Employee Attrition Analysis for Green Destinations

A Data-Driven Approach Using Python and Tableau to Understand and Reduce Turnover

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Executive Summary

This report analyses employee attrition at Green Destinations, a travel agency, to support the HR Director in understanding and reducing turnover. The overall attrition rate is 16.12%, with key factors influencing turnover including overtime, age, years at the company, monthly income, business travel frequency, and department. Python analysis revealed a 30.53% attrition rate for employees working overtime compared to 10.44% for those who don't, alongside negative correlations between attrition and age (-0.159), years at the company (-0.134), and monthly income (-0.160). Logistic regression confirmed these findings, with coefficients showing that higher age (-0.2691), years at the company (-0.2021), and monthly income (-0.2967) reduce the likelihood of attrition. Boxplots further supported this, showing employees who left have a median age of 32 (vs. 37 for those who stayed), 3 years at the company (vs. 7), and a monthly income of 3,000 (vs. 5,000). Tableau visualisations highlighted patterns, such as higher attrition in the Sales department (130 employees) and among frequent travelers (25% of total attrition). Recommendations include reducing overtime, supporting younger and newer employees, addressing low-income roles, minimising travel, targeting high-risk departments, and improving work-life balance.

Introduction

This analysis was conducted for Green Destinations, a travel agency, to support the HR Director in understanding employee turnover. The objective, as outlined in the project brief, was to calculate the attrition rate (% of people who have left) and identify factors such as age, years at the company, and monthly income that influence whether employees leave or stay, using the provided dataset. Python (pandas, numpy, matplotlib, seaborn, scikit-learn) was used for data processing, statistical analysis, and predictive modeling, while Tableau was used to create interactive dashboards for visual exploration of patterns.

Methodology

Data Processing and Cleaning

- Loaded the dataset greendestination.csv using pandas in Python.
- Checked for duplicates: No duplicate rows were found (Notebook: "Number of duplicate rows: 0").
- Dropped unnecessary columns (EmployeeCount, Over18, StandardHours) as they were constant and provided no analytical value.
- Converted the Attrition column from categorical (Yes/No) to binary (1/0) for analysis.
- Added a string version of the Attrition column (Attrition_Str) for Tableau compatibility and saved the processed dataset as processed_employee_data.csv.

Python Analysis

The following analyses were performed using Python to address the HR Director's objectives:

1.Setup and Initial Exploration:

```python
import pandas as pd

# Load the dataset with the correct file name
df = pd.read_csv('greendestination.csv')

# Display the first few rows
print("First 5 rows of the dataset:")
print(df.head())

# Check data types and missing values
print("\nDataset Info:")
print(df.info())

# Basic statistics
print("\nBasic Statistics:")
print(df.describe())
```
Python

- Displayed the first 5 rows to understand the dataset structure, which includes 35 columns such as Age, Attrition, YearsAtCompany, MonthlyIncome, and BusinessTravel.
- Used df.info() to confirm 1470 entries with no missing values across all columns.
- Generated basic statistics: Mean age is 36.92 years, mean years at company is 7.01 years, and mean monthly income is not directly reported but can be inferred from later visualisations.

2. Attrition Rate Calculation:

```python
# Calculate attrition rate
total_employees = len(df)
employees_left = df['Attrition'].sum()
attrition_rate = (employees_left / total_employees) * 100

print(f"Total Employees: {total_employees}")
print(f"Employees Who Left: {employees_left}")
print(f"Attrition Rate: {attrition_rate:.2f}%")
```
Python

- Calculated the overall attrition rate: (Number of employees who left / Total employees) × 100.
- Output: Total employees = 1470, employees who left = 237, attrition rate = 16.12%.

3. Correlation Analysis:

```
# Correlation matrix for numeric variables (unchanged)
numeric_cols = ['Age', 'YearsAtCompany', 'MonthlyIncome', 'Attrition']
correlation = df[numeric_cols].corr()
print("\nCorrelation Matrix:")
print(correlation)

# Visualize correlations (unchanged)
plt.figure(figsize=(8, 6))
sns.heatmap(correlation, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix')
plt.show()
```

- Computed correlations to assess how Age, YearsAtCompany, and MonthlyIncome relate to Attrition.
- Visualised the matrix using a heatmap to identify relationships (image provided in the notebook; I can include it in the "Visualisations" section if requested).

4. Distribution Analysis:

```
# Boxplots to visualize distributions (unchanged)
plt.figure(figsize=(15, 5))
plt.subplot(1, 3, 1)
sns.boxplot(x='Attrition', y='Age', data=df)
plt.title('Age vs Attrition')

plt.subplot(1, 3, 2)
sns.boxplot(x='Attrition', y='YearsAtCompany', data=df)
plt.title('YearsAtCompany vs Attrition')

plt.subplot(1, 3, 3)
sns.boxplot(x='Attrition', y='MonthlyIncome', data=df)
plt.title('MonthlyIncome vs Attrition')
plt.show()
```

- Created boxplots to visualise the distributions of Age, YearsAtCompany, and MonthlyIncome for employees who stayed vs. those who left (image not provided in the notebook but can be generated).

