NAME:SHIVAM MAKHIJA ROLL NO:32 D15C

Aim: Introduction to Data science and Data preparation using Pandas steps.

Theory:

Data preparation is a fundamental step in data science, involving the cleaning and transformation of raw data into a structured and analyzable format. Pandas, a powerful
The Python library provides efficient tools for handling missing values, encoding categorical data, and scaling numerical features. Proper preprocessing enhances dataset quality, ensuring consistency and reliability for further analysis and machine learning models.

Problem Statement:

The Placement Data dataset contains various attributes related to students' academic performance, placement status, and salary packages. The objective of this experiment is to:

● Identify key trends in student placements based on academic performance. ● Analyze the distribution of salary packages.
● Handle missing data and remove inconsistencies.
● Standardize and normalize the data for further analysis.

By cleaning the placement dataset and applying data preprocessing steps, the goal is to improve data reliability, analyze student performance trends, and provide valuable insights for academic and recruitment decisions.

Dataset Overview:

The dataset provides detailed insights into company layoffs, capturing various aspects of workforce reductions across different organizations. It includes multiple columns, each representing specific attributes related to the companies, their locations, and the nature of the layoffs. The dataset helps analyze trends and patterns in employee terminations and business impacts across industries. The columns featured in the dataset include:

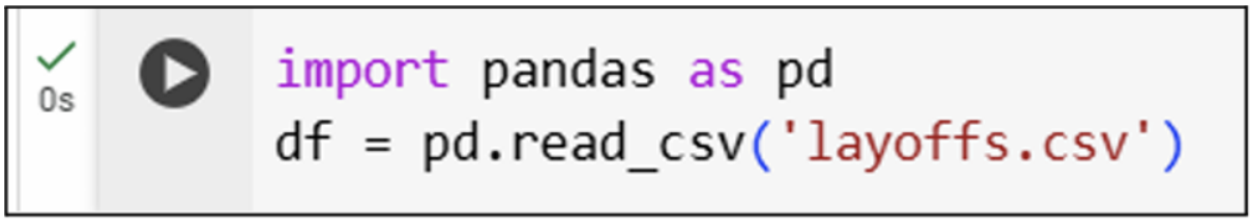
1. Company: Name of the company where layoffs occurred.
2. Location_HQ: Headquarters location of the company.
3. Region: Geographical region (if specified).
4. State: State where the headquarters is located.
5. Country: Country of the company's headquarters.
6. Continent: Continent where the company is based.
7. Laid_Off: Number of employees who were laid off.
8. Date_layoffs: Date on which the layoff event occurred.
9. Percentage: Proportion of total staff that was laid off..
10. Company_Size_before_Layoffs: Number of employees before the layoff.
11. Company_Size_after_layoffs: Number of employees after the layoff
12. Industry: Industry category the company belongs to

13. **Stage**: Business stage or funding round of the company (e.g., Seed, Series A, etc.). **Money_Raised_in__mil**: Total funds raised by the company in millions.
14. **Year**: Year in which the layoff took place.
    Longitude: Geographical longitude of the company's location.
15. **Latitude**: Geographical latitude of the company's location.

Steps:

Loading the Dataset:

The first step involves loading the dataset into a DataFrame using Pandas. This is typically done using the read_csv() function if the data is in CSV format:



Description of Dataset.

1. Information about the Dataset.

Use functions like .head(), .tail(), .shape, and .describe() to get a general idea of what the dataset looks like**.**

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1839 entries, 0 to 1838
Data columns (total 18 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   #                             1839 non-null   int64
 1   Company                       1839 non-null   object
 2   Location_HQ                   1839 non-null   object
 3   Region                        473 non-null    object
 4   State                         566 non-null    object
 5   Country                       1839 non-null   object
 6   Continent                     1839 non-null   object
 7   Laid_Off                      1677 non-null   float64
 8   Date_layoffs                  1839 non-null   object
 9   Percentage                    1667 non-null   object
 10  Company_Size_before_Layoffs   1585 non-null   object
 11  Company_Size_after_layoffs    1619 non-null   object
 12  Industry                      1839 non-null   object
 13  Stage                         1839 non-null   object
 14  Money_Raised_in__mil          1692 non-null   float64
 15  Year                          1839 non-null   int64
 16  latitude                      1839 non-null   float64
 17  longitude                     1839 non-null   float64
dtypes: float64(4), int64(2), object(12)
memory usage: 258.7+ KB
```

2. Drop the columns that are not useful.

