Foundations of Automated Database Tuning

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Scope and Purpose of This Tutorial

Motivate and enable students and young scientists to pursue research on the auto-tuning aspect of autonomic computing

Complementary to
- SIGMOD 02 and VLDB 02 tutorials (Shasha/Bonnet) on tuning techniques for DBAs
- VLDB 04 tutorial (Chaudhuri/Dageville/Lohman) on self-management features of DBMS products

Outline

- Part I: What Is It All About
- Part II: Five Auto-Tuning Paradigms
  1 Auto-Tuning as Tradeoff Elimination
  2 Auto-Tuning as Static Optimization with Deterministic Input
  3 Auto-Tuning as Static Optimization with Stochastic Input
  4 Auto-Tuning as Online Optimization
  5 Auto-Tuning as Feedback Control Loop
- Part III: Wrap-up

Part I: What Is It All About

- The Need for and Nature of Auto-Tuning
- State of the Art
  - Product Features
  - Scientific Principles
- Auto-Tuning Paradigms

Need for Auto-Tuning

- Total cost of ownership (TCO) for DBMS-based IT solution dominated by staff for system admin, management, and tuning
- Increasing complexity of multi-tier application services call for automated management
- DBMS offers hundreds of tuning kobs (system config-time, DB-load-time, startup-time, run-time parameters)

→ DBMS (and multi-tier IT systems) should be **autonomic (self-*)**: self-managing, self-monitoring, self-healing, **self-tuning**

Easy Solutions

- **Throw more hardware (KIWI method)**
  - Use this with caution
  - Where do you throw hardware?
- **Rules of Thumb approach**
  - Finding them is harder than you think
  - May simply not exist – oversimplified wrong solutions are not helpful

Nature of Auto-Tuning

ability to predict

workload × config → performance

!!! !!! ???

is key to finding the right knob setting

workload × config → performance goal

!!! ??? !!!

Many difficult ramifications:

- workloads at different levels and time scales
  - app-level vs. internal, long-term steady-state vs. next hour or minute
- variety of performance metrics
  - resource usage, response time, throughput
  - mean values vs. distributions
  - single-class vs. multi-class
- unknown, fluctuating, and evolving parameters

State of the Art: Product Features

Oracle 10g Self-Managing Database:
automatic database diagnostic monitor, automatic memory pool management, automatic workload repository, automatic routine administration, drill-down root-cause analysis, etc.

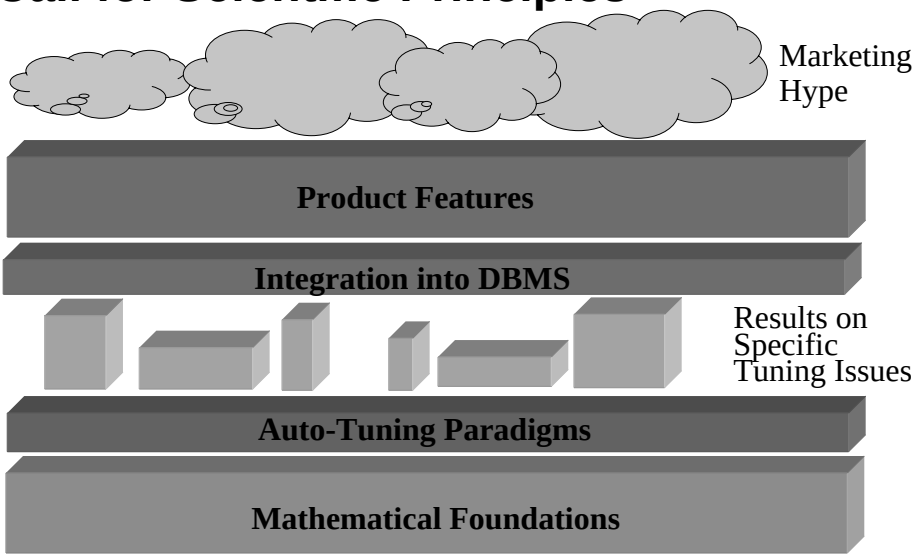
IBM DB2 Autonomic Technology:
index advisor, configuration advisor, health monitoring, learning query optimizer, etc.

Microsoft SQL Server Self-Tuning Features:
physical design wizard, continuous monitoring, statistics management, memory pressure analysis & heuristic resolution, etc.

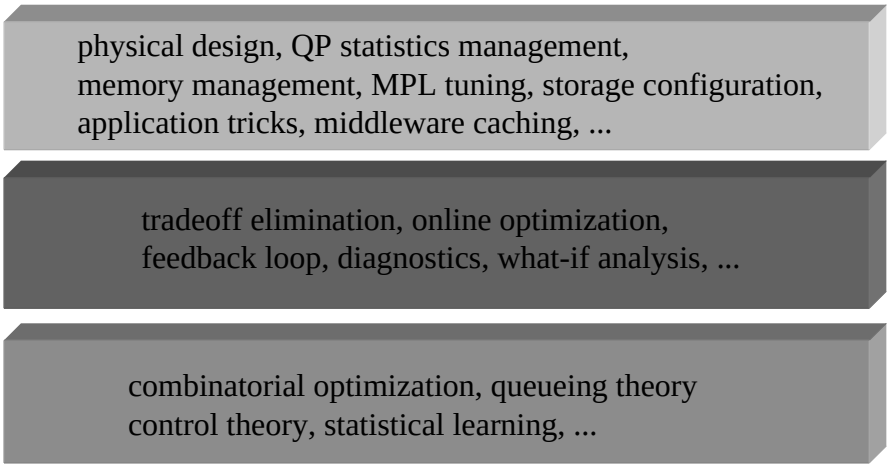
Storage systems: AutoRAID etc.

\+ great online profiling & analysis infrastructure
\+ viable solutions for specific tuning issues
– progress exaggerated by marketing
? fundamental principles

Call for Scientific Principles



Foundations, Paradigms, Tuning Issues



Auto-Tuning Paradigms

Aim: generalize from good approaches to specific tuning problems

Auto-tuning as:

- **tradeoff elimination** (ex. cache replacement)
- **static optimization** (ex. index selection)
- **stochastic prediction** (ex. capacity planning)
- **online optimization** (ex. memory governing)
- **feedback control loop** (ex. MPL tuning)
- what-if analysis (ex. bottleneck identification)
- statistical learning (ex. root-cause analysis)

General Literature

- D. Shasha, P. Bonnet: Database Tuning – Principles, Experiments, and Troubleshooting Techniques, Morgan Kaufmann, 2003 (see also tutorials at SIGMOD 2002 and VLDB 2002)
- S. Chaudhuri, B. Dageville, G. Lohman: Self-Managing Technology in Database, Management Systems, Tutorial Slides, VLDB 2004
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Part II: Five Auto-Tuning Paradigms

1 Auto-Tuning as Tradeoff Elimination
2 Auto-Tuning as Static Optimization with Deterministic Input
3 Auto-Tuning as Static Optimization with Stochastic Input
4 Auto-Tuning as Online Optimization
5 Auto-Tuning as Feedback Control Loop

1 Auto-Tuning as Tradeoff Elimination

Tuning parameters handle tradeoffs

If you can find a parameter setting that yields universally close-to-optimal performance
(across a wide spectrum of workloads and for several technology generations)
then the tuning knob can be eliminated !

Examples:
- B^+-tree (vs. hash index): scan vs. random-lookup performance
- Page size: disk IO efficiency vs. memory efficiency
- Striping unit: IO parallelism vs. disk throughput
- LRU-k-style caching: recency (LRU) vs. frequency (LFU)

Example: Caching Strategies

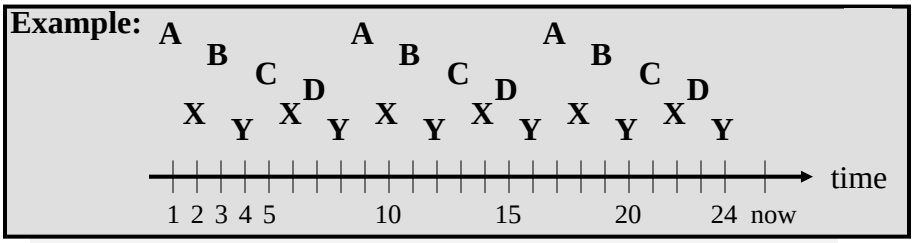
LRU: drop page that has been least recently used
LFU: drop page that has been least frequently used

Tradeoff recency vs. frequency:

LFU: optimal for static access probabilities, but has no aging

LRU: optimal if last access is indicative for next future access

LRU degrades for sequential only-once access
and is suboptimal for multiple page pools (e.g., index pages)



Hybrid **LRU/LFU strategies** have weights that are critical to tune
Using **multiple page-pool caches** (each with LRU) is a tuning nightmare

Example: LRU-k Caching Strategy

LRU-k: drop page with the oldest k-th last reference

estimates *heat (p)* = $\frac{k}{now - t_k(p)}$ optimal for IRM

extensions and variations for variable-size objects, non-uniform storage, etc.

