

A Semi-Decoupled Approach to Fast and Optimal Hardware-Software Co-Design of Neural Accelerators

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ABSTRACT

In view of the performance limitations of fully-decoupled designs for neural architectures and accelerators, hardware-software co-design has been emerging to fully reap the benefits of flexible design spaces and optimize neural network performance. Nonetheless, such co-design also enlarges the total search space to practically infinity and presents substantial challenges. While the prior studies have been focusing on improving the search efficiency (e.g., via reinforcement learning), they commonly rely on co-searches over the entire architecture-accelerator design space. In this paper, we propose a *semi*-decoupled approach to reduce the size of the total design space by orders of magnitude, yet without losing optimality. We first perform neural architecture search to obtain a small set of optimal architectures for one accelerator candidate. Importantly, this is also the set of (close-to-)optimal architectures for other accelerator designs based on the property that neural architectures' ranking orders in terms of inference latency and energy consumption on different accelerator designs are highly similar. Then, instead of considering all the possible architectures, we optimize the accelerator design only in combination with this small set of architectures, thus significantly reducing the total search cost. We validate our approach by conducting experiments on various architecture spaces for accelerator designs with different dataflows. Our results highlight that we can obtain the optimal design by only navigating over the reduced search space. The source code of this work is at <https://github.com/Ren-Research/CoDesign>.

KEYWORDS

Hardware-software co-design, neural accelerator, performance monotonicity

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1 INTRODUCTION

Neural architecture search (NAS) has been commonly used as a powerful tool to automate the design of efficient deep neural network

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(DNN) models [36]. As DNNs are being deployed on increasingly diverse devices such as tiny Internet-of-Things devices, state-of-the-art (SOTA) NAS is turning hardware-aware by further taking into consideration the target hardware as a crucial factor that affects the resulting performance (e.g., inference latency) of NAS-designed models [4, 8, 15, 25, 26, 30, 32].

Likewise, optimizing hardware accelerators built on Field Programmable Gate Array (FPGA) or Application-Specific Integrated Circuit (ASIC), as well as the corresponding dataflows (e.g., scheduling DNN computations and mapping them on hardware), is also critical for speeding up DNN execution [1, 11, 33].

While both NAS and accelerator optimization can effectively improve the DNN performance (in terms of, e.g., accuracy and latency), they are traditionally performed in a siloed manner, without fully unleashing the potential of design flexibilities. As shown in recent studies [16, 19], such a decoupled approach does not explore potentially better combinations of architecture-accelerator designs, leading to highly sub-optimal DNN performance. As a result, co-design of neural architectures and accelerators (a.k.a., hardware-software co-design) has been emerging to discover jointly optimal architecture-accelerator designs [3, 11, 12, 19, 20, 33].

A common approach to hardware-software co-design is to use a nested loop: the outer loop searches over the hardware space while the inner loop searches for the optimal architecture given the hardware choice in the outer loop, or vice versa (i.e., outer loop for architectures and inner loops for hardware) [12, 13]. Alternatively, one can also simultaneously search over the neural architecture and hardware spaces as a combined design choice [16].

While hardware-software co-design can further optimize DNN performance [34], it also exponentially enlarges the search space, presenting significant challenges. For example, the combination of architecture and accelerator design spaces can be up to 10^{861} [16]. Concretely, letting M and N be the sizes of the architecture space and hardware/accelerator space, respectively, the total search complexity is in the order of $O(MN)$. By contrast, the fully-decoupled approach (i.e., separately performing NAS and accelerator optimization) has a total complexity of $O(M + N)$, although it only results in sub-optimal designs.

Consequently, many studies have been focusing on speeding up the evaluation of co-design choices (e.g., using accuracy predictor and latency/energy simulation instead of actual measurement [5, 19, 29, 33]), and/or improving the search efficiency (e.g., reinforcement learning or evolutionary search to co-optimize architecture and hardware [11, 16, 19]). Nonetheless, due to the $O(MN)$ search space, the SOTA hardware-software co-design is still a time-consuming process, taking up a few or even tens of GPU hours for

each new deployment scenario (e.g., changing the latency and/or energy constraints) [12, 16].

Contributions. By settling in-between the fully-decoupled approach and the fully-coupled co-design approach, we propose a new *semi-decoupled* approach to reduce the size of the total co-search space $O(MN)$ by orders of magnitude, yet without losing design optimality. Our approach builds on the *latency and energy monotonicity* — the architectures’ ranking orders in terms of inference latency and energy consumption on different accelerators are highly correlated — and includes two stages. In **Stage 1**, we randomly choose a sample accelerator (a.k.a., a proxy accelerator), and then run hardware-aware NAS for K times to find a set \mathcal{P} consisting of $K = |\mathcal{P}|$ optimal architectures for this proxy. Clearly, compared to M and N , the size of \mathcal{P} is orders-of-magnitude smaller (e.g., 10-20 vs. 10^{18} [17]). Then, in **Stage 2**, instead of the entire architecture space as in the SOTA co-design, we only jointly search over the hardware space combined with the small set \mathcal{P} , which significantly reduces the total search space. Crucially, by latency and energy monotonicity, the set of optimal architectures is (approximately) the same for all accelerator designs, and hence selecting architectures out of \mathcal{P} can still yield the optimal or very close-to-optimal architecture design.

