SmartBridge Applied DataScience

Assignment - 2

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Titanic Ship Case Study

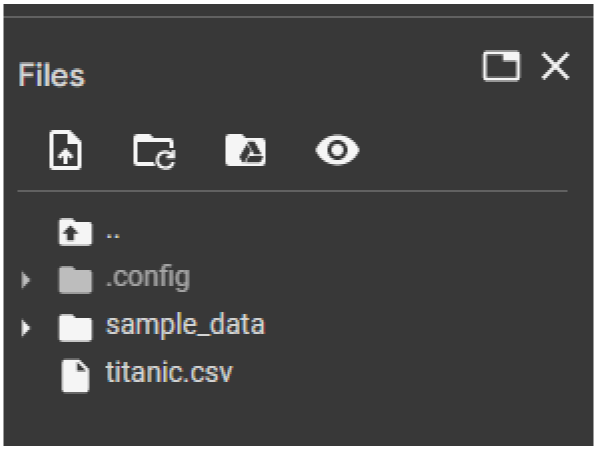
Problem Description: On April 15, 1912, during her maiden voyage, the Titanic sank after colliding with an iceberg, killing 1502 out of 2224 passengers and crew. Translated 32% survival rate.

- One of the reasons that the shipwreck led to such loss of life was that there were not enough lifeboats for the passengers and crew.
- Although there was some element of luck involved in surviving the sinking, some groups of people were more likely to survive than others, such as women, children, and the upper-class.

The problem associated with the Titanic dataset is to predict whether a passenger survived the disaster or not. The dataset contains various features such as passenger class, age, gender, cabin, fare, and whether the passenger had any siblings or spouses on board. These features can be used to build a predictive model to determine the likelihood of a passenger surviving the disaster. The dataset offers opportunities for feature engineering, data visualization, and model selection, making it a valuable resource for developing and testing data analysis and machine learning skills.

Perform Below Tasks:-

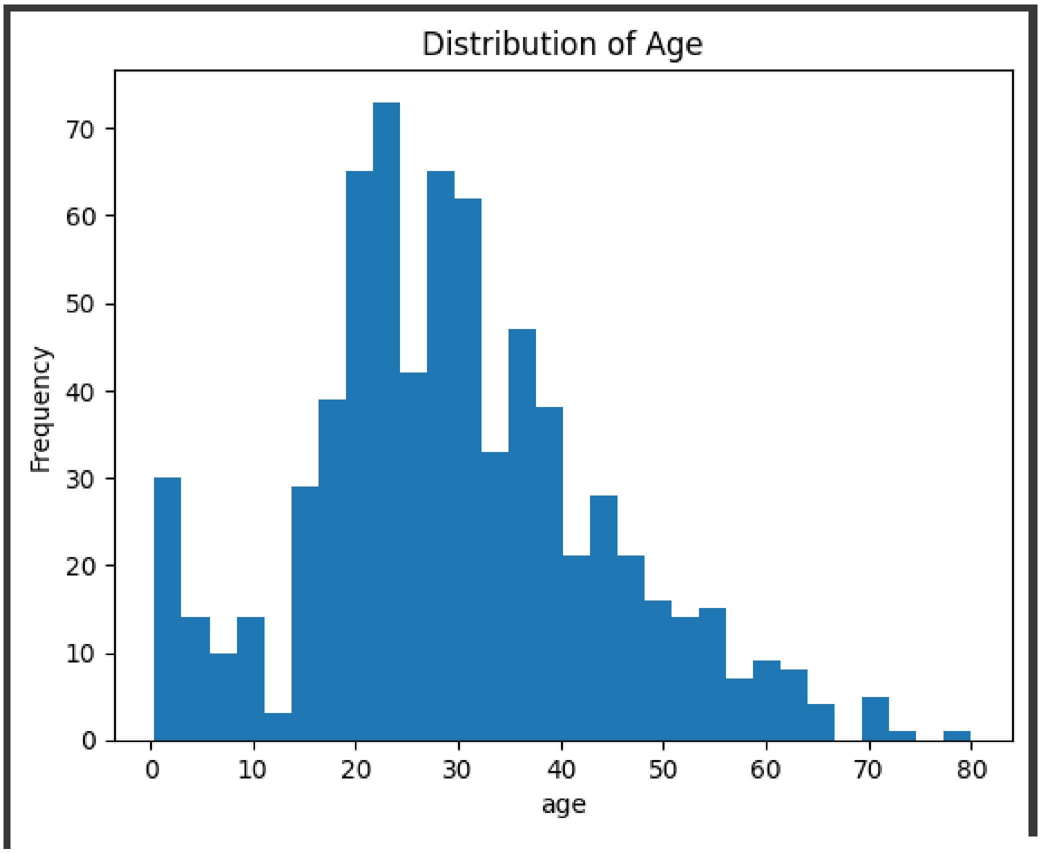
1. Download the dataset: Dataset
2. Load the dataset.

