Adaptive, Model-driven Autoscaling for Cloud Applications

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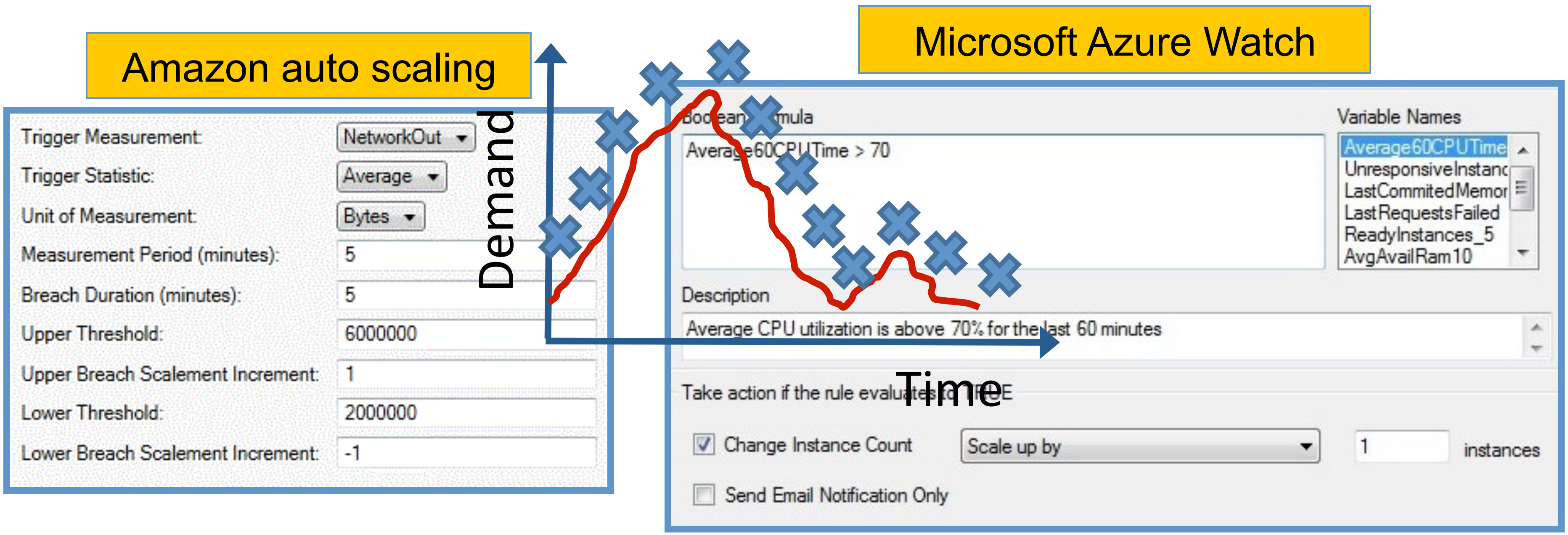
Motivation

- Businesses have started moving to the cloud for their IT needs
  - reduces capital cost of buying servers
  - allows for elastic resizing of applications that have dynamic workload demand
- Cloud Service Providers (CSPs) offer monitoring and rule-based triggers to enable dynamic scaling of applications

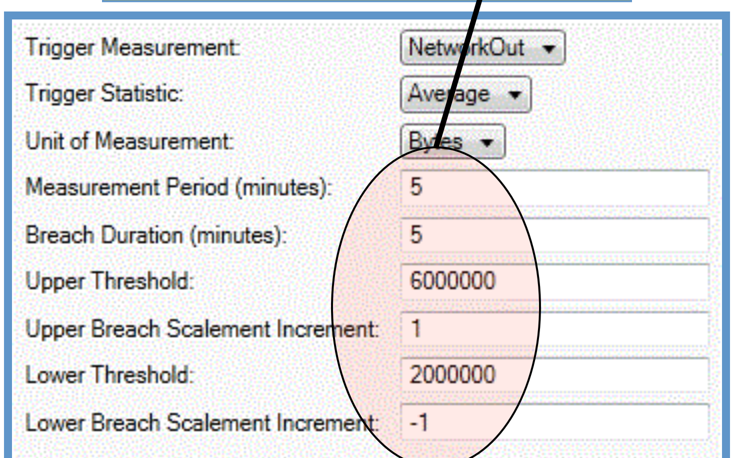


Motivation

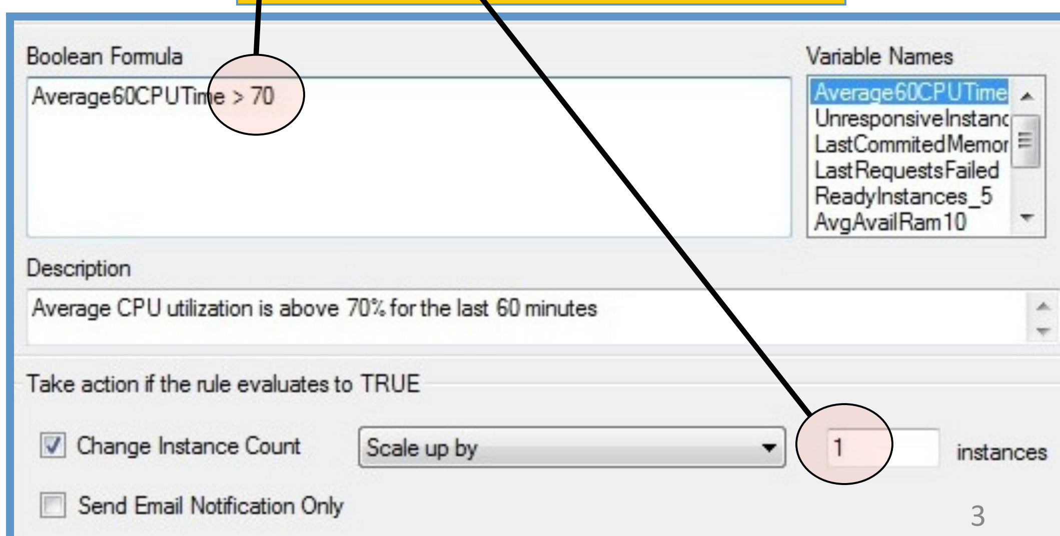
- The values have to be determined by the user
  - requires expert knowledge of application (CPU, memory, n/w thresholds)
  - requires performance modeling expertise (when and how to scale)

How to set these values ??