We validate our approach by conducting experiments on a state-of-the-art neural accelerator simulator MAESTRO [14]. Our results confirm that strong latency and energy monotonicity exist among different accelerator designs. More importantly, by using one candidate accelerator as the proxy and obtaining its small set of optimal architectures, we can reuse the same architecture set for other accelerator candidates during the hardware search stage.

2 PROBLEM FORMULATION

We focus on the design of a single neural architecture-accelerator pair. The main goal is to maximize the inference accuracy subject to a few design constraints such as inference latency, energy, and area [12]. Next, by denoting the neural architecture and hardware as a and h , respectively, we formulate the problem as follows:

$$\max_{a \in \mathcal{A}, h \in \mathcal{H}} \text{Accuracy}(a) \quad (1)$$

$$\text{s.t.,} \quad \text{Latency}(a, h) \leq L \quad (2)$$

$$\text{Energy}(a, h) \leq E \quad (3)$$

$$\text{HardwareResource}(h) \leq H, \quad (4)$$

where the objective $\text{Accuracy}(a)$ depends on the architecture,¹ the first two constraints are set on the inference latency and energy consumption that depend on both the architecture and hardware choices, and the last constraint is on the hardware configuration itself (e.g., area) and hence independent of the architecture. We denote the optimal design as (a^*, h^*) which solves the optimization problem Eqns. (1)–(4). Note that, because of the combinatorial nature of the problem, *optimality* is not in a mathematically strict sense; instead, a design (a, h) is often considered as *optimal* if it is good enough in practice (e.g., better than or competitive with SOTA designs).

Suppose that the architecture space \mathcal{A} and hardware space \mathcal{H} have $M = |\mathcal{A}|$ and $N = |\mathcal{H}|$ design choices, respectively, which

¹The inference accuracy also depends on the network weight trained on a dataset, which is not a decision variable in hardware-software co-design and hence omitted.

are both extremely large in practice. Thus, the co-design space $\mathcal{A} \times \mathcal{H}$ has a total of MN architecture-hardware combinations. This makes exhaustive search virtually impossible and adds significant challenges to co-design over the joint search space.

Remark. In our formulation, the notation of neural “architecture” $a \in \mathcal{A}$ can also broadly include other applicable design factors for the DNN model (e.g., weight quantization). Moreover, the hardware h implicitly includes the dataflow design, which is a downstream task based on the architecture and hardware choices. In the following, we also interchangeably use “accelerator” and “hardware” to refer to the hardware-dataflow combination unless otherwise specified. Thus, with different dataflows, the same hardware configuration will be considered as different $h \in \mathcal{H}$.

3 A SEMI-DECOPLED APPROACH

In this section, we first review the existing architecture-accelerator design approaches, and then present our semi-decoupled approach.

3.1 Overview of Existing Approaches

3.1.1 Fully decoupled approach. A straightforward approach is to separately optimize architectures and accelerators in a siloed manner by decoupling NAS from accelerator design [9, 29, 33]: first perform NAS to find *one* optimal architecture $\tilde{a} \in \mathcal{A}$, and then optimize the accelerator design for this particular architecture \tilde{a} ; or, alternatively, first optimize the accelerator $\tilde{h} \in \mathcal{H}$, and then perform NAS to find the optimal architecture for this particular accelerator \tilde{h} . This approach has a total complexity in the order of $O(M + N)$ where $M = |\mathcal{A}|$ and $N = |\mathcal{H}|$. But, the drawback is also significant: it does not fully exploit the flexibility of the co-design space and, as shown in several prior studies [12, 16, 19], can result in highly sub-optimal architecture-accelerator designs.

3.1.2 Fully coupled approach. As can be seen in Eqns. (2) and (3), the inference latency and energy consumption is jointly determined by the architecture and hardware choices. Such entanglement of architecture and hardware is the key reason for the SOTA hardware-software co-design.

Concretely, a general co-design approach is to use a nested loop [19]. For example, the outer loop searches over the hardware space, whereas the inner loop searches for the optimal architecture given the hardware choice in the outer loop. Alternatively, another equivalent approach is to first search for neural architectures in the outer loop and then search for accelerators in the inner loop.

Here, we use “outer loop for hardware and inner loop for architecture” as an example. While the actual search method can differ from one study to another (e.g., reinforcement learning vs. evolutionary search [5, 19]), this nested search can be mathematically formulated as a bi-level optimization problem below:

$$\text{Outer:} \quad \max_{h \in \mathcal{H}} \text{Accuracy}(a^*(h)) \quad (5)$$

$$\text{s.t.,} \quad \text{HardwareResource}(h) \leq H, \quad (6)$$

where, given a choice of h , the architecture $a^*(h) = a^*(h; L, E)$ solves the inner hardware-aware NAS problem:

$$\text{Inner:} \quad \max_{a \in \mathcal{A}} \text{Accuracy}(a) \quad (7)$$

$$\text{s.t.,} \quad \text{Latency}(a, h) \leq L \quad (8)$$

$$\text{Energy}(a, h) \leq E. \quad (9)$$

Table 1: Comparison of Different Approaches

Approach	Optimality	Complexity
Fully-decoupled separate design	No	$O(M + N)$
Fully-coupled co-design	Yes	$O(MN)$
Semi-decoupled co-design	Yes	$O(K(M + N))$

In Eqn. (5), $\text{Accuracy}(\cdot)$ is still decided by the architecture, although we use $a^*(h) = a^*(h; L, E)$ to emphasize that the architecture is specifically optimized for the given hardware candidate h .