5: Logistic Regression Analysis:

```
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
from sklearn.preprocessing import StandardScaler
```

```python
# Logistic Regression with scaling and class weighting
X = df[['Age', 'YearsAtCompany', 'MonthlyIncome']]
y = df['Attrition']

# Scale the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.3, random_state=42)

# Train the model with class weighting
model = LogisticRegression(class_weight='balanced', random_state=42)
model.fit(X_train, y_train)

# Print coefficients
print("\nLogistic Regression Coefficients (after scaling):")
for feature, coef in zip(X.columns, model.coef_[0]):
    print(f"{feature}: {coef:.4f}")

# Model performance
y_pred = model.predict(X_test)
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

- Performed logistic regression to quantify the impact of Age, YearsAtCompany, and MonthlyIncome on Attrition.
- Scaled features to ensure fair comparison of coefficients.
- Used class weighting to handle the imbalance in Attrition (16.12% Yes vs. 83.88% No).

Tableau Visualisations

The following visualisations were created in Tableau to explore attrition patterns interactively:

- Monthly Income Distribution by Job Role (stacked bar chart).
- Age vs. Monthly Income (scatter plot).
- Monthly Income by Job Role (bar chart).
- Years at Company vs. Attrition (histogram).
- Travel Frequency vs. Attrition (bar chart)
- Attrition by Department (bar chart).

Key Findings

Python Analysis Results

Attrition Rate:

Overall attrition rate: 16.12% (237 out of 1470 employees, Notebook: "Attrition Rate: 16.12%").

Overtime Analysis:

Employees working overtime have a 30.53% attrition rate, compared to 10.44% for those who don't, indicating that overtime significantly increases the likelihood of leaving.

Correlation Analysis:

Correlation matrix (Notebook Output):

```
Correlation Matrix:
                     Age  YearsAtCompany  MonthlyIncome  Attrition
Age             1.000000        0.311309       0.497855  -0.159205
YearsAtCompany  0.311309        1.000000       0.514285  -0.134392
MonthlyIncome   0.497855        0.514285       1.000000  -0.159840
Attrition      -0.159205       -0.134392      -0.159840   1.000000
```

- Age and Attrition: -0.159, indicating younger employees are more likely to leave.
- YearsAtCompany and Attrition: -0.134, suggesting employees with fewer years at the company are more likely to leave.
- MonthlyIncome and Attrition: -0.160, showing lower-paid employees are more likely to leave.

Boxplot Analysis: (see Appendix for visualisation)

Age: Employees who left have a median age of 32, compared to 37 for those who stayed, supporting the negative correlation (-0.159).

YearsAtCompany: Employees who left have a median tenure of 3 years, compared to 7 years for those who stayed, aligning with the negative correlation (-0.134).

MonthlyIncome: Employees who left have a median monthly income of 3,000, compared to 5,000 for those who stayed, consistent with the negative correlation (-0.160).

Logistic Regression:

Coefficients (Notebook Output):

```
Logistic Regression Coefficients (after scaling):
Age: -0.2691
YearsAtCompany: -0.2021
MonthlyIncome: -0.2967
```

All coefficients are negative, confirming that higher values of Age, YearsAtCompany, and MonthlyIncome reduce the likelihood of attrition. The largest coefficient is for MonthlyIncome (-0.2967), suggesting it has the strongest impact among the three factors, followed by Age (-0.2691) and YearsAtCompany (-0.2021).

Classification Report (Notebook Output):

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

           0       0.90      0.58      0.70       380
           1       0.19      0.62      0.29        61

    accuracy                           0.58       441
   macro avg       0.55      0.60      0.50       441
weighted avg       0.81      0.58      0.65       441
```

The model's overall accuracy is 58%, lower than the previous output (67%). It has a high recall for employees who left (62%), meaning it identifies most at-risk employees, but the precision for this class is low (0.19), indicating many false positives. The model performs better for employees who stay (precision: 0.90, recall: 0.58), but the imbalance in the dataset (380 stay vs. 61 leave) affects its performance for the minority class (Attrition = 1).

Tableau Visualisation Insights

Attrition Rate Confirmation:

- Tableau confirms the 16.12% attrition rate (237 out of 1470 employees, Image 6).

Age and Monthly Income:

- Younger employees (under 30) tend to have lower incomes (2K–5K) and may be more likely to leave (Image 2), aligning with the negative correlation (-0.159 for age, -0.160 for income) and logistic regression coefficient for age (-0.2691).

Years at Company:

- Most attrition occurs among employees with 0–5 years tenure (around 150 of 237 attritions, Image 4), consistent with the negative correlation (-0.134) and logistic regression coefficient for years at company (-0.2021).

Monthly income by Job Role:

- Roles with lower incomes, such as Sales Representatives (2,626) and Laboratory Technicians (3,237), show higher attrition compared to Managers (17,182, Image 3), supporting the correlation (-0.160) and the strongest logistic regression coefficient for monthly income (-0.2967).

