Import Dataset

```
import pandas as pd
from google.colab import data_table
data_table.enable_dataframe_formatter()

# Read CSV file with space delimiter
df = pd.read_csv('/content/Earthquake_Data.csv', delimiter=r'\s+')

# Print the first 5 rows of the data frame
display(df)
```

1 to 25 of 18030 entries Filter

index	Date(YYYY/MM/DD)	Time	Latitude	Longitude	Depth	Mag	Magt	Nst	Gap	Clo	RMS	SRC	EventID
0	1966/07/01	09:41:21.82	35.9463	-120.47	12.26	3.2	Mx	7	171	20	0.02	NCSN	-4540462
1	1966/07/02	12:08:34.25	35.7867	-120.3265	8.99	3.7	Mx	8	86	3	0.04	NCSN	-4540520
2	1966/07/02	12:16:14.95	35.7928	-120.3353	9.88	3.4	Mx	8	89	2	0.03	NCSN	-4540521
3	1966/07/02	12:25:06.12	35.797	-120.3282	9.09	3.1	Mx	8	101	3	0.08	NCSN	-4540522
4	1966/07/05	18:54:54.36	35.9223	-120.4585	7.86	3.1	Mx	9	161	14	0.04	NCSN	-4540594
5	1966/07/27	08:12:00.26	35.9103	-120.4397	8.02	3.0	Mx	10	158	12	0.02	NCSN	-4540837
6	1966/08/03	12:39:05.79	35.8137	-120.3527	6.59	3.4	Mx	10	131	2	0.05	NCSN	-4540891
7	1966/08/07	17:03:24.14	35.938	-120.4568	11.76	3.0	Mx	11	153	19	0.04	NCSN	-4540922
8	1966/08/19	22:51:20.04	35.914	-120.4272	1.67	3.3	Mx	6	165	11	0.1	NCSN	-4540969
9	1966/09/07	00:20:52.12	36.0032	-120.0317	10.61	3.4	Mx	13	258	27	0.14	NCSN	-4541046
10	1968/01/12	22:19:10.35	36.6453	-121.2497	6.84	3.0	ML	14	155	2	0.07	NCSN	-1001356
11	1968/02/09	13:42:37.05	37.1527	-121.5448	8.49	3.0	ML	25	157	7	0.08	NCSN	-1001405
12	1968/02/21	14:39:48.10	37.1783	-121.578	6.95	3.8	ML	29	142	4	0.1	NCSN	-1001431
13	1968/03/02	04:25:53.94	36.8343	-121.5447	5.35	3.0	Mx	17	106	5	0.16	NCSN	-1001455
14	1968/03/17	15:07:02.12	37.3088	-121.6615	4.39	3.0	ML	29	85	4	0.07	NCSN	-1001502
15	1968/03/21	21:54:59.94	37.0378	-121.7407	11.86	4.3	ML	29	133	6	0.1	NCSN	-1001514
16	1968/05/03	21:39:57.28	37.729	-122.1162	10.08	3.2	ML	23	161	19	0.04	NCSN	-1001592
17	1968/05/21	22:33:01.20	37.3577	-121.631	8.0	3.0	Mx	7	151	9	0.06	NCSN	-1001624
18	1968/05/25	09:41:04.33	37.4133	-121.8243	1.77	3.42	Mx	21	115	5	0.12	NCSN	-1001633
19	1968/05/25	11:46:48.64	37.4225	-121.8105	4.05	3.14	Mx	14	105	3	0.08	NCSN	-1001634
20	1968/05/30	08:03:01.06	38.1722	-123.2057	5.0	4.2	ML	38	324	91	0.3	NCSN	-1001645
21	1968/06/20	07:50:28.11	36.8142	-121.5412	6.8	3.5	ML	25	72	3	0.2	NCSN	-1001698
22	1968/08/08	19:41:31.32	37.4095	-121.758	8.35	3.2	ML	31	76	3	0.07	NCSN	-1001806
23	1968/08/19	09:05:27.25	36.4967	-121.8773	4.99	3.23	Mx	5	270	43	0.06	NCSN	-1001831
24	1968/09/26	20:01:14.08	37.018	-121.701	9.85	3.14	Mx	30	65	4	0.15	NCSN	-1001894

Show 25 per page 1 2 10 100 700 720 722

Preprocessing

No preprocessing required because the data is already clean and structured. We just have to change the column names to meaningful names.

```
new_column_names = ["Date(YYYY/MM/DD)",  "Time(UTC)", "Latitude(deg)", "Longitude(deg)", "Depth(km)", "Magnitude(ergs)
                    "Magnitude_type", "No_of_Stations", "Gap", "Close", "RMS", "SRC", "EventID"]

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

1 to 25 of 18030 entries Filter

index	Latitude(deg)	Longitude(deg)	Depth(km)	Magnitude(ergs)	Magnitude
1966-07-01 09:41:21.820000	35.9463	-120.47	12.26	3.2	Mx
1966-07-02 12:08:34.250000	35.7867	-120.3265	8.99	3.7	Mx
1966-07-02 12:16:14.950000	35.7928	-120.3353	9.88	3.4	Mx
1966-07-02 12:25:06.120000	35.797	-120.3282	9.09	3.1	Mx
1966-07-05 18:54:54.360000	35.9223	-120.4585	7.86	3.1	Mx
1966-07-27 08:12:00.260000	35.9103	-120.4397	8.02	3.0	Mx
1966-08-03 12:39:05.790000	35.8137	-120.3527	6.59	3.4	Mx
1966-08-07 17:03:24.140000	35.938	-120.4568	11.76	3.0	Mx
1966-08-19 22:51:20.040000	35.914	-120.4272	1.67	3.3	Mx
1966-09-07 00:20:52.120000	36.0032	-120.0317	10.61	3.4	Mx
1968-01-12 22:19:10.350000	36.6453	-121.2497	6.84	3.0	ML
1968-02-09 13:42:37.050000	37.1527	-121.5448	8.49	3.0	ML
1968-02-21 14:39:48.100000	37.1783	-121.578	6.95	3.8	ML
1968-03-02 04:25:53.940000	36.8343	-121.5447	5.35	3.0	Mx
1968-03-17 15:07:02.120000	37.3088	-121.6615	4.39	3.0	ML
1968-03-21 21:54:59.940000	37.0378	-121.7407	11.86	4.3	ML
1968-05-03 21:39:57.280000	37.729	-122.1162	10.08	3.2	ML
1968-05-21 22:33:01.200000	37.3577	-121.631	8.0	3.0	Mx
1968-05-25 09:41:04.330000	37.4133	-121.8243	1.77	3.42	Mx
1968-05-25 11:46:48.640000	37.4225	-121.8105	4.05	3.14	Mx
1968-05-30 08:03:01.060000	38.1722	-123.2057	5.0	4.2	ML
1968-06-20 07:50:28.110000	36.8142	-121.5412	6.8	3.5	ML

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 18030 entries, 1966-07-01 09:41:21.820000 to 2007-12-28 23:20:28.120000
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Latitude(deg)    18030 non-null  float64
 1   Longitude(deg)   18030 non-null  float64
 2   Depth(km)        18030 non-null  float64
 3   Magnitude(ergs)  18030 non-null  float64
 4   Magnitude_type   18030 non-null  object
 5   No_of_Stations   18030 non-null  int64
 6   Gap              18030 non-null  int64
 7   Close            18030 non-null  int64
 8   RMS              18030 non-null  float64
 9   SRC              18030 non-null  object
 10  EventID          18030 non-null  int64
dtypes: float64(5), int64(4), object(2)
memory usage: 1.7+ MB
```

Export Preprocessed dataset

Export the data into xlsx file

```
file_name = 'Earthquake_data_processed.xlsx'

# saving the excel
df.to_excel(file_name)
print('DataFrame is written to Excel File successfully.')
```

```
DataFrame is written to Excel File successfully.
```

```
import warnings
warnings.filterwarnings('ignore')
```

Partition the data into Training and Testing data

```
from sklearn.model_selection import train_test_split

# Select relevant columns
X = df[['Latitude(deg)', 'Longitude(deg)', 'Depth(km)', 'No_of_Stations']]
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)
```

Linear regression

Loading the model and fitting it with training data

```
from sklearn.linear_model import LinearRegression

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

```
▾ LinearRegression
LinearRegression()
```

Predict the testing data

Find the predicted values and evaluate it using metrics of linear regression

```
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))
```

```
R^2: 0.02, MSE: 0.19
```

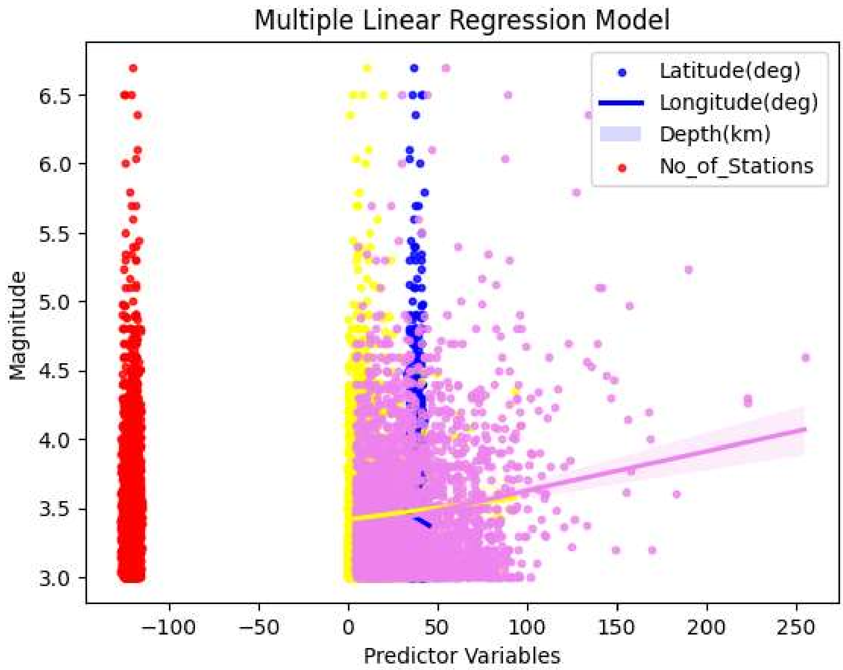
Predict for new data

```
# Predict on new data
new_data = [[33.89, -118.40, 16.17, 11], [37.77, -122.42, 8.05, 14]]
new_pred = regressor.predict(new_data)
print("New predictions:", new_pred)
```

```
New predictions: [3.447483   3.33027751]
```

Plot multiple linear regression model

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



SVM

Loading the model and fitting it with training data

```
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: -2.6273211125904736
```

Predict the testing data

Find the predicted values and evaluate it using metrics like MSE, r2

```
# 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: -2.63, MSE: 0.70
```

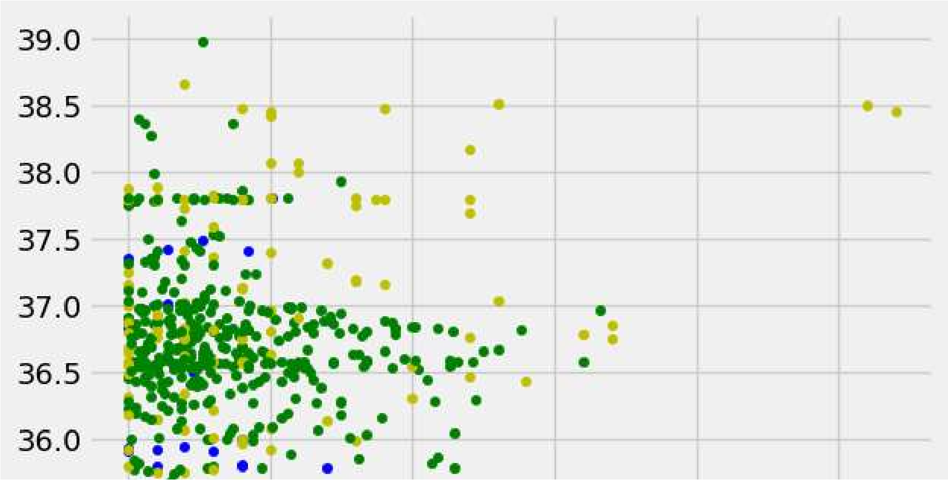
Predict for new data

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