But cache bookkeeping has time and space overhead:
- O(log M) time for priority queue maintenance
- M* > M entries in cache directory
  to remember k last accesses to M* pages

\+ overhead acceptable for improved cache hit rate
\+ add'l bookkeeping memory is small and uncritical to tune
→ improved implementations: 2Q, ARC

Lesson: substitute critical tuning param by robust 2nd-order params and accept small overhead

Lessons and Problems

Lessons:

find „sweet spot“ for tuning param by mathematical analyis and/or substitute „difficult“ param by „well-tempered“ param, and accept some overhead for making better run-time decisions

Problems:

- caching for multi-class workload with per-class goals
- extend 2Q / ARC methods to hierarchical & distributed caching
- combine caching & prefetching with response time guarantees
- systematic study & characterization of tuning-parameter sensitivities

Literature on Tradeoff Elimination:

- E.J. O‘Neil, P. O‘Neil, G. Weikum: The LRU-k Page Replacement Algorithm for Database Disk Buffering, SIGMOD 1993
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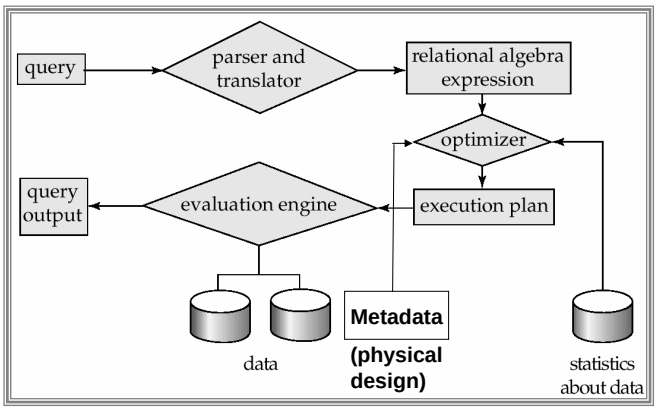
Auto-Tuning as Static Optimization with Deterministic Input

Physical Database Design

Overview of Database Systems



From "Database System Concepts" by Sliberschatz, Korth, Sudarshan, 5th edition, McGraw Hill.

Physical Database Design

- Performance of a query depends on execution plan
- Execution plan picked by optimizer depends on
  - Statistics created by the optimizer
  - Physical design Objects that exist
- Choice of statistics and physical design objects amortized
- Physical Design Configuration
  - Clustered Indexes + Non-clustered indexes + Materialized Views

Roadmap

- ***Why the problem is hard?***
- Abstract problem formulation
- Measuring goodness of a design
- Search: need for merging
- Search: leveraging the server
- Search: top-down vs. bottom-up

Is this a hard problem?

```
SELECT A,B,C
FROM R
WHERE 10 < A < 20
  AND 20 < B < 100

SELECT B,C,D
FROM R
WHERE 50 < B < 100
  AND 60 < 2*D < 80
```

Storage for (A,B,C) + (D,B,C) is too large!

```
UPDATE R
SET B=B+1
WHERE 10 < C < 20
```

We started fine, but progressively:

- Used statistical information
- Guessed how the optimizer would use statistics
- Guessed how the optimizer would use proposed indexes
- Gave up

Real Life Queries are Complex!

```
---
--- Galaxy target selection with spectroscopic redshifts
---
SELECT top 15  str(gal.ra,9,4) AS ra, str(gal.dec,8,4) AS dec,
               cast(spec.objTypeName AS CHAR(9)) AS type,
               str(spec.z,7,4) AS Z,
               fSpecZStatusN(spec.zStatus) AS status,
               fGetUrlSpecImg(spec.specObjID) AS Spectra
FROM
          @database..PhotoPrimary AS gal,
          @database..specObj AS spec
WHERE
          gal.objID = spec.bestObjID AND
          -- Our star-galaxy separation AND target selection
          psfMag_r - modelMag_r >= @delta_psf_model AND
          petroMag_r - extinction_r <= @maglim AND
          petroMag_r - 2.5*log10(2*@pi*petroR50_r*petroR50_r) < @SBlim AND
          -- Check flags
          (flags & @bad_flags) = 0 AND
          (((flags & @BLENDED) = 0) OR ((flags & @NODEBLEND) != 0)) AND
          -- Check spectro flags
                        NOT spec.zStatus IN (@FAILED, @NOT_MEASURED)
```

SKYSERVER SAMPLE QUERY

Roadmap

- Why the problem is hard?
- ***Abstract problem formulation***
- Measuring goodness of a design
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Physical Database Design as Static Optimization

- Workload
  - queries and updates
- Configuration
  - A set of indexes, materialized views and partitions from a search space
- Constraints
  - Upper bound on storage space for indexes
- Search: Pick a configuration with lowest *cost* for the given database and workload.

Roadmap

- *Why the problem is hard?*
- Abstract problem formulation
- ***Measuring goodness of a design***
  - *What-if Physical Design*
- Search: need for Merging
- Search: leveraging the server
- Search: top-down vs. bottom-up

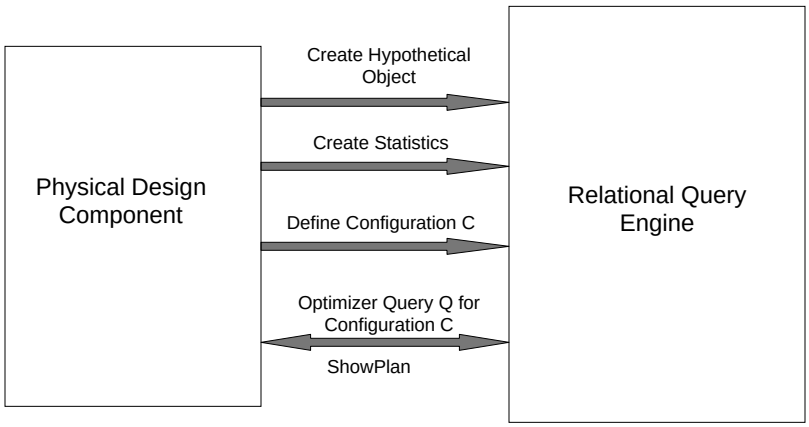
What is "cost"?

- Execution cost of the query
  - Requires physical design changes – too disruptive
- Optimizer Estimated Cost
  - Used to compare alternative plans for the *query*
- We choose optimizer estimated cost
  - Better than designing a new cost model
  - Estimate quantitatively the impact of physical design on workload (queries and updates)
    - e.g., if we add an index on T.c, which queries benefit and by how much?
  - Pitfalls: Never meant to compare across physical designs/Queries

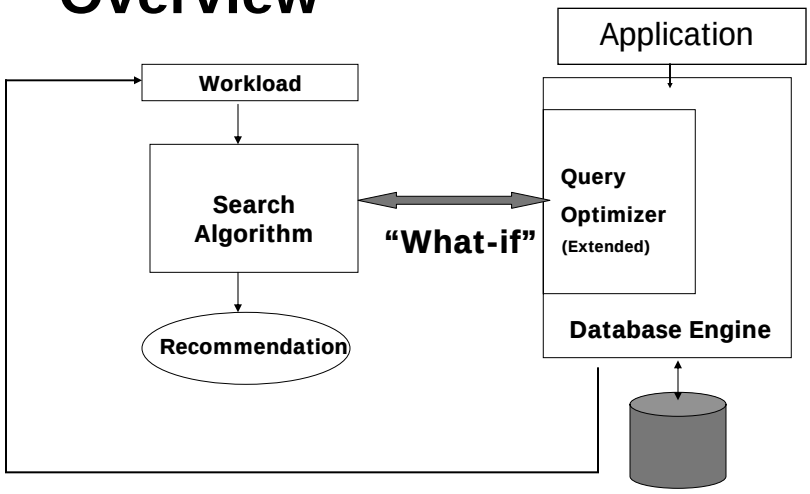
"What-If" Indexes

- Query Optimizer decides which plan to choose given a physical design
- Query optimizer does not require physical design to be materialized
  - Relies on statistics to choose right plan
    - Sampling based techniques for building statistic
- Sufficient to fake existence of physical design
  - Build approximate statistics
  - Change "meta-data" entry

Using What-If Analysis



"What-If" Architecture Overview



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Balancing Requirements of Multiple Queries

- Simple divide and conquer not enough
- Because, union of “best” configurations for each query may not be feasible
  - Violate storage constraints
  - Maintenance costs for update queries may rule out “ideal” indexes/MV
- Use locally suboptimal alternatives - need for “merging”

Characteristics of Merged Candidates

- A derived configuration from one or more seed configurations
- M_{12} is a "merged" candidate from parents P_1, P_2
  - If Q was using P_1, it can have a plan using M_{12}
  - New plans using M_{12} is not "much" more expensive
- Merging can
  - Introduce new logical objects (materialized views)
  - Introduce new physical structures (indexes)

Sample Algorithm: Index Merging Candidates

- Union of columns in I_1 and I_2
  - Index scan benefits preserved
  - Preserve seek benefits to at least one
- A common prefix of two indexes
  - Partial seek benefits
- Multiple thinner indexes
  - Replace covering indexes with Intersection/Union plans (A,B|C,F) [S] (B,E|F) = (B|F) + (A|C) + (E)

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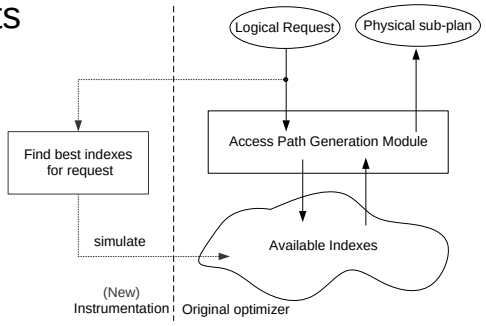
Optimizer as a Black Box?

