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



Choose Files WA_Fn-Us...-Attrition.csv

• WA_Fn-UseC_-HR-Employee-Attrition.csv(text/csv) - 227977 bytes, last modified: 9/20/2019 - 100% done Saving WA Fn-UseC -HR-Employee-Attrition.csv to WA Fn-UseC -HR-Employee-Attrition.csv

import pandas as pd

Load the dataset
df = pd.read_csv("WA_Fn-UseC_-HR-Employee-Attrition.csv")

View shape and first few rows
print("Dataset shape:", df.shape)
df.head()

→ Dataset shape: (1470, 35)

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	• • •	${\tt RelationshipSatisfaction}$	Standard
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1		1	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	2		4	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	4		2	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	5		3	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	7		4	

5 rows × 35 columns

Overview of dataset
df.info()

Check for missing values
df.isnull().sum()



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 object 1470 non-null DailyRate 3 1470 non-null int64 Department 1470 non-null object 1470 non-null DistanceFromHome int64 Education 1470 non-null int64 7 EducationField 1470 non-null object EmployeeCount 1470 non-null int64 EmployeeNumber 9 1470 non-null int64 EnvironmentSatisfaction 1470 non-null int64 11 Gender 1470 non-null object 12 HourlyRate 1470 non-null int64 JobInvolvement 1470 non-null int64 13 14 JobLevel 1470 non-null int64 JobRole 15 1470 non-null object 16 JobSatisfaction 1470 non-null int64 17 MaritalStatus 1470 non-null object MonthlyIncome 18 1470 non-null int64 19 MonthlyRate 1470 non-null int64 20 NumCompaniesWorked 1470 non-null int64 21 Over18 object 1470 non-null 22 OverTime 1470 non-null object 23 PercentSalaryHike 1470 non-null int64 PerformanceRating 24 1470 non-null int64 25 RelationshipSatisfaction 1470 non-null int64 26 StandardHours 1470 non-null int64 27 StockOptionLevel 1470 non-null int64 TotalWorkingYears 1470 non-null int64 28 TrainingTimesLastYear 1470 non-null int64 WorkLifeBalance 30 1470 non-null int64 YearsAtCompany 1470 non-null int64 31 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 0 0 Age Attrition 0 **BusinessTravel** 0 **DailyRate** 0 Department 0

0

DistanceFromHome

<class 'pandas.core.frame.DataFrame'>

0 Education EducationField 0 **EmployeeCount** 0 EmployeeNumber 0 **EnvironmentSatisfaction** 0 0 Gender HourlyRate 0 JobInvolvement 0 JobLevel 0 **JobRole** 0 **JobSatisfaction** 0 MaritalStatus 0 **MonthlyIncome** 0 MonthlyRate 0 NumCompaniesWorked 0 Over18 0 OverTime 0 PercentSalaryHike 0 0 PerformanceRating RelationshipSatisfaction 0 StandardHours 0 StockOptionLevel 0 TotalWorkingYears 0 TrainingTimesLastYear 0 WorkLifeBalance 0 YearsAtCompany 0 YearsInCurrentRole 0 YearsSinceLastPromotion 0 YearsWithCurrManager 0

dtype: int64

```
# Label encode the target variable

df['Attrition'] = df['Attrition'].map({'Yes': 1, 'No': 0})

# Get all object (text) columns

categorical_cols = df.select_dtypes(include='object').columns

print("Categorical columns:", list(categorical_cols))

→ Categorical columns: ['BusinessTravel', 'Department', 'EducationField', 'Gender', 'JobRole', 'MaritalStatus', 'Over18', 'OverTime']

# One-hot encode all remaining categorical columns

df_encoded = pd.get_dummies(df, drop_first=True)

# Confirm all columns are now numeric

df_encoded.info()

# Preview the encoded dataset

df_encoded.head()
```

<<class 'pandas.core.frame.DataFrame'>
 RangeIndex: 1470 entries, 0 to 1469
 Data columns (total 48 columns):