We see that, during the search for the optimal hardware h^* in the outer problem, the inner NAS problem is repeatedly solved as a subroutine and yields the optimal architecture $a^*(h) = a^*(h; L, E)$ given each hardware choice h set by the outer search. For notational convenience, we also use $a^*(h)$ to represent $a^*(h; L, E)$ without causing ambiguity.

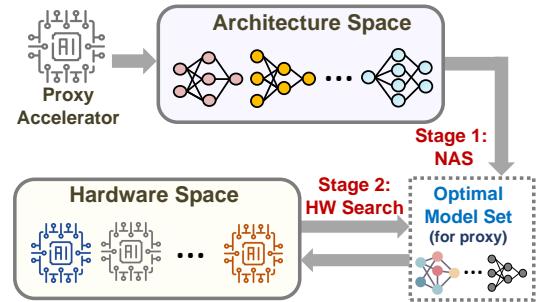
The focus of SOTA hardware-software co-design approaches have been primarily on speeding up the evaluation of architecture-hardware choices (e.g., using accuracy predictor and latency/energy simulation instead of actual measurement [5, 19, 29, 33]), and/or improving the search efficiency (e.g., reinforcement learning or evolutionary search to co-optimize architecture and hardware [11, 16, 19]). Nonetheless, evaluating one architecture-accelerator combination can still take up a few seconds in total (e.g., running MAESTRO to perform mapping/scheduling and estimate the latency and energy consumption takes 2–5 seconds on average [14]). Then, compounded by the exponentially large architecture and hardware space in the order of $O(MN)$, the total hardware-software co-design cost is very high (e.g., a few or even tens of GPU hours for each deployment scenario [16, 19]).

3.2 Semi-Decoupled Co-Design

We propose a semi-decoupled approach — partially decoupling NAS from hardware search to reduce the total co-search cost from $O(MN)$ to $O(K(M + N))$ in a principled manner, where K is orders-of-magnitude less than M and N .

Performance monotonicity. The key intuition underlying our semi-decoupled approach is the latency and energy performance monotonicity — given different accelerators, the architectures’ ranking orders in terms of both the inference latency and energy consumption are highly correlated. We can measure the ranking correlation in terms of the Spearman’s rank correlation coefficient (SRCC), whose value lies within $[-1, 1]$ with “1” representing the identical ranking orders [2].

It has been shown in a recent hardware-aware NAS study [18] that the architectures’ ranking orders in terms of inference latency are highly similar on different devices, with SRCCs often close to 0.9 or higher, especially among devices of the same platform (e.g., mobile phones). For example, if one architecture a_1 is faster than another architecture a_2 on one mobile phone, then it is very likely that a_1 is still faster than a_2 on another phone. One reason is that architectures are typically either computing-bound or memory-bound on devices of the same platform, which, by roofline analysis, results in similar rankings of their latencies [31]. Based on this property (a.k.a., latency monotonicity), it has been theoretically and empirically proved that the Pareto-optimal architectures on different devices are highly overlapping if not identical [18].

**Figure 1: Overview of our semi-decoupled approach.**

While the target hardware space chosen by the designer has many choices, it essentially covers one platform — neural accelerator under a set of hardware constraints. As a result, we expect latency monotonicity to be satisfied in our problem. Additionally, beyond the findings in [18], we observe in our experiments that *energy* monotonicity also holds: if one architecture a_1 is more energy-efficient than another architecture a_2 for one hardware choice, then it is very likely that a_1 is still more energy-efficient than a_2 for another hardware choice. Along with latency monotonicity, energy monotonicity will be later validated in our experiments. One reason for the energy monotonicity is that energy consumption is highly related to the inference latency with a strong correlation [15].

For simplicity, we use *performance* monotonicity to collectively refer to both latency and energy monotonicity.

Insights. The performance monotonicity leads to the following proposition, which generalizes the statement in [18] by considering both latency and energy monotonicity. We first note that, by solving the inner NAS problem under a set of latency and energy constraints in Eqns. (7)–(9), we can construct a set $\mathcal{P}(h) = (a_1^*(h; L_1, E_1), \dots, a_K^*(h; L_K, E_K))$ of optimal architectures covering the architectures along the Pareto boundary. The size $K = |\mathcal{P}(h)|$ of the optimal architecture set depends on the granularity of latency and energy constraints we choose. In practice, K in the order of a few tens (e.g., 10–30) is sufficient to cover a wide range of latency and energy constraints for our design target.

PROPOSITION 3.1. *Given performance monotonicity, the set of optimal architectures $\mathcal{P}(h) = (a_1^*(h; L_1, E_1), \dots, a_K^*(h; L_K, E_K))$ found by the inner hardware-aware NAS problem in Eqns. (7)–(9) is the same for all hardware choices, i.e., $\mathcal{P}(h_1) = \mathcal{P}(h_2)$, for all $h_1, h_2 \in \mathcal{H}$.*

PROOF. Consider two hardware choices $h_1, h_2 \in \mathcal{H}$. By performance monotonicity, we can replace the constraints $\text{Latency}(a, h_1) \leq L_1$ and $\text{Energy}(a, h_2) \leq E_1$ with another two equivalent constraints $\text{Latency}(a, h_2) \leq L_1'$ and $\text{Energy}(a, h_2) \leq E_1'$, respectively. By varying E_1 and L_1 over their feasible ranges, we obtain the optimal architecture set $\mathcal{P}(h_1)$ for h_1 . Accordingly, due to the equivalent latency and energy constraints for h_2 , we also obtain the optimal architecture set $\mathcal{P}(h_2)$ for h_2 , thus completing the proof. ■

