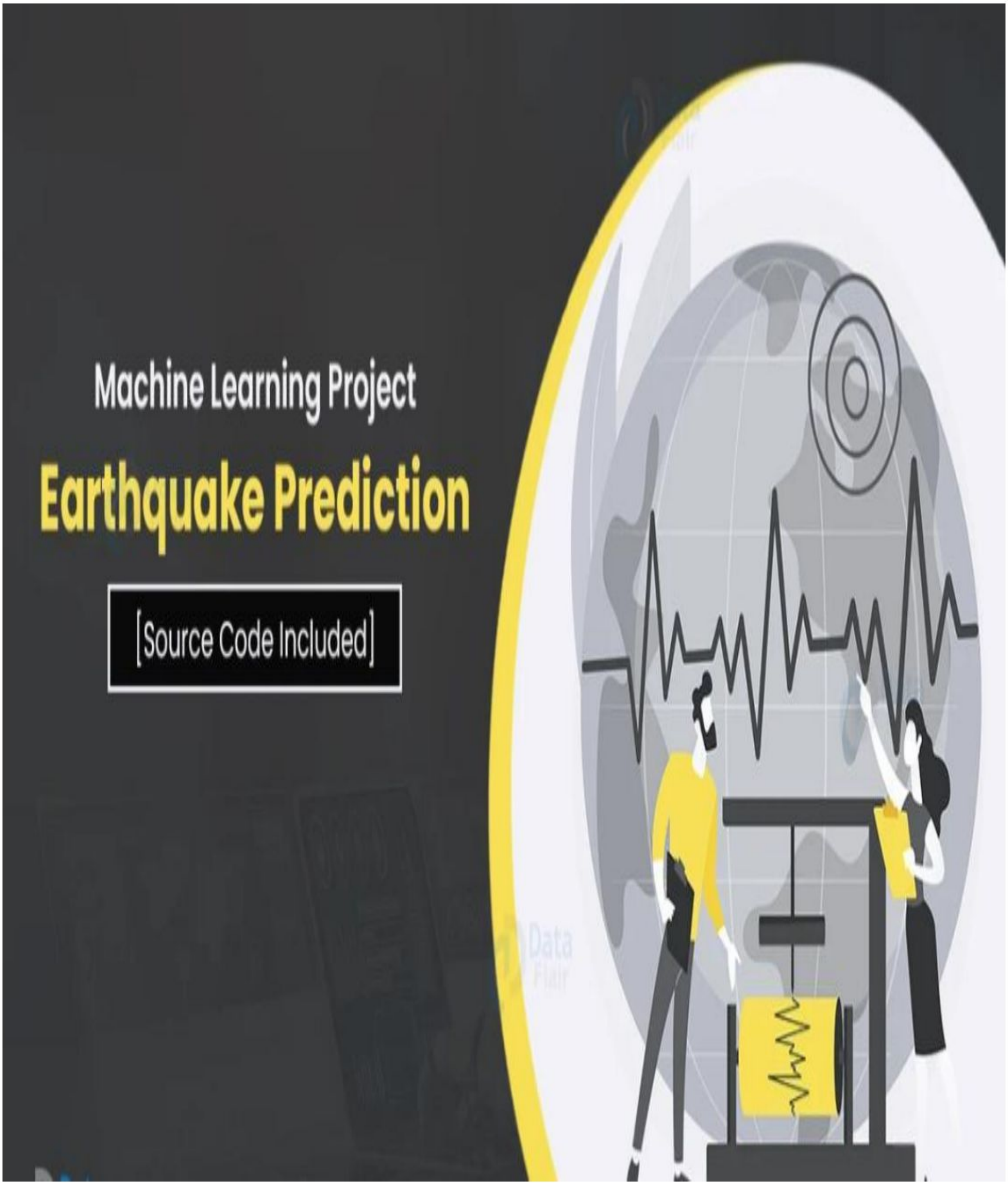

Machine Learning Project
Earthquake Prediction
[Source Code Included]

•

Earthquake Prediction System

Earthquakes were once thought to result from supernatural forces in the prehistoric era. Aristotle was the first to identify earthquakes as a natural occurrence and to provide some potential explanations for them in a truly scientific manner. One of nature's most destructive dangers is earthquakes. Strong earthquakes frequently have negative effects.

A lot of devastating earthquakes occasionally occur in nations like Japan, the USA, China, and nations in the middle and far east. Several major and medium-sized earthquakes have also occurred in India, which have resulted in significant property damage and fatalities. One of the most catastrophic earthquakes ever recorded occurred in Maharastra early on September 30, 1993. One of the main goals of researchers studying earthquake seismology is to develop effective predicting methods for the occurrence of the next severe earthquake event that may allow us to reduce the death toll and property damage.

