Learning State Representations for Query Optimization with Deep Reinforcement Learning

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ABSTRACT

We explore the idea of using deep reinforcement learning for query optimization. The approach is to build queries incrementally by encoding properties of subqueries using a learned representation.

In this paper, we focus specifically on the state representation problem and the formation of the state transition function. We show preliminary results and discuss how we can use the state representation to improve query optimization using reinforcement learning.

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1 INTRODUCTION

Query optimization is not a solved problem, and existing database management systems (DBMSs) still choose poor execution plans for some queries [5]. Because query optimization must be efficient in time and resources, existing DBMSs implement a key step of cardinality estimation by making simplifying assumptions about the data (e.g., inclusion principle, uniformity or independence assumptions). When these assumptions do not hold, cardinality estimation errors occur, leading to sub-optimal plan selections [5].

Recently, thanks to dropping hardware costs and growing datasets available for training, *deep learning* has successfully been applied to solving computationally intensive learning tasks in other domains. The advantage of these type of models comes from their ability to learn unique patterns and features of the data that are difficult to manually find or design [3].

In this paper, we explore the idea of training a deep learning model to predict query cardinalities. Instead of relying entirely on basic statistics and formulas to estimate cardinalities, we train a model to automatically learn important properties of the data to more accurately infer these estimates. Importantly, we use that model to learn subquery representations that can serve to derive the representation, and cardinality, of more complex queries and that can serve to build query plans bottom-up using deep reinforcement learning. As of today, there are few studies that have used deep learning techniques to solve database problems, although some have started to raise awareness for the potential of this method in our field [14]. Now is the time to explore this space, since we have the computational capabilities to run these models. In particular, we make two contributions in this paper: A succinct way of representing the state of a table (or subquery) using deep learning, and a principled way to enumerate plans for a given query using those states together with reinforcement learning.

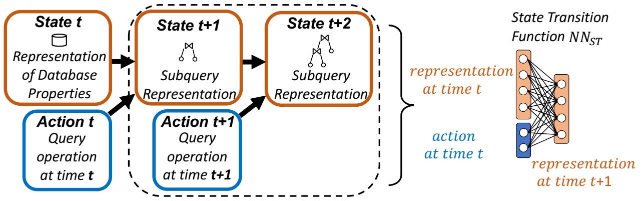
State t
Representation of Database Properties
Action t
Query operation at time t
State t+1
Subquery Representation
Action t+1
Query operation at time t+1
State t+2
Subquery Representation
State Transition Function NN_{ST}
representation at time t
action at time t
representation at time t+1

Figure 1: Given a database and a query, we use a neural network to generate a subquery representation. This representation can serve for cardinality estimation and for incrementally building query plans using reinforcement learning.

State Representation. A key challenge of this approach is how to represent queries and data. As a first contribution, we develop an approach that learns to *incrementally* generate a succinct representation of each subquery's intermediate results: The model takes as input a subquery and a new operation to predict the resulting subquery's representation. This representation can serve to derive the subquery's cardinality (Section 3).

Query Plan Enumeration. We also present an initial approach to using these representations to enumerate query plans through reinforcement learning. Reinforcement learning is a general purpose framework used for decision-making in contexts where a system learns by trial and error from rewards and punishment. We propose to use this approach to incrementally build a query plan by modeling it as a Markov process, where each decision is based on the properties of each state. Figure 1 illustrates our approach to query optimization. Given a query and a database, the model incrementally builds a query plan through a series of state transitions. In the initial state t in the figure, the system begins with a representation of the entire database. Given an action selected using reinforcement learning, the model transitions to a new state at $t+1$, having now constructed a larger subquery. Each action represents a query operation and each state captures a representation of the subquery's intermediate results. We train a state transition function (a neural network), NN_{ST}, to generate this representation. NN_{ST} is a recursive function that takes as input a previous subquery representation as well as an action at time t, to produce the subquery representation for time $t+1$.

