Reusing Auto-Schedules for Efficient DNN Compilation

Perry Gibson, José Cano
School of Computing Science, University of Glasgow, UK

Abstract

Auto-scheduling is a process where a search algorithm automatically explores candidate schedules (program transformations) for a given tensor program on a given hardware platform to improve its performance. However this can be a very time consuming process, depending on the complexity of the tensor program, and capacity of the target device, with often many thousands of program variants being explored. To address this, in this paper we introduce and demonstrate the idea of tuning-reuse, a novel approach to identify and re-use auto-schedules between tensor programs. We demonstrate this concept using Deep Neural Networks (DNNs), taking sets of auto-schedules from pre-tuned DNNs, and using them to reduce the inference time of a new DNN. Given a set of pre-tuned schedules, tuning-reuse provides its maximum speedup in less time than auto-scheduling using the state-of-the-art Ansor auto-scheduler. On a set of widely used DNN models, we apply tuning-reuse and achieve maximum speedups between 1.16× and 4.76×, while outperforming Ansor when given limited tuning time.

1 Introduction

Computationally expensive tensor programs such as deep neural networks (DNNs) have broad applications across fields such as computer vision [17, 18, 25, 32, 33], natural language processing [20, 21], scientific computing [23, 28, 44], and many more. To achieve high performance on these workloads, a range of efficient hand-tuned kernel libraries such as OpenBLAS [1] and oneDNN [2] for CPUs, and cuDNN [14] for NVIDIA GPUs, have been developed to accelerate the performance of common operations. However, these libraries require a great engineering effort to be optimized, do not necessarily see performance portability to new hardware architectures, and optimize for common cases often leaving novel operations with poor performance, such as capsule networks [36]. Reliance on hand-tuned kernel libraries can reduce the speed of adoption of new solutions [9], since communities in both academia and industry must wait for optimized operations to be developed by kernel library contributors. Schedule based approaches such as TVM [13] and Halide [30] can reduce some of these barriers by decoupling the high level description of the target algorithm from its user specified optimizations. This can make it easier to port algorithms to new systems, though still requires domain expertise to write an optimized schedule.

Ansor [45] is an auto-scheduling system which approaches the problem by extending the TVM deep learning compiler stack to enable automatic optimizations of workload schedules and produce more efficient code for a given workload and target device. This process automatically generates schedules, compared to the hand-tuned schedules and kernels required by TVM, cuDNN, etc. The approach can produce state-of-the-art inference time performance on a range of platforms and workloads, and in particular can show improvement compared to existing approaches on novel workloads such as capsule 2D convolution [36]. Ansor splits the computation graph into a set of workloads, where workloads are bundles of easily fused operations such as convolutional layers and their complementary activation function, which are tuned individually for a given device to produce their corresponding auto-schedules.

Note that this tuning process can be very time consuming, and specific to a given workload of a given size, e.g. if we tune a convolutional layer of some size and we are presented
with a new convolutional layer of a different size, we must tune the new layer from scratch. Figure 1 shows the tuning time of Ansor for a number of common deep neural networks (DNNs) on a common server-class CPU \(^1\), Intel Xeon E5-2620. We observe that even on this high-end CPU, tuning time takes several hours, which is a large initial upfront cost to reduce inference time when an application is deployed. If a range of applications are to be deployed on a given platform, this upfront cost may be further exacerbated, and may make the potential performance improvements of auto-scheduling impractical to achieve.

However, if we want to reduce our tuning time, we could sacrifice potential inference time improvements by stopping tuning early, or only tuning a subset of the workloads. These are practical approaches, however Ansor gets its performance from evaluating a vast array of possible schedules, and early stopping may miss performant schedules. Our main observation is that many applications, such as DNNs, feature a great deal of similarity between workloads in terms of the types of operations they compute, and the sizes of the tensors or multi-dimensional arrays involved. For example, most DNNs contain a limited set of operations such as convolutional layers, skip connections, activation functions, and pooling layers. The DNN models in Figure 1 contain 16 unique workload types (which we call workload classes), with every model having at least 2 workload classes in common with every other one, and often many more. Thus, if we have already found performant schedules on the target hardware platform, perhaps we can re-use this knowledge on other tensor programs which contain similar workloads.

In this paper we introduce the idea of tuning-reuse, a new approach which can improve execution performance for a given tensor program when available tuning time is limited. Tuning-reuse exploits the similarity between workloads containing the same operations, with varying data sizes, so that we can re-use schedules from other tensor programs. Thus, we can potentially achieve performance improvements, while reducing the costs associated with auto-scheduling.

The contributions of this paper include the following:

- **We introduce tuning-reuse**, a new approach to reduce the costs of auto-scheduling, by re-using tuning between tensor programs.

- **We discuss how tuning-reuse is enabled by the features of the compute schedule programming paradigm**, demonstrate the principles with an example using auto-schedules of two GEMM kernels of different sizes with each other, and tune the model ResNet18 using schedules from ResNet50.

- **We discuss in detail the key components of tuning-reuse**, such as workload classes, standalone evaluation, full evaluation; as well as a model selection heuristic, and optimizations to the compilation process.

- **We evaluate tuning-reuse by demonstrating the performance improvements for a number of representative DNN models, with a maximum speedup over untuned inference of between 1.16 \(\times\) and 4.76 \(\times\), while clearly outperforming Ansor when given limited search time.**

- **We discuss the ways in which tuning-reuse can be improved, both by reducing the costs in identifying performant schedules, and increasing the variety of pre-tuned schedules available. In addition we discuss the broader scope of tuning-reuse, and how it can be leveraged in practical applications.**

## 2 Schedules and auto-scheduling

Compute schedules is a programming paradigm which decouples the high-level description of an algorithm from the description of how it is to be optimized for a given hardware platform, seen in systems such as Halide [30], TVM [13], and RISE/ELEVATE [16]. The schedule is expressed in a domain-specific language, where optimization choices such as decisions about the intermediate storage and the order of computation are defined by the programmer as transformations to code of the algorithm. This separation can allow clearer reasoning about the performance impact of optimizations, when compared to defining the algorithm and its optimizations in the same code such as in system programming languages such as C, C++, and Rust. Additionally, a single algorithm can have multiple schedules for different cases, such as hardware architectures, or workload properties, as seen in TVM which defines different schedules for the same algorithm for CPUs and GPUs. Figure 2 shows a tensor program being decomposed into workloads. For example a workload could be a single layer of the neural network. Each workload corresponds to an algorithm (a high level description of the desired computation), and can have a schedule (the transformations to be applied to the algorithm) applied to it at compile time to produce efficient code for the target platform. Optimized workloads are composed together into a full program. Optimizations can include choices such as whether to unroll a loop, tiling, and where to apply vectorization.

