

TITLE

EMPLOYEE DATA ANALYSIS AND INSIGHTS

Prepared by: NIRMAL KUMAR

Date:11/03/2025

**Institution/Organization: KIET
GROUP OF INSTITUTIONS**

Course/Department: CSEAI

**University Roll No. :
242801100300162**

**Submitted to : Mr. Mayank
Lakhotia**

Background & Purpose

In modern organizations, employee data analysis is essential for making informed decisions regarding salaries, experience, and department-wise performance. Understanding salary trends, departmental variations, and experience-based compensation structures helps organizations

optimize workforce management, improve employee satisfaction, and ensure fair pay structures.

This project aims to **analyze and visualize employee data** to extract meaningful insights, such as:

- ✓ Identifying **salary trends** across departments
- ✓ Finding **correlation between salary & experience**
- ✓ Detecting **outliers in salaries**
- ✓ Understanding **departmental salary distribution**
- ✓ Exploring **employee demographics**

By leveraging **Python, Pandas, Seaborn, and Matplotlib**, this study provides a **data-driven approach** to employee analytics, helping HR professionals and management make strategic workforce decisions.

METHODOLOGY:

✂ Tools & Technologies Used

- **Python** – For data manipulation and analysis
- **Pandas** – For handling structured data (CSV file)

- **Matplotlib & Seaborn** – For visualizing salary distribution, correlations, and trends
- **Statistical Analysis** – Using correlation, outlier detection, and department-wise insights

Steps Followed

Step 1: Data Collection & Preprocessing

- The employee dataset (CSV format) was loaded into Python using Pandas.
- Initial checks were performed to inspect missing values and data types.

Step 2: Exploratory Data Analysis (EDA)

- **Summary statistics** were computed, including min, max, mean, and standard deviation of salary, experience, and other numerical attributes.
- **Department-wise average salary & experience** were analyzed.
- **Correlation analysis** was performed between salary and experience.

Step 3: Advanced Analysis & Outlier Detection

- **Outliers in salary** were detected using the **Interquartile Range (IQR) method**.
- Employees with **highest & lowest salaries** were identified.

Step 4: Data Visualization

- **Salary Distribution (Histogram with KDE)**
- **Experience vs Salary Scatterplot (Color-coded by department)**
- **Department-wise Salary Boxplot (To show salary spread)**
- **Salary Growth Trendline (Regression plot)**
- **Employee Distribution Pie Chart**

Step 5: Interpretation & Insights

- The results were analyzed to identify key patterns, correlations, and department-wise salary trends.

CODE TYPED:

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

```
# Load the employee data CSV file
file_path = "employee_data.csv" # Update if needed
df = pd.read_csv(file_path)
```

```
# Display basic dataset information
print("\n ✂ Basic Information:\n", df.info())
```

```
# Display first few rows
print("\n ✂ First Few Rows of the Dataset:\n",
df.head())
```

```
# ----- SUMMARY STATISTICS -----
```

```
print("\n ✂ Summary Statistics:\n", df.describe())
```

```
# ----- DEPARTMENT-WISE ANALYSIS -----
-----
```

```
# Average salary and experience by department
```

```
dept_analysis = df.groupby("Department")[["Salary",  
"Experience"]].mean()
```

```
print("\n ✂ Department-wise Average Salary and  
Experience:\n", dept_analysis)
```

```
# Count of employees in each department
```

```
dept_count = df["Department"].value_counts()
```

```
print("\n ✂ Employee Count per Department:\n",  
dept_count)
```

```
# ----- CORRELATION ANALYSIS -----
```

```
# Compute correlation between Experience & Salary
```

```
correlation = df[["Experience", "Salary"]].corr()
```

```
print("\n ✂ Correlation Between Experience &  
Salary:\n", correlation)
```

```
# ----- HIGHEST & LOWEST SALARY  
EMPLOYEES -----
```

```
highest_salary = df.loc[df["Salary"].idxmax()]
```

```
lowest_salary = df.loc[df["Salary"].idxmin()]
```

```
print("\n ✂ Employee with Highest Salary:\n",  
highest_salary)
```

```
print("\n ✂ Employee with Lowest Salary:\n",  
lowest_salary)
```

```
# ----- OUTLIER DETECTION -----
```

```
# Identify outliers in salary using IQR method
```

```
Q1 = df["Salary"].quantile(0.25)
```

```
Q3 = df["Salary"].quantile(0.75)
```

```
IQR = Q3 - Q1
```

```
lower_bound = Q1 - 1.5 * IQR
```

```
upper_bound = Q3 + 1.5 * IQR
```

```
outliers = df[(df["Salary"] < lower_bound) |  
(df["Salary"] > upper_bound)]
```

```
print("\n ✨ Outliers in Salary:\n", outliers if not  
outliers.empty else "No outliers detected.")
```

```
# ----- DATA VISUALIZATION -----
```

```
# Plot Salary Distribution
```

```
plt.figure(figsize=(8, 5))
```

```
sns.histplot(df["Salary"], bins=10, kde=True,  
color="blue")
```

```
plt.title("Salary Distribution")
```

```
plt.xlabel("Salary")
```

```
plt.ylabel("Frequency")
```

```
plt.show()
```

```
# Plot Experience vs Salary
```

```
plt.figure(figsize=(8, 5))
```

```
sns.scatterplot(x=df["Experience"], y=df["Salary"],  
hue=df["Department"], palette="coolwarm")
```

```
plt.title("Experience vs Salary")
```

```
plt.xlabel("Years of Experience")
```

```
plt.ylabel("Salary")
```

```
plt.show()
```



```
# Boxplot of Salary by Department
plt.figure(figsize=(10, 6))
sns.boxplot(x="Department", y="Salary", data=df,
palette="Set2")
plt.title("Salary Distribution by Department")
plt.xlabel("Department")
plt.ylabel("Salary")
plt.xticks(rotation=45)
plt.show()
```

```
# Salary Growth with Experience (Trendline)
plt.figure(figsize=(8, 5))
sns.regplot(x=df["Experience"], y=df["Salary"],
scatter_kws={"color": "red"}, line_kws={"color":
"black"})
plt.title("Salary Growth with Experience")
plt.xlabel("Experience (Years)")
plt.ylabel("Salary")
plt.show()
```

```
# Department-wise Employee Distribution (Pie Chart)
plt.figure(figsize=(6, 6))
plt.pie(dept_count, labels=dept_count.index,
autopct="%1.1f%%",
colors=sns.color_palette("pastel"))
plt.title("Employee Distribution by Department")
plt.show()
```

