A Sampling-based Learning Framework for Big Databases

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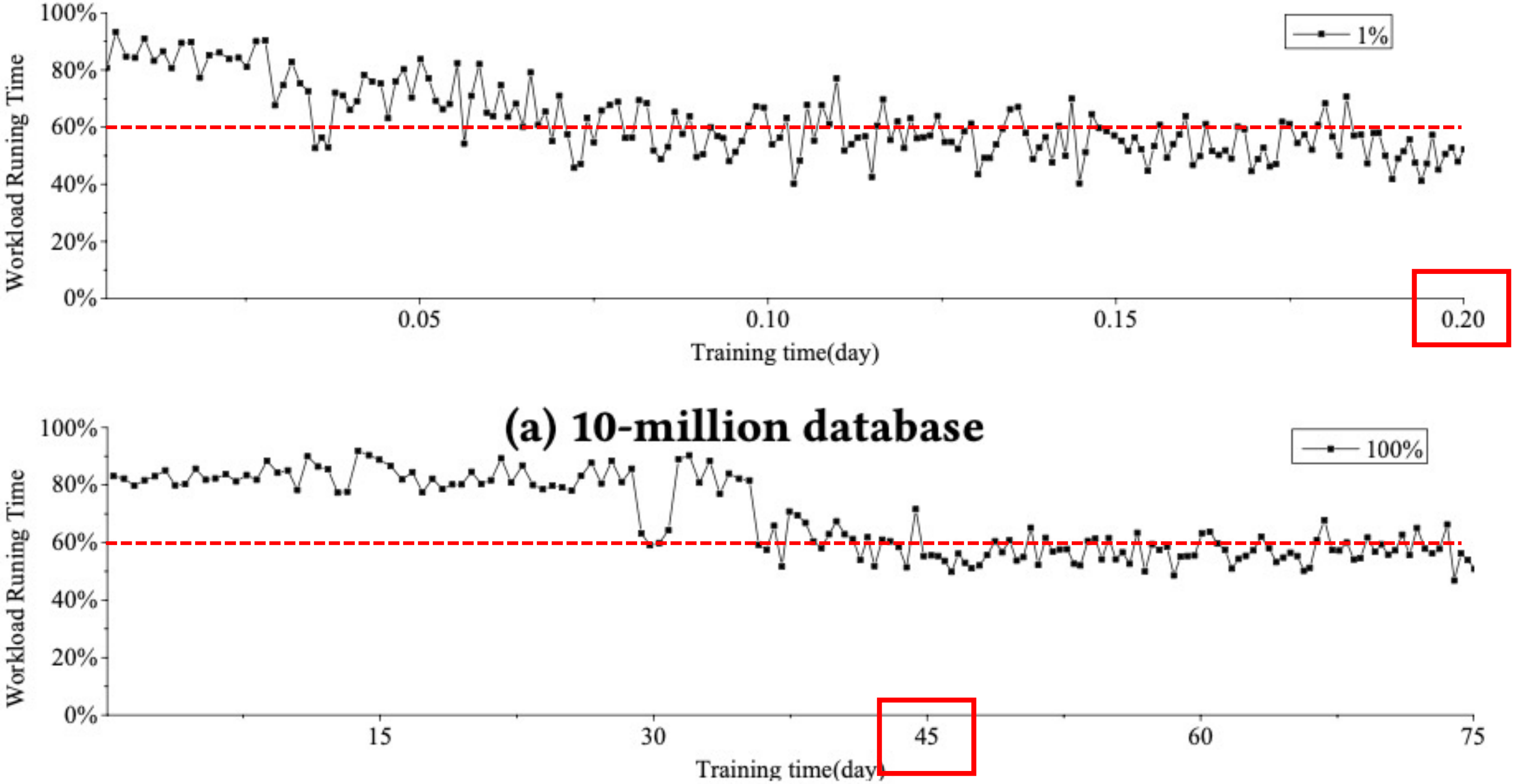
Background

Autonomous Database

- To get rid of the work from DBAs.
- Tune the database performance fully automatically.
- RL (Reinforcement learning) is a promising direction to go.
- Core challenge: the sample complexity （AlphaGo)

Reinforcement Learning & Large-scale Databases

- Too expensive → How to reduce the overhead?



