

# PROJECT 3 - EMPLOYEE ATTRITION ANALYSIS (HR ANALYTICS)

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## CODE

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score,
confusion_matrix

def load_data(filepath):
    try:
        data = pd.read_csv(filepath)
        print("Data loaded successfully!")
        print(f"Dataset shape: {data.shape}")
        print("The first 5 rows of the dataset:\n")
        print(data.head())
        return data
    except FileNotFoundError:
        print(f"Error: The file '{filepath}' was not found.")
        return None

def initial_cleaning(df):
    if df is None:
        return None

    print("\n--- Starting Initial Cleaning ---")
    # Dropping columns that have only one unique value (constants) ,
    these columns will provide no information
    cols_to_drop = [col for col in df.columns if df[col].nunique() ==
1]
    if cols_to_drop:
        df = df.drop(columns=cols_to_drop)
        print(f"Dropped constant columns: {cols_to_drop}")
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    df['Attrition_Numeric'] = df['Attrition'].map({'Yes': 1, 'No': 0})
#mapped 'Attrition' to numeric values (Yes=1, No=0)

    print("Initial Cleaning Complete")
    return df

def preprocess_and_encode(df):
    if df is None:
        return

    le=LabelEncoder()
    df['Gender_Encoded'] = le.fit_transform(df['Gender'])

    print("\n--- Starting Preprocessing and One-Hot-Encoding ---")
    categorical_cols = ['BusinessTravel', 'Department',
'EducationField', 'JobRole', 'MaritalStatus', 'OverTime']

    cols_to_encode = [col for col in categorical_cols if col in
df.columns]

    print(f"Original Columns to be encoded: {cols_to_encode} ")
    original_cols = set(df.columns)
    df_encoded = pd.get_dummies(df, columns=cols_to_encode ,
drop_first=True, dtype=int)
    cols_to_drop = ['Gender'] + cols_to_encode
    new_cols = set(df_encoded.columns)
    new_one_hot_cols = list(new_cols - original_cols)
    print(f"\n New one-hot columns created ({len(new_one_hot_cols)}):")
    if len(new_one_hot_cols) > 20:
        print(new_one_hot_cols)
    else:
        print(new_one_hot_cols)

    print('\n--- One-Hot Encoding Complete! ---')
    df_encoded = df_encoded.drop(columns=cols_to_drop ,
errors='ignore')
    return df_encoded

def perform_univariate_analysis(df):
    if df is None:
        return

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print("\n--- Starting Univariate Analysis ---")
sns.set_style("whitegrid")

# Attrition distribution
plt.figure(figsize=(7, 5))
sns.countplot(x='Attrition', data=df, palette='pastel' ,
hue='Attrition' , legend=False)
plt.title('Overall Employee Attrition Distribution', fontsize=16)
plt.xlabel('Attrition', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.savefig('univariate_attrition_distribution.png',
bbox_inches='tight')
print("Saved 'univariate_attrition_distribution.png'")

# Satisfaction Level Distribution
plt.figure(figsize=(10, 6))
sns.histplot(df['JobSatisfaction'], kde=True, bins=4,
color='skyblue')
plt.title('Job Satisfaction Level Distribution', fontsize=16)
plt.xlabel('Job Satisfaction (1=Low, 4=Very High)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.savefig('univariate_job_satisfaction.png', bbox_inches='tight')
print("Saved 'univariate_job_satisfaction.png'")

# Department Distribution
plt.figure(figsize=(10, 6))
sns.countplot(y='Department', data=df, palette='viridis',
order=df['Department'].value_counts().index , hue='Department' ,
legend=False)
plt.title('Employee Distribution by Department', fontsize=16)
plt.xlabel('Count', fontsize=12)
plt.ylabel('Department', fontsize=12)
plt.savefig('univariate_department_distribution.png',
bbox_inches='tight')
print("Saved 'univariate_department_distribution.png'")

print("--- Univariate Analysis Complete ---")

def perform_bivariate_analysis(df):
    if df is None:
        return

    print("\n--- Starting Bivariate Analysis (vs. Attrition) ---")

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# Attrition vs. Salary
plt.figure(figsize=(12, 7))
sns.boxplot(x='Attrition', y='MonthlyIncome', data=df,
palette='coolwarm' , hue='Attrition' , legend=False)
plt.title('Monthly Income vs. Attrition', fontsize=16)
plt.xlabel('Attrition', fontsize=12)
plt.ylabel('Monthly Income', fontsize=12)
plt.savefig('bivariate_attrition_vs_income.png',
bbox_inches='tight')
print("Saved 'bivariate_attrition_vs_income.png'")

