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Using Dependence Tree Model and Upward-Downward Algorithm for Network Loss Tomography

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Abstract: It is essential to have link-level performance data for understanding the features of a network. Network tomography is based on end-to-end measurement to infer the network internal information. Instead of using classical method, we use the dependence tree model and upward-downward algorithm to infer link loss ratio, which requires a relatively small number of free parameters by making Markov-like assumptions on the tree. The simulation result shows the method works efficiently and produces reasonable accurate results.
Keywords: network tomography, dependence tree, upward-downward algorithm

1. INTRODUCTION

To better design, control and manage the network, the characteristics of the network play an important role, which includes link loss ratio, link delay and etc. Routing algorithms, service strategies, security procedures, and performance verification can benefit from monitoring techniques that report such information. Monitoring techniques can be performed internally but it is impractical to measure characteristics directly at all internal devices for a number of reasons. A reasonable way is to infer the network internal behaviors by “external” end-to-end measurement. This problem is often referred to as network tomography[1].

There are several groups investigate methods for inferring the network internal loss ratio[2]-[6], they use maximum likelihood estimate and EM algorithm to calculate after measurement . In this paper, we use the tree model and upward-downward algorithm[7] to infer the link loss ratio, which requires a relatively small number of free parameters by making Markov-like assumptions on the tree.

A multicast probe traffic is added from the root node on the ongoing traffic. Analyses are done at several receivers based on the received probes and the link loss ratios are inferred. The key to this approach is that multicast traffic introduces correlation in the end-to-end losses measured by receivers. This correlation can, in turn, be used to infer the loss behavior of the links within the multicast routing tree spanning the sender and receivers.

The inherent structure of networks makes this problem ideally suitable to the dependence tree [7]. The dependence tree is a model for the joint probability distribution of an n-dimensional random vector, let X=(X1,X2,…,Xn) be a discrete fixed-length random vector and P(X) be the joint probability function of X. The dependence tree is defined by a three-element tuple {X,S,P}, S is the structure of the tree that defines the causal influences among the variables in X. If the tree structure is given and only the joint probabilities are unknown, then parameter estimation with missing data can be solved using upward-downward algorithm.

The rest of the paper is organized as follows. In Section 2 we present the model for multicast tree and describe the framework within which analysis will occur. We present the algorithm for computing packet loss estimations based on [7]. Section 3 presents the results of simulation experiments that validate our approach. The last section is devoted to concluding remark.

2. INFER LINK LOSS RATIO UNDER DEPENDENCE TREE MODEL

Here the loss of the probe packets is modeled on the logical multicast tree by a set of mutually independent Bernoulli processes, each operating on a different link. Losses are therefore independent for different links and different packets. A logical multicast tree is a special dependence tree, where observations only happen on the leaf nodes. Figure 1 is an expample of the dependence tree. We send probe packets from node 0, and receive at the leaf nodes. Each component of the vector X is a network node, X_i is assigned to the node i in the tree. A conditional probality $P(X_i|X_j)$ is associated with the edge in the tree, which means the success probability of node i having X_i received probe packets under the condition of its parent node j having X_j received probe packets.

Suppose a probe packet is sent from node 0, if node i received successfully, X_i=1, otherwise, X_i=0. And we can observe on the leaf nodes only, so there are three types of nodes as followed.

(1) Node 1 is the root node of the dependence tree;

(2) Leaf node $i \in S_{OM}$, which we can observe but its parent node is unobserved;

(3) Middle node $i \in S_{MM}$, which is unobserved and its parent node is unobserved too.

Define the parameters corresponding to a tree as equation (1), where $\pi(i)$ is the parent node of node i.

$$\theta = \{a_1^u = P(X_1 = u), a_i^{u,v} = P(X_i = u \mid X_{\pi(i)} = v) : 1 < i < n; u, v = 0 \text{ } or \text{ } 1\} \tag{1}$$

The data set for estimating the parameters of the tree consists of S samples of the random vector X, each sample is an independent n-dimensional vector $X^k=(X_1^k, X_2^k,\ldots X_n^k,)$, k=1,…,S that have some missing components, such as X_1-X_3 in Figure 1.

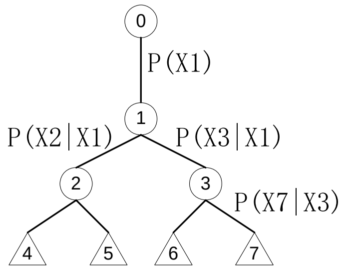

Figure 1. Multicast Tree Model

Until $|\theta^{(p)} - \theta^{(p-1)}| < \delta$

Output $a_i^{u,v}$

}

procedure upward-downward(k)

{ foreach node i

iterate up the tree, calculate $\beta_i(m)$、$\beta_{\pi(i)\backslash i}(m)$ [7]

foreach node i

iterate down the tree, calculate $\alpha_i(m)$ [7]

$$A_{i,k}^{m} \leftarrow \frac{\alpha_i(m)\beta_i(m)}{\sum_m \alpha_i(m)\beta_i(m)}$$

$$B_{i,k}^{m,m'} \leftarrow \frac{\alpha_{\pi(i)}(m')\beta_{\pi(i)\backslash i}(m')\beta_i(m)a_i^{m,m'}}{\sum_m \alpha_i(m)\beta_i(m)}$$

}

3. SIMULATION RESULTS

We evaluated our inference techniques through computer simulation and verified that they performed as expected. We used a software written in C++. We simulated the tree topology shown in Figures 1. Node 0 sent a multicast probes to the leaf nodes. Each link exhibited packet losses with temporal and spatial independence. We could configure each link with a different loss probability that held constant for the duration of a simulation run. Repeat the experiment 1000 times. We fed the losses observed by the leaves to a separate file that implements the inference calculation described earlier. For all node i, the initial values are $a_i^{u,v} = \begin{pmatrix} 1 & 0.5 \\ 0 & 0.5 \end{pmatrix}$. Iterate 30 times to converge. $\delta = 10^{(-4)}$, S=1000. Figure 2 compares the inferred packet loss ratio to the actual loss ratio.

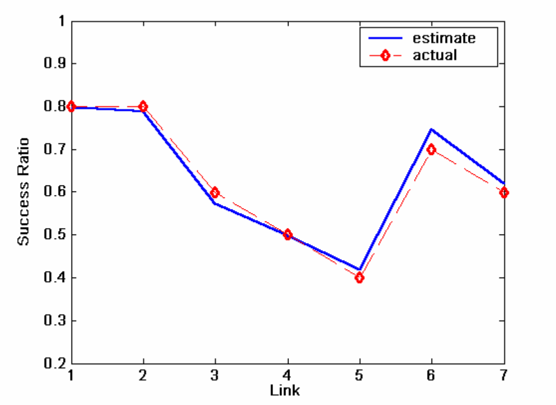

Figure 2. Success ratio of links

4. CONCLUSION

In this paper, we present a new approach to infer the link loss characteristic by end-to –end measurement. The inference method is built on the dependence tree model, which maps the link-level performance problem into a dependence tree. By exploiting the upward-downward algorithm to uncover link-level characteristics from incomplete data. The simulation result shows the method can produce reasonable accurate result. The result is almost identical to the result produced by other methods. We believe this technique would be an addition to the current study of network tomography.

We can use this model for network link delay tomography by defining the delay as discrete values. The dependence tree model can learn from incomplete data for both the conditional probabilities of links and the structure of the tree, we are investigating the methods to learn structure from data.

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