The Mystery Machine: End-to-end performance analysis of large-scale Internet services

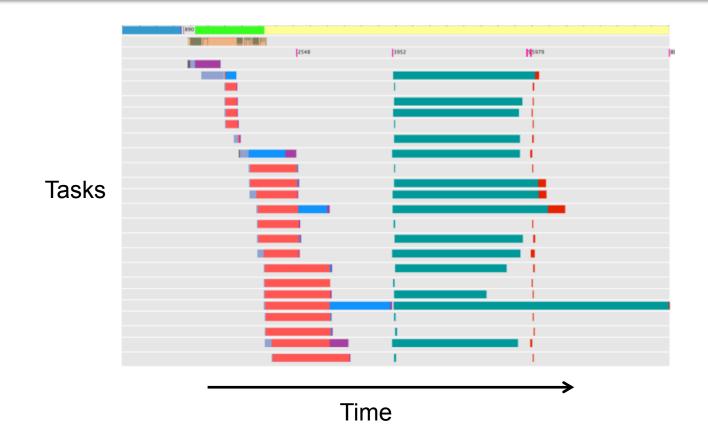
Michael Chow

David Meisner, Jason Flinn, Daniel Peek, Thomas F. Wenisch





Internet services are complex

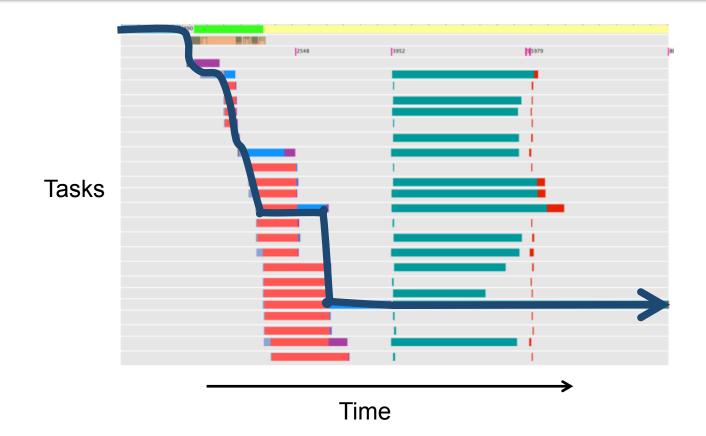


Scale and heterogeneity make Internet services complex





Internet services are complex

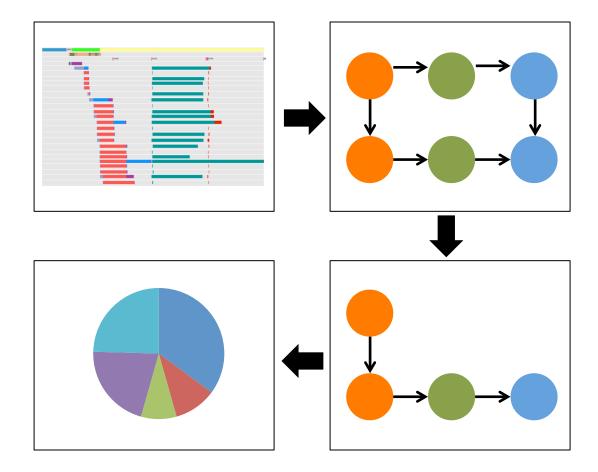


Scale and heterogeneity make Internet services complex





Analysis Pipeline

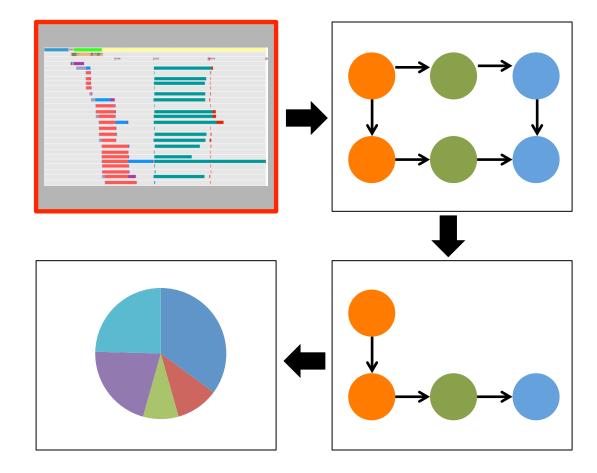






4

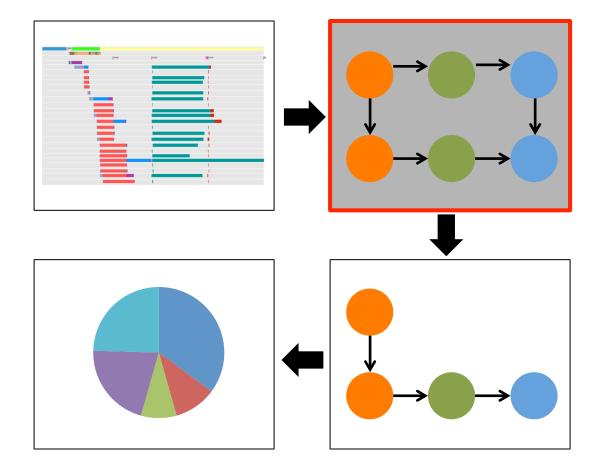
Step 1: Identify segments







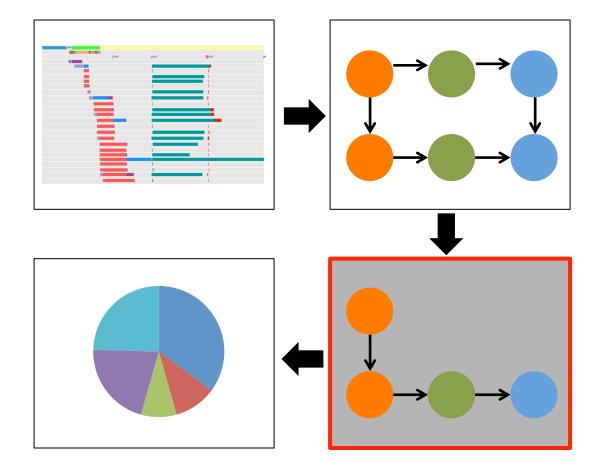
Step 2: Infer causal model







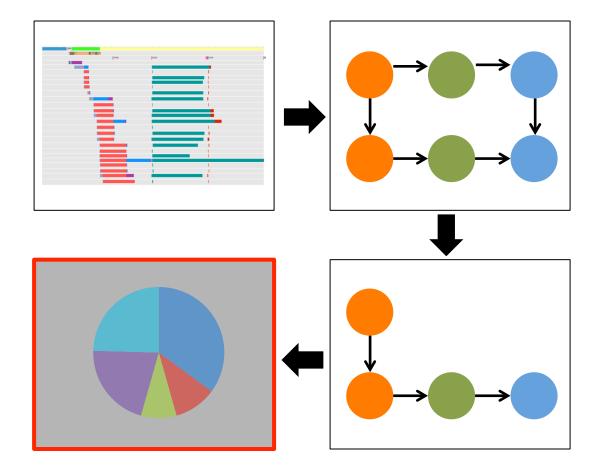
