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Joint work with Shivnath Babu, Songyun Duan, Nedyalkov Borisov, and Herodotous Herodotou Duke University 20th May 2009

AUTOMATED EXPERIMENT-DRIVEN MANAGEMENT OF (DATABASE) SYSTEMS

Claim:

- "Current" techniques for managing systems have limitations
 - Not adequate for end-to-end systems management
- Closing the loop
 - Experiment-driven management of systems

An example scenario

- A "CEO Query" does not meet the SLO
- Reason: Violates the response time objective
- Admin's observation: High disk activity
- Admin's dilemma:



- What corrective action should I take?
- How to validate the impact of my action?

- Hardware-level changes
 - Add more DRAM
- OS-level changes
 - Increase memory/CPU cycles (VMM)
 - Increase swap space
- DB-level changes
 - Partition the data
 - Update database statistics
 - Change physical database design indexes, schema, views
 - Tune the query/Manually change query plan
 - Change configuration parameters like buffer pool sizes, I/O daemons, and max connections

How to find the corrective action?

- Get more insight into the problem
 - Use domain knowledge
 - Admin's experience
 - Use apriori models if available
 - Fast prediction
 - Systems are complex
 - Hard to capture the behavior of the system apriori
 - Rely on "Empirical Analysis
 - More accurate prediction
 - Time-consuming
 - Sometimes the only choice!

How Admins do Empirical Analysis

- Conduct an experiment run with a prospective setting (trial)
 - Pay some extra cost, get new information in return
- Learn from observations (error)
- Repeat until satisfactory solution is found
- Automating the above process is what we call

Experiment-driven Management

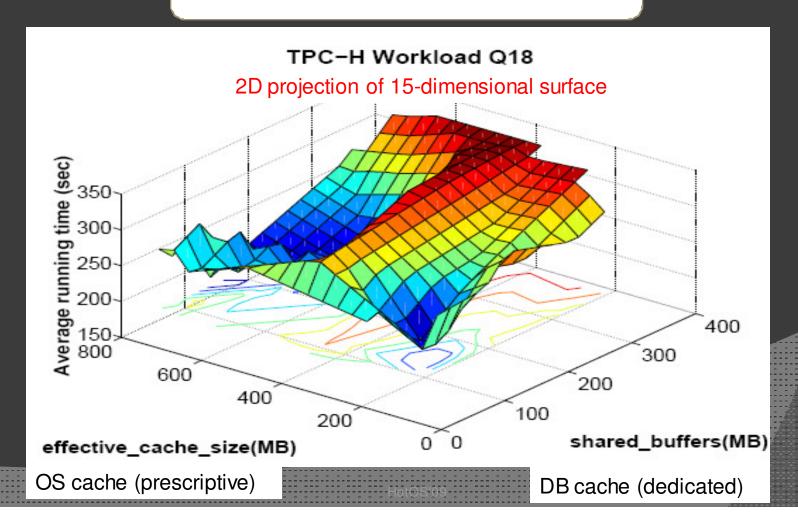
An example where experimentdriven management can be used

- Configuration parameter tuning
 - Database parameters (PostgreSQL-specific)
 - Memory distribution
 - shared_buffers, work_mem
 - I/O optimization
 - fsync, checkpoint_segments, checkpoint_timeout
 - Parallelism
 - max_connections
 - Optimizer's cost model
 - effective_cache_size, random_page_cost, default_statistics_target, enable_indexscan

