HOMEWORK 1

1. There are totally **12 features** in the training set. They are **PassengerId, Survived, Pclass, Name, Sex, Age, SibSp, Parch, Ticket, Fare, Cabin, Embarked**.

2. The features that are categorial are: **Survived, Pclass, Sex and Embarked.**

3. The features that are numerical are **PassengerID, Survived, Pclass, Age, SibSp, Parch and Fare**

4. The features that have mixed data type are **Ticket and Cabin**.

5. In training data, the features that contain blank, null or empty values are **Age (714 values), Cabin (204 values) and Embarked (889 values)**. Similarly, in the test data, the features that contain blank, null or empty values are **Age (332 values), Fare (417 values) and Cabin (91 values).**

6. The different data types in the training set are **float 64** (Age and Fare), **Object/String** (Name, Ticket, Cabin, Embarked) and **int 64** (PassengerId, Survived, Pclass, Sex, SibSp, and Parch)

   ##
   Output for questions from 1 through 6:

   Output for the training set:

```
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    int64
 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(6), object(4)
```

Output for the test set:

```
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  418 non-null    int64
 1   Pclass       418 non-null    int64
 2   Name         418 non-null    object
 3   Sex          418 non-null    object
 4   Age          332 non-null    float64
 5   SibSp        418 non-null    int64
 6   Parch        418 non-null    int64
 7   Ticket       418 non-null    object
 8   Fare         417 non-null    float64
 9   Cabin        91 non-null     object
 10  Embarked     418 non-null    object

dtypes: float64(2), int64(4), object(5)
```

Number of missing values in each feature of the training set:

```
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
```

Number of missing values in each feature of the testing set:

```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

##

7. The following are the statistical data to understand the distribution of numerical feature values across the samples:

##
Output for question 7:

```
[aahana@MacBook-Pro homework-1 % python3 main.py
       PassengerId    Survived      Pclass         Sex         Age       SibSp       Parch        Fare
count   891.000000  891.000000  891.000000  891.000000  714.000000  891.000000  891.000000  891.000000
mean    446.000000    0.383838    2.308642    0.647587   29.699118    0.523008    0.381594   32.204208
std     257.353842    0.486592    0.836071    0.477990   14.526497    1.102743    0.806057   49.693429
min       1.000000    0.000000    1.000000    0.000000    0.420000    0.000000    0.000000    0.000000
25%     223.500000    0.000000    2.000000    0.000000   20.125000    0.000000    0.000000    7.910400
50%     446.000000    0.000000    3.000000    1.000000   28.000000    0.000000    0.000000   14.454200
75%     668.500000    1.000000    3.000000    1.000000   38.000000    1.000000    0.000000   31.000000
max     891.000000    1.000000    3.000000    1.000000   80.000000    8.000000    6.000000  512.329200
```


```
       PassengerId    Survived      Pclass         Sex         Age       SibSp       Parch        Fare

