Data Analytics Assignment - G-15

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Decision Tree Employment Prediction

This project uses **Machine Learning** to predict whether a candidate is suitable for employment or not.

We use a **Decision Tree classifier** because:

- It works well with both numbers and categories.
- It is easy to explain visually.
- It mimics human decision-making (like asking step-by-step questions).

Dataset source
IBM HR Analytics (mapped to required fields).
Kaggle original: https://www.kaggle.com/datasets/pavansubhasht/ibm-hr-analytics-attrition-dataset

Deliverables

- Notebook with code + explanations.
- Visualized decision tree.
- Model performance metrics.
- Predictions for at least 3 hypothetical candidates with interpretation.
- Feature importance analysis.

Data Loading and Exploration

Import required libraries

Why these libraries?

- **pandas** → handles tables (like Excel in Python).
- **numpy** → supports math operations.
- **matplotlib** & **seaborn** → help us make plots.
- **train_test_split** → splits data into training and testing sets.
- **LabelEncoder** → converts text values (Yes/No) into numbers.
- **DecisionTreeClassifier** → the algorithm we use.
- **accuracy_score, confusion_matrix, classification_report** → evaluate model performance.

*Debug tip: If you see `ModuleNotFoundError`, run the `pip install` command at the top.

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier, plot_tree
# from sklearn.preprocessing import StandardScaler
# from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
```

Load the dataset

- We load the dataset into a DataFrame called `df_raw`.
- `.head()` shows the first 5 rows to confirm it loaded correctly.
- If you see a `FileNotFoundError`, check the file path and confirm the CSV is inside the **data/** folder.
- Run `df.columns` to see available column names before using them. This prevents `KeyError`.

Double-click (or enter) to edit

```
# Load the dataset
df = pd.read_csv('/content/drive/MyDrive/WA_Fn-UseC_-HR-Employee-Attrition.csv')
```

```
# Show first rows
display(df.head())
```

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

5 rows × 35 columns

Mapping dataset columns to assignment fields

- We **restructure the dataset** into exactly the features we need.
- Scaling `JobLevel` into a 0–100 test score makes it easier to interpret.
- We add a target column: `suitable_for_employment`.
  - Attrition = "Yes" → Not suitable (No).
  - Attrition = "No" → Suitable (Yes).

```
# Map dataset columns to our required features
df = pd.DataFrame({
    "age": df["Age"],
    "education_level": df["Education"],
    "years_of_experience": df["TotalWorkingYears"],
    "technical_test_score": df["JobLevel"].astype(float),
    "interview_score": df["PerformanceRating"].astype(float),
    "previous_employment": df["NumCompaniesWorked"].apply(lambda x: "Yes" if pd.
    notnull(x) and x > 0 else "No"),
    "suitable_for_employment": df["Attrition"].apply(lambda x: "No" if x ==
    "Yes" else "Yes")
})
```

```
df.head(5).style.hide(axis="index")
```

age	education_level	years_of_experience	technical_test_score	interview_score	previous_employment	suitable_for_employment
41	2	8	2.000000	3.000000	Yes	No
49	1	10	2.000000	4.000000	Yes	Yes
37	2	7	1.000000	3.000000	Yes	No
33	4	8	1.000000	3.000000	Yes	Yes
27	1	6	1.000000	3.000000	Yes	Yes

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
```

```
Data columns (total 7 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   age                     1470 non-null   int64
 1   education_level         1470 non-null   int64
 2   years_of_experience     1470 non-null   int64
 3   technical_test_score    1470 non-null   float64
 4   interview_score         1470 non-null   float64
 5   previous_employment     1470 non-null   object
 6   suitable_for_employment 1470 non-null   object
dtypes: float64(2), int64(3), object(2)
memory usage: 80.5+ KB
```

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

	0
age	0
education_level	0
years_of_experience	0
technical_test_score	0
interview_score	0
previous_employment	0
suitable_for_employment	0

dtype: int64

```
# check statistics of numeric columns
print("\nBasic descriptive stats for numeric columns:")
display(df.describe())
```

```
Basic descriptive stats for numeric columns:
```