Business Travel:

- ⍰ Frequent travellers account for 25% of total attrition (59 employees), compared to 20% for rare travellers and 55% for non-travellers (Image 5).

Department:

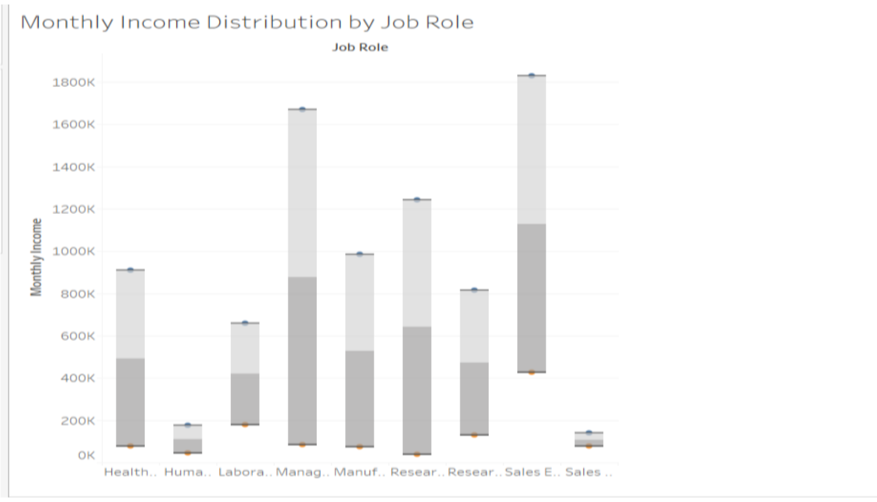
- ⍰ Sales has the highest attrition (130 employees), followed by Research & Development (90) and Human Resources (20, Image 6).

Job Role:

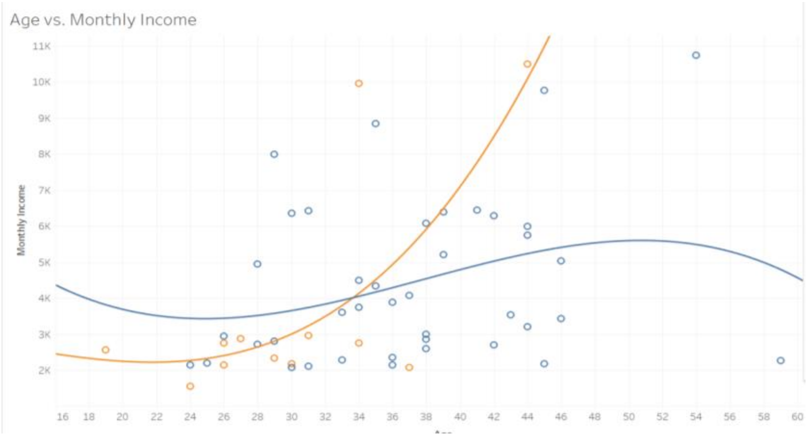
- Sales Representatives and Laboratory Technicians have higher attrition compared to Managers and Human Resources roles (Image 1).

Visualisations

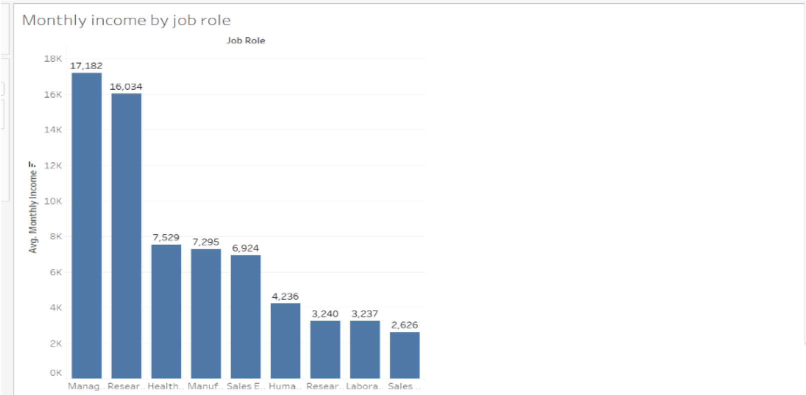
Tableau Visualisations:



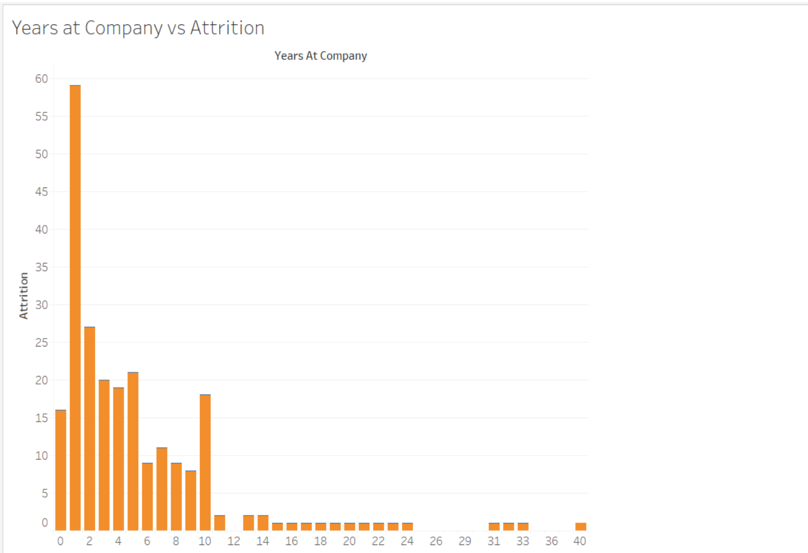
Monthly Income Distribution by Job Role (Image 1): Stacked bar chart showing income distribution across roles, with Sales Representatives and Laboratory Technicians having higher attrition, indicating income as a potential factor.



