In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv ("titanic_train.csv")
df.head()
```

Out[2]:

	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 [3]:
```
# upto here we are uploded "titanic dataset.csv" to jupyter notebook.
# and make df as a instance of our insurance dataset.
```

In [4]:
```
df.shape
# there are 891 rows and 12 columns are present in the data set.
```

Out[4]:
```
(891, 12)
```

In [5]:
```
df.columns
# here we can see the name of each column present in the data set.
```

Out[5]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

In [6]:
```
df.columns.unique()
# here we can se that the same result is occured, that means there there is not repetation of any column in the dataset.
```

Out[6]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

In [7]:
```
df.columns.nunique()
# the total no. of cloumns are same as we can check earlier in df.shape
```

Out[7]:
```
12
```

In [8]:
```
df.dtypes
# here can see that there are some different types of data is present in the given dataset like : [ int64, object, float64 ]
```

Out[8]:
```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

In [9]:
```
df.info()
#  here we can see that
# 1) total number for columns present : 12
# 2) total number of rows presnet : 891
# 3) total "data types present in data set" : 3 (i.e "object, int64 & float64")
#  out of which   2 columns of - float64
#                 5 column of - int64
#                 5 columns of - object
# 4)NULL VALUES are may present in our dataset.- "AGE", "CABIN" AND "EMBARKED", we have to chek further with other methods.
# 5) here we can also observe that thE data type of age "AGE" column is "float64", "age" could not be in DECIMALS,
#     so we have to change it from DECIMAL to INTEGER
```

```
<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 [ ]:

CHECKING NULL VALUES

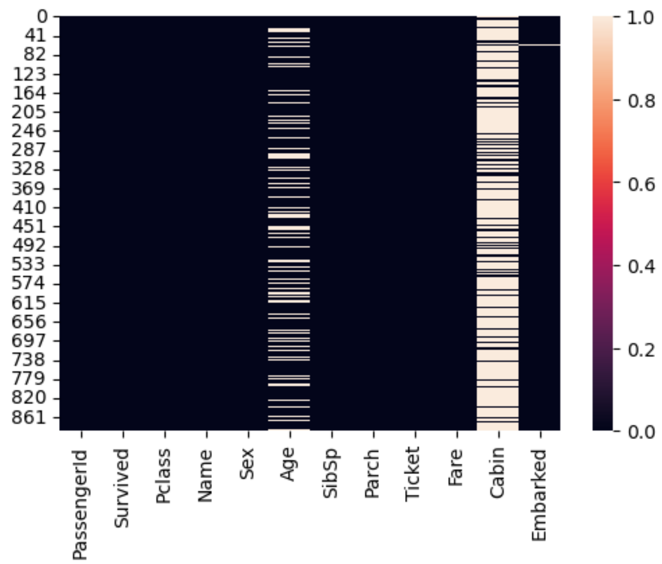
==

In [11]:
```
df.isnull().sum()
# Here we can see the NULL VALUES present in the cloumn "AGE", "CABIN", & "EMBARKED"
```

Out[11]:
```
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 [12]:
```
plt.figure(figsize=(6,4))
sns.heatmap(df.isnull())
# Here we can also check null values with the help of Heatmap
```

Out[12]: <AxesSubplot:>



In [13]:
```
# Now after finding null values we have to replace it .
```

In [14]:
```
df['Embarked'].isnull().sum()
# here we find two NULL VALUES present in EMBARKED column
# the Emarked column is also a categorical column with "object" category
# and here we find only 2 null values are present so we can replace it with MODE
#  for this we have to import 'SIMPLE IMPUTER' library from SKLEARN
```

Out[14]: 2

In [15]:
```
from sklearn.impute import SimpleImputer
```

In [16]:
```
imp = SimpleImputer(strategy="most_frequent")
```

In [17]:
```
df['Embarked']= imp.fit_transform(df['Embarked'].values.reshape(-1,1))
df.head(2)
```

Out[17]:

	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

In [18]:
```
df['Embarked'].isnull().sum()
```

Out[18]: 0

In [19]:
```
# Here we are successfully replaced the NAN VALUES of Embarked Column.
```

In [20]:
```
df['Age'].isnull().sum()
#  there are 177 NULL values are present in the age column.
# we can replace it with MEDIAN
```

Out[20]: 177

In [23]:
```
imp = SimpleImputer(strategy="mean")
```

In [24]:
```
df['Age']= imp.fit_transform(df['Age'].values.reshape(-1,1))
df.head(2)
```

Out[24]:

	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

In [25]:
```
df['Age'].isnull().sum()
```
Out[25]:
```
0
```

In [26]:
```
# here Null  values present in Age Column is also removed succesfully.
```

In [27]:
```
df['Cabin'].isnull().sum()
# there are 687 NULL values are present in the 'cabin' column.
# Cabins are the numbers which are alloted to the customers , if there are any missing values in it,
# so did'nt change it with Mean because 'Mean' number cabin may not be present ,
# so we can replace it with MEDIAN
```
Out[27]:
```
687
```

In [28]:
```
# Here we can see in the 'Cabin column'
#  out of Total entries (891), there (687) are NAN values are present
# so insted of repalcing, we can drop the 'cabin column'
```

In [29]:
```
df['Cabin'].dtypes
# Datatype is Object
```
Out[29]:
```
dtype('O')
```

In [30]:
```
df.shape
```
Out[30]:
```
(891, 12)
```

In [31]:
```
# here we can see that in "CABIN COLUMN" out of 891 rows, 687 NAN VALUES are present , that means most of the data is absent
# if we can replace it with "MODE" technique , then 687 rows are having same data, which we dont know what it should be...
# so insted of replacing/deleting NAN VALUES we can drop this column from our dataset.
```

In [32]:
```
df.drop('Cabin', axis = 1, inplace=True)
```

In [33]:
```
df.head(2)
```
Out[33]:

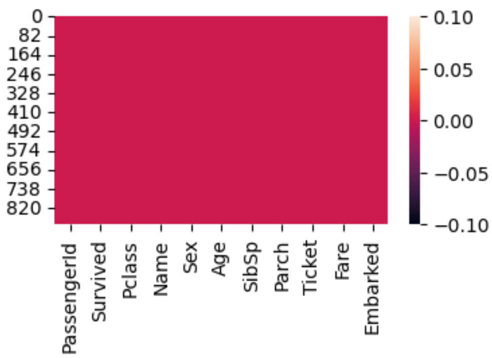
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C

In [34]:
```
# here we successfully drop the cabin cloumn
```

In [35]:
```
df.isnull().sum()
# Here as you can see we have successfully removed all the NAN VALUES from our DATASET
```
Out[35]:
```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       0
dtype: int64
```

In [36]:
```
plt.figure(figsize=(4,2))
sns.heatmap(df.isnull())
# NOW NO NULL VALUES ARE PRESENT IN DATASET
```

Out[36]:
```
<AxesSubplot:>
```



In [ ]:

CHECKING UNIQUE VALUES PRENSENT IN DATASET & UNIVARIATE ANALYSIS
==

In [38]:
```
df.columns
```

Out[38]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Embarked'],
      dtype='object')
```

In [39]:
```
df.head(2)
```

Out[39]:

	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

In [40]:
```
df.shape
```

Out[40]:
```
(891, 11)
```

In [41]:
```
df['Survived'].unique()
```

Out[41]:
```
array([0, 1], dtype=int64)
```

In [42]:
```
df['Survived'].nunique()
```

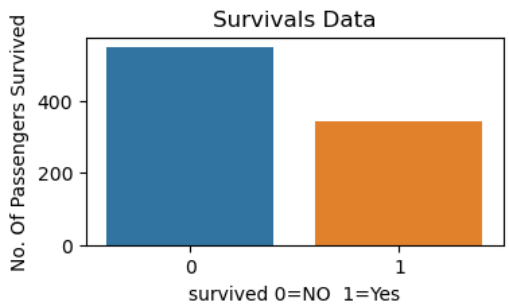
Out[42]:
```
2
```

In [43]:
```
df['Survived'].value_counts()
```

Out[43]:
```
0    549
1    342
Name: Survived, dtype: int64
```

In [44]:
```
plt.figure (figsize = (4,2), facecolor = "white")
plt.title('Survivals Data')
sns.countplot(x='Survived', data = df)
plt.xlabel('survived 0=NO  1=Yes', fontsize=10)
# plt.xticks(rotation=30, ha = 'right')
plt.ylabel('No. Of Passengers Survived')
# plt.yticks(rotation=30, ha = 'right')

# Here we can see that the Number Of Survivals are Less as Compared to Deaths.
```

Out[44]:
```
Text(0, 0.5, 'No. Of Passengers Survived')
```



In [45]:
```
df['PassengerId'].nunique()
# Here as we can see that the number of "nunique" values present in dataset is 891, same as total number of rows present.
#  that means we can say that there is no repetition in "Passenger id" column.
```

Out[45]:
```
891
```

In [46]:
```
df['Pclass'].nunique()
# The number of nunique values in "Pclass" column is only 3
# so we can say that it is a CATEGORICAL COLUMN
```

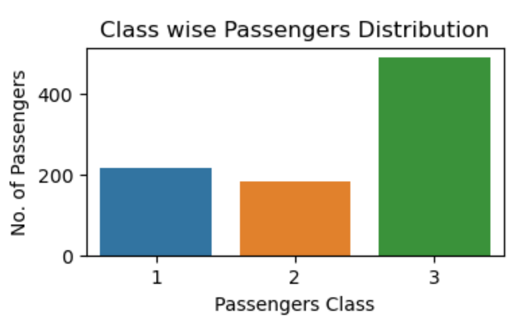
Out[46]:
```
3
```

In [47]:
```
df['Pclass'].value_counts()
# And out of this "Pclass" (Passenger class) we found that , there are most of the passengers are from "3" class, then "1" & "2
```

Out[47]:
```
3    491
1    216
2    184
Name: Pclass, dtype: int64
```

In [48]:
```
plt.figure (figsize = (4,2), facecolor = "white")
plt.title('Class wise Passengers Distribution')
sns.countplot(x='Pclass', data = df)
plt.xlabel('Passengers Class', fontsize=10)
# plt.xticks(rotation=30, ha = 'right')
plt.ylabel('No. of Passengers')
# plt.yticks(rotation=30, ha = 'right')

# here clearly we can see that majority of the passengrs are present in "class 3"
# and there is only slight differece between "class 2" & "class 1"
```

Out[48]:
```
Text(0, 0.5, 'No. of Passengers')
```



In [49]:
```
df['Name'].nunique()
#  similarly same for "name" column.
```

Out[49]:
```
891
```

In [50]:
```
df['SibSp'].nunique()
# The number of nunique values in "SibSp" column is only 7
# so we can say that it is a CATEGORICAL COLUMN
```

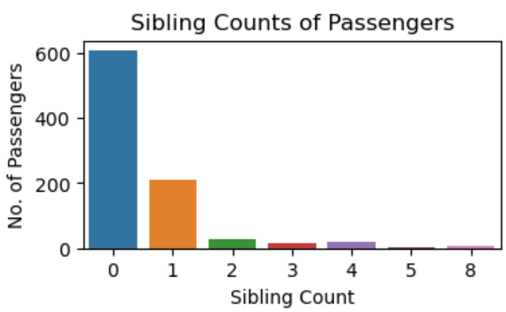
Out[50]:
```
7
```

In [51]:
```
df['SibSp'].value_counts()
# here we can see the "siblingcounts" , majority of "siblings count is 0 & 1"
#  then it goes further upto 5
```

Out[51]:
```
0    608
1    209
2     28
4     18
3     16
8      7
5      5
Name: SibSp, dtype: int64
```

In [52]:
```
plt.figure (figsize = (4,2), facecolor = "white")
plt.title('Sibling Counts of Passengers')
sns.countplot(x='SibSp', data = df)
plt.xlabel('Sibling Count', fontsize=10)
# plt.xticks(rotation=30, ha = 'right')
plt.ylabel('No. of Passengers', fontsize=10)

# here clearly we can see the no. of siblings counts present "0" is maximum and then "1".
# few of the passengers are in "2,3,4,5,8" category
```

Out[52]:
```
Text(0, 0.5, 'No. of Passengers')
```



In [53]:
```
df['Parch'].nunique()
# The number of nunique values in "Parch" column is only 7
# so we can say that it is a CATEGORICAL COLUMN
```

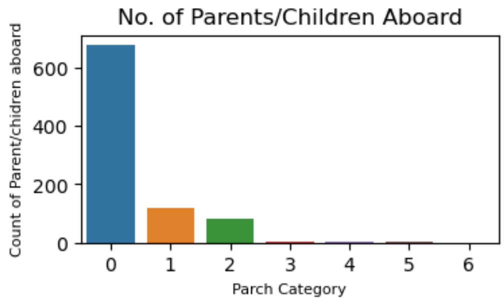
Out[53]:
```
7
```

In [54]:
```
df['Parch'].value_counts()
```

Out[54]:
```
0    678
1    118
2     80
5      5
3      5
4      4
6      1
Name: Parch, dtype: int64
```

In [55]:
```
plt.figure(figsize=(4,2),facecolor="white")
plt.title ('No. of Parents/Children Aboard')
sns.countplot(x='Parch',data=df)
plt.xlabel('Parch Category', fontsize=8)
# plt.xticks(rotation=30, ha = 'right')
plt.ylabel('Count of Parent/chidren aboard', fontsize=8)
# plt.yticks(rotation=0, ha = 'right')

# here we can see that most of the Passengers are in "0 parch category" and some of with "1,2" & only few of them in "3,4,5,6"
```

Out[55]:
```
Text(0, 0.5, 'Count of Parent/chidren aboard')
```



In [56]:
```
df['Ticket'].nunique()
# but here we can see the difference between no. of uniques present in "ticket" and Total no. of rows
#  but it is "ignoreble" because we know that there could be more then 1 passenger for a single ticket.
# so we can ignore this difference.
```

Out[56]:
```
681
```

In [57]:
```
df['Embarked'].nunique()
# The number of nunique values in "Embarked" column is only 3
# so we can say that it is a CATEGORICAL COLUMN
```

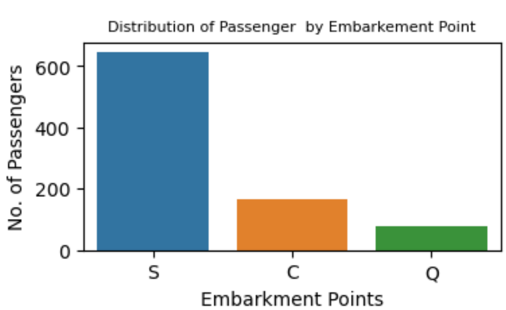
Out[57]:
```
3
```

In [58]:
```
df['Embarked'].value_counts()
# here we can find that the embarkment point of most of the passengers is "s"
#  then it goes on further deacrissing with "C" & "Q"
```

Out[58]:
```
S    646
C    168
Q     77
Name: Embarked, dtype: int64
```

In [59]:
```
plt.figure(figsize=(4,2),facecolor="white")
plt.title('Distribution of Passenger  by Embarkement Point',fontsize=8)
sns.countplot(x='Embarked', data=df)
plt.xlabel('Embarkment Points',fontsize=10)
# plt.xticks(rotation=30, ha = 'right')
plt.ylabel('No. of Passengers',fontsize=10)
# plt.yticks(rotation=0, ha = 'right')