TVM applies the compute schedule paradigm to the domain of DNN inference, compiling models ahead-of-time, and exploiting the predictability in data shapes. DNN models can be loaded from a range of deep learning frameworks, including PyTorch [29], TensorFlow [3], and ONNX [7]. TVM then applies pre-defined high-level optimizations to the whole computation graph, such as operator fusion (e.g., batch normalization layers can be completely removed from the graph for inference by combining their parameters with prior layers), and leverages its library of algorithms and schedules to

\(^1\)Note that auto-scheduling can be performed for both GPUs and CPUs, however it requires a CPU to generate the schedule variants as the problem is not suited for GPUs.
compile for backends including LLVM [24], OpenCL [40], CUDA [26], and more.

However, writing optimized schedules by hand requires domain expertise, including understanding of the algorithm’s design, and the behavior of the target hardware. In addition, an efficient schedule may not be efficient in all versions of the target algorithm, for example if the schedule was optimized with the assumption that the size of the inner loop would always be small. In this case, schedule optimizations which were used to exploit this assumed workload characteristic will not help, and may even hinder performance.

To adapt schedules to the diversity of workload sizes that a given algorithm may be parameterized by, AutoTVM [11] improved the performance portability of their schedules by leveraging auto-tuning, by exploring the impact of varying schedule parameters such as tile sizes, or loop re-orderings on the target platform for a given tensor program. This can bring high performance improvements, however as well as being a time-consuming process, auto-tuning still requires the schedule to be hand-written. Additionally the schedule designer must define the search space to explore, which requires further expertise. The chosen space could be either too large to easily find an efficient set of tuned parameters, or too restrictive and leave out more optimal configurations. For these reasons, auto-tuning hand-written schedules is difficult to scale, since schedules must be optimized for new hardware architectures, and novel algorithms must have schedules written from scratch, which requires large engineering efforts, which can be a barrier to the adoption of novel solutions such as novel DNN architectures [9].

Ansor [45] expands on the schedule model by introducing “auto-schedules”, where efficient schedules for given workloads are generated automatically for a given platform. This reduces the need for specialized workload and platform expertise to produce efficient code, especially when new operations are introduced. In this case, only the high-level algorithm needs to be written, and an efficient schedule for the target platform can be found via evolutionary fine-tuning. A large schedule space is explored (without needing to be defined by the designer, such as in AutoTVM), following applying rules and random perturbations to find an efficient schedule for a particular instantiation of a given operation. Auto-schedules in Ansor are tuned for a particular sub-graph, or workload, of a tensor program. If another tensor program contains an identical workload, such a convolutional layer featuring the same kernel sizes, input and output dimensions, then the schedule can be reused. However, if these parameters change, then new tuning must be performed.

3 Motivation

Auto-schedules included in Ansor [45] provide state-of-the-art performance on a number of benchmarks and hardware devices by speeding up the inference of tensor programs such as DNNs. Figure 3a shows an example of a simple computation Directed Acyclic Graph (DAG) for a tensor program, such as a DNN, with default untuned schedules. Each node of the graph represents a unit of computation, also known as a workload. In the figure, colors represent the workload class, i.e. the operations contained within (such as the layer type of a DNN), with there being three classes of workloads in this example, and four workloads in total. The shapes of the nodes represent the size of the data computed in the workload, which in this example varies with every workload. In this illustrative example, if we use Ansor to auto-schedule this model, as shown in Figure 3b, we see that we can speed up the inference time by $2 \times$, with a search time of 36, where all values are for illustrate purposes.

However, it should be noted that auto-scheduling is a very time consuming process, as shown in Figure 1, where the tuning time can be on the order of several hours for a whole DNN model, depending on the complexity of the tensor program. This high cost can be a bottleneck to deployment, since if we want to get the best inference time for a given DNN model on a target device, we must spend a long period of time exploring schedule space. Approaches to reduce the tuning time include reducing the time we allow the tuner, as shown in Figure 3c; only tuning a subset of the workloads in the model and shown in Figure 3d; or some combination of the two. These trade-offs can allow users to sacrifice potential improvements in performance, for reduced tuning time.

Our main observation in Figure 3 is that workloads of the same class, where class is represented as color, may produce auto-schedules with similar properties, since they define the same high level algorithm, just over varying data sizes.

The question posed by our observation is “What would be the performance impact of using a schedule from a different workload of the same class?” A related question is “How different will the optimizations found via auto-scheduling be between two workloads of the same class, but varying data sizes?” This will vary depending on the structure of the computations defining the class, with factors such as access patterns and costs of the loop body playing important roles; as well as the architecture of the target platform that the auto-schedule exploits, as different memory hierarchies and features such as vector-instruction size may make some optimizations more or less relevant. Perhaps having some
Thus, we define the process of re-using an auto-schedule for a given workload on a different workload as tuning-reuse. In Figure 3e we show an example of tuning-reuse, where we reduce tuning time by reusing auto-schedules. We re-use the auto-schedule for Workload 1 with Workload 2, to reduce the inference time without requiring any additional tuning. We use the auto-schedule of Workload 1 with itself, which we refer to as the “native schedule”. Note that we should expect some penalty when running Schedule 1 with Workload 2, compared to running a natively auto-schedule for Workload 2, since a native schedule will exploit the specific data sizes of the computation to find optimizations for the target hardware, and data size specific optimizations. This workload specific information would not be exploited by using Schedule 1 for the workload, as the schedule is tuned on a different workload. The target of tuning-reuse is to improve the inference time without additional search costs. The trade-off search time and performance improvement is interesting to explore and exploit, as long search times may not always be acceptable.

4 Tuning-reuse

First, in Section 4.1 we discuss some of the types of optimizations used by auto-scheduling, and discuss how tuning-reuse is possible, and can be beneficial. Then, in Section 4.2, we discuss the idea of workload classes, and how they are a key part of tuning-reuse. In Section 4.3 we explore some of the behaviors of tuning-reuse on a full DNN model (ResNet18), and in Sections 4.4 and 4.5 we discuss some of the other practical considerations for tuning-reuse.

