

Short Term Wireless Channel State Prediction Using Markov Models and Supervised Learning

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I. ABSTRACT

Packet error rate is one of the most important factors that determine the quality of service achieved over wireless networks. However, long term characteristics of the error process at the link-layer are not sufficient to guide decisions which may require short-term knowledge of the link state, such as, scheduling, and rate adaptation. We expect that transmitters will benefit from short term link state knowledge since avoiding transmitting during periods where channel quality is poor may save unnecessary transmissions and thus limit bandwidth wastage and energy usage. In this study two types of schemes are evaluated that exploit short-term phenomena of the error process at the link-layer in order to predict link state. The first scheme employs a Naive Bayes Classifier (NBC) while the second one relies on a Markov chain model. Preliminary simulation results derived from a simple topology reveal that the NBC-based scheme can predict failed transmission with an accuracy of up to 84.1%.

II. INTRODUCTION

Packet error rate is one of the most important factors that determine the quality of service achieved by any type of network. Especially for the case of wireless networks, extremely high packet error rates are observed due to phenomena, such as, interference, and signal attenuation.

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In order to counter high link-layer error rates, a broad range of studies for wireless networks are targeted at modelling long term characteristics of the error process, such as, average packet error rate and temporal correlation [5], [4]. Such models are used to guide routing decisions which involve selecting the paths that can minimize the expected number of link-layer transmissions [2], [3] or tune parameters of protocols at higher layers, such as, error control protocols (Automatic Repeat reQuest).

However, long term characteristics of the error process at the link-layer are not sufficient to guide decisions which may require short-term knowledge of the link state, such as, scheduling, and rate adaptation. We expect that transmitters will benefit from short term link state knowledge since avoiding transmitting during periods where channel quality is poor may save unnecessary transmissions and thus limit bandwidth wastage. An expected side effect of such a mechanism is increased overall throughput and lower delay since failed transmissions waste network resources and increase overall interference. The reduction of the unnecessary or failed transmissions leads to more energy efficient communication networks.

In this study we suggest two types of schemes that exploit short-term phenomena of the error process at the link-layer in order to predict link state. To be more precise, the proposed schemes estimate whether transmissions during the next time slots on a link will result in failures based on the recent history of that link's transmissions. The first prediction scheme employs *supervised learning* in order to classify each transmission as *failed* or *successful* while the second uses Markov chains to model transitions between link states as well as state sojourn times. These predictors can provide valuable guidance to scheduling schemes since transmitters can either avoid transmitting or transmit at a lower rate in case where a burst or moderate number of failures respectively is forecasted for the next set of transmissions. The importance of predicting both link state and its variability has also been outlined in [5].

For the rest of the study the terms predictor and prediction scheme will be used interchangeably. The same holds for Markov Chains and Markov models.

III. SIMULATION TESTBED AND DATA ACQUISITION

All of the prediction schemes proposed in this study are trained and tested on a time series of packet transmission outcomes of the form (t_i, x_i) where t_i denotes the time at which packet i was received across a link and x_i represents the transmission outcome. A value of 1 denotes a successful reception while 0 a failed one.

Time series data are generated using a patched version of Ns2 simulator which models both interference and noise and implements *SNR*- and *SINR*-based packet reception criteria. We simulate the simple topology depicted in Fig. 1 although we plan to employ more complicated topologies and data acquired from real testbeds. The simulation setup consists of eight single-radio nodes, all tuned at the same channel, using a fixed rate of 36 Mbps with the RTS/CTS mechanism disabled. In order to force for a lossy network

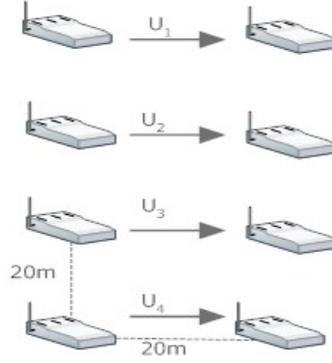


Fig. 1. Simulated topology

setup, the simulated topology is quite dense with horizontal and vertical distances between nodes being equal to 20 meters. Four flows, U_1, \dots, U_4 , are simulated for 200 seconds. To stress test our prediction schemes we pick-up the time series of the link exhibiting the higher loss rate (53.1%).

IV. PREDICTION SCHEMES BASED ON SUPERVISED LEARNING

The target of supervised learning techniques is to infer-predict the value of a class based on a number of input characteristics (features). During the training phase, a set of samples of the form (\vec{X}, \vec{Y}) is given as input to the learner where \vec{X} denotes the feature vector and \vec{Y} the vector of the target class values. In case of a single-valued categorical class, the learning problem becomes a classification problem.

$$h^* = \arg \max_h P(h|\vec{X}_i) = \arg \max_h P(h) \prod_{j=1}^N P(X_{ij}|h) \quad (1)$$

The classification technique employed in this study is the *Naive Bayes Classifier* (NBC). Assuming that N denotes the size of the feature vector, data for training and testing the suggested classifier are extracted by moving a sliding window of size $N + 1$ over the time series denoting the transmission outcomes (described in section III). This means that NBC will use the outcome of the past N transmissions in order to predict the outcome of the transmission during the next time slot. In this way, the first feature vector of the sample data will contain values x_1 to x_N , the second, x_2 to x_{N+1} , e.t.c. When a prediction is needed for a new sample $\vec{X}_i = (X_{i1}, \dots, X_{iN})$, NBC estimates the target class value h that satisfies equation (1), where $P(X_{ij}|h)$ are estimated for every feature j of every sample i during the training phase. The possible outcomes for h can be positive or negative denoting a prediction for a correct or failed transmission respectively. As stated in Section II, we are mostly interested in predicting transmissions that are going to be failed in order to minimize the number of unnecessary transmissions and thus increase the delivery ratio. Fig. 2 depicts the true negative rate achieved by the Naive Bayes Classifier for various sizes of the feature vector using a 80-20% mix of training and test data respectively.

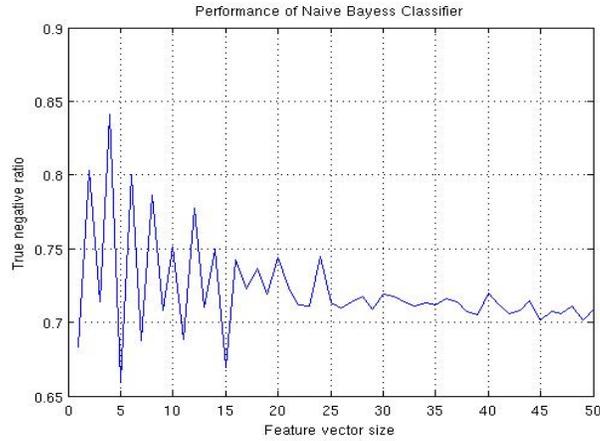


Fig. 2. Performance of the Naive Bayes Classifier

TABLE I

STATE CLASSIFICATION BASED ON ERROR PATTERN

State	# of failed tx's
Good	0-2/16
Medium	3-10/16
Bad	11-16/16

As this figure shows, the accuracy for correctly predicting failed transmissions (true negative rate) varies from 65.9% to 84.1% for feature vector sizes ranging from 1 to 50 suggesting that a scheduler using this predictor could decrease failed transmissions by up to 84.1%. It should be noted that NBC achieves the higher true negative rate when feature vectors with less than 10 features are used.

V. PREDICTION SCHEMES BASED ON MARKOV MODELS

In this study we explore whether Markov models can also capture and model short term characteristics of the error process (at the link layer) apart from longer term ones. Specifically we explore whether these models can predict if an error pattern will appear during the next time slots based on observations of successful or failed packet transmissions acquired from recent history. Notice that we are interested in predicting the error pattern that will appear within a window of successive transmissions instead of a single transmission in order to limit the prediction and scheduling overhead.

We split the time series acquired from the testbed described in Section III into consecutive windows of sizes 2, 4, 6, ..., 16 packets although we present preliminary results acquired using windows of 16 transmissions due to space limitations. For our preliminary evaluation we use a simple pattern in order to classify channel state to Good, Bad, and Medium which counts the number of failed transmissions observed within a window of 16 transmissions (Table I). Based on this state classification we compute the transition matrix and the mean sojourn time for the Markov Chain depicted in Fig. 3 for each state i

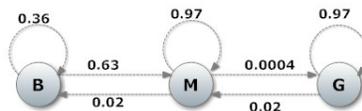


Fig. 3. The Markov chain and the transition probabilities

with $p_{i,i}$ denoting the self transition probability for that state.

Observing this figure reveals some interesting properties of the error process. First of all, the probabilities of moving to the Good state while being at the Bad and vice-versa are zero which means that the channel under consideration is not so bursty. This is largely due to the smoothness induced in the trace by the CBR traffic sources. Apart from that, the sojourn time for the Bad state is approximately 1.59 time slots which means that long bursts of errors are rare in the trace. Finally, the high self transition probabilities observed for both the Good and the Medium state suggest long periods of few or moderate errors.

VI. FUTURE WORK

There are several ongoing and future extensions concerning the issues addressed in this study. First of all, we plan to test our prediction schemes on arbitrary network topologies containing mobility and random traffic patterns. We are currently working on extending the NBC predictor in order to forecast a window of consecutive transmissions instead of forecasting only the next one. Apart from that we plan to compare NBC's performance with Auto-Regressive models and other classification techniques, such as, Neural Networks and Support Vector Machines. As far as the Markov model is concerned, we plan to evaluate its accuracy on predicting transitions between the three different states defined in Section V. Notice that the model proposed in this study is quite simple using a fixed window of transmissions in order to define a state as well as a simple error pattern to discriminate amongst them. We intend to try more sophisticated pattern recognition schemes in order to extract patterns in the error process and examine if they increase the prediction accuracy of the Markov model.

The long term goal of this study is to incorporate these predictors in scheduling schemes and examine, firstly, if they offer a significant increase in the delivery ratio and secondly if ceasing transmitters or lowering their rates saves enough network resources such that allow for higher overall network throughput. As an illustrative example, we plan to incorporate our Markov model into a predictor that based on it's current state it will estimate for how long will the channel remain in the same state (sojourn time) and after that time elapses which is the most probable state to move to. During each state traffic scheduling can be carried in such a way that reduces failed transmissions. In the medium state for example where a significant but not excess number of failures is observed, some form of coding may be used in order to hide link-layer losses from upper layer protocols. There are several types of coding schemes that can be used, such as, Forward Error Correction Codes (FEC), or variations of network coding that use redundancy.

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