```
New SVM predictions: [4.030623   3.68010607]
```

Plot model

```
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=='Mx').astype(int))
svm3.fit(features, (classes=='Md').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)', 'Depth(km)', 'Magnitude(ergs)',
       'Magnitude_type', 'No_of_Stations', 'Gap', 'Close', 'RMS', 'SRC',
       'EventID'],
      dtype='object')
array(['Mx', 'ML', 'Md', 'Mw'], dtype=object)
```

Naive Bayes

> **Note: Naive bayes is used for strings and numbers(categorically) it can be used for classification so it can be either 1 or 0 nothing in between like 0.5 (regression). Even if we force naive bayes and tweak it a little bit for regression the result is disappointing; A team experimented with this and achieve not so good results.**

`This code is just for predicting categorical data magnitude type with Naive Bayes`

```
import pandas as pd
import numpy as np
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
import matplotlib.pyplot as plt
import seaborn as sns

# Read CSV file with space delimiter
df = pd.read_csv('/content/Earthquake_Data.csv', delimiter=r'\s+')

new_column_names = ["Date(YYYY/MM/DD)",  "Time(UTC)", "Latitude(deg)", "Longitude(deg)", "Depth(km)", "Magnitude",
                    "Magnitude_Category", "No_of_Stations", "Gap", "Close", "RMS", "SRC", "EventID"]

df.columns = new_column_names

# Convert magnitude column to categorical data
df['Magnitude_Category'] = pd.cut(df['Magnitude'], bins=[0, 5, 6, 7, np.inf], labels=['Minor', 'Moderate', 'Strong', '

# Encode Magnitude Category
le = LabelEncoder()
df['Magnitude_Category_Encoded'] = le.fit_transform(df['Magnitude_Category'])

# Normalize latitude and longitude values
scaler = MinMaxScaler()
df[['Latitude(deg)', 'Longitude(deg)']] = scaler.fit_transform(df[['Latitude(deg)', 'Longitude(deg)']])

# Select features
X = df[['Latitude(deg)', 'Longitude(deg)', 'No_of_Stations']]
y = df['Magnitude_Category_Encoded']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Train the Gaussian Naive Bayes model on the training data
gnb = GaussianNB()
gnb.fit(X_train, y_train)
```

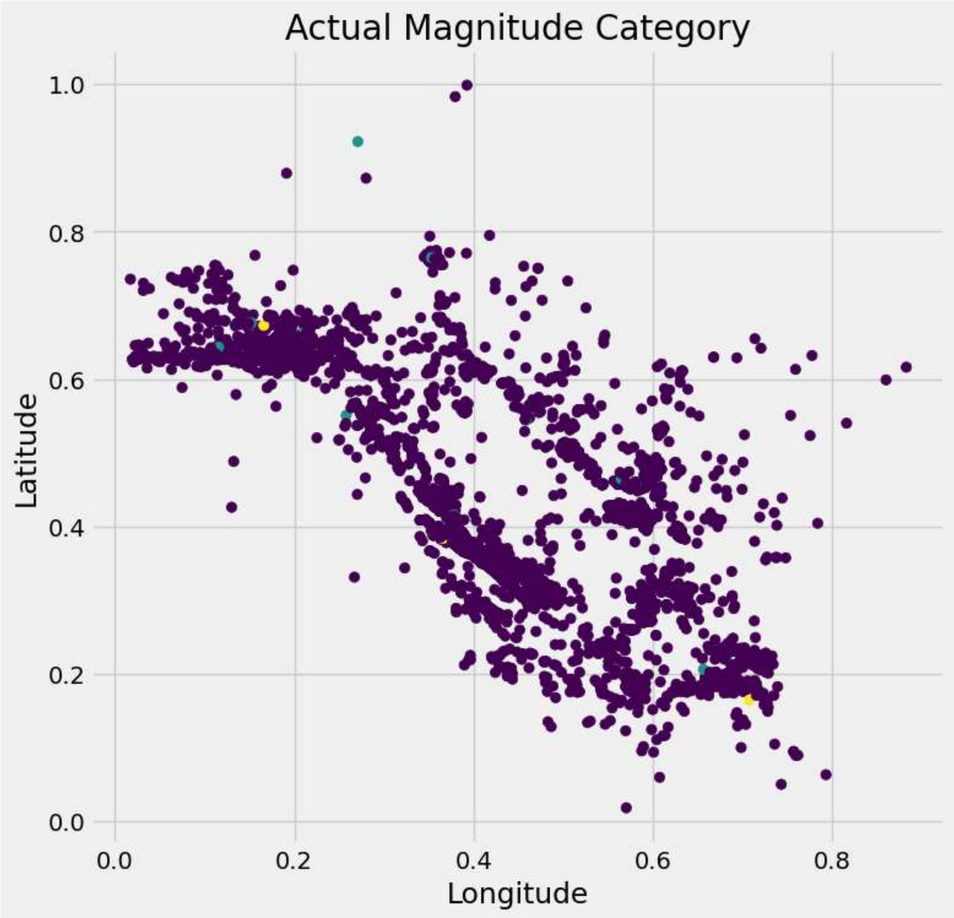
```
▾ GaussianNB
GaussianNB()
```

