Automatic Tuning of Tensorflow’s CPU Backend using Gradient-Free Optimization Algorithms

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Abstract. Modern deep learning (DL) applications are built using DL libraries and frameworks such as TensorFlow and PyTorch. These frameworks have complex parameters and tuning them to obtain good training and inference performance is challenging for typical users, such as DL developers and data scientists. Manual tuning requires deep knowledge of the user-controllable parameters of DL frameworks as well as the underlying hardware. It is a slow and tedious process, and it typically delivers sub-optimal solutions. In this paper, we treat the problem of tuning parameters of DL frameworks to improve training and inference performance as a black-box optimization problem. We then investigate applicability and effectiveness of Bayesian optimization (BO), genetic algorithm (GA), and Nelder-Mead simplex (NMS) to tune the parameters of TensorFlow’s CPU backend. While prior work has already investigated the use of Nelder-Mead simplex for a similar problem, it does not provide insights into the applicability of other more popular algorithms. Towards that end, we provide a systematic comparative analysis of all three algorithms in tuning TensorFlow’s CPU backend on a variety of DL models. Our findings reveal that Bayesian optimization performs the best on the majority of models. There are, however, cases where it does not deliver the best results.

Keywords: Deep learning · gradient-free optimizations · Gaussian process · auto-tuning

1 Introduction

In recent years, deep learning has gained significant momentum in academic research as well as in production to solve real-world problems. For example, deep learning applications in the areas of speech recognition (e.g., Amazon Alexa, Apple Siri, Google Assistant, etc.), language translation (e.g., Google Translate),
and recommendation systems (e.g., Netflix movie recommendations, Amazon product recommendations, etc.) are already part of everyday life. Interest in deep learning is fueled by the vast availability of both open-source and proprietary data as well as by the continuous development of heterogeneous computing platforms (e.g., CPU, GPU, TPU, etc.) and cloud resources (e.g., Amazon AWS, Google Cloud, Microsoft Azure, etc.) to process that data.

The availability of open-source deep learning software frameworks, such as PyTorch [11] and TensorFlow [1], along with the suites of neural network models [15] enables fast deployment of deep learning models. Although deep learning frameworks are relatively new software systems, they essentially employ software designs that are similar to other existing software systems, particularly compilers. Deep learning frameworks accept models written in high-level languages such as Python. Similar to the compilers for high-level languages, these models are either interpreted directly (as for Python itself) or converted (“lowered”, in compilers parlance, such as for C and C++ languages) into a low-level data-flow graph that is later executed. Before the models are executed, the framework runtime schedules the computations from their data-flow graphs onto the backends for the hardware devices [1]. Consequently, the training or inference performance of a deep learning model partly depends upon runtime’s scheduling decisions.

TensorFlow’s default CPU backend is implemented using an open-source library named Eigen [3]. TensorFlow’s Eigen CPU backend enables efficient execution on multicore CPUs by offering a configurable threading model to exploit the concurrency that is typically present in TensorFlow’s data-flow graphs. Specifically, vertices in TensorFlow’s data-flow graphs represent computations, and they can have data dependencies (i.e., input edges from other vertices) and control dependencies (i.e., a scheduling constraint specified by the user or TensorFlow framework). The Eigen CPU backend relies on PThreads library for multi-threading, and its threading model offers two configurable parameters: (i) \texttt{inter\_op\_parallelism\_threads}: the maximum number of independent computations to execute in parallel, and (ii) \texttt{intra\_op\_parallelism\_threads}: the maximum number of threads to use for executing a single computation. Unfortunately, the Eigen CPU backend has shown sub-optimal performance on several Intel Xeon CPU platforms [5, 10]. Consequently, Intel contributes with its own CPU backend to TensorFlow [17] that delivers orders of magnitude of performance improvement over the Eigen CPU backend. Intel’s CPU backend uses the OpenMP [9] library for multi-threading and adds another configurable parameter to TensorFlow’s threading model: (iii) \texttt{OMP\_NUM\_THREADS}: the number of OpenMP threads to use for executing a single computation with Intel’s backend.

