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Hybrid Active Learning and Dynamic Self-Training for Data Stream Classification

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Abstract— **Most of the data stream classification methods need plenty of labeled samples to achieve a reasonable result. However, in a real data stream environment, it is crucial and expensive to obtain labeled samples, unlike the unlabeled ones. Although Active learning is one way to tackle this challenge, it ignores the effect of unlabeled instances utilization that can help with strength supervised learning. This paper proposes a hybrid framework named "DSeSAL", which combines active learning and dynamic self-training to achieve both strengths. Also, this framework introduces variance based self-training that uses minimal variance as a confidence measure. Since an early mistake by the base classifier in self-training can reinforce itself by generating incorrectly labeled data, especially in multi-class condition. A dynamic approach to avoid classifier accuracy deterioration, is considered. The other capability of the proposed framework is controlling the accuracy reduction by specifying a tolerance measure. To overcome data stream challenges, i.e., infinite length and evolving nature, we use the chunking method along with a classifier ensemble. A classifier is trained on each chunk and with previous classifiers form an ensemble of M such classifiers. Experimental results on synthetic and real-world data indicate the performance of the proposed framework in comparison with other approaches.**

Keywords- Computer Science; Data Mining; Semi-supervised learning; Classification; Data Stream.

I. INTRODUCTION

In many applications, such as credit card transactions, ATM transactions, network data, web-usage data, stock market data, etc., large volumes of data are being generated continuously that can be characterized as data streams. Therefore, data stream classification has recently attracted much attention. For extracting knowledge or patterns from data streams, it is crucial to develop methods that analyze and process streams of data in multi-dimensional, multi-level, single pass, and online manner [1, 2, 3]. The general process of data stream mining is depicted in Fig. 1. Data streams may evolve in several ways: 1) The prior probability distribution $p(c)$ of class c may change. 2) The posterior probability distribution $p(c|x)$ of the class may change and 3) both the prior and posterior probabilities may change. In either case, the challenge is to build a classification model that is consistent with the current concept [4, 5]. Because of essential

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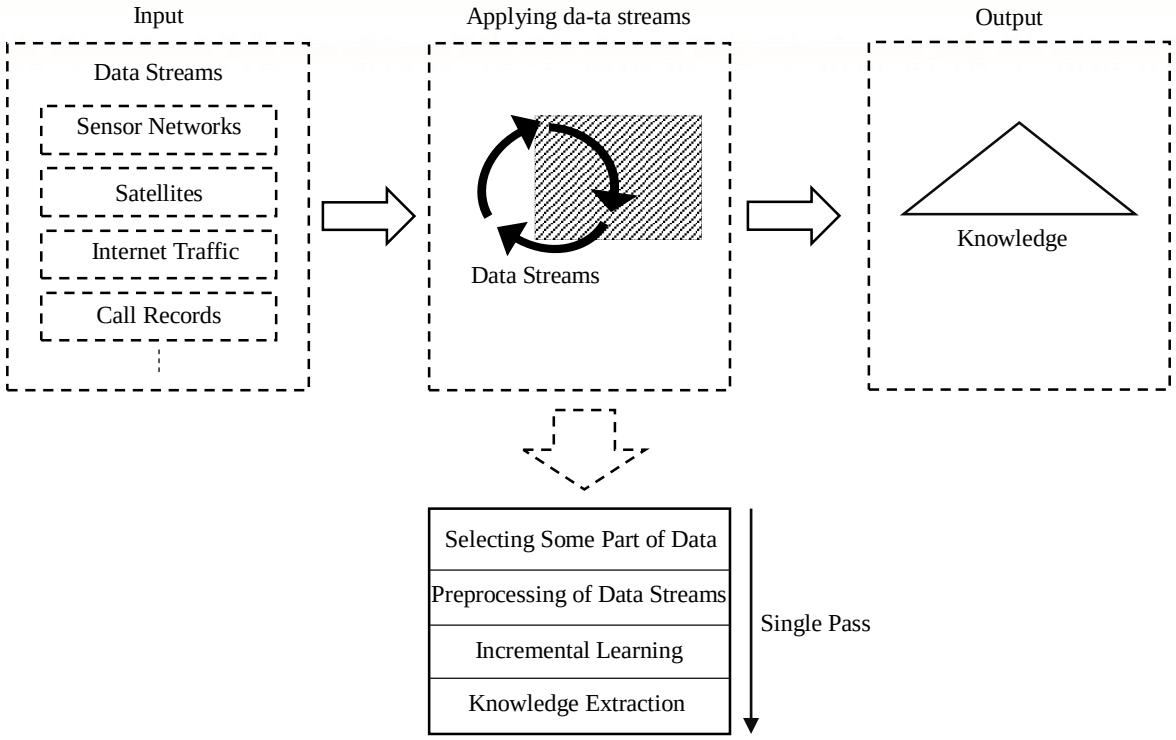


Fig. 1. General process of data stream mining

properties, i.e., increasing data volume and dynamic and evolving nature, mining data streams raised several challenges [6, 7, 8]. The length of data stream would be infinite and an algorithm is needed to process the data in one pass [7, 8]. Therefore, traditional learning algorithms that require several passes on the training data cannot be directly applied to the streaming environment [8, 9]. To solve this problem, ensemble classification techniques have been proposed.

Ensemble approaches have the advantage that they can be updated efficiently, and they can be easily made to adopt the changes in the stream. Several ensemble approaches have been devised for the classification of evolving data streams [10, 11, 12]. The general technique practiced by these approaches is that the data stream is divided into equal-sized chunks. Each of these chunks is used to train a classifier. An ensemble of *M* such classifiers is used to test unlabeled data.

Manual labeling of data is both costly and time-consuming [14, 15]. Therefore, labeled data may be very scared in a real streaming environment, where huge volumes of data appear at high speed. Thus, only a limited amount of training data may be available for building the classification models, leading to poorly trained classifiers [16, 17, 18]. One recently proposed solution to address this issue is to use active learning (AL) techniques which selectively label number of informative instances that can form an accurate predictive model [19, 20, 21]. The goal of active learning is to maximize the prediction accuracy by only labeling a limited number of instances. Meanwhile, the main challenge is about to identify "important" instances that should be labeled to improve the model training due to the fact that one could not afford to label all samples [18]. For example, uncertainty sampling [22, 23], query by committee (QBC) [20] or query by a margin [21] principles takes instances in which the current learners have the highest uncertainty as the most needed instances for labeling.

Thus, in practice, only small fraction of each data chunk is likely to be labeled, leaving a major portion of the chunk as unlabeled. By only selecting the most informative instances for labeling, active learning could reduce the labeling cost when labeled instances are hard to obtain [24]. Facing the same situation, semi-supervised learning utilizes unlabeled instances to strengthen trained classifiers on labeled instances [25, 26]. In general, active learning methods ignore the effect of unlabeled instances. However, unlabeled instances could strengthen supervised learning tasks under suitable assumptions. A variety of semi-supervised learning methods were proposed based on this idea. Semi-supervised learning methods can be used to strengthen active learners [24, 27, 28]. Therefore, this paper proposed a hybrid method that combines active learning and semi-supervised learning to come up with the mentioned challenges.

In this paper, we present a combination of AL and self-training approach to which we will refer as semi-supervised active learning for data stream mining (SeSAL). To the best of our knowledge, no semi-supervised active learning combination exists for data streams. We introduce minimal variance as a confidence measure in self-training. In multi-class conditions, AL performs better than SeSAL. The nature of Self-training causes this problem. Because of the small initial labeled set, with a high number of classes, self-training weaken itself by generating incorrectly labeled data that redound poor classifier. To avoid such an error propagation, we propose a dynamic self-training algorithm and apply it in our combination framework (DSeSAL). Concerning accuracy reduction in the iterations of self-training algorithm, we indicate a tolerance measure that prevents such downfall, stop

Algorithm 1 General AL framework

Given:
B: number of examples to be selected
L: set of labeled examples
P: set of unlabeled examples
U_M: utility function

Algorithm:
Loop until stopping criterion is met
1. Learn model M from L
2. For all $p_i \in P$: $u_{p_i} \leftarrow U_M(P_i)$
3. Select B examples $p_i \in P$ with highest utility u_{p_i}
4. Query human annotator for labels of all B examples
5. Move newly labeled examples from P to L

Return L

the semi-supervised approach and switch to AL phase. This procedure guarantees to derive a model to predict future instances' label as accurately as possible.

The rest of this paper is organized as follows: In the next section, related works are reviewed. In Section 3, active learning and semi-supervised learning are recalled as the foundation of our hybrid framework. In Section 4, the proposed framework is presented. Experimental results are reported in Sections 5. Section 6, includes the conclusion.

II. RELATED WORK

In addition to data stream classification, our research is closely related to the existing works on both semi-supervised and active learning. There have been many works in stream data classification. There are two main approaches: *single model classification* and *ensemble classification*. Single model classification techniques incrementally update their model with new data to cope with the evolution of the stream [1, 30]. These techniques usually require complex operations to modify the internal structure of the model and may have a poor performance if there is a concept-drift in the stream [4, 31, 32]. In data streams with continuous volumes, the classifier ensemble has shown to be effective in tackling data volume and concept drifting challenges [11, 33, 34]. [30] and [33] proposed a streaming ensemble algorithm that combines decision tree models using majority voting. Kolter and Maloof in [35] proposed an AddExp ensemble method by using weighted online learners to handle drifting concepts. [28, 36] and [37] have proposed a weighted ensemble framework for concept drifting data streams and proved that the error rate of a classifier ensemble is less than a single classifier trained from the aggregated data of all consecutive k chunks. These ensemble approaches have the advantage that they can be more efficiently built than updating a single model and they observe higher accuracy than their single model counterpart [4].

The combination of classifier ensemble and active learning has been reported in much research [19, 39, 40, 41]. Semi-supervised and active learning frameworks concerning data stream classification, are established research areas. Here, some recent and reliable research in this field is introduced. Clustering-training is a semi-supervised framework that select confident unlabeled samples using clustering. Then uses them to retrain the classifier incrementally which is proposed in [42, 43]. Yan Yu et al. in [44] propose an anomaly detection algorithm for evolving data stream based on semi-supervised learning, SSAD. The SSAD algorithm utilizes an attenuation rule to decrease the effect of historical data on the detection result, which can help the algorithm to learn from current data that characterizes the traffic pattern more accurately. SSAD also uses semi-supervised learning to extend labeled dataset as a training dataset to do with the problem of lack of the labeled data.

Realizing that labeling all stream data is expensive and extremely time-consuming, Fan et al. in [45], proposed an active mining (AM) framework that labels samples only if it is necessary. In short, AM uses a decision tree (trained from the currently labeled data) to compare the distributions of the incoming samples and the data collected by hand using the tree branches (without observing the class labels). If two sets of samples are subject to different distributions, then labeling process is triggered to randomly select a few incoming samples for labeling. Xingquan Zhu et al. in [37] propose a classifier ensemble based active learning framework, with an objective of maximizing the prediction accuracy of the classifier ensemble built from labeled stream data. We use this framework in our method and describe it in more details in the next section.

III. PRELIMINARY

In this section, we recall the two main principles of our hybrid proposed framework: Active learning and Semi-supervised learning.

A. Active Learning

Algorithm 1 describes the general AL framework. A utility function $U_M(P_i)$ is the core of each AL approach. It estimates how useful it would be for a specific base learner to have an unlabeled example labeled and, subsequently included in the training set [17].

B. Semi-Supervised Learning

There are many semi-supervised learning methods developed. Self-training learning is the one that needs only one classifier, which is important to meet the speed requirement [28]. We choose Self-training to strengthen the learning engine in AL framework with unlabeled instances. In self-training, first, a classifier is trained with the small amount of labeled data. The classifier is then used to classify the unlabeled data. Typically, the most confident unlabeled points, together with their predicted labels, are added to the training set. The

Algorithm 2 Self-training

Given:
Labeled data $\{(x_i, y_i)\}_{i=1}^{l}$, unlabeled data $\{x_i\}_{j=l+1}^{l+u}$

Algorithm:
1. Initially, let L = $\{(x_i, y_i)\}_{i=1}^{l}$ and U = $\{x_i\}_{j=l+1}^{l+u}$.
2. Repeat:
   3. Train f from L using supervised learning.
   4. Apply f to the unlabeled instances in U.
   5. Remove a subset S from U; add $\{(x, f(x)) | x \in S\}$ to *L*.

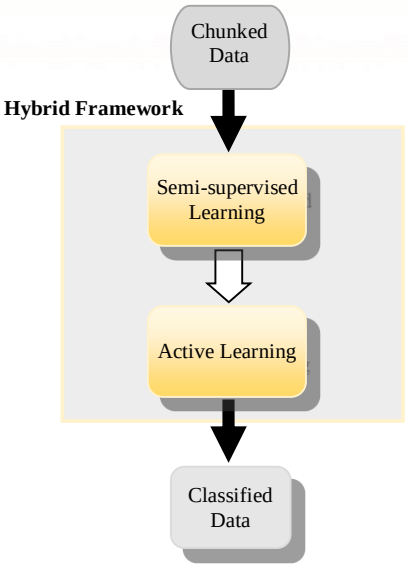


Fig. 3. Hybrid of Semi-supervised and Active Learning black box

classifier is re-trained and the procedure repeated [25, 29]. Note the classifier uses its own predictions to teach it. The overall process of self-training is shown in Algorithm 2.

IV. PROPOSED METHOD

There are two important properties in a real stream environment which lead to many challenges [3]; incremental growth of data volumes and continuous evolvement of decision concepts. In addition, massive volumes of data arrive at high speed, so labeled data may be rare, and it is not possible to manually label all the data as soon as they arrive. In this condition, the best way is to use the advantages of abundant unlabeled data. So, we introduce **DSeSAL** framework, to overcome such difficulties and challenges. In this framework, our contributions are as follows:

A. Combination of Active learning and self-training.

B. Introduce minimal variance as a confidence measure in self-training.

C. Propose a dynamic self-training algorithm and combination with active learning.

D. Indicate tolerance measure that prevents an accuracy reduction in the iteration of the self-training.

We apply semi-supervised learning with active learning in a hybrid manner that benefit from both unlabeled data and selective sampling scenario. The way we combine semi-supervised and active learning is shown in Fig. 2. Naturally, stream data could be stored in the buffer and processed when the buffer is full, so we divide the stream data into equal-sized (user-specified) chunks and exploit our learning process on each of them. Due to the limited number of labeled data in each chunk, we utilize unlabeled data to build a stronger model from each chunk, by applying a semi-supervised approach (Fig. 3).

In order to simplify the problem and deliver an applicable combining framework data streams, we

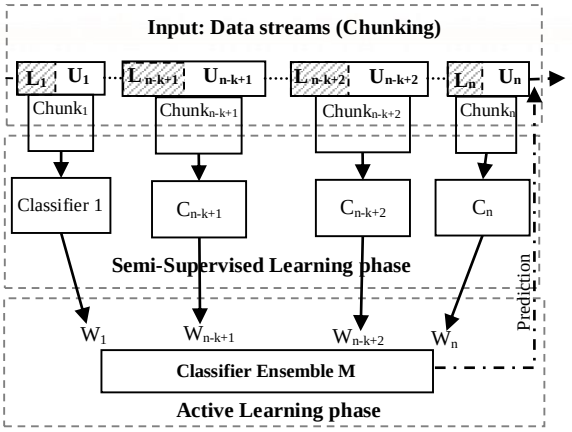


Fig. 2. A general classifier ensemble framework for learning from data streams

assume that the concepts in the data are constantly evolving, so the proposed framework is carried out on a regular basis, and the objective is to find important samples out of a certain number of newly arrived instances for labeling.

The proposed framework in Fig. 3 can be applied to a variety of stream applications as long as instance labeling is of concern. The employment of a classifier ensemble ensures that framework can handle massive volumes of stream data effectively and adopt the changes in the stream [1].

Based on the framework in Fig. 3, we assume that once the algorithm moves to chunk S_n, all instances in previous chunks, $\dots, S_{n-3}, S_{n-2}, S_{n-1}$, are inaccessible except classifiers built from them (i.e., $\dots, C_{n-3}, C_{n-2}, C_{n-1}$).

Relying on the above assumptions, the objective becomes labeling instances in data chunk S_n such that a classifier C_n built from the labeled and unlabeled instances in S_n. The classifier C_n along with the most recent $K-1$ classifiers $C_{n-k+1}, \dots, C_{n-1}$, can form a classifier ensemble with maximum prediction accuracy on unlabeled instances in S_n.

A. Variance Reduction for Error Minimization

In this part, we first argue that minimizing the classifier variance is equivalent to minimizing its error rate and then apply variance as a confidence measure in our semi-supervised approach. In addition, we shortly explain an active learning approach and optimal-weight calculation method that we use in the classifier ensemble.

- *Confidence measure in self-training*

Let x be an input instance and c_i is a class label and $p(c_i|x)$ is a classifier's probability estimation in classifying x, and then the actual probability $f_{c_i}(x)$ is shown as follows:

$$f_{c_i}(x) = p(c_i|x) + \varepsilon_i(x) \quad (1)$$

where $\varepsilon_i(x)$, is an added error. If we consider that the added error of the classifier mainly comes from two sources, i.e., classifier bias and variance [46, 47, 48], then the added error $\varepsilon_i(x)$ in (1) can be decomposed

into two terms, i.e., β_{c_i} and $\eta_{c_i}(x)$, where β_{c_i} represents the bias of the current learning algorithm, and $\eta_{c_i}(x)$ is a random variable that accounts for the variance of the classifier (with respect to class c_i), which gives [49, 50]:

$$f_{c_i}(x) = p(c_i|x) + \beta_{c_i} + \eta_{c_i}(x) \quad (2)$$

According to [51], classifiers that trained by using the same learning algorithm but different versions of the training data suffer from the same level of bias but different variance values. Assuming that we are using the same learning algorithm in our analysis, without loss of generality, we can ignore the bias term. Consequently, the learner's probability in classifying x into class c_i becomes:

$$f_{c_i}(x) = p(c_i|x) + \eta_{c_i}(x) \quad (3)$$

According to [51] concluded that the classifier's expected added error can be defined as:

$$\mathrm{Err}_{\mathrm{add}} = \frac{\sigma^2_{\eta_{c_i}} + \sigma^2_{\eta_{c_j}}}{s} = \frac{\sigma^2_{\eta_c}}{s} \quad (4)$$

Where $p'(.)$ denotes the derivate of $p(.)$ and $p(c_i|x^*)$ is the probability distribution of class i for all points x^*, $s = p'(c_j|x^*) - p'(c_i|x^*)$, which is independent of the trained model. $\eta_{c_i}(x)$ is a random variable that accounts for the variance of the classifier (with respect to class c_i) and $\sigma^2_{\eta_{c_i}}$ denotes the variance of $\eta_{c_i}(x)$. As Equation (4) indicates the expected added error of a classifier is proportional to its variance; thus, reducing this quantity reduces the classifier's expected error rate.

Based on the framework in Fig. 3, we apply variance-base self-training in SSL phase. The main idea is first to train a classifier on labeled data. The classifier is then used to predict the labels for the unlabeled data. A subset of the unlabeled data, jointly with their predicted labels, is then selected to augment the labeled data. Typically, this subset consists of few unlabeled instances with the most confident predictions. The classifier is now re-trained on the larger set of labeled data, and the procedure repeats [43]. We use C4.5 [53] as our base learner. For selecting a subset of unlabeled instances, we use minimum classifier variance on current unlabeled set in each chunk based on Fig. 3. Following above conclusion, smaller variance means the prediction of our model is more confident. In our system, $\sigma^2_{\eta_{c_i}}$ is calculated by:

$$\sigma^2_{\eta_{c_i}} = \frac{1}{|\Lambda_x|} \sum_{(x,c)\epsilon\Lambda_x} \left(y^x_{c_i} - f_{c_i}(x)\right)^2 \quad (5)$$

where Λ_x, an evaluation set ($\Lambda_x = L_n \cup \hat{I}_x$, where $\hat{I}_x$ denotes I_x with a predicted class label.), is used to calculate the classifier variance, $|\Lambda_x|$ denotes the number of instances in Λ_x, $y^x_{c_i}$ is the genuine class probability of instance x. If x is labeled as $\mathrm{class}c_i$, then $y^x_{c_i}$ is equal to 1; otherwise, it is equal to 0 and $f_{c_i}(x)$ denotes the probability of base classifier in classifying x into class c_i. Consequently, the variance of the classifier over all class $c_1, c_2, \ldots, c_l$ is given by:

$$\sigma^2_{\eta_c} = \sum_{i=1}^{l} \sigma^2_{\eta_{c_i}} \quad (6)$$

- *Variance and optimal weight classifier ensemble*

As shown in Fig. 3, k base classifiers form a classifier ensemble M. The probability of the ensemble M in classifying an instance x is given by a linear combination of the probabilities produced by all of its base classifier. Each classifier C_m has a weight value w^m. The probability of M in classifying x into class c_i is given by (7), where $f^m_{c_i}(x)$ denotes the probability of base classifier C_m in classifying x into class c_i, i.e.,

$$f^E_{c_i}(x) = \sum_{m=n-k+1}^{n} w^m f^m_{c_i}(x) \Big/ \sum_{m=n-k+1}^{n} w^m = p(c_i|x) + \sum_{m=n-k+1}^{n} w^m \eta^m_{c_i} \Big/ \sum_{m=n-k+1}^{n} w^m \quad (7)$$

This probability can be expresses as:

$$f^E_{c_i}(x) = p(c_i|x) + \eta^E_{c_i}(x) \quad (8)$$

where $\eta^E_{c_i}(x)$ is a random variable accounting for the variance of the classifier ensemble M with respect to class c_i, and

$$\eta^E_{c_i} = \sum_{m=n-k+1}^{n} w^m \eta^m_{c_i} \Big/ \sum_{m=n-k+1}^{n} w^m \quad (9)$$

The variance of $\eta^E_{c_i}(x)$ becomes

$$\sigma^2_{\eta^E_{c_i}} = \sum_{m=n-k+1}^{n} (w^m)^2 \sigma^2_{\eta^m_{c_i}} \Big/ \left(\sum_{m=n-k+1}^{n} w^m \right)^2 \quad (10)$$

$\sigma^2_{\eta^m_{c_i}}$ is explained in SSL Phase. The total variance of the ensemble M is then given by:

$$\sigma^2_{\eta^E} = \sum_{i=1}^{l} \sigma^2_{\eta^E_{c_i}} = \sum_{m=n-k+1}^{n} (w^m)^2 \sigma^2_{\eta^m_{c_i}} \Big/ \left(\sum_{m=n-k+1}^{n} w^m \right)^2 \quad (11)$$

According to (4), expected added error can be written as:

$$\mathrm{Err}^E_{\mathrm{add}} = \frac{\sigma^2_{\eta^E}}{S} \quad (12)$$

Equation (12) states that to minimize the error rate of a classifier ensemble, we can minimize its variance instead. This objective can be achieved through the adjustment of the weight value associated with each of

Algorithm 3 The DSeSAL method

Input: (1) current data chunk S_n; and (2) $k-1$ classifiers $C_{n-k+1}, \dots, C_m, \dots, C_{n-1}$ built from the most recent data chunks;
Parameters: (1) α, the percentage of instances should be labeled from S_n by AL; (2) β; maximum percentage of instances should be labeled from S_n by DSSL; (3) γ, # of instances labeled in each SSL iteration

Objective: Updated ensemble M

1. $L_n \leftarrow \emptyset$; $U_n \leftarrow S_n$
2. $L_n \leftarrow$ Randomly label a tiny portion, e.g. 1~2.5% of instances from U_n.
3. $E \leftarrow 0$ //recording the iteration of SSL ($E = \beta/\gamma$)
4. Build a classifier C_n from L_n and calculate the base model accuracy Acc_b.
5. **While** $L_n < |S_n|.\beta$ //SSL phase continue until reach the stop point
   5.1. **For** each instance I_x in U_n
      a. Use the current classifier to predict a class label for I_x.
      b. Build an evaluation set $\Lambda_x = L_n \cup \hat{I_x}$, where $\hat{I_x}$ denotes I_x with a predicted class label.
      c. Calculate the confidence measure (classifier variance) on Λ_x (Eqs. (5) and (6)).
      End For
   5.2. $j \leftarrow 0$ // recording the number of labeled instances in each SSL iteration
   5.3. Choose instance I_x in U_n with smallest variance, put labeled I_x into L_n, i.e. $L_n = L_n \cup I_x$; $U_n = U_n / I_x$.
   5.4. $j \leftarrow j + 1$
   5.5. **If** $j < \gamma$
      a. Repeat Step 5.3.
   5.6. **Else**
      a. $E = E + 1$
   5.7. Update classifier by a new L_n.
   5.8. Calculate the current model accuracy Acc_i.
   5.9. **If** $E = 1$
      a. calculates the tolerance value T (Eq. (11)).
   5.10. **If** $Acc_i < (Acc_{i-1} - \mathrm{T})$ OR $Acc_i < (Acc_{i-2} - \mathrm{T}/2)$
      a. Return the model to previous state.
      b. Return the L_n and U_n to previous state.
      c. break
   End While
6. Initialize weight value w^m for each classifier C_m, $m = n-k+1, \dots, n$, where w^m is equal to C_m's prediction accuracy on L_n.
7. Use $C_{n-k+1}, \dots, C_m, \dots, C_{n-1}$ to form a classifier ensemble M as shown in Fig. 1.
8. For each instance I_x in U_n, Calculate ensemble variance (Eq. (11)) as instance I_x's expected ensemble variance on M.
9. Choose instance I_x in U_n with largest variance, label I_x and put labeled I_x into L_n, i.e. $L_n = L_n \cup I_x$; $U_n = U_n / I_x$.
10. Recalculate the ensemble variance of each base classifier C_m on L_n and find optimum weight value w^m (Eq. (13)) for all base classifiers (update the ensemble by new weight values).
11. Check if α percentages of instances are labeled.

M's base classifier $\mathrm{C_m}$. In [37], an optimal-weight calculation method is applied to assign weight values to the classifiers such that they can form an ensemble with minimum error rate. To find the weight values $\mathrm{w^m, m = n-k+1, \dots, n}$, an optimization problem is solved, and then weight values for each individual classifier of the classifier ensemble M are given by:

$$w^m = \frac{1}{1 + \sigma^2_{\eta_c^m}\left(\sum_{t=n-k+1, t\neq m}^{n} 1/\sigma^2_{\eta_c^t}\right)} \qquad (13)$$

The minimization of the classifier ensemble error rate through variance reduction acts as a principle to actively select mostly needed instances for labeling.

B. A COMBINED FRAMEWORK OF DYNAMIC SELF-TRAINING AND ACTIVE LEARNING

The process of the DSeSAL method is given in Algorithm 3. Following the conclusions derived from Section IV, we propose a combined framework of AL and SSL approaches for data stream classification. We introduce variance-based self-training. Self-training is characterized by the fact that the learning process uses its own predictions to teach it.

On the other hand, in stream environments, initial labeled data may be very scarce. So, it is conceivable that an early mistake made by the base classifier (which is not perfect to start with, due to a small initial labeled set) can weaken itself by generating incorrectly labeled data. Re-training with this data will lead to an even worse classifier in the next iteration. It is so expected in multi-class condition. Due to the limited initial labeled set, the base classifier may not be able to identify and learn unseen classes. To alleviate this problem, we propose dynamic self-training, as shown on Steps 5.1 to 5.10 in Algorithm 3.

To avoid error propagation in self-training iterations, we specify a tolerance value T for accuracy reduction. In our system, T is calculated by:

$$\mathrm{T} = |\, Acc_b - Acc_1| \qquad (14)$$

where $\mathrm{Acc_b}$ is the base model accuracy on unlabeled data in the related chunk and $\mathrm{Acc_1}$ is the accuracy of the model that build from the first iteration in self-training. Self-training iterations continue provided:

$$Acc_i > (Acc_{i-1} - \mathrm{T}) \; and \; Acc_i > (Acc_{i-2} - \mathrm{T}/2) \qquad (15)$$

This condition prevents classifier accuracy deterioration and guarantees to derive a model to predict future instances' label as accurately as possible. The way that the condition in Equation (15) is applied in self-training algorithm, is shown in Fig 4. In Algorithm 3, steps 6 to 11, present the AL procedure.

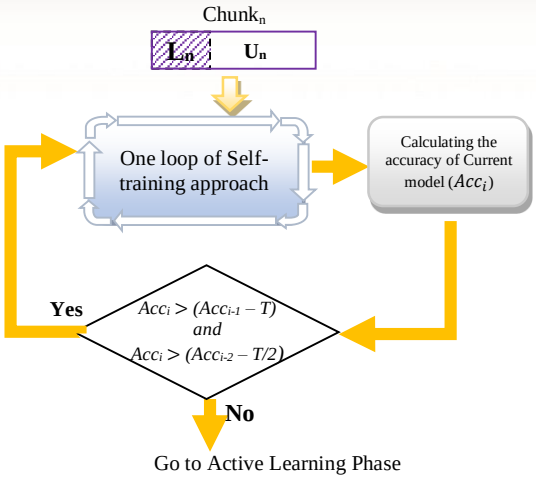


Fig. 4. Error propagation prevention condition in self-training process

Selecting the informative instance and update the ensemble are shown in Steps 6 to 9 and Step 10, respectively.

V. Experimental Result

A. Implementation

A set of experiments is carried out to compare our algorithm with the results of [37] (MV), random sampling (RS) and uncertainty sampling (US). All methods are implemented in MATLAB with an integration of WEKA data mining tool (Witten, & Frank, 2005). All the tests are conducted on a PC machine with a 2.71GH CPU and 2.0G memory.

B. Data Streams

Synthetic data: In order to simulate the magnitude and speed of concept drift in data streams, a hyper-plane based synthetic data stream generator is applied which is so popular in stream data mining research [11, 12, 33]. The hyper-plane of the data generation is controlled by a non-linear function defined by Equation (16). Given an instance x, its $f(x)$ value defined by Equation (16) determines its class label. Assume $f(x)$ value larger than a threshold θ indicates that x belongs to class A, otherwise, x belongs to class B, then changing the values of $a_i, i = 1, \dots, d$ and threshold θ may make an instance x have different probability $p(c_i|x)$ with respect to a particular class c_i.

$$f(x) = \sum_{i=1}^{d} \frac{a_i}{x_i + (x_i)^2} \qquad (16)$$

In Equation (16), d is the total dimensions of the input data x. Each dimension $x_i, i = 1, \dots, d$, is a value randomly generated in the range of [0, 1]. A weight value $a_i, i = 1, \dots, d$, is associated with each input dimension and the value of a_i is initialized randomly in the range of [0, 1] at the beginning. In data generation process, we will gradually change the value of a_i to simulate concept drifting. The general concept drifting is controlled through the following three parameters [1, 11, 33]: (1) t, controlling the magnitude of the concept drifting (in every N instances): (2) p, controlling the number of attributes whose weights are involved in the change; (3) h and $n_i \in \{-1, 1\}$, controlling the weight adjustment direction for attributes involved in the change. After the generation of each instance x, a_i is adjusted continuously by $n_i \cdot t / N$ (as long as a_i is involved in the concept drifting), and value a_0 is recalculated to change the decision boundaries (concept drifting). Meanwhile, after the generation of N instances, there is a h percentage of chances that weight change will invert its direction, i.e., $n_i = -n_i$ for all attributes ai involved in the change. In summary, c2-I100k-d10-p5-N1000-t0.1-h0.2 denotes a two-class data stream with 100k instances, each containing 10 dimensions. The concept drifting involves 5 attributes, and their weights change with a magnitude of 0.1 in every 1000 instances and weight inverts the direction with 20% of chance.

Table. I. Data characteristics of the real-world data used for evaluation

Name	# of instances	# of attributes	# of classes	Majority: Minority class ratio
Adult	48,842	15	2	0.761:0.239
Magic	19,020	10	2	0.351:0.649
Covtype	581,012	55	7	0.488:0.005
Shuttle	58,000	9	7	0.034:0.8
Letter	20,000	17	26	0.041:0.037

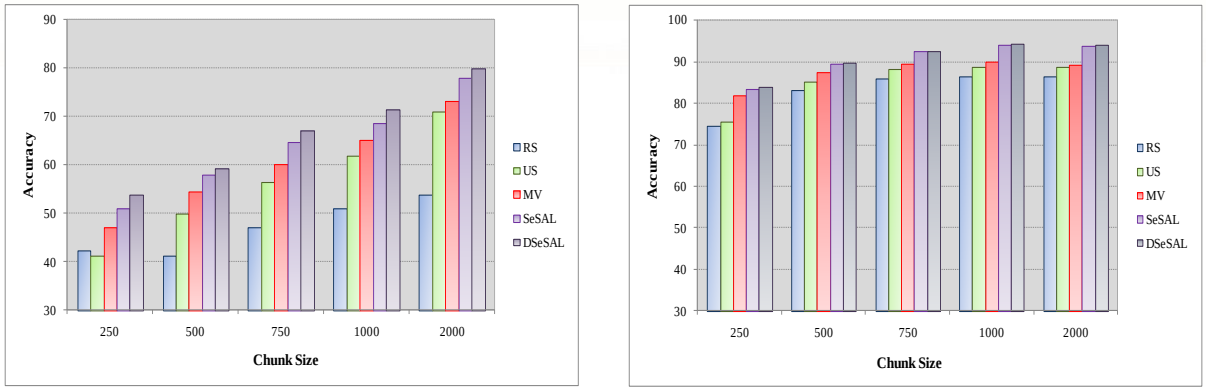
Real-world data: Due to the unavailability of public benchmark data streams (from classification perspectives), we select five relatively large datasets from UCI data repository [54] and treat them as data streams for our experiments. The datasets we selected are Adult, Magic Gamma Telescope, Covtype, Shuttle and Letter (as listed in Table 1).

Among these datasets, all of them except Letter are considered dense datasets, which means that a small portion of examples can learn genuine concepts quite well. The class distribution in the Covtype and Shuttle datasets are severely biased. Letter is a sparse dataset and 26 classes of examples are evenly distributed, and a small portion of examples are insufficient to learn genuine concepts underlying the data.

C. Evaluation

All results are 10-fold cross-validation accuracies which we set in Weka. C4.5 is our base learner in all experiments.

Learning with Fixed α and β Values: We apply our proposed framework to two types of synthetic data streams: two-class (Table 2) and four-class (Table 3). The accuracies in the tables denote an ensemble classifier's average accuracy in predicting instances in the current data chunk Sn, with chunk sizes varying from 250 to 2000. We fix the α and β values to 0.1 and set the k value to 10, which means that 10% of the instances are labeled for each data chunk, and only the



(a) (b)

Fig. 5. Average classification accuracy histogram on (α and β=0.1): (a) c2-I50k-d10-p5-N1000-t0.1-h0.2, (b) c4-I50k-d10-p5-N1000-t0.1-h0.2

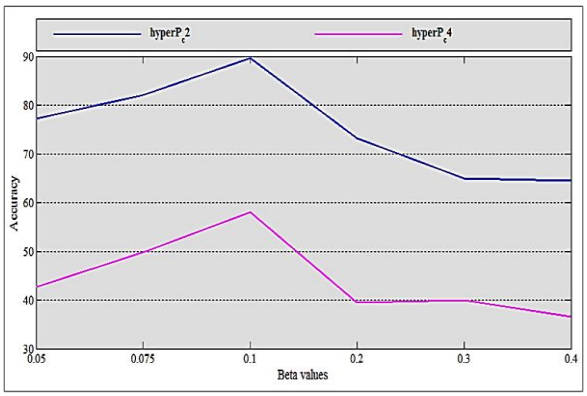


Fig. 6. SeSAL average accuracy on synthetic data (chunk size=500, α=0.1)

most recent ten classifiers are used to form a classifier ensemble.

The results from Table 2 and 3 indicate that the performance of all methods deteriorates as a consequence of the shrinking chunk size. This is because a smaller data chunk contains a few examples, and sparse training examples usually produce inferior learners in general. The advantage of having a small chunk size is the training efficiency.

For any particular method, Table 2 and 3 indicate that the results in multi-class data streams are significantly worse than a binary class data stream. This shows that learning from a multiclass data stream is more challenging than a binary class data stream.

Fig. 5 shows the results from Table 2 and 3 as two histograms. Comparing all five methods, we can easily conclude that SeSAL and DSeSAL receive the best performance across all data streams. The US is not an option for learning from data streams, and its performance is constantly worse than RS regardless of whether the underlying data are binary or multiple classes. The results from RS are surprisingly good, and it is generally quite difficult to beat RS with a substantial amount of improvement.

2) Learning with Different β Value: β is a percentage of instances should be labeled from S_n by self-training in SeSAL model. In Fig. 6, we compare SeSAL average accuracy w.r.t. different β values on synthetic data.

3) Learning with Different α Value: In Fig. 7, we compare all five methods w.r.t. different α values. Not surprisingly, when α value increases, all methods gain better prediction accuracies. This is due to the increasing number of labeled instances helps build strong base classifiers.

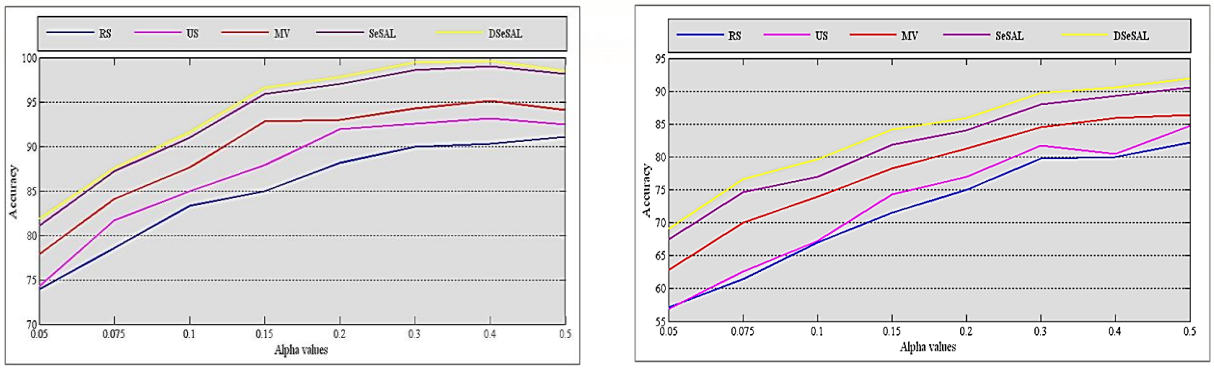
Overall, SeSAL, DSeSAL and MV achieve the best performance, and US is inferior to RS in the majority of the cases. For multiclass data streams, the performance of US is unsatisfactory and is largely inferior to the RS. To get the best performance and the lowest cost, we choose 0.1 for α value.

Table. II. Average classification accuracy on c4-I50k-d10-p5-N1000-t0.1-h0.2 (α and β=0.1)

Chunk Size	RS	US	MV	SeSAL	DSeSAL
250	74.54	75.51	81.84	83.35	**84.02**
500	83.07	85.16	87.62	**89.56**	**89.79**
750	86.10	88.14	89.48	**92.63**	**92.67**
1000	86.43	88.79	90.12	**94.17**	**94.37**
2000	86.47	88.69	89.16	**93.78**	**94.15**

Table. III. Average classification accuracy on c4-I50k-d10-p5-N1000-t0.1-h0.2 (α and β=0.1)

Chunk Size	RS	US	MV	SeSAL	DSeSAL
250	42.27	41.34	47.21	51.13	**53.76**
500	50.47	49.91	54.51	57.98	**59.24**
750	58.11	56.48	60.12	64.63	**67.04**
1000	63.08	61.92	65.14	68.52	**71.51**
2000	71.87	70.98	73.09	77.84	**79.86**



(a) (b)

Fig. 7. Classification average accuracy on (chunk size=500, β=0.1): (a) c2-I50k-d10-p5-N1000-t0.1-h0.2, (b) c4-I50k-d10-p5-N1000-t0.1-h0.211

4) Time Complexity and Runtime Performance: The time complexity of the proposed model in Algorithm 3 can be decomposed into two major parts: time complexity of semi-supervised phase and active learning part. As mentioned above, we use MV for Active learning phase. The time complexity of this phase is $O(N^2.M)$ [37].

same measure (variance) in semi-supervised and active learning phases of the unlabeled instance selection. The total time complexity is bounded by two important factors: 1) the number of instances in each chunk N and 2) the number of data chunks M. Because model training in each chunk is nonlinear w.r.t. the chunk size, we may prefer a relatively small chunk size to save the computational cost.

The time complexity of the semi-supervised part is also $O(N^2.M)$, where M is the number of chunks, each of which contains N instances. Because we use the

In Fig. 8, we report the system runtime performance, where the x-axis denotes the chunk size, and the y-axis denotes the average system runtime w.r.t. a single data chunk. Not surprisingly, RS has demonstrated itself to be the most efficient method due to its simple random selection nature. The MV, SeSAL and DSeSAL methods is the most time-consuming approach mainly because the calculation of the ensemble variance and the weight updating requires additional scanning in each chunk. The larger the chunk size, the more expensive the MV, SeSAL, and DSeSAL can be, because the weight we obtain the best tradeoff between computational cost and accuracy, when the chunk size is 500.

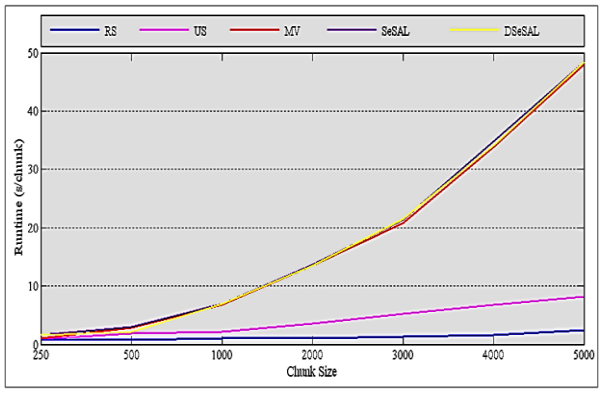


Fig. 8. System runtime with respect to different chunk sizes (c4-I50k-d10-p5-N1000-t0.1-h0.2 stream, α and β=0.1)

5) SeSAL and DSeSAL Performance on Real-World Data: For each data stream, we report its results using chunk size 500. We fix α and β value to 0.1 and set value k to 10, which means that only the most recent 10 classifiers are used to form a classifier ensemble. In Fig. 9, we report the algorithm performances on five real-world data.

According to the results illustrated in Table 4 and Fig. 9, SeSAL provides superior performance than MV on four datasets. These are dense datasets, which means that a small portion of examples can learn genuine concepts quite well. The Letter is a sparse dataset and 26 classes of examples are evenly distributed, and a small portion of examples are insufficient to learn genuine concepts underlying the data. In letter, SeSAL performs inferior to MV in the majority of cases, but DSeSAL solves this problem and provides a reasonable result. The performances of SeSAL and DSeSAL in binary class datasets are close to each other. In fact, DSeSAL eliminates the lack of SeSAL in multi-class problems.

Different from synthetic data streams where the decision concepts in data chunks gradually change following the formula given in Eq. (13), the data chunks of the real-world data do not share such property, and the concept drifting among data chunks are not clear to us (in fact, we do not even know the genuine concepts of the data). Because of this, we compare algorithms on two types of test sets. In Fig. 9,

Table. IV. Average accuracies on real-world datasets

Datasets	MV	SeSAL	DSeSAL
Adult	83.5756	**86.0346**	**86.1398**
Magic	79.1676	**83.3018**	**83.7278**
Covtype	66.9895	71.3863	**78.9498**
Shuttle	97.8795	98.8871	**99.567**
Letter	37.3099	27.9810	**47.3161**

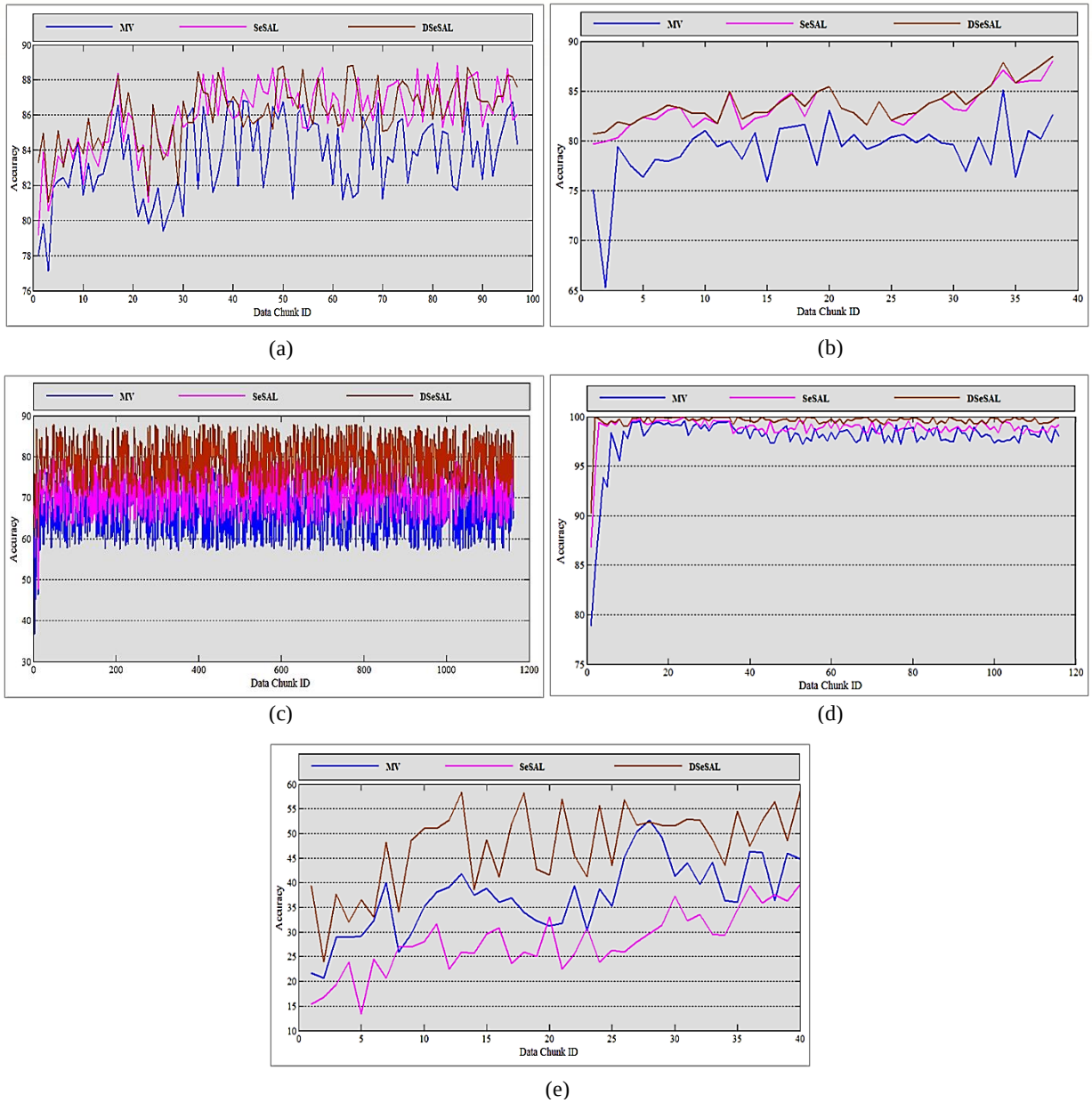


Fig. 9. Classifier ensemble accuracy on data chunk S¬¬n (chunk size=500, α and β=0.1): (a) Adult ,(b) Magic ,(c) CoverType ,(d) Shuttle ,(e) Letter

the algorithms are tested on all instances in data chunkS_n. In Fig. 10, the algorithms are tested on a separate test set generated from 10-fold cross-validation. The x-axis denotes the ratio of the initial labeled set to chunk size.

The results in Figs. 9 and 10 indicate that, overall, the accuracies evaluated on individual data chunks are slightly better than the accuracies acquired from the isolated test set. But overall, an algorithm's relative performance on each individual data chunk or on a separate test set does not make a big difference.

VI.CONCLUSION

In this paper, we propose a new research topic on the combination of active and semi-supervised learning for data streams with increasing data volumes and evolving nature. Our goal is to derive a model to predict future instances' label as accurately as possible. In a real stream environment, labeled data may be fairly scarce and labeling all data is quite difficult and expensive. Active learning and semi-supervised learning are two approaches to alleviate the burden of labeling large amounts of data. We use Active learning and semi-supervised learning to get the advantage of both methods, to boost the performance of learning algorithm.

In our proposed framework, we use self-training with a new confidence measure to take advantage of unlabeled instances to augment the performance of learning algorithm. In multiclass conditions, we face an error propagation and accuracy reduction in SSL phase. To address this problem, we propose a dynamic self-training algorithm (DSeSAL). We control the accuracy reduction by specifying a tolerance measure. Moreover, in our experiments on real data sets, we compared our algorithm with a fully supervised active learning method. The experiments show that the proposed method outperforms the compared methods.

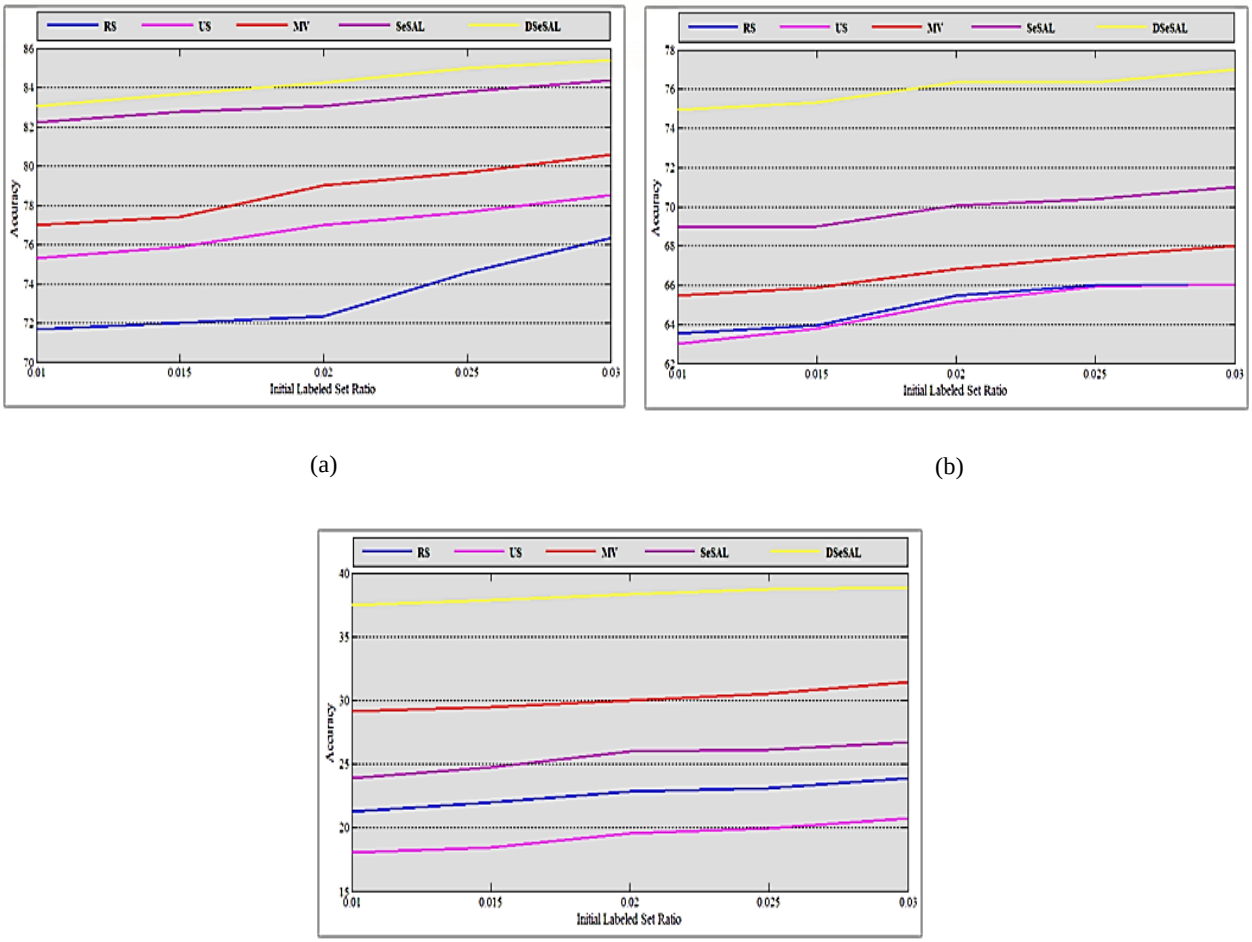


Fig. 10. Classifier ensemble accuracy on a separate test set (chunk size=500, α and β=0.1): (a) Adult, (b) CoverType, (c) Letter

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