

Improving Adaptive Bagging Methods for Evolving Data Streams

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Abstract. We propose two new improvements for bagging methods on evolving data streams. Recently, two new variants of Bagging were proposed: **ADWIN** Bagging and Adaptive-Size Hoeffding Tree (ASHT) Bagging. ASHT Bagging uses trees of different sizes, and **ADWIN** Bagging uses **ADWIN** as a change detector to decide when to discard underperforming ensemble members. We improve **ADWIN** Bagging using Hoeffding Adaptive Trees, trees that can adaptively learn from data streams that change over time. To speed up the time for adapting to change of Adaptive-Size Hoeffding Tree (ASHT) Bagging, we add an error change detector for each classifier. We test our improvements by performing an evaluation study on synthetic and real-world datasets comprising up to ten million examples.

1 Introduction

Data streams pose several challenges on data mining algorithm design. First, algorithms must make use of limited resources (time and memory). Second, by necessity they must deal with data whose nature or distribution changes over time. In turn, dealing with time-changing data requires strategies for detecting and quantifying change, forgetting stale examples, and for model revision. Fairly generic strategies exist for detecting change and deciding when examples are no longer relevant. Model revision strategies, on the other hand, are in most cases method-specific.

The following constraints apply in the Data Stream model:

1. Data arrives as a potentially infinite sequence. Thus, it is impossible to store it all. Therefore, only a small summary can be computed and stored.
2. The speed of arrival of data is fast, so each particular element has to be processed essentially in real time, and then discarded.
3. The distribution generating the items may change over time. Thus, data from the past may become irrelevant (or even harmful) for the current prediction.

Under these constraints the main properties of an ideal classification method are the following: high accuracy and fast adaption to change, low computational

cost in both space and time, theoretical performance guarantees, and a minimal number of parameters.

Ensemble methods are combinations of several models whose individual predictions are combined in some manner (for example, by averaging or voting) to form a final prediction. Often, ensemble learning classifiers provide superior predictive performance and they are easier to scale and parallelize than single classifier methods.

In [6] two new state-of-the-art bagging methods were presented: ASHT Bagging using trees of different sizes, and ADWIN Bagging using a change detector to decide when to discard underperforming ensemble members. This paper improves on ASHT Bagging by speeding up the time taken to adapt to changes in the distribution generating the stream. It improves on ADWIN Bagging by employing Hoeffding Adaptive Trees, trees that can adaptively learn from evolving data streams. The paper is structured as follows: the state-of-the-art Bagging methods are presented in Section 2. Improvements to these methods are presented in Section 3. An experimental evaluation is conducted in Section 4. Finally, conclusions and suggested items for future work are presented in Section 5.

2 Previous Work

2.1 Bagging using trees of different size (ASHT Bagging)

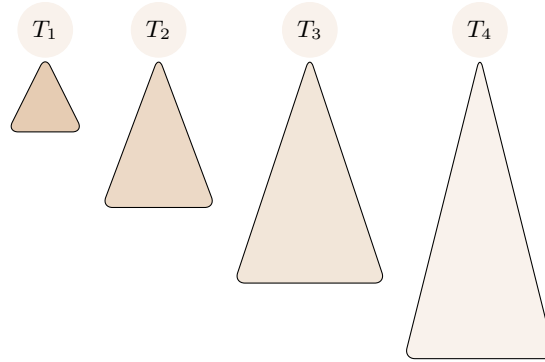


Fig. 1. An ensemble of trees of different size

In [6], a new method of bagging was presented using Hoeffding Trees of different sizes. A *Hoeffding tree* [10] is an incremental, anytime decision tree induction algorithm that is capable of learning from massive data streams, assuming that the distribution generating examples does not change over time. Hoeffding trees exploit the fact that a small sample can often be enough to choose an optimal splitting attribute. This idea is supported mathematically by

the Hoeffding bound, which quantifies the number of observations (in our case, examples) needed to estimate some statistics within a prescribed precision (in our case, the goodness of an attribute). More precisely, the Hoeffding bound states that with probability $1 - \delta$, the true mean of a random variable of range R will not differ from the estimated mean after n independent observations by more than:

$$\epsilon = \sqrt{\frac{R^2 \ln(1/\delta)}{2n}}.$$

A theoretically appealing feature of Hoeffding Trees not shared by many other incremental decision tree learners is that it has sound theoretical guarantees of performance. IADEM-2 [9] uses Chernoff and Hoeffding bounds to give similar guarantees. Using the Hoeffding bound one can show that the output of a Hoeffding tree is asymptotically nearly identical to that of a non-incremental learner using infinitely many examples. See [10] for details.

