Earthquake

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1 Analysis of Earthquake Frequency

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1.1 Abstract

Even leading science is unable to accuratly predict earthquakes. Instead earthquakes can be treated as a random event. Luckily, statistics has many well understood tools to understand these events.

1.2 The exponential distribution

$$Marginal\ Distribution = e^{-\lambda x} \tag{1}$$
$$Cumulative\ Distribution = \int MrgDist = 1 - e^{-\lambda x} \tag{2}$$

[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 is used to model events with a constant failure rate. That is, if the failure rate is F, 1/F events will 'fail' each timestep.

$$TODO : Define\ and\ prove\ failure\ rate \tag{3}$$
$$\tag{4}$$

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()
```

[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)
df.head()
```

[6]:
```
         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
```

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

[7]:
```
           Latitude     Longitude     Magnitude          Year  \
count  23228.000000  23228.000000  23228.000000  23228.000000
mean       1.385304     39.738244      5.882785   1992.719520
std       29.929647    125.755664      0.424059     14.437895
min      -77.080000   -179.997000      5.500000   1965.000000
25%      -18.719500    -76.384500      5.600000   1981.000000
```

```
50%       -3.684450   106.307500    5.700000  1994.000000
75%       24.968500   145.290250    6.000000  2005.000000
max       86.005000   179.998000    9.100000  2016.000000

       Rounded_Magnitude               Last_Quake  Last_Quake_days
count       23228.000000                    23228     23228.000000
mean            5.728194  0 days 19:37:17.121146         0.817559
std             0.402489  0 days 23:24:29.312558         0.975339
min             5.500000         0 days 00:00:00         0.000000
25%             5.500000         0 days 03:39:22         0.152338
50%             5.500000         0 days 11:42:44         0.488009
75%             6.000000  1 days 03:07:29.500000         1.130203
max             9.000000        10 days 05:30:13        10.229317
```

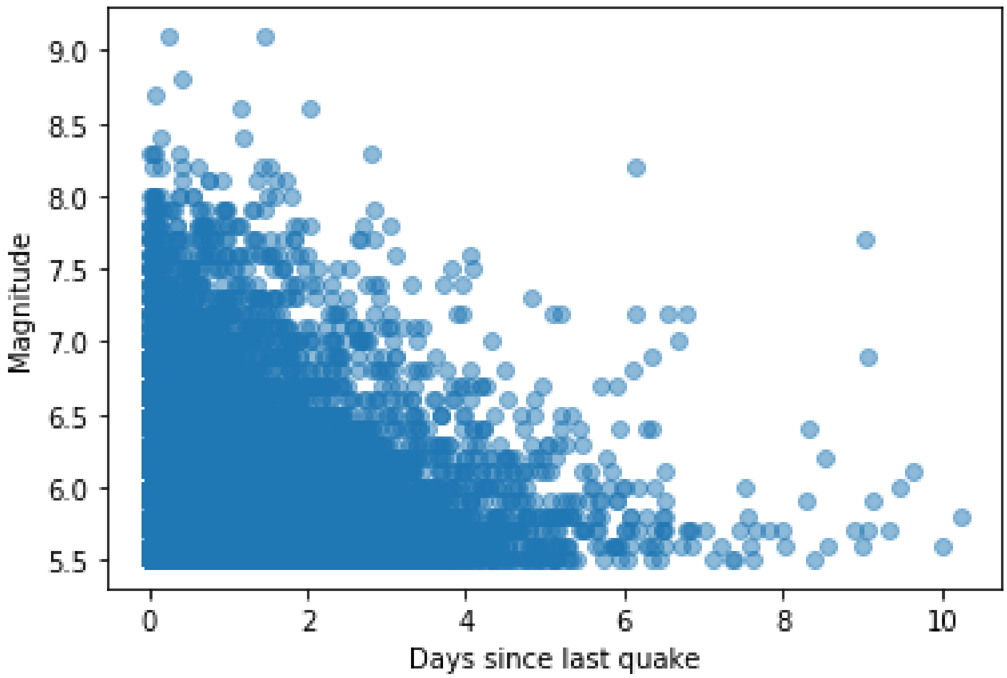
[8]:
```
len(df)
```

[8]: 23228

1.5 Does the strength of an earthquake depend on the time since the last earthquake?

Hypothesis: Assume the earth acts like a spring, constantly storing 'elastic' energy and releasing it in burst that we call earthquakes. Then big earthquakes are the result of a large buildup of energy. If an earthquake has not been recorded for a long time, the probability of a large quake is high.

[9]:
```
plt.scatter(df.Last_Quake_days,df.Magnitude, alpha=0.5)

plt.xlabel('Days since last quake')
plt.ylabel('Magnitude')
plt.show()
```



1.6 Big quakes are preceeded shortly by other quakes

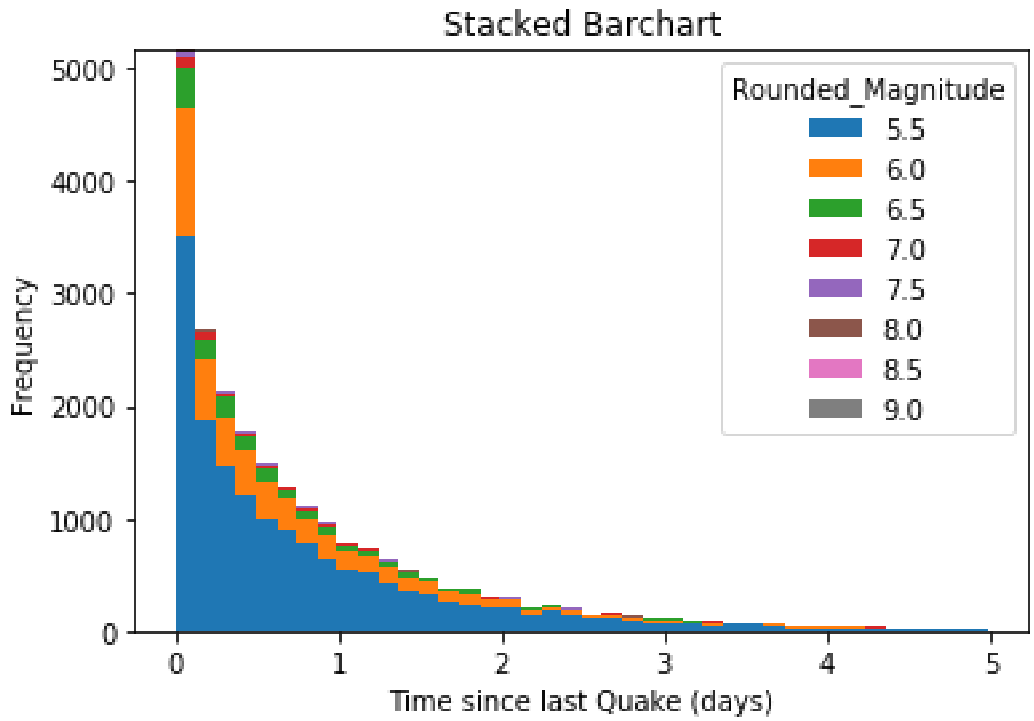
The hypothesis is **not supported**. In fact, the longer time without a quake, the higher probability that the next quake will be small.

However, this graph does not account for other factors like location and therefore the hypothesis cannot be proved inncorrect.

1.7 Fitting the data to the statistical Model

[10]:
```
(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)')
```

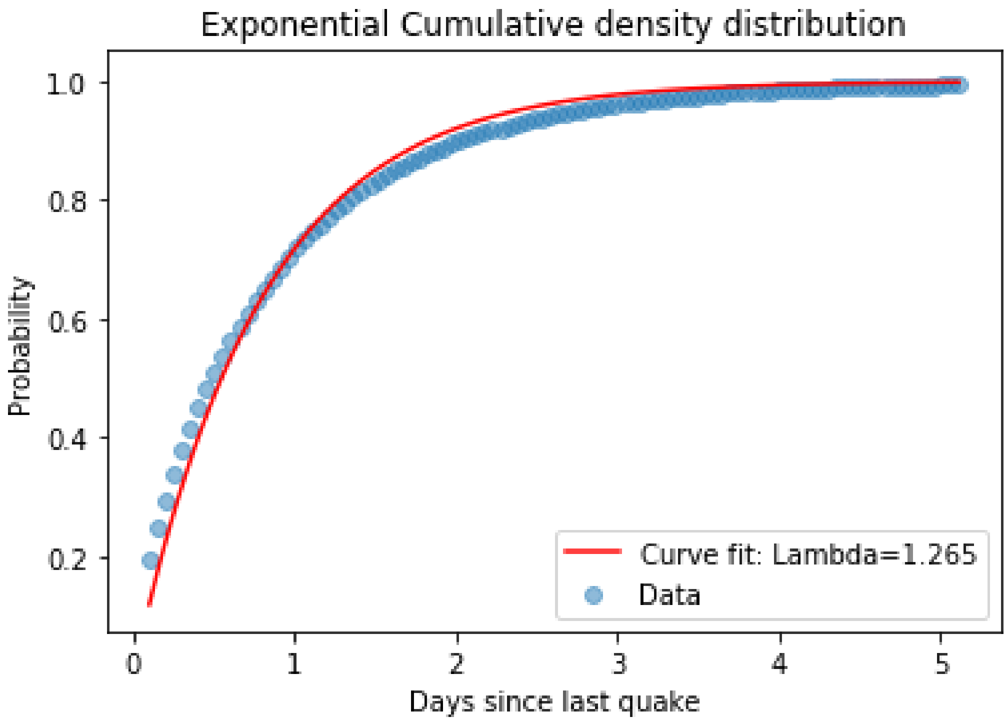
[10]:
```
Text(0.5, 0, 'Time since last Quake (days)')
```

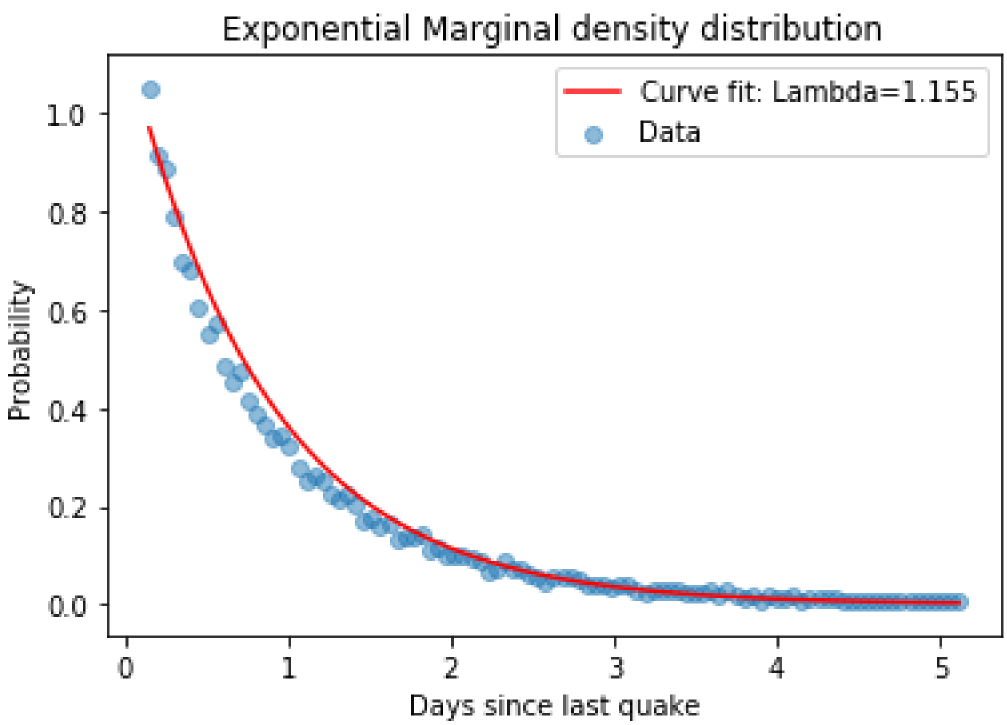


[11]:
```
def exp_plot(density, df):
    density = 100 # Plot resolution
    lamb = []
    # This okay becuase data is so dense. When data is more sparce, other␣
↪methods must be used.

    # 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

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

    popt, pcov = curve_fit(exp_cumulative_density, x, y) # Fit curve
    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()
    return lamb
```

[12]:
```
lamb = exp_plot(100,df)
global_lamb = np.mean(lamb)
print('lambda (avg): ' + str(global_lamb))
```


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


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

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

1.7.1 Mean and Variance

The exponential distribution has the propterty,

$$mean = \frac{1}{\lambda} \tag{5}$$

$$variance = \frac{1}{\lambda} \tag{6}$$

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.

[13]:
```
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

[14]:
```
print('P(Days >= 7) = %3.3f percent' %((1 -␣
↪exp_cumulative_density(7,global_lamb))*100))
```

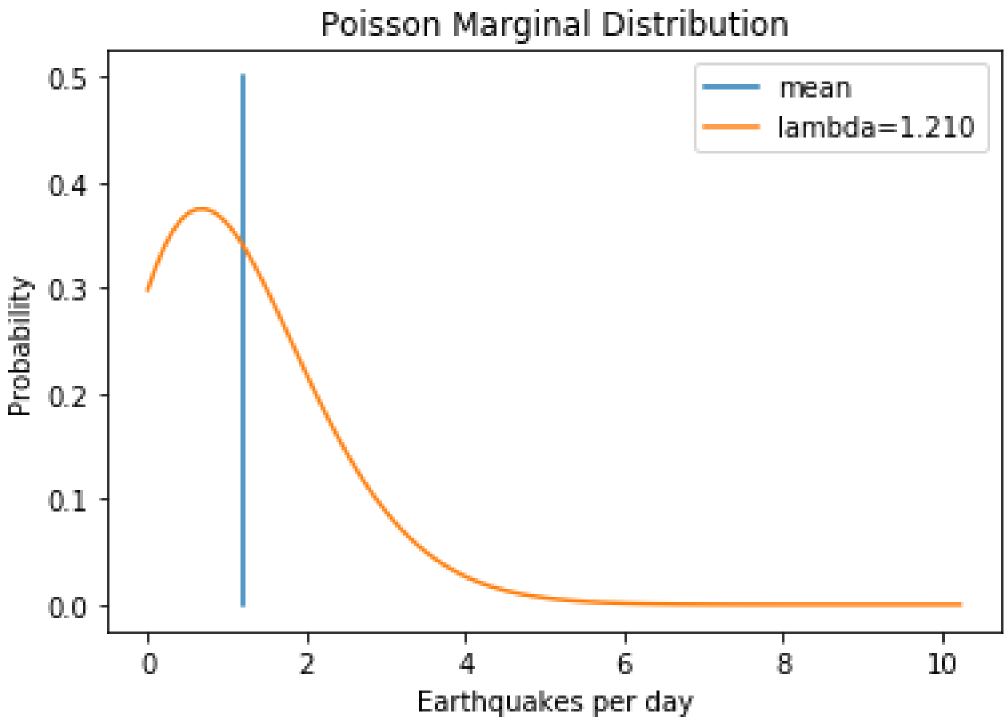
```
P(Days >= 7) = 0.021 percent
```

1.8 The Poisson Distribution

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

[15]:
```
def pois_plot(density, df, lamb, unit, max_x=None):
    if not max_x:
        max_x = df['Last_Quake_'+unit].max()
    x = np.linspace(0,max_x,density)

    plt.plot([lamb,lamb],[0,.5], label='mean') # Mark mean
    plt.plot(x,pois_marginal_density(x,lamb),label = 'lambda=%3.3f'%(lamb))

