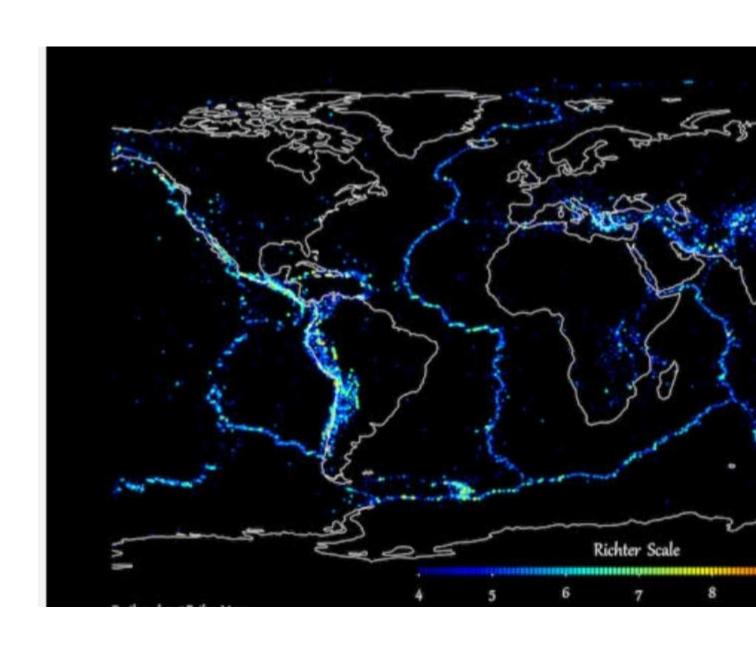
PREPROCESSING OF DATASET IN PREDICTION OF EARTHQUAKE USING PYTHON:



```
import numpy as np
import pandas as pd
import requests
from sklearn import preprocessing
import matplotlib.pyplot as plt
import seaborn as sns
from pandas.plotting import scatter_matrix
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
import time

from google.colab import drive
drive.mount('/content/drive')
df = pd.read_csv("/content/drive/MyDrive/Colab
Notebooks/earthquake_prediction/earthquake1.csv")
```

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force remount=True).

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24007 entries, 0 to 24006

Data columns (total 17 columns):

#	Column	Non-Null	Count	Dtype
0	id	24007	non-null	float64
1	date	24007	non-null	object
2	time	24007	non-null	object
3	lat	24007	non-null	float64
4	long	24007	non-null	float64
5	country	24007	non-null	object
6	city	11754	non-null	object
7	area	12977	non-null	object
8	direction	10062	non-null	object
9	dist	10062	non-null	float64
10	depth	24007	non-null	float64
11	жm	24007	non-null	float64
12	md	24007	non-null	float64
13	richter	24007	non-null	float64
14	mw	5003	non-null	float64
15	ms	24007	non-null	float64
16	mb	24007	non-null	float64

dtypes: float64(11), object(6)
memory usage: 3.1+ MB

df.describe()

df.describe()

	. 01.										
	Id	lat	long	dist	depth	xm	md	richte r	mw	ms	mb
C o u nt	2.400 700e +04	2400 7.000 000	2400 7.000 000	1006 2.000 000	2400 7.000 000	2400 7.000 000	2400 7.000 000	2400 7.000 000	5003 .000 000	2400 7.000 000	2400 7.000 000
M ea n	1.991 982e +13	37.92 9474	30.77 3229	3.175 015	18.49 1773	4.056 038	1.912 346	2.196 826	4.47 8973	0.677 677	1.690 561
st d	2.060 396e +11	2.205 605	6.584 596	4.715 461	23.21 8553	0.574 085	2.059 780	2.081 417	1.04 8085	1.675 708	2.146 108
m in	1.910 000e +13	29.74 0000	18.34 0000	0.100 000	0.000	3.500 000	0.000	0.000	0.00	0.000	0.000
2 5 %	1.980 000e +13	36.19 0000	26.19 5000	1.400	5.000	3.600	0.000	0.000	4.10 0000	0.000	0.000
5 0 %	2.000 000e +13	38.20 0000	28.35 0000	2.300 000	10.00 0000	3.900 000	0.000	3.500 000	4.70 0000	0.000	0.000
7 5 %	2.010 000e +13	39.36 0000	33.85 5000	3.600 000	22.40 0000	4.400 000	3.800	4.000 000	5.00 0000	0.000	4.100 000

m ax	2.020 000e +13	46.35 0000	48.00 0000	95.40 0000	225.0 0000 0	7.900 000	7.400 000	7.200 000	7.70 0000	7.900 000	7.100 000
---------	----------------------	---------------	---------------	---------------	--------------------	--------------	--------------	--------------	--------------	--------------	--------------

df.shape
output:

(24007, 17) df.head()

i d	date	tim e	lat	lo n g	co un tr y	ci ty	ar ea	directi on	dist	d e pt h	x m	m d	ri ch te r	m w	m s	m b	
0	2.00 0000 e+13	200 3.0 5.2 0	12: 17: 44 A M	3 9. 0 4	40. 38	tu rk ey	bi ng ol	baliklic ay	wes t		1 0	4 . 1	4. 1	0 . 0	N a N	0 . 0	0
1	2.01 0000 e+13	200 7.0 8.0 1	12: 03: 08 A M	4 0. 7 9	30. 09	tu rk ey	ko ca eli	bayrakt ar_izm it	wes t	0. 1	5 . 2	4 . 0	3. 8	4 . 0	N a N	0 . 0	0 . 0
2	1.98 0000 e+13	197 8.0 5.0 7	12: 41: 37 A M	3 8. 5 8	27. 61	tu rk ey	m an isa	hamza beyli	sout h_ wes t	0. 1	0 . 0	3 . 7	0. 0	0 . 0	N a N	0 . 0	3 . 7
3	2.00 0000 e+13	199 7.0 3.2 2	12: 31: 45	3 9. 4 7	36. 44	tu rk ey	si va s	kahvep inar_sa rkisla	sout h_ wes t	0. 1	1 0	3 . 5	3. 5	0 . 0	N a N	0 . 0	0

A M

```
12:
          200
                                    sa
                                                 sout
   2.00
                57:
                                         meseli
                                                                        0
                               tu
                                                                    4.
           0.0
                     0.
                         30.
                                    ka
                                                        0.
                                                   h_
4 0000
                 38
                               rk
                                        serdiv
                                                                    3
           4.0
                      8
                          24
                                                        1
                                                  wes
                                    ry
                                                               3
                                                                        0 N 0 0
   e+13
                 A
                               ey
                                             an
            2
                      0
                                                    t
                 M
```

I

df.columns

OUTPUT:

Data Preprocessing:

```
df = df.drop('id',axis=1)
import datetime
import time

timestamp = []
for d, t in zip(df['date'], df['time']):
    ts = datetime.datetime.strptime(d+' '+t, '%Y.%m.%d %I:%M:%S
%p')
    timestamp.append(time.mktime(ts.timetuple()))
timeStamp = pd.Series(timestamp)
df['Timestamp'] = timeStamp.values
final_data = df.drop(['date', 'time'], axis=1)
final_data = final_data[final_data.Timestamp != 'ValueError']
df = final_data
df.head()
```

lat	long		country	city	area dire	ection	dist	depth	X	m
0	39.04	40.38	turkey	bingol	baliklicay	west		0.1	10.0	4.
1	40.79	30.09	turkey	kocaeli	bayraktar_izmit	west		0.1	5.2	4.
2	38.58	27.61	turkey	manisa	hamzabeyli	south_we	st	0.1	0.0	3.
3	39.47	36.44	turkey	sivas	kahvepinar_sarkisl	a south_we	st	0.1	10.0	3.
4	40.80	30.24	turkey	sakarya	meseli_serdivan	south_we	st	0.1	7.0	4.

df.dtype:

```
float64
lat
           float64
long
country object object area object direction object donth
country
depth float64
           float64
хm
md
           float64
richter
mw
           float64
float64
            float64
ms
mb
             float64
          float64
Timestamp
dtype: object
# Data Encoding
label_encoder = preprocessing.LabelEncoder()
for col in df.columns:
    if df[col].dtype == 'object':
      label encoder.fit(df[col])
       df[col] = label encoder.transform(df[col])
df.dtypes
```

OUTPUT:

lat float64

```
lat
         long
                       country
                               city
                                                 direction
                                                              dist depth
                                      area
         long
                   float64
                   int64
         country
                     int64
         city
                     int64
         area
         direction
                    int64
                 float64
         dist
                   float64
         depth
         xm
                   float64
                   float64
         md
         richter
                    float64
                    float64
         mw
                    float64
         ms
         mb
                    float64
         Timestamp float64
         dtype: object
         df.isnull().sum()
         OUTPUT:
                        0
         lat
         long
                        0
         country
                        0
                        0
         city
         area
         direction
                       0
                   13945
         dist
         depth
                        0
                        0
         xm
         md
                        0
                        0
         richter
                    19004
         mw
                        0
         ms
         mb
                        0
         Timestamp
         dtype: int64
         # Imputing Missing Values with Mean
         si=SimpleImputer(missing values = np.nan, strategy="mean")
         si.fit(df[["dist", "mw"]])
         df[["dist", "mw"]] = si.transform(df[["dist", "mw"]])
         df.isnull().sum()
```

0

0

0

lat long

city

country

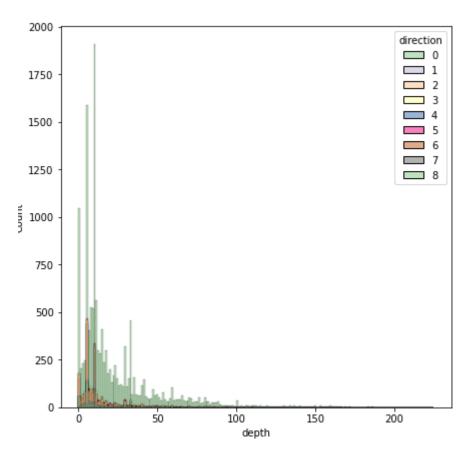
 \mathbf{xm}

```
area
direction 0
dist
          0
depth
           0
           0
xm
md
richter
mw
ms
            0
mb
Timestamp
            0
dtype: int64
```

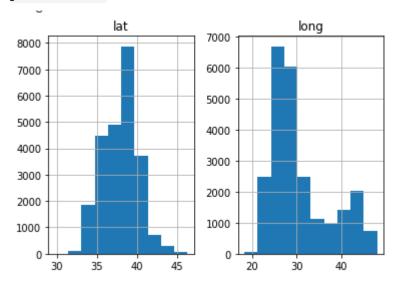
Data Visualization

```
import plotly.express as px
px.scatter(df, x='richter',y='xm', color="direction")

plt.figure(figsize=(7,7))
sns.histplot(data=df, x='depth', hue='direction',palette = 'Accent')
plt.show()
```

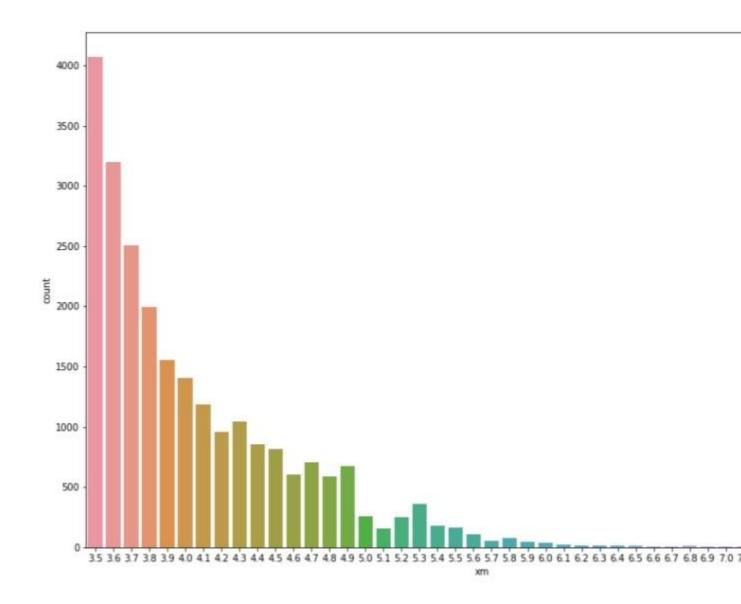


plt.figure(figsize=(7,7))
df[['lat','long']].hist()
plt.show()



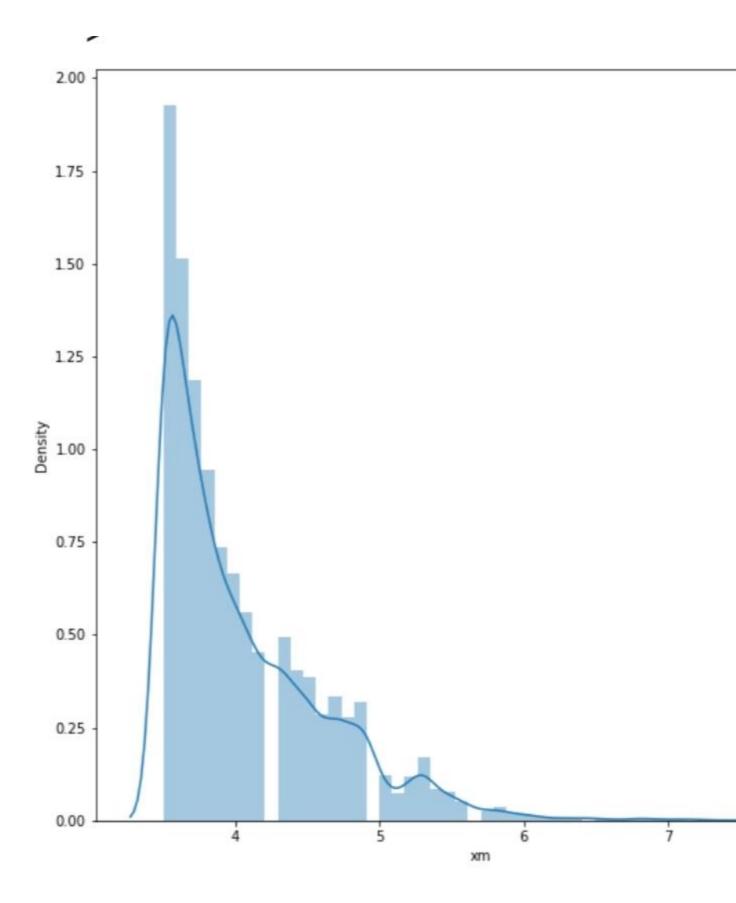
lat long country city area direction dist depth xm

plt.figure(figsize=(15,10))
sns.countplot(df.xm)
output:
<matplotlib.axes._subplots.AxesSubplot at 0x7f3d2346d400>



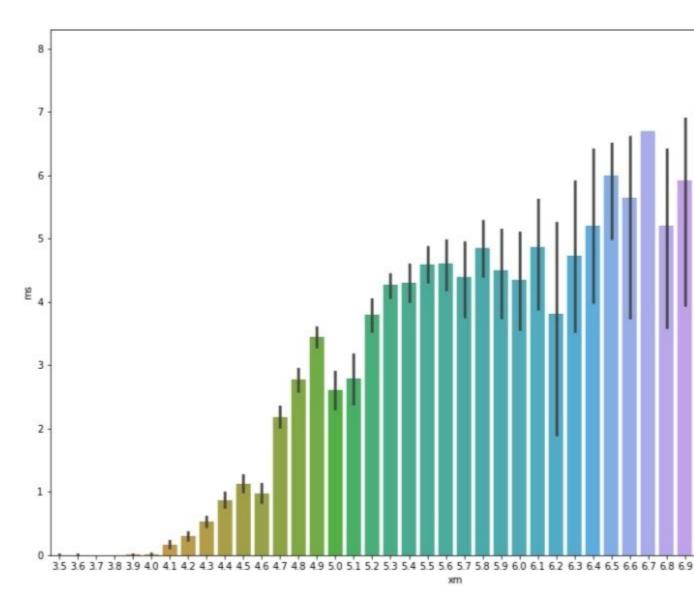
plt.figure(figsize=(10,10))
sns.distplot(df.xm)

<matplotlib.axes._subplots.AxesSubplot at 0x7f3d242a4d00>

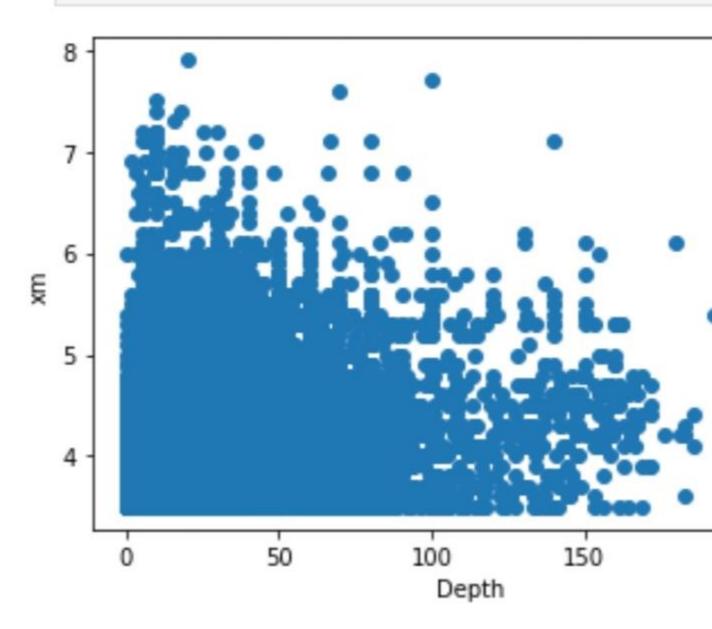


```
plt.figure(figsize=(15,10))
sns.barplot(x=df['xm'], y=df['ms'])
plt.xlabel('xm')
plt.ylabel('ms')
```

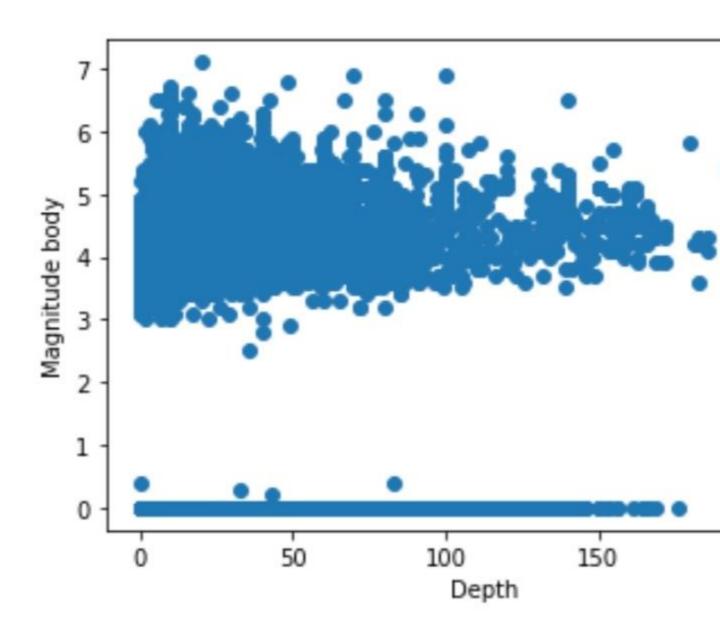
Text(0, 0.5, 'ms')



```
plt.scatter(df.depth, df.xm)
plt.xlabel("Depth")
plt.ylabel("xm")
```

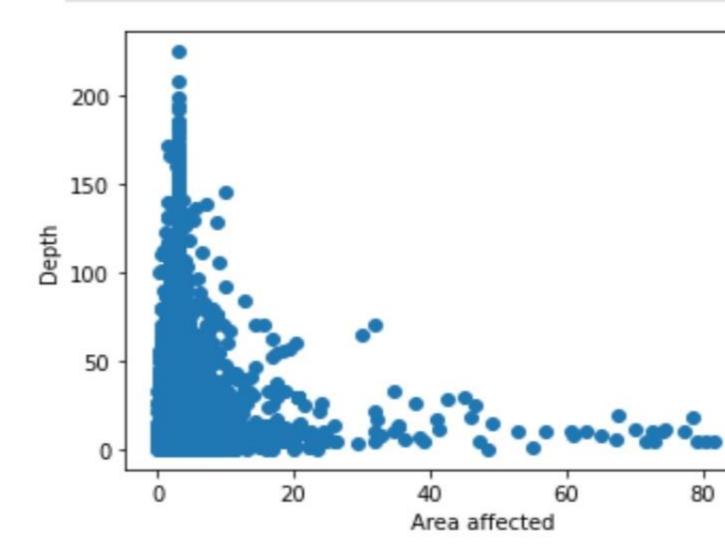


plt.scatter(df.depth, df.mb)
plt.xlabel("Depth")
plt.ylabel("Magnitude body")
plt.show()

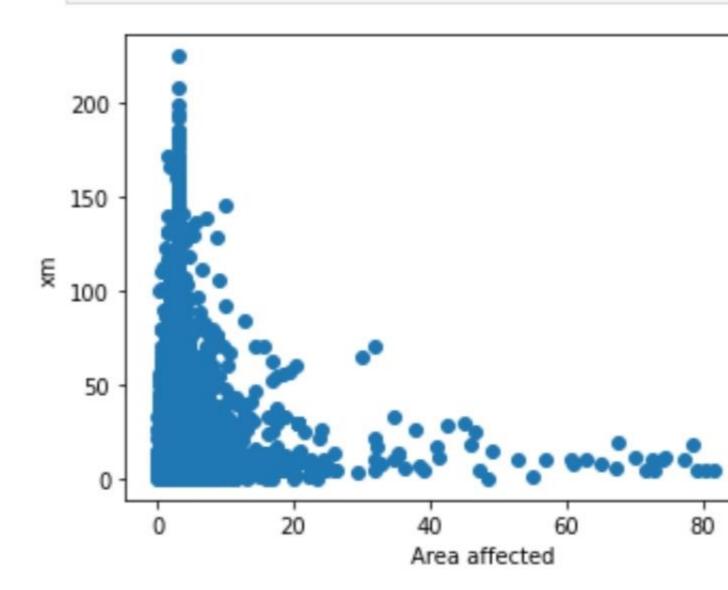


plt.scatter(df.dist, df.depth)
plt.xlabel("Area affected")
plt.ylabel("Depth")
plt.show()

htr. allow()



```
plt.scatter(df.dist, df.depth)
plt.xlabel("Area affected")
plt.ylabel("xm")
plt.show()
```



Correlation between Attributes

most_correlated = df.corr()['xm'].sort_values(ascending=False)
most_correlated

	1,000000
xm	1.000000
ms	0.699579
mb	0.628382
richter	0.426653
mw	0.420695
depth	0.302926

iat -	1	023	0.023	43	-0.21	43	0.029	-0.24	-0.01	0.051	-0.032	0.021	0.056	0.015
Buol	023	1	0.34	-0.21	-0.22	0.31	0.016	0.065	0.072	011	0.14	0.05	0.044	0.0034
country	0.023	0.34	1	-0.59	-0.52	-0.55	9.4e-16	-0.075	-0 056	0.16	0.19	0.016	-0.026	-0 081
dy.	-0.3	-0.21	-0.59	1			-0.019	017	011	-0.18	0.23	-0.0062	0.045	0.1
area	0.21	-0.22	-0.52	0.57	1	0.53	0.0017	016	013	-0.089	014	0.05	0.068	0.13
direction	03	-0.31	-0.55		053	1	0.023	019	0.088	-0.16	019	-0.025	0.022	0.08
dist -	0.029	0.016	9 4e-16	-0.019	0.0017	-0.023	1	0 012	0.0029	-0.0027	0.004	-0.0029	-0.0056	-5.7e-0
depth	-0.24	-0.065	-0.075	0.17	0.16	0.19	0 012	1	0.3	0.043	015	012	0.26	0.31
e -	-0.01	0.072	0.056	011	013	0.068	0.0029	0.3	1	0.24		0.42	0.7	0.63
pu-	0.051	011	016	-0.18	0.089	-0.16	-0.0027	0.043	024	1	0.24	0.33		-0 023
richter	-0.032	-0 14	-0 19	023	014	019	0.004	015	0.43	-0.24	1	0.09	0.42	0.24
wu	0.021	0.05	0016	-0.0062	0.05	-0.025	-0.0029	012	0.42	0.33	0.09	1	0.41	0.31
£ -	0.056	0.044	0.026	0.045	0.068	0.022	-0.0056	0.26	0.7		0.42	0.41	1	0.59
월 -	0.015	0.0034	-0.081	0.1	013	0.03	.5.7e-05	031	0.63	-0.023	0.24	031	0.59	1
Timestamp	-0.065	011	0.085	-0.042	-0.12	-0.048	0.0032	-0.2	-0.54	-0.39	-0.15	0.44	-0.68	-0.62
,	lat	long	country	city	area	direction	dist	depth	жm	md	richter	mw	ms	mb

