Towards Predicting Query Execution Time for Concurrent and Dynamic Database Workloads

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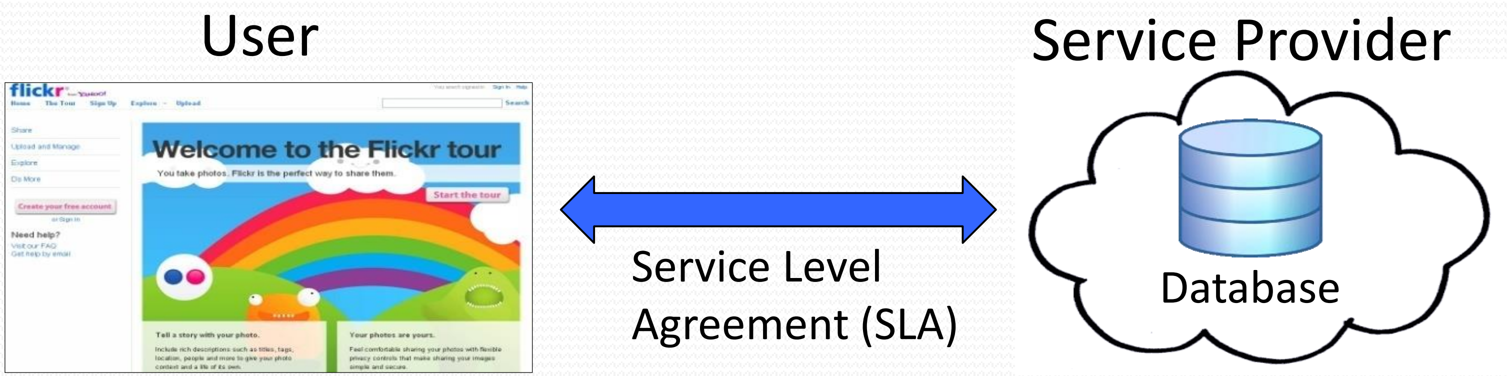
Background

- Database as a service (DaaS)



How can we predict the execution time of a query before it runs?

- Other applications
  - Admission control, query scheduling, progress monitoring, system sizing, etc.

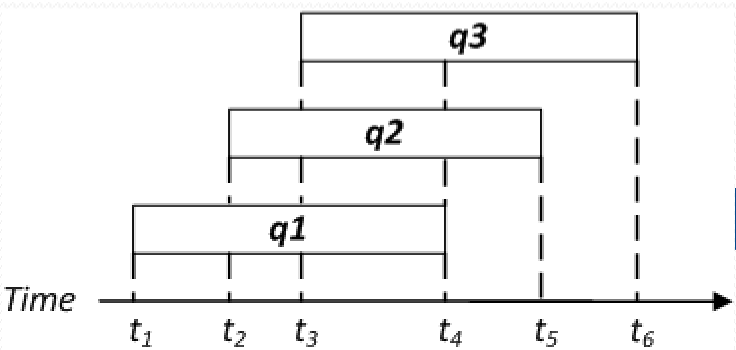
Motivation

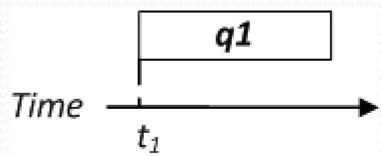
- Previous work
  - Standalone workloads [ICDE'09, ICDE'12, VLDB'12, ICDE'13]
  - Concurrent but *static* workloads [EDBT'11, SIGMOD'11]
- Real world database workloads
  - *Dynamic*: queries are not known *a priori*.

Our goal: Workloads that are *both* concurrent and dynamic!

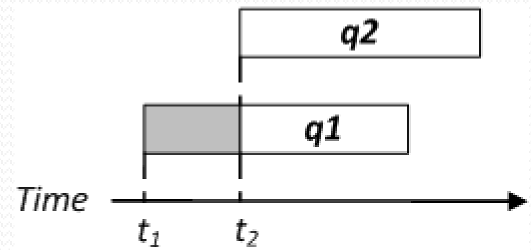
Problem Definition

At time t_i, predict the (*remaining*) execution time for each query in the mix.

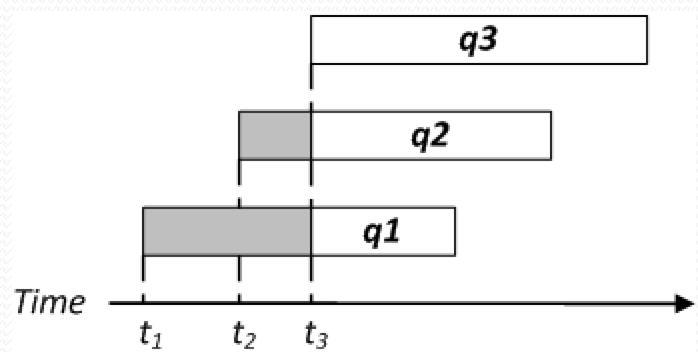




(a) At time t_1



(b) At time t_2



(c) At time t_3

Main Idea

Cost Unit	Value
c_s: seq_page_cost	1.0
c_r: rand_page_cost	4.0
c_t: cpu_tuple_cost	0.01
c_i: cpu_index_tuple_cost	0.005
c_o: cpu_operator_cost	0.0025

- PostgreSQL's cost model

$$\boxed{C = n_s c_s + n_r c_r + n_t c_t + n_i c_i + n_o c_o}$$

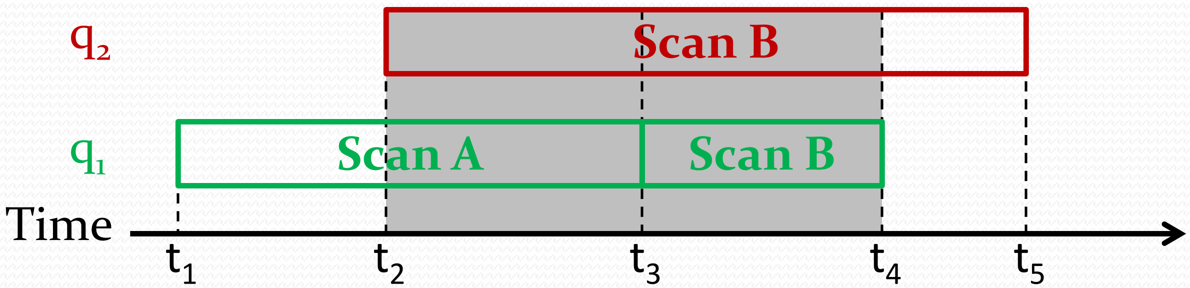
Wentao Wu, Yun Chi, Shenghuo Zhu, Junichi Tatemura, Hakan Hacigümüs, and Jeffrey F. Naughton, *Predicting query execution time: are optimizer cost models really unusable?* In ICDE, 2013.

