Day 23 – Practical EDA: Applying 7 Core Techniques on a Real Dataset

We learned the **theory of Exploratory Data Analysis (EDA)** — an essential first step in any data science or machine learning project.
We covered the **7 core EDA techniques**:

1. Variable Identification
2. Univariate Analysis
3. Bivariate Analysis
4. Outlier Detection
5. Missing Value Treatment
6. Variable Transformation
7. Variable Creation

What We will Do Today – Day 23

Today, we will put those 7 EDA techniques into **practical use** by applying them to a **real-world sample dataset** that contains common issues such as:

- Dirty text with special characters
- Mixed formats in numerical fields
- Missing values
- Inconsistent formatting

Dataset Preview

Name	Domain	Age	Location	Salary	Exp
Mike	`Datascience#$`	34 years	Mumbai	`5^00#0`	2+
Teddy^	Testing	45' yr	Bangalore	`10%%000`	<3
Umar#r	`Dataanalyst^^#`	NaN	NaN	`1$5%000`	4> yrs
Jane	`Ana^^lytics`	NaN	Hyderbad	`2000^0`	NaN
Uttam*	Statistics	67-yr	NaN	`30000-`	5+ year
Kim	NLP	55yr	Delhi	`6000^$0`	10+

Important Note

Even though this dataset has only 6 rows, the same EDA techniques we apply here can be used on datasets with **thousands or even millions of rows**.

EDA is not about size — it's about understanding, cleaning, and preparing your data for analysis and machine learning.

Plan of Action for Today

We will apply each of the 7 EDA techniques to this dataset in order to:

- Clean inconsistent and messy values
- Handle missing data
- Standardize column types
- Explore data patterns
- Prepare it for machine learning models

Load the Dataset

In [1]:
```
import pandas as pd

# Load the Excel file
df = pd.read_excel(r'C:\Users\aksha\OneDrive\Desktop\Dataset\EDA\Rawdata.xlsx')
```

Basic Data Inspection

In [2]:
```
df.head()  # Displays the first 5 rows
```

Out[2]:

	Name	Domain	Age	Location	Salary	Exp
0	Mike	Datascience#$	34 years	Mumbai	5^00#0	2+
1	Teddy^	Testing	45' yr	Bangalore	10%%000	<3
2	Uma#r	Dataanalyst^^#	NaN	NaN	1$5%000	4> yrs
3	Jane	Ana^^lytics	NaN	Hyderbad	2000^0	NaN
4	Uttam*	Statistics	67-yr	NaN	30000-	5+ year

In [3]:
```
df.tail()  # Displays the last 5 rows
```

Out[3]:

	Name	Domain	Age	Location	Salary	Exp
1	Teddy^	Testing	45' yr	Bangalore	10%%000	<3
2	Uma#r	Dataanalyst^^#	NaN	NaN	1$5%000	4> yrs
3	Jane	Ana^^lytics	NaN	Hyderbad	2000^0	NaN
4	Uttam*	Statistics	67-yr	NaN	30000-	5+ year
5	Kim	NLP	55yr	Delhi	6000^$0	10+

Shape and Columns

In [6]:
```
df.shape        # Returns (rows, columns)
```

Out[6]: (6, 6)

In [5]:
```
df.columns      # Lists all column names
```

Out[5]: Index(['Name', 'Domain', 'Age', 'Location', 'Salary', 'Exp'], dtype='object')

Dataset Summary Information

In [7]:
```
df.info()       # Overview of data types, non-null counts, and memory usage
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6 entries, 0 to 5
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Name      6 non-null      object
 1   Domain    6 non-null      object
 2   Age       4 non-null      object
 3   Location  4 non-null      object
 4   Salary    6 non-null      object
 5   Exp       5 non-null      object
dtypes: object(6)
memory usage: 420.0+ bytes
```

Missing Value Check

In [8]:
```
df.isnull()     # Returns a DataFrame showing True for missing cells
```