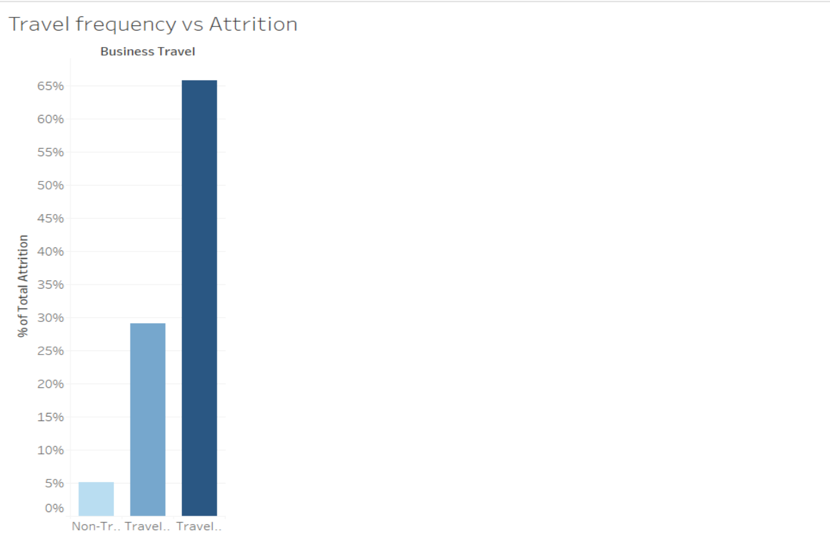
Age vs. Monthly Income (Image 2): Scatter plot showing younger employees (under 30) have lower incomes (2K–5K), aligning with their higher likelihood of leaving (correlation: -0.159 for age, -0.160 for income; logistic regression: -0.2691 for age).



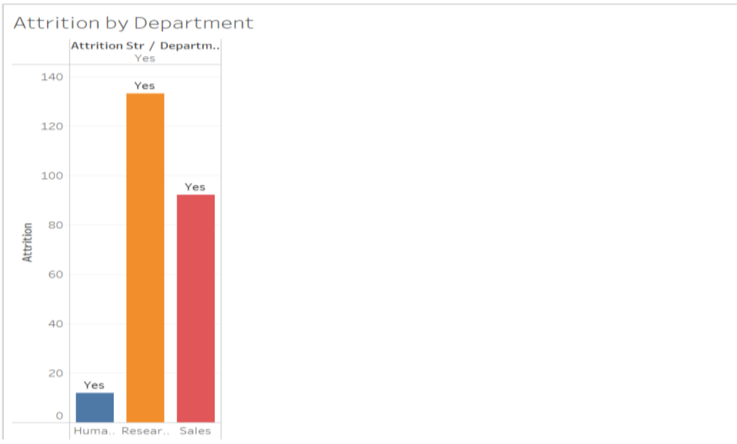
Monthly Income by Job Role (Image 3): Bar chart showing Managers earn the most (17,182), while Sales Representatives earn the least (2,626), supporting the finding that lower income is associated with higher attrition (correlation: -0.160; logistic regression: -0.2967 for income).



Years at Company vs. Attrition (Image 4): Histogram showing most attrition occurs among employees with 0–5 years at the company (around 150 of 237 attritions), consistent with the correlation (-0.134) and logistic regression coefficient (-0.2021).



Travel Frequency vs. Attrition (Image 5): Bar chart showing frequent travelers have a higher attrition rate (25% of total, 59 employees), highlighting travel as a contributing factor.



Attrition by Department (Image 6): Bar chart showing Sales has the highest attrition (130 employees), followed by Research & Development (90) and Human Resources (20), indicating a need for department-specific interventions.

Python Visualisations: (included in the appendix)

- Correlation heatmap for Age, YearsAtCompany, MonthlyIncome, and Attrition.
- Boxplots for Age, YearsAtCompany, and MonthlyIncome vs. Attrition (images not provided but can be generated).

