## A Reinforcement Learning Approach to Virtual Machines Auto-configuration

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# Why VM Autoconfiguration?

- □ Server consolidation is a primary usage of virtualization to reduce TCO
- ☐ In cloud systems, virtual machines need to be configured on-demand, in real time
- □ VMs need to be reconfigured dynamically
  - > Created from template
  - Migrated to a new host
  - > Resource demands/supplies vary with

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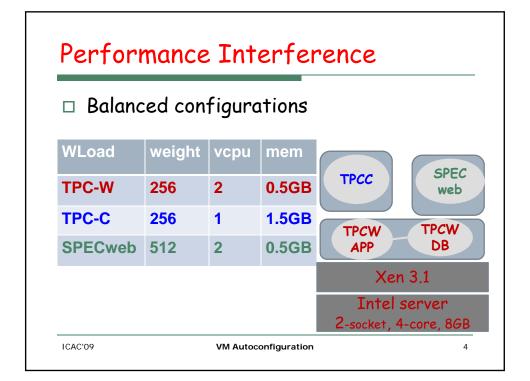
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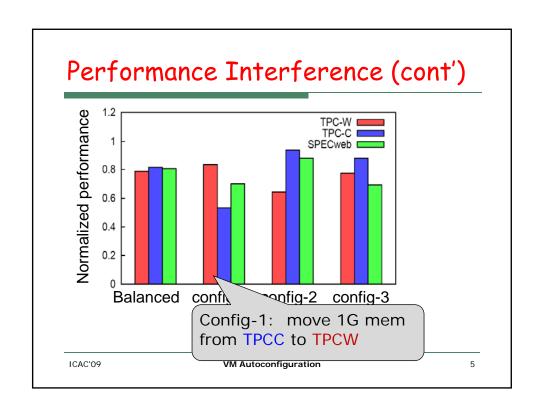
## Challenges in Online Autoconfig

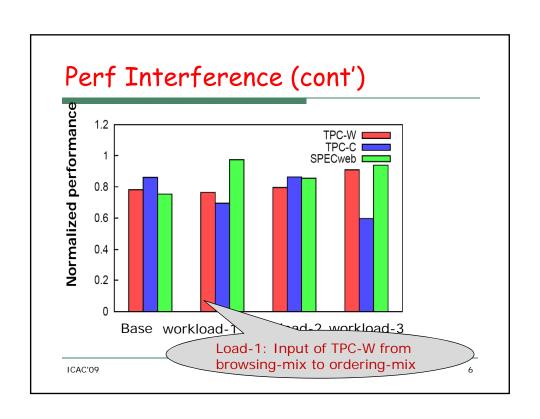
- □ A rich set of configurable parameters
  - > CPU, memory, I/O bandwidth, etc
- Heterogonous applications in the same physical platform
  - > Hungry for different types of resources
- □ Performance interference between VMs
  - > Centralized virtualization layer
- □ Delayed effect of reconfiguration
- Scale and real-time requirements make it even harder

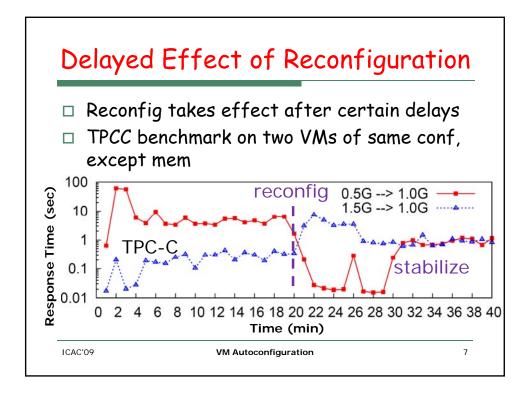
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#### Problem Statement

- □ For VMs to be run on the same physical platform, automate the resource (re)configuration process:
  - Optimize system-wide perf (utility func) under individual SLA constraints.
  - > SLA w. r.t. throughput or response time
- □ Multi-resources
  - CPU time (weighted scheduling in Xen),#virtual CPUs, Memory
- □ Work-conserving in resource allocation