Proposition 3.1 ensures that in the presence of performance monotonicity, the same set $\mathcal{P}(h)$ of optimal architectures apply to all $h \in \mathcal{H}$. Thus, we can also simply use \mathcal{P} to denote the set of optimal architectures, which are essentially *shared* by $h \in \mathcal{H}$. Note carefully that Proposition 3.1 does *not* mean that, given a specific pair of

Algorithm 1 Semi-Decoupled Architecture-Accelerator Co-Design

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1: Input: Architecture space  $\mathcal{A}$ , hardware space  $\mathcal{H}$ , sample hardware  $h_0 \in \mathcal{H}$ , and design constraints  $L, E, H$  in Eqns. (2), (3), (4)
2: Output: Optimal co-design  $(a^*, h^*)$ 
3: Initialization: Choose  $K$  latency and energy constraints  $(L_k, E_k)$  for  $k = 1, \dots, K$ , set  $\mathcal{P} = \emptyset$ , and randomly choose  $(a^*, h^*)$ ;
4: for  $k = 1, \dots, K$  do
5:   For constraints  $(L_k, E_k)$ , run hardware-aware NAS to get optimal architecture  $a_k^*(h_0; L_k, E_k)$ 
6:    $\mathcal{P} = \mathcal{P} \cup \{a_k^*(h_0; L_k, E_k)\}$ ;
7: end for
8: for each candidate hardware  $h \in \mathcal{H}$  do
9:   if  $HardwareResource(h) \leq H$  then
10:    Find optimal architecture  $a^*(h) \in \mathcal{P}$  satisfying the latency and energy constraint  $(L, E)$ 
11:    if  $Accuracy(a^*(h)) > Accuracy(a^*)$  then
12:       $(a^*, h^*) \leftarrow (a^*(h), h)$ 
13:    end if
14:  end if
15: end for

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latency and energy constraints, we will have the same architecture $a^*(h_1; L, E) = a^*(h_2; L, E)$ for two hardware choices $h_1, h_2 \in \mathcal{H}$.

Nonetheless, once we have found $\mathcal{P} \subset \mathcal{A}$, there is no need to jointly search over the entire architecture-hardware space $\mathcal{A} \times \mathcal{H}$ any more. Instead, it is sufficient to merely search over the restricted architecture-hardware space $\mathcal{P} \times \mathcal{H}$. Importantly, the set \mathcal{P} of optimal architectures is orders-of-magnitude smaller than the entire architecture space \mathcal{A} (e.g., a few tens vs. 10^{18} in the DARTS architecture space [17]), thus significantly reducing the total hardware-software co-design cost without losing optimality.

Algorithm. Our semi-decoupled approach has two stages, as illustrated in Fig. 1 and summarized in Algorithm 1.

Stage 1: We randomly choose a sample accelerator $h_0 \in \mathcal{H}$, which we refer to as the *proxy* accelerator, and run hardware-aware NAS for K times to find a set of optimal architectures $\mathcal{P} = \mathcal{P}(h_0) = (a_1^*(h_0; L_1, E_1), \dots, a_K^*(h_0; L_K, E_K))$. Specifically, \mathcal{P} is constructed by setting K different latency and energy constraints and accordingly solving the inner NAS problem in Eqns. (7)–(9) for K times. Thus, the search cost in Stage 1 is $O(KM)$ where $M = |\mathcal{A}|$.

Stage 2: We search for the optimal accelerator $h^* \in \mathcal{H}$. Specifically, given each candidate $h \in \mathcal{H}$ (selected by, e.g., reinforcement learning or evolutionary search [16, 19]), instead of searching over the entire architecture set \mathcal{A} , we obtain its corresponding optimal architecture $a^*(h)$ from the set $\mathcal{P} \subset \mathcal{A}$ constructed in Stage 1. Thus, the search cost in Stage 2 is $O(KN)$ where $N = |\mathcal{H}|$.

3.3 Discussion

In practice, performance monotonicity may not be perfectly satisfied. Thus, the optimal architecture $a^*(h)$ corresponding to a candidate accelerator $h \in \mathcal{H}$ may not always strictly belong to the optimal architecture set \mathcal{P} that is pre-constructed based on the proxy h_0 . Nonetheless, by only searching over \mathcal{P} for this candidate

accelerator h , we can still find an architecture $a \in \mathcal{P}$ that is *close-to-optimal*. In fact, to speed up the NAS process and find competitive architectures, it is very common to use proxy/substitute metrics (such as accuracy predictor or the neural tangent kernel [6]) which only have SRCC of around 0.5–0.9 with the true performance. In our problem, we can also view the architectures’ latency and energy performance on the proxy accelerator h_0 as the substitute performance on other accelerator candidates. Therefore, given the good albeit not necessarily close-to-perfect performance monotonicity, the architectures optimized specifically for the proxy are also sufficiently competitive ones for other accelerator candidates.

In [18], scalable hardware-aware NAS is proposed by utilizing latency monotonicity on various devices. Without considering energy consumption, a high SRCC (>0.9) for latency is needed to ensure that one proxy device’s optimal architectures are still close to optimal on another device. In our problem, such high SRCC values are not necessarily needed, because we consider both energy and latency – moderate SRCC values on two performance metrics are enough. This is reflected in both our experiments and prior studies (e.g., two proxy metrics having moderate SRCC values with the true accuracy can estimate the accuracy performance very well [6]).