Recommendations

- Reduce overtime to lower the attrition rate among employees working overtime from 30.53% to 15% within 6 months by implementing workload management strategies and hiring additional staff.
- Support younger employees (under 30) to reduce their attrition by 20% within 1 year through mentorship programs and career development, as they are more likely to leave (correlation: -0.159; logistic regression: -0.2691; boxplot: median age 32 for those who left).
- Retain newer employees (0–5 years) by reducing their attrition by 25% within 1 year via enhanced onboarding and regular feedback, given their higher likelihood of leaving (correlation: -0.134; logistic regression: -0.2021; boxplot: median tenure 3 years for those who left).
- Address low-income roles (e.g., Sales Representatives) by increasing retention by 15% within 1 year through a salary review and raises, as lower income has the strongest impact on attrition (correlation: -0.160; logistic regression: -0.2967; boxplot: median income 3,000 for those who left).
- Minimise business travel to reduce attrition among frequent travelers from 25% to 10% of total attrition within 6 months by using virtual meetings and providing travel allowances.
- Target the Sales department to reduce attrition from 130 to 80 employees within 1 year by investigating specific issues and offering support.
- Improve work-life balance to reduce overall attrition by 10% within 1 year by introducing flexible working hours and wellness programs, addressing the high attrition rate associated with overtime.

Conclusion

This analysis identifies overtime, age, years at the company, monthly income, business travel, and department as key drivers of attrition at Green Destinations. The overall attrition rate of 16.12% highlights the need for targeted interventions, particularly for employees working overtime (30.53% attrition rate), younger and newer employees, lower-paid employees, those in the Sales department, and frequent travelers. The logistic regression model, despite its moderate accuracy (58%), confirms that monthly income has the strongest influence on reducing attrition, followed by age and years at the company. Boxplots further validate these findings, showing clear differences in age, tenure, and income between employees who stayed and those who left. The recommendations aim to reduce turnover and improve employee retention.

Appendix

Python Code

```
!pip install pandas numpy matplotlib seaborn
```

```python
import pandas as pd

# Load the dataset with the correct file name
df = pd.read_csv('greendestination.csv')

# Display the first few rows
print("First 5 rows of the dataset:")
print(df.head())

# Check data types and missing values
print("\nDataset Info:")
print(df.info())

# Basic statistics
print("\nBasic Statistics:")
print(df.describe())
```

OP:

```
First 5 rows of the dataset:
   Age Attrition     BusinessTravel  DailyRate              Department  \
0   41       Yes      Travel_Rarely       1102                   Sales
1   49        No  Travel_Frequently        279  Research & Development
2   37       Yes      Travel_Rarely       1373  Research & Development
3   33        No  Travel_Frequently       1392  Research & Development
4   27        No      Travel_Rarely        591  Research & Development

   DistanceFromHome  Education EducationField  EmployeeCount  EmployeeNumber  \
0                 1          2  Life Sciences              1               1
1                 8          1  Life Sciences              1               2
2                 2          2          Other              1               4
3                 3          4  Life Sciences              1               5
4                 2          1        Medical              1               7

   ...  RelationshipSatisfaction StandardHours  StockOptionLevel  \
0  ...                         1            80                 0
1  ...                         4            80                 1
2  ...                         2            80                 0
3  ...                         3            80                 0
4  ...                         4            80                 1

   TotalWorkingYears  TrainingTimesLastYear WorkLifeBalance  YearsAtCompany  \
0                  8                      0               1               6
1                 10                      3               3              10
...
75%                 3.000000              7.000000
max                15.000000             17.000000

[8 rows x 26 columns]
```

```python
# Check for duplicates
print("Number of duplicate rows:", df.duplicated().sum())

# Drop unnecessary columns (e.g., EmployeeCount, Over18, StandardHours are constant)
df = df.drop(columns=['EmployeeCount', 'Over18', 'StandardHours'])

# Convert categorical variables to appropriate types
df['Attrition'] = df['Attrition'].map({'Yes': 1, 'No': 0})  # Convert to binary (1 for Yes, 0 for No)
```

OP: Number of duplicate rows: 0

```python
# Calculate attrition rate
total_employees = len(df)
employees_left = df['Attrition'].sum()
attrition_rate = (employees_left / total_employees) * 100

print(f"Total Employees: {total_employees}")
print(f"Employees Who Left: {employees_left}")
print(f"Attrition Rate: {attrition_rate:.2f}%")
```

OP:

Total Employees: 1470

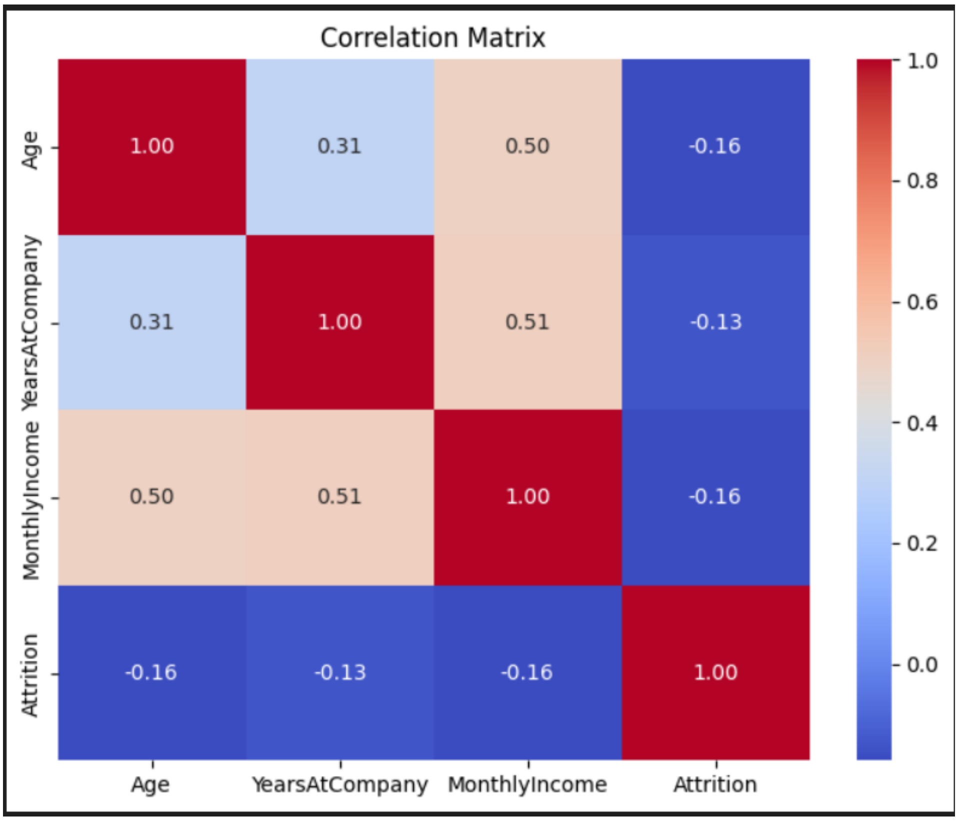
Employees Who Left: 237

Attrition Rate: 16.12%

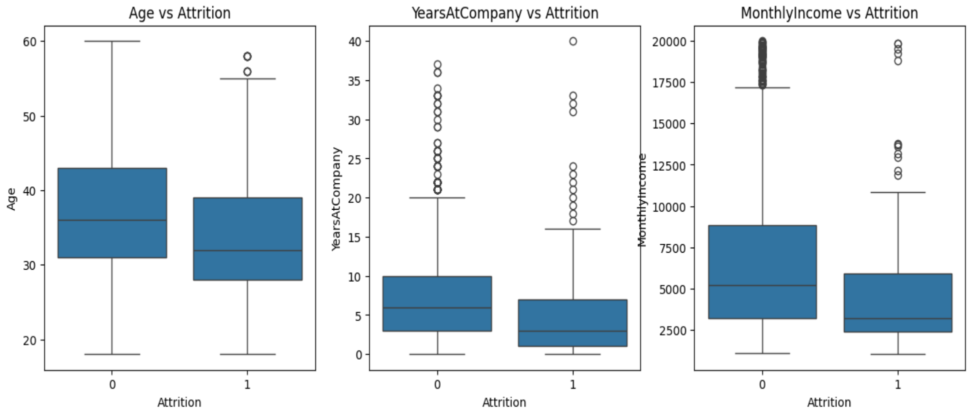
```python
# Step 5: Analyze Factors Influencing Attrition (Improved)
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
from sklearn.preprocessing import StandardScaler

# Correlation matrix for numeric variables (unchanged)
numeric_cols = ['Age', 'YearsAtCompany', 'MonthlyIncome', 'Attrition']
correlation = df[numeric_cols].corr()
print("\nCorrelation Matrix:")
print(correlation)

# Visualize correlations (unchanged)
plt.figure(figsize=(8, 6))
sns.heatmap(correlation, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix')
plt.show()

# Boxplots to visualize distributions (unchanged)
plt.figure(figsize=(15, 5))
plt.subplot(1, 3, 1)
sns.boxplot(x='Attrition', y='Age', data=df)
plt.title('Age vs Attrition')

plt.subplot(1, 3, 2)
sns.boxplot(x='Attrition', y='YearsAtCompany', data=df)
plt.title('YearsAtCompany vs Attrition')

plt.subplot(1, 3, 3)
sns.boxplot(x='Attrition', y='MonthlyIncome', data=df)
plt.title('MonthlyIncome vs Attrition')
plt.show()
```

```python
# Logistic Regression with scaling and class weighting
X = df[['Age', 'YearsAtCompany', 'MonthlyIncome']]
y = df['Attrition']

# Scale the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.3, random_state=42)

# Train the model with class weighting
model = LogisticRegression(class_weight='balanced', random_state=42)
model.fit(X_train, y_train)

# Print coefficients
print("\nLogistic Regression Coefficients (after scaling):")
for feature, coef in zip(X.columns, model.coef_[0]):
    print(f"{feature}: {coef:.4f}")

