Active Learning for ML Enhanced Database Systems

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Background

- ML enhanced databases are emerging
 - E.g., academic contributions on ML enhanced query optimizer, index advisor, or query latency predictor
- ML enhanced databases face challenges at deployments: the ML model's prediction error increases significantly
- Key reason:
 - Data distribution shift due to differences on table sizes,

Motivation Experiment

- ECP Task: given a query plan, predict its execution cost
- PRP Task: given two query plans, predict which is cheaper
- Applications: ML enhanced query optimizer or index advisor



table data distributions, and operator combinations on production workloads

ECP Task

Solution

- Actively collect additional training data for individual databases during deployments
 - Using B-instances or replicas to execute additional queries without impacting normal business operation
 - > Focus on "target test data" for specific prod. workload
 - E.g., the optimizer's plan space for a set of queries
- A general platform supporting various ML tasks for DBs

Active Learning

- Challenge: target test data can be large
 - E.g., optimizer enumerates hundreds of thousands of plans for complex queries
- Active learning: select best training data from a pool of test data to improve ML model

Active Data Collection Platform



 Typically define an informativeness score (e.g., uncertainty), then acquire the most informative labels

Holistic Active Learner

- Challenge: canonical active learning has not focused on several holistic challenges arising from DB deployments
 Noisy uncertainty, labeling cost differences, and batch-labeling before retraining
- HAL: a new active learning strategy that is robust, cost-sensitive, and batch-friendly
 - > Techniques: biased sampling, cost weighting, and redundancy rejection



Results

 Reduces up to 75% test error on new databases at deployments by executing ~100 queries

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