# A Parameter-Free Self-Training Algorithm for Dual Choice Strategy

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Abstract: In the field of machine learning, semi-supervised learning has become a research hotspot. Self-training algorithms, improve classification performance by iteratively adding selected high-confidence samples to the labeled sample set. However, existing methods often rely on parameter tuning for selecting high-confidence samples and fail to fully account for local neighborhood information and the information of labeled samples. To address these issues, this paper proposes a self-training algorithm with a parameter-free self-training algorithm for dual choice strategy. Firstly, the selection problem of K-value in KNN classifier is solved by using natural neighbors to capture the local information of each sample, and secondly, adaptive stable labels are defined to consider the information of labeled samples. On this basis, a decision tree classifier is introduced to combine the global information for double selection to further select high-confidence samples. We conducted experiments on 12 benchmark datasets and compared them with several self-training algorithms. The experimental results show that the FSTDC algorithm achieves significant improvement in classification accuracy.

## 1 INTRODUCTION

In the field of semi-supervised learning (SSL)(Van Engelen and Hoos, 2020), self-training algorithms play a crucial role, which aiming to improve the performance of classifiers by combining a small amount of labeled data with a large amount of unlabeled data. Li et al (Li et al., 2005) proposed the self-training with editing algorithm(SETRED), which uses data editing techniques to identify and reject potentially mislabeled samples from the labeling process. Despite the progress SETRED has made in improving the robustness of self-training, it relies on manually set thresholds. To overcome this limitation, Wu et al (Wu et al., 2018) proposed the self-training semi-supervised classification based on density peaks of data algorithm(STDP), which is based on the concept of density peak clustering (DPC)(Rodriguez and Laio, 2014) and is able to reveal the underlying data on data distributions of different shapes. The STDP algorithm does not rely on specific data distribution assumptions, thus expanding the application scope of self-training algorithms. Zhao et al(Zhao and Li, 2021) introduced the concept of natural neighbors based on STDP and proposed a semi-supervised self-training method based on density peaks and natural neighbors algorithm (STDPNaN). Furthermore, Li et al (Li et al., 2019) proposed a self-training method based on density peaks and an extended parameter-free local noise filter for k nearest neighbor (STDPNF). An extended parameter-free local noise filter (ENaNE) was proposed to address the problem of mislabeled samples in STDP. The design of ENaNE cleverly exploits the information of both labeled and unlabeled data, and efficiently filters noise. Wang et al(Wang et al., 2023) proposed a self-training algorithm based on the two-stage data editing method with mass-based dissimilarity (STDEMB) based on the previous work. The STDEMB algorithm, through a prototype tree design, which effectively edits mislabeled samples and selects high-confidence samples during self-training.

Based on the above algorithms, a parameter-free self-training algorithm for the dual selection strategy is designed. It is not only parameter-free, but also integrates the global and local information of the samples, while making full use of the information of the labeled samples. In addition, a decision tree classifier is introduced for high-confidence sample selection, which is extensively experimentally validated on several datasets, proving its

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effectiveness and superiority in SSL tasks.

# 2 RELATED WORK

## 2.1 Relevant Symbol

$X=\{x_1,...,x_n\}$ denotes a dataset containing $n$ samples.
$Y=\{y_1,\dots,y_n\}$ represents the set of labels.
$L=\{(x_1,y_1),\dots,(x_l,y_l)\}$ denotes a labeled sample set containing $l$ labeled samples.
$U=\{u_{l+1},\dots,u_n\}$ denotes the set of unlabeled samples, which contains $n-l$ unlabeled samples.

## 2.2 Self-Training Algorithm

The self-training algorithm is a semi-supervised learning strategy that iteratively improves the performance of a classification model by progressively integrating the high-confidence samples. The algorithm first trains an initial model on a limited amount of labeled data, and then the model generates pseudo-labels by predicting a large amount of unlabeled data. The most reliable part of them is selected to be added to the training set. Its general process is shown in the table below.

## 2.3 Comparison Algorithm

### 2.3.1 STDP

STDP uses density peaks in the data space to discover the structure of the data. It then integrates structural information into the self-training process by alternately selecting the 'previous' and 'next' unlabeled samples of a labeled sample and adding these samples and their predicted labels to the training set. This process is iterated until a more accurate classifier has been trained.

### 2.3.2 SETRED

The SETRED algorithm introduces data processing techniques. The algorithm captures the local structure of the data by constructing a neighborhood graph and uses a local cut edge weight statistic (CEW) to identify and exclude potentially mislabeled samples. The SETRED algorithm improves the generalization of the model by adding only those samples to the training set in each iteration that have passed the reliability test.

### 2.3.3 STDPNaN

Classification performance is improved by combining the concept of density peaks and natural neighbors. The algorithm first reveals the true structure and distribution of the data using improved density peak clustering without parameters (DPCNaN), and then continuously adds unlabeled samples with high confidence to the training set through self-training process, where an integrated classifier is used to improve the prediction capability.

### 2.3.4 STDEMB

The STDEMB algorithm is based on a two-stage data editing approach and mass-based dissimilarity to improve the performance of semi-supervised learning. It develops an innovative two-stage data editing strategy that effectively selects unlabeled samples with high confidence and explores the relationship between unlabeled samples and labeled samples through a prototype tree.

Algorithm 1: Self-training algorithm.

```
Input：$L$, $U$
Output：Classifier $C$
1.Initialise high confidence sample set $S=\varnothing$
2.While $U\neq\varnothing$ DO
3.   Train the classifier C using the labeled sample set $L$
4.   Assigning labels to unlabeled sample set $U$ using classifier $C$
5.   Select the high-confidence sample set $S$ from $U$
6.   $L\leftarrow L\cup S, U\leftarrow U-S$
7.End While
```

# 3 OUR ALGORITHM

## 3.1 Definitions

**Definition1(Natural Neighbors)**
In the field of data science, the concept of natural neighbors is a mathematical abstraction of the mutual recognition relationship in social network theory. The core of this concept lies in the fact that the neighborhood relationship between data points is mutual, i.e., one data point and another data point are each other's nearest neighbors at the same time. Natural neighbors do not require predefined parameters and are defined as follows:

$$NN(x_i) = \left\{ x_j \middle| x_j \in KNN(x_i), x_i \in KNN(x_j) \right\} \qquad (1)$$

where $KNN(x_i)$ denotes the nearest neighbors and $NN(x_i)$ denotes the set of natural neighbors.

**Definition 2(Natural Stabilization Structure)**
The natural stable structure is a special type of data form in which every data point in a dataset forms a natural neighbor relationship with at least one other data point. The existence of such a structure implies that the dataset exhibits an intrinsic stability in which the data points are connected to each other through mutually recognized neighbor relationships, constituting a stable structure known as the natural stable structure. For any data point $x_i$, there exists at least one that satisfies the following relationship:

$$x_i \in NN(x_j) \cup x_j \in NN(x_i), x_i \neq x_j \qquad (2)$$

**Definition 3(Natural Neighbor Label Set)**
The natural neighbor label set represents the set of labels of the natural neighbors of a sample.

$$y_{NN}(x_i) = \{ y_j | x_j \in NN(x_i) \} \qquad (3)$$

where $y_{NN}(x_i)$ denotes the set of natural neighborhood labels for sample $x_i$.

**Definition 4(Adaptive Stable Labels)**
Adaptively stable labels denote the class of labels with the highest number of occurrences in the set of natural neighborhood labels, which is represented as follows:

$$y_{AS}(x_i) = Mode(y_{NN}(x_i)) \qquad (4)$$

Where $y_{AS}(x_i)$ denotes the adaptive stable label of sample $x_i$ and $Mode(\bullet)$ is the function used to calculate the number of plurality in a set.

## 3.2 Description of the Algorithm

In order to fully consider the domain information of the samples and the information of the labeled samples, we designed the FSTDC algorithm. Firstly, it does not require preset parameters and is based on natural neighborhood adaptive learning. Secondly, it adopts a dual selection strategy based on decision tree classifier, which selects as high-confidence samples when and only when the adaptively stable labels and the predicted labels of the decision tree classifier match, which improves the quality of the selected high-confidence samples. The process of FSTDC algorithm is shown in the following table.

# 4 EXPERIMENTS

The experimental sessions of this study were executed in the same configuration of the computing environment, which consisted of a 64-bit Windows 10 operating system, 64 GB RAM, and an Intel Core i9 processor. The software environment used for the experiments was MATLAB 2023a.

## 4.1 Description of the Data Set

To validate the performance of FSTDC, we selected 12 datasets from UCI, the details are shown below.

Table 1: datasets details.

| index | dataset | samples | features | classes |
|---|---|---|---|---|
| 1 | AR | 1680 | 1024 | 120 |
| 2 | Australian | 690 | 14 | 2 |
| 3 | Balance | 625 | 4 | 3 |
| 4 | BUPA | 345 | 6 | 2 |
| 5 | Cleve | 303 | 13 | 8 |
| 6 | crx_uni | 690 | 15 | 2 |
| 7 | Ecoli | 336 | 7 | 8 |
| 8 | FERET32x32 | 1400 | 1024 | 200 |
| 9 | Glass | 214 | 9 | 6 |
| 10 | Haberman | 306 | 3 | 2 |
| 11 | ORL | 400 | 1024 | 40 |
| 12 | Yeast | 1484 | 1470 | 10 |

Algorithm 2: FSTDC algorithm.

```
Input：$L$, $U$
Output：Classifier $C$
While true
    Initializing KNN classifier using labeled samples
    Initialize $S=\varnothing$
    For each unlabeled sample $x_i$ in $U$
        Natural neighbors $NN(x_i)$ of $x_i$ obtained through equation (1)
        The set of natural neighborhood labels $y_{NN}(x_i)$ of $x_i$ is obtained through equation (3)
        Adaptive stabilization labels $y_{AS}(x_i)$ obtained by equation (4) for $x_i$
        Assigning predictive labels $y_{CART}(x_i)$ to unlabeled samples $x_i$ using decision tree classifiers
        If $y_{AS}(x_i) = y_{CART}(x_i)$
            Add $x_i$ to $S$
        End If
    If $S=\varnothing$
        Break
    End If
    $L = L \cup S, U = U - S$
End While
Return $C$
```

Table 2: The accuracy results of the algorithms.

| Datasets | STDP | SETRED | STDEMB | STDPNaN | FSTDC |
|---|---|---|---|---|---|
| AR | 78.19±1.07(4) | 78.44±1.23(3) | 77.62±1.14(5) | 84.67±1.23(2) | 91.76±1.04(1) |
| Australian | 64.15±3.43(5) | 64.17±2.30(4) | 67.87±2.86(2) | 64.86±3.15(3) | 68.92±2.39(1) |
| Balance | 76.64±1.89(3) | 77.12±2.15(2) | 75.08±5.73(4) | 74.71±2.21(5) | 80.95±6.58(1) |
| BUPA | 59.63±4.1(4) | 60.2±3.18(2) | 59.58±5.59(5) | 59.84±4.08(3) | 61.62±5.89(1) |
| Cleve | 75.22±5.67(5) | 76.12±5.61(4) | 78.58±5.07(2) | 78.2±4.77(3) | 79.69±2.21(1) |
| crx_uni | 63.68±2.92(4) | 65.26±3.59(3) | 67.96±3.43(2) | 63.44±3.9(5) | 69.25±2.8(1) |
| Ecoli | 89.88±2.77(3) | 88.84±3.53(5) | 89.15±3.8(4) | 90.94±2.1(2) | 91.09±1.81(1) |
| FERET32x32 | 84.11±0.76(3) | 83.88±0.73(4) | 83.8±0.99(5) | 88.53±1.5(2) | 97.47±0.44(1) |
| Glass | 76.79±5.52(5) | 77.62±3.82(4) | 78.35±4.22(3) | 78.91±5.93(2) | 79.90±4.13(1) |
| Haberman | 62.65±6.25(4) | 61.0±8.63(5) | 65.11±13.65(2) | 64.81±5.2(3) | 65.94±9.49(1) |
| ORL | 83.93±1.92(3) | 82.56±2.29(5) | 83.51±1.6(4) | 87.84±1.86(2) | 93.16±1.43(1) |
| Yeast | 87.17±2.51(3) | 87.73±2.51(1) | 87.06±1.93(4) | 86.88±1.48(5) | 87.51±2.15(2) |
| Wilcoxon | + | + | + | + | N/A |
| Ave.ACC | 75.17 | 75.25 | 76.14 | 76.97 | 80.61 |
| Ave.STD | 3.23 | 3.30 | 4.17 | 3.12 | 3.36 |

## 4.2 Experimental Setup

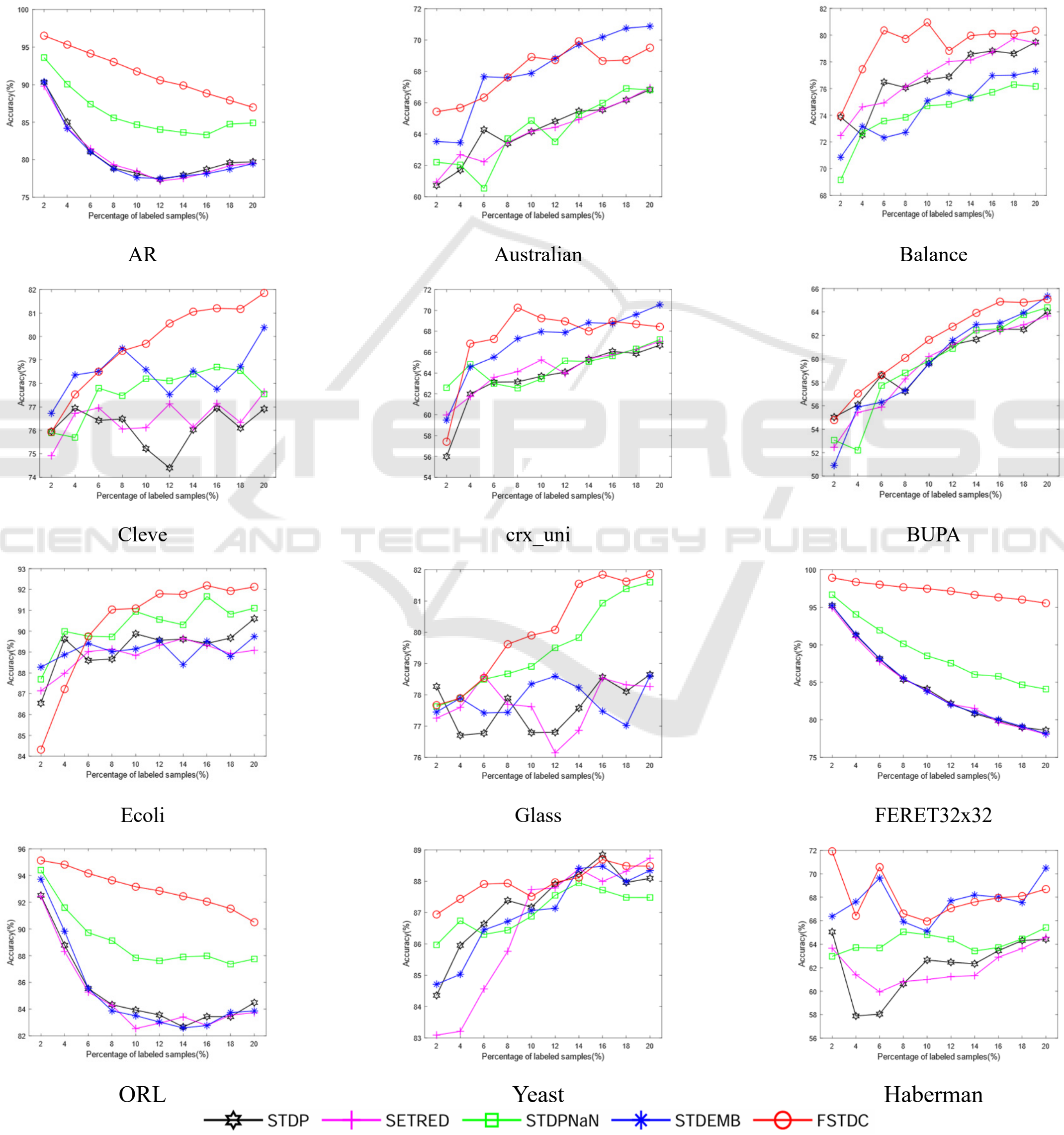
In the experiments, five existing self-training algorithms were selected for comparison in order to verify the performance of the FSTDC algorithm. For STDP and STDPNF, the parameter $\partial$ was set to 2. The threshold parameter $\theta$ was set to 0.1 for the SETRED algorithm, while the STDEMB algorithm was set to $k$ =7 and $\partial$ =0.5. These parameters followed the settings in the original literature for each algorithm. The significance of the experimental results was verified by Wilcoxon test at 90%

confidence level. In the experimental results, the symbol '+' indicates that our algorithm performs significantly better than the comparison algorithms; '-' indicates that the performance is significantly worse and '~' indicates that there is no significant difference in performance.

## 4.3 Analysis of Results

The table records the average accuracy of each algorithm on different datasets, and our algorithm is 5.44%, 5.36%, 4.47%, and 3.64% higher than that of the comparison algorithms, respectively, which proves the effectiveness of our algorithm.

Meanwhile, we also did experiments on the effect of the proportion of labeled samples on the classification performance, and the experimental results are shown in the figure below. From the figure, it can be seen that with the increase of the proportion of labeled samples, there is an upward trend in most of the datasets.



AR

Australian

Balance

Cleve

crx_uni

BUPA

Ecoli

Glass

FERET32x32

ORL

Yeast

Haberman

Figure 1: Classification accuracies of six algorithms with different proportions of labeled samples.

## 5 SUMMARY

To address the problem of selecting high-confidence samples for self-training algorithms in semi-supervised learning, we propose a parameter-free self-training algorithm for dual choice strategy (FSTDC). FSTDC considers the local information of the samples through the introduction of natural neighbors and defines natural stable labels, which take into account the information of the labeled samples. In addition, high-confidence samples are further selected by considering global information through a dual strategy. Extensive experiments were conducted and the experimental results proved the effectiveness of our proposed algorithm.

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