Titanic - Machine Learning from Disaster

Predicting survival on the Titanic

Data Dictionary

Variable	Definition	Key
survival	Survival	0 = No, 1 = Yes
pclass	Ticket class	1 = 1st, 2 = 2nd, 3 = 3rd
sex	Sex	
Age	Age in years	
sibsp	# of siblings / spouses aboard the Titanic	
parch	# of parents / children aboard the Titanic	
ticket	Ticket number	
fare	Passenger fare	
cabin	Cabin number	
embarked	Port of Embarkation	C = Cherbourg, Q = Queenstown, S = Southampton

In [ ]:
```
#importing the libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [ ]:
```
df = pd.read_csv('titanic_train.csv')
df.head()
```

Out[ ]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fa
0	631	1	1	Barkworth, Mr. Algernon Henry Wilson	male	80.0	0	0	27042	30.00
1	852	0	3	Svensson, Mr. Johan	male	74.0	0	0	347060	7.77
2	97	0	1	Goldschmidt, Mr. George B	male	71.0	0	0	PC 17754	34.65
3	494	0	1	Artagaveytia, Mr. Ramon	male	71.0	0	0	PC 17609	49.50
4	117	0	3	Connors, Mr. Patrick	male	70.5	0	0	370369	7.75

In [ ]:

```
df.shape
```

Out[ ]: (891, 12)

Data Preprocessing

In [ ]:

```
#removing the columns
df = df.drop(columns=['PassengerId','Name','Cabin','Ticket'], axis= 1)
```

In [ ]:

```
df.describe()
```

Out[ ]:

	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	29.361582	0.523008	0.381594	32.204208
std	0.486592	0.836071	13.019697	1.102743	0.806057	49.693429
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	22.000000	0.000000	0.000000	7.910400
50%	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	1.000000	3.000000	35.000000	1.000000	0.000000	31.000000
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [ ]:

```
#checking data types
df.dtypes
```

Out[ ]:
```
Survived      int64
Pclass        int64
Sex          object
Age         float64
SibSp         int64
Parch         int64
Fare        float64
Embarked     object
dtype: object
```

In [ ]:
```
#checking for unique value count
df.nunique()
```

Out[ ]:
```
Survived      2
Pclass        3
Sex           2
Age          88
SibSp         7
Parch         7
Fare        248
Embarked      3
dtype: int64
```

In [ ]:
```
#checking for missing value count
df.isnull().sum()
```

Out[ ]:
```
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    2
dtype: int64
```

Refining the data

In [ ]:
```
# replacing the missing values
df['Age'] =  df['Age'].replace(np.nan,df['Age'].median(axis=0))
df['Embarked'] = df['Embarked'].replace(np.nan, 'S')
```

In [ ]:
```
#type casting Age to integer
df['Age'] = df['Age'].astype(int)
```

In [ ]:
```
#replacing with 1 and female with 0
df['Sex'] = df['Sex'].apply(lambda x : 1 if x == 'male' else 0)
```

Categorising in groups i.e. Infant(0-5), Teen (6-20), 20s(21-30), 30s(31-40), 40s(41-50), 50s(51-60), Elder(61-100)

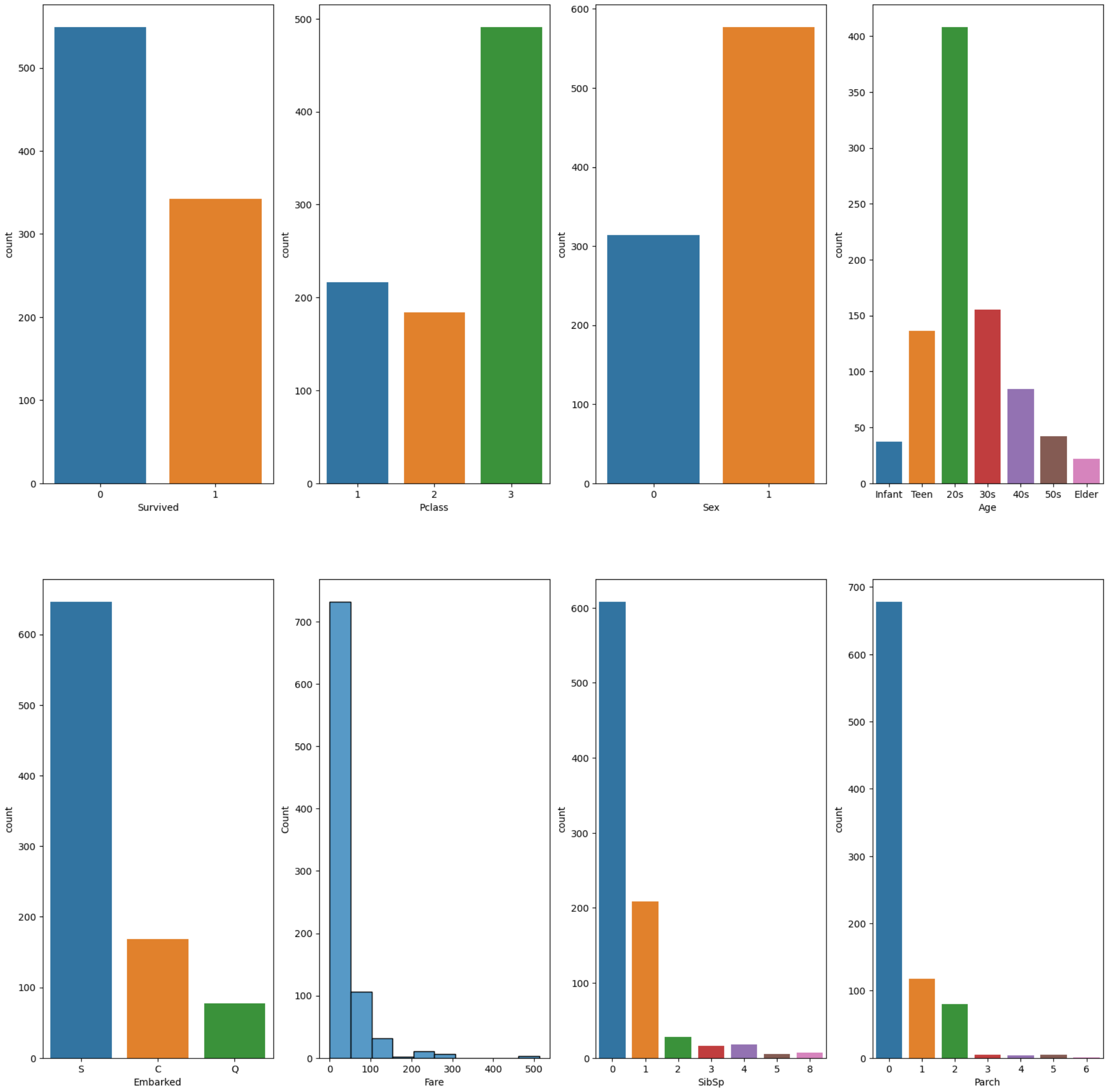
In [ ]:
```