Out[8]:

	Name	Domain	Age	Location	Salary	Exp
0	False	False	False	False	False	False
1	False	False	False	False	False	False
2	False	False	True	True	False	False
3	False	False	True	False	False	True
4	False	False	False	True	False	False
5	False	False	False	False	False	False

In [9]:
```
df.isna()       # Same as isnull(), both can be used interchangeably
```

Out[9]:

	Name	Domain	Age	Location	Salary	Exp
0	False	False	False	False	False	False
1	False	False	False	False	False	False
2	False	False	True	True	False	False
3	False	False	True	False	False	True
4	False	False	False	True	False	False
5	False	False	False	False	False	False

In [10]:
```
df.isnull().sum()    # Total number of missing values in each column
```

Out[10]:
```
Name        0
Domain      0
Age         2
Location    2
Salary      0
Exp         1
dtype: int64
```

Quick Tip:

- isnull() and isna() are functionally identical in Pandas.
- Use .sum() to quickly check how many missing values exist column-wise.

Rename DataFrame

In [11]:
```
emp = df  # Now you can use emp instead of df
```

In [12]:
```
emp
```

Out[12]:

	Name	Domain	Age	Location	Salary	Exp
0	Mike	Datascience#$	34 years	Mumbai	5^00#0	2+
1	Teddy^	Testing	45' yr	Bangalore	10%%000	<3
2	Uma#r	Dataanalyst^^#	NaN	NaN	1$5%000	4> yrs
3	Jane	Ana^^lytics	NaN	Hyderbad	2000^0	NaN
4	Uttam*	Statistics	67-yr	NaN	30000-	5+ year
5	Kim	NLP	55yr	Delhi	6000^$0	10+

Data Cleaning

Remove all non-word characters from the 'Name' column

In [13]:
```
# Remove all non-word characters from the 'Name' column
emp['Name'] = emp['Name'].str.replace(r'\W', '', regex=True)
```

In [14]:
```
emp
```

Out[14]:

	Name	Domain	Age	Location	Salary	Exp
0	Mike	Datascience#$	34 years	Mumbai	5^00#0	2+
1	Teddy	Testing	45' yr	Bangalore	10%%000	<3
2	Umar	Dataanalyst^^#	NaN	NaN	1$5%000	4> yrs
3	Jane	Ana^^lytics	NaN	Hyderbad	2000^0	NaN
4	Uttam	Statistics	67-yr	NaN	30000-	5+ year
5	Kim	NLP	55yr	Delhi	6000^$0	10+

.str.replace(r'\W', '', regex=True) means:

\W → Matches anything that is NOT a letter, number, or underscore

Removes special characters like @, #, !, spaces, etc.

Keeps only letters, digits, and underscores

Clean Domain Column

In [15]:
```
# Clean Domain Column
emp['Domain'] = emp['Domain'].str.replace(r'\W', '', regex=True)
# Removes symbols like #$%^ from the domain field
```

In [43]:
```
emp['Domain']
```

Out[43]:
```
0    Datascience
1        Testing
2    Dataanalyst
3      Analytics
4     Statistics
5            NLP
Name: Domain, dtype: object
```

Clean and Extract Numbers from Age Column

In [16]:
```
# Remove non-word characters
emp['Age'] = emp['Age'].str.replace(r'\W', '', regex=True)

# Extract numeric part from age using regex
emp['Age'] = emp['Age'].str.extract(r'(\d+)')b
```

In [44]:
```
emp['Age']
```

Out[44]:
```
0     34
1     45
2    NaN
3    NaN
4     67
5     55
Name: Age, dtype: object
```

`(\d+)` explanation:

\d → digit (0–9)

+ → one or more digits

() → capture only the number part
This extracts numbers like 34 from values like '34 years', '67-yr', etc.

