- The titanic and titanic2 data frames describe the survival status of individual passengers on the Titanic.
- The titanic data frame does not contain information from the crew, but it does contain actual ages of half of the passengers.
- The principal source for data about Titanic passengers is the Encyclopedia Titanica.

In [1]:
```python
# Importing the packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```python
# Reading the Dataset and checking the shape of the dataset
df = pd.read_csv("titanic_train.csv")
df.shape
```

Out[2]: (891, 12)

In [3]:
```python
df.head()
```

Out[3]:

	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

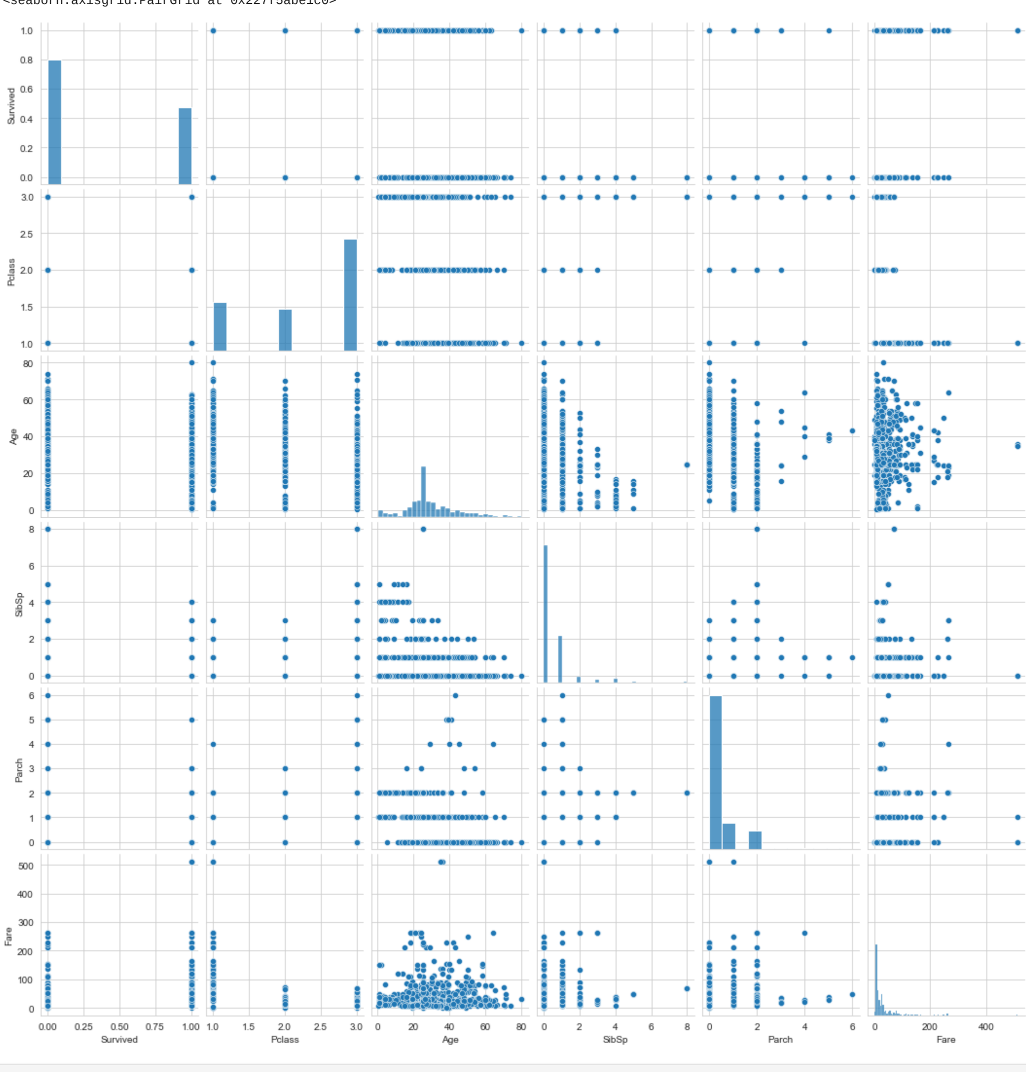
Variable Description

- Pclass Passenger Class :- Pclass (1 = 1st; 2 = 2nd; 3 = 3rd)
- survival :- Survival (0 = No; 1 = Yes)
- name :- Passenger Names
- sex :- Sex ["MALE","FEMALE"]
- age :- Age
- sibsp :- Number of Siblings/Spouses Aboard
- parch :- Number of Parents/Children Aboard
- ticket :- Ticket Number
- fare :- Passenger Fare (British pound)
- cabin :- Cabin
- embarked :- Port of Embarkation (C = Cherbourg; Q = Queenstown; S = Southampton)

