CS 5665 Homework #2
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All code, plots reside here:
https://github.com/karunmj/usu-coursework/tree/master/cs5660datasc/hw/hw2

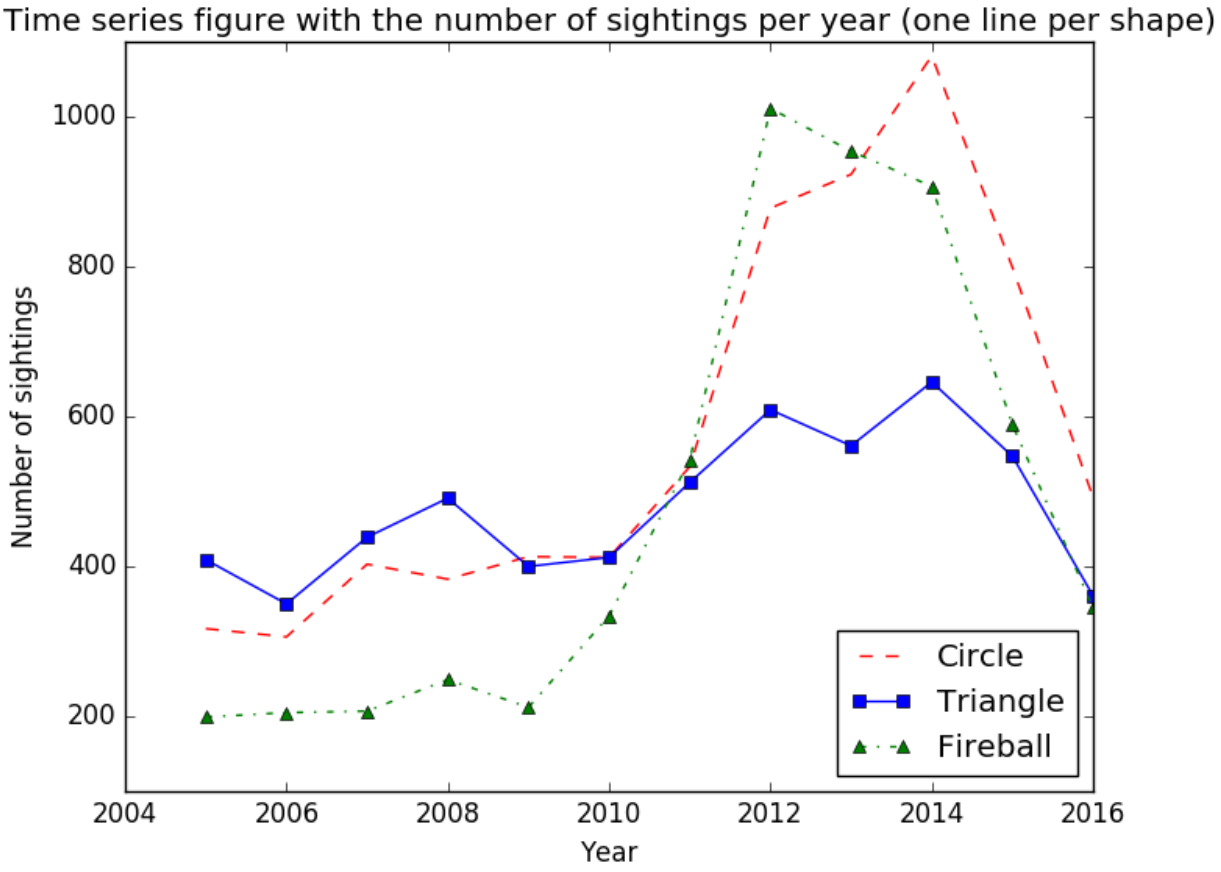
Data collection involved using request and beautiful soup libraries to get UFO data for circles, triangles and fireball shape sightings in the form of a Pandas data frame object in Python. The column labels include date of sighting, time of sighting, city, state, shape, duration, summary and posted date.

Data preprocessing involved including sighting between 1/1/2005 and 9/22/2016, representing duration of sighting in seconds and sightings in either of the 50 (+1 by including DC) states of US.

1. Box plot of duration of UFO sightings of each shape

(not done)

2. Time series figure with the number of sightings per year (one line per shape)



There seems to be higher number of sightings during 2012 to 2014 than the rest of years.

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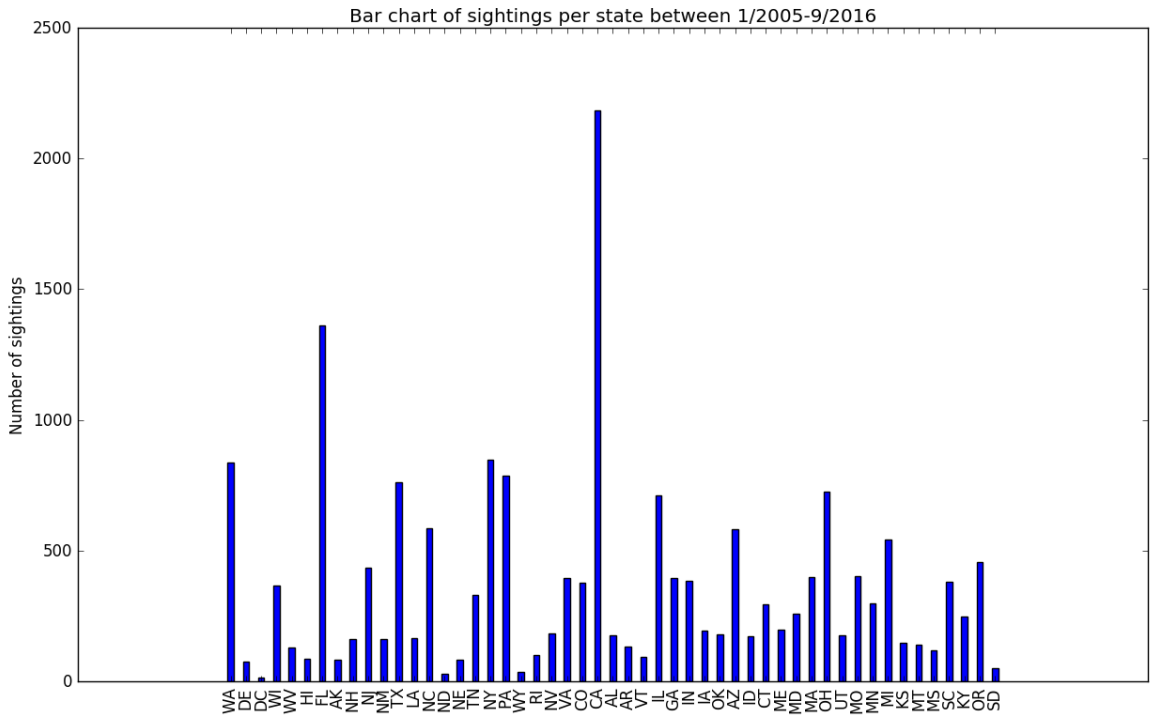
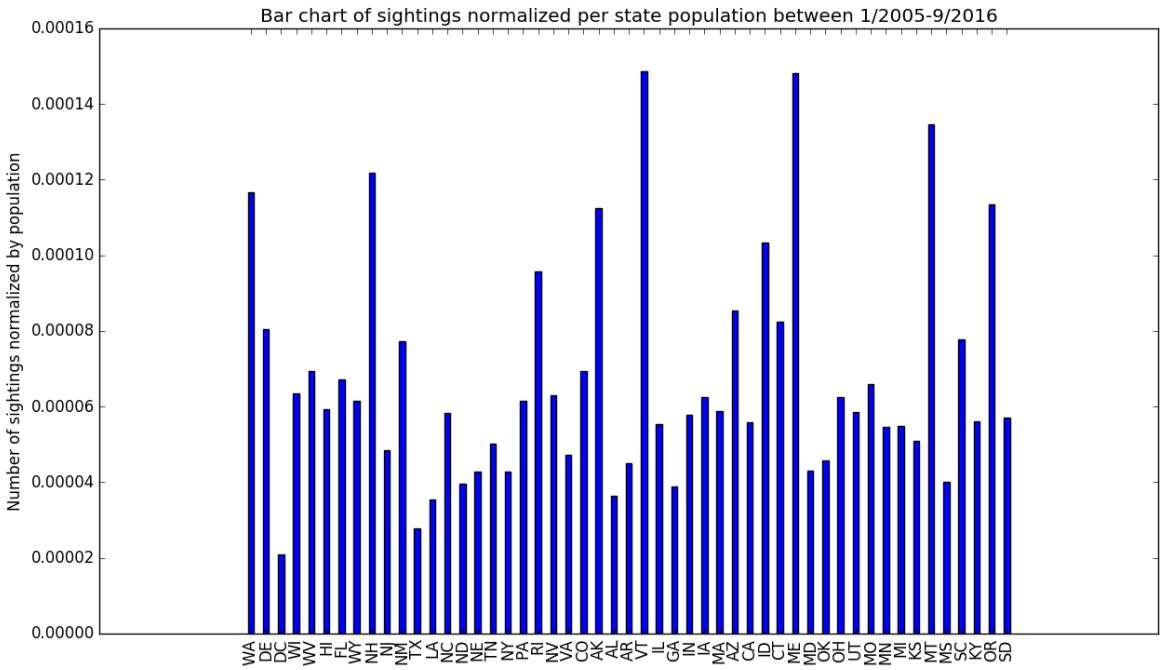
3. Bar chart for sightings of:
    a. Absolute numbers by state



    b. Normalized numbers, based on state population, by state



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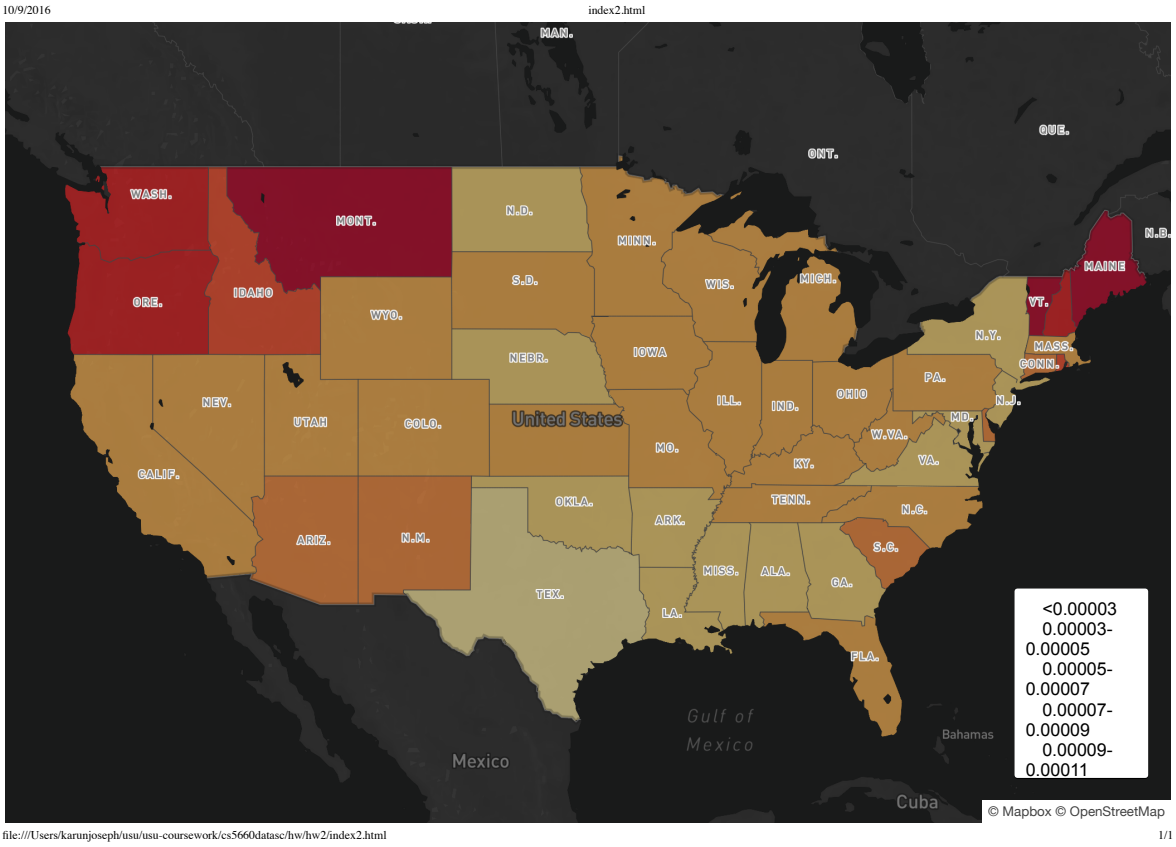
State population numbers were obtained from US Census API service for

4. Normalized sightings by state population visualized on a map

Mapbox Studio had been used to generate a static HTML page with the normalized sightings.



It looks like states like Montana, Vermont and Maine had the highest number of sightings. These states also have very low population, hence higher sightings per person. Also, these states have fewer cities that result in lower light pollution levels. Residents are more likely to see moving planetary objects like comets. meteors which could be mistaken for UFOs.

For classification, Python's sklearn tree package had been used to build the decision tree classifier. Since this package doesn't deal with categorical type of attribute directly [which is in our case], they had to be vectorized. For example, given an observation's attributes in training data set

time_of_day	region
night	s

it is converted to:

region=mw	region=ne	region=s	region=w	time_of_day=afternoon	time_of_day=evening	time_of_day=morning	time_of_day=night
0	0	1	0	0	0	0	1

Similarly, the class labels ‘Circle’, Fireball’ and ‘Triangle’ were mapped to 0, 1 and 2 respectively. Gini criterion had been used to build the classifier.

5. Classification accuracy of decision tree using test set data

Python’s sklearn metrics’ precision score had been used to calculate the ratio $\frac{t_p}{t_p + f_p}$, where t_p is the number of true positives and f_p the number of false positives, for each class

Circle	Fireball	Triangle
0.43863816	0.35789094	0.33474576

The accuracy from sklearn metrics’ accuracy_score is 0.391364661002

The confusion matrix of predicted vs true class labels of test set data were as follows

True label	Circle	1108	1067	197
	Fireball	733	991	117
	Triangle	685	711	158
		Circle	Fireball	Triangle
		Predicted label		

Overall, the decision tree classifier had done a poor job.

6. Illustration of built decision tree