(a) 10-million database

(b) 1-billion database

Questions at core of this paper

- What is the difference between the neural model trained in the sampled database and original database?
- How can we guarantee that the model trained in the sampled database is well-adopted to the original database?
- If model transfer incurs a high precision loss, how can we address the problem?

Motivation

Sampling

- How to reduce the overhead?

→ What if train the policy network on **a sampled database**

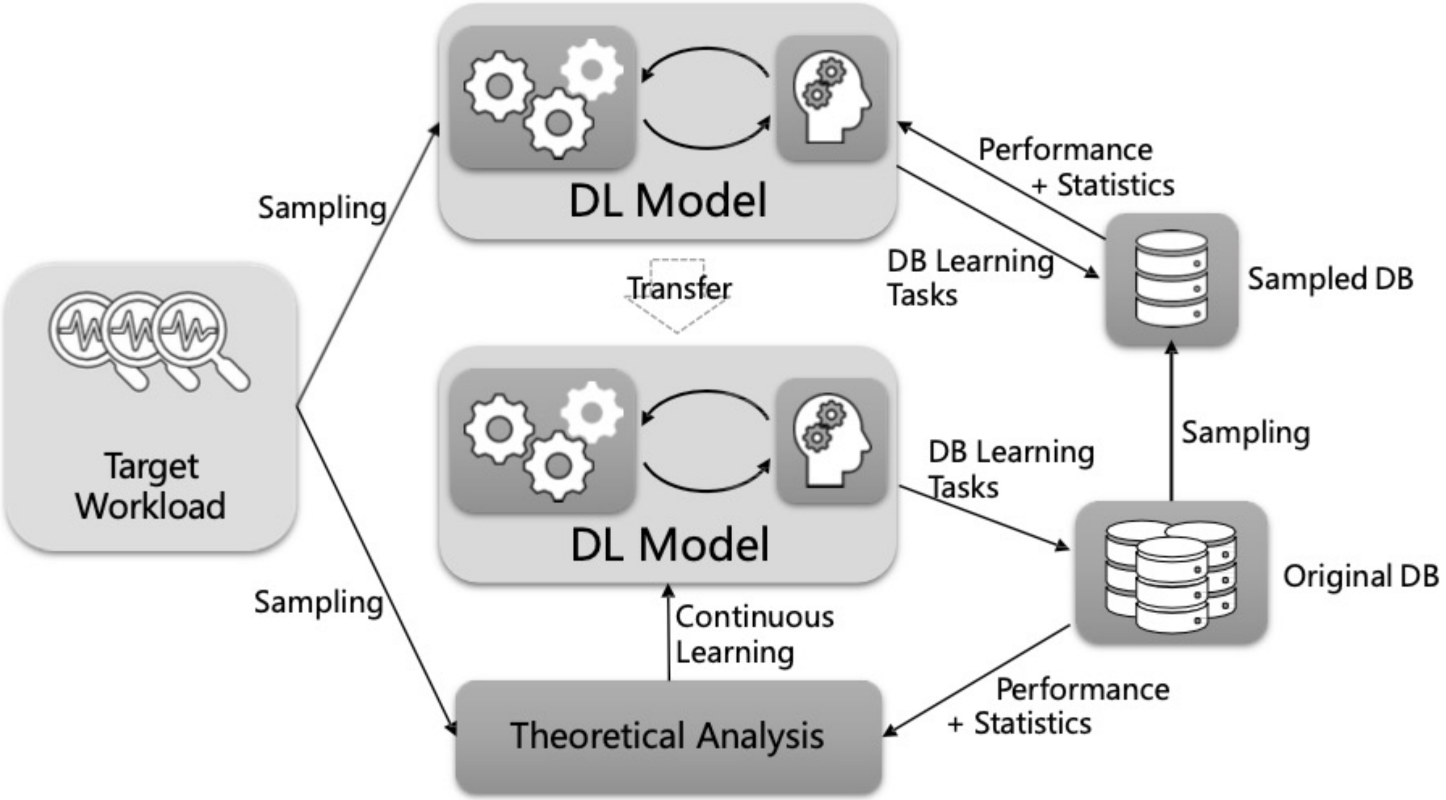
→ How do we do the sampling: towards mitigating **un-ignorable noises** and **prediction drifting**

