

On the Predictability of Large Transfer TCP Throughput

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Outline

TCP throughput prediction: problem statement and motivation

Formula-Based (FB) prediction

- A formula-based predictor
- Types of FB prediction errors
- Experimental evaluation

History-Based (HB) prediction

- Typical history-based predictors
- Dealing with outliers and level shifts
- Experimental evaluation

Predictability factors

What makes some paths less predictable than others?



Problem Statement and Motivation

Objective:

Predict the throughput of a bulk TCP transfer on a given path

Motivation:

- Server selection
- Overlay/multi-homed routing
- Load balancing
- Grid computing
- P2P downloading



Constraints and Assumptions

- Prediction is needed before the start of transfer
- Performing "test TCP transfer" just for prediction is too intrusive/slow
- Measuring certain "lightweight path characteristics" (e.g., loss rate or RTT) is not intrusive



Two Classes of TCP Throughput Predictors

Prediction Method	Basis	Inputs	Advantages	Issues
Formula Based (FB)	Analytical model for TCP throughput	Estimates of path's RTT and loss rate	No previous transfers required	Prediction accuracy?
History Based (HB)	Time series forecasting theory	History of previous TCP transfers on the same path	Prediction based on actual TCP transfers	Prediction accuracy?



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Main Contributions

- Evaluate prediction accuracy for FB and HB predictions
 - FB can be significantly inaccurate, especially for congestion-limited flows
 - HB is quite accurate even with simple linear predictors and sporadic previous samples
- Explain major causes of prediction errors in terms of underlying network and TCP behavior
 - Focus on cause-effect relations, rather than black box evaluation
- Study effects of path properties and transfer characteristics on prediction accuracy
 - Load, degree of multiplexing
 - Receiver window, transfer frequency



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TCP Throughput Model

Analytical model of the expected TCP throughput
 R as a function of several path characteristics

R = f(T, p) (p > 0)

- T, p: RTT and loss rate experienced during the flow
- We use PFTK model by Padhye et. al (Sigcomm '98)

$$R = \min\left(\frac{M}{T_{\sqrt{\frac{2bp}{3}} + T_{0}}\min(1, \sqrt{\frac{3bp}{8}})p(1+32p^{2})}, \frac{W}{T}}\right), p > 0$$

M: path MTU (Maximum Transfer Unit) W: TCP maximum congestion window T₀: TCP retransmission timeout b: segments released per new ACK



An FB Predictor

Measure loss rate p', RTT T' before the target flow starts

Typical measurement: periodic probing, e.g., Ping

Apply T' and p' to the throughput equation

 $\hat{R} = f(T', p') \quad (p' > 0)$

With the PFTK model...

$$\hat{R} = \min(\frac{M}{T'\sqrt{\frac{2bp'}{3}} + T_0\min(1,\sqrt{\frac{3bp'}{8}})p'(1+32p'^2)},\frac{W}{T'}), p' > 0$$



An FB Predictor

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Typical measurement: periodic probing, e.g., Ping

Apply T' and p' to the throughput equation

 $\hat{R} = f(T', p') \quad (p' > 0)$

With the PFTK model...

$$\hat{R} = \begin{cases} \min(\frac{M}{T'\sqrt{\frac{2bp'}{3}} + T_0 \min(1, \sqrt{\frac{3bp'}{8}}) p(1 + 32p'^2)}, \frac{W}{T'}), & \text{if } p' > 0\\ \min(A', \frac{W}{T'}), & \text{if } p' = 0 \end{cases}$$

A': available bandwidth estimation



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	 Potential Issues with FB Prediction Differences between T' and T, p' and p 				
		T', p'	Т, р		
	Temporal:	before flow	during flow		
	Sampling:	periodic probing	TCP "sampling"		
	Issue Additional load of the target flow may increase <i>T</i> , <i>p</i> Adaptive and bursty TCP sampling vs. non-adaptive periodic sampling		Effect		
			Overestimate throughput		
			Underestimate or overestimate throughput		

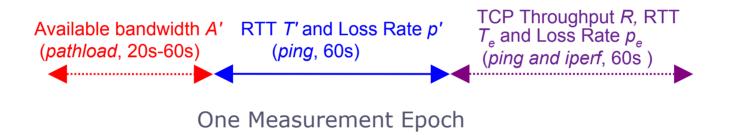


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Evaluation of Throughput Prediction Accuracy

Epoch:

 IPerf for TCP transfers, pathload for available bandwidth, ping (interval: 100ms, pkt size: 41bytes) for RTT & loss rate



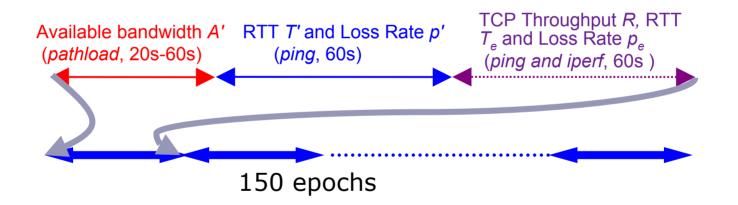


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Evaluation of Throughput Prediction Accuracy

Epoch:

 IPerf for TCP transfers, pathload for available bandwidth, ping (interval: 100ms, pkt size: 41bytes) for RTT & loss rate



- Each trace consists of 150 consecutive epochs
- We used 35 Internet paths; 7 traces on each path; hosts in US, Europe, Korea



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Prediction Error Metrics

Relative Error

$$E = \frac{R - R}{\min(R, R)}$$

 $\hat{R} = (1/w)$ R, and $\hat{R} = w$ R both have: |E| = w-1e.g., $\hat{R} = \frac{1}{2}$ R, and $\hat{R} = 2$ R both have: |E| = 1

Root Mean Square Relative Error

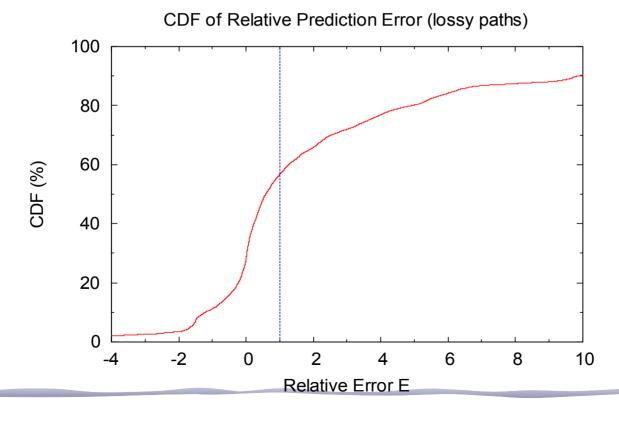
$$RMSRE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}E_{i}^{2}}$$



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CDF of FB Prediction Error

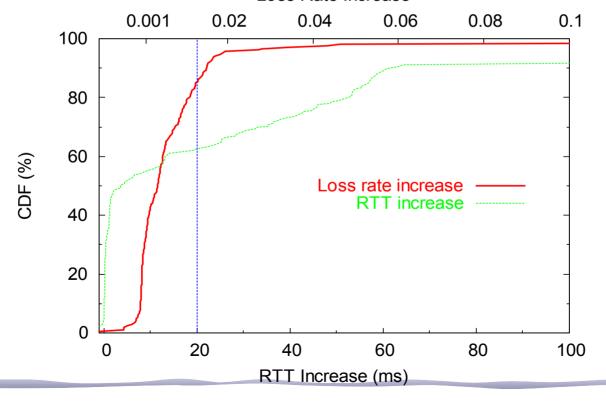
- Overestimation by >100% (E>1) for 40% of the measurements
- Dominance of overestimation errors (E>0)
 - Prevalent occurrences of T' < T and p' < p</p>



CDF of FB Prediction Error

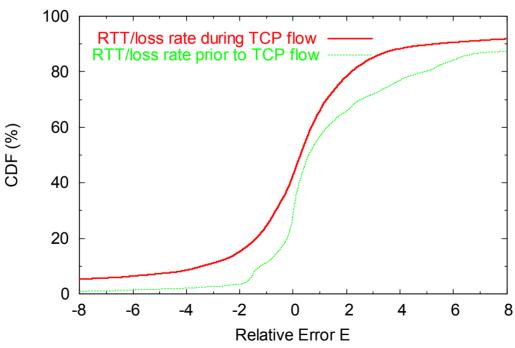
- Overestimation by >100% (E>1) for 40% of the measurements
- Dominance of overestimation errors (E>0)





Errors Due to Sampling Differences

- Prediction using Ping RTT & loss rate measurements during target flow
- Prediction errors are still significant, but overestimation & underestimation are almost symmetric



