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IMPORT LIBRARIES

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
```

IMPORT DATASET

In [3]:
```
df=pd.read_csv("WA_Fn-UseC_-HR-Employee-Attrition.csv")
```

In [4]:
```
df
```

Out[4]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	E
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	
...	...	...	...	...	...	...	...	...	
1465	36	No	Travel_Frequently	884	Research & Development	23	2	Medical	
1466	39	No	Travel_Rarely	613	Research & Development	6	1	Medical	
1467	27	No	Travel_Rarely	155	Research & Development	4	3	Life Sciences	
1468	49	No	Travel_Frequently	1023	Sales	2	3	Medical	
1469	34	No	Travel_Rarely	628	Research & Development	8	3	Medical	

1470 rows × 35 columns

In [5]:
```
df.head()
```

Out[5]:

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

5 rows × 35 columns

In [6]:

```
df.tail()
```

Out[6]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	E
1465	36	No	Travel_Frequently	884	Research & Development	23	2	Medical	
1466	39	No	Travel_Rarely	613	Research & Development	6	1	Medical	
1467	27	No	Travel_Rarely	155	Research & Development	4	3	Life Sciences	
1468	49	No	Travel_Frequently	1023	Sales	2	3	Medical	
1469	34	No	Travel_Rarely	628	Research & Development	8	3	Medical	

5 rows × 35 columns

In [7]:

```
df.shape
```

Out[7]:

```
(1470, 35)
```

In [8]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 35 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   Age                       1470 non-null   int64 
 1   Attrition                 1470 non-null   object
 2   BusinessTravel            1470 non-null   object
 3   DailyRate                 1470 non-null   int64 
 4   Department                1470 non-null   object
 5   DistanceFromHome          1470 non-null   int64 
 6   Education                 1470 non-null   int64 
 7   EducationField            1470 non-null   object
 8   EmployeeCount             1470 non-null   int64 
 9   EmployeeNumber            1470 non-null   int64 
 10  EnvironmentSatisfaction   1470 non-null   int64 
 11  Gender                    1470 non-null   object
 12  HourlyRate                1470 non-null   int64 
 13  JobInvolvement            1470 non-null   int64 
 14  JobLevel                  1470 non-null   int64 
 15  JobRole                   1470 non-null   object
 16  JobSatisfaction           1470 non-null   int64 
 17  MaritalStatus             1470 non-null   object
 18  MonthlyIncome             1470 non-null   int64 
 19  MonthlyRate               1470 non-null   int64 
 20  NumCompaniesWorked        1470 non-null   int64 
 21  Over18                    1470 non-null   object
 22  OverTime                  1470 non-null   object
 23  PercentSalaryHike         1470 non-null   int64 
 24  PerformanceRating         1470 non-null   int64 
 25  RelationshipSatisfaction  1470 non-null   int64 
 26  StandardHours             1470 non-null   int64 
 27  StockOptionLevel          1470 non-null   int64 
 28  TotalWorkingYears         1470 non-null   int64 
 29  TrainingTimesLastYear     1470 non-null   int64 
 30  WorkLifeBalance           1470 non-null   int64 
 31  YearsAtCompany            1470 non-null   int64 
 32  YearsInCurrentRole        1470 non-null   int64 
 33  YearsSinceLastPromotion   1470 non-null   int64 
 34  YearsWithCurrManager      1470 non-null   int64 
dtypes: int64(26), object(9)
memory usage: 402.1+ KB
```

In [9]:

```
df.describe()
```

Out[9]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	Environm
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1470.000000	
mean	36.923810	802.485714	9.192517	2.912925	1.0	1024.865306	
std	9.135373	403.509100	8.106864	1.024165	0.0	602.024335	
min	18.000000	102.000000	1.000000	1.000000	1.0	1.000000	
25%	30.000000	465.000000	2.000000	2.000000	1.0	491.250000	
50%	36.000000	802.000000	7.000000	3.000000	1.0	1020.500000	
75%	43.000000	1157.000000	14.000000	4.000000	1.0	1555.750000	
max	60.000000	1499.000000	29.000000	5.000000	1.0	2068.000000	

8 rows × 26 columns

In [10]:
```python
corr=df.corr()
corr
```

```
C:\Users\roopa\AppData\Local\Temp\ipykernel_22912\3182140910.py:1: FutureWarning: The de
fault value of numeric_only in DataFrame.corr is deprecated. In a future version, it wil
l default to False. Select only valid columns or specify the value of numeric_only to si
lence this warning.
  corr=df.corr()
```