EDA

In [110…
```python
sns.pairplot(df)
```

Out[110… <seaborn.axisgrid.PairGrid at 0x227f5abe1c0>



In [4]:
```python
#Check basic statistics for each columns:-

df.describe()
```

Out[4]:

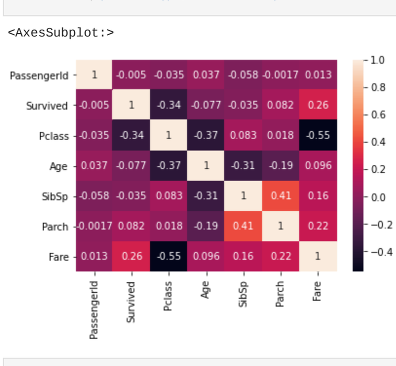
	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	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]:
```python
df.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
```

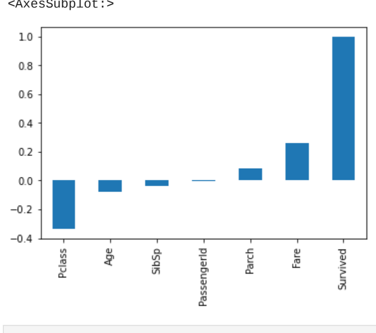
In [6]:
```python
# Correlation between the columns

sns.heatmap(df.corr() , annot=True)
```

Out[6]: <AxesSubplot:>



In [7]:
```python
df.corr()["Survived"].sort_values(ascending=True).plot(kind="bar")
```

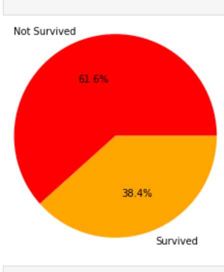
Out[7]: <AxesSubplot:>



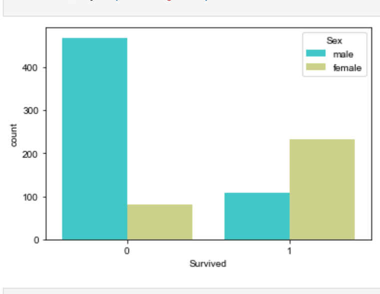
In [8]:
```python
# To check there is imblance in DataSet:-

df["Survived"].value_counts()
```

Out[8]:
```
0    549
1    342
Name: Survived, dtype: int64
```

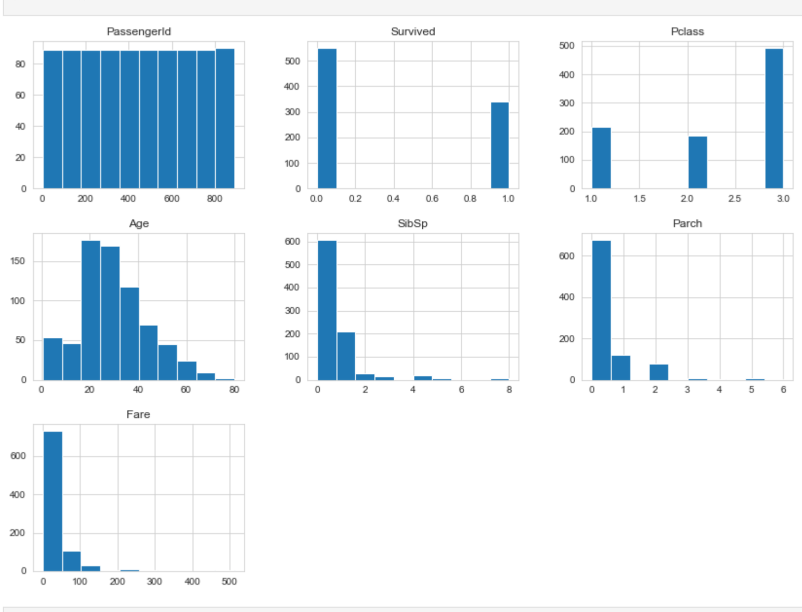
In [9]:
```python
# Pie chart of Survived Column for better visualization :-
plt.pie(df["Survived"].value_counts() ,
        labels = ["Not Survived","Survived"] ,
        colors= ["red","orange"] ,
        autopct = "%.1f%%",
        radius=1.2)
plt.show()
```