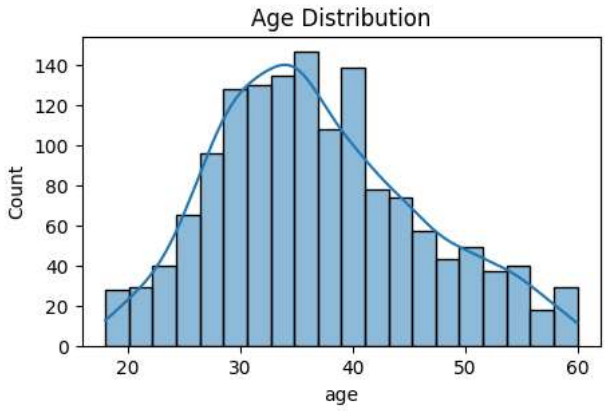
	age	education_level	years_of_experience	technical_test_score	interview_score
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.000000
mean	36.923810	2.912925	11.279592	2.063946	3.153741
std	9.135373	1.024165	7.780782	1.106940	0.360824
min	18.000000	1.000000	0.000000	1.000000	3.000000
25%	30.000000	2.000000	6.000000	1.000000	3.000000
50%	36.000000	3.000000	10.000000	2.000000	3.000000
75%	43.000000	4.000000	15.000000	3.000000	3.000000
max	60.000000	5.000000	40.000000	5.000000	4.000000

EDA(Exploratory Data Analysis)

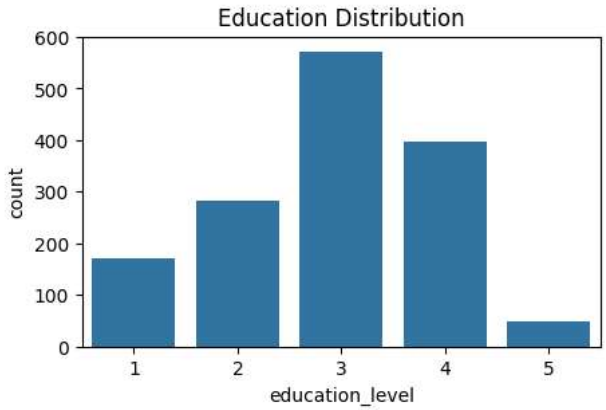
Understanding the dataset visually.

- Histograms showing the distribution of numbers like age
- Countplots showing how many candidates fall in each category

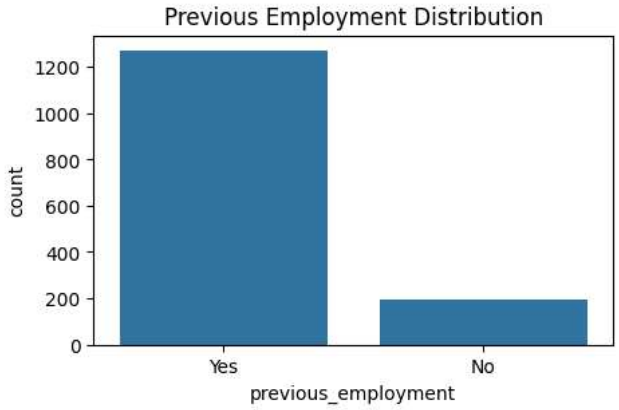
```
# Age distribution
plt.figure(figsize=(5,3))
sns.histplot(df['age'],bins=20, kde=True)
plt.title('Age Distribution')
plt.show()
```




```
# Education Distribution
plt.figure(figsize=(5,3))
sns.countplot(x='education_level', data=df).figsize=(5,2)
plt.title('Education Distribution')
plt.show()
```




```
# Previous employment distribution
plt.figure(figsize=(5,3))
sns.countplot(x ="previous_employment", data=df)
plt.title('Previous Employment Distribution')
plt.show()
```



Data Preprocessing

Preparing the dataset so the model can understand it.

steps

1. Encode categorical columns: `previous_employment` and `suitable_for_employment`.
2. Build feature matrix `X` using the columns required by the assignment.
3. Use `suitable_for_employment_enc` as the numeric target `y`.
4. Split into train (80%) and test (20%) sets with stratification.

