EDA on titanic data set

```
In [2]: !pip install pyforest
        Collecting pyforest
          Downloading pyforest-1.1.0.tar.gz (15 kB)
        Building wheels for collected packages: pyforest
          Building wheel for pyforest (setup.py): started
          Building wheel for pyforest (setup.py): finished with status 'done'
          Created wheel for pyforest: filename=pyforest-1.1.0-py2.py3-none-any.whl size=14607 sh
        a256=b0be22dca46381029ed0f8c0cfd596ca2e09d622658d1a6bc6455fcb9599cb60
          Stored in directory: c:\users\vikin\appdata\local\pip\cache\wheels\d5\1a\3e\6193fe1c56
        168f5df4aef57d8411033ba4611881135d495727
        Successfully built pyforest
        Installing collected packages: pyforest
        Successfully installed pyforest-1.1.0
        import pyforest
In [4]:
        data=pd.read_csv('Titanic-Train-Data.csv')
In [5]:
In [6]:
        data
```

Out[6]:		Passengerld	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embar
	0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	
	1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	0	PC 17599	71.2833	C85	
	2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	
	3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	
	4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	
	886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN	
	887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42	
	888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN	
	889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148	
	890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN	

891 rows × 12 columns

In [8]: data.shape

Out[8]: (891, 12)

In [9]: data.isna().sum()

```
PassengerId
                           0
Out[9]:
         Survived
                           0
         Pclass
                           0
         Name
                           0
         Sex
                           0
         Age
                         177
         SibSp
                           0
         Parch
                           0
                           0
         Ticket
         Fare
                           0
         Cabin
                         687
         Embarked
                           2
         dtype: int64
```

In [10]: data.describe()

Out[10]:

	Passengerld	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 [11]: data.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
dtyp	es: float64(2), int64(5), obj	ect(5)

memory usage: 83.7+ KB

In [13]: data.dtypes

```
PassengerId
                           int64
Out[13]:
         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 [22]:
         from sklearn.preprocessing import LabelEncoder
         from sklearn import preprocessing
In [24]:
         label_encoder=preprocessing.LabelEncoder()
         data['Sex']= label_encoder.fit_transform(data['Sex'])
         data['Sex'].value_counts()
              577
Out[24]:
              314
         Name: Sex, dtype: int64
         data
In [25]:
```

Out[25]:		Passengerld	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarke
	0	1	0	3	Braund, Mr. Owen Harris	1	22.0	1	0	A/5 21171	7.2500	NaN	(
	1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	0	38.0	1	0	PC 17599	71.2833	C85	(
	2	3	1	3	Heikkinen, Miss. Laina	0	26.0	0	0	STON/O2. 3101282	7.9250	NaN	(
	3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	0	35.0	1	0	113803	53.1000	C123	Ç
	4	5	0	3	Allen, Mr. William Henry	1	35.0	0	0	373450	8.0500	NaN	:
	886	887	0	2	Montvila, Rev. Juozas	1	27.0	0	0	211536	13.0000	NaN	•
	887	888	1	1	Graham, Miss. Margaret Edith	0	19.0	0	0	112053	30.0000	B42	Ç
	888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	0	NaN	1	2	W./C. 6607	23.4500	NaN	ţ
	889	890	1	1	Behr, Mr. Karl Howell	1	26.0	0	0	111369	30.0000	C148	(
	890	891	0	3	Dooley, Mr. Patrick	1	32.0	0	0	370376	7.7500	NaN	C

891 rows × 12 columns

In [26]: data=data.drop(['Ticket','Name','Cabin'],axis=1)
 data

Out[26]:		Passengerld	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
	0	1	0	3	1	22.0	1	0	7.2500	S
	1	2	1	1	0	38.0	1	0	71.2833	С
	2	3	1	3	0	26.0	0	0	7.9250	S
	3	4	1	1	0	35.0	1	0	53.1000	S
	4	5	0	3	1	35.0	0	0	8.0500	S
	886	887	0	2	1	27.0	0	0	13.0000	S
	887	888	1	1	0	19.0	0	0	30.0000	S
	888	889	0	3	0	NaN	1	2	23.4500	S
	889	890	1	1	1	26.0	0	0	30.0000	С
	890	891	0	3	1	32.0	0	0	7.7500	Q

891 rows × 9 columns

In [28]: data['Age'].median()

Out[28]: 28.

