In [1]:
```
import pandas as pd
```

In [2]:
```
data=pd.read_csv("/home/placement/Downloads/Titanic Dataset.csv")
```

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

Out[3]:

	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 [4]:
```
data.head()
```

Out[4]:

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

In [5]:
```
data.isna().sum()
```

Out[5]:
```
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
```

In [6]:
```
data['PassengerId'].unique()
```

Out[6]:
```
array([  1,   2,   3,   4,   5,   6,   7,   8,   9,  10,  11,  12,  13,
        14,  15,  16,  17,  18,  19,  20,  21,  22,  23,  24,  25,  26,
        27,  28,  29,  30,  31,  32,  33,  34,  35,  36,  37,  38,  39,
        40,  41,  42,  43,  44,  45,  46,  47,  48,  49,  50,  51,  52,
        53,  54,  55,  56,  57,  58,  59,  60,  61,  62,  63,  64,  65,
        66,  67,  68,  69,  70,  71,  72,  73,  74,  75,  76,  77,  78,
        79,  80,  81,  82,  83,  84,  85,  86,  87,  88,  89,  90,  91,
        92,  93,  94,  95,  96,  97,  98,  99, 100, 101, 102, 103, 104,
       105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117,
       118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130,
       131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142, 143,
       144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 155, 156,
       157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169,
       170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 180, 181, 182,
       183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194, 195,
       196, 197, 198, 199, 200, 201, 202, 203, 204, 205, 206, 207, 208,
       209, 210, 211, 212, 213, 214, 215, 216, 217, 218, 219, 220, 221,
       222, 223, 224, 225, 226, 227, 228, 229, 230, 231, 232, 233, 234,
       235, 236, 237, 238, 239, 240, 241, 242, 243, 244, 245, 246, 247,
       248, 249, 250, 251, 252, 253, 254, 255, 256, 257, 258, 259, 260,
       261, 262, 263, 264, 265, 266, 267, 268, 269, 270, 271, 272, 273,
       274, 275, 276, 277, 278, 279, 280, 281, 282, 283, 284, 285, 286,
       287, 288, 289, 290, 291, 292, 293, 294, 295, 296, 297, 298, 299,
       300, 301, 302, 303, 304, 305, 306, 307, 308, 309, 310, 311, 312,
       313, 314, 315, 316, 317, 318, 319, 320, 321, 322, 323, 324, 325,
       326, 327, 328, 329, 330, 331, 332, 333, 334, 335, 336, 337, 338,
       339, 340, 341, 342, 343, 344, 345, 346, 347, 348, 349, 350, 351,
       352, 353, 354, 355, 356, 357, 358, 359, 360, 361, 362, 363, 364,
       365, 366, 367, 368, 369, 370, 371, 372, 373, 374, 375, 376, 377,
       378, 379, 380, 381, 382, 383, 384, 385, 386, 387, 388, 389, 390,
       391, 392, 393, 394, 395, 396, 397, 398, 399, 400, 401, 402, 403,