- If you view optimizer as a black box, then for each configuration C and a query Q, you need an optimizer call to estimate cost
- In contrast, excessive co-dependence on optimizer code makes evolution hard
- Trade-off: make only broadest assumptions on optimizer that impact search space
  - Role of covering indexes

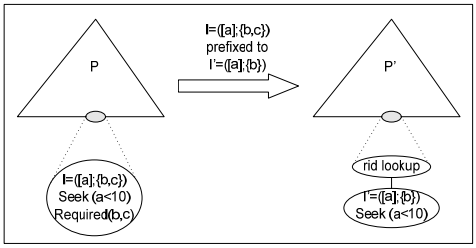
Generating the Candidate Indexes/Materialized Views

- Intercept index and view "*requests*"
  - Concise, no false negatives/positives
- Identify candidate indexes and views from requests



Estimating Cost without an Optimizer call

- If two configurations have the same set of relevant structures for a query, then the estimated costs for the query are equal
- Approximate cost by upper-bound via locally replacement of a structure



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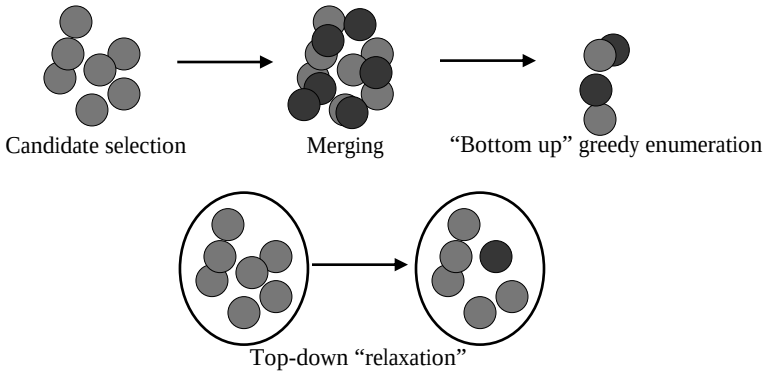
- ***Search: top-down vs. bottom-up***

Search Algorithm

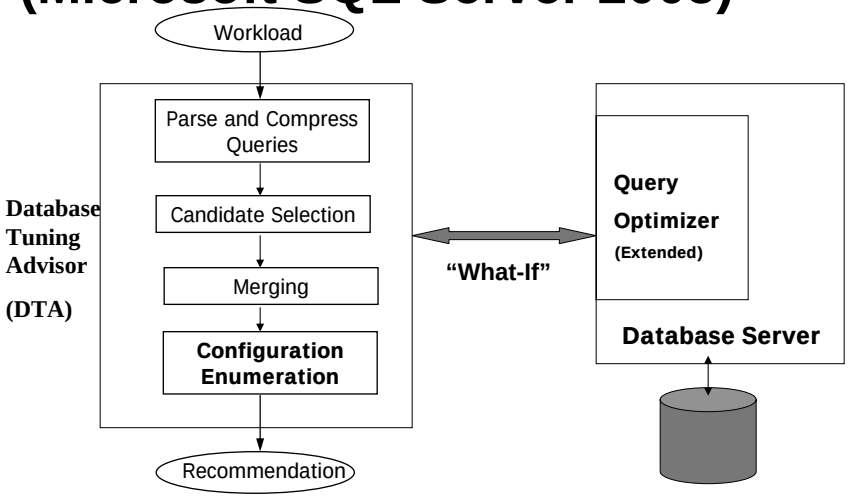
Search Space = “Locally Best” U “Merged”

- Indexes and Indexed Views need to be considered together
  - Cannot “break” into two sequential selection steps
- Search driven by reduction in optimizer estimated costs
  - *Top-Down*: Get an optimal structure and then modify it
  - *Bottom-up*: Grow by picking the next k-structures

Top-down and Bottom-Up

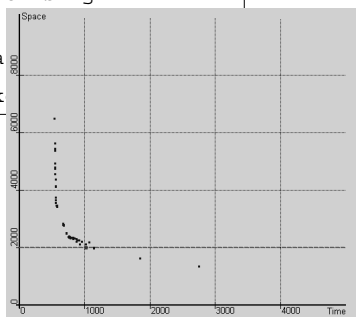


Example: Database Tuning Advisor (Microsoft SQL Server 2005)



Top-Down Search Algorithm [SIGMOD05]

1. Obtain **initial** configuration with **best** alternative for each request
2. While time is not exceeded
   a) Pick **some** configuration; **relax** it using the most promising "**merging**".
   b) Incrementally eva
   c) If best so far, k



Other Approaches

- [Agrawal et. al 2000] Bottom-up search
  - Incrementally add "most promising" structures
  - But, consider tight interactions
  - Initially exhaustive, degenerate into greedy
- [Valentin et.al. 2000] Knapsack + Genetic
  - Create a feasible solution through knapsack (ignore interactions)
  - Genetic mutations and generate new candidates

Lessons and Problems

- **Lessons:**
  - Precise static optimization problem
    - Challenges in cost definition
    - Complex search space – depends on server sophistication
- **Problems:**
  - How deeply to exploit optimizer
  - Uncertainty in cost estimation
  - Workload model
  - Search Algorithms (combinatorial optimization)

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Part 2: Five Auto-Tuning Paradigms

1 Auto-Tuning as Tradeoff Elimination
2 Auto-Tuning as Static Optimization with Deterministic Input
3 Auto-Tuning as Static Optimization with Stochastic Input
- **Capacity Planning**
- Example: Cache Sizing
- Queueing Theory
- Further Aspects and Lessons

4 Auto-Tuning as Online Optimization
5 Auto-Tuning as Feedback Control Loop

Auto-Tuning as Static Optimization with Stochastic Input

Capacity Planning and System Configuration

Workload varies statistically
Load may be unbounded
⇒ input is stochastic
⇒ can provide only stochastic guarantees

System Capacity Planning

Key issue for long-term tuning:
how big should you configure your system resources?

- CPU speed, #processors in SMP, #servers in server farm
- amount of memory, cache sizes
- #disks, disk types, storage controller types
- software parameters for (static) resource limitation

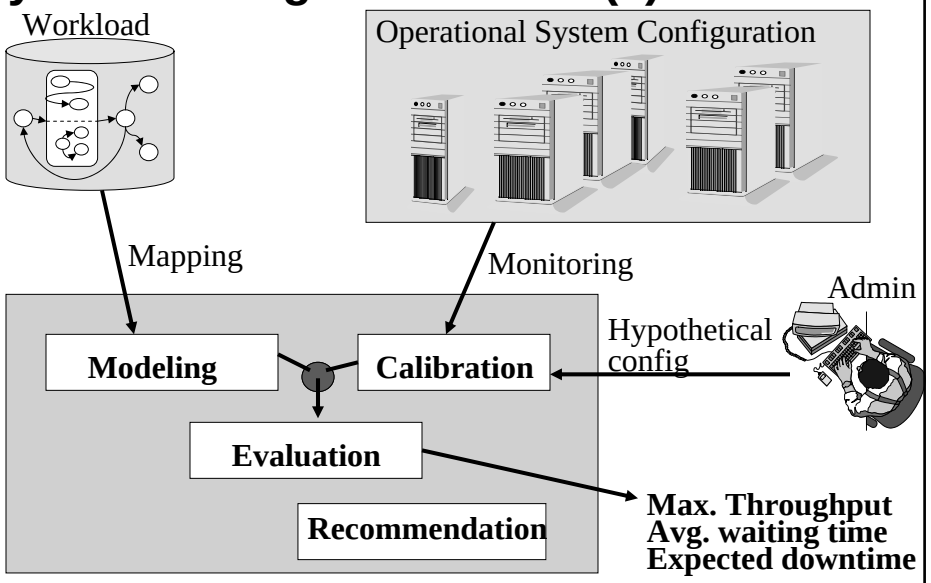
→ configure system so as to meet goals for

- performance: throughput, response time (mean or quantile)
- reliability and availability

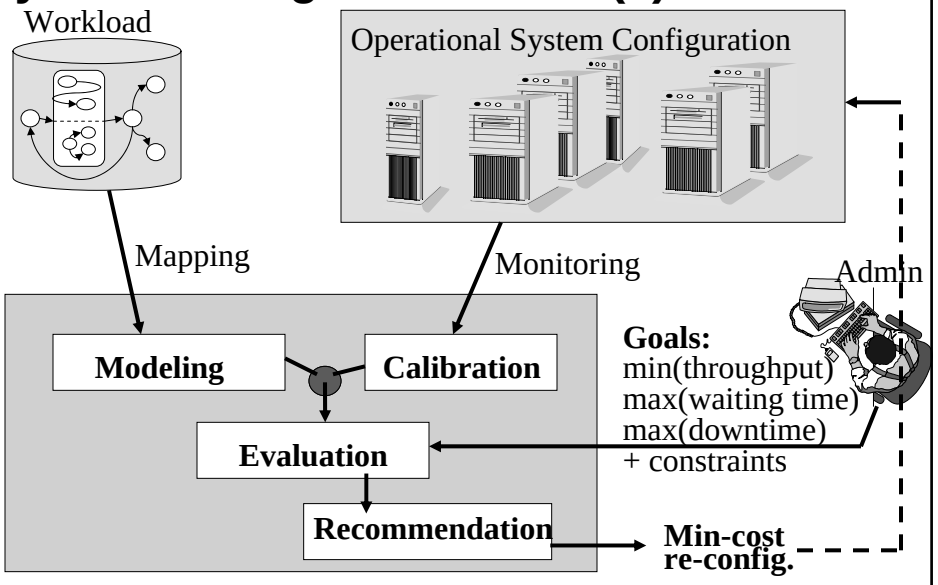
reasonably understood for OLTP server, HTTP server, etc.
not so well understood for DBMS, multi-tier Web Services

→ workload and complex system behavior approximated/abstracted by stochastic models

System Configuration Tool (1)



System Configuration Tool (2)



Part 2: Five Auto-Tuning Paradigms

Example: DBMS Cache Sizing

Cost / throughput consideration:

Keep page in cache if $C_{cache} < C_{disk}$

$$\Leftrightarrow 100\,KB\,\frac{1000\,\$}{1\,GB} < \frac{1000\,\$}{100\,s^{-1}}\,\lambda \qquad \Leftrightarrow \lambda > 0.01\,s^{-1}$$