4.1 Principles of Tuning-Reuse

To understand how tuning-reuse works, we must first briefly explain the relevant concepts of schedules, and auto-schedules. Let us consider an operation, such as a matrix-multiply, which has a fixed loop structure, but may have varying data sizes, as shown on lines 1-5 of Algorithm 1.

Let us consider an operation, such as a matrix-multiply, which has a fixed loop structure, but may have varying data sizes, as shown on lines 1-5 of Algorithm 1. There are a variety of code transformations which can be applied to this operation, some of which are applicable to all instantiations of the operation, and others which are specific to a particular input matrix size.

For example, some transformations are valid regardless of the data sizes involved, such as if we instruct a given loop to be unrolled to its maximum depth. No matter how many iterations are in a loop, it can be applied as long as we know the number of iterations ahead of time, thus it is valid regardless of if there are 3 iterations or 300,000. However, the performance benefit of the transformation will be different depending on the number of iterations, with relevant factors including the architecture of the underlying hardware, e.g., the features of its cache; and properties of the computation such as the cost of the loop body.

To contrast, some transformations may only be valid with a given data shape. For example, if we have a loop over the range \(0, N\) where \(N = 32\), we could apply a loop splitting optimization \(\text{Split}(N, 4, 8)\) that breaks the loop into two loops in the ranges \((0, 4)\) and \((4, 8)\), which would allow us to traverse the full 32 elements. If we try to apply this optimization to a similar loop where \(N = 128\), then splitting it into these two loops would produce invalid code, since we will not be able to cover the full space of the loop. However, if we reformulate our transformation such that we apply it as \(\text{Split}(N, (N/8), 8)\), our transformation becomes valid for all programs where \(N \in \mathbb{N} : 8 | N\).

Therefore some transformations can be applied to a workload regardless of the data-shape, others can be reformulated to be valid for more than one data-shape, and some may not be valid for any data-shape other than the one they were originally defined on. The performance benefits of these transformations may be data-shape dependent, for example a loop unrolling that brings benefit for a small loop range could bring a penalty for a larger loop range. However, we claim that even with large data-shape differences some of these
Algorithm 1: We look at two data sizes for the operation, workload, a row-major square matrix-multiply, as defined in this paper, when we apply the schedule produced for a given workload via auto-scheduling, and apply it to a workload other than the one the schedule was tuned for: we call this technique tuning-reuse.

Let us take a look at a simple example of an auto-scheduled workload, a row-major square matrix-multiply, as defined in Algorithm 1. We look at two data sizes for the operation, $C_1$ multiplying two $(512 \times 512)$ matrices $A_1B_1$, and $C_2$ multiplying two $1024 \times 1024$ matrices $A_2B_2$. We run Ansor auto-scheduling on the two workloads, with an improvement of $246 \times$ and $308 \times$ for $C_1$ and $C_2$ respectively, compared to using no schedule. The auto-scheduling of the two workloads produces different schedules, since they have different sizes. Additionally, auto-scheduling in Ansor is non-deterministic due to the use of genetic algorithms to mutate schedules, and a stochastic learned cost model to reduce evaluation costs; thus differences in the auto-schedule may emerge even when re-running Ansor for the same workload. Algorithm 1 shows the matrix-multiply computation, and a simplified representation of auto-schedules generated for $A_1B_1$ and $A_2B_2$ on an Intel Xeon E5-2620 CPU. Next, we briefly explain the schedule primitives used in this example.

- **Split([range],[factor]):** split a loop range into inner and outer ranges.
- **Reorder([set of ranges]):** specify a reordering of a set of nested loops.
- **Fuse([range],[range]):** fuse two consecutive loop ranges into a single range.
- **Parallel([range]):** mark an axis to be used for multi-threaded computation.
- **Unroll([range],[max unroll factor]):** unroll a loop range, up to a maximum depth.
- **Vectorize([range]):** apply SIMD vectorization to a range.
- **ComputeAt([output tensor],[axis]):** move a computation such that it is computed at a given axis.

We observe that we can apply tuning-reuse to the GEMM computations and still produce valid code: obtain performance within 5% of the native tuning for both kernels; and a speedup of near $270 \times$ when compared to the unmodified computation without a schedule. The core difference in the auto-schedules

| Algorithm 1 Auto-schedules for a GEMM operation |
|------------------------------------------------|
| $A$: input matrix of size $N \times K$           |
| $B$: input matrix of size $K \times M$           |
| $C$: output matrix of size $N \times M$          |

**Unmodified row-major matrix-multiply computation**

1: for $n \leftarrow 0$ to $N$ do
2: for $m \leftarrow 0$ to $M$ do
3: $C[n][m] \leftarrow 0$  \(\triangleright\) Initialize output value to zero
4: for $k \leftarrow 0$ to $K$ do
5: $C[n][m] += A[n][k] \times B[k][m]$  

**Simplified auto-schedule where $N = P = K = 512$**

6: $N_o, N_i \leftarrow \text{Split}(N,8)$
7: $N_{oo}, N_o \leftarrow \text{Split}(N_o,1)$  \(\triangleright\) note $N_o$ redefined
8: $N_{oo}, N_{oo} \leftarrow \text{Split}(N_{oo},16)$
9: $M_o, M_i \leftarrow \text{Split}(M,8)$
10: $M_{oo}, M_o \leftarrow \text{Split}(M_{oo},16)$
11: $K_o, K_i \leftarrow \text{Split}(K,1)$
12: $N_{oo}, N_{oo}, N_{oo}, M_{oo}, K_o, N_o, M_o, K_i, N_i, M_i$  
13: $N_{oo}, N_{oo}, N_{oo}, M_{oo}, K_o, N_o, M_o, K_i, N_i, M_i$  
14: $F_{NM} \leftarrow \text{Fuse}(N_{oo},M_{oo})$
15: $\text{Parallel}(F_{NM})$
16: $\text{Unroll}(F_{NM},512)$
17: $\text{Vectorize}(M_i)$

