# 02 - Exploratory Data Analysis (EDA)

In this notebook, we will:

- Load the **cleaned** dataset.
- Perform **univariate** analysis on numeric and categorical features.
- Perform **bivariate** analysis (e.g., scatter plots, boxplots).
- Generate a **correlation heatmap** for key numeric features.

## Import Libraries & Load Data

We start by importing the necessary libraries and then load the cleaned dataset (saved as `hr_data_cleaned.csv` from the previous notebook).

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

sns.set(style="whitegrid")
plt.rcParams["figure.figsize"] = (12, 8)

# Load the cleaned dataset
df = pd.read_csv("hr_data_cleaned.csv")
print("DataFrame shape:", df.shape)
df.head()
```

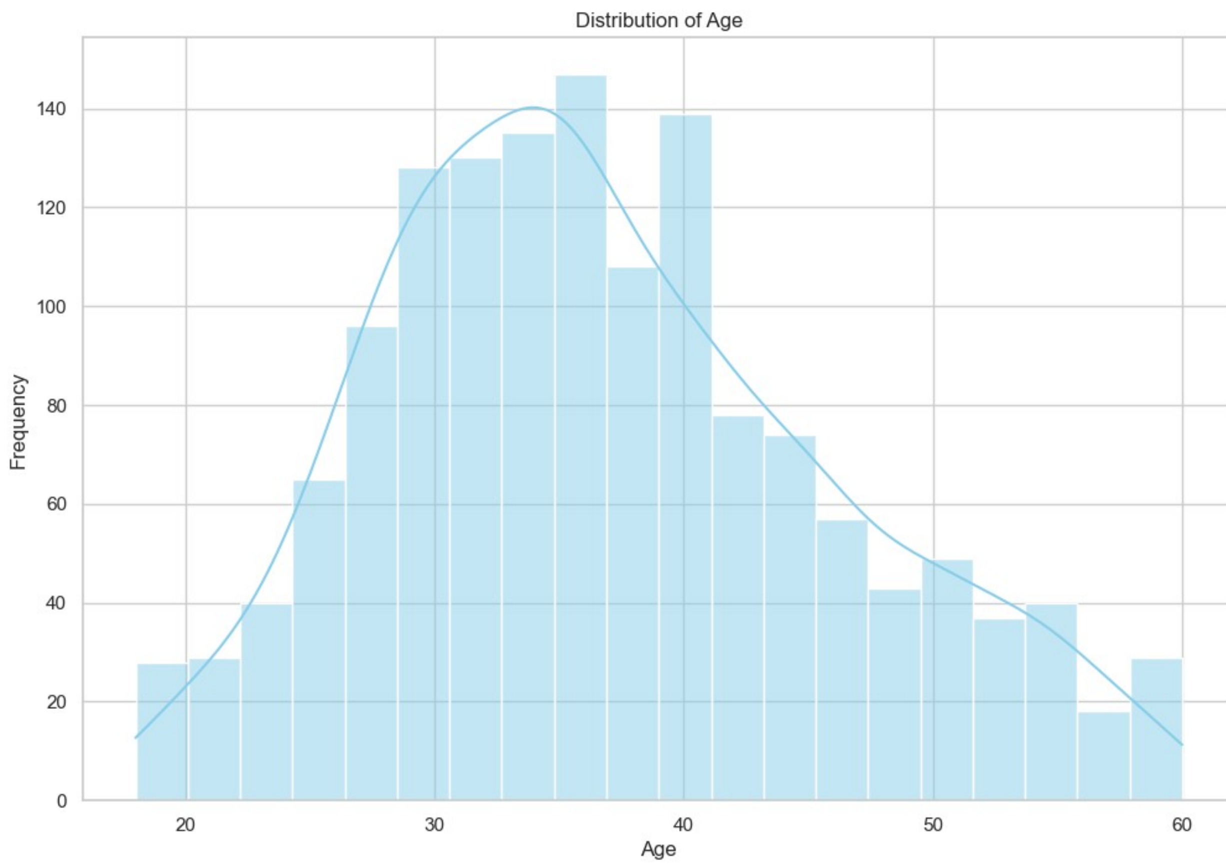
```
DataFrame shape: (1470, 36)

   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

   ...  StandardHours StockOptionLevel  TotalWorkingYears  \
0  ...             80                0                  8
1  ...             80                1                 10
2  ...             80                0                  7
3  ...             80                0                  8
4  ...             80                1                  6

   TrainingTimesLastYear  WorkLifeBalance YearsAtCompany
YearsInCurrentRole  \
0                      0                1              6
4
1                      3                3             10
7
2                      3                3              0
0
3                      3                3              8
7
4                      3                3              2
2

  YearsSinceLastPromotion  YearsWithCurrManager  TenureBucket
0                       0                     5           3-6
1                       1                     7          6-10
2                       0                     0           NaN
3                       3                     0          6-10
4                       2                     2            <3

[5 rows x 36 columns]
```

## Univariate Analysis: Numeric Features

Let's explore the distributions of some key numeric variables such as **Age** and **PercentSalaryHike**. We will use histograms with KDE plots for visualization.

