

# Data and Artificial Intelligence

## Cyber Shujaa Program

### Week 3 Assignment

#### Exploratory data analysis

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## Table of contents

## Table of Contents

Data and Artificial Intelligence .....	1
Cyber Shujaa Program.....	1
Week 1 Assignment Web Scraping and Data Handling in Python.....	1
Introduction .....	5
Objectives.....	5
Tasks Completed .....	5
Step 1: Initial data exploration .....	5
Code .....	5
code explanation.....	6
Screenshots of step 1 .....	6
Step 2: handling missing values and outliers .....	8
Code .....	9
code explanation.....	9
Screenshots of step 2:.....	10
Step 3: univariate analysis.....	11
Code .....	11
code explanation.....	12
Screenshots to the code:.....	13
Step 4: Bivariate Analysis .....	15
code explanation.....	17
Screenshots:.....	17
Step 5: Multivariate Analysis.....	19
Code .....	19
code explanation.....	19
screenshot to code:.....	19
Step 6: Outlier detection and handling.....	20
Code .....	20
code explanation.....	21
Screenshots of code .....	21
Step 7: target variable exploration.....	23
Code .....	23
code explanation.....	24
screenshots to code: .....	24

Link to Code .....	27
Conclusion.....	27

## Table of figures

Figure 1: screenshot showing the first 20 rows by running the command df.head(20) .....	7
Figure 2: screenshot showing the result of df.describe() .....	7
Figure 3: screenshot showing the result of df.nunique() and df.duplicated() .....	8
Figure 4: screenshot showing the result of df.isnull().sum() .....	8
Figure 5: screenshot showing age distribution while checking for skewness.....	10
Figure 6: screenshot showing the results after filling in the missing age values with median, and dropping the cabin column. It can be seen that now there are no null values and the columns are now 11 confirming the cabin column is dropped.....	11
Figure 7: screenshot showing age distribution of passengers .....	14
Figure 8: screenshot showing the no of passengers embarking on each location .....	14
Figure 9: screenshot showing the distribution of ticket prices.....	15
Figure 10: A boxplot of passenger ticket prices .....	15
Figure 11: screenshot showing distribution of sibsp.....	22
Figure 12: screenshot showing distribution of parch.....	22
Figure 13: relationship between passenger class and survival rate.....	25
Figure 14: relationship between embarkation point and survival rate .....	26
Figure 15: relationship between gender and class on survival (combined effect) .....	26

# Introduction

The assignment this week was on exploratory data analysis. Exploratory data analysis is the process of analysing datasets to summarize their main characteristics often using visual methods. Some common visuals in exploratory data analysis include histogram, boxplot, bar chart, KDE. In this week's assignment I developed hands-on experience on Exploratory Data Analysis using Kaggle Data Set and I published my work on Kaggle.

## Objectives

The purpose of this assignment is to practice exploratory data analysis steps:

1. initial data exploration
2. Handling Missing Values and Outliers
3. Univariate analysis
4. Bivariate analysis
5. Multivariate analysis
6. Target variable analysis

# Tasks Completed

These are the steps I took:

## Step 1: Initial data exploration

In this step, I explored my dataset to have an overview of it and to better understand it. I checked for the number of rows and columns, I checked for the data type of each column, I checked for duplicated rows, for null values and its descriptive summary such as mean and standard deviation. This allowed me to understand my dataset before performing any analysis

### Code

```
df.head(20)
```

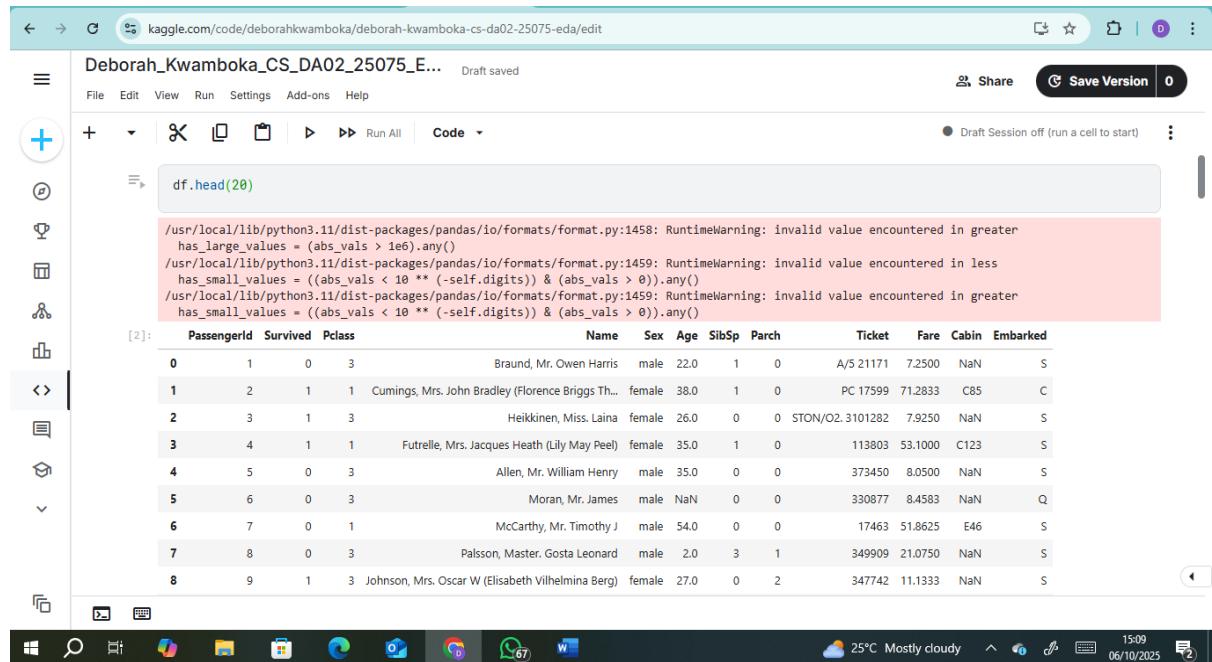
```
df.shape
```

`df.info()`  
`df.describe()`  
`df.nunique()`  
`df.duplicated()`  
`df.duplicated().sum()`  
`df.isnull()`  
`df.isnull().sum()`

#### [code explanation](#)

The line `df.head(20)` returns the first 20 rows of the dataset, allowing you to preview sample records. The command `df.shape` returns a tuple showing the total number of rows and columns. When you run `df.info()`, it prints a summary of the dataset including column names, data types, and the count of non-null values. The line `df.describe()` returns statistical summaries such as mean, standard deviation, minimum, and maximum values for all numeric columns. Using `df.nunique()` returns the number of unique values in each column. The command `df.duplicated()` returns a Boolean Series indicating whether each row is a duplicate, while `df.duplicated().sum()` returns the total number of duplicate rows. Similarly, `df.isnull()` returns a DataFrame of True or False values showing where data is missing, and `df.isnull().sum()` returns the total count of missing values in each column.

