Case Study on Bagging Stable Classifiers for Data Streams

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Abstract

Ensembles of classifiers are among the strongest classifiers in most data mining applications. Bagging ensembles exploit the instability of base-classifiers by training them on different bootstrap replicates. It has been shown that Bagging instable classifiers, such as decision trees, yield generally good results, whereas bagging stable classifiers, such as k-NN, makes little difference. However, recent work suggests that this cognition applies to the classical batch data mining setting rather than the data stream setting. We present an empirical study that supports this observation.

1. Introduction

Ensembles of classifiers are among the strongest classifiers in most data mining applications. By building multiple different models and combining the predictions of those, predictive accuracy typically improves over building just one model. Some well known ensemble techniques are Bagging [6], Boosting [18] and Stacking [10, 24]. Bagging exploits the instability of classifiers. The base-classifiers are trained on slightly different samples of the training set, yielding diverse models. Common decision tree induction algorithms are known to be *instable*, which makes them appropriate to be used in a bagging ensemble. Classifiers such as Naive Bayes and k-Nearest Neighbour are known to be *stable*, slight changes in the training set do not influence predictions. Breiman already showed that Bagging k-Nearest Neighbour does not yield accuracy improvement, when used in a classical batch data mining setting.

However, it is unknown whether this observation holds in the data stream setting. Data stream mining varies from the batch classification setting in various ways [3, 4, 11, 17, 20]. In the conventional batch setting, a finite amount of stationary data is provided and the goal is to build a model that fits the data as well as possible. When working with data streams, we should expect an infinite amount of data, where observations come in one by one and are being processed in that order. Furthermore, the nature of the data can change over time, known as *concept drift*. Classifiers should be able to detect when a learned model becomes obsolete and update it accordingly. All of these differences are not covered by the original work on Bagging [6].

In [20] some observations were reported that suggest that Bagging stable classifiers in the data stream setting actually does improve accuracy, even though gains are small. In this paper, we study the effect of bagging stable classifiers in the data stream setting. Our contribution is empirical evidence that suggests that bagging stable classifiers does improve predictive performance on data streams. Although the performance gains that can be obtained are small, this result can be seen as a form of meta-knowledge. It adds to the knowledge of how classifiers behave and what classifiers to use on what data. All results are made publicly available in OpenML [19, 22].

2. Related Work

The requirements for processing streams of data are: process one example at a time (and inspect it only once), use a limited amount of time and memory, and be ready to predict at any point in the stream [3, 17]. These requirements inhibit the use of most batch data mining algorithms. However, some algorithms can trivially be used or adapted to be used in a data stream setting, for example, NaiveBayes [15], k Nearest Neighbour (k-NN) [1, 25], and Stochastic Gradient Descent [5]. Also, many algorithms have been created specifically to operate on data streams. Most notably, the Hoeffding Tree [9] is a tree based algorithm that splits the data based on information gain, but uses only a small sample of the data determined by the Hoeffding bound. The Hoeffding bound gives an upper bound on the difference between the mean of a variable estimated after a number of observations and the true mean, with a certain probability [13].

Ensembles of classifiers are among the best performing learning algorithms in the traditional batch setting. Multiple models are produced that all vote for the label of a certain instance. The final prediction is made according to a predefined voting schema, e.g., the class with the most votes wins. In [12] it is proven that the error rate of an ensemble in the limit converges to the Bayes error rate if two conditions are met: first, the individual models must do better than random guessing, and second, the individual models must be diverse, meaning that their errors should not be correlated. For example, Bagging [6] exploits the instability of classifiers by training them on different *bootstrap replicates*: resamplings (with replacement) of the training set. Effectively, the training sets for various classifiers differ by the weights of their training examples. Two variants of Bagging have been designed specifically for the data stream setting. *Online Bagging* [16] draws the weight of each example from a $Poisson(1)$ distribution, which converges to the behavior of the classical Bagging algorithm if the number of examples is large. *Leveraging Bagging* draws the weights of each example from a $Poisson(\lambda)$ distribution, where λ is a parameter under the user's control (default value 6). Furthermore, the ensemble is equipped with the ADWIN drift detection method [2], making sure that obsolete ensemble members are replaced with new ones. Although Leveraged Bagging differs from classical Bagging techniques, it seems to work very well in practise [4, 20].

3. Experimental Setup

We will compare the predictive accuracy of stable classifiers with their accuracy when used in a bagged ensemble. We selected Naive Bayes and k-NN, as both are known to be stable classifiers [21], and have implementations available in the MOA framework [3]. k-NN seems to behave more stable with a higher value for k. We set $k = 10$, since this seems to be fairly stable. As for the Bagging techniques, we include both Online Bagging and Leveraging Bagging. Online Bagging is the most objective Bagging technique. Leveraging Bagging also includes a change detector, hence performance gains obtained by Leveraged Bagging schemas can be due to the change detector. The differences in accuracy are tested for significance using a Paired T-Test and the Wilcoxon Signed-Ranks Test, both explained in [8]. Note that when comparing multiple classifiers with each other, ideally a test suited for multiple classifiers should be used, e.g., the Nemenyi test. However, in this case we are only interested in the impact of bagging on the performance of these classifiers.

We use all data streams that are available in OpenML [22]. These cover both real world data streams and synthetically generated data streams, as is common in data stream literature [4, 17, 20]. We discuss a few of them in more detail.

SEA Concepts The SEA Concepts Generator generates three numeric attributes from a given distribution, of which only the first two are relevant. The class that needs to be predicted is whether these values exceed a certain threshold. Several SEA Concept generated data streams based on different data distributions can be joined together in order to simulate concept drift.

STAGGER The STAGGER Concepts Generatorgenerates descriptions of geometrical objects. Each instance describes the size, shape and color of such object. A STAGGER concept is a binary classification rule distinguishing between the two classes, e.g., all blue rectangles belong to the positive class.

Rotating Hyperplanes The Rotating Hyperplane Generator [14] generates a high-dimensional hyperplane. Instances represent a point in this high-dimensional space. The task is to predict whether such a point is within the hyperplane. Concept drift can be introduced by rotating and moving the hyperplane.

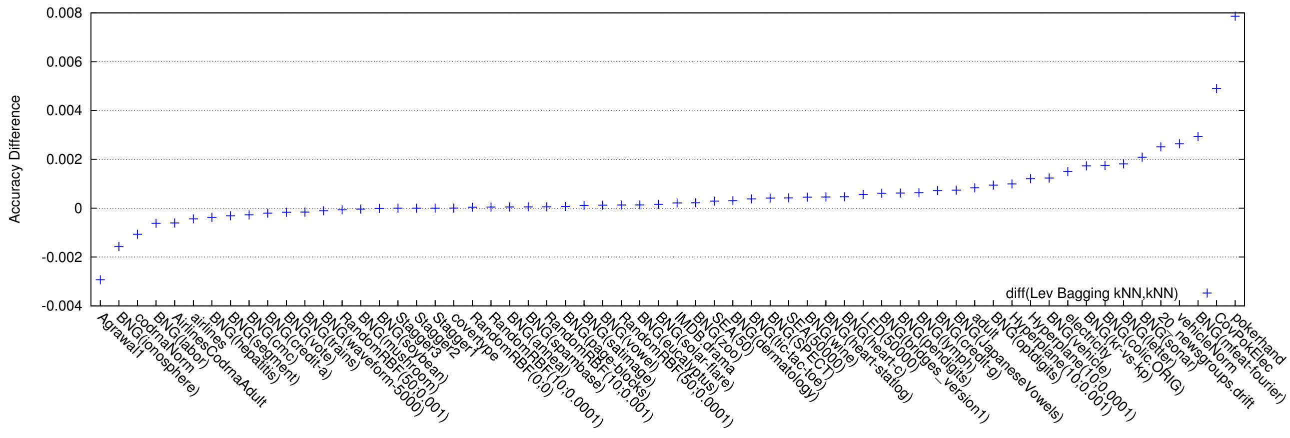
LED The LED Generator [7] generates instances based on a LED display. Attributes represent the various LED lights, and the task is to predict which digit is represented. In order to add noise, attributes can display the wrong value with a certain probability. Furthermore, additional (irrelevant) attributes can be added.

