Single-Training Collaborative Object Detectors
Adaptive to Bandwidth and Computation

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Abstract

In the past few years, mobile deep-learning deployment progressed by leaps and bounds, but solutions still struggle to accommodate its severe and fluctuating operational restrictions, which include bandwidth, latency, computation, and energy. In this work, we help to bridge that gap, introducing the first configurable solution for object detection that manages the triple communication-computation-accuracy trade-off with a single set of weights. Our solution shows state-of-the-art results on COCO–2017, adding only a minor penalty on the base EfficientDet-D2 architecture. Our design is robust to the choice of base architecture and compressor and should adapt well for future architectures.

1. Introduction

Mobile and embedded devices comprise most computing devices, both in raw number and market share [21]. The impact of bringing to them cutting-edge computer vision models can hardly be overstated, given their ubiquity.

Deep neural networks not only solidified core tasks of computer vision — such as image classification and object detection — but enabled many applications not even considered until then — such as style transfer, pose transfer, and natural image generation, to name a few. Much of current research focuses on the real-world deployment of those solutions. Even smaller models, like image classifiers, pose considerable challenges for deployment in mobile and embedded devices, while larger models, like object detectors, have comparatively lagged.

A crucial trend in improving that scenario is collaborative intelligence [4], which addresses dividing deep learning inference across multiple devices. In particular split computing [29] computes the first layers of a deep model in the local, mobile device while delegating the last layers to remote servers.

While promising, those ideas have yet to surmount the severe technical constraints of mobile devices, which include limitations of network bandwidth and latency, connection reliability, computational power, energy consumption, thermal dissipation, etc. Before becoming practical...
for widespread consumer deployment, solutions will have to become adaptable to multiple, realistic constraints.

Many “adaptive” deep learning models require separate training and weight-sets for each expected runtime condition. That imposes a severe compromise on the number of settings to which the model may adapt. Worse: separate weight-sets limit the responsiveness of the system and increase power consumption.

The main contribution of this work is breaking that compromise by proposing a configurable split object detector with a single set of weights. Our model is the first full-neural (i.e., without non-differentiable layers) split object detector adaptable for bandwidth with a single set of weights. It is the first split computer vision model flexible on-the-fly for both bandwidth and computation. Another contribution is an analytical survey of the recent literature on split models for computer vision.

The text follows the usual organization, with literature survey next, proposed technique in Section 3, experiments in Section 4, and conclusions/discussion last.

2. Related work

In this section, we focus on the recent literature on split computing without aiming at an exhaustive review of collaborative intelligence. Bajić et al. [4] compiled a very recent summary of the challenges in collaborative intelligence, while Wang et al. [38, Section V] and Shi et al. [34] organized comprehensive surveys of deep learning in edge computing, including collaborative intelligence. Table 1 summarizes the works within our scope: those that, at inference time, split the deep-learning network, adding lossy feature compression/decompression between the two halves. Works below the mid-line, which address object detection, are particularly related to ours.

Early works tended to focus on the feasibility of the concept, showing that split computing outperformed compressing the input image and offloading the inference entirely to a remote server [3, 10, 11, 16, 26]. In terms of bandwidth, the split solution was a strong contender, since unsupervised deep compression was already surpassing classical compression [5], but its on-device computational feasibility was far from clear. Eshratifar et al. [15] drew attention with a simple framework of autoencoding+JPEG compression analyzed under a power consumption model for wireless networks [20], showing clear gains over compressed input offloading in terms of bandwidth, latency, and device power consumption.

In contrast, recent split architectures for object detection show little concern for measuring computational costs, focusing on compressing the features and reducing bandwidth. That choice reflects the challenge of making split computing feasible for the task, as networks for object detection tend to branch on upper layers, creating a huge amount of communication. All existing solutions cope with that phenomenon by splitting the network before the branching stages (Figure 2). While Matsubara et al. [30] proposes a framework for distilling the encoders of split networks, other works focus on lightweight compression that forgoes retraining [12, 13].

As shown Table 1, even when existing works share the same task, the lack of standardization hinders direct comparison. In addition, many works assume unrealistic settings for the scenario of actual mobile applications (see [29, Section 3.2] for a lucid critique in that direction). Aside from Matsubara et al. [30, 29], Cohen et al. [13] are the only other authors known to use COCO-2017, but even among that limited set of works, lack of agreement on the metrics prevents direct comparison. In this work, we follow Matsubara et al., choosing the mAP@50:95 as a more challenging (and more robust) metric for object detection instead of the easier (and potentially noisier) mAP@50. Please refer to Section 4.1 for an explanation of the metric.

