Advances in Data Stream Mining with Concept Drift

Thesis · March 2017

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Recife

2017

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Thesis submitted to examination committee at Centro de Informática, Universidade Federal de Pernambuco, as partial requirement to promotion to Full Professorship.

Universidade Federal de Pernambuco – UFPE

Centro de Informática

Recife

2017

Barros, Roberto Souto Maior de

Advances in Data Stream Mining with Concept Drift / Roberto Souto Maior de Barros. – Recife, 2017.
158 p. : il. (algumas color.) ; 30 cm.

Thesis – Universidade Federal de Pernambuco – UFPE,
Centro de Informática, 2017.

1. Concept Drift. 2. Data Streams. 3. Concept Drift Detection Methods. 4. Ensemble. 5. Large-scale Evaluation. I. Roberto Souto Maior de Barros. II. Universidade Federal de Pernambuco. III. Centro de Informática
IV. Advances in Data Stream Mining with Concept Drift.

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Advances in Data Stream Mining with Concept Drift

Tese apresentada para banca examinadora no Centro de Informática da Universidade Federal de Pernambuco como requisito parcial para Promoção para o cargo de Professor Titular.

Trabalho aprovado. Recife, 14 de Março de 2017.

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Recife
2017

Abstract

Online learning regards extracting information from large quantities of data flowing rapidly and continuously (data streams), which are usually affected by changes in the data distribution (concept drift). Drift detection methods are software that mostly attempt to estimate the concept drift positions in data streams in order to substitute the base learner after these changes and ultimately improve accuracy. Ensembles of classifiers have also been proposed to address the problem of mining data streams, with or without explicit concept drift detection, and those ensembles which explicitly detect the drifts, sometimes, use concept drift detectors as auxiliary methods.

This thesis proposes two new concept drift detection methods (RDDM and WSTD) and a new ensemble algorithm (BOLE), which is configurable with an auxiliary concept drift detector, aimed at improving the detections of the drifts and the accuracy of current methods in data streams containing concept drift.

This thesis also performed large-scale comparisons of 15 drift detectors configurations and of five ensemble algorithms, configurable with drift detectors, for mining data streams with concept drift, using a large number of artificial datasets and two different base classifiers (Naive Bayes and Hoeffding Trees), aimed at adequately measuring how good the proposed methods are and also at verifying/challenging common beliefs in the area.

The results of the experiments suggest the three proposed methods are efficient in at least some scenarios and the best detectors in terms of accuracy are *not* necessarily those that detect the existing drifts closer to the correct positions, only detecting these. In addition, the auxiliary detectors, inside ensembles, that maximize the accuracy of the ensembles are also somewhat different from the best detectors in terms of either accuracy or detections. Finally, in most datasets, the choice of ensemble algorithm has much more impact on the final accuracy of the ensemble than the choice of concept drift detector.

Keywords: Data Streams, Concept Drift, Drift Detection, Ensemble, Online Learning.

Resumo

O aprendizado online tem como objetivo a extração de informações a partir de uma grande quantidade de dados coletados continuamente e em velocidade (fluxos de dados), que são normalmemente afetados por mudanças na sua distribuição (mudanças de conceito). Métodos detectores de mudanças de conceitos são algoritmos que tentam estimar as posições das mudanças de conceito em fluxos de dados visando substituir o classificador base após estas mudanças e melhorar a acurácia. Comitês de classificadores também já foram propostos para atacar o problema de mineração em fluxos de dados, com ou sem detecção explícita de mudanças de conceito, e, dentre os comitês que explicitamente detectam as mudanças, vários usam detectores como métodos auxiliares.

Esta tese propõe dois novos métodos detectores de mudanças de conceito (RDDM e WSTD) e um novo comitê de classificadores (BOLE), configurável com um detector de mudanças auxiliar, com o objetivo de melhorar as detecções das mudanças e a acurácia de outros métodos atuais para mineração em fluxos de dados contendo mudanças de conceito.

Esta tese também realizou comparações de larga escala com 15 configurações de detectores de mudanças e com 5 métodos de comitês, configuráveis com métodos detectores, para mineração em fluxos de dados com mudanças de conceito, usando um grande número de bases de dados artificiais e dois classificadores base (Naive Bayes e Hoeffding Trees), com o objetivo de medir adequadamente quão bons são os métodos propostos e também verificar/desafiar crenças comuns na área.

Os resultados dos experimentos sugerem que os três métodos propostos são eficientes em pelo menos alguns cenários e que os melhores detectores em termos de acurácia *não* são necessariamente aqueles que detecctam as mudanças mais próximo de suas posições corretas, detectando apenas estas. Além disto, os detectores auxiliares, dentro de comitês, que maximizam a acurácia dos comitês também não coincidem exatamente com os melhores detectores em termos de acurácia ou de detecções. Finalmente, na maioria das bases de dados, a escolha do algoritmo do comitê tem muito mais impacto na acurácia final do comitê do que a escolha do método auxiliar adotado para detectar as mudanças de conceito.

Palavras-chave: Fluxos de Dados, Mudança de Conceito, Detecção de Mudanças de Conceito, Comitês de Classificadores, Aprendizado Online.

List of Figures

List of Tables

Contents

1 Introduction

Data stream environments frequently contain very large amounts of data, which may be infinite, flowing rapidly and continuously. Applications aimed at mining data streams are usually required to process this information online, i.e., as they arrive, because it is often impractical or even impossible to store all the data. In other words, restrictions on usage of memory and run-time usually apply and multiple reading of the same instance of data is normally not allowed.

In addition, because these data are frequently collected over long periods of time, usually the data distribution will not be stationary. This phenomenon is commonly known as concept drift (GAMA et al., 2014), and concepts may recur (GONÇALVES JR.; BARROS, 2013). Machine learning and mining from data streams in the presence of concept drift is the scenario considered online learning in this work.

The most common categorization of concept drift is based on the speed of the changes. When the changes from one concept to another are sudden and/or rapid, they are called *abrupt* and, when the transitions between concepts occur over a number of instances, they are called *gradual*.

A different categorization of concept drift reflects the reason of change. A drift is *real* when a set of examples has legitimate class labels at one time and different legitimate labels at another time (KOLTER; MALOOF, 2007). Drifts are *virtual* when the target concepts remain the same but the data distribution changes (DELANY et al., 2005). In practice, they often occur together (TSYMBAL et al., 2008).

In the real world, there are many examples of online applications with concept drift (ŽLIOBAITĖ; PECHENIZKIY; GAMA, 2016), including monitoring data from sensors (LEE; WANG; RYU, 2007), TCP/IP traffic, or the purchase history of customers, filtering spam in e-mail messages (KATAKIS; TSOUMAKAS; VLAHAVAS, 2010), intrusion detection (LANE; BRODLEY, 1998), sentiment analysis (SMAILOVIC et al., 2014), as well as the detection of changes in weather or water temperature, among others.

Several directions have already been investigated to learn from data streams containing concept drift. One that is very common refers to concept drift detection methods (GONÇALVES JR. et al., 2014), lightweight software that focus on identifying changes in the data distribution. In general, these identifications are the result of monitoring the prediction results of a separate base classifier.

Many concept drift detection methods have been published over the years. The most well-known methods include Drift Detection Method (DDM) (GAMA et al., 2004), Early

Drift Detection Method (EDDM) (BAENA-GARCIA et al., 2006), Adaptive Windowing (ADWIN) (BIFET; GAVALDÀ, 2007), Statistical Test of Equal Proportions (STEPD) (NISHIDA; YAMAUCHI, 2007), Paired Learners (PL) (BACH; MALOOF, 2008), and EWMA for Concept Drift Detection (ECDD) (ROSS et al., 2012). From these, DDM and STEPD are among the most simple algorithms and, in spite of this, they present good all-round performance (GONÇALVES JR. et al., 2014).

Other more recent concept drift detectors have also been proposed, including Sequential Drift (SeqDrift) (PEARS; SAKTHITHASAN; KOH, 2014), Drift Detection Methods based on Hoeffding's Bounds (HDDM) (FRÍAS-BLANCO et al., 2015), and Fisher Test Drift Detector (FTDD) (CABRAL, 2017).

Another common approach is to use ensembles with a base learner and sometimes more sophisticated strategies and/or different weighting functions to compute the resulting classification, including Dynamic Weighted Majority (DWM) (KOLTER; MALOOF, 2007), Diversity for Dealing with Drifts (DDD) (MINKU; YAO, 2012), Adaptable Diversity-based Online Boosting (ADOB) (SANTOS et al., 2014), and Fast Adaptive Stacking of Ensembles (FASE) (FRÍAS-BLANCO et al., 2016). Some methods concentrate on detecting recurring concepts and reusing previous classifiers, e.g. Recurring Concept Drifts (RCD) (GONÇALVES JR.; BARROS, 2013).

Additionally, it is worth pointing out that many ensembles also rely on an auxiliary drift detection method (BIFET et al., 2009; MINKU; YAO, 2012; GONÇALVES JR.; BARROS, 2013; SANTOS et al., 2014; FRÍAS-BLANCO et al., 2016), etc.

Ensembles of concept drift detection methods sharing the same base classifier is another approach which was comparatively less explored (DU et al., 2014; MACIEL; SANTOS; BARROS, 2015).

In all these approaches, most methods have their own parameters and their optimal values vary depending on the datasets used, the type of drift these datasets have, the values of the other parameters, etc.

1.1 Objective and Motivation

The main objective of this work is to advance the state of the art in data stream mining, proposing new concept drift detection methods and ensembles that improve the detections of concept drifts and/or the resulting accuracy of existing methods. Moreover, this includes verifying/challenging the common wisdom in the area that (a) the best drift detection methods are necessarily those that detect all the existing concept drifts closer to their correct points, ideally detecting only these drifts, and (b) that ensembles which internally use concept drift detectors would deliver their best results when using the best drift detection methods according to the understanding given in (a).

The main motivation is the fact that the real world often does not behave according to the expectations or predictions of currently accepted theoretical models. In addition, in most given problems, different objectives usually require alternative solutions.

For example, cars are normally expected to remain in the main driveways at all times, irrespective of the reason they are being driven. This is certainly part of the best practices to avoid accidents in normal everyday driving. However, in car racing, where the objective is to go a certain distance as quickly as possible, this is not always the best strategy. In this scenario, a certain amount of sliding of the cars out of the main path of the track is often beneficial, especially in go karts and rally racing, and even in formula one racing.

Similarly, it might be that detecting the existing concept drifts very close to their exact positions, and only detecting these drifts, is not the best strategy to maximize the accuracy of the classifiers in some real-world problems. In other words, minimizing the distance of the true positive detections as well as the false negative and false positive detections might not be the best strategy to maximize accuracy in some scenarios. More specifically, a small amount of false negatives and/or false positives might indeed be beneficial, helping to improve the accuracy of the classifiers in some problems.

Another motivation is the belief that the objective of new methods should always be to actually work, e.g. to maximize the accuracy results, or to minimize the false negative and/or false positive detections, over a broad range of applications or at least for some specifically delimited scenario(s), irrespective of how complicated their technical details might be. Often, it seems the academic community has not been valuing this objective enough, giving more attention to technically complicated solutions, even when they do not seem to work very well.

1.2 Contributions

This thesis proposes two new concept drift detection methods and a new ensemble for data stream mining.

Reactive Drift Detection Method (RDDM) is a new detector inspired on DDM (GAMA et al., 2004). Among other heuristic modifications, it proposes to discard older instances of very long concepts aiming to detect drifts earlier, improving the precision of its detections and especially the final accuracy. These improvements in the accuracy results are specially substantial when the sizes of the concepts are many thousand instances long. Moreover, using its recommended default configuration, RDDM presents especially strong performance in datasets with gradual concept drifts, which are generally acknowledged as more difficult to detect and more common in real-world problems.

Wilcoxon Rank Sum Test Drift Detector (WSTD) is another novel drift detection method, inspired on STEPD (NISHIDA; YAMAUCHI, 2007), which provides an efficient implementation of the Wilcoxon rank-sum statistical test (WILCOXON, 1945) and applies it to detect concept drifts, improving the drift detections of STEPD as well as its accuracy in most scenarios. Even though WSTD presents strong all-round performance in the reported experiments, its accuracy improvements are usually larger in datasets with abrupt concept drifts. Finally, it is worth emphasizing its main strength is the precision of its detections of concept drifts.

Boosting-like Online Learning Ensemble (BOLE) is based on heuristic modifications to ADOB (SANTOS et al., 2014), which is a modified version of Oza and Russell's Online Boosting (OZA; RUSSELL, 2001). More precisely, BOLE weakens the requirements to allow the experts to vote and changes the concept drift detection method internally used, improving the ensemble accuracy in most situations. The first round of experiments, reported in Chapter 5, shows the improvements are specially evident when the concept drifts are frequent and/or abrupt, where the accuracy gains can be very high. However, despite its simplicity, the experiments of Chapter 7 confirm BOLE delivers very strong performance in most datasets, irrespective of drift detection method used.

The three proposed methods were implemented in Java to be run in the Massive Online Analysis (MOA) framework (BIFET et al., 2010). In addition, their source codes will soon be freely available — in fact, the source code of BOLE already is — and this permits further experiments by other researchers.

In addition, the work reported in this thesis carried out large-scale comparisons of both concept drift detection methods and ensembles for mining data streams affected by concept drift. More specifically, 15 different configurations of concept drift detectors are compared in terms of their final accuracies and of the precision of their detections of concept drift.

Then, *five* configurations of ensembles, that are parametrized with an auxiliary drift detector, are paired with each of *eight* selected drift detection methods configurations and the accuracies of these 40 combinations are compared among themselves as well as against the selected detectors' configurations individually.

All these comparisons were performed using a considerably large number of artificial datasets, with both abrupt and gradual concept drift versions of several sizes, using two different base classifiers, and were all run in the MOA framework.

The results of these large-scale experiments, still unpublished, provide indications, for two different base classifiers, of (a) the best concept drift detectors, both individually and as auxiliary methods inside ensembles, (b) the best ensembles, irrespective of drift detector adopted, and (c) the best ensemble-detector combinations. They also give indications of how much do the type of concept drift, the dataset generators, and the size of the concepts affect these answers. The three methods proposed in this thesis are all among the best in these experiments in at least some scenarios.

More specifically, these experiments were designed to answer the following research questions (RQ) for two very popular base classifiers in the data streams area, namely Naive Bayes (NB) (JOHN; LANGLEY, 1995) and Hoeffding Tree (HT) (HULTEN; SPENCER; DOMINGOS, 2001):

- **RQ1:** What are the best drift detectors in terms of accuracy in abrupt and gradual concept drift datasets?
- **RQ2:** What are the best concept drift detectors in terms of detections, measured by precision and recall (FAWCETT, 2006) and the Matthews Correlation Coefficient (MCC) metric (MATTHEWS, 1975), in the abrupt datasets?
- **RQ3:** Do the answers of **RQ1** and **RQ2** vary with the different dataset generators used in the experiments? How much?
- **RQ4:** Do the answers of **RQ1** and **RQ2** depend on the size of the concepts included in the datasets? How much?
- **RQ5:** In the same datasets, are the best methods of **RQ1** and **RQ2** the same? To what extent?
- **RQ6:** What are the best ensemble plus drift detector combinations in terms of final accuracy in abrupt and gradual concept drift datasets?
- **RQ7:** What are the best ensembles in terms of accuracy in abrupt and gradual drift datasets irrespective of the auxiliary concept drift detector used?
- **RQ8:** What are the best concept drift detectors as auxiliary methods in ensembles in terms of accuracy of the ensembles in abrupt and gradual concept drift datasets?
- **RQ9:** Do the answers of **RQ6**, **RQ7**, and **RQ8** vary with the different dataset generators used in the experiments? How much?
- **RQ10:** Do the answers of **RQ6**, **RQ7**, and **RQ8** depend on the size of the concepts included in the datasets? How much?
- **RQ11:** In the same datasets, are the best ensembles of **RQ6** and **RQ7** the same?
- **RQ12:** In the same datasets, are the best concept drift detectors of **RQ1**, **RQ6**, and **RQ8** the same? To what extent?

1.3 Organization

The rest of this thesis is organized in seven chapters. Chapter 2 reviews the literature on concept drift classification, covering both concept drift detection methods and concept drift ensembles. In addition, it introduces the artificial dataset generators and the real-world datasets that were used in the experiments reported in this thesis.

Chapter 3 describes RDDM in detail, including its motivation, heuristic assumptions, and algorithm. In addition, it presents the results of the experiments included in a paper currently submitted to a Journal.

Similarly, Chapter 4 introduces WSTD, describing the Wilcoxon rank-sum statistical test (WILCOXON, 1945) and its provided implementation, as well as the algorithm of WSTD in details. Additionally, it includes the results of the experiments reported in another paper, submitted to a different Journal.

Chapter 5 presents all the information about BOLE, including heuristic decisions, detailed description, and voting algorithm, as well as the results of the experiments reported in the paper published in the 2016 IEEE International Joint Conference on Neural Networks (IJCNN) (BARROS; SANTOS; GONÇALVES JR., 2016).

Chapter 6 reports on the large-scale comparison of concept drifts detection methods, presenting detailed information of all relevant aspects of the experiments and analysing its results regarding accuracy and detections using a large number of datasets. Specifically, it answers research questions **RQ1** to **RQ5**.

Similarly, Chapter 7 reports on the comprehensive comparison of ensembles for data stream mining. It includes tests with 40 different configurations, i.e. *five* different ensembles combined with each of *eight* drift detection methods versions, using the same datasets, and provides answers to research questions **RQ6** to **RQ12**.

Finally, Chapter 8 draws some conclusions and proposes future work.

2 Literature Survey

This chapter reviews the published literature on concept drift classification, both concept drift detection methods (Subsection 2.1) and ensembles (Subsection 2.2). More detailed descriptions are provided for DDM, STEPD, and ADOB, the methods that inspired the new detectors and the ensemble proposed in this thesis, RDDM, WSTD, and BOLE, respectively. In addition, this chapter describes the datasets (Subsection 2.3) that were used in the experiments reported in this thesis, including both artificial dataset generators and real-world datasets, all commonly used in experiments in the area.

2.1 Concept Drift Detection Methods

It is fairly common to use a concept drift detection method together with a base classifier to learn from data streams. In general, concept drift detectors analyse the prediction results of the base learner and apply some decision model to attempt to detect changes in the data distribution. The most well-known methods that follow this approach are DDM (GAMA et al., 2004), EDDM (BAENA-GARCIA et al., 2006), and STEPD (NISHIDA; YAMAUCHI, 2007).

Given a sequence of examples in the form of pairs $(\overrightarrow{x}_i, y_i)$, where $\overrightarrow{x}_i$ is a vector of attributes and y_i is its corresponding class, for each example, the base learner makes a prediction $(\hat{y}_i)$, which is then compared to the actual result (y_i) to decide whether the prediction was correct $(\hat{y}_i = y_i)$ or not $(\hat{y}_i \neq y_i)$.

Distinct drift detection methods use different strategies and/or statistics to monitor the performance of the base classifier and to decide when concept drifts occurred. Warning levels are also usually raised, using a lower confidence level, and indicate that concept drifts may occur. At these points, the methods prescribe that a new instance of the base classifier is created and starts to be trained in parallel. Eventually, when a concept drift is confirmed, this new instance will replace the original learner. On the other hand, when the warning is a false alarm, the new instance will be discarded.

Nevertheless, it is important to clarify that, in the MOA framework (BIFET et al., 2010), the drift detection methods merely signal the *warning* and *drift* positions. The interface with the base learners is actually handled by other classes of MOA.

2.1.1 DDM

DDM (GAMA et al., 2004) detects changes in a distribution by analyzing the error rate of the base classifier and its corresponding standard deviation. For each point i in the sequence of examples, DDM assumes the error rate p_i is the probability of making an incorrect prediction and its standard deviation is given by $s_i = \sqrt{\frac{p_i(1-p_i)}{i}}$.

Based on the Probably Approximately Correct (PAC) (MITCHELL, 1997) learning model, the authors of DDM argue the error rate p_i will decrease when the number of examples i increases, as long as the distribution of the examples remains stationary. Accordingly, an increase in the error rate suggests there was a change in the data distribution and the current base learner is thus likely to have become inefficient.

For each instance i, DDM updates the minimum values of the probability of error (p_{min}) and standard deviation (s_{min}) when $p_i + s_i < p_{min} + s_{min}$. These minimum values are then used in the detection of the warning and drift levels. They are both signaled when $p_i + s_i \geq p_{min} + \alpha * s_{min}$ for some α. Note α_w and α_d represent the chosen confidence intervals for the warning and drift levels, respectively, expressed as numbers of standard deviations.

In addition to α_w and α_d, DDM has a third parameter n, which is the minimum number of instances before the detection of a drift is permitted. The default values of these parameters are 2.0, 3.0, and 30, respectively. Note that the first two signify 95% and 99% confidence intervals, respectively.

2.1.2 STEPD

The basic idea of STEPD (NISHIDA; YAMAUCHI, 2007) is to monitor the accuracy of a base learner over two windows: a *recent* window, containing the last examples, and an *older* window, with all the other examples seen by the base learner after the last detected drift. The size of the *recent* window (w) is a parameter and its default value is 30. Warnings and drifts are signaled when a significant difference is detected on the examples of the *recent* window with respect to those of the *older* window.

The method assumes the accuracies of the base classifier over the two aforementioned windows should be the same, as long as the concept remains stationary. Accordingly, the criterion to signal warnings and drifts is a significant decrease in accuracy detected on the examples of the *recent* window with respect to those of the *older* window.

As DDM, STEPD also has two parametrized thresholds referring to significance levels for the detection of drifts and warnings: $\alpha_d = 0.003$ and $\alpha_w = 0.05$.

In STEPD, the comparison of the precisions over the two windows employ a hypothesis test of equal proportions with continuity correction, as presented in Equation 2.1 (NISHIDA; YAMAUCHI, 2007), where r_o is the number of correct predictions in the n_o examples of the *older* window, r_r is the number of correct predictions in the n_r (w) examples of the *recent* window, and $\hat{p} = (r_o + r_r)/(n_o + n_r)$.

$$T(r_o, r_r, n_o, n_r) = \frac{|r_o/n_o - r_r/n_r| - 0.5 \times (1/n_o + 1/n_r)}{\sqrt{\hat{p} \times (1 - \hat{p}) \times (1/n_o + 1/n_r)}} \tag{2.1}$$

The result of Equation 2.1 is then used to find the p-value in the standard normal distribution table (BLUMAN, 2014), which is later compared to the significance levels adopted for drifts and warnings. When p-value $< \alpha_w$ STEPD signals warnings. Concept drifts are detected when p-value $< \alpha_d$.

2.1.3 Other Methods

EDDM (BAENA-GARCIA et al., 2006) is similar to DDM but it monitors the distance between two consecutive classification errors, rather than the error rate, to identify concept drifts. Accordingly, when the concepts are stationary, the distance between two consecutive errors tends to increase and, when it decreases, warnings and drifts are triggered. Its authors claim EDDM is more adequate than DDM to detect gradual concept drifts while DDM is better suited for abrupt concept drifts. The parameters of EDDM and their respective default values are the minimum number of errors before the detection of drifts is permitted, $e = 30$, and thresholds for the detection of warnings and drifts, $w = 0.95$ and $d = 0.9$, respectively, which also represent 95% and 99% confidence intervals.

ADWIN (BIFET; GAVALDÀ, 2007) uses a sliding window of instances (W) with a variable size. When drifts are detected the size of W is reduced and the longer the concept the larger the size of W. Two dynamically adjusted sub-windows are stored, representing older and recent data. Drifts are detected when the difference on the averages between these sub-windows is higher than a given threshold. The parameters of ADWIN are a confidence level to reduce the window size – $\delta \in (0, 1)$ – and the minimum frequency of instances needed for the window size to be reduced – f. The default values of ADWIN in its implementation in the MOA framework are $\delta = 0.002$ and $f = 32$.

PL (BACH; MALOOF, 2008) uses two learners. One, the *stable* (S), uses all known instances for training, whereas the other, named *reactive* (R), only trains on the last W instances, a parameter that defines the number of instances of R. The number of instances incorrectly classified by S but correctly classified by R is kept updated and, if its proportion of W is greater then a parametrized percentage threshold θ, a drift is detected. After drifts are confirmed, S is replaced by R and R is reset. The parameters of PL and their defaults in MOA are $W = 12$ and $\theta = 0.2$.

ECDD (ROSS et al., 2012) was adapted from Exponentially Weighted Moving Average (EWMA) (ROBERTS, 1959) to be used in data streams subjected to concept drifts. EWMA detects significant changes in the mean of a sequence of random variables as long as the mean and standard deviation of the data are known in advance. However, in ECDD, the mean and standard deviation are not needed. The authors of ECDD defined three parameters but its MOA implementation only has two: the weights used to differentiate recent from old instances (λ) and the minimum number of instances before the detection of drifts is permitted (n). The default parameter values of ECDD in the MOA framework is one of the configurations used by its authors: λ=0.2 and n=30.

The authors of SeqDrift (PEARS; SAKTHITHASAN; KOH, 2014) wrote it was proposed to improve on some deficiencies of the ADWIN drift detector. It uses two sub-windows to represent old and new data. In its newer version, SeqDrift2, an extended version of SeqDrift1 (SAKTHITHASAN; PEARS; KOH, 2013), the old data is managed by the use of a reservoir sampling, a one pass method to obtain a random sample of fixed size from a data pool whose size is not known in advance. This technique presents computational efficiency in maintaining and sampling the reservoir. It also uses the Bernstein bound (BERNSTEIN, 1946) to compare the sample means of both sub-windows and, according to the authors, it presents good results compared to other published bounds, specially in distributions with low variance. The proposed parameters and their default values are the size of the pool (b=200) and the drift level (δ=0.01).

The HDDM authors (FRÍAS-BLANCO et al., 2015) propose to monitor the performance of the base learner by applying “some probability inequalities that assume only independent, uni-variate and bounded random variables to obtain theoretical guarantees for the detection of such distributional changes”. This is different than DDM, EDDM, and ECDD, for example, which assume that measured values are given according to a Bernoulli distribution. HDDM also provides bounds on both false positive and false negative rates, whereas ECDD only focuses on the false positive rate. Two main approaches have been proposed. The authors claim (FRÍAS-BLANCO et al., 2015) the first (A_Test, HDDM_A) “involves moving averages and is more suitable to detect abrupt changes” and the second (W_Test, HDDM_W) “follows a widespread intuitive idea to deal with gradual changes using weighted moving averages”. They have three common parameters, the confidence values for drifts (α_D =0.001) and warnings (α_W=0.005), and the direction of the error, which can be one-sided (t=0, only increments), default for HDDM_W, or two-sided (t=1, error increments and decrements), default for HDDM_A. Finally, HDDM_W has an extra parameter (λ=0.05) which is used to control how much weight is given to more recent data in comparison to older data.

FTDD is one of three concept drift detection methods (CABRAL, 2017) based on an efficient implementation of Fisher's exact test (FISHER, 1922). It was inspired on STEPD (NISHIDA; YAMAUCHI, 2007) and on the deficiency of its statistical test of equal proportions in situations where the data samples are small or imbalanced. This particular method detects drifts using Fisher's exact test instead of the test of equal proportions in all situations. The other two sibling methods adopt hybrid applications of Fisher's exact test. Both Fisher Proportions Drift Detector (FPDD) and Fisher Squared Drift Detector (FSDD) use Fisher's exact test only in the situations where the number of errors or the number of correct predictions in any of the two windows of STEPD, also adopted in all these three methods, is small. Otherwise, FPDD uses the test of equal proportions, just like STEPD, and FSDD adopts the chi-squared statistical test for homogeneity of proportions (BLUMAN, 2014). The three methods have the same three parameters of STEPD: recent window size $w = 30$ and significance levels $\alpha_d = 0.003$ and $\alpha_w = 0.05$.

2.2 Ensemble Methods

As previously discussed, ensembles of classifiers to learn for data streams with concept drift are also fairly common in the literature.

Bagging (BREIMAN, 1996) and Boosting (FREUND; SCHAPIRE, 1996) are well-known and general methods for improving the accuracy of other algorithms ("weak" learners). They both use a set of classifiers trained on the training data and combine them in an ensemble by aggregating the responses of each classifier to deliver better predictions but using different strategies. More specifically, Bagging uses different randomly generated bootstrap samples for training, by resampling from the training set with repetitions. Boosting, on the other hand, trains several classifiers using different distributions over the training data and varies the amount of diversity given to each classifier depending on their previous predictions. Notice that many boosting algorithms come with some theoretical guarantees about their results.

Oza and Russell's Online Bagging and Boosting (OZA; RUSSELL, 2001) both use a Poisson distribution to simulate the behavior of their corresponding offline algorithms in online environments. Adwin Online Bagging (Adwin OzaBag) (BIFET et al., 2009) is basically Oza and Russell's Online Bagging (OzaBag) using ADWIN to detect concept drifts. Similarly, Adwin Online Boosting (Adwin OzaBoost), available in the MOA framework, is Oza and Russell's Online Boosting (OzaBoost) equipped with ADWIN as its drift detector.

Leveraging Bagging (LevBag) (BIFET; HOLMES; PFAHRINGER, 2010) is a modified version of Oza and Russell's Online Bagging also adding ADWIN as a hard-coded concept drift detector. In addition, it introduces two changes. The first is to increase the value of diversity ($\lambda = 6$) in the Poisson distribution which, as a consequence, leads to an increase in the probability that experts train on the same instance. The second is to change the way the experts predict instances in order to increase diversity and reduce the correlation. With these modifications, LevBag usually delivers better accuracies than Adwin OzaBag.

DDD (MINKU; YAO, 2012; MINKU, 2010) is also a variation of Online Bagging and uses four ensembles of classifiers with high and low diversity, before and after a concept drift is detected. A preliminary study (MINKU; WHITE; YAO, 2010) analysed how these ensembles behaved in different sets of data, with abrupt and gradual drifts of different speeds and different lengths of concepts. Based on the obtained results, DDD tries to select the best weighted majority of ensembles before and after the concept drifts detected by a configurable auxiliary drift detector (default is EDDM). The parameters of DDD and their corresponding default values are $W = 1$, which controls its robustness to false alarms, and $\lambda_l = 1$ and $\lambda_h = 0.1$, which represent ensembles with low and high diversity, respectively.

FASE (FRÍAS-BLANCO et al., 2016) is another algorithm based on Oza and Russell's Online Bagging. It proposes to use a meta-classifier to combine the predictions from the set of base adaptive learners that compose the ensemble and to use HDDM_A for the detection of concept drifts, though it can be configured to use other methods. When a drift is detected, the worst classifier is removed from the ensemble and a new one is added. The proposed voting strategy is weighted and the weights are inversely proportional to the error rates of the components. According to its authors, FASE "is able to process the input data in constant time and space computational complexity". In addition to the auxiliary drift detector, the only parameter of FASE is the number of experts (default value is 10).

Online Boost-by-majority (Online BBM) (BEYGELZIMER; KALE; LUO, 2015) is an online version of Freund's BBM algorithm (FREUND, 1995). Online BBM does not require importance weighted online learning and can achieve results similar to other methods with fewer weak learners. Beygelzimer et al. also proposed another version of online boosting (AdaBoost.OL), which weighs the experts taking into account their accuracy (adaptive).

DWM (KOLTER; MALOOF, 2007) is a weighted ensemble that extends the Weighted Majority Algorithm (WMA) (BLUM, 1997) and aims to adapt to concept drifts without explicitly detecting them. DWM adds and removes classifiers according to its global performance: a classifier is added when the ensemble commits an error; the weight of each classifier is reduced when it commits an error; and a classifier is removed when its weight is very low, indicating it presented low accuracy on many examples.

Finally, the following two methods are ensembles of detectors rather than ensembles of classifiers, i.e. multiple drift detection methods share a single base learner.

e-Detector (DU et al., 2014) is a selective detector ensemble which aims to detect both abrupt and gradual concept drifts. It proposes to cluster detector candidates grouping by homogeneous methods and to use a Coefficient of Failure (CoF) to choose the best component of each cluster to form the ensemble. The detections of drifts and warnings of the ensemble are signalled when one of its components signals them and this strategy was named the early-find-early-report rule. The authors claim e-Detector improves the recall and false negative rates without significantly increasing the false positive rate of its detections and also that it has stronger generalization ability than the detectors.

Drift Detection Ensemble (DDE) (MACIEL; SANTOS; BARROS, 2015) is a configurable lightweight ensemble of detectors with three components that aims to deliver more precise detections of the drifts, improving the final accuracy with no substantial effect on the execution time. Its strategy for the detections is based on a sensitivity parameter, which specifies the minimum number of components needed to signal warnings and drifts. When the chosen sensitivity is 1, its strategy is similar to the early-find-early-report rule of e-Detector. The other sensitivity values (2 and 3) are intended to make DDE more robust to false positive detections, even though the true detections may be delayed.

2.2.1 ADOB

ADOB (SANTOS et al., 2014) is a boosting ensemble based on Oza and Russell's Online Boosting which uses a different strategy to speed up the experts recovery after concept drifts.

Algorithm 1 shows ADOB's pseudo-code adapted from (SANTOS et al., 2014). Notice that ADOB sorts the experts by accuracy before processing each instance (line 4). This modification affects the way diversity is distributed to the classifiers and tends to slightly improve the accuracy of the ensemble just after the concept drifts, especially when these drifts are abrupt.

When an instance d arrives, initially the expert with less accuracy will be selected. If d is correctly classified, it is assumed the other (more accurate) experts also have good chances of correctly classifying it (an error is unlikely).

Also, observe that λ is reduced when the classification is correct and increased if it is incorrect (lines 17 to 25). This makes the influence of an unlikely error on λ decrease as more instances are processed, because the next selected expert will be the one with the best accuracy (lines 6 to 8). So, experts with the worst accuracies, and most likely to make mistakes, will only be selected at the end.

Although ADOB can be easily configured to use any concept drift detection method, it was proposed using ADWIN to allow for a direct comparison with the original algorithm. The only other parameter of ADOB is the number of experts, with default value set to 10.

2.3 Datasets

This section describes the datasets chosen for the experiments of Chapters 3 to 7. They have all been previously used in the area and are publicly available, either in the MOA framework, from the MOA website, or at *https://sites.google.com/site/moaextensions*.

Artificial datasets are useful for the experiments since it is possible to define number, position, and size of the concept drifts and thus simulate different scenarios. Real-world

Algorithm 1: Adaptable Diversity-based Online Boosting (ADOB)

Input: ensemble size M, ensemble h, instance d, number of processed instances N

$minPos \leftarrow 1$; $maxPos \leftarrow M$;
$correct \leftarrow$ false;
$\lambda \leftarrow 1.0$; $\lambda^{sc} \leftarrow 0.0$; $\lambda^{sw} \leftarrow 0.0$;
sort h **by** accuracy **in** ascending order;
for $m \leftarrow 1$ **to** M **do**
    if *correct* **then**
        $pos \leftarrow maxPos$;
        $maxPos \leftarrow maxPos$ - 1;
    else
        $pos \leftarrow minPos$;
        $minPos \leftarrow minPos + 1$;
    end
    $K \leftarrow \text{Poisson}(\lambda)$;
    for $k \leftarrow 1$ **to** K **do**
        $h_{pos} \leftarrow \text{Learning}(h_{pos}, d)$;
    end
    if $h_{pos}(d)$ *was correctly classified* **then**
        $\lambda^{sc}_m \leftarrow \lambda^{sc}_m + \lambda$;
        $\lambda \leftarrow \lambda \left(\frac{N}{2\lambda^{sc}_m}\right)$;
        $correct \leftarrow$ true;
    else
        $\lambda^{sw}_m \leftarrow \lambda^{sw}_m + \lambda$;
        $\lambda \leftarrow \lambda \left(\frac{N}{2\lambda^{sw}_m}\right)$;
        $correct \leftarrow$ false;
    end
end
return h;

datasets are also important because they bring unpredictability and volume of data. In the latter, the number and position of the drifts are usually unknown.

2.3.1 Artificial Dataset Generators

Agrawal generator (AGRAWAL; IMIELINSKI; SWAMI, 1993; MACIEL; SANTOS; BARROS, 2015) stores information from people willing to receive a certain amount of loan. From this data, they should be classified as belonging to group A or group B. The attributes are: salary, commission, age, education level, zip code, value of the house, etc. To perform the classification, the authors proposed ten functions, each with different forms of evaluation. In addition, it is possible to add noise.

LED generator (BIFET et al., 2009; GONÇALVES JR.; BARROS, 2013; SANTOS et al., 2014) represents the problem of predicting the digit shown by a seven-segment LED display. It has 24 categorical attributes, 17 of which are irrelevant, and a categorical class, with ten possible values. Also, each attribute has 10% probability of being inverted (noise). Concept drifts are simulated by changing the position of the relevant attributes.

Mixed generator (GAMA et al., 2004; BAENA-GARCIA et al., 2006; GONÇALVES JR.; BARROS, 2013) has two boolean (v, w) and two numeric attributes (x, y). Each instance can be classified as positive or negative. They are classified as positive if at least two of the three following conditions are met: $v, w, y < 0.5 + 0.3\sin(3\pi x)$. To simulate a concept drift, the labels of the aforementioned conditions are reversed.

RandomRBF generator (BIFET et al., 2009; MACIEL; SANTOS; BARROS, 2015) uses n centroids with their centers, labels and weights randomly defined, and a Gaussian distribution to determine the values of m attributes. The chosen centroid also determines the class label of the example. This effectively creates a normally distributed hypersphere of examples surrounding each central point with varying densities which is very hard to learn. A concept drift is simulated by changing the positions of the centroids. This dataset generator has six classes, 40 attributes, and 50 centroids.

Sine generator (GAMA et al., 2004; BAENA-GARCIA et al., 2006; ROSS et al., 2012) has two numeric attributes (x, y) and two contexts: Sine1 and Sine2. In the former, a given instance will be classified as positive if the point is below the curve $y = sin(x)$. In the latter, the condition $y < 0.5 + 0.3\sin(3\pi x)$ must be satisfied. Concept drifts can be simulated either by alternating between Sine1 and Sine2 or by reversing the aforementioned conditions, i.e. points below the curves become negative.

Stagger generator (SCHLIMMER; GRANGER, 1986; SANTOS et al., 2014) has three attributes: $color \in \{green, blue, red\}$, $shape \in \{triangle, circle, rectangle\}$, and $size \in \{small, medium, large\}$. It also has three concepts: (1) $color = red \wedge size = small$; (2) $color = green \vee shape = circle$; and (3) $size = medium \vee size = large$. This dataset is usually employed to simulate abrupt concept drifts and is fairly simple to learn because the numbers of attributes and concepts are small and the concepts are not disjoint.

Waveform generator (BIFET et al., 2009; SANTOS; BARROS; GONÇALVES JR., 2015) has three-classes and 40 numerical attributes, with the last 19 used to produce noise. The goal of the problem is to detect the waveform generated by combining two of three base waves. To perform changes, the positions of the attributes representing a certain context are reversed.

2.3.2 Real-world Datasets

Airlines (BIFET et al., 2013; SANTOS; BARROS; GONÇALVES JR., 2015) is a binary dataset composed of 539,383 instances. The goal is to predict whether flights are delayed or not, based on a set of flight information. Its attributes are: name of the company, departure time, flight number, duration, airports of origin and destination, and day of the week.

Covertype (GONÇALVES JR.; BARROS, 2013; BIFET et al., 2009; MACIEL; SANTOS; BARROS, 2015) stores information on the forest cover type for 30x30 meter cells obtained from US Forest Service (USFS) Region 2 data and contains 581,012 instances and 54 attributes (numeric and categorical). The goal is to predict the forest cover type from cartographic variables. This real-world dataset is frequently used in the area.

In addition to the original dataset, another version with its instances sorted by the *elevation* attribute (IENCO et al., 2013) was also used and is referred to as *CovertypeSorted*. It induces gradual concept drifts on the class distribution: depending on the elevation, some types of vegetation disappear while others start to appear.

The Electricity dataset (GAMA et al., 2004; BAENA-GARCIA et al., 2006; KOLTER; MALOOF, 2007; MINKU; YAO, 2012; SANTOS et al., 2014) stores data collected from the Australian New South Wales Electricity Market where prices depend on market demand and supply – it has 45,312 instances and eight attributes. The prices are set every five minutes and the class label identifies the change of the price related to a moving average of the last 24 hours. The goal is to predict if the price will increase or decrease. It is probably the most used real dataset in the data streams area.

Pokerhand (BIFET et al., 2009; SANTOS; BARROS; GONÇALVES JR., 2015) represents the problem of identifying the value of a five-card hand in the game of Poker. It is constituted of five categorical and five numeric attributes and one categorical class with 10 possible values informing the value of the hand (one pair, two pairs, a sequence, etc.). In the original and harder to classify version of this dataset, with 1,000,000 instances, the cards are not ordered. This version is referred as *Pokerhand1M* in this work.

In addition to the original version, a modified version available at the MOA website (BIFET; HOLMES; PFAHRINGER, 2010; BIFET et al., 2010; GONÇALVES JR.; BARROS, 2013) was also used. In this normalized version, cards are sorted by rank and suit and duplicates were removed, resulting in 829,201 instances. This version is comparatively much more used than the original version.

Finally, Sensor Stream (ZHU, 2010) contains information collected from 54 sensors deployed in the Intel Berkeley Research Lab (temperature, humidity, light, and sensor voltage). It contains consecutive information recorded over a 2 months period, with one reading every 1-3 minutes. The sensor ID is the target attribute, which must be identified based on the sensor data and the corresponding recording time. This dataset is constituted of 2,219,803 instances, 5 attributes, and 54 classes. This is an interesting and intriguing dataset because, in addition to being much larger than the others, it delivers considerable variations in the accuracy performance of the methods.

3 Reactive Drift Detection Method

DDM (GAMA et al., 2004) is probably the best known and most used and cited concept drift detection method, especially because it presents reasonably good all-round performance (GONÇALVES JR. et al., 2014), despite being quite simple.

One of the well-known problems with DDM is that its performance usually worsens when the concepts are very large (SALPERWYCK; BOULLÉ; LEMAIRE, 2015), because it tends to become less sensitive to concept drifts, taking too many instances to detect the changes.

This chapter proposes RDDM, which is based on DDM and, among other heuristic modifications, adds an explicit mechanism to discard older instances of very long concepts to overcome or at least alleviate the performance loss problem of DDM. RDDM should deliver higher (or equal) global accuracy than DDM in most situations by detecting most drifts earlier than DDM would and, thus, it is claimed to be better than DDM.

In addition, this chapter presents the results of previous experiments included in a paper submitted to a journal. Using the MOA framework (BIFET et al., 2010), DDM, RDDM, ECDD, and STEPD were tested in a considerably large number of scenarios, with both artificial and real-world datasets, and the results were statistically evaluated.

The rest of this chapter is organized as follows: Section 3.1 describes RDDM and presents its implementation abstract pseudo-code; Section 3.2 details the configuration of this chapter experiments, discusses the results obtained, analyses the drift identifications, and performs statistical evaluations of accuracy and of memory and run-time consumption; and, finally, Section 3.3 introduces some conclusions.

3.1 Description of RDDM

This section provides a detailed description of RDDM, an original proposal to overcome deficiencies and thus improve the detections and accuracy results of DDM. This includes motivation and heuristic assumptions, as well as all important details of the corresponding implementation in MOA.

As already mentioned, the main idea behind RDDM is to periodically shorten the number of instances of very long stable concepts to tackle a known performance loss problem of DDM. It is assumed that such a drop is caused by decreased sensitivity to concept drifts as a result of very large number of instances belonging to a given concept. This occurs because, in concepts with *many thousands* instances, it takes a fairly large number of prediction errors to sufficiently affect the mean error rate and trigger the drifts.

Another symptom of the same problem is the fact that, at least in some scenarios, DDM tends to stay at the warning level for a very large number of instances. Besides causing DDM to slow down because of the extra instance of the base learner running in parallel, this behaviour might also make DDM fail to detect some of the existing gradual drifts, as the base learner is slowly adapting itself to the new concept without a drift detection.

Given this scenario, some design decisions were made to deal with the problem. Firstly, it was decided that, whenever the current concept became too long, measured by a chosen *maximum* number of instances, a softer concept drift, which was named RDDM drift, would be performed. This type of drift does *not* cause any modifications in the base learner. Instead, it triggers the recalculation of the DDM statistics used to detect the warning and drift levels using only a chosen smaller number of instances, more specifically, the most recent *minimum* instances seen in the concept.

A similar result might be achieved if a fixed-size window were adopted for the calculation of the DDM statistics. This possibility was considered, but it was discarded because it would change the usual behavior of DDM before it was really necessary and it would also be much more time-consuming, making RDDM slower than it is.

A second decision that was made was that RDDM drifts should *not* be performed during the warning level because this might very well cause a performance loss, especially if the warning period was too small. In such circumstances, the RDDM drift recalculation of the statistics might trigger a premature DDM concept drift in the following instance(s) without a sufficiently trained base learner.

On the other hand, such a decision could also mean not tackling the performance loss of DDM in those scenarios where the problem of excessively long warning periods occurred. This was the main motivation for the third design decision, which was to force a DDM drift whenever the number of instances under warning reached a certain limit. The rationale was that, in most of these situations, although not yet detected, a concept drift would already have taken place. Moreover, when this was not the case, such a decision should *not* cause much harm, as the alternative base learner would already have been trained over a reasonably large number of instances.

Another point that drew attention was that a warning level followed by a drift detection should actually mean that a concept drift had already occurred at least since the instance where the warning level was set. So, because the new base learner would have been trained from this position, hypothetically, the statistics of the method could also be calculated from this instance. Thus, in the DDM drifts that occur after a warning period, RDDM starts calculating the statistics of the new concept at the first instance of the warning period.

Finally, a single RDDM implementation is envisaged. Even so, it is plausible that different users may be willing to use RDDM with alternative values in the maximum and minimum number of instances related to the RDDM drift, as well as in the limit for the number of instances of warnings. For this reason, in addition to the parameters of DDM, three new parameters were added in RDDM and, after some experimentation, default values have been chosen for them. These are: $n = 129$, $\alpha_w = 1.773$, $\alpha_d = 2.258$, $maximum = 40,000$, $minimum = 7,000$, and $warnLimit = 1,400$.

3.1.1 Implementation

This subsection gives additional, more concrete, details of the RDDM implementation. Algorithm 2 shows a still abstract pseudo-code, corresponding to the Java code that implements RDDM in the MOA framework, release 2014.11.

The inputs to RDDM are a data stream; the parameters of DDM, i.e. the minimum number of instances (n) before drift detections are allowed and the levels for warning (α_w) and drift (α_d); the maximum size a concept is allowed to have (max); the reduced size of a stable concept (min); and the maximum number of instances that limits the warning level ($warnLimit$).

Line 1 of the pseudo-code shows the allocation of the array that stores the predictions of (up to) the last min instances of the current concept. Note that, in Java, array allocations are dynamic, so, the array will have the exact size (min) needed. It is also important to state that, for the sake of efficiency in the usage of memory and run-time, the adopted storage strategy in this array is that of a circular queue and the type chosen for its elements was the smallest numeric type available in Java (byte).

Lines 2–4 show a simplified high-level summary of the data that needs to be instantiated in the beginning.

Lines 7–12 refer to the main part of the RDDM algorithm. It is worth emphasizing that both DDM and RDDM implement their necessary adjustments after a drift detection when they receive the first instance of the new concept. Thus, the contents of attributes $rddmDrift$ and $ddmDrift$ at the beginning of the loop (line 5) are the ones set at the previous instance, in the last part of the algorithm.

In addition, notice that both types of drift are handled by the same piece of code. The difference between them is two-fold. Firstly, only the DDM drifts cause changes in the base learner — this is *not* implemented in the code of the detectors, since they only signal the drift points to other classes of the MOA implementation. The other difference is that the DDM drift detections implemented in the last part of the algorithm change the subset of the array that will be used in the recalculation of the statistics, whereas RDDM drifts use all the instances stored in the array.

Algorithm 2: Reactive Drift Detection Method (RDDM)

```
   Input: stream, n, α_w, α_d, max, min, warnLimit
1  storedPredictions ← NEW byte [min]
2  reset m_n, m_p, m_s, m_pmin, m_smin, m_psmin // Variables used in DDM statistics in its
   MOA implementation
3  rddmDrift ← ddmDrift ← false
4  numInstConcept ← numWarnings ← 0
5  foreach instance in stream do
6      pred ← prediction (instance)
7      if rddmDrift then
8          reset m_n, m_p, m_s, m_pmin, m_smin, m_psmin
9          Calculates DDM statistics using the elements of storedPredictions instead of pred (lines
            14-17; 19-24)
10         rddmDrift ← ddmDrift ← false
11         numInstConcept ← numWarnings ← 0
12     end
13     Inserts pred into array storedPredictions forgetting oldest value if it is already full (min
        instances)
14     m_p ← m_p + (pred − m_p) / m_n // Updates DDM statistics to consider pred
15     m_s ← sqrt (m_p × (1 − m_p) / m_n)
16     m_n ← m_n + 1
17     numInstConcept ← numInstConcept + 1
18     warningLevel ← false
19     if numInstConcept ≥ n then
20         if m_p + m_s < m_psmin then
21             m_pmin ← m_p
22             m_smin ← m_s
23             m_psmin ← m_p + m_s
24         end
25         if m_p + m_s > m_pmin + α_d × m_smin then
26             rddmDrift ← ddmDrift ← true
27             if numWarnings = 0 then
28                 storedPredictions ← pred
29             end
30         end
31         else
32             if m_p + m_s > m_pmin + α_w × m_smin then
33                 if numWarnings ≥ warnLimit then
34                     rddmDrift ← ddmDrift ← true
35                     storedPredictions ← pred
36                 end
37                 else
38                     warningLevel ← true
39                     numWarnings ← numWarnings + 1
40                 end
41             end
42             else
43                 numWarnings ← 0
44             end
45             if numInstConcept ≥ max and not warningLevel then
46                 rddmDrift ← true
47             end
48         end
49     end
50 end
```

In lines 13–24, the current instance prediction is stored in the circular queue and used to update the statistics. Notice line 19 guarantees that detections only take place after at least n instances.

The DDM drifts are detected and handled in lines 25–30, the warning scenarios are addressed in lines 32–41, whereas lines 42–43 capture the stable concept situations. In particular, is important to notice that the **if** in line 27 reduces the circular queue to a single instance, whenever a drift is detected without a previous warning, and the one in line 33 is responsible for limiting the size of the warning level. Finally, lines 45–47 detect and handle RDDM drifts, making sure they are never set during warnings.

3.1.2 Space and Time Complexity Analysis

Analyzing the space complexity of RDDM, it stores at most the last min values in a circular queue implemented using an array, reflecting the minimum size of stable concepts. Thus, RDDM has an $O(min)$ space complexity, whereas DDM has an $O(1)$ complexity.

Regarding the time complexity, RDDM performs more iterations when drifts occur, because of the size of *storedPredictions* (min). Despite this, and similarly to what Cormen et al. (CORMEN et al., 2009) wrote about the complexity of insertion sort, technically, it would be an abuse to say the running time of RDDM is $O(n \times min)$, where n is the number of processed instances, as this complexity is related to the execution time of at most $1/max$ instances.

Because the min iterations are only performed for a small subset of the n instances, stating that RDDM has time complexity $\Theta(n \times min)$ on the worst-case scenario is more adequate but does not reflect the total execution time for any dataset. So, its complexity is claimed to be $\Theta(n)$ in most datasets. In turn, the time complexity of DDM is $O(n)$.

3.1.3 Discarded Heuristics

It is worth mentioning that, in addition to the strategies that were implemented in RDDM, other heuristics have been tried and discarded. For instance, at the beginning of the investigation, the intention was to force DDM drifts in the situations in which the RDDM drifts are now applied. The main reason why it did not work was that it would discard the trained base learner and start again from scratch, which proved to be a damaging strategy, despite the fact that Naive Bayes (NB) (JOHN; LANGLEY, 1995), the base classifier used in the early experiments, usually learns new concepts very quickly.

The application of RDDM drifts during warning periods have also been tried. Despite not noticing any significant drop in performance inherent in this strategy, it was observed that, when these warning periods were not very short, such RDDM drifts would often be followed by DDM drifts. This information led to the decision that RDDM drifts should *not* occur under warning, i.e. more instances should be processed. Either a DDM drift would happen or RDDM would return to the stable concept state and then the RDDM drift would be effected.

Another attempted heuristic was to consider long periods of warning followed by a return to a stable concept state as if this warning period was uninterrupted until the subsequent concept drift. The rationale was that sometimes these long warning periods would be interrupted for a few instances only and such interruptions would destroy the classifier that was being trained in parallel. Even though this was true in the targeted scenario, this decision was impairing the results when the warning period was followed by another long period of stability because, in the next drift, the base learner would still retain information from the previous concept.

3.2 Experiments

This section describes all the relevant information on the experiments designed to test and evaluate RDDM against DDM and other drift detectors.

To allow for a fair comparison, all the drift detection methods used NB as base learner, chosen because it is simple, fast, efficient, and freely available, and is often used in experiments in the data stream area. Also, the first three parameters of RDDM were exceptionally set with the same values used by DDM, i.e. $n = 30$, $\alpha_w = 2$, $\alpha_d = 3$.

Four artificial dataset generators were selected to build abrupt and gradual concept drift versions of six different sizes, for a total of 48 artificial datasets. These are Agrawal generator, Mixed generator, Sine generator, and LED generator. They were all described in Subsection 2.3.1. In all these datasets, there are four concept drifts distributed at regular intervals. Thus, the size of the concepts in each dataset version of the same generator is different, covering six different scenarios.

Note the abrupt drifts were simulated by joining different concepts, whereas the gradual changes were generated using a probability function to increase the chance of selecting instances from the new concept instead of the old one. Finally, in the gradual concept drifts datasets, the changes last for 500 instances.

In the artificial datasets with up to 500,000 instances, the experiments were executed 30 times to calculate the accuracies of the methods and the mean results were computed with 95% confidence intervals. In the datasets with one million instances or more, the procedure was similar but the number of repetitions was set to 10.

In addition, three well-known real-world datasets were selected to complement the evaluation of RDDM – these are Airlines, Pokerhand, and Electricity, which were also previously described — in Subsection 2.3.2.

The first two real-world datasets were chosen because they are believed to be good fits for RDDM, as they are reasonably big and do not seem to have many concept drifts. In other words, their concepts are assumed to be long, creating opportunities to apply the main strategy of RDDM. The third was chosen because it is the most widely used real dataset in the data streams area and, also, it is one where RDDM was expected to perform similarly to DDM, since it is comparably small and contains many concept drifts.

The accuracy evaluation was performed using the Interleaved Test-Then-Train methodology, the *Basic Window* version of Prequential (GAMA et al., 2014). More specifically, each incoming instance is used initially for testing and subsequently for training. This means that every instance is used both for testing and for training and that the problem of training before testing on any given instance is avoided.

All the experiments were executed using a PC configured with an Intel Core i7 4790K processor, 16GB of 1866 MHz RAM, and a SSD, running the Ubuntu Desktop 14.04 LTS 64 bits operating system.

The following subsections present the results of the experiments and this includes analyses of accuracy, concept drift identifications, memory and run-time usage, as well as statistical evaluations over the 51 tested datasets.

3.2.1 Accuracy Results and Analysis

Table 1 presents the accuracies obtained for DDM, RDDM, ECDD, and STEPD, all tested on the artificial datasets affected by abrupt and gradual concept drifts, as well as on the real-world datasets. In each dataset generator, method and type of concept drift combination, the best result is written in **bold**.

Notice that, in absolute terms, RDDM improved the predictive accuracies of DDM in *all 51* tested configurations, i.e. the results improved in all sizes of concepts across all four tested dataset generators with both abrupt and gradual concept drifts as well as in the three real-world datasets, though some of these results are not statistically different.

Analyzing the results of the methods in the artificial datasets in more detail, one can see that, as the size of the datasets (and consequently of the concepts) increased, the accuracies of RDDM also increased in almost all cases and, when it did not, the performance loss was very small. Accordingly, except for the Mixed datasets, RDDM reached its best accuracies in the 3 million instances configurations. And although this was not the case in the Mixed datasets, the differences to the best results were 0.02% or smaller. The results of ECDD and STEPD followed a similar pattern.

In the case of DDM, this pattern did not occur, confirming that its performance tends to worsen when the concepts become very long. In all four generators, the largest versions were *not* those in which DDM attained its best accuracies. In five of the eight

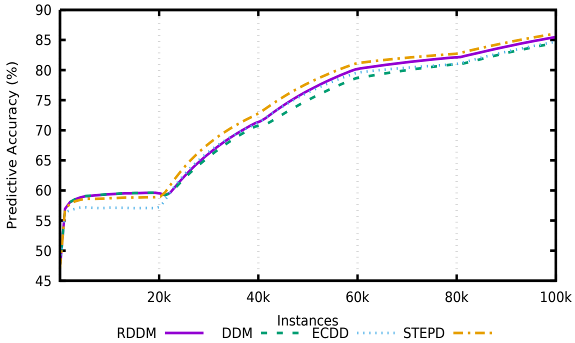
Table 1 – Mean accuracies of RDDM and the other methods in percentage (%), with 95% confidence intervals in the artificial datasets

DATASET	AGRAWAL				MIXED			
Artificial	DDM	RDDM	ECDD	STEPD	DDM	RDDM	ECDD	STEPD
Abr-50K	70.76±0.79	72.16±0.53	72.38±0.12	**73.45±0.25**	91.06±0.48	**91.34±0.10**	89.74±0.14	91.33±0.14
Abr-100K	72.36±0.63	73.20±0.45	72.39±0.08	**73.90±0.15**	91.14±0.56	**91.64±0.07**	89.78±0.10	91.48±0.09
Abr-500K	73.53±0.66	**74.45±0.35**	72.52±0.03	74.34±0.06	90.61±1.53	**91.93±0.03**	89.90±0.05	91.61±0.04
Abr-1M	74.62±0.35	**74.81±0.40**	72.53±0.04	74.36±0.09	90.73±2.30	**92.02±0.04**	89.95±0.05	91.66±0.03
Abr-2M	73.79±0.76	**74.96±0.15**	72.52±0.04	74.36±0.06	90.58±1.50	**92.01±0.03**	89.94±0.04	91.64±0.03
Abr-3M	73.89±1.17	**75.04±0.09**	72.52±0.03	74.37±0.05	88.39±3.61	**92.00±0.03**	89.93±0.04	91.62±0.03
Gr-50K	70.75±0.74	71.87±0.54	71.94±0.11	**72.73±0.27**	90.56±0.12	**90.61±0.11**	88.89±0.14	90.26±0.12
Gr-100K	72.11±0.67	73.08±0.46	72.16±0.10	**73.69±0.13**	91.27±0.07	**91.31±0.07**	89.35±0.10	90.95±0.09
Gr-500K	73.58±0.64	**74.39±0.35**	72.47±0.04	74.27±0.05	91.25±1.13	**91.89±0.02**	89.82±0.05	91.51±0.03
Gr-1M	74.72±0.36	**74.79±0.40**	72.50±0.05	74.31±0.09	91.90±0.15	**91.98±0.04**	89.91±0.05	91.60±0.03
Gr-2M	74.17±0.82	**74.95±0.15**	72.51±0.04	74.34±0.06	91.53±0.48	**92.00±0.03**	89.92±0.04	91.61±0.03
Gr-3M	72.96±1.68	**75.05±0.08**	72.51±0.04	74.35±0.05	90.38±1.15	**91.99±0.03**	89.92±0.04	91.61±0.03
DATASET	SINE				LED			
Artificial	DDM	RDDM	ECDD	STEPD	DDM	RDDM	ECDD	STEPD
Abr-50K	85.09±0.74	86.54±0.26	86.28±0.11	**87.10±0.12**	72.08±0.25	**72.41±0.13**	68.58±0.29	67.67±0.96
Abr-100K	85.00±0.82	86.59±0.27	86.29±0.10	**87.13±0.08**	72.82±0.19	**73.06±0.12**	68.91±0.21	68.83±0.70
Abr-500K	85.33±0.76	87.02±0.09	86.29±0.03	**87.19±0.03**	72.86±0.41	**73.60±0.07**	69.18±0.10	69.95±0.30
Abr-1M	83.33±2.75	87.18±0.07	86.33±0.03	**87.20±0.03**	73.28±0.20	**73.67±0.05**	69.20±0.13	70.02±0.20
Abr-2M	81.72±3.50	**87.22±0.03**	86.32±0.02	87.20±0.02	73.00±0.74	**73.78±0.05**	69.29±0.08	70.14±0.19
Abr-3M	82.30±2.84	**87.23±0.03**	86.32±0.02	87.20±0.02	71.94±1.15	**73.81±0.05**	69.34±0.07	70.13±0.17
Gr-50K	86.14±0.35	**86.37±0.26**	85.70±0.12	86.29±0.12	72.11±0.16	**72.19±0.13**	68.11±0.31	67.01±0.99
Gr-100K	86.33±0.39	86.59±0.28	85.96±0.09	**86.68±0.07**	72.73±0.21	**72.99±0.12**	68.69±0.22	68.59±0.65
Gr-500K	85.17±0.98	87.02±0.10	86.23±0.03	**87.10±0.03**	73.07±0.28	**73.60±0.07**	69.14±0.10	69.86±0.30
Gr-1M	83.63±2.33	**87.18±0.07**	86.29±0.03	87.15±0.04	73.09±0.42	**73.67±0.05**	69.19±0.14	69.98±0.21
Gr-2M	82.27±3.52	**87.21±0.04**	86.31±0.02	87.18±0.02	72.81±0.61	**73.78±0.06**	69.28±0.08	70.14±0.19
Gr-3M	81.85±3.49	**87.22±0.03**	86.31±0.02	87.18±0.02	72.68±1.02	**73.82±0.05**	69.33±0.07	70.12±0.17
Real	AIRLINES			POKERHAND			ELECTRICITY	
SIZE	DDM ECDD	RDDM STEPD	SIZE	DDM ECDD	RDDM STEPD	SIZE	DDM ECDD	RDDM STEPD
539K	67.72 64.73	**68.58** 65.73	829K	65.85 **79.80**	74.44 77.18	45K	82.58 **87.44**	83.01 84.47

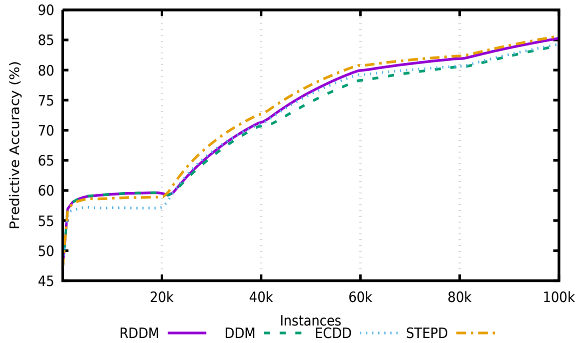
tested datasets, DDM obtained its top results in the one million instances versions, whereas in the other three this occurred in smaller versions. In other words, in all tested scenarios, when concepts had about 200,000 instances, the performance of DDM started to drop or had already dropped.

Another point to be highlighted is that RDDM obtained lower confidence intervals in 45 of the 48 tested dataset configurations. This indicates the performance of RDDM does not vary as much as that of DDM. The confidence intervals of ECDD and STEPD were reasonably close to those of RDDM in most datasets.

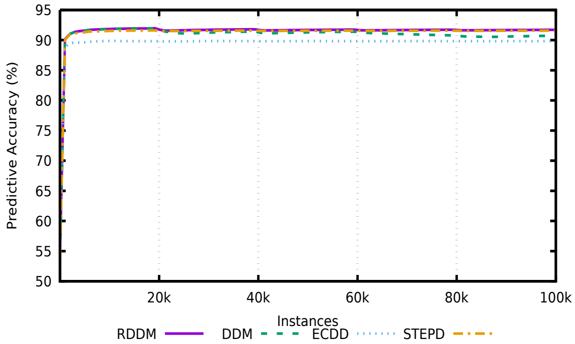
To better illustrate the results, Figures 1 and 2 graphically represent the accuracy results of the methods in the datasets with 100 thousand and three million instances, respectively. Each drift is represented by a vertical dotted line. One can observe that, before the first drift, the four methods behave in basically the same way in most datasets. This was to be expected because none of them indicated that a drift had occurred. One possible situation where the methods would diverge would be if there were a long sequence of instances at warning level but this was not the case in the first concept of the tested versions of the artificial datasets.



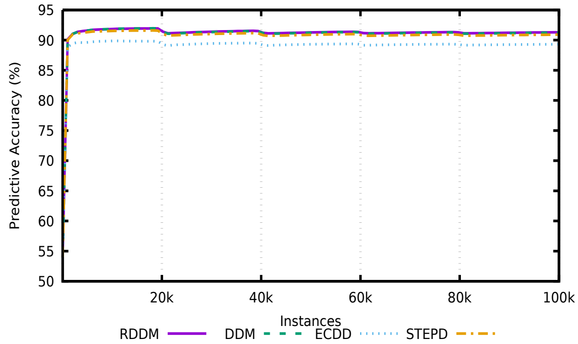
(a) Agrawal



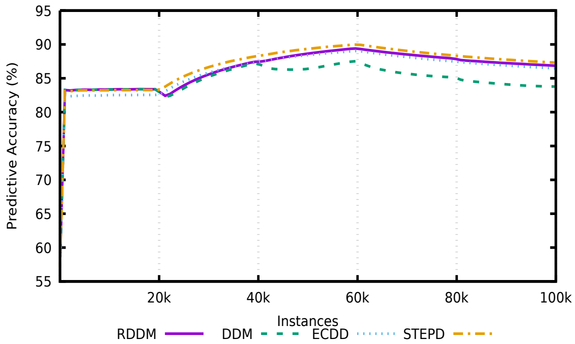
(b) Agrawal



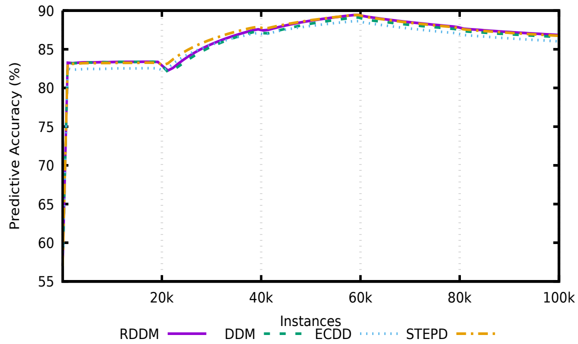
(c) Mixed



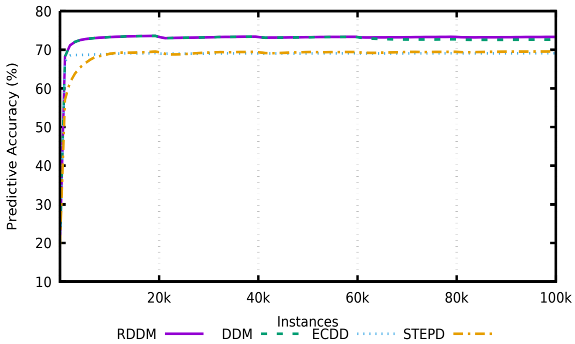
(d) Mixed



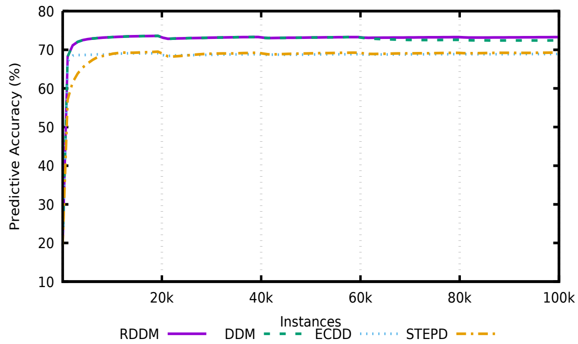
(e) Sine



(f) Sine

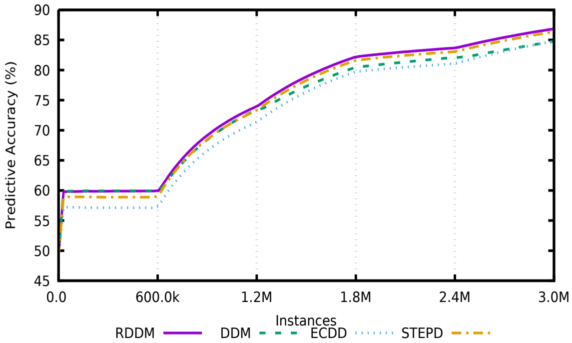


(g) LED

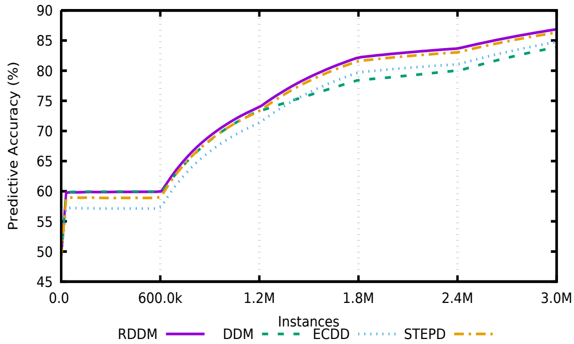


(h) LED

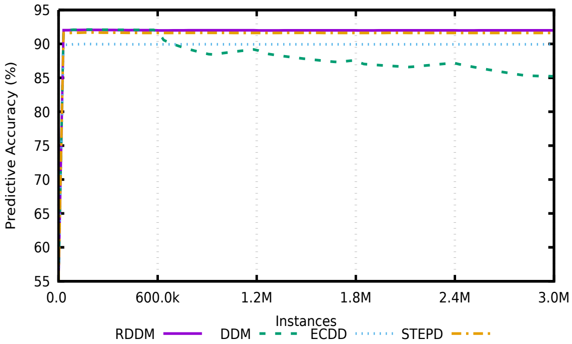
Figure 1 – RDDM: Accuracies in the datasets with 100,000 instances — Abrupt concept drifts versions are on the left and the gradual ones are on the right hand side



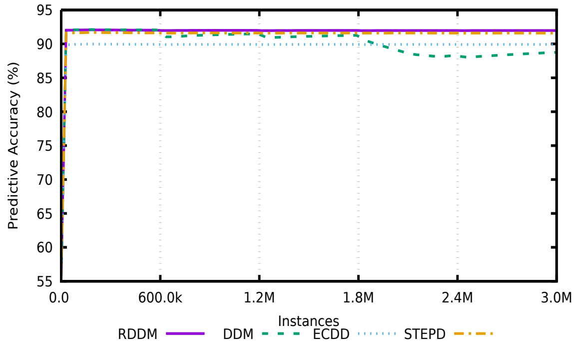
(a) Agrawal



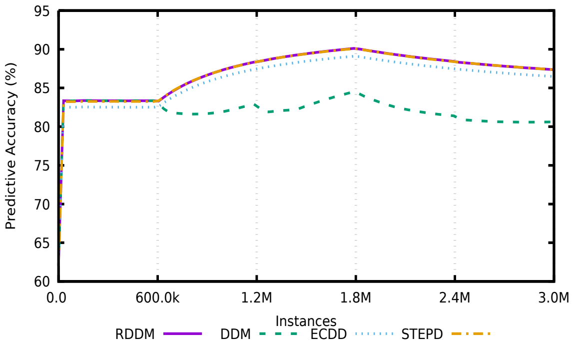
(b) Agrawal



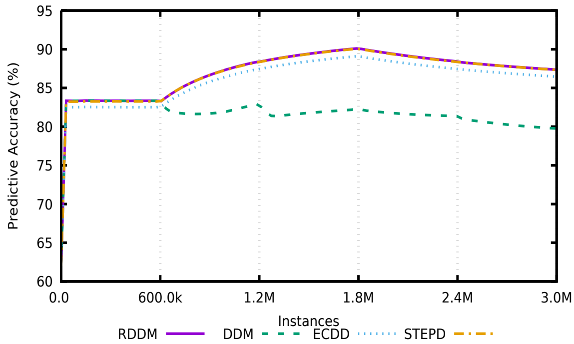
(c) Mixed



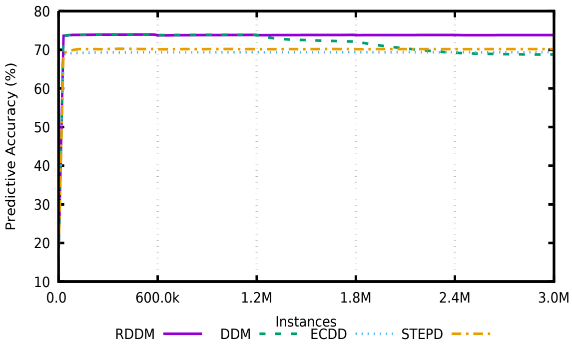
(d) Mixed



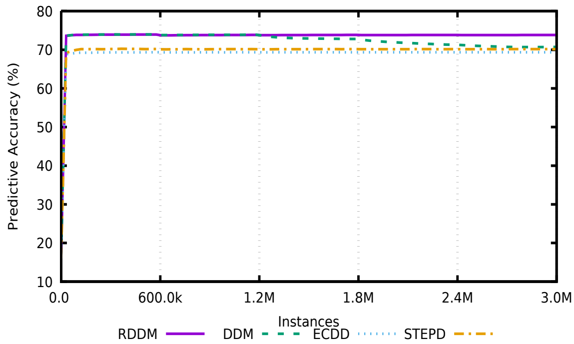
(e) Sine



(f) Sine



(g) LED



(h) LED

Figure 2 – RDDM: Accuracies in the datasets with 3 million instances — Abrupt concept drifts versions are on the left and the gradual ones are on the right hand side

Observe that, after the first drift, the methods started to diverge, with RDDM having a higher predictive accuracy when compared to DDM. The differences are subtle in the 100K datasets and increase with the rise in the number of instances.

Also, when comparing versions of the same datasets with different sizes, it may be seen that the distance of the curves is bigger in the 3M configurations than in their corresponding 100K configurations.

In addition, it is worth pointing out the performances of RDDM, ECDD, and STEPD followed similar patterns in most datasets, but often RDDM was slightly better.

The results in the real-world datasets were not that different from those of the artificial datasets. The biggest improvement of RDDM came in the pokerhand dataset, which is the largest of the three and is believed to be free from concept drifts.

The improvement in the electricity dataset, albeit small, was somewhat surprising, because neither the RDDM drift nor the long periods of warnings were supposed to be applicable. The use of instances of the warning period in the calculation of the statistics was the only modification that could be applicable.

In these two datasets, ECDD and STEPD were the best two methods, whereas in airlines they presented the lowest results.

3.2.2 Drift Identification Analysis

A different perspective about the performance of the methods can be obtained by analysing the concept drifts that each method identified. Table 2 presents, for each abrupt dataset configuration, the mean distance to the real drift points, the sensitivity (true positive rate), and the average number of false positives and false negatives of each method considering the repetitions.

The false positive detections regard identified drifts where none occurred and the false negatives refer to existing drifts that were not detected by the methods. In both, smaller numbers are better.

Notice that, to categorize the identifications of concept drifts, the detections were considered to be true positives if they occurred within 2% of the concept size after the correct drift point. For instance, in the 100,000 instances datasets, the concepts last for 20,000 instances and, thus, detections occurred up to 400 instances after the correct points were computed as true positives.

It is important to say that this analysis used only the abrupt datasets because the exact positions where the concept changes occur are known. In the gradual concept drift datasets, it is not clear how the positive identifications should be computed as there is no single drift point.

Table 2 – Concept drift identifications of RDDM and the other methods in the abrupt datasets

DATASET	METHOD	μDist	%TP	FP	FN	METHOD	μDist	%TP	FP	FN	DATASET
50K-Agrawal	DDM	273.00	52.5%	14.20	1.90	DDM	600.00	87.5%	28.60	0.50	1M-Agrawal
	RDDM	212.00	63.33%	2.70	1.47	RDDM	507.00	95%	37.50	0.20	
	ECDD	312.00	72.5%	82.83	1.10	ECDD	91.00	97.5%	1,806.9	0.10	
	STEPD	50.50	81.67%	40.80	0.73	STEPD	20.00	97.5%	608.00	0.10	
50K-Mixed	DDM	28.00	98.33%	0.77	0.07	DDM	138.50	92.5%	1.80	0.30	1M-Mixed
	RDDM	28.00	100%	0.07	0.00	RDDM	39.00	100%	28.50	0.00	
	ECDD	4.00	100%	61.53	0.00	ECDD	4.00	100%	1,285.0	0.00	
	STEPD	4.00	97.5%	9.77	0.10	STEPD	4.00	100%	226.70	0.00	
50K-Sine	DDM	62.00	72.5%	3.67	1.10	DDM	647.50	85%	4.80	0.60	1M-Sine
	RDDM	40.00	89.17%	0.77	0.43	RDDM	144.50	100%	30.80	0.00	
	ECDD	4.00	96.67%	83.83	0.13	ECDD	4.00	100%	1,746.6	0.00	
	STEPD	5.50	99.17%	15.33	0.03	STEPD	5.50	100%	289.90	0.00	
50K-LED	DDM	270.50	27.5%	3.10	2.90	DDM	4753.50	62.5%	2.00	1.50	1M-LED
	RDDM	247.50	25%	3.20	3.00	RDDM	575.00	87.5%	17.30	0.50	
	ECDD	15.50	74.17%	35.93	1.03	ECDD	89.00	100%	765.30	0.00	
	STEPD	98.50	77.50%	56.57	0.90	STEPD	83.50	92.5%	956.7	0.30	
100K-Agrawal	DDM	301.50	55%	23.47	1.80	DDM	1231.50	85%	31.90	0.60	2M-Agrawal
	RDDM	245.50	70.83%	1.77	1.17	RDDM	802.00	85%	69.40	0.60	
	ECDD	128.00	81.67%	175.47	0.73	ECDD	276.00	97.5%	3,580.9	0.10	
	STEPD	51.00	84.17%	68.93	0.63	STEPD	48.00	97.5%	1,180.2	0.10	
100K-Mixed	DDM	36.50	95.83%	1.37	0.17	DDM	239.50	97.5%	2.90	0.10	2M-Mixed
	RDDM	37.00	100%	0.40	0.00	RDDM	41.50	100%	52.60	0.00	
	ECDD	4.00	100%	128.67	0.00	ECDD	4.00	100%	2,576.2	0.00	
	STEPD	4.00	100%	22.63	0.00	STEPD	4.00	100%	459.60	0.00	
100K-Sine	DDM	108.00	73.33%	4.20	1.07	DDM	3103.50	80%	4.10	0.80	2M-Sine
	RDDM	55.50	86.67%	1.17	0.53	RDDM	334.50	100%	57.50	0.00	
	ECDD	4.00	97.5%	172.3	0.10	ECDD	4.00	100%	3,493.4	0.00	
	STEPD	5.00	99.17%	29.8	0.03	STEPD	4.50	100%	568.2	0.00	
100K-LED	DDM	531.50	39.17%	2.87	2.43	DDM	2463.50	75%	2.30	1.00	2M-LED
	RDDM	299.00	43.33%	2.53	2.27	RDDM	942.50	97.5%	32.10	0.10	
	ECDD	92.50	70%	74.80	1.20	ECDD	229.50	100%	1,521.4	0.00	
	STEPD	25.00	86.67%	105.63	0.53	STEPD	36.00	100%	1,904.3	0.00	
500K-Agrawal	DDM	569.50	67.5%	30.30	1.30	DDM	2770.50	75%	23.30	1.00	3M-Agrawal
	RDDM	359.50	80.83%	13.77	0.77	RDDM	576.00	92.5%	101.90	0.30	
	ECDD	306.50	82.5%	899.17	0.70	ECDD	100.50	97.5%	5,388.2	0.10	
	STEPD	44.50	95.83%	311.27	0.17	STEPD	51.00	97.5%	1,755.3	0.10	
500K-Mixed	DDM	99.00	95.83%	1.87	0.17	DDM	411.00	97.5%	2.40	0.10	3M-Mixed
	RDDM	43.50	100%	11.67	0.00	RDDM	44.50	100%	73.80	0.00	
	ECDD	4.00	100%	643.73	0.00	ECDD	4.00	100%	3,876.1	0.00	
	STEPD	4.00	100%	643.73	0.00	STEPD	4.00	100%	709.10	0.00	
500K-Sine	DDM	583.00	78.33%	4.40	0.87	DDM	5485.50	67.5%	4.40	1.30	3M-Sine
	RDDM	167.00	94.17%	14.33	0.23	RDDM	382.00	100%	69.90	0.00	
	ECDD	4.00	100%	874.5	0.00	ECDD	4.00	100%	5,210.7	0.00	
	STEPD	6.00	100%	145.73	0.00	STEPD	4.50	100%	847.9	0.00	
500K-LED	DDM	1928.00	55%	2.40	1.80	DDM	64846.00	50%	1.90	2.00	3M-LED
	RDDM	417.50	75.83%	10.70	0.97	RDDM	2516.50	82.5%	37.10	0.70	
	ECDD	128.00	92.5%	385.37	0.30	ECDD	59.00	100%	2,277.4	0.00	
	STEPD	71.50	94.17%	488.0	0.23	STEPD	22.00	97.5%	2,940.5	0.10	

Considering the mean distance of the concept drift detections, STEPD and ECDD achieved the best results in most tested datasets. To a lesser extent, these methods also presented the highest mean results in the sensitivity metric.

Regarding false negatives, STEPD and ECDD, again, presented the best results in most dataset versions. However, in many configurations, the results of RDDM were reasonably close and sometimes equal to them, especially in Mixed and Sine.

Nevertheless, these good results of STEPD and ECDD usually came at the cost of many false positive detections, hurting their accuracy results, especially in the largest datasets, and more severely in the case of ECDD.

Compared to DDM, RDDM identified the drifts closer to the correct points in 22 out of 24 datasets. In addition, RDDM correctly detected more drifts than DDM in most configurations. Also, the false negative results of RDDM were generally superior when directly compared to those of DDM.

Concerning the average number of false positives, RDDM presented lower results in the smaller datasets (50K and 100K), while DDM was better in the larger datasets. This was the only metric where DDM presented results that are superior to those of RDDM and the other tested drift detection methods.

To conclude, it is claimed RDDM presented the best balance between true and false positive detections. It achieves better accuracies than DDM by detecting more drifts and detecting them earlier. In comparison to ECDD and STEPD, its better accuracies result from much lower numbers of false positive detections.

3.2.3 Memory Results and Analysis

Table 3 presents the memory usage in bytes per second that DDM and RDDM required to process the different datasets.

Table 3 – Memory usage of DDM and RDDM in bytes per second, with 95% confidence intervals in the artificial datasets

DATASET	AGRAWAL		MIXED		SINE		LED	
Artificial	DDM	RDDM	DDM	RDDM	DDM	RDDM	DDM	RDDM
Abr-50K	5.84±0.31	8.79±0.47	1.62±0.12	3.24±0.19	1.72±0.11	3.43±0.20	31.73±1.42	35.74±1.14
Abr-100K	15.58±1.74	23.35±2.48	5.03±0.79	11.01±1.57	5.25±0.78	11.09±1.65	74.5±4.83	82.03±4.27
Abr-500K	294.48±60.78	435.42±88.07	131.5±28.73	272.66±59.21	136.72±29.55	275.32±59.93	953.64±154.17	1062.43±166.3
Abr-1M	335.01±101.4	517.28±152.6	163.24±65.28	340.64±135.07	163.22±62.67	331.02±128.1	1246.48±240.96	1413.92±245.1
Abr-2M	1257.5±462.9	1805.8±574.3	624.6±268.6	1197.3±476.8	622.1±266.5	1234.0±492.4	3873.4±1105.1	4384.9±1068.3
Abr-3M	2506.2±904.1	3738.7±1306	1361.7±592.2	2596.5±1045.5	1357.3±563	2614.4±1043.6	7578.8±2392.2	8507.6±2188.3
Gr-50K	5.76±0.29	8.97±0.42	1.6±0.11	3.51±0.21	1.62±0.12	3.59±0.25	30.88±0.9	37.11±1.48
Gr-100K	15.68±1.88	23.11±2.44	4.72±0.73	10.81±1.55	5.11±0.76	10.85±1.53	74.1±5.2	83.59±4.17
Gr-500K	291.32±58.68	441.75±88.27	129.65±28.4	271.58±59.84	134.02±29.49	281.65±59.85	932.06±153.24	1069.59±168.4
Gr-1M	364.59±128.9	525.4±160.75	157.23±60.81	304.67±111.62	168.02±69.48	324.72±124.75	1319.2±252.26	1479.08±241.9
Gr-2M	1210.1±441.2	1741.4±571.6	619.9±271.6	1181.5±459.4	673.3±292.1	1222.2±490	3946.4±1062.9	4408.8±1071.2
Gr-3M	2298.8±808.5	3726.4±1312.3	1260.7±517.5	2618.4±1058.8	1233.3±487.6	2670.4±1084.7	7522.6±2228.1	8554.9±2250.6
Real	AIRLINES			POKERHAND			ELECTRICITY	
SIZE	DDM	RDDM	SIZE	DDM	RDDM	SIZE	DDM	RDDM
539K	1274.88	1356.98	829K	187.69	163.44	45K	3.22	5.99

Analyzing the results, it is obvious that RDDM uses more memory than DDM in all tested scenarios. However, this was to be expected because, using the default configuration, RDDM stores 7,000 bytes of predictions in a circular queue to enable it to shrink the size of long concepts, recalculating the DDM statistics, as described at Subsection 3.1. In spite of this, the amount of memory consumed by RDDM was below 11K to process a three-million instances dataset, which is obviously negligible, in absolute terms, as even entrance-level modern computers have much more main memory available.

3.2.4 Run-time Results and Analysis

Table 4 presents the run-time consumption in seconds that DDM and RDDM needed to process each of the different tested datasets. Because none of them is a clear winner, the best result in each dataset version is written in **bold**.

Table 4 – Mean run-time in seconds of DDM and RDDM, with 95% confidence intervals in the artificial datasets

DATASET	AGRAWAL		MIXED		SINE		LED	
Artificial	DDM	RDDM	DDM	RDDM	DDM	RDDM	DDM	RDDM
Abr-50K	**1.44±0.06**	1.45±0.07	0.81±0.06	**0.79±0.05**	0.82±0.05	0.82±0.05	3.36±0.09	**3.26±0.08**
Abr-100K	**3.80±0.40**	3.88±0.40	**2.48±0.38**	2.67±0.38	**2.51±0.37**	2.66±0.39	7.78±0.44	**7.51±0.38**
Abr-500K	70.77±14.26	**70.69±14.23**	**64.26±14.06**	64.69±14.02	**64.84±14.11**	64.89±14.07	92.25±14.27	**90.81±14.28**
Abr-1M	**83.65±26.34**	84.54±25.50	**78.57±31.33**	80.47±31.80	78.12±30.77	**77.00±29.67**	124.73±24.61	**120.83±21.11**
Abr-2M	323.81±124.0	**297.83±99.3**	301.28±130.2	**280.71±111.7**	294.96±126.5	**287.18±114.9**	373.89±98.4	**364.79±87.5**
Abr-3M	656.70±253.1	**625.29±222.4**	666.57±292.5	**609.97±245.5**	657.86±282.7	**611.56±245.1**	742.38±217.5	**713.94±187.4**
Gr-50K	**1.43±0.06**	1.46±0.06	**0.82±0.05**	0.83±0.05	**0.80±0.06**	0.84±0.06	3.35±0.07	**3.30±0.09**
Gr-100K	3.85±0.42	**3.77±0.39**	**2.41±0.37**	2.57±0.37	**2.50±0.37**	2.56±0.37	7.74±0.43	**7.54±0.39**
Gr-500K	**70.96±14.15**	71.27±14.05	64.52±14.10	**64.13±14.10**	**64.49±14.16**	65.94±14.03	91.92±14.35	**91.30±14.28**
Gr-1M	90.97±31.66	**84.69±26.14**	78.41±31.20	**71.50±26.11**	79.15±32.12	**75.40±28.91**	127.83±24.43	**122.86±21.17**
Gr-2M	318.87±121.8	**290.04±98.2**	303.06±132.3	**275.27±107.1**	318.27±137.3	**283.55±114.2**	375.55±97.6	**362.89±85.5**
Gr-3M	**621.11±221.3**	625.60±222.7	**612.61±251.2**	613.56±247.6	**598.23±238.9**	622.26±253.4	723.48±195.5	**714.80±187.7**
Real	AIRLINES			POKERHAND			ELECTRICITY	
SIZE	DDM	RDDM	SIZE	DDM	RDDM	SIZE	DDM	RDDM
539K	61.96	**61.66**	829K	31.89	**25.80**	45K	**1.14**	1.20

One can see that DDM and RDDM presented comparable results when the size of the datasets was up to one million instances. When two million instances or more were used, RDDM became faster than DDM in almost all datasets, especially in the versions with abrupt concept drifts.

It is worth pointing out that computing the statistics in both DDM and RDDM is not a computationally heavy task. The task that takes most time to perform is training the base learner, and this situation is more time-consuming when the methods are at the warning level, because there are two classifiers running in parallel. In addition to the conditions in which DDM detects drifts, RDDM forces extra drifts when the number of instances of the warning level reaches a defined threshold. Since this situation is more likely to occur in larger datasets, such a result is to be expected.

Additionally, it is important to notice that, based on the reported results, the evaluation time is *not* directly proportional to the number of instances. As the number of instances rises, the evaluation time usually increases at a much greater rate. For example, when increasing the number of instances of the datasets from 50 thousand to three million (a 60-fold increase), the differences in their run-times range from a 215-fold increase (in the LED dataset) to a 822-fold increase (in the Mixed dataset).

3.2.5 Statistical Evaluation

Complementing the analysis of the reported results, a statistic named F_F, based on the nonparametric Friedman test (DEMSAR, 2006), was used to compare the accuracy results. The null hypothesis states that all methods are statistically equal and, when it is rejected, it means there is statistical difference in any of the methods but it does *not* specify which method(s). The Bonferroni-Dunn post-hoc test (DEMSAR, 2006) was used to compare RDDM (as base method) against the other methods and find this out.

