Plan-Structured Deep Neural Network Models for Query Performance Prediction

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ABSTRACT

Query performance prediction, the task of predicting the latency of a query, is one of the most challenging problems in database management systems. Existing approaches rely on features and performance models engineered by human experts, but often fail to capture the complex interactions between query operators and input relations, and generally do not adapt naturally to workload characteristics and patterns in query execution plans. In this paper, we argue that deep learning can be applied to the query performance prediction problem, and we introduce a novel neural network architecture for the task: a plan-structured neural network. Our approach eliminates the need for human-crafted feature selection and automatically discovers complex performance models both at the operator and query plan level. Our novel neural network architecture can match the structure of any optimizer-selected query execution plan and predict its latency with high accuracy. We also propose a number of optimizations that reduce training overhead without sacrificing effectiveness. We evaluated our techniques on various workloads and we demonstrate that our plan-structured neural network can outperform the state-of-the-art in query performance prediction.

1 INTRODUCTION

Query performance prediction (QPP), the task of predicting the latency of a query, is an important primitive for a wide variety of data management tasks, including admission control [51], resource management [48], and maintaining SLAs [8, 31]. QPP is also a notoriously difficult task, as the latency of a query is highly dependent on a number of factors, including, but not limited to, the execution plan chosen and the underlying data distribution. As database management systems become increasing complex, this task only gets more difficult: each new operator or physical design component can introduce new and complex interactions that can be very difficult to model. Optimizer cost models, even when precisely tuned, only attempt to differentiate between potential query execution plans, and serve as poor predictors of query latency on their own [13, 23].

Previous approaches to query performance prediction have focused on designing hand-derived metrics [9], training models based exclusively on plan-level information [54], proposing mathematical models of relational operators [25], or combining plan-level and operator-level information in ad-hoc ways [4]. All of these methods depend on intelligent human feature engineering, the task of selecting or deriving pieces of information from a query plan or query operator that might correlate with its latency. Feature engineering, as a manual process, generally requires significant effort from human experts, but, more importantly, scales poorly with the increasing complexity of database management systems.

In this paper, we present a class of deep neural networks (DNNs) capable of performing query performance prediction in a "human-free" manner. DNNs have shown tremendous performance on a number of machine learning tasks [46], and carry a number of advantages. First, deep neural networks require no human feature engineering beyond the architecture of the network. During training, neural networks automatically derive and invent combinations of their inputs that serve as useful features, drastically diminishing the need for human experts [20]. Second, DNNs are capable of learning complex models of their training data [15], alleviating the need for ad-hoc and human-derived models of relational operators and their combinatorial interactions.

Despite the proven track record and massive growth of DNNs, applying deep learning to query performance prediction is not a straight-forward task. DNNs, like many other machine learning algorithms, are designed to map input vectors to output vectors. However, to act as input to a DNN, query plans need to be carefully vectorized to effectively capture their performance-related properties, such as the tree-based structure of an execution plan, features of intermediate results, and all involved operators. Unfortunately, existing works applying neural networks to tree structured data [34, 49] are ill-suited for the query performance prediction task. Specifically, branch isolation, the fact that a particular relational operator can only affect the performance of its parents and not its siblings, combined with heterogeneous tree nodes, the fact that different operators have different properties (e.g., number of children, predicates, etc.), make query execution plans a unique structure.
We thus propose a novel deep neural network architecture, a plan-structured neural network, specifically crafted for predicting the latency of query execution plans in relational DBMSes. Critically, our structure uses a unique neural unit, a small neural network, for each logical operator supported by a DBMS’s execution engine. These neural units can model the latency of an operator while emitting “interesting” features to any subsequent operators in the query plan. These neural units can then be combined together into a tree shape isomorphic to the structure of a given execution plan, creating a single neural network which maps a query execution plan directly to a latency. By exploiting weight sharing, i.e., the property where the same neural unit is used for any instance of the same operator across plans, these neural units are capable of learning complex interactions between operators. When compared to simpler models [4, 9, 25, 54], our approach automatically models both the performance of individual operators and the interaction effects between operators, avoiding the need for costly human model design. This paper makes the following contributions:

- We introduce the notion of an operator-level neural unit, a deep neural network that models the behavior of logical relational operators. Neural units are designed to produce (a) latency estimates and (b) performance-related properties that might be useful for the latency prediction of their parent operator in the plan.
- We introduce plan-structured deep neural networks, a neural network model specifically designed to predict the latency of query execution plans by dynamically assembling operator-level neural units in a neural network isomorphic to a given query plan.
- We propose optimizations for efficiently training our novel neural network architecture, decreasing model training time by nearly an order of magnitude.
- We present experimental results demonstrating that our approach outperforms state-of-the-art techniques for query performance prediction.

Our work marks the beginning of a new line of research that aggressively uses deep learning to address complex data management problems. While query performance prediction has been studied extensively (e.g., [4, 9, 25, 54]), this is the first approach that completely eliminates human-engineered features and models as well as avoids simplified assumptions made by previous work in attempt to make the query performance prediction problem tractable by human experts.

In the next section, we provide background information about deep neural networks. Section 3 outlines unique properties of query execution plans that motivate our new deep neural network architecture. Section 4 describes our plan-structured neural network model, and how it can be applied to query execution plans. In Section 5, we describe critical optimizations to make training a neural network for query performance prediction tractable. We present experimental results in Section 6, describe related work in Section 7, and offer concluding remarks and directions for future work in Section 8.

2 NEURAL NETWORKS BACKGROUND

Deep neural networks (DNNs) have a long-ranging history [15], and have recently enjoyed a surge in popularity [20]. This section will cover the basics of DNNs and gradient descent, the primary method for training neural networks. A more detailed discussion can be found in [28].

A DNN model is structured in layers, where the first layer takes in a vector representing the input data, and each subsequent layer applies some transformation of the previous layer’s output. Each layer consists of nodes which receives input data, multiplies each input by a coefficient (weight), sums the result, and passes that sum through an activation function. The activation function introduces non-linearity, allowing neural networks to represent arbitrary functions [15]. Intuitively, activation functions help the network represent the extent that a particular input value affects the ultimate outcome (e.g., “is this feature helpful in predicting latency data without error?”), and hence determines whether and to what extent that value progresses further through the network to affect the ultimate outcome (i.e., a node’s output is “activated” or “deactivated”).

