In [1]:
```
# This Python 3 environment comes with many helpful analytics libraries instal
led
# It is defined by the kaggle/python docker image: https://github.com/kaggle/d
ocker-python
# For example, here's several helpful packages to load in

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# import other needed packages and functions
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.preprocessing import MinMaxScaler
from sklearn.feature_selection import SelectKBest
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier, ExtraTreesClassifier, Ada
BoostClassifier, GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import VotingClassifier
import lightgbm
from sklearn.model_selection import cross_val_score
import itertools


# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will lis
t all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# Any results you write to the current directory are saved as output.
```

```
/kaggle/input/titanic/train.csv
/kaggle/input/titanic/gender_submission.csv
/kaggle/input/titanic/test.csv
```

In [2]:
```
# read in csv files and make dfs
train_df = pd.read_csv("/kaggle/input/titanic/train.csv")
test_df = pd.read_csv("/kaggle/input/titanic/test.csv")

# make copy of test df for submission
submission = test_df.copy()

# combine train and test dfs into 1 df of all data
all_df = pd.concat([train_df, test_df], sort=False)
```

In [3]:

```python
# Define function to inspect data frames. Prints first few lines, determines size/shape of data frame,
# shows descriptive statistics, shows data types, shows missing or incomplete data, check for duplicate data.

def inspect_df(df):
    print('Header:')
    print('{}'.format(df.head()))
    print()
    print('Shape: {}'.format(df.shape))
    print()
    print('Statistics:')
    print('{}'.format(df.describe()))
    print()
    print('Info:')
    print('{}'.format(df.info()))

# use inspect_df on all_df

inspect_df(all_df)
```

```
Header:
   PassengerId  Survived  Pclass  \
0            1       0.0       3
1            2       1.0       1
2            3       1.0       3
3            4       1.0       1
4            5       0.0       3

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

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

Shape: (1309, 12)

Statistics:
       PassengerId    Survived       Pclass          Age        SibSp  \
count  1309.000000  891.000000  1309.000000  1046.000000  1309.000000
mean    655.000000    0.383838     2.294882    29.881138     0.498854
std     378.020061    0.486592     0.837836    14.413493     1.041658
min       1.000000    0.000000     1.000000     0.170000     0.000000
25%     328.000000    0.000000     2.000000    21.000000     0.000000
50%     655.000000    0.000000     3.000000    28.000000     0.000000
75%     982.000000    1.000000     3.000000    39.000000     1.000000
max    1309.000000    1.000000     3.000000    80.000000     8.000000

             Parch         Fare
count  1309.000000  1308.000000
mean      0.385027    33.295479
std       0.865560    51.758668
min       0.000000     0.000000
25%       0.000000     7.895800
50%       0.000000    14.454200
75%       0.000000    31.275000
max       9.000000   512.329200

Info:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1309 entries, 0 to 417
Data columns (total 12 columns):
PassengerId    1309 non-null int64
Survived       891 non-null float64
Pclass         1309 non-null int64
Name           1309 non-null object
Sex            1309 non-null object
Age            1046 non-null float64
SibSp          1309 non-null int64
Parch          1309 non-null int64
```

```
Ticket         1309 non-null object
Fare           1308 non-null float64
Cabin          295 non-null object
Embarked       1307 non-null object
dtypes: float64(3), int64(4), object(5)
memory usage: 132.9+ KB
None
```

In [4]:
```
# look at proportions of passengers by Pclass

all_df.Pclass.value_counts(normalize=True, sort=False)
```

Out[4]:
```
1    0.246753
2    0.211612
3    0.541635
Name: Pclass, dtype: float64
```

In [5]:
```
# look at proportions of passengers by Sex

all_df.Sex.value_counts(normalize=True)
```

Out[5]:
```
male      0.644003
female    0.355997
Name: Sex, dtype: float64
```

In [6]:
```
# inspect null values for Embarked

all_df[all_df.Embarked.isnull()]
```

Out[6]:

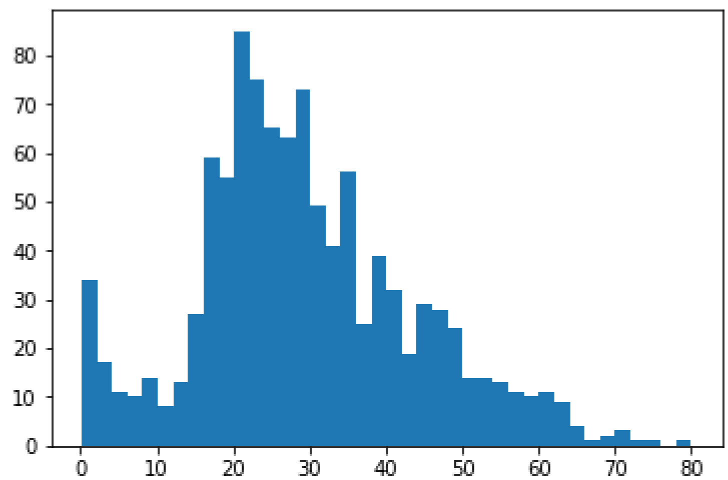
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
61	62	1.0	1	Icard, Miss. Amelie	female	38.0	0	0	113572	80.0	B28
829	830	1.0	1	Stone, Mrs. George Nelson (Martha Evelyn)	female	62.0	0	0	113572	80.0	B28

Looked up Mrs. Stone and Miss Icard online, they boarded in Southampton.

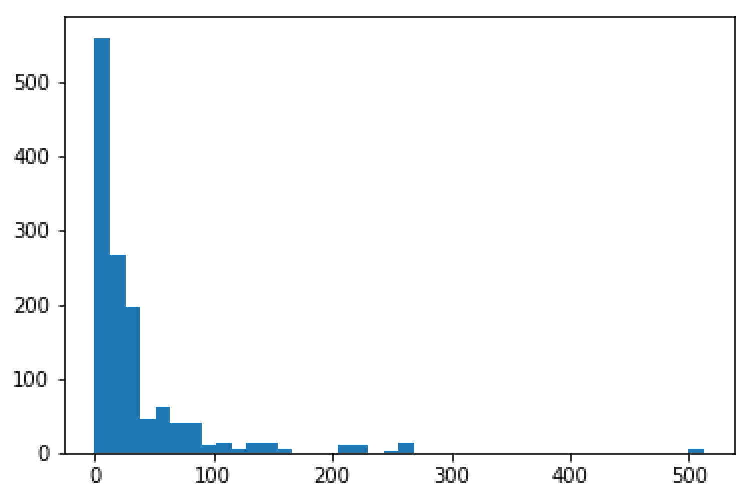
In [7]:
```
# fill missing values for Embarked with information found online

all_df.loc[[61, 829], ['Embarked']] = 'S'
```

In [8]:
```python
# plot histogram of Ages

plt.hist(data = all_df, x = 'Age', bins = 40);
```

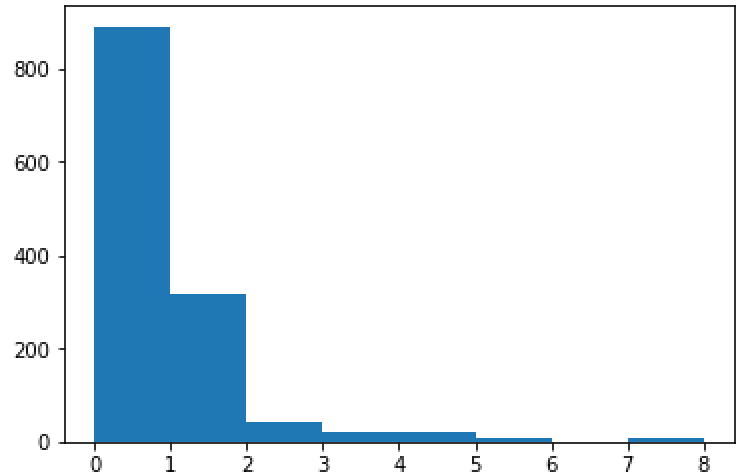
```
/opt/conda/lib/python3.6/site-packages/numpy/lib/histograms.py:824: RuntimeWa
rning: invalid value encountered in greater_equal
  keep = (tmp_a >= first_edge)
/opt/conda/lib/python3.6/site-packages/numpy/lib/histograms.py:825: RuntimeWa
rning: invalid value encountered in less_equal
  keep &= (tmp_a <= last_edge)
```