Amazon auto scaling



Microsoft Azure Watch



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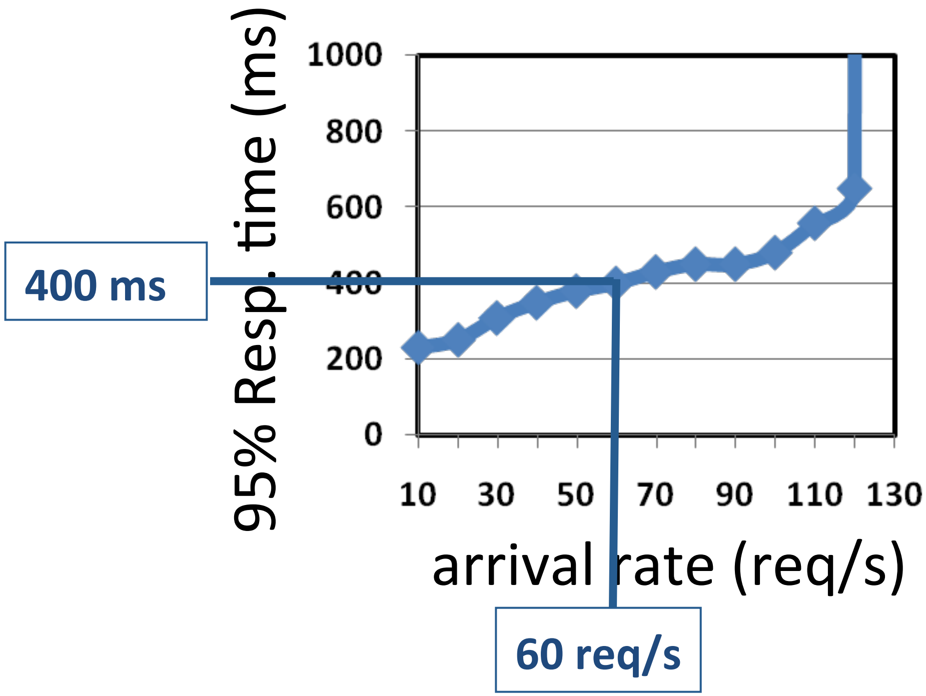
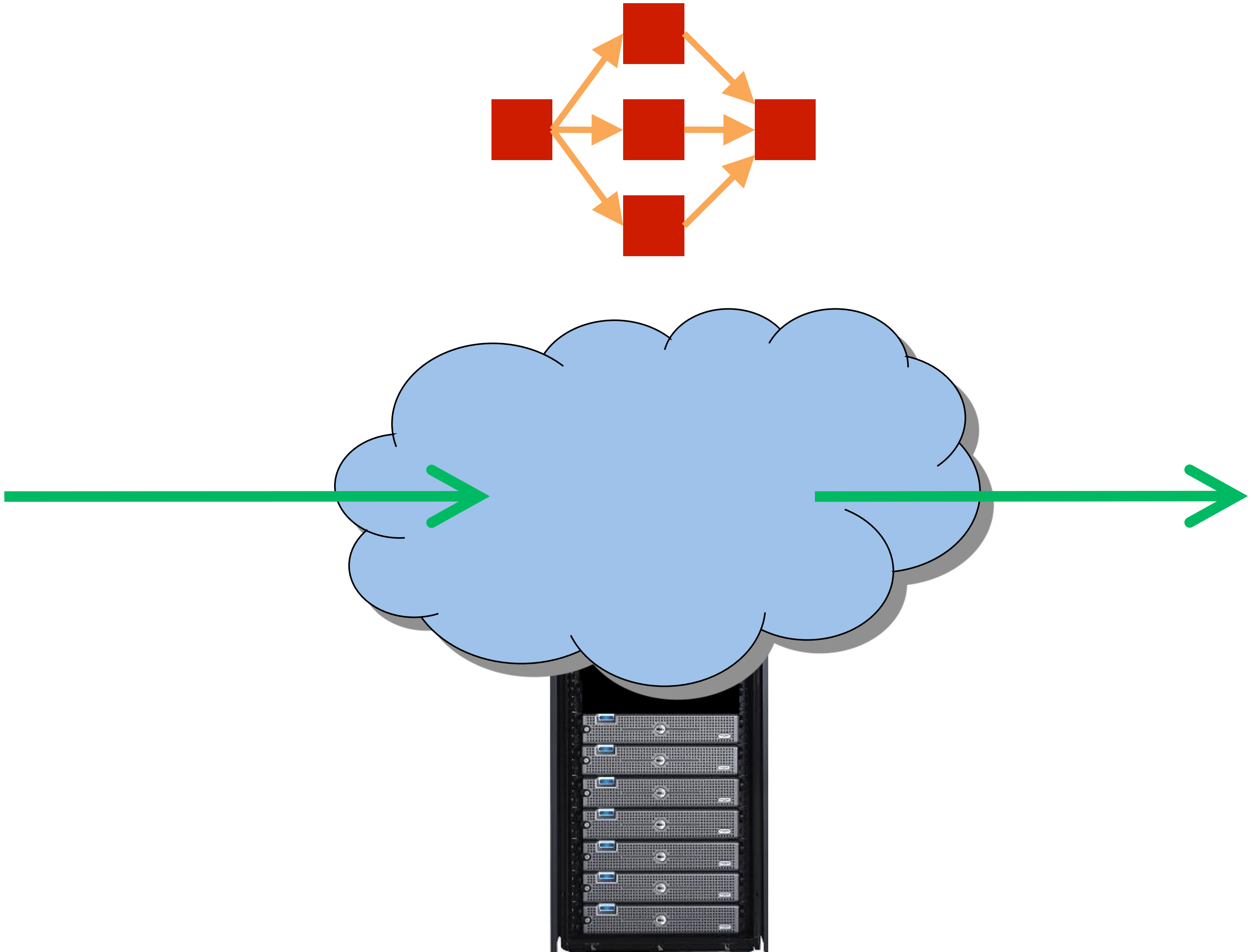


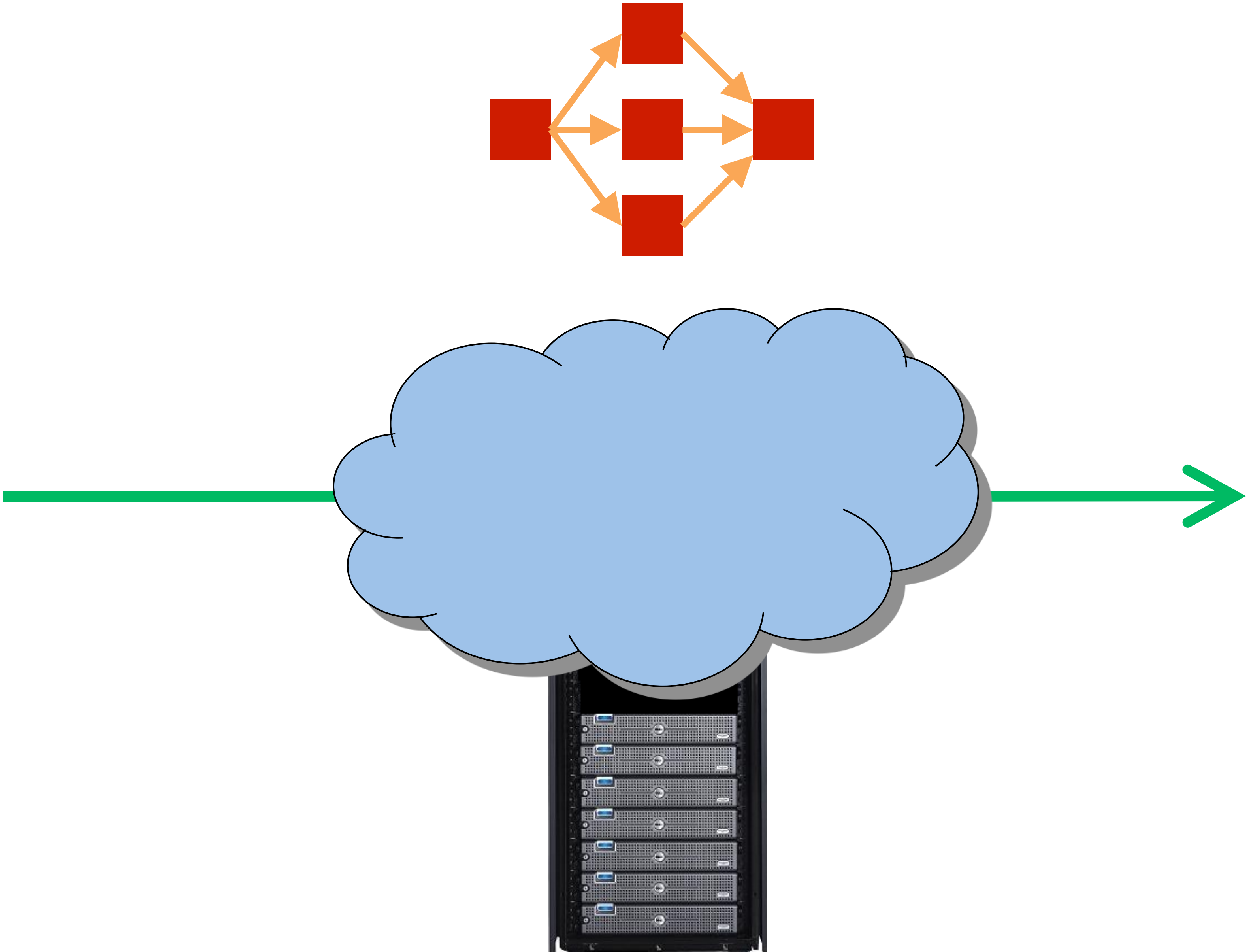
- ➢ Offline benchmarking
- ➢ Trial-and-error
- ➢ Expert application knowledge

