Predicting Titanic Survivors by Machine Learning

use machine learning to create a model that predicts which passengers survived the Titanic shipwreck

We are going to take the following approach:

1. Problem Definition
2. Data
3. Evaluation
4. Features
5. Modelling
6. Experimentation

1. Problem definition

In a statement

> Given demographic data about each passengers, can we predict whether or not they have survived the shipreck?

2. Data

> This data is originally a competition on Kaggle.

3. Evaluation

> Accuracy score is the percentage of passengers you correctly predict. If we can reach 95% accuracy at predicting whether or not a passenger has survived.

4. Features

Information about each section of data

Create data dictionary

- survival: Survival 0 = No, 1 = Yes
- pclass: Ticket class 1 = 1st, 2 = 2nd, 3 = 3rd
- sex: Sex
- Age: Age in years
- sibsp: # of siblings / spouses aboard the Titanic
- parch: # of parents / children aboard the Titanic
- ticket: Ticket number
- fare: Passenger fare
- cabin: Cabin number
- embarked: Port of Embarkation C = Cherbourg, Q = Queenstown, S = Southampton
- pclass: A proxy for socio-economic status (SES) 1st = Upper 2nd = Middle 3rd = Lower
- sibsp: The dataset defines family relations in this way...

  Sibling = brother, sister, stepbrother, stepsister

Spouse = husband, wife (mistresses and fiancés were ignored)

- parch: The dataset defines family relations in this way...

  Parent = mother, father

  Child = daughter, son, stepdaughter, stepson

  Some children travelled only with a nanny, therefore parch=0 for them.

In [1]:

```
# Prepare the tools

# Regular EDA
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# Import models from SkLearn
from sklearn.svm import LinearSVC
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier

# Model evaluations
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import precision_score, recall_score, f1_score
from sklearn.metrics import plot_roc_curve
```

Data

In [2]:

```
# load data
df = pd.read_csv('train.csv')
df.head()
```

Out[2]:

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

In [3]:

```
len(df)
```

Out[3]:

```
891
```

Data exploration (exploratory data analysis or EDA)

The goal here is to find out more about the data and become a subject matter expert on the dataset

1. What questions are you trying to solve?
2. What kind of data we have and how can we treat different types?
3. What's missing from the data and how you deal with it?
4. Where are the outliers? Should we care about it?
5. How can you add, change or remove features to get more out of data?

a. How many classifications do we have?

In [4]:

```
df['Survived'].value_counts()
```

Out[4]:

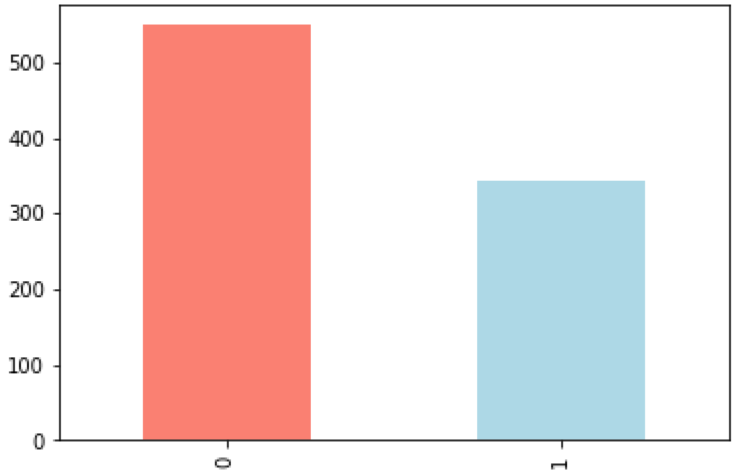
```
0    549
1    342
Name: Survived, dtype: int64
```

In [5]:

```
df['Survived'].value_counts().plot(kind = 'bar', color = ['salmon', 'lightblue'
])
```

Out[5]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff6a82c1780>
```



b. Let's see what type of data we have

In [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
PassengerId    891 non-null int64
Survived       891 non-null int64
Pclass         891 non-null int64
Name           891 non-null object
Sex            891 non-null object
Age            714 non-null float64
SibSp          891 non-null int64
Parch          891 non-null int64
Ticket         891 non-null object
Fare           891 non-null float64
Cabin          204 non-null object
Embarked       889 non-null object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.6+ KB
```

c. Missing data

In [7]:

```
df.isna().sum()
```

Out[7]:

```
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
```

Cabin has too many missing values, we will drop this feature to avoid confusion

d. Understand more

In [8]:

```
df.describe()
```

Out[8]:

