Project 1: Employee Attrition Analysis

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

data = pd.read_csv("Attrition data.csv", sep = ',')
data_frame = pd.DataFrame(data)

data_frame
```

```
      EmployeeID  Age Attrition     BusinessTravel
Department  \
0              1   51        No      Travel_Rarely
Sales
1              2   31       Yes  Travel_Frequently  Research &
Development
2              3   32        No  Travel_Frequently  Research &
Development
3              4   38        No         Non-Travel  Research &
Development
4              5   32        No      Travel_Rarely  Research &
Development
...          ...  ...       ...                ...
...
4405        4406   42        No      Travel_Rarely  Research &
Development
4406        4407   29        No      Travel_Rarely  Research &
Development
4407        4408   25        No      Travel_Rarely  Research &
Development
4408        4409   42        No      Travel_Rarely
Sales
4409        4410   40        No      Travel_Rarely  Research &
Development

      DistanceFromHome  Education EducationField  EmployeeCount
Gender  ...  \
0                    6          2  Life Sciences              1
Female  ...
1                   10          1  Life Sciences              1
Female  ...
2                   17          4          Other              1
Male  ...
```

```
3                      2          5  Life Sciences              1
Male  ...
4                     10          1        Medical              1
Male  ...
...                  ...        ...            ...            ...      ..
.  ...
4405                   5          4        Medical              1
Female  ...
4406                   2          4        Medical              1
Male  ...
4407                  25          2  Life Sciences              1
Male  ...
4408                  18          2        Medical              1
Male  ...
4409                  28          3        Medical              1
Male  ...

      TotalWorkingYears TrainingTimesLastYear YearsAtCompany  \
0                   1.0                     6              1
1                   6.0                     3              5
2                   5.0                     2              5
3                  13.0                     5              8
4                   9.0                     2              6
...                 ...                   ...            ...
4405               10.0                     5              3
4406               10.0                     2              3
4407                5.0                     4              4
4408               10.0                     2              9
4409                NaN                     6             21

      YearsSinceLastPromotion  YearsWithCurrManager
EnvironmentSatisfaction  \
0                           0                     0
3.0
1                           1                     4
3.0
2                           0                     3
2.0
3                           7                     5
4.0
4                           0                     4
4.0
...                       ...                   ...
...
4405                        0                     2
4.0
4406                        0                     2
4.0
4407                        1                     2
```

```
1.0
4408                           7                     8
4.0
4409                           3                     9
1.0

      JobSatisfaction  WorkLifeBalance  JobInvolvement
PerformanceRating
0                 4.0              2.0               3
3
1                 2.0              4.0               2
4
2                 2.0              1.0               3
3
3                 4.0              3.0               2
3
4                 1.0              3.0               3
3
...               ...              ...             ...
...
4405              1.0              3.0               3
3
4406              4.0              3.0               2
3
4407              3.0              3.0               3
4
4408              1.0              3.0               2
3
4409              3.0              NaN               4
3

[4410 rows x 29 columns]
```

Exploratory Data Analysis

```
data_frame.shape
```

```
(4410, 29)
```

```
data_frame.isnull()
data_frame.isnull().sum()
```

```
EmployeeID                 0
Age                        0
Attrition                  0
BusinessTravel             0
Department                 0
DistanceFromHome           0
Education                  0
EducationField             0
```

```
EmployeeCount                0
Gender                       0
JobLevel                     0
JobRole                      0
MaritalStatus                0
MonthlyIncome                0
NumCompaniesWorked          19
Over18                       0
PercentSalaryHike            0
StandardHours                0
StockOptionLevel             0
TotalWorkingYears            9
TrainingTimesLastYear        0
YearsAtCompany               0
YearsSinceLastPromotion      0
YearsWithCurrManager         0
EnvironmentSatisfaction     25
JobSatisfaction             20
WorkLifeBalance             38
JobInvolvement               0
PerformanceRating            0
dtype: int64
```

Columns NumCompaniesWorked, TotalWorkingYear, EnvironmentSatisfaction, JobSatisfaction and WorkLifeBalance have NULL values. As all of them have numerical values, it would be a good idea to fill the NULL values with the mean of the Data.

Calculating Mean for: NumCompaniesWorked, TotalWorkingYears, EnvironmentSatisfaction, JobSatisfaction and WorkLifeBalance

```
mean_value_column_1 = data_frame['NumCompaniesWorked'].mean()
data_frame['NumCompaniesWorked'].fillna(mean_value_column_1,
inplace=True)

mean_value_column_2 = data_frame['TotalWorkingYears'].mean()
data_frame['TotalWorkingYears'].fillna(mean_value_column_2,
inplace=True)

mean_value_column_3 = data_frame['EnvironmentSatisfaction'].mean()
data_frame['EnvironmentSatisfaction'].fillna(mean_value_column_3,
inplace=True)

mean_value_column_4 = data_frame['JobSatisfaction'].mean()
data_frame['JobSatisfaction'].fillna(mean_value_column_4,
inplace=True)

mean_value_column_5 = data_frame['WorkLifeBalance'].mean()
data_frame['WorkLifeBalance'].fillna(mean_value_column_5,
inplace=True)
```

```
data_frame.isnull()
data_frame.isnull().sum()
```

```
EmployeeID                 0
Age                        0
Attrition                  0
BusinessTravel             0
Department                 0
DistanceFromHome           0
Education                  0
EducationField             0
EmployeeCount              0
Gender                     0
JobLevel                   0
JobRole                    0
MaritalStatus              0
MonthlyIncome              0
NumCompaniesWorked         0
Over18                     0
PercentSalaryHike          0
StandardHours              0
StockOptionLevel           0
TotalWorkingYears          0
TrainingTimesLastYear      0
YearsAtCompany             0
YearsSinceLastPromotion    0
YearsWithCurrManager       0
EnvironmentSatisfaction    0
JobSatisfaction            0
WorkLifeBalance            0
JobInvolvement             0
PerformanceRating          0
dtype: int64
```

All NULL values have been replaced with the mean of their respective columns

```
data_frame.describe()
```

```
        EmployeeID          Age  DistanceFromHome    Education  
EmployeeCount  \
count  4410.000000  4410.000000       4410.000000  4410.000000  
4410.0
mean   2205.500000    36.923810          9.192517     2.912925  
1.0
std    1273.201673     9.133301          8.105026     1.023933  
0.0
min       1.000000    18.000000          1.000000     1.000000  
1.0
25%    1103.250000    30.000000          2.000000     2.000000
```

```
1.0
50%    2205.500000    36.000000          7.000000     3.000000
1.0
75%    3307.750000    43.000000         14.000000     4.000000
1.0
max    4410.000000    60.000000         29.000000     5.000000
1.0

          JobLevel  MonthlyIncome  NumCompaniesWorked
PercentSalaryHike  \
count  4410.000000    4410.000000         4410.000000
4410.000000
mean      2.063946   65029.312925            2.694830
15.209524
std       1.106689   47068.888559            2.493497
3.659108
min       1.000000   10090.000000            0.000000
11.000000
25%       1.000000   29110.000000            1.000000
12.000000
50%       2.000000   49190.000000            2.000000
14.000000
75%       3.000000   83800.000000            4.000000
18.000000
max       5.000000  199990.000000            9.000000
25.000000

       StandardHours  ...  TotalWorkingYears  TrainingTimesLastYear  \
count         4410.0  ...        4410.000000            4410.000000
mean             8.0  ...          11.279936               2.799320
std              0.0  ...           7.774275               1.288978
min              8.0  ...           0.000000               0.000000
25%              8.0  ...           6.000000               2.000000
50%              8.0  ...          10.000000               3.000000
75%              8.0  ...          15.000000               3.000000
max              8.0  ...          40.000000               6.000000