```
# Distribution of Age
plt.figure()
sns.histplot(df["Age"], kde=True, bins=20, color="skyblue")
plt.title("Distribution of Age")
plt.xlabel("Age")
plt.ylabel("Frequency")
plt.show()
```




The distribution appears roughly unimodal, with a peak around the mid 30s. Most employees seem to fall between their early 30s to early 40s, indicating a relatively young workforce.

```python
# Distribution of PercentSalaryHike
plt.figure()
sns.histplot(df["PercentSalaryHike"], kde=True, bins=15,
color="salmon")
plt.title("Distribution of Percent Salary Hike")
plt.xlabel("Percent Salary Hike")
plt.ylabel("Frequency")
plt.show()
```


The Percent Salary Hike distribution is heavily concentrated between roughly 11% and 15%, with a clear peak around 12%. It then tapers off toward the higher end (above 18%), this indicates that not a lot of employees get hikes higher than 16%. This will be interesting to see if age for example plays a part in the salary hike.

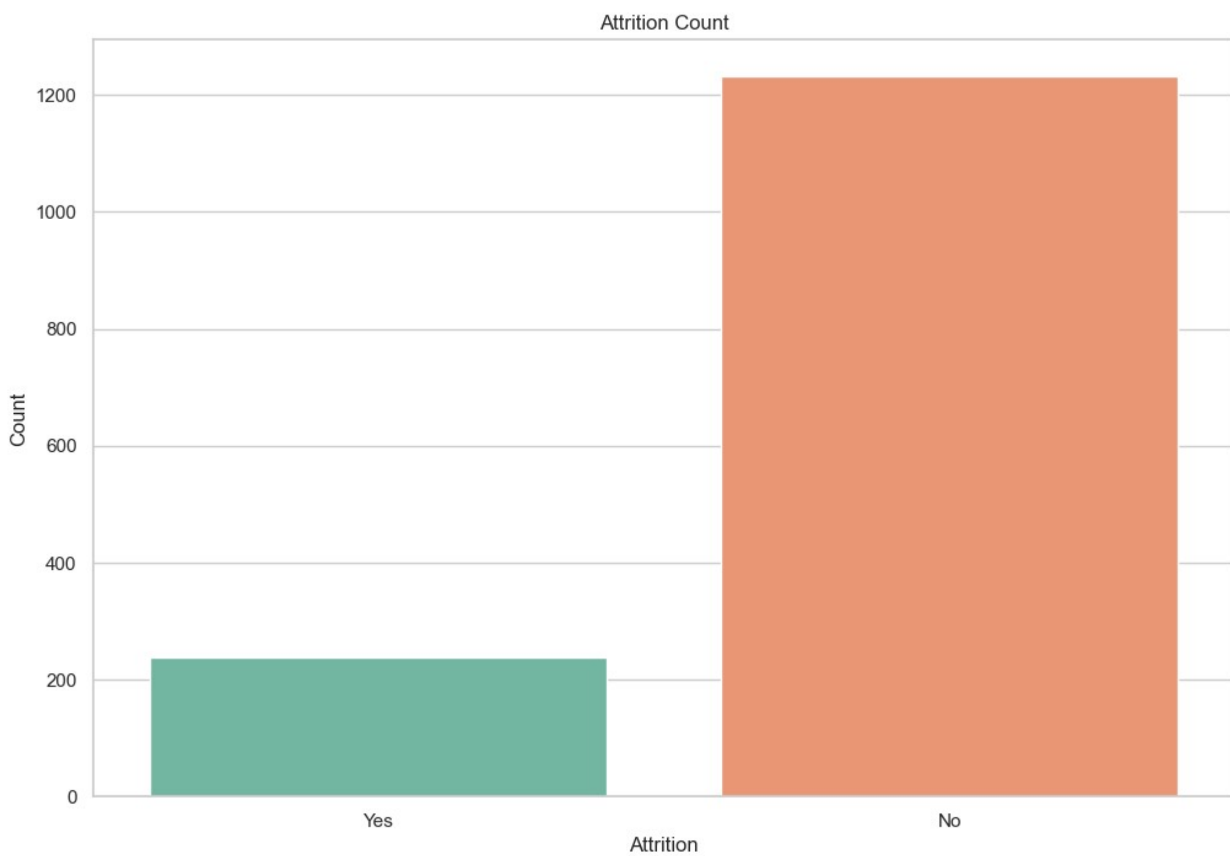
## Univariate Analysis: Categorical Features

Next, we look at the frequency distribution of categorical variables.
For example, we examine the **Attrition** status and the distribution of employees by **Department**.

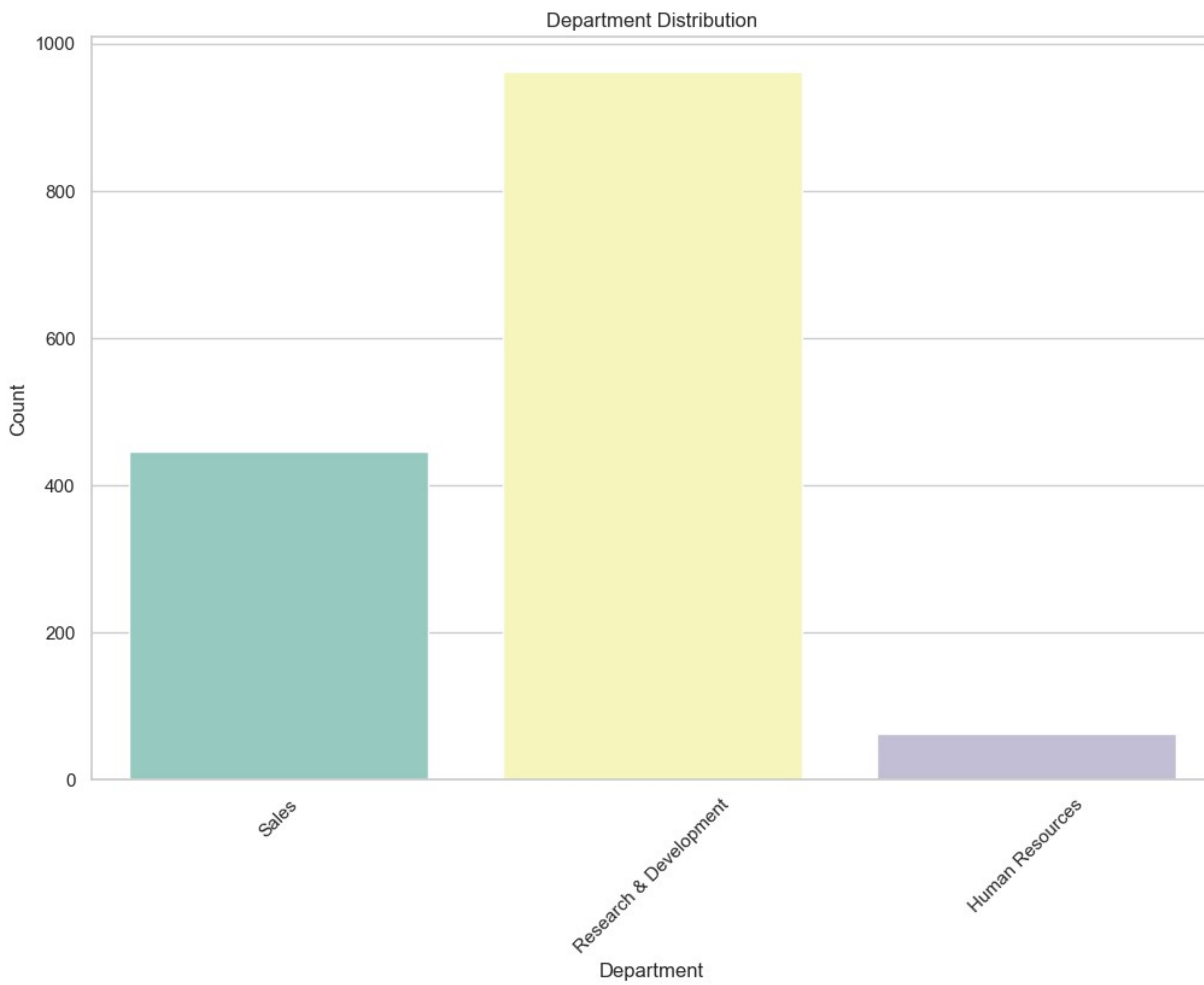
```
# Attrition count
plt.figure()
sns.countplot(x="Attrition", data=df, palette="Set2")
plt.title("Attrition Count")
plt.xlabel("Attrition")
plt.ylabel("Count")
plt.show()