	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

Survival by Departure

In [9]:

```
result = pd.crosstab(df.Survived, df.Embarked)
result
```

Out[9]:

Embarked	C	Q	S
Survived			
0	75	47	427
1	93	30	217

In [10]:

```
df['Embarked'].value_counts()
```

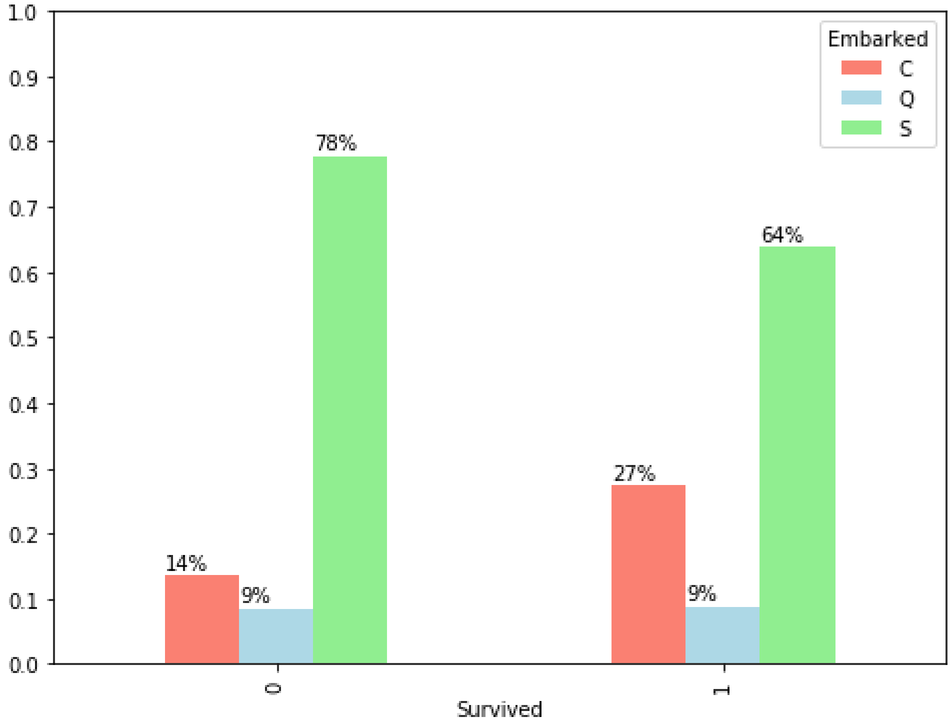
Out[10]:

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

In [11]:

```
# Too hard to see, let's plot
ax = (result.div(result.sum(1), axis=0)).plot(kind = 'bar',
                                              color = ['salmon', 'lightblue', 'light
green'],
                                                 figsize = (8,6))
plt.xticks(fontsize = 10)
# for spine in plt.gca().spines.values():
#     spine.set_visible(False)
plt.yticks(ticks = np.arange(0,1.1,0.1))

# Add this loop to add the annotations
for p in ax.patches:
    width, height = p.get_width(), p.get_height()
    x, y = p.get_xy()
    ax.annotate('{:.0%}'.format(height), (x, y + height + 0.01))
```



In [12]:

```
result.div(result.sum(0), axis = 1)
```

Out[12]:

Embarked	C	Q	S
Survived			
0	0.446429	0.61039	0.663043
1	0.553571	0.38961	0.336957

Interestingly, people who embarked at Cherbourg has a higher number of survivor compared to dead. This is not true for the other departures points

Survival by Class

In [13]:

```
sur_class = pd.crosstab(df.Survived, df.Pclass)
sur_class
```

Out[13]:

Pclass	1	2	3
Survived			
0	80	97	372
1	136	87	119

In [14]:

```
sur_class.div(sur_class.sum(0), axis = 1)
```

Out[14]:

Pclass	1	2	3
Survived			
0	0.37037	0.527174	0.757637
1	0.62963	0.472826	0.242363

As expected, people from first class has a much better chance of surviving compared to third class. 63% first class survived while only 24% of third class made it.