       YearsAtCompany  YearsSinceLastPromotion
YearsWithCurrManager  \
count     4410.000000              4410.000000          4410.000000

mean         7.008163                 2.187755             4.123129

std          6.125135                 3.221699             3.567327

min          0.000000                 0.000000             0.000000

25%          3.000000                 0.000000             2.000000

50%          5.000000                 1.000000             3.000000
```

```
75%          9.000000                 3.000000               7.000000

max         40.000000                15.000000              17.000000


       EnvironmentSatisfaction  JobSatisfaction  WorkLifeBalance  \
count              4410.000000      4410.000000      4410.000000
mean                  2.723603         2.728246         2.761436
std                   1.089654         1.098753         0.703195
min                   1.000000         1.000000         1.000000
25%                   2.000000         2.000000         2.000000
50%                   3.000000         3.000000         3.000000
75%                   4.000000         4.000000         3.000000
max                   4.000000         4.000000         4.000000

       JobInvolvement  PerformanceRating
count     4410.000000        4410.000000
mean         2.729932           3.153741
std          0.711400           0.360742
min          1.000000           3.000000
25%          2.000000           3.000000
50%          3.000000           3.000000
75%          3.000000           3.000000
max          4.000000           4.000000

[8 rows x 21 columns]
```

```
num = data_frame.select_dtypes(include=np.number).columns
len(num)
```

```
21
```

```
for i in num:
    print("The no.of unique values in",i,"are: ",
data_frame.loc[:,i].nunique())
```

```
The no.of unique values in EmployeeID are:  4410
The no.of unique values in Age are:  43
The no.of unique values in DistanceFromHome are:  29
The no.of unique values in Education are:  5
The no.of unique values in EmployeeCount are:  1
The no.of unique values in JobLevel are:  5
The no.of unique values in MonthlyIncome are:  1349
The no.of unique values in NumCompaniesWorked are:  11
The no.of unique values in PercentSalaryHike are:  15
The no.of unique values in StandardHours are:  1
The no.of unique values in StockOptionLevel are:  4
The no.of unique values in TotalWorkingYears are:  41
The no.of unique values in TrainingTimesLastYear are:  7
The no.of unique values in YearsAtCompany are:  37
```

```
The no.of unique values in YearsSinceLastPromotion are:  16
The no.of unique values in YearsWithCurrManager are:  18
The no.of unique values in EnvironmentSatisfaction are:  5
The no.of unique values in JobSatisfaction are:  5
The no.of unique values in WorkLifeBalance are:  5
The no.of unique values in JobInvolvement are:  4
The no.of unique values in PerformanceRating are:  2
```

Data Cleaning

```
data_frame.Over18.value_counts()
data_frame.groupby('StandardHours').size()
data_frame.groupby('EmployeeCount').size()
```

