# TEAM\_02\_CSCI599\_HW\_BIGDATA\_Report

## Data Preparation and Cleaning

We started with analyzing the UFO sightings data. The most important column identified was the location as it should be used to get the latitude and longitude using geocode API. We observed following nature of the location field in the data which were later exploited to decode the ISO region for the location.

1. Total number of sightings are 61067. Number of non-US sightings based on a cursory analysis is 9019. Out of these there are around 21k unique locations.
2. Most of the US sightings followed the notation of (county\_name, state\_code) For example: - Santa Cruz, CA.
3. Some US sightings are mostly random and has Freeway/Expressway names
4. There is no similar notation used in non-US sightings except for the countries Canada, Australia and some others. These countries have the country name in the location string.

Some other observations made about the datasets:

1. Some of the data is not clean, for eg. city is missing from the UFO sighting location
2. Row 19202 in TSV file is not of proper structure. (Eg. the description is there in the city column)
3. Inconsistent data in the JSON and TSV files. (Eg: Row 19202).

### Finding Nearest Airport

We used the following airport dataset**: -** <http://ourairports.com/data/airports.csv>

This file contains around 53k airports with the longitude, latitudes, iso\_country and iso\_region. First thing we had to do was get the latitudes and longitudes for the UFO sightings dataset and then compare it to the airports dataset to get the closest airport. The first instinct was to compare all the locations with all the airports. But soon we could see that it will be too many comparisons. Then we found that as most of the sightings are in US and there are around 22k airports corresponding to US region, we need to have a better strategy for reducing number of comparisons. So, we came up with the following strategy.

1. For all the US sightings, we will assume that it could be related to an airport in that state or the neighboring state. For this we created a key-value pair data structure which had every state’s neighboring state. Using the state codes of the neighboring states we formed ISO region codes such as US-CA (for USA California). We used these codes to narrow down on the list of airports to be compared to the UFO sighting location.
2. For non-US sightings we assume that the sightings will be related to the airports in that country alone. While getting the latitude and longitudes from geocode API, we also fire the reverse query to capture the ISO country code of that location. This helps reducing the number of comparisons in non-US sightings.

### Issues faced while getting longitude and latitudes from geocoding API

1. The OpenMaps geocode API would throw Too many requests error if overwhelmed with too many geocode requests. For this we had to store all the unique locations in pyMongo DB and then call the geocode API with a sleep of 1 second.
2. Some cities in US share names with cities in Canada and Mexico for such cases to get best results we had to include the name of country in the location query string.
3. Same city names across different states in USA. For these we had to include the state name in the location query string.

## Data Sets for additional 9 features:

### Dataset 1

**Mime Type** – Application/JSON

**Source** - <https://data.nasa.gov/Space-Science/Meteorite-Landings/gh4g-9sfh>

**Meteorite Landing** - based on year and location we can get to know if people confused a meteorite for a UFO

**Features:**

1. Name of closest meteorite
2. Distance of closest meteorite to each city for that particular year the UFO was sighted
3. Possibility that the sighting is mistaken (sighting happened at < 50 miles of Meteorite landing)

#### Features Extraction & Methodology.

Features extracted are closest Meteor name, Meteor Distance based on the longitude and latitude of meteor landing, and the possibility that the meteor could have been confused as a UFO sighting, which is based upon the threshold on the distance and the year in which the meteor landing happened. To narrow down the number of comparisons, we indexed all the meteor landings based on the year n which it happened and then compared it to UFO sightings of that year.

