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Self-training algorithm based on density peaks combining globally adaptive multi-local noise filter

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Abstract: Self-training algorithm can quickly train an supervised classifier through a few labeled samples and lots of unlabeled samples. However, self-training algorithm is often affected by mislabeled samples, and local noise filter is proposed to detect the mislabeled samples. Nevertheless, current local noise filters have the problems: (a) Current local noise filters ignore the spatial distribution of the nearest neighbors in different classes. (b) They can't perform well when mislabeled samples are located in the overlapping areas of different classes. To solve the above challenges, a new self-training algorithm based on density peaks combining globally adaptive multi-local noise filter (STDP-GAMNF) is proposed. Firstly, the spatial structure of data set is revealed by density peak clustering, and it is used for helping self-training to label unlabeled samples. In the meantime, after each epoch of labeling, GAMLNF can comprehensively judge whether a sample is a mislabeled sample from multiple classes or not, and will reduce the influence of edge samples effectively. The corresponding experimental results conducted on eighteen real-world data sets demonstrate that GAMLNF is not sensitive to the value of the neighbor parameter k , and it can be adaptive to find the appropriate number of neighbors of each class.

Keywords: Self-training algorithm, Density peaks clustering, Noise filter.

1 Introduction

Supervised learning is a popular research in machine learning and data mining. Although supervised learning can effectively make a lot of labeled samples to build a classifier, labeling samples usually need a lot of time and consume plenty of money. On the contrary, semi-supervised learning (SSL) (Li Y et al. [2019](#); Yuan Cet al. [2020](#)) can train a classifier using a few number of labeled samples and a large number of unlabeled samples, which has been successfully applied to many real applications, such as text classification(Tran et al. [2017](#)), face recognition(Liu et al. [2021](#)), medicine(Zhang et al. [2020](#)) and other fields.

SSL algorithm includes self-training algorithm(Li et al. [2019](#)), deep generative models(Pande et al. [2021](#)), co-training algorithm (Slivka et al. [2017](#)) and graph-based semi-supervised learning(Anis et al.

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2019). Self-training algorithm is widely used, since it does not need to consider initial assumptions of data set and is easy to be implemented. Self-training algorithm contains two steps. (a) A small amount of labeled samples are utilized to train an initial classifier. (b) The unlabeled samples with the highest confidence are selected and are predicted by the classifier, and then they are added into the training set. The two steps are repeated until the stop condition is reached.

How to improve the performance of self-training algorithm has been discussed and studied by many scholars in recent years. Gan et al.(2013) developed semi-supervised fuzzy C-means algorithm (SFCM) to find unlabeled samples which has strong discriminant ability in the local data structure, and unlabeled samples are relabeled through fuzzy C-means algorithm. However, the algorithm does not consider the global structure information of data set and can't obtain spatial structure on non spherical distribution data. Thus, Wu et al.(2018) proposed a self-training algorithm based on density peaks of data (STDP). The density peaks clustering (DPC) algorithm is used to discover the spatial structure of data set, which helps the self-training algorithm to relabel representative unlabeled samples.

Although STDP considers the global spatial structure of data sets, it will easily produce some mislabeled samples during the training process. If the mislabeled samples are added to the training data set, it will ultimately reduce the classification accuracy of the classifier(Wei Z et al. 2013). Thus, many self-training algorithms based on the local noise filters have been proposed, such as self-training based on density peaks clustering and cut edge weight statistic (STDPCWEWS) (Wei D et al. 2020), self-training method based on density peaks clustering with extended parameter-free local noise filter (STDPNF) (Li J et al. 2019) and multi-label self-training with editing (MLSTE) (I. Triguero et al. 2014). STDPCWEWS identifies mislabeled samples by cutting edges weight statistic. MLSTE adopts edited nearest neighbor (ENN) to filter out noisy samples while STDPNF uses natural neighbors to remove noisy samples. Despite these local noise filters can improve the classification accuracy of the classifiers, their main technical defects are as follows:

(a) Current local noise filters only consider the spatial distribution of the nearest neighbors within one class. Considering the different distribution of samples in different classes, local noise filters need different k nearest neighbors for different classes.

(b) Local noise filters based on k nearest neighbors are impacted by noise samples, especially when the size of surrounding labeled samples is small. Actually, when k value is very small, the local noise filters may ignore important nearest neighbors. Conversely, if k value is large, the local noise filters will be subjected to relabeled samples with the error class. Thus, it is unreasonable for ENN to utilize a fixed value k to detect relabeled samples. Therefore, an adaptive selection rule is quite significant and necessary.

(c) The decision rule of current local noise filters is majority rule, which is quite imprecise. Majority rule does not take effect when mislabeled samples are located in the overlapping areas of different classes. Thus, closer nearest neighbor contributes more to detection, and it acquires more voting weights(Mateos-García et al. 2016).

Based on the above analysis, a novel globally adaptive multi-local noise filter using harmonic mean distance(GAMLNF) is proposed. GAMLNF uses the idea of the local mean-based k nearest neighbor(LMKNN) (Mitani Y et al. 2006). Each class finds its correspondingly local average vector, which can take the spatial distribution of the nearest neighbors within each class into account (Gou J et al. 2014). Firstly, GAMLNF utilizes globally adaptive nearest neighbor selection rule (Pan Z et al. 2020), which calculates r globally nearest neighbors, and GAMLNF dynamically finds out k_i local nearest

neighbors of each class. Secondly, k_i multi-local mean vectors are calculated on the basis of k_i local nearest neighbors, and the sole pseudo mean vector is calculated, which effectively reduces the influence of mislabeled samples. Finally, GAMLNF calculates the distance between pseudo mean vector of each class and unlabeled samples by harmonic mean distance (Pan Z et al. 2017a, b). Naturally, GAMLNF can consider the influence of spatial distribution in each class. The strategies enable GAMLNF to improve the ability of detecting mislabeled samples, and the classification accuracy can be boosted.