TensorFlow’s configurable CPU threading model enables end-users to improve performance of their models by tuning TensorFlow to the target hardware. As mentioned in TensorFlow’s “Binary Configuration” section [14], a savvy user can tune the model by finding values of \texttt{inter\_op\_parallelism\_threads} and \texttt{intra\_op\_parallelism\_threads} by “finding the right configuration for their specific workload and environment”. The guide, however, does not discuss how to find the right configuration in practice. Unfortunately, it is unrealistic to expect
that a deep learning application developer or a data scientist would know the optimal parameter configurations as these configurations are intimately related to detailed knowledge of the framework and the underlying hardware. Considering this limitation, Intel provides specific configurations \cite{19} for popular deep learning models, such as ResNet50, on commonly-used Intel Xeon platforms, such as the latest generation Intel Xeon CPUs (codenamed IceLake). However, any deviation from this standard setup, for example with a new model or a new hardware platform, could mean that the provided settings may not deliver the optimal performance. The alternative of relying on the default values of the parameters can be acceptable in some situations such as early prototyping. However, they usually deliver sub-optimal performance \cite{5}.

A common approach to search for the optimal configuration is manual search. Manual search, however, is a tedious activity, leading to sampling only a few configurations, and it also relies on the expertise of the user. A naive approach of exhaustive search is feasible for small search spaces, but becomes unfeasible as the search time grows exponentially in the number of parameters. For instance, in our experiments, the exhaustive search run for the optimal configuration of TensorFlow’s threading model for ResNet50 inference took close to a month of CPU time on a multi-core Intel Xeon platform. The search space consisted of roughly 50000 points. While this could be acceptable in research and development settings, it would not be acceptable in production environments.

Hasabnis \cite{5} offers an excellent description of the problem and an auto-tuning solution, called TensorTuner, to configure TensorFlow’s threading model for CPU backend. Specifically, TensorTuner uses a black-box optimization algorithm named Nelder-Mead simplex. This solution addresses both the issues described earlier: obtaining the best performance and systematically configuring the parameters of the threading model. Nelder-Mead simplex, however, is a local optimization algorithm. And popular global optimization algorithms, such as Bayesian optimization and genetic algorithm, have been demonstrated to perform successfully in system tuning tasks \cite{8}. Hasabnis does not consider these alternatives and leaves the open question of the best algorithm for this problem.

In this paper, we analyze the effectiveness of Bayesian optimization, genetic algorithm, and Nelder-Mead simplex to tune TensorFlow’s threading model for various deep learning models. Unlike TensorTuner that focuses solely on deep learning models from image recognition domain, we consider models belonging to a variety of domains. Furthermore, we also consider a larger set of performance-sensitive parameters by considering batch size and KMP_BLOCKTIME, which are not considered by TensorTuner. Finally, we perform detailed comparative analysis of the performance of all three algorithms and discuss our findings.

1.1 Contributions

In this paper we make following contributions:

1. We evaluate and compare the effectiveness of Bayesian optimization, genetic algorithm, and Nelder-Mead simplex to automatically tune performance-critical parameters of TensorFlow’s Intel-CPU backend.
2. We consider several deep learning models, written for a variety of use cases such as image recognition, language translation, etc. Prior work for this problem has focused on the models used in image recognition only.

3. We analyze performance of each optimization algorithm. The analysis provides us insights on the performance behavior of the algorithms and the classes of problems for which they could be more successful.

This paper is organized as follows. Section 2 provides the necessary background information about TensorFlow and black-box optimization algorithms. Section 3 and Section 4 present our evaluation methodology and results, respectively. Section 5 presents the related work, while Section 6 concludes the paper.

2 Background

This section provides a brief introduction to TensorFlow, Bayesian optimization (BO), genetic algorithm (GA), and Nelder-Mead simplex (NMS) algorithm. The description is not meant to be exhaustive, but sufficient to understand the results presented in the experimental section.

2.1 TensorFlow

TensorFlow [1], initially released in 2015, is an open-source library for machine learning and deep learning that is developed by the Google brain team. It is a multi-system library that supports Linux, MacOS and Windows and is implemented primarily in Python, C++, and CUDA.

TensorFlow supports machine learning and deep Learning models implemented in languages such as Python and Javascript. It also offers high-level Keras APIs to enable quick model development and prototyping. It supports execution on various hardware devices such as CPUs, GPUs, TPUs, etc., and provides a variety of tools (e.g., TensorFlow eXtended, TensorFlow Lite, TensorFlow.js, etc.) that enable easy deployment of trained models on those devices.