- The *n*'s *won't* change!
  - Even if the query is running together with other queries

- Only the *c*'s *will* change!

Main Idea (Cont.)

- The c's change at boundaries of *phases* during execution.

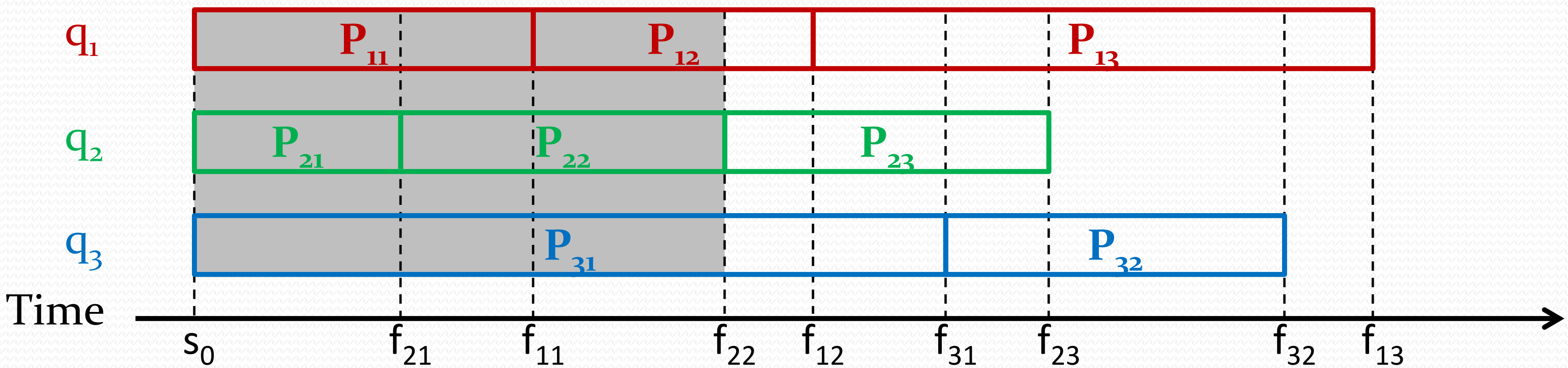


- What should be a *phase* of a query?
  - A phase = an *operator*?
  - *Pipelining* of operators => *interleaved* phases!

- We define a phase to be a *pipeline*.

Progressive Predictor

- The execution of a query mix can then be thought of as
  - multiple stages of *mixes of pipelines*



8 *mixes of pipelines* during the execution of the 3 queries

We need a predictor for a *mix of pipelines*!

Predictors for A Mix of Pipelines

- An approach based on machine learning
- An approach based on analytic models

Machine-Learning Based Approach

- CPU and I/O interactions are different
  - Separate the modeling of CPU and I/O interactions.

- Modeling CPU interactions (m CPU cores, n pipelines)
  - If $m \geq n$, then $c_{cpu} = \tau$ (same as the standalone case).
  - If $m < n$, then $c_{cpu} = \frac{n}{m} \cdot \tau$, assuming fair sharing.

- Modeling I/O interactions
  - Use machine learning.

Modeling I/O Interactions

- Previous work
  - Assume that *all* the queries are known beforehand.
  - Run *sample mixes* and *train* a regression model.
  - Apply to *static* workloads (e.g., report generation).
- It cannot be directly applied to *dynamic* workloads.
  - We do not know all the queries to be run.

Modeling I/O Interactions (Cont.)

Observation #1. Fixed DBMS => Fixed # *scan operators*

Observation #2.
Fixed DBMS + Fixed DB schema => Fixed # *scan types*

scan type = scan operator + table name (e.g., *index scan* over *orders*)

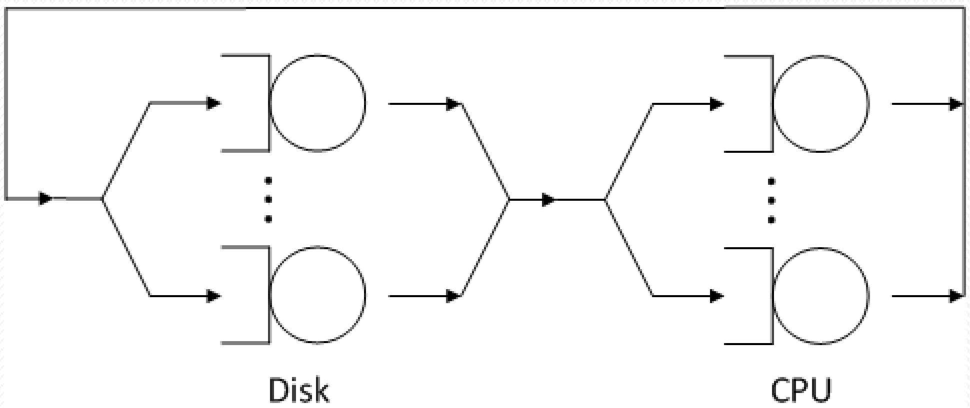
We can apply the machine-learning idea to *scan types* instead of query templates!

NB: Additional I/O's (e.g., from hash-joins) => Additional scans

Analytic-Model Based Approach

- Problem of the machine-learning based approach
  - Infinitely many *unknown* queries/query mixes

- Model the system with a queueing network.



1. Two *service centers*: Disk, CPU.
2. Pipelines *are customers*.
3. The c's are the *residence times per visit* of a customer.

Analytic-Model Based Approach (Cont.)

