BLUTune: Continuous Knobs Tuning

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Spencer Bryson, Connor Henderson, Parke Godfrey, Jarek Szlichta

Mohammed Alhamid, Vincent Corvinelli, Piotr Mierzejewski, Calisto Zuzarte

What is Knob Tuning?

- DBMS have dozens of knobs (configuration parameters) that control them
  - e.g. Sort heap size, buffer pool size, optimization levels, concurrency control, etc
- Knobs must be properly adjusted to achieve high performance and scalability
  - high throughput and low latency

Motivation

- Traditionally, databases rely on DBAs to tune the knobs
  - Non-trivial problem
  - Too many knobs
  - Requires an expert to spend a lot of time and effort (possibly several days)

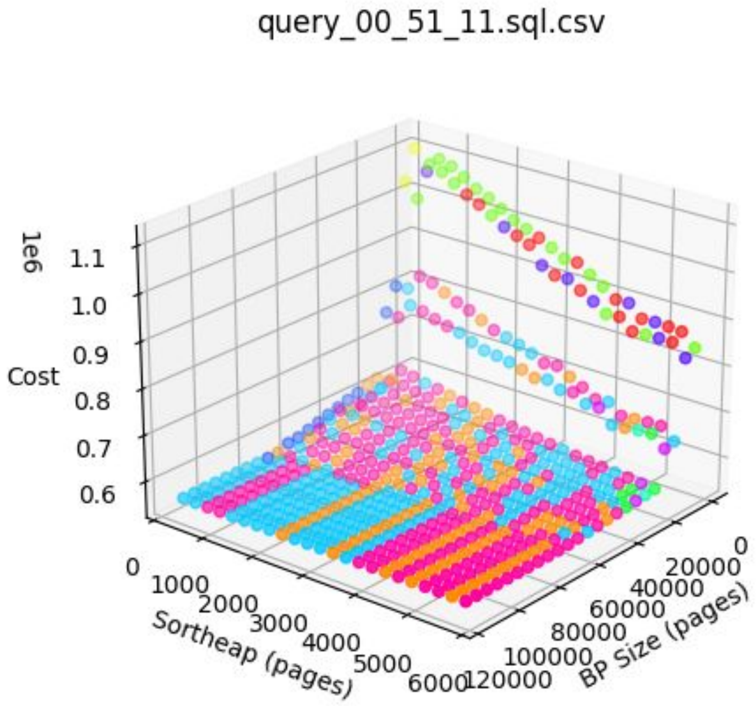
- As a workload evolves over time the configuration may no longer be optimal
  - Could cause poor performance until the knobs are re-tuned

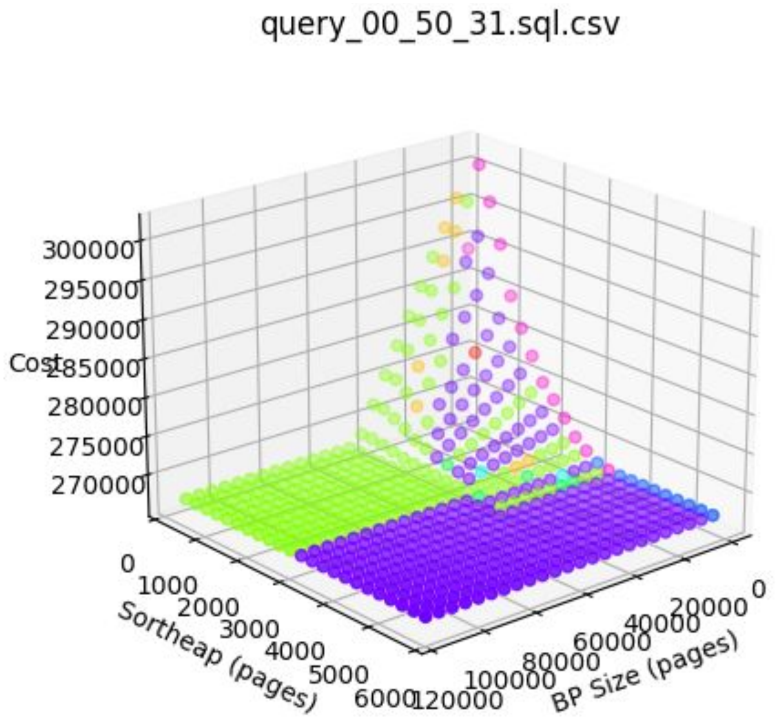
Automatic Knob Tuning

- A fully automated approach to optimally tune knobs is desired
  - Relieve the burden of tuning from experts
  - Find better configurations than experts
- Businesses and their applications are not static
  - Workloads can change overtime; so must the knobs
  - Cannot “set it and forget it”