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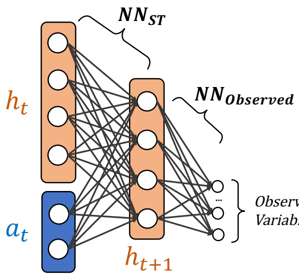


Figure 2: Learning the State Transition Function NN_{ST}: Given any h_t and a_t, we can extract a representation of a subquery through NN_{ST}. We train the function NN_{ST} by predicting properties from a set of observed variables. The function $NN_{Observed}$ defines the mapping between the hidden state and these observed variables.

Let us now motivate the setup that is laid out in Figure 1. Consider the dynamics of a query plan that is built bottom-up, one operation (action) at a time. At any stage t of the query plan, let's say a subquery has been built; let h_t, the state at t be represented by an n-dimensional real vector. Applying the next action, a_t to this current database state leads to the next state, h_{t+1}. The mapping, $NN_{ST} : (h_t, a_t) \rightarrow h_{t+1}$ is called the state transition function. In most applications of reinforcement learning, the state as well as the state transition function are known. For example, in the game of Go, each possible board position is a state and the process of moving from one board position to the next (the transition) is well-defined. Unfortunately, in the case of query plan enumeration, we cannot easily anticipate the state. The crux of our approach is to represent each state by using a finite dimensional real vector and *learn* the state transition function using a deep learning model. To guide the training process for this network, we use input signals and context defined from observed variables that are intimately associated with the state of the database. For example, throughout this work, we use the cardinality of each subquery at any stage of the plan as an observed variable. If a state h_t is represented succinctly with the right amount of information, then we should be able to learn a function, $NN_{observed}$, which maps this state to predicted cardinalities at stage t. We show both NN_{ST} and $NN_{observed}$ in Figure 2. As we train this model, the parameters of the networks will adjust accordingly based on longer sequences of query operations. With this model, each state will learn to accurately capture a representation. Once trained, we can fix this model and apply reinforcement learning to design an optimal action policy, leading to good query plans (Section 4).

Before describing our approach in more detail, we first briefly survey fundamental concepts about deep learning and reinforcement learning in the following section.

2 BACKGROUND

Deep Learning Deep learning models, also known as feedforward neural networks, are able to approximate a non-linear function, f [3]. These models define a mapping from an input x to an output y, through a set of learned parameters across several layers, θ. During training, the behavior of the inner layers are not defined by the input data, instead these models must learn how to use the layers to produce the correct output. Since there is no direct interaction between the layers and the input training data, these layers are called *hidden layers* [3].

These feedforward networks are critical in the context of representation learning. While training to meet some objective function, a neural network's hidden layers can indirectly learn a representation, which could then be used for other tasks [3]. There is a trade-off between preserving as much information as possible and learning useful properties about the data. Depending on the output of the network, the context of these representations can vary [3].

Reinforcement Learning Reinforcement learning models are able to map scenarios to appropriate actions, with the goal of maximizing a cumulative reward. Unlike supervised learning, the learner (the *agent*) is not explicitly shown which action is best. Instead, the agent must discover the best action through trial and error by either exploiting current knowledge or exploring unknown states [11]. At each timestep, t, the agent will observe a state of the environment, s_t and will select an action, a_t. The action selected depends on the policy, π. This policy can reenact several types of behaviors. As an example, it can either act greedily or balance between exploration and exploitation through an ϵ-greedy (or better) approach. The policy is driven by the expected rewards of each state, which the model must learn. Given the action selected, the model will arrive at a new state, s_{t+1}. The environment then sends the agent a reward, r_{t+1}, signaling the "goodness" of the action selected. The agent's goal is to maximize this total reward [11]. One approach is to use a value-based iteration technique, where the model records state-action values, $QL(s, a)$. These values specify the long-term desirability of the state by taking into account the rewards for the states that are likely to follow [11].