**Simplified auto-schedule where $N = P = K = 1024$**

18: $N_o, N_i \leftarrow \text{Split}(N,32)$
19: $M_o, M_i \leftarrow \text{Split}(M,256)$
20: $\text{Reorder}(N_o, M_o, N_i, M_i)$
21: $\tilde{N} \leftarrow N_i, \tilde{M} \leftarrow M_i$
22: Create Local Cache Buffer $D$ of size $\tilde{N} \times \tilde{M}$
23: $\tilde{N}_o, \tilde{N}_i \leftarrow \text{Split}(\tilde{N},1)$
24: $\tilde{N}_{oo}, \tilde{N}_o \leftarrow \text{Split}(\tilde{N}_o,16)$
25: $\tilde{N}_{oo}, \tilde{N}_{oo} \leftarrow \text{Split}(\tilde{N}_{oo},2)$
26: $\tilde{M}_o, \tilde{M}_i \leftarrow \text{Split}(\tilde{M},8)$
27: $\tilde{M}_{oo}, \tilde{M}_o \leftarrow \text{Split}(\tilde{M}_o,4)$
28: $\tilde{M}_{oo}, \tilde{M}_{oo} \leftarrow \text{Split}(\tilde{M}_{oo},8)$
29: $K_o, K_i = \text{Split}(K,4)$
30: $\text{Reorder}(\tilde{N}_{oo}, \tilde{M}_{oo}, \tilde{N}_{oo}, \tilde{M}_{oo}, K_o, \tilde{N}_o, \tilde{M}_o, K_i, \tilde{N}_i, \tilde{M}_i)$
31: $\text{ComputeAt}(D, M_o)$
32: $F_{NM} \leftarrow \text{Fuse}(N_o, M_o)$
33: $\text{Parallel}(F_{NM})$
34: $\text{Unroll}(F_{NM},64)$
35: $\text{Vectorize}(M_i)$

**Algorithm 2** High level definition of a workload class with a convolutional layer, bias addition, and ReLU activation.

1: Define placeholders for inputs $X$, weights $W$, and bias $B$
2: Pad the input $Xl \leftarrow \text{Pad}(X)$
3: $Y \leftarrow \text{Conv2d}(Xl)$
4: $Y \leftarrow Y + B$
5: $Y \leftarrow \text{ReLU}(Y)$
6: Return $Y$
produced for $A_1B_1$ and $A_2B_2$ is that the latter uses a temporary cache buffer to store intermediate results, as seen on Line 22. Other differences are the unroll factors chosen by the auto-scheduler: 512 for $A_1B_1$, as seen on Line 16; and 64 for $A_2B_2$ on Line 34. If we apply the $A_2B_2$ schedule to $A_1B_1$ we observe that the transformations being applied are still valid, since all of the loop variables being referenced exist in both computations, and no transformation is strongly dependent on a given data size.

4.2 Workload Classes

We briefly introduced the idea of workload classes in Figure 3, where we can re-use auto-schedules between workloads if they contain the same operations. We now discuss the concept in more detail. Workloads are the units of computation which we pass to the auto-scheduler, for example in neural networks a workload may be a layer. Often, workloads can contain several operations, especially when they can be fully fused to encompass the same loop structure (such as in the case of many activation functions like ReLU). For this work, we defer to the workload partitioning used in TVM, since the choices it makes are reasonable (such as combining activation functions and bias additions with larger layers such convolutional layers), and leads to state-of-the-art performance in many benchmarks [13]. For example, a convolutional layer followed by a ReLU activation function can be treated as a single workload, since we can fuse the operations such that the ReLU function is applied within the loop nest of the convolutional layer, as soon as all the partial sums for an output have been computed. This operation fusion saves a full traversal of the output data, and can thus reduce cache misses significantly. We define a workload class to be a set of workloads that share the same sequence of operations, regardless of their data sizes.

In Table 1 we observe the characteristics of the workloads and their classes, in the model ResNet18 [17]; a CNN defined on the ImageNet dataset [34]. Most workloads include a 2D convolutional layer, some of which include an activation function or a bias or skip-connection addition; however we also observe a fully connected layer, and some pooling layers. Some of the workloads are repeated more than once in the model\(^2\), however for the purposes of auto-scheduling repeated workloads are only tuned once, though may be given a higher proportion of the search time. Overall in ResNet18 we identify 6 workload classes, labeled A-F: with classes A, E, and F representing workloads featuring convolutional layers; B and C being max-pooling and average-pooling workloads; and D being the final fully connected layer. There are a variety of workload classes featuring convolutional layers, such as class label D, defined by padding input data, running a convolutional layer, followed by a ReLU activation, and then finally a skip-connection, which we describe in Algorithm 2. The steps can be further decomposed into lower level loop structures, such as those describing the Conv2d algorithm, however we do not include these details for brevity.

A workload of class E would be defined by the data size of its inputs and weights, and a schedule for this workload would apply transformations to the code in a manner similar to the one seen in Algorithm 1, albeit with a more complex initial loop structure. Much like the GEMM example in Section 4.1, we observe that schedules can be reused between workloads of the same class in ResNet18, even if they defined different sizes. Thus, we could run tuning-reuse using a schedule of class E on another workload of class E.

If we were to try applying a schedule from class E to another class, such as one defined by a fully-connected layer of class D it would be invalid, as the schedule would be attempting to apply transformations to input data and loops not present in the computation. In some cases even within the same class the generated code may be invalid, for example if the schedule defines a loop splitting factor which is larger than the loop itself. In Section 6.2 we discuss how a weak form of across-class tuning-reuse may be possible, however for now we assume tuning-reuse is only valid between workloads of the same class.

4.3 Applying tuning-reuse

Now that we have discussed the principles of tuning-reuse, including why it works, and how workload classes are relevant; next we look at how it behaves on a real DNN model.

| ID | Class | input_shape | kernel_shape | TVM Ops | Use Count |
|----|-------|-------------|--------------|---------|------------|
| 1  | A     | [1, 256, 14, 14] | [1, 512, 7, 7] | conv2d_add | 1          |
| 2  | A     | [1, 128, 28, 28] | [1, 256, 14, 14] | conv2d_add | 1          |
| 3  | A     | [1, 64, 56, 56] | [1, 256, 14, 14] | conv2d_add | 1          |
| 4  | E     | [1, 3, 224, 224] | [1, 112, 112, 112] | conv2d_bias_relu | 1 |
| 5  | E     | [1, 64, 56, 56] | [1, 64, 56, 56] | conv2d_bias_relu | 2          |
| 6  | E     | [1, 64, 56, 56] | [1, 64, 56, 56] | conv2d_bias_relu | 1          |
| 7  | F     | [1, 64, 56, 56] | [1, 64, 56, 56] | conv2d_bias_add_relu | 2 |
| 8  | E     | [1, 64, 56, 56] | [1, 128, 28, 28] | conv2d_bias_relu | 1          |
| 9  | E     | [1, 128, 28, 28] | [1, 128, 28, 28] | conv2d_bias_relu | 1          |
| 10 | F     | [1, 128, 28, 28] | [1, 128, 28, 28] | conv2d_bias_add_relu | 2 |
| 11 | E     | [1, 128, 28, 28] | [1, 128, 14, 14] | conv2d_bias_relu | 1          |
| 12 | E     | [1, 256, 14, 14] | [1, 256, 14, 14] | conv2d_bias_relu | 1          |
| 13 | F     | [1, 256, 14, 14] | [1, 256, 14, 14] | conv2d_bias_add_relu | 2 |
| 14 | E     | [1, 256, 14, 14] | [1, 512, 7, 7] | conv2d_bias_relu | 1          |
| 15 | E     | [1, 512, 7, 7] | [1, 512, 7, 7] | conv2d_bias_relu | 1          |
| 16 | F     | [1, 512, 7, 7] | [1, 512, 7, 7] | conv2d_bias_add_relu | 2 |