# Attrition vs. Department
plt.figure(figsize=(10, 6))

dept_attrition =
df.groupby('Department')['Attrition_Numeric'].mean().reset_index().sort
_values(by='Attrition_Numeric', ascending=False)
sns.barplot(x='Attrition_Numeric', y='Department',
data=dept_attrition, palette='plasma' , hue='Department' ,
legend=False)
plt.title('Attrition Rate by Department', fontsize=16)
plt.xlabel('Attrition Rate', fontsize=12)
plt.ylabel('Department', fontsize=12)
plt.savefig('bivariate_attrition_vs_department.png',
bbox_inches='tight')
print("Saved 'bivariate_attrition_vs_department.png'")

# Bivariate: Attrition vs. YearsAtCompany
plt.figure(figsize=(12, 7))
sns.kdeplot(df[df['Attrition'] == 'Yes']['YearsAtCompany'],
label='Attrition: Yes', fill=True, color='red')
sns.kdeplot(df[df['Attrition'] == 'No']['YearsAtCompany'],
label='Attrition: No', fill=True, color='blue')
plt.title('Years at Company vs. Attrition', fontsize=16)
plt.xlabel('Years at Company', fontsize=12)
plt.ylabel('Density', fontsize=12)
plt.legend()
plt.savefig('bivariate_attrition_vs_years_at_company.png',
bbox_inches='tight')
print("Saved 'bivariate_attrition_vs_years_at_company.png'")

print("--- Bivariate Analysis Complete ---")

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def generate_correlation_heatmap(df):
    if df is None:
        return

    print("\n--- Generating Correlation Heatmap ---")

    df_corr = df.copy()
    if 'Attribution' in df_corr.columns:
        df_corr = df_corr.drop(columns=['Attribution'])

    numeric_df = df_corr.select_dtypes(include=np.number)

    if numeric_df.empty:
        print("Error: No Numeric Data found for correlation Heatmap")

    plt.figure(figsize=(20, 16))
    correlation_matrix = numeric_df.corr()
    sns.heatmap(correlation_matrix, annot=True, fmt='.2f',
cmap='coolwarm', annot_kws={"size": 8} )
    plt.title('Correlation Heatmap of All Features', fontsize=20)
    plt.xticks(rotation=90)
    plt.yticks(rotation=0)
    plt.savefig('correlation_heatmap.png', bbox_inches='tight')
    print("Saved 'correlation_heatmap.png'")

    # Show top correlations with Attrition
    attrition_corr =
correlation_matrix['Attrition_Numeric'].sort_values(ascending=False)
    print("\nTop features correlated with Attrition (Positive):")
    print(attrition_corr[attrition_corr > 0][1:].head(10)) # Skip
itself
    print("\nTop features correlated with Attrition (Negative):")
    print(attrition_corr[attrition_corr <
0][1:].sort_values(ascending=True).head(10))

    print("--- Correlation Analysis Complete ---")

def derive_specific_insight(df):
    if df is None:
        return

    print("\n--- Deriving Specific Insight ---")

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    # using 1st quartile (bottom 25%) as the definition for "low
income"

    low_income_threshold = df['MonthlyIncome'].quantile(0.25)
    print(f"Defining 'Low Income' as <= ${low_income_threshold:.2f}
(1st Quartile)")

    # 2. Create the segments
    df['Experience_Group'] = pd.cut(df['YearsAtCompany'], bins=[-1, 2,
float('inf')], labels=['<3 Years', '3+ Years'])
    df['Income_Group'] = pd.cut(df['MonthlyIncome'], bins=[-1,
low_income_threshold, float('inf')], labels=['Low Income', 'Not Low
Income'])

    # 3. Analyze the target group
    target_group = df[
        (df['Experience_Group'] == '<3 Years') &
        (df['Income_Group'] == 'Low Income')
    ]

    if not target_group.empty:
        overall_attrition_rate = df['Attrition_Numeric'].mean()
        target_group_attrition_rate =
target_group['Attrition_Numeric'].mean()

        print(f"\nOverall Attrition Rate:
{overall_attrition_rate:.2%}")
        print(f"Target Group (<3 Yrs Exp, Low Income) Attrition Rate:
{target_group_attrition_rate:.2%}")

        if target_group_attrition_rate > overall_attrition_rate:
            print("\nInsight Confirmed: Attrition is significantly
higher among employees with < 3 years of experience and low income.")
        else:
            print("\nInsight Not Confirmed: The target group does not
have a higher attrition rate than the overall average.")