Step 3: Analyze individual requests







Step 4: Aggregate results







Challenges

- Previous methods derive a causal model
 - Instrument scheduler and communication
 - Build model through human knowledge

Need method that works at scale with heterogeneous components



Opportunities

Component-level logging is ubiquitous

Tremendous detail about a request's execution

 Handle a large number of requests Coverage of a large range of behaviors





The Mystery Machine

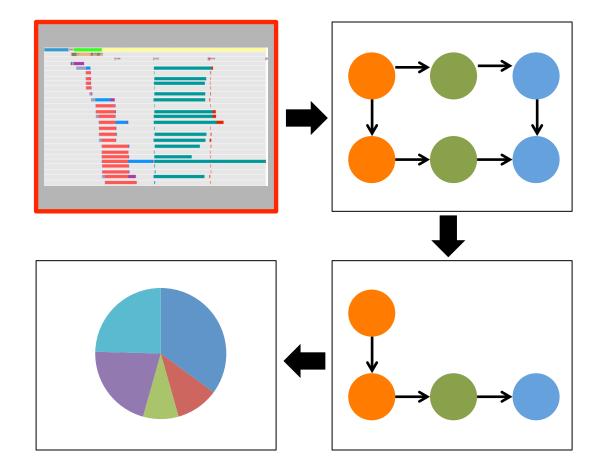
1) Infer causal model from large corpus of traces

- Identify segments
- Hypothesize all possible causal relationships
- Reject hypotheses with observed counterexamples
- 2) Analysis
 - Critical path, slack, anomaly detection, what-if