Challenges and Use Cases

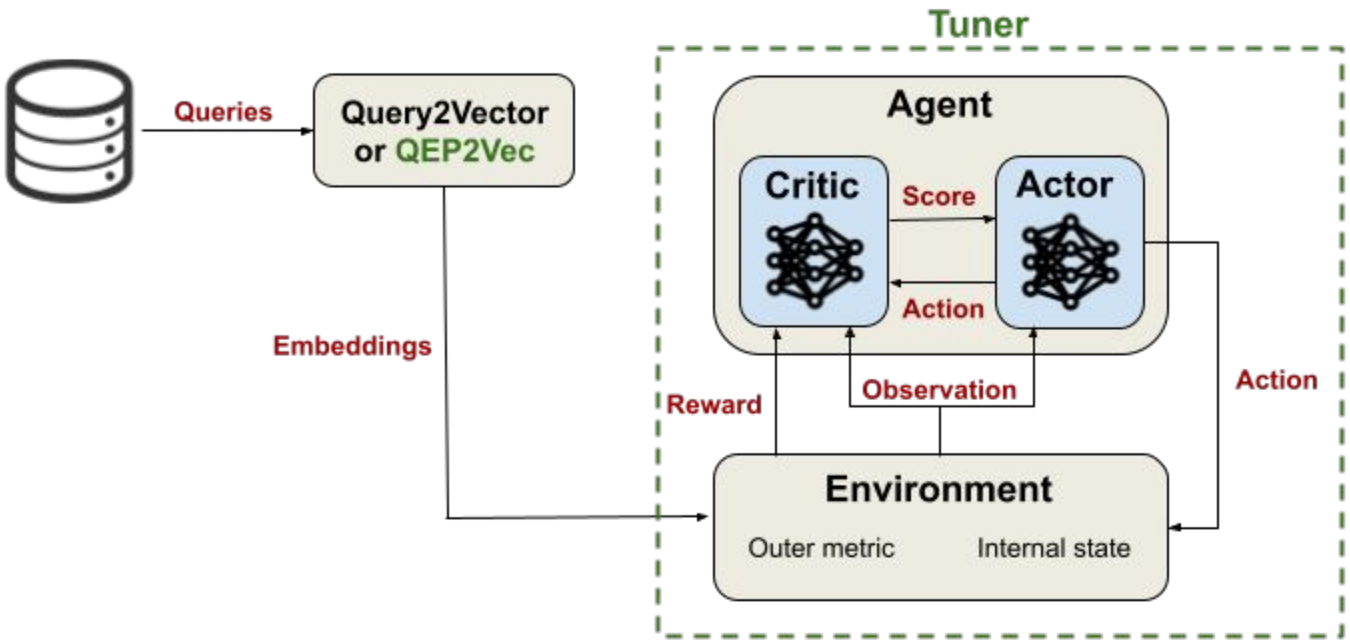
- Many knobs are continuous values
- Knobs can be interdependent
- One configuration does not fit all





Our Approach Architecture

- An intelligent ML solution driven by deep reinforcement learning
  - We use actor-critic network with policy-based learning to compute most likely best next action
  - embeddings to map high-dimensional queries into low-dimensional representation



Reward-driven learning

- The agent’s behaviour is driven by the designed reward function
  - Goal is to maximize the reward

- Our reward is based on change in query performance
  - Performance metric can be execution time or optimizer cost
  - We keep a cost history and apply exponential decay to steer the learning

- Our reward function also enforces limited resource constraints
  - i.e. the environment only has X amount of shared memory (sortheap, bpsize) e.g., cloud computing, must train the agent to stay within constraints

Execution time vs. Optimizer cost

- The overall goal of the agent is to minimize the execution time by finding a suitable configuration
  - Training on execution time can get prohibitively expensive as the complexity of the queries and the size of the database grows
    - The size of the database for prior works is mostly from 1GB to 10GB (we target 100GB+ large & complex query workloads)
- We've demonstrated that optimizer cost can be used in lieu of execution time
  - greatly speeds up training
  - 20 episodes in 7 hours vs. 5 episodes in 38 hours

Fine-tuning the model

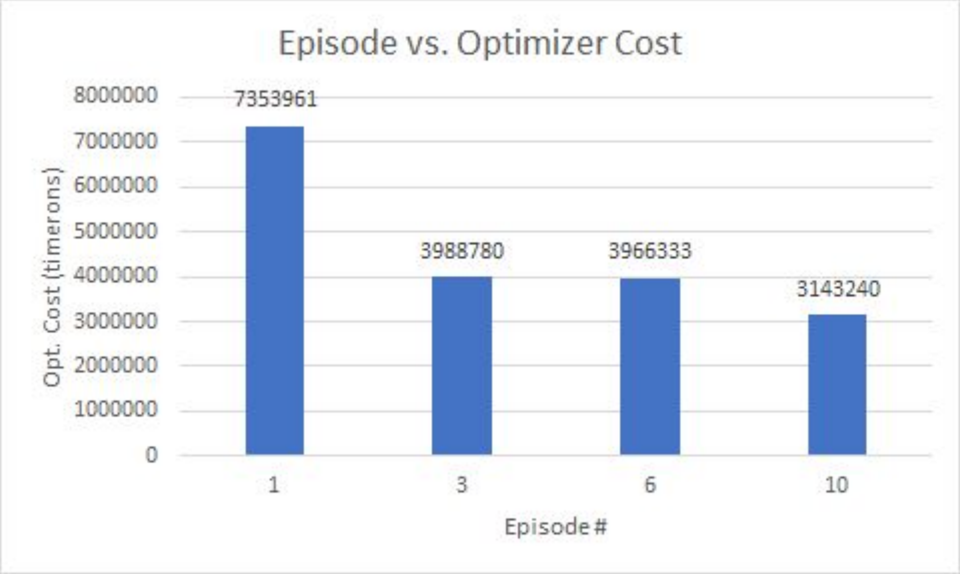
- Optimizer cost can be an effective measure of performance for various knob changes