# here we find the distribution of Passengerss from Embarkment Point 'S= Southampton' 'C = Cherbourg' & 'Q = Queenstown'
# majority of the passengers are embarked on 's= Southampton' point
# (C = Cherbourg; Q = Queenstown; S = Southampton)
# Here we finds that most of the passengers are from "S = Southampton port"
```

Out[59]:
```
Text(0, 0.5, 'No. of Passengers')
```



In [60]:
```
# So from the above analysis we found that, there may also NULL VALUES in some of the columns and
# The column are ==> "Pclass"  "sibsp"  "Parch"  "Embarked" is CATEGORICAL COLUMNS.
```

In [61]:
```
# UNIVARIATE ANALYSIS IS COMPLETED=====================================================================================
```

In [ ]:

BIVARIATE ANALYSIS
==

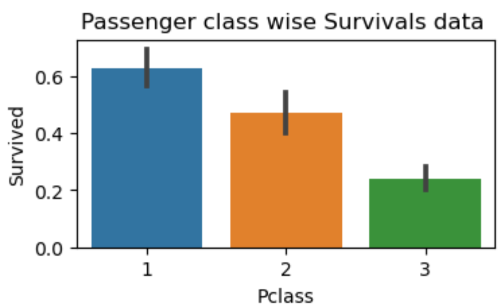
In [63]:
```
df.head(2)
```

Out[63]:

	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

In [64]:
```
# 1) First we have to check how many passengers are survived from different Passenger classes
```

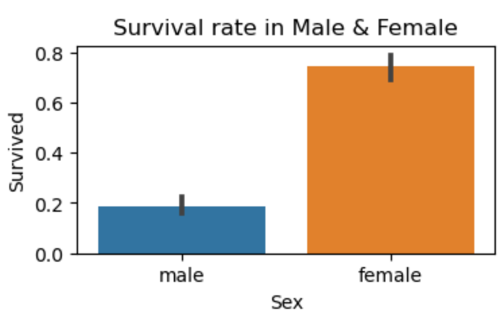
In [65]:
```
plt.figure (figsize = (4,2), facecolor = "white")
plt.title('Passenger class wise Survivals data ',fontsize=12)
sns.barplot (x = 'Pclass', y = 'Survived', data = df)
# plt.xticks(rotation=30, ha = 'right')
plt.show()

# here we can clearly see that the survials are only from "1 class"
#  because below '0.5 ' is not considerd as srvived
```



In [ ]:

In [66]:
```
# 2) we have to check the survival rate in 'Male' & 'Female'
```

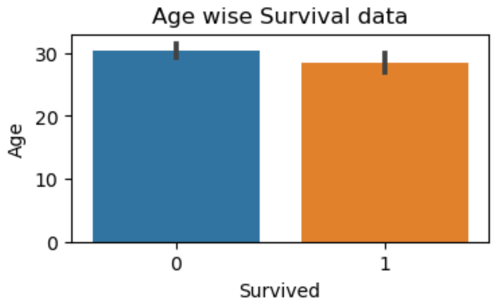
In [67]:
```
plt.figure (figsize = (4,2), facecolor = "white")
plt.title('Survival rate in Male & Female',fontsize=12)
sns.barplot (x = 'Sex', y = 'Survived', data = df)
# plt.xticks(rotation=30, ha = 'right')
plt.show()

# Survival Rate of Female's are verymuch Higher as compared to Male
```



In [ ]:

In [68]:
```
# 3) Now we are checking age wise survival data.
```

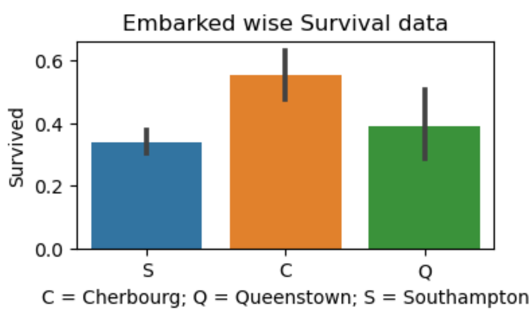
In [69]:
```
plt.figure (figsize = (4,2), facecolor = "white")
plt.title('Age wise Survival data',fontsize=12)
sns.barplot (x = 'Survived', y = 'Age', data = df)
# plt.xticks(rotation=30, ha = 'right')
plt.show()
# there is no such difference between this.
```



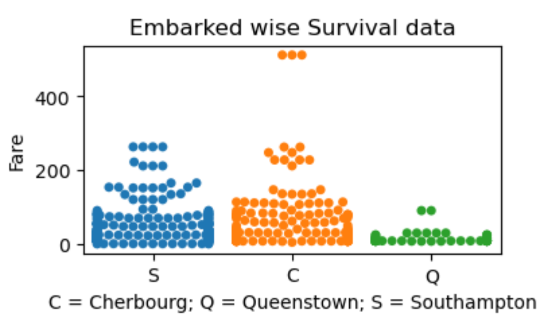
In [ ]:

In [70]:
```
# 4) Cheking rate of survivals acoording to Embarkemnet Point.
```

In [71]:
```
plt.figure (figsize = (4,2), facecolor = "white")
plt.title('Embarked wise Survival data',fontsize=12)
sns.barplot (x = 'Embarked', y = 'Survived', data = df)
plt.xlabel('C = Cherbourg; Q = Queenstown; S = Southampton')
# plt.xticks(rotation=30, ha = 'right')
plt.show()

# here we find that the survival rate is HIGHEST in 'C'= cherbourg > 'S'= Southampton > 'Q'= Queenstown
```



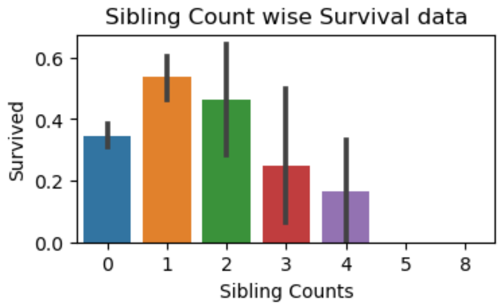
In [72]:
```
plt.figure (figsize = (4,2), facecolor = "white")
plt.title('Embarked wise Survival data',fontsize=12)
sns.swarmplot (x = 'Embarked', y = 'Fare', data = df)
plt.xlabel('C = Cherbourg; Q = Queenstown; S = Southampton')
# plt.xticks(rotation=30, ha = 'right')
plt.show()

# as in above graph we can see that the survival rate is higher of those passengers whose "Embarkement Point is 'C'= Cherbourg"
#  why is this ? because of their TICKET FAIR PRICES , clearly shown in below graph
```



In [ ]:

In [73]:
```
# 5) Cheking rate of survivals acoording to Siblings Count.
```

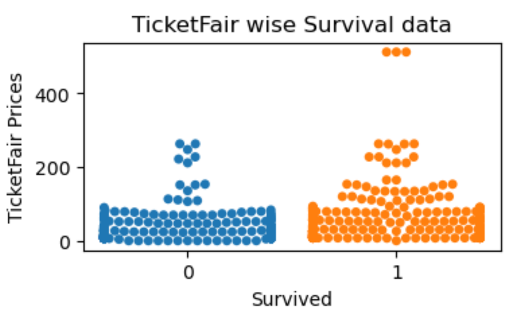
In [74]:
```
plt.figure (figsize = (4,2), facecolor = "white")
plt.title('Sibling Count wise Survival data',fontsize=12)
sns.barplot (x = 'SibSp', y = 'Survived', data = df)
plt.xlabel('Sibling Counts')
# plt.xticks(rotation=30, ha = 'right')
plt.show()

