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Energy based competitive learning

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ABSTRACT

This paper addresses the three important issues associated with competitive learning clustering, which are auto-initialization, adaptation to clusters of different size and sparsity, and eliminating the disturbance caused by outliers. Although many competitive learning methods have been developed to deal with some of these problems, few of them can solve all the three problems simultaneously. In this paper, we propose a new competitive learning clustering method termed *energy based competitive learning* (EBCL) to simultaneously tackle these problems. Auto-initialization is achieved by extracting samples of high energy to form a core point set, whereby connected components are obtained as initial clusters. To adapt to clusters of different size and sparsity, a novel competition mechanism, namely, *size-sparsity balance of clusters* (SSB), is developed to select a winning prototype. For eliminating the disturbance caused by outliers, another new competition mechanism, namely, *adaptive learning rate based on samples' energy* (ALR), is proposed to update the winner. Data clustering experiments on 2000 simulated datasets comprising clusters of different size and sparsity, as well as with outliers, have been performed to verify the effectiveness of the proposed method. Then we apply EBCL to automatic color image segmentation. Comparison results show that the proposed EBCL outperforms existing competitive learning algorithms.

1. Introduction

Competitive learning has received a significant amount of attention in the past decades [1,2]. Due to its adaptive on-line learning, it has been widely applied in the fields of data clustering [3], vector quantization [4], RBF net [5], shape detection [6,7], discrete-valued source separation [8], Markov model identification [9], component analysis [10], scheduling [11], *etc.* Among them, clustering analysis is still one of the most active fields. The issues such as auto-initialization, partitioning clusters of different size and sparsity, and eliminating the disturbance caused by outliers are the major topics in the literature of data clustering [12–14]. In this paper, we mainly focus on competitive learning for data clustering, and develop a new competitive learning clustering method termed *energy based competitive learning* (EBCL) that simultaneously has the advantages of auto-initialization, adaptation to clusters of different size and sparsity, and insensitivity to outliers.

1.1. Related work

Recent development of competitive learning clustering is mainly focused on the auto-initialization including estimating the number of clusters and allocating appropriate initial prototypes. *Rival penalized competitive learning* (RPCL) [3] proposed by Xu et al. is one of the most widely used competitive learning algorithms for automatic model selection. The basic idea is that not only the winning prototype is learned to adapt to the input, but also its rival (*i.e.*, the second winner) is delearned by a smaller delearning rate, such that the redundant prototypes can be automatically eliminated. Ma and Wang [15] provided a mathematical theory for the convergence of RPCL from the perspective of cost-function, and proposed a distance-sensitive RPCL (DSRPCL). For controlling the strength of rival penalization, Cheung proposed the *rival penalization controlled competitive learning* (RPCCL) [16]. Apart from the rival penalization mechanism, other model selection strategies have recently emerged, such as self-splitting proposed by Zhang and Liu [17] and competitive repetition suppression by Bacciu and Starita [18]. Although these methods can automatically estimate the number of clusters, they are mostly proposed for clusters of the same size and sparsity and their performances degenerate considerably when this requirement is not satisfied. Additionally, the disturbance caused by outliers may also affect their performances.

For adapting to the clusters of different size and sparsity, Xu further extended the original RPCL to the finite mixture modeling and multi-sets modeling, for instance, elliptic RPCL, which have been shown effective for clusters of complicated shapes [5,12]. NonGaussian structural RPCL is another effective approach of this type [19]. All these rival penalization mechanisms can be seen as special cases of the Bayesian Ying-Yang (BYY) harmony learning [2,19]. Very recently, another different model selection strategy, namely, *entropy regularized likelihood* (ERL), has been developed

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by Lu and Ip for Gaussian mixture fitting based on regularization theory [20]. These methods have made great improvement to the model selection for mixture models. However, relatively little attention has been paid to eliminating the disturbance caused by outliers. And experimental results demonstrate that the existence of outliers may significantly decrease the accuracies of both model selection and cluster label assignment. In the real-world applications, auto-initialization, adapting to the clusters of different size and sparsity, and eliminating the disturbance caused by outliers are of great importance. In this paper, we propose a new competitive learning clustering method termed *energy based competitive learning* (EBCL) to simultaneously address the three issues.

1.2. The proposed approach

The proposed method first computes the samples' energy as the normalized sum of the weights. Then samples with high energy are extracted to form a subset termed *core point set*, which can be divided into several connected components by marginal points, *i.e.*, samples with low energy. These separated components are taken as the initial clusters and their means as the initial prototypes. In this way, the number of clusters is automatically estimated and the prototypes are initiated. The initial prototypes require further refinement by competitive learning, such that not only the *core point set* but also the marginal samples are assigned with accurate cluster labels. Through defining the prototype energy by considering both the size and sparsity of the corresponding cluster, two basic observations on competitive learning are obtained:

- *Observation one*: the lower energy a *prototype* possesses, which implies that the corresponding cluster is either more sparsely distributed or of smaller size, the more samples this cluster should incorporate hereafter.
- *Observation two*: the higher energy a *sample* possesses, the more strongly it should attract the corresponding winning prototype.

Two new competition mechanisms are developed, respectively. Based on observation one, the first mechanism is the *size-sparsity balance of clusters* (SSB) to select a winning prototype. As shown in Fig. 1, this mechanism leads to the second advantage of EBCL, namely, adaptation to the clusters of different size and sparsity. From observation two, the second mechanism is the *adaptive learning rate based on samples' energy* (ALR) to update the winner, such that outliers with little or no energy will no longer affect the prototypes (Fig. 1). Therefore, the third advantage, namely, insensitivity to outliers, is achieved.

The remainder of the paper is organized as follows. Section 2 describes the proposed *energy based competitive learning* (EBCL) method. Experimental results are reported in Section 3. We conclude our paper in Section 4.

2. Energy based competitive learning

2.1. Problem formulation

Given a sample dataset $\mathcal{X}=\{\mathbf{x}_1,\ldots,\mathbf{x}_N\}$, data clustering seeks to find a finite (but not necessarily preselected) number K of clusters $\{\mathcal{C}_1,\ldots,\mathcal{C}_K\}$ such that some prespecified objective function J is minimized. For *classical competitive learning* (CCL), the number of clusters K should be preselected and the objective function is the *distortion measure*, given by the sum of the squared distances of each data point to its assigned prototype

$$J^{CCL}=\sum_{n=1}^{N}\|\mathbf{x}_n-\mathbf{w}_{k(n)}\|^2, \tag{1}$$

where $\mathbf{w}_k$ is the prototype of cluster $\mathcal{C}_k$, and $k(n)$ is a function assigning a sample $\mathbf{x}_n$ to $\mathcal{C}_{k(n)}$ (*i.e.*, $\mathbf{x}_n\in\mathcal{C}_{k(n)}$), computed as $k(n)=\operatorname{argmin}_{k\in\{1,\ldots,K\}}(\|\mathbf{x}_n-\mathbf{w}_k\|^2)$. The objective J^{CCL} is based on two assumptions that the *prior* probabilities of clusters are equal, *i.e.*, $P(\mathcal{C}_k)=1/K,\forall k=1,\ldots,K$, and the covariance matrix Σ_k of each cluster is equally proportional to the identity matrix, *i.e.*, $\Sigma_k\equiv\sigma^2 I$ [21]. Therefore, it is limited to the clusters of the same size and sparsity. To adapt to the clusters of different size and sparsity, in the proposed EBCL algorithm, we define a *prototype energy weighted squared distance* (PEWSD) objective function according to observation one as follows:

$$J^{EBCL}=\sum_{n=1}^{N}(E_{k(n)}\|\mathbf{x}_n-\mathbf{w}_{k(n)}\|^2), \tag{2}$$

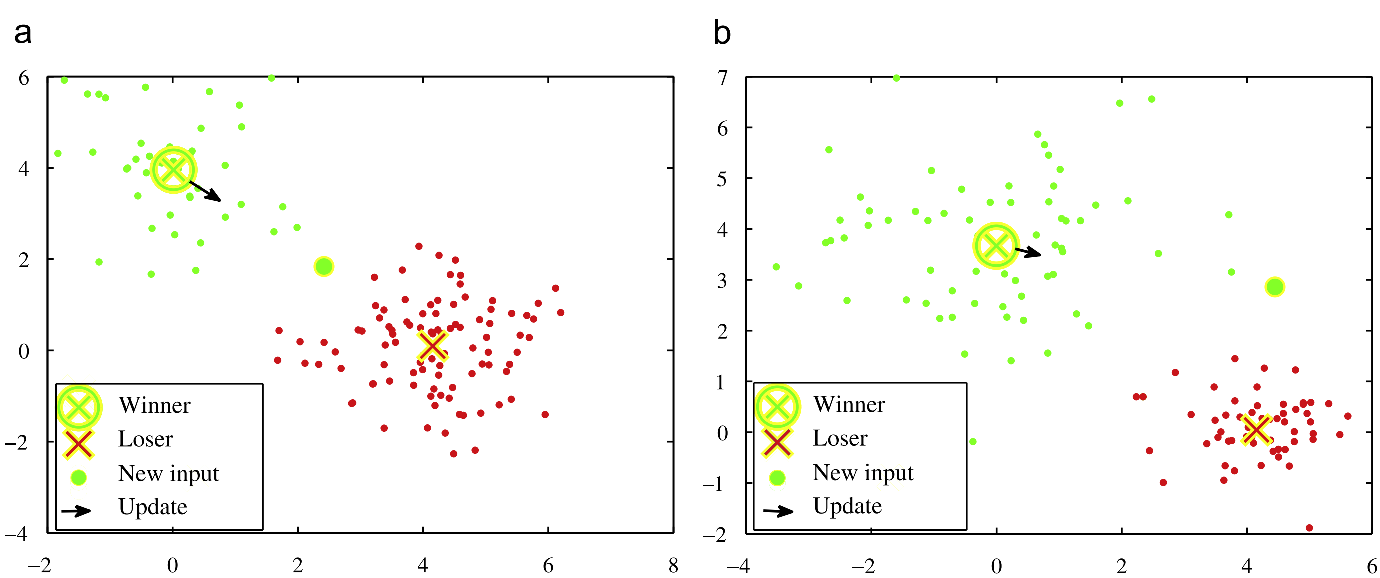

Fig. 1. Illustration of SSB and ALR mechanisms: (a) the top-left cluster has fewer samples and is sparser, so its prototype holds lower energy than that of the bottom-right; (b) although the top-left cluster has more samples yet distributes more sparsely, so its prototype holds lower energy. In both cases, when a new sample comes, the top-left cluster is more likely to be selected as the winner according to the SSB mechanism. Note that, the new sample in (a) has higher energy than that in (b), so the winning prototype in (a) is updated with a larger step size than that in (b) according to the ALR mechanism.