In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
df = pd.read_csv("https://raw.githubusercontent.com/dsrscientist/dataset1/master/titanic_train.csv", error_bad_li
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]:

```
df.shape
```

Out[3]: (891, 12)

In [4]:

```
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 [5]:

```
df.isnull().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
```

As we can see we have null values in Age and Cabin columns. Now we will fill null values with the help of Mean.

In [6]:

```
## Filling null values.
```

```
df['Age'].fillna(int(df['Age'].mean()), inplace=True)
df
```

Out[6]:

	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
...	...	...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	29.0	1	2	W./C. 6607	23.4500	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN	Q

891 rows × 12 columns

In [7]:

```
df.isnull().sum()
```

Out[7]:

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

Now we can see there is no null values in Age columns.

EDA

Lets try to analyze the target

In [8]:

```
## Lets try to analyze the target
df['Survived'].unique()
```

Out[8]:

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

In [9]:

```
df.Survived.value_counts().sort_index()
```

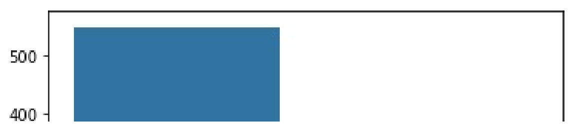
Out[9]:

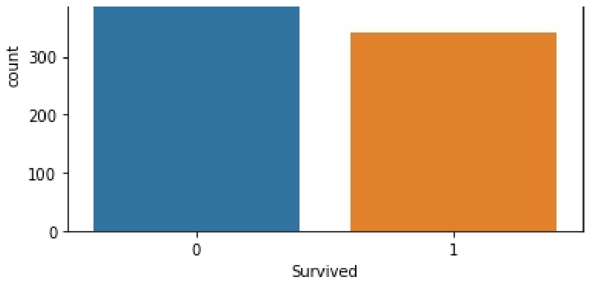
```
0    549
1    342
Name: Survived, dtype: int64
```

In [10]:

```
sns.countplot(x='Survived', data=df)
```

Out[10]: <AxesSubplot:xlabel='Survived', ylabel='count'>





In [12]:

```
df = df.drop("Cabin",axis = 1) ## as we can see we dont need cadin for the prediction.
df
```

Out[12]:

	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
...	...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	29.0	1	2	W./C. 6607	23.4500	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	Q

891 rows × 11 columns

In [13]:

```
df = df.drop("Name",axis = 1) ## as we can see we dont need Name for the prediction.
df
```

Out[13]:

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	male	22.0	1	0	A/5 21171	7.2500	S
1	2	1	1	female	38.0	1	0	PC 17599	71.2833	C
2	3	1	3	female	26.0	0	0	STON/O2. 3101282	7.9250	S
3	4	1	1	female	35.0	1	0	113803	53.1000	S
4	5	0	3	male	35.0	0	0	373450	8.0500	S
...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	male	27.0	0	0	211536	13.0000	S
887	888	1	1	female	19.0	0	0	112053	30.0000	S
888	889	0	3	female	29.0	1	2	W./C. 6607	23.4500	S
889	890	1	1	male	26.0	0	0	111369	30.0000	C
890	891	0	3	male	32.0	0	0	370376	7.7500	Q

891 rows × 10 columns

In [14]:

```
df = df.drop("Sex",axis = 1) ## as we can see we dont need Sex for the prediction.
df
```

Out[14]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	22.0	1	0	A/5 21171	7.2500	S
1	2	1	1	38.0	1	0	PC 17599	71.2833	C
2	3	1	3	26.0	0	0	STON/O2. 3101282	7.9250	S
3	4	1	1	35.0	1	0	113803	53.1000	S

4	5	0	3	35.0	0	0	373450	8.0500	S
...	...	...	...	...	...	...	...	...	...
886	887	0	2	27.0	0	0	211536	13.0000	S
887	888	1	1	19.0	0	0	112053	30.0000	S
888	889	0	3	29.0	1	2	W./C. 6607	23.4500	S
889	890	1	1	26.0	0	0	111369	30.0000	C
890	891	0	3	32.0	0	0	370376	7.7500	Q

891 rows × 9 columns

In [15]:

```
df = df.drop("Ticket",axis = 1) ## as we can see we dont need Ticket for the prediction.
df
```

Out[15]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare	Embarked
0	1	0	3	22.0	1	0	7.2500	S
1	2	1	1	38.0	1	0	71.2833	C
2	3	1	3	26.0	0	0	7.9250	S
3	4	1	1	35.0	1	0	53.1000	S
4	5	0	3	35.0	0	0	8.0500	S
...	...	...	...	...	...	...	...	...
886	887	0	2	27.0	0	0	13.0000	S
887	888	1	1	19.0	0	0	30.0000	S
888	889	0	3	29.0	1	2	23.4500	S
889	890	1	1	26.0	0	0	30.0000	C
890	891	0	3	32.0	0	0	7.7500	Q

891 rows × 8 columns

In [16]:

```
df = df.drop("Embarked",axis = 1) ## as we can see we dont need Embarked for the prediction.
df
```

Out[16]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
0	1	0	3	22.0	1	0	7.2500
1	2	1	1	38.0	1	0	71.2833
2	3	1	3	26.0	0	0	7.9250
3	4	1	1	35.0	1	0	53.1000
4	5	0	3	35.0	0	0	8.0500
...	...	...	...	...	...	...	...
886	887	0	2	27.0	0	0	13.0000
887	888	1	1	19.0	0	0	30.0000
888	889	0	3	29.0	1	2	23.4500
889	890	1	1	26.0	0	0	30.0000
890	891	0	3	32.0	0	0	7.7500

891 rows × 7 columns

In [17]:

```
# Add two columns to make a new column
df['Family'] = df['SibSp'] + df['Parch']
print('Updated DataFrame:')
print(df)
```

```
Updated DataFrame:
     PassengerId  Survived  Pclass   Age  SibSp  Parch     Fare  Family
0              1         0       3  22.0      1      0   7.2500       1
1              2         1       1  38.0      1      0  71.2833       1
2              3         1       3  26.0      0      0   7.9250       0
3              4         1       1  35.0      1      0  53.1000       1
4              5         0       3  35.0      0      0   8.0500       0
..           ...       ...     ...   ...    ...    ...      ...     ...
```

```
886          887          0        2  27.0      0       0  13.0000       0
887          888          1        1  19.0      0       0  30.0000       0
888          889          0        3  29.0      1       2  23.4500       3
889          890          1        1  26.0      0       0  30.0000       0
890          891          0        3  32.0      0       0   7.7500       0

[891 rows x 8 columns]
```

In [18]:
```
df = df.drop("Parch", axis = 1)
df
```

Out[18]:

	PassengerId	Survived	Pclass	Age	SibSp	Fare	Family
0	1	0	3	22.0	1	7.2500	1
1	2	1	1	38.0	1	71.2833	1
2	3	1	3	26.0	0	7.9250	0
3	4	1	1	35.0	1	53.1000	1
4	5	0	3	35.0	0	8.0500	0
...	...	...	...	...	...	...	...
886	887	0	2	27.0	0	13.0000	0
887	888	1	1	19.0	0	30.0000	0
888	889	0	3	29.0	1	23.4500	3
889	890	1	1	26.0	0	30.0000	0
890	891	0	3	32.0	0	7.7500	0

891 rows × 7 columns

In [19]:
```
df = df.drop("SibSp", axis = 1)
df
```

Out[19]:

	PassengerId	Survived	Pclass	Age	Fare	Family
0	1	0	3	22.0	7.2500	1
1	2	1	1	38.0	71.2833	1
2	3	1	3	26.0	7.9250	0
3	4	1	1	35.0	53.1000	1
4	5	0	3	35.0	8.0500	0
...	...	...	...	...	...	...
886	887	0	2	27.0	13.0000	0
887	888	1	1	19.0	30.0000	0
888	889	0	3	29.0	23.4500	3
889	890	1	1	26.0	30.0000	0
890	891	0	3	32.0	7.7500	0

891 rows × 6 columns

In [20]:
```
df.shape
```

Out[20]:
```
(891, 6)
```

Statistical Summary

In [21]:
```
df.describe()
```

Out[21]:

	PassengerId	Survived	Pclass	Age	Fare	Family
count	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.560236	32.204208	0.904602

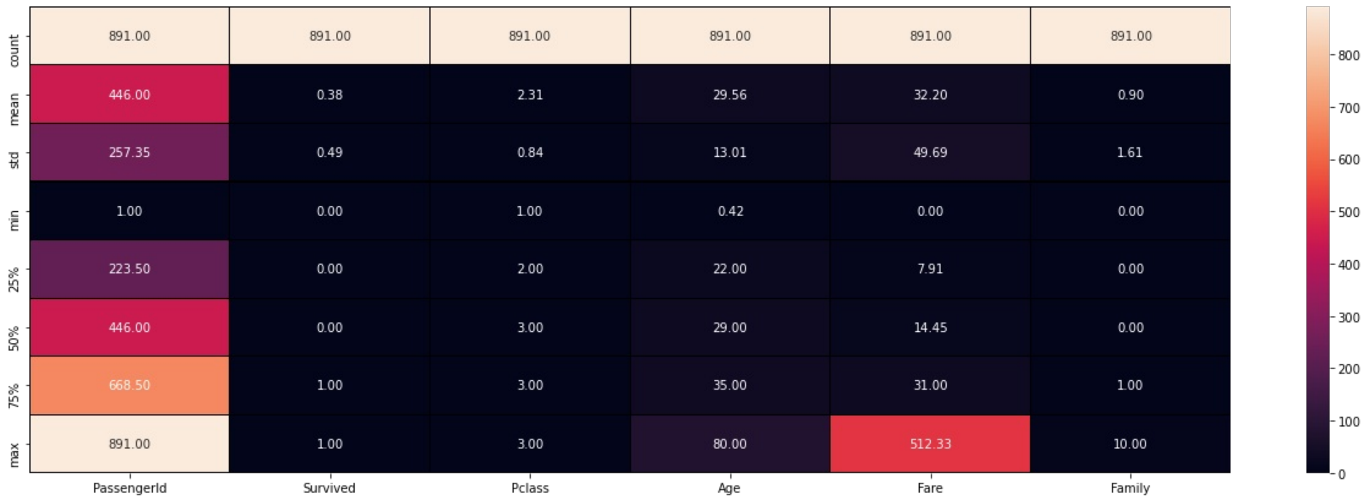
std	257.353842	0.486592	0.836071	13.005010	49.693429	1.613459
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	22.000000	7.910400	0.000000
50%	446.000000	0.000000	3.000000	29.000000	14.454200	0.000000
75%	668.500000	1.000000	3.000000	35.000000	31.000000	1.000000
max	891.000000	1.000000	3.000000	80.000000	512.329200	10.000000

In [22]:

```
#Heatmap using df.describe

import matplotlib.pyplot as plt
plt.figure(figsize=(22,7))
sns.heatmap(df.describe(), annot=True, linewidths=0.1, linecolor='black',fmt=".2f")
```

Out[22]: <AxesSubplot:>



Checking for nulls

In [23]:

```
df.isnull().sum()
```

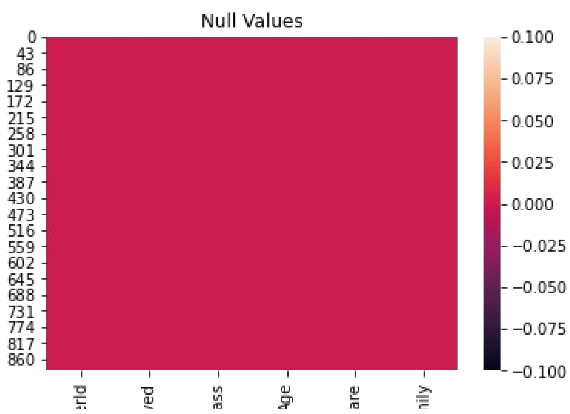
Out[23]:

```
PassengerId    0
Survived       0
Pclass         0
Age            0
Fare           0
Family         0
dtype: int64
```

In [24]:

```
sns.heatmap(df.isnull())
plt.title("Null Values")
plt.show
```

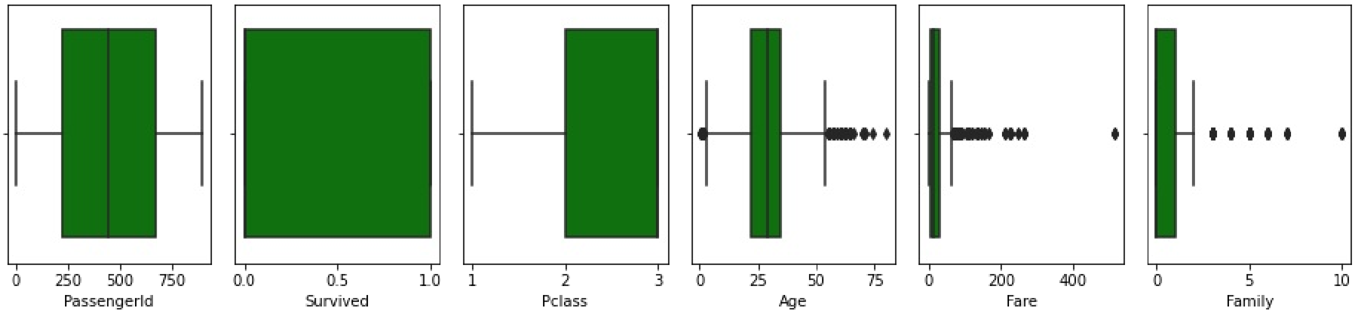
Out[24]: <function matplotlib.pyplot.show(close=None, block=None)>



In [25]:

```python
## Outlier checking: using box plot will check min value, max value and outliers.