Response-time guarantee:

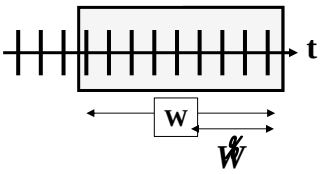
Minimum cache size M such that

$$RT_{percentile} = f(hit\ ratio,...) = f(g(M),...) \leq RT_{goal}$$

LRU-k Cache Hit Rate Prediction

with cache size M, page access probabilites $\beta_1, \beta_2, ...$

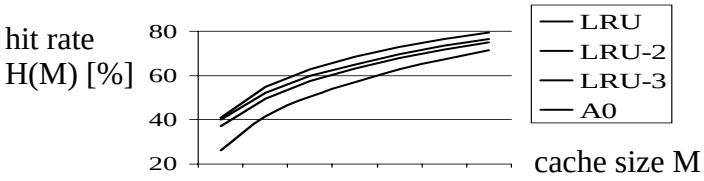
$$P(W) := E[\text{distinct pages referenced at least k times in window W}] = \sum_{i=1}^{n} \sum_{j=k}^{W} \binom{W}{j} \beta_i^j (1-\beta_i)^{W-j}$$



$$W := P^{-1}(M)$$

$$p_i := P[\text{page } i \text{ resides in cache}] \approx \sum_{j=k}^{W} \binom{W}{j} \beta_i^j (1-\beta_i)^{W-j}$$

$$H(M) := P[\text{reference is cache hit}] = \sum_{i=1}^{n} \beta_i p_i$$



LRU-k Response Time Prediction

with cache size M, page access probabilites $\beta_1, \beta_2, ...$,
disk characteristics, global load, ...

- *RT = f (hit rate, disk access time)*
- *disk access time = service time + queueing delay*

→ *need disk model*
→ *need queueing analysis*

rich repertoire of math, many models around,
but care needed in adopting models
→ need understanding of modeling & math

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- Capacity Planning
- Example: Cache Sizing
- **Queueing Theory**
- Further Aspects and Lessons

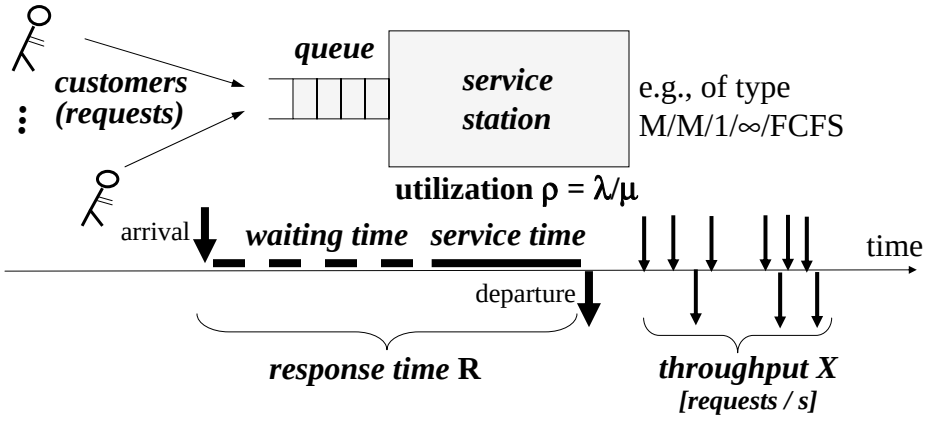
4 Auto-Tuning as Online Optimization
5 Auto-Tuning as Feedback Control Loop

Basics of Queueing Systems

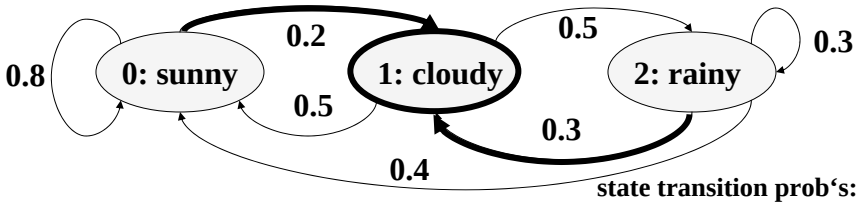
prob. distr. of interarrival time (e.g.: M = exp. distr.)
arrival rate λ

scheduling policy (e.g.: FCFS)

prob. distr. of service time S (e.g.: M = exp. distr.)
service rate μ



Markov Chains



state transition prob's: p_{ij}

$p0 = 0.8\ p0 + 0.5\ p1 + 0.4\ p2$
$p1 = 0.2\ p0 + 0.3\ p2$
$p2 = 0.5\ p1 + 0.3\ p2$
$p0 + p1 + p2 = 1$

$\Rightarrow$ $p0 \approx 0.657$, $p1 = 0.2$, $p2 \approx 0.143$

state prob's in step t: $p_i^{(t)} = P[S(t)=i]$

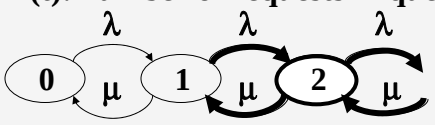
Markov property: $P[S(t)=i \mid S(0), ..., S(t-1)] = P[S(t)=i \mid S(t-1)]$

interested in stationary state probabilities:

$$p_j := \lim_{t\to\infty} p_j^{(t)} = \lim_{t\to\infty} \sum_k p_k^{(t-1)} p_{kj} \qquad p_j = \sum_k p_k p_{kj} \qquad \sum_j p_j = 1$$

M/M/1 Queueing Systems

N(t): number of requests in queue (or in service)



λ: arrival rate

μ: service rate

flow rate:

$$\lim_{\Delta t\to 0} \frac{P[\text{transition in } \Delta t]}{\Delta t}$$

flow balance equations:

$p_1\mu = p_0\lambda$ and $\boxed{p_{n-1}\lambda + p_{n+1}\mu = p_n(\lambda+\mu)}$ for $n \geq 1$

$\Rightarrow$ for $\rho := \frac{\lambda}{\mu} < 1$: $p_n = \rho^n(1-\rho)$ for $n \geq 0$

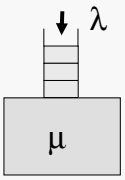
$$\Rightarrow \quad E[N] = \sum_{n=0}^{\infty} n\, p_n = \frac{\rho}{1-\rho} \quad \Rightarrow \quad \boxed{E[R] = \frac{E[N]}{\lambda} = \frac{E[S]}{1-\rho}}$$

response time distribution: $F_R(t) = P[R \leq t] = 1 - e^{-t/E[R]}$

but more complex for non-exponential service time

Insights (Example): Variability Matters

M/G/1:



with 2 workload classes

$S_1 = 0.01$ s $S_2 = 0.1$ s

$\lambda_1 = 40\ s^{-1}$ $\lambda_2 = 4\ s^{-1}$

$E[S] \approx 0.01818$ s

$E[S^2] \approx 0.00091\ s^2$

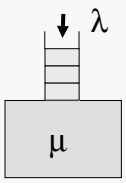
$\rho = 0.8$

$$\Rightarrow E[R] = E[S] + \frac{E[S^2]\rho}{2(1-\rho)E[S]}$$

$$\approx 0.01818 + \frac{0.00091 \cdot 0.8}{0.4 \cdot 0.01818}\ s$$

$$\boxed{\approx 0.118\ s}$$

M/D/1:



with 1 „average“ class

$S \approx 0.01818$ s

$\lambda = 44\ s^{-1}$

$E[S] \approx 0.01818$ s

$E[S^2] = 0.00033\ s^2$

$\rho = 0.8$

$$\Rightarrow E[R] = E[S] + \frac{E[S^2]\rho}{2(1-\rho)E[S]}$$

$$\approx 0.01818 + \frac{0.00033 \cdot 0.8}{0.4 \cdot 0.01818}\ s$$

$$\boxed{\approx 0.054\ s}$$

Other Queueing Systems

many variations and generalizations:

- queueing networks
- M/G/1 models with general service time distributions
- multiple request (customer) classes, with priorities
- service scheduling other than FIFO
- GI/G/1 models
- discrete-time models

Stochastic Response Time Prediction

for multi-zone disk with seek-time function $t_{seek}(x)$, Z tracks of capacity $C_{min} \le C_i \le C_{max}$, rotation time ROT, disk load λ_{disk}

$$f_R(t) = \sum_{i=1}^{n} \beta_i \, p_i \, f_{Rcache}(t) + \beta_i (1 - p_i) \, f_{Rdisk}(t)$$

$$f^*_R(s) = \sum_{i=1}^{n} \beta_i (1 - p_i) \, f^*_{Rdisk}(s)$$

$$f^*_{Rdisk} = f^*_{serv}(s) \frac{s(1-\rho)}{s - \lambda_{disk} + \lambda_{disk} f^*_{serv}(s)}$$

$$f^*_{serv}(s) = f^*_{seek}(s) f^*_{rot}(s) f^*_{trans}(s)$$

with M/G/1 queue:

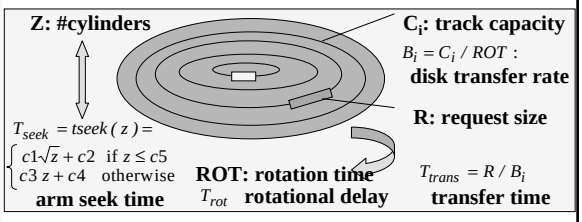
$$\lambda_{disk} = \lambda \sum_{i=1}^{n} \beta_i (1 - p_i)$$

$$\rho = \lambda_{disk} E[t_{serv}]$$

Modeling Disk Service Times for multi-zone disk

$$C_\nu = C_{min} + \frac{(C_{max} - C_{min}) \cdot (\nu - 1)}{Z - 1}$$

$$P[dist = k \mid on\ cyl\ i] = \begin{cases} C_\nu / C_{disk} & for\ k = 0 \\ (C_{\nu-k} + C_{\nu-k}) / C_{disk} & for\ 0 < k \le \nu \le Z-1-k \\ C_{\nu-k} / C_{disk} & for\ k > 0\ and\ i > Z-1-k \\ C_{\nu+k} / C_{disk} & for\ k > 0\ and\ \nu < k \end{cases}$$



$$f_{dist}(k) = P[dist = k] = \sum_i P[dist = k \mid on\ cyl\ i]$$

$$F_{seek}(t) = \begin{cases} F_{dist}(((t - c2)/c1)^2) & for\ t \le c1\sqrt{c5} + c2 \\ F_{dist}((t - c4)/c3) & otherwise \end{cases}$$

$$f_{rot}(s) = \frac{1}{ROT} \qquad f^*_{rot}(s) = \frac{1 - e^{-s\,ROT}}{s\,ROT}$$

$$C_\nu = C_{min} + \frac{(C_{max} - C_{min}) \cdot (\nu - 1)}{Z - 1} \qquad B_\nu = C_\nu / ROT \qquad P[B \le B_i] = \sum_{\nu=1}^{i} C_\nu \Big/ \sum_{\nu=1}^{Z} C_\nu$$

$$F_{rate}(r) = \frac{(C_{min}/ROT + r)(r - Zr + ZC_{min}/ROT - C_{max}/ROT)}{(C_{min} + C_{max}) Z (C_{min} - C_{max})/ROT^2}$$

$$F_{trans}(t) = \int_{r = C_{min}/ROT}^{C_{max}/ROT} f_{rate}(r) F_{size}(tr)\, dr$$

manageable with computer algebra tools like Maple or Matlab

Cache Sizing: Putting It All Together

We can now:

- predict the **cache hit ratio** and
  the **page-access response time** (mean and quantiles)
  for given cache size M
- predict **transaction response times** by accumulating page accesses
- solve for **smallest M** that satisfies **response time goal**

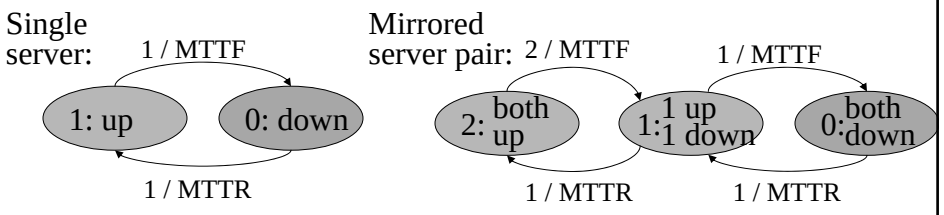
Part 2: Five Auto-Tuning Paradigms

Dependability Measures

- **Failure tolerance:** ability to recover from failures
- **Failure masking:** ability to hide failures from application program
- **Reliability:** time until failure (a random variable);
  usually given by the expectation value
- **Availability:** probability of service (at random time point);
  often given by #nines (e.g., 99.99 % ≈ 1 hour downtime per year)
- **Performability:** performance with consideration of
  service degradation due to (transient) component failures

Availability Example

only transient, repairable failures
availability = P[system is operational at random time point]



p0 / MTTR = p1 / MTTF
p1 /MTTF = p0 / MTTR
p0 + p1 = 1

$$\Rightarrow \quad p1 = \frac{MTTF}{MTTF + MTTR}$$

availability of server

p1 / MTTR = 2 p2 / MTTF
2 p2 / MTTF + p0 / MTTR =
p1 / MTTR + p1 / MTTF
p1 / MTTF = p0 / MTTR
p0 + p1 + p2 = 1

$$\Rightarrow \quad p2 \approx \frac{MTTF^2}{2}$$

availability of server pair

Lessons and Problems

Lessons:

- stochastic models are key to predicting performance for workloads with statistical fluctuation, and thus key for capacity planning and system configuration
- crude models are better than no models
- analytic model can be replaced/complemented by simulation models
- well established for mainframe, storage, network configuration, no coverage in DB teaching

Problems:

- from storage-level to DBMS-kernel-level queueing models
- automatic translation of SQL-level workloads into input for queueing models
- develop library of medium-grained DBMS components, each with its own performance prediction model
- develop composability methodology

Literature (1) on II.3: Static Optimization with Stochastic Input

- A. Allen: Probability, Statistics, and Queueing Theory with Computer Science Applications, Academic Press, 1990
- R. Nelson: Probability, Stochastic Processes, and Queueing Theory, Springer 1995
- R.A. Sahner, K.S. Trivedi, A. Puliafito: Performance and Reliability Analysis of Computer Systems, Kluwer, 1996
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- D.A. Menasce, V.A.F. Almeida: Capacity Planning for Web Performance – Metrics, Models, and Methods, Prentice Hall, 1998
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Literature (2) on II.3: Static Optimization with Stochastic Input

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- J. Wilkes, R.A. Golding, C. Staelin, T. Sullivan: The HP AutoRAID Hierarchical Storage System, ACM TOCS 14(1), 1996
- E.A.M. Shriver, A. Merchant, J. Wilkes: An Analytic Behavior Model for Disk Drives with Readahead Caches and Request Reordering, SIGMETRICS 1998
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Outline

- Part I: What Is It All About
- **Part II: Five Auto-Tuning Paradigms**
  - 1 Auto-Tuning as Tradeoff Elimination
  - 2 Auto-Tuning as Static Optimization with Deterministic Input
  - 3 Auto-Tuning as Static Optimization with Stochastic Input
  - **4 Auto-Tuning as Online Optimization**
  - 5 Auto-Tuning as Feedback Control Loop
- Part III: Wrap-up

Auto-Tuning as Online Optimization

Memory Governance Histogram Maintenance

Problem Formulation

- Memory = Other Processes + DB
- DB = Cache + Sum(WorkingQ-Memory)
- WorkingQ Memory = Sum (WorkingO-Memory)
- WorkingO-Memory assignment is a time varying function
- Solve the optimization problem at every reallocation point. Key factors are:
  - Current progress of each operator
  - Expected response time of queries and cache hit rate

Key Challenges

- Page replacement policy in Cache
  - LRU(k): based on online statistics
- Building *adaptive operators*
- *Allocation strategy* with imprecise knowledge on progress and predicted response time
  - Dynamic requirements, uncertainty over cardinality
  - Estimation of value of incremental memory

Making Hash Join Adaptive

- Memory fluctuation across “steps”
  - Adjust cluster size for partitioning buffers
  - Maximize size of write requests (e.g., flush largest partition to give up memory)
- Fluctuation during steps
  - +: Enlarge buffers for build as well as probe
  - -: Reduce partition buffer, not input buffers
- In Memory Hash -> Grace Hash -> Recursive Hash
- Role reversal between build and probe

ROC Framework

- ROC (Return on Consumption) = benefit/cost of incremental memory (or other resources)
  - Consider phases in an operator
  - Identify their dependence on incremental memory
  - Capture space-time product
  - ROC(M) = (T(M_0) – T(M))/(M*T(M) – M0*T(M0))
  - Optimization problem solved using simulated annealing
- Heuristic Threshold Strategy
  - Agree on a ROC threshold – how?
    - If ROC > threshold Then assign max Else assign min memory

Challenges in ROC Model

- Derive Δperf/ ΔMi for each operator
  - Decision to take away memory interacts with implied IO costs
  - Limited work on modeling adaptive join operators (Davidson 1995 thesis)
- Balancing across query groups in the workload may be important
  - Criticality (OLTP, OLAP, DSS)
  - Small, Medium or Large operands
- Reference: Resource Brokering framework based on ROC (Davidson, Graefe)

Example: Allocation in Microsoft SQL Server

- Compile Time
  - For each operator phase, min/max memory value is assigned (based on expected cardinalities)
  - For multiple concurrently executing phases, division is proportional to expected work
- Run time
  - At least min, but give Max if available but below a threshold of total memory
  - Queue, but don't preempt
  - Longest waiting operator first to free memory

Example: Allocation in Oracle 10g

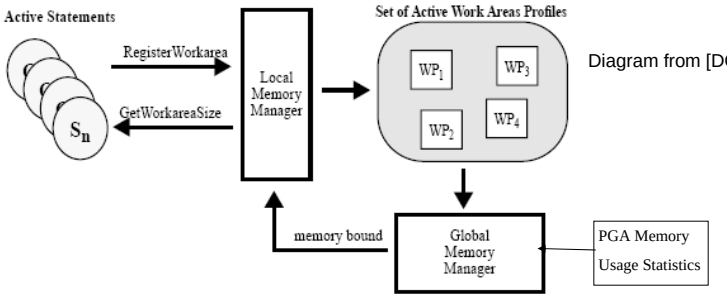

Diagram from [DG02]

Example: Allocation in Oracle 10g

- Global Memory Bound - g
  - Computed from the global limit on workspace and current workspace profiles
- To estimate a target working area size, following constraints are used
  - Below 5% of overall limit
  - At least min, at most (max_requirement, g)
  - Since “g” depends on current-state, there is a delayed effect
  - May require correction in a pro-active mode

Lessons and Problems

- **Lessons**
  - Cache (Buffer Pool) replacement reasonably solved
  - Static optimization not a feasible approach
  - Memory pressure can arise due to many different reasons
  - Use of built-in simulators (more opportunities)
- **Problems**
  - Allocation problem wide open
  - Incremental value of memory analysis open

References (Memory Management)

- Weikum G., Konig C., Kraiss A., Sinnwell, M. Towards Self-Tuning Memory Management for Data Servers, IEEE Data Engineering Bulletin 22(2): 3-11, 1999.
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- Brown K., Carey M., Livny M., Goal-Oriented Buffer Management Revisited, SIGMOD Conference,1996.
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References (Memory Management)

- Graefe G., Bunker R., Cooper S.: Hash Joins and Hash Teams in Microsoft SQL Server. VLDB 1998: 86-97
- Davison D.L., Graefe G.: Dynamic Resource Brokering for Multi-User Query Execution. SIGMOD Conference 1995: 281-292
- Davison D.L., Graefe G.: Memory-Contention Responsive Hash Joins. VLDB 1994: 379-390
- Dageville B., Zaït M.: SQL Memory Management in Oracle9i. VLDB 2002: 962-973
- Qi S., Dang M.: the DB2 UDB Memory Model, IBM DeveloperWorks.