Random RBF The Random RBF Generator generates a number of centroids. Each has a random position in Euclidean space, standard deviation, weight and class label. Each example is defined by its coordinates in Euclidean Space and a class label referring to a centroid close by. Centroids move at a certain speed, generating gradual concept drift.

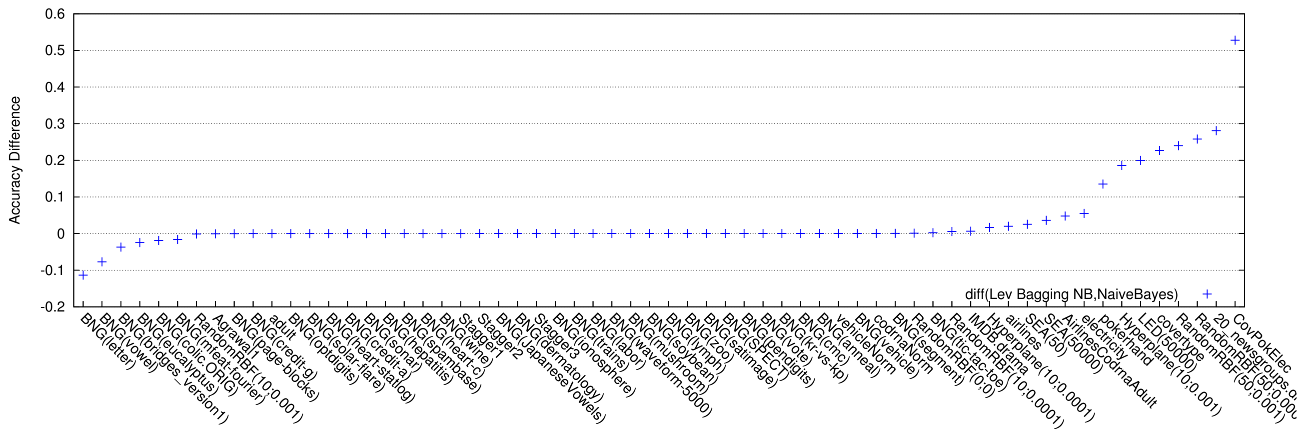
Bayesian Network The Bayesian Network Generator [20] takes a batch data set as input, build a Bayesian Network over it, and generates instances based on the probability tables. As the Bayesian Network does not change over time, it is unlikely that a native form of concept drift occurs in the data stream. The parameter set is the data set that was taken as input.

Composed Data Streams Common batch datasets can be appended to each other, forming one combined dataset covering all observations and attributes, containing small periods or abrupt concept drift. This is commonly done with the Covertype, Pokerhand and Electricity dataset [4, 17]. We applied a similar merge to the Airlines, CodeRNA and Adult dataset, forming "AirlinesCodernaAdult". The original datasets are normalized before this operation is applied.

IMDB.drama The IMDB dataset contains $120{,}919$ movie plots. Each movie is represented by a bag of words of the globally $1{,}000$ most occurring words. Originally, it is a multi-label dataset, with binary attributes whether it falls in a given genre. We predict whether it is in the drama genre, which is the most frequently occurring [17].



(a) Leveraged Bagging k-NN Vs. k-NN



(b) Leveraged Bagging Naive Bayes Vs. Naive Bayes

Figure 1. Performance differences between Leveraging Bagging ensemble and single classifiers.

20 **Newsgroups** The original 20 Newsgroup dataset contains $19,300$ newsgroup messages, each represented as a bag of words of the $1,000$ most occurring words. Each instance is part of at least one newsgroup. This data set is commonly converted into 20 binary classification problems, with the task to determine whether an instance belongs to a given newsgroup. We append these data sets to each other, resulting in one large binary-class dataset containing 386,000 records with 19 shifts in concept [17].