```
EmployeeCount
1    4410
dtype: int64
```

```
data_frame.drop(columns=['Over18', 'StandardHours', 'EmployeeCount',
'StockOptionLevel', 'TrainingTimesLastYear', 'DistanceFromHome'],
inplace=True)
```

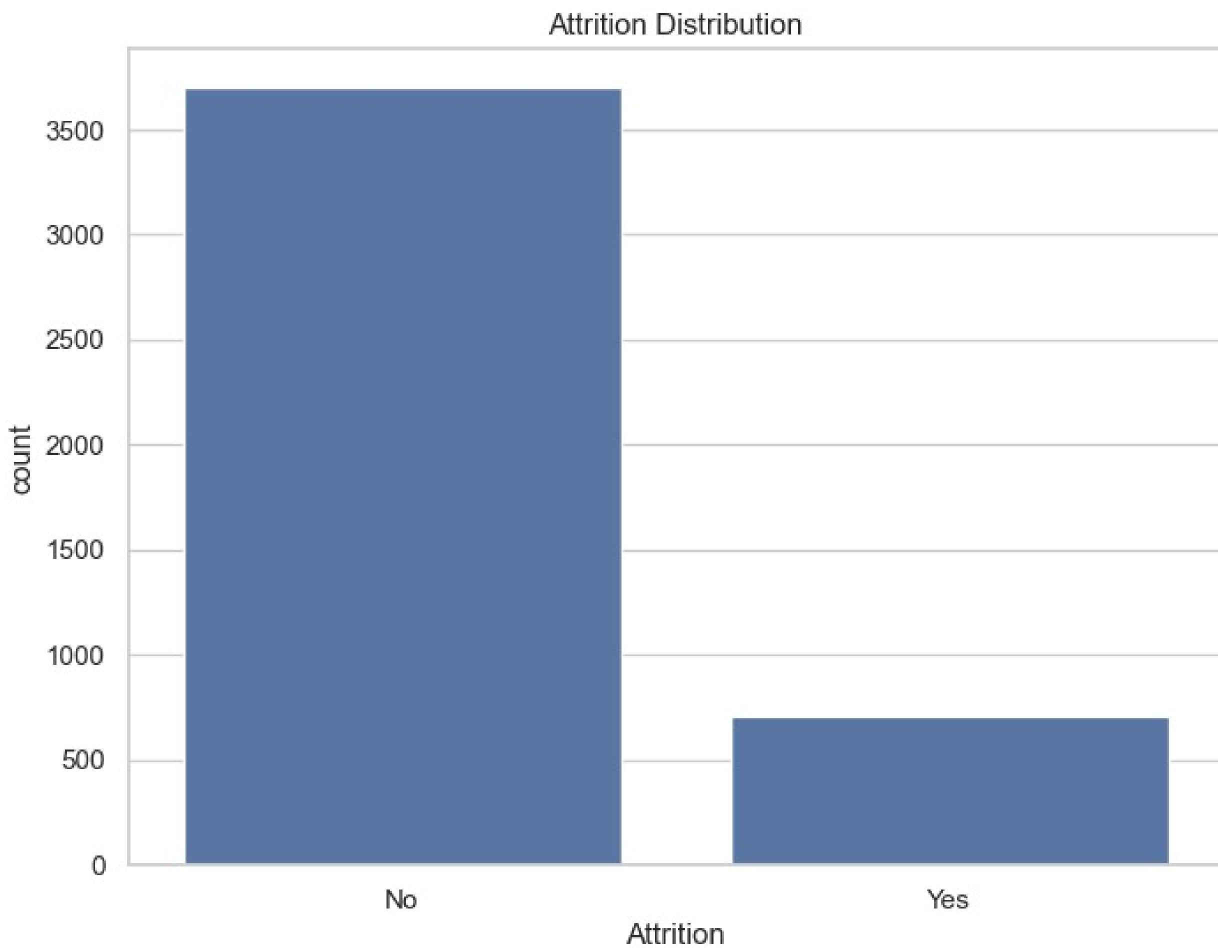
```
print(data_frame.duplicated().value_counts())
data_frame.drop_duplicates(inplace=True)
print(len(data_frame))
```

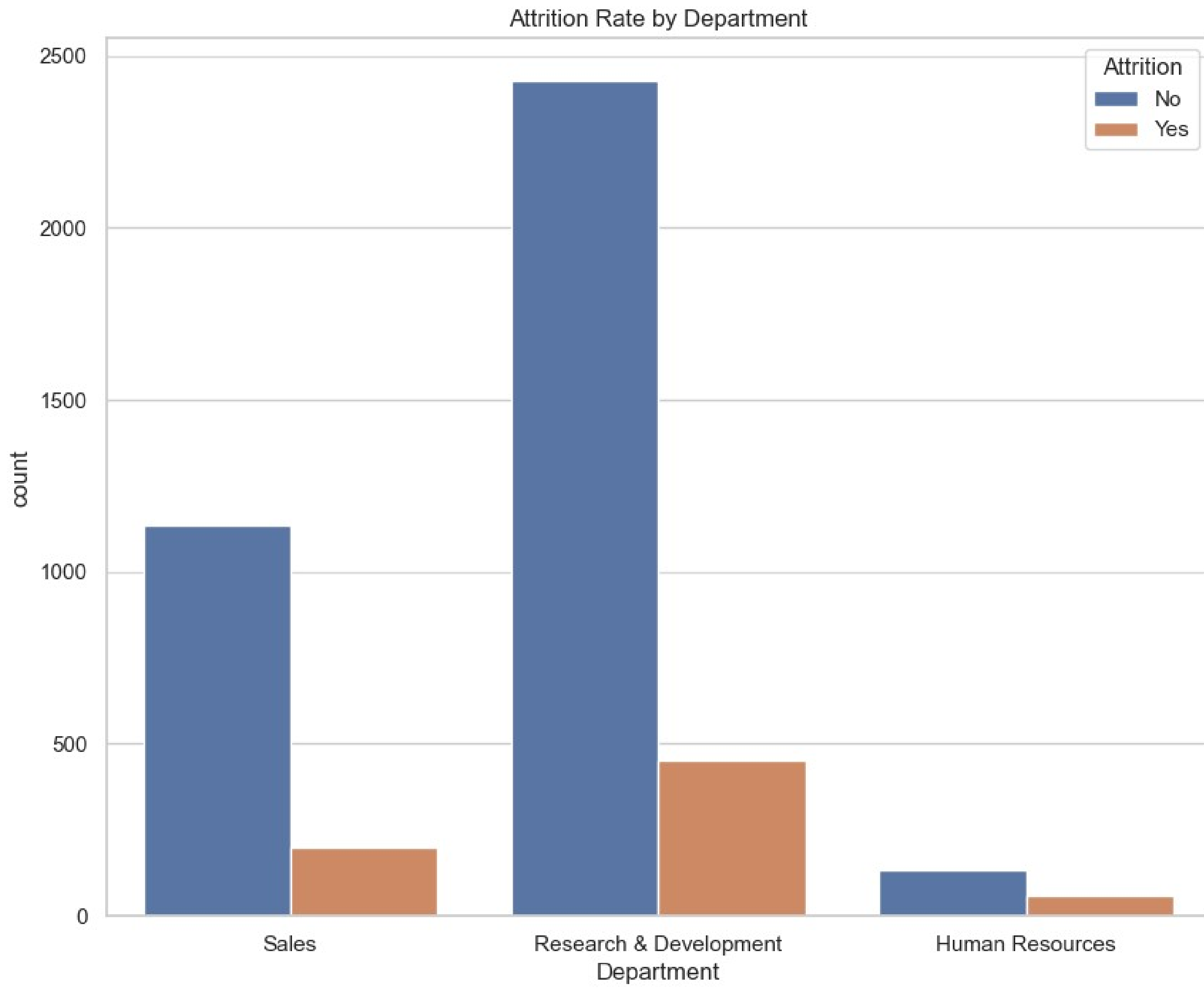
```
False    4410
Name: count, dtype: int64
4410
```

Data Visualization

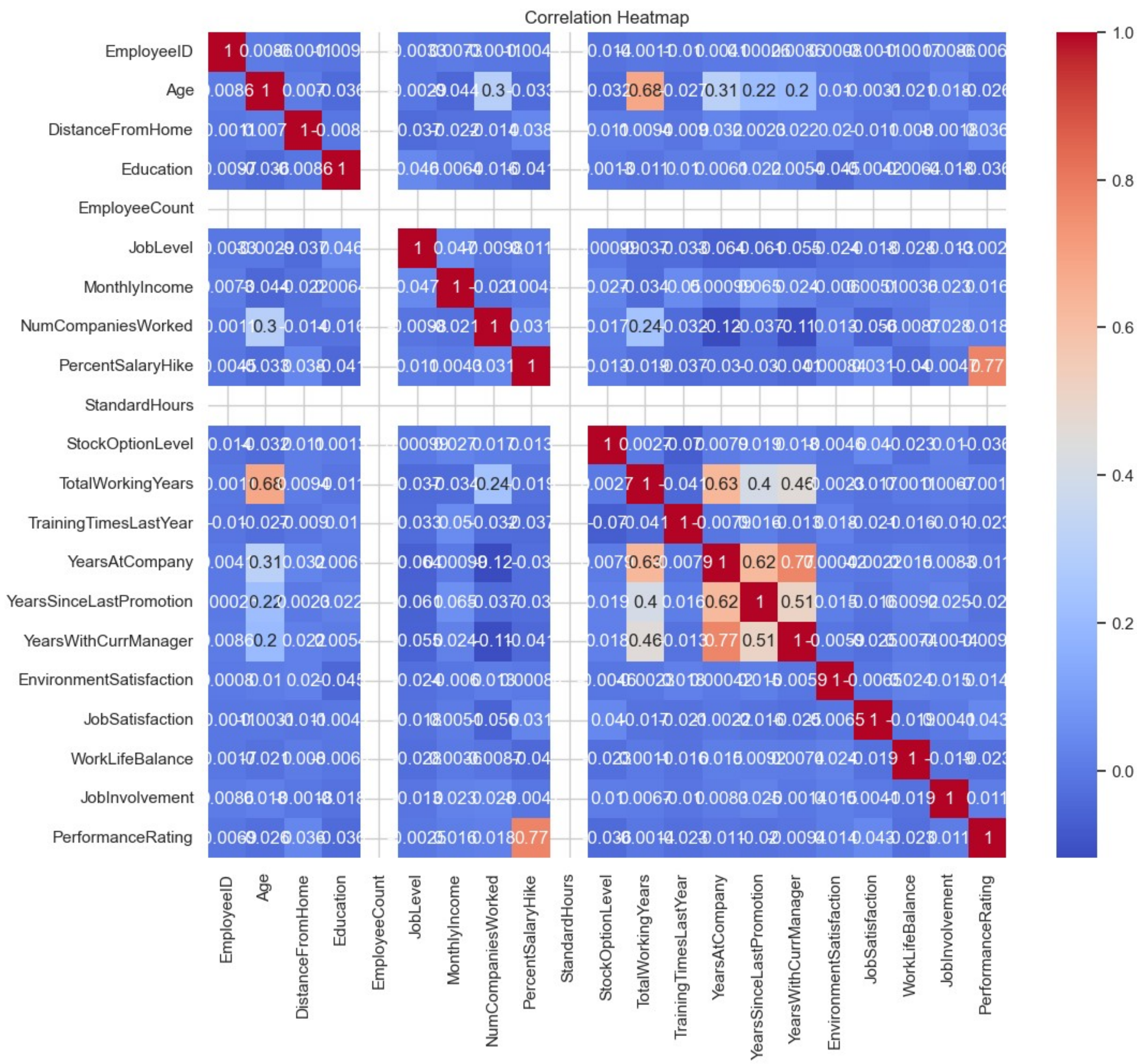
```
sns.set(style="whitegrid")

# Plot the distribution of attrition
plt.figure(figsize=(8, 6))
sns.countplot(x='Attrition', data=data)
plt.title('Attrition Distribution')
plt.show()

# Plot attrition rate by department
plt.figure(figsize=(10, 8))
sns.countplot(x='Department', hue='Attrition', data=data)
plt.title('Attrition Rate by Department')
plt.show()

# Only keep numeric columns for the correlation matrix
numeric_data = data.select_dtypes(include=['float64', 'int64'])

# Plot the correlation heatmap
```

```
plt.figure(figsize=(12, 10))
correlation_matrix = numeric_data.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