```
import pandas as pd
df = pd.read_csv('layoffs.csv')
cols = ['latitude', 'longitude']
df = df.drop(cols, axis=1)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1839 entries, 0 to 1838
Data columns (total 16 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   #                             1839 non-null   int64
 1   Company                       1839 non-null   object
 2   Location_HQ                   1839 non-null   object
 3   Region                        473 non-null    object
 4   State                         566 non-null    object
 5   Country                       1839 non-null   object
 6   Continent                     1839 non-null   object
 7   Laid_Off                      1677 non-null   float64
 8   Date_layoffs                  1839 non-null   object
 9   Percentage                    1667 non-null   object
 10  Company_Size_before_Layoffs   1585 non-null   object
 11  Company_Size_after_layoffs    1619 non-null   object
 12  Industry                      1839 non-null   object
 13  Stage                         1839 non-null   object
 14  Money_Raised_in__mil          1692 non-null   float64
 15  Year                          1839 non-null   int64
dtypes: float64(2), int64(2), object(12)
memory usage: 230.0+ KB
```

Columns Present in the Database are:

The .info() method provides insight into the structure of the dataset — data types, non-null values, and memory usage:

3. Now we will drop the rows with missing.

Sometimes, some columns do not contribute any meaningful information to the analysis. For example, StudentID might be dropped if it is only a unique identifier.

```
import pandas as pd
df = pd.read_csv('layoffs.csv')
cols = ['latitude', 'longitude']
df = df.drop(cols, axis=1)
df = df.dropna()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 403 entries, 2 to 1836
Data columns (total 16 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   #                            403 non-null    int64  
 1   Company                      403 non-null    object 
 2   Location_HQ                  403 non-null    object 
 3   Region                       403 non-null    object 
 4   State                        403 non-null    object 
 5   Country                      403 non-null    object 
 6   Continent                    403 non-null    object 
 7   Laid_Off                     403 non-null    float64
 8   Date_layoffs                 403 non-null    object 
 9   Percentage                   403 non-null    object 
 10  Company_Size_before_Layoffs  403 non-null    object 
 11  Company_Size_after_layoffs   403 non-null    object 
 12  Industry                     403 non-null    object 
 13  Stage                        403 non-null    object 
 14  Money_Raised_in__mil         403 non-null    float64
 15  Year                         403 non-null    int64  
dtypes: float64(2), int64(2), object(12)
memory usage: 53.5+ KB
```

4. Now we are creating dummy variables:

Categorical columns like Placement Training or Placement Status need to be converted to numeric format using dummy variables:

```
import pandas as pd
df = pd.read_csv('layoffs.csv')
cols = ['latitude', 'longitude']
df = df.drop(cols, axis=1)
df = df.dropna()
dummies = []
cols = ['State', 'Stage',]
for col in cols:
   dummies.append(pd.get_dummies(df[col]))
layoffs_dummies = pd.concat(dummies, axis=1)
df = pd.concat((df,layoffs_dummies), axis=1)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 403 entries, 2 to 1836
Data columns (total 32 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   #                           403 non-null    int64
 1   Company                     403 non-null    object
 2   Location_HQ                 403 non-null    object
 3   Region                      403 non-null    object
 4   State                       403 non-null    object
 5   Country                     403 non-null    object
 6   Continent                   403 non-null    object
 7   Laid_Off                    403 non-null    float64
 8   Date_layoffs                403 non-null    object
```

5. Taking care of missing data.

Instead of dropping, sometimes missing data is filled with appropriate values:

```
import pandas as pd
df = pd.read_csv('layoffs.csv')
df['Money_Raised_in__mil'] = df['Money_Raised_in__mil'].interpolate()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1839 entries, 0 to 1838
Data columns (total 18 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   #                             1839 non-null   int64
 1   Company                       1839 non-null   object
 2   Location_HQ                   1839 non-null   object
 3   Region                        473 non-null    object
 4   State                         566 non-null    object
 5   Country                       1839 non-null   object
 6   Continent                     1839 non-null   object
 7   Laid_Off                      1677 non-null   float64
 8   Date_layoffs                  1839 non-null   object
 9   Percentage                    1667 non-null   object
 10  Company_Size_before_Layoffs   1585 non-null   object
 11  Company_Size_after_layoffs    1619 non-null   object
 12  Industry                      1839 non-null   object
 13  Stage                         1839 non-null   object
 14  Money_Raised_in__mil          1839 non-null   float64
 15  Year                          1839 non-null   int64
 16  latitude                      1839 non-null   float64
 17  longitude                     1839 non-null   float64
dtypes: float64(4), int64(2), object(12)
memory usage: 258.7+ KB
```

6. Finding out outliners:

Outliers can skew the analysis. They can be detected using statistical methods like the IQR method or visualizations like box plots.

```python
import pandas as pd

# Load dataset
df = pd.read_csv('layoffs.csv')

# Interpolate missing values
df['Money_Raised_in__mil'] = df['Money_Raised_in__mil'].interpolate()

# Function to detect outliers using IQR
def find_outliers_iqr(data, column):
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = data[(data[column] < lower_bound) | (data[column] > upper_bound)]
    return outliers

# Find outliers in 'Money_Raised_in__mil' column
outliers = find_outliers_iqr(df, 'Money_Raised_in__mil')
print("Outliers based on IQR method:\n", outliers)
```

7. Normalization the columns: Normalization scales the data to a range (usually 0 to 1). It's useful when features have different units or scales:

```python
from sklearn.preprocessing import MinMaxScaler

# Initialize the MinMaxScaler
scaler = MinMaxScaler()

# Normalize the 'Money_Raised_in__mil' column
df['Money_Raised_Normalized'] = scaler.fit_transform(df[['Money_Raised_in__mil']])

print(df[['Money_Raised_in__mil', 'Money_Raised_Normalized']].head())
```

```
   Money_Raised_in__mil  Money_Raised_Normalized
0                  90.0                 0.000730
1                  45.0                 0.000361
2                   1.0                 0.000000
3                   6.0                 0.000041
4                  79.0                 0.000640
```

8. Standardization the columns :

Standardization rescales data to have a mean of 0 and a standard deviation of 1. It's particularly useful for algorithms like SVM or KNN:

```
from sklearn.preprocessing import StandardScaler

# Initialize the StandardScaler
scaler = StandardScaler()

# Standardize the 'Money_Raised_in__mil' column
df['Money_Raised_Standardized'] = scaler.fit_transform(df[['Money_Raised_in__mil']])

print(df[['Money_Raised_in__mil', 'Money_Raised_Standardized']].head())
```

```
   Money_Raised_in__mil  Money_Raised_Standardized
0                  90.0                  -0.133289
1                  45.0                  -0.143487
2                   1.0                  -0.153458
3                   6.0                  -0.152325
4                  79.0                  -0.135782
```

Conclusion:

In this experiment, we emphasized the significance of data preparation within the data science workflow using the Pandas library. Utilizing a student placement dataset, we carried out key preprocessing tasks such as addressing missing values, correcting data inconsistencies, encoding categorical features, and normalizing numerical attributes. These processes were crucial in converting the raw data into a well-organized and uniform format suitable for detailed analysis. Consequently, we were able to uncover valuable patterns in student placement trends, examine salary distributions, and assess the influence of academic performance, internships, soft skills, and training on placement outcomes. This data preparation enhanced the dataset's reliability and laid a solid groundwork for future analytical efforts and informed decision-making in both academic and recruitment settings.