Most earthquakes, or 90%, are natural and result from tectonic activity. 10% of the remaining characteristics are associated with volcanism, man-made consequences, or other variables. Natural earthquakes are those that occur naturally and are typically far more powerful than other kinds of earthquakes. The continental drift theory and the plate-tectonic theory are the two hypotheses that deal with earthquakes.

Random Forest

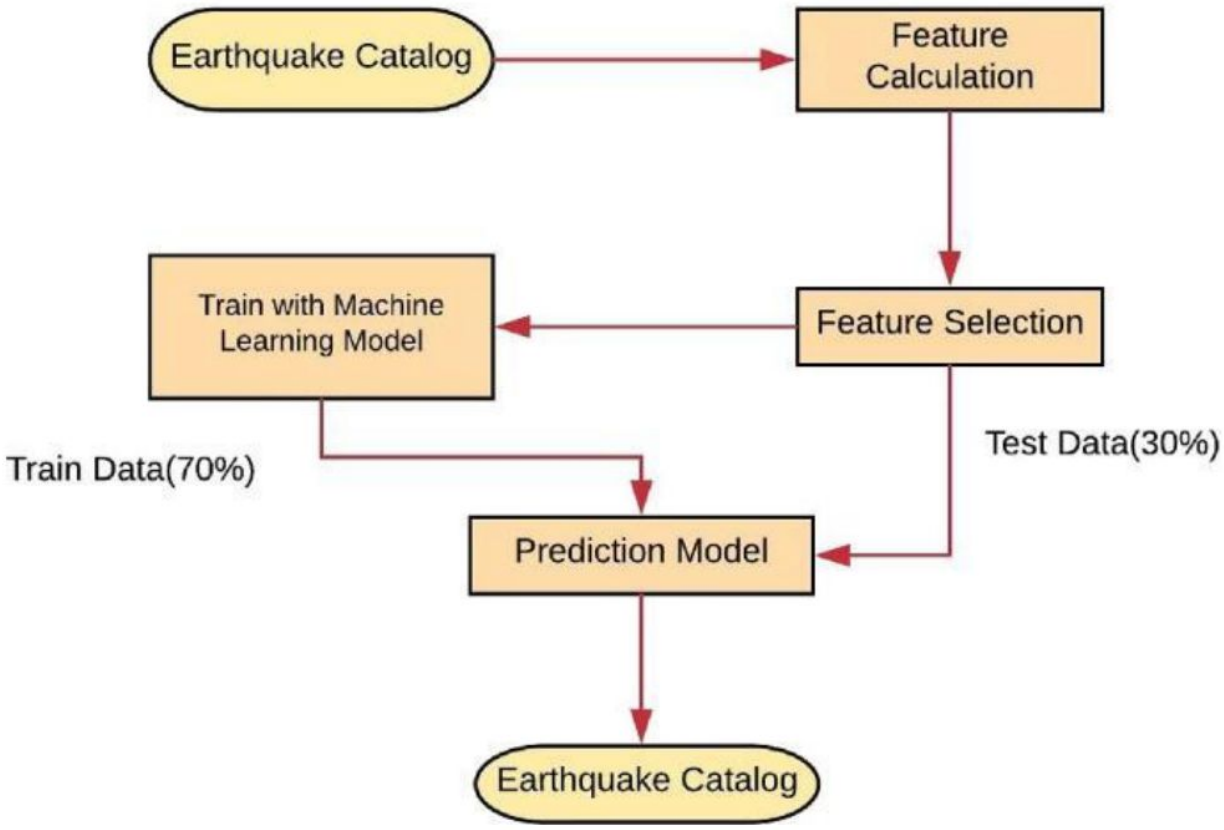
It is a type of machine learning algorithm that is very famous nowadays. It generates a random decision tree and combines it into a single forest. It features a decision model to increase accuracy. These trees divide the predictor space using a series of binary splits ("splits") on distinct variables. The tree's "root" node represents the entire predictor space. The final division of the predictor space is made up of the "terminal nodes," which are nodes that are not split. Depending on the value of one of the predictor variables, each nonterminal node divides into two descendant nodes, one on the left and one on the right. If a continuous predictor variable is smaller than a split point, the points to the left will be the smaller predictor points, and the points to the right will be the larger predictor points. The values of a categorical predictor variable Xi come from a small number of categories. To divide a node into its two descendants, a tree must analyze every possible split on each predictor variable and select the "best" split based on some criteria. A common splitting criterion in the context of regression is the mean squared residual at the node.

It is also a classification technique that uses ensemble learning. The random forest generates a root node feature by randomly dividing, which is the primary distinction between it and the decision tree. To enhance its accuracy, the Random forest chooses a random feature. The random forest approach is faster than the bagging and boosting method. In some circumstances, the neural network Support Vector Machine performs better when using the random forest.

