Yahoo SAMOA Lab2 --Test Performance of Non-parallel Naive Bayes Classifier

Li Huang

Computer Engineering and Computer Science

J.B. Speed School of Engineering

University of Louisville

l0huan08@gmail.com

2014.4.3

Abstract:

A Naive Bayes Classifier was implemented under Yahoo SAMOA platform. It is a non-parallel algorithm. This lab test the performance, including speed and correct rate, of this algorithm under different cluster setting: (1)single machine (2) two machine-cluster (3) three machine-cluster. The source data are from Kdd99[1] and Movie Review[2]. Vertical Hoeffding Decision Tree and another version of Naive Bayes classifier are also tested and compared.

[1] Kdd99 data: https://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html

[2] Movie Review data: https://www.cs.cornell.edu/people/pabo/movie-review-data/

Contents

1.Purpose: 3

2.Test environment: 3

3.Test settings 4

3.1 Algorithm 4

3.1.1 Introduction of Naive Bayes Classifier 4

3.1.2 Algorithms used in test 5

3.2 Test Data 9

3.3 Cluster modes 13

4. Test Result 13

4.1 Final result 14

5 Conclusion 17

Appendix 18

1. Detail of Test Result 18

1.1 Result file 18

1.2 log file 19

1.3 Raw Test Result 20

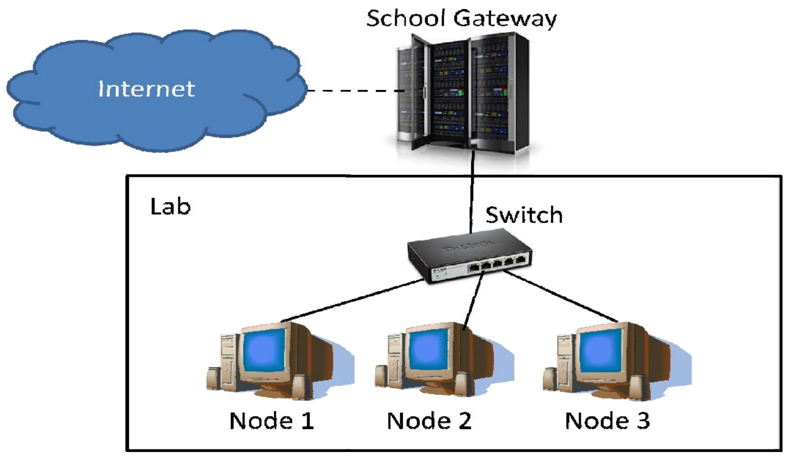
1.4 Average value of Test Result 24

1.Purpose:

To learn how to implement user-defined data mining algorithm under SAMOA platform, I tried to implement a Naive Bayes Classifier. The first version of my algorithm is tried to be as simple as possible, so it is non-parallel version. To test the characteristic and possibility of SAMOA, I test this algorithm on different cluster settings: Single-machine, Two-machine cluster, Three-machine cluster, to see if it is possible to get better performance when the cluster becomes larger(with more computing nodes). I also compared this algorithm with VHDT(Vertical Hoeffding Decision Tree) which has been integrated into SAMOA, as well as another version of my Naive Bayes classifier.

2.Test environment:

The test is running on a cluster composed by three computers. They are connected by a switch. The hardware and software configuration are shown below:



Hardware	Software
node1: Pentium4 1.8Ghz, 576 MB RAM node2: Pentium4 1.8Ghz, 768 MB RAM node3: Pentium4 2.35Ghz, 495 MB RAM	Ubuntu Linux Desktop ver12.04 32-bit Yahoo S4 ver0.6 Yahoo SAMOA ver0.0.1

3.Test settings

3 different test data are applied to the implemented Naive Bayes algorithm, the performances (speed and correct rate) are collected under 4 different cluster configuration.

3.1 Algorithm

3.1.1 Introduction of Naive Bayes Classifier

Consider the test data instance, X=(x1,x2,..xi,..xM), has M attributes a1,a2,a3,a4,a5,a6,a7,….ai,…aM. It may belong to K class C1,C2,…,Ck,…CK.

To decide which class it belongs, we need to calculate the probability that X belongs to class k, P(Ck|X), and find the maximum one.

(1) Bayes formula

Pk = P(Ck| X) = P(X|Ck)*P(Ck)/P(X) ……………………..(1)

Comparing Pj and Pk:

Pj / Pk = [P(X|Cj)*P(Cj)] / [P(X|Ck)*P(Ck)] …………………..(2)

(2) Independent assumption

Naive Bayes assumes all the attributes a1,a2,…,aM are independent, that
P(X|Ck)=P(x1,x2,x3,…,xM|Ck)=P(x1|Ck)*P(x2|Ck)*….*P(xi|Ck)*…P(xM|Ck) ………….(3)

Pj / Pk = [P(x1|Cj)*P(x2|Cj)*…P(xM|Cj)] / [P(x1|Ck)*P(x2|Ck)*…P(xM|Ck)] * P(Cj)/P(Ck) …………(4)

(3) Probability estimation

We can estimate by counting the training data:

P(Cj) = n(Cj) / N. …………….(5)

P(xi |Ck) = n(xi,Ck)/n(Ck). ……………(6)

where

n(Cj): number of instances in training data that belongs to class Cj.