Configuration parameter tuning

TPC-H Q18: Large Volume Customer Query

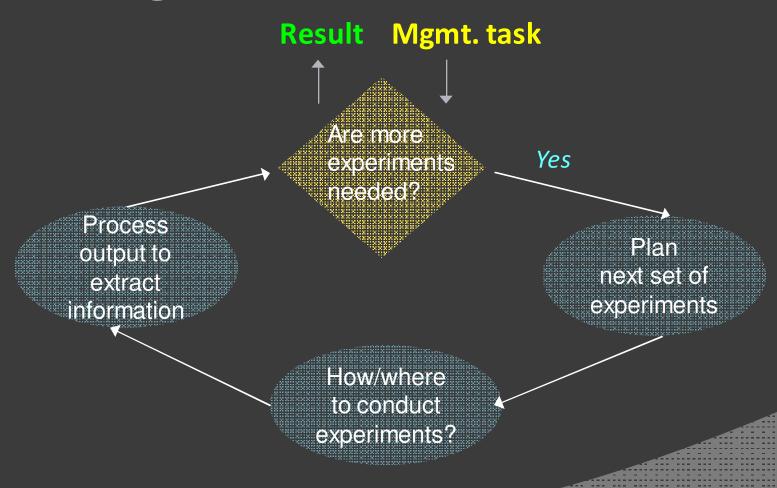
Data size: 4GB, Memory: 1GB



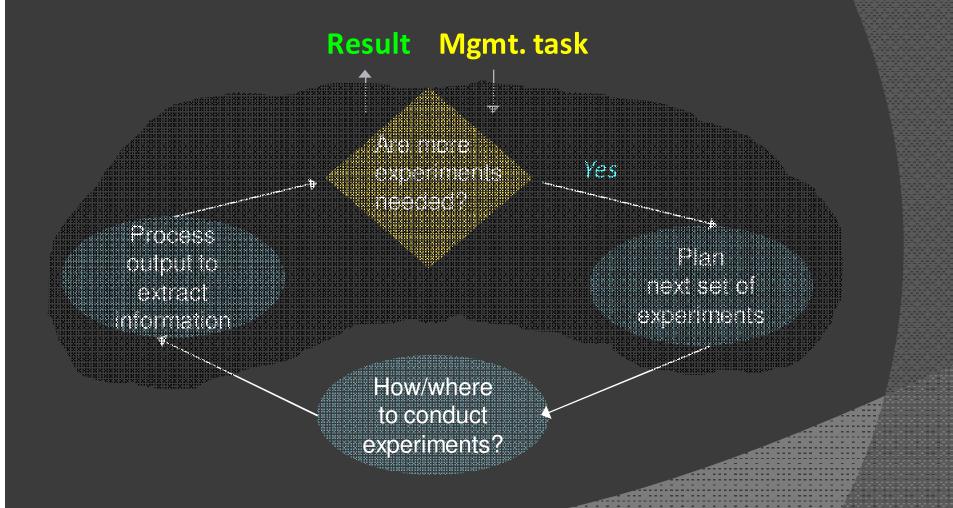
More examples where experimentdriven management can be used

- Configuration parameter tuning
- Problem diagnosis (troubleshooting), finding fixes, and validating the fixes
- Benchmarking
- Capacity planning
- Speculative execution
- Canary in server farm (James Hamilton, Amazon Web Services)

Workflow for Experiment-driven Management



Outline



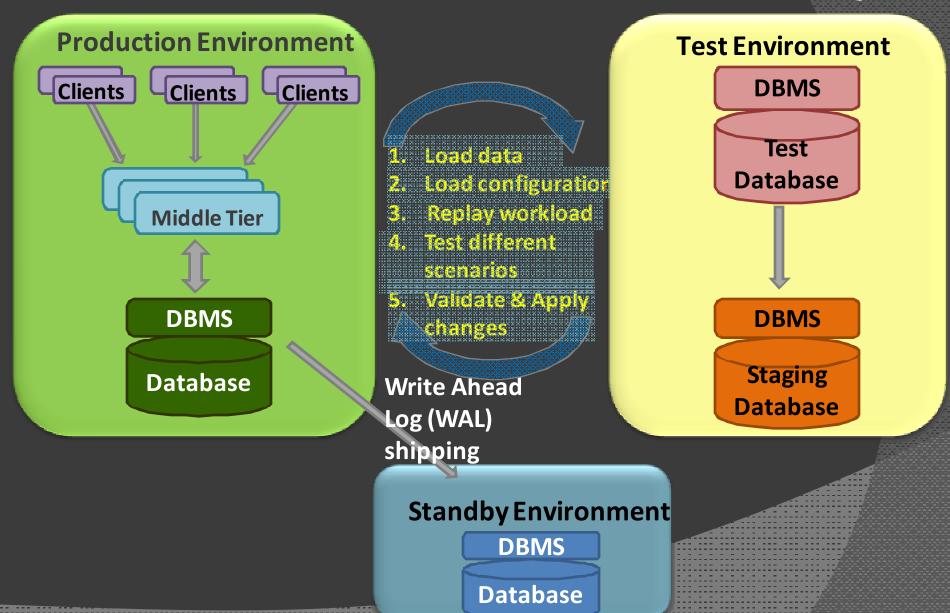
Challenges in setting up an experiment

- What is the right abstraction for an experiment?
- Ensuring representative workloads
 - Can be tuning task specific
 - Detecting deadlocks vs. performance tuning
- Ensuring representative data
 - Full copy vs. sampled data?

