Estimating Network Internal Link Loss Behavior From End-to-End Multi-cast Measurements

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***Abstract*— We study the use of multi-cast probes to infer network internal loss behavior from losses observed in multi-cast receivers. First part of the paper analyzes the estimation problem based on the assumption that there is no temporal correlation between link losses for different probes. We have applied Expectation-Maximization(EM) algorithm to this problem. We compared the results of EM with a direct approach developed in [2]. The second part of the paper is based on the assumption of Markov temporal correlation between packet losses. We applied EM algorithm to this problem with E-step approximated by Gibbs sampling, completely factorized variational and structured variational approximation. We observed from simulation that the links closer to observed nodes give more accurate results and that structured variational approximation improves simple variational approximation results considerably.**

***Index Terms*— estimation, network measurements, machine learning, Expectation-Maximization, Gibbs sampling**

I. Introduction

Internet has evolved from a small controlled network serving a few users to a massive and distributed network very rapidly. Determining statistical features of the network can help detect congestion, routing faults and anomalous traffic. However, the heterogeneous nature and the lack of centralized control for Internet makes cooperation for network measurements difficult. The collection of network statistics such as link delays and packet drop rates at each internal router can cause computing overhead in addition to consuming considerable bandwidth while transmitting these statistics back to a central processing unit. Even if these statistics can be collected, end-systems cannot rely on the network itself to cooperate in characterizing its own behaviour. In addition, gaining access to the internal nodes in an administratively diverse network can be difficult. Introducing new measurement mechanisms will require altering the product of companies, which is not feasible.

Network tomography is a new field developed to acquire network statistics without special-purpose cooperation from routers and without or little increase in network load. The main idea is to acquire the statistics about the network with either active probing or passive monitoring and then to extract hidden information about the network from these active or passive measurements. Extracting hidden information requires the estimation of a very large number of spatially distributed parameters(e.g. single link loss rates [1],[2], [4], delay distributions [3], [5], and traffic flow [6]).

This paper focuses on network tomography of inferring loss characteristics of internal network links from end-to-end loss reports at multi-cast receivers. The reason to use multi-cast in inference is its efficiency. N multi-cast servers causes a network load grow as N whereas N unicast probes increase the load of each link as N^2. A recent paper [2] presents an algorithm for inferring the loss behavior of the links within the multicast routing tree spanning the source and receivers from the correlation of the packet losses experienced by the multicast receivers. The main assumption in that paper is that link losses are described by independent Bernouilli processes. Their algorithm guarantee that the solution from the algorithm converges to the Maximum Likelihood estimation(MLE) of the link loss probabilities almost surely. In this paper, we compare the estimation results from their algorithm with the application of Expectation-Maximization(EM) algorithm to perform link-level loss inferences.

Assuming that all the link losses are independent Bernoulli processes ignores the presence of spatial and temporal correlations between losses. It is believed that large and long-lasting spatial dependence is unlikely in a real network due to traffic heterogeneity. However, both wired and wireless links can exhibit temporal correlations depending on the choice of probe process. If inter-probe time is large enough the sampling of link loss rates can be assumed to be independent. Then the link loss probabilities will just reflect the average behavior of this link over time. This information can be used in dynamic routing applications by choosing the path consisting of links with smaller loss probabilities. On the other hand, the network is usually modelled as a simple two-state Markov Chain, which has been shown to approximate the packet loss behavior over wired [7] and wireless [8] links fairly accurately. It is well known that packet loss in Internet often occurs in bursts. This is because of the fact that packets are dropped at the network routers successively during congestion. Most routers employ First-In-First-Out(FIFO) policy where successive packets are dropped if the buffer of the router is full. In wireless links, successive loss can also occur because of the fading characteristics of the channel. The decrease in channel gain during fading increases the bit error probability, which causes packets to be dropped as a result of Cyclic Redundancy Check(CRC). Determining the transition probability of Markov Chain can be used in adjusting the forward error correction (FEC) coding rate to minimize the irrecoverable loss probability[9]. The redundancy in the packets should be increased as the average duration that the path to destination is in “bad” state increases.

Based on the assumption of two-state Markov temporal structure of the loss behavior at each router, the transition probabilities can be estimated by using EM algorithm. Since the model is intractable for exact calculation, we utilized Gibbs sampling and two variational approximations. We consider two different distributions for variational approximation: one in which all the nodes are decoupled, and one in which the tree calculations are performed exactly and the time steps of the trees are decoupled.

The paper is organized as follows: In Section II, we describe the multicast tomography scenario and the intuition behind it. In Section III, we formally define the loss model. In Section IV, we describe the two algorithms for estimating the link loss probabilities of each internal link by ignoring temporal correlations: direct estimation and EM algorithm. In Section V, we present inference algorithms considering Markov temporal correlations by using Gibbs sampling, simple and structured variational approximations. After examining the performance of our methods in Section VI, concluding remarks are made in Section VII.

