Lecture #17

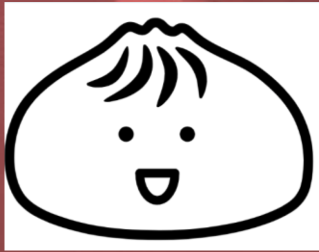
Carnegie Mellon University

Special Topics:

Self-Driving Database Management Systems

Bao: Making Learned Query Optimization Practical

Best Paper of SIGMOD’21



@Lichen Jin // 15-799 // Spring 2022

LAST CLASS

Automatic SQL Rewriting

→ Works at changing query at the SQL Language Level

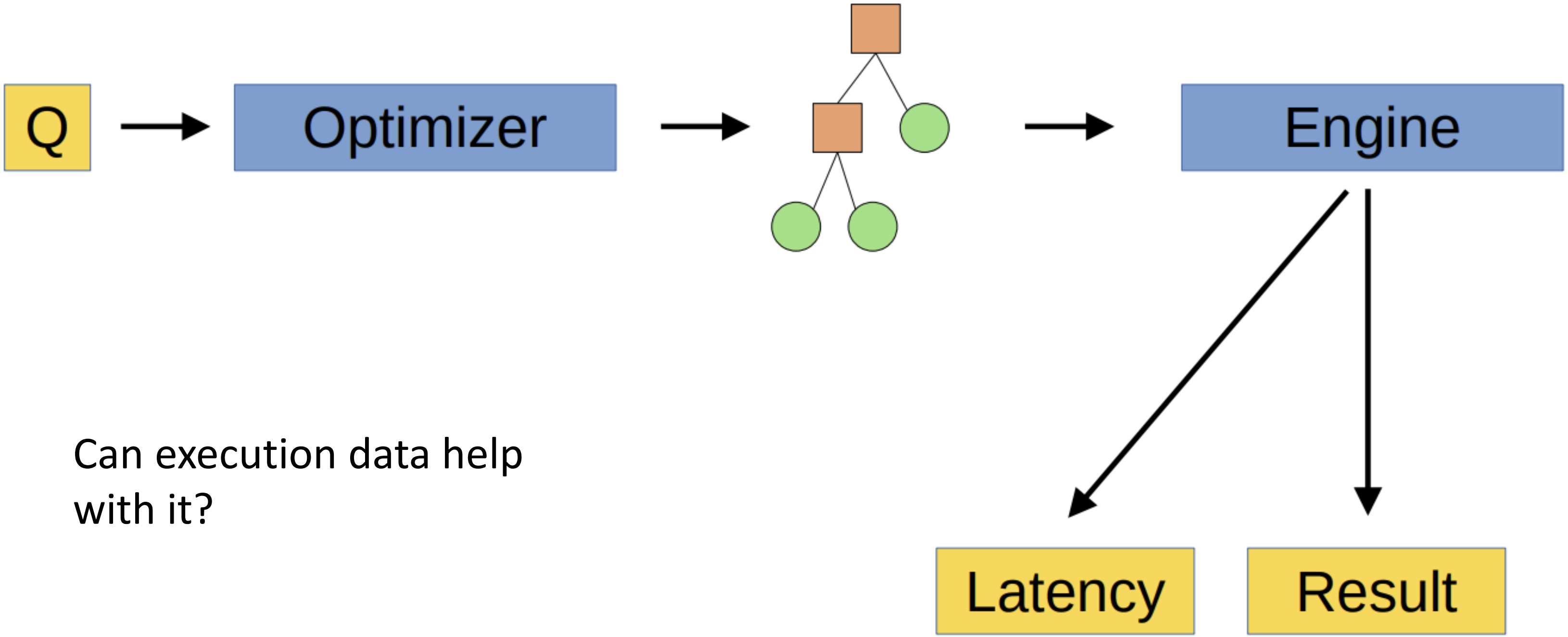
→ MCTS to efficiently enumerate and select based on rewriting rules

→ Deep Learning model to estimate tree node costs

TODAY'S AGENDA

→ Overview: Learned Query Optimization
→ Prior Work: Neo
→ Bao Introduction
→ Enumerating Query Hints
→ Contextual Multi-arm Bandit
→ Predictive Model: TCNN Cost Model
→ Integration and Improvements
→ Experiments
→ Parting Thought

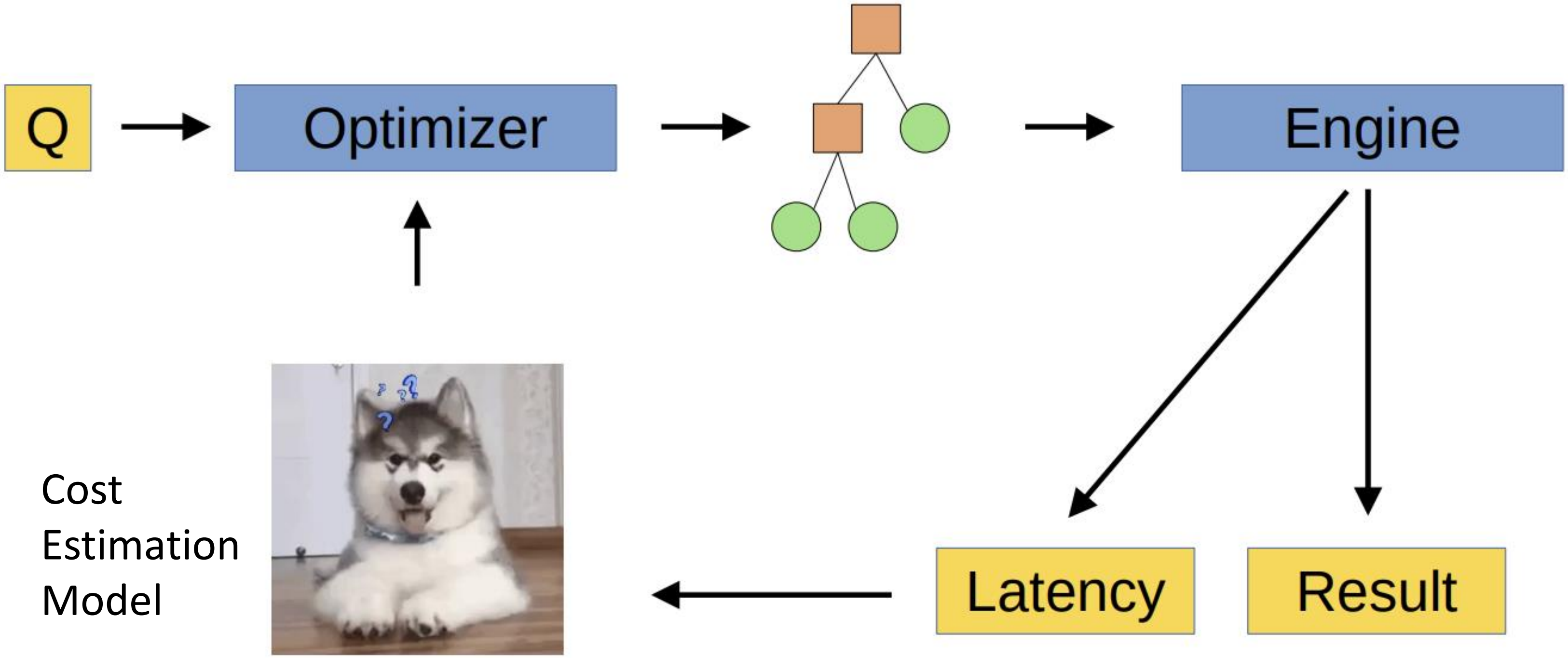
Overview: Learned Query Optimization



Can execution data help with it?