Execution modes. TensorFlow’s current version (version 2) supports two modes of execution: eager mode and graph mode. The eager mode is similar to Python’s interpreter mode in that Keras/Python APIs invoked by programmers are interpreted immediately. The graph mode, on the other hand, leverages the concept of lazy evaluation and builds an intermediate data-flow graph representation before executing it. Although the eager mode enables faster prototyping and model development, its performance is typically lower than the graph mode. This is because the graph mode can perform global optimizations over the data-flow graphs that are not possible in the eager mode.
import tensorflow as tf
from tf.keras import Input, Model
from tf.keras.layers import Dense
from tf.nn import relu

in_ = Input(shape=(3,),
            batch_size=2)
out = Dense(4,
            use_bias=True,
            activation=relu)(in_)
model = Model(in_, out)

Fig. 1: Python implementation of the model for \( y = Wx + b \)

Fig. 2: Data-flow graph for the model (yellow boxes show computations, while gray boxes show variables/tensors)

Fig. 3: TensorFlow model for \( y = Wx + b \) (left) and its data-flow graph (right)

**Tensors and data-flow graph.** TensorFlow’s data-flow graph represents high-level machine learning models by representing computations as vertices and inputs/outputs of the computations as incoming and outgoing edges. In TensorFlow, inputs and outputs of the computations are called tensors. This name, borrowed from algebra, indicates objects that can be represented as N-dimensional matrices. Edges in the data-flow graph carry tensors between the computations, and thus the name “data-flow” graph. Figure 3 shows a Python implementation of the model for \( (y = Wx + b) \), a basic operation of a neural network, written using TensorFlow’s Keras APIs. The figure also shows its corresponding data-flow graph. The arrows in the figure represent tensors, and the directions of the arrows correspond to the directions of the data flow.

**Scheduling and execution.** Edges in TensorFlow’s data-flow graph can represent two different types of dependencies: data dependencies and control dependencies. An edge that feeds an output of an operation \( X \) to an operation \( Y \) constitutes a data dependency of the operation \( Y \) on the operation \( X \). It means that the operation \( Y \) cannot be executed or scheduled for execution until the operation \( X \) has finished its execution. Control dependencies, on the other hand, represent scheduling constraints between the operations and can be inserted (by the user or automatically) to enforce a particular scheduling order. As an example, solid arrows in Figure 3 only show data dependencies. There are no control dependencies in the figure.

**CPU threading model.** Data and control dependencies in TensorFlow’s data-flow graph help in enforcing a particular execution order of the operations. However, the execution order can still be partial. In particular, operations in the data-flow graph that do not have any direct or indirect dependencies can be executed in any order. With reference to Figure 3, variables inputs and filter of MatMul can be
accessed either concurrently or serially (inputs after filter or vice versa.) TensorFlow’s threading model for multi-core CPU devices allows users to exploit this concurrency in the data-flow graphs by setting two parameters of the threading model: `inter_op_parallelism_threads` and `intra_op_parallelism_threads`. `inter_op_parallelism_threads` specifies the maximum number of operations that can be executed concurrently, while `intra_op_parallelism_threads` specifies the maximum number of threads that can be used by a single operation. Both parameters together restrict the total number of threads that will be used to execute a data-flow graph. Therefore, they are used to control over-subscription of a device. The default values of these parameters are decided by TensorFlow’s runtime depending on the underlying platform. The default values, however, are not adapted further to the input machine learning model, thus missing an opportunity for performance improvement.

### 2.2 Black-box Optimization Algorithms

Tuning the parameters of a software system to improve performance metrics, such as execution time or memory consumption, can be formulated as a black-box optimization problem. “Black-box” here refers to any system for which analytical description or gradients is not available, and instead it is only possible to query a configuration of the inputs and measure the corresponding output. Therefore, the problem cannot be solved with gradient-based techniques, but requires gradient-free optimization algorithms of non-linear systems. The algorithms investigated in this work belong to the class of gradient-free optimization algorithms, and all can solve this problem. However, they have fundamentally different behaviors as explained in the following sections.

Formally, a black-box has input $x \in X$, where $X$ is the solution space. Note that $X$ has, in general, $d$ dimensions, so $x = x_0, x_1, ..., x_{d-1}$. The system can be described by an objective function $f$, which is unknown but measurable. A measurement or evaluation corresponding to input $x$ would be $y = f(x)$. The optimization problem can be formulated as:

$$
\min_{x \in X} f(x)
$$

The solution to this problem would be an input configuration $x^* = \arg\min f(x)$, also called minimizer, and the only information that can be leveraged to find this solution is the history of past $n$ measurements $D = \{(x_i, y_i)\}_{i=0}^{n-1}$.

