Statistical Machine Learning Project 2

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# Required Tasks

The specific algorithmic tasks I needed to perform for this part of the project included:

* Initialize clusters using Strategy 1 and 2. Strategy 1 involves randomly picking the initial centers from the given samples. Strategy 2 involves picking only the first point randomly and picking points with ith center (i>1) such that the average distance of this chosen point to all previous centroids is maximal.
* Test the implementation with the number k of clusters ranging from 2-10.
* Plot the objective function value vs. the number of clusters k. Under each strategy, plot the objective function twice, each start from a different initialization.

## Initialization

* 1. Strategy 1

I have used the “NumPy” library for the Python programming language. It adds support for large, multi-dimensional arrays and matrices.

And for this whole project I have used vectorization to make calculations more efficient.

Each sample is represented as a 2D Vector.

I have used the random.sample to choose “k” random and unique points to avoid duplicate clusters.

I have then stored this in a Python list called all\_centers. The shape of this would be ( k x 2) Where k is the number of centroids.

* 1. Strategy 2

For this strategy, I choose the first point randomly using random.randint.

For the rest of the centroids, I built a function called *calc\_point\_distances()* which calculates the average distance of each point to the previously calculated centroids, stores them in a list in decreasing order and returns them.

I now iterate through this list until I find the first index which is not already present in *all\_clusters*. Hence I calculate the point with the maximum average distance which is not already present in *all\_clusters*. The reason for doing this and not just returning an argmax is because after considering a certain number of centers, the future centers get repeated. Hence this following method gives us unique centroids.

## K-Means Algorithm

I created a Python dictionary called *center\_points\_dict* which stores the cluster index as the key, and the points present in the cluster as its value. The key is an integer and the value is a list of lists.

For every iteration of KMeans these points get updated as well as all\_clusters get updated.

I have used Euclidean distance to assign a point to a cluster such that the Euclidean distance between the point and the centroid of the assigned cluster is the least among that of all the other centroids.

After each iteration I update all\_clusters by updating each centroid as the average of all the points present in that specific cluster. These points can be retrieved from *center\_points\_dict*.

I also created two plotting functions to visualize the centroids as well as all the points in their respective clusters after performing K-Means.

1. Objective Function

k – number of clusters

D – Total Sample set

- Samples in cluster i

– Centroid of cluster i.

1. Plotting the Objective Function vs Number of Graphs

I used matplotlib as my plotting library of choice.

I first created a function called *compute\_all\_objective\_costs()*, which calculated the final objective function cost after convergence for clusters ranging from 2-10, and also take the strategy as an input.

Since I created KMeans as a class, I just had to pass in number of clusters, strategy type, maximum number of iterations and the dataset path as parameters to the class instance.

I was then able to get the final objective cost for each instance each time with different number of clusters and a specific strategy time.

These costs were stored in a list and returned.

I then used matplotlib to plot these costs on the Y-axis and the number of clusters on the X-axis.

1. Results

|  |  |  |
| --- | --- | --- |
| Naive Bayes | Logistic Regression | |
| Unnormalized Gradients (lr=0.0008, epochs=250000) | Normalized gradients  (lr=0.08, epochs=2500000) |
| 69.53% | **79.97%** | **77.92%** |