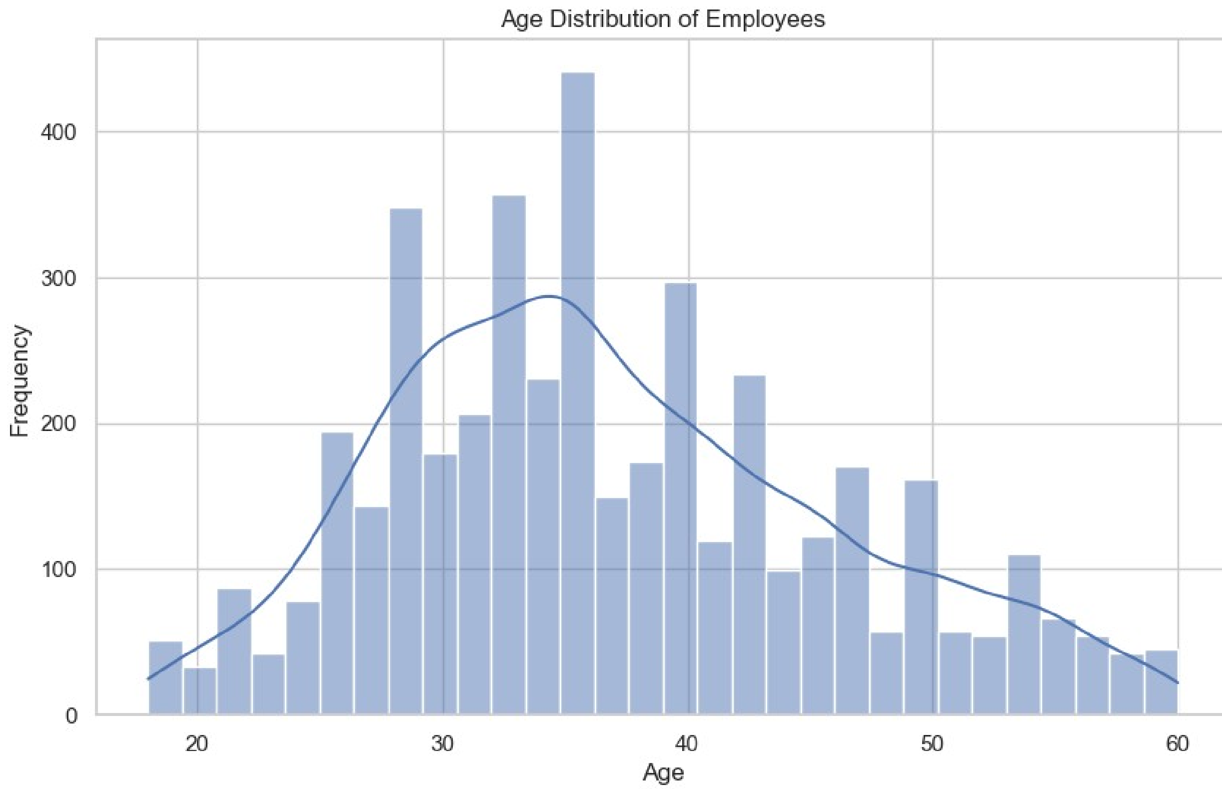


Attrition Rate by Department
Attrition
No
Yes
count
2500
2000
1500
1000
500
0
Sales
Research & Development
Human Resources
Department



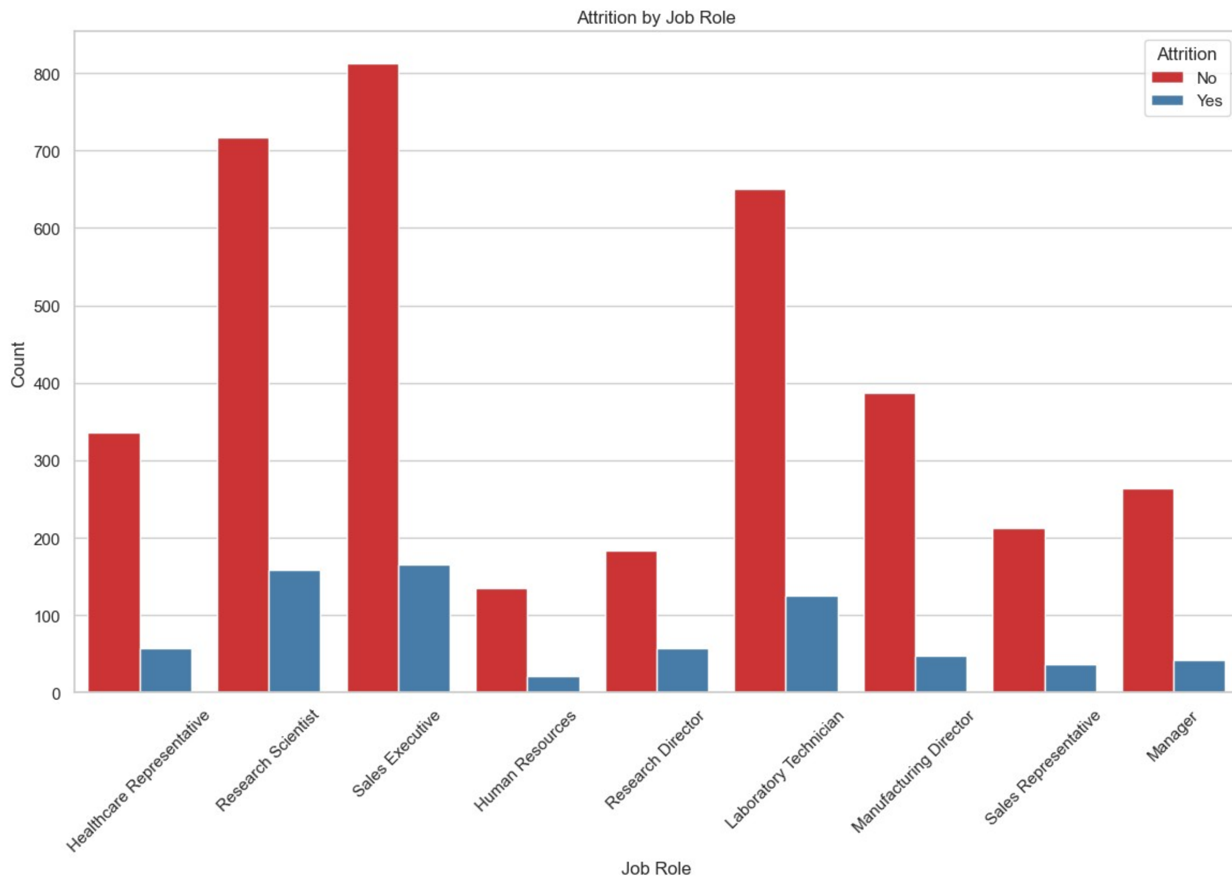
Distribution of age

```
plt.figure(figsize=(10, 6))
sns.histplot(data['Age'], kde=True, bins=30)
plt.title('Age Distribution of Employees')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



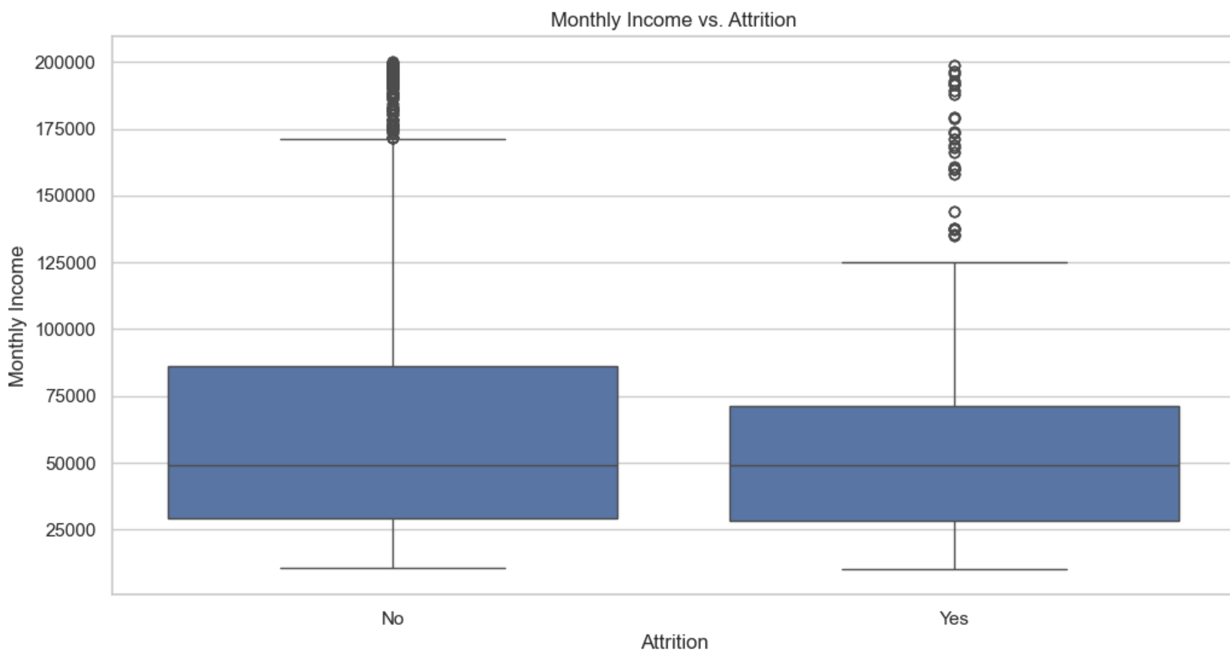
Attrition by Job Role

