predicting-survival-titanic

April 9, 2024

0.1 Project Name : Predicting Survival on Titanic using Artificial Neural Networks

0.1.1 Contribution : Individual

0.2 Data Dictionary

Column Name	Description
Pclass	Ticket class indicating the socio-economic status of the passenger
Survived	A binary indicator that shows whether the passenger survived (1) or not (0)
Name	The full name of the passenger
Sex	The gender of the passenger, denoted as either male or female
Age	The age of the passenger in years
SibSp	The number of siblings or spouses aboard the Titanic for the respective passenger
Parch	The number of parents or children aboard the Titanic for the respective passenger
Ticket	The ticket number assigned to the passenger
Fare	The fare paid by the passenger for the ticket
Cabin	The cabin number assigned to the passenger, if available
Embarked	The port of embarkation for the passenger
Boat	this column contains the identifier of the lifeboat they were rescued in
Body	this column contains the identification number of their recovered body, if applicable
Home.dest	The destination or place of residence of the passenger

[35]:
```python
# import library
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
sns.set(style='darkgrid', palette='Set2')
```

[36]:
```python
# load dataset
dataset = '/content/Titanic Dataset.csv'

df = pd.read_csv(dataset)
df.head()
```

[36]:
```
   pclass  survived                                             name     sex  \
0       1         1                    Allen, Miss. Elisabeth Walton  female
1       1         1                   Allison, Master. Hudson Trevor    male
2       1         0                     Allison, Miss. Helen Loraine  female
3       1         0             Allison, Mr. Hudson Joshua Creighton    male
4       1         0  Allison, Mrs. Hudson J C (Bessie Waldo Daniels)  female

     age  sibsp  parch  ticket      fare    cabin embarked boat   body  \
0  29.00      0      0   24160  211.3375       B5        S    2    NaN
1   0.92      1      2  113781  151.5500  C22 C26        S   11    NaN
2   2.00      1      2  113781  151.5500  C22 C26        S  NaN    NaN
3  30.00      1      2  113781  151.5500  C22 C26        S  NaN  135.0
4  25.00      1      2  113781  151.5500  C22 C26        S  NaN    NaN

                         home.dest
0                     St Louis, MO
1  Montreal, PQ / Chesterville, ON
2  Montreal, PQ / Chesterville, ON
3  Montreal, PQ / Chesterville, ON
4  Montreal, PQ / Chesterville, ON
```

0.3 Data Preprocessing 1

[37]:
```python
# checking the shape dataset
df.shape
```

[37]: (1309, 14)

Dropping the unecessary columns - name, cabin, boat, body, home.dest

[38]:
```python
# drop columns
drop_col = ['name', 'cabin', 'boat', 'body', 'home.dest']

df.drop(drop_col, axis=1, inplace=True)
df.dtypes
```

[38]:
```
pclass        int64
survived      int64
sex          object
age         float64
sibsp         int64
```

```
parch          int64
ticket        object
fare         float64
embarked      object
dtype: object
```

[39]:
```python
# moved the 'survived' column to the last column
df = pd.concat([df.drop(columns=['survived']), df[['survived']]], axis=1)
df.sample(5)
```

[39]:
```
      pclass     sex   age  sibsp  parch         ticket   fare embarked  \
375        2    male  28.0      0      0         248740  13.00        S
973        3    male   NaN      0      0  S.O./P.P. 251   7.55        S
583        2  female  40.0      0      0     C.A. 33595  15.75        S
484        2  female  34.0      0      0     C.A. 34260  10.50        S
1073       3    male   NaN      0      0         371060   7.75        Q

      survived
375          0
973          0
583          1
484          1
1073         0
```

[40]:
```python
# shwoing 10 values for ticket column
df.ticket.values[:10]
```

[40]:
```
array(['24160', '113781', '113781', '113781', '113781', '19952', '13502',
       '112050', '11769', 'PC 17609'], dtype=object)
```

because the ticket column is of the object data type, I will convert it to numeric

[41]:
```python
# convert ticket column to float
df.ticket = pd.to_numeric(df.ticket, errors='coerce')
```

[42]:
```python
# checking the dtype for ticket column
df.ticket.dtypes
```

[42]:
```
dtype('float64')
```

[43]:
```python
# checking null value
df.isnull().sum()
```

[43]:
```
pclass        0
sex           0
age         263
sibsp         0
```

```
parch         0
ticket      352
fare          1
embarked      2
survived      0
dtype: int64
```