CDF of Relative Prediction Error

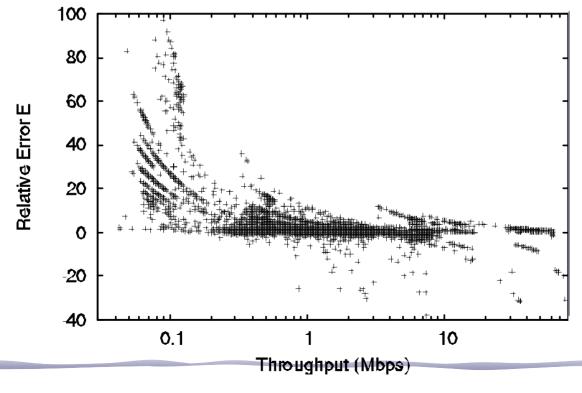


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Prediction Accuracy vs. Actual Throughput

Large errors are more common in lower-throughput paths

 Explanation: in a congested path, slight load increase causes large loss rate increase



Throughput vs. FB Predictability

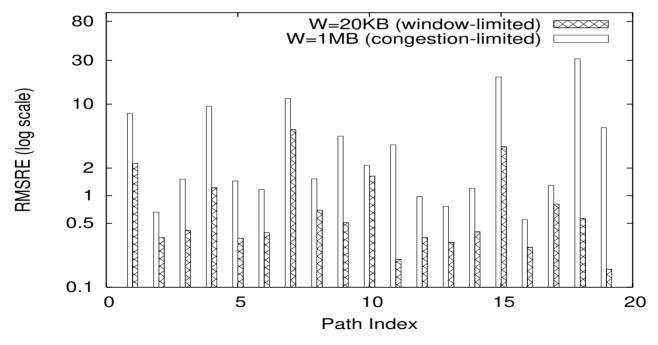


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Window-limited Flows

Throughput is more predictable for window-limited TCP flows

Explanation: window-limited flows do not saturate path's bottleneck



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History-Based Prediction

- General one-step forecasting problem $\hat{R}_n = f(R_1, R_2, ..., R_{n-1})$
- We only consider simple linear predictors
 - Moving Average (MA)

$$\hat{X}_{i+1} = \frac{1}{n} \sum_{k=i-n+1}^{i} X_k$$

Exponentially Weighted Moving Average (EWMA)

$$\hat{X}_{i+1} = \alpha X_i + (1 - \alpha) \hat{X}_i$$

- Non-seasonal Holt-Winters (HW)
 - An EWMA variation that captures the time series trend

$$\begin{aligned} \hat{X}_{i}^{f} &= \hat{X}_{i}^{s} + \hat{X}_{i}^{t} \\ \hat{X}_{i+1}^{s} &= \alpha X_{i} + (1 - \alpha) \hat{X}_{i}^{f} & --\text{smoothing} \\ \hat{X}_{i+1}^{t} &= \beta (\hat{X}_{i}^{s} - \hat{X}_{i-1}^{s}) + (1 - \beta) \hat{X}_{i-1}^{t} & --\text{trend} \end{aligned}$$



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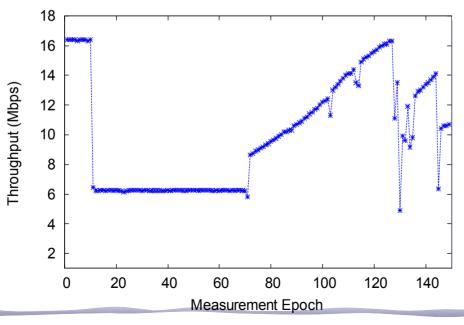
Level Shifts (LS) and Outliers (OL)

Why are LS and OL undesirable?

Cause large prediction errors and differences among predictors; complicate the analysis of HB predictability

