Get our environment set up

The first thing we'll need to do is load in the libraries and dataset we'll be using. We'll be working with a dataset containing information on earthquakes that occured between 1965 and 2016.

We have gathered this dataset from the publicly available domain Kaggle. We have used the �Significant Earthquakes, 1965-2016� dataset from Kaggle in the CSV format. It includes a record of the date, time, location, depth, magnitude, and source of every earthquake with a reported magnitude 5.5 or higher since 1965.

Documentation

Introduction

Earthquakes are regarded one of the most deadly natural catastrophes, since they may strike without warning. The percentage of mortality caused by earthquakes is over 50% greater than that of other natural catastrophes. According to the World Health Organization (WHO), earthquakes killed 750,000 people globally between 1998 and 2017. During this era, more than 125 million individuals were afflicted by earthquakes, meaning that they were either hurt or lost their homes and precious assets. In 2020, Americans lost USD 4.4 billion, owing to disastrous earthquakes. Seismic activity prediction is the ideal strategy for minimising earthquake-related economic and human calamities.

Machine learning (ML) techniques play a crucial role in prediction and forecasting in several sectors, including diverse catastrophes, such as floods, earthquakes, and landslides. Significant study has been performed, employing these strategies, to decrease the effect of the aforementioned calamities. These research have employed a number of machine learning methodologies, including artificial neural network, support vector machine, random forest, and convolutional neural network. In this work, we view the seismic activity prediction issue as a binary classification problem, and offer a deep neural network model for predicting the existence or otherwise of major seismic activity on top of training using the Random Forest technique as well.

Problem Statement

Several natural risks including fire, tsunami, flood, earthquake, etc., are hurting persons, buildings, animals, and other infrastructures. These dangers can not be halted but can be averted utilising numerous approaches as remote sensign, LiDAR, and seismic stations. One of the purposes of earthquake hazard analysis is to reduce the effect of earthquakes on civilization by limiting damage to buildings and infrastructure. Predicting seismic occurrences using continuous data and applying it in real-time to early warning systems or evaluating it offline to hunt for previously unpredicted earthquakes is an essential problem.

Dataset Used

We have used the publicly available dataset on Kaggle named "Significant Earthquakes, 1965-2016". It is a dataset in the CSV (Comma Separated Values) format. It provides a record of the date, time, location, depth, magnitude, and source of every earthquake of a recorded magnitude 5.5 or greater since 1965.

Dataset Preprocessing Steps

Several methods to clean the data were implemented to preprocess the data before use. The data was preprocessed by handling missing values, then scaling and normalization were done. The dates in the data was parsed, and inconsistent data entry was handled.

An environment was setup in form of a python notebook file. The required modules (Pandas, Numpy, Seaborn, Datetime) were downloaded and imported into the environment. The date columns were converted into datetime.

Feature Exploration

We have built a heatmap of the earthquake prone zones on the world map using data visualization methods provided in MatplotLib. The heatmap can be seen in the following slide.

Hybrid Learning

To create our data model, we have opted to use the Random Forest algorithm and a Neural Network algorithm. We have used the ensemble learning technique to intelligently choose the best performing algorithm for building the data model.

Random Forest Implementation

Leo Breiman and Adele Cutler are the creators of the widely used machine learning technique known as random forest, which mixes the output of several decision trees to produce a single outcome. We have used Scikit-Learn Python module to train our dataset using the Random Forest algorithm. We have fit the X and Y values on the regressor and built the data model and test it against the test dataset to achieve an accuracy of 87.49%, a sensitivity of 92.9% and a specificity of 64.1% as seen in the graph in the following slide

Neural Network Algorithm

We have used the Keras library to build a Neural Network for the dataset. A neural network is a collection of algorithms that aims to identify underlying links in a piece of data using a method that imitates how the human brain functions.

```
# modules we'll use
import pandas as pd
import numpy as np
import seaborn as sns
import datetime

# read in our data
earthquakes = pd.read_csv("../input/earthquake-database/database.csv")

# set seed for reproducibility
np.random.seed(0)
```

1) Check the data type of our date column

We are working with the "Date" column from the `earthquakes` dataframe. We investigate this column now and see if it looks like it contains dates and what the dtype of the column is.

```
# TODO: Your code here!
earthquakes['Date'].head()

0    01/02/1965
1    01/04/1965
2    01/05/1965
3    01/08/1965
4    01/09/1965
Name: Date, dtype: object
```

2) Convert our date columns to datetime

Most of the entries in the "Date" column follow the same format: "month/day/four-digit year". However, the entry at index 3378 follows a completely different pattern. We run the code cell below to see this.

```
earthquakes[3378:3383]

                          Date                      Time  Latitude
Longitude  \
3378  1975-02-23T02:58:41.000Z  1975-02-23T02:58:41.000Z     8.017
124.075
```

```
3379               02/23/1975                  03:53:36   -21.727
-71.356
3380               02/23/1975                  07:34:11   -10.879
166.667
3381               02/25/1975                  05:20:05    -7.388
149.798
3382               02/26/1975                  04:48:55    85.047
97.969

            Type  Depth  Depth Error  Depth Seismic Stations
Magnitude  \
3378  Earthquake  623.0          NaN                     NaN
5.6
3379  Earthquake   33.0          NaN                     NaN
5.6
3380  Earthquake   33.0          NaN                     NaN
5.5
3381  Earthquake   33.0          NaN                     NaN
5.5
3382  Earthquake   33.0          NaN                     NaN
5.6

     Magnitude Type  ...  Magnitude Seismic Stations  Azimuthal Gap  \
3378             MB  ...                         NaN            NaN
3379             MB  ...                         NaN            NaN
3380             MS  ...                         NaN            NaN
3381             MB  ...                         NaN            NaN
3382             MS  ...                         NaN            NaN

      Horizontal Distance  Horizontal Error  Root Mean Square
ID  \
3378                  NaN               NaN               NaN
USP0000A09
3379                  NaN               NaN               NaN
USP0000A0A
3380                  NaN               NaN               NaN
USP0000A0C
3381                  NaN               NaN               NaN
USP0000A12
3382                  NaN               NaN               NaN
USP0000A1H

     Source Location Source Magnitude Source    Status
3378     US              US                US  Reviewed
3379     US              US                US  Reviewed
3380     US              US                US  Reviewed
3381     US              US                US  Reviewed
3382     US              US                US  Reviewed

[5 rows x 21 columns]
```

This does appear to be an issue with data entry: ideally, all entries in the column have the same format. We can get an idea of how widespread this issue is by checking the length of each entry in the "Date" column.

```
date_lengths = earthquakes.Date.str.len()
date_lengths.value_counts()
```

```
10    23409
24        3
Name: Date, dtype: int64
```

Looks like there are two more rows that has a date in a different format. We Run the code cell below to obtain the indices corresponding to those rows and print the data.

```
indices = np.where([date_lengths == 24])[1]
print('Indices with corrupted data:', indices)
earthquakes.loc[indices]
```

```
Indices with corrupted data: [ 3378  7512 20650]

                           Date                      Time  Latitude  \
3378   1975-02-23T02:58:41.000Z  1975-02-23T02:58:41.000Z     8.017
7512   1985-04-28T02:53:41.530Z  1985-04-28T02:53:41.530Z   -32.998
20650  2011-03-13T02:23:34.520Z  2011-03-13T02:23:34.520Z    36.344

       Longitude        Type  Depth  Depth Error  Depth Seismic
Stations  \
3378     124.075  Earthquake  623.0          NaN
NaN
7512     -71.766  Earthquake   33.0          NaN
NaN
20650    142.344  Earthquake   10.1         13.9
289.0

       Magnitude Magnitude Type  ...  Magnitude Seismic Stations  \
3378         5.6             MB  ...                         NaN
7512         5.6             MW  ...                         NaN
20650        5.8            MWC  ...                         NaN

       Azimuthal Gap  Horizontal Distance  Horizontal Error  Root Mean
Square  \
3378             NaN                  NaN               NaN
NaN
7512             NaN                  NaN               NaN
1.30
20650           32.3                  NaN               NaN
1.06

               ID Source Location Source Magnitude Source    Status
3378   USP0000A09     US              US               US  Reviewed
```

```
7512    USP0002E81      US                US                HRV   Reviewed
20650   USP000HWQP      US                US               GCMT   Reviewed

[3 rows x 21 columns]
```

Given all of this information, we create a new column "date_parsed" in the `earthquakes` dataset that has correctly parsed dates in it.

We have now converted all the date columns into datetime.

```
# TODO: Your code here
earthquakes.loc[3378, "Date"] = "02/23/1975"
earthquakes.loc[7512, "Date"] = "04/28/1985"
earthquakes.loc[20650, "Date"] = "03/13/2011"
earthquakes['date_parsed'] = pd.to_datetime(earthquakes['Date'],
format="%m/%d/%Y")
```

3) Select the day of the month

Create a Pandas Series `day_of_month_earthquakes` containing the day of the month from the "date_parsed" column.

```
# try to get the day of the month from the date column
day_of_month_earthquakes = earthquakes['date_parsed'].dt.day
```

4) Plot the day of the month to check the date parsing

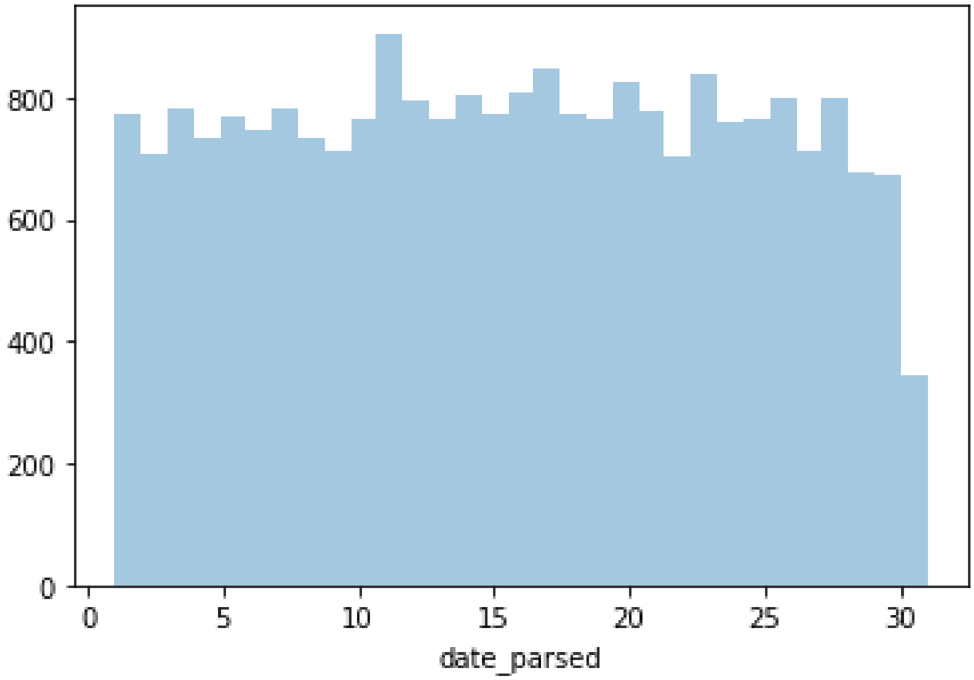
Plot the days of the month from your earthquake dataset.

```
# TODO: Your code here!
# remove na's
day_of_month_earthquakes = day_of_month_earthquakes.dropna()

# plot the day of the month
sns.distplot(day_of_month_earthquakes, kde=False, bins=31)
```

```
/opt/conda/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed
in a future version. Please adapt your code to use either `displot` (a
figure-level function with similar flexibility) or `histplot` (an
axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

```
<AxesSubplot:xlabel='date_parsed'>
```



Now we have visualized a graph that shows the days of the month. This data parsing is just for visualizing the data. When training, we import and use the dataset as it is.

Import Libraries and Dataset

Here we import the other neccessary libraries for further data visualization and import the dataset as well

Import the necessary libraries required for buidling the model and data analysis of the earthquakes.

```
import matplotlib.pyplot as plt

import os
print(os.listdir("../input"))

['database.csv']
```

Read the data from csv and also columns which are necessary for the model and the column which needs to be predicted.

```
data = pd.read_csv("../input/database.csv")
data.head()
```

```
          Date      Time    ...      Magnitude Source     Status
0  01/02/1965  13:44:18    ...                ISCGEM  Automatic
1  01/04/1965  11:29:49    ...                ISCGEM  Automatic
2  01/05/1965  18:05:58    ...                ISCGEM  Automatic
3  01/08/1965  18:49:43    ...                ISCGEM  Automatic
4  01/09/1965  13:32:50    ...                ISCGEM  Automatic

[5 rows x 21 columns]
```

```
data.columns
```

```
Index(['Date', 'Time', 'Latitude', 'Longitude', 'Type', 'Depth',
'Depth Error',
       'Depth Seismic Stations', 'Magnitude', 'Magnitude Type',
       'Magnitude Error', 'Magnitude Seismic Stations', 'Azimuthal
Gap',
       'Horizontal Distance', 'Horizontal Error', 'Root Mean Square',
'ID',
       'Source', 'Location Source', 'Magnitude Source', 'Status'],
      dtype='object')
```

Figure out the main features from earthquake data and create a object of that features, namely, Date, Time, Latitude, Longitude, Depth, Magnitude.

```
data = data[['Date', 'Time', 'Latitude', 'Longitude', 'Depth',
'Magnitude']]
data.head()
```

```
         Date      Time  Latitude  Longitude  Depth  Magnitude
0  01/02/1965  13:44:18    19.246    145.616  131.6        6.0
1  01/04/1965  11:29:49     1.863    127.352   80.0        5.8
2  01/05/1965  18:05:58   -20.579   -173.972   20.0        6.2
3  01/08/1965  18:49:43   -59.076    -23.557   15.0        5.8
4  01/09/1965  13:32:50    11.938    126.427   15.0        5.8
```

Here, the data is random we need to scale according to inputs to the model. In this, we convert given Date and Time to Unix time which is in seconds and a numeral. This can be easily used as input for the network we built.

```
import datetime
import time

timestamp = []
for d, t in zip(data['Date'], data['Time']):
    try:
        ts = datetime.datetime.strptime(d+' '+t, '%m/%d/%Y %H:%M:%S')
        timestamp.append(time.mktime(ts.timetuple()))
    except ValueError:
```

```
        # print('ValueError')
        timestamp.append('ValueError')

timeStamp = pd.Series(timestamp)
data['Timestamp'] = timeStamp.values

final_data = data.drop(['Date', 'Time'], axis=1)
final_data = final_data[final_data.Timestamp != 'ValueError']
final_data.head()
```

	Latitude	Longitude	Depth	Magnitude	Timestamp
0	19.246	145.616	131.6	6.0	-1.57631e+08
1	1.863	127.352	80.0	5.8	-1.57466e+08
2	-20.579	-173.972	20.0	6.2	-1.57356e+08
3	-59.076	-23.557	15.0	5.8	-1.57094e+08
4	11.938	126.427	15.0	5.8	-1.57026e+08

Visualization

Here, all the earthquakes from the database in visualized on to the world map which shows clear representation of the locations where frequency of the earthquake will be more.

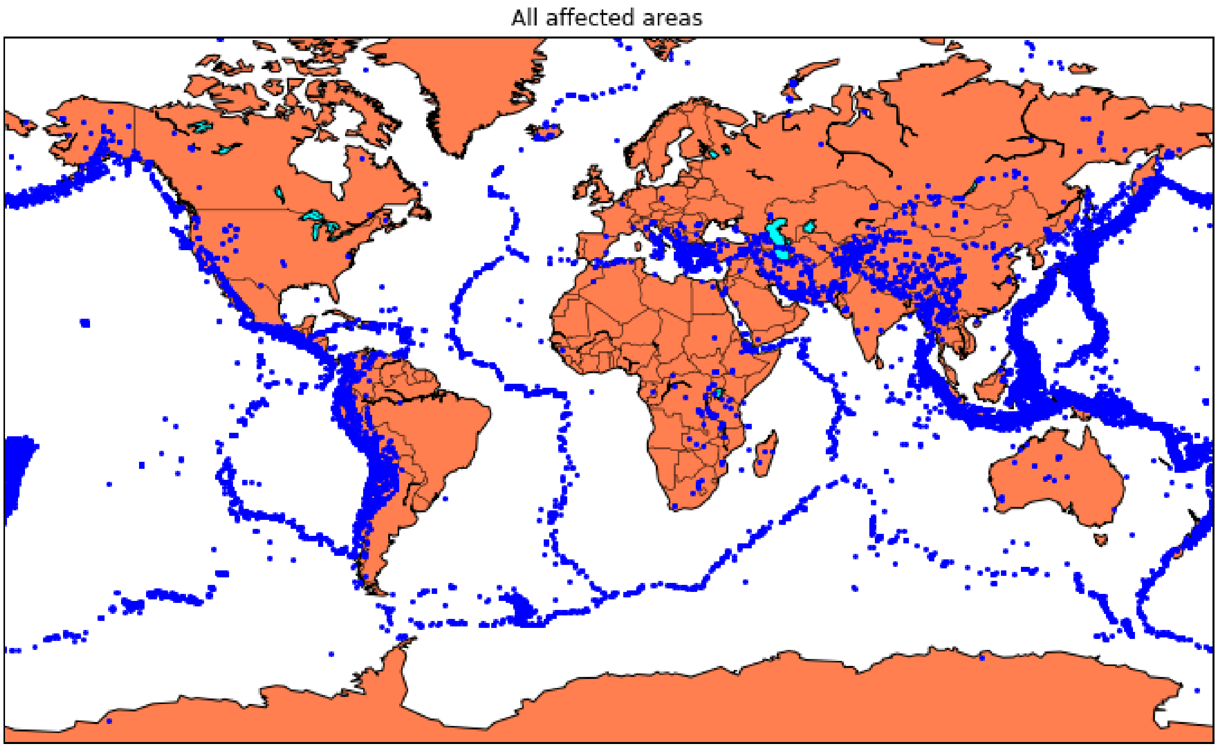
```
from mpl_toolkits.basemap import Basemap

m = Basemap(projection='mill',llcrnrlat=-80,urcrnrlat=80, llcrnrlon=-
180,urcrnrlon=180,lat_ts=20,resolution='c')

longitudes = data["Longitude"].tolist()
latitudes = data["Latitude"].tolist()
#m = Basemap(width=12000000,height=9000000,projection='lcc',
            #resolution=None,lat_1=80.,lat_2=55,lat_0=80,lon_0=-107.)
x,y = m(longitudes,latitudes)

fig = plt.figure(figsize=(12,10))
plt.title("All affected areas")
m.plot(x, y, "o", markersize = 2, color = 'blue')
m.drawcoastlines()
m.fillcontinents(color='coral',lake_color='aqua')
m.drawmapboundary()
m.drawcountries()
plt.show()
```

```
/opt/conda/lib/python3.6/site-packages/mpl_toolkits/basemap/
__init__.py:1704: MatplotlibDeprecationWarning: The axesPatch function
was deprecated in version 2.1. Use Axes.patch instead.
  limb = ax.axesPatch
/opt/conda/lib/python3.6/site-packages/mpl_toolkits/basemap/__init__.p
y:1707: MatplotlibDeprecationWarning: The axesPatch function was
deprecated in version 2.1. Use Axes.patch instead.
  if limb is not ax.axesPatch:
```



Splitting the Data

Firstly, split the data into Xs and ys which are input to the model and output of the model respectively. Here, inputs are TImestamp, Latitude and Longitude and outputs are Magnitude and Depth. Split the Xs and ys into train and test with validation. Training dataset contains 80% and Test dataset contains 20%.

```
X = final_data[['Timestamp', 'Latitude', 'Longitude']]
y = final_data[['Magnitude', 'Depth']]

from sklearn.cross_validation import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
print(X_train.shape, X_test.shape, y_train.shape, X_test.shape)
```

```
(18727, 3) (4682, 3) (18727, 2) (4682, 3)
```

```
/opt/conda/lib/python3.6/site-packages/sklearn/cross_validation.py:41:
DeprecationWarning: This module was deprecated in version 0.18 in
favor of the model_selection module into which all the refactored
classes and functions are moved. Also note that the interface of the
new CV iterators are different from that of this module. This module
will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

Training using Random Forest

Here, we used the RandomForestRegressor model to predict the outputs, we see the strange prediction from this with score above 80% which can be assumed to be best fit but not due to its predicted values.

```
from sklearn.ensemble import RandomForestRegressor

reg = RandomForestRegressor(random_state=42)
reg.fit(X_train, y_train)
reg.predict(X_test)
```

```
/opt/conda/lib/python3.6/site-packages/sklearn/ensemble/
weight_boosting.py:29: DeprecationWarning: numpy.core.umath_tests is
an internal NumPy module and should not be imported. It will be
removed in a future NumPy release.
  from numpy.core.umath_tests import inner1d
```

```
array([[  5.96,  50.97],
       [  5.88,  37.8 ],
       [  5.97,  37.6 ],
       ...,
       [  6.42,  19.9 ],
       [  5.73, 591.55],
       [  5.68,  33.61]])
```

```
reg.score(X_test, y_test)
```

```
0.8614799631765803
```

```
from sklearn.model_selection import GridSearchCV

parameters = {'n_estimators':[10, 20, 50, 100, 200, 500]}

grid_obj = GridSearchCV(reg, parameters)
grid_fit = grid_obj.fit(X_train, y_train)
best_fit = grid_fit.best_estimator_
best_fit.predict(X_test)
```

```
array([[  5.8888 ,  43.532  ],
       [  5.8232 ,  31.71656],
       [  6.0034 ,  39.3312 ],
       ...,
       [  6.3066 ,  23.9292 ],
       [  5.9138 , 592.151  ],
       [  5.7866 ,  38.9384 ]])
```

```
best_fit.score(X_test, y_test)
```

```
0.8749008584467053
```

Building the Neural Network model

In the above case it was more kind of linear regressor where the predicted values are not as expected. So, Now, we build the neural network to fit the data for training set. Neural Network consists of three Dense layer with each 16, 16, 2 nodes and relu, relu and softmax as activation function.

```
from keras.models import Sequential
from keras.layers import Dense

def create_model(neurons, activation, optimizer, loss):
    model = Sequential()
    model.add(Dense(neurons, activation=activation, input_shape=(3,)))
    model.add(Dense(neurons, activation=activation))
    model.add(Dense(2, activation='softmax'))

    model.compile(optimizer=optimizer, loss=loss,
metrics=['accuracy'])

    return model
```

```
Using TensorFlow backend.
```

In this, we define the hyperparameters with two or more options to find the best fit.

```
from keras.wrappers.scikit_learn import KerasClassifier

model = KerasClassifier(build_fn=create_model, verbose=0)

# neurons = [16, 64, 128, 256]
neurons = [16]
# batch_size = [10, 20, 50, 100]
batch_size = [10]
epochs = [10]
# activation = ['relu', 'tanh', 'sigmoid', 'hard_sigmoid', 'linear',
'exponential']
activation = ['sigmoid', 'relu']
# optimizer = ['SGD', 'RMSprop', 'Adagrad', 'Adadelta', 'Adam',
'Adamax', 'Nadam']
optimizer = ['SGD', 'Adadelta']
loss = ['squared_hinge']

param_grid = dict(neurons=neurons, batch_size=batch_size,
epochs=epochs, activation=activation, optimizer=optimizer, loss=loss)
```

Here, we find the best fit of the above model and get the mean test score and standard deviation of the best fit model.

```
grid = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=-1)
grid_result = grid.fit(X_train, y_train)

print("Best: %f using %s" % (grid_result.best_score_,
grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Best: 1.000000 using {'activation': 'relu', 'batch_size': 10,
'epochs': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer':
'Adadelta'}
0.936562 (0.000858) with: {'activation': 'sigmoid', 'batch_size': 10,
'epochs': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer':
'SGD'}
0.000000 (0.000000) with: {'activation': 'sigmoid', 'batch_size': 10,
'epochs': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer':
'Adadelta'}
0.646286 (0.411324) with: {'activation': 'relu', 'batch_size': 10,
'epochs': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer':
'SGD'}
1.000000 (0.000000) with: {'activation': 'relu', 'batch_size': 10,
'epochs': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer':
'Adadelta'}
```

The best fit parameters are used for same model to compute the score with training data and testing data.

```
model = Sequential()
model.add(Dense(16, activation='relu', input_shape=(3,)))
model.add(Dense(16, activation='relu'))
model.add(Dense(2, activation='softmax'))

model.compile(optimizer='SGD', loss='squared_hinge',
metrics=['accuracy'])

model.fit(X_train, y_train, batch_size=10, epochs=20, verbose=1,
validation_data=(X_test, y_test))
```

```
Train on 18727 samples, validate on 4682 samples
Epoch 1/20
18727/18727 [==============================] - 3s 134us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 2/20
18727/18727 [==============================] - 2s 122us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 3/20
18727/18727 [==============================] - 2s 118us/step - loss:
```

```
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 4/20
18727/18727 [==============================] - 2s 120us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 5/20
18727/18727 [==============================] - 2s 121us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 6/20
18727/18727 [==============================] - 3s 135us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 7/20
18727/18727 [==============================] - 2s 124us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 8/20
18727/18727 [==============================] - 2s 119us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 9/20
18727/18727 [==============================] - 2s 118us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 10/20
18727/18727 [==============================] - 2s 120us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 11/20
18727/18727 [==============================] - 2s 123us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 12/20
18727/18727 [==============================] - 2s 118us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 13/20
18727/18727 [==============================] - 2s 121us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 14/20
18727/18727 [==============================] - 2s 119us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 15/20
18727/18727 [==============================] - 2s 125us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 16/20
18727/18727 [==============================] - 2s 121us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 17/20
18727/18727 [==============================] - 2s 124us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 18/20
18727/18727 [==============================] - 2s 120us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 19/20
18727/18727 [==============================] - 2s 120us/step - loss:
0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
```

```
Epoch 20/20
18727/18727 [==============================] - 3s 135us/step - loss: 0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
```

```
<keras.callbacks.History at 0x7838b345a358>
```

```
[test_loss, test_acc] = model.evaluate(X_test, y_test)
print("Evaluation result on Test Data : Loss = {}, accuracy = {}".format(test_loss, test_acc))
```

```
4682/4682 [==============================] - 0s 22us/step
Evaluation result on Test Data : Loss = 0.5, accuracy = 0.018581802648440837
```

We see that the above model performs better but it also has lot of noise (loss) which can be neglected for prediction and use it for furthur prediction.

The above model is saved for furthur prediction that could be done with a user interface.

```
model.save('earthquake.h5')
```