Final report

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Abstract

We did more experiment with different parameters during the Milestone 4. We optimized the code and visualized the results as a video on youtube[7]. In this final report, we will summarize over the whole three-month project, demonstrate the results and point out some future work **TO_DO:** Added more words

1 Introduction

Climate change is an issue of ever increasing significance to both policy makers and the public, especially as the impact of climate change on global and local economies has become clear. People care about this critical issue, and this interest is reflected in news headlines and across global social media.

Geologists and climatologists have developed many traditional methods the get more insight of this problem. They look into evidences from temperature measurements and proxies, historical and archaeological evidence, glaciers, arctic sea ice loss, vegetation, precipitation, sea level change and so on. They have also built many satellites and monitoring stations that are collecting large volumes of data everyday to help with the analysis. However, these traditional methods are mostly based on hypothesis testing methods and can't make full use of these automatically collected data, as the data volume is too big to handle. It is natural that novel methods that are able to deal with big data can play an important role in the climate change research.

We developed a system to cluster and visualize the GHCN-D data[2]. GHCN-D is a dataset that contains daily weather observations over global land areas. Like its monthly counterpart, GHCN-Daily is a composite of climate records from numerous sources that were merged together and subjected to a common suite of quality assurance reviews. The archive includes the following meteorological elements: daily maximum temperature, daily minimum temperature, temperature at the time of observation, precipitation (i.e., rain, melted snow), snowfall, snow depth, other elements where available. The data we used dates from 1763 to 2014 and has approximately 100 Gigabytes total volume.

Our approach is a practical attempt to cluster, visualize and interpret the data, which brings insights into the change and may help to control negative effect.Further researches can be related to the patterns appeared in our result.

2 Contribution

TO_DO: todo contribution todo compare to existing work, find some work

3 The System Architecture

3.1 Description of the Architecture and Tools used

As is shown in Figure 1, our system has four main steps : Feature Extraction, Sampling, Clustering and Visualization. The tools we use includes Amazon Elastic MapReduce[1],

Scikit-learn[5] library and Google Map API[6]. The four steps are illustrated in details in the followling part.

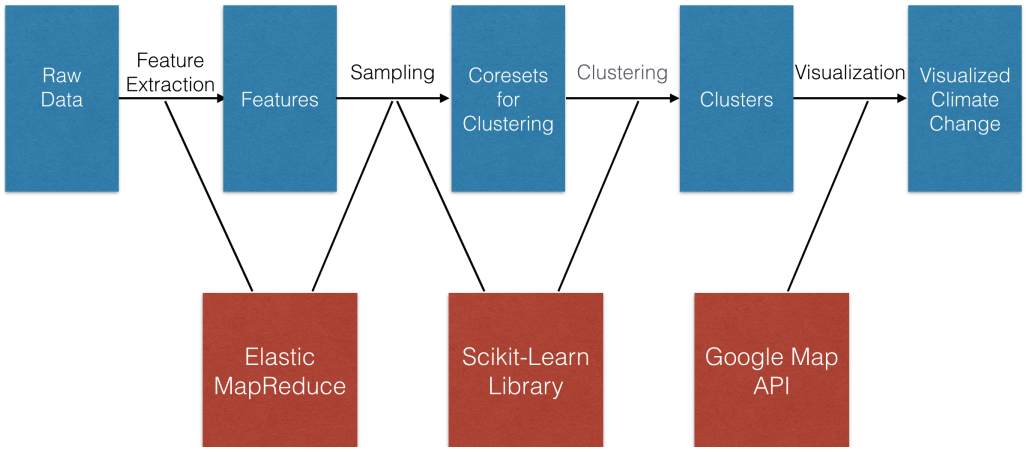


Figure 1: Architecture of our system

3.1.1 Feature Extraction

The raw data includes the climate data from 1763 to 2014, the total volume of raw data is about 100 Gigabytes, which is too big to fit in the memory. So we use Amazon Elastic MapReduce to calculate features. We use the same features setting with the previous milestone. The feature extraction consists of 3 sub-steps, including calculating features for existing data, filling in the missing value using the mean value of the feature value of all other existing data and normalizing data. Each of these sub-steps is done by a map-reduce task because of the huge volume of data. Through feature extraction, we get about 300 million 60-dimentional data points.

3.1.2 Sampling

We want to use all data points to run clustering. However, we use the k-means function in the scikit-learn library to compute clusters. It is impossible for that k-means function to run on 300 million of data points. We have two choices of handling this. One is to write a parallel k-means function that can run on Amazon EMR, the other one is to sample these data points so that the sample points are able to represent all the data points with the minimum loss of information. We choose the second approach and use coreset for k-means clustering. The coreset is a set of data points that is used to run the weighted k-means clustering. Each point in the coreset represents some original data points that are near to it. These data points are assigned the same label as the point in the coreset. The coreset sampling is done by an iterative step, where in each step, we uniformly sample some data points, calculate distance to the nearest point in the sampling set for every data point, remove data points whose distance to the nearest point in the sampling set are below median. Iterate this step until the number of remained data points is smaller than a pre-defined number and we get a coreset sampling of data.

todo

TO_DO: In addition to coreset sampling, we could also run on the whole feature,

3.1.3 Clustering

Having the coreset whose size is reasonable, we can run weighted k-means algorithm on the coreset and calculated all the centroids. The last step is to assign each data point to the nearest centroid and give that data a label. This step is also done by a map-reduce task.

3.1.4 Visualization

For the visualization part, we used the same technique that we have used in milestone 2. We used Google Map API to visualize the clustering result. For each year, all the stations in that year are placed on the map according to its location and the stations in the same cluster have the same color. We did an animation to show the change of clusters that reflects climate change.

3.2 Limits in Scalability and Possible Improvements

We have used most data that is available, however, due to the sampling process, the pattern of the result of clustering is not as obvious as the previous milestone. The main limit is the scalability of the clustering algorithm. I think coreset sampling is a good way to handle this, but due to the time limit, the coreset sampling we implemented has a lot of room for improvement and the clustering result is not as good as imagined. We would like to improve our sampling method and try different parameters for better sampling and clustering result. Also, we would like to write a parrallel k-means algorithm so that we can use more data points if possible.

4 Performance Measurements and Results

4.1 Performance metrics

There are three common performance metrics, we have our own way to measure:

- Execution time: one is run-time, the other is normalized instance hour;
- Memory-consumption & number of machines: peak memory of mapper and reducer, see Table 4.1. We use m3.2xlarge and one master, two cores;
- Solution quality: our project is quite innovative and there is no existing work. We can only compare our results with differnt parameters by topographical world map[8].

Generally, it would take four hours to run on the whole datasets, which is more than 100 instance hours.

Model	vCPU	Mem (GiB)	SSD Storage (GB)
m3.medium	1	3.75	1 x 4
m3.large	2	7.5	1 x 32
m3.xlarge	4	15	2 x 40
m3.2xlarge	8	30	2 x 80

Table 1: Instance types

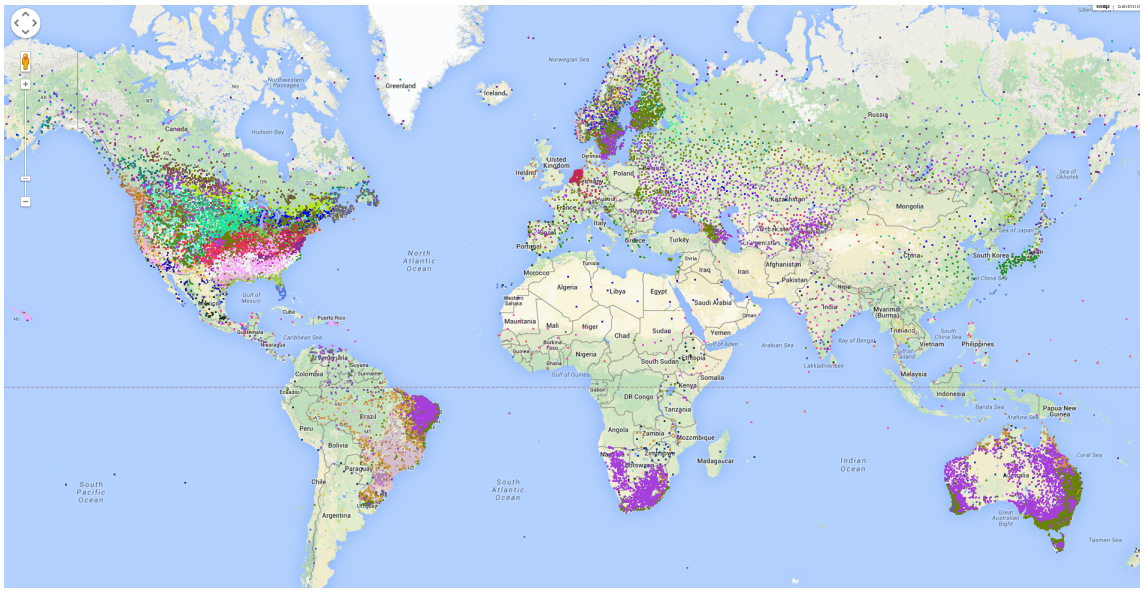
4.2 Result of recent four decades

Same as Milestone 3, we selected the year 1983, 1993, 2003 and 2013 to show the results. The size of raw compressed dataset is as showing in the Table 4.2.

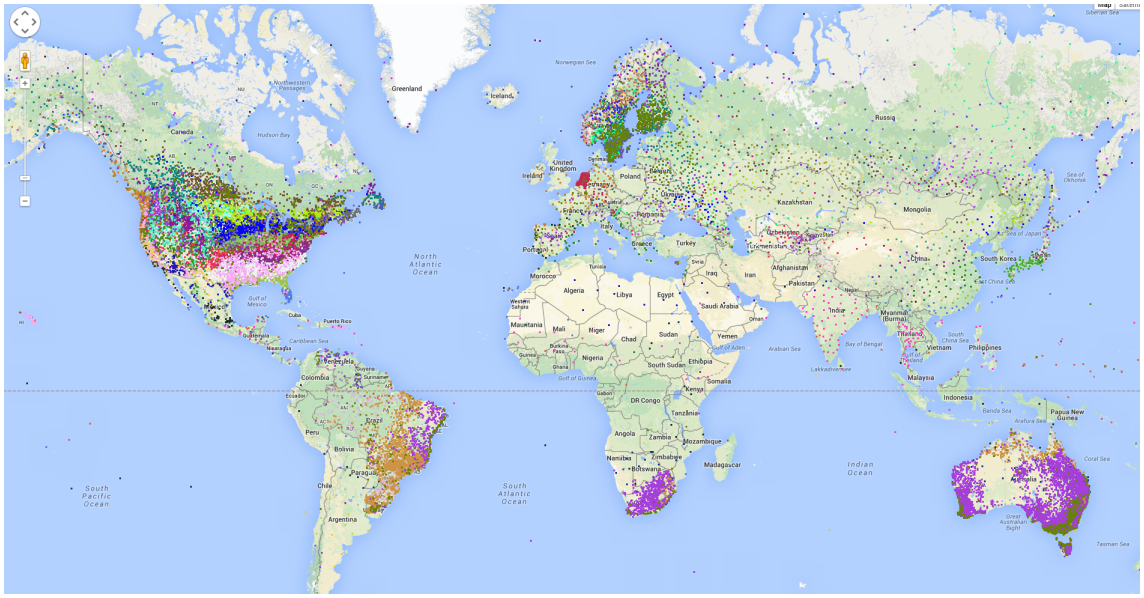
Year	1983	1993	2003	2013
Compressed Size	155MB	152MB	159MB	166MB
Original	912.4MB	899.7MB	960.7MB	987.2MB

Table 2: Size of dataset in selected years

We kept adjusting the parameters until we found the result is resonable. The following pictures are snapshots from 150 clusters, 500 iterations. From the pictures we can see that

