1. Importing the Data Set and Libraries

In [414]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
```

In [415]:

```
train.head(5)
```

Out[415]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500
1	2	1	1	Cumings, Mrs. John 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	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500

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

3. Superficial Analysis

In [416]:

```
train.shape[0]
```

Out[416]:

```
891
```

In [417]:

```
test.shape[0]
```

Out[417]:

```
418
```

In [418]:

```
train.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 [419]:

```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 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  
 7   Ticket       418 non-null    object 
 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
```

In [420]:

```
train.isnull().sum()
```

Out[420]:

```
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 [421]:

```
test.isnull().sum()
```

Out[421]:

```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

We can see that there is a lot of missing data in columns Cabin, Age and Embarked There are two approaches we can make, one is to simply delete all the rows with missing data and the other is trying to replace the missing values with data that makes sense

Since there are a lot of rich data in this rows, we'll choose the latter

4. Analyzing the Correlation

In [422]:

```
# Gender
males = train.loc[train['Sex'] == 'male']
survived_males = males.loc[train['Survived'] == 1]
s_m = survived_males['Survived'].shape[0]

females = train.loc[train['Sex'] == 'female']
survived_females = females.loc[train['Survived'] == 1]
s_f = survived_females['Survived'].shape[0]

dead_males = males.loc[train['Survived'] == 0]
d_m = dead_males['Survived'].shape[0]

dead_females = females.loc[train['Survived'] == 0]
d_f = dead_females['Survived'].shape[0]
```

In [423]:

```
gender_survived = pd.DataFrame(data={'Males':[d_m, s_m], 'Females':[d_f, s_f]})
gender_survived['Perc'] = (gender_survived['Females'] / (gender_survived['Males'] + gen
der_survived['Females'])).round(2)
gender_survived['Total'] = (gender_survived['Males'] + gender_survived['Females']).roun
d(0)


gender_survived = gender_survived.T
gender_survived.columns = ['Dead', 'Survived']

gender_survived
```

Out[423]:

	Dead	Survived
Males	468.00	109.00
Females	81.00	233.00
Perc	0.15	0.68
Total	549.00	342.00

With this approach, we can clearly see that females were more likely to survive than males. This Matrix shows us that only 15% of the dead were females and the 68% that survived were females as well.

In [424]:

```
# Age
survived = train.loc[train['Survived'] == 1]
age_survived = pd.DataFrame(survived['Age'].describe().round(2))

dead = train.loc[train['Survived'] == 0]
age_dead = pd.DataFrame(dead['Age'].describe().round(2))
```

In [425]:

```
age_survived
```

Out[425]:

	Age
count	290.00
mean	28.34
std	14.95
min	0.42
25%	19.00
50%	28.00
75%	36.00
max	80.00

In [426]:

```
age_dead
```

Out[426]:

	Age
count	424.00
mean	30.63
std	14.17
min	1.00
25%	21.00
50%	28.00
75%	39.00
max	74.00

Comparing the age

In [427]:

```
# Pclass
Pclass_s = pd.DataFrame(survived.groupby(['Pclass'])['Survived'].value_counts())
s = pd.DataFrame(data=[[1, 136], [2, 87], [3, 119]], columns=['Pclass', 'Survived'])
s
```

Out[427]:

	Pclass	Survived
0	1	136
1	2	87
2	3	119

In [428]:

```
Pclass_s = pd.DataFrame(dead.groupby(['Pclass'])['Survived'].value_counts())
d = pd.DataFrame(data=[[1, 80], [2, 97], [3, 372]], columns=['Pclass', 'Dead'])
d['Survived'] = s['Survived']
d['Fatality Rate'] = (d['Dead']/(d['Dead'] + d['Survived'])).round(2)
d
```

Out[428]:

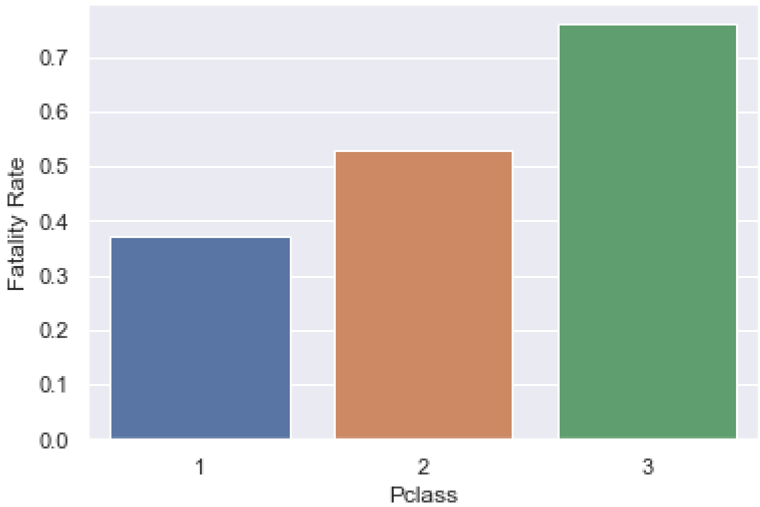
	Pclass	Dead	Survived	Fatality Rate
0	1	80	136	0.37
1	2	97	87	0.53
2	3	372	119	0.76

In [429]:

```
sns.barplot(x=d['Pclass'], y=d['Fatality Rate'])
```

Out[429]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20bad570048>
```



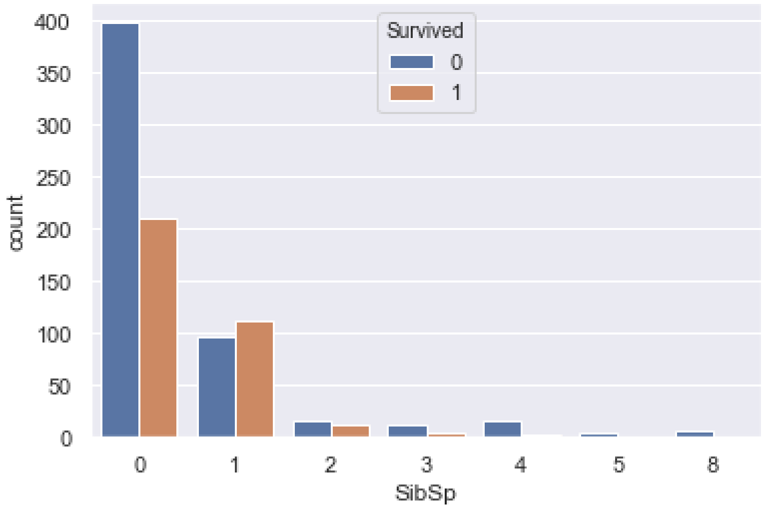
As we can see, people that were on the cheapest class had a much smaller chance of survival

In [430]:

```
#SibSp
sns.countplot(x=train['SibSp'], hue=train['Survived'])
```

Out[430]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20bad5b9548>
```

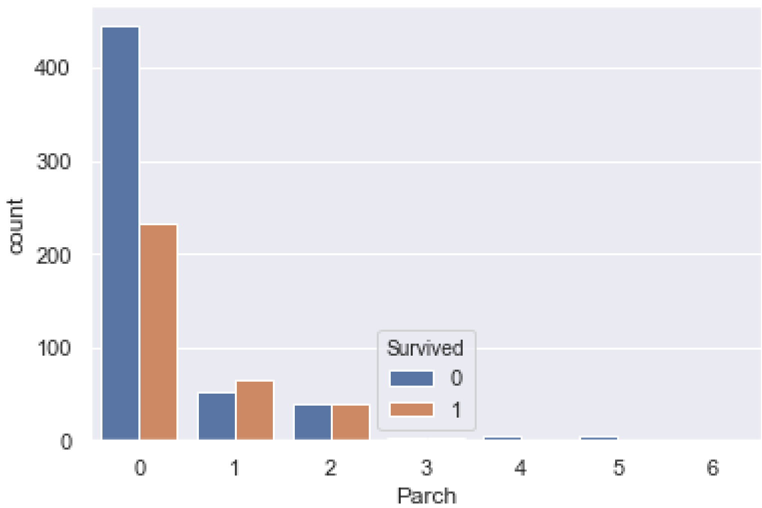


In [431]:

```
#Parch
sns.countplot(x=train['Parch'], hue=train['Survived'])
```

Out[431]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20bad649288>
```

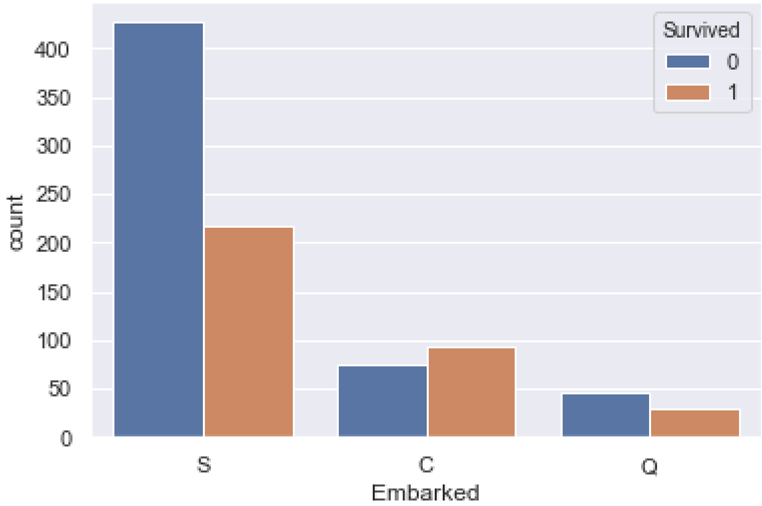


In [432]:

```
#Embarked
sns.countplot(x=train['Embarked'], hue=train['Survived'])
```

Out[432]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20bad6bb288>
```



5. Filling the values through feature engineering

In this process, we'll try to fill up the gaps in our data in order for the machine learning model to work

We'll do such by using statistic metrics and intuitive work in out database

In [433]:

```
train['Title'] = train['Name'].str.extract(' ([A-za-z]+)\.', expand=False)
test['Title'] = test['Name'].str.extract(' ([A-za-z]+)\.', expand=False)
```

In [434]:

```
train['Title'].value_counts()
```

Out[434]:

```
Mr          517
Miss        182
Mrs         125
Master       40
Dr            7
Rev           6
Col           2
Mlle          2
Major         2
Capt          1
Lady          1
Sir           1
Don           1
Countess      1
Ms            1
Mme           1
Jonkheer      1
Name: Title, dtype: int64
```

Title Map: Mr: 0 Miss: 1 Mrs: 2 Others:3

In [435]:

```
title_mapping = {"Mr": 0, "Miss": 1, "Mrs": 2,
                 "Master": 3, "Dr": 3, "Rev": 3, "Col": 3, "Major": 3, "Mlle": 3,"Count
ess": 3,
                 "Ms": 3, "Lady": 3, "Jonkheer": 3, "Don": 3, "Dona" : 3, "Mme": 3,"Cap
t": 3,"Sir": 3 }
```

In [436]:

```
train['Title'] = train['Title'].map(title_map)
test['Title'] = test['Title'].map(title_map)
```

In [437]:

```
train.head()
```

Out[437]:

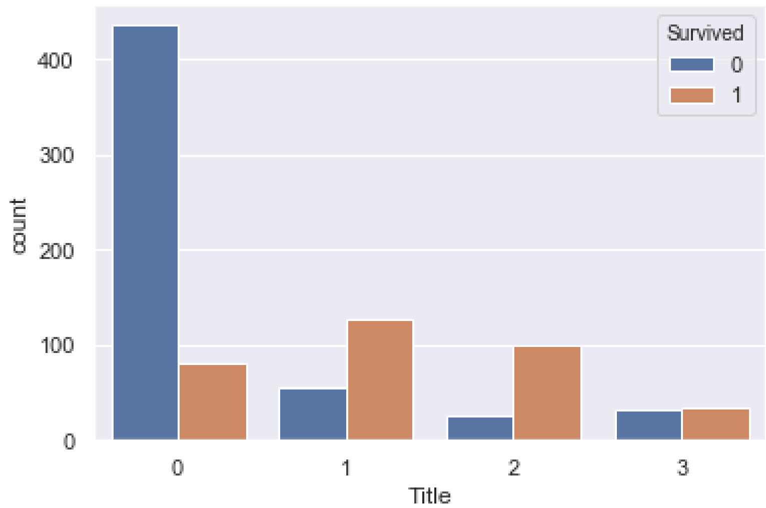
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500

In [438]:

```
sns.countplot(x=train['Title'], hue=train['Survived'])
```

Out[438]:

<matplotlib.axes._subplots.AxesSubplot at 0x20bad749b88>



In [439]:

```
# As we can see, "Mr" had a high chance of dying
```

In [440]:

```
sex_map = {"male":0, "female":1}
train['Sex'] = train['Sex'].map(sex_map)
test['Sex'] = test['Sex'].map(sex_map)
```

In [441]:

```
train['Age'].fillna(train.groupby('Title')['Age'].transform("median"), inplace=True)
test['Age'].fillna(test.groupby('Title')['Age'].transform("median"), inplace=True)
```

In [442]:

```
test['Title'] = test['Title'].fillna(3)
```

In [443]:

```
train.info()
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 13 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    int64  
 5   Age          891 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 
 12  Title        891 non-null    int64  
dtypes: float64(2), int64(7), object(4)
memory usage: 90.6+ KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  418 non-null    int64  
 1   Pclass       418 non-null    int64  
 2   Name         418 non-null    object 
 3   Sex          418 non-null    int64  
 4   Age          418 non-null    float64
 5   SibSp        418 non-null    int64  
 6   Parch        418 non-null    int64  
 7   Ticket       418 non-null    object 
 8   Fare         417 non-null    float64
 9   Cabin        91 non-null     object 
 10  Embarked     418 non-null    object 
 11  Title        418 non-null    float64
dtypes: float64(3), int64(5), object(4)
memory usage: 39.3+ KB
```

For the Age field, we succesfully filled the gaps using the categorization of the Title and Sex.

In [444]:

```
train['Embarked'] = train['Embarked'].fillna('S')
test['Embarked'] = test['Embarked'].fillna('S')
```

In [445]:

```
train.info()
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 13 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    int64  
 5   Age          891 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     891 non-null    object 
 12  Title        891 non-null    int64  
dtypes: float64(2), int64(7), object(4)
memory usage: 90.6+ KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  418 non-null    int64  
 1   Pclass       418 non-null    int64  
 2   Name         418 non-null    object 
 3   Sex          418 non-null    int64  
 4   Age          418 non-null    float64
 5   SibSp        418 non-null    int64  
 6   Parch        418 non-null    int64  
 7   Ticket       418 non-null    object 
 8   Fare         417 non-null    float64
 9   Cabin        91 non-null     object 
 10  Embarked     418 non-null    object 
 11  Title        418 non-null    float64
dtypes: float64(3), int64(5), object(4)
memory usage: 39.3+ KB
```

In [446]:

```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  418 non-null    int64  
 1   Pclass       418 non-null    int64  
 2   Name         418 non-null    object 
 3   Sex          418 non-null    int64  
 4   Age          418 non-null    float64
 5   SibSp        418 non-null    int64  
 6   Parch        418 non-null    int64  
 7   Ticket       418 non-null    object 
 8   Fare         417 non-null    float64
 9   Cabin        91 non-null     object 
 10  Embarked     418 non-null    object 
 11  Title        418 non-null    float64
dtypes: float64(3), int64(5), object(4)
memory usage: 39.3+ KB
```

Here we just use a arbitrary value to fill the embarked field

In [447]:

```
train.loc[train['Age'] <= 16, 'Age'] = 0
train.loc[ (train['Age'] > 16) & (train['Age'] <= 26), 'Age'] = 1
train.loc[ (train['Age'] > 26) & (train['Age'] <= 36), 'Age'] = 2
train.loc[ (train['Age'] > 36) & (train['Age'] <= 62), 'Age'] = 3
train.loc[ train['Age'] > 62, 'Age'] = 4

test.loc[train['Age'] <= 16, 'Age'] = 0
test.loc[ (test['Age'] > 16) & (test['Age'] <= 26), 'Age'] = 1
test.loc[ (test['Age'] > 26) & (test['Age'] <= 36), 'Age'] = 2
test.loc[ (test['Age'] > 36) & (test['Age'] <= 62), 'Age'] = 3
test.loc[ test['Age'] > 62, 'Age'] = 4
```

In order to use the data for a statistic model, we have to attribute a numeric value that makes sense with the data we currently own. So, we made a small library for the Age values

In [448]:

```
embarked_map = {"S": 0, "C": 1, "Q": 2}
train['Embarked'] = train['Embarked'].map(embarked_map)
test['Embarked'] = test['Embarked'].map(embarked_map)
```

In [449]:

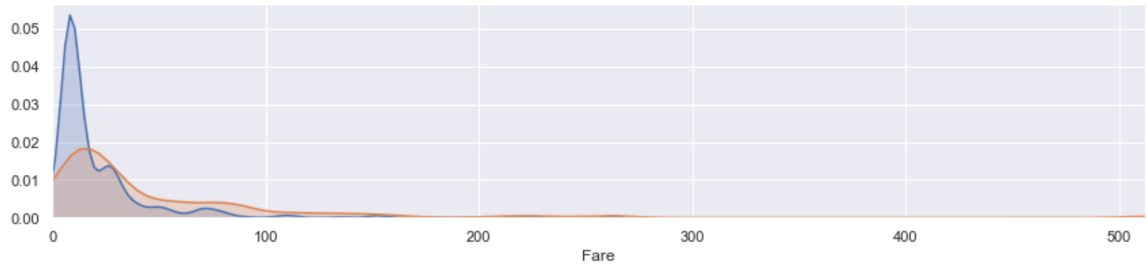
```
train['Fare'].fillna(train.groupby('Pclass')['Fare'].transform("median"), inplace=True)
test['Fare'].fillna(test.groupby('Pclass')['Fare'].transform("median"), inplace=True)
```

In [450]:

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

Out[450]:

```
<seaborn.axisgrid.FacetGrid at 0x20bad5698c8>
```



In [451]:

```
train.loc[train['Fare'] <= 17, 'Fare'] = 0
train.loc[ (train['Fare'] > 17) & (train['Fare'] <= 30), 'Fare'] = 1
train.loc[ (train['Fare'] > 30) & (train['Fare'] <= 100), 'Fare'] = 2
train.loc[ train['Fare'] > 100, 'Fare'] = 4

test.loc[test['Fare'] <= 17, 'Fare'] = 0
test.loc[ (test['Fare'] > 17) & (test['Fare'] <= 30), 'Fare'] = 1
test.loc[ (test['Fare'] > 30) & (test['Fare'] <= 100), 'Fare'] = 2
test.loc[ test['Fare'] > 100, 'Fare'] = 4
```

In [452]:

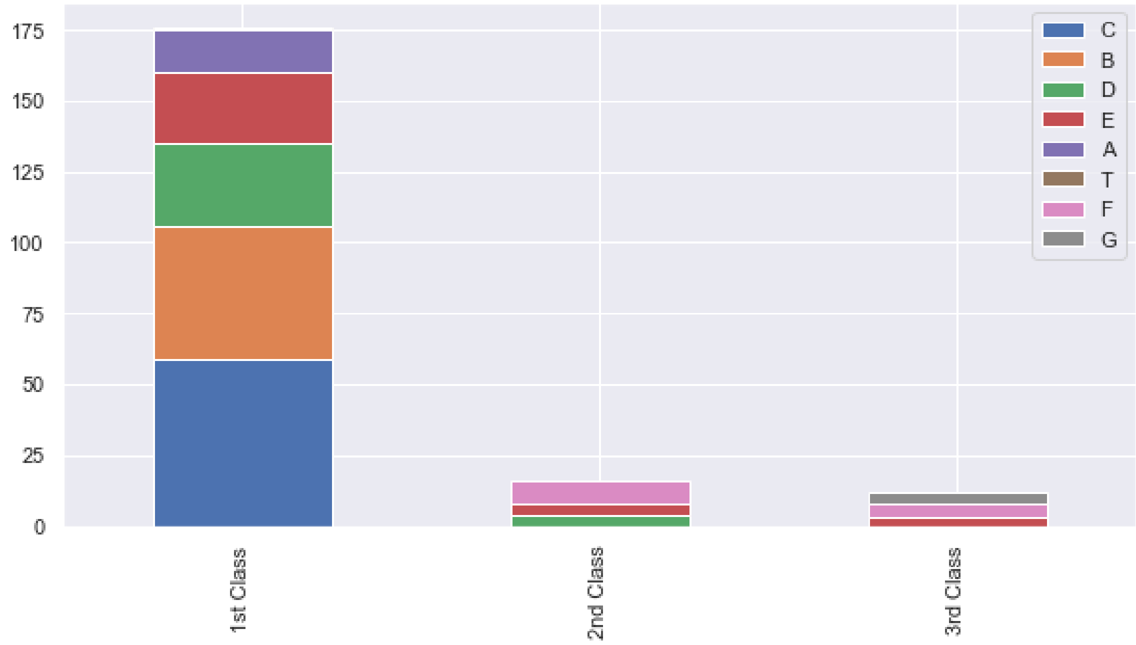
```
train['Cabin'] = train['Cabin'].str[:1]
test['Cabin'] = test['Cabin'].str[:1]
```

In [453]:

```
Pclass1 = train[train['Pclass']==1]['Cabin'].value_counts()
Pclass2 = train[train['Pclass']==2]['Cabin'].value_counts()
Pclass3 = train[train['Pclass']==3]['Cabin'].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))
```

Out[453]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20bad825f08>
```



In [454]:

```
cabin_map = {"A":0, "B":0.4, "C":0.8, "D":1.2, "E":1.6, "F":2, "G": 2.4, "T":2.8}
train['Cabin'] = train['Cabin'].map(cabin_map)
test['Cabin'] = test['Cabin'].map(cabin_map)
```

In [455]:

```
train['Cabin'].fillna(train.groupby('Pclass')['Cabin'].transform("median"), inplace=Tru
e)
test['Cabin'].fillna(test.groupby('Pclass')['Cabin'].transform("median"), inplace=True)
```

In [456]:

```
train.head()
```

Out[456]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cab
0	1	0	3	Braund, Mr. Owen Harris	0	1.0	1	0	A/5 21171	0.0	2
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	1	3.0	1	0	PC 17599	2.0	(
2	3	1	3	Heikkinen, Miss. Laina	1	1.0	0	0	STON/O2. 3101282	0.0	2
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	1	2.0	1	0	113803	2.0	(
4	5	0	3	Allen, Mr. William Henry	0	2.0	0	0	373450	0.0	2

In [457]:

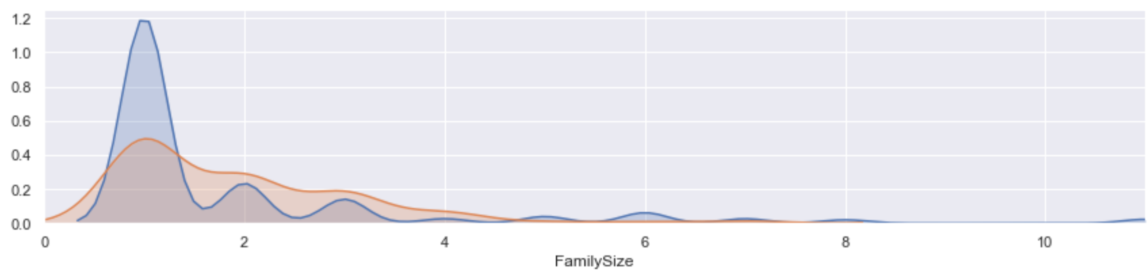
```
train['FamilySize'] = train['SibSp'] + train['Parch'] + 1
test['FamilySize'] = test['SibSp'] + test['Parch'] + 1
```

In [458]:

```
facet = sns.FacetGrid(train, hue='Survived', aspect=4)
facet.map(sns.kdeplot, "FamilySize", shade = True)
facet.set(xlim=(0, train['FamilySize'].max()))
```

Out[458]:

```
<seaborn.axisgrid.FacetGrid at 0x20bad8af108>
```



In [459]:

```
family_map = {1: 0, 2: 0.4, 3:0.8, 4:1.2, 5: 1.6, 6: 2, 7: 2.4, 8: 2.8, 9: 3.2, 10: 3.6
, 11: 4}
train['FamilySize'] = train['FamilySize'].map(family_map)
test['FamilySize'] = test['FamilySize'].map(family_map)
```

In [460]:

```
train = train.drop(['Ticket', 'SibSp', 'Parch', 'PassengerId', 'Name'], axis=1)
test = test.drop(['Ticket', 'SibSp', 'Parch', 'Name'], axis=1)
```

In [461]:

```
train_data = train.drop('Survived', axis=1)
target_train = train['Survived']
```

In [462]:

```
train_data.head()
```

Out[462]:

	Pclass	Sex	Age	Fare	Cabin	Embarked	Title	FamilySize
0	3	0	1.0	0.0	2.0	0	0	0.4
1	1	1	3.0	2.0	0.8	1	2	0.4
2	3	1	1.0	0.0	2.0	0	1	0.0
3	1	1	2.0	2.0	0.8	0	2	0.4
4	3	0	2.0	0.0	2.0	0	0	0.0

6. Machine Learning Section

In this section, we'll first choose the best model for the train dataset. For that, we will use some models described below and check their score.

In [463]:

```
# Importing Classifier Modules
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC

import numpy as np
```

In [464]:

```
##6.1 Cross Validation
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
k_fold = KFold(n_splits=10, shuffle=True, random_state=0)

#Here we choose to split the dataset into 10 parts in order to build the algorithm
```

In [465]:

```
##6.1.1 kNN Method
clf = KNeighborsClassifier(n_neighbors = 13)
scoring = 'accuracy'
score = cross_val_score(clf, train_data, target_train, cv=k_fold, n_jobs=1, scoring=sco
ring)
round(np.mean(score)*100, 2)
```

Out[465]:

81.82

In [466]:

```
##6.1.2 Decision Tree
clf = DecisionTreeClassifier()
scoring = 'accuracy'
score = cross_val_score(clf, train_data, target_train, cv=k_fold, n_jobs=1, scoring=sco
ring)
round(np.mean(score)*100, 2)
```

Out[466]:

79.8

In [467]:

```
##6.1.3 Random Forest
clf = RandomForestClassifier(n_estimators=13)
scoring = 'accuracy'
score = cross_val_score(clf, train_data, target_train, cv=k_fold, n_jobs=1, scoring=sco
ring)
round(np.mean(score)*100, 2)
```

Out[467]:

81.6

In [468]:

```
##6.1.4 Naive Bayes
clf = GaussianNB()
scoring = 'accuracy'
score = cross_val_score(clf, train_data, target_train, cv=k_fold, n_jobs=1, scoring=sco
ring)
round(np.mean(score)*100, 2)
```

Out[468]:

78.44

In [469]:

```
##6.1.4 SVM
clf = SVC()
scoring = 'accuracy'
score = cross_val_score(clf, train_data, target_train, cv=k_fold, n_jobs=1, scoring=sco
ring)
round(np.mean(score)*100,2)
```

Out[469]:

```
83.5
```

7. Testing

In [470]:

```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  418 non-null    int64  
 1   Pclass       418 non-null    int64  
 2   Sex          418 non-null    int64  
 3   Age          418 non-null    float64
 4   Fare         418 non-null    float64
 5   Cabin        418 non-null    float64
 6   Embarked     418 non-null    int64  
 7   Title        418 non-null    float64
 8   FamilySize   418 non-null    float64
dtypes: float64(5), int64(4)
memory usage: 29.5 KB
```

In [471]:

```
clf = SVC()
clf.fit(train_data, target_train)

test_data = test.drop("PassengerId", axis=1).copy()
prediction = clf.predict(test_data)
```

In [472]:

```
submission = pd.DataFrame({
        "PassengerId": test["PassengerId"],
        "Survived": prediction
    })

submission.to_csv('submission.csv', index=False)
```

In [473]:

```
submission = pd.read_csv('submission.csv')
submission.head()
```

Out[473]:

	PassengerId	Survived
0	892	0
1	893	1
2	894	0
3	895	0
4	896	1

In [ ]:

```
```