#### [Screenshots of step 1](#)

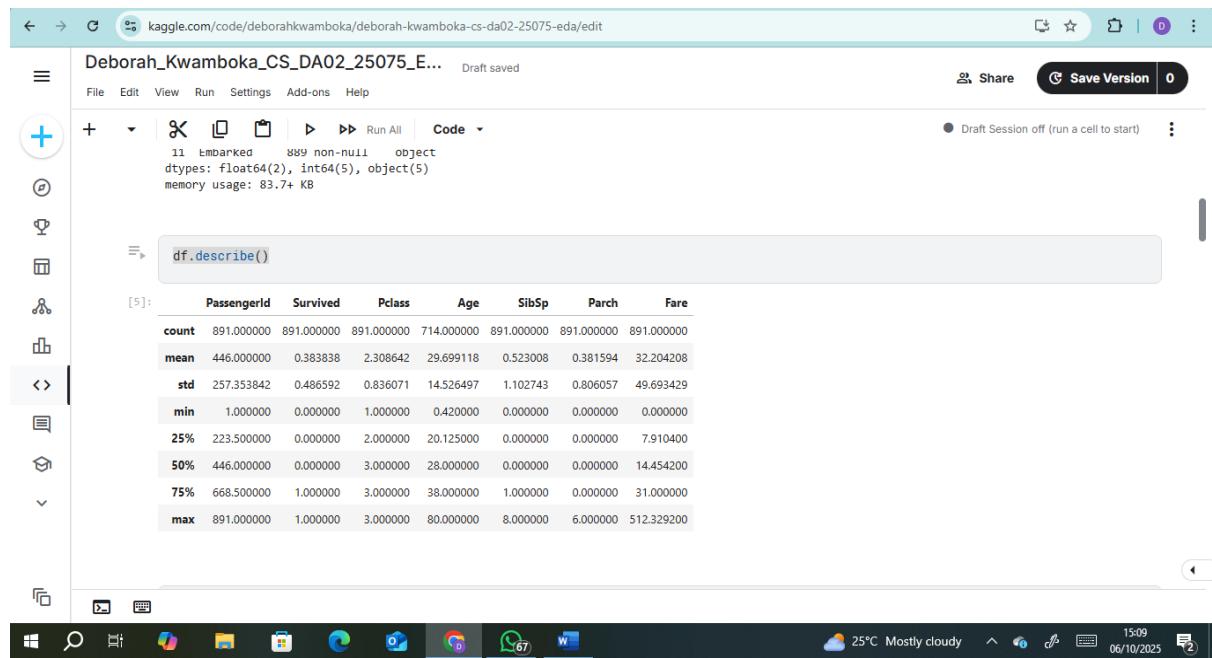


```
/usr/local/lib/python3.11/dist-packages/pandas/io/format.py:1458: RuntimeWarning: invalid value encountered in greater
has_large_values = (abs_vals > 1e+06).any()
/usr/local/lib/python3.11/dist-packages/pandas/io/format.py:1459: RuntimeWarning: invalid value encountered in less
has_small_values = ((abs_vals < 10 ** (-self.digits)) & (abs_vals > 0)).any()
/usr/local/lib/python3.11/dist-packages/pandas/io/format.py:1459: RuntimeWarning: invalid value encountered in greater
has_small_values = ((abs_vals < 10 ** (-self.digits)) & (abs_vals > 0)).any()

[2]:
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	Nan	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th... Heikkinen, Miss. Laina	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	26.0	0	0	STON/O2. 3101282	7.9250	Nan	S
3	4	1	1	Allen, Mr. William Henry	male	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Moran, Mr. James	male	NaN	0	0	373450	8.0500	Nan	S
5	6	0	3	McCarthy, Mr. Timothy J	male	54.0	0	0	330877	8.4583	Nan	Q
6	7	0	1	Palsson, Master. Gosta Leonard	male	2.0	3	1	17463	51.8625	E46	S
7	8	0	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	349909	21.0750	Nan	S
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	Nan	S

Figure 1: screenshot showing the first 20 rows by running the command `df.head(20)`

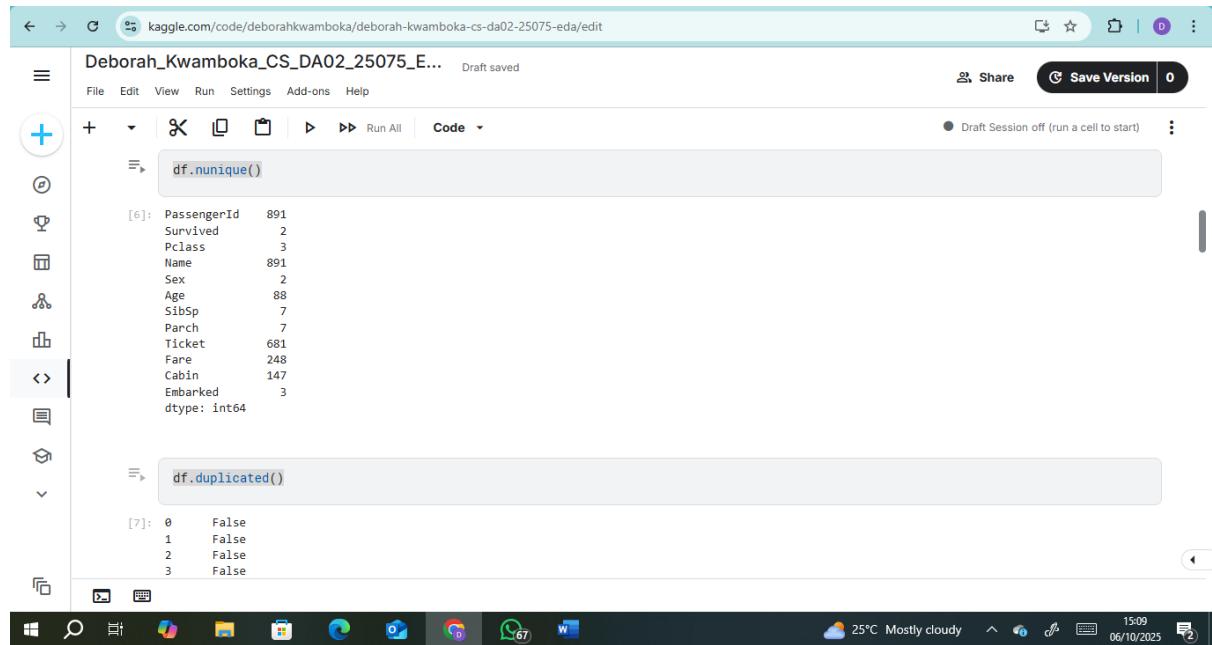


```
11 Embarked      889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.74 KB