DNNs end in an output layer: a layer responsible for mapping the output of the penultimate layer to a prediction. DNNs are trained on a dataset, consisting of pairs of inputs and targets, and aim to learn to accurately map a given input to the correct target. The quality of this mapping is measured by a loss function, which quantifies the difference between the neural network’s prediction (output) and the ground truth (target). DNNs learn via a process called gradient descent, a method that incrementally adjusts the transformation performed by each layer (i.e., the weights), to minimize the loss function. Training a DNN can be seen as a corrective feedback loop, rewarding weights that support correct guesses, punishing weights that lead to prediction errors, and slowly pushing the loss function towards smaller and smaller values. In the process, the network takes advantage of correlations and patterns in the underlying data, creating new, transformed representations of the data. Simultaneously, the network learns to recognize correlations between relevant features and optimal predictions. Next, we describe the above using more formal definitions, essential for the introduction of our techniques.
2.1 Layers

Each layer in a DNN is composed of an affine transformation of its input\(^1\) and a non-linear activation function. Given an input vector \(\hat{x}\) of size \(n \times 1\), the \(i\)-th layer of a network can be defined as a function \(t_i(\hat{x})\) that provides an output vector of size \(m\):

\[
t_i(\hat{x}) = S(W_i \times \hat{x} + b_i)
\]

where \(S\) is the activation function and \(W_i\) are the weights for the \(i\)-th layer, represented by a matrix of size \(m \times n\). The bias, \(b_i\), is an \(m \times 1\) vector representing the constant shift of an affine transform. Together, the weights and the biases represent the parameters of the neural network model, and control the properties of the transformation performed at each layer. The activation function, \(S\), represents some differentiable but non-linear function: popular choices include a sigmoid function or a rectified linear function [12].

Neural network layers are composed together by feeding the output of one layer into the input of the next. For a neural network with \(n\) layers, where \(\circ\) represents the function composition operator, a neural network can be defined as:

\[
N(\hat{x}) = t_n \circ t_{n-1} \circ \ldots \circ t_1
\]

For example, a two layer neural network \(N\) on an input vector \(\hat{x}\) could be represented as:

\[
N(\hat{x}) = t_2(t_1(\hat{x})) = S(W_2 \times S(W_1 \times \hat{x} + b_1) + b_2)
\]

2.2 Gradient descent

The first step to training a neural network \(N\) is defining a loss function, i.e. a function whose minimization is a suitable criteria for the network to provide a good prediction. Let us assume a set of training input vectors \(X\) and a labeling function \(l(\hat{x})\) that provides the corresponding target value for each vector \(\hat{x} \in X\). For example, if \(X\) is a set of vectors representing query plans, \(l(\hat{x})\) could be the latency of the query plan represented by the vector \(\hat{x}\). The neural network \(N\) can be trained to produce the target \(l(\hat{x})\) when fed \(\hat{x}\) by minimizing a loss function [44]. One popular loss function is \(L_2\) loss, or root mean squared error, which can be defined as:

\[
err(X) = \sqrt{\frac{1}{|X|} \sum_{\hat{x} \in X} (N(\hat{x}) - l(\hat{x}))^2}
\]

Given a loss function and a dataset, the next task is to adjust the weights and biases of the neural network to minimize the loss function. One popular technique for tweaking the weights and biases is with gradient descent [44]. Here, the activation function \(S\) is chosen to be differentiable so that the loss function can be differentiated with respect to any particular parameter. This allows us to calculate the gradient: the derivative of the loss function with respect to an arbitrary parameter (i.e. a weight in \(W_i\) or a bias in \(b_i\) for some \(i\)). This represents how the loss function is affected by the particular parameter (i.e., if a higher/lower weight/bias leads to higher/lower loss). The derivative of a particular parameter \(w\) (i.e., a single element inside of a weight matrix or bias vector) can be written as the following function:

\[
\nabla_w(err, X) = \frac{\partial err(X)}{\partial w}
\]

In other words, the gradient of a parameter of the neural network (weights and biases) is the derivative of the loss function with respect to this particular parameter. This gradient can then be evaluated given the input vectors \(X\) and their corresponding target values \(l(\cdot)\).

Gradient descent works by adjusting each weight of the neural network independently. The gradient descent algorithm first computes the gradient (Equation 4) of a given neural network parameter, \(w\). If the gradient is positive, meaning that an increase in this parameter would (locally) lead to an increase in the loss function, the weight \(w\) is increased. If the gradient is negative, meaning that an increase in this parameter would (locally) lead to a decrease in the loss function, the weight \(w\) is decreased. After adjusting the weight, the algorithm then repeats this procedure for each parameter in the network. This simple procedure is iterated until gradients of all parameters (weight and biases) are relatively flat (i.e., convergence).

In practice, computing the gradient for the entire dataset (i.e., all of input vectors and target values), is prohibitive. Thus, stochastic gradient descent instead takes a simple random sample of the input vectors and their corresponding target values and uses these to estimate the gradient [44].

3 DL-BASED LATENCY PREDICTION: CHALLENGES

Despite their numerous advantages, it is difficult to apply traditional deep neural networks to the query performance prediction task. A straightforward application of deep learning would be to model the whole query as a single neural network and use query plan features as the input vector. However, this naive approach ignores the fact that the query plan structure, features of intermediate results, and non-leaf operator are often correlated with query execution times and hence can be useful in any predictive analysis task.

Furthermore, query plans are diverse structures – the type and number of operators varies per plan, operators have different correlations with query performance, and operators have different sets of properties and hence different sets of predictive features. Traditional DNNs have static network architectures and deal with input vectors of fixed size.

\(^1\)Different application domains may use more complex transformations.
A naive solution to this problem might be to concatenate vectors together for each relational operator. For example, if a join operator has 9 properties and a filter operator has 7 properties, one could represent either a join or a filter operator with a vector of size $9 + 7 = 16$ properties. If the operator is a filter, the first 9 entries of the vector are simply 0, and the last 7 entries of the vector are populated. If the operator is a join, the first 9 entries of the vector are populated and last 7 entries are empty. The problem with this solution is sparsity: if one has many different operator types, the vectors used to represent them will have an increasingly larger proportion of zeros. Generally speaking, such sparsity represents a major problem for statistical techniques [22], and transforming sparse input into usable, dense input is still an active area of research [52, 53]. In other words, using sparse vectors to overcome heterogeneous tree nodes replaces one problem with a potentially harder problem.

**Position-independent operator behavior** As pointed out by previous work [13, 25], two instances of the same operator (e.g., join, selection, etc), will share similar performance characteristics, even when appearing within different plans or multiple times in the same plan. For example, in the case of a hash join, latency is strongly correlated with the size of the probe and search relations, and this correlation holds regardless of the operator’s position in the query execution plan. This indicates that one could potentially train a neural network model to predict the performance of a hash join operator, and that same model can be used any time the hash-join operator appears in a plan.

### 4 PLAN-STRUCTURED DNNs

Taking the above observations into account, this paper proposes a new tree-structured neural network architecture, in which the structure of the network matches the structure of a given query plan. This plan-structured neural network consists of operator-level neural networks (called neural units) and the entire query plan is modeled as a tree of neural units. On its own, each neural unit is expected to (1) predict the performance of an individual operator type – for example, the neural unit corresponding to a join predicts the latency of joins – as well as (2) “interesting” data regarding the operator that could be useful to the parent of the neural unit. The plan-level neural networks is expected to predict the execution time of a given query plan.

