```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

df=pd.read_csv(r'C:\Users\DELL\Desktop\VIKAS SINGH\Titanic-
Dataset.csv')

df.head(5)

   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age
SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0
1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
1
2                             Heikkinen, Miss. Laina  female  26.0
0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
1
4                           Allen, Mr. William Henry    male  35.0
0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S

df.tail(5)

     PassengerId  Survived  Pclass
Name  \
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

        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
```

# Typical Columns in the Titanic Dataset

Column Description

PassengerId- Unique identifier for each passenger

Survived- Whether the passenger survived (1) or not (0)

Pclass - Passenger class (1st, 2nd, 3rd)

Name - Full name

Sex Gender

Age Age in years

SibSp Number of siblings/spouses aboard

Parch Number of parents/children aboard

Ticket Ticket number

Fare Fare paid

Cabin Cabin number

Embarked Port of embarkation (C = Cherbourg, Q = Queenstown, S = Southampton)

```
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
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

```
df.dtypes
```

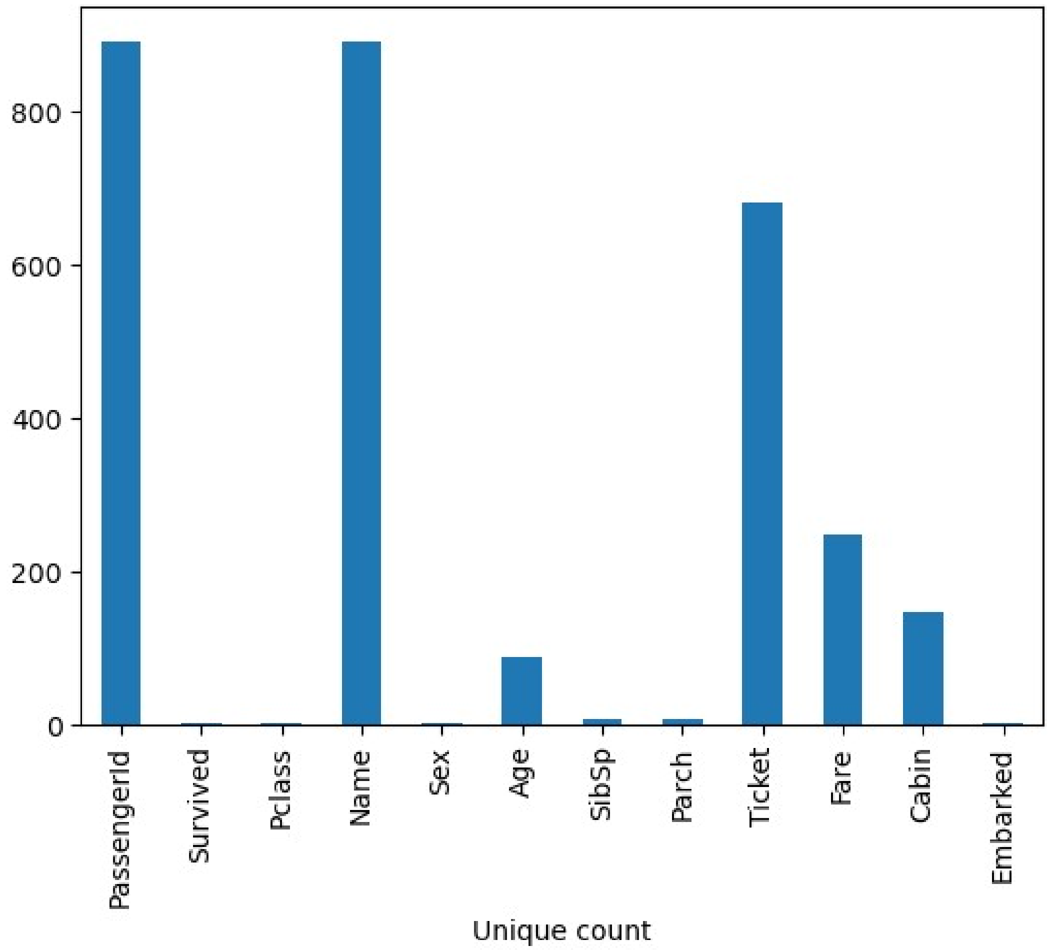
```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

```
df.describe() # basic stats for int data tpe
```

```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

- There are 891 records.
- the average age of passenger is 30 years old, 75 % ,population is under 38 years, max age is 80 may be a outlier in the dataset.
- The average fare is $ 32. 75 % passeger is under the 32$ ticket.

```
df.nunique().plot(kind='bar')
plt.xlabel('Unique count')
plt.show()
```



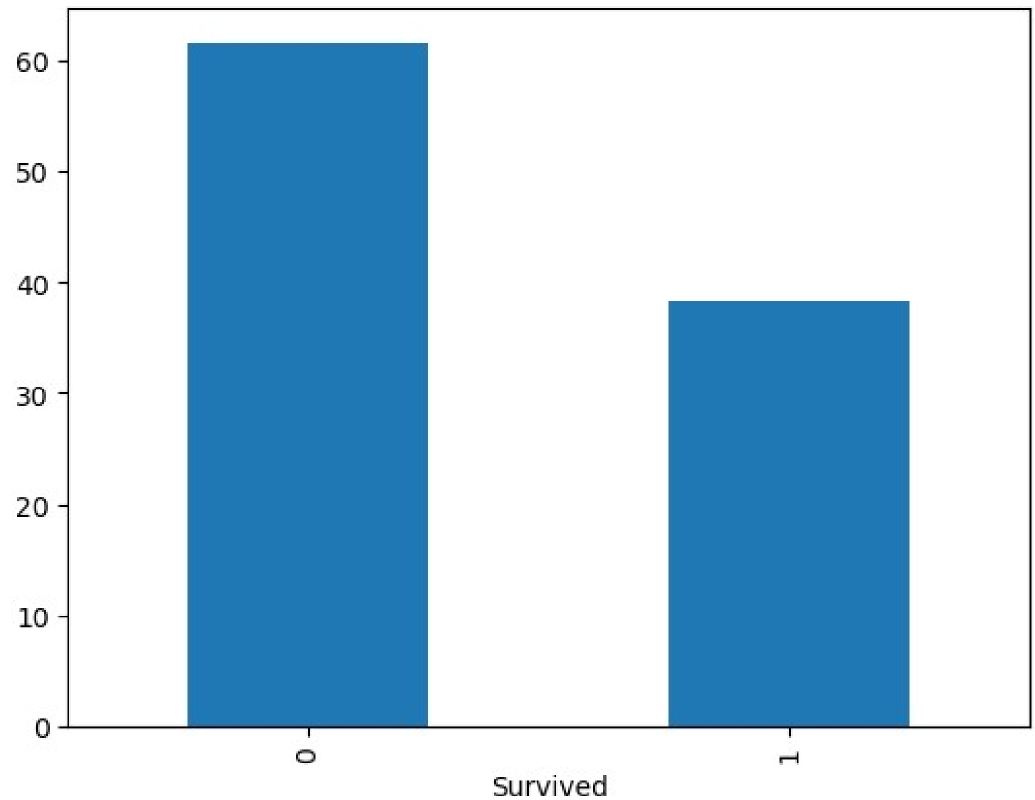

```
df.size
```

```
10692
```

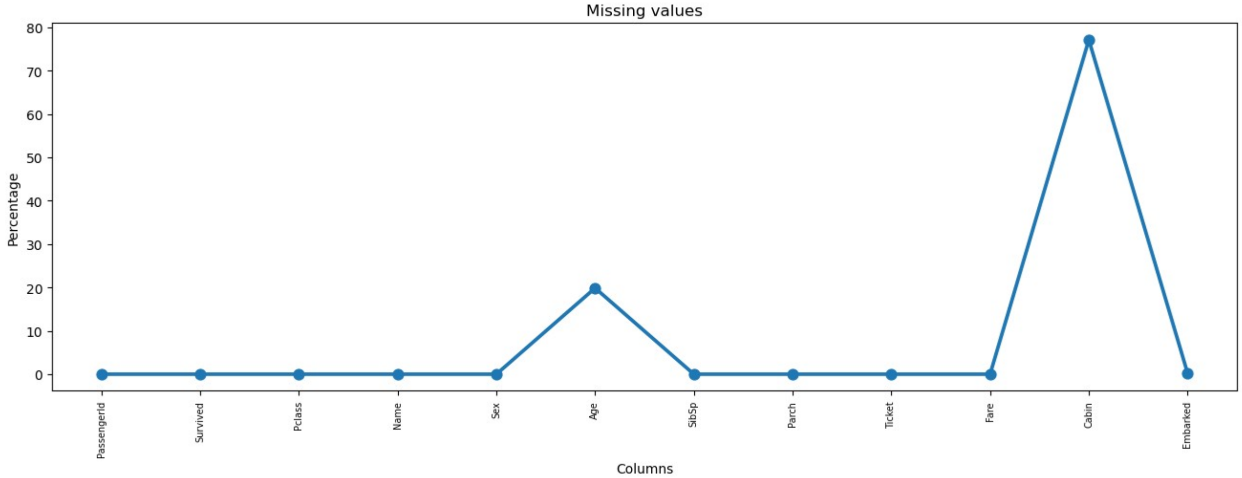
```
df.shape
```

```
(891, 12)
```

```
(100*df.Survived.value_counts()/len(df)).plot(kind='bar')
plt.show()

# very low pecentage of surviuval 61 : 39 ratio for survival
```



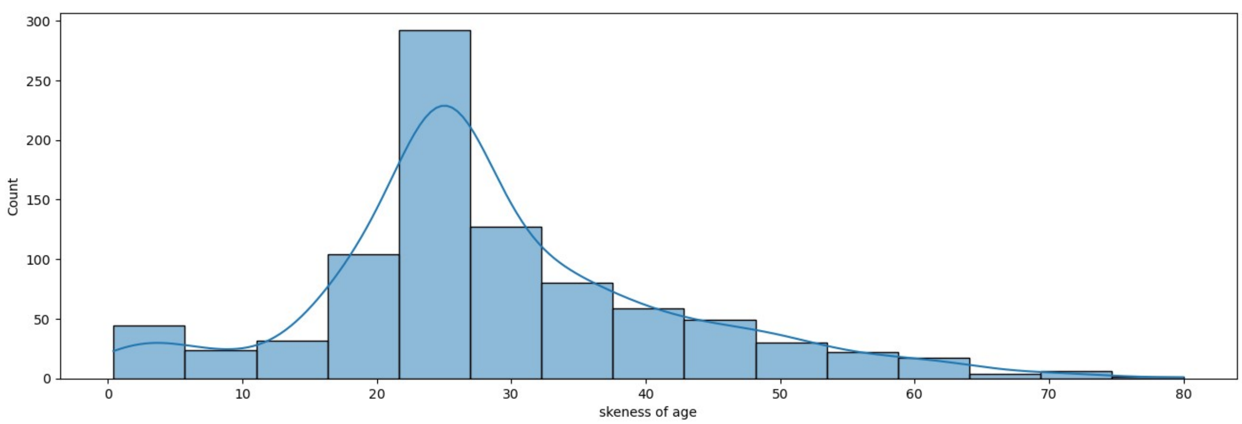

```
missing
=pd.DataFrame((df.isnull().sum()*100)/df.shape[0]).reset_index()
missing.columns = ['Column', 'MissingPercent']

plt.figure(figsize=(16,5))
ax=sns.pointplot(x='Column',y='MissingPercent',data=missing)
plt.xticks(rotation=90,fontsize=7)
plt.xlabel('Columns')
plt.ylabel('Percentage')
plt.title("Missing values")
plt.show()
```




## Missing Data - initial Intuition

- In the Age data, it is left skewed data, so we have identified the mean of people whose age between 20 to 30 as per skewness of data and replace the null values with that is Age.
- In the Cabin, there is 687 null values available, there is Pclass 1 value where 40 null values in Cabin
- In the Cabin, there is 687 null values available, there is Pclass 2 value where 168 null values in Cabin
- In the Cabin, there is 687 null values available, there is Pclass 3 value where 479 null values in Cabin
- 2 Values is null in the Embarked.