```
plt.figure(figsize=(14, 8))
sns.countplot(x='JobRole', hue='Attrition', data=data, palette='Set1')
plt.title('Attrition by Job Role')
plt.xlabel('Job Role')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



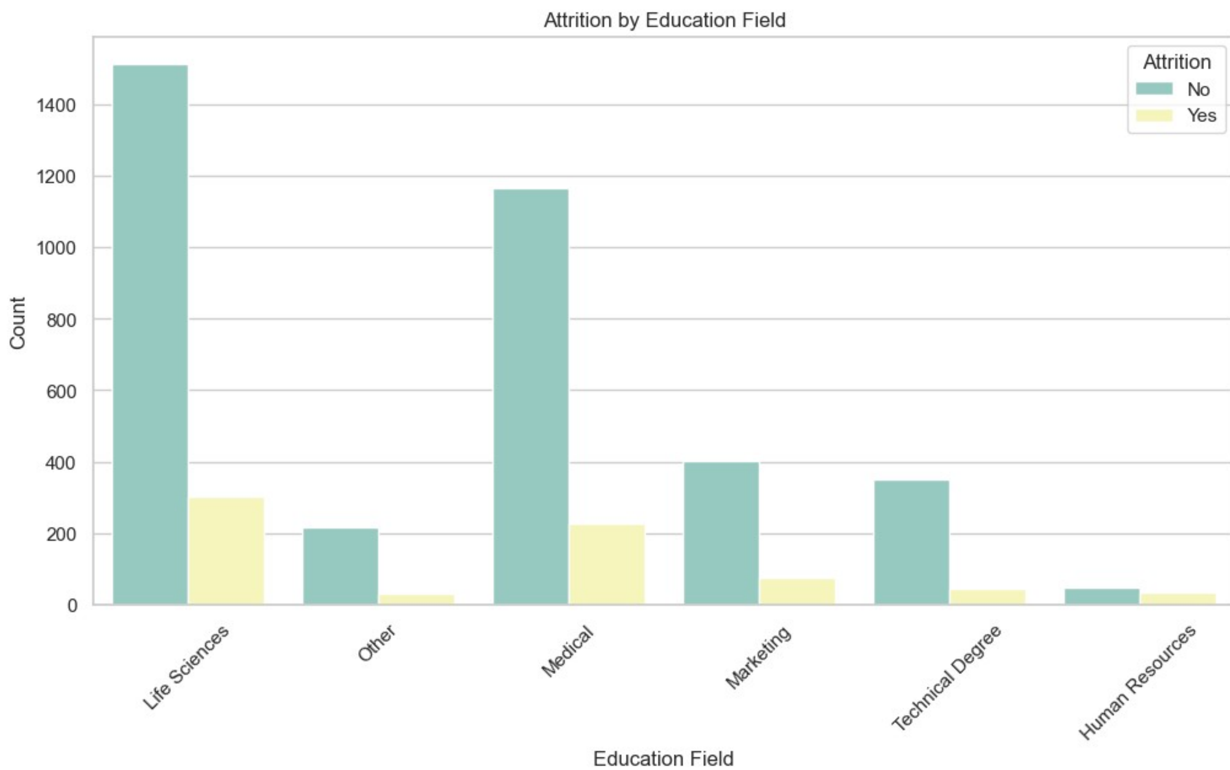
Monthly Income vs Attrition

```
plt.figure(figsize=(12, 6))
sns.boxplot(x='Attrition', y='MonthlyIncome', data=data)
plt.title('Monthly Income vs. Attrition')
plt.xlabel('Attrition')
plt.ylabel('Monthly Income')
plt.show()
```



