



Cloud Computing

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A View of Cloud Computing

Communications of the ACM Volume 53 Issue 4, April 2010

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History-Based Harvesting of Spare Cycles and Storage in Large-Scale Datacenters

12th USENIX Symposium on Operating Systems Design and Implementation (OSDI '16), November 2016

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Dynamic Resource Allocation Using Virtual Machines for Cloud Computing Environment

IEEE Transactions on Parallel and Distributed Systems Volume 24 Issue 6, June 2013

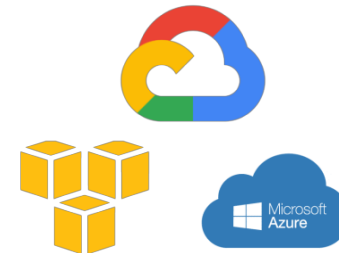
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Open Source Cloud Technologies

Third ACM Symposium on Cloud Computing (SoCC '12), October 2012

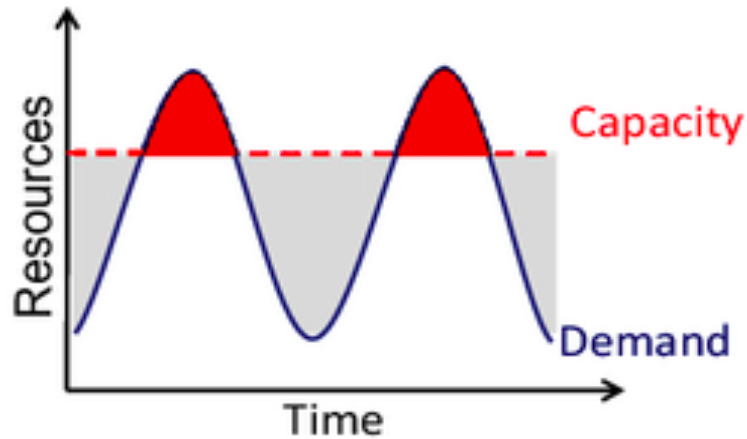
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Why Cloud Computing? (Berkeley)

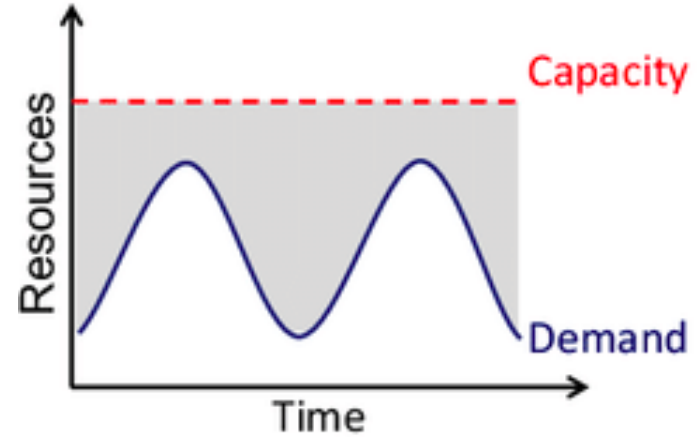


Cloud administrative	Client
<ul style="list-style-type: none">• Economy of scale (profitable)• Brand effect <p>Providers: Google, Microsoft, Amazon</p>	<ul style="list-style-type: none">• Pay as you go• Rewards conservative choices <ul style="list-style-type: none">➔ Surge computing➔ Reduce UpFront cost

Cloud Management Difficulties



Under-Provisioning



Over-Provisioning

Utility is Key!

Static Resource Allocation

- Main Goal: Efficient Task Scheduling

To achieve:

- Better Server Utilization

History-Based Harvesting of Spare Cycles and Storage in Large-Scale Datacenters

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History-Based Harvesting of Spare Cycles & Storage in Large-Scale Datacenters



- Smart task scheduling
- Smart data placement

Smart Task Scheduling



- Motivation/Main contribution
- History data observation
- Algorithm
- Experiment

Define Primary Tenant

Primary tenant

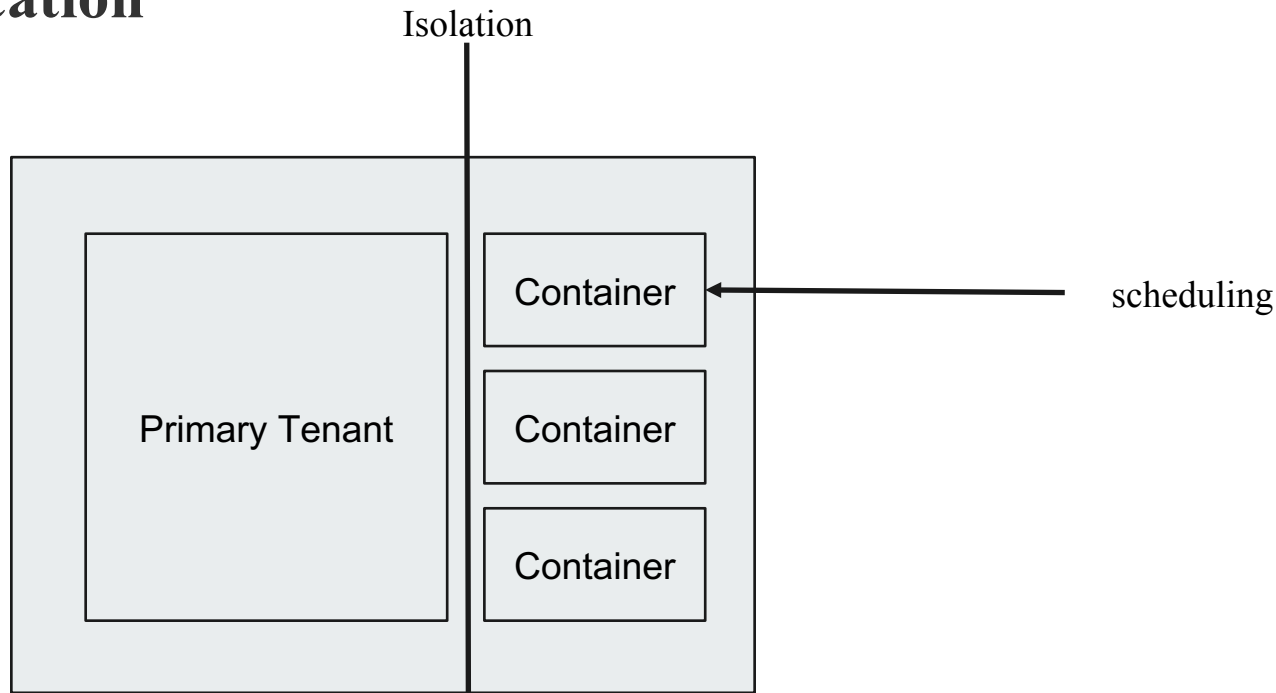


Result ranking server

Result ranking server

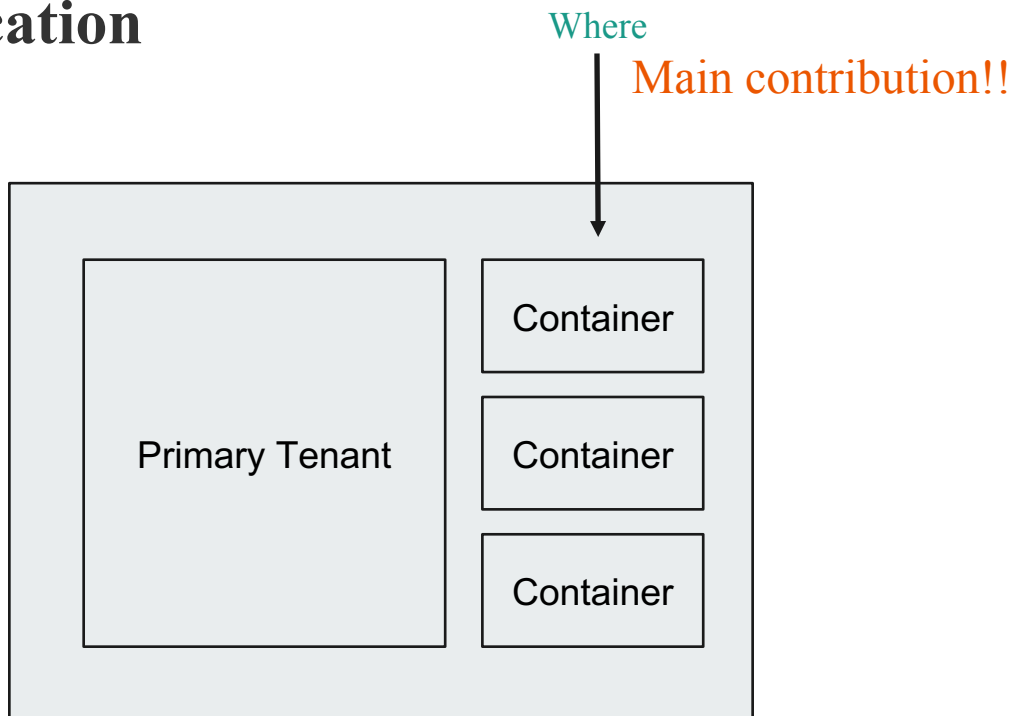
Result ranking server

Service Co-Location



History-Based Harvesting of Spare Cycles and Storage in Large-Scale Datacenters (2013)

Service Co-Location



History-Based Harvesting of Spare Cycles and Storage in
Large-Scale Datacenters (2013)

Smart Task Scheduling



- Motivation / Main contribution
- History data observation
- Algorithm
- Experiment

Tenant Characterization



Periodic

User facing application

Constant

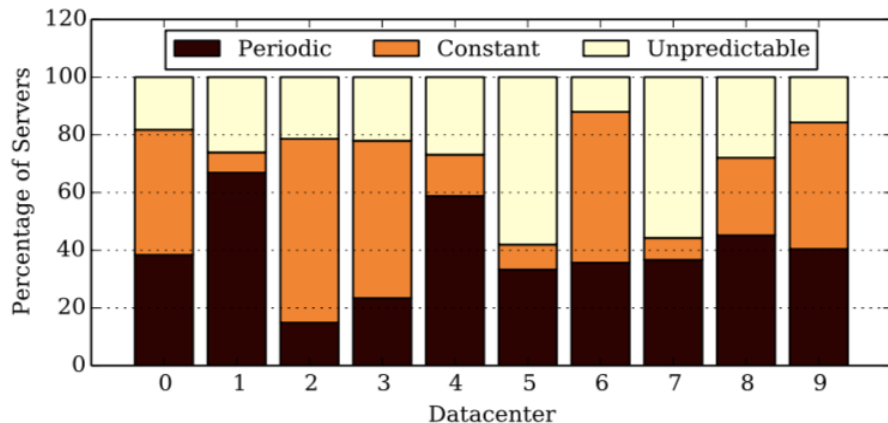
Web crawling

Batch Data analytics

Unpredictable

Testing

Why historical is good reference?



Constant and Period Tenant occupies majority of server (75% average)

Figure 3: Percentages of servers per class.

Smart Task Scheduling



- Motivation / Main contribution
- History data observation
- Algorithm
- Experiment

Objective

Type \ Priority	1st	2nd	3rd
	Constant	Periodic	Unpredictable
Long job			

For Long job, want to prioritize Long Contant jobs

Objective

Type \ Priority	1st	2nd	3rd
	Long job	Periodic	Unpredictable
Short job	Unpredictable	Periodic	Constant

Task scheduling



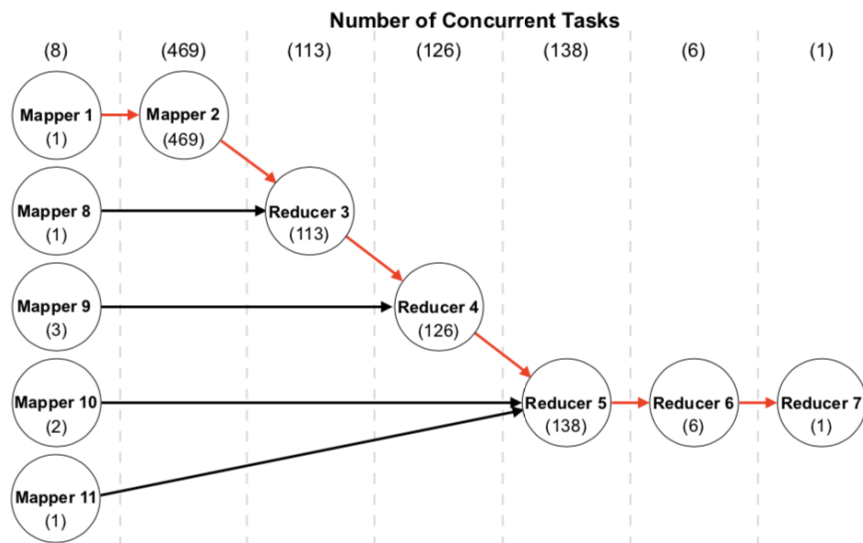
1. **Weights classes** for resource assignment
2. **Resource requirement** by DAG

Weighted setting



Priority Type	1st	2nd	3rd
Long job	constant	periodic	unpredictable
Short job	unpredictable	periodic	constant
Medium job	periodic	constant	unpredictable

Job resource requirement



**Most “crowdy” moment as
Job Resource Requirement**

Smart Task Scheduling



- Motivation / Main contribution
- History data observation
- Algorithm
- Experiment

Primary Tenant Latency Comparison

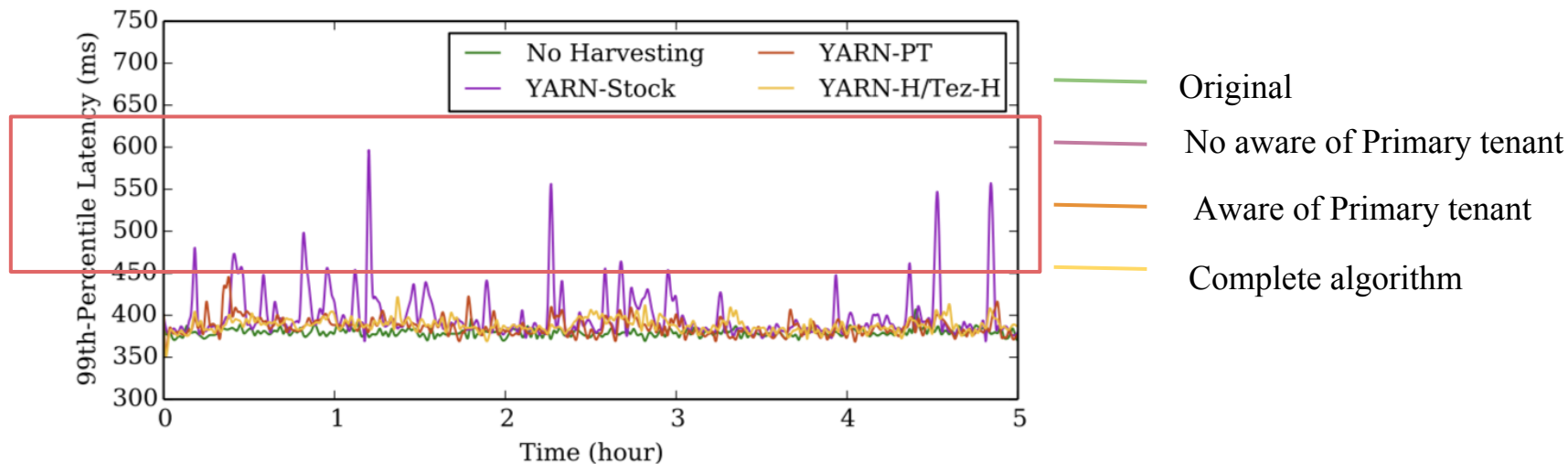


Figure 10: Primary tenant's tail latency in the real testbed for versions of YARN and Tez.

Secondary Tenant effect against Primary Tenant

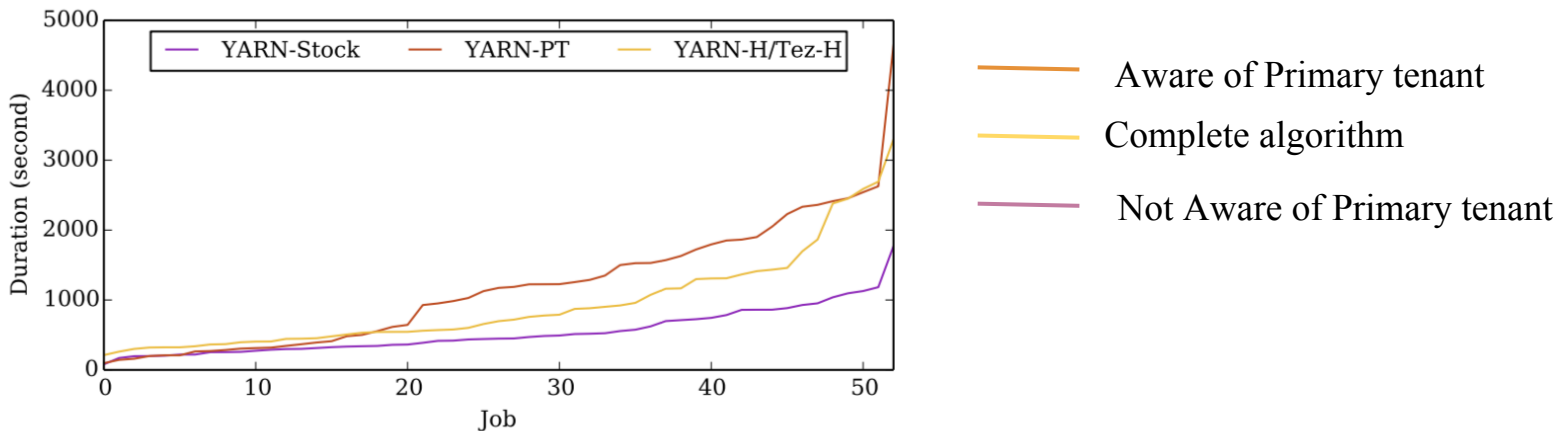


Figure 11: Secondary tenants' run times in the real testbed for versions of YARN and Tez.

History-Based Harvesting of Spare Cycles & Storage in Large-Scale Datacenters



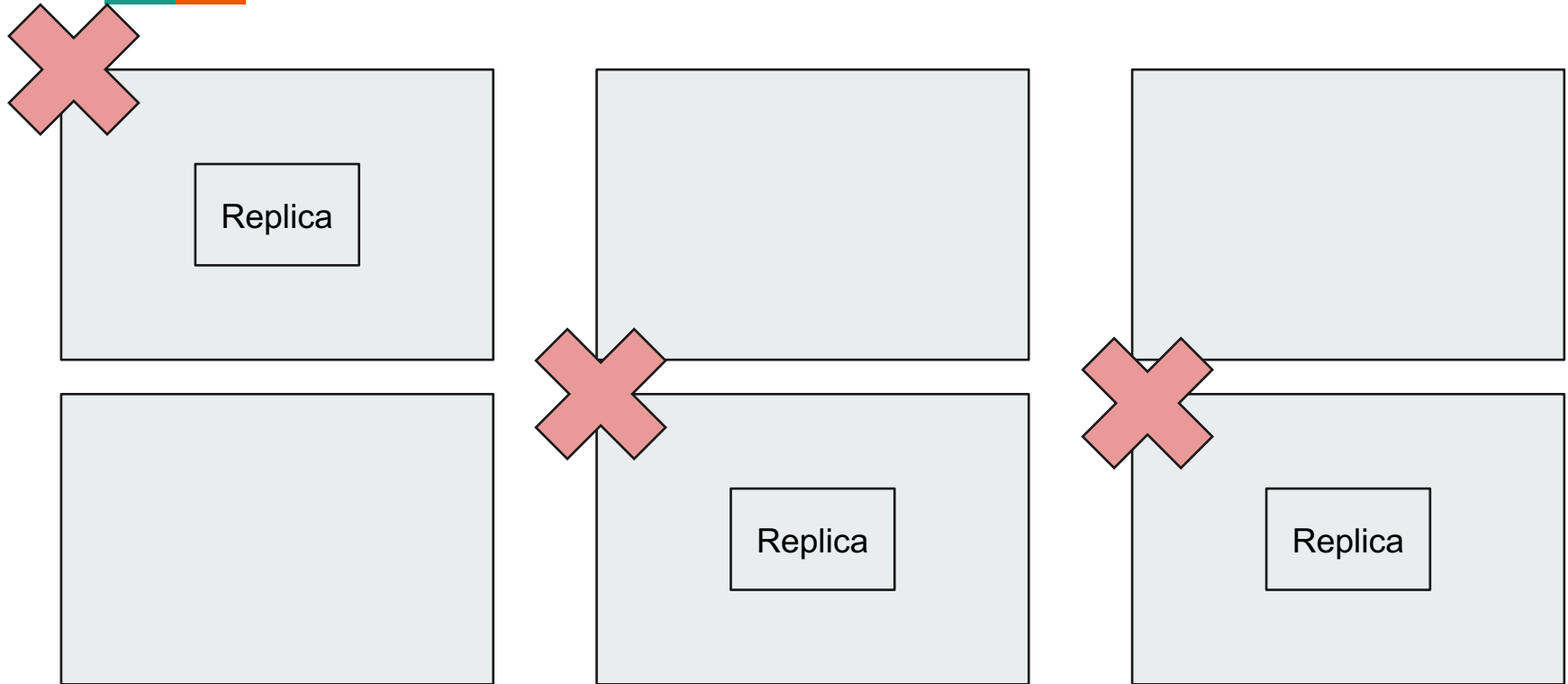
- Smart Task Scheduling
- Smart Data Placement

Smart Data Placement

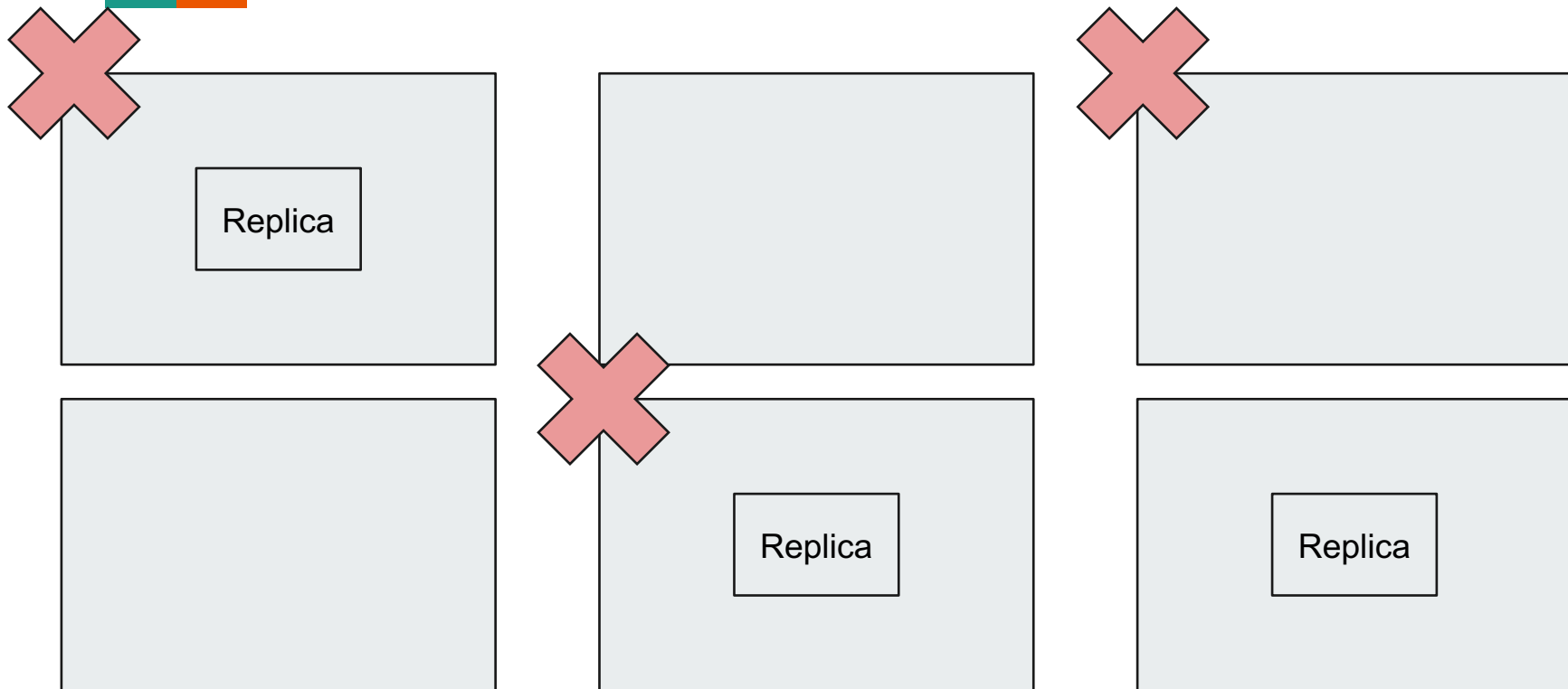


- Motivation / Main contribution
- History data observation
- Algorithm
- Experiment

Re-Image - Durability/Busy server - unavailable data



Ideal Data replica placement



Greedy Solution



Re-Image the disks the least / have lowest CPU utilizations.

Consistant Performance!!!

Smart Data Placement



- Motivation / Main contribution
- History data observation
- Algorithm
- Experiment

ReImages frequency CDF

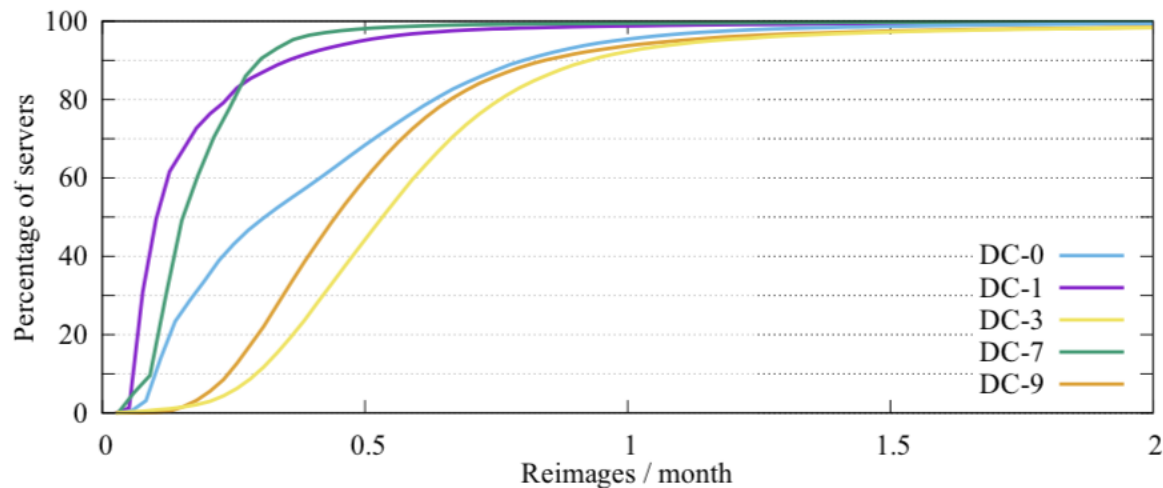


Figure 4: Per-server number of reimages in three years.

Diversity in reimage frequency

Change of ReImages frequency Group CDF

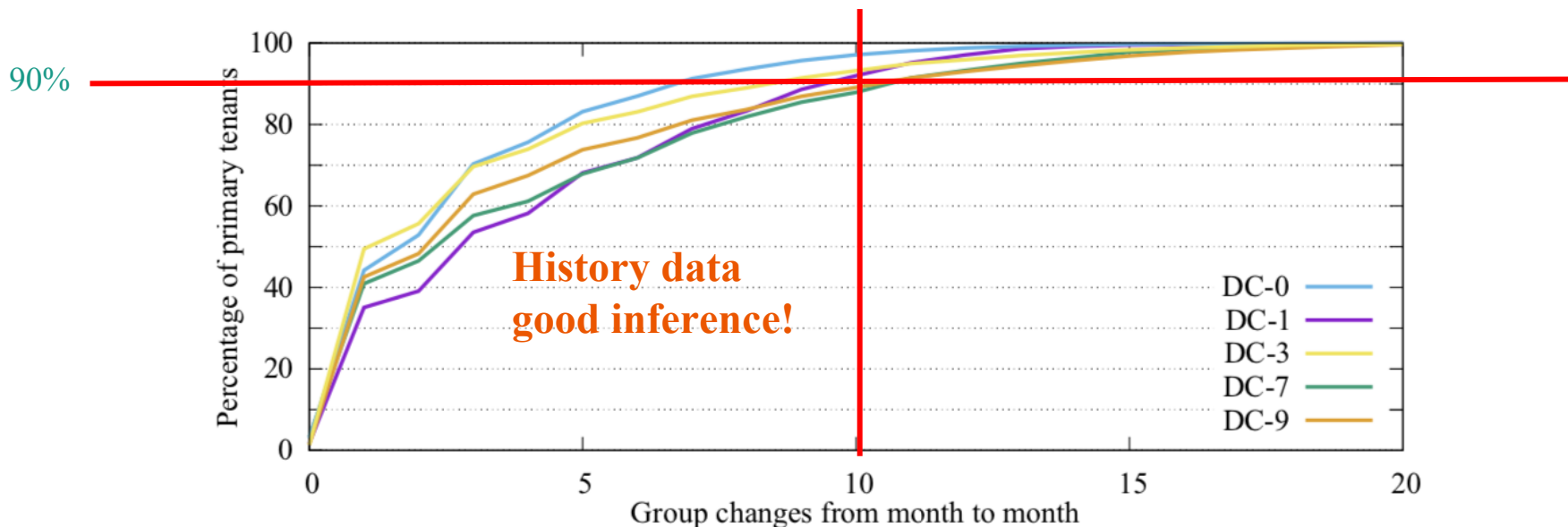


Figure 6: Number of times a primary tenant changed reimage frequency groups in three years.

- **Diversity in reimage frequency**
- **History data can be good inference!**

Smart Data Placement




- Motivation / Main contribution
- History data observation
- Algorithm
- Experiment




Take advantage of diversity!

utilization		High	Medium	Low
Reimage	Frequent			
	Intermediate			
	Infrequent			

smart data placement

utilization		High	Medium	Low
Reimage	Frequent			
	Intermediate			
	Infrequent			

Take advantage of diversity!

utilization		High	Medium	Low
Reimage	Frequent			
Intermediate				
Infrequent				

Classification Example

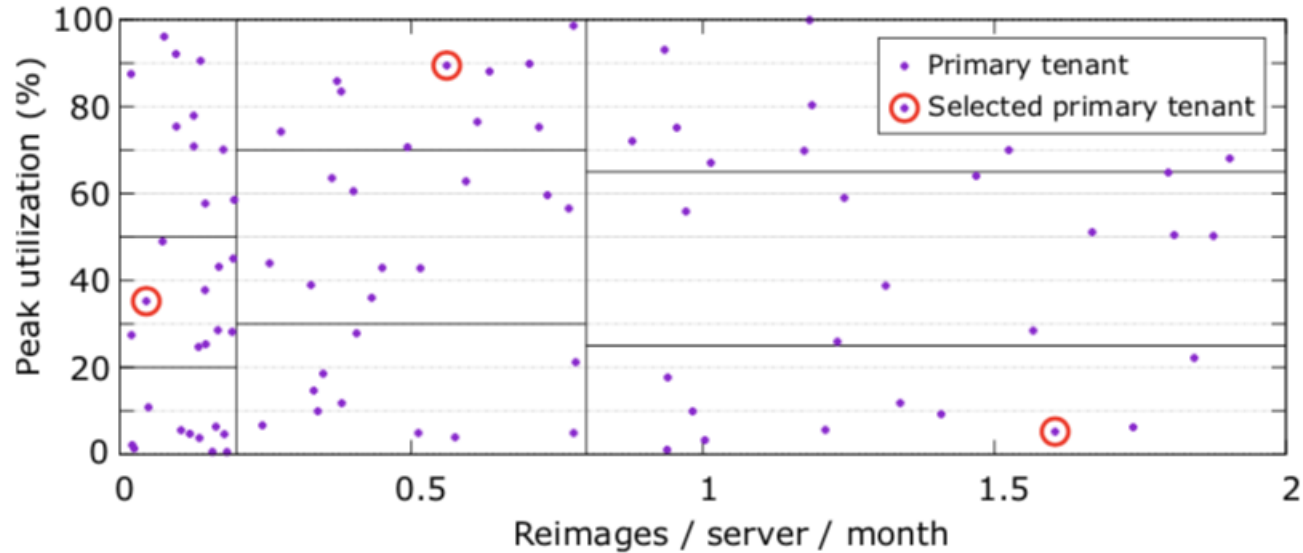


Figure 8: Two-dimensional clustering scheme.

Smart Data Placement



- Motivation / Main contribution
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- Algorithm
- Experiment

Primary Tenant Latency Comparison

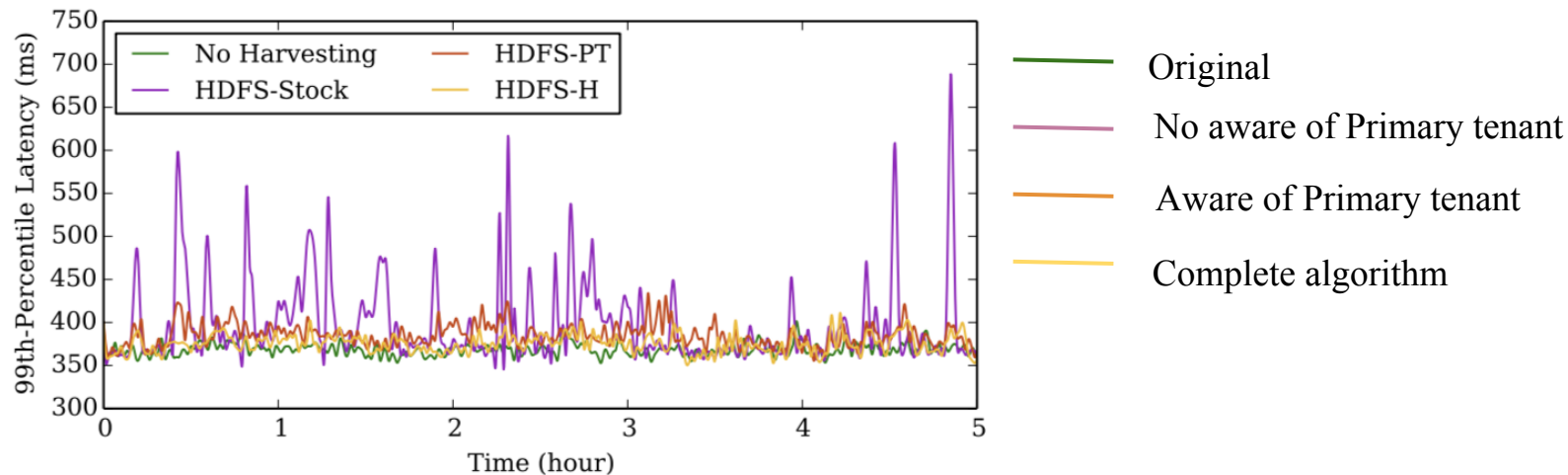


Figure 12: Primary tenant's tail latency in the real testbed for versions of HDFS.

Lost block Comparison

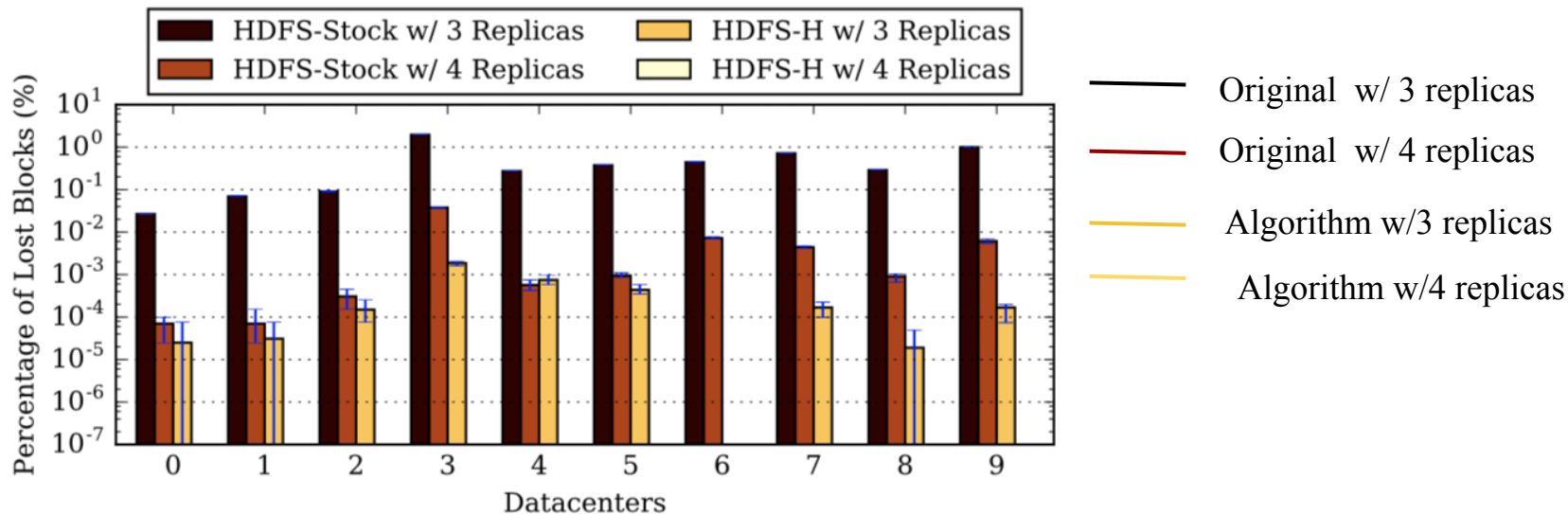


Figure 15: Lost blocks for two replication levels.

Failed Access Comparison

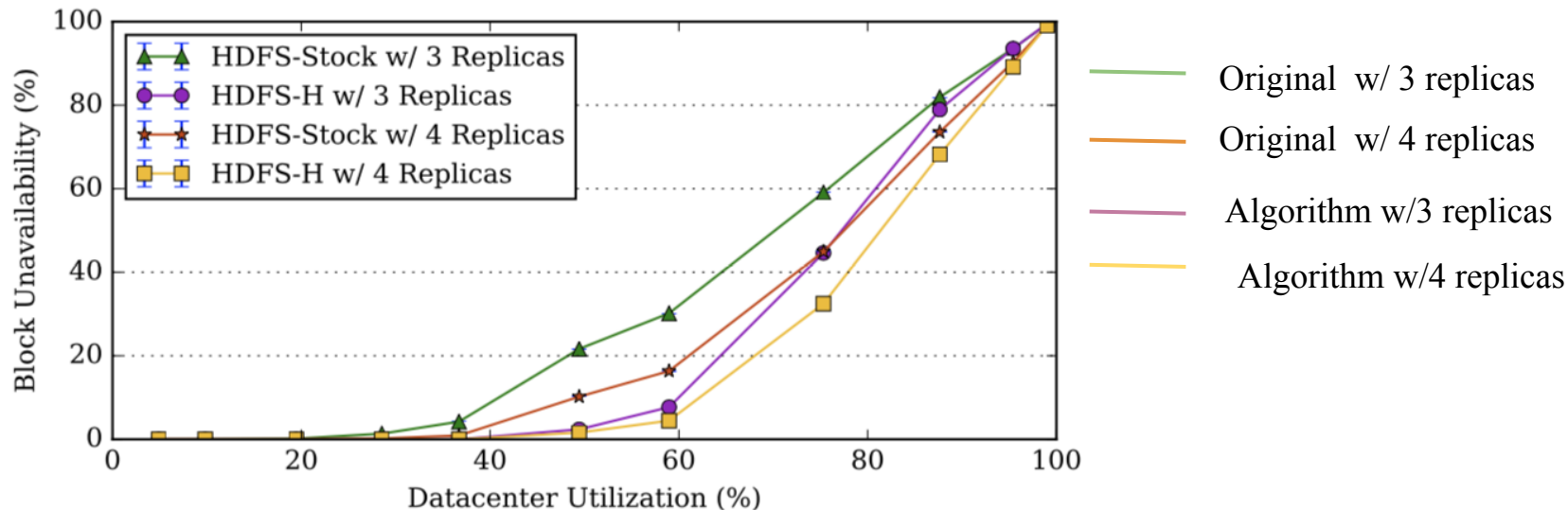


Figure 16: Failed accesses under linear scaling.

Main contribution Summary



- Interesting View of Historical Data
- Primary / Secondary Tenant Perspective
- Data Placement Algorithm
- Historical Data as Good Measure of Future

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Dynamic Resource Allocation

- Main Goal: Effective Load Prediction

A good Framework to achieve:

- Prevent Overload (Under-Provisioning)
- Green Computing when Possible (Over-Provisioning)

Cloud Manager Framework - Skewness

Skewness (a measure of balance)

→ Minimize skewness

→ Balance resource utilization

$$skewness(p) = \sqrt{\sum_{i=1}^n (r_i/\bar{r} - 1)^2}$$

- \bar{r} : average utilization of all resources
- r_i : utilization of resource i

Cloud Manager Framework - Migration

Trade-Off: Load Balancing \leftrightarrow Green Computing

Migration:

-  Hot Migration for HotSpot (too High utilization)
-  Cold Migration for ColdSpot (too Low utilization)

Cloud Manager Framework



Skewnesss



Hotspot, Coldspot

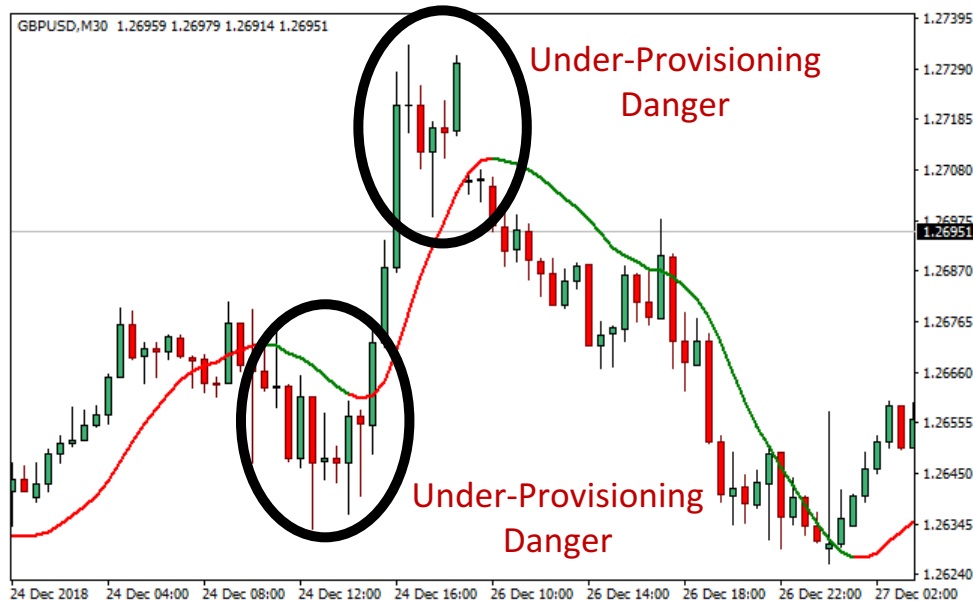


Load Prediction

Load Prediction - Original

No High Error!