Support Vector Classifier

There is a computer algorithm known as a support vector machine (SVM) that learns to name objects. For instance, by looking at hundreds or thousands of reports of both fraudulent and legitimate credit card activity, an SVM can learn to identify fraudulent credit card activity. A vast collection of scanned photos of handwritten zeros, ones, and other numbers can also be used to train an SVM to recognize handwritten numerals.

Additionally, SVMs have been successfully used in a growing number of biological applications. The automatic classification of microarray gene expression profiles is a typical use of support vector machines in the biomedical field. Theoretically, an SVM can examine the gene expression profile derived from a tumor sample or from peripheral fluid and arrive at a diagnosis or prognosis. An SVM could theoretically analyze the gene expression profile obtained from a tumor sample or from peripheral fluid and determine a diagnosis or prognosis.



Earthquake prediction model

Data Collection:

Obtain earthquake data from reliable sources such as the USGS Earthquake Catalog or seismic observatories.

Data Preprocessing:

Clean and preprocess the data:

Remove duplicates and irrelevant columns.

Handle missing values (e.g., by imputing or removing them).

Convert date/time information into a suitable format.

Feature engineering: Extract relevant features like earthquake depth, magnitude, location, etc.

Feature Scaling:

Normalize or standardize your feature data, especially if you're using algorithms sensitive to the scale of the features.

Data Splitting:

Split your data into training and testing sets. A typical split might be 80% for training and 20% for testing.

Model Selection:

Choose a machine learning algorithm suitable for your problem. For earthquake prediction, you might consider using techniques like decision trees, random forests, or neural networks.

Model Training:

Train your selected model on the training data.

Model Evaluation:

Evaluate your model's performance using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or others, depending on your specific goals.

Hyperparameter Tuning:

Optimize your model's hyperparameters for better performance.

Prediction:

Use your trained model to make predictions on the testing data.

Performance Assessment:

Assess how well your model performs and make adjustments as needed.

Deployment:

If the model is satisfactory, deploy it in a real-time environment for continuous earthquake prediction.

You'll need to implement these steps in your chosen programming language and environment. If you have specific questions or need code examples for any of these steps, feel free to ask for more guidance.

earthquakemagnitudepredicton

0.1 Importing Required Packaged

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import geopandas as gpd
import cufflinks as cf

%matplotlib inline
```

1 1) Data Source

[2]:
```
data = pd.read_csv("database.csv",
                   header=0,
                   index_col=None,
                   sep=","
                  )
```

[3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23412 entries, 0 to 23411
Data columns (total 21 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   Date                        23412 non-null  object
 1   Time                        23412 non-null  object
 2   Latitude                    23412 non-null  float64
 3   Longitude                   23412 non-null  float64
 4   Type                        23412 non-null  object
 5   Depth                       23412 non-null  float64
 6   Depth Error                 4461 non-null   float64
 7   Depth Seismic Stations      7097 non-null   float64
 8   Magnitude                   23412 non-null  float64
 9   Magnitude Type              23409 non-null  object
```

```
 10  Magnitude Error             327 non-null    float64
 11  Magnitude Seismic Stations  2564 non-null   float64
 12  Azimuthal Gap               7299 non-null   float64
 13  Horizontal Distance         1604 non-null   float64
 14  Horizontal Error            1156 non-null   float64
 15  Root Mean Square            17352 non-null  float64
 16  ID                          23412 non-null  object
 17  Source                      23412 non-null  object
 18  Location Source             23412 non-null  object
 19  Magnitude Source            23412 non-null  object
 20  Status                      23412 non-null  object
dtypes: float64(12), object(9)
memory usage: 3.8+ MB
```

1.0.1 Required Feautures

- **Latitude**
- **Longitude**
- **Depth**
- **Depth Error**
- **Root Mean Square**

[4]:
```
data = data[["Latitude","Longitude","Root Mean Square","Depth","Depth␣
↪Error","Magnitude"]]
```