# Department distribution
plt.figure()
sns.countplot(x="Department", data=df, palette="Set3")
plt.title("Department Distribution")
plt.xlabel("Department")
```

```python
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.show()

# Job Role distribution
plt.figure()
sns.countplot(x="JobRole", data=df, palette="Set3")
plt.title("JobRole Distribution")
plt.xlabel("JobRole")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.show()
```

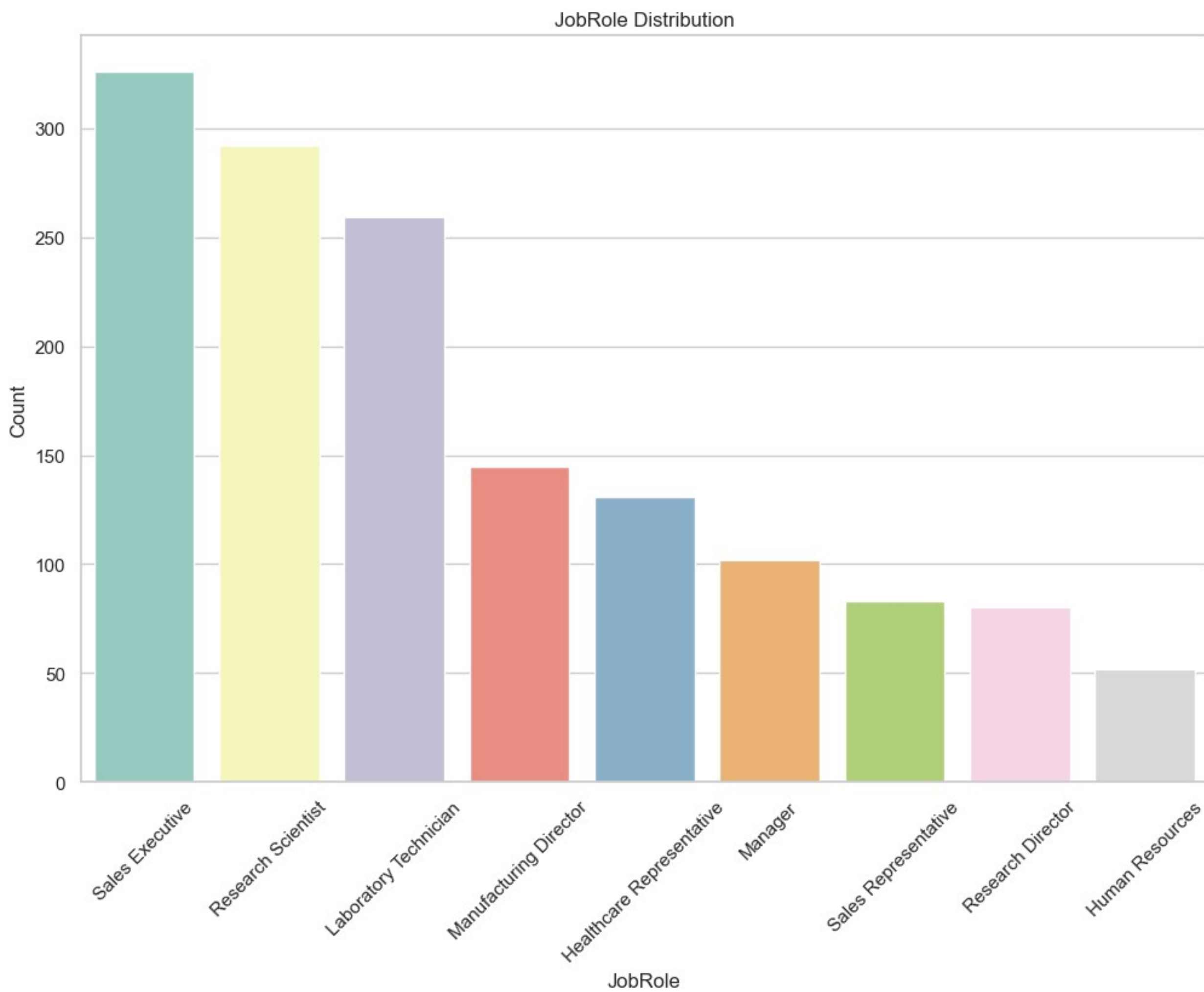
```
C:\Users\darre\AppData\Local\Temp\ipykernel_61876\2478731947.py:3:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x="Attrition", data=df, palette="Set2")
```



```
C:\Users\darre\AppData\Local\Temp\ipykernel_61876\2478731947.py:11:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x="Department", data=df, palette="Set3")
```