N: totally number of training instances.

n(xi,Ck): number of instances has value xi in attribute i, and belongs to class Ck.

Smoothing:

In practice, P(xi |Ck) = n(xi,Ck)/n(Ck) is too harsh and maybe can be divided by 0. So "smoothing" is applied:

P(xi |Ck) = (n(xi,Ck)+l) / (n(Ck)+l*J), …………(7)

that l and J are user-defined constants, usually l=1 and J=|ai|=number of distinct values of attribute i.

Deal with real attribute values:

However, counting n(xi,Ck) only works for nominal attribute and enumerate and small integer attribute. If attribute i are real values, we cannot count n(xi,Ck). So in this situation we must use other method to estimate P(xi|Ck). One way is assuming the values in attribute i among the instances belong to class Ck are in a specific distribution, that P(xi|Ck) can be calculate directly as same as the probability density f(xi) among the training data belongs to class Ck.

(4) Class labeling

After calculating every Pj while j=1,2,…K, we can find the max one, Pk, then we can output the class label of the test instance X is Ck.

3.1.2 Algorithms used in test

Three algorithms are applied and compared in this test.

(1) Naive Bayes Classifier - my version 4 (NB-4)

Several different versions of Naive Bayes algorithm were designed, and each version use different strategy and parallel topology. The "NB-4" is the 4^{th} version of Naive Bayes algorithm I designed.

NB-4 is a non-parallel Naive Bayes Classifier implemented by myself. It useS a single "ModelProcessor" to train the model and apply the model to calculate classification result. The core data structure is the statistic information for each attribute of training data:

A "matrix" to record n(xi, Ck) and a vector to record n(Ck).

Advantage: Fast and simple data structure

Disadvantage: Unfortunately, this algorithm can only handle data with nominal attributes, or enumerate(small integer) attributes. When the attribute are continuous real values or large integers, this algorithm will crash and cause error. So latter I designed NB-5 algorithm.

(2) Naive Bayes Classifier - my version 5 (NB-5)

This algorithm is designed to handle real values and large integer attributes in input data, which is a problem in "NB- 4". The code is totally different from NB-4, that NB-5 is copy and modified from the source code of Naive Bayes Classifier in MOA(Massive Online Analysis)[3]. This algorithm consider the values in a specific numeric attribute(integer or real) within a specific class as Gauss(Normal) distribution, that it can calculate:

P(xi| Ck) = probability density(x) in values belongs to class Ck = f(x|Ck)

$$= f(x,\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} . \qquad \text{......................(8)}$$

The parameter μ in this definition is the mean or expectation of the distribution (and also its median and mode). The parameter σ is its standard deviation;

When encounter new instance, this algorithm update the μ [i,k] and σ [i,k], which is corresponding to the distribution of attribute i's values within class k.

Advantages:

Simple; Able to process both numeric attributes and nominal attributes.

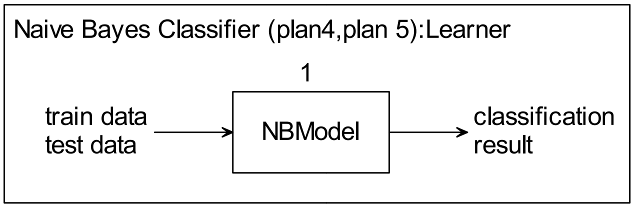
Disadvantages:

Not designed for parallel computing.

---

[3] MOA: http://moa.cms.waikato.ac.nz/

The streaming processing topology (in SAMOA terminology) of NB-4 and NB-5 are shown below:



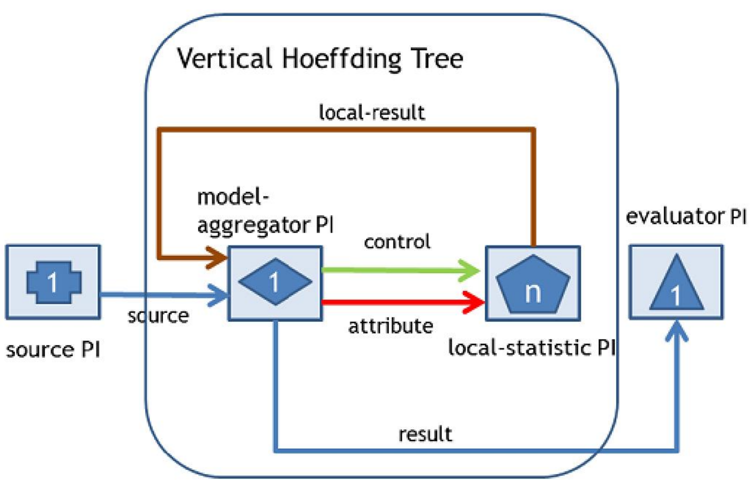
(3) Vertical Hoeffding Decision Tree (VHT)

This algorithm is the default classifier which has been implemented by SAMOA. It is a parallel algorithm that its speed can scale-up when the number of computing nodes increases.

VHDT is tested as a baseline to compare with my own Naive Bayes classifier. This algorithm is a parallel algorithm that would speed up with more computing nodes.

