Cost-Model Oblivious Database Tuning with Reinforcement Learning

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Is Query Optimization a Solved Problem?

- Current query optimizers depend on pre-determined cost models

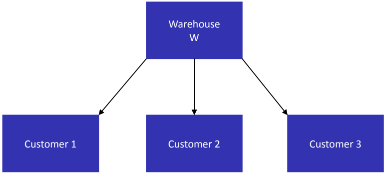
- But cost models can be highly erroneous

> the cardinality model. In my experience, the cost model may introduce errors of at most 30% for a given cardinality, but the cardinality model can quite easily introduce errors of ***many orders of magnitude***! I'll give a real-world example in a moment. With such errors, the wonder isn't "Why did the optimizer pick a bad plan?" Rather, the wonder is "Why would the optimizer ever pick a decent plan?"

Proposed Solution

- We propose and validate **a tuning strategy** to do without such a pre-defined model
- The process of database tuning is modelled as a **Markov decision process (MDP)**
- A reinforcement learning based algorithm is developed to **learn the cost function**
- COREIL replaces the need of **pre-defined knowledge** of cost in index tuning

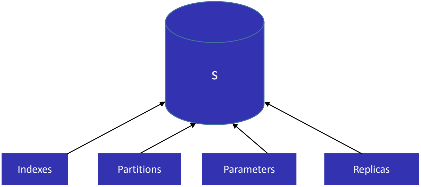
Problem



Queries
1) New order
2) Delivery
3) Stock

Tables
1) History
2) Stock
3) New orders
4) Stocks

Database Schema: **R**

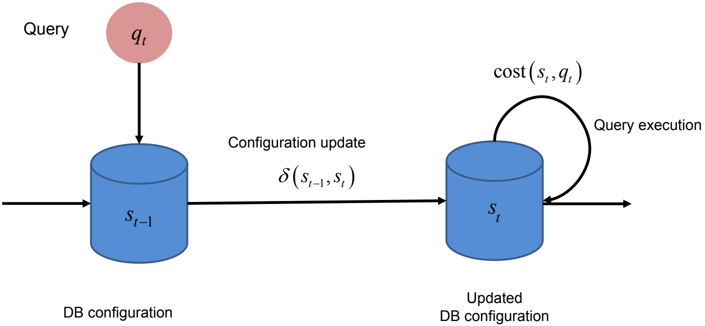


Set of all Database Configurations: **S = {s}**

...	.....
t = 201	Customer 1, New order
t = 202	Stock
t = 203	Customer 2, Delivery
...	.....

Schedule of queries and updates: **Q**

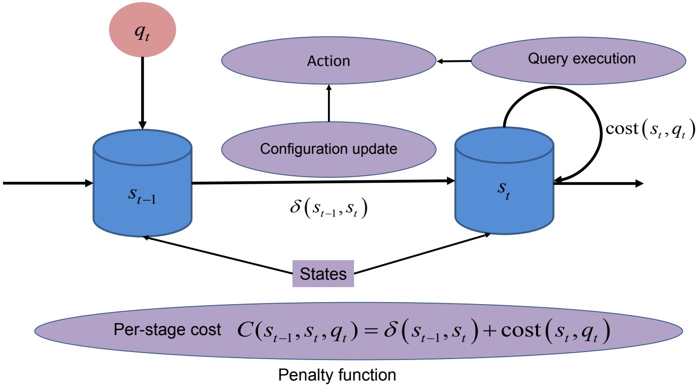
Transition



Per-stage cost

$$C(s_{t-1}, s_t, q_t) = \delta(s_{t-1}, s_t) + \mathrm{cost}(s_t, q_t)$$

Mapping to MDP



Policy: Sequence of configuration changes that minimizes the cumulative penalty

MDP Formulation

- **State**: Database configurations $s \in S$
- **Action**: Configuration changes $s_{t-1} \rightarrow S_t$ along with query q_t execution
- **Penalty function**: Per-stage cost of the action $C(s_{t-1}, s_t, \hat{q}_t)$
- **Transition function**: Transition from one state to another on an action are deterministic
- **Policy**: A sequence of configuration changes depending on the incoming queries

Problem Statement

- For a policy π and discount factor $0 < \gamma < 1$ the cumulative penalty function or the **cost-to-go function** can be defined as,

$$V^{\pi}(s) \triangleq \mathbb{E}\left[\sum_{t=1}^{\infty} \gamma^{t-1} C(s_{t-1}, s_t, \hat{q}_t)\right] \text{ satisfying } \begin{cases} s_0 = s \\ s_t = \pi(s_{t-1}, \hat{q}_t), \\ t \geq 1 \end{cases}$$

- **Goal**: Find out an optimal policy π^* that minimizes the cumulative penalty or the cost-to-go function

Policy Iteration

A **dynamic programming** approach to solve MDP

- Begin with an initial policy π_0 and initial configuration s_0
- Find an estimate $\overline{V}^{\pi_0}(s_0)$ of the cost-to-go function
- Incrementally improve the policy using the **Bellman equation** based on current estimate of the cost-to-go function

$$\overline{V}^{\pi_t}(s) = \min_{s' \in S} \left(\delta(s, s') + \mathbb{E}\left[cost(s', q) \right] + \gamma \overline{V}^{\pi_{t-1}}(s') \right)$$

- Carry on the improvement till there is no (or ϵ) change in policy

Problems with Policy Iteration

- **Problem 1**: The **curse of dimensionality** makes direct computation of $\overline{V}$ hard
- **Problem 2**: There may be **no proper model** available beforehand for the **cost function** $cost(s, q)$
- **Problem 3**: The **probability distribution of queries** being **unknown**, it impossible to compute the expected cost of query execution

Solutions: Adaptive Tuning Algorithm

- A **reduced subspace** is searched for a query $\hat{q}$ at state s that includes states s', such that $cost(s, \hat{q}) > cost(s', \hat{q})$
- The cost model can be **approximated using linear projection** given by

$$\delta(s, s') = cost(s, q(s, s')) \approx \boldsymbol{\zeta}^T \boldsymbol{\eta}(s, q(s, s'))$$

  where, **changing the configuration** from s to s' is considered as **executing a special query** $q(s, s')$
- Similar linear projection $\phi(s)$ can be used to approximate the cost-to-go function $\overline{V}^{\pi_t}(s)$
- These approximations are then **improved recursively** by minimizing the least square error

What is COREIL?

