DATA MINING AND MACHINE LEARNING

Question 1.

Introduction

The goal of this project is to predict if certain passengers on the Titanic in the given database would get survived in the Titanic crushor not via training decision tree models.

I will use the training data (the first 40 records from the entire given data set) to develop a prodictive model. And then test in the test data set.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set()
from IPython.display import display
```

In [2]:
```
train = pd.read_csv('titanic-train.csv')
test = pd.read_csv('titanic-test.csv')
```

In [3]:
```
train.dtypes
```

Out[3]:
```
PassengerId        int64
Survived           int64
PassengerClass     int64
Sex               object
Age                int64
SiblingSpouse      int64
ParentChild        int64
dtype: object
```

Data Dictionary

- PassengerId
- Survived: 0 = No | 1 = Yes.
- PassengerClass: (Ticket class) 1 = 1st class, 2 = 2nd class, 3 = 3rd class.
    - this field represent the social class of the passenger, whether the passenger is in hte first class, middle class, or the underline class.
- Sex: male or female
- Age: will categorize to 3 groups: 0 = child, 1 = teenager, and 2 = adult.
- SiblingSpouse: will categorize to 2 groups: 0 = zero, 1 = non-zero.
    - represent the number of siblings of the passenger on Titanic.
- ParentChild: will categorize to 2 groups: 0 = zero, 1 = non-zero
    - represent the number of parents and childs of the passenger on Titanic.

Training Dataset

In [4]:
```
train.head()
```

Out[4]:

	PassengerId	Survived	PassengerClass	Sex	Age	SiblingSpouse	ParentChild
0	1	0	3	male	22	1	0
1	2	1	1	female	38	1	0
2	3	1	3	female	26	0	0
3	4	1	1	female	35	1	0
4	5	0	3	male	35	0	0

For attributes with value in numeric data types:

In [5]:
```
train.describe()
```

Out[5]:

	PassengerId	Survived	PassengerClass	Age	SiblingSpouse	ParentChild
count	40.000000	40.000000	40.000000	40.000000	40.000000	40.000000
mean	20.500000	0.425000	2.300000	27.375000	0.900000	0.525000
std	11.690452	0.500641	0.853349	15.923998	1.104768	1.198022
min	1.000000	0.000000	1.000000	2.000000	0.000000	0.000000
25%	10.750000	0.000000	1.750000	17.250000	0.000000	0.000000
50%	20.500000	0.000000	3.000000	27.000000	1.000000	0.000000
75%	30.250000	1.000000	3.000000	38.000000	1.000000	0.250000
max	40.000000	1.000000	3.000000	66.000000	4.000000	5.000000

This shows that the PassengerId, Survived, PassengerClass, Age, SiblingSponse, and ParentChild attributes are numercial data.

For attributes with value in object data types:

In [6]:
```
train.describe(include=['O'])
```

Out[6]:

	Sex
count	40
unique	2
top	female
freq	22

This shows that among the 40 records in the training set, there were 22 female and the other 18 people were male.

In [7]:
```
print("More information about Train data: ")
train.info()
```

```
More information about Train data:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 40 entries, 0 to 39
Data columns (total 7 columns):
PassengerId       40 non-null int64
Survived          40 non-null int64
PassengerClass    40 non-null int64
Sex               40 non-null object
Age               40 non-null int64
SiblingSpouse     40 non-null int64
ParentChild       40 non-null int64
dtypes: int64(6), object(1)
memory usage: 2.3+ KB
```

Testing Dataset

In [8]:
```
test.head()
```

Out[8]:

	PassengerId	Survived	PassengerClass	Sex	Age	SiblingSpouse	ParentChild
0	41	0	1	male	65	0.0	1
1	42	1	2	female	21	0.0	0
2	43	0	3	male	29	0.0	0
3	44	1	2	female	5	1.0	2
4	45	0	3	male	11	5.0	2

In [9]:
```
test.describe()
```

Out[9]:

	PassengerId	Survived	PassengerClass	Age	SiblingSpouse	ParentChild
count	23.00000	23.000000	23.000000	23.000000	22.000000	23.000000
mean	52.00000	0.347826	2.478261	31.608696	1.000000	0.565217
std	6.78233	0.486985	0.730477	43.683510	1.690309	0.895752
min	41.00000	0.000000	1.000000	1.000000	0.000000	0.000000
25%	46.50000	0.000000	2.000000	16.500000	0.000000	0.000000
50%	52.00000	0.000000	3.000000	25.000000	0.000000	0.000000
75%	57.50000	1.000000	3.000000	29.500000	1.000000	1.500000
max	63.00000	1.000000	3.000000	221.000000	5.000000	2.000000

In [10]:
```
test.describe(include=['O'])
```

Out[10]:

	Sex
count	23
unique	2
top	male
freq	17

In [11]:
```
print("More information about Train data: ")
test.info()
```

```
More information about Train data:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23 entries, 0 to 22
Data columns (total 7 columns):
PassengerId       23 non-null int64
Survived          23 non-null int64
PassengerClass    23 non-null int64
Sex               23 non-null object
Age               23 non-null int64
SiblingSpouse     22 non-null float64
ParentChild       23 non-null int64
dtypes: float64(1), int64(5), object(1)
memory usage: 1.3+ KB
```

As the requirement, there are 40 entries in the train dataset, and the rest (23 entries) are in the test dataset.

In [12]:
```
train.isnull().sum()
```

Out[12]:
```
PassengerId       0
Survived          0
PassengerClass    0
Sex               0
Age               0
SiblingSpouse     0
ParentChild       0
dtype: int64
```

In [13]:
```
test.isnull().sum()
```

Out[13]:
```
PassengerId       0
Survived          0
PassengerClass    0
Sex               0
Age               0
SiblingSpouse     1
ParentChild       0
dtype: int64
```

This shows that there is a missing entrie for SiblingSpouse in the testing dataset.

1. Cleaing and Pre-Process the data

- Categorised the data based on the "Age" attribute:
  - lable "Child" for records whose age is <=12
  - lable "Teenage" for records whose age is >12 and <20
  - lable "Adult" for records whose age is >=20

In [14]:
```
titanic = [train,test]
```

1.1 Age

In [15]:
```
train['AgeGrp'] = -1
test['AgeGrp'] = -1
```

In [16]:
```
for dataset in titanic:
    dataset.loc[ dataset['Age'] <= 12, 'AgeGrp'] = 0,
    dataset.loc[(dataset['Age'] > 12) & (dataset['Age'] <= 20), 'AgeGrp'
] = 1,
    dataset.loc[ dataset['Age'] > 20, 'AgeGrp'] = 2
```

In [17]:
```
print("After categorize train data by Age: ")
train.head()
```

```
After categorize train data by Age:
```

Out[17]:

	PassengerId	Survived	PassengerClass	Sex	Age	SiblingSpouse	ParentChild	Age(
0	1	0	3	male	22	1	0	2
1	2	1	1	female	38	1	0	2
2	3	1	3	female	26	0	0	2
3	4	1	1	female	35	1	0	2
4	5	0	3	male	35	0	0	2

In [18]:
```
train.tail()
```

Out[18]:

	PassengerId	Survived	PassengerClass	Sex	Age	SiblingSpouse	ParentChild	Ag
35	36	0	3	female	18	1	0	1
36	37	0	3	male	7	4	1	0
37	38	0	3	male	21	0	0	2
38	39	1	1	female	49	1	0	2
39	40	1	2	female	29	1	0	2

- Categorize data into two groups based on the value of the attributes "SiblingSpouse' and 'ParentChild'.

1.2 Sex

Categorize data based on sex in to 0 = male, and 1 = female.

In [19]:
```
sex_mapping = {"male": 0, "female": 1}
for dataset in titanic:
    dataset['Sex'] = dataset['Sex'].map(sex_mapping)
```

In [20]:
```
# After categorizing based on Age:
train.head()
```

Out[20]:

	PassengerId	Survived	PassengerClass	Sex	Age	SiblingSpouse	ParentChild	AgeGr
0	1	0	3	0	22	1	0	2
1	2	1	1	1	38	1	0	2
2	3	1	3	1	26	0	0	2
3	4	1	1	1	35	1	0	2
4	5	0	3	0	35	0	0	2

In [21]:
```
train['SiblSpGrp'] = 0
train['PrtCldGrp'] = 0
test['SiblSpGrp']= 0
test['PrtCldGrp']= 0
```

In [22]:
```
for dataset in titanic:
    dataset.loc[ dataset['SiblSpGrp'] == 0, 'SiblSpGrp'] = 0,
    dataset.loc[ dataset['SiblSpGrp'] > 0, 'SiblSpGrp'] = 1,
    dataset.loc[ dataset['PrtCldGrp'] == 0, 'PrtCldGrp'] = 0,
    dataset.loc[ dataset['PrtCldGrp'] > 0, 'PrtCldGrp'] = 1,
```

After categorize train data by SiblingSpouse and ParentChild attributes:

In [23]:
```
train.head()
```

Out[23]:

	PassengerId	Survived	PassengerClass	Sex	Age	SiblingSpouse	ParentChild	AgeGr
0	1	0	3	0	22	1	0	2
1	2	1	1	1	38	1	0	2
2	3	1	3	1	26	0	0	2
3	4	1	1	1	35	1	0	2
4	5	0	3	0	35	0	0	2

In [24]:
```
train.tail()
```

Out[24]:

	PassengerId	Survived	PassengerClass	Sex	Age	SiblingSpouse	ParentChild	AgeG
35	36	0	3	1	18	1	0	1
36	37	0	3	0	7	4	1	0
37	38	0	3	0	21	0	0	2
38	39	1	1	1	49	1	0	2
39	40	1	2	1	29	1	0	2

2. State the attributes and the class label for building the decision tree model.

Since we are interested in whether the passenger had been servived in the Titanic Crash, we could drop the **Survived** field from the dataset, and use it as a individual variable. It is also the target we want to predict.

In [25]:
```
# drop "Survived" attribute from the dataset and store it in a new varia
ble.
train_target = train['Survived']
train_data = train.drop('Survived', axis=1)
train_data.dtypes
```

Out[25]:
```
PassengerId       int64
PassengerClass    int64
Sex               int64
Age               int64
SiblingSpouse     int64
ParentChild       int64
AgeGrp            int64
SiblSpGrp         int64
PrtCldGrp         int64
dtype: object
```

In [26]:
```
# for testing dataset
test_target = test['Survived']
test_data = test.drop('Survived', axis=1)
```

Now, for every passenger, there exist a corresponding record in the target[i] for data.loc[i].

Calculating Accuracy

In [27]:
```
# This function will return the accuracy score of the predict based on t
ruth
def accuracy_scr(predict, truth):
    if len(truth) == len(predict):
        return "Accuracy of Prediction {:.2f}%.".format((truth == predic
t).mean()*100)
    else:
        return "Error in matching."
```

In [28]:
```
pred = pd.Series(np.ones(10, dtype = int))
print(accuracy_scr(pred, train_target[:10]))
```

```
Accuracy of Prediction 60.00%.
```

Since we don't have any information about if passengers were survived, I just predict there is no people in the Titanic Crash been survived (without consider any other information).

In [29]:
```
def non_suvivor_pred(data):
    pred = []
    for _, p in data.iterrows():
        pred.append(0)
    return pd.Series(pred)
```

In [30]:
```
pred = non_suvivor_pred(train_data)
print(accuracy_scr(pred, train_target))
```

```
Accuracy of Prediction 57.50%.
```

Prediction based on single attribute

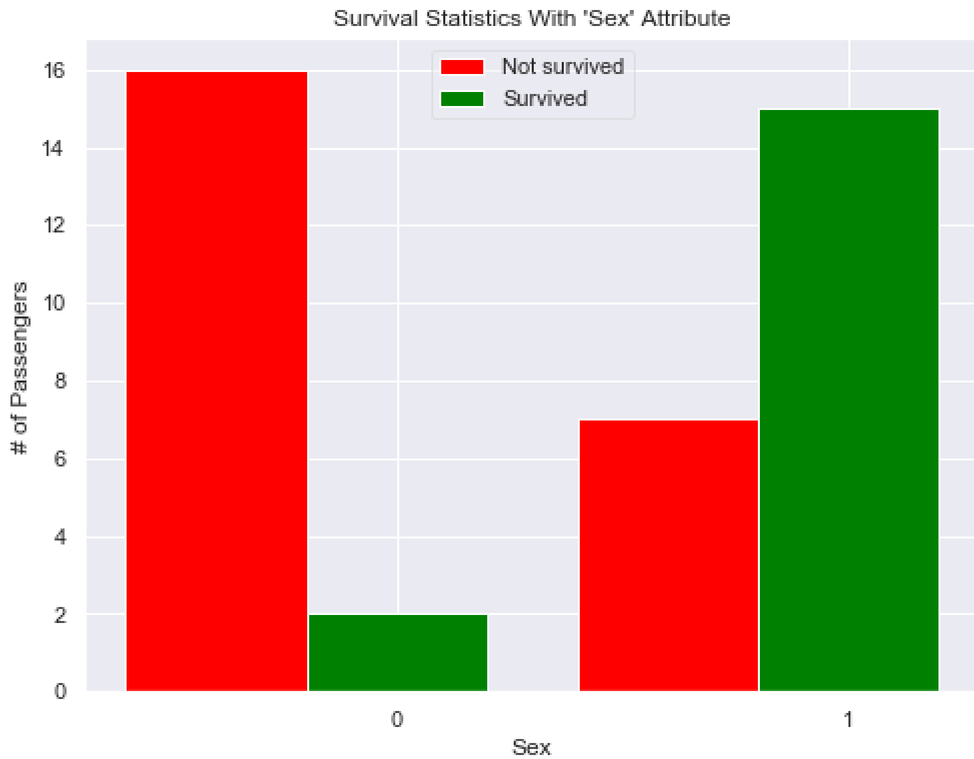
In [31]:
```
# This function will filter out the elements which do not match the filt
er_rule.
# Input: list
# Output: list
# filter_rule: a list of <attribute_name> <operator> <value>
def filter(data, filter_rule):
    attr, ope, val = filter_rule.split(" ")
    try:
        val = float(val)
    except:
        val = val.strip("\'\'")

    if ope == ">":
        matches = data[attr] > val
    elif ope == "<":
        matches = data[attr] < val
    elif ope == ">=":
        matches = data[attr] >= val
    elif ope == "<=":
        matches = data[attr] <= val
    elif ope == "==":
        matches = data[attr] == val
    elif ope == "!=":
        matches = data[attr] != val
    else: # invalid operator
        raise Exception("Invalid comparison operator.")

    # filter data and return result
    data = data[matches].reset_index(drop = True)
    return data
```

In [32]:
```
# This function will return the selected attribute with survival statist
ics.
def static_survival(data, attr, result, rules=[]):
    if attr not in data.columns.values:
        print("'{}' is not exist in Titanic data".format(attr))
        return False

    # merge back "Survived" attribute and other data
    all_train_data = pd.concat([data,result], axis = 1)

    for rule in rules:
        all_train_data = filter(all_train_data, rule)

    all_train_data = all_train_data[[attr, 'Survived']]

    plt.figure(figsize=(8,6))

    # 'Numerical' attributes
    if(attr == 'Age'):

        # Remove NaN values from Age data
        all_train_data = all_train_data[~np.isnan(all_train_data[attr])]

        bins = [0,12,20,all_train_data[attr].max()]

        # Overlay each bin's survival rates
        nonsurvival_values = all_train_data[all_train_data['Survived'] =
= 0][attr].reset_index(drop = True)
        survival_values = all_train_data[all_train_data['Survived'] == 1
][attr].reset_index(drop = True)
        plt.hist(nonsurvival_values, bins = bins, alpha = 0.4, color =
'red', label = 'Not survive')
        plt.hist(survival_values, bins = bins, alpha = 0.4, color = 'gre
en', label = 'Survived')

        # Add legend to plot
        plt.xlim(0, all_train_data[attr].max())
        plt.legend(framealpha = 0.6)

    # 'Categorical' features
    else:
        if(attr == 'Sex'):
            values = [0,1]
            # values = ['male', 'female']
        if (attr == 'PassengerClass'):
            values = [1,2,3]
        if (attr == 'AgeGrp'):
            values = [0,1,2]


        frame = pd.DataFrame(index = np.arange(len(values)), columns=(at
tr,'Survived','NonSurvived'))
        for i, value in enumerate(values):
            frame.loc[i] = [value, \
                     len(all_train_data[(all_train_data['Survived'] == 1)
& (all_train_data[attr] == value)]), \
```

```
                    len(all_train_data[(all_train_data['Survived'] == 0)
& (all_train_data[attr] == value)])]

        # Set the width of each bar
        bar_wid = 0.4

        # Display each category's survival rates
        for i in np.arange(len(frame)):
            nonsurv_bar = plt.bar(i-bar_wid, frame.loc[i]['NonSurvived'
], width = bar_wid, color = 'red')
            surv_bar = plt.bar(i, frame.loc[i]['Survived'], width = bar_
wid, color = 'green')

            plt.xticks(np.arange(len(frame)), values)
            plt.legend((nonsurv_bar[0], surv_bar[0]),('Not survived', 'S
urvived'), framealpha = 0.4)

    plt.xlabel(attr)
    plt.ylabel('# of Passengers')
    plt.title('Survival Statistics With \'%s\' Attribute'%(attr))
    plt.show()

    # Report number of passengers with missing values
    if sum(pd.isnull(all_train_data[attr])):
        nan_outcomes = all_train_data[pd.isnull(all_train_data[attr])][
'Survived']
        print("Passengers with missing '{}' values: {} ({} survived, {}
 did not survive)".format(attr, len(nan_outcomes), sum(nan_outcomes == 1
), sum(nan_outcomes == 0)))
```

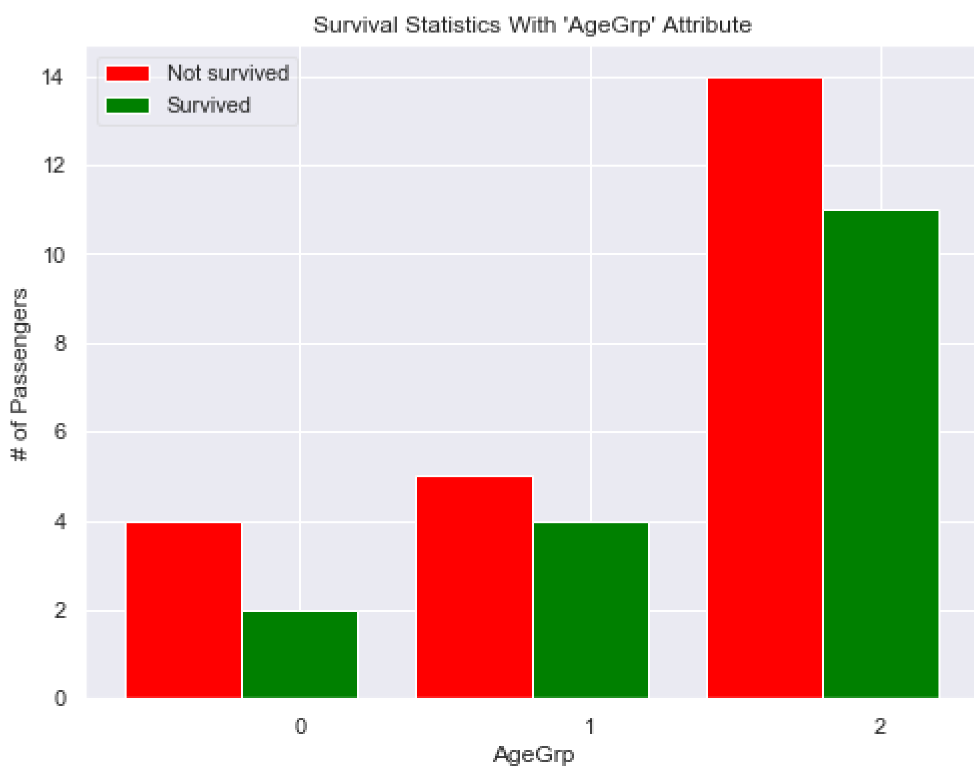
Consider how **Sex** will affect the survival for the passengers.

In [33]:
```
static_survival(train_data, 'Sex', train_target)
```

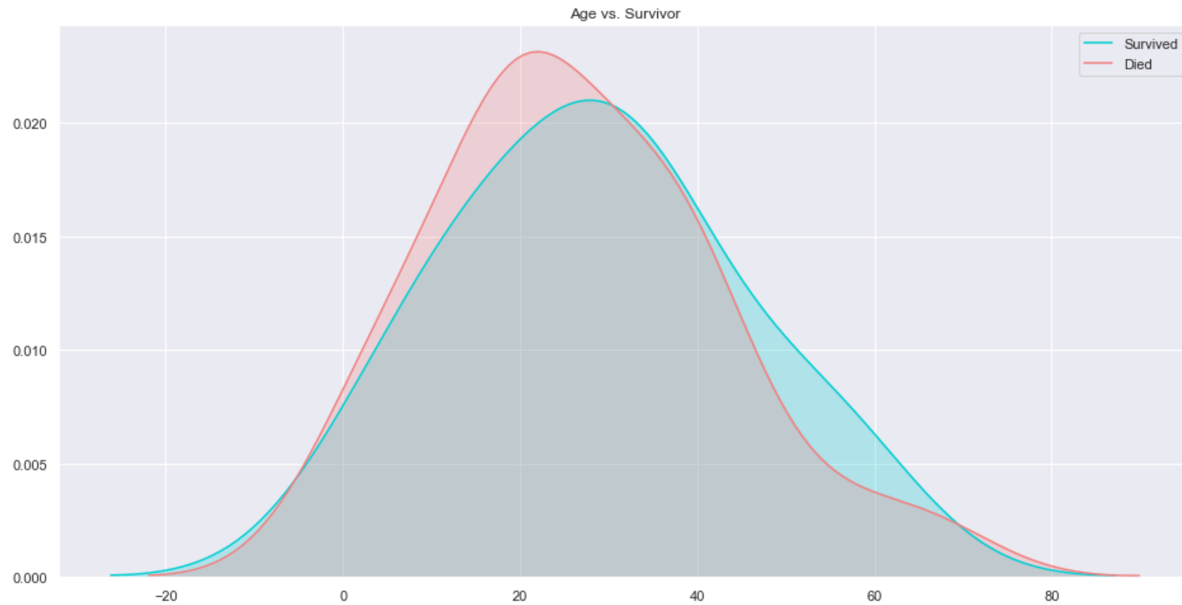


Consider how **Age** will affect the survival for the passengers.

In [34]:
```
static_survival(train_data, 'AgeGrp', train_target)
```

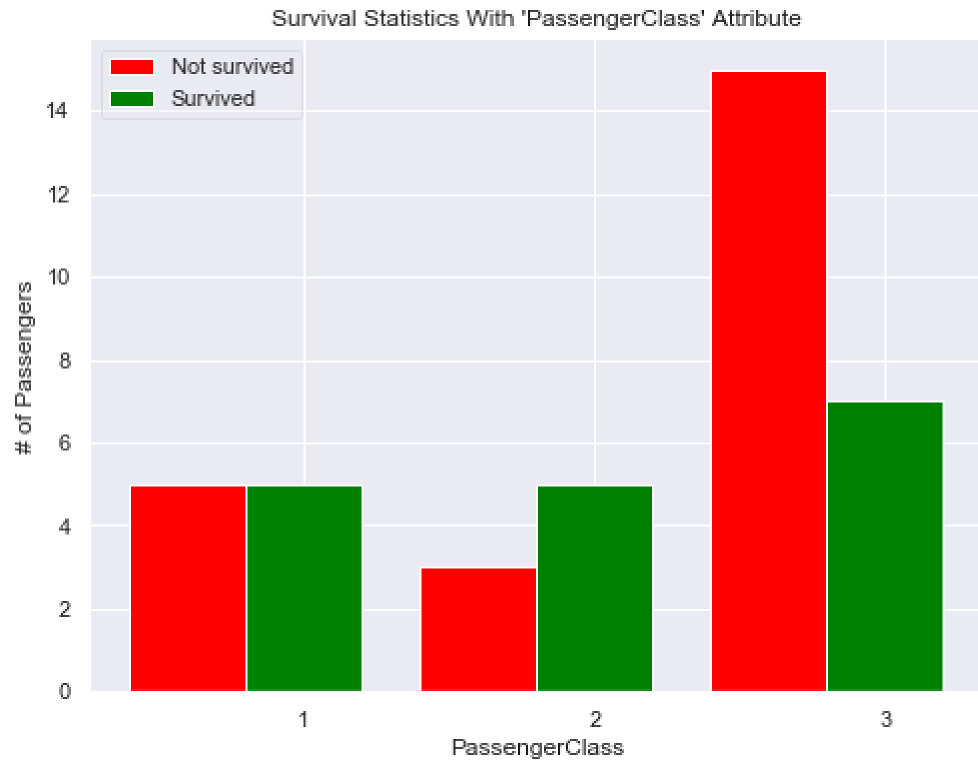


In [65]:
```
plt.figure(figsize=(16,8))
sns.kdeplot(train["Age"][train.Survived == 1], color="darkturquoise", sh
ade=True)
sns.kdeplot(train["Age"][train.Survived == 0], color="lightcoral", shade
=True)
plt.legend(['Survived', 'Died'])
plt.title('Age vs. Survivor')
plt.show()
```



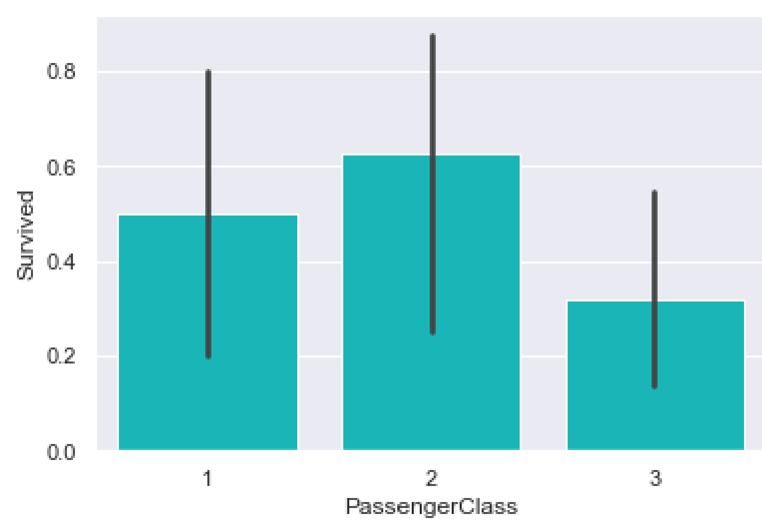
Consider how **PassengerClass** will affect the survival for the passengers.

In [35]:
```
static_survival(train_data, 'PassengerClass', train_target)
```



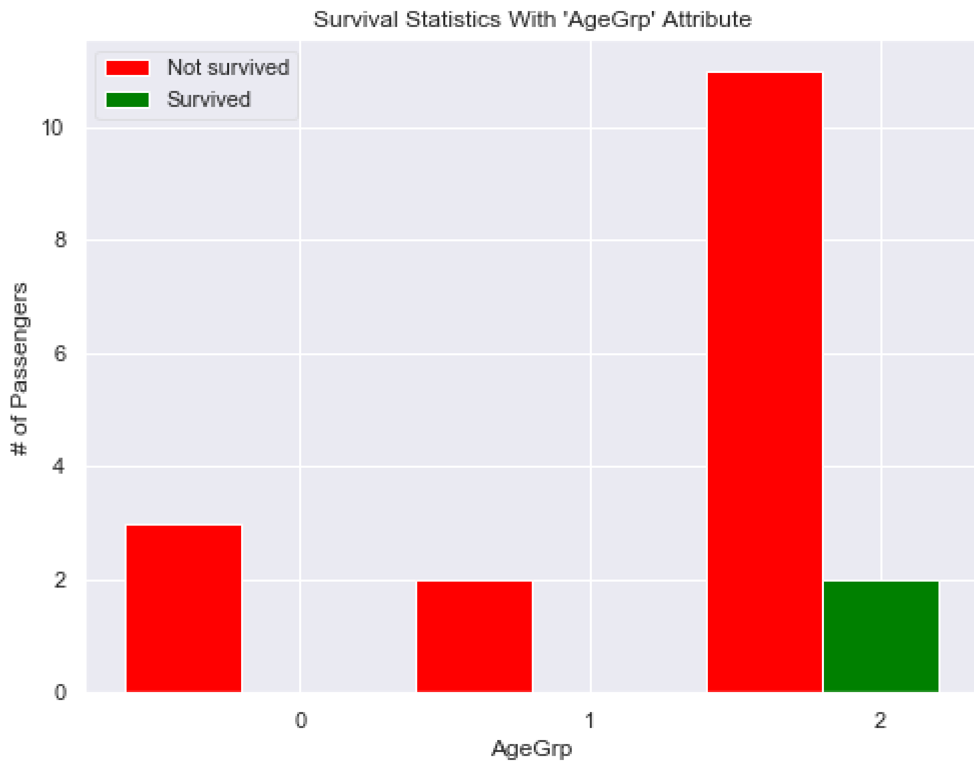
In [63]:
```
sns.barplot('PassengerClass', 'Survived', data=train, color="darkturquoi
se")
plt.show()
```

```
/anaconda3/envs/Udacity_PyTorch/lib/python3.6/site-packages/scipy/stat
s/stats.py:1713: FutureWarning: Using a non-tuple sequence for multidim
ensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr
[seq]`. In the future this will be interpreted as an array index, `arr
[np.array(seq)]`, which will result either in an error or a different r
esult.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

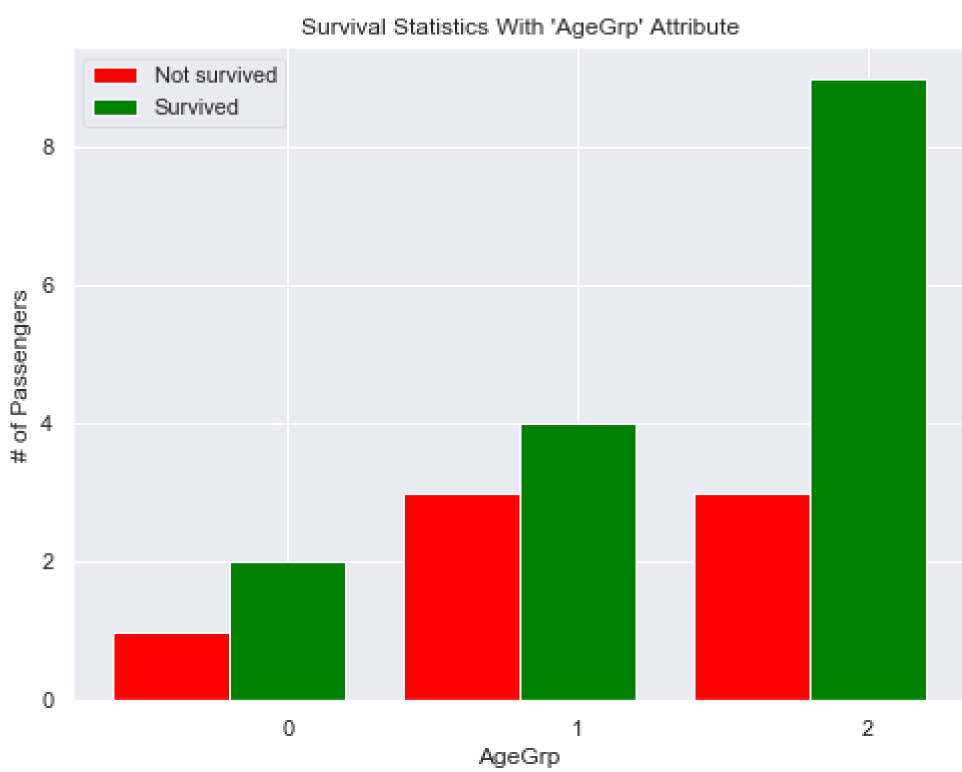


Prediction based on mutiple attributes

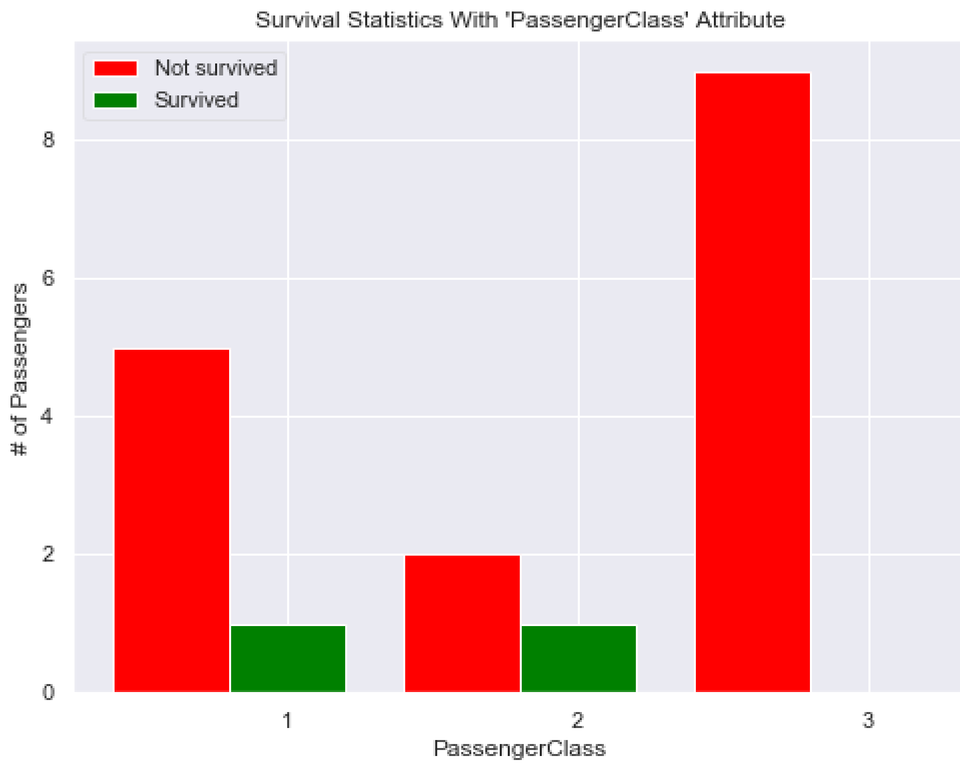
In [36]:
```
static_survival(train_data, 'AgeGrp', train_target, ["Sex == 0"])
```



In [37]:
```
static_survival(train_data, 'AgeGrp', train_target, ["Sex == 1"])
```



In [38]:
```
static_survival(train_data, 'PassengerClass', train_target, ["Sex == 0"
])
```



In [39]:
```
static_survival(train_data, 'PassengerClass', train_target, ["Sex == 1"
])
```

Modeling

In [40]:
```
# Importing Classifier Modules
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
```

Cross Validation

In [41]:
```
k_fold = KFold(n_splits=10, shuffle=True, random_state=0)
```

In [42]:
```
clf = DecisionTreeClassifier()
scoring = 'accuracy'
score = cross_val_score(clf, train_data, train_target, cv=k_fold, n_jobs
=1, scoring=scoring)
print(score)
```

```
[0.5  1.   0.25 0.5  0.5  0.25 0.75 0.5  0.75 1.  ]
```

decision tree model score

In [43]:
```
round(np.mean(score)*100, 2)
```

Out[43]:
```
60.0
```

Training the model

In [44]:
```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
from sklearn import tree
```

In [45]:
```
X_train, X_test, y_train, y_test = train_test_split(train_data, train_ta
rget, test_size=23/63, random_state=42)
```

In [46]:
```
dtclf = DecisionTreeClassifier()
dtclf.fit(X_train,y_train)
```

Out[46]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=N
one,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=N
one,
            splitter='best')
```

Test the model

Making predict:

In [47]:
```
y_train_pd = dtclf.predict(X_train)
y_test_pd = dtclf.predict(X_test)
```

Calculate the accuracy for training data nad test data:

In [48]:
```
train_accuracy = accuracy_scr(y_train_pd, y_train)
test_accuracy = accuracy_scr(y_test_pd, y_test)
print('The accuracy for training dataset is: ', train_accuracy)
print('The accuracy for testing dataset is: ', test_accuracy)
```

```
The accuracy for training dataset is:  Accuracy of Prediction 100.00%.
The accuracy for testing dataset is:  Accuracy of Prediction 66.67%.
```

In [49]:
```
pd.DataFrame(
    confusion_matrix(y_test, y_test_pd),
    columns=['Predicted Not Survival', 'Predicted Survival'],
    index=['True Not Survival', 'True Survival']
)
```

Out[49]:

	Predicted Not Survival	Predicted Survival
True Not Survival	7	4
True Survival	1	3

In [50]:
```
dt_tree = tree.DecisionTreeClassifier()
```

In [51]:
```
dt_tree
```

Out[51]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=N
one,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=N
one,
            splitter='best')
```

In [52]:
```
dt_tree.fit(X_train, y_train)
```

Out[52]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=N
one,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=N
one,
            splitter='best')
```

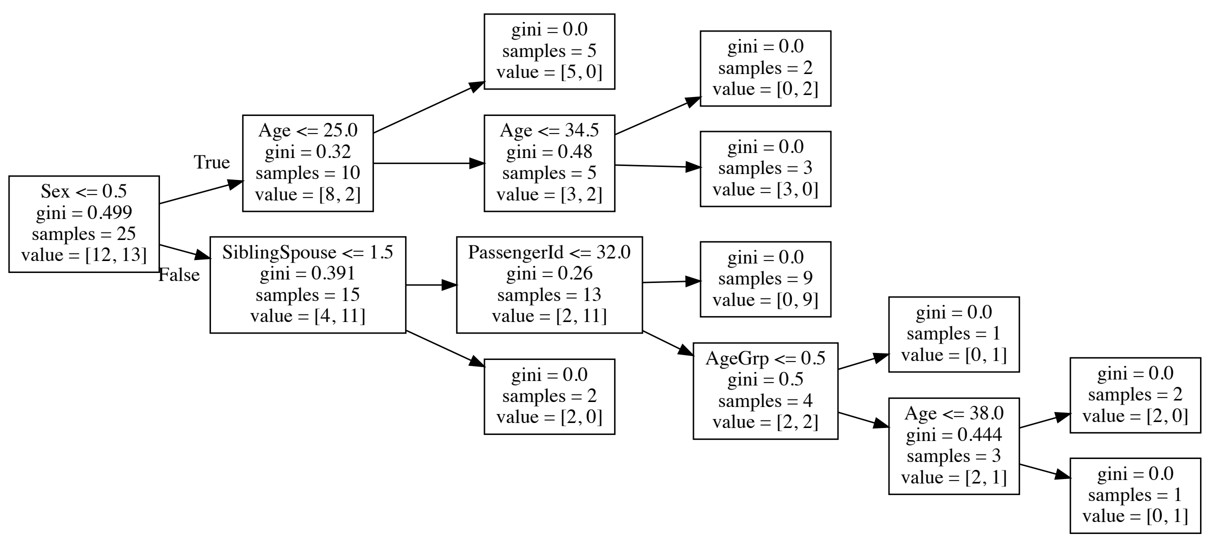
In [53]:
```
y_test_pd2 = dt_tree.predict(X_test)
test_accuracy = accuracy_scr(y_test_pd2, y_test)
print('The accuracy for testing dataset is: ', test_accuracy)
```

```
The accuracy for testing dataset is:  Accuracy of Prediction 60.00%.
```

In [59]:
```
import graphviz
```

In [61]:
```
dt_tree_view = tree.export_graphviz(dt_tree, out_file=None, feature_name
s=train_data.columns.values, rotate=True)
dt_tree_vis = graphviz.Source(dt_tree_view)
dt_tree_vis
```

Out[61]:



Using Gini index

- Gini index:
  - the Gini index is a cost function used to evaluate splits in the dataset.
  - each split involves a input attribute and a value corresponding to the attribute, which could be used to divide training models into 2 groups of rows.
- Gini score:
  - the gini score gives an idea of how well the split is by how mixed the classes are in the 2 groups generated by the split.
  - a perfect separation result in a Gini score is 0.
  - a worst result in a Gini score is 0.5 which separate 50/50 classes in each of the two groups.