[5]:
```

	PassengerId	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

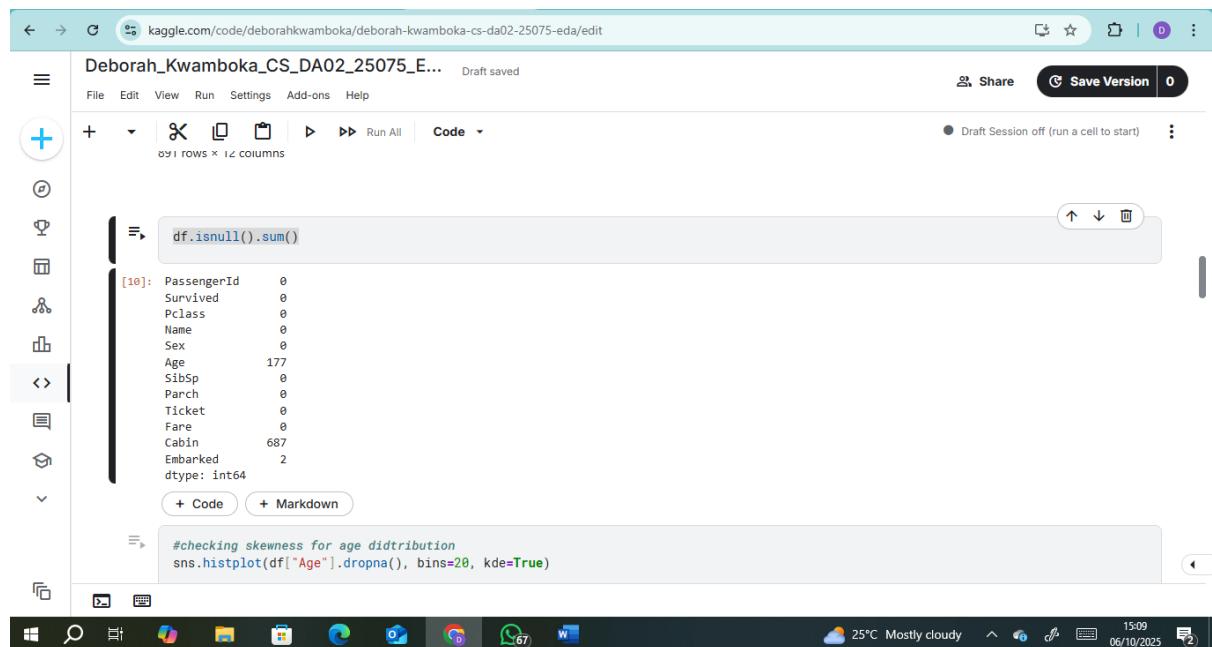
Figure 2: screenshot showing the result of `df.describe()`



```
[6]: df.nunique()
      PassengerId    891
      Survived        2
      Pclass          3
      Name           891
      Sex            2
      Age           88
      SibSp          7
      Parch          7
      Ticket         681
      Fare          248
      Cabin         147
      Embarked       3
      dtype: int64

[7]: df.duplicated()
      0    False
      1    False
      2    False
      3    False
```

Figure 3: screenshot showing the result of `df.nunique()` and `df.duplicated()`



```
[10]: df.isnull().sum()
      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
```

```
#checking skewness for age distribution
sns.histplot(df["Age"].dropna(), bins=20, kde=True)
```

Figure 4: screenshot showing the result of `df.isnull().sum()`

## Step 2: handling missing values and outliers

In this step I handled missing values. The age of passenger's column had 177 missing values, embarked column had 2 missing values and the cabin column had 687 missing values. I visualized the age distribution of passengers first and checked its skewness. It was right skewed hence it was appropriate to fill in the 177 missing values with the mean. I filled the

two missing values for the embarked column with the mode of that column. I dropped the 687 missing values for the cabin column since the number is high and I deemed it of no importance.

### Code

```
#checking skewness for age distribution
```

```
sns.histplot(df["Age"].dropna(), bins=20, kde=True)
```

```
plt.title("Age Distribution")
```

```
plt.xlabel("Age")
```

```
plt.ylabel("Frequency")
```

```
plt.show()
```

*#age distribution is positively skewed so i will fill in the 177 missing values of age column using median.*

```
df.fillna({"Age": df["Age"].median()}, inplace=True)
```

```
df["Age"].isnull().sum()
```

*#dropping the cabin column because it has many missing values and its really of no importance*

```
df = df.drop("Cabin", axis=1)
```

*#confirming if the column is dropped*

```
print(df.columns)
```

*#filling in the two missing values for embarked column with the mode*