In the highly unlikely event of very low SRCCs (e.g., 0.2) between the proxy and other accelerator candidates, we can enlarge \mathcal{P} by adding some approximately optimal architectures near the Pareto boundary (for the chosen proxy), such that they can be competitive choices for other candidate accelerators. Alternatively, we could use *a few* proxy accelerators, each having good latency and energy monotonicity with a subspace of accelerator design, and jointly construct an expanded set \mathcal{P} of optimal architectures in Stage 1. In any case, the set \mathcal{P} is orders-of-magnitude smaller than the entire architecture space or accelerator space.

Summary. The essence of our semi-decoupled approach is to use a proxy h_0 to find a small set of optimal architectures that also includes the actual optimal or *close-to-optimal* architectures for different accelerator candidates, thus reducing the total co-design complexity without losing optimality. This is significantly different from a typical fully-decoupled approach that pre-searches for *one* architecture and then find the matching accelerator, and also has a sharp contrast with a fully-coupled co-design approach that jointly searches over the entire architecture-accelerator space. The comparison of different approaches is also summarized in Table 1. Importantly, our approach focuses on reducing the search space complexity, and can be integrated with any actual NAS (Stage 1) and accelerator exploration techniques (Stage 2).

4 EXPERIMENT SETUP

We provide details of our experiment setup as follows.

Accelerator hardware space. We employ an open-source tool MAESTRO [14] to simulate DNNs on the accelerator and measure inference metrics (e.g., latency and energy). MAESTRO supports a wide range of accelerators, including global shared scratchpad (i.e., L2 scratchpad), local PE scratchpad (i.e., L1 scratchpad), NoC, and a PE array organized into different hierarchies or dimensions.

DNN dataflow. Dataflow decides the DNN partitioning and scheduling strategies, which affects inference latency and energy

performance. We consider three template dataflows: **KC-P** (motivated by NVDLA [21]), **YR-P** (motivated by Eyeriss [7]), and **X-P** (weight-stationary). Exhibiting different characteristics (e.g., temporal reuse of input activation and filter in YR-P vs. spatial reuse of input activation in KC-P), these representative dataflows are all supported by MAESTRO [14] and commonly used in SOTA hardware-software co-design [34].

Architecture space. We consider the following two spaces.

- **NAS-Bench-301:** It is a SOTA surrogate NAS benchmark built via deep ensembles and modeling uncertainty, which provides close-to-real predicted performances (i.e., accuracy and training time) of 10^{18} architectures on CIFAR-10 [24]. We consider the DARTS space [17], where each architecture is a stack of 20 convolutional cells, and each cell consists of seven nodes.

- **AlphaNet:** It is a new family of architectures on ImageNet discovered by applying a generalized α -divergence to supernet training [27]. Our search space is based on Table 7 of [27], with a slight variation that the channel width is fixed as "16, 16, 24, 32, 64, 112, 192, 216, 1792", and depth, kernel size, expansion ratio of the first and last inverted residual blocks are fixed as "1, 1", "3, 3", "1, 6", respectively. For other searchable inverted residual blocks, the candidate depth, kernel size, and expansion ratio are "2, 3, 4, 5, 6", "3, 5, 7", and "3, 4, 6", respectively.

Search strategy. Our approach can be integrated with any NAS and hardware search strategies. Here, we consider exhaustive search over a pre-sampled subspace. Specifically, for the NAS-Bench-301, we first sample 10k models. Then, based on the accuracy given by NAS-Bench-301 and FLOPs of these 10k models, we select 1017 models, including the Pareto-optimal front (in terms of predicted accuracy and FLOPs) and some random architectures. Similarly, for the AlphaNet space, we first sample 10k models and then select 1046 models based on the predicted accuracy given by the released accuracy predictor [10] and FLOPs. We consider a filtered space of 1k+ architectures (which include the Pareto-optimal ones out of the 10k sampled architectures), because using MAESTRO to measure the latency and energy of 10k models on thousands of different hardware-dataflow combinations is beyond our computational resource limit. For each of the three template dataflows, we sample 51 neural accelerators with different number of PEs, NoC bandwidth, and off-chip bandwidth per the MAESTRO document [22]. Specifically, the number of PEs can be chosen from "512, 256, 128, 64, 32, 16", candidate NoC bandwidths are from "300, 400, 500, 600, 700, 800, 900, 1000", and off-chip bandwidths are from "50, 100, 150, 200, 250, 275, 300, 325, 350". Note that some of our sampled hardware-dataflow pairs are not supported when running with KC-P and YR-P dataflows on MAESTRO. Thus, the actual numbers of sampled accelerators (i.e., hardware-dataflow combinations) are 133 for NAS-Bench-301 and 132 for AlphaNet, respectively. We also consider layer-wise mixture of different dataflows (Section 5.3) to create 5000 different hardware-dataflow combinations.

5 EXPERIMENTAL RESULTS

In this section, we present our experimental results. We show that strong performance monotonicity exists in the hardware design space, and highlight that our semi-decoupled approach can identify the optimal design at a much lower search complexity.