Source: Ryan Marcus

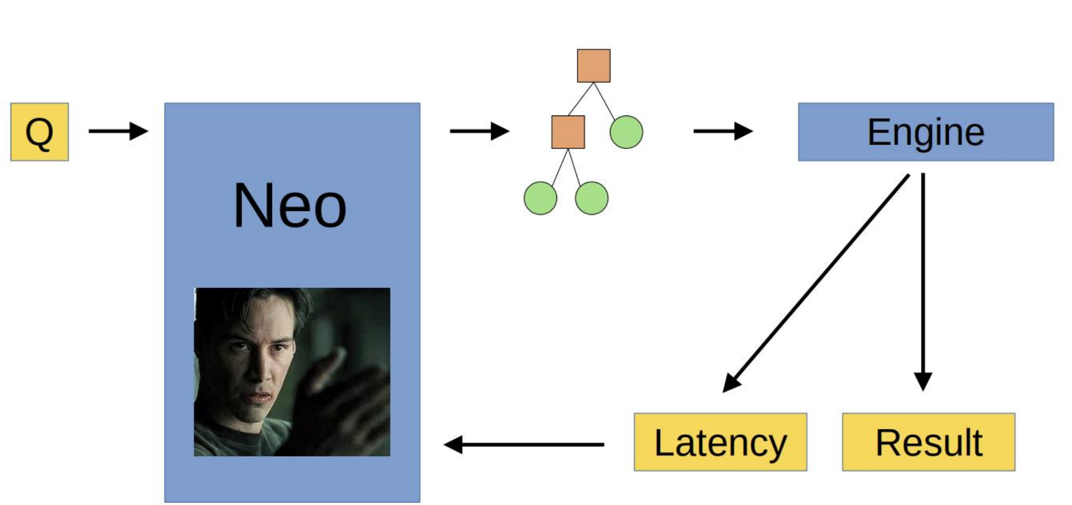
Overview: Learned Query Optimization



Source: Ryan Marcus

Prior Work: Neo

- → **Neural Optimizer**
- → Complete replacement of default query optimizer
- → List alternative plans based on expert rules
- → Deep Reinforcement Learning Guided Search



Source: Ryan Marcus

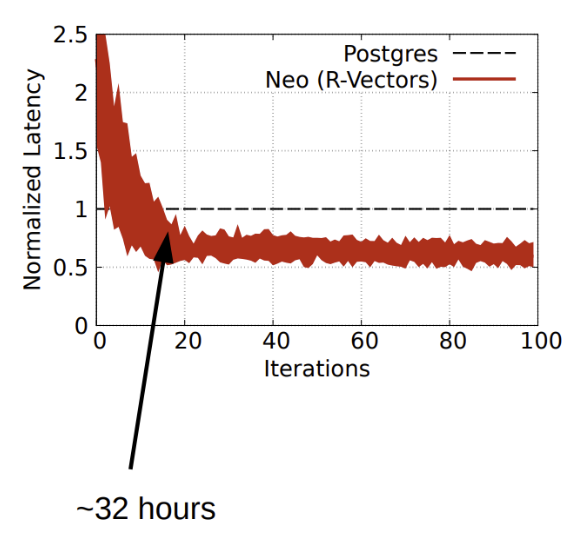
Prior Work: Neo

Promising Results But

Sample Inefficiency
→ Typically takes more than 1 day for pre-train

Brittleness to Workload and Schema Change
→ The encoding of cardinality estimate needs retrain

Tail Catastrophe
→ Deep RL making wrong estimations due to sample inefficiency



Other state-of-the-art: Similar Issues

Source: Ryan Marcus

Bao: Introduction

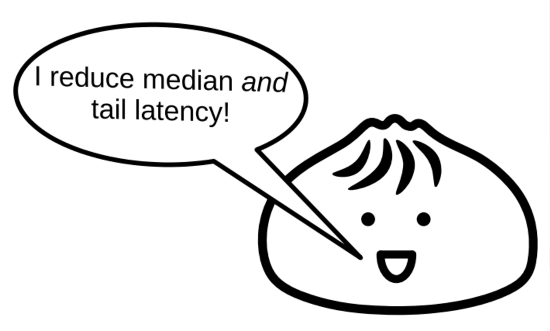
Bao: Bandit optimizer

By *steering* a traditional query optimizer, Bao:

→ Outperforms PG after *1 hour* of training

→ Reduces *99% latency*

→ *Adapts* to changes in workload, schema, and data.



Source: Ryan Marcus

Bao: Introduction

Three key points:

Offload Alternative Plan Enumeration
→ Query Hint Sets on top of the optimizer

Model Plan Selection as CMAB
→ Exploration and Exploitation
→ Reduce chances of wrong tail estimation

Deep Estimation Model
→ Tree Convolutional Neural Networks (TCNN)
→ Change-adaptive encoding approach

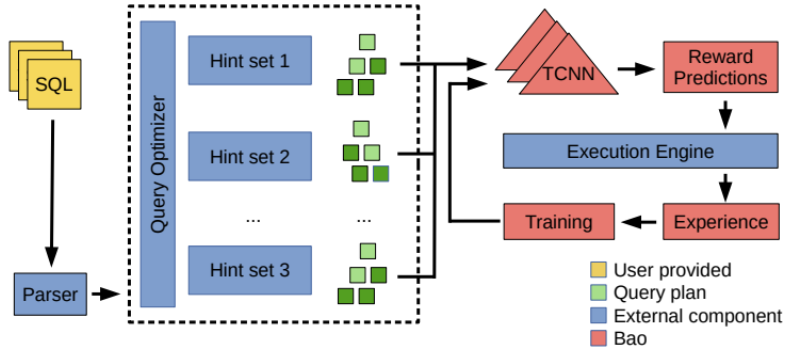


Figure 2: Bao system model

Query Hints

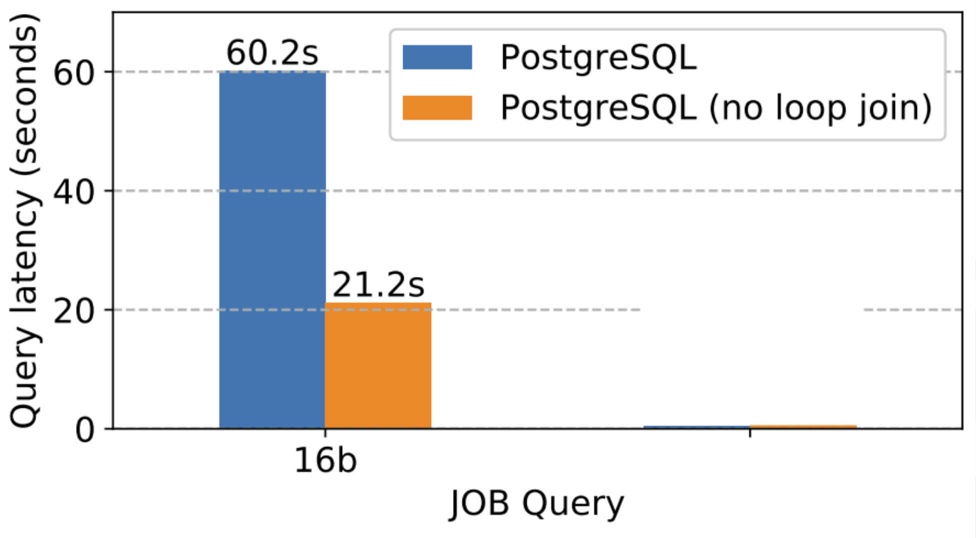
Slow query.

Run EXPLAIN.

- Loop join plan,
- Low selectivity

Try disabling loop join

- Huge improvement



Source: Ryan Marcus

Query Hints

Slow query.

Run EXPLAIN.