Key terms before preprocessing

- **Categorical variable**: column with discrete categories (e.g., "Yes"/"No").
- **Label encoding**: converting text categories to integers.
- **Feature matrix (X)**: input variables for the model.
- **Target vector (y)**: the label we want to predict.
- **Train/Test split**: partition data so the model trains on one set and is evaluated on another.

```
# import the libraries
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
```

```
# Encode categorical values
le = LabelEncoder()
df['suitable_for_employment_enc'] = le.fit_transform(df['suitable_for_employment'])
df['previous_employment_enc'] = le.fit_transform(df['previous_employment'])
```

```
df.head().style.hide(axis="index")
```

age	education_level	years_of_experience	technical_test_score	interview_score	previous_employment	suitable_for_employment	suitable_for_emplo
41	2	8	2.000000	3.000000	Yes	No	
49	1	10	2.000000	4.000000	Yes	Yes	
37	2	7	1.000000	3.000000	Yes	No	
33	4	8	1.000000	3.000000	Yes	Yes	
27	1	6	1.000000	3.000000	Yes	Yes	

```
# Seperate the Features (X) and the Target(Y)
X = df.drop(['suitable_for_employment', 'suitable_for_employment_enc', 'previous_employment'], axis=1)
y = df['suitable_for_employment_enc']
```

```
X.head().style.hide(axis="index")
```

age	education_level	years_of_experience	technical_test_score	interview_score	previous_employment_enc
41	2	8	2.000000	3.000000	1
49	1	10	2.000000	4.000000	1
37	2	7	1.000000	3.000000	1
33	4	8	1.000000	3.000000	1
27	1	6	1.000000	3.000000	1

```
# Split data
# - `stratify=y` ensures class proportions (Yes/No) are preserved in train and test sets.
# - `random_state=42` fixes randomness so results are reproducible across runs.
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)

print("Training samples:", X_train.shape[0])
print("Testing samples:", X_test.shape[0])
```

```
Training samples: 1176
Testing samples: 294
```

Train the Decision tree

- We create a **Decision Tree model**.
- `.fit()` trains the model with the training data.
- The tree learns decision rules step by step (like “If age > 30 → go left, else right”).

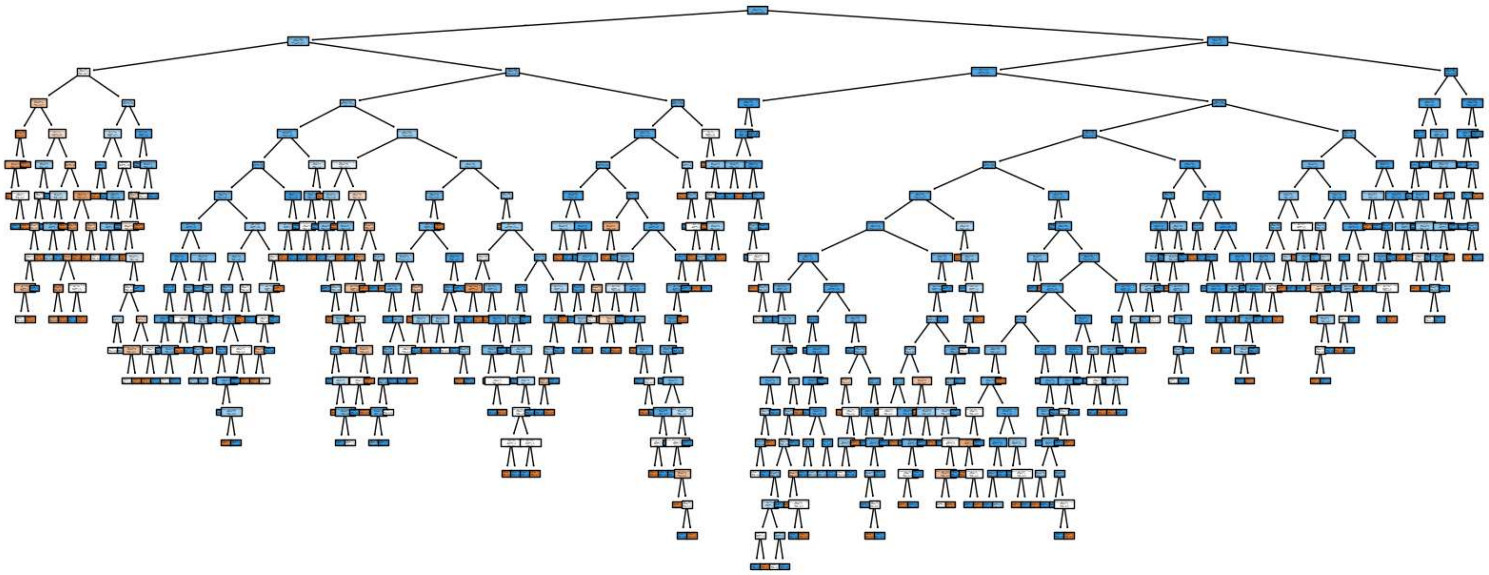
```
model = DecisionTreeClassifier(random_state=42)
model.fit(X_train, y_train)
```

```
DecisionTreeClassifier(random_state=42)
```