Where to conduct experiments in a 24X7 production environment?

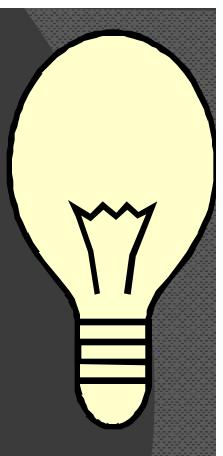
- Production system itself [USENIX'09, ACDC'09]
 - May impact user-facing workload
- Test system
 - Hard to replicate exact production settings
 - Manual set-up
- How and where to conduct experiments?
 - Without impacting user-facing workload
 - As close to production runs as possible

What do DB Administrators do today?



An idea

- How to conduct experiments?
 - Exploit underutilized resources
- Where to conduct experiments?
 - Production system, Standby system, Test system
 - ❖Need mechanisms and policies to utilize idle resources efficiently
 - > Mechanisms: Next slide
 - ➤ Policies: If CPU, memory, & disk utilization is below 10% for past 10 minutes, then resource X can be used for experiments



Mechanisms

Production Environment

Test Environment

Client

"Enterprises that have 99.999% availability have standby databases that are 99.999% idle", Oracle DBA's handbook

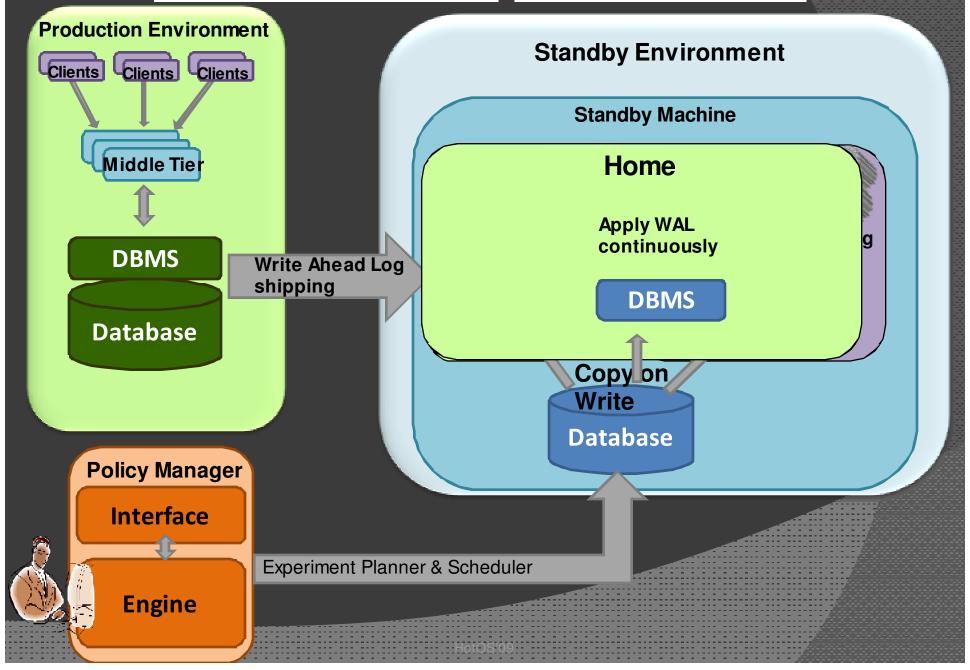
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Standby Environment