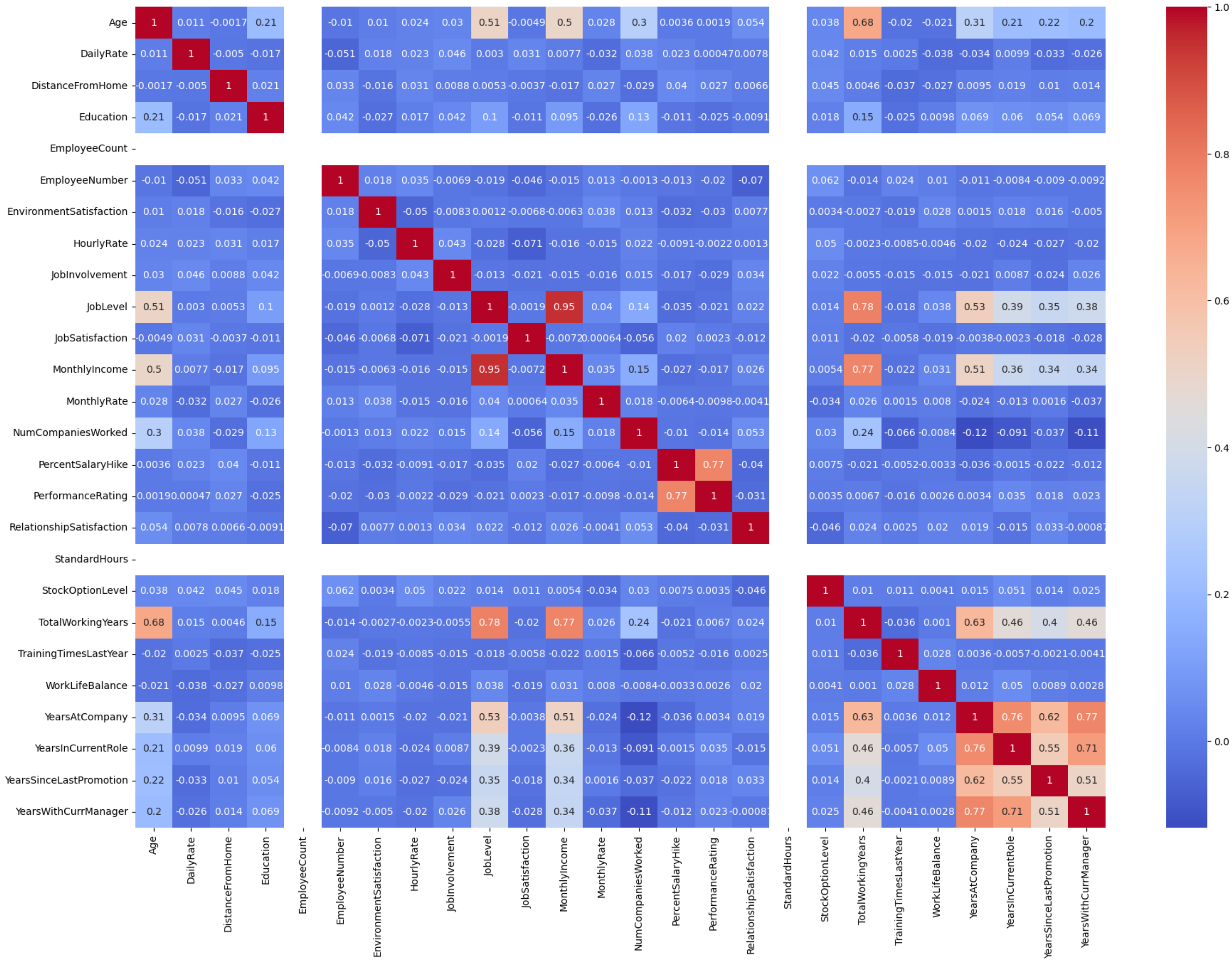
Out[10]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumbe
Age	1.000000	0.010661	-0.001686	0.208034	NaN	-0.01014
DailyRate	0.010661	1.000000	-0.004985	-0.016806	NaN	-0.05099
DistanceFromHome	-0.001686	-0.004985	1.000000	0.021042	NaN	0.03291
Education	0.208034	-0.016806	0.021042	1.000000	NaN	0.04207
EmployeeCount	NaN	NaN	NaN	NaN	NaN	Nal
EmployeeNumber	-0.010145	-0.050990	0.032916	0.042070	NaN	1.00000
EnvironmentSatisfaction	0.010146	0.018355	-0.016075	-0.027128	NaN	0.01762
HourlyRate	0.024287	0.023381	0.031131	0.016775	NaN	0.03517
JobInvolvement	0.029820	0.046135	0.008783	0.042438	NaN	-0.00688
JobLevel	0.509604	0.002966	0.005303	0.101589	NaN	-0.01851
JobSatisfaction	-0.004892	0.030571	-0.003669	-0.011296	NaN	-0.04624
MonthlyIncome	0.497855	0.007707	-0.017014	0.094961	NaN	-0.01482
MonthlyRate	0.028051	-0.032182	0.027473	-0.026084	NaN	0.01264
NumCompaniesWorked	0.299635	0.038153	-0.029251	0.126317	NaN	-0.00125
PercentSalaryHike	0.003634	0.022704	0.040235	-0.011111	NaN	-0.01294
PerformanceRating	0.001904	0.000473	0.027110	-0.024539	NaN	-0.02035
RelationshipSatisfaction	0.053535	0.007846	0.006557	-0.009118	NaN	-0.06986
StandardHours	NaN	NaN	NaN	NaN	NaN	Nal
StockOptionLevel	0.037510	0.042143	0.044872	0.018422	NaN	0.06222
TotalWorkingYears	0.680381	0.014515	0.004628	0.148280	NaN	-0.01436
TrainingTimesLastYear	-0.019621	0.002453	-0.036942	-0.025100	NaN	0.02360
WorkLifeBalance	-0.021490	-0.037848	-0.026556	0.009819	NaN	0.01030
YearsAtCompany	0.311309	-0.034055	0.009508	0.069114	NaN	-0.01124
YearsInCurrentRole	0.212901	0.009932	0.018845	0.060236	NaN	-0.00841
YearsSinceLastPromotion	0.216513	-0.033229	0.010029	0.054254	NaN	-0.00901
YearsWithCurrManager	0.202089	-0.026363	0.014406	0.069065	NaN	-0.00919

