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_avg
0	2022-01-10	339.33	4.2	Japan	33.299778	135.513876	69.870000	85.812667	81.2314
1	2022-01-10	84.74	4.3	Japan	33.299778	135.513876	73.267273	87.372000	87.6700
2	2022-01-11	46.28	4.4	Japan	33.299778	135.513876	74.916364	86.615333	86.4471
3	2022-01-11	34.49	4.6	Japan	33.299778	135.513876	71.993182	87.402667	86.2842
4	2022-01-11	380.35	4.2	Japan	33.299778	135.513876	87.038636	111.248000	139.1914

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_avg
0	2022-11-27	49.711	4.6	Japan	33.299778	135.513876	83.077636	89.482467	121.2292
1	2022-11-29	10.000	5.0	Japan	33.299778	135.513876	83.077636	89.482467	113.8895
2	2022-11-29	55.283	4.4	Japan	33.299778	135.513876	84.939636	92.501333	86.3178
3	2022-11-30	53.289	5.0	Japan	33.299778	135.513876	85.541909	95.401533	90.8515
4	2022-11-30	10.000	4.6	Japan	33.299778	135.513876	69.749136	91.681733	80.5734

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
```

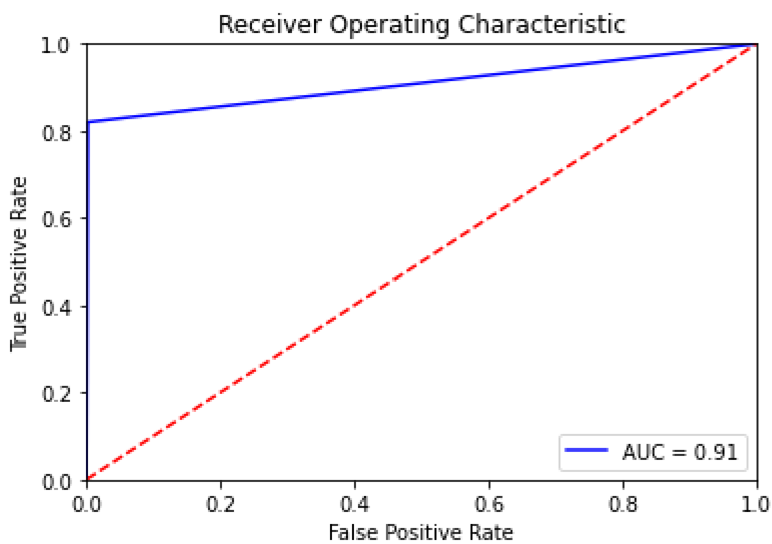
Out[11]:
```
GridSearchCV(estimator=AdaBoostClassifier(algorithm='SAMME',
                                          base_estimator=DecisionTreeClassi
fier(),
                                          learning_rate=0.6),
             param_grid={'base_estimator__max_depth': [2, 5, 7],
                         '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()
```

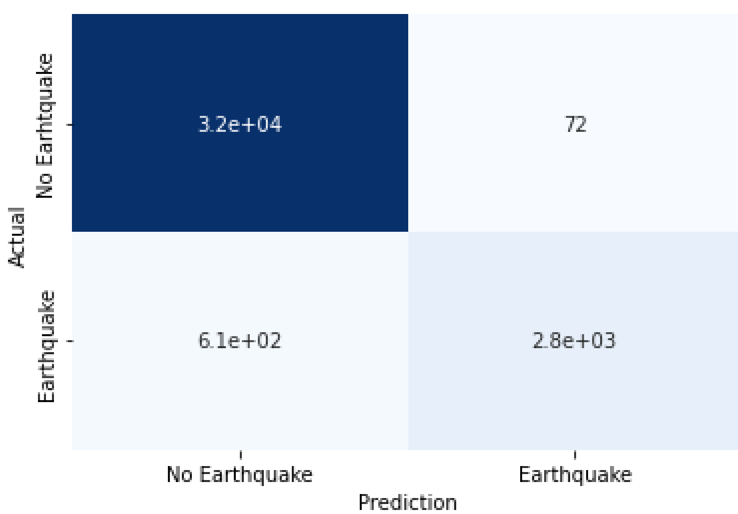
```
0.9089006038701254
AUC: 0.9089
```



In [14]:

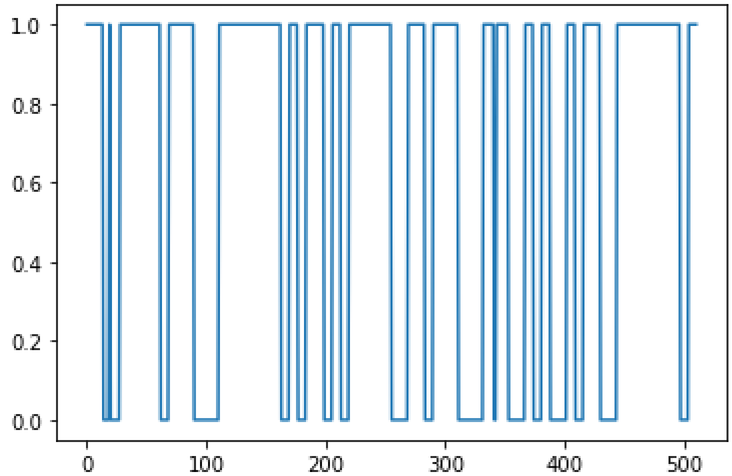
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
print('Confusion Matrix \n',confusion_matrix(y_test,pred_ABC))
print('Confusion Matrix \n',confusion_matrix(pred_ABC,y_test))
confusion_matrix= confusion_matrix(y_test,pred_ABC)
hm = sns.heatmap(confusion_matrix, annot=True, xticklabels=['No 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
 [[32410    72]
 [  606  2761]]
Confusion Matrix
 [[32410   606]
 [   72  2761]]

Recall TP/TP+FN =  0.82001782001782
```



