Task2:

Data Cleaning and Exploratory Data Analysis of Titanic Dataset

In [2]:
```
# For the analysis of titanic Data set load the file train.csv
```

Step 1:

Import all necessary Libraries

In [5]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import os
```

Step 2:

Download the titanic Dataset from kaggle and Load the file Train .csv file for analysis of data

In [8]:
```
train_df=pd.read_csv(r"C:\Users\seenu\Desktop\prodigy\titanic\train.csv")
train_df
```

Out[8]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	F
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0
...	...	...	...	...	...	...	...	...	...	
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7

891 rows × 12 columns

In [ ]:

Step 3:

Understand the data

In [11]:
```
train_df.shape   # It shows rows and columns
```

Out[11]:
```
(891, 12)
```

In [12]:
```
id(train_df)  #it gives address of data
```

Out[12]:
```
3212498633840
```

In [13]:
```
train_df.info()   #It gives information of train data
```

```
<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)
memory usage: 83.7+ KB
```

In [14]:
```
cat_col=train_df.select_dtypes(include=['object']).columns.tolist()   #displays cat
cat_col
```

Out[14]:
```
['Name', 'Sex', 'Ticket', 'Cabin', 'Embarked']
```

num_col=train_df.select_dtypes(include=['number']).columns.tolist() #Numerical variables
num_col

In [16]:
```
train_df.describe()  # It gives statistical information of tiatanic dataset
```

Out[16]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.00000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.20420
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.69342
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.00000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.91040
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.45420
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.00000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.32920

In [17]:

```
train_df.isnull().sum     # to check any missing values  (raw data)
```

Out[17]:

```
<bound method DataFrame.sum of      PassengerId  Survived  Pclass   Name    Sex  
Age  SibSp  Parch  Ticket  \
0          False     False    False  False  False  False  False  False   False
1          False     False    False  False  False  False  False  False   False
2          False     False    False  False  False  False  False  False   False
3          False     False    False  False  False  False  False  False   False
4          False     False    False  False  False  False  False  False   False
..           ...       ...      ...    ...    ...    ...    ...    ...     ...
886        False     False    False  False  False  False  False  False   False
887        False     False    False  False  False  False  False  False   False
888        False     False    False  False  False   True  False  False   False
889        False     False    False  False  False  False  False  False   False
890        False     False    False  False  False  False  False  False   False

      Fare  Cabin  Embarked
0    False   True     False
1    False  False     False
2    False   True     False
3    False  False     False
4    False   True     False
..     ...    ...       ...
886  False   True     False
887  False  False     False
888  False   True     False
889  False  False     False
890  False   True     False