Different classes of algorithms have been developed to address black-box systems, most notably model-based, evolutionary and heuristic, and all of them are iterative in nature.

Bayesian optimization (BO) is a model-based algorithm, meaning that it uses system evaluations to construct a surrogate model of the optimization objective, and leverages the knowledge of the model to guide the selection of the next configuration to evaluate. It is called Bayesian, because the model employed is probabilistic, often a Gaussian Process, which is fundamental to trade global exploration in the regions of large uncertainty with local exploitation around
the best solutions observed. This is different from more traditional models such as linear regression or neural network regression that only return a predicted value for each input. Instead, a probabilistic model returns both a prediction and an estimate of uncertainty for that prediction. This information is leveraged by BO at each iteration to guide the selection of candidate solutions. For this, predictions and uncertainties are used to evaluate an acquisition function, which takes large values in the vicinity of promising past measurements or in the regions with large uncertainty. After the initial model is ready, usually trained with a few random evaluations, BO starts a loop of iterations. First, it computes and maximizes the acquisition function. The solution maximizing the acquisition function is selected as the next configuration to evaluate. Second, this configuration is applied to the system and evaluated. Finally, the measurement provides a new data point, which is used to update the surrogate model.

In this work we use Gaussian Processes (GPs) as the surrogate models. The GP is highly “data-efficient”, thus it achieves good accuracy with a relatively small number of training points, and can be customized to model different classes of functions by changing its “kernel” function. Finally, GPs have convenient analytical properties that allow to train them with a closed-form approach. For the acquisition function we adopt “SMSEgo”, because it is fast to compute and delivers state-of-the-art performance. For each point in the solution space, this function accepts the prediction and the uncertainty from the surrogate model and estimates how likely they can extend the best evaluation observed so far. SMSEgo has been shown to have performance comparable to other best acquisition functions, which are harder to implement and require approximations.

Genetic algorithm (GA) belongs to the family of evolutionary algorithms, which draw inspiration from biological phenomena such as reproduction. Instead of building an internal model, at each iteration, GA relies upon a fitness function to select two “best parent configurations” from the history of the evaluated configurations. Then, the parent configurations are manipulated via crossover and mutation operations to generate a “child” configuration. GA reflects the process of natural evolution, in which genes determining a better adaptation are mixed together with occasional mutations, which leads to stronger and healthier generations. More formally, the GA would take the history as an input and reorder the input-output pairs based on a certain fitness function \( g(x_i, y_i) \). Then, it would pick the inputs of the two fittest pairs, called “parents”, and generate a new input by copying part of the components from the first parent and the other from the second parent. This operation is called crossover. Then, it might also change one or more component to purely random values. This is referred to as mutation. Evolutionary algorithms are broadly used for their ease of implementation and configuration.

Finally, Nelder-Mead simplex (NMS) is a direct search heuristic method that uses evaluations to build a simplex object in the space of objective function. The next configuration to evaluate is selected by manipulating the simplex via reflection, expansion and contraction operations. While simple to implement and intuitive, NMS has a tendency to get stuck in local optima.
3 Optimization Framework and Methodology

In this section, we describe our automated optimization methodology for black-box optimization of TensorFlow’s CPU backend.

Figure 4 shows the block diagram of the optimization setup. The optimization framework (on the left) has different components, and it runs on the host system. The algorithmic engines implement the black-box optimization algorithms described in the previous section: Bayesian optimization, genetic algorithm and Nelder-Mead simplex. The algorithm selection switch is configured to exercise one engine at a time. This ensures that all engines can use the same interface to TensorFlow for converting and applying the chosen parameters and the same data acquisition module to retrieve evaluation results and update the evaluation history. On the right, the system under test is the target system, and generically, it is any computing system that can execute TensorFlow models. The only requirement on the system is that it allows applying the parameters and measuring the corresponding output via some metric reporting subsystem (e.g. a log file in the simplest case). A clear separation of components ensures that the workload performance is not affected by interference from the optimization algorithm. It also enables us to run optimization algorithm on a relatively less-powerful machine than the target machine.