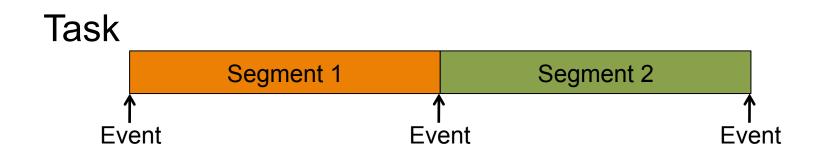
Step 1: Identify segments







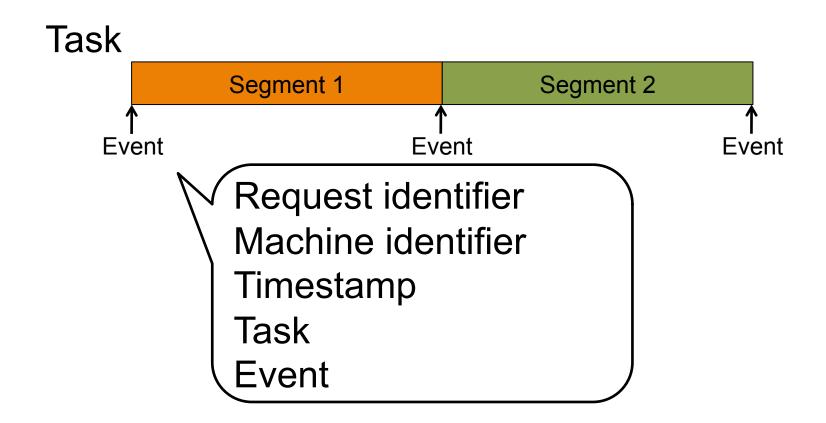
Define a minimal schema







Define a minimal schema

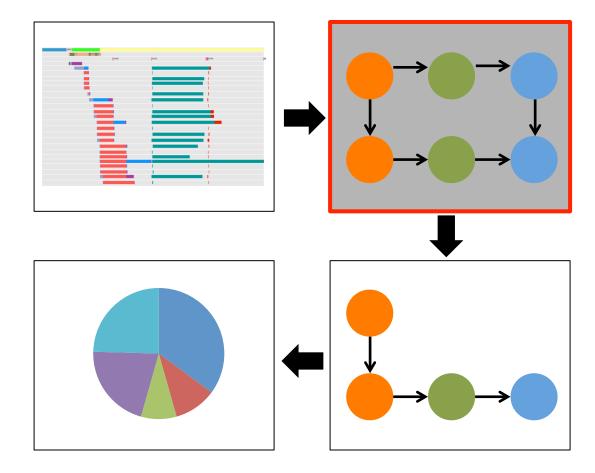


Aggregate existing logs using minimal schema





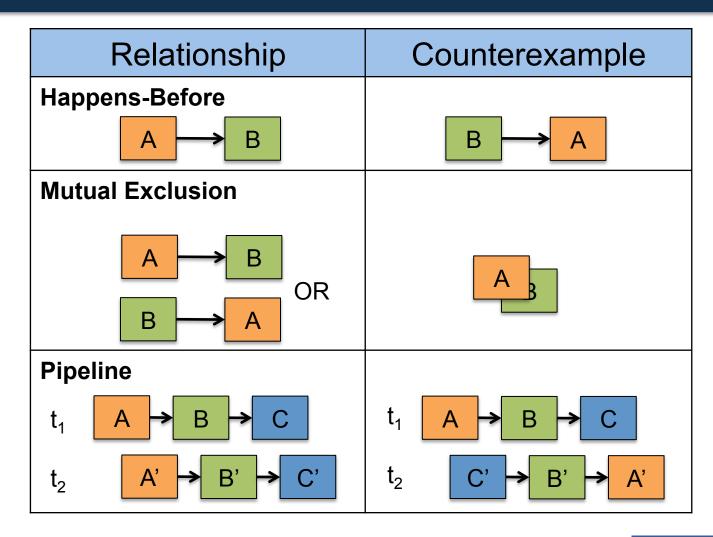
Step 2: Infer causal model



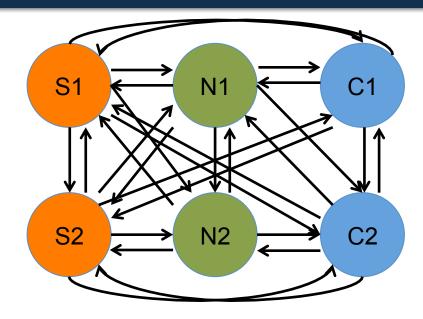




Types of causal relationships



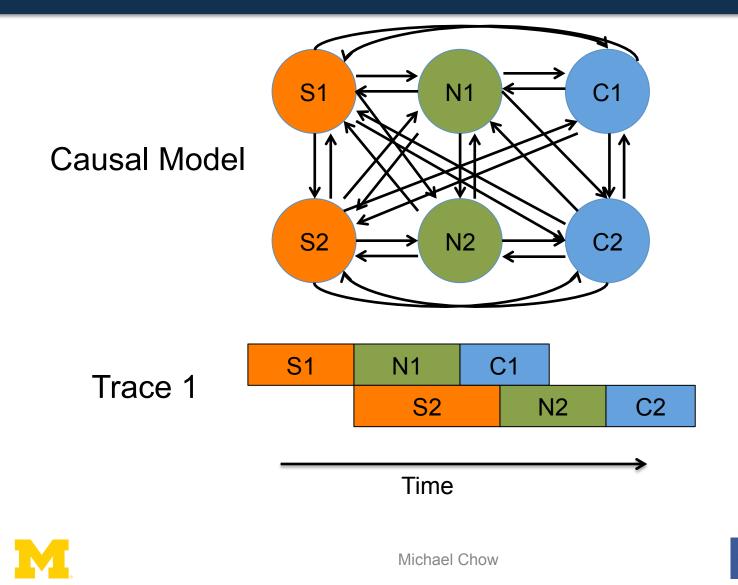




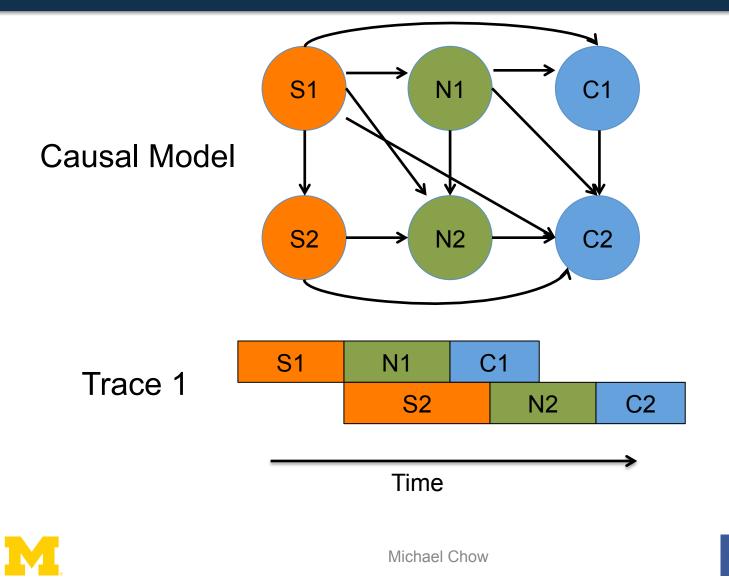
Causal Model



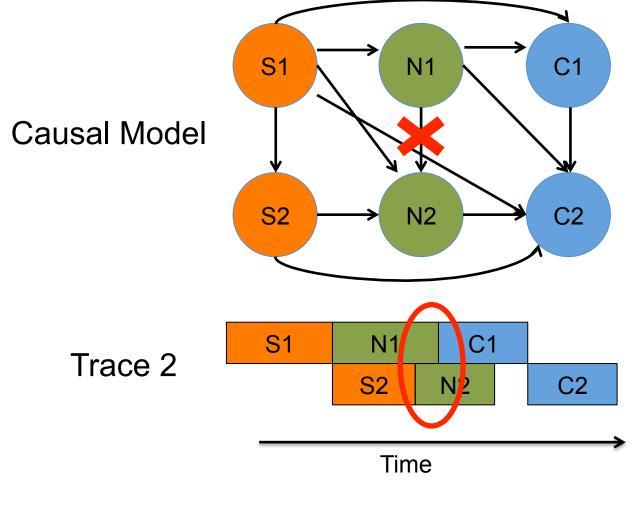






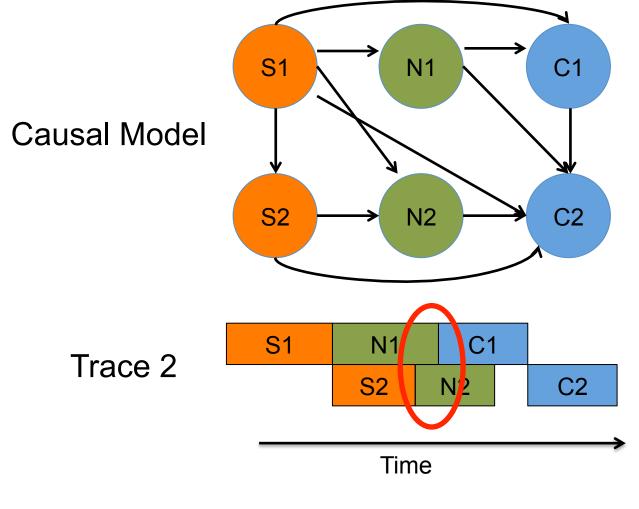






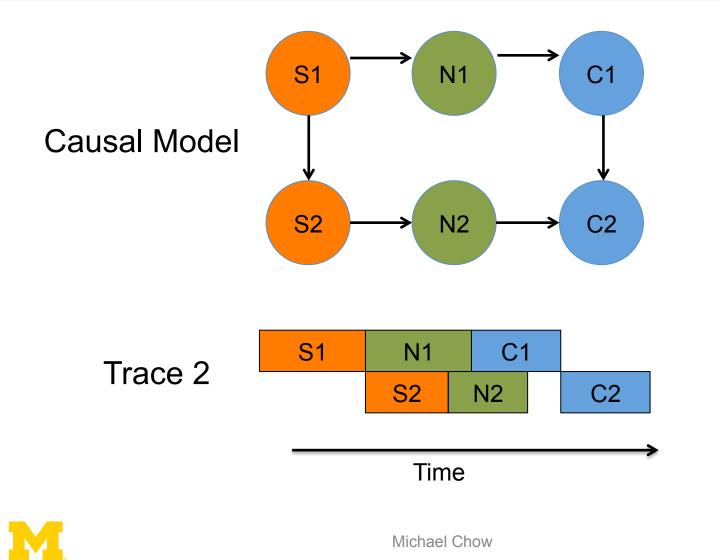






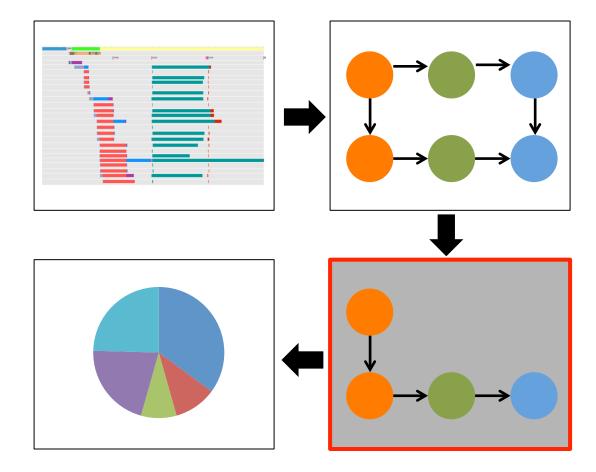








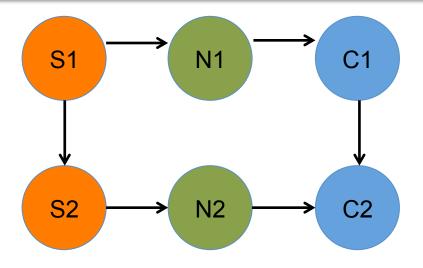
Step 3: Analyze individual requests

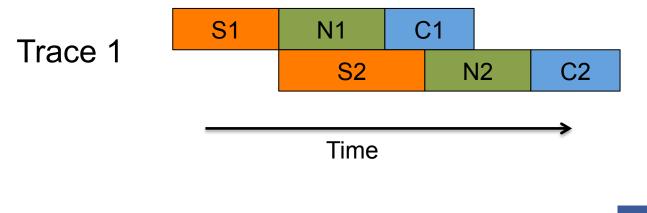






Critical path using causal model

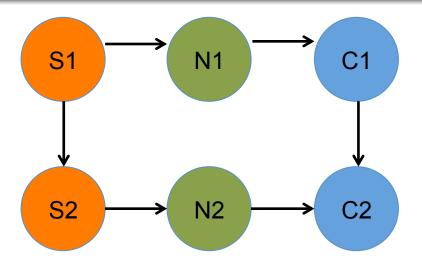


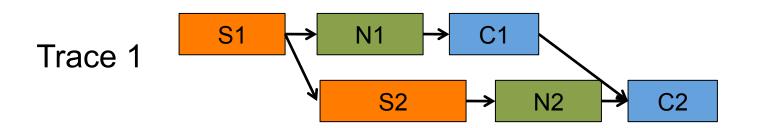


Michael Chow



Critical path using causal model

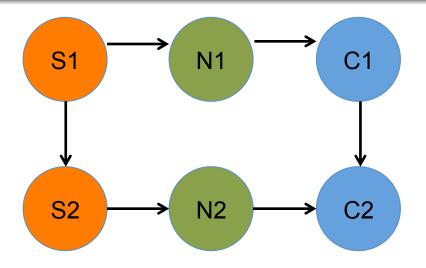


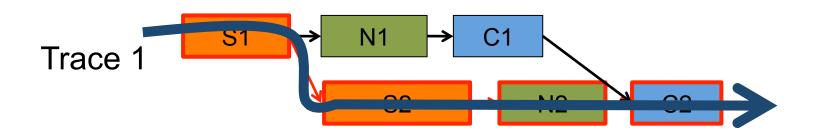






Critical path using causal model

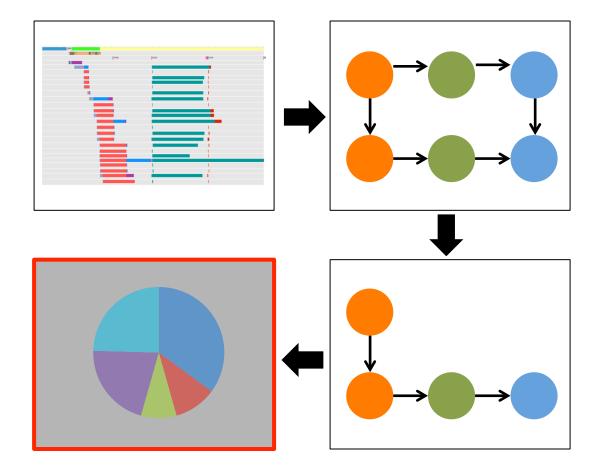








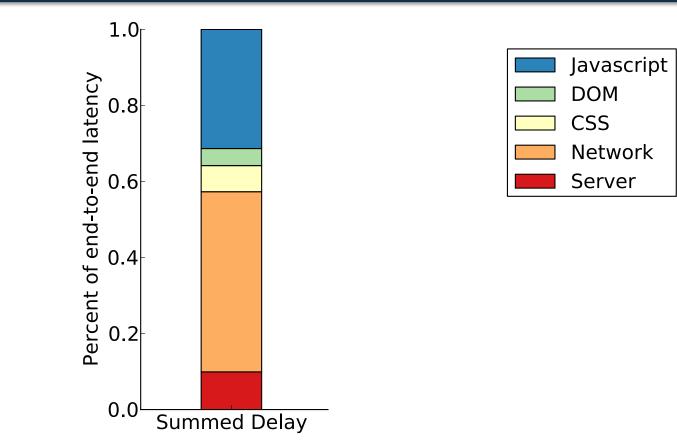
Step 4: Aggregate results







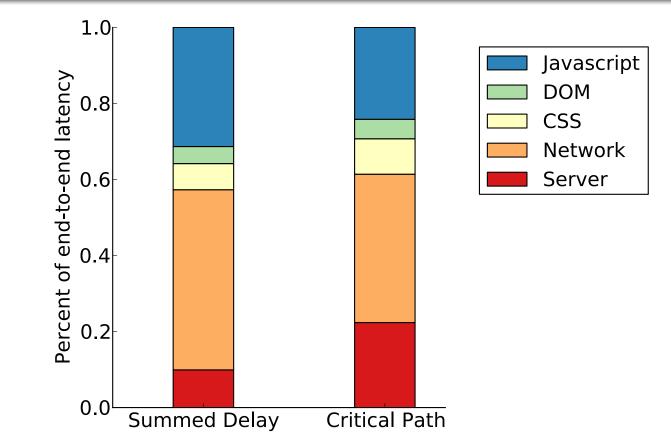
Inaccuracies of Naïve Aggregation







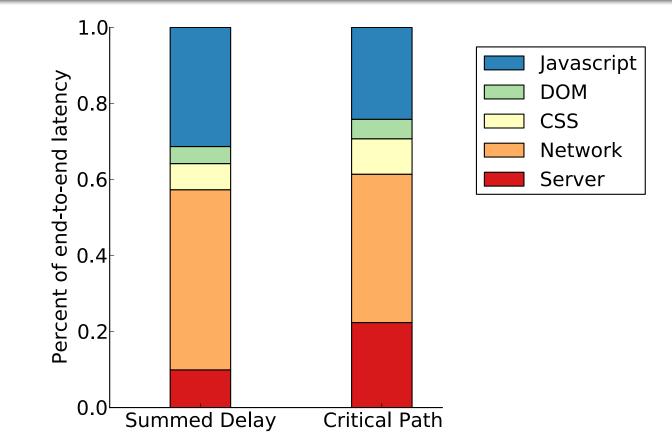
Inaccuracies of Naïve Aggregation







Inaccuracies of Naïve Aggregation



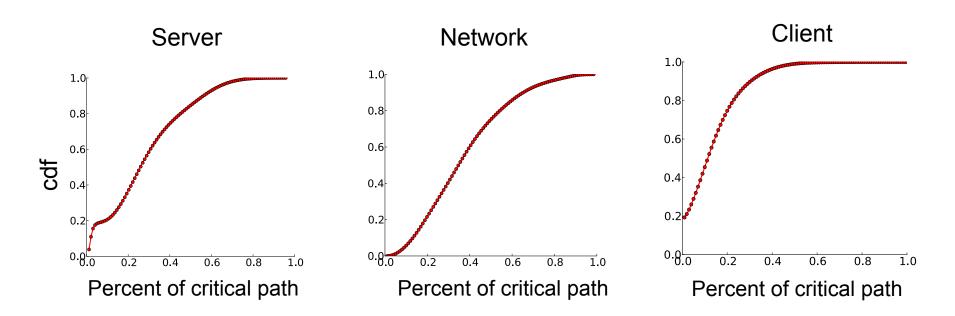
Need a causal model to correctly understand latency



