COMPOFA: COMPOUND ONCE-FOR-ALL NETWORKS FOR FASTER MULTI-PLATFORM DEPLOYMENT

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Paper under double-blind review

ABSTRACT

The emergence of CNNs in mainstream deployment has necessitated methods to design and train efficient architectures tailored to maximize the accuracy under diverse hardware & latency constrains. To scale these resource-intensive tasks with an increasing number of deployment targets, Once-For-All (OFA) proposed an approach to jointly train several models at once with a constant training cost. However, this cost remains as high as $O(10^3)$ GPU hours and also suffers from a combinatorial explosion of potentially sub-optimal model configurations. We find that the cost of this one-shot training is dependent on the size of the model design space, and hence seek to speed up the training by constraining the design space to configurations with better accuracy-latency trade-offs. We incorporate the insights of compound relationships between model depth & width to build *CompOFA*, a design space smaller by several orders of magnitude. We demonstrate a 50% cut in the training time, dollar cost, and CO_2 emissions over OFA due to the decreased interference in training this smaller design space. We also show that this smaller design space is dense enough to support equally accurate models for similar diversity of hardware and latency targets, as well as simplifying training and searching procedures.

1 INTRODUCTION

CNNs are emerging in mainstream deployment across diverse hardware platforms, latency requirements, and/or workload characteristics. This necessitates tailoring models for application-specific needs to maximize accuracy under their deployment constraints, by designing/searching new architectures, and training these architectures. These tasks are computationally intensive with respect to computational resources, time, expertise, and CO_2 emissions that need to be repeated for *each* deployment target.

Once-For-All (OFA) (Cai et al., 2020) recently proposed a way to evade the above hurdle through a novel progressive shrinking algorithm. In this approach, OFA decouples the search and train stages by training a family of models in a single-shot by sharing weights between a family of 10^{19} sub-networks of varying depth, width, kernel size, and image resolution.

The one-time training cost is expected to be amortized over the number of deployment platforms. However, this cost remains high in absolute terms, taking 1200 GPU hours for OFA. This massive computational requirement stems partially from the lack of latency or accuracy guided training of all possible combinations of model settings. This exhaustive approach exhibits a clear inefficiency in training a large portion of models that have sub-optimal accuracy-latency trade-offs. These extra models not only go un-utilized but also slow down the training process – the interference that exists in this large pool of models necessitates a phased training to stabilize their simultaneous optimization. Finally, searching for an optimal model from within this model family for a given deployment target is done via indirect estimations of latency and accuracy lookup tables.

On the other hand, common practices as well as empirical studies (Tan & Le, 2019; Radosavovic et al., 2020) have shown that model dimensions such as depth, width, and resolution are not orthogonal – models that obey some compound couplings between these dimensions produce a better accuracy-latency trade-off than those with unconstrained settings.

In this work, we show that the same or better accuracy-latency trade-offs can be achieved by model families smaller by several orders of magnitude. We reduce the search space and thus train time from $O(10^{19})$ models to 243, by leveraging two key insights: (1) the insight of compound coupling between model depth & width to prune away the models which are sub-optimal in their accuracy-latency trade-off, (2) 1ms density granularity on the accuracy/latency Pareto frontier is *sufficient* for practical systems deployments. We show that this size reduction allows for one-shot training that is simpler and for half the cost in terms of GPU time, dollars, and CO_2 emissions. This new search space named *CompOFA*, though smaller, is still dense enough to produce models covering the same range and density of latency targets for diverse hardware platforms as OFA, thus wasting far fewer models by several orders of magnitude.

2 Related Work

Efficient neural network design has been an active area of research due to the high computational complexity of CNNs. Neural Architecture Search (NAS) is being increasingly used to guide if not replace previously manual design processes. Early NAS techniques (Zoph et al., 2018; Zoph & Le, 2016) sampled several architectures and trained them from scratch every time, making them extremely compute-hungry. The technique of weight-sharing has emerged as one way to address these inefficiencies (Berman et al., 2020; Bender et al., 2018; Brock et al., 2017; Guo et al., 2019; Liu et al., 2018; Pham et al., 2018). These methods slice candidate sub-networks from a larger *super-network*, thereby sharing weights between them. Simultaneously, latency-guided NAS methods (Tan et al., 2019; Cai et al., 2018; Berman et al., 2020; Stamoulis et al., 2019; Wu et al., 2019) have sought to incorporate model complexity into their search to find efficient models for a given target latency on some hardware.