[44]:
```
# checking null value for age column
df[df.age.isnull()]
```

[44]:

	pclass	sex	age	sibsp	parch	ticket	fare	embarked	survived
15	1	male	NaN	0	0	NaN	25.9250	S	0
37	1	male	NaN	0	0	111427.0	26.5500	S	1
40	1	male	NaN	0	0	112379.0	39.6000	C	0
46	1	male	NaN	0	0	113798.0	31.0000	S	0
59	1	female	NaN	0	0	17770.0	27.7208	C	1
…	…	…	…	…	…	…	…	…	…
1293	3	male	NaN	0	0	NaN	8.0500	S	0
1297	3	male	NaN	0	0	NaN	7.2500	S	0
1302	3	male	NaN	0	0	2647.0	7.2250	C	0
1303	3	male	NaN	0	0	2627.0	14.4583	C	0
1305	3	female	NaN	1	0	2665.0	14.4542	C	0

[263 rows x 9 columns]

[45]:
```
# Replace the null value in the 'age' column with the mean
df.age.fillna(df.age.mean(), inplace=True)
df.age.isnull().sum()
```

[45]: 0

[46]:
```
# drop null value fot ticket column
df.dropna(subset=['ticket'], inplace=True)
df.ticket.isnull().sum()
```

[46]: 0

[47]:
```
# checking nullvalue for fare and embarked column
df[(df.fare.isnull()) | (df.embarked.isnull())]
```

[47]:

	pclass	sex	age	sibsp	parch	ticket	fare	embarked	survived
168	1	female	38.0	0	0	113572.0	80.0	NaN	1
284	1	female	62.0	0	0	113572.0	80.0	NaN	1
1225	3	male	60.5	0	0	3701.0	NaN	S	0

[48]:
```
# Replace the null value in the 'fare' column with the mean
df.fare.fillna(df.fare.mean(), inplace=True)
```

```
# drop null value for embarked column
df.dropna(subset=['embarked'], inplace=True)
```

[49]:
```
# checking null value again
df.isnull().sum()
```

[49]:
```
pclass      0
sex         0
age         0
sibsp       0
parch       0
ticket      0
fare        0
embarked    0
survived    0
dtype: int64
```

Because all columns no longer have null values, will be do checking duplicated values

[50]:
```
# checking duplicated values
df[df.duplicated()]
```

[50]:
```
      pclass     sex        age  sibsp  parch    ticket     fare embarked  \
384        2    male  29.881138      0      0  239853.0   0.0000        S
438        2  female  24.000000      1      2  220845.0  65.0000        S
528        2    male  29.881138      0      0  239853.0   0.0000        S
658        3  female   0.750000      2      1    2666.0  19.2583        C
714        3    male  32.000000      0      0    1601.0  56.4958        S
858        3    male  29.881138      0      0    1601.0  56.4958        S
945        3    male  29.881138      0      0    1601.0  56.4958        S
956        3  female  29.881138      3      1    4133.0  25.4667        S
957        3  female  29.881138      3      1    4133.0  25.4667        S
1002       3  female  29.881138      2      0  367226.0  23.2500        Q
1035       3    male  29.881138      1      1    2661.0  15.2458        C
1043       3  female  29.881138      1      0  367230.0  15.5000        Q
1185       3    male  29.881138      2      0    2662.0  21.6792        C
1186       3    male  29.881138      2      0    2662.0  21.6792        C

      survived
384          0
438          1
528          0
658          1
714          1
858          1
945          1
```

```
956           0
957           0
1002          1
1035          1
1043          1
1185          0
1186          0
```

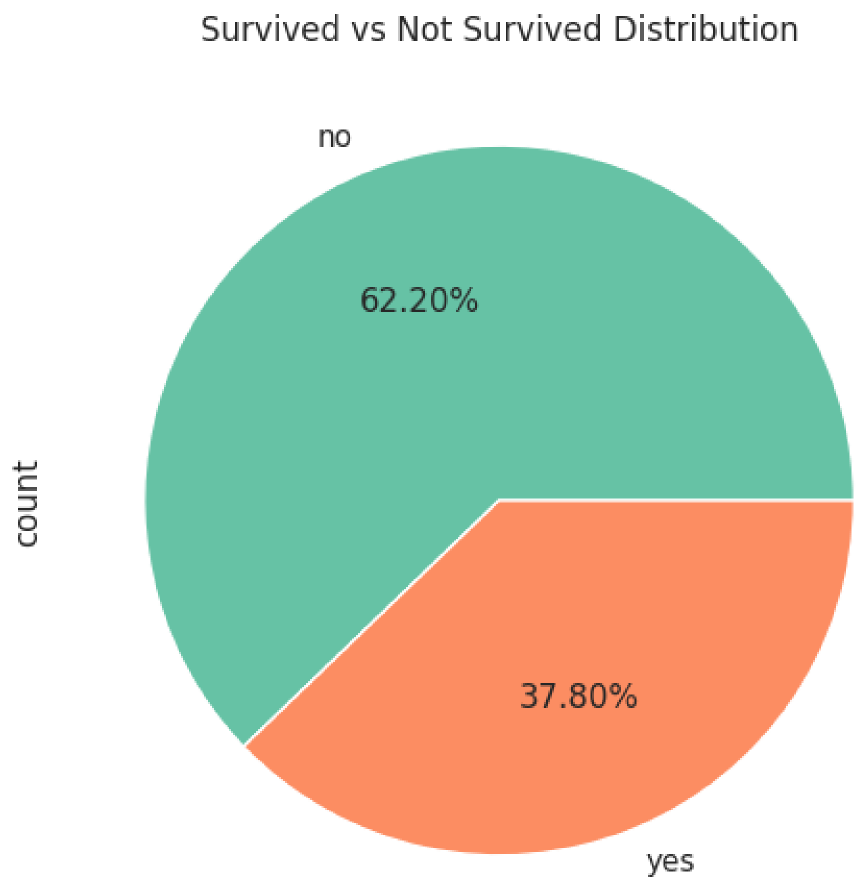
In my opinion, it is not necessary to delete duplicate values, so we continue to the next step