3 LEARNING A QUERY REPRESENTATION

Given as input a database D and a query Q, the first component of our approach is to apply deep learning to derive compact, yet informative representations of queries and the relations they produce. To ensure that these representations are informative, we focus on training these representations to predict subquery cardinalities.

3.1 Approach

There are two approaches that we could take. In the first approach, we could transform (Q, D) into a feature vector and train a deep network to take such vectors as input and output a cardinality value. As discussed in the introduction, the problem with this approach is that the size of the feature vector would have to grow with the complexity of databases and queries. This would result in very long, sparse vectors, which would require large training datasets.

Instead, we take a different approach, a recursive approach: We train a model to predict the cardinality of a query consisting of a single relational operation applied to a subquery as illustrated in Figure 2. This model takes as input a pair (h_t, a_t), where h_t is a vector representation of a subquery, while a_t is *a single relational operation on* h_t. Importantly, h_t is not a manually specified feature vector, but it is the latent representation that the model learns itself. The NN_{ST} function generates these representations by adjusting the weights based on feedback from the $NN_{Observed}$ function. This $NN_{Observed}$ function learns to map a subquery representation to predict a set of observed variables. As we train this model, we use back propagation to adjust the weights for both functions. In this

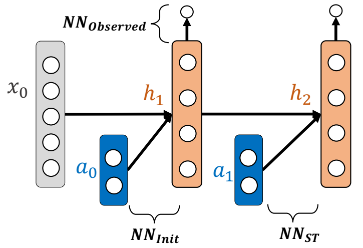


Figure 3: Combined Models NN_{init} and NN_{ST}

work, we only focus on predicting cardinalities, but we could extend the model to learn representations that enable us to capture additional properties such as more detailed value distributions or features of query execution plans, such as their memory footprint or runtime.

Before using the recursive NN_{ST} model, we must learn an additional function, NN_{init}, as shown in Figure 3. NN_{init} takes as input (x_0,a_0), where x_0 is a vector that captures the properties of the database D and a_0 is a single relational operator. The model outputs the cardinality of the subquery that executes the operation encoded in a_0 on D. We define the vector, x_0 to represent simple properties of the database, D. The list of properties we provide next is not definitive and more features can certainly be added. Currently, for each attribute in the dataset D, we use the following features to define x_0: the *min* value, the *max* value, the number of distinct values, and a representation of a 1-D equi-width histogram.

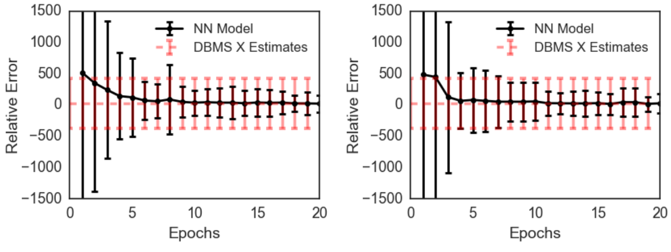
As shown in the figure, we then include the recursive model, NN_{ST}, that takes (h_t, a_t) as input and predicts the observed variables of the subqueries as well as the representation, h_{t+1} of the new subquery. We combine these models to train them together. During training, the weights are adjusted based on the combined loss from observed variable predictions. We want to learn an h_1 representation that captures not only enough information to predict the cardinality of that subquery but of other subqueries built by extending it.

3.2 Preliminary Results

We use the publicly available Internet Movie Data Base (IMDB) data set from the Join Order Benchmark (JOB) [5]. Unlike TPC-H and TPC-DS, the IMDB data set is real and includes skew and correlations across columns [5]. In our experiments, we use Python Tensorflow to implement our approach [1].