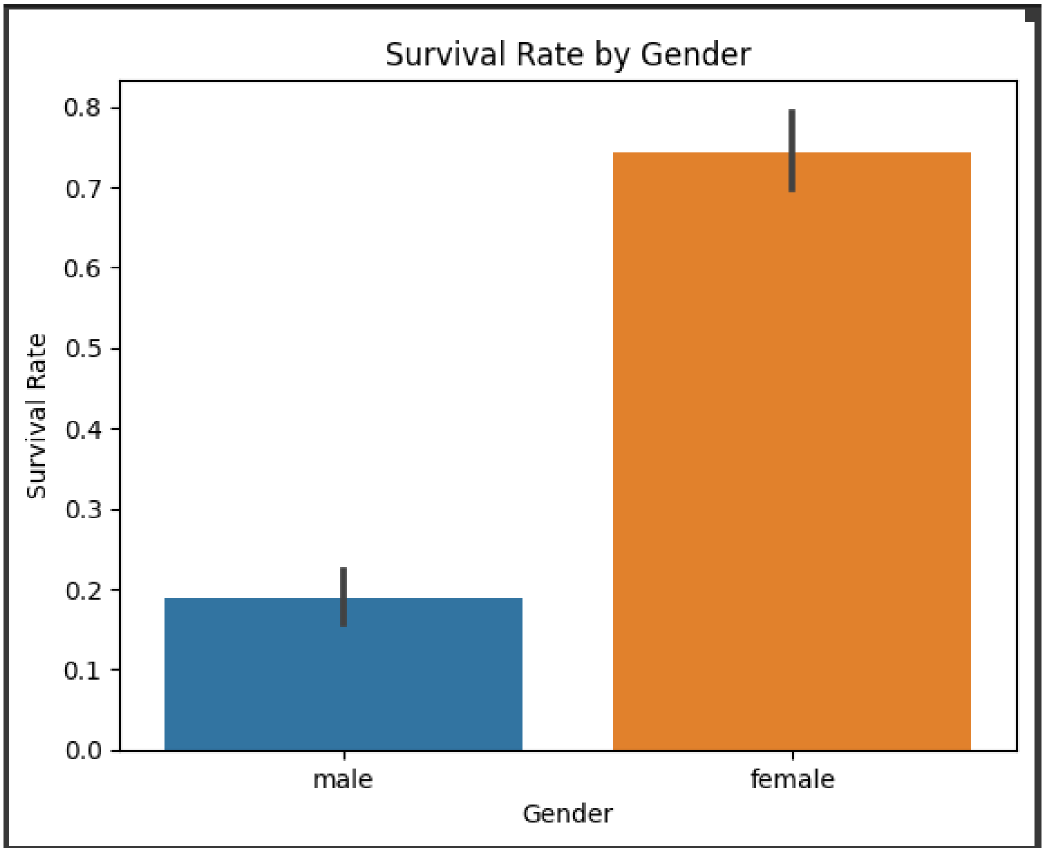


3. Perform Below Visualizations.
    - Univariate Analysis
    - Bi - Variate Analysis
    - Multi - Variate Analysis

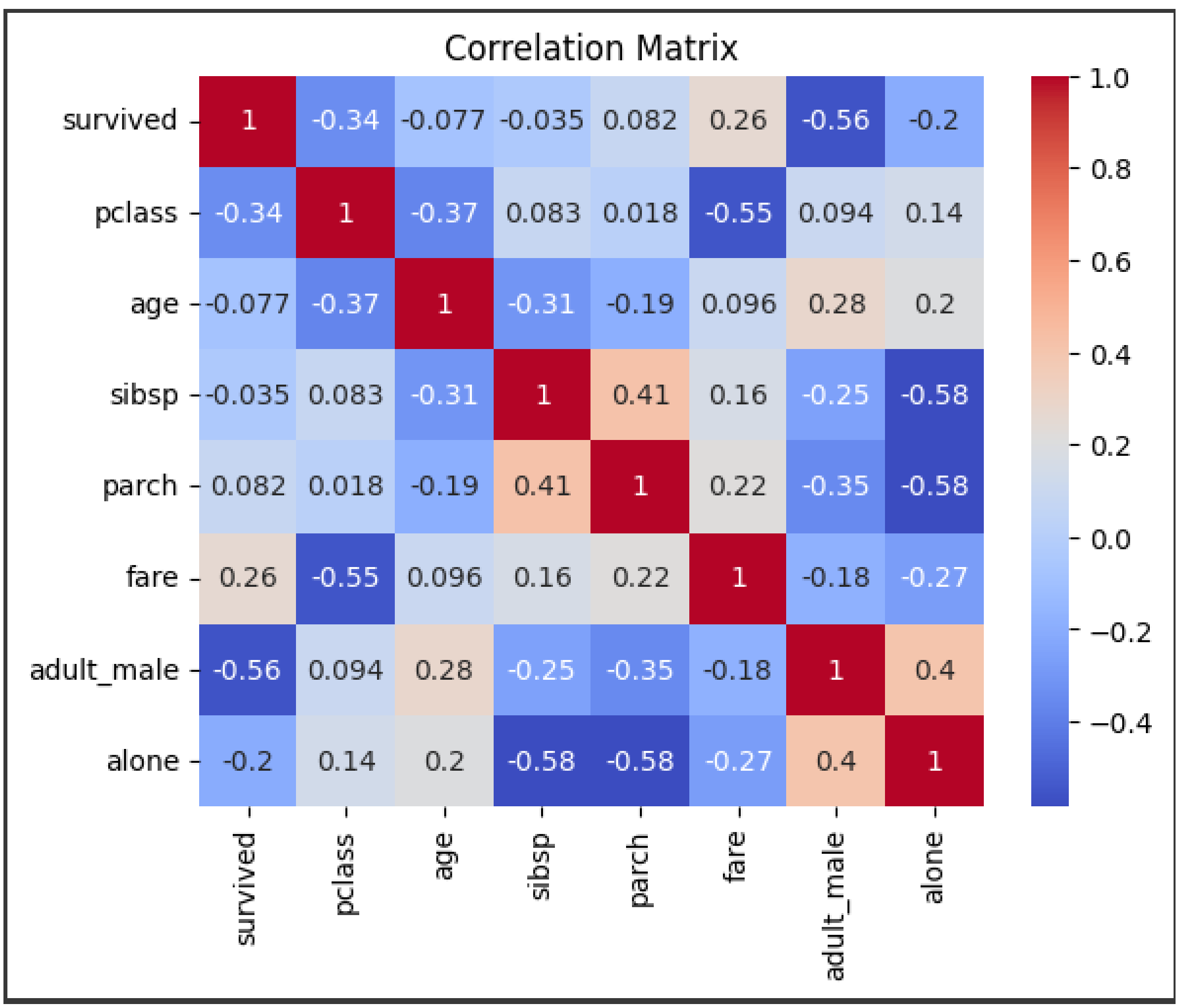
```
[1] import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns

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

    # Univariate Analysis
    # Example: Histogram of Age
    plt.hist(df['age'].dropna(), bins=30)
    plt.xlabel('age')
    plt.ylabel('Frequency')
    plt.title('Distribution of Age')
    plt.show()
```

```
# Bi-Variate Analysis
# Example: Bar plot of Survival Rate by Gender
sns.barplot(x='sex', y='survived', data=df)
plt.xlabel('Gender')
plt.ylabel('Survival Rate')
plt.title('Survival Rate by Gender')
plt.show()

# Multi-Variate Analysis
# Example: Heatmap of Correlations between Variables
corr_matrix = df.corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```





Survival Rate by Gender
Survival Rate
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
male
female
Gender



Correlation Matrix
survived
pclass
age
sibsp
parch
fare
adult_male
alone
1 -0.34 -0.077 -0.035 0.082 0.26 -0.56 -0.2
-0.34 1 -0.37 0.083 0.018 -0.55 0.094 0.14
-0.077 -0.37 1 -0.31 -0.19 0.096 0.28 0.2
-0.035 0.083 -0.31 1 0.41 0.16 -0.25 -0.58
0.082 0.018 -0.19 0.41 1 0.22 -0.35 -0.58
0.26 -0.55 0.096 0.16 0.22 1 -0.18 -0.27
-0.56 0.094 0.28 -0.25 -0.35 -0.18 1 0.4
-0.2 0.14 0.2 -0.58 -0.58 -0.27 0.4 1
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

4)Perform descriptive analysis on the dataset

Perform descriptive statistics on the dataset