count   891.000000  891.000000  891.000000  891.000000  714.000000  891.000000  891.000000  891.000000
mean    446.000000    0.383838    2.308642    0.647587   29.699118    0.523008    0.381594   32.204208
std     257.353842    0.486592    0.836071    0.477990   14.526497    1.102743    0.806057   49.693429
min       1.000000    0.000000    1.000000    0.000000    0.420000    0.000000    0.000000    0.000000
25%     223.500000    0.000000    2.000000    0.000000   20.125000    0.000000    0.000000    7.910400
50%     446.000000    0.000000    3.000000    1.000000   28.000000    0.000000    0.000000   14.454200
75%     668.500000    1.000000    3.000000    1.000000   38.000000    1.000000    0.000000   31.000000
max     891.000000    1.000000    3.000000    1.000000   80.000000    8.000000    6.000000  512.329200
```


##

8. First, the dtype of all the categorical features are converted to category and then the output is printed.

##

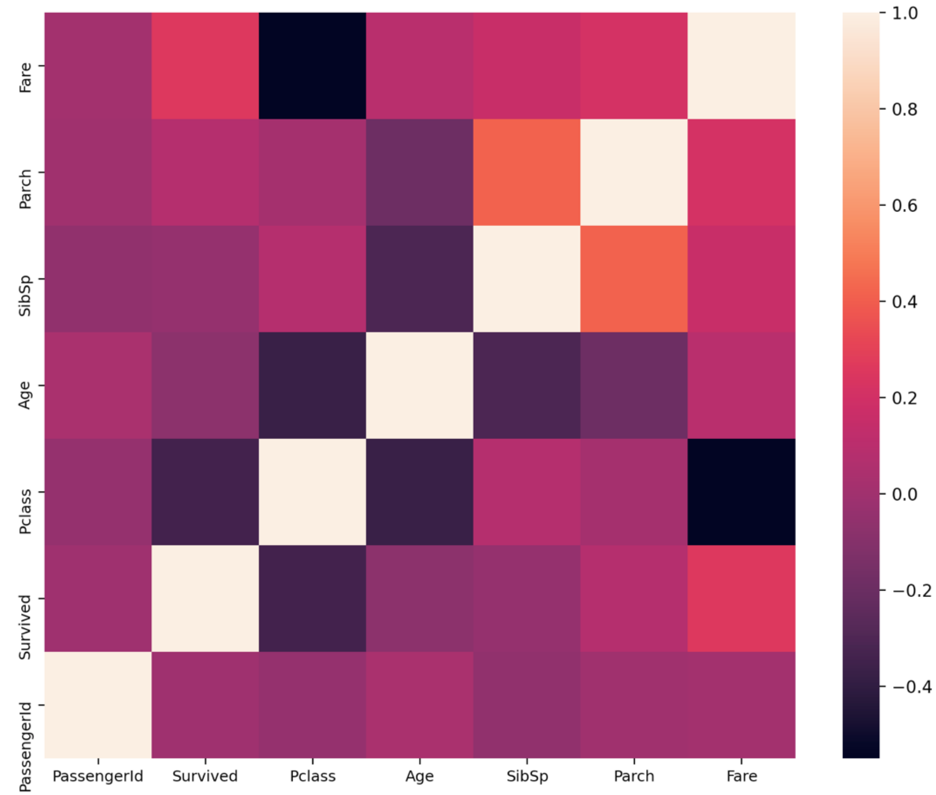
Output of question 8:

```
       Survived  Pclass   Sex Embarked
count       891     891   891      889
unique        2       3     2        3
top           0       3  male        S
freq        549     491   577      644
```

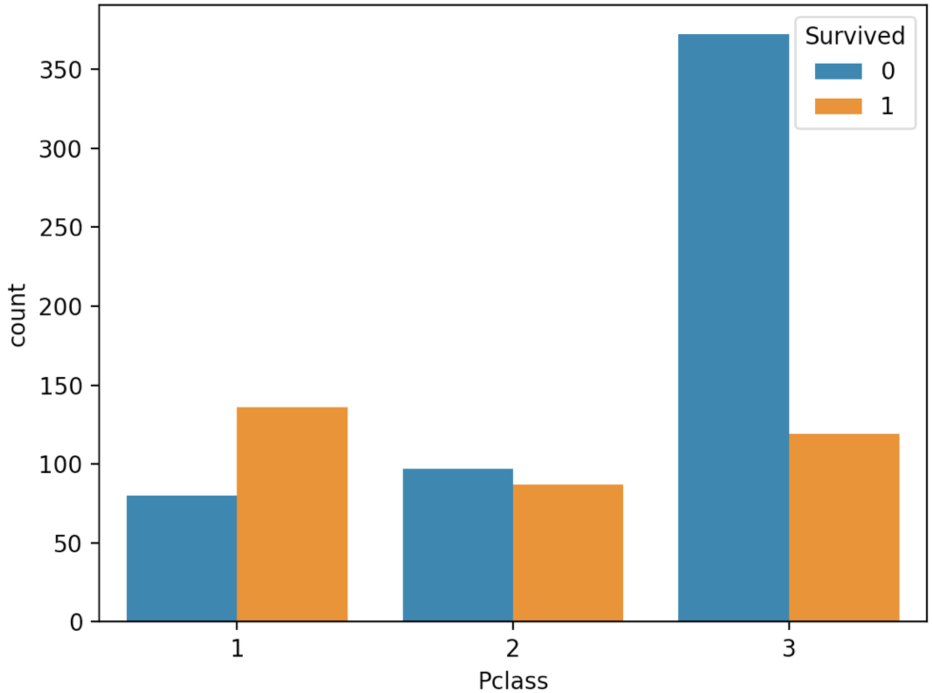
##

9. Yes, we should include this feature. When **Pclass = 1 there were 136 out of 216 passengers survived** which gives a surviving ratio of 0.62.

##
Output for question 9:



```
Survived    0    1
Pclass
1          80  136
2          97   87
3         372  119
```



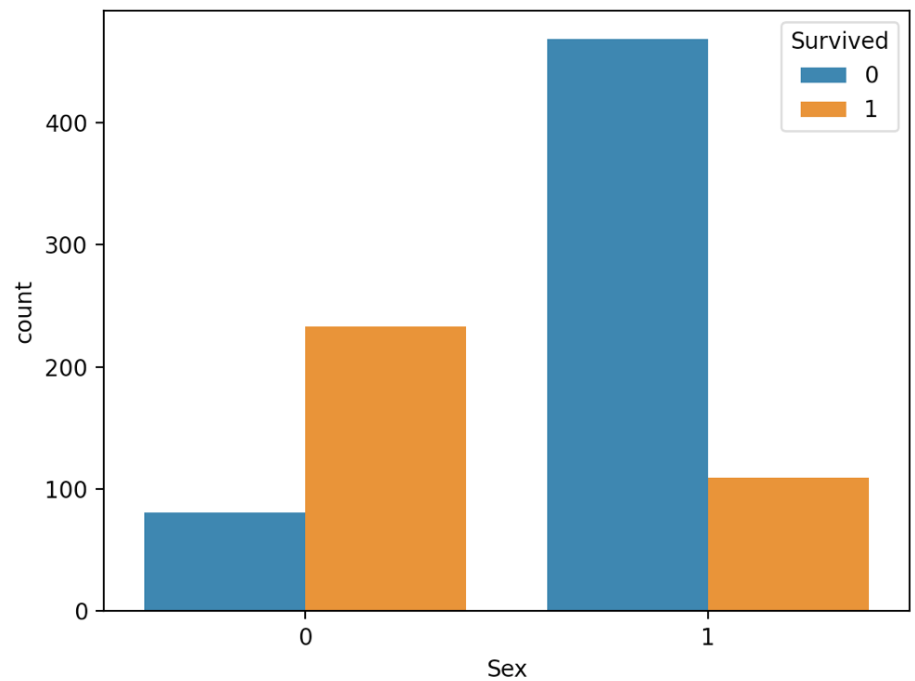
##

10. Yes, **women (233) are more likely to survive compared to men (189)**.

##

Output for question 10:

```
Survived    0    1
Sex
0          81   233
1         468   109
```



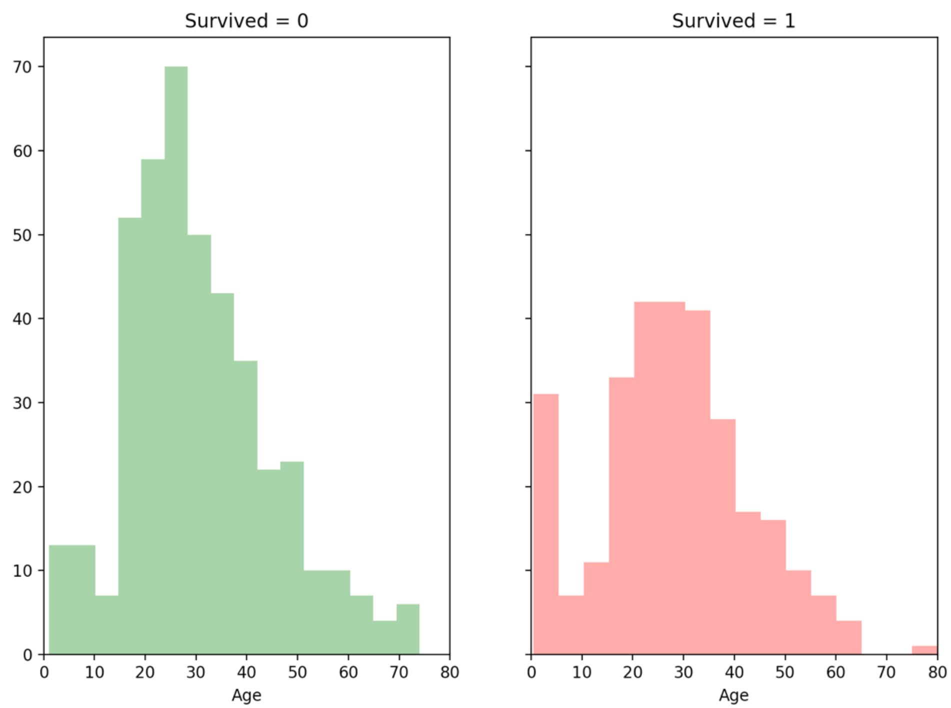
##

11. A) Yes, **infants under the age of 4 have high survival rate**.
B) Yes, **the oldest passenger survived**.
C) Yes, **a large number of people between the age 15 – 25 did not survive** (79 survived, 144 did not survive).

D) Yes, **we should consider age for our model training**.
E) Yes, **it makes it easier to analyze the data set**.

##

Output for question 11:



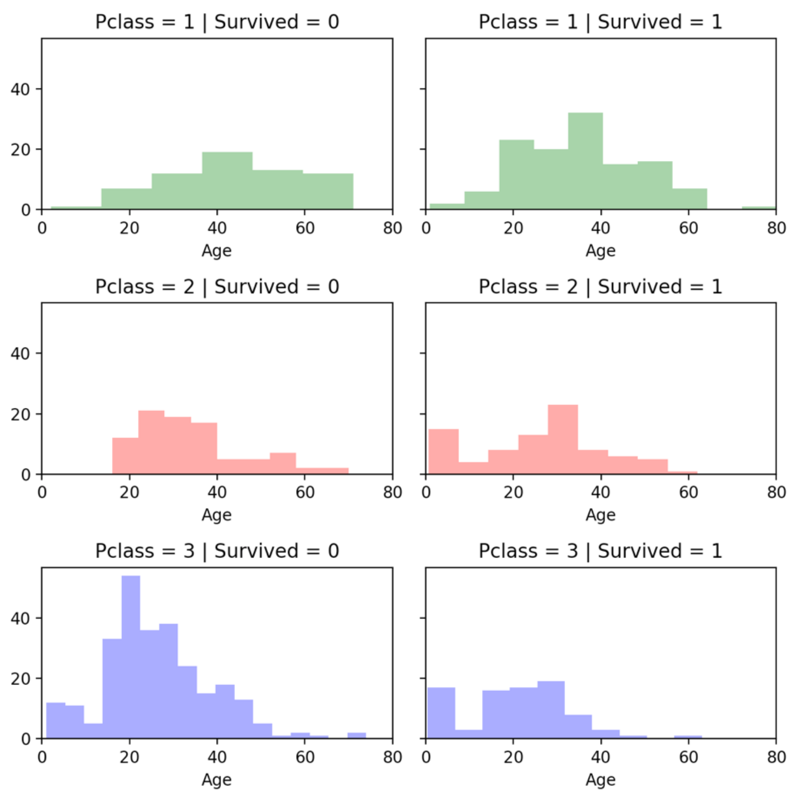