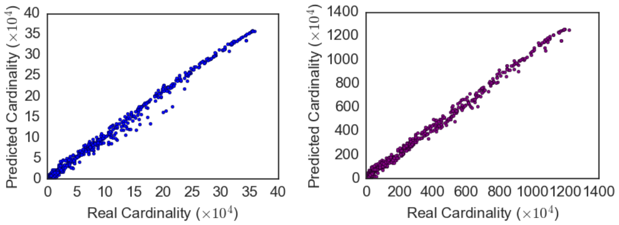
Training NN_{init}: As a first experiment, we initialize x_0 with properties of the IMDB dataset and train NN_{init} to learn h_1. a_0 represents a conjunctive selection operation over m attributes from the *aka_title* relation. We generate 20k unique queries, where 15k are used for training the model and the rest are used for testing. NN_{init} contains 50 hidden nodes in the hidden layer. We update the model via stochastic gradient descent with a loss based on relative error and a learning rate of .01.

In Figure 4a, we show the cardinality estimation results for selection queries where $m = 3$. On the x-axis, we show the number of epochs used during training and on the y-axis we show the relative error with the error bars representing the standard deviation. We compare our approach *NNModel* to estimates from a popular commercial DBMS. We use a commercial engine to ensure a strong baseline. With fewer epochs (less training) the NN_{init}'s cardinality predictions result in significant errors, but at the 6th epoch, the model performs similarly to the commercial system and then it starts to outperform it. We have also observed that increasing the number of training examples reduces the error variance.



(a) Predicting Cardinality (m = 3) **(b) Predicting Cardinality (m = 5)**

Figure 4: Learning h_1 for Selection Query



(a) Cardinality Predictions from $NN_{observed}$ and h_1 **(b) Cardinality Predictions from $NN_{observed}$ and h_2**

Figure 5: Learning Cardinalities on the Combined Model

In Figure 4b, we increase the number of columns in the selection to $m = 5$. In general, we observe that NN_{init} takes longer to converge once more columns are introduced. This is expected, as NN_{init} must learn about more joint distributions across more columns. Nevertheless, the model still manages to improve on the commercial engine's estimates by the 9th epoch.

Training NN_{init} and NN_{ST}: In the previous experiment, we only trained the NN_{init} model for selection queries over base data. For this next experiment, we predict the cardinality of a query containing both a selection and join operation by using the combined model. Here, a_0 represents the selection, while the subsequent action a_1 represents the join. Through this combined model, we can ensure that h_1 (the hidden state for the selection) captures enough information to be able to predict the cardinality after the join. In Figure 5, we show the cardinality prediction for h_1 and h_2. In these scatter plots, the x-axis shows the real cardinality, while the y-axis shows the predicted cardinality from the model. Although there is some variance, h_1 was able to hold enough information about the underlying data to make reasonable predictions for h_2.

Training this model takes ~535 seconds for 100 epochs. Cardinality predictions for each query takes ~.0004 seconds on average.

4 QUERY PLAN ENUMERATION WITH REINFORCEMENT LEARNING

In this section, we present and discuss our design to leverage the subquery representations from the section above, not only to estimate cardinalities, but to build query plans. Given a query, Q, we seek to identify a good query plan by combining our query representations from NN_{ST} with reinforcement learning.

We assume a model-free environment, where transition probabilities between states are not known. At s_0, the model only knows about D and Q. No query operations have yet taken place. The agent transitions to a new state by selecting an operation from query Q. At each state, we encode an additional contextual vector, u_t, which expresses the operations that remain to be done for Q. We now describe how to initialize the vector u_0 at time 0:

Given database D, we have a set of n relations $\mathcal{R} = \{rel_1, ..., rel_n\}$, where each rel_i contains a set of m attributes $\{att_{i_0}, ..., att_{i_m}\}$. The vector u_t represents a fixed set of equi-join predicates and one-dimensional selection predicates, $C = \{c_1, ...c_p\}$. We set the i-th coordinate in C accordingly if the corresponding predicate exists in the query Q. For example, c_1 could represent the following equi-join predicate, $rel_1.att_{1_0} = rel_2.att_{2_3}$. If this predicate exists in Q we encode it in u_t by updating the value of c_1 to 1, otherwise we set it to 0. For selections, we track one-dimensional ranged selections of the following form: $rel_i.att_{i_j} <= v$. For now, we allow each attribute to have at most one ranged filter in Q. If the selection predicate exists in Q, we place the value v in the corresponding element in C. Once the agent selects an action (query operation), a_t, we can update u_t by setting the corresponding element to 0.