- However, execution time captures some information that the optimizer fails with (inaccurate estimates, knob not factored in, etc)

- Thus, it is desirable to use the concept of transfer learning
  - first train up a model on minimizing optimizer cost, and then fine-tune the model by training on minimizing execution time

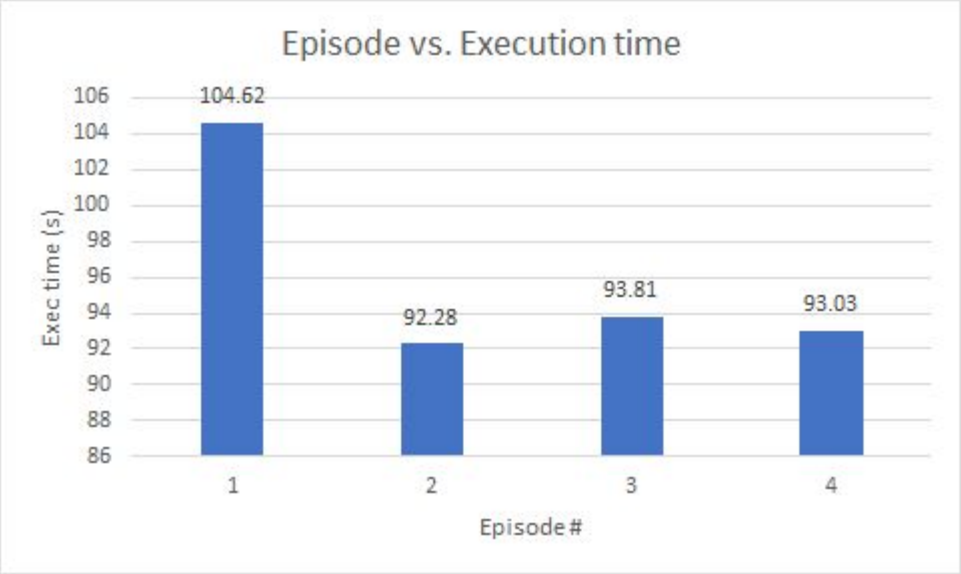
Results 1: Cost-only model

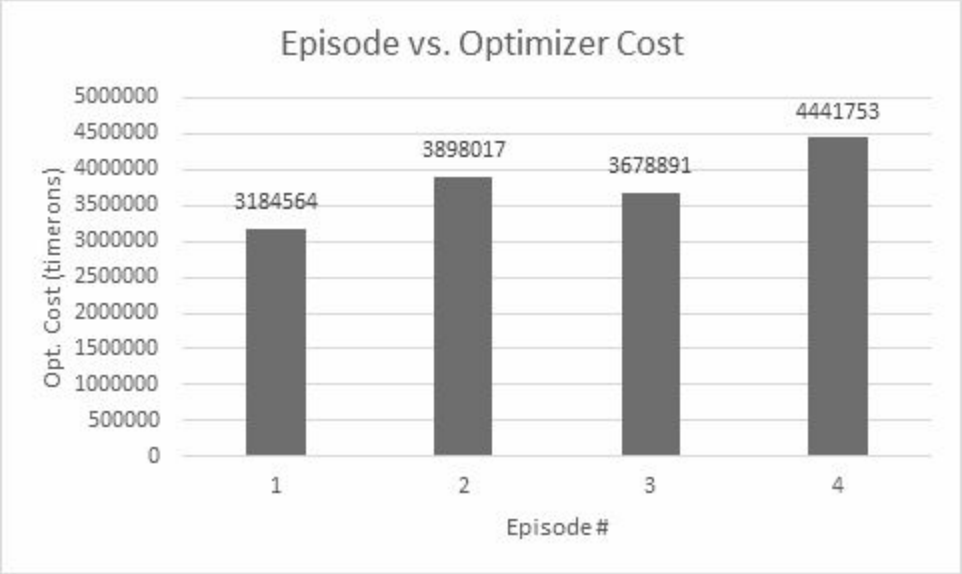
- Trained ONLY on cost
- **Time taken:** ~3.73 hours for 10 episodes (1000 iterations each)



Results 2: Fine-tuned on Execution time

- Continue training on the cost-only model with execution time
- **Time taken:** ~13.7 hours for 4 episodes (500 iterations each)





Result comparison

- Training only on cost produces a configuration that results in a total execution time of 107.91 seconds

- Fine-tuning the model above (transfer learning) leads to a execution time of 93 seconds

- This is an additional ~15% decrease which illustrates that fine-tuning the transfer learning component is beneficial

Thank-you