The Adaptive-Size Hoeffding Tree (ASHT) is derived from the Hoeffding Tree algorithm with the following differences:

- it has a value for the maximum number of split nodes, or *size*
- after one node splits, if the number of split nodes of the ASHT tree is higher than the maximum value, then it deletes some nodes to reduce its size

When the tree size exceeds the maximum size value, there are two different delete options:

- delete the oldest node, the root, and all of its children except the one where the split has been made. After that, the root of the child not deleted becomes the new root.
- delete all the nodes of the tree, that is, reset the tree to the empty tree

The intuition behind this method is as follows: smaller trees adapt more quickly to changes, and larger trees perform better during periods with little or no change, simply because they were built on more data. Trees limited to size s will be reset about twice as often as trees with a size limit of $2s$. This creates a set of different reset-speeds for an ensemble of such trees, and therefore a subset of trees that are a good approximation for the current rate of change. It is important to note that resets will happen all the time, even for stationary datasets, but this behaviour should not have a negative impact on the ensemble's predictive performance.

In [6] a new bagging method was presented that uses these Adaptive-Size Hoeffding Trees and that sets the size for each tree. The maximum allowed size for the n -th ASHT tree is twice the maximum allowed size for the $(n - 1)$ -th tree. Moreover, each tree has a weight proportional to the inverse of the square of its error, and it monitors its error with an exponential weighted moving average (EWMA) with $\alpha = .01$. The size of the first tree is 2.

With this new method, the authors attempted to improve bagging performance by increasing tree diversity. It has been observed [18] that boosting tends to produce a more diverse set of classifiers than bagging, and this has been cited as a factor in increased performance.

2.2 Bagging using ADWIN (ADWIN Bagging)

ADWIN [4] is a change detector and estimator that solves in a well-specified way the problem of tracking the average of a stream of bits or real-valued numbers. ADWIN keeps a variable-length window of recently seen items, with the property that the window has the maximal length statistically consistent with the hypothesis “there has been no change in the average value inside the window”.

More precisely, an older fragment of the window is dropped if and only if there is enough evidence that its average value differs from that of the rest of the window. This has two consequences: first, that change is reliably declared whenever the window shrinks; and second, that at any time the average over the existing window can be reliably taken as an estimate of the current average in the stream (barring a very small or very recent change that is still not statistically visible). A formal and quantitative statement of these two points (in the form of a theorem) appears in [4].

ADWIN is parameter- and assumption-free in the sense that it automatically detects and adapts to the current rate of change. Its only parameter is a confidence bound δ , indicating how confident we want to be in the algorithm’s output, a property inherent to all algorithms dealing with random processes.

Also important for our purposes, ADWIN does not maintain the window explicitly, but compresses it using a variant of the exponential histogram technique. This means that it keeps a window of length W using only $O(\log W)$ memory and $O(\log W)$ processing time per item.

Bagging using ADWIN is implemented as ADWIN Bagging where the Bagging method is the online bagging method of Oza and Russell [20] with the addition of the ADWIN algorithm as a change detector. The base classifiers used are Hoeffding Trees. When a change is detected, the worst classifier of the ensemble of classifiers is removed and a new classifier is added to the ensemble.

3 Improvements for Adaptive Bagging Methods

In this section we propose two new improvements for the adaptive bagging methods explained in the previous section.

3.1 ADWIN bagging using Hoeffding Adaptive Trees

The basic idea is to use Hoeffding trees, that are able to adapt to distribution changes instead of non-adaptive Hoeffding trees as the base classifier for the bagging ensemble method. We use the Hoeffding Adaptive Trees proposed in [5], where a new method for managing alternate trees is proposed. The general idea is simple: we place ADWIN instances at every node that will raise an alert whenever something worth attention happens at the node.

We use the variant of the *Hoeffding Adaptive Tree* algorithm (HAT for short) that uses ADWIN as a change detector. It uses one instance of ADWIN in each node, as a change detector, to monitor the classification error rate at that node.

A significant increase in that rate indicates that the data is changing with respect to the time at which the subtree was created. This was the approach used by Gama *et al.* in [12], using another change detector.

When any instance of ADWIN at a node detects change, we create a new alternate tree without splitting any attribute. Using two ADWIN instances at every node, we monitor the average error of the subtree rooted at this node and the average error of the new alternate subtree. When there is enough evidence (as witnessed by ADWIN) that the new alternate tree is doing better than the original decision subtree, we replace the original decision subtree by the new alternate subtree.

3.2 DDM bagging using trees of different size

We improve bagging using trees of different size, by adding a change detector for each tree in the ensemble to speed up the adaption to the evolving stream.