\(^2\)Note that in ResNet18 the 18 refers to the total number of convolutional and fully connected layers.
We take the ImageNet definition of ResNet18, and use the auto-schedules of ResNet50, a model chosen because it is likely to have good potential for tuning-reuse due to its similar structure. Our end-to-end tuning-reuse implementation has two stages: first we evaluate each workload/schedule pair as standalone programs; second we use this information to test if the best workload/schedule pairs chosen behave differently in the context of the full model.

4.3.1 Standalone execution

First, we evaluate each of the 18 workloads of ResNet18 with all compatible schedules of ResNet50. Figure 4 shows the inference time of all of these workload/schedule pairs running as standalone programs, separate from the full model. The purpose of this evaluation is to give us insights into which schedules give good performance improvements for each workload. We also evaluate the performance of a default fallback schedule, which we refer to as “untuned”.

We observe that there are six workload classes in ResNet18, with no schedules for classes F found in ResNet50. For class F, we use the default schedule provided by TVM, represented as a black bar. For workloads of class A we have 4 compatible schedules to try from ResNet50; workloads of class E can be compiled with 16 possible schedules; and for workloads of classes B, C, and D note that we only have one compatible schedule each. For class E, we observe that some schedules on some workloads produce invalid code, which we represent with a value of −1. There are 16 schedules of class E, from which 7 always produce invalid code for the workloads of ResNet18, hence we do not represent them in the graph. We also observe significant differences in inference time between schedules for some workloads: for example for workload 2, schedule A3 has over double the inference time of A4.

Running standalone is a reasonable proxy for performance in the full model, since the executed code of workloads in this context are independent function calls. Their only point of interaction is the output data of one workload being used as input data of a subsequent workload, which may have consequences for data locality. The independence of workloads assumption is used by Ansor, which tunes all workloads in isolation, and takes the best performing schedule for each. This is pragmatic, as it means that many more schedules can be evaluated due to reduced search costs, increasing the likelihood that a performant one can be found. However, our observation is that the independence assumption is too strong.

4.3.2 Full model evaluation

If instead of running each workload/schedule pair as its own program, we test how it reduces the inference time in the context of the full model, we observe that the “best” schedule chosen for each workload is not always the same. The red arrows in Figure 4 indicate which schedule provide the largest reduction in inference time when running the full model. For example, note that in workload 6 it is the fifth best schedule in standalone (E1) which gives the best reduction in the full model. Often it appears that the untuned workload is the best choice, but there are not many cases where it is chosen.

Our conclusion from this data is that the performance of a given workload/schedule pair ran as a standalone program can be a good proxy for its performance in the context of a full program; however we can get better information by testing schedules in the full tensor program. Taking the best performing schedules in standalone evaluation for each workload in ResNet18, we observe a speedup of 1.2× compared to the untuned model’s inference time. If we instead evaluate the pairs in the context of the full model, and take the best, then we get a maximum speedup of 1.21×. This is a modest improvement, however highlights how the maximum speedup of tuning-reuse can be increased.

However full evaluation is very expensive: every workload of the model must be compiled, and the full model must be run multiple times to get an average. A synthesis of the two approaches uses the information in standalone evaluation to prioritize the search in full evaluation. For example, we can reduce the priority of schedules which are unlikely to be useful, such those with higher inference times.

4.3.3 Approach

Combining these two stages, we evaluate an instantiation of tuning-reuse where: i) the user defines the number of full model evaluations they want to perform, ii) standalone execution of each workload/schedule pair is performed, iii) the performance of the model is measured using the best performing schedules, and iv) additional full evaluations are performed, changing a single schedule each time, to observe if it reduces inference time. For step iv) the workload/schedule pair to check on a given full evaluation is chosen based how expensive the workload is in the model, and how promising the schedule appeared in step ii).

Practically, we take the value of each workload’s inference time after step iii), apply the softmax function to represent the proportion of the model’s inference time the workload uses, and allocate the full-model evaluations proportionally. For example, if a user requested 20 full evaluations, and a workload represented 25% of model inference time, we would test up to 5 of the schedules of that workload in the full model. As discussed Section 4.3.2, we prioritize schedules to evaluate how promising they appeared in standalone execution. If we see an improvement, we keep this schedule, if not we discard the schedule and keep our previous choice.

Figure 5 shows how ResNet50 performs using this approach to tuning-reuse using schedules provided by ResNet50, as we increase the number of full evaluations. Zero evaluations represents the cost and speedup gained using only the top performing schedules according to standalone execu-
Figure 4: Inference time of ResNet18 workloads using ResNet50 schedules. The red arrow indicates the best schedule when tested in the full model, negative values denote schedules which produced invalid code.

Figure 5: Inference time of ResNet50 as we increase the number of permitted full-evaluations, using a schedule pool from ResNet50. The search time is shown as a red line, and we compare against Ansor given the same search time. With more full evaluations, more search time is required, and though this can potentially increase the performance, there is an upper bound for the speedup tuning-reuse can achieve given the available schedules since we cannot generate new, more optimal schedules. The yellow bar represents the speedup which the Ansor auto-scheduler given the same search time. Any optimization which reduces the search time needed for tuning-reuse makes it more competitive against Ansor as a solution.

4.4 Compiler optimizations

The dominating bottleneck in the search time of tuning-reuse is the cost to run full evaluations. Hence, reducing this cost can greatly improve the efficiency of tuning-reuse. Our observation is that between individual full-evaluations only one schedule for one workload is changed; the rest of the workloads are unchanged. Thus most of the compilation of the model will be redundant, and for ResNet50 we will be recompiling 17 of the 18 workloads using the same schedule. In theory we could reduce our compilation costs for ResNet50 by a factor of 18 by caching compiled workloads, and only recompiling the workload of interest. This makes the simplifying assumption that compilation of the workloads is the only compilation cost, and compilation costs are uniform between workloads.