[891 rows x 12 columns]>
```

As shown above wa can find out columns Age,cabin,Embarked have missing values

Step 4:

clean the data

4.1. Drop the less Used columns

In [21]:
```
train_df.drop(['Cabin','Ticket','Name','PassengerId'],axis=1)
```

Out[21]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	male	22.0	1	0	7.2500	S
1	1	1	female	38.0	1	0	71.2833	C
2	1	3	female	26.0	0	0	7.9250	S
3	1	1	female	35.0	1	0	53.1000	S
4	0	3	male	35.0	0	0	8.0500	S
...	...	...	...	...	...	...	...	...
886	0	2	male	27.0	0	0	13.0000	S
887	1	1	female	19.0	0	0	30.0000	S
888	0	3	female	NaN	1	2	23.4500	S
889	1	1	male	26.0	0	0	30.0000	C
890	0	3	male	32.0	0	0	7.7500	Q

891 rows × 8 columns

Dropped columns and reasons

- Cabin : Too many mising values and format is not standardized
- Ticket : Alphanumeric codes with no clear pattern hard to extract insights
- Name : Not useful for analysis directly(Mr/Mrs)
- PassengerId :Just an identifier not used for insights

4.2 Handle the Missing values

In [25]:
```
train_df['Age']=train_df['Age'].fillna(train_df['Age'].median())   #Here missing val
```

In [26]:
```
train_df['Age']
```

Out[26]:
```
0      22.0
1      38.0
2      26.0
3      35.0
4      35.0
       ...
886    27.0
887    19.0
888    28.0
889    26.0
890    32.0
Name: Age, Length: 891, dtype: float64
```

In [27]:
```
train_df['Embarked']=train_df['Embarked'].fillna(train_df['Embarked'].mode())
```

In [28]:
```
train_df['Embarked']
```

Out[28]:
```
0      S
1      C
2      S
3      S
4      S
      ..
886    S
887    S
888    S
889    C
890    Q
Name: Embarked, Length: 891, dtype: object
```

4.3 Convert into Categorical variables