[5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23412 entries, 0 to 23411
Data columns (total 6 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Latitude          23412 non-null  float64
 1   Longitude         23412 non-null  float64
 2   Root Mean Square  17352 non-null  float64
 3   Depth             23412 non-null  float64
 4   Depth Error       4461 non-null   float64
 5   Magnitude         23412 non-null  float64
dtypes: float64(6)
memory usage: 1.1 MB
```

[6]:
```
data.describe()
```

[6]:

	Latitude	Longitude	Root Mean Square	Depth	\
count	23412.000000	23412.000000	17352.000000	23412.000000	
mean	1.679033	39.639961	1.022784	70.767911	
std	30.113183	125.511959	0.188545	122.651898	
min	-77.080000	-179.997000	0.000000	-1.100000	

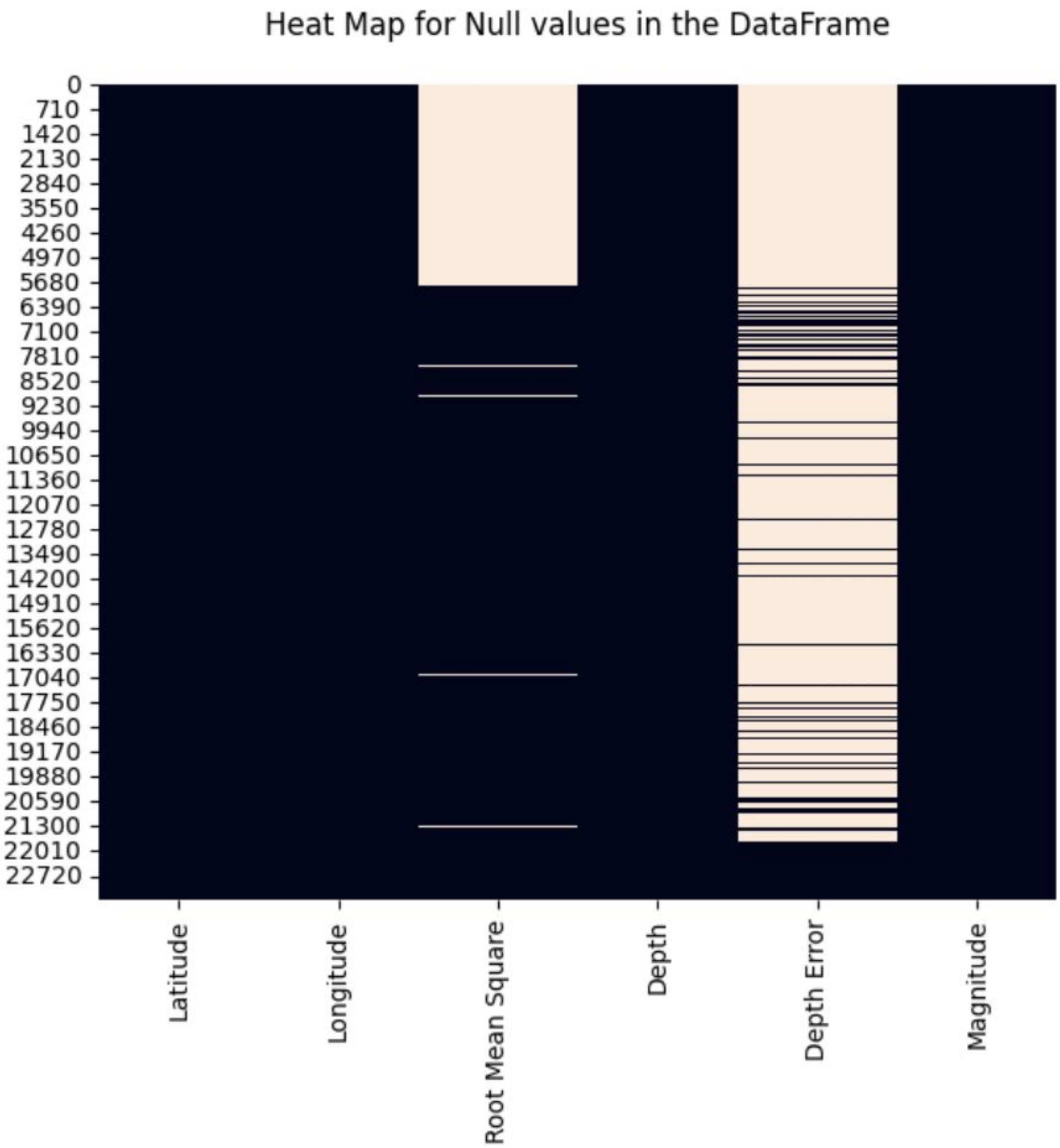
25%	-18.653000	-76.349750	0.900000	14.522500
50%	-3.568500	103.982000	1.000000	33.000000
75%	26.190750	145.026250	1.130000	54.000000
