Guyot: a Hybrid Learning- and Model-based RTT Predictive Approach

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Abstract—**Knowing the Round-Trip Time (RTT) between a client and a server is important for an online interactive multimedia service to provide satisfactory quality of user experience. Due to the intrinsic dynamics of the topology and routing strategies in the Internet, it is however challenging to predict the RTT accurately from limited information, e.g., only the IP pair of the client and server. To address this challenge, we propose *Guyot*, a hybrid learning- and model-based approach to predict RTT, which requires significantly smaller amount of data to be collected than traditional approaches, while achieving a similar prediction accuracy. Our design is based on a large-scale measurement study from a content provider's perspective. Based on an information gain analysis, we design a hybrid RTT prediction approach involving two types of predictions: (1) Learning-based prediction: We train a decision tree to predict RTT between IP pairs with large geographic distance, requiring only a small set of features to be collected. (2) Model-based prediction: We use a model-based framework to predict RTT between IP pairs with small distance, providing an accurate RTT prediction over time. By strategically dividing RTT prediction tasks to these two types according to the distance of the inferred geo-locations of the IPs, our prediction approach can scale with satisfactory accuracy. Our experiments further confirm the superiority of our design.**

I. Introduction

RTT between IP pairs is an important metric for online interactive services, which have seen a rapid growth on today's Internet, e.g., Massively Multiplayer Online Games (MMOGs) such as the World of Warcraft, attract millions of global players [1]. As RTT is one of the most important factors that affect the quality of experience in such online interactive applications, inferring RTT from basic information (e.g., IPs of a client and a server) is critical for service providers to evaluate and proactively improve the quality of experience for users in such applications [2]. Since the IP network is based on the design philosophy of best-effort forwarding, it is however difficult to directly calculate the RTT between any pair of IPs. To this end, previous works used models and learning frameworks to infer RTT, respectively.

Strategies based on modeling the Internet infrastructure. Madhyastha et al. [3] constructed an "atlas" of the Internet, i.e., a dataset of probing measurement, and predicted latency between two IPs by summing latencies of all segments in the routing path between the two IPs. Dabek et al. [4] proposed a decentralized synthetic coordinate system, using a virtual distance to estimate the latency between Internet hosts — Internet hosts are assigned a virtual coordinate and the "distance" between two hosts in the synthetic coordinate space is used to predict the RTT.

Strategies considering the Internet as a black-box. Belhaj et al. [5] constructed a mathematical model of the proposed Recurrent Neural Networks (RNNs), with two phases, (i.e., a learning process characterizing the RTT and a validation phase) to estimate RTT. A machine-learning technique known as the *Fixed-Share Experts Algorithm* was used by Nunes et al. [6] and each of several "experts" provides an estimated value. The weighted average of these estimate values is used to estimate the final RTT, with the weights updated after every RTT measurement.

The two types of strategies to infer RTT have the following limitations in the context of massive users in today's online applications: (1) For strategies based on the awareness of the Internet infrastructure, there is a huge amount of active or passive measurement load (e.g., maintaining updated topology knowledge and the latencies between routers), limiting the scalability of the RTT prediction system. (2) For strategies that consider the Internet as a black-box, they are not able to reflect the dynamics of RTT, as RTT is changing over time.

To address these two challenges, we propose *Guyot*: a hybrid learning- and model- based RTT predictive approach. Our contributions in this paper are summarized as follows.

▷ We carry out large-scale measurement studies on the characteristics of RTT in popular online services, based on traces provided by the CDN team of Tencent. Our results demonstrate that IP pairs that have different geographic distances have different RTT characteristics, e.g., IP pairs with a large geographic distance have much stable RTT measures than those with a small geographic distance.

▷ Motivated by our observations, we propose a hybrid RTT prediction approach for IPs with different distances, i.e., *inter-region* and *intra-region*. Our proposal combines the advantages of the "black-box" approaches that consider the Internet as a black box and model- based methods that take the Internet infrastructure into account seamlessly. For the inter-region IPs, we predict the RTT between them using a learning-based framework; and for the intra-region IPs, we predict the RTT between them using a model-based framework. A threshold is

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learnt from our measurements to determine which type an IP pair belongs to.

▷ Based on a prototype implementation, we have evaluated the performance of our proposal with real-world experiments. Our proposal is able to predict the class of RTT for large distance with an accuracy of about 80%, and for small distance, our proposal achieves the relative error within 10% for 70% of predictions.

