```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report

df = pd.read_csv("greendestination (1) (1).csv")
print("Shape of Dataset is : "df.shape)
print(df.head(5))
```

```
(1470, 35)
   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
2                  7                      3               3
0
3                  8                      3               3
8
4                  6                      3               3
2

  YearsInCurrentRole  YearsSinceLastPromotion  YearsWithCurrManager
0                  4                        0                     5
1                  7                        1                     7
2                  0                        0                     0
3                  7                        3                     0
4                  2                        2                     2

[5 rows x 35 columns]
```

```python
print(df.isnull().sum())
```

```
Age                         0
Attrition                   0
BusinessTravel              0
DailyRate                   0
Department                  0
DistanceFromHome            0
Education                   0
EducationField              0
EmployeeCount               0
EmployeeNumber              0
EnvironmentSatisfaction     0
Gender                      0
HourlyRate                  0
JobInvolvement              0
JobLevel                    0
JobRole                     0
JobSatisfaction             0
MaritalStatus               0
MonthlyIncome               0
MonthlyRate                 0
NumCompaniesWorked          0
Over18                      0
OverTime                    0
PercentSalaryHike           0
PerformanceRating           0
RelationshipSatisfaction    0
```

```
StandardHours               0
StockOptionLevel            0
TotalWorkingYears           0
TrainingTimesLastYear       0
WorkLifeBalance             0
YearsAtCompany              0
YearsInCurrentRole          0
YearsSinceLastPromotion     0
YearsWithCurrManager        0
dtype: int64
```

```
le = LabelEncoder()

for col in df.select_dtypes(include='object').columns:
    df[col] = le.fit_transform(df[col])

attrition_rate = (df['Attrition'].sum() / len(df)) * 100
print(f"Attrition Rate: {attrition_rate:.2f}%")
```

```
Attrition Rate: 16.12%
```

```
X = df.drop('Attrition', axis=1)
y = df['Attrition']

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

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

# Model : 1 - Logistic Regression

lr = LogisticRegression()
