

A Deep Learning Based Approach to Performance **Optimization in Big Data Systems**

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Motivation and Overall Architecture

Motivation

Our Framework

• To run an analytic task on a big data system, the execution requires setting the system parameter (θ).

The settings of θ have significant impact on user performance goals, such as

Cost Model

- For a finite set of well defined operators, one can manually construct a general purpose cost model by careful analysis.
- Big data systems do not have a fixed set of operators. Hence it is too complex to build a general cost model manually.

System Model

System parameters

- P_i: logical dataflow program description.
- θ : System configuration, such as the degree of parallelism and granularity of scheduling.
- HW: Hardware description.
- D: Data description.
- $O_i(t)$: Observations taken at time t,

latency (L), throughput, and cost. Also these goals are often contradict with each other.

- Nowadays, systems let users to set up θ , with no guarantee/prediction on the performance goals.
- Big data systems are very complex. It is hard for the user to set up θ to optimize the system performance.
- To our best knowledge, this is the first effort to have a framework, which is deeplearning based, for automatically building a cost model in-situ.

Multi-Objective Optimization

- Construct approximate Pareto Optimal Skyline efficiently.
- Explore Pareto Optimal plans that capture tradeoffs between various user performance goals.

Cost Model

Cost Model with Approximation

Deep Learning Approach

Workload characteristics

Train a deep auto-encoder I* to

Minimize avg(distance(O(t), O'(t))

includes latency, throughput, CPU, MEM, I/O, Network, etc.

Logical Plan

A complex analytical task (type i) can be modelled as a logical dataflow program, denote as P_i:



Physical Plan

A close look on a MR-pair in physical execution **plan**, with θ set to a particular value:

- A vector W_i is the description of P_i , denoted as $W_i(t)$.
- It is stable within a time period, but may evolve slowly over time.
- W_i is a hidden variable. So we need to lacksquareextract it from data (manually constructed) in some previous works).

Approximation

- $F(W_i(t), \theta, D, HW) + X_{\varepsilon}(t) = O_i(t)$
- X can be viewed as Random Noise, we focus on simulating F.
- when c is a small constant, we can use $W_i(t-c)$ in place of $W_i(t)$ as an approximation.
- $O_i(t) = F(W_i(t-c), \theta, D, HW)$ ullet



From code, we extract W.



With W extracted, the next step:

Train a neural network regression model F* as the cost model.

- For a P_i with enough training data: good result, predicting error is low, less than 10%.
- For new P_i without enough training data: still needs to improve.

Multi-Objective Optimization



System abstraction



Overall approach

- Pareto Optimal based.
- An algorithm to find the next interesting section to explore.
- Minimize uncertain space. Intuitively, it means where the pareto optimal skyline can be an arbitrary shape.
- When the user is not sure about how to distribute preference, it recommends best plans based on different algorithms.



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