# here we find that the Highest Survival is with 'Sibling Count 1 & 2 only'
```



In [ ]:

In [76]:
```
# 6) Cheking rate of survivals acoording to TicketFair Prices.
```

In [77]:
```
plt.figure (figsize = (4,2), facecolor = "white")
plt.title('TicketFair wise Survival data',fontsize=12)
sns.swarmplot (x = 'Survived', y = 'Fare', data = df)
plt.xlabel('Survived')
plt.ylabel('TicketFair Prices')
# plt.xticks(rotation=30, ha = 'right')
plt.show()

# Here we can clearly see that those passengers whose tickets Fair is very high,
# the possibility of surviving also high
```



In [ ]:

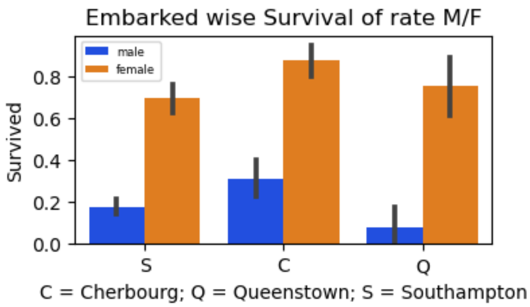
MULTIVARIATE ANALYSIS
==

In [79]:
```
df.head(5)
```

Out[79]:

	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 [98]:
```
plt.figure (figsize = (4,2), facecolor = "white")
plt.title('Embarked wise Survival of rate M/F')
sns.barplot (x= 'Embarked', y = 'Survived', hue = 'Sex', data= df, palette = "bright")
# plt.xticks(rotation=30, ha = 'right')
plt.xlabel('C = Cherbourg; Q = Queenstown; S = Southampton')
plt.legend(loc= 'upper left', fontsize=6)
plt.show()

# Here we find that , from all of three Embarked Points the Survival of females are Higher as compared to Males
```

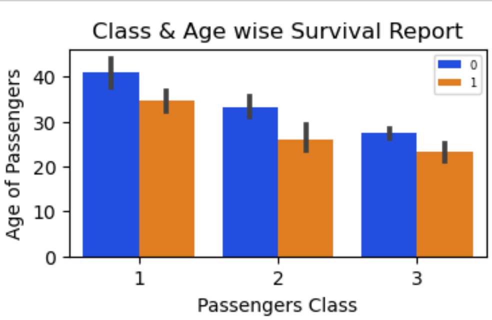


In [ ]:

In [97]:
```
plt.figure (figsize = (4,2), facecolor = "white")
plt.title('Age & Fare wise survivals report')
sns.scatterplot (x= 'Fare', y = 'Age', hue = 'Survived', data= df, palette = "bright")
# plt.xticks(rotation=30, ha = 'right')
plt.xlabel('Fare prices')
plt.ylabel('Age of Passengers')
plt.legend(loc= 'upper right', fontsize=6)
plt.show()
# As in the above graph it is clear that Higher the Ticket Fair - Hgher the Survival chances
```

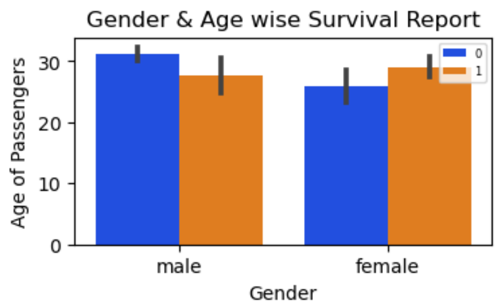
In [ ]:

In [100]:
```
plt.figure (figsize = (4,2), facecolor = "white")
plt.title('Class & Age wise Survival Report')
sns.barplot (x= 'Pclass', y = 'Age', hue = 'Survived', data= df, palette = "bright")
# plt.xticks(rotation=30, ha = 'right')
plt.xlabel('Passengers Class')
plt.ylabel('Age of Passengers')
plt.legend(loc= 'upper right', fontsize=6)
plt.show()

# Here we find that , in every class Lower Age Passengers are more able to survive as compared to Higher Age Passengers
```



In [ ]:

In [102]:
```
plt.figure (figsize = (4,2), facecolor = "white")
plt.title('Gender & Age wise Survival Report')
sns.barplot (x= 'Sex', y = 'Age', hue = 'Survived', data= df, palette = "bright")
# plt.xticks(rotation=30, ha = 'right')
plt.xlabel('Gender')
plt.ylabel('Age of Passengers')
plt.legend(loc= 'upper right', fontsize=6)
plt.show()

# Here we can find an intresting fact that: In MALE- Lower Age passengers are more able to survive as compared to Higher Age
#                                     But In Females- Higher Age passengers are more able to survive as compared to Lower Age
```

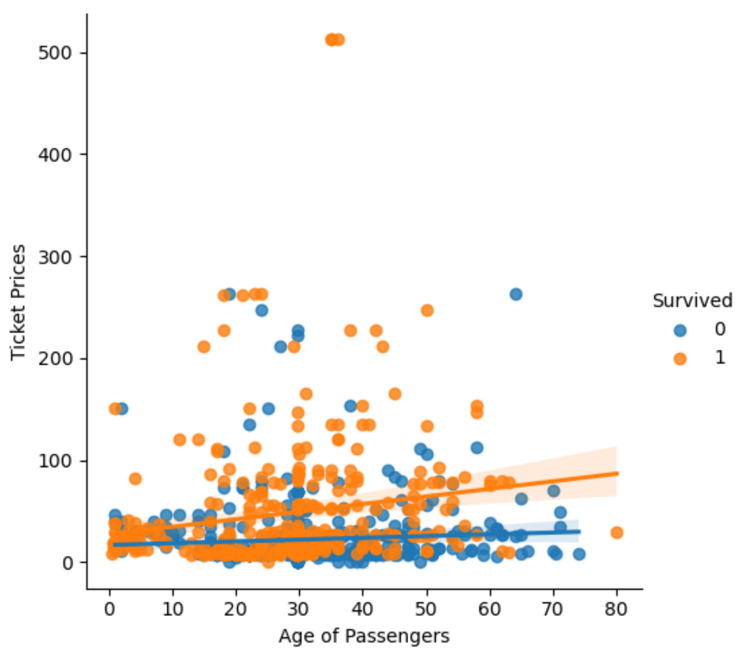


In [ ]:

In [116]:
```
plt.figure(figsize=(10,8))
sns.lmplot('Age','Fare',hue='Survived',data=df)
plt.xlabel('Age of Passengers',fontsize=10)
plt.ylabel('Ticket Prices')
```

Out[116]: Text(39.225756172839496, 0.5, 'Ticket Prices')

<Figure size 1000x800 with 0 Axes>



In [ ]:
```
# Most of the Higher Age Passengers are unable to survive only few of them are survived
# the Passengers who buy Higher Price Tickest are from Higher are Class & they are able to survive.
```

In [ ]:

CHECKING FOR OUTLIERS
==

In [118]:
```
df.describe()
```

Out[118]:

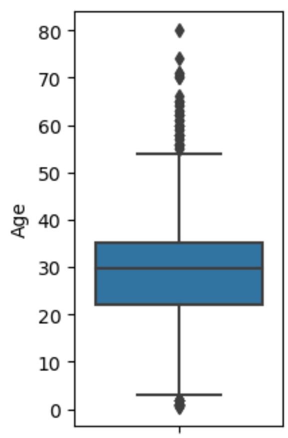
	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	13.002015	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	22.000000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	29.699118	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	35.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [ ]:
```
# here as we can see in the above table, we see a huge difference between 75% & Max of some columns,"Age","SibSp","Parch","Fare
#  due to which we can assume that there may presence of outliers, so we have to check this with "BOXPLOT METHOD"
# here above we also finds that "STANDARD DEVIATION" is very high in "P-id","Age","Fare". = very high SKEWNESS
```

In [119]:
```
df.columns
```

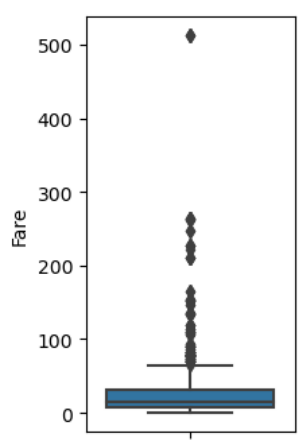
Out[119]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Embarked'],
      dtype='object')
```

