

EARTHQUAKE PREDICTION MODEL USING PYTHON

Phase 4 Submission Document:

Project: Earthquake Prediction:



INTRODUCTION:

- Earthquakes, natural phenomena of profound consequence, continue to evoke awe and trepidation due to their unpredictable nature.

- Their ability to cause devastation underscores the urgency of understanding and predicting these geological events.
- This study embarks on a journey through data analysis, modeling, and visualization, striving to accomplish the following key objectives:
 - Data Exploration:
 - Feature Engineering:
 - Model Building:
 - Multiclass Classification:
 - Visualization:

Data Exploration:

We initiate our exploration by delving into earthquake data sourced from reliable datasets. By meticulously examining this data, we gain insights into the temporal, spatial, and geological characteristics of earthquakes.

Feature Engineering:

The data presents various attributes that could influence earthquake magnitudes, such as geographical coordinates (latitude and longitude) and depth. Through feature engineering, we extract the most relevant variables to feed into our predictive models.

Model Building:

To predict earthquake magnitudes, we experiment with different machine learning models, beginning with a Linear Regression model to establish a baseline. We then advance to more sophisticated models like Support Vector Machines (SVM) to capture complex relationships within the data.

Multiclass Classification:

Beyond magnitude prediction, we also explore multiclass classification to categorize earthquakes into different magnitude types (e.g., 'ML', 'MS', 'MB'). This not only enhances our predictive abilities but also provides insights into the diversity of seismic events.

Visualization:

Throughout our analysis, we employ data visualization techniques to elucidate the geographical distribution of earthquakes and the performance of our models. Maps and scatter plots reveal patterns, correlations, and the efficacy of our predictions.

Loading DataSet:

Data loading in earthquake prediction is a crucial step in the process. It involves gathering and organizing relevant information to train and test predictive models Downloading

DataSet:

<https://www.kaggle.com/datasets/usgs/earthquake- database>

date	depth	mag	place	latitude	longitude	depth_avg_22	depth_avg_15	depth_avg_7	mag_avg_22	mag_avg_15	mag_avg_7
2020-07-14	6.70	1.58	Oklahoma	36.171483	-97.718347	6.717727	6.560000	7.100000	1.352273	1.271333	1.271333
2020-07-14	7.55	2.07	Oklahoma	36.171483	-97.718347	6.730000	6.682667	7.132857	1.372727	1.334667	1.334667
2020-07-14	7.39	1.89	Oklahoma	36.171483	-97.718347	6.747727	6.708667	6.940000	1.396818	1.377333	1.377333
2020-07-15	7.75	1.48	Oklahoma	36.171483	-97.718347	6.834545	6.764000	6.848571	1.383182	1.388667	1.388667
2020-07-15	7.81	1.50	Oklahoma	36.171483	-97.718347	6.841364	6.854667	6.964286	1.404545	1.385333	1.385333

Program :

```
import numpy as np
import pandas as pd
from sklearn import preprocessing;
from sklearn import model_selection;
from sklearn import linear_model;
import os
import datetime as dt
import matplotlib.pyplot as plt

df=pd.read_csv('database.csv')

new_column_names = ["Date(YYYY/MM/DD)", "Time(UTC)", "Latitude(deg)",
                    "Longitude(deg)","Type","Depth(km)", "Depth Error(km)",
                    "Depth Seismic Stations(km)"," Magnitude(ergs)",
                    "Magnitude_type", "Magnitude Error",
                    "Magnitude Seismic Stations","Azimuthal Gap",
                    "Horizontal Distance", "Horizontal Error",
                    " RootMeanSquare ", "ID ", "Source",
                    "Location Source", "Magnitude Source","Status"]

df.columns = new_column_names
ts = pd.to_datetime(df["Date(YYYY/MM/DD)"])
df = df.drop(["Date(YYYY/MM/DD)", "Time(UTC)"], axis=1)
df.index = ts
display(df)
```

Date(YYYY/MM/DD)	Latitude(deg)	Longitude(deg)	Type	Depth(km)	\
1965-01-02	19.2460	145.6160	Earthquake	131.60	
1965-01-04	1.8630	127.3520	Earthquake	80.00	
1965-01-05	-20.5790	-173.9720	Earthquake	20.00	
1965-01-08	-59.0760	-23.5570	Earthquake	15.00	
1965-01-09	11.9380	126.4270	Earthquake	15.00	
...	
2016-12-28	38.3917	-118.8941	Earthquake	12.30	
2016-12-28	38.3777	-118.8957	Earthquake	8.80	
2016-12-28	36.9179	140.4262	Earthquake	10.00	
2016-12-29	-9.0283	118.6639	Earthquake	79.00	
2016-12-30	37.3973	141.4103	Earthquake	11.94	

Date(YYYY/MM/DD)	Depth Error(km)	Depth Seismic Stations(km)	\
1965-01-02	NaN	NaN	
1965-01-04	NaN	NaN	
1965-01-05	NaN	NaN	
1965-01-08	NaN	NaN	
1965-01-09	NaN	NaN	
...	
2016-12-28	1.2	40.0	
2016-12-28	2.0	33.0	
2016-12-28	1.8	NaN	
2016-12-29	1.8	NaN	
2016-12-30	2.2	NaN	