max	86.005000	179.998000	3.440000	700.000000

	Depth Error	Magnitude
count	4461.000000	23412.000000
mean	4.993115	5.882531
std	4.875184	0.423066
min	0.000000	5.500000
25%	1.800000	5.600000
50%	3.500000	5.700000
75%	6.300000	6.000000
max	91.295000	9.100000

2 2) Feauture Exploration

2.1 Exploratory Data Analysis (EDA)

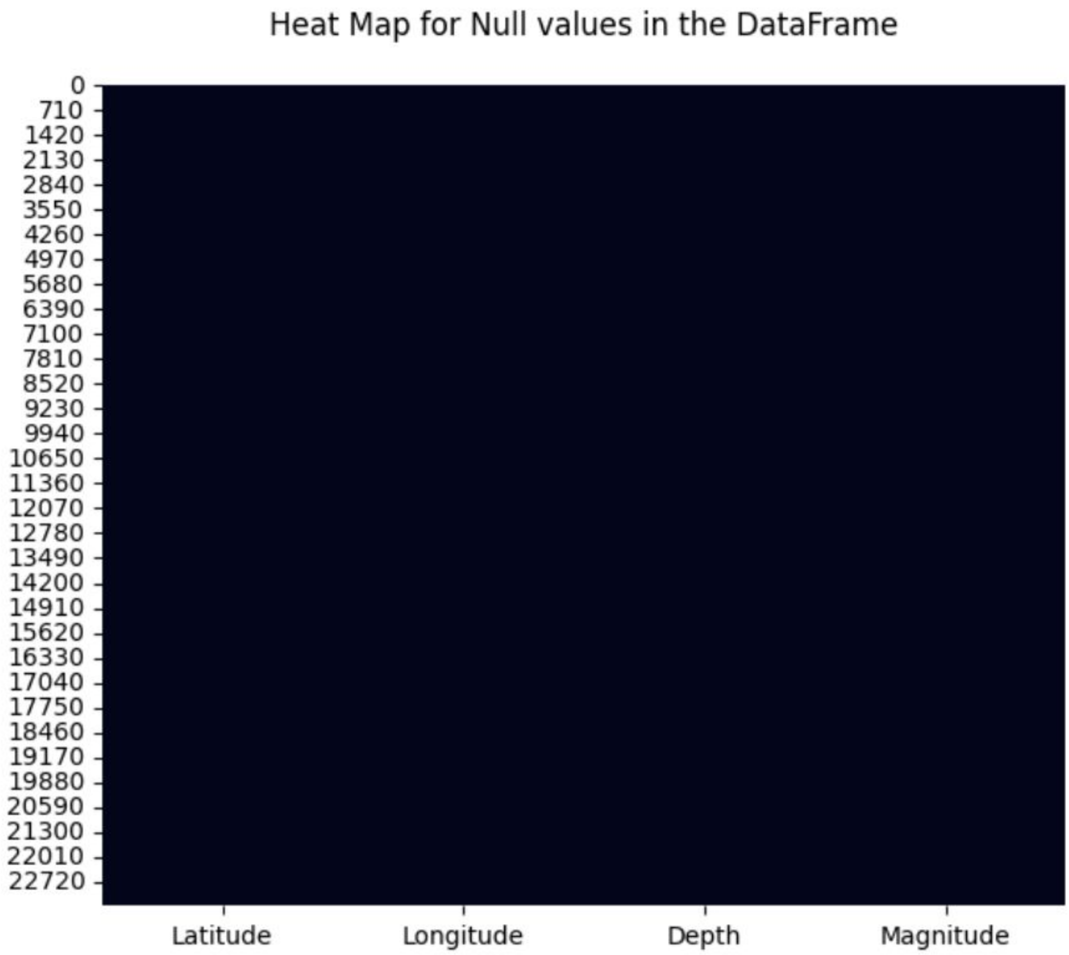
[7]:
```
plt.figure(figsize=(7,6))
sns.heatmap(data=data.isnull(),
            cbar=False)
txt = plt.title("\nHeat Map for Null values in the DataFrame\n")
```



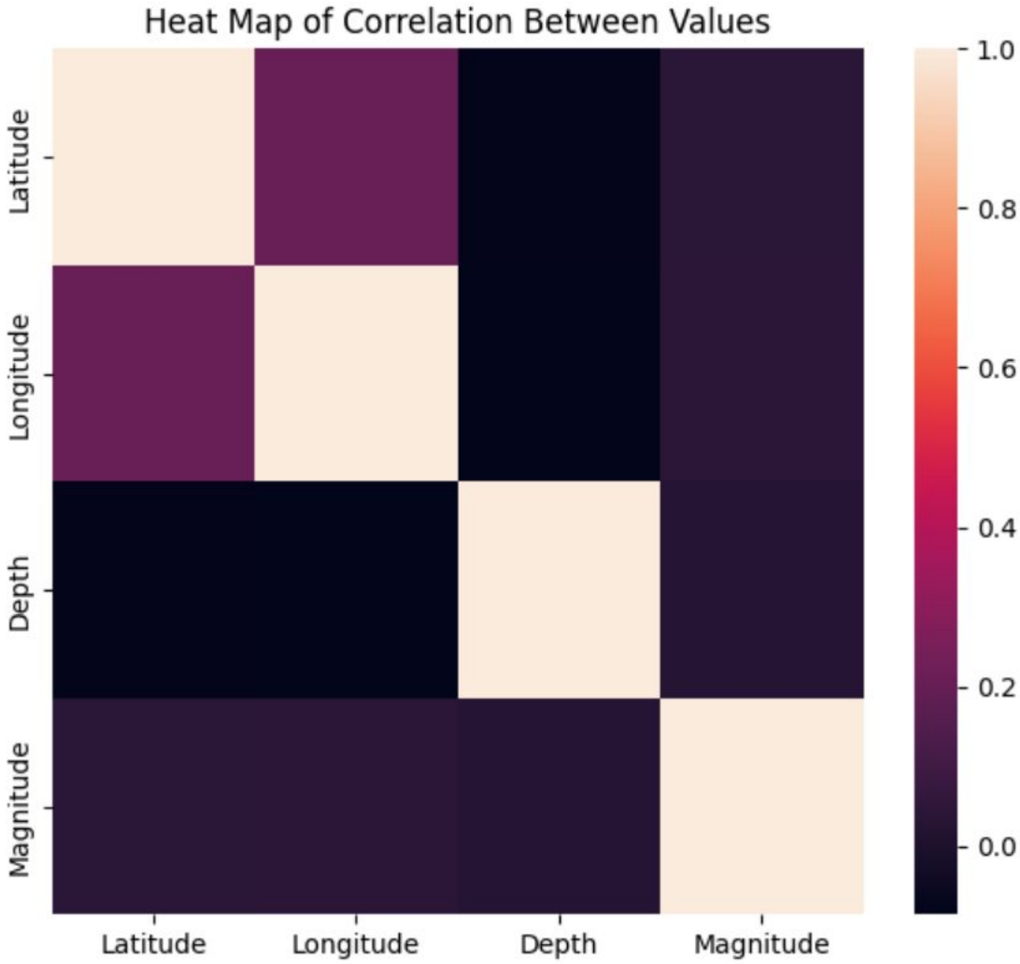
Dropping Depth Error And Root Mean Square, It is having null values and it is not gonna make much more change in model

[8]:
```
data = data.drop(["Depth Error","Root Mean Square"],axis=1)
```

[9]:
```
plt.figure(figsize=(7,6))
sns.heatmap(data=data.isnull(),
            cbar=False)
txt = plt.title("\nHeat Map for Null values in the DataFrame\n")
```



[10]:
```
plt.figure(figsize=(7,6))
sns.heatmap(data=data.corr())
txt = plt.title("Heat Map of Correlation Between Values")
```



[11]:
```
correlation = data['Depth'].corr(data['Magnitude'])
print(f"Correlation Between Depth and Magnitude is {correlation}")
correlation = data['Latitude'].corr(data['Magnitude'])
print(f"Correlation Between Lattitude and Magnitude is {correlation}")
correlation = data['Longitude'].corr(data['Magnitude'])
print(f"Correlation Between Longitude and Magnitude is {correlation}")
```

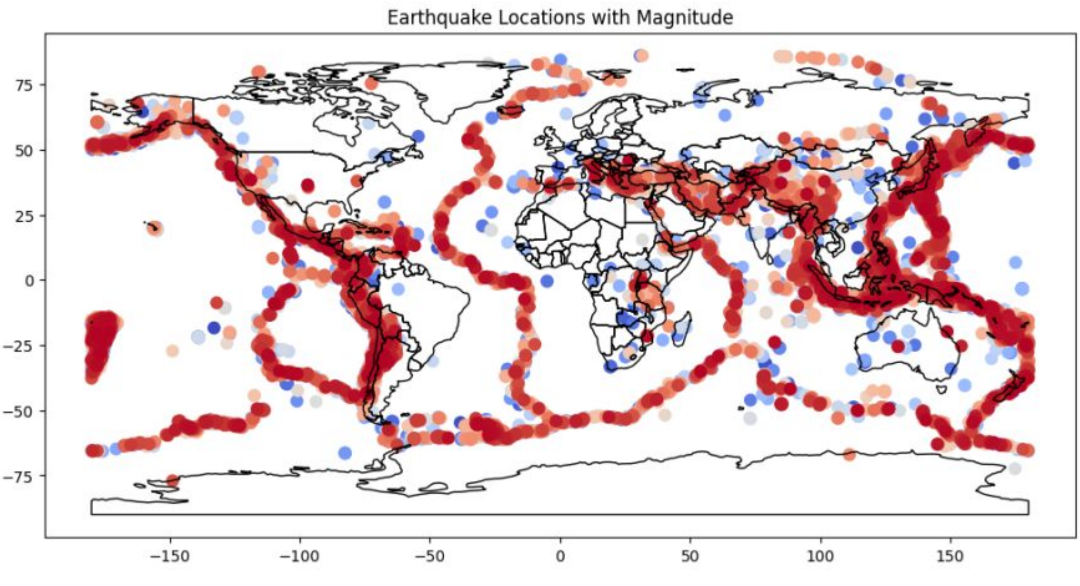
```
Correlation Between Depth and Magnitude is 0.023457312492053895
Correlation Between Lattitude and Magnitude is 0.03498650628261446
Correlation Between Longitude and Magnitude is 0.03857859753074192
```

[ ]:
```
```

3 3) Visualization

[12]:
```
df = data
gdf = gpd.GeoDataFrame(df, geometry=gpd.points_from_xy(df.Longitude, df.
 ↪Latitude))