```
plt.figure(figsize=(16,5))
sns.histplot(df.Age, bins=15,kde=True)
plt.xlabel('skeness of age')
plt.show()
```



```python
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
```

```python
Age = df[(df['Age'] >= 20) & (df['Age'] <= 30)]
Age.Age.mean()
```

```
25.091836734693878
```

```python
Age.describe()
```

```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   245.000000  245.000000  245.000000  245.000000  245.000000
mean    432.624490    0.355102    2.424490   25.091837    0.314286
std     254.982444    0.479524    0.757079    3.134410    0.610026
min       1.000000    0.000000    1.000000   20.000000    0.000000
25%     222.000000    0.000000    2.000000   22.000000    0.000000
50%     404.000000    0.000000    3.000000   25.000000    0.000000
75%     650.000000    1.000000    3.000000   28.000000    0.000000
max     890.000000    1.000000    3.000000   30.000000    3.000000

            Parch        Fare
count  245.000000  245.000000
mean     0.228571   27.101665
std      0.631158   42.826678
min      0.000000    0.000000
25%      0.000000    7.895800
50%      0.000000   10.500000
75%      0.000000   26.000000
max      4.000000  263.000000
```

```python
df.Cabin.isnull().sum()
```

```
687
```

```python
# Convert the 'Cabin' column to string, take the first character (deck
letter), and store it in a new 'Deck' column
df['Deck'] = df['Cabin'].astype(str).str[0]
```

```
df.groupby(['Pclass','Deck'])['Fare'].agg(Count='count', Max='max',
Sum='sum', Min = 'min',Mean = 'mean',std= 'std')
```

```
             Count       Max        Sum      Min        Mean
std
Pclass Deck

1      A        15   81.8583   594.3583   0.0000   39.623887
17.975333
       B        47  512.3292  5334.7709   0.0000  113.505764
109.301500
       C        99  512.3292  8982.8748   0.0000   90.736109
79.267897
       D        29  113.2750  1836.4043  25.9292   63.324286
26.172260
       E        25  134.5000  1393.5042  25.5875   55.740168
30.386910
       T         1   35.5000    35.5000  35.5000   35.500000
NaN
2      D         4   13.7917    52.6667  12.8750   13.166675
0.420829
       E         4   13.0000    46.3500  10.5000   11.587500
1.283469
       F       176   73.5000  3702.8250   0.0000   21.038778
13.598383
3      E         3   12.4750    33.0000   8.0500   11.000000
2.554775
       F       484   69.5500  6627.3701   0.0000   13.692913
11.856758
       G         4   16.7000    54.3250  10.4625   13.581250
3.601222
```

```
df[df['Pclass']==1].isnull().sum()
```

```
PassengerId     0
Survived        0
Pclass          0
Name            0
Sex             0
Age            30
SibSp           0
Parch           0
Ticket          0
Fare            0
Cabin          40
Embarked        2
Deck            0
dtype: int64
```

```
df[df['Pclass']==2].isnull().sum()
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age             11
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          168
Embarked         0
Deck             0
dtype: int64
```

```python
df[df['Pclass']==3].isnull().sum()
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            136
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          479
Embarked         0
Deck             0
dtype: int64
```

```python
df.groupby('Deck')[['Fare', 'Pclass']].agg(
    Count_Fare=('Fare', 'count'),
    Max_Fare=('Fare', 'max'),
    Count_Pclass=('Pclass', 'count'),
    Max_Pclass=('Pclass', 'max')
)
```

| Deck | Count_Fare | Max_Fare | Count_Pclass | Max_Pclass |
|---|---|---|---|---|
| A | 15 | 81.8583 | 15 | 1 |
| B | 47 | 512.3292 | 47 | 1 |
| C | 59 | 263.0000 | 59 | 1 |
| D | 33 | 113.2750 | 33 | 2 |
| E | 32 | 134.5000 | 32 | 3 |
| F | 13 | 39.0000 | 13 | 3 |
| G | 4 | 16.7000 | 4 | 3 |
| T | 1 | 35.5000 | 1 | 1 |
| n | 687 | 512.3292 | 687 | 3 |

```python
df['Deck'] = df['Deck'].replace('n',np.nan)
```

```python
df
```

```
     PassengerId  Survived  Pclass  \
0              1         0       3
1              2         1       1
2              3         1       3
3              4         1       1
4              5         0       3
..           ...       ...     ...
886          887         0       2
887          888         1       1
888          889         0       3
889          890         1       1
890          891         0       3

                                                  Name     Sex   Age
SibSp  \
0                              Braund, Mr. Owen Harris    male  22.0
1
1    Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
1
2                               Heikkinen, Miss. Laina  female  26.0
0
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
1
4                             Allen, Mr. William Henry    male  35.0
0
..                                                 ...     ...   ...
...
886                              Montvila, Rev. Juozas    male  27.0
0
887                       Graham, Miss. Margaret Edith  female  19.0
0
888           Johnston, Miss. Catherine Helen "Carrie"  female   NaN
1
889                              Behr, Mr. Karl Howell    male  26.0
0
890                                Dooley, Mr. Patrick    male  32.0
0

     Parch            Ticket     Fare Cabin Embarked Deck
0        0         A/5 21171   7.2500   NaN        S  NaN
1        0          PC 17599  71.2833   C85        C    C
2        0  STON/O2. 3101282   7.9250   NaN        S  NaN
3        0            113803  53.1000  C123        S    C
4        0            373450   8.0500   NaN        S  NaN
..     ...               ...      ...   ...      ...  ...
886      0            211536  13.0000   NaN        S  NaN
```

```
887       0            112053  30.0000   B42         S    B
888       2         W./C. 6607  23.4500   NaN         S  NaN
889       0            111369  30.0000  C148         C    C
890       0            370376   7.7500   NaN         Q  NaN

[891 rows x 13 columns]
```

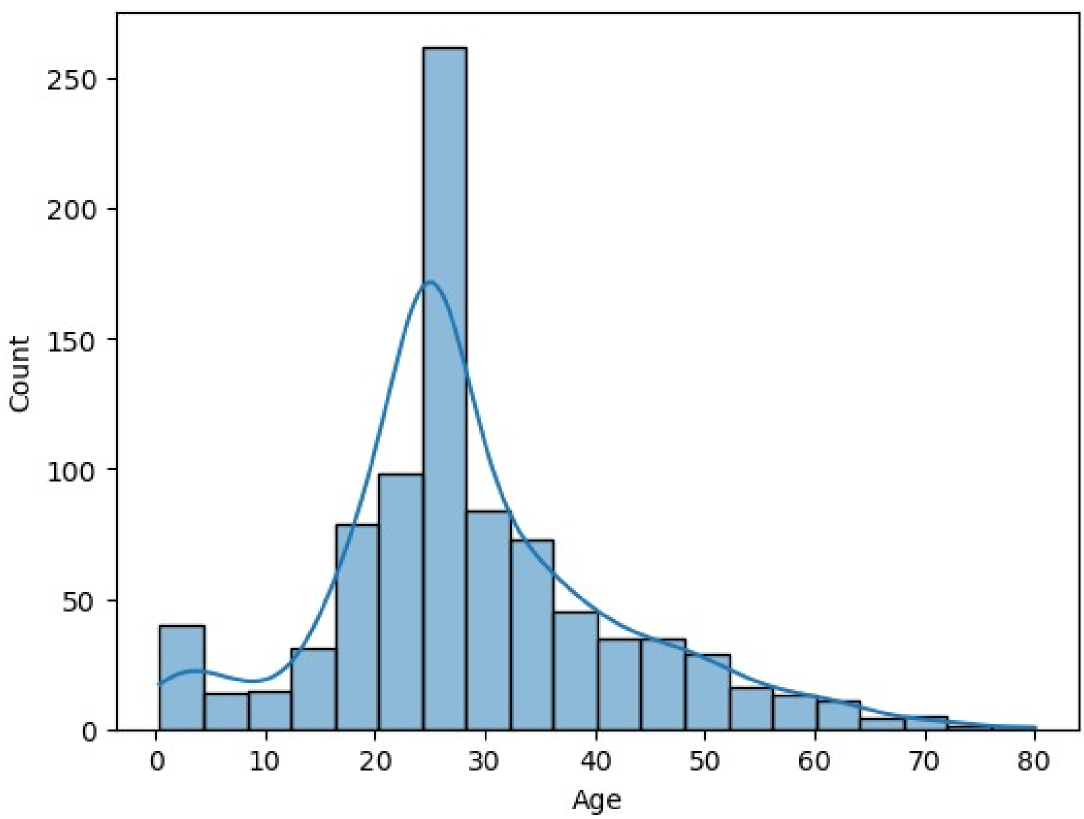
# Data Cleaning

on the basis of missing value intuition , we can fill the null values.

-in the Age, we can fill null with the age between (20 to 30 ) mean bcz aforesaid that the data is left skewed.

-in the Cabin value we should fill the null values on the basis of Pclass of passenger and

```
# fill the null vales in the age column
df.Age=df['Age'].fillna(Age.Age.mean())

sns.histplot(df['Age'],bins=20,kde=True)
plt.show()
```




```
## lets fil the null values in the Cabin
```

```
df.head()
```

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age
SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0
1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
1
2                             Heikkinen, Miss. Laina  female  26.0
0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
1
4                           Allen, Mr. William Henry    male  35.0
0

   Parch            Ticket     Fare Cabin Embarked Deck
0      0         A/5 21171   7.2500   NaN        S  NaN
1      0          PC 17599  71.2833   C85        C    C
2      0  STON/O2. 3101282   7.9250   NaN        S  NaN
3      0            113803  53.1000  C123        S    C
4      0            373450   8.0500   NaN        S  NaN
```

```
# Find most common deck per Pclass
deck_mode_per_class = df.groupby('Pclass')['Deck'].agg(lambda x:
x.mode()[0])
print(deck_mode_per_class)
```

```
Pclass
1    C
2    F
3    F
Name: Deck, dtype: object
```

```
# Fill missing Decks by class
def impute_deck(row):
    if pd.isnull(row['Cabin']):
        return deck_mode_per_class[row['Pclass']]
    else:
        return row['Deck']


df['Deck']= df.apply(impute_deck,axis=1)
```

```
df['Cabin']= df['Deck'] + "000"

df
```

```
     PassengerId  Survived  Pclass  \
0              1         0       3
1              2         1       1
2              3         1       3
3              4         1       1
4              5         0       3
..           ...       ...     ...
886          887         0       2
887          888         1       1
888          889         0       3
889          890         1       1
890          891         0       3

                                                  Name     Sex
Age  \
0                              Braund, Mr. Owen Harris    male
22.000000
1    Cumings, Mrs. John Bradley (Florence Briggs Th...  female
38.000000
2                               Heikkinen, Miss. Laina  female
26.000000
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)  female
35.000000
4                             Allen, Mr. William Henry    male
35.000000
..                                                 ...     ...
...
886                              Montvila, Rev. Juozas    male
27.000000
887                       Graham, Miss. Margaret Edith  female
19.000000
888           Johnston, Miss. Catherine Helen "Carrie"  female
25.091837
889                              Behr, Mr. Karl Howell    male
26.000000
890                                Dooley, Mr. Patrick    male
32.000000

     SibSp  Parch            Ticket     Fare Cabin Embarked Deck
0        1      0         A/5 21171   7.2500  F000        S    F
1        1      0          PC 17599  71.2833  C000        C    C
2        0      0  STON/O2. 3101282   7.9250  F000        S    F
3        1      0            113803  53.1000  C000        S    C
4        0      0            373450   8.0500  F000        S    F
..     ...    ...               ...      ...   ...      ...  ...
```

```
886      0      0           211536  13.0000  F000        S    F
887      0      0           112053  30.0000  B000        S    B
888      1      2       W./C. 6607  23.4500  F000        S    F
889      0      0           111369  30.0000  C000        C    C
890      0      0           370376   7.7500  F000        Q    F

[891 rows x 13 columns]
```

```
df.Embarked.mode()
```

```
0    S
Name: Embarked, dtype: object
```

