

WEIGHTED CLUSTERING ENSEMBLE WITH BASE CLUSTERING FREQUENCY AND DIVERSITY

Arko Banerjee, Suwendu Chandan Nayak and Chhabi Rani Panigrahi

ABSTRACT

Clustering Ensemble, also referred as Consensus Clustering, is a tool for enhancing the reliability and stability of data clustering by aggregating the base clusterings obtained by different clustering algorithms in the input ensemble. This study introduces a novel ensemble selection strategy for establishing consensus clustering. Our strategy avoids looking at the entire population of base clusterings in the ensemble in order to establish a quality consensus by carefully selecting a few base clusterings. The experimental results reveal that the suggested method's consensus clustering surpasses some other well-known clustering ensemble methods in terms of clustering accuracy for diverse data sets.

Index Terms Ensemble Clustering; Consensus; Frequency; Diversity.

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Biographical notes:

Arko Banerjee, arko.banerjee@gmail.com, Biju Patnaik University of Technology, Odisha, India.

Suwendu Chandan Nayak, suwendu2006@gmail.com, GITA Autonomous College Bhubaneswar, Odisha, India

Chhabi Rani Panigrahi, panigrahichhabi@gmail.com, Rama Devi Women's University, Bhubaneswar, Odisha, India

1. INTRODUCTION

Consensus Clustering is a technique in which the base clustering of an ensemble a data are optimally combined to generate a qualitatively enhanced clustering. The majority of the base clustering that make up the ensemble can be formed overly, and not all of them accurately represent the data's underlying structure. As a result, when forming a consensus, all clusterings are not need to be considered. In such a setting, the question naturally arises as to whether certain of the ensemble's base clusterings should be used selectively. The purpose of this study is to address the issue. The aim is to develop a mechanism for picking a subset of base clusterings that has a consensus that is on a par with or better than that of the ensemble as a whole. Each clustering in this method can be thought of as an expert's judgment, representing the possibility of an element fitting into a cluster. In our work, we consider the weighting of expert judgments in terms of the diversity and frequency of the relevant base clustering. The opinions of experts who regularly concur are regarded to be more qualified than those who concur infrequently. On the other hand, if one expert's view differs from that of other experts, her judgement should not be dismissed because it may contain vital insights into the structure of the data that other experts have missed. As a result, frequently occurring base clusterings that are varied in comparison to the whole ensemble may include useful information for the ultimate consensus. This hypothesis has been explored empirically for several types of data in this paper. The remainder of the paper is arranged as follows: Section 2 contains an overview of the pertinent literature. Section 3 discusses the weighing technique for a clustering that takes frequency and diversity into account. Chapter 4 details the proposed ensemble selection technique. Experiments in Section 5 demonstrate that the approaches outperform other widely used consensus clustering algorithms. Finally, Chapters 6 and 7 summarise the contribution of the paper.

2. RELATED WORK

The following is a description of the clustering ensemble problem: $S = \{s_1, s_2, \dots, s_n\}$ is the set of n data points.. A clustering P on S is described as a partition $P = \{C_1, C_2, \dots, C_k\}$ where each set $C_i \subseteq S$, also known as a cluster, is such that they are mutually exclusive i.e. $C_i \cap C_j = \emptyset$ and exhaustive i.e. $\cup C_i = S$. The distinction between any random partition and a clustering of S is that the clustering is such a partition that attempts to group comparable (closer) data points together in a single set (cluster) and dissimilar data points together in a separate set (cluster). A base clustering can be obtained by running a clustering algorithm on S . A collection of base clusterings $P = \{P_1, P_2, \dots, P_T\}$ can be produced by repeatedly running multiple clustering algorithms on S several times (say T times) or by repeatedly running the same method with varying initial values. The objective is to discover a definite clustering $P^* = \{C^* 1, C^* 2, \dots, C^* k\}$ that maximizes the consensus function mapping P to a final clustering P^* . This P^* is the consensus clustering, which is a median of $P_1, P_2, \dots,$ and P_T . In the literature, various works on consensus functions have been done. In this context, a great number of research papers on various areas of consensus clustering, such as novel algorithms, theoretical work [27], and applications, have recently been published [17] [18] [19] [20] [21] [22] [23] [24] [25] [26]. Fred et al. [4] generate an ensemble of clusterings using many iterations of the k-means method, which they then integrate into a co-association matrix. Following that, the coassociation matrix is used to construct the end clustering ensemble using a hierarchical single-link approach. According to Topchy et al. [12], the clustering ensemble problem can be formulated as a maximum likelihood estimation problem that can be solved using the EM algorithm. Caruana et al. [2] proposed that the ensemble be drawn from a trained model library. Gionis et al. [6] propose a

