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CAMPUS: VIT-AP

1. IMPORT THE LIBRARIES

```
In [1]: import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns
    from scipy import stats
    from sklearn.preprocessing import LabelEncoder
    from sklearn.preprocessing import StandardScaler
    from sklearn.model_selection import train_test_split
```

2. IMPORT THE DATASET

```
In [4]: df=pd.read_csv("Titanic-Dataset.csv")
```

In [5]: df

Out[5]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	0	PC 17599	71.2833
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500

891 rows × 12 columns

In [6]:

df.head()

Out[6]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Са
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	N
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	0	PC 17599	71.2833	(
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	٨
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C.
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	٨

In [7]: df.tail()

Out[7]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.00	NaN
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.00	B42
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.45	NaN
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.00	C148
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.75	NaN

In [8]: df.shape

Out[8]: (891, 12)

In [9]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):

#	Column	Non-Null Count	Dtype
0	PassengerId	891 non-null	int64
1	Survived	891 non-null	int64
2	Pclass	891 non-null	int64
3	Name	891 non-null	object
4	Sex	891 non-null	object
5	Age	714 non-null	float64
6	SibSp	891 non-null	int64
7	Parch	891 non-null	int64
8	Ticket	891 non-null	object
9	Fare	891 non-null	float64
10	Cabin	204 non-null	object
11	Embarked	889 non-null	object
-11			

dtypes: float64(2), int64(5), object(5)

memory usage: 83.7+ KB

In [10]: df.describe()

Out[10]:

	Passengerld	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75 %	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

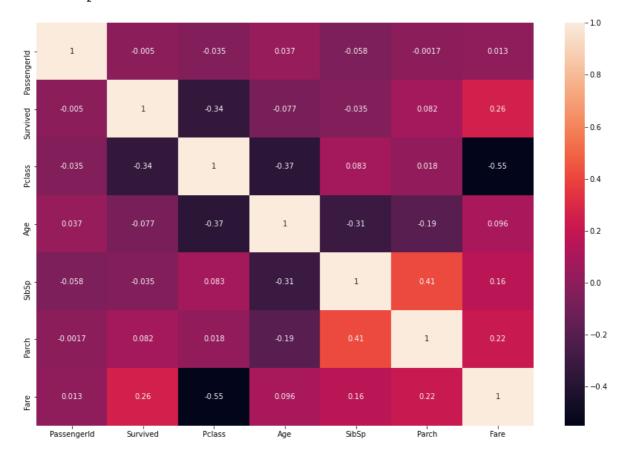
In [11]: corr=df.corr()
corr

Out[11]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
PassengerId	1.000000	-0.005007	-0.035144	0.036847	-0.057527	-0.001652	0.012658
Survived	-0.005007	1.000000	-0.338481	-0.077221	-0.035322	0.081629	0.257307
Pclass	-0.035144	-0.338481	1.000000	-0.369226	0.083081	0.018443	-0.549500
Age	0.036847	-0.077221	-0.369226	1.000000	-0.308247	-0.189119	0.096067
SibSp	-0.057527	-0.035322	0.083081	-0.308247	1.000000	0.414838	0.159651
Parch	-0.001652	0.081629	0.018443	-0.189119	0.414838	1.000000	0.216225
Fare	0.012658	0.257307	-0.549500	0.096067	0.159651	0.216225	1.000000

```
In [12]: plt.subplots(figsize=(15,10))
sns.heatmap(corr,annot=True)
```

Out[12]: <AxesSubplot:>



```
In [13]: df.Survived.value_counts()
```

Out[13]: 0 549 1 342

Name: Survived, dtype: int64

```
In [14]: df.Sex.value_counts()
```

Out[14]: male 577 female 314

Name: Sex, dtype: int64

In [15]: df.Embarked.value_counts()