```
C:\Users\darre\AppData\Local\Temp\ipykernel_61876\2478731947.py:20:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x="JobRole", data=df, palette="Set3")
```



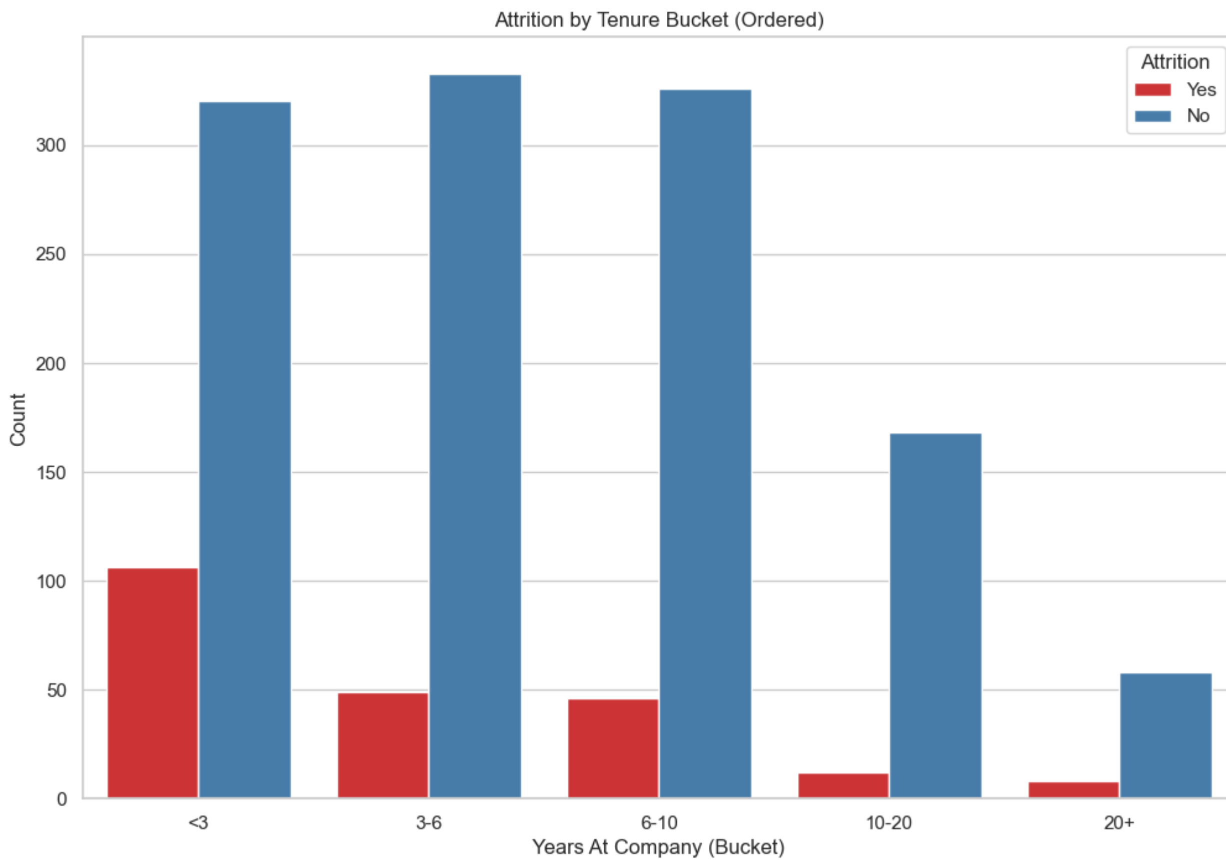

This just gives us an idea of the data we're working with. We see our dataset has a larger number of employees who has not faced attrition. Meanwhile majority of employees are from R&D. Very few employees from HR.

## Categorical Analysis: Attrition by Tenure Bucket

Here we visualize how attrition is distributed across different tenure buckets (a new feature we created in the data cleaning notebook).

```
df["TenureBucket"] = pd.Categorical(
    df["TenureBucket"],
    categories=["<3","3-6","6-10","10-20","20+"],
    ordered=True
)

