Titanic: Machine Learning from Disaster

Description

The sinking of the RMS Titanic is one of the most infamous shipwrecks in history. On April 15, 1912, during her maiden voyage, the Titanic sank after colliding with an iceberg, killing 1502 out of 2224 passengers and crew. This sensational tragedy shocked the international community and led to better safety regulations for ships.

One of the reasons that the shipwreck led to such loss of life was that there were not enough lifeboats for the passengers and crew. Although there was some element of luck involved in surviving the sinking, some groups of people were more likely to survive than others, such as women, children, and the upper-class.

Business Problem:

To apply the tools of machine learning to predict which passengers survived the tragedy.

Data

Taken data from : https://www.kaggle.com/c/titanic/data

Business objectives and Constraints

Objectives:
To predict which passengers survived the tragedy

Constraints:
Latency : Not required
Interpretability : It is good to have an uderstanding behind the passengers survival

Machine Learning Problem :

It is a classification Problem
Survived - 1,Not survived - 0

Performance metrics :

Accuracy
Confusion matrix

Features of the data:

survival : Survival 0 = No, 1 = Yes
PassengerId : Unique ID given to each and every passenger
Name : the name of the passenger
pclass : A proxy for socio-economic status (SES) 1st = Upper 2nd = Middle 3rd = Lower
sex : Sex
Age : Age in years (Age is fractional if less than 1. If the age is estimated, is it in the form of xx.5)
sibsp : siblings(brother, sister, stepbrother, stepsister)/ spouses(husband, wife (mistresses and fiancés were ignored)) aboard the Titanic
parch : parents(mother, father) / children(daughter, son, stepdaughter, stepson) aboard the Titanic /Some children travelled only with a nanny, therefore parch=0 for them.
ticket : Ticket number

ticket : Ticket number
fare : Passenger fare
cabin : Cabin number
embarked : Port of Embarkation C = Cherbourg, Q = Queenstown, S = Southampton

Libraries

In [216]:

```
import warnings
warnings.filterwarnings("ignore")
import os
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
import scikitplot as skplt
from sklearn.grid_search import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier as KNN
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
from keras.initializers import RandomNormal
from keras.utils import np_utils
from keras.models import Sequential
from keras.layers import Dense, Activation
from keras.layers.normalization import BatchNormalization
from keras.layers import Dropout
```

Load Data

In [270]:

```
train_data = pd.read_csv(r'C:\Users\Friend\AI\AI_datasets\Titanic\train.csv')
train_data.shape
```

Out[270]:

```
(891, 12)
```

In [74]:

```
train_data.head()
```

Out[74]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

In [5]:

```
test_data = pd.read_csv(r'C:\Users\Friend\AI\AI_datasets\Titanic\test.csv')
test_data.shape
```

Out[5]:

```
(418, 11)
```

In [8]:

```
test_data.head()
```

Out[8]:

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

Exploratory Data Analysis:

In [12]:

```
#columns of the data

train_data.columns
```

Out[12]:

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

Observations:

- Independent Variable - PassengerId,Pclass,Name,Sex,Age,SibSp,Parch,Ticket,Fare,Cabin,Embarked
- Dependent variable - Survived

In [13]:

```
#Datatypes of each Column

train_data.dtypes
```

Out[13]:

```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

In [38]:

```
#Statistical Analysis of features

train_data.describe()
```

Out[38]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [37]:

```
# Checking attribute values in PassengerId
print('length of unique values in PassengerId',len(set(train_data['PassengerId'])))
print('some of the unique values in PassengerId',list(set(train_data['PassengerId']))[0:5])
print('---------------------------------------------------------')

# Checking attribute values in Pclass
print('length of unique values in Pclass',len(set(train_data['Pclass'])))
print('unique values in Pclass',set(train_data['Pclass']))
print('---------------------------------------------------------')

# Checking attribute values in Name
print('length of unique values in Name',len(set(train_data['Name'])))
print('length of unique values in Name',len(set(train_data['Name'])))
print('---------------------------------------------------------')

# Checking attribute values in Sex
print('length of unique values in Sex',len(set(train_data['Sex'])))
print('unique values in Sex',set(train_data['Sex']))
print('---------------------------------------------------------')

# Checking attribute values in Age
print('length of unique values in Age',len(set(train_data['Age'])))
print('some of the unique values in Age',list(set(train_data['Age']))[0:5])
print('---------------------------------------------------------')

# Checking attribute values in SibSp
print('length of unique values in SibSp',len(set(train_data['SibSp'])))
print('unique values in SibSp',set(train_data['SibSp']))
print('---------------------------------------------------------')

# Checking attribute values in Parch
print('length of unique values in Parch',len(set(train_data['Parch'])))
print('unique values in Parch',set(train_data['Parch']))
print('---------------------------------------------------------')

# Checking attribute values in Ticket
print('length of unique values in Ticket',len(set(train_data['Ticket'])))
print('some of the unique values in Ticket',list(set(train_data['Ticket']))[0:5])
print('---------------------------------------------------------')

# Checking attribute values in Fare
print('length of unique values in Fare',len(set(train_data['Fare'])))
print('some of the unique values in Fare',list(set(train_data['Fare']))[0:5])
print('---------------------------------------------------------')

# Checking attribute values in Cabin
```

```
print('length of unique values in Cabin',len(set(train_data['Cabin'])))
print('some of the unique values in Cabin',list(set(train_data['Cabin']))[0:5])
print('---------------------------------------------------------')

# Checking attribute values in Embarked
print('length of unique values in Embarked',len(set(train_data['Embarked'])))
print('unique values in Embarked',set(train_data['Embarked']))
print('---------------------------------------------------------')

# Checking attribute values in Survived
print('length of unique values in Survived',len(set(train_data['Survived'])))
print('unique values in Survived',set(train_data['Survived']))
```

```
length of unique values in PassengerId 891
some of the unique values in PassengerId [1, 2, 3, 4, 5]
---------------------------------------------------------
length of unique values in Pclass 3
unique values in Pclass {1, 2, 3}
---------------------------------------------------------
length of unique values in Name 891
length of unique values in Name 891
---------------------------------------------------------
length of unique values in Sex 2
unique values in Sex {'male', 'female'}
---------------------------------------------------------
length of unique values in Age 265
some of the unique values in Age [nan, nan, 2.0, nan, 4.0]
---------------------------------------------------------
length of unique values in SibSp 7
unique values in SibSp {0, 1, 2, 3, 4, 5, 8}
---------------------------------------------------------
length of unique values in Parch 7
unique values in Parch {0, 1, 2, 3, 4, 5, 6}
---------------------------------------------------------
length of unique values in Ticket 681
some of the unique values in Ticket ['7552', '349910', '13214', 'SOTON/O.Q. 392087', '250646']
---------------------------------------------------------
length of unique values in Fare 248
some of the unique values in Fare [0.0, 512.3292, 4.0125, 5.0, 6.975]
---------------------------------------------------------
length of unique values in Cabin 148
some of the unique values in Cabin [nan, 'C91', 'B39', 'B18', 'D21']
---------------------------------------------------------
length of unique values in Embarked 4
unique values in Embarked {nan, 'C', 'S', 'Q'}
---------------------------------------------------------
length of unique values in Survived 2
unique values in Survived {0, 1}
```

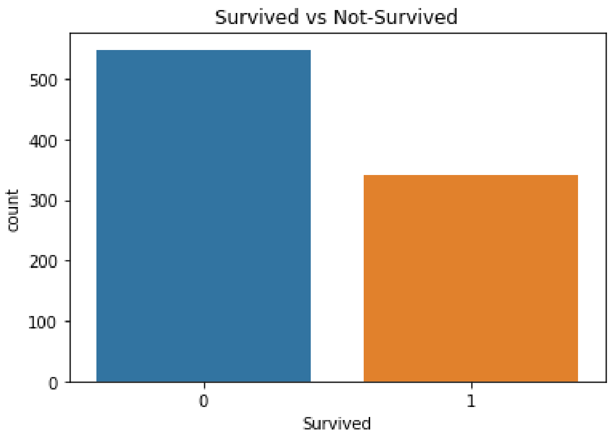
Observations:

- Independent variables:
  - PassengerId : Discrete value;unique identifier for each record in dataset
  - Pclass : Categorical(Ordinal)
  - Name : Text(unique)
  - Sex : Categorical(Nominal)
  - Age : Numeric(Continuous)
  - SibSp : Numeric(Discrete)
  - Parch : Numeric(Discrete)
  - Ticket : Text(Not unique)
  - Fare : Numeric(Continuous)
  - Cabin : Categorical(Nominal)
  - Embarked : Categorical(Nominal)
- Dependent Variable:
  - Survived : Numeric(Discrete)

In [271]:

```
# Distribution of output

sns.countplot(x ="Survived", data = train_data)
plt.title("Survived vs Not-Survived")
plt.show()
```

```
plt.show()
```



In [40]:

```
# Analysing Columns having missing/null vlaues

null_values = train_data.isnull().sum()
print(null_values)
```

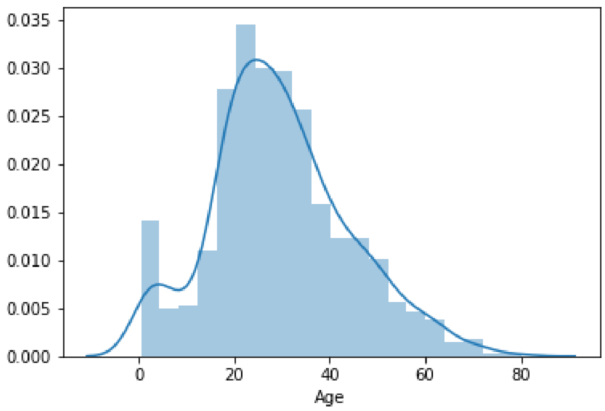
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

Observations: We see that apart from Age,Cabin and Embarked we do not have missing values in any other column.

In [84]:

```
# Analysing Age Column
print('percent of data missing',train_data['Age'].isnull().sum()*100/train_data.shape[0])

# Checking the distribution of Age
data = train_data[train_data['Age'].notnull()]['Age']
sns.distplot(data)
plt.show()
```

```
percent of data missing 19.865319865319865
```



Observations: Seems like Age column distribution is symmetric about mean with little noise,hence it would be good to replace it with median.

In [85]:

```
# Analysing Cabin Column
print('percent of data missing',train_data['Cabin'].isnull().sum()*100/train_data.shape[0])
```

```
percent of data missing 77.10437710437711
```

Observations: Seems like cabin data has lot of missing values,hence it is better that we drop it.

In [57]:

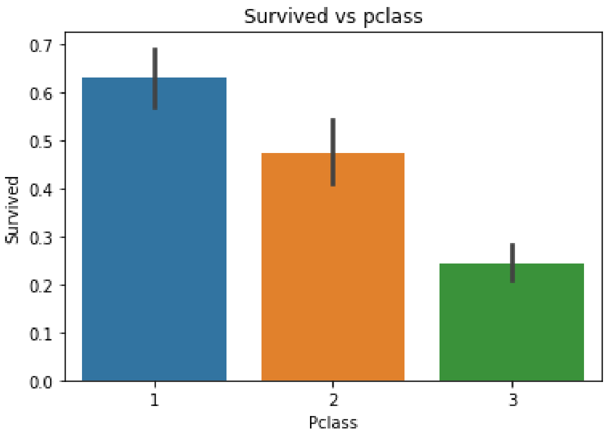
```
# Analysing Embarked Column
print(train_data['Embarked'].value_counts(dropna=False))
```

```
S      644
C      168
Q       77
NaN      2
Name: Embarked, dtype: int64
```

Observations: Found 2 null value in Embarked column,it could be better to replace them with the mode of the column.

In [89]:

```
# Analysis on pclass

sns.barplot(x="Pclass", y="Survived", data = train_data)
plt.title("Survived vs pclass")
plt.show()
```



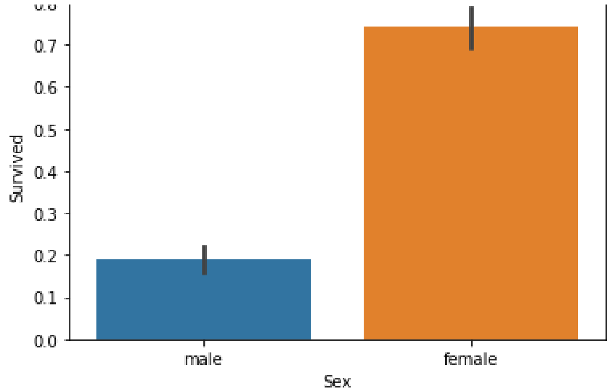
Observation:

From the barplot it is evident that

1. Above 60% of 1st class people has survived.
2. Around 45% of 2nd class people has survived.
3. Around 30% of 3rd calss people has survived.

In [91]:

```
# Analysis on Sex

sns.barplot(x="Sex", y="Survived", data = train_data)
plt.title("Survived vs pclass")
plt.show()
```



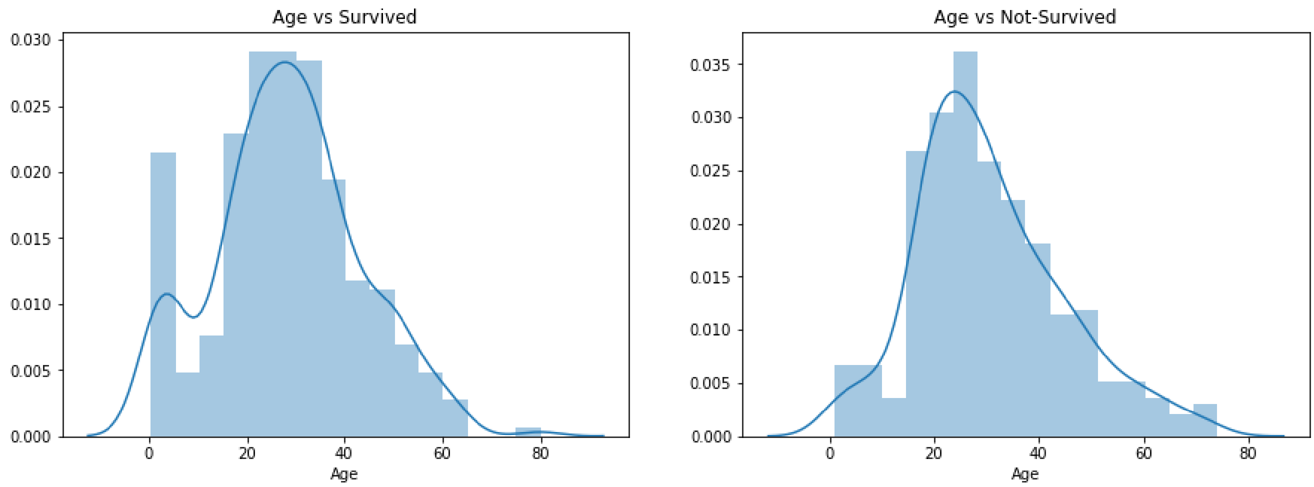
Observations:

From the barplot it is evident that

1. Around 70% to 80% of people who has survived are females.
2. Around 20 % of the people being males has survived.

In [100]:

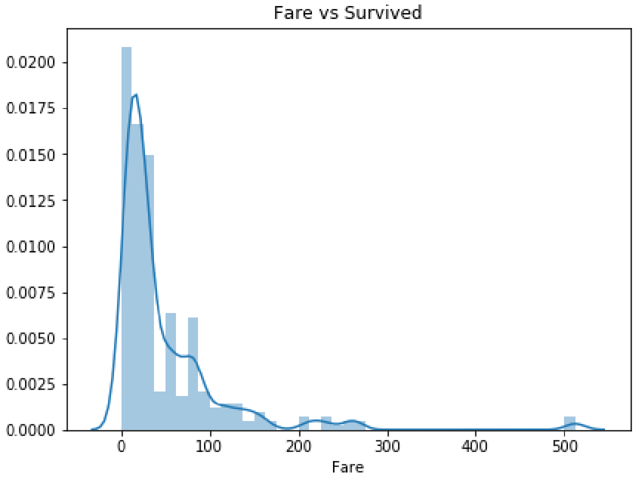
```
# Analysis on Age

data = train_data[train_data['Age'].notnull()]
plt.figure(figsize=(15,5))
plt.subplot(1, 2, 1)
sns.distplot(data[data.Survived  == 1]['Age'])
plt.title('Age vs Survived')
plt.subplot(1, 2, 2)
sns.distplot(data[data.Survived  == 0]['Age'])
plt.title('Age vs Not-Survived')
plt.show()
```

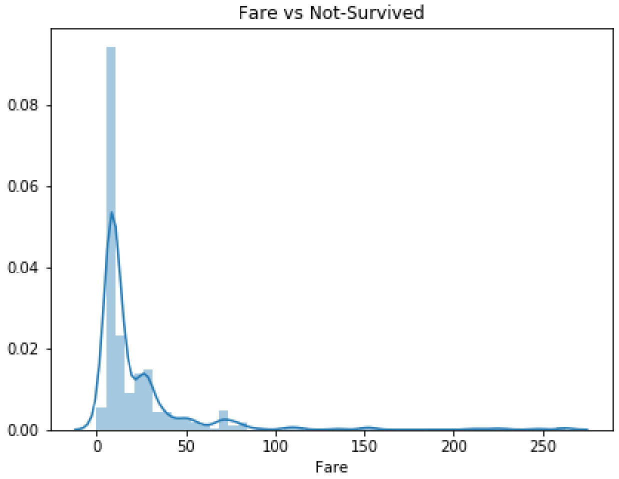


Observations: Nothing information to be drawn from age,since both survived and not-survived gives similar plots except that there is a difference in the shape at the range of 0 to 10.Seems like children have survived more.

In [106]:

```
# Analysis on Fare

plt.figure(figsize=(15,5))
plt.subplot(1, 2, 1)
sns.distplot(train_data[train_data.Survived  == 1]['Fare'])
plt.title('Fare vs Survived')
plt.subplot(1, 2, 2)
sns.distplot(train_data[train_data.Survived  == 0]['Fare'])
plt.title('Fare vs Not-Survived')
plt.show()
```





Observations:

From the plot it is clear that

1. Only 2% of people who have survived has a fare within 50 dollars.
2. About 8% of people has not survived who has same fare.

In [108]:

```
# Checking correlations between features.

train_data.corr()
```

Out[108]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
PassengerId	1.000000	-0.005007	-0.035144	0.036847	-0.057527	-0.001652	0.012658
Survived	-0.005007	1.000000	-0.338481	-0.077221	-0.035322	0.081629	0.257307
Pclass	-0.035144	-0.338481	1.000000	-0.369226	0.083081	0.018443	-0.549500
Age	0.036847	-0.077221	-0.369226	1.000000	-0.308247	-0.189119	0.096067
SibSp	-0.057527	-0.035322	0.083081	-0.308247	1.000000	0.414838	0.159651
Parch	-0.001652	0.081629	0.018443	-0.189119	0.414838	1.000000	0.216225
Fare	0.012658	0.257307	-0.549500	0.096067	0.159651	0.216225	1.000000

Observations:

1. Positive correlation : Fare,Parch
2. Negative correlation : Pclass,Age,SibSp,PassengerId
3. Fare vs Survived : Positive correlation indicating an increase in fare will increase the chances of survival
4. Parch vs Survived : Not highly correlated,but shows a positive correlation
5. Pclass vs Survived : Class is inversely propotional to chances of survival.1st class has higher chances of surviving than 2nd class ,2nd class has higher chances of survival than 3rd class.
6. Age vs Survived : Negative correlation indicating least the age,higher is the chance of survival.
7. Sibsp vs Survived : Negative correaltion indicating lesser is the number of sibblings/spouses,more are the chance of survival.
8. Need not worry about PassengerId since it is an unique identifier.
9. Highest positive correlation could be seen from Fare and survived indicating an increase in fare will increase the chances of survival.
10. Highest negative correlation could be seen from Pclass and Fare indicating,1st class paid more than 2nd class,and 2nd class paid more than 3rd class.

Data Preparation

In [238]:

```
#Fill null value with the mode(S) of the column
train_data["Embarked"].fillna("S", inplace = True)
print(train_data['Embarked'].value_counts(dropna=False))
```

```
S    646
C    168
Q     77
Name: Embarked, dtype: int64
```

In [239]:

```
#Fill null value with the median(S) of the column
train_data["Age"].fillna(train_data["Age"].median(), inplace = True)
```

In [240]:

```
#Drop "Cabin"-Lot of missing values, "Ticket"-Adds no onformation to the model,"Name"-Adds no informati
on to model,"PassengerId" -unique identifier.
train_data.drop(labels = ["Cabin", "Ticket","Name","PassengerId"], axis = 1, inplace = True)
```

In [241]:

```
train_data.isnull().sum()
```

Out[241]:

```
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    0
dtype: int64
```

In [242]:

```
train_data.columns
```

Out[242]:

```
Index(['Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare',
       'Embarked'],
      dtype='object')
```

Featurization

In [243]:

```
# convert sex,a categorical text column to categorical numeric.

set(train_data['Sex'])
```

Out[243]:

```
{'female', 'male'}
```

In [244]:

```
train_data.loc[train_data['Sex'] =='male', 'Sex'] = 1
train_data.loc[train_data['Sex'] == 'female','Sex'] = 0

set(train_data['Sex'])
```

Out[244]:

```
{0, 1}
```

In [245]:

```
# Convert Embarked a categorical column to Numerical.

set(train_data['Embarked'])
```

Out[245]:

```
{'C', 'Q', 'S'}
```

In [246]:

```
train_data.loc[train_data['Embarked'] =='C', 'Embarked'] = 1
train_data.loc[train_data['Embarked'] == 'Q','Embarked'] = 2
train_data.loc[train_data['Embarked'] == 'S','Embarked'] = 3

set(train_data['Embarked'])
```

Out[246]:

```
{1, 2, 3}
```

In [247]:

```
#Considering sibling+spouse+Parents+Children as family size
train_data["total_family"] = train_data["SibSp"] + train_data["Parch"] + 1
```

In [248]:

```
#Checking if the person is single(if single = 1 ,else = 0).
train_data["single"] = train_data.total_family.apply(lambda x: 1 if x == 1 else 0)
```

In [249]:

```
train_data.head()
```

Out[249]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	total_family	single
0	0	3	1	22.0	1	0	7.2500	3	2	0
1	1	1	0	38.0	1	0	71.2833	1	2	0
2	1	3	0	26.0	0	0	7.9250	3	1	1
3	1	1	0	35.0	1	0	53.1000	3	2	0
4	0	3	1	35.0	0	0	8.0500	3	1	1

Split Data

In [250]:

```
Y = train_data['Survived']
train_data.drop(labels = ['Survived'], axis = 1, inplace = True)
```

In [251]:

```
X_train, X_test, y_train, y_test = train_test_split(train_data, Y, test_size=0.30, random_state=42)
X_train.shape,X_test.shape,y_train.shape,y_test.shape
```

Out[251]:

((623, 9), (268, 9), (623,), (268,))

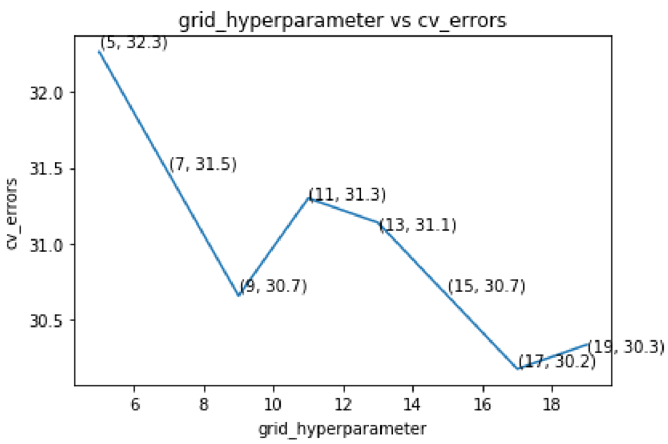
Machine Learning Models

K-NN

In [165]:

```
grid_hyperparameter = [{'n_neighbors':[5, 7, 9, 11, 13, 15, 17, 19]}]
print(grid_hyperparameter)

knn_model = GridSearchCV(KNN(algorithm = 'kd_tree'),grid_hyperparameter,scoring = 'accuracy', cv=3)
knn_model.fit(X_train,y_train)

#plot cv errors
errors = [(1-x[1])*100 for x in knn_model.grid_scores_]
plt.plot(grid_hyperparameter[0]['n_neighbors'],errors)
for xy in zip(grid_hyperparameter[0]['n_neighbors'],np.round(errors,1)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.xlabel('grid_hyperparameter')
plt.ylabel('cv_errors')
plt.title('grid_hyperparameter vs cv_errors')
plt.show()

k = knn_model.best_estimator_.get_params()['n_neighbors']
knn_train_score = knn_model.score(X_train,y_train)
knn_test_score = knn_model.score(X_test, y_test)
print('the best k-value is',k)
print('Accuracy of train data',knn_train_score)
print('Accuracy of test data',knn_test_score)

knn_model = KNN(n_neighbors= 9,algorithm = 'kd_tree')
knn_model.fit(X_train,y_train)

pred = knn_model.predict(X_test)
skplt.metrics.plot_confusion_matrix(y_test, pred, normalize=False)
```

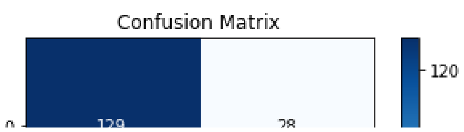
[{'n_neighbors': [5, 7, 9, 11, 13, 15, 17, 19]}]

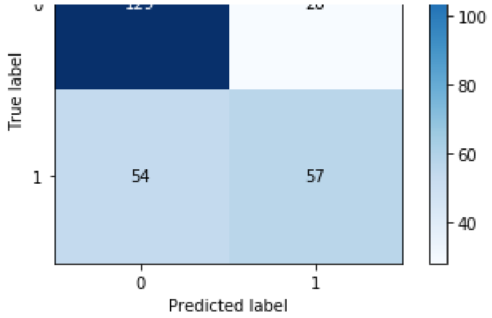


the best k-value is 17
Accuracy of train data 0.7399678972712681
Accuracy of test data 0.7052238805970149

Out[165]:

<matplotlib.axes._subplots.AxesSubplot at 0x168755565f8>



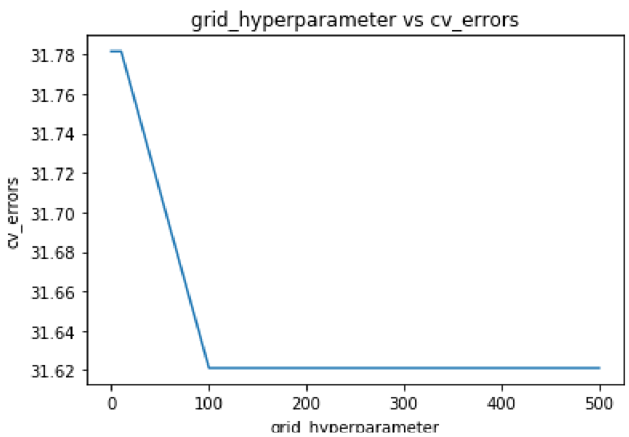


Naive Bayes

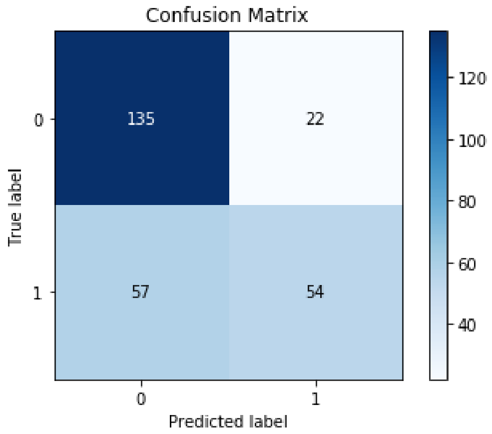
In [200]:

```
grid_hyperparameter = [{'alpha':[0.000001,0.00001, 0.0001, 0.001, 0.01, 1, 10, 100,500]}]
print(grid_hyperparameter)

NB_model = GridSearchCV(NB(),grid_hyperparameter,scoring = 'accuracy', cv=3)
NB_model.fit(X_train,y_train)

#plot cv errors
errors = [(1-x[1])*100 for x in NB_model.grid_scores_]
plt.plot(grid_hyperparameter[0]['alpha'],errors)
for xy in zip(grid_hyperparameter[0]['alpha'],np.round(errors,1)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.xlabel('grid_hyperparameter')
plt.ylabel('cv_errors')
plt.title('grid_hyperparameter vs cv_errors')
plt.show()

alpha = NB_model.best_estimator_.get_params()['alpha']
NB_train_score = NB_model.score(X_train,y_train)
NB_test_score = NB_model.score(X_test, y_test)
print('the best alpha-value is',alpha)
print('Accuracy of train data',NB_train_score)
print('Accuracy of test data',NB_test_score)

NB_model = NB(alpha = alpha)
NB_model.fit(X_train,y_train)

pred = NB_model.predict(X_test)
skplt.metrics.plot_confusion_matrix(y_test, pred, normalize=False)
plt.show()

#Features that are important in analysing people who could not survive
neg_probs = NB_model.feature_log_prob_[0, :].argsort()
print('Features important for not survived',np.take(X_train.columns, neg_probs[0:2]))

#Features that are important in analysing people who could survive
pos_probs = NB_model.feature_log_prob_[1, :].argsort()
print('Features important for survived',np.take(X_train.columns, pos_probs[0:2]))
```

```
[{'alpha': [1e-06, 1e-05, 0.0001, 0.001, 0.01, 1, 10, 100, 500]}]
```



```
the best alpha-value is 100
Accuracy of train data 0.680577849117175
Accuracy of test data 0.7052238805970149
```



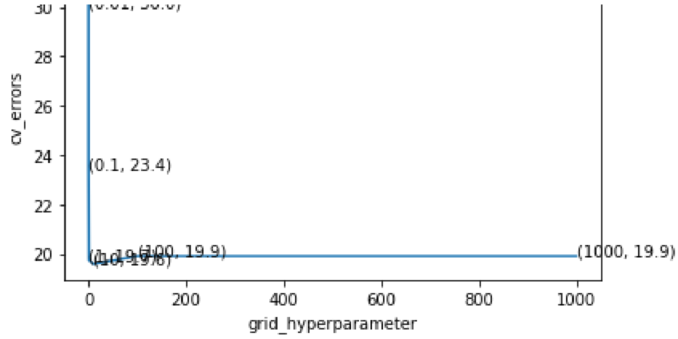

```
Features important for not survived Index(['Parch', 'SibSp'], dtype='object')
Features important for survived Index(['Sex', 'Parch'], dtype='object')
```

Logistic Regression

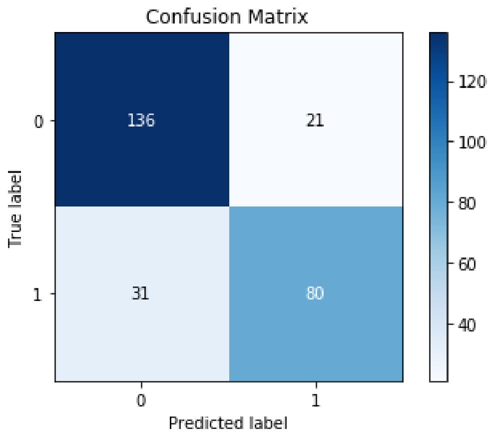
In [204]:

```python
grid_hyperparameter = [{'C':[0.0001,0.001,0.01,0.1,1,10,100,1000]}]
print(grid_hyperparameter)

LR_model = GridSearchCV(LogisticRegression(penalty='l2'),grid_hyperparameter,scoring = 'accuracy', cv=3
)
LR_model.fit(X_train,y_train)

#plot cv errors
errors = [(1-x[1])*100 for x in LR_model.grid_scores_]
plt.plot(grid_hyperparameter[0]['C'],errors)
for xy in zip(grid_hyperparameter[0]['C'],np.round(errors,1)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.xlabel('grid_hyperparameter')
plt.ylabel('cv_errors')
plt.title('grid_hyperparameter vs cv_errors')
plt.show()

C = LR_model.best_estimator_.get_params()['C']
LR_train_score = LR_model.score(X_train,y_train)
LR_test_score = LR_model.score(X_test, y_test)
print('the best C-value is',alpha)
print('Accuracy of train data',LR_train_score)
print('Accuracy of test data',LR_test_score)

LR_model = LogisticRegression(penalty='l2',C= C)
LR_model.fit(X_train,y_train)

pred = LR_model.predict(X_test)
skplt.metrics.plot_confusion_matrix(y_test, pred, normalize=False)
plt.show()

#Important Features
indx = LR_model.coef_.argsort()
print('Important Features',np.take(X_train.columns, indx[0][:2]))
```

```
[{'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]}]
```




```
the best C-value is 100
Accuracy of train data 0.7961476725521669
Accuracy of test data 0.8059701492537313
```




```
Important Features Index(['Sex', 'SibSp'], dtype='object')
```

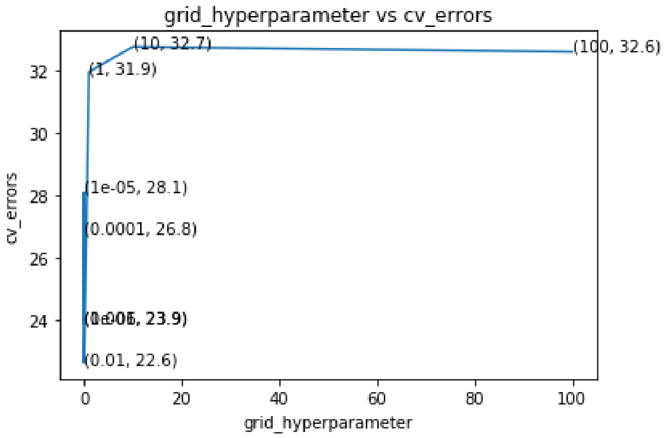
SVM

In [205]:

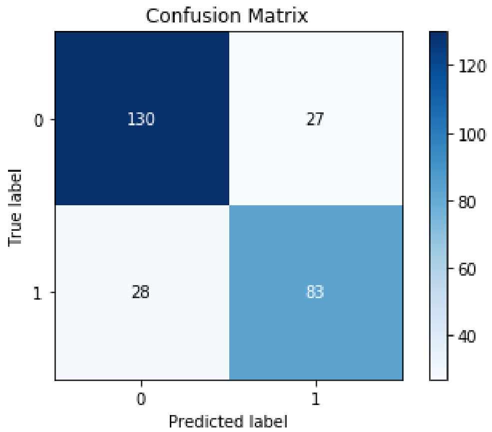
```
grid_hyperparameter = [{'alpha':[0.000001,0.00001, 0.0001, 0.001, 0.01, 1, 10, 100]}]
print(grid_hyperparameter)

SVM_model = GridSearchCV(SGDClassifier(penalty='l2',loss='hinge',max_iter=1000),grid_hyperparameter,sco
ring = 'accuracy', cv=3)
SVM_model.fit(X_train,y_train)

#plot cv errors
errors = [(1-x[1])*100 for x in SVM_model.grid_scores_]
plt.plot(grid_hyperparameter[0]['alpha'],errors)
for xy in zip(grid_hyperparameter[0]['alpha'],np.round(errors,1)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.xlabel('grid_hyperparameter')
plt.ylabel('cv_errors')
plt.title('grid_hyperparameter vs cv_errors')
plt.show()

SVM_alpha = SVM_model.best_estimator_.get_params()['alpha']
SVM_train_score = SVM_model.score(X_train,y_train)
SVM_test_score = SVM_model.score(X_test, y_test)
print('the best C-value is',alpha)
print('Accuracy of train data',SVM_train_score)
print('Accuracy of test data',SVM_test_score)

SVM_model = SGDClassifier(alpha = SVM_alpha,penalty='l2',loss='hinge',max_iter=1000)
SVM_model.fit(X_train,y_train)

pred = SVM_model.predict(X_test)
skplt.metrics.plot_confusion_matrix(y_test, pred, normalize=False)
plt.show()
```

```
#Important Features
indx = SVM_model.coef_.argsort()
print('Important Features',np.take(X_train.columns, indx[0][:2]))
```

```
[{'alpha': [1e-06, 1e-05, 0.0001, 0.001, 0.01, 1, 10, 100]}]
```




```
the best C-value is 100
Accuracy of train data 0.7752808988764045
Accuracy of test data 0.8022388059701493
```




```
Important Features Index(['Sex', 'single'], dtype='object')
```

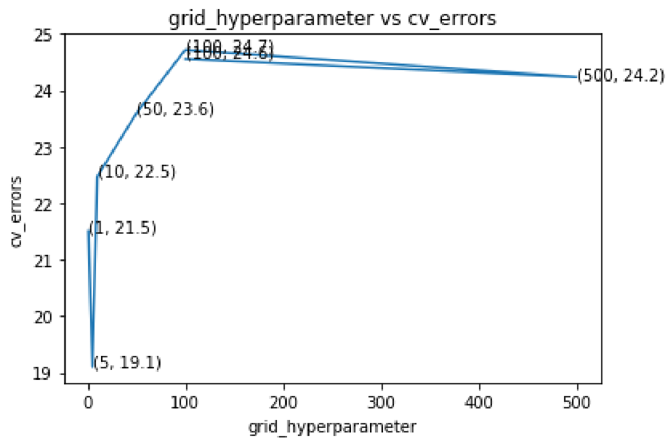
Decision Tress

In [214]:

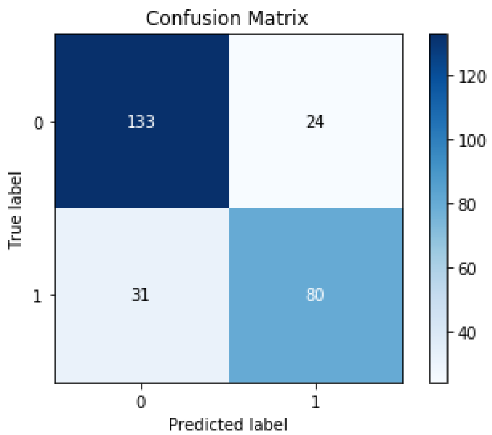
```
grid_hyperparameter = [{'max_depth':[1, 5, 10, 50, 100, 500, 100]}]
print(grid_hyperparameter)

DT_model = GridSearchCV(DecisionTreeClassifier(),grid_hyperparameter,scoring = 'accuracy', cv=3)
DT_model.fit(X_train,y_train)

#plot cv errors
errors = [(1-x[1])*100 for x in DT_model.grid_scores_]
plt.plot(grid_hyperparameter[0]['max_depth'],errors)
for xy in zip(grid_hyperparameter[0]['max_depth'],np.round(errors,1)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.xlabel('grid_hyperparameter')
plt.ylabel('cv_errors')
plt.title('grid_hyperparameter vs cv_errors')
plt.show()

DT_depth = DT_model.best_estimator_.get_params()['max_depth']
DT_train_score = DT_model.score(X_train,y_train)
DT_test_score = DT_model.score(X_test, y_test)
print('the best max_depth is',DT_depth)
print('Accuracy of train data',DT_train_score)
```

```
print('Accuracy of train data',DT_train_score)
print('Accuracy of test data',DT_test_score)

DT_model = DecisionTreeClassifier(max_depth = DT_depth)
DT_model.fit(X_train,y_train)

pred = DT_model.predict(X_test)
skplt.metrics.plot_confusion_matrix(y_test, pred, normalize=False)
plt.show()

#Important Features
indx = np.argsort(DT_model.feature_importances_)
print('Important Features',np.take(X_train.columns, indx[:2]))
```

```
[{'max_depth': [1, 5, 10, 50, 100, 500, 100]}]
```




```
the best max_depth is 5
Accuracy of train data 0.85553772070626
Accuracy of test data 0.7947761194029851
```




```
Important Features Index(['SibSp', 'single'], dtype='object')
```

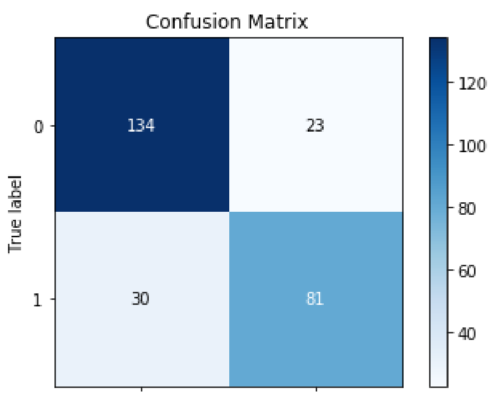
Random Forest

In [218]:

```
grid_hyperparameter = [{'n_estimators'  : [100, 200, 500, 1000, 2000],'max_depth':[5,10]}]
grid_hyperparameter

clf = GridSearchCV(RandomForestClassifier(criterion='gini'),grid_hyperparameter,scoring = 'accuracy', c
v=3)
clf.fit(X_train,y_train)

n_estimators = grid_hyperparameter[0]['n_estimators']
max_depth = grid_hyperparameter[0]['max_depth']
df = pd.DataFrame(clf.grid_scores_)
scores = np.array(df['mean_validation_score']).reshape(2,5)
```

```
fig, ax = plt.subplots()
plt.imshow(scores, interpolation='nearest')
plt.colorbar()
for i in range(len(max_depth)):
    for j in range(len(n_estimators)):
        text = ax.text(j, i, np.round(scores[i, j],3),
                       ha="center", va="center", color="w")
ax.set_xticks(np.arange(len(n_estimators)))
ax.set_yticks(np.arange(len(max_depth)))
ax.set_xticklabels(n_estimators)
ax.set_yticklabels(max_depth)
plt.xlabel('n_estimators')
plt.ylabel('max_depth')
ax.set_title("Grid Search f1 Score")
fig.tight_layout()
plt.show()

clf_n = clf.best_estimator_.get_params()['n_estimators']
clf_depth = clf.best_estimator_.get_params()['max_depth']
clf_train_score = clf.score(X_train,y_train)
clf_test_score = clf.score(X_test, y_test)
print('the best max_depth is',clf_depth)
print('the best max_depth is',clf_n)
print('Accuracy of train data',clf_train_score)
print('Accuracy of test data',clf_test_score)

clf = RandomForestClassifier(class_weight = 'balanced',n_estimators=clf_n, criterion='gini', max_depth=
clf_depth, random_state=42, n_jobs=-1)
clf.fit(X_train,y_train)

pred = clf.predict(X_test)
skplt.metrics.plot_confusion_matrix(y_test, pred, normalize=False)
plt.show()

#Important Features
indx = np.argsort(clf.feature_importances_)
print('Important Features',np.take(X_train.columns, indx[:2]))
```


```
the best max_depth is 5
the best max_depth is 100
Accuracy of train data 0.869983948635634
Accuracy of test data 0.8134328358208955
```




```
Important Features Index(['single', 'Parch'], dtype='object')
```

XGB

In [227]:

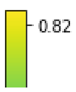
```
xg_n_estimator = clf.best_estimator_.get_params()['n_estimators']
xg_max_depths = clf.best_estimator_.get_params()['max_depth']
xg_train_score = clf.score(X_train,y_train)
xg_test_score = clf.score(X_test, y_test)
print('the best max_depth is',clf_depth)
print('the best max_depth is',clf_n)
print('Accuracy of train data',clf_train_score)
print('Accuracy of test data',clf_test_score)
```

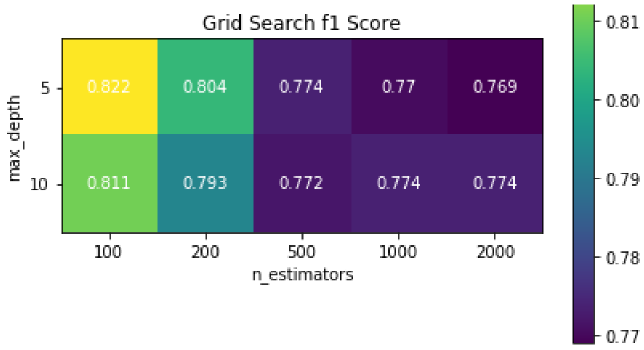
Out[227]:

```
[50, 100, 500, 1000, 2000]
```

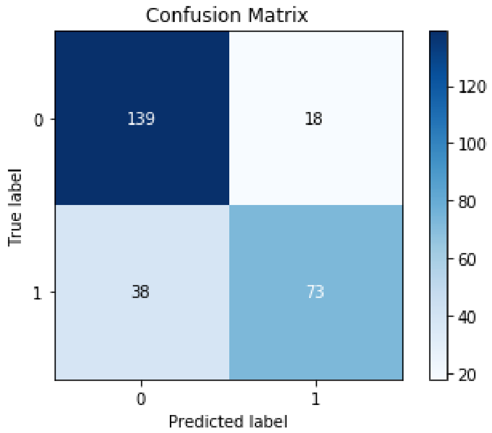
In [229]:

```
grid_hyperparameter = [{'n_estimators'  : [50,100,500,1000,2000],'max_depth':[5,10]}]

clf_XG = GridSearchCV(XGBClassifier(), grid_hyperparameter,scoring = 'accuracy',cv=3)
clf_XG.fit(X_train,y_train)

xg_n_estimators = grid_hyperparameter[0]['n_estimators']
xg_max_depth = grid_hyperparameter[0]['max_depth']
df = pd.DataFrame(clf_XG.grid_scores_)
scores = np.array(df['mean_validation_score']).reshape(2,5)
fig, ax = plt.subplots()
plt.imshow(scores, interpolation='nearest')
plt.colorbar()
for i in range(len(max_depth)):
    for j in range(len(n_estimators)):
        text = ax.text(j, i, np.round(scores[i, j],3),
                       ha="center", va="center", color="w")
ax.set_xticks(np.arange(len(n_estimators)))
ax.set_yticks(np.arange(len(max_depth)))
ax.set_xticklabels(n_estimators)
ax.set_yticklabels(max_depth)
plt.xlabel('n_estimators')
plt.ylabel('max_depth')
ax.set_title("Grid Search f1 Score")
fig.tight_layout()
plt.show()

xg_n_estimator = clf_XG.best_estimator_.get_params()['n_estimators']
xg_max_depths = clf_XG.best_estimator_.get_params()['max_depth']
xg_train_score = clf_XG.score(X_train,y_train)
xg_test_score = clf_XG.score(X_test, y_test)
print('the best max_depth is',xg_max_depths)
print('the best max_depth is',xg_n_estimator)
print('Accuracy of train data',xg_train_score)
print('Accuracy of test data',xg_test_score)


clf = XGBClassifier(class_weight = 'balanced',n_estimators=xg_n_estimator, criterion='gini', max_depth=
xg_max_depths, random_state=42, n_jobs=-1)
clf.fit(X_train,y_train)

pred = clf.predict(X_test)
skplt.metrics.plot_confusion_matrix(y_test, pred, normalize=False)
plt.show()
```






```
the best max_depth is 5
the best max_depth is 50
Accuracy of train data 0.8972712680577849
Accuracy of test data 0.7910447761194029
```



MLP

In [235]:

```
def plt_dynamic(x, vy, ty, ax, colors=['b']):
    ax.plot(x, vy, 'b', label="Validation Loss")
    ax.plot(x, ty, 'r', label="Train Loss")
    plt.legend()
    plt.grid()
    fig.canvas.draw()
```

In [264]:

```
output_dim = 1
input_dim = X_train.shape[1]
batch_size = 32
nb_epoch = 5
```

In [265]:

```
model_drop = Sequential()

model_drop.add(Dense(10,activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNormal(me
an=0.0, stddev=0.062, seed=None)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(10 ,activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125, see
d=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(output_dim, activation='sigmoid'))
```

```
model_drop.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_10 (Dense)             (None, 10)                100       
_________________________________________________________________
batch_normalization_7 (Batch (None, 10)                40        
_________________________________________________________________
dropout_7 (Dropout)          (None, 10)                0         
_________________________________________________________________
dense_11 (Dense)             (None, 10)                110       
_________________________________________________________________
batch_normalization_8 (Batch (None, 10)                40        
_________________________________________________________________
dropout_8 (Dropout)          (None, 10)                0         
_________________________________________________________________
dense_12 (Dense)             (None, 1)                 11        
=================================================================
Total params: 301
Trainable params: 261
Non-trainable params: 40
_________________________________________________________________
```

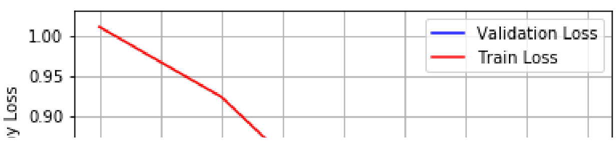
In [266]:

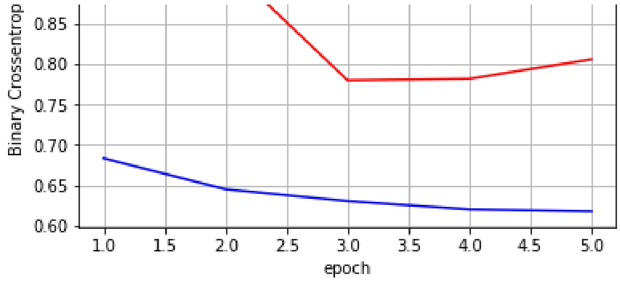
```
model_drop.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
history = model_drop.fit(X_train, y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validatio
n_data=(X_test, y_test))

score = model_drop.evaluate(X_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
```

```
Train on 623 samples, validate on 268 samples
Epoch 1/5
623/623 [==============================] - 1s 2ms/step - loss: 1.0106 - acc: 0.4928 - val_loss: 0.6834
- val_acc: 0.6045
Epoch 2/5
623/623 [==============================] - 0s 73us/step - loss: 0.9237 - acc: 0.5152 - val_loss: 0.6449
- val_acc: 0.7276
Epoch 3/5
623/623 [==============================] - 0s 70us/step - loss: 0.7800 - acc: 0.5811 - val_loss: 0.6303
- val_acc: 0.7052
Epoch 4/5
623/623 [==============================] - 0s 67us/step - loss: 0.7819 - acc: 0.5570 - val_loss: 0.6200
- val_acc: 0.6940
Epoch 5/5
623/623 [==============================] - 0s 70us/step - loss: 0.8060 - acc: 0.6003 - val_loss: 0.6176
- val_acc: 0.7127
Test score: 0.6175802928298267
Test accuracy: 0.7126865662745575
```

In [268]:

```
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch')
ax.set_ylabel('Binary Crossentropy Loss')

# list of epoch numbers
x = list(range(1,nb_epoch+1))

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.show()
```





Summary

In [267]:

```
from prettytable import PrettyTable

Table = PrettyTable()

Table.field_names  = ["Model", "Hyper_parameter", "Train score", "Test score"]

Table.add_row(["KNN", k, knn_train_score,knn_test_score])
Table.add_row(["Naive bayes", alpha,NB_train_score, NB_test_score])
Table.add_row(["Logistic Regression", C,LR_train_score, LR_test_score])
Table.add_row(["SVM", SVM_alpha,SVM_train_score, SVM_test_score])
Table.add_row(["Decision Tree", DT_depth,DT_train_score, DT_test_score])
Table.add_row(["Random Forest", [clf_n,clf_depth],clf_train_score, clf_test_score])
Table.add_row(["XGB", [xg_n_estimator,xg_max_depths],xg_train_score, xg_test_score])
Table.add_row(["MLP","",score[0], score[1]])

print(Table)
```

Model	Hyper_parameter	Train score	Test score
KNN	17	0.7399678972712681	0.7052238805970149
Naive bayes	100	0.680577849117175	0.7052238805970149
Logistic Regression	10	0.7961476725521669	0.8059701492537313
SVM	0.01	0.7752808988764045	0.8022388059701493
Decision Tree	5	0.85553772070626	0.7947761194029851
Random Forest	[100, 5]	0.869983948635634	0.8134328358208955
XGB	[50, 5]	0.8972712680577849	0.7910447761194029
MLP		0.6175802928298267	0.7126865662745575