theoretical framework for consensus clustering and a few consensus algorithms that are theoretically guaranteed to keep the final consensus's quality. Topchy et al. [13] describe two approaches that incorporate plurality voting and a partition space metric. Strehl and Ghosh [11] formulate the consensus clustering problem as a graph optimization problem and define the Normalized Mutual Information (NMI) of the ensemble of clusterings as a metric of consensus clustering quality. Nguyen and Caruana [16] propose the Iterative Voting Consensus (IVC) technique and its two variants for discovering clustering ensembles. By aiming to minimize/maximize a disagreement/agreement criterion function, the majority of the approaches listed above attempt to locate a clustering that is similar to the input ensemble of clusterings. Due to the disparate ways in which they generate the criterion function and the proposed heuristic for improving it, the results of various consensus clustering algorithms vary. All of these strategies take into account the entire ensemble of clusterings in order to arrive at a consensus clustering. However, many redundancies as well as diversity in constituent clusterings can be found in an ensemble. As a result, strategically selecting a subset of the whole ensemble of clusterings may improve the quality of the consensus outcome. Fern et al. refer to this as the Ensemble Selection Problem [3]. They provide three ensemble selection algorithms depending on the quality and variability of clusterings in the input ensemble. The first technique, Joint Criterion, develops a shared objective function based on diversity and quality. Cluster and Select (CAS) is the second approach, which determines a clustering of the clusterings in the ensemble based on a similarity measure. It discovers the consensus of all representative clusterings by selecting one representative clustering from each cluster of clusterings. The third technique, Convex Hull, uses the convex hull idea to determine the consensus of vertices in the ensemble expressed by average quality and diversity of clusterings. Cluster and Select outperforms the other two recommended approaches in the paper's experiments.

III. CLUSTERING WEIGHT BASED ON DIVERSITY AND FREQUENCY

The notions of variety and frequency of base clusterings in an ensemble are used in this part to present a novel approach of ensemble selection procedure. The ensemble of base clusterings P is supposed to be overly created by repeated iterations of the same or different algorithms. Because P is overly created, it's more possible that some of the clusterings will have numerous copies. Without losing generality, Assume that E is the set containing all (say, r) unique clusterings of P , where $E = \{P_1, P_2, \dots, P_r\}$. The terms listed below are defined.

A. Definition 1 (Frequency) The number of copies of P_i in P is called the frequency of P_i (denoted as v_i) in E .

B. Validity Measures Numerous validity or similarity metrics have been proposed in the literature to compare two clusterings [1][5][7][8][10][11][12][14]. We use the Adjusted Rand Index as a measure of similarity between two partitions in our empirical section. It is important to note, however, that the strategy suggested in this paper works with any metric or non-metric similarity measure and is not dependent on any specific similarity measure. In most cases, similarity measurements return a maximum value of 1 in the event of two identical clusterings and a minimum value of 0 in the case of absolute disagreement between two clusterings.

Definition 2 (Mean Similarity Index) The mean Similarity index (MSI) of a clustering P_i in E represents P_i 's average similarity to all clusterings in E and is indicated by $MSI(P_i, E)$ where, $r \geq i, j = 1, 2, \dots, r$

$$MSI(P_i, E) = \frac{1}{r-1} \sum_{j=1, j \neq i}^r SI(P_i, P_j) \quad (3)$$

Here, $SI(P_i, P_j)$ is a similarity measure index such as the Adjusted Rand Index.

C. Definition 3 (Diversity Index) In E , the diversity measure index of P_i is defined as follows. $DI(P_i, E) = 1 - MSI(P_i, E)$

(4) If P_i clusters in E as an outlier, $DI(P_i, E)$ is usually large (near to 1), and if P_i tends to the median of E , $DI(P_i, E)$ takes the smallest value (close to 0).