In [15]:

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



In [16]:

```python
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	2022-03-27	Haiti	18.630986	-73.595337	1.0
1	2022-03-30	Haiti	18.630986	-73.595337	1.0
2	2022-04-06	Haiti	18.630986	-73.595337	1.0
3	2022-04-15	Haiti	18.630986	-73.595337	1.0
4	2022-04-29	Haiti	18.630986	-73.595337	1.0
...	...	...	...	...	...
366	2022-12-08	Japan	33.299778	135.513876	1.0
367	2022-12-08	New Zealand	-33.654791	-61.980008	1.0
368	2022-12-08	Philippines	10.520730	123.935076	1.0
369	2022-12-08	Puerto Rico	18.059253	-66.850617	0.0
370	2022-12-08	U.S. Virgin Islands	18.932836	-64.701673	1.0

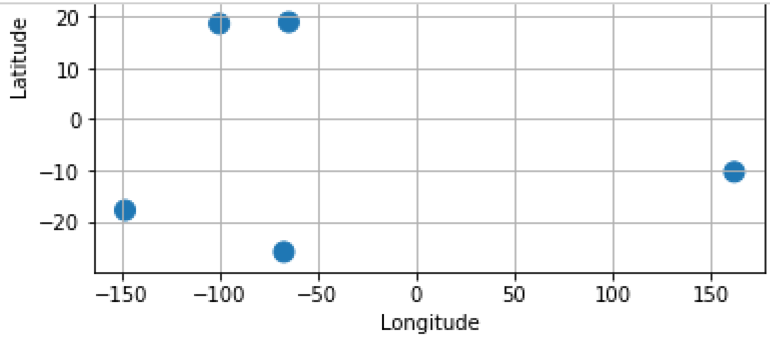
371 rows × 5 columns

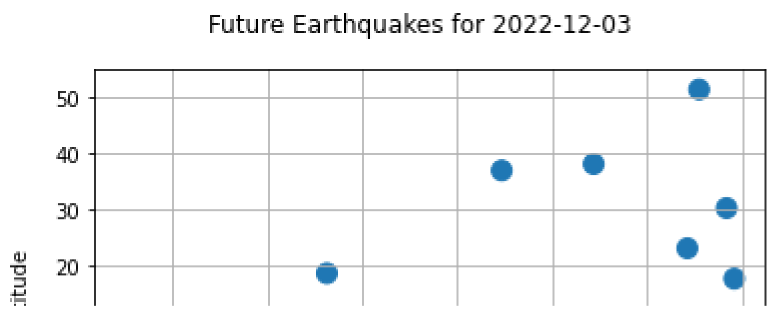
In [18]:

```python
# convert date to proper format for prediction
days = list(set([d for d in live_set['date'].astype(str) if d > dt.datetime.r
days.sort()
days
#Predict NaN outcome value in earthquake for next day 1.
predict_day=days[0]
predict_day
```

Out[18]: '2022-12-02'

```
In [19]: # 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()
```






```
In [20]: live_set.to_csv('dt_live_dataset.csv',index=False)
```

Random Forest Classifier

In [21]:

```
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[21]:

```
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]})
```

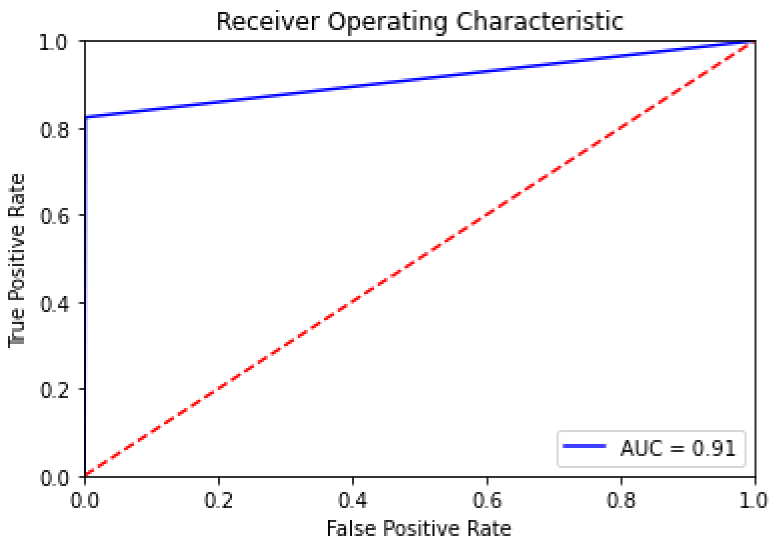
In [22]:

```
pred=CV_rfc.predict(X_test)
```

In [23]:

```
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()
```

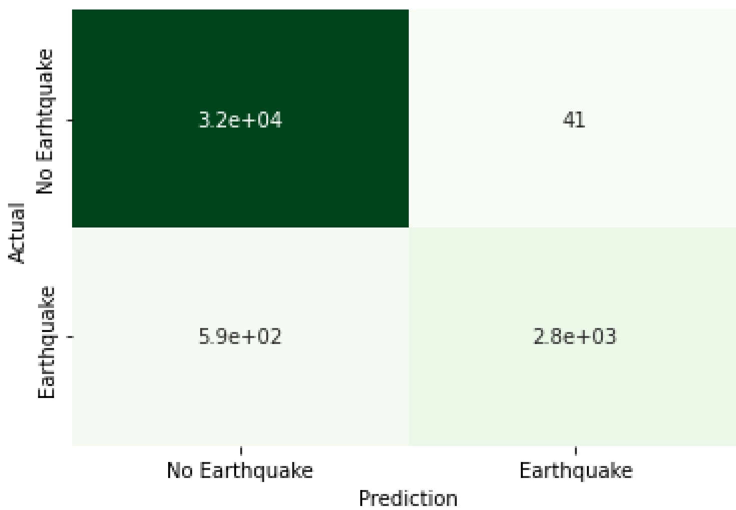
```
0.9113082931659374
AUC: 0.9113
```



In [24]:

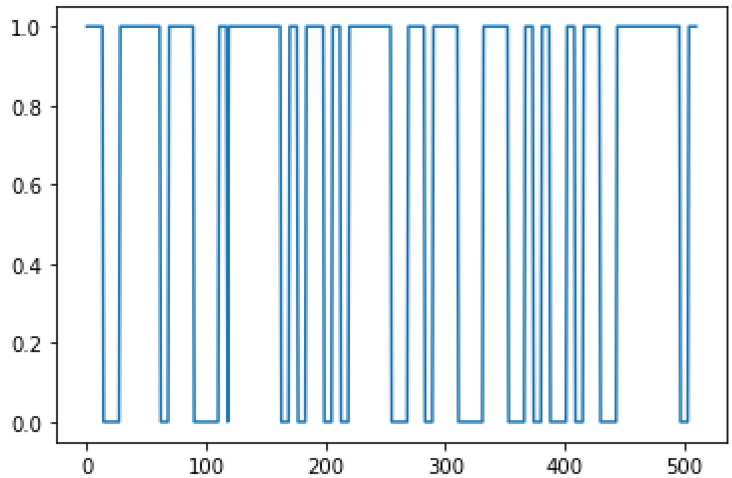
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
print('Confusion Matrix \n',confusion_matrix(y_test,pred))
print('Confusion Matrix \n',confusion_matrix(pred,y_test))
confusion_matrix= confusion_matrix(y_test,pred)
hm = sns.heatmap(confusion_matrix, annot=True, xticklabels=['No 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
 [[32441    41]
 [  593  2774]]
Confusion Matrix
 [[32441   593]
 [   41  2774]]

Recall 'TP/TP+FN' =  0.8238788238788238
```



In [25]:

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



In [26]:

```
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[26]:

	date	place	latitude	longitude	quake
366	2022-12-08	Japan	33.299778	135.513876	1.0
367	2022-12-08	New Zealand	-33.654791	-61.980008	1.0
368	2022-12-08	Philippines	10.520730	123.935076	1.0
369	2022-12-08	Puerto Rico	18.059253	-66.850617	0.0
370	2022-12-08	U.S. Virgin Islands	18.932836	-64.701673	1.0

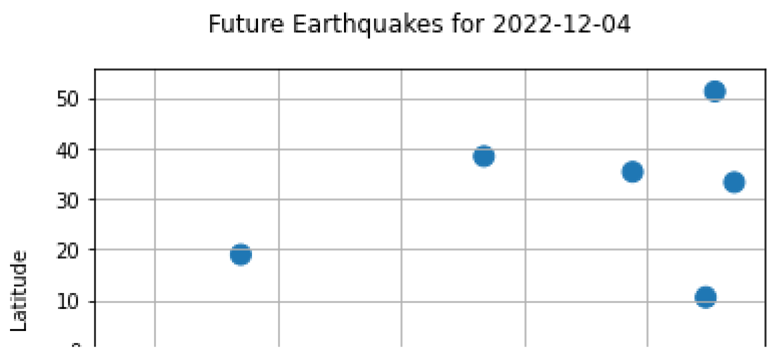
In [27]:

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

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

Out[27]: '2022-12-02'

In [28]:

```python
# 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()
```



In [29]:

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

XGBoost Algorithm

In [30]:

```
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)
```

```
[09:35:52] 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.
```

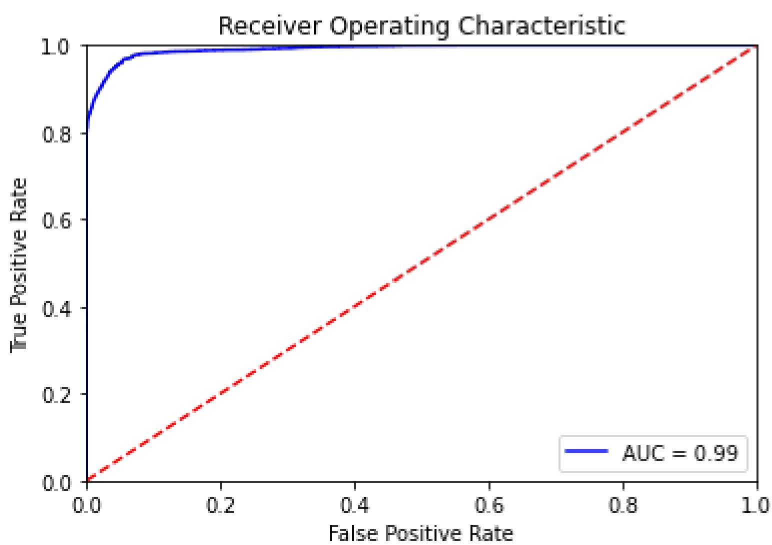
In [31]:

```
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 [32]:

```
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()
```

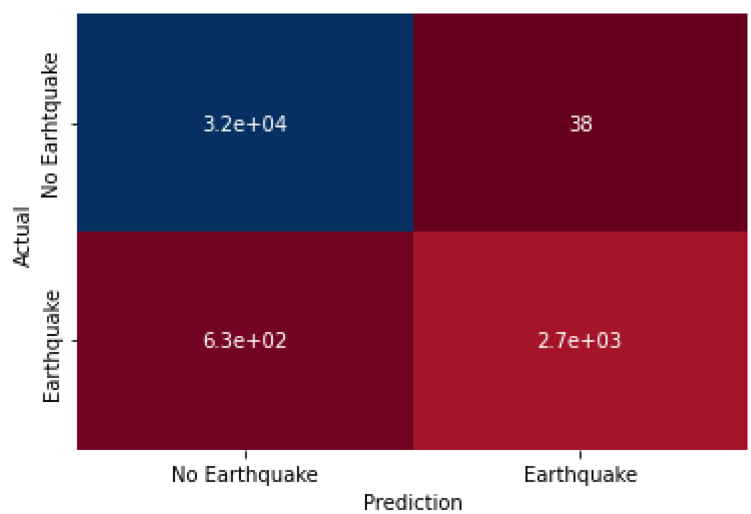
```
0.9911287551057271
AUC: 0.9911
```



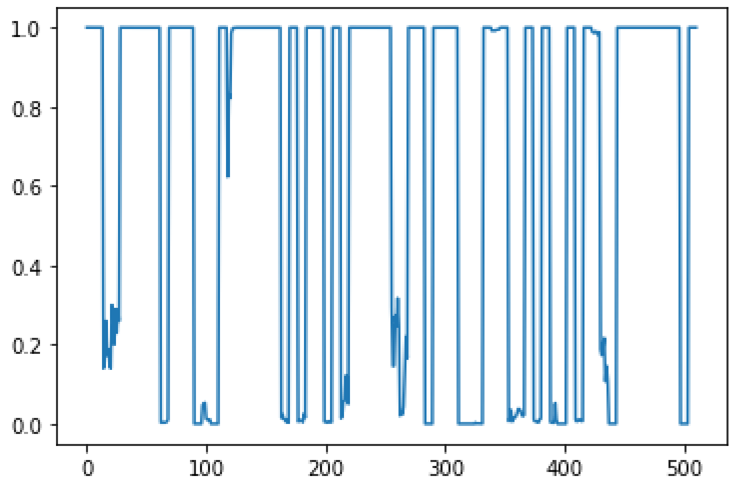
In [33]:

```python
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
 [[32444    38]
 [  631  2736]]
Confusion Matrix
 [[32444   631]
 [   38  2736]]

Recall 'TP/TP+FN' =  0.8125928125928126
```



In [34]:
```python
dlive = xgb.DMatrix(df_predict[features]) #, label=[])
preds = bst.predict(dlive)

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



In [35]:
```python
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()
```

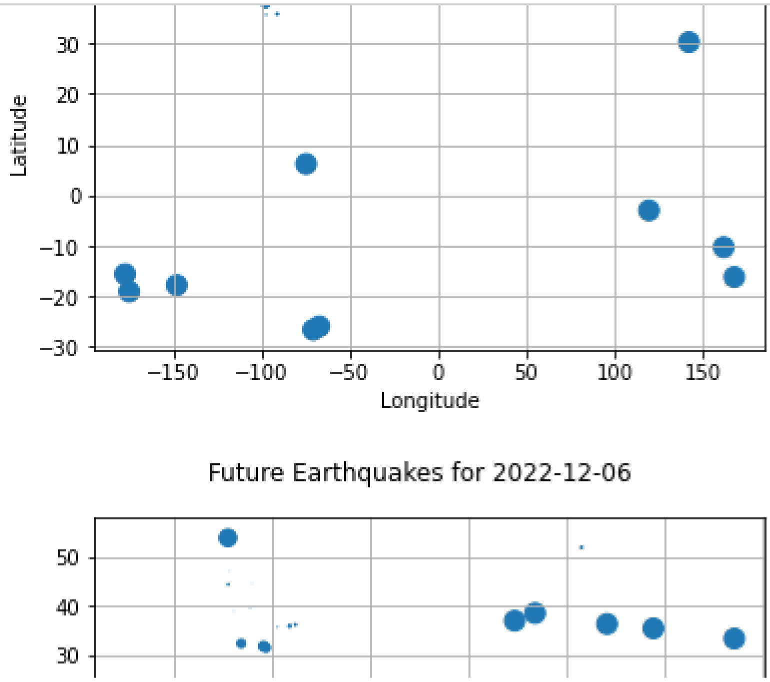
Out[35]:

	date	place	latitude	longitude	quake
366	2022-12-08	Japan	33.299778	135.513876	0.999870
367	2022-12-08	New Zealand	-33.654791	-61.980008	0.999807
368	2022-12-08	Philippines	10.520730	123.935076	0.999830
369	2022-12-08	Puerto Rico	18.059253	-66.850617	0.259874
370	2022-12-08	U.S. Virgin Islands	18.932836	-64.701673	0.988017

In [36]:
```python
# convert date to proper format for prediction
days = list(set([d for d in live_set['date'].astype(str) if d > dt.datetime.r
days.sort()

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

Out[36]: '2022-12-02'

In [37]:
```
# 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()
```



In [38]:
```
live_set.to_csv('xgb_live_dataset.csv',index=False)
```

Multi-Layer Precepton

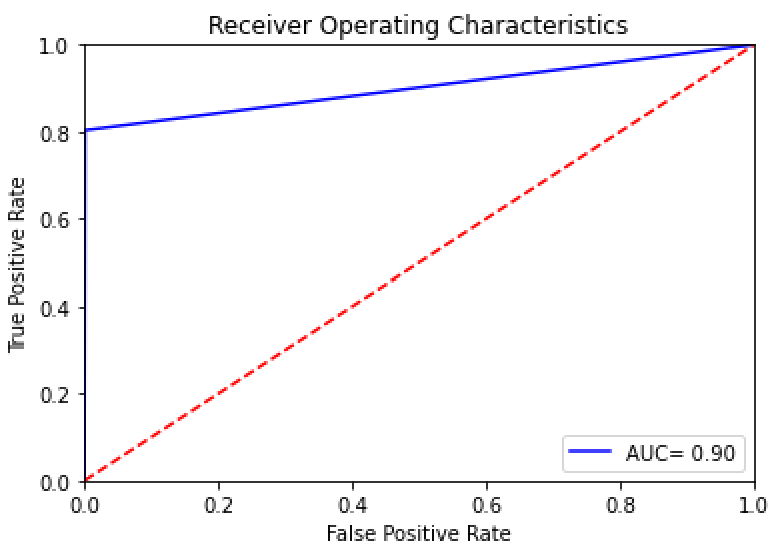
In [39]:
```
from keras.models import Sequential
from keras.layers import Dense

model = Sequential()
# Input Layer
model.add(Dense(128, activation='relu', input_dim=len(features)))
# Hidden Layer
model.add(Dense(64, activation='relu'))
model.add(Dense(32, activation='relu'))
model.add(Dense(16, activation='relu'))
model.add(Dense(8, activation='relu'))
# Output Layer
model.add(Dense(1, activation='sigmoid'))
# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accurac
```

In [40]:
```
#Train the model
model.fit(X_train,y_train,epochs=500,verbose=False);
```

In [41]:
```
pred_mlp=(model.predict(X_test) > 0.5).astype("int32")
```

In [42]:
```
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()
```

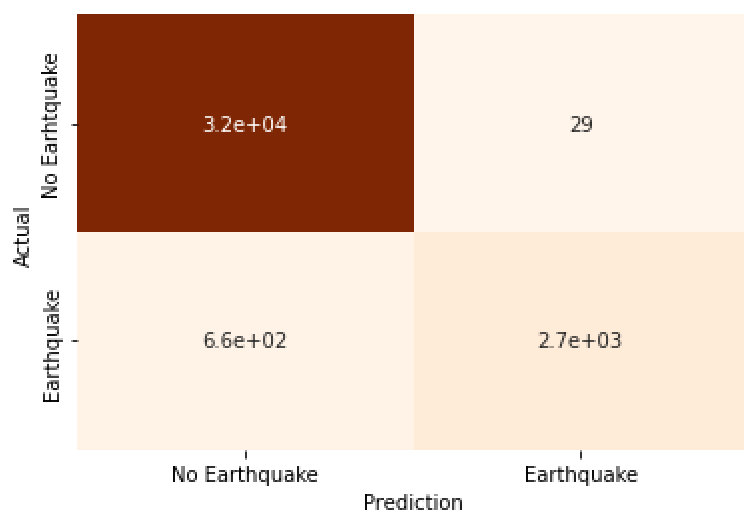
```
ROC_AUC_Score:  0.9012465006092245
AUC:  0.9012
```



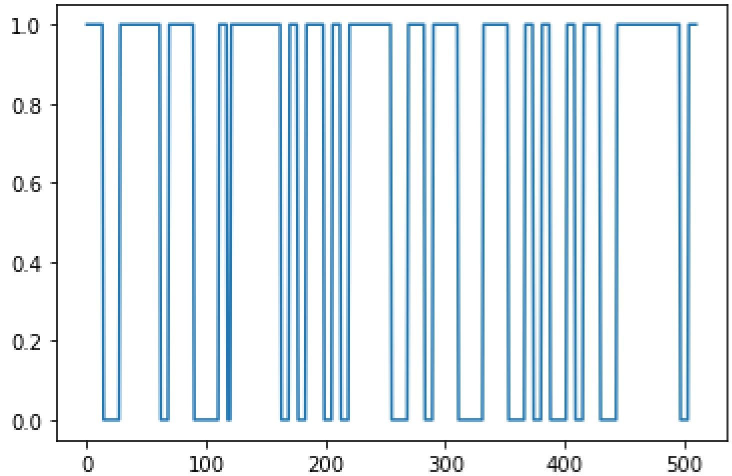
In [43]:

```
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
 [[32453    29]
 [  662  2705]]
Confusion Matrix
 [[32453   662]
 [   29  2705]]

Recall TP/TP+FN =  0.8033858033858033
```



In [44]:
```python
pred_mlp=(model.predict(df_predict[features]) > 0.5).astype("int32")
plt.plot(pred_mlp)
plt.show()
```



In [45]:
```python
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()
```

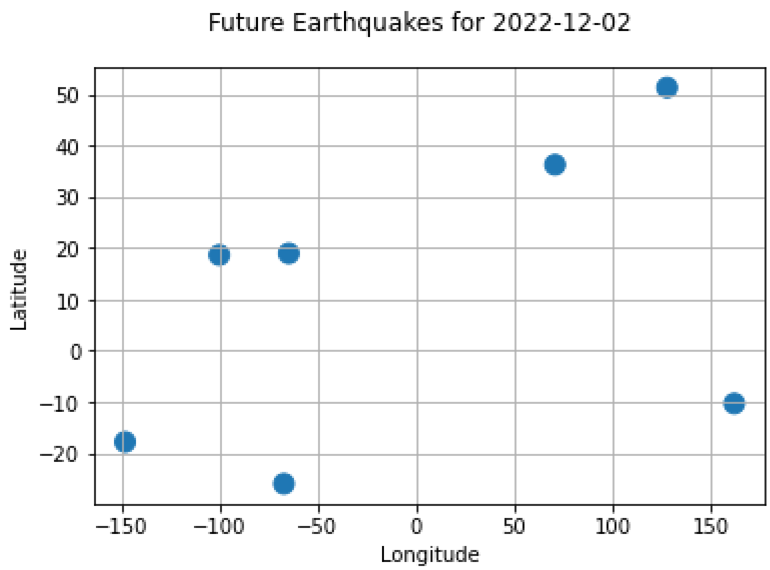
Out[45]:

	date	place	latitude	longitude	quake
366	2022-12-08	Japan	33.299778	135.513876	1.0
367	2022-12-08	New Zealand	-33.654791	-61.980008	1.0
368	2022-12-08	Philippines	10.520730	123.935076	1.0
369	2022-12-08	Puerto Rico	18.059253	-66.850617	0.0
370	2022-12-08	U.S. Virgin Islands	18.932836	-64.701673	1.0

In [46]:
```python
# convert date to proper format for prediction
days = list(set([d for d in live_set['date'].astype(str) if d > dt.datetime.r
days.sort()

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

Out[46]: '2022-12-02'

In [47]:
```python
# 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 2022-12-03

In [48]:
```python
live_set.to_csv('mlp_live_dataset.csv',index=False)
```

Comparing models and find the best outcome

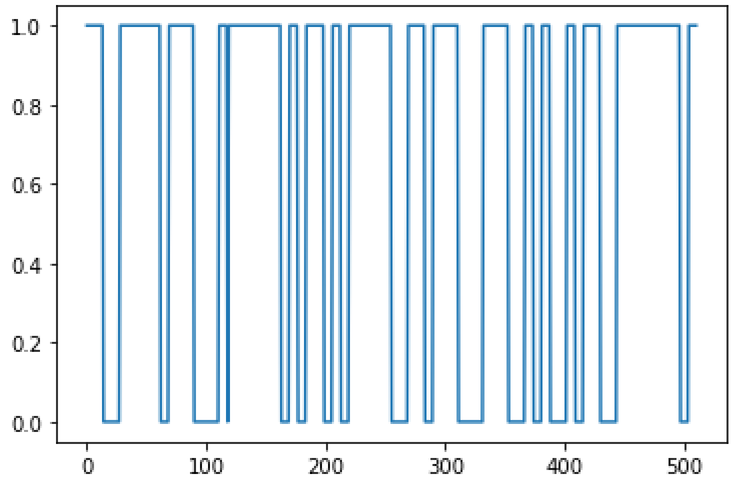
In [49]:
```python
best_recall=max([dtc,rfc,xgbc,mlpc])
print("Recall (Sensitivity): ",best_recall)
```

```
Recall (Sensitivity):  0.8238788238788238
```

```
In [50]:
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 [51]:

```
live_prediction(best_recall)
```



Future Earthquakes for 2022-12-02