The mapping of the optimization problem is realized as following. At each iteration, an algorithmic engine selects a configuration $x$ of TensorFlow’s threading model parameters. Through the TensorFlow interface, the configuration $x$ is converted into a command to set the values of parameters on the target system. Then, the optimization framework runs an evaluation on the target system and evaluates the objective function $f(x)$ of the metric of interest, such as images.
processed per second in the case of ResNet50. The evaluation provides a new data point, which is added to the global history of evaluations. In case of Bayesian optimization, this is then used to retrain the Gaussian process model, recompute the acquisition function and maximize to select the next configuration.

4 Evaluation

In this section, we discuss our evaluation of Genetic algorithm, Bayesian optimization, and Nelder-Mead simplex algorithm to tune the inference throughput of the selected deep learning models. In other words, the objective function was to maximize the throughput of performing inference over every model.

4.1 Experimental Setup

Before we present our results, we describe the evaluation setup.

**Hardware configurations:** We used a dual-socket, 22-core Intel Xeon E5-2699 v4 processor (codenamed Broadwell) as the host system and a dual-socket, 24-core 2nd-generation Intel Xeon Scalable Gold 6252 processor (codenamed Cascade Lake) as the target system. The processor for the host system was configured to run at 3.6 GHz with 384 GB of physical memory, while the processor for the target system was configured to run at 3.9 GHz with hyper-threading turned on and with 512 GB of physical memory. Both the servers were running Ubuntu-18.04 operating system.

**Software configurations:** We installed Intel-optimized TensorFlow v1.15 [17] on the target system to run the deep learning models. This TensorFlow version uses version v0.20.6 of Intel’s Math Kernel Library for Deep Neural Networks (oneDNN). oneDNN is an open-source, cross-platform high-performance library of basic building blocks for deep learning applications [7]. We used Python 3.7.7 to run the TensorFlow benchmarks.

**TensorFlow models:** Intel Model Zoo [6] provides a suite of popular deep learning models that are optimized for various versions of Intel-optimized TensorFlow. We used SSD Mobilenet, ResNet50, Transformer-LT, BERT, and NCF models from the Intel provided suite. We selected the models such that they cover a variety of application domains, such as image recognition, language translation.

**Configuration of the parameter search space:** We considered five parameters of TensorFlow’s threading model for our experiments. We described `inter_op_parallelism_threads` and `intra_op_parallelism_threads` parameters in the Background section (Section 2). We provide a brief background of the other three parameters below. In addition, we describe rationale for selecting particular ranges of values to tune these parameters. The range is defined with an upper bound, a lower bound, and a step size value as shown in Table 1.
**Table 1:** Tuning parameters and their ranges (min, max, step size)

| Parameters                        | Range  |
|-----------------------------------|--------|
| `inter_op_parallelism_threads`    | [1, 4, 1] |
| `intra_op_parallelism_threads`    | [1, 56, 1] |
| NCF                               | [64, 256, 64] |
| SSD-MobileNet                     | [64, 1024, 64] |
| ResNet50                          | [64, 1024, 64] |
| Transformer-LT                    | [64, 1024, 64] |
| BERT                              | [32, 64, 32] |
| KMP_BLOCKTIME                     | [0, 200, 10] |
| OMP_NUM_THREADS                   | [1, 56, 10] |

**inter_op_parallelism_threads:** Since this parameter controls the maximum number of concurrent operations from the data-flow graph, we set this parameter’s range from 1 to 4 at step size of 1. These values were obtained from Intel’s recommendation of setting this parameter based on the number of sockets.

**intra_op_parallelism_threads:** Since this parameter controls the maximum number of threads to be used for operations from the data-flow graphs, we set its range from 1 to 56 at the step size of 1. This decision was based on Intel’s recommendation of setting `intra_op_parallelism_threads` based on the number of cores in the system. Intel Xeon CPUs have per-socket core count of up to 56.

**batch_size:** This parameter controls the number of examples provided to the deep-learning models as input. Setting the value to 1 allows us to obtain latency of inference, while higher values allow us to obtain throughput. We note that the batch size is a performance-sensitive parameter — a multi-core system could be under-utilized for lower batch size values. Higher batch sizes thus allow us to explore the saturation points of a system. Furthermore, some models are computationally-less intensive than others. To ensure that the target system is saturated for all the models, we used different batch sizes for different models.

