

Enhanced clustering

Gianluca Bortoli
DISI - University of Trento
Student id: 179816
gianluca.bortoli@studenti.unitn.it

Martin Brugnara
DISI - University of Trento
Student id: 182904
mb@disi.unitn.eu

ABSTRACT

Keywords

Big data, Data mining, Clustering, Streaming, Parallel computation

1. INTRODUCTION

The clustering problem consists in grouping together data items that are “similar” to each other such that the inter-group similarity is high, while the intra-group one is low.

This challenge has received a lot of attention over the years. According to Jane and K. [12], the first specific study appeared in 1954 [6] and by now thousands of solutions have been proposed.

Data clustering has been used in many different disciplines, such as data mining [10], statistics [20, 1] and machine learning. The most common usages aim to gain insight to data (underlying structure) and for summarizing it through cluster prototypes (compression).

The concept of similarity varies a lot in the different contexts it can be applied. For example the Euclidean distance (L2) can be used when dealing with continuous values or the Jaccard similarity index, which computes similarity for generic sets of elements. Nonetheless, the underlying algorithm is agnostic with respect to the similarity measure that is applied to compute a distance between the elements in the data. Clustering can be also viewed as identifying the dense regions of the probability density of the data source [3].

The literature suggests two different approaches: *partitional* and *hierarchical*.

The first strategy needs some parameters to be set and known in advance. For example the *k-means*, which is one of the most popular and adopted algorithm, requires the number of cluster to be found (K).

The latter can be implemented both in a top down (divisive) or a bottom up (agglomerative) manner. Initially, the divisive algorithm treats all data as a single big cluster and later splits it until every object is separated [14]. On the contrary, the agglomerative starts considering each “element” as a *singleton* (a cluster composed of one element). Next, the most similar clusters are collapsed together until only one big cluster remains. Implicitly the merging order defines a clear hierarchy among the intermediate representations (dendrogram).

Clearly, both the above mentioned approaches to the clustering problem have their disadvantages. The partitional methods require prior knowledge on the data distribution, while the hierarchical ones imply the user interaction to de-

cide the dendrogram’s cut height. For a complete list of the various clustering technique flavours refer to Jan *et al.* review [12]. However, a solution that does not suffer from those is still an open challenge.

In this work we propose a completely autonomous system which merges the two strategies to overcome their weaknesses, meaning that it satisfies the following *Data Mining Desiderata*:

1. **streaming**: require one scan of the database, since reading from secondary memory is still the most costly I/O operation. Moreover the analysis can be stopped and restarted without having to re-process the whole data (“stop and resume” support). This property adds the capability to incorporate additional data with existing model efficiently (incremental computation).
2. **on-line “anytime” behaviour**: a “best” answer is always available at any time during the computation phase.
3. **limited memory**: the tool must work within the bounds of a given amount of main memory (RAM).

2. RELATED WORK

The most popular and simplest partitional algorithm is **k-means** [16]. Like every other solution belonging to this class, it requires the objective number of clusters (k) to be known a-priori. Unfortunately, there exists no mathematical formula to compute such parameter in advance, requiring the test to be run multiple times with different values in order to find the best solution according to some criterion (*e.g.* the Schwarz Criterion [18]). This algorithm is based on the notion of distance and it usually employs the Euclidean one. The resulting division into clusters can be also seen as a lossy compression of the points towards the centroids identifying the clusters. The main idea behind the k-means consists in minimizing an objective function. Usually the Mean Squared Error (MSE) is chosen, where the error is defined as the distance between each point and the centroid of the cluster it is assigned to. This process is iterative; initially k points are identified to be the centroids, then all the points are assigned to the nearest centroid (locally minimizing the MSE) and finally the centroids are recomputed as the barycenter of the clusters. The procedure continues until the convergence of the centroids’ locations. A noteworthy aspect is that the bootstrap phase, namely the initial centroids identification, highly influences the outcome.

Different centroids usually lead to different results, since the algorithm is designed to find a local optimum. Several

options for the bootstrap have been proposed like the one from Bradley and Fayyad [2]. They suggest to run the k-means algorithm M times using any initial centroid selection strategy on M different subsets of the initial data. After that, an optimal grouping of the $M \times k$ centroids identified in the previous runs has to be found. Given the small set size, a brute force approach is a reasonable option. Finally the “real” k-means will use those centroids as the initial ones.

Using a distance as a similarity measure implies that the clusters will have a spherical shape. It follows that the algorithm performs best when the input data have features values that are normally distributed.

Despite these disadvantages, many variants and optimizations have been proposed both by the industrial and academic communities [13, 15, 8].