Clean Location Column

In [17]:
```
emp['Location'] = emp['Location'].str.replace(r'\W', '', regex=True)
```

Clean Salary Column

In [18]:
```
emp['Salary'] = emp['Salary'].str.replace(r'\W', '', regex=True)
```

Extract Experience from Exp Column

In [19]:
```
emp['Exp'] = emp['Exp'].str.extract(r'(\d+)')
# Gets numeric part from values like 2+, 4> yrs, 5+ year
```

In [20]:
```
clean_data = emp.copy()
```

EDA Technique

Handle Missing Values in 'Age' Column

In [21]:
```
import numpy as np
import pandas as pd

# If 'Age' is not yet numeric, convert it
clean_data['Age'] = pd.to_numeric(clean_data['Age'])

# Fill missing Age values with the mean of the column
clean_data['Age'] = clean_data['Age'].fillna(np.mean(clean_data['Age']))
```

Handle Missing Values in 'Exp' Column

In [22]:
```
clean_data['Exp'] = pd.to_numeric(clean_data['Exp'])  # Ensure it's numeric
clean_data['Exp'] = clean_data['Exp'].fillna(np.mean(clean_data['Exp']))
```

Handle Missing Values in 'Location' Column (Categorical)

In [23]:
```
# Fill missing Location values with the most frequent value (mode)
clean_data['Location'] = clean_data['Location'].fillna(clean_data['Location'].mode
```

Convert Data Types

After cleaning, we should convert data types to appropriate formats for better performance and memory usage.

In [24]:
```
# Convert numeric columns to int
clean_data['Age'] = clean_data['Age'].astype(int)
clean_data['Exp'] = clean_data['Exp'].astype(int)
clean_data['Salary'] = clean_data['Salary'].astype(int)

# Convert object columns with limited unique values to category
clean_data['Name'] = clean_data['Name'].astype('category')
clean_data['Domain'] = clean_data['Domain'].astype('category')
clean_data['Location'] = clean_data['Location'].astype('category')
```

Final Check: Data Summary

In [25]:
```
clean_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6 entries, 0 to 5
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Name      6 non-null      category
 1   Domain    6 non-null      category
 2   Age       6 non-null      int32
 3   Location  6 non-null      category
 4   Salary    6 non-null      int32
 5   Exp       6 non-null      int32
dtypes: category(3), int32(3)
memory usage: 866.0 bytes
```

