Loading Libraries

In [1]:
```
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
```

Gathering Live Data

- Collecting live data from USGS.gov (United States Geological Survey)
- Using Aws services like Amazon EventBridge, Lambda to collect live-data periodically at midnight.(cron-job)
- Using S3 to store data in json format and converting it into .csv file.

In [2]:
```
# Downloading data from aws3
import boto3
s3= boto3.client('s3')
bucket_name='eq-data-csv-to-json-cron-job'
fileName = 'eq_data_csv_to_json_format.json'
fName='C:/Users/ratup/Desktop/ASP/DataSets/USGSgov/eq_json_format_data.json'
s3.download_file(Bucket=bucket_name,Key=fileName,Filename=fName)

df=pd.read_json(fName)
s=df.to_csv('all_month.csv',index=None)
```

In [3]:
```
df=pd.read_csv('all_month.csv')
```

Features in the dataset

- time ---- Time when the event occurred. Times are reported in milliseconds since the epoch.
- latitude ---- Decimals degrees latitude. Negative values for southern latitudes.
- longitutde ----Decimals degrees longitude. Negative values for western longitudes.
- depth ---- Depth of the event in kilometers.
- mag ---- Magnitude of event occurred.
- magType ---- The method or algorithm used to calculate the preferreds magnitude.
- nst ---- The total number ofseismic stations used to determine earthquake locations.
- gap ---- The largest azimuthal gap between azimuthally adjacent stations (in degrees).
- dmin ---- Horizontal distance from the epicenter to the nearest station (in degrees).
- rms ---- The root-mean-square (RMS) travel time residual, in sec, using all weights.
- net ---- The ID of data source contributor for event occured.
- id ---- A unique identifier for the event.

- types ---- A comma-seperated list of product types associated to this event.
- place ---- named geographic region near to the event.
- type ---- Type of seismic event.
- locationSource ---- The network that originally authored the reported the location of this event.
- magSource ---- Network that orginally authored the reported magnitude for this event.
- horizontalError ---- Uncertainty of reported location of the event in kilometers.
- depthError---- The depth erroe, three princcipal errora on a vertical line.
- magError ---- Uncertainty of reported magnitude of the event.
- magNst ---- The total number of seismic stations to calculate the magnitude of earthquake.
- status ---- Indicates whether the event has been reviewed by a human.

In [4]:
```
df.head()
```
Out[4]:

	time	latitude	longitude	depth	mag	magType	nst	gap	dmin	rms
0	2022-11-30T16:47:14.340Z	34.917667	-119.364667	2.48	1.33	ml	16.0	93.0	0.04567	0.24
1	2022-11-30T16:39:39.830Z	34.386833	-118.384833	11.84	1.28	ml	30.0	48.0	0.08044	0.27
2	2022-11-30T16:32:59.550Z	60.989300	-151.298300	58.20	1.20	ml	NaN	NaN	NaN	0.17
3	2022-11-30T16:03:14.977Z	63.962900	-149.859900	10.90	1.40	ml	NaN	NaN	NaN	0.86
4	2022-11-30T16:01:07.400Z	38.754501	-122.425835	6.40	2.06	md	18.0	67.0	NaN	0.09

5 rows × 22 columns

In [5]:
```
df.shape
```
Out[5]: (10159, 22)

In [6]:
```
df.describe()
```

Out[6]:

	latitude	longitude	depth	mag	nst	gap	
count	10159.000000	10159.000000	10159.000000	10157.000000	7797.000000	7797.000000	596
mean	39.055773	-116.229115	23.402517	1.697825	24.415929	113.588367	
std	20.221343	67.548727	58.941876	1.235994	23.803864	60.466778	
min	-64.241300	-179.978100	-3.740000	-1.600000	3.000000	13.000000	
25%	33.183750	-152.958550	3.150000	0.900000	9.000000	68.000000	
50%	38.814835	-122.797833	7.850000	1.490000	18.000000	99.000000	
75%	57.053100	-116.204267	16.000000	2.140000	32.000000	147.000000	
max	85.808800	179.983000	660.000000	7.300000	492.000000	352.540000	3

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10159 entries, 0 to 10158
Data columns (total 22 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   time             10159 non-null  object
 1   latitude         10159 non-null  float64
 2   longitude        10159 non-null  float64
 3   depth            10159 non-null  float64
 4   mag              10157 non-null  float64
 5   magType          10157 non-null  object
 6   nst              7797 non-null   float64
 7   gap              7797 non-null   float64
 8   dmin             5960 non-null   float64
 9   rms              10159 non-null  float64
 10  net              10159 non-null  object
 11  id               10159 non-null  object
 12  updated          10159 non-null  object
 13  place            10159 non-null  object
 14  type             10159 non-null  object
 15  horizontalError  6829 non-null   float64
 16  depthError       10159 non-null  float64
 17  magError         7457 non-null   float64
 18  magNst           7791 non-null   float64
 19  status           10159 non-null  object
 20  locationSource   10159 non-null  object
 21  magSource        10159 non-null  object
dtypes: float64(12), object(10)
memory usage: 1.7+ MB
```

Finding out the features which are list important and having many null values.So, that we can select best features for feature engineering and data wrangling.

In [8]:
```python
df.isnull().sum()
```

Out[8]:
```
time                 0
latitude             0
longitude            0
depth                0
mag                  2
magType              2
nst               2362
gap               2362
dmin              4199
rms                  0
net                  0
id                   0
updated              0
place                0
type                 0
horizontalError   3330
depthError           0
magError          2702
magNst            2368
status               0
locationSource       0
magSource            0
dtype: int64
```

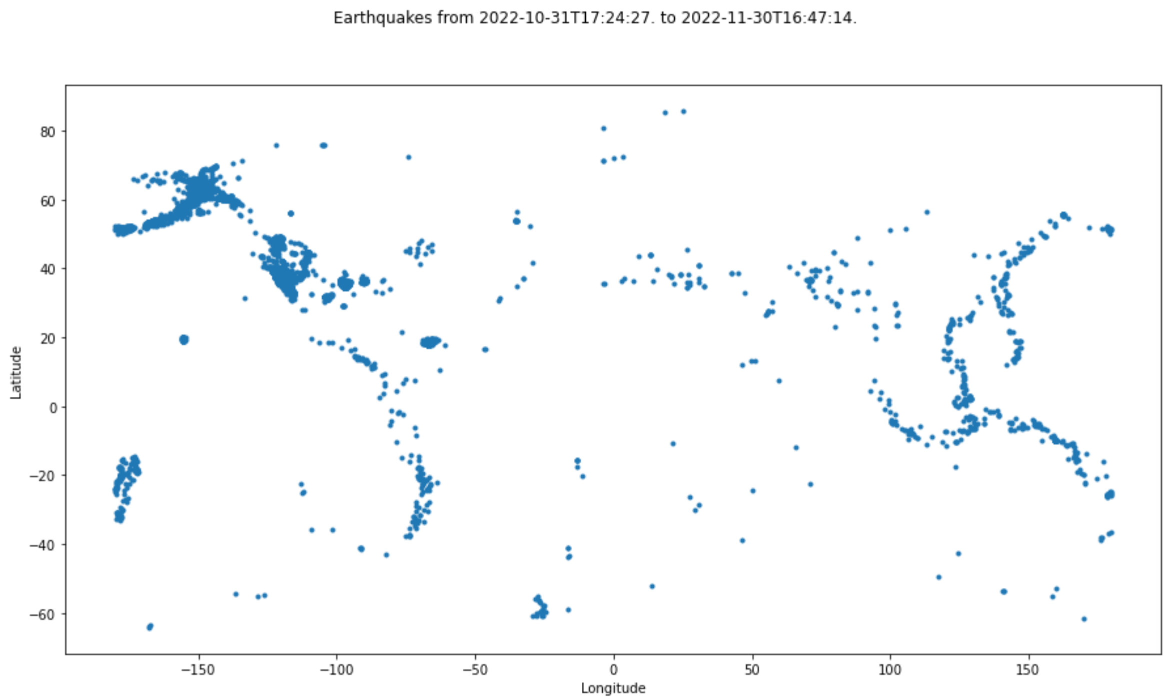
Visualize latitude and longitude features from dataframe to see where the points fall from the feature set.

In [9]:

```
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'].head(10500),rounding_factor),
         np.round(df['latitude'].head(10500),rounding_factor),
         linestyle='none', marker='.')

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



Extracting Date from time column.

In [10]:
```python
df = df.sort_values('time', ascending=True)

#Date extraction
df['date'] = df['time'].str[0:10]
df.head()
```

Out[10]:

	time	latitude	longitude	depth	mag	magType	nst	gap	dmin
10158	2022-10-31T17:24:27.320Z	34.333000	-116.840167	-1.41	1.16	ml	11.0	88.0	0.0183
10157	2022-10-31T17:25:47.194Z	61.112300	-141.225800	10.80	1.10	ml	NaN	NaN	NaN
10156	2022-10-31T17:27:36.010Z	19.240667	-155.408173	29.49	2.32	ml	13.0	135.0	NaN
10155	2022-10-31T17:31:39.790Z	19.458500	-155.597000	-1.38	1.94	ml	13.0	75.0	NaN
10154	2022-10-31T17:34:29.645Z	61.139900	-151.779100	78.90	1.70	ml	NaN	NaN	NaN

5 rows × 23 columns

Data cleaning for seperating 'place' column.Hence only consider city by seperating string by ','.

In [11]:
```python
# only keep the columns needed
df = df[['date','time' ,'latitude', 'longitude', 'depth', 'mag', 'place']]
# df['date'] = df['time'].str.split(', ', expand=True)
newdf = df['place'].str.split(', ', expand=True)
```

In [12]:
```python
newdf.head()
```

Out[12]:

	0	1	2
10158	8km N of Big Bear City	CA	None
10157	97 km ESE of McCarthy	Alaska	None
10156	Island of Hawaii	Hawaii	None
10155	28 km E of Honaunau-Napoopoo	Hawaii	None
10154	35 km WNW of Tyonek	Alaska	None

In [13]:
```python
df['place'] = newdf[1]
df = df[['date','latitude', 'longitude', 'depth', 'mag', 'place']]
```

In [14]:
```python
df.head()
```

Out[14]:

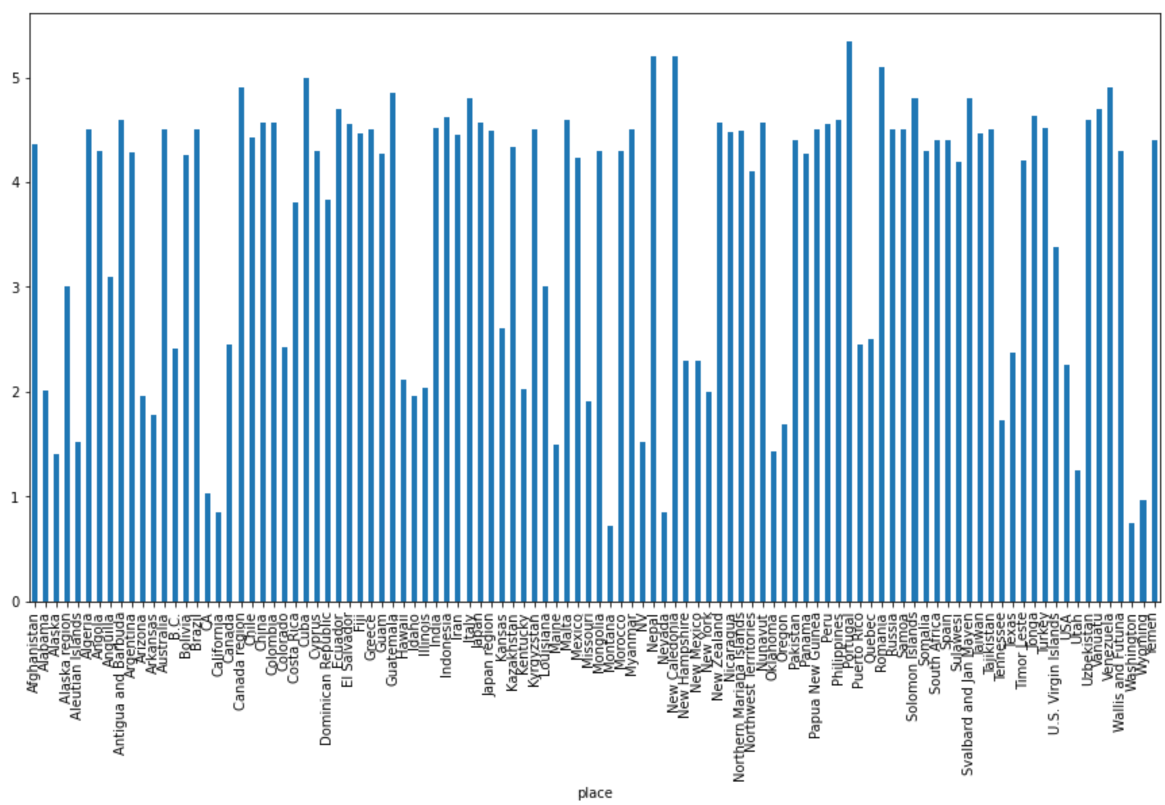
	date	latitude	longitude	depth	mag	place
10158	2022-10-31	34.333000	-116.840167	-1.41	1.16	CA
10157	2022-10-31	61.112300	-141.225800	10.80	1.10	Alaska
10156	2022-10-31	19.240667	-155.408173	29.49	2.32	Hawaii
10155	2022-10-31	19.458500	-155.597000	-1.38	1.94	Hawaii
10154	2022-10-31	61.139900	-151.779100	78.90	1.70	Alaska

In [15]:
```python
print('total locations:',len(set(df['place'])))
```

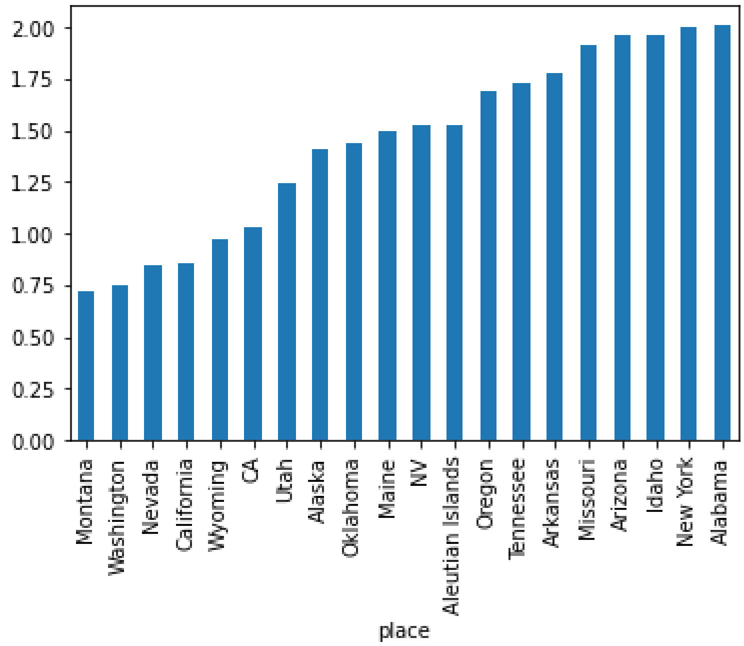
```
total locations: 105
```

Bar plot of mean magnitude vs place, as we can see from the graph, only few countries are considered as epicenter of dangerous since they have magnitude more than 2.8

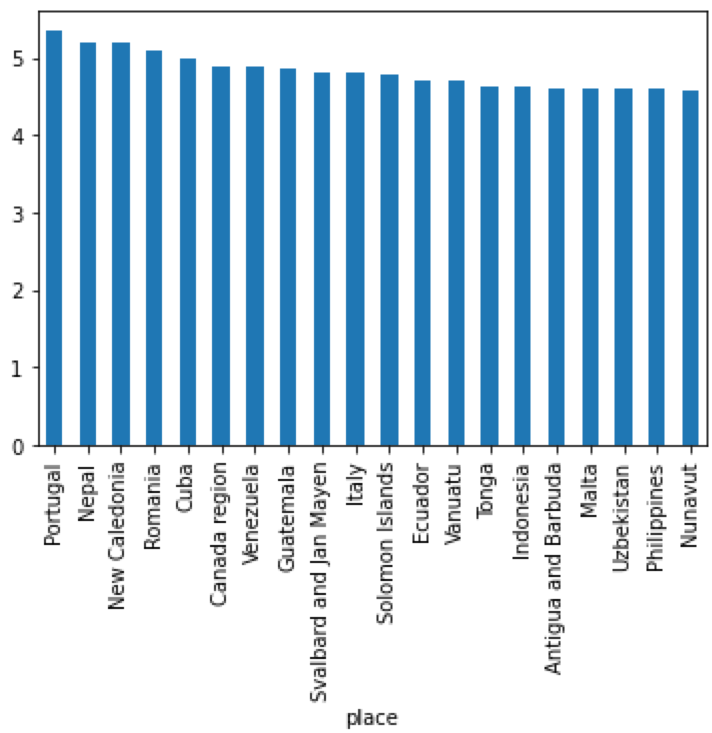
In [16]:
```python
df.groupby(['place'])['mag'].mean().plot(kind='bar',figsize=(15,8));
```



In [17]:
```
df.groupby(['place'])['mag'].mean().nsmallest(20).plot(kind='bar');
```



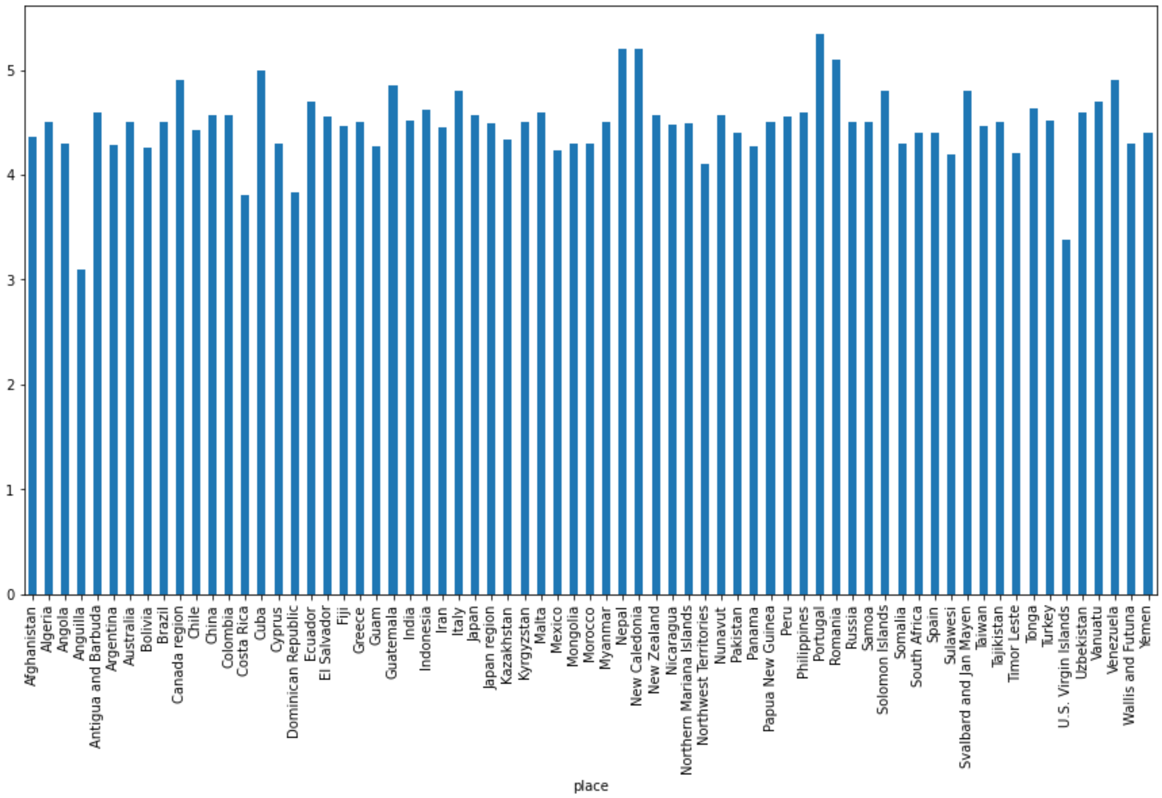
In [18]:
```
df.groupby(['place'])['mag'].mean().nlargest(20).plot(kind='bar');
```



Lets consider 3 as threshold for how high the earthquake has hit and lets visualize countries with more than 3 magnitude.

In [19]:
```
more_dangerous_places=df.groupby('place')['mag'].mean()
more_dangerous_places=more_dangerous_places[more_dangerous_places>3]
```

In [20]:
```
more_dangerous_places.plot(kind='bar',figsize= (15,8));
```



In [21]:
```
# calculate mean latitude and longitude for simplified locations

df_coords = df[['place','latitude', 'longitude']]
df_coords = df_coords.groupby(['place'], as_index=False).mean()
df_coords = df_coords[['place','latitude', 'longitude']]
```

In [22]:
```
df_coords.head()
```

Out[22]:

	place	latitude	longitude
0	Afghanistan	36.466317	70.820667
1	Alabama	33.201333	-86.110000
2	Alaska	59.194554	-155.376073
3	Alaska region	56.574000	-169.537500
4	Aleutian Islands	51.944034	-137.438036

Merge the two dataframes of mean latitude and longitude locations calculated above with dataframe only considering ['date','depth','mag','place'] as columns out of total features

In [23]:
```
df = df[['date','depth', 'mag', 'place']]
df = pd.merge(left=df, right=df_coords, how='inner', on=['place'])
df.head()

print('total locations:',len(set(df['place'])))
```

```
total locations: 104
```

In [24]:
```
print(set(df['place']))
```

```
{'Svalbard and Jan Mayen', 'Australia', 'Kyrgyzstan', 'California', 'Tong
a', 'Alaska', 'Kentucky', 'Montana', 'Guatemala', 'Aleutian Islands', 'Ango
la', 'Myanmar', 'Sulawesi', 'Washington', 'Canada region', 'New Hampshire',
'Alabama', 'Greece', 'Puerto Rico', 'New Zealand', 'Afghanistan', 'Missour
i', 'Northwest Territories', 'USA', 'Nicaragua', 'NV', 'Spain', 'Japan', 'I
daho', 'Iran', 'New York', 'Guam', 'Russia', 'Indonesia', 'Northern Mariana
Islands', 'Alaska region', 'B.C.', 'Italy', 'Ecuador', 'Algeria', 'Louisian
a', 'Chile', 'Tennessee', 'Malta', 'Brazil', 'South Africa', 'China', 'Paki
stan', 'Philippines', 'Argentina', 'Wallis and Futuna', 'New Caledonia', 'N
epal', 'Nevada', 'Kazakhstan', 'Cyprus', 'Antigua and Barbuda', 'CA', 'Queb
ec', 'Fiji', 'Japan region', 'Nunavut', 'Anguilla', 'Panama', 'Timor Lest
e', 'Morocco', 'Papua New Guinea', 'Canada', 'Dominican Republic', 'El Salv
ador', 'Portugal', 'Oregon', 'Uzbekistan', 'India', 'Samoa', 'Illinois', 'C
olorado', 'Bolivia', 'Venezuela', 'Taiwan', 'Cuba', 'Somalia', 'Kansas', 'V
anuatu', 'Yemen', 'Arizona', 'Peru', 'Turkey', 'Tajikistan', 'Maine', 'Texa
s', 'New Mexico', 'Arkansas', 'Mexico', 'Colombia', 'Utah', 'Solomon Island
s', 'Mongolia', 'Oklahoma', 'Hawaii', 'Wyoming', 'Romania', 'U.S. Virgin Is
lands', 'Costa Rica'}
```

In [25]:
```
df.head()
```

Out[25]:

	date	depth	mag	place	latitude	longitude
0	2022-10-31	-1.41	1.16	CA	36.644073	-120.132241
1	2022-10-31	7.96	1.57	CA	36.644073	-120.132241
2	2022-10-31	0.93	0.35	CA	36.644073	-120.132241
3	2022-10-31	4.90	1.32	CA	36.644073	-120.132241
4	2022-10-31	5.07	1.81	CA	36.644073	-120.132241

Feature Engineering and Data Wrangling

- Set rolling window size for future prediction based on past values with fixed window size in past.
- I have created 6 new features based on rolling window size on average depth and average magnitude.
- A final outcome 'mag_outcome' has been defined as target values and the output is considered as shifted values from set rolling window of past days e.g:'7'

In [26]:

```
eq_tmp = df.copy()

#rolling window size
DAYS_OUT_TO_PREDICT = 7

# loop through each zone and apply MA
eq_data = []
eq_data_last_days_out = []

for place in list(set(eq_tmp['place'])):
    temp_df = eq_tmp[eq_tmp['place'] == place].copy()

    #avg. depth of 22 days rolling period and so on..
    temp_df['depth_avg_22'] = temp_df['depth'].rolling(window=22,center=False
    temp_df['depth_avg_15'] = temp_df['depth'].rolling(window=15,center=False
    temp_df['depth_avg_7'] = temp_df['depth'].rolling(window=7,center=False).
    temp_df['mag_avg_22'] = temp_df['mag'].rolling(window=22,center=False).me
    temp_df['mag_avg_15'] = temp_df['mag'].rolling(window=15,center=False).me
    temp_df['mag_avg_7'] = temp_df['mag'].rolling(window=7,center=False).mear
    temp_df.loc[:, 'mag_outcome'] = temp_df.loc[:, 'mag_avg_7'].shift(DAYS_OU

    #days to predict value on earth quake data this is not yet seen or witnes

    eq_data_last_days_out.append(temp_df.tail(DAYS_OUT_TO_PREDICT))

    eq_data.append(temp_df)
```

In [27]:

```
# concat all location-based dataframes into master dataframe
eq_all = pd.concat(eq_data)
```

In [28]:

```
eq_all.head()
```

Out[28]:

	date	depth	mag	place	latitude	longitude	depth_avg_22	depth_avg_15	dep
9303	2022-11-23	10.000	4.7	Svalbard and Jan Mayen	71.41270	-3.69830	NaN	NaN	
9304	2022-11-24	10.964	4.9	Svalbard and Jan Mayen	71.41270	-3.69830	NaN	NaN	
9298	2022-11-21	10.000	4.5	Australia	-17.69460	123.41210	NaN	NaN	
9291	2022-11-18	43.700	4.4	Kyrgyzstan	39.53325	72.94525	NaN	NaN	
9292	2022-11-21	8.684	4.6	Kyrgyzstan	39.53325	72.94525	NaN	NaN	

In [29]:

```
# remove any NaN fields
eq_all = eq_all[np.isfinite(eq_all['depth_avg_22'])]
eq_all = eq_all[np.isfinite(eq_all['mag_avg_22'])]
eq_all = eq_all[np.isfinite(eq_all['mag_outcome'])]
```

In [30]:

```
eq_all.head()
```

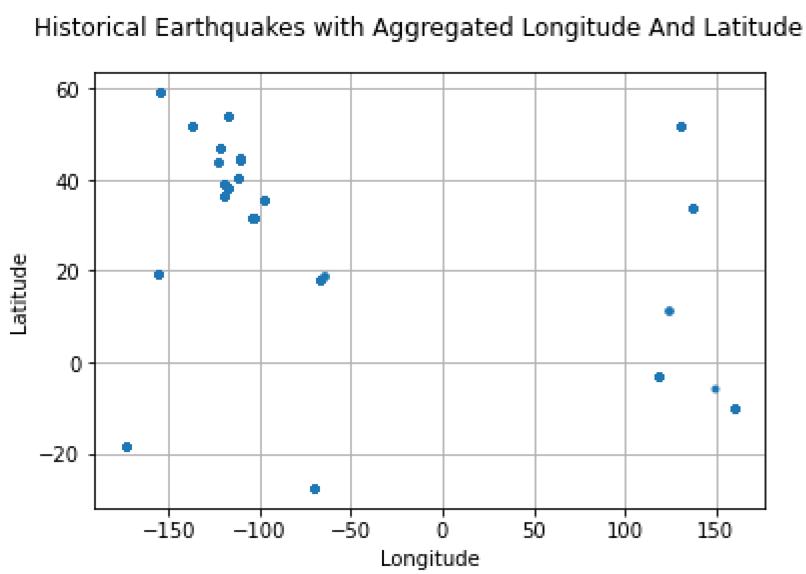
Out[30]:

	date	depth	mag	place	latitude	longitude	depth_avg_22	depth_avg_15	dept
7569	2022-11-06	7.2	0.8	California	39.251735	-119.621585	5.845455	6.946667	
7570	2022-11-08	12.1	1.7	California	39.251735	-119.621585	6.345455	7.206667	
7571	2022-11-08	4.9	0.8	California	39.251735	-119.621585	6.477273	7.533333	
7572	2022-11-08	6.1	0.7	California	39.251735	-119.621585	6.531818	7.940000	
7573	2022-11-08	4.3	0.3	California	39.251735	-119.621585	6.650000	8.173333	

Location after feature engineering

In [31]:

```
plt.plot(eq_all['longitude'],
         eq_all['latitude'],
         linestyle='none', marker='.')
plt.suptitle('Historical Earthquakes with Aggregated Longitude And Latitude')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.grid()
plt.show()
```



In [32]:
```
# keep our live data for predictions
eq_data_last_days_out = pd.concat(eq_data_last_days_out)


eq_data_last_days_out = eq_data_last_days_out[np.isfinite(eq_data_last_days_c
predict_unknown=eq_data_last_days_out
```

In [33]:
```
# here 'mag_outcome' has NaN because these are future outcome event to be pre
predict_unknown
```

Out[33]:

	date	depth	mag	place	latitude	longitude	depth_avg_22	depth_avg_15	dept
7649	2022-11-26	4.00	2.60	California	39.251735	-119.621585	7.500000	6.780000	
7650	2022-11-26	11.30	0.50	California	39.251735	-119.621585	7.731818	6.993333	
7651	2022-11-28	3.10	0.80	California	39.251735	-119.621585	7.077273	6.666667	
7652	2022-11-28	4.80	0.80	California	39.251735	-119.621585	6.931818	6.573333	
7653	2022-11-29	10.00	2.50	California	39.251735	-119.621585	6.954545	7.240000	
...	...	...	...	...	...	...	...	...	
8647	2022-11-27	5.13	3.18	U.S. Virgin Islands	19.030958	-64.815751	25.012727	20.194667	1
8648	2022-11-29	20.24	3.14	U.S. Virgin Islands	19.030958	-64.815751	25.071818	20.877333	1
8649	2022-11-29	38.61	2.85	U.S. Virgin Islands	19.030958	-64.815751	26.691364	21.302667	1
8650	2022-11-30	10.27	3.12	U.S. Virgin Islands	19.030958	-64.815751	25.930909	20.387333	1
8651	2022-11-30	7.00	3.60	U.S. Virgin Islands	19.030958	-64.815751	22.612727	18.320667	1

183 rows × 13 columns

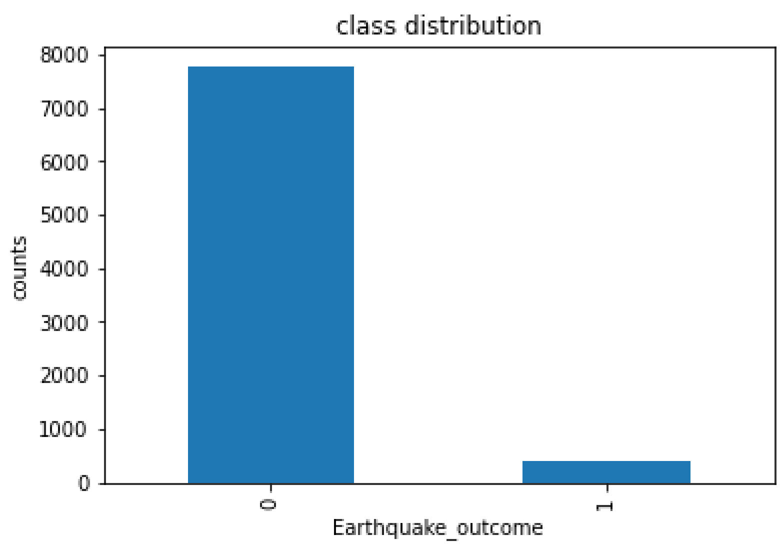
Considered magnitude above 2.5 as dangerous hence prediction outcome as '1'else '0'

In [34]:
```
eq_all['mag_outcome'] = np.where(eq_all['mag_outcome'] > 2.5, 1,0)
print(eq_all['mag_outcome'].describe())
eq_all['mag_outcome'].value_counts()
```

```
count    8149.000000
mean        0.047736
std         0.213220
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         1.000000
Name: mag_outcome, dtype: float64
```

Out[34]:
```
0    7760
1     389
Name: mag_outcome, dtype: int64
```

In [35]:
```
eq_all['mag_outcome'].value_counts().plot(kind='bar',)
plt.xlabel('Earthquake_outcome')
plt.ylabel('counts')
plt.title('class distribution');
```



Save the data of fixed rolling window and live unknown prediction data in sql database using sql engine

In [36]:
```
from sqlalchemy import create_engine
engine = create_engine('sqlite:///Earthquakedata.db')
eq_all.to_sql('Earthquake_features', engine, index=False,if_exists='replace')
```

In [37]:
```
engine = create_engine('sqlite:///Earthquakedata_predict.db')
predict_unknown.to_sql('Earthquake_predict', engine, index=False,if_exists='r
```