Michael Chow



High variance in critical path

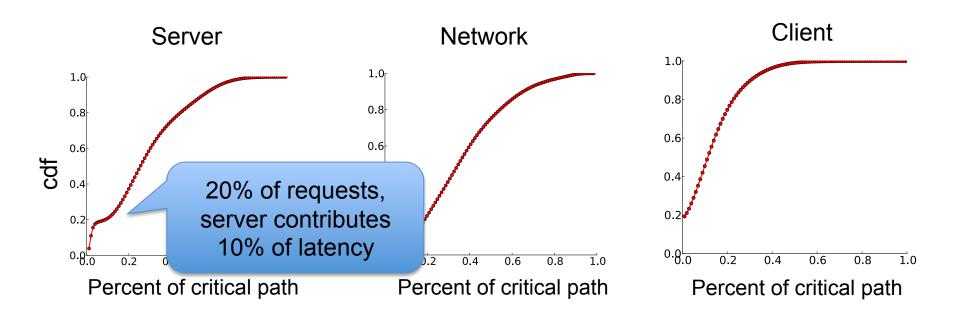


- Breakdown in critical path shifts drastically
 - Server, network, or client can dominate latency





High variance in critical path

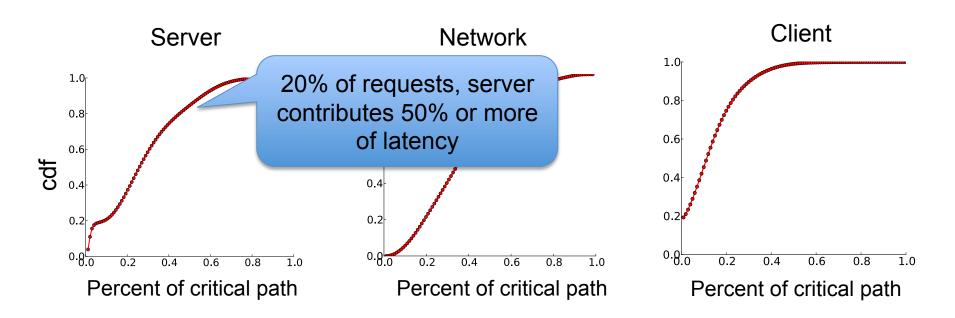


- Breakdown in critical path shifts drastically
 - Server, network, or client can dominate latency





High variance in critical path

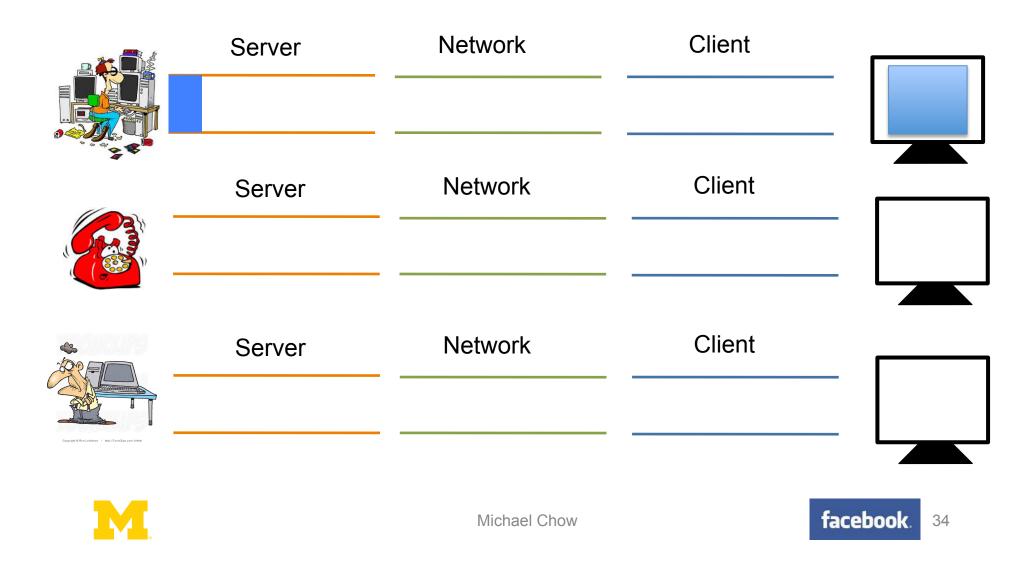


- Breakdown in critical path shifts drastically
 - Server, network, or client can dominate latency

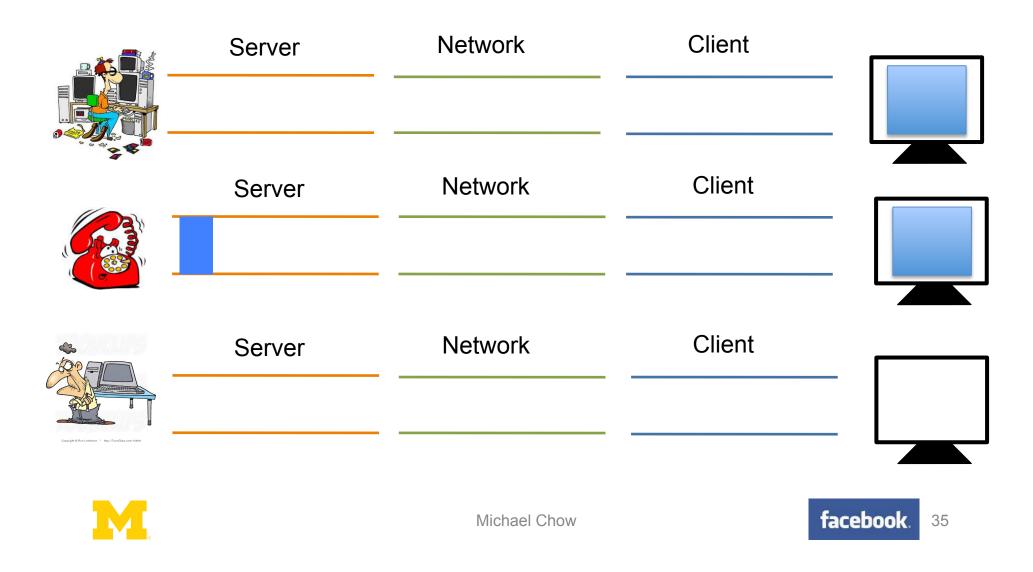




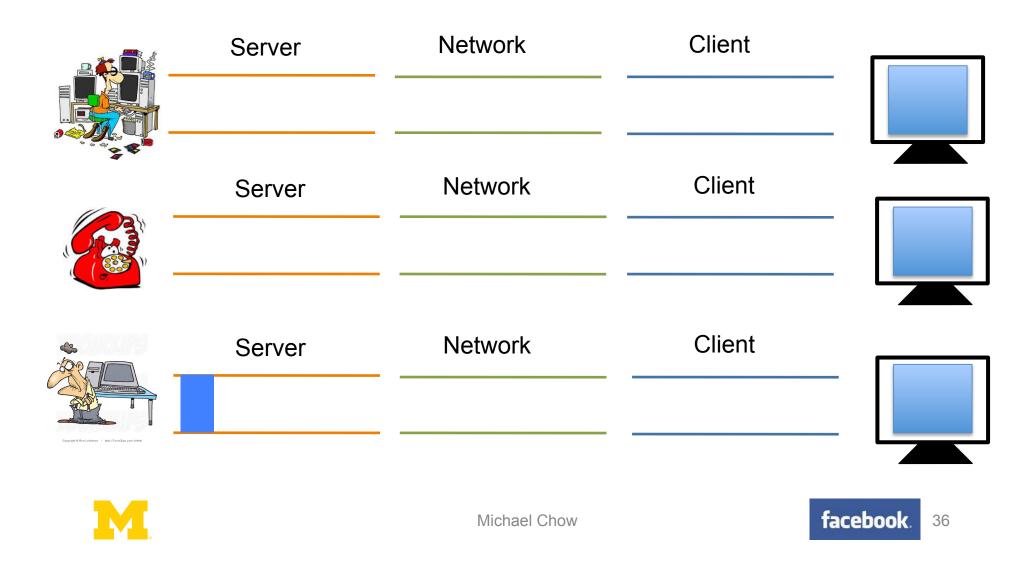
Diverse clients and networks



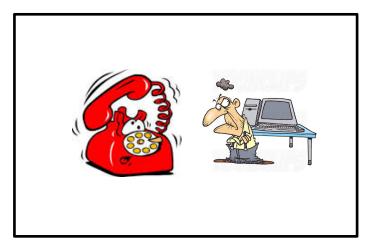
Diverse clients and networks



Diverse clients and networks



Differentiated service



Slack in server generation time Produce data slower End-to-end latency stays same



No slack in server generation time Produce data faster Decrease end-to-end latency

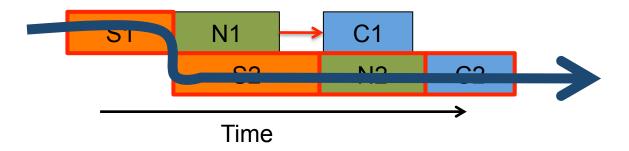
Deliver data when needed and reduce average response time





Additional analysis techniques

Slack analysis



- What-if analysis
 - Use natural variation in large data set





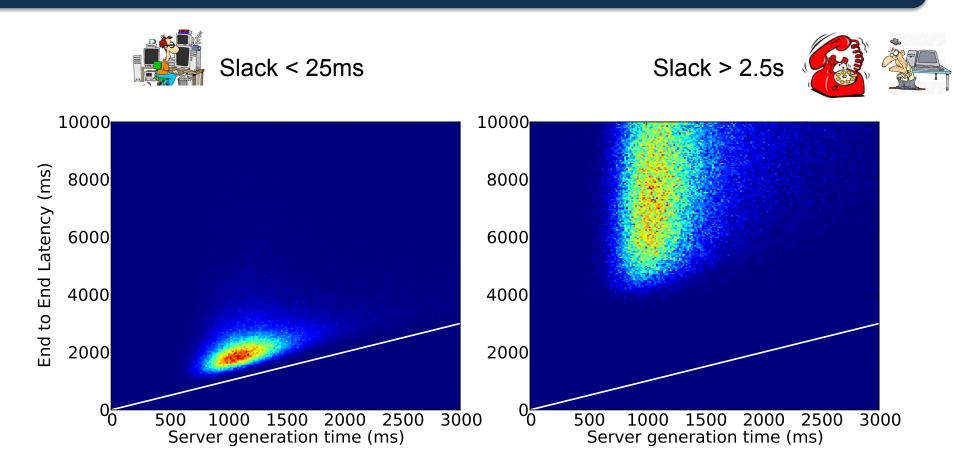
What-if questions

- Does server generation time affect end-toend latency?
- Can we predict which connections exhibit server slack?