26 rows × 26 columns

In [11]:
```python
plt.subplots(figsize=(22,15))
sns.heatmap(corr,annot=True,cmap="coolwarm")
```

Out[11]:
```
<Axes: >
```



In [12]:
```
df.Attrition.value_counts()
```

Out[12]:
```
No     1233
Yes     237
Name: Attrition, dtype: int64
```

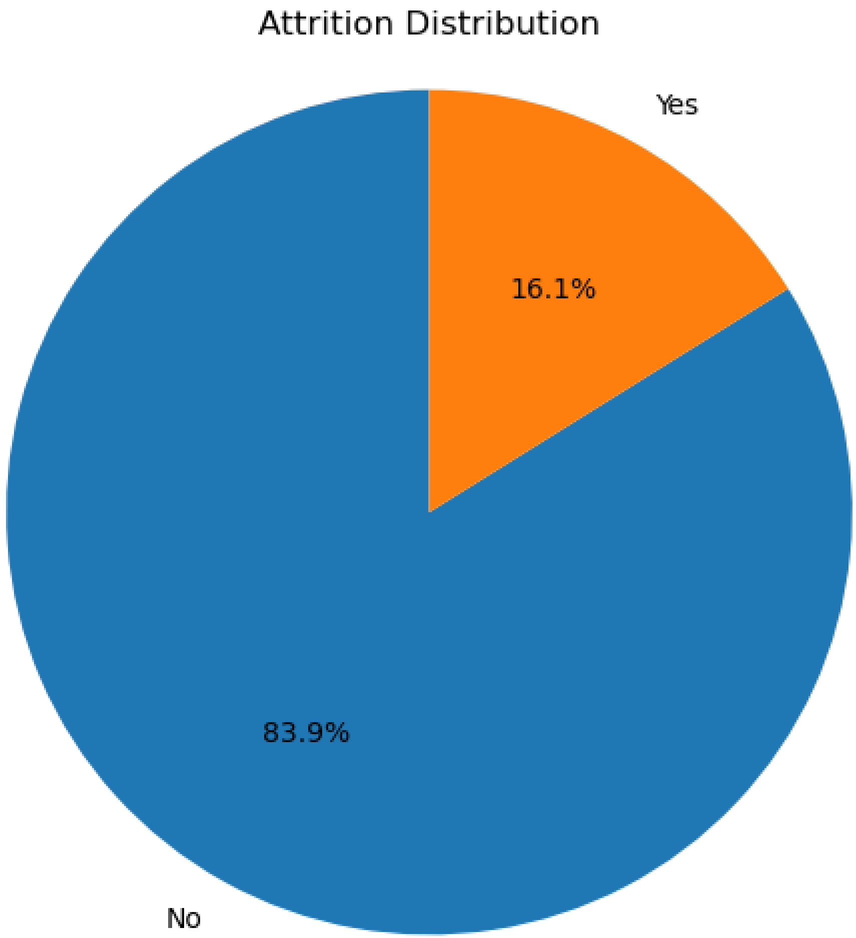
Checking for NULL Values

In [13]:
```
df.isnull().any()
```

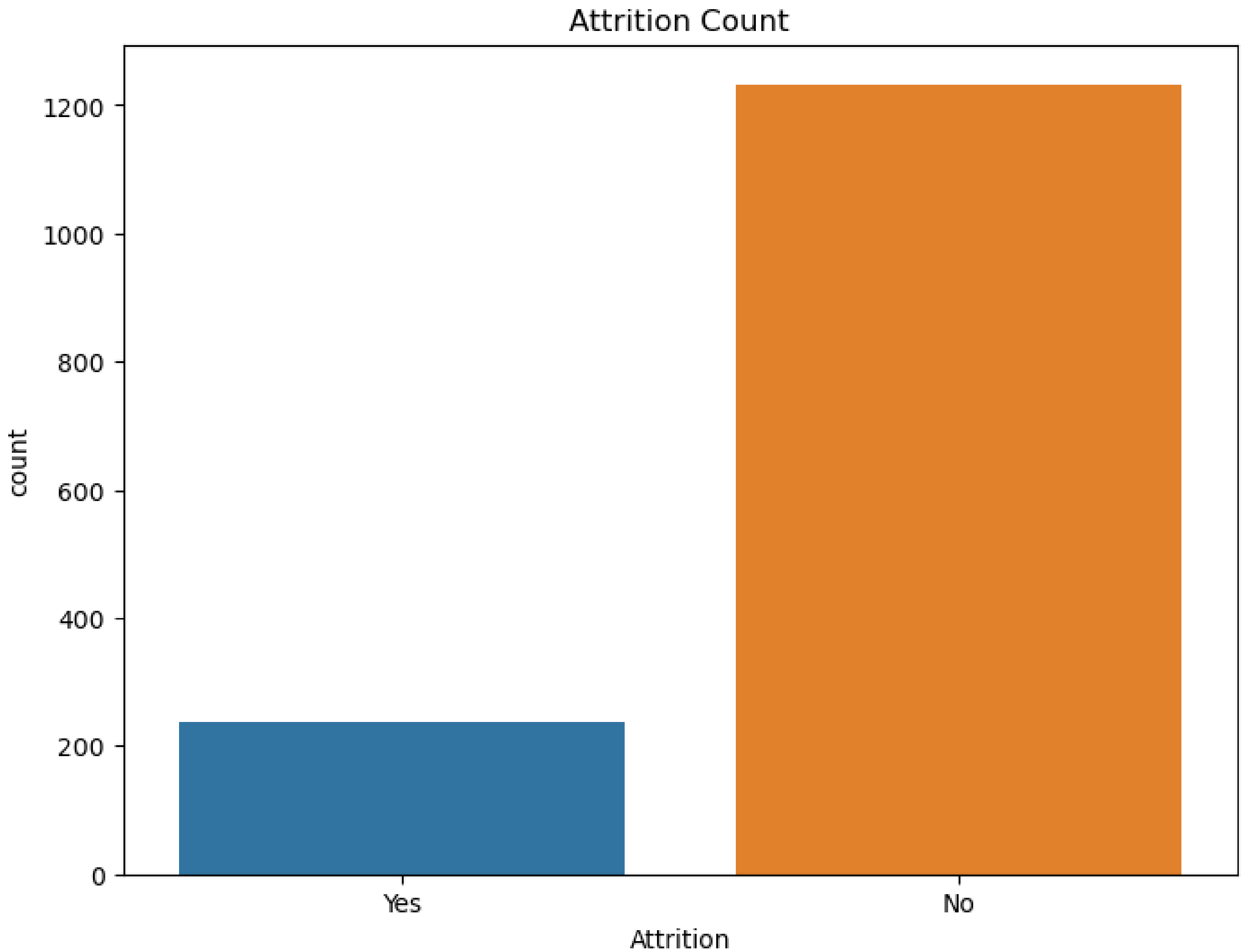
Out[13]:
```
Age                          False
Attrition                    False
BusinessTravel               False
DailyRate                    False
Department                   False
DistanceFromHome             False
Education                    False
EducationField               False
EmployeeCount                False
EmployeeNumber               False
EnvironmentSatisfaction      False
Gender                       False
HourlyRate                   False
JobInvolvement               False
JobLevel                     False
JobRole                      False
JobSatisfaction              False
MaritalStatus                False
MonthlyIncome                False
MonthlyRate                  False
NumCompaniesWorked           False
Over18                       False
OverTime                     False
PercentSalaryHike            False
PerformanceRating            False
RelationshipSatisfaction     False
StandardHours                False
StockOptionLevel             False
TotalWorkingYears            False
TrainingTimesLastYear        False
WorkLifeBalance              False
YearsAtCompany               False
YearsInCurrentRole           False
YearsSinceLastPromotion      False
YearsWithCurrManager         False
dtype: bool
```