Survival by number of parents / children aboard the Titanic

In [15]:

```
sur_parch = pd.crosstab(df.Survived, df.Parch)
sur_parch
```

Out[15]:

Parch	0	1	2	3	4	5	6
Survived							
0	445	53	40	2	4	4	1
1	233	65	40	3	0	1	0

we may think of outliers in this case but we'll keep this for now

Correlation Matrix

In [16]:

```
corr_matrix = df.corr()
fig, ax = plt.subplots(figsize = (15,10))
ax = sns.heatmap(corr_matrix,
                annot = True,
                linewidths = 0.5,
                fmt = '.2f',
                cmap = 'YlGnBu');
```

SibSp and Parch seem to be relate and to avoid multicolinearity, we can remove one of them from being features in the model.
Also, Ticket feature is not gonna affect the survival rate, so we'll drop it from the features

Features

```
Let's turn string features into categorical features
Let's fill in the missing values here for Age and Embarked
```

Make a copy of dataframe to mess with

In [17]:

```
df_tmp = df.copy()
df_tmp.head()
```

Out[17]:

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

3.a. Turn string features into categorical features

In [19]:

```
# Find all the columns with string values
for label, content in df_tmp.items():
    if pd.api.types.is_string_dtype(content):
        print(label)
```

```
Sex
Embarked
```

In [45]:

```
# Turn them into categorical values
def to_categorical(dataframe):
    '''
    Turn the values with string values into categorical
    '''
    for label, content in dataframe.items():
        if pd.api.types.is_string_dtype(content):
            dataframe[label] = content.astype('category').cat.as_ordered()
            dataframe['coded_'+label] = dataframe[label].cat.codes
```

In [51]:

```
to_categorical(df_tmp)
df_tmp.coded_Sex.head()
```

Out[51]:

```
0    1
1    0
2    0
3    0
4    1
Name: coded_Sex, dtype: int8
```

In [52]:

```
df_tmp.coded_Embarked.value_counts()
```

Out[52]:

```
 2    644
 0    168
 1     77
-1      2
Name: coded_Embarked, dtype: int64
```

In [53]:

```
df_tmp.dtypes
```

Out[53]:

```
PassengerId          int64
Survived             int64
Pclass               int64
Name              category
Sex               category
Age                float64
SibSp                int64
Parch                int64
Ticket            category
Fare               float64
Cabin             category
Embarked          category
coded_Name           int16
coded_Sex             int8
coded_Ticket         int16
coded_Cabin          int16
coded_Embarked        int8
dtype: object
```

Split data first to avoid leakage

In [56]:

```
np.random.seed(26)
# Split the dataframe into X and y
X = df_tmp.drop(['Survived', 'Cabin', 'Ticket', 'Name','Sex','Embarked','coded_N
ame', 'coded_Ticket','coded_Cabin'],
                axis = 1) # May consider drop SibSp or Parch later
y = df_tmp['Survived']
X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size  = 0.2)
X_train.shape, X_valid.shape
```

Out[56]:

```
((712, 8), (179, 8))
```

3.b. Fill Missing Numeric Value for Age

In [57]:

```
df_tmp[df_tmp['Age'].isnull() & df.Parch != 0]
```

Out[57]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
65	66	1	3	Moubarek, Master. Gerios	male	NaN	1	1	2661	15.2458
128	129	1	3	Peter, Miss. Anna	female	NaN	1	1	2668	22.3583
166	167	1	1	Chibnall, Mrs. (Edith Martha Bowerman)	female	NaN	0	1	113505	55.0000
176	177	0	3	Lefebre, Master. Henry Forbes	male	NaN	3	1	4133	25.4667
229	230	0	3	Lefebre, Miss. Mathilde	female	NaN	3	1	4133	25.4667
409	410	0	3	Lefebre, Miss. Ida	female	NaN	3	1	4133	25.4667
485	486	0	3	Lefebre, Miss. Jeannie	female	NaN	3	1	4133	25.4667
709	710	1	3	Moubarek, Master. Halim Gonios ("William George")	male	NaN	1	1	2661	15.2458