Not possible for CSPs !

View from user’s perspective

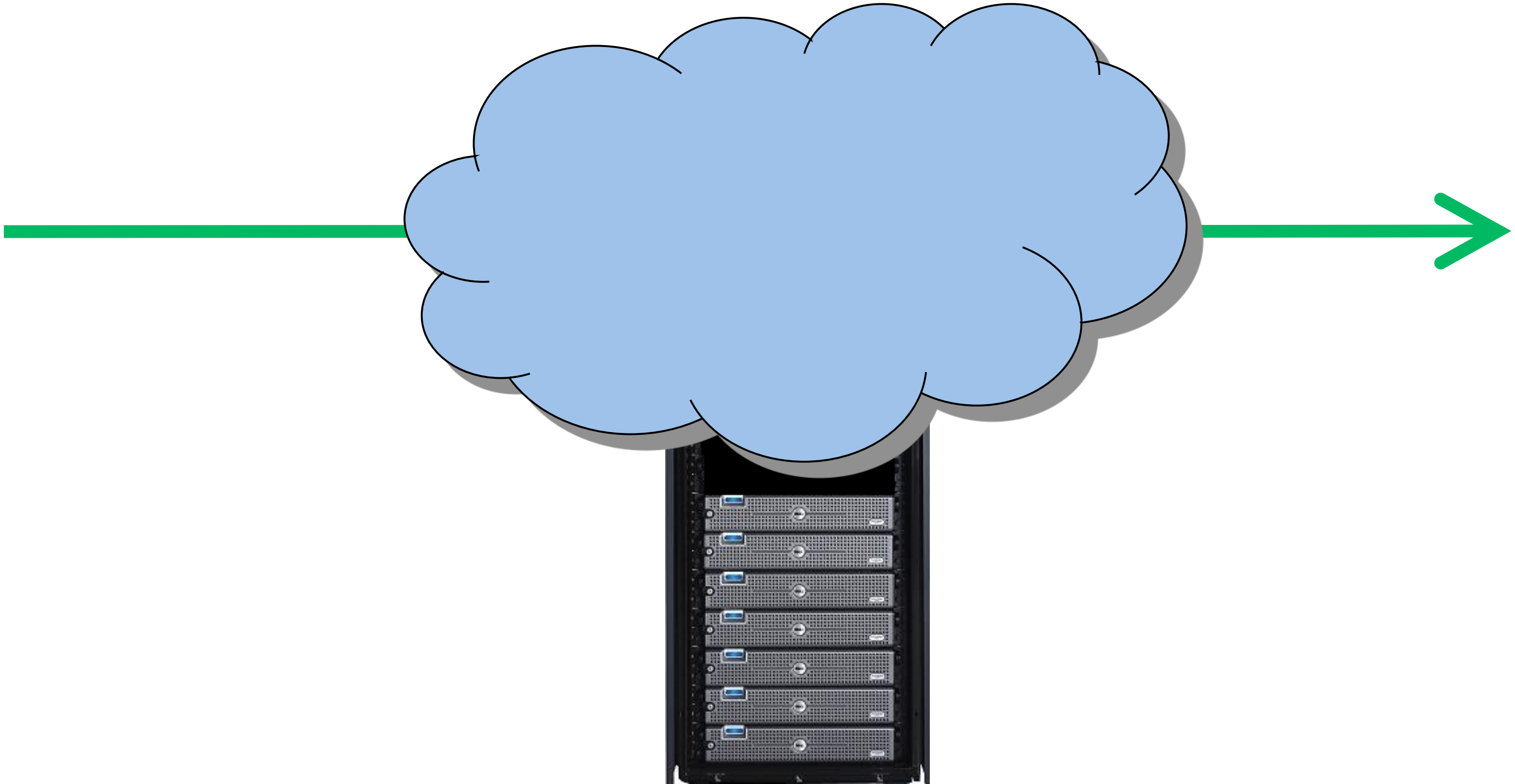


View from CSP's perspective

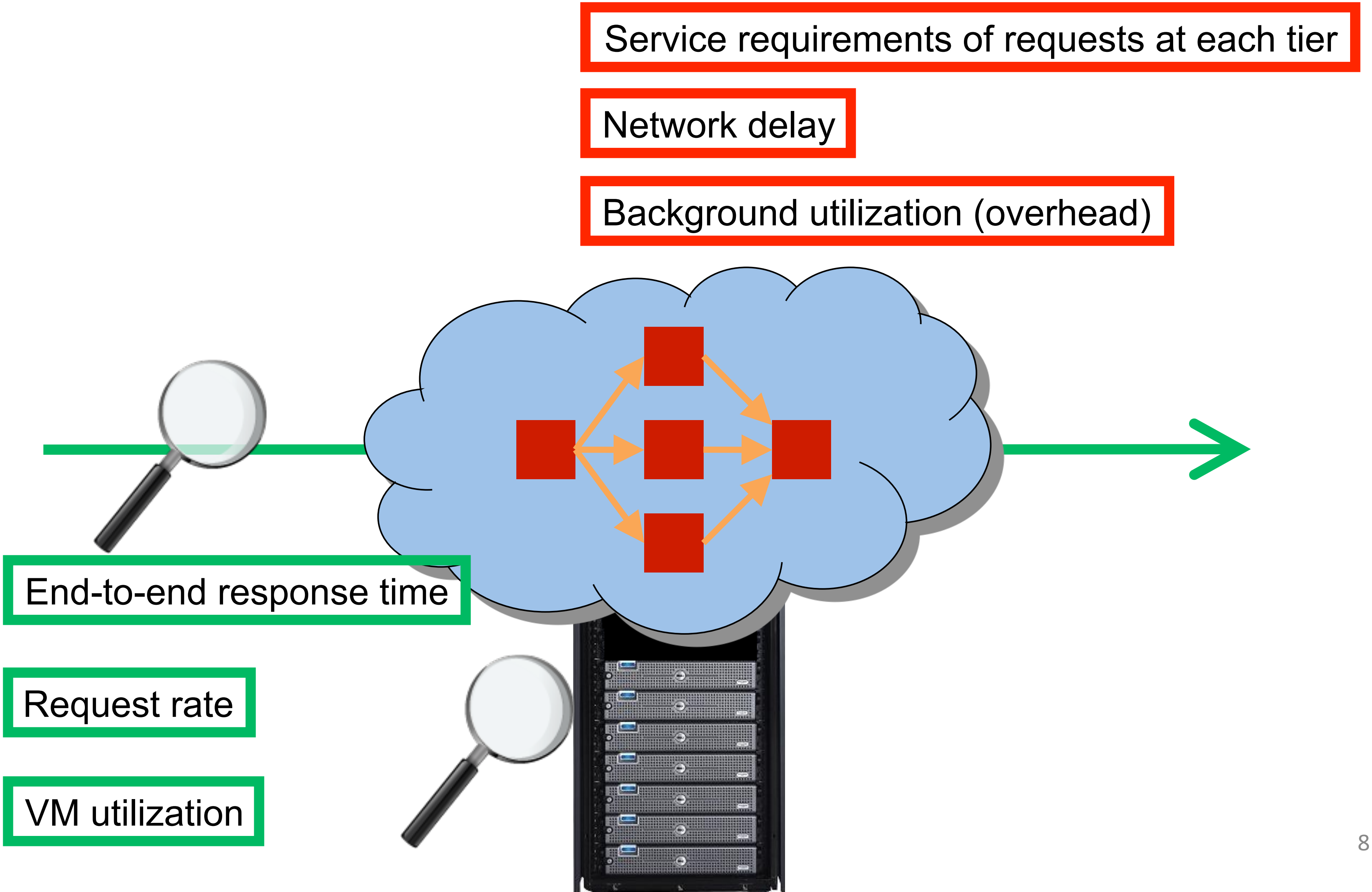


Problem statement

How to scale an unobservable cloud application to provide performance guarantees ?



DC2: High-level idea



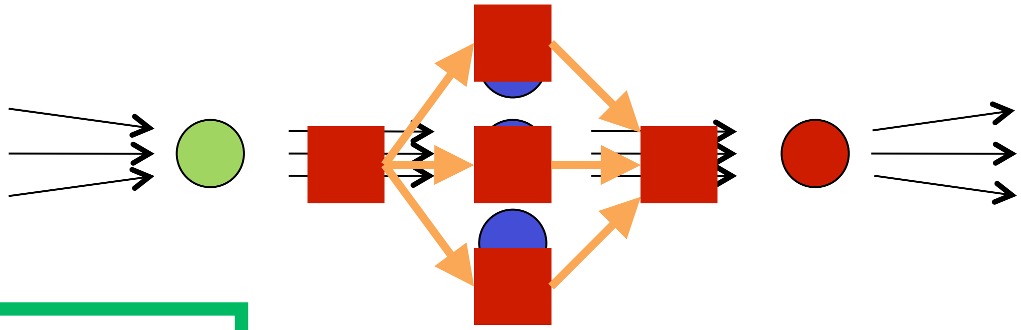
DC2: High-level idea

Kalman filtering

Service requirements of requests at each tier

Network delay

Background utilization (overhead)