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

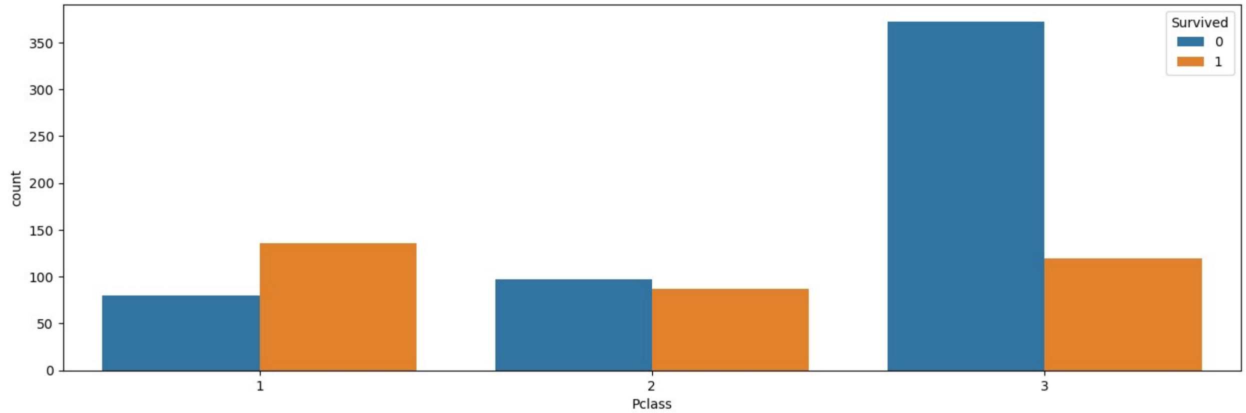
```
df.isnull().sum() # there is no nullvalues in  the data set
```

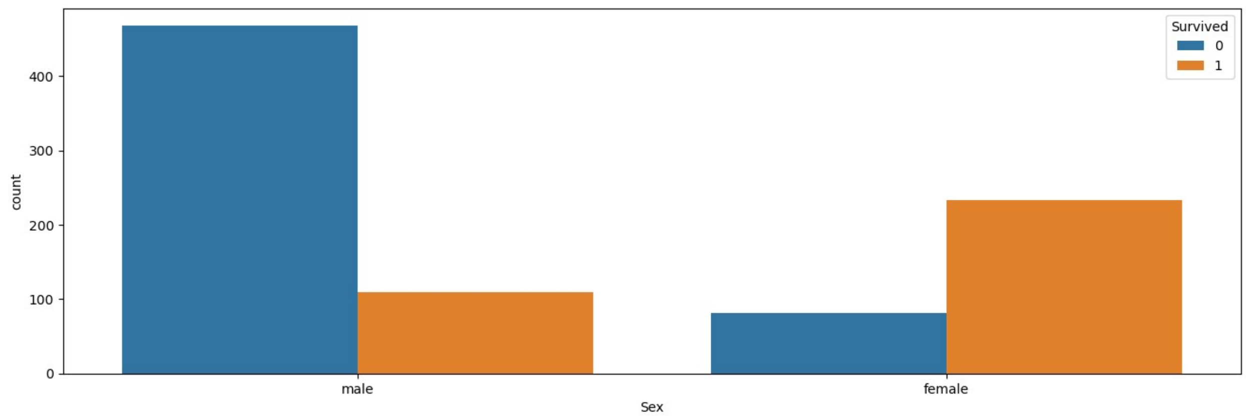
```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Cabin          0
Embarked       0
Deck           0
dtype: int64
```

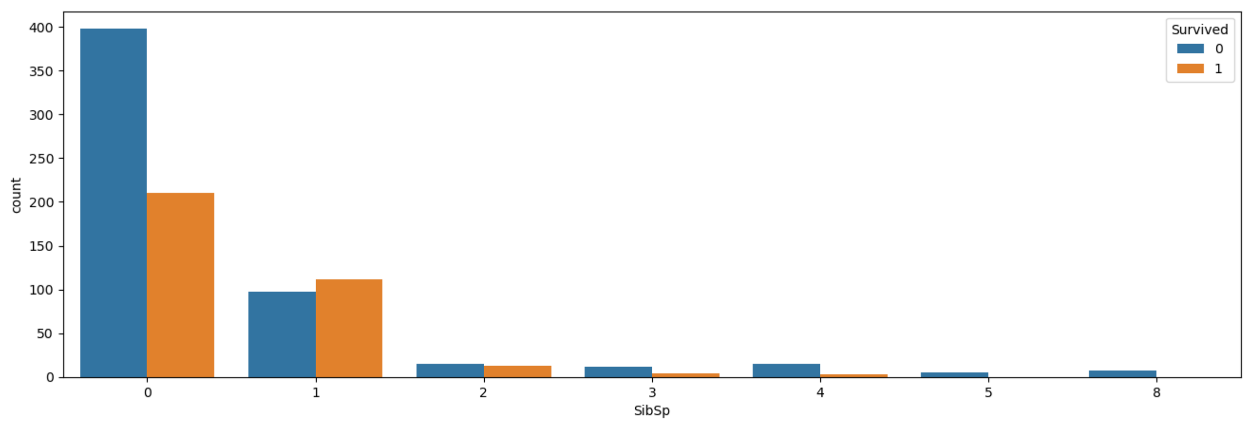
# Data Exploration

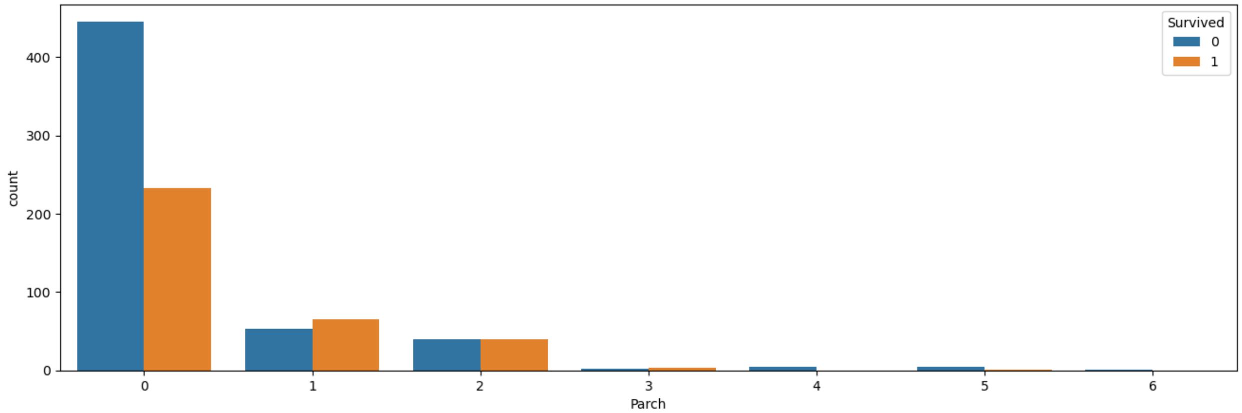
Univariate analysis

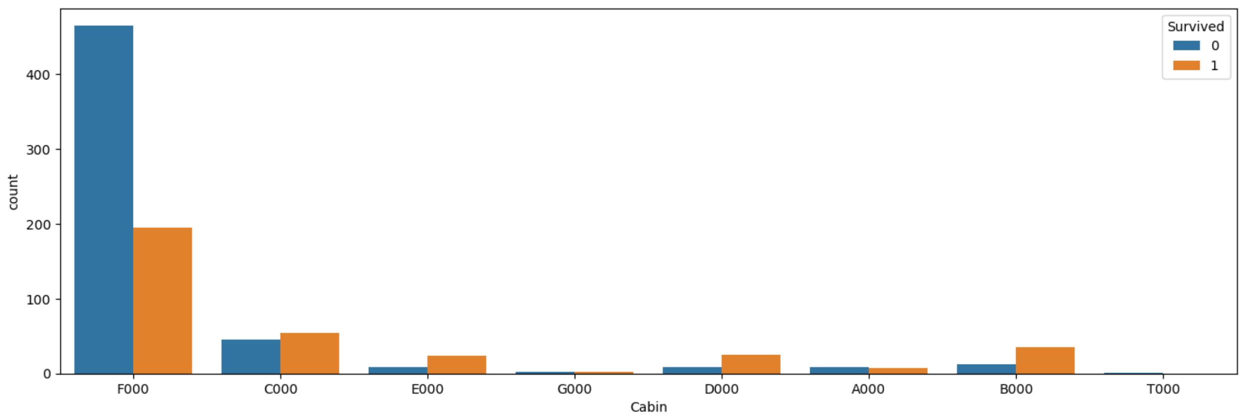
```
for i , predictor in 
enumerate(df.drop(columns=['Survived','PassengerId','Name','Age','Tick
et','Fare'],axis=1)):
    plt.figure(i,figsize=(16,5))
    sns.countplot(data=df,x= predictor,hue='Survived')
    plt.show()
```

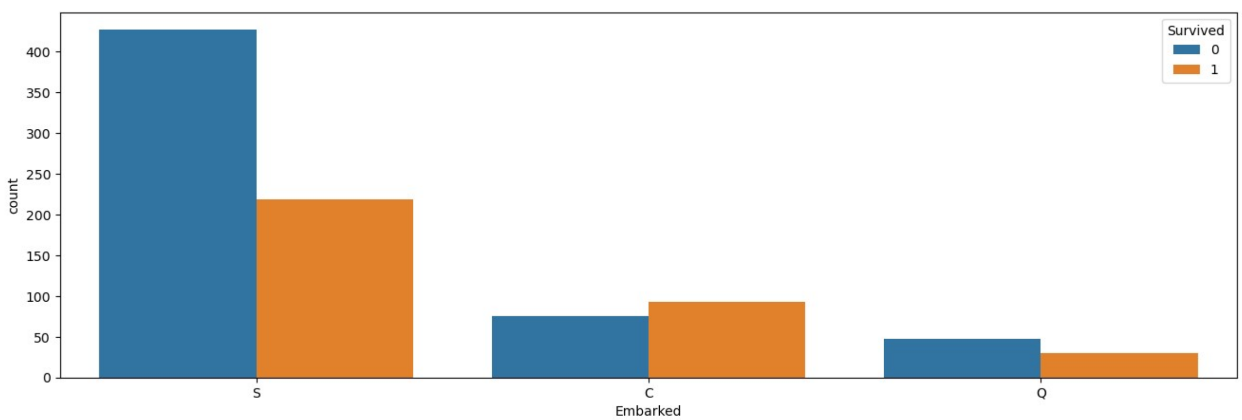

Survived
0
1
count
350
300
250
200
150
100
50
0
1
2
3
Pclass

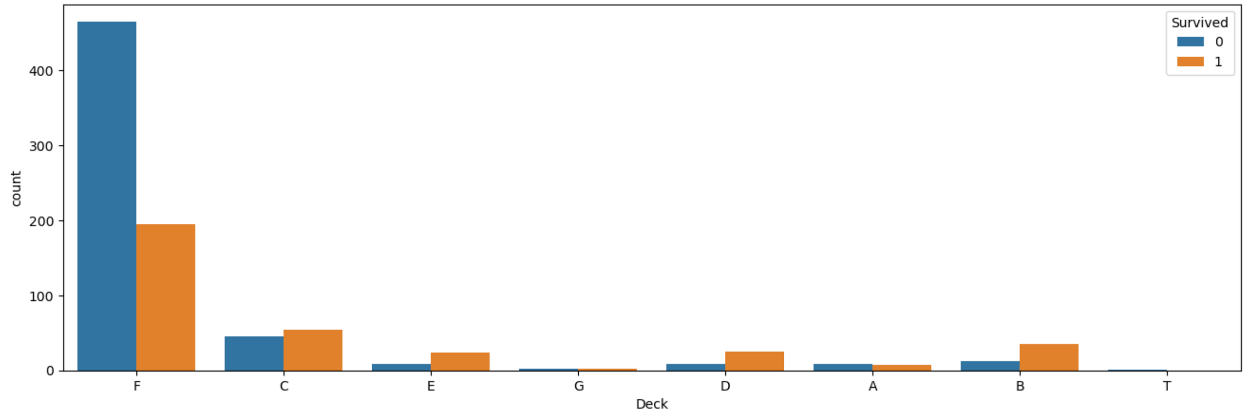

Survived
0
1
count
400
300
200
100
0
male
female
Sex


Survived
0
1
count
400
350
300
250
200
150
100
50
0
0
1
2
3
4
5
8
SibSp


Survived
0
1
count
0
100
200
300
400
0
1
2
3
4
5
6
Parch


Survived
0
1
count
0
100
200
300
400
F000
C000
E000
G000
D000
A000
B000
T000
Cabin