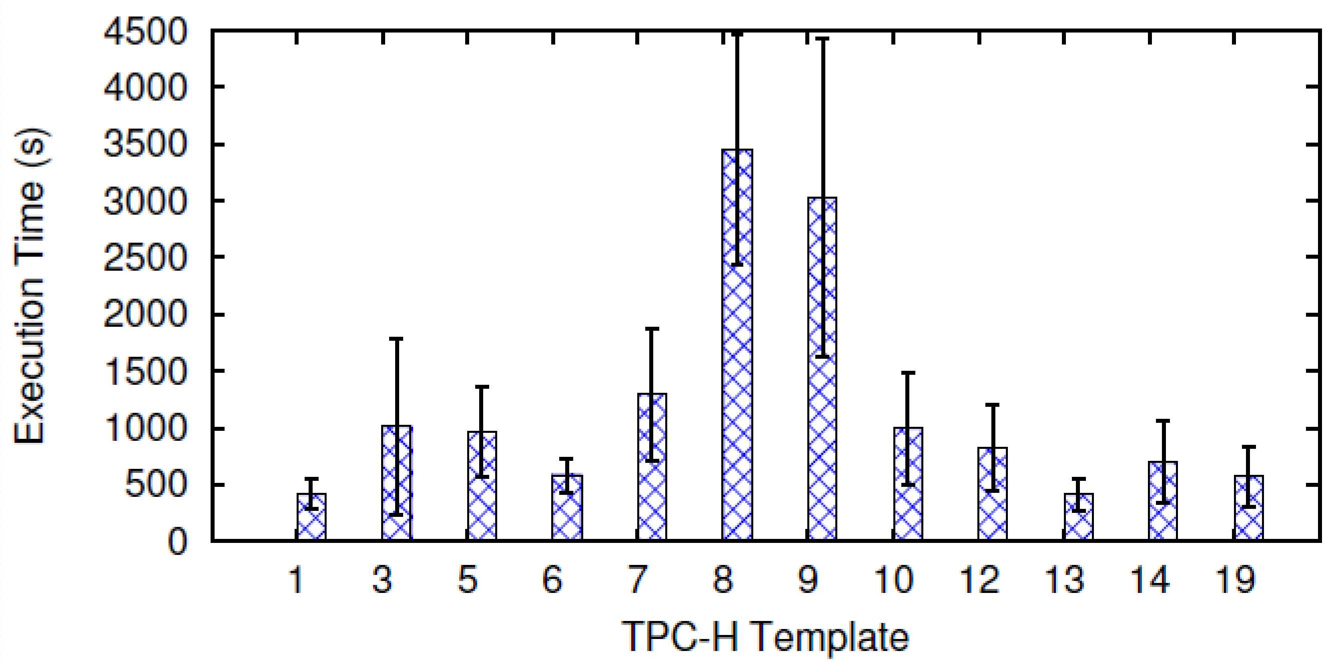
- The effect of the buffer pool
  - The buffer pool *cannot* be modeled as a *service center*.
- We used a model [SIGMETRICS'92]
  - For the "*clock*" algorithm used by PostgreSQL

Experimental Settings

- PostgreSQL 9.0.4, Linux 3.2.0-26
- TPC-H 10GB database
- Multiprogramming Level (MPL): 2 to 5
- Dual Intel 1.86GHz CPU, 4GB of memory

Workloads

- 2 TPC-H workloads & 3 micro-benchmarking workloads
  - TPC-H2: 12 templates (Q7, 8, 9 are more expensive)
  - MB1: *heavy index scans* with different data sharing rate.

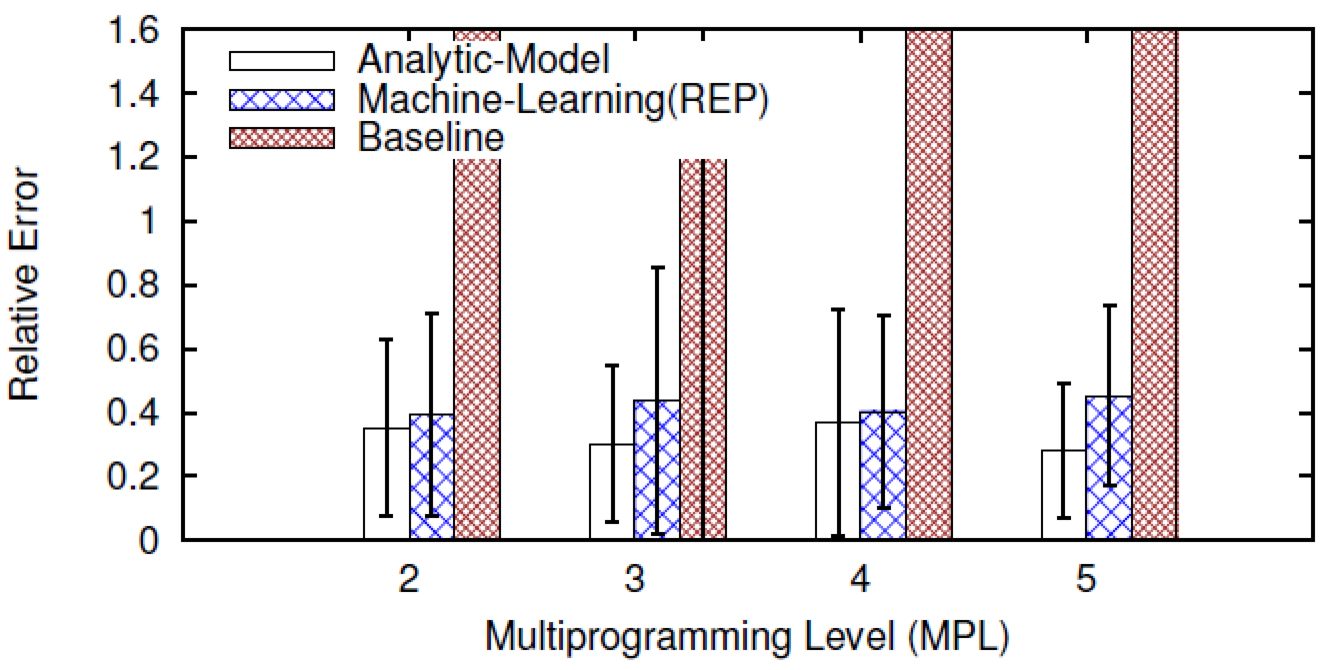


Baseline Approach

- For each query in the mix
  - Predict its time by using the *single-query* predictor.
- *Multiply* it with the MPL as the prediction.
- Intuitively, this approach *ignores* the impact of query interactions.