Next, we discuss our proposed model in more detail, starting with the operator-level neural units and moving on with the plan-structured neural network architecture.

#### 4.1 Operator-level neural units

Our proposed approach models each logic operator type supported by a DBMS’ execution engine with a unique neural unit, responsible for learning the performance of that particular operator type, e.g., a unique unit for joins, a unique unit for selections, etc. These neural units aim to represent sufficiently complex functions to model the performance of relational operators in a variety of contexts. For example, while a simple polynomial model of a join operator may
make predictions only based on estimated input cardinalities, our neural units will automatically identify the most relevant features out of a wide number of candidate inputs (e.g., underlying structure of the table, statistics about the data distribution, uncertainty in selectivity estimates, available buffer space, etc.), all without any hand-tuning.

**Input feature vectors** Let us define as $\hat{x} = F(x)$ a vector representation describing $x$, an instance of a relational operator. This vector will act as an input to the neural unit of that particular operator. These vectors could be extracted from the output of the query optimizer, and contain information such as: the type of operator (e.g., hash join or nested loop join for join operators, etc.), the estimated number of rows to be produced, the estimated number of I/Os required, etc. Many DBMSes expose this information through convenient APIs, such as EXPLAIN queries. For examples, see Appendix B, which lists the features used in our experimental study for several operators. Note that the size of the input vector may vary based on its corresponding operator: input vectors for join operators would have a different set of properties and thus different sizes than the input vectors for selection operators. However, every instance of a relational operator of a given type will have the same size of input vector, e.g. all join operators have the same size input vectors.

**Output vector** Performance information for an operator instance $x$ are often relevant to the performance of its parent operator in a query execution plan. To capture this, and allow for flow of information between operator-level neural units, each neural unit of an operator type will output both a latency prediction and a data vector. While the latency output predicts the operator’s latency, the output data vector represents “interesting” features from the child operator that are relevant to the performance of the parent operator. For example, a neural unit for a scan operator may produce a data vector that contains information about the expected distribution of the produced rows. We note these data vectors are learned automatically by the model during its training phase, without any human interference or selection of the features that appear in the output vector.

**Neural units** Next, we define a neural unit as a neural network $N_A$, with $A$ representing a type of relational operator, e.g. $N_{scan}$ is the neural unit for join operators. For each instance $a$ of the operator type $A$ in a given query plan, the neural unit $N_A$ takes as input the vector representation of the operator instance $a$, $\hat{x}_a$.

This input is fed through a number of hidden layers, with each hidden layer generating features by applying an activated affine transformation (as defined by Equation 1). These complex transformations can be learned automatically using gradient descent methods, which gradually adjusts the weights and bias of the neural unit $N_A$ in order to minimize its loss function (as described in Section 2.2). The last layer transforms the internal representation learned by the hidden layers into a latency prediction and an output data vector.

Formally, the output of a neural unit $N_A$ is defined as:

$$\tilde{p}_a = N_A(\tilde{a}), \text{ when } a \text{ is a leaf}$$

where $a$ is the instance of the operator type $A$. The output vector has a size of $d + 1$. The first element of the output vector represents the neural unit’s estimation of the operator’s latency, denoted as $\tilde{p}_a[l]$. The remaining $d$ elements represent the data vector, denoted as $\tilde{p}_a[d]$. We note that since the input vectors to different neural units will not have the same size, each neural unit may have different sizes of weight and bias vectors that define the neural unit, but their fundamental structure will be similar.

4.1.1 Leaf neural units (scan). The simplest neural units are those representing leaf nodes of the query plan tree and are responsible for accessing data from the database. Following PostgreSQL terminology, we refer to these as scan operators to distinguish them from the selection operator that filters out intermediate data.

For a given instance $s$ of the scan operator type $S$, the neural unit $N_S$ takes as input the raw vector representation of the operator instance $s$, $\hat{x}_s$, and produces an output vector $\tilde{p}_s$. Since these operators access stored data, their corresponding vectors include (among others) information about the input relation of the scan operator. These features are collected through the optimizer (or various system calls). We refer to the function collecting this information for an instance $a$ of the operator $A$ as $F(a)$.

Figure 2 shows an illustration of a neural unit for a scan operator $N_S$. The unit takes information from the query plan (e.g., index/table scan, optimizer’s cost, cardinality estimates, estimated I/Os, memory availability, etc) as input. By running the raw vector representation of a scan operator through many successive hidden layers, the neural unit can model complex interactions between the inputs. For example, a series of activated affine transformations might “trust” the optimizer’s cost model more for certain types of scans, or for scans over particular relations. The neural unit transforms the input vector into a latency prediction and an output data vector. Possible output data features here might be distribution information of the rows emitted by the scan.

![Figure 2: Neural unit corresponding to a scan operator, $N_S$. Input features are mapped through a number of hidden layers and one output layer.](image-url)
4.1.2 Internal neural units. Having constructed neural units for each leaf operator type, we next explain how the internal operators, i.e., operators with children in a query execution plan, can be modeled using neural units. Like leaf operators, the neural units for the internal operator instance $x$ of the query execution plan will take an operator-specific input vector into account, provided by the function $F(x)$. However, the performance of the internal operators depends also on the behavior of its children. Hence, each internal neural unit receives also as input the latency prediction and the output data vector of its children.

A neural unit for an internal operator type $A$ is represented as a neural network $N_A$. Given a query execution plan where an operator instance $a$ of type $A$ receives input from operators $x_i, i \in \{1, \ldots, n\}$, the input vector of $N_A$ will be the operator-related information produced by $F(a)$ in addition to the output vectors produced by the operator’s children:

$$\tilde{p}_a = N_A(F(a) \sim p_{x_1} \sim \cdots \sim p_{x_n})$$  \hfill (6)

where $\sim$ represents the vector concatenation operator.

Since the operator’s raw input vector and the outputs of its children’s neural units are concatenated together and passed as an input to another neural network, the loss function of the entire neural network architecture is still differentiable with respect to any weight. This guarantees that the network can still be trained using standard gradient descent methods.

Figure 3 shows an example of an internal neural unit, corresponding to a join operator, $N_{\circ} \sigma$. The unit takes information about the join operator itself (e.g., the type of join, the optimizer’s predicted cost, cardinality estimates, etc.) as well as information from the join operator’s children. Specifically, the join neural unit will receive both the data vector and latency output of its left and right child. These inputs are fed through a number of hidden layers and is transformed into a final output vector, where the first element of the output vector represents the predicted latency and the remaining elements represent the data output features. This allows $N_{\circ} \sigma$ to be further composed with other neural units.