[51]:
```
# descriptive statistics
df.describe(include='all')
```

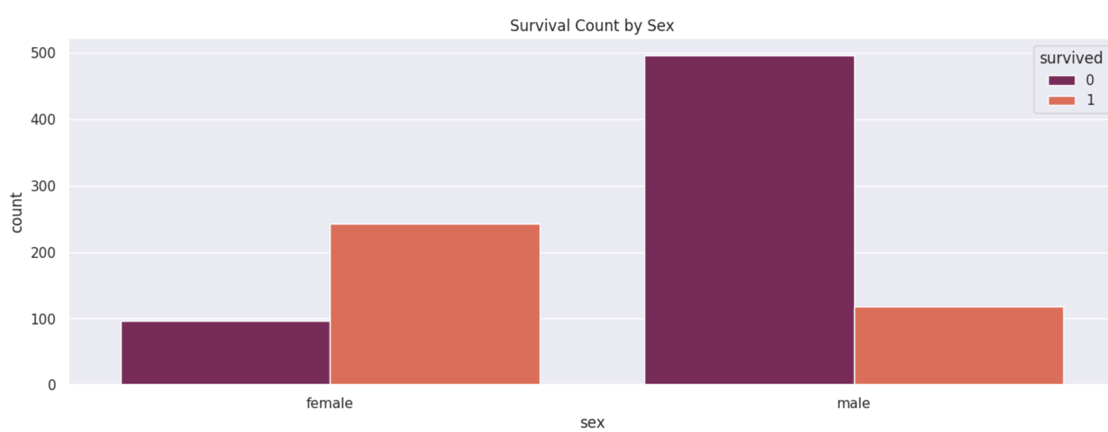
[51]:
```
            pclass   sex         age       sibsp       parch        ticket  \
count   955.000000   955  955.000000  955.000000  955.000000  9.550000e+02
unique         NaN     2         NaN         NaN         NaN           NaN
top            NaN  male         NaN         NaN         NaN           NaN
freq           NaN   615         NaN         NaN         NaN           NaN
mean      2.342408   NaN   29.657154    0.450262    0.341361  2.493228e+05
std       0.831150   NaN   12.765045    0.840776    0.765282  4.431056e+05
min       1.000000   NaN    0.330000    0.000000    0.000000  6.800000e+02
25%       2.000000   NaN   22.000000    0.000000    0.000000  1.995000e+04
50%       3.000000   NaN   29.881138    0.000000    0.000000  2.346860e+05
75%       3.000000   NaN   34.000000    1.000000    0.000000  3.474685e+05
max       3.000000   NaN   80.000000    4.000000    5.000000  3.101298e+06

              fare embarked    survived
count   955.000000      955  955.000000
unique         NaN        3         NaN
top            NaN        S         NaN
freq           NaN      662         NaN
mean     27.701066      NaN    0.378010
std      37.832230      NaN    0.485144
min       0.000000      NaN    0.000000
25%       7.883350      NaN    0.000000
50%      13.000000      NaN    0.000000
75%      27.900000      NaN    1.000000
max     263.000000      NaN    1.000000
```