```
df["Embarked"] = df["Embarked"].fillna(df["Embarked"].mode()[0])
```

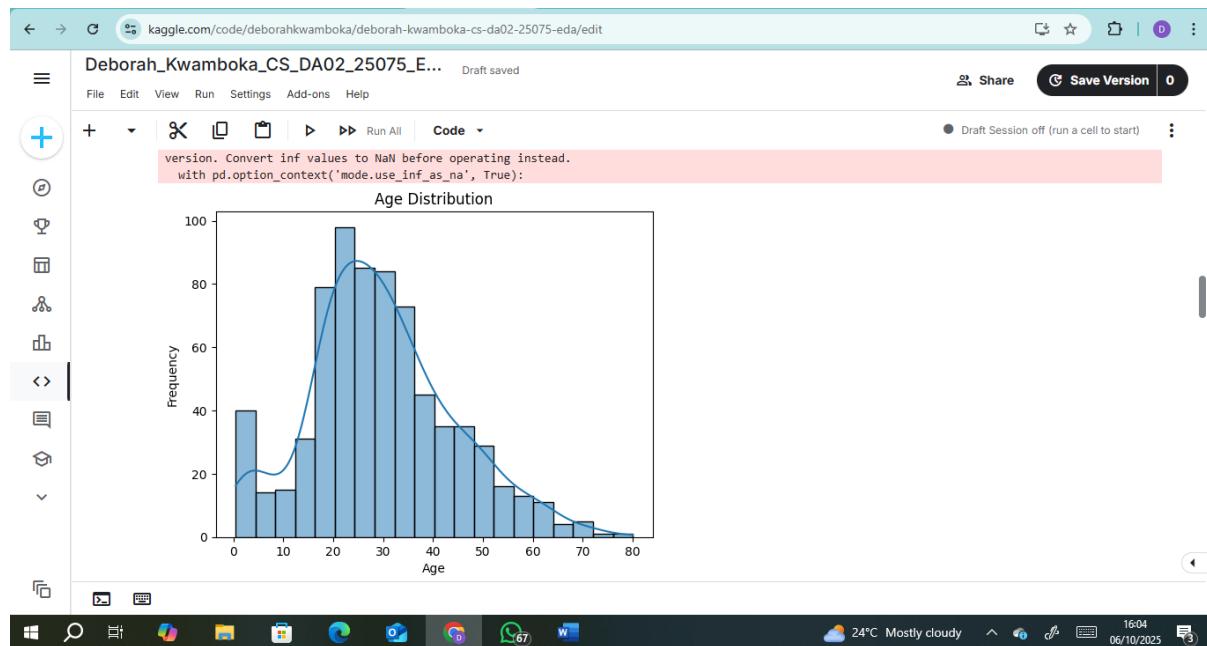
```
df["Embarked"].isnull().sum()
```

### code explanation

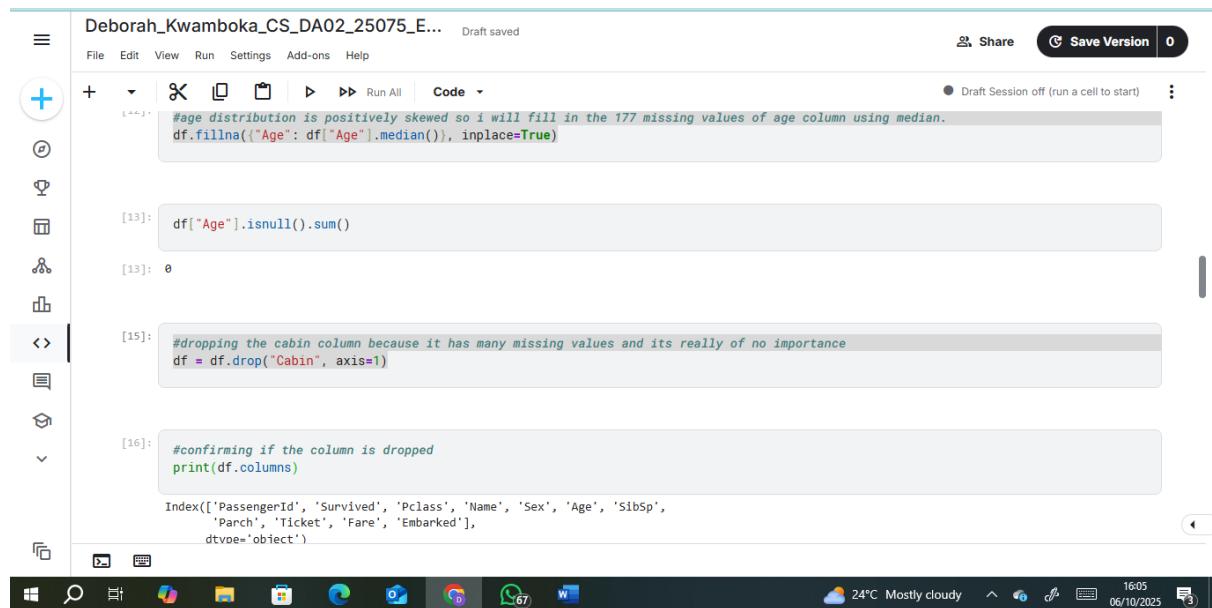
The line sns.histplot(df["Age"].dropna(), bins=20, kde=True) plots the distribution of the Age column after dropping missing values, showing how passenger ages are spread across 20

bins. The next three lines, plt.title("Age Distribution"), plt.xlabel("Age"), and plt.ylabel("Frequency"), label the plot, and plt.show() displays it. From the plotted histogram, the age distribution appears positively skewed, meaning most passengers were younger while a few were much older. To handle the 177 missing values in the Age column, the line df.fillna({"Age": df["Age"].median()}, inplace=True) replaces all missing ages with the median age, which is suitable for skewed data since the median is less affected by outliers. The line df["Age"].isnull().sum() then returns the count of remaining missing values in the Age column to confirm they were filled. The line df = df.drop("Cabin", axis=1) removes the Cabin column from the dataset because it contained too many missing values and was not useful for analysis. To verify that the column was successfully dropped, print(df.columns) returns the list of remaining column names. Finally, the line df["Embarked"] = df["Embarked"].fillna(df["Embarked"].mode()[0]) fills the two missing values in the Embarked column with the mode (most frequent value), and df["Embarked"].isnull().sum() confirms that no missing values remain.

### Screenshots of step 2:



*Figure 5: screenshot showing age distribution while checking for skewness*



```

Deborah_Kwamboka_CS_DA02_25075_E... Draft saved
File Edit View Run Settings Add-ons Help
+ X Run All Code
#age distribution is positively skewed so i will fill in the 177 missing values of age column using median.
df.fillna({"Age": df["Age"].median()}, inplace=True)

[13]: df["Age"].isnull().sum()

[13]: 0

[15]: #dropping the cabin column because it has many missing values and its really of no importance
df = df.drop("Cabin", axis=1)

[16]: #confirming if the column is dropped
print(df.columns)

Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Embarked'],
      dtype='object')

```

Figure 6: screenshot showing the results after filling in the missing age values with median, and dropping the cabin column. It can be seen that now there are no null values and the columns are now 11 confirming the cabin column is dropped

### Step 3: univariate analysis

In this step I examined each feature at a time to understand its distribution. I analysed the age distribution of passenger. I examined the number of passengers embarking from each location. I also did analysis on the distribution of ticket prices checking for skewness.

#### Code

#visualizing the age distribution of passengers through a histogram