**KMP_BLOCKTIME:** This and the next parameter are tunable parameters of OpenMP runtime library, and they are applicable to Intel-optimized TensorFlow, since its CPU backend relies on oneDNN library that uses OpenMP library. KMP_BLOCKTIME sets the time that a thread should wait before sleeping after completing the execution of a parallel region. Most deep-learning primitives in oneDNN are implemented using parallel-programming primitives such as parallel for. The block of code following this primitive is called “parallel region” in OpenMP. OpenMP tuning guide [9] recommends to set this parameter to 200, but our prior experiments demonstrated that value of 0 is also sometimes effective. Consequently, we set the range for this parameter from 0 to 200 with the step size of 10.

**OMP_NUM_THREADS:** This parameter is used to set the maximum number of threads to use in OpenMP parallel regions. Setting this parameter to a value higher than 1 enables parallel regions to use multiple cores of multi-core CPUs concurrently. Intel’s guide [19] recommends setting this parameter to the number of cores in the system. So we set the range of this parameter to be same as `inter_op_parallelism_threads`. 
Fig. 5: Results of auto-tuning TensorFlow’s threading model using Bayesian optimization, genetic algorithm, and Nelder-Mead simplex

4.2 Results

We now discuss the results of our tuning experiments. In our experiments, the models were configured to use 32-bit floating point (FP32) data type. Additionally, for ResNet50 model, we evaluated it with 8-bit integer (INT8) data type, which produces a compact model and also reduces its memory footprint.

Figure 5 shows the results of tuning the selected deep learning models using different optimization algorithms. The X axis in the figure represents tuning iterations (capped at 50), and the Y axis represents the throughput value (examples/second) — a higher throughput value represents better performance. Also, in the figure, green, blue and orange plots represent the performance of Nelder-Mead simplex, genetic algorithm, and Bayesian optimization, respectively.

Out of the 6 plots, the top 3 plots for SSD-MobileNet-FP32, ResNet50-FP32, and ResNet50-Int8 show similar characteristics. Specifically, Bayesian optimization and genetic algorithm perform similarly and deliver close to peak throughput, while Nelder-Mead simplex struggles with a considerable variation in the throughput. For the bottom 3 plots, namely Transformer-LT-FP32, BERT-FP32, and NCF-FP32, the optimization algorithms perform differently. Specifically, except for BERT-FP32, plots for Bayesian optimization and genetic algorithm for other two models look different. Additionally, while Bayesian optimization delivers the best performance on tuning NCF-FP32 throughput, it struggles on
Exhaustive sweep of ResNet50 Int8 throughput (imgs/sec) (V: inter_op_parallelism_threads, W: kmp_blocktime, X: intra_op_parallelism_threads, Y: omp_num_threads, Z: batch_size)

Fig. 6: Exhaustive sweep of ResNet50-INT8 throughput across all five parameters. Labels for different axes are in the legend. Colors indicate different throughput values (dark blue being the highest, and yellow being the lowest.)

BERT-FP32, for which Nelder-Mead simplex delivers the best throughput. For Transformer-LT model, genetic algorithm performs better than Nelder-Mead simplex and Bayesian optimization.

Overall, the results show that no single optimization algorithm consistently outperforms others in tuning the selected deep learning models. Nevertheless, Bayesian optimization demonstrates to be the most competitive overall for the selection of the models.

4.3 Comparison of the Optimization Algorithms

**Exhaustive sweep.** In order to understand the effect of different parameters on the performance of the deep learning models, we performed exhaustive sweep of ResNet50’s performance for INT8 precision across all the five parameters. Figure 6 shows the throughput of ResNet50 for different parameter values.

We report some salient observations from Figure 6:

- KMP BLOCKTIME of 0 delivers better performance than others, for a given value of inter_op_parallelism_threads. 3D plots become lighter in color as KMP BLOCKTIME value increases (from left to right).
All 3D plots have a common pattern: as the value of `OMP_NUM_THREADS` increases (along the Y-axis) the throughput also increases, suggesting that this parameter has considerable impact on the performance.

Performance does not vary considerably (and noticeably) for different values of `intra_op_parallelism_threads` (along the X-axis), suggesting that ResNet50's INT8 model does not utilize deep learning operators that leverage Eigen threadpool (which relies on the value of this parameter.) It also suggests that we can possibly drop this parameter from the list of tunable parameters to prune the search space.

Batch size (along the Z-axis) has relatively less impact on the throughput than other parameters, suggesting that it could be dropped from the list of tunable parameters as well.