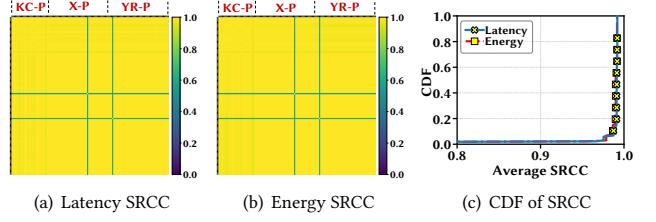


Figure 2: Performance monotonicity. We test 1017 models sampled in DARTS search space on 133 accelerators.

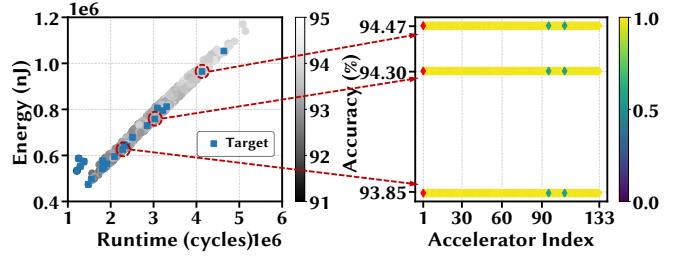


Figure 3: NAS-Bench-301. Left: The optimal models are marked in blue, and the grey scale indicates accuracy. Right: The accuracy of the model selected from the proxy's optimal model set. We test each accelerator as a different proxy. We also select two proxy accelerators (indexes 95 and 107) that have the lowest SRCCs with the target, and show the detailed results in Table 2.

5.1 NAS-Bench-301

5.1.1 Performance monotonicity. We first validate that strong latency and energy performance monotonicity, quantified in SRCC, holds between different accelerators. The results are shown in Fig. 2. We see that, except for two accelerator choices that have SRCC less than 0.6 with others, all the other accelerators have almost perfect performance monotonicity with SRCC greater than 0.97. We also plot in Fig. 2(c) the cumulative distribution function (CDF) of the average SRCC values for all the sampled accelerators, where for each accelerator h the “average” is over the SRCC values of all the accelerator pairs that include h . We see that the vast majority of the accelerators have average SRCC close to 1.

5.1.2 Effectiveness. To demonstrate the effectiveness, suppose that we have an optimal architecture-accelerator pair (a^*, h^*) produced by the SOTA hardware-software co-design. We refer to the optimal accelerator as the “Target”. By using our approach, in Stage 1, we first randomly choose a non-target accelerator h_0 as our proxy, and run hardware-aware NAS on this proxy to obtain the set \mathcal{P} of optimal architectures. Next, in Stage 2, we will search over the accelerator space, retrieve the corresponding architecture a_0^* from \mathcal{P} that best satisfies the latency and energy constraints, and keep the accelerator, whose corresponding architecture a_0^* has the highest accuracy, as the optimal accelerator. Thus, we prove the effectiveness of our approach if the architecture $a_0^* \in \mathcal{P}$ corresponding to the optimal accelerator found in Stage 2 produces (approximately) the same accuracy as a^* obtained using the SOTA co-design.

In our experiment, we consider a target optimal accelerator h^* as follows: 512 PEs, NoC bandwidth constraint 900, off-chip bandwidth

Accelerator Index	SRCC			Hardware Config.			Model Performance		
	Latency	Energy	PEs	NoC	Off-chip	Dataflow	Latency (cycles)	Energy (nJ)	Accuracy (%)
1 (target)	1	1	512	900	350	KC-P	2279256	626090	93.85
107	0.556	0.567	64	400	250	YR-P	2279256	626090	93.85
95	0.595	0.595	256	800	350	X-P	2279256	626090	93.85
1 (target)	1	1	512	900	350	KC-P	3027992	758928	94.30
107	0.556	0.567	64	400	250	YR-P	3027992	758928	94.30
95	0.595	0.595	256	800	350	X-P	3027992	758928	94.30
1 (target)	1	1	512	900	350	KC-P	4130699	964783	94.47
107	0.556	0.567	64	400	250	YR-P	4130699	964783	94.47
95	0.595	0.595	256	800	350	X-P	4130699	964783	94.47

Table 2: Hardware configuration of the target and two proxy accelerators, and performance metrics of the selected optimal models on each of them. “Accelerator Index” corresponds to the x -axis in right of Fig. 3, the models on the target accelerator correspond to the circled ones in left of Fig. 3, while the models on the two proxy accelerators correspond to the diamond marks located on the accelerator indexes. The architecture configuration of the target models is further illustrated in Table 3.

Target Model	Model Architecture			
	Normal Cell Config.	Normal Cell Concat.	Reduce Cell Config.	Reduce Cell Concat.
#1	(skip_connect, 0), (skip_connect, 1), (skip_connect, 0), (skip_connect, 2), (sep_conv_5x5, 0), (skip_connect, 1), (dil_conv_5x5, 4), (skip_connect, 2)	[2, 3, 4, 5]	(sep_conv_3x3, 1), (sep_conv_3x3, 0), (dil_conv_3x3, 2), (skip_connect, 0), (sep_conv_5x5, 2), (avg_pool_3x3, 0), (dil_conv_3x3, 3), (sep_conv_3x3, 1)	[2, 3, 4, 5]
	(skip_connect, 0), (max_pool_3x3, 1), (sep_conv_3x3, 0), (skip_connect, 1), (skip_connect, 0), ('sep_conv_5x5, 3), (avg_pool_3x3, 4), (sep_conv_5x5, 1)		(sep_conv_3x3, 1), (sep_conv_5x5, 0), (avg_pool_3x3, 0), (sep_conv_5x5, 1), (dil_conv_5x5, 3), (sep_conv_3x3, 2), (avg_pool_3x3, 4), (sep_conv_3x3, 0)	
	(dil_conv_5x5, 0), (skip_connect, 1), (max_pool_3x3, 0), (max_pool_3x3, 2), (sep_conv_5x5, 0), (dil_conv_3x3, 3), (dil_conv_5x5, 3), (dil_conv_5x5, 4)		(skip_connect, 0), (dil_conv_3x3, 1), (sep_conv_3x3, 1), (sep_conv_5x5, 2), (skip_connect, 1), (max_pool_3x3, 0), (skip_connect, 1), (sep_conv_5x5, 2)	