Original: Exponential (Weighted) Moving Average



- Slower trend
- Conservative trend

Load Prediction - FUSD

Improved: Fast Up Slow Down Algorithm

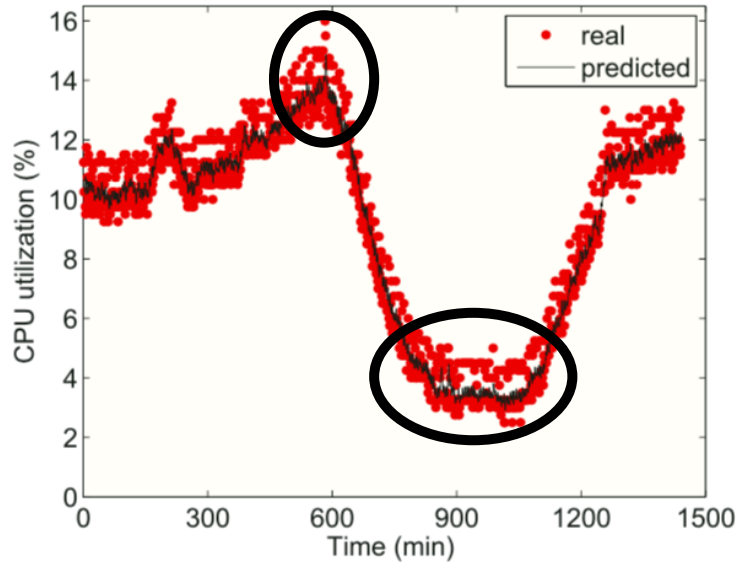
- Aggressive estimation when rising trend
- Conservative estimation when descending trend

$$E(t) = -|\alpha| \times E(t-1) + (1 + |\alpha|) \times O(t), -1 \leq \alpha \leq 0$$

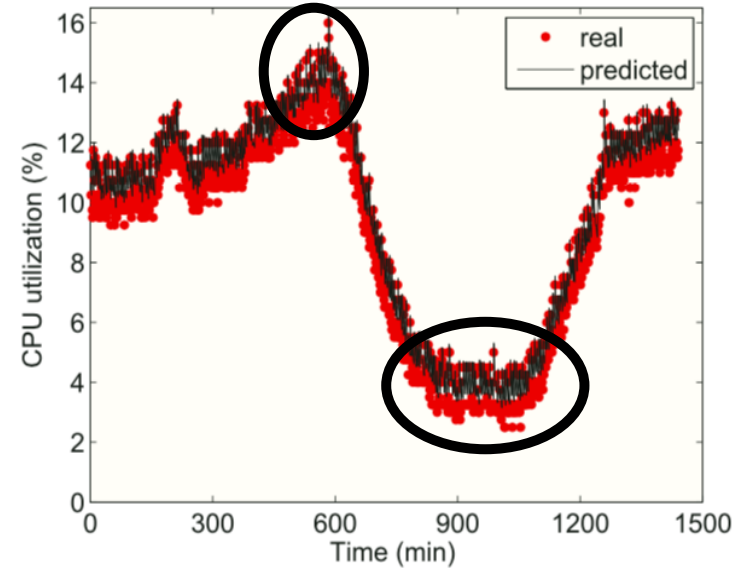
- $\uparrow \alpha$ for increasing trend
- $\downarrow \alpha$ for descending trend

根據（上升/下降） trend 而有不同參數

Load Prediction - FUSD

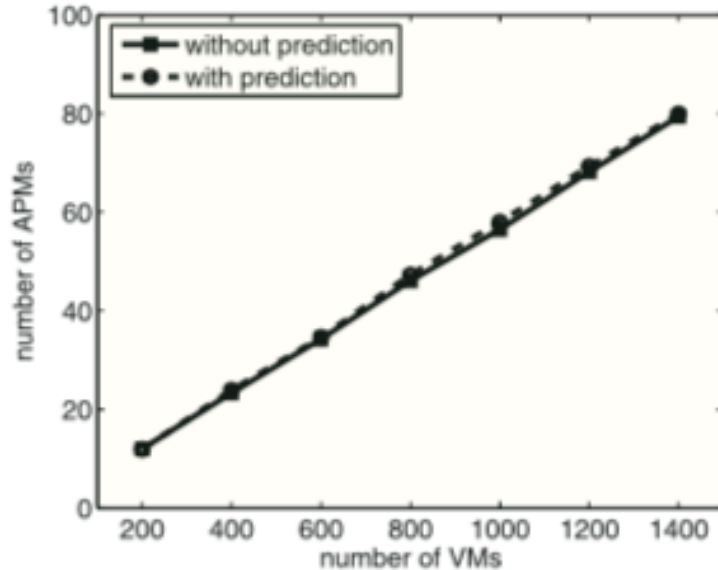


(a) EWMA: $\alpha = 0.7$, $W = 1$



(b) FUSD: $\uparrow \alpha = -0.2$, $\downarrow \alpha = 0.7$, $W = 1$

Dynamic Resource Allocation - Results



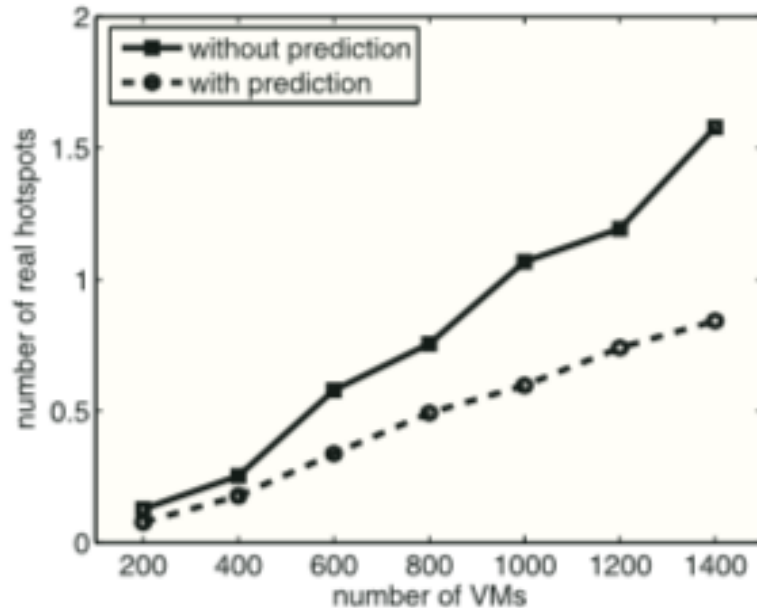
(b) number of APMs

(APM = Active Physical Machine)

With vs. Without Prediction

Results are almost the same!

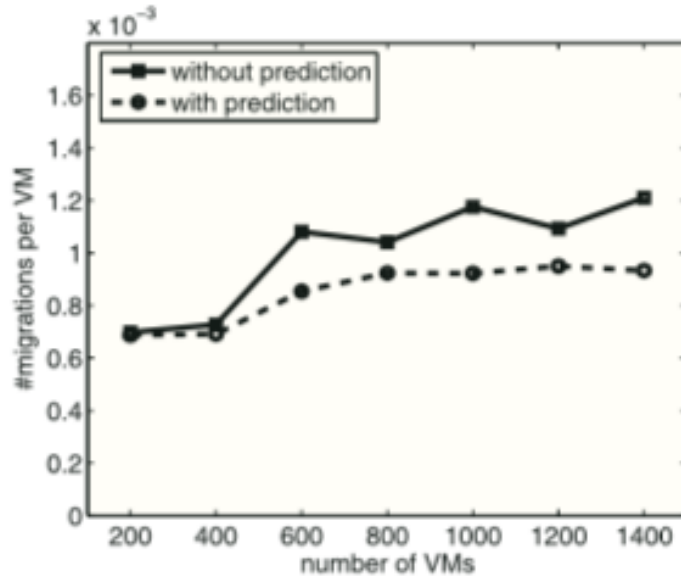
Dynamic Resource Allocation - Results



(a) number of hot spots

Notable decrease in hotspot

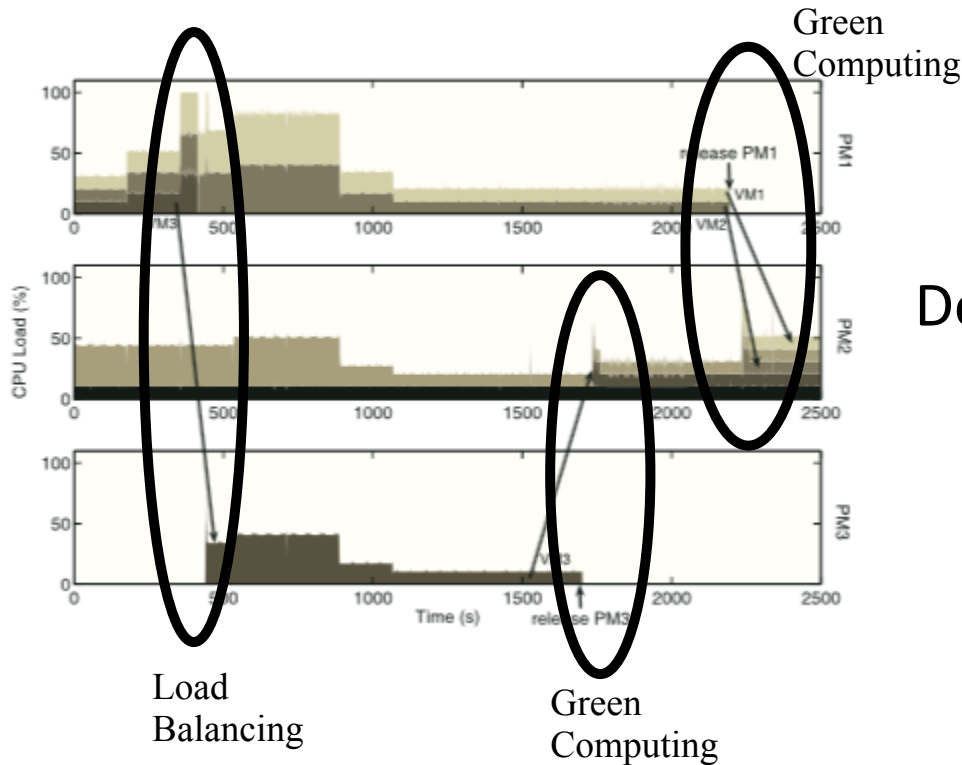
Dynamic Resource Allocation - Results



(c) number of migration

Notable decrease in migrations

Dynamic Resource Allocation - Results



Demonstration on Migration

Dynamic Resource Allocation

- Main Goal: Effective load prediction
- Contribution:
 - ✓ Cloud Manager Framework
 - ✓ Fast Up Slow Down Algorithm (FUSD)
 - ✓ Dynamic Green Computing

Comparison

Different aspects of utilization:

- Static utility optimization via Primary/Secondary tenant
 - Better allocating with concept of Secondary Tenant
 - Good Initialization
- Dynamic utility optimization via Minimizing Skewness
 - Live Migration
 - Support Green Computing

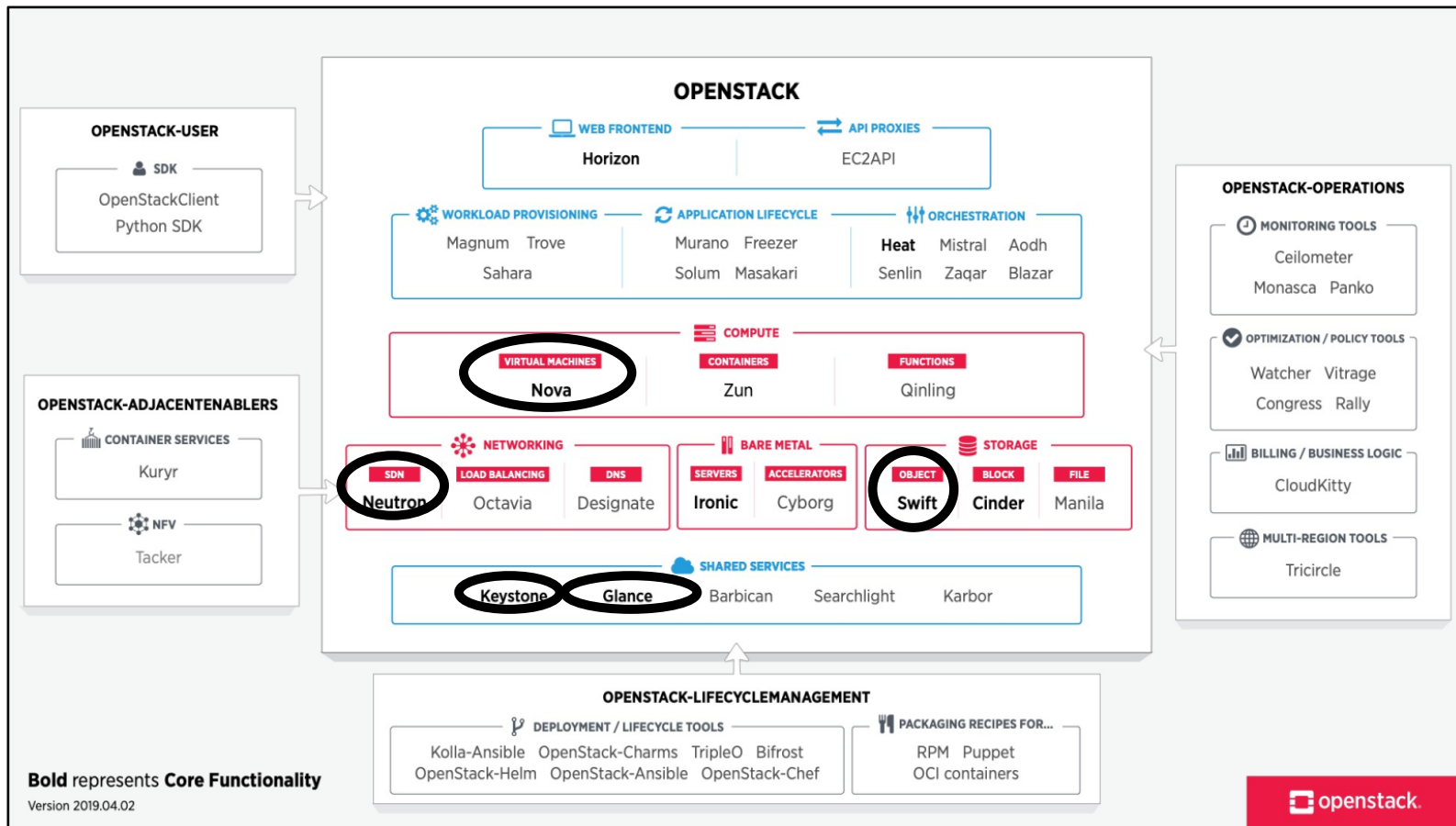
Idea

- Dynamic allocation: Better prediction via ML
- Static vs. Dynamic?
- Static + Dynamic

Cloud Framework - OpenStack

- Framework for Private Cloud
- Infrastructure as a Service (IaaS)
- Modularized component





OpenStack - Fast Deployment

- ➡ Image Management (Glance)
- ➡ Network Management (Neutron)
- ➡ VM Management (Nova)
- ➡ Storage Management (Swift)
- ➡ Identity Authentication (KeyStone)

OpenStack - MAAS (Metal As A Service)

- Image Management
- Network Management
- Basic Configurations (user, bashrc, ssh...)

 Fast Deployment