Out[15]: S 644 C 168

Q 77

Name: Embarked, dtype: int64

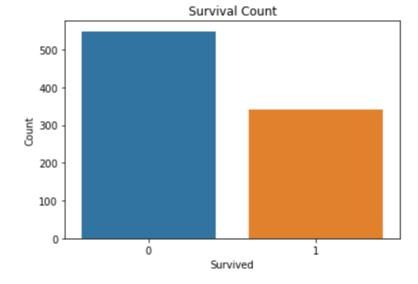
#3. CHECK FOR NULL VALUES

```
In [16]: df.isnull().any()
Out[16]: PassengerId
                          False
          Survived
                          False
          Pclass
                          False
          Name
                          False
          Sex
                          False
          Age
                           True
          SibSp
                          False
          Parch
                          False
          Ticket
                          False
          Fare
                          False
          Cabin
                           True
          Embarked
                           True
          dtype: bool
In [17]: df.isnull().sum()
Out[17]: PassengerId
                            0
          Survived
                            0
          Pclass
                            0
          Name
                            0
          Sex
                            0
          Age
                          177
          SibSp
                            0
          Parch
                            0
          Ticket
                            0
          Fare
                            0
          Cabin
                          687
          Embarked
                            2
          dtype: int64
          Fill null values in the 'Age' column with the mean age
In [18]: mean_age = df['Age'].mean()
          df['Age'].fillna(mean_age, inplace=True)
          Fill null values in the 'Embarked' column with the most common value
          most_common_embarked = df['Embarked'].mode()[0]
In [19]:
          df['Embarked'].fillna(most_common_embarked, inplace=True)
In [20]: | df.drop(['Cabin'],axis=1, inplace=True)
In [21]: |df.drop(['Ticket'],axis=1, inplace=True)
In [22]: df.drop(['Name'],axis=1,inplace=True)
```

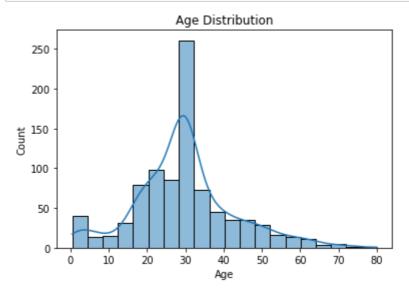
```
In [23]: print(df.isnull().sum())
```

PassengerId Survived 0 Pclass 0 Sex 0 Age 0 0 SibSp Parch 0 0 Fare Embarked 0 dtype: int64

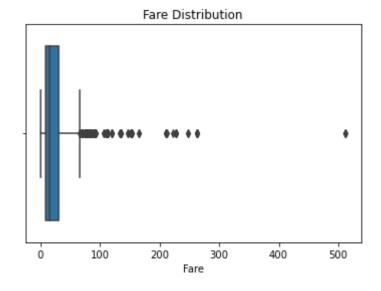
#4. Data Visualization



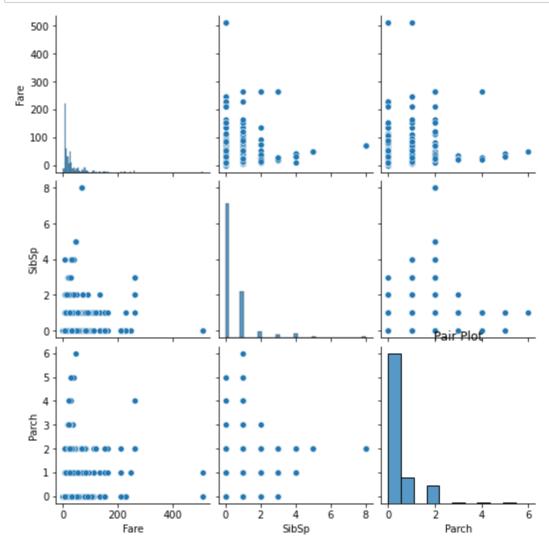
```
In [25]: #Visualize the distribution of the 'Age' column
    sns.histplot(data=df, x='Age', bins=20, kde=True)
    plt.title('Age Distribution')
    plt.xlabel('Age')
    plt.ylabel('Count')
    plt.show()
```



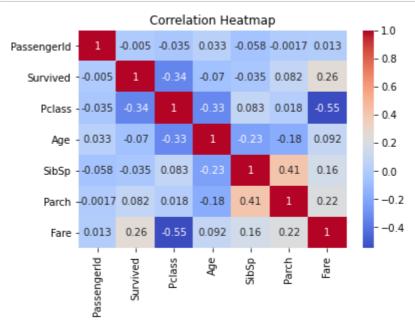
In [26]: #Visualize the distribution of the 'Fare' column and detect outliers we
sns.boxplot(data=df, x='Fare')
plt.title('Fare Distribution')
plt.xlabel('Fare')
plt.show()



```
In [27]: #Pair plot for selected numerical columns
    sns.pairplot(data=df[['Fare', 'SibSp', 'Parch']])
    plt.title('Pair Plot')
    plt.show()
```



```
In [28]: corr_matrix = df.corr()
    sns.heatmap(corr_matrix, annot=True,cmap='coolwarm')
    plt.title('Correlation Heatmap')
    plt.show()
```