Thus, we extend TVM to support incremental compilation, where we cache compiled workloads and purge compiled workloads from the cache which we want to recompile using a new schedule. This extension cannot be exploited by Ansor which only compiles the final model once. For ResNet50, this reduces the search time by an average of 33%, and a maximum of 46%. In Figure 5, and Section 5, we show results using reduced compilation costs.

4.5 Model selection

In Section 4.3 we demonstrated the core concepts of tuning-reuse using the model ResNet50, tuned from ResNet50. This was a reasonable choice, since the model architectures are similar (they belong to the same family of models); however we need a more robust approach to select the model we will use for tuning-reuse.

Table 2 shows a set of DNN models, their workload classes, the frequency of workloads of each class, and the proportion of the untuned inference time that workloads of a given class represent. For example ResNet50 has 6 workload classes representing 27 unique workloads (some workloads are repeated in the model); with classes including class A with four workloads, which represents 17% of the untuned inference time; 16 workloads of class E representing 67% of the inference time; and classes B, C, and D which represents a negligible proportion of the inference time. For brevity we do not include details of each class, however expensive workload classes tend to include convolutional layers or fully connected layers while cheaper classes tend to contain operations such as pooling layers.

When choosing a model, we want to maximize the likelihood that it will provide a good tuning for a target model. We hypothesized in Section 3 that perhaps similarities between

\[^3^\]This extension, as well as our implementation of tuning-reuse is available at github.com/xxx/yyy
the workloads (e.g., having the same kernel size, or similar memory footprint) could be used to predict how successful a given tuning-reuse for a workload using a given schedule would be. However, in our initial study we did not find any feature which had strong predictive power. Thus, in this paper we adopt a more coarse-grained approach which chooses a model to tune based on the number of available schedules of a given class, and the proportional cost of that workload class in untuned inference in the target model.

We define a selection heuristic which for a target model, chooses a tuning model which maximizes the number of available tuned schedules, giving preference for workload classes which represent a higher proportion of the untuned inference time. To avoid models with very high numbers of schedules dominating, we increase the influence of the untuned costs by squaring it, and reduce the influence of the number of schedules in the tuning model by taking the square root. Thus, we formulate our heuristic for a given target model $M$, which has a set of workload classes $C$, as choosing a tuning model $T$ which maximizes the following:

$$
\sum_{c \in C} P_c^2 \sqrt{|W_{Tc}|},
$$

where $P_c$ is the proportional cost of workload class $c$ in $M$, and $W_{Tc}$ is the set of workloads of class $c$ in the candidate model $T$. Looking at Table 2, we can see for ResNet50, that the model which maximizes Equation 1 is GoogLeNet; and the two versions of EfficientNet maximize each other.

However this heuristic is not guaranteed to make optimal decisions. For example, the heuristic chose GoogLeNet in part because it had a high number of schedules for class E, which represents 67% of ResNet50’s untuned inference time. This means that for each of the 16 workloads of class E in ResNet50, there are 49 schedules that may reduce the inference time. However, the 9 schedules of class E in VGG-16 may be better at reducing the overall inference time in ResNet50, even though there are fewer of them. A better predictive model of which schedules may perform well for when used in tuning-reuse for a given workload could improve the heuristic. However the heuristic gets reasonable results. Table 3 shows the maximum speedup achieved by running tuning-reuse for 5 full-evaluations for the top 3 models suggested by the heuristic. As we can see, the trend is that the best speedup is achieved by Choice 1, and the maximum speedup decreases with subsequent options.

In the next section, we present results of running the top choice given by the heuristic for each model, and compare against Ansor.

5 Evaluation

In this section we evaluate the performance of nine common DNN models, shown in Table 2, applying tuning-reuse using auto-schedules from the model selected using the heuristic described in Section 4.5. We analyze the impact of increasing the number of full model evaluations, and compare how well Ansor auto-scheduling from scratch performs when given the same search time.

5.1 Experimental Setup

In addition to ResNet18 discussed in Section 4, we evaluate 8 more models. All models are defined on the ImageNet dataset [34], and the machine used to evaluate the models includes an Intel Xeon E5-2620 CPU. Auto-scheduling, compilation, and inference are executed using the CPU.

ResNet18 and ResNet50 [17] have 18 and 50 layers respectively and consist of residual blocks. Each block contains two convolutional layers (that include between 64 and 2048 filters of size $3 \times 3$ and $1 \times 1$) and blocks are connected in a feed-forward manner. Additionally, there is a skip connection between the input and output of each block, which helps gradients propagate through the network [8]. These models also utilize batch normalization [19] after each convolution, though these layers are combined with the parameters of the convolutional layers such that they have zero cost.

AlexNet [22] consists of 5 convolutional layers, 3 max-pooling layers and 3 fully connected layers. Each convolutional layer consists of convolutional filters (different sizes are used including $3 \times 3$, $5 \times 5$ and $11 \times 11$) and a nonlinear activation function ReLU.

VGG-16 [38] is a feed-forward network with 13 convolutional layers and 3 fully connected layers. Each convolutional layer consists of convolutional filters (different sizes are used including $3 \times 3$, $5 \times 5$ and $11 \times 11$) and a nonlinear activation function ReLU.

MobileNetV2 [37] is a lighter weight model with 53 layers, many of which feature depthwise convolutions, which reduce the number of parameters and operations required. This makes it ideal for constrained edge devices.

EfficientNet [43] is a family of models, with a focus on scalability, variants of which continue to rank highly in the state-of-the-art for a range of standard datasets. The architecture of the smallest model, EfficientNetB0, was found using neural architecture search (NAS), and the accuracy of the model is improved by applying a novel scaling method which changes the architecture to increase the number of parameters and operations. There are sizes ranging from B0-B7, but in this paper we evaluate EfficientNetB0 and EfficientNetB4.

GoogLeNet [41] (or InceptionV1) is a 22 layer model, containing 9 so-called “inception” modules. It came first in the ILSVRC 2014 image classification challenge.

MNASNet [42] is an architecture designed for edge devices such as mobile phones, with an architecture generated using NAS.