```
sns.histplot(data=df, x="Age", bins=20, kde=True, color="blue")
```

```
plt.title("Age Distribution of Passengers")
```

```
plt.xlabel("Age")
```

```
plt.ylabel("Count")
```

```
plt.show()
```

#how many passengers embarked from each location

```
embark_counts = df["Embarked"].value_counts()
```

```
print(embarc_counts)
```

```
#checking if ticket prices are evenly distributed, or are they skewed?
```

```
# Histogram
```

```
plt.figure(figsize=(8,5))
```

```
sns.histplot(df["Fare"], bins=50, kde=True, color="purple")
```

```
plt.title("Distribution of Passenger Ticket Prices (Fare)")
```

```
plt.xlabel("Fare")
```

```
plt.ylabel("Count")
```

```
plt.show()
```

```
# Boxplot to see skew & outliers
```

```
plt.figure(figsize=(8,3))
```

```
sns.boxplot(x= df["Fare"], color="lightblue")
```

```
plt.title("Boxplot of Passenger Ticket Prices")
```

```
plt.xlabel("Fare")
```

```
plt.show()
```

### code explanation

The line `sns.histplot(data=df, x="Age", bins=20, kde=True, color="blue")` creates a histogram to visualize the distribution of passenger ages in the dataset `df`. The parameter `x="Age"` specifies that the `Age` column is being plotted, `bins=20` divides the ages into 20 equal intervals, and `kde=True` adds a Kernel Density Estimate (KDE) curve to show the smooth shape of the distribution. The `color="blue"` argument sets the histogram bars and KDE line to blue. The next three lines — `plt.title("Age Distribution of Passengers")`, `plt.xlabel("Age")`, and `plt.ylabel("Count")` add a title and label the x- and y-axes for better readability. Finally, `plt.show()` displays the plot. This visualization helps identify how ages

are spread across passengers, whether the distribution is skewed, and if there are any noticeable age groups or gaps in the data.

The line `embark_counts = df["Embarked"].value_counts()` returns the number of passengers who embarked from each location (C = Cherbourg, Q = Queenstown, S = Southampton) by counting how many times each embarkation point appears in the Embarked column. The line `print(embark_counts)` then displays these counts in descending order, helping identify which port most passengers boarded from.

Next, the code checks whether ticket prices (Fare) are evenly distributed or skewed. The block starting with `plt.figure(figsize=(8,5))` creates a figure for the histogram, and `sns.histplot(df["Fare"], bins=50, kde=True, color="purple")` plots the distribution of passenger fares across 50 bins. The `kde=True` adds a smooth density curve, and `color="purple"` sets the histogram color. The following lines — `plt.title()`, `plt.xlabel()`, and `plt.ylabel()` — label the plot, while `plt.show()` displays it. This histogram helps visualize whether most fares are concentrated in lower or higher ranges, revealing if the data is right-skewed.

The next block uses a boxplot to examine skewness and detect outliers. The line `plt.figure(figsize=(8,3))` defines the figure size, and `sns.boxplot(x=df["Fare"], color="lightblue")` creates a horizontal boxplot showing the median, quartiles, and outliers of the Fare variable. The title and label clarify the plot, and `plt.show()` displays it. The boxplot visually confirms whether there are extreme fare values (outliers) and supports conclusions about data skewness observed in the histogram.

[Screenshots to the code:](#)

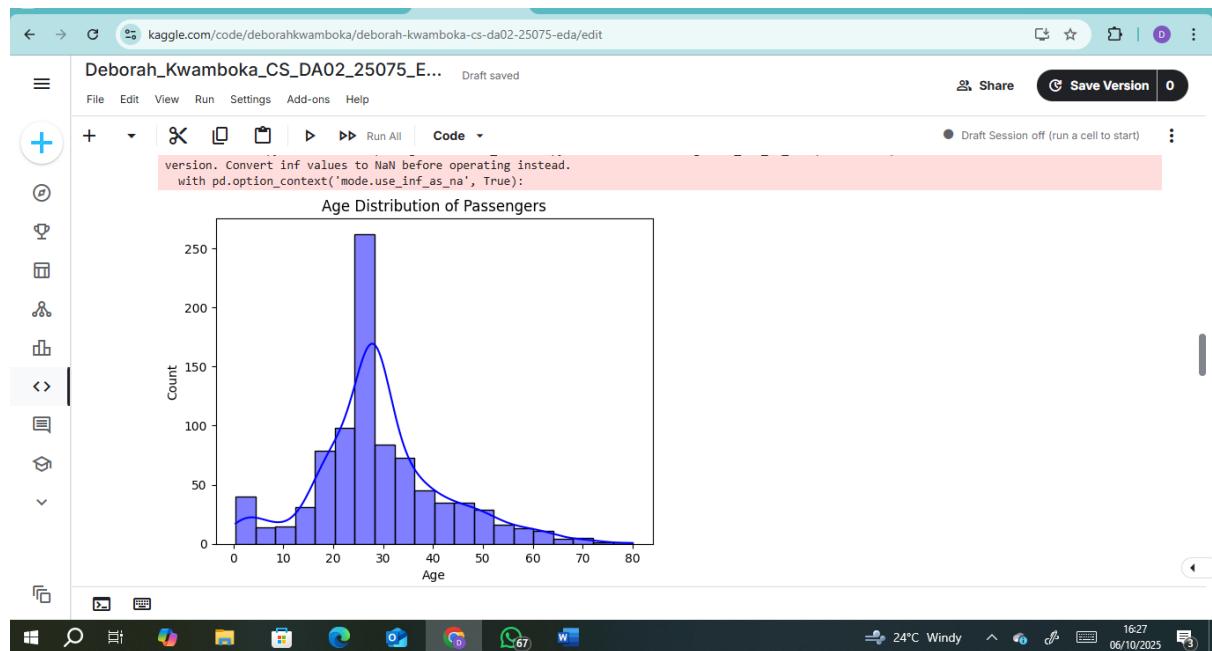
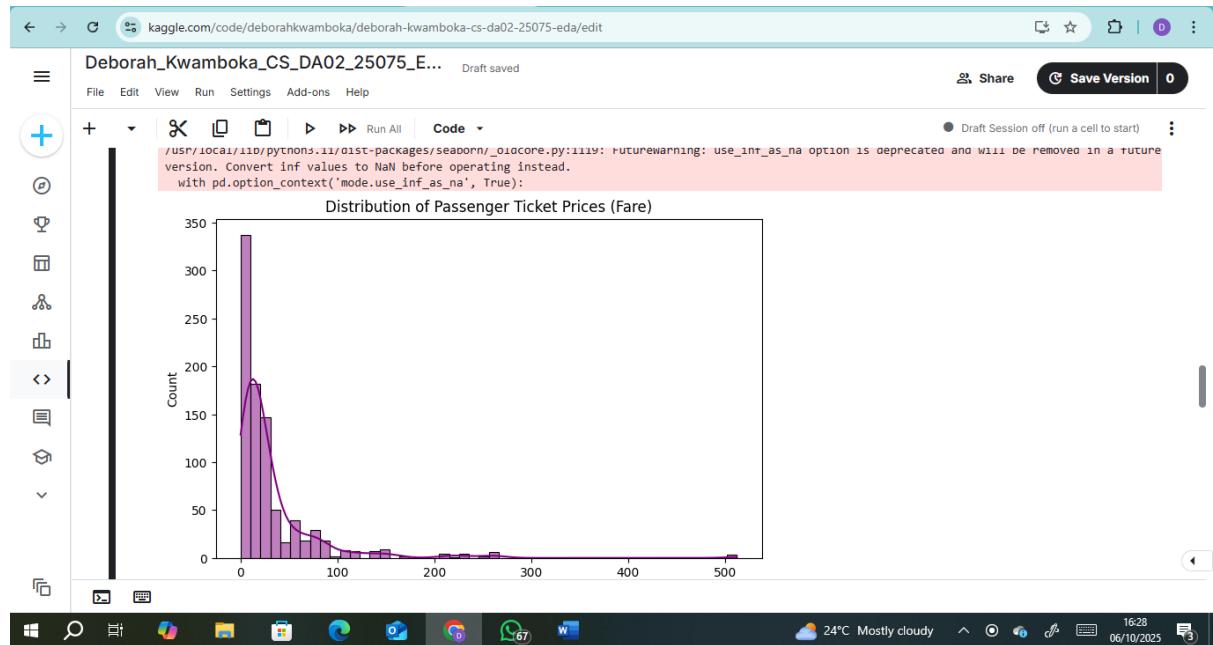


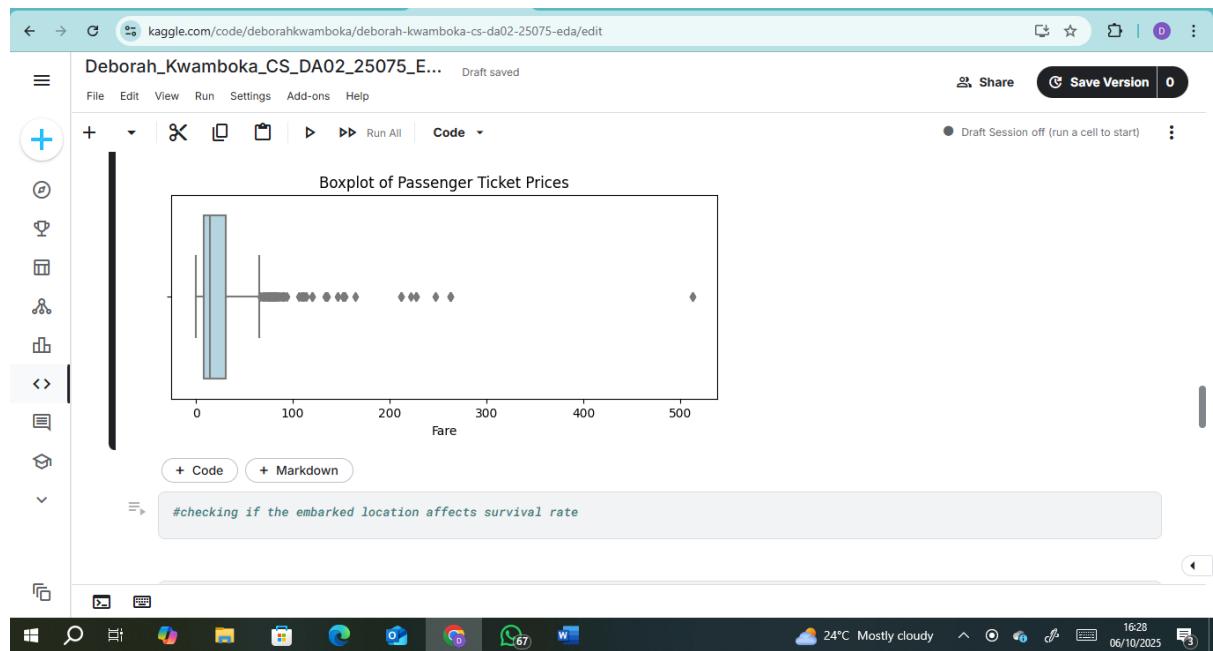
Figure 7: screenshot showing age distribution of passengers



Figure 8: screenshot showing the no of passengers embarking on each location



*Figure 9: screenshot showing the distribution of ticket prices*



*Figure 10: A boxplot of passenger ticket prices*

#### Step 4: Bivariate Analysis

In this step, I conducted bivariate analysis to explore how pairs of variables relate to each other. I examined pairs of features of interest. I analysed two variables at a time. I examined

if the fare changes depending on the Passenger class. I examined if age, younger or older affected the likelihood of survival. I analysed if the embarked location affected survival rate.

## Code

# 1. Relationship between Passenger Class and Fare