4.2 Trees of neural units

Next, we show how these neural units can be composed into tree structures isomorphic to any particular query execution plan. Figure 4 shows an example of a query execution plan and the isomorphic plan-structured neural network. Intuitively, each operator in a query execution plan is replaced with its corresponding neural unit, e.g., join operators are replaced with $N_{\circ} \sigma$, and the output of each neural unit is fed into the parent. The latency of the query execution plan is the first element of the output vector $\tilde{p}_r$, where $r$ is the instance operator on the root of the query execution plan. Note that the recursive definition (Equation 6) of $\tilde{p}_r$ will “replace” each relational operator with its corresponding neural unit in a top-down fashion.

Figure 5 shows an example of this construction. For the query execution plan shown in the bottom-right of the figure (two scans and a join), two instances of the scan neural unit and one instance of the join neural unit are created. The outputs of the scan units are concatenated together with
Figure 6: General neural network for latency prediction

Figure 6 shows a more general example, with a query plan (top left) and the corresponding neural network tree (right). Each neural unit, represented as trapezoids, takes in a number of inputs. For the leaf units (orange, corresponding to the table scans in the query plan), the inputs are information from the query plan (black arrows). The internal, non-leaf units take information from the query plan as well, but additionally take in the latency output (green arrows) and the data outputs (red arrows) of their children. The latency outputs represent the model’s estimate of the latency of each operator, and the data outputs contain information about each operator that may be useful to the parent operator (for example, the table scan neural unit may encode data about which relation is being read). Here, the two orange trapezoids correspond to the scan operators of $R_1$ and $R_2$ in the query plan, and thus use the same neural unit.

4.3 Model benefits

Our plan-structured neural network model eliminates a number of aforementioned challenges, while leveraging a number of plan-structured properties (see Section 3).

Branch isolation Since we know that any particular relational operator in a query execution plan can only affect the performance of its ancestors, and not its siblings or children, we say that a query execution plan exhibits branch isolation. The way we assemble neural units into trees respects this property: each neural unit passes information exclusively upwards. Intuitively, this upwards-only communication policy directly encodes knowledge about the structure of the query execution plan into the network architecture itself.

Heterogeneous tree nodes Operator-level neural unit accepts input vectors of different size depending on the operator they model while producing a fixed-sized output vector. This enables the structure of the plan-structured neural network to dynamically match any given query plan, thus making our model suitable to handle arbitrary plans. For example, regardless of if the child of a join operator is a filter (selection) or a scan, its child neural unit will produce a vector of a fixed size, allowing this output vector to be connected to the neural unit representing the join operator.

Position-independent operator behavior Since we expect a particular operator to have some common performance characteristics regardless of its position in the query execution plan, the same neural unit is used for every instance of a particular operator. Because the same query execution plan can contain multiple instance of the same operator type (e.g., multiple joins), our architecture can be considered a recurrent neural network [26], and as such benefits from weight sharing: since instances of the same operators share similar properties, representing them with a single neural unit (and thus a single set of weights and bias) is both efficient and effective. However, since distinct operator types are represented by different neural units (and thus will not share the same weights and bias), our approach can handle the heterogeneous nature of the query execution plan operators.

5 MODEL TRAINING

So far, we have discussed how to assemble neural units into trees matching the structure of a given query execution plan. In this section, we describe how these plan-structured neural networks are trained. Training is the process of progressively refining the network’s weights and bias (in our case, the weight and bias of the neural units included in a plan-structured neural network) to minimize the loss function using gradient descent (as discussed in Section 2).

Initially, each hidden layer, and the final latency and data vector output for each neural operator, will simply be a random activated affine transformation. In other words, the weights and bias that define the transformations (Equation 1) are initially picked randomly. Through repeated applications of gradient descent, these transformations are slowly tweaked to map their inputs slightly closer to the desired target outputs.

This training process is performed using a large corpus of executed query plans. Formally, for a dataset of executed query execution plans, let $D$ be the set of all query operator instances within those plans. Then, for each query operator $o \in D$, let $l(o)$ be the latency of the operator. The neural units are trained by minimizing the following loss function:

$$L_2(D) = \sqrt{\frac{1}{|D|} \sum_{o \in D} (\tilde{p}_o[I] - l(o))^2}$$  \hspace{1cm} (7)

where $\tilde{p}_o[I]$ represents the latency output of the operator $o$’s neural unit (the neural unit’s prediction).
Note that, if a particular query operator instance \( o \) is not a leaf in its query execution plan, the evaluation of its output \( \vec{p_o} \) will involve multiple neural units, based on the recursive definition given by Equation 6. The loss function \( L_s(D) \) thus represents the prediction accuracy of leaf operators, internal operators, and the root operator of a query execution plan. Minimizing this loss function thus minimizes the prediction error for all the operators in the training set.

Intuitively, Equation 7 is simply the combined differences between the latency the model predicted for each operator and the observed, “ground truth” latency. The loss function explicitly compares the predicted latency of a particular operator \( \vec{p_o}[l] \) with the “ground truth” latency \( l(op) \).

However, it is important to note that the loss function does not explicitly compare the data vector of the output \( \vec{p_o} \) to any particular value. The gradient descent algorithm is thus free to tweak the transformations creating the output data vector to produce useful information for the parent neural unit consuming the data vector output. To exemplify this, consider evaluating the output \( \vec{p_j} \) for a simple query plan involving the join of two relation scans, \( s_1 \) and \( s_2 \), as illustrated in Figure 5. Following Equation 6, and defining as \( N_j \) the neural unit for joins and \( N_s \) the neural unit for scans, we can expand the output vector \( \vec{p_j} \) as follows:

\[
\vec{p_j} = N_w(F(j) \leadsto \vec{p_{s_1}} \leadsto \vec{p_{s_2}})
= N_w(F(j) \leadsto N_s(F(s_1)) \leadsto N_s(F(s_2)))
= N_w(F(j) \leadsto [\vec{p_{s_1}}[l] \leadsto \vec{p_{s_1}}[d]] \leadsto [\vec{p_{s_2}}[l] \leadsto \vec{p_{s_2}}[d]])
\]

where \( \vec{p}_{s}[d] \) represents the output data vector for the neural unit of operator \( s \).

Thus, the transformations producing the output data vector for each neural unit are adjusted by the gradient descent algorithm to minimize the latency prediction error of their parents. In this way, each neural unit can learn what information about its represented operator type is relevant to the performance of the parent operator automatically, without expert human analysis. Because the training process does not push output data vectors to represent any pre-specified values, we refer to these values as opaque, as the exact semantics of the output data vector will likely vary significantly based on context, and may be difficult to interpret directly, as is generally the case with recurrent neural networks [26].

### 5.1 Training optimizations

The training overhead of our plan-structured neural network model can be significant due to the large number of operators that might appear in a query execution plan, and thus we wish to train multiple neural units in parallel. To address this challenge, we propose two optimizations over naive training methods. These techniques aim to improve the performance of computing the loss function of a plan-structured neural network (Equation 7) in the context of gradient descent. Section 5.1.1 explains how the loss function can be computed efficiently in a vectorized way. Section 5.1.2 notes that computing the loss function can be accelerated by exploiting the tree structure of a query execution plan.