**Insights from the dataset and its extracted features:**

<TODO>

### Dataset 2 – Census Data: **MIME Type – text/CSV**

**Sources**: <https://factfinder.census.gov/>

Open data source at <https://github.com/grammakov/USA-cities-and-states?files=1>

We have added around 8 missing entries to this data file. Including few here.

|  |  |  |
| --- | --- | --- |
| **City** | **County** | **State** |
| Oregon | Clackamas | Oregon |
| Murphy | Collin | Texas |
| Bloomington | Hennepin | Hennepin |

#### Features Extraction

Features extracted are Housing density, Population density, County. We imported the data using python 3 CSV library to read the respective columns from our input file. We grouped the UFO sightings data on Key of <State, County, Year>. We joined UFO dataset with this census data on the key <State,County,Year>

#### What we noticed about datasets and handling of issues if any:

* We took census data county wise for 2000 and 2010 years. For the years before 2000, the census data format is different and the demographic information is classified under different ethnic races.
* Problem with Alaska and District of Columbia states, as the structure of cities and counties does not align with the other states of America
* Puerto Rico data format, added united states suffix in the input data file to make format consistent with other states
* In the input file Input\_CountyCitiesList.CSV - removed the data related to District of Columbia as the County names were empty strings and also some junk data related to Postal Serrvice
* For some UFO sightings, year ‘Sighted at’ is given 0000. For such rows we considered ‘Reported at’ column.
* From the total UFO sightings there are 51547 sightings for valid 50 US states and out of which for 5883 sightings we could not map to the county due to the above-mentioned data issues.
* There are some incorrect locations of UFO sightings due to which we could not map given city, state to a county, state

Examples like:

* + Invalid locations like "Laporte, WA"
  + Ambiguous locations like “Silver Beach, NY”
  + Spelling mistakes: Seatle [Seattle], Lewiston [Lewistown]
  + Missing detail: Hollywood - [WestHollywood], Bluff - [Pine Bluff], Tawas - [East Tawas]

#### What questions the joined dataset allows us to answer:

* Are the highly sighted UFO locations densely populated or sparsely populated?
* <TO DO> Write answer

#### What clusters were revealed

We clustered Counties as Urban and Rural based on population density and housing density.

#### What similarity metrics produced more accurate measurements? Why?

<TO DO>

#### Any unintended consequences does the additional dataset suggest related to UFO sightings? (insights of the indirect features)

<TO DO>

#### Assumptions

Based on the source at <https://www2.census.gov/geo/pdfs/reference/GARM/Ch12GARM.pdf>, we define County as urban if population density (per sq mile) is > 1000 and housing density > 500 rural otherwise.

### **Dataset 3**

**Mime Type** – text/HTML

**Sci-Fi Movies (e.g. Star Wars, Star Trek) released -** based on the year of release of sci-fi movies and the year of the ufo sightings, we can predict if whether the ufo sighting was a delusion or not.

**Features:**

1. The number of sci-fi movies released in that year
2. The number of UFO sightings that took place in that year
3. ratio of number of movies released to number of sightings that took place in that year
4. based on the ratio, if it possible that due to a high influence of sci-fi movies, people imagined aircrafts to be UFO

**Source of the dataset acquired:** <https://en.wikipedia.org/wiki/Lists_of_science_fiction_films>

**Feature Extraction and Methodology:**

The dataset was available in HTML format in the form of multiple tables for each year. A simple python script - *wiki\_scifi.py* was written to extract the table contents from the links for each decade. All the extracted table contents from each decade was finally inserted into a csv file - *sci-fi\_database.csv*.

From the generated csv file and the original ufo\_awesome.json data file, the years were extracted based on the movie release date and the ufo sighted date and their respective counts were calculated. Once we had this data, we made an ***assumption that if the ratio of the number of ufo sightings to the number of movies in that year < 2***, then there is a high probability that the sci-fi movie had an impact on the person who sighted the UFO and probably mistook what they saw, for a UFO.

**Insights from the dataset and its extracted features:**

* There were 18 out of 82 years in which the ratio was less than 2.
* 21.95% of the years could be a possibility of delusion where the person confused an aircraft for a UFO after watching a sci-fi movie released in the same year.
* The unintended consequence seems to be the fact that such a huge sci-fi movie watching crowd could have been the reasons for confusing a flying object to be a UFO.