In order to better detect the mislabeled samples in STDP, a new self-training algorithm based on density peaks combining globally adaptive multi-local noise filter(STDP-GAMLNF) is proposed in this paper. Firstly, STDP-GAMLNF uses DPC to reveal the whole spatial structure of samples (Wu et al. 2018). Again, the unlabeled samples are relabeled according to the spatial structure. Next, by using the novel noise filter, a mislabeled sample is comprehensively detected from multiple classes, and the influence of edge samples and mislabeled samples are reduced effectively. Finally, the mislabeled samples will be removed, which will corrupt the spatial structure revealed by DPC. Space structure restoration (SSR) technology with doubly-linked list is used for storing spatial structure, and automatically connects the unlabeled "previous" samples with the nearest density peak one in the deleted samples. Thus, SSR can ensure that every unlabeled sample can be correctly relabeled.

The rest of the paper is organized as follows. Preliminaries are described in Section 2. In Section 3, STDP-GAMLNF are introduced. The comparison experiments are used to evaluate the performance of STDP-GAMLNF in Section 4. And the experimental results are discussed in Section 5. Section 6 concludes our work and future plans.

2 Preliminaries

In this section, notations used in this paper are first shown. Then, STDP, LMKNN and the harmonic mean distance will be described briefly.

2.1 Notations

In this paper, the notations are described in Table 1.

Table 1 The notations used in this paper.

ID	Notations	Explanations.
1	$T=\{(x_i, y_i) 1 \leq i \leq n\}$	x_i is the training samples, y_i is its corresponding label.
2	n	The size of data set.
3	$Y=\{y_i y_i \in \{w_i\}, i=1, 2, \dots, m\}$	The number of class.
4	$L=\{l_1, l_2, \dots, l_u\}$	The labeled data set.
5	$U=\{u_1, u_2, \dots, u_l\}$	The unlabeled data set.
6	w_j	The j th class of data set.
7	NN_j^r	The nearest neighbor set for class w_j with r nearest neighbors.
8	m_j	The local mean vector for class w_j .
9	$HMD(\cdot)$	The harmonic mean distance.
10	$AMD(\cdot)$	The arithmetic mean distance.
11	$d(x_i, x_j)$	The Euclidean distance between x_i and x_j .
12	PD	The probability difference between the highest probability and the lowest one.
13	β	Local density.
14	δ	The nearest local density sample.
15	L_j	The labeled samples set in class w_j .
16	$order$	The spatial structure revealed by DPC.
17	r_i	The number of nearest neighbors in class w_j .

2.2 STDP algorithm

STDP algorithm first uses DPC to reveal the whole spatial structure of the samples (Wu et al. 2018). DPC is a density-based clustering algorithm that can discover the global spatial structure of data and automatically find the number of clusters. DPC is based on the two assumptions:

- (a) The highest density sample in a cluster is the center sample of the cluster.
- (b) There is a large distance between centroid samples.

Based on two assumptions, DPC first calculates the local density β_i and the nearest local density sample δ_i for each sample x_i . The spatial structure of the data can be found by assigning x_i to its corresponding sample δ_i , where β_i and δ_i can be computed as:

$$\beta_i = \sum_j X(d_{ij} - d_c) \quad (1)$$

$$\delta_i = \begin{cases} 1, & x < 0 \\ 0, & x \geq 0 \end{cases}$$

$$\delta_i = \begin{cases} \min_{j: \beta_j < \beta_i} (d_{ij}), & \text{others} \\ \max_j (d_{ij}), & \forall j, \beta_j \geq \beta_i \end{cases} \quad (2)$$

STDP uses the global spatial structure revealed by DPC to select representative unlabeled samples for relabeling. The relabeling process is divided into two steps. Step 1 is iteratively to select and relabel all the unlabeled "next" samples of the labeled samples. Step 2 is iteratively to select and relabel all the unlabeled "previous" samples of the labeled samples. A general framework for STPD is shown in Fig. 1.

Fig. 1 The framework of STDP.

2.3 LMKNN algorithm

LMKNN algorithm is a very effective and simple classification algorithm in supervised learning (Mitani Y et al. 2006). It proposes a local mean vector and distance decision rule and considers the spatial distribution of the nearest neighbors of each class. The algorithm is immune to outliers, and can improve the accuracy of classification.

Suppose that $L_j = \{(x_i, y_i) | (1 \leq i \leq n_j)\}$, L_j is labeled samples set in class w_j , $\bigcup_{j=1}^w L_j = L$, and the parameter r represents the number of neighbors in each class. The unlabeled sample $x^* \in \mathbb{R}^d$ would be relabeled as following:

First of all, r samples nearest to x_i in L_j are calculated by local nearest neighbor(LNN) rule, which is given in Algorithm 1. $NN_j^r = \{(x_i, y_i) | y_i = w_j, 1 \leq i \leq r\}$ represents the r samples point nearest to x_i in the class w_j , then the r samples are sorted in ascending order.

Algorithm 1: LNN rule

Input: L, x_i .

Output: LNN_j (local nearest neighbor in class w_j)

Process:

- 1: The local Euclidean distance is calculated $\{d(x_i, y_i) | (y_i \in L, 1 \leq i \leq n)\}$.
  - 2: Sort $\{d(x_i, y_i) | (y_i \in L, 1 \leq i \leq n)\}$ by the ascending order.
  - 3: Select the first r samples as r nearest neighbor in class w_j based on sort $\{d(x_i, y_i) | (y_i \in L, 1 \leq i \leq n)\}$.
-

After that, the local mean vector m_j^r is calculated from the r nearest samples in each class

$$m_j^r = \frac{1}{r} \sum_{i=1}^r y_i, y_i \in NN_j^r \quad (3)$$

Finally, the local mean vector closest to unlabeled sample x_i is obtained, the class of x_i is the class of the local mean vector, which is calculated by Eq. (4)

$$w_c = \arg \min_{w_j} d(x, m_j^r) \quad (4)$$

where Euclidean distance is used to find the local mean vector nearest to x .