collist = df.columns.values
ncol = 30
nrows = 14
plt.figure(figsize=(ncol,3*ncol))
for i in range(0, len(collist)):
    plt.subplot(ncol, nrows,i+1)
    sns.boxplot(df[collist[i]], color = "green", orient = 'v')
    plt.tight_layout()
```

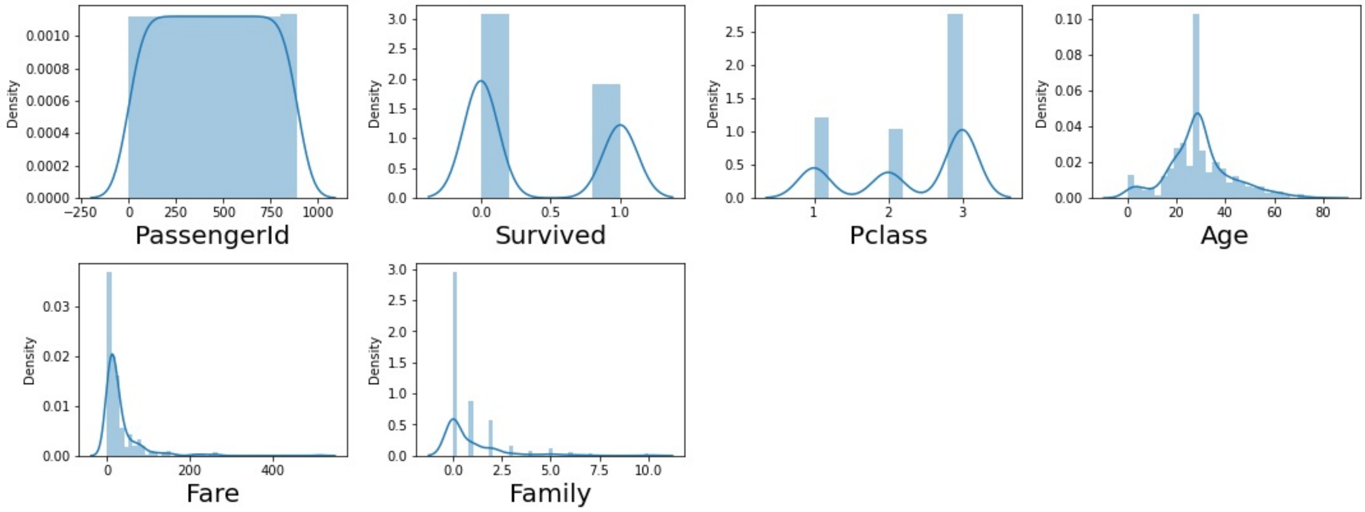


In [26]:

```python
#Data distribution:
#Dist Plot:

plt.figure(figsize = (15,8), facecolor = 'white')
plotnumber = 1   #initializing 1 to a name

for column in df:
    if plotnumber <= 11:
        ax = plt.subplot(3,4,plotnumber) #In 3 rows I want 4 columns to be plotted
        sns.distplot(df[column])
        plt.xlabel(column,fontsize = 20)
        plotnumber += 1
        plt.tight_layout()
```



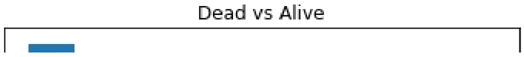
Most of the data is skewed

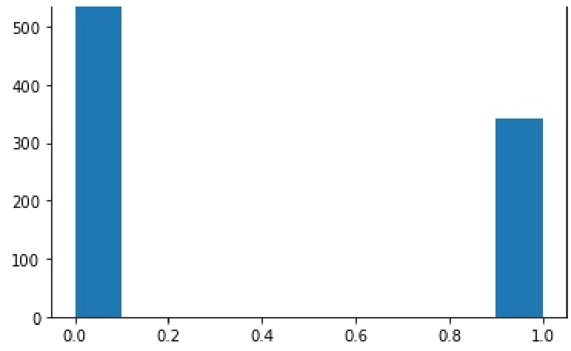
checking for class imbalance

In [27]:

```python
#Lets check if there is class imbalance

df["Survived"].hist(grid = False)
plt.title("Dead vs Alive")
plt.show()
```



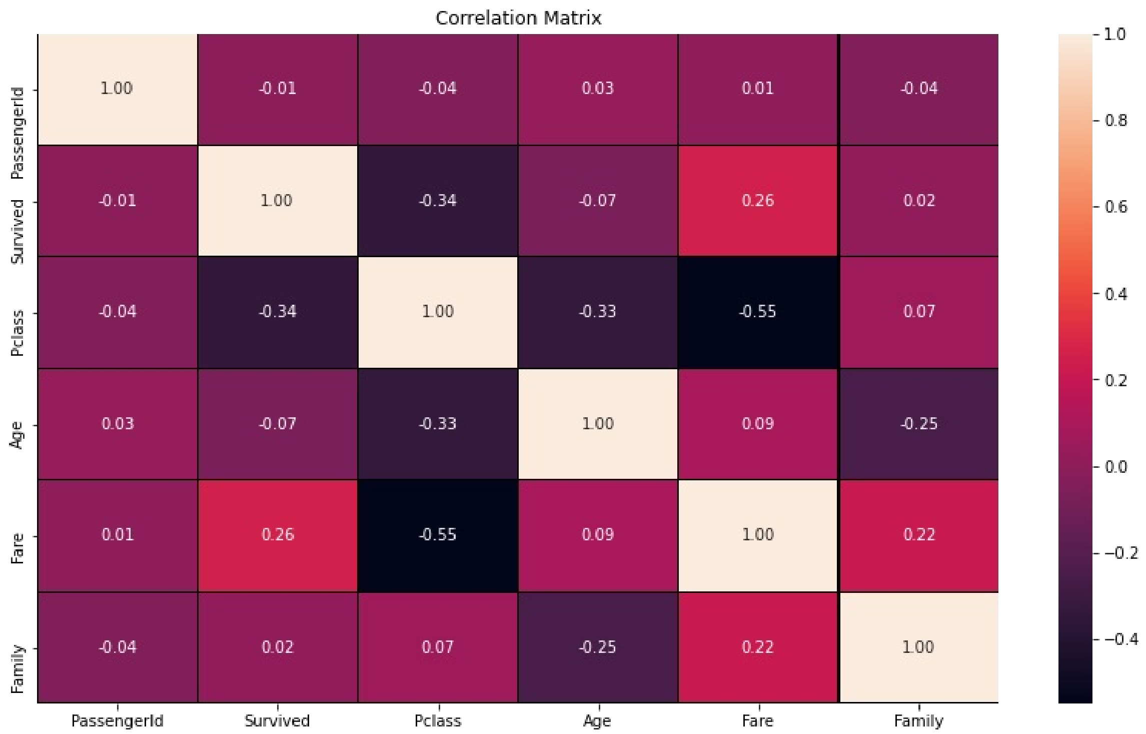


No class imbalance good to proceed

correlation

In [28]:

```
correlation = df.corr()
plt.figure(figsize=(14, 8))
sns.heatmap(correlation, annot=True, linewidths=0.1, linecolor='black', fmt="0.2f")
plt.title("Correlation Matrix")
plt.show()
```



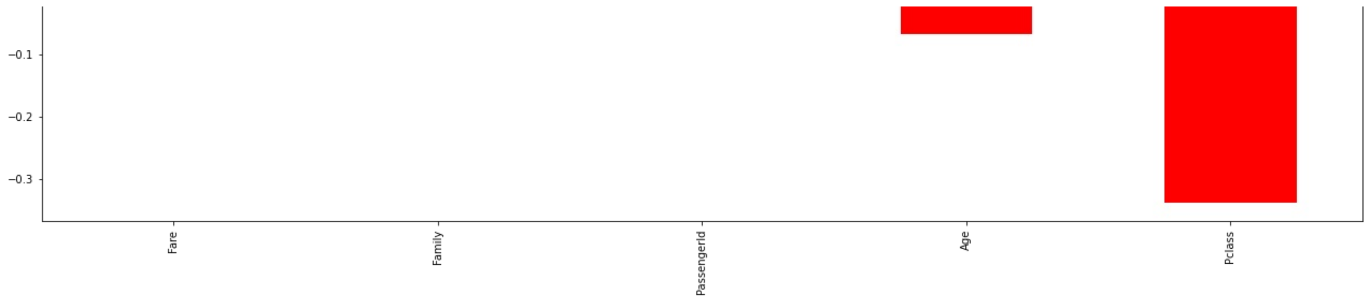
Outcome of Correlation;

Fare has 22 percent corr. with the target column which can be considered as a Good bond. Age has 25 percent corr. with the target column which can be considered as a good Bond. Pclass has 7 percent corr. with the target column which can be considered as a Weak bond. Survived has 2 percent corr. with the target column which can be considered as a very Weak bond. Passengerid has 4 percent corr. with the target column which can be considered as a Weak bond.

In [29]:

```
plt.figure(figsize=(22,7))
correlation['Survived'].sort_values(ascending=False).drop(['Survived']).plot(kind='bar',color='r')
```

Out[29]: <AxesSubplot:>



In [30]:

```
correlation['Survived'].sort_values(ascending=False)
```

Out[30]:

```
Survived       1.000000
Fare           0.257307
Family         0.016639
PassengerId   -0.005007
Age           -0.067814
Pclass        -0.338481
Name: Survived, dtype: float64
```

Observation: Min Correlation: PassengerID ; Max Correlation: Survived

lets divide data into features and label

In [31]:

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

Out[31]:

	PassengerId	Pclass	Age	Fare	Family
0	1	3	22.0	7.2500	1
1	2	1	38.0	71.2833	1
2	3	3	26.0	7.9250	0
3	4	1	35.0	53.1000	1
4	5	3	35.0	8.0500	0
...	...	...	...	...	...
886	887	2	27.0	13.0000	0
887	888	1	19.0	30.0000	0
888	889	3	29.0	23.4500	3
889	890	1	26.0	30.0000	0
890	891	3	32.0	7.7500	0

891 rows × 5 columns

Skewness

In [32]:

```
x.skew()
```

Out[32]:

```
PassengerId    0.000000
Pclass        -0.630548
Age            0.466268
Fare           4.787317
Family         2.727441
dtype: float64
```

power_tranform function

In [33]:

```python
# we will remove the skewness using power_tranform function
from sklearn.preprocessing import power_transform
x_new = power_transform(x ,  method = 'yeo-johnson')
x = pd.DataFrame(x_new,columns=x.columns)
```

In [34]:

```python
x.skew()
```

Out[34]:

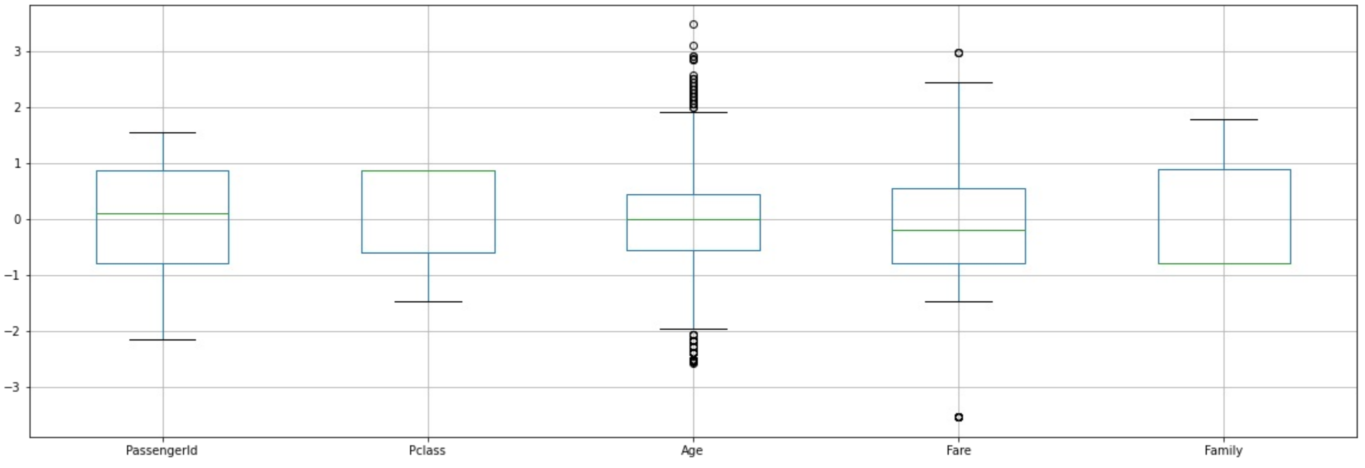
```
PassengerId   -0.283201
Pclass        -0.441438
Age            0.069162
Fare          -0.040329
Family         0.539231
dtype: float64
```

All values are under +/-0.5, skewness is handled.

Checking outliers:

In [35]:

```python
# plotting boxplot for all the columns
x.iloc[:,0:11].boxplot(figsize=[20,8])
plt.subplots_adjust(bottom=0.25)
plt.show()
```



Outliers Removal

ZScore Technique:

In [36]:

```python
from scipy.stats import zscore
import numpy as np
z=np.abs(zscore(x))
z.shape
```

Out[36]: (891, 5)

In [37]:

```python
threshold=3
print(np.where(z>3))
```

```
(array([179, 263, 271, 277, 302, 413, 466, 481, 597, 630, 633, 674, 732,
       806, 815, 822, 851], dtype=int64), array([3, 3, 3, 3, 3, 3, 3, 3, 3, 2, 3, 3, 3, 3, 3, 3, 2], dtype=int64)
)
```

In [38]:

```python
df_new=x[(z<3).all(axis=1)]
print(x.shape)
print(df_new.shape)
```

```
(891, 5)
(874, 5)
```

In [39]:

```
## Percentage data loss:
loss_percent=(891-874)/891*100
print(loss_percent)
```

```
1.9079685746352413
```

Data loss is in the acceptable range , good to proceed.

Finding Best Random_state:

In [40]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix,classification_report
from sklearn.model_selection import train_test_split
```