Survived
0
1
count
0
50
100
150
200
250
300
350
400
S
C
Q
Embarked




# Intuition from Univariate Analysis — Figure by Figure on Categorical Features

Pclass: The survival rate is high in 1st class and low in 3rd class.

Sex: The survival rate (percentage) is higher for females, but in absolute numbers, more males survived because there were more males onboard.

SibSp: Passengers with fewer or no siblings/spouses had a higher survival rate because they had less dependency.

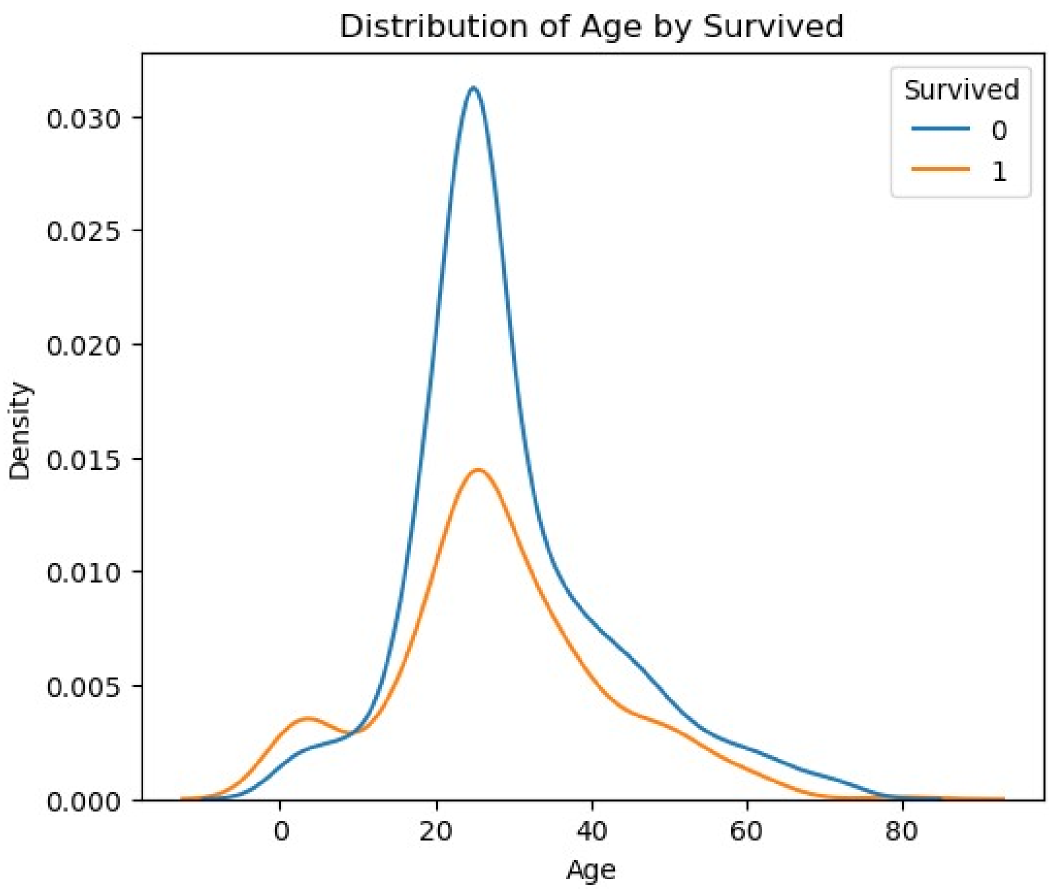
Parch: Passengers with fewer or no parents/children had a higher survival rate because they had less dependency.

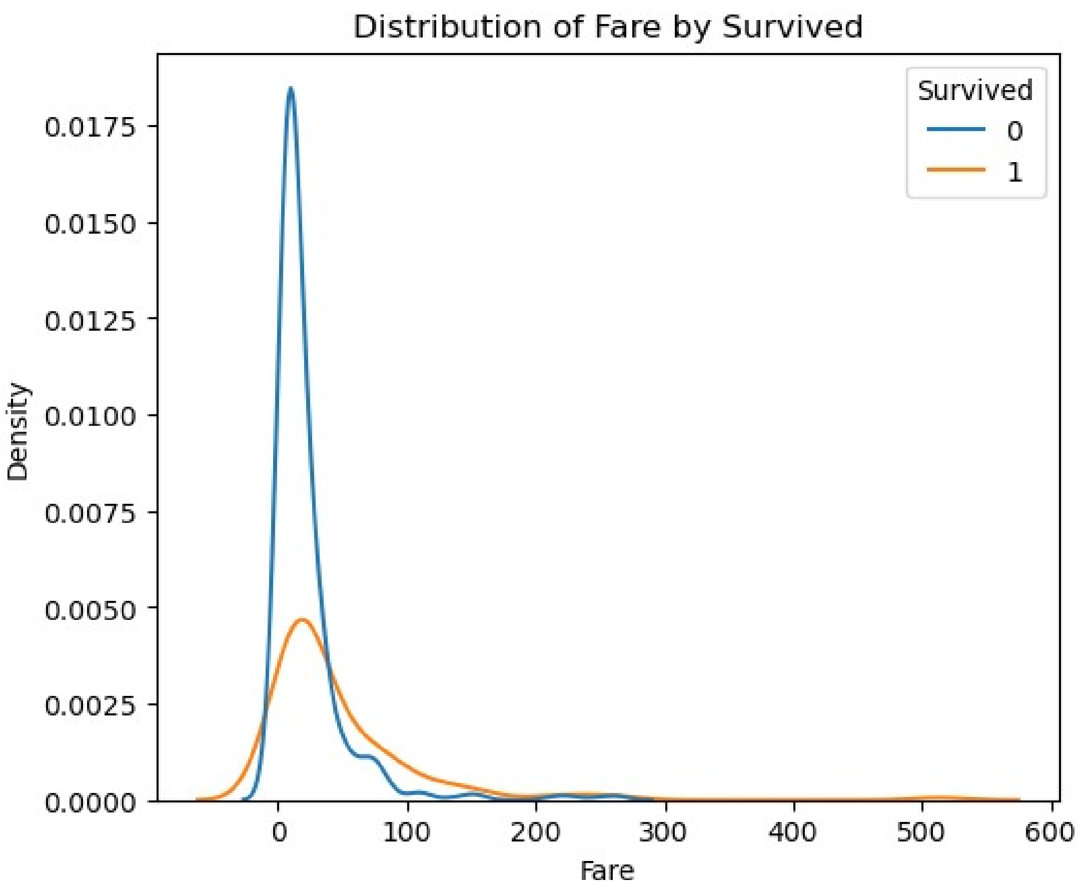
Cabin / Deck: Higher survival rates were seen in cabins on decks B, C, and D, but many survivors were also from F deck; overall, passengers who had cabin assignments survived more.

Embarked: More passengers who boarded at Southampton survived in absolute numbers (because most passengers boarded there), but the survival rate was highest among passengers who boarded at Cherbourg.

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

# Get a list of colors outside the loop
colors = sns.color_palette('tab10')  # or 'Set2', 'pastel', 'husl',
etc.
color_idx = 0

for col in df.columns:
    if df[col].dtype == 'int64' or df[col].dtype == 'float64':
        if col in ['PassengerId', 'Survived', 'Pclass', 'SibSp',
'Parch']:
            continue

        plt.figure(figsize=(6, 5))
        sns.kdeplot(data=df, x=col,
```

```
hue='Survived',color=colors[color_idx % len(colors)])
        plt.title(f'Distribution of {col} by Survived')
        plt.show()

        color_idx += 1  # move to next color
```



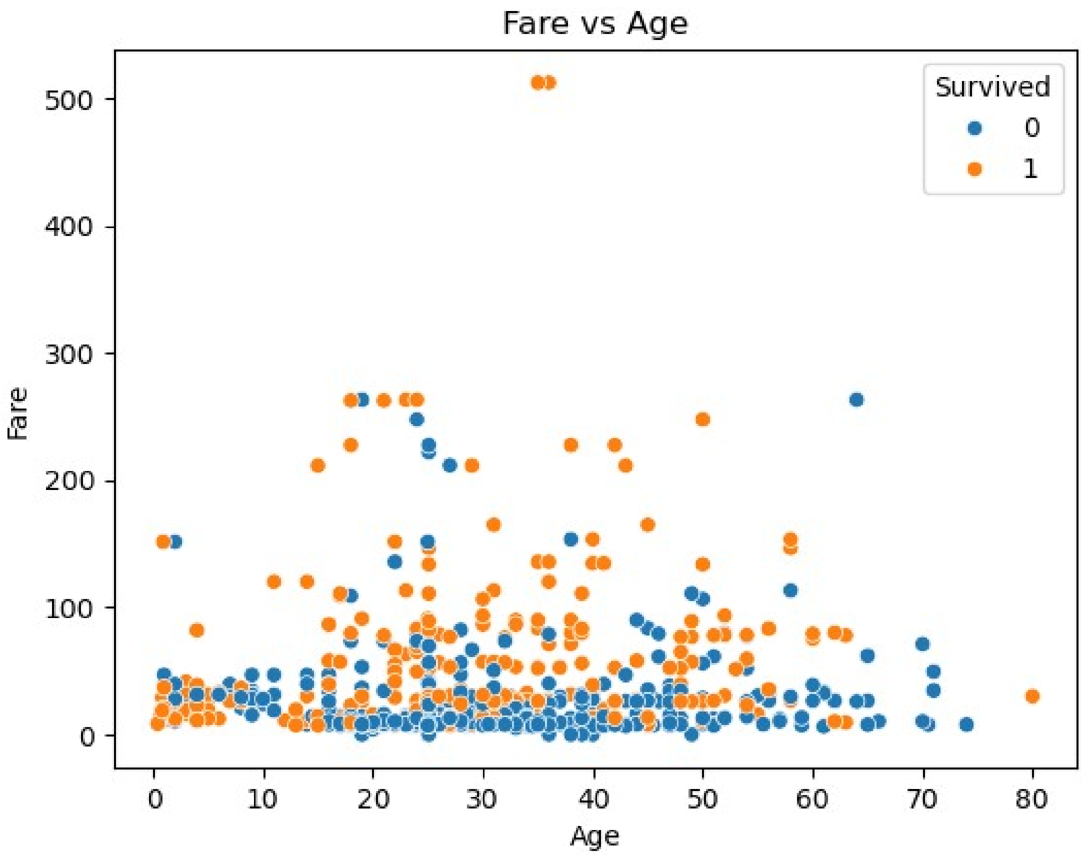



# BiVariate and Univariate analysis