       404, 405, 406, 407, 408, 409, 410, 411, 412, 413, 414, 415, 416,
       417, 418, 419, 420, 421, 422, 423, 424, 425, 426, 427, 428, 429,
       430, 431, 432, 433, 434, 435, 436, 437, 438, 439, 440, 441, 442,
       443, 444, 445, 446, 447, 448, 449, 450, 451, 452, 453, 454, 455,
       456, 457, 458, 459, 460, 461, 462, 463, 464, 465, 466, 467, 468,
       469, 470, 471, 472, 473, 474, 475, 476, 477, 478, 479, 480, 481,
       482, 483, 484, 485, 486, 487, 488, 489, 490, 491, 492, 493, 494,
       495, 496, 497, 498, 499, 500, 501, 502, 503, 504, 505, 506, 507,
```

```
       508, 509, 510, 511, 512, 513, 514, 515, 516, 517, 518, 519, 520,
       521, 522, 523, 524, 525, 526, 527, 528, 529, 530, 531, 532, 533,
       534, 535, 536, 537, 538, 539, 540, 541, 542, 543, 544, 545, 546,
       547, 548, 549, 550, 551, 552, 553, 554, 555, 556, 557, 558, 559,
       560, 561, 562, 563, 564, 565, 566, 567, 568, 569, 570, 571, 572,
       573, 574, 575, 576, 577, 578, 579, 580, 581, 582, 583, 584, 585,
       586, 587, 588, 589, 590, 591, 592, 593, 594, 595, 596, 597, 598,
       599, 600, 601, 602, 603, 604, 605, 606, 607, 608, 609, 610, 611,
       612, 613, 614, 615, 616, 617, 618, 619, 620, 621, 622, 623, 624,
       625, 626, 627, 628, 629, 630, 631, 632, 633, 634, 635, 636, 637,
       638, 639, 640, 641, 642, 643, 644, 645, 646, 647, 648, 649, 650,
       651, 652, 653, 654, 655, 656, 657, 658, 659, 660, 661, 662, 663,
       664, 665, 666, 667, 668, 669, 670, 671, 672, 673, 674, 675, 676,
       677, 678, 679, 680, 681, 682, 683, 684, 685, 686, 687, 688, 689,
       690, 691, 692, 693, 694, 695, 696, 697, 698, 699, 700, 701, 702,
       703, 704, 705, 706, 707, 708, 709, 710, 711, 712, 713, 714, 715,
       716, 717, 718, 719, 720, 721, 722, 723, 724, 725, 726, 727, 728,
       729, 730, 731, 732, 733, 734, 735, 736, 737, 738, 739, 740, 741,
       742, 743, 744, 745, 746, 747, 748, 749, 750, 751, 752, 753, 754,
       755, 756, 757, 758, 759, 760, 761, 762, 763, 764, 765, 766, 767,
       768, 769, 770, 771, 772, 773, 774, 775, 776, 777, 778, 779, 780,
       781, 782, 783, 784, 785, 786, 787, 788, 789, 790, 791, 792, 793,
       794, 795, 796, 797, 798, 799, 800, 801, 802, 803, 804, 805, 806,
       807, 808, 809, 810, 811, 812, 813, 814, 815, 816, 817, 818, 819,
       820, 821, 822, 823, 824, 825, 826, 827, 828, 829, 830, 831, 832,
       833, 834, 835, 836, 837, 838, 839, 840, 841, 842, 843, 844, 845,
       846, 847, 848, 849, 850, 851, 852, 853, 854, 855, 856, 857, 858,
       859, 860, 861, 862, 863, 864, 865, 866, 867, 868, 869, 870, 871,
       872, 873, 874, 875, 876, 877, 878, 879, 880, 881, 882, 883, 884,
       885, 886, 887, 888, 889, 890, 891])
```