# creating age groups - young (0-18), adult(18-30), middle aged(30-50), old (50-
df['Age'] = pd.cut(x=df['Age'], bins=[0, 5, 20, 30, 40, 50, 60, 100], labels = [
```

Exploratory Data Analysis

Plotting the Countplot to visualize the numbers

In [ ]:
```
# visulizing the count of the features
fig, ax = plt.subplots(2,4,figsize=(20,20))
sns.countplot(x = 'Survived', data = df, ax= ax[0,0])
sns.countplot(x = 'Pclass', data = df, ax=ax[0,1])
sns.countplot(x = 'Sex', data = df, ax=ax[0,2])
sns.countplot(x = 'Age', data = df, ax=ax[0,3])
sns.countplot(x = 'Embarked', data = df, ax=ax[1,0])
sns.histplot(x = 'Fare', data= df, bins=10, ax=ax[1,1])
sns.countplot(x = 'SibSp', data = df, ax=ax[1,2])
sns.countplot(x = 'Parch', data = df, ax=ax[1,3])
```

Out[ ]:
```
<Axes: xlabel='Parch', ylabel='count'>
```

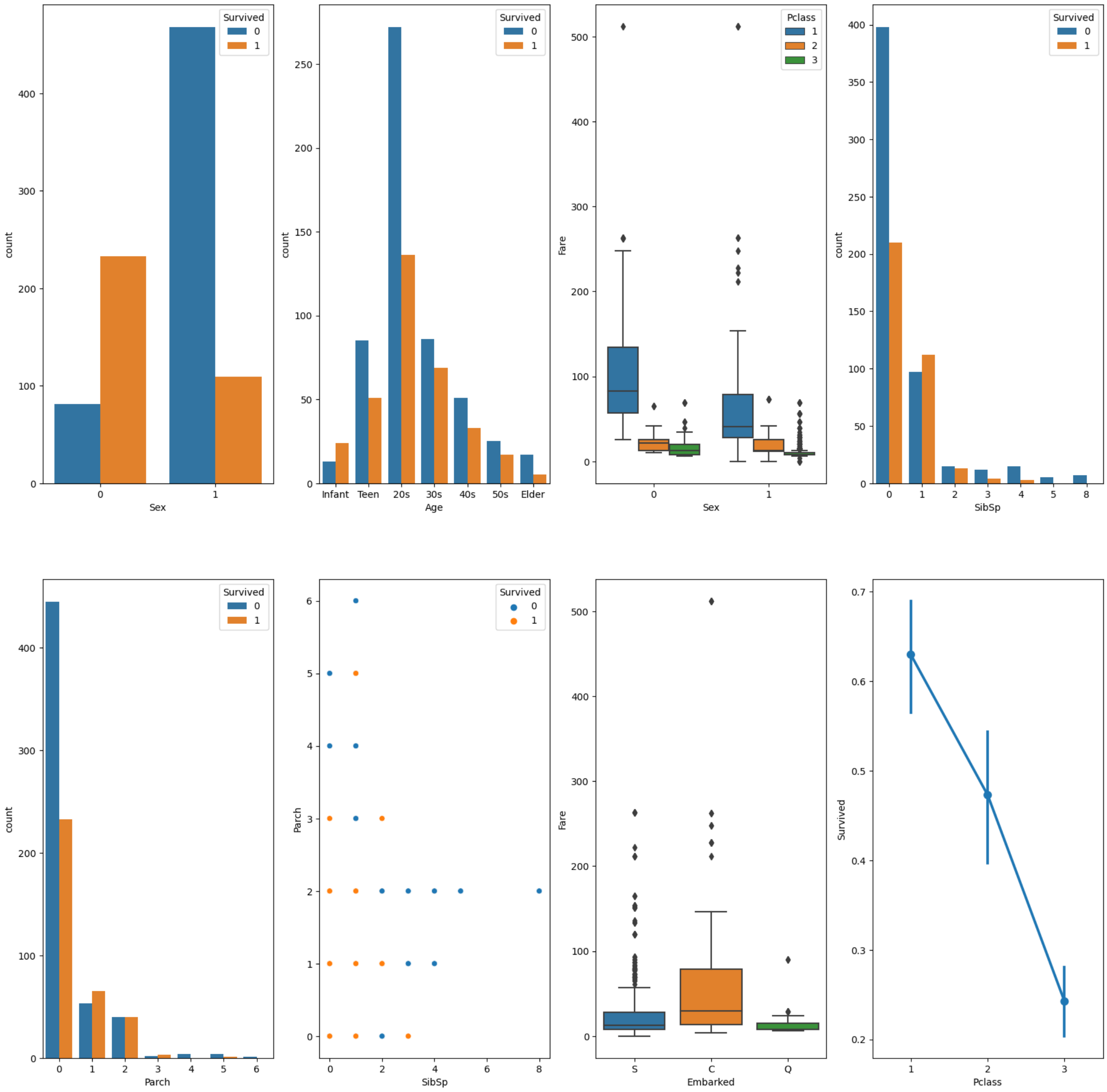


Visualizing the replationship between the features

In [ ]:
```
fig, ax = plt.subplots(2,4,figsize=(20,20))
sns.countplot(x = 'Sex', data = df, hue = 'Survived', ax= ax[0,0])
sns.countplot(x = 'Age', data = df, hue = 'Survived', ax=ax[0,1])
sns.boxplot(x = 'Sex',y='Fare', data = df, hue = 'Pclass', ax=ax[0,2])
sns.countplot(x = 'SibSp', data = df, hue = 'Survived', ax=ax[0,3])
sns.countplot(x = 'Parch', data = df, hue = 'Survived', ax=ax[1,0])
```