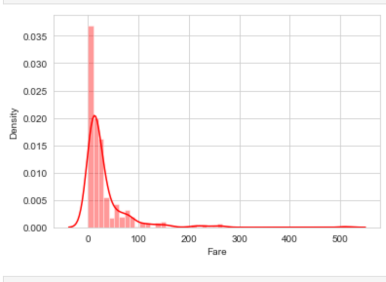
In [10]:
```python
# How many are survived w.r to Sex

sns.countplot("Survived",hue="Sex",data=df,palette="rainbow")
sns.set_style("whitegrid")
```



In [11]:
```python
# To check distribution of data and identify outliers:-

df.hist(figsize=(14,10))
plt.show()
```

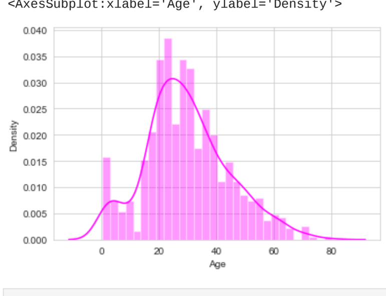


In [12]:
```python
# Distribution of Fare on datset

sns.distplot(df["Fare"],color="red")
sns.set_style("whitegrid")
```



In [13]:
```python
# Distibution of Age groups on dataset

sns.distplot(df["Age"],bins=30,color="magenta")
```

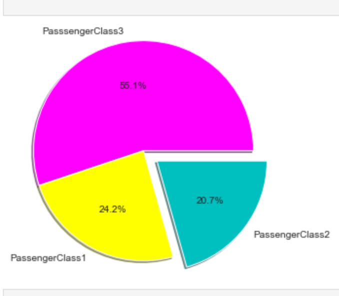
Out[13]: <AxesSubplot:xlabel='Age', ylabel='Density'>



In [14]:
```python
df["Pclass"].value_counts()
```

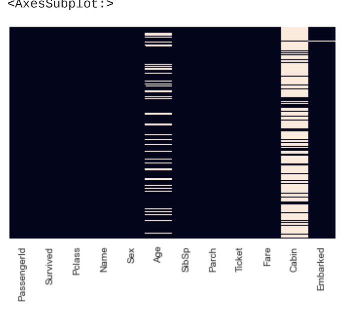
Out[14]:
```
3    491
1    216
2    184
Name: Pclass, dtype: int64
```

In [15]:
```python
# Pie chart of Pclass Column for better visualization :-

plt.pie(df["Pclass"].value_counts() ,
        labels = ["PasssengerClass3","PassengerClass1","PassengerClass2"] ,
        colors= ["magenta","yellow","c"] ,
        autopct = "%.1f%%",
        radius=1.3,
        shadow=True,
        explode=(0,0,0.2))
plt.show()
```



In [16]:
```python
# Checking nan values in the dataset using heatmap for better visualization

sns.heatmap(df.isna() , yticklabels=False,cbar=False)
```

Out[16]: <AxesSubplot:>



- If the dataset has more than 50% of null values we will drop that column
- If the dataset has less than 50% of null values we will fill the null values
- If the dataset has less than 5% of null values we will use dropna()

In [17]:
```python
df.drop("Cabin",axis=1,inplace=True)
```

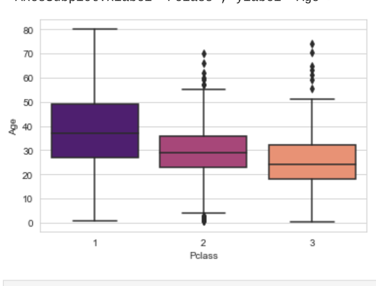
In [18]:
```python
df.head()
```

Out[18]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
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	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	S