In [58]:

```
X_valid["Age"].mean(), X_valid["Age"].median()
```

Out[58]:

```
(30.21964285714286, 29.0)
```

In [59]:

```
def fill_na_num(label):
    '''
    Fill missing values with median
    '''
    label.fillna(label.median(), inplace = True)
```

In [60]:

```
fill_na_num(X_train['Age'])
fill_na_num(X_valid['Age'])
```

```
/Users/PhuongMPham/anaconda3/lib/python3.7/site-packages/pandas/cor
e/generic.py:6130: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  self._update_inplace(new_data)
```

3.c. Fill Missing Categorical Value for Embarked

In [62]:

```
# Let's fill missing data
X_train['coded_Embarked'] = pd.Categorical(X_train['coded_Embarked']).codes + 1
X_valid['coded_Embarked'] = pd.Categorical(X_valid['coded_Embarked']).codes + 1
## Codes for missing values is -1 which we do not want, so we add 1 to make it
 0.
```

```
/Users/PhuongMPham/anaconda3/lib/python3.7/site-packages/ipykernel_l
auncher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy

/Users/PhuongMPham/anaconda3/lib/python3.7/site-packages/ipykernel_l
auncher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing
imports until
```

In [63]:

```
unique, counts = np.unique(pd.Categorical(X_train['coded_Embarked']).codes, retu
rn_counts=True)
dict(zip(unique, counts))
```

Out[63]:

```
{0: 2, 1: 137, 2: 63, 3: 510}
```

In [64]:

```
X_train.isna().sum()
```

Out[64]:

```
PassengerId       0
Pclass            0
Age               0
SibSp             0
Parch             0
Fare              0
coded_Sex         0
coded_Embarked    0
dtype: int64
```

In [65]:

```
X_valid.isna().sum()
```

Out[65]:

```
PassengerId       0
Pclass            0
Age               0
SibSp             0
Parch             0
Fare              0
coded_Sex         0
coded_Embarked    0
dtype: int64
```

In [66]:

```
y_train.isna().sum()
```

Out[66]:

```
0
```

In [67]:

```
y_valid.isna().sum()
```

Out[67]:

```
0
```

Now that our data is all numeric and does not contain any missing values. Let's start the baseline model

Model

We'll train and find patterns on training sets and test it on the test set

Refer to the scikit ML map to know which models we should use:

```
* Linear SVC
* Logistic Regression
* K-nearest Neighbors Classifier
* Random Forest Classifier
```

In [68]:

```
# Let's put all models in a dictionary
models = {'Linear SVC': LinearSVC(),
          'Logistic Regression': LogisticRegression(),
          'KNN': KNeighborsClassifier(),
          'Random Forest': RandomForestClassifier()}

# Create a function to run all types of model
def fit_n_score(models, X_train, X_valid, y_train, y_valid):
    '''
    Fits and Evaluate given Machine Learning Model
    models: dict of different Scikit Learn ML models
    X_train: training data (no labels)
    X_test: testing data (no labels)
    y_train: training label
    y_test: testing label
    '''
    # Set a random seed
    np.random.seed(26)
    # Create a model score empty dictionary
    score = {}
    # Fit and score each model
    for name, model in models.items():
        model.fit(X_train, y_train)
        score[name] = model.score(X_valid, y_valid)
    # Return the result dict
    return score
```

In [69]:

```
result = fit_n_score(models, X_train, X_valid, y_train, y_valid)
result
```

```
/Users/PhuongMPham/anaconda3/lib/python3.7/site-packages/sklearn/sv
m/_base.py:977: ConvergenceWarning: Liblinear failed to converge, in
crease the number of iterations.
  "the number of iterations.", ConvergenceWarning)
/Users/PhuongMPham/anaconda3/lib/python3.7/site-packages/sklearn/lin
ear_model/_logistic.py:764: ConvergenceWarning: lbfgs failed to conv
erge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as sh
own in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver option
s:
    https://scikit-learn.org/stable/modules/linear_model.html#logist
ic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

Out[69]:

```
{'Linear SVC': 0.7150837988826816,
 'Logistic Regression': 0.7821229050279329,
 'KNN': 0.6033519553072626,
 'Random Forest': 0.8044692737430168}
```

**Model Comparison

In [73]:

```
model_compare = pd.DataFrame(result, index = ['accuracy'])
model_compare
```

Out[73]:

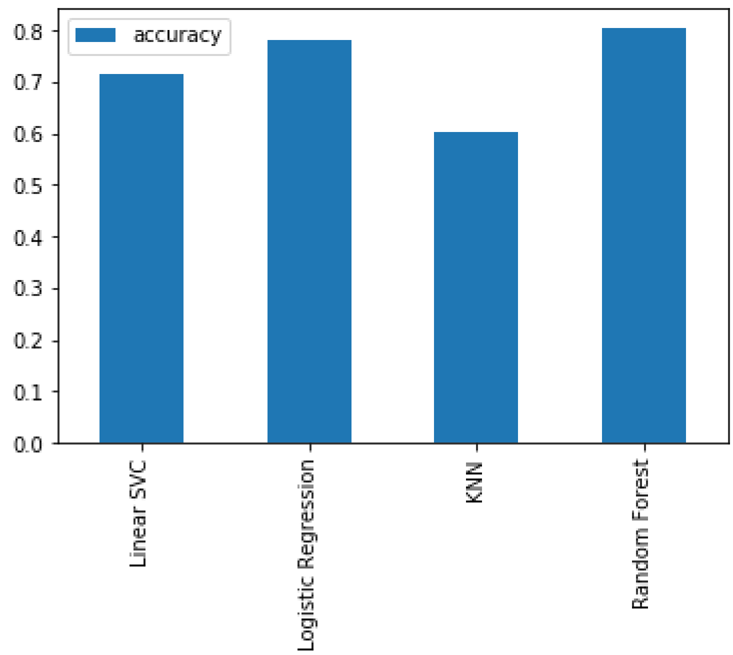
	Linear SVC	Logistic Regression	KNN	Random Forest
accuracy	0.715084	0.782123	0.603352	0.804469

In [75]:

```
model_compare.T.plot.bar()
```

Out[75]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff6adc45438>
```



Random Forest gave the best result. Let's tune `hyperparameters` to achieve a better accuracy

Experiments

Let's look at the following:

```
* HYPERPARAMETERS tuning
* Feature importance
* Confusion Matrix
* Cross-validation
* Precision
* Recall
* F1 score
* Classification Report
* ROC curve
* Area under the curve (AUC)
```

A. RandomizedSearchCV tune `Randomized Forest` and `Logistic Regression`

A1. Create a hypermeter grid for each model

In [88]:

```
# Hypermeter grid for Logistic Regression
log_reg_grid = {'C': [100, 10, 1.0, 0.1, 0.01],
                'penalty' : ['l2'],
               'solver': ['newton-cg', 'lbfgs', 'liblinear']}

# Hypermeter grid for Randomized Forest
rf_grid = {'n_estimators': np.arange(10,1000, 50),
           'max_features': ['sqrt', 'log2'],
           'max_depth': [None, 3, 5, 10],
           'min_samples_split': np.arange(2,20,2),
           'min_samples_leaf': np.arange(1,20,2)}
```

A2. Tune for Logistic Regression

In [79]:

```
# Use randomized Search to find the best hyperparameters combo
np.random.seed(26)
rs_log_reg = RandomizedSearchCV(LogisticRegression(),
                                param_distributions= log_reg_grid,
                                verbose = True)
# Fit random hyperparameters for tuning
rs_log_reg.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurr
ent workers.
/Users/PhuongMPham/anaconda3/lib/python3.7/site-packages/sklearn/lin
ear_model/_logistic.py:764: ConvergenceWarning: lbfgs failed to conv
erge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as sh
own in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver option
s:
    https://scikit-learn.org/stable/modules/linear_model.html#logist
ic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/Users/PhuongMPham/anaconda3/lib/python3.7/site-packages/sklearn/lin
ear_model/_logistic.py:764: ConvergenceWarning: lbfgs failed to conv
erge (status=1):
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Increase the number of iterations (max_iter) or scale the data as sh
own in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver option
s:
    https://scikit-learn.org/stable/modules/linear_model.html#logist
ic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/Users/PhuongMPham/anaconda3/lib/python3.7/site-packages/sklearn/lin
ear_model/_logistic.py:764: ConvergenceWarning: lbfgs failed to conv
erge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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own in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver option
s:
    https://scikit-learn.org/stable/modules/linear_model.html#logist
ic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/Users/PhuongMPham/anaconda3/lib/python3.7/site-packages/sklearn/lin
ear_model/_logistic.py:764: ConvergenceWarning: lbfgs failed to conv
erge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as sh
own in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver option
s:
    https://scikit-learn.org/stable/modules/linear_model.html#logist
ic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/Users/PhuongMPham/anaconda3/lib/python3.7/site-packages/sklearn/lin
ear_model/_logistic.py:764: ConvergenceWarning: lbfgs failed to conv
erge (status=1):
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```