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#### Related Work

- □ [Wildstrom08] Regression based value est for memory
  - Single memory resource, supervised learning, not adaptive
- ☐ [Soror08] Greedy search based config enumeration for database workloads
  - Single CPU resource, assumes independent calibration of different resources
- ☐ [Padala07, Padala09] Control theory based alloc of resources (CPU, i/o bw)
  - Assumes no interference between VMs due to the use of non-work-conserving mode
  - Delayed effect of memory config is not considered

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### Our Contribution

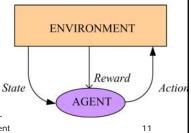
- □ A reinforcement learning approach for online auto-configuration of multiple resources (includes memory)
- □ Consideration of VM interferences in workconserving mode
- Consideration of delayed effect in resource allocation
- Prototyped in a VCONF framework and tested in real world applications

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# Reinforcement Learning

- □ Learning by interaction with env
  - > State: configuration of VMs (cpu, mem, time, etc)
  - Action: reconfiguration (increase/decrease/nop of resrc)
  - Immediate reward: w.r.t. response time or throughput
- □ Learning Objective
  - For a given state, find an action policy that would maximize long-run return



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# Reinforcement Learning (cont')

- $\ \square$  An optimal policy  $\pi^*$  is to select the action a in each state s that maximizes cumulative reward r
  - $Q^{\pi^*}(s_1, a_1) = r_0 + \gamma r_1 + \gamma^2 r_2 + ... \quad (0 \le \gamma < 1)$
- $\square$  An RL solution is to obtain good estimations of  $Q(s_t, a_t)$  based on interactions:  $(s_t, a_t, r_{t+1})$
- $\square$  Q(s<sub>t</sub>,a<sub>t</sub>) of each state-action pair is updated each time an interaction finishes:

$$Q(s_{t}, a_{t})=Q(s_{t}, a_{t})+a[r_{t+1}+\gamma^{*}Q(s_{t+1}, a_{t+1})-Q(s_{t}, a_{t})]$$

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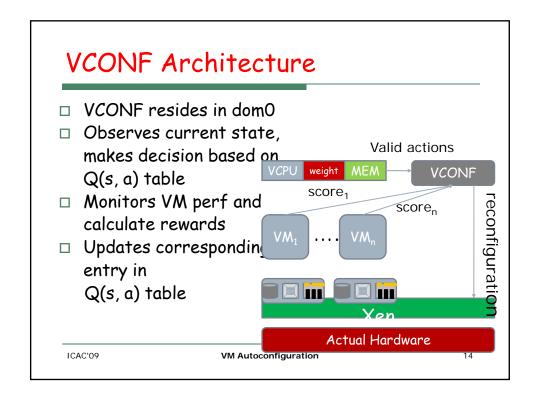
# RL for Autoconfiguration

- $\square$  State space:  $(mem_1, weight_1, vcpu_1,..., mem_n, weight_n, vcpu_n)$
- ☐ Action set: Inc, Dec, and Nop on each resource
- □ Rewards: summarized perf over hosting applications
  - > Score each VM based on normalized perf

$$reward = \begin{cases} \sqrt[n]{\prod_{i=1}^{n} w_{i} * score_{i}} & if \ for \ all \ score_{i} > 0; \\ -1 & otherwise \end{cases}$$

$$score = \frac{thrpt}{ref \ \_thrpt} - penalty$$

$$penalty = \begin{cases} 0, \ if \ resp \leq SLA; \\ \frac{resp}{SLA}, \ if \ resp > SLA. \end{cases}$$