        insight_data = df.groupby(['Experience_Group', 'Income_Group']
, observed=False)['Attrition_Numeric'].mean().reset_index()
        plt.figure(figsize=(10, 6))
        sns.barplot(x='Experience_Group', y='Attrition_Numeric',
hue='Income_Group', data=insight_data, palette='Set1')

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        plt.title('Attrition Rate by Experience and Income',
fontsize=16)
        plt.ylabel('Attrition Rate', fontsize=12)
        plt.xlabel('Experience Group', fontsize=12)
        plt.axhline(y=overall_attrition_rate, color='blue',
linestyle='--', label=f'Overall Avg ({overall_attrition_rate:.2%})')
        plt.legend()
        plt.savefig('insight_experience_vs_income.png',
bbox_inches='tight')
        print("Saved 'insight_experience_vs_income.png'")

    else:
        print("Could not analyze the target group (no data found for
this segment).")

    print("--- Specific Insight Analysis Complete ---")

def logistic_regression_model(df):
    if df is None:
        return

    print("\n--- Building a Logistic Regression Model ---")

    y = df['Attrition_Numeric']
    X = df.drop(columns=['Attrition_Numeric', 'Attrition'
, 'EmployeeNumber'], errors='ignore')
    X = X.select_dtypes(include=np.number)
    X = X.fillna(0)

    print(f"\nTraining Model with {len(X.columns)} features.")

    X_train , X_test, y_train , y_test =
train_test_split(X,y,test_size=0.2,random_state=42)

    scaler=StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)

    model=LogisticRegression(random_state=42,class_weight='balanced' ,
max_iter=1000)
    model.fit(X_train_scaled , y_train)

    y_pred = model.predict_proba(X_test_scaled)[: , 1] # for 'Yes'

```

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# print(len(y_pred))
# print(y_test)
boolarr = (y_pred > 0.66)
y_pred = boolarr.astype(int)

print("\nModel Evaluation Results:")

accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2%}")

print("\nConfusion Matrix:")
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted No', 'Predicted Yes'],
            yticklabels=['Actual No', 'Actual Yes'])
plt.title('Confusion Matrix', fontsize=14)
plt.savefig('confusion_matrix.png', bbox_inches='tight')
print("Saved 'confusion_matrix.png'")
print(cm)

print("\nClassification Report:")
report = classification_report(y_test, y_pred, target_names=['No
(0)', 'Yes (1)'])
print(report)

print("--- Model Building Complete ---")

def main():
    FILEPATH = './WA_Fn-UseC_-HR-Employee-Attrition.csv'
    data = load_data(FILEPATH)

    if data is not None:

        data = initial_cleaning(data.copy())

```



```

perform_univariate_analysis(data.copy())
perform_bivariate_analysis(data.copy())
derive_specific_insight(data.copy())
df_encoded = preprocess_and_encode(data)
generate_correlation_heatmap(df_encoded.copy())
logistic_regression_model(df_encoded.copy())

print("\n\nAnalysis complete!!")

if __name__ == "__main__":
    main()

```

## TERMINAL OUTPUT -

**"C:/Program Files/Python312/python.exe"**  
**c:/Users/Administrator/Desktop/Training/Milestone1\_17112025/milestone1.py**  
**Data loaded successfully!**  
**Dataset shape: (1470, 35)**  
**The first 5 rows of the dataset:**

	Age	Attrition	BusinessTravel	DailyRate	Department	...	WorkLifeBalance
	YearsAtCompany	YearsInCurrentRole	YearsSinceLastPromotion	YearsWithCurrManager			
0	41	Yes	Travel_Rarely	1102	Sales	...	1
4			0				6
5							
1	49	No	Travel_Frequently	279	Research & Development	...	3
10		7	1				
7							
2	37	Yes	Travel_Rarely	1373	Research & Development	...	3
0		0	0				
0							
3	33	No	Travel_Frequently	1392	Research & Development	...	3
8		7	3				
0							
4	27	No	Travel_Rarely	591	Research & Development	...	3
2		2	2				
2							

[5 rows x 35 columns]

