# Phase5

# Earthquake Prediction Model Using Python

I will take you through how to create a model for the task of Earthquake Prediction using Machine Learning and the Python programming language. Predicting earthquakes is one of the great unsolved problems in the earth sciences with the increase in the use of technology, many seismic monitoring stations have increased, so we can use machine learning and other data-driven methods to predict earthquakes.

## Earthquake Prediction Model with Machine Learning

It is well known that if a disaster occurs in one region, it is likely to happen again. Some regions have frequent earthquakes, but this is only a comparative amount compared to other regions.

So, predicting the earthquake with date and time, latitude and longitude from previous data is not a trend that follows like other things, it happens naturally.

I will start this task to create a model for earthquake prediction by importing the necessary python libraries:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
data = pd.read_csv("database.csv")
```

```
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')
```

Now let's see the main characteristics of earthquake data and create an object of these characteristics, 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 |

Since the data is random, so we need to scale it based on the model inputs. In this, we convert the given date and time to Unix time which is in seconds and a number.

| Import *date* | |
|---|---|
| | `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 |

# Data Visualization

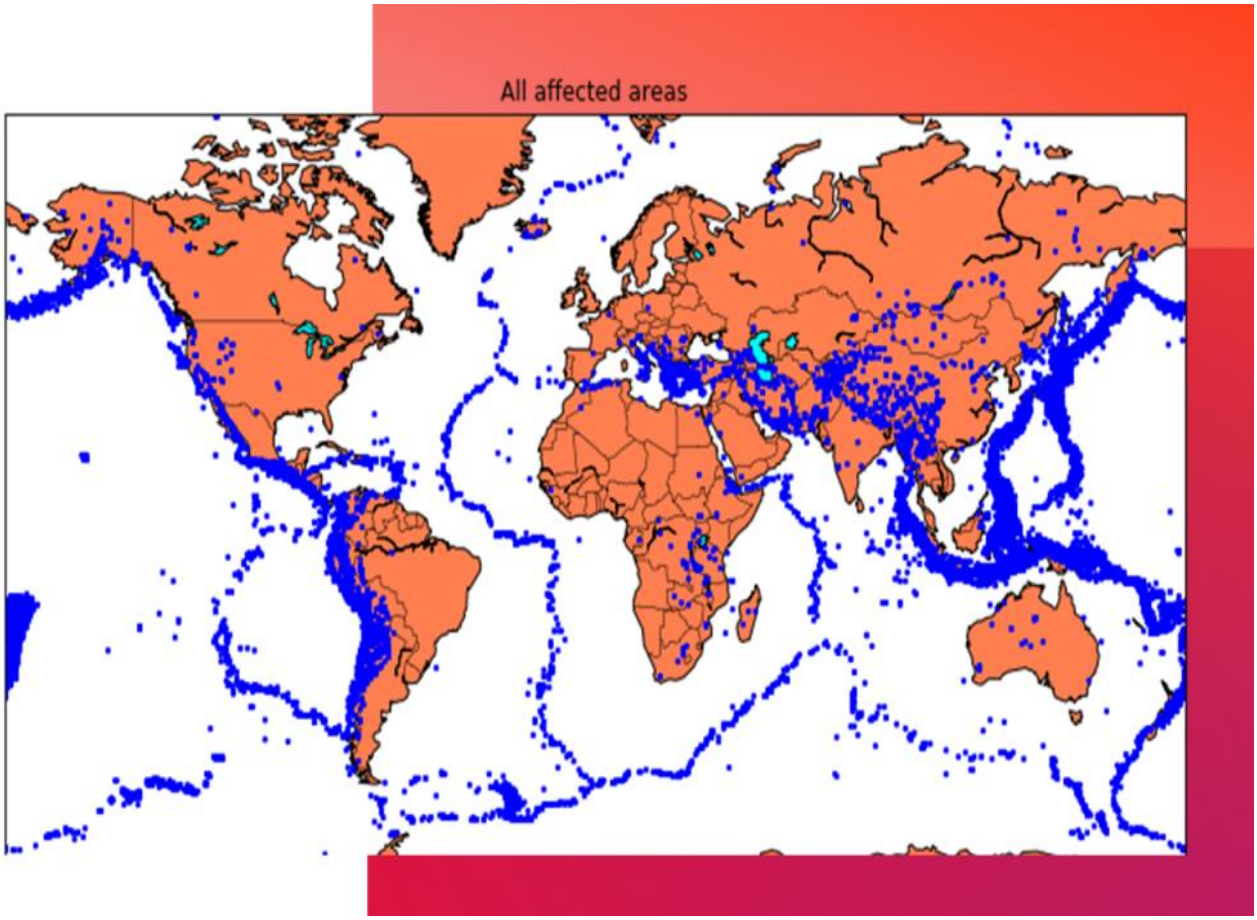
Now, before we create the earthquake prediction model, let's visualize the data on a world map that shows a clear representation of where the earthquake frequency will be more:

```
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()
```



# Splitting the Dataset

Now, to create the earthquake prediction model, we need to divide the data into Xs and ys which respectively will be entered into the model as inputs to receive the output from the model.
Here the inputs are TImestamp, Latitude and Longitude and the outputs are Magnitude and Depth. I'm going to split the xs and ys into train and test with validation. The training set contains 80% and the test set 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)
```

# Neural Network for Earthquake Prediction

Now I will create a neural network to fit the data from the training set. Our neural network will consist of three dense layers each with 16, 16, 2 nodes and reread. Relu and softmax will be used as activation functions:

```
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
```

Now we need to 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: 0.957655 using {'activation': 'relu', 'batch_size': 10, 'epochs': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'SGD'} 0.333316**

**(0.471398) 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'} 0.957655 (0.029957) with: {'activation': 'relu', 'batch_size': 10, 'epochs': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'SGD'} 0.645111 (0.456960) with: {'activation': 'relu', 'batch_size': 10, 'epochs': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'Adadelta'}**

In the step below, the best-fit parameters are used for the same model to calculate the score with the training data and the test 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))

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

**Evaluation result on Test Data : Loss = 0.5038455790406056, accuracy = 0.9241777017858995**

So we can see in the above output that our neural network model for earthquake prediction performs well. I hope you liked this article on how to create an earthquake prediction model with machine learning and the Python programming language.

## Feature engineering

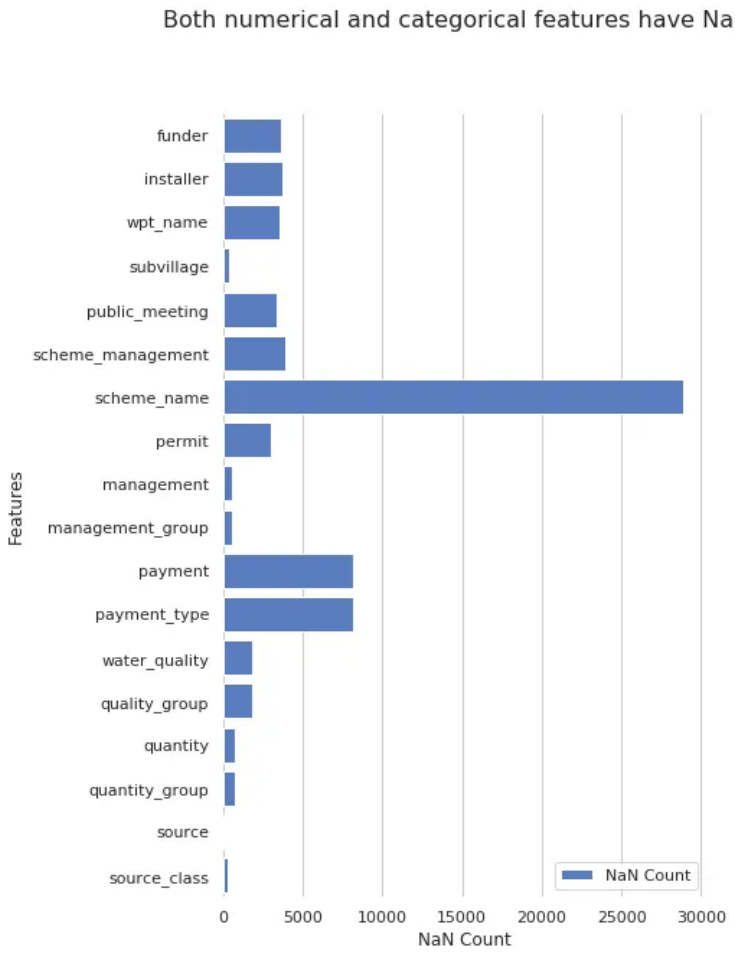
**Feature engineering** means identifying the relationships between independent and dependent features. Then the identified relationships we can add as polynomial or interaction features.

*Feature engineering step is the point of entry for successive iterations. This is a critical step and plays a greater role in predictions as compared to model validation.*

We can either drop columns with high cardinality and NaN values if needed. Also for numerical features, we can fill the NaN values with its mean, median or mode instead of dropping it. In the same way for categorical features, we can categorize the NaN as a separate category.