Figure 3 graphically presents the results of the test referring to the data at Table 1. The calculated ranks are 1.3137 for RDDM, 2.2353 for STEPD, 2.9804 for DDM, and 3.4706 for ECDD. Note the critical difference (0.612) is represented by a bar and methods connected to the base method by this bar are *not* statistically different. According to the results, RDDM is significantly better than the other three methods.

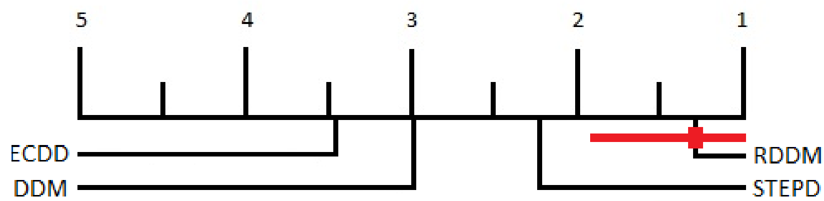


Figure 3 – Accuracy statistical comparison of RDDM and the other methods using Bonferroni-Dunn post-hoc test in the 51 tested datasets

In addition, the Wilcoxon signed-rank test (WILCOXON, 1945) has also been performed to evaluate the accuracy, memory, and run-time results of DDM and RDDM in the experiments with the artificial datasets. This test consists in ranking the differences in the performances of the methods using a set of databases. The null hypothesis, which suggests the methods have a similar performance, is based on the sum of their ranks and may be rejected or not (DEMSAR, 2006). The goal is to check whether the performances of DDM and RDDM are statistically different.

Table 5 presents the Wilcoxon signed-rank test results of the two methods in the tested datasets. Notice that larger numbers are superior in accuracy and inferior in both memory and run-time.

Table 5 – Wilcoxon signed-rank test of DDM and RDDM, with 95% confidence

Wilcoxon Test	Accuracy		Memory		Run-Time	
Methods	R+	R-	R+	R-	R+	R-
RDDM-DDM	1176	0	1176	0	302.5	874.5

Considering that the number of artificial datasets is 48, the corresponding critical value is 396, meaning that a result in either R+ or R− smaller or equal to 396 indicates a statistically significant difference.

Since, in all tested datasets, RDDM performed better than DDM in accuracy and worse in memory usage, the results of these evaluations were obvious and confirmed by the zeros in the DDM (R−) columns: RDDM was statistically superior in accuracy and statistically inferior in memory usage.

Because 302.5 is smaller than 396 and in run-time lower results are better, RDDM was also statistically better than DDM in run-time usage.

Given this last statistical result was not obvious from Table 4, the run-time usage was further investigated segmented by dataset generator. Table 6 presents these results.

Table 6 – Wilcoxon signed-rank test of DDM and RDDM run-time, with 95% confidence, in the artificial datasets segmented by generator

RUN-TIME	Agrawal		Mixed		Sine		LED	
Methods	R+	R-	R+	R-	R+	R-	R+	R-
RDDM-DDM	28.5	49.5	29	49	32	47	0	78

As the number of datasets in each generator is 12, the new critical value is 13, meaning the results of R+ or R− are now compared to 13. Thus, although RDDM achieved better results in all four segments, only in the 12 versions of LED is there a statistical difference between the methods.

Similarly, extra tests were run segmenting by size and the results returned statistical differences in favor of RDDM only in the two million instances segments.

3.3 Conclusion

This chapter presented RDDM, a new method for concept drift detection in data streams, rooted in DDM, and motivated by a drop in performance, caused by sensitivity loss, which usually affects DDM when the concepts become very long.

To evaluate RDDM against DDM, ECDD, and STEPD, experiments were run using 48 artificial dataset versions, with both abrupt and gradual concept drifts, as well as three real-world datasets, covering a reasonably large number of scenarios.

In these experiments, RDDM comprehensively outperformed DDM in accuracy, with smaller confidence intervals, and was also faster, especially in the larger datasets. And although these results came at the cost of more memory consumption, the absolute numbers are negligible for present-day computers.

Also, the accuracy of RDDM was significantly better than those of the three other methods. The advantage of RDDM to these methods is a better balance between true and false positive detections. RDDM is more accurate than DDM by detecting more drifts and detecting them earlier, and better than ECDD and STEPD because it presents much lower numbers of false positive detections.

Finally, note RDDM is subjected to more comprehensive testing in the experiments reported in Chapters 6 and 7.

4 Wilcoxon Rank Sum Test Drift Detector

This chapter proposes WSTD, which is a concept drift detection method inspired on STEPD. It changes the statistical test used to signal warnings and drifts and it also limits the size of the older window of STEPD. An efficient implementation of the rank sum test (WILCOXON, 1945) to calculate its ranks and p-value directly, without an explicit sort algorithm, is also provided.

Similarly to Chapter 3, this chapter also presents the results of previous experiments included in a paper submitted to a journal. WSTD was tested against ADWIN, DDM, EDDM, ECDD, and STEPD, using the MOA framework (BIFET et al., 2010), two different base classifiers, and a reasonably large number of scenarios, with both artificial and real-world datasets. In addition, statistical evaluations and drift identifications analysis of the results have also been performed.

The rest of the chapter is organized as follows: Section 4.1 describes the Wilcoxon rank sum test and its implementation; Section 4.2 details the proposed method (WSTD) and its abstract pseudo-code; Section 4.3 shows the experiments configuration and presents the results obtained, evaluating and statistically comparing accuracies and analysing the drift identifications; and, finally, Section 4.4 draws some conclusions.

4.1 Wilcoxon Rank Sum Test

In statistics, when tests and models do not conform to parametric standards, i.e. one cannot assume the data satisfy a known distribution, nonparametric standards are used.

The Wilcoxon rank sum test (WILCOXON, 1945) (also called Mann-Whitney U test) is a nonparametric test that can be used to determine whether two *independent* samples come from populations with the same distribution (LARSON; FARBER, 2010). This statistical test is applicable when the samples are independent and it is useful when measurements can be sorted on ordinal scale, i.e. when the values tend to a continuous variable but may not have a normal distribution.

The test is developed under the null hypothesis that the two samples have the same distribution, against the alternative that they have different distributions.

First, it is necessary to choose the significance level (α), sometimes called risk level, which is the probability of rejecting the null hypothesis when it is true. Then, critical values found in the standard table of normal distribution are established to be compared to the test statistic in order to determine the rejection criterion of the null hypothesis. They are related to α and, so, their values are fixed after α is identified.

After, the test prescribes that the $n_1 + n_2$ observations of the two samples must be combined and sorted in ascending order, resulting in a rank in the $[1, n_1 + n_2]$ interval for each observation.

In the case of ties (identical observations), their ranks are replaced by the mean of the ranks they would have if they were distinguishable. For example, if the seventh and eighth observations were identical, they would both be ranked as 7.5.

Also, the sum of the ranks of the observations of both samples are separately calculated and the smallest of the two ($\boldsymbol{R}$) is selected.

The test statistic is calculated by the generalized Equation $z = (R - \mu_R) \ / \ \sigma_R$. Note $\mu_R = n_1 \times (n_1 + n_2 + 1) \ / \ 2$ and $\sigma_R = \sqrt{n_1 \times n_2 \times (n_1 + n_2 + 1) \ / \ 12}$ are the population mean and standard deviation, respectively, and n_1 and n_2 represent the sizes of the smallest and of the largest sample, respectively.

The obtained z value is then used to reject the null hypothesis that the two samples have the same distribution when its value is in the rejection region (BLUMAN, 2014), accepting that the samples come from different distributions.

Another possibility, adopted in this work, is to determine the forcefulness of the null hypothesis by calculating the p-value and estimating the strength of evidence of the respective rejection or not that both samples have the same distribution.

The p-value is the probability obtained by finding the z value in the table of the normal distribution (BLUMAN, 2014). Thus, the null hypothesis that errors *are* equally distributed on both windows should be rejected *if and only if* the obtained p-value is smaller than the chosen significance level (α), otherwise it is accepted.

4.1.1 Implementation

Based on the aforementioned description, it is easy to see that computing the Wilcoxon rank sum text is relatively simple. However, the prescribed *sorting* of the observations can make it computationally expensive.

In the drift detection scenario, this operation would mean one ordering of the results for each new instance of data processed, even though the adoption of *insertion sort* (CORMEN et al., 2009) could possibly make it fairly efficient.

It is also worth writing that other generalizations have also been proposed to decrease the computational cost of the original test (PEROLAT et al., 2015).

However, as all the observations in the considered scenario are either 0 or 1, there will be only two rank values after the application of the test. And because the number of occurrences of both values are already calculated for both samples, it is possible to deduce these ranks by using mathematics, more specifically, the formula to calculate the sum of the elements of arithmetic series (AS), i.e. finite arithmetic progressions, making the use of an explicit *sort* unnecessary.

Given that (a) STEPD keeps track of the number of correct predictions r_o and r_r in the n_o and n_r examples of the *older* and *recent* windows, respectively, (b) the corresponding numbers of wrong predictions w_o and w_r are trivially calculated from them, and (c) in MOA 0 means true and 1 means false, the result of the *sort* of the Wilcoxon test is a sequence containing $r_o + r_r$ zeros followed by $w_o + w_r$ ones.

Consequently, the ranks of the first $r_o + r_r$ observations are all equal to the mean of the values of the AS that goes from 1 to $r_o + r_r$ with $r_o + r_r$ elements.

Then, given the sum of the elements of an AS is $(a_1 + a_n) \times n \ / \ 2$, where a_1 and a_n are its first and last element and n is the number of elements, the mean value of these elements is $(a_1 + a_n) \ / \ 2$, and the resulting rank is $rRanks = (1 + r_o + r_r) \ / \ 2$.

Similarly, the calculation of the rank of the remaining $w_o + w_r$ observations is given by $wRanks = r_o + r_r + (1 + w_o + w_r) \ / \ 2$.

The sum of the ranks of the elements of both samples are also straightforward: $sum_o = (rRanks \times r_o) + (wRanks \times w_o)$ and $sum_r = (rRanks \times r_r) + (wRanks \times w_r)$.

The rest of the provided implementation simply follows the previously presented description of the method and is omitted here.

4.2 Description of WSTD

As previously discussed in Section 2.1, STEPD maintains statistics of two windows of data and adopts the statistical test of equal proportions to detect changes in the data distribution as the means to signal the warnings and drifts points in the processed data stream.

Aiming to provide a method that identifies less false positive drifts than STEPD and is also statistically precise, this work proposes WSTD, a method that applies the Wilcoxon rank sum test in the detection of concept drifts.

WSTD works similarly to STEPD: it monitors the predictions of the base learner using two windows (*recent* and *older*), it relies on a statistical test to signal warnings and drifts, and it includes its three parameters and default values, i.e. the size of the *recent* window ($w = 30$) and the significance levels for the detection of drifts ($\alpha_d = 0.003$) and of warnings ($\alpha_w = 0.05$).

The default values of the three parameters were initially set to the same default values of STEPD to allow for a fair comparison of the methods. However, several exploratory experiments to search for better sets of values for both methods have been run later, including the use of a genetic algorithm (SANTOS; BARROS; GONÇALVES JR., 2015), but no significantly better set of values could be found over a large collection of datasets.

The main differences of the two methods are related to (a) the statistical test used to compare the samples and (b) the size of the *older* window.

In STEPD, the *older* window covers all the data instances seen before those of the *recent* window. The original intention was to adopt the same strategy in WSTD but it was noticed, experimentally, that the precision of the method would degrade when the concepts were very long, irrespective of base classifier, dataset generator, or type, frequency, and severity of drift.

For this reason, the size of the *older* window of WSTD was limited, using a fourth parameter w_2. Its default value was experimentally set to 4,000, but using 500 is enough to deliver similarly good results, especially if the base classifier is Hoeffding Tree (HT) (HULTEN; SPENCER; DOMINGOS, 2001).

Algorithm 3 presents the abstract pseudo-code of WSTD. Note the inputs are a data stream and the four parameters, i.e. the levels set for warnings and drifts and the sizes of the two windows.

Lines 1–4 show a simplified high-level summary of the data that needs to be instantiated in the beginning of the method. This includes the dynamic allocation of the two arrays, $storedPreds_r$ and $storedPreds_o$, used to store the prediction results of the *recent* and *older* windows, respectively. It also includes resetting the values of the variables that store the sizes (n_o and n_r), numbers of errors (w_o and w_r), and numbers of correct predictions (r_o and r_r) of the two windows.

As in the implementation of RDDM (Subsection 3.1.1), for the sake of efficiency in the usage of memory and run-time, the adopted storage strategy in both arrays is also that of a circular queue and the type chosen for the elements was the smallest numeric type available in Java (byte).

Lines 5–36 refer to the main part of the WSTD algorithm. It is worth saying WSTD implements its necessary adjustments after a concept drift detection when it receives the first instance of the new concept (lines 6–10), similarly to most detectors implemented in MOA. Therefore, the contents of attribute *changeDetected* at line 6 is the one set when the previous instance was processed. This is so because, in the MOA framework, changes in the base learner after the detection of concept drifts are *not* directly implemented in the code of any drift detectors – they only signal the drift points to other shared classes of the MOA implementation.

Notice that line 11 abstracts the updates needed in both windows every time a new instance of data is processed: the oldest instance of the *older* window is discarded, the

Algorithm 3: Wilcoxon rank sum test drift detector

```
   Input: Data Stream s, Recent Window Size w, Drift Level α_d, Warning Level α_w,
          Older Window Maximum Size w_2
1  storedPreds_r ← new byte [w]
2  storedPreds_o ← new byte [w_2]
3  n_o ← n_r ← w_o ← w_r ← r_o ← r_r ← 0
4  changeDetected ← false
5  foreach instance in s do
6      if changeDetected then
7          reset storedPreds_r, storedPreds_o
8          n_o ← n_r ← w_o ← w_r ← r_o ← r_r ← 0
9          changeDetected ← false
10     end
11     Updates predictions in older and recent windows
12     Updates stats of both windows: n_o, n_r, w_o, w_r, r_o, r_r
13     isWarningZone ← false
14     if n_o ≥ w then
15         rRanks ← (1 + r_o + r_r) / 2
16         wRanks ← r_o + r_r + ((1 + w_o + w_r) / 2)
17         sum_o ← (rRanks × r_o) + (wRanks × w_o)
18         sum_r ← (rRanks × r_r) + (wRanks × w_r)
19         if sum_o < sum_r then
20             R ← sum_o
21         end
22         else
23             R ← sum_r
24         end
25         aux ← n_o + n_r + 1
26         z ← (R − n_r × aux / 2) / sqrt (n_o × n_r × aux / 12)
27         p-value ← normalProbability (|z|)
28         p-value ← 2 × (1 − p-value)
29         if p-value < α_d then
30             changeDetected ← true
31         end
32         else if p-value < α_w then
33             isWarningZone ← true
34         end
35     end
36 end
```

oldest instance of the *recent* window is moved to the *older* window, and this new instance is included in the *recent* window. Accordingly, line 12 abstracts the code that reflects those changes in both windows statistics.

Observe line 14 guarantees that detections only take place after the *older* window has at least w instances, i.e. after $2 \times w$ processed instances, lines 15–28 detail the calculation of the p-value, and drifts and warnings are detected in lines 29–34.

4.3 Experiments

This section describes all the relevant information on the experiments designed to test and evaluate WSTD against STEPD and other detectors.

Firstly, all the methods have been tested with both Hoeffding Tree (HT) and Naive Bayes (NB) as base learners – they are the most frequently used in experiments in the area and their implementations are available in the MOA framework.

Three artificial dataset generators were chosen to built abrupt and gradual concept drift versions of three different sizes, for a total of 18 artificial datasets. These are Agrawal, Mixed, and Sine generators. They were all described in Subsection 2.3.1. In all of them, four concept drifts are distributed at regular intervals and the size of the concepts in each dataset version of the same generator is different, covering three different scenarios.

Again, the abrupt drifts were simulated by joining different concepts, whereas the gradual changes were generated using a probability function to increase the chance of selecting instances from the new concept instead of the old one. Once again, in the gradual concept drifts datasets, the changes last for 500 instances.

In all the artificial datasets, the experiments were executed 30 times to calculate the accuracies of the methods and the mean results were computed with 95% confidence intervals.

As in the previous chapter, in addition to the artificial datasets, three well-known real-world datasets were chosen to complement the evaluation of WSTD. These are Airlines, CovertypeSorted, and Pokerhand, all of them previously described in Subsection 2.3.2.

The accuracy evaluation was performed using Gama et al.'s Prequential methodology (GAMA; SEBASTIÃO; RODRIGUES, 2013) with a sliding window as its forgetting mechanism. Similarly to the Interleaved Test-Then-Train methodology, used in Chapter 3, each incoming instance is also used initially for testing and subsequently for training.

The remaining subsections introduce the results of the performed experiments, including analyses of accuracy and drift identifications of the six methods over the selected datasets using the two base learners.

4.3.1 Accuracy Results and Analysis

Tables 7 and 8 present the accuracy results of the six tested methods in all selected datasets as well as their ranks using HT and NB, respectively. In each dataset and in the ranks, the best result is written in **bold**.

Table 7 – Mean accuracies of WSTD and the other methods in percentage (%) using HT, with 95% confidence intervals in the artificial datasets

TYPE – SIZE	DATASET	ADWIN	DDM	EDDM	ECDD	STEPD	WSTD
Abrupt – 20K	Agrawal	64.27 (+-0.23)	64.93 (+-1.28)	64.79 (+-0.61)	63.83 (+-0.44)	64.96 (+-0.31)	**67.13 (+-0.79)**
	Mixed	90.13 (+-0.13)	88.96 (+-0.54)	89.30 (+-0.39)	89.37 (+-0.20)	**90.65 (+-0.17)**	90.64 (+-0.15)
	Sine	88.67 (+-0.14)	89.31 (+-0.14)	87.21 (+-0.19)	86.90 (+-0.19)	89.22 (+-0.20)	**89.93 (+-0.12)**
Abrupt – 50K	Agrawal	65.73 (+-0.15)	68.03 (+-1.98)	67.45 (+-0.82)	64.76 (+-0.64)	66.18 (+-0.29)	**71.83 (+-0.72)**
	Mixed	91.46 (+-0.12)	91.28 (+-0.37)	90.30 (+-0.17)	89.78 (+-0.14)	91.14 (+-0.10)	**92.05 (+-0.10)**
	Sine	89.88 (+-0.10)	91.06 (+-0.15)	88.97 (+-0.24)	87.12 (+-0.13)	90.37 (+-0.21)	**91.53 (+-0.13)**
Abrupt – 100K	Agrawal	66.48 (+-0.12)	71.01 (+-2.08)	69.42 (+-1.05)	66.25 (+-0.71)	66.89 (+-0.27)	**74.19 (+-0.56)**
	Mixed	91.77 (+-0.10)	92.79 (+-0.12)	91.42 (+-0.11)	89.75 (+-0.10)	91.23 (+-0.09)	**93.12 (+-0.06)**
	Sine	90.33 (+-0.08)	92.31 (+-0.09)	90.49 (+-0.21)	87.15 (+-0.10)	90.96 (+-0.16)	**92.59 (+-0.10)**
Gradual – 20K	Agrawal	63.38 (+-0.24)	**64.10 (+-1.17)**	64.00 (+-0.74)	62.94 (+-0.32)	64.05 (+-0.21)	62.69 (+-1.04)
	Mixed	86.88 (+-0.14)	87.29 (+-0.19)	**87.59 (+-0.16)**	86.69 (+-0.18)	87.30 (+-0.15)	87.36 (+-0.14)
	Sine	85.43 (+-0.11)	86.68 (+-0.14)	86.53 (+-0.13)	85.04 (+-0.18)	85.89 (+-0.12)	**86.69 (+-0.22)**
Gradual – 50K	Agrawal	65.32 (+-0.16)	68.46 (+-1.74)	67.30 (+-0.82)	64.95 (+-0.74)	65.77 (+-0.25)	**68.67 (+-1.09)**
	Mixed	89.97 (+-0.11)	**90.84 (+-0.10)**	90.33 (+-0.12)	88.69 (+-0.14)	89.81 (+-0.10)	90.75 (+-0.09)
	Sine	88.51 (+-0.10)	90.27 (+-0.10)	89.00 (+-0.25)	86.33 (+-0.14)	89.16 (+-0.20)	**90.32 (+-0.12)**
Gradual – 100K	Agrawal	66.23 (+-0.12)	71.72 (+-1.76)	69.25 (+-1.18)	65.79 (+-0.64)	66.63 (+-0.27)	**72.17 (+-0.88)**
	Mixed	91.01 (+-0.10)	92.42 (+-0.08)	91.49 (+-0.11)	89.20 (+-0.10)	90.64 (+-0.09)	**92.43 (+-0.06)**
	Sine	89.60 (+-0.07)	**92.00 (+-0.09)**	90.62 (+-0.20)	86.80 (+-0.12)	90.38 (+-0.15)	91.96 (+-0.09)
Real	Airlines	65.17	65.30	65.07	63.82	65.37	**65.40**
	Covertype	71.26	75.64	**76.39**	70.05	70.75	70.88
	Pokerhand	73.83	72.73	77.30	**78.62**	77.12	76.52
Rank	–	4.28571	2.47619	3.42857	5.61905	3.47619	**1.71429**

Table 8 – Mean accuracies of WSTD and the other methods in percentage (%) using NB, with 95% confidence intervals in the artificial datasets

TYPE-SIZE	DATASET	ADWIN	DDM	EDDM	ECDD	STEPD	WSTD
Abrupt-20K	Agrawal	64.09 (+-0.17)	63.08 (+-0.59)	61.73 (+-0.32)	62.37 (+-0.15)	64.38 (+-0.18)	**64.48 (+-0.27)**
	Mixed	90.46 (+-0.12)	90.26 (+-0.67)	89.79 (+-0.19)	89.41 (+-0.20)	90.95 (+-0.19)	**91.19 (+-0.13)**
	Sine	86.66 (+-0.17)	83.67 (+-1.77)	85.60 (+-0.60)	86.42 (+-0.16)	87.18 (+-0.16)	**87.21 (+-0.18)**
Abrupt-50K	Agrawal	65.51 (+-0.13)	63.64 (+-0.63)	62.81 (+-0.24)	62.80 (+-0.13)	65.12 (+-0.15)	**65.57 (+-0.14)**
	Mixed	91.43 (+-0.11)	90.85 (+-0.96)	90.07 (+-0.59)	89.82 (+-0.14)	91.43 (+-0.14)	**91.73 (+-0.10)**
	Sine	87.14 (+-0.12)	84.21 (+-1.32)	85.46 (+-0.66)	86.44 (+-0.11)	87.27 (+-0.12)	**87.40 (+-0.11)**
Abrupt-100K	Agrawal	**66.00 (+-0.08)**	64.17 (+-0.68)	63.31 (+-0.21)	62.89 (+-0.08)	65.40 (+-0.08)	65.96 (+-0.11)
	Mixed	91.75 (+-0.06)	90.70 (+-1.17)	90.02 (+-1.02)	89.81 (+-0.09)	91.54 (+-0.08)	**91.90 (+-0.06)**
	Sine	87.28 (+-0.08)	83.77 (+-1.40)	85.75 (+-0.52)	86.45 (+-0.10)	87.30 (+-0.08)	**87.43 (+-0.09)**
Gradual-20K	Agrawal	63.07 (+-0.18)	62.62 (+-0.51)	61.90 (+-0.34)	61.85 (+-0.13)	**63.31 (+-0.23)**	63.15 (+-0.41)
	Mixed	87.12 (+-0.15)	87.85 (+-0.17)	**87.98 (+-0.18)**	86.84 (+-0.19)	87.50 (+-0.16)	87.71 (+-0.16)
	Sine	84.03 (+-0.15)	84.64 (+-0.20)	**84.73 (+-0.17)**	84.17 (+-0.15)	84.36 (+-0.19)	84.60 (+-0.16)
Gradual-50K	Agrawal	**65.21 (+-0.13)**	63.92 (+-0.57)	62.80 (+-0.26)	62.53 (+-0.11)	64.77 (+-0.14)	65.17 (+-0.14)
	Mixed	90.05 (+-0.10)	**90.42 (+-0.11)**	90.17 (+-0.11)	88.78 (+-0.15)	90.12 (+-0.11)	90.40 (+-0.10)
	Sine	86.06 (+-0.09)	86.31 (+-0.26)	85.98 (+-0.17)	85.62 (+-0.12)	86.24 (+-0.12)	**86.63 (+-0.11)**
Gradual-100K	Agrawal	**65.84 (+-0.09)**	64.06 (+-0.63)	63.34 (+-0.22)	62.77 (+-0.08)	65.16 (+-0.09)	65.69 (+-0.11)
	Mixed	91.03 (+-0.07)	91.22 (+-0.07)	90.61 (+-0.09)	89.29 (+-0.09)	90.88 (+-0.08)	**91.23 (+-0.07)**
	Sine	86.74 (+-0.08)	86.58 (+-0.29)	86.16 (+-0.17)	86.01 (+-0.09)	86.73 (+-0.07)	**87.05 (+-0.09)**
Real	Airlines	**66.70**	65.35	65.18	63.66	65.73	66.68
	Covertype	67.73	67.14	66.41	67.39	67.62	**68.15**
	Pokerhand	73.69	61.98	77.47	**79.12**	77.18	76.38
Rank	–	2.88095	3.90476	4.47619	5.28571	2.83333	**1.61905**

Notice that, in absolute terms, WSTD improved the accuracies of STEPD in most tested datasets, i.e. the results improved in all sizes of concepts, across all dataset generators, with both abrupt and gradual concept drifts, as well as in two real-world datasets and in the two base learners, with few exceptions. A notable exception was the pokerhand dataset. In other words, the performance of WSTD was solid in all situations, with very subtle variations across the different scenarios.

Moreover, WSTD achieved the very best results in over 66% and 57% of the datasets with HT and NB, respectively. Consequently, it was the best ranked method with both base learners. From the other tested detectors, DDM and STEPD were the best performing methods in the tests and ECDD was the worst.

Complementing the analysis of the reported results, again, the F_F statistic was used with the Bonferroni-Dunn post-hoc test (DEMSAR, 2006) and WSTD was the base method. They were applied twice, once for the results using each base learner. The results are again presented using graphics where the critical difference (CD) is represented by a bar and methods that are connected to WSTD by the bar are *not* statistically different.

The results of the tests referring to the data at Tables 7 and 8 are summarized in Figures 4 and 5, respectively. According to Figure 4, using HT, WSTD was significantly better than all the other methods with the exception of DDM. On the other hand, when the base learner was NB (Figure 5), there was *no* statistical difference from WSTD to STEPD and ADWIN.

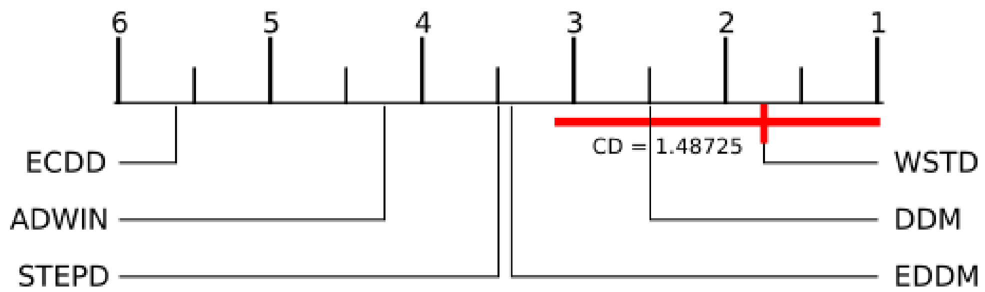


Figure 4 – Accuracy statistical comparison of WSTD and the other methods with Hoeffding Tree using the Bonferroni-Dunn post-hoc test on all tested datasets

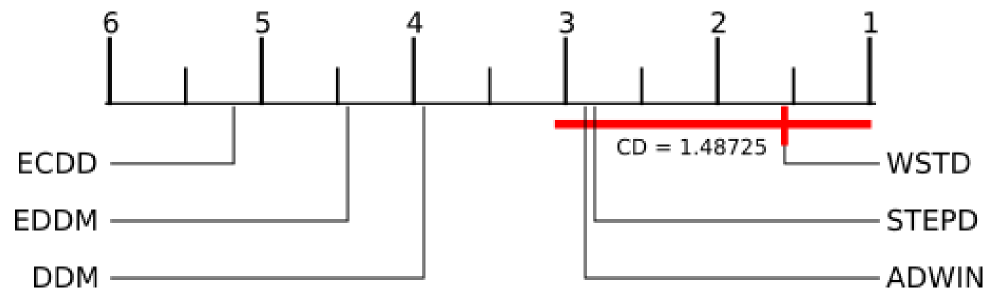


Figure 5 – Accuracy statistical comparison of WSTD and the other methods with Naive Bayes using the Bonferroni-Dunn post-hoc test on all tested datasets

4.3.2 Drift Identification Analysis

As explained in Subsection 3.2.2, a different perspective regarding the performance of the drift detectors can be obtained by analysing the number and position of the concept drifts identified by each method.

Table 9 presents, for each *abrupt* dataset configuration, the mean distance to the real drift points in the true positive drift identifications as well as the total number of false negatives (FN) and false positives (FP) of each method considering the 30 repetitions.

Table 9 – Concept drift identifications of WSTD and the other methods in the abrupt datasets using both base classifiers

RESULTS USING HOEFFDING TREE AS BASE CLASSIFIER								RESULTS USING NAIVE BAYES AS BASE CLASSIFIER						
DET.	μD	FN	FP	Prec.	Recall	MCC	DATASET	DET.	μD	FN	FP	Prec.	Recall	MCC
ADWIN	45.00	116	275	0.0143	0.03333	0.0216		ADWIN	70.00	117	265	0.0112	0.02500	0.0164
DDM	43.33	117	99	0.0294	0.02500	0.0269		DDM	70.00	119	103	0.0096	0.00833	0.0088
EDDM	56.00	115	664	0.0075	0.04167	0.0172	Agraw-20K	EDDM	40.00	119	688	0.0015	0.00833	0.0030
ECDD	**32.53**	**41**	970	0.0753	**0.65833**	0.2223		ECDD	**34.26**	52	915	0.0692	0.56667	0.1976
STEPD	44.00	60	276	0.1786	0.50000	0.2986		STEPD	46.67	**51**	208	0.2491	**0.57500**	0.3783
WSTD	37.31	53	**65**	**0.5076**	0.55833	**0.5323**		WSTD	47.41	66	**97**	**0.3576**	0.45000	**0.4010**
ADWIN	40.00	2	169	0.4111	0.98333	0.6358		ADWIN	40.00	**0**	155	0.4364	**1.00000**	0.6605
DDM	33.48	5	34	0.7718	0.95833	0.8600		DDM	43.70	1	12	0.9084	0.99167	0.9491
EDDM	44.06	24	261	0.2689	0.80000	0.4637	Mixed-20K	EDDM	51.97	44	291	0.2071	0.63333	0.3619
ECDD	**9.83**	2	739	0.1377	0.98333	0.3677		ECDD	**10.00**	**0**	765	0.1356	**1.00000**	0.3680
STEPD	11.25	**0**	187	0.3909	**1.00000**	0.6251		STEPD	**10.00**	**0**	104	0.5357	**1.00000**	0.7319
WSTD	17.33	**0**	**14**	**0.8955**	**1.00000**	**0.9463**		WSTD	16.50	**0**	**0**	**1.0000**	**1.00000**	**1.0000**
ADWIN	40.25	1	200	0.3730	0.99167	0.6081		ADWIN	40.17	**0**	110	0.5217	**1.00000**	0.7222
DDM	48.42	**0**	86	0.5825	**1.00000**	0.7632		DDM	49.76	38	94	0.4659	0.68333	0.5641
EDDM	31.77	58	696	0.0818	0.51667	0.2052	Sine - 20K	EDDM	39.40	37	780	0.0962	0.69167	0.2576
ECDD	**10.25**	1	966	0.1097	0.99167	0.3295		ECDD	**9.83**	2	945	0.1110	0.98333	0.3301
STEPD	13.28	1	184	0.3927	0.99167	0.6240		STEPD	14.33	**0**	162	0.4255	**1.00000**	0.6522
WSTD	17.83	**0**	**1**	**0.9917**	**1.00000**	**0.9959**		WSTD	18.75	**0**	**3**	**0.9756**	**1.00000**	**0.9877**
ADWIN	134.84	56	462	0.1217	0.53333	0.2546		ADWIN	145.81	58	254	0.1962	0.51667	0.3183
DDM	150.43	97	91	0.2018	0.19167	0.1966		DDM	144.00	115	**104**	0.0459	0.04167	0.0436
EDDM	107.50	116	802	0.0050	0.03333	0.0127	Agraw-50K	EDDM	70.00	119	778	0.0013	0.00833	0.0031
ECDD	**48.02**	29	2429	0.0361	0.75833	0.1653		ECDD	**58.07**	32	2282	0.0371	0.73333	0.1648
STEPD	63.37	31	574	0.1342	0.74167	0.3154		STEPD	75.47	**25**	429	0.1813	**0.79167**	0.3788
WSTD	51.70	**14**	**83**	**0.5608**	**0.88333**	**0.7038**		WSTD	81.70	32	105	**0.4560**	0.73333	**0.5782**
ADWIN	33.50	**0**	298	0.2871	**1.00000**	0.5357		ADWIN	34.50	**0**	190	0.3871	**1.00000**	0.6221
DDM	65.22	5	72	0.6150	0.95833	0.7677		DDM	73.05	2	23	0.8369	0.98333	0.9071
EDDM	103.64	65	517	0.0962	0.45833	0.2098	Mixed-50K	EDDM	138.17	49	402	0.1501	0.59167	0.2979
ECDD	**10.00**	2	1817	0.0610	0.98333	0.2447		ECDD	**10.00**	**0**	1846	0.0610	**1.00000**	0.2469
STEPD	10.42	**0**	466	0.2048	**1.00000**	0.4525		STEPD	10.50	**0**	290	0.2927	**1.00000**	0.5409
WSTD	15.75	**0**	**23**	**0.8392**	**1.00000**	**0.9161**		WSTD	15.33	**0**	**0**	**1.0000**	**1.00000**	**1.0000**
ADWIN	40.92	**0**	454	0.2091	**1.00000**	0.4572		ADWIN	41.50	**0**	142	0.4580	**1.00000**	0.6767
DDM	69.67	**0**	131	0.4781	**1.00000**	0.6914		DDM	88.85	33	110	0.4416	0.72500	0.5658
EDDM	80.97	58	852	0.0678	0.51667	0.1871	Sine - 50K	EDDM	79.19	46	1265	0.0553	0.61667	0.1844
ECDD	**10.18**	8	2448	0.0438	0.93333	0.2019		ECDD	**9.83**	1	2512	0.0452	0.99167	0.2116
STEPD	11.93	1	386	0.2356	0.99167	0.4833		STEPD	13.95	1	460	0.2055	0.99167	0.4514
WSTD	17.83	**0**	**5**	**0.9600**	**1.00000**	**0.9798**		WSTD	18.58	**0**	**4**	**0.9677**	**1.00000**	**0.9837**
ADWIN	162.95	25	838	0.1018	0.79167	0.2839		ADWIN	203.07	**6**	222	0.3393	**0.95000**	**0.5677**
DDM	230.27	83	**84**	0.3058	0.30833	0.3070		DDM	313.33	111	**114**	0.0732	0.07500	0.0740
EDDM	260.00	116	828	0.0048	0.03333	0.0126	Agraw-100K	EDDM	295.00	118	784	0.0025	0.01667	0.0064
ECDD	53.74	21	4745	0.0204	0.82500	0.1297		ECDD	**60.34**	31	4661	0.0187	0.74167	0.1177
STEPD	77.05	25	1114	0.0786	0.79167	0.2493		STEPD	96.47	18	778	0.1159	0.85000	0.3138
WSTD	**44.64**	**8**	127	**0.4686**	**0.93333**	**0.6613**		WSTD	106.47	18	184	**0.3566**	0.85000	0.5506
ADWIN	40.00	**0**	548	0.1796	**1.00000**	0.4238		ADWIN	40.00	**0**	164	0.4225	**1.00000**	0.6500
DDM	82.88	2	86	0.5784	0.98333	0.7542		DDM	99.04	5	41	0.7372	0.95833	0.8405
EDDM	276.86	69	627	0.0752	0.42500	0.1787	Mixed-100K	EDDM	272.21	52	460	0.1288	0.56667	0.2701
ECDD	**9.75**	1	3822	0.0302	0.99167	0.1729		ECDD	**9.83**	**0**	3860	0.0302	**1.00000**	0.1735
STEPD	12.33	**0**	1029	0.1044	**1.00000**	0.3231		STEPD	10.33	**0**	679	0.1502	**1.00000**	0.3875
WSTD	17.50	**0**	**12**	**0.9091**	**1.00000**	**0.9535**		WSTD	17.00	**0**	**0**	**1.0000**	**1.00000**	**1.0000**
ADWIN	39.92	**0**	952	0.1119	**1.00000**	0.3345		ADWIN	40.25	**0**	126	0.4878	**1.00000**	0.6984
DDM	91.42	**0**	103	0.5381	**1.00000**	0.7336		DDM	126.36	32	126	0.4112	0.73333	0.5491
EDDM	140.66	59	965	0.0595	0.50833	0.1738	Sine - 100K	EDDM	172.68	49	1543	0.0440	0.59167	0.1612
ECDD	16.05	6	5032	0.0222	0.95000	0.1449		ECDD	**10.00**	2	5168	0.0223	0.98333	0.1480
STEPD	**11.60**	1	686	0.1478	0.99167	0.3828		STEPD	13.42	**0**	893	0.1185	**1.00000**	0.3441
WSTD	16.75	**0**	**8**	**0.9375**	**1.00000**	**0.9682**		WSTD	18.17	**0**	**3**	**0.9756**	**1.00000**	**0.9877**
ADWIN	64.15	22.22	466.22	0.2011	0.81481	0.3950		ADWIN	72.81	20.11	180.89	0.3622	0.83241	0.5481
DDM	90.57	34.33	87.33	0.4557	0.71389	0.5667		DDM	112.01	50.67	80.78	0.4367	0.57778	0.5003
EDDM	122.38	75.56	690.22	0.0741	0.37037	0.1623	MEAN	EDDM	128.74	70.33	776.78	0.0763	0.41389	0.1717
ECDD	**22.26**	12.33	2552	0.0596	0.89722	0.2199		ECDD	**23.57**	13.33	2550.44	0.0589	0.88889	0.2176
STEPD	28.36	13.22	544.67	0.2075	0.88981	0.4171		STEPD	32.35	**10.56**	444.78	0.2527	**0.91204**	0.4643
WSTD	26.29	**8.33**	**37.56**	**0.7856**	**0.93056**	**0.8508**		WSTD	37.77	12.89	**44.00**	**0.7877**	0.89259	**0.8321**

The numbers of true positive (TP) and true negative (TN) detections were omitted because they can be easily calculated from the other information: $TP = 120 - FN$ and $TN = size \times 30 - 120 - FP$. Again, in each dataset and in the mean results, the best values are written in **bold**.

As in the results reported in Table 2 of Chapter 3, to compute true positives, the drifts detected within 2% of the concept size after the correct drift position were considered. For instance, in the 20K datasets, the concepts last for 4K instances and, thus, detections occurred up to 80 instances after the exact points were considered true positives. Once more, this analysis considered only the abrupt datasets because the exact positions of the concept drifts are known. The gradual drifts datasets have no single change point and, thus, it is not clear how the identifications should be classified as positive or negative, as previously explained.

Regarding the average distance of the true positives, ECDD and STEPD were the best methods in most datasets. However, these results often came at the cost of many false positive detections, hurting their accuracies. On the other hand, the detections of WSTD were usually fairly close to the best results.

As already explained, false negatives are related to existing drifts *not* detected by the methods and false positives refer to identified drifts where none exists. In both metrics, notably in the latter, WSTD was the best method. Note its perfect identifications in all versions of Mixed using NB. ECDD followed by EDDM and STEPD had the worst results in most datasets with both HT and NB.

Table 9 also presents results regarding the evaluation of the methods using *Precision* and *Recall* (FAWCETT, 2006) as well as the Matthews Correlation Coefficient (MCC) (MATTHEWS, 1975), also used by (LIU et al., 2016). In all of them, higher values indicate the corresponding methods perform better.

Precision, defined as TP / $(TP + FP)$, returns the proportion of predicted drifts that are existing drifts, whereas Recall, given by TP / $(TP + FN)$, is the proportion of the existing concept drifts that were correctly detected by each method.

The MCC criterion, defined below, was included because many other criteria are severely influenced by the imbalance ratio between the numbers of positive and negative samples (LIU et al., 2016). It returns values in the [-1, 1] interval and is based on the four values of the confusion matrix: TP, TN, FP, and FN.

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN)}} \tag{4.1}$$

Analysing the results of these three criteria, WSTD was much superior to all the other methods in both Precision and MCC with both HT and NB. In the case of Recall, in most tested datasets, WSTD presented similar results to those of ECDD and STEPD and was much better than ADWIN, DDM, and EDDM, returning the best mean with HT and the second best with NB.

Taking into consideration all the results of the experiments regarding accuracy (Subsection 4.3.1) and drift identifications, it is natural to conclude WSTD was the best performing method in this round of experiments.

4.3.3 Memory and Run-time Results and Analysis

Memory usage and mean run-time of the six methods have also been computed using HT and NB as base learners. Analysing them, we notice WSTD tends to consume slightly more memory and run-time than the other methods, especially with HT as base classifier. However, the absolute numbers are still negligible for modern computers and, for this reason, these results are omitted.

4.4 Conclusion

This chapter proposed WSTD, a new method to detect concept drifts in data streams using two windows of data, similarly to STEPD. More specifically, WSTD adopts the Wilcoxon rank sum statistical test, instead of the test of equal proportions used in STEPD, and limits the size of the *older* window. An efficient implementation of Wilcoxon's test was also provided.

WSTD was compared to five other well-known concept drift detectors, using both Hoeffding Tree (HT) and Naive Bayes (NB), several artificial datasets with abrupt and gradual concept drifts, and also real-world datasets.

In the experiments, WSTD was the top-ranked method in accuracy with both base learners and its predictive accuracies were the best in most datasets, though the results are stronger in the datasets with abrupt concept drifts. Moreover, it was significantly superior to all the other methods with at least one base learner.

Regarding drift detections, WSTD presented the lowest false negative and false positive identifications and delivered close results in the distance to the correct position of the true drifts. Moreover, it was also much better than the other detectors in the Precision and MCC criteria, with competitive results in Recall.

Thus, based on the results of these experiments, WSTD was declared the best performing drift detection method tested.

Finally, WSTD is also subjected to more comprehensive testing in the experiments reported in Chapters 6 and 7.

5 A Boosting-like Online Learning Ensemble

This chapter introduces BOLE. It is based on both ADOB (SANTOS et al., 2014) and OzaBoost (OZA; RUSSELL, 2001) and implements a few different strategies aimed at improving the accuracy results of these ensembles. More specifically, three different heuristic configuration strategies were implemented and empirically studied.

However, because some of the theoretical assumptions of boosting, and thus the associated theoretical guarantees, are deliberately being disregarded, the resulting ensemble was *not* called an online boosting variation. Instead, it is merely inspired on online boosting. Note the version based on OzaBoost was named OzaBole (OzaBole).

Similarly to Chapters 3 and 4, this chapter also includes the results of previous experiments. In this case, the paper was published in the 2016 IEEE International Joint Conference on Neural Networks (IJCNN) (BARROS; SANTOS; GONÇALVES JR., 2016).

This chapter is structured as follows: Section 5.1 details the proposed modifications and describes BOLE; Section 5.2 introduces the experiments configuration and analyses the results, including the corresponding statistical evaluation; and, finally, Section 5.3 presents some conclusions.

5.1 Proposed Heuristics and BOLE

This section provides detailed descriptions of the heuristic modifications proposed to online boosting algorithms, instantiated and tested in both ADOB and OzaBoost, aimed at improving their accuracies, particularly in datasets with frequent and/or abrupt concept drifts.

Many boosting methods are based on AdaBoost.M1 (FREUND; SCHAPIRE, 1996) and only permit a classifier to vote if its error is below 50%, the value associated to random guessing. However, when the problem is not binary, this 50% requirement is often too strong, as stated by Freund and Schapire (FREUND; SCHAPIRE, 1996).

Moreover, as AdaBoost.M1, these methods also stop processing a given instance of data as soon as they find a classifier with error greater than 50%. Discarding an instance because one of the classifiers presents low accuracy is probably a damaging strategy for online methods, as they only access each data once. This option was named the *50%-Break* voting strategy.

Even though the pseudo-code presented in their paper does not explicitly reproduce the aforementioned behavior of Adaboost.M1, Oza and Russell write nothing about doing anything differently regarding these features. Thus, in this case, it is reasonable to assume OzaBoost should replicate Adaboost.M1. And indeed this is how it is implemented in its corresponding code available in the MOA framework (BIFET et al., 2010).

Similarly, the aforementioned boosting behavior is not explicitly written in the ADOB paper (SANTOS et al., 2014) but it is also included in the corresponding implementation code available at *https://sites.google.com/site/moamethods*.

It is worth saying some online boosting methods are not based on AdaBoost.M1 and/or do not adopt such 50%-based condition and/or do not discard any instances, e.g. OSBoost (CHEN; LIN; LU, 2012).

Algorithm 4 shows a very abstract and deliberately much simplified pseudo-code corresponding to the java method *getVotesForInstance*, which implements the original voting computation of both tested boosting algorithms as implemented in the MOA framework.

Algorithm 4: Online boosting voting computation

Input: ensemble size M, instance x

for $m \leftarrow 1$ **to** M **do**
  Calculates the error ϵ_m
  if $\epsilon_m <= 0.5$ **then**
    Calculates the member weight w_m
    Calculates the member weighted vote wv_m
    Combines wv_m with other votes of instance x
  else
    break
  end
end
return *highest weighted combined vote for* x

Notice that the **if** statement written in the pseudo-code corresponds to the part of the code that only permits a classifier (weak hypothesis) to vote if its error is up to 50% and that its corresponding **else** clause contains a **break** which prevents an instance from being processed by the remaining classifiers after one of them fails the 50% condition.

It is worth pointing out that the corresponding **if** statement in the actual java code of method *getVotesForInstance* uses a different test condition, but this condition is met exactly when the error is greater than 0.5%, which is explicitly tested in method *getEnsembleMemberWeight*.

Following from the aforementioned observations, it was decided to try heuristic modifications, to examine different strategies. More specifically, three different modifications to generate ensembles were empirically tested, aimed at beating the precision accuracies of the corresponding online boosting methods. And to pursue higher accuracies, it was decided, perhaps boldly, to risk giving up boosting theoretical guarantees. As part of this process, some reasonable combinations were also compared.

The first two changes weaken the traditional boosting voting strategy and permit more classifiers to vote. The first scenario keeps the below 50% error requirement to vote but accepts the votes of all the classifiers in the ensemble that meet this 50% condition. This modification is simple and does not change the general idea of boosting. It was named the *50%-Continue* voting strategy.

The second (more permissive and daring) scenario adopts a higher error bound to accept the classifiers' votes and a slightly different strategy to aggregate them. Notice that, in the boosting original calculation, the weight of a classifier is positive when its classification error is below 50%. So, this modification requires some other arrangement in the calculation of the weights of the classifiers to prevent negative weights.

Finally, the third adaptation that was examined is the substitution of the drift detector internally used in both methods from ADWIN (BIFET; GAVALDÀ, 2007) to DDM (GAMA et al., 2004) because the results of a previous comparison of concept drift detectors (GONÇALVES JR. et al., 2014) concluded that the DDM was the best method *overall*. Other works that have used DDM as drift detector include Recurring Concept Drifts (GONÇALVES JR.; BARROS, 2013) and Active Learning Framework (ŽLIOBAITĖ et al., 2014). In this case, the change in the code is a mere parametrization of code already available in the MOA framework.

5.1.1 The BOLE Implementation

Because a single BOLE implementation is envisaged, one of the first design decisions made was to add new parameters to its implementation whenever necessary.

The implementation of the first modification is very simple and could be carried out by simply removing the **else** clause and the **break** command of the method *getVotes-ForInstance*. However, a new parameter called *breakVotes* was created, with possible values being 'y' and 'n': when it is set to 'y', BOLE will behave just like the original method; otherwise, the **break** command is never executed.

Similarly, for the second scenario, the parameter *errorBound* was created and it expects a positive value between 0.5 and 1.0. Note that values greater than 0.5 let more classifiers vote whereas smaller values would impose stronger restrictions on the voting.

To avoid negative weights in the classifiers allowed to vote, a simple shift strategy was adopted in the weights of *all* classifiers. Likewise, the value used in this shift strategy is a parameter, called *weightShift*, and its expected values are in the [0.0, 5.0] interval. When its value is set to 0.0, BOLE will calculate the weights just like the original method.

To minimize the shift strategy interference in the weights, *weightShift* should be the smallest value that avoids negative weights. For example, if the error bound is changed to 60%, *weightShift* should be *at least* 0.4055 because the original weighting function would generate a weight of approximately -0.4055 when the error of a classifier is 0.6. For the extreme error bound of 100%, the corresponding shift should be 5.0.

Notice *weightShift* can also be used to generate different weighting strategies in the ensemble, while maintaining the rest of the method behaving just like boosting. Higher values of *weightShift* would make the more accurate classifiers have comparatively smaller effects on the final results. When its value is high enough, i.e. it is greater than most of the classifiers original weights, the weighting function would tend to become very similar to a simple majority vote.

Nevertheless, neither this direction of investigation nor the combined effect of such strategy with the use of other values for the error bound have been thoroughly explored.

Algorithm 5 details BOLE's voting computation, again using a very abstract and much simplified pseudo-code, which represents the modified version of the java method *getVotesForInstance*.

Algorithm 5: BOLE's voting computation

Input: ensemble size M, instance x, $breakVotes$, $errorBound$, $weightShift$

for $m \leftarrow 1$ **to** M **do**
    Calculates the error ϵ_m
    if $\epsilon_m <= errorBound$ **then**
        Calculates the member weight w_m
        $w_m \leftarrow w_m + weightShift$
        Calculates the member weighted vote wv_m
        Combines wv_m with other votes of instance x
    else
        if $breakVotes =$ *'y'* **then**
            break
        end
    end
end
return *highest weighted combined vote for x*

5.2 Experiments

This section describes the experiments designed to test and evaluate these ideas. Specifically, using the MOA framework release 2012.08, some of the most meaningful combinations of the three proposed modifications implemented in ADOB and OzaBoost were tested among themselves as well as against other ensembles aimed at learning from data streams with concept drifts: DDD, DWM, and LevBag.

The Interleaved Test-Then-Train methodology was used to evaluate accuracy: each incoming instance is first tested and, then, it is used for training. This guarantees that every instance is used both for testing and training and avoids the problem of training before testing on any given instance.

Since neither ADOB nor OzaBoost use much execution time or memory, and also because the proposed modifications should not change this scenario, the methods are only compared in terms of accuracy.

5.2.1 Configuration of the Datasets

Four artificial dataset generators were picked, two of them were configured with abrupt concept drifts and the other two with gradual concept drifts. These are: Stagger, Agrawal, Mixed, and Waveform, all of them previously described.

Three versions of each of the four artificial datasets were generated (12 in total), with 10, 40, and 80 concept changes, respectively. They are all composed of 10,000 instances and have the concept drifts distributed at regular intervals.

The three versions of both Stagger and Agrawal have abrupt drifts and all versions of Mixed and Waveform have gradual changes. In all these gradual datasets, the length of the concept drifts was set to 50 instances. In the Agrawal datasets, 1% of noise was inserted in each of the six numeric attributes.

Finally, to compute the precision of the methods in the artificial datasets, the experiments were executed 40 times and the mean results were computed alongside with 95% confidence intervals.

Three real-world datasets, with very different number of instances and complexity, and previously used in the area have also been selected. These are Covertype, Electricity, and Pokerhand1M.

5.2.2 Parametrization of the Methods

As several methods have common parameters, these were all set similarly, for a fair comparison of their results. Likewise, the chosen base learner was a Hoeffding Tree (HT) (HULTEN; SPENCER; DOMINGOS, 2001) and the number of experts was set to 10 in all of them.

To detect drifts, OzaBoost, ADOB, and LevBag all use ADWIN. The only formal parameter of ADWIN is δ, the maximum global error, and its default value at MOA is 0.002. However, the ADWIN code available in the MOA framework has an informal parameter as an internal variable: the minimum number of processed instances necessary to reduce the window size (*mintClock*, set to 32). This configuration is referred as ADWIN$_{OLD}$.

On the other hand, based on partial results of ongoing and unpublished research, it is believed these are not the best parameter values for ADWIN when many concept drifts are expected. Thus, it was decided the experiments would run the detectors with a more sensitive to concept drifts parametrization, despite this making them more likely to raise false alarms. The chosen parametrization for ADWIN is: $\delta = 0.58$ and $mintClock = 70$. Notice that (a) changing the value of δ directly influences the sensibility of ADWIN and (b) increasing *mintClock* avoids consecutive detections, notably during gradual concept drifts.

In addition, aiming to separate the effect of this different configuration from those of the proposed modifications to the boosting methods, we also tested the original versions of ADOB and OzaBoost using this new setting.

The DDM implementation available in MOA has one formal parameter, the minimum number of processed instances before a drift can be detected (n), with default value 30, and two others hard-coded, representing the number of standard deviations to raise warnings ($w = 2$) and to detect drifts ($d = 3$). As in the case of ADWIN, we chose to use a different, more sensitive, configuration: $n = 7$, $w = 1.2$, and $d = 1.95$.

The parameters of the other methods were always set to their default values, as specified by their authors and their specific values are given below.

The parameters of DDD are W, which controls its robustness to false alarms and was set to 1, and λ_l and λ_h, which are the values that represent ensembles with low and high diversity, respectively set to 1 and 0.1.

DDD uses EDDM to detect changes. The parameters of EDDM with their respective default values are the number of instances ($n = 30$) and of errors ($e = 30$) before starting to detect changes, and the confidence levels to activate the warning level ($w = 0.95$) and to detect drifts ($d = 0.9$).

DWM uses three parameters: the time needed to verify if any expert will be added or removed and to update the weights of classifiers that incorrectly classifies the actual instance ($p = 50$); the decrement applied to the expert when it makes a mistake ($\beta = 0.5$); and the minimum value an expert must have to stay in the ensemble ($\theta = 0.01$) (KOLTER; MALOOF, 2007).

Finally, LevBag uses λ, which controls the weight of resampling and was set to 6.

5.2.3 Tested Versions of the Methods

Seven versions based on each of the two methods were tested. The first versions, named ADOB and OzaBoost, respectively, are their original versions, using the traditional boosting voting strategy (*50%-Break*) and ADWIN_{OLD}, the default configuration of

ADWIN. Versions 2 of both methods are similar but they use the new parametrization chosen for ADWIN.

The other five versions were named using BOLE and OzaBole, respectively, as they use the modified implementation code. Versions 1 use the *50%-Continue* voting strategy (breakVotes = 'n', errorBound=0.5, weightShift=0.0), the first proposed modification to the original methods, also adopting the new parametrization of ADWIN.

The BOLE_2 and OzaBole_2 versions both implement the two proposed modifications, again using the new parametrization of ADWIN. The parameter values chosen to let more classifiers vote were: breakVotes = 'n', errorBound=0.6, and weightShift=1.0. We named this combination the *60%-Continue* voting strategy. The second modification on its own (the *60%-Break* voting strategy) was not tested in this round of experiments.

Finally, versions 3, 4 and 5 of the new methods are similar to the respective versions 2 of the original methods, and versions 1 and 2 of the new methods, respectively, except for they all use DDM and its new parametrization, which were the drift detector and configuration originally chosen for BOLE.

5.2.4 Results and Accuracy Analysis

Tables 10 and 11 present the accuracies obtained for each of the seven variations based on ADOB and OzaBoost, respectively, and Table 12 gives the results of the other methods, all tested on the artificial and real-world datasets. In each dataset, the overall best result is written in **bold** and the best local results in the other tables are written in *italics*. Also, Rank_{ALL} is the mean of the rank positions that each configuration achieved over the 15 datasets, considering all 17 tested configurations.

Note that ADWIN_{OLD} with the *50%-Break* voting strategy corresponds to the methods' original configurations and the other ranks (Rank_{BOLE} and $\text{Rank}_{OZ.}$) are the means of the rank positions of each configuration within each table.

In all Stagger datasets, all the modifications improved the accuracy of both methods and their performances were close. The biggest increases came with OzaBole whereas the best accuracies were achieved by BOLE. Also, the improvements were higher in the versions with more concept drifts.

In Agrawal_{10D}, the accuracies remained similar in all configurations of both methods. In the other two data sets, the accuracies have increased 2%-3% in the versions using ADWIN with the new parametrization, and another 2%-3% when using DDM. BOLE_5 achieved the best accuracies in these Agrawal datasets with more concept drifts.

In Mixed_{10D}, the accuracies in both methods were similar, being slightly higher when using DDM. In Mixed_{40D}, the results increased by approximately 8% with the new

Table 10 – Mean accuracies in percentage (%), with 95% confidence intervals in artificial datasets, for ADOB/BOLE using different configurations of concept drift detector, its parameters (in the specific case of ADWIN), and voting strategy.

	ADOB ADWIN$_{OLD}$ 50%-Break	ADOB$_2$ ADWIN 50%-Break	BOLE$_1$ ADWIN 50%-Cont.	BOLE$_2$ ADWIN 60%-Cont.	BOLE$_3$ DDM 50%-Break	BOLE$_4$ DDM 50%-Cont.	BOLE$_5$ DDM 60%-Cont.
Stag.$_{10D}$	98.43±0.04	98.54±0.04	98.53±0.04	98.52±0.04	98.96±0.04	98.96±0.04	**98.97±0.04**
Stag.$_{40D}$	90.05±0.26	93.48±0.20	93.48±0.20	93.45±0.19	96.91±0.07	96.90±0.07	**96.92±0.07**
Stag.$_{80D}$	71.39±0.52	79.51±0.75	79.63±0.74	80.03±0.73	93.88±0.14	94.00±0.13	**94.08±0.12**
Agr.$_{10D}$	77.38±0.53	77.92±0.49	78.01±0.48	*78.19±0.44*	77.68±0.24	77.69±0.24	77.87±0.27
Agr.$_{40D}$	67.44±0.42	69.52±0.35	69.61±0.32	69.79±0.32	71.98±0.31	71.98±0.31	**72.07±0.29**
Agr.$_{80D}$	63.80±0.39	66.30±0.43	66.30±0.43	66.32±0.45	69.12±0.34	69.12±0.34	**69.21±0.33**
Mix.$_{10D}$	84.16±0.26	84.42±0.29	84.46±0.27	84.27±0.28	85.79±0.24	**85.81±0.23**	85.71±0.22
Mix.$_{40D}$	55.12±0.57	62.11±1.02	63.03±0.78	63.31±0.79	76.53±0.52	**76.55±0.52**	76.36±0.53
Mix.$_{80D}$	50.88±0.25	50.93±0.28	50.78±0.29	50.72±0.31	64.79±0.82	*64.81±0.82*	64.78±0.84
Wave$_{10D}$	77.08±0.36	77.06±0.36	77.17±0.35	76.76±0.36	77.45±0.36	*77.69±0.31*	77.55±0.31
Wave$_{40D}$	72.26±0.76	72.61±0.78	72.92±0.74	71.52±0.71	76.83±0.56	*77.08±0.56*	77.01±0.55
Wave$_{80D}$	70.72±1.05	71.24±1.03	71.56±1.03	71.04±1.02	76.14±0.92	*76.36±0.92*	76.31±0.93
Electric.	88.64	89.32	89.34	89.25	89.91	89.93	**90.04**
Covert.	85.52	85.26	85.29	85.25	*90.04*	*90.04*	90.03
Pokerh.	53.03	52.92	53.65	53.03	50.71	**53.70**	53.10
Rank$_{BOLE}$	6.3000	5.1333	4.3333	5.3000	3.0000	**1.8666**	2.0666
Rank$_{ALL}$	12.8333	10.2666	9.0000	10.4333	4.7333	**2.7333**	3.2666

Table 11 – Mean accuracies in percentage (%), with 95% confidence in artificial datasets, for OzaBoost/OzaBole, using similar configurations to those of Table 10.

	OzaBoost ADWIN$_{OLD}$ 50%-Break	OzaBoost$_2$ ADWIN 50%-Break	OzaBole$_1$ ADWIN 50%-Cont.	OzaBole$_2$ ADWIN 60%-Cont.	OzaBole$_3$ DDM 50%-Break	OzaBole$_4$ DDM 50%-Cont.	OzaBole$_5$ DDM 60%-Cont.
Stag.$_{10D}$	97.51±0.92	97.61±0.92	98.48±0.06	98.51±0.05	98.02±0.92	98.89±0.05	*98.91±0.04*
Stag.$_{40D}$	89.84±0.49	92.60±0.44	93.08±0.19	93.24±0.17	96.30±0.42	96.78±0.08	*96.81±0.08*
Stag.$_{80D}$	71.55±0.61	81.15±0.61	81.98±0.58	82.36±0.59	93.00±0.21	93.74±0.13	*93.87±0.12*
Agr.$_{10D}$	76.35±0.46	77.24±0.46	77.22±0.47	77.29±0.43	*77.61±0.27*	77.56±0.27	77.58±0.22
Agr.$_{40D}$	67.64±0.37	69.64±0.32	69.63±0.33	69.74±0.29	*71.83±0.31*	71.81±0.31	71.78±0.30
Agr.$_{80D}$	63.63±0.30	66.08±0.39	66.06±0.38	65.99±0.38	*68.79±0.36*	*68.79±0.36*	68.75±0.36
Mix.$_{10D}$	83.47±0.31	83.55±0.34	83.59±0.35	83.52±0.29	85.51±0.27	*85.55±0.25*	84.92±0.26
Mix.$_{40D}$	55.30±0.51	63.17±0.81	63.30±0.84	63.84±0.87	76.05±0.49	*76.09±0.49*	75.76±0.50
Mix.$_{80D}$	50.73±0.21	50.63±0.27	50.70±0.25	50.75±0.29	65.14±0.75	*65.20±0.76*	65.12±0.77
Wave$_{10D}$	77.56±0.39	77.51±0.38	77.82±0.34	78.20±0.40	77.59±0.34	77.79±0.32	**78.21±0.33**
Wave$_{40D}$	71.19±0.91	71.61±0.90	72.77±0.83	72.59±0.90	76.66±0.58	77.02±0.53	**77.61±0.53**
Wave$_{80D}$	69.77±1.05	70.53±0.97	71.30±0.94	71.87±0.97	75.58±0.92	76.05±0.88	**76.78±0.91**
Electric.	88.45	88.88	88.92	89.47	89.24	89.31	*89.75*
Covert.	85.45	84.90	84.91	85.63	89.70	89.73	**90.16**
Pokerh.	53.07	53.07	*53.67*	53.63	52.43	52.96	52.29
Rank$_{OZ.}$	6.4333	5.7000	4.6666	3.8666	2.9666	2.2333	**2.1333**
Rank$_{ALL}$	14.0333	12.3666	10.6000	9.2666	6.8333	5.4333	4.7333

ADWIN parametrization, and another 11% to 13% with DDM. In Mixed$_{80D}$ the versions using ADWIN had similar results but the change to DDM increased the results by more than 14%. BOLE$_4$ was the best classifier in the first two datasets.

Similarly, the accuracies in Waveform with fewer drifts improved slightly when using the proposed configurations. In the other versions, the accuracies increased a little with the new ADWIN parametrization and voting strategies. The change to DDM improved the results in about 4%. Here, OzaBole$_5$ was the best classifier in all three versions.

In the real-world datasets, the improvements were usually small and were not present in all combinations but, once again, the best result in each individual dataset was obtained by one of the modified ensembles.

Table 12 – BOLE: Mean accuracy in percentage (%) with 95% confidence in artificial datasets, for the other selected ensembles.

	DDD	DWM	LevBag
Stagger_{10D}	95.24±0.29	*95.75*±0.34	90.77±0.32
Stagger_{40D}	*88.11±0.36*	86.46±0.44	81.46±0.32
Stagger_{80D}	76.22±0.31	*77.19±0.40*	72.26±0.43
Agrawal_{10D}	76.44±0.30	73.10±0.42	**80.07±0.56**
Agrawal_{40D}	69.87±0.73	67.30±0.34	*70.64±0.31*
Agrawal_{80D}	*66.60±0.47*	64.47±0.38	64.95±0.46
Mixed_{10D}	*83.94±0.44*	83.70±0.37	75.49±0.68
Mixed_{40D}	*74.14±0.52*	72.34±0.65	53.72±0.73
Mixed_{80D}	**65.84±0.71**	61.60±0.58	44.64±0.35
Wave_{10D}	*77.70±0.35*	72.59±0.43	76.99±0.50
Wave_{40D}	*76.18±0.62*	71.60±0.70	74.71±0.62
Wave_{80D}	*74.62±0.99*	69.18±0.95	72.61±0.96
Electricity	86.17	88.52	*89.71*
Covertype	83.86	87.00	*88.13*
Pokerhand	*52.97*	46.36	52.18
Rank_{ALL}	10.4666	14.0000	12.0000

One interesting and promising result was the fact that the higher error bound for the votes of the classifiers also improved results in binary datasets, e.g. in stagger and electricity. This was a somewhat surprising result.

Notice that, in the mean ranks, all versions of BOLE have a better ranking than DDD, DWM, and LevBag. The same occurred with OzaBole, except for OzaBole_1. The best overall classifier was BOLE_4, closely followed by BOLE_5, and the worst were OzaBoost and DWM.

Once again, the F_F statistic (DEMSAR, 2006) was used but, this time, with the Nemenyi post-hoc test to verify which of the classifiers are statistically superior to the others. It was computed three times: one to compare the seven versions of Table 10, another for the seven versions of Table 11, and a third time comparing all the 17 configurations, generating the three rankings.

To find out which methods are statistically superior, the Nemenyi-test also uses a critical difference (CD) as a reference. The calculated CD value with 95% confidence for the comparison of all 17 versions was approximately 6.376. This means that each pair of methods with a ranking difference greater than 6.376 are statistically different.

BOLE_4 presented significant differences when compared to both versions of ADOB and OzaBoost, to BOLE_2, OzaBole_1, and OzaBole_2, as well as to DDD, DWM, and LevBag. BOLE_5 was also statistically superior to all these classifiers, except for OzaBole_2. Notice that BOLE_4 and BOLE_5 were the only two configurations to statistically outperform DDD, and that $BOLE_3$, $OzaBole_5$ and $OzaBole_4$ followed just behind, with several significant differences.

Figure 6 graphically represents these results, but notice that some configurations with intermediate results have been omitted to improve the presentation.

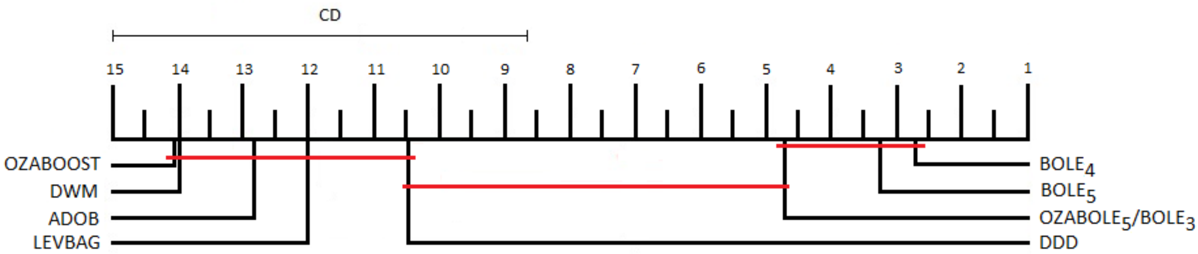


Figure 6 – Comparison results using the Nemenyi test with 95% confidence: groups of classifiers that are not significantly different are connected.

5.3 Conclusion

This chapter proposed different strategies aimed at increasing the accuracy of online boosting methods, particularly in scenarios where concept drifts are frequent and/or abrupt.

More specifically, the effects of (a) lessening the precondition that controls which experts are allowed to vote and of (b) replacing the concept drift detection method that is often used within several online learning methods were studied. In addition, a more aggressive parametrization was tried on these detectors, making them more sensitive to concept drifts, in spite of making them likely to raise more false alarms.

The results suggest that each of the proposed modifications are more effective than the others in different scenarios. In most cases, they contributed to improve the accuracies of both tested methods and, together, they statistically outperformed most other configurations in the tested datasets. So, the proposed modifications were all considered very successful, making $BOLE_4$ and $BOLE_5$ achieve the best rankings overall.

It is worthwhile pointing out that both versions of BOLE are subjected to more comprehensive testing in the experiments reported in Chapter 7.

Finally, to some extent, this work could be seen as an experimental exploration of the algorithmic solution space which might lead to provably better boosting algorithms in the future. In addition, both BOLE and OzaBole were implemented in the MOA framework and their codes are freely available at *https://sites.google.com/site/moamethods*.

6 A Large-scale Comparison of Detectors

This chapter presents a large-scale comparison of concept drifts detection methods, including detailed information of all relevant aspects of the experiments and analysing its results. More explicitly, 15 different configurations of concept drift detection methods are compared in terms of accuracy and of their detections. The results of this large-scale experiments give indications of the best concept drift detection methods configurations.

The experiments reported in this chapter were performed using seven artificial dataset generators, configured with both abrupt and gradual drift versions of several sizes, using two different base classifiers — Naive Bayes (NB) (JOHN; LANGLEY, 1995) and Hoeffding Tree (HT) (HULTEN; SPENCER; DOMINGOS, 2001), and run in the MOA framework (BIFET et al., 2010), release 2014.11.

More specifically, these experiments were designed to answer research questions **RQ1** to **RQ5**, introduced in Chapter 1 and repeated below:

- **RQ1:** What are the best drift detectors in terms of accuracy in abrupt and gradual concept drift datasets?
- **RQ2:** What are the best concept drift detectors in terms of detections, measured by precision and recall (FAWCETT, 2006) and the Matthews Correlation Coefficient(MCC) metric (MATTHEWS, 1975), in the abrupt datasets?
- **RQ3:** Do the answers of **RQ1** and **RQ2** vary with the different dataset generators used in the experiments? How much?
- **RQ4:** Do the answers of **RQ1** and **RQ2** depend on the size of the concepts included in the datasets? How much?
- **RQ5:** In the same datasets, are the best methods of **RQ1** and **RQ2** the same? To what extent?

The rest of this chapter is organized in five sections. Section 6.1 details all the relevant information about the experiments configuration; Section 6.2 analyses the accuracy results of the tested concept drift detection methods configurations and evaluates them statistically to answer **RQ1**; Section 6.3 inspects the results of the confusion matrix regarding the detections of the methods, i.e. false negatives (FN), false positives (FP), true negatives (TN), and true positives (TP), to answer **RQ2**; Section 6.4 provides additional perspectives on the results of the experiments, answering **RQ3**, **RQ4**, and **RQ5**; and, finally, Section 6.5 presents some conclusions and closes this chapter.

6.1 Experiments Configuration

This section provides all the relevant information about the experiments reported in this chapter. As in Chapter 4, all the concept drift detection methods have been tested with both Naive Bayes (NB) and Hoeffding Tree (HT) as base learners because they are the most frequently used classifiers in experiments in the area and their implementations are available in the MOA framework.

The tested methods are DDM, EDDM, ADWIN, ECDD, STEPD, SeqDrift2, HDDM_A, HDDM_W, and FTDD, all previously described in Section 2.1, in addition to RDDM and WSTD, proposed in Chapters 3 and 4, respectively. In the case of DDM and RDDM, three different sets of values were used on their common three parameters. The first versions, named DDM and RDDM_{30}, respectively, use the default configuration of DDM: $n = 30$, $\alpha_w = 2$, and $\alpha_d = 3$. The second versions, named DDM_7 and RDDM_7, respectively, set the values of the parametrization of DDM used by the default configuration of BOLE: $n = 7$, $\alpha_w = 1.2$, and $\alpha_d = 1.95$. Finally, the third version of the methods, named DDM_{129} and RDDM_{129}, respectively, follow the default values of RDDM: $n = 129$, $\alpha_w = 1.773$, and $\alpha_d = 2.258$. It is worth noting this arrangement was adopted to allow a more fair comparison of these two methods.

Six artificial dataset generators were chosen to build abrupt and gradual concept drift datasets of different sizes. In the tests using HT, there are five sizes of each dataset, with 10K, 20K, 50K, 100K, and 500K instances, respectively. In the case of NB, in addition to these five sizes, the tests used datasets with 1 million and 2 million instances as well. These larger datasets were *not* tested using HT only because of the excessive time needed to execute them.

The specific generators selected for these experiments are Agrawal, LED, Mixed, Random RBF, Sine, and Waveform, all previously described in Subsection 2.3.1. In the case of Agrawal, it was used twice: Agrawal_1 uses its first five functions (F1 to F5) and Agrawal_2 uses its remaining functions (F6 to F10), as these provide very different datasets.

As in Chapters 3 and 4, in all generated datasets, four concept drifts were distributed at regular intervals and, thus, the size of the concepts in each dataset version of the same generator is different, covering different scenarios.

As in previous experiments, abrupt drifts were simulated by joining different concepts, whereas gradual changes were generated using a probability function to increase the chance of selecting instances from the new concept instead of the old one. Once again, in the gradual concept drifts datasets, the changes last for 500 instances.

The experiments using artificial datasets with up to 100K instances were executed 30 times to calculate the accuracies of the methods and the mean results were computed with 95% confidence intervals. In the larger datasets there were only 10 repetitions.

Finally, as in Chapter 4, the accuracy evaluation used the Prequential methodology of Gama et al. (GAMA; SEBASTIÃO; RODRIGUES, 2013) with a sliding window of size 1000 (default in MOA) as its forgetting mechanism. In this methodology, each incoming instance is used initially for testing and subsequently for training.

6.2 Accuracy Results and Analysis

This section introduces the accuracy results of the concept drift detection methods tested configurations and examines them, including several statistical evaluations, to thoroughly answer **RQ1**.

Tables 13 and 14 present the accuracy results of the methods (split in two parts) as well as their ranks in the *abrupt* datasets using NB as base learner, also including the ranks considering all datasets (for completeness). In each dataset and in the ranks, the best result is written in **bold**.

Table 13 – Mean accuracies of Drift Detectors in percentage (%) in abrupt datasets, with 95% confidence intervals, using NB (Part 1)

DS Type and Size	DATASET FTDD	DDM WSTD	EDDM $HDDM_A$	ADWIN DDM_7	ECDD DDM_{129}	STEPD $RDDM_{30}$	SeqDrift2 $RDDM_7$	$HDDM_W$ $RDDM_{129}$
ABRUPT 10K	**$AGRAW_1$** 60.85 (+-0.29)	61.56 (+-0.52) 62.07 (+-0.36)	60.49 (+-0.38) 63.17 (+-0.32)	61.52 (+-0.30) 62.82 (+-0.20)	61.81 (+-0.31) 63.32 (+-0.27)	62.72 (+-0.35) 62.54 (+-0.28)	61.21 (+-0.37) 63.51 (+-0.22)	63.14 (+-0.26) **63.56 (+-0.26)**
	$AGRAW_2$ 79.15 (+-0.67)	72.68 (+-1.59) 80.69 (+-0.52)	70.83 (+-1.94) 80.11 (+-0.66)	78.36 (+-0.31) 81.22 (+-0.43)	80.99 (+-1.15) 79.51 (+-0.94)	81.43 (+-0.47) 73.73 (+-1.18)	77.61 (+-0.36) 81.34 (+-0.54)	**81.99 (+-0.34)** 79.63 (+-0.96)
	LED 67.20 (+-0.75)	69.57 (+-0.30) 67.60 (+-0.80)	67.52 (+-0.40) 69.72 (+-0.29)	62.40 (+-0.46) 69.54 (+-0.30)	67.48 (+-0.41) 69.85 (+-0.30)	61.03 (+-1.92) 69.54 (+-0.29)	58.87 (+-0.97) **69.99** (+-0.31)	69.28 (+-0.43) 69.80 (+-0.29)
	MIXED 90.39 (+-0.22)	89.74 (+-0.29) **90.41 (+-0.22)**	88.78 (+-0.33) 90.39 (+-0.21)	88.82 (+-0.26) 89.34 (+-0.67)	89.06 (+-0.29) 90.20 (+-0.24)	90.40 (+-0.28) 89.87 (+-0.23)	83.31 (+-0.20) 90.31 (+-0.23)	90.39 (+-0.22) 90.22 (+-0.23)
	RandRBF **31.08 (+-0.53)**	30.87 (+-0.59) 30.70 (+-0.56)	30.40 (+-0.45) 30.56 (+-0.43)	30.40 (+-0.50) 29.94 (+-0.46)	30.87 (+-0.64) 30.33 (+-0.45)	30.01 (+-0.51) 30.77 (+-0.49)	30.91 (+-0.53) 30.12 (+-0.44)	29.51 (+-0.43) 30.53 (+-0.43)
	SINE 86.75 (+-0.23)	85.10 (+-0.69) 86.76 (+-0.22)	85.35 (+-0.42) 86.62 (+-0.21)	85.59 (+-0.23) 84.86 (+-0.68)	86.23 (+-0.22) 85.83 (+-0.72)	**86.78 (+-0.21)** 86.03 (+-0.24)	80.92 (+-0.21) 86.73 (+-0.22)	86.77 (+-0.22) 86.58 (+-0.24)
	WAVEF. 78.06 (+-0.61)	78.49 (+-0.45) 78.79 (+-0.51)	78.53 (+-0.43) 78.73 (+-0.48)	78.37 (+-0.39) 78.96 (+-0.43)	78.33 (+-0.39) 79.16 (+-0.43)	**79.25 (+-0.42)** 78.56 (+-0.42)	78.41 (+-0.41) 79.23 (+-0.43)	79.18 (+-0.44) 79.12 (+-0.47)
ABRUPT 20K	**$AGRAW_1$** 62.02 (+-0.35)	63.08 (+-0.59) 64.48 (+-0.27)	61.73 (+-0.32) 64.82 (+-0.17)	64.09 (+-0.17) 64.33 (+-0.13)	62.37 (+-0.15) 64.75 (+-0.13)	64.38 (+-0.18) 64.32 (+-0.18)	63.70 (+-0.34) 64.87 (+-0.16)	64.16 (+-0.19) **64.89 (+-0.15)**
	$AGRAW_2$ 81.90 (+-0.41)	79.00 (+-0.87) 83.41 (+-0.40)	71.11 (+-1.52) 83.00 (+-0.50)	81.23 (+-0.35) 83.60 (+-0.34)	83.30 (+-0.18) 83.09 (+-0.51)	83.82 (+-0.37) 79.50 (+-0.82)	80.88 (+-0.34) 84.01 (+-0.27)	**84.13 (+-0.19)** 83.18 (+-0.56)
	LED 70.55 (+-0.47)	71.32 (+-0.25) 70.60 (+-0.44)	69.17 (+-0.27) 71.52 (+-0.18)	63.42 (+-0.57) 71.25 (+-0.36)	68.15 (+-0.42) 71.68 (+-0.18)	65.79 (+-1.63) 71.39 (+-0.18)	60.95 (+-1.04) **71.88 (+-0.19)**	70.79 (+-0.40) 71.74 (+-0.16)
	MIXED 91.18 (+-0.13)	90.26 (+-0.67) **91.19 (+-0.13)**	89.79 (+-0.19) 91.10 (+-0.12)	90.46 (+-0.12) 90.18 (+-0.51)	89.41 (+-0.20) 90.91 (+-0.22)	90.95 (+-0.19) 90.78 (+-0.14)	87.62 (+-0.14) 91.02 (+-0.14)	**91.19 (+-0.13)** 91.03 (+-0.15)
	RandRBF 31.15 (+-0.46)	30.79 (+-0.47) 30.70 (+-0.57)	30.92 (+-0.50) 30.69 (+-0.41)	30.46 (+-0.35) 30.15 (+-0.43)	**31.25 (+-0.62)** 30.42 (+-0.42)	29.65 (+-0.39) 30.76 (+-0.42)	31.14 (+-0.48) 30.17 (+-0.42)	29.32 (+-0.32) 30.50 (+-0.41)
	SINE 87.21 (+-0.19)	83.67 (+-1.77) 87.21 (+-0.18)	85.60 (+-0.60) 87.08 (+-0.18)	86.66 (+-0.17) 85.54 (+-0.67)	86.42 (+-0.16) 86.76 (+-0.48)	87.18 (+-0.16) 86.51 (+-0.23)	84.26 (+-0.17) 87.14 (+-0.18)	**87.22 (+-0.18)** 87.02 (+-0.19)
	WAVEF. 79.12 (+-0.44)	78.98 (+-0.29) 79.71 (+-0.28)	78.86 (+-0.28) 79.60 (+-0.26)	79.28 (+-0.29) 79.57 (+-0.23)	78.67 (+-0.25) 79.75 (+-0.28)	79.74 (+-0.22) 79.32 (+-0.30)	79.44 (+-0.27) **79.85 (+-0.25)**	**79.85 (+-0.24)** 79.78 (+-0.29)
ABRUPT 50K	**$AGRAW_1$** 63.55 (+-0.51)	63.64 (+-0.63) 65.57 (+-0.14)	62.81 (+-0.24) 65.67 (+-0.16)	65.51 (+-0.13) 65.22 (+-0.18)	62.80 (+-0.13) 65.53 (+-0.11)	65.12 (+-0.15) 65.36 (+-0.17)	65.55 (+-0.10) 65.63 (+-0.13)	64.61 (+-0.11) **65.73 (+-0.11)**
	$AGRAW_2$ 83.86 (+-0.50)	82.40 (+-1.16) 85.30 (+-0.25)	70.56 (+-0.86) 85.34 (+-0.22)	84.97 (+-0.20) 85.15 (+-0.31)	84.27 (+-0.09) 85.20 (+-0.22)	85.33 (+-0.19) 84.24 (+-0.43)	83.32 (+-0.39) **85.74 (+-0.08)**	85.60 (+-0.10) 85.38 (+-0.20)
	LED 72.23 (+-0.21)	71.66 (+-0.71) 72.10 (+-0.33)	70.06 (+-0.17) 72.81 (+-0.16)	64.76 (+-0.53) 72.51 (+-0.26)	68.73 (+-0.31) 72.81 (+-0.17)	68.73 (+-0.79) 72.67 (+-0.15)	65.00 (+-1.41) 72.78 (+-0.17)	71.63 (+-0.27) **72.89 (+-0.15)**
	MIXED 91.72 (+-0.10)	90.85 (+-0.96) **91.73 (+-0.10)**	90.07 (+-0.59) 91.63 (+-0.11)	91.43 (+-0.11) 90.77 (+-0.49)	89.82 (+-0.14) 91.39 (+-0.25)	91.43 (+-0.14) 91.41 (+-0.11)	90.29 (+-0.10) 91.56 (+-0.12)	91.72 (+-0.10) 91.57 (+-0.10)
	RandRBF 31.03 (+-0.49)	31.06 (+-0.50) 30.39 (+-0.54)	31.14 (+-0.42) 30.91 (+-0.40)	30.58 (+-0.34) 30.52 (+-0.40)	**31.32 (+-0.65)** 30.65 (+-0.42)	29.28 (+-0.30) 30.95 (+-0.39)	31.24 (+-0.51) 30.63 (+-0.31)	29.19 (+-0.31) 30.73 (+-0.36)
	SINE **87.40 (+-0.12)**	84.21 (+-1.32) **87.40 (+-0.11)**	85.46 (+-0.66) 87.26 (+-0.10)	87.14 (+-0.12) 86.45 (+-0.48)	86.44 (+-0.11) 86.87 (+-0.48)	87.27 (+-0.12) 86.79 (+-0.21)	86.19 (+-0.12) 87.34 (+-0.12)	**87.40 (+-0.12)** 87.22 (+-0.13)
	WAVEF. 79.92 (+-0.25)	79.60 (+-0.18) **80.21 (+-0.13)**	79.21 (+-0.16) 80.13 (+-0.15)	80.12 (+-0.13) 79.95 (+-0.15)	79.02 (+-0.16) 80.04 (+-0.17)	80.06 (+-0.13) 79.93 (+-0.17)	80.08 (+-0.13) 80.14 (+-0.13)	80.15 (+-0.14) 80.16 (+-0.14)

Table 14 – Mean accuracies of Drift Detectors in percentage (%) in abrupt datasets, with 95% confidence intervals, using NB (Part 2)

DS Type and Size	DATASET FTDD	DDM WSTD	EDDM $HDDM_A$	ADWIN DDM_7	ECDD DDM_{129}	STEPD $RDDM_{30}$	SeqDrift2 $RDDM_7$	$HDDM_W$ $RDDM_{129}$
ABRUPT 100K	**$AGRAW_1$**	64.17 (+-0.68)	63.31 (+-0.21)	66.00 (+-0.08)	62.89 (+-0.08)	65.40 (+-0.08)	66.06 (+-0.08)	64.81 (+-0.09)
	65.04 (+-0.47)	65.96 (+-0.11)	66.06 (+-0.08)	65.81 (+-0.09)	65.66 (+-0.31)	65.73 (+-0.17)	65.94 (+-0.09)	**66.08 (+-0.08)**
	$AGRAW_2$	84.29 (+-0.62)	70.20 (+-0.37)	86.05 (+-0.05)	84.49 (+-0.07)	85.84 (+-0.09)	84.49 (+-0.45)	86.09 (+-0.07)
	84.60 (+-0.47)	85.84 (+-0.31)	86.14 (+-0.09)	85.73 (+-0.35)	85.88 (+-0.20)	85.26 (+-0.34)	**86.23 (+-0.05)**	86.13 (+-0.04)
	LED	72.54 (+-0.40)	70.45 (+-0.17)	65.21 (+-0.53)	69.02 (+-0.22)	69.46 (+-0.60)	67.82 (+-1.18)	71.99 (+-0.23)
	72.94 (+-0.19)	72.85 (+-0.20)	73.37 (+-0.11)	72.90 (+-0.36)	73.35 (+-0.12)	73.23 (+-0.12)	73.21 (+-0.12)	**73.39 (+-0.12)**
	MIXED	90.70 (+-1.17)	90.02 (+-1.02)	91.75 (+-0.06)	89.81 (+-0.09)	91.54 (+-0.08)	91.19 (+-0.06)	**91.90 (+-0.06)**
	91.90 (+-0.06)	**91.90 (+-0.06)**	91.81 (+-0.07)	90.48 (+-0.75)	91.72 (+-0.09)	91.67 (+-0.06)	91.68 (+-0.07)	91.78 (+-0.06)
	RandRBF	31.38 (+-0.42)	31.49 (+-0.38)	30.59 (+-0.30)	31.51 (+-0.58)	29.12 (+-0.18)	31.41 (+-0.42)	29.30 (+-0.21)
	31.65 (+-0.45)	30.69 (+-0.44)	31.13 (+-0.34)	30.80 (+-0.33)	31.32 (+-0.31)	31.24 (+-0.35)	30.89 (+-0.22)	31.16 (+-0.28)
	SINE	83.77 (+-1.40)	85.75 (+-0.52)	87.28 (+-0.08)	86.45 (+-0.10)	87.30 (+-0.08)	86.82 (+-0.08)	**87.43 (+-0.09)**
	87.43 (+-0.09)	**87.43 (+-0.09)**	87.27 (+-0.10)	85.31 (+-1.01)	86.92 (+-0.36)	86.85 (+-0.20)	87.38 (+-0.08)	87.31 (+-0.10)
	WAVEF.	79.67 (+-0.22)	79.36 (+-0.21)	80.27 (+-0.10)	79.13 (+-0.13)	80.21 (+-0.10)	80.27 (+-0.10)	80.29 (+-0.12)
	80.23 (+-0.18)	**80.33 (+-0.10)**	80.27 (+-0.11)	80.08 (+-0.13)	80.09 (+-0.16)	80.05 (+-0.14)	80.23 (+-0.11)	80.25 (+-0.11)
ABRUPT 500K	**$AGRAW_1$**	64.72 (+-0.74)	63.73 (+-0.16)	66.39 (+-0.05)	62.96 (+-0.06)	65.58 (+-0.08)	**66.44 (+-0.04)**	64.88 (+-0.08)
	66.32 (+-0.07)	66.23 (+-0.06)	66.40 (+-0.05)	66.03 (+-0.34)	66.01 (+-0.20)	66.11 (+-0.22)	66.24 (+-0.04)	66.39 (+-0.06)
	$AGRAW_2$	85.89 (+-0.90)	70.43 (+-0.04)	**86.84 (+-0.03)**	84.75 (+-0.05)	86.28 (+-0.09)	86.54 (+-0.47)	86.56 (+-0.04)
	86.17 (+-0.64)	86.74 (+-0.11)	86.83 (+-0.06)	86.69 (+-0.10)	86.65 (+-0.09)	86.59 (+-0.18)	86.65 (+-0.06)	86.78 (+-0.06)
	LED	72.63 (+-0.60)	70.79 (+-0.16)	67.61 (+-1.10)	69.18 (+-0.14)	70.03 (+-0.29)	72.79 (+-0.38)	72.39 (+-0.26)
	73.49 (+-0.28)	73.45 (+-0.10)	**73.77 (+-0.11)**	73.31 (+-0.83)	73.49 (+-0.22)	73.59 (+-0.12)	73.48 (+-0.10)	73.75 (+-0.08)
	MIXED	91.21 (+-1.20)	90.68 (+-0.10)	92.04 (+-0.03)	89.94 (+-0.07)	91.64 (+-0.05)	91.93 (+-0.04)	**92.07 (+-0.03)**
	92.07 (+-0.03)	**92.07 (+-0.03)**	92.02 (+-0.05)	90.52 (+-1.39)	91.95 (+-0.11)	91.97 (+-0.05)	91.83 (+-0.03)	92.01 (+-0.03)
	RandRBF	**33.42 (+-0.35)**	33.36 (+-0.36)	30.78 (+-0.28)	33.26 (+-0.66)	29.07 (+-0.12)	33.15 (+-0.44)	29.40 (+-0.09)
	33.12 (+-0.31)	31.00 (+-0.29)	32.54 (+-0.29)	32.81 (+-0.41)	32.73 (+-0.34)	32.49 (+-0.25)	31.48 (+-0.22)	32.13 (+-0.26)
	SINE	79.19 (+-4.28)	83.63 (+-2.66)	87.36 (+-0.06)	86.45 (+-0.05)	87.35 (+-0.05)	87.28 (+-0.05)	87.39 (+-0.06)
	87.41 (+-0.06)	87.40 (+-0.06)	87.33 (+-0.07)	85.47 (+-2.26)	86.77 (+-0.50)	87.21 (+-0.10)	**87.41 (+-0.05)**	87.40 (+-0.06)
	WAVEF.	79.80 (+-0.30)	79.23 (+-0.33)	**80.39 (+-0.12)**	79.19 (+-0.10)	80.26 (+-0.11)	**80.39 (+-0.12)**	80.34 (+-0.11)
	80.39 (+-0.11)	80.38 (+-0.11)	80.38 (+-0.12)	80.22 (+-0.12)	80.23 (+-0.16)	80.07 (+-0.20)	80.33 (+-0.10)	80.37 (+-0.11)
ABRUPT 1M	**$AGRAW_1$**	64.28 (+-1.19)	63.62 (+-0.17)	66.49 (+-0.04)	62.98 (+-0.05)	65.67 (+-0.05)	**66.51 (+-0.04)**	64.95 (+-0.06)
	66.45 (+-0.07)	66.30 (+-0.05)	66.46 (+-0.05)	66.28 (+-0.10)	66.03 (+-0.26)	66.35 (+-0.05)	66.29 (+-0.04)	66.49 (+-0.05)
	$AGRAW_2$	85.99 (+-1.15)	70.44 (+-0.03)	**86.95 (+-0.02)**	84.77 (+-0.04)	86.34 (+-0.05)	86.89 (+-0.06)	86.61 (+-0.02)
	86.70 (+-0.27)	86.89 (+-0.05)	86.91 (+-0.03)	86.62 (+-0.22)	86.83 (+-0.08)	86.64 (+-0.27)	86.70 (+-0.03)	86.86 (+-0.02)
	LED	72.95 (+-0.35)	70.85 (+-0.16)	68.49 (+-1.32)	69.25 (+-0.12)	70.16 (+-0.30)	73.34 (+-0.20)	72.47 (+-0.14)
	73.49 (+-0.27)	73.52 (+-0.10)	**73.84 (+-0.06)**	73.55 (+-0.41)	73.65 (+-0.17)	73.70 (+-0.05)	73.53 (+-0.06)	73.82 (+-0.06)
	MIXED	90.11 (+-3.29)	89.60 (+-1.98)	92.09 (+-0.03)	89.97 (+-0.05)	91.67 (+-0.03)	92.03 (+-0.03)	**92.10 (+-0.03)**
	92.10 (+-0.03)	**92.10 (+-0.03)**	92.08 (+-0.03)	91.56 (+-0.66)	92.03 (+-0.06)	92.03 (+-0.04)	91.86 (+-0.04)	92.04 (+-0.04)
	RandRBF	33.40 (+-0.23)	**33.51 (+-0.21)**	30.74 (+-0.13)	33.16 (+-0.44)	29.03 (+-0.08)	33.49 (+-0.28)	29.32 (+-0.07)
	33.27 (+-0.21)	31.07 (+-0.23)	32.93 (+-0.21)	33.23 (+-0.25)	33.08 (+-0.33)	32.55 (+-0.19)	31.50 (+-0.18)	32.16 (+-0.13)
	SINE	81.76 (+-4.29)	83.47 (+-2.59)	87.42 (+-0.05)	86.48 (+-0.03)	87.36 (+-0.04)	87.38 (+-0.05)	87.43 (+-0.05)
	87.45 (+-0.05)	87.44 (+-0.05)	87.38 (+-0.07)	85.29 (+-2.70)	87.09 (+-0.17)	87.32 (+-0.07)	**87.45 (+-0.03)**	87.44 (+-0.04)
	WAVEF.	79.85 (+-0.36)	79.23 (+-0.31)	80.43 (+-0.07)	79.20 (+-0.08)	80.27 (+-0.07)	**80.44 (+-0.07)**	80.38 (+-0.08)
	80.40 (+-0.10)	80.40 (+-0.06)	80.41 (+-0.09)	80.26 (+-0.17)	80.18 (+-0.19)	80.35 (+-0.08)	80.35 (+-0.07)	80.41 (+-0.07)
ABRUPT 2M	**$AGRAW_1$**	64.12 (+-0.99)	63.37 (+-0.59)	66.55 (+-0.04)	62.98 (+-0.03)	65.66 (+-0.03)	**66.56 (+-0.04)**	64.95 (+-0.04)
	66.53 (+-0.04)	66.31 (+-0.02)	66.49 (+-0.05)	66.03 (+-0.76)	66.31 (+-0.19)	66.44 (+-0.04)	66.30 (+-0.02)	66.52 (+-0.03)
	$AGRAW_2$	84.94 (+-1.40)	70.45 (+-0.03)	**87.01 (+-0.02)**	84.78 (+-0.03)	86.34 (+-0.03)	86.98 (+-0.03)	86.63 (+-0.01)
	86.97 (+-0.04)	86.94 (+-0.03)	86.97 (+-0.02)	86.85 (+-0.10)	86.58 (+-0.50)	86.79 (+-0.09)	86.72 (+-0.02)	86.90 (+-0.02)
	LED	72.78 (+-0.72)	70.95 (+-0.12)	70.54 (+-0.98)	69.31 (+-0.08)	70.24 (+-0.23)	73.60 (+-0.20)	72.52 (+-0.07)
	73.77 (+-0.19)	73.64 (+-0.06)	**73.89 (+-0.05)**	73.65 (+-0.46)	73.59 (+-0.30)	73.78 (+-0.09)	73.57 (+-0.03)	73.87 (+-0.04)
	MIXED	89.91 (+-2.38)	89.96 (+-1.62)	92.06 (+-0.03)	89.95 (+-0.04)	91.64 (+-0.03)	92.03 (+-0.02)	**92.07 (+-0.02)**
	92.07 (+-0.02)	**92.07 (+-0.02)**	92.03 (+-0.02)	89.90 (+-1.50)	91.83 (+-0.15)	92.00 (+-0.03)	91.84 (+-0.04)	92.01 (+-0.03)
	RandRBF	33.58 (+-0.28)	**33.86 (+-0.15)**	30.98 (+-0.25)	33.07 (+-0.19)	29.00 (+-0.09)	33.27 (+-0.18)	29.31 (+-0.07)
	33.23 (+-0.14)	31.16 (+-0.16)	33.02 (+-0.20)	33.53 (+-0.17)	33.52 (+-0.13)	32.67 (+-0.18)	31.45 (+-0.12)	32.13 (+-0.13)
	SINE	77.48 (+-6.00)	84.62 (+-2.50)	87.44 (+-0.03)	86.47 (+-0.02)	87.36 (+-0.03)	87.41 (+-0.03)	87.44 (+-0.02)
	87.44 (+-0.03)	87.44 (+-0.02)	87.41 (+-0.02)	86.80 (+-0.82)	86.60 (+-0.80)	87.36 (+-0.02)	87.45 (+-0.03)	**87.47 (+-0.03)**
	WAVEF.	79.55 (+-0.29)	79.23 (+-0.29)	80.46 (+-0.03)	79.21 (+-0.04)	80.31 (+-0.04)	**80.48 (+-0.03)**	80.43 (+-0.04)
	80.47 (+-0.04)	80.46 (+-0.04)	80.47 (+-0.04)	80.36 (+-0.11)	80.16 (+-0.27)	80.39 (+-0.04)	80.38 (+-0.04)	80.46 (+-0.03)
NB ABRUPT	**RANK**	11.0102	12.0306	8.27551	11.6429	9.4898	8.04082	7.12245
	6.09184	5.55102	4.84694	9.33673	7.65306	8.21429	5.9898	**4.70408**
NB ALL	**RANK**	10.6071	11.551	8.7398	11.6786	10.2245	7.68367	7.28061
	6.91327	6.70918	4.87755	8.28061	7.10204	7.73469	6.2551	**4.36224**

Similarly, Tables 15 and 16 present the corresponding accuracy results of the methods (also split in two parts) as well as their ranks in the datasets configured with *gradual* concept drifts using NB as base learner, again including the ranks that consider all datasets (for completeness). In each dataset and in the ranks, the best result is written in **bold** as well.