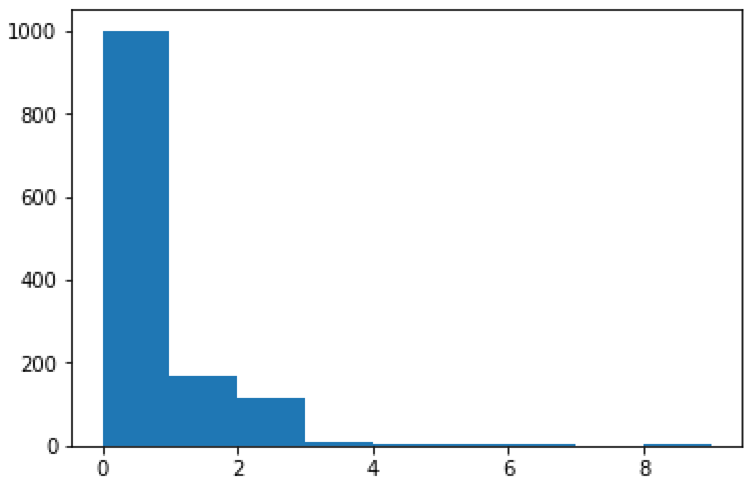
In [9]:
```python
# plot histogram of Fare

plt.hist(data = all_df, x = 'Fare', bins = 40);
```



In [10]:
```
# plot histogram of siblings and spouses

plt.hist(data = all_df, x = 'SibSp', bins = 8);
```



In [11]:
```
# plot histogram of parents and children

plt.hist(data = all_df, x = 'Parch', bins = 9);
```



In [12]:
```
# inspect columns and missing values again

all_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1309 entries, 0 to 417
Data columns (total 12 columns):
PassengerId    1309 non-null int64
Survived       891 non-null float64
Pclass         1309 non-null int64
Name           1309 non-null object
Sex            1309 non-null object
Age            1046 non-null float64
SibSp          1309 non-null int64
Parch          1309 non-null int64
Ticket         1309 non-null object
Fare           1308 non-null float64
Cabin          295 non-null object
Embarked       1309 non-null object
dtypes: float64(3), int64(4), object(5)
memory usage: 172.9+ KB
```

In [13]:
```
# find passenger with missing fare data

all_df[all_df.Fare.isnull()]
```

Out[13]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Er
152	1044	NaN	3	Storey, Mr. Thomas	male	60.5	0	0	3701	NaN	NaN	

In [14]:
```
# get average fare of each Pclass

all_df.Fare.groupby(all_df.Pclass).mean()
```

Out[14]:
```
Pclass
1    87.508992
2    21.179196
3    13.302889
Name: Fare, dtype: float64
```

In [15]:
```
#fill nan fare value with rounded mean for class 3

all_df.loc[152, ['Fare']] = 13
```

In [16]:
```
# fill missing values for ages with the mean age value for each passengers Pcl
ass and Sex

all_df.Age = all_df.Age.groupby([all_df.Pclass, all_df.Sex]).transform(lambda
x: x.fillna(x.mean()))
```

In [17]:
```
# Extract titles from names and make new Title column, then get survival rate
 of each title

all_df['Title'] = all_df.Name.str.extract(' ([A-Za-z]+)\.', expand=False)
all_df.Survived.groupby(all_df.Title).mean()
```

Out[17]:
```
Title
Capt        0.000000
Col         0.500000
Countess    1.000000
Don         0.000000
Dona             NaN
Dr          0.428571
Jonkheer    0.000000
Lady        1.000000
Major       0.500000
Master      0.575000
Miss        0.697802
Mlle        1.000000
Mme         1.000000
Mr          0.156673
Mrs         0.792000
Ms          1.000000
Rev         0.000000
Sir         1.000000
Name: Survived, dtype: float64
```