In [121]:
```
plt.figure (figsize = (2,4), facecolor = "white")
sns.boxplot(y='Age',data=df)
plt.show()
# here we can see the presence of Outliers
```



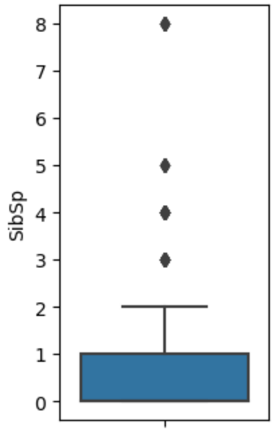
In [ ]:

In [123]:
```
plt.figure (figsize = (2,4), facecolor = "white")
sns.boxplot(y='Fare',data=df)
plt.show()
# here in the "Fare Cloumn" also we can see the huge no. of outliers are present
```



In [ ]:

In [128]:
```
plt.figure (figsize = (2,4), facecolor = "white")
sns.boxplot(y='SibSp',data=df)
plt.show()
# here we can also seen the outliers in 'Siblings count'
```



In [136]:
```
#  Here Before removing outliers we have to change our "object" columns into "integers"
```

In [ ]:

In [134]:
```
df.dtypes
```

Out[134]:
```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Embarked        object
dtype: object
```

In [135]:
```
df.head(2)
```

Out[135]:

	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

In [ ]:
```
# here some of the columns are having no such important relevance , so for better model we have to drop those columns.
```

In [137]:
```
df.drop('PassengerId', axis = 1, inplace=True)
```

In [140]:
```
df.drop('Name', axis = 1, inplace=True)
```

In [141]:
```
df.drop('Ticket', axis = 1, inplace=True)
```

In [142]:
```
df.head(2)
```

Out[142]:

	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

In [143]:
```
df.shape
# here above we removed 3 columns from our Dataset , now from 11, 8 columns are remain
```

Out[143]:
```
(891, 8)
```

In [145]:
```
df.columns
```
Out[145]:
```
Index(['Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare',
       'Embarked'],
      dtype='object')
```

In [ ]:
```
# Outof these 8 columns these are = Survived, Pclass, Age, Sibsp, Parch, Embarked    are categorical columns
```

In [146]:
```
df.dtypes
```
Out[146]:
```
Survived      int64
Pclass        int64
Sex          object
Age         float64
SibSp         int64
Parch         int64
Fare        float64
Embarked     object
dtype: object
```

In [ ]:
```
# here above 'sex' & 'Embarked' are object columns , so firstofall we have to have to change their data type.
```

In [ ]:

ENCODING TECHNIQUES
===

In [149]:
```
from sklearn.preprocessing import LabelEncoder
```

In [150]:
```
le = LabelEncoder()
```

In [152]:
```
df['Sex'] = le.fit_transform(df['Sex'])
df.head(5)

# Here below we can see that out 'Gender' column is converted into 0-1  from  Male-Female
```
Out[152]:

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

In [ ]:

In [153]:
```
df['Embarked'] = le.fit_transform(df['Embarked'])
df.head(5)
# similarly here Embarked also converted from S-C-Q to 2-0-1
```
Out[153]:

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

In [154]:
```
df.dtypes
# now here you can see 'Sex' & 'Embarked' columns type is changed from 'object' to 'int64'
# now we have two columns with 'float64' i.e 'Age' & 'Fare'
```
Out[154]:
```
Survived      int64
Pclass        int64
Sex           int64
Age         float64
SibSp         int64
Parch         int64
Fare        float64
Embarked      int32
dtype: object
```

In [ ]:
```
#  Now we can apply Z-SCORE METHOD------
```

In [ ]:

Removing Of OutLiers by applyin Z-Score Method
==

In [281]:
```
# We can't remove OUTLIERS from our TARGET COLUMN
```

In [132]:
```
from scipy.stats import zscore
```

In [155]:
```
z = np.abs(zscore(df))
z.head(5)

# by applying 'abs' (absolute method), we are getting
```

Out[155]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0.789272	0.827377	0.737695	0.592481	0.432793	0.473674	0.502445	0.585954
1	1.266990	1.566107	1.355574	0.638789	0.432793	0.473674	0.786845	1.942303
2	1.266990	0.827377	1.355574	0.284663	0.474545	0.473674	0.488854	0.585954
3	1.266990	1.566107	1.355574	0.407926	0.432793	0.473674	0.420730	0.585954
4	0.789272	0.827377	0.737695	0.407926	0.474545	0.473674	0.486337	0.585954

In [156]:
```
threshold = 3
print(np.where(z>3))
```

```
(array([ 13,  16,  25,  27,  50,  59,  68,  71,  86,  88,  96, 116, 118,
       119, 159, 164, 167, 171, 180, 182, 201, 233, 258, 261, 266, 278,
       299, 311, 324, 341, 360, 377, 380, 386, 437, 438, 438, 480, 493,
       527, 541, 542, 557, 567, 610, 630, 638, 672, 678, 679, 683, 686,
       689, 700, 716, 730, 736, 737, 742, 745, 774, 779, 787, 792, 813,
       824, 846, 850, 851, 858, 863, 885], dtype=int64), array([5, 4, 5, 6, 4, 4, 4, 4, 5, 6, 3, 3, 6, 4, 4, 4, 5, 4, 4, 4, 4,
4,
       6, 4, 4, 4, 6, 6, 4, 6, 5, 6, 6, 4, 5, 5, 6, 4, 3, 6, 4, 4, 6, 5,
       5, 3, 5, 3, 5, 6, 4, 4, 6, 6, 6, 6, 5, 6, 6, 3, 5, 6, 4, 4, 4, 4,
       4, 4, 3, 5, 4, 5], dtype=int64))
```

In [159]:
```
# here above we found 72 those values whose z-score is more then > 3
# i.e means we are having 72 outlier still present in our dataset, and we have to remove those outliers
```

In [165]:
```
df_new = df[(z<3).all(axis=1)]
df_new.shape
df_new
```

Out[165]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	1	22.000000	1	0	7.2500	2
1	1	1	0	38.000000	1	0	71.2833	0
2	1	3	0	26.000000	0	0	7.9250	2
3	1	1	0	35.000000	1	0	53.1000	2
4	0	3	1	35.000000	0	0	8.0500	2
...	...	...	...	...	...	...	...	...
886	0	2	1	27.000000	0	0	13.0000	2
887	1	1	0	19.000000	0	0	30.0000	2
888	0	3	0	29.699118	1	2	23.4500	2
889	1	1	1	26.000000	0	0	30.0000	0
890	0	3	1	32.000000	0	0	7.7500	1