Table 15 – Mean accuracies of Drift Detectors in percentage (%) in gradual datasets, with 95% confidence intervals, using NB (Part 1)

DS Type and Size	**DATASET** / FTDD	DDM / WSTD	EDDM / $HDDM_A$	ADWIN / DDM_7	ECDD / DDM_{129}	STEPD / $RDDM_{30}$	SeqDrift2 / $RDDM_7$	$HDDM_W$ / $RDDM_{129}$
	AGRAW$_1$	60.56 (+-0.38)	59.97 (+-0.32)	60.74 (+-0.18)	60.84 (+-0.26)	61.28 (+-0.30)	60.23 (+-0.27)	61.83 (+-0.25)
	59.27 (+-0.52)	60.80 (+-0.30)	61.25 (+-0.34)	61.69 (+-0.20)	**62.08 (+-0.29)**	60.20 (+-0.35)	61.94 (+-0.22)	62.05 (+-0.27)
	AGRAW$_2$	69.38 (+-1.23)	69.93 (+-1.53)	74.45 (+-0.48)	77.03 (+-1.08)	76.90 (+-0.89)	73.57 (+-0.65)	**77.89 (+-0.78)**
	71.82 (+-1.30)	75.61 (+-1.08)	76.12 (+-0.85)	76.19 (+-1.24)	74.01 (+-1.67)	69.29 (+-1.32)	76.55 (+-1.23)	74.29 (+-1.44)
	LED	67.78 (+-0.40)	66.69 (+-0.37)	60.92 (+-0.49)	65.16 (+-0.40)	59.51 (+-1.55)	58.41 (+-0.71)	66.72 (+-0.36)
GRAD.	63.11 (+-0.90)	64.40 (+-0.72)	67.65 (+-0.30)	67.41 (+-0.33)	67.75 (+-0.30)	67.83 (+-0.34)	67.63 (+-0.29)	**67.85 (+-0.29)**
	MIXED	83.65 (+-0.28)	84.16 (+-0.25)	83.04 (+-0.25)	83.02 (+-0.31)	83.28 (+-0.32)	83.50 (+-0.25)	83.74 (+-0.29)
10K	83.74 (+-0.24)	83.42 (+-0.27)	83.61 (+-0.27)	83.63 (+-0.26)	83.80 (+-0.30)	83.88 (+-0.27)	83.73 (+-0.27)	**83.89 (+-0.29)**
	RandRBF	30.81 (+-0.61)	30.46 (+-0.45)	30.50 (+-0.43)	30.91 (+-0.65)	29.78 (+-0.51)	**30.92 (+-0.52)**	29.41 (+-0.39)
	30.90 (+-0.56)	30.73 (+-0.61)	30.55 (+-0.47)	29.92 (+-0.50)	30.26 (+-0.44)	30.89 (+-0.52)	30.12 (+-0.45)	30.39 (+-0.44)
	SINE	81.32 (+-0.27)	81.71 (+-0.20)	80.90 (+-0.20)	81.20 (+-0.19)	80.73 (+-0.24)	81.10 (+-0.22)	81.63 (+-0.22)
	81.26 (+-0.20)	81.32 (+-0.21)	81.51 (+-0.20)	81.52 (+-0.23)	81.78 (+-0.19)	81.78 (+-0.22)	81.71 (+-0.19)	**81.85 (+-0.18)**
	WAVEF.	77.99 (+-0.43)	78.25 (+-0.37)	77.86 (+-0.39)	78.06 (+-0.37)	78.33 (+-0.38)	77.73 (+-0.41)	78.24 (+-0.39)
	76.65 (+-0.46)	77.54 (+-0.54)	77.82 (+-0.49)	78.52 (+-0.37)	78.59 (+-0.40)	77.87 (+-0.41)	**78.61 (+-0.41)**	78.46 (+-0.37)
	AGRAW$_1$	62.62 (+-0.51)	61.90 (+-0.34)	63.07 (+-0.18)	61.85 (+-0.13)	63.31 (+-0.23)	62.25 (+-0.38)	63.26 (+-0.16)
	61.14 (+-0.35)	63.15 (+-0.41)	63.92 (+-0.14)	63.69 (+-0.16)	63.81 (+-0.22)	63.62 (+-0.16)	63.87 (+-0.14)	**63.98 (+-0.13)**
	AGRAW$_2$	75.89 (+-1.02)	70.81 (+-1.58)	79.06 (+-0.31)	81.02 (+-0.92)	81.64 (+-0.38)	79.33 (+-0.25)	**82.27 (+-0.19)**
	78.79 (+-0.60)	79.76 (+-1.35)	80.47 (+-0.51)	81.81 (+-0.43)	80.65 (+-0.90)	76.58 (+-1.07)	82.13 (+-0.37)	80.79 (+-0.91)
	LED	70.54 (+-0.19)	69.29 (+-0.24)	62.53 (+-0.52)	67.21 (+-0.43)	64.11 (+-1.41)	60.56 (+-0.92)	69.36 (+-0.38)
GRAD.	67.66 (+-0.87)	68.68 (+-0.52)	70.43 (+-0.18)	70.40 (+-0.19)	70.61 (+-0.18)	70.61 (+-0.18)	70.61 (+-0.17)	**70.66 (+-0.18)**
	MIXED	87.85 (+-0.17)	87.98 (+-0.18)	87.12 (+-0.15)	86.84 (+-0.19)	87.50 (+-0.16)	87.83 (+-0.14)	87.99 (+-0.18)
20K	87.63 (+-0.16)	87.71 (+-0.16)	87.80 (+-0.18)	87.87 (+-0.16)	87.93 (+-0.19)	**88.01 (+-0.16)**	87.95 (+-0.18)	**88.01 (+-0.18)**
	RandRBF	30.89 (+-0.51)	30.77 (+-0.45)	30.37 (+-0.41)	**31.27 (+-0.61)**	29.70 (+-0.41)	31.06 (+-0.47)	29.31 (+-0.33)
	31.26 (+-0.45)	30.78 (+-0.57)	30.68 (+-0.44)	30.18 (+-0.49)	30.48 (+-0.39)	30.95 (+-0.42)	30.38 (+-0.38)	30.53 (+-0.47)
	SINE	84.64 (+-0.20)	84.73 (+-0.17)	84.03 (+-0.15)	84.17 (+-0.15)	84.36 (+-0.19)	84.38 (+-0.19)	84.92 (+-0.16)
	84.74 (+-0.17)	84.60 (+-0.16)	84.97 (+-0.15)	84.70 (+-0.20)	84.83 (+-0.17)	84.92 (+-0.19)	84.94 (+-0.16)	**84.98 (+-0.15)**
	WAVEF.	78.46 (+-0.29)	78.74 (+-0.25)	78.62 (+-0.22)	78.53 (+-0.23)	79.31 (+-0.26)	78.68 (+-0.26)	79.19 (+-0.26)
	78.15 (+-0.41)	78.73 (+-0.28)	78.90 (+-0.30)	79.32 (+-0.22)	79.29 (+-0.30)	78.76 (+-0.25)	**79.40 (+-0.27)**	79.22 (+-0.31)
	AGRAW$_1$	63.92 (+-0.57)	62.80 (+-0.26)	65.21 (+-0.13)	62.53 (+-0.11)	64.77 (+-0.14)	65.28 (+-0.13)	64.30 (+-0.12)
	62.87 (+-0.42)	65.17 (+-0.14)	**65.43 (+-0.11)**	65.02 (+-0.33)	65.34 (+-0.10)	65.13 (+-0.17)	65.27 (+-0.12)	65.38 (+-0.11)
	AGRAW$_2$	82.41 (+-0.96)	70.40 (+-0.80)	83.99 (+-0.30)	83.53 (+-0.09)	84.31 (+-0.21)	83.07 (+-0.42)	84.82 (+-0.10)
	82.75 (+-0.51)	83.90 (+-0.92)	84.57 (+-0.31)	84.73 (+-0.23)	84.67 (+-0.22)	83.75 (+-0.46)	**84.95 (+-0.13)**	84.77 (+-0.22)
	LED	72.30 (+-0.26)	70.25 (+-0.18)	64.49 (+-0.50)	68.35 (+-0.33)	68.17 (+-0.80)	64.62 (+-1.26)	71.17 (+-0.27)
GRAD.	71.62 (+-0.19)	71.48 (+-0.28)	72.48 (+-0.15)	72.39 (+-0.17)	72.61 (+-0.16)	72.50 (+-0.14)	72.43 (+-0.16)	**72.63 (+-0.15)**
	MIXED	90.42 (+-0.11)	90.17 (+-0.11)	90.05 (+-0.10)	88.78 (+-0.15)	90.12 (+-0.11)	90.37 (+-0.09)	90.47 (+-0.11)
50K	90.42 (+-0.11)	90.40 (+-0.10)	90.45 (+-0.11)	90.38 (+-0.10)	90.43 (+-0.10)	90.48 (+-0.11)	90.40 (+-0.09)	**90.50 (+-0.09)**
	RandRBF	30.94 (+-0.49)	31.10 (+-0.43)	30.59 (+-0.35)	**31.31 (+-0.66)**	29.32 (+-0.30)	31.08 (+-0.48)	29.28 (+-0.31)
	31.00 (+-0.49)	30.43 (+-0.53)	30.92 (+-0.37)	30.64 (+-0.47)	30.73 (+-0.41)	30.94 (+-0.41)	30.60 (+-0.30)	30.81 (+-0.35)
	SINE	86.31 (+-0.26)	85.98 (+-0.17)	86.06 (+-0.09)	85.62 (+-0.12)	86.24 (+-0.12)	86.29 (+-0.12)	86.76 (+-0.10)
	86.58 (+-0.11)	86.63 (+-0.11)	86.76 (+-0.10)	86.50 (+-0.13)	86.67 (+-0.11)	86.48 (+-0.21)	86.68 (+-0.12)	**86.78 (+-0.11)**
	WAVEF.	79.51 (+-0.21)	79.26 (+-0.20)	79.88 (+-0.18)	78.96 (+-0.16)	79.90 (+-0.12)	79.85 (+-0.20)	79.91 (+-0.14)
	79.42 (+-0.20)	79.80 (+-0.17)	79.89 (+-0.18)	79.87 (+-0.14)	79.90 (+-0.15)	79.78 (+-0.16)	**79.97 (+-0.13)**	79.95 (+-0.13)
	AGRAW$_1$	64.06 (+-0.63)	63.34 (+-0.22)	65.84 (+-0.09)	62.77 (+-0.08)	65.16 (+-0.09)	65.88 (+-0.08)	64.65 (+-0.08)
	64.33 (+-0.49)	65.69 (+-0.11)	**65.93 (+-0.09)**	65.71 (+-0.12)	65.69 (+-0.29)	65.71 (+-0.12)	65.77 (+-0.08)	65.92 (+-0.08)
	AGRAW$_2$	83.83 (+-0.81)	70.29 (+-0.32)	85.65 (+-0.10)	84.08 (+-0.11)	85.42 (+-0.09)	84.16 (+-0.45)	85.62 (+-0.08)
	84.03 (+-0.43)	85.51 (+-0.26)	85.70 (+-0.13)	85.59 (+-0.27)	85.61 (+-0.16)	85.07 (+-0.36)	85.76 (+-0.12)	**85.79 (+-0.06)**
	LED	72.34 (+-0.51)	70.51 (+-0.15)	65.42 (+-0.47)	68.83 (+-0.23)	69.17 (+-0.62)	68.51 (+-0.77)	71.76 (+-0.23)
GRAD.	72.47 (+-0.17)	72.46 (+-0.18)	73.22 (+-0.12)	73.14 (+-0.15)	73.27 (+-0.12)	73.18 (+-0.12)	73.07 (+-0.11)	**73.30 (+-0.12)**
	MIXED	91.22 (+-0.07)	90.61 (+-0.09)	91.03 (+-0.07)	89.29 (+-0.09)	90.88 (+-0.08)	91.21 (+-0.06)	91.27 (+-0.07)
100K	91.23 (+-0.07)	91.23 (+-0.07)	91.25 (+-0.07)	91.22 (+-0.07)	91.23 (+-0.07)	91.27 (+-0.07)	91.18 (+-0.07)	**91.29 (+-0.06)**
	RandRBF	31.41 (+-0.40)	31.56 (+-0.34)	30.62 (+-0.27)	31.53 (+-0.58)	29.14 (+-0.19)	31.48 (+-0.43)	29.25 (+-0.25)
	31.64 (+-0.45)	30.79 (+-0.40)	31.16 (+-0.33)	31.15 (+-0.34)	31.25 (+-0.36)	31.20 (+-0.35)	30.87 (+-0.25)	31.23 (+-0.30)
	SINE	86.58 (+-0.29)	86.16 (+-0.17)	86.74 (+-0.08)	86.01 (+-0.09)	86.73 (+-0.07)	86.86 (+-0.09)	**87.18 (+-0.09)**
	87.04 (+-0.09)	87.05 (+-0.09)	87.14 (+-0.09)	86.33 (+-1.08)	87.08 (+-0.11)	86.84 (+-0.20)	87.07 (+-0.08)	87.16 (+-0.09)
	WAVEF.	79.52 (+-0.18)	79.25 (+-0.20)	80.20 (+-0.12)	79.10 (+-0.13)	80.13 (+-0.10)	**80.25 (+-0.10)**	80.16 (+-0.12)
	79.95 (+-0.19)	80.21 (+-0.10)	80.20 (+-0.11)	80.10 (+-0.12)	79.98 (+-0.17)	80.02 (+-0.13)	80.17 (+-0.11)	80.13 (+-0.11)
	AGRAW$_1$	63.93 (+-0.91)	63.61 (+-0.17)	66.38 (+-0.04)	62.94 (+-0.06)	65.55 (+-0.07)	**66.41 (+-0.04)**	64.85 (+-0.08)
	66.27 (+-0.06)	66.20 (+-0.05)	66.38 (+-0.05)	66.18 (+-0.09)	65.66 (+-0.62)	66.22 (+-0.13)	66.19 (+-0.05)	66.36 (+-0.04)
	AGRAW$_2$	86.16 (+-0.34)	70.43 (+-0.04)	**86.74 (+-0.04)**	84.68 (+-0.06)	86.19 (+-0.07)	86.25 (+-0.63)	86.42 (+-0.04)
	86.05 (+-0.62)	86.61 (+-0.11)	**86.74 (+-0.05)**	86.63 (+-0.20)	86.57 (+-0.10)	86.49 (+-0.18)	86.55 (+-0.06)	86.67 (+-0.07)
	LED	72.69 (+-0.89)	70.80 (+-0.16)	67.26 (+-0.93)	69.15 (+-0.15)	69.98 (+-0.27)	72.66 (+-0.34)	72.31 (+-0.26)
GRAD.	73.35 (+-0.26)	73.35 (+-0.06)	**73.74 (+-0.11)**	73.69 (+-0.11)	73.60 (+-0.15)	73.55 (+-0.13)	73.45 (+-0.11)	73.72 (+-0.09)
	MIXED	91.76 (+-0.22)	90.70 (+-0.10)	91.88 (+-0.04)	89.83 (+-0.07)	91.51 (+-0.05)	91.93 (+-0.04)	91.93 (+-0.03)
500K	91.92 (+-0.03)	91.93 (+-0.03)	**91.94 (+-0.04)**	91.92 (+-0.03)	91.93 (+-0.03)	91.91 (+-0.03)	91.75 (+-0.03)	91.91 (+-0.03)
	RandRBF	**33.31 (+-0.43)**	33.27 (+-0.34)	30.80 (+-0.31)	33.26 (+-0.66)	29.08 (+-0.13)	33.18 (+-0.36)	29.40 (+-0.08)
	33.14 (+-0.32)	30.99 (+-0.26)	32.49 (+-0.40)	32.82 (+-0.37)	32.69 (+-0.35)	32.46 (+-0.36)	31.47 (+-0.16)	32.14 (+-0.26)
	SINE	84.02 (+-3.07)	84.05 (+-2.27)	87.26 (+-0.05)	86.36 (+-0.05)	87.24 (+-0.05)	87.29 (+-0.05)	87.35 (+-0.07)
	87.33 (+-0.04)	87.33 (+-0.04)	87.31 (+-0.06)	87.21 (+-0.07)	87.19 (+-0.21)	87.23 (+-0.13)	87.35 (+-0.06)	**87.39 (+-0.05)**
	WAVEF.	79.81 (+-0.29)	79.19 (+-0.22)	80.37 (+-0.12)	79.18 (+-0.11)	80.24 (+-0.11)	**80.38 (+-0.12)**	80.32 (+-0.11)
	80.35 (+-0.11)	80.33 (+-0.15)	80.35 (+-0.12)	80.21 (+-0.11)	80.09 (+-0.21)	80.19 (+-0.16)	80.30 (+-0.10)	80.33 (+-0.14)

Table 16 – Mean accuracies of Drift Detectors in percentage (%) in gradual datasets, with 95% confidence intervals, using NB (Part 2)

DS Type and Size	**DATASET** FTDD	DDM WSTD	EDDM $HDDM_A$	ADWIN DDM_7	ECDD DDM_{129}	STEPD $RDDM_{30}$	SeqDrift2 $RDDM_7$	$HDDM_W$ $RDDM_{129}$
	$AGRAW_1$	64.57 (+-0.85)	63.78 (+-0.30)	66.47 (+-0.04)	62.96 (+-0.05)	65.64 (+-0.05)	**66.49 (+-0.04)**	64.92 (+-0.06)
	66.43 (+-0.07)	66.29 (+-0.05)	66.45 (+-0.05)	65.97 (+-0.34)	66.19 (+-0.19)	66.33 (+-0.10)	66.27 (+-0.04)	66.44 (+-0.06)
	$AGRAW_2$	86.55 (+-0.29)	70.44 (+-0.03)	**86.90 (+-0.02)**	84.73 (+-0.04)	86.28 (+-0.04)	86.34 (+-0.61)	86.47 (+-0.11)
	86.56 (+-0.29)	86.76 (+-0.10)	86.83 (+-0.05)	86.77 (+-0.10)	86.78 (+-0.12)	86.65 (+-0.27)	86.66 (+-0.02)	86.81 (+-0.03)
	LED	72.21 (+-1.15)	70.82 (+-0.12)	68.94 (+-0.66)	69.23 (+-0.12)	70.12 (+-0.30)	73.38 (+-0.19)	72.44 (+-0.14)
GRAD.	73.61 (+-0.24)	73.46 (+-0.12)	**73.84 (+-0.06)**	73.78 (+-0.10)	73.63 (+-0.14)	73.72 (+-0.04)	73.52 (+-0.05)	73.79 (+-0.05)
	MIXED	91.89 (+-0.17)	90.70 (+-0.15)	92.00 (+-0.03)	89.92 (+-0.05)	91.60 (+-0.03)	**92.03 (+-0.03)**	**92.03 (+-0.03)**
1M	**92.03 (+-0.03)**	**92.03 (+-0.03)**	**92.03 (+-0.03)**	92.02 (+-0.03)	92.02 (+-0.03)	91.98 (+-0.04)	91.82 (+-0.03)	91.99 (+-0.03)
	RandRBF	33.37 (+-0.28)	**33.49 (+-0.15)**	31.02 (+-0.24)	33.16 (+-0.44)	29.03 (+-0.08)	**33.49 (+-0.26)**	29.33 (+-0.09)
	33.25 (+-0.21)	31.07 (+-0.24)	32.95 (+-0.25)	33.19 (+-0.33)	33.07 (+-0.23)	32.65 (+-0.24)	31.50 (+-0.17)	32.10 (+-0.15)
	SINE	79.93 (+-5.03)	85.98 (+-0.09)	87.37 (+-0.05)	86.43 (+-0.03)	87.30 (+-0.04)	87.38 (+-0.05)	87.43 (+-0.05)
	87.41 (+-0.05)	87.40 (+-0.05)	87.38 (+-0.07)	86.75 (+-1.08)	87.26 (+-0.12)	87.32 (+-0.05)	87.41 (+-0.04)	**87.45 (+-0.04)**
	WAVEF.	79.89 (+-0.32)	79.13 (+-0.27)	80.40 (+-0.08)	79.19 (+-0.08)	80.27 (+-0.06)	**80.43 (+-0.07)**	80.37 (+-0.08)
	80.39 (+-0.10)	80.38 (+-0.07)	80.40 (+-0.09)	80.25 (+-0.16)	80.18 (+-0.22)	80.25 (+-0.20)	80.34 (+-0.07)	80.40 (+-0.06)
	$AGRAW_1$	64.06 (+-1.10)	63.91 (+-0.23)	66.54 (+-0.04)	62.98 (+-0.03)	65.65 (+-0.04)	**66.55 (+-0.04)**	64.94 (+-0.04)
	66.52 (+-0.04)	66.30 (+-0.03)	66.49 (+-0.05)	66.44 (+-0.08)	66.27 (+-0.27)	66.40 (+-0.05)	66.28 (+-0.02)	66.51 (+-0.03)
	$AGRAW_2$	85.85 (+-0.87)	70.45 (+-0.03)	**86.98 (+-0.02)**	84.76 (+-0.04)	86.32 (+-0.03)	86.97 (+-0.03)	86.58 (+-0.01)
	86.87 (+-0.10)	86.87 (+-0.03)	86.95 (+-0.02)	86.89 (+-0.08)	86.59 (+-0.50)	86.77 (+-0.08)	86.70 (+-0.01)	86.88 (+-0.02)
	LED	71.68 (+-1.42)	71.00 (+-0.13)	70.62 (+-0.62)	69.31 (+-0.08)	70.23 (+-0.23)	73.58 (+-0.15)	72.50 (+-0.07)
GRAD.	73.74 (+-0.18)	73.60 (+-0.06)	**73.89 (+-0.05)**	**73.89 (+-0.06)**	73.73 (+-0.23)	73.78 (+-0.10)	73.56 (+-0.03)	73.86 (+-0.04)
	MIXED	88.51 (+-3.84)	89.50 (+-2.32)	92.02 (+-0.03)	89.92 (+-0.04)	91.60 (+-0.03)	**92.03 (+-0.02)**	**92.03 (+-0.03)**
2M	**92.03 (+-0.03)**	**92.03 (+-0.03)**	92.02 (+-0.02)	92.01 (+-0.03)	92.01 (+-0.03)	91.99 (+-0.03)	91.82 (+-0.03)	91.98 (+-0.03)
	RandRBF	33.57 (+-0.23)	**33.83 (+-0.15)**	30.90 (+-0.15)	33.07 (+-0.19)	29.00 (+-0.09)	33.26 (+-0.20)	29.31 (+-0.07)
	33.21 (+-0.14)	31.15 (+-0.15)	33.07 (+-0.19)	33.48 (+-0.15)	33.45 (+-0.14)	32.46 (+-0.20)	31.44 (+-0.12)	32.13 (+-0.10)
	SINE	80.81 (+-5.41)	82.86 (+-4.43)	87.40 (+-0.03)	86.45 (+-0.02)	87.33 (+-0.03)	87.41 (+-0.02)	87.45 (+-0.02)
	87.44 (+-0.03)	87.43 (+-0.02)	87.09 (+-0.67)	86.10 (+-2.38)	86.61 (+-1.15)	87.35 (+-0.02)	87.44 (+-0.03)	**87.46 (+-0.03)**
	WAVEF.	79.53 (+-0.30)	79.21 (+-0.29)	80.45 (+-0.03)	79.21 (+-0.04)	80.31 (+-0.04)	**80.48 (+-0.04)**	80.42 (+-0.05)
	80.47 (+-0.04)	80.45 (+-0.04)	80.46 (+-0.04)	80.40 (+-0.04)	80.04 (+-0.28)	80.40 (+-0.05)	80.38 (+-0.04)	80.45 (+-0.04)
NB	**RANK**	10.2041	11.0714	9.20408	11.7143	10.9592	7.32653	7.43878
GRAD.	7.73469	7.86735	4.90816	7.22449	6.55102	7.2551	6.52041	**4.02041**
NB	**RANK**	10.6071	11.551	8.7398	11.6786	10.2245	7.68367	7.28061
ALL	6.91327	6.70918	4.87755	8.28061	7.10204	7.73469	6.2551	**4.36224**

Tables 17 and 18 are similar to Tables 13 and 14 but refer to the results in the *abrupt* datasets using HT as base learner, instead of NB.

Table 17 – Mean accuracies of Drift Detectors in percentage (%) in abrupt datasets, with 95% confidence intervals, using HT (Part 1)

DS Type and Size	**DATASET** FTDD	DDM WSTD	EDDM $HDDM_A$	ADWIN DDM_7	ECDD DDM_{129}	STEPD $RDDM_{30}$	SeqDrift2 $RDDM_7$	$HDDM_W$ $RDDM_{129}$
	$AGRAW_1$	63.13 (+-0.56)	62.08 (+-0.34)	62.44 (+-0.25)	63.26 (+-0.33)	63.78 (+-0.38)	62.87 (+-0.33)	64.31 (+-0.37)
	62.64 (+-0.38)	63.44 (+-0.43)	64.47 (+-0.34)	63.98 (+-0.39)	64.62 (+-0.42)	63.16 (+-0.40)	**64.84 (+-0.36)**	64.69 (+-0.30)
	$AGRAW_2$	75.22 (+-1.80)	75.89 (+-1.76)	79.16 (+-0.35)	81.95 (+-0.27)	81.97 (+-0.43)	77.68 (+-0.35)	**82.59 (+-0.28)**
	79.41 (+-0.66)	81.07 (+-0.51)	81.56 (+-0.44)	81.75 (+-0.31)	81.54 (+-0.85)	76.13 (+-1.87)	82.24 (+-0.27)	81.58 (+-0.85)
	LED	69.56 (+-0.30)	67.46 (+-0.40)	61.98 (+-0.66)	67.35 (+-0.43)	60.78 (+-1.68)	58.49 (+-0.95)	69.24 (+-0.43)
ABRUPT	67.01 (+-0.74)	67.08 (+-1.00)	69.68 (+-0.30)	69.53 (+-0.30)	69.85 (+-0.30)	69.52 (+-0.29)	**69.97 (+-0.31)**	69.78 (+-0.29)
	MIXED	89.70 (+-0.29)	88.84 (+-0.29)	88.74 (+-0.27)	89.01 (+-0.28)	90.30 (+-0.29)	83.23 (+-0.20)	90.35 (+-0.22)
10K	90.33 (+-0.23)	**90.36 (+-0.22)**	90.32 (+-0.23)	89.24 (+-0.66)	89.94 (+-0.44)	89.82 (+-0.24)	90.27 (+-0.24)	90.17 (+-0.24)
	RandRBF	31.92 (+-0.44)	31.89 (+-0.41)	31.87 (+-0.39)	30.83 (+-0.64)	31.23 (+-0.50)	**32.32 (+-0.47)**	31.00 (+-0.41)
	32.26 (+-0.50)	30.93 (+-0.60)	32.06 (+-0.37)	31.47 (+-0.39)	31.89 (+-0.43)	32.22 (+-0.43)	31.64 (+-0.38)	32.01 (+-0.39)
	SINE	87.01 (+-0.72)	85.86 (+-0.28)	86.86 (+-0.17)	86.57 (+-0.27)	88.06 (+-0.19)	82.37 (+-0.14)	**88.40 (+-0.14)**
	88.37 (+-0.17)	88.38 (+-0.15)	88.39 (+-0.17)	86.71 (+-0.36)	87.76 (+-0.23)	87.82 (+-0.16)	87.84 (+-0.21)	87.98 (+-0.20)
	WAVEF.	78.45 (+-0.46)	78.55 (+-0.45)	78.33 (+-0.39)	78.30 (+-0.39)	**79.21 (+-0.42)**	78.38 (+-0.41)	79.15 (+-0.44)
	78.07 (+-0.58)	78.77 (+-0.51)	78.69 (+-0.48)	78.91 (+-0.42)	79.13 (+-0.44)	78.54 (+-0.42)	79.20 (+-0.43)	79.09 (+-0.47)
	$AGRAW_1$	64.93 (+-1.28)	64.79 (+-0.61)	64.27 (+-0.23)	63.83 (+-0.44)	64.96 (+-0.31)	64.15 (+-0.48)	66.60 (+-0.71)
	64.04 (+-0.76)	65.33 (+-0.48)	68.12 (+-0.48)	67.25 (+-0.44)	67.78 (+-0.44)	67.31 (+-0.49)	68.10 (+-0.46)	**68.19 (+-0.45)**
	$AGRAW_2$	81.19 (+-1.60)	78.28 (+-1.76)	83.27 (+-0.24)	83.49 (+-0.17)	84.56 (+-0.23)	82.81 (+-0.20)	**84.88 (+-0.14)**
	84.13 (+-0.24)	84.52 (+-0.23)	84.44 (+-0.26)	84.22 (+-0.20)	83.03 (+-1.30)	82.06 (+-1.24)	84.56 (+-0.21)	83.11 (+-1.31)
	LED	71.31 (+-0.25)	69.14 (+-0.26)	63.22 (+-0.58)	68.09 (+-0.42)	65.16 (+-1.59)	60.97 (+-1.17)	70.76 (+-0.41)
ABRUPT	70.51 (+-0.43)	70.25 (+-0.60)	71.52 (+-0.18)	71.30 (+-0.30)	71.68 (+-0.18)	71.38 (+-0.18)	**71.87 (+-0.19)**	71.73 (+-0.17)
	MIXED	88.96 (+-0.54)	89.30 (+-0.39)	90.13 (+-0.13)	89.37 (+-0.20)	90.65 (+-0.17)	87.80 (+-0.21)	**90.67 (+-0.14)**
20K	90.64 (+-0.15)	90.64 (+-0.15)	90.29 (+-0.15)	89.74 (+-0.36)	89.98 (+-0.30)	90.47 (+-0.16)	90.64 (+-0.15)	90.66 (+-0.14)
	RandRBF	31.82 (+-0.43)	32.28 (+-0.44)	32.10 (+-0.37)	31.23 (+-0.62)	31.43 (+-0.40)	**32.70 (+-0.41)**	31.15 (+-0.28)
	32.60 (+-0.45)	31.12 (+-0.54)	32.40 (+-0.34)	31.83 (+-0.30)	32.24 (+-0.37)	32.34 (+-0.36)	32.03 (+-0.33)	32.30 (+-0.37)
	SINE	89.31 (+-0.14)	87.21 (+-0.19)	88.67 (+-0.14)	86.90 (+-0.19)	89.22 (+-0.20)	86.80 (+-0.10)	89.92 (+-0.12)
	89.89 (+-0.13)	**89.93 (+-0.12)**	89.89 (+-0.13)	88.32 (+-0.27)	89.17 (+-0.16)	89.48 (+-0.14)	89.24 (+-0.18)	89.46 (+-0.14)
	WAVEF.	78.89 (+-0.22)	78.86 (+-0.27)	79.10 (+-0.26)	78.65 (+-0.25)	79.69 (+-0.22)	79.25 (+-0.24)	**79.74 (+-0.25)**
	79.05 (+-0.36)	79.46 (+-0.29)	79.41 (+-0.25)	79.44 (+-0.25)	79.62 (+-0.27)	79.27 (+-0.27)	**79.74 (+-0.26)**	79.64 (+-0.26)

Table 18 – Mean accuracies of Drift Detectors in percentage (%) in abrupt datasets, with 95% confidence intervals, using HT (Part 2)

DS Type and Size	**DATASET** FTDD	DDM WSTD	EDDM $HDDM_A$	ADWIN DDM_7	ECDD DDM_{129}	STEPD $RDDM_{30}$	SeqDrift2 $RDDM_7$	$HDDM_W$ $RDDM_{129}$
	AGRAW$_1$	68.03 (+-1.98)	67.45 (+-0.82)	65.73 (+-0.15)	64.76 (+-0.64)	66.18 (+-0.29)	66.84 (+-0.35)	70.68 (+-0.58)
	67.23 (+-0.89)	69.16 (+-0.72)	**72.57 (+-0.33)**	71.55 (+-0.31)	72.26 (+-0.37)	71.43 (+-0.80)	72.53 (+-0.31)	72.43 (+-0.31)
	AGRAW$_2$	83.60 (+-1.14)	74.08 (+-2.06)	84.98 (+-0.17)	84.40 (+-0.08)	85.95 (+-0.16)	84.19 (+-0.43)	**86.57 (+-0.09)**
	84.46 (+-0.44)	85.86 (+-0.42)	85.76 (+-0.32)	86.08 (+-0.21)	85.95 (+-0.35)	84.79 (+-0.49)	86.31 (+-0.16)	86.09 (+-0.19)
	LED	71.93 (+-0.48)	69.95 (+-0.24)	64.15 (+-0.55)	68.69 (+-0.32)	67.85 (+-1.10)	64.85 (+-1.35)	71.60 (+-0.27)
ABRUPT	72.20 (+-0.21)	71.99 (+-0.31)	72.81 (+-0.16)	72.56 (+-0.23)	72.80 (+-0.18)	72.66 (+-0.15)	72.76 (+-0.18)	**72.88 (+-0.15)**
	MIXED	91.28 (+-0.37)	90.30 (+-0.17)	91.46 (+-0.12)	89.78 (+-0.14)	91.14 (+-0.10)	90.56 (+-0.12)	**92.14 (+-0.08)**
50K	92.05 (+-0.09)	92.03 (+-0.11)	92.11 (+-0.07)	90.85 (+-0.15)	91.37 (+-0.14)	91.78 (+-0.11)	91.23 (+-0.13)	91.60 (+-0.14)
	RandRBF	32.54 (+-0.37)	32.45 (+-0.33)	32.23 (+-0.27)	**33.17 (+-0.32)**	31.10 (+-0.23)	32.62 (+-0.36)	30.97 (+-0.21)
	32.70 (+-0.42)	31.81 (+-0.38)	32.57 (+-0.30)	32.23 (+-0.29)	32.45 (+-0.31)	32.52 (+-0.28)	32.19 (+-0.21)	32.40 (+-0.28)
	SINE	91.06 (+-0.15)	88.97 (+-0.24)	89.88 (+-0.10)	87.12 (+-0.13)	90.37 (+-0.21)	90.23 (+-0.11)	91.54 (+-0.13)
	91.55 (+-0.15)	91.52 (+-0.13)	91.52 (+-0.14)	89.85 (+-0.43)	90.85 (+-0.19)	91.25 (+-0.13)	90.79 (+-0.23)	91.19 (+-0.14)
	WAVEF.	79.28 (+-0.20)	79.06 (+-0.15)	79.53 (+-0.16)	79.00 (+-0.17)	80.00 (+-0.15)	79.46 (+-0.21)	79.98 (+-0.15)
	79.37 (+-0.21)	79.63 (+-0.18)	79.58 (+-0.16)	79.80 (+-0.15)	79.73 (+-0.18)	79.47 (+-0.19)	**80.07 (+-0.15)**	79.94 (+-0.16)
	AGRAW$_1$	71.01 (+-2.08)	69.42 (+-1.05)	66.48 (+-0.12)	66.25 (+-0.71)	66.89 (+-0.27)	68.38 (+-0.32)	72.46 (+-0.39)
	70.38 (+-1.01)	71.62 (+-0.74)	74.74 (+-0.34)	74.60 (+-0.34)	74.80 (+-0.39)	74.19 (+-0.98)	**75.08 (+-0.31)**	74.85 (+-0.28)
	AGRAW$_2$	84.81 (+-0.83)	72.67 (+-1.67)	85.98 (+-0.11)	84.65 (+-0.07)	86.70 (+-0.10)	85.76 (+-0.55)	**87.67 (+-0.05)**
	85.86 (+-0.51)	87.40 (+-0.15)	87.44 (+-0.14)	87.01 (+-0.33)	87.02 (+-0.37)	85.84 (+-0.66)	87.43 (+-0.12)	87.17 (+-0.19)
	LED	72.65 (+-0.30)	70.32 (+-0.18)	64.79 (+-0.46)	68.97 (+-0.23)	69.04 (+-0.73)	67.90 (+-1.11)	71.97 (+-0.23)
ABRUPT	72.93 (+-0.18)	72.81 (+-0.20)	73.37 (+-0.11)	73.04 (+-0.21)	73.34 (+-0.12)	73.23 (+-0.12)	73.21 (+-0.12)	**73.39 (+-0.12)**
	MIXED	92.79 (+-0.12)	91.42 (+-0.11)	91.77 (+-0.10)	89.75 (+-0.10)	91.23 (+-0.09)	92.39 (+-0.07)	**93.15 (+-0.06)**
100K	93.13 (+-0.06)	93.09 (+-0.06)	93.12 (+-0.07)	91.25 (+-0.23)	92.20 (+-0.21)	92.89 (+-0.09)	91.67 (+-0.20)	92.46 (+-0.21)
	RandRBF	33.64 (+-0.26)	33.36 (+-0.32)	32.42 (+-0.24)	**34.86 (+-0.23)**	31.17 (+-0.16)	33.51 (+-0.18)	31.08 (+-0.12)
	33.32 (+-0.32)	32.45 (+-0.30)	32.87 (+-0.27)	32.70 (+-0.23)	32.94 (+-0.26)	33.08 (+-0.27)	32.52 (+-0.17)	32.80 (+-0.20)
	SINE	92.31 (+-0.09)	90.49 (+-0.21)	90.33 (+-0.08)	87.15 (+-0.10)	90.96 (+-0.16)	91.91 (+-0.10)	**92.61 (+-0.10)**
	92.61 (+-0.10)	92.59 (+-0.10)	92.57 (+-0.11)	91.68 (+-0.20)	92.13 (+-0.14)	92.39 (+-0.10)	92.06 (+-0.20)	92.41 (+-0.11)
	WAVEF.	79.35 (+-0.24)	79.40 (+-0.17)	79.55 (+-0.11)	79.12 (+-0.14)	**80.16 (+-0.11)**	79.53 (+-0.17)	80.03 (+-0.10)
	79.59 (+-0.19)	79.83 (+-0.15)	79.52 (+-0.17)	79.92 (+-0.13)	79.88 (+-0.17)	79.60 (+-0.16)	80.15 (+-0.12)	79.97 (+-0.14)
	AGRAW$_1$	76.88 (+-1.17)	73.47 (+-3.58)	66.86 (+-0.09)	66.81 (+-0.50)	68.36 (+-0.43)	71.46 (+-0.76)	75.04 (+-0.19)
	76.88 (+-1.59)	76.81 (+-0.65)	77.99 (+-0.79)	77.18 (+-3.15)	**79.42 (+-0.83)**	78.23 (+-1.10)	77.40 (+-0.63)	78.61 (+-0.52)
	AGRAW$_2$	88.22 (+-0.86)	75.48 (+-2.81)	86.86 (+-0.08)	84.85 (+-0.05)	87.35 (+-0.14)	89.24 (+-0.12)	89.17 (+-0.05)
	88.72 (+-0.52)	89.15 (+-0.09)	**89.29 (+-0.08)**	88.97 (+-0.24)	88.75 (+-0.70)	88.69 (+-0.21)	88.35 (+-0.15)	88.79 (+-0.14)
	LED	70.95 (+-0.92)	71.29 (+-0.23)	65.09 (+-0.30)	69.15 (+-0.15)	69.51 (+-0.38)	70.38 (+-0.69)	72.37 (+-0.26)
ABRUPT	**73.60 (+-0.10)**	73.25 (+-0.09)	73.57 (+-0.08)	73.44 (+-0.08)	73.46 (+-0.08)	73.32 (+-0.13)	73.47 (+-0.10)	73.58 (+-0.09)
	MIXED	94.80 (+-0.06)	93.72 (+-0.08)	92.15 (+-0.07)	89.88 (+-0.07)	91.59 (+-0.12)	94.72 (+-0.05)	**94.89 (+-0.05)**
500K	94.87 (+-0.07)	94.86 (+-0.06)	**94.89 (+-0.05)**	93.70 (+-0.28)	94.48 (+-0.13)	94.40 (+-0.19)	92.79 (+-0.27)	94.22 (+-0.14)
	RandRBF	35.88 (+-0.56)	37.06 (+-0.33)	32.56 (+-0.19)	**38.19 (+-0.09)**	31.18 (+-0.11)	35.80 (+-0.61)	31.00 (+-0.05)
	35.39 (+-0.39)	32.47 (+-0.15)	34.11 (+-0.27)	34.53 (+-0.79)	34.41 (+-0.34)	34.78 (+-0.34)	32.97 (+-0.22)	33.73 (+-0.24)
	SINE	95.63 (+-0.13)	94.75 (+-0.26)	90.64 (+-0.08)	87.20 (+-0.07)	91.84 (+-0.39)	95.57 (+-0.15)	95.80 (+-0.19)
	95.82 (+-0.20)	**95.82 (+-0.18)**	95.75 (+-0.18)	95.39 (+-0.11)	95.56 (+-0.18)	95.31 (+-0.23)	94.20 (+-0.34)	94.89 (+-0.30)
	WAVEF.	81.69 (+-0.19)	81.62 (+-0.08)	79.78 (+-0.16)	79.18 (+-0.11)	80.20 (+-0.10)	81.70 (+-0.14)	80.07 (+-0.11)
	81.74 (+-0.14)	80.75 (+-0.24)	81.09 (+-0.20)	79.97 (+-0.16)	81.15 (+-0.26)	80.62 (+-0.27)	80.15 (+-0.11)	80.17 (+-0.14)
HT	**RANK**	8.98571	11.2	11.8714	12.2286	9.4	10.1143	5.67143
ABRUPT	6.57143	7.0	**4.52857**	8.12857	6.15714	7.17143	5.88571	5.08571
HT	**RANK**	8.36429	10.4429	12.1357	12.1857	10.05	9.56429	5.98571
ALL	7.59286	7.90714	5.01429	7.76429	5.63571	6.50714	6.00714	**4.84286**

Similarly, Tables 19 and 20 are very much alike Tables 15 and 16 but refer to the results in the *gradual* datasets using HT as base learner, instead of NB.

Table 19 – Mean accuracies of Drift Detectors in percentage (%) in gradual datasets, with 95% confidence intervals, using HT (Part 1)

DS Type and Size	**DATASET** FTDD	DDM WSTD	EDDM $HDDM_A$	ADWIN DDM_7	ECDD DDM_{129}	STEPD $RDDM_{30}$	SeqDrift2 $RDDM_7$	$HDDM_W$ $RDDM_{129}$
	AGRAW$_1$	61.57 (+-0.47)	61.48 (+-0.27)	61.62 (+-0.19)	61.98 (+-0.20)	62.15 (+-0.25)	61.57 (+-0.26)	62.71 (+-0.22)
	61.33 (+-0.29)	61.77 (+-0.38)	62.27 (+-0.36)	62.66 (+-0.23)	62.87 (+-0.32)	61.18 (+-0.36)	62.81 (+-0.21)	**62.92 (+-0.27)**
	AGRAW$_2$	73.62 (+-1.59)	73.68 (+-1.57)	76.36 (+-0.31)	79.16 (+-0.25)	78.59 (+-0.50)	76.15 (+-0.33)	**79.66 (+-0.22)**
	74.56 (+-0.76)	77.35 (+-0.66)	78.27 (+-0.54)	79.01 (+-0.62)	78.65 (+-0.98)	74.00 (+-1.58)	79.50 (+-0.30)	78.65 (+-0.98)
	LED	67.76 (+-0.42)	66.62 (+-0.39)	60.20 (+-0.52)	65.10 (+-0.40)	59.39 (+-1.39)	58.10 (+-0.67)	66.68 (+-0.36)
GRAD.	62.88 (+-0.89)	63.99 (+-0.81)	67.58 (+-0.31)	67.35 (+-0.33)	67.72 (+-0.30)	67.80 (+-0.34)	67.62 (+-0.28)	**67.81 (+-0.29)**
	MIXED	83.49 (+-0.28)	**84.00 (+-0.26)**	82.85 (+-0.27)	82.84 (+-0.31)	83.04 (+-0.31)	83.27 (+-0.24)	83.55 (+-0.28)
10K	83.50 (+-0.23)	83.26 (+-0.27)	83.39 (+-0.27)	83.54 (+-0.27)	83.57 (+-0.29)	83.70 (+-0.27)	83.62 (+-0.28)	83.70 (+-0.31)
	RandRBF	32.00 (+-0.46)	31.74 (+-0.36)	31.73 (+-0.38)	30.87 (+-0.65)	30.99 (+-0.51)	**32.22 (+-0.48)**	30.94 (+-0.35)
	32.10 (+-0.52)	31.12 (+-0.64)	32.02 (+-0.39)	31.45 (+-0.39)	31.86 (+-0.40)	32.09 (+-0.44)	31.71 (+-0.36)	31.93 (+-0.38)
	SINE	82.43 (+-0.28)	82.26 (+-0.22)	81.43 (+-0.23)	81.50 (+-0.22)	81.48 (+-0.24)	81.97 (+-0.24)	82.57 (+-0.24)
	82.28 (+-0.24)	82.14 (+-0.22)	82.41 (+-0.27)	82.19 (+-0.25)	82.57 (+-0.21)	82.65 (+-0.23)	82.38 (+-0.25)	**82.66 (+-0.19)**
	WAVEF.	77.97 (+-0.43)	78.21 (+-0.40)	77.81 (+-0.38)	78.05 (+-0.37)	78.29 (+-0.39)	77.71 (+-0.40)	78.21 (+-0.39)
	76.68 (+-0.43)	77.57 (+-0.51)	77.82 (+-0.47)	78.51 (+-0.36)	**78.57 (+-0.40)**	77.86 (+-0.41)	78.56 (+-0.41)	78.42 (+-0.37)

Table 20 – Mean accuracies of Drift Detectors in percentage (%) in gradual datasets, with 95% confidence intervals, using HT (Part 2)

DS Type and Size	**DATASET** FTDD	DDM WSTD	EDDM $HDDM_A$	ADWIN DDM_7	ECDD DDM_{129}	STEPD $RDDM_{30}$	SeqDrift2 $RDDM_7$	$HDDM_W$ $RDDM_{129}$
	$AGRAW_1$	64.10 (+-1.17)	64.00 (+-0.74)	63.38 (+-0.24)	62.94 (+-0.32)	64.05 (+-0.21)	62.72 (+-0.65)	65.02 (+-0.58)
	61.47 (+-0.81)	64.61 (+-0.37)	66.30 (+-0.43)	66.12 (+-0.49)	66.53 (+-0.53)	65.95 (+-0.39)	66.48 (+-0.47)	**66.84 (+-0.40)**
	$AGRAW_2$	79.00 (+-1.91)	77.64 (+-1.69)	81.93 (+-0.20)	82.27 (+-0.14)	83.08 (+-0.24)	82.41 (+-0.24)	**83.42 (+-0.12)**
	82.21 (+-0.35)	82.94 (+-0.22)	82.98 (+-0.28)	83.16 (+-0.20)	82.55 (+-0.96)	79.82 (+-1.65)	83.38 (+-0.12)	82.64 (+-0.96)
	LED	70.54 (+-0.19)	69.25 (+-0.23)	62.43 (+-0.66)	67.16 (+-0.43)	64.25 (+-1.39)	60.15 (+-0.82)	69.32 (+-0.38)
GRAD.	67.67 (+-0.84)	68.57 (+-0.50)	70.42 (+-0.19)	70.38 (+-0.19)	70.61 (+-0.18)	70.60 (+-0.18)	70.60 (+-0.17)	**70.66 (+-0.19)**
	MIXED	87.29 (+-0.19)	**87.59 (+-0.16)**	86.88 (+-0.14)	86.69 (+-0.18)	87.30 (+-0.15)	87.53 (+-0.14)	87.32 (+-0.17)
20K	87.11 (+-0.16)	87.17 (+-0.17)	87.23 (+-0.18)	87.28 (+-0.15)	87.54 (+-0.17)	87.44 (+-0.17)	87.37 (+-0.17)	87.53 (+-0.18)
	RandRBF	31.80 (+-0.54)	32.33 (+-0.40)	32.02 (+-0.34)	31.25 (+-0.62)	31.21 (+-0.36)	**32.76 (+-0.37)**	31.06 (+-0.34)
	32.69 (+-0.44)	31.06 (+-0.53)	32.32 (+-0.37)	31.74 (+-0.41)	32.14 (+-0.41)	32.44 (+-0.34)	32.00 (+-0.34)	32.19 (+-0.35)
	SINE	86.68 (+-0.14)	86.53 (+-0.13)	85.43 (+-0.11)	85.04 (+-0.18)	85.89 (+-0.12)	86.55 (+-0.14)	86.77 (+-0.17)
	86.76 (+-0.11)	86.67 (+-0.10)	86.79 (+-0.13)	86.52 (+-0.17)	86.70 (+-0.14)	**86.88 (+-0.12)**	86.68 (+-0.16)	86.83 (+-0.13)
	WAVEF.	78.52 (+-0.25)	78.73 (+-0.25)	78.70 (+-0.21)	78.50 (+-0.23)	79.29 (+-0.23)	78.63 (+-0.24)	79.20 (+-0.24)
	78.36 (+-0.30)	78.78 (+-0.24)	78.78 (+-0.28)	79.21 (+-0.23)	79.12 (+-0.27)	78.74 (+-0.24)	**79.30 (+-0.26)**	79.10 (+-0.28)
	$AGRAW_1$	68.46 (+-1.74)	67.30 (+-0.82)	65.32 (+-0.16)	64.95 (+-0.74)	65.77 (+-0.25)	66.55 (+-0.28)	70.06 (+-0.52)
	65.95 (+-0.82)	67.93 (+-0.65)	71.39 (+-0.26)	70.77 (+-0.36)	71.27 (+-0.35)	70.84 (+-0.40)	71.30 (+-0.35)	**71.43 (+-0.31)**
	$AGRAW_2$	83.17 (+-1.16)	73.97 (+-2.05)	84.28 (+-0.25)	83.81 (+-0.10)	85.45 (+-0.15)	84.08 (+-0.43)	**85.95 (+-0.11)**
	83.88 (+-0.45)	85.29 (+-0.42)	85.19 (+-0.32)	85.66 (+-0.21)	85.63 (+-0.38)	84.38 (+-0.52)	85.84 (+-0.15)	85.69 (+-0.22)
	LED	72.33 (+-0.23)	70.22 (+-0.19)	63.84 (+-0.62)	68.32 (+-0.33)	67.97 (+-0.93)	64.66 (+-1.29)	71.15 (+-0.28)
GRAD.	71.61 (+-0.17)	71.36 (+-0.32)	72.47 (+-0.14)	72.41 (+-0.16)	72.61 (+-0.16)	72.50 (+-0.14)	72.42 (+-0.16)	**72.62 (+-0.15)**
	MIXED	90.84 (+-0.10)	90.33 (+-0.12)	89.97 (+-0.11)	88.69 (+-0.14)	89.81 (+-0.10)	90.62 (+-0.10)	**90.87 (+-0.09)**
50K	90.75 (+-0.08)	90.68 (+-0.09)	90.78 (+-0.09)	90.33 (+-0.14)	90.67 (+-0.11)	90.85 (+-0.09)	90.61 (+-0.11)	90.74 (+-0.09)
	RandRBF	32.53 (+-0.34)	32.56 (+-0.37)	32.17 (+-0.28)	**33.17 (+-0.32)**	31.08 (+-0.28)	32.71 (+-0.35)	31.01 (+-0.22)
	32.69 (+-0.43)	31.91 (+-0.38)	32.58 (+-0.29)	32.13 (+-0.26)	32.37 (+-0.29)	32.60 (+-0.31)	32.19 (+-0.21)	32.38 (+-0.28)
	SINE	90.27 (+-0.10)	89.00 (+-0.25)	88.51 (+-0.10)	86.33 (+-0.14)	89.16 (+-0.20)	90.11 (+-0.10)	**90.35 (+-0.10)**
	90.27 (+-0.11)	90.24 (+-0.12)	90.33 (+-0.11)	90.01 (+-0.14)	90.26 (+-0.10)	**90.35 (+-0.11)**	90.17 (+-0.12)	90.34 (+-0.09)
	WAVEF.	79.18 (+-0.23)	79.19 (+-0.16)	79.39 (+-0.18)	78.95 (+-0.16)	79.85 (+-0.13)	79.13 (+-0.23)	79.76 (+-0.15)
	79.01 (+-0.21)	79.44 (+-0.19)	79.44 (+-0.18)	79.74 (+-0.14)	79.58 (+-0.19)	79.53 (+-0.20)	**79.98 (+-0.15)**	79.71 (+-0.14)
	$AGRAW_1$	71.72 (+-1.76)	69.25 (+-1.18)	66.23 (+-0.12)	65.79 (+-0.64)	66.63 (+-0.27)	68.25 (+-0.24)	71.98 (+-0.36)
	69.51 (+-1.08)	70.90 (+-0.80)	74.25 (+-0.29)	73.80 (+-0.35)	74.04 (+-0.34)	73.37 (+-0.95)	**74.57 (+-0.30)**	74.43 (+-0.33)
	$AGRAW_2$	84.47 (+-0.82)	72.65 (+-1.65)	85.73 (+-0.09)	84.40 (+-0.06)	86.53 (+-0.12)	85.61 (+-0.56)	**87.36 (+-0.06)**
	85.59 (+-0.51)	86.98 (+-0.33)	87.14 (+-0.15)	86.97 (+-0.32)	86.89 (+-0.36)	85.68 (+-0.66)	87.30 (+-0.10)	86.97 (+-0.18)
	LED	72.54 (+-0.34)	70.40 (+-0.17)	64.60 (+-0.50)	68.79 (+-0.23)	68.75 (+-0.71)	68.48 (+-0.75)	71.74 (+-0.23)
GRAD.	72.53 (+-0.15)	72.40 (+-0.18)	73.21 (+-0.12)	73.14 (+-0.15)	73.27 (+-0.12)	73.18 (+-0.12)	73.06 (+-0.11)	**73.30 (+-0.12)**
	MIXED	92.42 (+-0.08)	91.49 (+-0.11)	91.01 (+-0.10)	89.20 (+-0.10)	90.64 (+-0.09)	92.32 (+-0.07)	**92.49 (+-0.07)**
100K	92.43 (+-0.06)	92.38 (+-0.06)	92.43 (+-0.08)	91.77 (+-0.16)	92.21 (+-0.13)	92.48 (+-0.07)	92.06 (+-0.13)	92.37 (+-0.08)
	RandRBF	33.67 (+-0.24)	33.34 (+-0.31)	32.51 (+-0.21)	**34.85 (+-0.20)**	31.16 (+-0.15)	33.59 (+-0.20)	31.04 (+-0.12)
	33.27 (+-0.32)	32.26 (+-0.25)	32.92 (+-0.26)	32.63 (+-0.21)	32.86 (+-0.23)	32.86 (+-0.21)	32.48 (+-0.16)	32.84 (+-0.19)
	SINE	92.00 (+-0.09)	90.62 (+-0.20)	89.60 (+-0.07)	86.80 (+-0.12)	90.38 (+-0.15)	91.89 (+-0.09)	92.00 (+-0.10)
	91.92 (+-0.09)	91.93 (+-0.10)	91.98 (+-0.09)	91.76 (+-0.14)	91.96 (+-0.08)	**92.02 (+-0.09)**	91.80 (+-0.13)	91.99 (+-0.09)
	WAVEF.	79.37 (+-0.25)	79.41 (+-0.17)	79.49 (+-0.12)	79.09 (+-0.13)	**80.10 (+-0.10)**	79.46 (+-0.17)	79.95 (+-0.10)
	79.28 (+-0.21)	79.47 (+-0.16)	79.47 (+-0.12)	79.85 (+-0.15)	79.84 (+-0.17)	79.57 (+-0.17)	**80.10 (+-0.11)**	79.81 (+-0.13)
	$AGRAW_1$	77.15 (+-1.11)	73.27 (+-2.14)	66.91 (+-0.12)	66.74 (+-0.52)	68.48 (+-0.32)	71.40 (+-0.72)	74.82 (+-0.23)
	77.36 (+-1.46)	77.66 (+-1.36)	78.14 (+-0.89)	76.66 (+-3.29)	79.09 (+-0.84)	**79.24 (+-0.97)**	77.60 (+-0.71)	78.12 (+-0.84)
	$AGRAW_2$	88.19 (+-0.87)	75.48 (+-2.82)	86.83 (+-0.09)	84.79 (+-0.04)	87.38 (+-0.14)	**89.22 (+-0.11)**	89.08 (+-0.04)
	88.63 (+-0.50)	89.14 (+-0.07)	89.20 (+-0.08)	88.99 (+-0.23)	88.75 (+-0.70)	88.63 (+-0.20)	88.41 (+-0.17)	88.74 (+-0.17)
	LED	71.62 (+-0.86)	71.35 (+-0.22)	65.48 (+-0.45)	69.12 (+-0.15)	69.43 (+-0.39)	70.52 (+-0.45)	72.30 (+-0.26)
GRAD.	73.53 (+-0.10)	73.19 (+-0.04)	73.53 (+-0.08)	73.43 (+-0.08)	73.35 (+-0.13)	73.33 (+-0.13)	73.42 (+-0.10)	**73.57 (+-0.09)**
	MIXED	**94.76 (+-0.05)**	93.66 (+-0.11)	92.06 (+-0.06)	89.76 (+-0.08)	91.46 (+-0.13)	94.70 (+-0.04)	**94.76 (+-0.04)**
500K	94.69 (+-0.04)	94.72 (+-0.05)	**94.76 (+-0.04)**	94.28 (+-0.16)	94.69 (+-0.07)	94.35 (+-0.15)	92.95 (+-0.26)	94.01 (+-0.14)
	RandRBF	36.05 (+-0.63)	36.94 (+-0.30)	32.61 (+-0.22)	**38.19 (+-0.09)**	31.18 (+-0.11)	35.59 (+-0.53)	31.00 (+-0.05)
	35.42 (+-0.36)	32.44 (+-0.14)	34.26 (+-0.29)	34.40 (+-0.88)	34.77 (+-0.40)	34.52 (+-0.37)	33.04 (+-0.22)	33.98 (+-0.28)
	SINE	95.57 (+-0.15)	94.62 (+-0.17)	90.55 (+-0.06)	87.14 (+-0.08)	91.92 (+-0.53)	95.56 (+-0.14)	**95.58 (+-0.17)**
	95.55 (+-0.16)	95.56 (+-0.17)	95.52 (+-0.19)	95.41 (+-0.13)	95.54 (+-0.17)	95.31 (+-0.22)	93.95 (+-0.34)	94.89 (+-0.32)
	WAVEF.	81.58 (+-0.19)	81.62 (+-0.08)	79.86 (+-0.13)	79.17 (+-0.11)	80.19 (+-0.10)	**81.76 (+-0.21)**	80.05 (+-0.11)
	81.55 (+-0.19)	80.62 (+-0.34)	81.09 (+-0.24)	80.06 (+-0.19)	81.31 (+-0.16)	80.63 (+-0.21)	80.13 (+-0.10)	80.18 (+-0.20)
HT	**RANK**	7.74286	9.68571	12.4	12.1429	10.7	9.01429	6.3
GRAD.	8.61429	8.81429	5.5	7.4	5.11429	5.84286	6.12857	**4.6**
HT	**RANK**	8.36429	10.4429	12.1357	12.1857	10.05	9.56429	5.98571
ALL	7.59286	7.90714	5.01429	7.76429	5.63571	6.50714	6.00714	**4.84286**

As in the previous three chapters, the accuracy results reported in Tables 13 to 20 were compared using the F_F statistic (DEMSAR, 2006). Note the null hypothesis states that all methods are statistically equal but, when it is rejected, it is necessary to use a post-hoc test to find out in what method(s) there is statistical difference. As in Chapter 5, we used the Nemenyi post-hoc test to compare all the methods against all the others.

Again, the results are presented using graphics where the critical difference (CD) is represented by bars and methods connected by a bar are *not* statistically different.

Figure 7 presents the evaluation of the concept drift detection methods based on the results of the experiments in the *abrupt* datasets using NB, i.e., those presented in Tables 13 and 14. According to the ranks, RDDM_{129}, HDDM_A, WSTD, RDDM_7, and FTDD are the best configurations in this subset of the tests, with no statistical difference between them or to the next two methods (HDDM_W and DDM_{129}), despite the comparatively worse ranks of the latter two. Also, notice that, in spite of this, only RDDM_{129} and HDDM_A are statistically better than the next three configurations (SeqDrift_2, RDDM_{30}, and ADWIN).

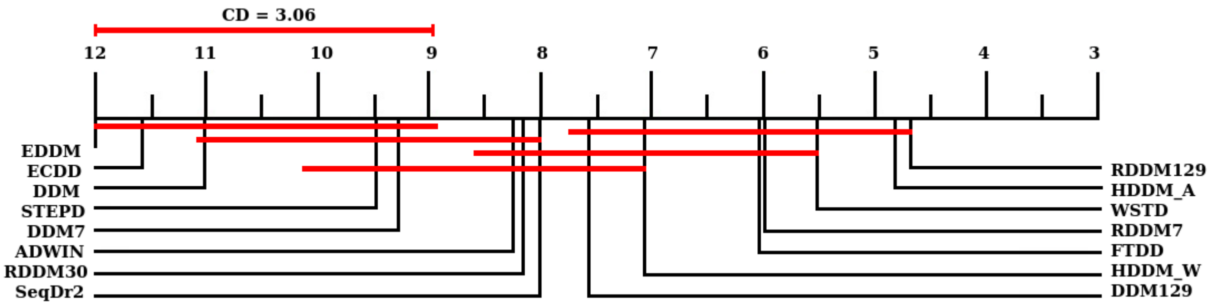


Figure 7 – Comparison results using the Nemenyi test of Detectors with NB in the abrupt datasets with 95% confidence.

Similarly, Figure 8 presents the corresponding evaluation based on the results of the *gradual* datasets using NB, i.e., those presented in Tables 15 and 16. In these datasets, the best results were those of RDDM_{129}, HDDM_A, RDDM_7, and DDM_{129}, with no statistical difference between them. However, in this scenario, only RDDM_{129} is statistically superior to the following six methods: DDM_7, RDDM_{30}, SeqDrift_2, HDDM_W, FTDD, and WSTD.

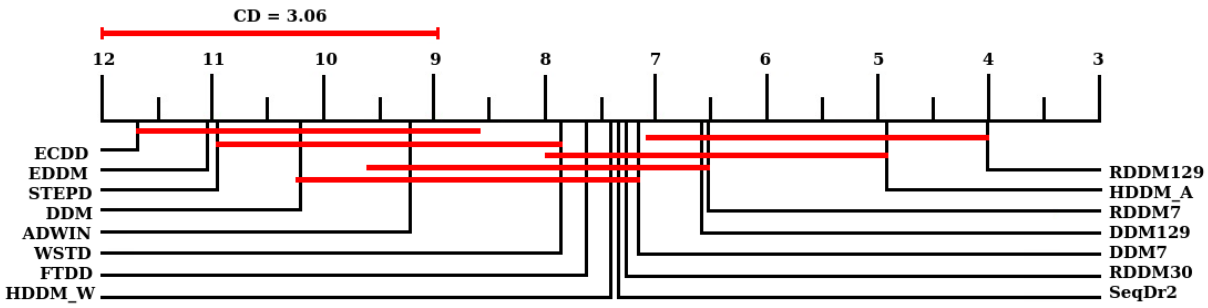


Figure 8 – Comparison results using the Nemenyi test of Detectors with NB in the gradual datasets with 95% confidence.

Figure 9 evaluates the accuracy results of the methods aggregating *all* the tests executed using NB as base learner. With this larger view of the data, the best methods are RDDM_{129} and HDDM_A, though RDDM_7 was also statistically similar to them. Again, the statistical differences from these three methods to the others are *not* the same: only

$RDDM_{129}$ is statistically superior to all the other 12 configurations, $HDDM_A$ is *not* statistically different to WSTD, FTDD, and DDM_{129}, whereas $RDDM_7$, in addition to these three, is also statistically similar to $HDDM_W$, $SeqDrift_2$, $RDDM_{30}$, and DDM_7.

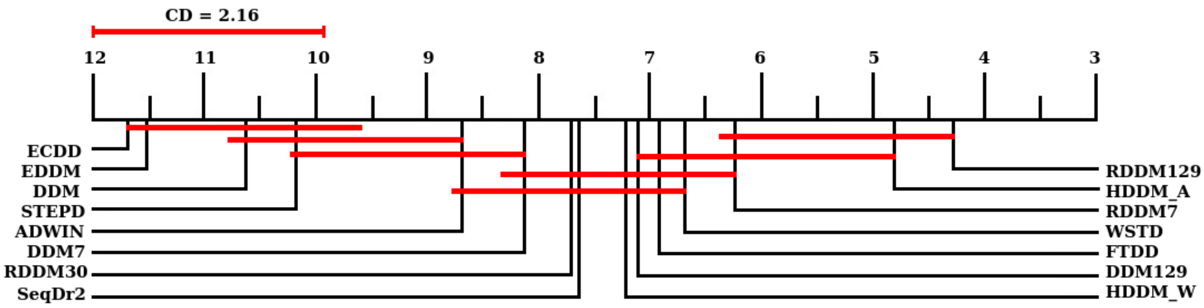


Figure 9 – Comparison results using the Nemenyi test of Detectors with NB in all artificial datasets with 95% confidence.

Figures 10, 11, and 12 represent the evaluations based on views similar to those of Figures 7, 8, and 9, respectively, but based on the tests using HT as base classifier. Figure 10 refers to the results of the experiments in the *abrupt* datasets, i.e., those presented in Tables 17 and 18. In this subset of the tests, nine different configurations are statistically similar: $HDDM_A$, $RDDM_{129}$, $HDDM_W$, $RDDM_7$, DDM_{129}, FTDD, WSTD, $RDDM_{30}$, and DDM_7. Despite this, only $HDDM_A$ and $RDDM_{129}$ are statistically better than the remaining six methods. For instance, the method with the third best rank, $HDDM_W$, is *not* superior to DDM or STEPD in this subset of the tests.

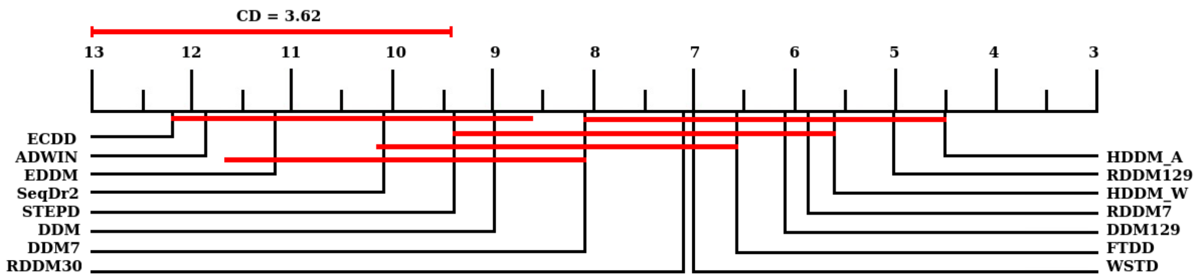


Figure 10 – Comparison results using the Nemenyi test of Detectors with HT in the abrupt datasets with 95% confidence.

Accordingly, Figure 11 corresponds to the evaluation referring to the results of the experiments in the *gradual* datasets using HT, i.e., those presented in Tables 19 and 20. In these datasets, eight methods presented statistically similar results: $RDDM_{129}$, DDM_{129}, $HDDM_A$, $RDDM_{30}$, $RDDM_7$, $HDDM_W$, DDM_7, and DDM. However, analogously to other previously discussed scenarios, only $RDDM_{129}$ is statistically superior to all the other seven tested configurations. More specifically, DDM_{129} is *not* superior to either FTDD or WSTD, whereas $HDDM_A$ is statistically indistinguishable from $SeqDrift_2$ as well as from FTDD and WSTD.

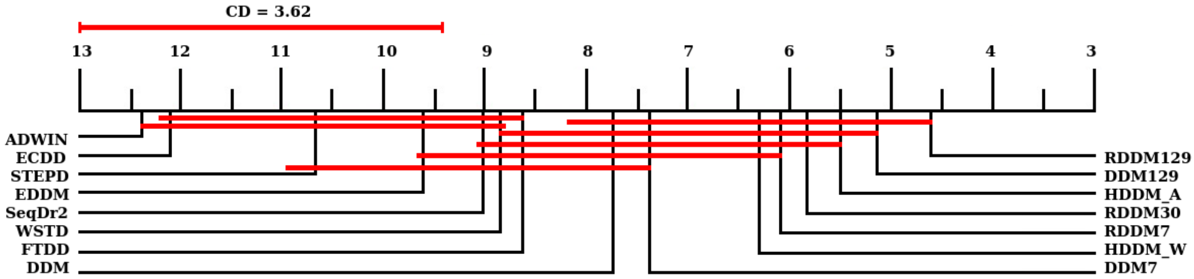


Figure 11 – Comparison results using the Nemenyi test of Detectors with HT in the gradual datasets with 95% confidence.

Figure 12 captures the evaluation of the accuracy results of the methods aggregating *all* the tests executed using HT as base learner, which is similar to the aggregation carried out for NB and represented in Figure 9. With this subset of the data, the best configurations are $RDDM_{129}$, $HDDM_A$, DDM_{129}, $HDDM_W$, $RDDM_7$, and $RDDM_{30}$, with no statistical difference among these six methods. Once again, $RDDM_{129}$ was the only of them to be significantly superior to all the other nine tested methods. In this scenario, $HDDM_A$ was *not* superior to FTDD, whereas DDM_{129} was *not* superior to FTDD, DDM_7, and WSTD.

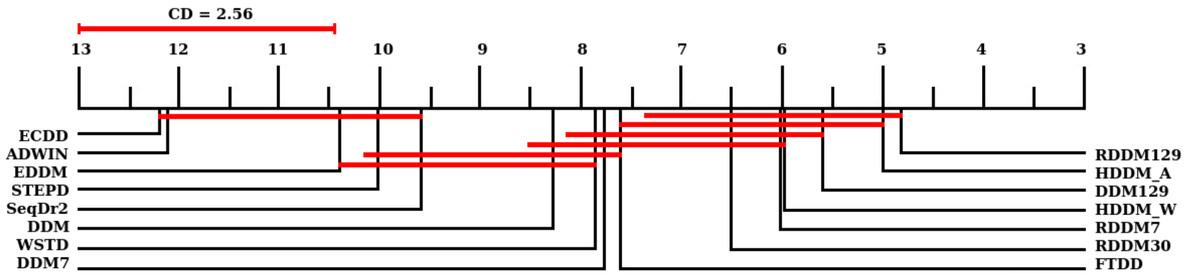


Figure 12 – Comparison results using the Nemenyi test of Detectors with HT in all artificial datasets with 95% confidence.

6.2.1 Discussion and Answer to RQ1

One telling fact that can easily be identified in these reported evaluations is that the most well-known and cited concept drift detection methods, namely DDM, EDDM, ADWIN, ECDD, and STEPD, are consistently ranked among the worst configurations in *all* of them.

It is also worth observing that WSTD and, to a lesser extent, FTDD and $HDDM_W$, delivered stronger performances in the abrupt datasets than in the gradual ones. On the other hand, the three configurations of RDDM were generally better in the gradual datasets, the exception being $RDDM_7$ using HT.

The description of **RQ1** was: *What are the best drift detectors in terms of accuracy in abrupt and gradual concept drift datasets?*

Based on the experiments reported in this chapter, the answer to **RQ1** is: even though there were slight variations in the results using the two base learners (NB and HT) as well as in the datasets configured with abrupt and gradual concept drifts, the overall best two concept drift detectors in terms of accuracy were clearly $RDDM_{129}$ and $HDDM_A$. Figure 13 corroborates this answer; it captures the evaluation of the accuracy results of the methods aggregating all the executed tests using both base classifiers.

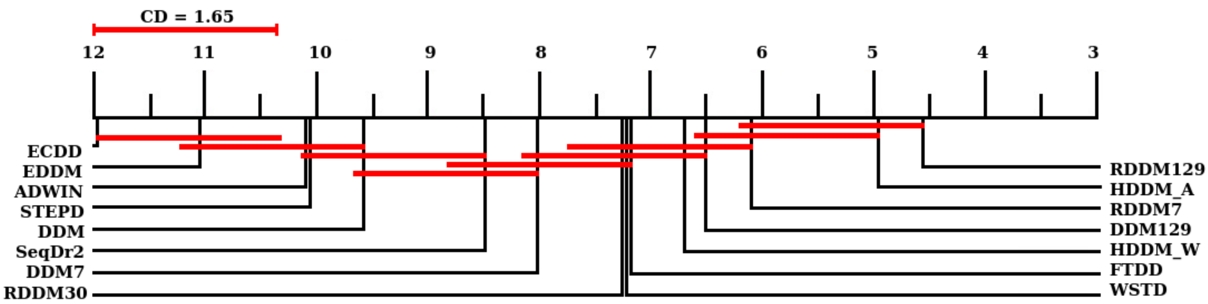


Figure 13 – Comparison results using the Nemenyi test of Detectors including all tested datasets with 95% confidence.

It is worth adding the highest differences in ranks between these two methods occurred in the gradual datasets, with both base learners. In addition, note RDDM_7 also presented a very consistent performance, achieving results that are statistically indistinguishable from those of RDDM_{129} and HDDM_A in *all* the included scenarios, in spite of having worse ranks in all of them.

6.3 Drift Detections Results and Analysis

Last section analysed the results of the experiments of this chapter based on the accuracy performance of the tested concept drift detectors. As previously mentioned in Chapters 3 and 4, analysing the concept drifts identifications of the methods can provide a different perspective concerning their performances.

For each *abrupt* dataset configuration, considering the number of repetitions adopted in the experiments, the mean distance to the exact drift positions of the true positive concept drift detections and the total number of false negatives (FN), false positives (FP), true negatives (TN), and true positives (TP) of each method were recorded.

As in the analyses presented in Chapters 3 and 4, the drifts detected within 2% of the concept size after the correct drift positions were computed as true positives. For instance, in the 500K datasets, the concepts last for 100K instances and, thus, detections occurred up to 2K instances after the perfect points were considered true positives.

Once again, this analysis only includes the *abrupt* datasets because the exact positions of the concept drifts are known. In the gradual drifts datasets, there are no single change points and, therefore, it is not clear when the drift identifications should be considered as positive or negative, as already explained.

Tables 21 and 22 summarize the *mean* concept drift identifications of the 15 tested configurations of the methods using NB as base learner, aggregating the results of different datasets by size. Notice that, in these aggregations, the mean distance was only calculated when the corresponding method detected at least one TP in at least five of the seven datasets considered in this procedure. The reason for the aggregation was the overwhelming amount of results. Nevertheless, the corresponding detailed raw data separated by size and dataset generator are included in Appendix A as Tables 32 to 45. Finally, in each dataset size, the best results are written in **bold**.

Table 21 – Detectors mean drift identifications in abrupt datasets using NB (Part 1)

Size	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
	DDM	N/A	91.29	79.43	299801	28.71	0.21536081	0.23928571	0.22599404
	EDDM	21.02	97.86	333.86	299546	22.14	0.05670214	0.18452381	0.09936743
	ADWIN	18.09	97.71	283.14	299597	22.29	0.08013609	0.18571429	0.12069909
	ECDD	**15.98**	51.43	343.57	299536	68.57	0.15696841	0.57142857	0.29493260
	STEPD	21.39	54.29	244.14	299636	65.71	0.29938773	0.54761905	0.38919120
	SeqDr2	N/A	110.71	244.14	299636	9.29	0.01935747	0.07738095	0.03416036
	HDDM$_W$	23.01	**50.00**	62.57	299817	**70.00**	**0.55023945**	**0.58333333**	**0.56203330**
10K	FTDD	26.75	68.00	**30.43**	**299850**	52.00	0.47492104	0.43333333	0.44750519
	WSTD	25.91	58.57	53.86	299826	61.43	0.50611196	0.51190476	0.49968641
	HDDM$_A$	25.19	66.14	42.14	299838	53.86	0.48893070	0.44880952	0.46626826
	DDM$_7$	23.09	64.71	515.71	299364	55.29	0.11962916	0.46071429	0.22339038
	DDM$_{129}$	26.81	77.43	113.57	299766	42.57	0.26894565	0.35476190	0.30529978
	RDDM$_{30}$	28.90	92.43	65.14	299815	27.57	0.23239479	0.22976190	0.23032441
	RDDM$_7$	24.98	79.00	148.00	299732	41.00	0.23545236	0.34166667	0.27866567
	RDDM$_{129}$	29.04	78.43	76.14	299804	41.57	0.32076519	0.34642857	0.33190985
	DDM	N/A	86.86	109.29	599771	33.14	0.21034528	0.27619048	0.23856965
	EDDM	46.20	94.14	426.71	599453	25.86	0.05489346	0.21547619	0.10528560
	ADWIN	52.00	68.71	397.86	599482	51.29	0.16843144	0.42738095	0.26113942
	ECDD	**19.49**	46.43	728.00	599152	73.57	0.08446048	0.61309524	0.22482403
	STEPD	29.91	41.29	360.00	599520	78.71	0.24276765	0.65595238	0.38613255
	SeqDr2	N/A	112.00	344.57	599535	8.00	0.00588235	0.06666667	0.01952594
	HDDM$_W$	30.58	**36.00**	104.14	599776	**84.00**	0.55438053	**0.70000000**	**0.61134384**
20K	FTDD	35.42	60.00	**30.29**	**599850**	60.00	0.54729776	0.50000000	0.51680121
	WSTD	30.34	47.71	57.43	599823	72.29	0.55316171	0.60238095	0.56839378
	HDDM$_A$	38.68	56.00	43.00	599837	64.00	**0.55897106**	0.53333333	0.54434613
	DDM$_7$	43.21	55.57	734.71	599145	64.43	0.12056323	0.53690476	0.23884044
	DDM$_{129}$	47.21	65.57	151.43	599729	54.43	0.28539982	0.45357143	0.35243981
	RDDM$_{30}$	48.46	85.43	73.14	599807	34.57	0.29776399	0.28809524	0.29254773
	RDDM$_7$	46.43	75.57	200.57	599679	44.43	0.23181177	0.37023810	0.28144029
	RDDM$_{129}$	51.76	68.43	84.71	599795	51.57	0.36887128	0.42976190	0.39678713
	DDM	120.97	76.00	131.71	1499748	44.00	0.24898461	0.36666667	0.29517924
	EDDM	74.28	97.14	542.57	1499337	22.86	0.03567264	0.19047619	0.07907518
	ADWIN	75.60	47.43	665.57	1499214	72.57	0.22125501	0.60476190	0.35153168
	ECDD	**31.05**	38.86	1824.43	1498055	81.14	0.03974312	0.67619048	0.16182681
	STEPD	42.87	34.57	740.43	1499140	85.43	0.13586017	0.71190476	0.30204413
	SeqDr2	193.88	32.14	415.57	1499464	87.86	0.36924018	0.73214286	0.49002033
	HDDM$_W$	45.39	**26.00**	267.71	1499612	**94.00**	0.44454349	**0.78333333**	0.56050015
50K	FTDD	52.48	49.86	**32.00**	**1499848**	70.14	0.61925646	0.58452381	0.59810310
	WSTD	46.92	36.71	87.14	1499793	83.29	0.55822341	0.69404762	0.61091974
	HDDM$_A$	79.65	42.14	41.29	1499839	77.86	**0.64212082**	0.64880952	**0.64422746**
	DDM$_7$	71.83	40.29	1128.71	1498751	79.71	0.11782836	0.66428571	0.25855308
	DDM$_{129}$	96.88	49.00	215.29	1499665	71.00	0.30357516	0.59166667	0.41163784
	RDDM$_{30}$	122.12	72.14	78.71	1499801	47.86	0.37626047	0.39880952	0.38685027
	RDDM$_7$	80.98	55.00	442.43	1499438	65.00	0.17153661	0.54166667	0.29360637
	RDDM$_{129}$	102.97	52.43	88.29	1499792	67.57	0.46634617	0.56309524	0.51008267

Table 22 – Detectors mean drift identifications in abrupt datasets using NB (Part 2)

Size	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
100K	DDM	204.85	72.14	174.71	2999705	47.86	0.25723574	0.39880952	0.30860128
	EDDM	202.43	98.43	601.86	2999278	21.57	0.02897979	0.17976190	0.06905262
	ADWIN	131.62	31.71	1122.14	2998758	88.29	0.25343920	0.73571429	0.41092081
	ECDD	**46.53**	35.71	3754.57	2996125	84.29	0.02027861	0.70238095	0.11780856
	STEPD	65.74	30.86	1398.86	2998481	89.14	0.07710190	0.74285714	0.23292182
	SeqDr2	211.75	25.86	546.29	2999334	94.14	0.37590183	0.78452381	0.51138103
	HDDM_W	56.88	**22.71**	538.57	2999341	**97.29**	0.37526402	**0.81071429**	0.50084294
	FTDD	92.38	42.14	**35.00**	**2999845**	77.86	0.65231578	0.64880952	0.64748698
	WSTD	66.78	31.29	134.86	2999745	88.71	0.52532686	0.73928571	0.60647479
	HDDM_A	134.13	33.00	44.71	2999835	87.00	**0.66887949**	0.72500000	**0.69497828**
	DDM_7	135.11	30.43	1664.29	2998216	89.57	0.10740748	0.74642857	0.25443678
	DDM_{129}	168.97	41.00	296.71	2999583	79.00	0.30258838	0.65833333	0.42904775
	RDDM_{30}	197.97	65.14	85.57	2999794	54.86	0.41192585	0.45714286	0.43368141
	RDDM_7	126.48	46.00	797.29	2999083	74.00	0.10512952	0.61666667	0.24736675
	RDDM_{129}	174.91	41.14	132.14	2999748	78.86	0.44586342	0.65714286	0.53468070
500K	DDM	741.68	18.57	69.57	4999890	21.43	0.34907419	0.53571429	0.41338053
	EDDM	N/A	34.57	209.29	4999751	5.43	0.02176624	0.13571429	0.05277863
	ADWIN	247.38	**3.57**	1230.86	4998729	**36.43**	0.23485506	**0.91071429**	0.42346639
	ECDD	192.27	7.14	6329.29	4993631	32.86	0.00485784	0.82142857	0.06231523
	STEPD	194.68	5.86	2259.29	4997701	34.14	0.01892386	0.85357143	0.12385034
	SeqDr2	272.54	6.00	174.43	4999786	34.00	0.36859607	0.85000000	0.53225076
	HDDM_W	125.42	4.71	919.00	4999041	35.29	0.21741224	0.88214286	0.34484252
	FTDD	276.01	10.00	**19.29**	**4999941**	30.00	0.61669329	0.75000000	0.67812226
	WSTD	**105.06**	8.57	197.71	4999762	31.43	0.33088496	0.78571429	0.46875125
	HDDM_A	361.69	5.14	23.71	4999936	34.86	**0.65789220**	0.87142857	**0.75179353**
	DDM_7	417.94	6.00	1124.00	4998836	34.00	0.07865136	0.85000000	0.22793336
	DDM_{129}	657.70	10.00	174.29	4999786	30.00	0.23819520	0.75000000	0.40202611
	RDDM_{30}	575.60	12.86	127.29	4999833	27.14	0.17513516	0.67857143	0.34338293
	RDDM_7	279.75	8.14	1403.14	4998557	31.86	0.02746512	0.79642857	0.14407302
	RDDM_{129}	327.37	5.86	236.14	4999724	34.14	0.13289249	0.85357143	0.33460783
1M	DDM	1553.96	16.14	64.71	9999895	23.86	0.38814302	0.59642857	0.45883160
	EDDM	2137.13	35.57	197.14	9999763	4.43	0.01696406	0.11071429	0.04190268
	ADWIN	336.89	**1.86**	2107.71	9997852	**38.14**	0.24230037	**0.95357143**	0.43113149
	ECDD	254.36	5.86	12628.71	9987331	34.14	0.00252568	0.85357143	0.04579650
	STEPD	368.54	4.14	4417.43	9995543	35.86	0.01017397	0.89642857	0.09322290
	SeqDr2	316.60	5.14	186.86	9999773	34.86	0.37357613	0.87142857	0.54299562
	HDDM_W	252.11	3.71	1846.57	9998113	36.29	0.18839435	0.90714286	0.29787809
	FTDD	452.36	8.14	**27.71**	**9999932**	31.86	0.55942488	0.79642857	0.66396386
	WSTD	**194.02**	8.71	375.29	9999585	31.29	0.26597309	0.78214286	0.39900764
	HDDM_A	564.46	3.00	36.71	9999923	37.00	**0.58364139**	0.92500000	**0.72423195**
	DDM_7	638.07	5.00	1612.57	9998347	35.00	0.05957505	0.87500000	0.20061074
	DDM_{129}	986.05	8.00	219.71	9999740	32.00	0.19754617	0.80000000	0.37756509
	RDDM_{30}	1045.05	8.29	249.71	9999710	31.71	0.11466734	0.79285714	0.29940348
	RDDM_7	464.59	6.29	2886.71	9997073	33.71	0.01453113	0.84285714	0.10778661
	RDDM_{129}	480.14	4.14	466.00	9999494	35.86	0.07599551	0.89642857	0.25917964
2M	DDM	2546.81	15.57	68.00	19999892	24.43	0.39353465	0.61071429	0.46604690
	EDDM	N/A	35.14	199.71	19999760	4.86	0.01909436	0.12142857	0.04610653
	ADWIN	**380.57**	**1.00**	2725.00	19997235	**39.00**	0.22769047	**0.97500000**	0.41922193
	ECDD	429.25	5.71	25271.71	19974688	34.29	0.00126957	0.85714286	0.03252877
	STEPD	683.54	**1.00**	8782.71	19991177	**39.00**	0.00551117	**0.97500000**	0.07163527
	SeqDr2	584.09	4.00	241.00	19999719	36.00	0.34956295	0.90000000	0.53356740
	HDDM_W	548.57	1.86	3670.00	19996290	38.14	0.16971330	0.95357143	0.26430638
	FTDD	659.11	5.43	**40.29**	**19999920**	34.57	**0.52839275**	0.86428571	**0.66775503**
	WSTD	799.99	5.86	704.43	19999256	34.14	0.22829732	0.85357143	0.36352025
	HDDM_A	845.14	1.86	66.71	19999893	38.14	0.48050850	0.95357143	0.65521805
	DDM_7	1065.66	5.00	2204.43	19997756	35.00	0.05470236	0.87500000	0.18786708
	DDM_{129}	1628.07	7.29	176.86	19999783	32.71	0.17425324	0.81785714	0.37084977
	RDDM_{30}	1959.20	5.71	443.57	19999516	34.29	0.07520331	0.85714286	0.25165899
	RDDM_7	530.24	4.86	5735.57	19994224	35.14	0.00750785	0.87857143	0.07920433
	RDDM_{129}	544.72	3.71	944.29	19999016	36.29	0.03906119	0.90714286	0.18692039

It is worthwhile pointing out that the numbers of the TN and TP detections could also be easily calculated. Given *rep* is the number of repetitions of the experiments, $TN = (size - 4) \times rep - FP$ and $TP = 4 \times rep - FN$.