Nevertheless, these methods yield a single model per run – both search *and* training must be repeated for new deployment targets. With compute costs as high as $O(10^4)$ GPU hours, this linear scaling is infeasible for an ever-growing need for multi-platform deployment. Once-For-All (OFA) (Cai et al., 2020) proposed to reduce this cost by using weight-sharing for a large model *family* that simultaneously supports many diverse latencies. They perform a one-time training of $O(10^{19})$ sub-networks, which can then be independently searched to support a given deployment target later, thus amortizing the training cost. However, this cost is still high at 1200 GPU hours. The large search space complicates training and searching, stemming from an unconstrained combinatorial explosion of model configurations.

On the contrary, empirical studies on neural network design spaces (Tan & Le, 2019; Radosavovic et al., 2020) have shown that model dimensions such as depth, width, resolution are not independent – underlying relations between them can be used to obtain an optimal accuracy-latency trade-off. This insight forms the basis of our work to constrain the design space of OFA networks while maintaining the same quality & diversity of models with reduced train and search costs.

Dynamic Neural Networks with weight-sharing across models of varying latencies have been explored before (Yu et al., 2018; Yu & Huang, 2019) but with much fewer models (e.g. 4 in Yu et al. (2018)) and few dimensions (e.g. only width) which make for much sparser and narrower support for diverse latency targets. We explore a middle ground between these works and Cai et al. (2020) to build design spaces that are tractable yet sufficiently diverse to support many latency targets and varying in multiple model dimensions.

Yu et al. (2020) proposed replacing OFA's multi-stage training by a single-stage one. However, its training cost remains high at over 2300 TPU hours for $O(10^{12})$ models. We propose a similar reduction of OFA's multi-stage training but halve the training cost in this process. While Yu et al. (2020) challenges the conventional training practices of weight-shared NAS, our work emphasizes on insights from Tan & Le (2019) and Radosavovic et al. (2020) to refine the network design space to good models and show that an intractably large cardinality is not necessary.

3 Motivation

3.1 Design Space Parametrization

Consider a network architecture $\mathcal{N}$ composed of m micro-architectural blocks, $B_1, B_2, \ldots, B_m$. Each block is parametrized by its depth, per-layer width, and per-layer kernel size as $B_i(d_i, W_i, K_i)$.

Here d_i denotes the number of layers (depth) in the block, and W_i and K_i are lists denoting the width & kernel sizes of each of these d_i layers.

Once-For-All(Cai et al., 2020) builds a family of networks $\mathcal{N}_1, \mathcal{N}_2, \ldots$ of varying accuracies and latencies. The weights of common layers and channels of a block B_i are shared across all the networks. The "block" used in OFA is the Inverted Residual from MobileNetV3 (Howard et al., 2019) and hence "width" here refers to the channel expansion ratio. d_i, w_{ij}, k_{ij} are sampled independently from sets $D = [2, 3, 4], W = [3, 4, 6], K = [3, 5, 7]$ respectively.

In OFA, each of these dimensions is treated as orthogonal. Hence, the resulting number of possible networks is enormous, with $O(10^{19})$ models for $m = 5$ blocks(Cai et al., 2020).

3.2 Compound Relation of Model Dimensions

The combinatorial explosion from just 3 independent model dimensions of D, W, K yields a model family with an enormous number of models. While the aim for jointly training "every possible model" in this large design space is to support a diverse range of hardware platforms, we note the following concerns that arise from this:

1. **Model dimensions are not orthogonal**
   Scaling model dimensions like depth, width, and resolution in higher FLOP regimes is a common practice and Tan & Le (2019) systematically showed that compound relations exist between these dimensions for achieving an optimal accuracy-latency trade-off. In particular, increasing model dimensions in accordance with a compound scaling rule gives better results than doing so independently. Radosavovic et al. (2020) elevated this concept to the model *population* level and found that a *quantized linear relation* between model depth and width yielded design spaces with a better concentration of well-performing models. These works solidified the common practice of jointly increasing model depth and width. Yet, all these other sub-optimal models are still included in the search space when all dimensions are treated as independent.
2. **Large model families complicate training & searching**
   The interference between OFA's sub-networks complicates their simultaneous optimization, and necessitates techniques like progressive shrinking (Cai et al., 2020) which slow down training time. Further, extracting models for a desired target cannot rely on simple enumeration and instead needs to rely on predicting model accuracy/latency. This further requires training these accuracy predictors specific to the trained model family and collecting latency look-up tables (Cai et al., 2018). With a more tractable cardinality, we could rely on more standard, faster approaches during training and improve "off-the-shelf" usability during search.
3. **Hardware latency differences below a certain granularity are noisy**
   Finally, the difference between unique architectures' accuracy or latency needs to be distinguishable during search. The original OFA design space covers a FLOP range of 120-560 MFLOPs. Within this range, there are $O(10^{19})$ architecture choices. Even if these models were uniformly distributed in buckets of 1 FLOP, we would still have an $O(10^{11})$ models in *each* FLOP target. This is not accounting for the fact that each of these models support variable resolution, which would further multiply the number of choices at each FLOP target. On any hardware, inference time below a certain threshold is expected to be indistinguishable from noise. This threshold can vary depending on application context or hardware (e.g. it can be upto 1-5 ms in serving scenarios). Irrespective of the threshold, having these many models with such fine-grained differences in their compute requirement is well below the minimum error resolution at which they can be meaningfully compared. This motivates us to consider that a design space that is sparser by several orders of magnitude might still support the same density and range of deployment targets.

Figure 1 shows heatmaps comparing accuracy and latency of OFA sub-networks with uniform depth and width for a fixed kernel size. A closer look into these heatmaps, depicts a monotonically increasing gradient across the diagonal of each of these two dimensional heatmaps. This observation precisely emphasizes a coefficient that dictates a relationship between the depth and the width configurations of a model. This suggests that by quantitatively conforming to this coupling between the model dimensions, we can aim toward reducing the network design space of an architecture without

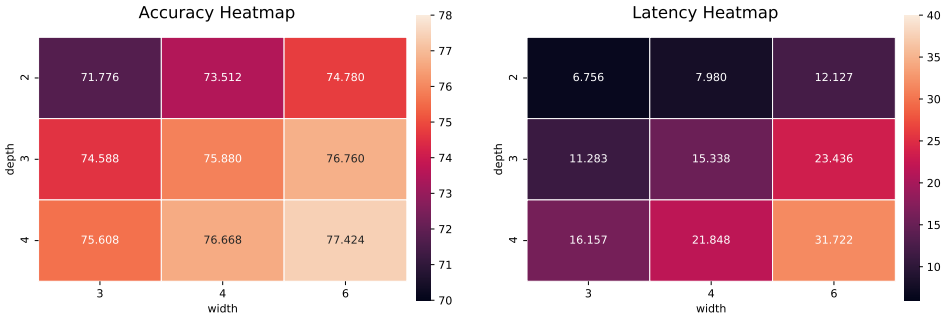

Figure 1: Accuracy and latency heatmaps for kernel size 5 with varying uniform depth and expansion ratios, as measured in MobileNetV3 architecture. Latency is measured on NVIDIA RTX 2080 Ti GPU with BS=64.

sacrificing on its accuracy. Subsequently, this further implies that OFA is unnecessarily training a lot more models than required and we additionally show in Appendix A.1 that OFA's model distribution also suffers from high variance. Conclusively, this leads us toward designing a solution that attempts to leverage these insights and thereby pruning out the redundant and ineffective sub-networks that are generated by the OFA architecture.

4 COMPOUND OFA

4.1 COUPLING HEURISTIC

Motivated by the above observations, we devise a simple heuristic to constrain the network design space by scaling or shrinking the depth and width dimensions together and not independently. Specifically, in each block, whenever we sample the ith largest depth $d_i \in D$, we correspondingly sample the ith largest width $w_i \in W$ for all d_i layers in the block. For instance, with $D = [2, 3, 4]$ and $W = [3, 4, 6]$, each block can have either two layers of channel expansion ratio 3, or three layers of ratio 4, or four layers of ratio 6.

