Towards Improved Provisioning and Utilization of Resources in Virtualized Environments

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PhD Defence Presentation

Computing-as-a-Service: The New Norm

Electricity Grid

Public Transport

Virtualization
Containers
Edge Computing
Serverless Computing

Enabling technology

- Software as a Service
- Platform as a Service
- Infrastructure as a Service

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1. Network-affinity aware CPU Usage Estimation

Prediction of virtualized CPU usage for inter-PM and intra-PM network communication between VMs

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Reduction of disk I/O by exploiting content similarity within and across virtual machines

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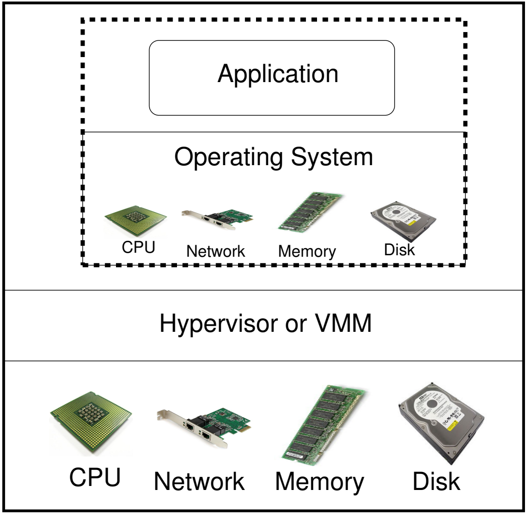
Tools and Deliverables

1. `WLoadGen`: A load generator for CPU, disk & network loads
2. `SimReplay`: A simulator for analyzing host cache effectiveness
3. `preadwritedump`: A kernel module for I/O request tracing

Resources Under Consideration



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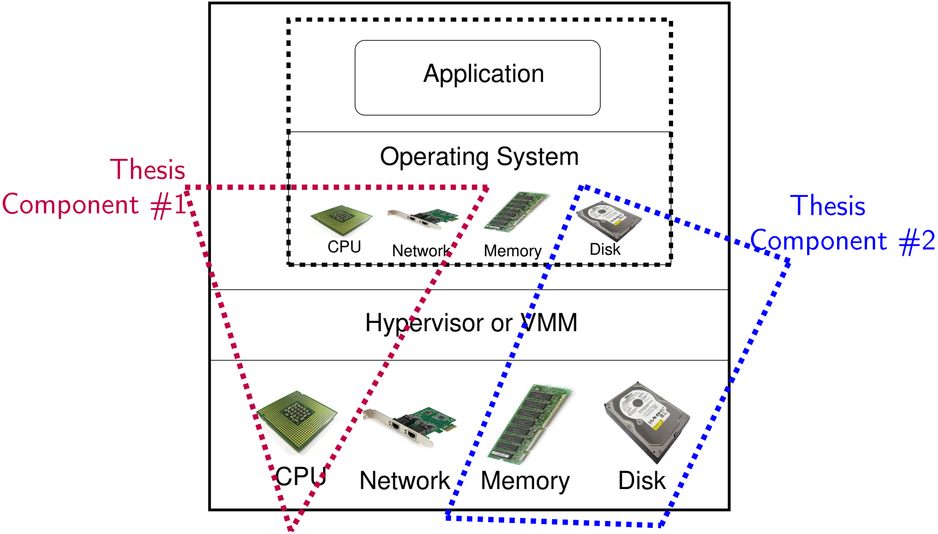

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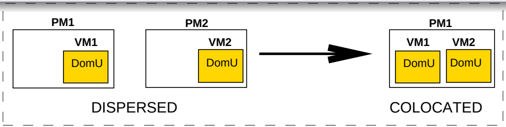
Reduction of disk I/O by exploiting content similarity within and across virtual machines

Network-affinity aware CPU Usage Estimation

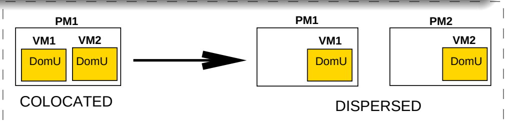
1. Event profiling study showing difference between *intra-PM* and *inter-PM* network code paths
2. Benchmarking of CPU usage in colocated and dispersed scenarios for a VM pair
3. Pair-wise linear regression model to predict total CPU when network traffic changes nature between intra-PM and inter-PM
4. Pair-wise linear regression model to predict differential CPU usage
5. Application of pair-wise models to predict for multi-VM scenarios

Migration-Enabled Resource/Performance Management

Colocate VMs for Resource Efficiency => intra-PM network traffic

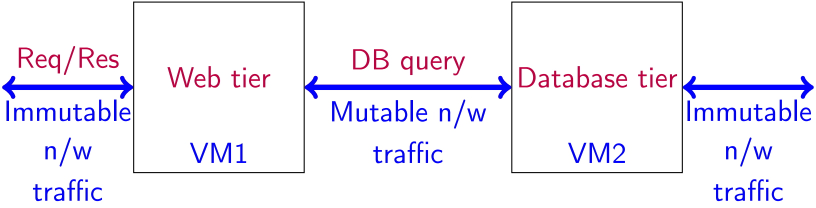


Disperse VMs for QoS => inter-PM network traffic



- Both colocation and dispersion need resource usage estimation
- Incorrect estimation is sub-optimal
  - Under-estimation => degraded performance
  - Over-estimation => wasted resources

Mutable and Immutable Network traffic for *Migratory* VMs



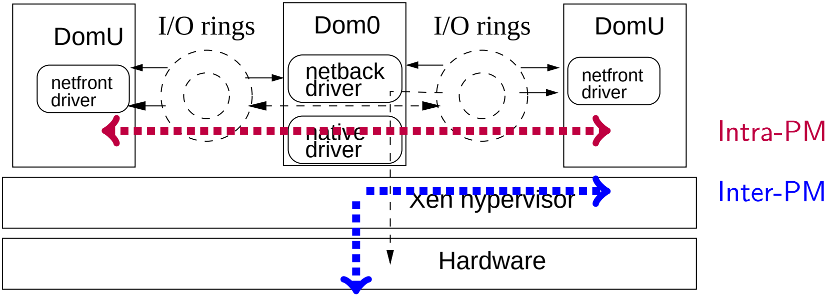
Definition of Mutable n/w traffic

For a VM pair, network traffic whose nature may *change between inter-PM and intra-PM*

Our hypothesis

Mutable network traffic has different CPU overheads in colocated and dispersed scenarios => ignoring affinity effects could result in incorrect CPU usage estimation

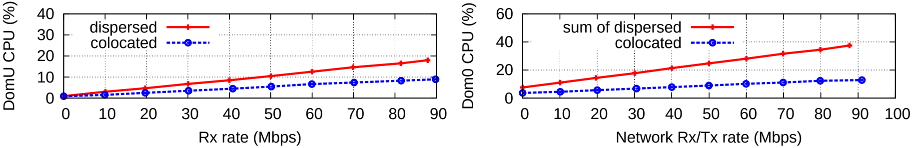
Communicating VMs (Xen-view)



- Dom0 overhead for DomU's I/O activity (network & disk)
- Intra-PM network traffic
  - Dom0 does not use native I/O drivers
  - Shared memory based copying of packets
- Less CPU overhead for *intra-PM* traffic compared to *inter-PM*
- Needs to be accounted for during VM migration

Effect of colocation on CPU usage for *Mutable* N/w traffic

Benchmarking setup: 2 VMs on 2 PMs—dispersed and colocated scenarios
Network load: Transmitted (Tx) by one VM and Received (Rx) by other



(a) Receiving DomU CPU util (b) Dom0 CPU util for Rx/Tx

Observations

- **DomU**: Rx increase from 20-90 Mbps =>decrease of 2-8% CPU util
- **Dom0**: Increase from 20-90 Mbps =>decrease of 9-25% CPU util

Effect of colocation on CPU usage for Immutable n/w traffic, CPU and disk loads

Benchmarking setup: 4 VMs on 4 PMs—dispersed and colocated scenarios

Table : Percentage CPU usage for Immutable Rx

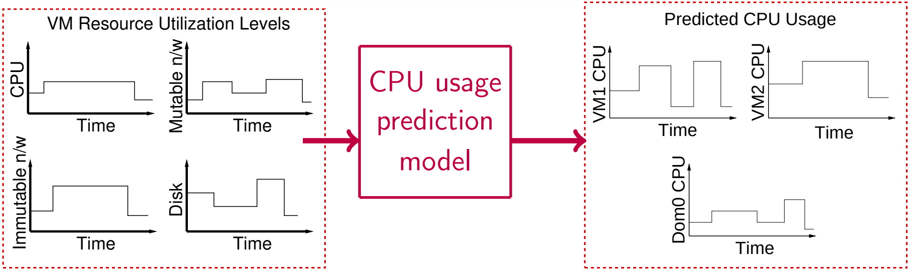
Immutable Rx (Mbps) ($< VM_1, VM_2 >$)	**% CPU utilization**	
	Dispersed case $VM_1, VM_2, \sum Dom0_i$	**Colocated case** $VM_1, VM_2, Dom0$
<20, 50>	4, 7, **18**	4, 7, **14**
<40, 10>	6, 2, 15	6, 2, 11
<60, 10>	8, 2, 18	8, 2, 14

