Learned Indexes for Dynamic Workloads

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Abstract
The recent proposal of learned index structures opens up a new perspective on how traditional range indexes can be optimized. However, the current learned indexes assume the data distribution is relatively static and the access pattern is uniform, while real-world scenarios consist of skew query distribution and evolving data. In this paper, we demonstrate that the missing consideration of access patterns and dynamic data distribution notably hinders the applicability of learned indexes. To this end, we propose solutions for learned indexes for dynamic workloads (called Doraemon). To improve the latency for skew queries, Doraemon augments the training data with access frequencies. To address the slow model re-training when data distribution shifts, Doraemon caches the previously-trained models and incrementally fine-tunes them for similar access patterns and data distribution. Our preliminary result shows that, Doraemon improves the query latency by 45.1% and reduces the model re-training time to 1/20.

1 Introduction
The pioneer study [27] on learned index structures arouses a lot of excitement around how machine learning can resculpt system components that have been decades-old, such as bloom filters [39], join queries [28] or even enable self-tuning databases [26].

The core insight of learned indexes is to view index as a distribution function from the keys to the index positions that can be approximated by deep neural networks. Nevertheless, their preliminary study assumes a relatively static distribution function, while in many real-world scenarios, the data is constantly evolving [12].

Typical approaches simply rely on re-training the whole model once the data distribution shifts notably from the training set used by the current model. However, such re-training is costly, because not only the model parameters need to be fine-tuned, but also that the model architecture needs to be searched again for better accuracy. Depending on the size of the hyperparameter search space, a basic architecture search technique such as grid search can easily take up to 10-100x the model training time [4, 31, 6].

Besides the inefficiency in handling dynamic workloads, the learned index paper also assumes a uniform access pattern (or query distribution). However, queries in real worlds tend to be skew, where some keys are much more frequently queried than the others [57, 14, 17, 33]. As a result, mispredicting a hot key is way more expensive, and we show that the originally proposed learned index model performs poorly under such scenarios. These two issues hinder the wider adoption of the learned indexes for real-world workloads.

In this paper, we propose Doraemon, a new learned index system for dynamic workloads where the data distribution and access pattern may be skew and evolving. To handle skewed access pattern, we first investigate and discuss why the original model fails to address this issue and then propose an approach that augments the training data with access frequencies. For the issue of model retraining, our insight is that the same model architecture can be reused for similar data distribution and access pattern. Based on this, Doraemon caches the trained models and simply fine-tunes them when a similar input distribution is encountered again. The preliminary result shows that, by augmenting dataset with the access frequency, the best model architecture has 45.1% performance improvement; by caching and reusing previous training result, the rebuilding time is reduced to 1/20 (from 40 mins to 2 mins).

2 Learned Indexes
In this section, we introduce the basic background of the original learned index structures [27]. The insight is that indexes can be viewed as functions from the data (key) to the values representing either record positions in a sorted array (for range index), in an unsorted array (for Hash-Index) or whether the data exists or not (for BitMap-Index). For the case of range index, the function
is effectively a cumulative distribution function (CDF). Given the CDF \( F \), the positions can be predicted by:

\[
p = F(\text{Key}) \times N
\]

where \( p \) is the position of the key and \( N \) is the total number of keys (see Figure 1 for examples).

The core idea is to approximate the CDF function \( F \) by machine learning models such as deep neural networks. While the choice of the model architectures can vary, the paper proposes a staged model architecture inspired by the multi-stage structure of B-Tree. The sub-model at each stage predicts which sub-models to be activated in the next stage while the leaf stage directly predicts the CDF values. The model is trained from the root stage to the leaf stage, and each stage is trained separately using the following loss function:

\[
L_l = \sum_{(x,y)} (f_l^i(M_lf_{l-1}(x)/N)) (x - y)^2 ; L_0 = \sum_{(x,y)} (f_0(x) - y)^2
\]

Here, \((x, y)\) is the key/position pair from the data to be indexed; \( L_l \) is the loss function of stage \( l \); \( f_{l-1}^j \) is the \( k^{th} \) sub-model of stage \( l \). \( f_{l-1}^j \) recursively executes the above equation until the root stage \( L_0 \).