# Model performance
y_pred = model.predict(X_test)
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

OP:



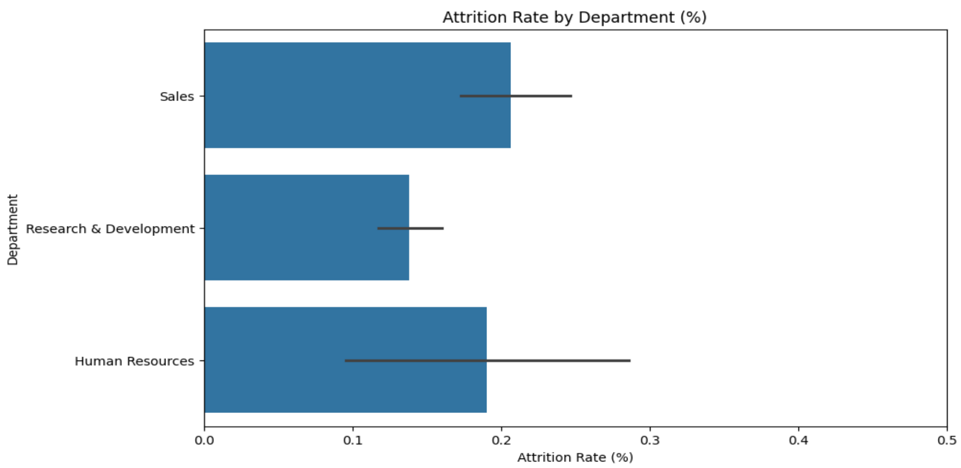
Correlation Heatmap: Visualises the correlation matrix for Age, YearsAtCompany, MonthlyIncome, and Attrition. The heatmap uses a 'coolwarm' color scheme, with red indicating positive correlations and blue indicating negative correlations. The negative correlations with Attrition are evident (e.g., -0.16 for MonthlyIncome).

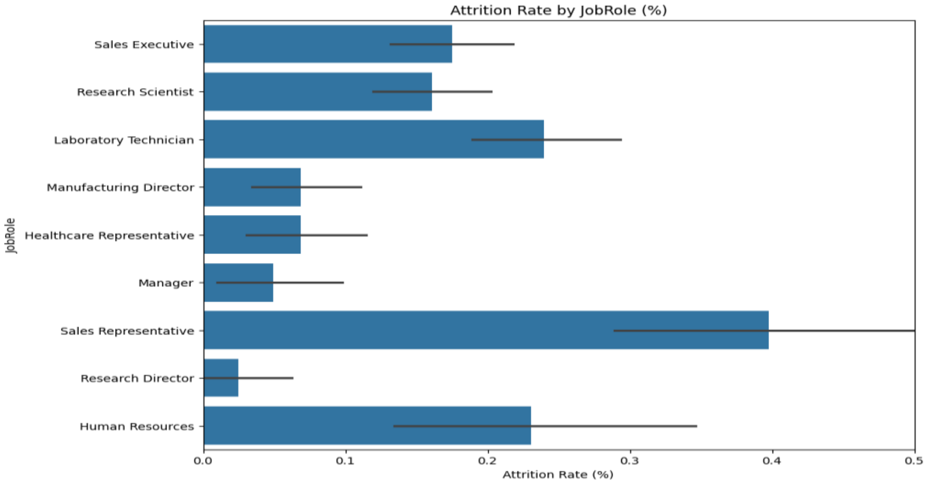


Boxplots for Age, YearsAtCompany, and MonthlyIncome vs. Attrition: Three boxplots showing the distributions of these variables for employees who stayed (Attrition = 0) and those who left (Attrition = 1). Employees who left have a median age of 32 (vs. 37 for those who stayed), 3 years at the company (vs. 7), and a monthly income of 3,000 (vs. 5,000).

```
# Analyze Attrition by Department and JobRole
# Calculate attrition rate by Department
print("\nAttrition Rate by Department:")
department_attrition = df.groupby('Department')['Attrition'].mean().sort_values(ascending=False) * 100
print(department_attrition)

# Visualize attrition by Department
plt.figure(figsize=(10, 6))
sns.barplot(x='Attrition', y='Department', data=df)
plt.title('Attrition Rate by Department (%)')
plt.xlabel('Attrition Rate (%)')
plt.xlim(0, 0.5)  # Since Attrition is 0/1, the mean will be between 0 and 1; adjust for better visualization
plt.show()

# Calculate attrition rate by JobRole
print("\nAttrition Rate by JobRole:")
jobrole_attrition = df.groupby('JobRole')['Attrition'].mean().sort_values(ascending=False) * 100
print(jobrole_attrition)

