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Evaluation Model for IP Network Routing Decision based on PCA-ANN

Kuang Hong, Yang Zongchang, Liu Jianxun
School of Arts, School of Information and Electrical Engineering, School of Computer Science and Engineering,
Hunan University of Science and Technology, Xiangtan 411201, China

Abstract - As an act of moving information across an internetwork from one source to one destination, routing is vital for network activities. The IP (Internet protocol) network is the so-called "best-effort" communication network in which the best-effort delivery is provided for hosts. Accordingly, routing decision is closely related with a wide variety of network applications. This study presents one called PCA ("principal component analysis")-ANN ("artificial neural networks") evaluation model for routing decision. The PCA technology is used to reduce the dimension of the route measurement data to present the most effective structure of the route measurement data for the ANN to perform further evaluation. The proposed PCA-Based model is evaluated by experiments. Experimental results show its potentiality.

***Keywords*：** *routing decision; PCA; ANN; evaluation model.*

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I. Introduction

Routing is a vital act in networks. It is defined as an act of moving information across an internetwork from one source to one destination. Along this way, at least one intermediate device typically is encountered and this particular device is called the router, which usually performs routing. So the router is used to connect to at least two networks to offers routing information in the process of transporting information between hosts. The IP(Internet protocol) network provides one so-called "best-effort" service of delivering datagrams between hosts. The best-effort delivery indicates that the network does not offer any guarantee of data being delivered. The transmitting rate, latency and loss of the delivery is unspecified. Thus, in most instances, network applications are always trying to seek routing in the best moving ways. In this study, a called PCA ("principal component analysis")-ANN ("artificial neural networks") evaluation model for IP network routing decision.

II. Evaluation Approach for Routing Decision

A. *Route-tracing-based Obtaining of Measurement Variables*

There are two fundamental actions are involved in the IP network routing. One is to determine optimal routing paths, and another is called packet switching to transport information groups (packets) through the internetwork. Undoubtedly, the packet is moved or switched straightforward. However, because the IP network provides the "best-effort" delivery, the path determination can be complicated. Basically, parameters for routing decision should at least include the following two variables,

1) Path Length, which is usually quantified as the so-called "hop count". It is defined as one metric measurement to quantify the amount of nodes or called "passes" along internetwork in transporting one packet between hosts through the internetwork.

2) Route Delay, it is defined as the length of time required to transport one packet between hosts through the internetwork. Actually, many factors, such as, the network bandwidth, the port queues at each router along the way and the physical distance between hosts, affect the route delay. Because the delay is one important variable for describing the routing, it is one common-used standard of measurement.

To acquire routing information, the so-called route-tracing is usually used [1]. The route-tracing is to display a list of nearside router interfaces of the routers along the path between hosts. The route-tracing uses the IP TTL ("time-to-live") field in the ICMP echo requests and ICMP time exceeded messages to determine the path from a source to a destination. By incrementing the TTL value by one for each ICMP echo request it sends and then waiting for an ICMP time exceeded message, the route-tracing works. The principle of the route-tracing is illustrated in Fig.1, where S denotes one source host, D denotes one destination and Rn: denotes routers.

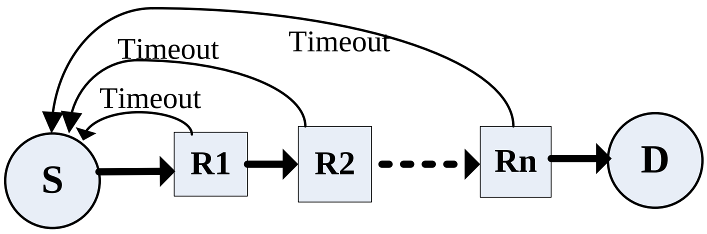

Figure 1. Illustration of the routing trace

B. *Evaluation Criteria*

To perform evaluation for routing decision, actually, it is one complex job. One simple solution may use one of the measured variables, however, which is a partial solution for the complicated job. . Accordingly, comprehensive solutions should be considered. The follows are the proposed evaluation criterions.

Assume a certain routing with path length of N (i.e., N nodes along the path) and delays from routers to a source host are measured as: $T_1 \ldots T_N$. Then, one routing of "good" performance should at least meet the two criteria as follows:

(1) Low path length and route delay. It can be quantified as: small values of N and average of ($T_1 \ldots T_N$): $\bar{T} = \frac{1}{N}\sum_{i=1}^{N} T_i$.