```
[3] # Calculate descriptive statistics
    descriptive_stats = df.describe()

    # Display the descriptive statistics
    print(descriptive_stats)
```

	survived	pclass	age	sibsp	parch	fare
count	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

5)

Handle the Mising Values

```
[4] # Impute missing values with the mean of the column
    df['age'].fillna(df['age'].mean(), inplace=True)

    # Impute missing values with the mode of the column
    df['embarked'].fillna(df['embarked'].mode()[0], inplace=True)
```

6)

Find the outliers and replace the outliers

[5]
```
import numpy as np
from scipy.stats import zscore

# Calculate z-scores for numerical columns
numeric_columns = ['age', 'fare']
z_scores = np.abs(zscore(df[numeric_columns]))

# Set a threshold for identifying outliers
threshold = 3

# Find indices of outliers based on z-scores
outlier_indices = np.where(z_scores > threshold)

# Replace outliers with the median of the column
df[numeric_columns] = np.where(z_scores > threshold, df[numeric_columns].median(), df[numeric_columns])
```

7)

Check for Categorical columns and perform encoding

[6]
```
# Identify categorical columns
categorical_columns = df.select_dtypes(include='object').columns

# Perform one-hot encoding
encoded_df = pd.get_dummies(df, columns=categorical_columns)

# Display the encoded DataFrame
print(encoded_df)
```

```
     survived  pclass        age  sibsp  parch     fare  adult_male  alone  \
0           0       3  22.000000      1      0   7.2500        True  False
1           1       1  38.000000      1      0  71.2833       False  False
2           1       3  26.000000      0      0   7.9250       False   True
3           1       1  35.000000      1      0  53.1000       False  False
4           0       3  35.000000      0      0   8.0500        True   True
..        ...     ...        ...    ...    ...      ...         ...    ...
886         0       2  27.000000      0      0  13.0000        True   True
887         1       1  19.000000      0      0  30.0000       False   True
888         0       3  29.699118      1      2  23.4500       False  False
889         1       1  26.000000      0      0  30.0000        True   True
890         0       3  32.000000      0      0   7.7500        True   True
```

```
     sex_female  sex_male  ...  deck_C  deck_D  deck_E  deck_F  deck_G  \
0             0         1  ...       0       0       0       0       0
1             1         0  ...       1       0       0       0       0
2             1         0  ...       0       0       0       0       0
3             1         0  ...       1       0       0       0       0
4             0         1  ...       0       0       0       0       0
..          ...       ...  ...     ...     ...     ...     ...     ...
886           0         1  ...       0       0       0       0       0
887           1         0  ...       0       0       0       0       0
888           1         0  ...       0       0       0       0       0
889           0         1  ...       1       0       0       0       0
890           0         1  ...       0       0       0       0       0
```