0.4 Eksploratory Data Analysis (EDA)

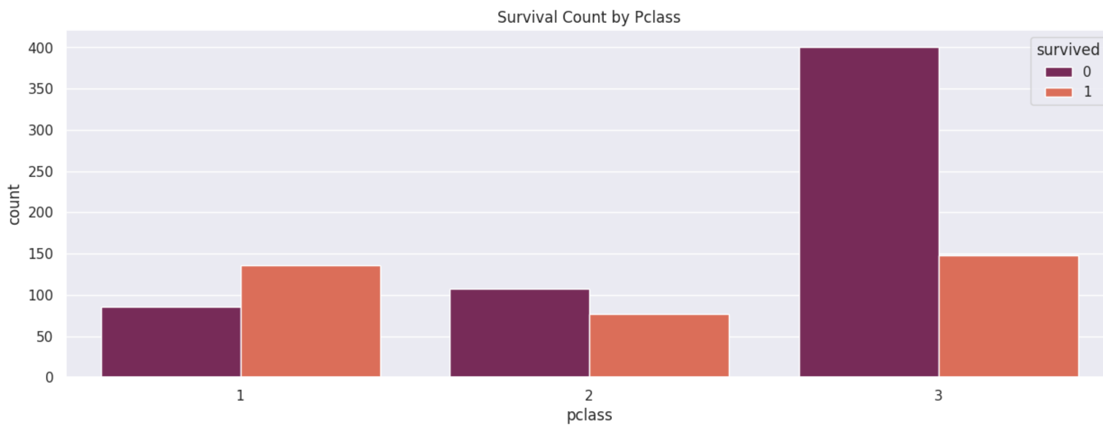
[53]:
```
plt.figure(figsize=(6,6))
df['survived'].value_counts().plot(kind='pie', autopct='%.2f%%', labels=['no',␣
↪'yes'])
plt.title('Survived vs Not Survived Distribution')
plt.show()
```



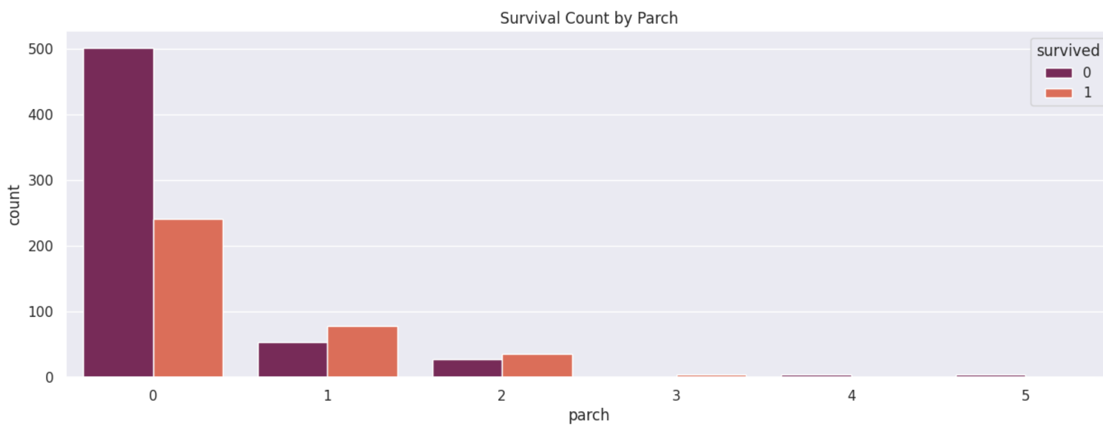
[54]:
```
plt.figure(figsize=(15,5))
sns.countplot(data=df, x='sex', hue='survived', palette='rocket')
plt.title('Survival Count by Sex')
plt.show()
```



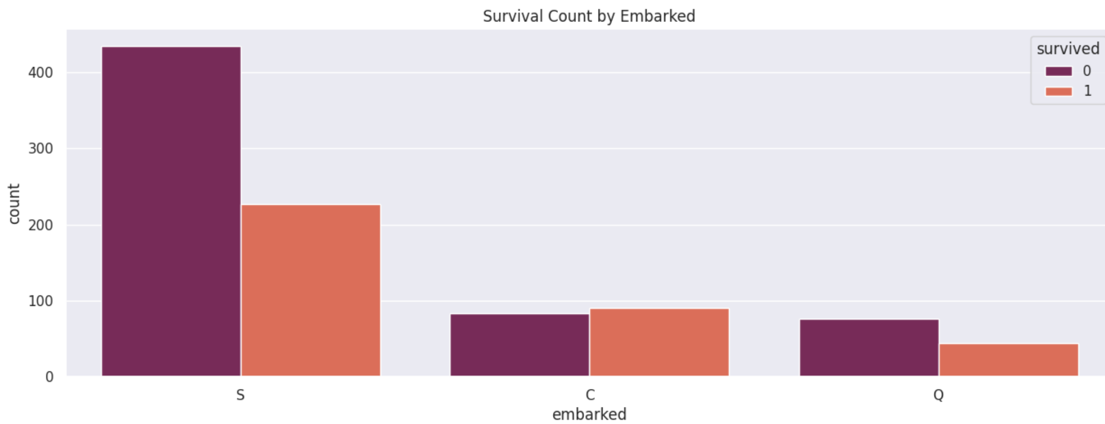
[55]:
```
plt.figure(figsize=(15,5))
sns.countplot(data=df, x='pclass', hue='survived', palette='rocket')
plt.title('Survival Count by Pclass')
plt.show()
```