COREIL is an **index tuner**, that

- instantiates our reinforcement learning framework
- tunes the configurations differing in their **secondary indexes**
- handles the configuration changes corresponding to the creation and deletion of indexes
- inherently **learns the cost** model and solve a MDP for optimal index tuning

COREIL: Realization of Adaptive Tuning

- For a given query $\hat{q}$, it searches in a reduced space that **includes** the set of **recommended indexes** for that query but **excludes** the set of **indexes being modified**

- To approximate $V^{\pi_t}(s)$, we define the feature mapping $\boldsymbol{\phi}(s)$ that indicates whether an index is modified by a configuration or not

- To approximate δ and $cost$, we define the feature mapping

$$\boldsymbol{\eta} = (\boldsymbol{\beta}^T, \boldsymbol{\alpha}^T)^T$$

- $\boldsymbol{\beta}(s, \hat{q})$ captures the **difference between the** recommended **index set** and that of the current configuration
- $\boldsymbol{\alpha}(s, \hat{q})$ indicates whether a **query modifies any index** in the current configuration

Dataset and Workload

- The dataset and workload conform to the TPC-C specification
- They are generated by the OLTP-Bench tool
- Response time of processing corresponding SQL statement is measured using IBM DB2
- The scale factor (SF) used here is 2
- We are comparing with WFIT algorithm that depends on what-if optimizer for the cost model

Efficiency

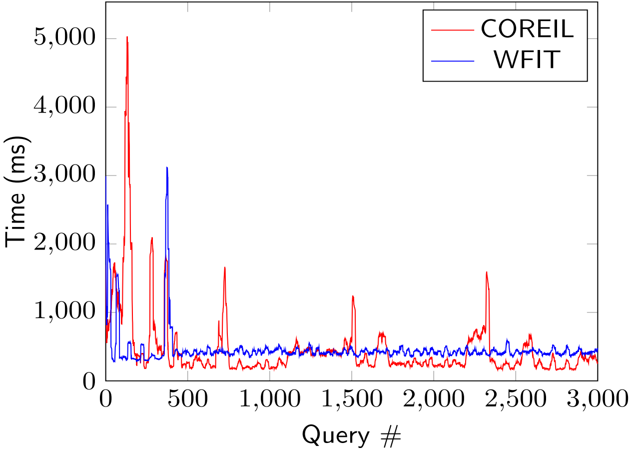


Figure : Efficiency = total time per query

Overhead Cost Analysis

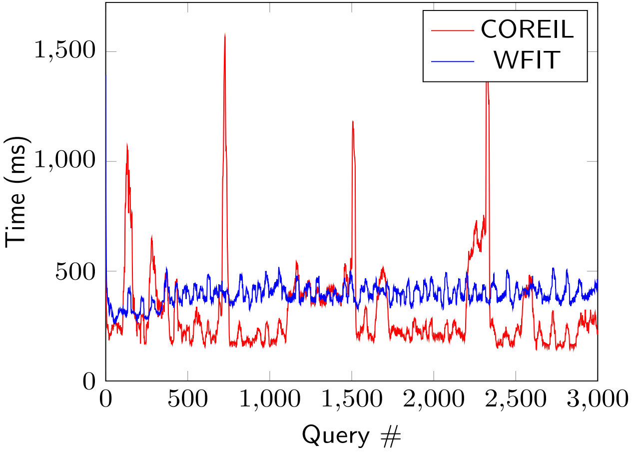


Figure : Overhead = Time of the optimization itself

Effectiveness

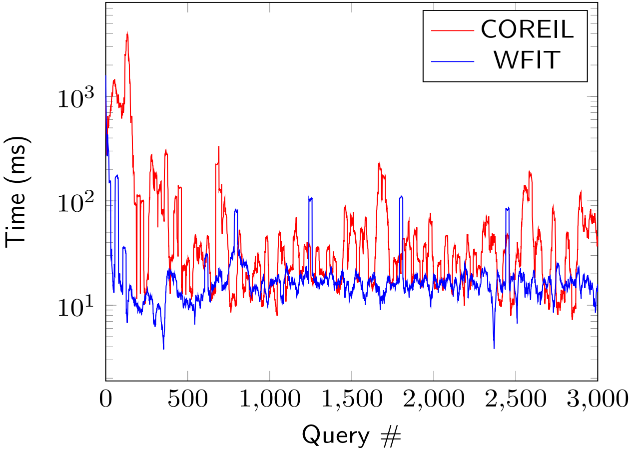


Figure : Effectiveness = Query execution time in the DBMS alone

Conclusion

- Database tuning can be modelled as a Markov decision process
- Our reinforcement learning algorithm solves the problem of cost-model oblivious database tuning
- COREIL instantiates the approach for index tuning problem
- It shows competitive performance with respect to the state-of-the-art WFIT algorithm

Future Work

- Validate the proposed algorithm on different datasets like TPC-H and benchmark for online index tuning
- Check sensitivity of COREIL on set-up and parameters
- Extend our approach to other aspects of database configuration, including partitioning and replication

Thank you