Auto-Tuning as Online Optimization

Histogram Maintenance

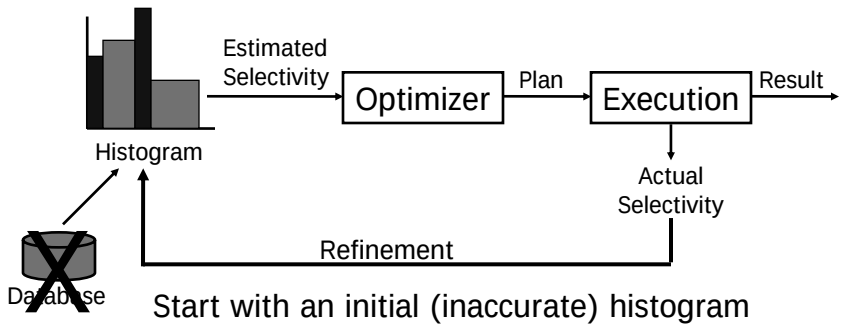
Histogram Maintenance

- Scenario 1: Insert/Deletes/Updates to relation take place
  - How can we avoid rebuilding histogram from scratch?
  - "Online incremental maintenance"
- Scenario 2: No updates to relation. But, trying to construct histograms by only looking at query executions
  - How can we modify histogram as we get "additional evidence"?
  - "Online incremental correction"
  - a.k.a Self Tuning Histograms

Online Incremental Correction

- Does not examine actual data set
- Assume uniformity and independence until feedback shows otherwise
- Uses Split and Merge techniques
  - Each query defines a potential new bucket if cardinality error is above threshold
  - Merge victims are chosen based on adjacency and similarity of density
- Goal: Error minimized if the workload is replayed.
- Contrast with online incremental maintenance technique..

Review: Self-tuning Histograms



Start with an initial (inaccurate) histogram and refine it based on feedback

Evaluation Metric for Online Incremental Correction

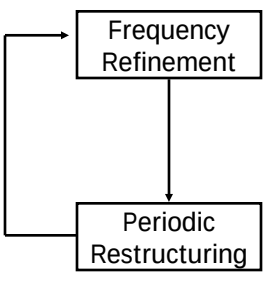
- **Absolute Error:**

$$E(D,H,W) = \frac{1}{|W|} \sum_{q \in W} \left| est(H,q) - act(D,q) \right|$$

- **Normalized Absolute Error:**

$$NAE(D,H,W) = \frac{\sum_{q \in W} |est(H,q) - act(D,q)|}{\sum_{q \in W} |est_{unif}(D,q) - act(D,q)|}$$

Refining STGrid Histograms

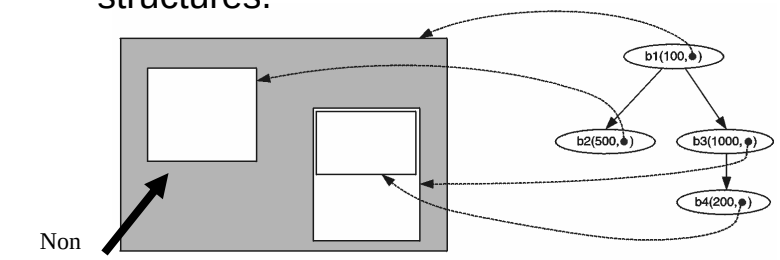


Observe error and accumulate information about data distribution in histogram buckets

Better bucket boundaries
Split high frequency buckets
Merge buckets with similar frequencies

Example: STHoles Histograms

- Tree structure among buckets.
- Buckets with holes: relaxes rectangular regions while using rectangular bucket structures.



$$est(H,q) = \sum_{b \in H} f(b) \frac{v(q \cap b)}{v(b)}$$

Refining STHoles Histograms

- Initialize histogram H assuming uniformity.
- For each query q in workload:

  1- Gather simple statistics from query results.

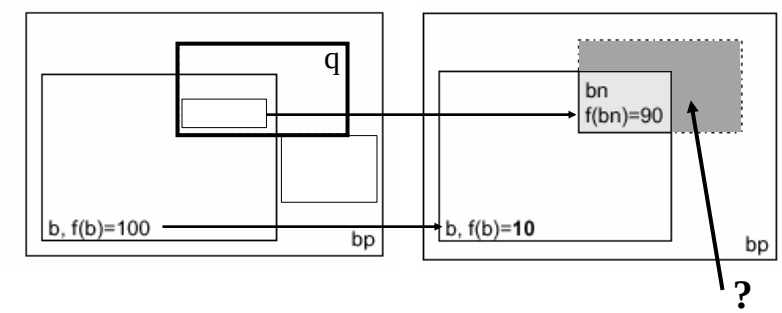
  2- Identify candidate holes and *drill* (add) them as new buckets in H.

  3- Merge superfluous buckets in H.

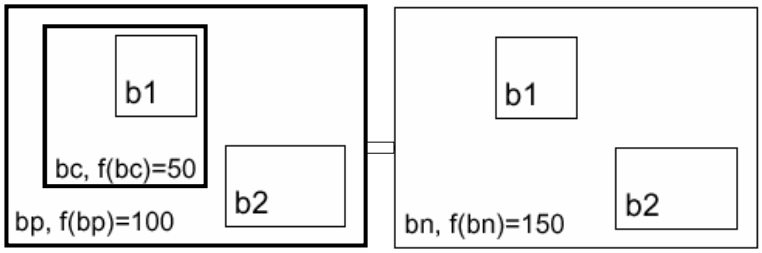
Drilling New Candidate Buckets

For each query *q* in workload and bucket b in histogram:

- Count how many tuples in result stream lie inside *q∩b.*
- Drill *q∩b* as a new bucket (child of *b*).



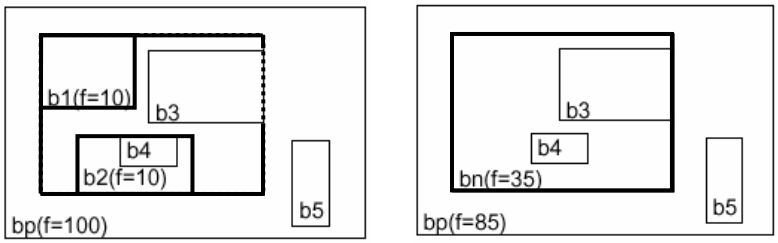
Parent-Child Merges



Eliminate buckets too similar to their parents.

Example: The interesting region in *bc* is covered by its child *b1*.

Sibling-Sibling Merges



- Consolidate buckets with similar densities that cover close regions.
- Extrapolate frequency distributions to yet unseen regions.

Lessons and Problems

- **Lessons**
  - Maintenance: Precise, online threshold driven
    - Needs auxiliary structures for correctness
  - Correction: An attractive approach because it avoids offline a priori decisions
- **Problems**
  - Correction:
    - Target optimization function alternatives
    - Analysis of convergence

References (Histogram Maintenance)

- Gibbons, P., Matias Y., Poosala V. Fast Incremental Maintenance of Approximate Histograms. *VLDB 1997.*
- Chung-Min Chen, Nick Roussopoulos: Adaptive Selectivity Estimation Using Query Feedback. SIGMOD Conference 1994: 161-172
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- Markl V., Megiddo N., Kutsch M., Tran T.M., Haas P., Srivastava U., Consistently Estimating the Selectivity of Conjuncts of Predicates. VLDB 2005

Part 2: Five Auto-Tuning Paradigms

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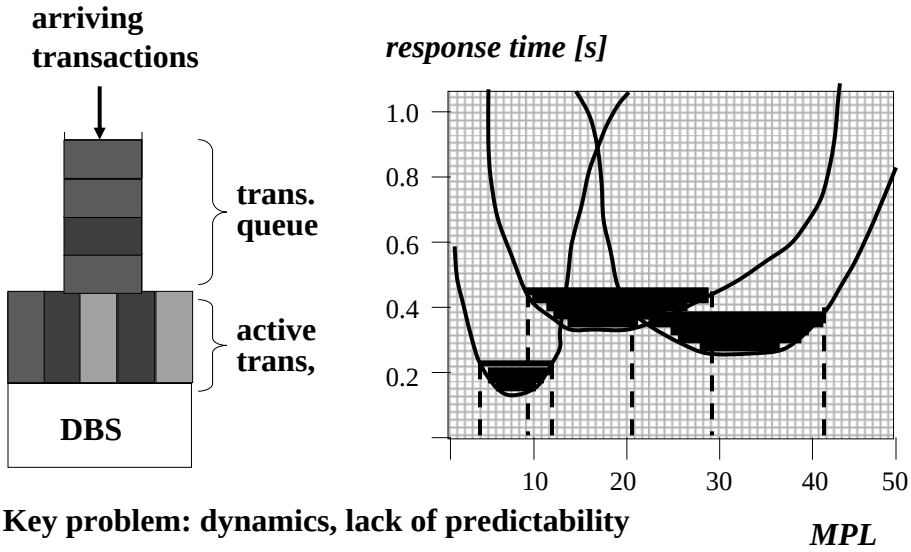
5 Auto-Tuning as Feedback Control Loop
- **Example: MPL Tuning Problem & Early Approaches**
- Feedback Control Theory
- Old Problem Reconsidered