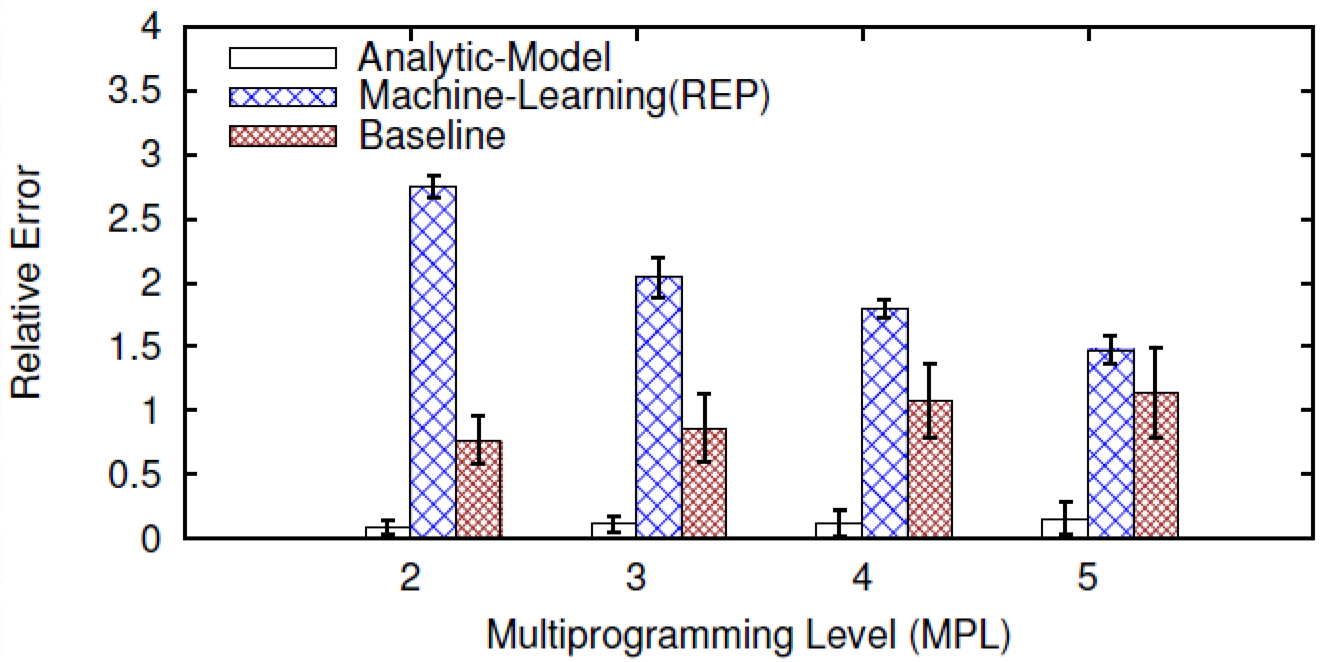
Prediction Accuracy

- On TPC-H2 (with more expensive templates)



Prediction Accuracy (Cont.)

- On MB1 (mixes of heavy index scans)



Overhead

- Both approaches
  - need to *calibrate* the optimizer's cost model.
- The machine-learning based approach
  - needs a *training* stage (usually *2 days*)
- The analytic-model based approach
  - needs to *evaluate* the analytic models (usually < *120 ms*)

Conclusion

- To the best of our knowledge, we are the first to
  - publish a technique to predict query execution times for workloads that are *both* concurrent and dynamic;
  - present a systematic exploration of its performance.

- We use *analytic-model* based approaches in addition to machine learning as used by previous work.

- We show that our analytic-model based approach can have *competitive* and often *better* prediction accuracy than a (*new*) machine-learning based approach.

Q & A

- Thank you☺

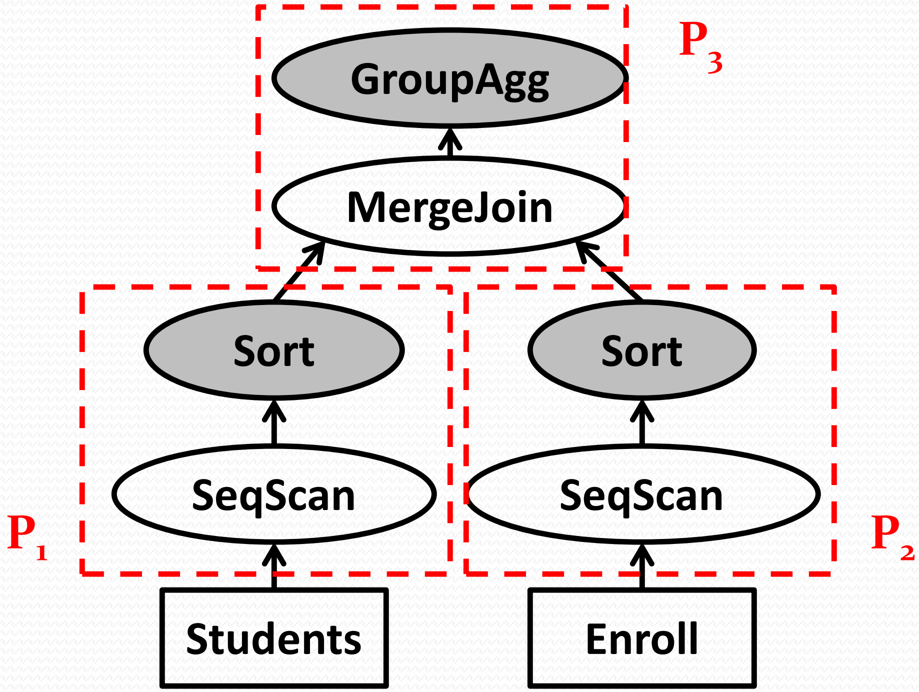
Backup Slides

From A Query Plan to Pipelines

Tables:
Students (<u>sid</u>, sname)
Enroll (<u>sid, cid</u>, grade)

SELECT S.sname, ***AVG*** (grade) **AS** gpa
FROM *Students* S, *Enroll* E
WHERE S.sid = E.sid
GROUP BY S.sname

The example query plan contains 3 pipelines with the execution order: $P_1P_2P_3$.



More Details of Queueing Network

Residence Time

Service Time

Queueing Time

$$R_{k,m} = \tau_k + Y_k \tau_k \sum_{j \neq m} Q_{k,j}$$

$$Q_{k,j} = \frac{V_{k,j} R_{k,j}}{\sum_{i=1}^{K} V_{i,j} R_{i,j}}$$ (Queue Length)

$$Y_k = \frac{1}{C_k} \rho^{4.464(C_k^{0.676}-1)}_M$$ (Correction Factor, $Y_k = 1$ if $C_k = 1$)

$$\rho_k = \frac{\tau_k}{C_k} \sum_{j=1}^{M} \frac{V_{k,j}}{\sum_{i=1}^{K} V_{i,j} R_{i,j}}$$ (Utility)

More Details of Buffer-Pool Model

- Recall the “clock” algorithm
  - The buffer pages are organized in a circular queue.
  - On a buffer miss, the clock pointer scans the pages and chooses the first page with count 0 for replacement.
  - If a page has a count greater than 0, then the count is decreased by 1.
  - On a buffer hit, the counter of the page is reset to its maximum value.