The rest of the paper is structured as follows. In Section II, we investigate the dynamic characteristics of RTT, and describe our motivation and design principle. *Guyot* is presented in Section III. In Section IV, we evaluate the performance of *Guyot*. Section V discusses the related work. We conclude in Section VI.

II. Design Principles Learnt from Measurement Studies

In this section, we carry out measurement studies to investigate the characteristics of RTT between any pairs of IPs. In particular, we study the impact of distance between IPs on the prediction of their RTT.

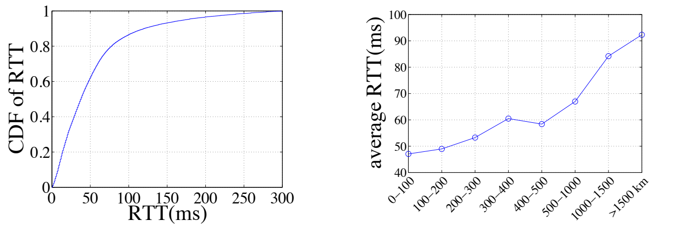
A. Measurement Methodology

First, we present our trace-driven measurement methodology.

1) Overview of Datasets: The datasets provided by the CDN team of Tencent consist of two parts:

Passive Measurement: The TCP traces record how the TCP connections that Tencent CDN servers serve their users. Our traces contain 146 million records, collected by 700 servers located in 24 different provinces in China in May 2013. Each of the records contains the following information: (1) The timestamp when a TCP connection is established, (2) The amount of data for the uplink and downlink transmission, (3) The latency between a client and the server, and (4) The time elapse to deliver the data. Among these logs, 92% of them have RTT smaller than 300 ms, which are typical latencies for real-time interactions [7].

Active Measurement: We also actively collect a large amount of traces regarding to the RTT and network topology. We use network diagnostic tools including *ping* and *traceroute*, which are widely used to determine connectivity and routing path in IP networks, to retrieve RTT and the routing paths periodically between several CDN servers those sampled for collecting the passive measurement data and randomly selected client IPs. Our active measurement is as follows: (1) We configure the ping tool to send 10 ICMP echo-request packets which consists of 64 bytes to the clients every minute. (2) In order to avoid stochastic fluctuation, we use the average RTT of 10 packets as the RTT in one minute, i.e., we collect 1440 items of RTT records for each client-server pair everyday, each record consists of timestamp when the packet is sent, the Time to Live (TTL) value and RTT the packet experiences.



(a) RTT distribution

(b) Average RTT in different distance ranges

Fig. 1: RTT distribution and RTT vs. geographic distance

2) Preprocessing of the Traces: Our preprocessing to the traces above is as follows.

Distance Preprocessing. Geographic distance is an important inference to the RTT between two IPs. In our study, we estimate the distance between IP pairs as follows. We translate an IP to a geo-location with a latitude and a longitude, and calculate the distance between any two IPs using the location information. In our distance preprocessing, we use several IP-to-location databases [8], [9] for cross validation, and only use logs with IPs that different databases provide the same location information.

RTT Preprocessing. In our dataset, over 90% logs have RTT smaller than 300 ms, and only a very small fraction of them have very large RTT. The reason may be that in these TCP connections, the clients encounter some network jitters or server load bursts. To eliminate the impact of such randomness, we have removed from our experiments the logs with RTT larger than 300 ms, as illustrated in Figure 1(a).

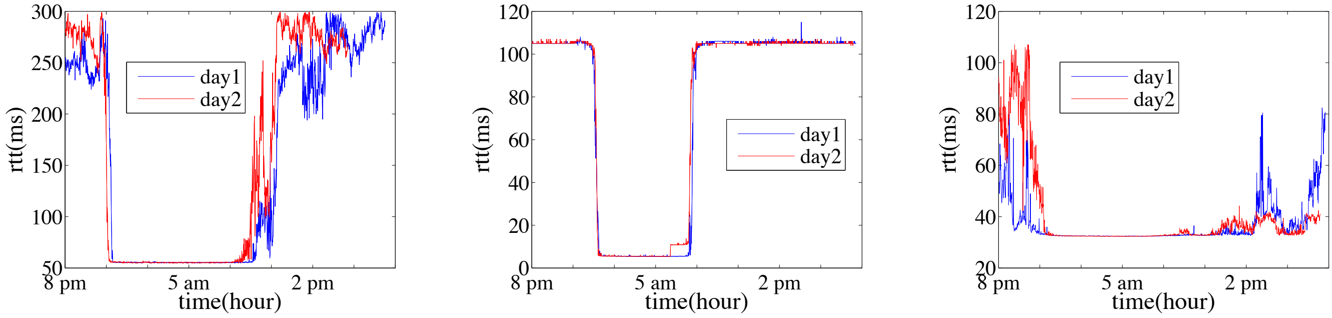
B. Features to Predict RTT in a Learning-based Framework