In [41]:

```
lr = LogisticRegression()
```

In [42]:

```
for i in range (0,1000):
    x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random_state=i)
    lr.fit(x_train,y_train)
    pred_train=lr.predict(x_train)
    pred_test=lr.predict(x_test)
    if round(accuracy_score(y_train,pred_train)*100,1)==round(accuracy_score(y_test,pred_test)*100,1):
        print(f"At random state {i}, The model performs very well")

        print(f"At random state {i}, the training accuracy is:- {accuracy_score(y_train,pred_train)*100}")
        print(f"At random state {i}, the testing accuracy is:- {accuracy_score(y_test,pred_test)*100}")
        print("\n")
```

```
At random state 224, The model performs very well
At random state 224, the training accuracy is:- 71.48876404494382
At random state 224, the testing accuracy is:- 71.50837988826815


At random state 432, The model performs very well
At random state 432, the training accuracy is:- 70.92696629213484
At random state 432, the testing accuracy is:- 70.94972067039106


At random state 529, The model performs very well
At random state 529, the training accuracy is:- 70.92696629213484
At random state 529, the testing accuracy is:- 70.94972067039106


At random state 536, The model performs very well
At random state 536, the training accuracy is:- 70.92696629213484
At random state 536, the testing accuracy is:- 70.94972067039106


At random state 663, The model performs very well
At random state 663, the training accuracy is:- 70.36516853932584
At random state 663, the testing accuracy is:- 70.39106145251397


At random state 678, The model performs very well
At random state 678, the training accuracy is:- 71.48876404494382
At random state 678, the testing accuracy is:- 71.50837988826815


At random state 720, The model performs very well
At random state 720, the training accuracy is:- 70.92696629213484
At random state 720, the testing accuracy is:- 70.94972067039106


At random state 758, The model performs very well
At random state 758, the training accuracy is:- 70.36516853932584
At random state 758, the testing accuracy is:- 70.39106145251397


At random state 873, The model performs very well
```

```
At random state 873, the training accuracy is:- 69.80337078651685
At random state 873, the testing accuracy is:- 69.83240223463687


At random state 899, The model performs very well
At random state 899, the training accuracy is:- 70.36516853932584
At random state 899, the testing accuracy is:- 70.39106145251397


At random state 930, The model performs very well
At random state 930, the training accuracy is:- 70.92696629213484
At random state 930, the testing accuracy is:- 70.94972067039106


At random state 969, The model performs very well
At random state 969, the training accuracy is:- 72.0505617977528
At random state 969, the testing accuracy is:- 72.06703910614524


At random state 990, The model performs very well
At random state 990, the training accuracy is:- 70.92696629213484
At random state 990, the testing accuracy is:- 70.94972067039106
```

Best training accuracy is 72.05%, best testing accuracy is 72.06% on Random_state 969

Creating Train-Test-split

In [43]:

```
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size = .20, random_state = 969)
```

In [44]:

```
print('Training Survived - \n', y_train.value_counts())
```

```
Training Survived -
 0    444
1    268
Name: Survived, dtype: int64
```

Logistic Regression

In [45]:

```
from sklearn.linear_model import LogisticRegression
LR = LogisticRegression()
LR.fit(x_train, y_train)
predlr = LR.predict(x_test)
print("Accuracy",accuracy_score(y_test, predlr)*100)
print(confusion_matrix(y_test,predlr))
print(classification_report(y_test,predlr))
```

```
Accuracy 72.06703910614524
[[85 20]
 [30 44]]
              precision    recall  f1-score   support

           0       0.74      0.81      0.77       105
           1       0.69      0.59      0.64        74

    accuracy                           0.72       179
   macro avg       0.71      0.70      0.71       179
weighted avg       0.72      0.72      0.72       179
```

for Logistic Regression, from above Confusion matrix, TP = 85, FP = 20, FN = 30, TN = 44. accuracy = 72%.

Decision Tree Classifier

In [46]:

```
from sklearn.tree import DecisionTreeClassifier
```

```
dt = DecisionTreeClassifier()
dt.fit(x_train, y_train)
preddt = dt.predict(x_test)
print("Accuracy",accuracy_score(y_test, preddt)*100)
print(confusion_matrix(y_test,preddt))
print(classification_report(y_test,preddt))
```

```
Accuracy 60.33519553072626
[[69 36]
 [35 39]]
              precision    recall  f1-score   support

           0       0.66      0.66      0.66       105
           1       0.52      0.53      0.52        74

    accuracy                           0.60       179
   macro avg       0.59      0.59      0.59       179
weighted avg       0.60      0.60      0.60       179
```

for Decision Tree Classifier, from above Confusion matrix, TP= 74, FP = 31, FN = 34, TN = 40. accuracy = 64%.

Random Forest Classifier

In [47]:

```
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier()
rf.fit(x_train, y_train)
predrf = dt.predict(x_test)
print("Accuracy",accuracy_score(y_test, predrf)*100)
print(confusion_matrix(y_test,predrf))
print(classification_report(y_test,predrf))
```

```
Accuracy 60.33519553072626
[[69 36]
 [35 39]]
              precision    recall  f1-score   support

           0       0.66      0.66      0.66       105
           1       0.52      0.53      0.52        74

    accuracy                           0.60       179
   macro avg       0.59      0.59      0.59       179
weighted avg       0.60      0.60      0.60       179
```

for Random Forest Classifier, from above Confusion matrix, TP = 74, FP = 31, FN = 34, TN = 40. accuracy = 64%.