The relevant document could be access at
https://github.com/yahoo/samoa/wiki/Vertical%20Hoeffding%20Tree%20Classifier

The topology diagram is shown below:

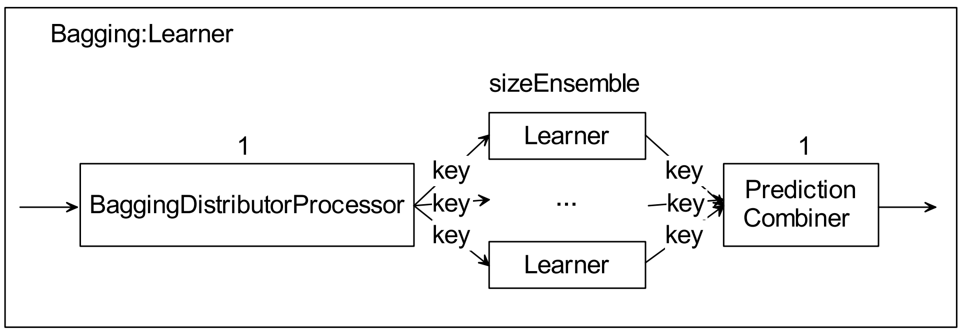


(4) Bagging

Bagging[4] is a ``bootstrap''[5] ensemble method that creates individuals for its ensemble by training each classifier on a random redistribution of the training set. The relevant introduction of Bagging algorithm could be found at http://people.cs.pitt.edu/~milos/courses/cs2750-Spring04/lectures/class23.pdf and http://www.cs.cmu.edu/afs/cs/project/jair/pub/volume11/opitz99a-html/node3.html .

Yahoo SAMOA has already contained a default Bagging algorithm (so called OzaBag, see http://moa.cms.waikato.ac.nz/details/classification/classifiers-2/)

The topology of Bagging algorithm in SAMOA is below:



In this lab, I tested Bagging algorithm with 3 different "Learner" as mentioned before: NB-4, NB-5, VHDT.

Prequential Evaluation Task

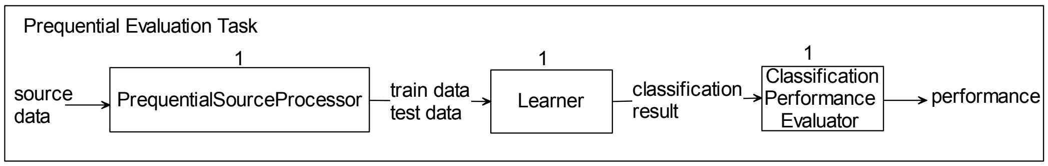
All the algorithms mentioned above were integrated in the "Prequential Evaluation Task" of SAMOA. This task is a basic framework of classify online data with user-defined classifiers. The task reads online data and send each instance to the learner(classifier) for training, and also classify this instance with this classifier; finally the classification results are output to a performance evaluator, and the classification performance (such as correct rate, F-measure, etc…) are showed.

---

[4] Breiman, L. 1996a. Bagging predictors . Machine Learning, 24(2), 123-140.

[5] Efron, B. Tibshirani, R. 1993. An Introduction to the Bootstrap. Chapman and Hall, New York.

The document can be found at https://github.com/yahoo/samoa/wiki/Prequential%20Evaluation%20Task , and its topology is:



In conclusion, the algorithms selected to compare are:

(1) Naive Bayes- my version 4 (NB-4)
(2) Niave Bayes- my version 5 (NB-5)
(3) Vertical Hoeffding Decision Tree (VHT)
(4) Bagging NB-4 (BagNB4)
(5) Bagging NB-5 (BagNB5)
(6) Bagging VHT (BagVHT)

3.2 Test Data

(1) Movie Review data

Movie Review Data are collections of movie-review documents labeled with respect to their overall sentiment polarity (positive or negative) and sentences labeled with respect to their subjectivity status (subjective or objective) or polarity. Basically, a movie review dataset contains many instances, and each instance is a movie review and a class label, "good movie" or "bad movie", of this review.

In this lab, I only use the preprocessed data from "polarity dataset 2.0", which contains 1000 positive and 1000 negative processed reviews. The preprocessed data is created by my classmate, Wen Long Sun. Moreover, I shuffled the order of instances that the "pos" and "neg" instances occur alternately. This data contains 2000 instances; each instance has about 1000 attributes and 1 class label, like below:

Movie Review													
Attribute	&	*	-	1	10	2	…	acc	adam	…	unit	visit	@@class@@
line 1	1	0	0	0	1	0	…	0	0	…	1	1	pos
line 2	0	0	1	0	0	0	…	1	0	…	0	1	neg

line 3	0	1	0	0	0	1	…	0	0	…	0	0	pos
…	…	…											

Each instance stands for a review document, and each attribute is the occurrence of a word in this document. For example, if the word “adam” occurs in this document, then the value of attribute “adam” should set to 1, otherwise set to 0. The last attribute “@@class@@” shows the sentiment polarity of each review document.

Size:

2000(instances) x 1172(attributes)

1000 instances are “pos”, and 1000 are “neg”.

(2) Kdd99 data

Kdd99 data can be found at https://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html.

Kdd99 data is created to build a predictive model (i.e. a classifier) capable of distinguishing between ``bad'' connections, called intrusions or attacks, and ``good'' normal connections.

The data contains about 5 Million instances, each with 41 attributes and 1 class label. Each instance is a connection record, including features such as “length (number of seconds) of the connection”, “type of the protocol”, “normal or error status of the connection”, etc. The class label is “normal” connection or 22 types of attacks, such as “buffer_overflow”, “guess_passwd”, etc.

The 22 types of attacks fall into four main categories:

- DOS: denial-of-service, e.g. syn flood;
- R2L: unauthorized access from a remote machine, e.g. guessing password;
- U2R: unauthorized access to local superuser (root) privileges, e.g., various ``buffer overflow'' attacks;
- probing: surveillance and other probing, e.g., port scanning.

The data is like:

Kdd99

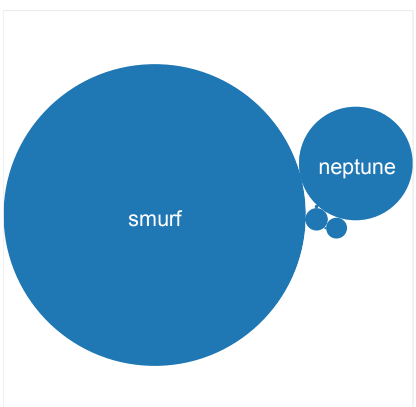
Attribute	duration	protocol_type	service	flag	src_bytes	dst_bytes	···	dst_host_srv_rerror_rate	class
line 1	0	tcp	http	SF	215	45076	···	0	normal
line 2	0	tcp	http	SF	162	4528		0	normal
line 3	0	tcp	http	SF	236	1228		0	smurf
line 4	0	tcp	http	SF	233	2032		0	neptune
…	…	…							…

It's **highly unbalanced** data that most of the instances are labeled "smurf".

Size:

4,898,431(instances) x 42(attributes)

class distribution: Total 23 classes. 87% are "smurf"(DOS attack), 12% are "neptune"(DOS attack), 0.48 % are "normal", as shown below:



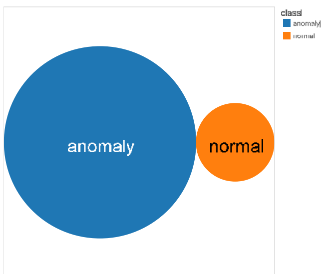
(3) NSL Kdd99 data

NSL Kdd99 data could be found at http://nsl.cs.unb.ca/NSL-KDD/ . It is an improvement of KDD99 that it is more efficient for training classifiers. It remove redundant records; it transforms class labels into only two types: “normal” and “anomaly”; it select the records to make it more balance.

Size:

125,973(instances) x 42(attributes)

class distribution: 86% anomaly,   14% normal



Finally, the three datasets are transformed into “ARFF”[6] file format to let SAMOA be able to read. They are:

data	file	total instance number	attribute number	class number	note
Movie Review data	m.arff	2000	1172	2	
NSL Kdd99 data	n.arff	125,973	42	2 (unbalance 86% anomaly, 14% normal)	NB-4 cannot process because it contains real value attribute.
Kdd99 data	k.arff	4,898,431	42	23 (unbalance, 87% smurf, 12% neptune, 0.48% normal)	NB-4 and VHT cannot process because it contains error values and real value attribute.

All the data could be downloaded from my Google drive:

https://drive.google.com/folderview?id=0B0k3wDoweGSZaWQ4c2IyaHhGSEk&usp=sharing

[6] http://www.cs.waikato.ac.nz/ml/weka/arff.html

3.3 Cluster modes

I test the different algorithms with different data, and I also need to test them in different cluster settings to see the parallel-computing scalability of the algorithms.

(1) Local mode (Local)

Only run task on node 3, in local mode without S4.

(2) S4 mode, single node (S4-1)

Run task on only node 3, with S4 platform.

(3) S4 mode, two nodes (S4-2)

Run task on cluster with 2 computing nodes (node 3 and node 2), with S4 platform.

(4) S4 mode, three nodes (S4-3)

Run task on cluster with 3 computing nodes (node 3, node2 and node 1), with S4 platform.

In conclusion, the test configurations can format as the combination table below:

Data: **movieReview, NSLKDD, KDD99**				
Algorithm/Cluster	**Local mode(single node)**	**S4, 1 node**	**S4, 2 node**	**S4, 3 node**
NB-4				
NB-5				
VHT				
BagNB4				
BagNB5				
BagVHT				

4. Test Result

The test result are collected from: (1)result files (2) log file (3) log(debug) information on the screen. Please see the middle output in Appendix. Here I only show the final rearranged result.

Measurements:

I measured 2 index for each test configuration [dataset + algorithm + cluster mode]:

(1) **Speed** (seconds/X instances):

How many time the algorithm spends on train and testing every X data. X's are different for different dataset. (MovieReview,X=1000; NslKdd,X=10,000; Kdd99,X=100,000)

(2) **Correct rate**.

The percentage of test data that correctly classified (output class=target class).