We firstly study the factors that affect RTT, including ISP, the period when the RTT is measured and the geo-distance between IP pairs.

1) ISP: Firstly, RTT is affected by the ISPs hosting the server and client. Figure 2 compares the RTT patterns over time (in two consecutive days), when servers are deployed in different ISPs, i.e., *China Mobile*, *China Unicom* and *China Telecom*. We have made the following observations: (1) The *shapes* of the curves (i.e., RTT over time) are highly affected by the hosting ISPs; (2) The fluctuation levels of the curves are also affected by ISPs; and (3) The averages of RTT are also affected by the hosting ISPs. In our RTT prediction design, ISP is thus an important factor to be considered.

2) Time: Next, we study the impact of time when the RTT is measured. From Figure 2, we observe that during the night about $11:00\ pm$ to $9:00\ am$, there is an obvious decrease in RTT, and the RTT oscillate during other periods. This can be easily explained by the daily Internet access pattern of users which incurs the variances of traffic and workload on routers and servers during different periods.

3) Geo-distance: In Figure 1(b), the curve represents the average RTT during one day versus the geographical distance between two IPs. We observe that as the distance between



(a) China Mobile (b) China Unicom (c) China Telecom

Fig. 2: RTT dynamics with different ISPs

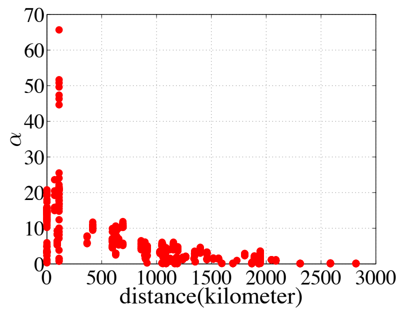


Fig. 3: RTT fluctuation versus the geo-distance between IPs

a server and a client increases, the average RTT generally increases as well, showing a positive correlation.

C. Demand for Model-based RTT Prediction Framework

Though learning-based framework may use minimized collection of features to "learn" the RTT between IPs, it provides inaccurate RTT predictions when the distance between IPs is not large enough, according to our measurement study.

1) RTT Fluctuation of Different IP Distances: We define a parameter α, to identify the extent of RTT fluctuation during a day in different distances, as follows, $\alpha = \frac{\max(RTT)-\min(RTT)}{\min(RTT)}$. In Figure 3, we plot the extent of fluctuation (α) versus the geo-distance between IPs. We observe a general trend that the level of fluctuation decreases as the geo-distance grows. As a result, for IPs with small geo-distance, we need to utilize a model-based approach that takes the under-layer topology of the infrastructure between IPs into account, to estimate the RTT.

2) Information-Gain Analysis: We further use an information gain approach [10] to study how we choose different approaches for RTT prediction. The information gain approach is based on the idea of entropy of a random variable X which is defined as (X): $H(X) = \sum_{i=1}^{n} -P(X = x_i)log_2 P(X = x_i)$, where $P(x_i)$ is the probability that $X = x_i$. The relationship of distance, ISP and RTT can be achieved by the relative mutual information gain, $I_{relative}(X; RTT) = \frac{H(RTT)-H(RTT|X)}{H(RTT)}$, where X denotes the geographic distance between the client and the server, or the ISP (ISPs are indexed).

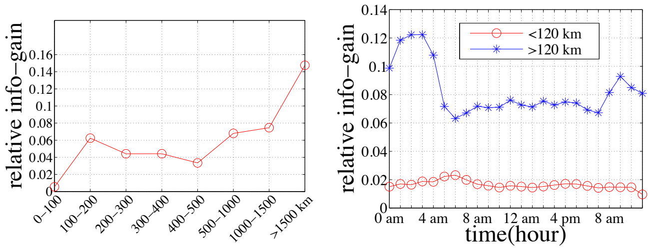
To study how we choose different prediction strategies based on the distance between IPs, we divide the distance between servers and clients into 8 categories, based on the distance distribution in our dataset, as follows: (1) $distance < 100$ km, (2) $100 \le distance < 200$ km, (3) $200 \le distance < 300$ km, (4) $300 \le distance < 400$ km, (5) $400 \le distance < 500$ km, (6) $500 \le distance < 1000$ km, (7) $1000 \le distance < 1500$ km, (8) $distance \ge 1500$ km. Note that for real prediction systems, the division may vary according to the real measurements.

Using the mutual information gain, we firstly study the correlation between the distance between two IPs and the RTT. In Figure 4(a), the curve represents the relative information gain between RTT and the geo-distance levels. We observe a positive correlation between the distance and the relative mutual information gain (the average RTT versus distance), indicating that for IPs with small distance, there are potentially other factors affecting the RTT, requiring a more detailed (e.g., the under-layer network topology) model-based prediction strategy. Kay et al. [11] summarized that RTT depends on the network topology and traffic conditions. Delay in each router depends on many factors such as the constant forwarding delay and variable queue delay. And the routers along the network path between the sending host and receiving host have a cumulative latency affect. In Section III, we will present the details how the network topology is considered in our prediction approach.

D. Choosing between Learning- and Model-based Approaches

Next, we investigate how we choose between the learning-based prediction and model-based prediction for different IP pairs. From Figure 3, we observe that the level of fluctuation are stable when the distances are larger then 120 kilometers compared with those smaller than 120 kilometers, i.e., there exists a threshold that can divide IP pairs according to their geographic distances into two groups which have dramatically different information gain with the RTT. We will show their information gain in the following part.

In our experiments, the threshold is around 120 kilometers. Please note that 120 kilometers is not applicable everywhere,



(a) Fine-grain level

(b) Coarse-grain level

Fig. 4: RTT relative mutual information gain vs. distance

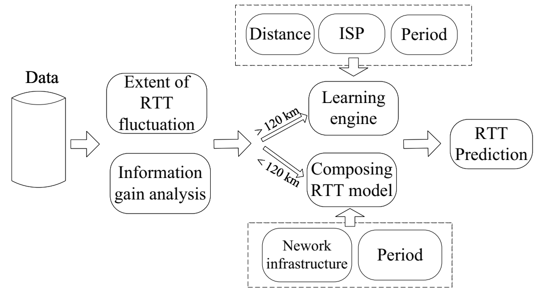


Fig. 5: The framework of our hybrid learning- and model-based (referred as composing RTT model) RTT prediction

we consider it as the threshold based on the analysis of collected traces. As illustrated in Figure 4(b), when the distance between IPs is below 120 kilometers, the mutual information gain is very small, indicating that there are many other factors determining the RTT; while when the distance is larger than 120 kilometers, the mutual information gain is relatively large. The reasons are as follows: (1) A larger distance means more random disturbances which maybe counteract each other; (2) The total RTT will become larger, therefore, some random disturbance is trivial related to the total RTT.

E. Principle Learnt: a Hybrid Predictive Structure

Based on studying the impact of different factors on RTT, and the information gain analysis, we have learnt a principle that can improve the prediction of RTT, between IPs with both short and large geographic distances. When the distance between the server and the client is larger than a threshold, the relative mutual information gain between the distance and the RTT is relatively large and the relative RTT fluctuation is small, indicating that a learning-based prediction can yield a good result. When the distance is smaller than the threshold, we observe that the relative RTT fluctuation is larger, indicating the more detailed investigation of the network infrastructure is still on demand to predict the RTT accurately.

III. Detailed Design of The Hybrid RTT Prediction

Based on the principles learnt, we next present the details of our RTT prediction design.

A. Framework

Figure 5 illustrates the framework of our hybrid approach, we choose between the learning-based strategy and model-based strategy to predict the RTT, according to the geographic distance between the two IPs. (1) For IP pairs with large distances, we use the learning-based strategy, in which a *decision tree* is trained to predict their RTT; (2) For IP pairs with small distances, we use the model-based strategy (referred as composing RTT model in Figure 5) in which a router-latency database is maintained, to predict their RTT.

B. Learning-based Prediction

1) Attributes for Constructing the Decision Tree: In the learning-based prediction, we build a decision tree for RTT prediction based on the different attributes' mutual information gains with RTT. According to our measurement study, we use the following attributes for the learning: (1) The distance between the client and the server, (2) The server's ISP provider, (3) The time when the measure is carried out. We divide the target attribute (i.e., RTT) into discrete levels for training the decision tree, by using a *K-means* algorithm with $K = 5$, e.g., the RTT levels for 9 am are as follows: (1) $10 \leq RTT < 30$ ms, (2) $30 \leq RTT < 42$ ms, (3) $42 \leq RTT < 61$ ms, (4) $61 \leq RTT < 94$ ms, (5) $94 \leq RTT \leq 195$ ms. Note that, the levels generated by the *K-means* depend on the distribution of RTT collected in one hour.

2) Constructing the Decision Tree: The internal nodes of the tree represent the test on the chosen attributes. Each branch descends from the node corresponding to the classification of the attribute. Leaf nodes represent the RTT level. In order to reduce the effect of the bias (towards attributes that have multiple levels) resulting from the use of information gain schemes, the information gain was divided by the Split Information, whose value depends on the number of values a categorical attribute and how uniformly those values are distributed [12]. The decision tree model is constructed using 10-fold cross-validation [13], i.e., each round takes 90% of the samples for training and the remaining 10% for test.

C. Model-based Prediction

For IPs with small geographic distance, we use a model-based strategy to predict their RTT.

1) Routing Path Discovery: Firstly, we use the traceroute tool for routing path discovery, and our hypothesis is that the network topology is stationary for at least for a finite period of time [14]. We retrieve the changing latencies of the intermediate routers along the network path by the ping tool.

2) Calculating Router Latencies in a Routing Path: For a specific routing path from a *source* (s) to a *destination* (d), there are several routers between them, denoted as $R_1, R_2, R_3 \ldots R_i, R_{i+1} \ldots R_n$. We calculate the latencies between consecutive routers ($L_{R_i,R_{i+1}}$) as follows, $L_{R_i,R_{i+1}} \leftarrow PING_{s,R_{i+1}} - PING_{s,R_i}$, where $PING_{s,R_{i+1}}$ is the actively ping'ed latency between the source s and the router R_{i+1}.

3) Constructing the Latency Database: Based on this history traces, we build a database, which is updated over time. The servers running our system periodically traceroute randomly selected client IPs, to retrieve routers in an intra region. Then, the servers ping these routers to retrieve the latencies between routers. These latencies are stored in a database for our model-based RTT prediction.

4) RTT Prediction: When the server predicts the RTT between it and a client, our design retrieves the path and router-latency information from the database, and calculate the predicted RTT by summing up the latencies of router pairs along the routing path between the server and the client.

D. Guyot: Trading Scalability for Accuracy

In our hybrid approach, the previous two strategies are selectively used. For IPs with large distances, we only need the IP pairs and get their distance and ISP information for the prediction. For IP pairs with small distances, to accurately predict the RTT between them, we will need to update the latency database frequently. Our design gives the system operation a chance to tradeoff between the prediction accuracy and the amount of information to be collected and maintained (e.g., in a database). In our evaluation, we will further present the results on such tradeoff.

IV. Evaluation

In this section, we evaluate the performance of our prediction approach. We aim to answer the following questions: (1) What is the accuracy of the learning-based prediction without information about the Internet infrastructure? (2) What is the accuracy of the model-based prediction? and (3) What is the overall performance of the hybrid approach?

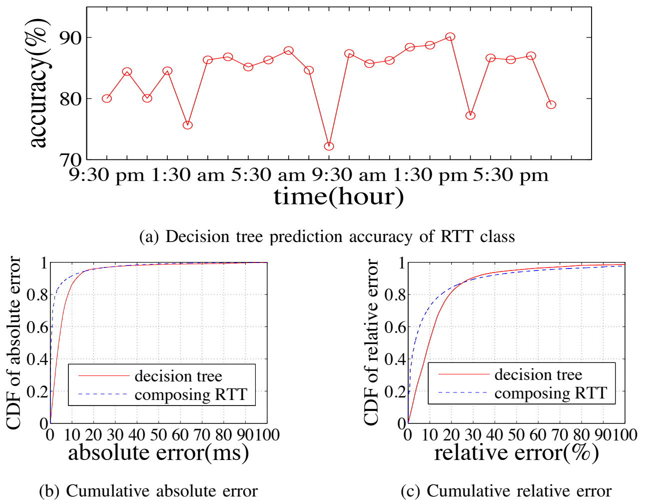
Our experiments are carried out as follows. We choose the prediction strategies according to the distance between IP pairs. For the learning-based prediction, we consider the centroid value of the class predicted by the decision tree, which is constructed based on the history traces collected in the previous hour, as the estimated RTT; for the model-based prediction, we get the RTT by composing the latency of each hop along the network path.