```
sns.scatterplot(x = 'SibSp', y = 'Parch', data = df,hue = 'Survived', ax=ax[1,1]
sns.boxplot(x = 'Embarked', y ='Fare', data = df, ax=ax[1,2])
sns.pointplot(x = 'Pclass', y = 'Survived', data = df, ax=ax[1,3])
```

Out[ ]: <Axes: xlabel='Pclass', ylabel='Survived'>



Data Preprocessing 2

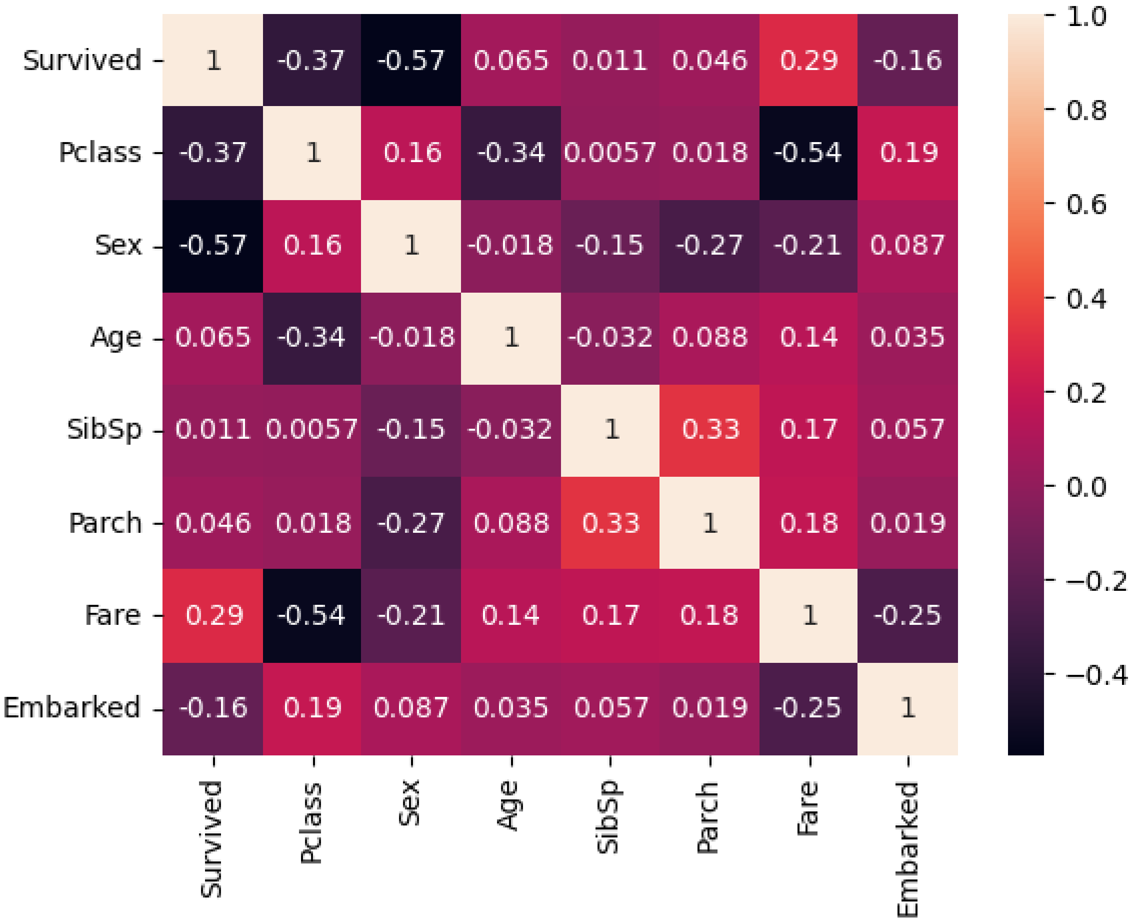
In [ ]:
```
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
le.fit(['S','C','Q'])
df['Embarked'] = le.transform(df['Embarked'])
```

In [ ]:
```
age_mapping = {
    'infant': 0,
    'teen': 1,
    '20s': 2,
    '30s': 3,
    '40s': 4,
    '50s': 5,
    'elder': 6}
df['Age'] = df['Age'].map(age_mapping)
df.dropna(subset=['Age'], axis= 0, inplace = True)
```

Coorelation Heatmap

In [ ]:
```
sns.heatmap(df.corr(), annot= True)
```

Out[ ]: <Axes: >



Separating the target and independent variable

In [ ]:
```
y = df['Survived']
x = df.drop(columns=['Survived'])
```

Model Training

Logistic Regression

In [ ]:
```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
lr
```

Out[ ]:
```
▾ LogisticRegression
LogisticRegression()
```

In [ ]:
```
lr.fit(x,y)
lr.score(x,y)
```