**Exploration-exploitation balance.** After obtaining the shape of the performance function for the ResNet50 INT8 model, we compared the effectiveness of all three optimization algorithms in obtaining optimal configurations. The objective here is to understand the tradeoff between exploitation and exploration delivered by all three algorithms. For this purpose, we plotted the ResNet50 INT8 throughput as a function of the sampled parameter values. Since we have 5 different parameters for tuning, we convert the 5-dimensional plot into multiple pairplots that represent throughput as a function of the pairs of the sampled parameter values. Figure 7a shows the ResNet50 INT8 pairplot for Nelder-Mead simple. For instance, the plot on the lower left corner between X and W in Figure 7a represents the ResNet50 INT8 throughput values in terms of X and W parameter values from the sampled configuration values. Darker values represent higher throughput values; lighter values represent lower throughput values. Figure 7c shows the pairplot for Bayesian optimization, and Figure 7b shows the pairplot for genetic algorithm.

There are a few interesting observations that emerge from these pairplots:

- Bayesian optimization samples min and max ranges of all the parameters (seen as squares in pairplots). At the same time, it also samples all the parameters fairly uniformly, displaying a fair balance between exploitation and exploration.
- Nelder-Mead simplex algorithm samples clusters of points, indicating that the algorithm has a higher chance of getting stuck in a local optimum. In other words, Nelder-Mead simplex devotes more time to exploitation, i.e. local search in the vicinity of the promising solutions. Note also that Nelder-Mead simplex presents another limitation in that it does not sample points along min and max ranges of some of the parameters (e.g., Y and Z),
- Genetic algorithm, on the other hand, has neither clusters of points nor samples along min and max ranges (e.g. parameter V, more white spaces in pairplots), indicating a poor exploration/exploitation balance.
- Bayesian optimization also has more darker points than Nelder-Mead simplex algorithm and Genetic algorithm, suggesting that Bayesian optimization delivers the best balance between exploitation and exploration. This is not
Fig. 7: Pairplots showing configurations sampled by different optimization algorithms across different parameters. Parameters: X = intra-op parallelism, Y = OMP NUM THREADS, Z = batch size, V = inter-op parallelism, W = KMP BLOCKTIME.
Table 2: Min/max ranges for different parameters vs. tunable ranges. Percentages are obtained by dividing the ranges of the sampled values by the tunable ranges. Parameters: X=\textit{intra\_op\_parallelism\_threads}, Y=\textit{omp\_num\_threads}, Z=\textit{batch\_size}, V=\textit{inter\_op\_parallelism\_threads}, W=\textit{kmp\_blocktime}

| Algorithm | ResNet50 Int8 | BERT-FP32 |
|-----------|--------------|-----------|
| Tunable range | X Y Z V W | X Y Z V W |
| Nelder-Mead simplex (min, max) | [7,43] [8,45] [192,1024] [1,4] [0,150] | [7,44] [6,45] [32,64] [1,4] [10,150] |
| Genetic algorithm (min,max) | [1,23] [1,19] [64,448] [1,2] [0,70] | [1,22] [1,23] [32,32] [1,3] [0,50] |
| Bayesian optimization (min,max) | [1,56] [1,56] [64,1024] [1,4] [0,200] | [1,56] [1,56] [32,64] [1,4] [0,200] |
| Nelder-Mead simplex sampled range(%) | 65 67 86 100 75 | 67 70 100 100 70 |
| Genetic algorithm sampled range(%) | 40 32 40 33 35 | 38 40 50 66 25 |
| Bayesian optimization sampled range(%) | 100 100 100 100 100 | 100 100 100 100 100 |

surprising, since this is one of the commonly known advantages of Bayesian optimization.

To further understand the exploration-exploitation behavior of all three algorithms, we obtained their pairplots for the BERT-FP32 model. Figures 7d, 7f, 7e shows the pairplots for Nelder-Mead simplex algorithm, Bayesian optimization, and genetic algorithm, respectively. Observations similar to those of ResNet50-INT8 can be made in BERT’s case also. Specifically, genetic algorithm neither has clusters of points nor samples min/max ranges, suggesting poor exploration-exploitation strategy. Nelder-Mead simplex algorithm has clusters of points, similar to that for ResNet50-INT8 model, suggesting that Nelder-Mead simplex algorithm exploits more than exploring the space (visible from not sampling min/max values of parameter V). However, it still samples better than genetic algorithm in a sense that there is much less white space in Nelder-Mead simplex’s pairplots than in genetics algorithm’s pairplots. Bayesian optimization, on the other hand, has a cluster of points as well as samples near min/max values, suggesting better balance between exploration and exploitation.