820 rows × 8 columns

In [166]:
```
df_new.shape
```

Out[166]:
```
(820, 8)
```

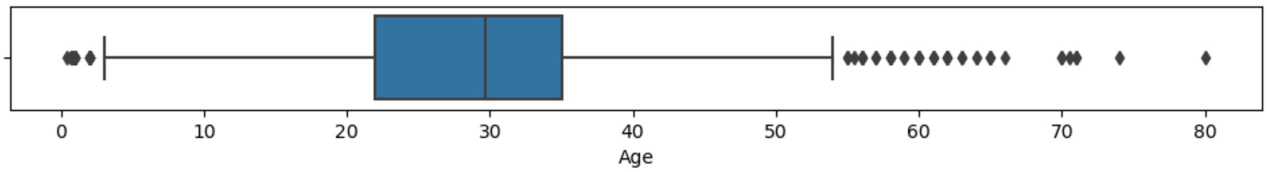
In [168]:
```
# here you can see our rows are reduced from 891-820, that means 71 Outliers are removed from our dataset.
```

In [ ]:

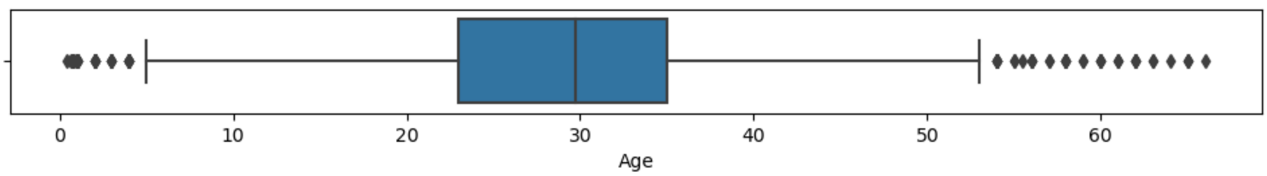
CHECKING REMOVAL OF OUTLIERS BY BOXPLOT (COMPARING 'df' & 'df_new')

==

In [170]:
```
plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='Age',data=df)
plt.show()

# it is the EARLIER (df dataset) PRESENCE OF OUTLIERS
```



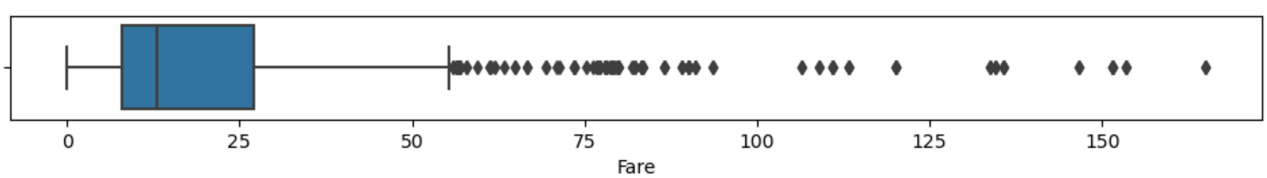
In [172]:
```
plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='Age',data=df_new)
plt.show()
# AND THIS IS AFTER APLLYING Z-SCORE , you can clearly see the diffrence between earlier one and this
# in earlier one the presence of OUTLIERS is upto - 80, and now it is removed upto - 65 Only
# outliers are removed
```



In [ ]:

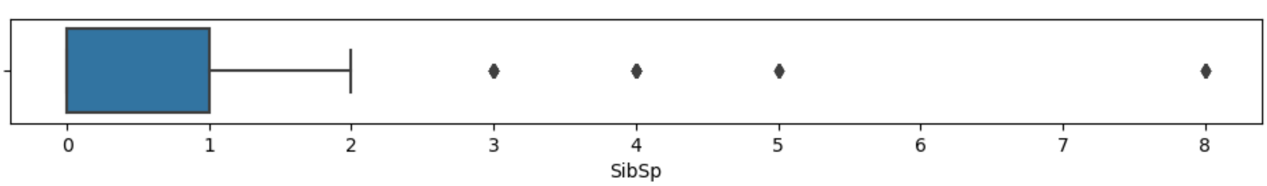
In [173]:
```
plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='Fare',data=df)
plt.show()
```

In [174]:
```
plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='Fare',data=df_new)
plt.show()
# AND THIS IS AFTER APLLYING Z-SCORE , you can clearly see the diffrence between earlier one and this
# in earlier one the presence of OUTLIERS is upto >500, and now it is reduced only upto - 155 to 160
# outliers are removed
```

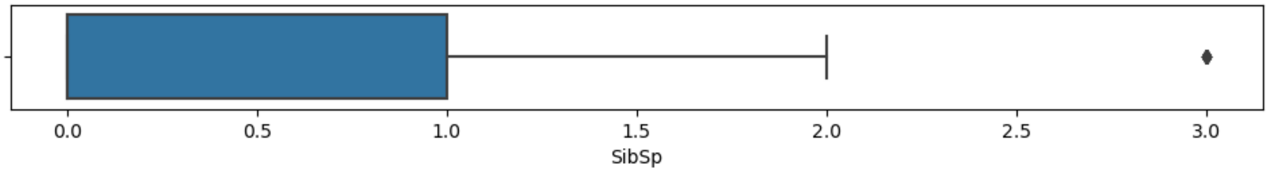


In [ ]:

In [175]:
```
plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='SibSp',data=df)
plt.show()
```



In [176]:
```
plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='SibSp',data=df_new)
plt.show()
# AND THIS IS AFTER APLLYING Z-SCORE , you can clearly see the diffrence between earlier one and this
# in earlier one the presence of OUTLIERS is upto - 8, now they are reduced upto 3
# those outliers are removed
```



In [ ]:

CHECKING SKEWNESS

===>>>

In [282]:
```
# the skewness shows the distribution of data, if the data is widely skewed that means it is not good for our model.
#  ideal range of skewness is ( -0.5 to +0.5)
# We can't remove skewness from our Target Column
```

In [179]:
```
df_new.skew()
```

Out[179]:
```
Survived    0.450825
Pclass     -0.632242
Sex        -0.664152
Age         0.318314
SibSp       1.979577
Parch       2.122629
Fare        2.318761
Embarked   -1.277386
dtype: float64
```

In [ ]:
```
# Here we can see the skewness in 'Parch', 'Fare' & 'Embarked'
# so we have to remove skewness from those columns by using 'cuberoot' method.
```

In [180]:
```
df_new['Parch'] = np.cbrt(df_new['Parch'])
```

In [181]:
```
df_new['SibSp'] = np.cbrt(df_new['SibSp'])
```

In [182]:
```
df_new['Embarked'] = np.cbrt(df_new['Embarked'])
```

In [184]:
```
df_new['Fare'] = np.cbrt(df_new['Fare'])
```

In [ ]:

In [185]:
```
df_new.skew()
```

Out[185]:
```
Survived    0.450825
Pclass     -0.632242
Sex        -0.664152
Age         0.318314
SibSp       1.018770
Parch       1.643259
Fare        0.708623
Embarked   -1.536414
dtype: float64
```

In [186]:
```
# here we can see that the skewness is removed as compared to earler.
#  we can't remove more skewness, there may be chance of huge dataloss.
```

In [187]:
```
df_new.head(5)
```

Out[187]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	1	22.0	1.0	0.0	1.935438	1.259921
1	1	1	0	38.0	1.0	0.0	4.146318	0.000000
2	1	3	0	26.0	0.0	0.0	1.993730	1.259921
3	1	1	0	35.0	1.0	0.0	3.758647	1.259921
4	0	3	1	35.0	0.0	0.0	2.004158	1.259921

In [188]:
```
df_new.shape
```
Out[188]:
```
(820, 8)
```

In [189]:
```
df_new.dtypes
```
Out[189]:
```
Survived      int64
Pclass        int64
Sex           int64
Age         float64
SibSp       float64
Parch       float64
Fare        float64
Embarked    float64
dtype: object
```