Metrics. For the model-based approach, we consider the absolute error and relative error of predicted RTT (in ms), defined as: $Error_{abs} = |RTT_{real} - RTT_{predict}|$, $Error_{rel} = \frac{Error_{abs}}{RTT_{real}}$. For the learning-based approach, besides these two errors, we also evaluate the *accurate ratio*, defined as the ratio of RTT which is predicted into the correct class.

A. Learning-based Prediction Performance

We firstly study the prediction performance of the learning-based approach. In Figure 6(a), the curve represents the accurate ratio for the learning-based approach over time. We observe that the learning-based prediction that only uses the ISP and distance information can achieve a high accuracy ratio of over 80%, to classify RTT into correct class. Besides, we observe that the accuracy ratio drops to the lowest value at around 9:30 am. The reason may be that the network suffers dynamics during this period.

Furthermore, we study the errors of the RTT predicted. In Figure 6(b)(c), the "decision tree" curves give the CDF of the absolute error and relative error in the learning-based prediction, respectively. We observe that our learning-based prediction achieves an absolute error within 10 ms for over 80% of the cases, and a relative error smaller than 10% for 50% of the cases, slightly better than traditional approaches that are based on the learning models, e.g., [4] which has a relative error of 10% for 40% cases.



(a) Decision tree prediction accuracy of RTT class

(b) Cumulative absolute error

(c) Cumulative relative error

Fig. 6: Evaluation of decision tree and composing RTT accuracy

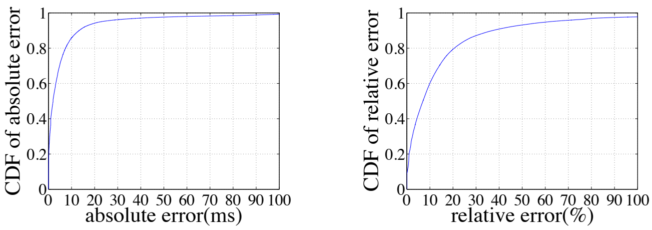
B. Model-based Prediction Performance

Next, we evaluate the model-based prediction. As illustrated in Figure 6(b)(c), the dot curves, referred as "composing RTT", show the CDF of the absolute error and relative error in the model-based predictions, respectively. We observe that over 90% (resp. 70%) of our predictions have an absolute error smaller than 10 ms (a relative error smaller than 10%). The results indicate that both predictions in our approach can work accurately when being used separately.

C. Hybrid Approach Performance

Finally, we study the overall performance of the hybrid prediction approach. We randomly select IP pairs from our dataset, with varying geographic distances. For an IP pair, we choose a prediction scheme from the learning-based and model-based schemes, to predict the RTT, according to our design. Figure 7(a)(b) illustrate the CDF of the absolute accuracy and relative accuracy for the overall prediction results. We observe that our hybrid approach achieves an absolute error below 10 ms for about 90% of the predictions.

Our results indicate that the model-based approach which achieves better prediction accuracy but requires very detailed information to be frequently collected from the Internet, and the learning-based approach which has a lower accuracy but requires a small amount of information for prediction, can be combined into a hybrid prediction, with promising RTT prediction results, for scalable systems.



(a) Cumulative absolute error

(b) Cumulative relative error

Fig. 7: Evaluation of overall hybrid approach

V. Related Work

RTT is critical to the users' quality of experience, it is concluded in [15] that latencies larger than 60 ms incur disturbing experience. A considerable amount of research has been done on the prediction of RTT.

A. Constructing Synthetic Coordinate Systems and Network Latency Databases

Many works have carried out on constructing the coordinate systems and network latency databases for predicting RTT.

Synthetic Coordinate system: Systems those belong to this kind all require global knowledge of node measurements. Landmark is one of the first techniques to calculate synthetic coordinates (e.g., GNP [16]) to predict Internet latency, however the choice of landmarks significantly affects system accuracy [17]. Dabek et al. proposed a decentralized synthetic coordinate system [4], using a virtual distance to estimate the latency between Internet hosts.