```
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own in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver option
s:
    https://scikit-learn.org/stable/modules/linear_model.html#logist
ic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/Users/PhuongMPham/anaconda3/lib/python3.7/site-packages/sklearn/lin
ear_model/_logistic.py:764: ConvergenceWarning: lbfgs failed to conv
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STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as sh
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    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver option
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```

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```

```
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s:
    https://scikit-learn.org/stable/modules/linear_model.html#logist
ic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
[Parallel(n_jobs=1)]: Done  50 out of  50 | elapsed:    1.9s finishe
d
```

Out[79]:

```
RandomizedSearchCV(estimator=LogisticRegression(),
                   param_distributions={'C': [100, 10, 1.0, 0.1, 0.0
1],
                                        'penalty': ['l2'],
                                        'solver': ['newton-cg', 'lbf
gs',
                                                   'liblinear']},
                   verbose=True)
```

In [80]:

```python
# The best params
rs_log_reg.best_params_
```

Out[80]:

```
{'solver': 'newton-cg', 'penalty': 'l2', 'C': 0.1}
```

In [81]:

```python
rs_log_reg.score(X_valid, y_valid)
```

Out[81]:

```
0.8044692737430168
```

`Logistic Regression` : 80.45% accuracy

A3. Tune for Random Forest

In [89]:

```
np.random.seed(26)
rs_rf = RandomizedSearchCV(RandomForestClassifier(),
                           param_distributions= rf_grid,
                           verbose = True)
# Fit random hyperparameters
rs_rf.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurr
ent workers.
[Parallel(n_jobs=1)]: Done  50 out of  50 | elapsed:   35.6s finishe
d
```

Out[89]:

```
RandomizedSearchCV(estimator=RandomForestClassifier(),
                   param_distributions={'max_depth': [None, 3, 5, 1
0],
                                        'max_features': ['sqrt', 'lo
g2'],
                                        'min_samples_leaf': array([
1,  3,  5,  7,  9, 11, 13, 15, 17, 19]),
                                        'min_samples_split': array([
2,  4,  6,  8, 10, 12, 14, 16, 18]),
                                        'n_estimators': array([ 10,
60, 110, 160, 210, 260, 310, 360, 410, 460, 510, 560, 610,
       660, 710, 760, 810, 860, 910, 960])},
                   verbose=True)
```

In [90]:

```
# The best hyperparameters are
rs_rf.best_params_
```

Out[90]:

```
{'n_estimators': 260,
 'min_samples_split': 6,
 'min_samples_leaf': 1,
 'max_features': 'sqrt',
 'max_depth': 5}
```

In [116]:

```
rs_rf.score(X_valid, y_valid)
```

Out[116]:

```
0.8156424581005587
```

Random Forest : 81.56% Accuracy

Our final model is Random Forest

B. Classification report

In [122]:

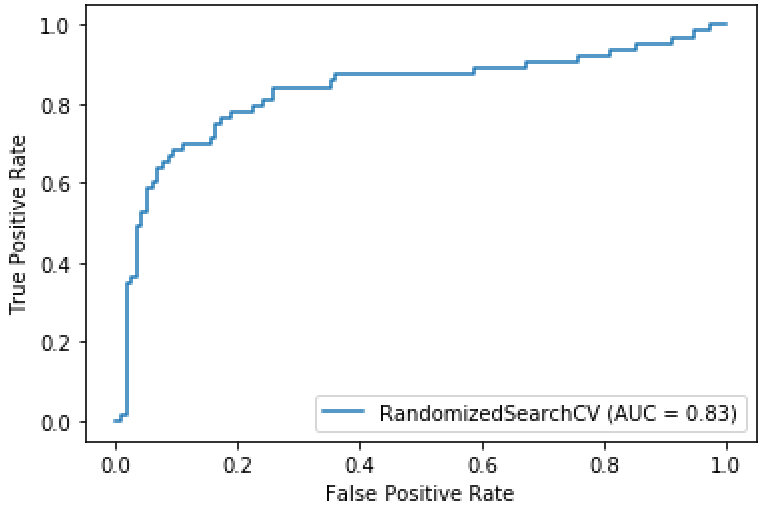
```
model = RandomForestClassifier(n_estimators= 260,
                              min_samples_split = 6,
                              min_samples_leaf = 1,
                              max_features = 'sqrt',
                              max_depth = 5)
model.fit(X_train, y_train)
y_preds = model.predict(X_valid)
```

In [123]:

```
plot_roc_curve(rs_rf, X_valid, y_valid)
```

Out[123]:

```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x7ff6ad385978>
```

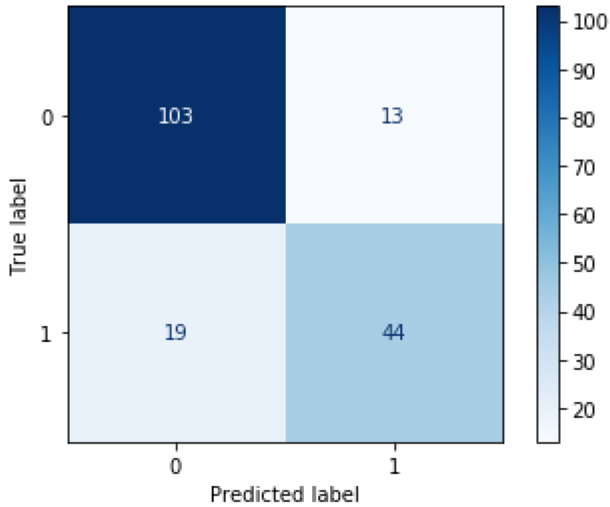


In [139]:

```python
from sklearn.metrics import plot_confusion_matrix
plot_confusion_matrix(model, X_valid, y_valid,
                      cmap=plt.cm.Blues)
```

Out[139]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x
7ff6afbc3fd0>
```



In [124]:

```python
print(classification_report(y_valid, y_preds))
```

```
              precision    recall  f1-score   support

           0       0.84      0.89      0.87       116
           1       0.77      0.70      0.73        63

    accuracy                           0.82       179
   macro avg       0.81      0.79      0.80       179
weighted avg       0.82      0.82      0.82       179
```

In [126]:

```
# Cross-validated accuracy
acc = cross_val_score(model,
                      X_train,
                      y_train,
                      cv = 5,
                      scoring = 'accuracy')
acc.mean()
```

Out[126]:

```
0.8174332709543977
```

In [127]:

```
# Cross-validated recall
recall = cross_val_score(model,
                      X_train,
                      y_train,
                      cv = 5,
                      scoring = 'recall')
recall.mean()
```

Out[127]:

```
0.6881818181818182
```

In [129]:

```
# Cross-validated precision
precision= cross_val_score(model,
                      X_train,
                      y_train,
                      cv = 5,
                      scoring = 'precision')
precision.mean()
```

Out[129]:

```
0.8399787291069076
```

In [130]:

```
# Cross-validated f1
f1 = cross_val_score(model,
                      X_train,
                      y_train,
                      cv = 5,
                      scoring = 'f1')
f1.mean()
```

Out[130]:

```
0.7548639398354141
```

In [133]:

```
# Summarize all metrics
metrics = pd.DataFrame({'Accuracy': acc.mean(),
                       'Precision': precision.mean(),
                        'Recall': recall.mean(),
                       'F1': f1.mean()},
                      index = ['Score'])
metrics
```

Out[133]:

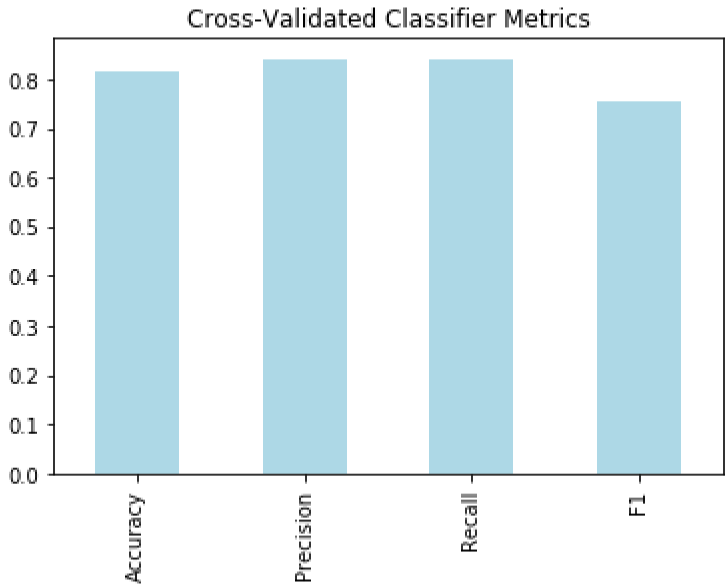
	Accuracy	Precision	Recall	F1
Score	0.817433	0.839979	0.840829	0.754864

In [136]:

```
# Visualize it
metrics.T.plot(kind = 'bar', color = 'lightblue', title ='Cross-Validated Classi
fier Metrics', legend = None)
```

Out[136]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff6b094b2b0>
```



Load test set

In [96]:

```
test_df = pd.read_csv('test.csv')
test_df.head()
```

Out[96]:

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

Explore Test Set data

In [99]:

```
len(test_df)
```

Out[99]:

```
418
```

In [100]:

```
test_df.dtypes
```

Out[100]:

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

Check for columns with string values

In [101]:

```
# Find columns with string values
for col, name in test_df.items():
    if pd.api.types.is_string_dtype(name):
        print(col)
```

```
Name
Sex
Ticket
Cabin
Embarked
```

In [103]:

```
# Convert columns into categorical values
to_categorical(test_df)
test_df.coded_Sex.head()
```

Out[103]:

```
0    1
1    0
2    1
3    1
4    0
Name: coded_Sex, dtype: int8
```

In [105]:

```
test_df.coded_Embarked.value_counts()
```

Out[105]:

```
2    270
0    102
1     46
Name: coded_Embarked, dtype: int64
```

Check for missing values

In [98]:

```
test_df.isna().sum()
```

Out[98]:

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

In [111]:

```
fill_na_num(test_df.Age)
fill_na_num(test_df.Fare)
test_df.isna().sum()
```

Out[111]:

```
PassengerId         0
Pclass              0
Name                0
Sex                 0
Age                 0
SibSp               0
Parch               0
Ticket              0
Fare                0
Cabin             327
Embarked            0
coded_Name          0
coded_Sex           0
coded_Ticket        0
coded_Cabin         0
coded_Embarked      0
dtype: int64
```

In [113]:

```
np.random.seed(26)
# Split the dataframe into X and y
X_test = test_df.drop(['Cabin', 'Ticket', 'Name','Sex','Embarked','coded_Name',
'coded_Ticket','coded_Cabin'],
                axis = 1) # May consider drop SibSp or Parch later

X_test.shape
```

Out[113]:

```
(418, 8)
```

In [114]:

```
X_test.isna().sum()
```

Out[114]:

```
PassengerId       0
Pclass            0
Age               0
SibSp             0
Parch             0
Fare              0
coded_Sex         0
coded_Embarked    0
dtype: int64
```

Predict Survival

In [138]:

```
result = model.predict(X_test)
result[:10]
```

Out[138]:

```
array([0, 0, 0, 0, 1, 0, 1, 0, 1, 0])
```

In [141]:

```
submission = pd.DataFrame(columns = ['PassengerId', 'Survived'])
submission
```

Out[141]:

PassengerId	Survived

In [144]:

```
submission['PassengerId'] = X_test['PassengerId']
submission['Survived'] = result
submission.head()
```

Out[144]:

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