Titanic Passanger Survival Analysis

1. Defining the problem statement¶

Complete the analysis of what sorts of people were likely to survive.

In particular, we ask you to apply the tools of machine learning to predict which passengers survived the Titanic tragedy.



```
In [2]: import os
   import pandas as pd
   import numpy as np
   train = pd.read_csv('train.xls')
   test = pd.read_csv('test.xls')
In [3]: train.head()
```

Harris Cumings, Mrs. John Bradley (Florence Briggs Th Heikkinen, Laina Futrelle, Mrs. Jacques Heath (Lily May Peel) Allen, Mr.	Out[3]:	Passenger	ld Surv	vived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
Mrs. John Bradley Female 38.0 1 0 PC 17599 71.2833		0	1	0	3	Mr. Owen	male	22.0	1	0		7.2500	NaN
2		1	2	1	1	Mrs. John Bradley (Florence Briggs	female	38.0	1	0	PC 17599	71.2833	C85
### A		2	3	1	3	Miss.	female	26.0	0	0		7.9250	NaN
## Tolumn Non-Null Count Dtype Column Non-Null Count Dippe Column Non-null int64 1 Survived 891 non-null int64 3 Name 891 non-null int64 3 Name 891 non-null int64 6 SibSp 891 non-null int64 6 SibSp 891 non-null int64 6 SibSp 891 non-null int64 7 Parch 891 non-null int64 8 Ticket 891 non-null object 9 Fare 891 non-null object 9 Fare 891 non-null object 11 Embarked 889 non-null object 12 Embarked 889 non-null object		3	4	1	1	Mrs. Jacques Heath (Lily May	female	35.0	1	0	113803	53.1000	C123
print("Train Shape:",train.shape) test.isnull().sum() print("Test Shape:",test.shape) Train Shape: (891, 12) Test Shape: (418, 11) In [5]: train.info() <class 'pandas.core.frame.dataframe'=""> RangeIndex: 891 entries, 0 to 890 Data columns (total 12 columns): # Column Non-Null Count Dtype</class>		4	5	0	3	William	male	35.0	0	0	373450	8.0500	NaN
Test Shape: (418, 11) In [5]: train.info() <class 'pandas.core.frame.dataframe'=""> RangeIndex: 891 entries, 0 to 890 Data columns (total 12 columns): # Column Non-Null Count Dtype</class>	In [4]:	<pre>print("Train Shape:",train.sha test.isnull().sum()</pre>											
<pre><class 'pandas.core.frame.dataframe'=""> RangeIndex: 891 entries, 0 to 890 Data columns (total 12 columns): # Column</class></pre>		•)								
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 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)	In [5]:	train.info()										
<pre>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)</pre>		RangeIndex: Data column # Column	891 e	ntrie al 12	es, 0 t 2 colum	o 890 ns): ount Dty	pe						
		0 Passen 1 Surviv 2 Pclass 3 Name 4 Sex 5 Age 6 SibSp 7 Parch 8 Ticket 9 Fare 10 Cabin 11 Embark dtypes: flo	11 int 11 int 11 obj 11 obj 11 int 11 int 11 int 11 obj 11 obj 11 obj 11 obj 11 obj	64 64 ect ect at64 64 ect at64 ect									
<pre>In [6]: test.info()</pre>	In [6]:	test.info()											

<class 'pandas.core.frame.DataFrame'> RangeIndex: 418 entries, 0 to 417 Data columns (total 11 columns): Non-Null Count Dtype Column ----------0 PassengerId 418 non-null int64 1 Pclass 418 non-null int64
2 Name 418 non-null object
3 Sex 418 non-null object
4 Age 332 non-null float64
5 SibSp 418 non-null int64
6 Parch 418 non-null int64 418 non-null object 7 Ticket 8 Fare 417 non-null float64 9 Cabin 91 non-null object 10 Embarked 418 non-null object dtypes: float64(2), int64(4), object(5) memory usage: 36.0+ KB

2. Data Dictionary

- Survived: 0 = No, 1 = Yes
- pclass: Ticket class 1 = 1st, 2 = 2nd, 3 = 3rd
- sibsp: # of siblings / spouses aboard the Titanic
- parch: # of parents / children aboard the Titanic
- ticket: Ticket number
- cabin: Cabin number
- embarked: Port of Embarkation C = Cherbourg, Q = Queenstown, S = Southampton

Total rows and columns

We can see that there are 891 rows and 12 columns in our training dataset.

```
In [7]: train.head(10)
```

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
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN
6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN
9	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	237736	30.0708	NaN
	2 3 4 5 6 7	 2 3 4 5 6 7 7 8 9 10 	2 3 1 3 4 1 4 5 0 5 6 0 6 7 0 7 8 0 8 9 1 9 10 1	2 3 1 3 3 4 1 1 3 4 5 0 3 5 6 0 3 6 7 0 1 7 8 0 3 9 1 3 9 1 3	1 2 1 1 Bradley (Florence Briggs Th Heikkinen, Miss. Laina Jacques Heath (Lily May Peel) Allen, Mr. Allen, Mr. Allen, Mr. MocCarthy, Mr. James McCarthy, Mr. Timothy J Alster. Gosta Leonard Johnson, Mrs. Gosta Leonard Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg) Nasser, Mrs. Achem)	1211Bradley (Florence Briggs Thfemale Briggs Th2313Heikkinen, Mrs. Allen, Mrs. Mrs. Jacques Peel)3411Futrelle, Mrs. Jacques Peel)4503Moran, Mr. James Mr. Jamesmale Henry5603Moran, Mr. James Mr. Jamesmale Timothy J7803McCarthy, Timothy Jmale Gosta Leonard8913Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)female Wilhelmina Berg)91012Nasser, Mrs. Mrs. Mrs. Nasser, Mrs. Mrs. Mrs. Oscar W Vilhelmina Berg)	1 2 1 1 Bradley (Florence Briggs Th female 38.0 2 3 1 3 Heikkinen, Miss. Laina female 26.0 3 4 1 1 Futrelle, Mrs. Jacques Heath (Lily May Peel) female 35.0 4 5 0 3 Moran, Mr. James Male NaN 5 6 0 3 Moran, Mr. James Male NaN 6 7 0 1 Mr. James McCarthy, Male McCarthy, Male Male male 54.0 7 8 0 3 Palsson, Master. Gosta Leonard male 2.0 8 9 1 3 Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg) 7 Nasser, Mrs. Mrs. Mrs. Mrs. Mrs. Mrs. Mrs. Mrs.	1 2 1 1 Bradley (Florence Briggs Th female 38.0 1 2 3 1 3 Miss. Laina female 26.0 0 3 4 1 1 Jacques Heath (Lily May Peel) female 35.0 1 4 5 0 3 William Mr. James male 35.0 0 5 6 0 3 Moran, Mr. James male NaN 0 6 7 0 1 McCarthy, Timothy J male 54.0 0 7 8 0 3 Palsson, Master. Gosta Leonard male 2.0 3 4 9 1 3 Oscar W (Elisabeth Vilhelmina Berg) female 27.0 0 9 10 1 2 Nicholas (Adele Achem) female 14.0 1	1 2 1 1 Bradley (Florence Briggs Th female 38.0 1 0 2 3 1 3 Miss. Laina female 26.0 0 0 0 3 4 1 1 Futrelle, Mrs. Heath (Lily May Peel) female 35.0 1 0 4 5 0 3 William Mr. James Male NaN 0 0 0 5 6 0 3 Moran, Mr. James Male NaN 0 0 0 6 7 0 1 Mr. James Male NaN 0 0 0 7 8 0 3 Moran, Mr. James Male NaN 0 0 0 7 8 0 3 Moran, Mr. Master. Gosta Leonard Leonard Leonard Naster. Gosta Leonard Naster. Gosta Leonard Naster. Gosta Leonard Naster. Gosta Leonard Naster. Mrs. Naster. Mrs. Naster. Mrs. Naster. Mrs. Naster. Mrs. Naster. Naster. Mrs.	1 2 1 1 Bradley (Florence Briggs Th female Briggs Th 38.0 1 0 PC 17599 2 3 1 3 Heikkinen, Miss. Laina female 26.0 0 0 STON/O2. 3101282 3 4 1 1 Jacques Mrs. Heath (Lij May Peel) female 35.0 1 0 113803 4 5 0 3 Moran, Mr. James male 35.0 0 0 373450 5 6 0 3 Moran, Mr. James male NaN 0 0 330877 6 7 0 1 Mr. Mr. James 54.0 0 0 17463 7 8 0 3 Moster, Gosta Leonard male 2.0 3 1 349909 8 9 1 3 Gosta Miss. Gosta W (Elisabeth Vilhelmina Berg) female 27.0 0 2 347742 9 10 1 2 Nicholas (Adele Achem) female 14.0 1 0 2337736 <td>1 2 1 1 Bradley (Florence Briggs Th female 38.0 1 0 PC 17599 71,2833 2 3 1 3 Heikkinen, Miss. Laina female 26.0 0 0 STON/O2. 3101282 7,9250 3 4 1 1 Heikkinen, Miss. Jacques female 26.0 0 0 STON/O2. 3101282 7,9250 4 5 0 3 Allen, Mr. Heath (Lily May Peel) female 35.0 1 0 113803 53.1000 5 6 0 3 Moran, Mr. James male 35.0 0 0 373450 8.0500 6 7 0 1 McCarthy, Mr. James male 54.0 0 0 330877 8.4583 7 8 0 3 McCarthy, Master. Gosta Leonard male 2.0 3 1 349909 21,0750 8 9 1 3 Misser, Mrs. Gosta Leonard Misser, Mrs. Gosta Misser, Misse</td>	1 2 1 1 Bradley (Florence Briggs Th female 38.0 1 0 PC 17599 71,2833 2 3 1 3 Heikkinen, Miss. Laina female 26.0 0 0 STON/O2. 3101282 7,9250 3 4 1 1 Heikkinen, Miss. Jacques female 26.0 0 0 STON/O2. 3101282 7,9250 4 5 0 3 Allen, Mr. Heath (Lily May Peel) female 35.0 1 0 113803 53.1000 5 6 0 3 Moran, Mr. James male 35.0 0 0 373450 8.0500 6 7 0 1 McCarthy, Mr. James male 54.0 0 0 330877 8.4583 7 8 0 3 McCarthy, Master. Gosta Leonard male 2.0 3 1 349909 21,0750 8 9 1 3 Misser, Mrs. Gosta Leonard Misser, Mrs. Gosta Misser, Misse

In [8]: train.describe()

Out[8]:		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 [9]:	test.	describe()						
Out[9]:		PassengerId	Pclass	Age	SibSp	Parch	Fare	
	count	418.000000	418.000000	332.000000	418.000000	418.000000	417.000000	-
	moon	1100 500000	2 265550	20 272500	0.447269	0.202244	25 627100	

:		Passengerld	Pclass	Age	SibSp	Parch	Fare
	count	418.000000	418.000000	332.000000	418.000000	418.000000	417.000000
	mean	1100.500000	2.265550	30.272590	0.447368	0.392344	35.627188
	std	120.810458	0.841838	14.181209	0.896760	0.981429	55.907576
	min	892.000000	1.000000	0.170000	0.000000	0.000000	0.000000
	25%	996.250000	1.000000	21.000000	0.000000	0.000000	7.895800
	50%	1100.500000	3.000000	27.000000	0.000000	0.000000	14.454200
	75%	1204.750000	3.000000	39.000000	1.000000	0.000000	31.500000
	max	1309.000000	3.000000	76.000000	8.000000	9.000000	512.329200

```
In [10]: train.isnull().sum()
                           0
         PassengerId
Out[10]:
         Survived
                           0
         Pclass
                           0
         Name
                           0
         Sex
                           0
                         177
         Age
         SibSp
                           0
         Parch
                           0
         Ticket
                           0
                           0
         Fare
         Cabin
                         687
         Embarked
                           2
         dtype: int64
In [11]: test.isnull().sum()
```

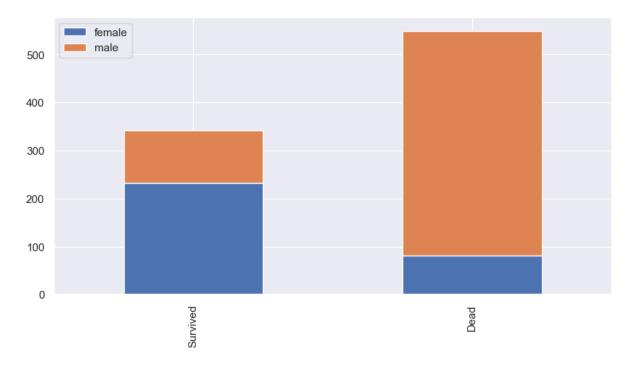
```
PassengerId
Out[11]:
                          0
         Pclass
         Name
         Sex
                         86
         Age
         SibSp
         Parch
                          0
         Ticket
                          0
         Fare
         Cabin
                        327
         Embarked
         dtype: int64
```

3. Data Visualization using Matplotlib and Seaborn packages.

Bar Chart for Categorical Features

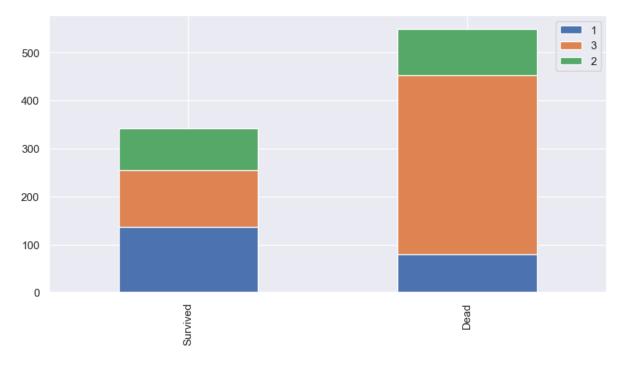
- Pclass
- Sex
- SibSp (# of siblings and spouse)
- Parch (# of parents and children)
- Embarked
- Cabin

```
In [13]: def bar_chart(feature):
    survived = train[train['Survived']==1][feature].value_counts()
    dead = train[train['Survived']==0][feature].value_counts()
    df = pd.DataFrame([survived,dead])
    df.index = ['Survived','Dead']
    df.plot(kind='bar',stacked=True, figsize=(10,5))
In [14]: bar_chart('Sex')
    print("Survived :\n",train[train['Survived']==1]['Sex'].value_counts())
```



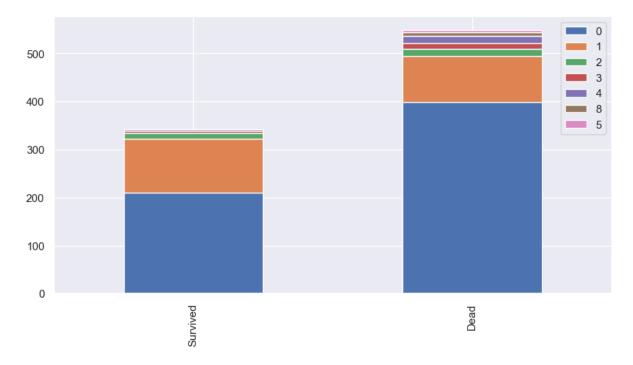
The Chart confirms Women more likely survivied than Men.

```
bar_chart('Pclass')
In [15]:
         print("Survived :\n",train[train['Survived']==1]['Pclass'].value_counts())
         print("Dead:\n",train[train['Survived']==0]['Pclass'].value_counts())
         Survived:
               136
          1
              119
               87
         Name: Pclass, dtype: int64
         Dead:
          3
               372
         2
               97
               80
         Name: Pclass, dtype: int64
```



The Chart confirms **1st class** more likely survivied than **other classes**. The Chart confirms **3rd class** more likely dead than **other classes**

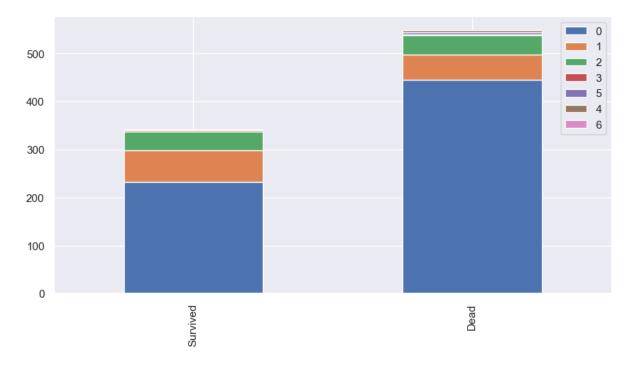
```
In [16]:
         bar_chart('SibSp')
          print("Survived :\n",train[train['Survived']==1]['SibSp'].value_counts())
         print("Dead:\n",train[train['Survived']==0]['SibSp'].value_counts())
         Survived:
                210
               112
          1
          2
                13
         3
                 4
         4
                 3
         Name: SibSp, dtype: int64
         Dead:
          0
                398
         1
                97
         4
                15
          2
                15
          3
                12
         8
                7
         5
                 5
         Name: SibSp, dtype: int64
```



The Chart confirms a **person aboarded with more than 2 siblings or spouse** more likely survived.

The Chart confirms a person aboarded without siblings or spouse more likely dead

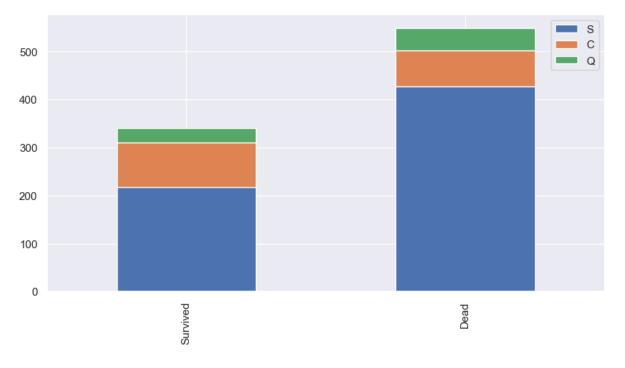
```
In [17]:
          bar chart('Parch')
          print("Survived :\n",train[train['Survived']==1]['Parch'].value_counts())
          print("Dead:\n",train[train['Survived']==0]['Parch'].value_counts())
         Survived:
                233
          1
                65
          2
                40
          3
                 3
                 1
         Name: Parch, dtype: int64
         Dead:
          0
                445
          1
                53
          2
                40
          5
                 4
          4
                 4
          3
                 2
          6
                 1
         Name: Parch, dtype: int64
```



The Chart confirms a person aboarded with more than 2 parents or children more likely survived.

The Chart confirms a person aboarded alone more likely dead

```
In [18]:
         bar_chart('Embarked')
          print("Survived :\n",train[train['Survived']==1]['Embarked'].value_counts())
          print("Dead:\n",train[train['Survived']==0]['Embarked'].value_counts())
         Survived:
          S
               217
               93
          C
                30
         Name: Embarked, dtype: int64
         Dead:
          S
               427
          C
                75
               47
         Q
         Name: Embarked, dtype: int64
```



The Chart confirms a **person aboarded from C** slightly more likely survived.

The Chart confirms a **person aboarded from Q** more likely dead.

The Chart confirms a **person aboarded from S** more likely dead.

4. Feature engineering

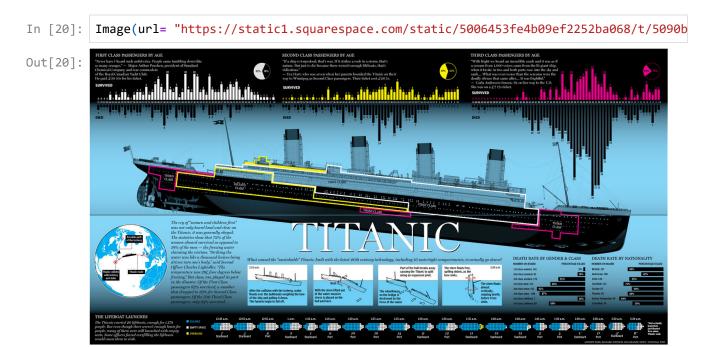
Feature engineering is the process of using domain knowledge of the data to create features (**feature vectors**) that make machine learning algorithms work.

feature vector is an n-dimensional vector of numerical features that represent some object. Many algorithms in machine learning require a numerical representation of objects, since such representations facilitate processing and statistical analysis.

In [19]: train.head()

Out[19]:		PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
	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

4.1 how titanic sank?



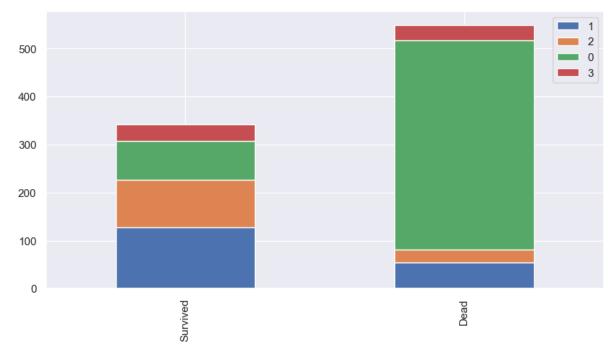
In [21]: train.head(10)

Out[21]:		PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
	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
	5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN
	6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46
	7	8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN
	8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN
	9	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	237736	30.0708	NaN

1.Title

```
In [22]: | train_test_data = [train,test]
         for dataset in train_test_data:
              dataset['Title'] = dataset['Name'].str.extract(' ([A-Za-z]+)\.', expand=False)
In [23]: train['Title'].value_counts()
         Mr
                      517
Out[23]:
                      182
         Miss
         Mrs
                      125
                       40
         Master
         Dr
                        7
                        6
         Rev
         Mlle
                        2
         Major
                        2
         Col
         Countess
                        1
         Capt
         Ms
                        1
         Sir
         Lady
                        1
         Mme
                        1
         Don
                        1
         Jonkheer
                        1
         Name: Title, dtype: int64
In [24]: test['Title'].value_counts()
         Mr
                    240
Out[24]:
                     78
         Miss
         Mrs
                     72
                     21
         Master
                      2
         Col
         Rev
                      2
         Ms
                      1
                      1
         Dr
         Name: Title, dtype: int64
         Title Map
         Mr: 0
         Miss: 1
         Mrs: 2
         Others: 3
In [25]: | title_mapping = {"Mr": 0, "Miss": 1, "Mrs": 2,
                           "Master": 3, "Dr": 3, "Rev": 3, "Col": 3, "Major": 3, "Mlle": 3, "C
                           "Ms": 3, "Lady": 3, "Jonkheer": 3, "Don": 3, "Dona": 3, "Mme": 3,
          for dataset in train test data:
              dataset['Title'] = dataset["Title"].map(title_mapping)
In [26]: dataset.head()
```

Out[26]:		PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
	0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
	1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
	2	894	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
	3	895	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
	4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S
In [27]:	te	st.head()										
Out[27]:		PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
Out[27]:	0	PassengerId 892	Pclass	Name Kelly, Mr. James	Sex male		SibSp 0	Parch 0	Ticket 330911	Fare 7.8292	Cabin NaN	Embarked Q
Out[27]:	0			Kelly, Mr.		34.5						
Out[27]:		892	3	Kelly, Mr. James Wilkes, Mrs. James (Ellen	male	34.5 47.0	0	0	330911	7.8292	NaN	Q
Out[27]:	1	892 893	3	Kelly, Mr. James Wilkes, Mrs. James (Ellen Needs) Myles, Mr. Thomas	male	34.5 47.0 62.0	0	0	330911 363272	7.8292	NaN NaN	Q
Out[27]:	1	892 893	3	Kelly, Mr. James Wilkes, Mrs. James (Ellen Needs) Myles, Mr. Thomas Francis Wirz, Mr.	male female male	34.5 47.0 62.0 27.0	0 1 0	0 0 0	330911 363272 240276	7.8292 7.0000 9.6875 8.6625	NaN NaN NaN	Q S

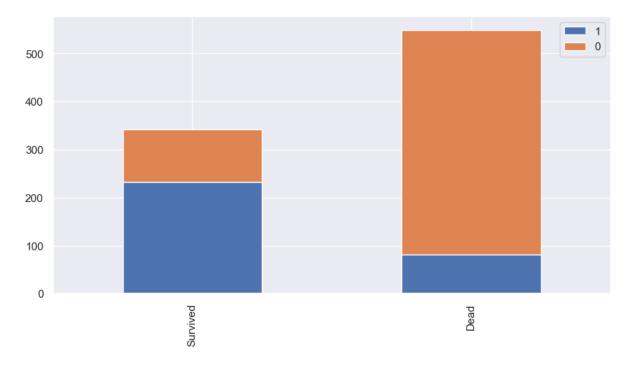


```
In [29]: train.drop('Name', axis=1, inplace=True)
test.drop('Name', axis=1, inplace=True)
```

In	۲30 T	:	train.head()

Out[30]:		PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
	0	1	0	3	male	22.0	1	0	A/5 21171	7.2500	NaN	S
	1	2	1	1	female	38.0	1	0	PC 17599	71.2833	C85	С
	2	3	1	3	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
	3	4	1	1	female	35.0	1	0	113803	53.1000	C123	S
	4	5	0	3	male	35.0	0	0	373450	8.0500	NaN	S

2.Sex



n [33]:	te	est.head()										
ut[33]:		Passengerld	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Title
	0	892	3	0	34.5	0	0	330911	7.8292	NaN	Q	0
	1	893	3	1	47.0	1	0	363272	7.0000	NaN	S	2
	2	894	2	0	62.0	0	0	240276	9.6875	NaN	Q	0
	3	895	3	0	27.0	0	0	315154	8.6625	NaN	S	0
	4	896	3	1	22.0	1	1	3101298	12.2875	NaN	S	2

3.Age

In [34]:				_								nplace= Tru lace= True)
In [35]:	tr	rain.head()										
Out[35]:		PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked 1
	0	1	0	3	0	22.0	1	0	A/5 21171	7.2500	NaN	S
	1	2	1	1	1	38.0	1	0	PC 17599	71.2833	C85	С
	2	3	1	3	1	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
	3	4	1	1	1	35.0	1	0	113803	53.1000	C123	S
	4	5	0	3	0	35.0	0	0	373450	8.0500	NaN	S

```
In [36]:
          facet = sns.FacetGrid(train, hue="Survived",aspect=4)
          facet.map(sns.kdeplot, 'Age', shade= True)
          facet.set(xlim=(0, train['Age'].max()))
          facet.add_legend()
          plt.show()
          C:\Users\Saketh\anaconda3\lib\site-packages\seaborn\axisgrid.py:848: FutureWarning:
          `shade` is now deprecated in favor of `fill`; setting `fill=True`.
          This will become an error in seaborn v0.14.0; please update your code.
            func(*plot args, **plot kwargs)
          C:\Users\Saketh\anaconda3\lib\site-packages\seaborn\axisgrid.py:848: FutureWarning:
          `shade` is now deprecated in favor of `fill`; setting `fill=True`.
          This will become an error in seaborn v0.14.0; please update your code.
            func(*plot_args, **plot_kwargs)
           0.04
           0.03
          Density
0.02
                                                                                             Survived
                                                                                             0
           0.01
           0.00
                       10
                                 20
                                           30
                                                              50
                                                                                 70
                                                                                           80
                                                    Age
          facet = sns.FacetGrid(train, hue="Survived",aspect=4)
In [37]:
          facet.map(sns.kdeplot, 'Age', shade= True)
          facet.set(xlim=(0, train['Age'].max()))
          facet.add legend()
          plt.xlim(10,50)
          C:\Users\Saketh\anaconda3\lib\site-packages\seaborn\axisgrid.py:848: FutureWarning:
          `shade` is now deprecated in favor of `fill`; setting `fill=True`.
          This will become an error in seaborn v0.14.0; please update your code.
            func(*plot_args, **plot_kwargs)
          C:\Users\Saketh\anaconda3\lib\site-packages\seaborn\axisgrid.py:848: FutureWarning:
          `shade` is now deprecated in favor of `fill`; setting `fill=True`.
          This will become an error in seaborn v0.14.0; please update your code.
            func(*plot_args, **plot_kwargs)
          (10.0, 50.0)
Out[37]:
           0.04
           0.03
          Density
0.02
                                                                                            Survived
                                                                                             0
                                                                                             ____ 1
           0.01
           0.00
```

Those who were 20 to 30 years old were more dead and more survived.

```
In [38]:
        train.info()
         test.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
                      891 non-null int64
             Survived
          2
             Pclass
                         891 non-null
                                        int64
          3
                         891 non-null
             Sex
                                      int64
                       891 non-null float64
             Age
          5
                       891 non-null
             SibSp
                                        int64
          6
             Parch
                         891 non-null
                                        int64
          7
             Ticket
                       891 non-null
                                        object
          8
            Fare
                         891 non-null
                                        float64
          9
             Cabin
                         204 non-null
                                        object
         10 Embarked
                         889 non-null
                                        object
         11 Title
                         891 non-null
                                        int64
         dtypes: float64(2), int64(7), object(3)
         memory usage: 83.7+ KB
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 418 entries, 0 to 417
        Data columns (total 11 columns):
                       Non-Null Count Dtype
             -----
                         -----
         0
             PassengerId 418 non-null
                                        int64
             Pclass 418 non-null
                                        int64
          2
             Sex
                         418 non-null
                                      int64
          3
             Age
                         418 non-null float64
          4
            SibSp
                       418 non-null int64
          5
             Parch
                       418 non-null int64
          6
             Ticket
                         418 non-null
                                        object
         7
             Fare
                         417 non-null
                                        float64
          8
             Cabin
                         91 non-null
                                        object
          9
             Embarked
                         418 non-null
                                        object
         10 Title
                         418 non-null
                                        int64
         dtypes: float64(2), int64(6), object(3)
         memory usage: 36.0+ KB
```

4.2 Binning

Binning/Converting Numerical Age to Categorical Variable

feature vector map:

child: 0young: 1

adult: 2

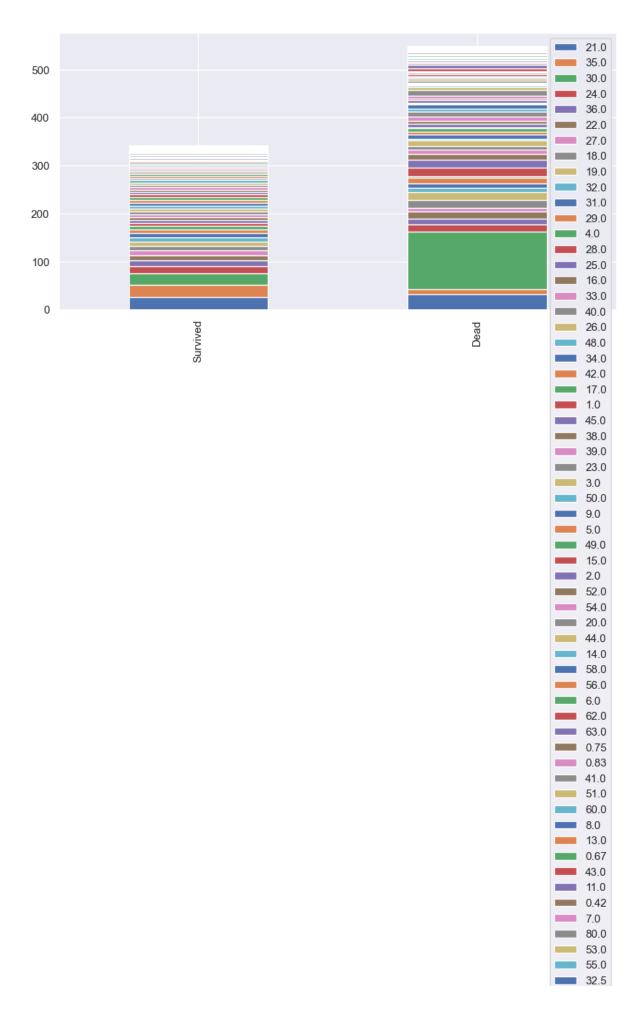
• mid-age: 3

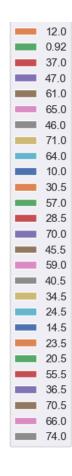
• senior: 4

In [39]:	tr	ain.head()											
Out[39]:		PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked [*]	1
	0	1	0	3	0	22.0	1	0	A/5 21171	7.2500	NaN	S	
	1	2	1	1	1	38.0	1	0	PC 17599	71.2833	C85	С	
	2	3	1	3	1	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S	
	3	4	1	1	1	35.0	1	0	113803	53.1000	C123	S	
	4	5	0	3	0	35.0	0	0	373450	8.0500	NaN	S	

Map the value of Age

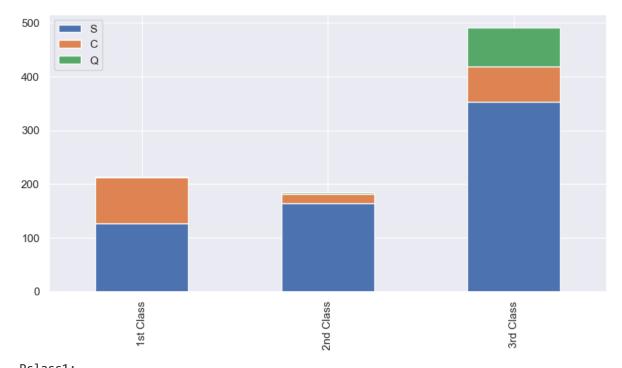
```
In [40]: train.head()
bar_chart('Age')
```





Map the value of Pclass

```
In [41]: Pclass1 = train[train['Pclass'] == 1]['Embarked'].value_counts()
    Pclass2 = train[train['Pclass'] == 2]['Embarked'].value_counts()
    Pclass3 = train[train['Pclass'] == 3]['Embarked'].value_counts()
    df = pd.DataFrame([Pclass1,Pclass2,Pclass3])
    df.index = ['1st Class','2nd Class','3rd Class']
    df.plot(kind = 'bar', stacked = True, figsize=(10,5))
    plt.show()
    print("Pclass1:\n",Pclass1)
    print("Pclass2:\n",Pclass2)
    print("Pclass3:\n",Pclass3)
```



```
Pclass1:
S 127
C 85
Q 2
Name: Embarked, dtype: int64
Pclass2:
S 164
```

17

Name: Embarked, dtype: int64

Pclass3: S 353 Q 72 C 66

C

Name: Embarked, dtype: int64

more than 50 % of 1st class are from S embark. more than 50 % of 2st class are from S embark. more than 50 % of 3st class are from S embark.

fill out missing embark with S embark

Map the value of Embarked

```
In [42]: for dataset in train_test_data:
    dataset['Embarked'] = dataset['Embarked'].fillna('S')
    train.head()
```

Out[42]:		PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked 1
	0	1	0	3	0	22.0	1	0	A/5 21171	7.2500	NaN	S
	1	2	1	1	1	38.0	1	0	PC 17599	71.2833	C85	С
	2	3	1	3	1	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
	3	4	1	1	1	35.0	1	0	113803	53.1000	C123	S
	4	5	0	3	0	35.0	0	0	373450	8.0500	NaN	S
In [43]:		barked_mapp r dataset i dataset['	n train_t	test_da	ta:		-	'].map	(embarked_	_mapping	;)	

```
dataset['Embarked'] = dataset['Embarked'].map(embarked_mapping)
```

Map the value of Fare

In [44]: train["Fare"].fillna(train.groupby("Pclass")["Fare"].transform("median"), inplace=T
 test["Fare"].fillna(test.groupby("Pclass")["Fare"].transform("median"), inplace=Tru
 train.head(10)

Out[44]:		Passengerld	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked 1
	0	1	0	3	0	22.0	1	0	A/5 21171	7.2500	NaN	0
	1	2	1	1	1	38.0	1	0	PC 17599	71.2833	C85	1
	2	3	1	3	1	26.0	0	0	STON/O2. 3101282	7.9250	NaN	0
	3	4	1	1	1	35.0	1	0	113803	53.1000	C123	0
	4	5	0	3	0	35.0	0	0	373450	8.0500	NaN	0
	5	6	0	3	0	30.0	0	0	330877	8.4583	NaN	2
	6	7	0	1	0	54.0	0	0	17463	51.8625	E46	0
	7	8	0	3	0	2.0	3	1	349909	21.0750	NaN	0
	8	9	1	3	1	27.0	0	2	347742	11.1333	NaN	0
	9	10	1	2	1	14.0	1	0	237736	30.0708	NaN	1

```
In [45]: facet = sns.FacetGrid(train, hue="Survived",aspect=4 )
    facet.map(sns.kdeplot, 'Fare', shade = True)
    facet.set(xlim = (0, train['Fare'].max()))
    facet.add_legend()
    plt.show()
```

In [46]:

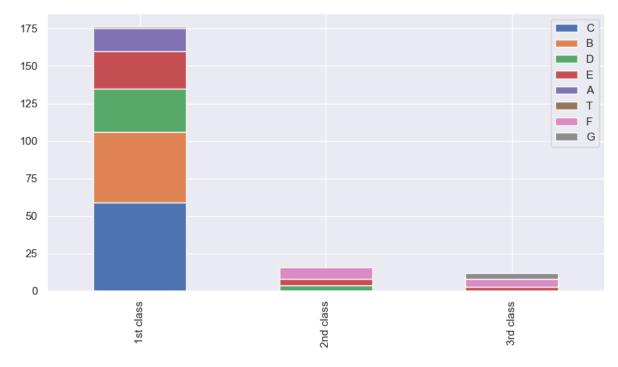
Out[46]:

```
C:\Users\Saketh\anaconda3\lib\site-packages\seaborn\axisgrid.py:848: FutureWarning:
`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.
  func(*plot_args, **plot_kwargs)
C:\Users\Saketh\anaconda3\lib\site-packages\seaborn\axisgrid.py:848: FutureWarning:
`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.
  func(*plot_args, **plot_kwargs)
 0.030
 0.025
 0.020
 0.015
                                                                                    Survived
                                                                                    0
 0.010
                                                                                     ____1
 0.005
 0.000
                   100
                                                  300
                                                                 400
                                                                                 500
                                           Fare
facet = sns.FacetGrid(train, hue="Survived",aspect=4)
facet.map(sns.kdeplot, 'Fare', shade= True)
facet.set(xlim=(0, train['Fare'].max()))
facet.add_legend()
plt.xlim(0, 20)
C:\Users\Saketh\anaconda3\lib\site-packages\seaborn\axisgrid.py:848: FutureWarning:
`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.
  func(*plot_args, **plot_kwargs)
C:\Users\Saketh\anaconda3\lib\site-packages\seaborn\axisgrid.py:848: FutureWarning:
`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.
  func(*plot args, **plot kwargs)
(0.0, 20.0)
 0.030
 0.025
 0.020
                                                                                    Survived
 0.015
                                                                                     0
 0.010
 0.005
 0.000
    0.0
              2.5
                        5.0
                                 7.5
                                           10.0
                                                     12.5
                                                                        17.5
                                                                                  20.0
                                                               15.0
                                           Fare
train.head()
```

In [47]:

Out[47]:	Passengerlo	l Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked 1
	0 1	C	3	0	22.0	1	0	A/5 21171	7.2500	NaN	0
	1 2	. 1	1	1	38.0	1	0	PC 17599	71.2833	C85	1
	2 3	3 1	3	1	26.0	0	0	STON/O2. 3101282	7.9250	NaN	0
	3	. 1	1	1	35.0	1	0	113803	53.1000	C123	0
	4 5	, c	3	0	35.0	0	0	373450	8.0500	NaN	0
In [48]:	n [48]: train.Cabin.value_counts().head()										
Out[48]:	B96 B98 G6 C23 C25 C27 C22 C26 F33 Name: Cabin,	4 4 4 3 3 dtype: i	.nt64								

Map the value of Cabin



```
In [52]: # fill missing Fare with median fare for each Pclass
    train["Cabin"].fillna(train.groupby("Pclass")["Cabin"].transform("median"), inplace
    test["Cabin"].fillna(test.groupby("Pclass")["Cabin"].transform("median"), inplace=T
```

Map the value of Family Size

```
train["FamilySize"] = train["SibSp"] + train["Parch"] + 1
In [53]:
         test["FamilySize"] = test["SibSp"] + test["Parch"] + 1
         facet = sns.FacetGrid(train, hue="Survived",aspect=4)
In [54]:
         facet.map(sns.kdeplot, 'FamilySize', shade= True)
         facet.set(xlim=(0, train['FamilySize'].max()))
         facet.add legend()
         plt.xlim(0)
         C:\Users\Saketh\anaconda3\lib\site-packages\seaborn\axisgrid.py:848: FutureWarning:
          `shade` is now deprecated in favor of `fill`; setting `fill=True`.
         This will become an error in seaborn v0.14.0; please update your code.
           func(*plot_args, **plot_kwargs)
         C:\Users\Saketh\anaconda3\lib\site-packages\seaborn\axisgrid.py:848: FutureWarning:
         `shade` is now deprecated in favor of `fill`; setting `fill=True`.
         This will become an error in seaborn v0.14.0; please update your code.
           func(*plot_args, **plot_kwargs)
         (0.0, 11.0)
Out[54]:
```

```
0.5

0.4

0.2

0.1

0.0

0.2

0.1

0.0

0.2

0.1

0.0

0.2

0.1

0.0

10

FamilySize
```

In [55]: family_mapping = {1: 0, 2: 0.4, 3: 0.8, 4: 1.2, 5: 1.6, 6: 2, 7: 2.4, 8: 2.8, 9: 3.
 for dataset in train_test_data:
 dataset['FamilySize'] = dataset['FamilySize'].map(family_mapping)

In [56]: train.head()

Out[56]:		PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	٦
	0	1	0	3	0	22.0	1	0	A/5 21171	7.2500	2.0	0	_
	1	2	1	1	1	38.0	1	0	PC 17599	71.2833	0.8	1	
	2	3	1	3	1	26.0	0	0	STON/O2. 3101282	7.9250	2.0	0	
	3	4	1	1	1	35.0	1	0	113803	53.1000	0.8	0	
	4	5	0	3	0	35.0	0	0	373450	8.0500	2.0	0	

```
In [57]: features_drop = ['Ticket','SibSp','Parch']
    train = train.drop(features_drop, axis = 1)
    test = test.drop(features_drop,axis=1)
    train = train.drop(['PassengerId'], axis=1)
```

```
In [58]: train_data = train.drop('Survived', axis = 1)
    target = train['Survived']
    train_data.shape, target.shape
```

Out[58]: ((891, 8), (891,))

In [59]: train_data.head(10)

Out[59]:		Pclass	Sex	Age	Fare	Cabin	Embarked	Title	FamilySize
	0	3	0	22.0	7.2500	2.0	0	0	0.4
	1	1	1	38.0	71.2833	0.8	1	2	0.4
	2	3	1	26.0	7.9250	2.0	0	1	0.0
	3	1	1	35.0	53.1000	0.8	0	2	0.4
	4	3	0	35.0	8.0500	2.0	0	0	0.0
	5	3	0	30.0	8.4583	2.0	2	0	0.0
	6	1	0	54.0	51.8625	1.6	0	0	0.0
	7	3	0	2.0	21.0750	2.0	0	3	1.6
	8	3	1	27.0	11.1333	2.0	0	2	0.8
	9	2	1	14.0	30.0708	1.8	1	2	0.4

5. Modelling

```
In [60]: from sklearn.neighbors import KNeighborsClassifier
    from sklearn.tree import DecisionTreeClassifier,ExtraTreeClassifier
    from sklearn.ensemble import RandomForestClassifier,ExtraTreesClassifier,BaggingCla
    from sklearn.naive_bayes import GaussianNB
    from sklearn.svm import SVC
    import numpy as np
```

In [61]: train.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 9 columns):

#	Column	Non-Null Count	Dtype					
0	Survived	891 non-null	int64					
1	Pclass	891 non-null	int64					
2	Sex	891 non-null	int64					
3	Age	891 non-null	float64					
4	Fare	891 non-null	float64					
5	Cabin	891 non-null	float64					
6	Embarked	891 non-null	int64					
7	Title	891 non-null	int64					
8	FamilySize	891 non-null	float64					
<pre>dtypes: float64(4), int64(5)</pre>								

memory usage: 62.8 KB

6.Cross Validation(k-fold)

```
from sklearn.model_selection import KFold
In [62]:
         from sklearn.model selection import cross val score
          k_fold = KFold(n_splits=10, shuffle=True, random_state=0)
In [63]: | clf = [KNeighborsClassifier(n_neighbors = 13),DecisionTreeClassifier(),
                RandomForestClassifier(n_estimators=13),GaussianNB(),SVC(),ExtraTreeClassifi
               GradientBoostingClassifier(n estimators=10, learning rate=1,max features=3, m
          def model fit():
             scoring = 'accuracy'
             for i in range(len(clf)):
                  score = cross_val_score(clf[i], train_data, target, cv=k_fold, n_jobs=1, sd
                  print("Score of Model",i,":",round(np.mean(score)*100,2))
         model_fit()
         Score of Model 0: 72.39
         Score of Model 1: 77.22
         Score of Model 2: 81.14
         Score of Model 3: 79.23
         Score of Model 4: 67.34
         Score of Model 5: 76.33
         Score of Model 6: 81.15
         Score of Model 7: 81.37
         Score of Model 8: 80.13
```

Score of **Model 4**: **83.5** Which is **Support Vector Machine**

7. Testing

```
In [64]: clf1 = SVC()
          clf1.fit(train_data, target)
          test_data = test.drop(['PassengerId'], axis=1)
          test_data
          prediction = clf1.predict(test_data)
In [65]: test_data['Survived'] = prediction
          test_data.head()
Out[65]:
             Pclass Sex Age
                                Fare Cabin Embarked Title FamilySize Survived
                 3
                     0 34.5
                              7.8292
                                        2.0
                                                         0
                                                                  0.0
                                                                             0
                 3
                     1 47.0
                              7.0000
                                        2.0
                                                         2
                                                                  0.4
                                                                             0
          2
                 2
                     0 62.0
                              9.6875
                                        2.0
                                                   2
                                                         0
                                                                  0.0
                                                                             0
                 3
                                                   0
                                                         0
                                                                             0
          3
                     0 27.0
                             8.6625
                                        2.0
                                                                  0.0
                 3
                     1 22.0 12.2875
                                        2.0
                                                   0
                                                         2
                                                                             0
                                                                  8.0
```

You can see that **Survived** Column which was predicted using this Support **Vector Machine Algorithm.**

```
In [66]: test_data_sample = pd.read_csv('test.xls')
    test_data_sample["Survived"] = prediction

In [67]: test_data_sample[['PassengerId','Survived']].to_csv("submission.csv", index = False)
In []:
```