Attrition by education field

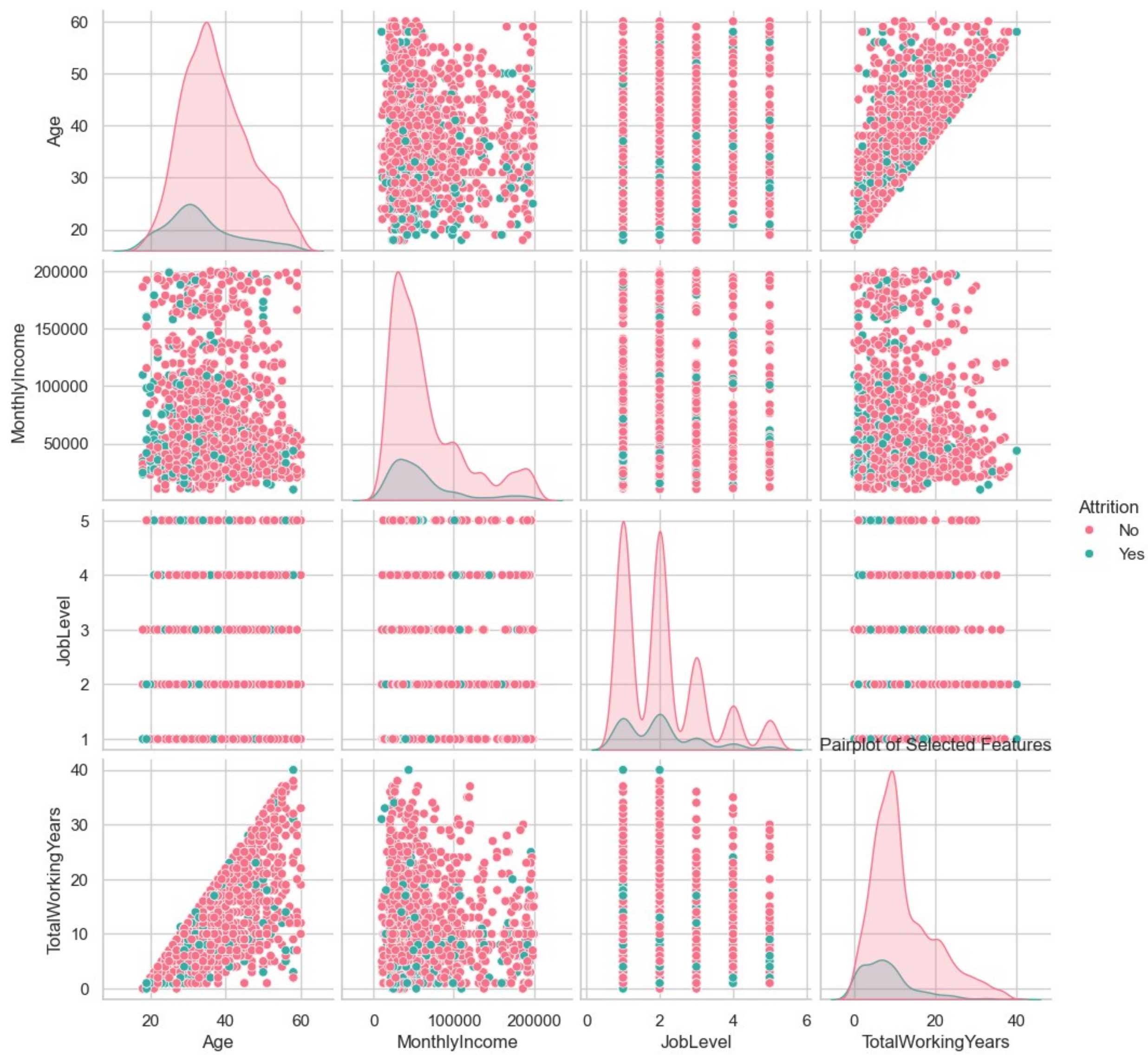
```
plt.figure(figsize=(12, 6))
sns.countplot(x='EducationField', hue='Attrition', data=data,
palette='Set3')
plt.title('Attrition by Education Field')
plt.xlabel('Education Field')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



Pairplot to Visualize Relationships

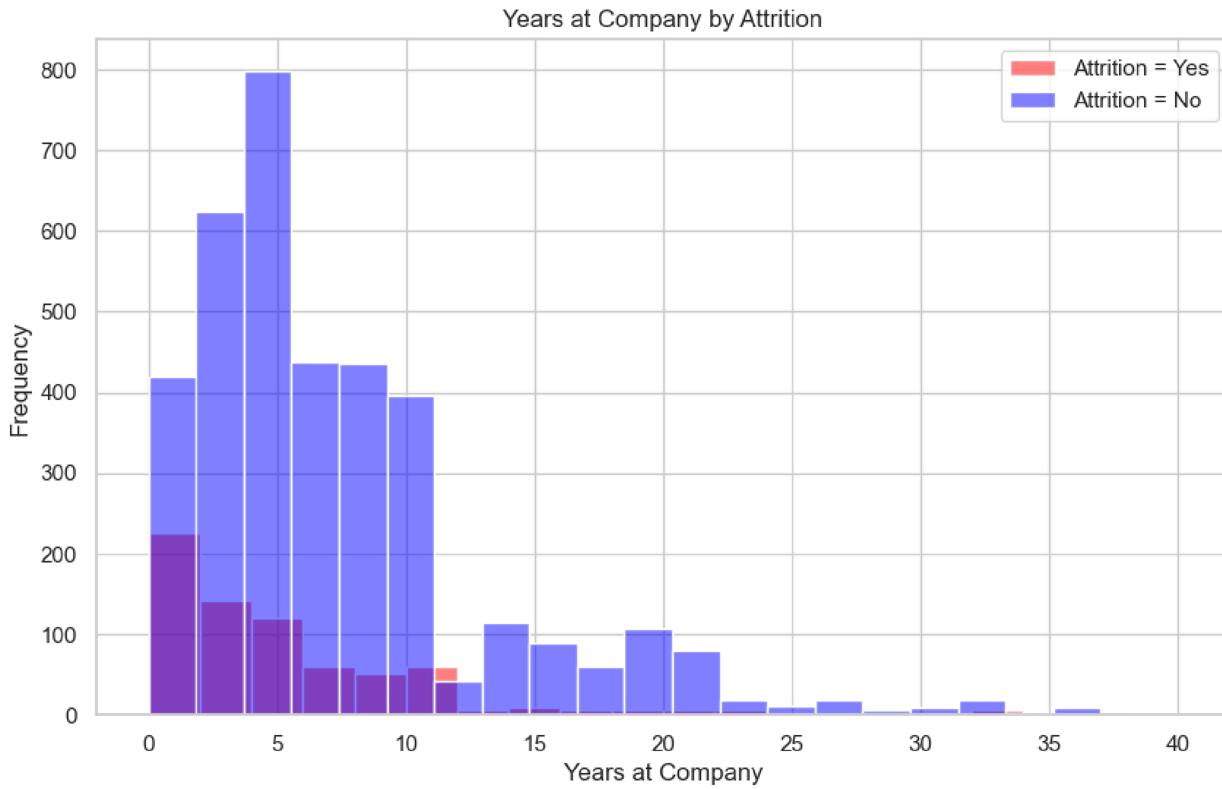
```
subset = data[['Age', 'MonthlyIncome', 'JobLevel',
'TotalWorkingYears', 'Attrition']]

# Create pairplot
sns.pairplot(subset, hue='Attrition', palette='husl')
plt.title('Pairplot of Selected Features')
plt.show()
```

```
C:\Users\anjan\AppData\Roaming\Python\Python311\site-packages\seaborn\
axisgrid.py:123: UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