Tables 23 and 24, presented below, are similar to Tables 21 and 22 except for they detail the *mean* drift identifications of the 15 tested configurations of the methods using HT as base classifier, instead of NB. Once again, in each dataset size, the best results are written in **bold**.

Accordingly, the results of different dataset generators were aggregated by their sizes, due to the large amount of raw data, and using the same criteria in the calculation of the mean distances of the true positive detections. In addition, note the corresponding detailed data separated by size and dataset generator are presented in Appendix B as Tables 46 to 55.

Table 23 – Detectors mean drift identifications in abrupt datasets using HT (Part 1)

Size	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
10K	DDM	N/A	90.00	78.57	299801	30.00	0.20602088	0.25000000	0.22516814
	EDDM	21.06	99.29	321.14	299559	20.71	0.05625867	0.17261905	0.09638524
	ADWIN	25.28	96.86	262.71	299617	23.14	0.08148672	0.19285714	0.12407030
	ECDD	**15.63**	50.00	344.14	299536	70.00	0.15983688	0.58333333	0.30080832
	STEPD	21.49	54.29	252.71	299627	65.71	0.29195356	0.54761905	0.38530818
	SeqDr2	N/A	108.43	246.57	299633	11.57	0.03061970	0.09642857	0.04812685
	$HDDM_W$	23.16	**49.86**	66.00	299814	**70.14**	**0.54903187**	**0.58452381**	**0.56110853**
	FTDD	26.86	67.57	**36.43**	**299844**	52.43	0.46170401	0.43690476	0.44347415
	WSTD	25.66	57.86	60.57	299819	62.14	0.50347745	0.51785714	0.50034705
	$HDDM_A$	23.97	65.29	41.14	299839	54.71	0.48818199	0.45595238	0.46980016
	DDM_7	23.21	63.43	484.57	299395	56.57	0.12794881	0.47142857	0.23371667
	DDM_{129}	28.05	76.29	115.43	299765	43.71	0.25812241	0.36428571	0.30159022
	$RDDM_{30}$	N/A	89.00	56.86	299823	31.00	0.26621177	0.25833333	0.26137608
	$RDDM_7$	27.06	74.43	139.43	299741	45.57	0.24892592	0.37976190	0.30250154
	$RDDM_{129}$	28.85	77.71	78.14	299802	42.29	0.30434020	0.35238095	0.32450253
20K	DDM	N/A	82.14	101.14	599779	37.86	0.21145381	0.31547619	0.25666822
	EDDM	45.54	92.00	401.00	599479	28.00	0.06657544	0.23333333	0.12229883
	ADWIN	47.90	67.14	388.14	599492	52.86	0.15184113	0.44047619	0.25347437
	ECDD	**19.33**	45.43	741.57	599138	74.57	0.08457360	0.62142857	0.22632111
	STEPD	28.64	43.57	397.14	599483	76.43	0.20534792	0.63690476	0.35203806
	SeqDr2	N/A	111.14	342.86	599537	8.86	0.01086303	0.07380952	0.02609195
	$HDDM_W$	31.81	**34.00**	104.71	599775	**86.00**	0.55281674	**0.71666667**	**0.61815446**
	FTDD	35.08	59.00	**37.14**	**599843**	61.00	0.52160225	0.50833333	0.51022193
	WSTD	30.66	48.43	72.29	599808	71.57	0.51587105	0.59642857	0.54532241
	$HDDM_A$	38.17	51.29	37.29	**599843**	68.71	**0.58967891**	0.57261905	0.57958938
	DDM_7	37.66	53.29	714.00	599166	66.71	0.11049923	0.55595238	0.23457819
	DDM_{129}	44.42	66.43	159.29	599721	53.57	0.22904237	0.44642857	0.31518365
	$RDDM_{30}$	48.08	86.57	68.71	599811	33.43	0.30325164	0.27857143	0.29012274
	$RDDM_7$	43.64	67.29	195.57	599684	52.71	0.22546217	0.43928571	0.30715549
	$RDDM_{129}$	39.75	70.43	94.43	599786	49.57	0.31092582	0.41309524	0.35500303
50K	DDM	107.53	67.43	133.57	1499746	52.57	0.27091152	0.43809524	0.33454889
	EDDM	83.04	100.29	485.29	1499395	19.71	0.03218228	0.16428571	0.07103979
	ADWIN	86.16	51.29	770.29	1499110	68.71	0.13514842	0.57261905	0.26843579
	ECDD	**30.05**	39.00	1848.43	1498032	81.00	0.03945008	0.67500000	0.16096799
	STEPD	41.33	35.43	814.57	1499065	84.57	0.11898320	0.70476190	0.28225088
	SeqDr2	192.12	39.14	447.57	1499432	80.86	0.31032494	0.67380952	0.42380236
	$HDDM_W$	42.44	**28.29**	263.43	1499617	**91.71**	0.42950086	**0.76428571**	0.54419086
	FTDD	47.57	49.86	45.00	1499835	70.14	0.55544102	0.58452381	0.56600695
	WSTD	42.18	38.43	114.00	1499766	81.57	0.47206154	0.67976190	0.55482955
	$HDDM_A$	66.13	39.57	**36.29**	**1499844**	80.43	**0.64264792**	0.67023810	**0.65515935**
	DDM_7	67.47	36.43	1299.00	1498581	83.57	0.09969151	0.69642857	0.23963326
	DDM_{129}	89.43	44.71	241.14	1499639	75.29	0.25490140	0.62738095	0.38853186
	$RDDM_{30}$	119.54	66.00	74.00	1499806	54.00	0.40963105	0.45000000	0.42883322
	$RDDM_7$	77.52	50.00	368.14	1499512	70.00	0.18452565	0.58333333	0.32124766
	$RDDM_{129}$	94.89	46.43	107.71	1499772	73.57	0.40462797	0.61309524	0.49456281

Table 24 – Detectors mean drift identifications in abrupt datasets using HT (Part 2)

Size	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
100K	DDM	167.74	62.86	156.00	2999724	57.14	0.28929211	0.47619048	0.35961077
	EDDM	189.17	101.57	513.29	2999367	18.43	0.02527367	0.15357143	0.06105986
	ADWIN	126.12	37.71	1429.71	2998450	82.29	0.10589051	0.68571429	0.25563339
	ECDD	**46.70**	34.43	3747.57	2996132	85.57	0.02058745	0.71309524	0.11962575
	STEPD	64.14	32.29	1491.71	2998388	87.71	0.06960340	0.73095238	0.22027472
	SeqDr2	205.43	31.14	607.43	2999273	88.86	0.29852841	0.74047619	0.43508194
	$HDDM_W$	52.51	**23.29**	525.00	2999355	**96.71**	0.37004855	**0.80595238**	0.49394895
	FTDD	67.67	40.14	65.00	2999815	79.86	0.56212360	0.66547619	0.60392649
	WSTD	61.17	31.86	176.14	2999704	88.14	0.44398637	0.73452381	0.55349065
	$HDDM_A$	103.87	32.71	**41.86**	**2999838**	87.29	**0.64862699**	0.72738095	**0.68563483**
	DDM_7	122.33	29.00	2058.71	2997821	91.00	0.09294739	0.75833333	0.23268517
	DDM_{129}	148.44	38.71	337.00	2999543	81.29	0.23888261	0.67738095	0.38582783
	$RDDM_{30}$	194.27	58.29	86.71	2999793	61.71	0.45083724	0.51428571	0.48094653
	$RDDM_7$	115.40	37.43	599.71	2999280	82.57	0.14707870	0.68809524	0.31248074
	$RDDM_{129}$	156.54	37.00	144.57	2999735	83.00	0.41384667	0.69166667	0.52781647
500K	DDM	756.68	18.43	57.43	4999903	21.57	0.30949461	0.53928571	0.39816468
	EDDM	1164.43	35.71	162.43	4999798	4.29	0.01818983	0.10714286	0.04237768
	ADWIN	268.07	6.29	2334.14	4997626	33.71	0.03257126	0.84285714	0.15245273
	ECDD	179.70	7.00	6281.57	4993678	33.00	0.00488386	0.82500000	0.06263832
	STEPD	211.14	5.57	2252.29	4997708	34.43	0.02029965	0.86071429	0.12795476
	SeqDr2	312.02	7.29	606.71	4999353	32.71	0.29114818	0.81785714	0.43796389
	$HDDM_W$	**129.87**	5.29	866.14	4999094	34.71	0.30080653	0.86785714	0.39234853
	FTDD	249.79	10.43	60.29	4999900	29.57	0.48771276	0.73928571	0.57320856
	WSTD	163.13	8.71	234.29	4999726	31.29	0.34552041	0.78214286	0.46900111
	$HDDM_A$	242.10	**3.43**	**43.00**	**4999917**	**36.57**	**0.59002590**	**0.91428571**	**0.71551232**
	DDM_7	340.68	7.86	1508.00	4998452	32.14	0.04074994	0.80357143	0.16920067
	DDM_{129}	528.23	8.71	180.14	4999780	31.29	0.16700785	0.78214286	0.35587683
	$RDDM_{30}$	488.13	10.71	103.86	4999856	29.29	0.25532757	0.73214286	0.42797920
	$RDDM_7$	281.64	7.57	1105.29	4998855	32.43	0.03917877	0.81071429	0.17304448
	$RDDM_{129}$	306.54	6.14	208.86	4999751	33.86	0.16135976	0.84642857	0.36595654

Considering the mean distance of the true positive detections, ECDD and STEPD achieved the best results in most tested datasets, especially in the lower sizes (up to 100K). However, these good results often came at the cost of many FP detections, hurting their accuracies, and this phenomenon was more severe in the case of ECDD. The other good methods in this metric were WSTD and $HDDM_W$: their results were usually close to those of the previous two methods and were often the best in the larger datasets.

Regarding the false negatives (and consequently true positives), several methods presented reasonably similar results. In no particular order, the best methods were ECDD, STEPD, $HDDM_W$, WSTD, $HDDM_A$, and DDM_7. In the larger datasets (from 100K), ADWIN and $SeqDrift_2$ also returned strong results in this metric.

In both aforementioned metrics, the results of FTDD and $RDDM_{129}$ were usually worse than the best results in each dataset but they were often reasonably close to them, especially in the larger datasets.

In the case of false positives (and consequently true negatives), FTDD and $HDDM_A$ were clearly the best two methods, FTDD being a distinct winner in the tests using NB and in the very small datasets (10K and 20K) with HT, whereas $HDDM_A$ was the best in most other datasets using HT. Despite being regularly behind the best two detectors in this metric, other configurations returned good results consistently, including DDM, WSTD, DDM_{129}, $RDDM_{30}$, and $RDDM_{129}$.

Analysing the results of Precision, the best methods were $HDDM_A$, FTDD, and WSTD. They provided the very best results in many scenarios and generally strong results in most other situations. $HDDM_W$ delivered very strong results in the smaller datasets but not so good results when the size of the datasets increased. It was also generally better using HT than using NB. On the other hand, the results of DDM were the opposite, progressively stronger with the increase in the size of the datasets and usually better using NB than using HT. Finally, $RDDM_{30}$ and $RDDM_{129}$ were rarely among the very best results but were consistently among the best 40% configurations in most datasets.

In the case of Recall, the differences were reasonably small in the results of a fairly large proportion of the tested configurations with both base learners, but the best methods were $HDDM_W$, ECDD, STEPD, WSTD, and $HDDM_A$, whereas EDDM was the worst.

To a considerable extent, the results of most configurations of the methods in the MCC criterion were directly related to their *Precision* results, which is probably a consequence of their close results in *Recall*. However, in MCC, $SeqDrift_2$ was much closer to the best methods than it was in *Precision*, though mostly in the tests using NB.

To conclude this section, lets repeat the description of **RQ2**: *What are the best concept drift detectors in terms of detections, measured by precision, recall, and the MCC metric, in the abrupt datasets?*

Based on this chapter's experiments, the answer to **RQ2** is: although there were minor variations in the data regarding the two base learners (NB and HT), the best concept drift detectors overall in terms of detections of concept drifts were $HDDM_A$, FTDD, WSTD, and $HDDM_W$. $RDDM_{129}$ was a consistent fifth place but reasonably far behind the very best configurations in most datasets.

6.4 Additional Research Questions

This section examines and answers the remaining three research questions this chapter proposed to answer, i.e., **RQ3**, **RQ4**, and **RQ5**.

The description of **RQ3** was: *Do the answers of **RQ1** and **RQ2** vary with the different dataset generators used in the experiments? How much?*

As expected, the answer to **RQ3** regarding accuracies (**RQ1**) is *yes*, there were considerable differences in the results when the data of the different dataset generators were separated and this phenomenon was more severe in the tests using HT. However, in general, the best methods ($RDDM_{129}$ and $HDDM_A$) delivered strong accuracy results in most dataset generators, the exception being randomRBF. In fact, the best methods in the randomRBF datasets are ECDD, EDDM, and $SeqDrift_2$, which did *not* present good results in the majority of the other datasets.

The answer to **RQ3** regarding the detections (**RQ2**) is also *yes*, there are variations in the results referring to different dataset generators but these are much more limited than they were in the case of the accuracies. In general, there were numerous changes in the order within the best four methods (HDDM$_A$, FTDD, WSTD, and HDDM$_W$), but these four remained the best in most dataset generators. As expected, the most notable exception was once again randomRBF: in these datasets, the best detections were those of SeqDrift$_2$, HDDM$_W$, HDDM$_A$, and RDDM$_{129}$.

The description of **RQ4** was: *Do the answers of **RQ1** and **RQ2** depend on the size of the concepts included in the datasets? How much?*

The answer to **RQ4** regarding accuracies (**RQ1**) is once again *yes*, there were substantial differences in the results of some configurations when the datasets of different sizes were separated. Note SeqDrift$_2$ and FTDD are the ones most affected by this phenomenon and both of them improved their results dramatically with the increase in the size of the datasets. On the other hand, the trend for both HDDM$_W$ and RDDM$_7$ was to consistently present worse ranks when the size of the datasets increased, though these variations were *not* nearly as large as those of SeqDrift$_2$ and FTDD.

The answer to **RQ4** regarding the detections (**RQ2**) is, one more time, *yes*, there were ample differences in the results of some methods when the datasets were separated by size. FTDD and, to a lesser extent, SeqDrift$_2$ again improved their detections when the size of the datasets increased, especially using NB as base classifier.

Finally, the description of **RQ5** was: *In the same datasets, are the best methods of **RQ1** and **RQ2** the same? To what extent?*

The answer is *no*. Looking exclusively to the results of the experiments using the abrupt datasets, it is clear that, in spite of some intersection among the best methods regarding their accuracies and detections, the very best methods are *not* exactly the same in the two criteria. The reason seems to be that false positive detections help to improve the accuracy results of some methods in many datasets, notably the three configurations of RDDM, instead of hurting them, as long as the numbers are not too big. However, this issue obviously needs to be further investigated for a more conclusive answer.

6.5 Conclusion

This chapter presented an extensive comparison and evaluation of concept drift detection methods. As was to be expected, no single drift detector is better than all the others in all situations, but both methods proposed in this thesis, RDDM and WSTD, presented solid results. The following chapter carries out fairly large experiments aiming to comprehensively evaluate ensembles for data stream mining focusing on methods that are configurable with concept drift detectors.

7 A comprehensive comparison of Ensembles

This chapter reports on the comprehensive experiments carried out to compare ensembles for mining data streams containing concept drifts. Detailed information about these experiments are provided and their results carefully analysed. More precisely, *five* ensemble versions that use auxiliary concept drift detection methods are paired with each of *eight* selected drift detectors configurations. The accuracies of these 40 combinations are then compared among themselves and against the selected detectors individually. The results of these experiments provide indications of the best ensemble-detector combinations, the best ensemble algorithms, and the best drift detectors to configure the ensembles.

The chosen ensembles for these experiments are ADOB (SANTOS et al., 2014), DDD (MINKU; YAO, 2012), and FASE (FRÍAS-BLANCO et al., 2016), as well as the $BOLE_4$ and $BOLE_5$ configurations proposed in Chapter 5. It would have been interesting to also include Leveraging Bagging (LevBag) (BIFET; HOLMES; PFAHRINGER, 2010) in the tests but, to make it possible, it would be necessary to change its implementation, because its concept drift detector (ADWIN) is hard-coded, rather than parametrized.

The selected detectors are a subset of the 15 used in the experiments of Chapter 6, namely: FTDD, WSTD, $HDDM_A$, DDM_7, DDM_{129}, $RDDM_{30}$, $RDDM_7$, and $RDDM_{129}$.

The experiments were also run in the MOA framework (BIFET et al., 2010), release 2014.11, and used the same datasets, base learners, and set ups adopted in the experiments of Chapter 6. The ensembles were all set up to use 10 experts and their specific parameters with respective default values, except for the auxiliary drift detector.

In particular, these experiments were designed to answer the additional research questions introduced in Chapter 1, **RQ6** to **RQ12**, repeated below:

- **RQ6:** What are the best ensemble plus drift detector combinations in terms of final accuracy in abrupt and gradual concept drift datasets?
- **RQ7:** What are the best ensembles in terms of accuracy in abrupt and gradual drift datasets irrespective of the auxiliary concept drift detector used?
- **RQ8:** What are the best concept drift detectors as auxiliary methods in ensembles in terms of accuracy of the ensembles in abrupt and gradual concept drift datasets?
- **RQ9:** Do the answers of **RQ6**, **RQ7**, and **RQ8** vary with the different dataset generators used in the experiments? How much?
- **RQ10:** Do the answers of **RQ6**, **RQ7**, and **RQ8** depend on the size of the concepts included in the datasets? How much?

- **RQ11:** In the same datasets, are the best ensembles of **RQ6** and **RQ7** the same?
- **RQ12:** In the same datasets, are the best concept drift detectors of **RQ1**, **RQ6**, and **RQ8** the same? To what extent?

Tables 25 to 31 show the ensemble accuracy results in the tests using the *abrupt* datasets (separated by size) and NB as base classifier. The first of these tables presents the results referring to the datasets with 10,000 instances. Also, observe the best result in each dataset is written in **bold**.

Table 25 – Mean accuracies of Ensembles in percentage (%) in 10K instances abrupt datasets, with 95% confidence intervals, using NB

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	60.77 (+-0.28)	60.77 (+-0.28)	60.80 (+-0.30)	60.14 (+-0.38)	63.60 (+-0.23)	60.85 (+-0.29)
	WSTD	62.26 (+-0.24)	62.26 (+-0.24)	62.39 (+-0.25)	61.74 (+-0.41)	63.85 (+-0.25)	62.07 (+-0.36)
	$HDDM_A$	62.18 (+-0.29)	62.17 (+-0.29)	62.32 (+-0.27)	62.45 (+-0.37)	63.97 (+-0.25)	63.17 (+-0.32)
	DDM_7	61.80 (+-0.22)	61.78 (+-0.22)	61.93 (+-0.20)	62.31 (+-0.33)	64.19 (+-0.20)	62.82 (+-0.20)
	DDM_{129}	62.67 (+-0.21)	62.66 (+-0.21)	62.85 (+-0.22)	62.78 (+-0.24)	64.11 (+-0.23)	63.32 (+-0.27)
	$RDDM_{30}$	61.21 (+-0.29)	61.20 (+-0.29)	61.26 (+-0.31)	61.73 (+-0.46)	63.93 (+-0.24)	62.54 (+-0.28)
	$RDDM_7$	62.75 (+-0.22)	62.73 (+-0.22)	62.88 (+-0.23)	63.14 (+-0.23)	**64.23 (+-0.25)**	63.51 (+-0.22)
	$RDDM_{129}$	62.63 (+-0.24)	62.62 (+-0.24)	62.79 (+-0.23)	62.81 (+-0.34)	64.11 (+-0.23)	63.56 (+-0.26)
$Agraw_2$	FTDD	82.04 (+-0.18)	82.05 (+-0.18)	82.09 (+-0.19)	78.18 (+-0.66)	81.74 (+-0.25)	79.15 (+-0.67)
	WSTD	82.58 (+-0.23)	82.58 (+-0.23)	82.64 (+-0.23)	79.83 (+-0.46)	81.97 (+-0.26)	80.69 (+-0.52)
	$HDDM_A$	82.43 (+-0.19)	82.44 (+-0.19)	82.47 (+-0.19)	79.12 (+-0.70)	81.83 (+-0.28)	80.11 (+-0.66)
	DDM_7	82.26 (+-0.19)	82.27 (+-0.19)	82.37 (+-0.19)	81.02 (+-0.59)	82.85 (+-0.17)	81.22 (+-0.43)
	DDM_{129}	81.52 (+-0.29)	81.53 (+-0.28)	81.68 (+-0.29)	79.40 (+-0.90)	82.20 (+-0.21)	79.51 (+-0.94)
	$RDDM_{30}$	79.62 (+-0.26)	79.63 (+-0.25)	79.69 (+-0.27)	73.51 (+-1.15)	82.06 (+-0.26)	73.73 (+-1.18)
	$RDDM_7$	82.21 (+-0.23)	82.21 (+-0.22)	82.33 (+-0.24)	81.09 (+-0.63)	**82.87 (+-0.16)**	81.34 (+-0.54)
	$RDDM_{129}$	81.44 (+-0.32)	81.45 (+-0.32)	81.58 (+-0.32)	79.43 (+-0.93)	82.21 (+-0.22)	79.63 (+-0.96)
LED	FTDD	66.40 (+-1.59)	68.49 (+-0.31)	68.09 (+-0.41)	65.81 (+-0.94)	68.25 (+-0.25)	67.20 (+-0.75)
	WSTD	67.88 (+-0.33)	67.95 (+-0.34)	68.13 (+-0.32)	68.26 (+-0.45)	67.27 (+-0.36)	67.60 (+-0.80)
	$HDDM_A$	68.92 (+-0.27)	68.99 (+-0.27)	69.03 (+-0.27)	68.59 (+-0.33)	68.64 (+-0.25)	69.72 (+-0.29)
	DDM_7	68.94 (+-0.27)	68.96 (+-0.27)	69.02 (+-0.27)	68.71 (+-0.30)	68.82 (+-0.27)	69.54 (+-0.30)
	DDM_{129}	68.79 (+-0.28)	68.81 (+-0.28)	68.86 (+-0.28)	68.66 (+-0.34)	68.58 (+-0.26)	69.85 (+-0.30)
	$RDDM_{30}$	68.38 (+-0.29)	68.41 (+-0.29)	68.45 (+-0.29)	68.53 (+-0.37)	68.56 (+-0.27)	69.54 (+-0.29)
	$RDDM_7$	69.02 (+-0.28)	69.04 (+-0.28)	69.09 (+-0.27)	69.08 (+-0.36)	68.83 (+-0.27)	**69.99 (+-0.31)**
	$RDDM_{129}$	68.76 (+-0.28)	68.78 (+-0.27)	68.82 (+-0.27)	68.59 (+-0.36)	68.58 (+-0.26)	69.80 (+-0.29)
Mixed	FTDD	90.47 (+-0.21)	90.47 (+-0.21)	90.47 (+-0.21)	88.05 (+-0.92)	89.87 (+-0.18)	90.39 (+-0.22)
	WSTD	90.44 (+-0.22)	90.44 (+-0.22)	**90.49 (+-0.22)**	88.02 (+-0.93)	89.85 (+-0.18)	90.41 (+-0.22)
	$HDDM_A$	90.40 (+-0.21)	90.39 (+-0.21)	90.41 (+-0.21)	87.40 (+-0.74)	89.95 (+-0.17)	90.39 (+-0.21)
	DDM_7	88.50 (+-0.26)	88.50 (+-0.27)	88.40 (+-0.24)	87.98 (+-0.85)	89.86 (+-0.20)	89.34 (+-0.67)
	DDM_{129}	90.13 (+-0.17)	90.13 (+-0.16)	90.14 (+-0.16)	88.02 (+-0.79)	89.89 (+-0.18)	90.20 (+-0.24)
	$RDDM_{30}$	89.96 (+-0.26)	90.01 (+-0.22)	90.00 (+-0.21)	88.87 (+-0.47)	89.92 (+-0.17)	89.87 (+-0.23)
	$RDDM_7$	89.78 (+-0.22)	89.77 (+-0.21)	89.83 (+-0.21)	89.10 (+-0.74)	89.87 (+-0.20)	90.31 (+-0.23)
	$RDDM_{129}$	90.22 (+-0.17)	90.22 (+-0.17)	90.23 (+-0.18)	87.55 (+-0.74)	89.89 (+-0.18)	90.22 (+-0.23)
RBF	FTDD	19.69 (+-0.79)	24.49 (+-0.71)	30.76 (+-0.68)	30.98 (+-0.59)	**31.71 (+-0.35)**	31.08 (+-0.53)
	WSTD	20.10 (+-1.07)	25.01 (+-0.83)	30.19 (+-0.66)	30.91 (+-0.65)	31.59 (+-0.39)	30.70 (+-0.56)
	$HDDM_A$	19.87 (+-0.84)	24.66 (+-0.71)	30.60 (+-0.63)	30.89 (+-0.54)	31.58 (+-0.36)	30.56 (+-0.43)
	DDM_7	20.06 (+-0.77)	24.40 (+-0.62)	30.62 (+-0.58)	30.15 (+-0.47)	31.18 (+-0.31)	29.94 (+-0.46)
	DDM_{129}	19.86 (+-0.84)	24.55 (+-0.66)	30.38 (+-0.54)	30.47 (+-0.47)	31.46 (+-0.30)	30.33 (+-0.45)
	$RDDM_{30}$	19.89 (+-0.85)	24.81 (+-0.74)	30.78 (+-0.69)	30.65 (+-0.57)	31.41 (+-0.34)	30.77 (+-0.49)
	$RDDM_7$	19.94 (+-0.77)	24.25 (+-0.82)	30.66 (+-0.57)	30.23 (+-0.39)	31.32 (+-0.29)	30.12 (+-0.44)
	$RDDM_{129}$	19.86 (+-0.84)	24.55 (+-0.66)	30.57 (+-0.54)	30.44 (+-0.40)	31.45 (+-0.31)	30.53 (+-0.43)
Sine	FTDD	88.64 (+-0.20)	88.66 (+-0.20)	88.67 (+-0.18)	84.62 (+-0.51)	86.38 (+-0.20)	86.75 (+-0.23)
	WSTD	88.68 (+-0.14)	88.70 (+-0.14)	**88.72 (+-0.14)**	85.07 (+-0.40)	86.40 (+-0.21)	86.76 (+-0.22)
	$HDDM_A$	88.66 (+-0.15)	88.68 (+-0.15)	88.69 (+-0.16)	84.83 (+-0.33)	86.42 (+-0.20)	86.62 (+-0.21)
	DDM_7	86.76 (+-0.18)	86.78 (+-0.19)	86.93 (+-0.19)	84.17 (+-0.70)	86.78 (+-0.20)	84.86 (+-0.68)
	DDM_{129}	88.42 (+-0.15)	88.44 (+-0.15)	88.46 (+-0.15)	84.47 (+-0.93)	86.45 (+-0.21)	85.83 (+-0.72)
	$RDDM_{30}$	88.22 (+-0.18)	88.24 (+-0.19)	88.26 (+-0.17)	85.16 (+-0.44)	86.30 (+-0.21)	86.03 (+-0.24)
	$RDDM_7$	88.19 (+-0.19)	88.21 (+-0.19)	88.30 (+-0.18)	86.03 (+-0.41)	86.77 (+-0.20)	86.73 (+-0.22)
	$RDDM_{129}$	88.55 (+-0.15)	88.57 (+-0.15)	88.60 (+-0.14)	85.38 (+-0.51)	86.45 (+-0.21)	86.58 (+-0.24)
Wavef.	FTDD	79.67 (+-0.47)	79.67 (+-0.48)	79.29 (+-0.48)	77.73 (+-0.58)	78.84 (+-0.44)	78.06 (+-0.61)
	WSTD	80.27 (+-0.35)	80.27 (+-0.35)	80.13 (+-0.38)	78.26 (+-0.52)	79.07 (+-0.40)	78.79 (+-0.51)
	$HDDM_A$	80.14 (+-0.40)	80.14 (+-0.41)	80.00 (+-0.42)	78.41 (+-0.52)	79.00 (+-0.43)	78.73 (+-0.48)
	DDM_7	**80.95 (+-0.35)**	**80.95 (+-0.35)**	80.88 (+-0.35)	79.08 (+-0.42)	79.81 (+-0.36)	78.96 (+-0.43)
	DDM_{129}	80.34 (+-0.36)	80.34 (+-0.37)	80.08 (+-0.43)	78.99 (+-0.52)	79.38 (+-0.39)	79.16 (+-0.43)
	$RDDM_{30}$	79.27 (+-0.37)	79.27 (+-0.37)	78.88 (+-0.37)	78.26 (+-0.44)	79.07 (+-0.41)	78.56 (+-0.42)
	$RDDM_7$	80.63 (+-0.34)	80.63 (+-0.34)	80.46 (+-0.34)	79.19 (+-0.43)	79.77 (+-0.35)	79.23 (+-0.43)
	$RDDM_{129}$	80.10 (+-0.35)	80.10 (+-0.36)	79.91 (+-0.41)	78.94 (+-0.46)	79.38 (+-0.39)	79.12 (+-0.47)

It is important to point out that, in all these tables, the last column, named *None*, refers to the results of the concept drift detectors without an ensemble.

The following tables cover the other dataset sizes used in the experiments with NB, i.e., 20,000, 50,000, 100,000, 500,000, 1 Million, and 2 Million instances.

Table 26 – Mean accuracies of Ensembles in percentage (%) in 20K instances abrupt datasets, with 95% confidence intervals, using NB

Dataset	Ensemble	ADOB	BOLE$_4$	BOLE$_5$	DDD	FASE	None
Agraw$_1$	FTDD	62.59 (+-0.23)	62.59 (+-0.22)	62.72 (+-0.21)	61.56 (+-0.44)	65.05 (+-0.12)	62.02 (+-0.35)
	WSTD	64.73 (+-0.19)	64.73 (+-0.19)	64.86 (+-0.18)	63.88 (+-0.31)	65.16 (+-0.12)	64.48 (+-0.27)
	HDDM$_A$	64.97 (+-0.21)	64.97 (+-0.21)	65.22 (+-0.21)	64.35 (+-0.19)	65.21 (+-0.11)	64.82 (+-0.17)
	DDM$_7$	63.36 (+-0.18)	63.35 (+-0.18)	63.55 (+-0.18)	64.10 (+-0.15)	65.30 (+-0.13)	64.33 (+-0.13)
	DDM$_{129}$	64.48 (+-0.17)	64.48 (+-0.17)	64.71 (+-0.17)	64.25 (+-0.22)	65.24 (+-0.12)	64.75 (+-0.13)
	RDDM$_{30}$	63.71 (+-0.23)	63.71 (+-0.23)	63.91 (+-0.26)	63.86 (+-0.16)	65.18 (+-0.13)	64.32 (+-0.18)
	RDDM$_7$	64.68 (+-0.17)	64.68 (+-0.17)	64.88 (+-0.16)	64.59 (+-0.17)	**65.31 (+-0.12)**	64.87 (+-0.16)
	RDDM$_{129}$	64.81 (+-0.22)	64.81 (+-0.22)	65.03 (+-0.22)	64.22 (+-0.23)	65.24 (+-0.12)	64.89 (+-0.15)
Agraw$_2$	FTDD	84.70 (+-0.12)	84.70 (+-0.12)	84.73 (+-0.12)	81.58 (+-0.44)	84.11 (+-0.14)	81.90 (+-0.41)
	WSTD	85.19 (+-0.14)	85.19 (+-0.14)	**85.23 (+-0.15)**	82.75 (+-0.47)	84.16 (+-0.14)	83.41 (+-0.40)
	HDDM$_A$	84.95 (+-0.10)	84.95 (+-0.10)	84.98 (+-0.10)	82.52 (+-0.56)	84.20 (+-0.11)	83.00 (+-0.50)
	DDM$_7$	84.59 (+-0.12)	84.60 (+-0.12)	84.71 (+-0.13)	83.38 (+-0.50)	84.77 (+-0.09)	83.60 (+-0.34)
	DDM$_{129}$	84.38 (+-0.14)	84.38 (+-0.14)	84.48 (+-0.14)	82.83 (+-0.54)	84.39 (+-0.12)	83.09 (+-0.51)
	RDDM$_{30}$	82.87 (+-0.18)	82.87 (+-0.18)	82.95 (+-0.21)	79.76 (+-0.76)	84.32 (+-0.11)	79.50 (+-0.82)
	RDDM$_7$	84.85 (+-0.11)	84.85 (+-0.11)	84.95 (+-0.11)	83.60 (+-0.38)	84.74 (+-0.09)	84.01 (+-0.27)
	RDDM$_{129}$	84.27 (+-0.15)	84.27 (+-0.15)	84.38 (+-0.14)	82.70 (+-0.46)	84.41 (+-0.12)	83.18 (+-0.56)
LED	FTDD	70.46 (+-1.12)	71.02 (+-0.22)	70.94 (+-0.23)	69.78 (+-0.37)	70.90 (+-0.16)	70.55 (+-0.47)
	WSTD	70.51 (+-0.29)	70.53 (+-0.29)	70.62 (+-0.28)	70.38 (+-0.24)	70.44 (+-0.25)	70.60 (+-0.44)
	HDDM$_A$	71.37 (+-0.18)	71.39 (+-0.18)	71.40 (+-0.19)	70.54 (+-0.23)	71.21 (+-0.16)	71.52 (+-0.18)
	DDM$_7$	71.35 (+-0.18)	71.36 (+-0.19)	71.39 (+-0.19)	70.81 (+-0.33)	71.41 (+-0.16)	71.25 (+-0.36)
	DDM$_{129}$	71.24 (+-0.19)	71.25 (+-0.19)	71.28 (+-0.19)	70.65 (+-0.23)	71.15 (+-0.16)	71.68 (+-0.18)
	RDDM$_{30}$	70.79 (+-0.19)	70.80 (+-0.19)	70.82 (+-0.19)	70.44 (+-0.22)	71.02 (+-0.18)	71.39 (+-0.18)
	RDDM$_7$	71.44 (+-0.18)	71.45 (+-0.18)	71.48 (+-0.18)	71.13 (+-0.27)	71.42 (+-0.16)	**71.88 (+-0.19)**
	RDDM$_{129}$	71.19 (+-0.19)	71.20 (+-0.19)	71.22 (+-0.20)	70.64 (+-0.22)	71.15 (+-0.16)	71.74 (+-0.16)
Mixed	FTDD	91.33 (+-0.15)	91.33 (+-0.15)	**91.37 (+-0.14)**	88.66 (+-0.81)	90.90 (+-0.11)	91.18 (+-0.13)
	WSTD	91.11 (+-0.17)	91.11 (+-0.17)	91.16 (+-0.15)	88.38 (+-0.77)	90.90 (+-0.11)	91.19 (+-0.13)
	HDDM$_A$	90.99 (+-0.16)	90.99 (+-0.16)	91.07 (+-0.16)	88.65 (+-0.56)	90.89 (+-0.10)	91.10 (+-0.12)
	DDM$_7$	89.07 (+-0.17)	89.06 (+-0.17)	89.18 (+-0.15)	88.45 (+-0.66)	90.88 (+-0.12)	90.18 (+-0.51)
	DDM$_{129}$	90.59 (+-0.13)	90.59 (+-0.13)	90.73 (+-0.13)	89.11 (+-0.60)	90.88 (+-0.10)	90.91 (+-0.22)
	RDDM$_{30}$	90.93 (+-0.15)	90.93 (+-0.15)	90.98 (+-0.14)	90.07 (+-0.37)	90.87 (+-0.10)	90.78 (+-0.14)
	RDDM$_7$	90.30 (+-0.17)	90.30 (+-0.17)	90.46 (+-0.15)	90.64 (+-0.34)	90.84 (+-0.12)	91.02 (+-0.14)
	RDDM$_{129}$	90.78 (+-0.15)	90.78 (+-0.15)	90.92 (+-0.14)	89.53 (+-0.49)	90.88 (+-0.10)	91.03 (+-0.15)
RBF	FTDD	19.49 (+-0.62)	23.62 (+-0.67)	30.74 (+-0.56)	30.88 (+-0.52)	**32.02 (+-0.31)**	31.15 (+-0.46)
	WSTD	19.67 (+-0.93)	24.16 (+-0.76)	30.40 (+-0.64)	30.73 (+-0.57)	31.98 (+-0.31)	30.70 (+-0.57)
	HDDM$_A$	19.54 (+-0.73)	23.80 (+-0.69)	30.78 (+-0.51)	30.80 (+-0.43)	31.87 (+-0.29)	30.69 (+-0.41)
	DDM$_7$	19.85 (+-0.62)	23.81 (+-0.44)	30.31 (+-0.45)	30.27 (+-0.37)	31.68 (+-0.24)	30.15 (+-0.43)
	DDM$_{129}$	19.56 (+-0.72)	23.74 (+-0.58)	30.41 (+-0.54)	30.45 (+-0.42)	31.88 (+-0.25)	30.42 (+-0.42)
	RDDM$_{30}$	19.62 (+-0.78)	23.92 (+-0.66)	30.68 (+-0.56)	30.85 (+-0.45)	31.99 (+-0.27)	30.76 (+-0.42)
	RDDM$_7$	19.89 (+-0.67)	23.60 (+-0.55)	30.49 (+-0.47)	30.17 (+-0.36)	31.64 (+-0.24)	30.17 (+-0.42)
	RDDM$_{129}$	19.56 (+-0.72)	23.69 (+-0.54)	30.50 (+-0.52)	30.51 (+-0.42)	31.85 (+-0.26)	30.50 (+-0.41)
Sine	FTDD	89.55 (+-0.14)	89.56 (+-0.14)	**89.60 (+-0.12)**	85.80 (+-0.44)	87.05 (+-0.17)	87.21 (+-0.19)
	WSTD	89.43 (+-0.14)	89.44 (+-0.14)	89.46 (+-0.13)	85.71 (+-0.33)	87.05 (+-0.17)	87.21 (+-0.18)
	HDDM$_A$	89.37 (+-0.13)	89.38 (+-0.13)	89.42 (+-0.13)	85.19 (+-0.34)	87.04 (+-0.16)	87.08 (+-0.18)
	DDM$_7$	87.72 (+-0.15)	87.73 (+-0.15)	87.88 (+-0.15)	85.03 (+-0.53)	87.36 (+-0.14)	85.54 (+-0.67)
	DDM$_{129}$	89.11 (+-0.15)	89.12 (+-0.15)	89.18 (+-0.13)	85.44 (+-0.75)	87.11 (+-0.16)	86.76 (+-0.48)
	RDDM$_{30}$	89.17 (+-0.14)	89.18 (+-0.14)	89.18 (+-0.13)	85.83 (+-0.30)	86.96 (+-0.16)	86.51 (+-0.23)
	RDDM$_7$	88.94 (+-0.13)	88.95 (+-0.13)	89.02 (+-0.12)	86.58 (+-0.31)	87.38 (+-0.15)	87.14 (+-0.18)
	RDDM$_{129}$	89.24 (+-0.15)	89.25 (+-0.15)	89.33 (+-0.14)	86.02 (+-0.33)	87.11 (+-0.16)	87.02 (+-0.19)
Wavef.	FTDD	80.54 (+-0.25)	80.54 (+-0.26)	80.30 (+-0.28)	78.73 (+-0.42)	79.74 (+-0.24)	79.12 (+-0.44)
	WSTD	81.04 (+-0.23)	81.04 (+-0.23)	80.98 (+-0.23)	79.17 (+-0.33)	79.97 (+-0.23)	79.71 (+-0.28)
	HDDM$_A$	80.81 (+-0.23)	80.81 (+-0.23)	80.77 (+-0.25)	79.21 (+-0.27)	79.88 (+-0.23)	79.60 (+-0.26)
	DDM$_7$	**81.58 (+-0.23)**	**81.58 (+-0.23)**	81.48 (+-0.23)	79.63 (+-0.23)	80.47 (+-0.21)	79.57 (+-0.23)
	DDM$_{129}$	81.02 (+-0.22)	81.02 (+-0.22)	80.91 (+-0.23)	79.59 (+-0.25)	80.14 (+-0.22)	79.75 (+-0.28)
	RDDM$_{30}$	80.17 (+-0.23)	80.20 (+-0.21)	79.90 (+-0.24)	78.98 (+-0.34)	79.95 (+-0.22)	79.32 (+-0.30)
	RDDM$_7$	81.32 (+-0.21)	81.32 (+-0.20)	81.19 (+-0.21)	79.82 (+-0.24)	80.47 (+-0.21)	79.85 (+-0.25)
	RDDM$_{129}$	80.79 (+-0.24)	80.79 (+-0.24)	80.71 (+-0.25)	79.61 (+-0.22)	80.14 (+-0.23)	79.78 (+-0.29)

Notice the number of tables to exhibit all the remaining accuracy results of these experiments is fairly big. For this reason, the remaining data are omitted from the text of this chapter. Even so, the results of the tests in the *gradual* datasets using NB as base learner are included in Appendix C as Tables 56 to 62.

Table 27 – Mean accuracies of Ensembles in percentage (%) in 50K instances abrupt datasets, with 95% confidence intervals, using NB

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	65.60 (+-0.27)	65.60 (+-0.27)	65.83 (+-0.30)	62.61 (+-0.51)	65.90 (+-0.12)	63.55 (+-0.51)
	WSTD	66.71 (+-0.15)	66.71 (+-0.15)	66.76 (+-0.15)	65.30 (+-0.18)	66.02 (+-0.12)	65.57 (+-0.14)
	$HDDM_A$	67.58 (+-0.12)	67.57 (+-0.12)	**67.78 (+-0.11)**	65.08 (+-0.20)	66.01 (+-0.11)	65.67 (+-0.16)
	DDM_7	65.14 (+-0.18)	65.14 (+-0.18)	65.39 (+-0.19)	65.16 (+-0.26)	66.05 (+-0.12)	65.22 (+-0.18)
	DDM_{129}	66.78 (+-0.14)	66.78 (+-0.14)	67.03 (+-0.15)	64.95 (+-0.21)	66.08 (+-0.10)	65.53 (+-0.11)
	$RDDM_{30}$	66.51 (+-0.16)	66.51 (+-0.16)	66.88 (+-0.15)	64.76 (+-0.23)	65.99 (+-0.11)	65.36 (+-0.17)
	$RDDM_7$	66.63 (+-0.14)	66.63 (+-0.14)	66.85 (+-0.15)	65.60 (+-0.11)	66.06 (+-0.11)	65.63 (+-0.13)
	$RDDM_{129}$	67.28 (+-0.10)	67.27 (+-0.10)	67.55 (+-0.12)	65.17 (+-0.20)	66.06 (+-0.11)	65.73 (+-0.11)
$Agraw_2$	FTDD	86.74 (+-0.12)	86.74 (+-0.12)	86.75 (+-0.12)	83.45 (+-0.49)	85.63 (+-0.09)	83.86 (+-0.50)
	WSTD	87.10 (+-0.09)	87.10 (+-0.09)	**87.12 (+-0.09)**	84.73 (+-0.37)	85.70 (+-0.09)	85.30 (+-0.25)
	$HDDM_A$	86.80 (+-0.10)	86.81 (+-0.10)	86.86 (+-0.10)	84.86 (+-0.28)	85.63 (+-0.10)	85.34 (+-0.22)
	DDM_7	86.33 (+-0.07)	86.33 (+-0.07)	86.48 (+-0.08)	85.07 (+-0.34)	85.92 (+-0.06)	85.15 (+-0.31)
	DDM_{129}	86.54 (+-0.11)	86.54 (+-0.11)	86.58 (+-0.11)	84.69 (+-0.38)	85.81 (+-0.06)	85.20 (+-0.22)
	$RDDM_{30}$	85.69 (+-0.13)	85.69 (+-0.14)	85.78 (+-0.13)	83.72 (+-0.46)	85.73 (+-0.06)	84.24 (+-0.43)
	$RDDM_7$	86.79 (+-0.08)	86.79 (+-0.09)	86.88 (+-0.10)	85.47 (+-0.17)	85.91 (+-0.05)	85.74 (+-0.08)
	$RDDM_{129}$	86.43 (+-0.13)	86.43 (+-0.13)	86.48 (+-0.13)	84.72 (+-0.35)	85.82 (+-0.06)	85.38 (+-0.20)
LED	FTDD	72.36 (+-0.17)	72.37 (+-0.17)	72.36 (+-0.16)	71.21 (+-0.30)	72.57 (+-0.17)	72.23 (+-0.21)
	WSTD	72.41 (+-0.19)	72.41 (+-0.19)	72.45 (+-0.19)	71.98 (+-0.23)	72.48 (+-0.15)	72.10 (+-0.33)
	$HDDM_A$	72.80 (+-0.16)	72.81 (+-0.16)	72.81 (+-0.16)	71.64 (+-0.23)	72.74 (+-0.15)	72.81 (+-0.16)
	DDM_7	72.72 (+-0.16)	72.72 (+-0.16)	72.73 (+-0.16)	72.31 (+-0.28)	72.80 (+-0.13)	72.51 (+-0.26)
	DDM_{129}	72.68 (+-0.17)	72.68 (+-0.17)	72.69 (+-0.17)	71.99 (+-0.21)	72.70 (+-0.14)	72.81 (+-0.17)
	$RDDM_{30}$	72.38 (+-0.17)	72.38 (+-0.17)	72.39 (+-0.17)	72.05 (+-0.19)	72.59 (+-0.14)	72.67 (+-0.15)
	$RDDM_7$	72.78 (+-0.15)	72.78 (+-0.15)	72.79 (+-0.15)	72.51 (+-0.16)	72.81 (+-0.14)	72.78 (+-0.17)
	$RDDM_{129}$	72.67 (+-0.16)	72.67 (+-0.16)	72.68 (+-0.16)	72.06 (+-0.24)	72.70 (+-0.14)	**72.89 (+-0.15)**
Mixed	FTDD	91.47 (+-0.17)	91.47 (+-0.17)	91.66 (+-0.13)	89.59 (+-0.77)	91.62 (+-0.10)	91.72 (+-0.10)
	WSTD	91.13 (+-0.17)	91.12 (+-0.17)	91.37 (+-0.14)	89.08 (+-0.65)	91.62 (+-0.10)	**91.73 (+-0.10)**
	$HDDM_A$	91.20 (+-0.15)	91.20 (+-0.15)	91.45 (+-0.12)	89.99 (+-0.47)	91.57 (+-0.10)	91.63 (+-0.11)
	DDM_7	89.58 (+-0.11)	89.58 (+-0.11)	89.86 (+-0.11)	88.99 (+-0.98)	91.56 (+-0.11)	90.77 (+-0.49)
	DDM_{129}	90.79 (+-0.12)	90.79 (+-0.12)	91.14 (+-0.10)	90.49 (+-0.55)	91.58 (+-0.10)	91.39 (+-0.25)
	$RDDM_{30}$	91.20 (+-0.18)	91.20 (+-0.18)	91.42 (+-0.15)	90.98 (+-0.25)	91.56 (+-0.10)	91.41 (+-0.11)
	$RDDM_7$	90.44 (+-0.20)	90.44 (+-0.20)	90.86 (+-0.12)	91.47 (+-0.11)	91.56 (+-0.10)	91.56 (+-0.12)
	$RDDM_{129}$	90.82 (+-0.21)	90.81 (+-0.21)	91.20 (+-0.15)	90.69 (+-0.47)	91.58 (+-0.10)	91.57 (+-0.10)
RBF	FTDD	19.46 (+-0.60)	23.28 (+-0.54)	31.09 (+-0.57)	31.16 (+-0.52)	**32.42 (+-0.23)**	31.03 (+-0.49)
	WSTD	19.10 (+-0.67)	23.22 (+-0.49)	30.46 (+-0.65)	30.63 (+-0.57)	32.24 (+-0.25)	30.39 (+-0.54)
	$HDDM_A$	19.49 (+-0.69)	23.32 (+-0.66)	30.93 (+-0.40)	30.95 (+-0.43)	32.26 (+-0.22)	30.91 (+-0.40)
	DDM_7	19.78 (+-0.61)	23.19 (+-0.38)	30.53 (+-0.36)	30.38 (+-0.47)	32.00 (+-0.19)	30.52 (+-0.40)
	DDM_{129}	19.40 (+-0.67)	23.17 (+-0.52)	30.64 (+-0.37)	30.73 (+-0.34)	32.20 (+-0.21)	30.65 (+-0.42)
	$RDDM_{30}$	19.56 (+-0.69)	23.09 (+-0.62)	31.03 (+-0.52)	30.85 (+-0.35)	32.25 (+-0.21)	30.95 (+-0.39)
	$RDDM_7$	19.62 (+-0.62)	23.12 (+-0.45)	30.73 (+-0.32)	30.46 (+-0.27)	32.02 (+-0.17)	30.63 (+-0.31)
	$RDDM_{129}$	19.41 (+-0.66)	23.10 (+-0.54)	30.91 (+-0.29)	30.71 (+-0.34)	32.21 (+-0.21)	30.73 (+-0.36)
Sine	FTDD	89.79 (+-0.13)	89.79 (+-0.13)	**89.90 (+-0.11)**	86.12 (+-0.33)	87.32 (+-0.11)	87.40 (+-0.12)
	WSTD	89.50 (+-0.13)	89.51 (+-0.14)	89.69 (+-0.11)	86.05 (+-0.34)	87.32 (+-0.11)	87.40 (+-0.11)
	$HDDM_A$	89.60 (+-0.16)	89.61 (+-0.15)	89.74 (+-0.14)	85.89 (+-0.33)	87.26 (+-0.11)	87.26 (+-0.10)
	DDM_7	88.41 (+-0.14)	88.42 (+-0.14)	88.57 (+-0.14)	85.61 (+-0.51)	87.55 (+-0.11)	86.45 (+-0.48)
	DDM_{129}	89.38 (+-0.14)	89.38 (+-0.14)	89.53 (+-0.13)	85.79 (+-0.91)	87.32 (+-0.11)	86.87 (+-0.48)
	$RDDM_{30}$	89.51 (+-0.18)	89.52 (+-0.18)	89.64 (+-0.15)	86.15 (+-0.36)	87.25 (+-0.11)	86.79 (+-0.21)
	$RDDM_7$	89.25 (+-0.12)	89.26 (+-0.12)	89.39 (+-0.11)	87.24 (+-0.18)	87.58 (+-0.10)	87.34 (+-0.12)
	$RDDM_{129}$	89.56 (+-0.15)	89.56 (+-0.15)	89.69 (+-0.14)	86.38 (+-0.35)	87.33 (+-0.11)	87.22 (+-0.13)
Wavef.	FTDD	81.14 (+-0.14)	81.14 (+-0.14)	81.06 (+-0.16)	79.58 (+-0.24)	80.37 (+-0.16)	79.92 (+-0.25)
	WSTD	81.59 (+-0.12)	81.59 (+-0.12)	81.55 (+-0.14)	79.88 (+-0.18)	80.49 (+-0.13)	80.21 (+-0.13)
	$HDDM_A$	81.44 (+-0.15)	81.44 (+-0.15)	81.41 (+-0.15)	79.75 (+-0.18)	80.42 (+-0.14)	80.13 (+-0.15)
	DDM_7	**81.91 (+-0.14)**	**81.91 (+-0.14)**	81.82 (+-0.13)	80.01 (+-0.15)	80.89 (+-0.14)	79.95 (+-0.15)
	DDM_{129}	81.48 (+-0.13)	81.48 (+-0.13)	81.43 (+-0.13)	79.89 (+-0.21)	80.50 (+-0.13)	80.04 (+-0.17)
	$RDDM_{30}$	81.10 (+-0.14)	81.10 (+-0.14)	81.05 (+-0.15)	79.84 (+-0.17)	80.39 (+-0.13)	79.93 (+-0.17)
	$RDDM_7$	81.66 (+-0.14)	81.66 (+-0.14)	81.58 (+-0.14)	80.11 (+-0.15)	80.91 (+-0.14)	80.14 (+-0.13)
	$RDDM_{129}$	81.44 (+-0.13)	81.44 (+-0.13)	81.39 (+-0.13)	80.01 (+-0.15)	80.50 (+-0.13)	80.16 (+-0.14)

Similarly, all the results of the experiments with the ensemble configurations using HT as base classifier are presented in Appendix D. Observe Tables 63 to 67 comprise the results of the tests in the *abrupt* datasets whereas Tables 68 to 72 refer to the tests in the *gradual* datasets.

As in Chapters 5 and 6, the obtained accuracy results were also compared using the F_F statistic (DEMSAR, 2006) and the Nemenyi post-hoc test to find out in what method(s) there is statistical difference.

Table 28 – Mean accuracies of Ensembles in percentage (%) in 100K instances abrupt datasets, with 95% confidence intervals, using NB

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	67.30 (+-0.22)	67.30 (+-0.22)	67.81 (+-0.24)	64.44 (+-0.40)	66.26 (+-0.08)	65.04 (+-0.47)
	WSTD	67.32 (+-0.12)	67.32 (+-0.12)	67.37 (+-0.13)	65.82 (+-0.12)	66.33 (+-0.07)	65.96 (+-0.11)
	$HDDM_A$	68.35 (+-0.10)	68.35 (+-0.10)	**68.54 (+-0.11)**	65.56 (+-0.18)	66.31 (+-0.07)	66.06 (+-0.08)
	DDM_7	66.06 (+-0.18)	66.06 (+-0.18)	66.40 (+-0.18)	65.48 (+-0.28)	66.40 (+-0.08)	65.81 (+-0.09)
	DDM_{129}	67.89 (+-0.15)	67.89 (+-0.15)	68.14 (+-0.15)	65.45 (+-0.30)	66.35 (+-0.07)	65.66 (+-0.31)
	$RDDM_{30}$	68.04 (+-0.10)	68.04 (+-0.10)	68.39 (+-0.10)	65.23 (+-0.18)	66.28 (+-0.07)	65.73 (+-0.17)
	$RDDM_7$	67.14 (+-0.14)	67.14 (+-0.14)	67.39 (+-0.13)	65.91 (+-0.07)	66.43 (+-0.07)	65.94 (+-0.09)
	$RDDM_{129}$	68.13 (+-0.10)	68.13 (+-0.10)	68.38 (+-0.10)	65.74 (+-0.14)	66.36 (+-0.07)	66.08 (+-0.08)
$Agraw_2$	FTDD	87.62 (+-0.11)	87.62 (+-0.11)	87.63 (+-0.11)	84.22 (+-0.54)	86.27 (+-0.06)	84.60 (+-0.47)
	WSTD	87.75 (+-0.05)	87.75 (+-0.05)	87.78 (+-0.05)	85.58 (+-0.31)	86.29 (+-0.05)	85.84 (+-0.31)
	$HDDM_A$	87.76 (+-0.08)	87.76 (+-0.08)	**87.83 (+-0.07)**	85.61 (+-0.20)	86.25 (+-0.05)	86.14 (+-0.09)
	DDM_7	87.08 (+-0.09)	87.09 (+-0.09)	87.27 (+-0.08)	85.60 (+-0.35)	86.32 (+-0.04)	85.73 (+-0.35)
	DDM_{129}	87.34 (+-0.09)	87.34 (+-0.09)	87.39 (+-0.09)	85.54 (+-0.33)	86.33 (+-0.04)	85.88 (+-0.20)
	$RDDM_{30}$	87.04 (+-0.09)	87.04 (+-0.09)	87.04 (+-0.09)	84.61 (+-0.43)	86.30 (+-0.04)	85.26 (+-0.34)
	$RDDM_7$	87.53 (+-0.06)	87.53 (+-0.06)	87.60 (+-0.06)	85.98 (+-0.16)	86.33 (+-0.04)	86.23 (+-0.05)
	$RDDM_{129}$	87.40 (+-0.07)	87.40 (+-0.07)	87.46 (+-0.08)	85.60 (+-0.30)	86.32 (+-0.04)	86.13 (+-0.04)
LED	FTDD	72.94 (+-0.14)	72.94 (+-0.14)	72.93 (+-0.14)	71.79 (+-0.20)	73.23 (+-0.13)	72.94 (+-0.19)
	WSTD	73.22 (+-0.12)	73.22 (+-0.12)	73.25 (+-0.12)	72.67 (+-0.21)	73.24 (+-0.11)	72.85 (+-0.20)
	$HDDM_A$	73.39 (+-0.12)	**73.40 (+-0.12)**	**73.40 (+-0.12)**	72.23 (+-0.17)	73.34 (+-0.11)	73.37 (+-0.11)
	DDM_7	73.31 (+-0.13)	73.32 (+-0.13)	73.32 (+-0.13)	72.74 (+-0.35)	73.38 (+-0.11)	72.90 (+-0.36)
	DDM_{129}	73.29 (+-0.13)	73.29 (+-0.13)	73.30 (+-0.13)	72.58 (+-0.17)	73.31 (+-0.11)	73.35 (+-0.12)
	$RDDM_{30}$	73.08 (+-0.13)	73.08 (+-0.13)	73.08 (+-0.13)	72.82 (+-0.21)	73.25 (+-0.11)	73.23 (+-0.12)
	$RDDM_7$	73.37 (+-0.12)	73.37 (+-0.12)	73.37 (+-0.12)	73.10 (+-0.15)	73.38 (+-0.11)	73.21 (+-0.12)
	$RDDM_{129}$	73.27 (+-0.13)	73.28 (+-0.13)	73.28 (+-0.13)	72.65 (+-0.21)	73.31 (+-0.11)	73.39 (+-0.12)
Mixed	FTDD	91.49 (+-0.10)	91.49 (+-0.10)	91.69 (+-0.08)	90.12 (+-0.55)	91.85 (+-0.06)	**91.90 (+-0.06)**
	WSTD	90.95 (+-0.17)	90.95 (+-0.17)	91.35 (+-0.11)	90.37 (+-0.57)	91.85 (+-0.06)	**91.90 (+-0.06)**
	$HDDM_A$	90.87 (+-0.18)	90.87 (+-0.18)	91.33 (+-0.12)	90.35 (+-0.44)	91.80 (+-0.06)	91.81 (+-0.07)
	DDM_7	89.65 (+-0.20)	89.65 (+-0.20)	90.09 (+-0.15)	89.11 (+-1.06)	91.78 (+-0.06)	90.48 (+-0.75)
	DDM_{129}	90.52 (+-0.19)	90.52 (+-0.19)	91.12 (+-0.10)	90.71 (+-0.70)	91.81 (+-0.05)	91.72 (+-0.09)
	$RDDM_{30}$	91.03 (+-0.16)	91.03 (+-0.16)	91.44 (+-0.12)	91.38 (+-0.24)	91.79 (+-0.06)	91.67 (+-0.06)
	$RDDM_7$	90.21 (+-0.14)	90.21 (+-0.14)	90.84 (+-0.09)	91.49 (+-0.17)	91.78 (+-0.06)	91.68 (+-0.07)
	$RDDM_{129}$	90.76 (+-0.17)	90.76 (+-0.17)	91.27 (+-0.12)	91.08 (+-0.40)	91.81 (+-0.05)	91.78 (+-0.06)
RBF	FTDD	19.28 (+-0.63)	23.05 (+-0.52)	31.15 (+-0.45)	31.67 (+-0.47)	**32.93 (+-0.20)**	31.65 (+-0.45)
	WSTD	18.81 (+-0.49)	22.90 (+-0.42)	30.37 (+-0.53)	30.77 (+-0.40)	32.58 (+-0.16)	30.69 (+-0.44)
	$HDDM_A$	19.34 (+-0.62)	22.84 (+-0.44)	30.55 (+-0.33)	31.32 (+-0.34)	32.73 (+-0.19)	31.13 (+-0.34)
	DDM_7	19.43 (+-0.61)	22.91 (+-0.43)	30.87 (+-0.37)	31.02 (+-0.36)	32.42 (+-0.11)	30.80 (+-0.33)
	DDM_{129}	19.15 (+-0.65)	22.76 (+-0.44)	30.89 (+-0.36)	31.16 (+-0.27)	32.66 (+-0.15)	31.32 (+-0.31)
	$RDDM_{30}$	19.44 (+-0.69)	22.52 (+-0.50)	31.18 (+-0.34)	31.25 (+-0.31)	32.72 (+-0.15)	31.24 (+-0.35)
	$RDDM_7$	19.66 (+-0.63)	22.82 (+-0.39)	30.92 (+-0.28)	30.74 (+-0.21)	32.41 (+-0.11)	30.89 (+-0.22)
	$RDDM_{129}$	19.35 (+-0.68)	22.67 (+-0.47)	30.82 (+-0.30)	31.12 (+-0.24)	32.66 (+-0.15)	31.16 (+-0.28)
Sine	FTDD	89.66 (+-0.19)	89.66 (+-0.19)	**89.89 (+-0.15)**	86.28 (+-0.28)	87.39 (+-0.09)	87.43 (+-0.09)
	WSTD	89.43 (+-0.15)	89.43 (+-0.15)	89.67 (+-0.12)	86.47 (+-0.29)	87.39 (+-0.09)	87.43 (+-0.09)
	$HDDM_A$	89.51 (+-0.18)	89.51 (+-0.18)	89.79 (+-0.14)	86.28 (+-0.40)	87.29 (+-0.09)	87.27 (+-0.10)
	DDM_7	88.81 (+-0.11)	88.82 (+-0.11)	88.96 (+-0.10)	85.95 (+-0.64)	87.59 (+-0.09)	85.31 (+-1.01)
	DDM_{129}	89.43 (+-0.12)	89.44 (+-0.12)	89.63 (+-0.10)	86.29 (+-0.47)	87.40 (+-0.09)	86.92 (+-0.36)
	$RDDM_{30}$	89.58 (+-0.16)	89.58 (+-0.16)	89.77 (+-0.12)	86.46 (+-0.25)	87.30 (+-0.09)	86.85 (+-0.20)
	$RDDM_7$	89.32 (+-0.13)	89.33 (+-0.13)	89.49 (+-0.11)	87.30 (+-0.12)	87.63 (+-0.08)	87.38 (+-0.08)
	$RDDM_{129}$	89.66 (+-0.09)	89.67 (+-0.09)	89.84 (+-0.08)	86.87 (+-0.27)	87.40 (+-0.09)	87.31 (+-0.10)
Wavef.	FTDD	81.44 (+-0.12)	81.44 (+-0.12)	81.42 (+-0.12)	79.90 (+-0.17)	80.59 (+-0.10)	80.23 (+-0.18)
	WSTD	81.70 (+-0.10)	81.70 (+-0.10)	81.69 (+-0.10)	80.12 (+-0.15)	80.66 (+-0.11)	80.33 (+-0.10)
	$HDDM_A$	81.62 (+-0.10)	81.62 (+-0.10)	81.60 (+-0.10)	80.11 (+-0.12)	80.57 (+-0.11)	80.27 (+-0.11)
	DDM_7	**81.88 (+-0.09)**	**81.88 (+-0.09)**	81.83 (+-0.09)	80.16 (+-0.13)	80.98 (+-0.10)	80.08 (+-0.13)
	DDM_{129}	81.56 (+-0.10)	81.56 (+-0.10)	81.53 (+-0.10)	80.11 (+-0.14)	80.65 (+-0.10)	80.09 (+-0.16)
	$RDDM_{30}$	81.38 (+-0.09)	81.38 (+-0.09)	81.35 (+-0.09)	79.99 (+-0.16)	80.58 (+-0.10)	80.05 (+-0.14)
	$RDDM_7$	81.75 (+-0.10)	81.75 (+-0.10)	81.71 (+-0.10)	80.27 (+-0.11)	81.03 (+-0.10)	80.23 (+-0.11)
	$RDDM_{129}$	81.58 (+-0.09)	81.58 (+-0.09)	81.56 (+-0.09)	80.14 (+-0.12)	80.66 (+-0.10)	80.25 (+-0.11)

It is worthwhile saying that the number of statistical comparisons carried out using the results of these experiments with ensembles was much larger than in the other chapters. This happened because the results were compared in three different dimensions: the ensemble-detector configurations, the ensembles irrespective of the detectors, and the detectors without regard to the ensembles.

For this reason, not all these statistical evaluations are explicitly presented here. Nevertheless, the best methods are always enumerated and the ranks have been used as subsidy to answer the research questions in Section 7.1.

Table 29 – Mean accuracies of Ensembles in percentage (%) in 500K instances abrupt datasets, with 95% confidence intervals, using NB

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	69.02 (+-0.14)	69.02 (+-0.14)	**69.31 (+-0.18)**	65.96 (+-0.22)	66.51 (+-0.04)	66.32 (+-0.07)
	WSTD	67.86 (+-0.11)	67.86 (+-0.11)	67.78 (+-0.13)	66.28 (+-0.07)	66.53 (+-0.05)	66.23 (+-0.06)
	$HDDM_A$	68.91 (+-0.13)	68.91 (+-0.13)	69.12 (+-0.14)	66.11 (+-0.15)	66.52 (+-0.04)	66.40 (+-0.05)
	DDM_7	67.31 (+-0.17)	67.31 (+-0.17)	67.75 (+-0.20)	66.14 (+-0.19)	66.73 (+-0.07)	66.03 (+-0.34)
	DDM_{129}	68.59 (+-0.19)	68.59 (+-0.19)	68.99 (+-0.18)	65.75 (+-0.26)	66.58 (+-0.04)	66.01 (+-0.20)
	$RDDM_{30}$	68.79 (+-0.16)	68.79 (+-0.16)	69.17 (+-0.14)	66.09 (+-0.12)	66.55 (+-0.05)	66.11 (+-0.22)
	$RDDM_7$	67.24 (+-0.14)	67.24 (+-0.14)	67.46 (+-0.15)	66.18 (+-0.06)	66.76 (+-0.06)	66.24 (+-0.04)
	$RDDM_{129}$	68.58 (+-0.21)	68.58 (+-0.21)	68.86 (+-0.18)	66.21 (+-0.13)	66.59 (+-0.06)	66.39 (+-0.06)
$Agraw_2$	FTDD	88.73 (+-0.12)	88.73 (+-0.12)	88.72 (+-0.12)	85.45 (+-0.81)	86.90 (+-0.06)	86.17 (+-0.64)
	WSTD	88.55 (+-0.07)	88.55 (+-0.07)	88.56 (+-0.06)	86.15 (+-0.37)	86.89 (+-0.04)	86.74 (+-0.11)
	$HDDM_A$	88.77 (+-0.04)	88.77 (+-0.04)	**88.78 (+-0.03)**	86.51 (+-0.30)	86.91 (+-0.04)	86.83 (+-0.06)
	DDM_7	88.23 (+-0.07)	88.23 (+-0.07)	88.37 (+-0.07)	86.75 (+-0.05)	86.75 (+-0.05)	86.69 (+-0.10)
	DDM_{129}	88.67 (+-0.06)	88.67 (+-0.06)	88.74 (+-0.06)	86.50 (+-0.27)	86.90 (+-0.04)	86.65 (+-0.09)
	$RDDM_{30}$	88.67 (+-0.06)	88.67 (+-0.06)	88.68 (+-0.05)	86.26 (+-0.35)	86.89 (+-0.05)	86.59 (+-0.18)
	$RDDM_7$	88.37 (+-0.07)	88.37 (+-0.07)	88.41 (+-0.07)	86.61 (+-0.07)	86.74 (+-0.04)	86.65 (+-0.06)
	$RDDM_{129}$	88.61 (+-0.05)	88.61 (+-0.05)	88.66 (+-0.04)	86.54 (+-0.20)	86.90 (+-0.04)	86.78 (+-0.06)
LED	FTDD	73.64 (+-0.09)	73.64 (+-0.09)	73.64 (+-0.09)	72.54 (+-0.29)	73.79 (+-0.09)	73.49 (+-0.28)
	WSTD	73.76 (+-0.11)	73.76 (+-0.11)	73.76 (+-0.11)	73.57 (+-0.12)	73.78 (+-0.08)	73.45 (+-0.10)
	$HDDM_A$	**73.80 (+-0.10)**	**73.80 (+-0.10)**	**73.80 (+-0.10)**	72.99 (+-0.28)	73.78 (+-0.09)	73.77 (+-0.11)
	DDM_7	73.74 (+-0.11)	73.74 (+-0.11)	73.74 (+-0.11)	73.62 (+-0.25)	73.77 (+-0.09)	73.31 (+-0.83)
	DDM_{129}	73.73 (+-0.11)	73.73 (+-0.11)	73.73 (+-0.11)	73.44 (+-0.17)	73.76 (+-0.09)	73.49 (+-0.22)
	$RDDM_{30}$	73.73 (+-0.10)	73.73 (+-0.10)	73.73 (+-0.10)	73.54 (+-0.16)	73.77 (+-0.08)	73.59 (+-0.12)
	$RDDM_7$	73.79 (+-0.10)	73.79 (+-0.10)	73.79 (+-0.10)	73.58 (+-0.10)	**73.80 (+-0.08)**	73.48 (+-0.10)
	$RDDM_{129}$	73.78 (+-0.10)	73.78 (+-0.10)	73.78 (+-0.10)	73.66 (+-0.10)	73.78 (+-0.09)	73.75 (+-0.08)
Mixed	FTDD	91.07 (+-0.24)	91.07 (+-0.24)	91.59 (+-0.15)	91.35 (+-0.79)	92.05 (+-0.03)	**92.07 (+-0.03)**
	WSTD	90.29 (+-0.37)	90.29 (+-0.37)	91.16 (+-0.32)	90.72 (+-0.85)	92.05 (+-0.03)	**92.07 (+-0.03)**
	$HDDM_A$	90.15 (+-0.33)	90.15 (+-0.33)	91.13 (+-0.19)	91.41 (+-0.51)	92.01 (+-0.04)	92.02 (+-0.05)
	DDM_7	89.73 (+-0.49)	89.73 (+-0.49)	90.42 (+-0.28)	89.87 (+-1.35)	92.01 (+-0.04)	90.52 (+-1.39)
	DDM_{129}	90.24 (+-0.30)	90.24 (+-0.30)	91.20 (+-0.19)	91.89 (+-0.13)	92.02 (+-0.04)	91.95 (+-0.11)
	$RDDM_{30}$	90.80 (+-0.23)	90.80 (+-0.23)	91.50 (+-0.12)	91.74 (+-0.28)	92.01 (+-0.04)	91.97 (+-0.05)
	$RDDM_7$	90.26 (+-0.26)	90.26 (+-0.26)	91.08 (+-0.12)	91.84 (+-0.05)	92.03 (+-0.02)	91.83 (+-0.03)
	$RDDM_{129}$	90.40 (+-0.29)	90.40 (+-0.29)	91.31 (+-0.21)	91.89 (+-0.21)	92.03 (+-0.03)	92.01 (+-0.03)
RBF	FTDD	18.88 (+-1.17)	21.50 (+-1.23)	32.43 (+-0.57)	33.49 (+-0.39)	**34.01 (+-0.17)**	33.12 (+-0.31)
	WSTD	18.90 (+-0.85)	22.07 (+-0.91)	31.26 (+-0.38)	31.08 (+-0.37)	33.18 (+-0.08)	31.00 (+-0.29)
	$HDDM_A$	19.10 (+-0.72)	22.37 (+-0.76)	31.58 (+-0.48)	32.77 (+-0.37)	33.73 (+-0.14)	32.54 (+-0.29)
	DDM_7	19.17 (+-0.93)	21.25 (+-1.30)	31.87 (+-0.51)	32.69 (+-0.42)	33.13 (+-0.11)	32.81 (+-0.41)
	DDM_{129}	18.53 (+-0.74)	21.95 (+-1.16)	31.78 (+-0.36)	32.46 (+-0.26)	33.69 (+-0.16)	32.73 (+-0.34)
	$RDDM_{30}$	18.66 (+-0.71)	21.49 (+-0.91)	31.75 (+-0.60)	32.33 (+-0.35)	33.66 (+-0.14)	32.49 (+-0.25)
	$RDDM_7$	18.80 (+-0.83)	22.13 (+-1.10)	31.57 (+-0.29)	31.35 (+-0.31)	33.09 (+-0.11)	31.48 (+-0.22)
	$RDDM_{129}$	18.93 (+-0.80)	21.11 (+-1.11)	31.52 (+-0.35)	32.01 (+-0.24)	33.65 (+-0.15)	32.13 (+-0.26)
Sine	FTDD	89.31 (+-0.33)	89.31 (+-0.33)	89.68 (+-0.25)	86.28 (+-0.71)	87.40 (+-0.06)	87.41 (+-0.06)
	WSTD	89.25 (+-0.26)	89.25 (+-0.26)	89.54 (+-0.20)	86.89 (+-0.39)	87.40 (+-0.06)	87.40 (+-0.06)
	$HDDM_A$	89.37 (+-0.34)	89.37 (+-0.34)	89.64 (+-0.26)	86.77 (+-0.41)	87.33 (+-0.07)	87.33 (+-0.07)
	DDM_7	89.13 (+-0.13)	89.13 (+-0.13)	89.31 (+-0.11)	86.08 (+-1.71)	87.54 (+-0.04)	85.47 (+-2.26)
	DDM_{129}	89.47 (+-0.18)	89.47 (+-0.19)	89.71 (+-0.19)	85.92 (+-1.13)	87.41 (+-0.06)	86.77 (+-0.50)
	$RDDM_{30}$	89.54 (+-0.22)	89.54 (+-0.22)	**89.83 (+-0.17)**	87.15 (+-0.14)	87.40 (+-0.06)	87.21 (+-0.10)
	$RDDM_7$	89.31 (+-0.21)	89.31 (+-0.21)	89.50 (+-0.15)	87.41 (+-0.07)	87.66 (+-0.05)	87.41 (+-0.05)
	$RDDM_{129}$	89.63 (+-0.23)	89.63 (+-0.23)	89.82 (+-0.16)	87.24 (+-0.14)	87.44 (+-0.06)	87.40 (+-0.06)
Wavef.	FTDD	81.64 (+-0.11)	81.64 (+-0.11)	81.64 (+-0.11)	80.08 (+-0.23)	80.58 (+-0.14)	80.39 (+-0.11)
	WSTD	81.71 (+-0.11)	81.71 (+-0.11)	81.71 (+-0.11)	80.32 (+-0.12)	80.62 (+-0.12)	80.38 (+-0.11)
	$HDDM_A$	81.63 (+-0.11)	81.63 (+-0.11)	81.63 (+-0.11)	80.26 (+-0.15)	80.54 (+-0.12)	80.38 (+-0.12)
	DDM_7	**81.87 (+-0.10)**	**81.87 (+-0.10)**	81.85 (+-0.10)	80.22 (+-0.11)	80.84 (+-0.10)	80.22 (+-0.12)
	DDM_{129}	81.57 (+-0.12)	81.57 (+-0.12)	81.56 (+-0.12)	80.12 (+-0.25)	80.60 (+-0.12)	80.23 (+-0.16)
	$RDDM_{30}$	81.56 (+-0.10)	81.56 (+-0.10)	81.56 (+-0.10)	80.24 (+-0.13)	80.58 (+-0.13)	80.07 (+-0.20)
	$RDDM_7$	81.80 (+-0.10)	81.80 (+-0.10)	81.79 (+-0.10)	80.36 (+-0.11)	81.06 (+-0.10)	80.33 (+-0.10)
	$RDDM_{129}$	81.66 (+-0.11)	81.66 (+-0.11)	81.65 (+-0.11)	80.33 (+-0.13)	80.64 (+-0.12)	80.37 (+-0.11)

In the evaluation of the ensemble-detector pairs, because of the large number of configurations, no explicit representation of the results is given. In the tests using NB, the $BOLE_5$+$HDDM_A$ pair was the best in the abrupt datasets, followed by $BOLE_5$+$RDDM_{129}$, $BOLE_5$+$RDDM_7$, $BOLE_5$+FTDD, and $BOLE_4$+$HDDM_A$. In the case of the gradual datasets, the best pairs were $BOLE_5$+$RDDM_{129}$, $BOLE_5$+$HDDM_A$, $BOLE_5$+DDM_{129}, $BOLE_5$+$RDDM_7$, and $BOLE_5$+$RDDM_{30}$. In all the datasets together, the bests ranks were those of $BOLE_5$+$HDDM_A$, $BOLE_5$+$RDDM_{129}$, $BOLE_5$+DDM_{129}, $BOLE_5$+$RDDM_7$, and $BOLE_4$+$HDDM_A$. In the three scenarios, the best pairs were statistically indistinguishable from each other as well as from a number of other combinations.

Table 30 – Mean accuracies of Ensembles in percentage (%) in 1 Million instances abrupt datasets, with 95% confidence intervals, using NB

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	68.77 (+-0.31)	68.77 (+-0.31)	69.08 (+-0.15)	66.25 (+-0.16)	66.54 (+-0.04)	66.45 (+-0.07)
	WSTD	68.00 (+-0.11)	68.00 (+-0.11)	67.95 (+-0.10)	66.40 (+-0.05)	66.59 (+-0.03)	66.30 (+-0.05)
	$HDDM_A$	69.00 (+-0.07)	69.00 (+-0.07)	69.18 (+-0.10)	66.28 (+-0.11)	66.55 (+-0.04)	66.46 (+-0.05)
	DDM_7	67.86 (+-0.17)	67.86 (+-0.17)	68.36 (+-0.21)	66.23 (+-0.25)	66.78 (+-0.04)	66.28 (+-0.10)
	DDM_{129}	68.71 (+-0.18)	68.71 (+-0.18)	69.19 (+-0.19)	65.82 (+-0.26)	66.63 (+-0.04)	66.03 (+-0.26)
	$RDDM_{30}$	69.05 (+-0.22)	69.05 (+-0.22)	**69.31 (+-0.18)**	66.27 (+-0.08)	66.60 (+-0.05)	66.35 (+-0.05)
	$RDDM_7$	67.42 (+-0.09)	67.42 (+-0.09)	67.60 (+-0.09)	66.24 (+-0.06)	66.84 (+-0.05)	66.29 (+-0.04)
	$RDDM_{129}$	68.65 (+-0.14)	68.65 (+-0.14)	68.95 (+-0.18)	66.48 (+-0.06)	66.65 (+-0.04)	66.49 (+-0.05)
$Agraw_2$	FTDD	88.83 (+-0.08)	88.83 (+-0.08)	88.87 (+-0.06)	86.19 (+-0.33)	86.98 (+-0.03)	86.70 (+-0.27)
	WSTD	88.68 (+-0.06)	88.68 (+-0.06)	88.67 (+-0.05)	86.24 (+-0.29)	86.96 (+-0.03)	86.89 (+-0.05)
	$HDDM_A$	88.91 (+-0.06)	88.91 (+-0.06)	**88.93 (+-0.06)**	86.43 (+-0.33)	86.97 (+-0.03)	86.91 (+-0.03)
	DDM_7	88.54 (+-0.06)	88.54 (+-0.06)	88.64 (+-0.05)	86.57 (+-0.37)	86.80 (+-0.02)	86.62 (+-0.22)
	DDM_{129}	88.86 (+-0.05)	88.86 (+-0.05)	88.90 (+-0.04)	86.54 (+-0.25)	86.99 (+-0.03)	86.83 (+-0.08)
	$RDDM_{30}$	88.85 (+-0.06)	88.85 (+-0.06)	88.89 (+-0.05)	86.35 (+-0.45)	86.96 (+-0.03)	86.64 (+-0.27)
	$RDDM_7$	88.46 (+-0.05)	88.46 (+-0.05)	88.49 (+-0.05)	86.68 (+-0.05)	86.78 (+-0.02)	86.70 (+-0.03)
	$RDDM_{129}$	88.84 (+-0.04)	88.84 (+-0.04)	88.87 (+-0.03)	86.86 (+-0.04)	86.97 (+-0.02)	86.86 (+-0.02)
LED	FTDD	73.81 (+-0.06)	73.81 (+-0.06)	73.81 (+-0.06)	72.95 (+-0.32)	73.83 (+-0.09)	73.49 (+-0.27)
	WSTD	73.85 (+-0.07)	73.85 (+-0.07)	73.86 (+-0.07)	73.74 (+-0.08)	73.87 (+-0.05)	73.52 (+-0.10)
	$HDDM_A$	73.87 (+-0.06)	73.87 (+-0.06)	73.87 (+-0.06)	73.48 (+-0.20)	73.86 (+-0.05)	73.84 (+-0.06)
	DDM_7	73.84 (+-0.06)	73.84 (+-0.06)	73.84 (+-0.06)	73.19 (+-0.53)	73.87 (+-0.06)	73.55 (+-0.41)
	DDM_{129}	73.83 (+-0.06)	73.83 (+-0.06)	73.83 (+-0.06)	73.28 (+-0.34)	73.86 (+-0.05)	73.65 (+-0.17)
	$RDDM_{30}$	73.84 (+-0.07)	73.84 (+-0.07)	73.84 (+-0.07)	73.63 (+-0.08)	73.86 (+-0.05)	73.70 (+-0.05)
	$RDDM_7$	**73.89 (+-0.07)**	**73.89 (+-0.07)**	**73.89 (+-0.07)**	73.65 (+-0.06)	**73.89 (+-0.05)**	73.53 (+-0.06)
	$RDDM_{129}$	73.87 (+-0.07)	73.87 (+-0.07)	73.87 (+-0.07)	73.80 (+-0.06)	73.88 (+-0.05)	73.82 (+-0.06)
Mixed	FTDD	90.91 (+-0.43)	90.91 (+-0.43)	91.53 (+-0.27)	90.78 (+-1.23)	**92.10 (+-0.03)**	**92.10 (+-0.03)**
	WSTD	90.23 (+-0.28)	90.23 (+-0.28)	91.21 (+-0.20)	90.41 (+-1.09)	**92.10 (+-0.03)**	**92.10 (+-0.03)**
	$HDDM_A$	90.12 (+-0.28)	90.12 (+-0.28)	91.20 (+-0.19)	91.86 (+-0.14)	92.08 (+-0.03)	92.08 (+-0.03)
	DDM_7	89.82 (+-0.23)	89.82 (+-0.23)	90.73 (+-0.13)	91.22 (+-0.81)	92.07 (+-0.03)	91.56 (+-0.66)
	DDM_{129}	90.68 (+-0.30)	90.68 (+-0.30)	91.44 (+-0.19)	91.86 (+-0.33)	92.08 (+-0.03)	92.03 (+-0.06)
	$RDDM_{30}$	90.55 (+-0.30)	90.55 (+-0.30)	91.46 (+-0.13)	91.93 (+-0.08)	92.07 (+-0.03)	92.03 (+-0.04)
	$RDDM_7$	90.35 (+-0.18)	90.35 (+-0.18)	91.14 (+-0.12)	91.88 (+-0.02)	92.07 (+-0.03)	91.86 (+-0.04)
	$RDDM_{129}$	90.28 (+-0.30)	90.28 (+-0.30)	91.32 (+-0.16)	92.02 (+-0.04)	92.08 (+-0.03)	92.04 (+-0.04)
RBF	FTDD	18.93 (+-1.14)	20.90 (+-1.24)	32.78 (+-0.51)	33.29 (+-0.26)	**34.01 (+-0.14)**	33.27 (+-0.21)
	WSTD	18.70 (+-0.64)	21.35 (+-0.93)	30.96 (+-0.35)	31.22 (+-0.09)	33.14 (+-0.08)	31.07 (+-0.23)
	$HDDM_A$	19.26 (+-0.93)	22.00 (+-1.02)	31.76 (+-0.38)	33.01 (+-0.27)	33.93 (+-0.04)	32.93 (+-0.21)
	DDM_7	18.82 (+-0.73)	21.31 (+-1.10)	32.19 (+-0.62)	33.16 (+-0.41)	33.16 (+-0.07)	33.23 (+-0.25)
	DDM_{129}	18.39 (+-0.67)	21.05 (+-1.30)	32.05 (+-0.34)	32.93 (+-0.30)	33.84 (+-0.07)	33.08 (+-0.33)
	$RDDM_{30}$	18.76 (+-0.66)	21.35 (+-1.07)	32.26 (+-0.29)	32.64 (+-0.11)	33.82 (+-0.05)	32.55 (+-0.19)
	$RDDM_7$	18.37 (+-0.52)	21.73 (+-0.86)	31.64 (+-0.15)	31.30 (+-0.16)	33.08 (+-0.04)	31.50 (+-0.18)
	$RDDM_{129}$	18.84 (+-0.87)	20.89 (+-0.71)	32.05 (+-0.26)	32.00 (+-0.11)	33.69 (+-0.04)	32.16 (+-0.13)
Sine	FTDD	89.34 (+-0.33)	89.35 (+-0.33)	89.69 (+-0.27)	86.36 (+-0.36)	87.44 (+-0.05)	87.45 (+-0.05)
	WSTD	89.44 (+-0.32)	89.44 (+-0.32)	89.71 (+-0.25)	86.82 (+-0.42)	87.44 (+-0.05)	87.44 (+-0.05)
	$HDDM_A$	89.15 (+-0.18)	89.15 (+-0.18)	89.48 (+-0.15)	86.60 (+-0.44)	87.39 (+-0.06)	87.38 (+-0.07)
	DDM_7	89.05 (+-0.14)	89.05 (+-0.14)	89.29 (+-0.12)	85.86 (+-1.88)	87.55 (+-0.04)	85.29 (+-2.70)
	DDM_{129}	89.56 (+-0.17)	89.56 (+-0.18)	**89.80 (+-0.13)**	86.41 (+-0.64)	87.44 (+-0.05)	87.09 (+-0.17)
	$RDDM_{30}$	89.39 (+-0.21)	89.39 (+-0.21)	89.71 (+-0.15)	87.22 (+-0.09)	87.45 (+-0.04)	87.32 (+-0.07)
	$RDDM_7$	89.54 (+-0.15)	89.54 (+-0.15)	89.70 (+-0.12)	87.46 (+-0.04)	87.69 (+-0.04)	87.45 (+-0.03)
	$RDDM_{129}$	89.33 (+-0.15)	89.33 (+-0.15)	89.65 (+-0.12)	87.36 (+-0.13)	87.48 (+-0.04)	87.44 (+-0.04)
Wavef.	FTDD	81.69 (+-0.06)	81.69 (+-0.06)	81.69 (+-0.06)	80.34 (+-0.12)	80.56 (+-0.07)	80.40 (+-0.10)
	WSTD	81.73 (+-0.06)	81.73 (+-0.06)	81.73 (+-0.06)	80.38 (+-0.09)	80.62 (+-0.07)	80.40 (+-0.06)
	$HDDM_A$	81.65 (+-0.08)	81.65 (+-0.08)	81.65 (+-0.08)	80.35 (+-0.12)	80.54 (+-0.08)	80.41 (+-0.09)
	DDM_7	**81.87 (+-0.07)**	**81.87 (+-0.07)**	81.86 (+-0.07)	80.15 (+-0.25)	80.78 (+-0.08)	80.26 (+-0.17)
	DDM_{129}	81.50 (+-0.10)	81.50 (+-0.10)	81.50 (+-0.10)	80.22 (+-0.24)	80.60 (+-0.08)	80.18 (+-0.19)
	$RDDM_{30}$	81.59 (+-0.06)	81.59 (+-0.06)	81.59 (+-0.06)	80.33 (+-0.09)	80.61 (+-0.07)	80.35 (+-0.08)
	$RDDM_7$	81.82 (+-0.06)	81.82 (+-0.06)	81.81 (+-0.06)	80.39 (+-0.07)	81.07 (+-0.07)	80.35 (+-0.07)
	$RDDM_{129}$	81.69 (+-0.05)	81.69 (+-0.06)	81.69 (+-0.06)	80.39 (+-0.07)	80.66 (+-0.07)	80.41 (+-0.07)

On the other hand, in the tests using HT, FASE+$HDDM_A$ was the best pair in the abrupt datasets, followed by FASE+DDM_{129}, $BOLE_5$+$HDDM_A$, FASE+$RDDM_{129}$, and FASE+$RDDM_{30}$. In the gradual datasets, the best pairs were FASE+DDM_{129}, FASE+$RDDM_{30}$, FASE+$HDDM_A$, FASE+$RDDM_{129}$, and FASE+DDM_7. In these two subsets, there were very few statistical differences, with over 30 indistinguishable pairs. In the evaluation with all the datasets, the bests ranks were those of FASE+DDM_{129}, FASE+$HDDM_A$, FASE+$RDDM_{30}$, FASE+$RDDM_{129}$, and $BOLE_5$+$HDDM_A$. In this last set, the best pairs were also statistically indistinguishable from each other and from several other combinations.

Table 31 – Mean accuracies of Ensembles in percentage (%) in 2 Million instances abrupt datasets, with 95% confidence intervals, using NB

Dataset	Ensemble	ADOB	BOLE$_4$	BOLE$_5$	DDD	FASE	None
Agraw$_1$	FTDD	68.97 (+-0.14)	68.97 (+-0.14)	69.31 (+-0.16)	66.35 (+-0.12)	66.58 (+-0.02)	66.53 (+-0.04)
	WSTD	68.12 (+-0.08)	68.12 (+-0.08)	68.07 (+-0.07)	66.41 (+-0.02)	66.61 (+-0.02)	66.31 (+-0.02)
	HDDM$_A$	69.07 (+-0.19)	69.07 (+-0.19)	69.29 (+-0.20)	66.32 (+-0.15)	66.58 (+-0.02)	66.49 (+-0.05)
	DDM$_7$	68.22 (+-0.18)	68.22 (+-0.18)	68.76 (+-0.16)	66.31 (+-0.22)	66.83 (+-0.02)	66.03 (+-0.76)
	DDM$_{129}$	69.00 (+-0.19)	69.00 (+-0.19)	**69.47 (+-0.17)**	65.85 (+-0.53)	66.67 (+-0.02)	66.31 (+-0.19)
	RDDM$_{30}$	69.12 (+-0.13)	69.12 (+-0.13)	69.33 (+-0.13)	66.27 (+-0.07)	66.64 (+-0.02)	66.44 (+-0.04)
	RDDM$_7$	67.62 (+-0.08)	67.62 (+-0.08)	67.78 (+-0.07)	66.28 (+-0.03)	66.88 (+-0.01)	66.30 (+-0.02)
	RDDM$_{129}$	68.78 (+-0.15)	68.78 (+-0.15)	69.05 (+-0.14)	66.44 (+-0.05)	66.68 (+-0.02)	66.52 (+-0.03)
Agraw$_2$	FTDD	88.98 (+-0.06)	88.98 (+-0.06)	88.98 (+-0.05)	86.29 (+-0.29)	87.03 (+-0.02)	86.97 (+-0.04)
	WSTD	88.74 (+-0.04)	88.74 (+-0.04)	88.72 (+-0.04)	86.49 (+-0.31)	86.99 (+-0.02)	86.94 (+-0.03)
	HDDM$_A$	89.03 (+-0.05)	89.03 (+-0.05)	**89.06 (+-0.04)**	86.54 (+-0.31)	87.02 (+-0.02)	86.97 (+-0.02)
	DDM$_7$	88.77 (+-0.07)	88.77 (+-0.07)	88.84 (+-0.06)	86.69 (+-0.32)	86.82 (+-0.01)	86.85 (+-0.10)
	DDM$_{129}$	88.94 (+-0.09)	88.94 (+-0.09)	89.01 (+-0.06)	86.51 (+-0.40)	87.02 (+-0.02)	86.58 (+-0.50)
	RDDM$_{30}$	88.96 (+-0.06)	88.96 (+-0.06)	88.98 (+-0.05)	86.55 (+-0.19)	87.00 (+-0.02)	86.79 (+-0.09)
	RDDM$_7$	88.57 (+-0.04)	88.57 (+-0.04)	88.60 (+-0.03)	86.72 (+-0.02)	86.81 (+-0.02)	86.72 (+-0.02)
	RDDM$_{129}$	88.95 (+-0.03)	88.95 (+-0.03)	88.97 (+-0.03)	86.91 (+-0.02)	87.00 (+-0.02)	86.90 (+-0.02)
LED	FTDD	73.92 (+-0.04)	73.92 (+-0.04)	73.92 (+-0.04)	73.32 (+-0.25)	73.93 (+-0.04)	73.77 (+-0.19)
	WSTD	73.92 (+-0.04)	73.92 (+-0.04)	73.92 (+-0.04)	73.82 (+-0.03)	73.93 (+-0.03)	73.64 (+-0.06)
	HDDM$_A$	73.93 (+-0.04)	73.93 (+-0.04)	73.93 (+-0.04)	73.72 (+-0.13)	73.92 (+-0.04)	73.89 (+-0.05)
	DDM$_7$	73.92 (+-0.04)	73.92 (+-0.04)	73.92 (+-0.04)	73.63 (+-0.31)	73.93 (+-0.04)	73.65 (+-0.46)
	DDM$_{129}$	73.91 (+-0.04)	73.91 (+-0.04)	73.91 (+-0.04)	73.75 (+-0.08)	73.93 (+-0.03)	73.59 (+-0.30)
	RDDM$_{30}$	73.89 (+-0.04)	73.89 (+-0.04)	73.89 (+-0.04)	73.71 (+-0.20)	73.93 (+-0.04)	73.78 (+-0.09)
	RDDM$_7$	**73.94 (+-0.04)**	**73.94 (+-0.04)**	**73.94 (+-0.04)**	73.71 (+-0.04)	**73.94 (+-0.03)**	73.57 (+-0.03)
	RDDM$_{129}$	73.93 (+-0.04)	73.93 (+-0.04)	73.93 (+-0.04)	73.87 (+-0.04)	**73.94 (+-0.03)**	73.87 (+-0.04)
Mixed	FTDD	90.58 (+-0.30)	90.58 (+-0.30)	91.57 (+-0.17)	91.72 (+-0.23)	92.06 (+-0.02)	**92.07 (+-0.02)**
	WSTD	90.10 (+-0.24)	90.10 (+-0.24)	91.15 (+-0.16)	91.83 (+-0.22)	92.06 (+-0.02)	**92.07 (+-0.02)**
	HDDM$_A$	90.22 (+-0.16)	90.22 (+-0.16)	91.27 (+-0.10)	91.90 (+-0.13)	92.04 (+-0.02)	92.03 (+-0.02)
	DDM$_7$	90.15 (+-0.15)	90.15 (+-0.15)	90.86 (+-0.14)	90.11 (+-1.75)	92.04 (+-0.02)	89.90 (+-1.50)
	DDM$_{129}$	90.59 (+-0.33)	90.59 (+-0.33)	91.39 (+-0.14)	89.96 (+-2.12)	92.05 (+-0.02)	91.83 (+-0.15)
	RDDM$_{30}$	90.71 (+-0.20)	90.71 (+-0.20)	91.52 (+-0.09)	91.97 (+-0.04)	92.04 (+-0.02)	92.00 (+-0.03)
	RDDM$_7$	90.32 (+-0.13)	90.32 (+-0.13)	91.11 (+-0.09)	91.86 (+-0.04)	92.04 (+-0.02)	91.84 (+-0.04)
	RDDM$_{129}$	90.22 (+-0.24)	90.22 (+-0.24)	91.36 (+-0.13)	92.00 (+-0.04)	92.05 (+-0.02)	92.01 (+-0.03)
RBF	FTDD	18.59 (+-0.76)	20.22 (+-1.13)	32.69 (+-0.30)	33.31 (+-0.17)	**34.14 (+-0.09)**	33.23 (+-0.14)
	WSTD	18.26 (+-0.38)	20.42 (+-0.84)	31.26 (+-0.18)	31.22 (+-0.15)	33.23 (+-0.08)	31.16 (+-0.16)
	HDDM$_A$	18.97 (+-1.02)	21.43 (+-1.10)	32.36 (+-0.26)	33.21 (+-0.19)	34.05 (+-0.09)	33.02 (+-0.20)
	DDM$_7$	18.43 (+-0.66)	20.77 (+-1.00)	32.83 (+-0.23)	33.32 (+-0.29)	33.20 (+-0.08)	33.53 (+-0.17)
	DDM$_{129}$	18.24 (+-0.46)	20.25 (+-1.25)	32.64 (+-0.16)	33.38 (+-0.19)	34.01 (+-0.10)	33.52 (+-0.13)
	RDDM$_{30}$	18.49 (+-0.51)	21.42 (+-0.93)	32.41 (+-0.18)	32.62 (+-0.23)	33.83 (+-0.08)	32.67 (+-0.18)
	RDDM$_7$	18.24 (+-0.48)	20.84 (+-0.94)	31.80 (+-0.12)	31.33 (+-0.10)	33.07 (+-0.14)	31.45 (+-0.12)
	RDDM$_{129}$	18.99 (+-0.95)	20.60 (+-0.86)	32.03 (+-0.25)	32.14 (+-0.12)	33.71 (+-0.07)	32.13 (+-0.13)
Sine	FTDD	89.21 (+-0.42)	89.21 (+-0.42)	89.53 (+-0.35)	86.69 (+-0.38)	87.44 (+-0.02)	87.44 (+-0.03)
	WSTD	89.46 (+-0.28)	89.46 (+-0.28)	**89.70 (+-0.22)**	86.57 (+-0.36)	87.44 (+-0.02)	87.44 (+-0.02)
	HDDM$_A$	89.20 (+-0.17)	89.20 (+-0.17)	89.47 (+-0.16)	87.08 (+-0.33)	87.41 (+-0.02)	87.41 (+-0.02)
	DDM$_7$	89.15 (+-0.17)	89.15 (+-0.17)	89.41 (+-0.11)	86.54 (+-0.82)	87.51 (+-0.02)	86.80 (+-0.82)
	DDM$_{129}$	89.22 (+-0.18)	89.26 (+-0.18)	89.58 (+-0.14)	85.86 (+-1.67)	87.44 (+-0.02)	86.60 (+-0.80)
	RDDM$_{30}$	89.38 (+-0.23)	89.38 (+-0.23)	89.66 (+-0.19)	87.29 (+-0.18)	87.46 (+-0.02)	87.36 (+-0.02)
	RDDM$_7$	89.38 (+-0.15)	89.38 (+-0.15)	89.53 (+-0.13)	87.46 (+-0.03)	87.70 (+-0.01)	87.45 (+-0.03)
	RDDM$_{129}$	89.33 (+-0.18)	89.33 (+-0.18)	89.58 (+-0.15)	87.45 (+-0.03)	87.50 (+-0.02)	87.47 (+-0.03)
Wavef.	FTDD	81.72 (+-0.03)	81.72 (+-0.03)	81.72 (+-0.03)	80.47 (+-0.04)	80.59 (+-0.03)	80.47 (+-0.04)
	WSTD	81.76 (+-0.04)	81.76 (+-0.04)	81.76 (+-0.04)	80.45 (+-0.04)	80.63 (+-0.04)	80.46 (+-0.04)
	HDDM$_A$	81.67 (+-0.03)	81.67 (+-0.03)	81.67 (+-0.03)	80.41 (+-0.08)	80.59 (+-0.04)	80.47 (+-0.04)
	DDM$_7$	81.81 (+-0.03)	81.81 (+-0.03)	81.81 (+-0.04)	80.31 (+-0.19)	80.77 (+-0.05)	80.36 (+-0.11)
	DDM$_{129}$	81.52 (+-0.07)	81.52 (+-0.07)	81.51 (+-0.08)	80.02 (+-0.26)	80.62 (+-0.05)	80.16 (+-0.27)
	RDDM$_{30}$	81.64 (+-0.03)	81.64 (+-0.03)	81.64 (+-0.03)	80.41 (+-0.05)	80.64 (+-0.04)	80.39 (+-0.04)
	RDDM$_7$	**81.83 (+-0.04)**	**81.83 (+-0.04)**	**81.83 (+-0.04)**	80.42 (+-0.04)	81.10 (+-0.04)	80.38 (+-0.04)
	RDDM$_{129}$	81.71 (+-0.03)	81.71 (+-0.03)	81.71 (+-0.03)	80.46 (+-0.04)	80.69 (+-0.04)	80.46 (+-0.03)

An interesting information that came out of this round of evaluations is that the choice of ensemble algorithm seems to have much more influence than the choice of detector on the final accuracy results. In addition, different algorithms were the best in the tests with the two selected base learners. In fact, based on the ranks, BOLE$_5$ dominated the set of best results using NB and FASE did the same in the experiments using HT. Even so, it is important to remember that a large number of combinations were statistically similar, especially in the tests using HT. Therefore, reaching a definitive conclusion regarding the best combinations based on these results would be premature.

The second round of statistical evaluations concentrated on the ensemble algorithms disregarding the influence of the different concept drift detection methods. In the tests using NB, the order of the ranks was exactly the same in the experiments with the *abrupt* datasets, with the *gradual* datasets, and with *all* the datasets. In the three subsets, $BOLE_5$ was the best, with statistical superiority to all the other ensembles. Additionally, there were statistical differences in most other pairs compared. The order of the ranks was: $BOLE_5$, FASE, $BOLE_4$, ADOB, None, and DDD.

Figure 14 shows the results of the evaluation considering *all* the datasets using the same graphical notation adopted in previous chapters, where the critical difference (CD) is represented by bars and methods connected by a bar are *not* statistically different. Note only FASE and $BOLE_4$ were statistically similar in this evaluation using NB. In the segments separated by type of concept drift (*abrupt* and *gradual*), the results were basically the same except that $BOLE_4$ and ADOB had similar results as well in both.

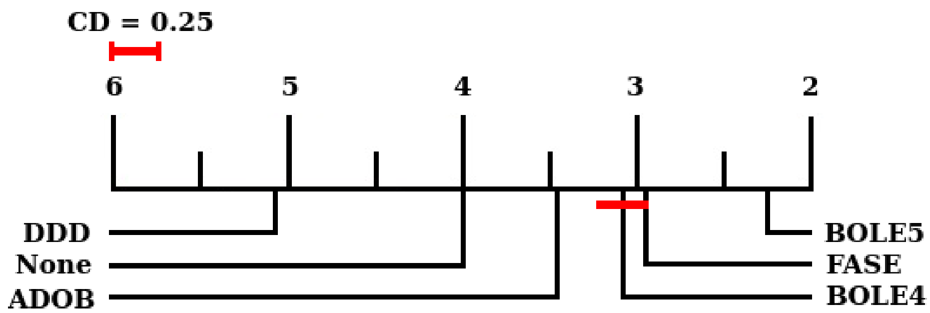


Figure 14 – Comparison results using the Nemenyi test of Ensembles, irrespective of Detectors, with NB in all artificial datasets with 95% confidence.

In the tests using HT, the order of the ranks was also exactly the same in the three subsets, with many statistical differences as well. However, this time, the order of the ranks was: FASE, $BOLE_5$, $BOLE_4$, None, ADOB, and DDD. Figure 15 represents the results of the evaluation considering *all* the datasets. These results and statistical similarities between the methods are basically identical to the ones considering only the *abrupt* datasets, despite the differences in the CD and in the ranks.

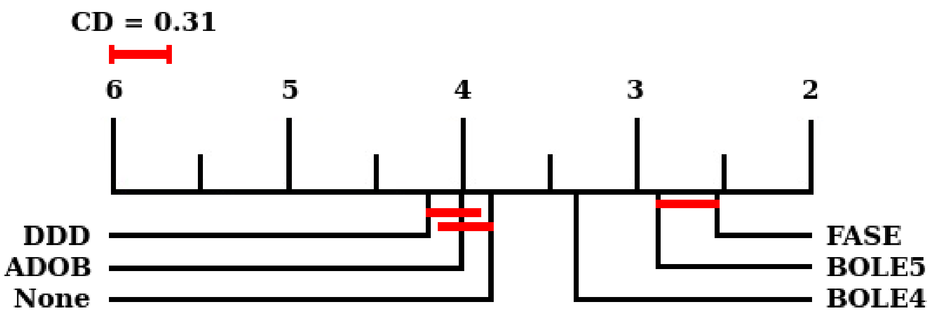


Figure 15 – Comparison results using the Nemenyi test of Ensembles, irrespective of Detectors, with HT in all artificial datasets with 95% confidence.

Figure 16 introduces the results referring to the evaluation in the *gradual* datasets, because the statistical similarities were a little bit different from the other two subsets. Notice that, in these gradual datasets, there is no statistical difference between either $BOLE_4$ and None or between None and DDD.

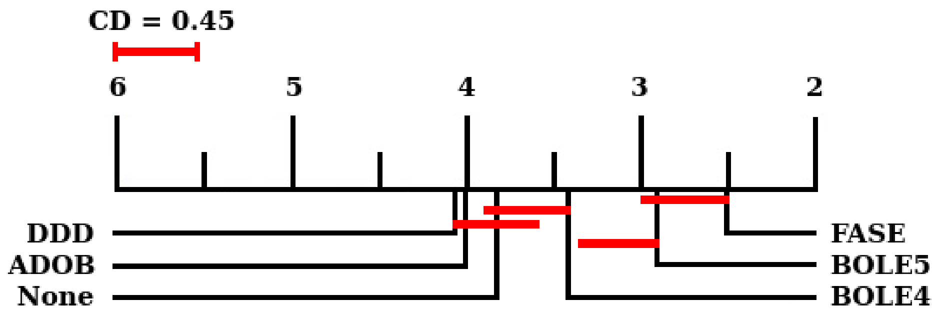


Figure 16 – Comparison results using the Nemenyi test of Ensembles, irrespective of Detectors, with HT in the gradual datasets with 95% confidence.

Finally, the third dimension refers to the statistical evaluation of the concept drift detectors inside ensembles ignoring the influence of the different ensemble algorithms. Figure 17 presents the evaluation based on the results of the experiments in the *abrupt* datasets using NB, i.e., those presented in Tables 25 to 31.

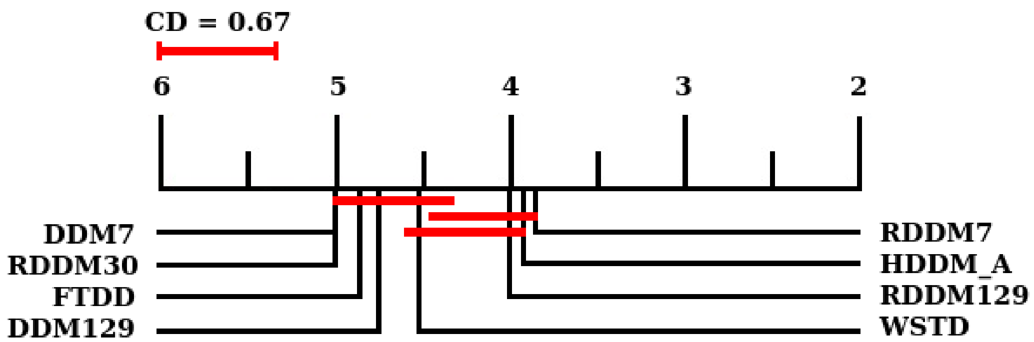


Figure 17 – Comparison results using the Nemenyi test of Detectors inside Ensembles with NB in the abrupt datasets with 95% confidence.

According to the results, $RDDM_7$, $HDDM_A$, and $RDDM_{129}$ are the best methods in this subset, with close ranks (all of them being statistically similar), followed by WSTD, DDM_{129}, FTDD, $RDDM_{30}$, and DDM_7. Also, notice that, in spite of this, only $RDDM_7$ is statistically better than WSTD.

Similarly, Figure 18 presents the corresponding evaluation based on the *gradual* datasets using NB. In these datasets, the best results were those of $RDDM_{129}$, $RDDM_7$, $HDDM_A$, and DDM_{129}, with no statistical differences, despite the fact that the ranks of the two RDDM configurations are much better than those of the other two. Nevertheless, in this scenario, only $RDDM_{129}$ is statistically superior to $RDDM_{30}$ and DDM_7. Also note the ranks of these two methods are reasonably close to those of $HDDM_A$ and DDM_{129}.

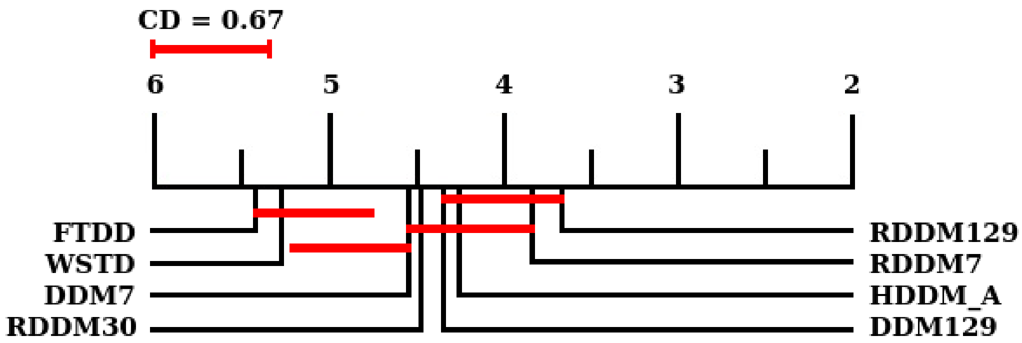


Figure 18 – Comparison results using the Nemenyi test of Detectors inside Ensembles with NB in the gradual datasets with 95% confidence.

Figure 19 evaluates the accuracy results of the methods aggregating *all* the tests using NB as base classifier. In this larger view of the data, the best methods are RDDM$_7$, RDDM$_{129}$, and HDDM$_A$, all three being statistically similar. Again, observe the statistical differences from these configurations to the others are *not* the same, as HDDM$_A$ is *not* statistically better than DDM$_{129}$. Considering the other methods, the only significant difference is between DDM$_{129}$ and FTDD.

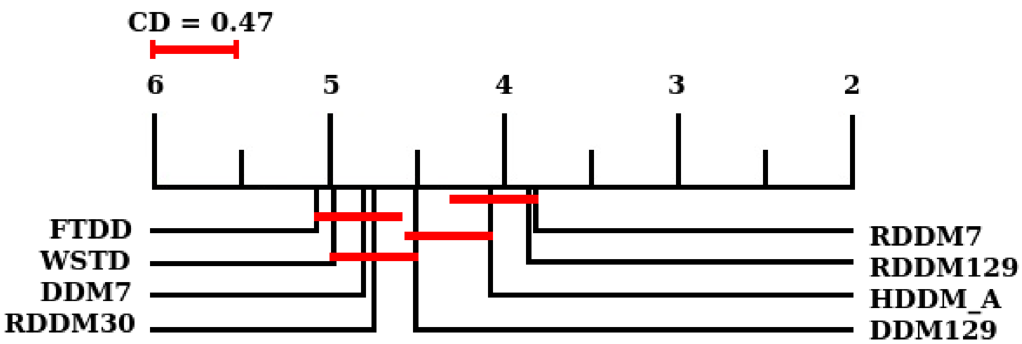


Figure 19 – Comparison results using the Nemenyi test of Detectors inside Ensembles with NB in all artificial datasets with 95% confidence.

Figures 20, 21, and 22 represent the evaluations based on views similar to those of Figures 17, 18, and 19, respectively, but based on the tests using HT as base learner. Figure 20 refers to the results of the experiments in the *abrupt* datasets. In this subset of the tests, HDDM$_A$ has the best rank and is the only method to achieve significant superiority to other methods, though DDM$_{129}$, RDDM$_{129}$, and RDDM$_7$ are also statistically indistinguishable. In spite of this, the other seven methods are all statistically similar.

Accordingly, Figure 21 presents the evaluation in the *gradual* datasets using HT. In these datasets, DDM$_{129}$ and RDDM$_{129}$ were the best configurations, followed by RDDM$_7$, RDDM$_{30}$, and HDDM$_A$, with no statistical differences among them. However, only DDM$_{129}$ is statistically superior to the other three tested configurations. Note RDDM$_{129}$ is *not* superior to DDM$_7$, whereas RDDM$_7$, RDDM$_{30}$, and HDDM$_A$ are only better than WSTD.

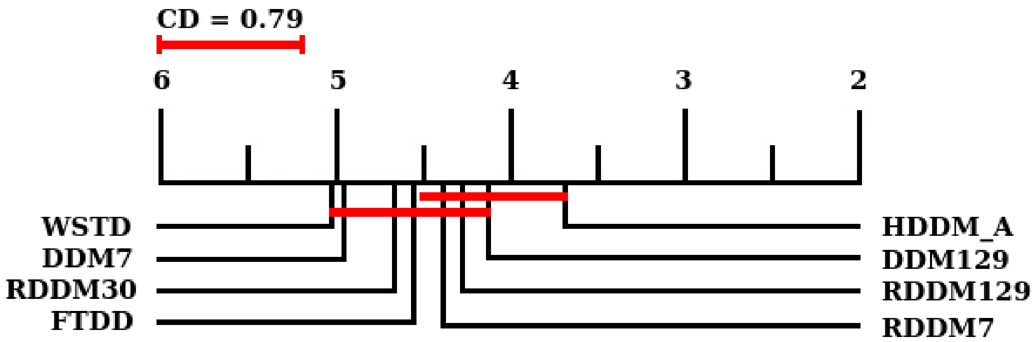


Figure 20 – Comparison results using the Nemenyi test of Detectors inside Ensembles with HT in the abrupt datasets with 95% confidence.

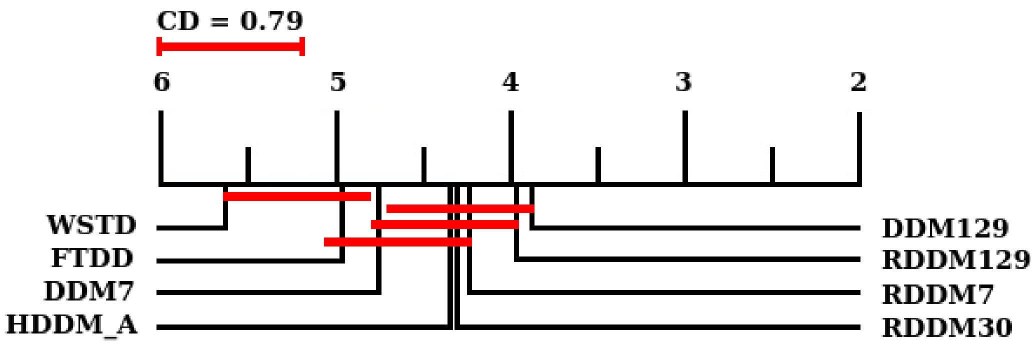


Figure 21 – Comparison results using the Nemenyi test of Detectors inside Ensembles with HT in the gradual datasets with 95% confidence.

Figure 22 captures the evaluation of the accuracy results aggregating *all* the tests using HT as base classifier. Considering this subset of the data, the best configurations were DDM_{129}, HDDM_A, RDDM_{129}, RDDM_7, and RDDM_{30}, with no statistical difference among these five methods, but only the first three were significantly superior to the remaining three, i.e., FTDD, DDM_7, and WSTD. In this scenario, RDDM_7 and RDDM_{30} were *not* superior to FTDD or DDM_7.

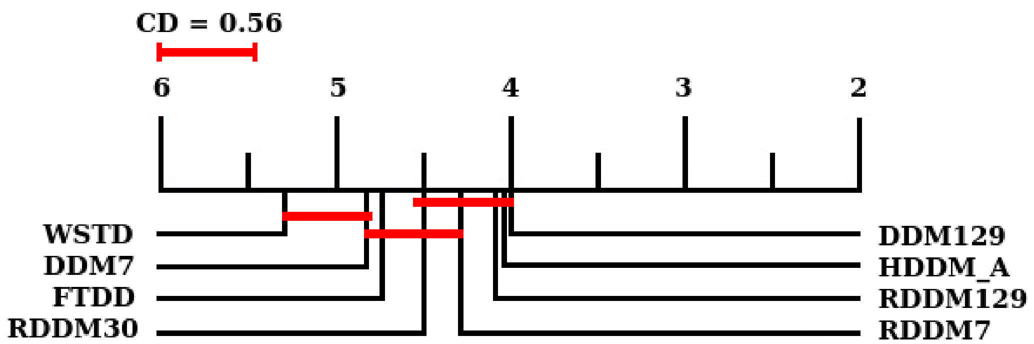


Figure 22 – Comparison results using the Nemenyi test of Detectors inside Ensembles with HT in all artificial datasets with 95% confidence.

7.1 Answer to Research Questions

This section examines and answers the remaining research questions this thesis proposed to investigate, i.e., **RQ6** to **RQ12**.

The description of **RQ6** was: *What are the best ensemble plus drift detector combinations in terms of final accuracy in abrupt and gradual concept drift datasets?*

Based on the experiments of this chapter, the answer to **RQ6** is: considerable variations happened in the results using the two base learners (NB and HT), with a large number of statistical similarities among different configurations. Even so, using NB, the chosen ensemble should be BOLE_5 combined with either HDDM_A or RDDM_{129}, irrespective of the type of concept drift.

Using HT, the chosen ensemble algorithm should probably be FASE but there is no clear choice of detector. In datasets with *abrupt* concept drifts the safer choice is HDDM_A, but the BOLE_5+HDDM_A combination could also be considered. In the ones with *gradual* changes, the detector could be either DDM_{129} or RDDM_{30}. Should the type of concept drift be unknown, either of the three aforementioned concept drift detection configurations could be paired with FASE.

The description of **RQ7** was: *What are the best ensembles in terms of accuracy in abrupt and gradual drift datasets irrespective of the auxiliary concept drift detector used?*

The answer to **RQ7** is simple: using NB, BOLE_5 was statistically superior to all the other algorithms in all the tested scenarios and, thus, it is an easy choice. Using HT, in all the three aggregations, FASE delivered the best ranks and is, therefore, declared the best choice, though BOLE_5 was always statistically similar.

The description of **RQ8** was: *What are the best concept drift detectors as auxiliary methods in ensembles in terms of accuracy of the ensembles in abrupt and gradual concept drift datasets?*

The answer to **RQ8** is: using NB, RDDM_7, RDDM_{129}, and HDDM_A were the best three configurations, with no statistical differences, but in different orders of ranks in the three scenarios: RDDM_7 was the best in the *abrupt* datasets and when *all* the datasets were considered, with RDDM_{129} being first in the *gradual* datasets. HDDM_A was second in the *abrupt* datasets and third in the other two scenarios.

Using HT, there were no statistical differences among DDM_{129}, HDDM_A, RDDM_{129}, and RDDM_7 in the three scenarios. However, based on their ranks, the best choices are probably HDDM_A, for *abrupt* datasets, and either DDM_{129} or RDDM_{129}, for *gradual* datasets. In the tests with *all* the datasets, the ranks of these three configurations were really close: the differences are negligible. The rank of RDDM_7 was *not* that much different either. Accordingly, when the type of concept drift is unknown, they are all good choices.

The description of **RQ9** was: *Do the answers of **RQ6**, **RQ7**, and **RQ8** vary with the different dataset generators used in the experiments? How much?*

The answer to **RQ9** regarding the combinations ensemble-detector (**RQ6**) is *yes*, there were considerable differences in the results of the ensembles in different dataset generators. In fact, in this scenario, BOLE_5 only dominated the best results in Agrawal_1 and Sine, also delivering the best rank in another two of the seven generators using NB, and in three generators using HT. The dominance of FASE using HT was restricted to two generators too: Agrawal_2 and Random RBF, the latter also in the tests using NB. Surprisingly, the *None* configurations (detectors without ensemble) dominated all the best results in the Mixed datasets using NB, whereas RDDM_{129} and RDDM_7 were first and third, respectively, in the Agrawal_1 datasets using HT. Another unexpected result was that, in the Sine datasets using HT, the choice of detector was as important as the choice of ensemble algorithm: the best results came with either BOLE_5, BOLE_4, or ADOB, always combined with FTDD in the abrupt datsets and RDDM_{30} in the gradual datasets.

The strict answer to **RQ9** regarding the ensemble algorithms (**RQ7**) is *yes*, there were some variations in the results considering the different dataset generators. However, BOLE_5 was consistently among the best algorithms using NB in all generators, with the exception of Random RBF, as well as in four of the seven generators using HT. On the other hand, FASE was often *not* the best method, even using HT, but delivered reasonably good results in the majority of the dataset generators with both base learners.

The answer to **RQ9** regarding the drift detectors inside ensembles (**RQ8**) is again *yes*, there were noticeable differences when the results of different dataset generators were separated. Even though RDDM_{129}, HDDM_A, and RDDM_7 consistently delivered good results, they did *not* dominate the ranks in the tests using any of the base learners. For instance, the most dominant detection method in specific dataset generators was FTDD, being the best in the Mixed and Random RBF datasets using both NB and HT whereas HDDM_A was the very best only in the Agrawal_2 datasets using NB. On the other hand, RDDM_{129} was the best in Agrawal_1 (using both classifiers) and in Sine using NB. Finally, RDDM_7 was dominant in Agrawal_2 using HT, in LED (using both base learners), and in Waveform using NB.

The description of **RQ10** was: *Do the answers of **RQ6**, **RQ7**, and **RQ8** depend on the size of the concepts included in the datasets? How much?*

The answer to **RQ10** regarding the combinations ensemble-detector (**RQ6**) is *yes*, there are variations, but they are comparatively small and limited to the smaller datasets, the 10K instances datasets, using both NB and HT. In these datasets, FASE combinations were the best using NB whereas RDDM_7 and RDDM_{129} (without an ensemble) achieved the best ranks using HT. Nevertheless, it is worth emphasizing that virtually no statistically significant difference happened in most sizes.

Strictly speaking, the answer to **RQ10** regarding the ensemble algorithms (**RQ7**) would also be *yes*, but the variations were restricted to the 10K and 20K *abrupt* datasets using HT. In the 10K abrupt datasets, $BOLE_5$ was ranked in front of FASE. In the 20K abrupt datasets, their ranks were absolutely the same. However, without separating the data by type of concept drift, the answer would be *no*, the size of the concepts did *not* change the results of **RQ7**. Interestingly, in all the tests using NB, the orders of the ranks were all very similar irrespective of the size of the datasets.

The answer to **RQ10** regarding the drift detectors inside ensembles (**RQ8**) is again *yes*, there were substantial variations in the results of some detectors when the datasets were separated by size. FTDD and $RDDM_7$ are the most affected ones. When the size of the datasets increased, again, FTDD improved its results dramatically whereas $RDDM_7$ consistently presented worse ranks, with both NB and HT. DDM_{129} also was worse with the increase in the size of the datasets, but only using NB. On the other hand, $RDDM_{30}$ improved its ranks in the larger datasets, but only in the ones with *abrupt* concept drifts.

The description of **RQ11** was: *In the same datasets, are the best ensembles of **RQ6** and **RQ7** the same?*

The answer to **RQ11** is definitely *yes*, in both **RQ6** and **RQ7** $BOLE_5$ was the best choice using NB and FASE was better using HT, despite not existing statistical differences in many scenarios, especially using HT.

Finally, the description of **RQ12** was: *In the same datasets, are the best concept drift detectors of **RQ1**, **RQ6**, and **RQ8** the same? To what extent?*

Before answering **RQ12**, to remind the reader, lets repeat the description of **RQ1**, addressed in Subsection 6.2.1: *What are the best drift detectors in terms of accuracy in abrupt and gradual concept drift datasets?*

The strict answer to **RQ12** is *no*, but they were *not* very different either, especially using NB, since all of them were restricted to $RDDM_{129}$, $HDDM_A$, and $RDDM_7$. In the tests using HT, the answer to **RQ6** brought new configurations to consider, namely DDM_{129} and $RDDM_{30}$, with the former also appearing in the answer to **RQ8**. However, despite not being recommended in the answer of **RQ1** (based on their ranks), both DDM_{129} and $RDDM_{30}$ were statistically similar to the recommended configurations using HT, fact that was captured by the evaluations presented in Figures 10, 11, and 12, Section 6.2.

7.2 Conclusion

This chapter reported on the extensive experiments designed to evaluate ensembles for data stream mining that are configurable with concept drift detectors. Chapter 8 presents conclusions and proposes future work, completing the main body of this thesis.

8 Conclusions

This thesis proposed to contribute towards advancing the state of the art of the area of data stream mining considering concept drift. Specifically, two new concept drift detection methods and a new ensemble approach were proposed in Chapters 3, 4, and 5, respectively, RDDM, WSTD, and BOLE.

RDDM was inspired in DDM (GAMA et al., 2004) and was motivated by a drop in performance (in both detections and accuracy), caused by sensitivity loss, which usually affects DDM when the concepts are very long. Despite its simplicity, RDDM delivers strong accuracy performance with both Naive Bayes (NB) and Hoeffding Tree (HT) and is especially good in datasets with *gradual* concept drifts.

WSTD is rooted in STEPD (NISHIDA; YAMAUCHI, 2007) and proposed an efficient implementation of the Wilcoxon rank sum test, without needing to sort the ranks, for detecting concept drifts, and aimed at identifying less false positive detections than STEPD. WSTD also delivers good accuracy results, especially in datasets with *abrupt* concept drifts, but its main strength is the precision of its detections of concept drifts using both NB and HT as base classifier.

BOLE is an ensemble based on the implementation of simple heuristic configuration strategies to ADOB (SANTOS et al., 2014) aiming to improve its accuracy results. The $BOLE_5$ version, which implements all the proposed heuristics, delivers very good results configured with different concept drift detectors using both NB and HT, but it is especially efficient using NB as base learner.

Further, this thesis proposed to verify/challenge common beliefs in the area. These beliefs are (a) the best concept drift detectors are necessarily the ones that detect all the existing concept drifts closer to their correct positions, ideally detecting only them, and (b) ensembles which use auxiliary drift detectors deliver their best results when using the best concept drift detection methods according to belief (a). In addition, to analyse these beliefs, this thesis introduced and answered 12 research questions.

Moreover, to answer these research questions, this thesis carried out *two* large-scale experiments, reported in Chapters 6 and 7, to evaluate and compare (a) 15 configurations of concept drift detection methods as well as (b) five ensembles for mining data streams containing concept drift which are configurable with auxiliary concept drift detectors.

More specifically, in Chapter 6, the concept drift detectors have been compared in terms of both their final accuracies and also the precision of their detections of concept drift, and the results were the basis for answering the first *five* research questions.

In Chapter 7, each of the ensembles were parametrized with *eight* selected concept drift detection methods configurations, chosen from the ones that delivered the best results in the experiments of Chapter 6, and the accuracies of these 40 combinations were compared among themselves and against the detectors individually. The results were the basis for answering the remaining *seven* research questions.

It is worth mentioning that these large-scale experiments were run in the MOA framework (BIFET et al., 2010), release 2014.11, using a considerably large number of artificial datasets, with *abrupt* and *gradual* concept drift versions of several sizes. Furthermore, these experiments were executed using two different base classifiers, namely NB and HT. To the best of my knowledge, these are the largest comparison evaluations ever reported in the area of data stream mining.

The results of these large-scale experiments give explicit indications of the best concept drift detectors, in terms of accuracy, detections, and as auxiliary methods inside ensembles; of the best ensemble algorithms, irrespective of drift detector adopted; as well as of the best ensemble-detector combinations. They also provided the basis that made it possible to analyse the influence of the type of concept drift, of the dataset generators, and of the size of the concepts on the performance of the methods.

It is worth emphasizing that two versions of RDDM, namely $RDDM_{129}$ and $RDDM_7$, were consistently among the very best concept drift detection configurations in terms of accuracy, both individually and as auxiliary methods to the ensembles, with both base learners. In addition, WSTD was one of the top methods according to the precision of its detections of concept drifts with both NB and HT. And, finally, one of the BOLE configurations ($BOLE_5$) was one of the two best ensemble algorithms in all the reported experiments, being statistically superior to all the other methods using NB as base classifier.

To conclude, it is also important to emphasize that the answers to the research questions addressed in this thesis indicated the common beliefs, often, do not correspond to reality. In particular, the top accuracy results of RDDM combined with its unremarkable precision in the detections of concept drift suggest that some degree of false positive detections can improve the accuracy results in many datasets, instead of hurting them. Nevertheless, to be conclusive, this issue demands further investigation.

8.1 Future Work

A number of other directions could be investigated as future work. Firstly, the performance loss problem of DDM, that inspired RDDM, is likely to affect other concept drift detectors as well, in particular EDDM (BAENA-GARCIA et al., 2006). Hence, those other methods could be identified and similar strategies could be implemented on them to check whether they are general.

The impact of the parametrization of the drift detectors in the final accuracy over different kinds of datasets could also be the subject of investigation: it is possible that the accuracies obtained in the experiments of this thesis could be improved further. In the particular case of WSTD, it might be that a different parametrization set allowing some more false positive detections could help improving its accuracies.

Experimenting with other statistical tests, and even combinations of such tests, could help to understand in which scenarios or situations each test is more efficient and such an investigation could lead to more efficient concept drift detection methods.

Note the heuristic strategies proposed for BOLE are general and might be applicable to other variations of online boosting. Therefore, it might be fruitful to select other methods such as Online Coordinate Boosting (OCBoost) (PELOSSOF et al., 2009), Fast and Light Classifier (FLC) (ATTAR; SINHA; WANKHADE, 2010), Online Non-Stationary Boosting (ONSB) (POCOCK et al., 2010), etc. to implement and further test these ideas.

Another direction of investigation regarding BOLE would be to try some other values as percentage limits for permitting the classifiers to vote. It might be that the best choice depends on how hard the problem is, for example, on the number of classes. Also, the impact of changing the 50% error bound and of shifting the values of the classifiers' weights in the distribution of diversity among the experts of the ensemble and in the final accuracies have not been thoroughly analysed: other functions could also be considered to prevent the use of negative weights.

Despite being very large, the evaluations reported in Chapters 6 and 7 could be incrementally expanded with other methods. In fact, recent methods such as Fast Hoeffding Drift Detection Method (FHDDM) (PESARANGHADER; VIKTOR, 2016) as well as Equal Means Z-Test Drift Detector (EMZD), FPDD, and FSDD (CABRAL, 2017) are already planned to be added in the comparison of the drift detection methods. Sometime in the near future, the source code of Leveraging Bagging (LevBag) (BIFET; HOLMES; PFAHRINGER, 2010) should also be modified to make its auxiliary concept drift detector become a parameter and permit its inclusion in the evaluation of the ensembles.

In both cases, i.e. the evaluations of drift detectors and ensembles, it should be interesting to include different scenarios in the artificial datasets, such as the 1 Million and 2 Million instances datasets also in the tests using HT, additional dataset generators, other frequencies of concept drifts, and longer transition periods in the gradual drifts datasets.

Finally, it is worth explicitly stating this research used an empirical approach. In addition, RDDM, WSTD, and BOLE were implemented in Java to be run in the MOA framework. The source code of BOLE is already freely available and those of the other methods will soon be released too, permitting further experiments by other researchers.

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Appendix

APPENDIX A – Drift Identifications with Detectors using NB

This appendix introduces the detailed raw data referring to the concept drift identifications of the 15 tested configurations of drift detection methods using NB as base learner. An aggregation of these results was presented in Chapter 6, Tables 21 and 22.

Table 32 – Concept drift identifications of Detectors in 10K instances abrupt datasets using NB (Part 1)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
Agrawal$_1$	DDM	N/A	120	92	299788	0	0.000000000	0.000000000	-0.000350362
	EDDM	20.00	116	565	299315	4	0.007029877	0.033333333	0.014453403
	ADWIN	0.00	119	142	299738	1	0.006993007	0.008333333	0.007200312
	ECDD	26.30	74	446	299434	46	0.093495935	0.383333333	0.188697409
	STEPD	30.65	89	159	299721	31	0.163157895	0.258333333	0.204905062
	SeqDr2	N/A	120	129	299751	0	0.000000000	0.000000000	-0.000414901
	HDDM$_W$	29.77	76	155	299725	44	0.221105528	0.366666667	0.284367586
	FTDD	35.00	118	37	299843	2	0.051282051	0.016666667	0.029014921
	WSTD	34.50	100	87	299793	20	0.186915888	0.166666667	0.176190074
	HDDM$_A$	33.33	111	111	299769	9	0.075000000	0.075000000	0.074629852
	DDM$_7$	32.14	106	617	299263	14	0.022187005	0.116666667	0.050022533
	DDM$_{129}$	36.00	115	152	299728	5	0.031847134	0.041666667	0.035986600
	RDDM$_{30}$	N/A	120	118	299762	0	0.000000000	0.000000000	-0.000396810
	RDDM$_7$	30.00	115	193	299687	5	0.025252525	0.041666667	0.031940575
	RDDM$_{129}$	35.00	118	125	299755	2	0.015748031	0.016666667	0.015795841
Agrawal$_2$	DDM	27.00	110	165	299715	10	0.057142857	0.083333333	0.068557218
	EDDM	22.50	112	175	299705	8	0.043715847	0.066666667	0.053518152
	ADWIN	10.00	116	446	299434	4	0.008888889	0.033333333	0.016454297
	ECDD	13.14	34	508	299372	86	0.144781145	0.716666667	0.321610585
	STEPD	17.78	30	407	299473	90	0.181086519	0.750000000	0.368095271
	SeqDr2	0.00	117	253	299627	3	0.011718750	0.025000000	0.016542460
	HDDM$_W$	27.16	32	51	299829	88	0.633093525	0.733333333	0.681236138
	FTDD	27.18	49	42	299838	71	0.628318584	0.591666667	0.609565837
	WSTD	26.86	34	36	299844	86	0.704918033	0.716666667	0.710651385
	HDDM$_A$	24.80	45	29	299851	75	0.721153846	0.625000000	0.671235910
	DDM$_7$	22.30	46	1249	298631	74	0.055933485	0.616666667	0.184837820
	DDM$_{129}$	26.09	74	214	299666	46	0.176923077	0.383333333	0.259999607
	RDDM$_{30}$	35.00	118	71	299809	2	0.027397260	0.016666667	0.021063485
	RDDM$_7$	26.90	62	231	299649	58	0.200692042	0.483333333	0.311041368
	RDDM$_{129}$	27.22	84	95	299785	36	0.274809160	0.300000000	0.286830512
LED	DDM	N/A	120	93	299787	0	0.000000000	0.000000000	-0.000352261
	EDDM	N/A	120	186	299694	0	0.000000000	0.000000000	-0.000498250
	ADWIN	24.00	110	639	299241	10	0.015408320	0.083333333	0.034947891
	ECDD	18.19	37	162	299718	83	0.338775510	0.691666667	0.483788598
	STEPD	23.55	58	792	299088	62	0.072599532	0.516666667	0.192920596
	SeqDr2	0.00	60	706	299174	60	0.078328982	0.500000000	0.197180879
	HDDM$_W$	19.55	32	61	299819	88	0.590604027	0.733333333	0.657959910
	FTDD	28.50	80	77	299803	40	0.341880342	0.333333333	0.337318061
	WSTD	25.52	53	197	299683	67	0.253787879	0.558333333	0.376075660
	HDDM$_A$	26.85	66	43	299837	54	0.556701031	0.450000000	0.500336524
	DDM$_7$	34.87	81	149	299731	39	0.207446809	0.325000000	0.259286461
	DDM$_{129}$	37.78	111	104	299776	9	0.079646018	0.075000000	0.076929822
	RDDM$_{30}$	N/A	120	90	299790	0	0.000000000	0.000000000	-0.000346531
	RDDM$_7$	34.83	91	76	299804	29	0.276190476	0.241666667	0.258075146
	RDDM$_{129}$	37.78	111	94	299786	9	0.087378641	0.075000000	0.080612437

Table 33 – Concept drift identifications of Detectors in 10K instances abrupt datasets using NB (Part 2)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
Mixed	DDM	33.61	1	2	299878	119	0.983471074	0.991666667	0.987555374
	EDDM	24.79	72	228	299652	48	0.173913043	0.400000000	0.263319359
	ADWIN	35.79	44	217	299663	76	0.259385666	0.633333333	0.404965452
	ECDD	10.09	4	337	299543	116	0.256070640	0.966666667	0.497226599
	STEPD	10.00	0	22	299858	120	0.845070423	1.000000000	0.919243399
	SeqDr2	N/A	120	261	299619	0	0.000000000	0.000000000	-0.000590290
	$HDDM_W$	16.33	0	0	299880	120	1.000000000	1.000000000	1.000000000
	FTDD	19.08	0	2	299878	120	0.983606557	1.000000000	0.991766100
	WSTD	18.58	0	0	299880	120	1.000000000	1.000000000	1.000000000
	$HDDM_A$	15.17	0	0	299880	120	1.000000000	1.000000000	1.000000000
	DDM_7	18.32	7	233	299647	113	0.326589595	0.941666667	0.554312911
	DDM_{129}	20.92	0	3	299877	120	0.975609756	1.000000000	0.987724656
	$RDDM_{30}$	35.00	0	0	299880	120	1.000000000	1.000000000	1.000000000
	$RDDM_7$	19.38	23	38	299842	97	0.718518519	0.808333333	0.762003563
	$RDDM_{129}$	21.25	0	1	299879	120	0.991735537	1.000000000	0.995857535
RandRBF	DDM	10.00	118	66	299814	2	0.029411765	0.016666667	0.021846108
	EDDM	18.33	114	297	299583	6	0.019801980	0.050000000	0.030851981
	ADWIN	0.00	119	276	299604	1	0.003610108	0.008333333	0.004880411
	ECDD	N/A	120	0	299880	0	0.000000000	0.000000000	0.000000000
	STEPD	30.00	117	132	299748	3	0.022222222	0.025000000	0.023155803
	SeqDr2	0.00	118	42	299838	2	0.045454545	0.016666667	0.027289341
	$HDDM_W$	28.00	115	130	299750	5	0.037037037	0.041666667	0.038875968
	FTDD	N/A	120	31	299849	0	0.000000000	0.000000000	-0.000203357
	WSTD	30.00	119	29	299851	1	0.033333333	0.008333333	0.016470785
	$HDDM_A$	N/A	120	64	299816	0	0.000000000	0.000000000	-0.000292208
	DDM_7	20.00	115	262	299618	5	0.018726592	0.041666667	0.027354384
	DDM_{129}	20.00	119	132	299748	1	0.007518797	0.008333333	0.007497647
	$RDDM_{30}$	0.00	119	87	299793	1	0.011363636	0.008333333	0.009391953
	$RDDM_7$	20.00	117	208	299672	3	0.014218009	0.025000000	0.018333093
	$RDDM_{129}$	30.00	117	129	299751	3	0.022727273	0.025000000	0.023426880
Sine	DDM	30.29	50	90	299790	70	0.437500000	0.583333333	0.504955252
	EDDM	21.95	38	535	299345	82	0.132901135	0.683333333	0.300819158
	ADWIN	38.75	56	176	299704	64	0.266666667	0.533333333	0.376784009
	ECDD	10.00	4	454	299426	116	0.203508772	0.966666667	0.443175082
	STEPD	12.75	0	91	299789	120	0.568720379	1.000000000	0.754021086
	SeqDr2	N/A	120	244	299636	0	0.000000000	0.000000000	-0.000570726
	$HDDM_W$	16.67	0	5	299875	120	0.960000000	1.000000000	0.979787729
	FTDD	18.92	0	3	299877	120	0.975609756	1.000000000	0.987724656
	WSTD	18.42	0	1	299879	120	0.991735537	1.000000000	0.995857535
	$HDDM_A$	18.13	8	11	299869	112	0.910569106	0.933333333	0.921849337
	DDM_7	15.75	7	708	299172	113	0.137637028	0.941666667	0.359529235
	DDM_{129}	21.89	9	89	299791	111	0.555000000	0.925000000	0.716367590
	$RDDM_{30}$	34.49	51	54	299826	69	0.560975610	0.575000000	0.567769496
	$RDDM_7$	18.74	33	157	299723	87	0.356557377	0.725000000	0.508170904
	$RDDM_{129}$	24.05	4	35	299845	116	0.768211921	0.966666667	0.861685733
Waveform	DDM	N/A	120	48	299832	0	0.000000000	0.000000000	-0.000253053
	EDDM	18.57	113	351	299529	7	0.019553073	0.058333333	0.033108195
	ADWIN	N/A	120	86	299794	0	0.000000000	0.000000000	-0.000338741
	ECDD	18.18	87	498	299382	33	0.062146893	0.275000000	0.130029925
	STEPD	25.00	86	106	299774	34	0.242857143	0.283333333	0.261997178
	SeqDr2	N/A	120	74	299806	0	0.000000000	0.000000000	-0.000314214
	$HDDM_W$	23.60	95	36	299844	25	0.409836066	0.208333333	0.292005764
	FTDD	31.82	109	21	299859	11	0.343750000	0.091666667	0.177350108
	WSTD	27.50	104	27	299853	16	0.372093023	0.133333333	0.222559439
	$HDDM_A$	32.86	113	37	299843	7	0.159090909	0.058333333	0.096118391
	DDM_7	18.28	91	392	299488	29	0.068883610	0.241666667	0.128389318
	DDM_{129}	25.00	114	101	299779	6	0.056074766	0.050000000	0.052592523
	$RDDM_{30}$	40.00	119	36	299844	1	0.027027027	0.008333333	0.014789265
	$RDDM_7$	25.00	112	133	299747	8	0.056737589	0.066666667	0.061095067
	$RDDM_{129}$	28.00	115	54	299826	5	0.084745763	0.041666667	0.059160010

Table 34 – Concept drift identifications of Detectors in 20K instances abrupt datasets using NB (Part 1)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
Agrawal$_1$	DDM	70.00	119	103	599777	1	0.009615385	0.008333333	0.008766883
	EDDM	40.00	119	688	599192	1	0.001451379	0.008333333	0.003000549
	ADWIN	70.00	117	265	599615	3	0.011194030	0.025000000	0.016435167
	ECDD	34.26	52	915	598965	68	0.069175992	0.566666667	0.197598469
	STEPD	46.67	51	208	599672	69	0.249097473	0.575000000	0.378280065
	SeqDr2	N/A	120	196	599684	0	0.000000000	0.000000000	-0.000255671
	HDDM$_W$	36.53	48	273	599607	72	0.208695652	0.600000000	0.353658627
	FTDD	51.54	107	39	599841	13	0.250000000	0.108333333	0.164462064
	WSTD	47.41	66	97	599783	54	0.357615894	0.450000000	0.401023480
	HDDM$_A$	56.58	82	96	599784	38	0.283582090	0.316666667	0.299520195
	DDM$_7$	55.86	91	804	599076	29	0.034813926	0.241666667	0.091269958
	DDM$_{129}$	68.89	111	178	599702	9	0.048128342	0.075000000	0.059845805
	RDDM$_{30}$	N/A	120	121	599759	0	0.000000000	0.000000000	-0.000200872
	RDDM$_7$	69.09	109	211	599669	11	0.049549550	0.091666667	0.067141780
	RDDM$_{129}$	76.00	115	125	599755	5	0.038461538	0.041666667	0.039832170
Agrawal$_2$	DDM	39.00	90	309	599571	30	0.088495575	0.250000000	0.148461664
	EDDM	42.00	110	183	599697	10	0.051813472	0.083333333	0.065473325
	ADWIN	57.08	48	449	599431	72	0.138195777	0.600000000	0.287690889
	ECDD	14.89	30	969	598911	90	0.084985836	0.750000000	0.252120233
	STEPD	17.10	27	622	599258	93	0.130069930	0.775000000	0.317229349
	SeqDr2	N/A	120	261	599619	0	0.000000000	0.000000000	-0.000295051
	HDDM$_W$	29.47	25	84	599796	95	0.530726257	0.791666667	0.648113401
	FTDD	29.89	33	35	599845	87	0.713114754	0.725000000	0.718976154
	WSTD	27.36	29	42	599838	91	0.684210526	0.758333333	0.720260430
	HDDM$_A$	29.63	39	33	599847	81	0.710526316	0.675000000	0.692475484
	DDM$_7$	30.93	34	2090	597790	86	0.039522059	0.716666667	0.167767355
	DDM$_{129}$	40.00	45	315	599565	75	0.192307692	0.625000000	0.346474328
	RDDM$_{30}$	61.67	96	80	599800	24	0.230769231	0.200000000	0.214688348
	RDDM$_7$	38.59	49	409	599471	71	0.147916667	0.591666667	0.295581137
	RDDM$_{129}$	47.81	47	85	599795	73	0.462025316	0.608333333	0.530049318
LED	DDM	N/A	120	117	599763	0	0.000000000	0.000000000	-0.000197523
	EDDM	80.00	119	204	599676	1	0.004878049	0.008333333	0.006116017
	ADWIN	46.76	83	1279	598601	37	0.028115502	0.308333333	0.092555662
	ECDD	22.74	47	414	599466	73	0.149897331	0.608333333	0.301722481
	STEPD	28.55	37	1002	598878	83	0.076497696	0.691666667	0.229653005
	SeqDr2	0.00	64	1304	598576	56	0.041176471	0.466666667	0.138117775
	HDDM$_W$	26.14	19	123	599757	101	0.450892857	0.841666667	0.615940241
	FTDD	34.41	61	70	599810	59	0.457364341	0.491666667	0.474096452
	WSTD	29.55	32	182	599698	88	0.325925926	0.733333333	0.488747736
	HDDM$_A$	45.94	51	40	599840	69	0.633027523	0.575000000	0.603241027
	DDM$_7$	57.50	56	167	599713	64	0.277056277	0.533333333	0.384234886
	DDM$_{129}$	63.59	81	89	599791	39	0.304687500	0.325000000	0.314538342
	RDDM$_{30}$	N/A	120	118	599762	0	0.000000000	0.000000000	-0.000198366
	RDDM$_7$	57.05	76	57	599823	44	0.435643564	0.366666667	0.399559932
	RDDM$_{129}$	61.52	87	85	599795	33	0.279661017	0.275000000	0.277177363
Mixed	DDM	43.70	1	12	599868	119	0.908396947	0.991666667	0.949108607
	EDDM	51.97	44	291	599589	76	0.207084469	0.633333333	0.361948344
	ADWIN	40.00	0	155	599725	120	0.436363636	1.000000000	0.660492912
	ECDD	10.00	0	765	599115	120	0.135593220	1.000000000	0.367994979
	STEPD	10.00	0	104	599776	120	0.535714286	1.000000000	0.731861606
	SeqDr2	N/A	120	261	599619	0	0.000000000	0.000000000	-0.000295051
	HDDM$_W$	14.17	0	0	599880	120	1.000000000	1.000000000	1.000000000
	FTDD	17.83	0	2	599878	120	0.983606557	1.000000000	0.991767754
	WSTD	16.50	0	0	599880	120	1.000000000	1.000000000	1.000000000
	HDDM$_A$	19.75	0	0	599880	120	1.000000000	1.000000000	1.000000000
	DDM$_7$	20.42	2	260	599620	118	0.312169312	0.983333333	0.553920492
	DDM$_{129}$	26.92	0	19	599861	120	0.863309353	1.000000000	0.929129705
	RDDM$_{30}$	44.91	4	0	599880	116	1.000000000	0.966666667	0.983188802
	RDDM$_7$	20.52	43	51	599829	77	0.601562500	0.641666667	0.621212903
	RDDM$_{129}$	26.97	1	12	599868	119	0.908396947	0.991666667	0.949108607

Table 35 – Concept drift identifications of Detectors in 20K instances abrupt datasets using NB (Part 2)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
RandRBF	DDM	N/A	120	78	599802	0	0.000000000	0.000000000	-0.000161272
	EDDM	30.00	117	385	599495	3	0.007731959	0.025000000	0.013549307
	ADWIN	40.00	118	402	599478	2	0.004950495	0.016666667	0.008720244
	ECDD	N/A	120	0	599880	0	0.000000000	0.000000000	0.000000000
	STEPD	54.00	115	251	599629	5	0.019531250	0.041666667	0.028243948
	SeqDr2	N/A	120	42	599838	0	0.000000000	0.000000000	-0.000118338
	HDDM_W	48.00	95	211	599669	25	0.105932203	0.208333333	0.148320617
	FTDD	50.00	118	34	599846	2	0.055555556	0.016666667	0.030323429
	WSTD	30.00	119	47	599833	1	0.020833333	0.008333333	0.013051493
	HDDM_A	N/A	120	83	599797	0	0.000000000	0.000000000	-0.000166361
	DDM_7	60.00	118	392	599488	2	0.005076142	0.016666667	0.008839342
	DDM_{129}	50.00	119	192	599688	1	0.005181347	0.008333333	0.006318997
	RDDM_{30}	60.00	119	120	599760	1	0.008264463	0.008333333	0.008099622
	RDDM_7	60.00	119	280	599600	1	0.003558719	0.008333333	0.005141399
	RDDM_{129}	55.00	118	174	599706	2	0.011363636	0.016666667	0.013523171
Sine	DDM	49.76	38	94	599786	82	0.465909091	0.683333333	0.564140873
	EDDM	39.40	37	780	599100	83	0.096176130	0.691666667	0.257592964
	ADWIN	40.17	0	110	599770	120	0.521739130	1.000000000	0.722248890
	ECDD	9.83	2	945	598935	118	0.111006585	0.983333333	0.330118655
	STEPD	14.33	0	162	599718	120	0.425531915	1.000000000	0.652239985
	SeqDr2	N/A	120	242	599638	0	0.000000000	0.000000000	-0.000284104
	HDDM_W	16.33	0	7	599873	120	0.944881890	1.000000000	0.972044682
	FTDD	19.00	0	3	599877	120	0.975609756	1.000000000	0.987727127
	WSTD	18.75	0	3	599877	120	0.975609756	1.000000000	0.987727127
	HDDM_A	25.88	1	4	599876	119	0.967479675	0.991666667	0.979494380
	DDM_7	22.94	1	916	598964	119	0.114975845	0.991666667	0.337402572
	DDM_{129}	31.10	2	144	599736	118	0.450381679	0.983333333	0.665405084
	RDDM_{30}	55.70	20	21	599859	100	0.826446281	0.833333333	0.829848493
	RDDM_7	25.47	34	230	599650	86	0.272151899	0.716666667	0.441471672
	RDDM_{129}	34.19	3	42	599838	117	0.735849057	0.975000000	0.846992582
Waveform	DDM	N/A	120	52	599828	0	0.000000000	0.000000000	-0.000131675
	EDDM	40.00	113	456	599424	7	0.015118790	0.058333333	0.029318689
	ADWIN	70.00	115	125	599755	5	0.038461538	0.041666667	0.039832170
	ECDD	25.22	74	1088	598792	46	0.040564374	0.383333333	0.124213373
	STEPD	38.69	59	171	599709	61	0.262931034	0.508333333	0.365419870
	SeqDr2	N/A	120	106	599774	0	0.000000000	0.000000000	-0.000188007
	HDDM_W	43.45	65	31	599849	55	0.639534884	0.458333333	0.541329337
	FTDD	45.26	101	29	599851	19	0.395833333	0.158333333	0.250255527
	WSTD	42.81	88	31	599849	32	0.507936508	0.266666667	0.367946163
	HDDM_A	54.29	99	45	599835	21	0.318181818	0.175000000	0.235858186
	DDM_7	54.85	87	514	599366	33	0.060329068	0.275000000	0.128448489
	DDM_{129}	50.00	101	123	599757	19	0.133802817	0.158333333	0.145366387
	RDDM_{30}	20.00	119	52	599828	1	0.018867925	0.008333333	0.012408119
	RDDM_7	54.29	99	166	599714	21	0.112299465	0.175000000	0.139973184
	RDDM_{129}	60.83	108	70	599810	12	0.146341463	0.100000000	0.120826687

Table 36 – Concept drift identifications of Detectors in 50K instances abrupt datasets using NB (Part 1)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
Agrawal$_1$	DDM	144.00	115	104	1499776	5	0.045871560	0.041666667	0.043645675
	EDDM	70.00	119	778	1499102	1	0.001283697	0.008333333	0.003067789
	ADWIN	145.81	58	254	1499626	62	0.196202532	0.516666667	0.318305052
	ECDD	58.07	32	2282	1497598	88	0.037130802	0.733333333	0.164794190
	STEPD	75.47	25	429	1499451	95	0.181297710	0.791666667	0.378764180
	SeqDr2	200.00	20	117	1499763	100	0.460829493	0.833333333	0.619659195
	HDDM$_W$	60.99	19	687	1499193	101	0.128172589	0.841666667	0.328343154
	FTDD	88.57	85	50	1499830	35	0.411764706	0.291666667	0.346507988
	WSTD	81.70	32	106	1499774	88	0.453608247	0.733333333	0.576713400
	HDDM$_A$	119.55	53	66	1499814	67	0.503759398	0.558333333	0.530305354
	DDM$_7$	121.95	38	1039	1498841	82	0.073148974	0.683333333	0.223421471
	DDM$_{129}$	132.89	75	167	1499713	45	0.212264151	0.375000000	0.282057929
	RDDM$_{30}$	150.00	118	122	1499758	2	0.016129032	0.016666667	0.016315650
	RDDM$_7$	121.49	46	358	1499522	74	0.171296296	0.616666667	0.324919868
	RDDM$_{129}$	150.00	84	101	1499779	36	0.262773723	0.300000000	0.280709145
Agrawal$_2$	DDM	107.62	57	426	1499454	63	0.128834356	0.525000000	0.259964419
	EDDM	50.00	116	174	1499706	4	0.022471910	0.033333333	0.027274303
	ADWIN	57.36	29	384	1499496	91	0.191578947	0.758333333	0.381073474
	ECDD	20.44	30	2482	1497398	90	0.034992224	0.750000000	0.161775370
	STEPD	23.57	22	1224	1498656	98	0.074130106	0.816666667	0.245900620
	SeqDr2	200.00	27	185	1499695	93	0.334532374	0.775000000	0.509124128
	HDDM$_W$	37.50	12	191	1499689	108	0.361204013	0.900000000	0.570114387
	FTDD	31.91	26	36	1499844	94	0.723076923	0.783333333	0.752581771
	WSTD	28.32	25	65	1499815	95	0.593750000	0.791666667	0.685575056
	HDDM$_A$	62.34	26	33	1499847	94	0.740157480	0.783333333	0.761419834
	DDM$_7$	51.24	31	3525	1496355	89	0.024626453	0.741666667	0.134875595
	DDM$_{129}$	68.72	34	545	1499335	86	0.136291601	0.716666667	0.312425801
	RDDM$_{30}$	120.68	46	73	1499807	74	0.503401361	0.616666667	0.557124247
	RDDM$_7$	68.83	43	938	1498942	77	0.075862069	0.641666667	0.220482038
	RDDM$_{129}$	74.77	32	100	1499780	88	0.468085106	0.733333333	0.585846019
LED	DDM	147.27	87	93	1499787	33	0.261904762	0.275000000	0.268312546
	EDDM	N/A	120	222	1499658	0	0.000000000	0.000000000	-0.000108824
	ADWIN	80.16	59	2987	1496893	61	0.020013123	0.508333333	0.100566023
	ECDD	26.85	31	1078	1498802	89	0.076263925	0.741666667	0.237681032
	STEPD	45.38	27	1697	1498183	93	0.051955307	0.775000000	0.200481005
	SeqDr2	157.14	22	2230	1497650	98	0.042096220	0.816666667	0.185213436
	HDDM$_W$	33.94	21	359	1499521	99	0.216157205	0.825000000	0.422216066
	FTDD	55.70	41	53	1499827	79	0.598484848	0.658333333	0.627665024
	WSTD	41.62	21	280	1499600	99	0.261213720	0.825000000	0.464156229
	HDDM$_A$	86.91	26	33	1499847	94	0.740157480	0.783333333	0.761419834
	DDM$_7$	103.86	32	169	1499711	88	0.342412451	0.733333333	0.501047142
	DDM$_{129}$	126.42	39	64	1499816	81	0.558620690	0.675000000	0.614025715
	RDDM$_{30}$	147.33	90	96	1499784	30	0.238095238	0.250000000	0.243913044
	RDDM$_7$	97.85	55	111	1499769	65	0.369318182	0.541666667	0.447213770
	RDDM$_{129}$	133.04	41	46	1499834	79	0.632000000	0.658333333	0.645003325
Mixed	DDM	73.05	2	23	1499857	118	0.836879433	0.983333333	0.907147892
	EDDM	138.17	49	402	1499478	71	0.150105708	0.591666667	0.297914396
	ADWIN	34.50	0	190	1499690	120	0.387096774	1.000000000	0.622131608
	ECDD	10.00	0	1846	1498034	120	0.061037640	1.000000000	0.246905887
	STEPD	10.50	0	290	1499590	120	0.292682927	1.000000000	0.540949477
	SeqDr2	200.00	0	141	1499739	120	0.459770115	1.000000000	0.678031631
	HDDM$_W$	13.17	0	0	1499880	120	1.000000000	1.000000000	1.000000000
	FTDD	18.00	0	2	1499878	120	0.983606557	1.000000000	0.991768746
	WSTD	15.33	0	0	1499880	120	1.000000000	1.000000000	1.000000000
	HDDM$_A$	29.08	0	0	1499880	120	1.000000000	1.000000000	1.000000000
	DDM$_7$	29.74	5	408	1499472	115	0.219885277	0.958333333	0.458977540
	DDM$_{129}$	39.42	0	57	1499823	120	0.677966102	1.000000000	0.823371324
	RDDM$_{30}$	67.17	0	2	1499878	120	0.983606557	1.000000000	0.991768746
	RDDM$_7$	30.93	23	192	1499688	97	0.335640138	0.808333333	0.520820268
	RDDM$_{129}$	38.67	0	13	1499867	120	0.902255639	1.000000000	0.949867264

Table 37 – Concept drift identifications of Detectors in 50K instances abrupt datasets using NB (Part 2)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
RandRBF	DDM	N/A	120	96	1499784	0	0.000000000	0.000000000	-0.000071559
	EDDM	30.00	116	396	1499484	4	0.010000000	0.033333333	0.018114499
	ADWIN	47.50	116	579	1499301	4	0.006861063	0.033333333	0.014950071
	ECDD	N/A	120	0	1499880	0	0.000000000	0.000000000	0.000000000
	STEPD	81.25	112	661	1499219	8	0.011958146	0.066666667	0.028053390
	SeqDr2	200.00	101	48	1499832	19	0.283582090	0.158333333	0.211850803
	$HDDM_W$	100.00	78	529	1499351	42	0.073555166	0.350000000	0.160312748
	FTDD	80.00	117	52	1499828	3	0.054545455	0.025000000	0.036875438
	WSTD	70.00	118	118	1499762	2	0.016666667	0.016666667	0.016587994
	$HDDM_A$	116.00	115	109	1499771	5	0.043859649	0.041666667	0.042674452
	DDM_7	74.29	106	545	1499335	14	0.025044723	0.116666667	0.053893990
	DDM_{129}	128.89	111	246	1499634	9	0.035294118	0.075000000	0.051339374
	$RDDM_{30}$	140.00	118	170	1499710	2	0.011627907	0.016666667	0.013826719
	$RDDM_7$	126.15	107	491	1499389	13	0.025793651	0.108333333	0.052708266
	$RDDM_{129}$	132.86	113	230	1499650	7	0.029535865	0.058333333	0.041400636
Sine	DDM	88.85	33	110	1499770	87	0.441624365	0.725000000	0.565799723
	EDDM	79.19	46	1265	1498615	74	0.055265123	0.616666667	0.184430601
	ADWIN	41.50	0	142	1499738	120	0.458015267	1.000000000	0.676736215
	ECDD	9.83	1	2512	1497368	119	0.045229951	0.991666667	0.211604872
	STEPD	13.95	1	460	1499420	119	0.205526770	0.991666667	0.451387143
	SeqDr2	200.00	0	128	1499752	120	0.483870968	1.000000000	0.695578661
	$HDDM_W$	16.42	0	10	1499870	120	0.923076923	1.000000000	0.960765720
	FTDD	19.67	0	2	1499878	120	0.983606557	1.000000000	0.991768746
	WSTD	18.58	0	4	1499876	120	0.967741935	1.000000000	0.983737442
	$HDDM_A$	44.08	0	8	1499872	120	0.937500000	1.000000000	0.968243254
	DDM_7	28.82	1	1490	1498390	119	0.073958981	0.991666667	0.270681590
	DDM_{129}	51.81	4	277	1499603	116	0.295165394	0.966666667	0.534106224
	$RDDM_{30}$	86.35	16	20	1499860	104	0.838709677	0.866666667	0.852561606
	$RDDM_7$	36.34	27	502	1499378	93	0.156302521	0.775000000	0.347948546
	$RDDM_{129}$	54.86	9	59	1499821	111	0.652941176	0.925000000	0.777135351
Waveform	DDM	165.00	118	70	1499810	2	0.027777778	0.016666667	0.021455980
	EDDM	78.33	114	561	1499319	6	0.010582011	0.050000000	0.022833518
	ADWIN	122.40	70	123	1499757	50	0.289017341	0.416666667	0.346959289
	ECDD	61.13	58	2571	1497309	62	0.023547284	0.516666667	0.110026302
	STEPD	50.00	55	422	1499458	65	0.133470226	0.541666667	0.268773069
	SeqDr2	200.00	55	60	1499820	65	0.520000000	0.541666667	0.530684467
	$HDDM_W$	55.74	52	98	1499782	68	0.409638554	0.566666667	0.481749006
	FTDD	73.50	80	29	1499851	40	0.579710145	0.333333333	0.439554011
	WSTD	72.88	61	37	1499843	59	0.614583333	0.491666667	0.549668066
	$HDDM_A$	99.56	75	40	1499840	45	0.529411765	0.375000000	0.445529509
	DDM_7	92.94	69	725	1499155	51	0.065721649	0.425000000	0.166974235
	DDM_{129}	130.00	80	151	1499729	40	0.209424084	0.333333333	0.264138542
	$RDDM_{30}$	143.33	117	68	1499812	3	0.042253521	0.025000000	0.032441884
	$RDDM_7$	85.28	84	505	1499375	36	0.066543438	0.300000000	0.141151831
	$RDDM_{129}$	136.56	88	69	1499811	32	0.316831683	0.266666667	0.290616983

Table 38 – Concept drift identifications of Detectors in 100K instances abrupt datasets using NB (Part 1)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
Agrawal$_1$	DDM	313.33	111	114	2999766	9	0.073170732	0.075000000	0.074042222
	EDDM	295.00	118	784	2999096	2	0.002544529	0.016666667	0.006410802
	ADWIN	203.07	6	222	2999658	114	0.339285714	0.950000000	0.567709803
	ECDD	60.34	31	4661	2995219	89	0.018736842	0.741666667	0.117727309
	STEPD	96.47	18	778	2999102	102	0.115909091	0.850000000	0.313827289
	SeqDr2	217.09	3	101	2999779	117	0.536697248	0.975000000	0.723367660
	HDDM$_W$	59.91	14	1376	2998504	106	0.071524966	0.883333333	0.251283619
	FTDD	152.41	66	64	2999816	54	0.457627119	0.450000000	0.453775870
	WSTD	106.47	18	184	2999696	102	0.356643357	0.850000000	0.550563237
	HDDM$_A$	171.57	37	76	2999804	83	0.522012579	0.691666667	0.600863499
	DDM$_7$	205.73	10	1401	2998479	110	0.072799471	0.916666667	0.258255288
	DDM$_{129}$	265.29	52	184	2999696	68	0.269841270	0.566666667	0.391003427
	RDDM$_{30}$	306.67	111	118	2999762	9	0.070866142	0.075000000	0.072865626
	RDDM$_7$	191.37	25	561	2999319	95	0.144817073	0.791666667	0.338545670
	RDDM$_{129}$	279.67	59	98	2999782	61	0.383647799	0.508333333	0.441586270
Agrawal$_2$	DDM	166.36	54	704	2999176	66	0.085714286	0.550000000	0.217054933
	EDDM	210.00	118	156	2999724	2	0.012658228	0.016666667	0.014479595
	ADWIN	70.94	24	423	2999457	96	0.184971098	0.800000000	0.384635407
	ECDD	27.58	21	5263	2994617	99	0.018463260	0.825000000	0.123264044
	STEPD	38.12	19	2068	2997812	101	0.046565237	0.841666667	0.197876168
	SeqDr2	204.17	24	185	2999695	96	0.341637011	0.800000000	0.522763943
	HDDM$_W$	39.62	14	398	2999482	106	0.210317460	0.883333333	0.430985380
	FTDD	31.81	26	35	2999845	94	0.728682171	0.783333333	0.755503635
	WSTD	46.12	17	77	2999803	103	0.572222222	0.858333333	0.700812283
	HDDM$_A$	101.60	20	34	2999846	100	0.746268657	0.833333333	0.788591487
	DDM$_7$	84.61	18	5011	2994869	102	0.019949149	0.850000000	0.130070577
	DDM$_{129}$	93.85	29	932	2998948	91	0.088954057	0.758333333	0.259657197
	RDDM$_{30}$	175.48	36	50	2999830	84	0.626865672	0.700000000	0.662410086
	RDDM$_7$	113.80	28	1587	2998293	92	0.054794521	0.766666667	0.204873108
	RDDM$_{129}$	107.85	27	132	2999748	93	0.413333333	0.775000000	0.565957746
LED	DDM	249.79	73	86	2999794	47	0.353383459	0.391666667	0.372006533
	EDDM	N/A	120	217	2999663	0	0.000000000	0.000000000	-0.000053793
	ADWIN	120.13	42	6015	2993865	78	0.012801576	0.650000000	0.091028927
	ECDD	42.99	33	2241	2997639	87	0.037371134	0.725000000	0.164493714
	STEPD	54.71	16	3169	2996711	104	0.031775130	0.866666667	0.165832017
	SeqDr2	194.59	9	3139	2996741	111	0.034153846	0.925000000	0.177633879
	HDDM$_W$	41.65	17	762	2999118	103	0.119075145	0.858333333	0.319642074
	FTDD	68.00	25	58	2999822	95	0.620915033	0.791666667	0.701098518
	WSTD	46.47	18	402	2999478	102	0.202380952	0.850000000	0.414718687
	HDDM$_A$	114.63	12	37	2999843	108	0.744827586	0.900000000	0.818738078
	DDM$_7$	156.22	22	176	2999704	98	0.357664234	0.816666667	0.540430832
	DDM$_{129}$	192.58	27	58	2999822	93	0.615894040	0.775000000	0.690868293
	RDDM$_{30}$	268.08	68	76	2999804	52	0.406250000	0.433333333	0.419549225
	RDDM$_7$	127.53	43	283	2999597	77	0.213888889	0.641666667	0.370426775
	RDDM$_{129}$	197.63	27	31	2999849	93	0.750000000	0.775000000	0.762387877
Mixed	DDM	99.04	5	41	2999839	115	0.737179487	0.958333333	0.840506991
	EDDM	272.21	52	460	2999420	68	0.128787879	0.566666667	0.270093000
	ADWIN	40.00	0	164	2999716	120	0.422535211	1.000000000	0.650009317
	ECDD	9.83	0	3860	2996020	120	0.030150754	1.000000000	0.173527975
	STEPD	10.33	0	679	2999201	120	0.150187735	1.000000000	0.387496762
	SeqDr2	200.00	0	141	2999739	120	0.459770115	1.000000000	0.678047568
	HDDM$_W$	15.08	0	0	2999880	120	1.000000000	1.000000000	1.000000000
	FTDD	18.83	0	2	2999878	120	0.983606557	1.000000000	0.991769077
	WSTD	17.00	0	0	2999880	120	1.000000000	1.000000000	1.000000000
	HDDM$_A$	43.50	0	0	2999880	120	1.000000000	1.000000000	1.000000000
	DDM$_7$	37.52	3	509	2999371	117	0.186900958	0.975000000	0.426843938
	DDM$_{129}$	52.58	0	72	2999808	120	0.625000000	1.000000000	0.790559928
	RDDM$_{30}$	89.17	0	12	2999868	120	0.909090909	1.000000000	0.953460682
	RDDM$_7$	54.24	35	481	2999399	85	0.150176678	0.708333333	0.326102445
	RDDM$_{129}$	52.76	4	25	2999855	116	0.822695035	0.966666667	0.891775601

Table 39 – Concept drift identifications of Detectors in 100K instances abrupt datasets using NB (Part 2)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
RandRBF	DDM	203.33	117	95	2999785	3	0.030612245	0.025000000	0.027629023
	EDDM	106.67	117	434	2999446	3	0.006864989	0.025000000	0.013025438
	ADWIN	292.50	100	742	2999138	20	0.026246719	0.166666667	0.066048562
	ECDD	N/A	120	0	2999880	0	0.000000000	0.000000000	0.000000000
	STEPD	201.25	104	1326	2998554	16	0.011922504	0.133333333	0.039746550
	SeqDr2	263.64	98	69	2999811	22	0.241758242	0.183333333	0.210501295
	HDDM_W	150.00	65	1032	2998848	55	0.050597976	0.458333333	0.152195289
	FTDD	241.67	114	60	2999820	6	0.090909091	0.050000000	0.067392411
	WSTD	145.00	114	221	2999659	6	0.026431718	0.050000000	0.036300707
	HDDM_A	252.17	97	115	2999765	23	0.166666667	0.191666667	0.178694877
	DDM_7	276.67	102	640	2999240	18	0.027355623	0.150000000	0.063971974
	DDM_{129}	251.76	103	308	2999572	17	0.052307692	0.141666667	0.086023398
	RDDM_{30}	180.00	116	213	2999667	4	0.018433180	0.033333333	0.024735486
	RDDM_7	233.10	91	775	2999105	29	0.036069652	0.241666667	0.093274806
	RDDM_{129}	289.33	105	335	2999545	15	0.042857143	0.125000000	0.073129921
Sine	DDM	126.36	32	126	2999754	88	0.411214953	0.733333333	0.549119785
	EDDM	172.68	49	1543	2998337	71	0.043990087	0.591666667	0.161230211
	ADWIN	40.25	0	126	2999754	120	0.487804878	1.000000000	0.698415628
	ECDD	10.00	2	5168	2994712	118	0.022323118	0.983333333	0.148026867
	STEPD	13.42	0	893	2998987	120	0.118460020	1.000000000	0.344128983
	SeqDr2	200.00	0	122	2999758	120	0.495867769	1.000000000	0.704164471
	HDDM_W	15.25	0	13	2999867	120	0.902255639	1.000000000	0.949869322
	FTDD	18.42	0	3	2999877	120	0.975609756	1.000000000	0.987729103
	WSTD	18.17	0	3	2999877	120	0.975609756	1.000000000	0.987729103
	HDDM_A	79.25	0	6	2999874	120	0.952380952	1.000000000	0.975899097
	DDM_7	43.14	2	2357	2997523	118	0.047676768	0.983333333	0.216434840
	DDM_{129}	76.12	4	350	2999530	116	0.248927039	0.966666667	0.490509061
	RDDM_{30}	115.48	16	35	2999845	104	0.748201439	0.866666667	0.805250207
	RDDM_7	51.94	27	962	2998918	93	0.088151659	0.775000000	0.261308807
	RDDM_{129}	61.47	4	174	2999706	116	0.400000000	0.966666667	0.621805578
Waveform	DDM	275.71	113	57	2999823	7	0.109375000	0.058333333	0.079849443
	EDDM	158.00	115	619	2999261	5	0.008012821	0.041666667	0.018183083
	ADWIN	154.43	50	163	2999717	70	0.300429185	0.583333333	0.418598031
	ECDD	128.44	43	5089	2994791	77	0.014905149	0.641666667	0.097619995
	STEPD	45.90	59	879	2999001	61	0.064893617	0.508333333	0.181544979
	SeqDr2	202.74	47	67	2999813	73	0.521428571	0.608333333	0.563188427
	HDDM_W	76.62	49	189	2999691	71	0.273076923	0.591666667	0.401924924
	FTDD	115.54	64	23	2999857	56	0.708860759	0.466666667	0.575140241
	WSTD	88.24	52	57	2999823	68	0.544000000	0.566666667	0.555199521
	HDDM_A	176.18	65	45	2999835	55	0.550000000	0.458333333	0.502060905
	DDM_7	141.88	56	1556	2998324	64	0.039506173	0.533333333	0.145050047
	DDM_{129}	250.63	72	173	2999707	48	0.217194570	0.400000000	0.294712917
	RDDM_{30}	250.91	109	95	2999785	11	0.103773585	0.091666667	0.097498527
	RDDM_7	113.40	73	932	2998948	47	0.048008172	0.391666667	0.137035613
	RDDM_{129}	235.69	62	130	2999750	58	0.308510638	0.483333333	0.386121894

Table 40 – Concept drift identifications of Detectors in 500K instances abrupt datasets using NB (Part 1)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
Agrawal$_1$	DDM	1311.90	19	19	4999941	21	0.525000000	0.525000000	0.524996200
	EDDM	N/A	40	265	4999695	0	0.000000000	0.000000000	-0.000020592
	ADWIN	216.00	0	92	4999868	40	0.303030303	1.000000000	0.550476818
	ECDD	290.26	1	7782	4992178	39	0.004986575	0.975000000	0.069670324
	STEPD	138.38	3	1453	4998507	37	0.024832215	0.925000000	0.151532265
	SeqDr2	230.00	0	42	4999918	40	0.487804878	1.000000000	0.698427362
	HDDM$_W$	172.82	1	2448	4997512	39	0.015681544	0.975000000	0.123618901
	FTDD	572.26	9	30	4999930	31	0.508196721	0.775000000	0.627573115
	WSTD	148.46	1	321	4999639	39	0.108333333	0.975000000	0.324989000
	HDDM$_A$	438.00	5	42	4999918	35	0.454545455	0.875000000	0.630652503
	DDM$_7$	461.58	2	937	4999023	38	0.038974359	0.950000000	0.192400512
	DDM$_{129}$	882.41	11	68	4999892	29	0.298969072	0.725000000	0.465560862
	RDDM$_{30}$	799.05	19	121	4999839	21	0.147887324	0.525000000	0.278631066
	RDDM$_7$	211.05	2	1013	4998947	38	0.036156042	0.950000000	0.185311992
	RDDM$_{129}$	398.24	6	181	4999779	34	0.158139535	0.850000000	0.366622231
Agrawal$_2$	DDM	450.00	14	324	4999636	26	0.074285714	0.650000000	0.219725011
	EDDM	N/A	40	49	4999911	0	0.000000000	0.000000000	-0.000008854
	ADWIN	202.75	0	150	4999810	40	0.210526316	1.000000000	0.458824585
	ECDD	140.94	8	9066	4990894	32	0.003517257	0.800000000	0.052973090
	STEPD	52.89	2	3181	4996779	38	0.011804908	0.950000000	0.105862045
	SeqDr2	294.44	4	61	4999899	36	0.371134021	0.900000000	0.577940629
	HDDM$_W$	34.86	5	632	4999328	35	0.052473763	0.875000000	0.214259271
	FTDD	89.70	7	15	4999945	33	0.687500000	0.825000000	0.753116380
	WSTD	96.47	6	95	4999865	34	0.263565891	0.850000000	0.473312772
	HDDM$_A$	253.95	2	14	4999946	38	0.730769231	0.950000000	0.833203662
	DDM$_7$	384.87	1	3240	4996720	39	0.011893870	0.975000000	0.107650458
	DDM$_{129}$	500.83	4	556	4999404	36	0.060810811	0.900000000	0.233927868
	RDDM$_{30}$	420.00	6	141	4999819	34	0.194285714	0.850000000	0.406369731
	RDDM$_7$	232.43	3	3167	4996793	37	0.011548065	0.925000000	0.103315490
	RDDM$_{129}$	278.95	2	305	4999655	38	0.110787172	0.950000000	0.324408192
LED	DDM	687.92	16	24	4999936	24	0.500000000	0.600000000	0.547718614
	EDDM	N/A	40	68	4999892	0	0.000000000	0.000000000	-0.000010431
	ADWIN	251.54	1	7492	4992468	39	0.005178595	0.975000000	0.071001237
	ECDD	276.92	1	3844	4996116	39	0.010043781	0.975000000	0.098917993
	STEPD	209.21	2	4888	4995072	38	0.007714170	0.950000000	0.085560153
	SeqDr2	210.00	0	961	4998999	40	0.039960040	1.000000000	0.199880863
	HDDM$_W$	79.74	1	1175	4998785	39	0.032125206	0.975000000	0.176958558
	FTDD	139.72	4	24	4999936	36	0.600000000	0.900000000	0.734844473
	WSTD	95.14	3	401	4999559	37	0.084474886	0.925000000	0.279520911
	HDDM$_A$	290.25	0	17	4999943	40	0.701754386	1.000000000	0.837706392
	DDM$_7$	412.50	0	116	4999844	40	0.256410256	1.000000000	0.506363810
	DDM$_{129}$	588.42	2	30	4999930	38	0.558823529	0.950000000	0.728614178
	RDDM$_{30}$	621.94	9	94	4999866	31	0.248000000	0.775000000	0.438399296
	RDDM$_7$	145.16	9	611	4999349	31	0.048286604	0.775000000	0.193429116
	RDDM$_{129}$	231.84	2	149	4999811	38	0.203208556	0.950000000	0.439365102
Mixed	DDM	300.26	1	29	4999931	39	0.573529412	0.975000000	0.747788510
	EDDM	1769.52	19	182	4999778	21	0.103448276	0.525000000	0.233033440
	ADWIN	40.00	0	57	4999903	40	0.412371134	1.000000000	0.642157639
	ECDD	10.00	0	6425	4993535	40	0.006187162	1.000000000	0.078607958
	STEPD	13.25	0	1118	4998842	40	0.034542314	1.000000000	0.185834848
	SeqDr2	200.00	0	48	4999912	40	0.454545455	1.000000000	0.674196626
	HDDM$_W$	17.25	0	0	4999960	40	1.000000000	1.000000000	1.000000000
	FTDD	20.00	0	0	4999960	40	1.000000000	1.000000000	1.000000000
	WSTD	18.75	0	0	4999960	40	1.000000000	1.000000000	1.000000000
	HDDM$_A$	91.75	0	0	4999960	40	1.000000000	1.000000000	1.000000000
	DDM$_7$	85.25	0	215	4999745	40	0.156862745	1.000000000	0.396050502
	DDM$_{129}$	117.44	1	58	4999902	39	0.402061856	0.975000000	0.626103386
	RDDM$_{30}$	128.50	0	112	4999848	40	0.263157895	1.000000000	0.512983430
	RDDM$_7$	53.55	9	959	4999001	31	0.031313131	0.775000000	0.155757106
	RDDM$_{129}$	54.50	0	197	4999763	40	0.168776371	1.000000000	0.410815922