```
df.head()

   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age
SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0
1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
1
2                             Heikkinen, Miss. Laina  female  26.0
0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
1
4                           Allen, Mr. William Henry    male  35.0
0
```

```
   Parch            Ticket     Fare Cabin Embarked Deck
0      0         A/5 21171   7.2500  F000        S    F
1      0          PC 17599  71.2833  C000        C    C
2      0  STON/O2. 3101282   7.9250  F000        S    F
3      0            113803  53.1000  C000        S    C
4      0            373450   8.0500  F000        S    F
```

```
sns.scatterplot(x='Age', y='Fare', data=df,hue='Survived')
plt.title('Fare vs Age')
plt.show()

# Correlation
print(df[['Age','Fare']].corr())
```



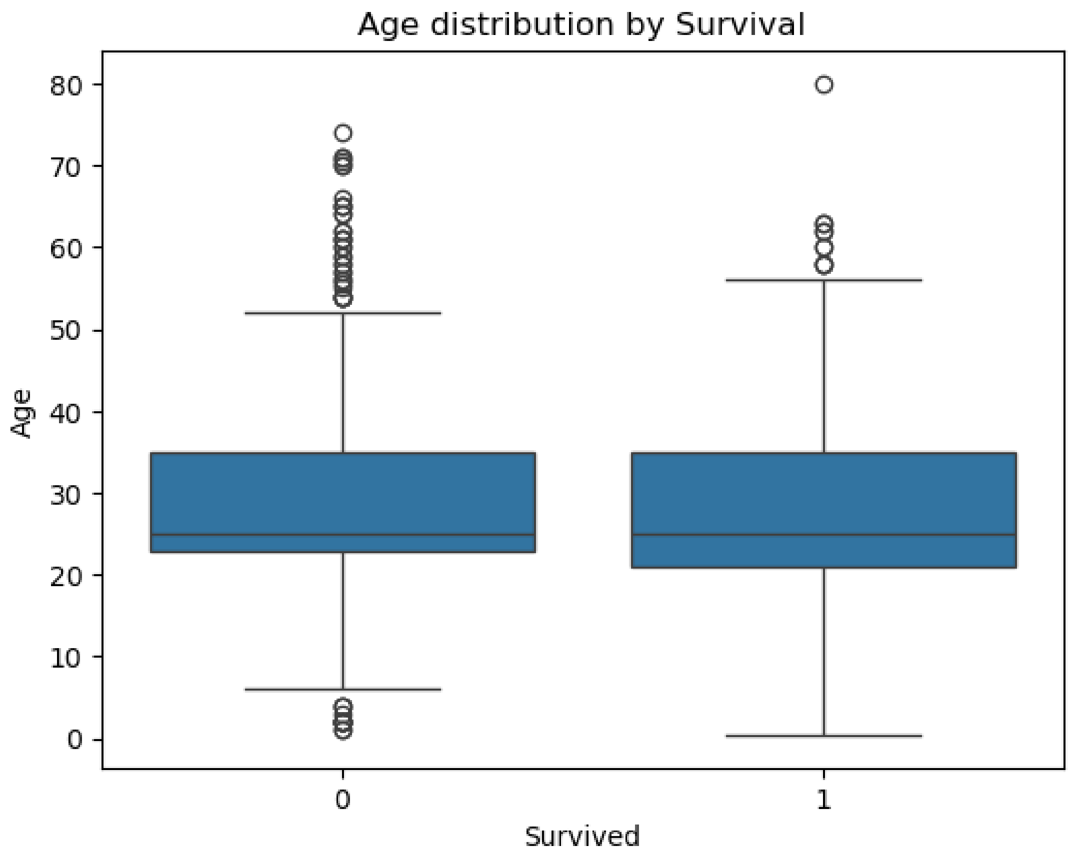

```
           Age      Fare
Age   1.000000  0.104769
Fare  0.104769  1.000000
```

## Interpretation:

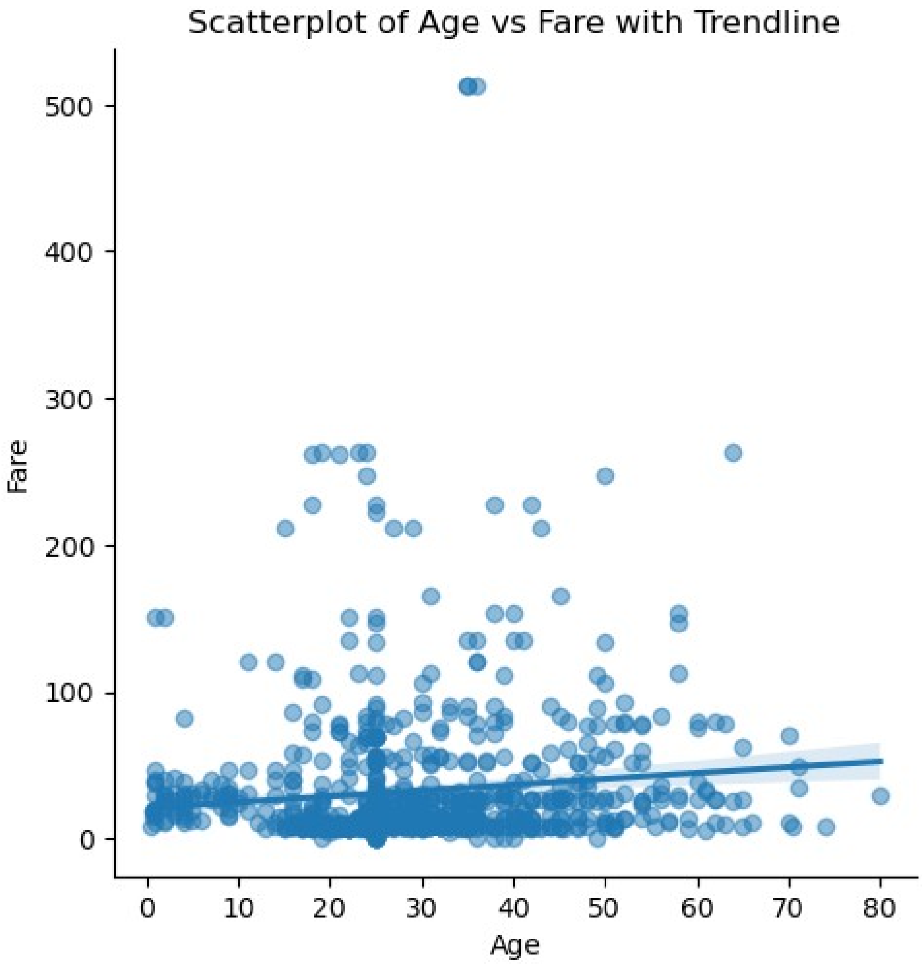
0.1048 means there's only a very weak positive relationship between a passenger's age and the fare they paid.

In plain words: older passengers tended to pay slightly more, but the effect is minor and probably not strongly predictive.

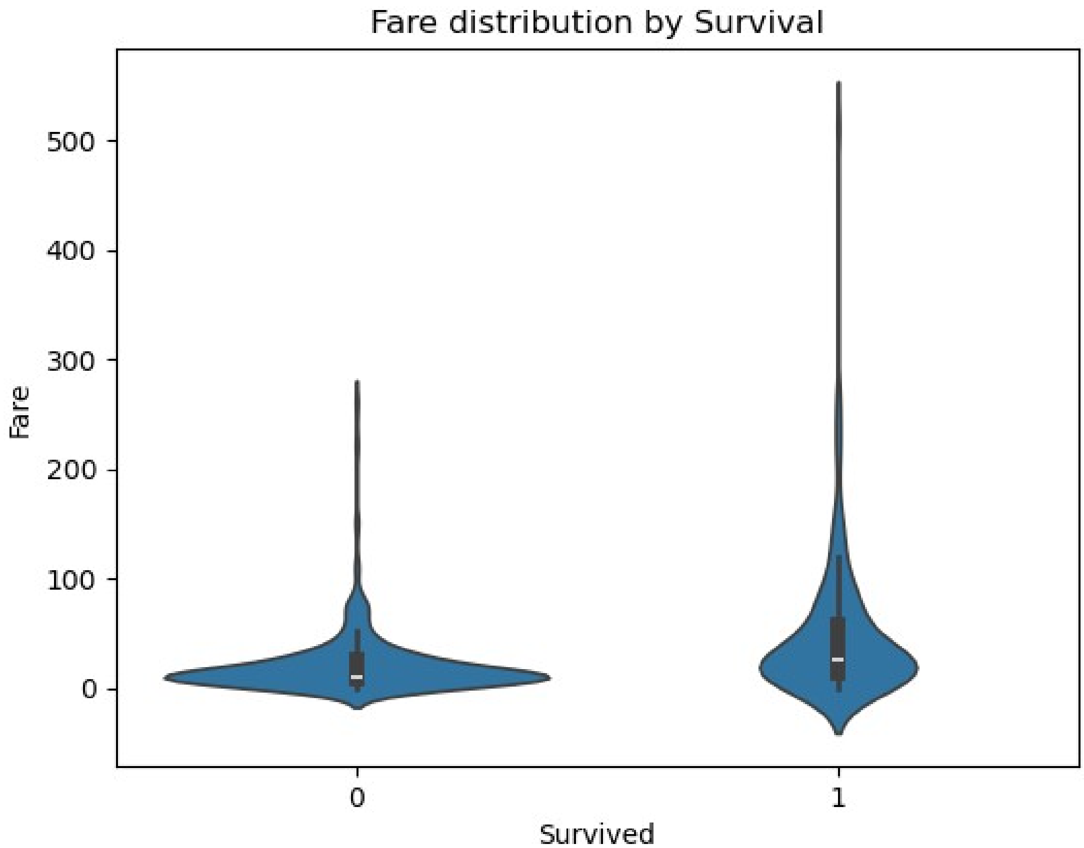
```
sns.boxplot(x='Survived', y='Age', data=df)
plt.title('Age distribution by Survival')
plt.show()
```



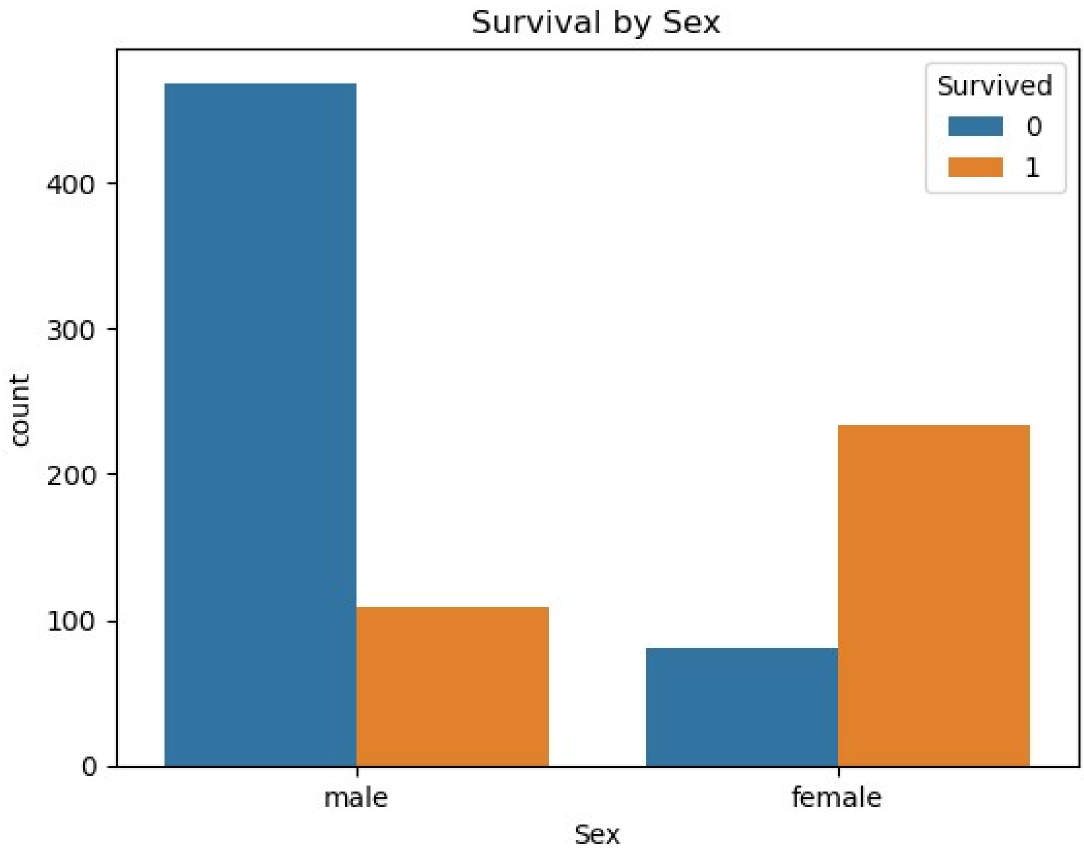

