

# SMART BRIDGE\_APPLIED DATA SCIENCE

## ASSIGNMENT - 1

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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 to complete the assignment:-

1. Download the dataset: [Dataset](#)
2. Load the dataset.
3. Perform Below Visualizations.
  - Univariate Analysis
  - Bi - Variate Analysis
  - Multi - Variate Analysis

✓  
2s



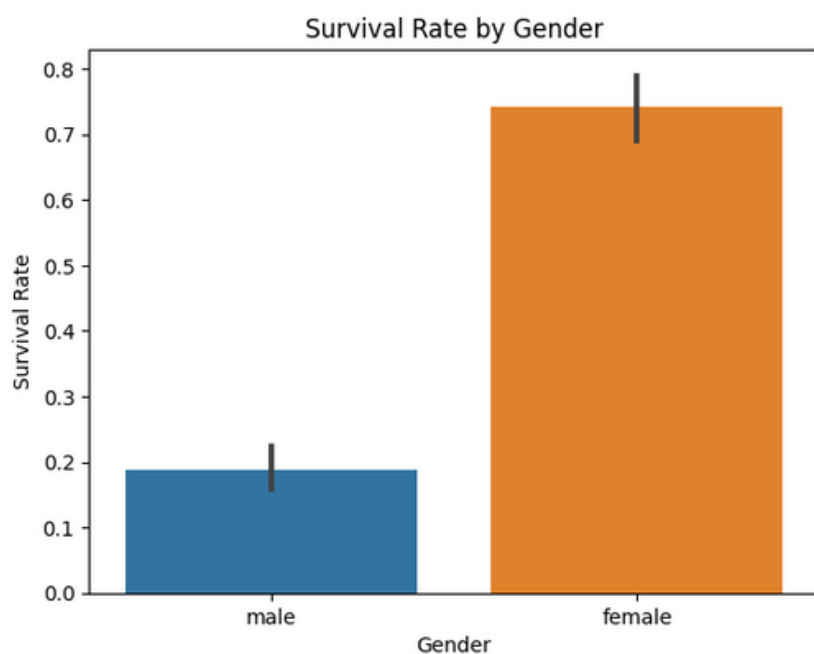
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

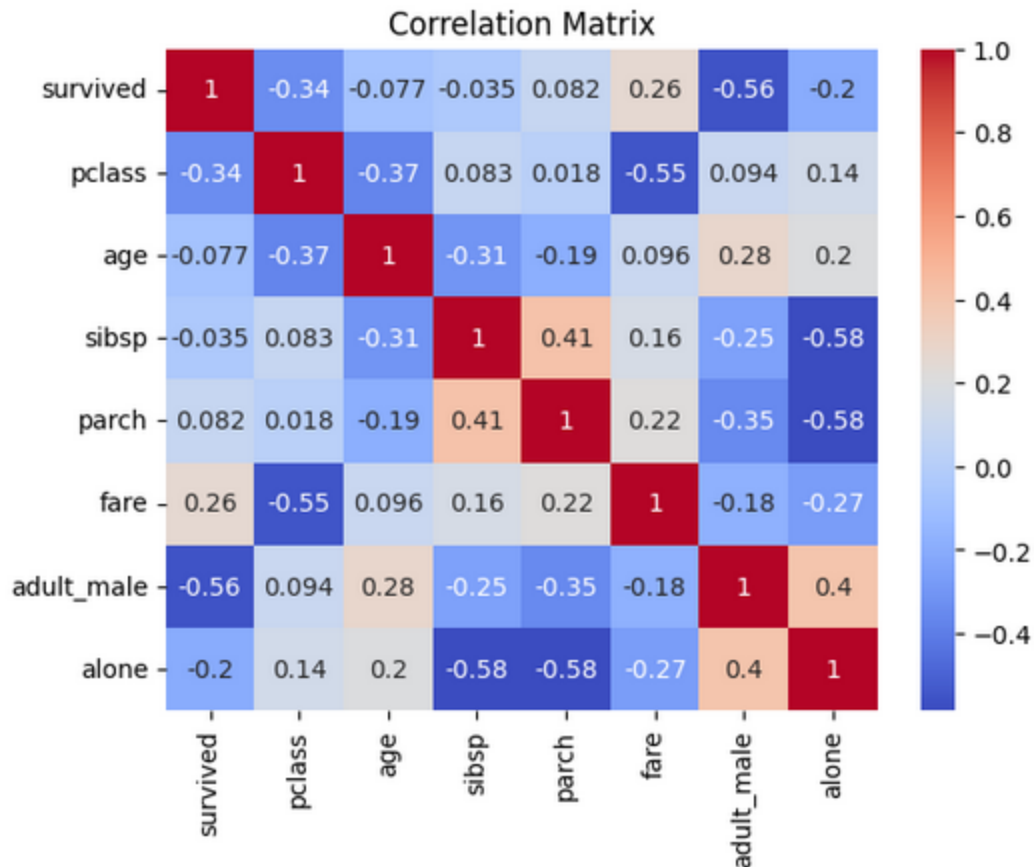
# Load the dataset
df = pd.read_csv('titanic.csv')

# 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()
```





Perform descriptive statistics on the dataset

```
[5] # 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

## Handle the Missing Values

```
✓ [6] # Impute missing values with the mean of the column  
0s 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)
```

## Find the outliers and replace the outliers

```
✓ [7] import numpy as np  
0s 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])
```

## Check for Categorical columns and perform encoding

```
✓ [8] # Identify categorical columns  
0s 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_Ch... 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

```

[891 rows x 31 columns]

Split the data into dependent and independent variables

```

[9] # 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]
0s
      pclass    sex  age  sibsp  parch    fare embarked  class  who  \
0         3   male  22.0     1     0   7.2500         S   Third  man
1         1  female  38.0     1     0  71.2833         C   First  woman
2         3  female  26.0     0     0   7.9250         S   Third  woman
3         1  female  35.0     1     0  53.1000         S   First  woman
4         3   male  35.0     0     0   8.0500         S   Third  man

      adult_male deck  embark_town alive  alone
0         True  NaN  Southampton    no  False
1        False    C    Cherbourg   yes  False
2        False  NaN  Southampton   yes   True
3        False    C    Southampton   yes  False
4         True  NaN  Southampton    no   True
0         0
1         1
2         1
3         1
4         0
Name: survived, dtype: int64

```

Scale the independent variables

```

✓ [10]
0s
import pandas as pd
from sklearn.preprocessing import StandardScaler

✓ [10]
0s
# 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())

```

```

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_Chernbourg 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]

```

Split the data into training and testing

```

[11] 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,)

```

**GOOGLE COLAB LINK**

**[https://colab.research.google.com/drive/1VF4\\_WGjyw053JcAAMzlnke8sYdBb2yD?usp=ssharing](https://colab.research.google.com/drive/1VF4_WGjyw053JcAAMzlnke8sYdBb2yD?usp=ssharing)**