    plt.title('Poisson Marginal Distribution')
    plt.xlabel('Earthquakes per '+unit[:-1])
    plt.ylabel('Probability')
    plt.legend()
```

[16]:
```
pois_plot(100,df,global_lamb,'days')
```



The Poisson distribution has the propterty,

$$mean = \lambda \quad (7)$$
$$variance = \lambda \quad (8)$$

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

1.8.1 Probability of 1 or more quakes in a day

[17]:
```
print('P(Quake > 1) = %3.3f percent' %((1 -␣
↪pois_cumulative_density(1,global_lamb))*100))
```

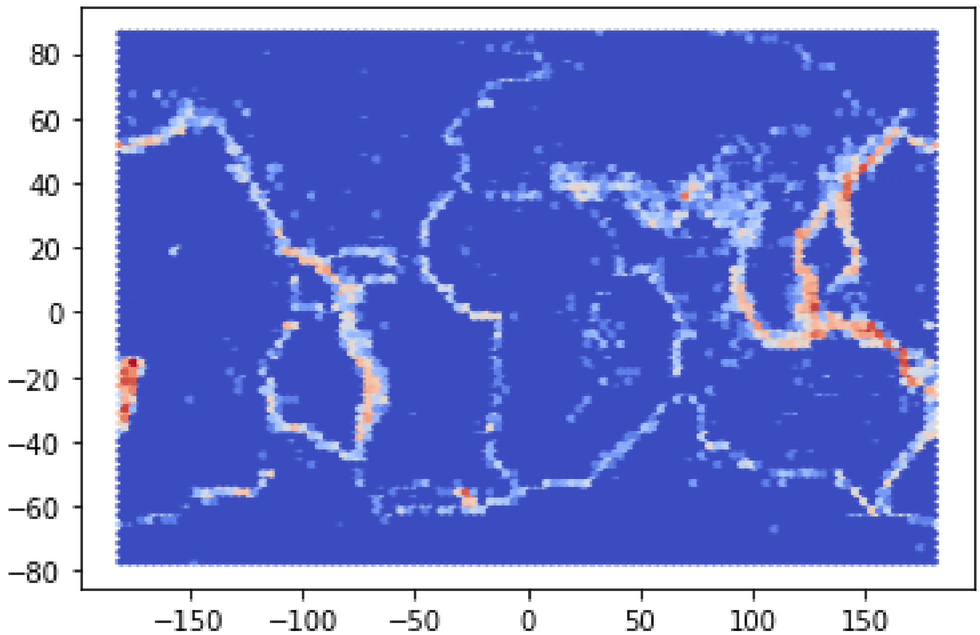
```
P(Quake > 1) = 70.176 percent
```

1.9 Localizing the model

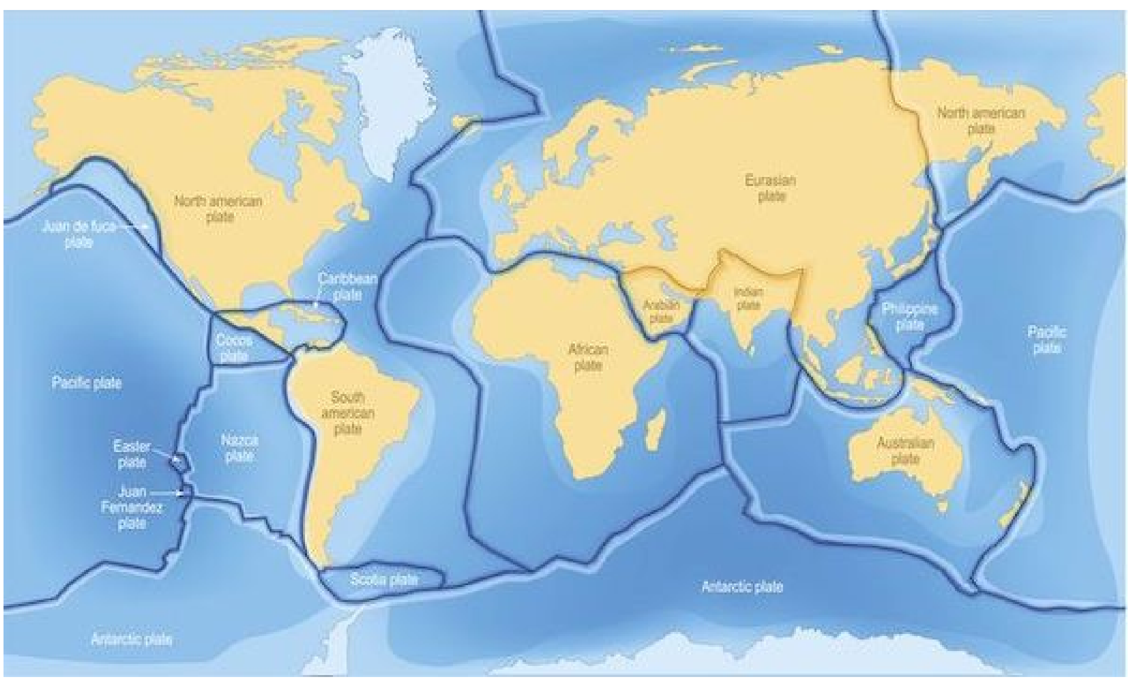
Earthquakes are more common at intersections of tectonic plates. Filtering the data to a local area can help residents assess and prepare for earthquakes.

[18]:
```
plt.hexbin(df.Longitude.values,df.Latitude.values, gridsize=100,␣
↪bins='log',cmap='coolwarm')
```

[18]: <matplotlib.collections.PolyCollection at 0x12766eeb8>



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.

[19]:
```
# Description:
#   Determines Euclidian (straight line) between 2 points. Does not consider␣
↪arc length, just straight distance
#   Assumes earth is a sphere with radius=1
#   So the poles are 2 units apart, the equator is sqrt(2) from each pole, not␣
↪pi and pi/2 like it would be with arc distance
# Input:
#   Dataframe with Latitude and Longitude components
#   2 arguments for Lat and Long of reference point
# Output:
#   Series containing distances to the reference point
def distance_from(df, Lat, Long):
    Lat = np.deg2rad(Lat) # Convert degrees to radians for numpy trig
    Long = np.deg2rad(Long)
    x_pos = np.cos(Lat)*np.sin(Long) # Convert spherical coordinates to␣
↪cartesian
    y_pos = np.cos(Lat)*np.cos(Long) # Assumes earths radius = 1
    z_pos = np.sin(Lat)

    data_Latitude_rad = np.deg2rad(df.Latitude) # Convert dataframe to radians
    data_Longitude_rad = np.deg2rad(df.Longitude)
    data_x_pos = np.cos(data_Latitude_rad)*np.sin(data_Longitude_rad) # Convert␣
↪to spherical
    data_y_pos = np.cos(data_Latitude_rad)*np.cos(data_Longitude_rad)
    data_z_pos = 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

[20]:
```
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])
```

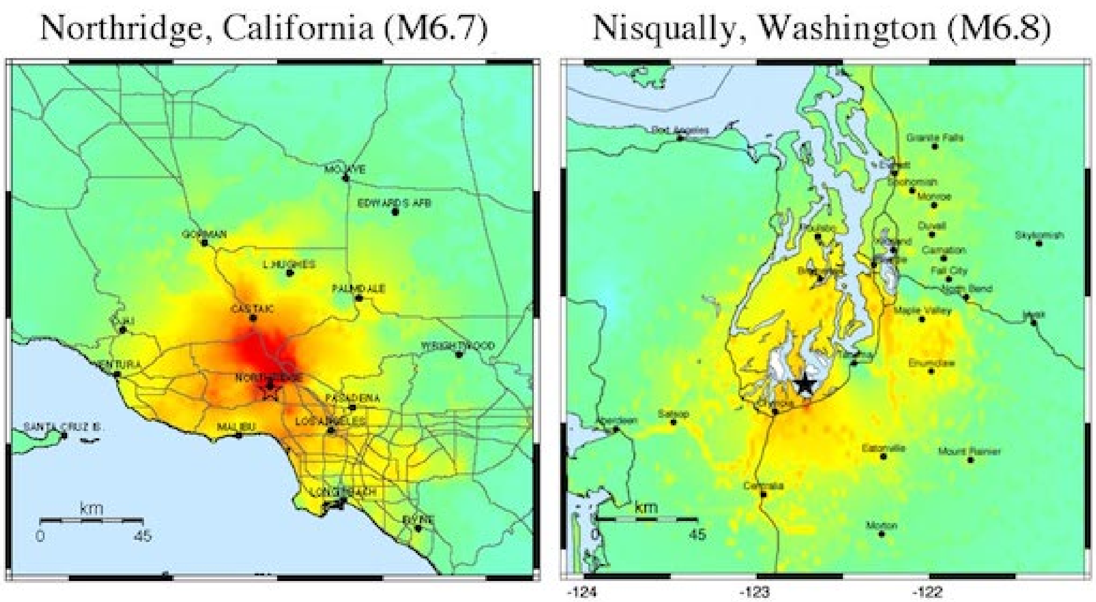
```
df.reset_index(drop=True, inplace=True)

df.head()
```

[20]:

```
         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    0.612724       1.583197     1.702209
1         1.275104    1.166416       1.228930     1.390338
2         3.030382    1.949312       1.782142     1.726013
3         0.779942    0.459641       1.518147     1.635202
4         1.002569    0.928365       1.334940     1.501385
```

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.