This significantly reduces the degrees of freedom in the design space. An additional consequence of this is that all layers within a block now have the same width, causing an extra reduction in the design space. Nevertheless, we will show in Section 5 that the design space is still diverse and dense enough to provide models for different deployment requirements.

For kernel size, we explore two possibilities – Fixed-Kernel and Elastic-Kernel. In fixed-kernel, we create a simplified search space with kernel sizes fixed to either 3 or 5 in each block, to match the original setting used in MobileNetV3. Thereby in this design space, depth (or width) alone can fully specify a block's configuration and this yields a family of $3^5 = 243$ models. In the elastic-kernel design space, we expand the kernel size, sampled from $K = [3, 5, 7]$ per layer, same as in OFA, and this results in a family of $(3^2 + 3^3 + 3^4)^5 \approx 10^{10}$ models. Unless otherwise specified, we use "CompOFA" to refer to the fixed-kernel design space.

4.2 TRAINING SPEEDUP

Cai et al. (2020) proposed a "progressive shrinking" approach to train the OFA sub-networks in a phased manner, starting with the largest model and then progressively including smaller sub-networks in training. At each batch, a different sub-network is sampled for forward/backward pass. If the expected time to complete one epoch in phase p is $\mathbb{E}(t_p)$ and the training is run for e_p number of epochs, then the total time to train a model family becomes $T_{family} \propto \sum_{p \in Phases} e_p \times \mathbb{E}(t_p)$.

Our goal is to reduce T_{family} while achieving the same level of accuracy-latency trade-off and supporting the same range of deployment scenarios. Since we do not wish to train bigger or smaller models themselves, we try to keep $\mathbb{E}(t_p)$ unchanged and target a reduction in the number of phases to reduce T_{family}.

While the number of models does not explicitly factor in T_{family}, note that it implicitly affects the count & duration of training phases – progressive shrinking was required in the first place due to interference between a large number of models. The maximum number of simultaneously trainable models in CompOFA's search space is smaller by 17 orders of magnitude. With this significantly smaller family size, we find that the interference between these models is reduced to the extent that we are now able to remove progressive shrinking altogether, and instead achieve the same accuracy with all trainable sub-networks included in training (see Section 5).

In Section 5 we show that this allows us to reduce the training time by 50%. Additionally, we show an ablation to confirm that this reduction in phases is only possible due to the reduced number of models in CompOFA, and not in the original large design space of OFA.

5 EXPERIMENTS

5.1 TRAINING SETUP

We train the full-sized CompOFA network ($D = [4], W = [6]$) on ImageNet (Deng et al., 2009) using the same base architecture of MobileNetV3 as OFA. We use a batch size of 1536 and a learning rate of 1.95 to train on 6 NVIDIA V100 GPUs. All other training hyperparameters are kept the same as OFA for accurate comparison.

Next, for CompOFA with fixed kernel sizes, we unlock all permissible model configurations ($D, W = [(2, 3), (3, 4), (4, 6)]$) in one stage, as opposed to progressively adding more configurations. We train this for 25 epochs with an initial learning rate of 0.06, followed by 120 epochs with an initial learning rate of 0.18 to obtain our final network. We sample $N_{sample} = 4$ models in each batch. The full network serves as a teacher model for knowledge distillation (Hinton et al., 2015). The comparison of the possible configurations and epoch durations for each training phase is summarized in Table 1.