In [30]:
```
train_df['Sex']=train_df['Sex'].map({'male':'0','female':'1'})
train_df['Embarked']=train_df['Embarked'].map({'S':0,'C':1,'Q':2})
```

In [31]:
```
train_df['Sex']
```

Out[31]:
```
0      0
1      1
2      1
3      1
4      0
      ..
886    0
887    1
888    1
889    0
890    0
Name: Sex, Length: 891, dtype: object
```

In [32]:
```
train_df['Embarked']
```

Out[32]:
```
0      0.0
1      1.0
2      0.0
3      0.0
4      0.0
      ...
886    0.0
887    0.0
888    0.0
889    1.0
890    2.0
Name: Embarked, Length: 891, dtype: float64
```

- Here we use mapping encoding to cange 'Sex ' categorical columns(male,female)value to numerical 0 and 1 numerical
- same as for 'Embarked' column value change =({s:'0','C':1,'Q':2)

In [34]:
```
#Now all useful data columns cleaned and encoded ready for Exploratory Data Analysi
```

In [35]:
```
train_df
```

Out[35]:

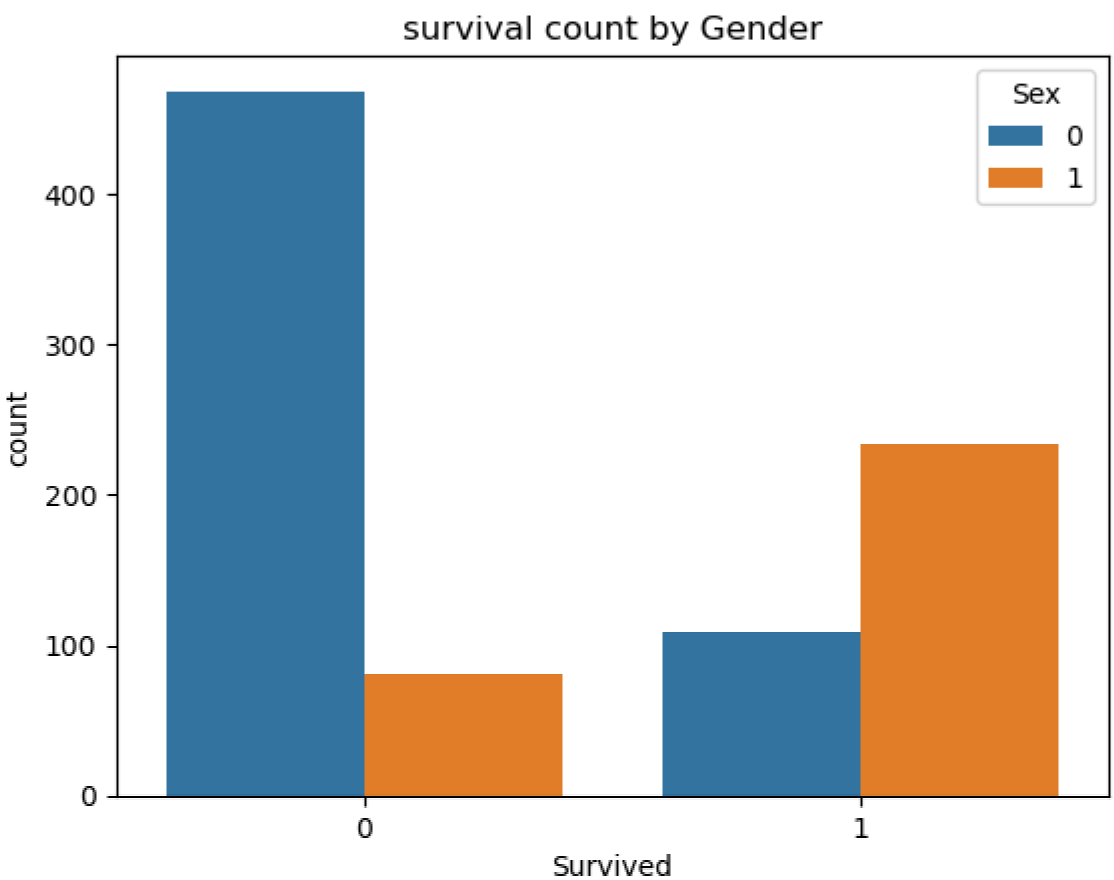
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	0	22.0	1	0	A/5 21171	7.2500
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	1	38.0	1	0	PC 17599	71.2833
2	3	1	3	Heikkinen, Miss. Laina	1	26.0	0	0	STON/O2. 3101282	7.9250
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	1	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	0	35.0	0	0	373450	8.0500
...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	0	27.0	0	0	211536	13.0000
887	888	1	1	Graham, Miss. Margaret Edith	1	19.0	0	0	112053	30.0000
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	1	28.0	1	2	W./C. 6607	23.4500
889	890	1	1	Behr, Mr. Karl Howell	0	26.0	0	0	111369	30.0000
890	891	0	3	Dooley, Mr. Patrick	0	32.0	0	0	370376	7.7500