SVM

In [48]:

```
from sklearn.svm import SVC

svc = SVC()
svc.fit( x_train, y_train)

ad_pred = svc.predict(x_test)
print("Accuracy", accuracy_score(y_test, ad_pred)*100)
print(confusion_matrix(y_test,ad_pred))
print(classification_report(y_test,ad_pred))
```

```
Accuracy 72.62569832402235
[[92 13]
 [36 38]]
              precision    recall  f1-score   support

           0       0.72      0.88      0.79       105
           1       0.75      0.51      0.61        74

    accuracy                           0.73       179
   macro avg       0.73      0.69      0.70       179
weighted avg       0.73      0.73      0.71       179
```

for SVM, from above Confusion matrix, TP = 92, FP = 13, FN = 36, TN = 38. accuracy = 73%. Lets check the CV scores for the above models, for overfitting.

Cross Validation

In [49]:
```
from sklearn.model_selection import cross_val_score

scr=cross_val_score(LR, x, y, cv=5)
print("Cross Validation score of LR model:", scr.mean())
```

```
Cross Validation score of LR model: 0.7015943757454021
```

In [50]:
```
scr=cross_val_score(dt, x, y, cv=5)
print("Cross Validation score of DT model:", scr.mean())
```

```
Cross Validation score of DT model: 0.640870001883121
```

In [51]:
```
scr=cross_val_score(rf, x, y, cv=5)
print("Cross Validation score of rf model:", scr.mean())
```

```
Cross Validation score of rf model: 0.6947649237336011
```

In [52]:
```
scr=cross_val_score(svc, x, y, cv=5)
print("Cross Validation score of SVC model:", scr.mean())
```

```
Cross Validation score of SVC model: 0.7161509007595255
```

Considering good CV score, SVC is performing better among all, we go ahead with SVC.

Hyper Parameter Tuning

In [53]:
```
from sklearn.model_selection import GridSearchCV

## Creating parameter list to pass in GridsearchCV
parameters = { "kernel" : ['linear', 'poly', 'rbf', 'sigmoid'], "gamma" : ['scale', 'auto'],
              "decision_function_shape" : ['ovo', 'ovr']}
```

In [54]:
```
GCV=GridSearchCV(SVC(),parameters,cv=5,scoring="accuracy")
GCV.fit(x_train,y_train) # Fitting the data in model
GCV.best_params_  # Printing the best parameter found by GridSearchCV
```

Out[54]:
```
{'decision_function_shape': 'ovo', 'gamma': 'scale', 'kernel': 'rbf'}
```

In [55]:
```
GCV_pred=GCV.best_estimator_.predict(x_test) # Prediciting with the best parameters
accuracy_score(y_test,GCV_pred) # Checking final accuracy
```

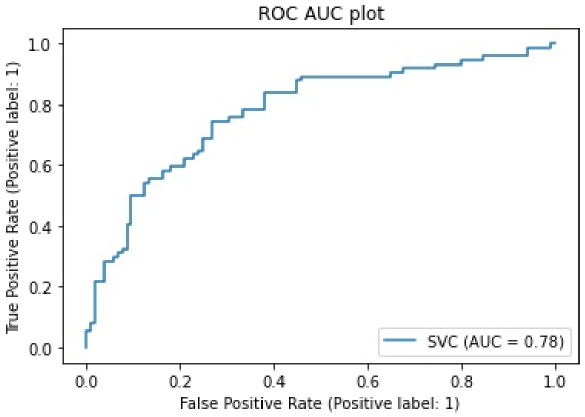
Out[55]:
```
0.7262569832402235
```

Accuracy of SVC after Hyper parameter tuning is 72.6%

ROC AUC Plot

In [56]:
```
from sklearn.metrics import plot_roc_curve
```

```
plot_roc_curve(GCV.best_estimator_,x_test,y_test)
plt.title("ROC AUC plot")
plt.show()
```



Final Accuracy is 72.6% & AUC score is 78%. which is good.

Saving the model in Pickle format

In [57]:

```
import pickle
filename = 'Titanic_project.pkl'
pickle.dump(rf, open(filename, 'wb'))
```

In [58]:

```
import numpy as np
a= np.array(y_test)
predicted=np.array(rf.predict(x_test))
df_com = pd.DataFrame({"Original":a,"Predicted":predicted }, index=range(len(a)))
df_com.head()
```

Out[58]:

	Original	Predicted
0	1	0
1	0	0
2	0	0
3	0	0
4	0	0

We can visualize there is no error in the Titanic prediction using the above model. Overall Our Model is Good.

In [ ]:

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