SCREENSHOTS:

```
NIRMAL_202401100300162.ipynb x +
colab.research.google.com/drive/1JAmox1N9dD_LQ60roFwsemj-qwF3mMzo

NIRMAL_202401100300162.ipynb ☆
File Edit View Insert Runtime Tools Help

Q Commands + Code + Text RAM Disk
plt.show()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20 entries, 0 to 19
Data columns (total 5 columns):
#   column      Non-Null Count  Dtype
---  ---
0   EmployeeID  20 non-null         int64
1   Age         20 non-null         int64
2   Department  20 non-null         object
3   Experience  20 non-null         int64
4   Salary      20 non-null         int64
dtypes: int64(4), object(1)
memory usage: 932.0+ bytes
Basic Information:
None

First Few Rows of the Dataset:
EmployeeID  Age  Department  Experience  Salary
0           1    23      Finance           8    93563
1           2    28      Finance          2    41742
2           3    37        HR           8    56905
3           4    23        HR          23   138397
4           5    55        IT          29   96879

Summary Statistics:
EmployeeID  Age  Experience  Salary
count      20.00000  20.000000  20.000000  20.000000
mean      10.50000  42.450000  16.750000  102503.150000
std         5.91608  13.092686  10.447236  32459.740566
min         1.00000  23.000000  2.000000  41742.000000
25%         5.75000  29.000000  8.000000  82244.750000
50%        10.50000  46.000000  15.500000  101315.500000
75%        15.25000  53.500000  24.250000  132247.500000
max        20.00000  58.000000  34.000000  144637.000000

3s completed at 10:30 AM
```

```
NIRMAL_202401100300162.ipynb x +
colab.research.google.com/drive/1JAmox1N9dD_LQ60roFwsemj-qwF3mMzo

NIRMAL_202401100300162.ipynb ☆
File Edit View Insert Runtime Tools Help

Q Commands + Code + Text RAM Disk
plt.show()

Department-wise Average Salary and Experience:
Department      Salary  Experience
Finance    93680.750    12.500000
HR         95687.125    12.375000
IT        112647.600    24.800000
Sales     115535.000    20.666667

Employee Count per Department:
Department
HR      8
IT      5
Finance 4
Sales   3
Name: count, dtype: int64

Correlation Between Experience & Salary:
Experience  Salary
Experience  1.000000  0.250745
Salary      0.250745  1.000000

Employee with Highest Salary:
EmployeeID      8
Age             46
Department      Finance
Experience       34
Salary          144637
Name: 7, dtype: object

Employee with Lowest Salary:
EmployeeID      2
Age             28
Department      Finance

3s completed at 10:30 AM
```