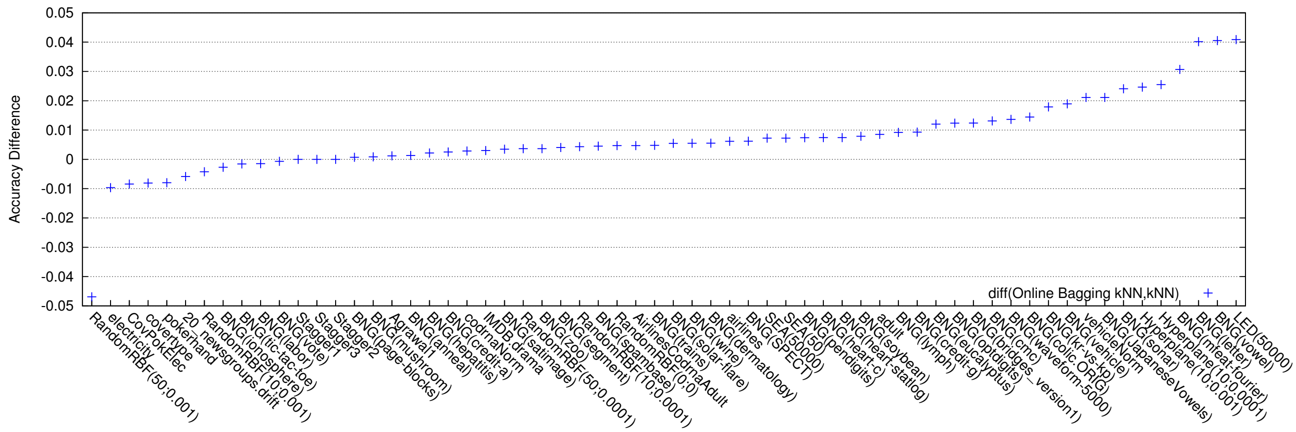
4. Results

Figure 1 and Figure 2 show the result of the experiments. The x-axis shows the dataset, the y-axis shows the difference in performance between the bagging schema and the single classifier. Note that the single classifier performed better on datasets where the difference is below zero, and vice versa for datasets where the difference is above zero. Datasets are ordered by this difference. For full reference, Table 3 contains all results.

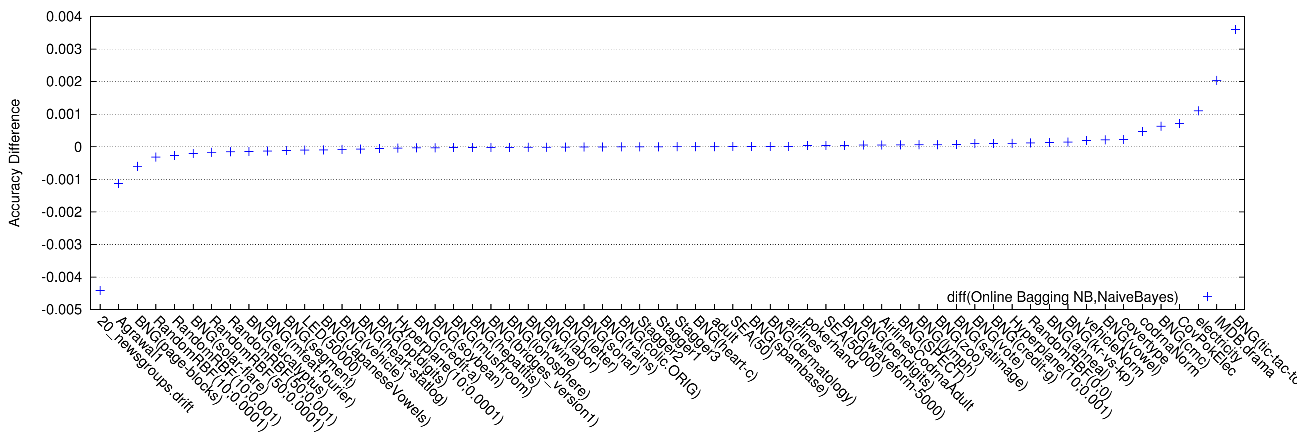
Figure 1(a) shows a similar trend as seen in the figure presented in [20]. There are few data streams on which k-NN performs best, but many data streams on which Leveraging Bagging k-NN performs best. A similar trend can be seen in the other figures.

One notable observation is the difference in scale between on one hand Figure 1(b) describing the effect of using Naive Bayes in a Leveraging Bagging schema and the other figures. In most cases, the effect of a Bagging schema can attribute to performance gains of few percentages. However in the case of Leveraged Bagging Naive Bayes, the performance gain can lead up to 50% (CovPokElec), but also other data sets show eminent improvements.

Among the 15 data streams on which Leveraged Bagging improves upon Naive Bayes the most, many presumably contain concept drift (see Section 3). Compared to



(a) Online Bagging k-NN Vs. k-NN



(b) Online Bagging Naive Bayes Vs. Naive Bayes

Figure 2. Performance differences between Online Bagging ensemble and single classifiers.

k-NN, its performance is quite poor on these data streams (see Table 3). Apparently, k-NN's natural protection against concept drift (it removes old instances as new ones come in) makes it perform quite well. When using Naive Bayes in a Leveraging Bagging schema, the change detector ensures that Naive Bayes also obtains this performance increase.

Figure 2(b) shows what we would expect to see when applying Bagging to a stable classifier. The differences in accuracy are small and the performance gains are equally divided between the single classifier and the bagging schema.

Table 1 shows which of the ensemble approaches were significantly better than the single classifiers according to the Wilcoxon Signed-Ranks Test [8, 23]. For example, we can see from this that Leveraging Bagging Naive Bayes is significantly better than using Naive Bayes as single classifier. Similarly, both Leveraging Bagging k-NN and Online Bagging k-NN are significantly better than just using k-NN.

In contrast to this, the T-Test found neither of the differences between classifiers statistically significant. This can be because the Wilcoxon Signed-Ranks Test bases its conclusion on the signs of a classifier; it only considers whether one schema was better, equal or worse on a given data stream. The T-Test bases its conclusion on actual scores. The fact that the Wilcoxon test found statistical evidence

Table 1. Wilcoxon Signed-Ranks Test results, 95% confidence.

Classifier	Online Bag.	Lev. Bag.
Naive Bayes	no	yes
k-NN	yes	yes

Table 2. T-Test results, 95% confidence.

Classifier	Online Bag.	Lev. Bag.
Naive Bayes	no	no
k-NN	no	no

that bagging actually improves the performance of stable classifiers in the data stream setting, but the T-Test not, leads to the belief that improvements can be obtained, but these are very limited.

5. Conclusions

We have performed a case study to establish empirically whether bagging stable classifiers yield performance gains in the data stream setting. Earlier work suggested that this could very well be the case [20]. However, these suggestions where based on the performance of a Leveraging Bagging schema, and could also be due to the change detector. We have compared the performance of two classifiers that are known to be stable using two bagging schemas. We find that, indeed, performance gains obtained by Leveraging Bagging schemas seem to be consistent, however they can plausibly be attributed to the accompanying change detector. The results obtained by the Online Bagging approach, which doesn't include a change detector, seem more ambiguous. Although its effect on Naive Bayes seems negligible, the difference of using Online Bagging with k-NN was found significantly better by the Wilcoxon Signed Ranks Test than just using k-NN. More research is required to give a decisive answer to the original question.

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Table 3. Accuracy per data stream, as obtained from OpenML [22].