```
C:\Users\DELL\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2k
fra8p0\LocalCache\local-packages\Python311\site-packages\sklearn\linear_model\_lo
gistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[ ]: 0.818577648766328

Decision Tree Classifier

In [ ]:
```python
from sklearn.tree import DecisionTreeClassifier
dtree = DecisionTreeClassifier()
dtree
```

Out[ ]:
```
▾ DecisionTreeClassifier

DecisionTreeClassifier()
```

In [ ]:
```python
dtree.fit(x,y)
dtree.score(x,y)
```

Out[ ]: 0.9404934687953556

Support Vector Machine (SVM)

In [ ]:
```python
from sklearn.svm import SVC
svm = SVC()
svm
```

Out[ ]:
```
▾ SVC

SVC()
```

In [ ]:
```python
svm.fit(x,y)
svm.score(x,y)
```

Out[ ]: 0.7024673439767779

K-Nearest Neighbor

In [ ]:
```python
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier()
knn
```

Out[ ]:
```
▾ KNeighborsClassifier

KNeighborsClassifier()
```

```
In [ ]: knn.fit(x,y)
        knn.score(x,y)
```

```
Out[ ]: 0.8127721335268505
```

From the above four model Decision Tree Classifier has the highest Training accuracy, so only Decision Tree Classifier will work on the Test Set.

Importing the test set

```
In [ ]: df2 = pd.read_csv('titanic_test.csv')
        df2.head()
```

Out[ ]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	
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

```
In [ ]: #removing the columns
        df2 = df2.drop(columns=['PassengerId','Name','Cabin','Ticket'], axis= 1)
```

Data Preprocessing the Test set

```
In [ ]: df2['Age'] =  df2['Age'].replace(np.nan,df2['Age'].median(axis=0))
        df2['Embarked'] = df2['Embarked'].replace(np.nan, 'S')
```

```
In [ ]: #type casting Age to integer
        df2['Age'] = df2['Age'].astype(int)
```

In [ ]:
```
#replacing with 1 and female with 0
df2['Sex'] = df2['Sex'].apply(lambda x : 1 if x == 'male' else 0)
```

In [ ]:
```
df2['Age'] = pd.cut(x=df2['Age'], bins=[0, 5, 20, 30, 40, 50, 60, 100], labels =
```

In [ ]:
```
le.fit(['S','C','Q'])
df2['Embarked'] = le.transform(df2['Embarked'])
```

In [ ]:
```
df2.dropna(subset=['Age'], axis= 0, inplace = True)
```

In [ ]:
```
df2.head()
```

Out[ ]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	1	2	1	0	7.2500	2
1	1	1	0	3	1	0	71.2833	0
2	1	3	0	2	0	0	7.9250	2
3	1	1	0	3	1	0	53.1000	2
4	0	3	1	3	0	0	8.0500	2