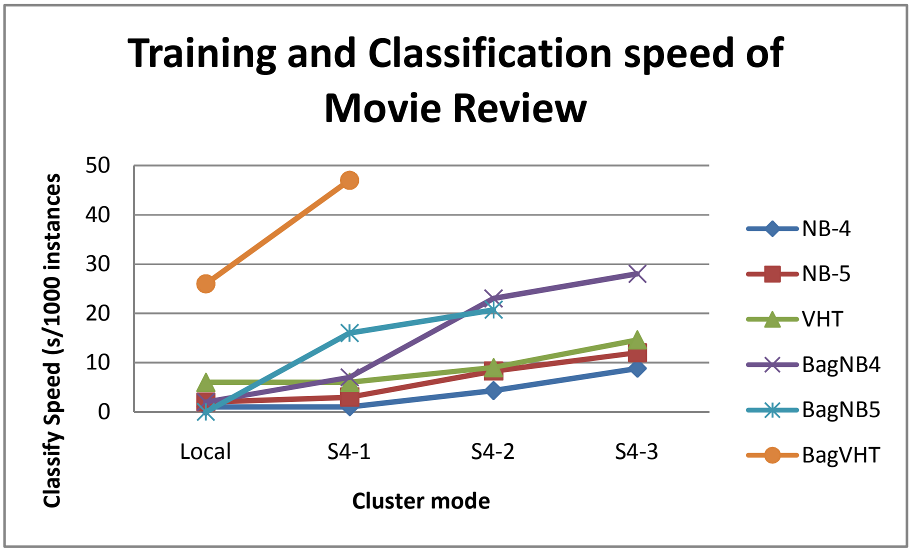
4.1 Final result

The table below shows the average speed of different algorithms running on different cluster modes and different datasets. Some cells in the table are blank, because the algorithm failed to run in the situation corresponding to this cell (See Appendix).

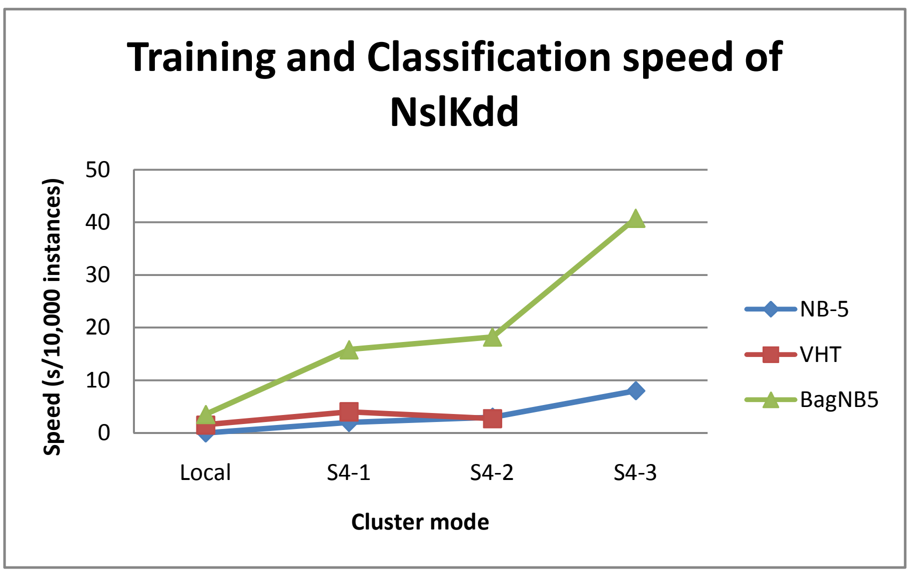
Average Speed (seconds / x instances)												
Algorithm/Dataset	**MovieRevew** (seconds/1000 instances)				**NslKdd** (seconds/10,000 instances)				**KDD99** (seconds/100,000 instances)			
Cluster mode	local	1 node	2 nodes	3 nodes	local	1 node	2 nodes	3 nodes	local	1 node	2 nodes	3 nodes
NB-4	1	1	4	9								
NB-5	2	3	8	12	<1	2	3	8	20	28	39	118
VHT	6	6	9	15	1.5	4	2.7					
BagNB4												
BagNB5					3.5	16	18	41	155	255	285	808
BagVHT												

We can draw the "speed graphs" from the tables above:

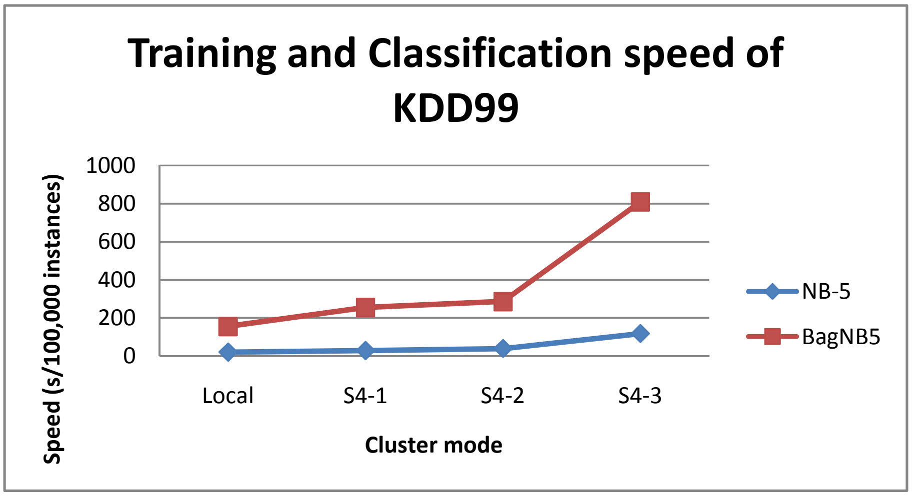
The vertical axis show the processing speed (Training + Classification time of every unit frequency of data).



Training and Classification speed of Movie Review
Classify Speed (s/1000 instances
50
40
30
20
10
0
Local
S4-1
S4-2
S4-3
Cluster mode
NB-4
NB-5
VHT
BagNB4
BagNB5
BagVHT

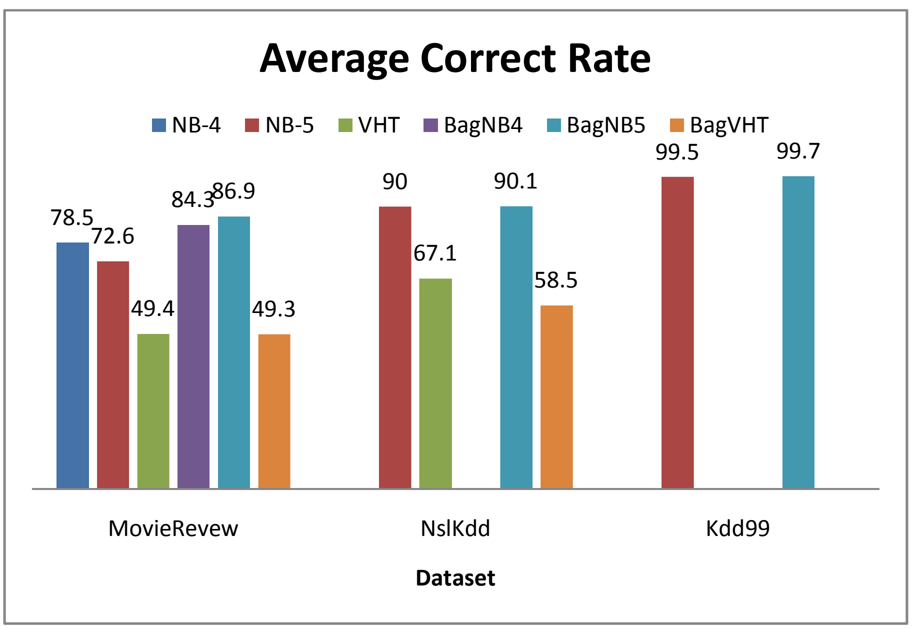


Training and Classification speed of NslKdd
Speed (s/10,000 instances)
50
40
30
20
10
0
Local
S4-1
S4-2
S4-3
Cluster mode
NB-5
VHT
BagNB5



The correct rate of different algorithms are basically stable among different cluster mode, so we can draw the correct rates table of different algorithms with different datasets.

Average Correct Rate (%)			
Algorithm/Dataset	**MovieRevew**	**NslKdd**	**Kdd99**
NB-4	78.5		
NB-5	72.6	90.0	99.5
VHT	49.4	67.1	
BagNB4	84.3		
BagNB5	86.9	90.1	99.7
BagVHT	49.3	58.5	



5 Conclusion

Comparing the speed of the algorithms, NB-4 > NB-5 > VHT (> means faster), and BagNB4 > BagNB5 > BagVHT; Simple algorithm was much faster than Bagging-assembled algorithm.

Comparing the correct rate, we can find NB-4 > NB-5 > VHT, and BagNB5 > BagVHT; Bagging-assembled Naive Bayes algorithms were better(about 10%) than pure Naive Bayes algorithms only for MovieReview dataset(for about 1000 attributes), but Bagging did not improve VHT for all dataset, neither did it improve Naive Bayes for KDD99 and NslKDD99 datasets.

Comparing compatibility of the algorithms, NB-4 cannot process float-type numeric attributes and VHT sometimes raise bugs such as "deserialization error" and "null point exception". Only NB-5 could run correctly with most of the data and cluster settings.

All the algorithms did not speed up with more computing nodes; instead, the performance decreased with more nodes. One reason is that NB-4 and NB-5 algorithms were not parallel structure. However, even the default VHT algorithm, which was claimed would "scale-up" by SAMOA developers, did not achieve better performance with more nodes.

In summary, NB-5 could achieve a correct rate of about 80% or more for selected datasets, which is much better than the default-VHT algorithm in SAMOA. In addition, its speed, 2s/1000 instances for 1000-attributes dataset, 20s/100,000 instances for 40-attributes dataset, is faster than VHT. Moreover, It can handle real(float) type numeric attributes with a "Normal Distribution" assumption. Some problems of SAMOA was found: (1) the default-Bagging algorithm in SAMOA did not improve correct rate but takes much more time than pure classifiers. (2) VHT did not speed up with more computing nodes.

In the future, I will try to improving NB-5 algorithm into parallel structure to make it speed up with more nodes.

Appendix

1. Detail of Test Result

1.1 Result file

The test result is output to the file “resultModeAlgorithmData”, such as “resultLocalBagP4m” (Local,BagNB4,m) or “resultS42P5k”(S4-2,NB-5,k). Each result file records the correct rate and Kappa statistics of the classification result. For example, resultS42P5k file is:

```
evaluation instances,classified instances,classifications correct (percent),Kappa Statistic (percent),Kappa Temporal Statistic (percent)

100000.0,100000.0,99.64,97.38271583414786,85.28209321340947

200000.0,200000.0,99.73349999999999,99.16494079571832,96.39889196675895

300000.0,300000.0,99.65833333333333,98.56872445672649,93.08973235353612
```

We can translate it to a CSV table:

evaluation instances	classified instances	classifications correct (percent)	Kappa Statistic (percent)	Kappa Temporal Statistic (percent)
100000	100000	99.64	97.38271583	85.28209321
200000	200000	99.7335	99.1649408	96.39889197
300000	300000	99.65833333	98.56872446	93.08973235

Because “Prequential Evaluation” task is online processor that train model, test(classify) the test instances, and evaluate the performance at the same time, the correct rate is changing while new instances come. This task can set an “evaluation frequency”, which means how many instances between two evaluation points. The table above shows 3 evaluation points at 100000,200000 and 30000 testing instances.