A *change detector* or *drift detection* method is an algorithm that takes as input a sequence of numbers and emits a signal when the distribution of its input changes. There are many such methods such as the CUSUM Test, the Geometric Moving Average test, etc. Change detection is not an easy task, since a fundamental limitation exists: the design of a change detector is a compromise between detecting true changes and avoiding false alarms. See [14] and [3] for a more detailed survey of change detection methods.

We use two drift detection methods (DDM and EDDM) proposed by Gama *et al.* [11] and Baena-García *et al.* [2]. These methods control the number of errors produced by the learning model during prediction. They compare the statistics of two windows: the first contains all of the data, and the second contains only the data from the beginning until the number of errors increases. Their methods do not store these windows in memory. They keep only statistics and a window of recent errors data.

The drift detection method (DDM) uses the number of errors in a sample of n examples, modelled by a binomial distribution. For each point i in the sequence that is being sampled, the error rate is the probability of misclassifying (p_i), with standard deviation given by $s_i = \sqrt{p_i(1 - p_i)/i}$. They assume (as stated in the PAC learning model [19]) that the error rate of the learning algorithm (p_i) will decrease while the number of examples increases if the distribution of the examples is stationary. A significant increase in the error of the algorithm, suggests that the class distribution is changing and, hence, the actual decision model is supposed to be inappropriate. Thus, they store the values of p_i and s_i when $p_i + s_i$ reaches its minimum value during the process (obtaining p_{min} and s_{min}). It then checks when the following conditions are triggered:

- $p_i + s_i \geq p_{min} + 2 \cdot s_{min}$ for the warning level. Beyond this level, the examples are stored in anticipation of a possible change of context.
- $p_i + s_i \geq p_{min} + 3 \cdot s_{min}$ for the drift level. Beyond this level the concept drift is supposed to be true, the model induced by the learning method is reset and a new model is learnt using the examples stored since the warning level triggered. The values for p_{min} and s_{min} are reset too.

This approach is good at detecting abrupt changes and gradual changes when the gradual change is not very slow, but has difficulties when the change is gradual and slow. In that case, the examples will be stored for a long time, the drift level then takes too long to trigger and the examples in memory can be exceeded.

Baena-García et al. proposed a new method EDDM [2] in order to improve DDM. It is based on the estimated distribution of the distances between classification errors. The window resize procedure is governed by the same heuristics.

4 Comparative Experimental Evaluation

Massive Online Analysis (MOA) [16] is a software environment for implementing algorithms and running experiments for online learning from data streams. The data stream evaluation framework and all algorithms evaluated in this paper were implemented in the Java programming language extending the MOA software. MOA includes a collection of offline and online methods as well as tools for evaluation. In particular, it implements boosting, bagging, and Hoeffding Trees, all with and without Naïve Bayes classifiers at the leaves.

One of the key data structures used in MOA is the description of an example from a data stream. This structure borrows from WEKA, where an example is represented by an array of double precision floating point values. This provides freedom to store all necessary types of value – numeric attribute values can be stored directly, and discrete attribute values and class labels are represented by integer index values that are stored as floating point values in the array. Double precision floating point values require storage space of 64 bits, or 8 bytes. This detail can have implications for memory usage.

We use the new experimental framework for concept drift presented in [6]. Considering data streams as data generated from pure distributions, we can model a concept drift event as a weighted combination of two pure distributions that characterizes the target concepts before and after the drift. This framework defines the probability that every new instance of the stream belongs to the new concept after the drift. It uses the sigmoid function, as an elegant and practical solution.

We see from Figure 2 that the sigmoid function

$$f(t) = 1/(1 + e^{-s(t-t_0)})$$

has a derivative at the point t_0 equal to $f'(t_0) = s/4$. The tangent of angle α is equal to this derivative, $\tan \alpha = s/4$. We observe that $\tan \alpha = 1/W$, and as $s = 4 \tan \alpha$ then $s = 4/W$. So the parameter s in the sigmoid gives the length of W and the angle α . In this sigmoid model we only need to specify two parameters : t_0 the point of change, and W the length of change.

Definition 1. *Given two data streams a , b , we define $c = a \oplus_{t_0}^W b$ as the data stream built joining the two data streams a and b , where t_0 is the point of change, W is the length of change and*

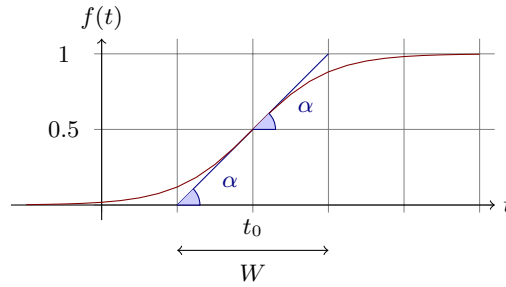


Fig. 2. A sigmoid function $f(t) = 1/(1 + e^{-s(t-t_0)})$.