plt.figure()
sns.countplot(
    x="TenureBucket",
    hue="Attrition",
```

```
    data=df,
    palette="Set1",
    order=["<3","3-6","6-10","10-20","20+"]
)
plt.title("Attrition by Tenure Bucket (Ordered)")
plt.xlabel("Years At Company (Bucket)")
plt.ylabel("Count")
plt.show()
```




From this we can see attrition decreases as years in the company increases, which is logical. Though 3-6 and 6-10 has almost the same level of attrition which is something interesting we can look into.

# Bivariate Analysis

## Monthly Income vs. Job Level

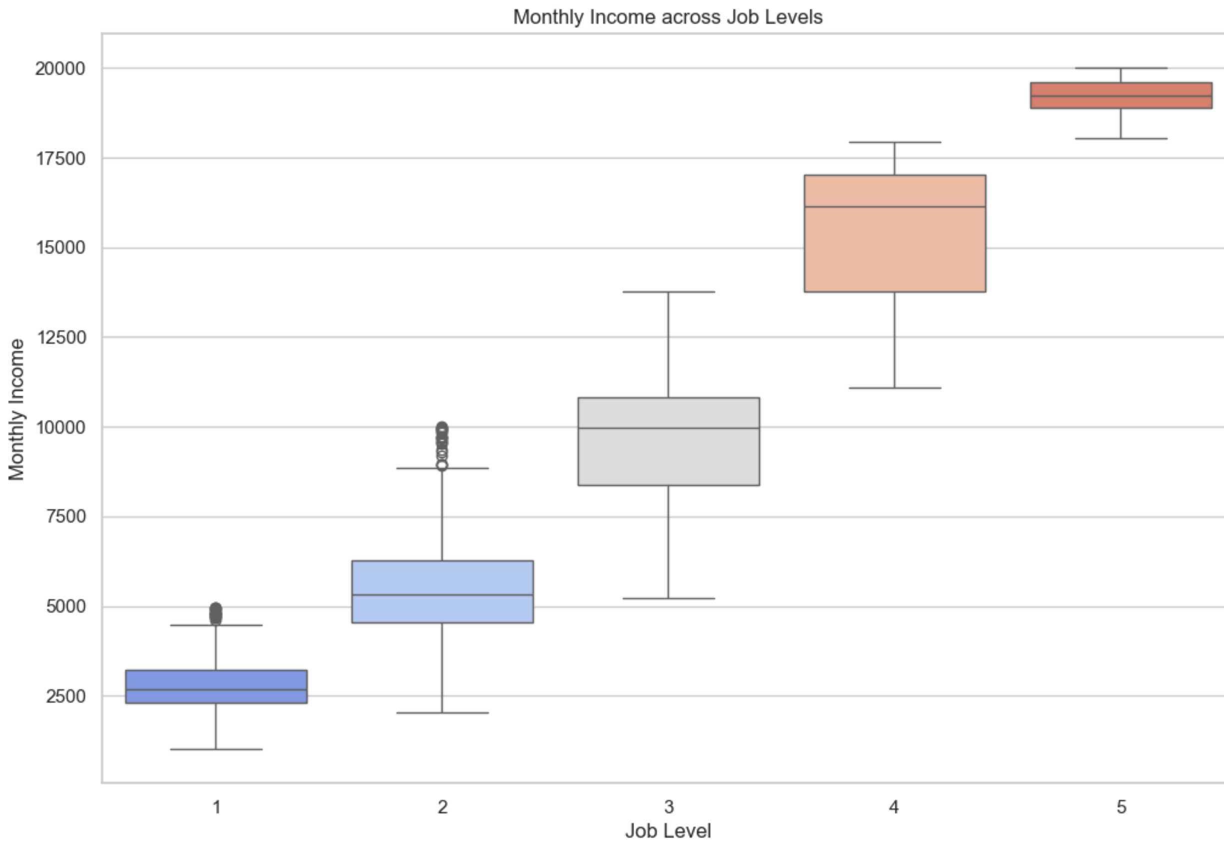
We use a boxplot to compare the **MonthlyIncome** across different **JobLevel** values.

## Total Working Years vs. Monthly Income by Attrition

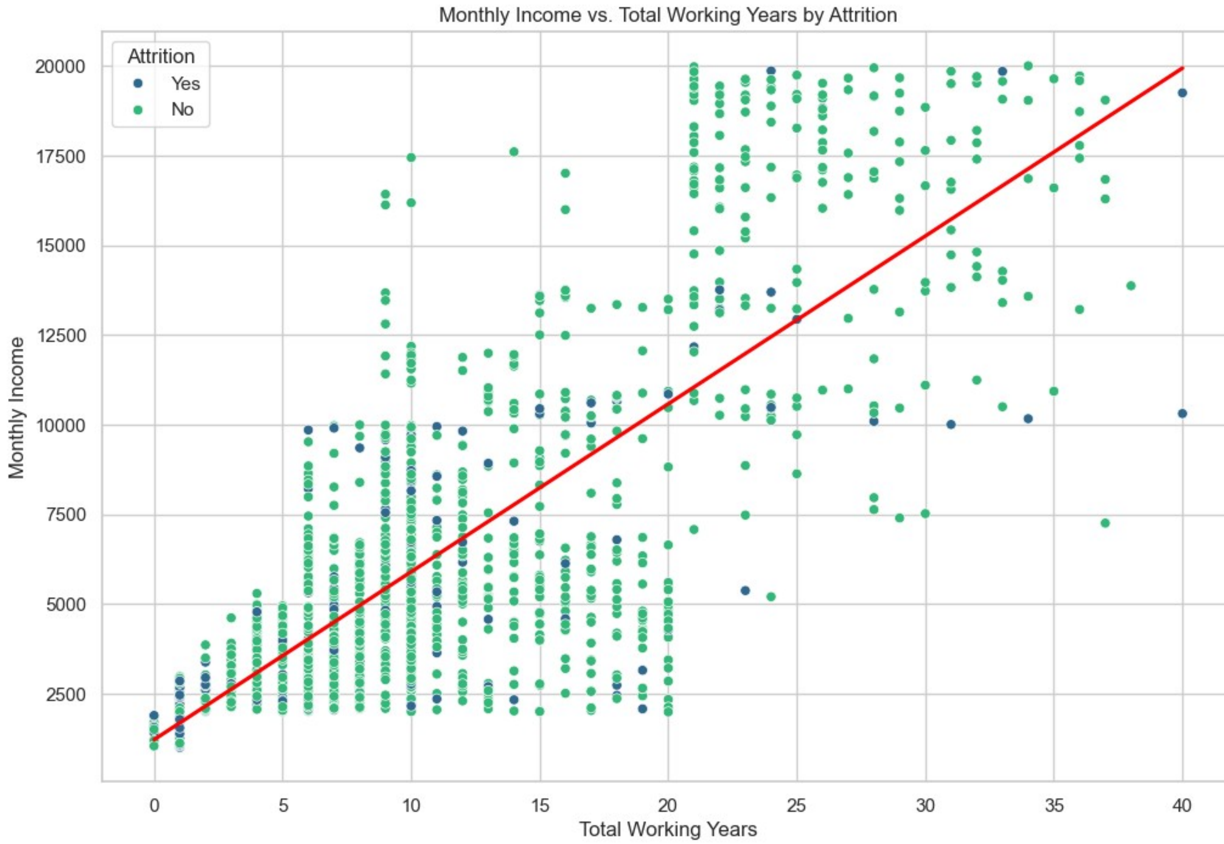
A scatter plot is created to see the relationship between **TotalWorkingYears** and **MonthlyIncome**, with data points colored by attrition status.

