In [1]:
```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
data=pd.read_csv(r"C:\Users\gunis\Downloads\Titanic Dataset.csv")
data
```

Out[2]:

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

891 rows × 12 columns

In [3]:
```
data.head()
```

Out[3]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN

In [4]:
```
data.describe()
```

Out[4]:

	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

In [5]:
```
data.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
```

In [6]:
```
data.shape
```

Out[6]:
```
(891, 12)
```

In [7]:
```
list(data)
```

Out[7]:
```
['PassengerId',
 'Survived',
 'Pclass',
 'Name',
 'Sex',
 'Age',
 'SibSp',
 'Parch',
 'Ticket',
 'Fare',
 'Cabin',
 'Embarked']
```

In [8]:
```
data1=data.drop(['PassengerId','Ticket','Cabin','Name','SibSp','Parch'],axis=1)
data1
```

Out[8]:

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

891 rows × 6 columns

In [9]:
```
data1.isna().sum()
```

Out[9]:
```
Survived      0
Pclass        0
Sex           0
Age         177
Fare          0
Embarked      2
dtype: int64
```

In [10]:
```
data1.fillna(35,inplace=True)
```

In [11]:
```
data1
```

Out[11]:

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

891 rows × 6 columns

In [12]:
```
data1['Sex']=data1['Sex'].map({'male':1,'female':0})
```

In [13]:
```
data1
```

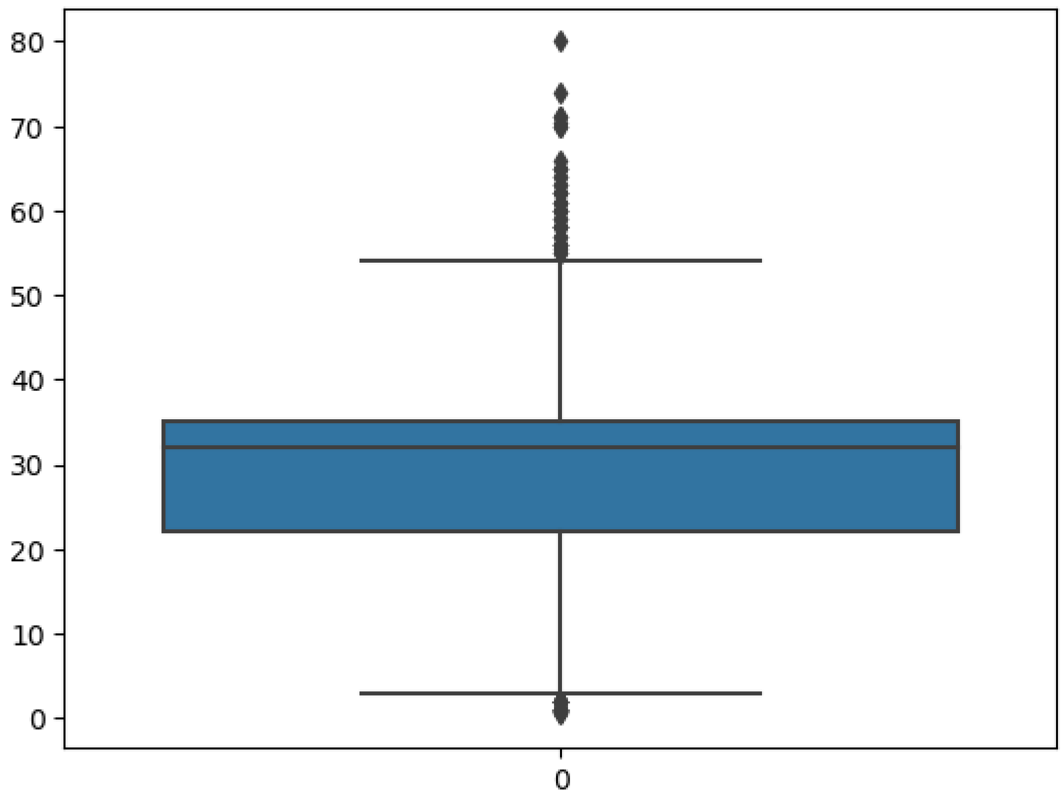
Out[13]:

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

891 rows × 6 columns

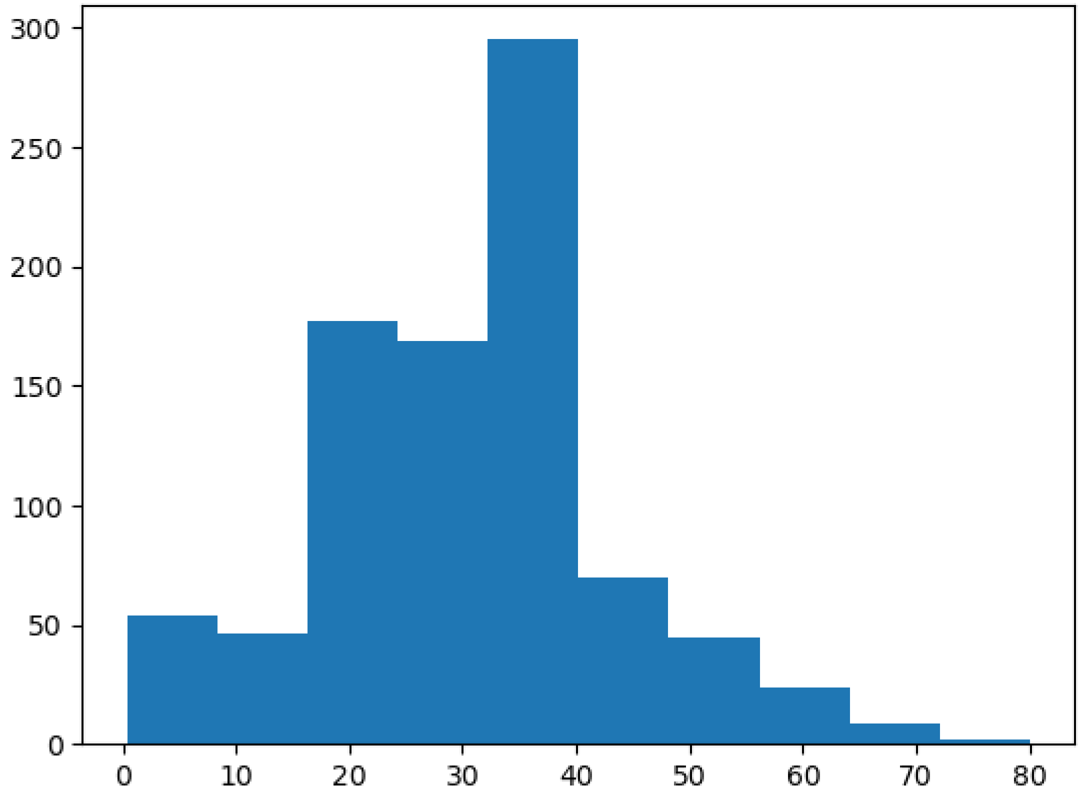
In [14]:
```
import seaborn as sb
import matplotlib.pyplot as plt
sb.boxplot(data1.Age)
```

