CS5425 Assignement2 Task2 Report

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Analyse the result

| medianScore | averageScore [| Dominant Domain (| • | Questions | |
|-------------|----------------|-------------------|-------------|-----------|-------|
| 1 | 2 | Deep-learning | (100.0%) | 94266 | |
| 1 | 2 | Algorithm | (100.0%) | 316131 | |
| 1 | 2 | Machine-Learning | (100.0%) | 364106 | |
| 1 | 2 | Computer-Systems | (100.0%) | 113597 | |
| 1 | 1 | Big-Data | (100.0%) | 149495 | |
| 1 | 3 | Silicon Valley | (100.0%) | 54756 | |
| 1 | 1 | Compute-Science | (100.0%) | 349779 | |
| 1 | 2 | Data-Analysis | (100.0%) | 358556 | |
| 2 | 3 | Software-Enginee | ring (67.0 | %) 21634 | |
| 2 | 3 | Security | (100.0%) | 180299 | |
| 2 | 3 | Internet-Service | -Providers | (100.0%) | 24001 |
| 3 | 5 | Programming-Lang | uage (100.0 | 9%) 13198 | |
| 4 | 7 | Cloud-services | (100.0%) | 10566 | |
| 9 | 10 | Big-Data | (100.0%) | 21830 | |
| 10 | 12 | Compute-Science | (100.0%) | 29063 | |
| 41 | 45 | Big-Data | (100.0%) | 2880 | |
| 44 | 53 | Data-Analysis | (100.0%) | 5419 | |
| 45 | | Compute-Science | (100.0%) | 3915 | |
| 69 | | Deep-learning | (100.0%) | 1190 | |
| 77 | | Security | (100.0%) | 1159 | |
| 87 | | Silicon Valley | (100.0%) | 619 | |
| 112 | | Machine-Learning | (100.0%) | 1739 | |
| 127 | | Compute-Science | (100.0%) | 884 | |
| 127 | 134 | Big-Data | (100.0%) | 561 | |
| 172 | 210 | Computer-Systems | | 359 | |
| 204 | 230 | Data-Analysis | (100.0%) | 529 | |
| 276 | | Compute-Science | (100.0%) | 237 | |
| 287 | | Big-Data | (100.0%) | 153 | |
| 316 | 430 | Algorithm | (100.0%) | 128 | |
| 331 | | Deep-learning | (100.0%) | 127 | |
| 489 | 585 | Security | (100.0%) | 68 | |
| 524 | 565 | Machine-Learning | (100.0%) | 214 | |
| 546 | 557 | Silicon Valley | (100.0%) | 34 | |
| 564 | | Big-Data | (100.0%) | 65 | |
| 580 | 621 | Compute-Science | (100.0%) | 62 | |
| 618 | 726 | Data-Analysis | (100.0%) | 63 | |
| 766 | 940 | Computer-Systems | (100.0%) | 26 | |
| 823 | 921 | Deep-learning | (100.0%) | 19 | |
| 1154 | 1192 | Big-Data | (100.0%) | 18 | |
| 1300 | | Compute-Science | (100.0%) | 16 | |
| 1474 | | Machine-Learning | | 49 | |
| 3335 | 3770 | Big-Data | (100.0%) | 3 | |
| 3636 | | Security | (100.0%) | 2 | |
| 4441 | | Machine-Learning | (100.0%) | 5 | |
| 10271 | 10271 | Compute-Science | (100.0%) | 2 | |

Ans: From the cluster result, we can observe that cluster result is good, normally one cluster contains only one tag.(Because we choose a big DomainSpread)

- 1) A lot of hot topics like Machine-Learning, Deep-learning, there exist a lot of questions, but most of them do not got a good answer.
- 2)The same tags can be cluster different clusters, because the cluster number is large than the domain numbers.
- 3) The cluster result is imbalance, because exist about one third of clusters size is lower than 100.

Analysis of the parameters in k-means

DomainSpread: it used to split the different questions by tag, it totally based on our requirement, if we want to split the different tags into different clusters, we need to use a big number, if we want

to focuses on the score and want to mixed the different tags, we can use a small number. Normally it will converged more quickly if we use number of changed points as converge condition.

KmeansKernels: The number of clusters, actually it is hard to choose a suitable cluster number. if the kmeansKernels is big, it will cost more time in each iteration, but will require less iteration number to converge. But the trend is a big kmeansKernels will need more time to converge and the total loss will be small.

KmeansEta: The converge condition, it's the average distance from each points to its centroids, the KmeansEta determined the cluster quality, a small KmeansEta means a good quality cluster, but will need more time to converge.

KmeansMaxIterations: Another converge condition, if we cannot meet the KmeansEta converge condition, we will use these to terminate our process. The big KmeansMaxIterations will cost more execution time normally.

Further discussion on the system performance

1) From Principle

We know, the quality of initial centroids is important for k-means, if we choose a suitable centroids, we will get a good cluster result and converge more quickly.

In my k-mean version, I just take distinct random points as initial centroids. Actually, we can use the kmean++ method to select the initial centroids. First we random pick one point, when we pick the second point, the probability we choose that point is inversely proportional to the distance between the two points. In that way, we can choose the initial centroids points that are sparse.

- 2)From the implementation
- 1) cache all the points
- 2) when we compute the points belong to which clusters or new centroids, we can parallel these 2 operations
- 3) we can use additional converge condition, for example, the number of points changed in this iterations.