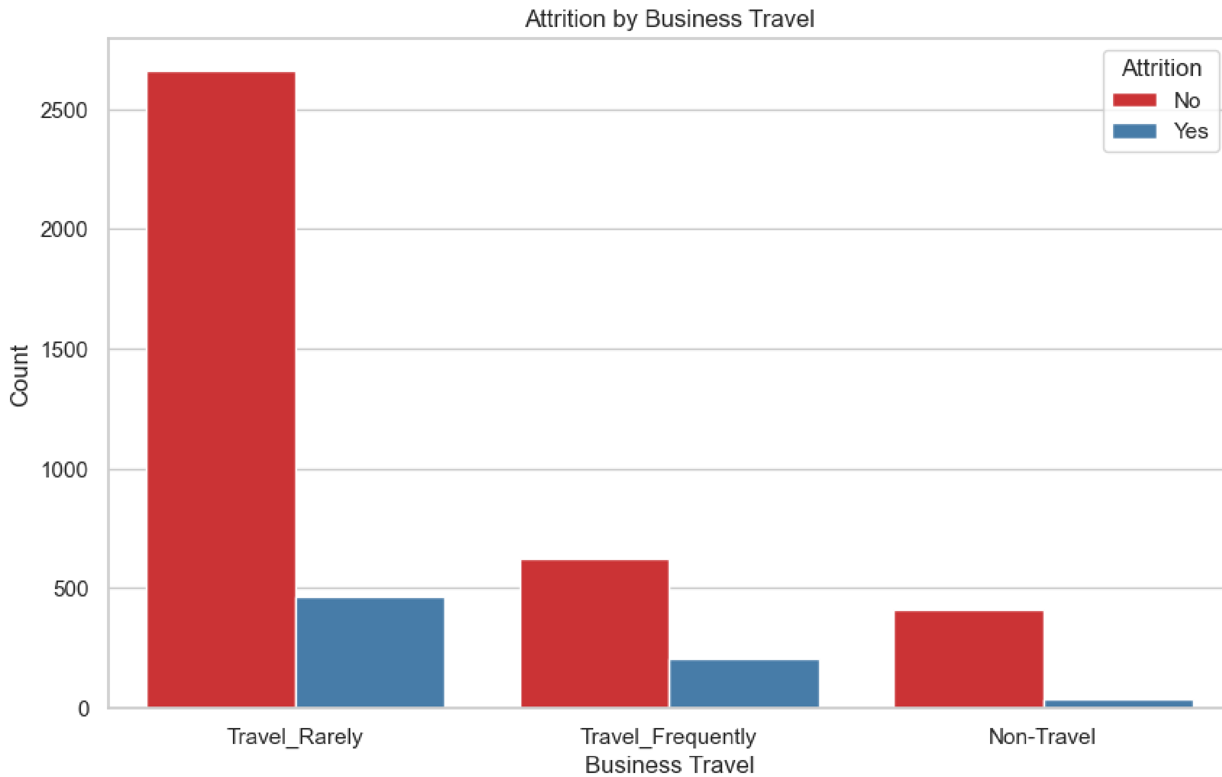
Attrition by Years at Company

```
plt.figure(figsize=(10, 6))
sns.histplot(data[data['Attrition'] == 'Yes']['YearsAtCompany'],
bins=20, color='red', alpha=0.5, label='Attrition = Yes')
sns.histplot(data[data['Attrition'] == 'No']['YearsAtCompany'],
bins=20, color='blue', alpha=0.5, label='Attrition = No')
plt.title('Years at Company by Attrition')
plt.xlabel('Years at Company')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```



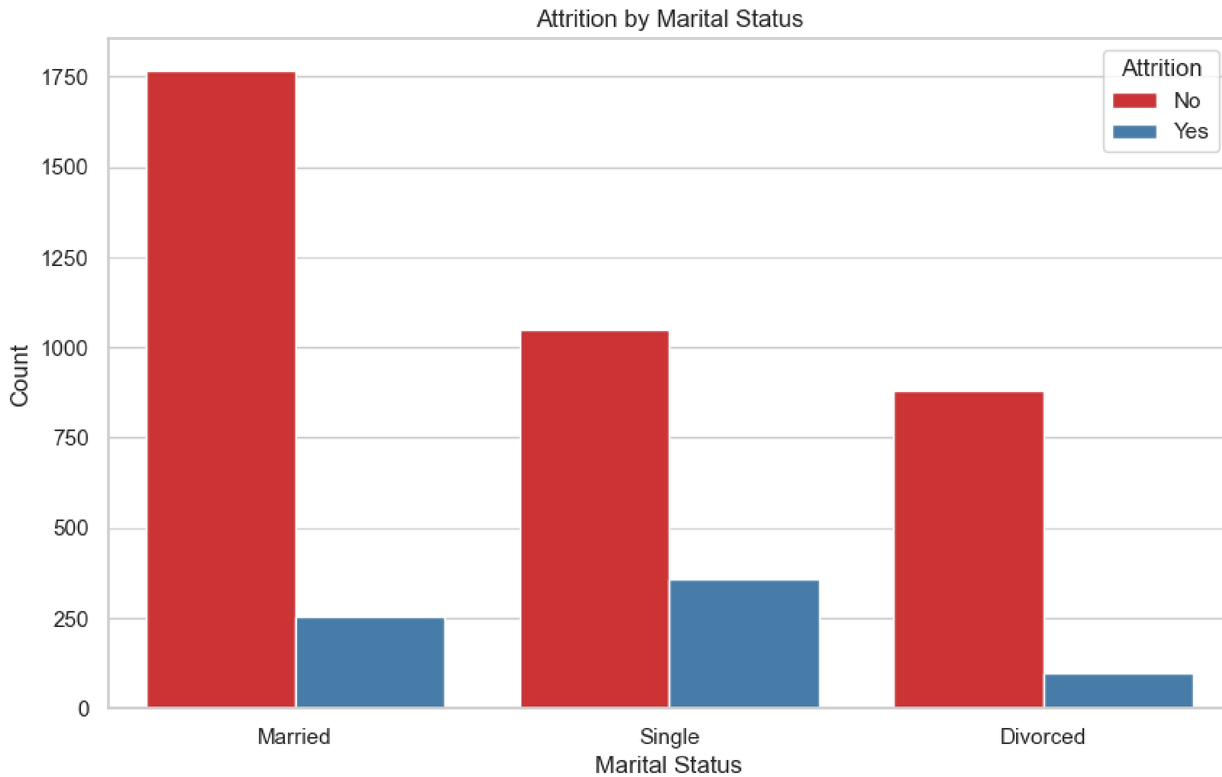
Attrition by Business Travel

```
plt.figure(figsize=(10, 6))
sns.countplot(x='BusinessTravel', hue='Attrition', data=data,
palette='Set1')
plt.title('Attrition by Business Travel')
plt.xlabel('Business Travel')
plt.ylabel('Count')
plt.show()
```



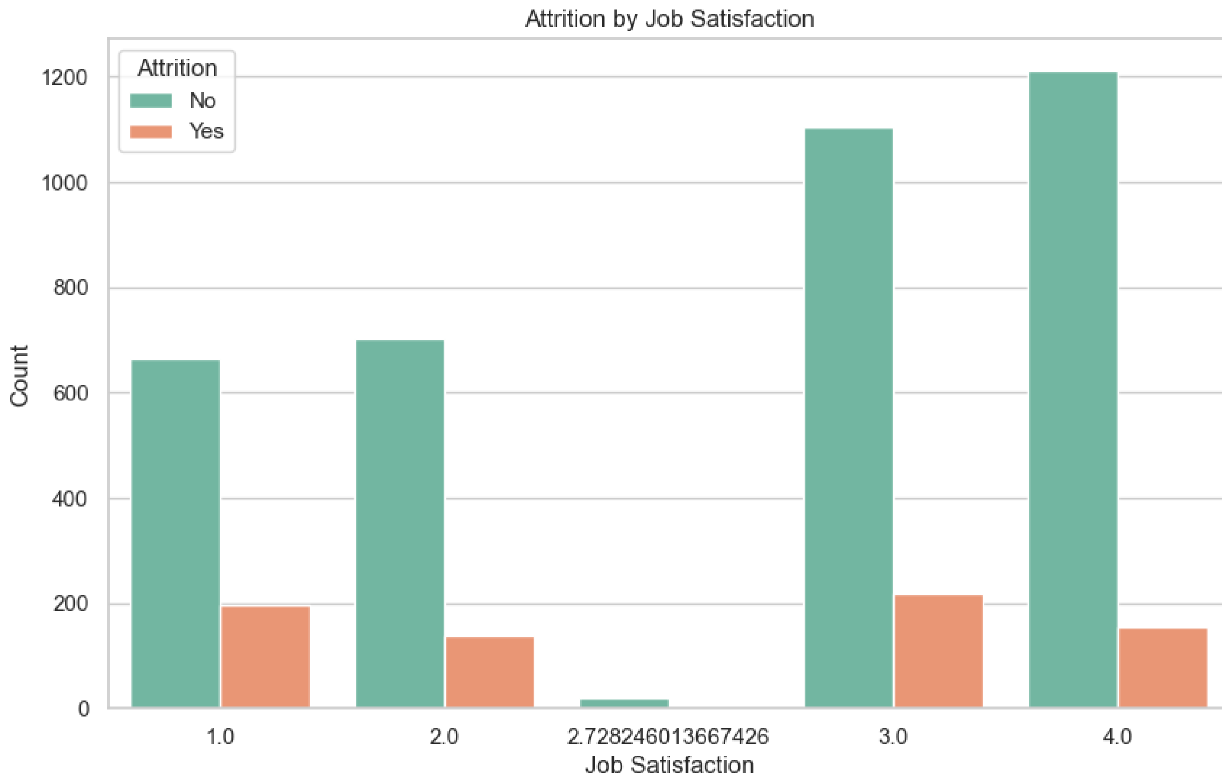
Attrition by Marital Status