In [19]:
```python
# Checking age w.r to PClass for equally filling the Age values.
# Not just directly applying mean of age and using fillna

sns.boxplot(df["Pclass"],df["Age"],data=df , palette="magma")
```

Out[19]: <AxesSubplot:xlabel='Pclass', ylabel='Age'>



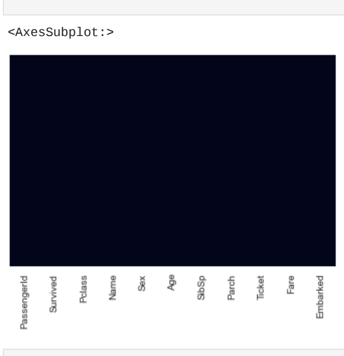
In [20]:
```python
def compute_age(cols):
    age = cols[0]
    pclass = cols[0]

    if pd.isna(age):
        if pclass == 1:
            return 38
        elif pclass == 2:
            return 28
        else:
            return 25
    else:
        return age
```

In [21]:
```python
df["Age"] = df[["Age","Pclass"]].apply(compute_age,axis=1)
```

In [22]:
```python
# Dropna for Embarked column which has 2-3% of nan values
df.dropna(inplace=True)
```

In [23]:
```python
sns.heatmap(df.isna(),yticklabels=False,cbar=False)
```

Out[23]: <AxesSubplot:>



In [24]:
```python
df.head()
```

Out[24]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
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	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	S

In [25]:
```python
# Droping columns which is no use

df.drop(["PassengerId","Name","Ticket"],axis=1,inplace=True)
```

In [26]:
```python
df.head()
```

Out[26]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	male	22.0	1	0	7.2500	S
1	1	1	female	38.0	1	0	71.2833	C
2	1	3	female	26.0	0	0	7.9250	S
3	1	1	female	35.0	1	0	53.1000	S
4	0	3	male	35.0	0	0	8.0500	S

In [27]:
```python
# Seprating independent variable and dependent variable

x = df.drop("Survived",axis=1)
y = df["Survived"]
```

In [32]:
```python
# Applying One Hot Encoder  for Embarked and Sex columns to chnage the categorical data into discrete variable

from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer

ct = ColumnTransformer([("encoder" ,
                   OneHotEncoder(),
                   ["Sex","Embarked"])], remainder="passthrough")

x = np.array(ct.fit_transform(x))
```

In [37]:
```python
x[:3]
```

Out[37]:
```
array([[ 0.    ,  1.    ,  0.    ,  0.    ,  1.    ,  3.    , 22.    ,
         1.    ,  0.    ,  7.25  ],
       [ 1.    ,  0.    ,  1.    ,  0.    ,  0.    ,  1.    , 38.    ,
         1.    ,  0.    , 71.2833],
       [ 1.    ,  0.    ,  0.    ,  0.    ,  1.    ,  3.    , 26.    ,
         0.    ,  0.    ,  7.925 ]])
```

In [38]:
```python
# Applying train_test_split on x y  variables

from sklearn.model_selection import train_test_split
Xtrain,Xtest,ytrain,ytest = train_test_split(x,
                                             y,
                                             test_size=0.25,
                                             random_state=1)
```

In [39]:
```python
# Default Paramters


from sklearn.metrics import accuracy_score , confusion_matrix , classification_report

from sklearn.neighbors import KNeighborsClassifier
knn  = KNeighborsClassifier(n_neighbors=4)

from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()

from sklearn.svm import SVC
svm = SVC()

from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier()

from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()
```

In [44]:
```python
def classifiers(model):
    model.fit(Xtrain,ytrain)
    ypred = model.predict(Xtest)

    print(f"Accuracy_Score:- {accuracy_score(ytest,ypred)}\n\n{confusion_matrix(ytest,ypred)}\n{classification_report(ytest,ypred)}")
    return model
```