Normalization of data:

```
# Using MinMaxScaler
scaler = preprocessing.MinMaxScaler()
d = scaler.fit_transform(df)
df = pd.DataFrame(d, columns=df.columns)
df.head()
```

l a t	lon g	cou ntr y	C it y	are a	dir ecti on	di st	de pt h	xm	md	ric hte r	mw	ms	m b	Timesta mp	a
0	0.5 599 04	0.7 430 88	0. 7 6	0.1 720 43	0.1 161 44	0. 8 7 5	0. 0	0.0 444 44	0.1 363 64	0.5 540 54	0.0 000 00	0.5 816 85	0. 0	0.00	0.8 668 75
1	0.6 652 62	0.3 961 56	0. 7 6	0.6 129 03	0.1 323 06	0. 8 7 5	0. 0	0.0 231 11	0.1 136 36	0.5 135 14	0.5 555 56	0.5 816 85	0. 0	0.00	0.9 062 52
2	0.5 322 10	0.3 125 42	0. 7 6	0.6 774 19	0.4 595 00	0. 7 5 0	0. 0	0.0 000 00	0.0 454 55	0.0 000 00	0.0 000 00	0.5 816 85	0. 0	0.52 1127	0.6 321 49
3	0.5 857 92	0.6 102 49	0. 7 6	0.8 709 68	0.5 130 61	0. 7 5 0	0. 0	0.0 444 44	0.0 000 00	0.4 729 73	0.0 000 00	0.5 816 85	0. 0	0.00 0000	0.8 091 18
4	0.6 658 64	0.4 012 14	0. 7 6	0.8 064 52	0.6 893 44	0. 7 5 0	0. 0	0.0 311 11	0.1 818 18	0.5 810 81	0.0 000 00	0.5 816 85	0. 0	0.00	0.8 375 35
Spli	tting th	e Datas	et												

```
X=np.array(df.drop('xm',axis=1))
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2
,random state=2)
```

Creating Models

1. Linear Regression

```
from sklearn.linear_model import LinearRegression
start1 = time.time()
linear=LinearRegression()
linear.fit(X_train,y_train)
ans1 = linear.predict(X_test)
end1 = time.time()
t1 = end1-start1

accuracy1=linear.score(X_test,y_test)
print("Accuracy of Linear Regression model is:",accuracy1)
```

Accuracy of Linear Regression model is: 0.63134131503029

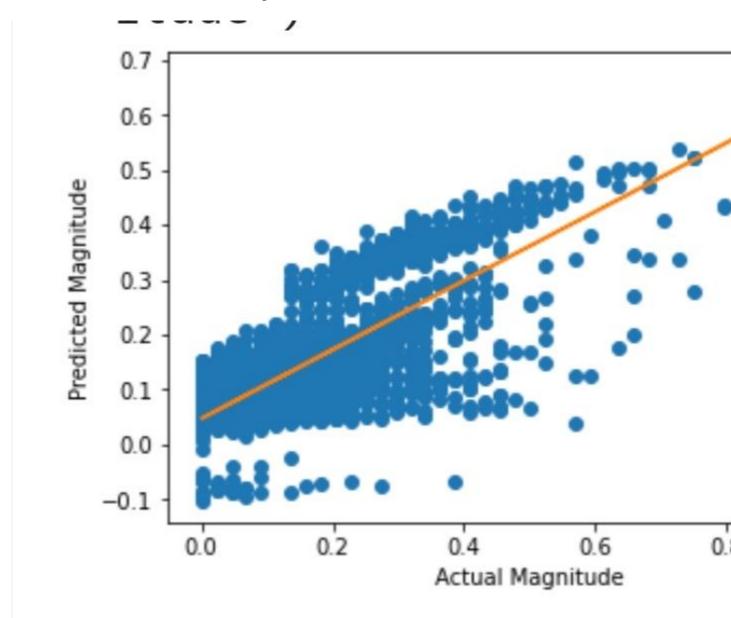
```
from sklearn import metrics
print("Linear Regression")
print('Mean Absolute Error:',
metrics.mean_absolute_error(y_test, ans1))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, ans1))
print('Root Mean Squared Error:',
np.sqrt(metrics.mean_squared_error(y_test, ans1)))
```

Linear Regression

```
Mean Absolute Error: 0.05878246463205686
Mean Squared Error: 0.00625827169726636
Root Mean Squared Error: 0.07910923901331854

plt.plot(y_test, ans1, 'o')
m, b = np.polyfit(y_test, ans1, 1)
plt.plot(y_test, m*y_test + b)
plt.xlabel("Actual Magnitude")
plt.ylabel("Predicted Magnitude")
```

Text(0, 0.5, 'Predicted Magnitude')



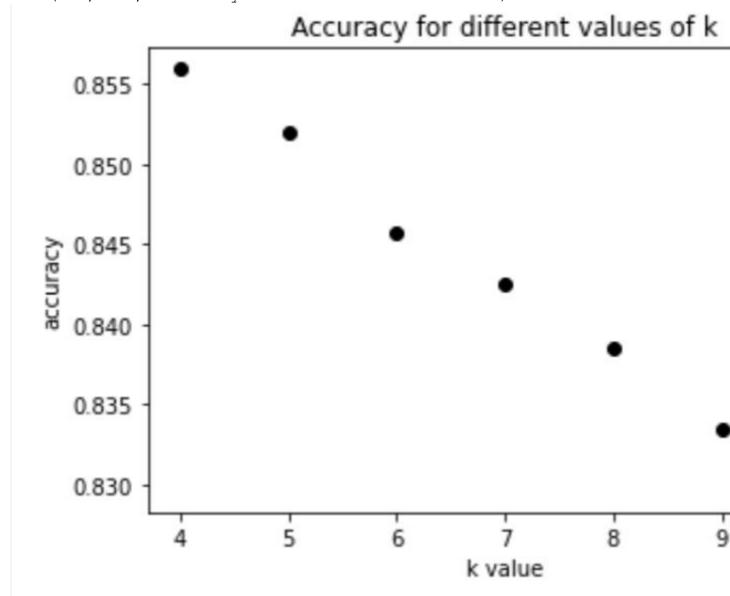
2. Decision Tree

from sklearn.tree import DecisionTreeRegressor

```
start2 = time.time()
regressor = DecisionTreeRegressor(random state = 40)
regressor.fit(X train,y train)
ans2 = regressor.predict(X test)
end2 = time.time()
t2 = end2-start2
accuracy2=regressor.score(X test,y test)
print("Accuracy of Decision Tree model is:",accuracy2)
Accuracy of Decision Tree model is: 0.9932960893884235
print("Decision Tree")
print('Mean Absolute Error:',
metrics.mean absolute error(y test, ans2))
print('Mean Squared Error:', metrics.mean squared error(y test,
ans2))
print('Root Mean Squared Error:',
np.sqrt(metrics.mean squared error(y test, ans2)))
Decision Tree
Mean Absolute Error: 0.0006909999621372331
Mean Squared Error: 0.00011380416561969702
Root Mean Squared Error: 0.010667903525046383
3.KNN Model
from sklearn.neighbors import KNeighborsRegressor
start3 = time.time()
knn = KNeighborsRegressor(n neighbors=6)
knn.fit(X train, y train)
ans3 = knn.predict(X test)
end3 = time.time()
t3 = end3-start3
accuracy3=knn.score(X test,y test)
print("Accuracy of KNN model is:",accuracy3)
Accuracy of KNN model is: 0.8457466919393031
print("KNN Model")
print('Mean Absolute Error:',
metrics.mean absolute error(y test, ans3))
print('Mean Squared Error:', metrics.mean squared error(y test,
ans3))
```

```
print('Root Mean Squared Error:',
np.sqrt(metrics.mean squared error(y test, ans3)))
KNN Model
Mean Absolute Error: 0.03305598677318794
Mean Squared Error: 0.002618571462992348
Root Mean Squared Error: 0.051171979275696854
import random
info = \{ \}
for i in range (10):
 k = random.randint(2,10)
  startk = time.time()
  knn = KNeighborsRegressor(n neighbors=k)
  knn.fit(X train, y train)
  ans3 = knn.predict(X test)
  endk = time.time()
  tk = endk-startk
  acc3=knn.score(X test,y test)
  info[k] = [acc3, tk]
for i in info:
 print("for k =",i,": accuracy =",info[i][0])
for k = 4: accuracy = 0.8559118607470738
for k = 9: accuracy = 0.8334625255508568
for k = 8: accuracy = 0.8384577534478264
for k = 6: accuracy = 0.8457466919393031
for k = 5: accuracy = 0.8519381145638621
for k = 10: accuracy = 0.8296048410841246
for k = 7: accuracy = 0.8425261199362686
x = list(info.keys())
yacc = []
for i in info:
  yacc.append(info[i][0])
plt.plot(x, yacc, 'o', color='black');
plt.xlabel("k value")
plt.ylabel("accuracy");
plt.title("Accuracy for different values of k")
```

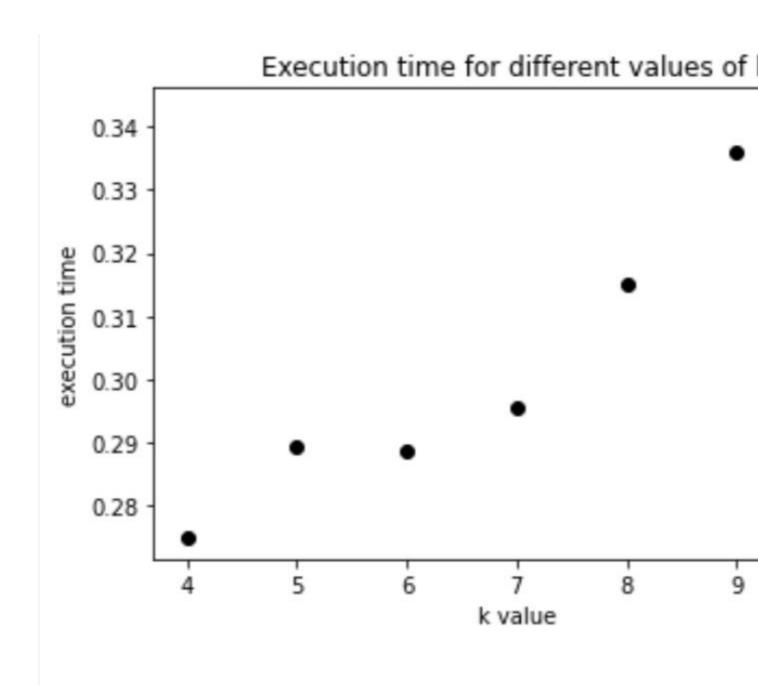
Text(0.5, 1.0, 'Accuracy for different values of k')



```
yt = []
for i in info:
   yt.append(info[i][1])
plt.plot(x, yt, 'o', color='black');
plt.xlabel("k value")
plt.ylabel("execution time");
plt.title("Execution time for different values of k")
```

output:

Text(0.5, 1.0, 'Execution time for different values of k')



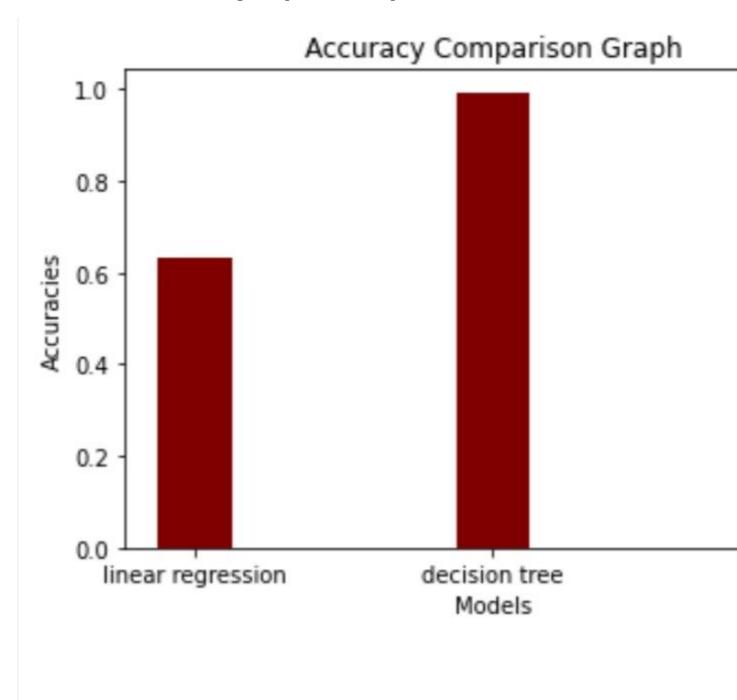
Comparison Graph:

1.Accuracy

```
models = ["linear regression","decision tree","knn"]
accuracies = [accuracy1,accuracy2,accuracy3]
plt.bar(models, accuracies, color = 'maroon', width = 0.25)
plt.xlabel("Models")
plt.ylabel("Accuracies")
plt.title("Accuracy Comparison Graph")
```

output:

Text(0.5, 1.0, 'Accuracy Comparison Graph')



2.Execution Time:

```
times = [t1,t2,t3]
plt.bar(models, times, color = 'maroon',
```

```
width = 0.25)
plt.xlabel("Models")
plt.ylabel("Execution Time")
plt.title("Execution Time Comparison Graph")
```

Text(0.5, 1.0, 'Execution Time Comparison Graph')

