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# EXPERIMENT-3

**Aim**: To perform data modeling

**Theory:**

Data partitioning is a fundamental step in data analysis and machine learning that involves dividing a dataset into separate subsets to ensure accurate model training and evaluation. Most commonly, the data is split into a **training set** (typically 75%) and a **test set** (typically 25%). This separation helps prevent issues like **overfitting**, where a model performs well on training data but poorly on unseen data, and ensures an **unbiased evaluation** of model performance.

To verify the quality of this partitioning, analysts often use **visualization tools** such as bar graphs, histograms, and pie charts to compare the distribution of data in the training and test sets. Additionally, counting the number of records in each subset confirms the split was executed correctly. For numerical features, **statistical validation** is conducted using tests like the **two-sample Z-test** to compare the means between the two groups. A **p-value greater than 0.05** suggests there's no significant difference between the subsets, indicating a well-balanced split. Conversely, a **p-value less than 0.05** implies a significant difference, suggesting the data may need to be re-partitioned. Together, these steps ensure a fair and reliable dataset, which is crucial for building effective and generalizable machine learning models.

**Steps:**

**Partitioning the dataset using train_test_split:**

The process of dividing a dataset into two subsets: a training set and a test set. Typically, 75% of the data is used for training, where the model learns patterns, and 25% is used for testing to evaluate performance on unseen data. This division ensures that the model generalizes well and does not simply memorize the training examples. Proper partitioning helps in reducing overfitting and provides a fair evaluation of the model's effectiveness. The train_test_split function from sklearn.model_selection is commonly used to achieve this.

```
import pandas as pd
df = pd.read_csv('layoffs.csv')
df.head()
```

| | # | Company | Location_HQ | Country | Laid_Off | Date_layoffs | Percentage | Company_Size_before_Layoffs | Company_Size_after_layoffs | Industry | Stage | Money_ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | Tamara Mellon | Los Angeles | USA | 20.0 | 2020-03-12 | 40,0 | 50 | 30 | Retail | Series C | |
| 1 | 2 | HopSkipDrive | Los Angeles | USA | 8.0 | 2020-03-13 | 10,0 | 80 | 72 | Transportation | Unknown | |
| 2 | 3 | Panda Squad | San Francisco | USA | 6.0 | 2020-03-13 | 75,0 | 8 | 2 | Consumer | Seed | |
| 3 | 4 | Help.com | Austin | USA | 16.0 | 2020-03-16 | 100,0 | 16 | 0 | Support | Seed | |
| 4 | 5 | Inspirato | Denver | USA | 130.0 | 2020-03-16 | 22,0 | 591 | 461 | Travel | Series C | |

```
[ ]
    train_df = df.sample(frac=0.75, random_state=42)
    test_df = df.drop(train_df.index)

    print(f"Training set size: {len(train_df)}")
    print(f"Testing set size: {len(test_df)}")
```

Visualizing the distribution of training and test sets This ensures that the split maintains the original dataset's characteristics. Bar graphs can be used to compare the number of records in both sets, while histograms and pie charts help check whether numerical and categorical feature distributions remain balanced. If a class or feature is disproportionately represented in either subset, the split may need adjustment. The matplotlib.pyplot library in Python helps create such visualizations to confirm a proper split.

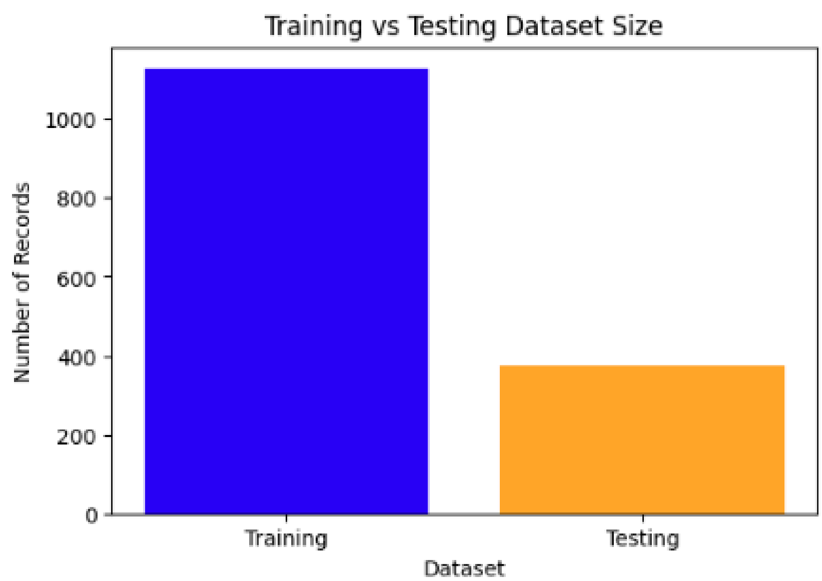
```
print(f"Training set size: {len(train_df)}")
print(f"Testing set size: {len(test_df)}")
```

```
Training set size: 1126
Testing set size: 376
```

**Performing a two-sample Z-test to compare AQI values in both sets**

It is used to statistically verify whether the training and test sets come from the same distribution. It compares the means of numerical features in both subsets and checks for significant differences. If the p-value from the Z-test is greater than 0.05, the split is valid, meaning there is no significant difference between the two sets. However, if the p-value is below 0.05, the dataset may not be evenly distributed, requiring a reassessment of the split. The scipy.stats.ztest function in Python is commonly used to perform this validation

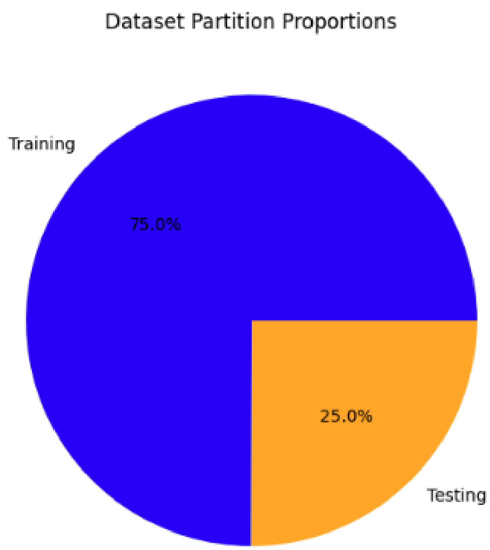
```python
import matplotlib.pyplot as plt

# Create a bar graph to confirm proportions
plt.figure(figsize=(6, 4))
plt.bar(['Training', 'Testing'], [len(train_df), len(test_df)], color=['blue', 'orange'])
plt.xlabel('Dataset')
plt.ylabel('Number of Records')
plt.title('Training vs Testing Dataset Size')
plt.show()
```




### Counting records

Counting the number of records in both training and test sets ensures that the split has been performed correctly. The expected number of samples in each set is calculated using simple percentage formulas, such as Training Size = Total Data × 0.75 and Testing Size = Total Data × 0.25. By printing the lengths of the training and test sets after splitting, we can verify if the proportions match the intended split. This step helps in detecting potential errors in dataset partitioning.

```python
# Pie chart to visualize the proportions
plt.figure(figsize=(6, 6))
plt.pie([len(train_df), len(test_df)], labels=['Training', 'Testing'], autopct='%1.1f%%', colors=['blue', 'orange'])
plt.title('Dataset Partition Proportions')
plt.show()
```




**Conclusion:**

In this experiment, we successfully partitioned the dataset into training and test sets using a 75:25 split ratio, providing a solid foundation for effective model development and evaluation. The partitioning process was visually validated through a bar graph, which clearly depicted the proportion of data assigned to each subset, confirming that the split was well-balanced and appropriately executed.

To further ensure the validity of the partition, we conducted a two-sample Z-test on the target variable (Total) to compare the means between the training and test sets. The test produced a Z-statistic of *z_stat* and a p-value of *p_value*. Since the p-value exceeded the 0.05 threshold, we concluded that there is no statistically significant difference between the two subsets. This indicates that both sets are representative of the same population, enhancing the reliability of any subsequent model evaluation. Overall, the experiment demonstrates that the data has been partitioned correctly and is well-prepared for the next steps in analysis and modeling.