```
plt.figure(figsize=(8,5))

sns.boxplot(x='Pclass', y='Fare', data=df, palette='cool')

plt.title('Relationship between Passenger Class and Fare')

plt.xlabel('Passenger Class')

plt.ylabel('Fare')

plt.show()
```

# 2. Relationship between Age and Survival

```
plt.figure(figsize=(8,5))

sns.boxplot(x='Survived', y='Age', data=df, palette='viridis')

plt.title('Effect of Age on Survival')

plt.xlabel('Survival (0 = No, 1 = Yes)')

plt.ylabel('Age')

plt.show()
```

# 3. Relationship between Embarked Location and Survival Rate

```
plt.figure(figsize=(8,5))

sns.barplot(x='Embarked', y='Survived', data=df, palette='magma')

plt.title('Survival Rate by Embarked Location')

plt.xlabel('Embarked Location')

plt.ylabel('Average Survival Rate')
```

`plt.show()`

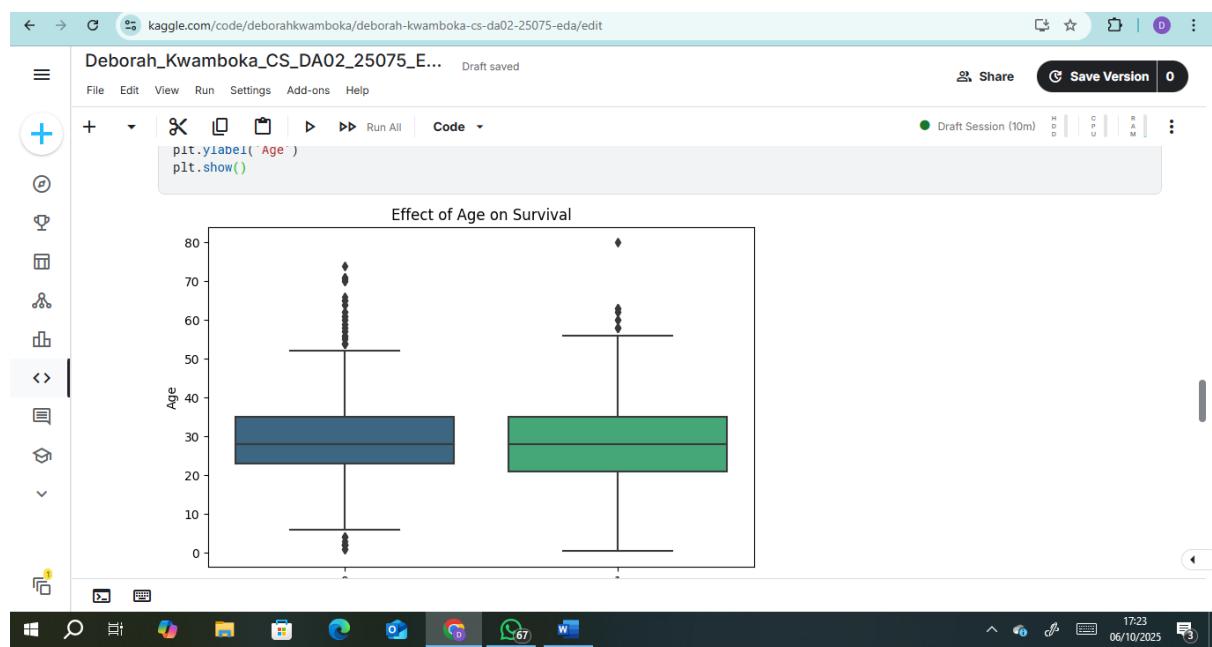
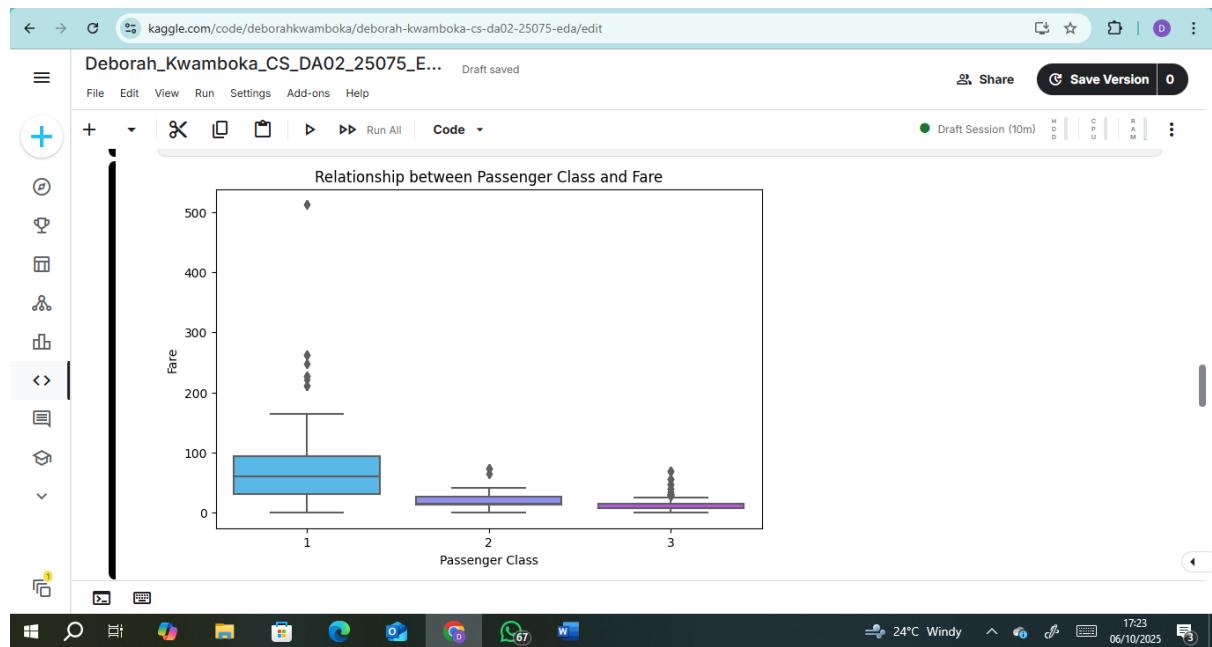
#### code explanation

The first block, `plt.figure(figsize=(8,5))`, creates a figure to control the plot size, and `sns.boxplot(x='Pclass', y='Fare', data=df, palette='cool')` plots a boxplot showing how ticket prices (Fare) vary across different Passenger Classes (Pclass). Each box represents the distribution of fares for a specific class showing that first-class passengers paid higher fares, while third-class passengers paid the lowest. The `palette='cool'` adds a blue-green color theme. The following lines add a title and axis labels, and `plt.show()` displays the plot. This visualization helps identify the relationship between class and fare, as well as any outliers in ticket prices.

The second block examines how Age relates to Survival. The line `sns.boxplot(x='Survived', y='Age', data=df, palette='viridis')` creates a boxplot comparing the age distribution of passengers who survived (1) versus those who did not (0). The plot shows whether survivors tended to be younger or older, and if there are notable differences between the two groups. The axis labels and title describe the plot, and `plt.show()` displays it.

The third block analyzes the relationship between Embarked location and survival rate. The line `sns.barplot(x='Embarked', y='Survived', data=df, palette='magma')` calculates the average survival rate for each embarkation point (C, Q, S) and displays it as a bar chart. Each bar's height represents the proportion of passengers who survived from that port. The title and labels clarify the meaning of the axes, and `plt.show()` renders the plot. This visualization helps determine whether passengers from certain embarkation points had higher survival chances. The results shows that its from point c.

#### Screenshots:





## Step 5: Multivariate Analysis

In this step I explored more complex relationships between three or more variables simultaneously. I aimed to detect interactions, combined effects, and hidden patterns that were not visible in bivariate analysis for example I analysed how Pclass, Age, and Fare jointly affect survival.

### Code

