SmartBridgeAppliedDataScience

Assignment-2

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TitanicShipCaseStudy

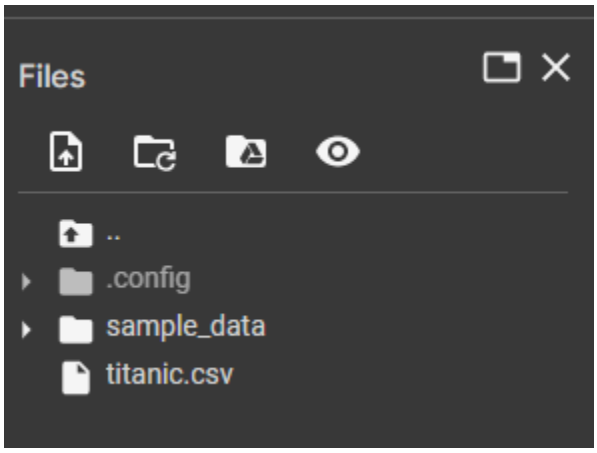
ProblemDescription: OnApril15,1912,duringhermaidenvoyage,theTitanic sank after colliding with an iceberg, killing 1502 out of 2224passengers and crew. Translated32% survival rate.

- Oneofthereasonsthattheshipwreckledtosuchlossoflifewasthattherewer enotenoughlifeboatsforthepassengersandcrew.
- Although there was some element of luck involved in surviving thesinking, some groups of people were more likely to survivethanothers,suchaswomen,children,andtheupper-class.

TheproblemassociatedwiththeTitanicdatasetistopredictwhetherapassengers urvivedthedisasterornot.Thedatasetcontainsvariousfeaturessuchaspassenger class,age,gender,cabin,fare,andwhetherthepassengerhadanysiblingsorspous esonboard.Thesefeaturescanbeusedtobuildapredictivemodeltodeterminethel ikelihoodofapassengersurvivingthedisaster.Thedatasetoffersopportunitiesfor featureengineering, data visualization, and model selection, making it a valuableresource for developing and testing data analysis and machine learningskills.

PerformBelowTasks:-

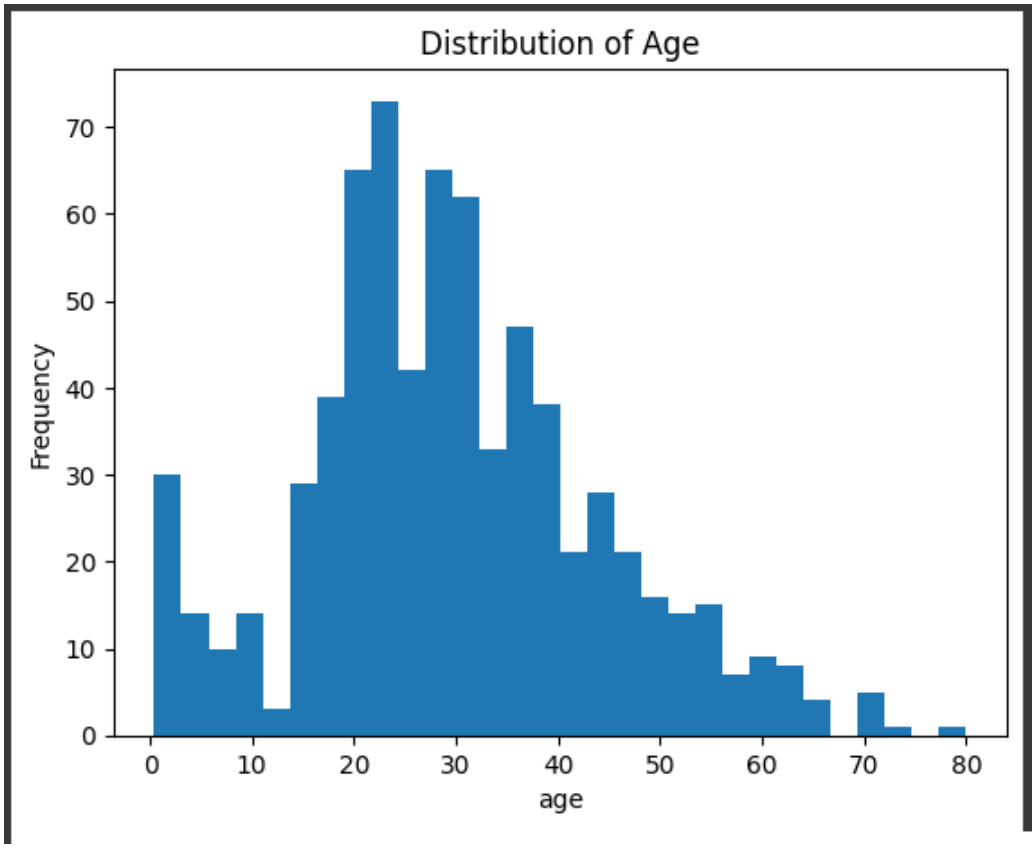
1. Downloadthedataset:Dataset
2. Loadthedataset.