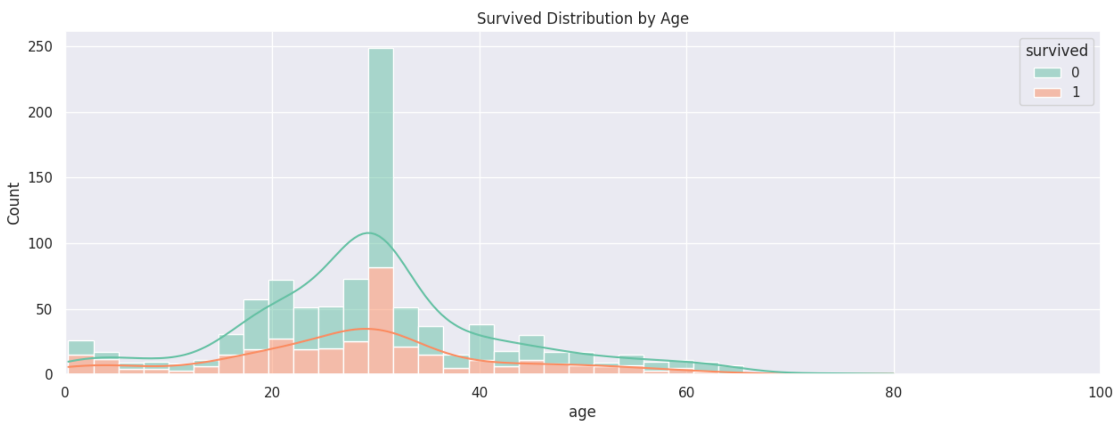
[56]:
```
plt.figure(figsize=(15,5))
sns.countplot(data=df, x='parch', hue='survived', palette='rocket')
plt.title('Survival Count by Parch')
plt.show()
```



[57]:
```
plt.figure(figsize=(15,5))
sns.countplot(data=df, x='embarked', hue='survived', palette='rocket')
plt.title('Survival Count by Embarked')
plt.show()
```



[58]:
```
plt.figure(figsize=(15, 5))
sns.histplot(data=df, x='age', hue='survived', multiple='stack',kde=True)
plt.title('Survived Distribution by Age')
plt.xlim(0,100)
plt.show()
```



0.5 Data Preprocessing Part 2

[59]:
```
# filter columns that have the object data type
for col in df:
  if df[col].dtypes == 'object':
    print(f'{col} : {df[col].unique()}')
```

```
sex : ['female' 'male']
embarked : ['S' 'C' 'Q']
```

[60]:

```
# label encoding
from sklearn.preprocessing import LabelEncoder

var = ['sex', 'embarked']
le = LabelEncoder()

for i in var:
    le.fit(df[i].unique())
    df[i]=le.transform(df[i])
    print(i,df[i].unique())
```

```
sex [0 1]
embarked [2 0 1]
```

[61]:

```
df.sample(5)
```

[61]:

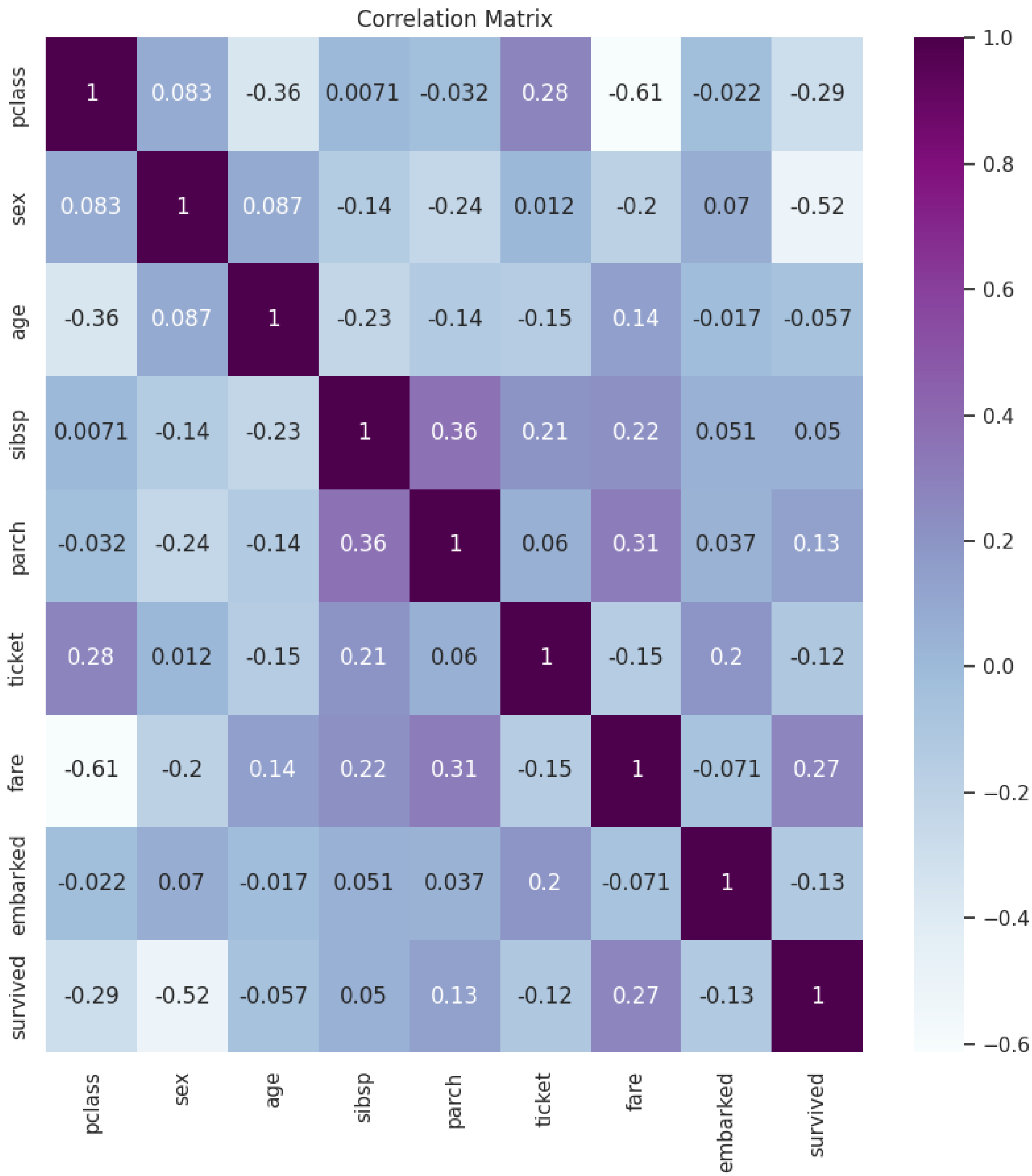
```
     pclass  sex        age  sibsp  parch    ticket     fare  embarked  \
589       2    0  29.000000      0      2   29103.0  23.0000         2
469       2    0  29.881138      0      0  226593.0  12.3500         1
440       2    0  48.000000      1      2  220845.0  65.0000         2
916       3    0   4.000000      0      1  349256.0  13.4167         0
128       1    1  47.000000      0      0  111320.0  38.5000         2

     survived
589         1
469         1
440         1
916         1
128         0
```

[62]:

```
# normalize the continuous variables
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

df[['ticket', 'fare']] = scaler.fit_transform(df[['ticket', 'fare']])
```

[63]:

```
# correlation matrix
plt.figure(figsize=(10,10))
sns.heatmap(df.corr(),annot=True,cmap='BuPu')
plt.title('Correlation Matrix')
plt.show()
```



[64]:
```python
X = df.drop('survived', axis=1)
y = df['survived']
```

[65]:
```python
# train test split
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
```

[66]:
```
len(X_train.columns)
```

[66]: 8

to predict whether the titanic people survived or not i will use the ANN model

[71]:
```
import tensorflow as tf
from tensorflow import keras

# define the ANN model
model = keras.Sequential([
    keras.layers.Dense(64, input_shape=(8,), activation='relu'),
    keras.layers.Dense(32, activation='relu'),
    keras.layers.Dense(1, activation='sigmoid')
])

# compile the model
model.compile(
    optimizer='adam',
    loss='binary_crossentropy',
    metrics=['accuracy']
)

# fitting the model
model.fit(X_train, y_train, epochs=10)
```

```
Epoch 1/10
24/24 [==============================] - 1s 4ms/step - loss: 1.5803 - accuracy:
0.5157
Epoch 2/10
24/24 [==============================] - 0s 2ms/step - loss: 0.6895 - accuracy:
0.5929
Epoch 3/10
24/24 [==============================] - 0s 2ms/step - loss: 0.6286 - accuracy:
0.6453
Epoch 4/10
24/24 [==============================] - 0s 2ms/step - loss: 0.6031 - accuracy:
0.6662
Epoch 5/10
24/24 [==============================] - 0s 2ms/step - loss: 0.5886 - accuracy:
0.6859
Epoch 6/10
24/24 [==============================] - 0s 2ms/step - loss: 0.5694 - accuracy:
0.6963
Epoch 7/10
24/24 [==============================] - 0s 2ms/step - loss: 0.5642 - accuracy:
0.7055
Epoch 8/10
```

```
24/24 [==============================] - 0s 3ms/step - loss: 0.5504 - accuracy:
0.7160
Epoch 9/10
24/24 [==============================] - 0s 2ms/step - loss: 0.5396 - accuracy:
0.7474
Epoch 10/10
24/24 [==============================] - 0s 2ms/step - loss: 0.5332 - accuracy:
0.7421
```