Out[14]: <Axes: >



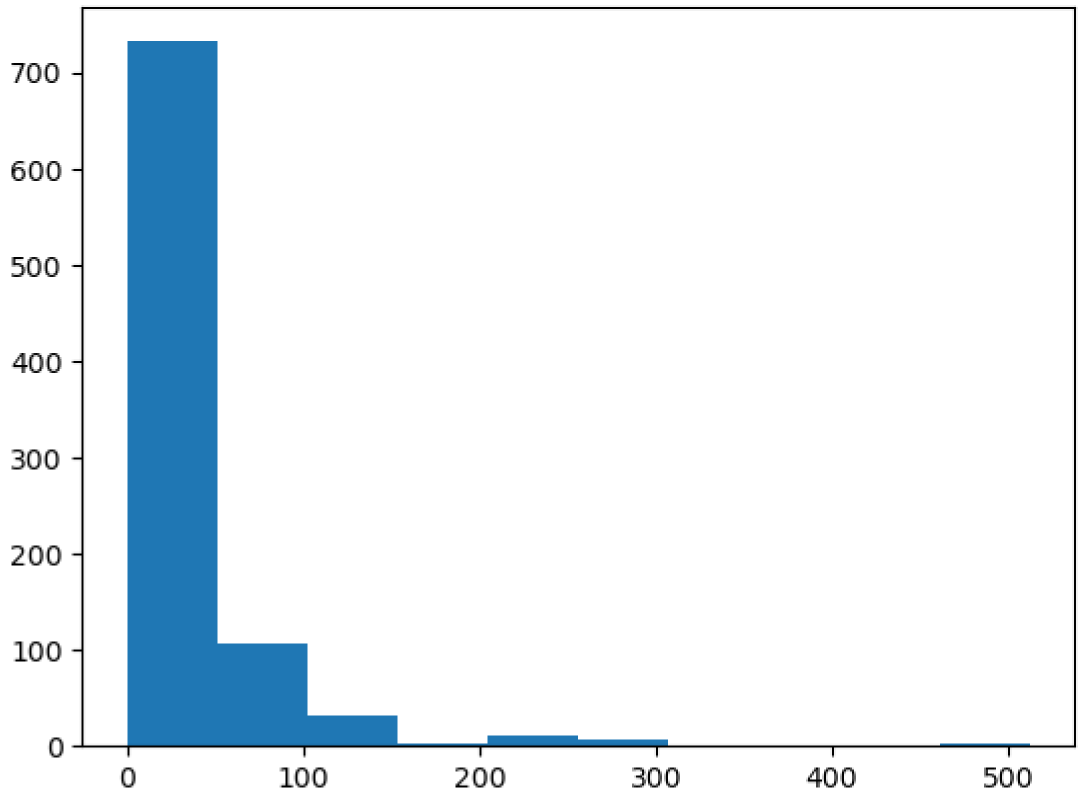
In [15]:
```
plt.hist(data1['Age'])
```

Out[15]:
```
(array([ 54.,  46., 177., 169., 295.,  70.,  45.,  24.,   9.,   2.]),
 array([ 0.42 ,  8.378, 16.336, 24.294, 32.252, 40.21 , 48.168, 56.126,
        64.084, 72.042, 80.   ]),
 <BarContainer object of 10 artists>)
```



In [16]:
```
plt.hist(data1['Fare'])
```

Out[16]:
```
(array([732., 106.,  31.,   2.,  11.,   6.,   0.,   0.,   0.,   3.]),
 array([  0.     ,  51.23292, 102.46584, 153.69876, 204.93168, 256.1646 ,
        307.39752, 358.63044, 409.86336, 461.09628, 512.3292 ]),
 <BarContainer object of 10 artists>)
```



In [17]:
```
data1.describe()
```

Out[17]:

	Survived	Pclass	Sex	Age	Fare
count	891.000000	891.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	0.647587	30.752155	32.204208
std	0.486592	0.836071	0.477990	13.173100	49.693429
min	0.000000	1.000000	0.000000	0.420000	0.000000
25%	0.000000	2.000000	0.000000	22.000000	7.910400
50%	0.000000	3.000000	1.000000	32.000000	14.454200
75%	1.000000	3.000000	1.000000	35.000000	31.000000
max	1.000000	3.000000	1.000000	80.000000	512.329200

In [18]:
```
data1['Age'].unique()
```

Out[18]:
```
array([22.  , 38.  , 26.  , 35.  , 54.  ,  2.  , 27.  , 14.  ,  4.  ,
       58.  , 20.  , 39.  , 55.  , 31.  , 34.  , 15.  , 28.  ,  8.  ,
       19.  , 40.  , 66.  , 42.  , 21.  , 18.  ,  3.  ,  7.  , 49.  ,
       29.  , 65.  , 28.5 ,  5.  , 11.  , 45.  , 17.  , 32.  , 16.  ,
       25.  ,  0.83, 30.  , 33.  , 23.  , 24.  , 46.  , 59.  , 71.  ,
       37.  , 47.  , 14.5 , 70.5 , 32.5 , 12.  ,  9.  , 36.5 , 51.  ,
       55.5 , 40.5 , 44.  ,  1.  , 61.  , 56.  , 50.  , 36.  , 45.5 ,
       20.5 , 62.  , 41.  , 52.  , 63.  , 23.5 ,  0.92, 43.  , 60.  ,
       10.  , 64.  , 13.  , 48.  ,  0.75, 53.  , 57.  , 80.  , 70.  ,
       24.5 ,  6.  ,  0.67, 30.5 ,  0.42, 34.5 , 74.  ])
```