DBMS

Database

Mechanisms: Workbench



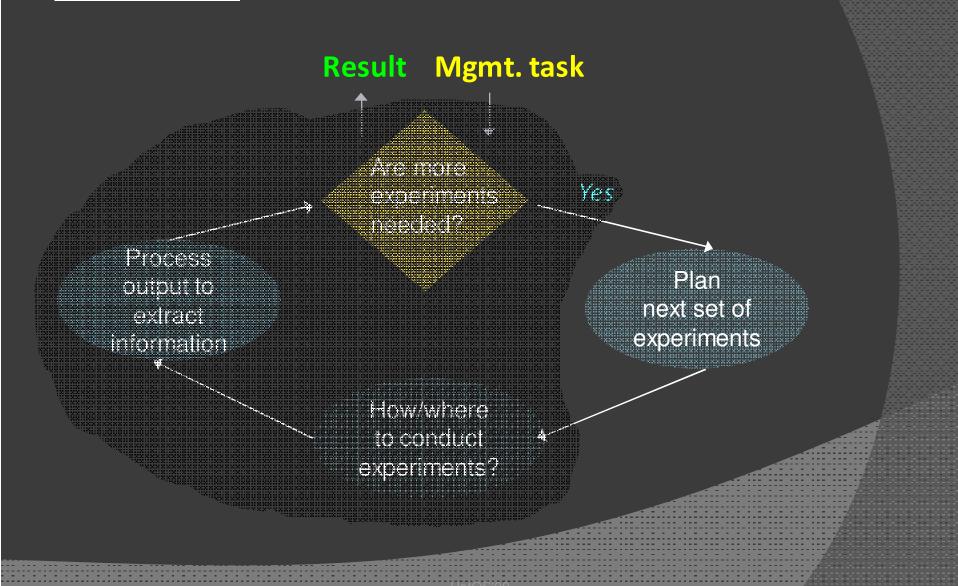
Workbench features

- Implemented using Solaris OS
 - Zones to isolate resources between home & garage containers
 - ZFS to create fast snapshots
 - Dtrace for resource monitoring

Overhead of workbench

Operation by workbench	Time (sec)	Description
Create Container	610	Create a new garage (one time process)
Clone Container	17	Clone a garage from already existing one
Boot Container	19	Boot garage from halt state
Halt Container	2	Stop garage and release resources
Reboot Container	2	Reboot the garage
Snapshot-R DB (5GB, 20GB)	7, 11	Create read-only snapshot of the database
Snapshot-RW DB (5GB, 20GB)	29, 62	Create read-write snapshot of database

Outline



Which experiments to run?

- Gridding
- Random Sampling
- Simulated Annealing
- Space-filling Sampling
 - Latin Hypercube Sampling
 - k-Furthest First Sampling
- Design of Experiments (Statistics)
 - Plackett-Burman
 - Fractional Factorial
- Can we do better than above?

Our approach

Adaptive Sampling

Bootstrapping:
Conduct initial set of experiments

Sequential Sampling: Select NEXT experiment based on previous samples Stopping Criteria:
Based on

Based on budget



- 1. Compute the utility of the experiment
- 2. Conduct experiment where utility is maximized
- 3. We used Gaussian Process for computing the utility

Results

- Empirical Setting
 - PostgreSQL v8.2: Tuning up to 30 parameters
 - 3 Sun Solaris machines with 3 GB RAM, 1.8 GHz processor
 - Workloads
 - TPC-H benchmark
 - SF = 1 (1GB, total database size = 5GB)
 - SF = 10 (10GB, total database size = 20GB)
 - TPC-W benchmark
 - Synthetic response surfaces

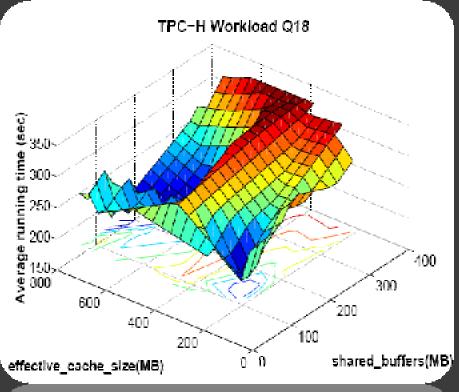
Results on Real Response Surfaces

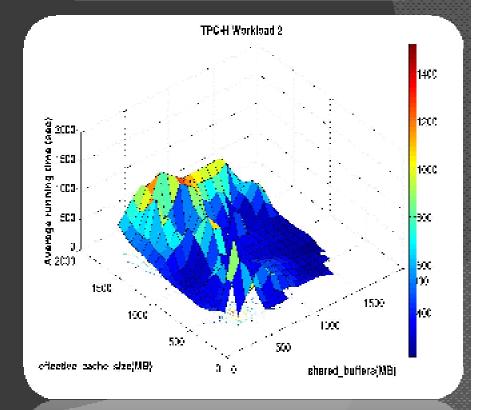
Simple Workload: W1-SF1

TPC-H Q18, Large Volume Customer Query

Complex Workload: W2-SF1

Random mix of 100 TPC-H Queries





effective_cache_size(MB)

shared_buffers(MB)

effective_pathe_size(MB)

