A Comparison of Online learning Naïve Bayes Classifier on RSS Feeds using SPARK

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Motivation & Problem Statement

Many practical applications rely on immediate data. The need for solutions to continuously conduct analyses as mathematical computations on large data amounts led to new technologies in the past years. Stream processing operates on real-time data for example through stream windowing and analytical operations within those. Since data distributions might not remain static over time a precomputed (batch) model for analysis

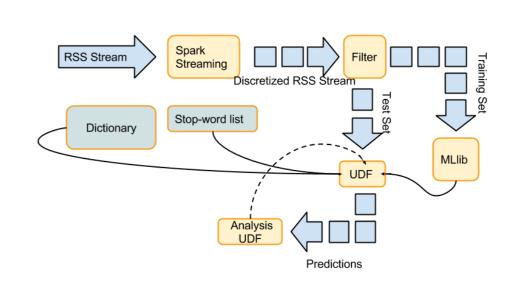
can produce poorly results after some time [1]. The reconstruction or updating of the underlying analytical model to receive accurate results is required. This problem is known as Concept Drift. In this project we are using unstructured streaming data from BBC RSS feeds in order to classify them to their corresponding category. We focus on the evaluation of a Naïve Bayes Classifier with different model-update approaches to compare their analytical performance according to Concept Drift.

Data & Setup

For our evaluation purposes of classifying streamed text data we are using RSS feeds from BCC. A RSS feed is a collection of tags in xml structure which contains tags for title, a description and an url among other tags. Only those listed are used in our application. Our data points are constructed from title and description of the feed, the URL gives us the respective label. Furthermore we are using Apache Spark for parallel execution of streaming and data classification. The machine learning library of Spark, MLlib, provides us with a Naive Bayes Classifier.

Streaming

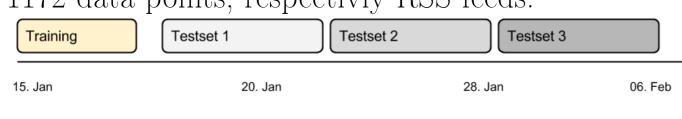
In order to deal with the continuous nature of the data, traditional programming primitives are not of much help. In order to make programmers's job easier, libraries providing higher lever abstractions are introduced. Knowing that, for a news feed classifier we need to split the 'main' stream into multiple streams to treat different portions of stream differently. For example, there needs to be at least two channels of streams branching out from the main one having the test items and training items. The main flow of the streaming logic we used is depicted in the figure. [2]



Methodology

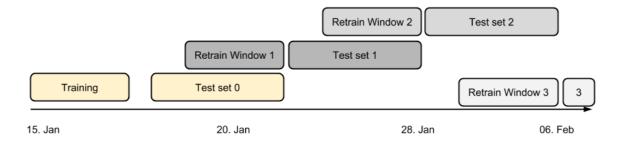
Batch

The batch or offline model implements a classic Traing-Testing-Phase setup. A subset training points are pre-collected from a stream and used to build a final model on which three testsets are applied. The batch model functions as a reference model to observe the performance of the initial training over time. For training 600 data points were taken collected in the first three days. The following four days with 1248 data points created the first test set for this model. A second and a third test set where created after the previous testphase and contained 1102 and 1172 data points, respectivly RSS feeds.



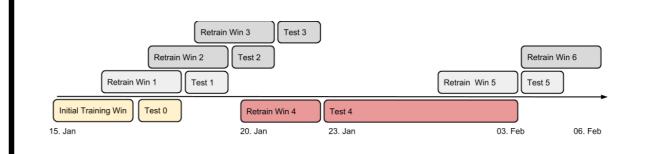
Bruteforce

On the other hand On-line Learning will change the model with the arriving of new data points. The bruteforce approach updates the model after a period of time through retraining. Based on a sliding window over the stream with a constant number of data points the model is rebuilt. The window size for the bruteforce model contains as well 600 data points. After 1000 test points we retrained it with the last 600 data points arrived. We then waited for 1000 data points and second retrain phase with the same window size followed which was tested also with 1000 new data points.



Threshold-triggered

As a variation of the bruteforce model-update the threshold triggered one will rebuild the model on a sliding window as soon as the accuracy of our model is beneth a certain threshold. The window size of the error-triggered model is constructed like the other szenarios out of 600 datapoints. Due to our observations an diserable accurency threshold of 63% seamed reasonable. A sanity window of testpoints ensures that at least 300 new data points arrive and based on their performance the model is rebuild.