(2) Low fluctuation of time-delays (T_i) to indicate one relatively stable environment for delivery. It can be quantified as: the small variance of ($T_1 \ldots T_N$): $\sigma_X^2 = \frac{1}{N}\sum_{i=1}^{N}(T_i - \bar{T})^2$.

III. PCA-ANN-BASED ROUTING DECISION MODEL

A. Principal Component Analysis (PCA)

The PCA ("principal component analysis") also known as the Karhunen-Loève transform (KLT), is one of the most popular methods for feature generation and dimensionality reduction in data analysis [2]. It is an orthogonal linear transformation to transform the data to a new coordinate system.

Suppose given a random vector (column vectors) $\boldsymbol{x}_{N\times 1}$, and its mean μ_x:

$$\mu_x = E[\boldsymbol{x}] \tag{1}$$

Define covariance matrix $\boldsymbol{C}_x$ of $\boldsymbol{x}$:

$$\boldsymbol{C}_x = E\{[\boldsymbol{x} - u_x][\boldsymbol{x} - u_x]^T\} \tag{2}$$

From the definition, if follows that $\boldsymbol{C}_x$ is always symmetric. Let $\boldsymbol{A}$ be a matrix consisting of orthogonal eigenvectors of the covariance matrix $\boldsymbol{C}_x$ which are denoted as columns vectors:

$$\boldsymbol{A} = (\boldsymbol{a}_1, \boldsymbol{a}_2, \ldots \boldsymbol{a}_N) \tag{3}$$

Where, $\boldsymbol{a}_i^T \boldsymbol{a}_j = 0 (i \neq j)$ and $A^{-1} = A^T$

By transforming the vector $\boldsymbol{x}$, we get the vector $\mathbf{y}$ as follows,

$$\boldsymbol{y}_{N\times 1} = \boldsymbol{A}^T(\boldsymbol{x} - \mu_x) \tag{4}$$

Where, $\boldsymbol{y}$ is a point in the orthogonal coordinate system defined by the eigenvectors. Components (elements) y_i of $\boldsymbol{y}$ can be viewed as the coordinates (weights) in the orthogonal base:

$$\boldsymbol{y} = \boldsymbol{A}^T(\boldsymbol{x} - \mu_k) \quad \rightarrow y_i = \boldsymbol{a}_i^T(\boldsymbol{x} - \mu_x) = (\boldsymbol{x} - \mu_x)^T \boldsymbol{a}_i \tag{5}$$

We can reconstruct the original vector $\boldsymbol{x}$ from $\boldsymbol{y}$ by a linear combination of the orthogonal basis vectors. That is, from *Eq*.(4) and *Eq*.(5), we have

$$\boldsymbol{x} - \mu_x = \sum_{i=1}^{N} y_i \boldsymbol{a}_i = \sum_{i=1}^{N} \boldsymbol{a}_i^T(\boldsymbol{x} - \mu_x)\boldsymbol{a}_i = \sum_{i=1}^{N} \boldsymbol{a}_i(\boldsymbol{x} - \mu_x)^T \boldsymbol{a}_i \tag{6}$$

Instead of using all the eigenvectors of the covariance matrix, we may represent the data in terms of only a few basis vectors of the orthogonal basis. If selecting m principal eigenvectors $\boldsymbol{A}_m = (\boldsymbol{a}_1, \boldsymbol{a}_{2\ldots}\boldsymbol{a}_m)$, from *Eq*.(6), we can reconstruct or approximate $\boldsymbol{x}$ by:

$$\hat{\boldsymbol{x}} = \sum_{i=1}^{m} \boldsymbol{a}_i^T(\boldsymbol{x} - \mu_x)\boldsymbol{a}_i + \mu_x = \sum_{i=1}^{m} \boldsymbol{a}_i(\boldsymbol{x} - \mu_x)^T \boldsymbol{a}_i + \mu_x \tag{7}$$

In this way, it minimizes the mean-square-error (MSE) between the vector $\boldsymbol{x}$ and its representation (approximation) $\hat{\boldsymbol{x}}$ with given m principal eigenvectors [29,31-32]

$$E\left[\|\boldsymbol{x} - \hat{\boldsymbol{x}}\|^2\right] = E\left[\sum_{i=m+1}^{N} \|\boldsymbol{a}_i(\boldsymbol{x} - \mu_x)^T \boldsymbol{a}_i\|^2\right] = \sum_{i=m+1}^{N} \boldsymbol{a}_i^T C_x \boldsymbol{a}_i = \sum_{i=m+1}^{N} \lambda_i \tag{8}$$

That is, by picking the m eigenvectors having the largest eigenvalues, we lose as little information as possible in the mean-square sense. From *Eqs*.(**5**)-.(**8**) , we see that, representation $\hat{\boldsymbol{x}}$ (minus the mean**)** is the projection of $\boldsymbol{x}$ **(**minus the mean**)** into the subspace spanned by the principal m eigenvectors.

B. Artificial Neural Networks (ANN) Mode

The ANN ("artificial neural networks "or "neural networks") [2-7] is one of the commonly-used paradigms for computing. It is inspired by the animal's nervous system. Then the ANN works simulating the way of the animal brain in processing information. It is widely used in ML ("machine learning" as well as PR ("pattern recognition").

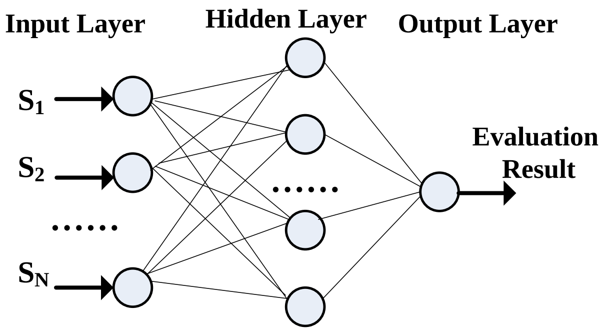

Figure 2. A classical ANN model with 3 layers

The BP-ANN is known as the so-called "feed-forward back-propagation artificial neural network". The BP refers to the "Back-Propagated Delta Rule Networks". It was developed from the called "simple Delta rule", which indicates extra hidden layers are the layers additionally added and connected between the input and output layers. The typical network topology (Fig.2) is defined to be feed-forward. That is, the input-information-flow is allowed forwardly from the input layer to the hidden layer(s), and then to the output layer. While the error is computed at the final output layer and then distributed back through the network layers, which is called the backward propagation of errors. The hidden layer is very import because with the hidden layer, the ANN can become more "intelligent" to "learn" to provide a description or mapping for the input-information. The classical BP-ANN model usually uses one hidden layer. Of course, the ANN may

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be more powerful when it has more than one single hidden layer. Their input/output graph usually uses the called “S function”.

When number of layers and number of units in each layer have been determined, we are going to train the ANN to modify or update weights and thresholds of the network to minimize the prediction error. Finally, after the training, the network is ready for testing or working. That is, the ANN applied to “learn” from some different data that are used in the “training’. As the ANN has been trained, it can work well, such as, it correctly recognize the input-data in a suitable way. It should be careful of the two issues called “under-fitting” and “over-fitting” in the training.

C. The Proposed PCA-ANN Evaluation Method

. Accordingly, the proposed evaluation method for the network routing decision is illustrated in Fig.3.

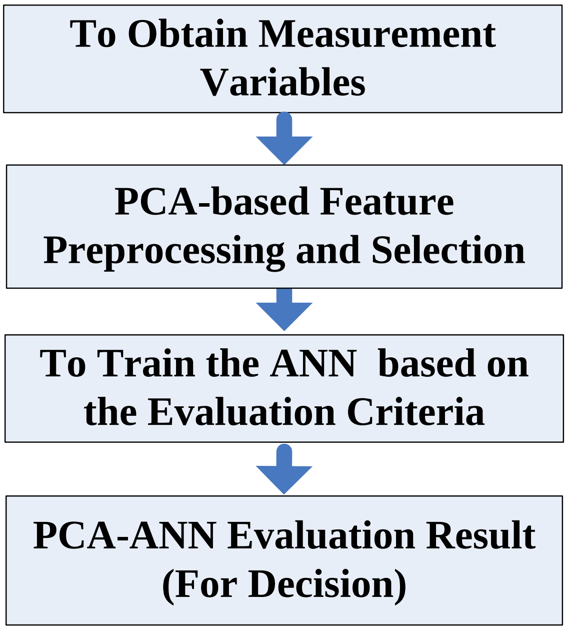

Figure 3: The proposed evaluation method for routing decision

In the proposed evaluation model, it is consisted of four stages, which are: (1) to obtain routing measurement variables, (2) to PCA-based feature preprocessing and selection, (3) to train the ANN based on the evaluation criteria, and (4) the PCA-ANN works to yield evaluation result for routing decision.

IV. EXPERIMENT RESULTS

The training of the BP-ANN can be analogous to a baby or child learning something from the input instances. When the examples are chosen better, and with a sufficient amount of training, the ANN will be able to work well. The best training procedure is to “learn” a wide variety of examples to show much enough different characteristics. It is important to select appropriate examples or instances for the “training”.

Six groups of learning samples (S1, S2…S6) listed in TableI are chosen for training the PCA-ANN model. Where, the default route length is 30. If route length is less than 30, the left T value will be set to 0. The waiting-time for each reply is 1000 milliseconds. The T value is set as -1 if wait timeout for one reply. The expected evaluation value scores its routing communication performance.

In the PCA-ANN evaluation model for routing decision, the ANN one classical 3-layers structure. That is, one input layer with 30 nodes, one hidden layer with 40 nodes and one output layer with one node to yield result. After training the BP-ANN model, 5 different routings (R1, R2…R5) are chosen to test the PCA-ANN model. Results are listed in Table 2. The evaluation results show that they follow the evaluation rules properly, and yield acceptable values for routing decision reference.

TABLE I. TRAINING DATASET FOR THE PCA-ANN MODEL

Ti (delay of every hop)	***Routing Trace***					
	S1	S2	S3	S4	S5	S6
T1	-1	1	5	20	20	50
T2	-1	0	5	20	20	50
T3	-1	0	5	20	20	50
T4	-1	0	5	20	20	100
T5	-1	0	5	20	20	100
T6	-1	0	5	20	20	100
T8	-1	0	5	20	20	100
T9	-1	0	5	20	20	100
T10	-1	0	5	20	20	100
T11	-1	0	0	20	30	100
T12	-1	0	0	20	40	200
T13	-1	0	0	20	80	200
T14	-1	0	0	20	70	200
T15	-1	0	0	20	100	200
T16	-1	0	0	0	100	200
T17	-1	0	0	0	100	200
T18	-1	0	0	0	100	300
T19	-1	0	0	0	100	500
T20	-1	0	0	0	100	900
T21	-1	0	0	0	100	900
T22	-1	0	0	0	100	-1
T23	-1	0	0	0	150	-1
…	…	…	…	…	…	…
T29	-1	0	0	0	250	-1
T30	-1	0	0	0	250	-1
Expected evaluation value	0.00	100.00	85.00	70.00	60.00	30.00

TABLE II. EVALUATION RESULTS FOR ROUTING DECISION

Ti (delay of every hop)	Routing Trace				
	R1	R2	R3	R4	R5
T1	20	17	10	10	20
T2	20	17	10	10	20
T3	20	17	10	10	20
T4	20	19	10	10	20
T5	20	20	10	10	20
T6	17	20	80	10	20
T7	90	21	80	41	100
T8	90	135	90	42	100
T9	100	135	250	100	290
T10	901	140	250	100	290
T11	978	152	250	120	290

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T12	990	-1	250	120	-1
T13	998	-1	250	0	300
T14	-1	-1	250	0	-1
T15	0	-1	0	0	-1
T16	0	-1	0	0	-1
T17	0	-1	0	0	-1
T18	0	-1	0	0	-1
T19	0	-1	0	0	-1
T20	0	0	0	0	-1
T21	0	0	0	0	-1
T22	0	0	0	0	-1
T23	0	0	0	0	0
…	…	…	…	…	…
T29	0	0	0	0	0
T30	0	0	0	0	0
Evaluation Value	56.84	45.23	65,12	76.55	40.83

V. CONCLUSIONS

Routing as an act of moving information across an internetwork from one source to one destination is a vital act in networks. The IP(Internet protocol) network provides one so-called “best-effort” service of delivering data between hosts. The best-effort delivery means that the network does not offer any guarantee of data being delivered. In this study, a PCA-ANN-based evaluation model for routing decision is proposed and applied to experiments. Experimental results show its potentiality. The evaluation results follow the proposed evaluation criteria properly. The proposed method may benefit other applications. However, to further investigate or improve the proposed method is still included in the future study.

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