Observations

1. No change in DomU CPU usage between colocated and dispersed
2. Dom0 CPU usage change of 4% for extra Dom0 instance (constant)
3. Similar observations for other workloads—CPU and disk read/write

Problem: Affinity-aware Resource Requirement Estimation

Given a pair of VMs and their resource utilization levels, predict the CPU resource requirement of DomU & Dom0, when VM placement scenario changes between dispersed and colocated.



For VM1 and VM2 (dispersed)

(colocated)

Core Idea

Since correlation of CPU usage with all other resources usage is linear, build linear prediction models

Linear Regression Modeling for CPU Estimation

Parameters in the models

- **CPU** metrics: user, system, iowait
- **Disk** metrics: read blocks/second, write blocks/second
- **Mutable and immutable** network metrics: Rx and Tx Kbps

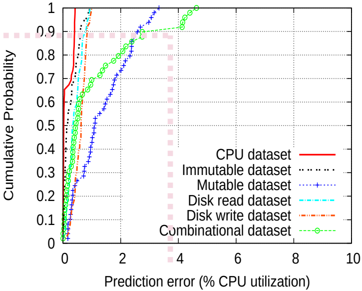
DomU Models

$$CPU_{colocated} = f(CPU, Disk, Mutable, Immutable)_{dispersed}$$
$$CPU_{dispersed} = f(CPU, Disk, Mutable, Immutable)_{colocated}$$

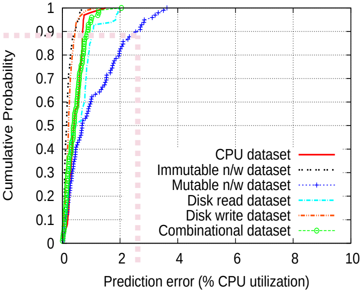
Dom0 Models

$$CPU_{colocated} = f(CPU_1, Disk_1, Mutable_1, Immutable_1, CPU_2, Disk_2, Mutable_2, Immutable_2)_{dispersed}$$
$$CPU_{dispersed} = f(CPU_1, Disk_1, Mutable_1, Immutable_1)_{colocated}$$

Prediction for Synthetic workloads - Xen Dom0 model



(a) Dispersed to colocated

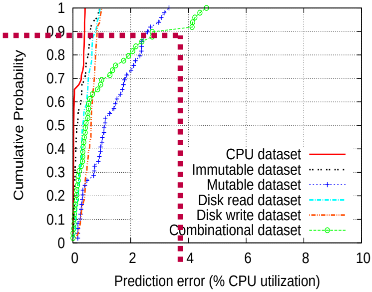


(b) Colocated to dispersed

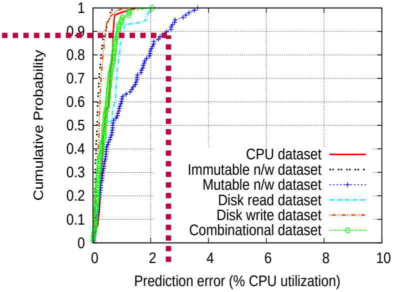
Observations

90^{th} percentile prediction error within 3% absolute CPU utilization, and maximum error 5-6% absolute CPU (Similarly for RUBiS workload as well)

Prediction for Synthetic workloads - Xen Dom0 model



(a) Dispersed to colocated



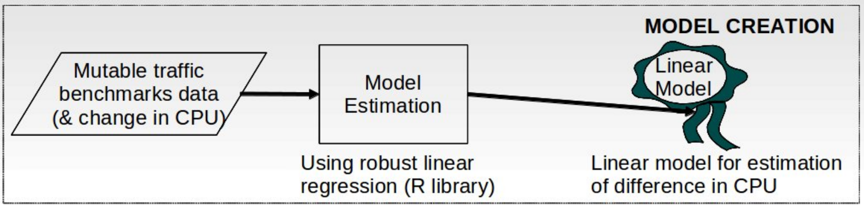
(b) Colocated to dispersed

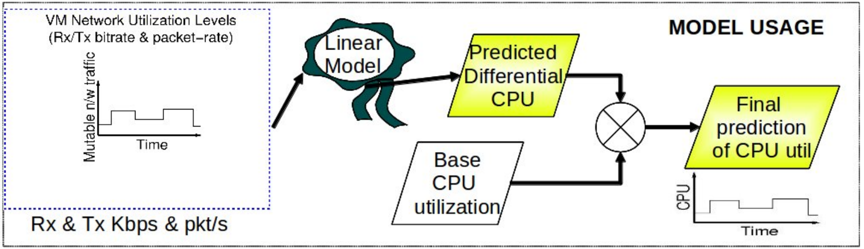
Observations

90^{th} percentile prediction error within 3% absolute CPU utilization, and maximum error 5-6% absolute CPU (Similarly for RUBiS workload as well)

Building an Enhanced Prediction Model

Because "differential" CPU usage is only due to mutable n/w traffic





Evaluation of Differential CPU Prediction Models

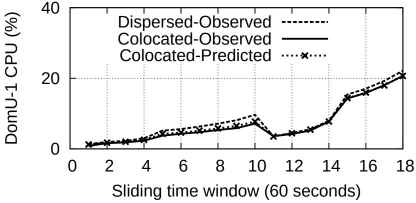


Figure : Colocated DomU-1 (Synthetic)

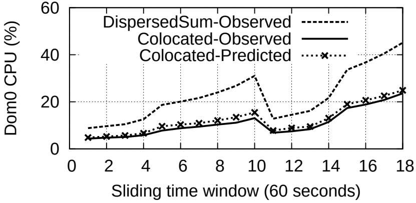


Figure : Colocated Dom0 (Synthetic)

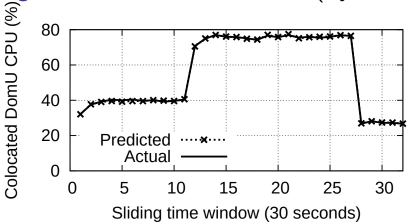


Figure : Colocated DomU-1 (RUBiS)

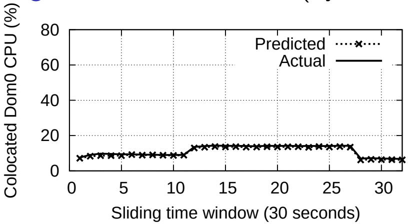
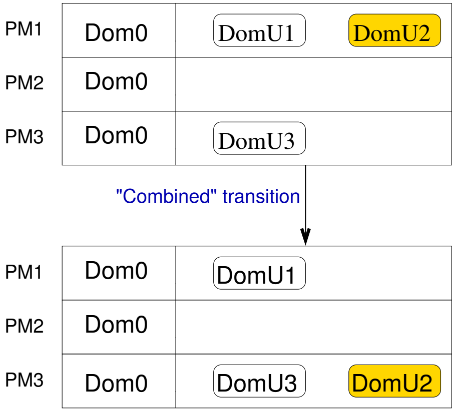


Figure : Colocated Dom0 (RUBiS)

Result

Maximum prediction error between 1-2% absolute CPU utilization.

Applying Pair-wise Models to Multi-VM Scenarios



Two-step prediction for combined transition

1. Predict using *dispersion model*
2. Predict using *colocation model* on previous prediction

Evaluated for multi-hop transitions

Table : Maximum error in Dom0 CPU utilization prediction

Transition	Max error (% absolute CPU)		
	Dom0-PM1	Dom0-PM2	Dom0-PM3
Transition (i)	0.75	-	-
Transition (ii)	1.99	-	0.85
Transition (iii)	-	0.51	0.43

Summary and Conclusions

- **Colocation of mutually-communicating VMs impacts their CPU requirement**
  - DomU: For Rx, increase from 20 to 90 Mbps => decrease from 2% to 8% CPU requirement
  - Dom0: Increase from 20 to 90 Mbps => decrease from 9% to 25% CPU requirement
- **Simple linear model shown to predict "differential" CPU requirement from mutable n/w traffic profiles**
  - Synthetic and RUBiS workloads: Max error within 1.5% absolute CPU utilization for both DomU and Dom0 models
  - Multi-VM scenario: Max error within 2% for all transitions

Publications

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VM Disk I/O Reduction by Host-cache Manipulation

1. Analysis of existing work (IODEDUP) to show inconsistent performance
2. Redirection of I/O requests from within VMs and implicitly manipulate host-cache in content-deduplicated fashion
3. Evaluation using public dataset available online
4. Case for generation of realistic I/O deduplication benchmarks

Publication

DRIVE: Using Implicit Caching Hints to achieve Disk I/O Reduction in Virtualized Environments. Proceedings of the 21st International Conference on High Performance Computing (HiPC), 2014. Sujesha Sudevalayam, Purushottam Kulkarni, Rahul Balani and Akshat Verma.

Effect of Data Similarity on Host-cache Effectiveness

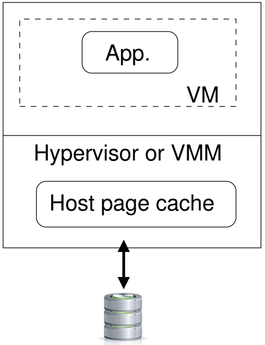


Figure : Typical virtualized system

Two optimization avenues

1. Duplicate I/O
2. Duplicate content in cache

Two orthogonal solutions

1. I/O deduplication (IODEDUP[1]) : but causes cache inclusiveness problem
2. Memory deduplication (Satori[2]) : dedupes after data is fetched

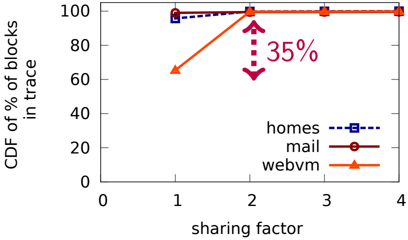
Sources of data similarity

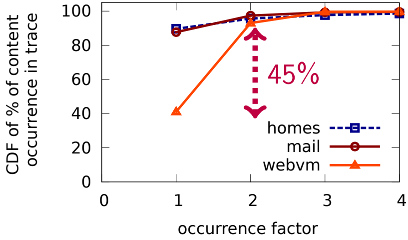
Similar operating systems, libraries, binaries, file copies,

Aim of this work

Improve host-cache effectiveness *using* I/O deduplication techniques,

Traces[1] used for evaluation: Similarity study





Observations

- *homes* & *mail* traces have 95% blocks with sharing factor 1, whereas *webvm* trace has 35% blocks with sharing factor 2
- In *webvm* trace, 45% content occur twice, compared to 6-10% in *homes* and *mail* traces

Conclusions

webvm trace is likely to benefit the most from I/O deduplication

Existing[2] I/O deduplication technique: IODEDUP [3]

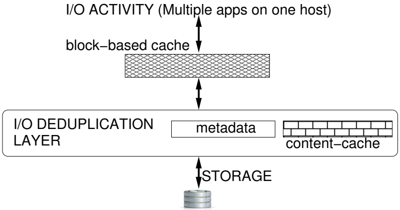


Figure : System Architecture of IODEDUP

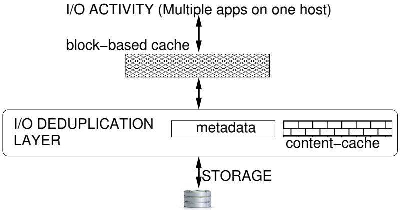
Functioning

- Creates and maintains content-based cache
- Intercepts read requests & services without accessing disk if possible

[2] Other related work for I/O deduplication & reduction discussed in thesis.

[3] *I/O Deduplication: Utilizing Content Similarity to Improve I/O Performance*

Existing[2] I/O deduplication technique: IODEDUP [3]



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Drawbacks

- Content-cache *sizing* needs exploration
- Block-cache still faces *duplicate content* problem

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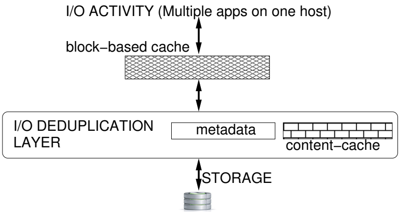

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Functioning

- Creates and maintains content-based cache
- Intercepts read requests & services without accessing disk if possible

Our contribution

- Perform *study of cache effectiveness* for IODEDUP system, using a custom simulator

[2] Other related work for I/O deduplication & reduction discussed in thesis.

[3] *I/O Deduplication: Utilizing Content Similarity to Improve I/O Performance*

Study of cache effectiveness for IODEDUP

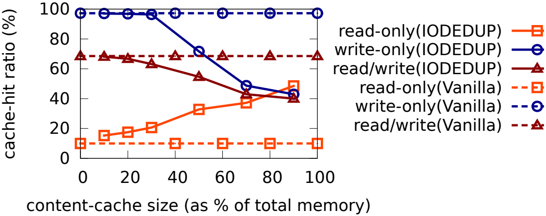


Figure : Cache-hit ratios for IODEDUP for *webvm* trace. Total cache 512 MB

Observations

1. Read-only trace has lowest performance at content-cache of 10% & highest at 90%
2. Write-only performance varies reverse, i.e., highest at 10% and lowest at 90%
3. At content-cache setting of 90%, read-only performance is 4× Vanilla, but read/write performance 42% worse than Vanilla.

Conclusion

Inconsistency in achievable cache effectiveness

Fundamental issues preventing efficient I/O reduction

Issues

1. IODEDUP system [1] has cache inclusiveness problem
2. Memory deduplication [2] works after data is already fetched from disk

Naive solution

- Operate host cache in fully-deduplicated fashion, such that only data not present in cache will ever be fetched from disk

Challenges in implementing naive solution

1. Needs change to cache datastructures and/or algorithms
2. Needs metadata updates per cache insertion
3. Needs invasive monitoring & metadata updates per cache eviction

DRIVE: Using implicit caching hints to achieve disk I/O reduction in virtualized environments

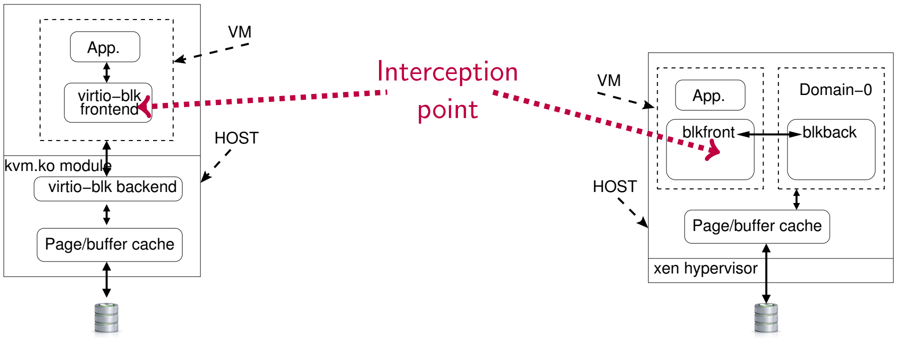
Our Approach

- Augment the virtual disk driver to **use implicit caching hints** to achieve an approximately fully-deduplicated host cache

System Requirements for DRIVE

1. Intercept block read *request* path for metadata lookup and I/O redirection, if present
2. Intercept block read *return* path for metadata update, if not previously present
3. Intercept block write *request* path for metadata invalidation
4. Maintain implicit caching hints within metadata to aid efficient I/O redirection.

Block request interception-point for DRIVE



(a) KVM split-driver architecture

(b) Xen split-driver architecture

Interception within VM's front-end driver

- De-coupling of the front-end and back-end drivers enables simple I/O redirection
- Results in implicit manipulation of host-cache as a content-deduplicated cache
- Exploits individual workload's content self-similarity, useful irrespective of co-hosted VMs
- Implementation within generic `virtio` drivers obviates dependence on VMM & guest OS

DRIVE metadata store: semantics and usage

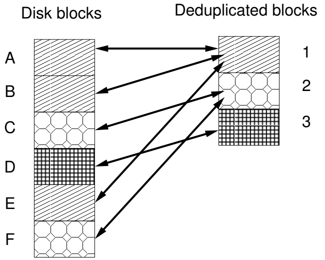


Figure : Semantics of metadata store.

DRIVE metadata store: semantics and usage

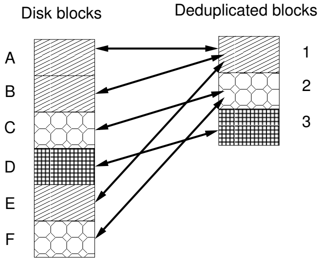


Figure : Semantics of metadata store.

Obtaining and using hints for I/O redirection

1. When a block is fetched, it is "known" to be cached
2. Above is noted in metadata, marked as *leader*
3. For next redirection, *leader* is used

DRIVE metadata store: semantics and usage

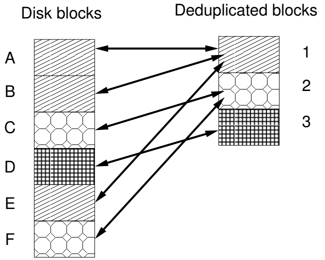


Figure : Semantics of metadata store.

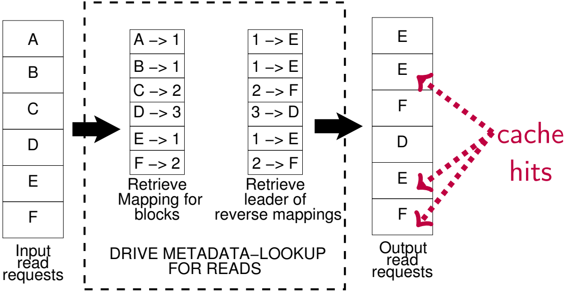


Figure : Example of read request redirection in DRIVE

Obtaining and using hints for I/O redirection

1. When a block is fetched, it is "known" to be cached
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3. For next redirection, *leader* is used

Evaluating host-cache effectiveness in DRIVE system

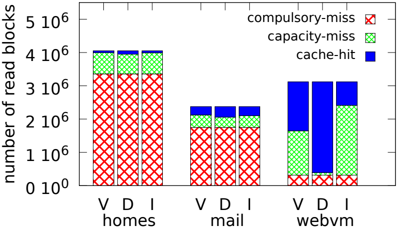


Figure : Classification of read responses

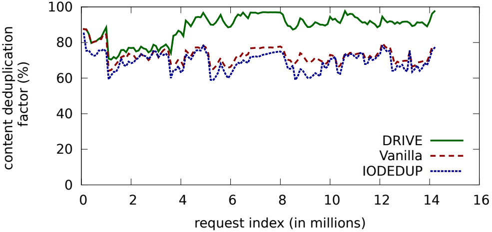


Figure : Content deduplication factor of page cache upon *webvm* trace.

Conclusions

- Both *homes* and *mail* workloads have huge number of compulsory misses, whereas the *webvm* workload has significantly fewer.
- DRIVE decreases number of capacity misses to 5% of Vanilla
- DRIVE achieves up to 97% deduplication in block-cache

Identifying similarity in multiple virtual machines

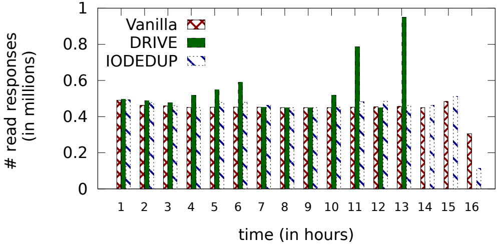


Figure : Read response throughput for aggregated (*homes*+*webvm*) trace.

Table : Performance for aggregated trace replay

Scheme	Cache-hit ratio (%)	Disk reads reduced(%)	Avg. read response latency (msec)
Vanilla	61.2	1.6	7.9
DRIVE	67.6	18.5	6.5
IODEDUP	62.4	4.3	7.7

Conclusions

- DRIVE completes earlier due to higher number of responses per hour on average[4].
- Huge margin in percentage of disk reads reduced

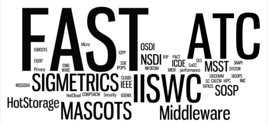
Summary of DRIVE

1. Performs implicit caching hint-based I/O redirection
2. Simulation-based evaluation shows promise—up to 97% content-deduplicated cache achieved
3. Further analysis requires more production traces

[4] Throughput derived from measured cache-hits & disk-reads and assumed latency values.

Dataset survey for I/O deduplication traces

To find other public datasets that can be used for our evaluation



(a) Conference-name tag cloud

(b) Year-of-publication tag cloud

Three types of workloads used in literature

1. Synthetic benchmarks
2. Production I/O traces
3. Production filesystem datasets

Our requirement

I/O traces having content representation as well—not available publicly.

Literature survey for "realistic" dataset generation

Types of datasets generated

1. I/O traces (without content) [4, 5, 6, 7, 8]
2. Filesystem content (without I/O traces) [9]

Relevant characteristics for I/O traces[5]

Block accessed distribution & Jump distances—*spatial locality*
Run lengths & Block reuse distances—*temporal locality*

General approach

1. Capture Multi-dimensional distributions and/or Markov models
2. Use above captured models to create new traces with similar properties
3. Vary appropriate parameters to create different traces as necessary

[5] *webvm* and *homes* trace characterization presented in thesis.