Data Visualization

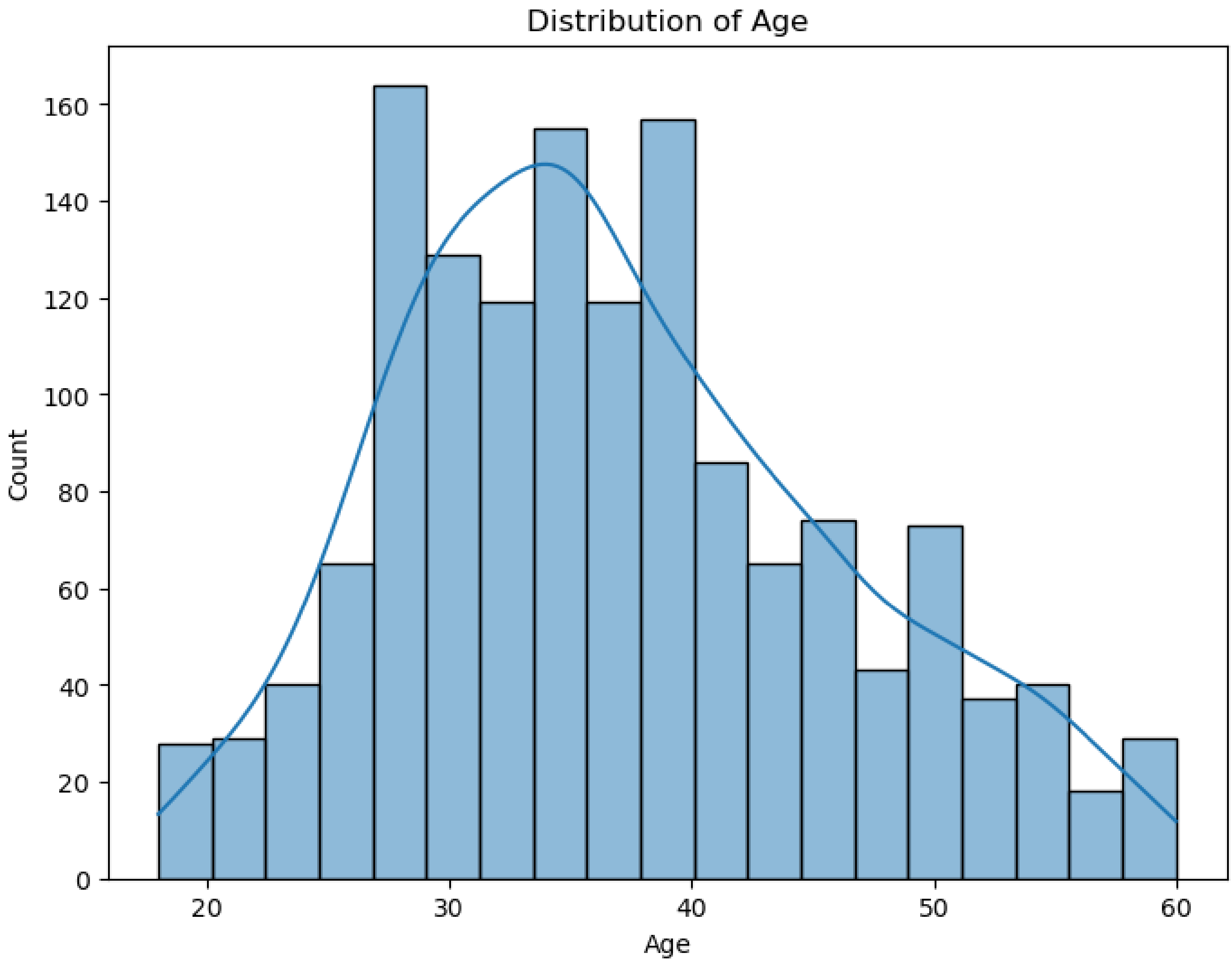
In [14]:
```
attrition_counts = df['Attrition'].value_counts()
plt.figure(figsize=(6, 6))
plt.pie(attrition_counts, labels=attrition_counts.index, autopct='%1.1f%%', startangle=9
plt.title('Attrition Distribution')
plt.axis('equal')

plt.show()
```



In [15]:
```
plt.figure(figsize=(8, 6))
sns.countplot(x="Attrition", data=df)
plt.title("Attrition Count")
plt.show()
```

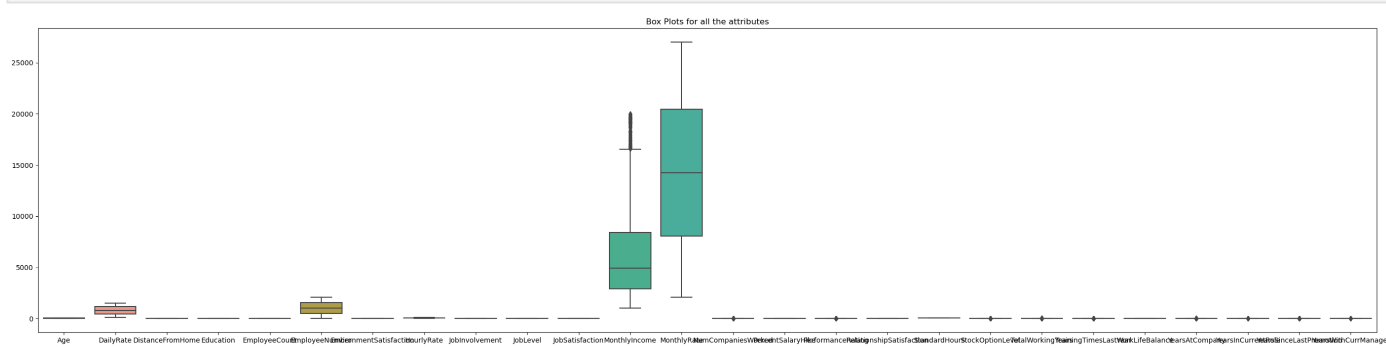


In [16]:
```
plt.figure(figsize=(8, 6))
sns.histplot(data=df, x="Age", kde=True)
plt.title("Distribution of Age")
plt.show()
```