```
sns.scatterplot(data=df, x='Age', y='Fare', hue='Survived', style='Pclass',
palette='coolwarm')
```

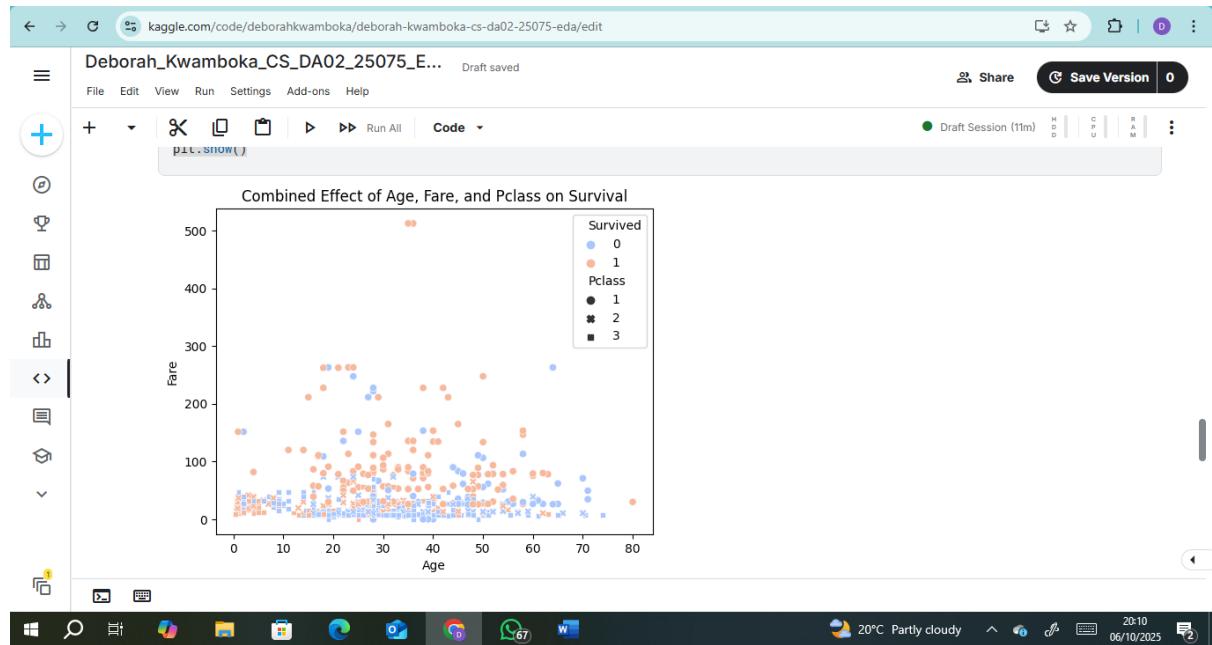
```
plt.title("Combined Effect of Age, Fare, and Pclass on Survival")
```

```
plt.show()
```

### code explanation

This line of code `sns.scatterplot(data=df, x='Age', y='Fare', hue='Survived', style='Pclass', palette='coolwarm')` creates a scatter plot that shows how Age and Fare jointly affect survival, where the color (hue) represents whether a passenger survived and the marker style (style) represents the passenger class, helping to visualize the combined influence of age, fare, and class on survival patterns.

### screenshot to code:



## Step 6: Outlier detection and handling

The intention of this step was to explore different ways to handle outliers, which include removing, capping, imputing, or leaving them as is. Removing outliers in Fare may help for predictive models, but could hide important insights for understanding passenger wealth.

The Age variable had a few mild outliers but most values were within a reasonable human range, so I decided to retain them to preserve data authenticity.

### Code

```
plt.figure(figsize=(10, 8))