Content-defined characterization of *webvm* trace

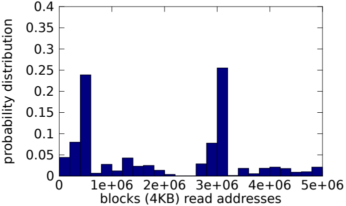


Figure : (a) Block access distribution

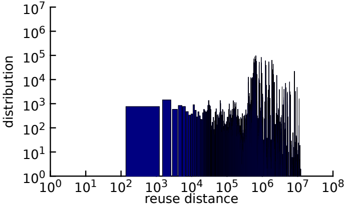


Figure : (c) Block reuse distribution

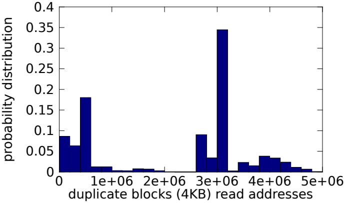


Figure : (b) Duplicate block distrib

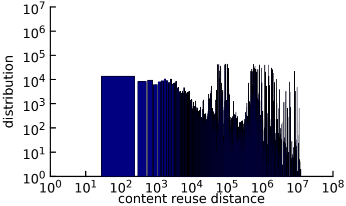


Figure : (d) Content reuse distribution

Observations

- Even duplicate content access has spatial locality property
- Temporal locality is higher for content than block

DRIVE system summary & conclusions

- In this component, we addressed I/O reduction via deduplication
- We analyzed existing work (IODEDUP) and showed that its performance is inconsistent depending on the read/write request-mix of the workload.
- We presented design & implementation of our DRIVE system
- Simulation evaluation shows promise—achieves 97% content deduplication of the host cache.
- We concluded with a survey of publicly available datasets, as well as benchmark generation literature, to make the case that future work towards I/O deduplication benchmarks is necessary

Bibliography I

Ricardo Koller and Raju Rangaswami.
I/O Deduplication: Utilizing Content Similarity to Improve I/O Performance.
In Proceedings of the USENIX Conference on File and Storage Technologies (FAST), pages 211–224, 2010.

Grzegorz Miłós, Derek G. Murray, Steven Hand, and Michael A. Fetterman.
Satori: Enlightened Page Sharing.
In Proceedings of the USENIX Annual Technical Conference (ATC), pages 1–14, 2009.

Ricardo Koller and Raju Rangaswamy.
Trace: I/O Deduplication: Utilizing Content Similarity to Improve I/O Performance.
Website.
http://sylab-srv.cs.fiu.edu/doku.php?id=projects:iodedup:start.

Sriram Sankar and Kushagra Vaid.
Storage Characterization for Unstructured Data in Online Services Applications.
In Proceedings of the IEEE International Symposium on Workload Characterization (IISWC), IISWC '09, pages 148–157. IEEE Computer Society, 2009.

C. Delimitrou, S. Sankar, K. Vaid, and C. Kozyrakis.
Storage I/O Generation and Replay for Datacenter Applications.
In Proceedings of the IEEE International Symposium on Performance Analysis of Systems and Software (ISPASS), pages 123–124, April 2011.

Christina Delimitrou, Sriram Sankar, Kushagra Vaid, and Christos Kozyrakis.
Accurate Modeling and Generation of Storage I/O for Datacenter Workloads, 2011.

Bibliography II

V. Tarasov, S. Kumar, J. Ma, D. Hildebrand, A. Povzner, G. Kuenning, and E. Zadok.
Extracting Flexible, Replayable Models from Large Block Traces.
In Proceedings of the 10th USENIX Conference on File and Storage Technologies (FAST), FAST'12, pages 22–22. USENIX Association, 2012.

Zachary Kurmas, Jeremy Zito, Lucas Trevino, and Ryan Lush.
Generating a Jump Distance Based Synthetic Disk Access Pattern, 2006.

Vasily Tarasov, Amar Mudrankit, Will Buik, Philip Shilane, Geoff Kuenning, and Erez Zadok.
Generating Realistic Datasets for Deduplication Analysis.
In Proceedings of the USENIX Conference on Annual Technical Conference, pages 24–24, 2012.