Table 1: Training schedule, duration, and GPU hour comparisons for OFA and CompOFA. CompOFA reduces the training time of OFA by 50% with a fixed kernel space. The columns K, D, W represent the sets of possible model dimensions (as in Section 3.1). While CompOFA allows all sub-networks to be trained after the teacher network, OFA progresses to the full search space with multiple phases of similar duration. See Appendix A.2 for CompOFA with Elastic Kernel

(a) Once-For-All (Cai et al., 2020) (Elastic Kernel)

Phase	K	D	W	N_{sample}	**Epochs**	**Wall Time**	**GPU Hours**
Teacher	7	4	6	1	180	28h 45m	172h 30m
Elastic Kernel	3, 5, 7	4	6	1	125	26h 51m	161h 06m
Elastic Depth-1	3, 5, 7	3, 4	6	2	25	7h 46m	46h 36m
Elastic Depth-2	3, 5, 7	2, 3, 4	6	2	125	38h 32m	231h 12m
Elastic Width-1	3, 5, 7	2, 3, 4	4, 6	4	25	10h 06m	60h 36m
Elastic Width-2	3, 5, 7	2, 3, 4	3, 4, 6	4	125	51h 03m	306h 18m
Total					**605**	**163h 03m**	**978h 18m**

(b) CompOFA (Fixed Kernel)

Phase	K	D	W	N_{sample}	**Epochs**	**Wall Time**	**GPU Hours**
Teacher	7	4	6	1	180	28h 45m	172h 30m
Compound	–	2, 3, 4	3, 4, 6	4	25	8h 43m	52h 18m
Compound	–	2, 3, 4	3, 4, 6	4	125	44h 47m	268h 42m
Total					**330**	**82h 15m**	**493h 30m**

5.2 TRAINING TIME AND COST

By using just one stage of training after the teacher model, instead of multiple stages of the same duration, we are able to reduce the training cost of CompOFA by 50%. Our reproduction of OFA's training scheme on 6 GPUs takes 978 GPU hours while CompOFA-Fixed Kernel finishes in 493

Table 2: Monetary cost and CO_2 emission comparison for OFA & CompOFA. Monetary cost is based on hourly price of 1 NVIDIA V100 on Google Cloud. CO_2 emission estimation is based on Strubell et al. (2019)

Method	**Cost**	CO_2 **emission**
OFA	\$2.4k	277 lbs
CompOFA (Elastic Kernel)	\$1.7k	196 lbs
CompOFA (Fixed Kernel)	\$1.2k	138 lbs

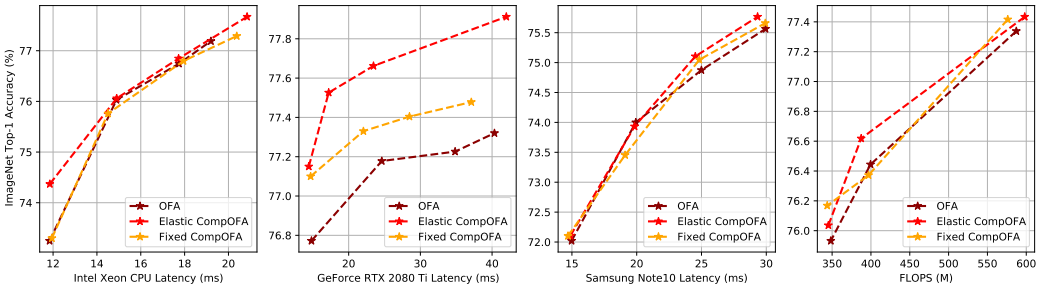

Figure 2: CompOFA networks consistently achieve comparable and higher ImageNet accuracies for similar latency and FLOP constraints on CPU, GPU and mobile platforms.

GPU hours, as shown in Table 1. Table 2 shows the translation of this time reduction in terms of dollar cost and CO_2 emissions. Note that the total duration of an epoch with the same design space configuration is comparable as we do not target a speedup by training smaller models – instead, the speedup stems largely due to halving the number of epochs, by way of reducing the phases for training. This reduction is in turn possible due to a smaller, constrained design space.

5.3 Accuracy-Latency Trade-off

After training CompOFA networks, we carried out an evolutionary search (Real et al., 2019) to retrieve specialized sub-networks for diverse hardware deployment scenarios, as done in OFA. The evolutionary search fetches sub-networks that maximize accuracy subject to a target efficiency (latency or FLOPs) constraint. Similar to OFA, we use a 3-layer accuracy predictor common across all platforms. For latency, we use a lookup-table based latency estimator for Samsung Note 10 CPU provided by Cai et al. (2020). For other hardware platforms – namely NVIDIA GeForce RTX 2080 Ti GPU and the Intel(R) Xeon(R) Gold 6226 CPU – we measured actual latency with a batch size of 64 and 1 respectively. The estimated accuracies of the best models returned by this search were then verified on the actual ImageNet validation set.