- ➢ Loop join plan,
- ➢ Low selectivity

Try disabling loop join

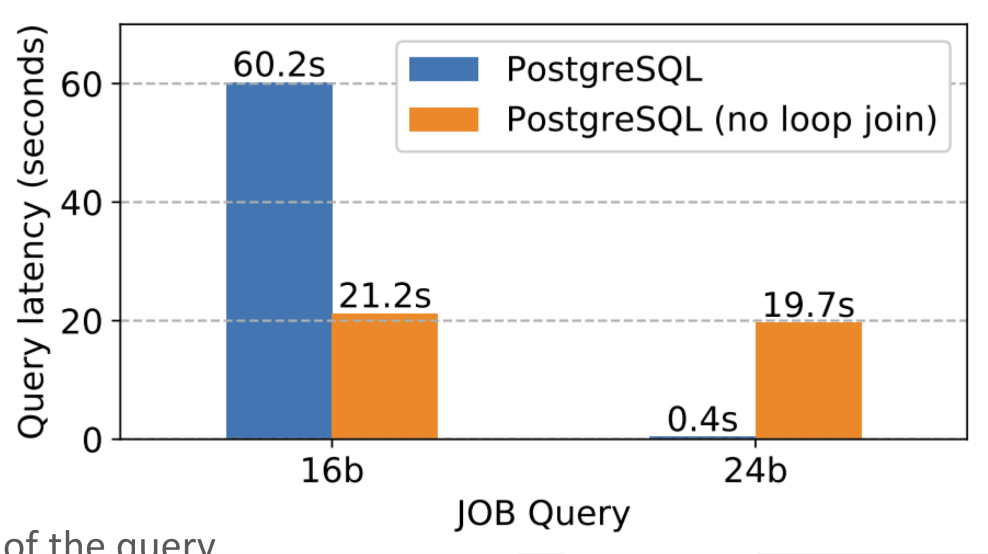
- ➢ Huge improvement

Apply this hint globally

- ➢ … other regressions,

Undo that, need local hints. Now What?

- ➢ Opt 1: Apply the hint to every instance of the query
- ➢ Opt 2: Set as default, find regressions, add hints to those queries
- ➢ Opt 3: Give up



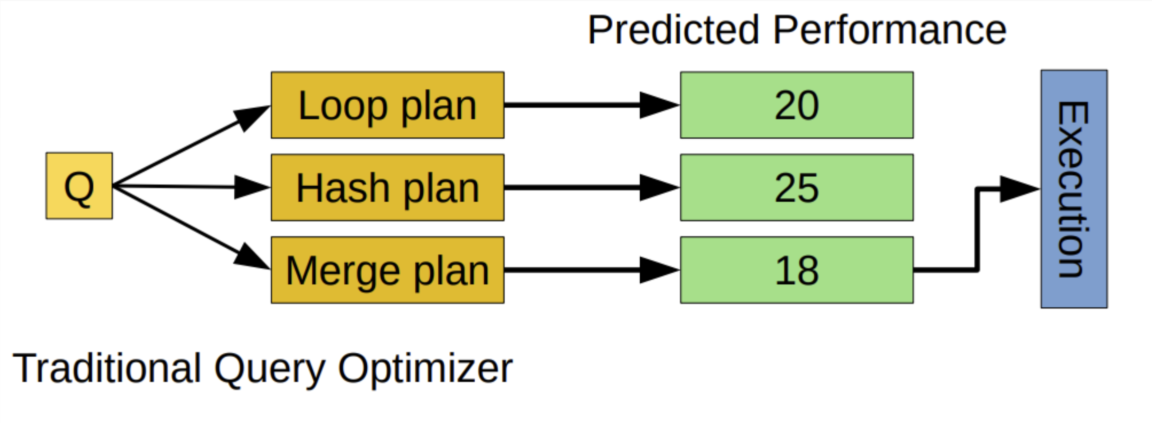
Source: Ryan Marcus

Enumerating Query Hints

Query Hint Set: A combination of configuration knobs.
→ Example: enable nested loop join

Query plans are enumerated using different query hint sets.

Bao tries to automatically determine the optimal hint to use.



Source: Ryan Marcus

Contextual Multi-arm Bandit

Suppose you are in a casino

But don't know which bandit wins money

Time = 1

$+

$-

$++

$--

Contextual Multi-arm Bandit

Suppose you are in a casino

But don’t know which bandit wins money

Time = 2

$-

$++

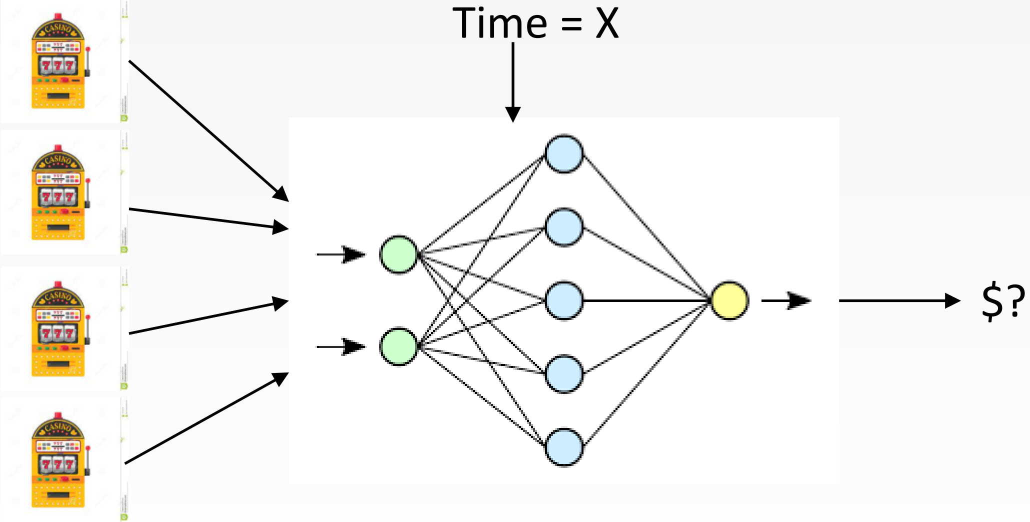
$--

$+

Contextual Multi-arm Bandit

Suppose you are in a casino

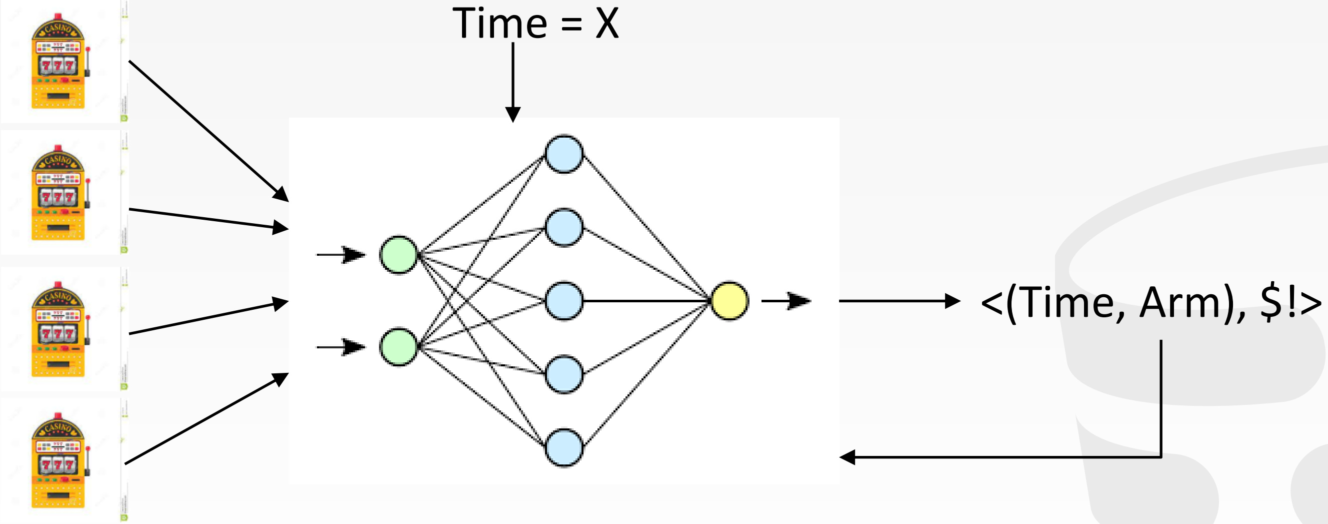
You want a mental model to estimate the best



Contextual Multi-arm Bandit

You really try the 'best' for ground truth

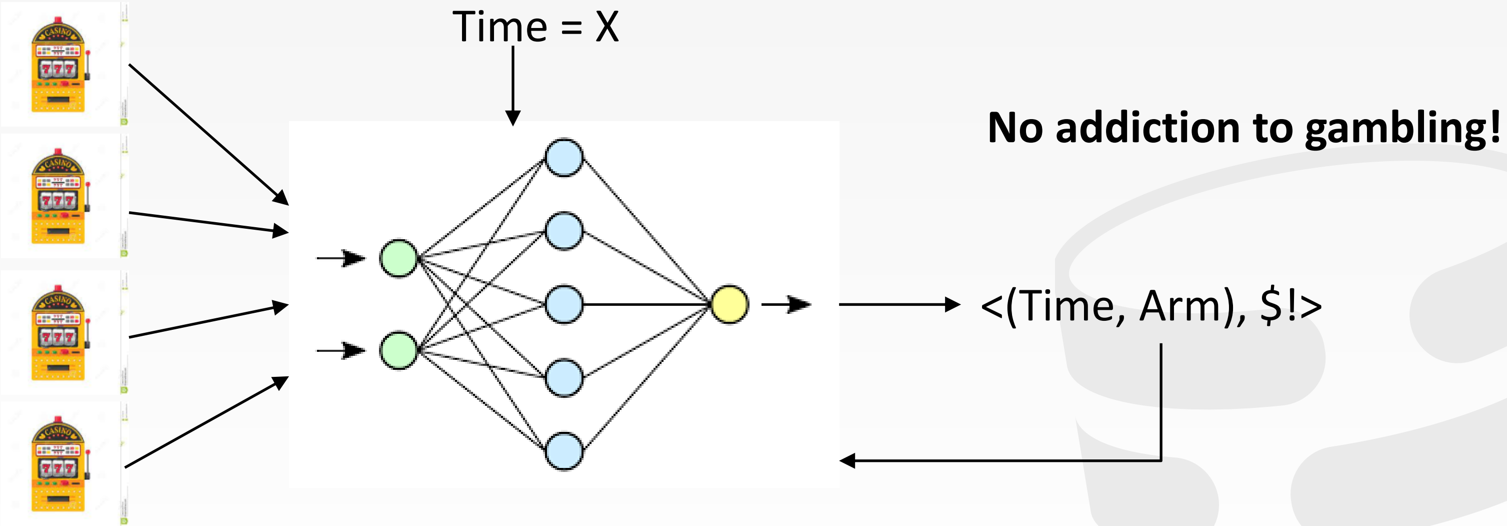
Used for updating the model



Contextual Multi-arm Bandit

Suppose you are in a casino

The model gradually estimates better on winning

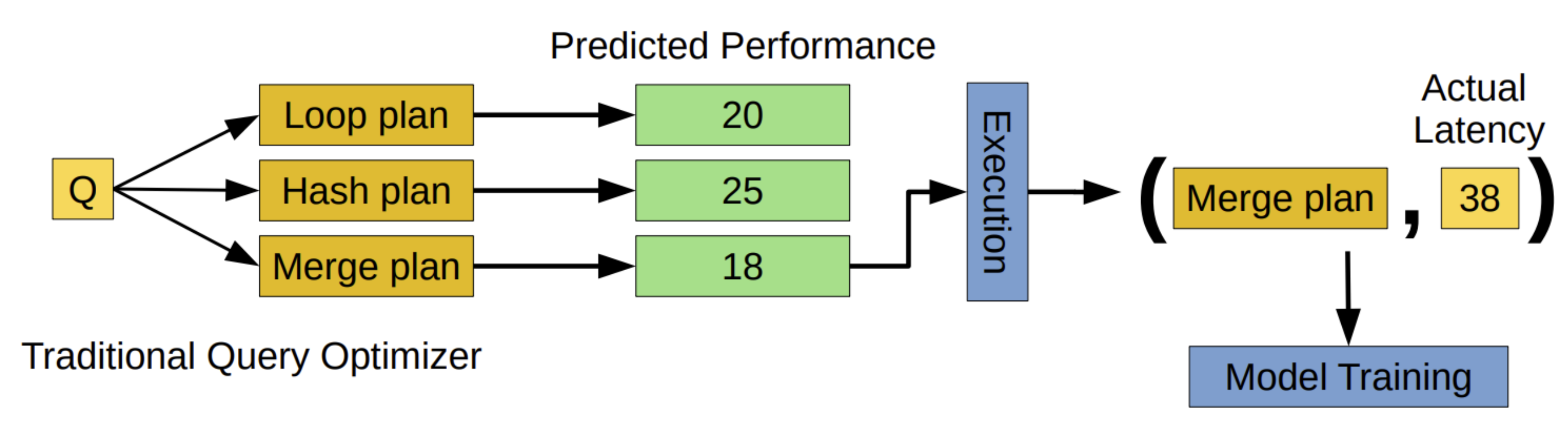


Mapping Back to Query Hints

Consider different hints as arms in a CMAB

Predictive Model (Query Latency Predict)