```
# Use the trained model to make predictions on the testing data
y_pred = gnb.predict(X_test)



# Calculate the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print('Accuracy:', accuracy)

# Calculate and print the confusion matrix and classification report
cm = confusion_matrix(y_test, y_pred)
print('Confusion Matrix:\n', cm)

cr = classification_report(y_test, y_pred, labels=[0, 1, 2, 3], target_names=['Minor', 'Moderate', 'Strong', 'Major'])
print('Classification Report:\n', cr)
```

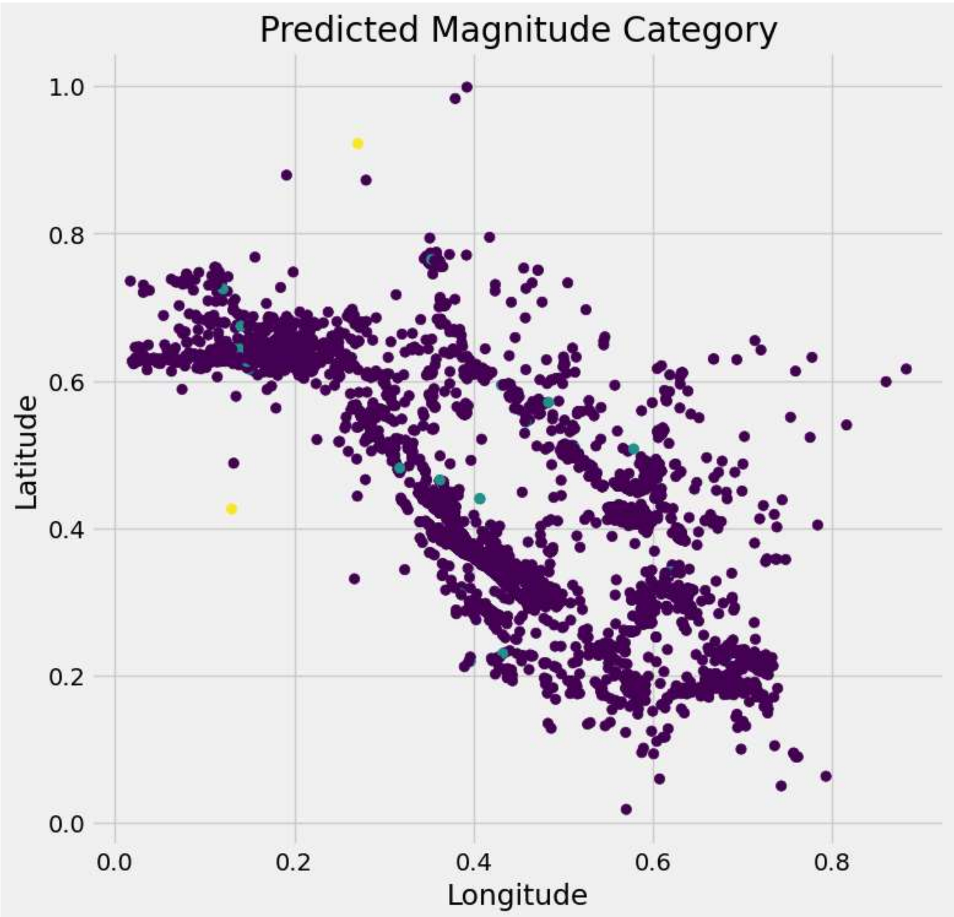
```
Accuracy: 0.9853947125161767
Confusion Matrix:
 [[5327   35    1]
 [  38    3    1]
 [   4    0    0]]
Classification Report:
               precision    recall  f1-score   support

       Minor       0.00      0.00      0.00         0
    Moderate       0.99      0.99      0.99      5363
      Strong       0.08      0.07      0.07        42
       Major       0.00      0.00      0.00         4

   micro avg       0.99      0.99      0.99      5409
```

```
    macro avg       0.27      0.27      0.27      5409
 weighted avg       0.98      0.99      0.98      5409
```

```
# Create a scatter plot of actual vs predicted values
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(" ")


# Create a heatmap of the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, cmap='Blues', fmt='g')
plt.xlabel('Predicted Magnitude Category')
plt.ylabel('Actual Magnitude Category')
plt.show()
print(" ")

cr = classification_report(y_test, y_pred, labels=[0, 1, 2, 3], target_names=['Minor', 'Moderate', 'Strong', 'Major'],
# Convert classification report dictionary to DataFrame
cr_df = pd.DataFrame(cr).transpose()

# Create bar plot of classification report scores
plt.figure(figsize=(8, 6))
sns.barplot(x=cr_df.index, y=cr_df['f1-score'])
plt.xlabel('Magnitude Category')
plt.ylabel('F1 Score')
plt.title('F1 Score by Magnitude Category')
plt.show()
print(" ")
```

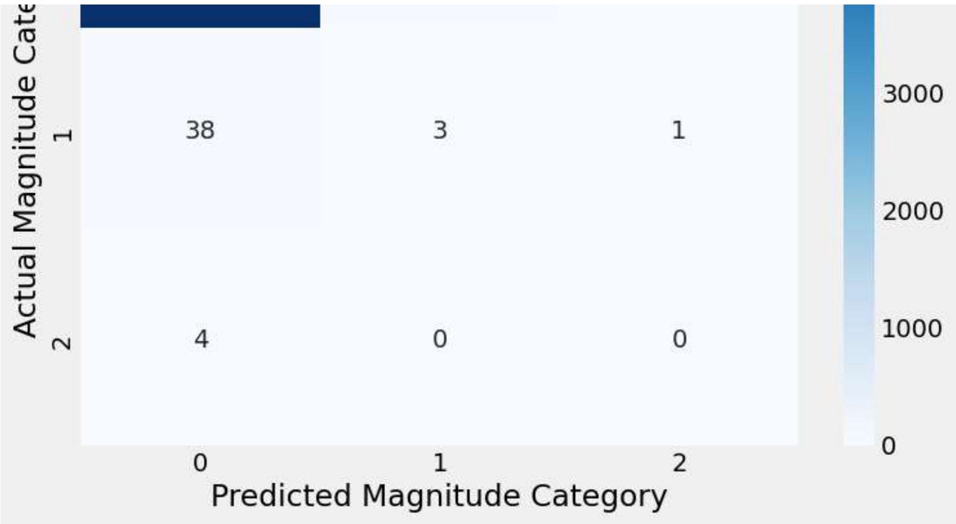


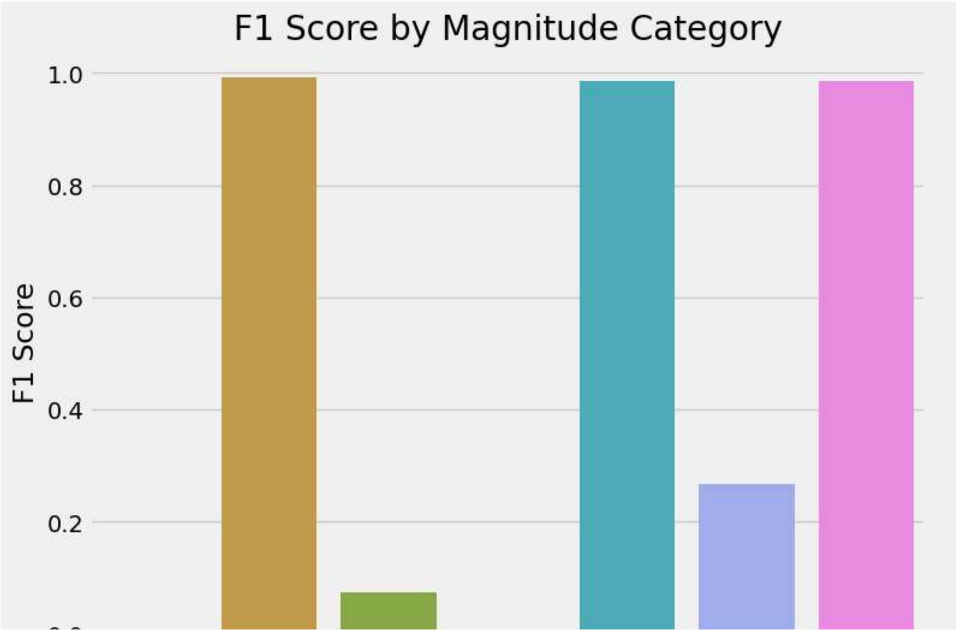
Actual Magnitude Category
Latitude
Longitude
0.0
0.2
0.4
0.6
0.8
1.0



Predicted Magnitude Category
Latitude
Longitude
0.0
0.2
0.4
0.6
0.8
1.0

5327
35
1
0
egory
5000
4000





Random Forest

Loading the model and fitting it with training data

```
from sklearn.ensemble import RandomForestRegressor

# Initialize a random forest regressor with 100 trees
rf = RandomForestRegressor(n_estimators=100, random_state=42)

# Fit the regressor to the training data
rf.fit(X_train, y_train)
```

```
▾ RandomForestRegressor
RandomForestRegressor(random_state=42)
```

Predict the testing data and evaluate it

Find the predicted values and evaluate it using metrics like MSE, r2

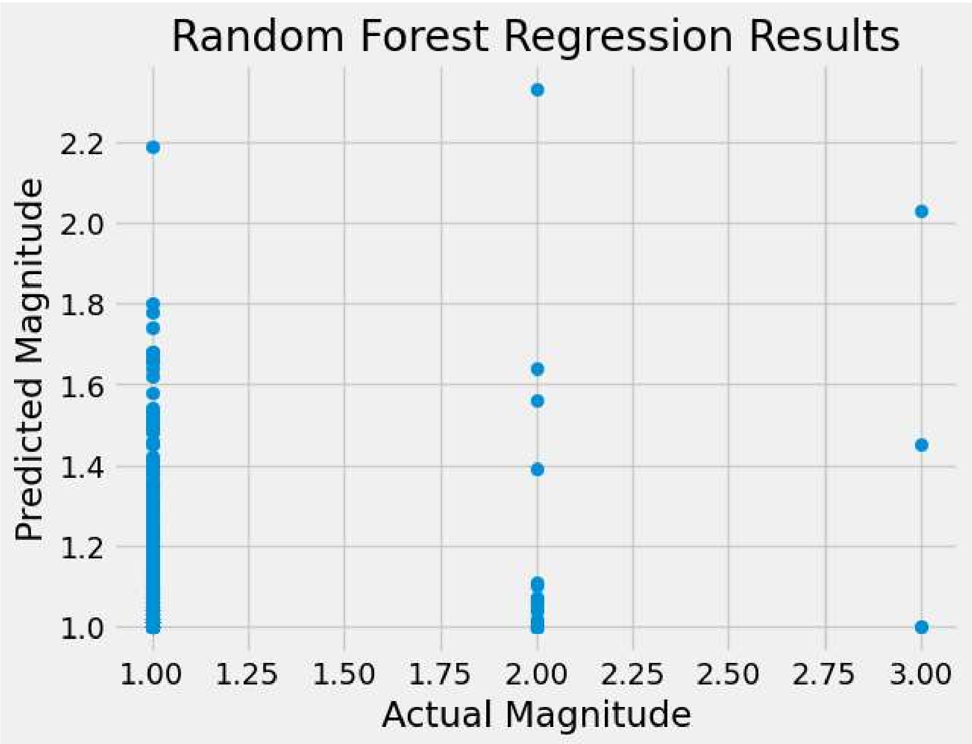
```
# Predict the target variable on the test data
y_pred = rf.predict(X_test)

# Evaluate the performance of the model using mean squared error and R^2 score
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

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

print('Mean Squared Error: ', mse)
print('R^2 Score: ', r2)
```

```
Mean Squared Error:  0.012586078757626l8
R^2 Score:  -0.18318898696107633
```

Plot model

Scatter plot

```
# Plot the predicted and actual values
plt.scatter(y_test, y_pred)
plt.xlabel('Actual Magnitude')
plt.ylabel('Predicted Magnitude')
plt.title('Random Forest Regression Results')
plt.show()
```



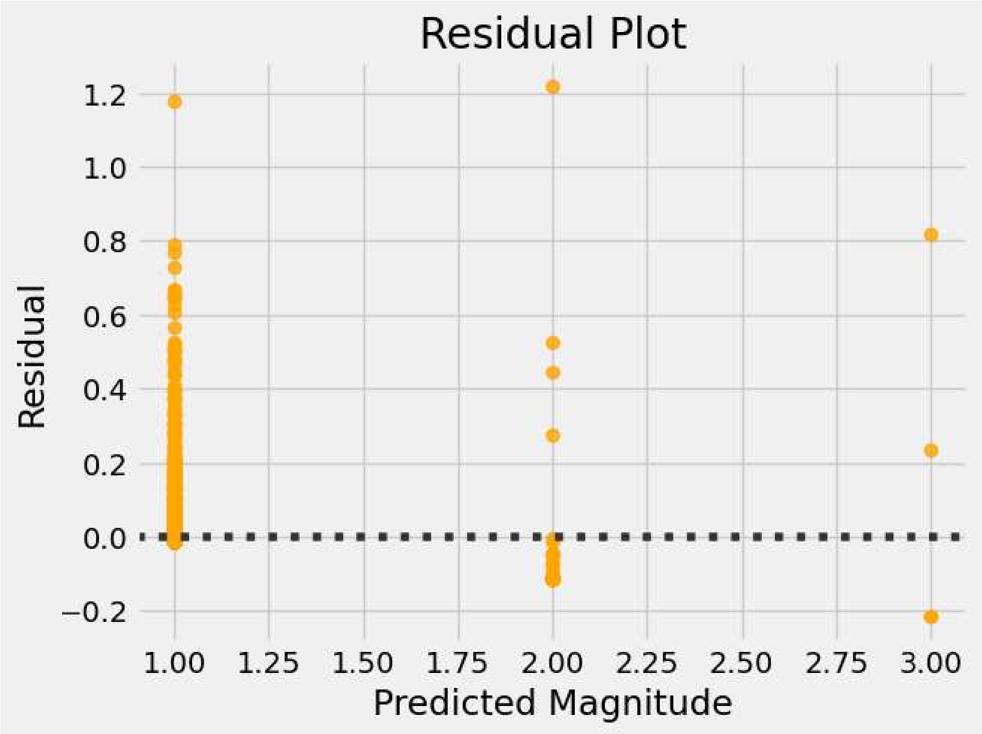
Feature Importance

This plot shows the importance of each feature in the model. You can create a feature importance plot using the feature_importances_ attribute of the random forest model.

Residual Plot

A residual plot shows the difference between the actual values and the predicted values. You can create a residual plot using the residplot() function from the seaborn library.

```
import seaborn as sns
sns.residplot(x= y_test, y =y_pred, color='orange')
plt.xlabel('Predicted Magnitude')
plt.ylabel('Residual')
plt.title('Residual Plot')
plt.show()
```



Actual vs. Predicted Line Plot

Actual vs. Predicted Line Plot: A line plot can be used to show the trend of the actual and predicted values over time (if the data is time-series). You can create a line plot using the plot() function.

```
plt.plot(y_test.index[:20], y_test[:20], color='blue', label='Actual Magnitude')
plt.plot(y_test.index[:20], y_pred[:20], color='orange', label='Predicted Magnitude')
plt.xlabel('Index')
plt.ylabel('Magnitude')
plt.title('Actual vs. Predicted Line Plot')
plt.legend()
plt.show()
```