Figure 2 reports the performances of accuracy-latency trade-off for CompOFA and OFA networks. We observe that the best model in CompOFA for evaluated latency targets are at least as accurate, despite their significantly smaller family size *and* training budget. This result validates our intuition behind the simple heuristic that aids in creating a smaller design space without losing out on Pareto-optimality or density of the generated models.

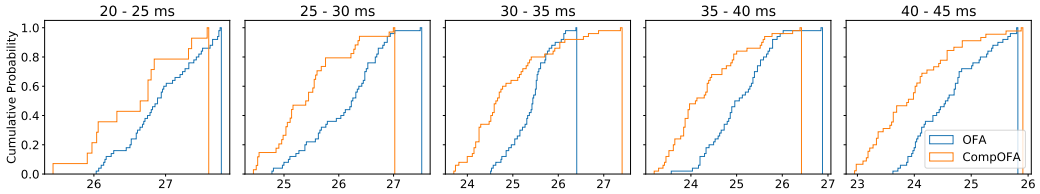

Figure 3: CDF comparisons of 50 randomly sampled models sampled in latency buckets of 5ms each. CompOFA has a higher fraction of its population at or better than a given classification error.

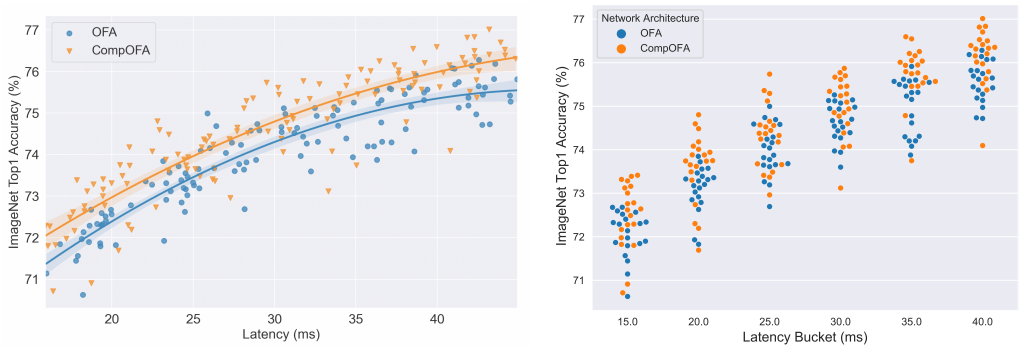

Figure 4: Random sampling of 20 models in each latency bucket of 5ms for CompOFA & OFA actual latency (left) and bucketed latency (right). CompOFA yields a higher average accuracy, i.e. as a population it has a higher concentration of accurate models. The shaded regions in the left plot show the 95% confidence interval of the average accuracy.

5.4 Design Space Comparison

Apart from individual models, we further evaluate CompOFA at a population level through a statistical sampling of design space as introduced by Radosavovic et al. (2020; 2019). Using Samsung Note 10 as sample hardware, we divide the supported range of latencies into buckets of 5ms each. For each latency bucket, we randomly sample 50 models in OFA and CompOFA. Figure 3 plots the cumulative distribution function (CDF) of classification error for each of these latency buckets. In each bucket, CompOFA's CDFs lie above those of OFA, showing that CompOFA has a higher fraction of models that exceed a given accuracy. Additionally in Figures 4, we show 20 of these models in each bucket for each search space, demonstrating that the average accuracy of a randomly picked model from CompOFA is higher than that in OFA. The takeaway of both these evaluations is that not only does CompOFA yield competitive *best* models at a given latency, but a better *concentration* of accurate models with fewer sub-optimal models – i.e. a more accurate overall model population.