Control Predictors
Control Predictors

Actions: ignore OL, restart predictor upon LS UTAH-LULEA

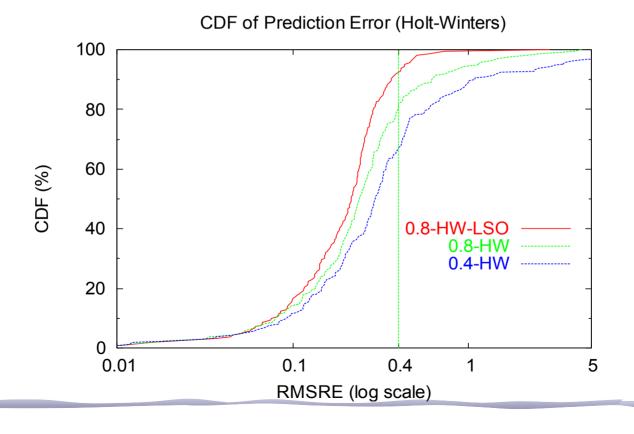




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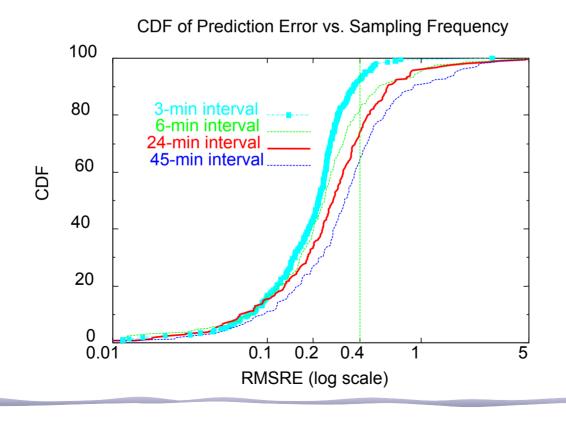
Overall HB Prediction Accuracy

- HB prediction is much more accurate than FB prediction
- 90% of traces have RMSREs < 0.4 (with LS/OL detection)</p>
- With LS/OL detections, the choices of predictor and of predictor parameters make little difference



Effect of Measurement Frequency

- Longer measurement period does not degrade accuracy significantly
 - Even with single transfer every 24 minutes, RMSRE is below 0.4 in 75% of the traces



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Predictability factors

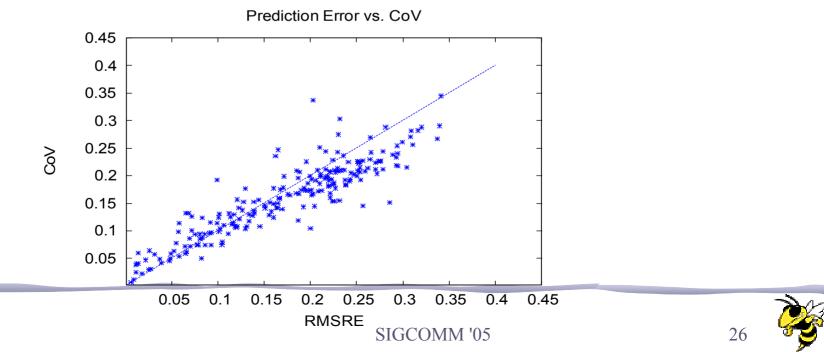
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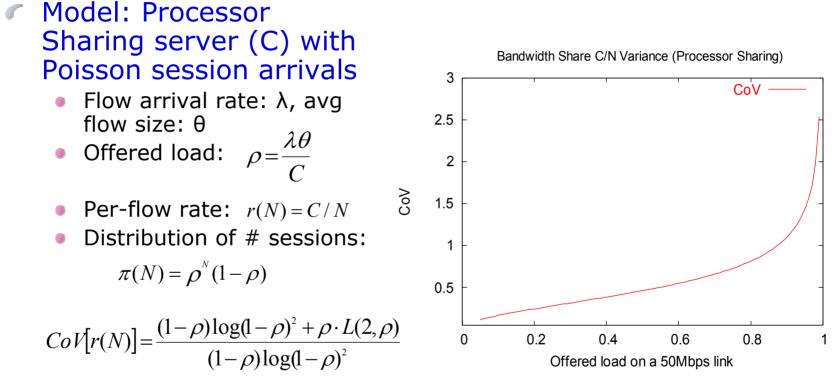
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What makes throughput more predictable on some paths than on others?

- Factors examined:
 - Link utilization
 - Degree of statistical multiplexing
- Approach:
 - Analyze the Coefficient of Variation (CoV) of the marginal distribution of TCP throughput
 - CoV \propto time series prediction error



Impact of Load (congestion-limited flow)



- CoV of per-session throughput increases with the offered load
- So, relative prediction error increases with offered load



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Impact of Degree of Multiplexing

- Consider the avail-bw A at non-congested Processor Sharing server (C)
 - Traffic model: N homogenous flows with rate limit: r, flow arrival rate: λ (Poisson), avg flow size: θ

$$CoV[A] = CoV[C-Y] = \frac{1}{\sqrt{E[N]}} \frac{\rho \cdot C}{C(1-\rho)}$$

- Conclusion: provided that utilization remains constant, CoV of available bandwidth decreases as number of flows increases
 - So, we expect lower prediction error as number of flows increases



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Conclusions

- FB prediction for congestion-limited TCP flows can cause major errors
 - Main reason: loss rate and RTT increase due to target flow
- HB prediction is much more accurate
 - Even with very simple predictors and sporadic previous transfers
- Path HB-predictability depends on load and degree of multiplexing at bottleneck link
 - Hardest-to-predict paths: heavily utilized bottleneck link, loaded with just a few flows