Table 3: Architecture configuration of the target models in Fig. 3. The first row (i.e., target model #1) corresponds to the leftmost circled model in Fig. 3, and second row corresponds to the middle circled model, etc. These are the configurations for each convolutional cell constructing a complete model, which is a stack of 20 cells. For detailed explanation of the operations in the DARTS search space, please refer to [17] and [24].

constraint 350, and KC-P dataflow. In Fig. 3, we plot all the optimal architectures under various latency and energy constraints.² Then, we set three representative latency and energy consumption constraints, with their corresponding optimal models circled in red. Next, we test each of the other 132 accelerators as the proxy, and find the corresponding set \mathcal{P} , which includes about 20 optimal architectures for that proxy. Then, we select the architecture from \mathcal{P} whose latency and energy are closest to the design constraints on the target accelerator. We see that by using *any* of the 132 accelerators as the proxy, our approach can still find the optimal architecture that has (nearly) the same accuracy as that found by using SOTA hardware-software co-design. Importantly, even the proxy accelerator that has the lowest SRCC with the target can yield an competitive architecture with a good accuracy.

5.1.3 *Total search cost.* We now compare the total search cost incurred by exhaustive search over our sampled space. Using the coupled SOTA approach, the co-serach evaluates $133*1017 \approx 135K$ architecture-accelerator designs. In Stage 1 of our approach, we

²MAESTRO returns the runtime cycles, instead of actual time, for the inference latency.

choose one proxy and evaluate 1017 architectures to obtain 20 optimal architectures for different latency and energy constraints. As we use exhaustive search, we do not need to run 20 times. In Stage 2, we evaluate the remaining 132 accelerators combined with the selected 20 architectures. Thus, the total search cost of our approach is $132*20+1017 \approx 3.7K$, which is significantly less than 135K. While reinforcement learning or evolutionary search can improve the efficiency (especially on larger spaces), the order of the total cost remains the same. Moreover, when the architecture and accelerator spaces are larger, the relative advantage of our approach is even more significant.

5.2 AlphaNet

We now turn to the AlphaNet architecture space, and show the results in Fig. 4 and Fig. 5. While the SRCC values are lower than those in the NAS-Bench-301 case, they are still generally very high (e.g., mostly >0.9). Crucially, as shown in Fig. 5, our approach can successfully find an architecture that has (almost) the same accuracy as that obtained by using the SOTA coupled approach.

Accelerator Index	SRCC			Hardware Config.			Model Config.		
	Latency	Energy	PEs	NoC	Off-chip	Dataflow	Latency (cycles)	Energy (nJ)	Accuracy (%)
1 (target)	1	1	512	900	350	KC-P	2061611	614779	69.60
64	0.638	0.945	512	400	350	X-P	2061611	602782	69.58
91	0.775	0.945	32	800	250	X-P	2046476	610891	69.60
1 (target)	1	1	512	900	350	KC-P	3367489	965462	71.18
64	0.638	0.945	512	400	350	X-P	3367489	965462	71.18
91	0.775	0.945	32	800	250	X-P	3367489	965462	71.18
1 (target)	1	1	512	900	350	KC-P	5923046	1858261	71.76
64	0.638	0.945	512	400	350	X-P	5923046	1858261	71.76
91	0.775	0.945	32	800	250	X-P	5923046	1858261	71.76

Table 4: Hardware configuration of the target and two proxy accelerators, and performance metrics of the selected optimal models on each of them. “Accelerator Index” corresponds to the x -axis in right of Fig. 5, models on the target accelerator correspond to the circled ones in left of Fig. 5, while the selected optimal models on proxy accelerators correspond to the diamond marks locating on the accelerator indexes. The architecture configuration of the target models is further illustrated in Table 5.

Target Model	Resolution	Model Architecture					
		Width	Kernel Size	Expansion Ratio	Depth		
#1	224	16, 16, 24, 32, 64, 112, 192, 216, 1792	3, 3, 3, 3, 3, 3, 3	1, 4, 4, 6, 6, 5, 6	1, 3, 4, 3, 3, 3, 1		
#2	288	16, 16, 24, 32, 64, 112, 192, 216, 1792	3, 3, 3, 3, 3, 7, 3	1, 4, 4, 5, 4, 5, 6	1, 3, 3, 3, 4, 4, 1		
#3	288	16, 16, 24, 32, 64, 112, 192, 216, 1792	3, 3, 5, 7, 7, 7, 3	1, 6, 6, 5, 5, 6	1, 6, 6, 3, 6, 6, 1		

Table 5: Architecture configuration of target models in Fig. 5. The first row (i.e., target model #1) corresponds to the leftmost circled model in Fig. 5, and second row corresponds to the middle circled model, etc. For detailed explanation of the operations in AlphaNet search space, please refer to [28].