End-to-end response time

Request rate

VM utilization

DC2: High-level idea

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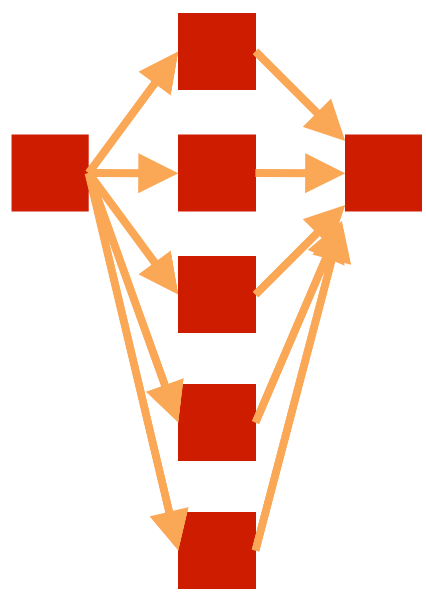

End-to-end response time

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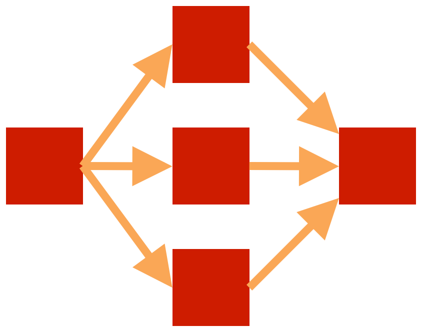
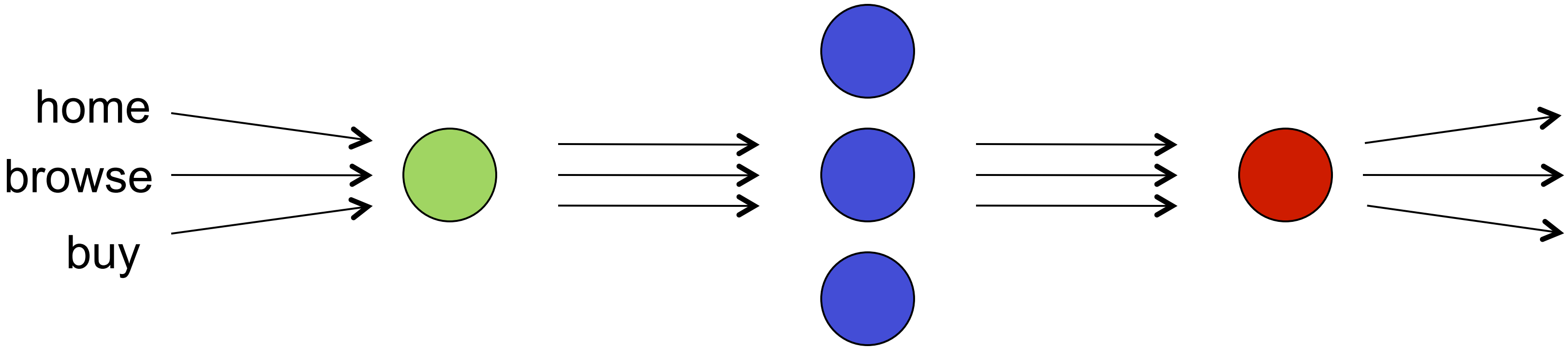
VM utilization

DC2: Modeling



multi-tier queueing network model



DC2: Modeling

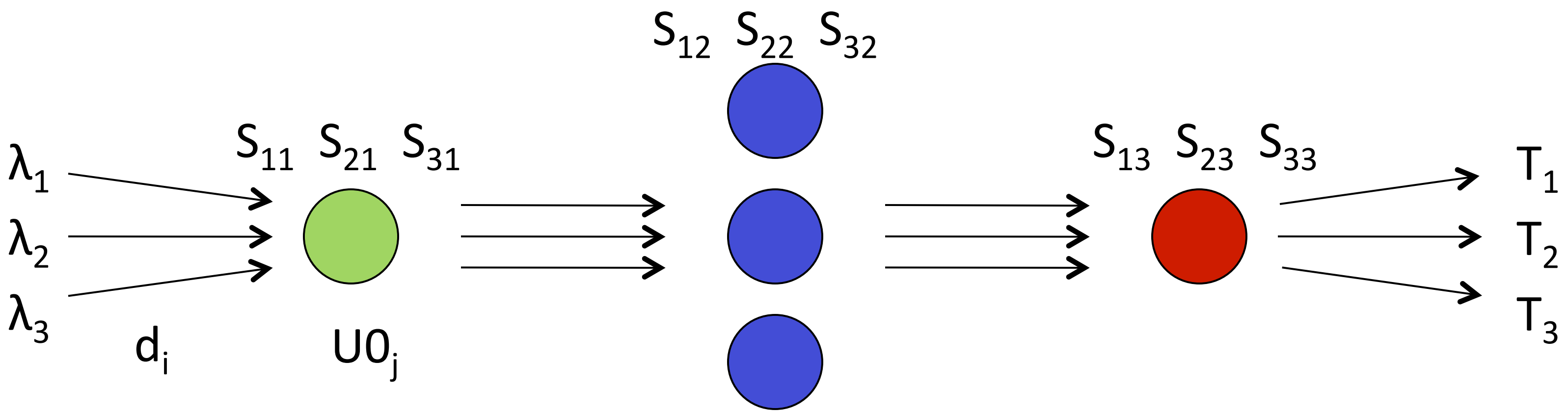
Parameters:

- λ_i – Request rate for class i
- T_i – Response time for class i
- S_{ij} – Service requirement for class i at tier j
- d_i – Network latency for class i
- $U0_j$ – Background utilization on tier j
- U_j – Utilization of tier j

24 parameters

$$T_i = d_i + \sum_j \frac{S_{ij}}{1 - U_j}$$

6 equations



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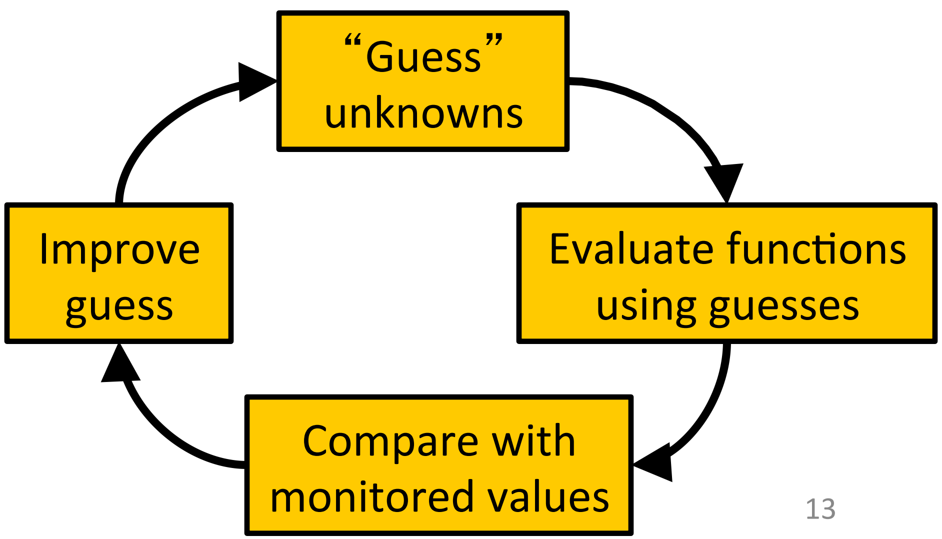
$$T_i = d_i + \sum_j \frac{S_{ij}}{1 - U_j}$$

$$U_j = U0_j + \sum_i \lambda_i S_{ij}$$

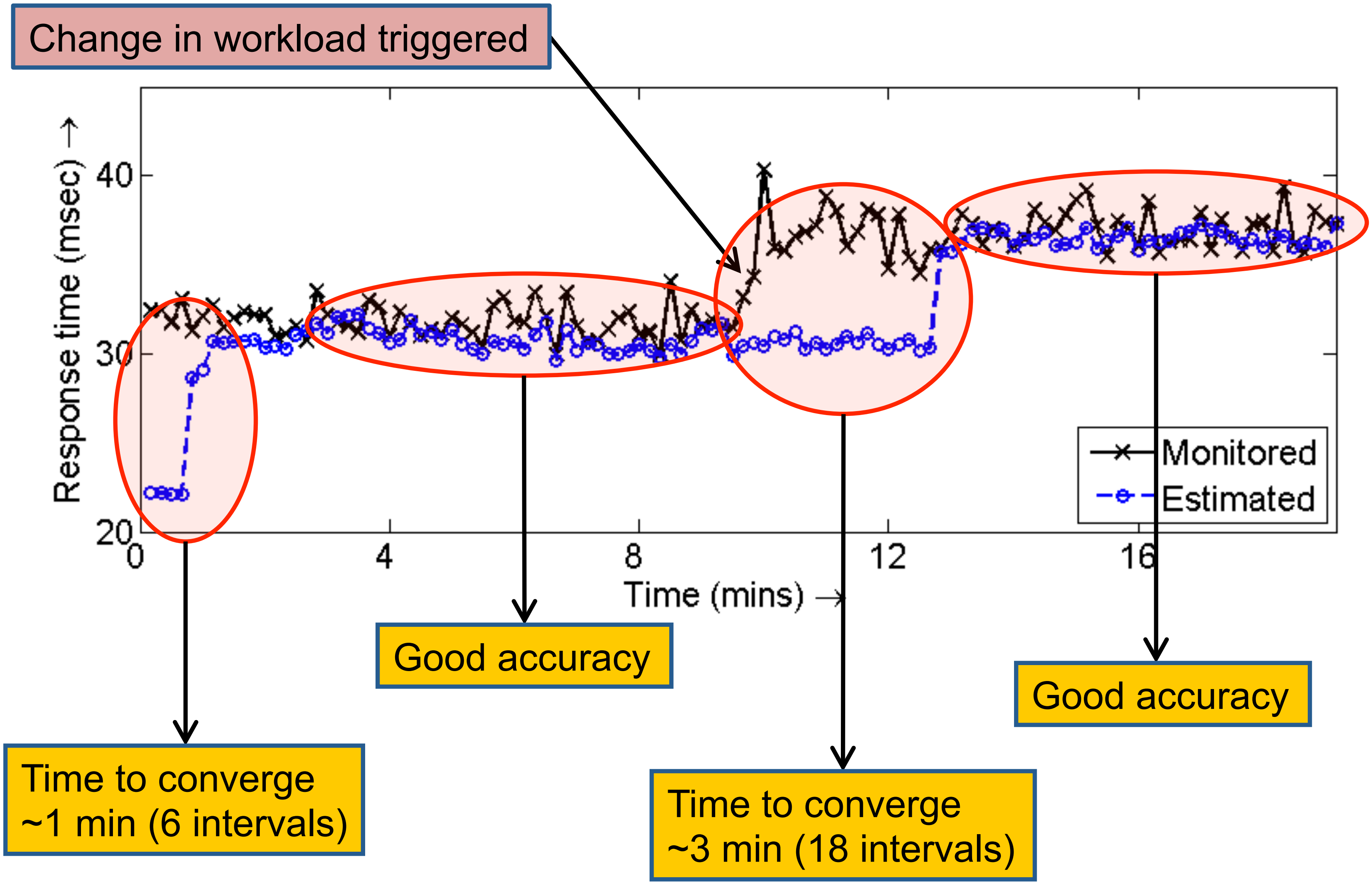
24 parameters
9 known + 15 unknown

6 equations

- Underdetermined system
- Need to "infer" unknowns
- Can leverage monitored values



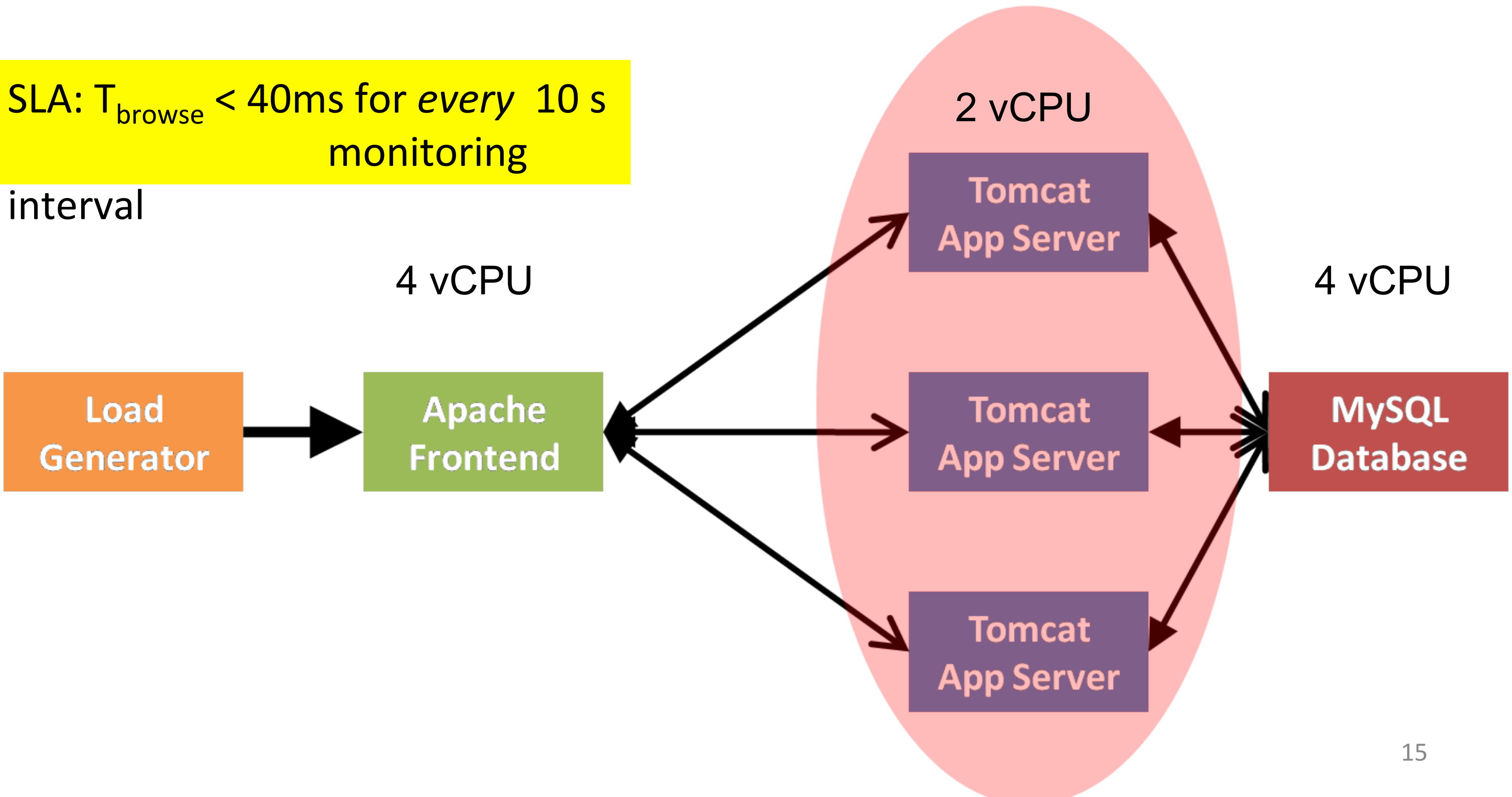
Kalman filtering + Queueing: Evaluation



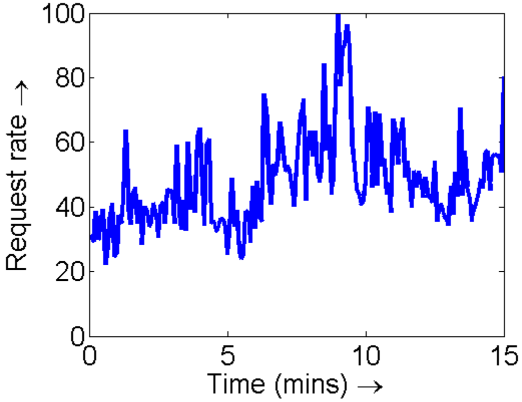
RUBiS

- RUBiS is an open source benchmark inspired by ebay.com
- Hosted on SoftLayer hypervisors via OpenStack
- We focus on scaling Tomcat app tier

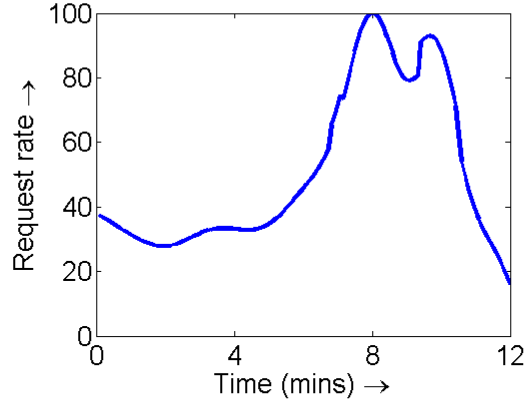
SLA: $T_{browse} < 40$ms for *every* 10 s monitoring interval



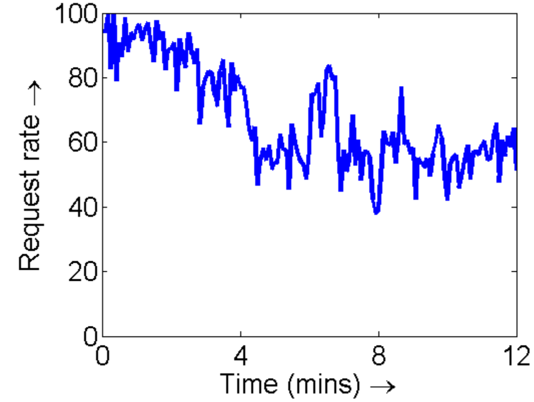
DC2: All traces



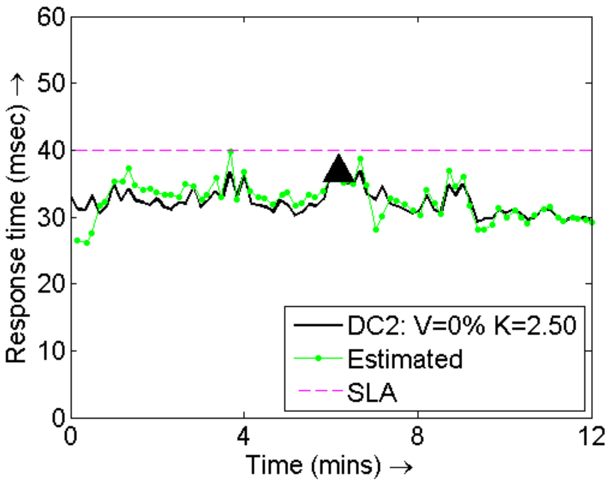
Bursty trace [WITS]