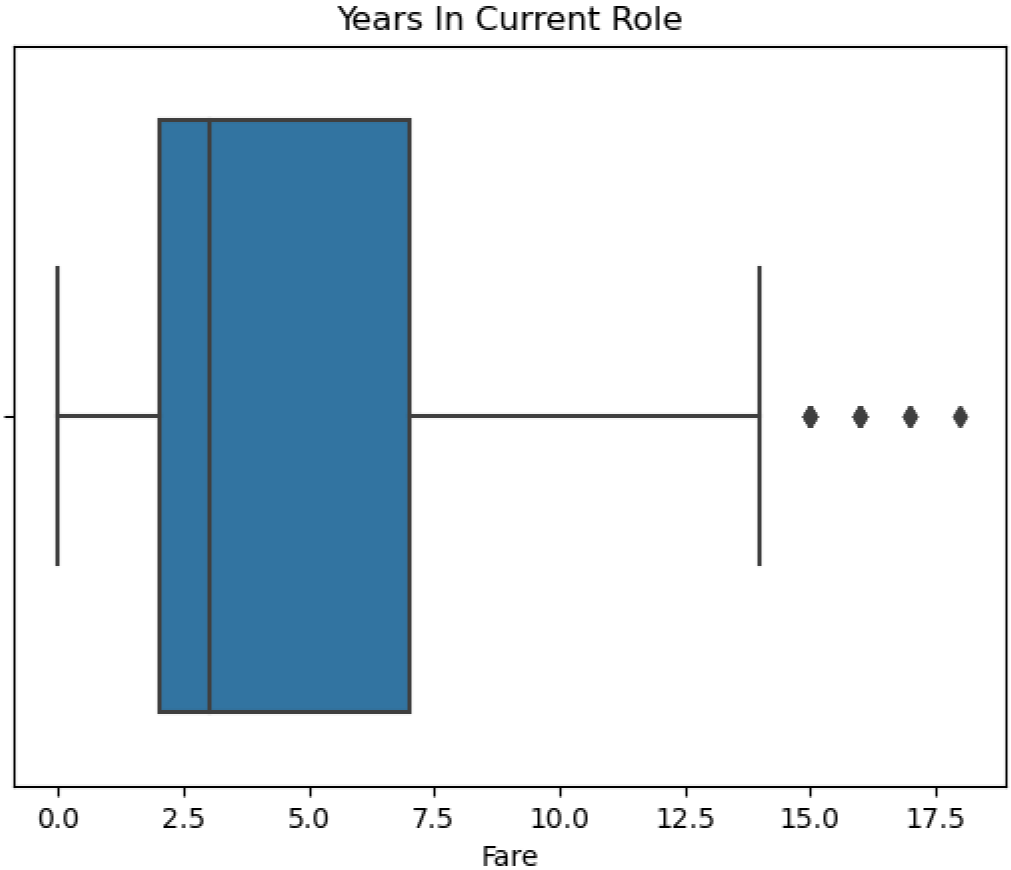


Outlier Detection

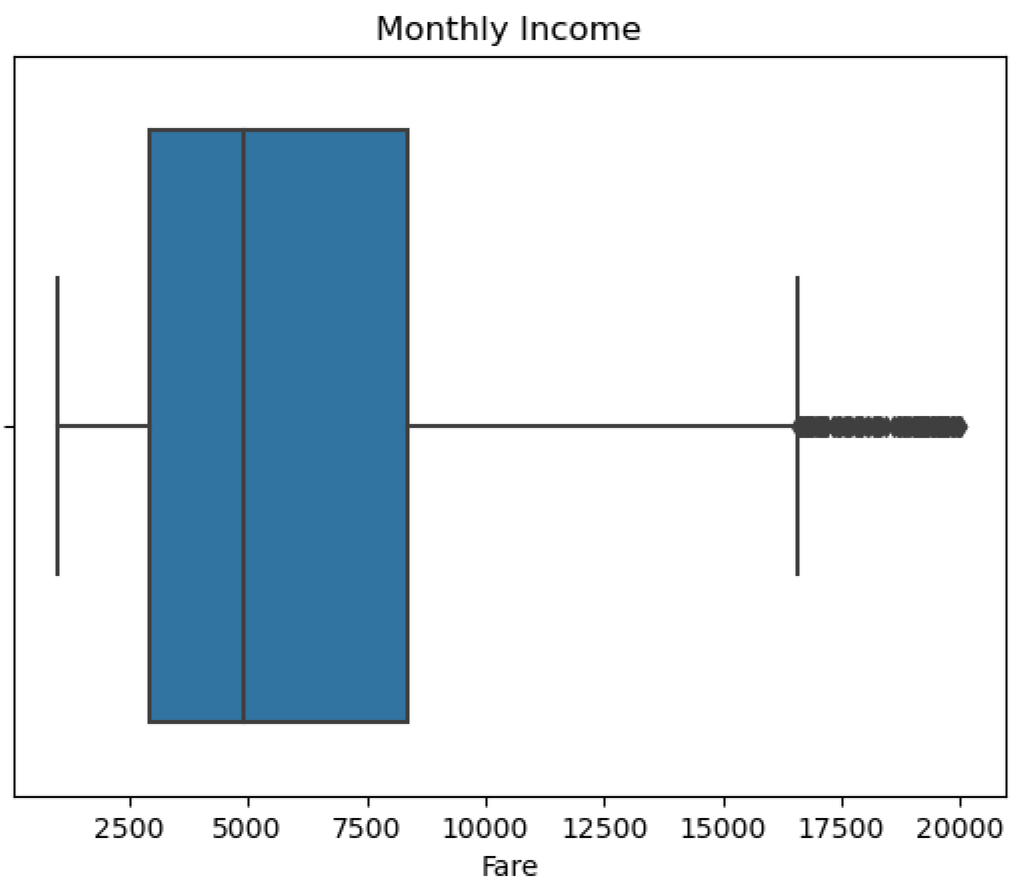
In [17]:
```
plt.figure(figsize=(35, 8))
sns.boxplot(data=df)
plt.title('Box Plots for all the attributes')
plt.show()
```



In [18]:
```
sns.boxplot(data=df, x='YearsInCurrentRole')
plt.title('Years In Current Role')
plt.xlabel('Fare')
plt.show()
```



In [19]:
```