```
plt.figure(figsize=(10, 6))
sns.countplot(x='MaritalStatus', hue='Attrition', data=data,
palette='Set1')
plt.title('Attrition by Marital Status')
plt.xlabel('Marital Status')
plt.ylabel('Count')
plt.show()
```



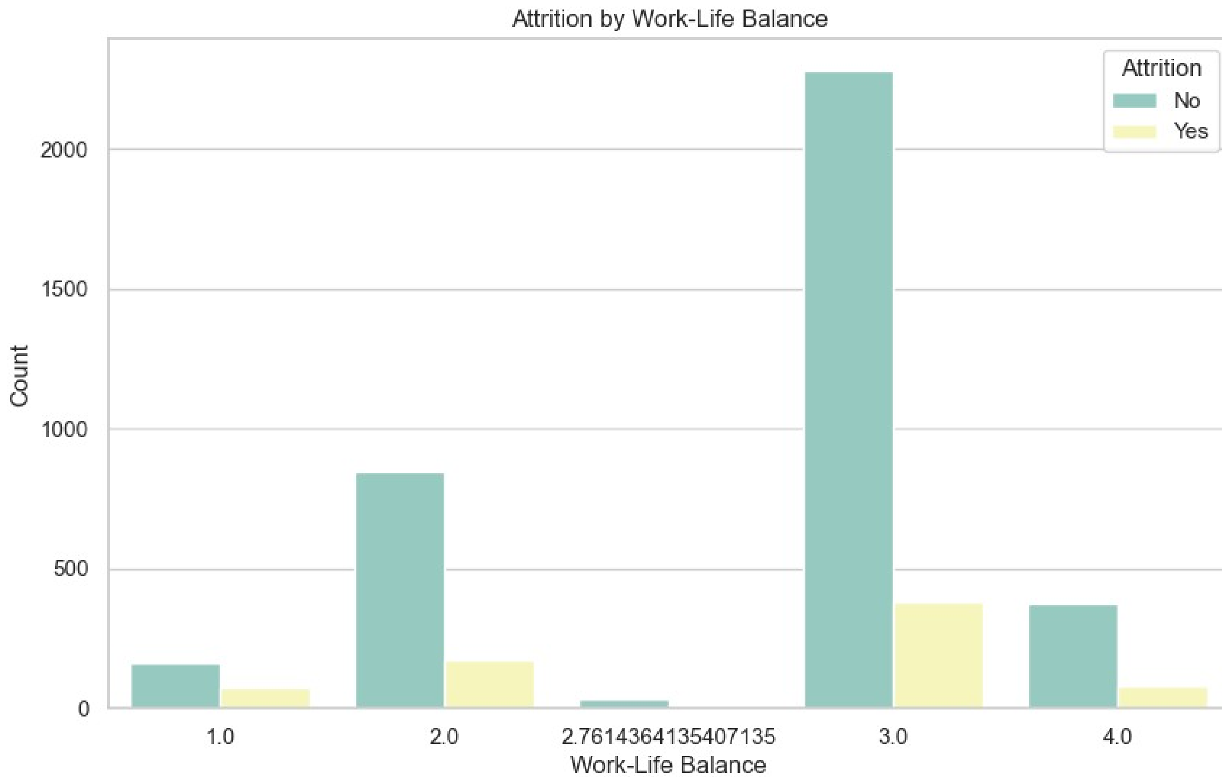
Attrition by Job Satisfaction

```
plt.figure(figsize=(10, 6))
sns.countplot(x='JobSatisfaction', hue='Attrition', data=data,
palette='Set2')
plt.title('Attrition by Job Satisfaction')
plt.xlabel('Job Satisfaction')
plt.ylabel('Count')
plt.show()
```



Attrition by Work-Life Balance

```
plt.figure(figsize=(10, 6))
sns.countplot(x='WorkLifeBalance', hue='Attrition', data=data,
palette='Set3')
plt.title('Attrition by Work-Life Balance')
plt.xlabel('Work-Life Balance')
plt.ylabel('Count')
plt.show()
```



Model Building and Evaluation

```
data_encoded = pd.get_dummies(data, drop_first=True)
X = data_encoded.drop('Attrition_Yes', axis=1)
y = data_encoded['Attrition_Yes']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

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

model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

print('Confusion Matrix:')
print(confusion_matrix(y_test, y_pred))
print('\nClassification Report:')
print(classification_report(y_test, y_pred))
print('\nAccuracy Score:')
print(accuracy_score(y_test, y_pred)*100)
```

```
Confusion Matrix:
[[1115    0]
 [  27  181]]

Classification Report:
              precision    recall  f1-score   support

       False       0.98      1.00      0.99      1115
        True       1.00      0.87      0.93       208

    accuracy                           0.98      1323
   macro avg       0.99      0.94      0.96      1323
weighted avg       0.98      0.98      0.98      1323


Accuracy Score:
97.95918367346938
```

1. Attrition by Department Insight: Certain departments may have higher attrition rates compared to others. Actionable Step: Focus on departments with higher attrition rates to identify specific issues and develop targeted retention strategies.
2. Attrition by Job Role Insight: Different job roles might experience varying levels of attrition. Actionable Step: Investigate the job roles with higher attrition to understand the underlying reasons, such as job satisfaction, workload, or career advancement opportunities.
3. Monthly Income vs. Attrition Insight: There might be a correlation between monthly income and attrition rates. Actionable Step: If lower-income employees are leaving at higher rates, consider reviewing compensation structures and offering competitive salaries.
4. Overtime and Attrition Insight: Employees who work overtime frequently might have higher attrition rates. Actionable Step: Evaluate workload and work-life balance policies. Consider implementing measures to reduce overtime and improve employee well-being.
5. Years at Company and Attrition Insight: Attrition rates might vary based on the tenure of employees. Actionable Step: Identify critical periods where attrition spikes (e.g., after 1 year, 3 years). Develop engagement and development programs targeted at these key tenure milestones.
6. Correlation Heatmap Insight: The correlation heatmap reveals relationships between various numeric features and attrition. Actionable Step: Use this information to identify factors that are strongly correlated with attrition and focus on them for deeper analysis and action.
7. Attrition by Business Travel Insight: Employees who travel frequently for business might have different attrition rates compared to those who do not. Actionable Step: Assess the impact of business travel on employee satisfaction and retention. Consider policies that minimize travel-related stress.
8. Job Satisfaction and Work-Life Balance Insight: These factors can have a significant impact on employee retention. Actionable Step: Conduct surveys and focus groups to understand employee satisfaction and work-life balance. Implement programs to enhance these aspects.

9. Education and Attrition Insight: Employees with different educational backgrounds might have varying attrition rates. Actionable Step: Tailor professional development and career advancement opportunities to different educational backgrounds.
10. Attrition by Marital Status Insight: Marital status might influence attrition rates. Actionable Step: Consider family-friendly policies and benefits to support employees with different personal situations.

Summary of Recommendations: Targeted Retention Strategies: Focus on departments, job roles, and tenure periods with higher attrition. Compensation Review: Ensure competitive salaries and benefits, especially for lower-income roles. Work-Life Balance: Implement policies to reduce overtime and enhance work-life balance. Employee Development: Provide career development opportunities and clear advancement paths. Employee Well-being: Offer programs that support employee well-being, such as flexible work arrangements and wellness programs. Family-Friendly Policies: Consider implementing policies that support employees with families, such as parental leave and childcare support.