world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))

fig, ax = plt.subplots(figsize=(12, 8))
world.boundary.plot(ax=ax, linewidth=1, color='k')

gdf.plot(ax=ax, markersize=df['Magnitude'] * 10, cmap='coolwarm', legend=True)

ax.set_title('Earthquake Locations with Magnitude')
# plt.legend(title='Magnitude')

plt.show()
```

```
/tmp/ipykernel_33037/249791788.py:4: FutureWarning:

The geopandas.dataset module is deprecated and will be removed in GeoPandas 1.0.
You can get the original 'naturalearth_lowres' data from
https://www.naturalearthdata.com/downloads/110m-cultural-vectors/.
```



[13]:
```
df = pd.DataFrame(data)

fig = df.iplot(
```

```
    kind='scattergeo',
    lon='Longitude',
    lat='Latitude',
    size='Magnitude',
    text='Magnitude',
    colorscale='YlOrRd',
    dimensions=(800, 600),
    title='Earthquake Locations with Magnitude',
    asFigure=True
)

fig.update_geos(
    projection_type="natural earth",
    coastlinecolor="black",
    landcolor="white",
    showland=True,
    showcoastlines=True,
    showocean=True,
    oceancolor="lightblue"
)

# Show the plot
fig.show()
```

[14]:
```
df = pd.DataFrame(data)
plt.figure(figsize=(20,20))
fig = px.scatter_geo(
    df,
    lat='Latitude',
    lon='Longitude',
    color='Magnitude',
    size='Magnitude',
    hover_name='Magnitude',
    projection='natural earth'
)

fig.update_geos(showcoastlines=True, coastlinecolor="Black", showland=True,␣
 ↪landcolor="lightgray")

fig.show()
```

```
<Figure size 2000x2000 with 0 Axes>
```

[ ]:

4 4) Data Splitting

[15]:
```
from sklearn.model_selection import train_test_split
```

[16]:
```
X = data.drop("Magnitude",axis=1)
y = data["Magnitude"]
```

[17]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33,␣
↪random_state=42)
```

[ ]:
```

```

5 5) Model Development

[18]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
```

```
2023-10-04 18:35:28.257319: I tensorflow/core/util/port.cc:110] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn them
off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2023-10-04 18:35:28.284433: I tensorflow/tsl/cuda/cudart_stub.cc:28] Could not
find cuda drivers on your machine, GPU will not be used.
2023-10-04 18:35:28.318832: I tensorflow/tsl/cuda/cudart_stub.cc:28] Could not
find cuda drivers on your machine, GPU will not be used.
2023-10-04 18:35:28.319665: I tensorflow/core/platform/cpu_feature_guard.cc:182]
This TensorFlow binary is optimized to use available CPU instructions in
performance-critical operations.
To enable the following instructions: AVX2 AVX512F AVX512_VNNI FMA, in other
operations, rebuild TensorFlow with the appropriate compiler flags.
2023-10-04 18:35:29.468449: W
tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Could not
find TensorRT
```

5.0.1 Scaling the feautures

[19]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

[20]:
```
model = keras.Sequential([
    layers.Dense(64, activation='relu', input_shape=(3,)),
    layers.Dense(32, activation='relu'),
```

```
    layers.Dense(1)
])
```

[21]:
```
model.compile(optimizer='adam',
              loss='mean_squared_error',
             )
```

[22]:
```
model.summary()
```

```
Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 64)                256

 dense_1 (Dense)             (None, 32)                2080

 dense_2 (Dense)             (None, 1)                 33

=================================================================
Total params: 2369 (9.25 KB)
Trainable params: 2369 (9.25 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

6 6) Training and Evaluation

[23]:
```
history = model.fit(X_train,
                    y_train,
                    epochs=25,
                    batch_size=32,
                    validation_split=0.2,
                    validation_data=(X_test,y_test))
```