Auto-Tuning as Feedback Control Loop

MPL Tuning (Admission Control)

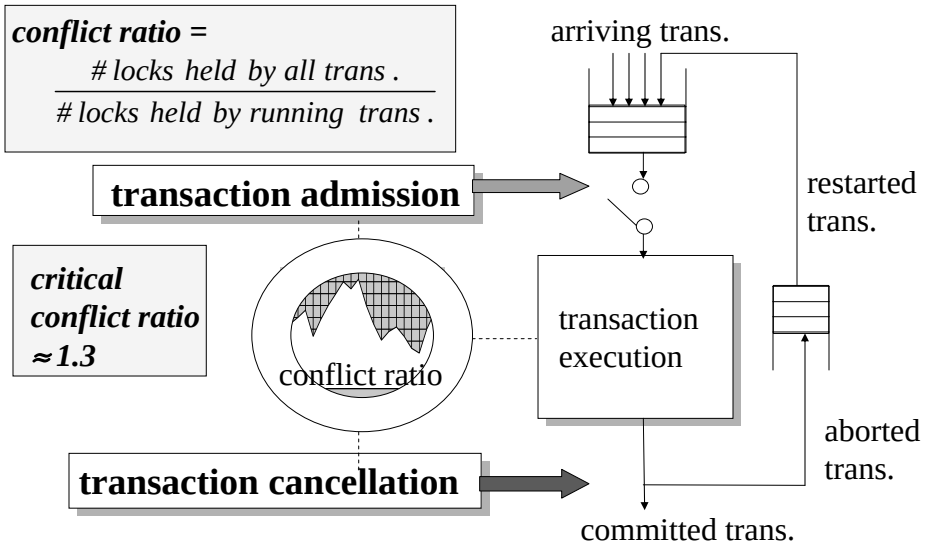
- No full-fledged predictive model of system behavior
- Errors in estimation of parameters and modeling
- Rapid workload evolution: bursts and shifts
  → feedback control
  - is adaptive
  - can work with black-box system,
  - and has theoretical underpinnings

MPL Tuning with Multiple Load Classes



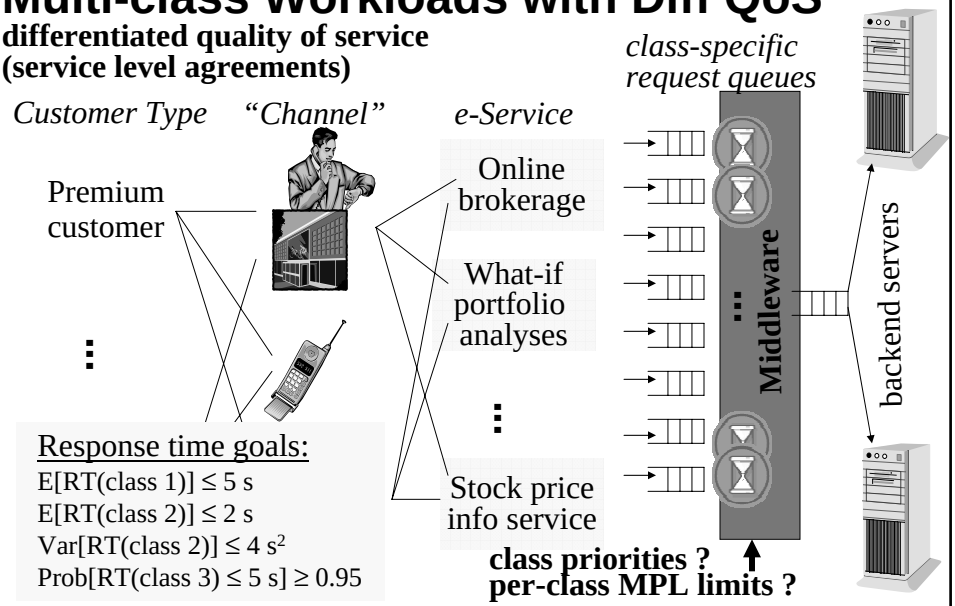
Key problem: dynamics, lack of predictability

Adaptive Load Control for Avoidance of Lock-Contention Thrashing



Multi-class Workloads with Diff QoS

differentiated quality of service (service level agreements)



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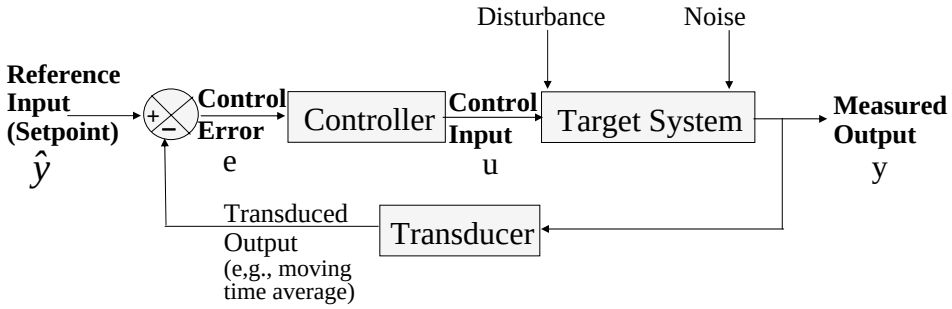
- **Feedback Control Theory**
- Old Problem Reconsidered

Basics of Feedback Control Theory

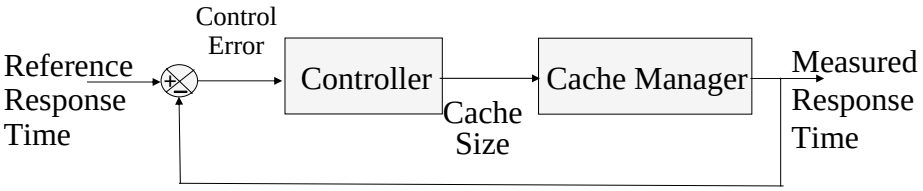
(following J.L. Hellerstein et al.: Feedback Control of Computing Systems, Wiley, 2004)



closed loop with feedback possible even for black-box system;
open loop (feedforward control) possible only with predictive model

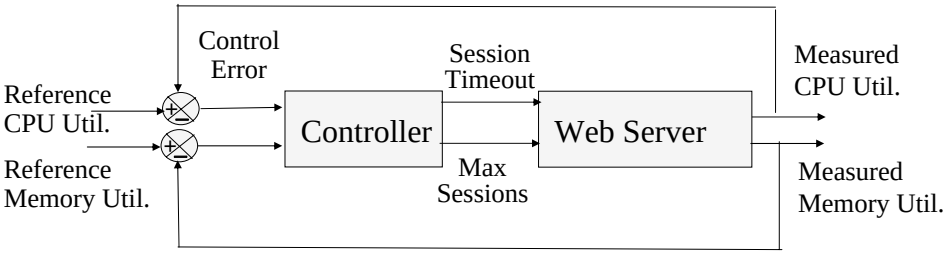
Application examples: thermostat, control valves, cruise control, ABS, building control (heating, energy, etc.)

Example: Dynamic Cache Sizing



SISO controller (single input, single output)

Example: Web Server



MIMO controller (multiple inputs, multiple outputs)

SASO Properties (1)

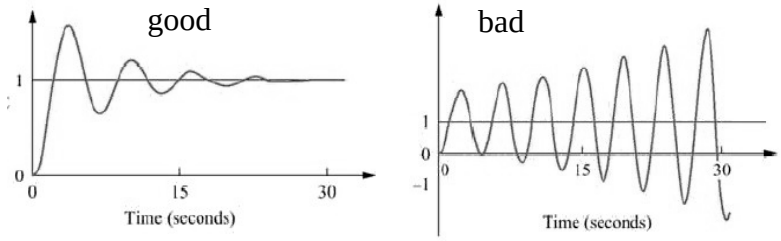
Desired guarantees:

stability – bounded input results in bounded output (BIBO)

accuracy – low error between reference and measured output

short settling time – fast convergence to steady state after excitement

low overshoot – low deviation from steady-state behavior



SASO Properties (2)

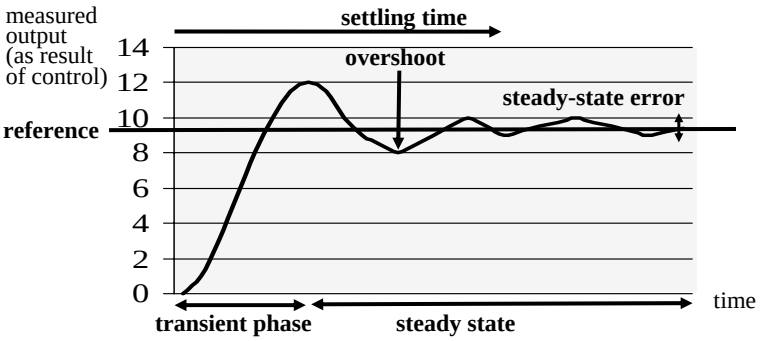
Desired guarantees:

stability – bounded input results in bounded output (BIBO)

accuracy – low error between reference and measured output

short settling time – fast convergence to steady state after excitement

no overshoot – low deviation from steady-state behavior



First-order Linear Models

described by difference equation with discrete time:

$$y(k+1) = ay(k) + bu(k)$$ with coefficients a, b

higher-order controller considers y(k-1), y(k-2), ...
non-linear behavior may be linearly approximated
parameters a, b derived from system model or estimated by regression

Examples:
- linearize M/M/1/K model, to control queue limit K based on resp. time
- MIMO controller for MPL and memory:

$$CPU(k+1) = a_{11}CPU(k) + a_{12}Mem(k) + b_{11}Timeout(k) + b_{12}Sessions(k)$$
$$Mem(k+1) = a_{21}CPU(k) + a_{22}Mem(k) + b_{21}Timeout(k) + b_{22}Sessions(k)$$

Transfer Function for Guaranteed Behavior

$$F(z) = \frac{Y(z)}{U(z)}$$ — Z transform of output / Z transform of input

$$U(z) = \sum_{k=0}^{\infty} u(k) z^{-k} = G_u(1/z)$$
with generating function G_u

Transfer function of linear first-order model with y(0)=0 :

$$y(k+1) = ay(k) + bu(k)$$
$$\Rightarrow zY(z) - zy(0) = aY(z) + bU(z) \quad \Rightarrow Y(z) = \frac{bU(z)}{z-a}$$
$$\Rightarrow \boxed{F(z) = b/(z-a)}$$

Theorem: system is stable iff all poles of G(z) have abs ≤ 1
(poles: roots of denominator polynomial)

more theorems about convergence, steady-state error,
transient responses, settling times, overshoot, oscillation, etc.