2.4 The harmonic mean distance

The harmonic mean distance is defined as $HMD(\cdot)$ (Pan Z et al. 2017a, b), which is used to measure the distance between the unlabeled sample x and n local mean vector of labeled samples in class w $LAM_w(x) = \{m_w^i | 1 \leq i \leq n\}$. The harmonic mean distance $HMD(x, \{m_w^i\}_{i=1}^n)$ is defined as

$$HMD(x, \{m_w^i\}_{i=1}^n) = \frac{n}{\sum_{i=1}^n \frac{1}{d(x, m_w^i)}} \quad (5)$$

In order to explain the difference between harmonic average distance and arithmetic mean distance, the proof is given.

The arithmetic mean distance is used to measure the distance between an unlabeled sample x and n local mean vector set in class w $LAM_w(x) = \{m_w^i | 1 \leq i \leq n\}$, which is denoted as $AMD(x, \{m_w^i\}_{i=1}^n)$, as in

Eq. (6), the value of $d(x, m_w^i)$ is represented $\frac{\partial AMD(x, \{m_w^i\}_{i=1}^n)}{\partial d(x, m_w^i)}$. Eq. (7) can prove that $\frac{\partial AMD(x, \{m_w^i\}_{i=1}^n)}{\partial d(x, m_w^i)} = \frac{1}{n}$,

which can prove that the distance between the unlabeled sample x and the local average vector has the same weight, so it can not give more weight to the nearest local average vector.

$$AMD(x, \{m_w^i\}_{i=1}^n) = \frac{\sum_{i=1}^n d(x, m_w^i)}{n} \quad (6)$$

$$\frac{\partial AMD(x, \{m_w^i\}_{i=1}^n)}{\partial d(x, m_w^i)} = \frac{\partial [\frac{\sum_{i=1}^n d(x, m_w^i)}{n}]}{\partial d(x, m_w^i)} = \frac{\partial [\sum_{i=1}^n d(x, m_w^i)]}{\partial d(x, m_w^i)} \times \frac{1}{n} = \frac{1}{n} \quad (7)$$

Similarly, Eq. (8) can prove that $\frac{\partial HMD(x, \{m_w^i\}_{i=1}^n)}{\partial d(x, m_w^i)}$ is inversely proportional to the value of $d^2(x, m_w^i)$.

Compared with the arithmetic average distance, the harmonic average distance will pay more attention to the local average vector of the labeled samples which is the closet to the unlabeled sample x .

$$\begin{aligned} \frac{\partial HMD(x, \{m_w^i\}_{i=1}^n)}{\partial d(x, m_w^i)} &= \frac{\partial [\frac{n}{\sum_{i=1}^n \frac{1}{d(x, m_w^i)}}]}{\partial d(x, m_w^i)} = n \times \left(\frac{1}{\partial d(x, m_w^i) \times \sum_{i=1}^n \frac{1}{d(x, m_w^i)}} \right)^2 \\ &= \frac{HMD^2(x, \{m_w^i\}_{i=1}^n)}{n \times d^2(x, m_w^i)} = \frac{1}{n} \times \frac{HMD^2(x, \{m_w^i\}_{i=1}^n)}{d^2(x, m_w^i)} \end{aligned} \quad (8)$$

3 The proposed algorithm

Fig. 2 shows the framework of STDP-GAMLNF, which is mainly divided into three parts. The first part is to discover the spatial structure of data set via DPC. The second part is to relabel the unlabeled "next" samples of labeled samples according to the spatial structure, and use GAMLNF to detect mislabeled samples. If it is detected as a mislabeled sample, SSR is used to repair the spatial structure to ensure that each unlabeled sample can be relabeled. Otherwise, the unlabeled sample is added to L . Finally, the unlabeled "previous" samples of the labeled samples are relabeled according to the updated spatial structure. GAMLNF is used to detect mislabeled samples, and SSR is used to repair the spatial structure. After that, all unlabeled samples are relabeled as labeled samples, and the labeled samples can train a better supervised classifier.

Fig. 2 The framework of STDP-GAMLNF.

3.1 Globally adaptive multi-local noise filter using harmonic mean distance

In the semi-supervised learning environment, GAMLNF can adaptively find the appropriate k parameters to detect and delete the mislabeled samples, which can effectively improve the algorithm accuracy.

Inspired by the improved algorithm GAKNN of LMKNN summarized in 2.3, we first use GANN to find the neighbors of labeled sample around relabeled samples. Specifically, the labeled sample set L has m classes, GANN can adaptively find r_i nearest neighbors in each class around the relabeled sample x_i , as shown in Algorithm 2.

Algorithm 2: GANN

Input: L, x .

Output: $GANN_j$ (local nearest neighbors in class w_j), r_i .

Process:

- 1: The global Euclidean distance is calculated $\{d(x_i, y_i) | (y_i \in L, 1 \leq i \leq n)\}$.
  - 2: Sort $\{d(x_i, y_i) | (y_i \in L, 1 \leq i \leq n)\}$ in the ascending order.
  - 3: The k nearest labeled samples closet to relabeled sample x_i are obtained, where $k=r \times M$.
  - 4: $i=1$
  - 5: $r_i=0$
  - 6: while $i \leq k$
  - 7:   If the class of labeled samples x_i is w_j , x_i is regarded as the k_i -th nearest neighbor in class w_j .
  - 8: $r_i=r_i+1$
  - 9: end while
-

When GANN adaptively finds r_i nearest neighbors in each class, the multi-local average vector $MLMV_j^r = \{m_j^s | 1 \leq s \leq k\}$ in each class can be calculated, where m_j^s is the local average vector, and is calculated by first s nearest neighbor in class w_j , its calculation is shown in Eq. (9).

$$m_j^s = \frac{1}{s} \sum_{i=1}^s y_i, y_i \in GANN_j^s \quad (9)$$

Closer local average vector contributes more to detection, so it acquires more voting weights. Thus, $HMD(x_i, m_j^r), m_j^r \subseteq MLMV_j^r$ of Eq. (5) is used to calculate the pseudo average vector m_j^* . In particular, if there isn't any neighbors in class w_j , then $d(x_i, w_j) = \infty$. Lastly, the closest pseudo average vector to the relabeled sample x_i is calculated by the Euclidean distance. If the relabeled sample is not in accordance with the class of m_j^* , the relabeled sample is considered as a mislabeled sample and is deleted from U .

Otherwise, it is added to the L set. GAMLNF is shown in Algorithm 3.

The computational complexity of GAMLNF mainly occurs in the search of global nearest neighbor (Stage 1), the pseudo average vector calculation (Stage 2) and the Euclidean distance calculation (Stage 3). In Stage 1, GAMLNF obtains k global nearest neighbors from n labeled samples according to Algorithm 2. Therefore, it is easy to calculate the computational complexity as $O(nk)$.

In Stage 2, GAMLNF first needs to calculate $m \times r$ local average vectors, and then calculate m pseudo average vectors through the harmonic average distance. Hence, it is easy to see that the computational complexity is $O(mr)$ according to Algorithm 3.

In Stage 3, GAMLNF obtains the closest pseudo-average vector to x from the m pseudo-average vectors and its complexity is $O(m)$.

Algorithm 3: GAMLNF**Input:** U^{re} (reabeled sample), L (labeled sample)**Output:** U^{re} (Updated reabeled samples), L^{re} (Updated labeled samples)**Process:**

```

1   while  $i \leq n$ 
2       while  $j \leq m$ 
3           Find the  $GANN_j$  of  $x_i$  in class  $w_j$  by Algorithm 1 .
4           if  $GANN_j \neq \emptyset$ 
5               The multi-local average vector  $MLMV_j^r$  is calculated in class  $w_j$ , according to the Eq.
               (9).
6                $m_j^r \subseteq MLMV_j^r$  is used to calculate the pseudo average vector  $m_j^*$  in class  $w_j$ , according to
                $HMD(x_i, m_j^r)$ .
7                $d(x_i, w_j)$  is calculated in class  $w_j$ , according to the Euclidean distance from  $x_i$  to  $m_j^*$ 
8           else
9                $d(x_i, w_j) = \infty$ 
10        end while.
11        Sort  $\{d(x_i, w_j) | (1 \leq j \leq r_j)\}$  in the ascending order.
12        The class  $w^*$  of  $d(x_i, w_j)$  with the shortest distance is obtained based on sort  $\{d(x_i, w_j) | (1 \leq j \leq r_j)\}$ .
13        if  $c^* \neq c^{re}$ 
14            Delete the sample  $x_i$  from  $U$ 
15        else Add the sample  $x_i$  to  $L$ 
16    end while.

```

3.2 Space structure restoration

GMLNF will be used to detect and delete the mislabeled samples. However, it will corrupt the spatial structure disclosed by DPC. As shown in Fig. 3, the circles and triangles represent real class w_1 and class w_2 , the green and blue represent labeled samples as w_1 and w_2 , colorless symbols represent unlabeled samples. As shown in Fig. 3(a), each sample will be designated to nearest and highest local density sample in the spatial structure disclosed by DPC. The unlabeled "next" samples will be relabeled by the spatial structure. However, as shown in Fig. 3(b), when the unlabeled "next" samples x_2 and x_3 are designated to an relabeled sample x_1 , and there are no "previous" other samples between x_2 and x_3 . If x_1 is mislabeled sample and x_1 is deleted by the GMLNF, the spatial structure will be corrupted, x_2 and x_3 can not be relabeled.

Accordingly, SSR algorithm is proposed. As shown in Fig. 3(c), the doubly-linked list structure is used to store the spatial structure. When x_1 is deleted by the noise filter, the nearest highest local density sample x_4 is obtained by the doubly-linked list structure, then x_2 and x_3 are designated to x_4 . When the unlabeled sample x_4 is relabeled, the unlabeled samples x_2 and x_3 will have the chance to be relabeled. SSR algorithm is shown in Algorithm 4.

(a)The spatial structure disclosed by DPC

(b)The spatial structure is corrupted

(c)The spatial structure is repaired

Fig. 3 Space structure restoration step diagram

Algorithm 4: SSR**Input:** x (deleted sample), L (labeled data set), U (unlabeled data set), $order$ (spatial structure)**Output:** $order$ **Process:**

```

1:  $P = order(x, previous)$ 
2:  $k = length(p)$ 
3:  $i = 1$ 
4: while  $i \leq k$ 
5:      $i = find(P_i, U)$ , where  $P_i$  is the  $i$ -th sample in  $P$ . //return 1 when  $P_i$  is found in  $U$ ,
       otherwise return 0.
6:      $z = order(P_i, previous)$ 
7:      $j = find(z, L)$  //return 1 when  $z$  is found in  $L$ , otherwise return 0.
8:     if  $(i == 1 \& \& j == 1)$ 
9:          $order(P_i, next) = order(x, next)$ 
10:    end while.

```

3.3 Self-training algorithm based on density peaks combining globally adaptive multi-local noise filter

The whole algorithm consists of five steps. At Step 1-Step 4, DPC algorithm is used to reveal the spatial structure of the data set. The spatial structure is stored in the form of doubly-linked list. At the same time, L is used to train the initial classifier C . Step 5-Step 11 are a process of iteratively training classifier C . Firstly, according to the order of spatial structure, the unlabeled "next" sample of a labeled sample is relabeled by the classifier C . Then the unlabeled samples are detected by GAMLNF. SSR is applied to the mislabeled samples which may cause the corruption of spatial structure, and then the relabeled samples are added to the L . Finally, the classifier C is trained on the basis of updated L . Step 12-Step 18 will be iteratively training classifier C with operate as similar as Step 5-Step 11.

STDP-GAMLNF can not only consider the global spatial structure revealed by DPC, but also consider the spatial structure in each class by GANN algorithm. Simultaneously, GAMLNF can adaptively find r_i local nearest neighbors from the k global nearest neighbors in each class. GAMLNF adopts the harmonic average distance to give more voting weight to the nearest neighbor. Based on the above improvements, STDP-GAMLNF can quickly train an effective supervised classifier.

Algorithm 5: STDP-GAMLNF

Input: L, U

Output: The trained classifier C

Process:

- 1: Calculate ρ_i for each sample x_i of L and U according to Eq. (1)
  - 2: Calculate δ_i for each sample x_i of L and U according to Eq. (2)
  - 3: Establish the structure of data space by making each sample x_i designates to its unique nearest sample ρ_i
  - 4: Train a classifier C using L
  - 5: Repeat until all the "next" samples of samples of L are selected from U
  - 6: $U^{re} = \text{Select } T \text{ from } U$, where each sample x_j is the "next" samples of samples of L according to the structure of data space
  - 7: Update the current unlabeled dataset $U = U - U^{re}$
  - 8: Label the samples of U^{re} with the trained classifier C
  - 9: GAMLNF is used to detect false labeled samples of U^{re} , and SSR is used to repair the spatial structure
  - 10: Update the current labeled dataset $U = U \cup U^{re}$
  - 11: Retrain the classifier C with U
  - 12: Repeat until all the samples are selected from U
  - 13: $U^{re} = \text{Select } T \text{ from } U$, where each sample x_j is the "previous" samples of samples of L according to the structure of data space
  - 14: Update the current unlabeled dataset $U = U - U^{re}$
  - 15: Label the samples of U^{re} with the trained classifier C
  - 16: GAMLNF is used to detect false labeled samples of U^{re} , and SSR is used to repair the spatial structure
  - 17: Update the current labeled dataset $L = L \cup U^{re}$
  - 18: Retrain the classifier C with L
  - 19: Return the classifier C
-

4 Experiments

4.1. Data sets and setting of experiments

We use a PC with 32G memory, Core i5 CPU and 64-bit operating system to run some experiments, in order to verify the efficiency of the proposed algorithm. Also, MATLAB2016b and PyCharm2021 are utilized to program.

In order to prove the effectiveness of STPD-GAMLNF, 18 benchmark data sets of experiments are selected from UCI (Asuncion A 2007) repositories. The data sets are described in Table 2.

Table 2 The descriptions of UCI data sets.

ID	Data sets	Size	Attributes	Class	Abbreviation
1	Australian_Credit_Approval	690	2	2	ACA
2	biodegradation	1055	41	2	BIO
3	Blood_Transfusion_Service_Center	748	4	2	BTSC
4	Avila	20867	12	12	AVI
5	Contraceptive_Method_Choice_Data_Set	1473	9	3	CMCDS
6	Gauss50	2000	50	2	GAU
7	german	1000	24	2	GER
8	Image_segmentation	2310	19	7	IS
9	Indian_Liver_Patient_Dataset	583	10	2	ILPD
10	mammographic_masses	961	5	2	MM
11	Segmentation	2130	19	7	SEG
12	spambase	4601	57	2	SPA
13	Tic_Tac_Toe_Endgame	958	9	2	TTTE
14	Website_Phishing	1353	9	3	WP
15	WaveForm	5000	21	3	WAV
16	Wireless_Indoor_Localization	2000	7	4	WIL
17	Banana	8800	2	2	BAN
18	letter	15534	16	26	LET

The training set is randomly divided into the labeled sample set L and the unlabeled sample set U . Four experiments are used to verify the effectiveness of the proposed algorithm. 10-fold cross-validation is used in all the experiments. Brief descriptions are listed as follows:

(a) Experiment 1 is a comparative experiment between STDPGAMLNF and other representative algorithm. Mean accuracy, variance, ROC, AUC work as evaluation indexes, and the ratio of L is set at 20%. The CART is selected as the base classifier.

(b) Experiment 2 compares the effect of the noise filter with the representative noise filter in STDP. Kappa coefficient is used as evaluation index, and the ratio of L is set at 20%. CART and KNN are selected as the base classifier.

(c) Experiment 3 studies the influence of k value on the proposed algorithm. KNN is selected as the base classifier.

(d) Experiment 4 studies the impact of the proportion of labeled samples on the noise filter. The evaluation indexes are accuracy and variance, and the ratio of L is set from 10%~90%. The base classifier adopts KNN.

4.2 Experiment 1: comparisons between our algorithm and existing representative work.

This experiment compares our algorithm with some representative algorithms to prove the effectiveness of STDPGAMLNF. Mean accuracy, variance, ROC, AUC will be used to prove the ability of our noise filter to detect mislabeled samples in this experiment. The ROC curve for multi-classification is calculated as:

Suppose the number of test samples is n and that of class is w . After the training, the probability of each test sample in each class is calculated, and matrix $\mathbf{P}$ with $w \times n$ is obtained. Each row represents the probability value of a test sample in each class (sorted by class label). Correspondingly, the label of each test sample is converted into a one-hot encoding form, and each position is used to label whether it belongs to the corresponding class, which can also get label matrix $\mathbf{L}$.

Under each class, the probability of n test samples of the class (column in matrix $\mathbf{P}$) can be calculated. Therefore, according to each corresponding column in the probability matrix $\mathbf{P}$ and the label matrix $\mathbf{L}$, the False Positive Rate (FPR) and the True Positive Rate (TPR) under each threshold can be calculated to draw a ROC curve. In this way, w ROC curves can be drawn. At last, average the w ROC curves to get the final ROC curve and AUC value.

Comparison algorithms and our algorithm are shown in Table 3. And dc parameter of the proposed algorithm will be discussed in detail in STDP (2018), so dc of the algorithms is set as recommended in STDP. The introduction of the comparison algorithms are as follows:

(a) Self-training with editing (SETRED) (Li M et al. 2005) combines CEWS to filter out noisy samples via self-training algorithm.

(b) Multi-label self-training with editing (MLSTE) (Wei et al. 2013) use ENN to detect noisy samples by self-training algorithm. Although MLSTE is applied to multi-label tasks, it can also be applied to the single-label tasks.

(c) Self-training with SFCM (STSFCM) (Gan et al. 2013) is a clustering algorithm, which is used to guide self-training method to train an effective classifier.

(d) Self-training with DPC (STDP) (Wu D et al. 2018) integrate the structure of feature space revealed by DPC into the self-training process to train an effective classifier.

(e) STDP integrated by parameter-free local noise filter (STDPNF) (Li J et al. 2019) is parameter-free and can remove mislabeled samples by exploiting the information of both labeled data and unlabeled data.

As shown in Table 4, the accuracy of STDP-GAMNF is better than that of the comparison algorithms. Compared with STDPNF, it can accurately detect mislabeled samples better and can consider the spatial structure within each class. 12 out of 18 data sets' average accuracy of STDP-GAMNF is better than that of the comparison algorithms, and good stability can be seen from the variance. However, in AVI and MM data sets, the average accuracy of STDP-GAMNF is lower than that of STDP. The distribution of the two data sets is totally even, and the correctly marked samples are deleted during the noise filter detection, causing massive samples reductions in $\mathbf{L}$ set. Finally, it leads to a decrease in the average accuracy rate. Meanwhile, according to Table 5, 9 out of 18 data sets' AUC value are improved compared with STDP, which proves that STDPGAMLNF can not only improve the average accuracy but also increase the AUC value to get better classification effect. Figure 4 and Figure 5 respectively show the ROC of the two-class data set BIO and the multi-class data set CMCDS. It can be seen that STDP-GAMNF can increase ROC in each class and solve the data skew problem.

Table 3 Comparison algorithms and parameters in experiment 1.

Abbreviation	Algorithms	Parameters
SETRED	Self-training with editing	$\theta = 0.1$
MLSTE	Multi-label self-training with editing	$k = 10$
STSFCM	Self-training with SFCM	Threshold $\varepsilon_1 = 1/n$ (n is the number of classes)
STDP	Self-training with DPC	$P_a = 2$. Please refer to the original literature
STDPNF	STDP combining PNF	$P_a = 2$.
STDPGAMLNF	Ours algorithm	$P_a = 2$. $r=k \times n$ (n is the number of classes)

Table 4 Experimental results (MCA $\pm$ STD) of comparison algorithms.

Data sets	ST_SFCM	MLSTE	SETRED	STDP	STDPNF	Ours
ACA	83.91 $\pm$ 5.48	67.82 $\pm$ 4.77	68.55 $\pm$ 8.02	83.91 $\pm$ 6.08	83.91 $\pm$ 6.08	84.05$\pm$5.87
BIO	82.93 $\pm$ 2.89	71.07 $\pm$ 5.46	74.39 $\pm$ 5.36	83.03 $\pm$ 2.74	84.25$\pm$2.76	83.78 $\pm$ 2.93
BTSC	78.74 $\pm$ 3.12	77.01 $\pm$ 2.53	79.27 $\pm$ 3.22	79.27 $\pm$ 2.59	79.01 $\pm$ 3.38	80.21$\pm$2.94
AVI	89.83 $\pm$ 0.59	68.41 $\pm$ 0.8	70.34 $\pm$ 0.82	90.31$\pm$0.85	90.02 $\pm$ 0.72	90.02 $\pm$ 0.54
CMCDS	52.53 $\pm$ 3.75	50.57 $\pm$ 3.75	51.72 $\pm$ 4.69	54.77 $\pm$ 4.46	53.35 $\pm$ 3.79	55.66$\pm$3.15
GAU	74.9 $\pm$ 1.85	92.65$\pm$1.39	88.05 $\pm$ 2.76	71.9 $\pm$ 3.26	73.95 $\pm$ 3.1	78.4 $\pm$ 3.09
GER	71.5 $\pm$ 3.92	68.9 $\pm$ 5.3	69.1 $\pm$ 4.12	72.9 $\pm$ 4.84	73.4 $\pm$ 4.52	74.6$\pm$3.27
IS	91.99 $\pm$ 1.06	80.56 $\pm$ 2.95	87.22 $\pm$ 1.53	93.33 $\pm$ 1.4	93.76 $\pm$ 1.31	94.15$\pm$0.77
ILPD	70.15 $\pm$ 5.16	56.76 $\pm$ 8.88	67.39 $\pm$ 7.6	68.93 $\pm$ 4.54	71.35 $\pm$ 4.77	72.21$\pm$3.91
MM	83.55 $\pm$ 2.95	76.27 $\pm$ 5.11	78.98 $\pm$ 4.32	83.45 $\pm$ 4.7	83.56$\pm$4.91	81.79 $\pm$ 5.47
SEG	91.60 $\pm$ 2.06	83.63 $\pm$ 2.36	86.06 $\pm$ 1.92	93.33 $\pm$ 1.99	93.42 $\pm$ 1.63	94.19$\pm$1.54
SPA	89.28 $\pm$ 1.46	74.59 $\pm$ 2.41	74.01 $\pm$ 2.8	89 $\pm$ 1.65	89.39 $\pm$ 1.52	89.54$\pm$1.01
TTTE	69.61 $\pm$ 4.92	60.54 $\pm$ 2.13	64.08 $\pm$ 4.56	70.02 $\pm$ 5.08	69.61 $\pm$ 4.92	71.07$\pm$4.91
WP	86.98 $\pm$ 3.02	84.47 $\pm$ 4.17	84.92 $\pm$ 4.23	87.87 $\pm$ 2.73	87.57 $\pm$ 2.52	88.83$\pm$2.86
WAV	78.38 $\pm$ 1.75	80.7 $\pm$ 1.46	83.48$\pm$1.17	77.98 $\pm$ 1.55	78.38 $\pm$ 1.53	79.96 $\pm$ 1.41
WIL	93.55 $\pm$ 1.55	97.2 $\pm$ 1.13	97.7$\pm$1.03	92.4 $\pm$ 1.82	94.8 $\pm$ 1.22	95.6 $\pm$ 1.34
BAN	90.22 $\pm$ 1.04	87.79 $\pm$ 1.19	89.95 $\pm$ 1.05	90.37 $\pm$ 0.82	90.85 $\pm$ 1.06	91.62$\pm$0.90
LET	75.82 $\pm$ 0.95	75.11 $\pm$ 0.77	81.54 $\pm$ 0.88	77.28 $\pm$ 0.94	77.5 $\pm$ 0.56	81.26$\pm$0.69

Table 5 Experimental results (AUC) of comparison algorithms.

Data sets	ST_SFCM	MLSTE	SETRED	STDp	STDpNF	Ours
ACA	0.89	0.78	0.76	0.91	0.9	0.89
BIO	0.85	0.85	0.89	0.83	0.87	0.89
BTSC	0.79	0.78	0.73	0.74	0.78	0.79
AVI	0.96	0.88	0.89	0.96	0.96	0.95
CMCDS	0.65	0.59	0.6	0.63	0.67	0.71
GAU	0.79	0.92	0.83	0.75	0.78	0.84
GER	0.73	0.59	0.59	0.72	0.68	0.63
IS	0.96	0.94	0.96	0.96	0.97	0.98
ILPD	0.62	0.79	0.68	0.55	0.64	0.66
MM	0.81	0.82	0.84	0.86	0.86	0.86
SEG	0.98	0.94	0.95	0.98	0.98	0.98
SPA	0.98	0.92	0.91	0.98	0.98	0.98
TTTE	0.83	0.45	0.57	0.55	0.58	0.61
WP	0.87	0.85	0.80	0.88	0.87	0.88
WAV	0.89	0.91	0.92	0.88	0.88	0.89
WIL	0.97	0.98	0.98	0.97	0.97	0.98
BAN	0.92	0.92	0.95	0.94	0.94	0.93
LET	0.91	0.92	0.95	0.9	0.91	0.93

(a)STDP-GAMNF

(b)MLSTE

(c)SETRED

(d)ST_SFCM

(e)STDP

(f)STDPNF

Fig. 4 ROC of biodegradation data set

Fig. 5 ROC of Contraceptive_Method_Choice data set

4.3 Experiment 2: comparisons between the proposed noise filter and existing ones

In order to prove the effectiveness of GAMNF, we selected 6 representative noise filters ENN (2017), RNN (1967), ALLKNN (2019), MENN (2000), CEWS (2020), PNF (2019) for comparison. To compare their abilities of solving the problem of mislabeling, STDP algorithm is chosen to combine the 6 noise filters (STDP_ENN, STDP_RNN, STDP_ALLKNN, STDP_MENN, STDP_CEWS, STDP_PNF).

Table 6 shows the comparison algorithm and related parameters.

Experiment 2 uses the kappa coefficient to judge the quality of the noise filter, which can not only check the consistency and measure the classification accuracy, but also judge the ability of unbalanced classification (W. Pei et al. 2020). The calculation method of kappa coefficient is shown in Eq. (9) where p_o is classification accuracy. The calculation method of p_e is shown in Eq. (10), where the total number of samples is n , the number of real samples in each class is $a_1, a_2, \dots, a_c$, and the predicted number of samples in each class is $b_1, b_2, \dots, b_c$.

$$\text{kappa} = \frac{p_o - p_e}{1 - p_e} \quad (9)$$

$$p_e = \frac{a_1 \times b_1 + a_2 \times b_2 + \dots + a_c \times b_c}{n \times n} \quad (10)$$

Table 7 and Table 8 shows the experimental results of GAMNF in STDP and other comparison algorithms. The base classifiers in Table 7 and Table 8 are respectively selected as KNN and CART.

From Table 7 and Table 8, when the base classifier is KNN, 11 out of 16 data sets' kappa coefficient of our algorithm are better than the comparison algorithms. When the base classifier is CART, 7 out of 16 data sets' kappa coefficient of our algorithm are better than the comparison algorithm. In summary, the overall accuracy of STDP_GAMLNF is higher than the comparison algorithm, and the effect is better when the base classifier is KNN. However, the performances of the two base classifiers on the MM and TTTE data sets perform not well. In particular, all the noise filters on the TTTE data set lead to the accuracy reduction, because the spatial structure revealed by DPC has been sufficient to support the training of the self-training algorithm. Furthermore, the noise filter will interfere the relabel samples, resulting in the deletion of too many unlabeled samples, which will corrupt the complete spatial structure. While STDP_GAMLNF can effectively detect mislabeled samples by multi-local mean vectors, and uses harmonic average distance to focus on local mean vectors close to the relabeled samples in each class, so as to achieve better detection ability.

Table 6 Comparison algorithms and parameters in experiment 2.

Abbreviation	Algorithms	Parameters
STDP	Self-training with DPC	$P_a = 2$.
STDP_ENN	STDP combining ENN	$P_a = 2, k=3$.
STDP_RENN	STDP combining RENN	$P_a = 2, k=3$.
STDP_ALLKNN	STDP combining ALLKNN	$P_a = 2, k=3$.
STDP_MENN	STDP combining MENN	$P_a = 2, k=3$.
STDPNF	STDP combining PNF	$P_a = 2$.
STDP_CEWS	STDP combining CEWS	$P_a = 2, \theta=0.1$.
STDP_GAMLNF	Our algorithm	$P_a = 2, r=k \times n$ (n is the number of classes)

Table 7 Experimental results of kappa with KNN as base classifier.

Data sets	STDP	STDP_ ENN	STDP_ RENN	STDP_AL LKNN	STDP_ MENN	STDP_PNF	STDP_CEWS	Ours
ACA	0.3632	0.3466	0.3466	0.3467	0.3466	0.3645	0.3685	0.3761
BIO	0.4885	0.4806	0.4806	0.4823	0.4806	0.4996	0.4882	0.504
BTSC	0.2700	0.2605	0.2605	0.2605	0.2605	0.27	0.2641	0.2829
AVI	0.6246	0.6244	0.6248	0.6363	0.6244	0.6301	0.6234	0.6617
CMCDS	0.2598	0.24	0.24	0.238	0.2357	0.2535	0.2375	0.2638
GAU	0.7945	0.7993	0.7993	0.7702	0.7993	0.7945	0.7747	0.7886
GER	0.2754	0.2699	0.2699	0.2313	0.2699	0.2664	0.2655	0.2772
IS	0.8738	0.8753	0.8753	0.8819	0.8758	0.8738	0.8723	0.891
ILPD	0.2679	0.2312	0.2312	0.2795	0.2312	0.2665	0.2855	0.2632
MM	0.5771	0.5834	0.5834	0.5859	0.5954	0.5732	0.5928	0.5711
SEG	0.8546	0.8586	0.8586	0.8667	0.8586	0.8596	0.8606	0.8834
SPA	0.4455	0.4413	0.4418	0.4288	0.4417	0.4381	0.4409	0.4721
TTTE	0.1919	0.2573	0.2573	0.2414	0.2158	0.223	0.1894	0.2511
WP	0.7362	0.748	0.748	0.747	0.746	0.74	0.7363	0.7316
WAV	0.7554	0.7553	0.7553	0.7533	0.755	0.7578	0.7458	0.7692
WIL	0.9611	0.9618	0.9618	0.9625	0.9618	0.9618	0.9625	0.9718

Table 8 Experimental results of kappa with CART as base classifier.

Data sets	STDP	STDP_ ENN	STDP_ RENN	STDP_AL LKNN	STDP_ MENN	STDP_PNF	STDP_CEWS	Ours
ACA	0.6698	0.6602	0.6836	0.6655	0.66	0.6698	0.6698	0.6727
BIO	0.6197	0.6408	0.6312	0.6096	0.6408	0.6412	0.6015	0.6338
BTSC	0.2895	0.2813	0.2813	0.2809	0.2813	0.2622	0.2755	0.2936
AVI	0.8739	0.8425	0.8327	0.8319	0.8425	0.8695	0.8772	0.8683
CMCDS	0.3009	0.3179	0.316	0.3017	0.3238	0.2778	0.3078	0.3125
GAU	0.4367	0.5616	0.5451	0.5487	0.5604	0.478	0.4769	0.5665
GER	0.3307	0.3556	0.3489	0.3439	0.3555	0.3597	0.3594	0.3367
IS	0.922	0.9250	0.926	0.9412	0.9235	0.9270	0.928	0.9316
ILPD	0.2278	0.2857	0.2429	0.2385	0.2974	0.2664	0.2599	0.2977
MM	0.6675	0.6971	0.6751	0.6679	0.6522	0.6703	0.672	0.6337
SEG	0.9219	0.9123	0.9245	0.9219	0.9123	0.9229	0.9235	0.9321
SPA	0.7684	0.7872	0.7858	0.8002	0.7955	0.7764	0.7648	0.7792
TTTE	0.357	0.3421	0.2522	0.3396	0.3303	0.3461	0.3546	0.3474
WP	0.7786	0.764	0.769	0.7775	0.7576	0.7742	0.779	0.7985
WAV	0.6691	0.7056	0.7177	0.7181	0.7056	0.675	0.6712	0.6989
WIL	0.8983	0.9391	0.9398	0.9411	0.9391	0.9304	0.9003	0.9411

4.4 Experiment 3: sensitivity of noise filters to the neighborhood k value

In GAMLNF r depends on k , which should be specially concentrated on. Therefore, GAMLNF only need to consider whether it is sensitive to k or not. The compared algorithm selects noise filters with k values, such as ENN, RNN, ALLKNN, and MENN. In order to better compare the sensitivity of

each noise filter to the value of k , k is tested and from 1 to 10, the average accuracy of k is used to find the variance. The smaller the variance is, the less sensitive the noise filter is to k .

The experimental results are shown in Figure 6. It is clear that the variance of GAMLNF is much lower than other noise filters, and it can achieve an adaptive global search for the appropriate k_i for each class. Although GAMLNF is not as stable as ALLKNN on the ILPD data set, it has a better classification effect. Single pseudo-average vector is obtained for k_i local average vector in each class, and the true class of the relabeled samples by pseudo-average vectors is obtained.

Fig. 6 Variance results of different K values

4.5 Experiment 4: the impact of ratio of labeled samples

The experimental parameters are consistent with Table 6. Simultaneously, STDP_MENN, STDP_PNF and STDP_GAMLNF perform better than other algorithms in Experiment 2, so they are used as compared algorithms. Figure 7 shows that the ratio of L (10%~90%) affects the average accuracy in different data sets.

As shown in Figure 7, GAMLNF performs better than the comparison algorithm on ACA, BIO, IS, ILPD, SEG, and TTTE data sets. GAMLNF calculates the most suitable local average vector for each class globally, which can achieve the effect of improving the classification accuracy through multiple average center. But on IS, ILPD, and TTTE data sets, when the ratio of L is 10%, the classification effect is significantly lower than the compared algorithms. GAMLNF need to find local average vector in each class, and if the ratio of L is too small, GANN can not find enough local neighbors in each class, and the global neighbors belong to a certain class. It is especially important to note that all algorithms can increase the accuracy of the algorithm when the labeled samples ratio increase, especially when the ratio of L is from 10%~50%.

Fig. 7 ACC of different algorithms with respect to different percentages of L on 6 data sets

5 Conclusions and future study

In this paper, we firstly explain in detail how we use GAMLNF to detect mislabeled samples. Then, we introduce how to repair the spatial structure damaged by the noise filter. In the end, we propose our STDP-GAMLNF algorithm framework. Specifically, the spatial structure of the data sets is revealed by DPC, and then the spatial structure is used to help self-training to label unlabeled samples. Meanwhile, GAMLNF is used to detect whether the relabeled sample is mislabeled sample or not, after each epoch of

labeling. SSR technology can reconstruct the corrupted space structure. Besides, all the experiments clearly show that (a) Compared with mainstream methods, the proposed algorithm can effectively improve the average accuracy and AUC value. (b) GAMLNF's ability to detect mislabeled samples is better than other comparison algorithms. (c) The presented algorithm is not sensitive to the neighbor parameter k value and can be adaptive to find the appropriate number of neighbors of each class. (d) The average accuracy of the algorithm will be improved when the ratio of L increases, and it can be better than other comparison algorithms in most cases.

In future work, we will consider how to improve the noise filter to promote the detection of mislabeled samples, when there exist extremely few labeled samples. We find that the increasing number of labeled samples can significantly improve the accuracy of the algorithm. Therefore, we also consider how to relabel the incorrectly labeled samples through the updated spatial structure for the sake of making the labeled samples not be simply deleted.

Compliance with ethical standards

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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Authorship contributions

Shuaijun Li: Conceptualization, Methodology, Validation, Formal analysis, Data Curation, Writing-Original Draft.

Jia Lu: Supervision, Writing - Review & Editing.

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