Date(YYYY/MM/DD)	Magnitude(ergs)	Magnitude_type	Magnitude Error	\
1965-01-02	6.0	MW	NaN	
1965-01-04	5.8	MW	NaN	
1965-01-05	6.2	MW	NaN	
1965-01-08	5.8	MW	NaN	
1965-01-09	5.8	MW	NaN	
...	
2016-12-28	5.6	ML	0.320	
2016-12-28	5.5	ML	0.260	
2016-12-28	5.9	MWW	NaN	
2016-12-29	6.3	MWW	NaN	
2016-12-30	5.5	MB	0.029	

Date(YYYY/MM/DD)	Magnitude	Seismic Stations	Azimuthal Gap	\
------------------	-----------	------------------	---------------	---

1965-01-02	NaN	NaN
1965-01-04	NaN	NaN
1965-01-05	NaN	NaN
1965-01-08	NaN	NaN
1965-01-09	NaN	NaN
...
2016-12-28	18.0	42.47
2016-12-28	18.0	48.58
2016-12-28	NaN	91.00
2016-12-29	NaN	26.00
2016-12-30	428.0	97.00

Date(YYYY/MM/DD)	Horizontal Distance	Horizontal Error	RootMeanSquare \
1965-01-02	NaN	NaN	NaN
1965-01-04	NaN	NaN	NaN
1965-01-05	NaN	NaN	NaN
1965-01-08	NaN	NaN	NaN
1965-01-09	NaN	NaN	NaN
...
2016-12-28	0.120	NaN	0.1898
2016-12-28	0.129	NaN	0.2187
2016-12-28	0.992	4.8	1.5200
2016-12-29	3.553	6.0	1.4300
2016-12-30	0.681	4.5	0.9100

Date(YYYY/MM/DD)	ID	Source Location	Source Magnitude	Source \
1965-01-02	ISCGEM860706	ISCGEM	ISCGEM	ISCGEM
1965-01-04	ISCGEM860737	ISCGEM	ISCGEM	ISCGEM
1965-01-05	ISCGEM860762	ISCGEM	ISCGEM	ISCGEM
1965-01-08	ISCGEM860856	ISCGEM	ISCGEM	ISCGEM
1965-01-09	ISCGEM860890	ISCGEM	ISCGEM	ISCGEM
...
2016-12-28	NN00570710	NN	NN	NN
2016-12-28	NN00570744	NN	NN	NN
2016-12-28	US10007NAF	US	US	US
2016-12-29	US10007NL0	US	US	US
2016-12-30	US10007NTD	US	US	US

Date(YYYY/MM/DD)	Status
1965-01-02	Automatic
1965-01-04	Automatic
1965-01-05	Automatic
1965-01-08	Automatic
1965-01-09	Automatic
...	...
2016-12-28	Reviewed
2016-12-28	Reviewed

```
2016-12-28      Reviewed
2016-12-29      Reviewed
2016-12-30      Reviewed
```

```
[23412 rows x 19 columns]
```

```
df.info()
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 23412 entries, 1965-01-02 00:00:00 to 2016-12-30 00:00:00
Data columns (total 19 columns):
```

#	Column	Non-Null Count	Dtype
0	Latitude(deg)	23412 non-null	float64
1	Longitude(deg)	23412 non-null	float64
2	Type	23412 non-null	object
3	Depth(km)	23412 non-null	float64
4	Depth Error(km)	4461 non-null	float64
5	Depth Seismic Stations(km)	7097 non-null	float64
6	Magnitude(ergs)	23412 non-null	float64
7	Magnitude_type	23409 non-null	object
8	Magnitude Error	327 non-null	float64
9	Magnitude Seismic Stations	2564 non-null	float64
10	Azimuthal Gap	7299 non-null	float64
11	Horizontal Distance	1604 non-null	float64
12	Horizontal Error	1156 non-null	float64
13	RootMeanSquare	17352 non-null	float64
14	ID	23412 non-null	object
15	Source	23412 non-null	object
16	Location Source	23412 non-null	object
17	Magnitude Source	23412 non-null	object
18	Status	23412 non-null	object

```
dtypes: float64(12), object(7)
```

```
memory usage: 3.6+ MB
```

Date(YYYY/MM/DD)	Latitude(deg)	Longitude(deg)	Type	Depth(km)	\
1965-01-02 00:00:00	19.246	145.616	Earthquake	131.6	
1965-01-04 00:00:00	1.863	127.352	Earthquake	80.0	
1965-01-05 00:00:00	-20.579	-173.972	Earthquake	20.0	
1965-01-08 00:00:00	-59.076	-23.557	Earthquake	15.0	
1965-01-09 00:00:00	11.938	126.427	Earthquake	15.0	

Date(YYYY/MM/DD)	Depth Error(km)	Depth Seismic Stations(km)	\
1965-01-02 00:00:00	NaN	NaN	

1965-01-04 00:00:00	NaN	NaN
1965-01-05 00:00:00	NaN	NaN
1965-01-08 00:00:00	NaN	NaN
1965-01-09 00:00:00	NaN	NaN

Date(YYYY/MM/DD)	Magnitude(ergs)	Magnitude_type	Magnitude	Error	\
1965-01-02 00:00:00	6.0	MW		NaN	
1965-01-04 00:00:00	5.8	MW		NaN	
1965-01-05 00:00:00	6.2	MW		NaN	
1965-01-08 00:00:00	5.8	MW		NaN	
1965-01-09 00:00:00	5.8	MW		NaN	

Date(YYYY/MM/DD)	Magnitude	Seismic Stations	Azimuthal Gap	\
1965-01-02 00:00:00		NaN	NaN	
1965-01-04 00:00:00		NaN	NaN	
1965-01-05 00:00:00		NaN	NaN	
1965-01-08 00:00:00		NaN	NaN	
1965-01-09 00:00:00		NaN	NaN	

Date(YYYY/MM/DD)	Horizontal Distance	Horizontal Error	RootMeanSquare	\
1965-01-02 00:00:00	NaN	NaN	NaN	
1965-01-04 00:00:00	NaN	NaN	NaN	
1965-01-05 00:00:00	NaN	NaN	NaN	
1965-01-08 00:00:00	NaN	NaN	NaN	
1965-01-09 00:00:00	NaN	NaN	NaN	

Date(YYYY/MM/DD)	ID	Source Location	Source Magnitude	Source	\
1965-01-02 00:00:00	ISCGEM860706	ISCGEM	ISCGEM	ISCGEM	
1965-01-04 00:00:00	ISCGEM860737	ISCGEM	ISCGEM	ISCGEM	
1965-01-05 00:00:00	ISCGEM860762	ISCGEM	ISCGEM	ISCGEM	
1965-01-08 00:00:00	ISCGEM860856	ISCGEM	ISCGEM	ISCGEM	
1965-01-09 00:00:00	ISCGEM860890	ISCGEM	ISCGEM	ISCGEM	

Date(YYYY/MM/DD)	Status
1965-01-02 00:00:00	Automatic
1965-01-04 00:00:00	Automatic
1965-01-05 00:00:00	Automatic
1965-01-08 00:00:00	Automatic
1965-01-09 00:00:00	Automatic


```
df.shape
(23412, 19)
```

```
df.describe()
```

	Latitude(deg)	Longitude(deg)	Depth(km)	Depth Error(km)	\
count	23412.000000	23412.000000	23412.000000	4461.000000	
mean	1.679033	39.639961	70.767911	4.993115	
std	30.113183	125.511959	122.651898	4.875184	
min	-77.080000	-179.997000	-1.100000	0.000000	
25%	-18.653000	-76.349750	14.522500	1.800000	
50%	-3.568500	103.982000	33.000000	3.500000	
75%	26.190750	145.026250	54.000000	6.300000	
max	86.005000	179.998000	700.000000	91.295000	

	Depth Seismic Stations(km)	Magnitude(ergs)	Magnitude Error	\
count	7097.000000	23412.000000	327.000000	
mean	275.364098	5.882531	0.071820	
std	162.141631	0.423066	0.051466	
min	0.000000	5.500000	0.000000	
25%	146.000000	5.600000	0.046000	
50%	255.000000	5.700000	0.059000	
75%	384.000000	6.000000	0.075500	
max	934.000000	9.100000	0.410000	

	Magnitude Seismic Stations	Azimuthal Gap	Horizontal Distance	\
count	2564.000000	7299.000000	1604.000000	
mean	48.944618	44.163532	3.992660	
std	62.943106	32.141486	5.377262	
min	0.000000	0.000000	0.004505	
25%	10.000000	24.100000	0.968750	
50%	28.000000	36.000000	2.319500	
75%	66.000000	54.000000	4.724500	
max	821.000000	360.000000	37.874000	

	Horizontal Error	RootMeanSquare
count	1156.000000	17352.000000
mean	7.662759	1.022784
std	10.430396	0.188545
min	0.085000	0.000000
25%	5.300000	0.900000
50%	6.700000	1.000000
75%	8.100000	1.130000
max	99.000000	3.440000

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Index: 23412 entries, 1965-01-02 00:00:00 to 2016-12-30 00:00:00
```

```
Data columns (total 19 columns):
```

#	Column	Non-Null Count	Dtype
---	-----	-----	-----
0	Latitude(deg)	23412 non-null	float64

1	Longitude(deg)	23412 non-null	float64
2	Type	23412 non-null	object
3	Depth(km)	23412 non-null	float64
4	Depth Error(km)	4461 non-null	float64
5	Depth Seismic Stations(km)	7097 non-null	float64
6	Magnitude(ergs)	23412 non-null	float64
7	Magnitude_type	23409 non-null	object
8	Magnitude Error	327 non-null	float64
9	Magnitude Seismic Stations	2564 non-null	float64
10	Azimuthal Gap	7299 non-null	float64
11	Horizontal Distance	1604 non-null	float64
12	Horizontal Error	1156 non-null	float64
13	RootMeanSquare	17352 non-null	float64
14	ID	23412 non-null	object
15	Source	23412 non-null	object
16	Location Source	23412 non-null	object
17	Magnitude Source	23412 non-null	object
18	Status	23412 non-null	object

dtypes: float64(12), object(7)
memory usage: 3.6+ MB

df.isnull().sum()

Latitude(deg)	0
Longitude(deg)	0
Type	0
Depth(km)	0
Depth Error(km)	18951
Depth Seismic Stations(km)	16315
Magnitude(ergs)	0
Magnitude_type	3
Magnitude Error	23085
Magnitude Seismic Stations	20848
Azimuthal Gap	16113
Horizontal Distance	21808
Horizontal Error	22256
RootMeanSquare	6060
ID	0
Source	0
Location Source	0
Magnitude Source	0
Status	0

dtype: int64

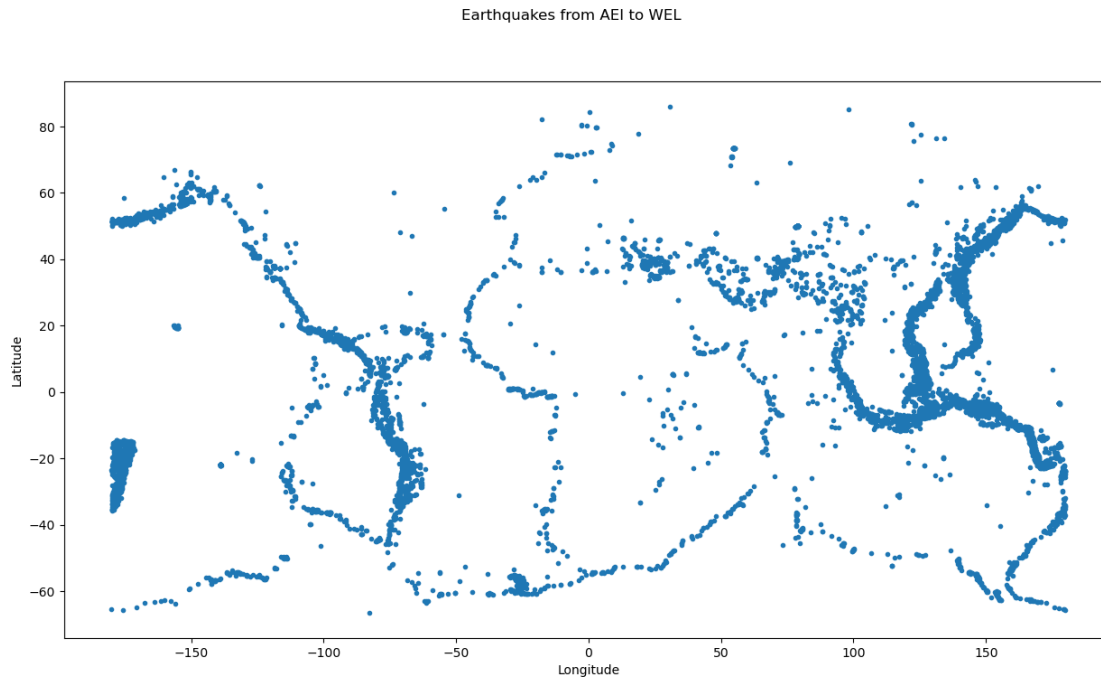
rounding_factor = 10

fig, ax = plt.subplots(figsize=(15,8))

latitude and longitude of earthquake site of top 10500 samples.

```
plt.plot(np.round(df['Longitude(deg)'].head(10500),rounding_factor),
         np.round(df['Latitude(deg)'].head(10500),rounding_factor),
         linestyle='none', marker='.')
```

```
plt.suptitle('Earthquakes from ' + str(np.min(df['Location Source']))[:20] +
' to ' + str(np.max(df['Location Source']))[:20])
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```



```
df = df.sort_values('Location Source', ascending=True)
#Date extraction
df['Date'] = df['Location Source'].str[0:10]
df.head()
```

Date(YYYY/MM/DD)	Latitude(deg)	Longitude(deg)	Type	Depth(km)	\
1992-05-12 00:00:00	59.691	-153.482	Earthquake	138.8	
1991-05-01 00:00:00	62.476	-151.413	Earthquake	114.2	
1995-12-30 00:00:00	63.212	-150.605	Earthquake	137.3	
1995-10-06 00:00:00	65.170	-148.565	Earthquake	9.1	
1993-11-20 00:00:00	60.025	-153.003	Earthquake	116.3	

Date(YYYY/MM/DD)	Depth Error(km)	Depth Seismic Stations(km)	\
1992-05-12 00:00:00	NaN	NaN	
1991-05-01 00:00:00	NaN	NaN	
1995-12-30 00:00:00	NaN	NaN	
1995-10-06 00:00:00	NaN	NaN	
1993-11-20 00:00:00	NaN	NaN	

Date(YYYY/MM/DD)	Magnitude(ergs)	Magnitude_type	Magnitude Error	\
------------------	-----------------	----------------	-----------------	---

1992-05-12 00:00:00	5.6	MW	NaN
1991-05-01 00:00:00	6.3	MW	NaN
1995-12-30 00:00:00	5.7	MW	NaN
1995-10-06 00:00:00	5.8	MS	NaN
1993-11-20 00:00:00	5.9	MW	NaN

Date(YYYY/MM/DD)	Magnitude	Seismic Stations	Azimuthal Gap	\
1992-05-12 00:00:00		NaN	NaN	
1991-05-01 00:00:00		NaN	NaN	
1995-12-30 00:00:00		NaN	NaN	
1995-10-06 00:00:00		64.0	NaN	
1993-11-20 00:00:00		NaN	NaN	

Date(YYYY/MM/DD)	Horizontal Distance	Horizontal Error	RootMeanSquare	\
1992-05-12 00:00:00	NaN	NaN	NaN	
1991-05-01 00:00:00	NaN	NaN	NaN	
1995-12-30 00:00:00	NaN	NaN	NaN	
1995-10-06 00:00:00	NaN	NaN	NaN	
1993-11-20 00:00:00	NaN	NaN	NaN	

Date(YYYY/MM/DD)	ID	Source	Location	Source	Magnitude	Source	\
1992-05-12 00:00:00	USP000577C	US		AEI		HRV	
1991-05-01 00:00:00	USP0004R34	US		AEI		NC	
1995-12-30 00:00:00	USP00079V0	US		AEI		HRV	
1995-10-06 00:00:00	USP00074KV	US		AEI		US	
1993-11-20 00:00:00	USP00063Z5	US		AEI		HRV	

Date(YYYY/MM/DD)	Status	Date
1992-05-12 00:00:00	Reviewed	AEI
1991-05-01 00:00:00	Reviewed	AEI
1995-12-30 00:00:00	Reviewed	AEI
1995-10-06 00:00:00	Reviewed	AEI
1993-11-20 00:00:00	Reviewed	AEI

```
file_name = 'database.csv'
print('DataFrame is written to Excel File successfully.')
print(df.columns)
```

```
DataFrame is written to Excel File successfully.
Index(['Latitude(deg)', 'Longitude(deg)', 'Type', 'Depth(km)',
       'Depth Error(km)', 'Depth Seismic Stations(km)', 'Magnitude(ergs)',
       'Magnitude_type', 'Magnitude Error', 'Magnitude Seismic Stations',
       'Azimuthal Gap', 'Horizontal Distance', 'Horizontal Error',
       'RootMeanSquare ', 'ID ', 'Source', 'Location Source',
```

```

        'Magnitude Source', 'Status', 'Date'],
        dtype='object')

import warnings
warnings.filterwarnings('ignore')

from sklearn.model_selection import train_test_split

# Select relevant columns
X = df[['Latitude(deg)', 'Longitude(deg)', 'Depth(km)']]
y = df[' Magnitude(ergs)']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=0)

from sklearn.linear_model import LinearRegression

# Train the linear regression model
regressor = LinearRegression()
regressor.fit(X_train, y_train)

LinearRegression()

from sklearn.metrics import r2_score, mean_squared_error

scores= {"Model name": ["Linear regression", "SVM", "Random Forest"], "mse":
[], "R^2": []}

# Predict on the testing set
y_pred = regressor.predict(X_test)

# Compute R^2 and MSE
r2 = r2_score(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)

scores['mse'].append(mse)
scores['R^2'].append(r2)

print("R^2: {:.2f}, MSE: {:.2f}".format(r2, mse))

```

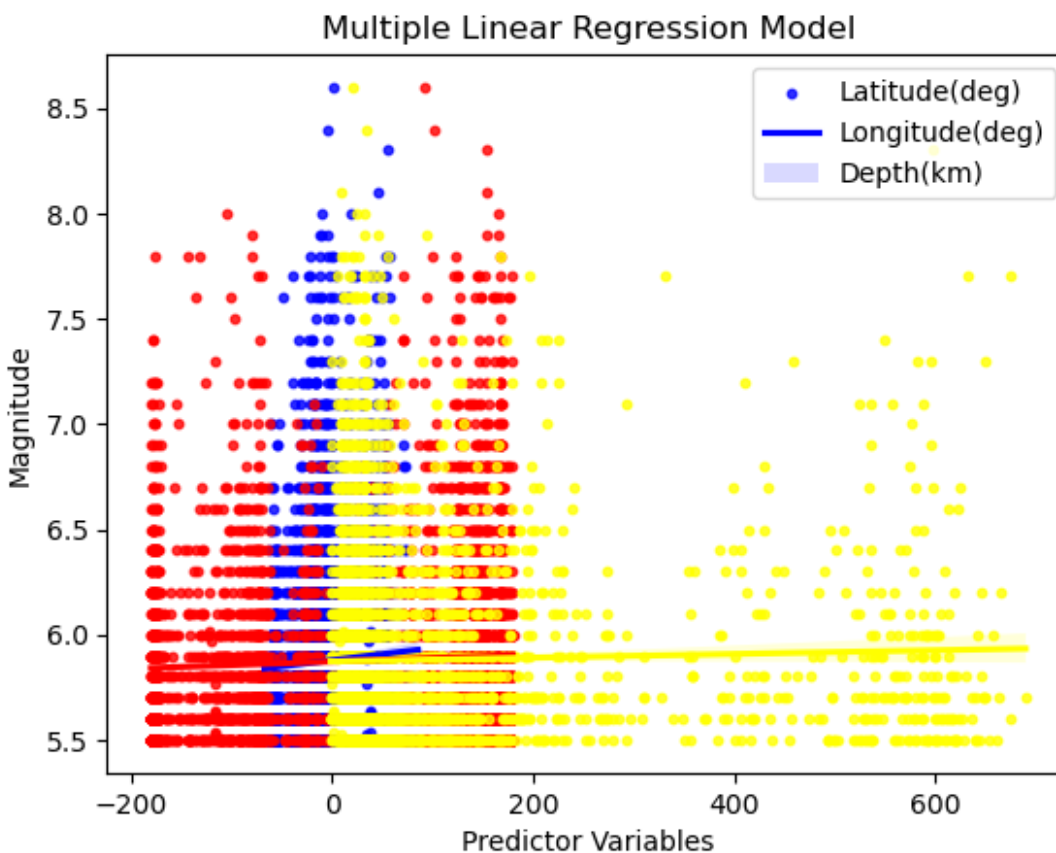
R²: 0.00, MSE: 0.18

```
new_data = [[33.89, -118.40, 16.17], [37.77, -122.42, 8.05]]
new_pred = regressor.predict(new_data)
print("New predictions:", new_pred)
```

New predictions: [5.87417003 5.87453261]

```
import seaborn as sns
import matplotlib.pyplot as plt

# Plot the regression line
sns.regplot(x=X_test['Latitude(deg)'], y=y_test, color='blue',
            scatter_kws={'s': 10})
sns.regplot(x=X_test['Longitude(deg)'], y=y_test, color='red',
            scatter_kws={'s': 10})
sns.regplot(x=X_test['Depth(km)'], y=y_test, color='yellow',
            scatter_kws={'s': 10})
plt.legend(labels=['Latitude(deg)', 'Longitude(deg)', 'Depth(km)'])
plt.xlabel('Predictor Variables')
plt.ylabel('Magnitude')
plt.title('Multiple Linear Regression Model')
plt.show()
```



```

from sklearn.svm import SVR

# Select a subset of the training data
subset_size = 500
X_train_subset = X_train[:subset_size]
y_train_subset = y_train[:subset_size]

# Create an SVM model
svm = SVR(kernel='rbf', C=1e3, gamma=0.1)

# Train the SVM model on the subset of data
svm.fit(X_train_subset, y_train_subset)

# Evaluate the model on the test set
score = svm.score(X_test, y_test)
print("Test score:", score)

Test score: -0.1688371824477879

# Predict on the testing set
y_pred_svm = svm.predict(X_test)

# Compute R^2 and MSE
r2_svm = r2_score(y_test, y_pred_svm)
mse_svm = mean_squared_error(y_test, y_pred_svm)

scores['mse'].append(mse_svm)
scores['R^2'].append(r2_svm)

print("SVM R^2: {:.2f}, MSE: {:.2f}".format(r2_svm, mse_svm))

SVM R^2: -0.17, MSE: 0.21

# Predict on new data
new_pred_svm = svm.predict(new_data)
print("New SVM predictions:", new_pred_svm)

New SVM predictions: [5.88892086 5.88874738]

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib import style
from sklearn.svm import SVC

style.use('fivethirtyeight')

```



```

# create mesh grids
def make_meshgrid(x, y, h =.02):
    x_min, x_max = x.min() - 1, x.max() + 1
    y_min, y_max = y.min() - 1, y.max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max,
h))
    return xx, yy

# plot the contours
def plot_contours(ax, clf, xx, yy, **params):
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    out = ax.contourf(xx, yy, Z, **params)
    return out

# color = ['y', 'b', 'g', 'k']

subset_size = 500

# modify the column names based on the dataset
features = df[[' Magnitude(ergs)', 'Latitude(deg)']][:subset_size].values
classes = df['Magnitude_type'][:subset_size].values

# create 3 svm with rbf kernels
svm1 = SVC(kernel = 'rbf')
svm2 = SVC(kernel = 'rbf')
svm3 = SVC(kernel = 'rbf')
svm4 = SVC(kernel = 'rbf')

# fit each svm's
svm1.fit(features, (classes=='ML').astype(int))
svm2.fit(features, (classes=='MS').astype(int))
svm3.fit(features, (classes=='MB').astype(int))

fig, ax = plt.subplots()
X0, X1 = features[:, 0], features[:, 1]
xx, yy = make_meshgrid(X0, X1)

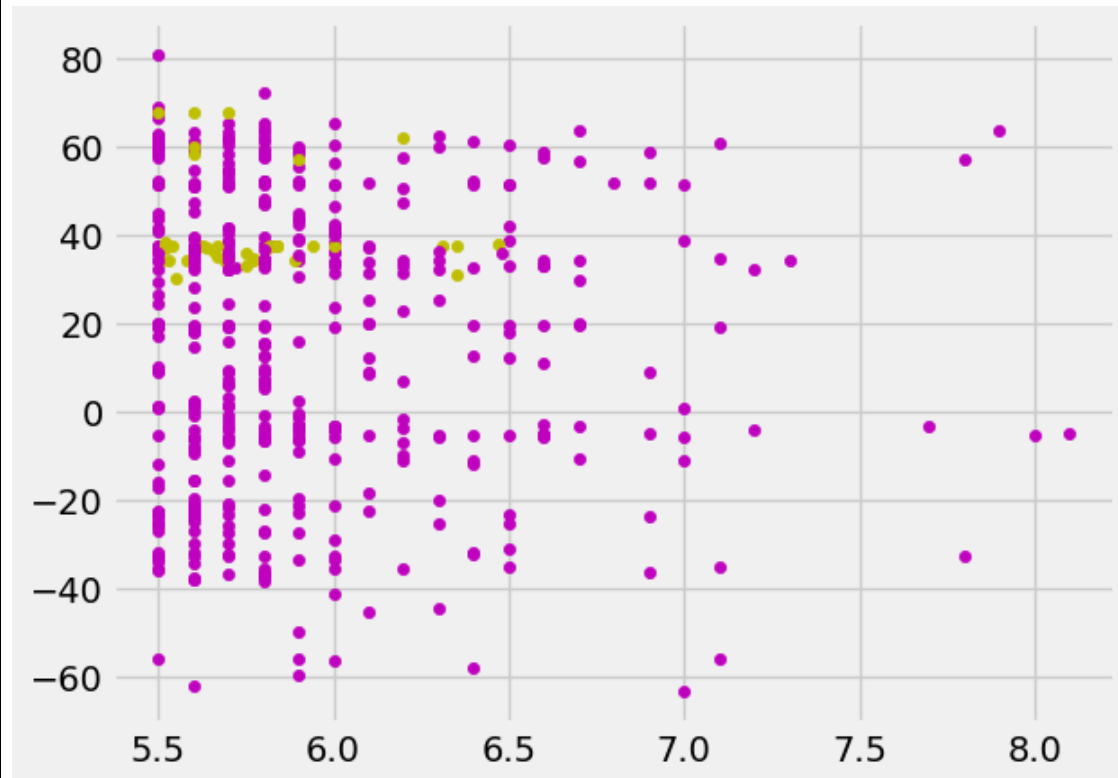
# plot the contours
'''
plot_contours(ax, svm1, xx, yy, cmap = plt.get_cmap('hot'), alpha = 0.8)
plot_contours(ax, svm2, xx, yy, cmap = plt.get_cmap('hot'), alpha = 0.3)
plot_contours(ax, svm3, xx, yy, cmap = plt.get_cmap('hot'), alpha = 0.5)
'''
color = ['y', 'b', 'g', 'k', 'm']

```

```

for i in range(subset_size):
    if classes[i] == 'ML':
        plt.scatter(features[i][0], features[i][1], s = 20, c = color[0])
    elif classes[i] == 'Mx':
        plt.scatter(features[i][0], features[i][1], s = 20, c = color[1])
    elif classes[i] == 'Md':
        plt.scatter(features[i][0], features[i][1], s = 20, c = color[2])
    else:
        plt.scatter(features[i][0], features[i][1], s = 20, c = color[4])
plt.show()

```



```

print(df.columns)
df['Magnitude_type'].unique()

```

```

Index(['Latitude(deg)', 'Longitude(deg)', 'Type', 'Depth(km)',
      'Depth Error(km)', 'Depth Seismic Stations(km)', 'Magnitude(ergs)',
      'Magnitude_type', 'Magnitude Error', 'Magnitude Seismic Stations',
      'Azimuthal Gap', 'Horizontal Distance', 'Horizontal Error',
      'RootMeanSquare ', 'ID ', 'Source', 'Location Source',
      'Magnitude Source', 'Status', 'Date'],
      dtype='object')

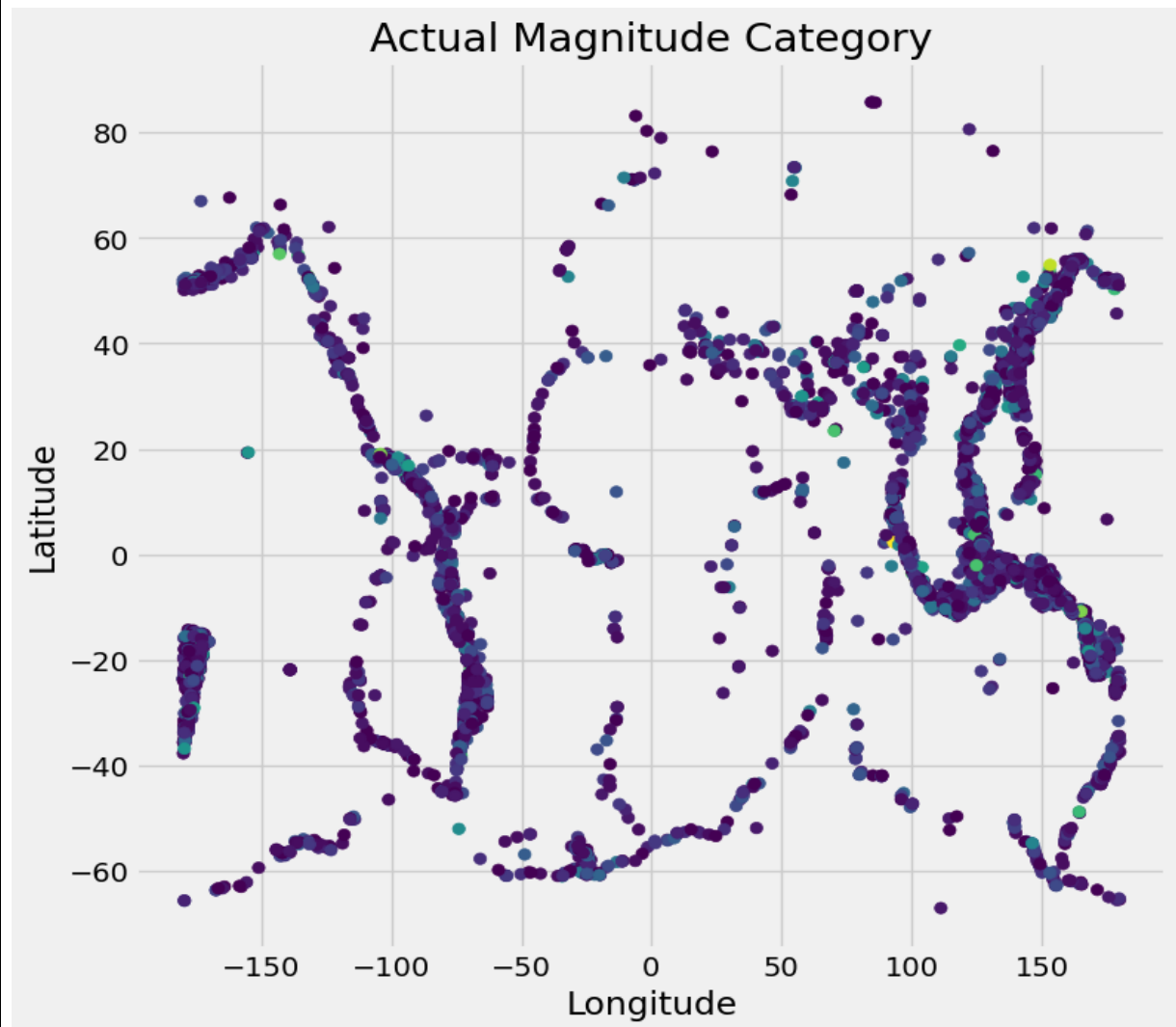
array(['MW', 'MS', 'MWC', 'MWW', 'MWB', 'MB', 'ML', nan, 'MH', 'MWR',