- How to adapt the model to the original database

→ **Transfer** the model to the original database

A Transferable Sampling-based Framework

1. Train a model on an unbiased sampled database
2. Transfer the trained model to the original database

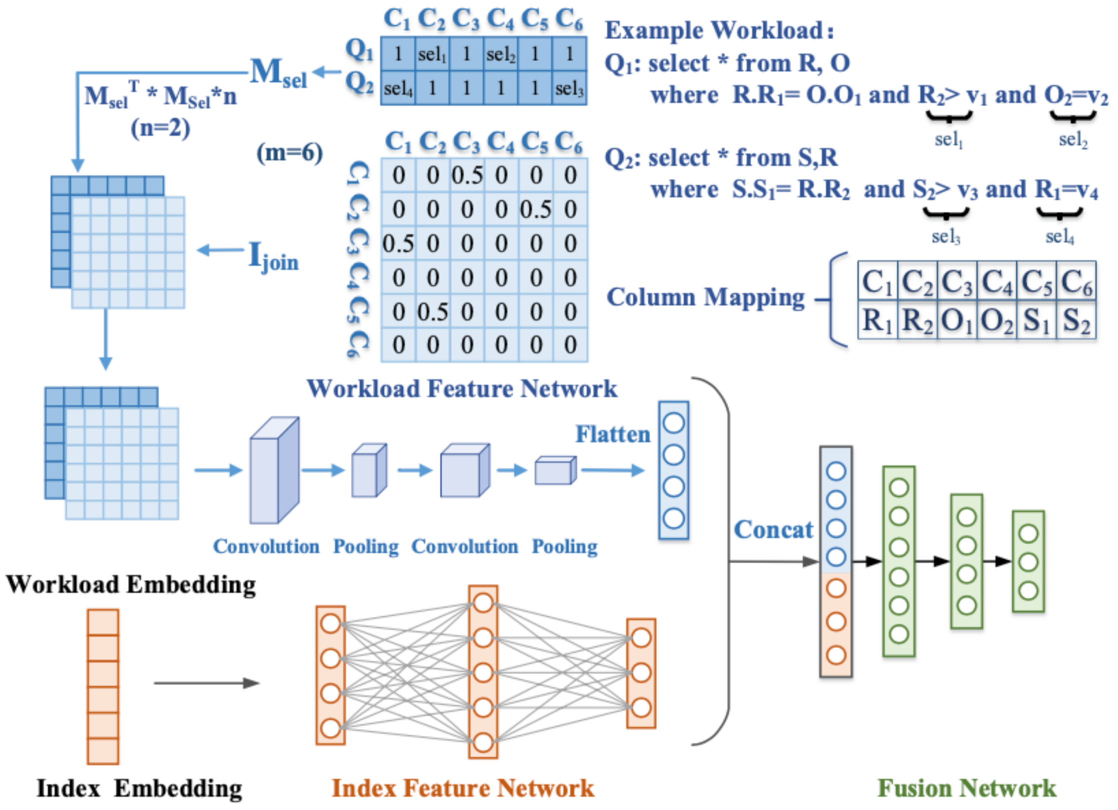


Method

Taking the index recommendation task as an example

Initial Training Phase -- Q function

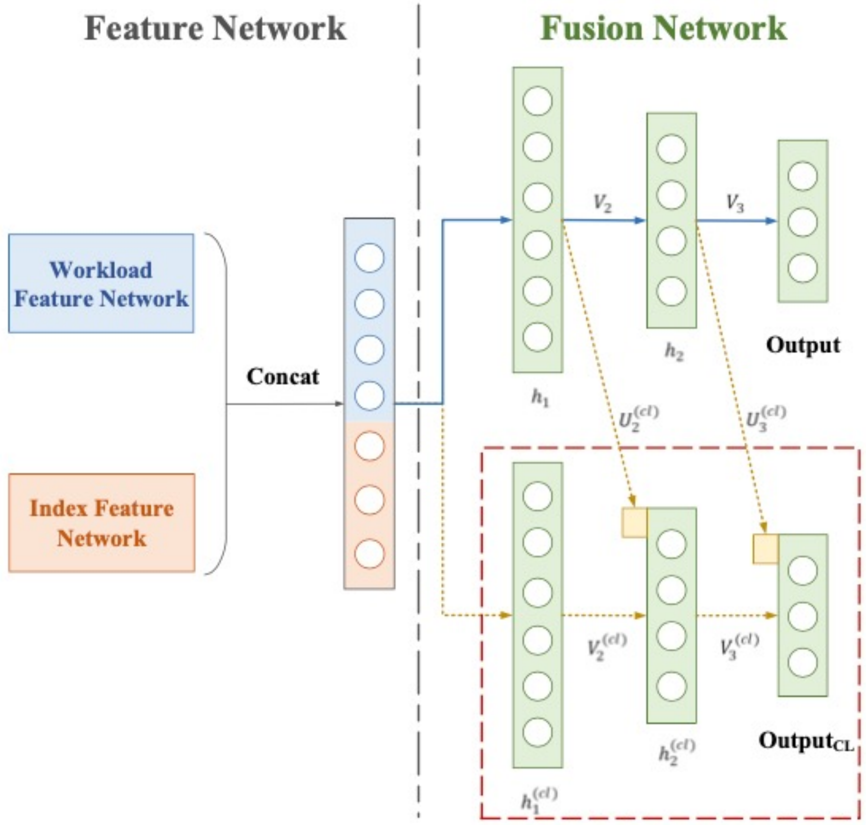
- A workload feature network.
  -> consider select, join and etc.
- An index feature network.
- A fusion network merging the representations.



$I_{Index} = [existsIndex(C_1), Type(C_1), \ldots, existsIndex(C_m), Type(C_m)]$

Continuous Learning Phase

- Step 1: Locate the outliers for the transferred model
- Step 2: Tune the model with a new branch



Lower and Upper Bound --- Robustness (noises)

Suppose the correct class for an input $\bar{x}$ on D' is i^* ($i^* = 0$ or 1), we define the margin function for a neural model $f(x)$ as:

$$g(x) = f_{i^*}(x) - f_i(x)$$

$$Pr(g(x) \geq 0) \geq 1 - \epsilon$$