Table 41 – Concept drift identifications of Detectors in 500K instances abrupt datasets using NB (Part 2)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
RandRBF	DDM	N/A	40	35	4999925	0	0.000000000	0.000000000	-0.000007483
	EDDM	635.00	38	112	4999848	2	0.017543860	0.050000000	0.029604394
	ADWIN	791.54	14	687	4999273	26	0.036465638	0.650000000	0.153934514
	ECDD	N/A	40	0	4999960	0	0.000000000	0.000000000	0.000000000
	STEPD	602.22	22	2263	4997697	18	0.007891276	0.450000000	0.059544299
	SeqDr2	533.33	28	33	4999927	12	0.266666667	0.300000000	0.282836631
	$HDDM_W$	479.31	11	1789	4998171	29	0.015951595	0.725000000	0.107506298
	FTDD	846.67	37	40	4999920	3	0.069767442	0.075000000	0.072328729
	WSTD	212.50	36	454	4999506	4	0.008733624	0.100000000	0.029527106
	$HDDM_A$	872.27	18	68	4999892	22	0.244444444	0.550000000	0.366659433
	DDM_7	1064.38	24	342	4999618	16	0.044692737	0.400000000	0.133686642
	DDM_{129}	1417.00	30	175	4999785	10	0.054054054	0.250000000	0.116233049
	$RDDM_{30}$	1141.18	23	148	4999812	17	0.103030303	0.425000000	0.209243576
	$RDDM_7$	637.10	9	973	4998987	31	0.030876494	0.775000000	0.154666995
	$RDDM_{129}$	816.52	17	258	4999702	23	0.081850534	0.575000000	0.216928280
Sine	DDM	538.75	8	39	4999921	32	0.450704225	0.800000000	0.600465307
	EDDM	1122.31	27	553	4999407	13	0.022968198	0.325000000	0.086373430
	ADWIN	41.50	0	61	4999899	40	0.396039604	1.000000000	0.629312937
	ECDD	48.50	0	8782	4991178	40	0.004534119	1.000000000	0.067276708
	STEPD	15.75	0	1442	4998518	40	0.026990553	1.000000000	0.164264327
	SeqDr2	200.00	0	44	4999916	40	0.476190476	1.000000000	0.690062523
	$HDDM_W$	16.75	0	81	4999879	40	0.330578512	1.000000000	0.574954917
	FTDD	20.00	0	5	4999955	40	0.888888889	1.000000000	0.942808570
	WSTD	19.50	0	24	4999936	40	0.625000000	1.000000000	0.790567518
	$HDDM_A$	155.25	0	6	4999954	40	0.869565217	1.000000000	0.932504249
	DDM_7	137.00	0	1766	4998194	40	0.022148394	1.000000000	0.148797081
	DDM_{129}	253.08	1	216	4999744	39	0.152941176	0.975000000	0.386148734
	$RDDM_{30}$	329.44	4	170	4999790	36	0.174757282	0.900000000	0.396578985
	$RDDM_7$	120.00	4	1729	4998231	36	0.020396601	0.900000000	0.135459098
	$RDDM_{129}$	104.25	0	311	4999649	40	0.113960114	1.000000000	0.337569290
Waveform	DDM	1161.25	32	17	4999943	8	0.320000000	0.200000000	0.252977533
	EDDM	1415.00	38	236	4999724	2	0.008403361	0.050000000	0.020479057
	ADWIN	188.33	10	77	4999883	30	0.280373832	0.750000000	0.458557037
	ECDD	387.00	0	8406	4991554	40	0.004735970	1.000000000	0.068760508
	STEPD	331.07	12	1470	4998490	28	0.018691589	0.700000000	0.114354436
	SeqDr2	240.00	10	32	4999928	30	0.483870968	0.750000000	0.602410681
	$HDDM_W$	77.20	15	308	4999652	25	0.075075075	0.625000000	0.216599682
	FTDD	243.70	13	21	4999939	27	0.562500000	0.675000000	0.616184536
	WSTD	144.62	14	89	4999871	26	0.226086957	0.650000000	0.383341463
	$HDDM_A$	430.34	11	19	4999941	29	0.604166667	0.725000000	0.661828484
	DDM_7	380.00	15	1252	4998708	25	0.019577134	0.625000000	0.110584501
	DDM_{129}	844.74	21	117	4999843	19	0.139705882	0.475000000	0.257594701
	$RDDM_{30}$	589.09	29	105	4999855	11	0.094827586	0.275000000	0.161474456
	$RDDM_7$	558.95	21	1370	4998590	19	0.013678906	0.475000000	0.080571321
	$RDDM_{129}$	407.31	14	252	4999708	26	0.093525180	0.650000000	0.246545804

Table 42 – Concept drift identifications of Detectors in 1 Million instances abrupt datasets using NB (Part 1)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
	DDM	1979.52	19	17	9999943	21	0.552631579	0.525000000	0.538636837
	EDDM	2350.00	39	272	9999688	1	0.003663004	0.025000000	0.009559187
	ADWIN	218.50	0	94	9999866	40	0.298507463	1.000000000	0.546355797
	ECDD	345.50	0	15587	9984373	40	0.002559672	1.000000000	0.050553759
	STEPD	135.68	3	2772	9997188	37	0.013171947	0.925000000	0.110363592
	SeqDr2	225.00	0	41	9999919	40	0.493827160	1.000000000	0.702726928
	HDDM$_W$	177.18	1	4889	9995071	39	0.007913961	0.975000000	0.087818821
Agrawal$_1$	FTDD	790.00	4	38	9999922	36	0.486486486	0.900000000	0.661691491
	WSTD	248.25	0	628	9999332	40	0.059880240	1.000000000	0.244696708
	HDDM$_A$	683.50	0	77	9999883	40	0.341880342	1.000000000	0.584703095
	DDM$_7$	839.74	1	1121	9998839	39	0.033620690	0.975000000	0.181042277
	DDM$_{129}$	1262.50	8	95	9999865	32	0.251968504	0.800000000	0.448967448
	RDDM$_{30}$	1418.80	15	188	9999772	25	0.117370892	0.625000000	0.270838814
	RDDM$_7$	283.24	3	2095	9997865	37	0.017354597	0.925000000	0.126684997
	RDDM$_{129}$	589.21	2	367	9999593	38	0.093827160	0.950000000	0.298550111
	DDM	1204.00	5	286	9999674	35	0.109034268	0.875000000	0.308871217
	EDDM	N/A	40	49	9999911	0	0.000000000	0.000000000	-0.000004427
	ADWIN	184.50	0	153	9999807	40	0.207253886	1.000000000	0.455247971
	ECDD	306.92	1	18069	9981891	39	0.002153744	0.975000000	0.045781126
	STEPD	75.00	0	6079	9993881	40	0.006537016	1.000000000	0.080827235
	SeqDr2	415.79	2	65	9999895	38	0.368932039	0.950000000	0.592015919
	HDDM$_W$	61.18	6	1262	9998698	34	0.026234568	0.850000000	0.149316985
Agrawal$_2$	FTDD	250.57	5	21	9999939	35	0.625000000	0.875000000	0.739508790
	WSTD	147.30	3	177	9999783	37	0.172897196	0.925000000	0.399908200
	HDDM$_A$	569.25	0	19	9999941	40	0.677966102	1.000000000	0.823386187
	DDM$_7$	363.33	1	5032	9994928	39	0.007690791	0.975000000	0.086571089
	DDM$_{129}$	738.46	1	622	9999338	39	0.059001513	0.975000000	0.239838920
	RDDM$_{30}$	955.53	2	351	9999609	38	0.097686375	0.950000000	0.304628360
	RDDM$_7$	262.16	3	6985	9992975	37	0.005269154	0.925000000	0.069785454
	RDDM$_{129}$	268.42	2	658	9999302	38	0.054597701	0.950000000	0.227736764
	DDM	1316.40	15	20	9999940	25	0.555555556	0.625000000	0.589253913
	EDDM	N/A	40	75	9999885	0	0.000000000	0.000000000	-0.000005477
	ADWIN	393.33	1	13016	9986944	39	0.002987361	0.975000000	0.053932284
	ECDD	575.25	0	7653	9992307	40	0.005199532	1.000000000	0.072080183
	STEPD	188.38	3	9567	9990393	37	0.003852561	0.925000000	0.059662853
	SeqDr2	190.00	0	1040	9998920	40	0.037037037	1.000000000	0.192440082
	HDDM$_W$	324.50	0	2317	9997643	40	0.016970725	1.000000000	0.130256644
LED	FTDD	144.71	6	32	9999928	34	0.515151515	0.850000000	0.661722472
	WSTD	58.38	3	827	9999133	37	0.042824074	0.925000000	0.199018716
	HDDM$_A$	650.00	0	24	9999936	40	0.625000000	1.000000000	0.790568466
	DDM$_7$	515.38	1	152	9999808	39	0.204188482	0.975000000	0.446184456
	DDM$_{129}$	812.78	4	49	9999911	36	0.423529412	0.900000000	0.617392934
	RDDM$_{30}$	1276.57	5	171	9999789	35	0.169902913	0.875000000	0.385566733
	RDDM$_7$	142.86	12	1251	9998709	28	0.021892103	0.700000000	0.123777597
	RDDM$_{129}$	413.68	2	311	9999649	38	0.108882521	0.950000000	0.321612840
	DDM	500.00	3	18	9999942	37	0.672727273	0.925000000	0.788841707
	EDDM	3240.00	28	156	9999804	12	0.071428571	0.300000000	0.146378336
	ADWIN	40.00	0	60	9999900	40	0.400000000	1.000000000	0.632453635
	ECDD	10.00	0	12850	9987110	40	0.003103181	1.000000000	0.055670397
	STEPD	10.00	0	2267	9997693	40	0.017338535	1.000000000	0.131660944
	SeqDr2	200.00	0	48	9999912	40	0.454545455	1.000000000	0.674198244
	HDDM$_W$	15.50	0	0	9999960	40	1.000000000	1.000000000	1.000000000
Mixed	FTDD	18.50	0	0	9999960	40	1.000000000	1.000000000	1.000000000
	WSTD	15.50	0	0	9999960	40	1.000000000	1.000000000	1.000000000
	HDDM$_A$	93.25	0	5	9999955	40	0.888888889	1.000000000	0.942808806
	DDM$_7$	104.62	1	393	9999567	39	0.090277778	0.975000000	0.296676908
	DDM$_{129}$	216.25	0	82	9999878	40	0.327868852	1.000000000	0.572595987
	RDDM$_{30}$	128.75	0	283	9999677	40	0.123839009	1.000000000	0.351902692
	RDDM$_7$	495.00	8	1958	9998002	32	0.016080402	0.800000000	0.113404290
	RDDM$_{129}$	64.74	2	353	9999607	38	0.097186701	0.950000000	0.303848227

Table 43 – Concept drift identifications of Detectors in 1 Million instances abrupt datasets using NB (Part 2)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
RandRBF	DDM	3217.50	36	41	9999919	4	0.088888889	0.100000000	0.094277062
	EDDM	1980.00	39	176	9999784	1	0.005649718	0.025000000	0.011876282
	ADWIN	1089.71	6	1302	9998658	34	0.025449102	0.850000000	0.147064316
	ECDD	N/A	40	0	9999960	0	0.000000000	0.000000000	0.000000000
	STEPD	1226.25	16	4467	9995493	24	0.005344021	0.600000000	0.056595635
	SeqDr2	764.71	23	38	9999922	17	0.309090909	0.425000000	0.362438249
	HDDM$_W$	795.59	6	3621	9996339	34	0.009302326	0.850000000	0.088899372
	FTDD	1609.00	30	47	9999913	10	0.175438596	0.250000000	0.209423195
	WSTD	645.00	36	781	9999179	4	0.005095541	0.100000000	0.022556516
	HDDM$_A$	1095.33	10	93	9999867	30	0.243902439	0.750000000	0.427695933
	DDM$_7$	1666.67	19	409	9999551	21	0.048837209	0.525000000	0.160114147
	DDM$_{129}$	2233.18	18	248	9999712	22	0.081481481	0.550000000	0.211687988
	RDDM$_{30}$	1706.67	16	246	9999714	24	0.088888889	0.600000000	0.230933295
	RDDM$_7$	877.84	3	1793	9998167	37	0.020218579	0.925000000	0.136741666
	RDDM$_{129}$	1235.45	7	490	9999470	33	0.063097514	0.825000000	0.228148592
Sine	DDM	849.41	6	48	9999912	34	0.414634146	0.850000000	0.593663646
	EDDM	2845.63	24	481	9999479	16	0.032193159	0.400000000	0.113466978
	ADWIN	40.75	0	44	9999916	40	0.476190476	1.000000000	0.690064041
	ECDD	9.50	0	17466	9982494	40	0.002284931	1.000000000	0.047759188
	STEPD	13.25	0	2899	9997061	40	0.013610071	1.000000000	0.116645299
	SeqDr2	200.00	0	44	9999916	40	0.476190476	1.000000000	0.690064041
	HDDM$_W$	15.25	0	141	9999819	40	0.220994475	1.000000000	0.470097180
	FTDD	18.75	0	18	9999942	40	0.689655172	1.000000000	0.830454051
	WSTD	18.00	0	45	9999915	40	0.470588235	1.000000000	0.685992797
	HDDM$_A$	207.50	0	9	9999951	40	0.816326531	1.000000000	0.903507496
	DDM$_7$	247.11	2	2477	9997483	38	0.015109344	0.950000000	0.119791252
	DDM$_{129}$	539.74	2	335	9999625	38	0.101876676	0.950000000	0.311093618
	RDDM$_{30}$	489.50	0	300	9999660	40	0.117647059	1.000000000	0.342992025
	RDDM$_7$	235.68	3	3308	9996652	37	0.011061286	0.925000000	0.101132351
	RDDM$_{129}$	156.92	1	552	9999408	39	0.065989848	0.975000000	0.253646134
Waveform	DDM	1810.91	29	23	9999937	11	0.323529412	0.275000000	0.298276795
	EDDM	270.00	39	171	9999789	1	0.005813953	0.025000000	0.012047904
	ADWIN	391.47	6	85	9999875	34	0.285714286	0.850000000	0.492802399
	ECDD	279.00	0	16776	9983184	40	0.002378687	1.000000000	0.048730857
	STEPD	931.21	7	2871	9997089	33	0.011363636	0.825000000	0.096804752
	SeqDr2	220.69	11	32	9999928	29	0.475409836	0.725000000	0.587085865
	HDDM$_W$	375.56	13	696	9999264	27	0.037344398	0.675000000	0.158757652
	FTDD	335.00	12	38	9999922	28	0.424242424	0.700000000	0.544947011
	WSTD	225.71	19	169	9999791	21	0.110526316	0.525000000	0.240880573
	HDDM$_A$	652.41	11	30	9999930	29	0.491525424	0.725000000	0.596953650
	DDM$_7$	729.67	10	1704	9998256	30	0.017301038	0.750000000	0.113895042
	DDM$_{129}$	1099.41	23	107	9999853	17	0.137096774	0.425000000	0.241378716
	RDDM$_{30}$	1339.50	20	209	9999751	20	0.087336245	0.500000000	0.208962430
	RDDM$_7$	955.36	12	2817	9997143	28	0.009841828	0.700000000	0.082979920
	RDDM$_{129}$	632.59	13	531	9999429	27	0.048387097	0.675000000	0.180714813

Table 44 – Concept drift identifications of Detectors in 2 Million instances abrupt datasets using NB (Part 1)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
Agrawal$_1$	DDM	3246.84	21	16	19999944	19	0.542857143	0.475000000	0.507795441
	EDDM	N/A	40	208	19999752	0	0.000000000	0.000000000	-0.000004561
	ADWIN	209.75	0	78	19999882	40	0.338983051	1.000000000	0.582221374
	ECDD	328.00	0	31384	19968576	40	0.001272912	1.000000000	0.035649894
	STEPD	514.00	0	5595	19994365	40	0.007098492	1.000000000	0.084240761
	SeqDr2	220.00	0	44	19999916	40	0.476190476	1.000000000	0.690064800
	HDDM$_W$	406.50	0	9745	19990215	40	0.004087890	1.000000000	0.063921028
	FTDD	1006.92	1	65	19999895	39	0.375000000	0.975000000	0.604668283
	WSTD	116.22	3	1324	19998636	37	0.027185893	0.925000000	0.158571789
	HDDM$_A$	987.00	0	118	19999842	40	0.253164557	1.000000000	0.503153121
	DDM$_7$	916.49	3	1480	19998480	37	0.024390244	0.925000000	0.150196644
	DDM$_{129}$	1967.06	6	147	19999813	34	0.187845304	0.850000000	0.399583374
	RDDM$_{30}$	3222.37	2	357	19999603	38	0.096202532	0.950000000	0.302308771
	RDDM$_7$	354.62	1	4386	19995574	39	0.008813559	0.975000000	0.092688936
	RDDM$_{129}$	690.51	1	700	19999260	39	0.052774019	0.975000000	0.226832036
Agrawal$_2$	DDM	2158.24	6	319	19999641	34	0.096317280	0.850000000	0.286125667
	EDDM	N/A	40	49	19999911	0	0.000000000	0.000000000	-0.000002214
	ADWIN	189.75	0	172	19999788	40	0.188679245	1.000000000	0.434370375
	ECDD	961.75	0	35808	19964152	40	0.001115822	1.000000000	0.033374011
	STEPD	211.54	1	11802	19988158	39	0.003293641	0.975000000	0.056650749
	SeqDr2	635.00	0	68	19999892	40	0.370370370	1.000000000	0.608579585
	HDDM$_W$	41.94	4	2567	19997393	36	0.013830196	0.900000000	0.111558152
	FTDD	825.75	0	27	19999933	40	0.597014925	1.000000000	0.772666888
	WSTD	170.25	0	383	19999577	40	0.094562648	1.000000000	0.307507458
	HDDM$_A$	763.00	0	31	19999929	40	0.563380282	1.000000000	0.750586043
	DDM$_7$	572.82	1	7575	19992385	39	0.005122143	0.975000000	0.070654802
	DDM$_{129}$	1128.61	4	264	19999696	36	0.120000000	0.900000000	0.328630851
	RDDM$_{30}$	894.86	5	637	19999323	35	0.052083333	0.875000000	0.213473743
	RDDM$_7$	170.81	3	13573	19986387	37	0.002718589	0.925000000	0.050126952
	RDDM$_{129}$	334.10	1	1414	19998546	39	0.026841019	0.975000000	0.161765406
LED	DDM	2368.33	10	23	19999937	30	0.566037736	0.750000000	0.651557577
	EDDM	N/A	40	67	19999893	0	0.000000000	0.000000000	-0.000002588
	ADWIN	225.75	0	16580	19983380	40	0.002406739	1.000000000	0.049038186
	ECDD	917.25	0	15214	19984746	40	0.002622263	1.000000000	0.051188556
	STEPD	286.25	0	19043	19980917	40	0.002096106	1.000000000	0.045761454
	SeqDr2	230.00	0	1345	19998615	40	0.028880866	1.000000000	0.169938001
	HDDM$_W$	331.05	2	4694	19995266	38	0.008030431	0.950000000	0.087332295
	FTDD	464.32	3	35	19999925	37	0.513888889	0.925000000	0.689453540
	WSTD	266.58	2	1355	19998605	38	0.027279253	0.950000000	0.160976233
	HDDM$_A$	663.16	2	114	19999846	38	0.250000000	0.950000000	0.487338158
	DDM$_7$	794.00	0	158	19999802	40	0.202020202	1.000000000	0.449464800
	DDM$_{129}$	1260.86	5	82	19999878	35	0.299145299	0.875000000	0.511615765
	RDDM$_{30}$	2455.56	4	318	19999642	36	0.101694915	0.900000000	0.302528721
	RDDM$_7$	418.40	15	2462	19997498	25	0.010052272	0.625000000	0.079252531
	RDDM$_{129}$	375.56	4	674	19999286	36	0.050704225	0.900000000	0.213616278
Mixed	DDM	748.46	1	29	19999931	39	0.573529412	0.975000000	0.747790275
	EDDM	5727.65	23	152	19999808	17	0.100591716	0.425000000	0.206761278
	ADWIN	40.00	0	58	19999902	40	0.408163265	1.000000000	0.638875639
	ECDD	9.00	0	25762	19974198	40	0.001550267	1.000000000	0.039348069
	STEPD	12.00	0	4596	19995364	40	0.008628128	1.000000000	0.092877042
	SeqDr2	200.00	0	48	19999912	40	0.454545455	1.000000000	0.674199053
	HDDM$_W$	15.00	0	0	19999960	40	1.000000000	1.000000000	1.000000000
	FTDD	19.00	0	0	19999960	40	1.000000000	1.000000000	1.000000000
	WSTD	17.00	0	0	19999960	40	1.000000000	1.000000000	1.000000000
	HDDM$_A$	205.00	0	5	19999955	40	0.888888889	1.000000000	0.942808924
	DDM$_7$	144.00	0	479	19999481	40	0.077071291	1.000000000	0.277613842
	DDM$_{129}$	447.69	1	128	19999832	39	0.233532934	0.975000000	0.477171947
	RDDM$_{30}$	250.00	0	516	19999444	40	0.071942446	1.000000000	0.268217430
	RDDM$_7$	26.25	8	3847	19996113	32	0.008249549	0.800000000	0.081226426
	RDDM$_{129}$	51.62	3	779	19999181	37	0.045343137	0.925000000	0.204793792

Table 45 – Concept drift identifications of Detectors in 2 Million instances abrupt datasets using NB (Part 2)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
RandRBF	DDM	5258.75	32	29	19999931	8	0.216216216	0.200000000	0.207948575
	EDDM	N/A	40	93	19999867	0	0.000000000	0.000000000	-0.000003050
	ADWIN	1405.00	4	2014	19997946	36	0.017560976	0.900000000	0.125709704
	ECDD	N/A	40	0	19999960	0	0.000000000	0.000000000	0.000000000
	STEPD	2081.62	3	8993	19990967	37	0.004097453	0.925000000	0.061548053
	SeqDr2	2363.64	18	104	19999856	22	0.174603175	0.550000000	0.309887630
	$HDDM_W$	1277.78	4	7129	19992831	36	0.005024424	0.900000000	0.067231026
	FTDD	1756.43	26	89	19999871	14	0.135922330	0.350000000	0.218109504
	WSTD	4651.43	26	1544	19998416	14	0.008985879	0.350000000	0.056070573
	$HDDM_A$	2311.11	4	145	19999815	36	0.198895028	0.900000000	0.423088528
	DDM_7	3113.81	19	409	19999551	21	0.048837209	0.525000000	0.160118823
	DDM_{129}	3572.07	11	238	19999722	29	0.108614232	0.725000000	0.280612949
	$RDDM_{30}$	2711.54	14	425	19999535	26	0.057649667	0.650000000	0.193573252
	$RDDM_7$	913.85	1	3597	19996363	39	0.010726073	0.975000000	0.102254305
	$RDDM_{129}$	1413.78	3	997	19998963	37	0.035783366	0.925000000	0.181927707
Sine	DDM	1493.75	8	41	19999919	32	0.438356164	0.800000000	0.592185539
	EDDM	4726.00	25	615	19999345	15	0.023809524	0.375000000	0.094484764
	ADWIN	40.75	0	64	19999896	40	0.384615385	1.000000000	0.620172681
	ECDD	88.25	0	34934	19965026	40	0.001143707	1.000000000	0.033789185
	STEPD	14.75	0	5682	19994278	40	0.006990563	1.000000000	0.083597708
	SeqDr2	200.00	0	42	19999918	40	0.487804878	1.000000000	0.698429562
	$HDDM_W$	15.00	0	270	19999690	40	0.129032258	1.000000000	0.359208179
	FTDD	18.25	0	20	19999940	40	0.666666667	1.000000000	0.816496173
	WSTD	17.75	0	81	19999879	40	0.330578512	1.000000000	0.574958410
	$HDDM_A$	227.00	0	12	19999948	40	0.769230769	1.000000000	0.877057756
	DDM_7	476.41	1	3201	19996759	39	0.012037037	0.975000000	0.108324216
	DDM_{129}	941.32	2	277	19999683	38	0.120634921	0.950000000	0.338528298
	$RDDM_{30}$	727.25	0	569	19999391	40	0.065681445	1.000000000	0.256280269
	$RDDM_7$	450.00	2	6483	19993477	38	0.005827327	0.950000000	0.074390704
	$RDDM_{129}$	168.97	1	1106	19998854	39	0.034061135	0.975000000	0.182229730
Waveform	DDM	2553.33	31	19	19999941	9	0.321428571	0.225000000	0.268925221
	EDDM	4315.00	38	214	19999746	2	0.009259259	0.050000000	0.021512064
	ADWIN	552.97	3	109	19999851	37	0.253424658	0.925000000	0.484165559
	ECDD	271.25	0	33800	19966160	40	0.001182033	1.000000000	0.034351644
	STEPD	1664.59	3	5768	19994192	37	0.006373816	0.925000000	0.076771105
	SeqDr2	240.00	10	36	19999924	30	0.454545455	0.750000000	0.583873186
	$HDDM_W$	1752.70	3	1285	19998675	37	0.027987897	0.925000000	0.160893965
	FTDD	523.13	8	46	19999914	32	0.410256410	0.800000000	0.572890796
	WSTD	360.67	10	244	19999716	30	0.109489051	0.750000000	0.286557285
	$HDDM_A$	759.70	7	42	19999918	33	0.440000000	0.825000000	0.602493807
	DDM_7	1442.07	11	2129	19997831	29	0.013438369	0.725000000	0.098696445
	DDM_{129}	2078.89	22	102	19999858	18	0.150000000	0.450000000	0.259805196
	$RDDM_{30}$	3452.80	15	283	19999677	25	0.081168831	0.625000000	0.225230775
	$RDDM_7$	1377.78	4	5801	19994159	36	0.006167552	0.900000000	0.074490454
	$RDDM_{129}$	778.52	13	940	19999020	27	0.027921406	0.675000000	0.137277814

APPENDIX B – Drift Identifications with Detectors using HT

This appendix presents detailed raw results regarding the concept drift detections of the 15 tested configurations of drift detectors using HT as base learner. Aggregated results were presented in Chapter 6, Tables 23 and 24.

Table 46 – Concept drift identifications of Detectors in 10K instances abrupt datasets using HT (Part 1)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
Agrawal$_1$	DDM	N/A	120	85	299795	0	0.000000000	0.000000000	-0.000336765
	EDDM	21.25	112	558	299322	8	0.014134276	0.066666667	0.029862097
	ADWIN	10.00	118	142	299738	2	0.013888889	0.016666667	0.014782842
	ECDD	23.83	60	483	299397	60	0.110497238	0.500000000	0.234458500
	STEPD	31.43	85	163	299717	35	0.176767677	0.291666667	0.226668519
	SeqDr2	0.00	108	149	299731	12	0.074534161	0.100000000	0.085910083
	HDDM$_W$	30.20	70	176	299704	50	0.221238938	0.416666667	0.303242291
	FTDD	36.67	114	49	299831	6	0.109090909	0.050000000	0.073605562
	WSTD	33.20	95	82	299798	25	0.233644860	0.208333333	0.220332056
	HDDM$_A$	28.00	110	107	299773	10	0.085470085	0.083333333	0.084033172
	DDM$_7$	31.43	99	750	299130	21	0.027237354	0.175000000	0.068127417
	DDM$_{129}$	30.00	114	169	299711	6	0.034285714	0.050000000	0.040941017
	RDDM$_{30}$	N/A	120	101	299779	0	0.000000000	0.000000000	-0.000367105
	RDDM$_7$	33.75	112	217	299663	8	0.035555556	0.066666667	0.048166423
	RDDM$_{129}$	36.00	115	136	299744	5	0.035460993	0.041666667	0.038021750
Agrawal$_2$	DDM	25.00	108	144	299736	12	0.076923077	0.100000000	0.087289885
	EDDM	24.44	102	240	299640	18	0.069767442	0.150000000	0.101776758
	ADWIN	17.14	113	359	299521	7	0.019125683	0.058333333	0.032729513
	ECDD	13.54	38	494	299386	82	0.142361111	0.683333333	0.311382505
	STEPD	17.22	30	402	299478	90	0.182926829	0.750000000	0.369966097
	SeqDr2	0.00	117	231	299649	3	0.012820513	0.025000000	0.017354542
	HDDM$_W$	27.47	37	59	299821	83	0.584507042	0.691666667	0.635675795
	FTDD	25.43	50	49	299831	70	0.588235294	0.583333333	0.585614126
	WSTD	26.59	35	39	299841	85	0.685483871	0.708333333	0.696691660
	HDDM$_A$	24.08	44	39	299841	76	0.660869565	0.633333333	0.646816722
	DDM$_7$	22.86	43	1072	298808	77	0.067014795	0.641666667	0.206566665
	DDM$_{129}$	23.85	68	221	299659	52	0.190476190	0.433333333	0.286881795
	RDDM$_{30}$	34.62	107	59	299821	13	0.180555556	0.108333333	0.139592563
	RDDM$_7$	26.45	58	192	299688	62	0.244094488	0.516666667	0.354766618
	RDDM$_{129}$	24.74	82	89	299791	38	0.299212598	0.316666667	0.307531044
LED	DDM	N/A	120	93	299787	0	0.000000000	0.000000000	-0.000352261
	EDDM	N/A	120	186	299694	0	0.000000000	0.000000000	-0.000498250
	ADWIN	20.00	109	645	299235	11	0.016768293	0.091666667	0.038320124
	ECDD	18.40	39	162	299718	81	0.333333333	0.675000000	0.474059255
	STEPD	24.75	61	819	299061	59	0.067198178	0.491666667	0.180985831
	SeqDr2	0.00	56	721	299159	64	0.081528662	0.533333333	0.207813781
	HDDM$_W$	19.55	32	61	299819	88	0.590604027	0.733333333	0.657959910
	FTDD	28.50	80	90	299790	40	0.307692308	0.333333333	0.319973297
	WSTD	25.00	52	242	299638	68	0.219354839	0.566666667	0.352173075
	HDDM$_A$	27.22	66	43	299837	54	0.556701031	0.450000000	0.500336524
	DDM$_7$	35.26	82	140	299740	38	0.213483146	0.316666667	0.259647553
	DDM$_{129}$	37.78	111	102	299778	9	0.081081081	0.075000000	0.077626465
	RDDM$_{30}$	N/A	120	90	299790	0	0.000000000	0.000000000	-0.000346531
	RDDM$_7$	35.00	90	77	299803	30	0.280373832	0.250000000	0.264474038
	RDDM$_{129}$	37.78	111	94	299786	9	0.087378641	0.075000000	0.080612437

Table 47 – Concept drift identifications of Detectors in 10K instances abrupt datasets using HT (Part 2)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
Mixed	DDM	33.90	2	4	299876	118	0.967213115	0.983333333	0.975229940
	EDDM	24.26	73	234	299646	47	0.167259786	0.391666667	0.255508049
	ADWIN	35.79	44	218	299662	76	0.258503401	0.633333333	0.404274692
	ECDD	10.08	2	330	299550	118	0.263392857	0.983333333	0.508632058
	STEPD	10.00	0	29	299851	120	0.805369128	1.000000000	0.897380212
	SeqDr2	N/A	120	263	299617	0	0.000000000	0.000000000	-0.000592549
	$HDDM_W$	16.33	0	0	299880	120	1.000000000	1.000000000	1.000000000
	FTDD	19.08	0	7	299873	120	0.944881890	1.000000000	0.972039008
	WSTD	18.58	0	0	299880	120	1.000000000	1.000000000	1.000000000
	$HDDM_A$	14.83	0	0	299880	120	1.000000000	1.000000000	1.000000000
	DDM_7	18.51	6	209	299671	114	0.352941176	0.950000000	0.578817009
	DDM_{129}	21.17	0	5	299875	120	0.960000000	1.000000000	0.979787729
	$RDDM_{30}$	35.25	0	0	299880	120	1.000000000	1.000000000	1.000000000
	$RDDM_7$	19.15	14	39	299841	106	0.731034483	0.883333333	0.803499109
	$RDDM_{129}$	21.50	0	2	299878	120	0.983606557	1.000000000	0.991766100
RandRBF	DDM	N/A	120	58	299822	0	0.000000000	0.000000000	-0.000278171
	EDDM	20.00	117	200	299680	3	0.014778325	0.025000000	0.018711110
	ADWIN	30.00	118	195	299685	2	0.010152284	0.016666667	0.012501967
	ECDD	N/A	120	0	299880	0	0.000000000	0.000000000	0.000000000
	STEPD	30.00	118	153	299727	2	0.012903226	0.016666667	0.014216621
	SeqDr2	0.00	118	42	299838	2	0.045454545	0.016666667	0.027289341
	$HDDM_W$	28.00	115	130	299750	5	0.037037037	0.041666667	0.038875968
	FTDD	N/A	120	32	299848	0	0.000000000	0.000000000	-0.000206611
	WSTD	30.00	119	32	299848	1	0.030303030	0.008333333	0.015685281
	$HDDM_A$	N/A	120	56	299824	0	0.000000000	0.000000000	-0.000273332
	DDM_7	20.00	116	202	299678	4	0.019417476	0.033333333	0.024930552
	DDM_{129}	30.00	118	84	299796	2	0.023255814	0.016666667	0.019355502
	$RDDM_{30}$	N/A	120	72	299808	0	0.000000000	0.000000000	-0.000309938
	$RDDM_7$	28.00	115	148	299732	5	0.032679739	0.041666667	0.036465549
	$RDDM_{129}$	30.00	118	95	299785	2	0.020618557	0.016666667	0.018184547
Sine	DDM	30.75	40	121	299759	80	0.398009950	0.666666667	0.514869379
	EDDM	21.38	55	495	299385	65	0.116071429	0.541666667	0.250162430
	ADWIN	38.75	56	190	299690	64	0.251968504	0.533333333	0.366229486
	ECDD	9.74	4	445	299435	116	0.206773619	0.966666667	0.446722995
	STEPD	12.00	0	94	299786	120	0.560747664	1.000000000	0.748713491
	SeqDr2	N/A	120	246	299634	0	0.000000000	0.000000000	-0.000573062
	$HDDM_W$	17.00	0	0	299880	120	1.000000000	1.000000000	1.000000000
	FTDD	19.67	0	4	299876	120	0.967741935	1.000000000	0.983732193
	WSTD	18.75	0	0	299880	120	1.000000000	1.000000000	1.000000000
	$HDDM_A$	16.81	4	5	299875	116	0.958677686	0.966666667	0.962648890
	DDM_7	15.64	3	667	299213	117	0.149234694	0.975000000	0.381001499
	DDM_{129}	23.57	8	126	299754	112	0.470588235	0.933333333	0.662565516
	$RDDM_{30}$	35.12	36	39	299841	84	0.682926829	0.700000000	0.691285719
	$RDDM_7$	18.51	19	174	299706	101	0.367272727	0.841666667	0.555747057
	$RDDM_{129}$	23.62	4	75	299805	116	0.607329843	0.966666667	0.766107517
Waveform	DDM	N/A	120	45	299835	0	0.000000000	0.000000000	-0.000245016
	EDDM	15.00	116	335	299545	4	0.011799410	0.033333333	0.019174498
	ADWIN	N/A	120	90	299790	0	0.000000000	0.000000000	-0.000346531
	ECDD	18.18	87	495	299385	33	0.062500000	0.275000000	0.130402924
	STEPD	25.00	86	109	299771	34	0.237762238	0.283333333	0.259226521
	SeqDr2	N/A	120	74	299806	0	0.000000000	0.000000000	-0.000314214
	$HDDM_W$	23.60	95	36	299844	25	0.409836066	0.208333333	0.292005764
	FTDD	31.82	109	24	299856	11	0.314285714	0.091666667	0.169561465
	WSTD	27.50	104	29	299851	16	0.355555556	0.133333333	0.217547300
	$HDDM_A$	32.86	113	38	299842	7	0.155555556	0.058333333	0.095039122
	DDM_7	18.80	95	352	299528	25	0.066312997	0.208333333	0.116925987
	DDM_{129}	30.00	115	101	299779	5	0.047169811	0.041666667	0.043973552
	$RDDM_{30}$	N/A	120	37	299843	0	0.000000000	0.000000000	-0.000222169
	$RDDM_7$	28.57	113	129	299751	7	0.051470588	0.058333333	0.054392000
	$RDDM_{129}$	28.33	114	56	299824	6	0.096774194	0.050000000	0.069294336

Table 48 – Concept drift identifications of Detectors in 20K instances abrupt datasets using HT (Part 1)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
Agrawal$_1$	DDM	43.33	117	99	599781	3	0.029411765	0.025000000	0.026936900
	EDDM	56.00	115	664	599216	5	0.007473842	0.041666667	0.017185887
	ADWIN	45.00	116	275	599605	4	0.014336918	0.033333333	0.021563072
	ECDD	32.53	41	970	598910	79	0.075309819	0.658333333	0.222288629
	STEPD	44.00	60	276	599604	60	0.178571429	0.500000000	0.298585956
	SeqDr2	0.00	116	224	599656	4	0.017543860	0.033333333	0.023913796
	HDDM$_W$	37.53	31	261	599619	89	0.254285714	0.741666667	0.434103999
	FTDD	50.00	102	57	599823	18	0.240000000	0.150000000	0.189609357
	WSTD	48.04	74	125	599755	46	0.269005848	0.383333333	0.320960416
	HDDM$_A$	40.00	55	69	599811	65	0.485074627	0.541666667	0.512487374
	DDM$_7$	54.77	76	858	599022	44	0.048780488	0.366666667	0.133304448
	DDM$_{129}$	59.09	98	179	599701	22	0.109452736	0.183333333	0.141434682
	RDDM$_{30}$	30.00	119	122	599758	1	0.008130081	0.008333333	0.008030222
	RDDM$_7$	56.67	87	282	599598	33	0.104761905	0.275000000	0.169471083
	RDDM$_{129}$	61.58	101	147	599733	19	0.114457831	0.158333333	0.134416603
Agrawal$_2$	DDM	34.44	93	253	599627	27	0.096428571	0.225000000	0.147040586
	EDDM	28.18	98	259	599621	22	0.078291815	0.183333333	0.119539988
	ADWIN	56.67	39	344	599536	81	0.190588235	0.675000000	0.358460455
	ECDD	15.40	33	1018	598862	87	0.078733032	0.725000000	0.238553940
	STEPD	17.89	30	541	599339	90	0.142630745	0.750000000	0.326813300
	SeqDr2	N/A	120	233	599647	0	0.000000000	0.000000000	-0.000278769
	HDDM$_W$	33.89	25	78	599802	95	0.549132948	0.791666667	0.659261601
	FTDD	30.11	31	37	599843	89	0.706349206	0.741666667	0.723735981
	WSTD	28.28	27	37	599843	93	0.715384615	0.775000000	0.744542862
	HDDM$_A$	31.74	34	21	599859	86	0.803738318	0.716666667	0.758909552
	DDM$_7$	33.17	38	1811	598069	82	0.043317485	0.683333333	0.171540916
	DDM$_{129}$	41.25	56	270	599610	64	0.191616766	0.533333333	0.319467683
	RDDM$_{30}$	59.35	89	63	599817	31	0.329787234	0.258333333	0.291756904
	RDDM$_7$	43.15	47	254	599626	73	0.223241590	0.608333333	0.368324762
	RDDM$_{129}$	47.38	59	53	599827	61	0.535087719	0.508333333	0.521445742
LED	DDM	N/A	120	118	599762	0	0.000000000	0.000000000	-0.000198366
	EDDM	80.00	119	203	599677	1	0.004901961	0.008333333	0.006132263
	ADWIN	43.41	79	1314	598566	41	0.030258303	0.341666667	0.101129499
	ECDD	22.74	47	414	599466	73	0.149897331	0.608333333	0.301722481
	STEPD	28.05	38	1134	598746	82	0.067434211	0.683333333	0.214264607
	SeqDr2	0.00	67	1282	598598	53	0.039700375	0.441666667	0.131910191
	HDDM$_W$	26.14	19	123	599757	101	0.450892857	0.841666667	0.615940241
	FTDD	34.41	61	81	599799	59	0.421428571	0.491666667	0.455077458
	WSTD	30.00	31	239	599641	89	0.271341463	0.741666667	0.448440066
	HDDM$_A$	46.38	51	41	599839	69	0.627272727	0.575000000	0.600491522
	DDM$_7$	57.85	55	166	599714	65	0.281385281	0.541666667	0.390242893
	DDM$_{129}$	63.68	82	90	599790	38	0.296875000	0.316666667	0.306467959
	RDDM$_{30}$	N/A	120	118	599762	0	0.000000000	0.000000000	-0.000198366
	RDDM$_7$	57.05	76	57	599823	44	0.435643564	0.366666667	0.399559932
	RDDM$_{129}$	62.12	87	85	599795	33	0.279661017	0.275000000	0.277177363
Mixed	DDM	33.48	5	34	599846	115	0.771812081	0.958333333	0.860000879
	EDDM	44.06	24	261	599619	96	0.268907563	0.800000000	0.463656177
	ADWIN	40.00	2	169	599711	118	0.411149826	0.983333333	0.635750124
	ECDD	9.83	2	739	599141	118	0.137689615	0.983333333	0.367725289
	STEPD	11.25	0	187	599693	120	0.390879479	1.000000000	0.625106095
	SeqDr2	0.00	115	261	599619	5	0.018796992	0.041666667	0.027696994
	HDDM$_W$	13.92	0	3	599877	120	0.975609756	1.000000000	0.987727127
	FTDD	17.50	0	11	599869	120	0.916030534	1.000000000	0.957086066
	WSTD	17.25	0	12	599868	120	0.909090909	1.000000000	0.953453053
	HDDM$_A$	38.33	0	5	599875	120	0.960000000	1.000000000	0.979791814
	DDM$_7$	14.05	4	446	599434	116	0.206405694	0.966666667	0.446503751
	DDM$_{129}$	20.79	6	102	599778	114	0.527777778	0.950000000	0.708018112
	RDDM$_{30}$	29.49	42	25	599855	78	0.757281553	0.650000000	0.701538271
	RDDM$_7$	14.73	29	149	599731	91	0.379166667	0.758333333	0.536100633
	RDDM$_{129}$	15.05	19	93	599787	101	0.520618557	0.841666667	0.661876058

Table 49 – Concept drift identifications of Detectors in 20K instances abrupt datasets using HT (Part 2)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
RandRBF	DDM	N/A	120	59	599821	0	0.000000000	0.000000000	-0.000140259
	EDDM	35.00	118	269	599611	2	0.007380074	0.016666667	0.010793554
	ADWIN	40.00	118	283	599597	2	0.007017544	0.016666667	0.010510088
	ECDD	N/A	120	0	599880	0	0.000000000	0.000000000	0.000000000
	STEPD	47.50	116	279	599601	4	0.014134276	0.033333333	0.021405869
	SeqDr2	N/A	120	42	599838	0	0.000000000	0.000000000	-0.000118338
	$HDDM_W$	50.91	98	223	599657	22	0.089795918	0.183333333	0.128059784
	FTDD	50.00	118	34	599846	2	0.055555556	0.016666667	0.030323429
	WSTD	30.00	119	50	599830	1	0.019607843	0.008333333	0.012654169
	$HDDM_A$	N/A	120	69	599811	0	0.000000000	0.000000000	-0.000151681
	DDM_7	30.00	117	272	599608	3	0.010909091	0.025000000	0.016217030
	DDM_{129}	N/A	120	118	599762	0	0.000000000	0.000000000	-0.000198366
	$RDDM_{30}$	70.00	116	87	599793	4	0.043956044	0.033333333	0.038110487
	$RDDM_7$	56.67	117	235	599645	3	0.012605042	0.025000000	0.017475342
	$RDDM_{129}$	0.00	118	117	599763	2	0.016806723	0.016666667	0.016540678
Sine	DDM	48.42	0	86	599794	120	0.582524272	1.000000000	0.763178066
	EDDM	31.77	58	696	599184	62	0.081794195	0.516666667	0.205220707
	ADWIN	40.25	1	200	599680	119	0.373040752	0.991666667	0.608116810
	ECDD	10.25	1	966	598914	119	0.109677419	0.991666667	0.329522642
	STEPD	13.28	1	184	599696	119	0.392739274	0.991666667	0.623974622
	SeqDr2	N/A	120	244	599636	0	0.000000000	0.000000000	-0.000285277
	$HDDM_W$	16.83	0	0	599880	120	1.000000000	1.000000000	1.000000000
	FTDD	18.25	0	5	599875	120	0.960000000	1.000000000	0.979791814
	WSTD	18.25	0	0	599880	120	1.000000000	1.000000000	1.000000000
	$HDDM_A$	18.25	0	5	599875	120	0.960000000	1.000000000	0.979791814
	DDM_7	20.93	2	902	598978	118	0.115686275	0.983333333	0.337017717
	DDM_{129}	29.23	3	212	599668	117	0.355623100	0.975000000	0.588729113
	$RDDM_{30}$	51.58	0	2	599878	120	0.983606557	1.000000000	0.991767754
	$RDDM_7$	23.02	14	224	599656	106	0.321212121	0.883333333	0.532538090
	$RDDM_{129}$	30.33	0	82	599798	120	0.594059406	1.000000000	0.770699813
Waveform	DDM	N/A	120	59	599821	0	0.000000000	0.000000000	-0.000140259
	EDDM	43.75	112	455	599425	8	0.017278618	0.066666667	0.033563223
	ADWIN	70.00	115	132	599748	5	0.036496350	0.041666667	0.038790523
	ECDD	25.22	74	1084	598796	46	0.040707965	0.383333333	0.124434785
	STEPD	38.50	60	179	599701	60	0.251046025	0.500000000	0.354115959
	SeqDr2	N/A	120	114	599766	0	0.000000000	0.000000000	-0.000194974
	$HDDM_W$	43.45	65	45	599835	55	0.550000000	0.458333333	0.501988468
	FTDD	45.26	101	35	599845	19	0.351851852	0.158333333	0.235929444
	WSTD	42.81	88	43	599837	32	0.426666667	0.266666667	0.337206299
	$HDDM_A$	54.29	99	51	599829	21	0.291666667	0.175000000	0.225805238
	DDM_7	52.82	81	543	599337	39	0.067010309	0.325000000	0.147220579
	DDM_{129}	52.50	100	144	599736	20	0.121951220	0.166666667	0.142366372
	$RDDM_{30}$	N/A	120	64	599816	0	0.000000000	0.000000000	-0.000146082
	$RDDM_7$	54.21	101	168	599712	19	0.101604278	0.158333333	0.126618621
	$RDDM_{129}$	61.82	109	84	599796	11	0.115789474	0.091666667	0.102864918

Table 50 – Concept drift identifications of Detectors in 50K instances abrupt datasets using HT (Part 1)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
Agrawal$_1$	DDM	150.43	97	91	1499789	23	0.201754386	0.191666667	0.196583210
	EDDM	107.50	116	802	1499078	4	0.004962779	0.033333333	0.012658378
	ADWIN	134.84	56	462	1499418	64	0.121673004	0.533333333	0.254626950
	ECDD	48.02	29	2429	1497451	91	0.036111111	0.758333333	0.165260776
	STEPD	63.37	31	574	1499306	89	0.134238311	0.741666667	0.315425714
	SeqDr2	186.52	31	333	1499547	89	0.210900474	0.741666667	0.395418386
	HDDM$_W$	48.21	8	565	1499315	112	0.165435746	0.933333333	0.392860534
	FTDD	79.18	71	95	1499785	49	0.340277778	0.408333333	0.372700791
	WSTD	56.63	22	179	1499701	98	0.353790614	0.816666667	0.537470744
	HDDM$_A$	78.33	18	46	1499834	102	0.689189189	0.850000000	0.765362315
	DDM$_7$	99.38	23	1353	1498527	97	0.066896552	0.808333333	0.232383249
	DDM$_{129}$	121.74	51	184	1499696	69	0.272727273	0.575000000	0.395935822
	RDDM$_{30}$	158.46	94	111	1499769	26	0.189781022	0.216666667	0.202710636
	RDDM$_7$	105.06	41	306	1499574	79	0.205194805	0.658333333	0.367459826
	RDDM$_{129}$	128.47	48	114	1499766	72	0.387096774	0.600000000	0.481881150
Agrawal$_2$	DDM	111.59	57	419	1499461	63	0.130705394	0.525000000	0.261847041
	EDDM	37.78	111	234	1499646	9	0.037037037	0.075000000	0.052597150
	ADWIN	60.55	29	421	1499459	91	0.177734375	0.758333333	0.367038625
	ECDD	24.00	25	2604	1497276	95	0.035198222	0.791666667	0.166706210
	STEPD	27.98	21	1075	1498805	99	0.084327087	0.825000000	0.263624465
	SeqDr2	200.00	28	152	1499728	92	0.377049180	0.766666667	0.537604423
	HDDM$_W$	38.74	17	182	1499698	103	0.361403509	0.858333333	0.556912108
	FTDD	32.11	30	37	1499843	90	0.708661417	0.750000000	0.729015487
	WSTD	32.29	24	59	1499821	96	0.619354839	0.800000000	0.703879753
	HDDM$_A$	40.64	26	27	1499853	94	0.776859504	0.783333333	0.780072036
	DDM$_7$	58.30	20	3696	1496184	100	0.026343519	0.833333333	0.147908455
	DDM$_{129}$	78.94	26	517	1499363	94	0.153846154	0.783333333	0.347053617
	RDDM$_{30}$	120.59	52	61	1499819	68	0.527131783	0.566666667	0.546504279
	RDDM$_7$	73.90	38	604	1499276	82	0.119533528	0.683333333	0.285684790
	RDDM$_{129}$	80.12	34	77	1499803	86	0.527607362	0.716666667	0.614878263
LED	DDM	147.58	87	93	1499787	33	0.261904762	0.275000000	0.268312546
	EDDM	N/A	120	226	1499654	0	0.000000000	0.000000000	-0.000109800
	ADWIN	75.33	60	3179	1496701	60	0.018524236	0.500000000	0.095931733
	ECDD	26.97	31	1074	1498806	89	0.076526225	0.741666667	0.238089959
	STEPD	48.84	25	2073	1497807	95	0.043819188	0.791666667	0.186054931
	SeqDr2	158.33	24	2254	1497626	96	0.040851064	0.800000000	0.180573156
	HDDM$_W$	33.94	21	359	1499521	99	0.216157205	0.825000000	0.422216066
	FTDD	55.70	41	60	1499820	79	0.568345324	0.658333333	0.611653448
	WSTD	42.02	21	320	1499560	99	0.236276850	0.825000000	0.441436792
	HDDM$_A$	87.77	26	32	1499848	94	0.746031746	0.783333333	0.764435765
	DDM$_7$	104.46	28	168	1499712	92	0.353846154	0.766666667	0.520795647
	DDM$_{129}$	126.42	39	64	1499816	81	0.558620690	0.675000000	0.614025715
	RDDM$_{30}$	147.67	90	96	1499784	30	0.238095238	0.250000000	0.243913044
	RDDM$_7$	96.94	58	116	1499764	62	0.348314607	0.516666667	0.424164627
	RDDM$_{129}$	133.04	41	46	1499834	79	0.632000000	0.658333333	0.645003325
Mixed	DDM	65.22	5	72	1499808	115	0.614973262	0.958333333	0.767669630
	EDDM	103.64	65	517	1499363	55	0.096153846	0.458333333	0.209803516
	ADWIN	33.50	0	298	1499582	120	0.287081340	1.000000000	0.535746490
	ECDD	10.00	2	1817	1498063	118	0.060981912	0.983333333	0.244725071
	STEPD	10.42	0	466	1499414	120	0.204778157	1.000000000	0.452453903
	SeqDr2	200.00	0	162	1499718	120	0.425531915	1.000000000	0.652292844
	HDDM$_W$	14.92	0	3	1499877	120	0.975609756	1.000000000	0.987728609
	FTDD	18.92	0	28	1499852	120	0.810810811	1.000000000	0.900441933
	WSTD	15.92	0	26	1499854	120	0.821917808	1.000000000	0.906588970
	HDDM$_A$	16.33	0	6	1499874	120	0.952380952	1.000000000	0.975898121
	DDM$_7$	20.68	3	1060	1498820	117	0.099405268	0.975000000	0.311204007
	DDM$_{129}$	32.69	1	282	1499598	119	0.296758105	0.991666667	0.542428488
	RDDM$_{30}$	62.77	1	31	1499849	119	0.793333333	0.991666667	0.886964015
	RDDM$_7$	26.80	23	291	1499589	97	0.250000000	0.808333333	0.449469059
	RDDM$_{129}$	34.33	0	138	1499742	120	0.465116279	1.000000000	0.681962964

Table 51 – Concept drift identifications of Detectors in 50K instances abrupt datasets using HT (Part 2)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
RandRBF	DDM	N/A	120	76	1499804	0	0.000000000	0.000000000	-0.000063670
	EDDM	80.00	118	278	1499602	2	0.007142857	0.016666667	0.010790131
	ADWIN	150.00	119	410	1499470	1	0.002433090	0.008333333	0.004355577
	ECDD	N/A	120	0	1499880	0	0.000000000	0.000000000	0.000000000
	STEPD	77.27	109	669	1499211	11	0.016176471	0.091666667	0.038327486
	SeqDr2	200.00	105	52	1499828	15	0.223880597	0.125000000	0.167238048
	$HDDM_W$	94.17	84	566	1499314	36	0.059800664	0.300000000	0.133794047
	FTDD	73.33	117	53	1499827	3	0.053571429	0.025000000	0.036543746
	WSTD	70.00	118	126	1499754	2	0.015625000	0.016666667	0.016056134
	$HDDM_A$	120.00	114	75	1499805	6	0.074074074	0.050000000	0.060796409
	DDM_7	89.09	109	421	1499459	11	0.025462963	0.091666667	0.048169650
	DDM_{129}	134.44	111	159	1499721	9	0.053571429	0.075000000	0.063297988
	$RDDM_{30}$	170.00	119	121	1499759	1	0.008196721	0.008333333	0.008184741
	$RDDM_7$	130.71	106	453	1499427	14	0.029978587	0.116666667	0.058993405
	$RDDM_{129}$	140.00	114	163	1499717	6	0.035502959	0.050000000	0.042041616
Sine	DDM	69.67	0	131	1499749	120	0.478087649	1.000000000	0.691408630
	EDDM	80.97	58	852	1499028	62	0.067833698	0.516666667	0.187053228
	ADWIN	40.92	0	454	1499426	120	0.209059233	1.000000000	0.457160752
	ECDD	10.18	8	2448	1497432	112	0.043750000	0.933333333	0.201883506
	STEPD	11.93	1	386	1499494	119	0.235643564	0.991666667	0.483341042
	SeqDr2	200.00	0	133	1499747	120	0.474308300	1.000000000	0.688669908
	$HDDM_W$	16.92	0	1	1499879	120	0.991735537	1.000000000	0.995858863
	FTDD	17.75	0	7	1499873	120	0.944881890	1.000000000	0.972048085
	WSTD	16.75	0	6	1499874	120	0.952380952	1.000000000	0.975898121
	$HDDM_A$	18.33	0	5	1499875	120	0.960000000	1.000000000	0.979794264
	DDM_7	32.31	3	1454	1498426	117	0.074474857	0.975000000	0.269330352
	DDM_{129}	42.67	0	273	1499607	120	0.305343511	1.000000000	0.552528673
	$RDDM_{30}$	70.83	0	2	1499878	120	0.983606557	1.000000000	0.991768746
	$RDDM_7$	32.31	3	327	1499553	117	0.263513514	0.975000000	0.506819766
	$RDDM_{129}$	43.92	0	83	1499797	120	0.591133005	1.000000000	0.768830471
Waveform	DDM	100.71	106	53	1499827	14	0.208955224	0.116666667	0.156084860
	EDDM	88.33	114	488	1499392	6	0.012145749	0.050000000	0.024485898
	ADWIN	108.00	95	168	1499712	25	0.129533679	0.208333333	0.164190393
	ECDD	61.13	58	2567	1497313	62	0.023583111	0.516666667	0.110110396
	STEPD	49.49	61	459	1499421	59	0.113899614	0.491666667	0.236528642
	SeqDr2	200.00	86	47	1499833	34	0.419753086	0.283333333	0.344819727
	$HDDM_W$	50.19	68	168	1499712	52	0.236363636	0.433333333	0.319965819
	FTDD	56.00	90	35	1499845	30	0.461538462	0.250000000	0.339645177
	WSTD	61.67	84	82	1499798	36	0.305084746	0.300000000	0.302476356
	$HDDM_A$	101.48	93	63	1499817	27	0.300000000	0.225000000	0.259756522
	DDM_7	68.04	69	941	1498939	51	0.051411290	0.425000000	0.147641491
	DDM_{129}	89.14	85	209	1499671	35	0.143442623	0.291666667	0.204452736
	$RDDM_{30}$	106.43	106	96	1499784	14	0.127272727	0.116666667	0.121787102
	$RDDM_7$	76.92	81	480	1499400	39	0.075144509	0.325000000	0.156142174
	$RDDM_{129}$	104.38	88	133	1499747	32	0.193939394	0.266666667	0.227341887

Table 52 – Concept drift identifications of Detectors in 100K instances abrupt datasets using HT (Part 1)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
Agrawal$_1$	DDM	230.27	83	84	2999796	37	0.305785124	0.308333333	0.307028751
	EDDM	260.00	116	828	2999052	4	0.004807692	0.033333333	0.012555909
	ADWIN	162.95	25	838	2999042	95	0.101822079	0.791666667	0.283855783
	ECDD	53.74	21	4745	2995135	99	0.020437655	0.825000000	0.129703374
	STEPD	77.05	25	1114	2998766	95	0.078577337	0.791666667	0.249341697
	SeqDr2	195.88	23	607	2999273	97	0.137784091	0.808333333	0.333678583
	HDDM$_W$	46.29	4	1052	2998828	116	0.099315068	0.966666667	0.309787749
	FTDD	98.78	38	191	2999689	82	0.300366300	0.683333333	0.453014929
	WSTD	55.91	10	279	2999601	110	0.282776350	0.916666667	0.509099498
	HDDM$_A$	101.04	5	50	2999830	115	0.696969697	0.958333333	0.817261328
	DDM$_7$	157.89	6	1725	2998155	114	0.061990212	0.950000000	0.242596693
	DDM$_{129}$	205.36	23	197	2999683	97	0.329931973	0.808333333	0.516398245
	RDDM$_{30}$	238.37	71	96	2999784	49	0.337931034	0.408333333	0.371440477
	RDDM$_7$	168.81	11	411	2999469	109	0.209615385	0.908333333	0.436312493
	RDDM$_{129}$	204.95	21	108	2999772	99	0.478260870	0.825000000	0.628125962
Agrawal$_2$	DDM	144.57	50	604	2999276	70	0.103857567	0.583333333	0.246075088
	EDDM	45.00	116	231	2999649	4	0.017021277	0.033333333	0.023765083
	ADWIN	80.71	22	670	2999210	98	0.127604167	0.816666667	0.322762422
	ECDD	28.64	17	5325	2994555	103	0.018975682	0.858333333	0.127471229
	STEPD	42.79	16	1805	2998075	104	0.054478785	0.866666667	0.217203926
	SeqDr2	206.19	23	157	2999723	97	0.381889764	0.808333333	0.555579015
	HDDM$_W$	59.74	6	394	2999486	114	0.224409449	0.950000000	0.461689942
	FTDD	29.35	27	40	2999840	93	0.699248120	0.775000000	0.736139249
	WSTD	40.99	19	90	2999790	101	0.528795812	0.841666667	0.667119639
	HDDM$_A$	67.80	20	33	2999847	100	0.751879699	0.833333333	0.791550750
	DDM$_7$	93.96	14	6601	2993279	106	0.015804383	0.883333333	0.117990005
	DDM$_{129}$	116.17	26	755	2999125	94	0.110718492	0.783333333	0.294439861
	RDDM$_{30}$	161.50	40	66	2999814	80	0.547945205	0.666666667	0.604380558
	RDDM$_7$	112.57	19	876	2999004	101	0.103377687	0.841666667	0.294913606
	RDDM$_{129}$	124.69	24	91	2999789	96	0.513368984	0.800000000	0.640837900
LED	DDM	249.79	73	72	2999808	47	0.394957983	0.391666667	0.393284715
	EDDM	N/A	120	219	2999661	0	0.000000000	0.000000000	-0.000054040
	ADWIN	121.04	43	6241	2993639	77	0.012187401	0.641666667	0.088236656
	ECDD	43.56	33	2240	2997640	87	0.037387194	0.725000000	0.164529103
	STEPD	61.05	25	3509	2996371	95	0.026359600	0.791666667	0.144328058
	SeqDr2	196.40	9	3055	2996825	111	0.035060013	0.925000000	0.179977867
	HDDM$_W$	41.65	17	762	2999118	103	0.119075145	0.858333333	0.319642074
	FTDD	68.00	25	100	2999780	95	0.487179487	0.791666667	0.621016041
	WSTD	46.92	16	459	2999421	104	0.184724689	0.866666667	0.400077298
	HDDM$_A$	115.28	12	35	2999845	108	0.755244755	0.900000000	0.824443975
	DDM$_7$	158.85	16	168	2999712	104	0.382352941	0.866666667	0.575627062
	DDM$_{129}$	190.98	28	60	2999820	92	0.605263158	0.766666667	0.681187071
	RDDM$_{30}$	268.08	68	76	2999804	52	0.406250000	0.433333333	0.419549225
	RDDM$_7$	125.26	44	278	2999602	76	0.214689266	0.633333333	0.368701348
	RDDM$_{129}$	197.63	27	31	2999849	93	0.750000000	0.775000000	0.762387877
Mixed	DDM	82.88	2	86	2999794	118	0.578431373	0.983333333	0.754170811
	EDDM	276.86	69	627	2999253	51	0.075221239	0.425000000	0.178727536
	ADWIN	40.00	0	548	2999332	120	0.179640719	1.000000000	0.423801726
	ECDD	9.75	1	3822	2996058	119	0.030195382	0.991666667	0.172930485
	STEPD	12.33	0	1029	2998851	120	0.104438642	1.000000000	0.323114250
	SeqDr2	200.00	0	156	2999724	120	0.434782609	1.000000000	0.659363329
	HDDM$_W$	14.67	0	3	2999877	120	0.975609756	1.000000000	0.987729103
	FTDD	17.58	0	12	2999868	120	0.909090909	1.000000000	0.953460682
	WSTD	17.33	0	21	2999859	120	0.851063830	1.000000000	0.922527979
	HDDM$_A$	21.67	0	7	2999873	120	0.944881890	1.000000000	0.972049219
	DDM$_7$	27.95	3	1923	2997957	117	0.057352941	0.975000000	0.236392424
	DDM$_{129}$	43.95	1	479	2999401	119	0.198996656	0.991666667	0.444191676
	RDDM$_{30}$	86.67	0	24	2999856	120	0.833333333	1.000000000	0.912867278
	RDDM$_7$	28.69	13	657	2999223	107	0.140052356	0.891666667	0.353334800
	RDDM$_{129}$	47.75	0	221	2999659	120	0.351906158	1.000000000	0.593194937

Table 53 – Concept drift identifications of Detectors in 100K instances abrupt datasets using HT (Part 2)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
RandRBF	DDM	N/A	120	74	2999806	0	0.000000000	0.000000000	-0.000031412
	EDDM	300.00	119	238	2999642	1	0.004184100	0.008333333	0.005848771
	ADWIN	300.83	108	522	2999358	12	0.022471910	0.100000000	0.047325325
	ECDD	N/A	120	0	2999880	0	0.000000000	0.000000000	0.000000000
	STEPD	185.50	100	1361	2998519	20	0.014482259	0.166666667	0.049006086
	SeqDr2	226.67	105	63	2999817	15	0.192307692	0.125000000	0.155016285
	HDDM_W	130.42	72	1116	2998764	48	0.041237113	0.400000000	0.128335146
	FTDD	163.33	111	58	2999822	9	0.134328358	0.075000000	0.100345680
	WSTD	162.00	115	241	2999639	5	0.020325203	0.041666667	0.029045763
	HDDM_A	216.00	105	79	2999801	15	0.159574468	0.125000000	0.141202805
	DDM_7	245.56	102	548	2999332	18	0.031802120	0.150000000	0.068988505
	DDM_{129}	264.17	108	173	2999707	12	0.064864865	0.100000000	0.080493153
	RDDM_{30}	300.00	119	143	2999737	1	0.006944444	0.008333333	0.007563773
	RDDM_7	229.23	94	701	2999179	26	0.035763411	0.216666667	0.087940883
	RDDM_{129}	275.00	110	207	2999673	10	0.046082949	0.083333333	0.061919405
Sine	DDM	91.42	0	103	2999777	120	0.538116592	1.000000000	0.733551713
	EDDM	140.66	59	965	2998915	61	0.059454191	0.508333333	0.173762561
	ADWIN	39.92	0	952	2998928	120	0.111940299	1.000000000	0.334521710
	ECDD	16.05	6	5032	2994848	114	0.022153129	0.950000000	0.144935891
	STEPD	11.60	1	686	2999194	119	0.147826087	0.991666667	0.382831645
	SeqDr2	200.00	0	133	2999747	120	0.474308300	1.000000000	0.688685176
	HDDM_W	16.42	0	1	2999879	120	0.991735537	1.000000000	0.995859029
	FTDD	16.92	0	7	2999873	120	0.944881890	1.000000000	0.972049219
	WSTD	16.42	0	7	2999873	120	0.944881890	1.000000000	0.972049219
	HDDM_A	23.17	0	7	2999873	120	0.944881890	1.000000000	0.972049219
	DDM_7	41.48	5	1546	2998334	115	0.069235400	0.958333333	0.257513716
	DDM_{129}	55.58	0	310	2999570	120	0.279069767	1.000000000	0.528243248
	RDDM_{30}	92.25	0	3	2999877	120	0.975609756	1.000000000	0.987729103
	RDDM_7	44.17	5	291	2999589	115	0.283251232	0.958333333	0.520979868
	RDDM_{129}	56.25	0	72	2999808	120	0.625000000	1.000000000	0.790559928
Waveform	DDM	207.50	112	69	2999811	8	0.103896104	0.066666667	0.083195728
	EDDM	112.50	112	485	2999395	8	0.016227181	0.066666667	0.032813188
	ADWIN	137.41	66	237	2999643	54	0.185567010	0.450000000	0.288930087
	ECDD	128.44	43	5069	2994811	77	0.014963078	0.641666667	0.097810204
	STEPD	58.69	59	938	2998942	61	0.061061061	0.508333333	0.176097376
	SeqDr2	212.90	58	81	2999799	62	0.433566434	0.516666667	0.473273313
	HDDM_W	58.39	64	347	2999533	56	0.138957816	0.466666667	0.254599594
	FTDD	79.75	80	47	2999833	40	0.459770115	0.333333333	0.391459593
	WSTD	88.60	63	136	2999744	57	0.295336788	0.475000000	0.374515167
	HDDM_A	182.12	87	82	2999798	33	0.286956522	0.275000000	0.280886499
	DDM_7	130.63	57	1900	2997980	63	0.032093734	0.525000000	0.129687756
	DDM_{129}	162.86	85	385	2999495	35	0.083333333	0.291666667	0.155841584
	RDDM_{30}	213.00	110	199	2999681	10	0.047846890	0.083333333	0.063095273
	RDDM_7	99.09	76	984	2998896	44	0.042801556	0.366666667	0.125182190
	RDDM_{129}	189.53	77	282	2999598	43	0.132307692	0.358333333	0.217689281

Table 54 – Concept drift identifications of Detectors in 500K instances abrupt datasets using HT (Part 1)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
Agrawal$_1$	DDM	593.46	14	25	4999935	26	0.509803922	0.650000000	0.575645881
	EDDM	1775.00	36	298	4999662	4	0.013245033	0.100000000	0.036372988
	ADWIN	249.46	3	1440	4998520	37	0.025050779	0.925000000	0.152197899
	ECDD	201.79	1	7880	4992080	39	0.004924864	0.975000000	0.069237172
	STEPD	175.14	3	1722	4998238	37	0.021034679	0.925000000	0.139460670
	SeqDr2	182.86	5	896	4999064	35	0.037593985	0.875000000	0.181348077
	HDDM$_W$	61.03	1	1719	4998241	39	0.022184300	0.975000000	0.147043772
	FTDD	100.77	1	156	4999804	39	0.200000000	0.975000000	0.441580757
	WSTD	56.92	1	248	4999712	39	0.135888502	0.975000000	0.363984002
	HDDM$_A$	176.25	0	45	4999915	40	0.470588235	1.000000000	0.685991254
	DDM$_7$	300.63	8	902	4999058	32	0.034261242	0.800000000	0.165534084
	DDM$_{129}$	447.95	1	88	4999872	39	0.307086614	0.975000000	0.547178078
	RDDM$_{30}$	352.58	9	69	4999891	31	0.310000000	0.775000000	0.490147250
	RDDM$_7$	144.86	3	663	4999297	37	0.052857143	0.925000000	0.221100188
	RDDM$_{129}$	194.10	1	129	4999831	39	0.232142857	0.975000000	0.475744786
Agrawal$_2$	DDM	335.36	12	208	4999752	28	0.118644068	0.700000000	0.288173961
	EDDM	120.00	37	81	4999879	3	0.035714286	0.075000000	0.051743965
	ADWIN	154.00	0	865	4999095	40	0.044198895	1.000000000	0.210217146
	ECDD	141.76	6	9053	4990907	34	0.003741609	0.850000000	0.056325600
	STEPD	115.25	0	2240	4997720	40	0.017543860	1.000000000	0.132423563
	SeqDr2	302.56	1	47	4999913	39	0.453488372	0.975000000	0.664941129
	HDDM$_W$	50.28	4	682	4999278	36	0.050139276	0.900000000	0.212409485
	FTDD	183.14	5	16	4999944	35	0.686274510	0.875000000	0.774911043
	WSTD	193.08	1	107	4999853	39	0.267123288	0.975000000	0.510332533
	HDDM$_A$	171.50	0	15	4999945	40	0.727272727	1.000000000	0.852801586
	DDM$_7$	303.78	3	4024	4995936	37	0.009111056	0.925000000	0.091759684
	DDM$_{129}$	440.54	3	327	4999633	37	0.101648352	0.925000000	0.306622769
	RDDM$_{30}$	207.81	8	124	4999836	32	0.205128205	0.800000000	0.405087888
	RDDM$_7$	175.68	3	2763	4997197	37	0.013214286	0.925000000	0.110523106
	RDDM$_{129}$	164.41	6	233	4999727	34	0.127340824	0.850000000	0.328987456
LED	DDM	774.62	27	45	4999915	13	0.224137931	0.325000000	0.269890821
	EDDM	N/A	40	80	4999880	0	0.000000000	0.000000000	-0.000011314
	ADWIN	397.75	0	10405	4989555	40	0.003829584	1.000000000	0.061819205
	ECDD	327.63	2	3821	4996139	38	0.009847111	0.950000000	0.096679108
	STEPD	161.58	2	5593	4994367	38	0.006748357	0.950000000	0.080018815
	SeqDr2	189.19	3	3124	4996836	37	0.011705157	0.925000000	0.104016352
	HDDM$_W$	79.74	1	1175	4998785	39	0.032125206	0.975000000	0.176958558
	FTDD	83.75	8	180	4999780	32	0.150943396	0.800000000	0.347488134
	WSTD	108.65	3	667	4999293	37	0.052556818	0.925000000	0.220471065
	HDDM$_A$	197.75	0	134	4999826	40	0.229885057	1.000000000	0.479456877
	DDM$_7$	181.03	1	359	4999601	39	0.097989950	0.975000000	0.309084083
	DDM$_{129}$	291.11	4	182	4999778	36	0.165137615	0.900000000	0.385508913
	RDDM$_{30}$	643.64	7	123	4999837	33	0.211538462	0.825000000	0.417747378
	RDDM$_7$	146.67	10	579	4999381	30	0.049261084	0.750000000	0.192194194
	RDDM$_{129}$	322.43	3	129	4999831	37	0.222891566	0.925000000	0.454057698
Mixed	DDM	158.50	0	20	4999940	40	0.666666667	1.000000000	0.816494948
	EDDM	1940.00	39	194	4999766	1	0.005128205	0.025000000	0.011305372
	ADWIN	40.00	0	1183	4998777	40	0.032706460	1.000000000	0.180827877
	ECDD	10.00	0	6418	4993542	40	0.006193868	1.000000000	0.078650604
	STEPD	13.75	0	1542	4998418	40	0.025284450	1.000000000	0.158986327
	SeqDr2	200.00	0	54	4999906	40	0.425531915	1.000000000	0.652324550
	HDDM$_W$	16.50	0	2	4999958	40	0.952380952	1.000000000	0.975899878
	FTDD	16.00	0	6	4999954	40	0.869565217	1.000000000	0.932504249
	WSTD	16.25	0	8	4999952	40	0.833333333	1.000000000	0.912870199
	HDDM$_A$	24.75	0	0	4999960	40	1.000000000	1.000000000	1.000000000
	DDM$_7$	67.63	2	1227	4998733	38	0.030039526	0.950000000	0.168907660
	DDM$_{129}$	99.50	0	193	4999767	40	0.171673820	1.000000000	0.414327398
	RDDM$_{30}$	79.23	1	69	4999891	39	0.361111111	0.975000000	0.593361740
	RDDM$_7$	29.19	3	880	4999080	37	0.040348964	0.925000000	0.193171259
	RDDM$_{129}$	44.00	0	182	4999778	40	0.180180180	1.000000000	0.424468634

Table 55 – Concept drift identifications of Detectors in 500K instances abrupt datasets using HT (Part 2)

Dataset	Detector	μD	FN	FP	TN	TP	Precision	Recall	MCC
RandRBF	DDM	1730.00	39	38	4999922	1	0.025641026	0.025000000	0.025310785
	EDDM	1500.00	39	89	4999871	1	0.011111111	0.025000000	0.016654883
	ADWIN	667.78	22	511	4999449	18	0.034026465	0.450000000	0.123719247
	ECDD	N/A	40	0	4999960	0	0.000000000	0.000000000	0.000000000
	STEPD	722.78	22	2262	4997698	18	0.007894737	0.450000000	0.059557376
	SeqDr2	861.54	27	45	4999915	13	0.224137931	0.325000000	0.269890821
	HDDM_W	452.76	11	1915	4998045	29	0.014917695	0.725000000	0.103961632
	FTDD	1110.00	37	41	4999919	3	0.068181818	0.075000000	0.071501904
	WSTD	607.50	36	465	4999495	4	0.008528785	0.100000000	0.029178175
	HDDM_A	627.60	15	65	4999895	25	0.277777778	0.625000000	0.416660083
	DDM_7	1092.67	25	415	4999545	15	0.034883721	0.375000000	0.114353073
	DDM_{129}	1254.29	26	118	4999842	14	0.106060606	0.350000000	0.192657440
	RDDM_{30}	1164.67	25	88	4999872	15	0.145631068	0.375000000	0.233681862
	RDDM_7	796.79	12	926	4999034	28	0.029350105	0.700000000	0.143310704
	RDDM_{129}	879.05	19	228	4999732	21	0.084337349	0.525000000	0.210407385
Sine	DDM	151.50	0	35	4999925	40	0.533333333	1.000000000	0.730294187
	EDDM	487.14	19	317	4999643	21	0.062130178	0.525000000	0.180589062
	ADWIN	42.25	0	1629	4998331	40	0.023966447	1.000000000	0.154785783
	ECDD	10.00	0	8448	4991512	40	0.004712535	1.000000000	0.068589890
	STEPD	13.75	0	826	4999134	40	0.046189376	1.000000000	0.214899386
	SeqDr2	200.00	0	48	4999912	40	0.454545455	1.000000000	0.674196626
	HDDM_W	20.25	0	0	4999960	40	1.000000000	1.000000000	1.000000000
	FTDD	16.00	0	0	4999960	40	1.000000000	1.000000000	1.000000000
	WSTD	17.00	0	0	4999960	40	1.000000000	1.000000000	1.000000000
	HDDM_A	22.00	0	0	4999960	40	1.000000000	1.000000000	1.000000000
	DDM_7	107.75	0	521	4999439	40	0.071301248	1.000000000	0.267009023
	DDM_{129}	95.75	0	110	4999850	40	0.266666667	1.000000000	0.516392099
	RDDM_{30}	75.00	0	42	4999918	40	0.487804878	1.000000000	0.698427362
	RDDM_7	44.62	1	472	4999488	39	0.076320939	0.975000000	0.272773745
	RDDM_{129}	49.50	0	138	4999822	40	0.224719101	1.000000000	0.474038921
Waveform	DDM	1553.33	37	31	4999929	3	0.088235294	0.075000000	0.081342148
	EDDM	N/A	40	78	4999882	0	0.000000000	0.000000000	-0.000011172
	ADWIN	325.24	19	306	4999654	21	0.064220183	0.525000000	0.183601937
	ECDD	387.00	0	8351	4991609	40	0.004767012	1.000000000	0.068985871
	STEPD	275.71	12	1581	4998379	28	0.017402113	0.700000000	0.110337196
	SeqDr2	248.00	15	33	4999927	25	0.431034483	0.625000000	0.519029702
	HDDM_W	228.50	20	570	4999390	20	0.033898305	0.500000000	0.130166387
	FTDD	238.89	22	23	4999937	18	0.439024390	0.450000000	0.444473819
	WSTD	142.50	20	145	4999815	20	0.121212121	0.500000000	0.246171780
	HDDM_A	474.84	9	42	4999918	31	0.424657534	0.775000000	0.573676413
	DDM_7	331.25	16	3108	4996852	24	0.007662835	0.600000000	0.067757056
	DDM_{129}	1068.46	27	243	4999717	13	0.050781250	0.325000000	0.128451094
	RDDM_{30}	894.00	25	212	4999748	15	0.066079295	0.375000000	0.157400950
	RDDM_7	633.68	21	1454	4998506	19	0.012898846	0.475000000	0.078238139
	RDDM_{129}	492.31	14	423	4999537	26	0.057906459	0.650000000	0.193990926

APPENDIX C – Ensemble Results with NB

This appendix includes Tables 56 to 62 which contain the detailed results of the experiments with the ensembles configurations in the gradual datasets using Naive Bayes (NB) as base classifier. These results, omitted from Chapter 7, are again separated by size of the datasets.

Table 56 – Mean accuracies of Ensembles in percentage (%) in 10K instances gradual datasets, with 95% confidence intervals, using NB

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	60.33 (+-0.25)	60.33 (+-0.25)	60.31 (+-0.27)	59.06 (+-0.47)	62.10 (+-0.24)	59.27 (+-0.52)
	WSTD	61.16 (+-0.30)	61.16 (+-0.30)	61.24 (+-0.29)	60.68 (+-0.29)	62.23 (+-0.21)	60.80 (+-0.30)
	$HDDM_A$	61.15 (+-0.27)	61.14 (+-0.27)	61.23 (+-0.27)	60.83 (+-0.30)	62.26 (+-0.23)	61.25 (+-0.34)
	DDM_7	60.85 (+-0.20)	60.83 (+-0.20)	61.05 (+-0.16)	61.48 (+-0.24)	62.68 (+-0.19)	61.69 (+-0.20)
	DDM_{129}	61.62 (+-0.20)	61.61 (+-0.21)	61.81 (+-0.21)	61.51 (+-0.35)	62.64 (+-0.18)	62.08 (+-0.29)
	$RDDM_{30}$	60.67 (+-0.24)	60.66 (+-0.23)	60.81 (+-0.23)	59.70 (+-0.38)	62.39 (+-0.20)	60.20 (+-0.35)
	$RDDM_7$	61.56 (+-0.19)	61.54 (+-0.19)	61.71 (+-0.21)	61.82 (+-0.21)	**62.69 (+-0.22)**	61.94 (+-0.22)
	$RDDM_{129}$	61.55 (+-0.19)	61.54 (+-0.19)	61.76 (+-0.22)	61.40 (+-0.36)	62.64 (+-0.18)	62.05 (+-0.27)
$Agraw_2$	FTDD	78.39 (+-0.30)	78.39 (+-0.30)	78.51 (+-0.26)	71.42 (+-1.07)	78.69 (+-0.22)	71.82 (+-1.30)
	WSTD	79.21 (+-0.23)	79.21 (+-0.23)	79.16 (+-0.23)	75.21 (+-0.88)	78.95 (+-0.23)	75.61 (+-1.08)
	$HDDM_A$	79.02 (+-0.21)	79.02 (+-0.22)	78.96 (+-0.27)	75.39 (+-0.55)	78.86 (+-0.28)	76.12 (+-0.85)
	DDM_7	78.91 (+-0.21)	78.91 (+-0.21)	79.18 (+-0.20)	76.76 (+-1.10)	**79.56 (+-0.20)**	76.19 (+-1.24)
	DDM_{129}	78.66 (+-0.29)	78.66 (+-0.29)	78.85 (+-0.33)	73.03 (+-1.59)	79.14 (+-0.25)	74.01 (+-1.67)
	$RDDM_{30}$	76.91 (+-0.32)	76.91 (+-0.33)	76.87 (+-0.33)	68.68 (+-0.87)	79.12 (+-0.24)	69.29 (+-1.32)
	$RDDM_7$	79.21 (+-0.19)	79.21 (+-0.19)	79.41 (+-0.20)	76.02 (+-1.35)	79.44 (+-0.21)	76.55 (+-1.23)
	$RDDM_{129}$	78.48 (+-0.27)	78.48 (+-0.27)	78.61 (+-0.26)	73.52 (+-1.42)	79.14 (+-0.25)	74.29 (+-1.44)
LED	FTDD	59.43 (+-2.17)	65.82 (+-0.36)	65.03 (+-0.46)	62.59 (+-0.93)	66.31 (+-0.28)	63.11 (+-0.90)
	WSTD	64.64 (+-1.29)	66.24 (+-0.30)	66.23 (+-0.30)	65.50 (+-0.54)	65.64 (+-0.30)	64.40 (+-0.72)
	$HDDM_A$	67.38 (+-0.27)	67.42 (+-0.27)	67.36 (+-0.27)	66.99 (+-0.30)	67.10 (+-0.27)	67.65 (+-0.30)
	DDM_7	67.53 (+-0.27)	67.55 (+-0.26)	67.59 (+-0.27)	67.48 (+-0.32)	67.07 (+-0.26)	67.41 (+-0.33)
	DDM_{129}	67.61 (+-0.29)	67.63 (+-0.29)	67.66 (+-0.29)	67.07 (+-0.27)	67.02 (+-0.27)	67.75 (+-0.30)
	$RDDM_{30}$	66.59 (+-0.37)	66.79 (+-0.35)	66.61 (+-0.34)	66.74 (+-0.51)	67.04 (+-0.25)	67.83 (+-0.34)
	$RDDM_7$	67.54 (+-0.28)	67.56 (+-0.28)	67.62 (+-0.27)	67.56 (+-0.32)	67.08 (+-0.25)	67.63 (+-0.29)
	$RDDM_{129}$	67.50 (+-0.29)	67.52 (+-0.28)	67.52 (+-0.28)	67.24 (+-0.28)	67.02 (+-0.27)	**67.85 (+-0.29)**
Mixed	FTDD	84.45 (+-0.17)	84.45 (+-0.17)	84.39 (+-0.19)	80.82 (+-0.47)	83.73 (+-0.21)	83.74 (+-0.24)
	WSTD	83.40 (+-0.21)	83.39 (+-0.21)	83.41 (+-0.20)	82.08 (+-0.51)	83.61 (+-0.24)	83.42 (+-0.27)
	$HDDM_A$	83.88 (+-0.20)	83.87 (+-0.20)	83.90 (+-0.20)	81.71 (+-0.48)	83.69 (+-0.24)	83.61 (+-0.27)
	DDM_7	81.89 (+-0.18)	81.88 (+-0.17)	81.87 (+-0.18)	83.67 (+-0.28)	83.67 (+-0.26)	83.63 (+-0.26)
	DDM_{129}	83.69 (+-0.21)	83.69 (+-0.20)	83.70 (+-0.20)	83.26 (+-0.39)	83.61 (+-0.26)	83.80 (+-0.30)
	$RDDM_{30}$	84.68 (+-0.21)	84.68 (+-0.21)	**84.70 (+-0.20)**	82.53 (+-0.41)	83.76 (+-0.26)	83.88 (+-0.27)
	$RDDM_7$	82.72 (+-0.23)	82.71 (+-0.23)	82.72 (+-0.23)	83.65 (+-0.29)	83.70 (+-0.24)	83.73 (+-0.27)
	$RDDM_{129}$	83.69 (+-0.20)	83.69 (+-0.20)	83.72 (+-0.20)	83.41 (+-0.38)	83.61 (+-0.26)	83.89 (+-0.29)
RBF	FTDD	19.60 (+-0.79)	24.86 (+-0.89)	30.68 (+-0.65)	30.76 (+-0.56)	**31.79 (+-0.40)**	30.90 (+-0.56)
	WSTD	19.93 (+-0.99)	24.95 (+-0.85)	30.36 (+-0.62)	30.79 (+-0.62)	31.66 (+-0.39)	30.73 (+-0.61)
	$HDDM_A$	19.85 (+-0.87)	24.80 (+-0.85)	30.52 (+-0.63)	30.75 (+-0.52)	31.61 (+-0.34)	30.55 (+-0.47)
	DDM_7	20.03 (+-0.81)	24.64 (+-0.69)	30.68 (+-0.49)	30.07 (+-0.49)	31.17 (+-0.36)	29.92 (+-0.50)
	DDM_{129}	19.82 (+-0.86)	24.94 (+-0.78)	30.59 (+-0.52)	30.56 (+-0.48)	31.54 (+-0.30)	30.26 (+-0.44)
	$RDDM_{30}$	19.84 (+-0.87)	24.89 (+-0.88)	30.60 (+-0.62)	30.71 (+-0.55)	31.57 (+-0.35)	30.89 (+-0.52)
	$RDDM_7$	19.99 (+-0.80)	24.33 (+-0.80)	30.68 (+-0.46)	30.30 (+-0.49)	31.21 (+-0.36)	30.12 (+-0.45)
	$RDDM_{129}$	19.82 (+-0.86)	24.93 (+-0.79)	30.72 (+-0.53)	30.63 (+-0.44)	31.51 (+-0.30)	30.39 (+-0.44)
Sine	FTDD	82.48 (+-0.15)	82.51 (+-0.15)	82.65 (+-0.15)	79.50 (+-0.49)	81.68 (+-0.20)	81.26 (+-0.20)
	WSTD	81.87 (+-0.16)	81.89 (+-0.16)	81.97 (+-0.16)	79.63 (+-0.35)	81.60 (+-0.19)	81.32 (+-0.21)
	$HDDM_A$	82.46 (+-0.19)	82.48 (+-0.19)	82.48 (+-0.19)	79.98 (+-0.51)	81.71 (+-0.20)	81.51 (+-0.20)
	DDM_7	80.59 (+-0.24)	80.61 (+-0.23)	80.75 (+-0.24)	81.44 (+-0.28)	81.82 (+-0.21)	81.52 (+-0.23)
	DDM_{129}	82.54 (+-0.19)	82.56 (+-0.19)	82.62 (+-0.17)	81.18 (+-0.35)	81.77 (+-0.21)	81.78 (+-0.19)
	$RDDM_{30}$	83.28 (+-0.17)	**83.30 (+-0.18)**	83.29 (+-0.17)	80.69 (+-0.47)	81.79 (+-0.20)	81.78 (+-0.22)
	$RDDM_7$	81.62 (+-0.20)	81.64 (+-0.20)	81.72 (+-0.21)	81.62 (+-0.18)	81.80 (+-0.21)	81.71 (+-0.19)
	$RDDM_{129}$	82.62 (+-0.18)	82.64 (+-0.19)	82.65 (+-0.18)	81.40 (+-0.39)	81.77 (+-0.21)	81.85 (+-0.18)
Wavef.	FTDD	78.49 (+-0.41)	78.49 (+-0.42)	78.31 (+-0.41)	76.54 (+-0.45)	78.08 (+-0.34)	76.65 (+-0.46)
	WSTD	79.18 (+-0.39)	79.18 (+-0.39)	78.94 (+-0.38)	77.31 (+-0.46)	78.17 (+-0.34)	77.54 (+-0.54)
	$HDDM_A$	79.10 (+-0.39)	79.10 (+-0.40)	78.84 (+-0.38)	77.72 (+-0.48)	78.19 (+-0.38)	77.82 (+-0.49)
	DDM_7	**80.71 (+-0.32)**	**80.71 (+-0.33)**	80.58 (+-0.31)	78.62 (+-0.40)	79.26 (+-0.35)	78.52 (+-0.37)
	DDM_{129}	79.75 (+-0.36)	79.75 (+-0.36)	79.43 (+-0.37)	78.60 (+-0.41)	78.60 (+-0.34)	78.59 (+-0.40)
	$RDDM_{30}$	78.86 (+-0.35)	78.86 (+-0.35)	78.60 (+-0.36)	77.76 (+-0.44)	78.28 (+-0.36)	77.87 (+-0.41)
	$RDDM_7$	80.03 (+-0.35)	80.03 (+-0.35)	79.85 (+-0.36)	78.56 (+-0.40)	79.25 (+-0.36)	78.61 (+-0.41)
	$RDDM_{129}$	79.38 (+-0.37)	79.38 (+-0.37)	79.15 (+-0.38)	78.36 (+-0.42)	78.60 (+-0.34)	78.46 (+-0.37)

Table 57 – Mean accuracies of Ensembles in percentage (%) in 20K instances gradual datasets, with 95% confidence intervals, using NB

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	61.96 (+-0.20)	61.96 (+-0.21)	62.01 (+-0.20)	60.77 (+-0.42)	64.37 (+-0.12)	61.14 (+-0.35)
	WSTD	63.84 (+-0.18)	63.84 (+-0.18)	63.95 (+-0.17)	62.71 (+-0.27)	64.39 (+-0.11)	63.15 (+-0.41)
	$HDDM_A$	63.98 (+-0.22)	63.98 (+-0.22)	64.24 (+-0.22)	63.49 (+-0.18)	64.43 (+-0.11)	63.92 (+-0.14)
	DDM_7	62.93 (+-0.13)	62.92 (+-0.13)	63.17 (+-0.13)	63.53 (+-0.15)	64.36 (+-0.13)	63.69 (+-0.16)
	DDM_{129}	64.07 (+-0.20)	64.07 (+-0.19)	64.33 (+-0.18)	63.55 (+-0.13)	64.50 (+-0.12)	63.81 (+-0.22)
	$RDDM_{30}$	63.29 (+-0.17)	63.28 (+-0.17)	63.47 (+-0.17)	62.96 (+-0.25)	64.38 (+-0.13)	63.62 (+-0.16)
	$RDDM_7$	64.04 (+-0.19)	64.04 (+-0.18)	64.21 (+-0.18)	63.65 (+-0.16)	64.43 (+-0.14)	63.87 (+-0.14)
	$RDDM_{129}$	64.29 (+-0.21)	64.29 (+-0.21)	**64.58 (+-0.21)**	63.55 (+-0.12)	64.49 (+-0.12)	63.98 (+-0.13)
$Agraw_2$	FTDD	83.00 (+-0.12)	83.00 (+-0.13)	82.99 (+-0.13)	78.72 (+-0.41)	82.57 (+-0.19)	78.79 (+-0.60)
	WSTD	83.44 (+-0.12)	83.45 (+-0.12)	83.44 (+-0.13)	79.93 (+-0.92)	82.70 (+-0.12)	79.76 (+-1.35)
	$HDDM_A$	83.27 (+-0.14)	83.27 (+-0.14)	83.25 (+-0.18)	79.44 (+-0.53)	82.64 (+-0.17)	80.47 (+-0.51)
	DDM_7	83.13 (+-0.13)	83.14 (+-0.13)	83.30 (+-0.12)	81.55 (+-0.51)	83.14 (+-0.12)	81.81 (+-0.43)
	DDM_{129}	82.66 (+-0.19)	82.66 (+-0.19)	82.81 (+-0.21)	80.08 (+-0.68)	82.86 (+-0.15)	80.65 (+-0.90)
	$RDDM_{30}$	81.51 (+-0.19)	81.51 (+-0.19)	81.54 (+-0.19)	76.19 (+-1.03)	82.76 (+-0.15)	76.58 (+-1.07)
	$RDDM_7$	83.34 (+-0.11)	83.34 (+-0.11)	**83.49 (+-0.11)**	82.23 (+-0.36)	83.07 (+-0.13)	82.13 (+-0.37)
	$RDDM_{129}$	82.73 (+-0.17)	82.73 (+-0.17)	82.90 (+-0.18)	80.12 (+-0.81)	82.87 (+-0.15)	80.79 (+-0.91)
LED	FTDD	68.10 (+-1.32)	69.53 (+-0.24)	69.20 (+-0.29)	67.02 (+-0.73)	69.81 (+-0.15)	67.66 (+-0.87)
	WSTD	69.53 (+-0.27)	69.63 (+-0.24)	69.69 (+-0.22)	69.55 (+-0.27)	69.19 (+-0.18)	68.68 (+-0.52)
	$HDDM_A$	70.51 (+-0.18)	70.52 (+-0.18)	70.53 (+-0.18)	69.61 (+-0.16)	70.24 (+-0.15)	70.43 (+-0.18)
	DDM_7	70.56 (+-0.18)	70.57 (+-0.18)	70.59 (+-0.18)	70.44 (+-0.20)	70.41 (+-0.17)	70.40 (+-0.19)
	DDM_{129}	70.55 (+-0.18)	70.57 (+-0.18)	70.59 (+-0.18)	69.97 (+-0.24)	70.29 (+-0.17)	70.61 (+-0.18)
	$RDDM_{30}$	70.20 (+-0.17)	70.21 (+-0.17)	70.22 (+-0.17)	69.83 (+-0.24)	70.19 (+-0.17)	70.61 (+-0.18)
	$RDDM_7$	70.57 (+-0.17)	70.58 (+-0.17)	70.60 (+-0.17)	70.58 (+-0.21)	70.41 (+-0.15)	70.61 (+-0.17)
	$RDDM_{129}$	70.50 (+-0.17)	70.51 (+-0.17)	70.53 (+-0.18)	70.17 (+-0.26)	70.29 (+-0.17)	**70.66 (+-0.18)**
Mixed	FTDD	88.45 (+-0.12)	88.45 (+-0.12)	88.44 (+-0.12)	85.17 (+-0.37)	87.84 (+-0.14)	87.63 (+-0.16)
	WSTD	87.68 (+-0.13)	87.67 (+-0.13)	87.68 (+-0.13)	85.99 (+-0.37)	87.82 (+-0.14)	87.71 (+-0.16)
	$HDDM_A$	88.00 (+-0.10)	88.00 (+-0.10)	88.00 (+-0.11)	85.59 (+-0.46)	87.89 (+-0.15)	87.80 (+-0.18)
	DDM_7	86.49 (+-0.18)	86.49 (+-0.18)	86.48 (+-0.18)	87.85 (+-0.15)	87.81 (+-0.15)	87.87 (+-0.16)
	DDM_{129}	87.86 (+-0.15)	87.86 (+-0.14)	87.88 (+-0.15)	87.24 (+-0.37)	87.82 (+-0.15)	87.93 (+-0.19)
	$RDDM_{30}$	88.55 (+-0.14)	88.55 (+-0.14)	**88.56 (+-0.15)**	86.92 (+-0.43)	87.86 (+-0.16)	88.01 (+-0.16)
	$RDDM_7$	87.30 (+-0.15)	87.30 (+-0.15)	87.31 (+-0.15)	87.89 (+-0.15)	87.83 (+-0.16)	87.95 (+-0.18)
	$RDDM_{129}$	87.92 (+-0.13)	87.92 (+-0.13)	87.94 (+-0.14)	87.29 (+-0.41)	87.81 (+-0.16)	88.01 (+-0.18)
RBF	FTDD	19.49 (+-0.61)	23.67 (+-0.65)	30.95 (+-0.62)	31.06 (+-0.50)	**32.05 (+-0.33)**	31.26 (+-0.45)
	WSTD	19.59 (+-0.92)	23.80 (+-0.69)	30.42 (+-0.56)	31.05 (+-0.59)	31.90 (+-0.33)	30.78 (+-0.57)
	$HDDM_A$	19.56 (+-0.70)	23.78 (+-0.63)	30.65 (+-0.39)	30.74 (+-0.50)	31.89 (+-0.32)	30.68 (+-0.44)
	DDM_7	19.89 (+-0.63)	23.94 (+-0.50)	30.60 (+-0.36)	30.12 (+-0.41)	31.59 (+-0.29)	30.18 (+-0.49)
	DDM_{129}	19.56 (+-0.73)	23.80 (+-0.58)	30.82 (+-0.48)	30.58 (+-0.44)	31.88 (+-0.27)	30.48 (+-0.39)
	$RDDM_{30}$	19.60 (+-0.73)	23.97 (+-0.68)	30.86 (+-0.46)	30.69 (+-0.43)	31.81 (+-0.31)	30.95 (+-0.42)
	$RDDM_7$	19.95 (+-0.70)	23.65 (+-0.58)	30.79 (+-0.41)	30.27 (+-0.37)	31.62 (+-0.24)	30.38 (+-0.38)
	$RDDM_{129}$	19.57 (+-0.73)	23.79 (+-0.60)	30.82 (+-0.40)	30.59 (+-0.38)	31.86 (+-0.27)	30.53 (+-0.47)
Sine	FTDD	86.29 (+-0.16)	86.30 (+-0.16)	86.35 (+-0.14)	82.17 (+-0.40)	84.79 (+-0.16)	84.74 (+-0.17)
	WSTD	86.05 (+-0.13)	86.06 (+-0.13)	86.05 (+-0.12)	82.75 (+-0.40)	84.82 (+-0.18)	84.60 (+-0.16)
	$HDDM_A$	86.49 (+-0.14)	86.50 (+-0.15)	86.51 (+-0.14)	82.07 (+-0.35)	84.97 (+-0.16)	84.97 (+-0.15)
	DDM_7	85.10 (+-0.20)	85.11 (+-0.20)	85.22 (+-0.20)	84.81 (+-0.18)	84.98 (+-0.16)	84.70 (+-0.20)
	DDM_{129}	86.50 (+-0.13)	86.52 (+-0.13)	86.54 (+-0.12)	83.46 (+-0.46)	84.93 (+-0.17)	84.83 (+-0.17)
	$RDDM_{30}$	86.87 (+-0.11)	**86.88 (+-0.11)**	86.87 (+-0.11)	83.65 (+-0.44)	84.96 (+-0.15)	84.92 (+-0.19)
	$RDDM_7$	85.90 (+-0.15)	85.91 (+-0.15)	85.94 (+-0.14)	84.87 (+-0.17)	84.96 (+-0.16)	84.94 (+-0.16)
	$RDDM_{129}$	86.57 (+-0.14)	86.58 (+-0.14)	86.58 (+-0.13)	83.93 (+-0.46)	84.93 (+-0.17)	84.98 (+-0.15)
Wavef.	FTDD	79.18 (+-0.34)	79.20 (+-0.34)	78.92 (+-0.30)	77.73 (+-0.35)	79.14 (+-0.24)	78.15 (+-0.41)
	WSTD	80.21 (+-0.23)	80.21 (+-0.23)	80.10 (+-0.24)	78.41 (+-0.34)	79.15 (+-0.21)	78.73 (+-0.28)
	$HDDM_A$	80.24 (+-0.25)	80.24 (+-0.25)	80.13 (+-0.26)	78.63 (+-0.25)	79.06 (+-0.25)	78.90 (+-0.30)
	DDM_7	**81.29 (+-0.24)**	**81.29 (+-0.24)**	81.17 (+-0.23)	79.32 (+-0.25)	80.17 (+-0.22)	79.32 (+-0.22)
	DDM_{129}	80.69 (+-0.22)	80.69 (+-0.22)	80.55 (+-0.23)	79.35 (+-0.27)	79.60 (+-0.23)	79.29 (+-0.30)
	$RDDM_{30}$	79.74 (+-0.25)	79.78 (+-0.24)	79.54 (+-0.23)	78.59 (+-0.30)	79.29 (+-0.26)	78.76 (+-0.25)
	$RDDM_7$	80.84 (+-0.22)	80.84 (+-0.22)	80.71 (+-0.22)	79.37 (+-0.25)	80.16 (+-0.22)	79.40 (+-0.27)
	$RDDM_{129}$	80.40 (+-0.25)	80.40 (+-0.25)	80.27 (+-0.25)	79.06 (+-0.29)	79.62 (+-0.23)	79.22 (+-0.31)

Table 58 – Mean accuracies of Ensembles in percentage (%) in 50K instances gradual datasets, with 95% confidence intervals, using NB

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	64.79 (+-0.25)	64.79 (+-0.25)	64.95 (+-0.27)	62.40 (+-0.41)	65.62 (+-0.11)	62.87 (+-0.42)
	WSTD	66.40 (+-0.13)	66.40 (+-0.13)	66.50 (+-0.14)	64.78 (+-0.17)	65.66 (+-0.10)	65.17 (+-0.14)
	$HDDM_A$	67.15 (+-0.15)	67.14 (+-0.15)	**67.34 (+-0.15)**	64.90 (+-0.17)	65.68 (+-0.09)	65.43 (+-0.11)
	DDM_7	65.00 (+-0.19)	65.00 (+-0.19)	65.26 (+-0.19)	64.90 (+-0.24)	65.70 (+-0.11)	65.02 (+-0.33)
	DDM_{129}	66.61 (+-0.17)	66.61 (+-0.17)	66.89 (+-0.16)	64.84 (+-0.17)	65.71 (+-0.10)	65.34 (+-0.10)
	$RDDM_{30}$	66.34 (+-0.12)	66.34 (+-0.12)	66.72 (+-0.12)	64.76 (+-0.17)	65.70 (+-0.10)	65.13 (+-0.17)
	$RDDM_7$	66.32 (+-0.15)	66.32 (+-0.15)	66.51 (+-0.15)	65.18 (+-0.14)	65.70 (+-0.11)	65.27 (+-0.12)
	$RDDM_{129}$	66.92 (+-0.13)	66.92 (+-0.13)	67.18 (+-0.12)	64.98 (+-0.17)	65.71 (+-0.10)	65.38 (+-0.11)
$Agraw_2$	FTDD	86.06 (+-0.11)	86.06 (+-0.11)	86.06 (+-0.12)	81.89 (+-0.48)	85.02 (+-0.13)	82.75 (+-0.51)
	WSTD	86.47 (+-0.08)	86.48 (+-0.08)	**86.49 (+-0.09)**	83.22 (+-0.31)	85.07 (+-0.12)	83.90 (+-0.92)
	$HDDM_A$	86.26 (+-0.08)	86.26 (+-0.08)	86.31 (+-0.09)	83.44 (+-0.31)	85.06 (+-0.13)	84.57 (+-0.31)
	DDM_7	85.87 (+-0.11)	85.87 (+-0.11)	85.99 (+-0.10)	84.62 (+-0.32)	85.27 (+-0.08)	84.73 (+-0.23)
	DDM_{129}	86.04 (+-0.11)	86.04 (+-0.11)	86.08 (+-0.11)	83.78 (+-0.32)	85.14 (+-0.10)	84.67 (+-0.22)
	$RDDM_{30}$	85.33 (+-0.14)	85.33 (+-0.14)	85.43 (+-0.16)	82.98 (+-0.50)	85.15 (+-0.11)	83.75 (+-0.46)
	$RDDM_7$	86.31 (+-0.09)	86.31 (+-0.09)	86.42 (+-0.09)	84.90 (+-0.15)	85.22 (+-0.08)	84.95 (+-0.13)
	$RDDM_{129}$	85.99 (+-0.12)	86.00 (+-0.12)	86.08 (+-0.12)	84.16 (+-0.33)	85.13 (+-0.10)	84.77 (+-0.22)
LED	FTDD	71.85 (+-0.15)	71.86 (+-0.15)	71.84 (+-0.15)	70.73 (+-0.19)	72.08 (+-0.16)	71.62 (+-0.19)
	WSTD	72.01 (+-0.17)	72.02 (+-0.17)	72.06 (+-0.17)	71.55 (+-0.20)	71.95 (+-0.15)	71.48 (+-0.28)
	$HDDM_A$	72.49 (+-0.16)	72.49 (+-0.16)	72.50 (+-0.16)	71.27 (+-0.19)	72.42 (+-0.14)	72.48 (+-0.15)
	DDM_7	72.48 (+-0.15)	72.49 (+-0.15)	72.50 (+-0.15)	72.37 (+-0.15)	72.50 (+-0.14)	72.39 (+-0.17)
	DDM_{129}	72.51 (+-0.15)	72.51 (+-0.16)	72.52 (+-0.16)	71.79 (+-0.23)	72.47 (+-0.14)	72.61 (+-0.16)
	$RDDM_{30}$	72.25 (+-0.16)	72.26 (+-0.16)	72.26 (+-0.16)	71.78 (+-0.23)	72.36 (+-0.14)	72.50 (+-0.14)
	$RDDM_7$	72.50 (+-0.15)	72.51 (+-0.15)	72.52 (+-0.15)	72.47 (+-0.16)	72.51 (+-0.14)	72.43 (+-0.16)
	$RDDM_{129}$	72.48 (+-0.15)	72.48 (+-0.15)	72.49 (+-0.15)	71.95 (+-0.23)	72.47 (+-0.14)	**72.63 (+-0.15)**
Mixed	FTDD	90.67 (+-0.10)	90.67 (+-0.09)	90.72 (+-0.10)	88.63 (+-0.43)	90.40 (+-0.09)	90.42 (+-0.11)
	WSTD	90.05 (+-0.14)	90.05 (+-0.14)	90.17 (+-0.12)	89.25 (+-0.33)	90.40 (+-0.09)	90.40 (+-0.10)
	$HDDM_A$	90.31 (+-0.14)	90.31 (+-0.14)	90.46 (+-0.11)	88.85 (+-0.47)	90.44 (+-0.10)	90.45 (+-0.11)
	DDM_7	88.97 (+-0.16)	88.97 (+-0.16)	89.19 (+-0.15)	90.39 (+-0.10)	90.42 (+-0.09)	90.38 (+-0.10)
	DDM_{129}	90.11 (+-0.12)	90.11 (+-0.12)	90.30 (+-0.11)	88.91 (+-0.72)	90.42 (+-0.10)	90.43 (+-0.10)
	$RDDM_{30}$	90.63 (+-0.15)	90.63 (+-0.15)	**90.77 (+-0.12)**	89.00 (+-0.55)	90.41 (+-0.09)	90.48 (+-0.11)
	$RDDM_7$	89.69 (+-0.13)	89.69 (+-0.13)	89.92 (+-0.11)	90.40 (+-0.09)	90.42 (+-0.09)	90.40 (+-0.09)
	$RDDM_{129}$	90.23 (+-0.12)	90.23 (+-0.12)	90.37 (+-0.10)	90.11 (+-0.34)	90.42 (+-0.10)	90.50 (+-0.09)
RBF	FTDD	19.45 (+-0.60)	23.08 (+-0.45)	31.07 (+-0.45)	31.25 (+-0.52)	**32.47 (+-0.26)**	31.00 (+-0.49)
	WSTD	19.08 (+-0.66)	23.12 (+-0.57)	30.10 (+-0.57)	30.71 (+-0.51)	32.22 (+-0.26)	30.43 (+-0.53)
	$HDDM_A$	19.44 (+-0.66)	23.26 (+-0.54)	30.80 (+-0.36)	30.95 (+-0.41)	32.25 (+-0.24)	30.92 (+-0.37)
	DDM_7	19.77 (+-0.61)	23.18 (+-0.39)	30.48 (+-0.32)	30.50 (+-0.41)	31.98 (+-0.19)	30.64 (+-0.47)
	DDM_{129}	19.38 (+-0.66)	23.12 (+-0.55)	30.82 (+-0.34)	30.73 (+-0.34)	32.13 (+-0.22)	30.73 (+-0.41)
	$RDDM_{30}$	19.55 (+-0.69)	23.22 (+-0.73)	30.78 (+-0.40)	30.75 (+-0.39)	32.19 (+-0.23)	30.94 (+-0.41)
	$RDDM_7$	19.62 (+-0.62)	23.08 (+-0.44)	30.78 (+-0.31)	30.52 (+-0.32)	31.92 (+-0.16)	30.60 (+-0.30)
	$RDDM_{129}$	19.40 (+-0.66)	23.15 (+-0.56)	31.04 (+-0.32)	30.54 (+-0.31)	32.15 (+-0.20)	30.81 (+-0.35)
Sine	FTDD	88.87 (+-0.09)	88.87 (+-0.09)	88.92 (+-0.09)	84.42 (+-0.33)	86.57 (+-0.11)	86.58 (+-0.11)
	WSTD	88.56 (+-0.11)	88.56 (+-0.11)	88.64 (+-0.11)	84.76 (+-0.42)	86.60 (+-0.11)	86.63 (+-0.11)
	$HDDM_A$	88.81 (+-0.12)	88.81 (+-0.12)	88.88 (+-0.11)	84.51 (+-0.54)	86.69 (+-0.11)	86.76 (+-0.10)
	DDM_7	87.77 (+-0.17)	87.77 (+-0.17)	87.88 (+-0.16)	86.43 (+-0.17)	86.75 (+-0.11)	86.50 (+-0.13)
	DDM_{129}	88.72 (+-0.11)	88.73 (+-0.11)	88.80 (+-0.11)	85.43 (+-0.34)	86.71 (+-0.11)	86.67 (+-0.11)
	$RDDM_{30}$	89.04 (+-0.12)	89.05 (+-0.12)	**89.12 (+-0.10)**	85.94 (+-0.29)	86.70 (+-0.11)	86.48 (+-0.21)
	$RDDM_7$	88.24 (+-0.11)	88.24 (+-0.11)	88.38 (+-0.09)	86.66 (+-0.12)	86.76 (+-0.12)	86.68 (+-0.12)
	$RDDM_{129}$	88.75 (+-0.13)	88.75 (+-0.13)	88.82 (+-0.11)	86.30 (+-0.25)	86.71 (+-0.11)	86.78 (+-0.11)
Wavef.	FTDD	80.62 (+-0.12)	80.62 (+-0.12)	80.47 (+-0.14)	79.09 (+-0.22)	80.14 (+-0.14)	79.42 (+-0.20)
	WSTD	81.20 (+-0.14)	81.20 (+-0.14)	81.17 (+-0.13)	79.53 (+-0.18)	80.24 (+-0.13)	79.80 (+-0.17)
	$HDDM_A$	81.15 (+-0.15)	81.15 (+-0.14)	81.12 (+-0.15)	79.75 (+-0.18)	80.20 (+-0.13)	79.89 (+-0.18)
	DDM_7	**81.82 (+-0.14)**	**81.82 (+-0.14)**	81.75 (+-0.14)	79.90 (+-0.13)	80.76 (+-0.13)	79.87 (+-0.14)
	DDM_{129}	81.39 (+-0.12)	81.39 (+-0.12)	81.34 (+-0.12)	79.75 (+-0.18)	80.29 (+-0.13)	79.90 (+-0.15)
	$RDDM_{30}$	80.94 (+-0.13)	80.94 (+-0.13)	80.88 (+-0.14)	79.63 (+-0.18)	80.18 (+-0.13)	79.78 (+-0.16)
	$RDDM_7$	81.56 (+-0.14)	81.56 (+-0.14)	81.46 (+-0.14)	79.96 (+-0.14)	80.77 (+-0.13)	79.97 (+-0.13)
	$RDDM_{129}$	81.24 (+-0.11)	81.24 (+-0.11)	81.19 (+-0.12)	79.82 (+-0.15)	80.30 (+-0.13)	79.95 (+-0.13)

Table 59 – Mean accuracies of Ensembles in percentage (%) in 100K instances gradual datasets, with 95% confidence intervals, using NB

Dataset	Ensemble	ADOB	BOLE$_4$	BOLE$_5$	DDD	FASE	None
Agraw$_1$	FTDD	67.07 (+-0.20)	67.07 (+-0.20)	67.59 (+-0.20)	63.75 (+-0.47)	66.09 (+-0.08)	64.33 (+-0.49)
	WSTD	67.18 (+-0.13)	67.18 (+-0.13)	67.20 (+-0.13)	65.53 (+-0.14)	66.14 (+-0.07)	65.69 (+-0.11)
	HDDM$_A$	68.31 (+-0.11)	68.31 (+-0.11)	**68.50 (+-0.12)**	65.15 (+-0.16)	66.15 (+-0.08)	65.93 (+-0.09)
	DDM$_7$	66.02 (+-0.15)	66.02 (+-0.15)	66.35 (+-0.15)	65.53 (+-0.16)	66.24 (+-0.07)	65.71 (+-0.12)
	DDM$_{129}$	67.78 (+-0.13)	67.78 (+-0.13)	68.04 (+-0.14)	65.36 (+-0.14)	66.20 (+-0.07)	65.69 (+-0.29)
	RDDM$_{30}$	67.87 (+-0.14)	67.87 (+-0.14)	68.22 (+-0.11)	64.98 (+-0.19)	66.15 (+-0.09)	65.71 (+-0.12)
	RDDM$_7$	67.01 (+-0.14)	67.01 (+-0.14)	67.23 (+-0.14)	65.73 (+-0.09)	66.24 (+-0.07)	65.77 (+-0.08)
	RDDM$_{129}$	68.10 (+-0.09)	68.10 (+-0.09)	68.32 (+-0.10)	65.54 (+-0.16)	66.19 (+-0.07)	65.92 (+-0.08)
Agraw$_2$	FTDD	87.35 (+-0.11)	87.35 (+-0.11)	87.36 (+-0.11)	83.14 (+-0.48)	85.92 (+-0.06)	84.03 (+-0.43)
	WSTD	87.44 (+-0.07)	87.44 (+-0.07)	87.48 (+-0.07)	84.43 (+-0.33)	85.91 (+-0.06)	85.51 (+-0.26)
	HDDM$_A$	87.46 (+-0.07)	87.47 (+-0.07)	**87.53 (+-0.07)**	84.43 (+-0.30)	85.93 (+-0.06)	85.70 (+-0.13)
	DDM$_7$	86.88 (+-0.09)	86.88 (+-0.09)	87.07 (+-0.08)	85.67 (+-0.24)	85.98 (+-0.05)	85.59 (+-0.27)
	DDM$_{129}$	87.14 (+-0.09)	87.14 (+-0.09)	87.19 (+-0.09)	84.98 (+-0.32)	85.95 (+-0.06)	85.61 (+-0.16)
	RDDM$_{30}$	86.89 (+-0.08)	86.89 (+-0.08)	86.90 (+-0.08)	84.18 (+-0.40)	85.97 (+-0.06)	85.07 (+-0.36)
	RDDM$_7$	87.34 (+-0.07)	87.34 (+-0.07)	87.40 (+-0.07)	85.81 (+-0.08)	85.99 (+-0.05)	85.76 (+-0.12)
	RDDM$_{129}$	87.24 (+-0.06)	87.24 (+-0.06)	87.30 (+-0.07)	85.00 (+-0.36)	85.96 (+-0.06)	85.79 (+-0.06)
LED	FTDD	72.74 (+-0.13)	72.74 (+-0.13)	72.72 (+-0.12)	71.48 (+-0.26)	73.02 (+-0.11)	72.47 (+-0.17)
	WSTD	72.98 (+-0.13)	72.98 (+-0.13)	73.00 (+-0.13)	72.51 (+-0.17)	72.99 (+-0.10)	72.46 (+-0.18)
	HDDM$_A$	73.26 (+-0.11)	73.27 (+-0.11)	73.27 (+-0.12)	72.10 (+-0.16)	73.23 (+-0.11)	73.22 (+-0.12)
	DDM$_7$	73.23 (+-0.12)	73.24 (+-0.12)	73.24 (+-0.12)	73.01 (+-0.17)	73.26 (+-0.11)	73.14 (+-0.15)
	DDM$_{129}$	73.23 (+-0.12)	73.23 (+-0.12)	73.24 (+-0.12)	72.42 (+-0.21)	73.22 (+-0.11)	73.27 (+-0.12)
	RDDM$_{30}$	73.05 (+-0.12)	73.05 (+-0.12)	73.06 (+-0.12)	72.64 (+-0.19)	73.14 (+-0.11)	73.18 (+-0.12)
	RDDM$_7$	73.25 (+-0.12)	73.25 (+-0.12)	73.26 (+-0.12)	73.16 (+-0.10)	73.25 (+-0.11)	73.07 (+-0.11)
	RDDM$_{129}$	73.22 (+-0.12)	73.22 (+-0.12)	73.23 (+-0.12)	72.59 (+-0.23)	73.22 (+-0.11)	**73.30 (+-0.12)**
Mixed	FTDD	91.14 (+-0.10)	91.13 (+-0.10)	91.26 (+-0.09)	90.01 (+-0.38)	91.25 (+-0.06)	91.23 (+-0.07)
	WSTD	90.47 (+-0.17)	90.47 (+-0.17)	90.73 (+-0.13)	90.07 (+-0.55)	91.24 (+-0.06)	91.23 (+-0.07)
	HDDM$_A$	90.55 (+-0.14)	90.55 (+-0.14)	90.91 (+-0.08)	88.88 (+-0.57)	91.26 (+-0.06)	91.25 (+-0.07)
	DDM$_7$	89.43 (+-0.17)	89.43 (+-0.17)	89.87 (+-0.12)	91.16 (+-0.12)	91.26 (+-0.06)	91.22 (+-0.07)
	DDM$_{129}$	90.34 (+-0.20)	90.34 (+-0.20)	90.83 (+-0.11)	88.75 (+-0.73)	91.25 (+-0.06)	91.23 (+-0.07)
	RDDM$_{30}$	90.94 (+-0.12)	90.94 (+-0.12)	91.26 (+-0.08)	90.06 (+-0.56)	91.24 (+-0.06)	91.27 (+-0.07)
	RDDM$_7$	89.90 (+-0.18)	89.89 (+-0.18)	90.39 (+-0.11)	91.18 (+-0.07)	91.26 (+-0.06)	91.18 (+-0.07)
	RDDM$_{129}$	90.37 (+-0.20)	90.37 (+-0.20)	90.87 (+-0.11)	90.90 (+-0.39)	91.24 (+-0.06)	**91.29 (+-0.06)**
RBF	FTDD	19.28 (+-0.63)	22.93 (+-0.47)	30.81 (+-0.42)	31.62 (+-0.44)	**32.88 (+-0.19)**	31.64 (+-0.45)
	WSTD	18.80 (+-0.49)	22.88 (+-0.41)	30.20 (+-0.51)	30.94 (+-0.50)	32.63 (+-0.17)	30.79 (+-0.40)
	HDDM$_A$	19.34 (+-0.62)	22.82 (+-0.41)	30.61 (+-0.37)	30.98 (+-0.36)	32.64 (+-0.17)	31.16 (+-0.33)
	DDM$_7$	19.42 (+-0.61)	22.90 (+-0.40)	31.04 (+-0.30)	30.80 (+-0.40)	32.39 (+-0.13)	31.15 (+-0.34)
	DDM$_{129}$	19.15 (+-0.65)	22.82 (+-0.49)	30.72 (+-0.34)	31.14 (+-0.28)	32.64 (+-0.15)	31.25 (+-0.36)
	RDDM$_{30}$	19.44 (+-0.69)	22.53 (+-0.50)	30.88 (+-0.37)	31.23 (+-0.39)	32.66 (+-0.14)	31.20 (+-0.35)
	RDDM$_7$	19.65 (+-0.63)	22.79 (+-0.39)	30.84 (+-0.26)	30.80 (+-0.23)	32.40 (+-0.11)	30.87 (+-0.25)
	RDDM$_{129}$	19.34 (+-0.68)	22.74 (+-0.53)	30.84 (+-0.29)	31.06 (+-0.25)	32.62 (+-0.15)	31.23 (+-0.30)
Sine	FTDD	89.41 (+-0.13)	89.41 (+-0.13)	89.55 (+-0.09)	85.41 (+-0.36)	87.02 (+-0.08)	87.04 (+-0.09)
	WSTD	89.11 (+-0.11)	89.12 (+-0.11)	89.27 (+-0.09)	85.84 (+-0.43)	87.03 (+-0.08)	87.05 (+-0.09)
	HDDM$_A$	89.29 (+-0.12)	89.29 (+-0.12)	89.45 (+-0.11)	85.50 (+-0.41)	87.09 (+-0.09)	87.14 (+-0.09)
	DDM$_7$	88.46 (+-0.13)	88.46 (+-0.13)	88.63 (+-0.12)	87.04 (+-0.09)	87.22 (+-0.09)	86.33 (+-1.08)
	DDM$_{129}$	89.13 (+-0.13)	89.14 (+-0.13)	89.32 (+-0.10)	85.73 (+-0.39)	87.15 (+-0.08)	87.08 (+-0.11)
	RDDM$_{30}$	89.46 (+-0.14)	89.46 (+-0.14)	**89.60 (+-0.10)**	86.59 (+-0.22)	87.11 (+-0.09)	86.84 (+-0.20)
	RDDM$_7$	88.98 (+-0.13)	88.98 (+-0.13)	89.12 (+-0.11)	87.08 (+-0.08)	87.25 (+-0.08)	87.07 (+-0.08)
	RDDM$_{129}$	89.36 (+-0.08)	89.36 (+-0.08)	89.51 (+-0.07)	86.86 (+-0.18)	87.15 (+-0.08)	87.16 (+-0.09)
Wavef.	FTDD	80.93 (+-0.11)	80.93 (+-0.11)	80.90 (+-0.11)	79.75 (+-0.16)	80.46 (+-0.10)	79.95 (+-0.19)
	WSTD	81.50 (+-0.09)	81.50 (+-0.09)	81.48 (+-0.09)	79.88 (+-0.13)	80.51 (+-0.09)	80.21 (+-0.10)
	HDDM$_A$	81.52 (+-0.09)	81.52 (+-0.09)	81.50 (+-0.09)	79.94 (+-0.13)	80.46 (+-0.10)	80.20 (+-0.11)
	DDM$_7$	**81.85 (+-0.09)**	**81.85 (+-0.09)**	81.79 (+-0.09)	80.16 (+-0.11)	80.91 (+-0.09)	80.10 (+-0.12)
	DDM$_{129}$	81.52 (+-0.10)	81.52 (+-0.10)	81.49 (+-0.10)	79.97 (+-0.17)	80.54 (+-0.10)	79.98 (+-0.17)
	RDDM$_{30}$	81.32 (+-0.09)	81.32 (+-0.09)	81.29 (+-0.10)	79.92 (+-0.14)	80.48 (+-0.10)	80.02 (+-0.13)
	RDDM$_7$	81.68 (+-0.10)	81.68 (+-0.10)	81.64 (+-0.10)	80.21 (+-0.10)	80.95 (+-0.10)	80.17 (+-0.11)
	RDDM$_{129}$	81.47 (+-0.10)	81.47 (+-0.10)	81.46 (+-0.10)	80.00 (+-0.11)	80.55 (+-0.09)	80.13 (+-0.11)

Table 60 – Mean accuracies of Ensembles in percentage (%) in 500K instances gradual datasets, with 95% confidence intervals, using NB

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	68.88 (+-0.11)	68.88 (+-0.11)	**69.23 (+-0.13)**	65.85 (+-0.15)	66.48 (+-0.03)	66.27 (+-0.06)
	WSTD	67.80 (+-0.12)	67.80 (+-0.12)	67.71 (+-0.16)	66.24 (+-0.05)	66.53 (+-0.04)	66.20 (+-0.05)
	$HDDM_A$	68.80 (+-0.12)	68.80 (+-0.12)	69.06 (+-0.16)	66.15 (+-0.16)	66.50 (+-0.03)	66.38 (+-0.05)
	DDM_7	67.13 (+-0.21)	67.13 (+-0.21)	67.66 (+-0.22)	65.83 (+-0.80)	66.68 (+-0.05)	66.18 (+-0.09)
	DDM_{129}	68.70 (+-0.13)	68.70 (+-0.13)	69.07 (+-0.13)	65.75 (+-0.27)	66.58 (+-0.04)	65.66 (+-0.62)
	$RDDM_{30}$	68.78 (+-0.15)	68.78 (+-0.15)	69.17 (+-0.13)	65.86 (+-0.24)	66.52 (+-0.04)	66.22 (+-0.13)
	$RDDM_7$	67.19 (+-0.14)	67.18 (+-0.14)	67.41 (+-0.13)	66.21 (+-0.05)	66.71 (+-0.05)	66.19 (+-0.05)
	$RDDM_{129}$	68.50 (+-0.16)	68.50 (+-0.16)	68.80 (+-0.16)	66.29 (+-0.16)	66.57 (+-0.04)	66.36 (+-0.04)
$Agraw_2$	FTDD	88.65 (+-0.11)	88.65 (+-0.11)	88.65 (+-0.10)	84.64 (+-0.79)	86.82 (+-0.06)	86.05 (+-0.62)
	WSTD	88.50 (+-0.08)	88.50 (+-0.08)	88.49 (+-0.07)	85.78 (+-0.29)	86.80 (+-0.06)	86.61 (+-0.11)
	$HDDM_A$	88.73 (+-0.04)	88.73 (+-0.04)	**88.75 (+-0.04)**	85.71 (+-0.33)	86.84 (+-0.04)	86.74 (+-0.05)
	DDM_7	88.18 (+-0.07)	88.19 (+-0.07)	88.33 (+-0.07)	86.72 (+-0.07)	86.70 (+-0.04)	86.63 (+-0.20)
	DDM_{129}	88.63 (+-0.07)	88.63 (+-0.07)	88.67 (+-0.06)	86.02 (+-0.38)	86.85 (+-0.04)	86.57 (+-0.10)
	$RDDM_{30}$	88.63 (+-0.04)	88.63 (+-0.04)	88.68 (+-0.04)	86.16 (+-0.33)	86.83 (+-0.06)	86.49 (+-0.18)
	$RDDM_7$	88.33 (+-0.06)	88.33 (+-0.06)	88.37 (+-0.06)	86.53 (+-0.07)	86.65 (+-0.04)	86.55 (+-0.06)
	$RDDM_{129}$	88.65 (+-0.04)	88.65 (+-0.04)	88.68 (+-0.04)	86.70 (+-0.06)	86.83 (+-0.04)	86.67 (+-0.07)
LED	FTDD	73.61 (+-0.12)	73.61 (+-0.12)	73.60 (+-0.11)	72.46 (+-0.21)	73.73 (+-0.09)	73.35 (+-0.26)
	WSTD	73.71 (+-0.11)	73.71 (+-0.11)	73.71 (+-0.11)	73.61 (+-0.11)	73.72 (+-0.09)	73.35 (+-0.06)
	$HDDM_A$	**73.79 (+-0.11)**	**73.79 (+-0.11)**	**73.79 (+-0.11)**	73.00 (+-0.26)	73.75 (+-0.09)	73.74 (+-0.11)
	DDM_7	73.75 (+-0.11)	73.75 (+-0.11)	73.75 (+-0.11)	73.58 (+-0.19)	73.76 (+-0.10)	73.69 (+-0.11)
	DDM_{129}	73.74 (+-0.11)	73.74 (+-0.11)	73.74 (+-0.11)	73.29 (+-0.28)	73.75 (+-0.09)	73.60 (+-0.15)
	$RDDM_{30}$	73.73 (+-0.10)	73.73 (+-0.10)	73.74 (+-0.10)	73.47 (+-0.16)	73.74 (+-0.08)	73.55 (+-0.13)
	$RDDM_7$	73.76 (+-0.10)	73.77 (+-0.10)	73.77 (+-0.10)	73.57 (+-0.10)	73.77 (+-0.10)	73.45 (+-0.11)
	$RDDM_{129}$	**73.79 (+-0.11)**	**73.79 (+-0.11)**	**73.79 (+-0.11)**	73.66 (+-0.10)	73.77 (+-0.09)	73.72 (+-0.09)
Mixed	FTDD	90.94 (+-0.33)	90.94 (+-0.33)	91.42 (+-0.17)	90.86 (+-0.73)	91.92 (+-0.03)	91.92 (+-0.03)
	WSTD	90.26 (+-0.25)	90.26 (+-0.25)	91.05 (+-0.16)	90.93 (+-0.77)	91.93 (+-0.03)	91.93 (+-0.03)
	$HDDM_A$	90.43 (+-0.26)	90.43 (+-0.26)	91.20 (+-0.12)	90.46 (+-0.74)	91.93 (+-0.03)	**91.94 (+-0.04)**
	DDM_7	89.77 (+-0.37)	89.77 (+-0.37)	90.42 (+-0.19)	91.82 (+-0.22)	91.93 (+-0.03)	91.92 (+-0.03)
	DDM_{129}	90.46 (+-0.28)	90.46 (+-0.28)	91.28 (+-0.12)	90.71 (+-0.73)	91.93 (+-0.03)	91.93 (+-0.03)
	$RDDM_{30}$	90.48 (+-0.33)	90.48 (+-0.33)	91.36 (+-0.18)	91.81 (+-0.11)	91.93 (+-0.03)	91.91 (+-0.03)
	$RDDM_7$	90.40 (+-0.22)	90.40 (+-0.22)	91.02 (+-0.13)	91.77 (+-0.04)	91.92 (+-0.03)	91.75 (+-0.03)
	$RDDM_{129}$	90.05 (+-0.26)	90.05 (+-0.26)	91.19 (+-0.13)	91.75 (+-0.18)	91.93 (+-0.03)	91.91 (+-0.03)
RBF	FTDD	18.87 (+-1.17)	21.55 (+-1.24)	32.18 (+-0.71)	33.35 (+-0.42)	**33.86 (+-0.17)**	33.14 (+-0.32)
	WSTD	18.90 (+-0.84)	22.08 (+-0.91)	31.00 (+-0.52)	31.28 (+-0.29)	33.19 (+-0.12)	30.99 (+-0.26)
	$HDDM_A$	19.09 (+-0.71)	22.35 (+-0.75)	31.11 (+-0.39)	32.54 (+-0.37)	33.72 (+-0.14)	32.49 (+-0.40)
	DDM_7	19.17 (+-0.93)	21.25 (+-1.31)	32.14 (+-0.30)	33.00 (+-0.47)	33.09 (+-0.10)	32.82 (+-0.37)
	DDM_{129}	18.53 (+-0.73)	21.94 (+-1.16)	31.82 (+-0.34)	32.63 (+-0.40)	33.68 (+-0.10)	32.69 (+-0.35)
	$RDDM_{30}$	18.66 (+-0.71)	21.47 (+-0.90)	31.46 (+-0.33)	32.33 (+-0.32)	33.60 (+-0.16)	32.46 (+-0.36)
	$RDDM_7$	18.80 (+-0.83)	22.16 (+-1.11)	31.69 (+-0.27)	31.35 (+-0.19)	33.08 (+-0.10)	31.47 (+-0.16)
	$RDDM_{129}$	18.94 (+-0.80)	21.10 (+-1.11)	31.63 (+-0.41)	31.90 (+-0.33)	33.62 (+-0.12)	32.14 (+-0.26)
Sine	FTDD	89.20 (+-0.16)	89.20 (+-0.16)	89.57 (+-0.13)	85.81 (+-0.68)	87.33 (+-0.05)	87.33 (+-0.04)
	WSTD	89.33 (+-0.21)	89.33 (+-0.21)	89.60 (+-0.14)	87.01 (+-0.21)	87.33 (+-0.06)	87.33 (+-0.04)
	$HDDM_A$	89.14 (+-0.11)	89.14 (+-0.11)	89.54 (+-0.07)	85.72 (+-0.66)	87.31 (+-0.06)	87.31 (+-0.06)
	DDM_7	89.03 (+-0.21)	89.03 (+-0.21)	89.26 (+-0.17)	86.30 (+-1.89)	87.46 (+-0.05)	87.21 (+-0.07)
	DDM_{129}	89.44 (+-0.14)	89.44 (+-0.14)	**89.69 (+-0.11)**	86.40 (+-0.54)	87.36 (+-0.06)	87.19 (+-0.21)
	$RDDM_{30}$	89.36 (+-0.12)	89.36 (+-0.12)	89.68 (+-0.07)	87.12 (+-0.15)	87.37 (+-0.07)	87.23 (+-0.13)
	$RDDM_7$	89.37 (+-0.15)	89.37 (+-0.15)	89.53 (+-0.14)	87.35 (+-0.06)	87.58 (+-0.05)	87.35 (+-0.06)
	$RDDM_{129}$	89.27 (+-0.15)	89.27 (+-0.15)	89.56 (+-0.13)	87.35 (+-0.08)	87.39 (+-0.07)	87.39 (+-0.05)
Wavef.	FTDD	81.60 (+-0.12)	81.60 (+-0.12)	81.60 (+-0.12)	79.99 (+-0.22)	80.55 (+-0.10)	80.35 (+-0.11)
	WSTD	81.68 (+-0.10)	81.68 (+-0.10)	81.67 (+-0.10)	80.26 (+-0.21)	80.58 (+-0.12)	80.33 (+-0.15)
	$HDDM_A$	81.61 (+-0.11)	81.61 (+-0.11)	81.61 (+-0.11)	80.24 (+-0.13)	80.51 (+-0.12)	80.35 (+-0.12)
	DDM_7	**81.84 (+-0.09)**	**81.84 (+-0.09)**	81.82 (+-0.09)	80.28 (+-0.11)	80.83 (+-0.11)	80.21 (+-0.11)
	DDM_{129}	81.49 (+-0.14)	81.49 (+-0.14)	81.48 (+-0.14)	80.08 (+-0.20)	80.60 (+-0.11)	80.09 (+-0.21)
	$RDDM_{30}$	81.52 (+-0.11)	81.52 (+-0.11)	81.52 (+-0.11)	80.23 (+-0.15)	80.58 (+-0.12)	80.19 (+-0.16)
	$RDDM_7$	81.79 (+-0.10)	81.79 (+-0.10)	81.78 (+-0.10)	80.35 (+-0.09)	81.05 (+-0.10)	80.30 (+-0.10)
	$RDDM_{129}$	81.63 (+-0.11)	81.63 (+-0.11)	81.63 (+-0.11)	80.30 (+-0.14)	80.62 (+-0.12)	80.33 (+-0.14)

Table 61 – Mean accuracies of Ensembles in percentage (%) in 1 Million instances gradual datasets, with 95% confidence intervals, using NB

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	68.84 (+-0.28)	68.84 (+-0.28)	69.21 (+-0.14)	66.28 (+-0.13)	66.53 (+-0.03)	66.43 (+-0.07)
	WSTD	67.99 (+-0.05)	67.99 (+-0.05)	67.94 (+-0.06)	66.36 (+-0.04)	66.58 (+-0.03)	66.29 (+-0.05)
	$HDDM_A$	69.03 (+-0.16)	69.03 (+-0.16)	69.23 (+-0.14)	66.26 (+-0.14)	66.55 (+-0.03)	66.45 (+-0.05)
	DDM_7	67.79 (+-0.21)	67.79 (+-0.21)	68.35 (+-0.20)	66.36 (+-0.09)	66.79 (+-0.04)	65.97 (+-0.34)
	DDM_{129}	68.69 (+-0.21)	68.69 (+-0.21)	69.13 (+-0.13)	65.85 (+-0.42)	66.62 (+-0.03)	66.19 (+-0.19)
	$RDDM_{30}$	68.97 (+-0.17)	68.97 (+-0.17)	**69.29 (+-0.15)**	66.27 (+-0.09)	66.61 (+-0.04)	66.33 (+-0.10)
	$RDDM_7$	67.38 (+-0.12)	67.38 (+-0.12)	67.56 (+-0.11)	66.27 (+-0.07)	66.80 (+-0.05)	66.27 (+-0.04)
	$RDDM_{129}$	68.68 (+-0.13)	68.68 (+-0.13)	68.95 (+-0.15)	66.41 (+-0.06)	66.65 (+-0.03)	66.44 (+-0.06)
$Agraw_2$	FTDD	88.86 (+-0.06)	88.86 (+-0.06)	88.87 (+-0.06)	85.73 (+-0.16)	86.94 (+-0.02)	86.56 (+-0.29)
	WSTD	88.66 (+-0.05)	88.66 (+-0.05)	88.64 (+-0.05)	86.26 (+-0.28)	86.90 (+-0.03)	86.76 (+-0.10)
	$HDDM_A$	88.94 (+-0.02)	88.94 (+-0.02)	**88.95 (+-0.03)**	86.05 (+-0.38)	86.95 (+-0.03)	86.83 (+-0.05)
	DDM_7	88.52 (+-0.06)	88.52 (+-0.06)	88.63 (+-0.07)	86.77 (+-0.17)	86.78 (+-0.02)	86.77 (+-0.10)
	DDM_{129}	88.83 (+-0.08)	88.83 (+-0.08)	88.87 (+-0.07)	86.16 (+-0.40)	86.96 (+-0.02)	86.78 (+-0.12)
	$RDDM_{30}$	88.87 (+-0.05)	88.87 (+-0.05)	88.90 (+-0.04)	86.35 (+-0.46)	86.93 (+-0.02)	86.65 (+-0.27)
	$RDDM_7$	88.46 (+-0.04)	88.46 (+-0.04)	88.49 (+-0.03)	86.67 (+-0.04)	86.73 (+-0.02)	86.66 (+-0.02)
	$RDDM_{129}$	88.82 (+-0.04)	88.82 (+-0.04)	88.86 (+-0.03)	86.82 (+-0.04)	86.93 (+-0.02)	86.81 (+-0.03)
LED	FTDD	73.79 (+-0.09)	73.79 (+-0.09)	73.79 (+-0.09)	72.85 (+-0.36)	73.84 (+-0.06)	73.61 (+-0.24)
	WSTD	73.82 (+-0.07)	73.82 (+-0.07)	73.82 (+-0.07)	73.75 (+-0.06)	73.85 (+-0.05)	73.46 (+-0.12)
	$HDDM_A$	73.87 (+-0.06)	73.87 (+-0.06)	73.87 (+-0.06)	73.23 (+-0.30)	73.85 (+-0.05)	73.84 (+-0.06)
	DDM_7	73.85 (+-0.07)	73.85 (+-0.07)	73.85 (+-0.07)	73.71 (+-0.19)	73.86 (+-0.06)	73.78 (+-0.10)
	DDM_{129}	73.83 (+-0.07)	73.83 (+-0.07)	73.83 (+-0.07)	73.40 (+-0.21)	73.85 (+-0.05)	73.63 (+-0.14)
	$RDDM_{30}$	73.84 (+-0.07)	73.84 (+-0.07)	73.84 (+-0.07)	73.62 (+-0.16)	73.86 (+-0.05)	73.72 (+-0.04)
	$RDDM_7$	73.87 (+-0.07)	73.87 (+-0.07)	73.87 (+-0.07)	73.64 (+-0.06)	**73.88 (+-0.06)**	73.52 (+-0.05)
	$RDDM_{129}$	73.87 (+-0.07)	73.87 (+-0.07)	**73.88 (+-0.07)**	73.79 (+-0.10)	73.87 (+-0.05)	73.79 (+-0.05)
Mixed	FTDD	91.03 (+-0.19)	91.03 (+-0.19)	91.56 (+-0.09)	91.61 (+-0.34)	**92.03 (+-0.03)**	**92.03 (+-0.03)**
	WSTD	90.10 (+-0.21)	90.10 (+-0.21)	91.14 (+-0.16)	91.63 (+-0.35)	**92.03 (+-0.03)**	**92.03 (+-0.03)**
	$HDDM_A$	90.14 (+-0.19)	90.14 (+-0.19)	91.22 (+-0.14)	90.35 (+-0.53)	**92.03 (+-0.03)**	**92.03 (+-0.03)**
	DDM_7	89.88 (+-0.33)	89.88 (+-0.33)	90.70 (+-0.17)	91.47 (+-0.51)	**92.03 (+-0.03)**	92.02 (+-0.03)
	DDM_{129}	90.59 (+-0.38)	90.59 (+-0.38)	91.43 (+-0.13)	91.05 (+-0.23)	**92.03 (+-0.03)**	92.02 (+-0.03)
	$RDDM_{30}$	90.77 (+-0.34)	90.77 (+-0.34)	91.56 (+-0.17)	91.83 (+-0.11)	**92.03 (+-0.03)**	91.98 (+-0.04)
	$RDDM_7$	90.29 (+-0.22)	90.29 (+-0.22)	91.07 (+-0.12)	91.85 (+-0.04)	92.02 (+-0.03)	91.82 (+-0.03)
	$RDDM_{129}$	90.18 (+-0.28)	90.18 (+-0.28)	91.27 (+-0.12)	91.92 (+-0.08)	**92.03 (+-0.03)**	91.99 (+-0.03)
RBF	FTDD	18.93 (+-1.14)	20.97 (+-1.29)	32.36 (+-0.47)	33.43 (+-0.25)	**34.14 (+-0.10)**	33.25 (+-0.21)
	WSTD	18.70 (+-0.64)	21.36 (+-0.93)	31.22 (+-0.37)	31.29 (+-0.19)	33.16 (+-0.07)	31.07 (+-0.24)
	$HDDM_A$	19.27 (+-0.95)	22.02 (+-1.03)	31.58 (+-0.49)	33.26 (+-0.30)	33.96 (+-0.06)	32.95 (+-0.25)
	DDM_7	18.82 (+-0.73)	21.32 (+-1.10)	32.59 (+-0.32)	33.00 (+-0.44)	33.14 (+-0.06)	33.19 (+-0.33)
	DDM_{129}	18.39 (+-0.67)	21.05 (+-1.30)	31.82 (+-0.41)	33.03 (+-0.26)	33.91 (+-0.06)	33.07 (+-0.23)
	$RDDM_{30}$	18.76 (+-0.66)	21.37 (+-1.09)	32.38 (+-0.35)	32.61 (+-0.22)	33.75 (+-0.08)	32.65 (+-0.24)
	$RDDM_7$	18.37 (+-0.51)	21.73 (+-0.87)	31.70 (+-0.17)	31.37 (+-0.16)	33.09 (+-0.04)	31.50 (+-0.17)
	$RDDM_{129}$	18.83 (+-0.86)	20.89 (+-0.70)	31.94 (+-0.18)	32.09 (+-0.17)	33.67 (+-0.08)	32.10 (+-0.15)
Sine	FTDD	89.41 (+-0.25)	89.41 (+-0.25)	89.69 (+-0.17)	86.25 (+-0.51)	87.41 (+-0.05)	87.41 (+-0.05)
	WSTD	89.29 (+-0.27)	89.29 (+-0.27)	89.57 (+-0.23)	86.73 (+-0.44)	87.41 (+-0.06)	87.40 (+-0.05)
	$HDDM_A$	89.27 (+-0.18)	89.27 (+-0.18)	89.54 (+-0.14)	86.34 (+-0.64)	87.39 (+-0.06)	87.38 (+-0.07)
	DDM_7	89.15 (+-0.13)	89.15 (+-0.13)	89.40 (+-0.10)	85.89 (+-1.88)	87.51 (+-0.04)	86.75 (+-1.08)
	DDM_{129}	89.45 (+-0.16)	89.45 (+-0.16)	89.68 (+-0.12)	86.46 (+-0.61)	87.42 (+-0.05)	87.26 (+-0.12)
	$RDDM_{30}$	89.48 (+-0.12)	89.48 (+-0.12)	89.73 (+-0.10)	87.23 (+-0.18)	87.45 (+-0.05)	87.32 (+-0.05)
	$RDDM_7$	89.39 (+-0.13)	89.39 (+-0.13)	89.56 (+-0.11)	87.41 (+-0.04)	87.66 (+-0.03)	87.41 (+-0.04)
	$RDDM_{129}$	89.58 (+-0.16)	89.58 (+-0.16)	**89.81 (+-0.11)**	87.37 (+-0.11)	87.47 (+-0.05)	87.45 (+-0.04)
Wavef.	FTDD	81.66 (+-0.06)	81.66 (+-0.06)	81.66 (+-0.06)	80.23 (+-0.12)	80.53 (+-0.07)	80.39 (+-0.10)
	WSTD	81.72 (+-0.06)	81.72 (+-0.06)	81.72 (+-0.06)	80.35 (+-0.10)	80.59 (+-0.06)	80.38 (+-0.07)
	$HDDM_A$	81.66 (+-0.07)	81.66 (+-0.07)	81.65 (+-0.07)	80.34 (+-0.10)	80.53 (+-0.08)	80.40 (+-0.09)
	DDM_7	81.80 (+-0.08)	81.80 (+-0.08)	81.79 (+-0.08)	80.29 (+-0.21)	80.77 (+-0.08)	80.25 (+-0.16)
	DDM_{129}	81.54 (+-0.09)	81.54 (+-0.09)	81.54 (+-0.09)	79.85 (+-0.27)	80.57 (+-0.08)	80.18 (+-0.22)
	$RDDM_{30}$	81.60 (+-0.07)	81.60 (+-0.07)	81.60 (+-0.07)	80.23 (+-0.22)	80.60 (+-0.07)	80.25 (+-0.20)
	$RDDM_7$	**81.81 (+-0.07)**	**81.81 (+-0.07)**	**81.81 (+-0.07)**	80.38 (+-0.07)	81.06 (+-0.07)	80.34 (+-0.07)
	$RDDM_{129}$	81.68 (+-0.05)	81.68 (+-0.05)	81.68 (+-0.05)	80.39 (+-0.08)	80.65 (+-0.06)	80.40 (+-0.06)

Table 62 – Mean accuracies of Ensembles in percentage (%) in 2 Million instances gradual datasets, with 95% confidence intervals, using NB

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	69.04 (+-0.20)	69.04 (+-0.20)	69.35 (+-0.15)	66.30 (+-0.16)	66.57 (+-0.02)	66.52 (+-0.04)
	WSTD	68.08 (+-0.04)	68.08 (+-0.04)	68.01 (+-0.05)	66.40 (+-0.03)	66.62 (+-0.02)	66.30 (+-0.03)
	$HDDM_A$	69.06 (+-0.16)	69.06 (+-0.16)	69.28 (+-0.17)	66.22 (+-0.17)	66.57 (+-0.03)	66.49 (+-0.05)
	DDM_7	68.14 (+-0.10)	68.14 (+-0.10)	68.69 (+-0.16)	65.76 (+-0.72)	66.82 (+-0.03)	66.44 (+-0.08)
	DDM_{129}	69.06 (+-0.23)	69.06 (+-0.23)	**69.49 (+-0.16)**	66.09 (+-0.36)	66.66 (+-0.02)	66.27 (+-0.27)
	$RDDM_{30}$	69.21 (+-0.11)	69.21 (+-0.11)	69.42 (+-0.12)	66.27 (+-0.07)	66.63 (+-0.02)	66.40 (+-0.05)
	$RDDM_7$	67.57 (+-0.07)	67.57 (+-0.07)	67.72 (+-0.06)	66.27 (+-0.04)	66.87 (+-0.02)	66.28 (+-0.02)
	$RDDM_{129}$	68.78 (+-0.12)	68.78 (+-0.12)	69.04 (+-0.09)	66.50 (+-0.04)	66.68 (+-0.02)	66.51 (+-0.03)
$Agraw_2$	FTDD	88.87 (+-0.12)	88.87 (+-0.12)	88.89 (+-0.10)	86.26 (+-0.30)	87.00 (+-0.02)	86.87 (+-0.10)
	WSTD	88.74 (+-0.02)	88.74 (+-0.02)	88.72 (+-0.02)	86.21 (+-0.27)	86.95 (+-0.02)	86.87 (+-0.03)
	$HDDM_A$	89.03 (+-0.04)	89.03 (+-0.04)	**89.04 (+-0.04)**	86.29 (+-0.27)	87.01 (+-0.02)	86.95 (+-0.02)
	DDM_7	88.75 (+-0.04)	88.75 (+-0.04)	88.84 (+-0.04)	86.85 (+-0.11)	86.80 (+-0.01)	86.89 (+-0.08)
	DDM_{129}	89.00 (+-0.08)	89.00 (+-0.08)	89.03 (+-0.07)	85.93 (+-0.29)	87.01 (+-0.02)	86.59 (+-0.50)
	$RDDM_{30}$	88.96 (+-0.05)	88.96 (+-0.05)	89.00 (+-0.03)	86.51 (+-0.16)	86.97 (+-0.02)	86.77 (+-0.08)
	$RDDM_7$	88.58 (+-0.05)	88.58 (+-0.05)	88.61 (+-0.04)	86.70 (+-0.02)	86.78 (+-0.02)	86.70 (+-0.01)
	$RDDM_{129}$	88.94 (+-0.03)	88.94 (+-0.03)	88.97 (+-0.03)	86.89 (+-0.02)	86.97 (+-0.02)	86.88 (+-0.02)
LED	FTDD	73.91 (+-0.04)	73.91 (+-0.04)	73.91 (+-0.04)	73.38 (+-0.34)	73.92 (+-0.03)	73.74 (+-0.18)
	WSTD	73.92 (+-0.04)	73.92 (+-0.04)	73.92 (+-0.04)	73.82 (+-0.03)	73.92 (+-0.04)	73.60 (+-0.06)
	$HDDM_A$	73.93 (+-0.04)	73.93 (+-0.04)	73.93 (+-0.04)	73.69 (+-0.15)	73.93 (+-0.04)	73.89 (+-0.05)
	DDM_7	73.92 (+-0.04)	73.92 (+-0.04)	73.92 (+-0.04)	73.67 (+-0.32)	73.92 (+-0.03)	73.89 (+-0.06)
	DDM_{129}	73.91 (+-0.04)	73.91 (+-0.04)	73.91 (+-0.04)	72.66 (+-1.84)	73.92 (+-0.03)	73.73 (+-0.23)
	$RDDM_{30}$	73.89 (+-0.04)	73.89 (+-0.04)	73.89 (+-0.04)	73.73 (+-0.20)	73.92 (+-0.04)	73.78 (+-0.10)
	$RDDM_7$	73.93 (+-0.04)	73.93 (+-0.04)	73.93 (+-0.04)	73.70 (+-0.03)	**73.94 (+-0.04)**	73.56 (+-0.03)
	$RDDM_{129}$	73.93 (+-0.04)	73.93 (+-0.04)	73.93 (+-0.04)	73.85 (+-0.03)	73.93 (+-0.04)	73.86 (+-0.04)
Mixed	FTDD	90.53 (+-0.33)	90.53 (+-0.33)	91.47 (+-0.12)	91.43 (+-0.41)	**92.03 (+-0.02)**	**92.03 (+-0.03)**
	WSTD	89.95 (+-0.35)	89.95 (+-0.35)	91.10 (+-0.21)	91.76 (+-0.18)	**92.03 (+-0.02)**	**92.03 (+-0.03)**
	$HDDM_A$	90.20 (+-0.22)	90.20 (+-0.22)	91.26 (+-0.11)	91.50 (+-0.48)	92.02 (+-0.02)	92.02 (+-0.02)
	DDM_7	89.99 (+-0.21)	89.99 (+-0.21)	90.92 (+-0.13)	91.78 (+-0.25)	**92.03 (+-0.02)**	92.01 (+-0.03)
	DDM_{129}	90.66 (+-0.22)	90.66 (+-0.22)	91.47 (+-0.13)	91.56 (+-0.37)	**92.03 (+-0.02)**	92.01 (+-0.03)
	$RDDM_{30}$	90.60 (+-0.22)	90.60 (+-0.22)	91.46 (+-0.10)	91.95 (+-0.04)	92.02 (+-0.03)	91.99 (+-0.03)
	$RDDM_7$	90.19 (+-0.17)	90.19 (+-0.17)	91.04 (+-0.12)	91.84 (+-0.03)	92.02 (+-0.02)	91.82 (+-0.03)
	$RDDM_{129}$	90.27 (+-0.16)	90.27 (+-0.16)	91.32 (+-0.12)	92.00 (+-0.03)	92.02 (+-0.03)	91.98 (+-0.03)
RBF	FTDD	18.61 (+-0.76)	20.24 (+-1.15)	32.47 (+-0.37)	33.25 (+-0.15)	**34.13 (+-0.07)**	33.21 (+-0.14)
	WSTD	18.26 (+-0.38)	20.42 (+-0.84)	31.25 (+-0.12)	31.24 (+-0.11)	33.21 (+-0.06)	31.15 (+-0.15)
	$HDDM_A$	18.97 (+-1.02)	21.43 (+-1.10)	32.30 (+-0.29)	33.35 (+-0.18)	34.08 (+-0.07)	33.07 (+-0.19)
	DDM_7	18.43 (+-0.66)	20.77 (+-1.00)	32.69 (+-0.29)	33.23 (+-0.26)	33.18 (+-0.07)	33.48 (+-0.15)
	DDM_{129}	18.24 (+-0.46)	20.25 (+-1.25)	32.67 (+-0.24)	33.51 (+-0.14)	33.99 (+-0.09)	33.45 (+-0.14)
	$RDDM_{30}$	18.49 (+-0.51)	21.42 (+-0.93)	32.25 (+-0.26)	32.86 (+-0.33)	33.82 (+-0.07)	32.46 (+-0.20)
	$RDDM_7$	18.24 (+-0.48)	20.84 (+-0.94)	31.78 (+-0.12)	31.30 (+-0.16)	33.06 (+-0.15)	31.44 (+-0.12)
	$RDDM_{129}$	18.99 (+-0.95)	20.60 (+-0.86)	32.06 (+-0.09)	32.01 (+-0.10)	33.73 (+-0.06)	32.13 (+-0.10)
Sine	FTDD	89.03 (+-0.26)	89.03 (+-0.26)	89.45 (+-0.21)	86.28 (+-0.44)	87.43 (+-0.03)	87.44 (+-0.03)
	WSTD	89.49 (+-0.21)	89.49 (+-0.21)	**89.69 (+-0.16)**	87.00 (+-0.36)	87.43 (+-0.03)	87.43 (+-0.02)
	$HDDM_A$	89.06 (+-0.14)	89.06 (+-0.14)	89.37 (+-0.09)	86.49 (+-0.94)	87.41 (+-0.02)	87.09 (+-0.67)
	DDM_7	89.29 (+-0.12)	89.29 (+-0.12)	89.52 (+-0.10)	85.77 (+-2.05)	87.50 (+-0.02)	86.10 (+-2.38)
	DDM_{129}	89.40 (+-0.18)	89.42 (+-0.18)	89.65 (+-0.14)	85.50 (+-2.48)	87.43 (+-0.02)	86.61 (+-1.15)
	$RDDM_{30}$	89.25 (+-0.18)	89.25 (+-0.18)	89.58 (+-0.12)	87.36 (+-0.04)	87.46 (+-0.02)	87.35 (+-0.02)
	$RDDM_7$	89.33 (+-0.09)	89.33 (+-0.09)	89.51 (+-0.08)	87.45 (+-0.02)	87.68 (+-0.01)	87.44 (+-0.03)
	$RDDM_{129}$	89.35 (+-0.14)	89.35 (+-0.14)	89.60 (+-0.10)	87.45 (+-0.03)	87.49 (+-0.02)	87.46 (+-0.03)
Wavef.	FTDD	81.71 (+-0.02)	81.71 (+-0.02)	81.71 (+-0.02)	80.34 (+-0.12)	80.60 (+-0.04)	80.47 (+-0.04)
	WSTD	81.75 (+-0.04)	81.75 (+-0.04)	81.75 (+-0.04)	80.44 (+-0.04)	80.61 (+-0.04)	80.45 (+-0.04)
	$HDDM_A$	81.67 (+-0.03)	81.67 (+-0.03)	81.67 (+-0.03)	80.43 (+-0.06)	80.60 (+-0.04)	80.46 (+-0.04)
	DDM_7	81.82 (+-0.06)	81.82 (+-0.06)	81.81 (+-0.06)	80.32 (+-0.19)	80.79 (+-0.07)	80.40 (+-0.04)
	DDM_{129}	81.48 (+-0.10)	81.48 (+-0.10)	81.48 (+-0.11)	80.10 (+-0.29)	80.61 (+-0.05)	80.04 (+-0.28)
	$RDDM_{30}$	81.62 (+-0.03)	81.62 (+-0.03)	81.62 (+-0.03)	80.41 (+-0.05)	80.64 (+-0.04)	80.40 (+-0.05)
	$RDDM_7$	**81.83 (+-0.04)**	**81.83 (+-0.04)**	81.82 (+-0.04)	80.42 (+-0.04)	81.09 (+-0.03)	80.38 (+-0.04)
	$RDDM_{129}$	81.71 (+-0.03)	81.71 (+-0.03)	81.71 (+-0.03)	80.44 (+-0.04)	80.69 (+-0.04)	80.45 (+-0.04)

APPENDIX D – Ensemble Results with HT

This appendix shows the detailed results of the experiments with the ensembles configurations using Hoeffding Tree (HT) as base learner, also omitted from Chapter 7, separated by type of concept drift as well as size of the datasets. Tables 63 to 67 contain the results in the abrupt datasets and Tables 68 to 72 the ones in the gradual datasets.

Table 63 – Mean accuracies of Ensembles in percentage (%) in 10K instances abrupt datasets, with 95% confidence intervals, using HT

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	60.43 (+-0.49)	60.48 (+-0.48)	60.75 (+-0.47)	62.53 (+-0.36)	64.21 (+-0.35)	62.64 (+-0.38)
	WSTD	62.67 (+-0.47)	62.67 (+-0.48)	63.01 (+-0.45)	63.43 (+-0.35)	64.21 (+-0.27)	63.44 (+-0.43)
	$HDDM_A$	62.62 (+-0.58)	62.60 (+-0.58)	63.06 (+-0.53)	63.94 (+-0.45)	64.60 (+-0.38)	64.47 (+-0.34)
	DDM_7	61.74 (+-0.42)	61.73 (+-0.43)	62.08 (+-0.40)	63.70 (+-0.31)	64.31 (+-0.29)	63.98 (+-0.39)
	DDM_{129}	62.29 (+-0.53)	62.28 (+-0.53)	62.82 (+-0.46)	64.07 (+-0.44)	64.69 (+-0.36)	64.62 (+-0.42)
	$RDDM_{30}$	60.95 (+-0.57)	60.99 (+-0.57)	61.62 (+-0.50)	62.74 (+-0.42)	64.60 (+-0.34)	63.16 (+-0.40)
	$RDDM_7$	62.54 (+-0.49)	62.52 (+-0.47)	62.95 (+-0.45)	64.70 (+-0.44)	64.45 (+-0.29)	**64.84 (+-0.36)**
	$RDDM_{129}$	62.48 (+-0.52)	62.47 (+-0.52)	62.96 (+-0.50)	64.15 (+-0.34)	64.71 (+-0.36)	64.69 (+-0.30)
$Agraw_2$	FTDD	80.49 (+-0.30)	80.52 (+-0.30)	80.79 (+-0.27)	79.05 (+-0.42)	81.58 (+-0.27)	79.41 (+-0.66)
	WSTD	81.67 (+-0.35)	81.70 (+-0.34)	81.94 (+-0.33)	80.17 (+-0.53)	81.86 (+-0.26)	81.07 (+-0.51)
	$HDDM_A$	81.23 (+-0.33)	81.26 (+-0.32)	81.56 (+-0.31)	80.72 (+-0.40)	81.79 (+-0.28)	81.56 (+-0.44)
	DDM_7	81.72 (+-0.24)	81.72 (+-0.24)	81.90 (+-0.24)	81.85 (+-0.28)	**82.60 (+-0.17)**	81.75 (+-0.31)
	DDM_{129}	81.53 (+-0.31)	81.56 (+-0.33)	81.72 (+-0.28)	81.49 (+-0.52)	82.38 (+-0.19)	81.54 (+-0.85)
	$RDDM_{30}$	78.60 (+-0.31)	78.62 (+-0.31)	78.91 (+-0.29)	76.80 (+-1.38)	82.16 (+-0.19)	76.13 (+-1.87)
	$RDDM_7$	82.03 (+-0.21)	82.05 (+-0.21)	82.23 (+-0.23)	81.88 (+-0.26)	82.57 (+-0.19)	82.24 (+-0.27)
	$RDDM_{129}$	81.22 (+-0.35)	81.26 (+-0.36)	81.47 (+-0.32)	81.42 (+-0.49)	82.39 (+-0.19)	81.58 (+-0.85)
LED	FTDD	65.07 (+-2.07)	68.48 (+-0.31)	68.05 (+-0.37)	65.93 (+-0.94)	68.05 (+-0.25)	67.01 (+-0.74)
	WSTD	67.78 (+-0.36)	68.12 (+-0.34)	68.22 (+-0.32)	68.31 (+-0.37)	66.93 (+-0.39)	67.08 (+-1.00)
	$HDDM_A$	68.67 (+-0.29)	69.01 (+-0.27)	69.04 (+-0.27)	68.73 (+-0.29)	68.52 (+-0.26)	69.68 (+-0.30)
	DDM_7	68.71 (+-0.30)	69.03 (+-0.26)	69.09 (+-0.25)	68.79 (+-0.31)	68.85 (+-0.27)	69.53 (+-0.30)
	DDM_{129}	68.55 (+-0.30)	68.84 (+-0.27)	68.88 (+-0.28)	68.69 (+-0.35)	68.50 (+-0.26)	69.85 (+-0.30)
	$RDDM_{30}$	68.12 (+-0.30)	68.41 (+-0.28)	68.43 (+-0.28)	68.53 (+-0.38)	68.48 (+-0.27)	69.52 (+-0.29)
	$RDDM_7$	68.81 (+-0.32)	69.12 (+-0.27)	69.16 (+-0.27)	69.19 (+-0.35)	68.84 (+-0.27)	**69.97 (+-0.31)**
	$RDDM_{129}$	68.49 (+-0.29)	68.78 (+-0.26)	68.82 (+-0.26)	68.62 (+-0.38)	68.50 (+-0.26)	69.78 (+-0.29)
Mixed	FTDD	89.99 (+-0.23)	89.99 (+-0.22)	90.16 (+-0.22)	88.45 (+-0.76)	89.84 (+-0.18)	90.33 (+-0.23)
	WSTD	90.04 (+-0.22)	90.05 (+-0.21)	90.18 (+-0.21)	87.58 (+-0.90)	89.83 (+-0.19)	**90.36 (+-0.22)**
	$HDDM_A$	89.93 (+-0.21)	89.93 (+-0.20)	90.09 (+-0.20)	87.68 (+-0.65)	89.96 (+-0.17)	90.32 (+-0.23)
	DDM_7	88.73 (+-0.26)	88.75 (+-0.25)	88.83 (+-0.23)	87.32 (+-0.83)	89.80 (+-0.21)	89.24 (+-0.66)
	DDM_{129}	89.83 (+-0.24)	89.84 (+-0.23)	90.01 (+-0.23)	87.41 (+-0.74)	89.92 (+-0.19)	89.94 (+-0.44)
	$RDDM_{30}$	89.73 (+-0.23)	89.73 (+-0.22)	89.83 (+-0.21)	88.65 (+-0.46)	89.91 (+-0.18)	89.82 (+-0.24)
	$RDDM_7$	89.59 (+-0.21)	89.60 (+-0.20)	89.77 (+-0.20)	88.83 (+-0.65)	89.84 (+-0.21)	90.27 (+-0.24)
	$RDDM_{129}$	89.89 (+-0.23)	89.90 (+-0.23)	90.09 (+-0.23)	87.51 (+-0.68)	89.92 (+-0.19)	90.17 (+-0.24)
RBF	FTDD	21.39 (+-0.95)	24.90 (+-0.76)	31.40 (+-0.58)	31.86 (+-0.55)	**32.50 (+-0.43)**	32.26 (+-0.50)
	WSTD	21.61 (+-0.98)	25.14 (+-0.72)	30.89 (+-0.64)	31.06 (+-0.65)	32.41 (+-0.36)	30.93 (+-0.60)
	$HDDM_A$	21.08 (+-0.88)	24.73 (+-0.77)	31.94 (+-0.51)	31.84 (+-0.39)	32.49 (+-0.41)	32.06 (+-0.37)
	DDM_7	20.54 (+-0.79)	24.65 (+-0.55)	31.74 (+-0.51)	31.48 (+-0.38)	31.56 (+-0.38)	31.47 (+-0.39)
	DDM_{129}	20.92 (+-0.87)	24.89 (+-0.89)	31.94 (+-0.58)	31.82 (+-0.37)	32.22 (+-0.35)	31.89 (+-0.43)
	$RDDM_{30}$	20.99 (+-0.90)	24.70 (+-0.79)	31.80 (+-0.61)	31.87 (+-0.51)	32.38 (+-0.40)	32.22 (+-0.43)
	$RDDM_7$	20.46 (+-0.76)	24.58 (+-0.56)	32.12 (+-0.48)	31.63 (+-0.33)	31.53 (+-0.34)	31.64 (+-0.38)
	$RDDM_{129}$	20.94 (+-0.87)	24.89 (+-0.87)	31.97 (+-0.52)	31.90 (+-0.43)	32.17 (+-0.35)	32.01 (+-0.39)
Sine	FTDD	89.90 (+-0.26)	89.92 (+-0.26)	**89.99 (+-0.27)**	87.17 (+-0.31)	88.43 (+-0.18)	88.37 (+-0.17)
	WSTD	89.59 (+-0.24)	89.62 (+-0.25)	89.64 (+-0.24)	87.21 (+-0.36)	88.44 (+-0.16)	88.38 (+-0.15)
	$HDDM_A$	89.64 (+-0.24)	89.66 (+-0.24)	89.71 (+-0.23)	87.43 (+-0.31)	88.58 (+-0.18)	88.39 (+-0.17)
	DDM_7	88.30 (+-0.24)	88.33 (+-0.25)	88.31 (+-0.25)	86.51 (+-0.46)	88.21 (+-0.17)	86.71 (+-0.36)
	DDM_{129}	89.50 (+-0.23)	89.53 (+-0.24)	89.56 (+-0.22)	86.93 (+-0.26)	88.49 (+-0.19)	87.76 (+-0.23)
	$RDDM_{30}$	89.63 (+-0.28)	89.65 (+-0.28)	89.68 (+-0.28)	87.33 (+-0.23)	88.58 (+-0.17)	87.82 (+-0.16)
	$RDDM_7$	89.47 (+-0.20)	89.49 (+-0.21)	89.50 (+-0.21)	87.52 (+-0.29)	88.26 (+-0.17)	87.84 (+-0.21)
	$RDDM_{129}$	89.42 (+-0.24)	89.45 (+-0.25)	89.45 (+-0.25)	87.34 (+-0.28)	88.48 (+-0.20)	87.98 (+-0.20)
Wavef.	FTDD	79.93 (+-0.31)	80.06 (+-0.32)	79.24 (+-0.37)	77.90 (+-0.51)	78.94 (+-0.44)	78.07 (+-0.58)
	WSTD	80.37 (+-0.30)	80.50 (+-0.30)	80.02 (+-0.33)	78.37 (+-0.50)	79.06 (+-0.42)	78.77 (+-0.51)
	$HDDM_A$	80.29 (+-0.31)	80.42 (+-0.30)	79.82 (+-0.36)	78.54 (+-0.48)	78.99 (+-0.43)	78.69 (+-0.48)
	DDM_7	80.86 (+-0.24)	**80.98 (+-0.25)**	80.77 (+-0.26)	79.06 (+-0.44)	79.77 (+-0.35)	78.91 (+-0.42)
	DDM_{129}	80.52 (+-0.31)	80.65 (+-0.31)	80.19 (+-0.34)	79.11 (+-0.46)	79.36 (+-0.38)	79.13 (+-0.44)
	$RDDM_{30}$	79.79 (+-0.34)	79.92 (+-0.33)	79.10 (+-0.39)	78.34 (+-0.45)	78.98 (+-0.40)	78.54 (+-0.42)
	$RDDM_7$	80.79 (+-0.32)	80.91 (+-0.31)	80.52 (+-0.34)	79.17 (+-0.43)	79.74 (+-0.36)	79.20 (+-0.43)
	$RDDM_{129}$	80.39 (+-0.32)	80.52 (+-0.31)	79.94 (+-0.36)	79.03 (+-0.40)	79.37 (+-0.38)	79.09 (+-0.47)

Table 64 – Mean accuracies of Ensembles in percentage (%) in 20K instances abrupt datasets, with 95% confidence intervals, using HT

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	60.20 (+-0.47)	60.19 (+-0.47)	60.46 (+-0.42)	61.83 (+-0.81)	66.27 (+-0.35)	64.04 (+-0.76)
	WSTD	63.38 (+-0.39)	63.38 (+-0.38)	63.60 (+-0.37)	65.53 (+-0.54)	66.08 (+-0.28)	65.33 (+-0.48)
	$HDDM_A$	65.88 (+-0.55)	65.87 (+-0.55)	66.05 (+-0.47)	67.27 (+-0.44)	68.44 (+-0.36)	68.12 (+-0.48)
	DDM_7	64.16 (+-0.49)	64.15 (+-0.49)	64.27 (+-0.45)	67.00 (+-0.51)	68.08 (+-0.42)	67.25 (+-0.44)
	DDM_{129}	65.46 (+-0.55)	65.46 (+-0.55)	65.67 (+-0.51)	66.97 (+-0.53)	**68.54 (+-0.33)**	67.78 (+-0.44)
	$RDDM_{30}$	65.08 (+-0.58)	65.08 (+-0.58)	65.13 (+-0.48)	66.00 (+-0.69)	68.42 (+-0.34)	67.31 (+-0.49)
	$RDDM_7$	65.70 (+-0.60)	65.68 (+-0.60)	65.98 (+-0.50)	67.99 (+-0.49)	68.20 (+-0.38)	68.10 (+-0.46)
	$RDDM_{129}$	66.00 (+-0.56)	66.00 (+-0.57)	66.17 (+-0.50)	67.38 (+-0.48)	68.52 (+-0.32)	68.19 (+-0.45)
$Agraw_2$	FTDD	82.79 (+-0.16)	82.81 (+-0.16)	82.87 (+-0.17)	83.31 (+-0.22)	83.97 (+-0.23)	84.13 (+-0.24)
	WSTD	83.72 (+-0.20)	83.74 (+-0.20)	83.88 (+-0.21)	83.80 (+-0.21)	84.32 (+-0.19)	84.52 (+-0.23)
	$HDDM_A$	83.30 (+-0.21)	83.32 (+-0.21)	83.46 (+-0.21)	83.63 (+-0.29)	84.36 (+-0.22)	84.44 (+-0.26)
	DDM_7	83.79 (+-0.18)	83.80 (+-0.18)	83.85 (+-0.17)	84.25 (+-0.25)	**84.83 (+-0.11)**	84.22 (+-0.20)
	DDM_{129}	83.40 (+-0.25)	83.41 (+-0.25)	83.45 (+-0.26)	83.44 (+-0.37)	84.56 (+-0.13)	83.03 (+-1.30)
	$RDDM_{30}$	81.39 (+-0.30)	81.40 (+-0.31)	81.38 (+-0.31)	81.00 (+-1.04)	84.44 (+-0.14)	82.06 (+-1.24)
	$RDDM_7$	84.03 (+-0.17)	84.04 (+-0.17)	84.15 (+-0.17)	84.14 (+-0.32)	**84.83 (+-0.12)**	84.56 (+-0.21)
	$RDDM_{129}$	83.45 (+-0.28)	83.46 (+-0.28)	83.58 (+-0.28)	83.34 (+-0.31)	84.57 (+-0.13)	83.11 (+-1.31)
LED	FTDD	70.89 (+-0.19)	71.05 (+-0.19)	71.00 (+-0.20)	69.86 (+-0.38)	70.84 (+-0.16)	70.51 (+-0.43)
	WSTD	70.48 (+-0.29)	70.64 (+-0.28)	70.72 (+-0.28)	70.39 (+-0.25)	70.26 (+-0.24)	70.25 (+-0.60)
	$HDDM_A$	71.26 (+-0.17)	71.41 (+-0.17)	71.42 (+-0.17)	70.43 (+-0.21)	71.18 (+-0.16)	71.52 (+-0.18)
	DDM_7	71.24 (+-0.21)	71.40 (+-0.19)	71.42 (+-0.19)	70.88 (+-0.30)	71.42 (+-0.17)	71.30 (+-0.30)
	DDM_{129}	71.13 (+-0.19)	71.28 (+-0.19)	71.31 (+-0.19)	70.59 (+-0.25)	71.13 (+-0.16)	71.68 (+-0.18)
	$RDDM_{30}$	70.60 (+-0.18)	70.75 (+-0.17)	70.77 (+-0.17)	70.41 (+-0.24)	70.98 (+-0.18)	71.38 (+-0.18)
	$RDDM_7$	71.34 (+-0.20)	71.49 (+-0.18)	71.52 (+-0.18)	71.12 (+-0.29)	71.41 (+-0.16)	**71.87 (+-0.19)**
	$RDDM_{129}$	71.08 (+-0.18)	71.23 (+-0.18)	71.26 (+-0.18)	70.63 (+-0.23)	71.13 (+-0.16)	71.73 (+-0.17)
Mixed	FTDD	91.29 (+-0.13)	91.29 (+-0.13)	**91.45 (+-0.12)**	88.95 (+-0.68)	90.85 (+-0.11)	90.64 (+-0.15)
	WSTD	91.01 (+-0.15)	91.01 (+-0.14)	91.21 (+-0.15)	88.28 (+-0.66)	90.85 (+-0.11)	90.64 (+-0.15)
	$HDDM_A$	90.89 (+-0.20)	90.90 (+-0.19)	91.10 (+-0.19)	88.27 (+-0.47)	90.83 (+-0.11)	90.29 (+-0.15)
	DDM_7	89.84 (+-0.19)	89.84 (+-0.19)	89.97 (+-0.18)	88.84 (+-0.56)	90.89 (+-0.13)	89.74 (+-0.36)
	DDM_{129}	90.83 (+-0.15)	90.83 (+-0.14)	91.02 (+-0.13)	89.42 (+-0.34)	90.88 (+-0.11)	89.98 (+-0.30)
	$RDDM_{30}$	91.13 (+-0.16)	91.13 (+-0.15)	91.29 (+-0.16)	89.80 (+-0.44)	90.86 (+-0.12)	90.47 (+-0.16)
	$RDDM_7$	90.62 (+-0.17)	90.63 (+-0.17)	90.79 (+-0.15)	90.54 (+-0.27)	90.88 (+-0.12)	90.64 (+-0.15)
	$RDDM_{129}$	90.85 (+-0.15)	90.85 (+-0.15)	91.07 (+-0.14)	89.29 (+-0.42)	90.89 (+-0.11)	90.66 (+-0.14)
RBF	FTDD	20.96 (+-0.84)	23.48 (+-0.42)	31.90 (+-0.57)	32.04 (+-0.43)	**33.09 (+-0.30)**	32.60 (+-0.45)
	WSTD	20.82 (+-0.81)	24.16 (+-0.64)	30.70 (+-0.60)	31.15 (+-0.57)	32.89 (+-0.27)	31.12 (+-0.54)
	$HDDM_A$	20.31 (+-0.80)	23.40 (+-0.48)	32.19 (+-0.44)	32.27 (+-0.38)	32.99 (+-0.30)	32.40 (+-0.34)
	DDM_7	20.35 (+-0.69)	23.66 (+-0.35)	32.09 (+-0.46)	31.89 (+-0.33)	32.08 (+-0.26)	31.83 (+-0.30)
	DDM_{129}	20.34 (+-0.78)	23.69 (+-0.47)	32.19 (+-0.45)	32.15 (+-0.38)	32.72 (+-0.32)	32.24 (+-0.37)
	$RDDM_{30}$	20.36 (+-0.81)	23.55 (+-0.53)	31.91 (+-0.48)	32.30 (+-0.36)	32.86 (+-0.31)	32.34 (+-0.36)
	$RDDM_7$	19.97 (+-0.63)	23.76 (+-0.35)	32.27 (+-0.39)	32.02 (+-0.34)	32.14 (+-0.28)	32.03 (+-0.33)
	$RDDM_{129}$	20.30 (+-0.77)	23.80 (+-0.56)	32.31 (+-0.40)	32.24 (+-0.31)	32.69 (+-0.31)	32.30 (+-0.37)
Sine	FTDD	91.54 (+-0.21)	91.56 (+-0.21)	**91.58 (+-0.21)**	88.35 (+-0.39)	90.17 (+-0.12)	89.89 (+-0.13)
	WSTD	91.52 (+-0.24)	91.53 (+-0.25)	91.57 (+-0.23)	88.27 (+-0.32)	90.14 (+-0.12)	89.93 (+-0.12)
	$HDDM_A$	91.43 (+-0.22)	91.44 (+-0.22)	91.46 (+-0.20)	88.11 (+-0.42)	90.22 (+-0.12)	89.89 (+-0.13)
	DDM_7	90.09 (+-0.26)	90.10 (+-0.26)	90.08 (+-0.26)	88.63 (+-0.28)	89.83 (+-0.11)	88.32 (+-0.27)
	DDM_{129}	91.33 (+-0.21)	91.34 (+-0.21)	91.31 (+-0.19)	88.58 (+-0.29)	90.12 (+-0.13)	89.17 (+-0.16)
	$RDDM_{30}$	91.38 (+-0.27)	91.40 (+-0.27)	91.41 (+-0.24)	88.85 (+-0.28)	90.19 (+-0.13)	89.48 (+-0.14)
	$RDDM_7$	91.12 (+-0.23)	91.14 (+-0.23)	91.12 (+-0.22)	89.01 (+-0.26)	89.91 (+-0.11)	89.24 (+-0.18)
	$RDDM_{129}$	91.28 (+-0.23)	91.29 (+-0.23)	91.33 (+-0.23)	88.31 (+-0.30)	90.11 (+-0.13)	89.46 (+-0.14)
Wavef.	FTDD	81.23 (+-0.19)	81.30 (+-0.19)	80.82 (+-0.20)	79.43 (+-0.25)	80.43 (+-0.22)	79.05 (+-0.36)
	WSTD	81.13 (+-0.18)	81.20 (+-0.18)	80.75 (+-0.19)	79.52 (+-0.26)	80.39 (+-0.18)	79.46 (+-0.29)
	$HDDM_A$	81.14 (+-0.21)	81.21 (+-0.21)	80.64 (+-0.24)	79.60 (+-0.26)	80.40 (+-0.21)	79.41 (+-0.25)
	DDM_7	81.54 (+-0.18)	**81.60 (+-0.17)**	81.34 (+-0.19)	79.70 (+-0.21)	80.55 (+-0.19)	79.44 (+-0.25)
	DDM_{129}	81.36 (+-0.20)	81.42 (+-0.20)	80.95 (+-0.21)	79.80 (+-0.24)	80.42 (+-0.22)	79.62 (+-0.27)
	$RDDM_{30}$	81.13 (+-0.19)	81.20 (+-0.20)	80.56 (+-0.22)	79.49 (+-0.23)	80.33 (+-0.20)	79.27 (+-0.27)
	$RDDM_7$	81.50 (+-0.21)	81.56 (+-0.20)	81.15 (+-0.22)	79.82 (+-0.26)	80.53 (+-0.20)	79.74 (+-0.26)
	$RDDM_{129}$	81.29 (+-0.17)	81.36 (+-0.17)	80.88 (+-0.19)	79.83 (+-0.27)	80.41 (+-0.22)	79.64 (+-0.26)

