Bayllocator: A proactive system to predict server utilization and dynamically allocate memory resources using Bayesian networks and ballooning

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Motivation

- Consolidation of virtual machines is the norm
- Most systems are idle most of the time, so we can overcommit resources
- * However, when they need to do their job, they need their resources
 - * ... and could benefit if others don't need theirs
- * Reactive resource allocation may not be fast enough
 - The allocation mechanism is sometimes slow in itself

Problem statement and approach

To get a flexible approach on improving utilization efficiency of hardware resources in a single hypervisor running virtual machines

Approach:

 A proactive system to predict server load using Bayesian networks, and dynamically allocate resources on virtual machines running on a single hypervisor to provide more efficient utilization of the physical hardware

 Currently only focused on dynamic memory allocation using ballooning

Ballooning

- A kernel module is loaded into the kernel of the VM
- It can be controlled from the hypervisor to allocate or release memory
- The VM will therefore believe to have the same amount of memory, but have some of it locked



Bayllocator will ...

- Assume an over-provisioned environment
- Make a prediction of how much memory each VM needs + a defined percentage
- * Ensure that a VM's min/max values are not violated
- Avoid Hypervisor swapping
- Distribute excessive memory fairly to all VMs
- Claim memory fairly

Prediction Algorithm

- Memory consumption is divided into categories
 - * Each category spans 100MB, f.e 400_500MB
- * Given the input of: VM, weekday, time interval and current consumption, a probability is calculated for all categories
- Each probability is multiplied with a number representing the category
 - In our case: 400_500MB -> 450MB * P(400_500MB)

Simple example

1. Calculate new probabilities using Bayesian network
\$ QueryNet .R TestServer1.dat FMU \
> Monday h07 m55_59 mem_100_200

mem_100_200, 0.148 mem_200_300, 0.306 mem_300_400, 0.492 mem_400_500, 0.054

2. Use probabilities to calculate memory demand $150 \cdot 0.148 = 22.2$ $250 \cdot 0.306 = 76.5$ $350 \cdot 0.492 = 172.2$ $450 \cdot 0.054 = 24.3$ 22.2 + 76.5 + 172.2 + 24.3 = 295.2 MB

The redistribution of wealth

- There may not be enough memory to meet all the predicted allocations
- *Fair* Large VM's will need more memory, but should be expected to share more too
- In practice, use a percentage rather than memory values when awarding / claiming memory

Experimental setup

- * Both generated data and replays of real data
- * Single KVM hypervisor with several VM's
- Special script mimicked workloads inside the VM
- Collected usage data into a DB and wrote a prototype using R and Perl

Results - Simulated data



Results - Real-life replay



Predictions start

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Predictions start

Results - Learning periods and accuracy

- * The more observed data, the better the accuracy of the predictions
- A fundamental difficulty with using historical data is that you need historical data
 - High-quality historical data is hard to come by
 - * Often times underlying trends or gaps pollute the data

Discussion

- A virtual machine will never get less memory than has ever been observed on it*
- "Why not choose the category with the highest probability, instead of calculating the sum?"
- * "What is the training time?"
- * "Why use only temporal parameters?"
- * "Can I run it and expand on the bayesian network myself?"
- Bayllocator is not about reactive, flashmob-mitigation

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Future work

- Weight-lifting for servers: If we knew the signs of a flashmob, we could train the model for it.
- Investigate the outer limits of ballooning under extreme circumstances
- Comparison with memory de-duplication
- Combining Bayllocator with reactive behavior

Thank you!

Questions?

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