BASIL: Automated IO Load Balancing across Storage Devices

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USENIX FAST - February 25, 2010



Outline

Problem Description & Motivation

- BASIL Modeling & Load Balancing
- Experimental Framework & Results
- Conclusions & Future Work

Datacenter Automation—State of the Art



Automated Load Balancing of CPU and Memory resources across a cluster of servers using **live migration**.

e.g., **VMware DRS** (Distributed Resource Scheduler)













Management Nightmares

IO load balancing? Virtual disk placement?



Storage Devices





Shoulders of Giants

Much characterization & modeling work precedes us

 Workload Characterization Kavalanekar et al: IISWC '08 Gulati et al: VPACT '09

Minerva, Hippodrome, Table-based Alvarez et al: ACM Trans. On Computing '01 Anderson et al: FAST '02

Analytical device models
 Uysal et al: MASCOTS '01
 Shriver et al: SIGMETRICS '98
 Merchant et al: IEEE Trans. Computing '96
 Ruemmler & Wilkes: IEEE Computer '94

Relative fitness modeling

Mesnier et al: SIGMETRICS '07

CART models

Wang et al: MASCOTS '04

Novel features

- Latency as primary metric
- Online and lightweight
- Different goal compared to existing literature

Latency as Main Metric—Why?



11

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BASIL Sketch

Online modeling

- Workload : capture dynamic behavior
- Device : capture device performance

Load balancing based on

- Workload and device models
- Assign workloads to device in proportion to their metrics

Workload Modeling



I/O Workload Modeling

Percentiles Data collected per-virtual disk

- Outstanding IOs
- IO Size

- Read/Write Ratio
- Randomness

Methodology

• Analyze impact of each parameter on latency



Percentiles Data collected per-virtual disk

- Outstanding IOs
- IO Size

- Read/Write Ratio
- Randomness

Latency varies linearly with #Outstanding IOs



Percentiles Data collected per-virtual disk

Outstanding IOs

• IO Size

- Read/Write Ratio
- Randomness

Latency varies linearly with IO Size



I/O Workload Modeling

Percentiles Data collected per-virtual disk

Outstanding IOs

Read/Write Ratio

IO Size
 Randomness

Latency varies linearly with %Reads



I/O Workload Modeling

Percentiles Data collected per-virtual disk

- Outstanding IOs
 Read/Write Ratio
- IO Size

Randomness

Latency varies linearly or Remains flat with %Randomness



Percentiles Data collected per-virtual disk

- Outstanding IOs
- IO Size

- Read/Write Ratio
- Randomness
- Workload Model denoted as W

 $W = (OIO + K_1) \cdot (IOsize + K_2) \cdot (Read\%/100 + K_3) \cdot (Random\%/100 + K_4)$

K values fit from empirical data

• $K_1 = 1.3$ • $K_2 = 51$ • $K_4 = 0.6$

OIO is the main contributor for most cases IO Size impacts only when change is large Read% and Random% have less impact, except extreme scenarios



Device performance can vary widely

- Different number of disks: 4 vs.16 disk LUN
- Different disk types: FC vs. SATA
- RAID type
- % Disk occupancy

BUT, device characteristics are hidden from hosts





Device Performance estimation

- <OIO, Latency> pairs collected using a reference workload
- Linear fit approximation of the pairs
- Slope indicates relative performance of the device

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Online Device Modeling—Issues

- Generally expect positive slope values
- We observe negative slope values in some cases
 - Large write IO bursts in real applications going to cache
 - IO size variation for different Outstanding IOs



Online Device Modeling—Solution

Filter out data from collected samples Writes: <*Read OIOs, Read latency* > pairs Large IOs: filter out if IO size > 32 KB • Sequential IOs: filter out if sequentiality > 90 % **Considering only Read IOs** Slope = 0.7368 Average Read IO Latency (in ms) 12 10 8 Slope = 0.3525B Linear Fit (DVD Store 4-disk LUN) 2 Linear Fit (DVD Store 8-disk LUN) 0 2 12 0 14 16 4 10 Outstanding IOs

Key Takeaways

Slopes are indicative of relative performance

- 4 vs. 8 disks, other factors are constant
- FC better than SATA, other factors kept constant

Incorporates cache effects

• Lower slope for arrays with smaller cache



Online modeling

- Online modeling is highly useful in practice
- Filtering of online input needed to handle extreme workloads

Load Balancing



Load Balancing

Recall Workload metric: W_i

 $W_i = (OIO + K_1) \cdot (IOsize + K_2) \cdot (Read\%/100 + K_3) \cdot (Random\%/100 + K_4)$

Recall Device metric: P_i

- 1 / slope of linear fit between <Read OIO, Read latency>
- Define Normalized Load on a device: NL

$$NL = \frac{\sum \text{Workload metric } W_i \text{ on a device } j}{P_j}$$

Load balancing

- Assign workloads to devices in proportion to their performance
- Heuristic: Equalize NL across data stores

Initial placement of virtual disks

Pick device with minimum NL

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Experimental Setup

- 2 hosts running VMware ESX 4.0 hypervisor
 - 8 to 13 virtual machines (VMs) mix of Windows, Linux OSes
 - 6 Data stores
- Devices (LUNs) spread across EMC CLARiiON & NetApp FAS-3140
- Workloads
 - Real Apps: Swingbench (DBMS: Oracle), DVD Store (DBMS: SQL)
 - Filebench: varmail, OLTP, webserver
 - Iometer configurations: OLTP, Workstation, Exchange Server, Web Server
 - <u>http://blogs.msdn.com/tvoellm/archive/2009/05/07/useful-io-profiles-for-simulating-various-workloads.aspx</u>











Three devices for micro-benchmark experiments

Device	#disks	Array	RAID	P= 1/slope
3diskLun	3	EMC Clariion	RAID-5	0.6
6diskLun	6	EMC Clariion	RAID-5	1.4
9diskLun	9	EMC Clariion	RAID-5	1.8

P: higher is better

Three devices for real-workload experiments

Device	#disks	Array	RAID	P= 1/slope
EMC	6 FC	EMC Clariion	RAID-5	1.10
NetApp-SP	6 FC	NetApp FAS 3140	RAID-5	0.83
Netapp-DP	7 SATA	NetApp FAS 3140	RAID-6	0.48



Summary: 500 Runs

Random placement vs. BASIL (80th percentile values)

- \geq 25% improvement in IOPS
- \geq 33% decrease in overall latency (computed using IOPS as weights)



Summary: 100 Initial Placements

Random initial placement vs. BASIL (50th percentile values)

- \geq 53% improvement in IOPS
- \geq 45% decrease in overall latency (computed using IOPS as weights)



Summary: Enterprise Workloads

Human Experts vs. BASIL

- 13 VMs: 3 DVDstore, 2 Swingbench, 4 mail servers, 2 oltp, 2 webservers
- 2 ESX hosts, 3 storage devices



BASIL provides lowest average latency and similar throughput

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Conclusions and Future Work

BASIL provides

- Practical online workload and device models
- Efficient initial placement
- Load balancing results in higher utilization, lower overall latency

Future Work

- K_i values: static vs. dynamic
- Try out alternate workload models
- Separate device modeling for reads & writes
- Detailed cost-benefit metric for storage vmotions