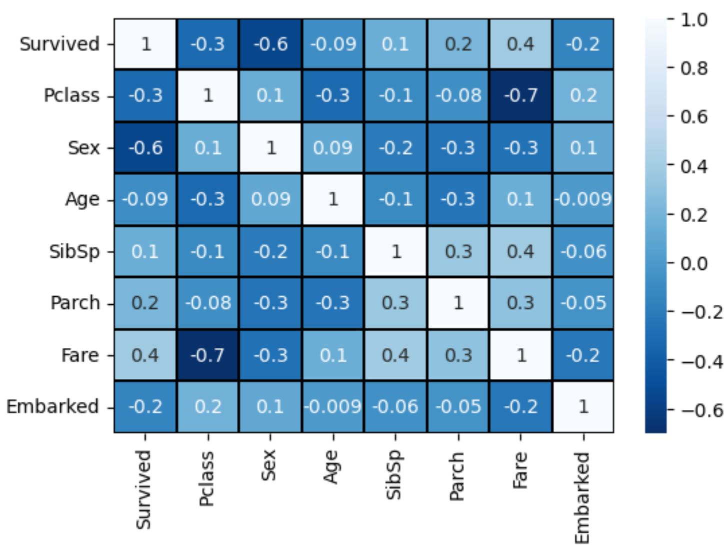
In [ ]:
```

```

CHECKING CORRELATION (GRAPHICALLY)
==

In [192]:
```
# FINDING CORRELATION GRAPHICALLY
```

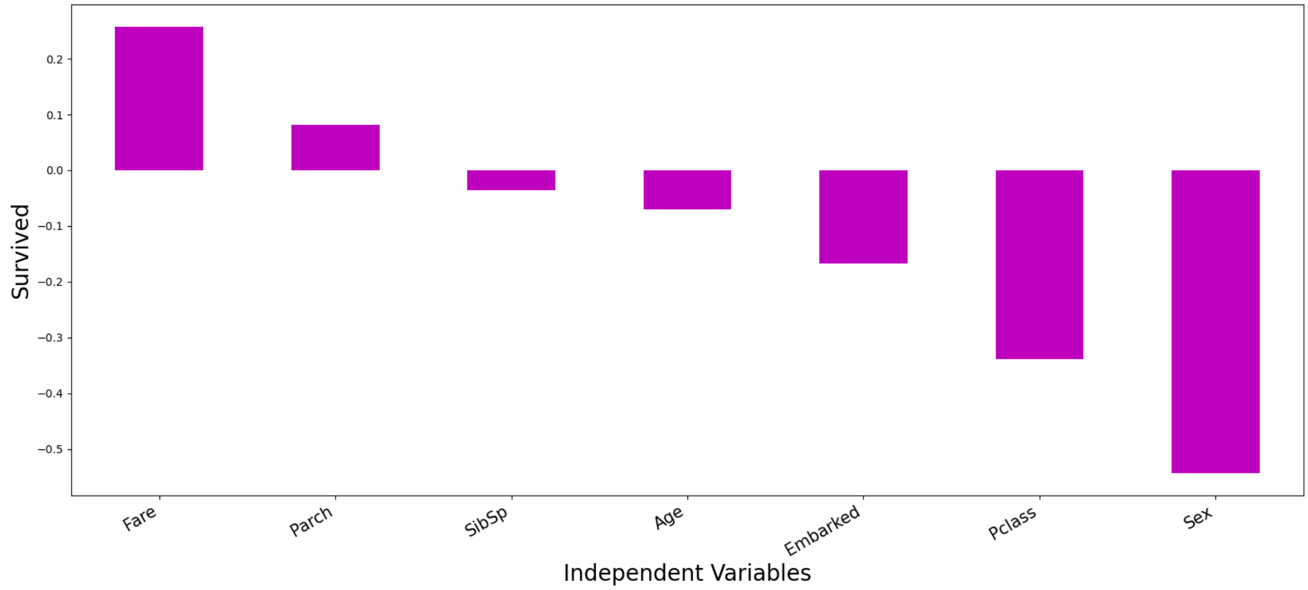
In [194]:
```
cor = df_new.corr()
```

In [195]:
```
plt.figure (figsize = (6,4), facecolor = "white")
sns.heatmap(df_new.corr(),linewidth=0.1,fmt="0.1g",linecolor="black",annot=True,cmap="Blues_r")
plt.yticks(rotation=0);
plt.show()

# here we can't see that there is such any correlation in between the variables
```



In [197]:
```
cor['Survived'].sort_values(ascending=False)
# here we can see in the correltion of all independent vaules with Target Column = 'Survived'
#  there no such any huge correation with target column.
```
Out[197]:
```
Survived     1.000000
Fare         0.363961
Parch        0.210930
SibSp        0.145722
Age         -0.090926
Embarked    -0.154194
Pclass      -0.322306
Sex         -0.554888
Name: Survived, dtype: float64
```

In [198]:
```
plt.figure(figsize=(20,8))
df.corr()['Survived'].sort_values(ascending=False).drop(['Survived']).plot(kind='bar',color="m")
plt.xlabel('Independent Variables',fontsize=20)
plt.xticks(rotation=30,ha='right',fontsize=15)
plt.ylabel('Survived',fontsize =20)
plt.title=("Correlation with Survived")
plt.show()

# here we can see that there no such any positive correlation, insted neagativly correlated independts are more.
```



In [ ]:

DIVIDING DATA INTO INDEPENDENT & TARGET VARIABLE
==

In [201]:
```
df_new.head(2)
```

Out[201]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	1	22.0	1.0	0.0	1.935438	1.259921
1	1	1	0	38.0	1.0	0.0	4.146318	0.000000

In [202]:
```
df_new.columns
```

Out[202]:
```
Index(['Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare',
       'Embarked'],
      dtype='object')
```

In [203]:
```
x = df[['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare',
       'Embarked']]
```

In [205]:
```
y = df[['Survived']]
```

In [ ]:

APPLYING SCALING TECHNIQUES
==>>>>>>

In [211]:
```
# we can't apply SCALING TECHNIQUES on TARGET VARIABLE
```

In [208]:
```
from sklearn.preprocessing import StandardScaler
```

In [209]:
```
st = StandardScaler()
```

In [210]:
```
x = st.fit_transform(x)
x
```

Out[210]:
```
array([[ 0.82737724,  0.73769513, -0.5924806 , ..., -0.47367361,
        -0.50244517,  0.58595414],
       [-1.56610693, -1.35557354,  0.63878901, ..., -0.47367361,
         0.78684529, -1.9423032 ],
       [ 0.82737724, -1.35557354, -0.2846632 , ..., -0.47367361,
        -0.48885426,  0.58595414],
       ...,
       [ 0.82737724, -1.35557354,  0.        , ...,  2.00893337,
        -0.17626324,  0.58595414],
       [-1.56610693,  0.73769513, -0.2846632 , ..., -0.47367361,
        -0.04438104, -1.9423032 ],
       [ 0.82737724,  0.73769513,  0.17706291, ..., -0.47367361,
        -0.49237783, -0.67817453]])
```

