Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import warnings
import datetime as dt
import pytz as tz
import matplotlib.pyplot as plt
from sklearn import preprocessing
from sklearn import model_selection
from sklearn.model_selection import train_test_split
from sqlalchemy import create_engine
import xgboost as xgb
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
from sklearn.metrics import roc_auc_score
from sklearn.metrics import recall_score
from sklearn.metrics import confusion_matrix
```

In [2]:
```
# Ignore the warnings
warnings.simplefilter('ignore')
```

Load training and prediction window data from saved sql databases

In [3]:
```
engine =create_engine('sqlite:///Earthquakedata.db')
df_features = pd.read_sql_table('Earthquake_features',con=engine)
```

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

Out[4]:

	date	depth	mag	place	latitude	longitude	depth_avg_22	depth_avg_15	depth_a
0	2022-11-06	7.2	0.8	California	39.251735	-119.621585	5.845455	6.946667	9.22
1	2022-11-08	12.1	1.7	California	39.251735	-119.621585	6.345455	7.206667	9.3
2	2022-11-08	4.9	0.8	California	39.251735	-119.621585	6.477273	7.533333	8.64
3	2022-11-08	6.1	0.7	California	39.251735	-119.621585	6.531818	7.940000	8.10
4	2022-11-08	4.3	0.3	California	39.251735	-119.621585	6.650000	8.173333	7.50

In [5]:
```
engine =create_engine('sqlite:///Earthquakedata_predict.db')
df_predict = pd.read_sql_table('Earthquake_predict',con=engine)
```

In [6]:
```
# Live data to be predicted on after being trained of rolling period for next
#Hence NaN outcome that has to be predicted

df_predict.head()
```

Out[6]:

	date	depth	mag	place	latitude	longitude	depth_avg_22	depth_avg_15	depth_a
0	2022-11-26	4.0	2.6	California	39.251735	-119.621585	7.500000	6.780000	7.5(
1	2022-11-26	11.3	0.5	California	39.251735	-119.621585	7.731818	6.993333	9.07
2	2022-11-28	3.1	0.8	California	39.251735	-119.621585	7.077273	6.666667	8.0
3	2022-11-28	4.8	0.8	California	39.251735	-119.621585	6.931818	6.573333	7.15
4	2022-11-29	10.0	2.5	California	39.251735	-119.621585	6.954545	7.240000	7.37

Training is done by considering 22,15 & 7 days window past features rolling average and outcome data is shifted to next 7 Days.

In [7]:
```
# Selection of features that are needed for prediction and hence consider onl

features = [f for f in list(df_features) if f not in ['date', 'lon_box_mean',
 'lat_box_mean', 'mag_outcome', 'mag', 'place',
 'combo_box_mean',  'latitude',
 'longitude']]

# splitting traing and testing dataset with trainging size = 70% and test = 3
X_train, X_test, y_train, y_test = train_test_split(df_features[features],
                    df_features['mag_outcome'], test_size=0.3, random_state=
```

In [8]:
```
features
```

Out[8]:
```
['depth',
 'depth_avg_22',
 'depth_avg_15',
 'depth_avg_7',
 'mag_avg_22',
 'mag_avg_15',
 'mag_avg_7']
```

Machine Learning & Boosting algorithms

Decision Tree with Ada Boost Classifier

In [9]:
```
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV

param_grid = {
              "base_estimator__max_depth" :   [2,5,7],
              "n_estimators": [200, 400, 600]
             }

# base estimator
tree = DecisionTreeClassifier()

# adaboost with the tree as base estimator
# learning rate is arbitrarily set to 0.6,
ABC = AdaBoostClassifier(
    base_estimator=tree,
    learning_rate=0.6,
    algorithm="SAMME")
```

In [10]:
```
# run grid search
grid_search_ABC = GridSearchCV(ABC,
                               param_grid=param_grid,
                               scoring = 'roc_auc',
                               return_train_score=True,
                               verbose = 1)
```

In [11]:
```
grid_search_ABC.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits
```

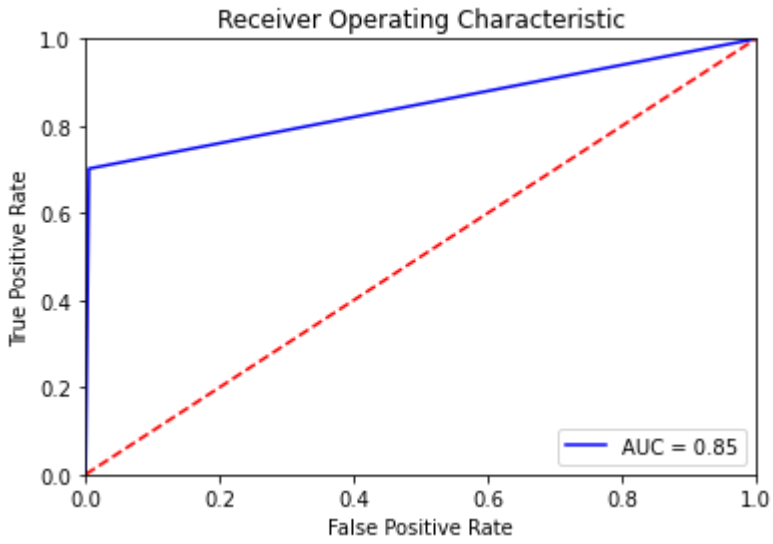
Out[11]:
```
GridSearchCV(estimator=AdaBoostClassifier(algorithm='SAMME',
                                          base_estimator=DecisionTreeClassi
fier(),
                                          learning_rate=0.6),
             param_grid={'base_estimator__max_depth': [2, 5, 7],
                         'n_estimators': [200, 400, 600]},
             return_train_score=True, scoring='roc_auc', verbose=1)
```

In [12]:
```
pred_ABC=grid_search_ABC.predict(X_test)
```

In [13]:

```
print(roc_auc_score(y_test, pred_ABC))

fpr, tpr, _ = roc_curve(y_test, pred_ABC)
roc_auc = auc(fpr, tpr)
print('AUC:', np.round(roc_auc,4))

plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

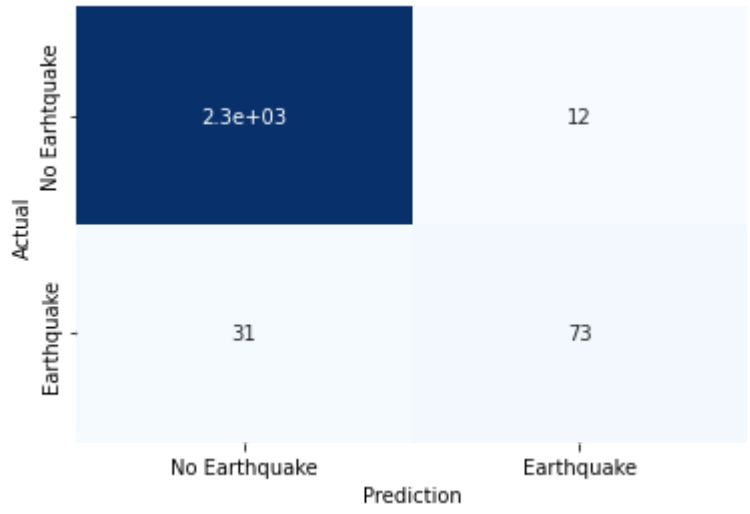
```
0.8483985311996846
AUC: 0.8484
```



In [14]:

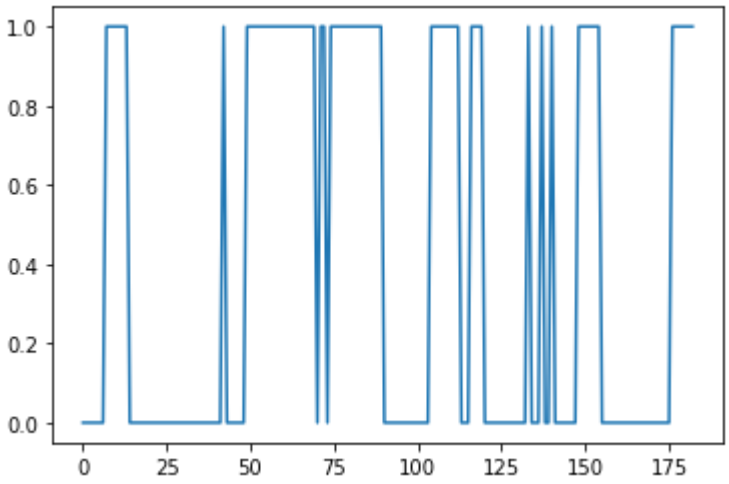
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
print('Confusion Matrix \n',confusion_matrix(y_test,pred_ABC))
print('Confusion Matrix \n',confusion_matrix(pred_ABC,y_test))
confusion_matrix= confusion_matrix(y_test,pred_ABC)
hm = sns.heatmap(confusion_matrix, annot=True, xticklabels=['No Earthquake',
                 yticklabels=['No Earhtquake', 'Earthquake'],
                 cbar=False, cmap='Blues')
hm.set_xlabel("Prediction")
hm.set_ylabel("Actual")
hm
dtc=recall_score(y_test,pred_ABC)
print("\nRecall TP/TP+FN = ",dtc)
```

```
Confusion Matrix
 [[2329   12]
 [  31   73]]
Confusion Matrix
 [[2329   31]
 [  12   73]]

Recall TP/TP+FN =  0.7019230769230769
```



In [15]:

```
pred_ABC=grid_search_ABC.predict(df_predict[features])
plt.plot(pred_ABC)
plt.show()
```



In [16]:
```
live_set = df_predict[['date', 'place', 'latitude', 'longitude']]
live_set.loc[:,'quake'] = pred_ABC
# aggregate down dups
live_set = live_set.groupby(['date', 'place'], as_index=False).mean()

# increment date to include DAYS_OUT_TO_PREDICT
live_set['date']= pd.to_datetime(live_set['date'],format='%Y-%m-%d')
live_set['date'] = live_set['date'] + pd.to_timedelta(7,unit='days')