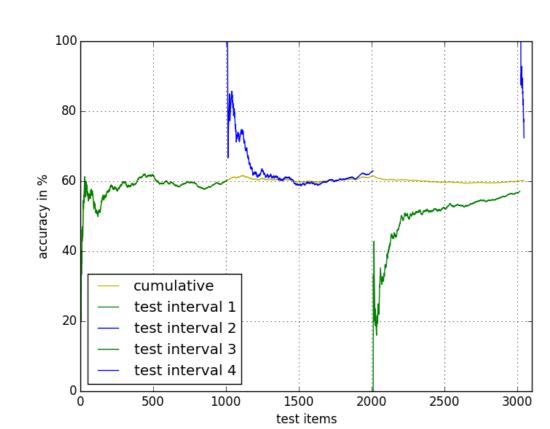


Incremental

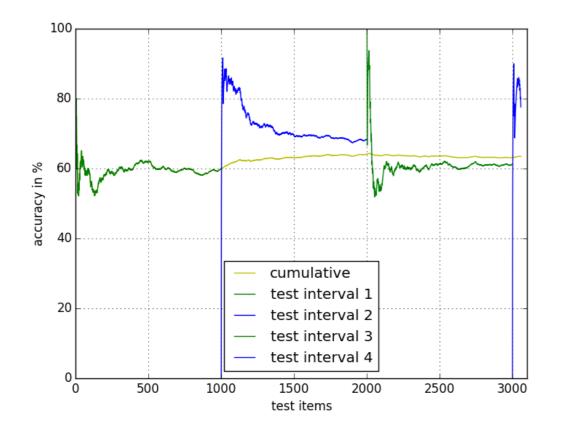
In the incremental model, unlike the other update models, following an initial training-only phase, all the incoming stream items are always used for training right after the prediction. So, this way the immidiate information whether the prediction was good or bad can be used for improving the model on the fly. In other words, predictive model building and testin phases perfectly overlap in incremental model update method. We used this to achieve a real-time response to the changes in the data arguably making the text mining application more resillant to the conceptual drifts. The initial traing size of 600 is used for this model update method as well.

Results

To evaluate the performance of our classification approaches we used the cumulative accuracy per interval and the cumulative accuracy over all points which. The batch/ offline method performs similar the first two test phase with but seams decreasing in the last interval.

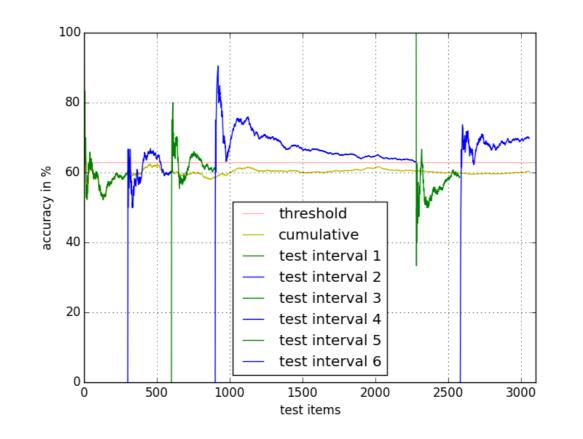


In the second scenario we applied the bruteforce model which rebuilt the model in the beginning of every interval.

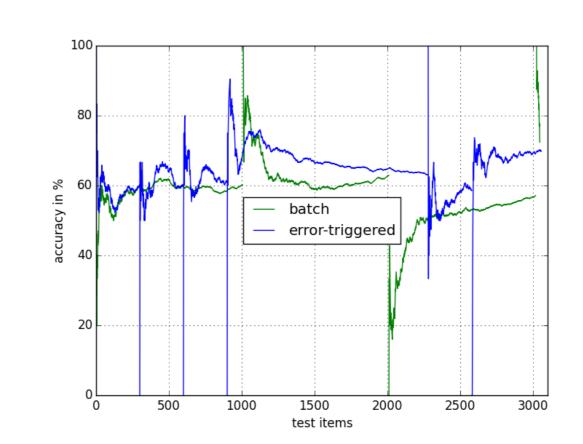


In comparison with the batch version the bruteforce model gets higher accuracies in the intervals.

For the error-triggered model we set a threshold at 63% of accuracy at which the model is recreated. After each model recreation, a sanity interval of 300 items takes place. In our experiments, we saw that the accuracy did not go below for a long time delaying the retraining period. Then two more retraining phases follow.

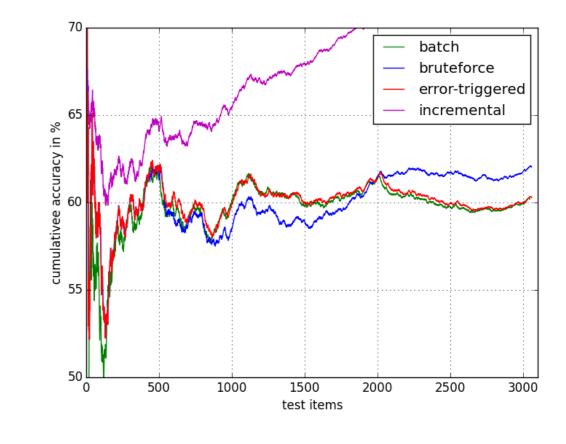


In comparison to the batch update model, errortriggered has higher interval accuracy but due to the short retraining intervals, their accuracy results are similar on average.



Bruteforce and error-triggered methods have both higher interval accuracies in the test phases around the data points of 1000 and 2000. This might be caused by concept drift.

The incremental one clearly outperformed all the other model-update methods although the learning rate was mostly between 0.02 and 0 except for three peak times when it is around 0.6.



Literatur

[1] CÉSAR A. ASTUDILLO AND JAVIER I. GONZALEZ Concept Drift Detection Using Online Bayesian Classifier, Proceedings of the XXXII International Conference of The Chilean Computer Science Society, 2013.

[2] ZAHARIA, MATEI AND DAS, TATHAGATA AND LI, HAOYUAN AND SHENKER, SCOTT AND STOICA, ION, Discretized Streams: An Efficient and Fault-tolerant Model for Stream Processing on Large Clusters, Proceedings of the 4th USENIX Conference on Hot Topics in Cloud Ccomputing, 2012.