lr.fit(X_train, y_train)

y_pred_lr = lr.predict(X_test)

print("Logistic Regression Accuracy:", accuracy_score(y_test,
y_pred_lr))
print(confusion_matrix(y_test, y_pred_lr))
print(classification_report(y_test, y_pred_lr))
```

```
Logistic Regression Accuracy: 0.891156462585034
[[249   6]
 [ 26  13]]
              precision    recall  f1-score   support

           0       0.91      0.98      0.94       255
```

```
           1       0.68      0.33      0.45        39

    accuracy                           0.89       294
   macro avg       0.79      0.65      0.69       294
weighted avg       0.88      0.89      0.87       294
```

```
# Model : 2 - Decision Tree

dt = DecisionTreeClassifier(random_state=42)
dt.fit(X_train, y_train)

y_pred_dt = dt.predict(X_test)

print("Decision Tree Accuracy:", accuracy_score(y_test, y_pred_dt))
```

```
Decision Tree Accuracy: 0.7653061224489796
```

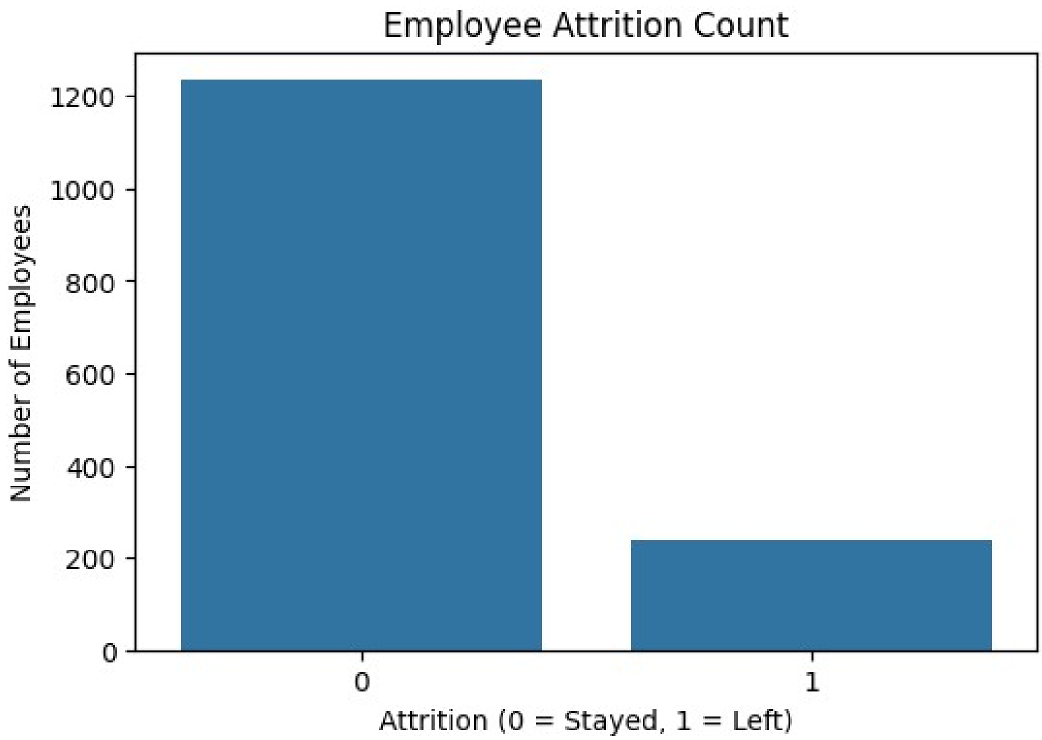
```
# model : 3 - Random Forest [BEST MODEL]

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

y_pred_rf = rf.predict(X_test)

print("Random Forest Accuracy:", accuracy_score(y_test, y_pred_rf))
print(confusion_matrix(y_test, y_pred_rf))
```

```