--- Starting Initial Cleaning ---

Dropped constant columns: ['EmployeeCount', 'Over18', 'StandardHours']

## Initial Cleaning Complete

--- Starting Univariate Analysis ---

Saved 'univariate\_attrition\_distribution.png'

Saved 'univariate\_job\_satisfaction.png'

Saved 'univariate\_department\_distribution.png'

--- Univariate Analysis Complete ---

--- Starting Bivariate Analysis (vs. Attrition) ---

Saved 'bivariate\_attrition\_vs\_income.png'

Saved 'bivariate\_attrition\_vs\_department.png'

Saved 'bivariate\_attrition\_vs\_years\_at\_company.png'

--- Bivariate Analysis Complete ---

--- Deriving Specific Insight ---

Defining 'Low Income' as  $\leq \$2911.00$  (1st Quartile)

Overall Attrition Rate: 16.12%

Target Group (<3 Yrs Exp, Low Income) Attrition Rate: 38.60%

Insight Confirmed: Attrition is significantly higher among employees with < 3 years of experience and low income.

Saved 'insight\_experience\_vs\_income.png'

--- Specific Insight Analysis Complete ---

--- Starting Preprocessing and One-Hot-Encoding ---

Original Columns to be encoded: ['BusinessTravel', 'Department', 'EducationField', 'JobRole', 'MaritalStatus', 'OverTime']

New one-hot columns created (20):

['EducationField\_Marketing', 'MaritalStatus\_Married', 'JobRole\_Laboratory Technician', 'JobRole\_Sales Executive', 'Department\_Research & Development', 'EducationField\_Technical Degree', 'Department\_Sales', 'JobRole\_Sales Representative', 'JobRole\_Manager', 'EducationField\_Other', 'JobRole\_Research Director', 'JobRole\_Manufacturing Director', 'EducationField\_Medical', 'MaritalStatus\_Single', 'OverTime\_Yes', 'JobRole\_Research Scientist', 'EducationField\_Life Sciences', 'BusinessTravel\_Travel Frequently', 'JobRole\_Human Resources', 'BusinessTravel\_Travel Rarely']

--- One-Hot Encoding Complete! ---

--- Generating Correlation Heatmap ---

Saved 'correlation\_heatmap.png'

Top features correlated with Attrition (Positive):

OverTime\_Yes 0.246118

MaritalStatus\_Single 0.175419

JobRole\_Sales Representative 0.157234

BusinessTravel\_Travel\_Frequently 0.115143  
JobRole\_Laboratory Technician 0.098290  
Department\_Sales 0.080855  
DistanceFromHome 0.077924  
EducationField\_Technical Degree 0.069355  
EducationField\_Marketing 0.055781  
NumCompaniesWorked 0.043494  
Name: Attrition\_Numeric, dtype: float64

Top features correlated with Attrition (Negative):

TotalWorkingYears -0.171063  
JobLevel -0.169105  
YearsInCurrentRole -0.160545  
MonthlyIncome -0.159840  
Age -0.159205  
YearsWithCurrManager -0.156199  
StockOptionLevel -0.137145  
YearsAtCompany -0.134392  
JobInvolvement -0.130016  
JobSatisfaction -0.103481

Name: Attrition\_Numeric, dtype: float64

--- Correlation Analysis Complete ---

--- Building a Logistic Regression Model ---

Training Model with 44 features.

Model Evaluation Results:

Accuracy: 81.29%

Confusion Matrix:

Saved 'confusion\_matrix.png'

[[219 36]

[ 19 20]]

Classification Report:

	precision	recall	f1-score	support
No (0)	0.92	0.86	0.89	255
Yes (1)	0.36	0.51	0.42	39
accuracy		0.81		294
macro avg	0.64	0.69	0.65	294
weighted avg	0.85	0.81	0.83	294

--- Model Building Complete ---

Analysis complete!!

#### INSIGHTS DERIVED -

--- Deriving Specific Insight ---

Defining 'Low Income' as  $\leq \$2911.00$  (1st Quartile)

Overall Attrition Rate: 16.12%

Target Group (<3 Yrs Exp, Low Income) Attrition Rate: 38.60%

Insight Confirmed: Attrition is significantly higher among employees with < 3 years of experience and low income.

Saved 'insight\_experience\_vs\_income.png'

--- Specific Insight Analysis Complete ---

#### OUTPUT VISUALIZATIONS -