#### 5.1.1 Batch training

Gradient descent minimizes a neural network’s loss function by tweaking each weight by a small amount based on the gradient of that weight (Equation 4). Ideally, the gradient of each weight should be evaluated over the whole training set. However, since neural networks are trained over very large datasets, naive implementations of gradient descent are space prohibitive. Furthermore, since real-world neural networks can have a significant number of weights, naive implementations of gradient descent which update each weight sequentially are time prohibitive.

To reduce space usage, modern differentiable programming frameworks [2, 39] preform training in batches. Instead of computing the gradient using the entire dataset (which cannot effectively fit into memory), simple random samples (called batches or mini-batches) are drawn from the data and used to estimate the gradient and adjust the weights. This widely-adopted technique is called stochastic gradient descent [44]. Since each sample is selected at random, the estimation of the gradient is unbiased [7].

To reduce the time required, modern neural network libraries take advantage of vectorization (i.e., applying mathematical operators to entire vectors simultaneously) to speed up their models. To do so, neural networks are assumed to be using a fixed architecture, e.g. an architecture that does not change based on the particular input. This is the case in many applications, such as computer vision. By assuming a fixed architecture, libraries can assume that the symbolic gradient of each weight will be identical for each item in the batch (i.e., the derivative of any weight can be computed using the same sequence of mathematical operations), and thus their computation can be vectorized.

Stochastic gradient descent and vectorization work very well for neural networks where the structure of the network does not change based on the inputs. However, these optimization poses a challenge for our proposed plan-structured neural network model: if two samples (i.e., query plan) in a batch have different tree structures, the symbolic derivative for a given weight will be varying depending on the input sample, and thus the sequence of mathematical operations needed to compute the derivative of two given weights can differ. Thus, vectorization cannot be directly applied.

One solution might be to group the training set into query execution plans with identical structure, and then use each

#### 5.1.2 Vectorization

Vectorization is the process of applying mathematical operations to entire vectors simultaneously, rather than on individual elements. This can be done by taking advantage of libraries that can automatically vectorize mathematical operators. However, this comes at a cost: vectorization increases the amount of memory required to store the data vectors.

To address this, we propose using a technique called batch training, which involves dividing the training set into smaller batches and computing the gradient for each batch separately. This reduces the amount of memory required to store the data vectors, but increases the number of gradient computations required.

Another technique is to use a technique called stochastic gradient descent, which involves randomly sampling a portion of the training set at each iteration. This reduces the amount of memory required to store the data vectors, but increases the variance of the gradient estimates.

Finally, we propose using a technique called lazy evaluation, which involves evaluating the data vectors only when they are needed. This reduces the amount of memory required to store the data vectors, but increases the time required to compute the gradient estimates.

These techniques can be combined to achieve a balance between memory usage and computation time. However, it is important to note that the optimal balance will depend on the specific application and the available resources.
This approach avoids biasing the gradient estimate while still gaining efficiency from batch processing.

5.1.2 Information sharing in subtrees. Let us assume that of type is the root operator of a query execution plan, and is the sole child of that operator. When computing the loss function of the query execution plan’s neural network, estimating the latency prediction error of the root, \((\hat{p}_c[l] - l(r))\) in Equation 7, requires us to compute the output vector of its child, \(\hat{p}_c\), as an intermediate value. This follows from the definition of \(\hat{p}_c\) in Equation 6, based on which \(\hat{p}_r = N_R(F(r) \sim \hat{p}_c)\). Since computing the loss function will also require computing \(\hat{p}_c\), i.e. in the term \((\hat{p}_c - l(c))\), we can avoid a significant redundant computation by caching the value of \(\hat{p}_c\) so that it only needs to be computed once.

More generally, for an arbitrary root \(r \in D\) of a query execution plan, we can compute the error of each neural unit in the plan’s neural network rooted at \(r\) in a bottom-up fashion: first, for each leaf node \(leaf\) in the tree rooted at \(r\), compute and store the output the neural units corresponding to the leaf nodes, \(p_{leaf}\). Then, compute and sum the \((p_{leaf}[l] - l(leaf))^2\) values, storing the result into a global accumulator variable. Once all the leaf nodes have been resolved in this way, repeat the process moving one level up the tree. When the root of the tree has been reached, the global accumulator value will contain the \((\hat{p}_c[l] - l(x))^2\) values for every operator \(x\) in the tree rooted at \(r\). The global accumulator contains the sum of the squared differences between the predicted latency and the actual latency for every node in the tree. Applying this technique over every plan-structured neural network in \(D\) can greatly accelerate the computation of our loss function as defined in Equation 7.

6 EXPERIMENTAL RESULTS

In this section, we describe the experimental study we conducted for our proposed plan-based neural network model. In all our experiments, our queries were executed on PostgreSQL [1] on a single node with an Intel Xeon CPU E5-2640 v4 processor, 32GB of RAM, and a solid-state drive.

Workload We conducted experiments using TPC-H [42], a decision support benchmark, and TPC-DS [36], a decision support benchmark with a focus on higher volumes of data and more complex queries. All TPC-H query templates were used but only seventy (70) TPC-DS query templates are compatible with PostgreSQL (without modification), hence we use only these templates for TPC-DS. For both benchmarks, 20,000 queries were executed with a scale factor of 100GB.

Each query was executed from a “cold cache” state (both the OS and PostgreSQL cache) in isolation (no multiprocessing). Execution times and execution plans were recorded using PostgreSQL’s EXPLAIN ANALYZE capability. The input features used for each neural unit are those that PostgreSQL makes available through the EXPLAIN command before a query is executed. See Appendix B for a listing.

Training data The queries were split into a training set and a testing set in two different ways. For the TPC-DS queries, all of the instances of 10 randomly selected query templates are “held out” of the training set (e.g., the neural network trains on 60 query templates, and the performance of the network is measured on 40 query templates, and the performance of the network is measured on the unseen 10 query templates). For the TPC-H data, since there are not enough query templates to use the same strategy, 10% of the queries, selected at random, are “held out” of the training set (e.g., the neural network trains on 90% of the data, and the performance of the network is measured on the other 10%).

Neural networks Unless otherwise stated, each neural unit had 5 hidden layers, each with 128 neurons each. The data output size was set to \(d = 32\). Rectified linear units (ReLUs [12]) were used as activation functions. Standard stochastic gradient descent (SGD) was used to train the network.
with a learning rate of 0.001 and a momentum of 0.9. Training was conducted over 1000 epochs (full passes over the training queries), which consistently produced the reported results. We used the PyTorch [39] library to implement the neural network, and we used its built-in SGD implementation.

**Evaluation techniques** We compare our plan-based neural network model (QPP Net) with three other latency prediction approaches:

1. **SVM-based models (SVM)**: We implemented the learning-based approach proposed in [4], the state-of-the-art in latency prediction for relational queries with no explicit human modeling. Here, a regression variant of SVM (Support Vector Machine) models are built for each operator while selective applications of plan-level models are used in situations where the operator-level models are likely to be inaccurate. In contrast to our approach, the set of input vectors for both the operator and plan level models are hand-picked through extensive experimentation.