```
     embark_town_Cherbourg  embark_town_Queenstown  embark_town_Southampton  \
0                        0                       0                        1
1                        1                       0                        0
2                        0                       0                        1
3                        0                       0                        1
4                        0                       0                        1
..                     ...                     ...                      ...
886                      0                       0                        1
887                      0                       0                        1
888                      0                       0                        1
889                      1                       0                        0
890                      0                       1                        0
```

```
     alive_no  alive_yes
0           1          0
1           0          1
2           0          1
3           0          1
4           1          0
..        ...        ...
886         1          0
887         0          1
888         1          0
889         0          1
890         1          0
```

8)

Split the data into dependent and independent variables

```
[7] # Split into dependent (target) variable and independent variables
    X = df.drop('survived', axis=1)  # Independent variables
    y = df['survived']  # Dependent (target) variable

    # Display the independent variables
    print(X.head())

    # Display the dependent variable
    print(y.head())
```

9) Scale the independent variables

Scale the independent variables

```
[ ] import pandas as pd
    from sklearn.preprocessing import StandardScaler


    # Split into dependent (target) variable and independent variables
    X = df.drop('survived', axis=1)  # Independent variables
    y = df['survived']  # Dependent (target) variable

    # Perform one-hot encoding on categorical variables
    X_encoded = pd.get_dummies(X)

    # Perform scaling
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X_encoded)

    # Display the scaled independent variables
    scaled_df = pd.DataFrame(X_scaled, columns=X_encoded.columns)
    print(scaled_df.head())
```

```
     pclass       age     sibsp     parch      fare  adult_male     alone  \
0  0.827377 -0.592704  0.432793 -0.473674 -0.654170    0.811922 -1.231645
1 -1.566107  0.695087  0.432793 -0.473674  1.549441   -1.231645 -1.231645
2  0.827377 -0.270757 -0.474545 -0.473674 -0.630941   -1.231645  0.811922
3 -1.566107  0.453626  0.432793 -0.473674  0.923690   -1.231645 -1.231645
4  0.827377  0.453626 -0.474545 -0.473674 -0.626639    0.811922  0.811922

   sex_female  sex_male  embarked_C  ...    deck_C    deck_D    deck_E  \
0   -0.737695  0.737695   -0.482043  ... -0.266296 -0.196116 -0.193009
1    1.355574 -1.355574    2.074505  ...  3.755222 -0.196116 -0.193009
2    1.355574 -1.355574   -0.482043  ... -0.266296 -0.196116 -0.193009
3    1.355574 -1.355574   -0.482043  ...  3.755222 -0.196116 -0.193009
4   -0.737695  0.737695   -0.482043  ... -0.266296 -0.196116 -0.193009
```

```
     deck_F    deck_G  embark_town_Cherbourg  embark_town_Queenstown  \
0 -0.121681 -0.067153              -0.482043               -0.307562
1 -0.121681 -0.067153               2.074505               -0.307562
2 -0.121681 -0.067153              -0.482043               -0.307562
3 -0.121681 -0.067153              -0.482043               -0.307562
4 -0.121681 -0.067153              -0.482043               -0.307562

   embark_town_Southampton  alive_no  alive_yes
0                 0.619306  0.789272  -0.789272
1                -1.614710 -1.266990   1.266990
2                 0.619306 -1.266990   1.266990
3                 0.619306 -1.266990   1.266990
4                 0.619306  0.789272  -0.789272

[5 rows x 30 columns]
```

10)

Split the data into training and testing

[8]
```python
from sklearn.model_selection import train_test_split

# Split into dependent (target) variable and independent variables
X = df.drop('survived', axis=1)  # Independent variables
y = df['survived']  # Dependent (target) variable

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Display the shapes of the subsets
print("Training set shape:", X_train.shape, y_train.shape)
print("Testing set shape:", X_test.shape, y_test.shape)
```

```
Training set shape: (712, 14) (712,)
Testing set shape: (179, 14) (179,)
```

GoogleColab Link:

https://colab.research.google.com/drive/1KFfKWKOOprGK0BNlbzZEb2yMkM_xTHZn?usp=sharing