Predicting Traffic Patterns in Software Defined Networks

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Abstract

Just the prediction part

1 Introduction

The predictability of network traffic is the main aim of the thesis. Usually, there are two different category of network prediction: short and long period predictions. The short forecast is used to guess values in terms of seconds or minutes. Instead, the long one is adopted to estimate the future workload. Therefore, it favors the possibility to produce better planning and decision. To be able to predict future load of a network, we have to create a model of its behaviors. On the changing of a model we have different characteristics such as the correctness of the prediction and its adaptability.

There are two type of models: **Supervised** and **Unsupervised**. The *Supervised* algorithms takes as a input a set of objects and the desired output. The set of objects it is called training data. The learning algorithm analyzes the training data and produces an inferred function that its behavior is checked with the last input. The internal structure of the model is changed according to the error between the forecast and the desired result. Instead, the *Unsupervised* learning tries to find hidden structure in unlabeled data. The difference with the *Supervised* learning algorithms is that there is no error or reward signal to evaluate a potential solution.

We focus over the long term prediction and only on supervised classifier. The decision of which classifier chose has been taken conducting an experiment in a small simulated network. We simulate a normal scenario of daily network usage through a network of 4 nodes. We repeat the simulation thirty times collecting at each execution statistics of the links utilization in terms of network bandwidth and the load of the switches. From this information, we have created different dataset changing the features used and the numbers of the last observations. Then, we have tested the prediction precision and recall of different algorithm at the varying of the distinct datasets.

The implementation of the prediction is designed in four different phases

- Observer
- Analyzing
- Plan
- Execute

A graphical representation of the interconnection between the four modules is given in Figure 1.

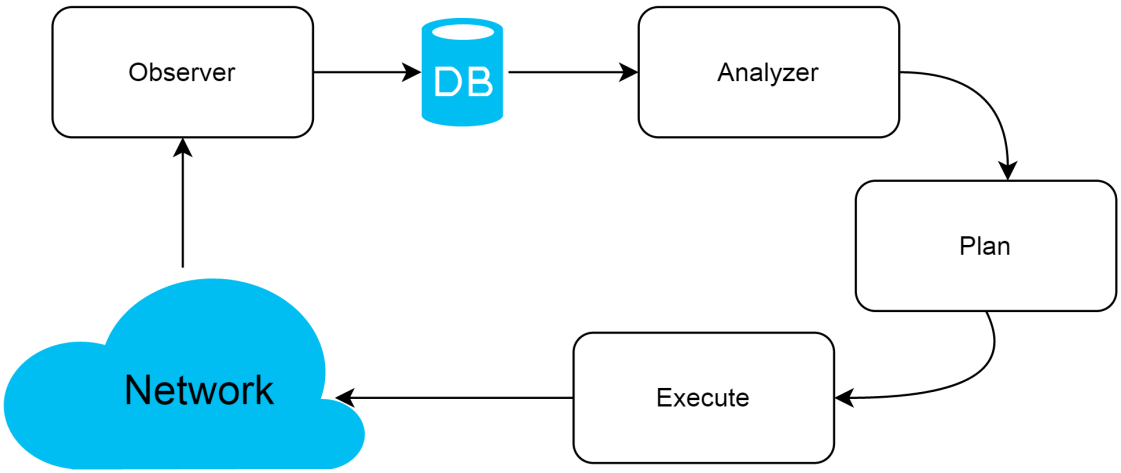

Figure 1: The different phases of the prediction

Observer. It is implemented as a daemon in the cloud application. Every few minute it launches a python script which queries the network controller via *REST API* and then stores the result inside a *nosql* database. The information saved regards the network load, switches and flows.

Analyzing. It is done looking through the information inside the database. A java application collects the data from the database and converts the knowledge in the Attribute-Relation File Format (ARFF). This format is an ASCII text file that describes a list of instances sharing a set of attributes. The application depends on the *weka* (Waikato Environment for Knowledge Analysis) package, a well known suite of learning machine algorithms developed by the University of Waikato. The ARFF files are read by the weka package and used to produce the model that is adopted to make predictions.

Plan. It is demanded to the Administrator. He or she can write rules to specify what to do when a particular event occurs. In the cloud application the administrator has the possibility to create the rules that are stored inside the FloodLight controller.

Execute. It is implemented by the controller. It monitors the network and every few minutes it makes predictions using the previously generated model. When it perceives from a forecast that some rules can be applied, it fires them.

Further, every module is uncoupled from the others. This design decision of modularity gives us the possibility to change or upgrade every module whenever there is the necessity. This feature is crucial for the prediction phase. We can test new classifiers or the addiction of new features in a separate and controlled network without

affecting the production one. Moreover, we can hot swapping the model using the cloud interface. We have designed the controller to work with a different model for each switch. This decision brings the possibility to predict when a particular node will be overloaded with more precision and recall.

2 Prediction over the Network

2.1 Configuration

We have set up a small simulation to decide which classifier algorithm works better for our purpose. The candidates were the following:

- *NaiveBayes* [6]: is a classifier based on the Bayes theorem. It assumes independence between the features of the model. It is in the family of simple probabilistic classifiers.
- *SMO* [10, 7, 5]: It is an algorithm that employs the support vector machines. The classifier learns by solving an optimization problem.
- *BayesNet* [2]: It uses the K2 learning algorithm that is in the family of the Naive Bayes. It uses a hill climbing algorithm restricted by an order on the variables of the model.
- *MultilayerPerceptron* [12, 1]: It is the most known application of the neural network that uses the back-propagation technique to adjust its internal structure.
- *J*48: It is a java implementation of the C4.5 [11] decision tree algorithm.
- K^* (*KStar*) [3]: It is an instance-based classifier. It classifies a new instance using the one that is more near to one it has learned in terms of entropy.
- *ZeroR*: This is the dumbest classifier of the list. We have chosen to test it so we can measure other classifiers by how well they do compared to this minimal level of performance. Given a certain data set, ZeroR permits to find out what is the minimum performance we may expect.

To found the most promising classifier, we have created a network of 4 nodes shows in Figure 2. In this network we have generate traffic from the node $H1$ directed to

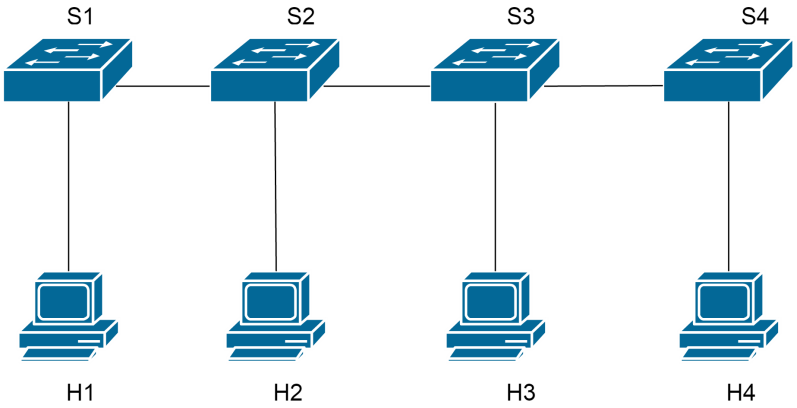

Figure 2: Topology of the network used to test the different classifiers

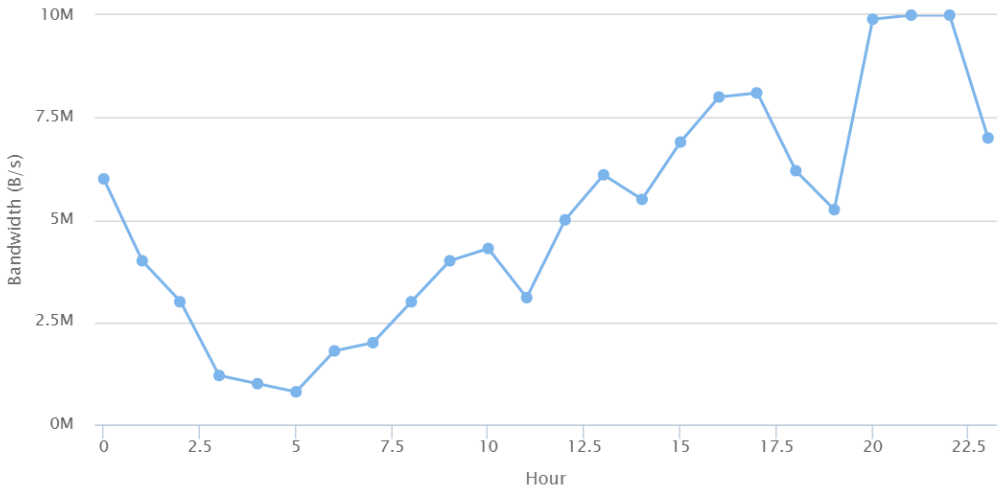

Figure 3: Graph of the bandwidth simulation of a daily usage of the network

$H4$ for a day respecting to the scenario predefined. The graph bandwidth generated is shown in Figure 3.

The creation of the network relies on the virtualization of the hardware components. Therefore, we have simulated it using Mininet [8] with OpenFlow [9] switches that have links of $10MB$ capacity. The chosen controller is FloodLight [4], an open source controller for Software Defined Network.

2.2 DataSet

In addiction to the independent variable of which classifier perform better, we have to find which information is most useful as a feature to the model to increase its prediction accuracy. Our aim is to estimate the future load of the network in terms of bandwidth required. To be able to classify it correctly, we have store the raw information taken from the controller inside buckets. Moreover, we have tested if the introduction of the derivative of the bandwidth helps or not the overall quality of the models. The last variable investigated is the number of precedent measurements passed to the prediction module. The results of our tests products five different datasets:

- **200**: We use $200KBytes$ as dimension of buckets and we use only the last 5 measurement of bandwidth.
- **500**: The size of the buckets are of $500KBytes$ and the remaining features are the same as before.
- **500_D**: The buckets are $500KBytes$ large, but now in addiction to the last 5 calculation we have the derivative between the consecutive values.
- **500_D_8**: The bucket are still of the same size but we increase the number of previous bandwidth to 8 and we use the derivative.
- **500_D_10**: This configuration is the same as before, but the number of previous data is increased to 10.

2.3 Evaluation

The testing of the various datasets and classifiers is conducted using the classic ten fold cross validation. Usually the classifiers are evaluated using the $RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y(t)-\hat{y}(t))^2}{n}}$ where $y(t)$ is the real output and $\hat{y(t)}$ is the calculated one. For our purpose, we have decided to take care about the maximal error in terms of distance between the class guessed and the real one. This is possible because we can induce an order between classes since they correspond to a numerical range of Bytes. Moreover, we consider the average of this distance called σ. We considered also the percentage score of the models to classify correctly the instances and the coverage. The results of this evaluation are presented in the next tables.

	Max Error	% Correct	σ	RMSE	Precision	Recall	Coverage (0.95)
NaiveBayes	23	34,33	3,31	0,1437	0,2756	0,2836	50,75
SMO	27	33,59	3,52	0,1371	0,2207	0,3284	91,80
ZeroR	45	10,45	23,52	0,1372	0,0109	0,1045	98,51
BayesNet	19	37,31	3,30	0,1311	0,2738	0,3657	67,16
MPL	43	35,82	3,90	0,1393	0,2626	0,2985	66,42
J48	43	33,58	3,87	0,1399	0,3206	0,3582	45,52
KStar	43	38,06	3,66	0,1579	0,2803	0,2985	40,30

Table 1: Results for **200**

	Max Error	% Correct	σ	RMSE	Precision	Recall	Coverage (0.95)
NaiveBayes	9	50,75	1,27	0,1964	0,4763	0,4627	70,1493
SMO	10	41,79	1,40	0,2064	0,3707	0,4478	97,7612
ZeroR	18	10,45	9,10	0,2103	0,0215	0,1045	97,7612
BayesNet	7	43,28	1,37	0,1881	0,4059	0,4776	82,0896
MPL	17	48,51	1,31	0,2007	0,4359	0,4552	71,6418
J48	17	49,25	1,35	0,2080	0,3914	0,4254	55,2239
KStar	17	50,75	1,44	0,2204	0,4608	0,4403	53,7313

Table 2: Results for **500**

	Max Error	% Correct	σ	RMSE	Precision	Recall	Coverage (0.95)
NaiveBayes	7	45,52	1,38	0,2105	0,4572	0,4478	56,7164
SMO	10	41,79	1,40	0,2063	0,3813	0,4328	97,7612
ZeroR	18	10,45	9,10	0,2103	0,0202	0,0896	97,7612
BayesNet	7	43,28	1,37	0,1823	0,4809	0,5224	86,5672
MPL	7	49,25	1,19	0,2035	0,4496	0,4478	67,9104
J48	17	52,24	1,40	0,2026	0,4823	0,4701	64,9254
KStar	9	41,04	1,54	0,2350	0,4428	0,4030	43,2836

Table 3: Results for **500_D**

	Max Error	% Correct	σ	RMSE	Precision	Recall	Coverage (0.95)
NaiveBayes	17	43,28	1,67	0,2216	0,4480	0,4328	52,2388
SMO	7	55,22	1,03	0,2056	0,6230	0,6493	99,2537
ZeroR	18	10,45	9,10	0,2103	0,0224	0,1119	97,7612
BayesNet	7	51,49	1,18	0,1794	0,4489	0,5299	76,8657
MPL	17	60,45	1,12	0,1746	0,6070	0,5821	75,3731
J48	17	58,96	1,25	0,1974	0,5071	0,5000	61,1940
KStar	17	40,30	1,95	0,2460	0,3735	0,3582	36,5672

Table 4: Results for **500_D_8**

	Max Error	% Correct	σ	RMSE	Precision	Recall	Coverage (0.95)
NaiveBayes	8	38,81	1,67	0,2321	0,3503	0,3433	47,0149
SMO	9	46,27	1,40	0,2064	0,3780	0,4328	98,5075
ZeroR	18	10,45	9,10	0,2103	0,0190	0,0821	97,7612
BayesNet	7	48,51	1,28	0,1932	0,4203	0,5000	72,3881
MPL	17	47,01	1,49	0,2126	0,3819	0,3955	60,4478
J48	8	43,28	1,37	0,2045	0,4201	0,4478	69,4030
KStar	17	36,57	2,02	0,2601	0,3113	0,2836	28,3582

Table 5: Results for **500_D_10**

2.4 Discussion

Number of Classes. The number of classes in the first dataset is $\frac{10\text{MB}}{0.2\text{MB}} = 50$. In all the others the classes are 20. Changing the total interval in which the classifier have to choose is a crucial design feature. With wider range the classifier has less difficulties to correctly classifies an instance and makes better predictions. Nevertheless this gives us less information because the forecast are more general and tell us that the future traffic will be in a bigger interval. With this knowledge we have less capacity of reaction. On the other hand, having smaller classes helps us to have mo

Derivative.

Number of previous measurement.

Avere 50% di successo -¿ 10 volte meglio di sparare a caso $1/20 = 5\%$

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