Separating the traget and independent variable

In [ ]:
```
x = df2.drop(columns=['Survived'])
y = df2['Survived']
```

Predicting using Decision Tree Classifier

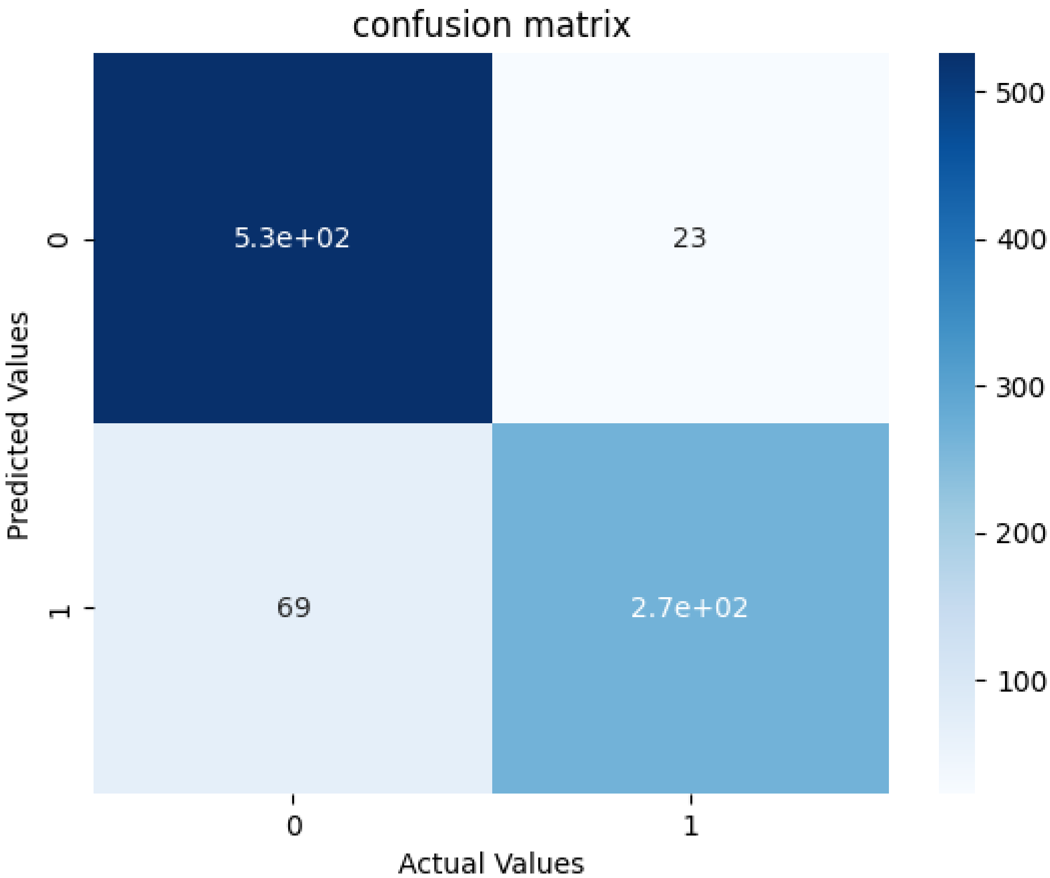
In [ ]:
```
tree_pred = dtree.predict(x)
```

In [ ]:
```
from sklearn.metrics import accuracy_score
accuracy_score(y, tree_pred)
```

Out[ ]: 0.8959276018099548

Confusion Matrix

In [ ]:
```
from sklearn.metrics import confusion_matrix
sns.heatmap(confusion_matrix(y,tree_pred),annot= True, cmap = 'Blues')
plt.ylabel('Predicted Values')
plt.xlabel('Actual Values')
plt.title('confusion matrix')
plt.show()
```


confusion matrix
5.3e+02
23
69
2.7e+02
Predicted Values
Actual Values
0
1
0
1
500
400
300
200
100