- $\Pr[c(t) = a(t)] = e^{-4(t-t_0)/W} / (1 + e^{-4(t-t_0)/W})$
- $\Pr[c(t) = b(t)] = 1 / (1 + e^{-4(t-t_0)/W})$.

In order to create a data stream with multiple concept changes, we can build new data streams joining different concept drifts:

$$(((a \oplus_{t_0}^{W_0} b) \oplus_{t_1}^{W_1} c) \oplus_{t_2}^{W_2} d) \dots$$

4.1 Datasets for concept drift

Synthetic data has several advantages – it is easier to reproduce and there is little cost in terms of storage and transmission. For this paper we use the data generators most commonly found in the literature.

SEA Concepts Generator This artificial dataset contains abrupt concept drift, first introduced in [23]. It is generated using three attributes, where only the two first attributes are relevant. All the attributes have values between 0 and 10. The points of the dataset are divided into 4 blocks with different concepts. In each block, the classification is done using $f_1 + f_2 \leq \theta$, where f_1 and f_2 represent the first two attributes and θ is a threshold value. The most frequent values are 9, 8, 7 and 9.5 for the data blocks. In our framework, SEA concepts are defined as follows:

$$(((SEA_9 \oplus_{t_0}^W SEA_8) \oplus_{2t_0}^W SEA_7) \oplus_{3t_0}^W SEA_{9.5})$$

Rotating Hyperplane It was used as testbed for CVFDT versus VFDT in [17]. A hyperplane in d -dimensional space is the set of points x that satisfy

$$\sum_{i=1}^d w_i x_i = w_0 = \sum_{i=1}^d w_i$$

where x_i , is the i th coordinate of x . Examples for which $\sum_{i=1}^d w_i x_i \geq w_0$ are labeled positive, and examples for which $\sum_{i=1}^d w_i x_i < w_0$ are labeled negative. Hyperplanes are useful for simulating time-changing concepts, because

we can change the orientation and position of the hyperplane in a smooth manner by changing the relative size of the weights. We introduce change to this dataset adding drift to each weight attribute $w_i = w_i + d\sigma$, where σ is the probability that the direction of change is reversed and d is the change applied to every example.

Random RBF Generator This generator was devised to offer an alternate complex concept type that is not straightforward to approximate with a decision tree model. The RBF (Radial Basis Function) generator works as follows: A fixed number of random centroids are generated. Each center has a random position, a single standard deviation, class label and weight. New examples are generated by selecting a center at random, taking weights into consideration so that centers with higher weight are more likely to be chosen. A random direction is chosen to offset the attribute values from the central point. The length of the displacement is randomly drawn from a Gaussian distribution with standard deviation determined by the chosen centroid. 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. Only numeric attributes are generated. Drift is introduced by moving the centroids with constant speed. This speed is initialized by a drift parameter.

LED Generator This data source originates from the CART book [7]. An implementation in C was donated to the UCI [1] machine learning repository by David Aha. The goal is to predict the digit displayed on a seven-segment LED display, where each attribute has a 10% chance of being inverted. It has an optimal Bayes classification rate of 74%. The particular configuration of the generator used for experiments (led) produces 24 binary attributes, 17 of which are irrelevant.

Data streams may be considered infinite sequences of (x, y) where x is the feature vector and y the class label. Zhang et al. [24] observe that $p(x, y) = p(x|t) \cdot p(y|x)$ and categorize concept drift in two types:

- *Loose Concept Drifting (LCD)* when concept drift is caused only by the change of the class prior probability $p(y|x)$,
- *Rigorous Concept Drifting (RCD)* when concept drift is caused by the change of the class prior probability $p(y|x)$ and the conditional probability $p(x|t)$

Note that the Random RBF Generator has RCD drift, and the rest of the dataset generators have LCD drift.

4.2 Real-World Data

It is not easy to find large real-world datasets for public benchmarking, especially with substantial concept change. The UCI machine learning repository [1] contains some real-world benchmark data for evaluating machine learning techniques. We consider three of the largest: Forest Covertype, Poker-Hand, and Electricity.

	Hyperplane Drift .0001			Hyperplane Drift .001		
	Time	Acc.	Mem.	Time	Acc.	Mem.
BagADWIN 10 HAT	3025.87	91.36 ± 0.13	9.91	2834.85	91.12 ± 0.15	1.23
DDM Bag10 ASHT W	1321.64	91.60 ± 0.09	0.85	1351.16	91.43 ± 0.07	2.10
EDDM Bag10 ASHT W	1362.31	91.43 ± 0.13	3.15	1371.46	91.17 ± 0.11	2.77
NaiveBayes	86.97	83.40 ± 2.11	0.01	86.87	77.54 ± 2.93	0.01
NBADWIN	308.85	91.30 ± 0.90	0.06	295.19	90.58 ± 0.59	0.06
HT	157.71	86.09 ± 1.60	9.57	159.43	82.99 ± 1.88	10.41
HT DDM	174.10	89.36 ± 0.24	0.04	180.51	89.07 ± 0.26	0.01
HT EDDM	207.47	88.73 ± 0.38	13.23	193.07	87.97 ± 0.51	2.52
HAT	500.81	89.75 ± 0.25	1.72	431.6	89.40 ± 0.30	0.15
BagADWIN 10 HT	1306.22	91.18 ± 0.12	11.40	1308.08	90.86 ± 0.15	5.52
Bag10 HT	1236.92	87.07 ± 1.64	108.75	1253.07	84.13 ± 1.79	114.14
Bag10 ASHT	1060.37	90.85 ± 0.53	2.68	1070.44	90.39 ± 0.33	2.69
Bag10 ASHT W	1055.87	91.38 ± 0.26	2.68	1073.96	91.01 ± 0.18	2.69
Bag10 ASHT R	995.06	91.44 ± 0.09	2.95	1016.48	91.17 ± 0.12	2.14
Bag10 ASHT W+R	996.52	91.62 ± 0.08	2.95	1024.02	91.40 ± 0.10	2.14
Bag5 ASHT W+R	551.53	90.83 ± 0.06	0.08	562.09	90.75 ± 0.06	0.09
OzaBoost	974.69	86.68 ± 1.19	130.00	959.14	84.47 ± 1.49	123.75

Table 1. Comparison of algorithms. Accuracy is measured as the final percentage of examples correctly classified over the 1 or 10 million test/train interleaved evaluation. Time is measured in seconds, and memory in MB. The best individual accuracies are indicated in boldface.

Forest Coverttype Contains the forest cover type for 30 x 30 meter cells obtained from US Forest Service (USFS) Region 2 Resource Information System (RIS) data. It contains 581,012 instances and 54 attributes, and it has been used in several papers on data stream classification [13, 21].

Poker-Hand Consists of 1,000,000 instances and 11 attributes. Each record of the Poker-Hand dataset is an example of a hand consisting of five playing cards drawn from a standard deck of 52. Each card is described using two attributes (suit and rank), for a total of 10 predictive attributes. There is one Class attribute that describes the “Poker Hand”. The order of cards is important, which is why there are 480 possible Royal Flush hands instead of 4.

Electricity Is another widely used dataset described by M. Harries [15] and analysed by Gama [11]. This data was collected from the Australian New South Wales Electricity Market. In this market, the prices are not fixed and are affected by demand and supply of the market. The prices in this market are set every five minutes. The ELEC dataset contains 45,312 instances. Each example of the dataset refers to a period of 30 minutes, i.e. there are 48 instances for each time period of one day. The class label identifies the change of the price related to a moving average of the last 24 hours. The class

	SEA W= 50000			RandomRBF No Drift 50 centers		
	Time	Acc.	Mem.	Time	Acc.	Mem.
BagADWIN 10 HAT	154.91	88.88 \pm 0.05	2.35	5378.75	95.34 \pm 0.06	119.17
DDM Bag10 ASHT W	44.02	88.72 \pm 0.05	0.65	1230.43	93.09 \pm 0.05	3.21
EDDM Bag10 ASHT W	48.95	88.60 \pm 0.05	0.90	1317.58	93.28 \pm 0.03	3.76
NaiveBayes	5.52	84.60 \pm 0.03	0.00	111.12	72.04 \pm 0.02	0.01
NBADWIN	12.40	87.83 \pm 0.07	0.02	396.01	72.04 \pm 0.02	0.08
HT	7.20	85.02 \pm 0.11	0.33	154.67	93.80 \pm 0.10	6.86
HT DDM	7.88	88.17 \pm 0.18	0.16	185.15	93.77 \pm 0.12	13.72
HT EDDM	8.52	87.87 \pm 0.22	0.06	185.89	93.75 \pm 0.14	13.81
HAT	20.96	88.40 \pm 0.07	0.18	794.48	93.80 \pm 0.10	9.28
BagADWIN 10 HT	53.15	88.58 \pm 0.10	0.88	1238.50	95.34 \pm 0.06	67.79
Bag10 HT	30.88	85.38 \pm 0.06	3.36	995.46	95.35 \pm 0.05	71.26
Bag10 ASHT	35.30	88.02 \pm 0.08	0.91	1009.62	80.08 \pm 0.14	3.73
Bag10 ASHT W	35.69	88.27 \pm 0.08	0.91	986.90	92.84 \pm 0.05	3.73
Bag10 ASHT R	33.74	88.38 \pm 0.06	0.84	913.74	90.03 \pm 0.03	2.65
Bag10 ASHT W+R	33.56	88.51 \pm 0.06	0.84	925.65	92.85 \pm 0.05	2.65
Bag5 ASHT W+R	20.00	87.80 \pm 0.06	0.05	536.61	80.82 \pm 0.07	0.06
OzaBoost	39.97	86.64 \pm 0.06	4.00	964.75	94.85 \pm 0.03	206.60

Table 2. Comparison of algorithms. Accuracy is measured as the final percentage of examples correctly classified over the 1 or 10 million test/train interleaved evaluation. Time is measured in seconds, and memory in MB.

level only reflect deviations of the price on a one day average and removes the impact of longer term price trends.