THEOREM 1. *Let $f(x)$ be a K-class neural classifier and x_0 is its input. We define the noise δ as $||x - x_0||_p \leq \delta$ for $p \geq 1$. Let $g(x)$ be the margin function. Suppose the input vector X follows some given distribution $\mathcal{D}$ with mean x_0. For a constant $a \geq 0$, there exists a lower bound $\mathcal{L}$ and upper bound $\mathcal{U}$ for the probability $\mathcal{L} \leq Pr(g(x) \geq a) \leq \mathcal{U}$, where*

$$\mathcal{L} = 1 - F_{g^L(x)}(a)$$

and

$$\mathcal{U} = 1 - F_{g^U(x)}(a)$$

$F_Z(z)$ is the cumulative distribution function (CDF) of the random variable Z.

$$g^L(x) = A^L x + b^L$$

$$g^U(x) = A^U x + b^U$$

Note that if X follows a normal distribution with a mean μ and variance Σ, the linear combination $Z = wX + v$ also follows the normal distribution with a mean $\mu_z = w\mu + v$ and variance $\sigma_z = w\Sigma w^T$. The CDF of Z can be estimated as:

$$\frac{1}{2}(1 + erf(\frac{z - \mu_z}{\sigma_z\sqrt{2}}))$$

where erf represents the Gauss error function defined as:

$$erf(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt$$

Merging the definitions for CDF of Z, μ_L, μ_U, σ_L and σ_U. We have

$$\mathcal{L} \approx \frac{1}{2} - \frac{1}{2} erf(\frac{a - \mu_L}{\sigma_L\sqrt{2}}))$$

$$\mathcal{U} \approx \frac{1}{2} - \frac{1}{2} erf(\frac{a - \mu_U}{\sigma_U\sqrt{2}}))$$