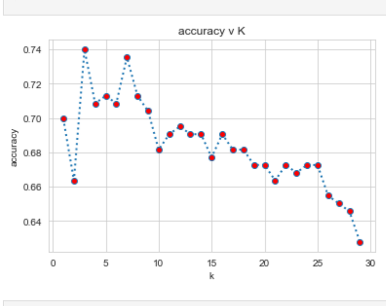
In [45]:
```python
classifiers(knn)
```

```
Accuracy_Score:- 0.7085201793721974

[[117  21]
 [ 44  41]]
              precision    recall  f1-score   support

           0       0.73      0.85      0.78       138
           1       0.66      0.48      0.56        85

    accuracy                           0.71       223
   macro avg       0.69      0.67      0.67       223
weighted avg       0.70      0.71      0.70       223
```

Out[45]: KNeighborsClassifier(n_neighbors=4)

In [67]:
```python
# Using n_neighbors
for improving the accuracy

accuracy = []
n = list(range(1,30))

for i in n:
        knn = KNeighborsClassifier(n_neighbors=i)
        knn.fit(Xtrain,ytrain)
        ypred = knn.predict(Xtest)

        ac = accuracy_score(ytest,ypred)
        accuracy.append(ac)
```

In [68]:
```python
plt.plot(n,accuracy,ls=":",lw=2,marker="o",markerfacecolor="red")
plt.title("accuracy v K")
plt.xlabel("k")
plt.ylabel("accuracy")
plt.show()
```



In [71]:
```python
knn = KNeighborsClassifier(n_neighbors=3)
classifiers(knn)
```

```
Accuracy_Score:- 0.7399103139013453

[[110  28]
 [ 30  55]]
              precision    recall  f1-score   support

           0       0.79      0.80      0.79       138
           1       0.66      0.65      0.65        85

    accuracy                           0.74       223
   macro avg       0.72      0.72      0.72       223
weighted avg       0.74      0.74      0.74       223
```

Out[71]: KNeighborsClassifier(n_neighbors=3)

In [59]:
```python
classifiers(lr)
```

```
Accuracy_Score:- 0.8430493273542601

[[119  19]
 [ 16  69]]
              precision    recall  f1-score   support

           0       0.88      0.86      0.87       138
           1       0.78      0.81      0.80        85

    accuracy                           0.84       223
   macro avg       0.83      0.84      0.83       223
weighted avg       0.84      0.84      0.84       223
```

Out[59]: LogisticRegression()

In [48]:
```python
classifiers(svm)
```

```
Accuracy_Score:- 0.6502242152466368

[[113  25]
 [ 53  32]]
              precision    recall  f1-score   support

           0       0.68      0.82      0.74       138
           1       0.56      0.38      0.45        85

    accuracy                           0.65       223
   macro avg       0.62      0.60      0.60       223
weighted avg       0.64      0.65      0.63       223
```

Out[48]: SVC()

In [49]:
```python
classifiers(dt)
```

```
Accuracy_Score:- 0.7937219730941704

[[115  23]
 [ 23  62]]
              precision    recall  f1-score   support

           0       0.83      0.83      0.83       138
           1       0.73      0.73      0.73        85

    accuracy                           0.79       223
   macro avg       0.78      0.78      0.78       223
weighted avg       0.79      0.79      0.79       223
```

Out[49]: DecisionTreeClassifier()

In [50]:
```python
classifiers(rf)
```

```
Accuracy_Score:- 0.8251121076233184

[[119  19]
 [ 20  65]]
              precision    recall  f1-score   support

           0       0.86      0.86      0.86       138
           1       0.77      0.76      0.77        85

    accuracy                           0.83       223
   macro avg       0.81      0.81      0.81       223
weighted avg       0.82      0.83      0.82       223
```

Out[50]: RandomForestClassifier()

Conclusion

. BEST SCORES

- LOGISTIC REGRESSION CLASSIFIER HAVE **84%** OF ACCURACY.
- RANDOM FOREST CLASSIFIER HAVE **83%** OF ACCURACY.
- DECISION TREE CLASSIFIER HAVE **79%** OF ACCURACY.
- K-NEAREST NEIGHBORS HAVE **74%** OF ACCURACY.
- SUPPORT VECTOR CLASSIFIER HAVE **65%** OF ACCURACY.

- Default Logisitc Regression is performing well because the dataset is well linearly seprable and the datapoints are not overlapping.
- The Dataset is also small not much samples are present.
- We can improve the Logistic Regression accuracy and also decrease the FN values by optimising thresshold values

In [ ]: