Earthquake

September 11, 2019

1 Analysis of Earthquake Frequency

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1.1 Abstract

This project will demonstrate the effectiveness of common statistical distributions at modeling random natural phenomena.

1.2 The exponential distribution

Marginal Distribution:

$$e^{-\lambda x} \tag{1}$$

Cumulative Distribution:

$$\int Marginal\ Dist = 1 - e^{-\lambda x} \tag{2}$$

[1]:
```
def exp_marginal_density(x, lamb): # The derivative of CDF
    return lamb * np.exp(-lamb * x)

def exp_cumulative_density(x, lamb): # The integral of MDF
    return 1 - np.exp(-lamb * x)
```

The exponential distribution models the time **between** events, but it can be transformed to model the **number of events** in each timestep.

1.3 The Poisson Distribution

[2]:
```
def pois_marginal_density(k,lamb):
    a = lamb**k
    b = np.exp(-lamb)
    c = gamma(k+1)
    return (a * b) / c

def pois_cumulative_density(k,lamb):
    s = 0
    for x in range(k):
```

```
        s += np.exp(-lamb)*(lamb**x)/gamma(k+1)
    return s
```

1.4 About the data

The dataset is available on Kaggle

The filtered set contains 23228 earthquakes from all over the world reported between 1965 and 2016. This set only contains significant earthquakes with a magnitude >5.5. There are **thousands** of small, unnoticable earthquakes every day that are not contained in this set.

Magnitude	Effects	Estimated Number Each Year
<2.5	Usually not felt, only recorded by seismograph.	900,000
2.5-5.4	Often felt, but only minor damage	30,000
5.5-6.0	Slight damage to buildings	500
6.1-6.9	May cause lots of damage in populated areas	100
7.0-7.9	Serious Damage	20
>8.0	Can totally destroy communities	1 every 5-10 years

(Source, geo.mtu.edu)

[3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.optimize import curve_fit
from scipy.special import gamma

from pandas.plotting import register_matplotlib_converters
register_matplotlib_converters()
```

1.5 Reading and processing the data

[4]:
```
Fields = ['Date','Time','Latitude','Longitude','Type','Magnitude','Source'] #␣
 ↪Only import used columns
df = pd.read_csv('database.csv', usecols=Fields)
```

[5]:
```
# Cleaning
df = df[df.Date.str.len() < 15] # Removes 3 rows with malformed dates
df = df[df.Type.isin(['Earthquake'])] # removes nuclear explosions and rock␣
 ↪bursts
```

[6]:
```
# Calculations
df['Datetime'] = pd.to_datetime(df.Date +' '+ df.Time) #convert strings to␣
 ↪datetime object
```

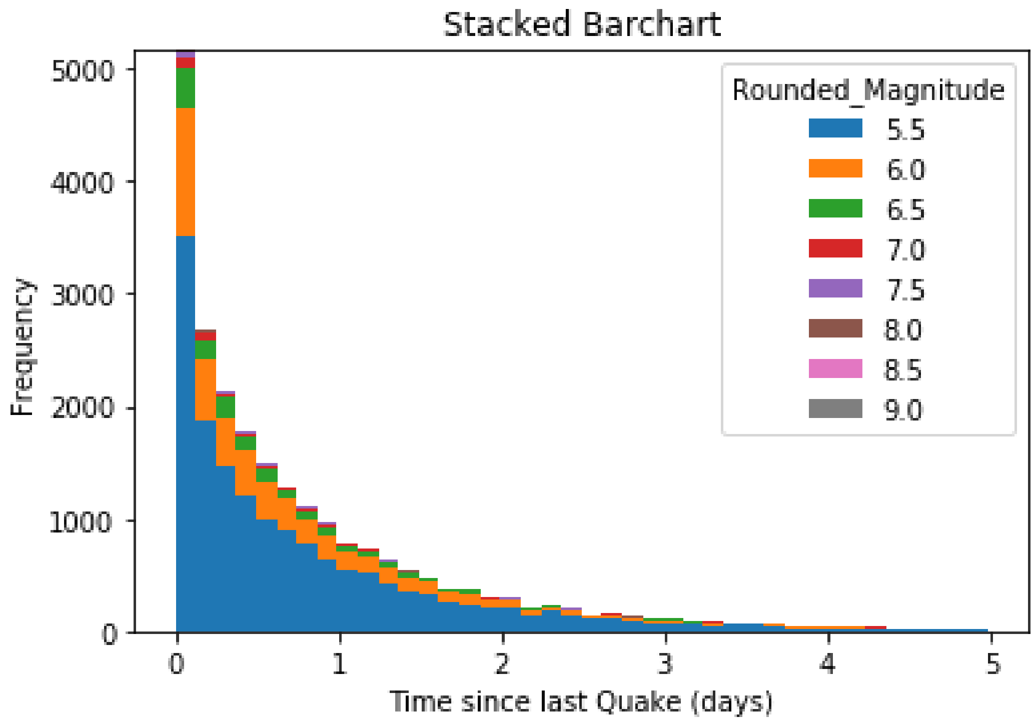
```
df['Year'] = df['Datetime'].map(lambda x: x.year) #get year of datetime object␣
↪for plotting

#for grouping magnitudes
df['Rounded_Magnitude'] = np.floor(df.Magnitude * 2) / 2 #scaling rounds to the␣
↪nearest half instad of whole number.

df['Last_Quake'] = df.Datetime.diff() #get frequency data
df = df[df['Last_Quake'].notna()]
df['Last_Quake_days'] = df['Last_Quake'].map(lambda x: x.total_seconds()/
↪(24*60*60)) # Convert to days

df.reset_index(drop=True, inplace=True)
```

[7]:
```
df.head()
```

[7]:
```
         Date      Time  Latitude  Longitude        Type  Magnitude  Source  \
0  01/04/1965  11:29:49     1.863    127.352  Earthquake        5.8  ISCGEM
1  01/05/1965  18:05:58   -20.579   -173.972  Earthquake        6.2  ISCGEM
2  01/08/1965  18:49:43   -59.076    -23.557  Earthquake        5.8  ISCGEM
3  01/09/1965  13:32:50    11.938    126.427  Earthquake        5.8  ISCGEM
4  01/10/1965  13:36:32   -13.405    166.629  Earthquake        6.7  ISCGEM

             Datetime  Year  Rounded_Magnitude      Last_Quake  \
0 1965-01-04 11:29:49  1965                5.5 1 days 21:45:31
1 1965-01-05 18:05:58  1965                6.0 1 days 06:36:09
2 1965-01-08 18:49:43  1965                5.5 3 days 00:43:45
3 1965-01-09 13:32:50  1965                5.5 0 days 18:43:07
4 1965-01-10 13:36:32  1965                6.5 1 days 00:03:42

   Last_Quake_days
0         1.906609
1         1.275104
2         3.030382
3         0.779942
4         1.002569
```

1.6 Fitting the data to the statistical Model

[8]:
```
(df[df.Last_Quake_days < 5].
↪pivot(columns='Rounded_Magnitude')['Last_Quake_days']).plot(kind = 'hist',␣
↪stacked=True,bins=40)
plt.title('Stacked Barchart')
plt.xlabel('Time since last Quake (days)')
plt.show()
```

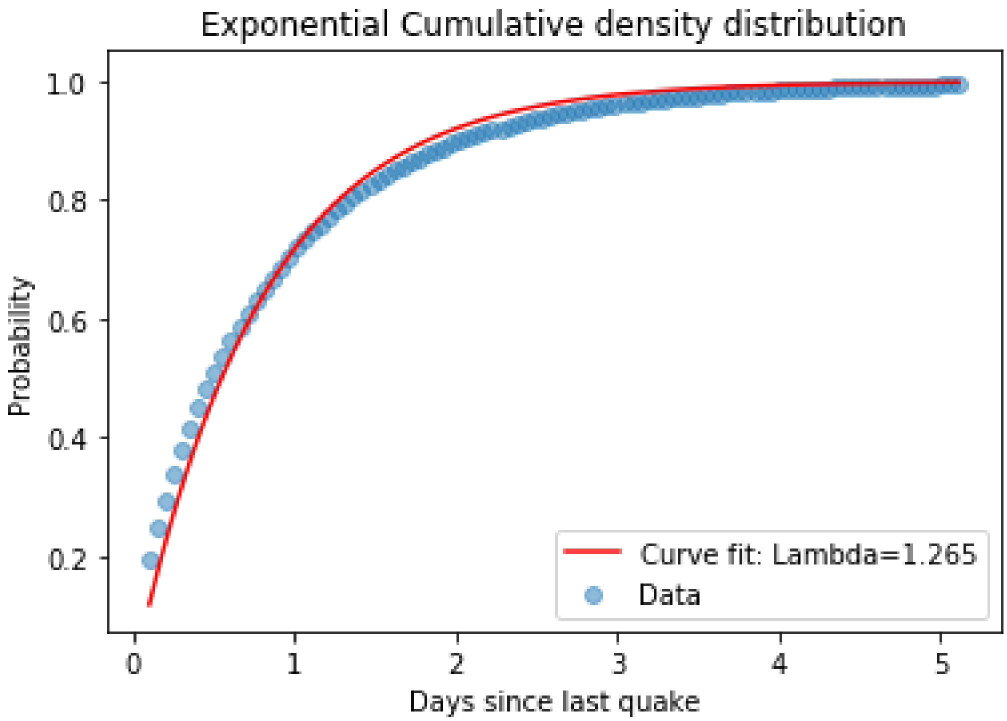


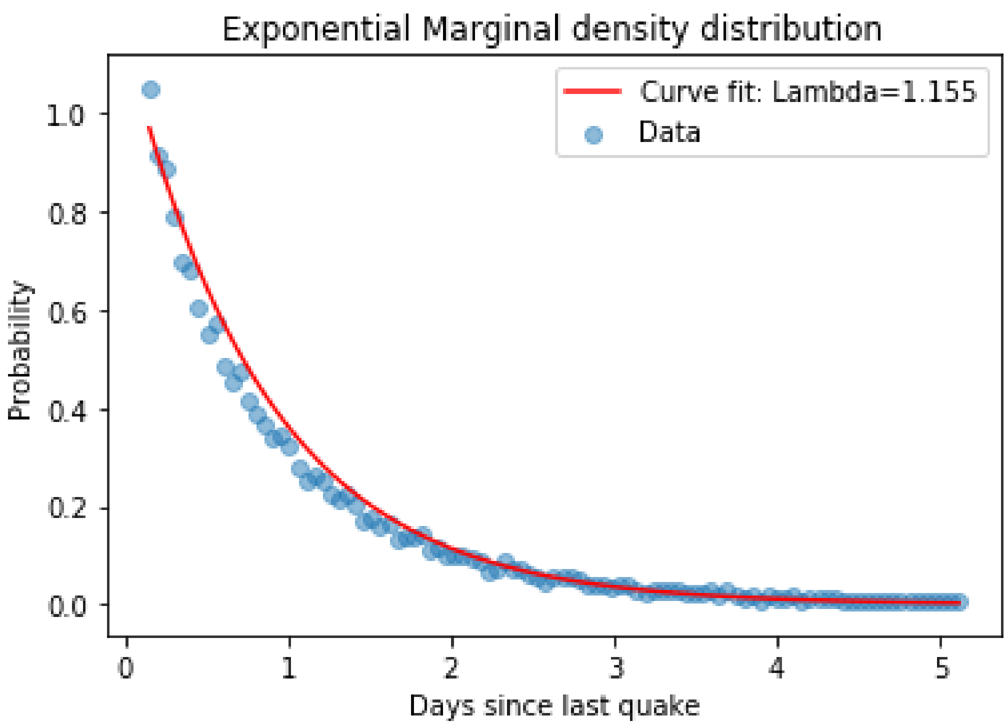
1.7 Global Exponential Model

[9]:

```
density = 100 # Plot resolution
lamb = []
# This is okay becuase data is so dense. When data is more sparce, other␣
↪methods must be used.

# Cumulative Distribution
max_x = df.Last_Quake_days.max()
x = np.linspace(0.1,.5*max_x,density) # x does not include 0 to avoid skewing␣
↪data during derivative
y = np.zeros(density)
for i in range(density):
    y[i] = len(df[df.Last_Quake_days < x[i]]) / len(df) # Count earthquakes␣
↪less than tolerance, divide by size of list to get probability
# Plot data
plt.scatter(x,y, alpha=0.5, label='Data')
# Fit curve
popt, pcov = curve_fit(exp_cumulative_density, x, y)
plt.plot(x, exp_cumulative_density(x, *popt), 'r-',label='Curve fit: Lambda=%5.
↪3f' % tuple(popt)) # Plot fit curve
lamb.append(popt)
```

```
plt.title('Exponential Cumulative density distribution')
plt.xlabel('Days since last quake')
plt.ylabel('Probability')
plt.legend()

#Marginal Distribution
plt.figure() # New plot
dx = np.diff(x)
dy = np.diff(y)
new_x = x[1:] # becuase np.diff()

plt.scatter(new_x,dy/dx, alpha=0.5, label='Data') # Plot data

popt, pcov = curve_fit(exp_marginal_density, new_x, dy/dx) # Fit curve
plt.plot(new_x, exp_marginal_density(new_x, *popt), 'r-',label='Curve fit:␣
↪Lambda=%5.3f' % tuple(popt)) # Plot fit curve
lamb.append(popt)

plt.title('Exponential Marginal density distribution')
plt.xlabel('Days since last quake')
plt.ylabel('Probability')
plt.legend()

plt.show()

global_lamb = np.mean(lamb)
print('lambda (avg): ' + str(global_lamb))
```


Exponential Cumulative density distribution
1.0
0.8
0.6
0.4
0.2
Probability
Curve fit: Lambda=1.265
Data
0
1
2
3
4
5
Days since last quake


Exponential Marginal density distribution
1.0
0.8
0.6
0.4
0.2
0.0
Probability
Curve fit: Lambda=1.155
Data
0
1
2
3
4
5
Days since last quake

```
lambda (avg): 1.209864762554936
```

1.7.1 Mean and Variance

The exponential distribution has the propterty,

$$mean = \frac{1}{\lambda} \tag{3}$$

$$variance = \frac{1}{\lambda} \tag{4}$$

Using $\lambda = avg(1.265, 1.155) = 1.210$, **on average** earthquakes occour every 0.826 days. This closely agreees with the calculated mean of the dataset with small error.

[10]:
```
mean = df.Last_Quake_days.mean()
error = abs(mean - (1/global_lamb))/ mean
print('mean: %3.3f, error %3.3f' % (mean,error))
```

```
mean: 0.818, error 0.011
```

1.7.2 Probability of a week without a strong earthquake

[11]:
```
print('P(Days >= 7) = %3.3f percent' %((1 -␣
↪exp_cumulative_density(7,global_lamb))*100))
```

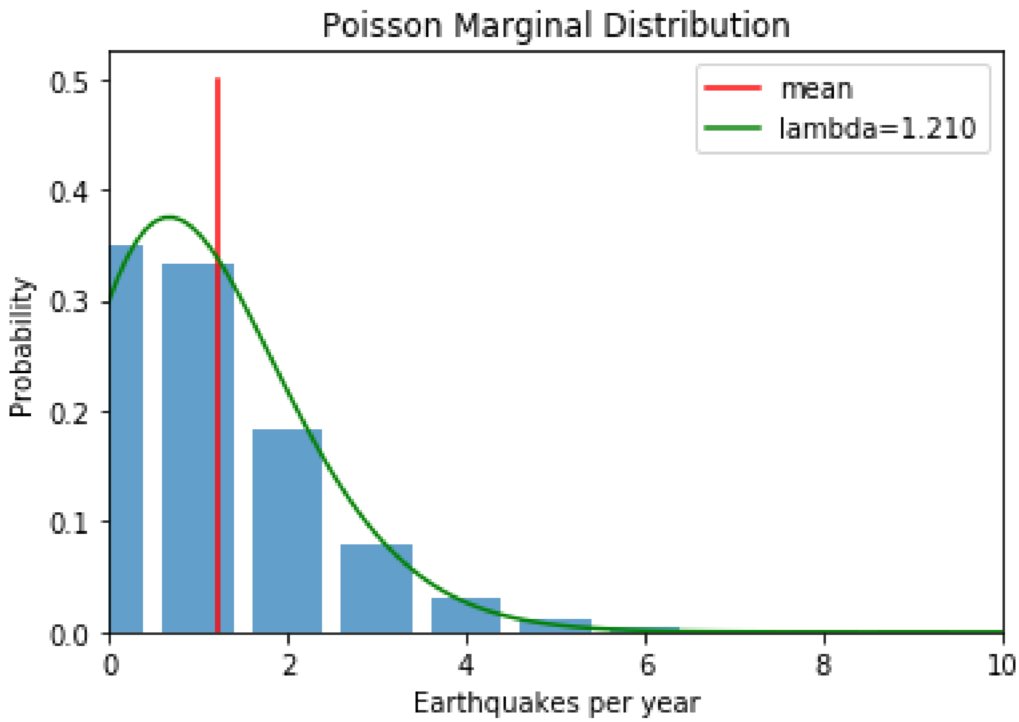
```
P(Days >= 7) = 0.021 percent
```

1.8 The Poisson Distribution

Using the lambda from the exponential distribution fitting, the Poisson distribution can be easily calcualted.

[12]:
```
max_x = df['Last_Quake_days'].max()
x = np.linspace(0,max_x,density)

plt.plot([global_lamb,global_lamb],[0,.5], label='mean',c='r') # Mark mean
plt.plot(x,pois_marginal_density(x,global_lamb),label = 'lambda=%3.
↪3f'%(global_lamb), c='g')

plt.title('Poisson Marginal Distribution')
plt.xlabel('Earthquakes per year')
plt.ylabel('Probability')
plt.legend()

counts = df.Date.groupby(df.Date).count().value_counts()
total_days = int((df.Datetime.max()-df.Datetime.min())/np.timedelta64(1,'D'))
days_w_no_quake = total_days - df.Date.nunique()
counts[0] = days_w_no_quake
plt.bar(counts.index, counts/total_days, alpha=0.7)
```

```
plt.xlim(0,10)
plt.show()
```



The Poisson distribution has the propterty,

$$mean = \lambda \tag{5}$$
$$variance = \lambda \tag{6}$$

So, **on average** earth will have 1.210 eathquakes **per day**.

1.8.1 Probability of 1 or more quakes in a day

```
[13]: print('P(Quake > 1) = %3.3f percent' %((1 -
      ↪pois_cumulative_density(1,global_lamb))*100))
```

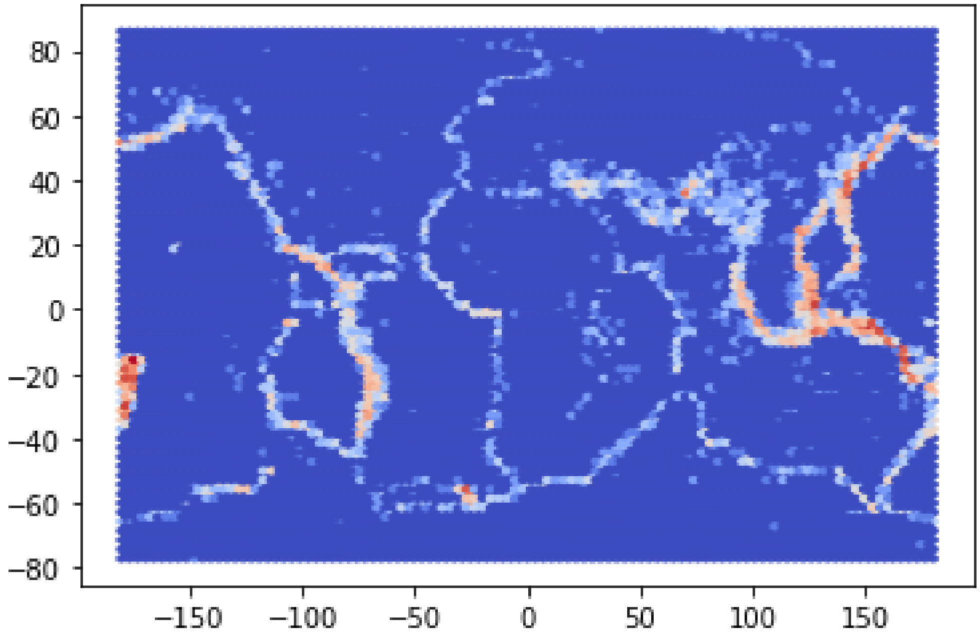
```
P(Quake > 1) = 70.176 percent
```

1.9 Localizing the model

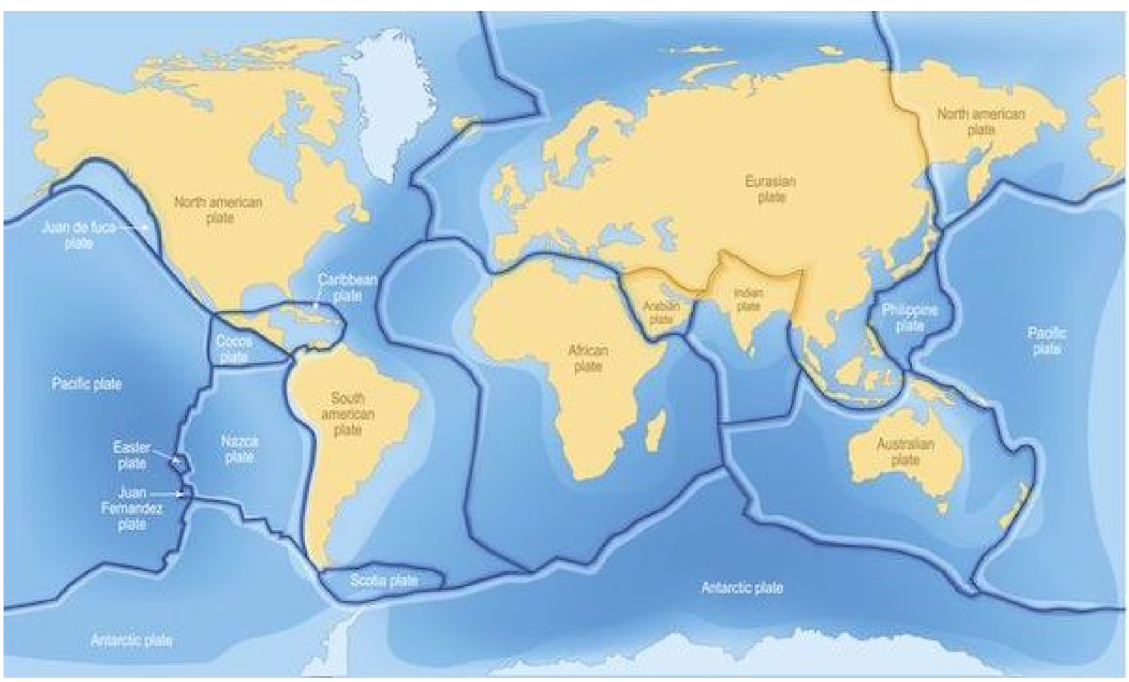
Earthquakes are more common at intersections of tectonic plates. Filtering the data to a local area can help residents assess and prepare for earthquakes.

```python
[14]: plt.hexbin(df.Longitude.values,df.Latitude.values, gridsize=100,
      bins='log',cmap='coolwarm')
```

```
[14]: <matplotlib.collections.PolyCollection at 0x12a07f470>
```



1.9.1 Map of tectonic plates



1.10 Filtering by local distance

1.10.1 About the distance Funciton

Subtracting latitude and longitude of a quake will not return the distance. The data will be skewed due to the same effect that makes Greenland appear nearly as large as Africa on a 2d map.

Instead Lat/Long points define a point in spherical space and can be converted to an x,y,z triple in cartesian space. Then the euclidian distance between quakes and the reference point can be accuratly calculated.

[15]:
```
#   Determines Euclidian (straight line) between 2 points. Does not consider␣
↪arc length, just straight distance
#   So the poles are 2 units apart, the equator is sqrt(2)*r from each pole,␣
↪not pi*r and pi/2*r like it would be with arc distance
def distance_from(df, Lat, Long):
    Lat = np.deg2rad(Lat) # Convert degrees to radians for numpy trig
    Long = np.deg2rad(Long)
    earth_radius = 6371 # km
    x_pos = earth_radius * np.cos(Lat)*np.sin(Long) # Convert spherical␣
↪coordinates to cartesian
    y_pos = earth_radius * np.cos(Lat)*np.cos(Long) # Assumes earths radius = 1
    z_pos = earth_radius * np.sin(Lat)

    data_Latitude_rad = np.deg2rad(df.Latitude) # Convert dataframe to radians
    data_Longitude_rad = np.deg2rad(df.Longitude)
    data_x_pos = earth_radius * np.cos(data_Latitude_rad)*np.
↪sin(data_Longitude_rad) # Convert to spherical
    data_y_pos = earth_radius * np.cos(data_Latitude_rad)*np.
↪cos(data_Longitude_rad)
    data_z_pos = earth_radius * np.sin(data_Latitude_rad)
    return ( (data_x_pos - x_pos)**2 + (data_y_pos - y_pos)**2 + (data_z_pos -␣
↪z_pos)**2)**(1/2) # Pythagoras3D
```

1.10.2 Sampling some cities

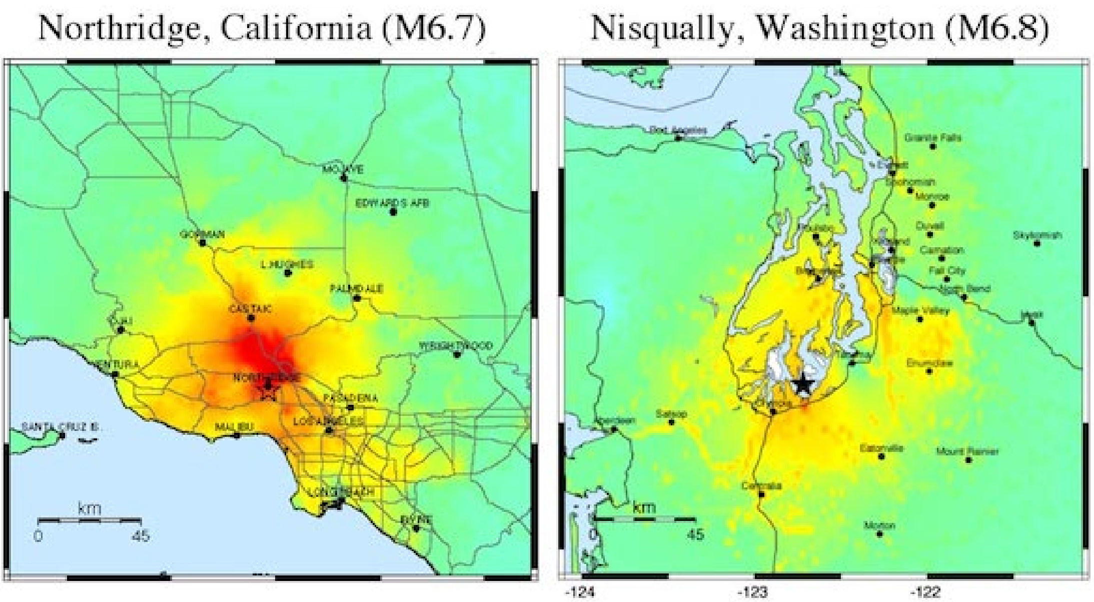
[16]:
```
Tokyo = [35.67,139.65]
San_Fran = [37.77,-122.42]
Denver = [39.74,-104.99]

df['Dist_Tokyo'] = distance_from(df,Tokyo[0],Tokyo[1])
df['Dist_San_Fran'] = distance_from(df,San_Fran[0],San_Fran[1])
df['Dist_Denver'] = distance_from(df,Denver[0],Denver[1])

df.reset_index(drop=True, inplace=True)

df.head()
```

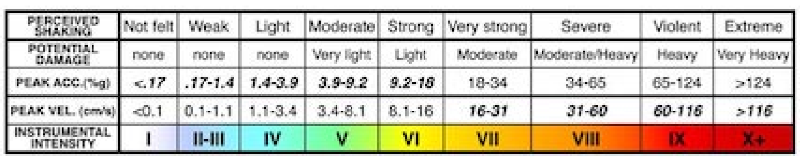
[16]:

```
         Date      Time  Latitude  Longitude        Type  Magnitude  Source  \
0  01/04/1965  11:29:49     1.863    127.352  Earthquake        5.8  ISCGEM
1  01/05/1965  18:05:58   -20.579   -173.972  Earthquake        6.2  ISCGEM
2  01/08/1965  18:49:43   -59.076    -23.557  Earthquake        5.8  ISCGEM
3  01/09/1965  13:32:50    11.938    126.427  Earthquake        5.8  ISCGEM
4  01/10/1965  13:36:32   -13.405    166.629  Earthquake        6.7  ISCGEM

             Datetime  Year  Rounded_Magnitude      Last_Quake  \
0 1965-01-04 11:29:49  1965                5.5 1 days 21:45:31
1 1965-01-05 18:05:58  1965                6.0 1 days 06:36:09
2 1965-01-08 18:49:43  1965                5.5 3 days 00:43:45
3 1965-01-09 13:32:50  1965                5.5 0 days 18:43:07
4 1965-01-10 13:36:32  1965                6.5 1 days 00:03:42

   Last_Quake_days    Dist_Tokyo  Dist_San_Fran   Dist_Denver
0         1.906609   3903.666462   10086.546238  10844.773500
1         1.275104   7431.237762    7829.511117   8857.842876
2         3.030382  12419.068617   11354.027774  10996.431875
3         0.779942   2928.373019    9672.115135  10417.868876
4         1.002569   5914.613093    8504.900890   9565.323488
```

1.10.3 How far away can you feel a strong quake?

The US Geological Program (USGS) cites that even somewhat large earhquakes dissapate quickly over an area. The tremors can hardly be felt more than just 100km or about 1 degree away.





PERCEIVED SHAKING	Not felt	Weak	Light	Moderate	Strong	Very strong	Severe	Violent	Extreme
POTENTIAL DAMAGE	none	none	none	Very light	Light	Moderate	Moderate/Heavy	Heavy	Very Heavy
PEAK ACC.(%g)	<.17	.17-1.4	1.4-3.9	3.9-9.2	9.2-18	18-34	34-65	65-124	>124
PEAK VEL.(cm/s)	<0.1	0.1-1.1	1.1-3.4	3.4-8.1	8.1-16	16-31	31-60	60-116	>116
INSTRUMENTAL INTENSITY	I	II-III	IV	V	VI	VII	VIII	IX	X+

There are clearly other factors to consider before estimating damages. Soil composition can affect energy dissapation and other secondary effects like tsunamis can cause significant damage from greater distances.

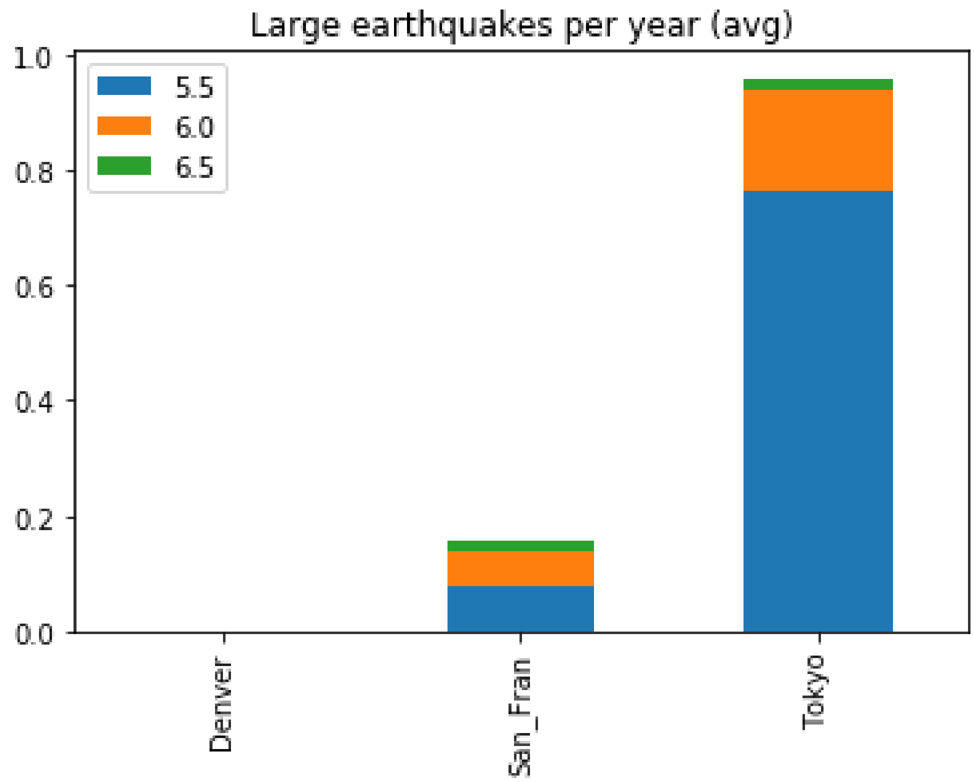
[17]:
```
# distance_from returns a the distance in kilometers between 2 points.
# Euclidian distance, not arc distance
q = pd.DataFrame.from_dict({'Latitude': [San_Fran[0]], 'Longitude':␣
↪[San_Fran[1]]})
distance_from(q,34.05,-118.24) # Distance to LA
```

[17]:
```
0    558.990744
dtype: float64
```

1.11 Comparing the frequency of earthquakes in 3 large cities.

[18]:
```
Local_Dist = 100
years = 2016-1965

Denver_Local_Counts = df[df.Dist_Denver < Local_Dist].Rounded_Magnitude.
↪value_counts() / years
San_Fran_Local_Counts = df[df.Dist_San_Fran < Local_Dist].Rounded_Magnitude.
↪value_counts() / years
```

```
Tokyo_Local_Counts = df[df.Dist_Tokyo < Local_Dist].Rounded_Magnitude.
 ↪value_counts() / years

counts = pd.concat({'Denver':Denver_Local_Counts, 'San_Fran':
 ↪San_Fran_Local_Counts, 'Tokyo':Tokyo_Local_Counts}, axis = 1).fillna(0)
counts.transpose().plot(kind='bar',stacked=True)

plt.title('Large earthquakes per year (avg)')
plt.show()
```



1.11.1 Earthquake frequency in Tokyo

[19]:
```
tokyo_df = df[df.Dist_Tokyo < Local_Dist]
# Calculations
tokyo_df['Last_Quake'] = tokyo_df.Datetime.diff()
tokyo_df = tokyo_df[tokyo_df['Last_Quake'].notna()]
tokyo_df['Last_Quake_years'] = tokyo_df['Last_Quake'].map(lambda x: x.
 ↪total_seconds()/(365*24*60*60)) # Last Quake (s)

tokyo_df.reset_index(drop=True, inplace=True)
tokyo_df.head()
```

```
/usr/local/lib/python3.7/site-packages/ipykernel_launcher.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing imports
until
```

[19]:

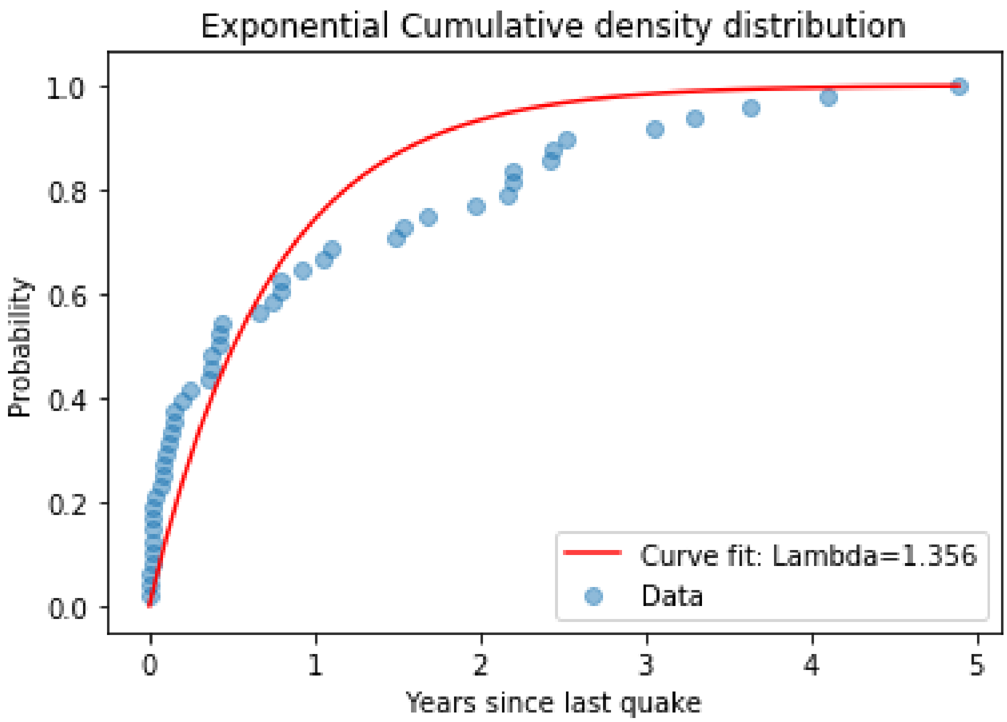
```
         Date      Time  Latitude  Longitude        Type  Magnitude  Source  \
0  09/15/1967  00:28:39    35.607    140.738  Earthquake        5.8  ISCGEM
1  07/01/1968  10:45:12    35.999    139.348  Earthquake        6.1  ISCGEM
2  07/22/1971  22:07:21    35.518    138.976  Earthquake        5.6  ISCGEM
3  09/30/1973  06:17:53    35.606    140.447  Earthquake        5.9      US
4  10/01/1973  14:16:23    35.716    140.561  Earthquake        5.6      US

             Datetime  Year  Rounded_Magnitude         Last_Quake  \
0 1967-09-15 00:28:39  1967                5.5  891 days 18:56:40
1 1968-07-01 10:45:12  1968                6.0  290 days 10:16:33
2 1971-07-22 22:07:21  1971                5.5 1116 days 11:22:09
3 1973-09-30 06:17:53  1973                5.5  800 days 08:10:32
4 1973-10-01 14:16:23  1973                5.5    1 days 07:58:30

   Last_Quake_days  Dist_Tokyo  Dist_San_Fran  Dist_Denver  Last_Quake_years
0         1.241238   98.569397    7644.968728  8474.988294          2.443258
1         4.794919   45.601298    7706.335966  8517.359487          0.795694
2         1.419352   63.242601    7752.862234  8563.203859          3.058832
3         0.695035   72.374801    7662.202260  8488.883038          2.192714
4         1.332292   82.428106    7649.836055  8476.991232          0.003650
```

[20]:

```python
# Cumulative Distribution
max_x = tokyo_df.Last_Quake_years.max()
x = np.array(sorted(tokyo_df.Last_Quake_years.values))
y = np.arange(1,len(tokyo_df)+1)/len(tokyo_df)
dense_x = np.linspace(0,max_x,50)

plt.scatter(x,y, alpha=0.5, label='Data') # Plot data

popt, pcov = curve_fit(exp_cumulative_density, x, y) # Fit curve
plt.plot(dense_x, exp_cumulative_density(dense_x, *popt), 'r-',label='Curve fit:
↪ Lambda=%5.3f' % tuple(popt)) # Plot fit curve
tokyo_lamb = popt[0]

plt.title('Exponential Cumulative density distribution')
plt.xlabel('Years since last quake')
plt.ylabel('Probability')
```

```
plt.legend()
```

[20]: <matplotlib.legend.Legend at 0x12a13cf28>

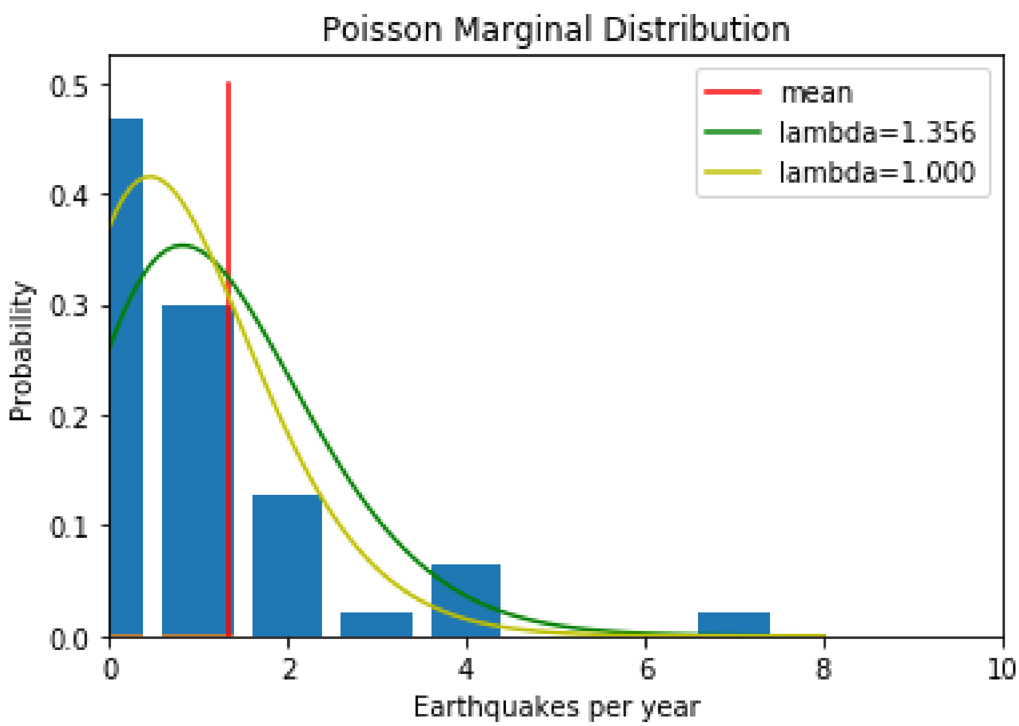


[21]:
```
len(tokyo_df)
```

[21]: 48

[26]:
```
x = np.linspace(0,8,100)

plt.plot([tokyo_lamb,tokyo_lamb],[0,.5], label='mean',c='r') # Mark mean
plt.plot(x,pois_marginal_density(x,tokyo_lamb),label = 'lambda=%3.
 ↪3f'%(tokyo_lamb), c='g')
manual_fit = 1
plt.plot(x,pois_marginal_density(x,manual_fit),label = 'lambda=%3.
 ↪3f'%(manual_fit), c='y')

plt.title('Poisson Marginal Distribution')
plt.xlabel('Earthquakes per year')
plt.ylabel('Probability')
plt.legend()

years = tokyo_df.Datetime.map(lambda x: x.year)
```

```
total_years = years.max()-years.min()
years_w_no_quake = total_years - years.nunique()
counts = years.groupby(years).count().value_counts()
counts[0] = years_w_no_quake
plt.bar(counts.index,counts/(years.max()-years.min()))

total_days = int((df.Datetime.max()-df.Datetime.min())/np.timedelta64(1,'D'))
days_w_no_quake = total_days - df.Date.nunique()
plt.bar(counts.index, counts/total_days, alpha=0.7)
plt.xlim(0,10)
plt.show()
```



[25]:
```
print('P(Quake > 1, lambda = 1.35) = %3.3f percent' %((1 -␣
 ↪pois_cumulative_density(1,tokyo_lamb))*100))
print('P(Quake > 1, lambda = 1) = %3.3f percent' %((1 -␣
 ↪pois_cumulative_density(1,1))*100))
```

```
P(Quake > 1, lambda = 1.35) = 74.219 percent
P(Quake > 1, lambda = 1) = 63.212 percent
```

Fit The global data is dense enough to sample at linearly spaced points, but this set is more sparse. Optimizing on this set suffers from sampling bias. Lambda ~= 1 visually appears to be a better fit.

Tokyo Conclusions Using the properties of Poisson distributions, Tokyo has on average **more than 1 large earthquakes per year.** The ancient, coastal city has been built from the ground up with the danger of earthquakes in mind. Traditionally, buildings in Tokyo were made of wood becuase the wood flexes during earthquakes instead of crumbling like bricks or concrete. However, wood building cause other forms of danger. In 1923, a **8.3** magnitude earthquake hit Tokyo. A fire had broken out in one of the wooden buildings and quickly spread throughout the city killing 142,000 people, more than the earthquake itself. (source)

Modern structures in Tokyo use elaborate damping methods to dissapate energy as it travels through the building.

Other solutions completely isolate the building from the ground by sitting on rollers.

```
[ ]:
```