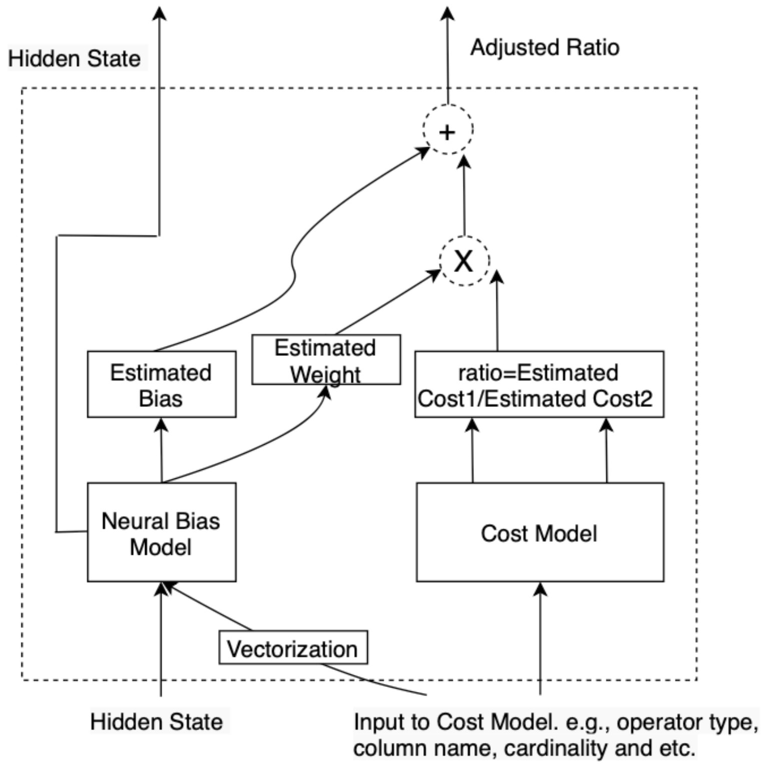
$$\delta = argmax_{i=0}^{m} |\sum_j \log(\frac{1}{Sel(Q_j, C_i)})^2 - \sum_j \log(\frac{1}{Sel'(Q_j, C_i)})^2|$$