```
import seaborn as sns
import matplotlib.pyplot as plt

sns.lmplot(x='Age', y='Fare', data=df, scatter_kws={'alpha':0.5})
plt.title('Scatterplot of Age vs Fare with Trendline')
plt.show()
```



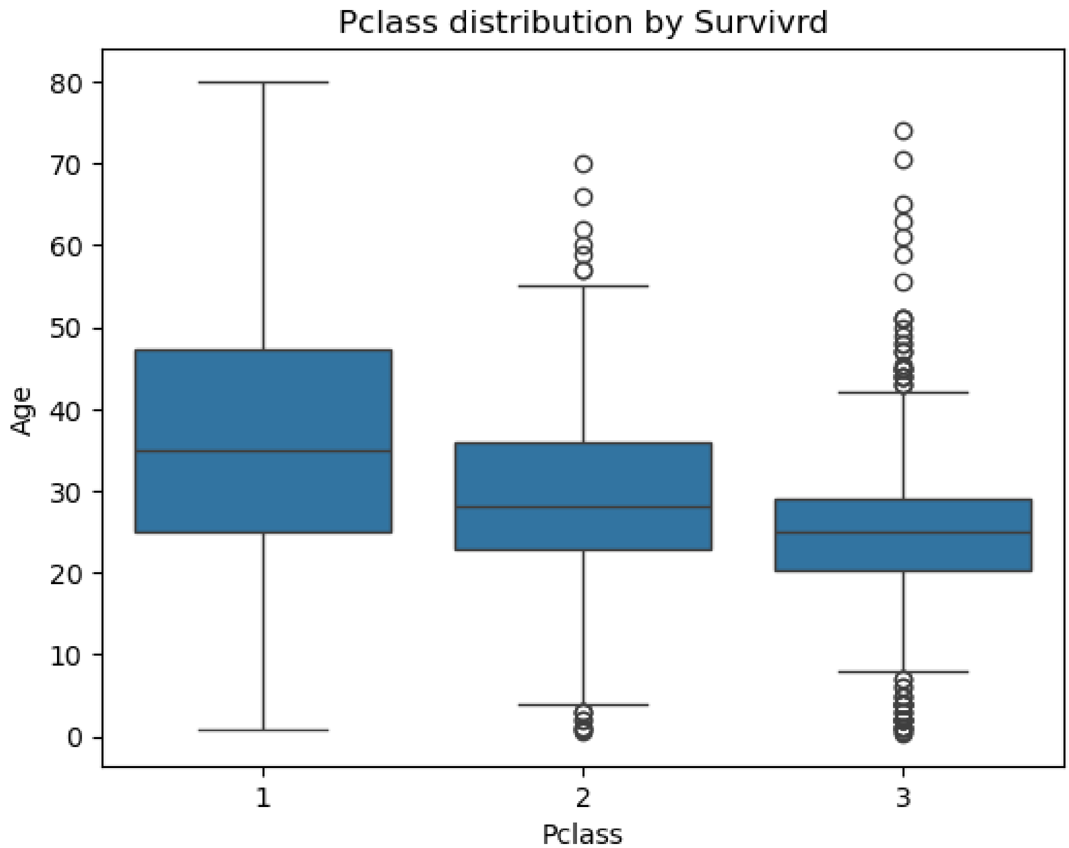

```
sns.violinplot(x='Survived', y='Fare', data=df)
plt.title('Fare distribution by Survival')
plt.show()
```



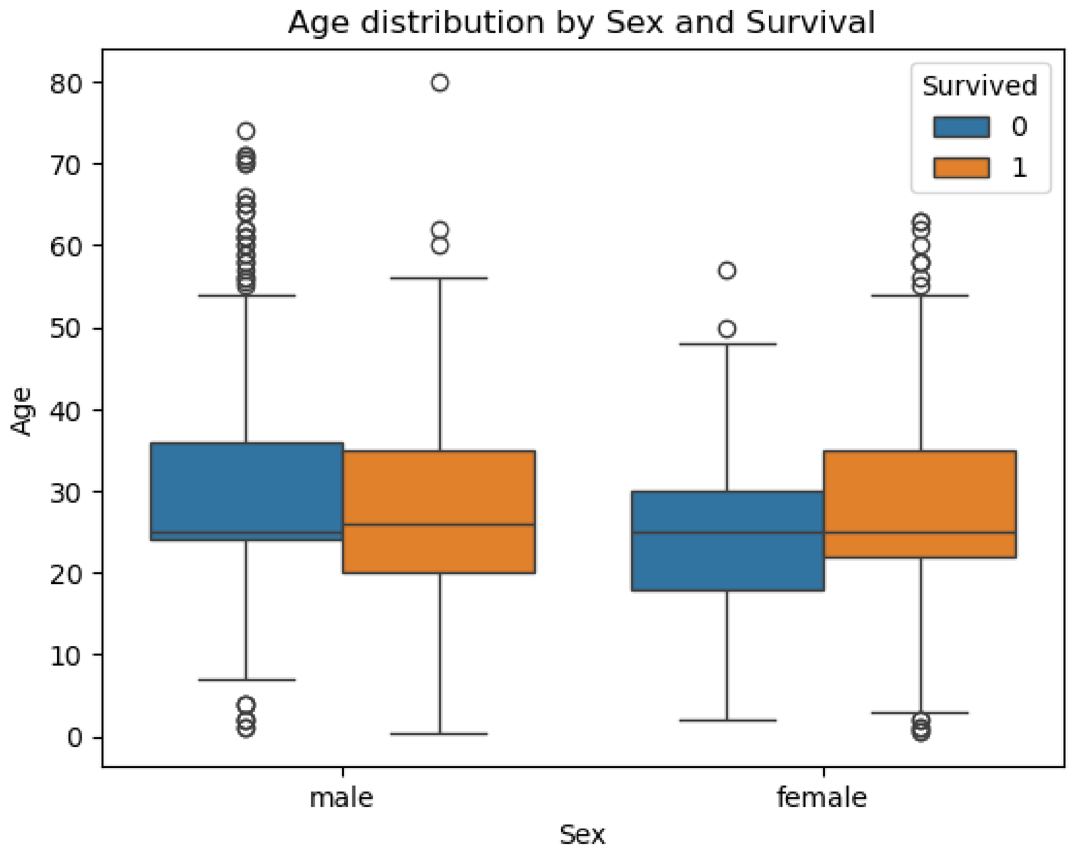

```
sns.countplot(x='Sex', hue='Survived', data=df)
plt.title('Survival by Sex')
plt.show()
```



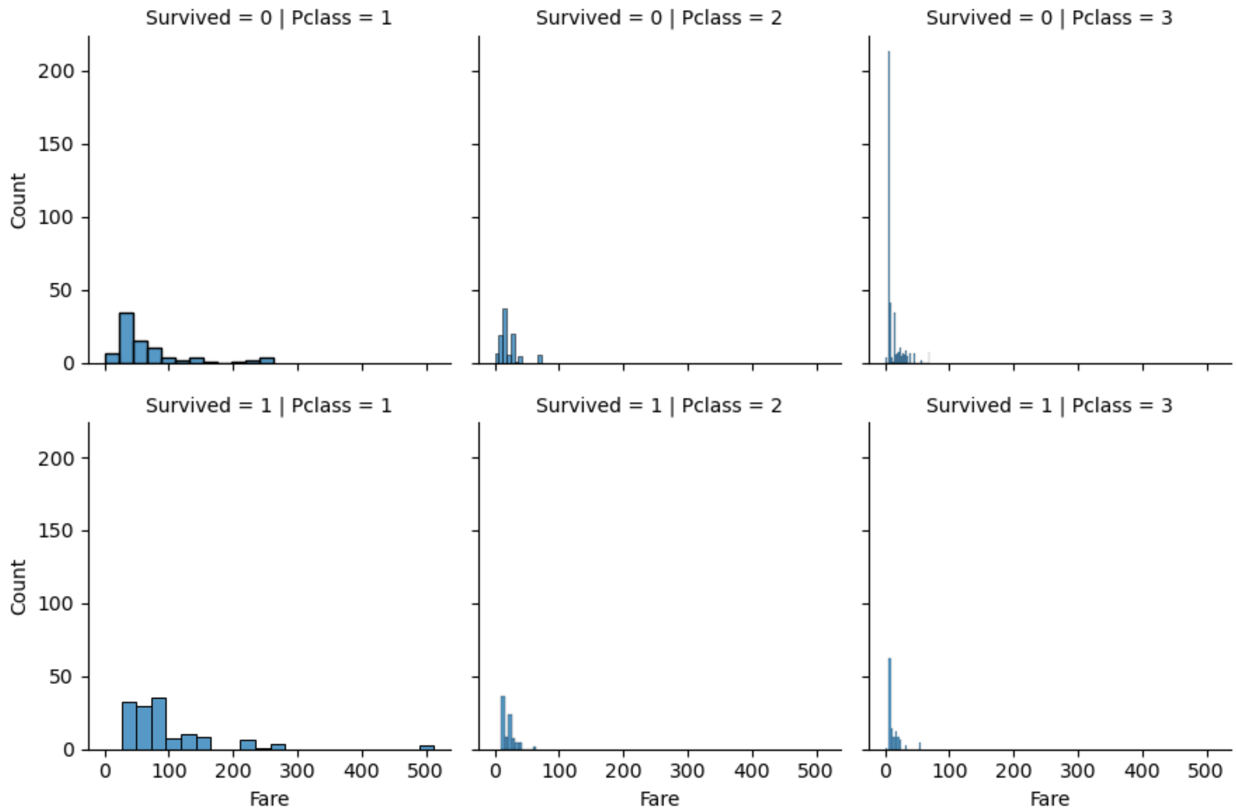