In [7]:
```
data['Survived'].unique()
```

Out[7]:
```
array([0, 1])
```

In [8]:
```
data['Pclass'].unique()
```

Out[8]:
```
array([3, 1, 2])
```

In [9]:
```
data['Age'].unique()
```

Out[9]:
```
array([22.  , 38.  , 26.  , 35.  ,   nan, 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 [10]:
```
data1=data.drop(['PassengerId','Ticket','Cabin','Name','SibSp','Parch'],axis=1)
data1
```

Out[10]:

	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 [11]:
```
list(data1)
```

Out[11]:
```
['Survived', 'Pclass', 'Sex', 'Age', 'Fare', 'Embarked']
```

In [12]:
```
data1.isna().sum()
```

Out[12]:
```
Survived      0
Pclass        0
Sex           0
Age         177
Fare          0
Embarked      2
dtype: int64
```

In [13]:
```
data1.shape
```

Out[13]:
```
(891, 6)
```

In [14]:
```
data1['Sex']=data1['Sex'].map({'male':1,'female':0})
data1
```

Out[14]:

	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	NaN	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 [15]:
```
data1['Pclass'].unique()
```

Out[15]:
```
array([3, 1, 2])
```

In [16]:
```
data2=data1.fillna(data1.median())
data2
```

```
/tmp/ipykernel_11595/2983102192.py:1: FutureWarning: The default value of numeric_only in DataFrame.median
is deprecated. In a future version, it will default to False. In addition, specifying 'numeric_only=None' i
s deprecated. Select only valid columns or specify the value of numeric_only to silence this warning.
  data2=data1.fillna(data1.median())
```

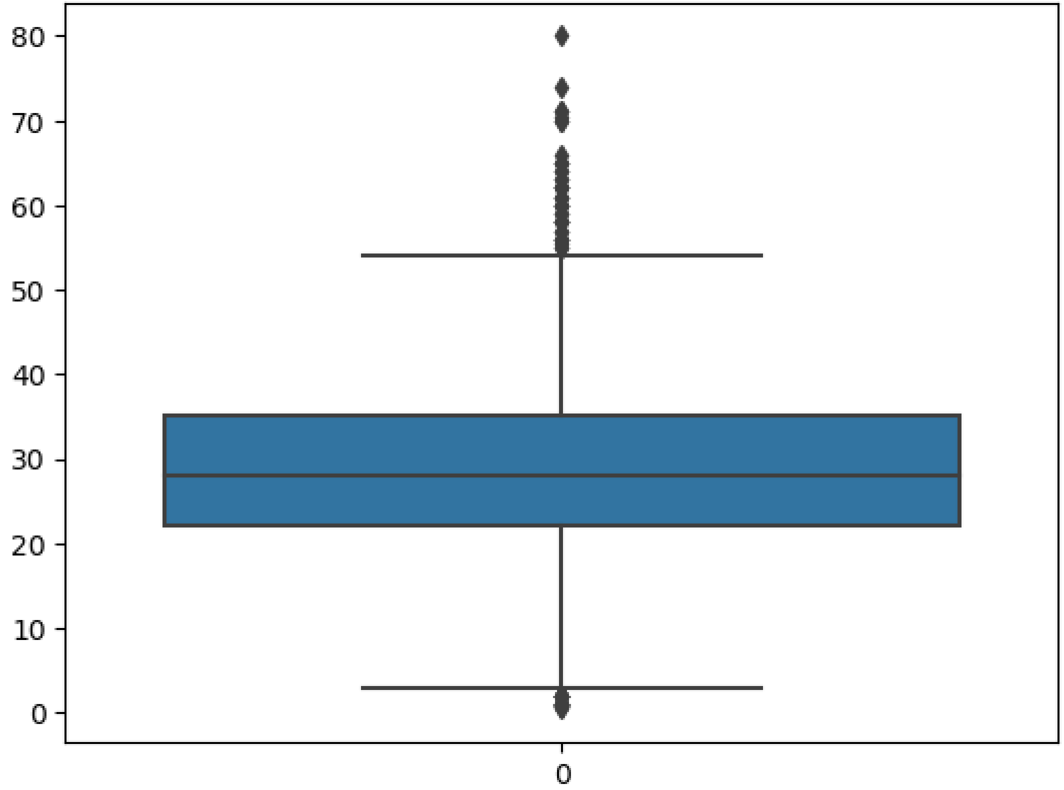
Out[16]:

	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	28.0	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

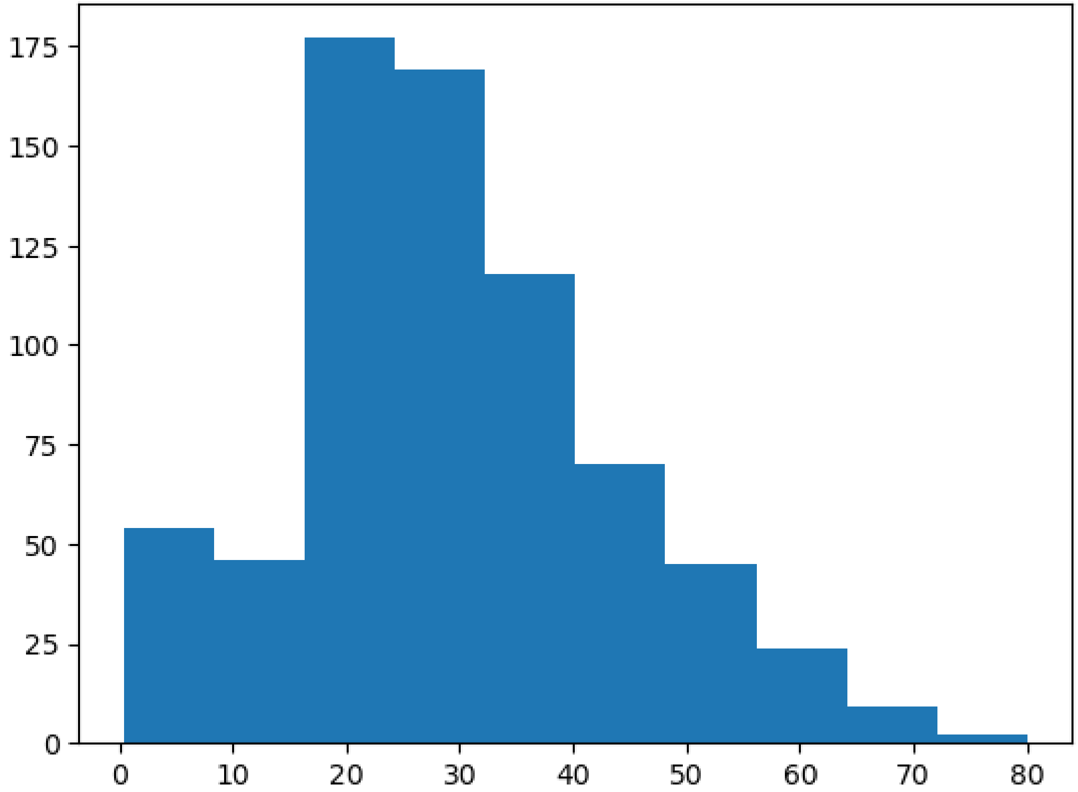
In [17]:
```
import seaborn as sns
import matplotlib.pyplot as plt
sns.boxplot(data2.Age)
```

Out[17]:
```
<Axes: >
```



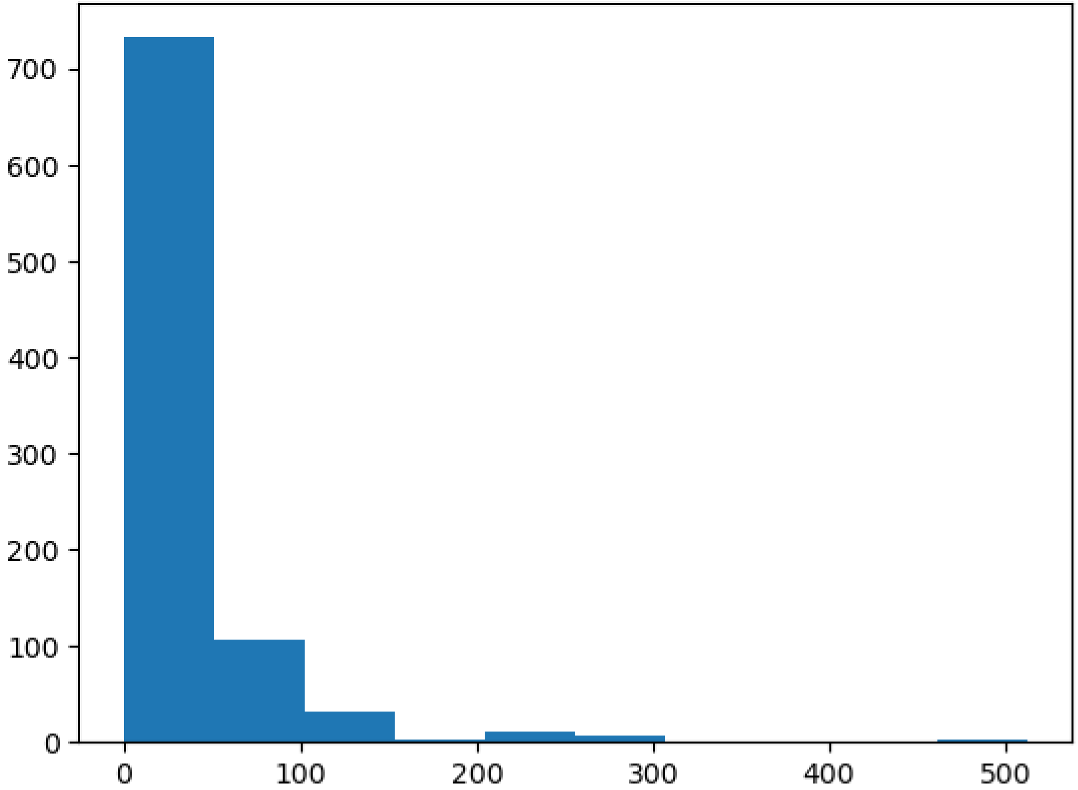
In [18]:
```
plt.hist(data1['Age'])
```

Out[18]:
```
(array([ 54.,  46., 177., 169., 118.,  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 [19]:
```
plt.hist(data2['Fare'])
```