Network Latency Database: Madhyastha et al. [3], [18] constructed an "atlas" of the Internet and utilized it to compose the segments of the path to predict the RTT between the IP pairs.

B. Training Black-boxes

Other works considered the Internet as a black-box. Some classic machine-learning algorithms (e.g., Recurrent Neural Networks [5], *Fixed-Share Experts Algorithm* [6]) are utilized to estimate the RTT based on the collected traces, with the training and validation phases.

Our study is based on a real-world measurement of RTT characteristics in today's online applications, and we propose a hybrid approach to combine the benefits of the two types of RTT predictions.

VI. Conclusion

In this paper, based on a large-scale measurement and information gain analysis, we propose Guyot, a hybrid apporach for RTT prediction, which balances the system scalability and prediction accuracy: (1) Learning-based framework which considers the network as a black-box, (2) Model-based framework which predicts RTT by composing the RTT between router pairs along a routing path. We use two modulars for two different cases: inter-region and intra-region RTT predictions. In particular, for IP pairs with a large geographic distance, our learning-based scheme uses a data-driven machine learning approach and only needs some public free IP-Geo information without any extra cost; while for IP pairs belong to the intra-region category, we construct an infrastructure database of latencies between routers, which is then used to compose the RTT along the network path. By carefully dividing the RTT predictions to these two types, our design achieves a high prediction accuracy and makes the prediction approach scalable for large-scale systems.

Acknowledgement

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References

[1] "http://www.blizzard.com/."
[2] C. Ly, C.-H. Hsu, and M. Hefeeda, "Irs: A detour routing system to improve quality of online games," *Multimedia, IEEE Transactions on*, vol. 13, no. 4, pp. 733–747, Aug 2011.
[3] H. V. Madhyastha, T. Anderson, A. Krishnamurthy, N. Spring, and A. Venkataramani, "A structural approach to latency prediction," in *ACM SIGCOMM*, 2006.
[4] F. Dabek, R. Cox, F. Kaashoek, and R. Morris, "Vivaldi: A decentralized network coordinate system," in *ACM SIGCOMM*, 2004.
[5] S. Belhaj and M. Tagina, "Modeling and prediction of the internet end-to-end delay using recurrent neural networks." *JNW*, 2009.
[6] B. A. A. Nunes, K. Veenstra, W. Ballenthin, S. Lukin, and K. Obraczka, "A machine learning approach to end-to-end rtt estimation and its application to tcp," in *ICCCN*, 2011.
[7] D. J. Roberts, P. M. Sharkey, and P. Sandoz, "A real-time, predictive architecture for distributed virtual reality," in *ACM Siggraph Workshop Simulation & Interaction in Virtual Environments*, 1995.
[8] "http://www.cz88.net/."
[9] "http://www.maxmind.com."
[10] A. Balachandran, V. Sekar, A. Akella, S. Seshan, I. Stoica, and H. Zhang, "Developing a predictive model of quality of experience for internet video," in *ACM SIGCOMM*, 2013.
[11] R. Kay, "Pragmatic network latency engineering fundamental facts and analysis," *CPacket Networks*, 2009.
[12] J. R. Quinlan, *C4. 5: programs for machine learning*. Morgan kaufmann, 1993, vol. 1.
[13] T. M. Mitchell, *Machine learning. WCB*. McGraw-Hill Boston, 1997.
[14] V. Paxson, "End-to-end routing behavior in the internet," *IEEE/ACM Transactions on Networking*, 1997.
[15] P. Quax, P. Monsieurs, W. Lamotte, D. De Vleeschauwer, and N. Degrande, "Objective and subjective evaluation of the influence of small amounts of delay and jitter on a recent first person shooter game," in *Proceedings of 3rd ACM SIGCOMM Workshop on Network and System Support for Games*, 2004.
[16] T. E. Ng and H. Zhang, "Predicting internet network distance with coordinates-based approaches," in *IEEE INFOCOM*, 2002.
[17] L. Tang and M. Crovella, "Geometric exploration of the landmark selection problem," in *Passive and Active Network Measurement*. Springer, 2004, pp. 63–72.
[18] H. V. Madhyastha, T. Isdal, M. Piatek, C. Dixon, T. Anderson, A. Krishnamurthy, and A. Venkataramani, "iplane: An information plane for distributed services," in *OSDI*, 2006.