To select good query plans, we need to provide the model with a reward. This reward must either be given at each state or once the entire query plan has been constructed. Currently, we are using the negative of our system's cardinality estimates at each step. The limitation is that this approach only optimizes logical query plans. We plan to extend the reward function in future work to also capture physical query plan properties. In particular, one approach is to use the negative of the query execution time as the reward.

Ultimately, the goal of the agent is to discover an optimal policy, π^*, which determines which action the agent will take given the state. As the agent explores the states, the model can update the state-action values for the function $QL(s, a)$, through Q-learning. Q-learning is an *off-policy* algorithm, that uses two different policies to ensure convergance of the state-action values [9, 11, 12]. One is a *behavior* policy, which determines which actions to select next. In practice, this is usually an ϵ-greedy policy [8, 9], but other policies can be used as well. The other is the *target* policy, usually a greedy strategy, which determines how values should be updated.

Initially, all state-action pairs are random values. At each timestep, the agent selects an action and observes the reward, r_{t+1} at state s_{t+1}. As the agent explores, these state-action pairs will converge to represent the expected reward of the states in future timesteps. At each state transition, each $QL(s, a)$ is updated as follows:

$$QL(s_t, a_t) \leftarrow QL(s_t, a_t) + \alpha[r_{t+1} + \gamma max_{a'} QL(s_{t+1}, a') - QL(s_t, a_t)]$$

Where the $max_{a'} QL(s_{t+1}, a')$ represents the maximum value from s_{t+1} given the target policy. We compute the subsequent state given the state transition function, NN_{ST}.

Open Problems: Many open problems remain for the above design. As we indicated above, the first open problem is the choice of reward function and its impact on query plan selection. Another open problem is that the state-space is large even when we only consider selections and join operators as possible actions. Thus, the Q-learning algorithm as initially described is impractical as the state-action values are estimated separately for each unique subquery. In other words, for each query that we train, it is unlikely that we will run into the same *exact* series of states for a separate query. Thus, a better approach is to consider approximate solutions to find values for $QL(s, a)$. We can learn a function, $\hat{QL}(s, a, w)$ to approximate $QL(s, a)$ given parameter weights w. This allows the model to generalize the value of a state-action pairs given previous experience with different (but similar) states.

5 RELATED WORK

Eddies [2] gets rid of the optimizer altogether and instead of building query plans, uses an eddy to determine the sequence of operators based on a policy. Tzoumas *et al.* [13] took this a step further and transformed it into a reinforcement learning problem where each state represents a tuple along with metadata about which operators still need to be applied and each action represents which operator to run next. Since the eddies framework does not build traditional query plans, their work does not consider learning representations of intermediate relations. Leo [10], was one of the first approaches to automatically adjust an optimizer's estimates based on past mistakes. This requires successive runs of similar queries to make adjustments. Liu *et al.* [6] use neural networks to solve the cardinality estimation problem, but focus on selection queries only. Work by Kraska *et al.* [4] uses a mixture of neural networks to learn the distribution of an attribute to build fast indexes. Our goal is to learn the correlation across several columns and to build query plans. Work by Marcus *et al.* [7] also uses a deep reinforcement learning technique to determine join order for a fixed database. Each state also represents a subquery, but our approach models each state as a latent vector that is learned through a neural network and is propagated to other subsequent states. Their approach uses a policy gradient to determine the best action, while our technique proposes to use a value-based iteration approach.

6 CONCLUSION

In this work, we described a model that uses deep reinforcement learning for query optimization. By encoding basic information about the data, we use deep neural networks to incrementally learn state representations of subqueries. As future work, we propose to use these state representations in conjunction with a reinforcement learning model to learn optimal plans.

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