Table 2: Workload features

| ID | Model               | Workload classes (number of workloads, percentage of inference time)                                                                 | Tuning Model   |
|----|---------------------|------------------------------------------------------------------------------------------------------------------------------------|----------------|
| M1 | ResNet50            | A (4, 17%); B (1, 0%); C (1, 0%); D (1, 6%); E (16, 67%); G (4, 10%)                                                            | GoogLeNet      |
| M2 | AlexNet             | B (3, 0%); D (1, 6%); E (5, 14%); H (2, 80%); I (1, 0%)                                                                         | VGG16          |
| M3 | VGG16               | B (5, 0%); D (1, 1%); E (9, 59%); H (2, 40%); I (1, 0%)                                                                         | GoogLeNet      |
| M4 | MobileNetV2         | A (7, 15%); C (1, 0%); D (1, 24%); J (8, 32%); K (5, 15%); L (10, 14%)                                                          | EfficientNetB4 |
| M5 | EfficientNetB0      | A (14, 9%); C (11, 4%); D (1, 12%); K (5, 9%); M (8, 39%); N (12, 27%); O (7, 0%)                                       | EfficientNetB4 |
| M6 | EfficientNetB4      | A (16, 11%); C (13, 3%); D (1, 10%); K (7, 14%); M (9, 39%); N (14, 23%); O (9, 0%)                                       | EfficientNetB4 |
| M7 | GoogLeNet           | B (10, 1%); C (1, 0%); D (1, 4%); E (49, 95%)                                                                                 | ResNet50       |
| M8 | MnasNet1.0          | A (7, 17%); D (1, 25%); E (9, 31%); K (5, 15%); P (12, 13%)                                                                   | GoogLeNet      |

Table 3: Heuristic choices

| Model         | Choice 1        | Choice 2       | Choice 3       |
|---------------|-----------------|----------------|----------------|
| ResNet50      | M7 (1.17×)      | M8 (1.0×)      | M3 (1.09×)     |
| AlexNet       | M3 (4.81×)      | M7 (1.05×)     | M1 (1.03×)     |
| VGG16         | M7 (1.19×)      | M1 (1.0×)      | M8 (1.0×)      |
| MobileNetV2   | M6 (1.17×)      | M5 (1.21×)     | M8 (1.19×)     |
| EfficientNetB0| M6 (1.22×)      | M4 (1.08×)     | M8 (1.09×)     |
| EfficientNetB4| M5 (1.15×)      | M4 (1.04×)     | M8 (1.03×)     |
| GoogLeNet     | M4 (1.15×)      | M3 (1.04×)     | M8 (1.0×)      |
| MnasNet1.0    | M7 (1.28×)      | M1 (1.25×)     | M3 (1.18×)     |

5.2 Results

Figure 6 shows the results of running tuning-reuse across the 8 models, with each model being tuned using the model suggested by our heuristic described in Section 4.5.

For ResNet50, we have 27 workloads in total, with some workloads repeated throughout the model. In Figure 6a we observe a speedup of 1.16× after the first stage of tuning-reuse (zero full evaluations), which takes 559 seconds; and gets its maximum speedup of 1.2× after 10 full evaluations, or 885 seconds. Ansor given the same time gets a speedup of 1.03× after the first stage (0 evaluations), and 1.13× after 10 full evaluations. After 40 full evaluations, or 1712 seconds, Ansor is able to find a set of schedules which outperforms tuning-reuse. However ResNet50 achieves its best time after only 10 full evaluations, and tuning-reuse’s target is to keep the number of full evaluations low through intelligent schedule selection.

For AlexNet, we have 12 workloads, across 5 classes, with the tuning provided by GoogLeNet. In Figure 6b we observe significant speedups, up to 4.84×. The maximum search time for AlexNet is low compared to other models, due to the smaller number of workloads. However we observe that Ansor also finds a high speedup after a short period time, reaching a similar speedup to tuning-reuse in 20 full evaluations, or 355...
seconds. We discuss this behavior in Section 5.3.

MobileNetV2 (tuned with EfficientNetB4) sees a maximum speedup of $1.22 \times$, and even after 50 full evaluations Ansor does not find a set of schedules which can outperform tuning-reuse. The search costs of MobileNetV2 are low, at most 640 seconds. This is partially due to over half of its workloads (those of classes J and L) not being tuned by EfficientNetB4. Tuning with a model which included those classes could increase the maximum speedup, though would increase the search time.

EfficientNetB0, also tuned with EfficientNetB4, gets a maximum speedup of $1.27 \times$; and like MobileNetV2, Ansor does not outperform tuning-reuse given 50 full evaluations. The search time for the model is much higher than most other models, over 990 seconds to complete the first stage (0 evaluations), and almost 3000 seconds to perform 50 full evaluations. This is because there are 58 workloads to evaluate, and even with the compiler optimizations discussed in Section 4.4 the costs of combining many compiled workloads together into a single binary are non-negligible. For EfficientNetB4 (tuned with EfficientNetB0), the situation is similar with a high search time due to 69 workloads. The maximum speedup is $1.15 \times$, which is lower than EfficientNetB0, and after 40 and 50 evaluations Ansor has sufficient time reach a higher speedup.

GoogLeNet features 61 workloads, and reaches a maximum speedup of $1.15 \times$ after 5 full evaluations. Like the two EfficientNet models, higher number of workloads make the search time high, up to 2732 seconds. After 40 full evaluations Ansor is able to find the same speedup.

MnasNet1.0 tuned with GoogLeNet achieves a maximum speedup of $1.28 \times$ after 10 full evaluations, or 615 seconds. After 50 full evaluations Ansor is still unable to provide a competitive time, with its highest speedup being $1.18 \times$.

Finally, for VGG16 we have 18 workloads, across 5 classes. The heuristic tells us that we should select GoogLeNet, as seen in Table 3. The maximum speedup of $1.19 \times$ is reached after the first stage (0 evaluations), however very quickly Ansor outperforms tuning-reuse with a maximum speedup of $1.61 \times$. Section 5.3 explores this poor performance.

Overall, these results show that tuning-reuse can outperform the state-of-the-art auto-scheduler Ansor when given a limited amount of search time. Tuning-reuse has the largest speedups relative to Ansor between 0 and 10 full evaluations, which should be considered the target.