To deploy the learned index, the approximation error needs to be corrected. First, the prediction error can be bounded by looking at the maximum distance \( \sigma \) between the predicted and the true positions for each key. Hence, if \( \text{pos} \) is the predicted position by the learned index, the true position is guaranteed to be within \([\text{pos} - \sigma, \text{pos} + \sigma]\), and a binary search can be used. The error bound \( \sigma \) is thus a critical indicator of the effectiveness of the learned index. The smaller \( \sigma \) is, the more effective is the index.

There are several limitations of the original learned index. First, the CDF should be relatively static. Otherwise, the model needs to be re-trained for better approximations. Since insertion and deletion are very common, learned indexes can be quite slow due to the high cost of re-training. Second, the model assumes all the keys are being uniformly queried, while in reality, the prediction error of a hotter key has much more impact on the overall performance.

We explain how Doraemon addresses these issues in the following sections. Section 3 investigates quantitatively how learned indexes perform under different access patterns (Sec 3.1) and data distribution (Sec 3.2). We then propose our solutions in section (Sec 4) using data augmentation (Sec 4.1) and model caching (Sec 4.2). We also discuss other components in our system (Sec 4.3) and related works (Sec 5).

### 3 Challenges with Dynamic Workloads

In this section, we will discuss the challenges posed by dynamic workloads with a simple example of 2 stages learned index. We found that the choice of model architecture is affected by both query distribution and data distribution.

Table 1 compares three different model architectures with different datasets and workloads. Each dataset has 200M integer keys, but with different distributions as shown in Figure 1. The uniform workload evenly reads every key. The skewed workloads have 95% queries reading 5% hot keys, but in different ranges. All three architectures have 200k linear models at the second stage and only their first stages are different.

Table 1: The best model architecture and the corresponding average search time (in ns) with different datasets and workloads.

| Dataset | Skewed 1 | Skewed 2 | Skewed 3 | Uniform  |
|---------|----------|----------|----------|----------|
|         | Arch     | Time(ns) | Arch     | Time(ns) |
| D1      | NN16     | 321      | LIN      | 252      | NN16     | 282      |
| D2      | NN8      | 319      | LIN      | 316      | NN8      | 301      |
| D3      | LIN      | 293      | LIN      | 281      | LIN      | 278      |
| D4      | NN8      | 314      | LIN      | 289      | LIN      | 288      |
|         | NN16     | 375      | LIN      | 344      | NN16     | 350      |

Figure 1: Above figures show the CDF of dataset D1, D2, D3 and D4. The y-axis is the normalized CDF for each dataset. The x-axis indicates the key space where key generated from.
LIN: The first stage is a linear regression model.

• NN8: The first stage is a one hidden layer 8-width Neural Network (NN)

• NN16: The first stage is a one hidden layer 16-width Neural Network (NN)

There is an interesting observation based on the results. By shifting either the workload or the dataset, the best architecture is undecidable. For example, for the first row in Table 1, LIN is the best with workload Skewed 2, but even worse than B-Tree with workload Skewed 1 (1120 vs. 396 ns). Next, we will discuss the reasons behind such a phenomenon.

3.1 The Query Distribution

Querying a key with learned index has two steps: first, it predicts the position by model computation; Second, it tries to find the actual position using binary search in a bounded range. However, its latency usually depends on the binary search, as it takes much longer time than model computation, (6/7–25/26) in our evaluation. Further, the search area is decided by the error bound \(1\) of the last stage model who has the key. Thus, we have the following observation.

A skew workload’s performance is dominated by the hot models’ error bound. Hot model is defined as the last stage model who holds a hot (frequently accessed) key. Given a workload, all models’ error bounds can vary across different model architectures, including the hot models’. As a result, the best architecture varies for the workloads with different query distributions. Figure 2 shows the error bound (y-axis) of the model where the key (x-axis) is located. Two lines represent two architectures, LIN and NN16, trained with dataset of D1. For the average error bound, NN16’s is smaller than LIN’s (5.32 vs. 6.58). Thus, with uniform workload, NN16 has better performance than LIN (375 vs. 406 ns). However, for the key range from \(3.5 \times 10^8\) to \(4.6 \times 10^8\), LIN’s average error bound is smaller than NN16’s (4.56 vs. 4.86). As a result, LIN has better performance than NN16 (252 vs. 310 ns) with workload Skewed 2.