# SibSp distribution
plt.subplot(2, 2, 1)
sns.histplot(df['SibSp'], bins=8, kde=True, color='skyblue')
plt.title("Distribution of SibSp (Siblings/Spouses Aboard)")
plt.xlabel("SibSp")
plt.ylabel("Count")
```

```
plt.subplot(2, 2, 2)

sns.boxplot(x=df['SibSp'], color='lightcoral')

plt.title("Boxplot of SibSp")

plt.xlabel("SibSp")

# Parch distribution

plt.subplot(2, 2, 3)

sns.histplot(df['Parch'], bins=8, kde=True, color='lightgreen')

plt.title("Distribution of Parch (Parents/Children Aboard)")

plt.xlabel("Parch")

plt.ylabel("Count")

plt.subplot(2, 2, 4)

sns.boxplot(x=df['Parch'], color='orange')

plt.title("Boxplot of Parch")

plt.xlabel("Parch")

plt.tight_layout()

plt.show()
```

#### code explanation

The above block of code detects outliers in siblings/spouse and parent/children distribution

#### Screenshots of code



Figure 11: screenshot showing distribution of sibsp



Figure 12: screenshot showing distribution of parch

From the screenshots above it can be seen that sibsp and parch have a few outliers. I decided to retain them as they are true values that show the relationship that was there among the passengers that boarded.

## Step 7: target variable exploration

In this step I analysed the Target/Dependent Variable Survived and explored the distribution of the target variable (Survived) using countplots and bar plots. I examined how balanced or imbalanced the dataset is and what factors (like age, gender, class, or embarkation point) may influence survival. I also used combined plots to detect interaction effects.

### Code

```
#target variable exploration
```

```
sns.countplot(data=df, x='Survived', palette='pastel')
```

```
plt.title("Distribution of Survival")
```

```
plt.xlabel("Survival (0 = No, 1 = Yes)")
```

```
plt.ylabel("Count")
```

```
plt.show()
```

```
sns.catplot(data=df, x='Embarked', y='Survived', hue='Pclass', kind='bar', palette='viridis')
```

```
plt.title("Survival Rate by Embarkation Port and Passenger Class")
```

```
plt.show()
```

```
#factors influencing survival
```

```
sns.barplot(data=df, x='Sex', y='Survived', palette='coolwarm')
```

```
plt.title("Survival Rate by Gender")
```

```
plt.show()
```

```
sns.barplot(data=df, x='Pclass', y='Survived', palette='mako')
```

```
plt.title("Survival Rate by Passenger Class")
```

```
plt.show()
```

```
sns.barplot(data=df, x='Embarked', y='Survived', palette='viridis')
```

```
plt.title("Survival Rate by Embarkation Point")
```

```
plt.show()
```

```
#combined plots to determine interaction effects
```

```
sns.catplot(data=df, x='Pclass', y='Survived', hue='Sex', kind='bar', palette='husl')
```

```
plt.title("Interaction between Gender and Class on Survival")
```

```
plt.show()
```

### code explanation

The line `sns.catplot(data=df, x='Embarked', y='Survived', hue='Pclass', kind='bar', palette='viridis')` generates a bar chart comparing survival rates across embarkation ports while distinguishing passengers by class, showing how both factors interact to influence survival.

The line `sns.barplot(data=df, x='Sex', y='Survived', palette='coolwarm')` displays the average survival rate for each gender, revealing that females had a much higher chance of survival than males. Similarly, `sns.barplot(data=df, x='Pclass', y='Survived', palette='mako')` shows the survival rate by passenger class, where first-class passengers survived more often than those in third class, while `sns.barplot(data=df, x='Embarked', y='Survived', palette='viridis')` examines survival differences by embarkation point.

Finally, `sns.catplot(data=df, x='Pclass', y='Survived', hue='Sex', kind='bar', palette='husl')` creates a combined bar plot that shows the interaction between gender and class on survival, illustrating that females in higher classes had the highest survival rates while males in lower classes had the lowest.

### screenshots to code:



Figure 13: relationship between passenger class and survival rate

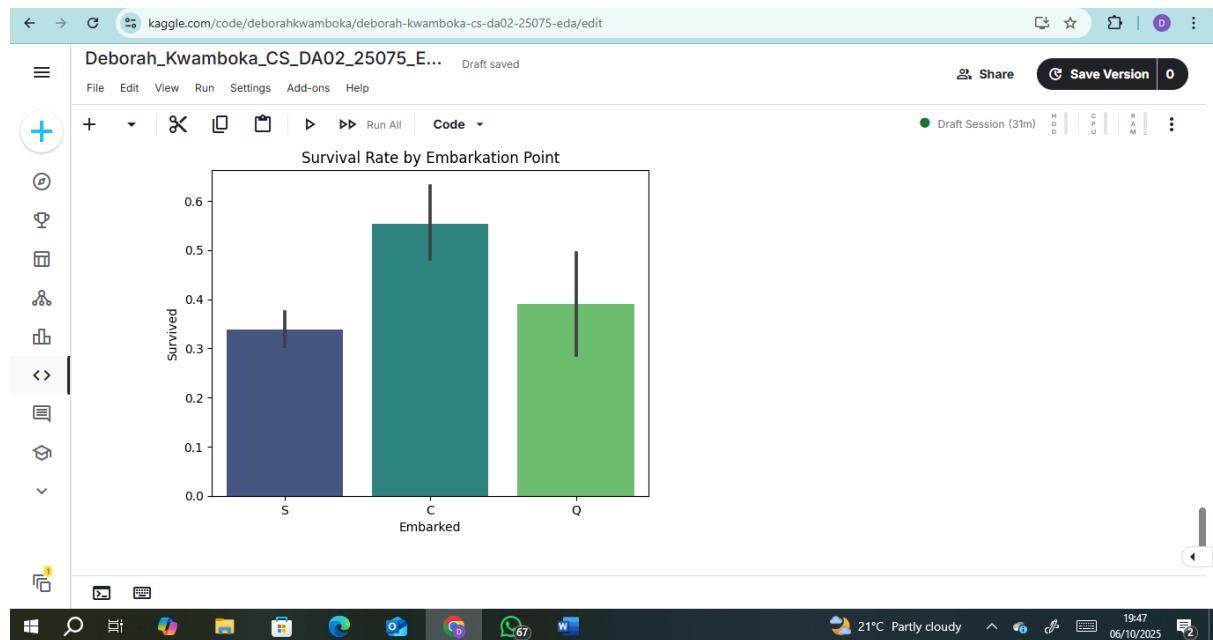


Figure 14: relationship between embarkation point and survival rate



Figure 15: relationship between gender and class on survival (combined effect)

## Link to Code

**Link to Code:** <https://www.kaggle.com/code/deborahkwamboka/deborah-kwamboka-cs-da02-25075-eda>

## Conclusion

This week I gained insights and hands on experience on exploratory data analysis. It was interesting to get an overview of a dataset and dive deeper into summarizing and understanding the data with visualizations. Through exploratory data analysis I was able to analyse the relationship between one or more variables in a data set. This week's assignment has given me practical experience of visualizing data and detecting and handling outliers.