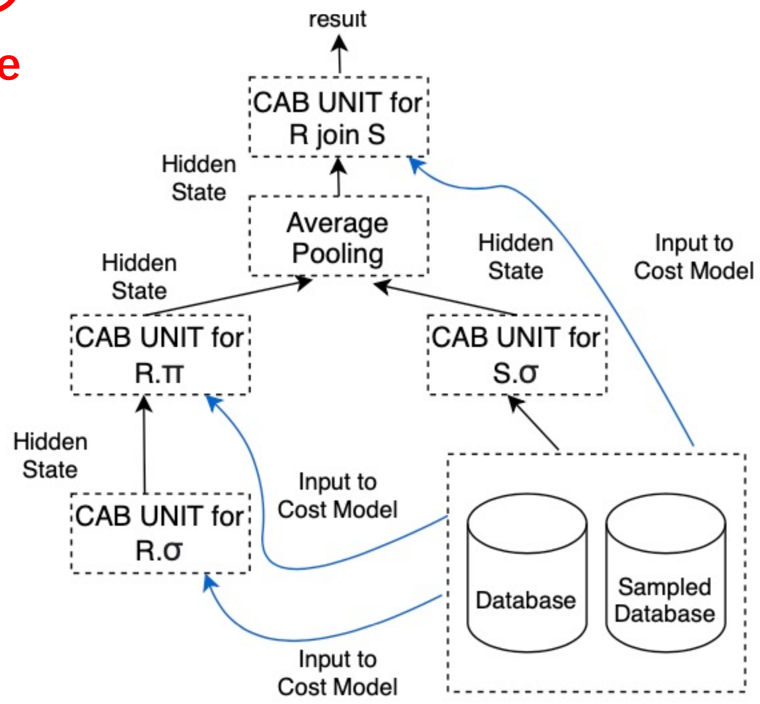
Normalization of Rewards — Robustness

- To guarantee the model returns **the consistent prediction results** for both **the original database** and **any sampled database**

$$r_{norm}(q_i, s_i) = \boxed{\frac{R(q_i, 1)}{R(q_i, \rho_i)}} * RT(q_i, I)$$

Learnable





Experiments

Setting

- **Benchmark**

  TPC-H benchmark, JOBbenchmark

- **Server**

  Intel Xeon Processor E5 2660 v2 (25M Cache, 2.20 GHz)

- **Database**

  PolarDB, Intel Xeon Platinum 8163 CPU (25M Cache, 2.50GHz

- **GPU**

  V100

- **Notation**

  Default: on the whole database

  Percona: a RL baseline

  Lift: a RL baseline

  Random: random sampled

  IR-Mirror-NR:

  - reward normalization
  - continuous learning techniques

  IR-OR: no mirror

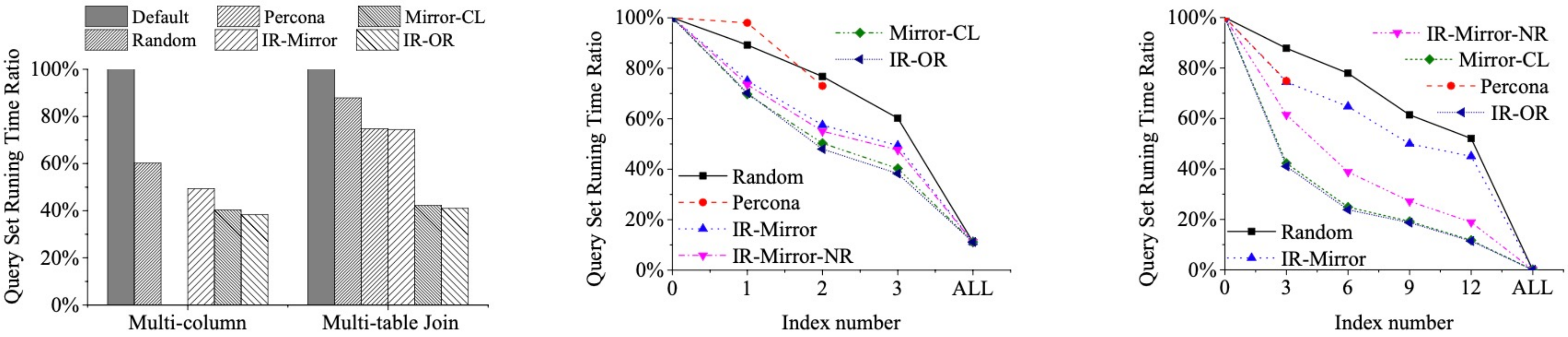
  IR-Mirror: without the optimizations

  Mirror-CL: all the optimizations

Main Result

Data Size	IR-Mirror-NR (per V100)	Lift(mins per V100)
8 Million(0.8%)	41 mins	77 mins
16 Million(1.6%)	119 mins	186 mins
32 Million(3.2%)	314 mins	386 mins
1 Billion (100%)	45 days	Not Converge

Table 1: Training Time with Varied Sampling Rate



(a) Overall Performance **(b) Index number(Multi-column)** **(c) Index number(Multi-table Join)**

Conclusion

Contributions

- Mirror reduces the training overhead by transferring a trained policy network.
- Based on the theoretic bounds, Mirror adopts a continuous learning technique to refine the model on the original database.
- Experiments demonstrate promising results.

Thanks! & QA