Save Cleaned Data to CSV

In [26]:
```
clean_data.to_csv('Clean_data.csv', index=False)
```

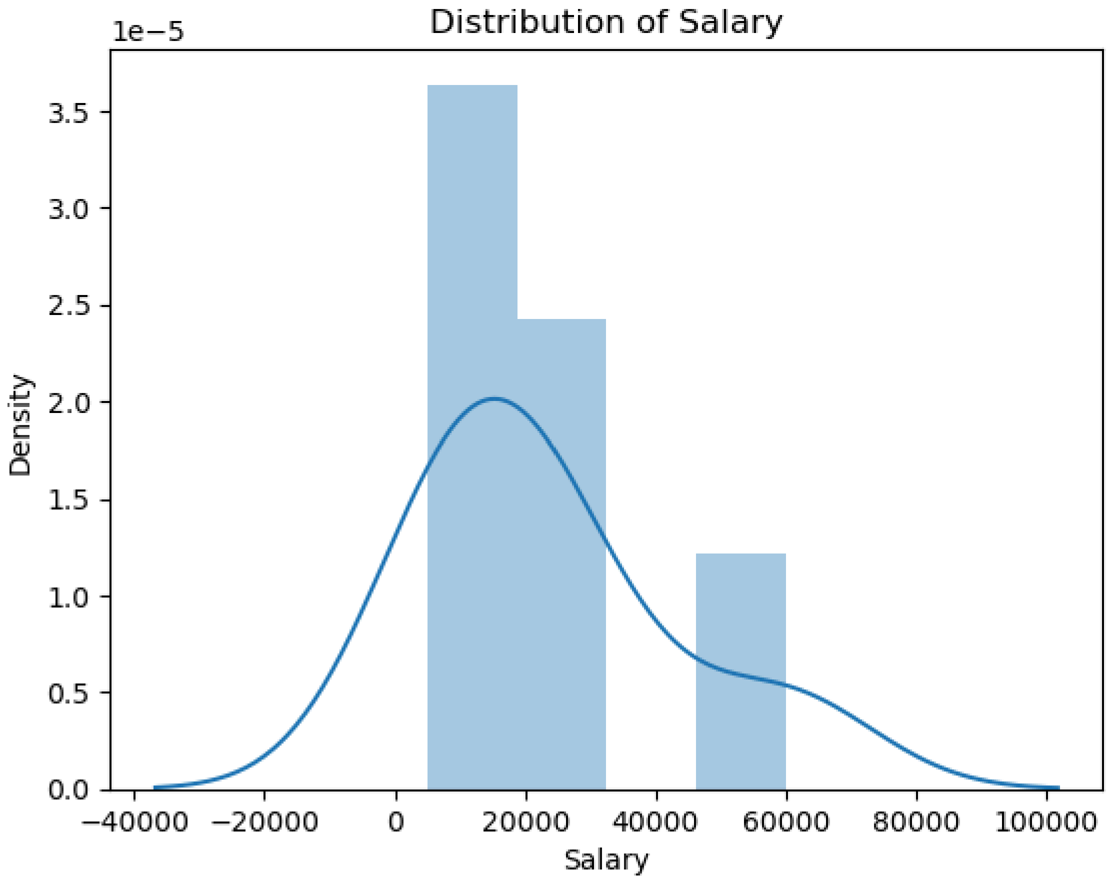
In [27]:
```
# Check your current working directory using:
import os
os.getcwd()
```

Out[27]:
```
'C:\\Users\\aksha\\OneDrive\\Desktop\\Full stack Data Science course\\GITHUB Uplo
ads\\4_EDA_Exploratory_Data_Analysis'
```