5.5 Effect of Number of Phases

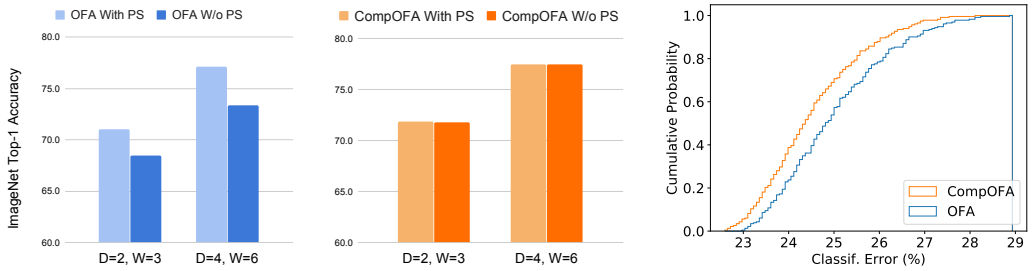

Figure 5: **Left and Center:** Comparing accuracies with and without progressive shrinking (PS). OFA suffers upto 3.7% accuracy drop when progressive shrinking is removed. For CompOFA, no such accuracy drop is seen when compared to the longer training with progressive shrinking.
Right: CDF of model configurations *common* to OFA & CompOFA. CompOFA does not lose accuracy despite its smaller cardinality and smaller training budget.

Cai et al. (2020) showed that OFA networks suffer a top-1 accuracy drop of up to 3.7% when progressive shrinking is removed, showing its role in resolving interference. With $O(10^{19})$ models interfering with each other for simultaneous optimization of their weights, a phased approach is needed to stabilize training by gradually train model configurations. In CompOFA, our primary method of reducing the training time is by reducing the number of phases in training. We repeat a similar ablation to compare the effect of progressive shrinking in OFA & CompOFA. For both design

Table 3: Average search duration for four target latencies in OFA and CompOFA, when measuring real latency without lookup tables

Network Architecture	Avg. Search Time
OFA	18 hours
CompOFA (Elastic Kernel)	9 hours
CompOFA (Fixed Kernel)	**5 minutes**

spaces, we train with & without progressive shrinking and compare the accuracies of common sub-networks. Figure 5 shows CompOFA achieves the same accuracy with and without progressive shrinking. We attribute this to lower interference between sub-networks in a design space smaller by 17 orders of magnitude.

Next, we build a CDF of model configurations in CompOFA and then extract the same sub-networks from OFA. Figure 5 shows that CompOFA still maintains a slightly higher accuracy despite comparing the same models in both spaces. Thus, models discarded in the process of constraining the design space do not add to the accuracy of OFA or CompOFA – the retained models can achieve the same (if not better) accuracy independent of any potential collaboration from these discarded models.

5.6 Search time

The intractable cardinality of OFA necessitated the use of latency estimators as a proxy to real latency measurement. With a significantly smaller design space, this need is removed – avoiding the time and effort of building these latency tables eases "off-the-shelf" usability of CompOFA. We introduce a simple memoization technique during the evolutionary search to cache the measured latencies of model architectures and hence avoid its re-measurement, which is only practical with the smaller search space. Table 3 reports the average run time of NAS algorithms for 4 latency targets with this optimization added to both CompOFA and OFA, reducing the search time to just 5 minutes for CompOFA Fixed-Kernel. We also show that the evolutionary search converges in fewer iterations for CompOFA, in Appendix A.3

6 Conclusion

We build upon Once-For-All (OFA) networks to propose *CompOFA* – a design space for OFA networks using compound couplings between model dimensions, which speeds up the process of one-shot training & neural architecture search with hardware efficiency in the loop.

We use the insight of compound coupling between models to identify that training all possible models in the OFA design space is unnecessary. We propose a simple heuristic to constrain the design space to this compound coupling, and show that this can still attain the same optimal accuracy-latency trade-off. We point out that intractably large search spaces have latency granularities that are too fine for real hardware, and that CompOFA's much smaller search space is sufficiently dense to produce efficient models at the same range, density, and diversity of latency/hardware targets.

We show that this smaller cardinality reduces interference in weight-shared training to the extent that we can afford to train CompOFA to the same accuracy with a 50% reduction in the training budget.

Finally, during the search stage, we demonstrate that this reduced search space eliminates the time and effort needed to build latency lookup tables, thus improving the ease of "off-the-shelf" usability of our method in the real-world settings.