```
[aahana@MacBook-Pro homework-1 % python3 main.py
     PassengerId  Survived  Pclass                                  Name  Sex   Age  SibSp  Parch Ticket  Fare Cabin Embarked
630          631         1       1  Barkworth, Mr. Algernon Henry Wilson    1  80.0      0      0  27042  30.0   A23        S
```

##

12. A) Yes, **Pclass = 3 had most passengers, out of which many did not survive.**
    B) Yes, **infant passengers (age <= 4) tend to survive**.
    C) Yes, **most passengers in Pclass = 1 survive**.
    D) Yes, **Pclass varies in terms of age distribution of passengers**.
    E) Yes, **Pclass data set seems to provide vital information for our machine learning model**.

##

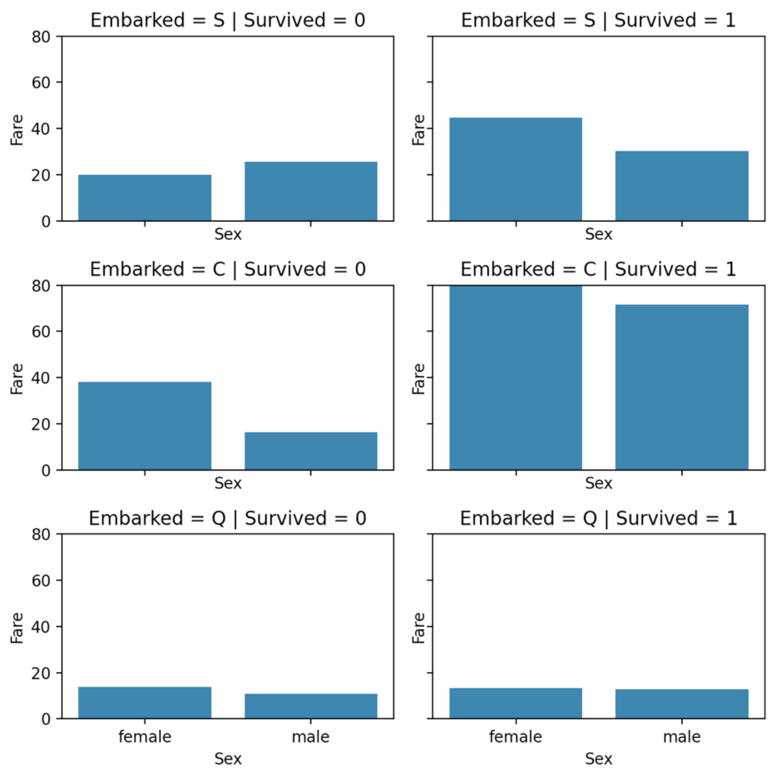
Output for question 12:



##

13. A) Yes, **those passengers that embarked to Southampton and Cherbourg with higher fare tickets seemed to have a higher survival rate as compared to those that traveled with lower fare tickets. Passengers that embarked to Queenstown seem to have very similar survival rate irrespective of the ticket fare.**
    B) Yes, **we should consider banding fare feature**. The fare feature seems to group well in those intervals of probably 10 – 20..

    ##
    Output for question 13:



##

14. There is a total of 891 ticket entries out of which about 681 are unique ticket values. Hence, **the duplication rate is 23.56% and remaining 76.43% of the ticket values are unique**. Duplication rate is calculated using the formula**, rate of duplicates = (total records - unique records)/total records.** However, the ticket feature does not seem to provide any useful information and thus we can drop this column.

    ##
    Output for question 14:

    ```
    Total number of ticket entries  891
    Number of unique ticket values  681
    Total ticket duplicate rate is  23.569023569023567 %
    ```

    ##

15. Yes, I would drop the Cabin feature. There are 891 entries in the train_df data set and 418 features in the test_df data set. The total number of entries for each feature in the combined data set is 1309 entries. Out of this, **the cabin feature has 1014 entries that are null valued**. Hence, we can go ahead and drop this feature.

    ##
    Output for Question 15:

    Train_df:

    ```
    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
```