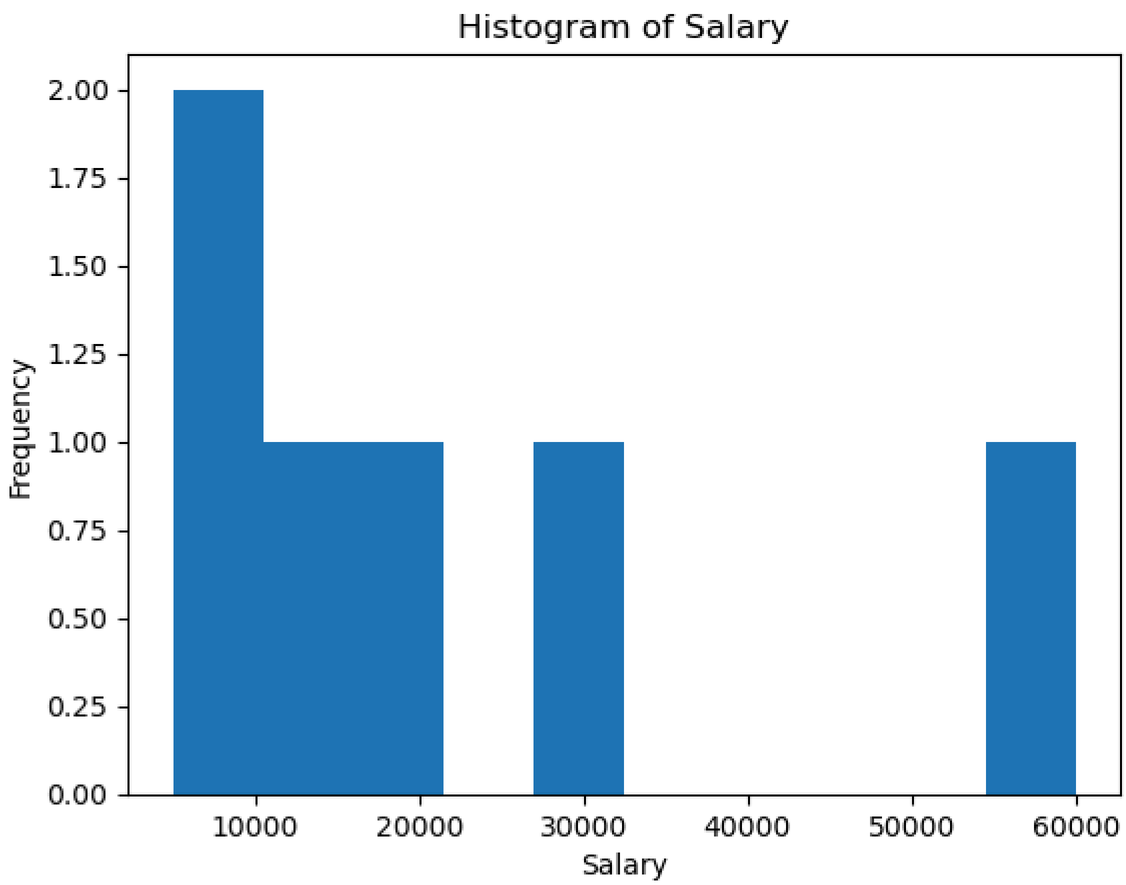
In [28]:
```
# Import Libraries
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Univariate Visualization

In [29]:
```
# Distribution Plot - Salary
sns.distplot(clean_data['Salary'])  # KDE + Histogram
plt.title("Distribution of Salary")
plt.show()
```



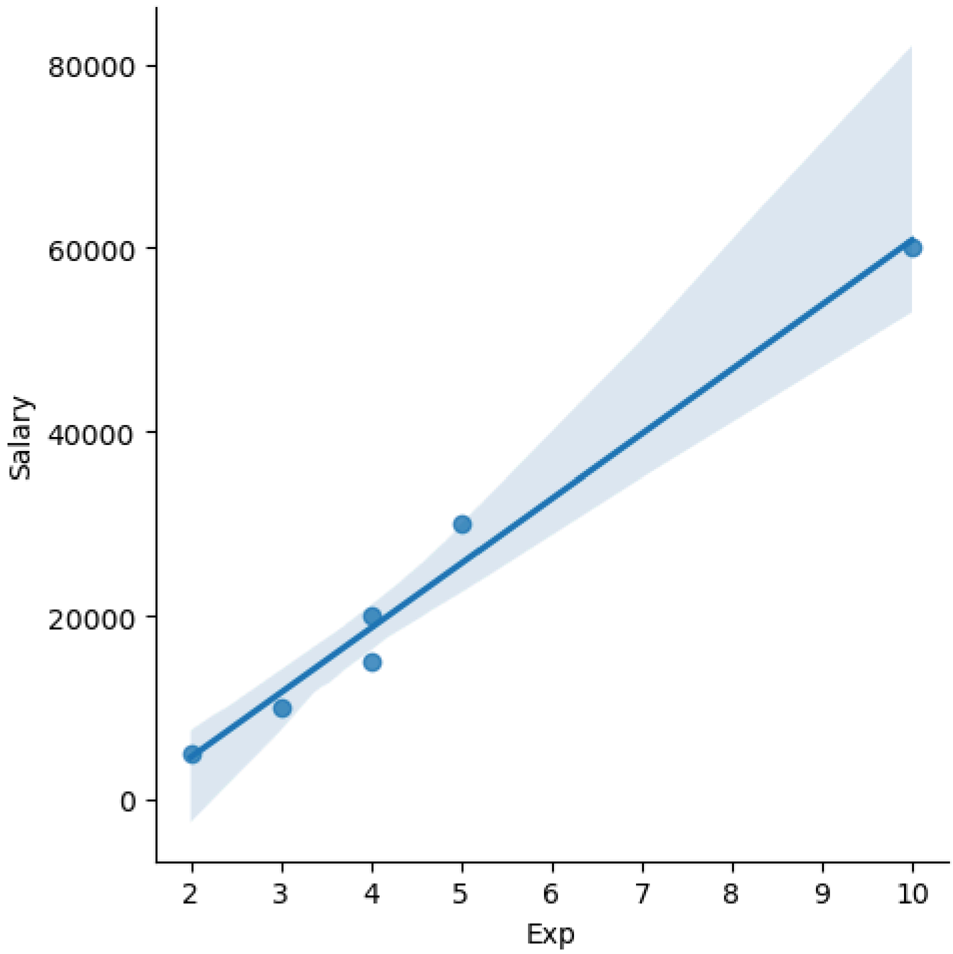
In [30]:
```
# Histogram - Salary
plt.hist(clean_data['Salary'])
plt.title("Histogram of Salary")
plt.xlabel("Salary")
plt.ylabel("Frequency")
plt.show()
```



Bivariate Visualization

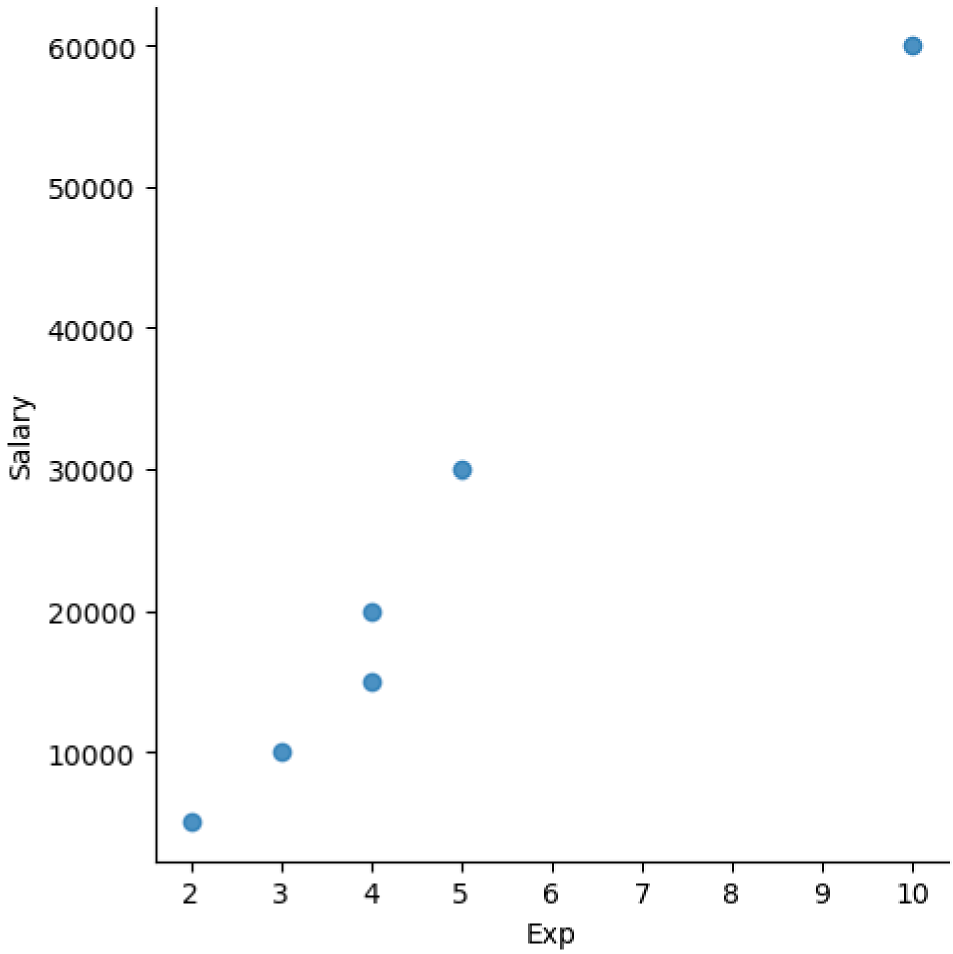
In [31]:
```
# Scatter Plot with Regression Line - Exp vs Salary
sns.lmplot(data=clean_data, x='Exp', y='Salary')  # Includes regression line
```

Out[31]: <seaborn.axisgrid.FacetGrid at 0x213490bd3a0>



In [32]:
```
# Scatter Plot without Regression Line - Exp vs Salary
sns.lmplot(data=clean_data, x='Exp', y='Salary', fit_reg=False)
```

Out[32]:
```
<seaborn.axisgrid.FacetGrid at 0x2134a267d10>
```



Slicing and Indexing

In [34]:
```