Experience: <Plan, Latency>



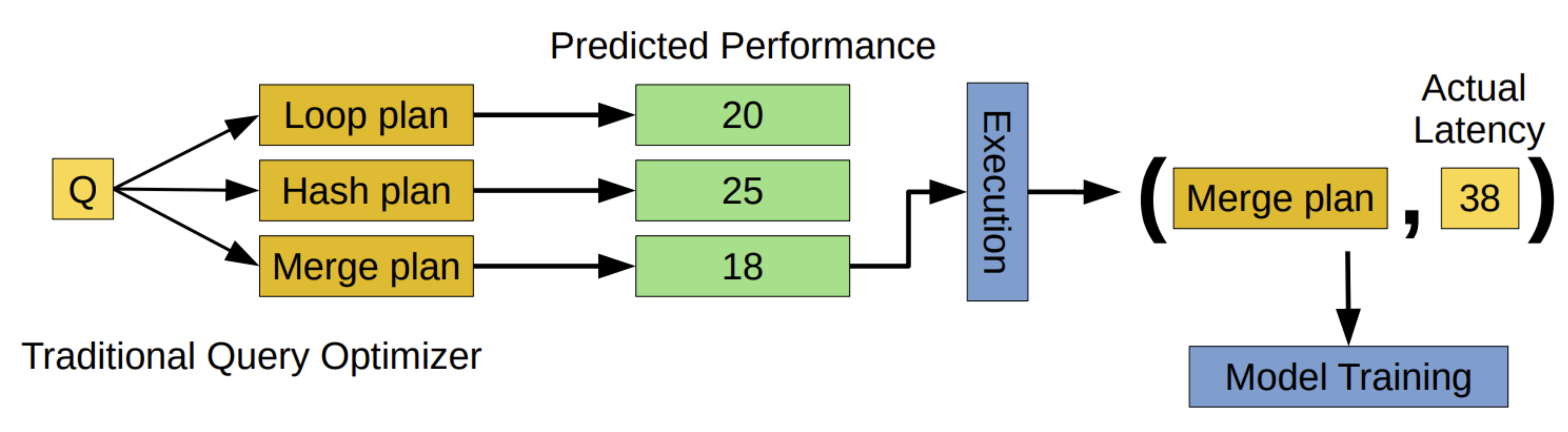
Source: Ryan Marcus

Mapping Back to Query Hints

Exploration-Exploitation Tradeoff

→ Losing Exploration: Local optimal, Wrong estimations

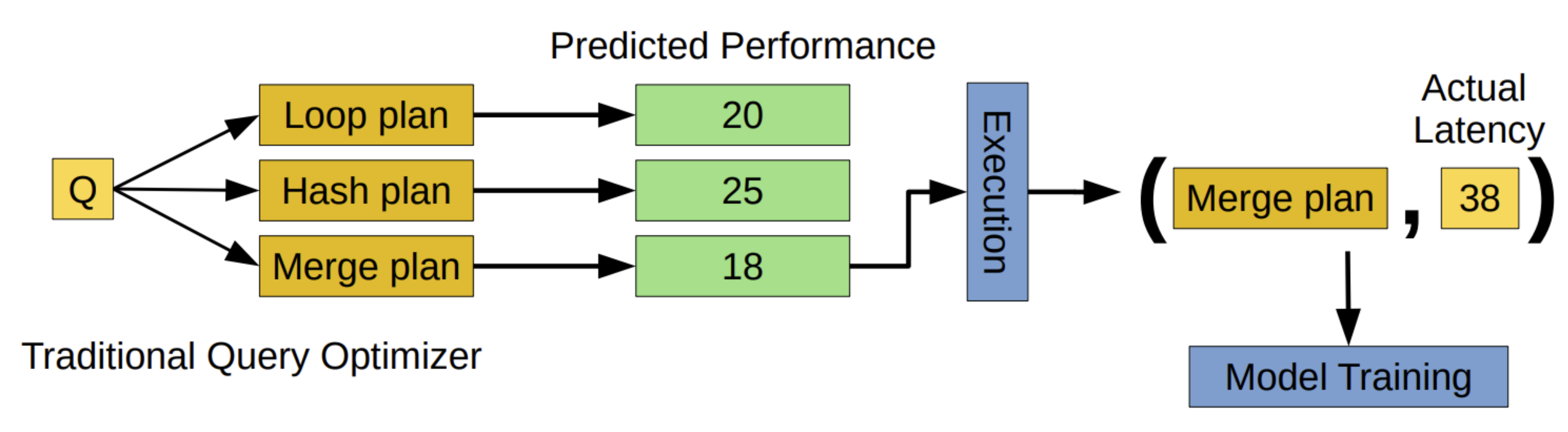
→ Losing Exploitation: Model cannot converge



Source: Ryan Marcus

Mapping Back to Query Hints

Exploration-Exploitation Tradeoff
→ Solution: Thompson Sampling



Source: Ryan Marcus

CMAB in Bao: Thompson Sampling

An old, well-studied algorithm for balancing exploration and exploitation.

Usual ML training (exploitation)	Weight = E[Weight | data]
Pick a random model (exploration)	Weight = sample P(Weight)
Sample model weights (Thompson Sampling)	Weight = sample P(Weight | data)

Source: Ryan Marcus

CMAB in Bao: Thompson Sampling

An old, well-studied algorithm for balancing exploration and exploitation.

Usual ML training (exploitation)	Weight = E[Weight | data]
Pick a random model (exploration)	Weight = sample P(Weight)
Sample model weights (Thompson Sampling)	Weight = sample P(Weight | data)

Bao Implementation: Retrain on a random sampled data set sized |E|, randomly drawn from E with replacement

Other complex approaches: Bayesian Networks

Source: Ryan Marcus

Predictive Model: TCNN Cost Model

Tree Convolutional Network: Efficient catching correlation as high-level patterns between operators in the tree structure.

→ Long chain of merge joins without sort.

→ Bushy tree of hash operators.

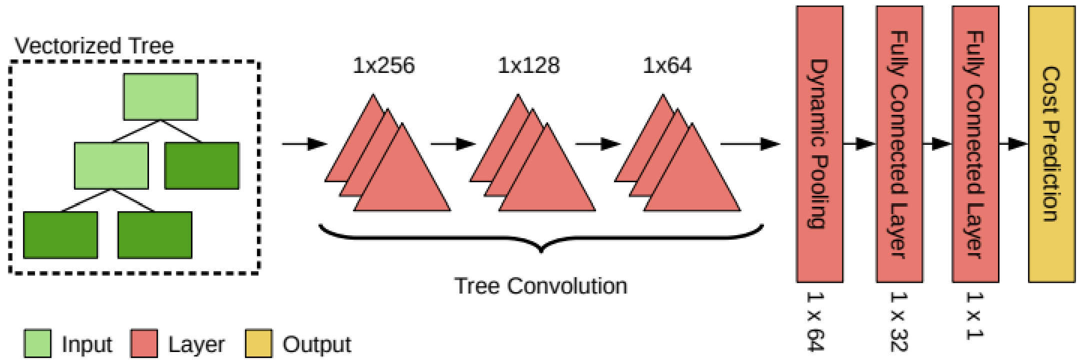


Figure 5: Bao prediction model architecture

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Predictive Model: Plan Encoding

Binarize: All internal nodes have two children; *supply with null node*

Multiple Children*: Convert to Binary*

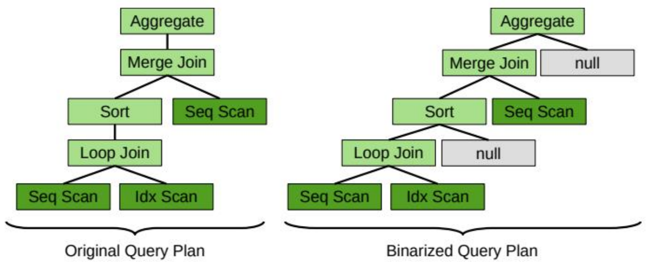

Figure 3: Binarizing a query plan tree

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Predictive Model: Plan Encoding

Binarize: All internal nodes have two children; *supply with null node*

Multiple Children*: Convert to Binary*

Vectorize: One-hot encoding of operator type, card. Estimator, cost

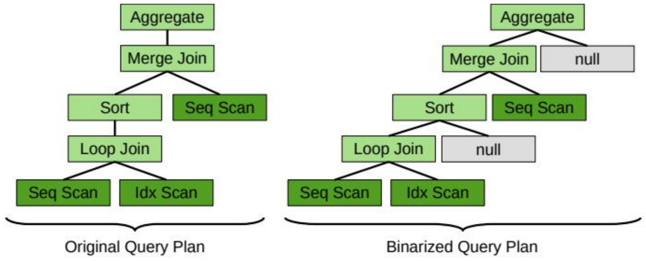

Figure 3: Binarizing a query plan tree

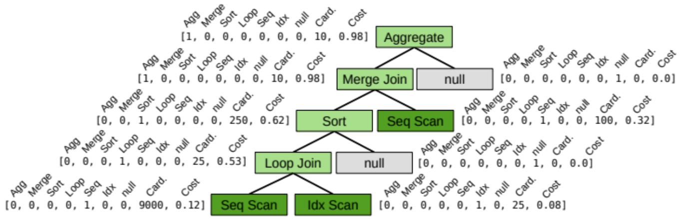

Figure 4: Vectorized query plan tree (vector tree)

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Integration and Improvements

→ Generate query plans based on hint sets
→ Select the "best" query hint set predicted by TCNN, execute the corresponding plan
→ Add ground truth to Experience data

→ Retrain with Thompson Sampling *per n executions*
→ Only keep *most recent k* as Experience data

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PostgreSQL Integration

Per-query Activation
→ SET enable_bao TO [on/off]

Active vs. advisor mode
→ Active: use bao to select query plan
→ Advisor: default; implicitly train the model

Triggered Exploration
→ Mark query as critical to avoid regression
→ Weighted retrain on critical misprediction

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PostgreSQL Integration

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Triggered Exploration
→ Mark query as critical to avoid regression
→ Weighted retrain on critical misprediction

```
switch (arm) {
case 0:
  enable_hashjoin = true;
  enable_indexscan = true;
  enable_mergejoin = true;
  enable_nestloop = true;
  enable_seqscan = true;
  enable_indexonlyscan = true;
  break;

case 1:
  enable_hashjoin = true;
  enable_indexonlyscan = true;
  enable_indexscan = true;
  enable_mergejoin = true;
  enable_seqscan = true;
  break;
case 2:
  enable_hashjoin = true;
  enable_indexonlyscan = true;
  enable_nestloop = true;
  enable_seqscan = true;
  break;
```

```
#ifndef BAO_CONFIGS_H
#define BAO_CONFIGS_H

#include "c.h"

#define BAO_MAX_ARMS 26

// Each Bao config variable is linked to a Postgre
// See the string docs provided to the PG functior
static bool enable_bao = false;
static bool enable_bao_rewards = false;
static bool enable_bao_selection = false;
static char* bao_host = NULL;
static int bao_port = 9381;
static int bao_num_arms = 5;
static bool bao_include_json_in_explain = false;
#endif
```

Source Code:
https://github.com/learnedsystems/BaoForPostgreSQL/tree/master/pg_extension

Experiment: Settings

	Size	Queries	WL	Data	Schema
IMDb	7.2 GB	5000	Dynamic	Static	Static
Stack	100 GB	5000	Dynamic	Dynamic	Static
Corp	1 TB	2000	Dynamic	Static[a]	Dynamic

[a]The schema change did not introduce new data, but did normalize a large fact table.