# Visualize attrition by JobRole
plt.figure(figsize=(10, 8))
sns.barplot(x='Attrition', y='JobRole', data=df)
plt.title('Attrition Rate by JobRole (%)')
plt.xlabel('Attrition Rate (%)')
plt.xlim(0, 0.5)  # Adjust for better visualization
plt.show()
```

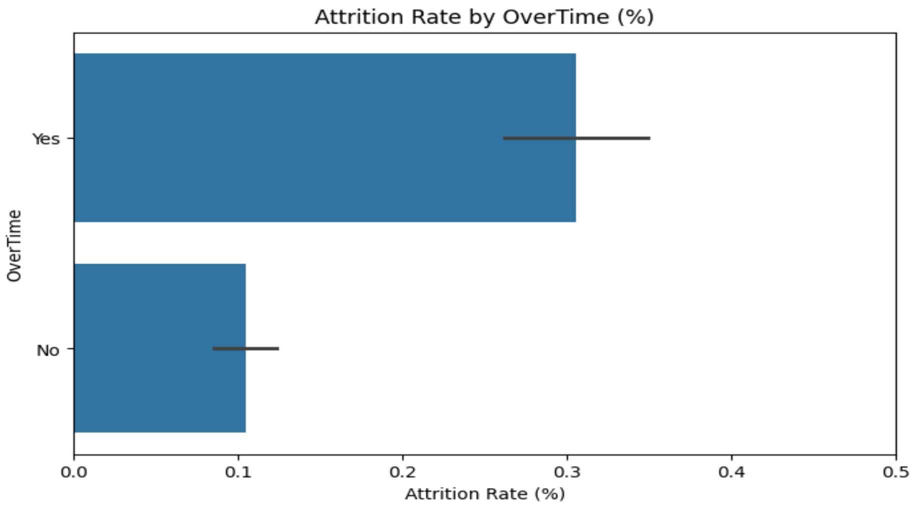
OP:

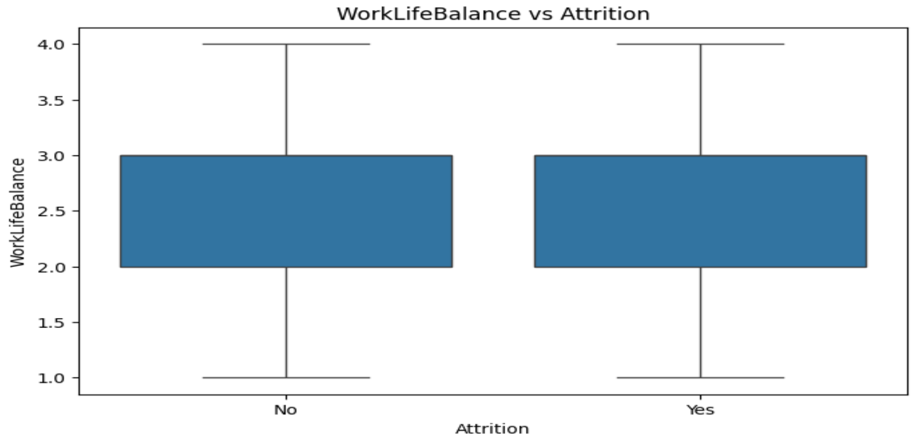




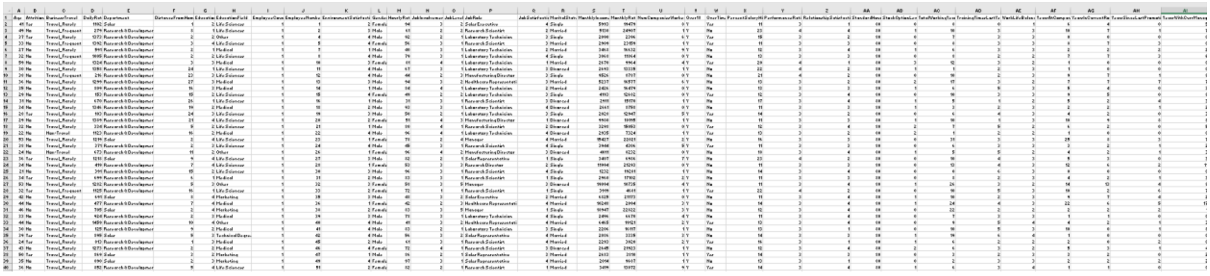

```
# Calculate attrition rate by OverTime
print("\nAttrition Rate by OverTime:")
overtime_attrition = df.groupby('OverTime')['Attrition'].mean().sort_values(ascending=False) * 100
print(overtime_attrition)

# Visualize attrition by OverTime
plt.figure(figsize=(8, 5))
sns.barplot(x='Attrition', y='OverTime', data=df)
plt.title('Attrition Rate by OverTime (%)')
plt.xlabel('Attrition Rate (%)')
plt.xlim(0, 0.5)  # Since Attrition is 0/1, the mean will be between 0 and 1
plt.show()

# Analyze WorkLifeBalance by Attrition
print("\nAverage WorkLifeBalance by Attrition:")
worklifebalance_attrition = df.groupby('Attrition')['WorkLifeBalance'].mean()
print(worklifebalance_attrition)

# Visualize WorkLifeBalance vs Attrition
plt.figure(figsize=(8, 5))
sns.boxplot(x='Attrition', y='WorkLifeBalance', data=df)
plt.title('WorkLifeBalance vs Attrition')
plt.xticks([0, 1], ['No', 'Yes'])  # Label Attrition as No/Yes for clarity
plt.show()
```

OP:





Dataset Overview



Sample rows from greendestination.csv to illustrate the data structure.