clean_data[:]        # All rows
```

Out[34]:

	Name	Domain	Age	Location	Salary	Exp
0	Mike	Datascience	34	Mumbai	5000	2
1	Teddy	Testing	45	Bangalore	10000	3
2	Umar	Dataanalyst	50	Bangalore	15000	4
3	Jane	Analytics	50	Hyderbad	20000	4
4	Uttam	Statistics	67	Bangalore	30000	5
5	Kim	NLP	55	Delhi	60000	10

In [35]:
```
clean_data[0:6:2]    # Every second row from first 6
```

Out[35]:

	Name	Domain	Age	Location	Salary	Exp
0	Mike	Datascience	34	Mumbai	5000	2
2	Umar	Dataanalyst	50	Bangalore	15000	4
4	Uttam	Statistics	67	Bangalore	30000	5

In [36]:
```
clean_data[::-1]     # Reverse order of rows
```

Out[36]:

	Name	Domain	Age	Location	Salary	Exp
5	Kim	NLP	55	Delhi	60000	10
4	Uttam	Statistics	67	Bangalore	30000	5
3	Jane	Analytics	50	Hyderbad	20000	4
2	Umar	Dataanalyst	50	Bangalore	15000	4
1	Teddy	Testing	45	Bangalore	10000	3
0	Mike	Datascience	34	Mumbai	5000	2

Splitting Features (X_iv) and Target (y_dv)

In [37]:
```
X_iv = clean_data[['Name', 'Domain', 'Age', 'Location', 'Exp']]  # Independent var
```

In [38]:
```
X_iv
```