[71]:
```
<keras.src.callbacks.History at 0x7e0acc469c30>
```

[90]:
```
# evaluate the model
model.evaluate(X_test, y_test)
```

```
6/6 [==============================] - 0s 6ms/step - loss: 0.5317 - accuracy:
0.7801
```

[90]:
```
[0.5317214131355286, 0.7801046967506409]
```

[91]:
```
# do a predict and show 5 result the predict
yp = model.predict(X_test)
yp[:5]
```

```
6/6 [==============================] - 0s 2ms/step
```

[91]:
```
array([[0.59424615],
       [0.7199342 ],
       [0.21613458],
       [0.4685506 ],
       [0.22969034]], dtype=float32)
```

[92]:
```
# filtering where val < 0.5 convert to 0 and else convert to 1
y_pred = []
for i in yp:
  if i < 0.5:
    y_pred.append(0)
  else:
    y_pred.append(1)
```

[93]:
```
# show 5 pred result
y_pred[:5]
```

[93]:
```
[1, 1, 0, 0, 0]
```

[94]:
```
# show 5 the test result
y_test[:5]
```

[94]:
```
293     1
626     0
976     0
1044    1
571     0
Name: survived, dtype: int64
```

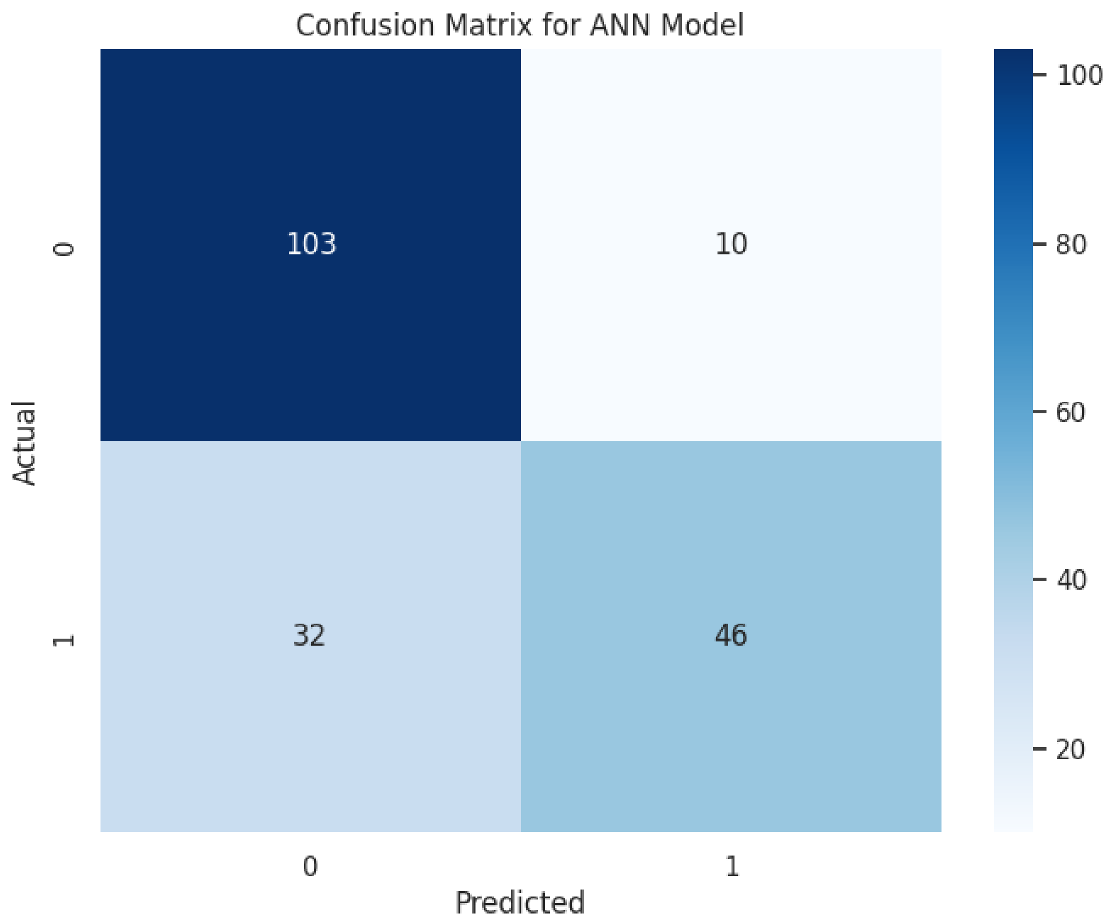
of the 5 samples we took, it can be seen that only 3 predictions were correct for the 5 samples taken