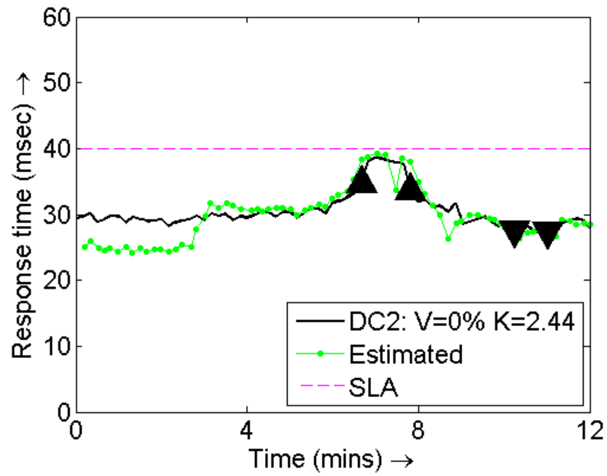


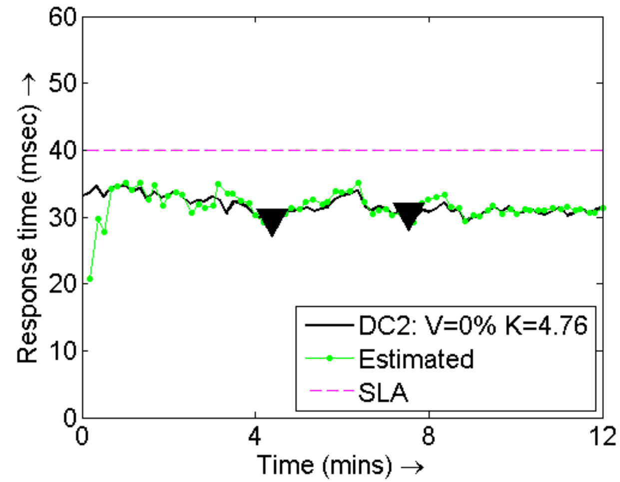
Hill trace [ITA]



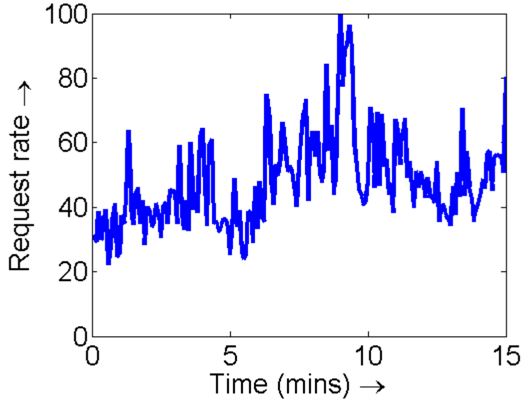
Rampdown trace [WITS]







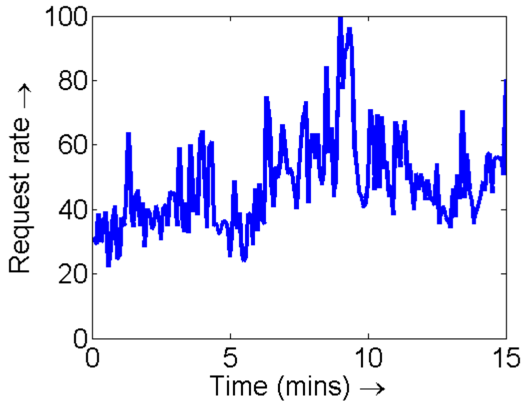
Bursty trace: All policies



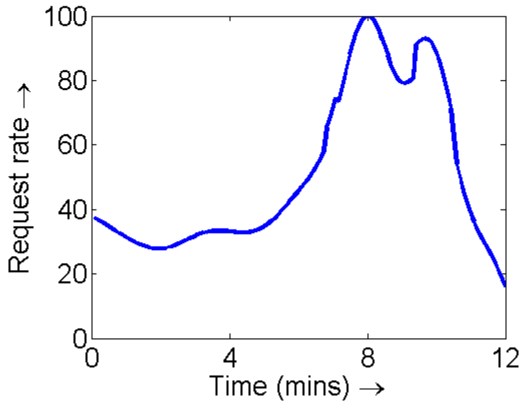
Bursty trace [WITS]

DC2	V=0% K=2.50
THRES(30,60)	V=0% K=2.50

All traces: All policies



Bursty trace [WITS]



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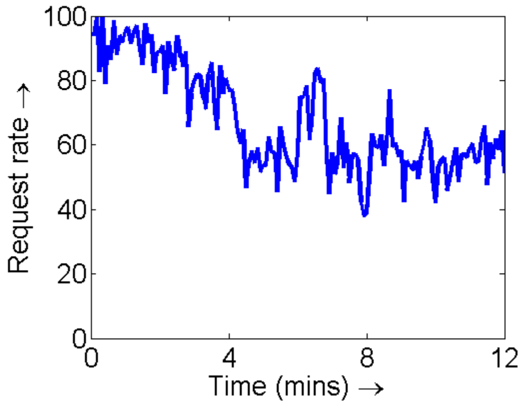

Rampdown trace [WITS]

	Bursty trace [WITS]	Hill trace [ITA]	Rampdown trace [WITS]
DC2	V=0% K=2.50	V=0% K=2.44	V=0% K=4.76
THRES(30,60)	V=0% K=2.50	V=6.66% K=2.56	V=0% K=6.00

Limitations and future work

- Evaluation limited to dynamic web applications
  - Currently investigating Hadoop-type applications
- Only applies to stateless tiers
  - DB scaling would be challenging
- Scaling algorithm can be modified
- Kalman Filtering can be replaced by other black-box approaches
  - Machine Learning approaches?
- Non-zero convergence time

Conclusions

- Need for adaptive scaling services for (opaque) cloud applications
  - Application agnostic
  - Robust to arrival patterns
- Existing commercial offerings do not suffice: rule-based
- Existing auto-scaling research solutions do not apply due to lack of visibility and control of opaque cloud applications

- Our solution: Dependable Compute Cloud (DC2)
  - Does not require offline benchmarking or expert knowledge
  - Can adapt to dynamic changes in workload
- Well suited for cloud users who lack expertise in system modeling and application knowledge

Thank You !

Conclusions

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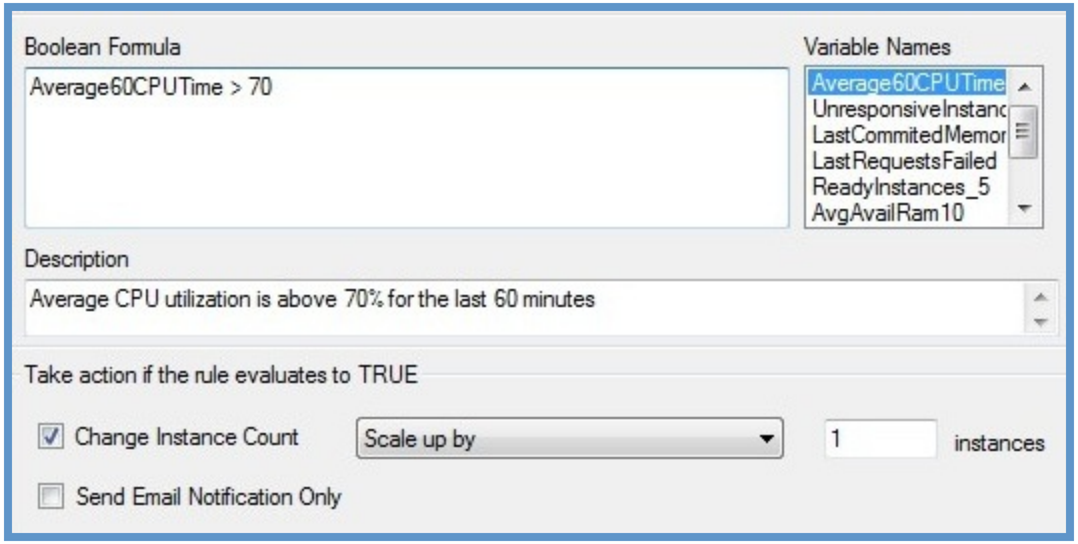
Backup

Existing CSP solutions

- Resource usage triggers
  - Amazon Auto Scaling, Microsoft Azure Watch, VMware AppInsight, CiRBA
- Request rate for specific software (ex: apache)
  - RightScale
- Latency/VM
  - Amazon Elastic Load balancing
- Web site response time
  - Scalr

User has to set values



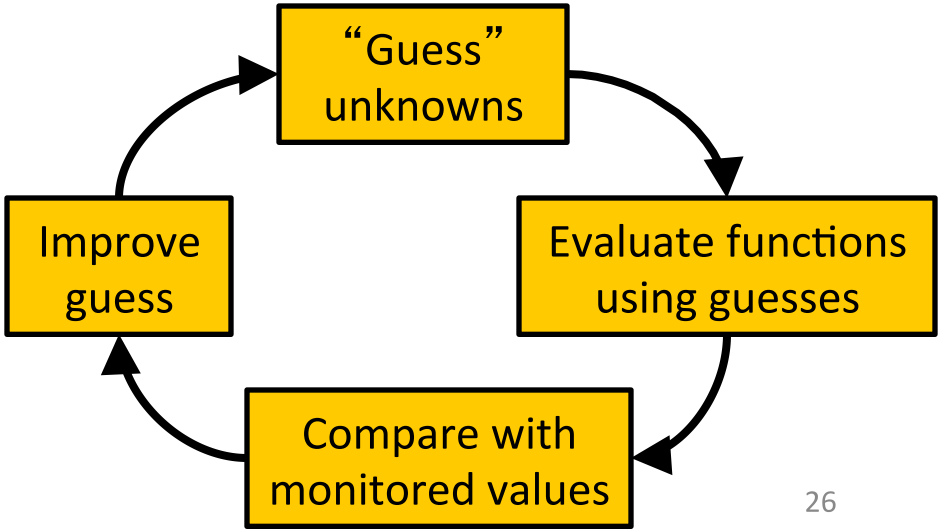
All workloads: All policies (Bursty trace)

- Rule-based policies like THRES require tuning and are not robust
- Other auto-scaling policies require control of application
- DC2 is *superior* to THRES and *does not* require application control

	Base	MoreDB	MoreWeb	MoreApp
STATIC-OPT	V=0% K=3.00	V=0% K=4.00	V=0% K=3.00	V=0% K=3.00
DC2	V=0% K=2.50	V=0% K=3.66	V=0% K=2.94	V=0% K=2.87
THRES(30,60)	V=0% K=2.50	V=3.06% K=3.40	V=2.04% K=2.98	V=0% K=3.00

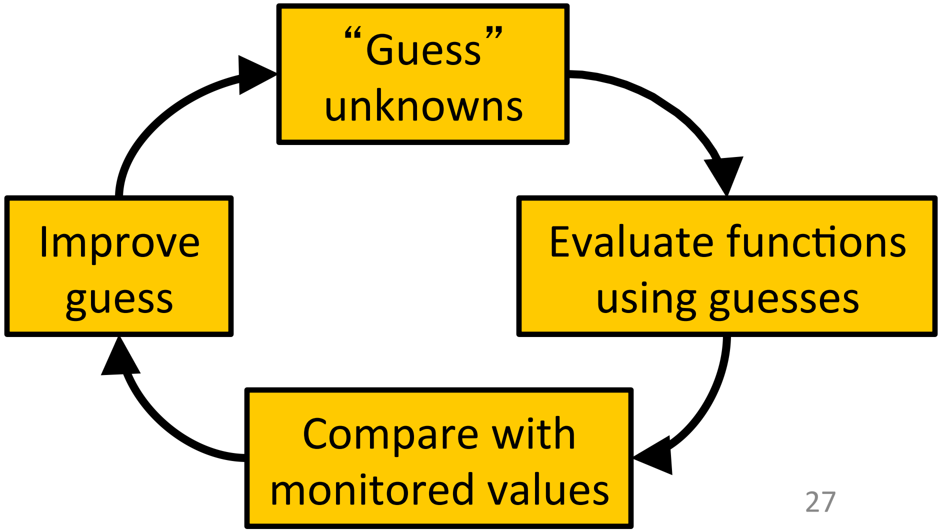
Kalman filtering

- KF is a reactive, feedback-based estimation approach that has only recently been employed for computer systems
- KF automatically learns the (*possibly changing*) system parameters, for any system, including combination of workloads
- We extend KF to a 3-tier 3-workload-class system
- Based on KF estimation, DC2 automatically, and *proactively,* detects which tier is the bottleneck, and how to resolve the bottleneck (scale VMs)
  - do not require any knowledge of application, except topology

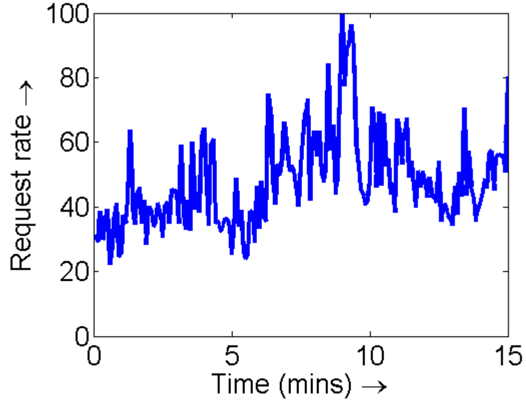


Kalman filtering + Queueing

- KF can be integrated with system models (ex, queueing models) to improve accuracy and convergence
- Model *need not* be accurate
  - KF leverages (true) monitored values to account for model inaccuracies
  - Well suited for approximate system models such as queueing-theoretic models
  - Can use other models as well, ex: machine-learning based models



All traces: All policies



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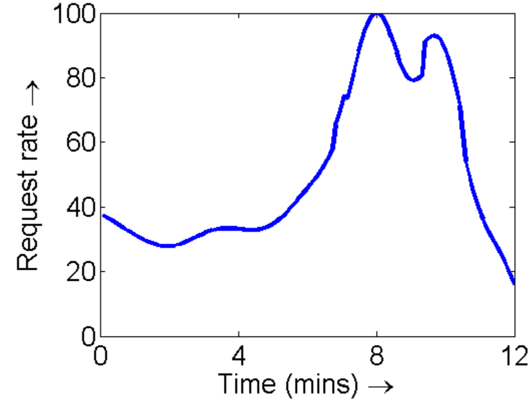

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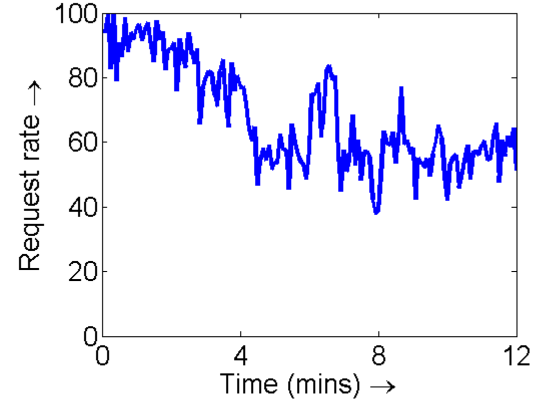

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THRES(30,50)	V=0% K=2.79	V=0% K=2.72	V=0% K=6.00
THRES(40,60)	V=2.02% K=2.19	V=15.87% K=2.13	V=0% K=4.62