Out[38]:

	Name	Domain	Age	Location	Exp
0	Mike	Datascience	34	Mumbai	2
1	Teddy	Testing	45	Bangalore	3
2	Umar	Dataanalyst	50	Bangalore	4
3	Jane	Analytics	50	Hyderbad	4
4	Uttam	Statistics	67	Bangalore	5
5	Kim	NLP	55	Delhi	10

In [39]:
```
y_dv = clean_data[['Salary']]                                         # Dependent var
```

In [40]:
```
y_dv
```

Out[40]:

	Salary
0	5000
1	10000
2	15000
3	20000
4	30000
5	60000

One-Hot Encoding for Categorical Variables

In [41]:
```
imputation = pd.get_dummies(clean_data)  # Converts categories to 0/1 columns
```

In [42]:
```
imputation
```

Out[42]:

	Age	Salary	Exp	Name_Jane	Name_Kim	Name_Mike	Name_Teddy	Name_Umar	N
0	34	5000	2	False	False	True	False	False	
1	45	10000	3	False	False	False	True	False	
2	50	15000	4	False	False	False	False	True	
3	50	20000	4	True	False	False	False	False	
4	67	30000	5	False	False	False	False	False	
5	55	60000	10	False	True	False	False	False	

We’re now ready to move on to model building, feature selection, and machine learning in the next phase.