3.2 The Data Distribution

An advantage of using complex models (e.g., neural networks) at the first stage is that it can approximate the complex distribution which cannot be fitted with linear model. As a result, for those distributions, the complex network is able to dispatch the data more evenly than simple models, which is good for the uniform workload. For example, NN16 is better than both NN8 and LIN (375 vs. 390 vs. 406 ns) for D1 with the uniform workload, as it can approximate the D1 (Figure 1.a) more precisely.

Complex model is good for the complex distribution, but not always. This is because of the computation cost of complex models. Figure 3 shows that with the first stage model getting more complex, even though the binary search time decreases, but the model computation time increases. Because of this tradeoff, for D3 that exhibits relatively complex distribution (Figure 1.c), LIN has better performance than NN16 (367 vs. 350 ns) — NN16 has better performance than LIN at the binary search (317 vs. 336 ns), but it is also penalized by the higher computation cost (50 vs. 14 ns).

4 Proposed Solution

To achieve learned indexes’ best performance, we propose a new learned index system for dynamic workloads called Doraemon (Figure 4). Doraemon incorporates read access pattern using the Training Set Generator and the Finalizer and reuses pre-trained models using the Counselor.

4.1 Incorporate Read Access Pattern

To incorporate read access pattern, an intuitive solution is to increase the contribution of frequently accessed keys during the training process. This can be achieved by creating multiple copies of those keys in the training set. For
example, considering a training set of \{(a, 0), (b, 1), (c, 2)\}, where the first element is the key and the second is its position. If the accessed ratio is 1:2:1, then we double \(b\) in the training set, which becomes \{(a, 0), (b, 1), (b, 1), (c, 2)\}. In this way, the model will be trained with (b, 1) two times more than others, the prediction accuracy of \(b\) can be improved. We evaluate this intuitive solution with the workload of Skewed 3 and the dataset D1. With the new training set, the best architecture we can find is NN16 with 275 ns average search time, which is close to the previous best architecture, 282 ns. This is because the intuitive solution does not improve the error bounds of the second stage models which decide the search time. In the above evaluation, the average error bound does not improve much (5.21 vs. 5.31).

“Stretch” the dataset. Instead of improving the prediction accuracy of the hot keys, we should focus on the error bounds of the models containing the hot keys (hot models). Since the models assigned with few keys tend to have small error bounds, we try to reduce the number of keys handled by the hot models by “stretching” the dataset. If a key is frequently accessed, we would like to increase the distance between it with its neighbors, the key before or after it. It can be achieved by simply shifting the position labels. Specifically, given a key with position \(p\) before “stretching”, if its access frequency is \(f_i\) and the dataset size is \(N\) then we need to shift its position to be \(p + (n - 1)/2\), and shift all keys after it with \(n - 1\). For the above example, the training set of \{(a, 0), (b, 1), (c, 2)\} with access frequency 1:2:1 will be augmented to \{(a, 0), (b, 1.5), (c, 3)\}. Figure 5 shows the CDF of dataset 1 before and after “stretching” with the access pattern in workload Skewed 3.

Training Set Generator takes the workload and dataset as input, extracts the access pattern by uniformly sampling from the workload and stretches the dataset according to the access pattern. Then it sends the stretched training set to Counselor to get a tuned model.

Before using the returned model from Counselor, the Finalizer needs to retrain the last stage models with the original dataset. This is because the position of each key in the stretched training set is changed, we need to repair the position information with the original dataset. This process is considerably fast as last models are usually linear models. For example, it only takes 118 \(\mu s\) to retrain one last model with 1000 keys.

4.2 Reuse Pre-trained Models

After incorporating the access pattern, the only factor affecting the model architecture is data distribution. We notice that the best model architecture tends to be the same for similar data distributions. As a result, DoraeMon is able to cache a mapping from data distributions to models for future reusing.

This is done by the Counselor component, which includes four modules:

Analyzer: extracts distribution information by uniformly sampling \(K\) records from the generated training set, then normalize both key and position to \([0, 1]\). However, \(K\) needs to be large enough to avoid breaking the distribution.

Model cache: maintains a mapping from the distribution of previous training set to their learning model’s architecture and parameters. If it receives a distribution from Analyzer, it will finds the entry in the map with the most similar distribution based on the mean square error. Then, it will send the model’s information in that entry to Fine Tuner. Furthermore, if the similarity is below a threshold, it will also start the auto-tuning process.