D. Definition 4 (Weight of a clustering in E) In E , weight of clustering P_i is defined as, $w_i = DI(P_i, E) \times v_i$

(5) Clustering weights w_i s are critical for prioritizing certain clusterings within the ensemble, taking both diversity and frequency into account; in terms of the experts-analogy, this implies that a point of view that is

endorsed by a sizable group of experts but deviates from the thoughts of certain other experts does have a great significance.

3. PROPOSED WORK

The proposed method begins with E , which is composed of the unique base clusterings of P . These unique clusterings are listed in non-increasing order of their weights w_i . With the help of any known clustering ensemble algorithm, the first k sorted clusterings are picked for determining the consensus. The Ensemble Selection algorithm's pseudo code is shown below. Algorithm: ESFD INPUT: P (Collection of base clusterings), k (size of new ensemble) OUTPUT: Consensus Clustering P^* METHOD: 1. Compute E , which is the collection of unique base clusterings in P and their associated frequencies, v_i 's according to definition-1. 2. Using definition-2, calculate the Mean Similarity Index (MSI) for each clustering in E . 3. For each clustering in E , compute the Diversity Index (DI) using definition-3. 4. Calculate the weight w_i by definition-4 for each clustering P_i in E . 5. Arrange E 's clusterings in descending order of w_i 6. Assume E' is the collection of the top k sorted clusterings in E . 7. Using any clustering ensemble approach, calculate clustering ensemble on E' . If a clustering has a higher weight, it is more likely to provide reliable and innovative information in the consensus generation process. Clusterings with a lower weight, on the other hand, may be deemed outliers in the ensemble. The proposed approach is referred to as Ensemble Selection using Frequency and Diversity throughout the remainder of this paper (ESFD). The ESFD technique aims to create an ensemble with a high degree of variety and low redundancy. We use three examples to demonstrate the relevance of considering both frequency and diversity rather than these two parameters alone. Case1: ensemble selection based solely on diversity Case2: ensemble selection based solely on frequency Case3: ensemble selection based on both frequency and diversity (ESFD). Figure 1 illustrates the results of all three scenarios using yeast data [15]. We create an ensemble of 100 clusterings of yeast data and apply ESFD in the said order of weights. The validity of the consensus is measured using the Adjusted Rand index (AR) in each scenario, and the results are plotted by changing the ensemble size. The size of the ensemble and the value of AR are depicted on the x-axis and y-axis, respectively, in Figure 1. The subset of the ensemble considered by eliminating the last 'a' clusterings in the ensemble is denoted by $x=a$. Figure 1 shows that the weight that takes into account both frequency and diversity gets a greater maximum and average AR value than the other two situations. Other well-known data, like as Ecoli, Segmentation, and Chart [15], have also shown similar traits, that are discussed in the experimental section

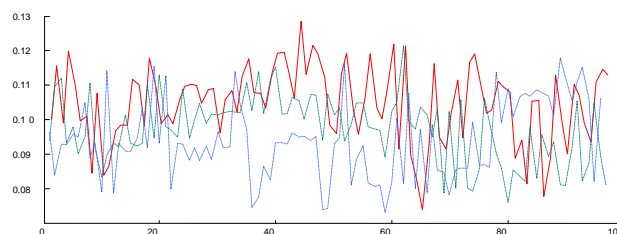


Fig 1: AR values plotted against different ensemble sizes. Green, blue, and red lines show ESFD weighted with diversity, frequency, and frequency-diversity, respectively

3.1 EXPERIMENTAL ANALYSIS

This part begins by describing the data sets used in the empirical evaluation and the basic experimental setups. The ESFD results are then compared to those obtained using the Cluster and Select (CAS) technique [3]. The experiments make use of real-world data sets obtained from the University of California, Irvine's machine learning data repository [15]. It's worth mentioning that all datasets have supervised categorization. The datasets are selected, since some are popular in the field of cluster analysis while others are less well-known but present a significant challenge to conventional clustering algorithms due to their high dimensionality [29]. Using various random initializations, the K-means algorithm is used to generate an ensemble of base clusterings of data. Individual set of data are divided into three different ensembles E1, E2 and E3, each of which contains 200 clustering. Each set of data is subjected [30] to three different categories of testing. In the first category of test, CSPA and HGPA are used on the whole ensemble[31], whereas in the second and third category of tests, CAS and ESFD have been used for clustering selection[32] on the whole ensemble, and then CSPA and HGPA are used to obtain final consensus, respectively. The quality of experimental results is determined by their similarity to the ground truth class labels provided with the data. The adjusted rand index (AR) is applied to compare consensus and ground truth clustering. The AR is a variant of the Rand Index, a well-known validity metric that statistically corrects for the latter's lack of invariance when random clusterings are chosen [7]. AR has been chosen as a validity measure since it is straightforward to compute and has been used in a large number of previous studies. Let P_i and P_j be two clusterings. $P_i = \{C_1, C_2, \dots, C_k\}$ and $P_j = \{C'_1, C'_2, \dots, C'_k\}$.

Then AR is defined as [11]

$$AR(P, P_{ij}) = \frac{a^0 - a^3}{a^1 + a^2 - a^3} \quad (1)$$

where, $j, i, k, s, t, 1, 2, 0, 1, 2, 3, s, t, r=1, s=1, M, m, m', a \times a, a = , a = , a = , a = 2, 2, 2, n, 2, \cap, \cap, \cap, |, |, |, |, |, \cap, \cup, \cup, \cup, |, \cup, \sum, \sum, \sum$ (2) Here, $M_{st} = |C_s \cap C'_t|$, $m_s = |C_s|$ and $m'_t = |C'_t|$, where C_s and C'_t are clusters of the clusterings P_i and P_j , respectively. If P_i and P_j are identical clusterings, the AR returns a maximum value of 1, and a minimum value of 0 if P_i and P_j are random clusterings. In tables II, III, and IV, the term 'CSPA' refers to a clustering ensemble that uses CSPA across the entire ensemble; 'CAS-CSPA' refers to a clustering ensemble that uses CSPA on a subset of clusterings chosen by CAS from the the whole ensemble; similarly 'ESFD-CSPA' refers to a clustering ensemble that uses CSPA on a subset of clusterings chosen by ESFD from the whole ensemble. Likewise, terms for HGPA are defined. On to eliminate the user-defined parameter 'k', which specifies the number of sorted clusterings chosen in the ESFD technique, in 'ESFD-CSPA', the subset of clusterings with a weight (w_i) greater than the ensemble mean weight is chosen. In the Chart, Segmentation, Ecoli, Yeast, and Iris datasets, ESFD surpasses CAS. ESFD performs similarly to CAS in the Glass and Wine datasets (not reported). CAS surpasses the ESFD when used with vehicle data. According to Table 1, ESFD beats CAS on Chart and Segmentation data utilizing both CSPA and HGPA. Concerning ground-truth clustering, Figure 3 illustrates the consensus clusterings produced by ESFD and CAS using Chart data. Sammon Mapping is used to reduce the dimension of Chart data [9]. The accuracy of projection is determined using the stress function indicated at the beginning of Figure 3

TABLE 1. SEGMENTATION DATA AND CHART DATA OUTCOMES

	Chart			Segmentation		
	<i>E1</i>	<i>E2</i>	<i>E3</i>	<i>E1</i>	<i>E2</i>	<i>E3</i>
CSPA	.6392	.6459	.6520	.3605	.3551	.4779
CAS- CSPA	.7416	.6730	.6889	.4907	.3797	.4805
ESFD- CSPA	.7815	.7210	.7027	.5169	.4061	.4869
HGPA	.4572	.4724	.4819	.1330	.2479	.2394
CAS- HGPA	.5891	.5511	.5533	.3458	.3887	.3503
ESFD- HGPA	.6029	.5881	.5591	.3567	.3989	.3563

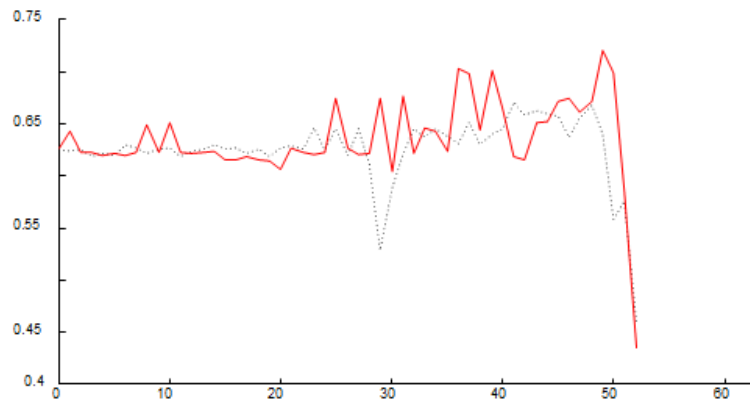


Fig 4. On the Second ensemble (*E2*) of chart data, the black line depicts CAS

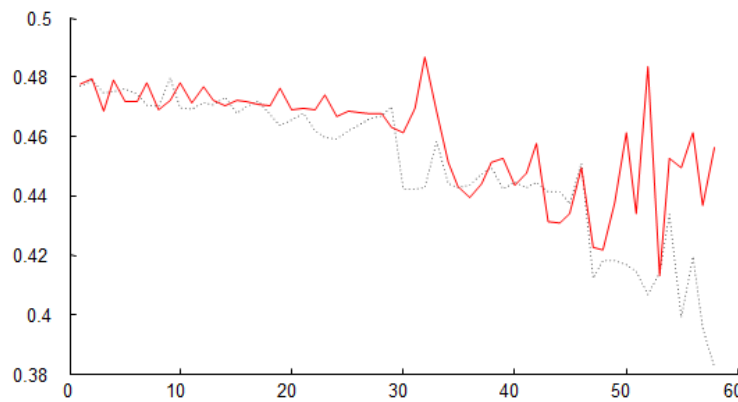


Fig 5. On the third ensemble (*E3*) of Segmentation data, the black line depicts CAS-CSPA and the red line shows ESFD-CSPA, respectively

Table 2 shows that on both the Ecoli and Yeast datasets, ESFD-CSPA/HGPA produces superior results than CAS. Table 3 reveals that ESFD-CSPA/HGPA outperforms CAS on Iris data, whereas CAS outperforms ESFD on Vehicle data

TABLE 2. YEAST DATA AND ECOLI DATA OUTCOMES

	Ecoli			Yeast		
	<i>E1</i>	<i>E2</i>	<i>E3</i>	<i>E1</i>	<i>E2</i>	<i>E3</i>
CSPA	.2104	.2956	.2827	.0972	.1008	.0869
CAS-CSPA	.2561	.3284	.3098	.1018	.1274	.1111
ESFD- CSPA	.2609	.3366	.3118	.1128	.1287	.1127
HGPA	.3454	.3313	.3116	.1013	.1153	.099
CAS- HGPA	.3623	.3521	.3327	.1220	.1226	.1101
ESFD- HGPA	.3673	.3593	.3338	.1224	.1244	.1201

TABLE 3. IRIS DATA AND VEHICLE DATA OUTCOMES

	Iris			Vehicle		
	<i>E1</i>	<i>E2</i>	<i>E3</i>	<i>E1</i>	<i>E2</i>	<i>E3</i>
CSPA	.7139	.7139	.7139	.1206	.1319	.1149
CAS- CSPA	.7414	.7414	.7414	.1451	.1519	.1211
ESFD- CSPA	.8014	.8014	.8014	.1344	.1398	.1159
HGPA	.6151	.6151	.6151	.0988	.1010	.0991
CAS- HGPA	.7221	.7221	.7221	.1133	.1235	.1011
ESFD- HGPA	.7460	.7460	.7460	.12015	.1133	.0996

4 CONCLUSIONS

We demonstrate in this research that carefully selecting a subset of the population of clusterings from an ensemble can result in a better consensus than evaluating the whole ensemble for consensus. According to our proposed method, weight of clustering in combination with frequency and diversity may encode considerable information for a meaningful consensus. When the actual number of clusters is considered, tests on a variety of benchmark datasets demonstrate that our method aids in improving clustering accuracy.

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