

ANALYSIS OF THE TITANIC DATASET

OVERVIEW OF THE DATASET

The titanic dataset contains different data types:

PassengerId: Unique identifier for each of the passengers

Survived: Binary indicator of survival where (0= Did not survive, 1=Survived)

Pclass: Passenger class (1=First class, 2=Second class, 3=Third class)

Name: Full name of the passenger

Sex: Gender of the passenger (male or female)

SibSp: Number of siblings or spouses on board

Parch: Number of parents or children on board

Ticket: Ticket Number

Fare: Amount paid for the ticket by a passenger

Cabin: Cabin number

Embarked: Port where the passenger Embarked (C=Cherbourg, Q= Queenstown, S=Southampton)

LOADING THE DATASET

The first step involves loading the data, getting an overview of the data and understanding the structure.

```

1  # Import libraries
2  import pandas as pd
3  import seaborn as sns
4  import matplotlib.pyplot as plt
5
6  # Load CSV file
7  TITANIC = pd.read_csv('train.csv')
8
9  # Viewing the first rows of the dataset
10 print(TITANIC.head())
11
12 # Viewing the last rows of the dataset
13 print(TITANIC.tail())
14
15 # Viewing a random line
16 print(TITANIC.sample())
17
18 # Overview of the data
19 print(TITANIC.info())
20

```

```

PassengerId  Survived  Pclass
0            1         0       3
1            2         1       1  Cumings, Mrs. John Bradley (Florence Briggs Th...
2            3         1       3  Heikkinen, Miss. Laina
3            4         1       1  Futrelle, Mrs. Jacques Heath (Lily May Peel)
4            5         0       3  Allen, Mr. William Henry
PassengerId  Survived  Pclass
886          887         0       2  Montvila, Rev. Juozas
887          888         1       1  Graham, Miss. Margaret Edith
888          889         0       3  Johnston, Miss. Catherine Helen "Carrie"
889          890         1       1  Behr, Mr. Karl Howell
890          891         0       3  Dooley, Mr. Patrick
PassengerId  Survived  Pclass
522          523         0       3  Lahoud, Mr. Sarkis
Name Sex Age SibSp Parch Ticket Fare Cabin Embarked
0 male 22.0 1 0 A/5 21171 7.2500 NaN S
1 female 38.0 1 0 PC 17599 71.2833 C85 C
2 female 26.0 0 0 STON/O2. 3101282 7.9250 NaN S
3 female 35.0 1 0 113803 53.1000 C123 S
4 male 35.0 0 0 373450 8.0500 NaN S
Name Sex Age SibSp Parch Ticket Fare Cabin Embarked
886 male 27.0 0 0 211536 13.00 NaN S
887 female 19.0 0 0 112053 30.00 B42 S
888 female NaN 1 2 W./C. 6607 23.45 NaN S
889 male 26.0 0 0 111369 30.00 C148 C
890 male 32.0 0 0 370376 7.75 NaN Q
Name Sex Age SibSp Parch Ticket Fare Cabin Embarked
522 male NaN 0 0 2624 7.225 NaN C
<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
dtypes: float64(2), int64(5), object(5)