live_set
```

Out[16]:

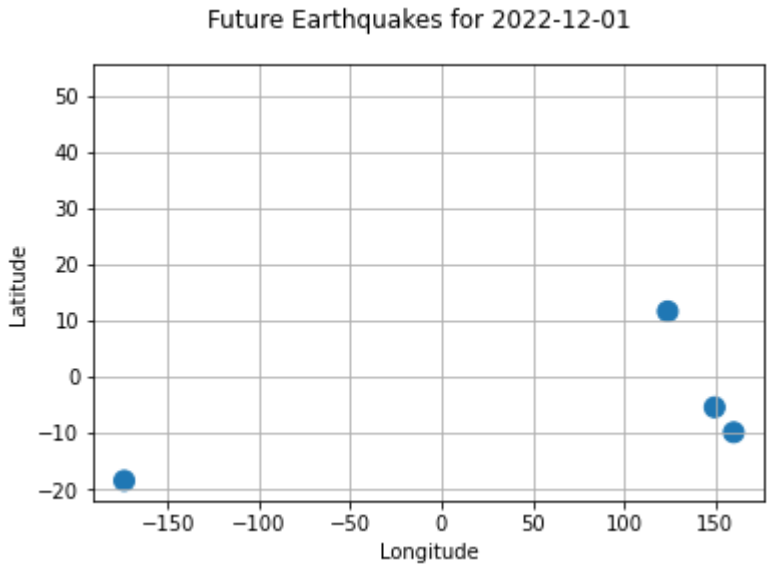
	date	place	latitude	longitude	quake
0	2022-11-25	Papua New Guinea	-5.524528	149.714707	1.0
1	2022-11-27	Papua New Guinea	-5.524528	149.714707	1.0
2	2022-11-28	Montana	44.863002	-111.066538	0.0
3	2022-11-28	Papua New Guinea	-5.524528	149.714707	1.0
4	2022-11-28	Tonga	-18.591112	-174.017210	1.0
...	...	...	...	...	...
87	2022-12-07	Puerto Rico	18.114459	-66.833591	0.0
88	2022-12-07	Russia	52.017591	130.222957	1.0
89	2022-12-07	Texas	31.575240	-103.698497	0.5
90	2022-12-07	U.S. Virgin Islands	19.030958	-64.815751	1.0
91	2022-12-07	Utah	40.225939	-112.244823	0.0

92 rows × 5 columns

In [17]:
```
# convert date to proper format for prediction
days = list(set([d for d in live_set['date'].astype(str) if d > dt.datetime.n
days.sort()

# Predict NaN outcome value in earthquake for next day 1.
predict_day=days[0]
predict_day
```

Out[17]: '2022-12-01'

In [18]:
```
# place, date, lat and long with earthquake probability for next 7 days
for i in range(0,7):
    live_set_tmp = live_set[live_set['date'] == days[i]]
    plt.scatter(live_set_tmp['longitude'], live_set_tmp['latitude'], s=(live_
    plt.suptitle('Future Earthquakes for ' + days[i])
    plt.xlabel('Longitude')
    plt.ylabel('Latitude')
    plt.grid()
    plt.show()
```



Future Earthquakes for 2022-12-02

In [19]:
```
live_set.to_csv('dt_live_dataset.csv',index=False)
```

Random Forest Classifier

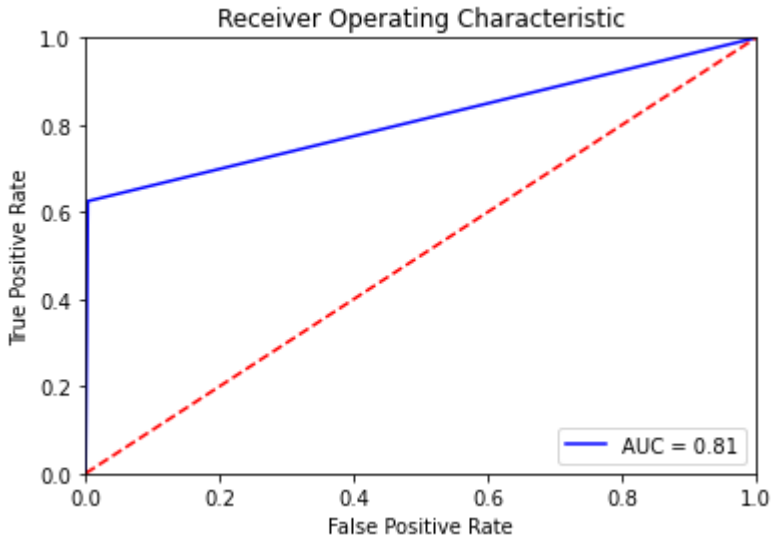
In [20]:
```
from sklearn.datasets import make_classification
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(n_jobs=-1,max_features= 'sqrt' ,n_estimators=50,

param_grid = {
    'n_estimators': [200, 700],
    'max_features': ['auto', 'sqrt', 'log2']
}
# GridSearch of parameter tunning.
CV_rfc = GridSearchCV(estimator=rfc, param_grid=param_grid, cv= 5)
CV_rfc.fit(X_train, y_train)
```

Out[20]:
```
GridSearchCV(cv=5,
             estimator=RandomForestClassifier(max_features='sqrt',
                                              n_estimators=50, n_jobs=-1,
                                              oob_score=True),
             param_grid={'max_features': ['auto', 'sqrt', 'log2'],
                         'n_estimators': [200, 700]})
```

In [21]:
```
pred=CV_rfc.predict(X_test)
```

In [22]:
```
print(roc_auc_score(y_test, pred))

fpr, tpr, _ = roc_curve(y_test, pred)
roc_auc = auc(fpr, tpr)
print('AUC:', np.round(roc_auc,4))

plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

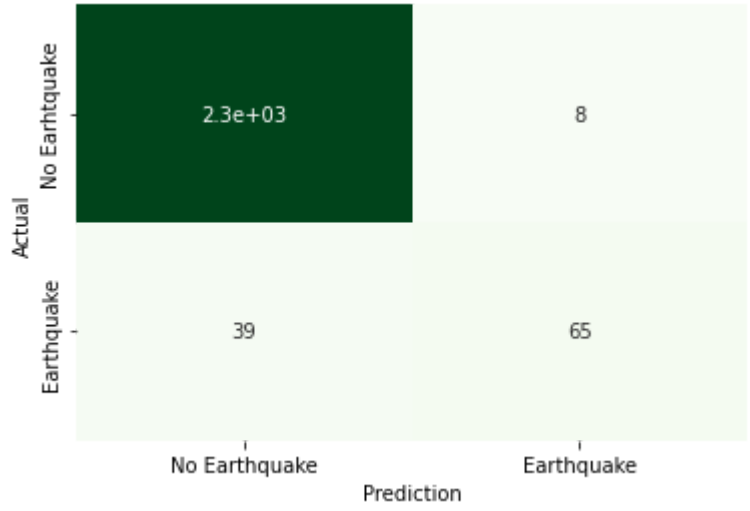
```
0.8107913284920975
AUC: 0.8108
```



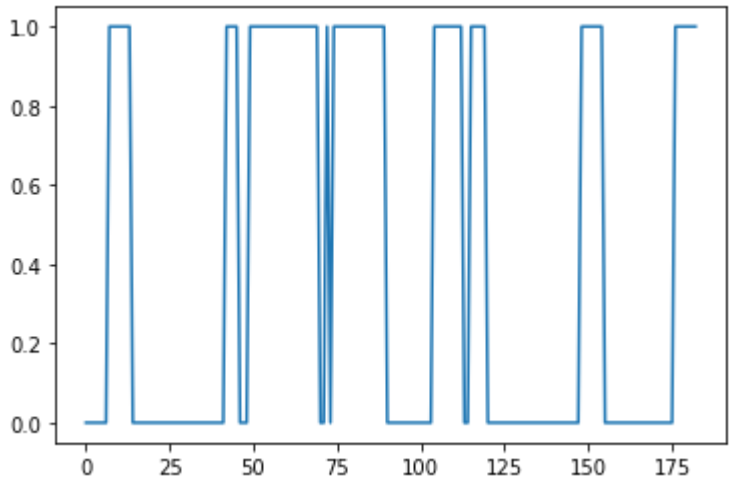
In [23]:

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
print('Confusion Matrix \n',confusion_matrix(y_test,pred))
print('Confusion Matrix \n',confusion_matrix(pred,y_test))
confusion_matrix= confusion_matrix(y_test,pred)
hm = sns.heatmap(confusion_matrix, annot=True, xticklabels=['No Earthquake',
                 yticklabels=['No Earhtquake', 'Earthquake'],
                 cbar=False, cmap='Greens')
hm.set_xlabel("Prediction")
hm.set_ylabel("Actual")
hm
rfc=recall_score(y_test,pred)
print("\nRecall 'TP/TP+FN' = ", rfc)
```

```
Confusion Matrix
 [[2333    8]
 [  39   65]]
Confusion Matrix
 [[2333   39]
 [   8   65]]

Recall 'TP/TP+FN' =  0.625
```



In [24]:
```
pred=CV_rfc.predict(df_predict[features])
plt.plot(pred)
plt.show()
```



In [25]:
```
live_set = df_predict[['date', 'place', 'latitude', 'longitude']]
live_set.loc[:,'quake'] = pred
# aggregate down dups
live_set = live_set.groupby(['date', 'place'], as_index=False).mean()

# increment date to include DAYS_OUT_TO_PREDICT
live_set['date']= pd.to_datetime(live_set['date'],format='%Y-%m-%d')
live_set['date'] = live_set['date'] + pd.to_timedelta(7,unit='d')
live_set.tail()
```

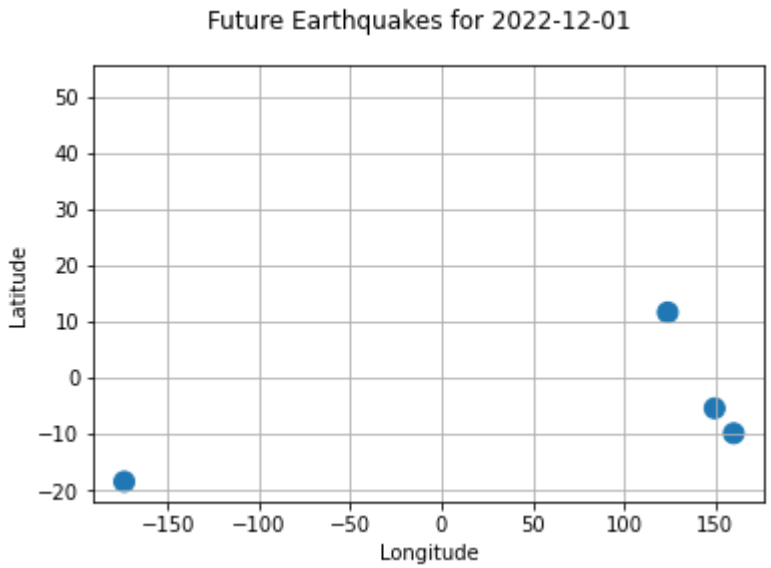
Out[25]:

	date	place	latitude	longitude	quake
87	2022-12-07	Puerto Rico	18.114459	-66.833591	0.5
88	2022-12-07	Russia	52.017591	130.222957	1.0
89	2022-12-07	Texas	31.575240	-103.698497	0.0
90	2022-12-07	U.S. Virgin Islands	19.030958	-64.815751	1.0
91	2022-12-07	Utah	40.225939	-112.244823	0.0

In [26]:
```
# convert date to proper format for prediction
days = list(set([d for d in live_set['date'].astype(str) if d > dt.datetime.n
days.sort()

# Predict NaN outcome value in earthquake for next day 1.
predict_day=days[0]
predict_day
```

Out[26]: '2022-12-01'

In [27]:
```
# place, date, lat and long with earthquake probability for next 7 days
for i in range(0,7):
    live_set_tmp = live_set[live_set['date'] == days[i]]
    plt.scatter(live_set_tmp['longitude'], live_set_tmp['latitude'], s=(live_
    plt.suptitle('Future Earthquakes for ' + days[i])
    plt.xlabel('Longitude')
    plt.ylabel('Latitude')
    plt.grid()
    plt.show()
```



Future Earthquakes for 2022-12-02

In [28]:
```
live_set.to_csv('rfc_live_dataset.csv',index=False)
```

XGBoost Algorithm

In [29]:

```
from xgboost import XGBClassifier
import xgboost as xgb

dtrain = xgb.DMatrix(X_train[features], label=y_train)
dtest = xgb.DMatrix(X_test[features], label=y_test)

param = {
        'objective': 'binary:logistic',
        'booster': 'gbtree',
        'eval_metric': 'auc',
        'max_depth': 6,  # the maximum depth of each tree
        'eta': 0.003,  # the training step for each iteration
        'silent': 1}  # logging mode - quiet}  # the number of classes that e
num_round = 5000  # the number of training iterations
bst = xgb.train(param, dtrain, num_round)
preds = bst.predict(dtest)
```

```
[23:57:05] WARNING: C:\Windows\Temp\abs_557yfx631l\croots\recipe\xgboost-sp
lit_1659548953302\work\src\learner.cc:576:
Parameters: { "silent" } might not be used.

  This could be a false alarm, with some parameters getting used by languag
e bindings but
  then being mistakenly passed down to XGBoost core, or some parameter actu
ally being used
  but getting flagged wrongly here. Please open an issue if you find any su
ch cases.
```

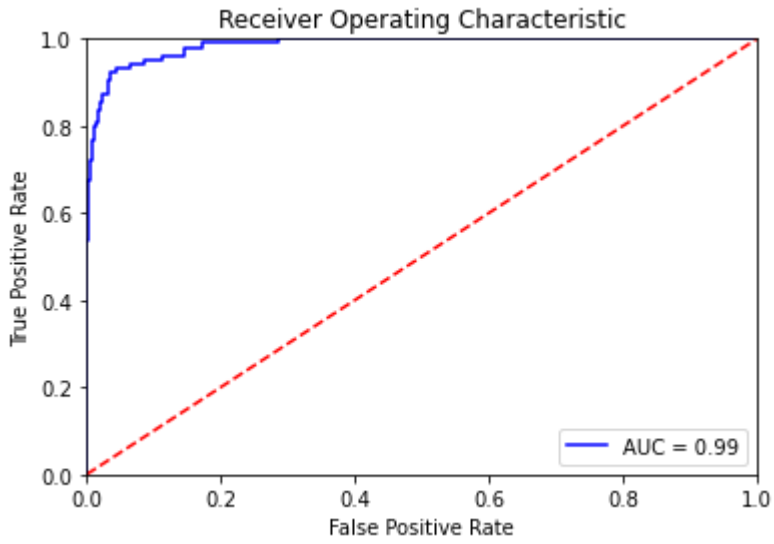
In [30]:

```
ypred_bst = np.array(bst.predict(dtest,ntree_limit=bst.best_iteration))
ypred_bst  = ypred_bst > 0.5
ypred_bst = ypred_bst.astype(int)
```

In [31]:

```
print (roc_auc_score(y_test, preds))
fpr, tpr, _ = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)
print('AUC:', np.round(roc_auc,4))
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

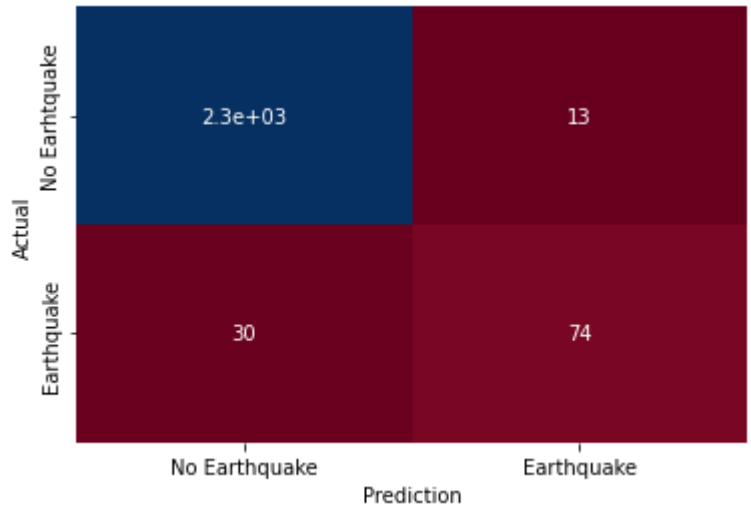
```
0.9854064666644761
AUC: 0.9854
```



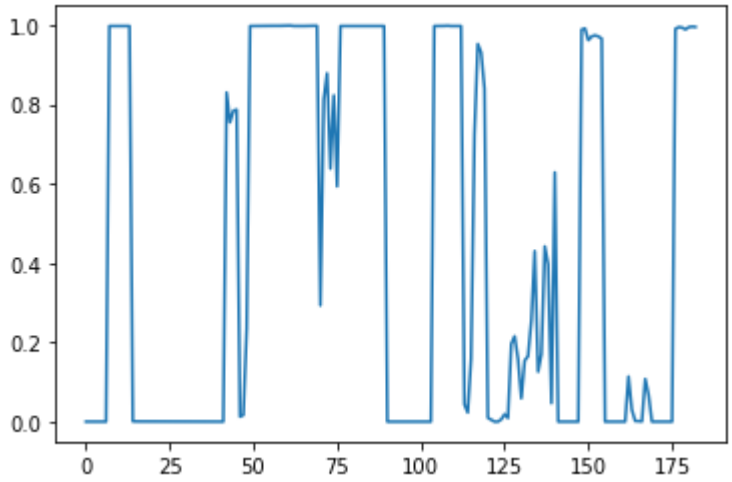
In [32]:

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
print('Confusion Matrix \n',confusion_matrix(y_test,ypred_bst))
print('Confusion Matrix \n',confusion_matrix(ypred_bst,y_test))
confusion_matrix= confusion_matrix(y_test,ypred_bst)
hm = sns.heatmap(confusion_matrix, annot=True, xticklabels=['No Earthquake',
                 yticklabels=['No Earhtquake', 'Earthquake'],
                 cbar=False, cmap='RdBu')
hm.set_xlabel("Prediction")
hm.set_ylabel("Actual")
xgbc=recall_score(y_test,ypred_bst)
print("\nRecall 'TP/TP+FN' = ", xgbc)
```

```
Confusion Matrix
 [[2328   13]
 [  30   74]]
Confusion Matrix
 [[2328   30]
 [  13   74]]

Recall 'TP/TP+FN' =  0.7115384615384616
```



In [33]:
```
dlive = xgb.DMatrix(df_predict[features]) #, label=[])
preds = bst.predict(dlive)

plt.plot(preds)
plt.show()
```



In [34]:
```
live_set = df_predict[['date', 'place', 'latitude', 'longitude']]
live_set.loc[:,'quake'] = preds
# aggregate down dups
live_set = live_set.groupby(['date', 'place'], as_index=False).mean()

# increment date to include DAYS_OUT_TO_PREDICT
live_set['date']= pd.to_datetime(live_set['date'],format='%Y-%m-%d')
live_set['date'] = live_set['date'] + pd.to_timedelta(7,unit='d')

live_set.tail()
```

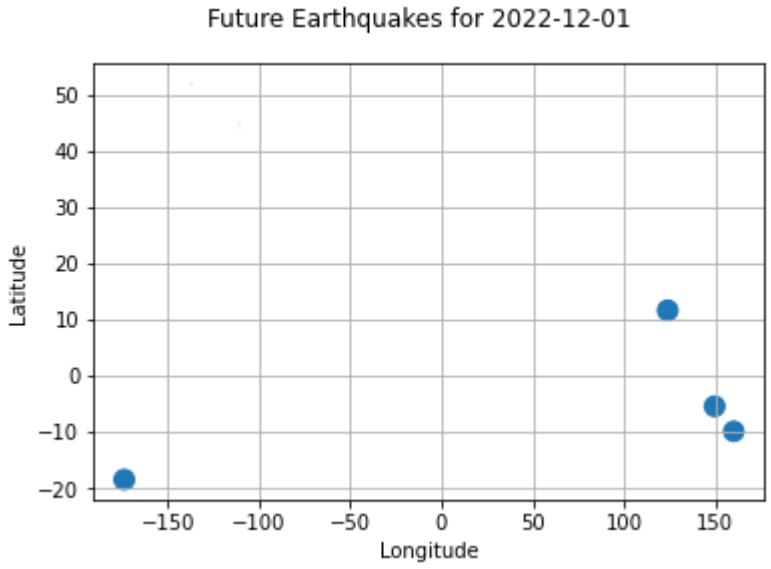
Out[34]:

	date	place	latitude	longitude	quake
87	2022-12-07	Puerto Rico	18.114459	-66.833591	0.431800
88	2022-12-07	Russia	52.017591	130.222957	0.997943
89	2022-12-07	Texas	31.575240	-103.698497	0.210647
90	2022-12-07	U.S. Virgin Islands	19.030958	-64.815751	0.995819
91	2022-12-07	Utah	40.225939	-112.244823	0.000064

In [35]:
```
# convert date to proper format for prediction
days = list(set([d for d in live_set['date'].astype(str) if d > dt.datetime.n
days.sort()

# Predict NaN outcome value in earthquake for next day 1.
predict_day=days[0]
predict_day
```

Out[35]: '2022-12-01'

In [36]:
```
# place, date, lat and long with earthquake probability for next 7 days
for i in range(0,7):
    live_set_tmp = live_set[live_set['date'] == days[i]]
    plt.scatter(live_set_tmp['longitude'], live_set_tmp['latitude'], s=(live_
    plt.suptitle('Future Earthquakes for ' + days[i])
    plt.xlabel('Longitude')
    plt.ylabel('Latitude')
    plt.grid()
    plt.show()
```



Future Earthquakes for 2022-12-02

In [37]:
```
live_set.to_csv('xgb_live_dataset.csv',index=False)
```

Multi-Layer Precepton

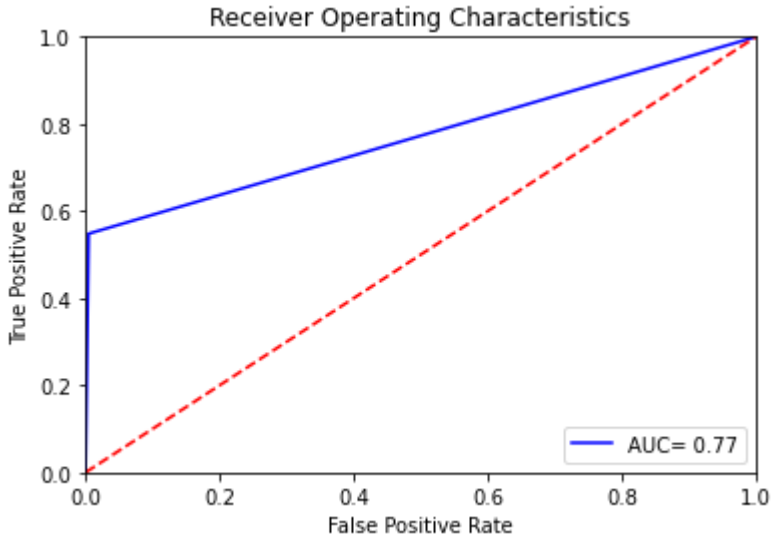
In [38]:
```
from keras.models import Sequential
from keras.layers import Dense

model = Sequential()
# Input layer
model.add(Dense(32, activation='relu', input_dim=len(features)))
# Hidden Layer
model.add(Dense(16, activation='relu'))
# Output Layer
model.add(Dense(1, activation='sigmoid'))
# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accurac
```

In [39]:
```
#Train the model
model.fit(X_train,y_train,epochs=200,verbose=False);
```

In [40]:
```
pred_mlp=(model.predict(X_test) > 0.5).astype("int32")
```

In [41]:
```
print("ROC_AUC_Score: ",roc_auc_score(y_test,pred_mlp))
fpr,tpr,_= roc_curve(y_test,pred_mlp)
roc_auc=auc(fpr,tpr)
print('AUC: ',np.round(roc_auc,4))

plt.title('Receiver Operating Characteristics')
plt.plot(fpr,tpr,'b',label='AUC= %0.2f'%roc_auc)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([0,1])
plt.ylim([0,1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

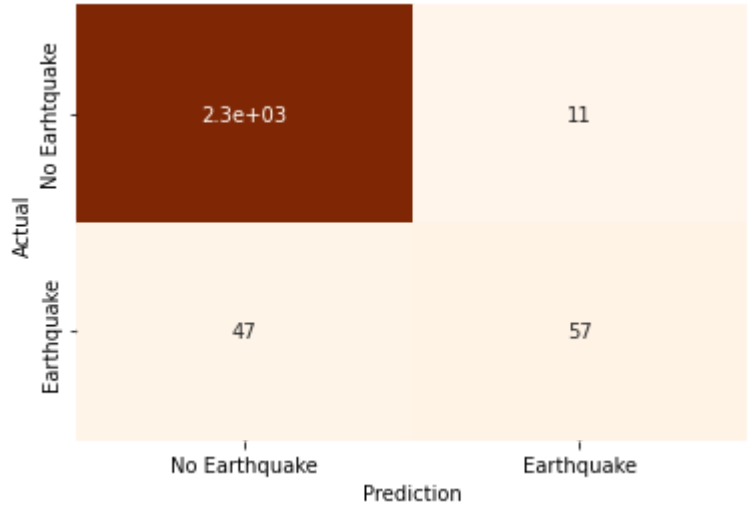
```
ROC_AUC_Score:  0.7716890382150955
AUC:  0.7717
```



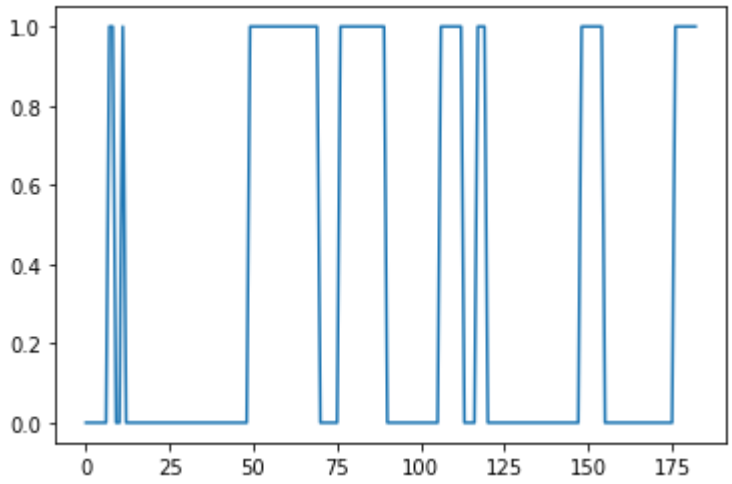
In [42]:

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
print('Confusion Matrix \n',confusion_matrix(y_test,pred_mlp))
print('Confusion Matrix \n',confusion_matrix(pred_mlp,y_test))
confusion_matrix= confusion_matrix(y_test,pred_mlp)
hm = sns.heatmap(confusion_matrix, annot=True, xticklabels=['No Earthquake',
                 yticklabels=['No Earhtquake', 'Earthquake'],
                 cbar=False, cmap='Oranges')
hm.set_xlabel("Prediction")
hm.set_ylabel("Actual")
hm
mlpc=recall_score(y_test,pred_mlp)
print("\nRecall TP/TP+FN = ",mlpc)
```

```
Confusion Matrix
 [[2330   11]
 [  47   57]]
Confusion Matrix
 [[2330   47]
 [  11   57]]

Recall TP/TP+FN =  0.5480769230769231
```



In [43]:
```
pred_mlp=(model.predict(df_predict[features]) > 0.5).astype("int32")
plt.plot(pred_mlp)
plt.show()
```



In [44]:
```
live_set = df_predict[['date', 'place', 'latitude', 'longitude']]
live_set.loc[:,'quake'] = pred_mlp
# aggregate down dups
live_set = live_set.groupby(['date', 'place'], as_index=False).mean()

# increment date to include DAYS_OUT_TO_PREDICT
live_set['date']= pd.to_datetime(live_set['date'],format='%Y-%m-%d')
live_set['date'] = live_set['date'] + pd.to_timedelta(7,unit='d')

live_set.tail()
```

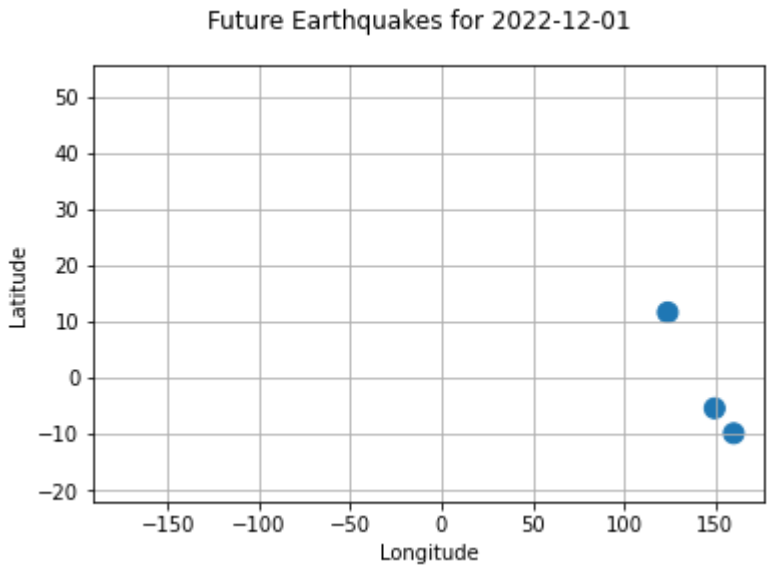
Out[44]:

	date	place	latitude	longitude	quake
87	2022-12-07	Puerto Rico	18.114459	-66.833591	0.0
88	2022-12-07	Russia	52.017591	130.222957	1.0
89	2022-12-07	Texas	31.575240	-103.698497	0.0
90	2022-12-07	U.S. Virgin Islands	19.030958	-64.815751	1.0
91	2022-12-07	Utah	40.225939	-112.244823	0.0

In [45]:
```
# convert date to proper format for prediction
days = list(set([d for d in live_set['date'].astype(str) if d > dt.datetime.n
days.sort()

# Predict NaN outcome value in earthquake for next day 1.
predict_day=days[0]
predict_day
```

Out[45]: '2022-12-01'

In [46]:
```
# place, date, lat and long with earthquake probability for next 7 days
for i in range(0,7):
    live_set_tmp = live_set[live_set['date'] == days[i]]
    plt.scatter(live_set_tmp['longitude'], live_set_tmp['latitude'], s=(live_
    plt.suptitle('Future Earthquakes for ' + days[i])
    plt.xlabel('Longitude')
    plt.ylabel('Latitude')
    plt.grid()
    plt.show()
```



Future Earthquakes for 2022-12-02

In [47]:
```
live_set.to_csv('mlp_live_dataset.csv',index=False)
```

Comparing models and find the best outcome

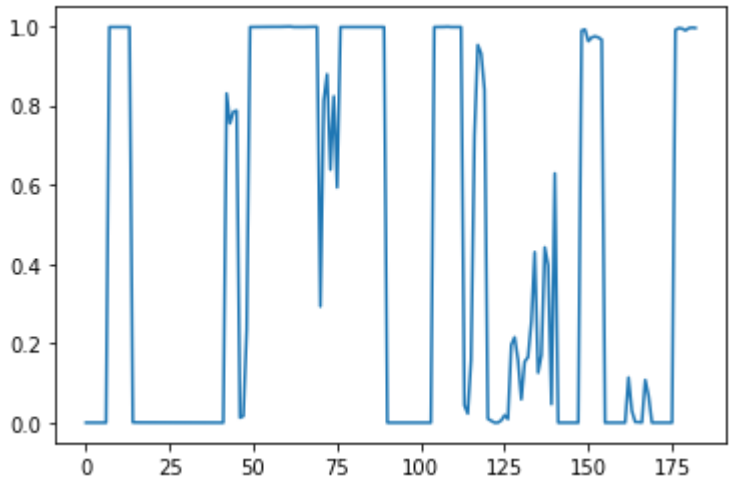
In [48]:
```
best_recall=max([dtc,rfc,xgbc,mlpc])
print("Recall (Sensitivity): ",best_recall)
```

```
Recall (Sensitivity):  0.7115384615384616
```

In [49]:

```
import datetime as dt
def live_prediction(x):
    if x== dtc:
        pred=grid_search_ABC.predict(df_predict[features])
    elif x==rfc:
        pred=CV_rfc.predict(df_predict[features])
    elif x==xgbc:
        dlive = xgb.DMatrix(df_predict[features]) #, label=[])
        pred = bst.predict(dlive)
    elif x==mlpc:
        pred=(model.predict(df_predict[features]) > 0.5).astype("int32")
    plt.plot(pred)
    plt.show()

    live_set = df_predict[['date', 'place', 'latitude', 'longitude']]
    live_set.loc[:,'quake'] = pred
    # aggregate down dups
    live_set = live_set.groupby(['date', 'place'], as_index=False).mean()

    # increment date to include DAYS_OUT_TO_PREDICT
    live_set['date']= pd.to_datetime(live_set['date'],format='%Y-%m-%d')
    live_set['date'] = live_set['date'] + pd.to_timedelta(7,unit='d')

    live_set.tail()

    # convert date to proper format for prediction
    days = list(set([d for d in live_set['date'].astype(str) if d > dt.dateti
    days.sort()

    # Predict NaN outcome value in earthquake for next day 1.
    predict_day=days[0]
    predict_day

    # place, date, lat and long with earthquake probability for next 7 days
    for i in range(0,7):
        live_set_tmp = live_set[live_set['date'] == days[i]]
        plt.scatter(live_set_tmp['longitude'], live_set_tmp['latitude'], s=(l
        plt.suptitle('Future Earthquakes for ' + days[i])
        plt.xlabel('Longitude')
        plt.ylabel('Latitude')
        plt.grid()
        plt.show()

    live_set.to_csv('best_recall_live_dataset.csv',index=False)
```

In [50]:
```
live_prediction(best_recall)
```



Future Earthquakes for 2022-12-01