Overall, these experiments suggest that Bayesian optimization maintains a fair balance between exploration and exploitation and can sample solutions in different regions of the search space. Nelder-Mead simplex algorithm and genetic algorithm, instead, struggle to maintain this balance, although Nelder-Mead simplex algorithm in these cases ends up exploring more than genetic algorithm. This can also been seen from the data in Table 2, which shows the sampled ranges, shown as (min,max), for different parameters against their tunable ranges for different optimization algorithms. As can be seen, Bayesian optimization explores
min and max values of all the parameters, both in case of ResNet50-INT8 and BERT-FP32. It explores 100% of the tunable ranges for all the parameters for both the models. Genetic algorithm, on the other hand, explores less than 50% of the ranges for most of the parameters for both the models, suggesting that it exploits more than explores.

In summary, we found that no single optimization algorithm can be used to find the optimal throughput for the selected deep learning workloads. Nevertheless, Bayesian optimization demonstrates a more robust and reliable behavior and delivers quality solutions with a limited number of iterations. Besides, each algorithm took different time to search the maximum throughput. For instance, Nelder-Mead simplex algorithm took a relatively short amount of time for searching the maximum throughput in BERT-FP32 compared with the others. Similarly, genetic algorithm took less time to search for the maximum throughput than Bayesian optimization in SSD-MobileNet-FP32. Moreover, we run our experiments multiple times, and we observed that the throughput values with both genetic algorithm and Bayesian optimization are very close in SSD-MobileNet-FP32, ResNet50-FP32 and BERT-FP32 model.

5 Related Work

In the machine learning domain, auto-tuning is routinely applied to the problem of hyper-parameter tuning. Although, there exists a number of commercial and open-source hyper-parameter tuning systems such as HyperOpt [2], MOE [20], Spearmint [13], AutoWeka [16], SigOpt [12], Google’s Vizier [4], etc., we are not aware of existing work that systematically analyzes tuning of performance-sensitive parameters of TensorFlow framework on multi-core CPU platforms used in data centers. The closest to our work is TensorTuner [5], which uses Nelder-Mead simplex algorithm to tune TensorFlow’s CPU backend. This work, however, neither considers other optimization algorithms nor provides insights into the applicability of Nelder-Mead simplex algorithm to the problem. Nelder-Mead simplex is known to be a local optimization algorithm, and global optimization algorithms such as Bayesian optimization and genetic algorithm exist already. We seek to provide this comparative evaluation and analysis among different optimization algorithms on several TensorFlow models, written for a variety of usecases such as image recognition, language translation, and recommendation system. TensorTuner, on the other hand, focuses on models used in image recognition problem. We also consider a larger set of performance-sensitive tunable parameters, thus expanding the search space of the configurations. Our work, in this sense, can be considered as an extension of TensorTuner.

Alternative to the auto-tuning based approach considered in this work, Wang et al. [15] develops a formula to set `inter_op_parallelism_threads` and `intra_op_parallelism_threads` by analyzing the data-flow graphs of the deep learning models. They develop this formula by analyzing data-flow graphs of various models and their relationship with the optimal values of these parameters. Their approach, however, treats TensorFlow’s CPU backend as a white-box and
requires intrusive changes to the TensorFlow framework. Furthermore, operating as a part of TensorFlow framework, this approach cannot set other performance-sensitive parameters such as batch\_size. Nevertheless, it is a promising approach in a sense that it can directly set the values of the parameters by analyzing data-flow graph of a model and thus eliminate the need of multiple rounds of online or offline tuning.

6 Conclusion

Overall, our evaluation across a variety of deep learning models for TensorFlow demonstrates that Bayesian optimization generally maintains good balance between exploration and exploitation (explores 100% of the tunable ranges for all the parameters for ResNet50-INT8 and BERT-FP32 models) and explores most of the search spaces, if not all. Genetic algorithm, on the other hand, explores less than 50% of the ranges for several models and struggles to maintain the balance between exploration and exploitation. Nelder-Mead simplex falls in between Bayesian optimization and genetic algorithm in terms of the exploration-exploitation balance. Nonetheless, we also found out that no particular optimization algorithm performs the best across all the models — Nelder-Mead simplex performs the best on BERT-FP32, while it lags behind Bayesian optimization and genetic algorithm on the others.

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