II. Multicast Tomography

We consider a scenario in which a single source sends multicast packets to a number of receives. The source and these receivers form a multicast tree such that the source is the root and the receivers are the leaves of the tree. We assume that we can measure the traffic only at the leaves of the tree, which gives us the information whether a packet sent from the sender reaches the receivers or not. This information can be obtained through some kind of feedback such as acknowledgements. We also assume that the multicast tree remains unchanged during the measurement through fixed routing tables.

The basic idea of using multicast traffic to estimate the loss probabilities associated with each individual link is the exploitation of the correlation between the receiver traffic characteristics sharing common subpaths. One packet is generated at the source. Then if the packet successfully reaches the destination, it is replicated for each child of the node in the tree. The paths from the source to two receivers share some common path and then diverge at some point. Then if one of them receives the packet, this means that the multi-cast packet successfully passed through the common path and the packet loss is due to one of the links in the non-common part of their paths. Exploiting this kind of correlation for all receivers allows us to resolve the losses occurring on all links.

III. Loss Modeling

Consider the tree-structured network associated with the multi-cast source and its receivers. Let $T = (V, L)$ denote the logical tree consisting of the set of nodes V, including the source and receivers, and the set of links L. The difference between the physical tree and logical tree is that each node in the logical tree has at least two children except the source node. Logical tree simply models the chain of links with one child as one composite link since it is not possible to differentiate between these links from the multi-cast receiver traffic characteristics. The root of the tree, node 0, is the source of all the packets and the leaves of the tree, set R, are the multi-cast receivers. We also denote the set of children of node j by $d(j)$ and the parent of node j other than the node 0 as $f(j)$.

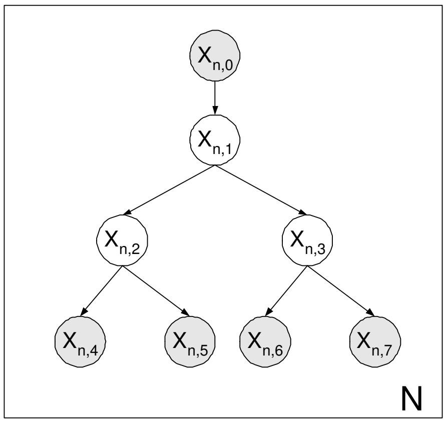

Fig. 1. Graphical representation for independent packet loss at each link for each probe

The loss model for the case ignoring temporal characteristics assumes independent loss characteristic at each probe sampling. The passage of probes at each time is described by a stochastic process $X = (X_{n,k})_{k \in V}$ where each $X_{n,k}$ is 0 or 1. $X_{n,k} = 1$ means that packet reached node k. Since packets are generated at the source, $X_{n,0} = 1$. If $X_{n,k} = 1$ then for j a child of k, $X_{n,j} = 1$ with probability α_j and $X_{n,j} = 0$ with probability $1 - \alpha_j$. If $X_{n,k} = 0$ then for j a child of k, $X_{n,j} = 0$. The graphical representation of this loss model is shown in Figure 1

The loss model for the case considering Markov temporal correlations assumes 2-state Markov Chain for each state. The passage of probes is described by the stochastic process $X = (X_{n,k})_{k \in V}$ where each $X_{n,k}$ is 0 or 1. $X_{n,k} = 1$ means that packet reached node k at time t. Since packets are generated at the source, $X_{n,0} = 1$ for all n. If $X_{n,k} = 1$ then for j a child of k, $X_{n,j} = 1$ with probability $p_{j,1}$ if $X_{n-1,j} = 0$ and with probability $1 - p_{j,0}$ if $X_{n-1,j} = 1$. This is represented by a 2-state Markov Chain shown in Figure 2. If $X_{n,k} = 0$ then for j a child of k, $X_{n,j} = 0$. The Markov loss model is shown as a graphical model in Figure 3.

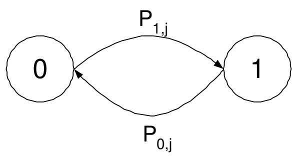

Fig. 2. Markov Chain associated with node j

IV. Inference Algorithms Ignoring Temporal Correlations

The outcome of each probe sent from the root of the tree to the leaves is whether or not a copy of the probe is received at each multicast receiver, which is denoted as $X_R = (X_k)_{k \in R}$.

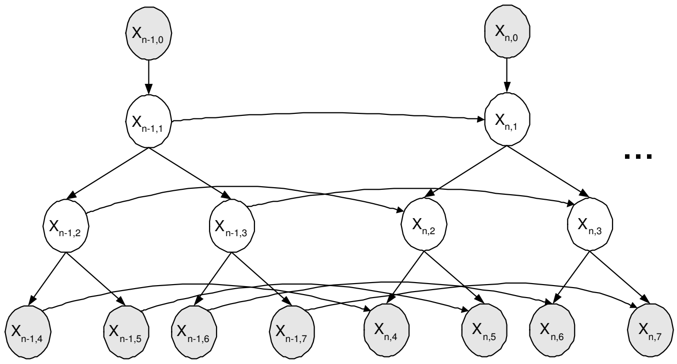

Fig. 3. Graphical representation for packet loss with Markov temporal correlation

The goal here is to estimate the probability that the packets will not be dropped in each node, which is independent of previous and following time steps. Let's denote the probability mass function of X_R for a single outcome x and for a given set of link probabilities $\alpha = (\alpha_k)_{k \in V}$ as $p(x;\alpha) = P_\alpha(X_R = x)$ by using the notation in [2].

The probability of N independent observations $x^1, x^2, ..., x^N$ is then given by:

$$p(x^1, ..., x^N) = \Pi_{n=1}^{N} p(x^n; \alpha) \tag{1}$$

The log likelihood function is used throughout the paper:

$$L(\alpha) = logp(x^1, ..., x^N) = \Sigma_{n=1}^{N} logp(x^n; \alpha) \tag{2}$$

Both of the following estimations of α are based on Maximum Likelihood Estimator(MLE). Direct estimation algorithm in Section IV-A is based on maximizing the likelihood without any constraint on the set α and then proving that the optimizing α converges to the actual α as the number of observations go to infinity. Expectation-Maximization(EM) algorithm described in Section IV-B is a more general approach to the maximum likelihood parameter estimation problem.

A. Direct Estimation Algorithm

Direct estimation algorithm described in [2] is based on solving the likelihood equation

$$\frac{\partial L}{\alpha_k} = 0, k \in V \tag{3}$$

without any range restriction on the set α by finding an algorithm to find its unique solution under some conditions and then proving that this result converges to the maximum likelihood estimate as the number of observations N goes to infinity.

Let $\Omega(k)$ be the set of outcomes x such that $x_j = 1$ for at least one receiver $j \in R$ which is a descendant of k, and let $\gamma_k = P_\alpha(\Omega(k))$. An estimate of γ_k is given by

$$\widehat{\gamma_k} = \sum_{x \in \Omega(k)} \widehat{p}(x) \tag{4}$$

where $\widehat{p}(x) = n(x)/N$ is the observed proportion of times outcome x is obtained.

Let's then define $G = \{(\gamma_k)_{k \in V} : \gamma_k > 0 \forall k; \gamma_k < \sum_{j \in d(k)} \gamma_j \forall k \in V \setminus R\}$. It is proven in [2] that if $\widehat{\gamma} \in G$ the the unique solution of likelihood function is expressed as follows: If we define $(\widehat{A}_k)_{k \in V}$ for the root node by $\widehat{A}_0 = 1$, for leaf nodes $k \in R$ by $\widehat{A}_k = \widehat{\gamma}_k$ and for all the other nodes $k \in V \setminus R$ as the unique solution in $(0, 1]$ of

$$1 - \frac{\widehat{\gamma}_k}{\widehat{A}_k} = \prod_{j \in d(k)} (1 - \frac{\widehat{\gamma}_j}{\widehat{A}_k}) \tag{5}$$

Then for $k \in V \setminus 0$, $\widehat{\alpha}_k = \frac{\widehat{A}_k}{\widehat{A}_{f(k)}}$.

In [2], it is proved that this solution is the MLE with probability 1 for sufficiently large n.

B. EM Algorithm

EM algorithm provides a general approach to the maximum likelihood parameter estimation problem in statistical problems with latent variables. In this problem, the observed variables are $X_{0,t} = 1$ and X_R and the latent variables are $X_{V \setminus \{0,R\}}$. The complete log likelihood for this problem is given in Equation 6 where $\alpha_{1,j}$ is $P(X_{n,j} = 1 | X_{n,i} = 1)$ and $\alpha_{1,j}$ is $P(X_{n,j} = 0 | X_{n,i} = 0)$. Then the expected complete log likelihood is in Equation 7. The final goal is to estimate $\alpha_{1,j}$ for each node $j \in V \setminus \{0\}$. The maximum likelihood estimate of $\alpha_{1,j}$ for the case of complete data is given in Equation 8 where the second equation results from the fact that $P(X_{n,j} = 1, X_{n,f(j)} = 0) = 0$.

This was the M-step of the EM algorithm. Since we do not know $X_{n,j}$ except the root and the leaves of the tree, we have to find $E(X_{n,j})$ for $n \in 1, 2, ..., N$ and $j \in V \setminus \{R, 0\}$. Here, we did this estimation using *sum-product algorithm* at each time n.

EM algorithm starts with a random initial set α. Then it iterates between E-step where the sum product algorithm is implemented to compute the posterior probabilities of hidden nodes in the tree with a fixed set α and M-step where the posterior probabilities from E-step is used to maximize the expected log likelihood of observation with respect to the set α.

V. Inference Algorithms Based on Markovian Temporal Correlations

The outcome of each probe sent at time n from the root of the tree to the leaves is whether or not a copy of the probe is received at each multicast receiver, which is denoted as $X_{n,R} = (X_{n,k})_{k \in R}$. The goal here is to estimate the transition probabilities for the 2-state Markov Chain in each node.

The transition probabilities of the Markov Chain of each node can be estimated via EM algorithm. The algorithm starts with random initial transition probabilities. The procedure then iterates between computing the posterior probabilities of hidden nodes by fixing the transition probabilities and using these posterior probabilities to maximize the log likelihood with respect to transition probabilities.

The M-step of the algorithm is tractable. We first write down the expression for the probability model in Equation 9. This factorized form of the probability makes the M-step of the

$$L(\alpha, x) = \sum_{n=1}^{N} \sum_{\substack{(i,j) \in L \\ j \in d(i)}} log(\begin{array}{l} (\alpha_{1,j})^{X_{n,i}X_{n,j}}(1-\alpha_{1,j})^{X_{n,i}(1-X_{n,j})} \\ (\alpha_{2,j})^{(1-X_{n,i})(1-X_{n,j})}(1-\alpha_{2,j})^{(1-X_{n,i})X_{n,j}}) \end{array} \tag{6}$$

$$E(L(\alpha, x)) = \sum_{n=1}^{N} \{ \sum_{\substack{(i,j) \in L \\ j \in d(i)}} (\begin{array}{l} E(X_{n,i}X_{n,j})log(\alpha_{1,j}) + E(X_{n,i}(1-X_{n,j}))log(1-\alpha_{1,j}) + \\ E((1-X_{n,i})(1-X_{n,j}))log(\alpha_{2,j}) + E((1-X_{n,i})X_{n,j})log(1-\alpha_{2,j}))\} \end{array} \tag{7}$$

$$\begin{aligned} \widehat{\alpha_{1,j}} &= \frac{\sum_{n=1}^{N} E(X_{n,f(j)}X_{n,j})}{\sum_{n=1}^{N} E(X_{n,f(j)})} \\ &= \frac{\sum_{n=1}^{N} E(X_{n,j})}{\sum_{n=1}^{N} E(X_{n,f(j)})} \end{aligned} \tag{8}$$

$$\begin{aligned} P(\{X_{n,0}, X_{n,1}, X_{n,2}, X_{n,3}, X_{n,4}, X_{n,5}, X_{n,6}, X_{n,7}\}) = \; & \pi_1(X_{1,1}|X_{1,0}) \\ & \pi_2(X_{1,2}|X_{1,1})\pi_3(X_{1,3}|X_{1,2})\pi_4(X_{1,4}|X_{1,2}) \\ & \pi_5(X_{1,5}|X_{1,2})\pi_6(X_{1,6}|X_{1,3})\pi_7(X_{1,7}|X_{1,3}) \\ & \textstyle\prod_{n=2}^{N}\{ \\ & a_1(X_{n,1}|X_{n,0}X_{n-1,1}) \\ & a_2(X_{n,2}|X_{n,1}, X_{n-1,2})a_3(X_{n,3}|X_{n,2}, X_{n-1,3}) \\ & a_4(X_{n,4}|X_{n,2}, X_{n-1,4})a_5(X_{n,5}|X_{n,2}, X_{n-1,5}) \\ & a_6(X_{n,6}|X_{n,3}, X_{n-1,6})a_7(X_{n,7}|X_{n,3}, X_{n-1,7}) \\ & \} \end{aligned} \tag{9}$$

$$p_{1,j} = \frac{\sum_{n=2}^{N} E((1-X_{n-1,j})X_{n,j}X_{n,f(j)})}{\sum_{n=2}^{N} E((1-X_{n-1,j})X_{n,f(j)})} \tag{10}$$

$$p_{0,j} = \frac{\sum_{n=2}^{N} E(X_{n-1,j}(1-X_{n,j})X_{n,f(j)})}{\sum_{n=2}^{N} E(X_{n-1,j}X_{n,f(j)})} \tag{11}$$

algorithm completely tractable. The M step estimates for the parameters $p_{1,j}$ and $p_{0,j}$ for $j \in V \setminus \{0\}$ are given in Equation 10.

Markov property can be used to obtain factorizations across time steps. However, the marginalization through summing over all possible unobserved states in each time makes the inference intractable. Therefore, we now describe the methods of obtaining approximate posterior probabilities.

A. Inference Based on Gibbs Sampling

Gibbs sampling is one of the simplest Monte Carlo sampling procedures. The procedure start with a random setting of hidden states and then updates the value of the hidden states according to the distribution conditioned on the all other states and the fixed parameters. Since the sequence of the overall states defines a Markov Chain, the samples from this Markov Chain can be used to determine the posterior probabilities of hidden nodes after the chain converges. The sampling from a hidden state variable at time n depends only on a few nodes at time n, $n-1$ and $n+1$. $X_{n,j}$ sampled from

$$\begin{aligned} P(X_{n,j}\| \quad & X_{n,f(j)}, X_{n,d(j)}, X_{n-1,j}, \\ & X_{n-1,d(j)}, X_{n+1,j}, X_{n+1,f(j)}). \end{aligned}$$

Then the first, second and third order statistics in Equation 10 can be collected by using the states visited after the Markov Chain is in steady state.

B. Inference Based on Completely Factorized Variational Mean Field Approach

The basic idea of completely factorized variational mean field approach is to approximate the posterior distribution of hidden variables by completely factorized distribution such that the Kullback-Leibler divergence between the new distribution and original posterior distribution is minimized. The new distribution in this case is given in Equation 12. Then the variational parameters in this model, the success probabilities $\lambda_{n,j}$ for $j \in 1,2,3$ and $n \in 1,2,...,N$, are obtained by minimizing KL divergence with respect to these variational parameters. This distribution is illustrated in Figure 4.

C. Inference Based on Structured Variational Mean Field Approach

The main goal of structured variational mean field approach is to decrease the performance loss caused by the oversimplified nature of completely factorized approximation. Structured

$$Q(\{X_{n,1}, X_{n,2}, X_{n,3}\} \| \lambda) = \prod_{n=1}^{N} q_{n,1}(X_{n,1}) q_{n,2}(X_{n,2}) q_{n,3}(X_{n,3}) \tag{12}$$

Real	Gibbs	Factorized	Structured
p_{11}=0.7	0.5520	0.5604	0.5647
p_{10}=0.6	0.4482	0.4396	0.4650
p_{21}=0.7	0.4307	0.4291	0.5718
p_{20}=0.6	0.6549	0.7150	0.5725
p_{31}=0.7	0.3928	0.3094	0.7164
p_{30}=0.6	0.6051	0.6960	0.2984
p_{41}=0.8	0.8166	0.5431	0.9515
p_{40}=0.2	0.2853	0.0718	0.0952
p_{51}=0.7	0.7263	0.6480	0.7324
p_{50}=0.6	0.6388	0.6687	0.6287
p_{61}=0.2	0.2649	0.2712	0.2307
p_{60}=0.8	0.7874	0.7810	0.8153
p_{71}=0.7	0.6006	0.6945	0.6702
p_{70}=0.6	0.6402	0.5697	0.5869

TABLE I
CONVERGED VALUES OF EM ALGORITHM WITH DIFFERENT APPROXIMATION METHODS

method removes some of the couplings in the original graph to obtain a simplified distribution Q. Here, we have chosen forest of trees as the Q distribution by removing the horizontal couplings as shown in Figure 5. The Q distribution is then given in Equation 13.

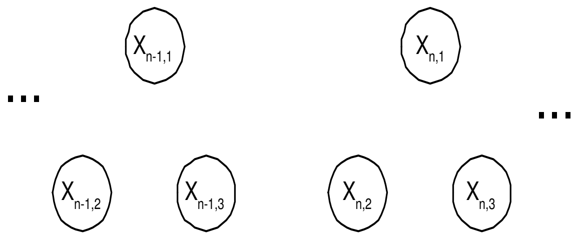

Fig. 4. Graphical representation for completely factorized variational approximation

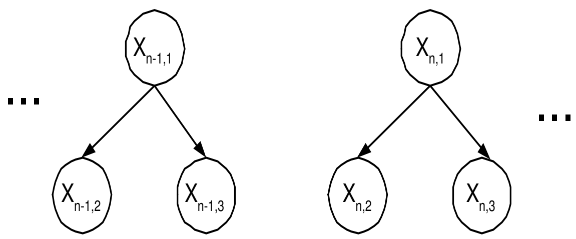

Fig. 5. Graphical representation for structured variational approximation as a forest of trees

The variational parameters for this distribution $\lambda_{n,1}$, $\lambda_{n,12,11}$, $\lambda_{n,12,00}$, $\lambda_{n,13,11}$, $\lambda_{n,13,00}$ are $P(X_{n,1} = 1)$, $P(X_{n,2} = 1|X_{n,1} = 1)$, $P(X_{n,2} = 0|X_{n,1} = 0)$, $P(X_{n,3} = 1|X_{n,1} = 1)$ and $P(X_{n,2} = 0|X_{n,1} = 0)$ respectively. They are again estimated by minimizing KL divergence with respect to this parameters.

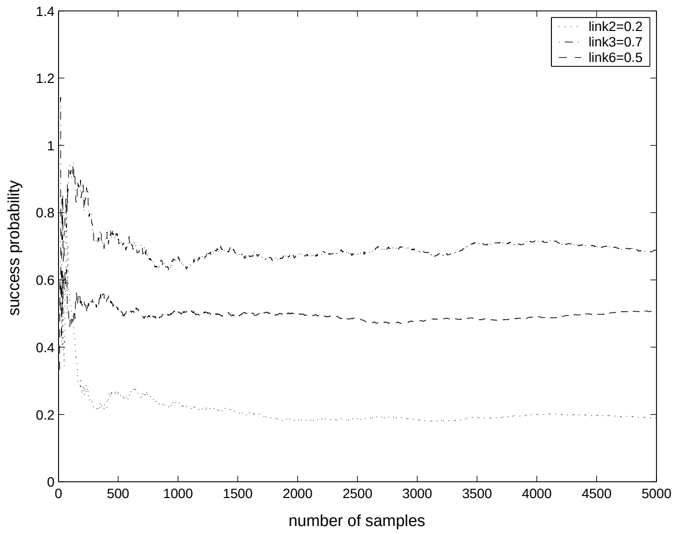

Fig. 6. Direct algorithm for 4-leaf tree with α = [0.6,0.2,0.7,0.6,0.4,0.5,0.5]

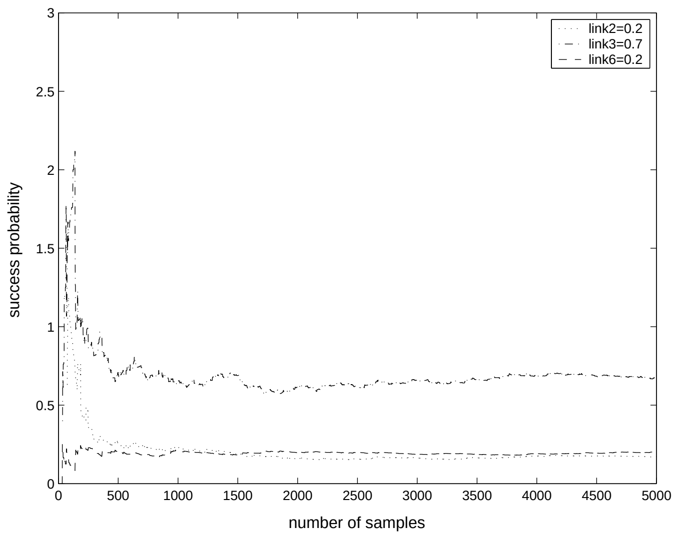

Fig. 7. Direct algorithm for 4-leaf tree with α = [0.6,0.2,0.7,0.6,0.2,0.2,0.3]

VI. SIMULATION RESULTS

Simulation is performed in MATLAB with the tree topology shown in Figure 1. Node 0 sends a sequence of multicast probes. Each link packet loss either is independent or evolves according to a 2-state Markov Chain. The losses observed at the leaves are then evaluated to infer the link characteristics, which is either the link success probability or the transition probabilities of Markov Chain governing the behavior of that link.

We first simulated the network with independent packet losses for each probe. Figures 6 and 7 show the converged values obtained by direct estimation algorithm described in Section IV-A for different number of samples for 2 different

$$Q(\{X_{n,1}, X_{n,2}, X_{n,3}\}|\lambda) = \prod_{n=1}^{N} q_{n,1}(X_{n,1}) q_{n,2}(X_{n,2}|X_{n,1}) q_{n,3}(X_{n,3}|X_{n,1}) \tag{13}$$

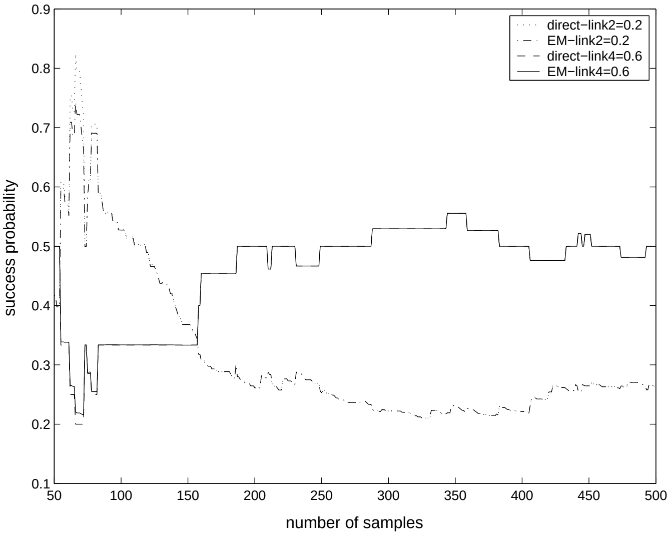

Fig. 8. Comparison of direct and EM algorithms for 4-leaf tree with α = [0.6,0.2,0.7,0.6,0.4,0.5,0.5]

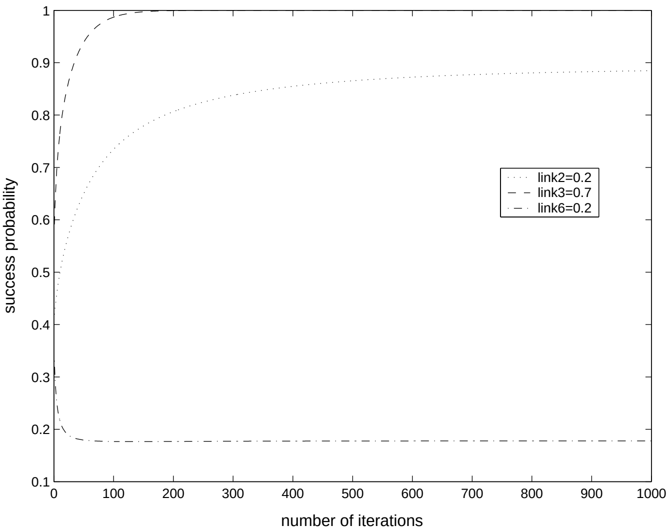

Fig. 9. Convergence of EM for 100 samples with α = [0.6,0.2,0.7,0.6,0.2,0.2,0.3]

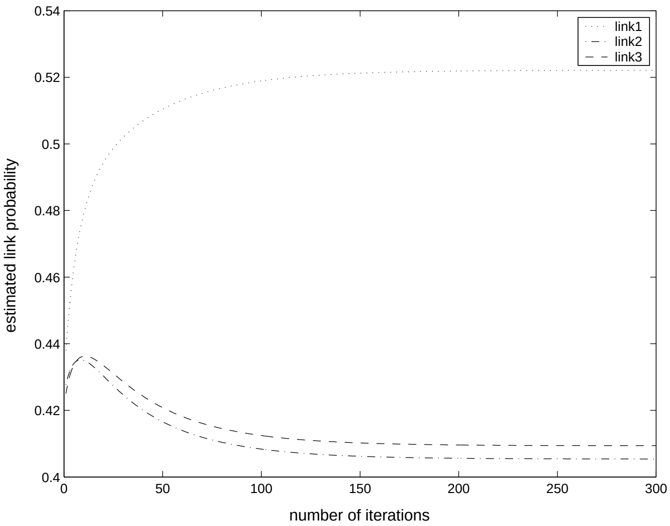

Fig. 10. Convergence of EM with 2-state Markov links of $p_{0j} = p_{1j} = 0.8$

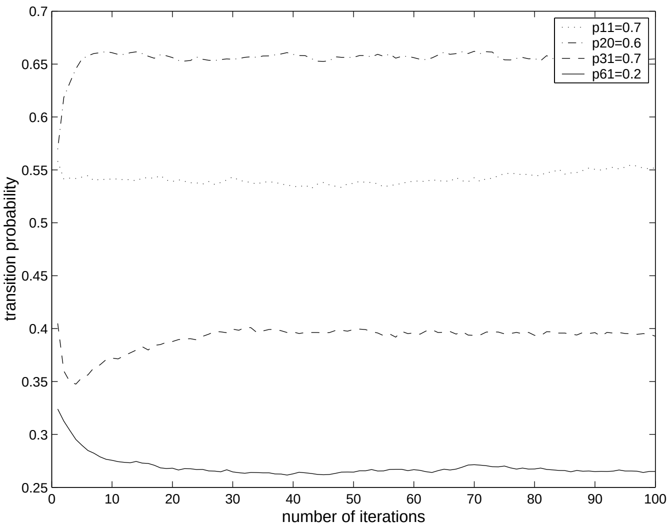

Fig. 11. EM algorithm with Gibbs sampling

set of link probabilities. As proved in [2], the link probabilities converges to the actual values as the number of samples increases. However, for small number of samples, the estimated link loss probabilities are even greater than 1. This was expected since the solution to this problem is obtained by finding extremum points of the likelihood function without putting any constraint on the link probabilities.

Figure 8 shows the estimated link probabilities for direct estimation and EM algorithms for the first set of link probabilities. There is slight difference in their behavior when the number of samples is low but then they exhibit exactly the same behavior as the number of samples increases. Figure 9 shows the convergence of EM algorithm as the number of iterations increases for 100 samples when the direct estimation algorithm gives link loss probabilities greater than 1. We can see that the converged values are like the clipped values of direct estimation estimates.