In [18]:
```
# get value counts for title occurences

all_df.Title.value_counts()
```

Out[18]:
```
Mr          757
Miss        260
Mrs         197
Master       61
Rev           8
Dr            8
Col           4
Major         2
Mlle          2
Ms            2
Sir           1
Don           1
Lady          1
Mme           1
Dona          1
Jonkheer      1
Capt          1
Countess      1
Name: Title, dtype: int64
```

In [19]:
```
# Replace uncommon titles with more common values and view new occurences

all_df.Title = all_df.Title.replace(['Capt', 'Col', 'Dr', 'Major', 'Rev', 'Do
n', 'Sir', 'Jonkheer'], 'Mr')
all_df.Title = all_df.Title.replace(['Ms', 'Mlle'], 'Miss')
all_df.Title = all_df.Title.replace(['Mme', 'Lady', 'Countess', 'Dona'], 'Mrs'
)
all_df.Title.value_counts()
```

Out[19]:
```
Mr        783
Miss      264
Mrs       201
Master     61
Name: Title, dtype: int64
```

In [20]:
```
# combine sibsp and parch to one family column
all_df['Fam'] = all_df.SibSp + all_df.Parch

# make ticket frequency column for number of occurences of ticket number
all_df['Ticket_Frequency'] = all_df.groupby('Ticket')['Ticket'].transform('cou
nt')

# make column for solo vs travel with family
all_df.loc[all_df['Fam'] == 0, 'Solo'] = 1
all_df.loc[all_df['Ticket_Frequency'] == 1, 'Solo'] = 1
all_df.Solo = all_df.Solo.fillna(0)

# bin fare column to 9 quantiles and encode as ordinal
all_df['Fare'] = pd.qcut(all_df.Fare, q=9, labels=np.arange(1,10))

# bin age column to 10 quantiles and encode as ordinal
all_df['Age'] = pd.qcut(all_df.Age, q=10, labels=np.arange(1,11))

# one-hot encode sex column and capitalize sex columns for consistency
all_df = pd.concat([all_df, pd.get_dummies(all_df.Sex)], axis=1)
all_df.rename(columns={'male':'Male', 'female':'Female'}, inplace=True)

# one-hot encode embarked column
all_df = pd.concat([all_df, pd.get_dummies(all_df.Embarked, prefix='Embarked'
)], axis=1)

# one-hot encode title column
all_df = pd.concat([all_df, pd.get_dummies(all_df.Title)], axis=1)

# drop unwanted columns (name, sex, cabin, embarked and title have been replac
ed with one hot encoding, ticket replaced with ticket frequency,
# cabin has too many missing values, sibsp and parch replaced with fam and sol
o columns)
all_df = all_df.drop(columns=['Name', 'Sex', 'Ticket', 'Cabin', 'SibSp', 'Parc
h', 'Embarked', 'Title'])

# inspect columns and number of values for resulting df
all_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1309 entries, 0 to 417
Data columns (total 17 columns):
PassengerId         1309 non-null int64
Survived            891 non-null float64
Pclass              1309 non-null int64
Age                 1309 non-null category
Fare                1309 non-null category
Fam                 1309 non-null int64
Ticket_Frequency    1309 non-null int64
Solo                1309 non-null float64
Female              1309 non-null uint8
Male                1309 non-null uint8
Embarked_C          1309 non-null uint8
Embarked_Q          1309 non-null uint8
Embarked_S          1309 non-null uint8
Master              1309 non-null uint8
Miss                1309 non-null uint8
Mr                  1309 non-null uint8
Mrs                 1309 non-null uint8
dtypes: category(2), float64(2), int64(4), uint8(9)
memory usage: 86.4 KB
```

In [21]:

```
# inspect survival rates for number of family members onboard

all_df.Survived.groupby(all_df.Fam).mean()
```