In [19]:
```
data1.groupby(['Age']).count()
```

Out[19]:

Age	Survived	Pclass	Sex	Fare	Embarked
0.42	1	1	1	1	1
0.67	1	1	1	1	1
0.75	2	2	2	2	2
0.83	2	2	2	2	2
0.92	1	1	1	1	1
...	...	...	...	...	...
70.00	2	2	2	2	2
70.50	1	1	1	1	1
71.00	2	2	2	2	2
74.00	1	1	1	1	1
80.00	1	1	1	1	1

88 rows × 5 columns

In [20]:
```
data1['Pclass']=data1['Pclass'].map({1:'f',2:'s',3:'Third'})
```

In [21]:
```
data1.isna().sum()
```

Out[21]:
```
Survived    0
Pclass      0
Sex         0
Age         0
Fare        0
Embarked    0
dtype: int64
```

In [22]:
```
data2=pd.get_dummies(data1,dtype=int)
data2
```

Out[22]:

	Survived	Sex	Age	Fare	Pclass_Third	Pclass_f	Pclass_s	Embarked_35	Embarked_C	Eml
0	0	1	22.0	7.2500	1	0	0	0	0	
1	1	0	38.0	71.2833	0	1	0	0	1	
2	1	0	26.0	7.9250	1	0	0	0	0	
3	1	0	35.0	53.1000	0	1	0	0	0	
4	0	1	35.0	8.0500	1	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	
886	0	1	27.0	13.0000	0	0	1	0	0	
887	1	0	19.0	30.0000	0	1	0	0	0	
888	0	0	35.0	23.4500	1	0	0	0	0	
889	1	1	26.0	30.0000	0	1	0	0	1	
890	0	1	32.0	7.7500	1	0	0	0	0	

891 rows × 11 columns

In [ ]:

In [23]:
```
data2.shape
```

Out[23]:
```
(891, 11)
```

In [24]:
```
data2.head(500)
```

Out[24]:

	Survived	Sex	Age	Fare	Pclass_Third	Pclass_f	Pclass_s	Embarked_35	Embarked_C	En
0	0	1	22.0	7.2500	1	0	0	0	0	
1	1	0	38.0	71.2833	0	1	0	0	1	
2	1	0	26.0	7.9250	1	0	0	0	0	
3	1	0	35.0	53.1000	0	1	0	0	0	
4	0	1	35.0	8.0500	1	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	
495	0	1	35.0	14.4583	1	0	0	0	1	
496	1	0	54.0	78.2667	0	1	0	0	1	
497	0	1	35.0	15.1000	1	0	0	0	0	
498	0	0	25.0	151.5500	0	1	0	0	0	
499	0	1	24.0	7.7958	1	0	0	0	0	

500 rows × 11 columns

In [25]:

```
cor_mat=data2.corr()
cor_mat
```

Out[25]:

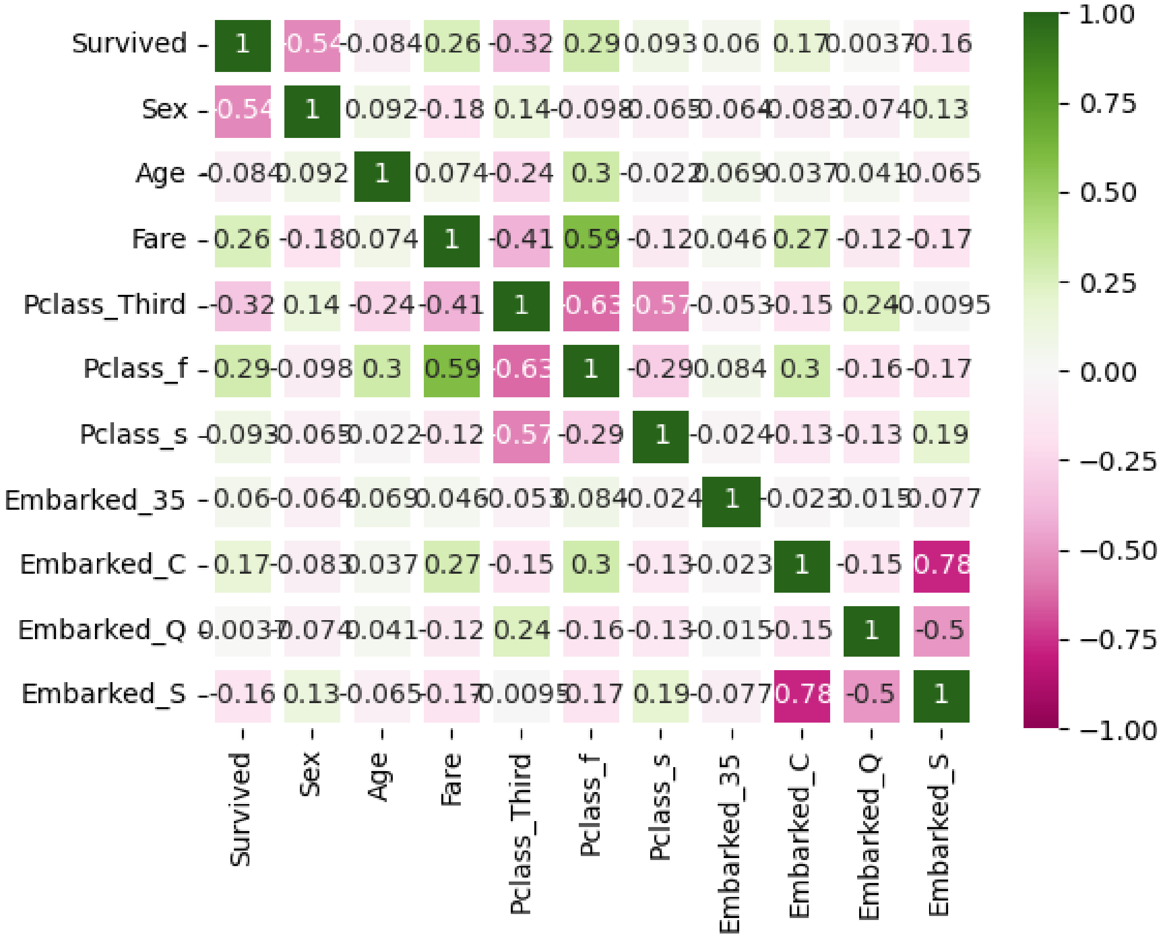
	Survived	Sex	Age	Fare	Pclass_Third	Pclass_f	Pclass_s	Embar
Survived	1.000000	-0.543351	-0.083713	0.257307	-0.322308	0.285904	0.093349	0.
Sex	-0.543351	1.000000	0.091930	-0.182333	0.137143	-0.098013	-0.064746	-0.
Age	-0.083713	0.091930	1.000000	0.074199	-0.242412	0.302149	-0.022021	0.
Fare	0.257307	-0.182333	0.074199	1.000000	-0.413333	0.591711	-0.118557	0.
Pclass_Third	-0.322308	0.137143	-0.242412	-0.413333	1.000000	-0.626738	-0.565210	-0.
Pclass_f	0.285904	-0.098013	0.302149	0.591711	-0.626738	1.000000	-0.288585	0.
Pclass_s	0.093349	-0.064746	-0.022021	-0.118557	-0.565210	-0.288585	1.000000	-0.
Embarked_35	0.060095	-0.064296	0.069343	0.045646	-0.052550	0.083847	-0.024197	1.
Embarked_C	0.168240	-0.082853	0.036953	0.269335	-0.153329	0.296423	-0.125416	-0.
Embarked_Q	0.003650	-0.074115	0.040528	-0.117216	0.237449	-0.155342	-0.127301	-0.
Embarked_S	-0.155660	0.125722	-0.065062	-0.166603	-0.009511	-0.170379	0.192061	-0.