Random Forest Accuracy: 0.8639455782312925
[[250   5]
 [ 35   4]]
```

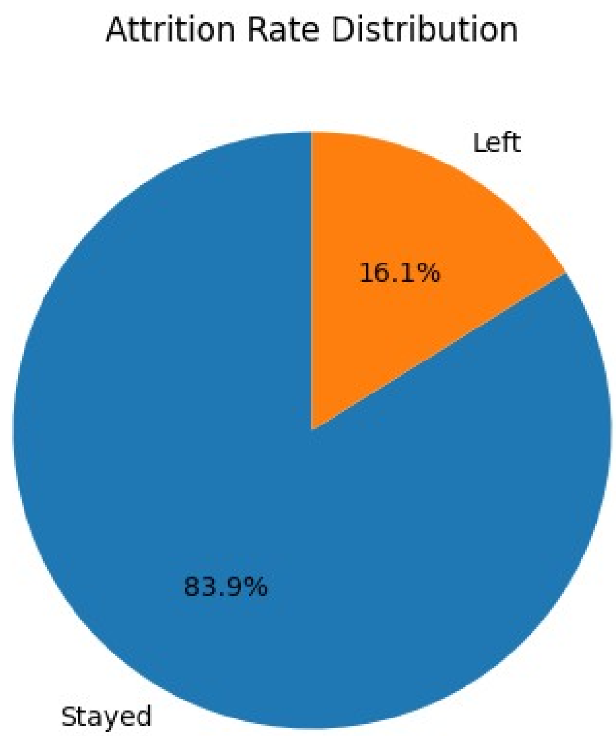
```
importances = rf.feature_importances_
features = X.columns

feature_imp = pd.DataFrame({
    'Feature': features,
    'Importance': importances
}).sort_values(by='Importance', ascending=False)

print(feature_imp)
```

```
                     Feature  Importance
17             MonthlyIncome    0.074968
21                  OverTime    0.064823
0                        Age    0.056865
2                  DailyRate    0.050505
27         TotalWorkingYears    0.048104
18               MonthlyRate    0.047090
8             EmployeeNumber    0.045296
11                HourlyRate    0.043352
4           DistanceFromHome    0.042012
```

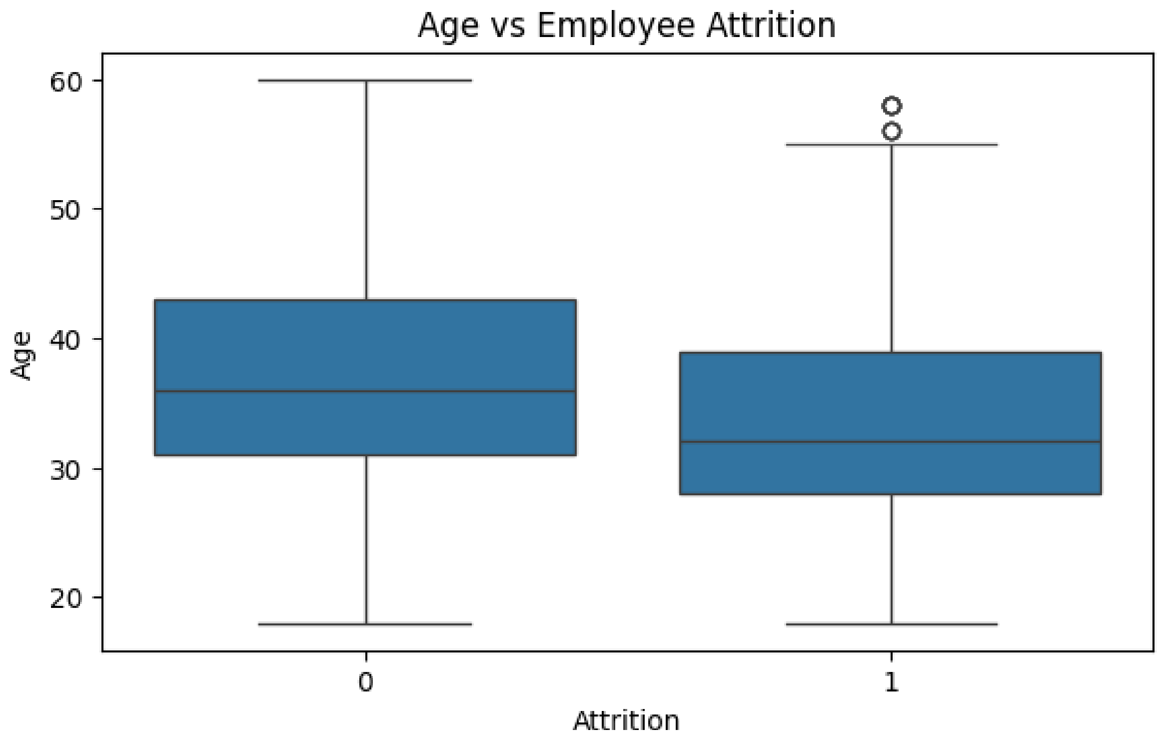
```
30            YearsAtCompany    0.041914
19        NumCompaniesWorked    0.036035
14                   JobRole    0.032731
22         PercentSalaryHike    0.032530
26          StockOptionLevel    0.031840
33      YearsWithCurrManager    0.028512
31        YearsInCurrentRole    0.027299
13                  JobLevel    0.026893
32   YearsSinceLastPromotion    0.026549
28     TrainingTimesLastYear    0.025413
15           JobSatisfaction    0.025368