```
# Boxplot: Monthly Income across Job Levels
plt.figure()
sns.boxplot(x="JobLevel", y="MonthlyIncome", data=df,
palette="coolwarm")
plt.title("Monthly Income across Job Levels")
plt.xlabel("Job Level")
plt.ylabel("Monthly Income")
plt.show()

# Scatter plot: TotalWorkingYears vs. MonthlyIncome by Attrition
plt.figure()
sns.scatterplot(x="TotalWorkingYears", y="MonthlyIncome",
hue="Attrition", data=df, palette="viridis")
# Add a regression line (correlation line)
sns.regplot(x="TotalWorkingYears", y="MonthlyIncome", data=df,
scatter=False, color="red", ci=None)
plt.title("Monthly Income vs. Total Working Years by Attrition")
plt.xlabel("Total Working Years")
plt.ylabel("Monthly Income")
plt.show()
```

```
C:\Users\darre\AppData\Local\Temp\ipykernel_13012\2068821318.py:3:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.boxplot(x="JobLevel", y="MonthlyIncome", data=df,
palette="coolwarm")
```



Monthly Income across Job Levels
Monthly Income
20000
17500
15000
12500
10000
7500
5000
2500
1
2
3
4
5
Job Level

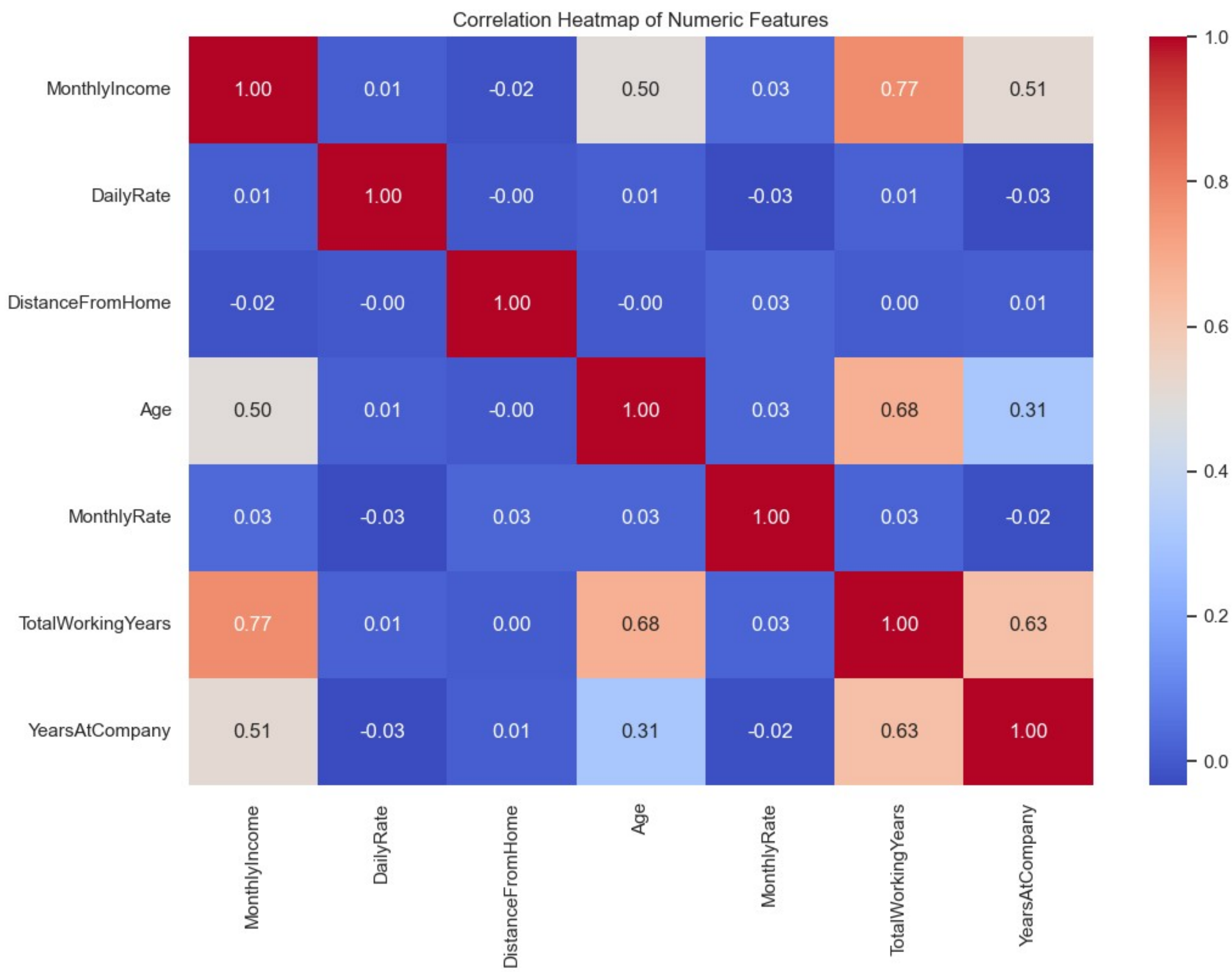



This boxplot shows a clear positive relationship between job level and monthly income. As job level increases, the median monthly income rises significantly. The scaterplot also suggest a positive relationship between Monthly Income and Total Working Years. We can determine the correlation value with a heatmap below.

# Multivariate Analysis: Correlation Heatmap

We now generate a correlation heatmap for selected numeric features to understand the relationships and potential multicollinearity among them.

```
# Define the numeric columns of interest
numeric_cols = ["MonthlyIncome", "DailyRate", "DistanceFromHome",
"Age",
                "MonthlyRate", "TotalWorkingYears", "YearsAtCompany"]

plt.figure()
corr = df[numeric_cols].corr()
sns.heatmap(corr, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap of Numeric Features")
plt.show()
```




From this heatmap, a few notable relationships stand out:

- **MonthlyIncome** has a strong positive correlation with **TotalWorkingYears** (0.77), indicating that employees with more overall experience tend to earn higher salaries.
- **MonthlyIncome** also shows a moderate correlation (0.51) with **YearsAtCompany**, suggesting that tenure at the current organization also plays a role in pay, though less strongly than total experience.
- **Age** correlates significantly with **TotalWorkingYears** (0.68) but less so with **YearsAtCompany** (0.31). This implies older employees have more experience but their experience may not be in the same company.
- **DistanceFromHome**, **DailyRate**, and **MonthlyRate** don't seem to have much correlation with other features. In fact it seems daily rate and monthly rate don't seem to mean how much they are paid in a day or a month.