Visualize Tree

- This shows the actual **decision tree**.
- Each node asks a Yes/No question.
- Each branch narrows down to a prediction.
- Helps explain the model visually.

```
plt.figure(figsize=(20,8))
plot_tree(model, feature_names=X.columns, class_names=["No","Yes"], filled=True)
plt.show()
```



Predict Hypothetical Candidates

- We test 3 hypothetical candidates:
  - Young with little experience → maybe No.
  - Experienced with high scores → Yes.
  - Average scores and experience → borderline case.
- The model predicts each candidate's suitability.

```
candidates = pd.DataFrame({
    "age": [25, 40, 30, 45, 7],
    "education_level": [2, 5, 4, 6, 0],
    "years_of_experience": [2, 15, 5, 18, 0.5],
    "technical_test_score": [60, 100, 80, 97, 2],
    "interview_score": [3, 4, 2, 8, 4],
    "previous_employment_enc": [1, 1, 0, 2, 1]
})
preds = model.predict(candidates)
candidates["Predicted Suitability"] = preds
candidates["Predicted Suitability"] = candidates["Predicted Suitability"].map({0:"No",1:"Yes"})
candidates.style.hide(axis="index")
```

age	education_level	years_of_experience	technical_test_score	interview_score	previous_employment_enc	Predicted Suitability
25	2	2.000000	60	3	1	Yes
40	5	15.000000	100	4	1	Yes
30	4	5.000000	80	2	0	Yes
45	6	18.000000	97	8	2	Yes
7	0	0.500000	2	4	1	Yes

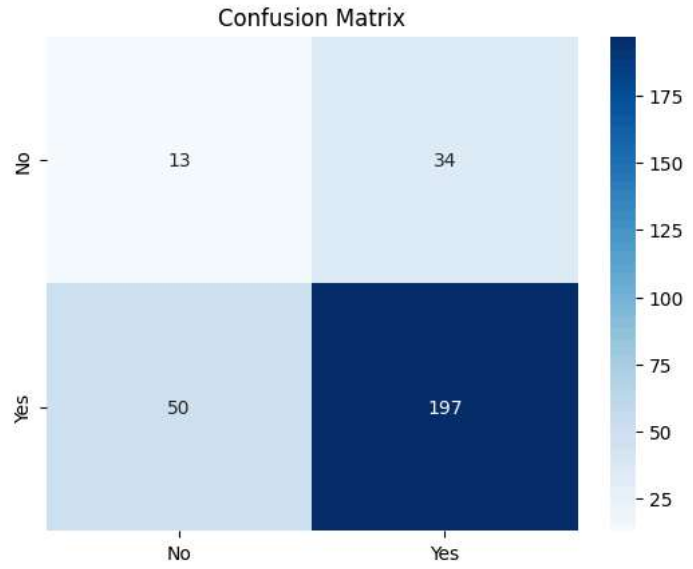
Evaluate Model

Interpreting model evaluation

- **Accuracy** tells us the overall fraction of correct predictions.
- **Confusion matrix** shows true positives and negatives, and false positives and negatives.
    - Check false negatives (suitable candidates predicted not suitable) if missing a good hire is costly.
- **Precision** = among predicted Yes, how many truly are Yes.
- **Recall** = among actual Yes, how many were found by the model.
- **F1-score** balances precision and recall; useful with imbalanced classes.

```
y_pred = model.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))

print("\nConfusion Matrix:")
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["No","Yes"], yticklabels=["No","Yes"])
plt.title("Confusion Matrix")
plt.show()

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.7142857142857143

Confusion Matrix:
```




```
Classification Report:
              precision    recall  f1-score   support

           0       0.21      0.28      0.24        47
           1       0.85      0.80      0.82       247

    accuracy                           0.71       294
   macro avg       0.53      0.54      0.53       294
weighted avg       0.75      0.71      0.73       294
```

Feature Importance

- Values reflect how often and how well a feature was used to split nodes in the tree.
- Higher values mean the feature was more useful to reduce impurity and make decisions.

```
importances = pd.Series(model.feature_importances_, index=X.columns)
importances.sort_values().plot(kind='barh',figsize=(5,2))
plt.xlabel("Importance (higher = more influence)")
plt.tight_layout()
plt.title("Feature Importance")
plt.show()
```