The size of these datasets is small, compared to tens of millions of training examples of synthetic datasets: 45,312 for ELEC dataset, 581,012 for CoverType, and 1,000,000 for Poker-Hand. Another important fact is that we do not know when drift occurs or indeed if there is any drift. We may simulate RCD concept drift, joining the three datasets, merging attributes, and supposing that each dataset corresponds to a different concept.

$$\text{CovPokElec} = (\text{CoverType} \oplus_{581,012}^{5,000} \text{Poker}) \oplus_{1,000,000}^{5,000} \text{ELEC}$$

As all examples need to have the same number of attributes, we simple concatenate all the attributes, and set the number of classes to the maximum number of classes of all the datasets. The attribute values for a type not currently selected is a constant one, for example, zero.

4.3 Results

We use the datasets for evaluation explained in the previous sections. The experiments were performed on a 2.0 GHz Intel Core Duo PC machine with 2 Gigabyte

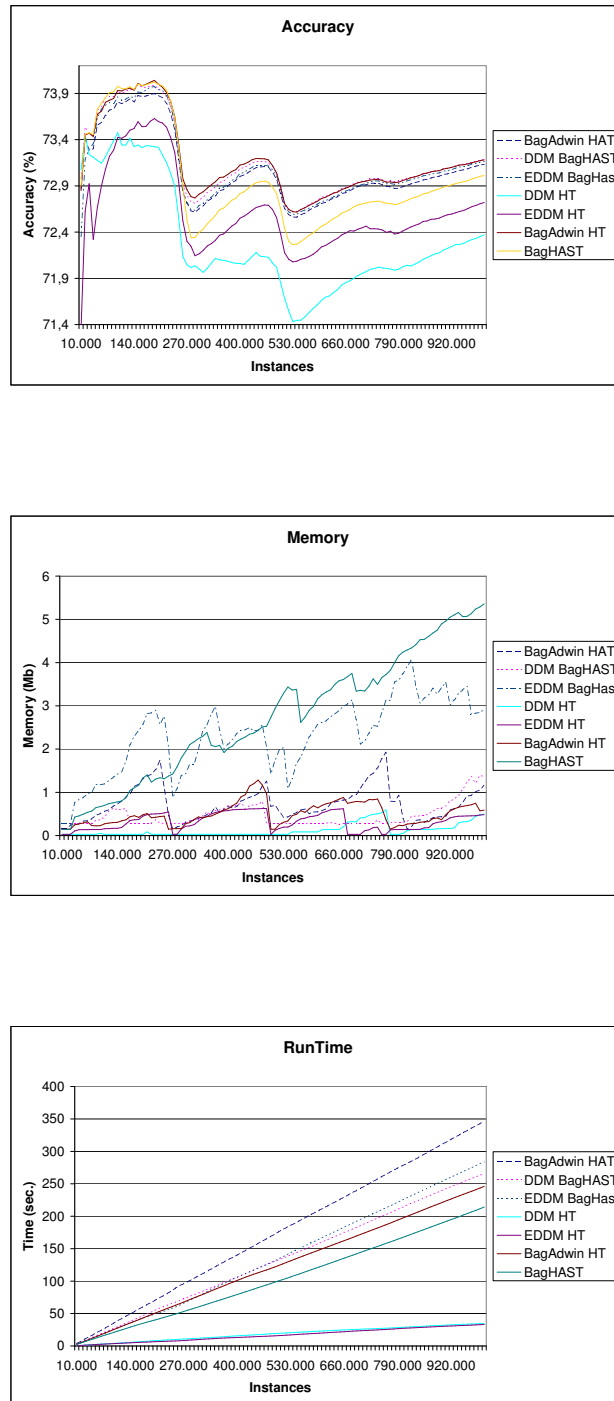


Fig. 3. Accuracy, runtime and memory on dataset LED with three concept drifts.

	RandomRBF Drift .0001 50 centers			RandomRBF Drift .001 50 centers		
	Time	Acc.	Mem.	Time	Acc.	Mem.
BagADWIN 10 HAT	2706.91	85.98 \pm 0.04	0.51	1976.62	67.20 \pm 0.03	0.10
DDM Bag10 ASHT W	1349.65	83.77 \pm 0.15	0.53	1441.22	70.01 \pm 0.31	3.09
EDDM Bag10 ASHT W	1366.65	84.20 \pm 0.46	0.71	1422.31	69.99 \pm 0.35	0.71
NaiveBayes	111.47	53.21 \pm 0.02	0.01	113.37	53.18 \pm 0.02	0.01
NBADWIN	272.58	68.05 \pm 0.02	0.05	249.1	62.19 \pm 0.02	0.04
HT	189.25	63.40 \pm 0.10	9.86	186.47	55.40 \pm 0.02	8.90
HT DDM	199.95	76.40 \pm 0.08	0.02	206.41	62.40 \pm 1.91	0.03
HT EDDM	214.55	76.39 \pm 0.57	0.09	203.41	63.23 \pm 0.71	0.02
HAT	413.53	79.12 \pm 0.08	0.09	294.94	65.32 \pm 0.03	0.01
BagADWIN 10 HT	1326.12	85.28 \pm 0.03	0.26	1354.03	67.20 \pm 0.03	0.03
Bag10 HT	1362.66	71.01 \pm 0.06	106.20	1240.89	58.17 \pm 0.03	88.52
Bag10 ASHT	1124.40	74.76 \pm 0.04	3.05	1133.51	66.25 \pm 0.02	3.10
Bag10 ASHT W	1104.03	75.55 \pm 0.05	3.05	1106.26	66.81 \pm 0.02	3.10
Bag10 ASHT R	1069.76	83.48 \pm 0.03	3.74	1085.99	67.78 \pm 0.02	2.35
Bag10 ASHT W+R	1068.59	84.20 \pm 0.03	3.74	1101.10	69.14 \pm 0.02	2.35
Bag5 ASHT W+R	557.20	79.45 \pm 0.06	0.09	587.46	67.53 \pm 0.02	0.10
OzaBoost	1312.00	71.64 \pm 0.07	105.94	1266.75	58.21 \pm 0.05	88.36

Table 3. Comparison of algorithms. Accuracy is measured as the final percentage of examples correctly classified over the 1 or 10 million test/train interleaved evaluation. Time is measured in seconds, and memory in MB.

main memory, running Ubuntu 8.10. The evaluation methodology used was Interleaved Test-Then-Train on 10 runs: every example was used for testing the model before using it to train. This interleaved test followed by train procedure was carried out on 10 million examples from the hyperplane and RandomRBF datasets, and one million examples from the SEA dataset. Tables 1, 2 and 3 reports the final accuracy, and speed of the classification models induced on synthetic data. Table 4 shows the results for real datasets: Forest CoverType, Poker Hand, and CovPokElec. The results for the Electricity dataset were structurally similar to those for the Forest CoverType dataset and therefore not reported. Additionally, the learning curves and model growth curves for LED dataset are plotted (Figure 3).

The first, and baseline, algorithm (HT) is a single Hoeffding tree, enhanced with adaptive Naive Bayes leaf predictions. Parameter settings are $n_{min} = 1000$, $\delta = 10^{-8}$ and $\tau = 0.05$, as used in [10]. The HT DDM and HT EDDM are Hoeffding Trees with drift detection methods as explained in Section 3.2.

Bag10 is Oza and Russell online bagging using ten classifiers and Bag5 only five. BagADWIN is the online bagging version using ADWIN explained in Section 2.2. As described earlier, we implemented the following new variants of bagging:

- ADWIN Bagging using Hoeffding Adaptive Trees.

	Cover Type			Poker			CovPokElec		
	Time	Acc.	Mem.	Time	Acc.	Mem.	Time	Acc.	Mem.
BagADWIN 10 HAT	317.75	85.48	0.2	267.41	88.63	13.74	1403.40	87.16	0.62
DDM Bag10 ASHT W	249.92	88.39	6.09	128.17	75.85	1.51	876.18	84.54	19.74
EDDM Bag10 ASHT W	207.10	86.72	0.37	141.96	85.93	12.84	828.63	84.98	48.54
NaiveBayes	31.66	60.52	0.05	13.58	50.01	0.02	91.50	23.52	0.08
NBADWIN	127.34	72.53	5.61	64.52	50.12	1.97	667.52	53.32	14.51
HT	31.52	77.77	1.31	18.98	72.14	1.15	95.22	74.00	7.42
HT DDM	40.26	84.35	0.33	21.58	61.65	0.21	114.72	71.26	0.42
HT EDDM	34.49	86.02	0.02	22.86	72.20	2.30	114.57	76.66	11.15
HAT	55.00	81.43	0.01	31.68	72.14	1.24	188.65	75.75	0.01
BagADWIN 10 HT	247.50	84.71	0.23	165.01	84.84	8.79	911.57	85.95	0.41
Bag10 HT	138.41	83.62	16.80	121.03	87.36	12.29	624.27	81.62	82.75
Bag10 ASHT	213.75	83.34	5.23	124.76	86.80	7.19	638.37	78.87	29.30
Bag10 ASHT W	212.17	85.37	5.23	123.72	87.13	7.19	636.42	80.51	29.30
Bag10 ASHT R	229.06	84.20	4.09	122.92	86.21	6.47	776.61	80.01	29.94
Bag10 ASHT W+R	198.04	86.43	4.09	123.25	86.76	6.47	757.00	81.05	29.94
Bag5 ASHT W+R	116.83	83.79	0.23	57.09	75.87	0.44	363.09	77.65	0.95
OzaBoost	170.73	85.05	21.22	151.03	87.85	14.50	779.99	84.69	105.63