sns.boxplot(data=df, x='MonthlyIncome')
plt.title('Monthly Income')
plt.xlabel('Fare')
plt.show()
```



In [20]:
```
from scipy import stats
```

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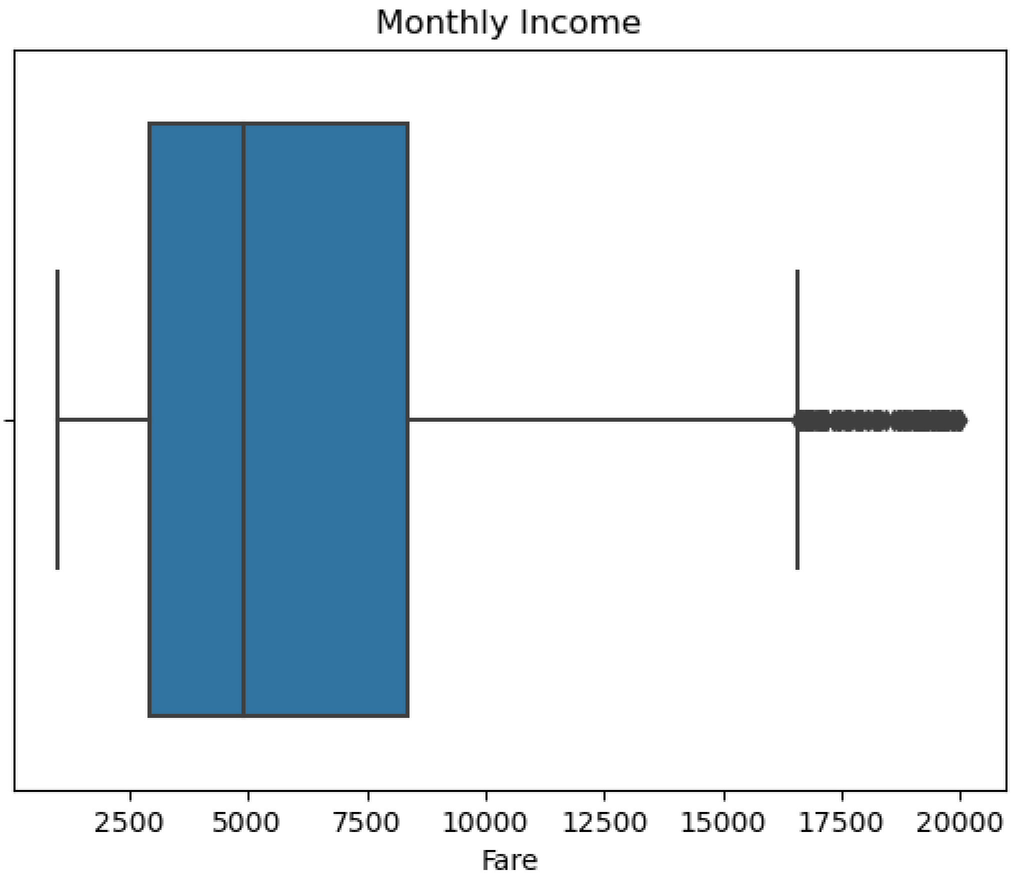
```
z_scores = stats.zscore(df['MonthlyIncome'])
z_score_threshold = 3
df_cleaned = df[(np.abs(z_scores) <= z_score_threshold)]
```