Data #	columns (total 48 columns): Column	Non-Null Count	Dtype
0	Age	1470 non-null	int64
1	Attrition	1470 non-null	int64
2	DailyRate	1470 non-null	int64
3	DistanceFromHome	1470 non-null	int64
4	Education	1470 non-null	int64
5			
	EmployeeCount	1470 non-null	int64
6	EmployeeNumber	1470 non-null	int64
7	EnvironmentSatisfaction	1470 non-null	int64
8	HourlyRate	1470 non-null	int64
9	JobInvolvement	1470 non-null	int64
10	JobLevel	1470 non-null	int64
11	JobSatisfaction	1470 non-null	int64
12	MonthlyIncome	1470 non-null	int64
13	MonthlyRate	1470 non-null	int64
14	NumCompaniesWorked	1470 non-null	int64
15	PercentSalaryHike	1470 non-null	int64
16	PerformanceRating	1470 non-null	int64
17	RelationshipSatisfaction	1470 non-null	int64
18	StandardHours	1470 non-null	int64
19	StockOptionLevel	1470 non-null	int64
20	TotalWorkingYears	1470 non-null	int64
21	TrainingTimesLastYear	1470 non-null	int64
22	WorkLifeBalance	1470 non-null	int64
23	YearsAtCompany	1470 non-null	int64
24	YearsInCurrentRole	1470 non-null	int64
25	YearsSinceLastPromotion	1470 non-null	int64
26	YearsWithCurrManager	1470 non-null	int64
27	BusinessTravel Travel Frequently	1470 non-null	bool
28	BusinessTravel Travel Rarely	1470 non-null	bool
29	Department Research & Development	1470 non-null	bool
30	Department Sales	1470 non-null	bool
31	EducationField_Life Sciences	1470 non-null	bool
32	EducationField Marketing	1470 non-null	bool
33	EducationField Medical	1470 non-null	bool
34	EducationField_Other	1470 non-null	bool
35	EducationField_Technical Degree	1470 non-null	bool
36	Gender Male	1470 non-null	bool
30 37	JobRole Human Resources		bool
		1470 non-null	
38	JobRole_Laboratory Technician	1470 non-null	bool
39	JobRole_Manager	1470 non-null	bool
40	JobRole_Manufacturing Director	1470 non-null	bool
41	JobRole_Research Director	1470 non-null	bool
42	JobRole_Research Scientist	1470 non-null	bool
43	JobRole_Sales Executive	1470 non-null	bool
44	JobRole_Sales Representative	1470 non-null	bool
45	MaritalStatus_Married	1470 non-null	bool
46	MaritalStatus_Single	1470 non-null	bool
47	OverTime_Yes	1470 non-null	bool
	es: bool(21), int64(27)		
memoi	ry usage: 340.4 KB		
		(0)(0,0,0)	0.001.00

https://colab.research.google.com/drive/1taK3SDRYB8FmYQX3dV0HemaUjihCf0WX#scrollTo=2IXfhgQYAUN2&printMode=true

	Age	Attrition	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement	•••	JobRole_Laboratory Technician	,
0	41	1	1102	1	2	1	1	2	94	3		False	
1	49	0	279	8	1	1	2	3	61	2		False	
2	37	1	1373	2	2	1	4	4	92	2		True	
3	33	0	1392	3	4	1	5	4	56	3		False	
4	27	0	591	2	1	1	7	1	40	3		True	

5 rows × 48 columns

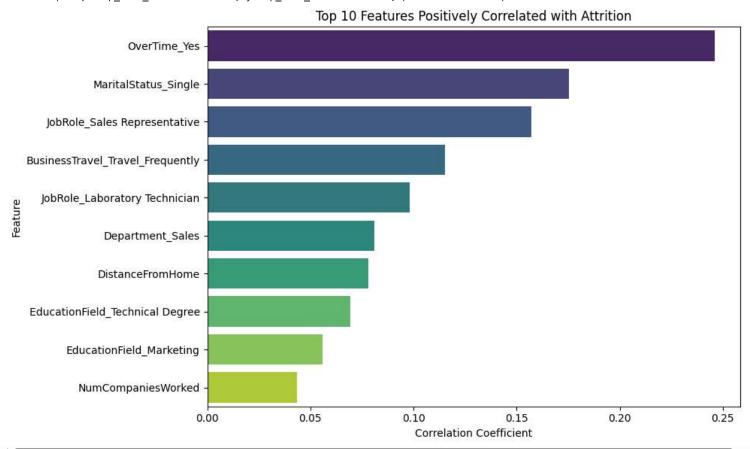
Check correlation with 'Attrition'
corr = df_encoded.corr()['Attrition'].sort_values(ascending=False)
print(corr)

→ ▼	Attrition	1.000000	
_	OverTime_Yes	0.246118	
	MaritalStatus_Single	0.175419	
	JobRole_Sales Representative	0.157234	
	BusinessTravel_Travel_Frequently	0.115143	
	<pre>JobRole_Laboratory Technician</pre>	0.098290	
	Department_Sales	0.080855	
	DistanceFromHome	0.077924	
	EducationField_Technical Degree	0.069355	
	EducationField_Marketing	0.055781	
	NumCompaniesWorked	0.043494	
	JobRole_Human Resources	0.036215	
	Gender_Male	0.029453	
	<pre>JobRole_Sales Executive</pre>	0.019774	
	MonthlyRate	0.015170	
	PerformanceRating	0.002889	
	JobRole_Research Scientist	-0.000360	
	HourlyRate	-0.006846	
	EmployeeNumber	-0.010577	
	PercentSalaryHike	-0.013478	
	EducationField_Other	-0.017898	
	Education	-0.031373	
	EducationField_Life Sciences	-0.032703	
	YearsSinceLastPromotion	-0.033019	
	RelationshipSatisfaction	-0.045872	
	EducationField_Medical	-0.046999	
	BusinessTravel_Travel_Rarely	-0.049538	
	DailyRate	-0.056652	
	TrainingTimesLastYear	-0.059478	
	WorkLifeBalance	-0.063939	

```
-0.082994
     JobRole_Manufacturing Director
    JobRole Manager
                                         -0.083316
     Department Research & Development
                                         -0.085293
     JobRole Research Director
                                         -0.088870
    MaritalStatus Married
                                         -0.090984
     EnvironmentSatisfaction
                                         -0.103369
     JobSatisfaction
                                         -0.103481
    JobInvolvement
                                         -0.130016
    YearsAtCompany
                                         -0.134392
     StockOptionLevel
                                         -0.137145
    YearsWithCurrManager
                                         -0.156199
                                         -0.159205
    MonthlyIncome
                                         -0.159840
    YearsInCurrentRole
                                         -0.160545
    JobLevel
                                         -0.169105
    TotalWorkingYears
                                         -0.171063
     EmployeeCount
                                               NaN
     StandardHours
                                               NaN
    Name: Attrition, dtype: float64
import matplotlib.pyplot as plt
import seaborn as sns
# Drop Attrition itself and get top correlations
top_corr_features = corr.drop('Attrition').head(10)
plt.figure(figsize=(10, 6))
sns.barplot(x=top_corr_features.values, y=top_corr_features.index, palette="viridis")
plt.title("Top 10 Features Positively Correlated with Attrition")
plt.xlabel("Correlation Coefficient")
plt.ylabel("Feature")
plt.tight layout()
plt.show()
```

→ <ipython-input-9-9e38d110ffad>:8: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect. sns.barplot(x=top_corr_features.values, y=top_corr_features.index, palette="viridis")



Example: MonthlyIncome vs Attrition sns.boxplot(x='Attrition', y='MonthlyIncome', data=df) plt.title("Monthly Income vs Attrition") plt.show()




```
# Define X and y
X = df_encoded.drop('Attrition', axis=1)
y = df_encoded['Attrition']

from sklearn.model_selection import train_test_split
# 80/20 split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
# Initialize models
dt = DecisionTreeClassifier(random_state=42)
rf = RandomForestClassifier(random_state=42)
# Train models
dt.fit(X_train, y_train)
rf.fit(X_train, y_train)
```

```
\overline{\pm}
            RandomForestClassifier
      RandomForestClassifier(random state=42)
# Predict
dt pred = dt.predict(X test)
rf pred = rf.predict(X test)
# Define a function for evaluation
def evaluate_model(name, y_true, y_pred):
    print(f"\n{name} Results:")
    print("Accuracy:", accuracy_score(y_true, y_pred))
    print("Precision:", precision score(y true, y pred))
    print("Recall:", recall score(y true, y pred))
    print("F1 Score:", f1_score(y_true, y_pred))
# Evaluate both
evaluate model("Decision Tree", y test, dt pred)
evaluate model("Random Forest", y test, rf pred)
\overline{2}
     Decision Tree Results:
     Accuracy: 0.7755102040816326
     Precision: 0.17073170731707318
     Recall: 0.1794871794871795
     F1 Score: 0.175
     Random Forest Results:
     Accuracy: 0.8775510204081632
     Precision: 0.8
     Recall: 0.10256410256410256
     F1 Score: 0.181818181818182
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
# Get feature importances
importances = rf.feature_importances_
features = X.columns
# Create a DataFrame
feat df = pd.DataFrame({'Feature': features, 'Importance': importances})
feat_df = feat_df.sort_values(by='Importance', ascending=False)
# Plot top 10 important features
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feat df.head(10), palette="coolwarm")
plt.title('Top 10 Important Features Driving Attrition')
```

```
plt.tight_layout()
plt.show()
```

<ipython-input-16-d6fcb16262f4>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect. sns.barplot(x='Importance', y='Feature', data=feat_df.head(10), palette="coolwarm")

Top 10 Important Features Driving Attrition MonthlyIncome -OverTime_Yes -DailyRate -EmployeeNumber -Age TotalWorkingYears -MonthlyRate -HourlyRate -DistanceFromHome -YearsAtCompany -0.00 0.01 0.02 0.03 0.04 0.05 0.06 0.07 Importance

from sklearn.linear_model import LogisticRegression from sklearn.neighbors import KNeighborsClassifier from sklearn.ensemble import GradientBoostingClassifier import xgboost as xgb from sklearn.ensemble import VotingClassifier # Initialize models lr = LogisticRegression(max_iter=1000) knn = KNeighborsClassifier()

```
gb = GradientBoostingClassifier()
xgb model = xgb.XGBClassifier(use label encoder=False, eval metric='logloss')
# Voting classifier (ensemble of top models)
voting clf = VotingClassifier(estimators=[
   ('lr', lr), ('knn', knn), ('rf', rf), ('gb', gb), ('xgb', xgb_model)
], voting='soft')
models = {
   "Logistic Regression": lr,
   "K-Nearest Neighbors": knn,
   "Gradient Boosting": gb,
   "XGBoost": xgb model,
   "Voting Classifier": voting clf
from sklearn.metrics import accuracy score, precision score, recall score, f1 score
for name, model in models.items():
   model.fit(X train, y train)
   y pred = model.predict(X test)
   print(f"\n{name}")
   print("Accuracy:", accuracy_score(y_test, y_pred))
   print("Precision:", precision score(y test, y pred))
   print("Recall:", recall score(y test, y pred))
   print("F1 Score:", f1 score(y test, y pred))
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.
    Increase the number of iterations (max_iter) or scale the data as shown in:
        https://scikit-learn.org/stable/modules/preprocessing.html
    Please also refer to the documentation for alternative solver options:
        https://scikit-learn.org/stable/modules/linear model.html#logistic-regression
      n iter i = check optimize result(
    Logistic Regression
    Accuracy: 0.8673469387755102
    Precision: 0.5
    Recall: 0.1794871794871795
    F1 Score: 0.2641509433962264
    K-Nearest Neighbors
    Accuracy: 0.8537414965986394
    Precision: 0.35714285714285715
    Recall: 0.1282051282051282
    F1 Score: 0.18867924528301888
    Gradient Boosting
    Accuracy: 0.8775510204081632
    Precision: 0.6
    Recall: 0.23076923076923078
```