More Details of Buffer-Pool Model (Cont.)

Model the "clock" algorithm by using a Markov chain.

$$\sum_{p=1}^{P} S_p \left(1 - \frac{1}{\left(1 + \frac{n_0}{m}\frac{r_p}{S_p}\right)^{I_p+1}}\right) - B = 0 \quad \text{(steady-state condition)}$$

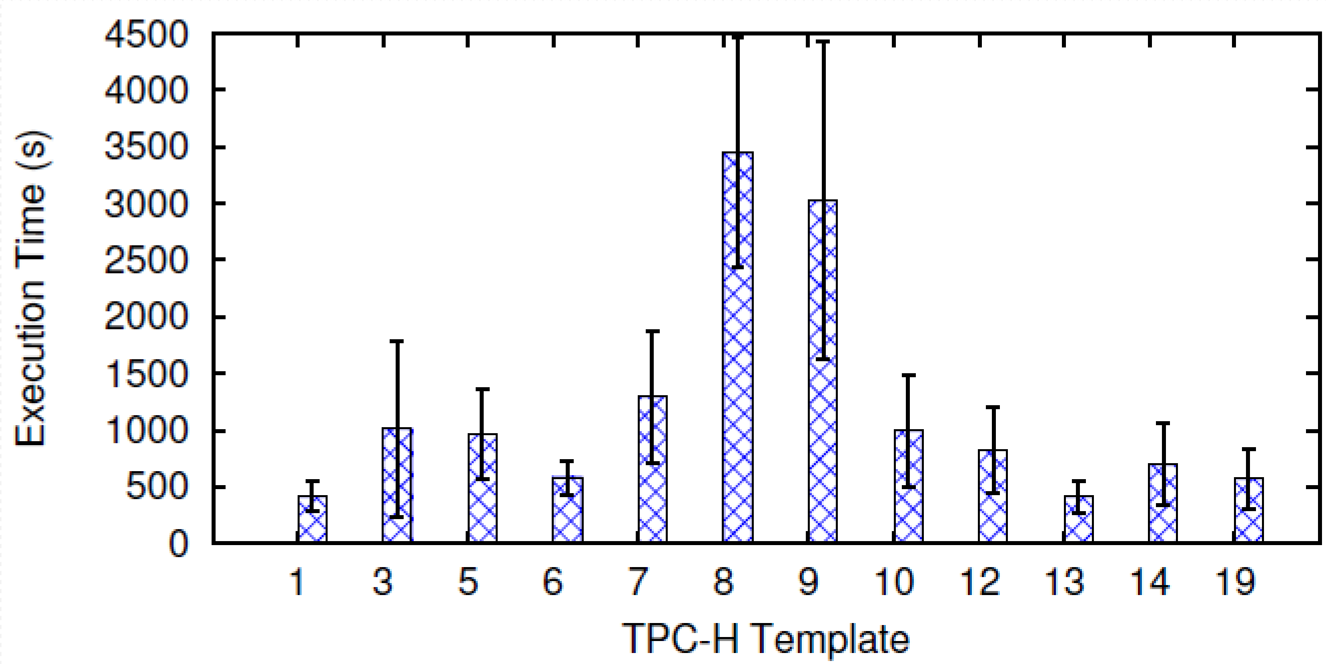
$$N_p = S_p \left(1 - \frac{1}{\left(1 + \frac{n_0}{m}\frac{r_p}{S_p}\right)^{I_p+1}}\right) \quad \text{(\# pages in the buffer)} \qquad h_p = \frac{N_p}{S_p} \quad \text{(buffer hit rate)}$$

$$m_p = 1 - h_p = \left[\left(1 + \frac{n_0}{m}\frac{r_p}{S_p}\right)^{I_p+1}\right]^{-1} \quad \text{(buffer miss rate)}$$

expected # accesses to a page in the partition *p*

Workloads

- TPC-H workloads
  - TPC-H1: 9 light to moderate TPC-H query templates
  - TPC-H2: TPC-H1 + 3 more expensive templates (Q7, 8, 9)
  - Create query mixes with Latin Hypercube Sampling (LHS).

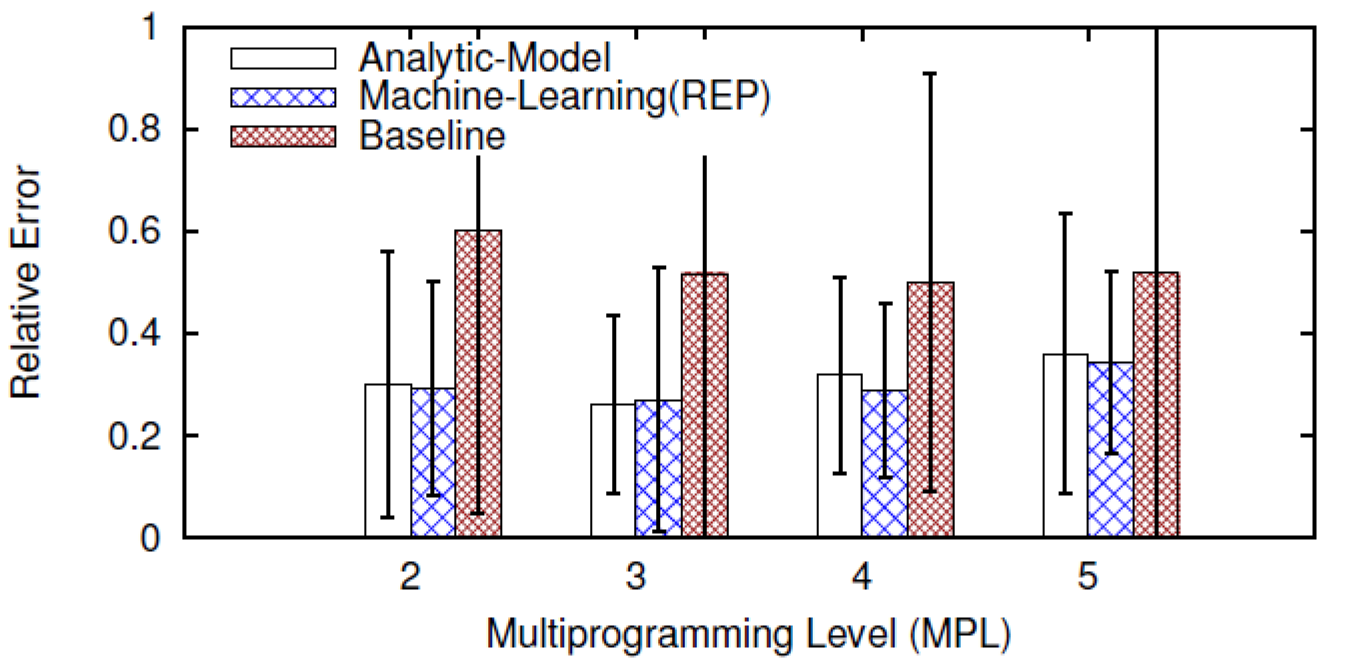


Workloads (Cont.)