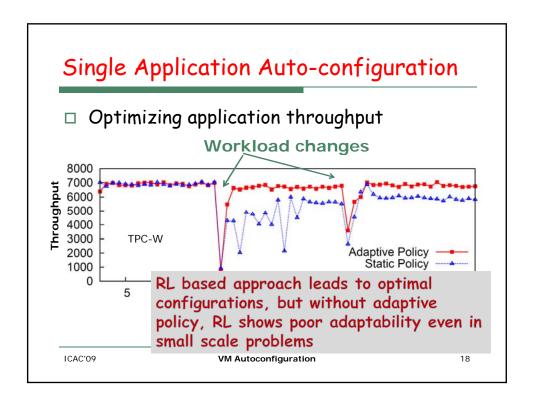
## Adaptability and Scalability

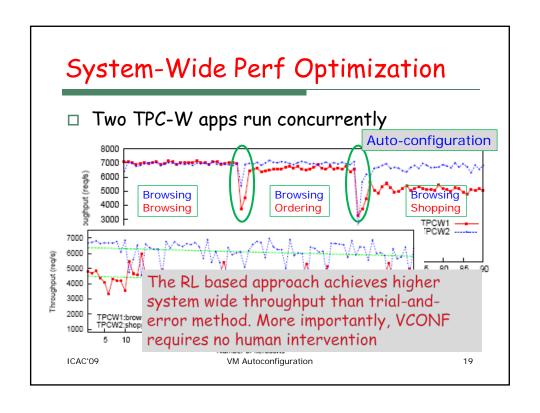
- Trivial implementation would lead to poor adaptability and scalability
- Adaptability
  - > Revise existing policy when environment changes
  - > Poor adaptability due to slow start
- □ Scalability
  - The size of the Q(s,a) table grows exponentially with the state variables

## Model-based RL and Function Approx

- ☐ Build env models from collected traces
  - $> (s_t, a_t) \rightarrow r_t$
  - Batch update Q(s, a) using simulated interactions from the models
  - > Continuously update the models with new traces
  - > Model-based RL is more data efficient
  - Model reuse when similar resource demands detected
- Replace look-up table based Q with neural network based function approximation

#### **Experimental Results** □ Settings > SPECweb, TPC-C, TPC-W as applications Xen vm ver3.1 on 2-socket quad-core CPU ronm TPCW APP ce of Two instances of TPC-W ed re Ьd TPCW DB1 TPCW APP1 TPCC Ιı testl eneou SPEC ered esour

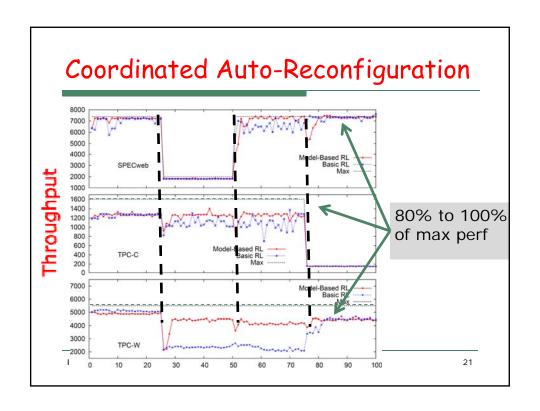




# VM Auto-configuration in Clouds

- □ Heterogeneous VMs
- □ Large problem size
  - > More VMs, more resources considered

	TPC-W	TPC-C	SPECweb
Workload-1	600 browsing	50 warehouses, 10 terminals	800 banking
Workload-2	600 ordering	50 warehouses, 10 terminals	800 banking
Workload-3	600 browsing	50 warehouses, 1 terminals	800 banking
Workload-4	600 browsing	50 warehouses, 10 terminals	200 banking



## Conclusion

- VCONF shows the applicability of RL algorithms in VM auto-configuration
  - RL-based agent is able to obtain optimal (near-optimal) policies in small scale problems
  - In clouds with a large problem size, model-based RL shows better adaptability and scalability
- □ Future work
  - Consider more resources, such as I/O, shared cache
  - Integrate migration as an additional dimension in the RL framework
- □ Auto-configuration of appliances in clouds [see ICDCS'09]

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# Thank you!

## Questions?

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