2. **Resource-Based Features (RBF)**: We also implemented a predictive model that take as input the features proposed by [25]. Although these features are picked for predicting resource utilization of query operators and by extension query plans, resource usage can be a good indicator of query performance in non-concurrent query executions. Hence we modified the MART regression trees used in [25] to predict query latency. Similarly to the SVM approach, the input features of this model are hand-picked and not automatically engineered as in QPP Net. However, unlike the SVM approach, the RBF approach uses human-derived models for capturing operator interactions.

3. **Tuned Analytic Model (TAM)**: We also implemented a version of the tuned optimizer cost model model proposed in [13]. This approach uses the optimizer cost model estimate to predict query latency. First, some “calibration queries” are ran to determine the coefficients for the “calibrated cost model.” Then, this calibrated cost model is used to predict the query latency using the optimizer’s cardinality estimates as inputs. The TAM approach is thus entirely human-engineered, except for a sparse number of tuned parameters that are adjusted using special calibration queries.

**Evaluation metrics** To evaluate the prediction accuracy of these techniques, we use two metrics: **relative prediction error** and **mean absolute prediction error**. The relative prediction error has been used in [4, 25] and can be defined as follows. Letting \( Q \) be the set of test queries, letting \( \text{predicted}(q \in Q) \) be the predicted latency of \( q \), and letting \( \text{actual}(q \in Q) \) be the actual latency, the relative prediction error is:

\[
\frac{1}{|Q|} \sum_{q \in Q} \frac{\text{actual}(q) - \text{predicted}(q)}{\text{actual}(q)}
\]

However, the “relative error” metric has several known flaws [50]. Specifically, relative error systematically favors underestimates due to the asymmetry in the error function. No matter how bad an under-prediction is, the worst value the relative error can take on is 0. However, for over-predictions, the relative error is unbounded, hence the asymmetry. Because of the issues with relative error, we also report the mean absolute error, a standard metric for evaluating regression [41], which symmetrically penalizes under and over estimations:

\[
\frac{1}{|Q|} \sum_{q \in Q} |\text{actual}(q) - \text{predicted}(q)|
\]

A useful property of mean absolute error is that it shares the same units as the regression target. In our case, since we are predicting a quantity in units of time, the units of the mean absolute error are also time units.

We also report \( R(q) \), the maximum of the ratio between the actual and the predicted and the ratio between the predicted and the actual (not to be confused with the coefficient of determination):

\[
R(q) = \max \left( \frac{\text{actual}(q)}{\text{predicted}(q)}, \frac{\text{predicted}(q)}{\text{actual}(q)} \right)
\]

Intuitively, the \( R(q) \) value represents the “factor” by which a particular estimate was off. For example, if a model estimates a query’s \( q \) latency to be 2 minutes, but the latency of the query is actually 1 minute, the \( R(q) \) value would be 2, as the model was off by a factor of two. Similarly, if the model estimates a query’s latency to be 2 minutes, but the latency of the query is actually 4 minutes, the \( R(q) \) value would also be 2, as the model was again off by a factor of two.

### 6.1 Prediction Accuracy

The accuracy of each method at estimating the latency of queries in the TPC-H and TPC-DS workloads are shown in Figure 7a. The results reveal that our neural network approach outperforms the other baselines. The relative error improved by 9% (TPC-DS) and 5% (TPC-H) over RBF, by 25% (TPC-DS) and 24% (TPC-H) over SVM and by 28% (TPC-DS) and 21% (TPC-H) over TAM. In terms of absolute error, the average error decreased by 11 minutes (TPC-DS) and 7 minutes (TPC-H) from RBF, and by 18 minutes (TPC-DS) and 15 minutes (TPC-H) from SVM and 21 minutes (TPC-DS) and 13 minutes (TPC-H) from TAM.

The larger improvement seen in TPC-DS is due to two factors: (1) the fact that the average TPC-DS query plan has
more operators in it than the average TPC-H query plan (22 operators vs 18 operators), resulting in QPP Net being able to take advantage of a larger amount of training data, and (2), QPP Net is capable of learning the more complex interactions present in the TPC-DS workload effectively. Overall, the hand-picked features used by the other techniques fail to capture the complex interaction between operators, while our automatic features selection approach outperforms all human-crafted techniques, with more significant gains when the query workload is more complex.

6.1.1 Prediction distribution. We analyzed how frequently each model’s prediction was within a certain relative range of the correct latency. We report the percentage of the test set for which each model’s prediction was closer than a factor of 1.5 of the actual latency, between a factor of 1.5 and 2 of the actual latency, and greater than a factor of 2 from the actual latency. Tables 1a and 1b display the results for TPC-DS and TPC-H, respectively.

For both workloads, QPP Net has the best performance in terms of the proportion of the test set with an error factor less than 1.5. A high percentage of its predictions (89% for TPC-DS and 93% for TCP-H) are only within a factor of 1.5 of the actual latency, outperforming TAM by 38% (TPC-DS) and 15% (TPC-H), SVM by 21% (both TPC-H and TPC-DS) and RBF by 4% (TPC-DS) and 5% (TPC-H). The results indicate that our approach offers predictions closer to the real latency for a significantly higher number of queries.

### Table 1: Percentage of the test set where a particular model’s estimate was within a factor of 1.5 of the correct latency, within some factor between 1.5 and 2, and not within a factor of 2.

| Model     | $R \leq 1.5$ | $1.5 < R < 2.0$ | $2.0 \geq R$ |
|-----------|--------------|-----------------|--------------|
| QPP Net   | 89%          | 7%              | 4%           |
| TAM       | 51%          | 22%             | 27%          |
| SVM       | 68%          | 15%             | 17%          |
| RBF       | 85%          | 6%              | 9%           |

(a) TPC-DS

| Model     | $R \leq 1.5$ | $1.5 < R < 2.0$ | $2.0 \geq R$ |
|-----------|--------------|-----------------|--------------|
| QPP Net   | 93%          | 6%              | 1%           |
| TAM       | 78%          | 17%             | 5%           |
| SVM       | 72%          | 20%             | 8%           |
| RBF       | 88%          | 6%              | 6%           |

(b) TPC-H

We additionally plot the distribution of $R(g)$ values in Figure 7b, in the style of cumulative density function. Each plot shows the largest $R(g)$ value achieved for a given percentage of the test set. For example, on the left hand graph for the QPP Net line, at 0.93 on the x-axis, the y-axis value is "1.5". This signifies that QPP Net’s prediction was within at least a factor of 1.5 for 93% of the testing data. For both datasets, QPP Net’s curve has a smaller slope, and does not spike until it is much closer to 1 than the other curves. This means the our estimates are within a lower error factor for a larger portion of the testing queries compared with the other techniques.