- Micro-benchmarking workloads
  - MB1: mixes of *heavy index scans* with different data sharing rate.
  - MB2: mixes mingled with both *sequential scans* and *index scans*.
  - MB3: similar to MB2, but we replace the scans with real *TPC-H queries* that contain the corresponding scans.

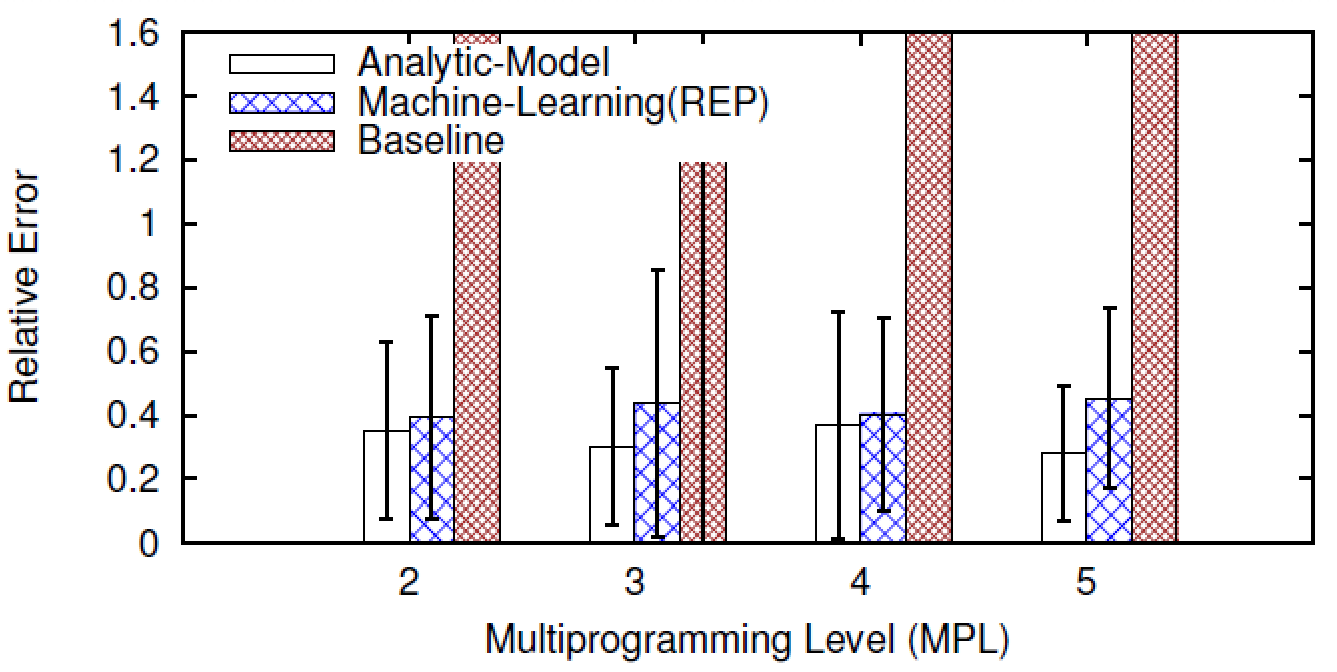
Prediction Accuracy

- On TPC-H1 (light to moderate templates)



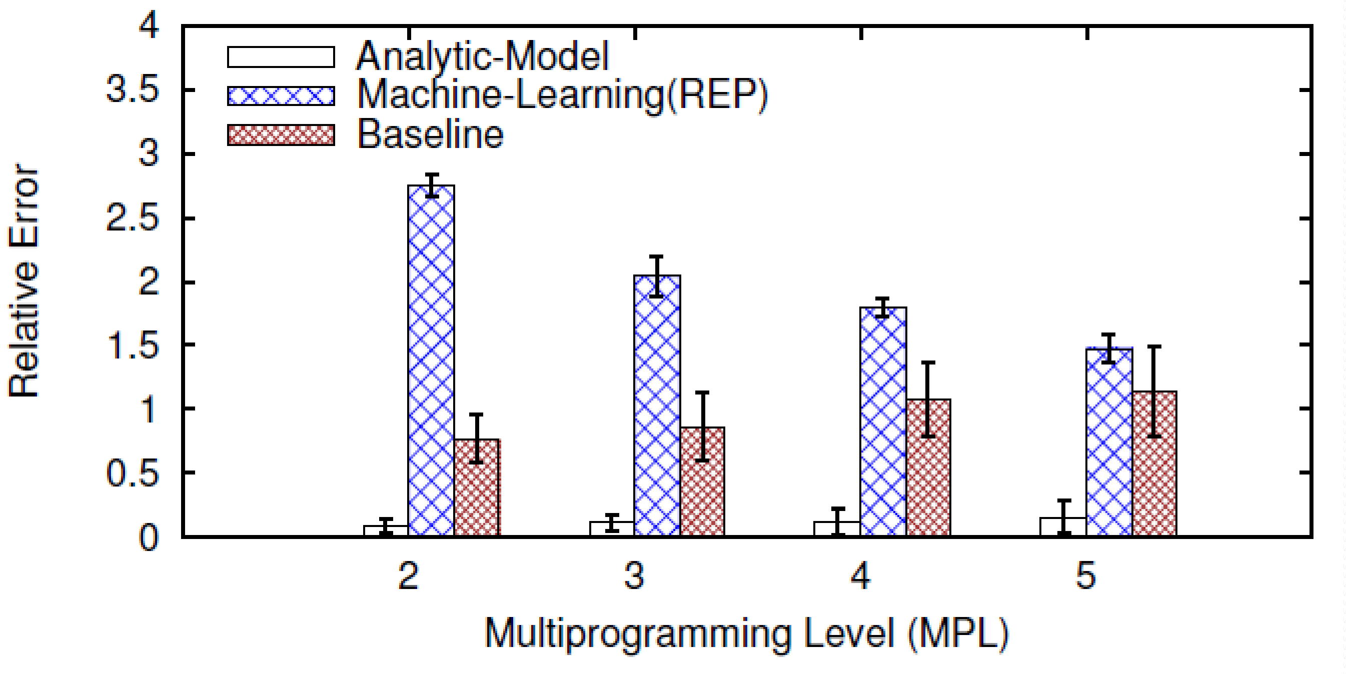
Prediction Accuracy (Cont.)