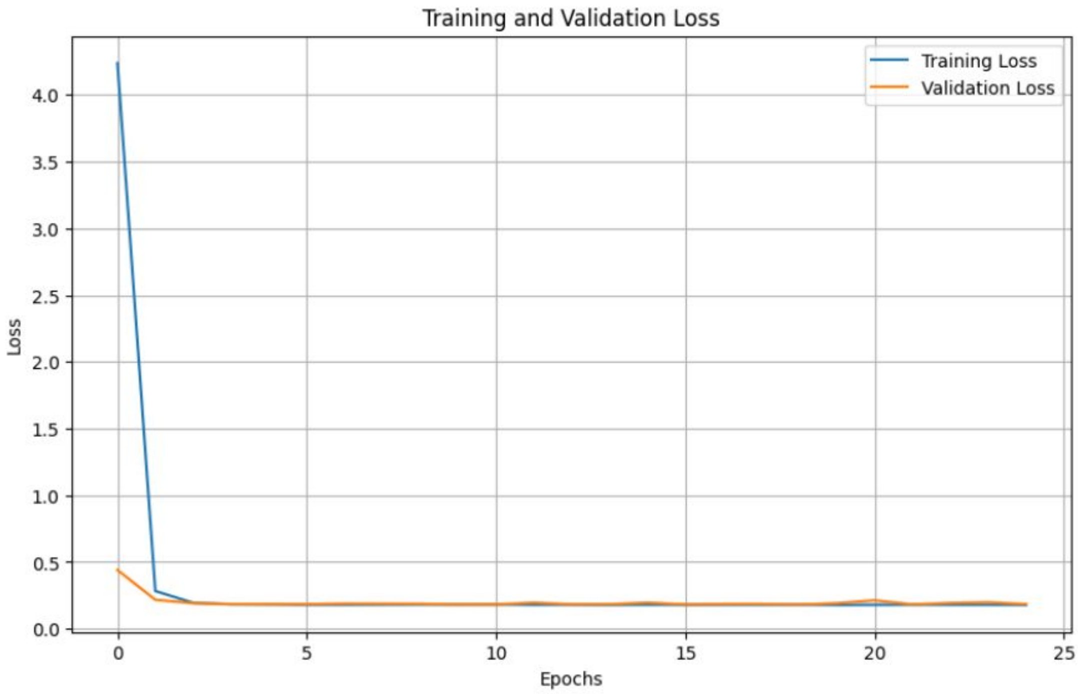
```
Epoch 1/25
491/491 [==============================] - 2s 2ms/step - loss: 4.2382 -
val_loss: 0.4398
Epoch 2/25
491/491 [==============================] - 1s 2ms/step - loss: 0.2826 -
val_loss: 0.2169
Epoch 3/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1940 -
val_loss: 0.1913
Epoch 4/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1831 -
val_loss: 0.1851
Epoch 5/25
```

```
491/491 [==============================] - 1s 2ms/step - loss: 0.1821 -
val_loss: 0.1843
Epoch 6/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1800 -
val_loss: 0.1837
Epoch 7/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1796 -
val_loss: 0.1881
Epoch 8/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1805 -
val_loss: 0.1874
Epoch 9/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1812 -
val_loss: 0.1867
Epoch 10/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1814 -
val_loss: 0.1822
Epoch 11/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1819 -
val_loss: 0.1818
Epoch 12/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1798 -
val_loss: 0.1955
Epoch 13/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1803 -
val_loss: 0.1826
Epoch 14/25
491/491 [==============================] - 1s 1ms/step - loss: 0.1788 -
val_loss: 0.1834
Epoch 15/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1802 -
val_loss: 0.1955
Epoch 16/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1799 -
val_loss: 0.1816
Epoch 17/25
491/491 [==============================] - 1s 1ms/step - loss: 0.1798 -
val_loss: 0.1854
Epoch 18/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1796 -
val_loss: 0.1856
Epoch 19/25
491/491 [==============================] - 1s 1ms/step - loss: 0.1806 -
val_loss: 0.1812
Epoch 20/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1783 -
val_loss: 0.1910
Epoch 21/25
```

```
491/491 [==============================] - 1s 2ms/step - loss: 0.1795 -
val_loss: 0.2128
Epoch 22/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1805 -
val_loss: 0.1824
Epoch 23/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1796 -
val_loss: 0.1927
Epoch 24/25
491/491 [==============================] - 1s 3ms/step - loss: 0.1800 -
val_loss: 0.1982
Epoch 25/25
491/491 [==============================] - 1s 3ms/step - loss: 0.1785 -
val_loss: 0.1841
```

[24]:

```python
plt.figure(figsize=(10, 6))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title('Training and Validation Loss')
plt.grid(True)
plt.show()
```



[25]:
```
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error on Test Set: {mse:.2f}")
```

```
242/242 [==============================] - 0s 1ms/step
Mean Squared Error on Test Set: 0.18
```

[26]:
```
model.evaluate(X_test,y_test)
```

```
242/242 [==============================] - 0s 1ms/step - loss: 0.1841
```

[26]:
```
0.18406274914741516
```

6.1 Conclusion:

Mean Squared Error on Test Data : 0.19

[ ]:
```

```