Table 65 – Mean accuracies of Ensembles in percentage (%) in 50K instances abrupt datasets, with 95% confidence intervals, using HT

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	62.73 (+-0.52)	62.73 (+-0.52)	62.73 (+-0.48)	65.98 (+-1.11)	68.73 (+-0.45)	67.23 (+-0.89)
	WSTD	63.98 (+-0.33)	63.98 (+-0.33)	64.08 (+-0.30)	70.43 (+-0.50)	69.25 (+-0.61)	69.16 (+-0.72)
	$HDDM_A$	68.32 (+-0.32)	68.32 (+-0.32)	68.36 (+-0.25)	71.31 (+-0.30)	72.38 (+-0.23)	**72.57 (+-0.33)**
	DDM_7	67.90 (+-0.28)	67.90 (+-0.28)	67.89 (+-0.28)	71.35 (+-0.26)	72.17 (+-0.22)	71.55 (+-0.31)
	DDM_{129}	68.59 (+-0.30)	68.58 (+-0.30)	68.71 (+-0.30)	71.25 (+-0.32)	72.38 (+-0.20)	72.26 (+-0.37)
	$RDDM_{30}$	67.99 (+-0.26)	67.99 (+-0.26)	68.07 (+-0.25)	70.81 (+-0.44)	72.45 (+-0.23)	71.43 (+-0.80)
	$RDDM_7$	68.79 (+-0.29)	68.79 (+-0.29)	69.02 (+-0.28)	71.68 (+-0.25)	72.29 (+-0.23)	72.53 (+-0.31)
	$RDDM_{129}$	68.68 (+-0.23)	68.68 (+-0.23)	68.86 (+-0.21)	71.47 (+-0.28)	72.31 (+-0.22)	72.43 (+-0.31)
$Agraw_2$	FTDD	84.01 (+-0.29)	84.02 (+-0.29)	84.02 (+-0.26)	83.69 (+-0.53)	86.41 (+-0.08)	84.46 (+-0.44)
	WSTD	85.51 (+-0.09)	85.51 (+-0.09)	85.54 (+-0.10)	85.50 (+-0.44)	86.40 (+-0.08)	85.86 (+-0.42)
	$HDDM_A$	84.97 (+-0.18)	84.97 (+-0.18)	84.99 (+-0.18)	85.74 (+-0.33)	86.42 (+-0.08)	85.76 (+-0.32)
	DDM_7	85.28 (+-0.11)	85.29 (+-0.12)	85.32 (+-0.10)	86.22 (+-0.14)	86.58 (+-0.06)	86.08 (+-0.21)
	DDM_{129}	85.21 (+-0.08)	85.22 (+-0.08)	85.27 (+-0.09)	85.60 (+-0.37)	86.51 (+-0.08)	85.95 (+-0.35)
	$RDDM_{30}$	84.33 (+-0.21)	84.33 (+-0.21)	84.35 (+-0.22)	84.66 (+-0.58)	86.44 (+-0.08)	84.79 (+-0.49)
	$RDDM_7$	85.53 (+-0.08)	85.53 (+-0.08)	85.58 (+-0.08)	86.36 (+-0.16)	**86.60 (+-0.07)**	86.31 (+-0.16)
	$RDDM_{129}$	85.17 (+-0.13)	85.18 (+-0.13)	85.25 (+-0.13)	85.62 (+-0.29)	86.50 (+-0.08)	86.09 (+-0.19)
LED	FTDD	72.41 (+-0.17)	72.47 (+-0.17)	72.46 (+-0.17)	71.41 (+-0.27)	72.45 (+-0.15)	72.20 (+-0.21)
	WSTD	72.41 (+-0.18)	72.48 (+-0.18)	72.52 (+-0.18)	72.05 (+-0.22)	72.34 (+-0.17)	71.99 (+-0.31)
	$HDDM_A$	72.75 (+-0.16)	72.81 (+-0.16)	72.82 (+-0.16)	71.68 (+-0.22)	72.74 (+-0.15)	72.81 (+-0.16)
	DDM_7	72.70 (+-0.17)	72.76 (+-0.16)	72.77 (+-0.16)	72.28 (+-0.25)	72.80 (+-0.13)	72.56 (+-0.23)
	DDM_{129}	72.62 (+-0.16)	72.67 (+-0.16)	72.68 (+-0.16)	71.92 (+-0.20)	72.70 (+-0.14)	72.80 (+-0.18)
	$RDDM_{30}$	72.34 (+-0.16)	72.40 (+-0.17)	72.41 (+-0.16)	72.03 (+-0.19)	72.57 (+-0.15)	72.66 (+-0.15)
	$RDDM_7$	72.74 (+-0.16)	72.80 (+-0.16)	72.81 (+-0.16)	72.53 (+-0.17)	72.81 (+-0.13)	72.76 (+-0.18)
	$RDDM_{129}$	72.61 (+-0.16)	72.67 (+-0.16)	72.68 (+-0.16)	71.98 (+-0.23)	72.70 (+-0.14)	**72.88 (+-0.15)**
Mixed	FTDD	93.15 (+-0.12)	93.15 (+-0.12)	93.21 (+-0.12)	90.33 (+-0.75)	92.42 (+-0.09)	92.05 (+-0.09)
	WSTD	92.90 (+-0.12)	92.90 (+-0.12)	92.95 (+-0.11)	89.39 (+-0.74)	92.40 (+-0.09)	92.03 (+-0.11)
	$HDDM_A$	92.85 (+-0.14)	92.85 (+-0.14)	92.91 (+-0.13)	89.82 (+-0.56)	92.42 (+-0.09)	92.11 (+-0.07)
	DDM_7	91.89 (+-0.11)	91.89 (+-0.11)	91.93 (+-0.11)	91.34 (+-0.48)	91.75 (+-0.11)	90.85 (+-0.15)
	DDM_{129}	92.59 (+-0.13)	92.60 (+-0.13)	92.66 (+-0.13)	90.77 (+-0.60)	92.01 (+-0.12)	91.37 (+-0.14)
	$RDDM_{30}$	93.17 (+-0.14)	93.17 (+-0.14)	**93.22 (+-0.14)**	91.32 (+-0.38)	92.39 (+-0.09)	91.78 (+-0.11)
	$RDDM_7$	92.52 (+-0.20)	92.52 (+-0.20)	92.58 (+-0.19)	91.54 (+-0.36)	91.76 (+-0.11)	91.23 (+-0.13)
	$RDDM_{129}$	92.66 (+-0.12)	92.66 (+-0.12)	92.73 (+-0.12)	90.62 (+-0.61)	92.01 (+-0.12)	91.60 (+-0.14)
RBF	FTDD	20.63 (+-0.73)	23.39 (+-0.64)	32.63 (+-0.31)	32.98 (+-0.39)	**33.67 (+-0.24)**	32.70 (+-0.42)
	WSTD	20.29 (+-0.72)	23.06 (+-0.48)	31.80 (+-0.57)	32.24 (+-0.49)	33.40 (+-0.24)	31.81 (+-0.38)
	$HDDM_A$	19.99 (+-0.64)	22.92 (+-0.52)	32.58 (+-0.39)	32.78 (+-0.33)	33.25 (+-0.23)	32.57 (+-0.30)
	DDM_7	19.99 (+-0.65)	23.19 (+-0.32)	32.45 (+-0.35)	32.12 (+-0.36)	32.45 (+-0.18)	32.23 (+-0.29)
	DDM_{129}	20.18 (+-0.73)	23.35 (+-0.41)	32.64 (+-0.33)	32.45 (+-0.34)	32.99 (+-0.20)	32.45 (+-0.31)
	$RDDM_{30}$	20.05 (+-0.65)	23.10 (+-0.60)	32.53 (+-0.38)	32.61 (+-0.30)	33.20 (+-0.24)	32.52 (+-0.28)
	$RDDM_7$	19.81 (+-0.70)	23.32 (+-0.30)	32.54 (+-0.32)	32.25 (+-0.25)	32.39 (+-0.18)	32.19 (+-0.21)
	$RDDM_{129}$	19.96 (+-0.76)	23.46 (+-0.42)	32.68 (+-0.31)	32.62 (+-0.22)	32.99 (+-0.20)	32.40 (+-0.28)
Sine	FTDD	94.32 (+-0.19)	**94.33 (+-0.19)**	**94.33 (+-0.18)**	91.07 (+-0.31)	91.95 (+-0.11)	91.55 (+-0.15)
	WSTD	93.91 (+-0.17)	93.92 (+-0.17)	93.92 (+-0.17)	90.78 (+-0.27)	91.96 (+-0.11)	91.52 (+-0.13)
	$HDDM_A$	93.97 (+-0.18)	93.97 (+-0.18)	93.99 (+-0.18)	90.77 (+-0.37)	91.96 (+-0.11)	91.52 (+-0.14)
	DDM_7	92.69 (+-0.25)	92.69 (+-0.25)	92.67 (+-0.25)	91.14 (+-0.23)	91.63 (+-0.12)	89.85 (+-0.43)
	DDM_{129}	93.67 (+-0.21)	93.67 (+-0.21)	93.66 (+-0.21)	90.85 (+-0.26)	91.90 (+-0.11)	90.85 (+-0.19)
	$RDDM_{30}$	94.18 (+-0.17)	94.18 (+-0.17)	94.17 (+-0.17)	91.39 (+-0.22)	91.95 (+-0.12)	91.25 (+-0.13)
	$RDDM_7$	93.57 (+-0.23)	93.58 (+-0.23)	93.54 (+-0.23)	91.21 (+-0.24)	91.64 (+-0.12)	90.79 (+-0.23)
	$RDDM_{129}$	93.86 (+-0.20)	93.87 (+-0.20)	93.88 (+-0.20)	91.23 (+-0.25)	91.90 (+-0.11)	91.19 (+-0.14)
Wavef.	FTDD	82.66 (+-0.14)	82.69 (+-0.13)	82.46 (+-0.13)	80.68 (+-0.20)	81.83 (+-0.18)	79.37 (+-0.21)
	WSTD	82.22 (+-0.14)	82.25 (+-0.14)	81.79 (+-0.16)	80.56 (+-0.19)	81.66 (+-0.13)	79.63 (+-0.18)
	$HDDM_A$	82.40 (+-0.12)	82.42 (+-0.12)	82.08 (+-0.13)	80.67 (+-0.16)	81.95 (+-0.14)	79.58 (+-0.16)
	DDM_7	82.25 (+-0.13)	82.27 (+-0.12)	81.82 (+-0.15)	80.71 (+-0.19)	81.34 (+-0.14)	79.80 (+-0.15)
	DDM_{129}	82.47 (+-0.12)	82.50 (+-0.11)	82.05 (+-0.12)	80.80 (+-0.15)	81.68 (+-0.12)	79.73 (+-0.18)
	$RDDM_{30}$	82.70 (+-0.14)	**82.72 (+-0.13)**	82.39 (+-0.15)	80.67 (+-0.17)	81.93 (+-0.11)	79.47 (+-0.19)
	$RDDM_7$	82.16 (+-0.14)	82.18 (+-0.14)	81.58 (+-0.13)	80.51 (+-0.20)	81.20 (+-0.13)	80.07 (+-0.15)
	$RDDM_{129}$	82.44 (+-0.12)	82.47 (+-0.12)	81.94 (+-0.10)	80.76 (+-0.16)	81.58 (+-0.13)	79.94 (+-0.16)

Table 66 – Mean accuracies of Ensembles in percentage (%) in 100K instances abrupt datasets, with 95% confidence intervals, using HT

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	65.45 (+-0.53)	65.45 (+-0.53)	65.20 (+-0.44)	71.56 (+-0.82)	71.09 (+-0.54)	70.38 (+-1.01)
	WSTD	65.02 (+-0.42)	65.02 (+-0.42)	64.90 (+-0.35)	73.12 (+-0.41)	71.73 (+-0.61)	71.62 (+-0.74)
	$HDDM_A$	69.96 (+-0.20)	69.96 (+-0.20)	70.07 (+-0.20)	73.97 (+-0.29)	74.38 (+-0.22)	74.74 (+-0.34)
	DDM_7	69.25 (+-0.21)	69.25 (+-0.21)	69.31 (+-0.20)	73.86 (+-0.35)	74.54 (+-0.24)	74.60 (+-0.34)
	DDM_{129}	69.92 (+-0.26)	69.92 (+-0.26)	70.04 (+-0.26)	73.71 (+-0.36)	74.52 (+-0.24)	74.80 (+-0.39)
	$RDDM_{30}$	70.22 (+-0.31)	70.22 (+-0.31)	70.26 (+-0.29)	73.41 (+-0.72)	74.54 (+-0.21)	74.19 (+-0.98)
	$RDDM_7$	70.08 (+-0.21)	70.08 (+-0.21)	70.24 (+-0.21)	74.04 (+-0.23)	74.54 (+-0.22)	**75.08 (+-0.31)**
	$RDDM_{129}$	70.17 (+-0.26)	70.17 (+-0.26)	70.26 (+-0.25)	73.94 (+-0.26)	74.57 (+-0.21)	74.85 (+-0.28)
$Agraw_2$	FTDD	85.32 (+-0.31)	85.32 (+-0.31)	85.31 (+-0.28)	85.25 (+-0.55)	87.55 (+-0.05)	85.86 (+-0.51)
	WSTD	86.44 (+-0.08)	86.44 (+-0.08)	86.45 (+-0.07)	86.72 (+-0.45)	87.64 (+-0.05)	87.40 (+-0.15)
	$HDDM_A$	86.19 (+-0.11)	86.20 (+-0.11)	86.21 (+-0.10)	87.20 (+-0.11)	87.61 (+-0.05)	87.44 (+-0.14)
	DDM_7	86.00 (+-0.08)	86.00 (+-0.08)	86.00 (+-0.08)	87.20 (+-0.34)	87.64 (+-0.06)	87.01 (+-0.33)
	DDM_{129}	85.95 (+-0.13)	85.96 (+-0.13)	85.94 (+-0.12)	86.79 (+-0.40)	87.62 (+-0.05)	87.02 (+-0.37)
	$RDDM_{30}$	85.45 (+-0.15)	85.46 (+-0.15)	85.45 (+-0.15)	85.65 (+-0.55)	87.59 (+-0.06)	85.84 (+-0.66)
	$RDDM_7$	86.16 (+-0.07)	86.16 (+-0.07)	86.18 (+-0.07)	87.54 (+-0.15)	**87.66 (+-0.05)**	87.43 (+-0.12)
	$RDDM_{129}$	85.82 (+-0.20)	85.82 (+-0.20)	85.84 (+-0.19)	87.14 (+-0.26)	87.61 (+-0.06)	87.17 (+-0.19)
LED	FTDD	73.02 (+-0.14)	73.05 (+-0.14)	73.04 (+-0.13)	72.10 (+-0.19)	73.18 (+-0.12)	72.93 (+-0.18)
	WSTD	73.22 (+-0.12)	73.25 (+-0.12)	73.27 (+-0.12)	72.76 (+-0.20)	73.19 (+-0.11)	72.81 (+-0.20)
	$HDDM_A$	73.38 (+-0.12)	**73.41 (+-0.12)**	**73.41 (+-0.12)**	72.38 (+-0.16)	73.34 (+-0.11)	73.37 (+-0.11)
	DDM_7	73.30 (+-0.12)	73.33 (+-0.12)	73.33 (+-0.12)	72.88 (+-0.21)	73.38 (+-0.11)	73.04 (+-0.21)
	DDM_{129}	73.26 (+-0.13)	73.29 (+-0.13)	73.30 (+-0.13)	72.70 (+-0.18)	73.31 (+-0.12)	73.34 (+-0.12)
	$RDDM_{30}$	73.05 (+-0.13)	73.08 (+-0.13)	73.09 (+-0.13)	72.88 (+-0.19)	73.23 (+-0.11)	73.23 (+-0.12)
	$RDDM_7$	73.36 (+-0.12)	73.39 (+-0.12)	73.40 (+-0.12)	73.11 (+-0.15)	73.38 (+-0.11)	73.21 (+-0.12)
	$RDDM_{129}$	73.24 (+-0.12)	73.27 (+-0.13)	73.28 (+-0.13)	72.74 (+-0.19)	73.31 (+-0.12)	73.39 (+-0.12)
Mixed	FTDD	95.26 (+-0.11)	95.26 (+-0.11)	95.31 (+-0.11)	92.11 (+-0.34)	93.33 (+-0.06)	93.13 (+-0.06)
	WSTD	94.79 (+-0.12)	94.79 (+-0.12)	94.83 (+-0.12)	92.06 (+-0.43)	93.31 (+-0.06)	93.09 (+-0.06)
	$HDDM_A$	95.00 (+-0.11)	95.00 (+-0.11)	95.05 (+-0.11)	91.85 (+-0.28)	93.34 (+-0.06)	93.12 (+-0.07)
	DDM_7	93.52 (+-0.18)	93.52 (+-0.18)	93.54 (+-0.17)	92.70 (+-0.22)	92.55 (+-0.11)	91.25 (+-0.23)
	DDM_{129}	94.49 (+-0.16)	94.49 (+-0.16)	94.54 (+-0.16)	92.58 (+-0.22)	93.00 (+-0.09)	92.20 (+-0.21)
	$RDDM_{30}$	95.39 (+-0.12)	95.40 (+-0.12)	**95.43 (+-0.12)**	92.59 (+-0.24)	93.31 (+-0.07)	92.89 (+-0.09)
	$RDDM_7$	94.47 (+-0.19)	94.47 (+-0.19)	94.50 (+-0.19)	92.73 (+-0.25)	92.53 (+-0.10)	91.67 (+-0.20)
	$RDDM_{129}$	94.61 (+-0.16)	94.61 (+-0.16)	94.66 (+-0.16)	92.44 (+-0.31)	93.00 (+-0.09)	92.46 (+-0.21)
RBF	FTDD	20.14 (+-0.70)	23.19 (+-0.37)	**34.31 (+-0.28)**	34.02 (+-0.29)	34.23 (+-0.25)	33.32 (+-0.32)
	WSTD	19.84 (+-0.63)	22.83 (+-0.37)	32.23 (+-0.30)	32.80 (+-0.34)	33.54 (+-0.18)	32.45 (+-0.30)
	$HDDM_A$	19.67 (+-0.62)	22.62 (+-0.50)	32.66 (+-0.23)	33.46 (+-0.34)	33.50 (+-0.16)	32.87 (+-0.27)
	DDM_7	19.72 (+-0.68)	22.89 (+-0.37)	32.62 (+-0.22)	32.88 (+-0.31)	32.59 (+-0.11)	32.70 (+-0.23)
	DDM_{129}	20.08 (+-0.72)	22.87 (+-0.39)	32.66 (+-0.25)	33.25 (+-0.26)	33.26 (+-0.16)	32.94 (+-0.26)
	$RDDM_{30}$	19.62 (+-0.61)	22.55 (+-0.55)	32.60 (+-0.28)	33.35 (+-0.26)	33.42 (+-0.14)	33.08 (+-0.27)
	$RDDM_7$	19.62 (+-0.61)	22.91 (+-0.37)	32.61 (+-0.22)	32.61 (+-0.17)	32.58 (+-0.09)	32.52 (+-0.17)
	$RDDM_{129}$	19.71 (+-0.78)	23.00 (+-0.40)	32.57 (+-0.28)	33.01 (+-0.20)	33.26 (+-0.15)	32.80 (+-0.20)
Sine	FTDD	96.27 (+-0.07)	96.28 (+-0.07)	96.28 (+-0.06)	92.16 (+-0.28)	93.11 (+-0.07)	92.61 (+-0.10)
	WSTD	96.19 (+-0.13)	96.19 (+-0.13)	96.19 (+-0.13)	92.14 (+-0.26)	93.11 (+-0.08)	92.59 (+-0.10)
	$HDDM_A$	96.29 (+-0.10)	96.29 (+-0.10)	**96.30 (+-0.10)**	92.11 (+-0.35)	93.11 (+-0.07)	92.57 (+-0.11)
	DDM_7	95.06 (+-0.17)	95.06 (+-0.17)	95.05 (+-0.17)	92.70 (+-0.21)	92.95 (+-0.07)	91.68 (+-0.20)
	DDM_{129}	95.95 (+-0.13)	95.95 (+-0.13)	95.94 (+-0.12)	92.58 (+-0.23)	93.10 (+-0.07)	92.13 (+-0.14)
	$RDDM_{30}$	96.22 (+-0.11)	96.22 (+-0.11)	96.22 (+-0.11)	92.58 (+-0.22)	93.11 (+-0.08)	92.39 (+-0.10)
	$RDDM_7$	95.84 (+-0.14)	95.84 (+-0.14)	95.82 (+-0.14)	92.68 (+-0.20)	92.93 (+-0.08)	92.06 (+-0.20)
	$RDDM_{129}$	96.00 (+-0.13)	96.00 (+-0.13)	96.01 (+-0.13)	92.49 (+-0.25)	93.10 (+-0.07)	92.41 (+-0.11)
Wavef.	FTDD	83.42 (+-0.10)	**83.44 (+-0.10)**	83.33 (+-0.11)	81.27 (+-0.17)	82.22 (+-0.16)	79.59 (+-0.19)
	WSTD	82.62 (+-0.08)	82.63 (+-0.08)	82.22 (+-0.10)	81.22 (+-0.13)	82.29 (+-0.12)	79.83 (+-0.15)
	$HDDM_A$	82.77 (+-0.10)	82.78 (+-0.10)	82.44 (+-0.10)	81.08 (+-0.15)	82.29 (+-0.15)	79.52 (+-0.17)
	DDM_7	82.64 (+-0.10)	82.65 (+-0.10)	82.25 (+-0.10)	80.81 (+-0.14)	81.64 (+-0.11)	79.92 (+-0.13)
	DDM_{129}	82.95 (+-0.10)	82.97 (+-0.10)	82.45 (+-0.13)	81.09 (+-0.15)	82.17 (+-0.11)	79.88 (+-0.17)
	$RDDM_{30}$	83.18 (+-0.08)	83.19 (+-0.08)	82.88 (+-0.08)	81.02 (+-0.15)	82.41 (+-0.10)	79.60 (+-0.16)
	$RDDM_7$	82.62 (+-0.11)	82.64 (+-0.11)	82.08 (+-0.12)	80.72 (+-0.13)	81.44 (+-0.09)	80.15 (+-0.12)
	$RDDM_{129}$	82.85 (+-0.11)	82.87 (+-0.11)	82.41 (+-0.12)	81.01 (+-0.12)	82.05 (+-0.11)	79.97 (+-0.14)

Table 67 – Mean accuracies of Ensembles in percentage (%) in 500K instances abrupt datasets, with 95% confidence intervals, using HT

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	68.97 (+-1.09)	68.97 (+-1.08)	68.75 (+-0.89)	76.38 (+-0.75)	76.44 (+-0.59)	76.88 (+-1.59)
	WSTD	67.53 (+-1.27)	67.53 (+-1.27)	66.93 (+-0.99)	76.35 (+-0.47)	76.94 (+-0.38)	76.81 (+-0.65)
	$HDDM_A$	72.69 (+-0.46)	72.69 (+-0.46)	72.71 (+-0.45)	76.50 (+-0.27)	77.65 (+-0.57)	77.99 (+-0.79)
	DDM_7	72.11 (+-0.54)	72.11 (+-0.54)	72.05 (+-0.45)	75.59 (+-3.16)	78.44 (+-0.48)	77.18 (+-3.15)
	DDM_{129}	72.96 (+-0.90)	72.96 (+-0.90)	72.89 (+-0.81)	77.55 (+-0.74)	78.12 (+-0.43)	**79.42 (+-0.83)**
	$RDDM_{30}$	73.34 (+-0.51)	73.34 (+-0.51)	73.35 (+-0.46)	77.25 (+-0.42)	77.73 (+-0.49)	78.23 (+-1.10)
	$RDDM_7$	71.38 (+-0.32)	71.38 (+-0.32)	71.42 (+-0.33)	76.02 (+-0.40)	78.69 (+-0.28)	77.40 (+-0.63)
	$RDDM_{129}$	72.70 (+-1.01)	72.70 (+-1.01)	72.67 (+-0.86)	77.16 (+-0.51)	78.25 (+-0.43)	78.61 (+-0.52)
$Agraw_2$	FTDD	87.96 (+-0.15)	87.97 (+-0.15)	87.90 (+-0.12)	88.75 (+-0.50)	89.33 (+-0.07)	88.72 (+-0.52)
	WSTD	87.76 (+-0.06)	87.76 (+-0.07)	87.74 (+-0.06)	89.04 (+-0.14)	89.35 (+-0.05)	89.15 (+-0.09)
	$HDDM_A$	87.73 (+-0.11)	87.73 (+-0.11)	87.70 (+-0.08)	89.23 (+-0.16)	89.34 (+-0.09)	89.29 (+-0.08)
	DDM_7	87.42 (+-0.07)	87.42 (+-0.07)	87.33 (+-0.09)	88.32 (+-0.64)	**89.38 (+-0.05)**	88.97 (+-0.24)
	DDM_{129}	87.48 (+-0.17)	87.48 (+-0.17)	87.39 (+-0.16)	89.13 (+-0.35)	**89.38 (+-0.06)**	88.75 (+-0.70)
	$RDDM_{30}$	87.41 (+-0.16)	87.41 (+-0.16)	87.34 (+-0.14)	88.42 (+-0.45)	89.29 (+-0.07)	88.69 (+-0.21)
	$RDDM_7$	87.34 (+-0.09)	87.34 (+-0.09)	87.32 (+-0.08)	88.74 (+-0.12)	89.11 (+-0.05)	88.35 (+-0.15)
	$RDDM_{129}$	87.49 (+-0.23)	87.49 (+-0.23)	87.45 (+-0.22)	89.04 (+-0.26)	89.27 (+-0.05)	88.79 (+-0.14)
LED	FTDD	73.73 (+-0.11)	73.74 (+-0.12)	73.74 (+-0.12)	72.91 (+-0.22)	73.78 (+-0.09)	73.60 (+-0.10)
	WSTD	73.75 (+-0.10)	73.76 (+-0.10)	73.76 (+-0.11)	73.56 (+-0.09)	73.76 (+-0.08)	73.25 (+-0.09)
	$HDDM_A$	73.78 (+-0.10)	73.79 (+-0.10)	73.79 (+-0.10)	73.21 (+-0.15)	73.80 (+-0.09)	73.57 (+-0.08)
	DDM_7	73.77 (+-0.11)	73.77 (+-0.11)	73.77 (+-0.11)	73.52 (+-0.15)	**73.81 (+-0.09)**	73.44 (+-0.08)
	DDM_{129}	73.76 (+-0.11)	73.77 (+-0.11)	73.77 (+-0.11)	73.52 (+-0.15)	73.78 (+-0.09)	73.46 (+-0.08)
	$RDDM_{30}$	73.70 (+-0.11)	73.71 (+-0.11)	73.71 (+-0.11)	73.35 (+-0.15)	73.75 (+-0.09)	73.32 (+-0.13)
	$RDDM_7$	73.77 (+-0.11)	73.78 (+-0.10)	73.78 (+-0.10)	73.56 (+-0.10)	73.80 (+-0.08)	73.47 (+-0.10)
	$RDDM_{129}$	73.75 (+-0.11)	73.76 (+-0.11)	73.76 (+-0.11)	73.57 (+-0.07)	73.79 (+-0.09)	73.58 (+-0.09)
Mixed	FTDD	**98.86 (+-0.02)**	**98.86 (+-0.02)**	**98.86 (+-0.03)**	94.90 (+-0.38)	95.22 (+-0.06)	94.87 (+-0.07)
	WSTD	98.78 (+-0.03)	98.78 (+-0.03)	98.79 (+-0.03)	94.55 (+-0.42)	95.21 (+-0.05)	94.86 (+-0.06)
	$HDDM_A$	98.76 (+-0.05)	98.76 (+-0.05)	98.77 (+-0.05)	94.64 (+-0.23)	95.21 (+-0.04)	94.89 (+-0.05)
	DDM_7	98.48 (+-0.06)	98.48 (+-0.06)	98.48 (+-0.06)	95.34 (+-0.08)	94.79 (+-0.09)	93.70 (+-0.28)
	DDM_{129}	98.63 (+-0.03)	98.63 (+-0.03)	98.63 (+-0.03)	94.97 (+-0.32)	95.07 (+-0.07)	94.48 (+-0.13)
	$RDDM_{30}$	98.69 (+-0.04)	98.69 (+-0.04)	98.69 (+-0.04)	94.96 (+-0.23)	95.19 (+-0.05)	94.40 (+-0.19)
	$RDDM_7$	98.65 (+-0.04)	98.65 (+-0.04)	98.65 (+-0.05)	94.11 (+-0.09)	94.51 (+-0.09)	92.79 (+-0.27)
	$RDDM_{129}$	98.68 (+-0.04)	98.68 (+-0.04)	98.69 (+-0.04)	94.64 (+-0.26)	95.05 (+-0.06)	94.22 (+-0.14)
RBF	FTDD	22.94 (+-2.68)	29.55 (+-0.83)	**37.44 (+-0.40)**	36.96 (+-0.28)	36.51 (+-0.27)	35.39 (+-0.39)
	WSTD	18.63 (+-0.51)	22.17 (+-0.77)	32.95 (+-0.12)	33.04 (+-0.23)	33.65 (+-0.19)	32.47 (+-0.15)
	$HDDM_A$	18.90 (+-0.94)	26.00 (+-1.10)	35.38 (+-0.24)	35.27 (+-0.54)	34.83 (+-0.24)	34.11 (+-0.27)
	DDM_7	18.63 (+-0.71)	27.74 (+-1.45)	35.37 (+-0.48)	34.78 (+-0.29)	33.45 (+-0.13)	34.53 (+-0.79)
	DDM_{129}	20.90 (+-1.62)	25.90 (+-1.13)	35.68 (+-0.25)	35.18 (+-0.47)	34.95 (+-0.18)	34.41 (+-0.34)
	$RDDM_{30}$	21.17 (+-1.79)	26.48 (+-1.52)	35.93 (+-0.31)	35.08 (+-0.30)	35.16 (+-0.22)	34.78 (+-0.34)
	$RDDM_7$	19.72 (+-0.91)	22.32 (+-1.09)	33.17 (+-0.21)	33.07 (+-0.23)	33.16 (+-0.12)	32.97 (+-0.22)
	$RDDM_{129}$	20.45 (+-1.73)	25.76 (+-1.24)	35.30 (+-0.38)	34.59 (+-0.33)	34.61 (+-0.20)	33.73 (+-0.24)
Sine	FTDD	**98.70 (+-0.05)**	**98.70 (+-0.05)**	**98.70 (+-0.04)**	96.34 (+-0.28)	96.41 (+-0.19)	95.82 (+-0.20)
	WSTD	98.66 (+-0.06)	98.66 (+-0.06)	98.66 (+-0.06)	96.59 (+-0.31)	96.38 (+-0.18)	95.82 (+-0.18)
	$HDDM_A$	98.68 (+-0.03)	98.68 (+-0.03)	98.68 (+-0.03)	96.42 (+-0.36)	96.39 (+-0.20)	95.75 (+-0.18)
	DDM_7	98.51 (+-0.05)	98.51 (+-0.05)	98.50 (+-0.05)	96.66 (+-0.16)	96.40 (+-0.09)	95.39 (+-0.11)
	DDM_{129}	98.53 (+-0.04)	98.53 (+-0.04)	98.52 (+-0.04)	96.62 (+-0.22)	96.43 (+-0.18)	95.56 (+-0.18)
	$RDDM_{30}$	98.64 (+-0.06)	98.64 (+-0.06)	98.63 (+-0.06)	96.41 (+-0.29)	96.35 (+-0.15)	95.31 (+-0.23)
	$RDDM_7$	98.57 (+-0.03)	98.57 (+-0.03)	98.56 (+-0.03)	95.32 (+-0.19)	95.77 (+-0.11)	94.20 (+-0.34)
	$RDDM_{129}$	98.59 (+-0.05)	98.59 (+-0.05)	98.59 (+-0.05)	96.21 (+-0.32)	96.33 (+-0.18)	94.89 (+-0.30)
Wavef.	FTDD	83.88 (+-0.07)	83.88 (+-0.07)	83.87 (+-0.07)	84.00 (+-0.24)	**84.08 (+-0.16)**	81.74 (+-0.14)
	WSTD	82.85 (+-0.08)	82.85 (+-0.08)	82.54 (+-0.11)	83.01 (+-0.42)	83.73 (+-0.14)	80.75 (+-0.24)
	$HDDM_A$	83.02 (+-0.11)	83.03 (+-0.10)	82.68 (+-0.09)	83.49 (+-0.20)	83.78 (+-0.11)	81.09 (+-0.20)
	DDM_7	83.06 (+-0.11)	83.06 (+-0.11)	82.65 (+-0.14)	82.56 (+-0.51)	82.43 (+-0.26)	79.97 (+-0.16)
	DDM_{129}	83.62 (+-0.10)	83.63 (+-0.09)	83.29 (+-0.12)	83.35 (+-0.29)	83.83 (+-0.12)	81.15 (+-0.26)
	$RDDM_{30}$	83.53 (+-0.09)	83.53 (+-0.09)	83.31 (+-0.10)	82.88 (+-0.39)	83.69 (+-0.10)	80.62 (+-0.27)
	$RDDM_7$	82.86 (+-0.07)	82.86 (+-0.07)	82.54 (+-0.08)	80.96 (+-0.16)	81.71 (+-0.10)	80.15 (+-0.11)
	$RDDM_{129}$	83.16 (+-0.07)	83.17 (+-0.07)	82.88 (+-0.09)	82.29 (+-0.28)	83.22 (+-0.13)	80.17 (+-0.14)

Table 68 – Mean accuracies of Ensembles in percentage (%) in 10K instances gradual datasets, with 95% confidence intervals, using HT

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	58.42 (+-0.39)	58.51 (+-0.40)	58.82 (+-0.38)	60.73 (+-0.48)	62.28 (+-0.20)	61.33 (+-0.29)
	WSTD	60.54 (+-0.39)	60.54 (+-0.39)	60.99 (+-0.37)	61.57 (+-0.33)	62.12 (+-0.23)	61.77 (+-0.38)
	$HDDM_A$	60.70 (+-0.46)	60.68 (+-0.47)	61.25 (+-0.41)	62.01 (+-0.33)	62.33 (+-0.28)	62.27 (+-0.36)
	DDM_7	60.37 (+-0.40)	60.36 (+-0.41)	60.60 (+-0.40)	62.76 (+-0.24)	62.55 (+-0.23)	62.66 (+-0.23)
	DDM_{129}	61.00 (+-0.39)	60.99 (+-0.39)	61.52 (+-0.33)	62.25 (+-0.20)	62.64 (+-0.22)	62.87 (+-0.32)
	$RDDM_{30}$	59.56 (+-0.55)	59.56 (+-0.56)	60.19 (+-0.47)	61.22 (+-0.37)	62.57 (+-0.24)	61.18 (+-0.36)
	$RDDM_7$	60.94 (+-0.46)	60.92 (+-0.45)	61.25 (+-0.43)	62.80 (+-0.26)	62.67 (+-0.25)	62.81 (+-0.21)
	$RDDM_{129}$	60.72 (+-0.42)	60.72 (+-0.43)	61.21 (+-0.39)	62.39 (+-0.32)	62.59 (+-0.22)	**62.92 (+-0.27)**
$Agraw_2$	FTDD	77.36 (+-0.38)	77.39 (+-0.37)	77.70 (+-0.32)	74.28 (+-0.66)	78.86 (+-0.28)	74.56 (+-0.76)
	WSTD	78.68 (+-0.26)	78.71 (+-0.27)	78.99 (+-0.28)	76.19 (+-0.76)	79.15 (+-0.25)	77.35 (+-0.66)
	$HDDM_A$	77.68 (+-0.33)	77.71 (+-0.33)	78.04 (+-0.30)	77.55 (+-0.54)	79.16 (+-0.27)	78.27 (+-0.54)
	DDM_7	78.65 (+-0.23)	78.65 (+-0.23)	78.75 (+-0.23)	79.25 (+-0.38)	**79.82 (+-0.17)**	79.01 (+-0.62)
	DDM_{129}	78.28 (+-0.35)	78.31 (+-0.36)	78.51 (+-0.34)	78.54 (+-0.80)	79.65 (+-0.18)	78.65 (+-0.98)
	$RDDM_{30}$	76.05 (+-0.30)	76.07 (+-0.31)	76.37 (+-0.30)	75.09 (+-1.07)	79.54 (+-0.15)	74.00 (+-1.58)
	$RDDM_7$	78.84 (+-0.21)	78.85 (+-0.21)	78.95 (+-0.21)	79.36 (+-0.37)	79.77 (+-0.19)	79.50 (+-0.30)
	$RDDM_{129}$	78.19 (+-0.33)	78.22 (+-0.34)	78.43 (+-0.32)	78.50 (+-0.77)	79.66 (+-0.18)	78.65 (+-0.98)
LED	FTDD	57.46 (+-2.54)	65.75 (+-0.45)	64.94 (+-0.53)	62.59 (+-0.97)	66.01 (+-0.33)	62.88 (+-0.89)
	WSTD	64.47 (+-1.06)	66.30 (+-0.33)	66.34 (+-0.36)	65.19 (+-0.53)	65.30 (+-0.37)	63.99 (+-0.81)
	$HDDM_A$	67.18 (+-0.32)	67.49 (+-0.28)	67.40 (+-0.28)	67.02 (+-0.29)	66.96 (+-0.27)	67.58 (+-0.31)
	DDM_7	67.37 (+-0.29)	67.69 (+-0.25)	67.73 (+-0.25)	67.55 (+-0.31)	67.05 (+-0.27)	67.35 (+-0.33)
	DDM_{129}	67.31 (+-0.30)	67.62 (+-0.27)	67.66 (+-0.27)	67.09 (+-0.28)	67.08 (+-0.28)	67.72 (+-0.30)
	$RDDM_{30}$	66.26 (+-0.37)	66.94 (+-0.27)	66.75 (+-0.28)	66.69 (+-0.52)	67.02 (+-0.25)	67.80 (+-0.34)
	$RDDM_7$	67.39 (+-0.33)	67.69 (+-0.28)	67.74 (+-0.29)	67.59 (+-0.31)	67.05 (+-0.28)	67.62 (+-0.28)
	$RDDM_{129}$	67.20 (+-0.32)	67.53 (+-0.28)	67.54 (+-0.28)	67.22 (+-0.29)	67.08 (+-0.28)	**67.81 (+-0.29)**
Mixed	FTDD	83.86 (+-0.21)	83.86 (+-0.21)	83.97 (+-0.22)	80.64 (+-0.46)	83.58 (+-0.24)	83.50 (+-0.23)
	WSTD	83.26 (+-0.21)	83.27 (+-0.20)	83.38 (+-0.20)	81.79 (+-0.54)	83.41 (+-0.23)	83.26 (+-0.27)
	$HDDM_A$	83.52 (+-0.19)	83.53 (+-0.19)	83.61 (+-0.18)	81.26 (+-0.57)	83.57 (+-0.26)	83.39 (+-0.27)
	DDM_7	82.03 (+-0.22)	82.05 (+-0.21)	82.07 (+-0.21)	83.45 (+-0.25)	83.62 (+-0.26)	83.54 (+-0.27)
	DDM_{129}	83.34 (+-0.24)	83.35 (+-0.23)	83.44 (+-0.22)	82.86 (+-0.39)	83.50 (+-0.28)	83.57 (+-0.29)
	$RDDM_{30}$	84.18 (+-0.21)	84.18 (+-0.21)	**84.26 (+-0.21)**	82.50 (+-0.42)	83.67 (+-0.25)	83.70 (+-0.27)
	$RDDM_7$	82.82 (+-0.16)	82.83 (+-0.16)	82.88 (+-0.17)	83.41 (+-0.29)	83.63 (+-0.24)	83.62 (+-0.28)
	$RDDM_{129}$	83.61 (+-0.22)	83.61 (+-0.21)	83.71 (+-0.21)	83.15 (+-0.40)	83.52 (+-0.28)	83.70 (+-0.31)
RBF	FTDD	21.38 (+-0.89)	24.87 (+-0.82)	31.42 (+-0.65)	31.70 (+-0.50)	**32.58 (+-0.40)**	32.10 (+-0.52)
	WSTD	21.81 (+-1.08)	25.46 (+-0.83)	30.95 (+-0.64)	30.97 (+-0.61)	32.49 (+-0.40)	31.12 (+-0.64)
	$HDDM_A$	21.12 (+-0.88)	24.82 (+-0.89)	31.93 (+-0.59)	31.94 (+-0.43)	32.55 (+-0.39)	32.02 (+-0.39)
	DDM_7	20.57 (+-0.84)	25.31 (+-0.77)	31.84 (+-0.57)	31.56 (+-0.44)	31.58 (+-0.35)	31.45 (+-0.39)
	DDM_{129}	21.02 (+-0.86)	24.69 (+-0.78)	31.98 (+-0.53)	31.85 (+-0.39)	32.19 (+-0.34)	31.86 (+-0.40)
	$RDDM_{30}$	21.03 (+-0.87)	24.79 (+-0.88)	31.58 (+-0.63)	31.97 (+-0.46)	32.53 (+-0.38)	32.09 (+-0.44)
	$RDDM_7$	20.44 (+-0.78)	25.07 (+-0.73)	32.08 (+-0.47)	31.56 (+-0.42)	31.62 (+-0.35)	31.71 (+-0.36)
	$RDDM_{129}$	21.01 (+-0.86)	24.72 (+-0.81)	32.12 (+-0.49)	31.86 (+-0.40)	32.18 (+-0.35)	31.93 (+-0.38)
Sine	FTDD	83.36 (+-0.24)	83.38 (+-0.24)	**83.48 (+-0.24)**	80.59 (+-0.34)	83.07 (+-0.18)	82.28 (+-0.24)
	WSTD	82.53 (+-0.21)	82.55 (+-0.22)	82.52 (+-0.21)	81.19 (+-0.34)	82.95 (+-0.19)	82.14 (+-0.22)
	$HDDM_A$	82.70 (+-0.27)	82.72 (+-0.27)	82.79 (+-0.25)	80.70 (+-0.41)	83.05 (+-0.17)	82.41 (+-0.27)
	DDM_7	81.34 (+-0.23)	81.37 (+-0.23)	81.41 (+-0.22)	82.40 (+-0.20)	82.89 (+-0.18)	82.19 (+-0.25)
	DDM_{129}	82.62 (+-0.20)	82.64 (+-0.20)	82.75 (+-0.19)	81.74 (+-0.35)	82.97 (+-0.18)	82.57 (+-0.21)
	$RDDM_{30}$	83.25 (+-0.25)	83.27 (+-0.25)	83.43 (+-0.24)	81.94 (+-0.39)	83.09 (+-0.17)	82.65 (+-0.23)
	$RDDM_7$	82.12 (+-0.17)	82.15 (+-0.16)	82.15 (+-0.16)	82.44 (+-0.20)	82.89 (+-0.18)	82.38 (+-0.25)
	$RDDM_{129}$	82.81 (+-0.23)	82.84 (+-0.23)	82.91 (+-0.23)	82.25 (+-0.30)	82.96 (+-0.18)	82.66 (+-0.19)
Wave	FTDD	79.45 (+-0.35)	79.58 (+-0.35)	78.68 (+-0.36)	76.90 (+-0.39)	78.07 (+-0.38)	76.68 (+-0.43)
	WSTD	79.82 (+-0.33)	79.95 (+-0.34)	79.39 (+-0.39)	77.52 (+-0.41)	78.18 (+-0.38)	77.57 (+-0.51)
	$HDDM_A$	79.79 (+-0.32)	79.92 (+-0.32)	79.25 (+-0.35)	77.84 (+-0.43)	78.20 (+-0.40)	77.82 (+-0.47)
	DDM_7	80.63 (+-0.27)	**80.75 (+-0.28)**	80.52 (+-0.30)	78.57 (+-0.39)	79.21 (+-0.35)	78.51 (+-0.36)
	DDM_{129}	80.27 (+-0.32)	80.40 (+-0.32)	79.86 (+-0.34)	78.62 (+-0.43)	78.57 (+-0.35)	78.57 (+-0.40)
	$RDDM_{30}$	79.49 (+-0.35)	79.62 (+-0.35)	78.81 (+-0.37)	77.83 (+-0.43)	78.25 (+-0.37)	77.86 (+-0.41)
	$RDDM_7$	80.47 (+-0.30)	80.59 (+-0.30)	80.16 (+-0.32)	78.60 (+-0.42)	79.19 (+-0.36)	78.56 (+-0.41)
	$RDDM_{129}$	80.07 (+-0.32)	80.20 (+-0.32)	79.64 (+-0.35)	78.31 (+-0.43)	78.57 (+-0.35)	78.42 (+-0.37)

Table 69 – Mean accuracies of Ensembles in percentage (%) in 20K instances gradual datasets, with 95% confidence intervals, using HT

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	59.95 (+-0.50)	59.94 (+-0.50)	60.13 (+-0.46)	60.42 (+-0.69)	65.31 (+-0.36)	61.47 (+-0.81)
	WSTD	62.77 (+-0.33)	62.77 (+-0.33)	62.94 (+-0.29)	63.87 (+-0.63)	64.84 (+-0.30)	64.61 (+-0.37)
	$HDDM_A$	65.04 (+-0.52)	65.03 (+-0.52)	65.09 (+-0.47)	65.59 (+-0.48)	66.67 (+-0.31)	66.30 (+-0.43)
	DDM_7	63.62 (+-0.47)	63.61 (+-0.47)	63.71 (+-0.44)	66.46 (+-0.45)	66.85 (+-0.33)	66.12 (+-0.49)
	DDM_{129}	64.35 (+-0.49)	64.35 (+-0.49)	64.64 (+-0.48)	66.11 (+-0.43)	67.08 (+-0.32)	66.53 (+-0.53)
	$RDDM_{30}$	64.22 (+-0.51)	64.22 (+-0.51)	64.41 (+-0.43)	66.05 (+-0.35)	67.03 (+-0.38)	65.95 (+-0.39)
	$RDDM_7$	64.55 (+-0.48)	64.54 (+-0.48)	64.84 (+-0.46)	66.88 (+-0.33)	66.76 (+-0.33)	66.48 (+-0.47)
	$RDDM_{129}$	64.25 (+-0.42)	64.25 (+-0.43)	64.51 (+-0.39)	66.55 (+-0.36)	**67.13 (+-0.37)**	66.84 (+-0.40)
$Agraw_2$	FTDD	81.27 (+-0.23)	81.28 (+-0.24)	81.33 (+-0.23)	81.14 (+-0.23)	82.29 (+-0.21)	82.21 (+-0.35)
	WSTD	82.27 (+-0.16)	82.29 (+-0.16)	82.46 (+-0.16)	81.89 (+-0.30)	82.83 (+-0.16)	82.94 (+-0.22)
	$HDDM_A$	81.67 (+-0.17)	81.69 (+-0.18)	81.86 (+-0.17)	81.95 (+-0.29)	82.86 (+-0.20)	82.98 (+-0.28)
	DDM_7	82.20 (+-0.20)	82.21 (+-0.20)	82.25 (+-0.18)	82.83 (+-0.35)	83.37 (+-0.13)	83.16 (+-0.20)
	DDM_{129}	81.74 (+-0.20)	81.75 (+-0.20)	81.77 (+-0.22)	81.92 (+-0.60)	83.19 (+-0.12)	82.55 (+-0.96)
	$RDDM_{30}$	79.92 (+-0.28)	79.94 (+-0.29)	79.89 (+-0.27)	79.01 (+-0.82)	82.87 (+-0.15)	79.82 (+-1.65)
	$RDDM_7$	82.49 (+-0.16)	82.50 (+-0.16)	82.61 (+-0.16)	82.72 (+-0.46)	83.29 (+-0.12)	**83.38 (+-0.12)**
	$RDDM_{129}$	82.11 (+-0.25)	82.13 (+-0.25)	82.23 (+-0.25)	82.00 (+-0.59)	83.19 (+-0.12)	82.64 (+-0.96)
LED	FTDD	69.27 (+-0.32)	69.60 (+-0.22)	69.35 (+-0.21)	67.02 (+-0.75)	69.66 (+-0.14)	67.67 (+-0.84)
	WSTD	69.45 (+-0.23)	69.64 (+-0.23)	69.70 (+-0.24)	69.35 (+-0.27)	69.07 (+-0.18)	68.57 (+-0.50)
	$HDDM_A$	70.39 (+-0.17)	70.53 (+-0.16)	70.55 (+-0.16)	69.59 (+-0.20)	70.21 (+-0.17)	70.42 (+-0.19)
	DDM_7	70.46 (+-0.20)	70.62 (+-0.18)	70.64 (+-0.18)	70.47 (+-0.19)	70.41 (+-0.16)	70.38 (+-0.19)
	DDM_{129}	70.45 (+-0.17)	70.59 (+-0.16)	70.62 (+-0.16)	69.93 (+-0.24)	70.24 (+-0.17)	70.61 (+-0.18)
	$RDDM_{30}$	70.05 (+-0.17)	70.19 (+-0.16)	70.21 (+-0.16)	69.81 (+-0.24)	70.20 (+-0.17)	70.60 (+-0.18)
	$RDDM_7$	70.49 (+-0.20)	70.64 (+-0.18)	**70.66 (+-0.18)**	70.56 (+-0.18)	70.41 (+-0.16)	70.60 (+-0.17)
	$RDDM_{129}$	70.37 (+-0.17)	70.52 (+-0.16)	70.54 (+-0.16)	70.19 (+-0.22)	70.24 (+-0.17)	**70.66 (+-0.19)**
Mixed	FTDD	87.97 (+-0.14)	87.97 (+-0.13)	**88.09 (+-0.13)**	85.48 (+-0.43)	87.72 (+-0.15)	87.11 (+-0.16)
	WSTD	87.40 (+-0.14)	87.41 (+-0.14)	87.49 (+-0.13)	85.92 (+-0.36)	87.67 (+-0.14)	87.17 (+-0.17)
	$HDDM_A$	87.32 (+-0.15)	87.32 (+-0.14)	87.41 (+-0.14)	85.97 (+-0.45)	87.71 (+-0.16)	87.23 (+-0.18)
	DDM_7	86.35 (+-0.16)	86.36 (+-0.15)	86.46 (+-0.15)	87.63 (+-0.15)	87.68 (+-0.15)	87.28 (+-0.15)
	DDM_{129}	87.24 (+-0.14)	87.24 (+-0.14)	87.34 (+-0.15)	87.34 (+-0.38)	87.76 (+-0.16)	87.54 (+-0.17)
	$RDDM_{30}$	87.80 (+-0.13)	87.81 (+-0.13)	87.92 (+-0.12)	86.70 (+-0.44)	87.73 (+-0.16)	87.44 (+-0.17)
	$RDDM_7$	86.86 (+-0.17)	86.86 (+-0.17)	86.98 (+-0.16)	87.61 (+-0.17)	87.69 (+-0.17)	87.37 (+-0.17)
	$RDDM_{129}$	87.40 (+-0.12)	87.40 (+-0.12)	87.51 (+-0.12)	87.59 (+-0.28)	87.76 (+-0.16)	87.53 (+-0.18)
RBF	FTDD	20.91 (+-0.82)	23.80 (+-0.60)	31.75 (+-0.51)	32.20 (+-0.45)	**33.02 (+-0.32)**	32.69 (+-0.44)
	WSTD	21.01 (+-0.88)	24.31 (+-0.61)	30.42 (+-0.52)	31.13 (+-0.57)	32.87 (+-0.30)	31.06 (+-0.53)
	$HDDM_A$	20.27 (+-0.81)	23.80 (+-0.56)	32.31 (+-0.39)	32.32 (+-0.38)	32.92 (+-0.32)	32.32 (+-0.37)
	DDM_7	20.33 (+-0.68)	23.78 (+-0.46)	32.11 (+-0.40)	31.90 (+-0.38)	32.05 (+-0.27)	31.74 (+-0.41)
	DDM_{129}	20.38 (+-0.78)	24.16 (+-0.75)	32.40 (+-0.33)	32.16 (+-0.35)	32.72 (+-0.30)	32.14 (+-0.41)
	$RDDM_{30}$	20.30 (+-0.83)	23.84 (+-0.62)	31.93 (+-0.44)	32.20 (+-0.43)	32.90 (+-0.31)	32.44 (+-0.34)
	$RDDM_7$	19.98 (+-0.64)	24.00 (+-0.38)	32.35 (+-0.39)	31.98 (+-0.35)	32.01 (+-0.26)	32.00 (+-0.34)
	$RDDM_{129}$	20.28 (+-0.78)	23.83 (+-0.58)	32.34 (+-0.36)	32.18 (+-0.31)	32.72 (+-0.31)	32.19 (+-0.35)
Sine	FTDD	87.98 (+-0.17)	87.99 (+-0.17)	**88.03 (+-0.18)**	84.71 (+-0.34)	87.27 (+-0.12)	86.76 (+-0.11)
	WSTD	86.84 (+-0.20)	86.85 (+-0.19)	86.86 (+-0.18)	85.13 (+-0.30)	87.27 (+-0.12)	86.67 (+-0.10)
	$HDDM_A$	86.89 (+-0.15)	86.90 (+-0.15)	86.93 (+-0.15)	84.39 (+-0.32)	87.33 (+-0.12)	86.79 (+-0.13)
	DDM_7	86.01 (+-0.18)	86.02 (+-0.18)	85.94 (+-0.19)	86.82 (+-0.15)	87.22 (+-0.11)	86.52 (+-0.17)
	DDM_{129}	86.76 (+-0.17)	86.77 (+-0.17)	86.83 (+-0.17)	85.72 (+-0.36)	87.22 (+-0.13)	86.70 (+-0.14)
	$RDDM_{30}$	87.35 (+-0.21)	87.36 (+-0.21)	87.46 (+-0.20)	85.55 (+-0.43)	87.30 (+-0.11)	86.88 (+-0.12)
	$RDDM_7$	86.61 (+-0.18)	86.62 (+-0.19)	86.60 (+-0.19)	86.95 (+-0.12)	87.22 (+-0.11)	86.68 (+-0.16)
	$RDDM_{129}$	86.83 (+-0.19)	86.84 (+-0.19)	86.87 (+-0.20)	86.27 (+-0.32)	87.25 (+-0.13)	86.83 (+-0.13)
Wavef.	FTDD	81.02 (+-0.20)	81.09 (+-0.21)	80.40 (+-0.25)	79.23 (+-0.25)	80.11 (+-0.24)	78.36 (+-0.30)
	WSTD	81.01 (+-0.20)	81.07 (+-0.19)	80.65 (+-0.23)	79.20 (+-0.24)	80.07 (+-0.20)	78.78 (+-0.24)
	$HDDM_A$	81.04 (+-0.20)	81.10 (+-0.20)	80.57 (+-0.22)	79.29 (+-0.23)	79.96 (+-0.27)	78.78 (+-0.28)
	DDM_7	81.34 (+-0.20)	81.40 (+-0.19)	81.14 (+-0.20)	79.47 (+-0.24)	80.26 (+-0.20)	79.21 (+-0.23)
	DDM_{129}	81.26 (+-0.20)	81.32 (+-0.19)	80.83 (+-0.21)	79.61 (+-0.25)	80.14 (+-0.20)	79.12 (+-0.27)
	$RDDM_{30}$	80.99 (+-0.19)	81.05 (+-0.19)	80.44 (+-0.20)	79.20 (+-0.25)	80.09 (+-0.23)	78.74 (+-0.24)
	$RDDM_7$	81.35 (+-0.19)	**81.41 (+-0.19)**	80.96 (+-0.21)	79.51 (+-0.24)	80.26 (+-0.22)	79.30 (+-0.26)
	$RDDM_{129}$	81.10 (+-0.19)	81.16 (+-0.18)	80.67 (+-0.21)	79.46 (+-0.25)	80.13 (+-0.20)	79.10 (+-0.28)

Table 70 – Mean accuracies of Ensembles in percentage (%) in 50K instances gradual datasets, with 95% confidence intervals, using HT

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	62.68 (+-0.58)	62.67 (+-0.58)	62.69 (+-0.53)	65.93 (+-1.23)	68.18 (+-0.40)	65.95 (+-0.82)
	WSTD	64.25 (+-0.50)	64.25 (+-0.50)	64.24 (+-0.42)	68.79 (+-0.54)	68.07 (+-0.42)	67.93 (+-0.65)
	$HDDM_A$	67.70 (+-0.20)	67.70 (+-0.20)	67.74 (+-0.22)	70.29 (+-0.25)	71.19 (+-0.21)	71.39 (+-0.26)
	DDM_7	67.60 (+-0.28)	67.60 (+-0.28)	67.59 (+-0.28)	70.79 (+-0.29)	**71.59 (+-0.22)**	70.77 (+-0.36)
	DDM_{129}	67.96 (+-0.28)	67.96 (+-0.28)	68.06 (+-0.27)	70.56 (+-0.25)	71.52 (+-0.21)	71.27 (+-0.35)
	$RDDM_{30}$	67.80 (+-0.29)	67.80 (+-0.29)	67.90 (+-0.28)	70.29 (+-0.34)	71.46 (+-0.23)	70.84 (+-0.40)
	$RDDM_7$	68.56 (+-0.24)	68.55 (+-0.24)	68.77 (+-0.25)	71.25 (+-0.27)	71.57 (+-0.23)	71.30 (+-0.35)
	$RDDM_{129}$	68.24 (+-0.21)	68.24 (+-0.21)	68.39 (+-0.21)	70.90 (+-0.31)	71.48 (+-0.21)	71.43 (+-0.31)
$Agraw_2$	FTDD	83.20 (+-0.29)	83.21 (+-0.29)	83.23 (+-0.25)	82.76 (+-0.42)	85.80 (+-0.09)	83.88 (+-0.45)
	WSTD	84.74 (+-0.11)	84.74 (+-0.11)	84.78 (+-0.10)	83.99 (+-0.44)	85.82 (+-0.10)	85.29 (+-0.42)
	$HDDM_A$	84.34 (+-0.19)	84.35 (+-0.19)	84.35 (+-0.18)	84.48 (+-0.37)	85.84 (+-0.09)	85.19 (+-0.32)
	DDM_7	84.82 (+-0.13)	84.82 (+-0.13)	84.84 (+-0.11)	85.83 (+-0.15)	**86.03 (+-0.08)**	85.66 (+-0.21)
	DDM_{129}	84.69 (+-0.13)	84.70 (+-0.13)	84.75 (+-0.12)	85.20 (+-0.56)	85.91 (+-0.09)	85.63 (+-0.38)
	$RDDM_{30}$	83.85 (+-0.21)	83.85 (+-0.21)	83.98 (+-0.20)	84.29 (+-0.64)	85.88 (+-0.10)	84.38 (+-0.52)
	$RDDM_7$	84.87 (+-0.09)	84.87 (+-0.10)	84.93 (+-0.10)	85.86 (+-0.15)	86.00 (+-0.08)	85.84 (+-0.15)
	$RDDM_{129}$	84.63 (+-0.14)	84.64 (+-0.14)	84.71 (+-0.13)	85.47 (+-0.30)	85.89 (+-0.09)	85.69 (+-0.22)
LED	FTDD	71.94 (+-0.15)	72.00 (+-0.16)	71.98 (+-0.16)	70.94 (+-0.18)	72.00 (+-0.16)	71.61 (+-0.17)
	WSTD	72.00 (+-0.18)	72.06 (+-0.18)	72.11 (+-0.19)	71.54 (+-0.21)	71.79 (+-0.16)	71.36 (+-0.32)
	$HDDM_A$	72.44 (+-0.16)	72.50 (+-0.16)	72.51 (+-0.16)	71.43 (+-0.19)	72.42 (+-0.14)	72.47 (+-0.14)
	DDM_7	72.47 (+-0.16)	72.53 (+-0.15)	72.54 (+-0.15)	72.40 (+-0.15)	72.52 (+-0.14)	72.41 (+-0.16)
	DDM_{129}	72.45 (+-0.15)	72.51 (+-0.15)	72.52 (+-0.15)	71.87 (+-0.20)	72.46 (+-0.14)	72.61 (+-0.16)
	$RDDM_{30}$	72.21 (+-0.15)	72.27 (+-0.16)	72.28 (+-0.16)	71.78 (+-0.19)	72.35 (+-0.15)	72.50 (+-0.14)
	$RDDM_7$	72.46 (+-0.16)	72.53 (+-0.15)	72.54 (+-0.15)	72.46 (+-0.16)	72.51 (+-0.14)	72.42 (+-0.16)
	$RDDM_{129}$	72.43 (+-0.15)	72.49 (+-0.15)	72.50 (+-0.15)	71.98 (+-0.18)	72.46 (+-0.14)	**72.62 (+-0.15)**
Mixed	FTDD	91.72 (+-0.11)	91.72 (+-0.11)	91.75 (+-0.10)	89.43 (+-0.31)	91.08 (+-0.08)	90.75 (+-0.08)
	WSTD	91.04 (+-0.10)	91.04 (+-0.10)	91.04 (+-0.10)	89.98 (+-0.35)	91.05 (+-0.09)	90.68 (+-0.09)
	$HDDM_A$	91.23 (+-0.11)	91.24 (+-0.11)	91.26 (+-0.11)	88.45 (+-0.59)	91.09 (+-0.09)	90.78 (+-0.09)
	DDM_7	90.59 (+-0.11)	90.59 (+-0.11)	90.59 (+-0.10)	90.89 (+-0.08)	90.82 (+-0.10)	90.33 (+-0.14)
	DDM_{129}	91.29 (+-0.10)	91.29 (+-0.10)	91.31 (+-0.10)	89.15 (+-0.65)	90.98 (+-0.09)	90.67 (+-0.11)
	$RDDM_{30}$	91.77 (+-0.14)	91.77 (+-0.14)	**91.81 (+-0.13)**	89.23 (+-0.51)	91.05 (+-0.09)	90.85 (+-0.09)
	$RDDM_7$	90.85 (+-0.14)	90.86 (+-0.14)	90.88 (+-0.14)	90.93 (+-0.08)	90.85 (+-0.10)	90.61 (+-0.11)
	$RDDM_{129}$	91.33 (+-0.09)	91.33 (+-0.09)	91.37 (+-0.09)	90.25 (+-0.47)	90.98 (+-0.09)	90.74 (+-0.09)
RBF	FTDD	20.61 (+-0.74)	23.21 (+-0.55)	32.79 (+-0.31)	32.97 (+-0.39)	**33.68 (+-0.27)**	32.69 (+-0.43)
	WSTD	20.23 (+-0.67)	22.99 (+-0.44)	31.80 (+-0.48)	32.39 (+-0.48)	33.47 (+-0.28)	31.91 (+-0.38)
	$HDDM_A$	19.93 (+-0.60)	22.92 (+-0.51)	32.56 (+-0.33)	32.71 (+-0.31)	33.29 (+-0.22)	32.58 (+-0.29)
	DDM_7	19.97 (+-0.64)	23.15 (+-0.34)	32.36 (+-0.35)	32.36 (+-0.29)	32.36 (+-0.18)	32.13 (+-0.26)
	DDM_{129}	20.15 (+-0.73)	23.31 (+-0.40)	32.59 (+-0.33)	32.57 (+-0.31)	33.00 (+-0.23)	32.37 (+-0.29)
	$RDDM_{30}$	20.00 (+-0.64)	23.01 (+-0.58)	32.52 (+-0.32)	32.54 (+-0.29)	33.13 (+-0.23)	32.60 (+-0.31)
	$RDDM_7$	19.78 (+-0.70)	23.30 (+-0.27)	32.48 (+-0.29)	32.23 (+-0.23)	32.37 (+-0.19)	32.19 (+-0.21)
	$RDDM_{129}$	19.87 (+-0.72)	23.39 (+-0.39)	32.60 (+-0.29)	32.50 (+-0.27)	32.99 (+-0.22)	32.38 (+-0.28)
Sine	FTDD	91.93 (+-0.18)	91.94 (+-0.18)	91.96 (+-0.17)	89.03 (+-0.27)	90.86 (+-0.11)	90.27 (+-0.11)
	WSTD	91.37 (+-0.19)	91.37 (+-0.19)	91.36 (+-0.19)	89.76 (+-0.31)	90.84 (+-0.10)	90.24 (+-0.12)
	$HDDM_A$	91.77 (+-0.21)	91.77 (+-0.21)	91.80 (+-0.19)	88.87 (+-0.28)	90.87 (+-0.12)	90.33 (+-0.11)
	DDM_7	90.98 (+-0.24)	90.98 (+-0.24)	90.95 (+-0.24)	90.60 (+-0.19)	90.76 (+-0.11)	90.01 (+-0.14)
	DDM_{129}	91.71 (+-0.20)	91.71 (+-0.20)	91.72 (+-0.20)	89.84 (+-0.29)	90.85 (+-0.10)	90.26 (+-0.10)
	$RDDM_{30}$	92.25 (+-0.20)	92.25 (+-0.20)	**92.27 (+-0.20)**	89.95 (+-0.29)	90.86 (+-0.10)	90.35 (+-0.11)
	$RDDM_7$	91.08 (+-0.16)	91.09 (+-0.16)	91.10 (+-0.15)	90.70 (+-0.10)	90.79 (+-0.11)	90.17 (+-0.12)
	$RDDM_{129}$	91.65 (+-0.22)	91.65 (+-0.22)	91.69 (+-0.22)	90.25 (+-0.22)	90.85 (+-0.10)	90.34 (+-0.09)
Wavef.	FTDD	82.58 (+-0.12)	82.61 (+-0.12)	82.35 (+-0.14)	80.39 (+-0.18)	81.90 (+-0.19)	79.01 (+-0.21)
	WSTD	82.10 (+-0.14)	82.13 (+-0.14)	81.73 (+-0.15)	80.55 (+-0.20)	81.85 (+-0.16)	79.44 (+-0.19)
	$HDDM_A$	82.37 (+-0.11)	82.39 (+-0.11)	82.01 (+-0.12)	80.66 (+-0.18)	81.89 (+-0.19)	79.44 (+-0.18)
	DDM_7	82.18 (+-0.11)	82.20 (+-0.11)	81.79 (+-0.14)	80.51 (+-0.17)	81.27 (+-0.13)	79.74 (+-0.14)
	DDM_{129}	82.50 (+-0.13)	82.53 (+-0.13)	82.02 (+-0.13)	80.68 (+-0.15)	81.71 (+-0.14)	79.58 (+-0.19)
	$RDDM_{30}$	82.63 (+-0.11)	**82.66 (+-0.11)**	82.32 (+-0.12)	80.51 (+-0.17)	82.04 (+-0.14)	79.53 (+-0.20)
	$RDDM_7$	82.20 (+-0.13)	82.22 (+-0.13)	81.63 (+-0.14)	80.45 (+-0.16)	81.12 (+-0.13)	79.98 (+-0.15)
	$RDDM_{129}$	82.48 (+-0.13)	82.50 (+-0.13)	81.99 (+-0.13)	80.81 (+-0.14)	81.63 (+-0.15)	79.71 (+-0.14)

Table 71 – Mean accuracies of Ensembles in percentage (%) in 100K instances gradual datasets, with 95% confidence intervals, using HT

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	64.69 (+-0.35)	64.68 (+-0.35)	64.62 (+-0.32)	70.32 (+-0.98)	70.64 (+-0.61)	69.51 (+-1.08)
	WSTD	64.94 (+-0.54)	64.94 (+-0.54)	64.87 (+-0.48)	72.13 (+-0.54)	71.13 (+-0.48)	70.90 (+-0.80)
	$HDDM_A$	69.89 (+-0.18)	69.89 (+-0.19)	70.01 (+-0.18)	73.23 (+-0.25)	73.74 (+-0.22)	74.25 (+-0.29)
	DDM_7	69.21 (+-0.22)	69.21 (+-0.22)	69.23 (+-0.22)	73.32 (+-0.31)	73.87 (+-0.22)	73.80 (+-0.35)
	DDM_{129}	69.83 (+-0.24)	69.83 (+-0.24)	69.94 (+-0.23)	73.45 (+-0.26)	73.92 (+-0.22)	74.04 (+-0.34)
	$RDDM_{30}$	69.81 (+-0.31)	69.81 (+-0.31)	69.88 (+-0.30)	73.00 (+-0.65)	73.95 (+-0.27)	73.37 (+-0.95)
	$RDDM_7$	69.80 (+-0.20)	69.80 (+-0.20)	69.97 (+-0.20)	73.46 (+-0.28)	73.94 (+-0.19)	**74.57 (+-0.30)**
	$RDDM_{129}$	70.05 (+-0.21)	70.04 (+-0.21)	70.13 (+-0.22)	73.43 (+-0.33)	73.95 (+-0.22)	74.43 (+-0.33)
$Agraw_2$	FTDD	84.87 (+-0.28)	84.87 (+-0.28)	84.84 (+-0.26)	84.17 (+-0.57)	87.26 (+-0.05)	85.59 (+-0.51)
	WSTD	86.05 (+-0.07)	86.06 (+-0.07)	86.07 (+-0.06)	86.11 (+-0.35)	87.33 (+-0.06)	86.98 (+-0.33)
	$HDDM_A$	85.87 (+-0.15)	85.88 (+-0.15)	85.87 (+-0.14)	86.49 (+-0.20)	87.33 (+-0.06)	87.14 (+-0.15)
	DDM_7	85.82 (+-0.06)	85.82 (+-0.06)	85.83 (+-0.06)	87.02 (+-0.34)	**87.43 (+-0.04)**	86.97 (+-0.32)
	DDM_{129}	85.76 (+-0.12)	85.76 (+-0.12)	85.77 (+-0.11)	86.49 (+-0.51)	87.34 (+-0.06)	86.89 (+-0.36)
	$RDDM_{30}$	85.36 (+-0.17)	85.36 (+-0.17)	85.36 (+-0.15)	85.61 (+-0.57)	87.28 (+-0.07)	85.68 (+-0.66)
	$RDDM_7$	85.91 (+-0.07)	85.92 (+-0.07)	85.93 (+-0.06)	87.35 (+-0.13)	87.42 (+-0.05)	87.30 (+-0.10)
	$RDDM_{129}$	85.76 (+-0.13)	85.77 (+-0.13)	85.76 (+-0.13)	86.90 (+-0.26)	87.33 (+-0.06)	86.97 (+-0.18)
LED	FTDD	72.88 (+-0.13)	72.91 (+-0.13)	72.90 (+-0.13)	71.80 (+-0.19)	72.99 (+-0.11)	72.53 (+-0.15)
	WSTD	73.00 (+-0.12)	73.04 (+-0.12)	73.05 (+-0.12)	72.54 (+-0.18)	72.90 (+-0.11)	72.40 (+-0.18)
	$HDDM_A$	73.24 (+-0.11)	73.27 (+-0.11)	73.27 (+-0.11)	72.31 (+-0.16)	73.22 (+-0.11)	73.21 (+-0.12)
	DDM_7	73.22 (+-0.12)	73.25 (+-0.12)	73.25 (+-0.12)	73.07 (+-0.13)	73.26 (+-0.11)	73.14 (+-0.15)
	DDM_{129}	73.20 (+-0.12)	73.23 (+-0.12)	73.24 (+-0.12)	72.64 (+-0.16)	73.21 (+-0.11)	73.27 (+-0.12)
	$RDDM_{30}$	73.03 (+-0.12)	73.06 (+-0.12)	73.06 (+-0.12)	72.78 (+-0.18)	73.13 (+-0.12)	73.18 (+-0.12)
	$RDDM_7$	73.24 (+-0.12)	73.27 (+-0.12)	73.28 (+-0.12)	73.13 (+-0.12)	73.26 (+-0.11)	73.06 (+-0.11)
	$RDDM_{129}$	73.20 (+-0.12)	73.22 (+-0.12)	73.23 (+-0.12)	72.66 (+-0.20)	73.21 (+-0.11)	**73.30 (+-0.12)**
Mixed	FTDD	93.91 (+-0.13)	93.91 (+-0.13)	93.93 (+-0.13)	91.67 (+-0.24)	92.67 (+-0.06)	92.43 (+-0.06)
	WSTD	93.37 (+-0.07)	93.37 (+-0.07)	93.37 (+-0.08)	91.80 (+-0.27)	92.66 (+-0.07)	92.38 (+-0.06)
	$HDDM_A$	93.91 (+-0.14)	93.91 (+-0.14)	93.93 (+-0.14)	91.58 (+-0.29)	92.66 (+-0.06)	92.43 (+-0.08)
	DDM_7	93.03 (+-0.15)	93.03 (+-0.15)	93.02 (+-0.15)	92.53 (+-0.08)	92.37 (+-0.08)	91.77 (+-0.16)
	DDM_{129}	93.77 (+-0.11)	93.77 (+-0.11)	93.78 (+-0.10)	91.27 (+-0.33)	92.58 (+-0.07)	92.21 (+-0.13)
	$RDDM_{30}$	**94.26 (+-0.11)**	**94.26 (+-0.11)**	**94.26 (+-0.10)**	92.21 (+-0.18)	92.66 (+-0.07)	92.48 (+-0.07)
	$RDDM_7$	93.35 (+-0.13)	93.35 (+-0.13)	93.37 (+-0.13)	92.53 (+-0.07)	92.38 (+-0.08)	92.06 (+-0.13)
	$RDDM_{129}$	93.91 (+-0.13)	93.91 (+-0.13)	93.94 (+-0.13)	92.35 (+-0.17)	92.58 (+-0.07)	92.37 (+-0.08)
RBF	FTDD	20.28 (+-0.86)	23.46 (+-0.77)	**34.31 (+-0.29)**	34.13 (+-0.30)	34.26 (+-0.22)	33.27 (+-0.32)
	WSTD	19.84 (+-0.63)	22.80 (+-0.35)	32.20 (+-0.23)	32.69 (+-0.25)	33.75 (+-0.20)	32.26 (+-0.25)
	$HDDM_A$	19.67 (+-0.62)	22.62 (+-0.50)	32.54 (+-0.24)	33.49 (+-0.30)	33.56 (+-0.20)	32.92 (+-0.26)
	DDM_7	19.73 (+-0.68)	22.87 (+-0.37)	32.59 (+-0.21)	32.82 (+-0.27)	32.62 (+-0.11)	32.63 (+-0.21)
	DDM_{129}	20.09 (+-0.72)	22.89 (+-0.40)	32.50 (+-0.22)	33.21 (+-0.25)	33.29 (+-0.19)	32.86 (+-0.23)
	$RDDM_{30}$	19.61 (+-0.60)	22.51 (+-0.55)	32.75 (+-0.23)	33.32 (+-0.25)	33.47 (+-0.16)	32.86 (+-0.21)
	$RDDM_7$	19.62 (+-0.61)	22.91 (+-0.37)	32.61 (+-0.19)	32.61 (+-0.16)	32.57 (+-0.12)	32.48 (+-0.16)
	$RDDM_{129}$	19.72 (+-0.78)	23.02 (+-0.41)	32.57 (+-0.20)	32.89 (+-0.22)	33.24 (+-0.15)	32.84 (+-0.19)
Sine	FTDD	95.00 (+-0.15)	95.00 (+-0.15)	95.00 (+-0.14)	91.53 (+-0.22)	92.54 (+-0.07)	91.92 (+-0.09)
	WSTD	94.71 (+-0.16)	94.71 (+-0.16)	94.71 (+-0.16)	91.60 (+-0.28)	92.53 (+-0.08)	91.93 (+-0.10)
	$HDDM_A$	95.11 (+-0.14)	95.11 (+-0.14)	95.11 (+-0.13)	90.98 (+-0.27)	92.56 (+-0.07)	91.98 (+-0.09)
	DDM_7	94.44 (+-0.16)	94.45 (+-0.16)	94.44 (+-0.16)	92.49 (+-0.12)	92.50 (+-0.07)	91.76 (+-0.14)
	DDM_{129}	95.02 (+-0.10)	95.02 (+-0.10)	95.02 (+-0.10)	91.69 (+-0.33)	92.54 (+-0.07)	91.96 (+-0.08)
	$RDDM_{30}$	**95.32 (+-0.12)**	**95.32 (+-0.12)**	95.31 (+-0.12)	92.05 (+-0.25)	92.56 (+-0.08)	92.02 (+-0.09)
	$RDDM_7$	94.65 (+-0.13)	94.65 (+-0.13)	94.65 (+-0.13)	92.55 (+-0.08)	92.50 (+-0.08)	91.80 (+-0.13)
	$RDDM_{129}$	94.93 (+-0.15)	94.93 (+-0.15)	94.96 (+-0.14)	92.14 (+-0.24)	92.54 (+-0.07)	91.99 (+-0.09)
Wavef.	FTDD	83.39 (+-0.08)	**83.40 (+-0.08)**	83.30 (+-0.09)	81.47 (+-0.27)	82.33 (+-0.15)	79.28 (+-0.21)
	WSTD	82.63 (+-0.09)	82.64 (+-0.09)	82.23 (+-0.11)	81.18 (+-0.20)	82.24 (+-0.13)	79.47 (+-0.16)
	$HDDM_A$	82.78 (+-0.11)	82.79 (+-0.11)	82.48 (+-0.11)	81.07 (+-0.17)	82.33 (+-0.13)	79.47 (+-0.12)
	DDM_7	82.59 (+-0.10)	82.61 (+-0.10)	82.16 (+-0.12)	80.88 (+-0.16)	81.61 (+-0.12)	79.85 (+-0.15)
	DDM_{129}	83.00 (+-0.10)	83.01 (+-0.10)	82.50 (+-0.11)	81.12 (+-0.16)	82.19 (+-0.13)	79.84 (+-0.17)
	$RDDM_{30}$	83.20 (+-0.08)	83.22 (+-0.08)	82.93 (+-0.09)	81.03 (+-0.16)	82.43 (+-0.09)	79.57 (+-0.17)
	$RDDM_7$	82.62 (+-0.11)	82.63 (+-0.11)	82.09 (+-0.13)	80.67 (+-0.13)	81.39 (+-0.10)	80.10 (+-0.11)
	$RDDM_{129}$	82.85 (+-0.11)	82.87 (+-0.12)	82.40 (+-0.12)	81.00 (+-0.16)	82.10 (+-0.13)	79.81 (+-0.13)

Table 72 – Mean accuracies of Ensembles in percentage (%) in 500K instances gradual datasets, with 95% confidence intervals, using HT

Dataset	Ensemble	ADOB	$BOLE_4$	$BOLE_5$	DDD	FASE	None
$Agraw_1$	FTDD	68.11 (+-0.79)	68.11 (+-0.79)	68.03 (+-0.78)	76.72 (+-0.43)	76.15 (+-0.45)	77.36 (+-1.46)
	WSTD	67.34 (+-0.97)	67.34 (+-0.97)	67.00 (+-0.89)	76.11 (+-0.51)	76.40 (+-0.60)	77.66 (+-1.36)
	$HDDM_A$	72.87 (+-0.63)	72.87 (+-0.63)	72.84 (+-0.58)	76.17 (+-0.46)	77.16 (+-0.35)	78.14 (+-0.89)
	DDM_7	71.96 (+-0.66)	71.96 (+-0.66)	71.96 (+-0.65)	75.47 (+-3.10)	77.81 (+-0.23)	76.66 (+-3.29)
	DDM_{129}	72.56 (+-0.84)	72.56 (+-0.84)	72.54 (+-0.72)	76.50 (+-0.78)	77.45 (+-0.50)	79.09 (+-0.84)
	$RDDM_{30}$	72.77 (+-0.37)	72.77 (+-0.37)	72.79 (+-0.32)	76.71 (+-0.53)	77.34 (+-0.39)	**79.24 (+-0.97)**
	$RDDM_7$	71.88 (+-0.75)	71.88 (+-0.75)	71.87 (+-0.69)	76.36 (+-0.32)	77.87 (+-0.31)	77.60 (+-0.71)
	$RDDM_{129}$	72.40 (+-0.82)	72.40 (+-0.82)	72.37 (+-0.73)	76.79 (+-0.45)	77.48 (+-0.49)	78.12 (+-0.84)
$Agraw_2$	FTDD	87.95 (+-0.15)	87.95 (+-0.15)	87.87 (+-0.14)	88.36 (+-0.49)	89.25 (+-0.09)	88.63 (+-0.50)
	WSTD	87.61 (+-0.06)	87.62 (+-0.06)	87.60 (+-0.06)	88.66 (+-0.15)	89.26 (+-0.05)	89.14 (+-0.07)
	$HDDM_A$	87.69 (+-0.08)	87.69 (+-0.08)	87.65 (+-0.09)	88.90 (+-0.18)	89.27 (+-0.09)	89.20 (+-0.08)
	DDM_7	87.40 (+-0.11)	87.40 (+-0.11)	87.33 (+-0.12)	88.28 (+-0.67)	89.27 (+-0.08)	88.99 (+-0.23)
	DDM_{129}	87.39 (+-0.15)	87.40 (+-0.15)	87.31 (+-0.14)	89.03 (+-0.35)	**89.31 (+-0.06)**	88.75 (+-0.70)
	$RDDM_{30}$	87.30 (+-0.20)	87.30 (+-0.20)	87.24 (+-0.18)	88.52 (+-0.46)	89.21 (+-0.06)	88.63 (+-0.20)
	$RDDM_7$	87.20 (+-0.07)	87.20 (+-0.07)	87.18 (+-0.05)	88.66 (+-0.11)	89.04 (+-0.05)	88.41 (+-0.17)
	$RDDM_{129}$	87.39 (+-0.20)	87.39 (+-0.20)	87.35 (+-0.19)	88.95 (+-0.29)	89.20 (+-0.06)	88.74 (+-0.17)
LED	FTDD	73.70 (+-0.12)	73.71 (+-0.12)	73.71 (+-0.12)	72.88 (+-0.17)	73.72 (+-0.09)	73.53 (+-0.10)
	WSTD	73.72 (+-0.10)	73.73 (+-0.10)	73.73 (+-0.10)	73.53 (+-0.11)	73.71 (+-0.10)	73.19 (+-0.04)
	$HDDM_A$	73.77 (+-0.10)	73.77 (+-0.11)	73.77 (+-0.10)	73.32 (+-0.19)	73.76 (+-0.09)	73.53 (+-0.08)
	DDM_7	73.76 (+-0.11)	73.77 (+-0.11)	73.77 (+-0.11)	73.49 (+-0.10)	**73.78 (+-0.09)**	73.43 (+-0.08)
	DDM_{129}	73.77 (+-0.11)	73.77 (+-0.11)	**73.78 (+-0.11)**	73.38 (+-0.13)	73.76 (+-0.09)	73.35 (+-0.13)
	$RDDM_{30}$	73.71 (+-0.11)	73.72 (+-0.11)	73.72 (+-0.11)	73.40 (+-0.15)	73.72 (+-0.09)	73.33 (+-0.13)
	$RDDM_7$	73.76 (+-0.11)	73.77 (+-0.11)	73.77 (+-0.11)	73.55 (+-0.09)	73.77 (+-0.09)	73.42 (+-0.10)
	$RDDM_{129}$	73.76 (+-0.11)	73.77 (+-0.11)	73.77 (+-0.11)	73.56 (+-0.09)	73.76 (+-0.09)	73.57 (+-0.09)
Mixed	FTDD	98.63 (+-0.03)	98.63 (+-0.03)	98.64 (+-0.03)	94.91 (+-0.29)	95.08 (+-0.06)	94.69 (+-0.04)
	WSTD	98.48 (+-0.04)	98.48 (+-0.04)	98.49 (+-0.04)	95.04 (+-0.15)	95.08 (+-0.06)	94.72 (+-0.05)
	$HDDM_A$	98.60 (+-0.04)	98.60 (+-0.04)	98.60 (+-0.03)	94.01 (+-0.33)	95.07 (+-0.05)	94.76 (+-0.04)
	DDM_7	98.43 (+-0.06)	98.43 (+-0.06)	98.43 (+-0.06)	95.14 (+-0.18)	94.87 (+-0.09)	94.28 (+-0.16)
	DDM_{129}	98.61 (+-0.03)	98.61 (+-0.03)	98.61 (+-0.03)	93.97 (+-0.26)	95.04 (+-0.05)	94.69 (+-0.07)
	$RDDM_{30}$	**98.65 (+-0.03)**	**98.65 (+-0.03)**	**98.65 (+-0.03)**	94.97 (+-0.25)	95.06 (+-0.05)	94.35 (+-0.15)
	$RDDM_7$	98.51 (+-0.05)	98.51 (+-0.05)	98.52 (+-0.04)	94.09 (+-0.10)	94.45 (+-0.09)	92.95 (+-0.26)
	$RDDM_{129}$	98.61 (+-0.03)	98.61 (+-0.03)	98.62 (+-0.03)	94.82 (+-0.26)	95.01 (+-0.09)	94.01 (+-0.14)
RBF	FTDD	22.91 (+-2.81)	29.87 (+-0.34)	**37.31 (+-0.21)**	36.91 (+-0.40)	36.92 (+-0.25)	35.42 (+-0.36)
	WSTD	18.64 (+-0.51)	22.25 (+-0.80)	32.86 (+-0.09)	33.06 (+-0.22)	33.56 (+-0.11)	32.44 (+-0.14)
	$HDDM_A$	18.73 (+-0.91)	27.18 (+-1.07)	35.56 (+-0.32)	35.04 (+-0.53)	34.87 (+-0.25)	34.26 (+-0.29)
	DDM_7	18.66 (+-0.74)	28.28 (+-1.14)	35.20 (+-0.36)	34.76 (+-0.46)	33.45 (+-0.18)	34.40 (+-0.88)
	DDM_{129}	21.11 (+-1.86)	26.33 (+-1.46)	35.71 (+-0.24)	35.17 (+-0.36)	35.04 (+-0.17)	34.77 (+-0.40)
	$RDDM_{30}$	21.57 (+-2.19)	26.63 (+-1.47)	35.65 (+-0.21)	35.18 (+-0.42)	35.10 (+-0.27)	34.52 (+-0.37)
	$RDDM_7$	19.71 (+-0.90)	22.52 (+-1.35)	33.26 (+-0.20)	33.12 (+-0.26)	33.21 (+-0.14)	33.04 (+-0.22)
	$RDDM_{129}$	20.63 (+-1.97)	26.18 (+-1.48)	35.00 (+-0.28)	34.62 (+-0.34)	34.69 (+-0.20)	33.98 (+-0.28)
Sine	FTDD	98.39 (+-0.03)	98.39 (+-0.03)	98.39 (+-0.03)	96.45 (+-0.21)	96.34 (+-0.13)	95.55 (+-0.16)
	WSTD	98.38 (+-0.08)	98.38 (+-0.08)	98.39 (+-0.08)	96.55 (+-0.22)	96.30 (+-0.14)	95.56 (+-0.17)
	$HDDM_A$	98.36 (+-0.07)	98.36 (+-0.07)	98.36 (+-0.07)	96.09 (+-0.30)	96.35 (+-0.15)	95.52 (+-0.19)
	DDM_7	98.33 (+-0.08)	98.33 (+-0.08)	98.32 (+-0.08)	96.55 (+-0.15)	96.33 (+-0.15)	95.41 (+-0.13)
	DDM_{129}	98.39 (+-0.06)	98.39 (+-0.06)	98.39 (+-0.05)	96.44 (+-0.23)	96.33 (+-0.15)	95.54 (+-0.17)
	$RDDM_{30}$	**98.43 (+-0.06)**	**98.43 (+-0.07)**	98.42 (+-0.06)	96.37 (+-0.15)	96.29 (+-0.13)	95.31 (+-0.22)
	$RDDM_7$	98.36 (+-0.03)	98.36 (+-0.03)	98.35 (+-0.03)	95.20 (+-0.21)	95.69 (+-0.11)	93.95 (+-0.34)
	$RDDM_{129}$	98.42 (+-0.06)	98.42 (+-0.06)	98.42 (+-0.05)	96.27 (+-0.23)	96.29 (+-0.14)	94.89 (+-0.32)
Wavef.	FTDD	83.86 (+-0.10)	83.86 (+-0.10)	83.84 (+-0.09)	**84.17 (+-0.19)**	**84.17 (+-0.10)**	81.55 (+-0.19)
	WSTD	82.86 (+-0.09)	82.87 (+-0.09)	82.56 (+-0.12)	83.45 (+-0.14)	83.72 (+-0.10)	80.62 (+-0.34)
	$HDDM_A$	83.04 (+-0.06)	83.04 (+-0.06)	82.76 (+-0.09)	83.56 (+-0.31)	83.85 (+-0.10)	81.09 (+-0.24)
	DDM_7	83.10 (+-0.14)	83.10 (+-0.14)	82.61 (+-0.24)	82.70 (+-0.49)	82.41 (+-0.22)	80.06 (+-0.19)
	DDM_{129}	83.57 (+-0.10)	83.57 (+-0.10)	83.22 (+-0.14)	83.06 (+-0.41)	83.92 (+-0.10)	81.31 (+-0.16)
	$RDDM_{30}$	83.49 (+-0.10)	83.50 (+-0.10)	83.31 (+-0.13)	82.86 (+-0.42)	83.68 (+-0.07)	80.63 (+-0.21)
	$RDDM_7$	82.89 (+-0.09)	82.89 (+-0.08)	82.62 (+-0.10)	80.95 (+-0.16)	81.69 (+-0.12)	80.13 (+-0.10)
	$RDDM_{129}$	83.10 (+-0.08)	83.11 (+-0.08)	82.84 (+-0.12)	82.12 (+-0.51)	83.21 (+-0.24)	80.18 (+-0.20)