6.1.2 Errors by query template. Figure 8 shows the mean absolute error of the queries in the test set grouped by the TPC-DS query template (note the log scale). For this experiment, we use a “hold one out” strategy: the model is trained using all but one of the query templates, and then the performance on the held-out query template is measured.

For each template, the mean absolute error of QPP Net is either lower or within 5% of the other models. Results for TPC-H are similar, but as TPC-H has far fewer templates, we omit the graph. We therefore conclude that QPP Net can accurately predict the latency of queries across a wide variety of query templates.

Generally, QPP Net’s performance greatly exceeds the other models on the query templates with the highest average latency (e.g. TPC-DS templates 6, 17, 81). A plot of the mean latency of each query template is provided in Appendix A. While the mean absolute error on these templates exceeds that of the other templates, the relative performance of QPP Net compared to the other models increases significantly. Thus, compared with other models, QPP Net performs especially well on long-running queries.
6.2 Training Overhead

In this section, we evaluate various properties and behaviors of the neural network model during training, including analyzing the effectiveness of our proposed optimizations.

**Optimizations** Here, we evaluate the two training optimizations introduced in Section 5: (a) information sharing, caching and reusing computations that are shared by multiple nodes, and (b) batch sampling, grouping trees with similar structures into batches in order to take advantage of vector processing.

We evaluated these optimizations by training the neural network until the network converged to the best-observed accuracy. We trained the network with no optimizations, the batching optimization alone, the information sharing optimization alone, and with both optimizations. Figure 9a shows the results for both datasets. Without either optimization, training the neural network for either dataset takes well over a week. The new optimizations, information sharing is the more significant in these experiments, bringing the training time down from over a week to a little under 3 days. Both optimizations combined bring the training down to only slightly over 24 hours.

We also measured the memory usage of the information sharing approach, which requires additional space to cache results. The size of the cache was minuscule in comparison to the size of the neural network’s weights, with the cache size never exceeding 20MB. We conclude that both the information sharing and batch sampling optimizations are worthwhile for accelerating the time needed to train the neural network.

**Training convergence** Next, we investigate the performance of the model over time during training. After each training epoch (a full pass over the training queries), we evaluated and recorded the mean absolute error across the test set. The results for TPC-H are shown in Figure 9b, and the results for TPC-DS are shown in Figure 9c. On both plots, the blue, green and red lines show the performance of TAM, SVM, and RBF, respectively. While the neural network model did not converge until epoch 1000 (approximately 28 hours for both datasets), the performance of the neural network begins to exceed the performance of SVM at around epoch 250 (7 hours) with TPC-H, or after 150 epochs (4.5 hours) for TPC-DS. The neural network begins to exceed the performance of RBF after around 350 epochs (10 hours) for TPC-H, or after 250 epochs for TPC-DS (7 hours). We conclude that the training overhead required for QPP Net to achieve competitive performance is reasonable for a variety of datasets.

Both Figure 9b and Figure 9c show the classic, inverse-exponential behavior of neural networks during training. At the start of the training, the neural network decreases its mean absolute error by 20 in just 100 epochs (epochs 0 through 100). However, later in the training, it takes 100 epochs to decrease the mean absolute error by just 2 (epochs 400 through 500). Thus, each additional epoch returns smaller and smaller benefits, requiring a large number of additional epochs to get small gains towards the end of training.

It is possible that using other optimization methods besides stochastic gradient descent, such as Adam [16], might speed up training. We leave such experiments to future work.

6.3 Network architecture

For all of the experiments so far, we have used 5 hidden layers each with 128 neurons for each neural unit. While a 5 layer, 128 neuron network would be considered rather small by modern standards, one needs to consider that in our model, each neural unit in the plan-based neural network has these dimensions. When assembled together into a tree, the network is much larger (one to two orders of magnitude). However, choosing the number of hidden layers and number of neurons is a difficult task. While there is no theoretically-best number of hidden layers or number of neurons per layer, good values can be found experimentally. Intuitively, “deeper” (i.e., more hidden layers) architectures enable more feature engineering, as additional layers add additional transformations of the inputs [20]. On the other hand, “taller” (i.e., larger hidden layers) architectures allow each feature transformation to be richer, as they have more weights and thus carry more data [46].

We analyze four of the variables at play when trying to find the correct network configuration: the number of hidden layers, the number of neurons, the maximum accuracy the network can reach, and the time it takes to train the network.
Figure 9: Training overhead results

Figure 10: Effect of the number of neurons on accuracy (relative to 128 neurons) and training time.

Figure 11: Effect of the number of hidden layers on accuracy (relative to 5 hidden layers) and training time.

Generally, increasing either the number of hidden layers or the number or neurons results in an increase in training time due to an increase in the number of weights. Thus, setting the number of neurons or number of hidden layers too high will result in unacceptably long training times. But, if the number of neurons or hidden layers is set too low, the network might not have enough weights to learn the underlying data distribution well enough. We thus seek the number of neurons and hidden layers that will minimize training time while still giving peak or near-peak accuracy.

Varying the number of neurons Figure 10 shows the training time and relative accuracy when varying the number of neurons inside each of the five hidden layers. With an extremely small number of neurons (8 neurons), training time is low (6 hours), but accuracy is extremely poor; QPP Net achieves less than 15% of the accuracy that the 128-neuron network does. On the other hand, using an extremely large number of neurons causes the training time to skyrocket: with 1024 neurons per hidden layer, training time is nearly four times what is required for the 128 neuron network, with only a tiny increase in accuracy (less than 1%).

One may notice that the training time seems to grow with the log of the number of neurons at first, but then eventually becomes linear. This is because neural networks are trained on GPUs equipped with highly-parallel vector processing units. There is thus sublinear increases in training time until there is approximately one weight per vector processing core, after which the training time changes as expected. When the number of neurons greatly exceeds the capacity of the GPU, the slowdown will become worse than linear.

Varying the number of hidden layers Figure 11 shows a similar experiment, this time varying the number of hidden layers and keeping the number of neurons fixed at 128. Note that connecting two layers with 128 neurons to each other requires a matrix of size $128 \times 128$, so each additional hidden layer adds on the order of $2^{14}$ additional weights.

Increasing the number of hidden layers has a similar behavior to increasing the number of neurons: initially, each...
increase brings about a small increase in training time but a large jump in accuracy. Eventually, adding another hidden layer produces a much larger jump in training time and a much smaller jump in accuracy. From Figure 11, we can conclude that adding more than 5 hidden layers, at least when the size of each hidden layer is 128 neurons, does not bring about much benefit.

7 RELATED WORK

Query performance prediction There exist a number of approaches that leverage machine learning and statistical analysis to address the problem of query performance prediction. We already discussed and compared with [4, 13, 25] in our experimental study. [11] focuses on predicting multiple query resource usage metrics simultaneously (but not execution times). Both [38, 59] predict statistics about queries in XML databases. [56] demonstrating that optimizer cost models can be used to predict query performance if one is willing to sample a percentage of the underlying data.