Table 4. Comparison of algorithms on real data sets. Time is measured in seconds, and memory in MB. The results are based on a single run. Unlike synthetic datasets, it is not straightforward to add randomization to real datasets such that meaningful datasets and analysis of performance variances are obtained.

- Bagging ASHT using the DDM drift detection method
- Bagging ASHT using the EDDM drift detection method

In general terms, we observe that ensemble methods perform better than single classifier methods, and that explicit drift detection is better. However, these improvements come at a cost of runtime and memory. In fact, the results indicate that memory is not as big an issue as the runtime accuracy tradeoff. We observe that the variance in accuracy goes up when the drift increases, and vice versa. All classifiers have a small accuracy variance for the dataset RandomRBF with no drift, as shown in Table 2.

RCD drift produces much greater differences than LCD - for example, the best result in Table 3 goes down 16% when increasing the drift from 0.0001 to 0.001 - in Hyperplane the same change in drift elicits only a fractional change in accuracy. For RCD drift all methods drop significantly. The bagging methods have the most to lose and go down between 14-17% (top three) and 10-18% (bottom of table). The base methods have less to lose going down (0-14%).

For all datasets one of the new methods always wins in terms of accuracy. Specifically, on the nine analysed datasets: BagADWIN 10 HAT wins four times out of nine, DDM Bag10 ASHT W wins three times, DDM Bag10 ASHT W wins once; this relationship is consistent in the following way: whenever the single HAT beats Bag10 ASHT W, then BagADWIN 10 HAT beats DDM Bag10 ASHT W, and vice

versa. Note that the bad result for DDM Bag10 ASHT W on the Poker dataset must be due to too many false positive drift predictions that wrongly keep the model too small (this can be verified by observing the memory usage in this case), which is mirrored by the behavior of HT DDM on the Poker dataset.

The new improved ensemble methods presented in this paper are slower than the old ones, with BagADWIN 10 HAT being worst, because it pays twice: through the addition of ADWIN and HAT, the latter being slower than HT by a factor between two and five. Change detection can be time-consuming, the extreme case being Naive Bayes vs. NBAdwin, where Naive Bayes can be up to six times faster. However, change detection helps accuracy, with improvements of up to 20 percentage points (see, for example, CovPokElec).

Non-drift-aware non-adaptive ensembles like Bag10 HT and OzaBoost usually need the most memory, sometimes by a very large margin. Bag10 ASHT W+R needs a lot more memory than Bag5 ASHT W+R, because the last trees in a Bag N ASHT W+R needs as much space as the full Bag N-1 ASHT W+R ensemble.

Recall that data stream evaluation is fundamentally three-dimensional. When adding adaptability to evolving data streams using change detector methods, we increase the run-time, obtaining more accurate methods. For example, adding a change detector DDM to HT, or to Bag10 ASHT W, in Table 1, we observe a higher cost in runtime, but also an improvement in accuracy.

5 Conclusions and Future Work

We have presented two new improvements for bagging methods, using Hoeffding Adaptive Trees and change detection methods. In general terms, we observe that using explicit drift detection methods we improve accuracy. However, these improvements come at a cost of runtime and memory. It seems that the cost of improving accuracy in bagging methods for data streams, is large in runtime, but small in memory.

As future work, we would like to build new ensemble methods that perform with an accuracy similar to the methods presented in this paper, but using less runtime. These new methods could be a boosting ensemble method, or a bagging method using new change detection strategies. We think that a boosting method could improve bagging performance by increasing tree diversity, as it is shown by the increased performance of boosting for the traditional batch learning setting. This could be a challenging topic since in [6], the authors didn't find any boosting method in the literature [20, 22, 8] that outperformed bagging in the streaming setting.

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