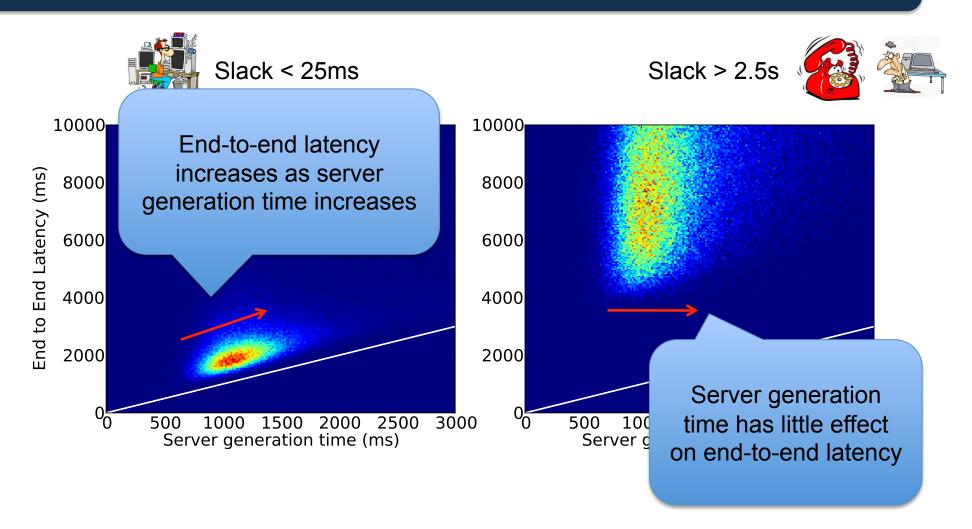
Server slack analysis







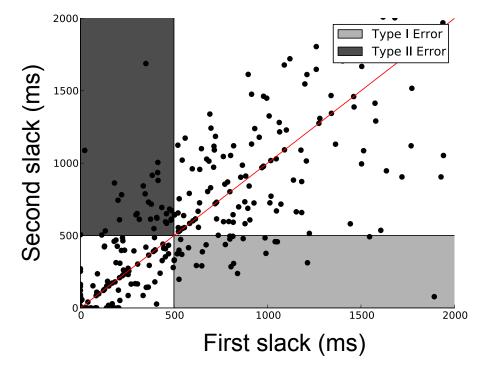
Server slack analysis





Predicting server slack

- Predict slack at the receipt of a request
- Past slack is representative of future slack



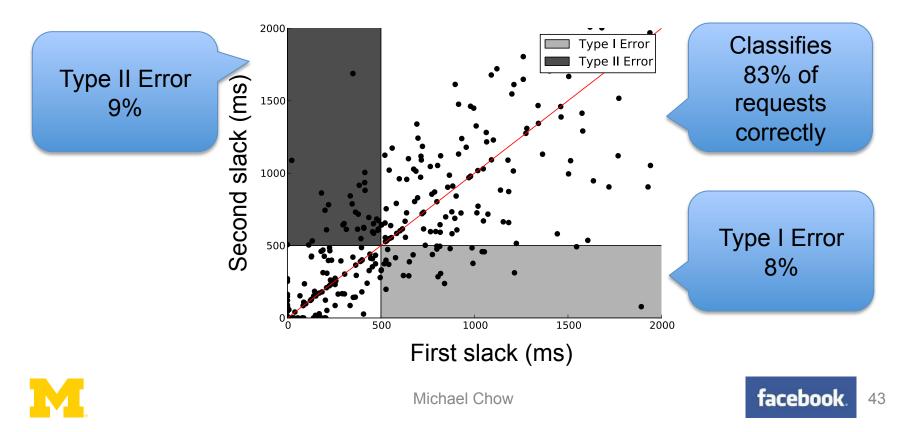


Michael Chow

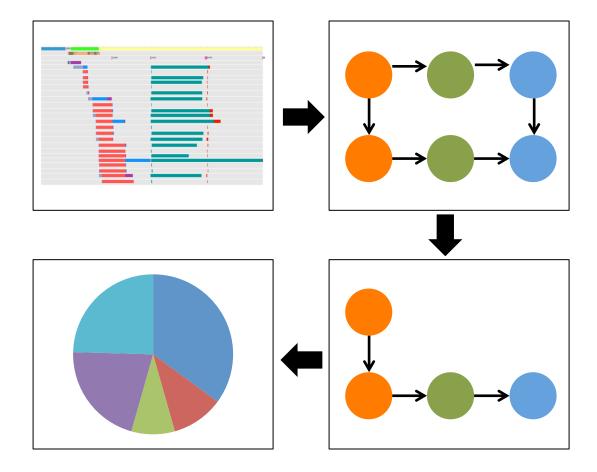


Predicting server slack

- Predict slack at the receipt of a request
- Past slack is representative of future slack



Conclusion







Questions





Michael Chow