0

shared buffers/MBI

200

200

1000

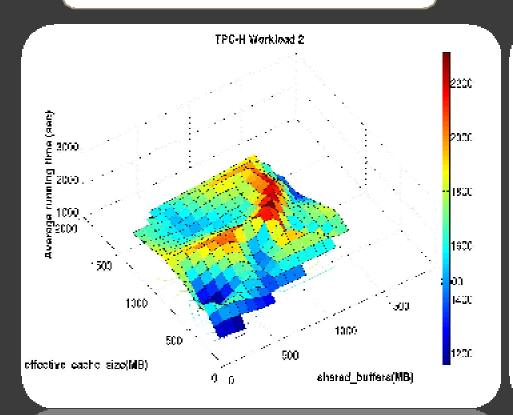
Results on Real Response Surfaces

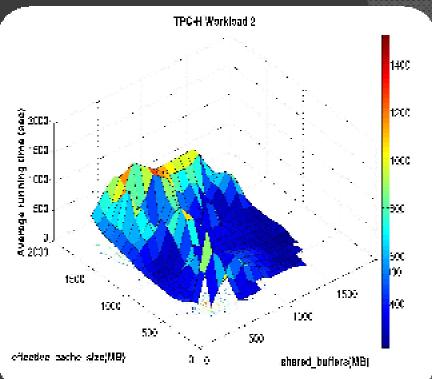
Complex Workload: W2-SF10

Random mix of 100 TPC-H Queries

Complex Workload: W2-SF1

Random mix of 100 TPC-H Queries





effeedive_cashe_size(MB)

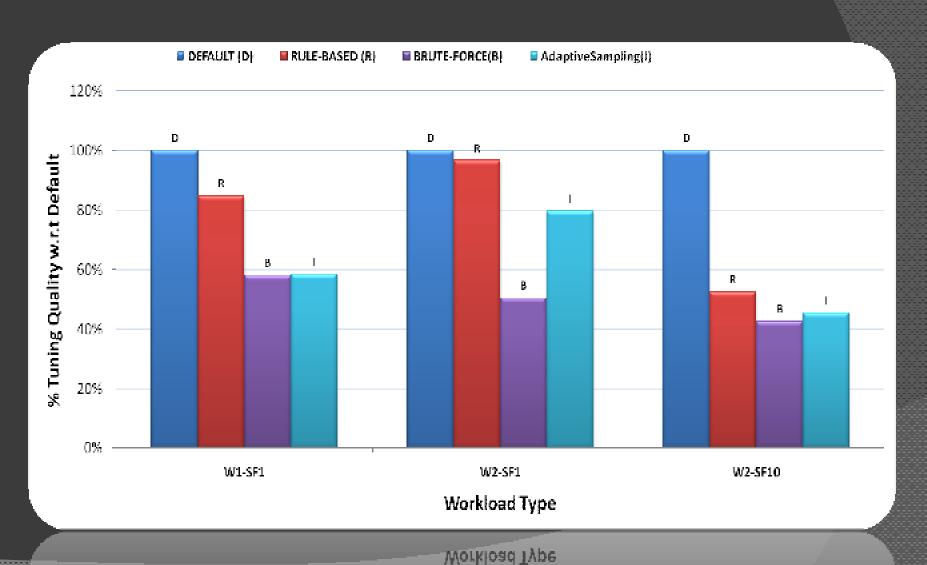
o p ahnrad buffera(MB)

effeedive_cashe_size(MB)

shared buffers(MB)

Comparison of Tuning Quality

W1-SF1



HotOGWS-SET

W2-SF10

Comparison of Tuning time

Cutoff time for each query: 90 minutes

	BruteForce	AdaptiveSampling
W1-SF1	8 hours	1.4 hours
W2-SF1	21.7 days	4.6 days
W2-SF10	68 days 14.8 days	

- We further reduced the time using techniques
 - Workload compression
 - Database specific information

Conclusion

- Experiment-driven management is an essential part of system administration
 - Our premise: Experiments should be supported as first-class citizens in systems
 - Compliments existing approaches
- Experiments in the cloud the time has come!

Q & A

Thanks!