5. Detect and Handle Outliers

```
In [29]:
         z_scores = np.abs(stats.zscore(df['Age']))
         max_threshold=3
         outliers = df['Age'][z_scores > max_threshold]
         # Print and visualize the outliers
         print("Outliers detected using Z-Score:")
         print(outliers)
         Outliers detected using Z-Score:
         96
                71.0
         116
                70.5
         493
                71.0
         630
                80.0
         672
                70.0
         745
                70.0
         851
                74.0
         Name: Age, dtype: float64
```

```
In [30]: z_scores = np.abs(stats.zscore(df['Fare']))
    max_threshold=3
    outliers = df['Fare'][z_scores > max_threshold]

# Print and visualize the outliers
    print("Outliers detected using Z-Score:")
    print(outliers)
```

```
Outliers detected using Z-Score:
27
       263.0000
88
       263.0000
118
       247.5208
258
       512.3292
299
       247.5208
311
       262.3750
341
       263.0000
377
       211.5000
380
       227.5250
438
       263.0000
527
       221.7792
557
       227.5250
679
       512.3292
689
       211.3375
700
       227.5250
716
       227.5250
730
       211.3375
737
       512.3292
742
       262.3750
779
       211.3375
Name: Fare, dtype: float64
```

```
In [31]: column_name = 'Fare'

# Calculate the first quartile (Q1) and third quartile (Q3)
Q1 = df[column_name].quantile(0.25)
Q3 = df[column_name].quantile(0.75)

# Calculate the IQR
IQR = Q3 - Q1

# Define the lower and upper bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter rows with values outside the IQR bounds
df_cleaned = df[(df[column_name] > lower_bound) & (df[column_name] < upper

# Display the original and cleaned DataFrame sizes
print(f"Original DataFrame size: {df.shape}")
print(f"Cleaned DataFrame size: {df_cleaned.shape}")
df_cleaned</pre>
```

Original DataFrame size: (891, 9) Cleaned DataFrame size: (775, 9)

Out[31]:

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	0	3	male	22.000000	1	0	7.2500	S
2	3	1	3	female	26.000000	0	0	7.9250	S
3	4	1	1	female	35.000000	1	0	53.1000	S
4	5	0	3	male	35.000000	0	0	8.0500	S
5	6	0	3	male	29.699118	0	0	8.4583	Q
886	887	0	2	male	27.000000	0	0	13.0000	S
887	888	1	1	female	19.000000	0	0	30.0000	S
888	889	0	3	female	29.699118	1	2	23.4500	S
889	890	1	1	male	26.000000	0	0	30.0000	С
890	891	0	3	male	32.000000	0	0	7.7500	Q

775 rows × 9 columns

```
In [ ]:
In [43]: df=df_cleaned
In [44]: x=df.drop('Survived', axis=1)
y=df['Survived']
```

```
In [45]: x.head()
```

Out[45]:

	PassengerId	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	3	male	22.000000	1	0	7.2500	S
2	3	3	female	26.000000	0	0	7.9250	S
3	4	1	female	35.000000	1	0	53.1000	S
4	5	3	male	35.000000	0	0	8.0500	S
5	6	3	male	29.699118	0	0	8.4583	Q

```
In [46]: y.head()
```

```
Out[46]: 0
```

- 0 (
- 2
- 3
- 4

5 0

Name: Survived, dtype: int64

#7. Perform Encoding

```
In [47]: en = LabelEncoder()
x['Sex'] = en.fit_transform(x['Sex'])
```

In [48]: x.head()

Out[48]:

	PassengerId	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	3	1	22.000000	1	0	7.2500	S
2	3	3	0	26.000000	0	0	7.9250	S
3	4	1	0	35.000000	1	0	53.1000	S
4	5	3	1	35.000000	0	0	8.0500	S
5	6	3	1	29.699118	0	0	8.4583	Q

```
In [49]: x = pd.get_dummies(x,columns=['Embarked'])
```

In [50]: x.head()

Out[50]:

	PassengerId	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked_C	Embarked_Q	Eml
0	1	3	1	22.000000	1	0	7.2500	0	0	
2	3	3	0	26.000000	0	0	7.9250	0	0	
3	4	1	0	35.000000	1	0	53.1000	0	0	
4	5	3	1	35.000000	0	0	8.0500	0	0	
5	6	3	1	29.699118	0	0	8.4583	0	1	

#8. Feature Scaling

```
In [51]: scale = StandardScaler()
    x[['Age', 'Fare']] = scale.fit_transform(x[['Age', 'Fare']])
In [52]: x.head()
```

Out[52]:

In []:

	Passengerld	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked_C	Embarked_Q	Er
0	1	3	1	-0.556219	1	0	-0.779117	0	0	
2	3	3	0	-0.243027	0	0	-0.729373	0	0	
3	4	1	0	0.461654	1	0	2.599828	0	0	
4	5	3	1	0.461654	0	0	-0.720161	0	0	
5	6	3	1	0.046606	0	0	-0.690071	0	1	

#9. Splitting the data into Train and Test