```
sns.boxplot(x='Pclass', y='Age', data=df)
plt.title('Pclass distribution by Survivrd')
plt.show()
```



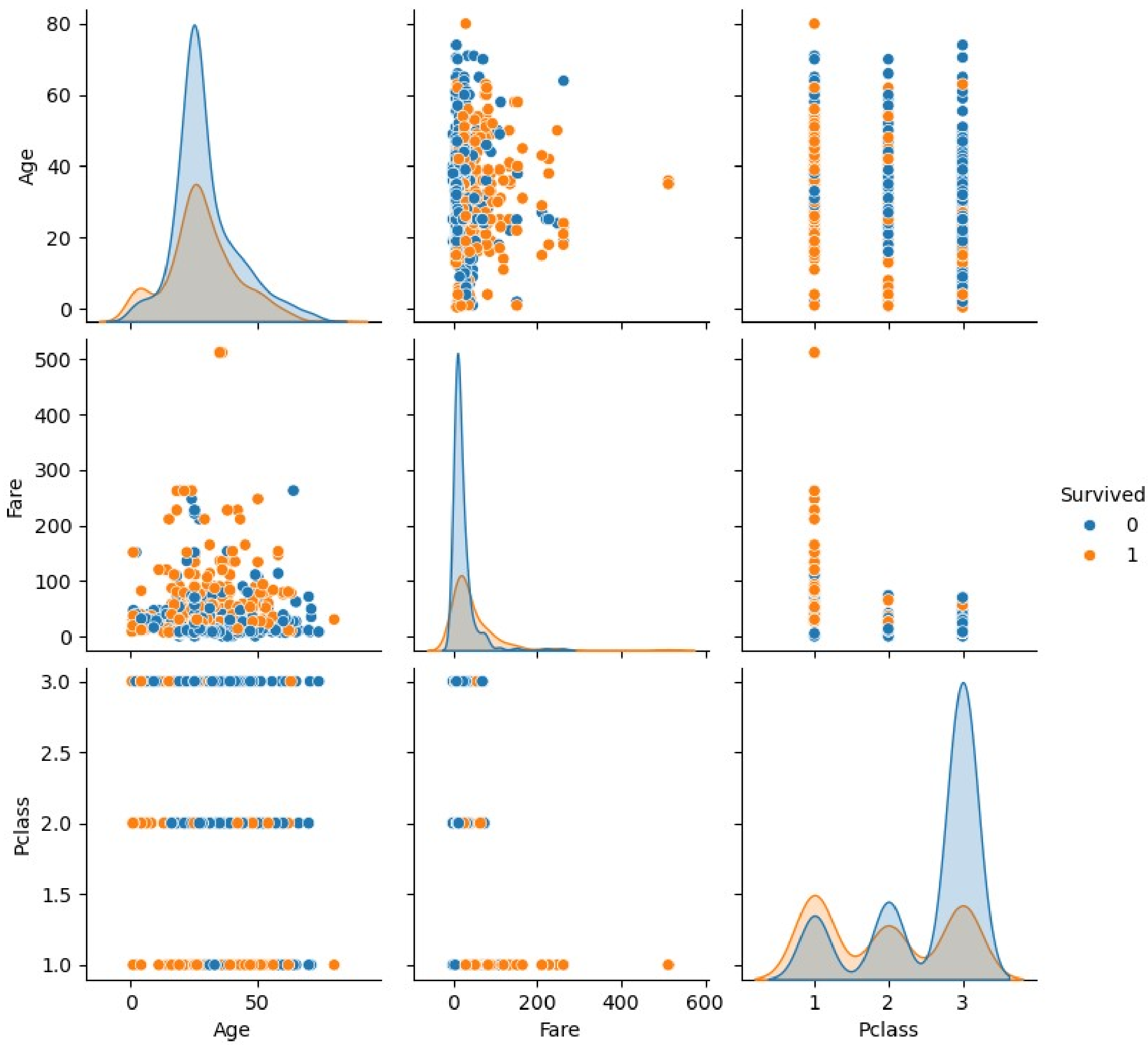

```
sns.boxplot(x='Sex', y='Age', hue='Survived', data=df)
plt.title('Age distribution by Sex and Survival')
plt.show()
```




```
# Fare distribution by class and survival
g = sns.FacetGrid(df, col='Pclass', row='Survived')
g.map(sns.histplot, 'Fare')
plt.show()
```

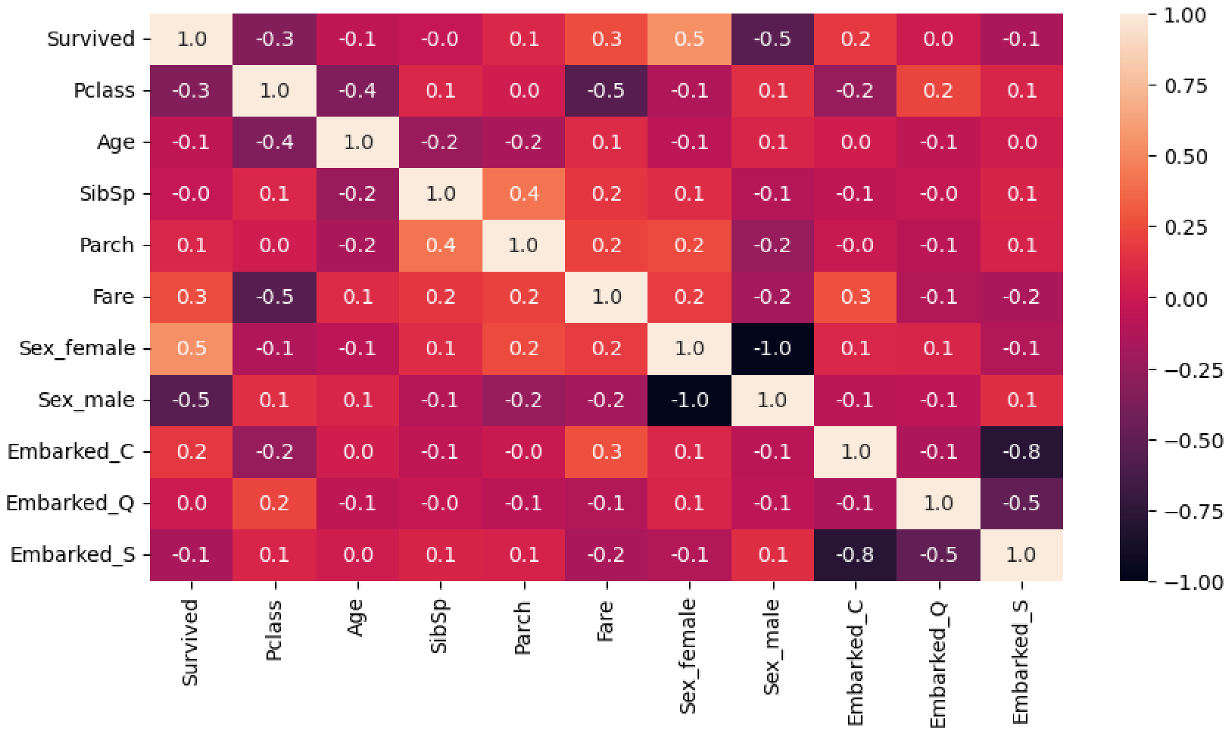



```
# Pairplot with hue on survival
sns.pairplot(df[['Age', 'Fare', 'Pclass', 'Survived']].dropna(),
hue='Survived')
plt.show()
```




```
df_dummies=pd.get_dummies(df.drop(columns=['Ticket','Name','PassengerI
d','Deck','Cabin'],axis=1),dtype=int) # get_dummies is method to
convert the categorical value into int

df_dummies.head()

   Survived  Pclass   Age  SibSp  Parch     Fare  Sex_female  Sex_male
\
0         0       3  22.0      1      0   7.2500           0         1

1         1       1  38.0      1      0  71.2833           1         0

2         1       3  26.0      0      0   7.9250           1         0

3         1       1  35.0      1      0  53.1000           1         0
```

```
4          0          3  35.0        0        0    8.0500                 0          1


   Embarked_C  Embarked_Q  Embarked_S
0           0           0           1
1           1           0           0
2           0           0           1
3           0           0           1
4           0           0           1

plt.figure(figsize=(10,5))
sns.heatmap(df_dummies.corr(),annot=True,fmt=".1f")
plt.show()
```




```
#TEST TRAIN SCALING THE DATA

df_sc=df[['Survived','Age','Fare']]

df_sc.head()

   Survived   Age     Fare
0         0  22.0   7.2500
1         1  38.0  71.2833
2         1  26.0   7.9250
3         1  35.0  53.1000
4         0  35.0   8.0500
```

```python
#test and train the data
from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test=train_test_split(df_sc.drop(columns='Survived',axis=1),df['Survived'],test_size=.3,random_state=0)

x_train.shape,x_test.shape,y_train.shape,y_train.shape
```

```
((623, 2), (268, 2), (623,), (623,))
```

```python
#scaled the age and fare on scale
from sklearn.preprocessing import StandardScaler

scaler=StandardScaler()

x_train_scaled=scaler.fit_transform(x_train)
x_test_scaled=scaler.transform(x_test)

x_train_scaled=pd.DataFrame(x_train_scaled,columns=x_train.columns)
x_test_scaled=pd.DataFrame(x_test_scaled,columns=x_test.columns)

x_train_scaled.head(),x_test_scaled.head()
```

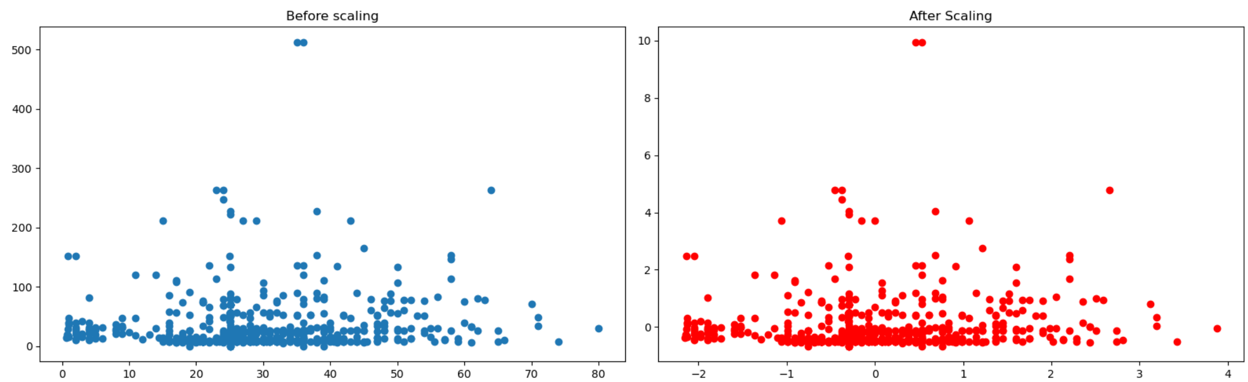
```
(         Age      Fare
 0  1.674835 -0.122530
 1  1.522726  0.918124
 2 -2.127894  0.299503
 3  1.902999  0.929702
 4 -0.295599 -0.373297,
          Age      Fare
 0 -0.295599 -0.373297
 1 -0.295599 -0.516566
 2 -1.671567 -0.069128
 3 -0.295599  2.365514
 4  0.001634 -0.356965)
```