I choose proper evaluation frequencies for different datasets, they are:

Dataset	m	n	k

Evaluation frequency	1000	10,000	100,000

1.2 log file

Except the result file, the classification task also output log information to screen. The log information contains running status, error message, debug information, and the most important one--running time of the task. I copy the logs from screen and save them to files.

For example, the log file "logS41P5m" records the log information of running the NB-5 algorithm with MovieReview data on S4-single-node mode:

```
SAMOA: Scalable Advanced Massive Online Analysis Platform

Version: 0.0.1

Copyright: Copyright Yahoo! Inc 2013

Web: http://github.com/yahoo/samoa



17:03:36.880 [S4 platform loader] INFO  c.y.l.s.l.classifiers.hl.NaiveBayes -
==============================================

17:03:36.885 [S4 platform loader] INFO  c.y.l.s.l.classifiers.hl.NaiveBayes - Begin init
NaiveBayes Classifier topology.

17:03:36.901 [S4 platform loader] INFO  c.y.l.s.l.classifiers.hl.NaiveBayes - Sucessfully
initializing NaiveBayes classifier topology.

17:03:36.924 [S4 platform loader] INFO  org.apache.s4.core.App - Init prototype
[com.yahoo.labs.samoa.topology.impl.S4EntranceProcessingItem].

17:03:36.931 [S4 platform loader] INFO  org.apache.s4.core.App - Init prototype
[com.yahoo.labs.samoa.topology.impl.S4ProcessingItem].

17:03:36.937 [S4 platform loader] INFO  org.apache.s4.core.App - Init prototype
[com.yahoo.labs.samoa.topology.impl.S4ProcessingItem].

17:03:36.938 [S4 platform loader] INFO  c.y.l.samoa.topology.impl.S4DoTask - Starting
DoTaskApp... App Partition [0]

17:03:37.063 [STREAM-0_PROCESSING-ITEM-0] INFO  c.y.l.s.l.c.hl.NBModelProcessor -
```

NBModelProcessor created, id = 0 17:03:37.164 [STREAM-0_PROCESSING-ITEM-0] INFO c.y.l.s.l.c.hl.NBModelProcessor - K=2,A=1172 17:03:41.099 [STREAM-1_PROCESSING-ITEM-1] INFO c.y.l.s.e.EvaluatorProcessor - **3 seconds for 1000 instances** 17:03:41.109 [STREAM-1_PROCESSING-ITEM-1] INFO c.y.l.s.e.EvaluatorProcessor - evaluation instances = 1,000 classified instances = 1,000 classifications correct (percent) = 70.3 Kappa Statistic (percent) = 40.968 Kappa Temporal Statistic (percent) = 41.879

The underlined part shows the processing speed (training time + test time) of this classification algorithm, which is 3s/1000 instances.

1.3 Raw Test Result

The tables below are raw performance results I recorded.

MovieReview evaluation frequency: 1000				
Algorithm/Cluster	**Local**	**S4-1**	**S4-2**	**S4-3**
NB-4	**speed (second/1000 instance):** 1 **correct rate:** 77.4% 77.7%	**speed(s/1000 instances)**: 1 **correct rate:** 77.7% 77.7%	**speed(s/1000 instances)**: 4 2 7 **Correct rate:** 78.1% 79.2% 80.0%	**speed(s/1000 instances)**: 7 9 10 9 9 **Correct rate** 77.8% 80.3% 81.0% 81.7% 81.5%

NB-5	**speed(s/1000 instances)**: 2 2 **correct rate:** 70.3% 73.8%	**speed(s/1000 instances):** 3 **correct rate:** 70.3%	**speed(s/1000 instances):** 13 6 6 **correct rate:** 70.7% 74.8% 76.6%	**speed(s/1000 instances):** 20 10 6 11 13 **correct rate:** 71.0% 75.8% 77.4% 78.7% 78.8%
VHT	6 50.2%	6 48.2%	8 9 10 deserializer error 48.4% 49.5% 49.4%	20 8 13 18 14 49.0% 50.9% 50.1% 50.9% 50.1%
BagNB4	2 2 76.9% 77.2%	7 88.1%	11 6 6 86.7% 85.1% 84.5%	38 22 24 87.5% 85.8% 85.0%
BagNB5	0 0 0 0 92.2% 91.4% 90.9% 90.5%	16 85.7%	32 17 13 84.8% 82.8% 82.5%	Zookeeper session expired
BagVHT	26 48.4%	47 50.12%	OutOfMemoryError	Serialization error

NSL KDD99 **evaluation frequency: 10,000**	

speed(second/10,000 instance) **correct rate**					
Algorithm/Cluster	**Local**	**S4-1**	**S4-2**	**S4-3**	**Note**
NB-4	-	-	-	-	NB-4 cannot process real value attributes
NB-5	**speed** 0 0 0 0 **correct rate:** 90.1% 90.0% 89.9% 89.8%	3 2 2 1 90.1% 89.9% 89.8% 89.8%	4 3 2 3 3 3 90.1% 90.1% 89.8% 89.7% 89.8% 89.8%	21 8 5 5 8 5 4 90.3% 90.1% 89.8% 89.8% 89.8% 89.8% 89.8%	
VHT	3 1 1 1 78.0% 85.1% 87.8% 89.3%	9 3 3 2 3 69.5% 80.5% 84.1% 86.1% 87.5%	3 1 1 1 1 9 deserializer error 53.0% 53.3% 53.2% 53.2% 53.0% 53.1%	deserializer error 53.0% 53.3% 53.1% 53.2% 53.0% 53.0% 53.0%	
BagNB4	-	-	-	-	NB-4 cannot process real

					value attribute s
BagNB5	4 4 3 3 90.1% 90.0% 89.97% 89.9%	18 15 15 15 90.2% 90.0% 89.9% 89.9%	28 19 17 15 15 15 90.2% 90.0% 89.9% 89.8% 89.9% 89.9%	56 40 41 36 31 90.1% 89.9% 89.9% 89.8% 89.8%	
BagVHT	NullPointerExc eption	NullPointerExc eption 59.2% 60.7%	deserializer error 57.0%	deserializer error	

KDD99 **evaluation frequency: 100,000** **speed(second/10,000 instance)** **correct rate**					
Algorithm/Cluste r	**Local**	**S4-1**	**S4-2**	**S4-3**	**Note**
NB-4	-	-	-	-	NB-4 cannot process real value attribute s
NB-5	**speed(secon d/10,000 instance)** 19, 20, 21 **correct rate:** 99.7%, 99.7%,	**speed** 28, 28, 29 **correct rate:** 99.7%, 99.7%, 99.7%	49,29, 99.6%, 99.7%	**speed** 274, 108, 69, 69, 70 **correct rate:** 99.7%, 99.1% ,	808 99.8%

	99.7%, 99.3%			99.3%,99.3%, 98.5%	
VHT	-	-	-	-	VHT cannot handle error values in dataset
BagNB4	-	-	-	-	NB-4 cannot process real value attribute s
BagNB5	**speed** 133 147, 165, 175 **correct rate:** 99.7%, 99.7%, 99.7%,99.3%	**speed** 249, 261 **correct:** 99.7%, 99.8%	302, 275, 279 99.8%, 99.8%, 99.7%		
BagVHT	-	-	-	-	VHT cannot process error values in dataset

1.4 Average value of Test Result

MovieReview **evaluation frequency: 1000** **speed(second/1000 instance)** **correct rate(low~high)**				
Algorithm/Cluster	**Local**	**S4-1**	**S4-2**	**S4-3**
NB-4	1 77.4%~77.7%	1 77.7%	4.3 78.1%~80.0%	8.8 77.8%~81.7%
NB-5	2 70.3%~73.8%	3 70.3%	8.3 70.7%~76.6%	12 71.0%~78.8%
VHT	6	6	9	14.6

	50.2%	48.2%	48.4%~49.5% deserializer error	49.0%~50.9%
BagNB4	2 76.9%~77.2%	7 88.1%	23 86.7%~84.5%	28 87.5%~85.0%
BagNB5	0 92.2%~90.5%	16 85.7%	20.7 84.8%~82.5%	Zookeeper session expired
BagVHT	26 48.4%	47 50.12%	OutOfMemoryError	Serialization error

NSL KDD99 **evaluation frequency: 10,000** **speed(second/10,000 instance)** **correct rate**					
Algorithm/ Cluster	**Local**	**S4-1**	**S4-2**	**S4-3**	**Note**
NB-4	-	-	-	-	NB-4 cannot process real value attributes
NB-5	0 90.1%~89.8%	2 90.1%~89.8%	3 90.1%~89.8%	8 90.3%~89.8%	
VHT	1.5 78.0%~89.3%	4 69.5%~87.5%	2.7 deserializer error 53.0%~53.3%	deserializer error 53.0%~53.3%	
BagNB4	-	-	-	-	NB-4 cannot process real value attributes
BagNB5	3.5 90.1%~89.9%	15.8 90.2%~89.9%	18.2 90.2%~89.9%	40.8 90.1%~89.8%	
BagVHT	NullPointerException	NullPointerException 59.2%~60.7%	deserializer error 57.0%	deserializer error	

KDD99 **evaluation frequency: 100,000** **speed(second/100,000 instance)** **correct rate**	

Algorithm/ Cluster	**Local**	**S4-1**	**S4-2**	**S4-3**	**Note**
NB-4	-	-	-	-	NB-4 cannot process real value attributes
NB-5	20 99.7%~99.3%	28.3 99.7%	39 99.6%~99.7%	118 99.7% ~98.5%	
VHT	-	-	-	-	VHT cannot handle error values in dataset
BagNB4	-	-	-	-	NB-4 cannot process real value attributes
BagNB5	155 99.7%~99.3%	255 99.7%~99.8%	285.3 99.8%~99.7%	808 99.8%	
BagVHT	-	-	-	-	VHT cannot process error values in dataset