5.3 Fully connected layers and VGG16

If we look at Table 2, we observe that VGG16 contains 2 workloads of class H, which represent 40% of the inference time. Despite having no schedules of class H, GoogLeNet is chosen by the heuristic, since it has a high number of class E schedules. What the heuristic does not capture is that these workloads of class H contain fully-connected layers, which have higher potential for speedup in TVM. If instead we tune VGG16 with AlexNet (since AlexNet contains 2 schedules of class H) we observe in Figure 6i that we increase the maximum speedup to $1.45 \times$, up from $1.19 \times$. This is despite class H representing a smaller fraction of VGG16’s inference time.

For brevity, we did not explain the operations present in every workload class in Table 1. However, if we compare workload classes H and E, we see that class H is defined by a fully connected layer; and class E is defined by a convolutional layer. Both classes also contain additional operations including a tensor addition and ReLU. This exposes a simplifying assumption of the heuristic, that was not as evident with other experiments: that the potential improvement for workloads of a given class is uniform.

To show the flaw in this assumption, we generate 6 workloads of varying sizes, 3 for each class H and E, and run the auto-scheduler on each for 100 program variants. After tuning, we observe on average that workloads of class H get a speedup of $33.4 \times$, whereas workloads of class E only get a speedup of $1.23 \times$. This suggests that it is easier to find better schedules for workloads containing fully connected layers, than 2D convolutional operations. Section 6.1 discusses how we might exploit this knowledge.

6 Discussion

Our evaluation highlights some important limitations of auto-scheduling, namely that it is possible to outperform it when we require less compilation time if we leverage tuning-reuse. The results in Section 5 show that tuning-reuse can be a viable tool in future tensor program deployments, in situations where search time is limited, and other tuned models are available. In this section, we discuss how tuning-reuse could be further improved to make it a more attractive solution.

6.1 Improvements to baseline tuning-reuse

Increased schedule pool size: Section 4.5 discusses how given a set of pre-tuned models and a target model, we can select a model which is likely to give higher performance improvements. However, in principle we could use all of the tuned schedules we have available in Table 2. The caveat to consider is that this could translate into a very high number of schedules to evaluate, which would increase search time significantly.

More intelligent schedule selection: As discussed in the previous section, a larger schedule pool could improve our maximum speedup, but also increase our search time. In Section 4.5 we discussed how we did not identify features of workloads and schedules which could help predict if a given schedule would provide a performant tuning-reuse. However, this does not discount a pattern which could be identified using more complex statistical methods or machine learning.
Being able to better predict a schedule’s performance could allow us to devise a better heuristic than the one described in Section 4.5, as well as requiring fewer schedules to be evaluated, since bad schedules could be discarded without any measurement. This would reduce search time, and make tuning-reuse more competitive. Additionally, we could leverage information about the differences in potential speedup for each workload class, as discussed in Section 5.3 to improve our schedule selection.

Reducing search costs: In Section 4.4 we discussed and implemented incremental compilation in TVM which reduced the needed search time for tuning-reuse. A more optimized implementation of this extension could reduce search times further, for example caching the parsing of the model definition, as well as more efficiently combing workloads together into a single executable binary.

6.2 Across class tuning-reuse

Thus far we have assumed that workloads of different classes are not suitable for tuning-reuse. However some workload classes are themselves similar, for example class E is characterized by a convolutional layer, a bias addition, and a ReLU activation function; whereas class F contains all of these operations, and a skip connection. Thus we may be able to relax the same-class requirement for tuning-reuse in this case, by removing parts of the schedule which reference tensors not present in the class. For radically different workload classes, such as class E and class D (which features a fully connected layer), tuning-reuse would not be possible. This is because the loop structures are inherently incompatible.

7 Related Work

Schedule based computation was popularized in Halide [30], however it does not provide all of the graph level optimizations available in TVM [13]. TVM builds on the ideas of Halide to bring a usable schedule compiler for deep learning. Other works include RISE/ELEVATE [16] which are well defined functional languages for compute declaration and scheduling respectively.

Auto-tuning frameworks, especially for compute-schedule based systems like TVM are a popular area of research. AutoTVM [11] takes hand-engineered schedules for operations, and explores parameter tunings across a space defined by the schedule author, such as tiling sizes, unrolling factors, and others. Choices to efficiently explore these potentially large spaces vary, with AutoTVM including approaches such as gradient boosting [12] and genetic algorithms. Chameleon [4] improves the search strategies of AutoTVM by leveraging reinforcement learning. MetaTune [35] improves auto-tuning parameter selection for systems like AutoTVM. In ATF [31], the authors look at more efficient auto-tuning techniques, with a focus on modeling when parameters have inter-dependencies among them.

Regarding auto-scheduling, FlexTensor [46] is an auto-scheduling system similar to Ansor, though relies on more hand written templates, thus seeing worse performance on some benchmarks. LIFT [39] explores the use of rewrite rules on high level representations of programs to generate OpenCL code, though it does not explore its large search space as efficiently as Ansor. The Tiramisu deep learning compiler [6] recently added support for an auto-scheduling system [5]. None of these approaches exploit the notion of tuning-reuse to reduce search time.

The reuse of bundles of optimizations has been seen in other works beyond tensor programs. For example Martins et al. [27] looks at similarities between C functions to cluster them into groups, and applies compiler passes based on group membership. In tuning-reuse we have more domain specific knowledge we can leverage, since we are in the space of tensor programs with well-defined operations. CompilerGym [15] exposes LLVM compiler optimizations to reinforcement learning agents via the OpenAI Gym [10]. Like Martins et al., its focus is on more general purpose program optimization, and does not exploit domain specific knowledge of tensor programs.

Overall, tuning-reuse builds on existing work of domain specific schedule based programming paradigms such as Halide and TVM, and the ideas of auto-scheduling framework introduced by Ansor. Other works have exploited similarity between programs to make compilation optimization more efficient. Tuning-reuse’s novelty comes from leveraging this workload similarity in the domain of schedule based tensor compilers to reduce search costs.

8 Conclusion

In this paper we proposed “tuning-reuse” as a new approach to exploit similarities in tensor programs to reduce efficient schedules found via auto-scheduling. We have discussed how tuning-reuse is feasible in a compute/schedule programming paradigm, and explained the key components necessary to accelerate tuning of a full model. We defined an implementation of tuning-reuse, and evaluated the performance on 9 models, with a maximum performance speedup of between 1.16× and 4.76×, while clearly outperforming Ansor when given limited search time. For future work, we will explore how tuning-reuse can be used to bootstrap auto-scheduling, as well as investigate its relevance to NAS.

Availability

Our complete implementation of tuning-reuse is available at https://www.github.com/xxx/yyy.
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