OLAP Workload:
→ Tail Dominate Pattern
→ Dynamic Changes
→ IMDb (Default)
Machine Types:
→ GCP N1-2; N1-4 (Default); N1-8; N1-16

Baseline Databases:
→ PostgreSQL (Default); Comsys [Oracle]
→ Bao integrated in corresponding DBMS

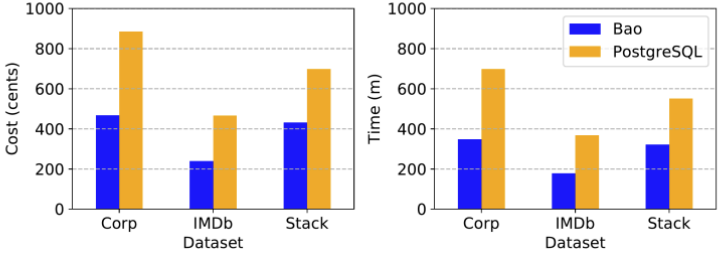
Concurrency: 1 (Default), 2, 4
Bao configuration: n=100, k=2000

Model:
3 Layer convolution, 2 Linear, Relu, Batch Norm; Adam Batch=16; epoch=100 with early stop

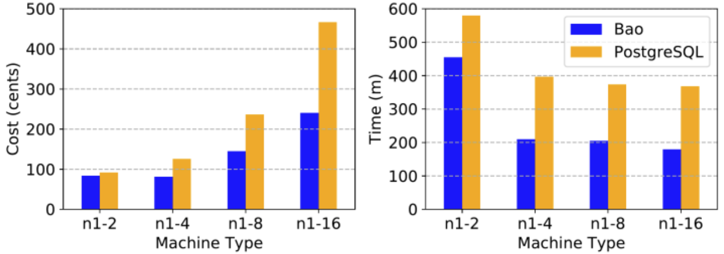
Time-split training:
Model only updated with data collected from previous time split

Experiment: Results

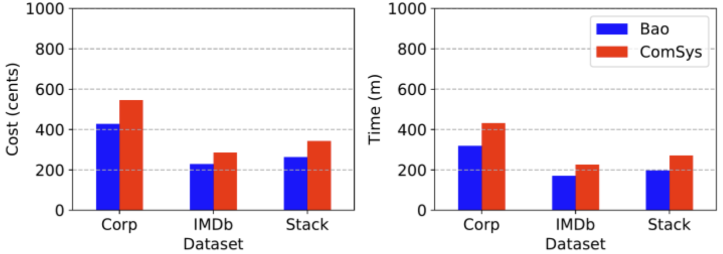
Significant Lower Cost and Runtime



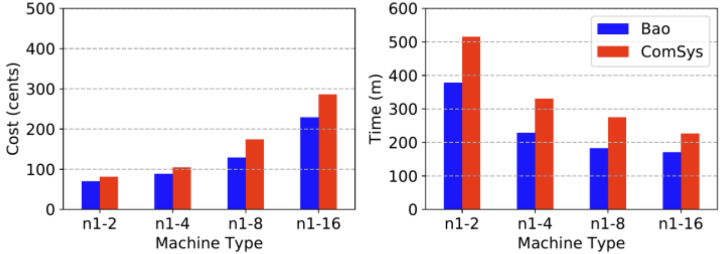
(a) Across our three evaluation datasets, Bao on the PostgreSQL engine vs. PostgreSQL optimizer on the PostgreSQL engine.



(a) Across four different VM types, Bao on the PostgreSQL engine vs. PostgreSQL optimizer on the PostgreSQL engine.



(b) Across our three evaluation datasets, Bao on the ComSys engine vs. ComSys optimizer on the ComSys engine.



(b) Across four different VM types, Bao on the ComSys engine vs. ComSys optimizer on the ComSys engine.

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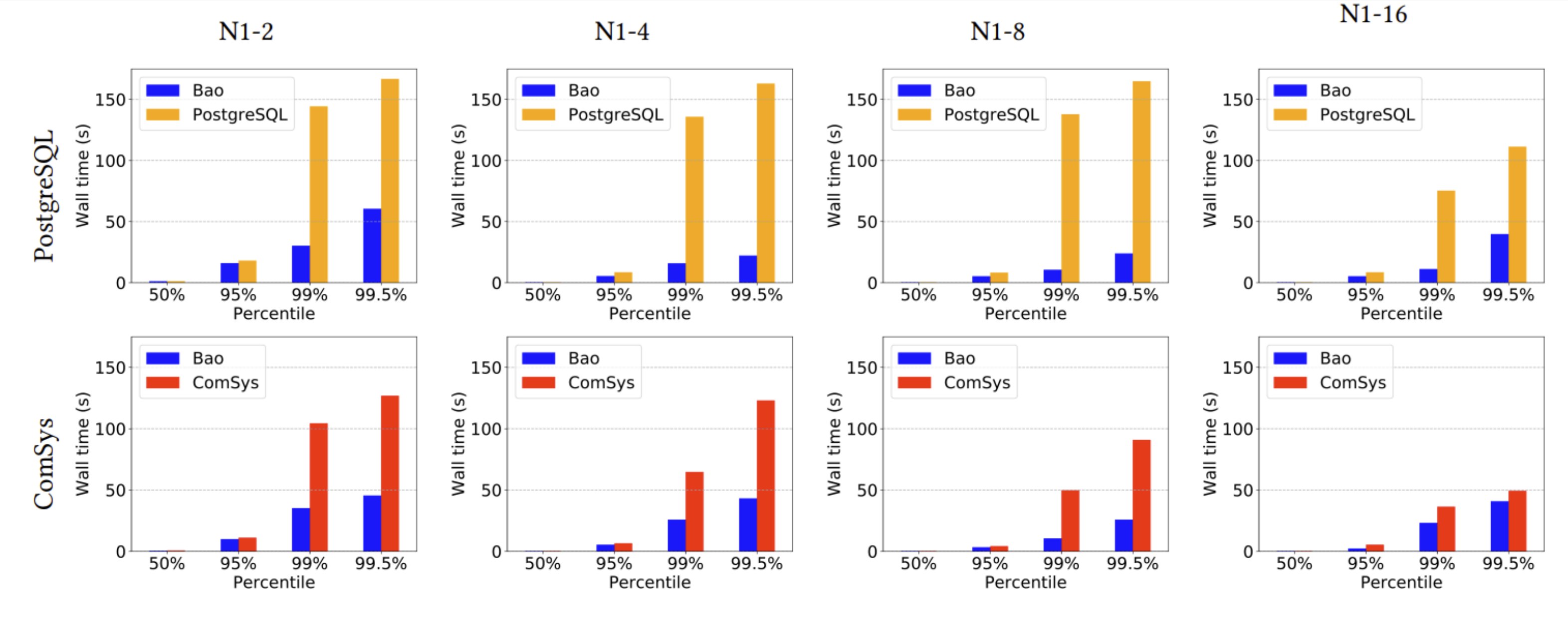
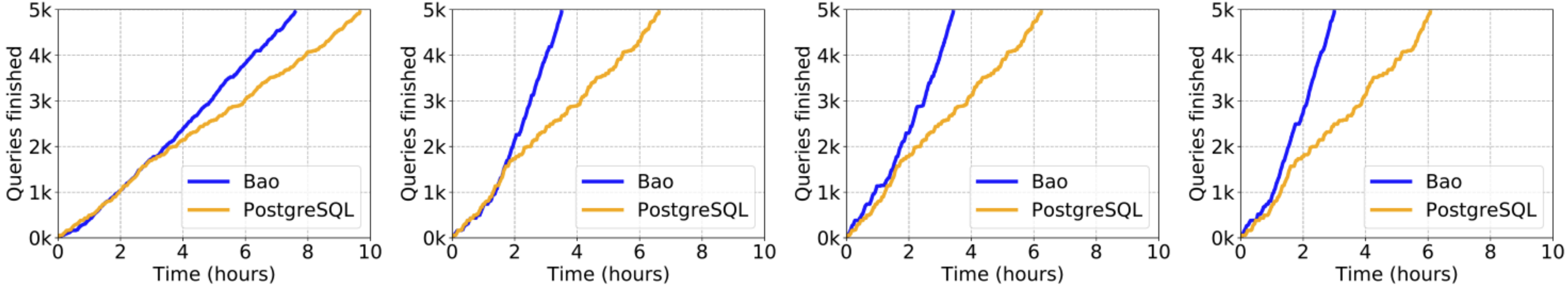
Tail Latency Analysis