All of the above gains have a common enabling root – a tractable design space cardinality, which in turn is enabled by the insight of compound couplings to identify and constrain the search to patterns of optimal neural network designs.

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A Appendix

A.1 Extra Models in OFA

Figure 6 depicts the stratification of the latency levels into multiple buckets of size 5ms each and uniformly sampled 100 sub-networks of OFA for each bucket. This box-plot helps in uncovering the considerable variance between the maximum and minimum accuracies of the models of the same latency bucket in OFA. This variance is mainly caused due to OFA's enormous search space that contains redundant models that do not improve the overall accuracy of the model distribution belonging to a certain latency bucket.

A.2 Training Schedule for CompOFA-Elastic Kernel

Table 4 shows the training schedule for CompOFA with Elastic Kernel. Compared to OFA, the training budget is reduced by 31%.

Table 4: CompOFA (Elastic Kernel)

Phase	K	D	W	N_{sample}	**Epochs**	**Wall Time**	**GPU Hours**
Teacher	7	4	6	1	180	28h 45m	172h 30m
Elastic Kernel	3, 5, 7	4	6	1	125	26h 51m	161h 06m
Compound	3, 5, 7	2, 3, 4	3, 4, 6	4	25	9h 21m	56h 06m
Compound	3, 5, 7	2, 3, 4	3, 4, 6	4	125	48h 01m	288h 06m
Total					**455**	**112h 58m**	**677h 48m**

A.3 Faster Convergence of NAS

An evolutionary algorithm is set to converge after a certain number of iterations (N) beyond which the fitness value of the population (P) does not improve significantly. OFA runs NAS with a setting of $N = 500$ iterations for a population of size $|P| = 100$. Figure 7 demonstrates that the search time of NAS could further be reduced by reducing the number of iterations to $N = 300$ and $N = 50$

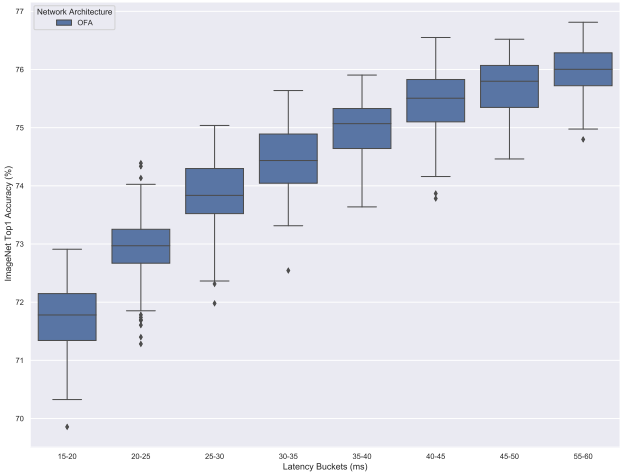

Figure 6: Distribution of accuracies of the randomly sampled models from OFA

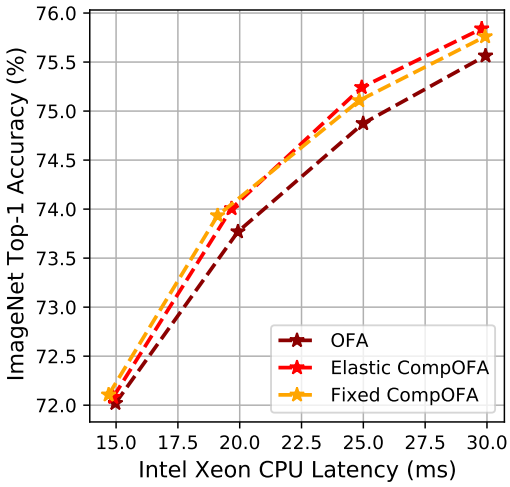

Figure 7: ImageNet accuracies and latencies on Samsung Note10 with reduced NAS iterations for CompOFA.

for CompOFA Elastic-Kernel and CompOFA Fixed-Kernel respectively, without losing out on their Pareto-optimality. Coupled with the removal of the latency predictor, these CompOFA-specific optimizations to the search are effective in reducing the search time and improving direct usability of CompOFA.