Out[21]:

```
Fam
0     0.303538
1     0.552795
2     0.578431
3     0.724138
4     0.200000
5     0.136364
6     0.333333
7     0.000000
10    0.000000
Name: Survived, dtype: float64
```

In [22]:

```
# bin fam column values and get value counts

all_df.Fam = pd.cut(all_df.Fam, bins=[0, 1, 4, 7, 11], include_lowest=True, ri
ght=False, labels=[1, 2, 3, 4])
all_df.Fam.value_counts()
```

Out[22]:

```
1    790
2    437
3     63
4     19
Name: Fam, dtype: int64
```

In [23]:
```
# inspect survival rate for number of people traveling in group

all_df.Survived.groupby(all_df.Ticket_Frequency).mean()
```

Out[23]:
```
Ticket_Frequency
1     0.270270
2     0.513812
3     0.653465
4     0.727273
5     0.333333
6     0.210526
7     0.208333
8     0.384615
11    0.000000
Name: Survived, dtype: float64
```

In [24]:
```
# bin ticket frequency column values and get value counts

all_df.Ticket_Frequency = pd.cut(all_df.Ticket_Frequency, bins=[0, 2, 5, 9, 12
], right=False, labels=[1, 2, 3, 4])
all_df.Ticket_Frequency.value_counts()
```

Out[24]:
```
1    713
2    475
3    110
4     11
Name: Ticket_Frequency, dtype: int64
```

In [25]:
```
# make list of all columns and view it

cols = list(all_df)
cols
```

Out[25]:
```
['PassengerId',
 'Survived',
 'Pclass',
 'Age',
 'Fare',
 'Fam',
 'Ticket_Frequency',
 'Solo',
 'Female',
 'Male',
 'Embarked_C',
 'Embarked_Q',
 'Embarked_S',
 'Master',
 'Miss',
 'Mr',
 'Mrs']
```

In [26]:
```
# use min max scaler to scale all feature columns to range 0-1

scaler = MinMaxScaler()
all_df[cols] = scaler.fit_transform(all_df[cols])
```

In [27]:
```
# make array of survived labels (training), drop survived column from all_df,
 split all_df into features (training) and test_df, and make array of feature
 column names

labels = all_df.loc[:890, 'Survived']
all_df = all_df.drop(columns = 'Survived')
features = all_df.iloc[:891]
test_df = all_df.iloc[891:]
feat_names = features.columns.values
```

In [28]:
```
# use SelectKBest to narrow down to top features and use result to transform t
rain and test features dfs

k = SelectKBest(k=11)
k.fit(features, labels)
k_scores = (k.scores_)
features = k.transform(features)
test_df = k.transform(test_df)
```

In [29]:
```
# make df to show scores for all features and print

feat_scores = pd.DataFrame()
feat_scores['Feature'] = feat_names
feat_scores['Score'] = k_scores
feat_scores
```

Out[29]:

	Feature	Score
0	PassengerId	0.022285
1	Pclass	115.031272
2	Age	0.118749
3	Fare	108.327062
4	Fam	6.313788
5	Ticket_Frequency	17.149390
6	Solo	47.368609
7	Female	372.405724
8	Male	372.405724
9	Embarked_C	25.895987
10	Embarked_Q	0.011846
11	Embarked_S	20.374460
12	Master	6.503635
13	Miss	112.860827
14	Mr	414.442624
15	Mrs	122.387505

In [30]:

```
# split training data into train and test subsets for validation

features_train, features_test, labels_train, labels_test = train_test_split(fe
atures, labels, test_size=0.2, random_state=3)
```

In [31]:

```
# setup base classifiers

gb = GradientBoostingClassifier()
rf = RandomForestClassifier()
et = ExtraTreesClassifier()
ab = AdaBoostClassifier()
dt = DecisionTreeClassifier()
lr = LogisticRegression(solver='liblinear')
kn = KNeighborsClassifier()
svc = SVC(gamma='auto', probability=True)
gnb = GaussianNB()
```

In [32]:
```python
# get train base classifiers and get initial validation scores

gb.fit(features_train, labels_train)
print('GB Score:', gb.score(features_test, labels_test))
rf.fit(features_train, labels_train)
print('RF Score:', rf.score(features_test, labels_test))
et.fit(features_train, labels_train)
print('ET Score:', et.score(features_test, labels_test))
ab.fit(features_train, labels_train)
print('AB Score:', ab.score(features_test, labels_test))
dt.fit(features_train, labels_train)
print('DT Score:', dt.score(features_test, labels_test))
lr.fit(features_train, labels_train)
print('LR Score:', lr.score(features_test, labels_test))
kn.fit(features_train, labels_train)
print('KN Score:', kn.score(features_test, labels_test))
svc.fit(features_train, labels_train)
print('SVC Score:', svc.score(features_test, labels_test))
gnb.fit(features_train, labels_train)
print('GNB Score:', gnb.score(features_test, labels_test))
```

```
GB Score: 0.8156424581005587
RF Score: 0.8212290502793296
ET Score: 0.8156424581005587
AB Score: 0.8044692737430168
DT Score: 0.8156424581005587
LR Score: 0.8212290502793296
KN Score: 0.8044692737430168

/opt/conda/lib/python3.6/site-packages/sklearn/ensemble/forest.py:245: Future
Warning: The default value of n_estimators will change from 10 in version 0.2
0 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/ensemble/forest.py:245: Future
Warning: The default value of n_estimators will change from 10 in version 0.2
0 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)

SVC Score: 0.8044692737430168
GNB Score: 0.7821229050279329
```

In [33]:
```
# use gridsearch to tune base classifier hyperparameters

alg = gb
params = {'n_estimators': (10, 25, 50, 100), 'learning_rate': (0.01, 0.1, 0.5,
1, 5, 10)}
clf = GridSearchCV(alg, params, cv = 5, scoring = 'accuracy', n_jobs = -1)
clf.fit(features_train, labels_train)
print("Best Parameters:", clf.best_params_)
print("Best Score:", clf.best_score_)
gb = clf.best_estimator_
```

```
Best Parameters: {'learning_rate': 0.01, 'n_estimators': 100}
Best Score: 0.8286516853932584

/opt/conda/lib/python3.6/site-packages/sklearn/model_selection/_search.py:81
4: DeprecationWarning: The default of the `iid` parameter will change from Tr
ue to False in version 0.22 and will be removed in 0.24. This will change num
eric results when test-set sizes are unequal.
  DeprecationWarning)
```

In [34]:
```
# use gridsearch to tune base classifier hyperparameters

alg = rf
params = {'n_estimators': (10, 25, 50, 100), 'min_samples_split': (2, 3, 4, 5,
10), 'min_samples_leaf': (1, 2, 3, 4, 5)}
clf = GridSearchCV(alg, params, cv = 5, scoring = 'accuracy', n_jobs = -1)
clf.fit(features_train, labels_train)
print("Best Parameters:", clf.best_params_)
print("Best Score:", clf.best_score_)
rf = clf.best_estimator_
```

```
Best Parameters: {'min_samples_leaf': 5, 'min_samples_split': 3, 'n_estimator
s': 25}
Best Score: 0.8300561797752809
```

In [35]:
```
# use gridsearch to tune base classifier hyperparameters

alg = et
params = {'n_estimators': (10, 25, 50, 100), 'min_samples_split': (2, 3, 4, 5,
10), 'min_samples_leaf': (1, 2, 3, 4, 5)}
clf = GridSearchCV(alg, params, cv = 5, scoring = 'accuracy', n_jobs = -1)
clf.fit(features_train, labels_train)
print("Best Parameters:", clf.best_params_)
print("Best Score:", clf.best_score_)
et = clf.best_estimator_
```

```
Best Parameters: {'min_samples_leaf': 4, 'min_samples_split': 4, 'n_estimator
s': 10}
Best Score: 0.8370786516853933
```

In [36]:
```
# use gridsearch to tune base classifier hyperparameters

alg = ab
params = {'n_estimators': (10, 25, 50, 100), 'learning_rate': (0.01, 0.1, 0.5,
1, 5, 10)}
clf = GridSearchCV(alg, params, cv = 5, scoring = 'accuracy', n_jobs = -1)
clf.fit(features_train, labels_train)
print("Best Parameters:", clf.best_params_)
print("Best Score:", clf.best_score_)
ab = clf.best_estimator_
```

```
Best Parameters: {'learning_rate': 1, 'n_estimators': 10}
Best Score: 0.8146067415730337
```

In [37]:
```
# use gridsearch to tune base classifier hyperparameters

alg = dt
params = {'min_samples_split': (2, 3, 4, 5, 10), 'min_samples_leaf': (1, 2, 3,
4, 5)}
clf = GridSearchCV(alg, params, cv = 5, scoring = 'accuracy', n_jobs = -1)
clf.fit(features_train, labels_train)
print("Best Parameters:", clf.best_params_)
print("Best Score:", clf.best_score_)
dt = clf.best_estimator_
```

```
Best Parameters: {'min_samples_leaf': 1, 'min_samples_split': 4}
Best Score: 0.8174157303370787
```

In [38]:
```
# use gridsearch to tune base classifier hyperparameters

alg = lr
params = {'penalty': ('l1', 'l2'), 'C': (0.01, 0.1, 0.5, 1, 5, 10), 'max_iter'
: (100, 500)}
clf = GridSearchCV(alg, params, cv = 5, scoring = 'accuracy', n_jobs = -1)
clf.fit(features_train, labels_train)
print("Best Parameters:", clf.best_params_)
print("Best Score:", clf.best_score_)
lr = clf.best_estimator_
```

```
Best Parameters: {'C': 10, 'max_iter': 100, 'penalty': 'l1'}
Best Score: 0.8188202247191011
```

In [39]:
```
# use gridsearch to tune base classifier hyperparameters

alg = kn
params = {'n_neighbors': (2, 3, 4, 5, 10, 20)}
clf = GridSearchCV(alg, params, cv = 5, scoring = 'accuracy', n_jobs = -1)
clf.fit(features_train, labels_train)
print("Best Parameters:", clf.best_params_)
print("Best Score:", clf.best_score_)
kn = clf.best_estimator_
```

```
Best Parameters: {'n_neighbors': 10}
Best Score: 0.8117977528089888
```

In [40]:
```
# use gridsearch to tune base classifier hyperparameters

alg = svc
params = {'C': (0.01, 0.1, 0.5, 1, 5, 10), 'kernel': ('linear', 'poly', 'rbf',
'sigmoid')}
clf = GridSearchCV(alg, params, cv = 5, scoring = 'accuracy', n_jobs = -1)
clf.fit(features_train, labels_train)
print("Best Parameters:", clf.best_params_)
print("Best Score:", clf.best_score_)
svc = clf.best_estimator_
```

```
Best Parameters: {'C': 10, 'kernel': 'poly'}
Best Score: 0.824438202247191
```

In [41]:
```
# retrain base classifiers and get validation scores

gb.fit(features_train, labels_train)
print('GB Score:', gb.score(features_test, labels_test))
rf.fit(features_train, labels_train)
print('RF Score:', rf.score(features_test, labels_test))
et.fit(features_train, labels_train)
print('ET Score:', et.score(features_test, labels_test))
ab.fit(features_train, labels_train)
print('AB Score:', ab.score(features_test, labels_test))
dt.fit(features_train, labels_train)
print('DT Score:', dt.score(features_test, labels_test))
lr.fit(features_train, labels_train)
print('LR Score:', lr.score(features_test, labels_test))
kn.fit(features_train, labels_train)
print('KN Score:', kn.score(features_test, labels_test))
svc.fit(features_train, labels_train)
print('SVC Score:', svc.score(features_test, labels_test))
gnb.fit(features_train, labels_train)
print('GNB Score:', gnb.score(features_test, labels_test))
```

```
GB Score: 0.8379888268156425
RF Score: 0.8379888268156425
ET Score: 0.8212290502793296
AB Score: 0.7988826815642458
DT Score: 0.8156424581005587
LR Score: 0.8212290502793296
KN Score: 0.8324022346368715
SVC Score: 0.8379888268156425
GNB Score: 0.7821229050279329
```

In [42]:
```
# setup voting classifier and get initial cross val score

vote = VotingClassifier(estimators=[('gb',gb), ('rf',rf), ('et',et), ('ab',ab
), ('dt',dt), ('lr',lr), ('kn',kn), ('svc',svc), ('gnb',gnb)], voting='soft')
vote.fit(features, labels)
cross_val_score(vote, features, labels, cv=5, scoring='accuracy').mean()
```

Out[42]:
```
0.8283140889719685
```

In [43]:
```
# retrain voting classifier and get validation score

vote.fit(features_train, labels_train)
print('Voting Score:', vote.score(features_test, labels_test))
```

```
Voting Score: 0.8324022346368715
```

In [44]:
```
# use itertools combinations to make list of tuples of all possible different
 combinations of classifiers

clfs = [('gb',gb), ('rf',rf), ('et',et), ('ab',ab), ('dt',dt), ('lr',lr), ('k
n',kn), ('svc',svc), ('gnb',gnb)]
combs = []

for i in range(2, len(clfs)+1):
    comb = [list(x) for x in itertools.combinations(clfs, i)]
    combs.extend(comb)
```

In [45]:
```python
# Tune voting classifier to use best combination of base classifiers

alg = vote
params = {'estimators': combs}
clf = GridSearchCV(alg, params, cv = 5, scoring = 'accuracy', n_jobs = -1)
clf.fit(features, labels)
print("Best Parameters:", clf.best_params_)
print("Best Score:", clf.best_score_)
vote = clf.best_estimator_
```

```
Best Parameters: {'estimators': [('gb', GradientBoostingClassifier(criterion
='friedman_mse', init=None,
                           learning_rate=0.01, loss='deviance', max_depth=3,
                           max_features=None, max_leaf_nodes=None,
                           min_impurity_decrease=0.0, min_impurity_split=Non
e,
                           min_samples_leaf=1, min_samples_split=2,
                           min_weight_fraction_leaf=0.0, n_estimators=100,
                           n_iter_no_change=None, presort='auto',
                           random_state=None, subsample=1.0, tol=0.0001,
                           validation_fraction=0.1, verbose=0,
                           warm_start=False)), ('rf', RandomForestClassifier
(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=None, max_features='auto', max_leaf_nodes=No
ne,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=5, min_samples_split=3,
                       min_weight_fraction_leaf=0.0, n_estimators=25,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)), ('dt', DecisionTreeClas
sifier(class_weight=None, criterion='gini', max_depth=None,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=4,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=None, splitter='best')), ('kn', KNeighbor
sClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=10, p=2,
                     weights='uniform')), ('svc', SVC(C=10, cache_size=200, c
lass_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto', kernel='poly',
    max_iter=-1, probability=True, random_state=None, shrinking=True, tol=0.0
01,
    verbose=False))]}
Best Score: 0.8361391694725028
```

In [46]:
```python
# retrain voting classifier and get validation score

vote.fit(features_train, labels_train)
print('Voting Score:', vote.score(features_test, labels_test))
```

```
Voting Score: 0.8324022346368715
```

In [47]:

```
# retrain voting classifier with full train set, use to make probability predi
ctions and make df of probs, set threshold for probablities and use to convert
probs to predictions

vote.fit(features, labels)
pred_prob = pd.DataFrame(vote.predict_proba(test_df))
threshold = 0.55
y_pred = pred_prob.applymap(lambda x: 1 if x>threshold else 0)
```

In [48]:

```
# add predictions submission df as survived column, drop all columns but passe
nger ID and survived, write submission to csv without index to generate submis
sion file

submission['Survived'] = y_pred[1].astype(int)
submission = submission[['PassengerId', 'Survived']]
submission.to_csv('submission.csv', index=False)
```