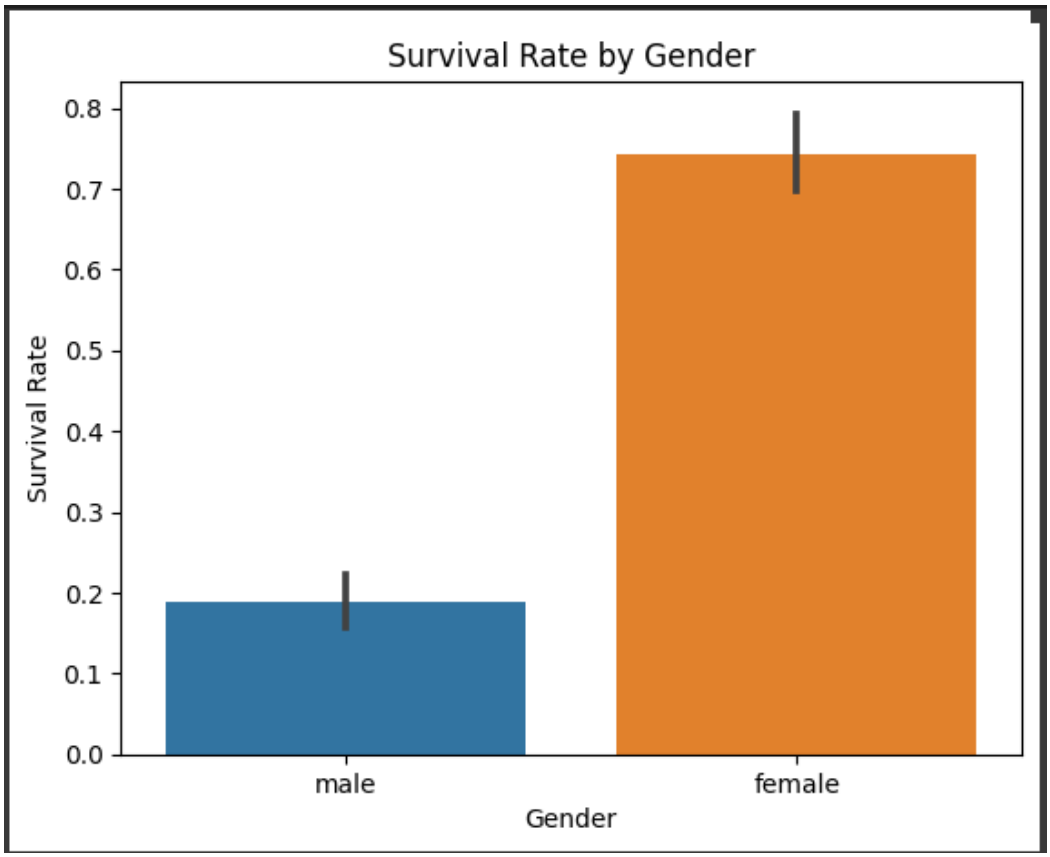


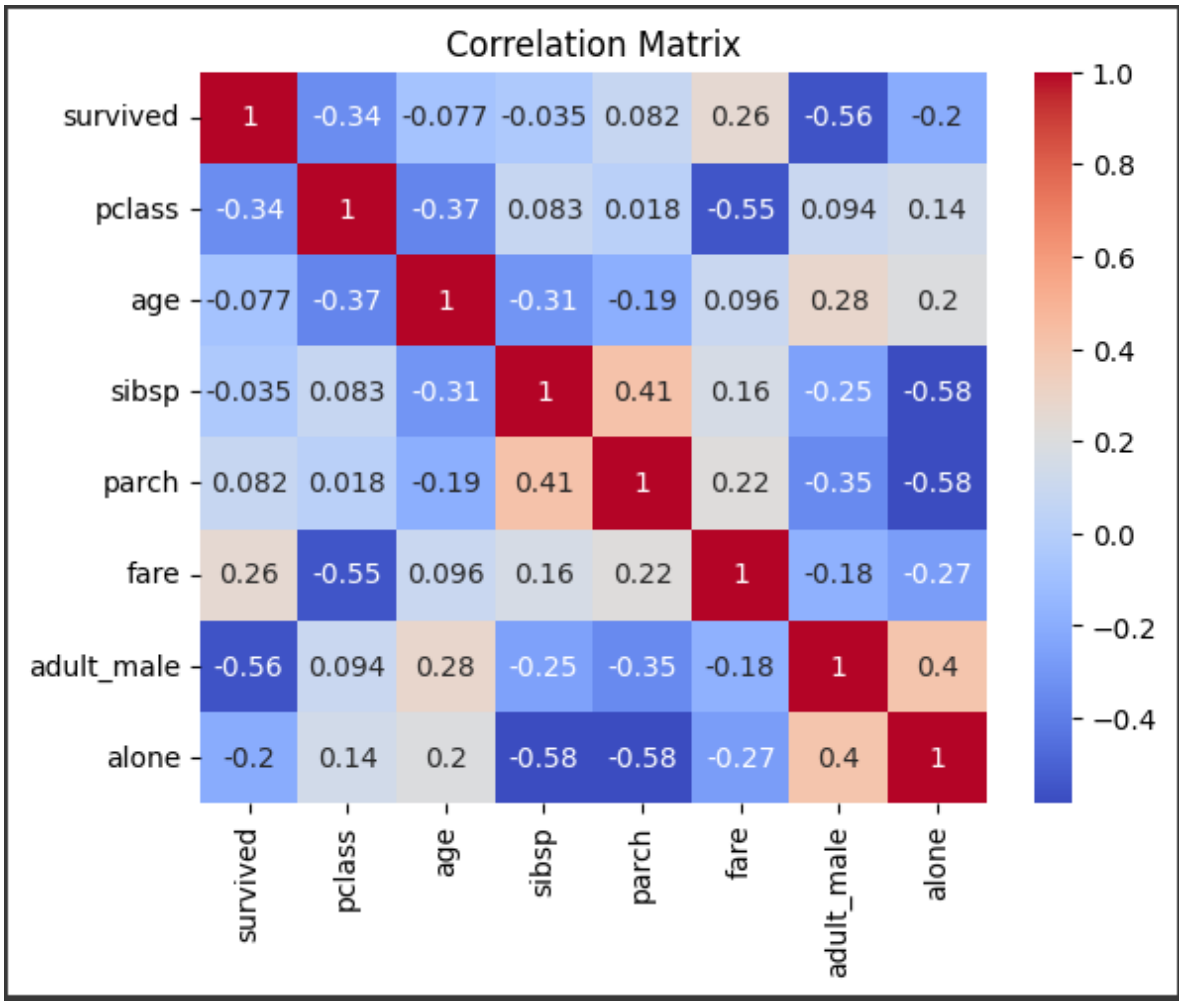
3. PerformBelowVisualizations.
   - UnivariateAnalysis
   - Bi-VariateAnalysis
   - Multi-VariateAnalysis

```
[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()
```

```python
# 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
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
male
female
Gender


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

4)Performdescriptiveanalysisonthedataset

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)Scaletheindependentvariables

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] 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,)
```