In [21]:
```
sns.boxplot(data=df_cleaned, x='MonthlyIncome')
plt.title('Monthly Income')
plt.xlabel('Fare')
plt.show()
```



So the outliers are in large quantity, and they are inside the threshold, so let us not remove the outliers

SPLITTING INDEPENDENT AND DEPENDENT VARIABLES

In [22]:
```
x= df.drop(columns=["Attrition"])
y = df["Attrition"]
```

In [23]:
```
x.head()
```

Out[23]:

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCour
0	41	Travel_Rarely	1102	Sales	1	2	Life Sciences	
1	49	Travel_Frequently	279	Research & Development	8	1	Life Sciences	
2	37	Travel_Rarely	1373	Research & Development	2	2	Other	
3	33	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	
4	27	Travel_Rarely	591	Research & Development	2	1	Medical	

5 rows × 34 columns

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In [24]:
```
y.head()
```

Out[24]:
```
0    Yes
1     No
2    Yes
3     No
4     No
Name: Attrition, dtype: object
```

ENCODING

In [25]:
```
categorical_features = x.select_dtypes(include=['object']).columns.tolist()
x_encoded = pd.get_dummies(x, columns=categorical_features, drop_first=True)
```

In [26]:
```
x_encoded.head()
```

Out[26]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction
0	41	1102	1	2	1	1	2
1	49	279	8	1	1	2	3
2	37	1373	2	2	1	4	4
3	33	1392	3	4	1	5	4
4	27	591	2	1	1	7	1

5 rows × 47 columns

FEATURE SCALING

In [27]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
x_scaled = pd.DataFrame(scaler.fit_transform(x_encoded), columns=x_encoded.columns)
```

In [28]:
```
x_scaled.head()
```

Out[28]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfact
0	0.446350	0.742527	-1.010909	-0.891688	0.0	-1.701283	-0.660
1	1.322365	-1.297775	-0.147150	-1.868426	0.0	-1.699621	0.254
2	0.008343	1.414363	-0.887515	-0.891688	0.0	-1.696298	1.169
3	-0.429664	1.461466	-0.764121	1.061787	0.0	-1.694636	1.169
4	-1.086676	-0.524295	-0.887515	-1.868426	0.0	-1.691313	-1.575

5 rows × 47 columns

In [29]:
```
x=x_scaled
```

Train and test split

In [30]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42
```

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In [31]:
```python
# Import the necessary libraries
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from joblib import dump
```

In [32]:
```python
logreg_model = LogisticRegression(random_state=42)
dt_model = DecisionTreeClassifier(random_state=42)
```

In [33]:
```python
logreg_model.fit(x_train, y_train)
dt_model.fit(x_train, y_train)
```

Out[33]:
```
▼ DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

In [34]:
```python
logreg_predictions = logreg_model.predict(x_test)

dt_predictions = dt_model.predict(x_test)

logreg_accuracy = accuracy_score(y_test, logreg_predictions)
print("Logistic Regression Accuracy:", logreg_accuracy)

dt_accuracy = accuracy_score(y_test, dt_predictions)
print("Decision Tree Accuracy:", dt_accuracy)

logreg_report = classification_report(y_test, logreg_predictions)
print("Classification Report for Logistic Regression:\n", logreg_report)

dt_report = classification_report(y_test, dt_predictions)
print("Classification Report for Decision Tree Classifier:\n", dt_report)

logreg_conf_matrix = confusion_matrix(y_test, logreg_predictions)
print("Confusion Matrix for Logistic Regression:\n", logreg_conf_matrix)

dt_conf_matrix = confusion_matrix(y_test, dt_predictions)
print("Confusion Matrix for Decision Tree Classifier:\n", dt_conf_matrix)
```

```
Logistic Regression Accuracy: 0.8809523809523809
Decision Tree Accuracy: 0.7721088435374149
Classification Report for Logistic Regression:
              precision    recall  f1-score   support

          No       0.92      0.95      0.93       255
         Yes       0.56      0.46      0.51        39

    accuracy                           0.88       294
   macro avg       0.74      0.70      0.72       294
weighted avg       0.87      0.88      0.88       294

Classification Report for Decision Tree Classifier:
              precision    recall  f1-score   support

          No       0.87      0.86      0.87       255
         Yes       0.17      0.18      0.17        39

    accuracy                           0.77       294
   macro avg       0.52      0.52      0.52       294
weighted avg       0.78      0.77      0.78       294

Confusion Matrix for Logistic Regression:
 [[241  14]
 [ 21  18]]
Confusion Matrix for Decision Tree Classifier:
 [[220  35]
 [ 32   7]]
```

In [ ]:

In [ ]:

In [ ]: