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Analysis of Placement for Electronics and Communication Engineering Students using Multiple Clustering

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Abstract:
Inspired by the success of supervised bagging and boosting algorithms, we propose non-adaptive and adaptive re-sampling schemes for the integration of multiple independent and dependent clustering. We investigate the effectiveness of bagging techniques, comparing the efficacy of sampling with and without replacement, in conjunction with several consensus algorithms. In our adaptive approach, individual partitions in the ensemble are sequentially generated by clustering specially selected subsamples of the given data set. The sampling probability for each data point dynamically depends on the consistency of its previous assignments in the ensemble. New subsamples are then drawn to increasingly focus on the problematic regions of the input feature space. The comparison of adaptive and non-adaptive approaches is a new avenue for research, and this study helps to pave the way for the useful application of distributed data mining methods.

Keywords: Python, MATLAB, ECE, prediction, branch, data, clustering.

INTRODUCTION

Exploratory placement data analysis and, in particular, data clustering can significantly benefit from combining various multiple data set partitions. Clustering ensembles can provide better solutions in terms of its robustness, novelty and stability. Moreover, the parallelization capabilities are a natural fit for the demands of distributed data mining. Achieving stability in the process, combination of multiple clusterings presents difficulties.

However, similar to the ensembles of supervised classifiers using boosting algorithms (Brieman 1998), a more accurate consensus clustering can be obtained if contributing partitions take into account the previously determined solutions. Unfortunately, it is not possible to mechanically apply the decision fusion algorithms from the supervised (classification) to the unsupervised (clustering) domain. New objective functions for guiding partition generation and the subsequent decision integration process are necessary in order to guide further refinement. Frossyniotis et al. (2004) apply the general principle of boosting to provide a consistent partitioning of a data set. At each boosting iteration, a new training set is created and the final clustering solution is produced by aggregating the multiple clustering results through a weighted voting.

We proposed a simple method an adaptive approach to partition generation that generally makes use of previous clustering history. In clustering process, the ground truth in the form of class labels is not available. Hence, we need to have an alternative measure of performance for an ensemble of partitions. We could obtain clustering consistency for various data set points by evaluating a previous history of cluster assignments for each data set point within the sequence generated of partitions. Clustering consistency serves for adapting the data sampling to the current state of an ensemble during partition generation. The goal of adaptation is to improve confidence in cluster assignments by concentrating sampling distribution on problematic regions of the feature space. In other words, by focusing attention on the data points with the least consistent clustering assignments, one can better approximate (indirectly) the inter-cluster boundaries.

The four main objectives are:
1. A detailed taxonomy of clustering ensemble approaches,
2. Critical and Unaddressed issues in applying resampling methods,
3. To provide a detailed comparison of bootstrap v/s sub-sampling ensemblegeneration,
4. Finally, to study adaptive partitioning ensembles.

EXPERIMENTAL SETUP

Classifiers

Pattern recognition has a wide variety of applications in various fields; hence it is not possible to develop with a specific single type of classifier that can produce Pattern recognition has a wide variety of applications in various fields; hence it is not possible to develop with a specific single type of classifier that can produce

The taxonomy of different consensus functions for clustering combination is shown in Figure 2.1. Several methods are known to create partitions for clustering ensembles. This taxonomy presents solutions for the generative procedure as well.

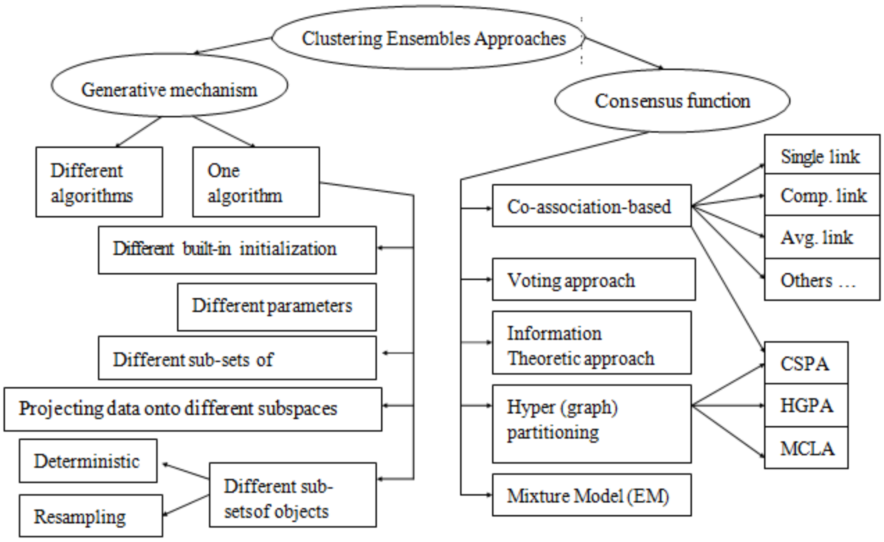

Figure 2.1 Taxonomy of different approaches to clustering combination

Distributed data clustering deals with the combination of partitions from many data sub-sets (usually disjoint). The combined final clustering can be constructed centrally either by combining explicit cluster labels of data points or, implicitly, through the fusion of cluster prototypes (e.g., centroid-based). We analyze the first approach, namely, the clustering combination via consensus functions operating on multiple labelings of the different subsamples of a data set. This study seeks to answer the question of the optimal size and granularity of the component partitions.