Fine Tuner: incrementally trains the model retrieved from the model cache with the training set.

Auto-tuner: uses grid search to find the best model architecture in the given search space. It performs auto-tuning at the background and sends the result to the Fi-
nalizer component.

4.3 Discussion

Detecting the change of distribution and access pattern. Doraemon will start to run on detecting the change of distribution or access pattern. The detection must be timely with few false positive. For currently design, we simply detect this by monitoring the degradation of the performance. However, we can use similar technique in [24] to improve the accuracy.

Extract the distribution feature from a dataset. Currently, we simply extract the distribution by uniformly sampling the dataset. However, to avoid breaking the distribution, the sample rate varies across different dataset. As a result, it is challengen to decide the sample rate.

Compute the similarity. Our sampled distribution representation can be regarded as a type of sequential data, for which there are many machine learning models are targeting [18] [11]. We believe we can further leverage learning to learn a better similarity metric.

Efficiently find the similar distribution in Model Cache. There can be thousands to millions entries in the Model Cache. As a result, finding the entry with most similar distribution is considerably cost. To solve this issue, we plan to use methods like [38] [22] to first filter out the most relevant entries before the comparison.

Improve Auto-tuner efficiency. Grid search is slow. To speed up the search, there are works that use Gaussian process to optimize the search process [50] [6] [8]. Similar ideas are also used in database system optimization [16] [51].

5 Related Works

Data Augmentation: Augmenting training data is a common technique in machine learning to avoid over-fitting and improve generalizability. Many researchers have been conducting including generating samples through transformation [11], distortion [49] [54], oversampling [9] and from minority class to deal with data imbalance [29] [20] [3]. As a contrast, the goal of our data augmentation is not to improve generalizability, but to guide the model to overfit more on keys of high frequency.

Automatic Machine Learning (AutoML): Despite the success of machine learning, designing models is still a time-consuming task and require domain expertise. To ease the problem, many works have been focusing on automatic design and tuning ML models. Automatic hyperparameter tuning reduces the tuning efforts by means of grid search [4] [31] [6], random search [5] [6], Bayesian optimization [50] [8], etc. The search time is usually proportional to the number of combinations of the hyperparameters to be explored. Neural Architec-

ture Search (NAS) [47] [2] [60] [34] [59] [61] [41] [62] [35] are more recent attempts to design neural network architectures automatically using model-based optimization strategies such as deep reinforcement learning or progressive search. These methods usually require tons of computation resources, making it hard to be deployed in resource-critical scenarios like index lookup directly.

Despite the resource concerns, it is still an open question for AutoML to handle dynamically-changing data distribution [21]. As a result, in Doraemon, we combine AutoML with the Model Cache to avoid the costly search for similar data distribution.

Indexes in Databases Indexing is a fundamental component of real-world databases. Some indexes use hybrid design to serve hot keys and cold keys respectively by using different data structures, using different storage, and compressing the cold data [57] [14] [17] [33]. Widely used trie-based indexes [12] [50] usually work the best with near uniform data distribution. To adapt them to less ideal data distributions, Leis et al. use dynamic fanout to optimize trie height [32]. Morrison et al. remove unnecessary nodes [40], and Binna et al. aggregate nodes to form a more balanced structure [7].

Transfer Learning: Transferring machine learning models learned from one task to another different but related task is an active research direction [45] [13] [44]. Common practice includes reusing learned representations from pre-trained models and fine-tuning from old weights [48] [55] [15] [42]. In Doraemon, models are fine-tuned from the weights obtained from the similar data distribution, which is easier than transferring models trained from another distribution.

Data-driven optimizations for system: Many system optimizations can be approached by machine learning models trained from historical data. In the area of database, examples include cardinality estimation [30] [25] [53] [46], join order planning [28] [57] [43] and configuration tuning [52]. Besides database, works have been done to improve buffer management systems [10], sorting algorithms [53], memory page prefetching [19] [56] and memory controller [25] and scheduling [26]. Many of these scenarios face similar challenges of dealing with shifting data distribution, which could be other applications of our model caching mechanism.

6 Conclusion

This paper proposes a system which can incorporate the query distribution in the training set to improve the query performance, and reuse the pre-trained model to reduce the re-trained cost.

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