Test_df:

```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

```
Out of 1309 entries in the cabin feature, the number of null values in Cabin feature are:  1014
entries.
```

```
###################################################################################################
```

16. All female entries in the Sex feature are assigned as 1 and all male entries in the Sex feature are assigned as 0.

```
###################################################################################################
```

Output for question 16:

```
0       0
1       1
2       1
```

```
3      1
4      0
      ..
886    0
887    1
888    1
889    0
890    0
Name: Sex, Length: 891, dtype: int64
```

##

17. All Nan values in the Age feature are replaced using K-Nearest Neighbor algorithm, where k = 5.

##

Output for question 17:

Some of the original and modified (using KNN algorithm) Age values are:

```
22.0 22.0
38.0 38.0
26.0 26.0
35.0 35.0
35.0 35.0
nan 29.69911764705882
54.0 54.0
2.0 2.0
27.0 27.0
14.0 14.0
4.0 4.0
58.0 58.0
20.0 20.0
39.0 39.0
14.0 14.0
```

```
55.0 55.0
2.0 2.0
nan 29.69911764705882
31.0 31.0
nan 29.69911764705882
35.0 35.0

The number of Nan values in the Age column is:  0

####################################################################################################
```

18. The training data set has 2 missing values. The common frequency (mode) in the 'Embarked' feature is S. Hence, the two empty values are filled with S.

```
####################################################################################################
```

Output for question 18:

```
The mode for Embarked freature is:  0    S
dtype: object
The number of empty values in Embarked feature is:  2
After filling the empty values, the number of empty values in the Embarked feature is:  0
The following are the values in the Embarked feature:  0      S

1      C
2      S
3      S
4      S
      ..
886    S
887    S
888    S
889    C
890    Q
```

```
Name: Embarked, Length: 891, dtype: object

##################################################################################################
```

19. There is only one empty data in the Fare feature of the testing data set. This empty value is filled with the mode (most common frequency) of the fare feature. The mode is 7.75.

```
##################################################################################################
```

Output for question 19

```
In the testing dataset, The mode for Fare freature is:  0    7.75
dtype: float64
The number of empty values in Fare feature is:  1
After filling the empty values, the number of empty values in the Fare feature is:  0
The following are the values in the Fare feature:  0        7.8292

1        7.0000
2        9.6875
3        8.6625
4       12.2875
         ...
413      8.0500
414    108.9000
415      7.2500
416      8.0500
417     22.3583
Name: Fare, Length: 418, dtype: float64

##################################################################################################
```

20. The Fare feature has been binned and corresponding ordinal values (0, 1, 2 and 3) are assigned.

##
Output for question 20:

```
   PassengerId  Survived  Pclass  ... Cabin Embarked  Fare_bin
0            1         0       3  ...   NaN        S         0
1            2         1       1  ...   C85        C         3
2            3         1       3  ...   NaN        S         1
3            4         1       1  ...  C123        S         3
4            5         0       3  ...   NaN        S         1

[5 rows x 13 columns]
```

##

GitHub link to the code:

https://github.com/monicabernard/CAP-5610_Machine-Learning.git