891 rows × 12 columns

Step 5: Exploaratory Data Analysis

5.1. Survival by Gender

In [38]:
```
import seaborn as sns
sns.countplot(x='Survived',hue='Sex',data=train_df)
plt.title('survival count by Gender')
plt.show()
```



📈 Insights from the plot

The X-axis left side graph(0) shows deaths, the right side shows survivors(1), and the color(blue=male, orange=female) split tells us how gender impacted survival.

🟦 Blue Bars (Sex = 0 → Male)

- Most males did not survive (left bar is very tall for Survived = 0).
- Only a small number of males survived (right blue bar is much shorter).

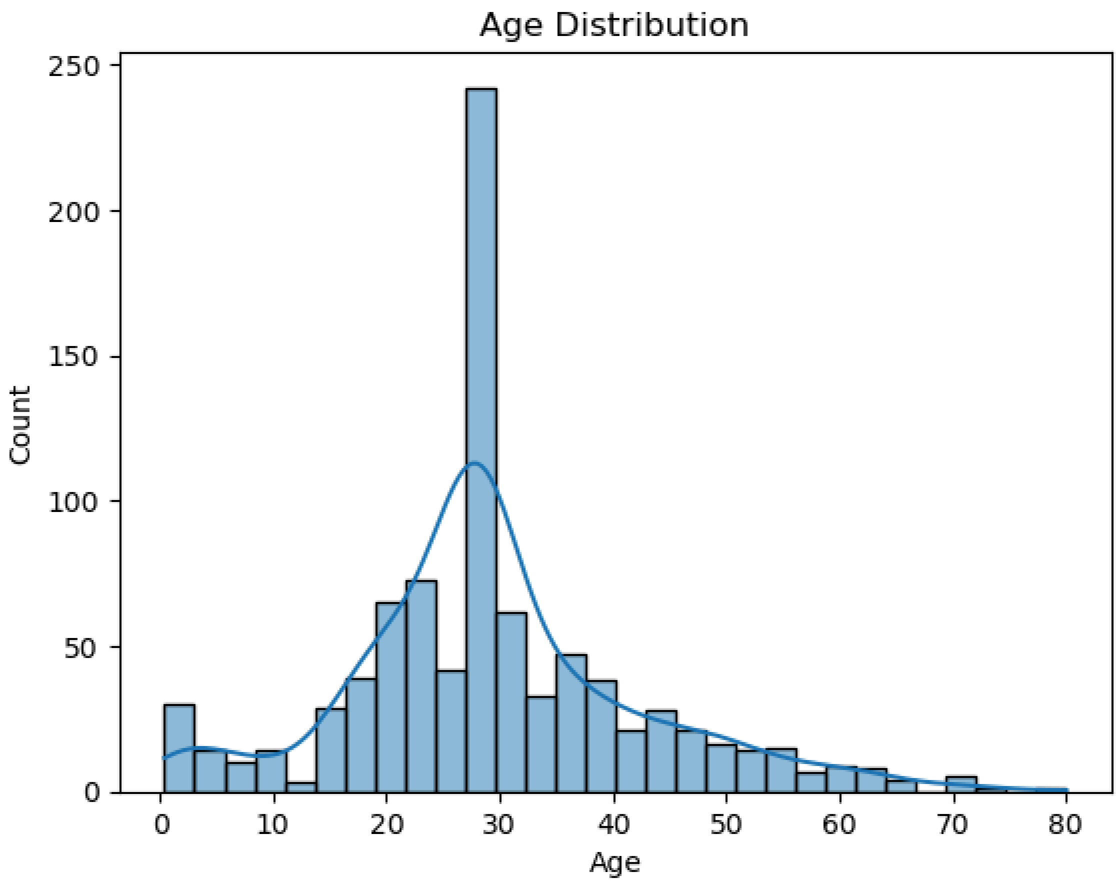
🟧 Orange Bars (Sex = 1 → Female)

- Most females survived (right orange bar is taller than left).

- Fewer females died (left orange bar is shorter)

5.2.Age Distribution

In [41]:
```
sns.histplot(train_df['Age'],kde=True)
plt.title('Age Distribution')
plt.show()
```



📊 Detailed Insights from the Age Distribution Plot

Right-Skewed Distribution:

- The histogram shows a slight right-skew, meaning more passengers were younger.
- The peak (mode) occurs around 20–30 years, indicating this was the most common age group.

KDE Line Adds Smoothing:

- The smooth KDE curve helps us understand the underlying distribution.
- It confirms that the majority of passengers were young adults.

Children (0–10 years):

- A noticeable spike near age 0–10 indicates that a number of children were on board, although fewer than adults.

Ages 30–50:

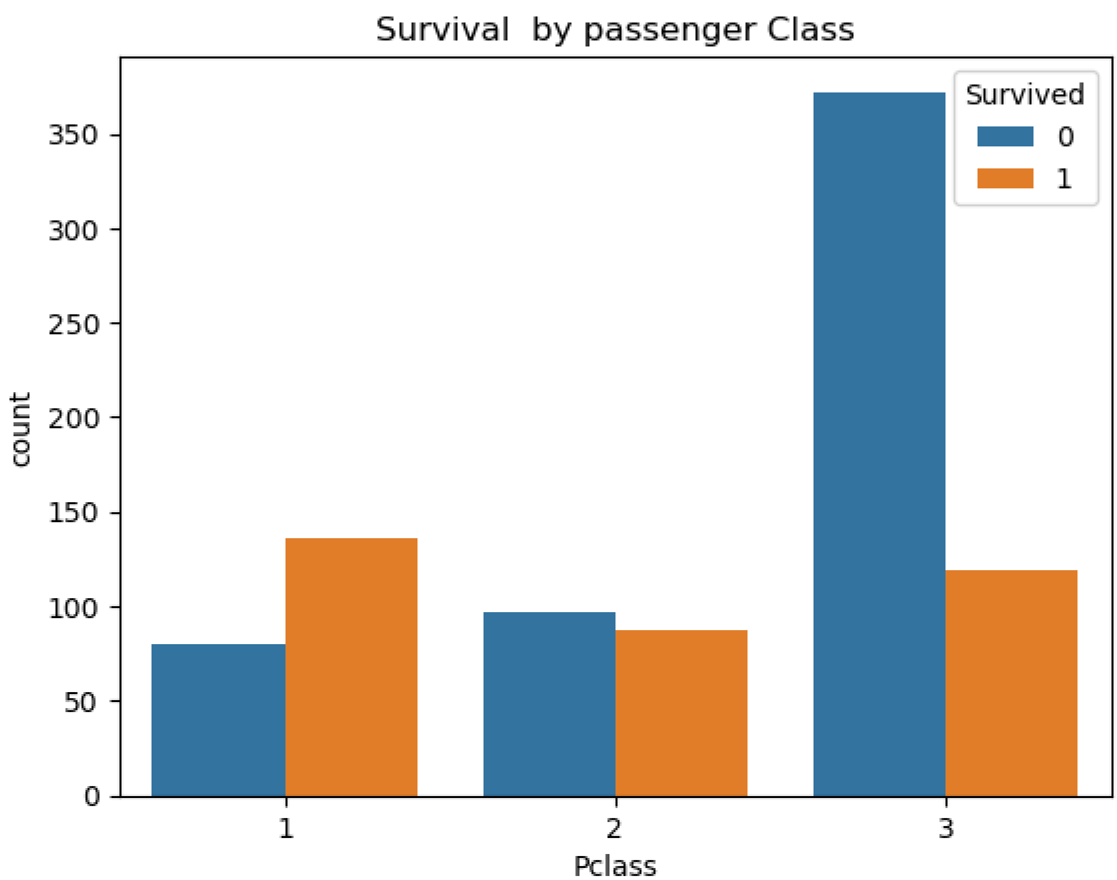
- There is a moderate number of passengers between 30 and 50 years, forming a broad plateau in the KDE line.