All these techniques suffer from similar drawbacks: first, they require human experts to analyze the properties of an operator or query execution plan and determine how they should be transformed into features for a machine learning algorithm, whereas our deep-learning approach requires no such feature engineering. Second, while some of these approaches model plans, operators, or a combination thereof, none of them learn the interactions between various combinations of operators, as the approach presented here does.

A number of techniques [9, 10, 54] extend to concurrent query performance prediction for analytical queries. These techniques assume a-priori knowledge of query templates [10], query structure [54] and/or require extensive offline training on representative queries [9]. Furthermore, their proposed input features, metrics and models are hand-tuned to handle only analytical tasks, which make them less applicable to diverse workloads.

Cardinality estimation Works on cardinality estimation are fundamentally related to query performance prediction, as an operator’s cardinality often correlates with its latency. Techniques for cardinality estimation include robust statistical techniques [5, 19, 32], adaptive histograms [3, 47], and deep learning [17, 27]. While query cardinalities are certainly an indicator of latency, translating even an accurate cardinality estimate for each operator in a query execution plan to a total plan latency is by no means a trivial task. However, a technique predicting operator cardinalities could be easily integrated into our deep neural network by inserting the cardinality estimate of each operator into its neural units input vector. The neural network could then learn the relationship between these estimates and the latency of the entire query execution plan.

Progress estimators Work on query progress indicators [21, 24, 29, 33, 57] essentially amounts to frequently updating a prediction of a query’s latency. These approaches estimate the latency of a query as it is running, and the estimate that these techniques make at the very start of the query’s execution may be quite inaccurate, but are quickly refined and corrected during the early stages of a query’s progress. This greatly limits their applicability for ahead-of-time query performance prediction, and thus we do not compare against any of these techniques directly.

Deep learning We are not the first to apply deep learning to database management problems. Deep learning has seen a recent groundswell of activity in the systems community [55], including several works on query optimization [30, 37], entity matching [35], index selection [40, 45], indexes themselves [18], and cardinality estimation [17, 27].

8 CONCLUSIONS AND FUTURE WORK

We have introduce a novel neural network architecture designed specifically to address the challenges of query performance prediction. The architecture allows for plan-structured neural networks (networks that predict the execution time of a given query plan) to be constructed by assembling operator-level neural units (neural networks that predict the latency of a given operator) to form a tree-based structure that matches the structure of the query plan generated by the optimizer. We motivated the need for this novel model, described its architecture and have shown how the model can be effectively trained through two optimizations. Experimental results demonstrate that our approach outperforms state-of-the-art solutions, with manageable training overhead.

Future work could advance in a number of directions. For example, the neural network architecture presented here could be adapted to handle concurrent queries. Doing so would require understanding the resource usage requirements of the two queries, and whether or not two queries will have to compete for resources. Furthermore, the neural network architecture presented here was used to predict the performance of queries executed on a bare-metal server. However, in a cloud environment, performance can vary greatly based on the time of day, or seemingly randomly. Techniques to capture the relative performance of the system (e.g., monitoring I/O rates, CPU cycles, etc.), and ways of making the neural network model aware of performance fluctuations, could be investigated. Improvements to the training time of neural network could be investigated. For example, using a different optimizer [16] or taking advantage of transfer learning techniques [6, 58] may prove fruitful.
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A TPC-DS TEMPLATE LATENCY
Figure 12 shows the mean latency for each of the TPC-DS query templates.

B FEATURES
Table 2 describes the values used as inputs for our neural units. The first column lists the name of the quantity. The second column describes which PostgreSQL operators use a particular type of input. The third column describes how
the particular value is encoded into an input suitable for a neural network. The encoding strategies are:

- **Numeric**: the value is encoded as a numeric value, scaled so that the mean of the value across the training set is zero and the variance is one. At inference time, the same scaling values are used. This is known as “whitening”, and is a standard practice in deep learning [39].
- **Boolean**: the value is encoded as either a zero or a one.
- **One-hot**: the value is categorical, and is encoded as a one-hot vector, e.g. a vector with a single “1” element where the rest of the elements are “0”.

The first five values, in the first section of the table, represent information that is available for every PostgreSQL operator. Thus, these values are included in all neural units. The next section of the table (“Join Type” to “Sort Method”), corresponds to information used by the join neural unit. The third section (“Relation Name” to “Scan Direction”) refers to the inputs used for the scan neural unit, and, depending on the selected physical operator type (e.g., index scan, table scan), some values may be missing. Missing values are set to zero. The final section of the table (“Strategy” to “Operator”) lists the inputs used for the aggregate neural unit.

| Feature                  | PostgreSQL operators | Encoding | Description                                           |
|--------------------------|-----------------------|----------|-------------------------------------------------------|
| Plan Width               | All                   | Numeric  | Optimizer’s estimate of the width of each output row  |
| Plan Rows                | All                   | Numeric  | Optimizer’s estimate of the cardinality of the output of the operator |
| Plan Buffers             | All                   | Numeric  | Optimizer’s estimate of the memory requirements of an operator |
| Estimated I/Os           | All                   | Numeric  | Optimizer’s estimate of the number of I/Os performed  |
| Total Cost               | All                   | Numeric  | Optimizer’s cost estimate for this operator, plus the subtree |
| Join Type                | Joins                | One-hot  | One of: semi, inner, anti, full                       |
| Parent Relationship      | Joins                | One-hot  | When the child of a join. One of: inner, outer, subquery |
| Hash Buckets             | Hash                 | Numeric  | # hash buckets for hashing                             |
| Hash Algorithm           | Hash                 | One-hot  | Hashing algorithm used                                |
| Sort Key                 | Sort                 | One-hot  | Key for sort operator                                 |
| Sort Method              | Sort                 | One-hot  | Sorting algorithm, e.g. “quicksort”, “top-N heapsort”, “external sort” |
| Relation Name            | All Scans            | One-hot  | Base relation of the leaf                             |
| Attribute Mins           | All Scans            | Numeric  | Vector of minimum values for relevant attributes      |
| Attribute Medians        | All Scans            | Numeric  | Vector of median values for relevant attributes       |
| Attribute Maxs           | All Scans            | Numeric  | Vector of maximum values for relevant attributes      |
| Index Name               | Index Scans          | One-hot  | Name of index                                         |
| Scan Direction           | Index Scans          | Boolean  | Direction to read the index (forward or backwards)    |
| Strategy                 | Aggregates           | One-hot  | One of: plain, sorted, hashed                         |
| Partial Mode             | Aggregate            | Boolean  | Eligible to participate in parallel aggregation       |
| Operator                 | Aggregate            | One-hot  | The aggregation to perform, e.g. max, min, avg        |

Table 2: QPP Net Inputs