```

TASK 1: DATA CLEANING

This step involves identifying missing values, outliers and duplicates.

```

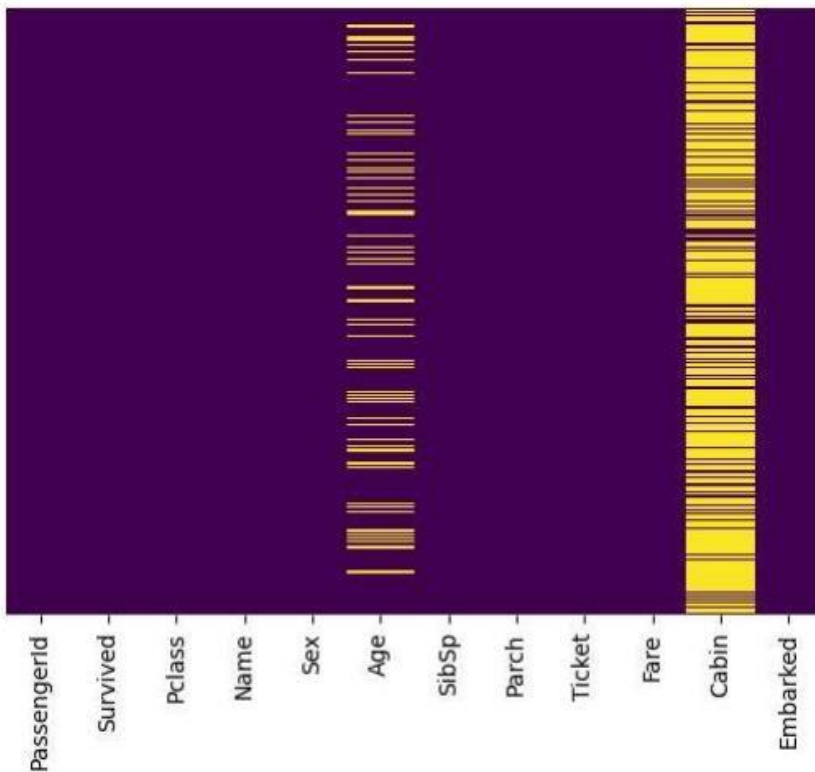
21 # Checking columns with missing values
22 print(TITANIC.isnull().sum())
23
24 # Heatmap to show the missing values in each column
25 sns.heatmap(TITANIC.isnull(), yticklabels=False, cmap="viridis", cbar=False)
26
27 # show the plot
28 plt.show()

```

```

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

```



From the output there are no duplicates in the data but there are missing values in three columns, i.e. Age column, Cabin Column and Embarked Column.

- **Cabin:** Since the Cabin column contains a significant number of missing values it is dropped. The Name and Ticket Columns are also dropped alongside the cabin column since they are not used for further data analysis.
- **Embarked:** There are 2 missing entries in the embarked column. These two entries are replaced with the mode of the column.
- **Age:** To replace the missing values in the age column, we use the median of the age.

```

30 # Dropping columns
31 TITANIC.drop(columns=["Cabin", "Name", "Ticket"], axis=1, inplace=True)
32
33 # Filling null values in the 'Embarked' column with the mode (most frequent value)
34 TITANIC["Embarked"] = TITANIC["Embarked"].fillna(TITANIC["Embarked"].mode()[0])
35
36 # Filling missing age values with the median
37 TITANIC['Age'].fillna(TITANIC["Age"].median(), inplace=True)
38
39 # Confirming that there are no null values
40 print(TITANIC.isnull().sum())

```

```

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

```

To remove the outliers, we use the interquartile range method. In this method, outliers are defined as values outside the range of:

$Q1 - 1.5 * IQR$ and $Q3 + 1.5 * IQR$

where $Q1$ is the first quartile, $Q3$ is the third quartile and IQR is the interquartile range.

```

49 # Remove outliers in Age
50 TITANIC = TITANIC[(TITANIC['Age'] >= lower_bound_age) & (TITANIC['Age'] <= upper_bound_age)]
51
52 # For Fare
53 Q1_fare = TITANIC['Fare'].quantile(0.25)
54 Q3_fare = TITANIC['Fare'].quantile(0.75)
55 IQR_fare = Q3_fare - Q1_fare
56 lower_bound_fare = Q1_fare - 1.5 * IQR_fare
57 upper_bound_fare = Q3_fare + 1.5 * IQR_fare
58
59 # Remove outliers in Fare
60 TITANIC = TITANIC[(TITANIC['Fare'] >= lower_bound_fare) & (TITANIC['Fare'] <= upper_bound_fare)]

```

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	0	3	male	22.0	1	0	7.2500	S
2	3	1	3	female	26.0	0	0	7.9250	S
3	4	1	1	female	35.0	1	0	53.1000	S
4	5	0	3	male	35.0	0	0	8.0500	S
5	6	0	3	male	28.0	0	0	8.4583	Q
..
886	887	0	2	male	27.0	0	0	13.0000	S
887	888	1	1	female	19.0	0	0	30.0000	S
888	889	0	3	female	28.0	1	2	23.4500	S
889	890	1	1	male	26.0	0	0	30.0000	C
890	891	0	3	male	32.0	0	0	7.7500	Q

[718 rows x 9 columns]