16             MaritalStatus    0.025151
9    EnvironmentSatisfaction    0.024602
6             EducationField    0.023972
12            JobInvolvement    0.022657
24  RelationshipSatisfaction    0.020104
29           WorkLifeBalance    0.019841
5                  Education    0.018488
1             BusinessTravel    0.012577
3                 Department    0.011564
10                    Gender    0.007987
23         PerformanceRating    0.004958
7              EmployeeCount    0.000000
25             StandardHours    0.000000
20                    Over18    0.000000

# 1. Attrition Count
plt.figure(figsize=(6,4))
sns.countplot(x='Attrition', data=df)
plt.title("Employee Attrition Count")
plt.xlabel("Attrition (0 = Stayed, 1 = Left)")
plt.ylabel("Number of Employees")
plt.show()
```



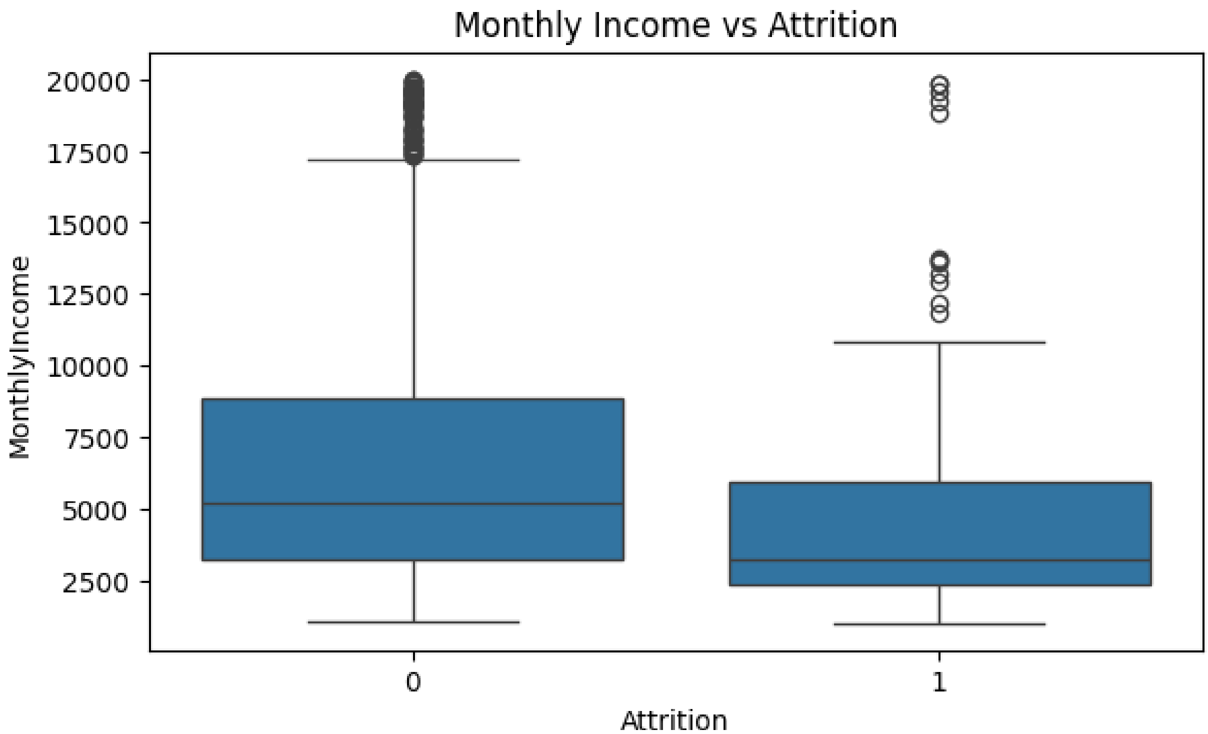

```python
# 2. Attrition Rate Pie Chart
plt.figure(figsize=(5,5))
df['Attrition'].value_counts().plot(
    kind='pie',
    autopct='%1.1f%%',
    startangle=90,
    labels=['Stayed', 'Left']
)
plt.title("Attrition Rate Distribution")
plt.ylabel("")
plt.show()
```



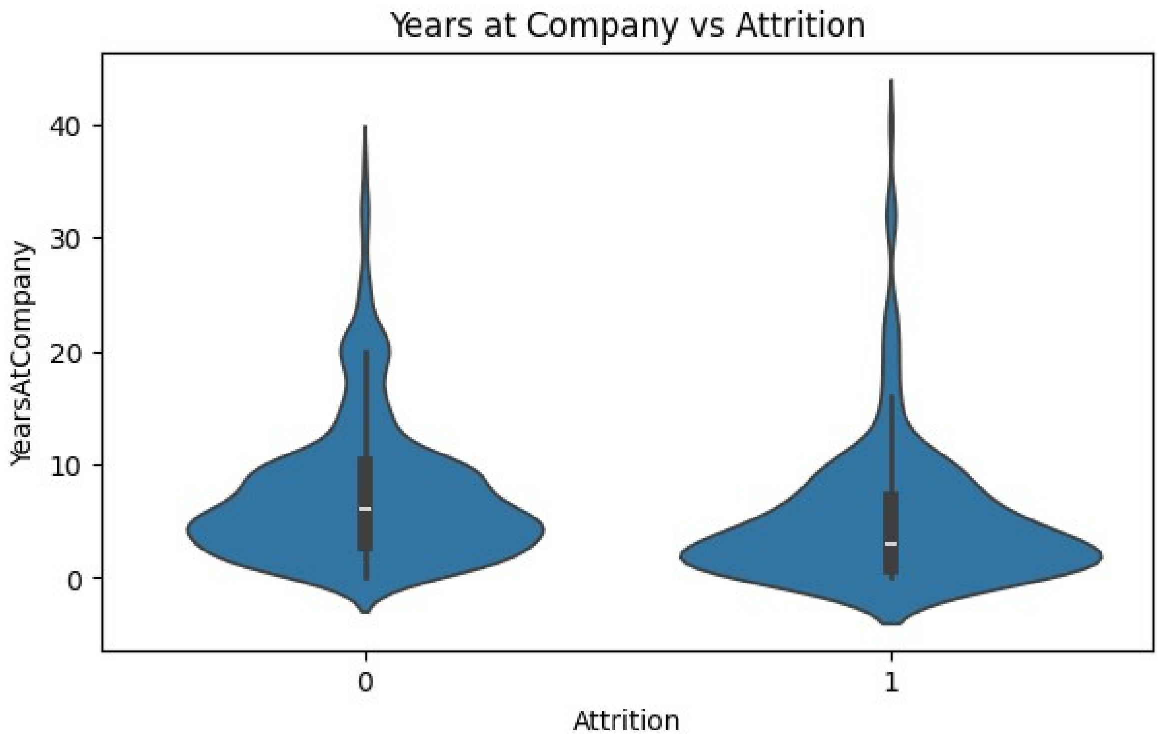

```
# 3. Age vs Attrition
plt.figure(figsize=(7,4))
sns.boxplot(x='Attrition', y='Age', data=df)