In [212]:
```
xf = pd.DataFrame(data=x)
print(xf)

# here we get our dataset (xf) after applying SCALING TECHING (STANDARD SCALER)
```

```
            0         1         2         3         4         5         6
0    0.827377  0.737695 -0.592481  0.432793 -0.473674 -0.502445  0.585954
1   -1.566107 -1.355574  0.638789  0.432793 -0.473674  0.786845 -1.942303
2    0.827377 -1.355574 -0.284663 -0.474545 -0.473674 -0.488854  0.585954
3   -1.566107 -1.355574  0.407926  0.432793 -0.473674  0.420730  0.585954
4    0.827377  0.737695  0.407926 -0.474545 -0.473674 -0.486337  0.585954
..        ...       ...       ...       ...       ...       ...       ...
886 -0.369365  0.737695 -0.207709 -0.474545 -0.473674 -0.386671  0.585954
887 -1.566107 -1.355574 -0.823344 -0.474545 -0.473674 -0.044381  0.585954
888  0.827377 -1.355574  0.000000  0.432793  2.008933 -0.176263  0.585954
889 -1.566107  0.737695 -0.284663 -0.474545 -0.473674 -0.044381 -1.942303
890  0.827377  0.737695  0.177063 -0.474545 -0.473674 -0.492378 -0.678175

[891 rows x 7 columns]
```

In [213]:
```
df_new.columns
```

Out[213]:
```
Index(['Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare',
       'Embarked'],
      dtype='object')
```

In [214]:
```
column = ['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare',
       'Embarked']
```

In [215]:
```
xf.columns = column
```

In [216]:
```
xf.head(1)
```

Out[216]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0.827377	0.737695	-0.592481	0.432793	-0.473674	-0.502445	0.585954

In [ ]:
```
# similarly for target column.
```

In [217]:
```
yf = y
```

In [221]:
```
yf.head(2)
```

Out[221]:

	Survived
0	0
1	1

In [ ]:

FINDING MULTICOLINEARITY
==

In [223]:
```
# We have to find the multicollinearity between the features and to remove it we can use VIF (VARIANCE INFLATION FACTOR)
# we can not apply VIF on the TARGET COLUMN
# for apllyin VIF we have to import some libraries as follows
```

In [224]:
```
import statsmodels.api as sm
from scipy import stats
from statsmodels .stats.outliers_influence import variance_inflation_factor
```

In [225]:
```
# here we are making "def function" for calculating VIF
def calc_vif(xf):
    vif = pd.DataFrame()
    vif["FETURES"] = xf.columns
    vif["VIF FACTOR"] = [variance_inflation_factor(xf.values,i) for i in range (xf.shape[1])]
    return (vif)
```

In [226]:
```
xf.shape
```

Out[226]:
```
(891, 7)
```

In [227]:
```
yf.shape
```

Out[227]:
```
(891, 1)
```

In [229]:
```
calc_vif(xf)
# here we didn't find MULTICOLINEARITY between the independent Columns.
```

Out[229]:

	FETURES	VIF FACTOR
0	Pclass	1.671580
1	Sex	1.108869
2	Age	1.205639
3	SibSp	1.282325
4	Parch	1.322550
5	Fare	1.648696
6	Embarked	1.079324

In [ ]:

RESAMPLING (SMOTE)
==

In [239]:
```
xf.shape
```

Out[239]:
```
(891, 7)
```

In [240]:
```
yf.shape
```

Out[240]:
```
(891, 1)
```

In [233]:
```
yf.value_counts()
```

Out[233]:
```
Survived
0           549
1           342
dtype: int64
```

In [235]:
```
#  here above we can see that the distribution of values with the unique number is very irregular,  therfore we have to make the
#  equal by using RESAMPLING TECHNIQUE.
```

In [236]:
```
from imblearn.over_sampling import SMOTE
```

In [237]:
```
smt = SMOTE()
```

In [241]:
```
trainx, trainy = smt.fit_resample(xf,yf)
```

In [242]:
```
trainy.value_counts()
# here as you can see below the immbalancenes is cleared now.
```

Out[242]:
```
Survived
0           549
1           549
dtype: int64
```

In [245]:
```
trainx.shape
```

Out[245]:
```
(1098, 7)
```

In [246]:
```
trainy.shape
```
Out[246]:
```
(1098, 1)
```

In [247]:
```
# here above we can see that, we appied SMOTE SUCCEFULLY ON THE DATASET,
# and BALANCE the dataset
```

In [ ]:

FINDING THE BEST RANDOM STATE FOR THE MODEL
===

APPLYING TRAIN TEST SPLIT
==

In [249]:
```
# here we can see that out Target Column - 'SURVIVED' is categorical column.
# we can aplly Multiple ML Model and test the prediction.
```

In [231]:
```
from sklearn.model_selection import train_test_split
```

In [250]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

In [251]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [252]:
```
dtc = DecisionTreeClassifier
```

In [253]:
```
maxaccu = 0
maxrs = 0

for i in range(1,200):
    x_train,x_test,y_train,y_test = train_test_split(trainx,trainy,test_size=0.20,random_state=i)
    dtc = DecisionTreeClassifier()
    dtc.fit(x_train,y_train)
    pred = dtc.predict(x_test)
    acc = accuracy_score(y_test,pred)

    if acc > maxaccu :
        maxaccu = acc
        maxrs = i

print ("Best accuracy is",maxaccu, "at random state", maxrs)
```
```
Best accuracy is 0.8636363636363636 at random state 193
```

In [ ]:
```
# here above we can find the MAXIMUM ACCURACY of 86% is occurs on random state= 193
```

FINDING BEST PERAMETERS WITH GRIDSEARCH CV
===

In [255]:
```
from sklearn.model_selection import GridSearchCV
```

In [256]:
```
grid_param = {'criterion':['gini','entropy']}
```

In [257]:
```
gd_sr = GridSearchCV (estimator=dtc, param_grid= grid_param, scoring="accuracy",cv=5)
```

In [258]:
```
gd_sr.fit(trainx,trainy)
```
Out[258]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(),
             param_grid={'criterion': ['gini', 'entropy']}, scoring='accuracy')
```

In [259]:
```
best_perameter = gd_sr.best_params_
print(best_perameter)
```
```
{'criterion': 'entropy'}
```

In [261]:
```
# here we can find the best perameter for the model is "entropy"
```

In [262]:
```
best_result = gd_sr.best_score_
print(best_result)
```
```
0.806068908260689
```

In [263]:
```
print(round(best_result,2))
```

```
0.81
```

In [264]:
```
#  the best score is .81
```

In [265]:
```
# now applying the model with "entropy" parameter and "193" randomstate
```

In [276]:
```
final_model = DecisionTreeClassifier (criterion="entropy")
```

In [267]:
```
 x_train,x_test,y_train,y_test = train_test_split(xf,yf,test_size=0.20,random_state=193)
```

In [277]:
```
final_model.fit(x_train,y_train)
final_model.score(x_train,y_train)
final_model_pred = final_model.predict(x_test)
print(accuracy_score(y_test,final_model_pred))
print(confusion_matrix(y_test,final_model_pred))
print(classification_report(y_test,final_model_pred))
```

```
0.770949720670391
[[89 15]
 [26 49]]
              precision    recall  f1-score   support

           0       0.77      0.86      0.81       104
           1       0.77      0.65      0.71        75

    accuracy                           0.77       179
   macro avg       0.77      0.75      0.76       179
weighted avg       0.77      0.77      0.77       179
```

In [ ]:
```
# here above we can see that the accuracy of our model is = 81%
```

CREATING FUNCTION TO PREDICT
===

In [273]:
```
def pred_func(s):
    s= s.reshape(1,7)
    st = dtc1.predict(s)
    print(st)

    if st == 0:
        print("not survived")
    elif (st == 1):
        print ("survived")
```

In [274]:
```
s= np.array([0.827377,0.737695,-0.592481,0.432793,-0.473674,-0.502445,0.585954])
pred_func(s)
```

```
[0]
not survived
```

In [ ]:

SAVING MODEL
===

In [279]:
```
import pickle
```

In [280]:
```
file_name = 'titanic_prediction.pkl'
pickle.dump(final_model,open(file_name,'wb'))
```

In [ ]:

== FINISHED ==

In [ ]:

In [ ]: