UNIVERSIDADE FEDERAL DO AMAZONAS
INSTITUTO DE COMPUTAÇÃO - ICOMP
PROGRAMA DE PÓS-GRADUAÇÃO EM INFORMÁTICA – PPGI

Handling Concept Drift Based on Data Similarity and Dynamic Classifier Selection

Felipe Azevedo Pinagé

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Tese apresentada ao Programa de Pós-Graduação em Informática do Instituto de Computação da Universidade Federal do Amazonas como requisito parcial para a obtenção do grau de Doutor em Informática.

Orientadora: Eulanda Miranda dos Santos

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Thesis presented to the Graduate Program in Informatics of the Institute of Computing of the Federal University of Amazonas in partial fulfillment of the requirements for the degree of Doctor in Informatics.

Advisor: Eulanda Miranda dos Santos

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Resumo

Em aplicações do mundo real, algoritmos de aprendizagem de máquina podem ser usados para detecção de spam, monitoramento ambiental, detecção de fraude, fluxo de cliques na Web, dentre outros. A maioria desses problemas apresenta ambientes que sofrem mudanças com o passar do tempo, devido à natureza dinâmica de geração dos dados e/ou porque envolvem dados que ocorrem em fluxo. O problema envolvendo tarefas de classificação em fluxo contínuo de dados tem se tornado um dos maiores desafios na área de aprendizagem de máquina nas últimas décadas, pois, como os dados não são conhecidos de antemão, eles devem ser aprendidos à medida que são processados. Além disso, devem ser feitas previsões rápidas a respeito desses dados para dar suporte à decisões muitas vezes tomadas em tempo real. Atualmente, métodos baseados em monitoramento da acurácia de classificação são geralmente usados para detectar explicitamente mudanças nos dados. Entretanto, esses métodos podem tornar-se inviáveis em aplicações práticas, especialmente devido a dois aspectos: a necessidade de uma realimentação do sistema por um operador humano, e a dependência de uma queda significativa da acurácia para que mudanças sejam detectadas. Além disso, a maioria desses métodos é baseada em aprendizagem incremental, onde modelos de predição são atualizados para cada instância de entrada, fato que pode levar a atualizações desnecessárias do sistema. A fim de tentar superar todos esses problemas, nesta tese são propostos dois métodos semi-supervisionados de detecção explícita de mudanças em dados, os quais baseiam-se na estimação e monitoramento de uma métrica de pseudo-erro. O modelo de decisão é atualizado somente após a detecção de uma mudança. No primeiro método proposto, o pseudo-erro é monitorado a partir de métricas de similaridade calculadas entre a distribuição atual e distribuições anteriores dos dados. O segundo método proposto utiliza seleção dinâmica de classificadores para aumentar a precisão do cálculo do pseudo-erro. Como consequência, nosso método possibilita que conjuntos de classificadores online sejam criados a partir de auto-treinamento. Os experimentos apresentaram resultados competitivos quando comparados inclusive com métodos baseados em aprendizagem incremental totalmente supervisionada. A proposta desses dois métodos, especialmente do segundo, é relevante por permitir que tarefas de detecção e reação a mudanças sejam aplicáveis em diversos problemas práticos alcançando altas taxas de acurácia, dado que, na maioria dos problemas práticos, não é possível obter o rótulo de uma instância imediatamente após sua classificação feita pelo sistema.

Abstract

In real-world applications, machine learning algorithms can be employed to perform spam detection, environmental monitoring, fraud detection, web click stream, among others. Most of these problems present an environment that changes over time due to the dynamic generation process of the data and/or due to streaming data. The problem involving classification tasks of continuous data streams has become one of the major challenges of the machine learning domain in the last decades because, since data is not known in advance, it must be learned as it becomes available. In addition, fast predictions about data should be performed to support often real time decisions. Currently in the literature, methods based on accuracy monitoring are commonly used to detect changes explicitly. However, these methods may become infeasible in some real-world applications especially due to two aspects: they may need human operator feedback, and may depend on a significant decrease of accuracy to be able to detect changes. In addition, most of these methods are also incremental learning-based, since they update the decision model for every incoming example. However, this may lead the system to unnecessary updates. In order to overcome these problems, in this thesis, two semi-supervised methods based on estimating and monitoring a pseudo error are proposed to detect changes explicitly. The decision model is updated only after changing detection. In the first method, the pseudo error is calculated using similarity measures by monitoring the dissimilarity between past and current data distributions. The second proposed method employs dynamic classifier selection in order to improve the pseudo error measurement. As a consequence, this second method allows classifier ensemble online self-training. The experiments conducted show that the proposed methods achieve competitive results, even when compared to fully supervised incremental learning methods. The achievement of these methods, especially the second method, is relevant since they lead change detection and reaction to be applicable in several practical problems reaching high accuracy rates, where usually is not possible to generate the true labels of the instances fully and immediately after classification.

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Chapter 1

Introduction

The design of robust classification systems to deal with dynamic environments has attracted considerable attention in machine learning and pattern recognition. In real-world applications, some changes occur in the environments along with time. This problem, named as concept drift, has a direct impact on classification systems performance, since these systems tend to decrease their effectiveness, i.e. high recognition rates may not be achieved.

Some problems, such as anti-spam filters, weather predictions, monitoring systems, fraud detection, customer preferences and environmental monitoring present dynamic environments. For example, in anti-spam filtering, features that characterize a spam can evolve over time. Besides, important features used to classify spam may be irrelevant in the future (Kuncheva, 2004). Thus, the anti-spam filter needs a mechanism to detect changes in order to adapt itself to new patterns of spams.

There are many studies in the literature that propose new methods to design classification systems which are able to detect changes and adapt its knowledge without compromise the system accuracy. However, several methods have focused on either detecting changes based on monitoring the success rate of the system or retraining classifiers without explicitly detecting changes. In the first case, it is necessary to reduce the performance of the system suddenly in order to detect changes, which certainly implies damage to the system. The main disadvantage of the second group of approaches is the computational cost involved, since the system updates constantly, even if changes do not occur. Moreover, when the system is based on single classifiers, as soon as the new concept is learned, the old concept may be forgotten. Such a behavior may lead the system to a catastrophic forgetting.

1.1 Problem Statement

In the literature related to classification systems for dynamic environment, we can find different problems, such as, given a set of known concepts, the data distribution drifts from one to another, or even to an unknown concept. This phenomenon is named concept drift. When it occurs, the decision model has to be adapted in order to keep high classification performance. Taking into account that classifying data in this kind of environment is a generic problem, methods that adapt the system to drifts might be applied to several practical problems.

One strategy used in this context is blind adaptation. In this case, the system is periodically updated with no verification of changing occurrence. There may be drawbacks to blind adaptation, since this approach may lead to unnecessary system updates and high computational cost. These interesting observations make us to believe that the best moment to update a classification system is after a change occurrence. In this way, the system will not spend an unnecessary computational cost, and all relevant changes will be noticed. On the other hand, many of the explicit detection methods have two characteristics in common: changing detection is performed based on accuracy monitoring and supervised incremental learning.

The first characteristic may lead the system to be critically affected by high classification error rates; there will be slow reaction to concept drifts; and the detectors will not be fast enough to cope with slow gradual drifts. Besides, these approaches rely on the assumption that there is an oracle able to indicate whether or not the classification system predicts the correct label for the unknown samples.

However, the existence of such an oracle may not be assured in practical applications, such as medical diagnoses and environmental monitoring. In addition, it is important to say that for practical applications, we usually do not have previous knowledge of the incoming data labels. In this thesis, we propose that the oracle might be part of the methods. We propose two methods, which present mechanisms to estimate labels for each instance, and based on these labels, the classification error is monitored. Here, we call this mechanism as pseudo error.

In terms of incremental learning, the system is updated for every incoming example, which may increase the high labelling cost of the system. Again, the main problem is related to using labeled data for the incremental learning process, since due to the massive quantity of incoming data, labeling the whole data is time-consuming and requires human intervention. In addition, true labels of newly streaming data instances are not immediately available. It is important to mention that incremental learning may detect drifts and blind adaptation does not present drift detection. These interesting observations motivated us to propose a changing detector not based on accuracy monitoring or supervised learning.

One way to detect changes different from accuracy monitoring may be by monitoring data distributions over different data windows. These distributions are compared using a statistical test, given that the concept remains stable when the distributions are similar. Otherwise, a change is detected. According to (Adae and Berthold, 2013), a window type is defined by two terms: the first term refers to the start position of the window and can either be *fixed* or *sliding*; the second term refers to the width of the window and it can be of *constant* or *growing* size. The window should be described as subparts of the overall stream, since it is not intended to store the whole information. It can also allows concepts, whose information was forgotten by the system, to reappear over time.

However, in classification problems involving changing data, there may be different types of drifts, such as abrupt, gradual, incremental, etc. These different changes must to be treated according to its characteristics, i.e., some of them must be ignored, others detected, etc. Thus, the different window combinations may be sensitive enough to deal with changes by taking into account these characteristics. In this thesis, monitoring data distributions is investigated.

Moreover, after changing detection, a system adaptation to these changes must be conducted. Strategies for reaction to drifts may be based on single classifier or ensemble of classifiers. Generally, handling concept drift using single classifiers is not very effective especially due to the following two reasons. First, after training a classifier, its knowledge will not adapt to changes unless the classifier is retrained. Second, if the classifier is retrained after each time period, it will forget the previously learned concepts, which may lead to catastrophic forgetting, especially when the environment presents recurring changes.

An alternative to single classifier is to use ensemble of classifiers. Drift detection using ensemble may use different window sizes, thresholds or heuristics. According to the literature, these methods are better in maintaining previous knowledge than methods based on single classifiers. Moreover, ensembles are robust on reacting to new concepts and on reacting to recurrent concepts. Due to ensembles' advantages we also employ classifier ensembles in this work. Precisely, in order to allow the ensemble to be most likely correct for classifying each new sample individually, we employ dynamic classifier selection, which is defined as a strategy that assumes each ensemble member as an expert in some regions of competence. In dynamic selection, a region of competence is defined for each unknown instance individually and the most competent classifier for that region is selected to assign the label to the unknown instance.

Therefore, the problem considered in this work is expressed in the following question: *How to update a classification system at the right moment when a drift occurs, considering different types of drifts avoiding loss of accuracy and high labeling cost in such a manner that its accuracy and drift detection rate may be similar or better than current solutions in the literature?*

1.2 Objetives

The main objective of this work is to propose methods based on pseudo error monitoring to deal with data stream by explicitly detecting drifts and reacting to them without compromising the classification performance and reducing the labeling cost, while reaching similar or superior accuracy and detection rates when compared to current solutions.

The specific objectives are:

1. To organize the meaning of several terms commonly used in the literature devoted to classification problems in data streams, such as novelty detection, concept drift, one-class classification, etc.
2. To develop two drift detectors based on pseudo error monitoring and focused on reducing the labeling process.
3. To develop an ensemble creation method based on online learning by self-training.

1.3 Contributions

Firstly, in this thesis, we propose a changing detector method, which works by measuring dissimilarity between old and new incoming data in order to detect when data distribution starts to drift. This method is our first proposal to avoid drift detection based on error monitoring and periodical updates, since it focus on detecting drifts explicitly in an unsupervised way, by monitoring a pseudo error and updating the decision model just after drift detections. The estimation of the pseudo error is the main novelty of this method due to the fact that it allows simulating the most common supervised drift detectors to be also used by unsupervised and semi-supervised strategies. However, even though the detection module is unsupervised, the reaction phase of this method updates incrementally in a fully supervised way. This first proposed method was published in (Pinagé and Santos, 2015) entitled “A Dissimilarity-based Drift Detection Method” and presented in the 27th IEEE International Conference on Tools with Artificial Intelligence (ICTAI 2015).

Secondly, still focusing on practical problems and taking into account the drawbacks detected in the first proposed method, such as fully supervised updating, we present a new semi-supervised detection method based on ensemble classifiers, which works by using dynamic classifier selection to choose an expert member to make a prediction, assumed as “true label”, which is used to monitor the pseudo error. Thus, it also allows the most common supervised drift detectors to be used on the pseudo error-monitoring task. In addition, each sample labeled according to the class assigned by the expert is used in the online ensemble generation process, leading to an online ensemble self-training. Therefore, this method deals with concept drift using unlabeled data for the detection phase and a small amount of labeled data for the reaction phase. This work was submitted to the journal Springer Data Mining and Knowledge Discovery and it is currently under review.

Finally, as marginal contribution, we also show in this thesis that there are a lot of concepts related to data stream problems which are used in the literature to define different problems, such as novelty detection and concept drift. As a result of this literature survey, an overview was reported in (Pinagé et al., 2016) entitled “Classification Systems in Dynamic Environments: An Overview” published in WIRES Data Mining and Knowledge Discovery Journal.

1.4 Thesis Organization

The introduction of this thesis presented the context, motivation, problem statement, and the objectives. The next chapters of this work are organized as follows:

In Chapter 2, **Concepts and Definitions**, presents a discussion about the differences between the concepts used in the literature to define data stream problems. Moreover, the main types of events, fundamental concepts of machine learning, and the main approaches of generic solutions to deal with data streams are described.

In Chapter 3, **Related Work**, the most common methods proposed to detect changes and adapt to them are presented. This chapter is divided into three categories of methods (Supervised, Unsupervised and Semi-Supervised methods) and a comparative analysis among current solutions is also presented.

In Chapter 4, **Dissimilarity-based Drift Detection Method** (DbDDM), we describe our first proposed method and its constituent modules: dissimilarity module; and drift detection module.

In Chapter 5, **Dynamic Selection-based Drift Detector** (DSDD), we describe a new proposed method and its constituent modules: ensemble creation; selection module; and detection module.

Finally, in Chapter 6, **Conclusion**, our conclusions, as well as the next steps of this work are discussed.

Chapter 2

Concepts and Definitions

The aim of this chapter is to clarify different concepts used in the literature, such as concept drift definition, categorization of types of change, and different groups of current solutions to deal with the concept drift problem.

2.1 Understanding the Problem

Several different concepts may be related to dynamic environment problems. In this chapter, the main concepts are presented aiming on describing their definitions and the relation among each other.

2.1.1 Novelty Detection

One of the main critical challenges in the literature when using classification systems in dynamic environments is called novelty detection. According to Miljkovic (2010), novelty refers to abnormal patterns embedded in a large amount of normal data, or when the data do not fit the expected behavior. Traditionally, novelty detection is related to statistical approaches for outlier detection, which can be based on monitoring the unconditional probability distribution (Kuncheva, 2004)(Markou & Singh, 2003). According to Kuncheva (2004), when only unlabeled data is available, one simple statistical scheme to detect novelties works on comparing the probability estimate $p(x)$ to a fixed threshold Θ, i.e. when $p(x) > \Theta$, x is classified based on knowledge obtained during the training step. Otherwise, x may be assumed as a novel object.

Gama et al (2014) also call novelty detection by *virtual drift*, which corresponds to change in data distribution that leads to change in the decision boundary but does not affect the target concept.

In work presented in (Morsier et al, 2012), the authors advocate that often in novelty detection problems only few labels or even none are available. In this way, it is possible to use semi-supervised or unsupervised classification systems. In the context of novelty detection using supervised learning, there is only available the knowledge about normal patterns. Thus, the novelties are assumed to be those data not clustered with the normal data, but which are spread in low density regions. Moreover, according to Faria et al (2016), novelty detection aims to detect emergent patterns and then incorporate them into the normal model. Finally, it is important to distinguish novelty detection from outlier detection, given that the first is related to data distribution and system accuracy decreasing, and the second is rare and does not compromise the accuracy.

2.1.2 Concept Drift

In the machine learning community, the term concept is employed to define the whole distribution of the data used to perform classification, regression or unsupervised tasks in a certain point of time. Usually, it is expected a stable underlying data generating mechanism, i.e. the concept does not evolve over time. However, as mentioned in the introduction, it has been shown that the learning context (target environment) changes over time in many real-world problems. In this case, researchers have referred to this problem as concept drift.

Therefore, concept drift occurs when data distributions change over time unexpectedly and in unpredictable ways. Widmer (1994) defines concept drift as follows: “In many real-world domains, the context in which some concepts of interest depend may change, resulting in more or less abrupt and radical changes in the definition of the target concept. The change in the target concept is known as concept drift”.

The change of underlying unknown probability distribution, which represents the concept drift, can be defined such as $P_j\ (x, \omega)\ \neq\ P_k\ (x, \omega)$, where x represents a data instance, ω represents a class, and the change occurs from time t_j to time t_k, where $t_j < t_k$. According to Hee Ang et al (2013), this means that, in a changing environment, an optimal prediction function for $P_j\ (x, \omega)$ is no longer optimal for $P_k\ (x, \omega)$. Moreover, concept drifts are the changes that may compromise the classification accuracy.

Hence, a very important challenge arises when it is observed that the learning concepts start to drift. According to Bose et al (2014), concept drift solutions should focus on two main directions: how to detect drifts (changes); and how to adapt the predictive model to drifts. These are no trivial tasks since there are different types of changes and the classification system should be robust to ones and sensitive to others. Many algorithms have been developed to handle concept drift and some of them will be described in Chapter 3.

In addition, the concept drift is the consequence of context change, which is directly related to the features and can be either hidden (called hidden contexts) or explicit. Harries and Sammut (1998) define context as follows: "Context is any attribute whose values tend to be stable over contiguous intervals of time when a hidden attribute occurs."

2.1.3 One-Class Classification

Here, only one class is well sampled (normal data) while samples from other classes (abnormal data) are not available. In One-Class Classification we know only the probability density $p(x|\omega_T)$, where x represents a data instance and ω_T is the normal class. The problem focus on making a description of a normal set of objects, as well as on detecting objects that do not belong to the learned description.

Therefore, the term One-Class Classification is used when the learning is semi-supervised. Assuming a dynamic environment problem, few labels on "unchanged" regions may be available and none on "changed" regions, which may be detected as novelties (Camps-Valls & Bruzzone, 2009). According to Le et al (2011), in real-world applications is easier and cheaper collecting normal data, while the abnormal data are expensive and are not always available.

We will focus on concept drift detection throughout this work. Whatever the definition used to drift detection in the literature, different types of events can occur. The main types of events are described in the next section.

2.2 Main Events in Data Streams

Since in data streams a massive amount of examples arrive, it is very common the occurrence of different events which may lead this kind of problem to be a challenge task. Adae & Berthold (2013) say that an event can be any irregularity in data behavior, i.e., the current observations may not be related to previous concepts. These events may be divided into two categories: 1) anomalies; and 2) drifts.

2.2.1 Anomalies

According to Chandola et al (2009), anomalies refer to patterns in data that do not conform to the expected behavior. However, anomalies are not incorporated to the normal model after their detection, since they do not represent a new concept. In the literature, the most common types of mentioned anomalies are: noise and rare event.

- Noise: Meaningless data that cannot be interpreted correctly and should not be taken into account on classification tasks, but can be used to improve system robustness for the underlying distribution. A difficult problem in handling concept drift is distinguishing between true concept drift and noise. An ideal learner should combine robustness to noise and sensitivity to concept drift as much as possible.
- Rare event: This is classified as an outlier. Assuming that these events are rare, they can be dealt with as abnormal data and discarded by the system. However, a concise group of examples classified as outliers should be considered as a novelty, since those events are no longer rare.

2.2.2 Drifts

There are different types of drift that may compromise the classification accuracy of a system due to the appearance of new concepts, for instance gradual, incremental and abrupt, or the reappearance of previous concepts, called recurring concepts, as described in this section.

Gradual Drift: Here, a concept C1 is gradually replaced by a new concept C2. Therefore, the new concept takes over almost imperceptibly, leading to a period of uncertainty between two stable states. Since a change occurs between two consecutive time points t_1 and t_2, there is a sub-space A′ of the whole instance space A whose concepts are different from the remaining data, because both concepts coexist in such a period of mixed distributions. The new concept takes over almost imperceptibly and the change may not be detected. Consequently, it increases the misclassification rate, since some of the new examples will be classified according to the old concept, as shown in Fig. 2.1.

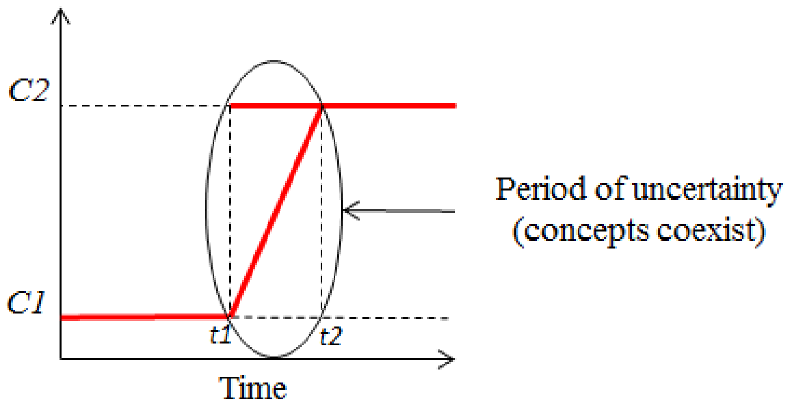


Figure 2.1. Gradual drift: when both concepts C1 and C2 coexist between t1 and t2, while C1 disappears gradually.

Incremental Drift: When the concept evolves slowly over time. Some researchers use the terms incremental and gradual as synonyms, considering them as the same type of change. However, according to Brzezinski (2010) and Bose et al (2014), a change is assumed to be incremental when variables slowly change their values over time, but there are no examples of two distributions mixed. The old concept $C1$ disappears slowly until be completely replaced by the new concept $C2$, as shown in Fig. 2.2.

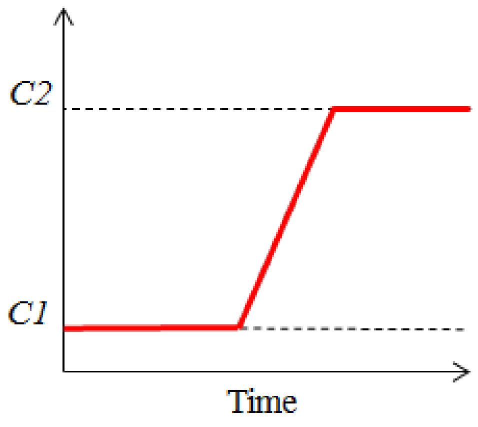


Figure 2.2. Incremental drift: when concept C1 is slowly replaced by C2.

Abrupt Drift: Also called sudden concept drift, it occurs when the source distribution at time t, denoted S_t, is suddenly replaced by a different distribution in S_{t+1}. In other words, a concept $C1$ is substituted by concept $C2$, and $C1$ disappears exactly at the moment of this replacement (see Fig. 2.3). These drifts directly decrease the classification accuracy since the generated classifier is trained on a different class distribution. Several methods designed to cope with abrupt changes use falling confidence of classification to detect a change occurrence.

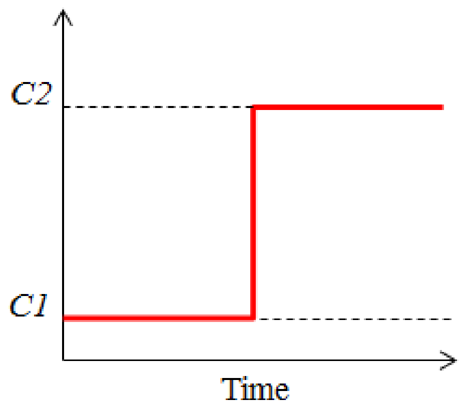


Figure 2.3. Abrupt drift: when the concept C1 disappears at the moment that C2 appears.

Recurring Concepts: Concepts that disappear but may reappear in the future, i.e. temporary changes, which are reverted after some time (see Fig 2.4). This happens especially due to the fact that several hidden contexts may reappear at irregular time intervals. In real-world environments, many natural phenomena can occur cyclically, for instance weather changes, biological systems, customer habits, etc. This kind of drift is not regularly periodic, thus it is not possible to know when the concepts might reappear. Recurring concepts can occur in both gradual and abrupt ways. Gomes et al (2014) assume that when a concept reappears, normally the context previously associated with it also reappears.

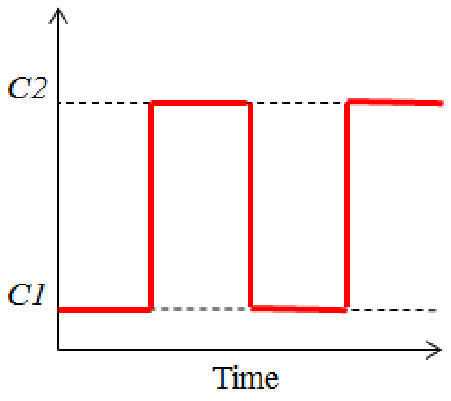


Figure 2.4. Recurring concept: when concepts (C1 or C2) that disappeared can reappear over time.

In the occurrence of any type of event, there are many alternative strategies based on machine learning techniques to treat them. The main concepts of machine learning and the generic solutions are described in the next section.

2.3 Fundamental Concepts of Machine Learning

Before we discuss about the methods proposed to handle concept drifts presented in Chapter 3, it is necessary to describe the main concepts of machine learning used to compose these methods.

In this work, we focus on classification systems, which learn a rule from data to extract knowledge and then to be able to make predictions to unknown instances. This rule is a decision model that explains the process underlying the data. The creation of these decision models can be based on different learning categories, as follows: supervised, unsupervised, and semi-supervised learning.

In addition, it is possible to create decision models by combining multiple learners that complement each other to attain higher accuracy, when compared to the accuracy achieved by its members, the so-called ensemble of classifiers. In this section, we describe the three different learning categories; and we discuss how to generate decision models using ensemble of classifiers.

2.3.1 Machine Learning Categories

Supervised learning uses known dataset (input data x and an output Y) to lead an algorithm to learn the mapping function from the input to the output, such as $Y = f(x)$, to make predictions. Its goal is to use labeled training dataset to build a decision model that will learn how to predict the output (Y) of new unseen input data. Usually, a test dataset is used to validate the model.

Whilst in supervised learning the aim is to provide correct labels to learn a mapping from the input to an output, in unsupervised learning there is no labeled data, i.e., there is only the input data. The aim is to find the correlations in the input data, since there is a structure over the input space such that certain patterns occur more often than others do. The focus is to recognize what generally happens and what does not. In statistics, this is called *density estimation* (Alpaydin, 2009).

One method for density estimation is *cluster analysis,* where the aim is to find hidden patterns or groupings over the input data. Clusters may be modeled using a measure of similarity based upon metrics such as distance, variance, rotation, etc.

Finally, there are problems where typically we may find a large amount of unlabeled data but only a small amount of labeled data. In this context, the category of machine learning techniques called semi-supervised learning may be employed. These problems fall between both supervised and unsupervised learning.

Therefore, many practical problems do not present fully labels available. In addition, it can be expensive or time-consuming to label the whole stream of data, especially where a human expert is required to provide these labels. In addition, the true labels of newly streaming data instances are not immediately available. In this way, semi-supervised techniques focus on labeling a small quantity of instances and using supervised or unsupervised learning techniques to learn the structure in the underlying data distribution.

Based on the fact that unlabeled data may be cheap and easy to collect and store, we can use supervised learning to make the best guess predictions for the unlabeled data; use these predictions as *true labels* to feed back the supervised learning algorithm as training data; and then, use the model to make predictions on new unknown instances. This semi-supervised learning method is called *self-training* and it is summarized in Algorithm 2.1.

```
input:   $x$: incoming unlabeled example;
         $H$: classifier;
         $L$: labeled dataset;

begin
$train\ H\ with\ training\ data\ L$;
for $each\ x$ do
         $classify\ x\ using\ H$;
         if $confidence\ score > threshold$ do
                  $add(L, x)$;  //include $x$ to training data
         end
end
end
```

Algorithm 2.1. Self-training algorithm used on combining supervised and unsupervised learning.

2.3.2 Ensemble of Classifiers

Ensemble of classifiers combines simple decision models aiming to overcome single classifiers in tasks requiring a robust and adaptive system. In practice, the use of ensemble of classifiers has presented a significant improvement related to classification systems based on single classifiers. In addition, the applicability of ensembles extends due to several techniques available in the literature to generate them.

2.3.2.1 Generation of Ensemble of Classifiers

There are different strategies to generate ensemble classifiers. A possible strategy is to manipulate the decision models involved in the system, such as using different types of classifiers (Ruta & Gabrys, 2005), different architecture of classifiers (Ruta & Gabrys, 2007), and different initialization parameters (Altinçay, 2007).

Another possible strategy is to manipulate the data used. For instance, using different data sources, different pre-processing techniques, different methods of sampling, among others. It is important to say that the generation of ensemble of classifiers is mainly defined by the classifier members and how to combine their decisions by means of a combining function.

In this way, we call by homogeneous, the ensemble classifiers composed by the same base learners created with different model parameters; and heterogeneous, ensembles composed by different base learners. We describe here the four most common methods used in the literature to generate ensemble classifiers, precisely bagging, boosting, randomization and stacking.

- **Bagging** (Bootstrap AGGreatING): proposed by Breiman (1996) aiming to produce several decision structures. It generates different data subsets of the same size from the original training dataset. Each training dataset may get two or more copies of the same instances, which provide diversity to the ensemble. This strategy is very suitable for machine learning algorithms called "unstable". According to Breiman (1996), unstable learning algorithms are the ones where any variation in the incoming data leads to huge changes in the model.
- **Boosting**: different decision models are generated by different training subsets, as in Bagging. However, Boosting is an iterative algorithm, where new classifiers are influenced by the output from previous classifiers. The change in the training data distribution for the new models is based on the misclassified instances by previous models. In this way, Boosting try to improve the performance of each new model. It is intuitive that each new model becomes an "expert" for instances that were misclassified by all the previous models.
- **Random subspace**: proposed by Ho (1998), one randomly selects r features (subspace) from the p-dimensional dataset to construct each classifier, where $r < p$. The ensemble final decision is a combination of individual classifiers' decisions, such as a simple majority voting rule. This method may be used for both constructing and aggregating classifiers.
- **Stacking**: this technique presents different base learners whose outputs are combined by a meta-learner. We can say that the base learners are the level-0 models, and the meta-learner is the level-1 model. The outputs of the different experts (base learners) are input for the meta-learner, which presents better performance.

2.3.2.2 Combining Member Decisions

There are two popular solutions to combine individual decisions of ensemble members: fusion and selection. (1) Fusion focus on providing an ensemble consensus by employing some rule, such as majority vote; whilst (2) Selection chooses the most competent member of the ensemble to classify the next incoming example.

Fusion assumes that ensemble members make decisions independently, i.e., they classify different examples in different ways. The idea is to combine individual results in order to improve the performance of the prediction (Kittler et al, 1998). However, in most real-world problems, this assumption cannot be verified. In this case, there are no guarantees that ensemble of classifiers will present higher performance than a single classifier (Smits, 2002). In the literature, there are several combination rules, such as: majority voting, maximum rule, minimum rule, median rule, naive bayes, among others.

Selection assumes the assumption that each classifier member is an expert in some regions of competence of the problem (Parikh, 2007)(Zhu et al, 2004). We call the selection static or dynamic whether the regions of competence are defined during the training phase or for the new unknown sample, respectively. Since dynamic selection chooses an expert for every incoming data, it may be a useful strategy to adapt the system given a concept drift occurrence, which is investigated in this work.

2.3.2.3 Dynamic Classifier Selection

A framework for dynamic selection of classifiers is usually divided into 3 steps: 1) classifier generation; 2) definition of regions of competence; and 3) dynamic selection. The first step is executed using any generation method mentioned above, such as bagging and boosting, in order to create an initial ensemble of classifiers. The second step focus on generating regions of competence by using a training or a validation datasets, since the assumption here is that each ensemble member is an expert in some regions of competence. The final step uses some mechanism to choose the most competent member to classify the unknown examples. Precisely, in dynamic selection, a region of competence is defined for each unknown instance individually and the most competent classifier for that region is selected to assign the label to the unknown instance.

Woods et al (1997) proposed a method called DCS-LA (*Dynamic Classifier Selection with Local Accuracy*). In this method, the authors use a heterogeneous ensemble composed by five classifiers. Basically, the method determines the K nearest neighbors of the current example x to evaluate the accuracy of the classifier members. Finally, the most accurate member is used to classify x. A very similar method, proposed by Giacinto & Roli (2000), also determines the K nearest neighbors to x, the difference is that their similarity must be higher than a specified threshold.

Kuncheva (2000) proposed a method based on clustering and selection. The ensemble was composed by MLP (*MultiLayer Perceptrons*) with different number of nodes in the hidden layer. This method works as follows: clusters are generated using a training or a validation set. Then, the cluster whose centroid is nearest to x is chosen as x's neighborhood. Finally, similar to the methods previously described, the most accurate member over the x's neighborhood is used to classify it.

All the works mentioned in this section determine a neighborhood for the current example. In general, these methods use validation dataset and an algorithm to calculate the K nearest neighbors of the instance. Especially noteworthy is the fact that the size of the validation dataset may critically affect the performance of the ensemble based on local accuracy, which may be a drawback to using this kind of solution for online systems.

2.4 Generic Solutions for Data Stream Problems

The generic solutions available in the literature for classification problems with concept drift may be divided into different categories. It is important to know these categories to better understand the methods used to handle concept drift. Such a diversity of approaches is due to the different aspects taken into account, for instance: incoming data, number of classifiers, incremental or non-incremental learning, and active or passive strategies.

2.4.1 Incoming Data

In real-world problems, the environments are non-stationary and the data arrive sequentially over time, i.e., in a stream of data. For example, in environmental monitoring, online video frames may be the data that arrive sequentially to the system. In this context, the first categorization of approaches takes into account the organization of the input data, which can be based on stream or batches. This choice depends on the velocity that the data are acquired and the framework employed to make decisions. In data streams, the complexity of the problem increases due to the high velocity and amount of input information provided to the system, in addition to massive storage capacity requirements. Therefore, these dynamic environments often require fast and real-time responses, besides constraints on memory usage and testing time.

There are windowing techniques, which are frequently used to handle concept drift in these cases. They provide a mechanism of forgetting to select the new examples to train the classifier, thus eliminating examples, which came from old concept distribution. One of the most common windowing techniques is the sliding windows. This method selects the most recent examples to train the classifiers.

The literature has shown that window size is the key issue for employing classifier windowing techniques successfully, since using windows of fixed size can be a dilemma. On the one hand, small windows of examples will allow quick reaction to changes, but it often causes misdetection, leading to accuracy reduction in period of stability. On the other, large windows of examples may contain data from different concepts, making the adaptation to new concepts slower. As a consequence, large windows-based techniques often fail to adapt to sudden drifts (Brzezinski & Stefanowski, 2014).

Classification systems trained using batches of examples over time are more prone to concept drift. Besides, these systems may face other substantial problem, the so-called Catastrophic Forgetting. This problem arises when classification systems learn new concepts, leading old useful information being forgotten. As mentioned in Section 2.2, in real applications some concepts can appear and disappear repeatedly. According to Chen et al (2012), the consequence of ignoring old useful information can be catastrophic.

2.4.2 Number of Classifiers

Another way to divide robust solutions to deal with concept drift is based on the number of classifiers used to make a decision: ensemble of classifiers or single classifiers. Generally, handling concept drift using single classifiers is not very effective especially due to the following two reasons. First, after training a classifier, its knowledge will not adapt to changes unless the classifier is retrained. Second, if the classifier is retrained after each time period, it will forget the previously learned concepts, which may lead to catastrophic forgetting, especially when the environment presents recurring changes. Hence, traditional single classifiers are feasible only on static environment problems.

Classifier ensembles have been successfully applied to cope with data streams problems. Rather than designing a new robust and well-adapted classifier, an ensemble of classifiers can be used to increase the system power of decision. According to the literature, classifier ensembles have presented significant performance improvements when compared to classification systems based on single classifiers. In studies like (Altinçay, 2007) (Tremblay et al, 2004) (Zhang et al, 2008) (Valentini, 2003) (Ruta & Gabrys, 2007), the authors conclude that ensembles of kNN (k-Nearest Neighbors), SVM (Support Vector Machine) and Neural Networks present superior performances than single kNN, SVM and Neural Network, respectively.

Concept drift detection using ensemble of classifiers based on labeled data can make use of different window sizes, thresholds or heuristics. For example, we can use the nearest mean classifier and update it with new observations without any forgetting, as proposed by Kuncheva (2008). The details of some solutions using ensemble of classifiers are presented in the next Chapter.

2.4.3 Incremental Learning x Non-Incremental Learning

This third categorization takes into account whether or not the data are reutilized. Incremental learning has focused on sequential data processing (stream or batch) and cannot pass by the same examples more than once (Ditzler & Polikar, 2013). Otherwise, it is considered non-incremental.

In this context, Kuncheva (2004) affirms that the term incremental learning can be also called online learning, whose definition is: data stream processing with constraints of runtime and memory capacity to improve computational systems.

Minku & Yao (2012) advocate that online learning is useful for applications dealing with streams of data, and they adopt the following definition for it: online learning algorithms process each training example once, without the need of storage or reprocessing. The decision model makes a prediction when an example becomes available, allowing the system to learn from the example and to update the learning model. This definition adopted by Minku & Yao

(2012) for online learning is termed by Ditzler & Polikar (2013) as one-pass learning, but using batch training data.

Hence, online learning may be considered a particular case of incremental learning. Moreover, the latter refers to learning machines that are also used to model continuous processes, but also deals with incoming data in chunks, instead of having to process each training example separately. In this way, one-pass learning is also another particular case of incremental learning, while learning methods that require access to previous data cannot be considered incremental.

Finally, we conclude that incremental learning, including both online and one-pass learning, uses every incoming example to updates the system, even though the examples are processed in chunks or separately.

2.4.4 Blind Strategy x Active Strategy

Finally, this approach divides the concept drift solutions into blind and active strategies, based on whether or not a drift detection mechanism is employed as a component of the solution. The idea of blind strategies is to update the system constantly using new input data without detecting changes. We can say that the detection mechanism is implicit in the method.

Some solutions based on ensemble classifiers use dynamic combination rules and heuristics of disposal of learning to always keep the system updated. For instance, (Zhang et al, 2008)(Rodríguez & Kuncheva, 2008)(Karnick et al, 2008)(Muhlbaier et al, 2009) proposed to assign weights to each classifier member based on its previous performances. Thus, the ensemble classifier members with the highest classification performances get the highest weights when combined to obtain the final decision.

The main disadvantage of blind strategies is the computational cost involved, using ensemble classifiers or not. Since the system updates constantly, even if changes do not occur, this may lead to increase processing time by updating the system unnecessarily. An alternative to blind strategies is to use active strategies, which explicitly employ detection mechanism. In this context, the system adapts its knowledge to new information only after it perceives environment changes.

2.5 Discussion

In this chapter we have presented some concepts and definitions related to our research. It has been observed that concept drift is a problem that may affect different applications in different ways, due to the diversity of possible drifts. In the context of solutions for the problem of concept drift, it has been shown that these solutions may be divided according to some aspects, such as: incoming data, number of classifiers, etc. These solutions may also be categorized into supervised, unsupervised and semi-supervised methods, as the literature review related to our work detailed in the next Chapter. Then, the two methods proposed in this work for handling different types of changes are presented in Chapter 4 and Chapter 5.

Chapter 3

Related Work

This chapter presents a literature review on studies whose focus is on handling concept drift. Taking into account that we propose in this work two methods to deal with concept drift, one unsupervised and another semi-supervised, we divided these studies into three categories: supervised methods, which include active strategies, called here drift detectors and blind methods; unsupervised and semi-supervised methods. Drift detectors and blind methods are described first. Then, unsupervised and semi-supervised methods are discussed.

3.1 Supervised Methods

These methods use fully labeled data to compose their mechanism to deal with concept drifts, and are divided into two subcategories. This categorization takes into account whether or not drifts are explicitly or implicitly detected, drift detectors (whose strategy is often based on error monitoring) and blind methods (whose strategy is often based on periodical updates) respectively.

3.1.1 Drift Detectors

Drift detectors compose a category of methods that utilizes statistical tests to monitor the class distribution over time and to reset the decision model when a concept drift is detected. Based on the definitions presented in the previous chapter, these methods are active strategies. We present three drift detectors based on single classifiers and one drift detector based on ensemble classifiers. All drift detectors discussed here update the decision model after drift detection.

The most popular drift detector is called *Drift Detection Method* (DDM), proposed by Gama & Castillo (2006). This algorithm detects drifts based on online classification error rate motivated by *probably approximately correct* (PAC) learning model (Mitchell, 1997). PAC assumes that, if the distribution of the examples is stationary, the error rate of the learning algorithm will decrease as the number of examples increases. Thus, an increase of this error rate suggests a change in class distribution, leading the current model to be outdated.

DDM uses statistical tests to calculate the prequential error. The prequential error is the average error obtained by the prediction of each incoming example, calculated in an online way (Dawid & Vovk, 1999). The rule used to obtain the prequential error on time step t is presented in the Equation 3.1. Where err_{ex} is 0 if the prediction of the current example ex is wrong and 1 if it is correct; and num_{ex} is the number of incoming examples until time step t.

$$err(t) = err(t-1) + err_{ex}(t) - err(t-1)/num_{ex} \tag{3.1}$$

DDM defines two thresholds, called warning level and drift level, which are reached if conditions (Equation 3.2) or (Equation 3.3) are satisfied, respectively. The p value represents the prequential error rate of the learning algorithm, while s denotes its standard deviation. The registers p_{min} and s_{min} are set during the training phase, and are updated if after each incoming example (i) the current register $p_i + s_i$ is lower than $p_{min} + s_{min}$.

$$p_i + s_i \geq p_{min} + 2 * s_{min} \tag{3.2}$$

$$p_i + s_i \geq p_{min} + 3 * s_{min} \tag{3.3}$$

For instance, given that the error rate of the current model reaches the warning level at example k_n, while the drift level is reached at example k_p, in DDM, it is assumed that the concept changes at k_p and a new context is declared between k_n and k_p. In the adaptation process, the new decision model should be generated using only the new context, i.e., the same classifier is retrained using examples stored between k_n and k_p.

The main drawback to this strategy is that the velocity of the changes critically affects DDM. Consequently, if a very slow gradual change takes place, the system will not be able to detect it. In order to overcome this drawback, Baena et al (2006) proposed the *Early Drift Detection Method* (EDDM). The basic idea of EDDM is that the distance between two consecutive errors will increase by improving the predictions of the decision model. Similar to DDM, two thresholds are defined when using EDDM, also called warning level and drift level.

EDDM calculates the distance (p') between two consecutive errors and their standard deviation (s'), and stores the maximum values of p' and s' to register the point where the distance between two errors is maximum($p'_{max} + 2 * s'_{max}$). According to Baena et al (2006), the warning level is reached when the Equation 3.4 is lower than α (they set α to 0,95), and the drift level is reached when the same Equation 3.4 is lower than β (they set β to 0,9).

$$(p'_i + 2 * s'_i)/(p'_{max} + 2 * s'_{max}) \tag{3.4}$$

Here, however, the thresholds must be used to monitor the decrease on the distance between two errors. And also, the adaptation process is basically the same as used in DDM, i.e. the decision model is updated using only the new context, ranging from warning and drift levels.

EDDM starts the search for concept drifts after calculating 30 classification errors, due to the fact that the authors intended to estimate the distance distribution between two consecutive errors in order to compare it with further distributions. The results attained by EDDM were better than the results provided by DDM in some databases. In addition, EDDM was able to detect gradual changes earlier even when the changes were very slow. Even though, EDDM was not robust enough to noisy datasets.

Another popular drift detector was proposed by Nishida & Yamauchi (2007), called *Detection Method Using Statistical Testing* (STEPD), which is based on two accuracies: the recent one and the overall one. The recent accuracy is calculated for a recent set of examples, called W, while the overall accuracy is calculated for the whole set of examples from the beginning of learning, except for the recent W examples. STEPD relies on two assumptions: (a) if the accuracy of a classifier for recent W examples is equal to the overall accuracy, then the target concept is stationary; (b) a significant decrease on recent accuracy suggests concept drift.

STEPD compares the statistic T presented in Equation 3.5 to the percentile of standard normal distribution to obtain the observed level (P) of significance, and defines two levels of significance as thresholds. In order to better clarify the comparison among drift detectors, we also call these two levels of significance as warning and drift levels. The algorithm starts by storing examples when P is lower than the warning level, and retrain the classifier when P is lower than the drift level. The classifier retraining is conducted using examples stored between both levels.

$$T(r_o r_r n_o n_r) = \frac{|r_o/n_o - r_r/n_r| - 0.5(1/n_o + 1/n_r)}{\sqrt{\hat{p}}(1-\hat{p})(1/n_o + 1/n_r)} \tag{3.5}$$

Here, r_o is the number of correct classifications considering overall examples (n_o), except the recent W examples, r_r is the number of correct classifications among W examples (n_r), and $\hat{p} = (r_o + r_r)/(n_o + n_r)$.

According to Nishida & Yamauchi (2007), in comparison to EDDM and DDM, STEPD presented the highest performances for abrupt changes and noises. However, EDDM detected gradual changes better than STEPD, while DDM well detected abrupt changes, but its detection speed was the slowest one.

These supervised-based methods summarized so far have focused on dealing with concept drift by explicitly detecting drifts using single classifiers. However, as mentioned in Chapter 2, approaches based on single classifiers may be prone to catastrophic forgetting. An alternative to these previous methods is to use drift detectors combined with classifier ensembles to react to drifts more quickly.

Following this idea, Minku & Yao (2012) proposed the *Diversity for Dealing with Drift* (DDD). This method processes each example at a time and maintains ensembles with different diversity levels in order to deal with concept drift. Basically, DDD generates a pool of classifiers using a modified version (Minku & Yao, 2010) of online bagging (Oza & Russell, 2001), as follows. Whenever a training example is available, it is presented N times for each base learner, and the classification is performed by weighted majority vote, as in offline bagging. Then, the classifier members are separated into two subsets of classifiers: (1) low diversity; and (2) high diversity ensembles.

It is important to note that there is no generally accepted formal definition of diversity yet. The researchers are still investigating how diversity should be measured and what means this measure. Johansson et al (2007) suggest that diversity is almost an axiom based on the assumption that classifier members must be diverse to assure that an ensemble will more likely present good generalization. Since there is no consensus about which proposed diversity measure is the best one, DDD measures diversity using Q statistic, recommend by Kuncheva & Whitaker (2003), due to its simplicity and easy interpretation. Minku & Yao (2012) consider that high/low diversity refers to high/low average Q statistic.

The aim of using high/low diversity ensembles is the assumption that the accuracy of the ensembles may be similar (not the same) or very distinct, according to the severity and the speed of each type of drift. For instance, the authors observed that high diversity ensembles achieve better accuracy rates when dealing with low severity and high speed drifts.

DDD operates in two modes: before and after drift detection. In the first mode, the low diversity ensemble and the high diversity ensemble are generated using incoming examples. Then, the after drift detection mode is triggered when there is no convergence about the concept. DDD monitors the low diversity ensemble using a drift detector, namely EDDM. In this last mode, the low/high diversity ensembles generated in the first mode are assigned as old low/high diversity ensembles and the first mode is reactivated in order to create new low/high diversity ensembles.

In general, DDD aims to learn new concepts using the information learned from the old concepts, i.e., by training the old high diversity ensemble on new concept, allowing its diversity to be lower. Minku & Yao (2012) have presented experiments using artificial and real-world data to show that DDD usually achieves similar or even better accuracy than EDDM.

3.1.2 Blind Methods

Aside the drift detectors, there is a category of blind methods which update their knowledge base by adding, removing or updating classifiers periodically. As mentioned in the previous chapter, these methods are also called passive strategies. Many blind solutions using ensemble of classifiers have been proposed to handle concept drift in online and incremental learning contexts. In these solutions, each example can be processed separately or in chunks (blocks of data).

Some of the most known algorithms based on ensemble classifiers utilize the passive strategy to build ensembles by adding members using every incoming data and removing members by employing different strategies: removing the oldest member, e.g. *Streaming Ensemble Algorithm* (SEA)(Street & Kim, 2001); or removing the poorest performing member to be replaced by a new classifier, such as *Dynamic Weighted Majority* (DWM)(Kolter & Maloof, 2007) and Learn++NSE for *NonStationary Environment* (Muhlbaier & Polikar, 2007).

For instance, the Learn++NSE method trains a new classifier for every incoming chunk of data. Thus, a performance monitoring mechanism is conducted using new and old data. Then, the average error is combined to majority voting to determine a voting weight to each classifier. In this way, the poorest performing classifier on the current concept is discarded. Another example is the SEA method, which trains a new classifier for every incoming chunk of data and increases or decreases the quality of its classifiers based on accuracy. This method removes the oldest member in a fixed-size ensemble.

Based on DWM strategy, Sidhu et al (2013) proposed a novel online ensemble approach called *Early Dynamic Weighted Majority* (ERDWM). The weighted strategy is undertaken using three options: (1) decreasing the weight of members whose local prediction is incorrect; (2) increasing the weight of members whose local prediction is correct but global prediction is incorrect; and (3) no performing weight update when both local and global predictions are correct.

ERDWM focus on the highest performing classifier members in order to reduce the chances of incorrect global prediction, main problem detected in DWM. In addition, ERDWM reduces the need of creating new classifier members and consequently, it decreases time and memory resources requirements. Even though, Sidhu et al (2013) conclude that ERDWM does not outperform EDDM in terms of memory and execution time. On the other hand, ERDWM is better in maintaining previous knowledge to aid making predictions.

Another work using passive strategy is presented by Brzezinski & Stefanowski (2014). They propose a method called *Accuracy Updated Ensemble* (AUE2), which combines the principles of chunk-based ensemble with incremental-based components and it presents a mechanism to achieve high predictions in occurrence of different types of drift at relatively low computational costs. In AUE2, a new ensemble classifier member is created after each incoming data chunk of examples and it replaces the poorest performing member. The remaining ensemble members are updated according to their accuracy. The weighting calculated according to Equation 3.6 is used to combine information about the accuracy of classifiers and the current class distribution.

$$\omega_{ij} = \frac{1}{MSE_r + MSE_{ij} + \epsilon} \tag{3.6}$$

where MSE_{ij} denotes the estimate of the error prediction of each classifier on each data chunk, while the value of MSE_r is the mean square error of a randomly predicting classifier and is used as a reference point to the current class distribution. Moreover, ϵ denotes a small positive value added to avoid the division by zero problem. Equation 3.5 is used to update the weight of the remaining classifier members.

In addition, in (Brzezinski & Stefanowski, 2014), the authors assume that the most recent incoming data chunk (B_i) is the best representation of the current and near-future data distribution. This way, a classifier C', trained on B_i, is treated as the best possible (or perfect) classifier and its weight is assigned by Equation 3.7.

$$\omega_{C'} = \frac{1}{MSE_r + \epsilon} \tag{3.7}$$

According to the authors, AUE2 achieves higher classification accuracy than its predecessors (Accuracy Weighted Ensemble - AWE and SEA) in the presence of slow gradual drifts. Besides, ensemble members can be retrained, which makes AUE2 less dependent on chunk size and it allows using smaller chunks without compromise its accuracy. Finally, to solve the problem of memory usage, AUE2 sets a memory usage limit (threshold) that, when exceeded, decreases the size of classifier members.

A recent framework proposed by (Almeida et al, 2016), called Dynamic Selection Based Drift Handler (DYNSE), uses dynamic ensemble selection to choose an expert subset of classifiers to assign a label to an incoming instance. DYNSE intends to deal with concept drift by building a new classifier using every most recent incoming data, organized in batches of samples, which are also used to replace a validation dataset at each update. Instead of discarding the oldest classifiers as classical methods do, DYNSE is designed to keep as much classifier members as possible. When a new instance x arrives, this method works as follows: a region of competence is identified as the set of k nearest neighbors over samples contained in a validation dataset surrounding x. Then, a subset of classifiers is dynamically selected to predict the x's label. Even using dynamic selection of classifiers, this method is in the category of blind methods based on supervised learning, since it is assumed that the method receives a large enough batch of supervised instances every month to adapt the system.

3.2 Unsupervised Methods

Different from the strategies mentioned before, this category of methods intends to handle concept drift even if only unlabeled data are available. In such a context, there are many data stream problems, which have only unlabeled data to be dealt with. In this section, some unsupervised strategies are described.

The method proposed by (Fanizzi et al, 2008), is applicable in two problems: concept drift (change of known concepts) and novelty detection (change of unknown concept). An isolated cluster in the search space represents this last problem. In their method, samples are divided into clusters. The maximum distance between clusters' instances and medoids is computed to establish a decision boundary for each cluster. The union of the boundaries of all clusters is called global decision boundary. The new unseen incoming examples that fall outside this global decision boundary are not considered "normal" and need a further analysis. In this way, these examples are stored in a short-term memory for grouping new clusters, which might indicate concept drift or novelty detection.

Another work based on dissimilarity measures between data employed to detect concept drift is found in (Otey & Parthasarathy, 2005). In this work, the authors calculate the dissimilarity between two windows ($\bar{X}$ and $\bar{Y}$) considering three components: distance, rotation and variance. For the distance component, its dissimilarity D_{dist} is computed by means of Euclidean distance between the centroids of each dataset ($\mu_{\bar{X}}$ and $\mu_{\bar{Y}}$), according to Equation 3.8:

$$D_{dist}(\bar{X}, \bar{Y}) = |\mu_{\bar{X}} - \mu_{\bar{Y}}| \tag{3.8}$$

For the rotation component, its dissimilarity D_{rot} is defined as the sum of the angles between the components (Equation 3.9). Since the columns X and Y are unit vectors, it follows that the diagonal of the matrix X^TY is the cosine of the angles between the corresponding principal components:

$$D_{rot}(\bar{X}, \bar{Y}) = trace\left(cos^{-1}\left(abs(X^TY)\right)\right) \tag{3.9}$$

For the variance component, its dissimilarity D_{var} is defined by the symmetric relative entropy (SRE) between the distributions of the random variables $V_{\bar{X}}$ and $V_{\bar{Y}}$, as shown in Equation 3.10:

$$D_{var}(\bar{X}, \bar{Y}) = SRE(V_{\bar{X}}, V_{\bar{Y}}) \tag{3.10}$$

Finally, (Otey & Parthasarathy, 2005) define the resultant dissimilarity D_{final} according to Equation 3.11:

$$D_{final}(\bar{X}, \bar{Y}) = D_{dist} * D_{rot} * D_{var} \tag{3.11}$$

It is worth noting that, even though the method proposed by (Otey & Parthasarathy, 2005) is applicable to detect drifts, learning process is not involved. In addition, this method deals with incoming data in batch. The authors, however, suggest an alternative incremental form of anomaly and change detection. This incremental method may calculate $D_{final}\left(\overline{X}, \overline{X} \cup \{x\}\right)$, where x denotes the first sample following the window. In this way, it is possible to verify how much D_{final} may increase when the data point x is included. This measure may indicate a concept drift. This work inspired the first method proposed in this thesis, as described in the next Chapter. First, however, the next section discusses the semi-supervised strategies available in the literature.

3.3 Semi-supervised Methods

Even though unsupervised drift detectors are assumed to be the solution for dealing with fully unlabeled data, these methods must assume some structure to the underlying distribution of data, must store clusters in a short-term memory and their decisions depend on similarity/dissimilarity measures. All these aspects may compromise system performances in online practical problems. In order to avoid storing examples and to provide more confident decision models, semi-supervised methods may be an interesting alternative since they usually allow working with a small amount of labeled data and a large amount of unlabeled data.

Wu et al (2012) proposed the SUN (*Semi-supervised classification algorithm for data streams with concept drifts and UNlabeled data*). Basically, SUN divides the streaming data into two sets: training and testing dataset. First, at the training phase, the method builds a growing decision tree incrementally and generates concept clusters in the leaves using labeled information. The unlabeled data are labeled according to the majority-class of their nearest cluster. Then, SUN suggests a concept drift based on the deviation measured in terms of distance, radius, etc., between old and new concept cluster. Secondly, at the test phase, the examples are evaluated using the current decision tree.

However, SUN searches for concept drifts only during the training phase, where samples contained in the training set are assigned to true labels or to pseudo-labels. During the test phase, the method assumes that all concepts described in the data stream are already known. Moreover, in terms of drift detection, the results attained by SUN are worse than its baseline, since SUN produces more false detections, missing detections and larger delays of drift reactions.

Another semi-supervised strategy for dealing with concept drift in the context of data streams was proposed by Kantardzic et al (2010). Here, however, instead of using single classifiers, the authors employed ensemble of classifiers. Their online method calculates similarity measures to select suspicious examples, which are assumed to belong to the new concept. Suspicious examples are samples that must be labeled in order to improve the accuracy of the current classifier. The incoming streaming examples are clustered in the *current distribution* and the suspicious examples are put together to form the *new regions*. This method does not build a new classifier for the ensemble periodically and it also does not detect the moment when drifts occur. The system update works as follows: when the number of examples assigned to a cluster *new region* reaches the predefined minimum number of examples, the ensemble requests a human expert to label them. After such a labeling process, the ensemble builds a new member classifier and removes the oldest one.

One more recent semi-supervised method based on ensemble classifiers is called SAND (*Semi-Supervised Adaptive Novel Class Detection and Classification over Data Stream*) proposed by Haque et al (2016). SAND maintains a window *W* to monitor estimates of classifier confidence on recent data instances. It means that a decreasing of classifier confidence suggests a concept drift. In order to update the ensemble, SAND uses the recent chunk and selects some instances (by classifier confidence) to be labeled and to be included in the training dataset for a new model (which replaces the oldest one). In this way, SAND deals with the concept drift problem updating the ensemble always with the most recent concept.

3.4 A Comparative Analysis of the Current Methods

All methods described in this chapter are listed in Table 3.1. This table highlights how these methods are divided according to the approach of generic solutions presented in Chapter 2. In addition, Table 3.1 also shows the type of changes that each method intends to deal with. Finally, for drift detectors, the measure used for drift detection is mentioned too.

DDM, EDDM and STEPD represent the same configuration of approaches. The main difference between these three drift detectors is the statistical test employed. These methods are based on single classifier, which is replaced after drift detection. Moreover, incoming data arrive in a stream, updating the current decision model incrementally (online learning). When warning level is reached, the samples update a kind of alternative decision model. However, alternative model only replaces the current decision model when drift level is reached. Since DDM, EDDM and STEPD pass by the same sample just once, these methods are assumed to be online.

We also consider DDM, EDDM and STEPD as active methods, since the drift detection is explicit in their strategies. However, these methods include every incoming sample to the decision models (current or alternative), i.e. the system does not update only after drift detection. Actually, the system is updated as the incoming samples arrive. These methods are robust at handling abrupt and gradual drifts. However, EDDM performs better when gradual drifts are very slow because it is based on distance between error occurrences.

Table 3.1. Compilation of related work reported in literature grouped according to the approach of generic solutions for dynamic environments problems.

Category	Method	Classifiers	Learning	Strategy	Detection based on	Proposed to deal with
Drift Detectors	**DDM**	Single	Online	Active	Error monitoring	Abrupt/Gradual drifts and noises
	EDDM	Single	Online	Active	Error monitoring	Abrupt/Gradual (slow) drifts
	STEPD	Single	Online	Active	Error monitoring	Abrupt/Gradual drifts and noises
	DDD	Ensemble	Incremental	Active	It depends on detection method used	Abrupt/Gradual (slow) drifts and noises
Blind Methods	**SEA**	Ensemble	One-Pass	Blind	-	Abrupt drifts and noises
	Learn++NSE	Ensemble	One-Pass	Blind	-	All drifts
	DWM	Ensemble	Online	Blind	-	Noises
	ERDWM	Ensemble	Online	Blind	-	Recurring concepts and noises
	AUE2	Ensemble	One-Pass	Blind	-	All drifts and noises
	DYNSE	Ensemble	One-Pass	Blind	-	All drifts and noises
Unsupervised Methods	**Fanizzi et al, 2008**	Single	One-Pass	Active	Dissimilarity	-
	Otey & Parthasarathy 2005	-	-	Active	Dissimilarity	Abrupt drifts and blips
Semi-Supervised Methods	**SUN**	Single	Online	Blind	-	All drifts and noises
	Kantardzic et al, 2010	Ensemble	Online	Blind	-	All drifts
	SAND	Ensemble	One-Pass	Active	Classifier Confidence Scores	All drifts
Our Proposed Methods	**DbDDM**	Single	Online	Active	Pseudo-error monitoring	All drifts
	DSDD	Ensemble	Online	Active	Pseudo-error monitoring	All drifts

Blind methods based on ensemble classifiers are better in maintaining previous knowledge than methods based on single classifier. Blind methods also use incremental learning divided into online learning, when the incoming data arrive as stream (DWM, ERDWM and DDD), and one-pass learning, when incoming data arrive as batch (SEA, AUE2 and DYNSE). Except for DDD, all the methods based on ensemble classifiers mentioned in this chapter use passive strategies to handle concept drifts. These methods are robust on reacting to new concepts. In addition, due to the ensemble of classifiers, they are also robust on reacting to recurrent concepts. However, in period of stable concepts, they remain updating the system unnecessarily.

In despite of the fact that DDD uses active strategy, this method needs an algorithm to detect changes. However, as mentioned before, since the authors used EDDM only at the changing detection phase, DDD is considered an incremental learning method, as shown in Table 3.1. Besides, it is assumed that DDD is an incremental learning method because it allows choosing a drift detector, which passes by each sample only once.

The unsupervised methods described in this chapter are based on clustering. In (Fanizzi et al, 2008), even though incoming data arrive on stream, first this method waits to form a cluster. Then, it integrates the created cluster to the model. Since it presents explicit drift detection, this method is assumed as an active strategy. The method proposed by Otey & Parthasarathy (2005) is totally based on data distribution. Therefore, it does not use either a classifier or learning. In addition, this method presents active strategy for data stream. It is better on detecting abrupt drifts due to the fact that the change should occur from one window to another one. The incremental form of change detection suggested by the authors may handle gradual drifts.

The semi-supervised methods mentioned in this work aim to update their systems to deal with evolving data streams. They handle concept drifts by updating their systems using a small selected amount of the most recent labeled examples. On the one hand, except for SAND, they do not present high performance on detecting drifts at the right moments when they occur. On the other, these semi-supervised methods present high accuracy rates and reduce the computational cost of the labeling process.

In addition, most of the methods based on ensemble classifiers, in both blind and semi-supervised categories, make their predictions by majority voting as ensemble fusion function. DYNSE is an exception, since it makes predictions based on dynamic classifier selection. Classifier fusion assumes error independence among ensemble's component members. This means that the classifier members are supposed to misclassify different patterns. In this way, the combination of classifier members' decision would improve the final classification performance. However, when the condition of independence is no verified, there is no guarantee that the combination of classifiers will outperform single classifiers (Kuncheva, 2002). In order to avoid the assumption of independence of classifier members, methods for classifier selection have been used as alternative to classifier fusion.

In order to achieve the objectives of this research, the blind methods are practically infeasible, due to the following reasons. First, to be able to react to all changes, a system based on passive strategy must be updated in short time intervals, leading to high computational cost. Second, if the system is updated in large time intervals, some changes may not be noticed by the system.

These drawbacks allow us to believe that the best moment for system update is after change detection. In this way, the system will not spend an unnecessary computational cost, and all relevant changes will be noticed. Therefore, drift detectors may be considered better than blind strategies, because they are based on explicit detection of changes.

In addition, as confirmed in this chapter, ensemble of classifiers achieves better performance on handling many types of drifts, when compared to single classifiers. However, most of the ensemble-based techniques available in the literature are blind strategies. The exception is DDD. However, as mentioned before, this method needs a drift detector.

In terms of active methods, they are based on error monitoring, dissimilarity between incoming data, or classifier confidence. Error monitoring-based methods need an operator feedback to indicate if the error rate has increased, i.e., it is necessary to know the true labels of the whole data. However, in stream data problems, the true labels are not always available. In this context, the dissimilarity-based methods take advantage, due to the fact that they detect drifts on unlabeled data and do not need to wait for error rate increasing to detect drifts. Even though, these methods must assume some structure to the underlying distribution of data, must store clusters in a short-term memory and their decisions depend on similarity/dissimilarity measures. All these aspects may compromise system performances in online practical problems.

During the adaptation process, all systems described in this chapter follow a standard process: drift detectors based on single classifiers replace the classifiers after drift detection using the most recent data to update their models, while ensemble-based, for both active and passive strategies, create new ensemble members using the most current data. What makes the difference in the adaptation process of ensemble-based methods is the identification of the right moment to replace old members, such as intended by Minku & Yao (2012) in DDD and Haque et al (2016) in SAND.

Therefore, there are many open problems on employing classification systems to deal with concept drift. In this work, we present two methods. Both proposed methods focus on detecting drifts explicitly in an unsupervised way by monitoring a pseudo error and updating the decision model just after drift detections. The estimation of the pseudo error is the main novelty of our methods, since it allows simulating the most common supervised drift detectors to be also used by unsupervised and semi-supervised methods.

Our two proposed methods (DbDDM and DSDD) are included in Table 3.1. All the details about the configurations of these proposed methods, experiments and results are summarized in the two next chapters.

Chapter 4

Dissimilarity-based Drift Detection Method

This work intends to overcome the following drawbacks identified in the current methods for data stream problems: classification error rate monitoring and unnecessary system updates. In this way, in order to avoid detecting changes based on performance monitoring, we propose a method to detect drifts by monitoring the dissimilarity between past and current data distributions. The decision model is kept until drift detection to avoid unnecessary updates, i.e. the model is reset to posterior incoming data as soon as a drift is detected. We call our method Dissimilarity-based Drift Detection Method (DbDDM).

A conventional prediction system for stable concepts is used to start the system, when it is necessary an initial decision model to predict every incoming sample. Thus, the unknown data arrive in a stream toward DbDDM, which detects drifts based on dissimilarity between the current sample and past data. It is important to mention that this past data represent small clusters created by grouping the most recent past data, which are updated with every incoming sample.

For the system reaction phase, as long as DbDDM does not alarm drift detection, the current decision model keeps classifying the incoming samples. When a concept drift occurs, the reference clusters are reset using the most recent incoming data. This chapter describes the whole method in details, as well as the results attained by experiments conducted using artificial and real datasets.

The proposed DbDDM may be included in the category of drift detectors, since it resets the decision model when a concept drift is observed. DbDDM is divided into two modules: (1) dissimilarity calculation; and (2) drift detection.

The first module is motivated by work (Otey & Parthasarathy, 2005). The authors advocate that an incremental form of anomaly detection for data stream applications may be achieved by calculating $D(\overline{\boldsymbol{W}}, \overline{\boldsymbol{W}} \cup \{X_i\})$, where $\overline{\boldsymbol{W}}$ is a sliding window of k samples, X_i is the first sample following the window, and D is the resulting dissimilarity measure. In our method, we implement this incremental form of anomaly detection. It is important to mention that these authors originally worked only with cluster of samples, i.e. they calculated $D(\overline{\boldsymbol{W}}, \overline{\boldsymbol{Z}})$, where $\overline{\boldsymbol{W}}$ and $\overline{\boldsymbol{Z}}$ are both windows of data. Moreover, their method did not involve learning, i.e., their aim was to identify whether or not $\overline{\boldsymbol{W}}$ and $\overline{\boldsymbol{Z}}$ were significantly different.

The second module of DbDDM is inspired by DDM and EDDM using statistical process control (SPC). As mentioned in the last chapter, DDM and EDDM are both incremental learning-based and accuracy monitoring-based methods. Here, however, in order to avoid accuracy monitoring, our method uses SPC to verify when the dissimilarity between the current unknown samples and previous known data reaches the warning or the drift level.

DbDDM works as follows. First, a classifier is trained using samples contained in a training dataset. Then, the training dataset is partitioned into *c* clusters, where *c* indicates the number of classes, to be used as reference clusters. We call each group of class by cluster C^n. For instance, two classes will result in two clusters: C^1 and C^2. Afterwards, the classifier will assign a label for each new (unknown) sample X_i one at a time, such as incoming data in a stream.

We extend the conventional prediction system to handle concept drift taking into account only data distribution (Figure 4.1). The aim is to detect concept drifts by analyzing the dissimilarity between the current sample and the reference clusters, and then to update the classifier to new concept. Since our drift detector is based on SPC, it may be adaptable to any SPC statistical test. We have employed the statistical tests performed in DDM and EDDM. In order to better describe this overview scheme, we divided it into three sections: dissimilarity module; drift detection module based on DDM; and drift detection module based on EDDM.

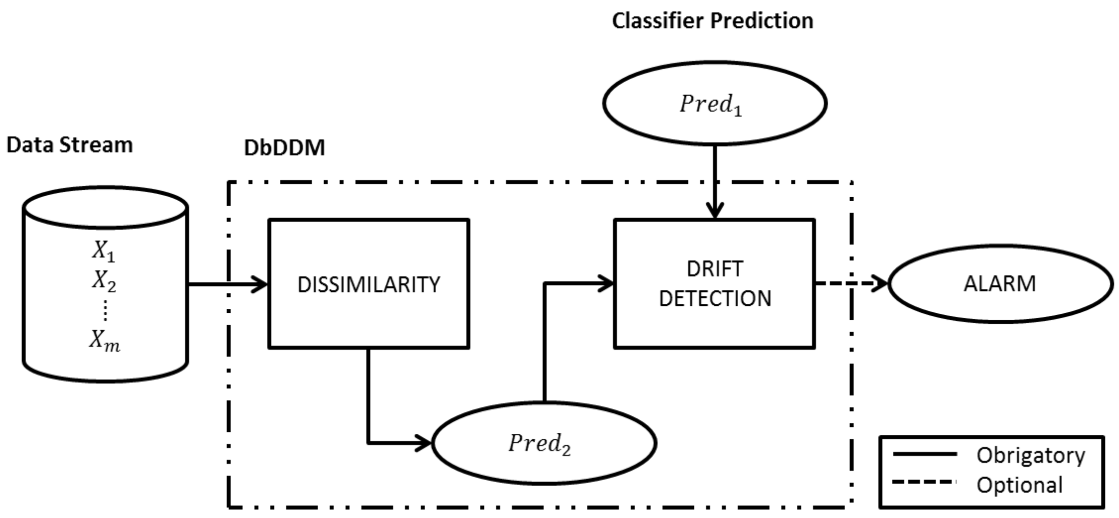


Figure 4.1. Overview scheme of the proposed method: It starts with every incoming example being predicted by dissimilarity module. This dissimilarity prediction is compared to the classifier prediction by the drift detection module in order to calculate when the assumed dissimilarity prediction error suggests a concept drift.

4.1 Dissimilarity Module

The dissimilarity module may also be divided into two levels: (1) dissimilarity measurement; and (2) cluster update. In the first level, for instance, given a n-classes problem, there are n initial clusters (C^1, C^2,..., C^n). For each incoming sample X_i, the method calculates its dissimilarity to each cluster: $D_1(C^1, C^1 \cup \{X_i\})$, $D_2(C^2, C^2 \cup \{X_i\})$ up to $D_n(C^n, C^n \cup \{X_i\})$.

Afterwards, it is assigned to X_i the class represented by the cluster less dissimilar to it. It is important to mention that the dissimilarity measurement is considered as a parameter for this module. Therefore, we used the measurements according to Equation 3.10, defined in the last chapter, as proposed by (Otey & Parthasarathy, 2005). It is a combination of three components: distance, rotation and variance.

As it can be observed, classification error is not taken into account at the first level. The second level is devoted to update the reference clusters, which is conducted as follows: the real label of X_i is verified, and X_i is used to update the correct cluster by removing the oldest sample and adding X_i. Therefore, the cluster update level is a supervised component of DbDDM.

It is important to say that the same initial clusters C^n are used as input of the dissimilarity module for the next sample and so on. Meanwhile, the class prediction by dissimilarity is used as input for the next module: the drift detection module. We can observe all steps involved in the dissimilarity module in Algorithm 4.1.

```
input:  $X_i$: incoming stream sample;
        RefClusters: set of k reference clusters;
output: $Pred_2$: dissimilarity prediction;
        $D_r$: dissimilarity measure related to the class predicted in $Pred_2$;
        RefClusters: updated reference clusters;

begin
for $each\ C_k \in$ RefClusters do $D_k(X_i, C^k)$;
$D_r \coloneqq \min(D)$;                                  //lower dissimilarity measure
return $C^k | \min(D)$;                                   //cluster less dissimilar
$Pred_2 \coloneqq class(C^k | \min(D))$;                  //class label predicted
RefClusters $\coloneqq update(C^k | label(X_i) \in C^k)$; //update based on true label
end
```

Algorithm 4.1. DbDDM Dissimilarity module algorithm.

4.2 Drift Detection Module based on DDM

The drift detection module receives two predictions to X_i as input: the classifier prediction ($Pred_1$), and the dissimilarity prediction ($Pred_2$). Precisely, $Pred_1$ denotes the class assigned by the classifier to sample X_i, while $Pred_2$ denotes the class of the cluster less dissimilar to X_i. It is important to mention that we do not evaluate whether or not the classifier made the right decision on assigning the selected class to X_i. We assume that $Pred_2$ is the reference to know if $Pred_1$ is correct or wrong.

Given that C^r is the cluster related to the class predicted in $Pred_2$, when $D_r(C^r, C^r \cup \{X_i\})$ is lower than the average dissimilarity calculated by all dissimilarities in this concept ($mean(D)$), $Pred_2$ is considered a correct reference prediction. Otherwise, it is a wrong reference prediction.

In this way, we use the prediction $Pred_2$ in order to calculate the SPC based on a pseudo prequential error p_i with standard deviation given by: $s_i = \sqrt{p_i(1-p_i)/i}$. In our method, the SPC (such as the dissimilarity measurements) is a parameter, i.e., it is possible to choose the same statistical test used by DDM, EDDM, STEPD or any other method based on SPC.

To better understanding the method, here, we describe it using the SPC-based DDM. This pseudo prequential error increases as $Pred_1$ is considered incorrect by $Pred_2$. Otherwise, p_i decreases. On the one hand, it is important to remember that p_i is not based on classification error, but it is only based on data dissimilarity. On the other, p_i is like a simulation of classification error and that is the reason why we called it by pseudo prequential error.

A significant increase in the pseudo prequential error indicates that new examples are very dissimilar to previous samples. This behavior suggests that the class distribution is changing. Consequently, it may be necessary to update the decision model. Thus, the system stores the values of p_i and s_i when $p_i + s_i$ reaches its minimum value during the process (obtaining p_{min} and s_{min}). And it checks when the following conditions triggers:

- **Warning level** ($p_i + s_i > p_{min} + \alpha * s_{min}$): Beyond this level, the system maintains the current decision model but it suggests that the concept is starting to change. Thus, it initiates to count the number of times the system reaches the warning level.
- **Drift level** ($p_i + s_i > p_{min} + \beta * s_{min}$): To achieve this level, the system has to reach the warning level at least *n* times. Beyond the drift level, the system resets the reference clusters to the next m samples of each class, forgets the old decision model and uses these same samples to create a new decision model. Finally, all the previous known parameters are also reinitialized.
- **In control level**: When the pseudo prequential error does not reach the warning level or the drift level, the system assumes that the concept is stable, so it just maintains the current decision model.

In experiments discussed in the next section, the values used for α and β have been defined empirically after some experimentation and they have been set to 1.55 and 1.70, respectively. In addition, since n and m are user defined, we set both n and m to 30, as Gama et al (2014) for detectors based on statistical process control. We can observe all the steps for drift detection module in Algorithm 4.2.

```
input:   $Pred_1$: classification prediction;
         $Pred_2$: dissimilarity prediction;
         $D_r$: dissimilarity measure related to the class predicted in $Pred_2$;
output:  level: in control, warning or drift;
         $NewClusters$: clustering after drift level;

begin
if $Pred_1 = Pred_2$ then
         if $D_r(X_i, C^r) \leq mean(D)$ then
                  $p_i = p_{i-1} - p_{i-1}/n$;                //$Pred_1$ is correct
         else     $p_i = p_{i-1} + (1 - p_{i-1})/n$;          //$Pred_1$ is incorrect
else //$Pred_1 \neq Pred_2$
         if $D_r(X_i, C^r) \leq mean(D)$ then
                  $p_i = p_{i-1} + (1 - p_{i-1})/n$;          //$Pred_1$ is incorrect
         else     $p_i = p_{i-1} - p_{i-1}/n$;                //$Pred_1$ is correct
$s_i = sqrt(p_i * (1 - p_i)/n)$;                              //Standard deviation

if $p_i + s_i > p_{min} + \beta * s_{min}$ and $wl\_num\_\min > 30$ then
         $NewClusters = accumulate(posteriori\_samples)$;
         return(drift, $replace(Model, NewClusters)$);
         $initialize(p, s, n, p_{min}, s_{min}, wl\_num\_\min)$;
else     if $p_i + s_i > p_{min} + \alpha * s_{min}$ then
                  return(warning, $maintain(Model)$);
                  $wl\_num\_\min{++}$;
else     return(inControl, $maintain(Model)$);
end
```

Algorithm 4.2. DDM-based drift detection module algorithm.

4.3 Drift Detection Module based on EDDM

We can observe all the steps for drift detection module based on EDDM in the Algorithm 4.3. This EDDM-based module also uses the dissimilarity prediction $Pred_2$ to assure whether or not the classifier prediction $Pred_1$ is correct. However, the EDDM statistical test is based on distance between two consecutive errors. It assumes that when the decision model needs to be updated, the distance between errors will decrease. As in EDDM, we calculate the average distance between two pseudo (by dissimilarity) errors p'_i and its standard deviation s'_i. We store the p'_{max} and s'_{max} obtained when $p'_i + 2 * s'_i$ reaches its maximum value. The method defines two thresholds for warning and drift level.

- **Warning level** $(p'_i + 2 * s'_i)/(p'_{max} + 2 * s'_{max}) < \alpha$: Beyond this level, the system maintains the current decision model but it suggests that the concept is starting to change. Thus, it initiates to count the number of times the system reaches the warning level.
- **Drift level** $(p'_i + 2 * s'_i)/(p'_{max} + 2 * s'_{max}) < \beta$: To achieve this level, the system has to reach the warning level at least n times. Beyond drift level, the system resets the reference clusters to the next m samples of each class, forgets the old decision model and uses these same samples to create a new decision model. Finally, all the previous known parameters are also reinitialized.
- **In control level**: When the statistical test does not reach the warning/drift level, the system assumes that the concept is stable and maintains the current decision model.

```
input:   $Pred_1$: classification prediction;
         $Pred_2$: dissimilarity prediction;
         $D_r$: dissimilarity measure related to the class predicted in $Pred_2$;
output:  level: in control, warning or drift;
         $NewClusters$: clustering after drift level;

begin
if $Pred_1 = Pred_2$ then
         if $D_r(X_i, C^r) > mean(D)$ then
                  $dist = number\ of\ examples\ between\ two\ last\ errors$;
                  $p'_i = p'_{i-1} + (dist - p'_{i-1})/num\_errors$;          $//Pred_1$ is incorrect
                  $s'_i = sqtr((dist - p'_i) * (dist - p'_{i-1})/num\_errors)$;
else $//Pred_1 \neq Pred_2$
         if $D_r(X_i, C^r) > mean(D)$ then
                  $dist = number\ of\ examples\ between\ two\ last\ errors$;
                  $p'_i = p'_{i-1} + (dist - p'_{i-1})/num\_errors$;          $//Pred_1$ is correct
                  $s'_i = sqtr((dist - p'_i) * (dist - p'_{i-1})/num\_errors)$;

if  $(p'_i + 2 * s'_i)/(p'_{max} + 2 * s'_{max}) < \beta$ and $wl\_num\_\min > 30$ then
         $NewClusters = accumulate(posteriori\_samples)$;
         return(drift, $replace(Model, NewClusters)$);
         $initialize(p, s, n, p_{min}, s_{min}, wl\_num\_\min)$;
else     if  $(p'_i + 2 * s'_i)/(p'_{max} + 2 * s'_{max}) < \alpha$ then
                  return(warning, $maintain(Model)$);
                  $wl\_num\_\min{++}$;
else     return(inControl, $maintain(Model)$);
end
```

Algorithm 4.3. EDDM-based drift detection module algorithm.

In this work, the values used for α and β have been defined empirically after some experimentation and they have been set to 0.22 and 0.10, respectively. In addition, since n and m are user defined, we set both n and m to the number of 30 samples as it is done in (Gama et al, 2014).

As can be observed in the description of our method, DbDDM, based on both DDM and EDDM, detects drifts without the need of an error monitoring phase, which may lead the system to predict the drift earlier. In addition, DbDDM updates the system just only after drift detection, avoiding a high computational cost with unnecessary updates. In next section, we analyze DbDDM experimentally.

4.4 Experiments and Results

The objective of these experiments is to compare the best version of our detection method to the two most common baselines (DDM and EDDM) and find out its main weakness and advantages. We have used SVM (Support Vector Machines) as learning algorithm with the drift detection methods investigated. The drift detectors were implemented in Matlab 7.10 over Windows 7 in a notebook based on Intel Core i7 3520M@2,90 GHz processor using LibSVM implementations of the learning algorithms. First, however, we will present details related to the databases investigated in our experiments.

4.4.1 Databases

The main aspect taken into account to choose the databases for the experiments is related to the type of concept drifts we intend to handle. Accordingly, we observed that most of the current methods handle abrupt and gradual drifts, while some methods handle recurrent concepts. In our experiments, we intend to deal with these same types of drifts.

However, since our method is based only on data dissimilarity with no label knowledge to detect drifts, we have to avoid datasets in which the classification is reversed in each concept, like SINE1. In this case, only the dissimilarity and a posteriori probability are not sufficient to detect drifts since there is only a reversion on class distribution. This observation is verified in this thesis, since SINE1 database is used in our experiments. In addition, given that DbDDM also uses supervised incremental learning, we have included SINE1 dataset to be evaluated in our experiments.

Besides SINE1, we have used some artificial datasets used by Gama & Castillo (2006), Baena et al (2006), Nishida & Yamauchi (2007) and Minku & Yao (2012), since we also intend to compare our results to the results reported by the DDM and EDDM authors. All artificial databases investigated are described below:

- SINE1. **Abrupt concept drift, noise-free examples**. This dataset presents two relevant attributes. Each attribute has values uniformly distributed in [0,1]. Classification is positive, if a point lies below the curve given by $y = \sin(x)$, otherwise it is negative. After concept drift, the classification is reversed.
- GAUSS. **Abrupt concept drift, noisy examples**. The examples are labeled according to two different but overlapped Gaussian, $N([0,0],1])$ for positive examples and $N([2,0],4)$ for negative examples. The overlapping can be considered as noise. After each concept drift, the classification is reversed.
- CIRCLE. **Gradual concept drift, noise-free examples**. This dataset presents the same relevant attributes as SINE1. But the examples are labeled according to a circular function: its label is positive if an example is inside the circle, otherwise is negative. The gradual drift occurs due to displacing the center of the circle and growing its radius. This dataset has four contexts defined by four circles:

center	[0.2,0.5]	[0.4,0.5]	[0.6,0.5]	[0.8,0.5]
radius	0.15	0.2	0.25	0.3

- SINE1G. **Very slow gradual drift, noise-free examples**. This dataset presents the same classification function of SINE1, but there is a transition time between old and new concepts. The old concept disappears gradually and the probability of selecting an example from the new concept becomes higher after the transition time.

All these artificial datasets have two classes and each class is represented by 50% of the examples. Also, in all datasets, each 1000 examples represent a concept, except in SINE1G, which have 2000 examples in each concept and 1000 examples of transition from one concept to another.

4.4.2 Comparison of DbDDM versions: DDM-based vs EDDM-based

The objective of these experiments is to evaluate the performance of the two versions of our proposed method, called here DbDDM (DDM-based) and DbEDDM (EDDM-based) on the databases described before. Both methods are compared in terms of prequential error and drift detection. It is important to mention that the performance of the learning algorithm is not the aim of these experiments. Instead, we investigate the potential of the compared methods to detect drifts and to react to them quickly. Even though, the errors shown in all experiments presented here are real prequential errors, i.e., the final classification performance.

We first analyze the performance of both methods on abrupt changing datasets. In Figure 4.2, we can see the behavior of both methods on SINE1 dataset (noise-free), respectively. DbDDM presents lower prequential error and smaller delays to detect drifts. However, DbDDM and DbEDDM present behaviors quite similar.

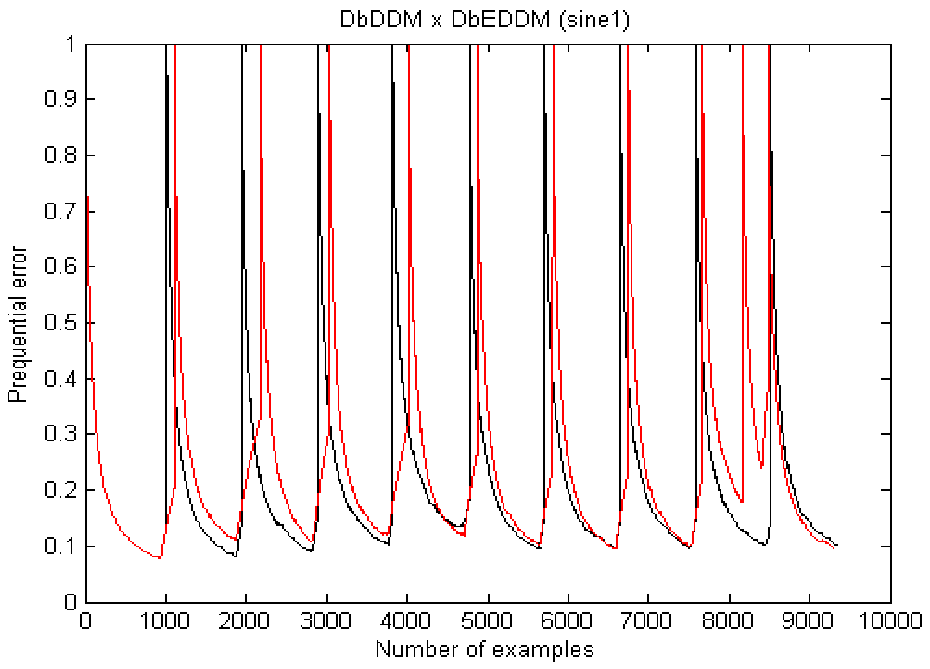


Figure 4.2. Prequential error of our proposed method on SINE1. DbDDM (black) and DbEDDM (red).

When dealing with a noisy dataset (GAUSS, Figure 4.3), both DbDDM and DbEDDM fail to address concept drift. However, they present different behaviors. While DbDDM presents several misdetections, DbEDDM overreacts to noisy (false detections). These inconclusive behaviors may be due to the misinterpretation of the noisy data by dissimilarity measures, which may provide an unexpected behavior of the not-real prequential error, responsible to reach the thresholds.

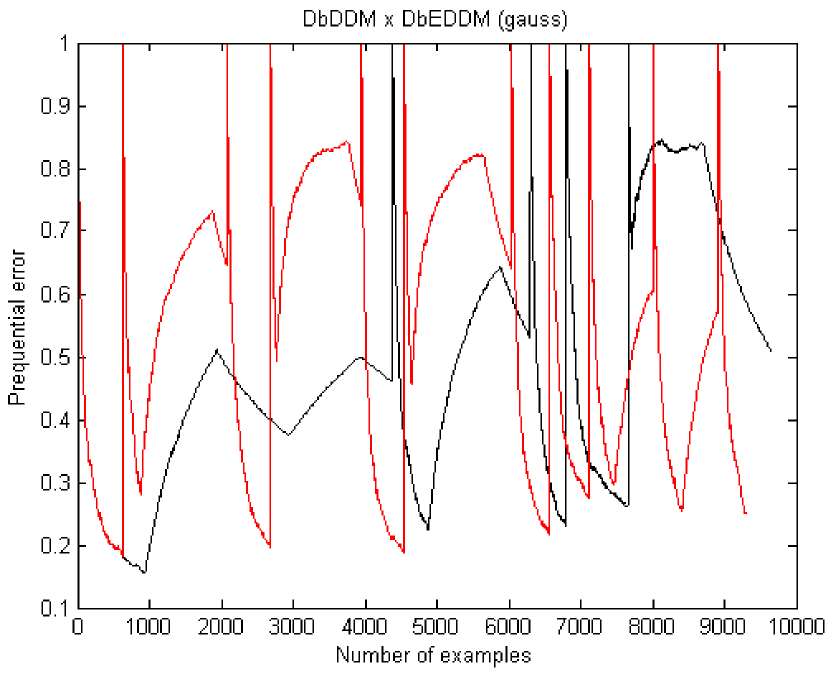


Figure 4.3. Prequential error of our proposed method on GAUSS. DbDDM (black) and DbEDDM (red).

Finally, we evaluate the performance of both methods on gradual changing datasets. According to the literature, EDDM is assumed to be better in this kind of problem. We can see in Figure 4.4 and Figure 4.5 the behavior of both methods on CIRCLE and SINE1G (noise-free), respectively. In CIRCLE dataset (Figure 4.4), both methods are quite similar, but during the second concept (examples between 1000 and 2000), DbEDDM achieves lower prequential error than DbDDM. However, DbDDM detects the last concept (from example 3000) earlier than DbEDDM.

On SINE1G (very slow gradual drift), DbDDM attained higher prequential error and several false detections, while DbEDDM detected drifts with larger delays. Figure 4.5 illustrates this comparison.

Based on the results shown in this section, we can conclude that DbDDM outperformed DbEDDM, since it was mostly effective with earlier drift detections, except on SINE1G, and it achieved lower prequential error. As a consequence, in the next section, we compare DbDDM to the most common baselines found in the literature, DDM and EDDM.

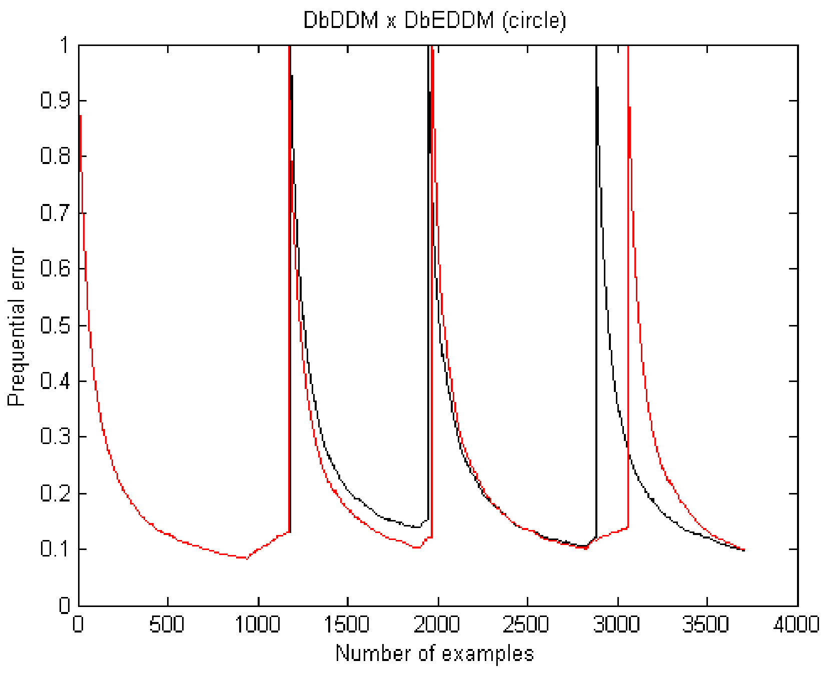


Figure 4.4. Prequential error of our proposed method on CIRCLE. DbDDM (black) and DbEDDM (red).

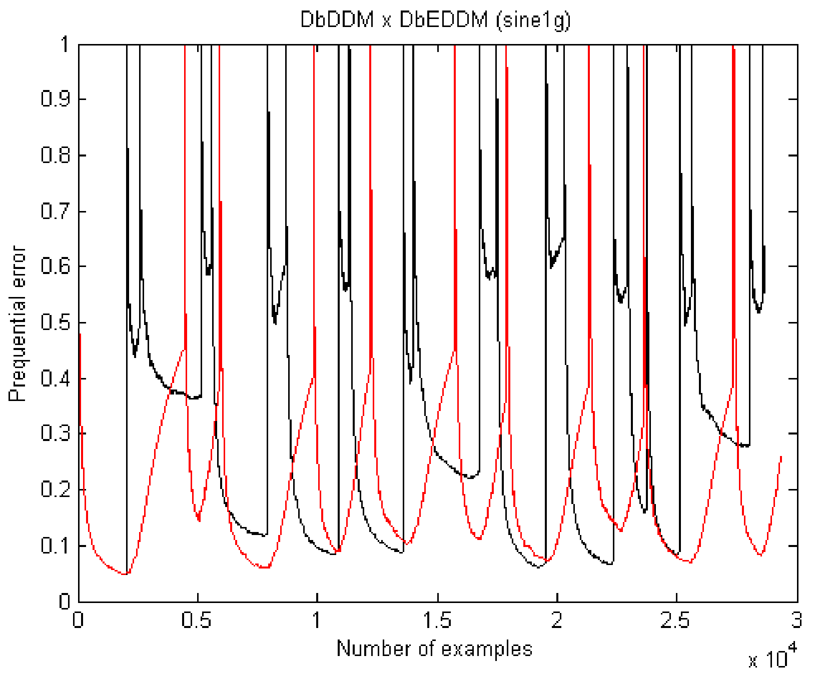


Figure 4.5. Prequential error of our proposed method on SINE1G. DbDDM (black) and DbEDDM (red).

4.4.3 Comparison between DbDDM and baselines

The purpose of these experiments is to analyze the performance of our detection method when compared to the most common drift detectors based on single classifiers and error monitoring, precisely DDM and EDDM. It is important to say that the performance of the learning algorithm is not the aim of these experiments, but the capability to detect drifts and to react to them quickly. Although, the errors plotted for all experiments presented in this chapter are real prequential errors, i.e., the final classification performance.

In Figure 4.6, it is shown how DbDDM deals with an abrupt changing problem (SINE1 dataset). This figure also shows the comparison among DbDDM, DDM and EDDM. It is possible to observe that DDM and EDDM present lower prequential error rates than DbDDM. In all experiments, the three investigated drift detectors present a detection delay. However, DDM and EDDM present smaller delays when compared to DbDDM. It is worth noting that, in general, DbDDM really detects drifts at the right moment (every 1000 examples) and reacts to them by decreasing the prequential error rate, in despite of the fact that DbDDM works solely based on data dissimilarity.

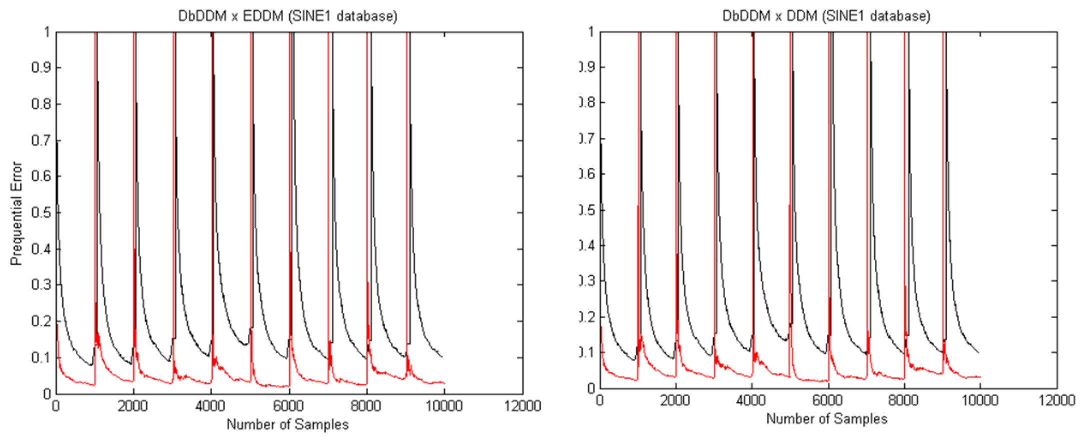
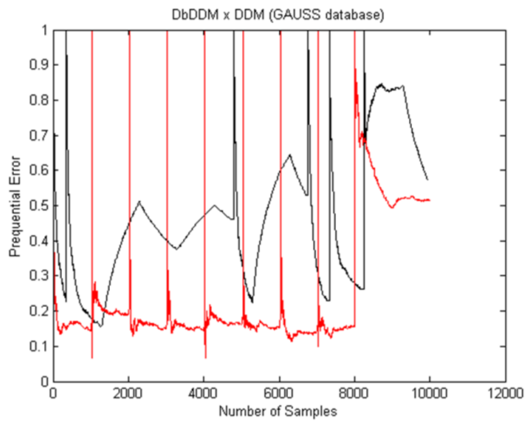


Figure 4.6. Prequential error on SINE1 dataset. Left: DbDDM (black) and DDM (red); Right: DbDDM (black) and EDDM (red).

In Figure 4.7, it is possible to observe the prequential error of DbDDM, DDM and EDDM on GAUSS database. In this case, we confirm that, among the investigated methods, DDM is the only method able to detect drift at the right moment for GAUSS database. EDDM presents several false detections, but it maintains the low prequential error rate. Finally, DbDDM may not handle with drift in problems with noisy examples.



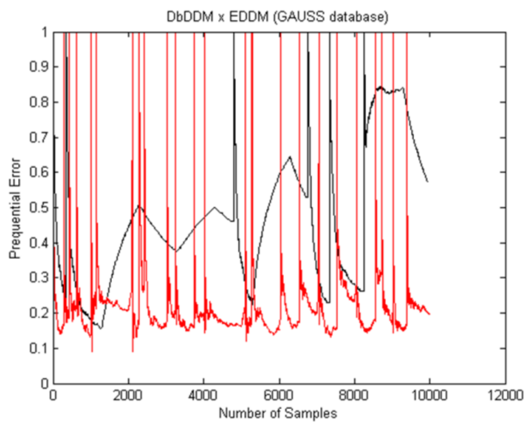
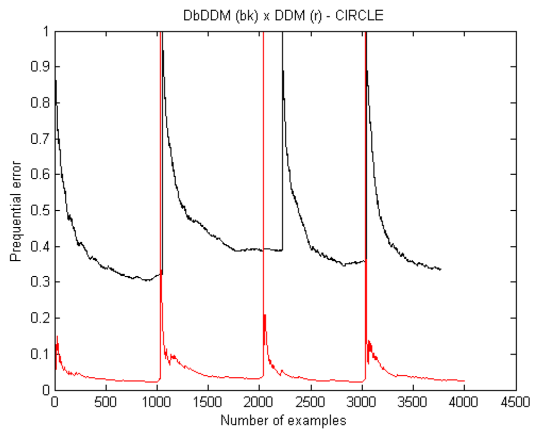


Figure 4.7. Prequential error on GAUSS dataset. Left: DbDDM (black) and DDM (red); Right: DbDDM (black) and EDDM (red).

In Figure 4.8, we can observe the behaviors of DbDDM compared to DDM and EDDM on gradual changing dataset (CIRCLE). In both experiments, DDM and EDDM present lower prequential error rate and smaller delays to drift detection than DbDDM. The delays presented by DbDDM on CIRCLE database are huge. For instance, the second drift detection occurs 300 samples after the real drift. Therefore, we may assume that DbDDM performs better on abrupt than on gradual changes.



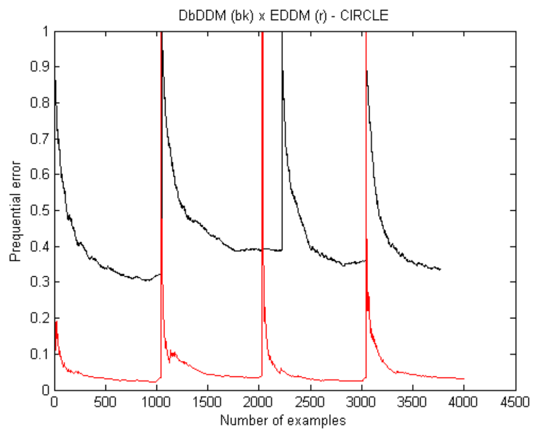


Figure 4.8. Prequential error on CIRCLE dataset. Left: DbDDM (black) and DDM (red); Right: DbDDM (black) and EDDM (red).

In Figure 4.9, we compare the prequential error rates attained by the investigated methods on a very slow gradual drift dataset (SINE1G). It is possible to observe that DbDDM performs better than DDM, reaching more frequently lower prequential error rates and earlier detections. When compared to EDDM, our detection method also presents promising results, performing better sometimes. However, in some transition phases from one concept to another, the three methods suggest drift more than once.

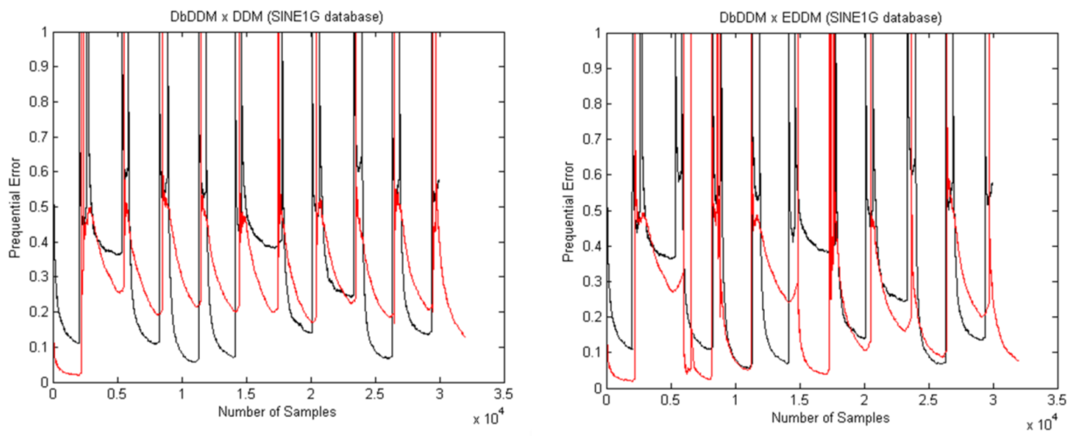


Figure 4.9. Prequential error on SINE1G dataset. Left: DbDDM (black) and DDM (red); Right: DbDDM (black) and EDDM (red).

It is not surprising that our experiments have shown that DbDDM does not perform better than DDM and EDDM in all datasets. On the one hand, taking into account that DbDDM monitors a pseudo prequential error whereas DDM and EDDM rely on real prequential errors, DbDDM was not expected to outperform DDM and EDDM. On the other, it is very interesting to observe that DbDDM presents performance almost similar to those attained by the other methods. Therefore, these results allow us to confirm that the main objective of this work may be achieved, i.e. designing drift detectors not based on recognition rate monitoring is effective. In addition, DbDDM outperforms DDM and EDDM in terms of computational costs.

4.4.4 Computational Cost Analysis

Concerning the amount of system updates, our method takes advantage over DDM and EDDM. Since our method uses batch mode classification learning, it updates the decision model only once after every drift detection, leading to low learning computational cost. In contrast, DDM and EDDM often involve high learning computational cost, as a result of updating the decision model for every incoming sample, even when the concept is stable, due to incremental learning.

In Table 4.1, we can observe the high differences in terms of learning computational cost when we compare our proposed method to DDM and EDDM. These two baselines spend more than a hundred times the learning computational cost of our method.

Table 4.1. Average Computational Cost of Learning (seconds).

Learning time (s)				
Dataset	**DDM**	**EDDM**	**DbDDM**	**DbEDDM**
SINE1	0,8304	0,8136	0,005	0,0019
GAUSS	0,8145	0,7861	0,0037	0,0087
CIRCLE	0,3744	0,5133	0,0035	0,0042
SINE1G	2,5545	2,6352	0,0141	0,0065

Summarizing, DbDDM is able to cope with abrupt and very slow gradual drifts but it does not detect drift in problems containing noisy examples. In addition, DbDDM is able to handle unlabeled data and avoid blind update. As a consequence, DbDDM reduces the computational costs involved on updating the classifier model whilst keeping low prequential error rates. Finally, our method may be improved. In this work, the same statistical tests performed in DDM and EDDM were employed, but this method may be also adaptable to the same statistical test used in STEPD, for instance.

4.5 Final Considerations

The goal of this first proposed method was to detect drifts at the right moment even when there is no fully labeled data available. Besides, this method does not update the system constantly. It uses the dissimilarity between current and past data to predict a pseudo prequential error, and it can use the same statistical tests conducted in traditional drift detectors, such as DDM and EDDM to suggest drift detections. Our method maintains the decision model until a drift detection. Once a change is observed, the system reacts by updating the decision model using new examples.

Given that the proposed method detects drifts considering unlabeled data and reacts to them avoiding periodical updates, the classification error rates and the system reaction delays achieved by our method were very promising, but subjected to more analysis aiming to decrease the prequential error.

Finally, despite the detection phase of DbDDM being unsupervised, we use labeled examples to update the reference clusters incrementally. Since we intend to reduce the labeling process time focusing on practical application problems, we present in the next chapter a new drift detection method. This new method employs ensemble of classifiers to improve the results attained by DbDDM, precisely, it applies dynamic selection of classifiers in order to improve the pseudo prequential error effectiveness, leading also to a self-training online learning process.

Chapter 5

Dynamic Selection-based Drift Detector

The Dynamic Selection-based Drift Detector (DSDD) proposed in this work creates an ensemble of classifiers to make online predictions. Since we intend to deal with unlabeled data, as in our first method, we propose a strategy to simulate the classification error to be monitored, as follows. For each incoming example, we assume the ensemble prediction as its true label. In order to allow the ensemble to be most likely correct for classifying each new sample individually, we employ dynamic classifier selection. Then, a drift detector is applied so as to monitor a pseudo-error for each ensemble member. This prediction is also used to update every ensemble member incrementally. Hence, it generates a process of ensemble self-training. Then, when one member detects a drift, all members are updated.

This method may be included in the category of Drift Detectors and Semi-supervised methods, since it resets the decision model when a concept drift is detected and it uses an ensemble of classifiers based on self-training online learning. Our method is divided into three modules: (1) ensemble generation; (2) dynamic classifier selection; and (3) drift detection, as illustrated in Figure 5.1.

The first module is focused on generating an online ensemble of classifiers. Even though several techniques for online classifier ensembles have been proposed in the literature, in this work the classifier ensemble is generated using a modified version (Minku et al, 2010) of online bagging (Oza & Russel, 2001), which includes ensemble diversity. In the original online bagging, each classifier member is trained using n copies of each incoming example, where n tends to

$Poisson(1)$ distribution. The modified version includes a parameter λ for the $Poisson(\lambda)$ distribution, where higher/lower λ values lead to lower/higher diversity in the ensemble.

Since our method is online and, in order to detect drifts in unlabeled data, the second module is intended to select the most competent ensemble member to classify each incoming example. Thus, for each new (unknown) example x_i, one ensemble member is selected to assign a label $Pred_i$ one at a time, such as incoming data in a stream. If a drift is detected, the dynamic classifier selection module is updated with a new labeled validation dataset. This is the supervised step of our method.

Finally, the third module is designed to detect drift. Assuming the prediction $Pred_i$ provided by the previous module as the true label, a drift detector is then applied for each ensemble member, so as to monitor individual pseudo-errors. $Pred_i$ is compared to the output provided by each classifier member. $Pred_i$ is also used to update every ensemble member incrementally as a self-training process. When t members detect a drift, all members and the validation dataset are updated.

The dynamic selection method for the second module and the drift detector for the third module are parameter to be adjusted in DSDD. In addition, other parameters also need to be set, such as: ensemble size (T); number of labeled examples to initiate the online bagging (m); number of members that need to reach the drift level (t); size of initial validation dataset (S); and the number of nearest neighbors to be used by dynamic selection method (kNN).

The aim of DSDD is to overcome strategies for drift detection based on error monitoring or system constant update, especially in practical problems whose data are not fully labeled. In this way, the idea is to detect drift by monitoring pseudo-errors and to update the system only after drift detection. In order to better describe the overview scheme shown in Figure 5.1, we divided this chapter into three sections: ensemble creation, selection module, and detection module.

5.1 Ensemble Creation

Motivated by the advantages of classifier ensembles highlighted in the literature concerning data stream problems, our method is intended to construct diverse ensembles. In addition, the classifier ensembles must be designed to allow incremental learning.

Hence, in the ensemble creation module, we employ a modified version of online bagging (Minku et al, 2010), summarized in Algorithm 5.1, as follows. The first m incoming examples are manually labeled to start the online bagging training process. For each classifier member, each training example is presented n times, where n is defined by $Poisson(\lambda)$ distribution. It is important to observe that, as mentioned before, low λ values lead to high diversity among ensemble members.

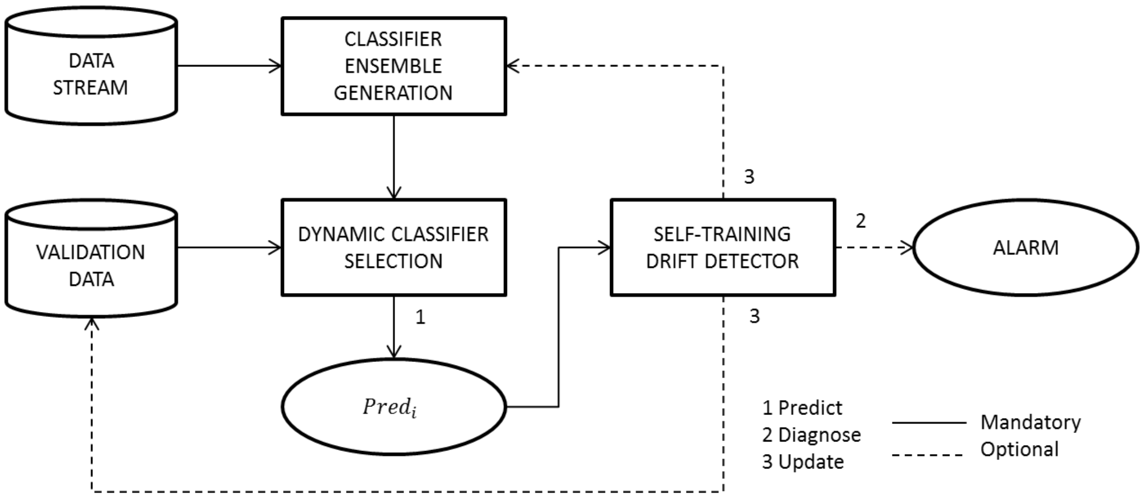


Figure 5.1. Overview scheme of the proposed method (DSDD).

After such a supervised online bagging including the first m incoming examples, online bagging keeps updating the ensemble incrementally, as it is expected. Here, however, the incoming examples after m are no longer manually labeled. The next module (Selection Module) provides a pseudo true label for every incoming example.

Therefore, online bagging is adapted to work as a self-training method. We have initialized the online bagging as supervised in order to generate an accurate ensemble and then to be incrementally updated by self-training.

The base classifiers used in this work are Hoeffding Trees. This choice is especially due to the fact that bagging is used to improve the performance of unstable algorithms, such as decision trees (Breiman, 1996).

5.2 Selection Module

It was mentioned in Chapter 2 that classifier selection is defined as a strategy that assumes each ensemble member as an expert in some regions of competence. Thus, rather than combining all t classifiers generated by online bagging using a fusion function, dynamic selection chooses a winning classifier over samples contained in an independent validation dataset, to assign the label to each x_i incoming sample.

```
input:  $x$: incoming example;
        $M$: ensemble;
        $T$: ensemble size;

begin
for $each\ x$ do
        for $j = 1\ to\ T$ do
                $K = Poisson(\lambda)$;
        while $K > 0$ do
                $M_j = IncrementalUpdate(M_j; x)$;
                $K = K - 1$;
        end
end
end
```

Algorithm 5.1. Online ensemble creation.

There are several different dynamic classifier selection methods reported in the literature. In this work, we employ methods based on the assumption that the best-performing classifier over the local region (k-nearest neighbors) obtained from a validation dataset surrounding x_i is the most confident classifier to label it individually. Hence, the second module of our method is designed to work with a validation dataset, which is created with a small amount of labeled examples.

Two dynamic classifier selection methods are investigated: *Dynamic Classifier Selection with Local Accuracy* (DCS-LA) (Woods et al, 1997) and *Dynamic Classifier Selection based on Multiple Classifier Behavior* (DS-MCB) (Giacinto & Roli, 2001). These methods follow the *Nearest Neighbor Rule* (NN-Rule) (Britto Jr et al, 2014), where methods search for the k-nearest neighbors (kNN) of x_i in the validation dataset. Each ensemble member is evaluated over the kNN of x_i and the best performing classifier is selected to predict x_i.

DCS-LA is a popular accuracy-based method for dynamic classifier selection with two different versions: *Overall Local Accuracy* (OLA) and *Local Class Accuracy* (LCA). The OLA is computed as the amount of neighbors of x_i correctly classified by each member classifier c_j. Then, the member (c^*) with the highest OLA is selected to classify x_i (Equation 5.1).

$$c_x^* = argmax_j(OLA_j) \tag{5.1}$$

In the LCA version, for each member classifier c_j, it is computed the number of neighbors of x_i for which c_j has correctly assigned class ω, but considering only those examples whose label (ω_t) is the same class predicted for x_i (ω_x). In this way, the best member classifier for the current example (c_x^*) is the one with the highest LCA (Equation 5.2).

$$c_x^* = argmax_j\left(LCA_j\right) \mid \omega_t = \omega_x \tag{5.2}$$

DS-MCB is a behavior-based method that uses a similarity function to measure the degree of similarity (Sim) of the output of all classifier members. First, for the incoming example x_i is computed the vector MCB_x of class labels assigned by all classifier members. Thus, for each x_i in the local region (kNN) is also computed the vector $MCB_{k,t}$ of class labels assigned by all classifier members. The method computes the similarity between MCB_x and each $MCB_{k,t}$ to find a new local region (kNN'), i.e., the examples in kNN with the MCB most similar to MCB_x (Equation 5.3). Finally, kNN' is used to select the most accurate classifier by overall local accuracy (OLA), such as DCS-LA, to classify x_i.

$$kNN' = kNN' \cup k_t \mid Sim\left(MCB_x, MCB_{k,t}\right) > threshold \tag{5.3}$$

Finally, in this module, the prediction ($Pred_i$) assigned by the selected classifier is assumed as the true label of x_i and used in the next module, whatever the dynamic selection strategy used to select the most confident classifier to label x_i. We may observe these steps in Algorithm 5.2. In the next module, the new validation dataset is collected to replace the current one when a concept drift occurs.

5.3 Detection Module

In the detection module, we apply a drift detector for each ensemble member. However, since most of the drift detectors are designed to cope only with labeled data, these methods must be tailored to support unlabeled data. In order to accomplish this requirement, in our method we assume that $Pred_i$ is the x_i's true label. Therefore, as in our previous method, our assumption is that any drift detector based on SPC available in the literature may be used to detect drift in the unsupervised detection module of our proposed method.

```
input:   $x$: incoming example;
         $M$: ensemble;
         $T$: ensemble size;
         $S$: labeled validation dataset;
output:  $expert$: member selected to classify $x$;
         $pseudoLabel$: expert member prediction;

begin
for $each\ x$ do
         $kNN = kNearestNeighbours(S;\ x)$;
         for $j = 1\ to\ T$ do
                  $pmcj = evaluate(Mj\ ;\ kNN)$;      //performance of each member
         end
         $expert = selectClassifier(M;\ pmc)$;       //member with best performance
         $pseudoLabel = predict(expert;\ x)$;        //this prediction is assumed as true label
end
end
```

Algorithm 5.2. Selection module algorithm.

In this work, we have tailored two supervised drift detectors to work as unsupervised methods: DDM and EDDM. It works as follows; a pseudo prequential error rate is monitored for each classifier member using $Pred_i$. For instance, given an ensemble M composed of 10 classifiers M_j, where $j = 1 \ldots 10$, there are 10 pseudo prequential error rates to be monitored simultaneously and individually, i.e. 10 local drift detection processes are conducted. Thus, the set of pairs $(Pred_i, x_i)$ which rely on the local warning level (denoted by S_j) is stored to further update its respective classifier member.

In terms of DDM, for each member classifier, the warning level and drift level are reached if conditions (Equation 3.1) or (Equation 3.2) are satisfied, respectively. The p value represents the pseudo error rate of the member classifier, while s denotes its standard deviation. The registers p_{min} and s_{min} are set during the training phase, and are updated if after each incoming example (i) the current register $p_i + s_i$ is lower than $p_{min} + s_{min}$.

On the other hand, when using EDDM's SPC, our method calculates the distance (p') between two consecutive pseudo errors and their standard deviation (s'), and stores the maximum values of p' and s' to register the point where the distance between two errors is maximum ($p'_{max} + 2 * s'_{max}$). According to Baena et al (2006), the warning level is reached when the Equation 3.3 is lower than α, and the drift level is reached when the same Equation 3.3 is lower than β. These two thresholds are defined experimentally. In our experiments, we set α=0,95 and β=0,9.

In this detection module, when the first classifier member M_j reaches its drift level, the whole system is updated and all parameters (such as prequential error and standard deviation) are reset, i.e., each classifier member M_j is updated using its own subset S_j.

However, it is important to mention that only the subset of M_j is labeled and used as new validation dataset, in order to reduce the labeling processing time. For the remaining classifiers, the label of each x_i contained in each S_j is assumed to be its respective $Pred_i$.

In addition, all members are also updated incrementally based on $Pred_i$ due to online bagging self-training, as discussed previously in this chapter. We can observe all the steps executed by the detection module in Algorithm 5.3.

In next section, we present experimental results to verify the performance of our proposed method compared to baselines over several databases. We also compare this method to our DbDDM method.

5.4 Experiments and Results

A series of experiments has been carried out to evaluate our semi-supervised drift detection method. Four different versions of combinations of dynamic selection methods and drift detectors are investigated: DCS-LA+DDM, DCS-LA+EDDM, DS-MCB+DDM and DS-MCB+EDDM. The best version is then compared to SAND, which is a semi-supervised baseline method described in Chapter 3, and to the supervised baseline DDM. Finally, the method proposed in this chapter is also compared to our first proposed method DbDDM.

As mentioned before, we have used online bagging as ensemble creation strategy and Hoeffding Trees as base learning algorithms. The drift detectors were implemented in Matlab 7.10 over Windows 7 in a machine based on Intel Core i7 3520M@2,90 GHz processor using WEKA implementations of the learning algorithms. First, however, we will present details related to the databases investigated in our experiments.

```
input:  $x$: incoming example;
        $M$: current ensemble;
        $R$: alternative ensemble;
        $T$: ensemble size;
        $S$: labeled validation dataset;

begin
for $each\ x$ do
        for $j = 1\ to\ T$ do
                if $p_j reaches\ DriftLevel$ then
                        $labeling(S_j)$;    //validation dataset for selection module
                        $p_j = 1$;
                        for $j = 1\ to\ T$ do
                                $replace(M_j, R_j)$;
                        end
                        break;              //go to the next example
                end
                else if $p_j reaches\ WarningLevel$ then
                        $S_j = add(x)$;
                        $IncrementalUpdate(R_j, x)$;
                end
                else
                        $reset(S_j)$;
                        $IncrementalUpdate(M_j, x)$;
                end
        end
end
end
```

Algorithm 5.3. Detection module algorithm.

In our experiments, we set the following parameters: ensemble size (T) to 10; number of labeled examples to initiate the online bagging (m) to 30; number of members that need to reach the drift level (t) to 1; size of initial validation dataset (S) to 30; and the number of nearest neighbors to be used by the dynamic selection method (kNN) to 10. The methods selected to adjust the second and the third modules are described in section 5.4.2.

5.4.1 Databases

Here, we describe the datasets used for the experiments. Some of artificial datasets, such as SINE1, CIRCLE and SINE1G, are described in Section 4.4.1, previous chapter. Besides SINE1, CIRCLE and SINE1G, and also investigated LINE, which is described below:

- LINE. **Abrupt concept drift, noise-free examples**. This dataset presents two relevant attributes, both assuming values uniformly distributed in [0,1]. The classification function is given by $y = -a_0 + a_1x_1$, where a_0 can assume different values to define different concepts. In this dataset, there are two concepts with high severity.

This artificial dataset has two classes and each class is represented by 50% of the examples, and each 1000 examples represent a concept. Besides these artificial datasets, we have used real datasets in our experiments. It is important to mention that, in the context of real data, we do not know when the drifts occur and which type of drifts occur. The real datasets are described below:

- ELEC2. According to Gama et al. (2006), this dataset is composed of 45312 instances dated from 7 May 1996 to 5 December 1998. Each example of the database refers to a period of 30 minutes and has 5 fields: day of week, time stamp, NSW electricity demand, Vic electricity demand, the scheduled electricity transfer between states and the class label. The latter identifies the change of the price related to a moving average of the last 24 hours.
- LUXEMBOURG. It was constructed using European Social Survey 2002-2007. The task focus on classifying a subject with respect to the internet usage, whether is high or low. Each data sample is represented as a 20-dimensional feature vector. These features were selected as general demographic representation. The dataset is balanced 977 + 924 samples for each class. More details about the dataset creation and data source are found in (Zliobaite, 2011) and (R. Jowell and the Central Coordinating Team, 2003; 2005; 2007).
- KDDCUP99. This is the dataset used for The Third International Knowledge Discovery and Data Mining Tools Competition, which was held in conjunction with KDD-99 The Fifth International Conference on Knowledge Discovery and Data Mining. This dataset

contains simulated intrusions in a military network traffic based on data collected during 7 weeks. KDDCUP99 has approximately 4.900.000 examples, which contain 41 features and are labeled as “bad” (intrusions or attacks) or “good” (normal) connections. We use for our experiments a set containing 10% of the original dataset examples.

5.4.2 Comparison of Different Versions of the Proposed Method

The purpose of these experiments is to compare the performance of our detection method in different versions of combinations of dynamic selection methods and drift detectors. The combinations experimented in this work are: DCS-LA+DDM, DCS-LA+EDDM, DS-MCB+DDM and DS-MCB+EDDM. These versions are used for experiments in both artificial and real datasets. All experiments in this work using DCS-LA are based on OLA version.

The aim of this comparison is to select the version of our method considered with the best performance to be compared to the baselines (DbDDM, SAND and DDM).

5.4.2.1 Experiments on Artificial Datasets

First, we analyze the results obtained on experiments using artificial datasets, which allow getting true, false and missing detections, as well as average detection delays, since it is well known the right moment when the drifts occur.

In Figure 5.2, we can observe the prequential error in artificial datasets using the dynamic selection method DCS-LA combined to DDM (red lines) and EDDM (blue lines). These plots present datasets containing abrupt drifts, such as SINE1 and LINE, and gradual drifts, such as CIRCLE and SINE1G.

Both versions using DCS-LA as dynamic selection strategy present results quite similar on abrupt drift datasets SINE1 and LINE in terms of detecting drifts at the right moment and keeping low prequential error. For the gradual drift datasets CIRCLE and SINE1G, it is more difficult to identify a pattern behavior due to the fact that there are drift detections at the right moment, but detections with long delays and detections before drift are also verified. Even though, both versions keep low prequential error rates when new concepts appear. In all experiments, delays in the drift detections are verified, but we may point out that DCS-LA+EDDM detects drifts earlier than DCS-LA+DDM.

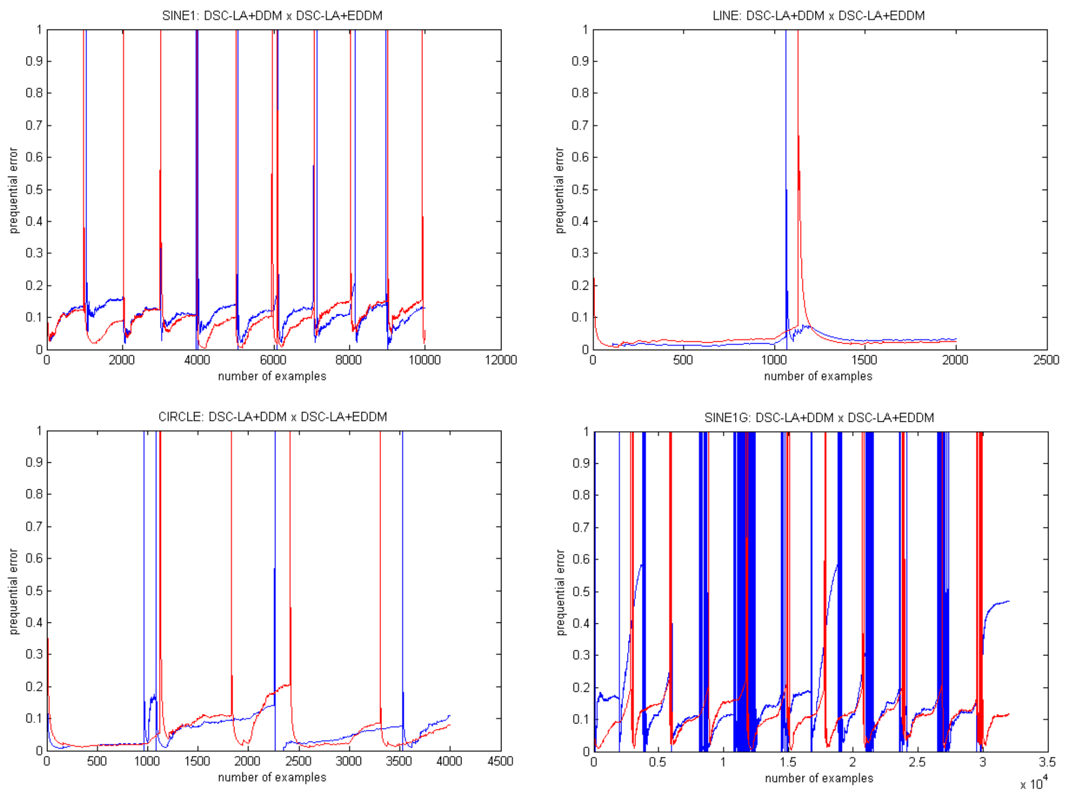


Figure 5.2. Prequential error of versions DCS-LA+DDM (red lines) and DCS-LA+EDDM (blue lines) on artificial datasets. Top Left: SINE1; Top Right: LINE; Bottom Left: CIRCLE; Bottom Right: SINE1G.

Figure 5.3 shows plots presenting the prequential error in artificial datasets obtained when using the dynamic selection method DS-MCB combined to DDM (red lines) and EDDM (blue lines). For the abrupt drift datasets (SINE1 and LINE), both versions with DS-MCB detected drift at the right moment and decreased the prequential error rate. However, DS-MCB+EDDM outperformed DS-MCB+DDM since it presents a smaller number of false detections on SINE1 and earlier reaction on LINE datasets. For CIRCLE, both versions missed detections. Finally, for SINE1G dataset, DS-MCB+EDDM did not detect the last drifts.

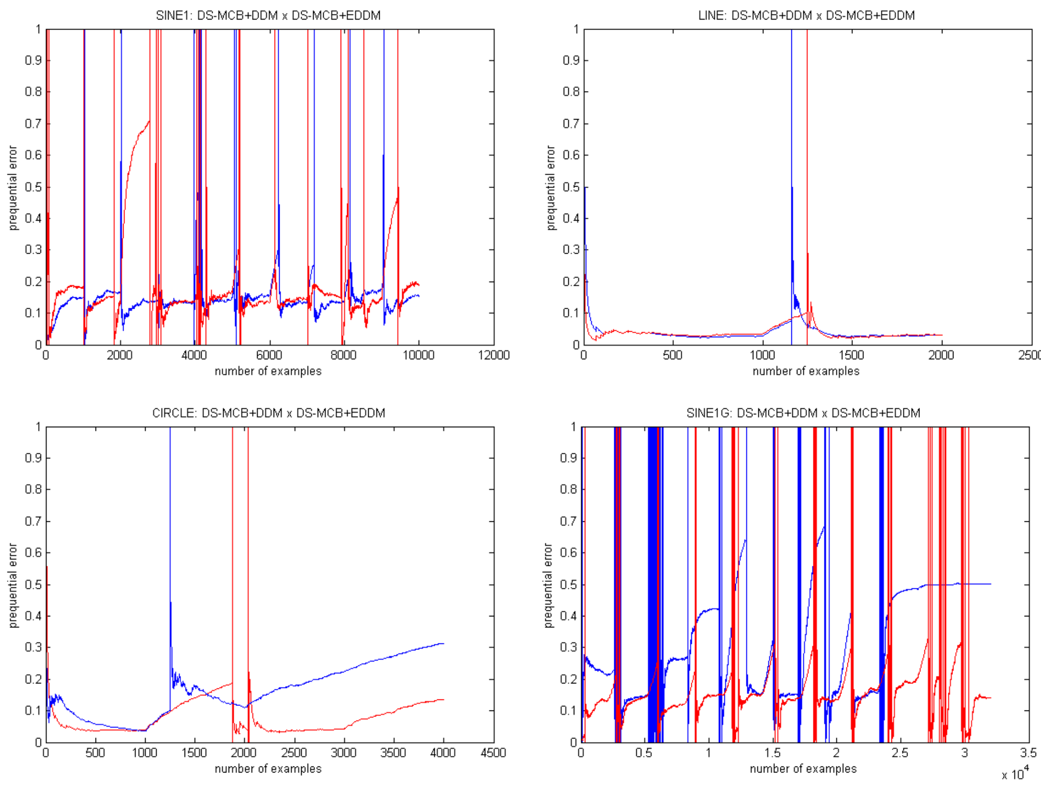


Figure 5.3. Prequential error of versions DS-MCB+DDM (red lines) and DS-MCB+EDDM (blue lines) on artificial datasets. Top Left: SINE1; Top Right: LINE; Bottom Left: CIRCLE; Bottom Right: SINE1G.

If we compare the two versions with DS-MCB to the versions with DCS-LA, some observations can be made from these results: (1) the proposed method using DCS-LA combined to both drift detectors was able to decrease the prequential error rate while learning the new concept before it ended, even with no access to the whole data labels; (2) the two versions using DS-MCB detected all the abrupt drifts but failed to detect some gradual drifts. Table 5.1 summarizes the comparison among all four versions of the proposed method in terms of accuracy, total number of true detections, false detections and missing detections for each dataset. The items presented in Table 5.1 are defined as follows:

- **Accuracy**: the percentage of examples correctly classified in the whole dataset;
- **Average detection delay**: the average number of examples between drift occurrence and true drift detection of all concept drifts. In SINE1G, detections during all transition period are not considered delayed;
- **True detections**: drift detections at the right moments. For abrupt drifts, we consider only the first detection after drift occurrence; for gradual drifts, we consider all the detections occurred in the transition period from one concept to another;

- **False detections**: for abrupt drifts, we consider all the detections after true detection in the same concept; for gradual drifts, we consider all the detections out of transition period since any detection have occurred in the transition period, otherwise, we use the same rule used for abrupt drifts;
- **Missing detections**: concept drifts which are not detected by the method, i.e. false negatives.

From this table, it is possible to observe that only versions including DS-MCB present missing detections on datasets with gradual drifts. This result may be due to the similarity function, which provides wrong new local regions in the transition period. On the other hand, the two versions involving DCS-LA are able to detect all drifts in all datasets. In the next section, we present experimental results to verify whether or not these results are observed considering real datasets.

Table 5.1. Classification accuracy (acc), average detection delay (delay), total number of true detections (TD), false detections (FD) and missing detections (MD) of different versions of DSDD in each artificial dataset.

DSDD version	Dataset	acc(%)	delay	TD	FD	MD
DCS-LA+DDM	SINE1	87,91	27	9	2	0
	LINE	94,8	130	1	0	0
	CIRCLE	90,33	280	3	1	0
	SINE1G	81,13	0	35	2	0
DCS-LA+EDDM	SINE1	85,23	25	9	1	0
	LINE	96,4	65	1	0	0
	CIRCLE	91,1	287	3	1	0
	SINE1G	77,7	0	49	22	0
DS-MCB+DDM	SINE1	74,64	70	9	11	0
	LINE	92,6	246	1	0	0
	CIRCLE	84,42	32	1	1	2
	SINE1G	75,26	0	33	12	0
DS-MCB+EDDM	SINE1	80,14	65	9	4	0
	LINE	94,3	161	1	0	0
	CIRCLE	75,35	248	1	0	2
	SINE1G	63,43	0	36	10	2

5.4.2.2 Experiments on Real Datasets

In these datasets, we do not know where the changes occur and which types of changes exist. Therefore, we are not able to measure true detections, false detections and missing detections. In this way, we present the behavior of the prequential error and the total number of detections over each dataset. The parameters settings are the same used for experiments in artificial datasets.

Figure 5.4 presents the prequential error attained by versions with DCS-LA combined to DDM (red lines) and EDDM (blue lines) on real datasets. For ELEC2, both versions detect a high quantity of drifts during the dataset but they keep low prequential error rates. In LUXEMBOURG, each version finds drifts in different moments of the dataset and they both keep low prequential error rates. In KDDCUP99, we plot the prequential error rate for the 100.000 first examples in order to provide a better visualization of the result; however, both versions with DCS-LA were able to keep low prequential error rates during the whole dataset presenting a high amount of drift detections.

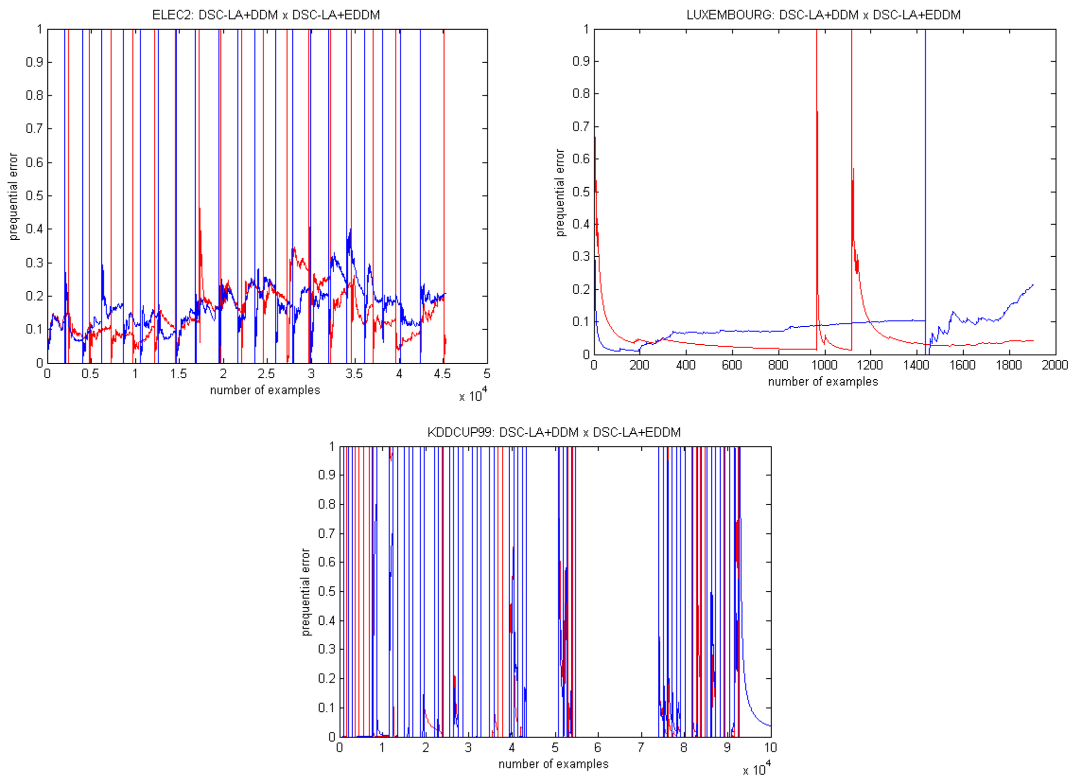


Figure 5.4. Prequential error of versions DCS-LA+DDM (red lines) and DCS-LA+EDDM (blue lines) on real datasets. Top Left: ELEC2; Top Right: LUXEMBOURG; Bottom: KDDCUP99.

In Figure 5.5, we can observe the prequential error of the versions with DS-MCB combined to DDM (red lines) and EDDM (blue lines) on real datasets. In ELEC2, the results are quite similar to the results using DCS-LA: a lot of detections during the dataset and decreasing the prequential error. In LUXEMBOURG, DS-MCB+DDM was able to decrease the prequential error rate after first detection, while DS-MCB+EDDM keeps the prequential error stable after detection. In KDDCUP99, both versions keep low prequential error rates, but it is possible to observe that DS-MCB+EDDM presents less detections than DS-MCB+DDM, and consequently lower accuracy rate.

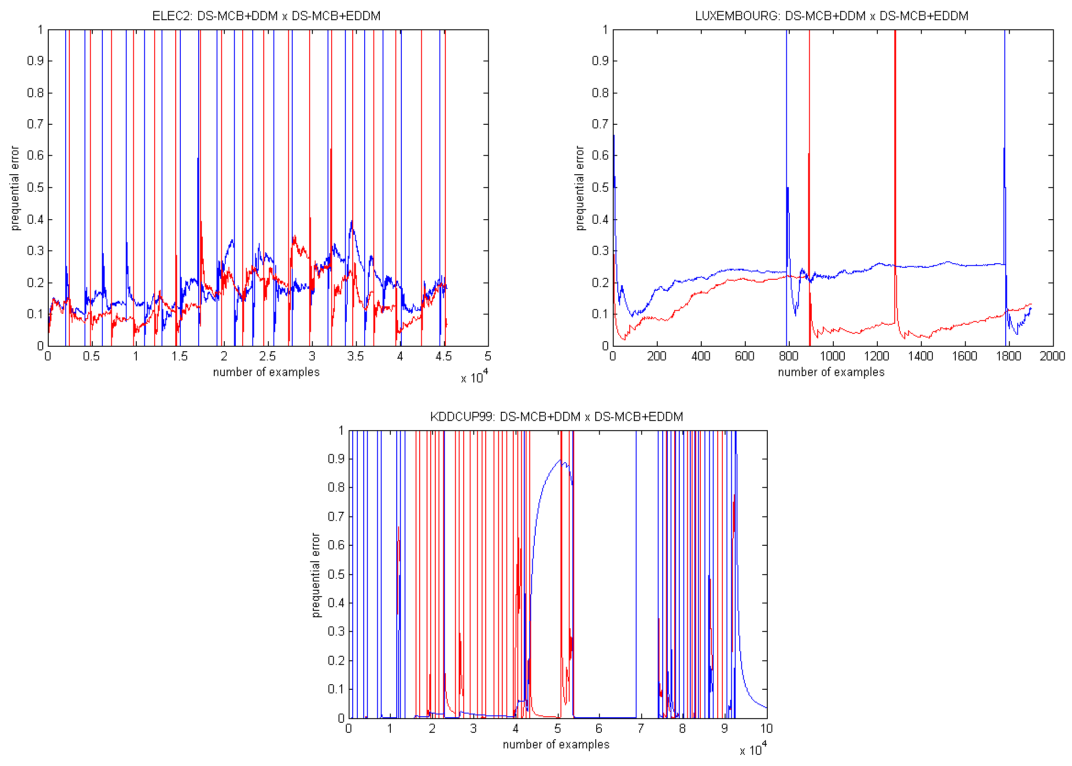


Figure 5.5. Prequential error of versions DS-MCB+DDM (red lines) and DS-MCB+EDDM (blue lines) on real datasets. Top Left: ELEC2; Top Right: LUXEMBOURG; Bottom: KDDCUP99.

Table 5.2 presents the classification accuracy and total number of detections attained by the four versions of DSDD at the end of each dataset. The same behavior pointed out for the artificial datasets was observed for the real databases investigated: versions using DCS-LA outperformed the DS-MCB-based versions. In terms of accuracy rates, for ELEC2 dataset, DCS-LA+DDM was slightly superior to DCS-LA+EDDM, while the difference between DCS-LA+DDM and DS-MCB-based versions was higher. Even though, the performances attained by all four versions are quite similar, since they present accuracy rates ranging from 81,12% to 84,16%.

Table 5.2. Classification accuracy (acc) and total number of detections of different versions of DSDD in each real dataset.

DSDD version	Dataset	acc(%)	Detections
DCS-LA+DDM	ELEC2	84,16	18
	LUXEMBOURG	97,53	2
	KDDCUP99	96,28	258
DCS-LA+EDDM	ELEC2	83,03	20
	LUXEMBOURG	87,01	1
	KDDCUP99	95,13	262
DS-MCB+DDM	ELEC2	81,12	17
	LUXEMBOURG	83,75	2
	KDDCUP99	95,82	266
DS-MCB+EDDM	ELEC2	81,45	21
	LUXEMBOURG	76,12	2
	KDDCUP99	90,92	206

Finally, these accuracies show that our DCS-LA+DDM version is able to cope with drifts presented in LUXEMBOURG and KDDCUP99 datasets classifying correctly more than 90% of the examples, in despite of using labels partially only. On the other hand, DS-MCB+EDDM presents the lowest accuracy rates for LUXEMBOURG (76,12%) and KDDCUP99 (90,92%), it may due to the concepts with small number of examples or to the sensitivity to outliers.

In response to the question posed in the beginning of this section, i.e., which is the best version of DSDD? DCS-LA+DDM may be deemed to be the best strategy. First, based on the classification accuracy results, this version attained the highest rate in 5 datasets (2 artificial and the 3 real datasets) out of a total of 7 datasets investigated. In addition, DCS-LA+DDM does not present missing detections in none of the artificial datasets. In this way, we choose the version DCS-LA+DDM to be compared to the baselines in the next section, due to its best performances in high accuracy rates and true detections.

5.4.3 Comparison of the Proposed Method to Baselines

In these experiments, we intend to compare the best version of DSDD selected by previous experiments (DCS-LA+DDM) to DbDDM and two different baselines. The first baseline is SAND, a semi-supervised method such as ours; and the second baseline is the supervised method DDM. The objective of this comparison is to show that our method is able to deal with concept drifts even when there are no fully labels available. We choose DDM because it is part of the selected version of DSDD.

It is important to mention that there is no comparison in terms of prequential error due to the fact that SAND does not provide results in prequential error. Thus, the comparison summarized in Tables 5.3 and 5.4 is performed by taking into account other measures such as accuracy, delay, true and false detections, etc.

5.4.3.1 Experiments on Artificial Datasets

For these experiments, we include the number of labeled examples as evaluation metric for the methods. In addition, Table 5.3 also presents the classification accuracy, average detection delay, total number of true detections, false detections and missing detections of our method DCS-LA+DDM, DbDDM, SAND and DDM at the end of each dataset. DCS-LA+DDM was able to detect all drifts in all datasets such as DDM. In SINE1G dataset, our method presents a high quantity of true detections in all experiments, but it is important to say that the detections were suggested in the transition period of 1000 examples. In addition, DCS-LA+DDM reaches high accuracy rates such as both baselines.

DbDDM presents accuracy rates quite similar to the other methods investigated. Although this method uses 100% of the labeled examples, the detection module monitors a pseudo-error. DbDDM detects all drifts at the right moment with no false or missing detections.

The results achieved using DDM were expected, since it is a supervised drift detector. DDM presented the best performance on attaining the highest accuracy rates, with no false detections or missing detections. However, in terms of accuracy rates, the rates reached by DCS-LA+DDM and SAND were on average 6% lower than DDM's accuracy rates for SINE1, LINE and CIRCLE datasets, while both semi-supervised methods outperformed DDM in SINE1G dataset. Especially noteworthy is the fact that the semi-supervised methods dealt with only 5% of labeled data, on average, in order to attain these high accuracy rates.

In terms of number of labeled examples, our method selects those examples that rely on warning level by statistical tests; while SAND selects those examples based on classifier confidence lower than a threshold. In this way, SAND presents a more robust method to select few examples among more recent examples to be labeled. However, in datasets such as SINE1 and SINE1G, SAND presents more missing detections than true detections. Such a weak result may be due to the classification function of these datasets. Since the classification is reversed after concept drifts, in this case, the classifier confidence will remain high but the predictor will classify data incorrectly. In addition, SAND is strongly dependent on fine-tuning the threshold parameter. SAND missed 8 true detections in SINE1 dataset and 7 true detections in SINE1G dataset. While in LINE and CIRCLE datasets, SAND takes advantage since it presents lower detection delays.

From this table, some observations can be made:

- Our semi-supervised drift detector outperformed the semi-supervised baseline SAND in all aspects investigated, except for the percentage of labeled examples.
- When comparing our two proposed methods, except for LINE dataset, DbDDM achieved higher accuracy rates. In terms of detection delay, DCS-LA+DDM presents higher delay, in general. The same scenario is observed when false detection is taken into account. Therefore, we may conclude that, in practical problems, when the true labels of newly instances are immediately available, DbDDM is more effective than DCS-LA+DDM.

Table 5.3. Classification accuracy (acc), average detection delay (delay) number of true detections (TD), false detections (FD), missing detections (MD) and percentage of labeled examples (lbl) in each dataset.

Method	dataset	acc(%)	delay	TD	FD	MD	lbl(%)
DCS-LA+DDM (DSDD)	SINE1	87,91	27	**9**	2	**0**	1,6
	LINE	94,8	130	**1**	**0**	**0**	0,25
	CIRCLE	90,33	280	**3**	1	**0**	1,05
	SINE1G	81,13	**0**	35	2	**0**	0,5
DbDDM	SINE1	91,37	73	**9**	**0**	**0**	100
	LINE	93,20	92	**1**	**0**	**0**	100
	CIRCLE	92,82	154	**3**	**0**	**0**	100
	SINE1G	**83,95**	**0**	20	**0**	**0**	100
SAND	SINE1	84,25	95	1	**0**	8	**0,03**
	LINE	94,9	83	**1**	**0**	**0**	**0,1**
	CIRCLE	91,4	**15**	**3**	3	**0**	**0,1**
	SINE1G	83,12	**0**	3	**0**	7	**0,02**
DDM	SINE1	**96,28**	**11**	**9**	**0**	**0**	100
	LINE	**97,55**	**25**	**1**	**0**	**0**	100
	CIRCLE	**96,8**	32	**3**	**0**	**0**	100
	SINE1G	79,67	**0**	**13**	**0**	**0**	100

5.4.3.2 Experiments on Real Datasets

As mentioned before, with real datasets we can evaluate the classification accuracy, the total number of detections and the percentage of labeled examples in the whole dataset. In order to compare DSDD to DbDDM, SAND and DDM, we choose again the version DCS-LA+DDM due to the best performance at decreasing prequential error in both real datasets.

In Table 5.4, we can observe that DCS-LA+DDM presents the highest accuracy rate in LUXEMBOURG dataset followed by DbDDM, and both probably find two true detections. SAND takes advantage in accuracy on ELEC2 while our method reaches accuracy rates quite similar to DbDDM and DDM. However, in ELEC2, DCS-LA-DDM presents the smallest number of detections, which implies in lower computational costs. In addition, our method and SAND reach high accuracy rates even using a limited number of labeled examples.

In terms of the KDDCUP99 dataset, our method reaches higher accuracy rates than DbDDM and accuracy rates quite similar to DDM, despite using only 23,01% of labeled examples. In addition, for this last dataset, SAND reaches the lowest accuracy rates compared to the other investigated methods.

Table 5.4. Classification accuracy (acc), total number of detections, and percentage of labeled examples (lbl) in each real dataset.

method	Dataset	acc(%)	detections	lbl(%)
DCS-LA+DDM (DSDD)	ELEC2	84,16	18	0,4
	LUXEMBOURG	**97,53**	2	6,0
	KDDCUP99	96,28	258	23,01
DbDDM	ELEC2	81,55	78	100
	LUXEMBOURG	93,61	2	100
	KDDCUP99	90,11	192	100
SAND	ELEC2	**94,62**	44	**0,1**
	LUXEMBOURG	85,11	1	**1,0**
	KDDCUP99	74,81	190	**0,5**
DDM	ELEC2	83,06	128	100
	LUXEMBOURG	79,80	0	100
	KDDCUP99	**99,91**	53	100

It is also important to mention that both semi-supervised methods DCS-LA+DDM and SAND outperformed DDM on real datasets, except for KDDCUP99, which was not an expected result, since DDM is a supervised method. These interesting results indicate that semi-supervised methods, besides reducing the dependence on labeled data, may also deal very effectively with drifts in real application problems.

5.5 Final Considerations

The DSDD also intends to deal with data streams in practical problems since it detects drifts and reacts to them considering unlabeled data. Its main goals are to estimate the pseudo error to be monitored, and to overcome the main DbDDM's drawback, i.e. supervised reference cluster update.

To ensure good online predictions to be assumed as "true labels" and to estimate the pseudo error, we use dynamic classifier selection in a diverse ensemble of classifiers generated by online bagging. The predicted label is used to update each ensemble member incrementally.

To detect drifts, drift detectors are applied independently and simultaneously for each ensemble member. They monitor different prequential pseudo error rates until the first member suggests a drift detection. This is moment when the whole ensemble is updated using recent examples.

This proposed method is flexible enough to be adjusted to different dynamic classifier selection techniques and different drift detectors. We experimented four different combinations using real and artificial datasets in order to select the best one to be compared to other baselines. The best results were attained to the combination DCS-LA+DDM.

Moreover, we compared this DSDD version (DCS-LA+DDM) to three baselines, DbDDM, SAND and DDM. Our method achieved competitive results in terms of accuracy rates, drift detection at the right moments and drift reaction delays. In addition, DSDD and SAND were able to achieve good performances even using a limited amount of labeled data. Finally, the DSDD outperformed DDM over real datasets, which is an unexpected result since DDM is a supervised method.

Chapter 6

Conclusions

This work proposes two new methods to be applied in practical problems involving data stream, such as spam filtering and fraud detection. The objective of the proposed methods is to maintain low error rates, even in the presence of concept drifts, by detecting drifts and adapting the classification system to the new concepts. The main goals of this work is to avoid strategies that detect drifts relied on system performance decreasing, i.e. based on error monitoring; and to avoid blind update-based strategies, which update the system constantly, whatever the drift detection is implicit or explicit.

The first proposed method, DbDDM, is based on two modules: dissimilarity and detection, which share the same application, but can be used in collaboration or independently. DbDDM uses the dissimilarity calculated between current and past data to estimate the pseudo prequential error. Based on pseudo prequential error values, DbDDM may employ the same statistical tests conducted in traditional drift detectors to suggest drifts. In this work, DDM and EDDM were investigated as drift detectors for DbDDM. This proposed method also maintains the decision model until drift detection, when the system reacts by updating the decision model (current classifier and reference clusters) using the next examples by one-pass learning, and consequently, forgetting the previous knowledge. However, even though this method does not use the true label for drift detection, it deals with clusters which are updated incrementally in a fully supervised way.

It is important to mention that in practical problems we may not assume that the true labels of the instances are fully and immediately available after classification, as expected for DbDDM.

Therefore, we propose another method that, besides avoiding the same drawbacks dealt with by DbDDM, also focuses on reducing the labeling process. In this case, the drift detection task is fully unsupervised, while labeled samples are needed just to update the model, i.e., after drift detection. Besides, if the concept is stable, all online system updates are based on self-training. The most relevant differences between our two proposed methods are highlighted in Table 6.1.

This second proposed method, DSDD, is based on three modules: ensemble creation, classifier selection and drift detection. First, it creates an ensemble of classifiers using the modified online bagging (Minku & Yao, 2010), which includes diversity between ensemble members. Afterwards, the ensemble classifier estimates online predictions by means of dynamic selection of classifier, i.e., the best performing classifier (expert) on a validation dataset is selected to predict each unknown example. These predictions are assumed as "true labels", making possible to apply any common drift detector for each ensemble member. The ensemble's assigned prediction is used for online learning self-training. After drift detection, both validation dataset and the whole ensemble of classifiers are update.

Table 6.1. Relevant differences between DbDDM and DSDD.

Method	**Classifiers**	**Incremental Learning**	**Classifier Updates**	**Pseudo-error Estimator**	**After Drift Detection**
DbDDM	Single	Supervised (clusters)	One-Pass	Dissimilarity	Update of Reference Clusters and Classifier
DSDD	Ensemble	Self-Training (ensemble)	Online	Expert Classifier	Update of Validation Dataset and Ensemble Classifiers

We consider DbDDM as a first attempt to reach our objectives. However, it was possible to detect some drawbacks, such as fully supervised learning or the use of dissimilarity measure to provide predictions to be assumed as true labels. The experiments presented promising results and, despite these drawbacks, it is possible to follow the idea of monitoring pseudo error.

For the DSDD, we avoid DbDDM's drawbacks by using semi-supervised learning and providing "true labels" by dynamic classifier selection. Our semi-supervised DSDD presents competitive results when compared to DbDDM and another semi-supervised method (SAND). However, it is important to say that SAND provides drift detections by monitoring windows with the most recent examples; and drift reactions by batch learning. On the other hand, DSDD deals with drifts by processing each incoming example separately (online learning) following the configuration of ideal drift detection method for practical problems discussed in Section 3.4.

In addition, when compared to a supervised method (DDM), DSDD attained performances quite similar or even better, such as the classification accuracy reached on all investigated real datasets. These results were not expected since DDM is a supervised drift detector.

6.1 Limitations and Future Work

Given that the second proposed method (DSDD) is accomplished using unlabeled data and avoiding blind updates, the drift detections, classification error rates and the system reaction delays attained by our method may be assumed to be very promising, but subjected to more analysis aiming to decrease the prequential error rates and leading drift reactions to be faster.

This method reacts to drifts by replacing the whole ensemble of classifiers when a concept drift is detected. This may increase the prequential error rate when recurring concepts are involved. In addition, it may increases the reaction delay since all classifier members represent the same concept and all of them need to be replaced after drift detection.

For future work, in the drift reaction system, an alternative to overcome the drawbacks mentioned before is to remove the poorest performing member classifier when adding a new member containing examples of the new concept. In this way, it is possible to maintain previous knowledge and, consequently, reducing prequential error rates and the reaction delay

Moreover, DSDD experiments used dynamic selection methods of a single classifier. The selection module of DSDD may also be adjusted to use dynamic ensemble selection methods such as KNORA (*k-Nearest-Oracles*) proposed by Ko et al (2008); since there is more than one expert, it may assure better predictions in transition periods between different concepts.

Another issue to investigate is the ensemble generation process. The proposed method creates a diverse ensemble by online bagging using self-training. Other ensemble generation techniques (such as mentioned in section 2.3.2.1) may be combined to self-training and adapted to online systems.

Finally, our proposed method, DSDD, uses semi-supervised learning selecting a small number of examples to be labeled by applying statistical tests on pseudo error monitoring. There are others example query strategies (Settles, 2010) that may be investigated to reduce the labeling process, such as query by ensemble that label those examples for which the ensemble members disagree the most.

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