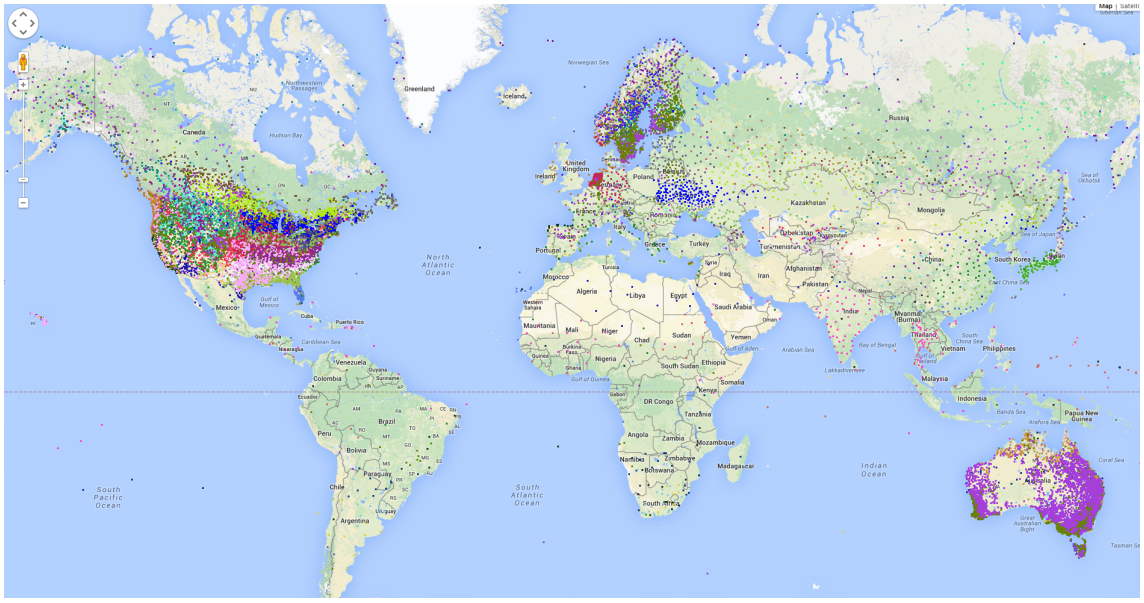


1983

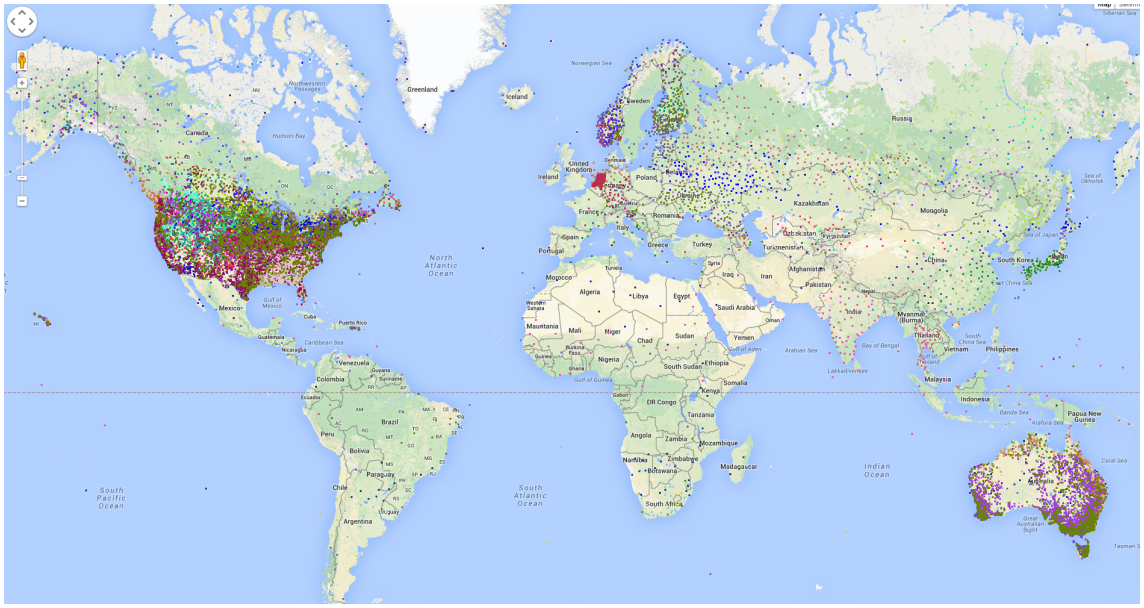


1993

Figure 2: Clustering results of 1983 and 1993.



2003



2013

Figure 3: Clustering results of 2003 and 2013.

there do exist some pattern in the same region in different years. But generally, the shape of clusters would note be the same.

Compared with results in milestone 3, there are two major improvements.

- More clusters (which are different colors) are observed;
- Less mising points on the map;

4.3 Result of more than a century

At next step, we adjusted the parameter to less clusters. Because the former years have really small recorded weawther information, it's unnecessary to run many clusters. When we run with 90 clusters, 500 iterations to check if there is any similar pattern to the extent of a century. We have chosen the years 1876, 1896, 1904, 1940, and 2010 with the size shown in Table 4.3. The values are varying from $900K$ to $184M$[1].

Year	1876	1896	1904	1940	2010
Compressed	900KB	18MB	32MB	73MB	184MB
Original	5.5MB	110.2MB	201.7MB	441.4MB	1GB

Table 3: Size of dataset in selected years

Here we observed a similar result as before.

4.4 Result of recent 11 years

We also extracted the result from 2003 to 2013, made a video by Python which is now available on Youtube[7].

5 Conclusion

Althgouh the result of our project is quite subjective, there is an optimal number of clusters. After enough iterations, the result remains a good quality. For the ones with less number of clusters, it would take less time to compute while for bigger number of clusters, it would take more time. From [5]'s website, there is a note for the complexity of algorithm:

> The k-means problem is solved using Lloyds algorithm.
>
> The average complexity is given by $O(knT)$, were n is the number of samples and T is the number of iteration.
>
> The worst case complexity is given by $O(n^{(k+2/p)})$ with n = n_samples, p = n_features. (D. Arthur and S. Vassilvitskii, 'How slow is the k-means method?' SoCG2006)
>
> In practice, the k-means algorithm is very fast (one of the fastest clustering algorithms available), but it falls in local minima. Thats why it can be useful to restart it several times.

Where in our experiment, we choose 150 clusters and 500 iterations. The solution quality would improve if we use more 'useful' data. We throw away the station which have huge number of missing values. The more 'useful' data we use, the more computational effort would take. So that's the trade-off.

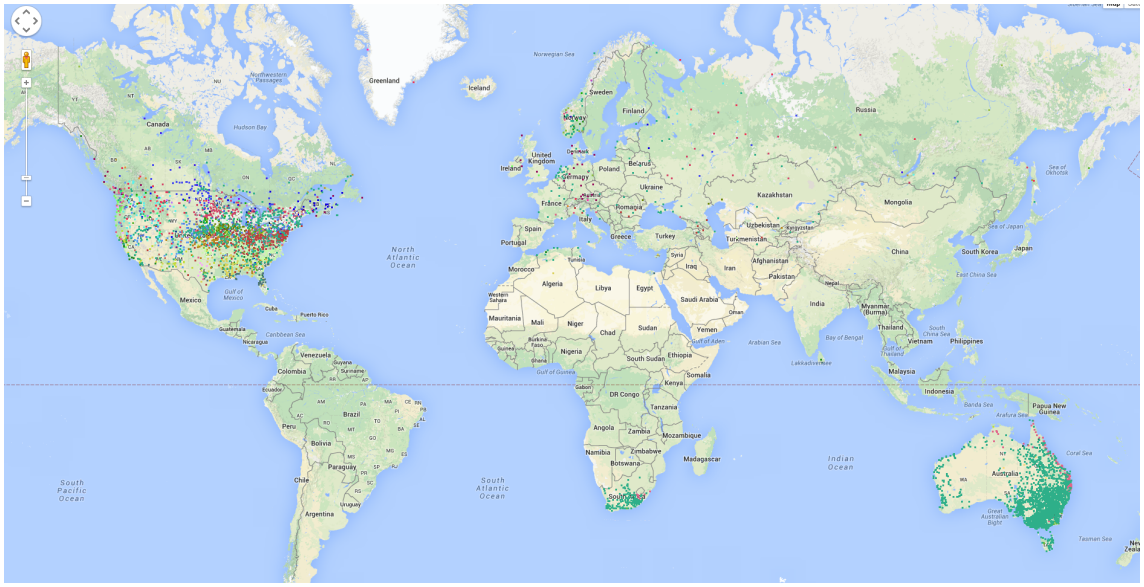
5.1 Difficulties

We encountered several difficulties during the projects. The top major ones is following:

- The size of Dataset is too big to fit in the memory;
- Too in-efficient to run K-means on the whole dataset;
- Install Python tools in the remote machine.

[1]The results before 1876 is meaningless since there were not enough data.

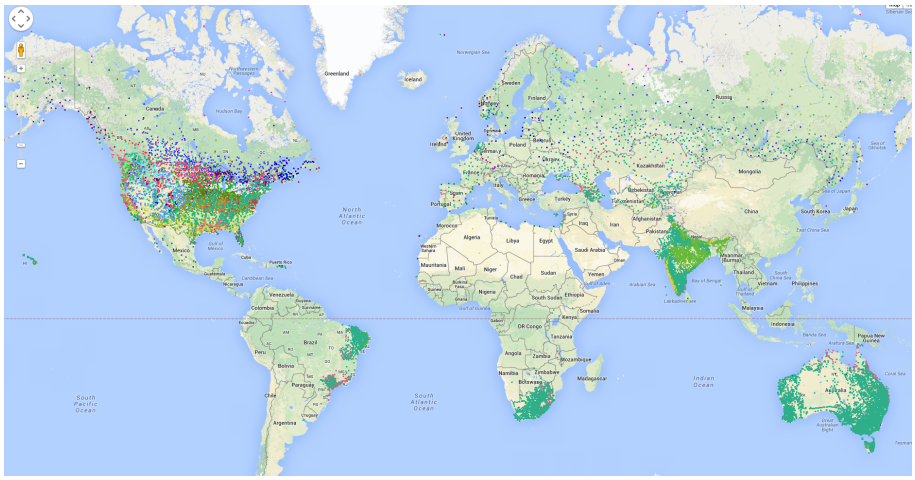
1876



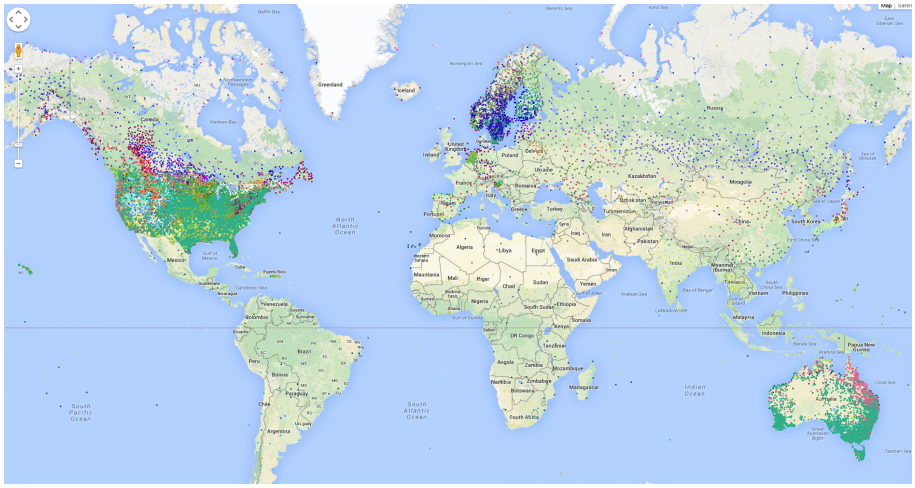
1896

Figure 4: Clustering results of 1876 and 1896.

1904



1940



2010

Figure 5: Clustering results of 1904, 1940 and 2010.

5.2 Lecture Learned

From this project, we learned quite a lot lessons, which could be improved when we do future big data project:

- Debug thoroughly before implementing it in a distributed system;
- Save the log whenever necessary.

6 Future Work

In future, we have two directions to go to improve our system: one is related with features, the other is about the clustering algorithm:

- Create more features and do feature selection;
- Other clustering algorithms, maybe GMM.

References

[1] http://aws.amazon.com/elasticmapreduce/

[2] Peterson, Thomas C., and Russell S. Vose. "An overview of the Global Historical Climatology Network temperature database." Bulletin of the American Meteorological Society 78.12 (1997): 2837-2849.

[3] https://boto.readthedocs.org/en/latest/

[4] http://aws.amazon.com/de/s3/

[5] http://scikit-learn.org/stable/

[6] https://developers.google.com/maps/?hl=de

[7] https://www.youtube.com/watch?v=xQfEk978IE4&list=UUkzQg0KkXhibidSnmizd4Vg&index=2

[8] http://www.ngdc.noaa.gov/mgg/image/color_etopo1_ice_low.jpg