```python
np.round(x_train_scaled.describe(),1)
```

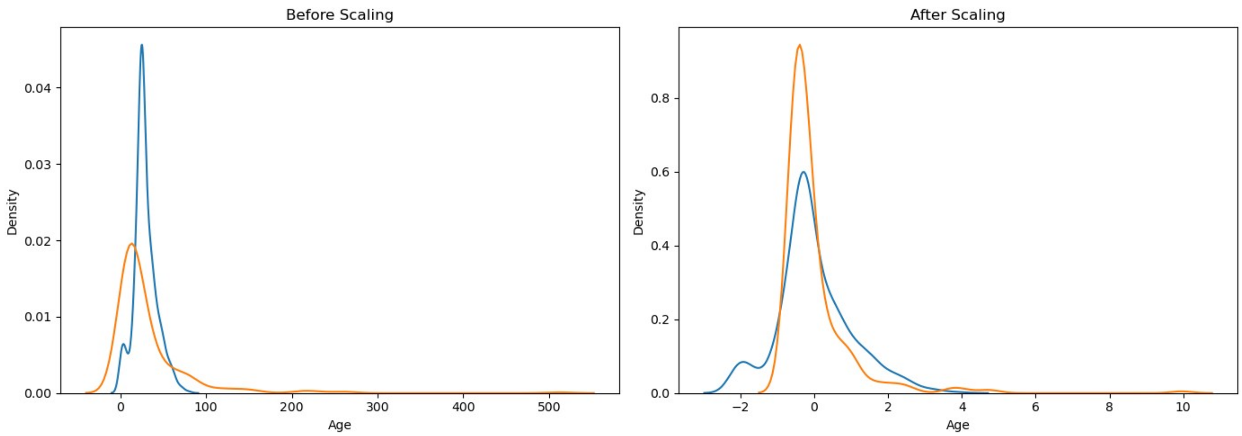
|  | Age | Fare |
|---|---|---|
| count | 623.0 | 623.0 |
| mean | 0.0 | 0.0 |
| std | 1.0 | 1.0 |
| min | -2.2 | -0.7 |
| 25% | -0.5 | -0.5 |
| 50% | -0.3 | -0.4 |
| 75% | 0.5 | -0.0 |
| max | 3.9 | 10.0 |

# Effect of scaling

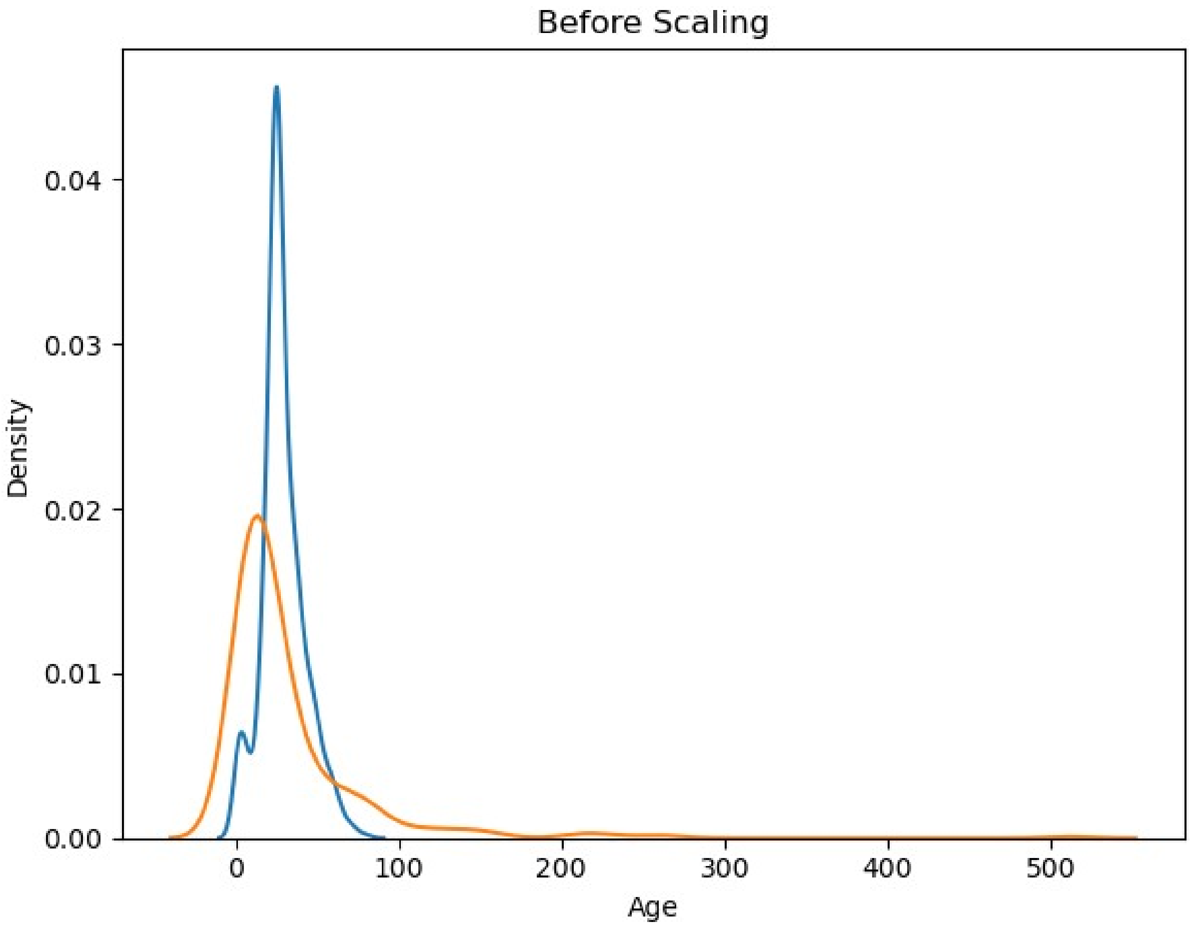
```
#plot the subplotb before scale and after scale
fig,(ax1,ax2)=plt.subplots(1,2,figsize=(16,5))
ax1.scatter(x_train['Age'],x_train['Fare'])
ax1.set_title('Before scaling')
ax2.scatter(x_train_scaled['Age'],x_train_scaled['Fare'],color='red')
plt.title('After Scaling')
plt.tight_layout()
plt.show()
```



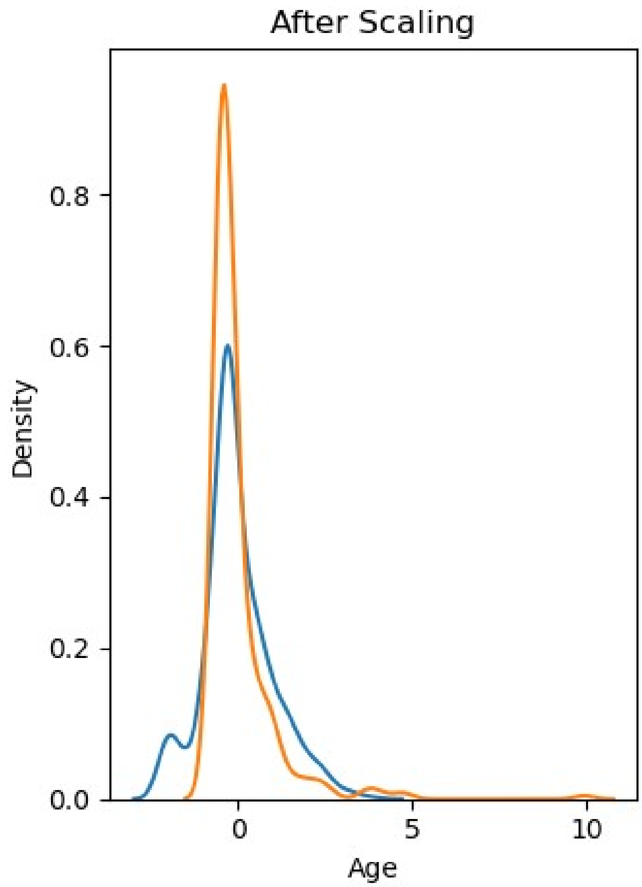

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


# Create the subplot figure (1 row, 2 columns)
plt.figure(figsize=(14, 5))

# Before scaling
plt.subplot(1, 2, 1)
sns.kdeplot(x_train['Age'])
sns.kdeplot(x_train['Fare'])
plt.title('Before Scaling')

# After scaling
plt.subplot(1, 2, 2)
sns.kdeplot(x_train_scaled['Age'])
sns.kdeplot(x_train_scaled['Fare'])
plt.title('After Scaling')

plt.tight_layout()
plt.show()
```




```python
plt.figure(figsize=(12,5))

# BEFORE SCALING
plt.subplot(1,2,1)
sns.kdeplot(x_train['Age'])
sns.kdeplot(x_train['Fare'])
plt.title('Before Scaling')
plt.tight_layout()
plt.show()

# AFTER SCALING
plt.subplot(1,2,2)
sns.kdeplot(x_train_scaled['Age'])
sns.kdeplot(x_train_scaled['Fare'])
plt.title('After Scaling')
plt.tight_layout()
plt.show()
```

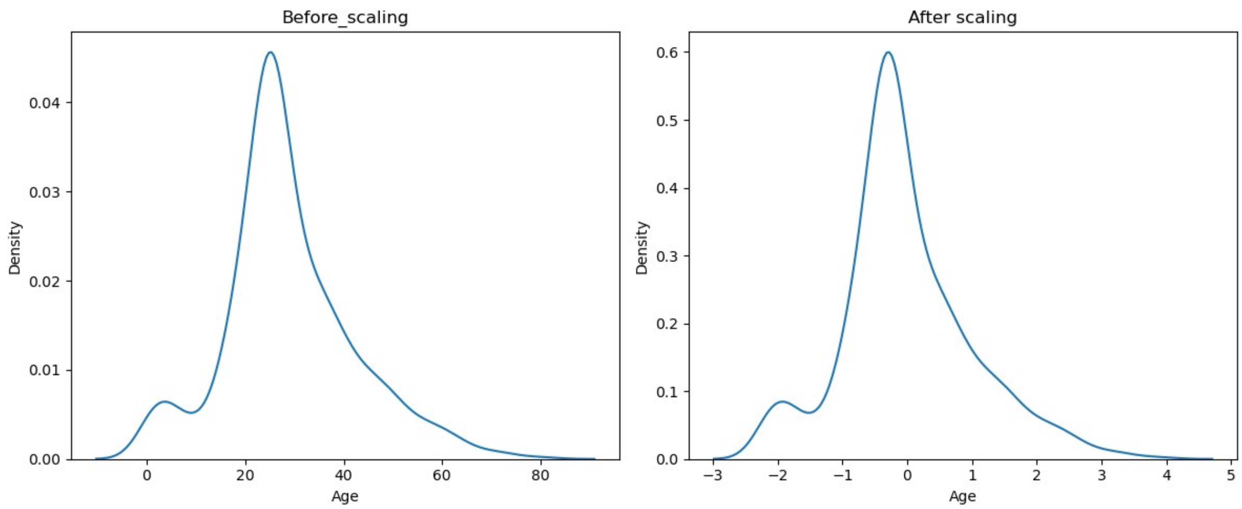


Before Scaling
Density
Age
0.00
0.01
0.02
0.03
0.04
0
100
200
300
400
500




# COMPARISON OF DISTRIBUTION

```
# the distribution should be betweem age and estimated salry before scaling and after scaling
# with the help of subplot

fig,(ax1,ax2)=plt.subplots(1,2,figsize=(12,5))

#befroe and after scaling of age
sns.kdeplot(x_train.Age,ax=ax1)
ax1.set_title("Before_scaling")
sns.kdeplot(x_train_scaled.Age,ax=ax2)
ax2.set_title('After scaling')
#plt.legend()
plt.tight_layout()
plt.show()
```




```
## COMPARISON OF DISTRIBUTION

# the distribution should be betweem age and fare before scaling and
after scaling
# with the help of subplot

fig,(ax1,ax2)=plt.subplots(1,2,figsize=(12,5))

#befroe and after scaling of age
sns.kdeplot(x_train.Fare,ax=ax1)
ax1.set_title("Before_scaling")
sns.kdeplot(x_train_scaled.Fare,ax=ax2)
ax2.set_title('After scaling')
#plt.legend()
plt.tight_layout()
plt.show()
```