plt.title("Age vs Employee Attrition")
plt.show()
```



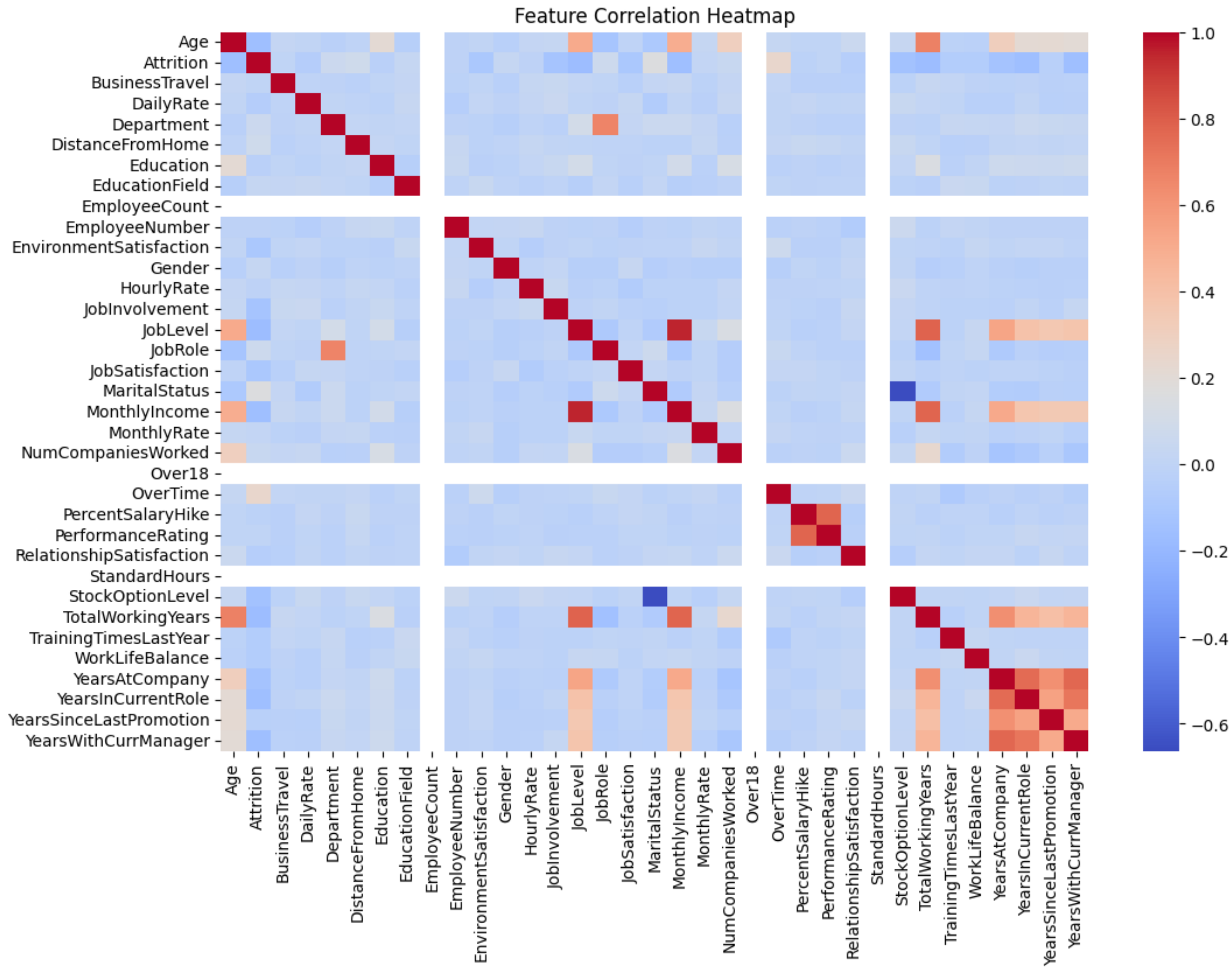

```
# 4. Monthly Income vs Attrition
plt.figure(figsize=(7,4))
sns.boxplot(x='Attrition', y='MonthlyIncome', data=df)
plt.title("Monthly Income vs Attrition")
plt.show()
```




```python
# 5. Years at Company vs Attrition
plt.figure(figsize=(7,4))
sns.violinplot(x='Attrition', y='YearsAtCompany', data=df)
plt.title("Years at Company vs Attrition")
plt.show()
```




```
# 6. Correlation Heatmap
plt.figure(figsize=(12,8))
sns.heatmap(df.corr(), cmap='coolwarm', annot=False)
plt.title("Feature Correlation Heatmap")
plt.show()
```


Feature Correlation Heatmap
Age
Attrition
BusinessTravel
DailyRate
Department
DistanceFromHome
Education
EducationField
EmployeeCount
EmployeeNumber
EnvironmentSatisfaction
Gender
HourlyRate
JobInvolvement
JobLevel
JobRole
JobSatisfaction
MaritalStatus
MonthlyIncome
MonthlyRate
NumCompaniesWorked
Over18
OverTime
PercentSalaryHike
PerformanceRating
RelationshipSatisfaction
StandardHours
StockOptionLevel
TotalWorkingYears
TrainingTimesLastYear
WorkLifeBalance
YearsAtCompany
YearsInCurrentRole
YearsSinceLastPromotion
YearsWithCurrManager
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6