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

Authors:
Ahmet Anil Pala & Franziska Adler

TU Berlin
Advanced Information Management III
Scalable Data Analytics and Data Mining

Motivation & Problem Statement

Many practical applications rely on immidiate data. The need for solutions to continously conduct analyses as mathmatical 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 analitical 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. 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 coresponding category. We focuss 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 classifing streamed textdata 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. Those listed are used in our applicaton. Our data points are constructed from title and description of the feed, the url gives us the respective label. Furthermore we are using SPARK for parallel execution of streaming and data classification. The available library for Machine Learning Algorithms MLlib provides us with a Naive Bayes Classifier.

Streaming

In order to deal with the contonious 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 below.

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

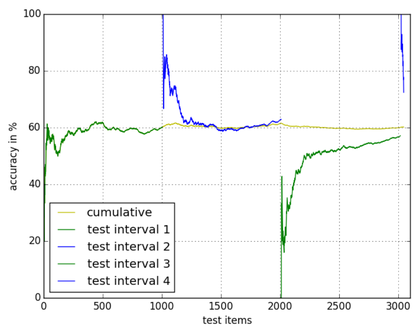
As a variation of the bruteforce model-update the threshold triggered one will rebuild the model on a sliding window as soon as the accuracy of our model is beneth a certain threshold. The window size of the error-triggered model is constructed like the other szenarios out of 600 datapoints. Due to our 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

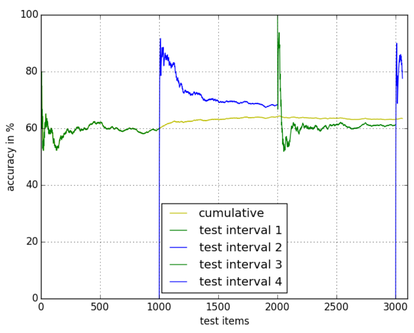
In the incremental model, unlike the other update models, following an initial training-only phase, all the incoming stream items are always used for training right after the prediction. So, this way the immidiate information whether the prediction was good or bad can be used for improving the model 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.

Results

To evaluate the performance of our classification approaches we used the cumulative accurency per interval and the cumulative accurancy over all points which are at this time not in the training set. The batch/ offline szenario performs similar the first two test phase with but seams decreasing in the last interval.

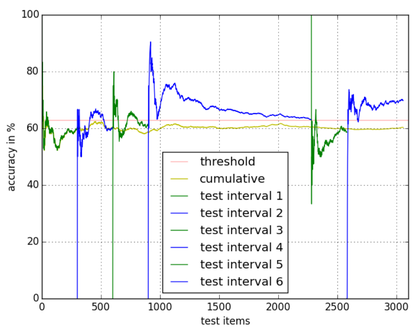


In the second szenario we applied the bruteforce model which rebuilt the model in the beginning of every interval.

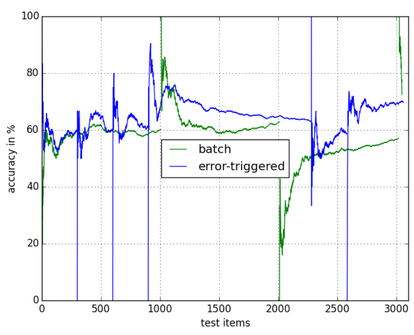


In comparison with the batch version the bruteforce model gets higher accuracies in the intervals.

For the error-triggered model we set a threshold at 63% of accuracy at which the model is recreated. Since we included a sanity point set the rebuilt takes place three times after the 300 sanity points and stays then constant for 1380 points after which two retraining phases follow.

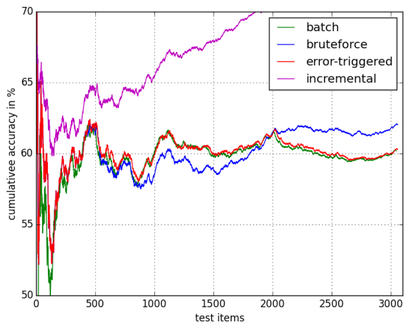


In comparison batch and error-triggered the error-triggered has higher interval accuracy but due to the short retraining intervals avaraged they are similar.



Despite bruteforce and error-triggered methods have both higher interval accuracies around the phase of testpoints 1000 to 2000 which might be caused by concept drift.

The incremental one



Literatur

[1] M. Hallo & L. Dadf,*Depressing literature title*, page 33, NoPressQL, 1883.

[2] K. Sullivan, *Monotonously down draggin words*, page 1, Academic Press, 2001.