Also based on the water table data set, we can engineer few features like:

- NaN values in **longitude** and **latitude** updated with its mean.




```
# Apply mean for missing values of latitude
and longitude
```

```
mean_longitude =
df['longitude'].mean()
df['longitude'] =
df['longitude'].apply(lambda x:
mean_longitude if round(x, 2) == 0
else x)
mean_latitude = df['latitude'].mean()
df['latitude'] =
df['latitude'].apply(lambda x:
mean_latitude if round(x, 2) == 0
else x)
```

- Binary feature to identify if **funder** has at least funded 5 pumps. In the same was identify if **installer** has installed at least 5 pumps.

| | |
|---|---|
| | # Identify items who have funded atleast 5 pumps |
| | if str(row) == "nan": |
| | return np.nan |
| | |
| | value_count = value_count_series.get(row) |
| | |
| | if value_count < count: |
| | return 0 |
| | else: |
| | return 1 |
| | |
| | # Create a column to indicate funder with atleast 5 pumps maintained. |
| | value_count_funder = df.funder.value_counts() |
| | df['funder_aleast_5'] = df['funder'].apply(atleast, |
| | args=(value_count_funder,)) |
| | |
| | # Create a column to indicate installer with atleast 5 pumps maintained. |
| | value_count_installer = df.installer.value_counts() |
| | df['installer_aleast_5'] = df['installer'].apply(atleast, |
| | args=(value_count_installer,)) |

- Split the **date_recorded** into **year_recorded** and **month_recorded**. Even group in different bins.

```
# split year from date_recorded
return int(row.split('-')[0])

def compute_month_recorded(row):
# split year from date_recorded
return int(row.split('-')[1])

# Fetch Year and Month of date recorded
df['year_recorded'] = df['date_recorded'].apply(compute_year_recorded)
df['month_recorded'] = df['date_recorded'].apply(compute_month_recorded)
```

- Compute the age of pump based on **construction_year** and **year_recorded**.

## Hyper-parameter tuning

**Hyper-parameter optimization** or **tuning** is the problem of choosing a set of optimal hyper-parameters for a learning algorithm. The same kind of machine learning model can require different constraints, weights or learning rates to generalize different data patterns. These measures are called hyper-parameters, and have to be tuned so that the model can optimally solve the machine learning problem. Hyper-parameter optimization finds a tuple of hyper-parameters that yields an optimal model which minimizes a predefined loss function on given independent data. The objective function takes a tuple of hyper-parameters and returns the associated loss. Cross-validation is often used to estimate this generalization performance.

Here let me illustrate tuning of parameters **max_depth** and **min_child_weight** of **XGBClassifier**.

**max_depth (int) —** Maximum tree depth for base learners.

- Used to control over-fitting as higher depth will allow model to learn relations very specific to a particular sample.
- Typical values: 3–9

**min_child_weight (int)** — Minimum sum of instance weight(hessian) needed in a child.

- Used to control over-fitting. Higher values prevent a model from learning relations which might be highly specific to the particular sample selected for a tree.
- Too high values can lead to under-fitting hence, it should be tuned using CV. Typical values: 1–5

```
from sklearn.preprocessing import RobustScaler
from xgboost import XGBClassifier

# Create pipeline
pipeline = make_pipeline(\
ce.BinaryEncoder(),
RobustScaler(),
XGBClassifier(learning_rate=0.1, n_estimators=1000,
max_depth=4, min_child_weight=6,
gamma=0, subsample=0.8,
colsample_bytree=0.8,
objective= 'multi:softmax', num_class=3,
scale_pos_weight=1,
seed=42, n_jobs=4))

# Model validation.
```

```
from sklearn.model_selection import GridSearchCV

param_grid = {
'xgbclassifier__max_depth': range(3, 10, 2),
'xgbclassifier__min_child_weight': range(1, 6, 2)
}

gridsearch1 = GridSearchCV(pipeline, param_grid=param_grid, cv=2,
scoring='accuracy', verbose=20)

gridsearch1.fit(X_train, y_train)

# Interpret the results.

# Best cross validation score
print('Cross Validation Score:', gridsearch1.best_score_)

# Best parameters which resulted in the best score
print('Best Parameters:', gridsearch1.best_params_)
```

During second iteration best value for **max_depth was 5**. Now it is **6**. So in the third iteration let us reconfirm the value of max_depth. Now let us keep **min_child_weight** parameter fixed to 1.

```
param_grid3 = {
 'xgbclassifier__max_depth': [5, 6, 7],
```

```
    'xgbclassifier__min_child_weight': [1]
    }

    gridsearch3 = GridSearchCV(pipeline, param_grid=param_grid3, cv=2,
    scoring='accuracy', verbose=20)

    gridsearch3.fit(X_train, y_train)

    # Interpret the results of Iteration 3

    # Best cross validation score
    print('Cross Validation Score:', gridsearch3.best_score_)

    # Best parameters which resulted in the best score
    print('Best Parameters:', gridsearch3.best_params_)
```

Output from third iteration of parameter tuning:

- **Cross Validation Score:** 0.7936251402918O7
- **Best Parameters:** {'xgbclassifier__max_depth': 6, 'xgbclassifier__min_child_weight': 1}

From third iteration we can confirm the values of **max_depth** as **6**. In the same way, we can pickup other parameters and tune for their optimized values.

As the model performance increases, it becomes exponentially difficult to tune.