Non-Adaptive Algorithms

Boot-strap (sampling with replacement) and that of sub-sampling (without replacement) can discern various statistics from replicate sub-sets of data while the samples in both casesare independent of each other. Our goal is to obtain a reliable clustering with measurable uncertainty from a set of various *k*-means partitions. The major idea of the approach is to integrate and combine multiple partitions methods developed by clustering of pseudo-samples of a data set.

Similarity-Based Algorithm

The first algorithm family is based on the co-association matrix, and employs a group of hierarchical clustering algorithms to find the final target partition. In this type, similarity-based clustering algorithms are used as the consensus function. Hierarchical clustering consensus functions with single-, complete-, and average-linkage criteria were used to obtain a target consensus clustering. Pseudo-code of these algorithms is shown in Figure 3.1. The parameter *k* in both algorithms is the number of clusters in every component partition. If the value of *k* is too large then the partitions will overfit the data set, and if *k*is too small then the number of clusters may not be large enough to capture the true structure of data set. In addition, if the total number of clusterings, *B*, in the combination is too small then the effective sample size for the estimates of distances between co- association values is also insufficient, resulting in a larger variance. In the rest of this chapter "*k*" stands for number of clusters inevery partition, "*B*" for number of partitions/pseudo-samples (in both the bootstrap and the sub-sampling algorithms), and "*S*" for the sample size.

Consensus Functions

A consensus function is used to maps a given set of partitions to a target partition. In this experiment we have employed four types of consensus functions: Co-association based functions, Quadratic Mutual Information Algorithm (QMI), Hypergraph partitioning and Voting approach

Critical Issues in Resampling

Let us emphasize the challenging points of using resampling techniques for maintaining diversity of partitions and estimation of co-association values: Variable number of samples, Repetitive data points (objects), Similarity estimation, Missing labels, Re-labeling, Adaptation of the k-means algorithm. A consensus clustering can be found by using an agglomerative clustering algorithm (e.g., single linkage) applied to such a co-association matrix constructed from all the points. The quality of the consensus solution depends on the accuracy of similarity values as estimated by the co-association values. The least reliable co-association values come from the points located in the problematic areas of the feature space. Therefore, our adaptive strategy is to increase the sampling probability for such points as we proceed with the generation of different partitions in the ensemble. The sampling probability can be adjusted not only by analyzing the co-association matrix, which is of quadratic complexity $O(N^2)$, but also by applying the less expensive $O(N + K^3)$ estimation of clustering consistency for the data points. Again, the motivation is that the points with the least stable cluster assignments, namely those that frequently change the cluster they are assigned to, require an increased presence in the data subsamples. In this case, a label correspondence problem must be approximately solvedto obtain the same labeling of clusters throughout the ensemble's partitions. By default, the cluster labels in different partitions are arbitrary. To make the correspondence problem more tractable, one needs to re-label each partition in the ensemble using some fixed reference partition. Table 3.1 illustrates how four different partitions of twelve points can be re-labeled using the first partition as a reference.

RESULTS AND DISCUSSION

Experimental Study on Non-Adaptive Approaches

The experiments were performed on several data sets, including two challenging artificial problem, the "Halfrings" data set, and the "2-Spiral" data set, two data sets fromUCI repository, the "Iris" and "Wine" and two other real world data set, the "ECE" and "Star/Galaxy" data sets. A summary of data set characteristics is shown in Table 3.1.

Input: D – data set of N points
B – number of partitions to be combined
M – number of clusters in the consensus partition σ
K – number of clusters in the partitions of the ensemble
Γ – chosen consensus function operating on cluster labels
$\mathbf{p}$ – sampling probabilities (initialized to $1/N$ for all the points)
Reference Partition $\leftarrow$ k-means(D)
for i=1 to B
  Draw a subsample X_i from D using sampling probabilities $\mathbf{p}$
  Cluster the sample X_i: $\pi(i) \leftarrow k$-means(X_i)
  Re-label partition $\pi(i)$ using the reference partition
  Compute the consistency indices for the data points in D
  Adjust the sampling probabilities $\mathbf{p}$
end
Apply consensus function Γ to ensemble Π to find the partition σ
Validate the target partition σ (optional)
return σ // *consensus partition*

Figure 3.1 Algorithms for adaptive clustering ensembles

Data Sets

The Halfrings and 2-Spiral data set, as shown in Figure 5.7, consist of two clusters, though the clusters are unbalanced with 100- and 300-point patterns in the Halfrings data set and balanced in the 2-Spiral. The *k*-means algorithm by itself is not able to detect the two natural clusters since it implicitly assumes hyperspherical clusters. 3-Gaussian is a simulated data set that includes three unbalanced classes with 50, 100, and 150 data points. The Wine data set described in Aeberhard et al. (1992) contains the value of the chemical composition of wines grown in the same region but derived from three different cultivars. The patterns are described by the quantities of thirteen constituents (features) found in each of the three types of wines. There are 178 samples in total. The figure 3.3(a) and 3.3(b) shows the intake of ECE students from 2004 to 2022, also the admitted ECE students from the academic year 2004 to 2022, the classification and distributation pattern from 2014 to 2022 are discussed with the average salary, the trends are improving as per the IT sector demand and projects, the average salary is not impressive, with respect to core sector.

Table 3.1: A summary of data sets characteristics

	No. of Classes	*No. of Features*	*No. of Patterns*	*Patterns per class*
Star/Galaxy	2	14	4192	2082-2110
Wine	3	13	178	59-71-48
ECE	2	6	227	64-163
Iris	3	4	150	50-50-50
3-Gaussian	3	2	300	50-100-150
Halfrings	2	2	400	100-300
2-Spirals	2	2	200	100-100

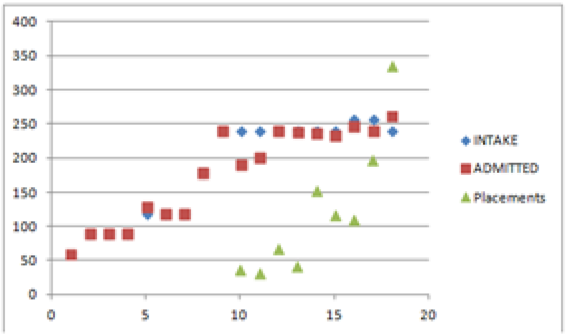

Figure 3.3(a): Pattern of intake, admitted and placement data-sets.

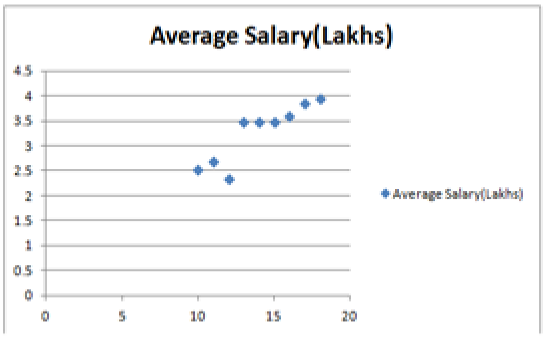

Figure 3.3(b): Pattern of average salary data-sets.

The ECE data set (Minaei & Punch, 2003) is extracted from the activity log in a web-based course using an online educational system developed at Michigan State University (MSU): the Learning Online Network with Computer-Assisted Personalized Approach (ECE-CAPA). The data set includes the student and course information on an introductory physics course (ECE-PHY), collected during the spring semester 2002. This course included 12 homework sets with a total of 184 problems, all of which were completed online using ECE-CAPA. The data set consists of 227 student records from one of the two groups: “Passed” for the grades above 2.0, and “Failed” otherwise. Each sample contains 6 features.

The Iris data set contains 150 samples in 3 classes of 50 samples each, where each class refers to a type of iris plant. One class is linearly separable from the other two, and each sample has four continuous-valued features. The Star/Galaxy data set described in Odewahn (1992) has a significantly larger number of samples (N=4192) and features (d=14). The task is to separate observed objects into stars or galaxies. Domain experts manually provided true labels for these objects.

For all these data sets the number of clusters, and their assignments, are known. Therefore, one can use the misassignment (error) rate of the final combined partition as a measure of performance of clustering combination quality. One can determine the error rate after solving the correspondence problem between the labels of derived and known clusters. The Hungarian method for solving the minimal weight bipartite matching problem can efficiently solve this label correspondence problem.

The Role of Algorithm's Parameters

The bootstrap experiments probe the accuracy of partition combination as a function of the resolution of partitions (value of k) and the number of partitions, B (number of partitions to be merged).

One of our goals was to determine the minimum number of bootstrap samples, B, necessary to form high-quality combined cluster solutions. In addition, different values of$k$ in the k-means algorithm provide different levels of resolution for the partitions in the combinations. We studied the dependence of the overall performance on the number of clusters, k. In particular, clustering on the bootstrapped samples was performed for the values of B in the range [5, 1000] and the values of k in the interval [2, 20].

Analogously, the size of the pseudosample, S, in subsampling experiments is anotherimportant parameter. Our experiments were performed with different subsample sizes in the interval

[N/20, $3N$/4], where N is the size of the original data sample. Thus, in thecase of the Halfrings, S was taken in the range [20, 300] where the original sample size is N=400, while in the case of the Galaxy data set, parameter S was varied in the range [200,3000] where N=4192. Therefore, in resampling without replacement, we analyzed how the clustering accuracy was influenced by three parameters: number of clusters, k, in every clustering, number of drawn samples, B, and the sample size, S. Note that all the experiments were repeated 20 times and the average error rate for 20 independent runs is reported, except for the Star/Galaxy data where 10 runs were performed.

The experiments employed eight different consensus functions: co-association-based functions (single link, average link, and complete link), hypergraph algorithms (HGPA, CSPA, MCLA), the QMI algorithm, as well as a Voting-based function.

The Role of Consensus Functions (Bootstrap algorithm)

Perhaps the single most important design element of the combination algorithm is the choice of a consensus function. In the Halfrings data set the true structure of the data set (100% accuracy) was obtained using co-association-based consensus functions (both single and average link) in the case of k=15 and number of partitions taking part in the combination where B≥100. None of the other six consensus methods converged to an acceptable error rate for this data set.

For the Wine data set an optimal accuracy of 73% was obtained with both the hypergraph-CSPA algorithm and co-association-based method using average link (AL) with different parameters as shown in Table 5.6. For the ECE data set the optimal accuracy of 79% was achieved only by co-association-based (using the AL algorithm) consensus function. This accuracy is comparable to the results of the k-NN classifier, multilayer perceptron, naïve Bayes classifier, and some other algorithms when the "*ECE*" data set is classified in a supervised framework based on labeled patterns (Minaei & Punch, 2003).

For the "*Iris*" data set, the hypergraph consensus function, HPGA algorithm led tothe best results when k ≥ 10. The AL and the QMI algorithms also gave acceptableresults, while the single link and average link did not demonstrate a reasonable convergence. Figure 5..7.3.1 shows that the optimal solution could not be found for the Iris data set with k in the range [2, 5], while the optimum was reached fork ≥ 10 with only B≥10 partitions. For the Star/Galaxy data set the CSPA function (similarity-based hypergraph algorithm) could not be used due to its computational complexity because it has a quadratic complexity in the number of patterns $O(kN^2B)$.

The HGPA function and SL did not converge at all, as shown in Table 5.5. Voting and complete link also did not yield optimal solutions. However, the MCLA, the QMI and the AL functions led to an error rate of approximately 10%, which is better than the performance of an individual k-means result (21%). The major problem in co-association-based functions is that they are computationally expensive. The complexity of these functions is very high ($O(kN^2d^2)$)and therefore, it is not effective to use the co-association-based functions as a consensus function for the large data sets. Note that the QMI algorithm did not work well when the number of partitions exceeded 200, especially when the value of k was large. This might be due to the fact thatthe core of the QMI algorithm operates in k–dimensional space. The performance of the k-means algorithm degrades considerably when B is large (>100) and, therefore, theQMI algorithm should be used with smaller values of B.

CONCLUSION

Concluding Remarks

A new approach to combine partitions is proposed by resampling of original data. This study showed that meaningful consensus partitions for the entire data set of objects emerge from clusterings of bootstrap and subsamples of small size. Empirical studies were conducted on various simulated and real data sets for different consensus functions, number of partitions in the combination and number of clusters in each component, for both bootstrap (*with* replacement) and subsampling (*without* replacement). The results demonstrate that there is a trade-off between the number of clusters per component and the number of partitions, and the sample size of each partition needed in order to perform the combination process converges to an optimal error rate. The bootstrap technique was recently applied in (Dudoit & Fridlyand, 2003; Fisher & Buhmann, 2003; Monti et al., 2003) to create a diversity in clusterings ensemble. However, our work extends the previous studies by using a more flexible subsampling algorithm for ensemble generation. We also provided a detailed comparative study of several consensus techniques. The challenging points of using resampling techniques for maintaining diversity of partitions were discussed in this chapter. We showed that there exists a critical fraction of data such that the structure of entire data set can be perfectly detected. Subsamples of small sizes can reduce costs and measurement complexity for many explorative data mining tasks with distributed sources of data. We have extended clustering ensemble framework by adaptive data sampling mechanism for generation of partitions. We dynamically update sampling probability to focus on more uncertain and problematic points by on-the-fly computation of clustering consistency. Empirical results demonstrate improved clustering accuracy and faster convergence as a function of the number of partitions in the ensemble. Further study of alternative resampling methods, such as the balanced (stratified) andrecentered bootstrap methods are critical for more generalized and effective results. This work has been published in (Minaei et al., 2004a; Minaei et al. 2004b, Topchy et al. 2004).

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