ECHO: Recreating Network Traffic Maps for Datacenters with Tens of Thousands of Servers

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Motivation

Network Performance and Efficiency ightarrow critical for DC operation

Scalable Topologies

- Dragonfly, Fat tree, Clos, etc.
- Hotspot detection & elimination

Flow Control

- Load balancing
- Speculative flow control
- Hedera, etc.

Network Switches Design

- Low latency RPCs
- RAMCloud, etc.

Software-defined DC networks

- OpenFlow
- Nicira, etc.



Where to find representative traffic patterns??

Executive Summary

- Network Workload Model: A scheme that accurately and concisely captures the traffic of a DC workload
 - □ User patterns only emerge in large-scale \rightarrow scalability
 - **Different** level of detail per application \rightarrow modularity/configurability
- □ Prior work on network modeling → mostly single-node, temporal behavior
 □ No spatial patterns, scalability and modularity
- ECHO addresses limitations of previous schemes:
 - System-wide network modeling: Not confined to a single-node
 - Locality-aware: Accounts for spatial network traffic patterns
 - Hierarchical: Adjusts the level of granularity to the needs of each app/study
 - Scalable: Scales to DCs with ~30,000 servers
 - Lightweight: Low and upper-bound modeling overheads
 - Validated: ECHO is validated against real traces from applications in production DCs

Outline

- Simple Temporal Model
- DC Network Traffic Characterization
- ECHO Design
- Model Validation

Distribution Fitting Model

- Most well-known modeling approach for network
- Single-node as opposed to system-wide!
- Capture temporal patterns in per-server network traffic
- Identify known distributions (e.g., Gaussian, Poisson, Zipf, etc.) in network activity traces
- Represent server network activity as a superposition of identified distributions

$$BW = \sum_{i=0}^{N} Distributions = \sum_{i=0}^{N_1} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu_i}{\sigma_i})^2} |_{t_{istart}}^{t_{istop}} + \sum_{i=0}^{N_2} \frac{\lambda^k e^{-\lambda}}{k!} |_{t_{istart}}^{t_{istop}} + \sum_{i=0}^{N_3} f_{others} |_{t_{istart}}^{t_{istop}} + \dots$$

Distribution Fitting Model

- Capture temporal patterns in perserver network traffic
- Identify known distributions (e.g., Gaussian, Poisson, Zipf, etc.) in network
 activity traces
- Represent server network activity as a superposition of identified distributions
- Model = Gaussian +
 Exponential +
 Gaussian +
 Gaussian +
 Constant



Validation: Deviation between original and synthetic is 4.9% on average

Distribution Fitting Model

Positive:

- Simple, accurate and concise
- Captures temporal patterns in network activity
- Facilitates traffic characterization (traffic is expressed as well-studied distributions)

Negative:

- × Does not track spatial patterns
- × Bursts in network activity not easily emulated by known distributions → would complicate the model
- × Non-modular design

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Methodology

Workloads:

- Entire Websearch application
- □ Combine → Websearch query results aggregator
- \square Render \rightarrow Websearch query results display

Experimental systems are production DCs with:

- 30,000 servers running Websearch
- 360 servers running Combine
- 1350 servers running Render
- We collect per-server bandwidth traces of data sent and received over a period of 5 months (at 5msec granularity)

Understanding Network-wide Behavior

Temporal variations of network traffic

- Fluctuation over time
- Differences between workloads

Average spatial patterns in network activity

- Locality in network traffic
- Impact of application functionality to locality

Temporal variations in spatial patterns

- Changes over different time scales
- Changes for different types of workloads



- Most servers are greatly underutilized
 → significant overprovisioning for latency-critical apps
- \Box Some servers have higher utilization \rightarrow mostly well load-balanced
- Similarity in network activity patterns over time
- Model should: capture fluctuation, remove information redundancy



 \Box Clearer diurnal patterns \rightarrow 31 dark and 31 light vertical bands



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- □ Higher utilization → not as much overprovisioning for servers that aggregate query results



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- □ Higher utilization → not as much overprovisioning for servers that aggregate query results
- Not equally load-balanced \rightarrow impact of queries serviced by each server

Spatial Patterns in Network Activity



 \Box High spatial locality \rightarrow Most accesses are confined within the same rack

The model should preserve the spatial locality (within racks & hotspots)

Spatial Patterns in Network Activity



- \Box High spatial locality \rightarrow Most accesses are confined within the same rack
- The model should preserve the spatial locality (within racks & hotspots)
- □ A few servers communicate with most of the machines → cluster scheduler, aggregators, monitoring servers

Spatial Patterns in Network Activity



- □ In contrast, Combine has less spatial locality → most servers talk to many machines
- \Box Consistent with its functionality \rightarrow query aggregation



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- However, at finer granularity there are differences



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 - Software updates
 - Changes in traffic due to user load
 - Background processes (e.g., garbage collection, logging, etc.)



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- However, at finer granularity there are differences
 - Software updates
 - Changes in traffic due to user load
 - Background processes (e.g., garbage collection, logging, etc.)
- Fine-grain patterns important for studies focused on specific hours of the day 22

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Model Requirements

Don't just model a node. Model the whole DC!

Requirements:

- 1. Average activity over time and space
- 2. Per-server activity fluctuation over time
- 3. Spatial patterns in network traffic
- 4. Individual server-to-server communication

Model Design – Spatial Aspects



- $\Box \quad \text{Hierarchical Markov Chain: groups of racks} \rightarrow \text{racks} \rightarrow \text{individual servers}$
- Configurable granularity based on app/study requirements
- Captures spatial patterns in network traffic: fine-grain transitions are explored within each coarse state

 most locality confined within a rack

Model Design – Temporal Aspects



- Captures temporal patterns in network traffic

 multiple models used
 over time
- Number of models is a function of the workload's activity fluctuations
- □ Switching between models allows compression in replay → fast experimentation

Hierarchical vs. Flat Model



- Hierarchical: explore fine grain transitions within coarse states
- \Box Flat: explore all fine grain states \rightarrow exponential increase in transition count
- Even for problems with a few hundred servers the model becomes intractable
- No loss in accuracy with the hierarchical model since locality is mostly confined within racks

Model Construction



- Collect system-wide network activity traces
- Cluster network requests based on
 - Sender/receiver server IDs
 - Type (rd/wr) and size of request (MB)
 - Inter-arrival time between requests (ms)
- □ Compute transition probabilities between states (e.g., S1→ S2: 90% 8KB read requests, 10msec inter-arrival time)

Cloud Node: Modeling Server Subsets

- □ Focus on specific interesting activity patterns → Validating the model in server subsets (a few hundred servers)
- Network activity is not necessarily selfcontained in those server subsets
- Cloud Node: Emulate all network activity to and from servers external to the studied server subset
- Maintains accuracy of per-server load while enabling more fine-grain validation



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Validation

- 1. Temporal variations of network activity
- 2. Spatial patterns of network activity
- 3. Individual server interactions (one-to-one communication patterns)

Validation – Temporal Patterns



Less than 8% deviation between original and synthetic workload, on average across server subsets

Validation – Spatial Patterns



average across server subsets

Validation – Indiv. Server Interactions



- 12% deviation between original and synthetic for a weekday
- 9% deviation between original and synthetic for a day of the weekend

Validation – Benefits of Hierarchy



28% deviation

9.1% deviation

4.4% deviation

Motivation: Revisited

- Scalable Topologies
 - Dragonfly, Fat tree, Clos, hotspot detection & elimination
- Flow Control
 - Load balancing
 - Speculative flow control, Hedera, etc.
- Network Switches Design
 - High port count designs, low latency RPCs, RAMCloud, etc.
- Software-defined DC networks
 - OpenFlow, Nicira, etc.
- Security attacks
 - Real-time deviation from modeled behavior

Retraining for major sw updates, major system configuration changes

Low overhead process

Conclusions

- ECHO leverages validated analytical models to capture the temporal and spatial access patterns in DC network activity
- □ It preserves the intensity and characteristics of DC network traffic
- It adjusts the granularity of representation to the app/study demands
- It is scalable and lightweight
- Decouples network system studies from access to large-scale applications

Future work

- Use ECHO for network system studies without the requirement for full application deployment
- Expand similar concepts to other subsystems.

Questions??

Thank you