- On TPC-H2 (with more expensive templates)



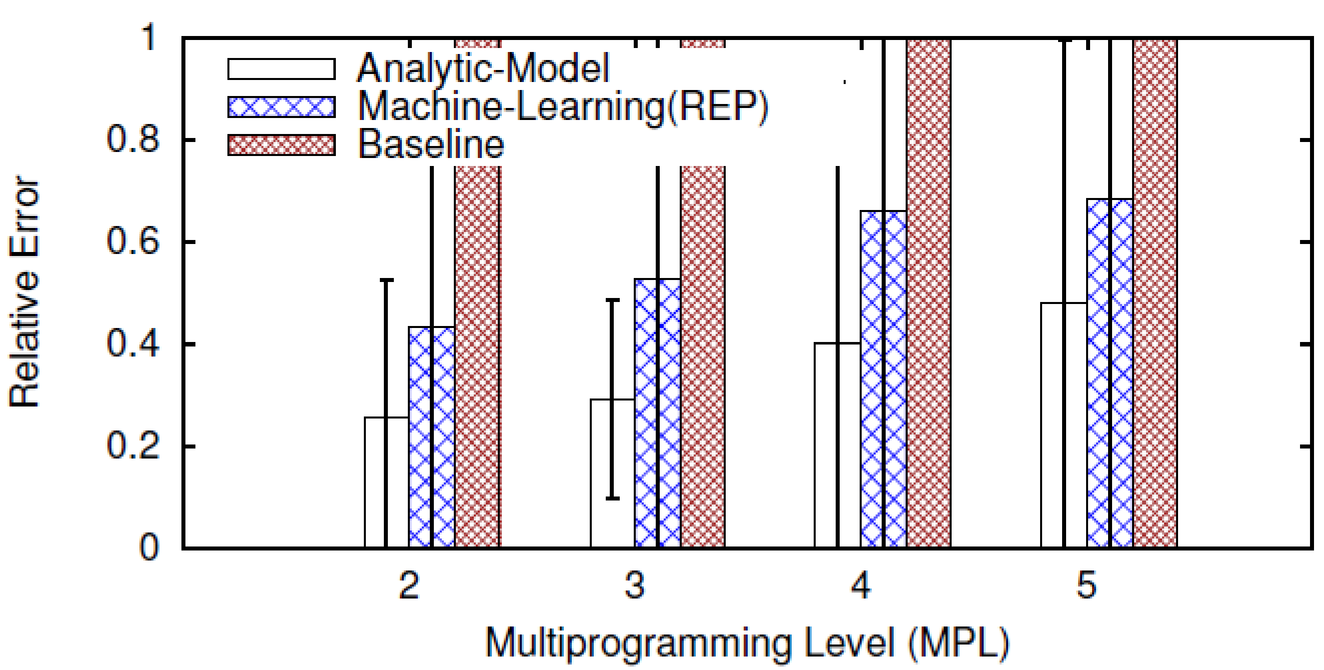
Prediction Accuracy (Cont.)

- On MB1 (mixes of heavy index scans)



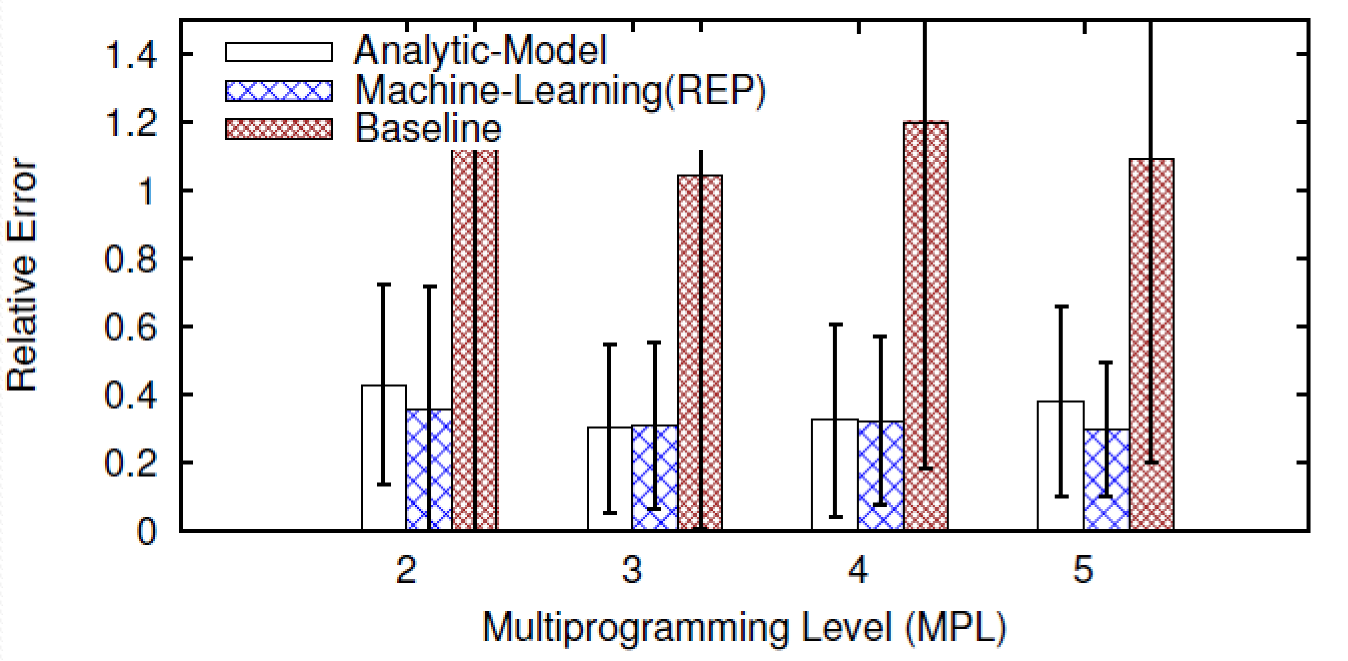
Prediction Accuracy (Cont.)