Controller Design

Proportional Control (P Control):

$$u(k) = K_p e(k) \quad \text{with control error} \quad e(k) = y(k) - \hat{y}$$

Integral Control (I Control):

$$u(k) = u(k-1) + K_I e(k)$$

PI Control:

$$u(k) = u(k-1) + (K_P + K_I) e(k) - K_P e(k-1)$$

rich results on SASO properties

plus many more controller types

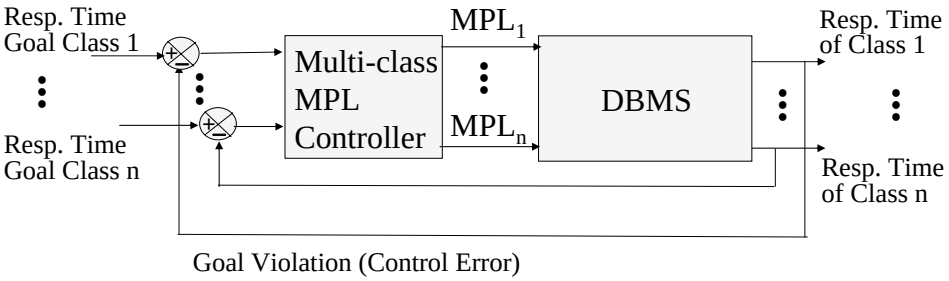
Part 2: Five Auto-Tuning Paradigms

1 Auto-Tuning as Tradeoff Elimination
2 Auto-Tuning as Static Optimization with Deterministic Input
3 Auto-Tuning as Static Optimization with Stochastic Input
4 Auto-Tuning as Online Optimization
5 Auto-Tuning as Feedback Control Loop
- Example: MPL Tuning Problem & Early Approaches
- Feedback Control Theory
- **Old Problem Reconsidered**

MIMO Controller for Multi-class DBMS

for lock-contention (and memory-contention) avoidance

Intriguing (and obvious?) approach:



but a viable solution is not that simple!

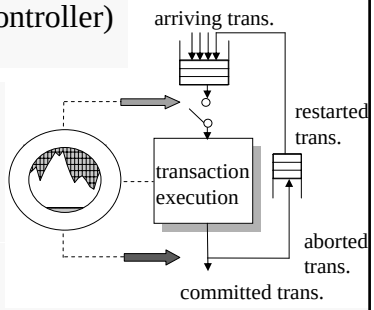
Lock-Contention Thrashing Reconsidered

Reference input metric is crucial:

response time or wait time (to drive MPL controller) do not work robustly

need deeper insight and math to identify viable metrics and setpoints:

- conflict ratio: $\frac{\#\ locks\ held\ by\ all\ trans.}{\#\ locks\ held\ by\ running\ trans.}$
  - should be < 1.3 (backed up by math analysis)
- wait depth:
  - wait depth of running trans.: 0
  - wait depth of trans. blocked by trans. at depth i: i+1
  - limit wait depth to 1 by cancelling trans. that are blocked and block other trans.



Details of control steps are crucial:
cancellation victim selection and restart waiting

Lessons and Problems

Lessons:

- feedback control adequate for tuning issues with limited predictive/causal understanding
- no panacea: controller design can be an art
- controller fine-tuning (e.g., sampling rates) can be critical
- can (and must) be combined with other paradigms (queueing models, regression, etc.)

Problems:

- extend successful work on Web & mail servers to DBMS
- full-fledged MIMO controller for multi-class MPL tuning problem (and memory allocation) in DBMS
- from stochastic or convergence guarantees to hard predictability („bounded surprise“)
- integrate control theory into curriculum

Literature (1) on II.5: Feedback Control Loop

- J.L. Hellerstein, Y. Diao, S. Parekh, D.M. Tilbury: Feedback Control of Computing Systems, Wiley 2004 (see also tutorial at SIGMETRICS 2005)
- G.F. Franklin, J.D. Powell, M.L. Workman: Digital Control of Dynamic Systems, Addison-Wesley, 1998
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Literature (2) on II.5: Feedback Control Loop

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- G. Weikum, C. Hasse, A. Moenkeberg, P. Zabback: The COMFORT Automatic Tuning Project, Information Systems 19(5), 1994
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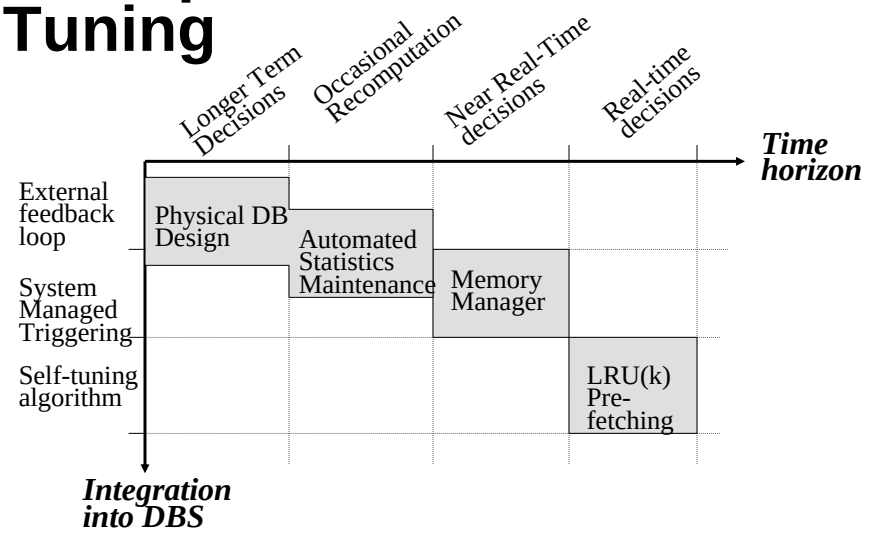
- S. Parekh, K. Rose, Y. Diao, V. Chang, J. Hellerstein, S. Lightstone, M. Huras: Throttling Utilities in the IBM DB2 Universal Database Server, American Control Conference, 2004

Outline

- Part I: What Is It All About
- Part II: Five Auto-Tuning Paradigms
  - 1 Auto-Tuning as Tradeoff Elimination
  - 2 Auto-Tuning as Static Optimization with Deterministic Input
  - 3 Auto-Tuning as Static Optimization with Stochastic Input
  - 4 Auto-Tuning as Online Optimization
  - 5 Auto-Tuning as Feedback Control Loop
- **Part III: Wrap-up**

The Spectrum for Self-Tuning



Other Notable Areas for Automated Tuning

- Statistics management
- Monitoring progress of SQL queries
- Choice of isolation levels
- Application tuning
- Tuning of middleware caching

Monitoring Infrastructure

- Only a very tiny part of the state of the server is accesible
- A flexible infrastructure for looking at system snapshot and its aggregation is useful
- DBMS Servers now provide
  - "Snapshot" of the state of the server
    - Extension: SQLCM: aggregation over stream of system events (ICDE 2004)
  - Historical system event data warehouse

Diagnostics/Troubleshooting

- Requires a careful model of the system
  - Distinguish normal from unusual
  - Analyze events as well as phases of execution over a time interval (Dias et.al. CIDR 2005)
- Decision trees frequently used
  - E.g., I/O bottleneck split into disk load imbalance, too many seeks, poor cache hit rate, insufficient bandwidth

"Learning" != "Magic"

- Conceptually enticing to say that the system will "learn from observation"
- Learning requires hard work
  - Identifying a learning model (not necessarily a typical ML model)
  - Several thresholds
  - Essentially, "fits" the parameters given observation
- Learning is a valuable tool but not a shortcut for thinking

Rethinking Systems: Wishful Thinking?

- VLDB 2000 Vision paper (Chaudhuri and Weikum 2000)
- Enforce Layered approach and Strong limits on interaction (narrow APIs)
  - Package as components of modest complexity
  - Encapsulation must be equipped with self-tuning
- Featurism can be a curse
  - Don't abuse extensibility - Eliminate 2nd order optimization

Final Words

- **Self-Tuning servers crucial for bounding cost**
  - Policy based adaptive control "observe-predict-react"
  - Monitoring infrastructure – leverage workload and events
  - What-if analysis
  - Mathematical tools
  - Deep understanding of local systems needed
    - Some limited successes so far
    - Plenty of opportunities/challenges