IMDB: Significant Lower Tail Latency



Analysis over Runtime

IMDB-PostgreSQL: Model converges in a few hours

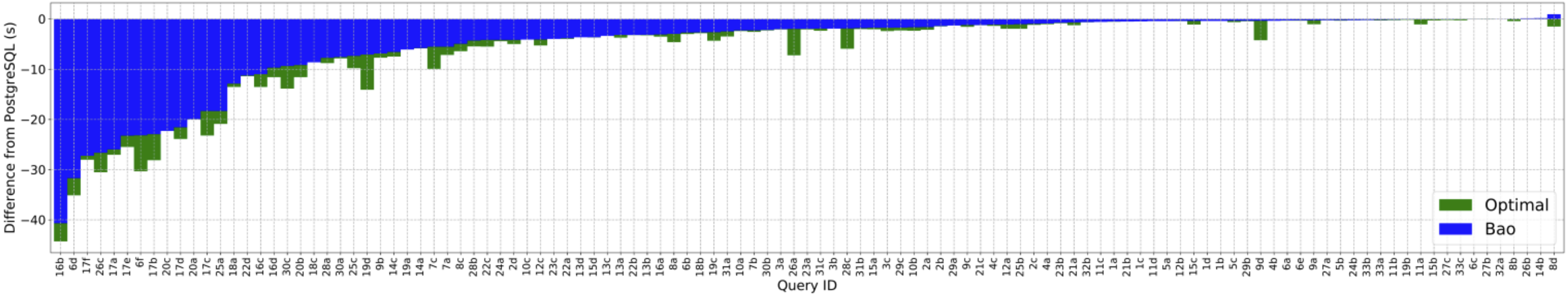


(a) VM type N1-2 (b) VM type N1-4 (c) VM type N1-8 (d) VM type N1-16

Figure 10: Number of IMDb queries processed over time for Bao and the PostgreSQL optimizer on the PostgreSQL engine. The IMDb workload contains 5000 unique queries which vary over time.

Per-query Analysis

IMDB-PostgreSQL: Only 3 of 105 has minor regression
Mostly with significant improvement



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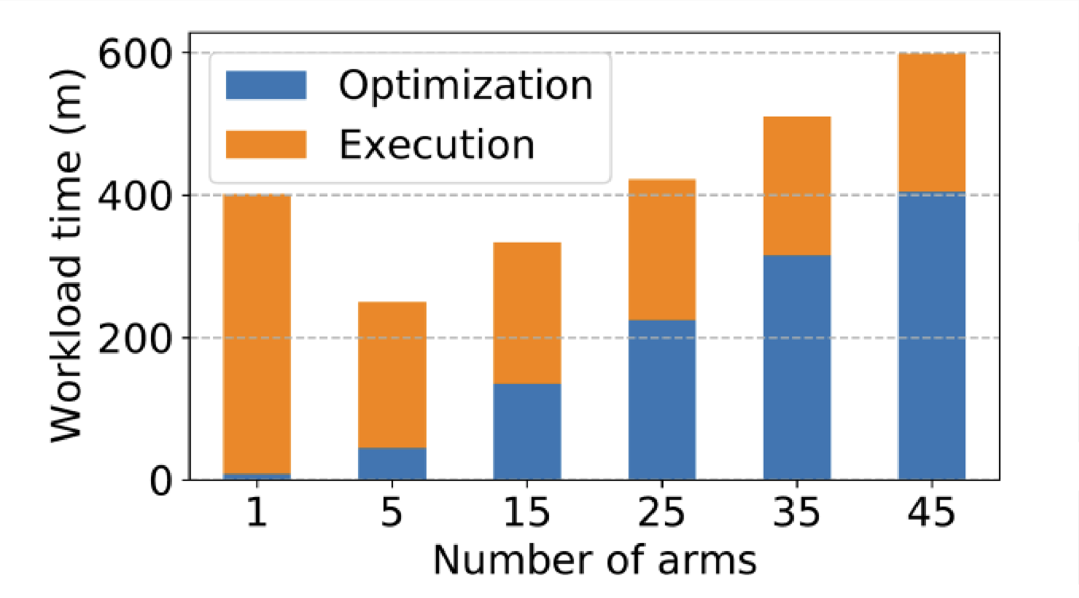
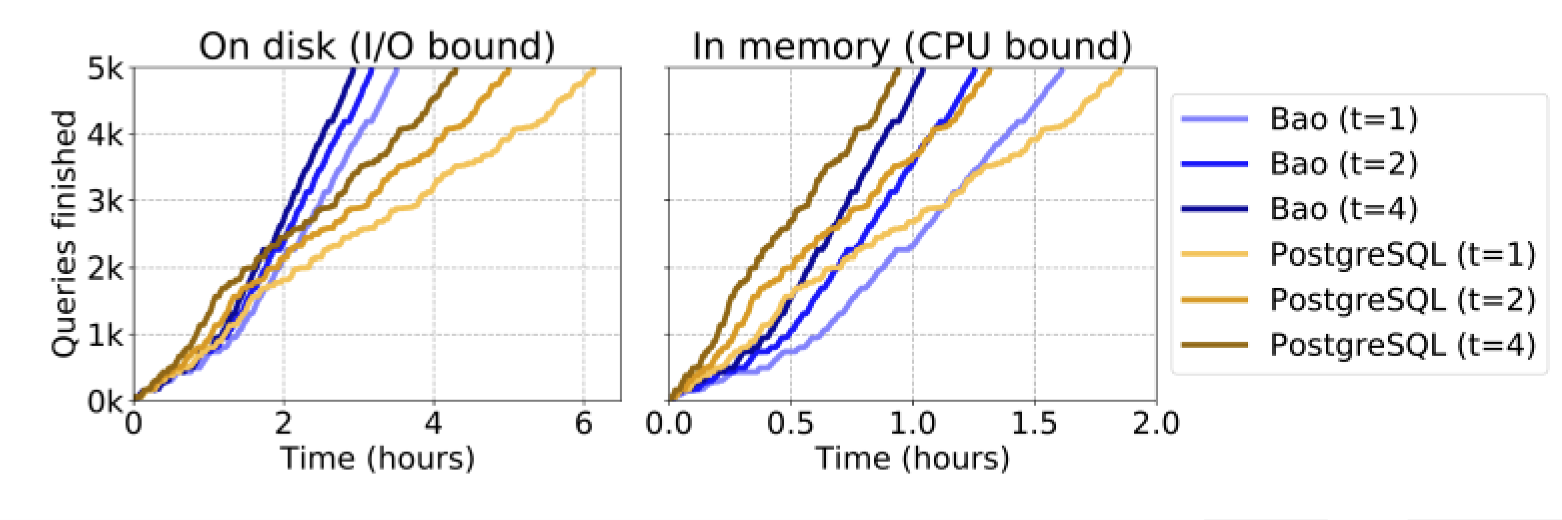
Varying # of Arms (Hint Sets)

IMDB-PostgreSQL: 48 arms ordered by observed benefits
Only a few arms is sufficient for optimization