We simulated the network with Markov temporal characteristics of equal transition probability of 0.8 with the EM algorithm for independent link losses. We observe from Figure 10 that the convergence rate decreases and the convergence value is almost equal to the stationary distribution.

We then performed the simulation over the network with Markov temporal correlations. Figure 11, Figure 12 and Fig-

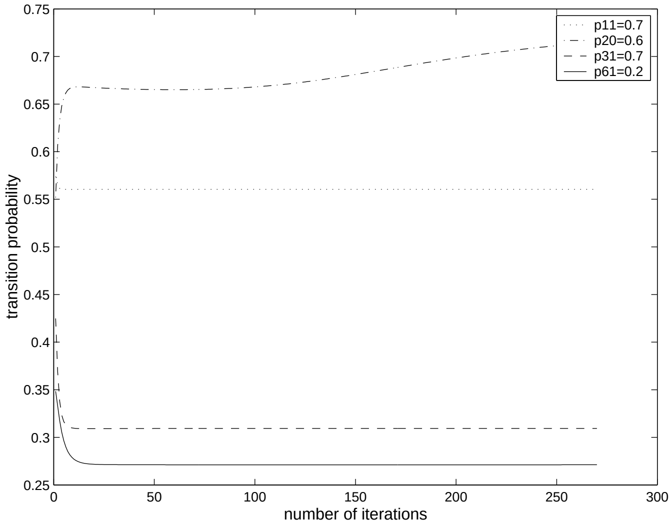

Fig. 12. EM algorithm with completely factorized variational approximation

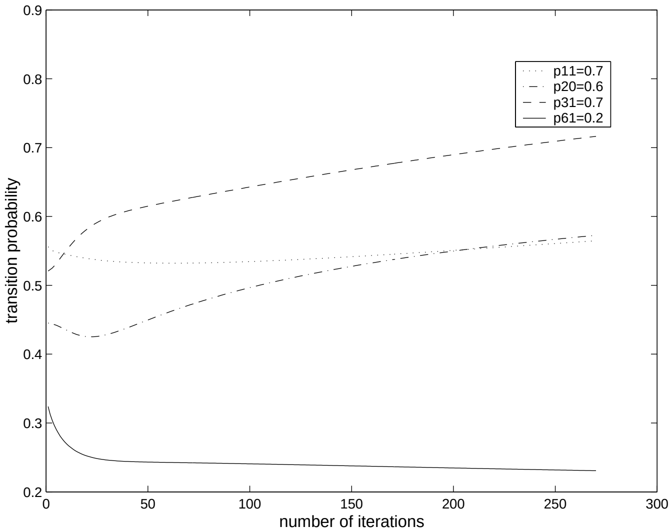

Fig. 13. EM algorithm with structured variational approximation

ure 13 show the results of EM algorithm from Gibbs sampling, completely factorized and structured variational approximation respectively. Table I gives the exact converged values for all the links and all the approximation methods. The link probabilities of the leaves are very close to the real values whereas the probabilities of the links higher in the tree exhibit a lot of error. The structured variational approximation performs much better than the completely factorized one. Structured variational approximation sometimes performs better than Gibbs sampling. This is probably caused because of insufficient number of sampling in Gibbs sampling.

VII. Conclusion

Determining link level loss characteristics of a network is essential in detecting congestion areas, routing faults, anomalous traffic for dynamic routing and video coding applications. Performing these measurements at each router may not be feasible because of the heterogeneous nature and the lack of centralized control for Internet. Even if this is possible, computing and communication overhead may not be tolerable.

Multi-cast based link level loss inference is chosen against unicast based approaches because of its efficiency. We first applied EM algorithm to the link loss estimation problem and compared the results with the direct estimation algorithm developed in [2] based on independent link losses over time. Simulations show that the behavior of EM and direct estimation algorithms are the same as the number of samples increases. If the number of samples is small, direct estimation algorithm can give link probability estimation outside $(0, 1]$ range since it is does not put any constraint on the link probabilities but it is proved to converge to the actual values as the number of samples increases. For small number of samples, the EM algorithm estimations are almost the clipped version of those of direct algorithm.

We then applied the above algorithm to the links with Markov temporal characteristics. We saw that the converged value is almost the steady state distribution of Markov Chain and the convergence is much slower. We then applied EM algorithm to the transition probability estimation problem of Markov chain at each link. We applied 3 techniques for the E-step: Gibbs sampling, completely factorized and structured mean field approximation. We observed that the estimation error for transition probabilities decreases as the links are closer to the observed nodes. We also observed that structured variational approximation performs much better than the completely factorized one as expected. It even performs better than Gibbs sampling due to possibly not enough sampling in Gibbs sampling.

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