip install shap
```

```
Requirement already satisfied: shap in /usr/local/lib/python3.11/dist-packages (0.47.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from shap) (2.0.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from shap) (1.15.2)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-packages (from shap) (1.6.1)
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages (from shap) (2.2.2)
Requirement already satisfied: tqdm>=4.27.0 in /usr/local/lib/python3.11/dist-packages (from shap) (4.67.1)
Requirement already satisfied: packaging>20.9 in /usr/local/lib/python3.11/dist-packages (from shap) (24.2)
Requirement already satisfied: slicer==0.0.8 in /usr/local/lib/python3.11/dist-packages (from shap) (0.0.8)
Requirement already satisfied: numba>=0.54 in /usr/local/lib/python3.11/dist-packages (from shap) (0.60.0)
Requirement already satisfied: cloudpickle in /usr/local/lib/python3.11/dist-packages (from shap) (3.1.1)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.11/dist-packages (from shap) (4.13.2)
Requirement already satisfied: llvmlite<0.44,>=0.43.0dev0 in /usr/local/lib/python3.11/dist-packages (from numba>=0.54->shap) (0.43
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11/dist-packages (from pandas->shap) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas->shap) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas->shap) (2025.2)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn->shap) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn->shap) (3.6.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.8.2->pandas->shap) (1.17
```

```
import shap
import matplotlib.pyplot as plt

# For tree models, use TreeExplainer; for linear models, use LinearExplainer
explainer = shap.Explainer(log_model, X_train)
shap_values = explainer(X_test)

# Summary plot (feature importance)
shap.plots.beeswarm(shap_values)
```




```
# Display SHAP value for a single prediction
shap.initjs()
shap.plots.force(shap_values[0])
```