In [32]: data['Age']=data['Age'].fillna(value=28)
 data

Out[32]:		Passengerld	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
	0	1	0	3	1	22.0	1	0	7.2500	S
	1	2	1	1	0	38.0	1	0	71.2833	С
	2	3	1	3	0	26.0	0	0	7.9250	S
	3	4	1	1	0	35.0	1	0	53.1000	S
	4	5	0	3	1	35.0	0	0	8.0500	S
	886	887	0	2	1	27.0	0	0	13.0000	S
	887	888	1	1	0	19.0	0	0	30.0000	S
	888	889	0	3	0	28.0	1	2	23.4500	S
	889	890	1	1	1	26.0	0	0	30.0000	С
	890	891	0	3	1	32.0	0	0	7.7500	Q

891 rows × 9 columns

```
In [34]: data['Age'].isna().sum()
```

Out[34]:

In [35]: data.isna().sum()

```
PassengerId
                           0
Out[35]:
                           0
          Survived
          Pclass
                           0
                           0
          Sex
          Age
                           0
          SibSp
                           0
          Parch
                           0
          Fare
                           0
                           2
          Embarked
          dtype: int64
          data['Embarked'].value_counts()
In [36]:
                644
Out[36]:
                168
                 77
          Name: Embarked, dtype: int64
In [38]:
          g=data.groupby('Survived')
          g['Embarked'].value_counts()
          Survived Embarked
Out[38]:
                                   427
                     S
                     С
                                    75
                     Q
                                    47
                     S
          1
                                   217
                     С
                                    93
                     Q
                                    30
          Name: Embarked, dtype: int64
          data['Embarked']=data['Embarked'].fillna(value='S')
In [42]:
In [43]:
          data
               PassengerId Survived Pclass Sex Age SibSp Parch
Out[43]:
                                                                      Fare Embarked
            0
                        1
                                 0
                                         3
                                              1 22.0
                                                          1
                                                                 0
                                                                    7.2500
                                                                                   S
                                                                                   С
                        2
                                                 38.0
                                                                   71.2833
            1
                                  1
                                         1
                                              0
                                                          1
                                                                 0
            2
                        3
                                         3
                                                 26.0
                                                          0
                                                                    7.9250
                                                                                   S
                                  1
                                                                   53.1000
                                                                                   S
            3
                        4
                                  1
                                         1
                                                35.0
                                                          1
                                                                 0
                                              0
                        5
                                 0
                                         3
                                                          0
                                                                                   S
            4
                                                 35.0
                                                                 0
                                                                    8.0500
          886
                      887
                                 0
                                         2
                                              1 27.0
                                                          0
                                                                 0 13.0000
                                                                                   S
                                                                                   S
          887
                       888
                                              0 19.0
                                                          0
                                                                   30.0000
                                         1
          888
                       889
                                 0
                                         3
                                              0 28.0
                                                                 2 23.4500
                                                                                   S
                                                          1
                                                                                   С
          889
                       890
                                  1
                                         1
                                              1 26.0
                                                          0
                                                                   30.0000
          890
                       891
                                  0
                                         3
                                              1 32.0
                                                          0
                                                                    7.7500
                                                                                   Q
         891 rows × 9 columns
In [46]:
          from sklearn.preprocessing import LabelEncoder
          from sklearn import preprocessing
```

label_encoder=preprocessing.LabelEncoder()

Loading [MathJax]/extensions/Safe.js

data['Embarked']=label_encoder.fit_transform(data['Embarked'])

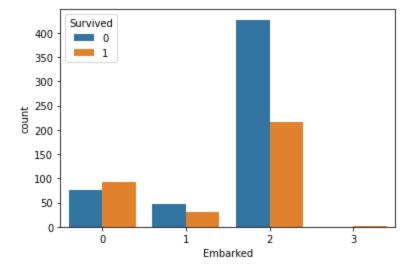
```
Out[46]: 2 644
0 168
1 77
3 2
Name: Embarked, dtype: int64
In [47]: sns.countplot(data['Embarked'], hue=data['Survived'])
```

C:\Users\vikin\anaconda3\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWa rning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

plt.show()

data['Embarked'].value_counts()



```
In [49]: data['Embarked'].value_counts()

Out[49]: 2    644
    0    168
    1    77
    3    2
    Name: Embarked, dtype: int64

In [50]: data
```

	Passengerld	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	0	3	1	22.0	1	0	7.2500	2
1	2	1	1	0	38.0	1	0	71.2833	0
2	3	1	3	0	26.0	0	0	7.9250	2
3	4	1	1	0	35.0	1	0	53.1000	2
4	5	0	3	1	35.0	0	0	8.0500	2
886	887	0	2	1	27.0	0	0	13.0000	2
887	888	1	1	0	19.0	0	0	30.0000	2
888	889	0	3	0	28.0	1	2	23.4500	2
889	890	1	1	1	26.0	0	0	30.0000	0
890	891	0	3	1	32.0	0	0	7.7500	1

891 rows × 9 columns

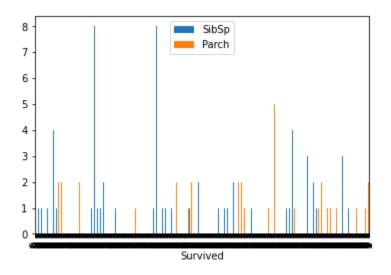
In [51]: data.corr()

Out [51]:							
	\cap	+	Г	5	7	1	
	υu	L	L	J	т.	л	

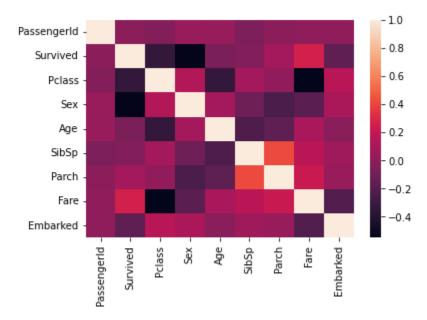
Out[50]:

	Passengerld	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarke
Passengerld	1.000000	-0.005007	-0.035144	0.042939	0.034212	-0.057527	-0.001652	0.012658	0.01308
Survived	-0.005007	1.000000	-0.338481	-0.543351	-0.064910	-0.035322	0.081629	0.257307	-0.16351
Pclass	-0.035144	-0.338481	1.000000	0.131900	-0.339898	0.083081	0.018443	-0.549500	0.15711
Sex	0.042939	-0.543351	0.131900	1.000000	0.081163	-0.114631	-0.245489	-0.182333	0.10405
Age	0.034212	-0.064910	-0.339898	0.081163	1.000000	-0.233296	-0.172482	0.096688	-0.01420
SibSp	-0.057527	-0.035322	0.083081	-0.114631	-0.233296	1.000000	0.414838	0.159651	0.06665
Parch	-0.001652	0.081629	0.018443	-0.245489	-0.172482	0.414838	1.000000	0.216225	0.03832
Fare	0.012658	0.257307	-0.549500	-0.182333	0.096688	0.159651	0.216225	1.000000	-0.22122
Embarked	0.013083	-0.163517	0.157112	0.104057	-0.014205	0.066654	0.038322	-0.221226	1.00000

data.plot(x="Survived", y=['SibSp','Parch'], kind='bar') In [57]: plt.show()



Out[58]: <AxesSubplot:>



Out[60]:		Survived	Pclass	Sex	Age	Fare	Family
	0	0	3	1	22.0	7.2500	2
	1	1	1	0	38.0	71.2833	2
	2	1	3	0	26.0	7.9250	1
	3	1	1	0	35.0	53.1000	2
	4	0	3	1	35.0	8.0500	1
	886	0	2	1	27.0	13.0000	1
	887	1	1	0	19.0	30.0000	1
	888	0	3	0	28.0	23.4500	4
	889	1	1	1	26.0	30.0000	1

1 32.0

7.7500

891 rows × 6 columns

Loading [MathJax]/extensions/Safe.js [n,y_train]

890

```
In [61]: x=data.drop('Survived', axis=1).values
    y=data['Survived'].values

In [62]: from sklearn.linear_model import LogisticRegression
    from sklearn.model_selection import train_test_split

In [64]: x_train, x_test, y_train, y_test=train_test_split(x, y, test_size=0.3, random_state=100)

In [65]: from sklearn.metrics import accuracy_score

In [68]: lr=LogisticRegression()
```

```
lrpred=lr.predict(x_test)
In [70]: accuracy_score(y_test,lrpred)
         0.7910447761194029
Out[70]:
In [72]:
         from sklearn.model_selection import GridSearchCV
In [74]:
         c_space=np.logspace(-5,8,15)
         param_grid={'C':c_space}
         logreg_cv=GridSearchCV(lr,param_grid,cv=5)
         logreg_cv.fit(x_train,y_train)
         print('T L R P:{}',format(logreg_cv.best_params_))
         print('the best score is{}', format(logreg_cv.best_score_))
         T L R P:{} {'C': 31.622776601683793}
         the best score is{} 0.8042193548387097
 In [ ]:
```