Another important clustering algorithm is the “Density-based spatial clustering of applications with noise”, more commonly known as **DBSCAN** [9]. As the name suggests, it is a density-based approach to the clustering problem, meaning that it groups together points with many others in the neighborhood and penalizes the ones in low density areas (outliers). The original version of DBSCAN relies on two user-provided parameters, namely *minPts* and ϵ . The *minPts* variable represents the minimum number of points that must lie in a circle of radius ϵ (neighborhood).

This algorithm exploits the *density-reachability* to define three classes of points:

- *core*: set of points that have at least *minPts* neighbors.
- *reachable*: set of points that are in the neighborhood of a *core* point, but are not *core* points themselves.
- *outlier*: set of points that have less than *minPts* points in their neighborhood.

As happens with the k-means, DBSCAN has the disadvantage of requiring its parameters *minPts* and ϵ to be known in advance. One possible solution is to let a domain expert deal with it, providing sensible parameters based on his prior and deep knowledge of the dataset. Moreover, DBSCAN lacks in flexibility since it uses a single “is dense” threshold derived from the two input parameters.

Some techniques for estimating such parameters have been proposed in the literature, resulting in an extended version of the algorithm known as EDBSCAN [7, 17]. It improves the handling of local density variation that exists within the clusters and dynamically chooses the best *minPts* and ϵ values for the current run. For good clustering results, such significant density variation might be allowed within a cluster if the objective is not a large number of smaller unimportant clusters. Furthermore, it tries to detect the clusters with different shapes and sizes that differ in local density.

As opposed to k-means, DBSCAN is able to find arbitrarily-shaped clusters, since it does not employ a distance to measure similarity. Moreover, the notion of density-reachability is not symmetric. Hence, this is the key property that allows to find clusters with any shape rather than only ones normally distributed.

There exist also mixed approaches that try to combine the advantages of both the partitional and the hierarchical models to overcome the respective weaknesses.

A noteworthy application is the **BFR** [3] algorithm proposed by Bradley, Fayyad and Reina. It addresses the problem of clustering very large databases that do not fit in main memory, where scanning data at each iteration step is extremely costly. This can be generalized to scenarios where random reading operations are costly or not possible (*e.g.* streaming data, hard disk, non-materialized views). The main idea behind BFR is to use sufficient statistics [11] to represent groups of points.

In more detail, first the algorithm has to be initialized with k points, which are designated as the initial centroids. After that, it fetches data filling the preallocated RAM buffer, and then it updates the internal model (*i.e.* it runs a classic k-means on the buffered data) and classifies the singleton items into the following sets in order to perform *data compression*:

1. *discard*: points that can be discarded after updating the sufficient statistics of the cluster they are assigned to.
2. *compression*: non discarded points that do not belong to any of the k clusters, but can be summarized and represented by other sufficient statistics.
3. *retained*: points that do not belong to any of the previous classes. They are kept as is in the buffer.

This data compression procedure is used to eliminate data points that are not useful anymore from main memory, thus allowing the buffer to continuously accommodate new data. To achieve this, *primary* data compression removes data points that are unlikely to change cluster membership in future iterations thresholding the Mahalanobis radius [5] around a candidate centroid and summarizing all the items within that area (discard set). Moreover, *secondary* data compression aims at finding sub-clusters of points that are very close to each other that were not compressed during the primary step (compression set).

Unfortunately, the BFR algorithm suffers from the cluster’s shape issue as the k-means. Therefore, this approach is able to deal only with data that follows a Gaussian distribution.

3. PROBLEM DEFINITION

Clustering is the task of gathering items in a way that elements belonging to the same group (the *cluster*) are more similar to each other than the ones assigned to the others.

More formally, given an input:

- $X = \{x_0, \dots, x_n\}$, the initial set of elements.
- $d : X \times X \rightarrow \mathbb{R}$, a *metric* measuring the similarity.

The final goal is to find the cluster configuration

$$C = \{c_0, \dots, c_m\} \mid \bigcup_C = X$$

partitioning X into m clusters, maximizing the intra-cluster distance (dual problem of minimizing inter-cluster distance):

$$\arg\max_C \sum_{c \in C} \sum_{i,j}^{|c|} d(c_i, c_j) \quad (1)$$

Challenges

The concept of clustering is simple and powerful; moreover, its versatility and generality are its greatness and at the same time source of many difficulties.

Given the only strict requirement to be the definition of a metric over the domain of X , clustering is applied to a wide variety of problems. Clearly, each domain offers different optimization opportunities and particular challenges. In particular, the choice of the metric heavily influences the final outcome quality. As a result even the medical [19], the mechanical engineering [21] and the mobile networks [4] literatures features different studies that address this particular challenge suggesting highly specialized distance functions.

Once the proper metric is identified, the following huge influencing factors are the mathematical definitions of “intra-cluster” and “inter-cluster” distances. They vary a lot in the different implementation leading to completely different clustering configurations. For example, when performing agglomerative clustering three methods are widely used to define the distance between two clusters: average, minimum, and maximum distance. The average approach uses the barycenters, while the minimum (maximum) relies upon the minimal (maximal) distance between any two points belonging to a different clusters.

4. SOLUTION

5. CONCLUSIONS AND FUTURE WORK

6. REFERENCES

- [1] J. D. Banfield and A. E. Raftery. Model-based gaussian and non-gaussian clustering. *Biometrics*, pages 803–821, 1993.
- [2] P. S. Bradley and U. M. Fayyad. Refining initial points for k-means clustering. In *ICML*, volume 98, pages 91–99. Citeseer, 1998.
- [3] P. S. Bradley, U. M. Fayyad, C. Reina, et al. Scaling clustering algorithms to large databases. In *KDD*, pages 9–15, 1998.
- [4] H. Cheng, J. Cao, X. Wang, S. K. Das, and S. Yang. Stability-aware multi-metric clustering in mobile ad hoc networks with group mobility. *Wireless Communications and Mobile Computing*, 9(6):759–771, 2009.
- [5] R. Duda. O. and hart, pe (1973) pattern classification and scene analysis. *New York: Willey*, 6.
- [6] J. Durbin and A. Stuart. Callbacks and clustering in sample surveys: An experimental study. *Journal of the Royal Statistical Society. Series A (General)*, 117(4):387–428, 1954.
- [7] M. T. Elbatta and W. M. Ashour. A dynamic method for discovering density varied clusters. *International Journal of Signal Processing, Image Processing and Pattern Recognition*, 6(1):123–134, 2013.
- [8] C. Elkan. Using the triangle inequality to accelerate k-means. In *ICML*, volume 3, pages 147–153, 2003.
- [9] M. Ester, H.-P. Kriegel, J. Sander, X. Xu, et al. A density-based algorithm for discovering clusters in large spatial databases with noise. In *Kdd*, volume 96, pages 226–231, 1996.
- [10] U. M. Fayyad, G. Piatetsky-Shapiro, P. Smyth, and R. Uthurusamy. *Advances in knowledge discovery and data mining*, volume 21. AAAI press Menlo Park, 1996.
- [11] R. A. Fisher. On the mathematical foundations of theoretical statistics. *Philosophical Transactions of the Royal Society of London. Series A, Containing Papers of a Mathematical or Physical Character*, 222:309–368, 1922.
- [12] A. K. Jain. Data clustering: 50 years beyond k-means. *Pattern recognition letters*, 31(8):651–666, 2010.
- [13] T. Kanungo, D. M. Mount, N. S. Netanyahu, C. D. Piatko, R. Silverman, and A. Y. Wu. An efficient k-means clustering algorithm: Analysis and implementation. *IEEE transactions on pattern analysis and machine intelligence*, 24(7):881–892, 2002.
- [14] L. Kaufman and P. J. Rousseeuw. *Finding groups in data: an introduction to cluster analysis*, volume 344. John Wiley & Sons, 2009.
- [15] A. Likas, N. Vlassis, and J. J. Verbeek. The global k-means clustering algorithm. *Pattern recognition*, 36(2):451–461, 2003.
- [16] J. MacQueen et al. Some methods for classification and analysis of multivariate observations. In *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*, volume 1, pages 281–297. Oakland, CA, USA., 1967.
- [17] A. Ram, A. Sharma, A. S. Jalal, A. Agrawal, and R. Singh. An enhanced density based spatial clustering of applications with noise. In *Advance Computing Conference, 2009. IACC 2009. IEEE International*, pages 1475–1478. IEEE, 2009.
- [18] G. Schwarz et al. Estimating the dimension of a model. *The annals of statistics*, 6(2):461–464, 1978.
- [19] V. Siless, S. Medina, G. Varoquaux, and B. Thirion. A comparison of metrics and algorithms for fiber clustering. In *Pattern Recognition in Neuroimaging (PRNI), 2013 International Workshop on*, pages 190–193. IEEE, 2013.
- [20] H. C. Tijms. *Stochastic models: an algorithmic approach*, volume 303. John Wiley & Sons Inc, 1994.
- [21] S. E. Wilding and D. T. Fullwood. Clustering metrics for two-phase composites. *Computational Materials Science*, 50(7):2262–2272, 2011.