Dataset	k-NN	Online Bag. k-NN	Lev.Bag. k-NN	NB	Online Bag. NB	Lev.Bag. NB
20_newsgroups.drift	0.987	0.981	0.989	0.702	0.698	0.983
adult	0.819	0.828	0.820	0.824	0.824	0.824
Agrawal(1)	0.642	0.643	0.639	0.885	0.884	0.885
airlines	0.672	0.678	0.671	0.646	0.646	0.665
AirlinesCodrnaAdult	0.775	0.780	0.775	0.659	0.659	0.707
BNG(anneal)	0.892	0.893	0.892	0.846	0.846	0.846
BNG(bridges_version1)	0.692	0.704	0.692	0.743	0.743	0.706
BNG(cmc)	0.472	0.485	0.472	0.512	0.512	0.512
BNG(colic.ORIG)	0.715	0.729	0.717	0.814	0.814	0.795
BNG(credit-a)	0.860	0.862	0.860	0.831	0.831	0.831
BNG(credit-g)	0.729	0.738	0.729	0.766	0.766	0.766
BNG(dermatology)	0.964	0.969	0.964	0.986	0.986	0.986
BNG(eucalyptus)	0.483	0.495	0.483	0.514	0.514	0.489
BNG(heart-c)	0.848	0.856	0.849	0.868	0.868	0.868
BNG(heart-statlog)	0.845	0.852	0.845	0.867	0.867	0.867
BNG(hepatitis)	0.887	0.889	0.887	0.877	0.877	0.877
BNG(ionosphere)	0.859	0.856	0.857	0.795	0.795	0.795
BNG(JapaneseVowels)	0.768	0.790	0.769	0.761	0.761	0.761
BNG(kr-vs-kp)	0.859	0.877	0.861	0.851	0.851	0.851
BNG(labor)	0.922	0.921	0.922	0.905	0.905	0.905
BNG(letter)	0.353	0.394	0.355	0.439	0.439	0.326
BNG(lymph)	0.861	0.870	0.862	0.861	0.861	0.861
BNG(mfeat-fourier)	0.691	0.722	0.694	0.832	0.832	0.817
BNG(mushroom)	0.964	0.965	0.964	0.927	0.927	0.927
BNG(optdigits)	0.891	0.903	0.892	0.906	0.906	0.906
BNG(page-blocks)	0.901	0.902	0.901	0.790	0.789	0.790
BNG(pendigits)	0.787	0.795	0.788	0.767	0.767	0.767
BNG(satimage)	0.813	0.817	0.813	0.783	0.783	0.783
BNG(segment)	0.811	0.815	0.811	0.806	0.806	0.807
BNG(solar-flare)	0.746	0.751	0.746	0.768	0.767	0.768
BNG(sonar)	0.745	0.769	0.747	0.755	0.755	0.755
BNG(soybean)	0.822	0.830	0.822	0.902	0.902	0.902
BNG(spambase)	0.626	0.630	0.626	0.665	0.665	0.665
BNG(SPECT)	0.808	0.814	0.808	0.756	0.756	0.756
BNG(tic-tac-toe)	0.748	0.746	0.748	0.717	0.720	0.719
BNG(trains)	0.923	0.928	0.923	0.887	0.887	0.887
BNG(vehicle)	0.566	0.585	0.567	0.483	0.483	0.484
BNG(vote)	0.942	0.941	0.941	0.918	0.918	0.918
BNG(vowel)	0.357	0.397	0.357	0.370	0.370	0.293
BNG(waveform-5000)	0.830	0.844	0.830	0.846	0.846	0.846
BNG(wine)	0.917	0.923	0.918	0.920	0.920	0.920
BNG(zoo)	0.923	0.926	0.923	0.928	0.928	0.928
codrnaNorm	0.894	0.897	0.893	0.745	0.746	0.746
covertype	0.922	0.914	0.922	0.605	0.605	0.832
CovPokElec	0.784	0.776	0.789	0.242	0.243	0.770
electricity	0.784	0.774	0.785	0.734	0.735	0.789
Hyperplane(10;0.0001)	0.833	0.858	0.834	0.913	0.913	0.929
Hyperplane(10;0.001)	0.833	0.858	0.834	0.709	0.709	0.895
IMDB.drama	0.606	0.609	0.606	0.602	0.604	0.609
LED(50000)	0.642	0.683	0.642	0.540	0.540	0.739
pokerhand	0.693	0.686	0.701	0.596	0.596	0.731
RandomRBF(0;0)	0.890	0.895	0.890	0.512	0.512	0.513
RandomRBF(10;0.0001)	0.893	0.897	0.893	0.521	0.521	0.527
RandomRBF(10;0.001)	0.883	0.879	0.883	0.520	0.519	0.518
RandomRBF(50;0.0001)	0.894	0.897	0.894	0.310	0.310	0.568
RandomRBF(50;0.001)	0.840	0.793	0.840	0.291	0.291	0.531
SEA(50)	0.869	0.876	0.869	0.839	0.839	0.864
SEA(50000)	0.864	0.871	0.864	0.839	0.839	0.875
Stagger(1)	1.000	1.000	1.000	1.000	1.000	1.000
Stagger(2)	1.000	1.000	1.000	1.000	1.000	1.000
Stagger(3)	1.000	1.000	1.000	1.000	1.000	1.000
vehicleNorm	0.713	0.734	0.715	0.807	0.807	0.807