In [26]:

```
import seaborn as sb
sb.heatmap(cor_mat,vmax=1,vmin=-1,annot=True,linewidths=5,cmap='PiYG')
```

Out[26]:

```
<Axes: >
```



In [27]:
```
data.groupby('Survived').count()
```

Out[27]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
Survived											
0	549	549	549	549	424	549	549	549	549	68	549
1	342	342	342	342	290	342	342	342	342	136	340

In [28]:
```
data2['Survived'].unique
```

Out[28]:
```
<bound method Series.unique of 0      0
1      1
2      1
3      1
4      0
      ..
886    0
887    1
888    0
889    1
890    0
Name: Survived, Length: 891, dtype: int64>
```

In [29]:
```
y=data2['Survived']
x=data2.drop(['Survived'],axis=1)
```

In [30]:
```
x
```

Out[30]:

	Sex	Age	Fare	Pclass_Third	Pclass_f	Pclass_s	Embarked_35	Embarked_C	Embarked_Q
0	1	22.0	7.2500	1	0	0	0	0	0
1	0	38.0	71.2833	0	1	0	0	1	0
2	0	26.0	7.9250	1	0	0	0	0	0
3	0	35.0	53.1000	0	1	0	0	0	0
4	1	35.0	8.0500	1	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...
886	1	27.0	13.0000	0	0	1	0	0	0
887	0	19.0	30.0000	0	1	0	0	0	0
888	0	35.0	23.4500	1	0	0	0	0	0
889	1	26.0	30.0000	0	1	0	0	1	0
890	1	32.0	7.7500	1	0	0	0	0	1

891 rows × 10 columns

In [31]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.33,random_state=42)
```

In [32]:
```
from sklearn.linear_model import LogisticRegression
classifier=LogisticRegression()
classifier.fit(x_train,y_train)
```

Out[32]:
```
▾ LogisticRegression
LogisticRegression()
```

In [33]:
```
ypred=classifier.predict(x_test)
ypred
```

Out[33]:
```
array([0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1,
       0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
       1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0,
       0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1,
       0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0,
       0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0,
       1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0,
       0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 1, 1, 0], dtype=int64)
```

In [34]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test,ypred)
```

Out[34]:
```
array([[155,  20],
       [ 37,  83]], dtype=int64)
```

In [35]:
```
from sklearn.metrics import accuracy_score
accuracy_score(y_test,ypred)
```

Out[35]: 0.8067796610169492

In [36]:
```
cor_mat=data2.corr()
cor_mat
```

Out[36]:

	Survived	Sex	Age	Fare	Pclass_Third	Pclass_f	Pclass_s	Embar
Survived	1.000000	-0.543351	-0.083713	0.257307	-0.322308	0.285904	0.093349	0.
Sex	-0.543351	1.000000	0.091930	-0.182333	0.137143	-0.098013	-0.064746	-0.
Age	-0.083713	0.091930	1.000000	0.074199	-0.242412	0.302149	-0.022021	0.
Fare	0.257307	-0.182333	0.074199	1.000000	-0.413333	0.591711	-0.118557	0.
Pclass_Third	-0.322308	0.137143	-0.242412	-0.413333	1.000000	-0.626738	-0.565210	-0.
Pclass_f	0.285904	-0.098013	0.302149	0.591711	-0.626738	1.000000	-0.288585	0.
Pclass_s	0.093349	-0.064746	-0.022021	-0.118557	-0.565210	-0.288585	1.000000	-0.
Embarked_35	0.060095	-0.064296	0.069343	0.045646	-0.052550	0.083847	-0.024197	1.
Embarked_C	0.168240	-0.082853	0.036953	0.269335	-0.153329	0.296423	-0.125416	-0.
Embarked_Q	0.003650	-0.074115	0.040528	-0.117216	0.237449	-0.155342	-0.127301	-0.
Embarked_S	-0.155660	0.125722	-0.065062	-0.166603	-0.009511	-0.170379	0.192061	-0.