- This age range appears more evenly distributed.

Fewer Elderly Passengers:

Very few passengers were above 60 years, and the frequency drops sharply after age 60.

5.3.Survival by class

In [44]:
```
sns.countplot(x='Pclass',hue='Survived',data=train_df)
plt.title('Survival  by passenger Class')
plt.show()
```



📊 Graph Overview

- X-axis: Passenger Class (Pclass – 1st, 2nd, 3rd).
- Hue: Survival status (0 = Did not survive, 1 = Survived).
- Y-axis: Number of passengers.
- Bars: Represent counts, split into survivors and non-survivors for each class.

🔍 Insights

1. 1st Class Had the Highest Survival Rate:

- The light-colored (survived) bar is taller than the dark (non-survived) bar.

Shows that most 1st class passengers survived.

2. 3rd Class Faced the Highest Fatality Rate:

- The dark bar dominates, indicating that majority of 3rd class passengers did not survive.

Survival chances were significantly lower in this class.

3. 2nd Class Shows Balanced Distribution:

- The bars for survival and non-survival are more evenly split, suggesting a moderate survival rate for 2nd class.

Clear Socioeconomic Impact on Survival:

- The trend indicates that higher class = higher chance of survival.

Access to lifeboats and priority during evacuation likely favored 1st class.

📝 Summary

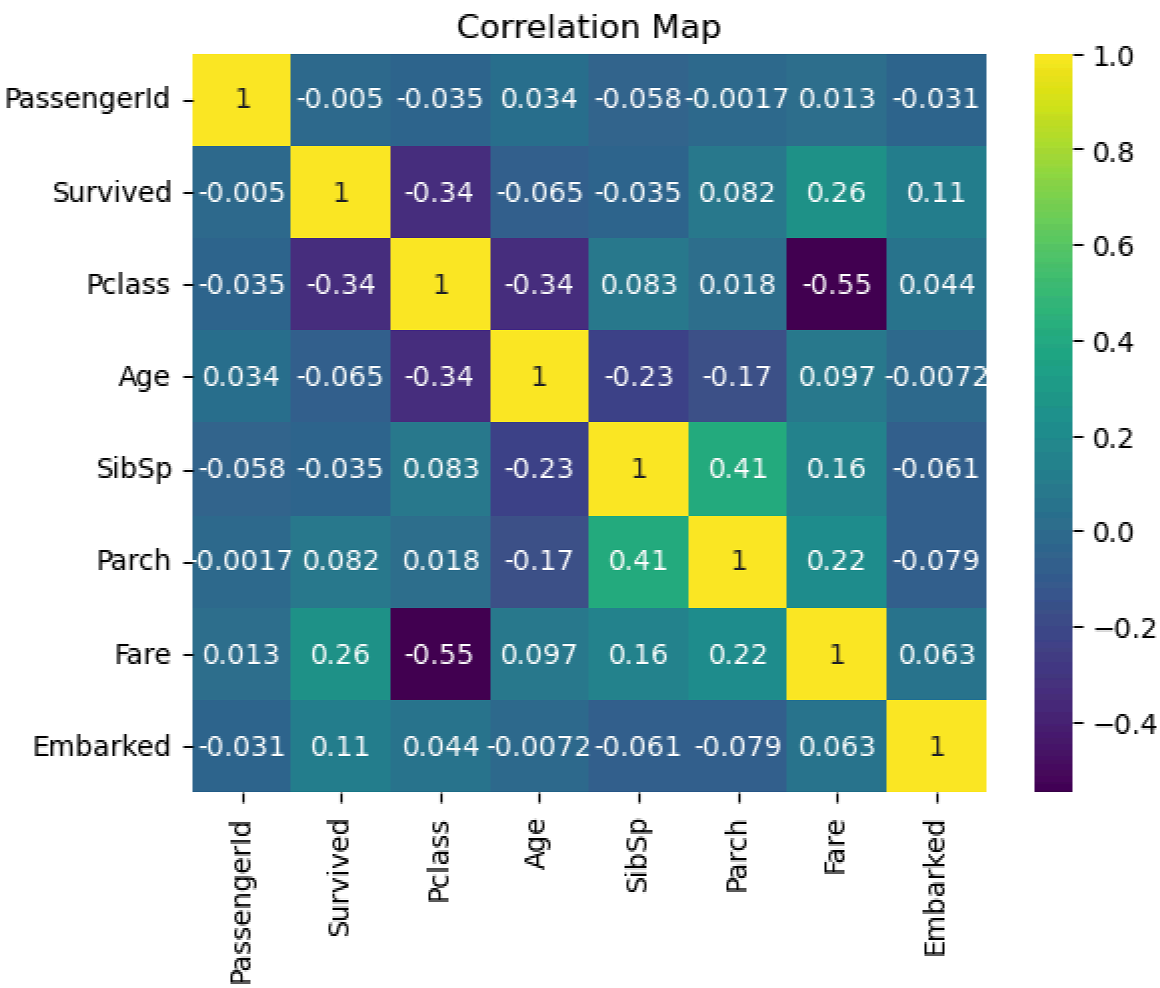
- Survival was strongly correlated with passenger class.
- 1st class passengers had the best chance, followed by 2nd, and 3rd class had the worst outcomes.
- This highlights the role of socioeconomic status in survival, a key pattern in the Titanic dataset.

5.4 Correlation Map

In [57]:

```
sns.heatmap(train_df.corr(numeric_only=True),annot=True,cmap='viridis')
plt.title('Correlation Map')
```

```
plt.show()
```



	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare	Embarked
PassengerId	1	-0.005	-0.035	0.034	-0.058	-0.0017	0.013	-0.031
Survived	-0.005	1	-0.34	-0.065	-0.035	0.082	0.26	0.11
Pclass	-0.035	-0.34	1	-0.34	0.083	0.018	-0.55	0.044
Age	0.034	-0.065	-0.34	1	-0.23	-0.17	0.097	-0.0072
SibSp	-0.058	-0.035	0.083	-0.23	1	0.41	0.16	-0.061
Parch	-0.0017	0.082	0.018	-0.17	0.41	1	0.22	-0.079
Fare	0.013	0.26	-0.55	0.097	0.16	0.22	1	0.063
Embarked	-0.031	0.11	0.044	-0.0072	-0.061	-0.079	0.063	1

Abouth the heat map

- A correlation heatmap shows the linear relationship between numerical features.
- Values range from -1 to +1:
  - +1: Perfect positive correlation
  - -1: Perfect negative correlation
  - : No correlation
- Generated using sns.heatmap() with cmap='coolwarm' .

📌 Key Insights:

- 🎯 Correlations with Survival (Survived):

🔹 **Sex (0.54) – Strongest positive correlation** → Being female (typically encoded as 1) was strongly associated with survival.

🔹 **Fare (0.26) – Moderate positive correlation** → Higher fare passengers had a better chance of survival (likely wealthier).

🔹 **Pclass (-0.34) – Moderate negative correlation**→ Lower class number (1st class) had better survival; higher class (3rd) had lower survival chances.

📉 Other Feature Relationships:

- 🔹 **SibSp & Parch (0.41)** – Moderate positive correlation

→ Passengers with siblings/spouses often also had parents/children aboard.

- 🔹 **Pclass & Fare (-0.55)** – Strong negative correlation
- Higher class passengers paid more fare (1st class had higher fares).
- 🔹 **Age & Parch (-0.17)** – Mild negative correlation

→ Younger passengers more likely traveled with parents.

✅ Summary Points:

- 🚺Gender is the most influential factor in survival (females had better chances).
- 💰 Wealth (indicated by Fare & Pclass) significantly influenced survival.

Traveling with family (SibSp/Parch) has mild correlation with other factors, but limited influence on survival.

- 👶 Age shows weak correlation with survival but may be more influential when

combined with other features (like family presence or class).

In [ ]:
```

```