Out[19]:
```
(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 [20]:
```
data2.isna().sum()
```

Out[20]:
```
Survived    0
Pclass      0
Sex         0
Age         0
Fare        0
Embarked    2
dtype: int64
```

In [21]:
```
data2.fillna(35,inplace=True)
```

In [22]:
```
data2.isna().sum()
```

Out[22]:
```
Survived    0
Pclass      0
Sex         0
Age         0
Fare        0
Embarked    0
dtype: int64
```

In [23]:
```
data2.describe()
```

Out[23]:

	Survived	Pclass	Sex	Age	Fare
count	891.000000	891.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	0.647587	29.361582	32.204208
std	0.486592	0.836071	0.477990	13.019697	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	28.000000	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 [24]:
```
data['Age'].unique()
```

Out[24]:
```
array([22.  , 38.  , 26.  , 35.  ,   nan, 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 [25]:
```
data3=data2.groupby(['Age']).count()
data3
```

Out[25]:

	Survived	Pclass	Sex	Fare	Embarked
Age					
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 [26]:
```
data2['Pclass']=data2['Pclass'].map({1:'F',2:'S',3:'T'})
```

In [27]:
```
data2.head(10)
```

Out[27]:

	Survived	Pclass	Sex	Age	Fare	Embarked
0	0	T	1	22.0	7.2500	S
1	1	F	0	38.0	71.2833	C
2	1	T	0	26.0	7.9250	S
3	1	F	0	35.0	53.1000	S
4	0	T	1	35.0	8.0500	S
5	0	T	1	28.0	8.4583	Q
6	0	F	1	54.0	51.8625	S
7	0	T	1	2.0	21.0750	S
8	1	T	0	27.0	11.1333	S
9	1	S	0	14.0	30.0708	C

In [28]:
```
data4=pd.get_dummies(data2)
data4
```

Out[28]:

	Survived	Sex	Age	Fare	Pclass_F	Pclass_S	Pclass_T	Embarked_35	Embarked_C	Embarked_Q	Embarked_S
0	0	1	22.0	7.2500	0	0	1	0	0	0	1
1	1	0	38.0	71.2833	1	0	0	0	1	0	0
2	1	0	26.0	7.9250	0	0	1	0	0	0	1
3	1	0	35.0	53.1000	1	0	0	0	0	0	1
4	0	1	35.0	8.0500	0	0	1	0	0	0	1
...	...	...	...	...	...	...	...	...	...	...	...
886	0	1	27.0	13.0000	0	1	0	0	0	0	1
887	1	0	19.0	30.0000	1	0	0	0	0	0	1
888	0	0	28.0	23.4500	0	0	1	0	0	0	1
889	1	1	26.0	30.0000	1	0	0	0	1	0	0
890	0	1	32.0	7.7500	0	0	1	0	0	1	0