- On MB2 (mixes of sequential scans/index scans)



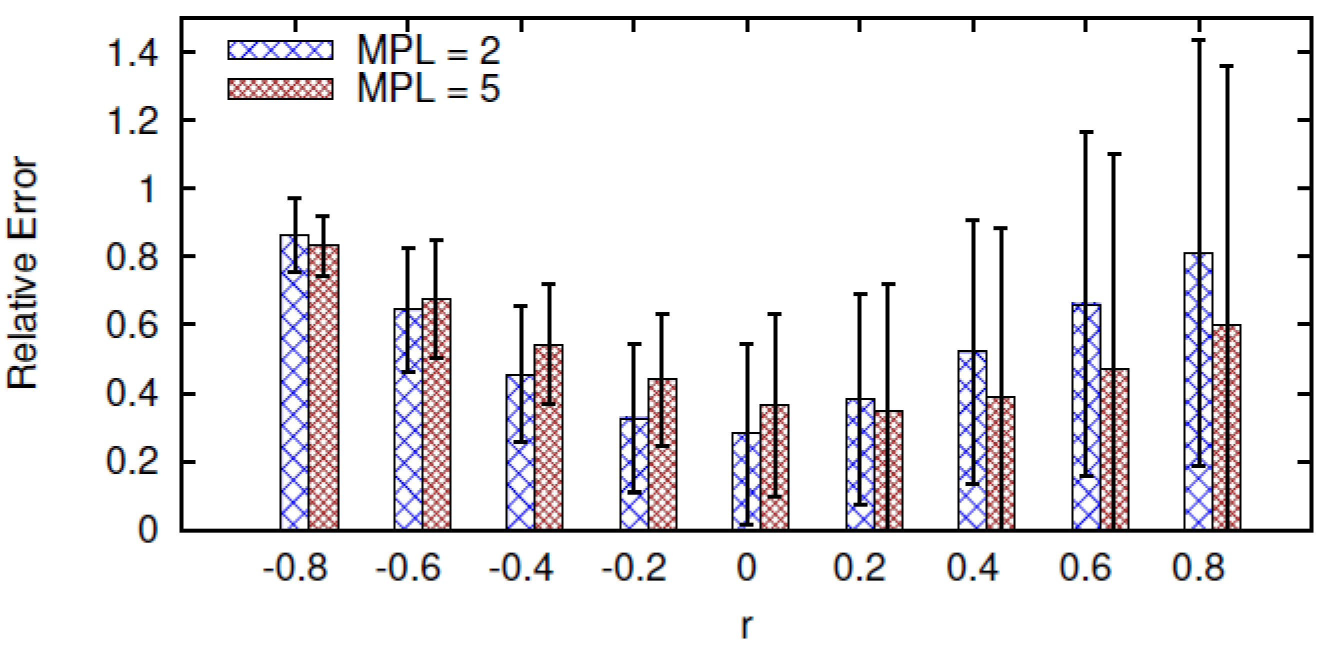
Prediction Accuracy (Cont.)

- On MB3 (similar to MB2, but with TPC-H queries)



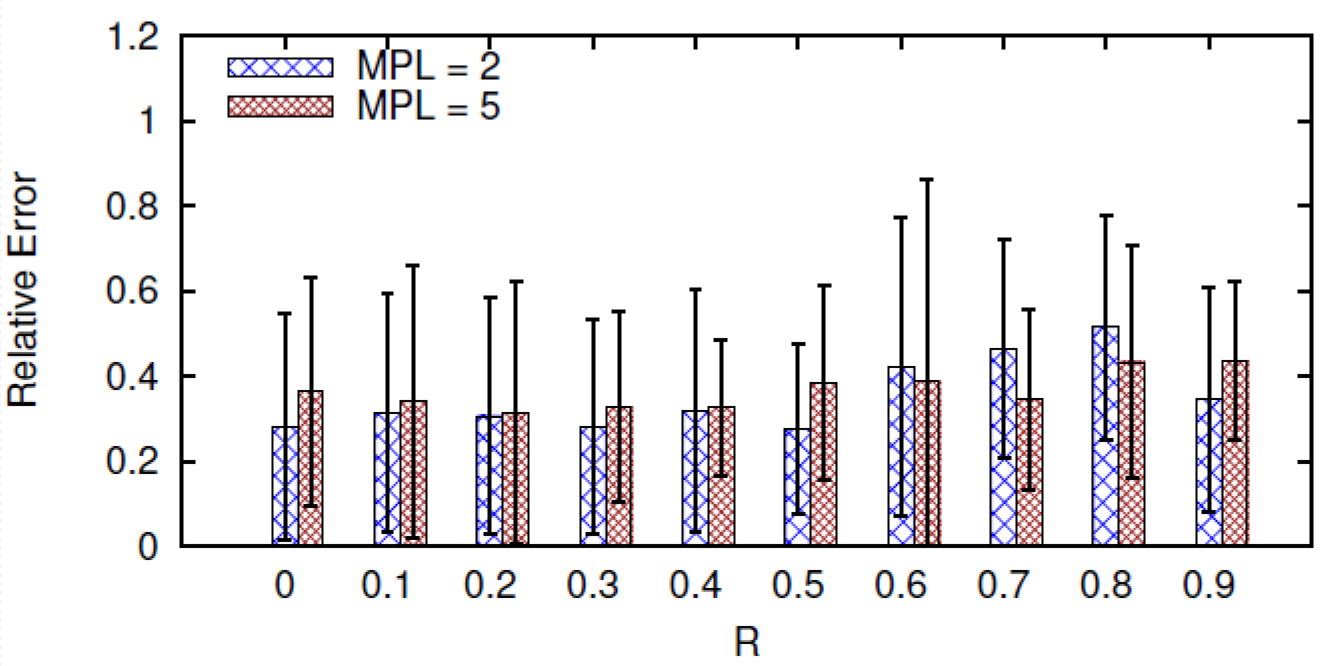
Sensitivity to Errors in Cardinality Estimates

- On TPC-H1, with *biased* errors



Sensitivity to Errors in Cardinality Estimates (Cont.)

- On TPC-H1, with *unbiased* errors



Additional Overhead (Analytic-Model Based Approach)