0.6 Model Evaluation

[84]:
```python
# classification report
from sklearn.metrics import confusion_matrix, classification_report

print(classification_report(y_test, y_pred))
```

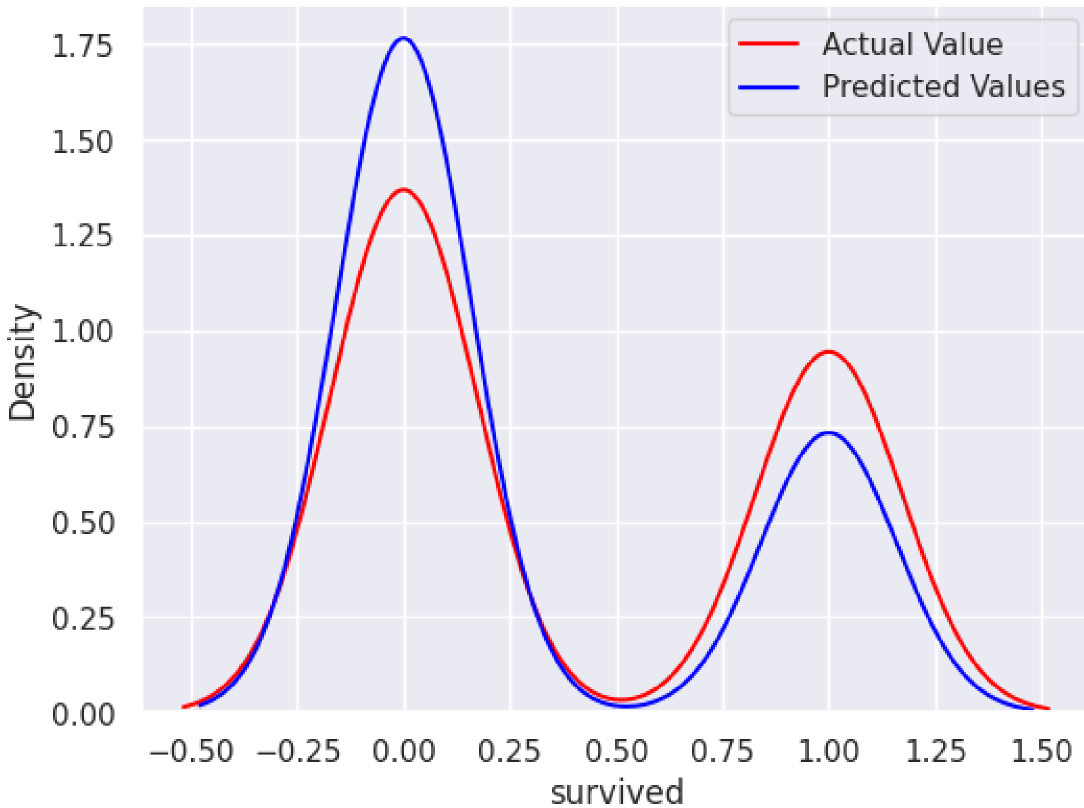
```
              precision    recall  f1-score   support

           0       0.76      0.91      0.83       113
           1       0.82      0.59      0.69        78

    accuracy                           0.78       191
   macro avg       0.79      0.75      0.76       191
weighted avg       0.79      0.78      0.77       191
```

[83]:
```python
# confusion metrix heatmap
plt.figure(figsize=(8,6))
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True,fmt='d',cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix for ANN Model')
plt.show()
```



[95]:
```
# distribution plot
ax = sns.distplot(y_test, hist=False, color='r', label='Actual Value')
sns.distplot(y_pred, hist=False, color='b', label='Predicted Values' , ax=ax)
plt.legend()
```

[95]:
```
<matplotlib.legend.Legend at 0x7e0abfe789d0>
```



Actual Value
Predicted Values
Density
survived
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
1.25
1.50