891 rows × 11 columns

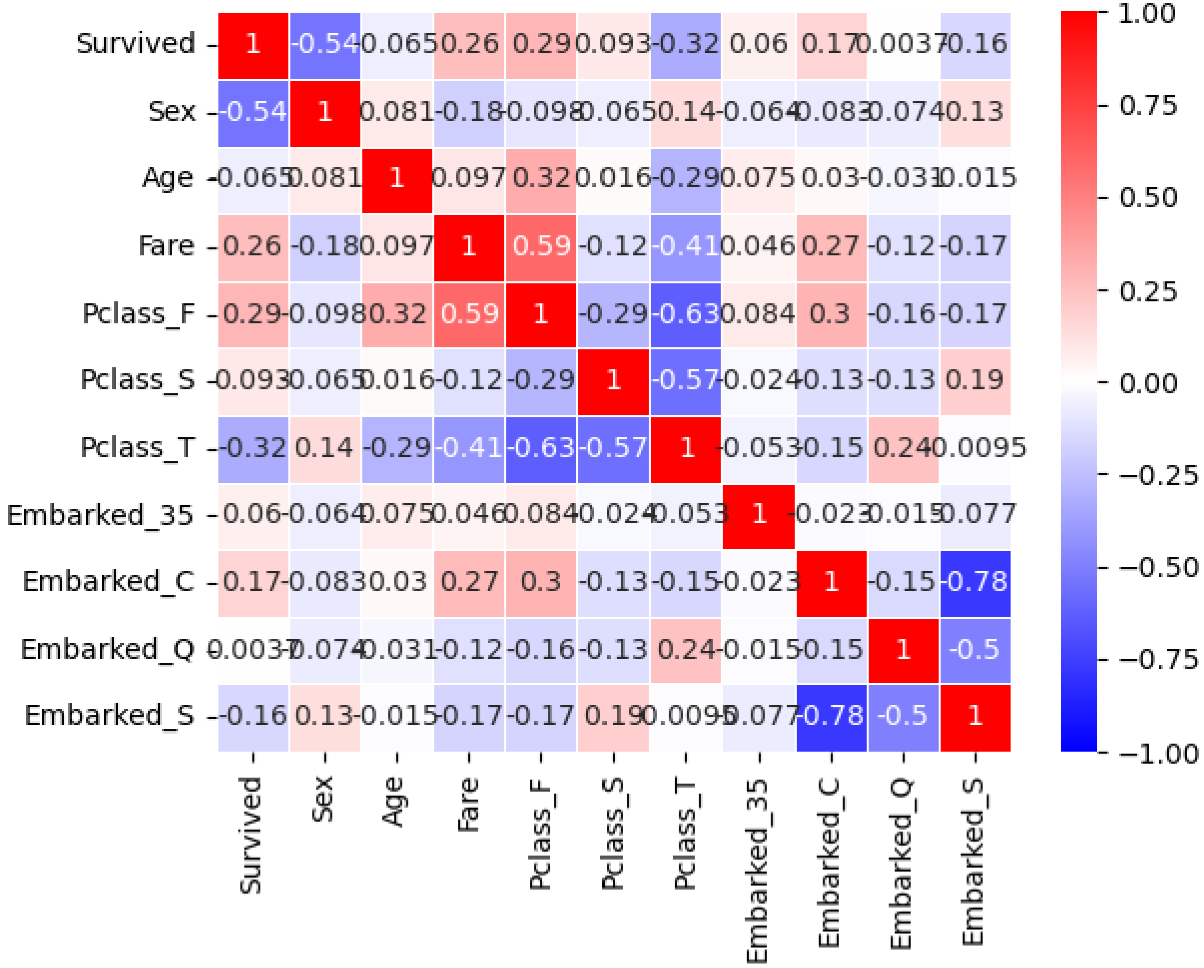
In [29]:
```
cor=data4.corr()
cor
```

Out[29]:

	Survived	Sex	Age	Fare	Pclass_F	Pclass_S	Pclass_T	Embarked_35	Embarked_C	Embarked_Q	Embarked_S
Survived	1.000000	-0.543351	-0.064910	0.257307	0.285904	0.093349	-0.322308	0.060095	0.168240	0.003650	-0.155660
Sex	-0.543351	1.000000	0.081163	-0.182333	-0.098013	-0.064746	0.137143	-0.064296	-0.082853	-0.074115	0.125722
Age	-0.064910	0.081163	1.000000	0.096688	0.323896	0.015831	-0.291955	0.075229	0.030248	-0.031415	-0.014665
Fare	0.257307	-0.182333	0.096688	1.000000	0.591711	-0.118557	-0.413333	0.045646	0.269335	-0.117216	-0.166603
Pclass_F	0.285904	-0.098013	0.323896	0.591711	1.000000	-0.288585	-0.626738	0.083847	0.296423	-0.155342	-0.170379
Pclass_S	0.093349	-0.064746	0.015831	-0.118557	-0.288585	1.000000	-0.565210	-0.024197	-0.125416	-0.127301	0.192061
Pclass_T	-0.322308	0.137143	-0.291955	-0.413333	-0.626738	-0.565210	1.000000	-0.052550	-0.153329	0.237449	-0.009511
Embarked_35	0.060095	-0.064296	0.075229	0.045646	0.083847	-0.024197	-0.052550	1.000000	-0.022864	-0.014588	-0.076588
Embarked_C	0.168240	-0.082853	0.030248	0.269335	0.296423	-0.125416	-0.153329	-0.022864	1.000000	-0.148258	-0.778359
Embarked_Q	0.003650	-0.074115	-0.031415	-0.117216	-0.155342	-0.127301	0.237449	-0.014588	-0.148258	1.000000	-0.496624
Embarked_S	-0.155660	0.125722	-0.014665	-0.166603	-0.170379	0.192061	-0.009511	-0.076588	-0.778359	-0.496624	1.000000

In [30]:
```
import seaborn as sns
sns.heatmap(cor,vmax=1,vmin=-1,annot=True,linewidths=.5,cmap='bwr')
```

Out[30]: <Axes: >



In [31]:
```
data4.groupby('Survived').count()
```

Out[31]:

	Sex	Age	Fare	Pclass_F	Pclass_S	Pclass_T	Embarked_35	Embarked_C	Embarked_Q	Embarked_S
Survived										
0	549	549	549	549	549	549	549	549	549	549
1	342	342	342	342	342	342	342	342	342	342

In [32]:
```
y=data4['Survived']
x=data4.drop('Survived',axis=1)
```

In [33]:
```
y
```

Out[33]:
```
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 [34]:
```
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 [35]:
```
x_test.head(5)
```

Out[35]:

	Sex	Age	Fare	Pclass_F	Pclass_S	Pclass_T	Embarked_35	Embarked_C	Embarked_Q	Embarked_S
709	1	28.0	15.2458	0	0	1	0	1	0	0
439	1	31.0	10.5000	0	1	0	0	0	0	1
840	1	20.0	7.9250	0	0	1	0	0	0	1
720	0	6.0	33.0000	0	1	0	0	0	0	1
39	0	14.0	11.2417	0	0	1	0	1	0	0

In [36]:
```
x_train.head(5)
```

Out[36]:

	Sex	Age	Fare	Pclass_F	Pclass_S	Pclass_T	Embarked_35	Embarked_C	Embarked_Q	Embarked_S
6	1	54.0	51.8625	1	0	0	0	0	0	1
718	1	28.0	15.5000	0	0	1	0	0	1	0
685	1	25.0	41.5792	0	1	0	0	1	0	0
73	1	26.0	14.4542	0	0	1	0	1	0	0
882	0	22.0	10.5167	0	0	1	0	0	0	1

In [37]:
```
y_test.head(5)
```

Out[37]:
```
709    1
439    0
840    0
720    1
39     1
Name: Survived, dtype: int64
```

In [38]:
```
y_train.head(5)
```

Out[38]:
```
6      0
718    0
685    0
73     0
882    0
Name: Survived, dtype: int64
```

In [39]:
```
from sklearn.linear_model import LogisticRegression
classifier=LogisticRegression()
classifier.fit(x_train,y_train)
```

```
/home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWa
rning: 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 (https://scikit-learn.org/stable/modules/pre
processing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.or
g/stable/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
```

Out[39]:
```
▾ LogisticRegression
LogisticRegression()
```

In [40]:
```
y_pred=classifier.predict(x_test)
```

In [41]:
```
y_pred
```

Out[41]:
```
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, 1, 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])
```

In [42]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test,y_pred)
```

Out[42]:
```
array([[154,  21],
       [ 37,  83]])
```

In [43]:
```
from sklearn.metrics import accuracy_score
accuracy_score(y_test,y_pred)
```

Out[43]:
```
0.8033898305084746
```

In [44]:
```
y
```

Out[44]:
```
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 [ ]:

In [ ]: