titanic-survival-prediction-ml

October 9, 2024

[71]:
```python
# linear algebra
import numpy as np

#Common Model Algorithms
from sklearn import svm, tree, linear_model, neighbors, naive_bayes, ensemble,␣
↪discriminant_analysis, gaussian_process
from xgboost import XGBClassifier

#Common Model Helpers
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn import feature_selection
from sklearn import model_selection
from sklearn import metrics
from sklearn.model_selection import ShuffleSplit

#ignore warnings
import warnings
warnings.filterwarnings('ignore')
print('-'*25)

# data visualization
import seaborn as sns
%matplotlib inline
from matplotlib import pyplot as plt
from matplotlib import style

# Algorithms
from sklearn import linear_model
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC, LinearSVC
from sklearn.naive_bayes import GaussianNB
```

```
#Configure Visualization Defaults
#%matplotlib inline = show plots in Jupyter Notebook browser
%matplotlib inline
# mpl.style.use('ggplot')
# sns.set_style('white')
# pylab.rcParams['figure.figsize'] = 12,8
```

----

1. Question or problem definition

The competition is simple: Use the Titanic passenger data (name, age, price of ticket, etc) to try to predict who will survive and who will die.

Get the data

[72]:
```
# Get the data
import pandas as pd

sub_df = pd.read_csv("/home/pc13/Desktop/Untitled Folder/titanic/test.csv")
df = pd.read_csv("/home/pc13/Desktop/Untitled Folder/titanic/train.csv")
# df = pd.concat([train_df, test_df])

df.columns.values
```

[72]:
```
array(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'], dtype=object)
```

There are 11 features and one target variable (survived).

"PassengerId", **"Ticket"** and **"Name"** would be highly correlated with the survival rate as they are unique values for each customer. However, they are too specific to be used for modeling. We need to generalize these fields.

[8]:
```
print('Descriptive statistics of train_df:\n')
df.describe(include = 'all')
```

```
Descriptive statistics of train_df:
```

[8]:

	PassengerId	Survived	Pclass	Name	Sex	\
count	891.000000	891.000000	891.000000	891	891	
unique	NaN	NaN	NaN	891	2	
top	NaN	NaN	NaN	Braund, Mr. Owen Harris	male	
freq	NaN	NaN	NaN	1	577	
mean	446.000000	0.383838	2.308642	NaN	NaN	
std	257.353842	0.486592	0.836071	NaN	NaN	
min	1.000000	0.000000	1.000000	NaN	NaN	
25%	223.500000	0.000000	2.000000	NaN	NaN	

```
50%      446.000000    0.000000    3.000000                     NaN    NaN
75%      668.500000    1.000000    3.000000                     NaN    NaN
max      891.000000    1.000000    3.000000                     NaN    NaN

               Age       SibSp       Parch  Ticket        Fare    Cabin  \
count   714.000000  891.000000  891.000000     891  891.000000      204
unique         NaN         NaN         NaN     681         NaN      147
top            NaN         NaN         NaN  347082         NaN  B96 B98
freq           NaN         NaN         NaN       7         NaN        4
mean     29.699118    0.523008    0.381594     NaN   32.204208      NaN
std      14.526497    1.102743    0.806057     NaN   49.693429      NaN
min       0.420000    0.000000    0.000000     NaN    0.000000      NaN
25%      20.125000    0.000000    0.000000     NaN    7.910400      NaN
50%      28.000000    0.000000    0.000000     NaN   14.454200      NaN
75%      38.000000    1.000000    0.000000     NaN   31.000000      NaN
max      80.000000    8.000000    6.000000     NaN  512.329200      NaN

       Embarked
count       889
unique        3
top           S
freq        644
mean        NaN
std         NaN
min         NaN
25%         NaN
50%         NaN
75%         NaN
max         NaN
```

[9]:

```
df.head(5)
```

[9]:

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
```

```
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

[10]:
```python
sub_df.head(5)
```

[10]:
```
   PassengerId  Pclass                                          Name     Sex  \
0          892       3                              Kelly, Mr. James    male
1          893       3              Wilkes, Mrs. James (Ellen Needs)  female
2          894       2                     Myles, Mr. Thomas Francis    male
3          895       3                              Wirz, Mr. Albert    male
4          896       3  Hirvonen, Mrs. Alexander (Helga E Lindqvist)  female

    Age  SibSp  Parch   Ticket     Fare Cabin Embarked
0  34.5      0      0   330911   7.8292   NaN        Q
1  47.0      1      0   363272   7.0000   NaN        S
2  62.0      0      0   240276   9.6875   NaN        Q
3  27.0      0      0   315154   8.6625   NaN        S
4  22.0      1      1  3101298  12.2875   NaN        S
```

Now we can safely drop the Name feature from training and testing datasets. We also do not need the PassengerId feature in the training dataset.

[11]:
```python
df.shape, sub_df.shape
```

[11]:
```
((891, 12), (418, 11))
```

The values in the second column (**"Survived"**) can be used to determine whether each passenger survived or not:

- if it's a "1", the passenger survived.
- if it's a "0", the passenger died.

2. Wrangle, prepare, cleanse the data

—- Start the data cleaning—-

We need to make sure the data is clean before starting your analysis. As a reminder, we should check for:

- Duplicate records
- Consistent formatting
- Missing values
- Obviously wrong values (x)

Duplicate Records How many duplicate transaction records are there?

```
[12]: #Find the number duplicate record
print('df - Number of duplicate Record:', df.duplicated().sum())

print('sub_df - Number of duplicate Record:', sub_df.duplicated().sum())
```

```
df - Number of duplicate Record: 0
sub_df - Number of duplicate Record: 0
```

Missing Values How many missing values are there?

```
[13]: #Find the number of null per each columns
print('Columns in df with null values:\n')
print(df)
print("-"*30)

print('Columns in sub_df with null values:\n')
print(sub_df.isnull().sum())
print("-"*30)
```

```
Columns in df with null values:

     PassengerId  Survived  Pclass  \
0              1         0       3
1              2         1       1
2              3         1       3
3              4         1       1
4              5         0       3
..           …         …     …
886          887         0       2
887          888         1       1
888          889         0       3
889          890         1       1
890          891         0       3

                                                  Name     Sex   Age  SibSp  \
0                              Braund, Mr. Owen Harris    male  22.0      1
1    Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                               Heikkinen, Miss. Laina  female  26.0      0
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                             Allen, Mr. William Henry    male  35.0      0
..                                                 …     …   …    …
886                              Montvila, Rev. Juozas    male  27.0      0
887                       Graham, Miss. Margaret Edith  female  19.0      0
888           Johnston, Miss. Catherine Helen "Carrie"  female   NaN      1
889                              Behr, Mr. Karl Howell    male  26.0      0
890                                Dooley, Mr. Patrick    male  32.0      0

     Parch            Ticket     Fare Cabin Embarked
```

```
0        0         A/5 21171   7.2500   NaN        S
1        0          PC 17599  71.2833   C85        C
2        0  STON/O2. 3101282   7.9250   NaN        S
3        0            113803  53.1000  C123        S
4        0            373450   8.0500   NaN        S
..     …               …       …    …      …
886      0            211536  13.0000   NaN        S
887      0            112053  30.0000   B42        S
888      2        W./C. 6607  23.4500   NaN        S
889      0            111369  30.0000  C148        C
890      0            370376   7.7500   NaN        Q

[891 rows x 12 columns]
------------------------------
Columns in sub_df with null values:

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

[14]:

```python
combine = [df, sub_df]
```

Converting a categorical feature Now we can convert features which contain strings to numerical values. This is required by most model algorithms. Doing so will also help us in achieving the feature completing goal.

Let us start by converting Sex feature to a new feature called Gender where female=1 and male=0.

[15]:

```python
for dataset in combine:
    dataset['Sex'] = dataset['Sex'].map( {'female': 1, 'male': 0} ).astype(int)

df.head()
```

[15]:

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
```

```
4            5          0       3

                                                Name  Sex   Age  SibSp  Parch  \
0                            Braund, Mr. Owen Harris    0  22.0      1      0
1  Cumings, Mrs. John Bradley (Florence Briggs Th…    1  38.0      1      0
2                             Heikkinen, Miss. Laina    1  26.0      0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)    1  35.0      1      0
4                           Allen, Mr. William Henry    0  35.0      0      0

             Ticket     Fare Cabin Embarked
0         A/5 21171   7.2500   NaN        S
1          PC 17599  71.2833   C85        C
2  STON/O2. 3101282   7.9250   NaN        S
3            113803  53.1000  C123        S
4            373450   8.0500   NaN        S
```

There is misssing value in Age, Cabin and Embarked.

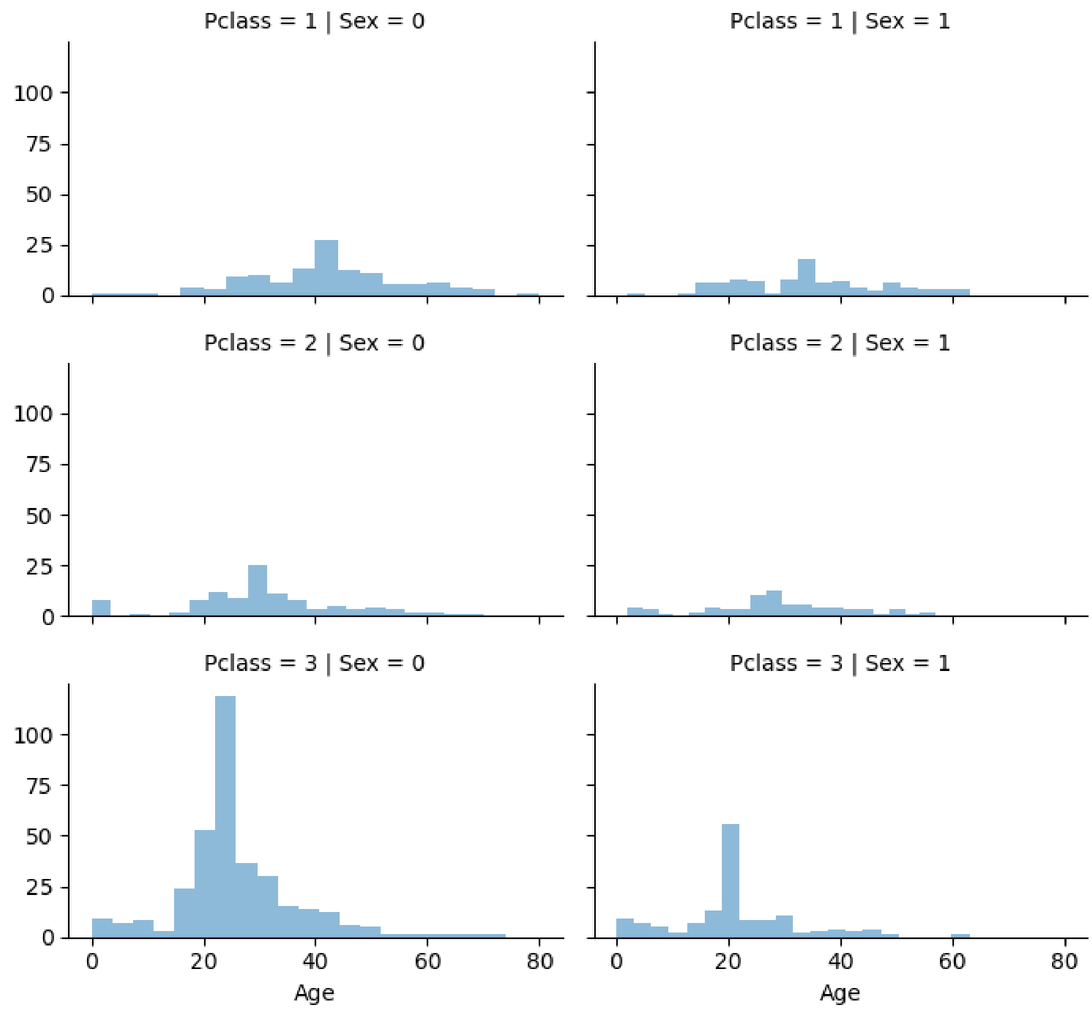
Handle missing value - numerical continuous variable Now we should start estimating and completing features with missing or null values. We will first do this for the Age feature.

We can consider three methods to complete a numerical continuous feature.

1. A simple way is to generate random numbers between mean and standard deviation.
2. More accurate way of guessing missing values is to use other correlated features. In our case we note correlation among Age, Gender, and Pclass. Guess Age values using median values for Age across sets of Pclass and Gender feature combinations. So, median Age for Pclass=1 and Gender=0, Pclass=1 and Gender=1, and so on…
3. Combine methods 1 and 2. So instead of guessing age values based on median, use random numbers between mean and standard deviation, based on sets of Pclass and Gender combinations.

Method 1 and 3 will introduce random noise into our models. The results from multiple executions might vary. We will prefer method 2

[21]:
```python
import seaborn as sns
import matplotlib.pyplot as plt

# Assuming df is your DataFrame
grid = sns.FacetGrid(df, row='Pclass', col='Sex', height=2.2, aspect=1.6)
grid.map(plt.hist, 'Age', alpha=.5, bins=20)
grid.add_legend()
plt.show()
```



Let us start by preparing an empty array to contain guessed Age values based on Pclass x Gender combinations.

[22]:
```
guess_ages = np.zeros((2,3))
guess_ages
```

[22]:
```
array([[0., 0., 0.],
       [0., 0., 0.]])
```

Now we iterate over Sex (0 or 1) and Pclass (1, 2, 3) to calculate guessed values of Age for the six combinations.

[23]:
```
for dataset in combine:
    for i in range(0, 2):
        for j in range(0, 3):
            guess_df = dataset[(dataset['Sex'] == i) & (dataset['Pclass'] ==␣
 ↪j+1)]['Age'].dropna()
```

```python
            # age_mean = guess_df.mean()
            # age_std = guess_df.std()
            # age_guess = rnd.uniform(age_mean - age_std, age_mean + age_std)

            age_guess = guess_df.median()

            # Convert random age float to nearest .5 age
            guess_ages[i,j] = int( age_guess/0.5 + 0.5 ) * 0.5

    for i in range(0, 2):
        for j in range(0, 3):
            dataset.loc[ (dataset.Age.isnull()) & (dataset.Sex == i) & (dataset.
 ↪Pclass == j+1),'Age'] = guess_ages[i,j]

    dataset['Age'] = dataset['Age'].astype(int)

df.head()
```

[23]:

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name  Sex  Age  SibSp  Parch  \
0                            Braund, Mr. Owen Harris    0   22      1      0
1  Cumings, Mrs. John Bradley (Florence Briggs Th…    1   38      1      0
2                             Heikkinen, Miss. Laina    1   26      0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)    1   35      1      0
4                           Allen, Mr. William Henry    0   35      0      0

             Ticket     Fare Cabin Embarked
0         A/5 21171   7.2500   NaN        S
1          PC 17599  71.2833   C85        C
2  STON/O2. 3101282   7.9250   NaN        S
3            113803  53.1000  C123        S
4            373450   8.0500   NaN        S
```

Handle missing value - categorical variable Embarked feature takes S, Q, C values based on port of embarkation. Our training dataset has two missing values. We simply fill these with the most common occurance.

[24]:

```python
#Find the value count of train_df['Embarked']
print('Value count of Embarked variable in train_df:\n')
print(df['Embarked'].value_counts())
```

```
print("-"*30)

# Find the mode of train_df['Embarked']
freq_port = df.Embarked.dropna().mode()[0]
print('Mode of Embarked variable in train_df: ',freq_port)
```

```
Value count of Embarked variable in train_df:

Embarked
S    644
C    168
Q     77
Name: count, dtype: int64
------------------------------
Mode of Embarked variable in train_df:  S
```

[25]:
```
#Fill the null value of Embarked with the most common occurance

for dataset in combine:
    dataset['Embarked'] = dataset['Embarked'].fillna(freq_port)

df.head()
```

[25]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name  Sex  Age  SibSp  Parch  \
0                            Braund, Mr. Owen Harris    0   22      1      0
1  Cumings, Mrs. John Bradley (Florence Briggs Th…    1   38      1      0
2                             Heikkinen, Miss. Laina    1   26      0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)    1   35      1      0
4                           Allen, Mr. William Henry    0   35      0      0

             Ticket     Fare Cabin Embarked
0         A/5 21171   7.2500   NaN        S
1          PC 17599  71.2833   C85        C
2  STON/O2. 3101282   7.9250   NaN        S
3            113803  53.1000  C123        S
4            373450   8.0500   NaN        S
```

[26]:
```
#Converting categorical feature to numeric

for dataset in combine:
```

```
    dataset['Embarked'] = dataset['Embarked'].map({"S": 1, "C": 2, "Q": 3})

df.head()
```

[26]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name  Sex  Age  SibSp  Parch  \
0                            Braund, Mr. Owen Harris    0   22      1      0
1  Cumings, Mrs. John Bradley (Florence Briggs Th…    1   38      1      0
2                             Heikkinen, Miss. Laina    1   26      0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)    1   35      1      0
4                           Allen, Mr. William Henry    0   35      0      0

             Ticket     Fare Cabin  Embarked
0         A/5 21171   7.2500   NaN         1
1          PC 17599  71.2833   C85         2
2  STON/O2. 3101282   7.9250   NaN         1
3            113803  53.1000  C123         1
4            373450   8.0500   NaN         1
```

Handle missing value in Fare Fare feature is fractional value. Our training dataset has one missing values. We simply fill these with the mean.

[27]:
```
for dataset in combine:
    dataset['Fare'].fillna(dataset['Fare'].dropna().mean(), inplace=True)
    dataset['Fare'] = dataset['Fare'].astype(np.int64)
```

0.0.1 Creating new feature extracting from existing (Add Computed Column)

We want to analyze if Name feature can be engineered to extract titles and test correlation between titles and survival, before dropping Name and PassengerId features.

In the following code we extract Title feature using regular expressions. The RegEx pattern `(\w+\.)` matches the first word which ends with a dot character within Name feature. The `expand=False` flag returns a DataFrame.

Observations.

When we plot Title, Age, and Survived, we note the following observations.

- Most titles band Age groups accurately. For example: Master title has Age mean of 5 years.
- Survival among Title Age bands varies slightly.
- Certain titles mostly survived (Mme, Lady, Sir) or did not (Don, Rev, Jonkheer).

Decision.

- We decide to retain the new Title feature for model training.

[28]:
```
for dataset in combine:
    dataset['Title']  = dataset.Name.str.extract(' ([A-Za-z]+)\.', expand=False)
```

[29]:
```
pd.crosstab(df["Title"], sub_df['Sex'])
```

[29]:
```
Sex       0   1
Title
Don       1   0
Dr        3   0
Master   14   9
Miss     64  37
Mme       1   0
Mr      145  83
Mrs      37  21
Rev       1   2
```

We can replace many titles with a more common name or classify them as Rare.

[30]:
```
for dataset in combine:
    dataset['Title'] = dataset['Title'].replace(['Lady', 'Countess','Capt',␣
↪'Col','Don', 'Dr', 'Major', 'Rev', 'Sir', 'Jonkheer', 'Dona'], 'Rare')
    dataset['Title'] = dataset['Title'].replace('Mlle', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Ms', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Mme', 'Mrs')
```

[31]:
```
for dataset in combine:
    dataset['Title'] = dataset['Title'].map({"Mr": 1, "Miss": 2, "Mrs": 3,␣
↪"Master": 4, "Rare": 5})
    dataset['Title'] = dataset['Title'].fillna(0)

df.head()
```

[31]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name  Sex  Age  SibSp  Parch  \
0                            Braund, Mr. Owen Harris    0   22      1      0
1  Cumings, Mrs. John Bradley (Florence Briggs Th…    1   38      1      0
2                             Heikkinen, Miss. Laina    1   26      0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)    1   35      1      0
4                           Allen, Mr. William Henry    0   35      0      0
```

```
              Ticket  Fare Cabin  Embarked  Title
0          A/5 21171     7   NaN         1      1
1           PC 17599    71   C85         2      3
2   STON/O2. 3101282     7   NaN         1      2
3             113803    53  C123         1      3
4             373450     8   NaN         1      1
```

Handle missing value - Highly incomplete (Cabin) A computed column, Deck, is created because it is slightly more general than Cabin.

[32]:
```
for dataset in combine:
    dataset['Deck'] = dataset['Cabin'].str.slice(0,1)
    dataset['Deck'] = dataset['Deck'].map({"A": 1, "B": 2, "C": 3, "D": 4, "E":␣
 ↪5, "F":6,"G":7, "T":8})
    dataset['Deck'] = dataset['Deck'].fillna(0)
    dataset['Deck'] = dataset['Deck'].astype(np.int64)
```

[33]:
```
#Find the number of null per each columns
print('Columns in df with null values:\n')
print(df.isnull().sum())
print("-"*30)

print('Columns in sub_df with null values:\n')
print(sub_df.isnull().sum())
print("-"*30)
```

```
Columns in df with null values:

PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         0
Title            0
Deck             0
dtype: int64
------------------------------
Columns in sub_df with null values:

PassengerId      0
```

```
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          327
Embarked         0
Title            0
Deck             0
dtype: int64
------------------------------
```

Create new feature combining existing features We can create a new feature for FamilySize which combines Parch and SibSp. This will enable us to drop Parch and SibSp from our datasets.

[34]:
```
for dataset in combine:
    dataset['FamilySize'] = dataset['SibSp'] + dataset['Parch'] + 1
```

[35]:
```
for dataset in combine:
    dataset['IsAlone'] = 0
    dataset.loc[dataset['FamilySize'] == 1, 'IsAlone'] = 1
```

Drop Useless Column The **Name, PassengerId**, **Ticket** and **Cabin** should not have a bearing on the analysis. We also do not need the PassengerId feature in the training dataset

Now we can safely drop the **Name, PassengerId** and **Ticket** feature from training and testing datasets. We also do not need the PassengerId feature in the training dataset

[36]:
```
#Duplicate variable - Fare & Age
# for dataset in combine:
#     dataset['FareB'] = dataset['Fare']
#     dataset['AgeB'] = dataset['Age']
```

[37]:
```
#Binning variable - Fare & Age
for dataset in combine:
    #Fare Bins/Buckets using qcut or frequency bins: https://pandas.pydata.org/
 ↪pandas-docs/stable/generated/pandas.qcut.html
    dataset['FareBin'] = pd.qcut(dataset['Fare'], 4)

    #Age Bins/Buckets using cut or value bins: https://pandas.pydata.org/
 ↪pandas-docs/stable/generated/pandas.cut.html
    dataset['AgeBin'] = pd.cut(dataset['Age'].astype(int), 5)
```

[38]:
```
# for dataset in combine:
#     dataset.loc[ dataset['FareB'] <= 7.91, 'FareB'] = 0
#     dataset.loc[(dataset['FareB'] > 7.91) & (dataset['FareB'] <= 14.454),␣
↪'FareB'] = 1
#     dataset.loc[(dataset['FareB'] > 14.454) & (dataset['FareB'] <= 31),␣
↪'FareB']   = 2
#     dataset.loc[ dataset['FareB'] > 31, 'FareB'] = 3
#     dataset['FareB'] = dataset['FareB'].astype(int)

combine = [df, sub_df]

df.head(10)
```

[38]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3
5            6         0       3
6            7         0       1
7            8         0       3
8            9         1       3
9           10         1       2

                                                Name  Sex  Age  SibSp  Parch  \
0                            Braund, Mr. Owen Harris    0   22      1      0
1  Cumings, Mrs. John Bradley (Florence Briggs Th…    1   38      1      0
2                             Heikkinen, Miss. Laina    1   26      0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)    1   35      1      0
4                           Allen, Mr. William Henry    0   35      0      0
5                                   Moran, Mr. James    0   25      0      0
6                            McCarthy, Mr. Timothy J    0   54      0      0
7                     Palsson, Master. Gosta Leonard    0    2      3      1
8  Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)    1   27      0      2
9                Nasser, Mrs. Nicholas (Adele Achem)    1   14      1      0

             Ticket  Fare Cabin  Embarked  Title  Deck  FamilySize  IsAlone  \
0         A/5 21171     7   NaN         1      1     0           2        0
1          PC 17599    71   C85         2      3     3           2        0
2  STON/O2. 3101282     7   NaN         1      2     0           1        1
3            113803    53  C123         1      3     3           2        0
4            373450     8   NaN         1      1     0           1        1
5            330877     8   NaN         3      1     0           1        1
6             17463    51   E46         1      1     5           1        1
7            349909    21   NaN         1      4     0           5        0
8            347742    11   NaN         1      3     0           3        0
```

```
9           237736    30    NaN          2       3     0            2         0

         FareBin          AgeBin
0  (-0.001, 7.0]    (16.0, 32.0]
1  (31.0, 512.0]    (32.0, 48.0]
2  (-0.001, 7.0]    (16.0, 32.0]
3  (31.0, 512.0]    (32.0, 48.0]
4    (7.0, 14.0]    (32.0, 48.0]
5    (7.0, 14.0]    (16.0, 32.0]
6  (31.0, 512.0]    (48.0, 64.0]
7   (14.0, 31.0]   (-0.08, 16.0]
8    (7.0, 14.0]    (16.0, 32.0]
9   (14.0, 31.0]   (-0.08, 16.0]
```

[39]:
```
for dataset in combine:
    #Fare Bins/Buckets using qcut or frequency bins
    dataset['FareBin'] = pd.qcut(dataset['Fare'], 4)
    #Age Bins/Buckets using cut or value bins
    dataset['AgeBin'] = pd.cut(dataset['Age'].astype(int), 5)
```

[40]:
```
# for dataset in combine:
#     dataset.loc[ dataset['AgeB'] <= 16, 'AgeB'] = 0
#     dataset.loc[(dataset['AgeB'] > 16) & (dataset['AgeB'] <= 32), 'AgeB'] = 1
#     dataset.loc[(dataset['AgeB'] > 32) & (dataset['AgeB'] <= 48), 'AgeB'] = 2
#     dataset.loc[(dataset['AgeB'] > 48) & (dataset['AgeB'] <= 64), 'AgeB'] = 3
#     dataset.loc[ dataset['AgeB'] > 64, 'AgeB'] = 4
# train_df.head()

combine = [df, sub_df]
df.head()
```

[40]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name  Sex  Age  SibSp  Parch  \
0                            Braund, Mr. Owen Harris    0   22      1      0
1  Cumings, Mrs. John Bradley (Florence Briggs Th…    1   38      1      0
2                             Heikkinen, Miss. Laina    1   26      0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)    1   35      1      0
4                           Allen, Mr. William Henry    0   35      0      0

            Ticket  Fare Cabin  Embarked  Title  Deck  FamilySize  IsAlone  \
0        A/5 21171     7   NaN         1      1     0           2        0
```

```
1          PC 17599    71   C85          2       3      3            2         0
2  STON/O2. 3101282     7   NaN          1       2      0            1         1
3            113803    53  C123          1       3      3            2         0
4            373450     8   NaN          1       1      0            1         1

        FareBin         AgeBin
0  (-0.001, 7.0]  (16.0, 32.0]
1  (31.0, 512.0]  (32.0, 48.0]
2  (-0.001, 7.0]  (16.0, 32.0]
3  (31.0, 512.0]  (32.0, 48.0]
4    (7.0, 14.0]  (32.0, 48.0]
```

Convert Formats We will convert categorical data to dummy variables for mathematical analysis. There are multiple ways to encode categorical variables; we will use the sklearn and pandas functions.

In this step, we will also define our x (independent/features/explanatory/predictor/etc.) and y (dependent/target/outcome/response/etc.) variables for data modeling.

[41]:
```
#CONVERT: convert objects to category using Label Encoder for train and test/
 ↪validation dataset

#code categorical data
label = LabelEncoder()
for dataset in combine:
    dataset['Sex_Code'] = label.fit_transform(dataset['Sex'])
    dataset['Embarked_Code'] = label.fit_transform(dataset['Embarked'])
    dataset['Title_Code'] = label.fit_transform(dataset['Title'])
    dataset['AgeBin_Code'] = label.fit_transform(dataset['AgeBin'])
    dataset['FareBin_Code'] = label.fit_transform(dataset['FareBin'])


#define y variable aka target/outcome
Target = ['Survived']

#define x variables for original features aka feature selection
data1_x = ['Sex','Pclass', 'Embarked', 'Title','SibSp', 'Parch', 'Age', 'Fare',␣
 ↪'FamilySize', 'IsAlone'] #pretty name/values for charts
data1_x_calc = ['Sex_Code','Pclass', 'Embarked_Code', 'Title_Code','SibSp',␣
 ↪'Parch', 'Age', 'Fare'] #coded for algorithm calculation
data1_xy =  Target + data1_x
print('Original X Y: ', data1_xy, '\n')


#define x variables for original w/bin features to remove continuous variables
data1_x_bin = ['Sex_Code','Pclass', 'Embarked_Code', 'Title_Code',␣
 ↪'FamilySize', 'AgeBin_Code', 'FareBin_Code']
```

```
data1_xy_bin = Target + data1_x_bin
print('Bin X Y: ', data1_xy_bin, '\n')


#define x and y variables for dummy features original
data1_dummy = pd.get_dummies(df[data1_x])
data1_x_dummy = data1_dummy.columns.tolist()
data1_xy_dummy = Target + data1_x_dummy
print('Dummy X Y: ', data1_xy_dummy, '\n')

data1_dummy.head()
```

```
Original X Y:  ['Survived', 'Sex', 'Pclass', 'Embarked', 'Title', 'SibSp',
'Parch', 'Age', 'Fare', 'FamilySize', 'IsAlone']

Bin X Y:  ['Survived', 'Sex_Code', 'Pclass', 'Embarked_Code', 'Title_Code',
'FamilySize', 'AgeBin_Code', 'FareBin_Code']

Dummy X Y:  ['Survived', 'Sex', 'Pclass', 'Embarked', 'Title', 'SibSp', 'Parch',
'Age', 'Fare', 'FamilySize', 'IsAlone']
```

[41]:

	Sex	Pclass	Embarked	Title	SibSp	Parch	Age	Fare	FamilySize	IsAlone
0	0	3	1	1	1	0	22	7	2	0
1	1	1	2	3	1	0	38	71	2	0
2	1	3	1	2	0	0	26	7	1	1
3	1	1	1	3	1	0	35	53	2	0
4	0	3	1	1	0	0	35	8	1	1

[42]:
```
df = df.drop(['PassengerId','Name','Ticket','Cabin'], axis=1)
sub_df = sub_df.drop(['Name','Ticket','Cabin'], axis=1)

combine = [df, sub_df]
df.shape, sub_df.shape
```

[42]: ((891, 19), (418, 19))

[43]:
```
## check for data type
print("Training Data:\n")
df.head()
```

```
Training Data:
```

[43]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Title	Deck	\
0	0	3	0	22	1	0	7	1	1	0	
1	1	1	1	38	1	0	71	2	3	3	

```
2         1       3    1   26       0       0     7          1      2     0
3         1       1    1   35       1       0    53          1      3     3
4         0       3    0   35       0       0     8          1      1     0

   FamilySize  IsAlone         FareBin         AgeBin  Sex_Code  Embarked_Code  \
0           2        0  (-0.001, 7.0]  (16.0, 32.0]         0              0
1           2        0  (31.0, 512.0]  (32.0, 48.0]         1              1
2           1        1  (-0.001, 7.0]  (16.0, 32.0]         1              0
3           2        0  (31.0, 512.0]  (32.0, 48.0]         1              0
4           1        1    (7.0, 14.0]  (32.0, 48.0]         0              0

   Title_Code  AgeBin_Code  FareBin_Code
0           0            1             0
1           2            2             3
2           1            1             0
3           2            2             3
4           0            2             1
```

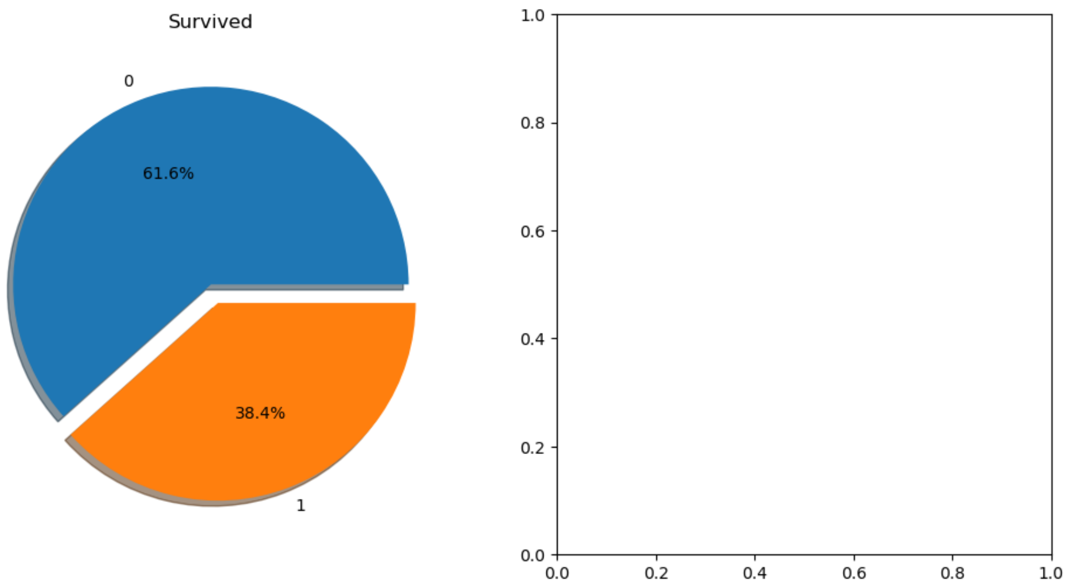
[44]:
```python
## check for data type
print("Testing Data:\n")
df.head()
```

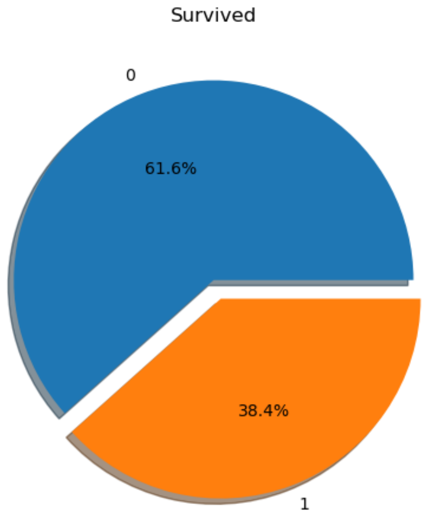
```
Testing Data:
```

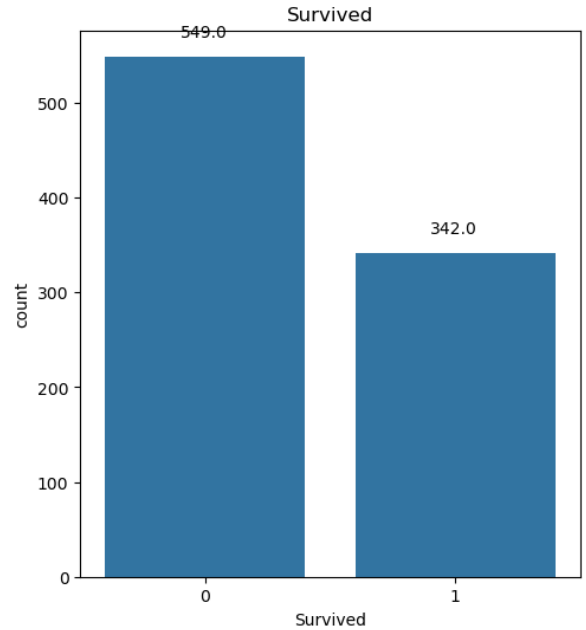
[44]:
```
   Survived  Pclass  Sex  Age  SibSp  Parch  Fare  Embarked  Title  Deck  \
0         0       3    0   22      1      0     7         1      1     0
1         1       1    1   38      1      0    71         2      3     3
2         1       3    1   26      0      0     7         1      2     0
3         1       1    1   35      1      0    53         1      3     3
4         0       3    0   35      0      0     8         1      1     0

   FamilySize  IsAlone         FareBin         AgeBin  Sex_Code  Embarked_Code  \
0           2        0  (-0.001, 7.0]  (16.0, 32.0]         0              0
1           2        0  (31.0, 512.0]  (32.0, 48.0]         1              1
2           1        1  (-0.001, 7.0]  (16.0, 32.0]         1              0
3           2        0  (31.0, 512.0]  (32.0, 48.0]         1              0
4           1        1    (7.0, 14.0]  (32.0, 48.0]         0              0

   Title_Code  AgeBin_Code  FareBin_Code
0           0            1             0
1           2            2             3
2           1            1             0
3           2            2             3
4           0            2             1
```

3. EDA (Exploratory Data Analysis) - Analyze, identify patterns, and explore the data Analysis

[46]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Survived rate

# Pie Chart
f, ax = plt.subplots(1, 2, figsize=(12, 6))
df['Survived'].value_counts().plot.pie(explode=[0, 0.1], autopct='%1.1f%%',␣
↪ax=ax[0], shadow=True)
ax[0].set_title('Survived')
ax[0].set_ylabel('')

# Bar chart - count
sns.countplot(x='Survived', data=df, ax=ax[1])  # Use 'x' instead of a␣
↪positional argument
ax[1].set_title('Survived')

for p in ax[1].patches:
    ax[1].annotate('{:.1f}'.format(p.get_height()), (p.get_x() + 0.3, p.
↪get_height() + 20))

plt.show()
```







- The plots show that number of passengers survived the accident.
- Only 350 out of 891 passengers (38.4%) survived in the training set.

'female': 1, 'male': 0

[47]:
```
eda_df = df.copy()
eda_df['Sex'] =  eda_df['Sex'].map( { 0: 'male',1:'female'} )
eda_df['Deck'] =  eda_df['Deck'].map( {0: 'Missing', 1: 'A', 2: 'B',3:'C',4:
↪'D',5:'E',6:'F',7:'G',8:'T'} )
eda_df['Embarked'] =  eda_df['Embarked'].map( {0: 'Missing', 1: 'S', 2: 'C',3:
↪'Q'} )
eda_df['Title'] =  eda_df['Title'].map( {0: 'Missing', 1: 'Mr', 2: 'Miss',3:
↪'Mrs',4:'Master',5:'Rare'} )
# eda_df['Survived'] =  eda_df['Survived'].map( {0: 'No',1:'Yes'} )
eda_df['Pclass'] =  eda_df['Pclass'].map( {0: 'Missing',1:'Upper',2:'Middle',3:
↪'Lower'} )
eda_df['IsAlone'] =  eda_df['IsAlone'].map( {0: 'No',1:'Yes'} )
```

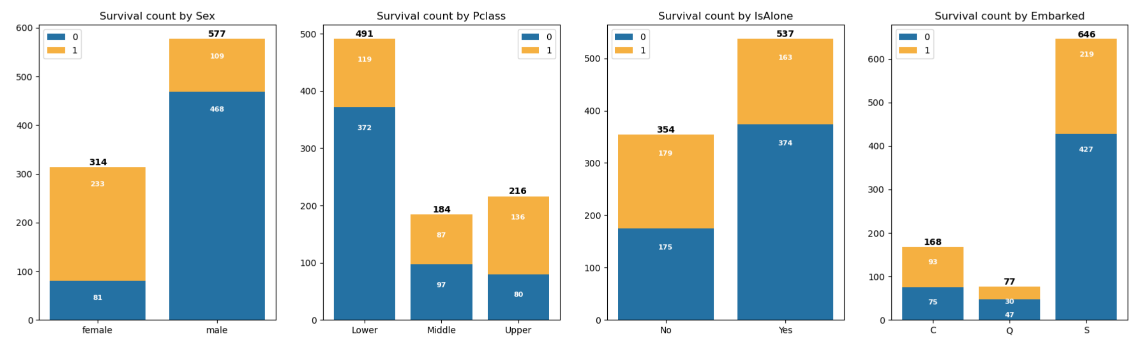
[48]:
```
import seaborn as sns

fig1 = eda_df.groupby(['Sex', 'Survived'])['Survived'].count().unstack().
↪fillna(0)
fig2 = eda_df.groupby(['Pclass', 'Survived'])['Survived'].count().unstack().
↪fillna(0)
fig3 = eda_df.groupby(['IsAlone', 'Survived'])['Survived'].count().unstack().
↪fillna(0)
```

```python
fig4 = eda_df.groupby(['Embarked', 'Survived'])['Survived'].count().unstack().
 ↪fillna(0)
```

[49]:
```python
colors = ['#2471A3', '#F5B041']

def stacked_barchart(fig,ax):
    bottom = np.zeros(len(fig))

    for i, col in enumerate(fig.columns):
        ax.bar(
          fig.index, fig[col], bottom=bottom, label=col, color=colors[i])
        bottom += np.array(fig[col])

    totals = fig.sum(axis=1)
    y_offset = 4
    for i, total in enumerate(totals):
        ax.text(totals.index[i], total + y_offset, round(total), ha='center',
              weight='bold')

    # Let's put the annotations inside the bars themselves by using a
    # negative offset.
    y_offset = -40

    # For each patch (basically each rectangle within the bar), add a label.
    for bar in ax.patches:
        ax.text(
          # Put the text in the middle of each bar. get_x returns the start
          # so we add half the width to get to the middle.
          bar.get_x() + bar.get_width() / 2,
          # Vertically, add the height of the bar to the start of the bar,
          # along with the offset.
          bar.get_height() + bar.get_y() + y_offset,
          # This is actual value we'll show.
          round(bar.get_height()),
          # Center the labels and style them a bit.
          ha='center',
          color='w',
          weight='bold',
          size=8
      )
```

[50]:
```python
fig,ax=plt.subplots(1,4,figsize=(22,6))

stacked_barchart(fig1,ax[0])
ax[0].set_title('Survival count by Sex')
ax[0].legend()
```

```
stacked_barchart(fig2,ax[1])
ax[1].set_title('Survival count by Pclass')
ax[1].legend()

stacked_barchart(fig3,ax[2])
ax[2].set_title('Survival count by IsAlone')
ax[2].legend()

stacked_barchart(fig4,ax[3])
ax[3].set_title('Survival count by Embarked')
ax[3].legend()

plt.show()
```



[51]:
```
display(df[['AgeBin', 'Survived']].groupby(['AgeBin'], as_index=False).mean().
  ↪sort_values(by='Survived', ascending=False))
## Analyze FamilySize feature with survived
display(df[['FamilySize', 'Survived']].groupby(['FamilySize'], as_index=False).
  ↪mean().sort_values(by='Survived', ascending=False))
## Analyze Pclass feature with survived
display(df[['Pclass', 'Survived']].groupby(['Pclass'], as_index=False).mean().
  ↪sort_values(by='Survived', ascending=False))
## Analyze sex feature with survived
display(df[["Sex", "Survived"]].groupby(['Sex'], as_index=False).mean().
  ↪sort_values(by='Survived', ascending=False))
## Analyze SibSp feature with survived
display(df[["SibSp", "Survived"]].groupby(['SibSp'], as_index=False).mean().
  ↪sort_values(by='Survived', ascending=False))
## Analyze Parch feature with survived
display(df[["Parch", "Survived"]].groupby(['Parch'], as_index=False).mean().
  ↪sort_values(by='Survived', ascending=False))
## Analyze IsAlone feature with survived
display(df[['IsAlone', 'Survived']].groupby(['IsAlone'], as_index=False).mean().
  ↪sort_values(by='Survived', ascending=False))
```

	AgeBin	Survived
0	(-0.08, 16.0]	0.550000
3	(48.0, 64.0]	0.434783
2	(32.0, 48.0]	0.412037
1	(16.0, 32.0]	0.337374
4	(64.0, 80.0]	0.090909

	FamilySize	Survived
3	4	0.724138
2	3	0.578431
1	2	0.552795
6	7	0.333333
0	1	0.303538
4	5	0.200000
5	6	0.136364
7	8	0.000000
8	11	0.000000

	Pclass	Survived
0	1	0.629630
1	2	0.472826
2	3	0.242363

	Sex	Survived
1	1	0.742038
0	0	0.188908

	SibSp	Survived
1	1	0.535885
2	2	0.464286
0	0	0.345395
3	3	0.250000
4	4	0.166667
5	5	0.000000
6	8	0.000000

	Parch	Survived
3	3	0.600000
1	1	0.550847
2	2	0.500000
0	0	0.343658
5	5	0.200000
4	4	0.000000
6	6	0.000000

	IsAlone	Survived
0	0	0.505650
1	1	0.303538

Sex

- The number of men on board the ship is much higher than the number of women, but the number of women saved is more than twice that of the number of males survived.
- The survival rates for a women on the ship is around 75% while that for men in around 19%.

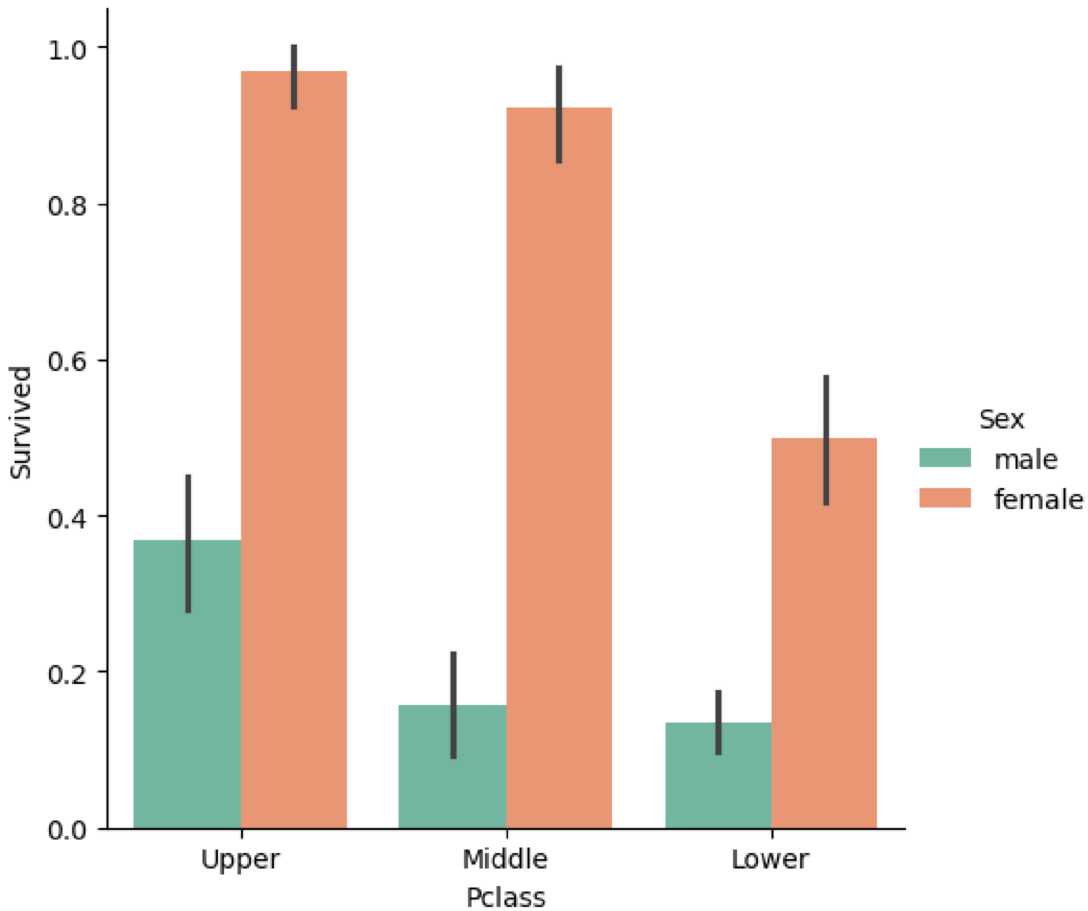
Pclass

- Passenegers Of Pclass 1 has a very high priority to survive.
- The number of Passengers in Pclass 3 were a lot higher than Pclass 1 and Pclass 2, but still the number of survival from pclass 3 is low compare to them.
- Pclass 1 %survived is around 63%, for Pclass2 is around 48%, and Pclass3 survived is around 25%

[52]:
```
pd.crosstab([eda_df.Sex,eda_df.Survived],eda_df.Pclass,margins=True)
```

[52]:
```
Pclass           Lower  Middle  Upper  All
Sex    Survived
female 0            72       6      3   81
       1            72      70     91  233
male   0           300      91     77  468
       1            47      17     45  109
All                491     184    216  891
```

[54]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Use catplot instead of factorplot
sns.catplot(x='Pclass', y='Survived', hue='Sex', data=eda_df, palette='Set2',␣
 ↪kind='bar', order=['Upper', 'Middle', 'Lower'])

plt.show()
```



- Female from Upper class is about 95-96% survived. Only 3 out of 94 Women from Upper class died.
- Female Upper class has high priority to survive
- Lower class female has more survived rate than Upper class male.

Features Correlation with Survived:

[55]:
```
plt.figure(figsize=(8, 12))
heatmap = sns.heatmap(df.corr()[['Survived']].sort_values(by='Survived',␣
↪ascending=False), vmin=-1, vmax=1, annot=True, cmap='BrBG')
heatmap.set_title('Features Correlating with Survived', fontdict={'fontsize':
↪18}, pad=16);
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Cell In[55], line 2
      1 plt.figure(figsize=(8, 12))
----> 2 heatmap = sns.heatmap(df.corr()[['Survived']].sort_values(by='Survived' ␣
↪ascending=False), vmin=-1, vmax=1, annot=True, cmap='BrBG')
```

```
      3 heatmap.set_title('Features Correlating with Survived',␣
↪fontdict={'fontsize':18}, pad=16)

File ~/miniconda3/lib/python3.12/site-packages/pandas/core/frame.py:11049, in␣
↪DataFrame.corr(self, method, min_periods, numeric_only)
  11047 cols = data.columns
  11048 idx = cols.copy()
> 11049 mat = data.to_numpy(dtype=float, na_value=np.nan, copy=False)
  11051 if method == "pearson":
  11052     correl = libalgos.nancorr(mat, minp=min_periods)

File ~/miniconda3/lib/python3.12/site-packages/pandas/core/frame.py:1993, in␣
↪DataFrame.to_numpy(self, dtype, copy, na_value)
   1991 if dtype is not None:
   1992     dtype = np.dtype(dtype)
-> 1993 result = self._mgr.as_array(dtype=dtype, copy=copy, na_value=na_value)
   1994 if result.dtype is not dtype:
   1995     result = np.asarray(result, dtype=dtype)

File ~/miniconda3/lib/python3.12/site-packages/pandas/core/internals/managers.py:
↪1694, in BlockManager.as_array(self, dtype, copy, na_value)
   1692         arr.flags.writeable = False
   1693 else:
-> 1694     arr = self._interleave(dtype=dtype, na_value=na_value)
   1695     # The underlying data was copied within _interleave, so no need
   1696     # to further copy if copy=True or setting na_value
   1698 if na_value is lib.no_default:

File ~/miniconda3/lib/python3.12/site-packages/pandas/core/internals/managers.py:
↪1747, in BlockManager._interleave(self, dtype, na_value)
   1741 rl = blk.mgr_locs
   1742 if blk.is_extension:
   1743     # Avoid implicit conversion of extension blocks to object
   1744 
   1745     # error: Item "ndarray" of "Union[ndarray, ExtensionArray]" has no
   1746     # attribute "to_numpy"
-> 1747     arr = blk.values.to_numpy(  # type: ignore[union-attr]
   1748         dtype=dtype,
   1749         na_value=na_value,
   1750     )
   1751 else:
   1752     arr = blk.get_values(dtype)

File ~/miniconda3/lib/python3.12/site-packages/pandas/core/arrays/base.py:568,␣
↪in ExtensionArray.to_numpy(self, dtype, copy, na_value)
    539 def to_numpy(
    540     self,
    541     dtype: npt.DTypeLike | None = None,
```

```
    542     copy: bool = False,
    543     na_value: object = lib.no_default,
    544 ) -> np.ndarray:
    545     """
    546     Convert to a NumPy ndarray.
    547 
   (…)
    566     numpy.ndarray
    567     """
--> 568     result = np.asarray(self, dtype=dtype)
    569     if copy or na_value is not lib.no_default:
    570         result = result.copy()

File ~/miniconda3/lib/python3.12/site-packages/pandas/core/arrays/_mixins.py:81 
 ↪in ravel_compat.<locals>.method(self, *args, **kwargs)
     78 @wraps(meth)
     79 def method(self, *args, **kwargs):
     80     if self.ndim == 1:
---> 81         return meth(self, *args, **kwargs)
     83     flags = self._ndarray.flags
     84     flat = self.ravel("K")

File ~/miniconda3/lib/python3.12/site-packages/pandas/core/arrays/categorical.py:
 ↪1664, in Categorical.__array__(self, dtype, copy)
   1662 ret = take_nd(self.categories._values, self._codes)
   1663 if dtype and np.dtype(dtype) != self.categories.dtype:
-> 1664     return np.asarray(ret, dtype)
   1665 # When we're a Categorical[ExtensionArray], like Interval,
   1666 # we need to ensure __array__ gets all the way to an
   1667 # ndarray.
   1668 return np.asarray(ret)

TypeError: float() argument must be a string or a real number, not 'pandas._libs.
 ↪interval.Interval'
```

- Sex is positively corrlated with Survived (with a Person's correlation coefficient of 0.54) ; Female is more likely to survive
- Pclass is negatively correlated with Survived(with a Pearson's correlation coefficient of -0.34) ; Obviously, better the ticket class (1 = 1st/Upper ; 2 = 2nd/Middle; 3 = 3rd/Lower), higher the chance of survival.
- Those important feature for prediction the Survived people

Correlation between features:

[ ]:
```
# get correlations
df_corr = df.corr()
```

```
fig, ax = plt.subplots(figsize=(12, 10))
# mask
mask = np.triu(np.ones_like(df_corr, dtype=np.bool))
# adjust mask and df
mask = mask[1:, :-1]
corr = df_corr.iloc[1:,:-1].copy()

# color map
# cmap = sb.diverging_palette(0, 230, 90, 60, as_cmap=True)

# plot heatmap
sns.heatmap(corr, mask=mask, annot=True, fmt=".2f",
           linewidths=5, cmap='BrBG', vmin=-1, vmax=1,
           cbar_kws={"shrink": .8}, square=True)
# ticks
yticks = [i.upper() for i in corr.index]
xticks = [i.upper() for i in corr.columns]
plt.yticks(plt.yticks()[0], labels=yticks, rotation=0)
plt.xticks(plt.xticks()[0], labels=xticks)
# title
title = 'Correlation Matrix\n'
plt.title(title, loc='left', fontsize=18)
plt.show()
```

According to the analysis, passengers were more likely to survive if:

- they had a high class ticket
- they were women
- they were young
- they embarked from Cherbourg

On the contrary, being a third class old man from Southampton lowered your chances of survival.

[56]:
```
df = df.drop(['AgeBin'], axis=1)
df = df.drop(['FareBin'], axis=1)
sub_df = sub_df.drop(['AgeBin'], axis=1)
sub_df = sub_df.drop(['FareBin'], axis=1)
```

4. Acquire training and testing data

[57]:
```
X_train = df.drop("Survived", axis=1)
Y_train = df["Survived"]
X_test  = sub_df.drop("PassengerId", axis=1).copy()
X_train.shape, Y_train.shape, X_test.shape
```

[57]: ((891, 16), (891,), (418, 16))

5. Model, predict and solve the problem

Now we are ready to train a model and predict the required solution. There are 60+ predictive modelling algorithms to choose from. We must understand the type of problem and solution requirement to narrow down to a select few models which we can evaluate. Our problem is a classification and regression problem. We want to identify relationship between output (Survived or not) with other variables or features (Gender, Age, Port…). We are also perfoming a category of machine learning which is called supervised learning as we are training our model with a given dataset. With these two criteria - Supervised Learning plus Classification and Regression, we can narrow down our choice of models to a few. These include:

Logistic Regression KNN or k-Nearest Neighbors Support Vector Machines Naive Bayes classifier Decision Tree Random Forrest Perceptron Artificial neural network RVM or Relevance Vector Machine

Split Training and Testing Data

[58]:
```
#define y variable aka target/outcome
Target = ['Survived']

#define x variables for original features aka feature selection
data1_x = ['Sex','Pclass', 'Embarked', 'Title','SibSp', 'Parch', 'Age', 'Fare',␣
 ↪'FamilySize', 'IsAlone'] #pretty name/values for charts
data1_x_calc = ['Sex_Code','Pclass', 'Embarked_Code', 'Title_Code','SibSp',␣
 ↪'Parch', 'Age', 'Fare'] #coded for algorithm calculation
data1_xy =  Target + data1_x
print('Original X Y: ', data1_xy, '\n')


#define x variables for original w/bin features to remove continuous variables
data1_x_bin = ['Sex_Code','Pclass', 'Embarked_Code', 'Title_Code',␣
 ↪'FamilySize', 'AgeBin_Code', 'FareBin_Code']
data1_xy_bin = Target + data1_x_bin
print('Bin X Y: ', data1_xy_bin, '\n')
```

```
Original X Y:  ['Survived', 'Sex', 'Pclass', 'Embarked', 'Title', 'SibSp',
'Parch', 'Age', 'Fare', 'FamilySize', 'IsAlone']

Bin X Y:  ['Survived', 'Sex_Code', 'Pclass', 'Embarked_Code', 'Title_Code',
'FamilySize', 'AgeBin_Code', 'FareBin_Code']
```

[59]:
```
#split train and test data with function defaults
#random_state -> seed or control random number generator: https://www.quora.com/
 ↪What-is-seed-in-random-number-generation
train1_x, test1_x, train1_y, test1_y = model_selection.
 ↪train_test_split(df[data1_x_calc], df[Target], random_state = 0)
train1_x_bin, test1_x_bin, train1_y_bin, test1_y_bin = model_selection.
 ↪train_test_split(df[data1_x_bin], df[Target] , random_state = 0)
train1_x_dummy, test1_x_dummy, train1_y_dummy, test1_y_dummy = model_selection.
 ↪train_test_split(data1_dummy[data1_x_dummy], df[Target], random_state = 0)
```

```
print("Data1 Shape: {}".format(df.shape))
print("Train1 Shape: {}".format(train1_x.shape))
print("Test1 Shape: {}".format(test1_x.shape))

train1_x_bin.head()
```

```
Data1 Shape: (891, 17)
Train1 Shape: (668, 8)
Test1 Shape: (223, 8)
```

[59]:

```
     Sex_Code  Pclass  Embarked_Code  Title_Code  FamilySize  AgeBin_Code  \
105         0       3              0           0           1            1
68          1       3              0           1           7            1
253         0       3              0           0           2            1
320         0       3              0           0           1            1
706         1       2              0           2           1            2

     FareBin_Code
105             0
68              0
253             2
320             0
706             1
```

[66]:

```
#Machine Learning Algorithm (MLA) Selection and Initialization
MLA = [
    #Ensemble Methods
    ensemble.AdaBoostClassifier(),
    ensemble.BaggingClassifier(),
    ensemble.ExtraTreesClassifier(),
    ensemble.GradientBoostingClassifier(),
    ensemble.RandomForestClassifier(),

    #Gaussian Processes
    gaussian_process.GaussianProcessClassifier(),

    #GLM
    linear_model.LogisticRegressionCV(),
    linear_model.PassiveAggressiveClassifier(),
    linear_model.RidgeClassifierCV(),
    linear_model.SGDClassifier(),
    linear_model.Perceptron(),

    #Navies Bayes
    naive_bayes.BernoulliNB(),
```

```
    naive_bayes.GaussianNB(),

    #Nearest Neighbor
    neighbors.KNeighborsClassifier(),

    #SVM
    svm.SVC(probability=True),
    svm.NuSVC(probability=True),
    svm.LinearSVC(),

    #Trees
    tree.DecisionTreeClassifier(),
    tree.ExtraTreeClassifier(),

    #Discriminant Analysis
    discriminant_analysis.LinearDiscriminantAnalysis(),
    discriminant_analysis.QuadraticDiscriminantAnalysis(),


    #xgboost: http://xgboost.readthedocs.io/en/latest/model.html
    XGBClassifier()
    ]



#split dataset in cross-validation with this splitter class: http://
 ↪scikit-learn.org/stable/modules/generated/sklearn.model_selection.
 ↪ShuffleSplit.html#sklearn.model_selection.ShuffleSplit
#note: this is an alternative to train_test_split
cv_split = model_selection.ShuffleSplit(n_splits = 10, test_size = .3,␣
 ↪train_size = .6, random_state = 0 ) # run model 10x with 60/30 split␣
 ↪intentionally leaving out 10%

#create table to compare MLA metrics
MLA_columns = ['MLA Name', 'MLA Parameters','MLA Train Accuracy Mean', 'MLA␣
 ↪Test Accuracy Mean', 'MLA Test Accuracy 3*STD' ,'MLA Time']
MLA_compare = pd.DataFrame(columns = MLA_columns)

#create table to compare MLA predictions
MLA_predict = df[Target]

#index through MLA and save performance to table
row_index = 0
for alg in MLA:

    #set name and parameters
    MLA_name = alg.__class__.__name__
```

```
    MLA_compare.loc[row_index, 'MLA Name'] = MLA_name
    MLA_compare.loc[row_index, 'MLA Parameters'] = str(alg.get_params())

    #score model with cross validation: http://scikit-learn.org/stable/modules/
 ↪generated/sklearn.model_selection.cross_validate.html#sklearn.
 ↪model_selection.cross_validate
    cv_results = model_selection.cross_validate(alg, df[data1_x_bin],␣
 ↪df[Target], cv  = cv_split, return_train_score=True)

    MLA_compare.loc[row_index, 'MLA Time'] = cv_results['fit_time'].mean()
    MLA_compare.loc[row_index, 'MLA Train Accuracy Mean'] =␣
 ↪cv_results['train_score'].mean()
    MLA_compare.loc[row_index, 'MLA Test Accuracy Mean'] =␣
 ↪cv_results['test_score'].mean()
    #if this is a non-bias random sample, then +/-3 standard deviations (std)␣
 ↪from the mean, should statistically capture 99.7% of the subsets
    MLA_compare.loc[row_index, 'MLA Test Accuracy 3*STD'] =␣
 ↪cv_results['test_score'].std()*3   #let's know the worst that can happen!


    #save MLA predictions - see section 6 for usage
    alg.fit(df[data1_x_bin], df[Target])
    MLA_predict[MLA_name] = alg.predict(df[data1_x_bin])

    row_index+=1


#print and sort table: https://pandas.pydata.org/pandas-docs/stable/generated/
 ↪pandas.DataFrame.sort_values.html
MLA_compare.sort_values(by = ['MLA Test Accuracy Mean'], ascending = False,␣
 ↪inplace = True)
MLA_compare
#MLA_predict
```

[66]:

```
                           MLA Name  \
21                    XGBClassifier
4            RandomForestClassifier
5         GaussianProcessClassifier
14                              SVC
3        GradientBoostingClassifier
2              ExtraTreesClassifier
15                            NuSVC
1                 BaggingClassifier
13             KNeighborsClassifier
0                AdaBoostClassifier
17           DecisionTreeClassifier
```

```
20  QuadraticDiscriminantAnalysis
18            ExtraTreeClassifier
6           LogisticRegressionCV
16                     LinearSVC
8              RidgeClassifierCV
19    LinearDiscriminantAnalysis
12                    GaussianNB
11                   BernoulliNB
9                  SGDClassifier
10                    Perceptron
7    PassiveAggressiveClassifier

                                     MLA Parameters MLA Train Accuracy Mean  \
21  {'objective': 'binary:logistic', 'base_score':…                  0.8897
4   {'bootstrap': True, 'ccp_alpha': 0.0, 'class_w…                0.893071
5   {'copy_X_train': True, 'kernel': None, 'max_it…                0.867228
14  {'C': 1.0, 'break_ties': False, 'cache_size': …                0.834457
3   {'ccp_alpha': 0.0, 'criterion': 'friedman_mse'…                0.868352
2   {'bootstrap': False, 'ccp_alpha': 0.0, 'class_…                0.893071
15  {'break_ties': False, 'cache_size': 200, 'clas…                0.829213
1   {'bootstrap': True, 'bootstrap_features': Fals…                0.888015
13  {'algorithm': 'auto', 'leaf_size': 30, 'metric…                0.855618
0   {'algorithm': 'SAMME.R', 'estimator': None, 'l…                0.822285
17  {'ccp_alpha': 0.0, 'class_weight': None, 'crit…                0.893071
20  {'priors': None, 'reg_param': 0.0, 'store_cova…                0.819476
18  {'ccp_alpha': 0.0, 'class_weight': None, 'crit…                0.893071
6   {'Cs': 10, 'class_weight': None, 'cv': None, '…                0.820599
16  {'C': 1.0, 'class_weight': None, 'dual': 'auto…                 0.81573
8   {'alphas': (0.1, 1.0, 10.0), 'class_weight': N…                0.814794
19  {'covariance_estimator': None, 'n_components':…                0.813858
12           {'priors': None, 'var_smoothing': 1e-09}                0.802247
11  {'alpha': 1.0, 'binarize': 0.0, 'class_prior':…                0.797753
9   {'alpha': 0.0001, 'average': False, 'class_wei…                0.768352
10  {'alpha': 0.0001, 'class_weight': None, 'early…                0.760112
7   {'C': 1.0, 'average': False, 'class_weight': N…                0.733708

   MLA Test Accuracy Mean MLA Test Accuracy 3*STD  MLA Time
21               0.829851                0.063757   0.03143
4                0.828731                0.058691  0.125983
5                0.828358                0.038453  0.090771
14               0.827612                0.048484  0.037755
3                0.826493                0.050868  0.101426
2                0.823507                0.076914  0.093583
15               0.822388                0.051832  0.042894
1                0.820522                0.073651  0.020466
13               0.817164                0.060489  0.002537
0                0.815672                0.052073  0.077164
```

17	0.813433	0.068274	0.002677
20	0.81194	0.067388	0.002456
18	0.810075	0.086629	0.002534
6	0.807463	0.053964	0.105646
16	0.806343	0.063016	0.002889
8	0.802612	0.059328	0.003642
19	0.802612	0.059328	0.002855
12	0.796269	0.068494	0.002545
11	0.789552	0.046479	0.003022
9	0.760448	0.163969	0.004192
10	0.756716	0.140956	0.003205
7	0.733582	0.138661	0.002759

[67]:
```
#barplot using https://seaborn.pydata.org/generated/seaborn.barplot.html
sns.barplot(x='MLA Test Accuracy Mean', y = 'MLA Name', data = MLA_compare,␣
 ↪color = 'm')

#prettify using pyplot: https://matplotlib.org/api/pyplot_api.html
plt.title('Machine Learning Algorithm Accuracy Score \n')
plt.xlabel('Accuracy Score (%)')
plt.ylabel('Algorithm')
```

[67]:
```
Text(-128.90277777777777, 0.5, 'Algorithm')
```

Rank the model We can use binary cross entropy or logistic loss as the loss function and any metric like accuracy or/and ROC AUC score as a metric to evaluate the results.

We can now rank our evaluation of all the models to choose the best one for our problem. While both Decision Tree and Random Forest score the same, we choose to use Random Forest as they correct for decision trees' habit of overfitting to their training set.

[68]:
```
# First XGBoost model for Pima Indians dataset
from numpy import loadtxt
from xgboost import XGBClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# fit model
model = XGBClassifier()
model.fit(X_train, Y_train)
# make predictions for test data
Y_pred = model.predict(X_test)
```

6. Visualize, report, and present the problem solving steps and final solution

7. Submit the results

[69]:
```
submission = pd.DataFrame({
        "PassengerId": sub_df["PassengerId"],
        "Survived": Y_pred
    })

submission.to_csv('submission.csv', index=False)
print("Your submission was successfully saved!")
```

```
Your submission was successfully saved!
```

[70]:
```
submission = pd.DataFrame({
    "PassengerId": sub_df["PassengerId"],
    "Survived": Y_pred
})

# Specify the full path where you want to save the file
submission.to_csv('/home/pc13/Desktop/submission.csv', index=False)

print("Your submission was successfully saved!")
```

```
Your submission was successfully saved!
```