1.10.4 Calculating the local distance threshold

More precicely, 100km == 0.899 deg, but lets round up to 1 degree

[21]:
```python
# Uses the radius of the earth to calculate the arc of 100 km

earth_radius = 6371 # kilometers
earth_circumfrence = earth_radius * 3.14 * 2
km_per_deg = earth_circumfrence / 360
print(100/km_per_deg)
```

```
0.8997777548945409
```

1 degree maps to 0.017 in the distance space.

[22]:
```python
# Calculates distance between Lat/Long points (0,0) and (0,1)

q = pd.DataFrame.from_dict({'Latitude': [0], 'Longitude': [0]})
distance_from(q,0,1)
```

[22]:
```
0    0.017453
dtype: float64
```

For reference, the distance between San Francisco and Los Angeles is 0.088

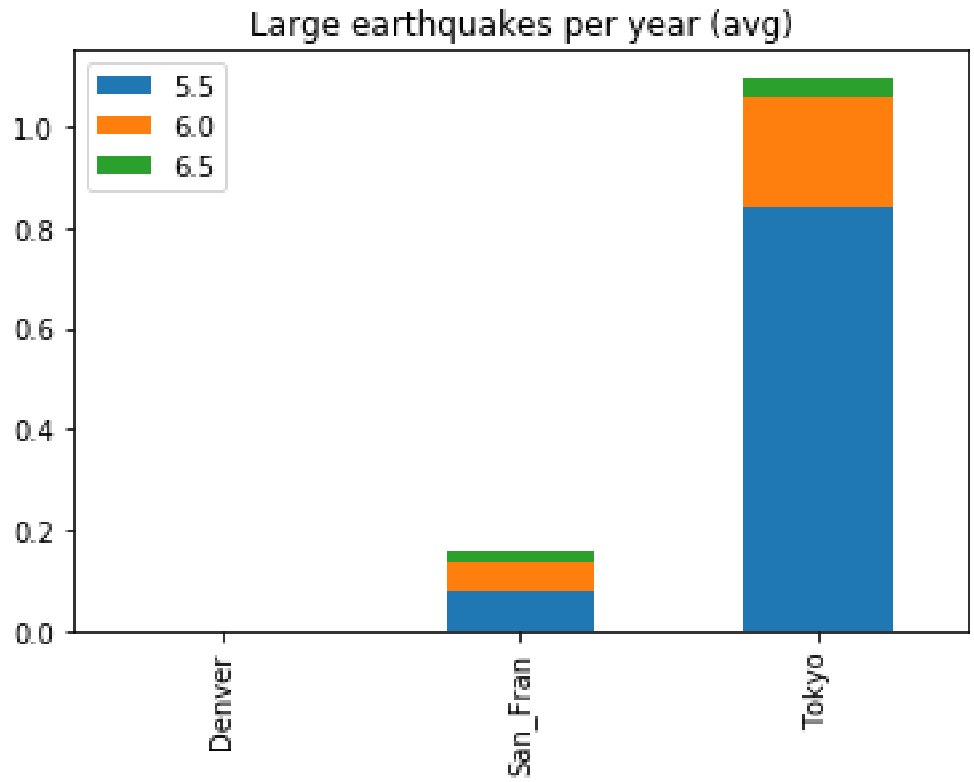
[23]:
```
# Calculate the distance (in the arbitrary distance space) between SF and LA
q = pd.DataFrame.from_dict({'Latitude': [San_Fran[0]], 'Longitude':␣
 ↪[San_Fran[1]]})
distance_from(q,34.05,-118.24) # Distance to LA
```

[23]:
```
0    0.08774
dtype: float64
```

1.11 Comparing the frequency of earthquakes in 3 large cities.

[24]:
```
Local_Dist = .017
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)')
```

[24]:
```
Text(0.5, 1.0, 'Large earthquakes per year (avg)')
```



1.11.1 Earthquake frequency in Tokyo

[25]:
```
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
```

[25]:

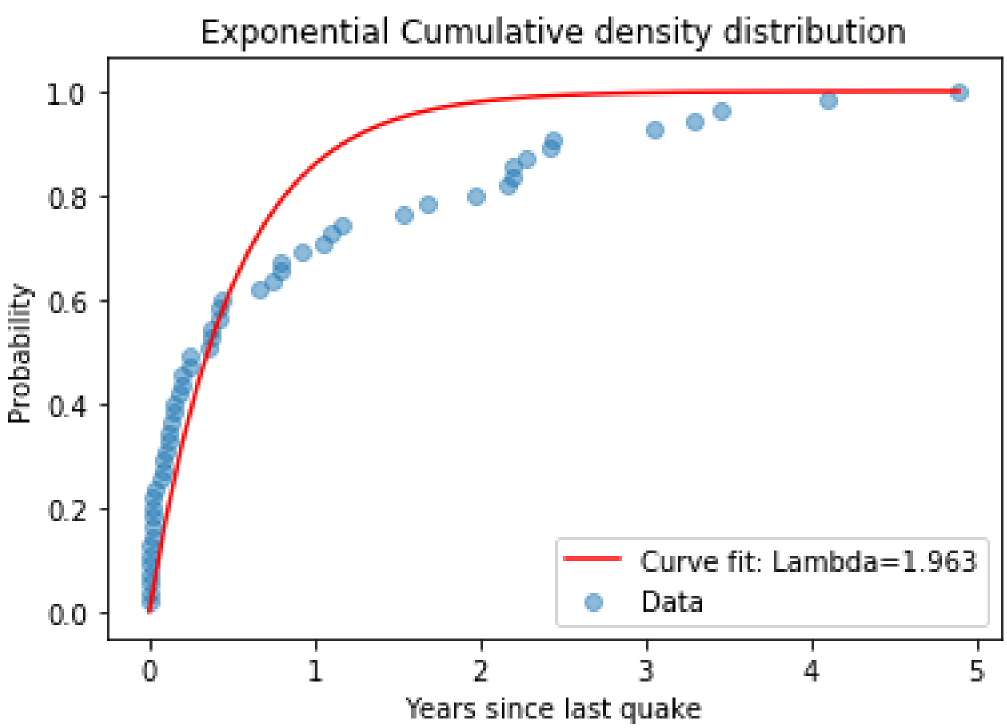
```
         Date      Time  Latitude  Longitude        Type  Magnitude  Source  \
0  09/15/1967  00:28:39    35.607    140.738  Earthquake        5.8  ISCGEM
1  07/01/1968  10:45:12    35.999    139.348  Earthquake        6.1  ISCGEM
2  07/22/1971  22:07:21    35.518    138.976  Earthquake        5.6  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    0.015472       1.199964     1.330245          2.443258
1         4.794919    0.007158       1.209596     1.336895          0.795694
2         1.419352    0.009927       1.216899     1.344091          3.058832
3         0.695035    0.011360       1.202669     1.332426          2.192714
4         1.332292    0.012938       1.200728     1.330559          0.003650
```

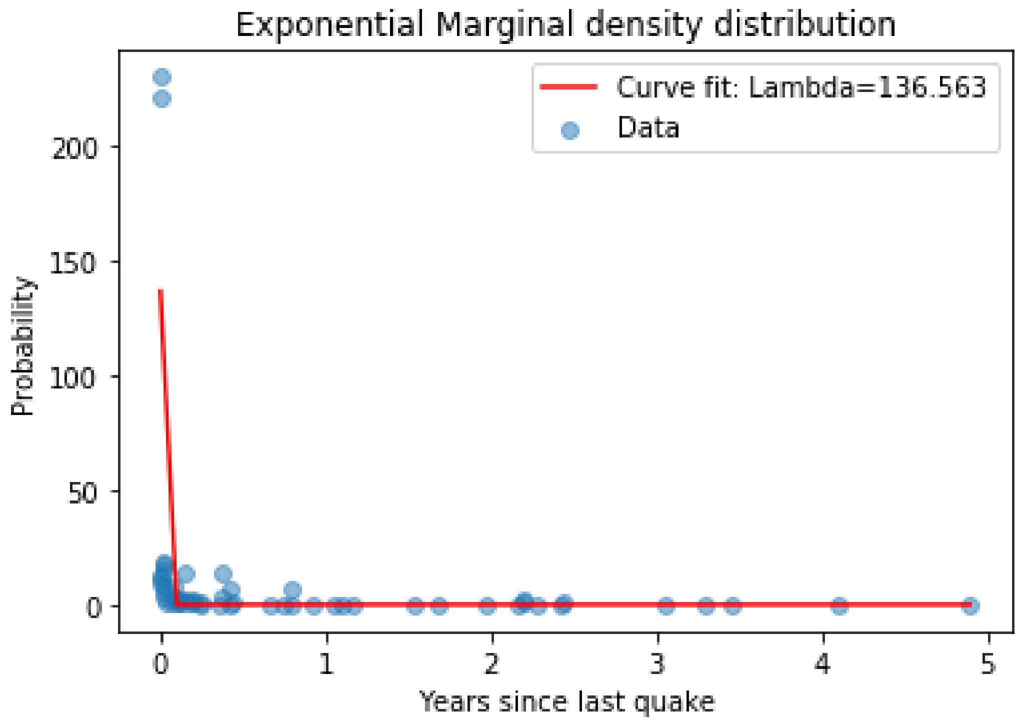
[26]:

```
def tokyo_plot(tokyo_df): #Redefinition of exp_plot to handle sparse data.␣
↪exp_plot better handles very dense data as it doesnt plot every point.
    lamb = []
    # 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
    lamb.append(popt)

    plt.title('Exponential Cumulative density distribution')
    plt.xlabel('Years 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(dense_x, exp_marginal_density(dense_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('Years since last quake')
    plt.ylabel('Probability')
    plt.legend()

    plt.show()
    return lamb
```

[27]:
```
lamb = tokyo_plot(tokyo_df)
tokyo_lamb = lamb[0]
```



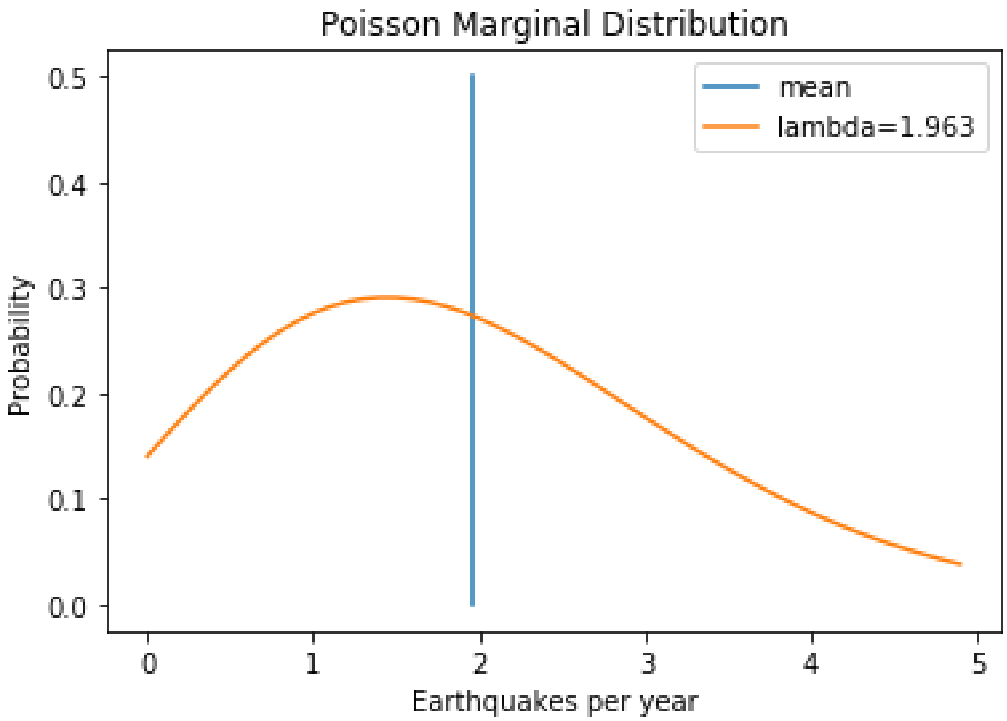


[28]:
```
len(tokyo_df)
```

[28]: 55

Fit and numerical Error The data subset includes only 55 data points. Additionally, the marginal distribution is caluclated using a first order numerical approcimation. While the cumulative distribution has some significant apperent error, the lambda from the cumulative distribution will be used in the following calculations.

[29]:
```
pois_plot(50,tokyo_df,tokyo_lamb,'years')
```



[30]:
```
print('P(Quake > 1) = %3.3f percent' %((1 -␣
↪pois_cumulative_density(1,tokyo_lamb))*100))
```

```
P(Quake > 1) = 85.959 percent
```

Tokyo Conclusions Using the properties of Poisson distributions, Tokyo has on average **nearly 2 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.

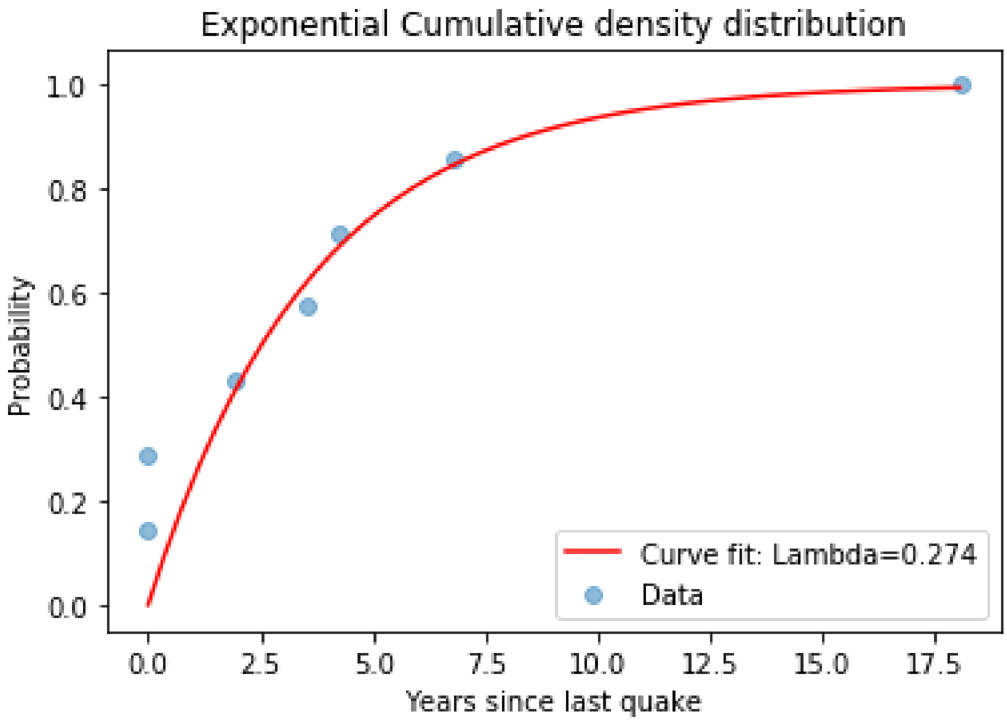
1.11.2 San Francisco

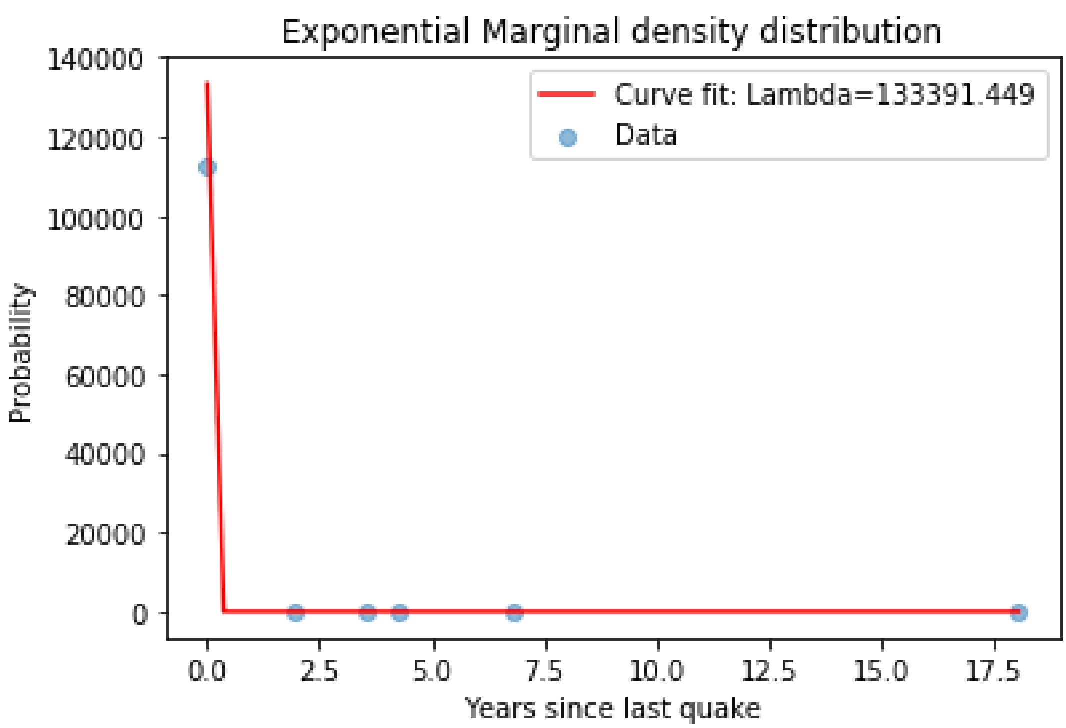
[31]:
```
San_Fran_df = df[df.Dist_San_Fran < Local_Dist]
# Calculations
San_Fran_df['Last_Quake'] = San_Fran_df.Datetime.diff()
San_Fran_df = San_Fran_df[San_Fran_df['Last_Quake'].notna()]
San_Fran_df['Last_Quake_years'] = San_Fran_df['Last_Quake'].map(lambda x: x.
 ↪total_seconds()/(365*24*60*60))

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
```

[31]:
```
         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    0.015472       1.199964     1.330245          2.443258
1         4.794919    0.007158       1.209596     1.336895          0.795694
2         1.419352    0.009927       1.216899     1.344091          3.058832
3         0.695035    0.011360       1.202669     1.332426          2.192714
4         1.332292    0.012938       1.200728     1.330559          0.003650
```

[32]:
```
lamb = tokyo_plot(San_Fran_df)
San_Fran_lamb = lamb[0]
print(San_Fran_lamb)
```


Exponential Cumulative density distribution
Probability
1.0
0.8
0.6
0.4
0.2
0.0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Years since last quake
Curve fit: Lambda=0.274
Data


Exponential Marginal density distribution
Probability
140000
120000
100000
80000
60000
40000
20000
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Years since last quake
Curve fit: Lambda=133391.449
Data

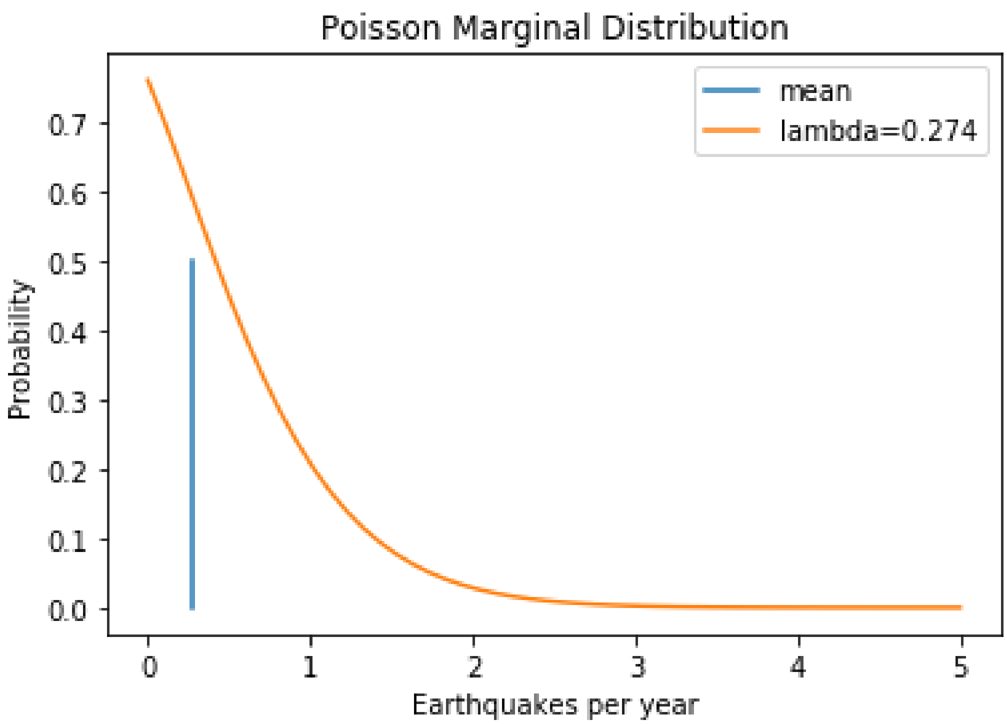
```
[0.27389501]
```

[33]:
```
len(San_Fran_df)
```

[33]:
```
7
```

Fit and numerical Error Now with even less datapoints, the numerical approximation begins to fall apart. Lambda from the cumulative distribution will be used again in the following calculations.

[34]:
```
pois_plot(50, San_Fran_df, San_Fran_lamb,'years',5)
```

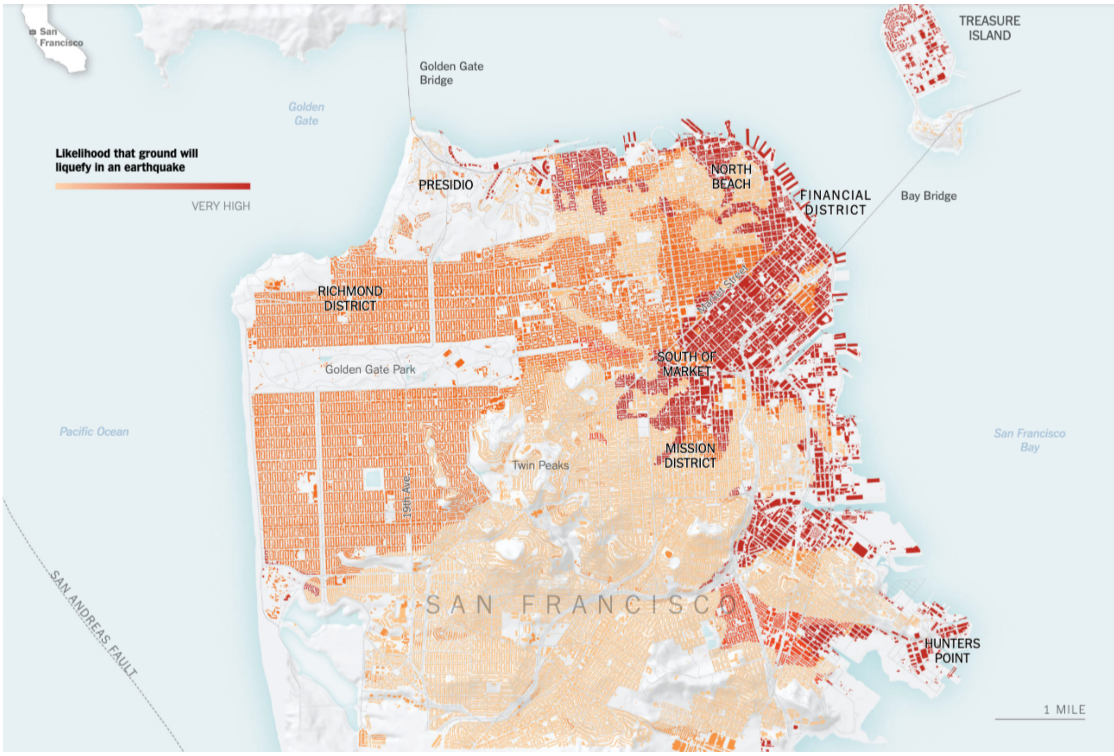


[35]:
```
print('P(Quake > 1) = %3.3f percent' %((1 -␣
↪pois_cumulative_density(1,San_Fran_lamb))*100))
```

```
P(Quake > 1) = 23.959 percent
```

San Francisco Conclusions San Francisco has significanly less earthquakes than tokyo, but the city is not entirely safe. Residents can expect a large earthquake every 3.64 years ($1/\lambda$).

Is San Francisco Ready? The coastal peninsula is largely composed of sand and other loose soils giving it a high risk of liquefaciton. Even building dampers won't help when the ground holding the foundation begins to flow like water.



(source, NY Times)