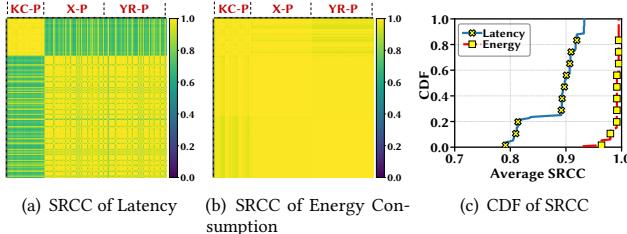


Figure 4: Performance monotonicity. We test 1046 models sampled in AlphaNet search space on 132 accelerators.

5.3 Layer-wise Mixed Dataflow

Ideally, each layer of a DNN model can be switched between accelerator hardware and dataflows to search for the best combination (especially in the multi-accelerator design case) [34]. To account for this, we divide each model into 22 parts: first and last convolutional layer, and evenly into 20 groups for all intermediate layers. For each part, it can be executed on any of our 51 sampled hardware configurations following any dataflow. We sample 5000 different mixtures for our models in NAS-Bench-301 and AlphaNet spaces, and report the SRCC results in Fig. 6 and 7, respectively. The results confirm again that strong performance monotonicity exists and ensures the effectiveness of our approach. We omit the optimal accuracy results due to the lack of space, while noting that they are similar to Figs. 3 and 5.

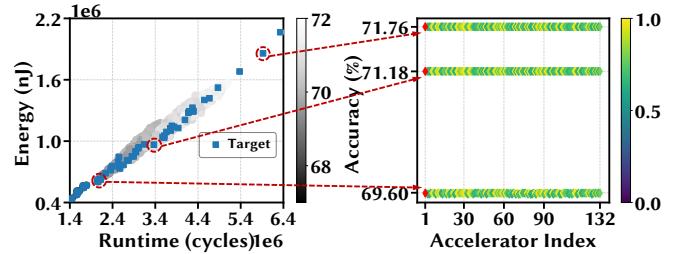


Figure 5: AlphaNet. Left: The optimal models are marked in blue, and the grey scale indicates accuracy. Right: The accuracy of the model selected from the proxy’s optimal model set. We test each accelerator as a different proxy. We select two proxy accelerators (indexes 64 and 91) and show the detailed results in Table 4.

6 RELATED WORK

NAS and accelerator design. Hardware-aware NAS has been actively studied to incorporate characteristics of target device and automate the design of optimal architectures subject to latency and/or energy constraints [4, 8, 15, 19, 23, 25, 32, 35]. These studies do not explore the hardware design space. A recent NAS study [18] explores latency monotonicity to scale up NAS across different devices, but it only considers latency constraints and, like other NAS studies, does not explore the hardware design space. In parallel, there have also been studies on automating the design of accelerators for

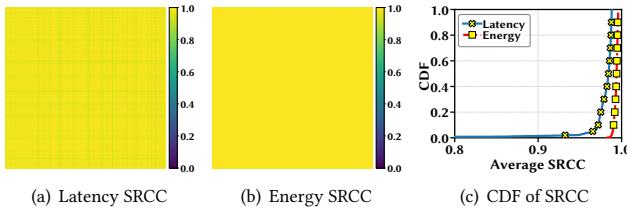


Figure 6: Performance monotonicity. We test 1017 models sampled in DARTS on 5000 accelerators with layer-wise mixed dataflows.

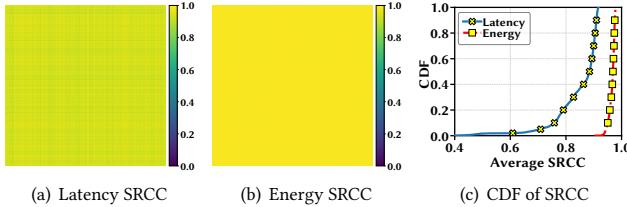


Figure 7: Performance monotonicity. We test 1046 models sampled in AlphaNet on 5000 accelerators with layer-wise mixed dataflows.

DNNs [33]. But, NAS and accelerator design have been traditionally studied in a siloed manner, resulting in sub-optimal designs.

Architecture-accelerator co-design. The studies on jointly optimizing architectures and accelerators have been quickly expanding. For example, [34] jointly optimizes neural architectures and ASIC accelerators using reinforcement learning, [13] performs a two-level (fast and slow) hardware exploration for each candidate neural architecture, [12] adopts a set of manually selected models as the hot start state for acceleration exploration, and [16] co-designs neural architecture, hardware configuration and dataflow, and employs evolutionary search to reduce the search cost. These studies primarily focus on improving the search efficiency given a certain search space. By contrast, we use a principled approach to reducing the total search space, without losing optimality.

7 CONCLUSION

In this paper, we reduce the total hardware-software co-design cost by semi-decoupling NAS from accelerator design. Concretely, we demonstrate latency and energy monotonicity among different accelerators, and use just one proxy accelerator’s optimal architecture set to avoid searching over the entire architecture space. Compared to the SOTA co-designs, our approach can reduce the total design complexity by orders of magnitude, without losing optimality. Finally, we validate our approach via experiments on two search spaces – NAS-Bench-301 and AlphaNet.

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