Varying Concurrency and Memory

IMDB-PostgreSQL: Good performance when I/O bound
High CPU usage contention when CPU bound



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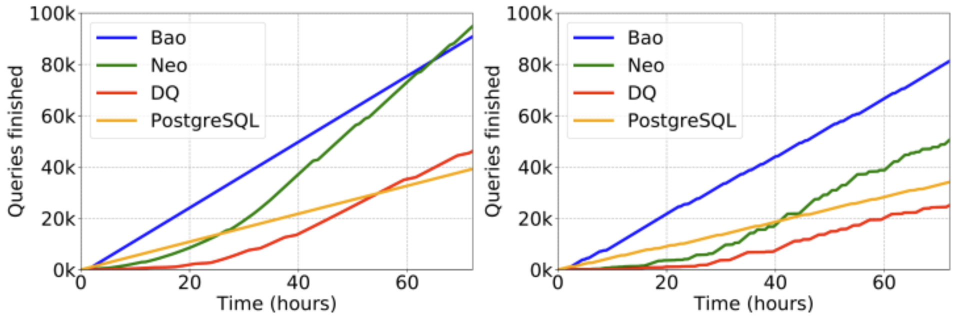
Adaptivity Analysis

Bao better adapts to changes compared to state-of-the-art

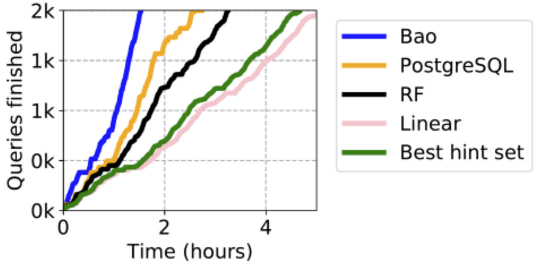


(a) Stable query workload (b) Dynamic query workloads

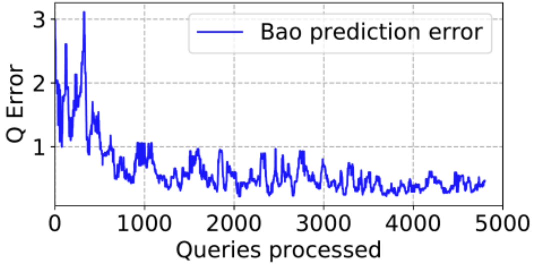
Figure 14: Comparison of number of queries finished over time for Bao, Neo [51], DQ [40], and PostgreSQL for a stable query workload (left) and a dynamic query workload (right).

Modeling Evaluation

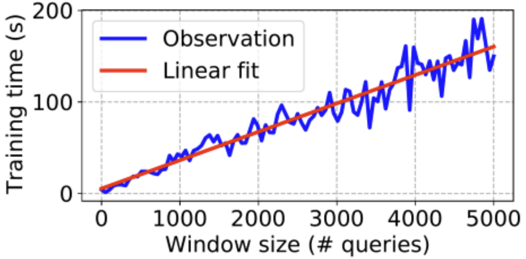
→ TCNN is necessary for Query Latency Predict
→ Bao avoids regression when model not converged
→ GPU time linear to the experience window size



(a) Random forest (RF) and linear models (Linear) used as Bao's model. "Best hint set" is the single best hint set. IMDb, N1-16 VM, on PostgreSQL.



(b) Median Q-Error (0 is a perfect prediction) of Bao's predictive model vs. the number of queries processed. IMDb workload on N1-16 VM using PostgreSQL engine.



(c) Simulated and observed time to train Bao's performance prediction model (GPU) based on the sliding window size (number of queries used during each training iteration).

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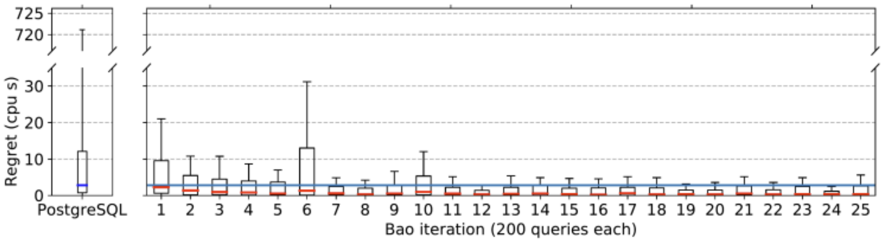
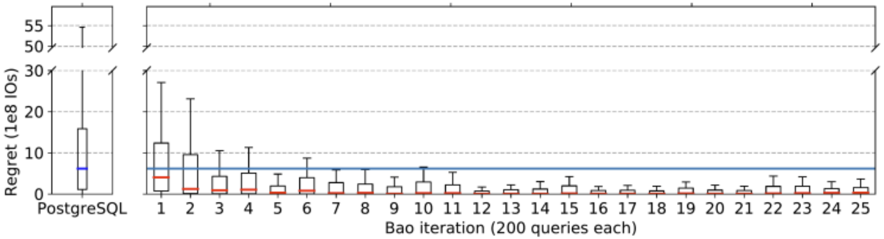
Model Regret (Loss) Analysis

$$R_q = \left(P(B(q)(q)) - \min_i P(HSet_i(q)) \right)^2$$



(a) CPU time regret



(b) Physical I/O regret

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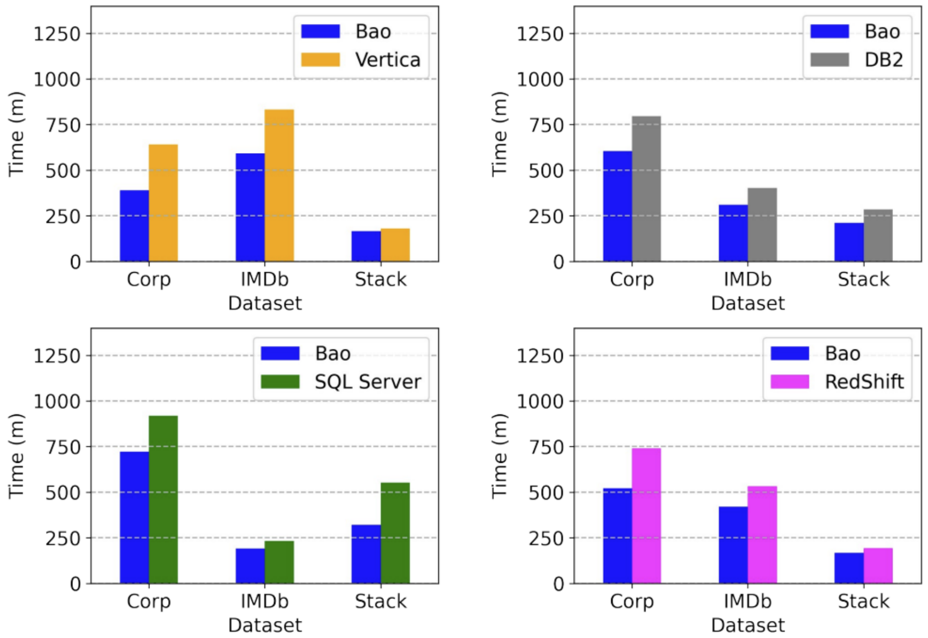
Bao on Distributed Databases

After SIGMOD submission: **Applying Bao to distributed systems**

Bao works on commercial and distributed systems as well



(3 node clusters, each ran on their preferred cloud provider with the cheapest nodes available)

Source: Ryan Marcus

PARTING THOUGHTS

→ Support searching on larger enumeration space (different query hints at different points) with approaches like MCTS

→ Inject learnt query optimizer changes to lower level like JIT bytecode with minimum recompiling

→ Why Bao eliminates tail latency better? Just the model is better sampled and hence more accurate?

→ Not suitable for OLTP optimizing? (Simple queries, no tail patterns)

PERMUTABLE COMPILED QUERIES: DYNAMICALLY ADAPTING COMPILED QUERIES WITHOUT RECOMPILING
VLDB 2020

NEXT CLASS

→ ~~Query Optimization II~~

→ P2 Discussion