      'MD'], dtype=object)

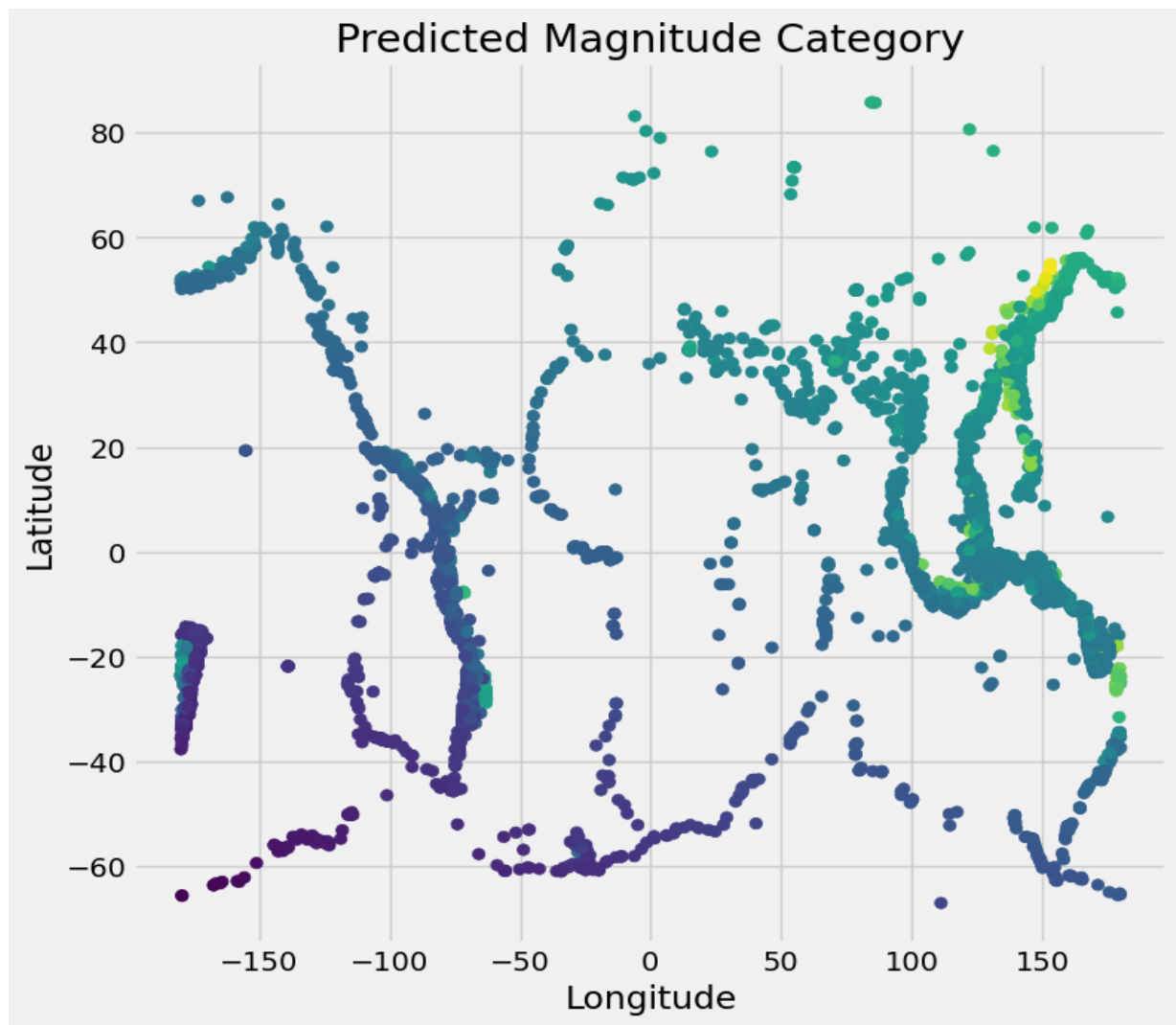
```

```

plt.figure(figsize=(8, 8))
plt.scatter(X_test['Longitude(deg)'], X_test['Latitude(deg)'], c=y_test,
            cmap='viridis')
plt.title('Actual Magnitude Category')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
print(" ")
plt.figure(figsize=(8, 8))
plt.scatter(X_test['Longitude(deg)'], X_test['Latitude(deg)'], c=y_pred,
            cmap='viridis')
plt.title('Predicted Magnitude Category')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
print(" ")

```





Conclusion:

- In conclusion, our analysis shed light on the potential of machine learning in earthquake prediction. While the models offered valuable insights and predictability, they represent just the beginning of a much broader field of research.
- Earthquake prediction remains a challenging domain, and our study serves as a foundational effort to enhance the accuracy and reliability of such predictions.