2.1. Configurability

An issue with existing art is the lack of standard terminology. In this work, we define configurable models as those able to change operational parameters (e.g., bandwidth) without needing a separate set of weights for each setting — at least on the encoder (the “half” of the model that resides on the local device). Let the reader beware that literature employs the terms “adaptive”, “dynamic”, “flexible”, and others with an array of meanings, ranging from relatively rigid models, trained separately (with a different weight-set) for each operational condition, until highly flexible models, able to select different computation paths on-the-fly based on each input (e.g., using early exits) [36, 39].

Multiple sets of weights, in addition to storage costs, hinder the model’s time performance, as models must stop for potentially several inference cycles to load the weights to memory [25]. Weight reloading may also severely impact battery life, as memory transfer and storage access use orders of magnitude more power than arithmetic computation (see [17 apud [41]).

The simplest way to provide bandwidth configurability, i.e., the ability to adapt the size of the representation between the encoder and the decoder (the “half” of the model that resides on the remote server) is to have an adjustable compressor. Straightforward approaches such as Principal Component Analysis [3] are easily parameterizable on-the-fly, but tend to discard important information (e.g., the spatial structure of tensors). In contrast, optimized quantization schemes [13] are very computation-efficient but have a limited ability of compressing representations on their own, constituting only one piece among others for most codec pipelines.
### Table 1. Summary of the state of the art on split computing featuring lossy compression. Tasks: Auto Encoder, Classification, Image Retrieval, Instance Segmentation, Keypoint Detection, Object Detection. Conf<sub>BW</sub> indicates works configurable in the sense of Section 2.1.

| Ref | Year | Tasks | Techniques / Architectures | Datasets | Conf<sub>BW</sub> |
|-----|------|-------|-----------------------------|----------|------------------|
| [26] | 2018 | C AE | Training from scratch / Custom Architecture | ImageNet | No               |
| [16] | 2019 | C    | Training from scratch / ResNet-50 | ImageNet (subset) | No               |
| [15] | 2019 | C    | Compression-augmented training (JPEG) / ResNet | ImageNet (subset) | Yes              |
| [3]  | 2019  | C    | PCA / MobileNet-v2 (0.25-1.0) | ImageNet | Yes              |
| [27] | 2019 | C    | Head network distillation / DenseNet (169 & 201), ResNet-152, Inception-v3 | Caltech-101 | No               |
| [32] | 2020 | C    | Fine-tuning / ResNet | CIFAR-100 | No               |
| [28] | 2020 | C    | Fine-tuning, Knowledge distillation, Head network distillation / MobileNet-v2 (1.0), MnasNet (0.5, 1.0), DenseNets (169, 201), ResNet-152, Inception-v3 | No | No               |
| [33] | 2020 | C    | Fine-tuning, Structured pruning / ResNet-18 | CIFAR-10 | No               |
| [18] | 2020 | C    | Fine-Tuning / MobileNet-v2 (1.0) | CIFAR-10, CIFAR-100 | No               |
| [22] | 2020 | C    | Fine-tuning, Structured pruning / VGG-16 | CIFAR-100 | No               |
| [10] | 2018 | OD   | Compression-augmented training (HEVC) / YOLO-9000-v2 | VOC<sub>2007</sub> | Yes             |
| [11] | 2018 | C OD AE | Custom deep feature CODEC / YOLO-v2, Darknet-19<sub>448</sub>, VGG-16, ResNet | VOC<sub>2007</sub> | No               |
| [9]  | 2019 | C OD IR | HEVC Compression without retraining / VGG-16, ResNet (50, 101, 152), Faster RCNN | ImageNet (subset), PKU, VehicleID, VOC<sub>2007</sub> | Yes             |
| [12] | 2020 | OD   | Channel selection + Reconstructive decoder / YOLO-v3 | COCO<sub>2014</sub> | No               |
| [13] | 2020 | OD   | Entropy-constrained quantizer / YOLO-v3 | COCO<sub>2017</sub> mAP<sub>@50</sub> | Yes             |
| [29] | 2020 | OD IS | Head network distillation / Faster RCNN, Mask RCNN | COCO<sub>2017</sub> mAP<sub>@50:95</sub> | No               |
| [30] | 2020 | OD IS KD | Generalized head network distillation / Faster RCNN, Mask RCNN | COCO<sub>2017</sub> mAP<sub>@50:95</sub> | No               |

On the opposite end of the sophistication spectrum, full-fledged image and video compression schemes, like JPEG and HVEC, may be employed on the features. The compressor may be introduced only during inference time, e.g., by applying HEVC to the output of the convolutional layers, treating the collection of feature maps output by the channels of a layer across a given batch as if they were successive temporal frames [9]. Instead, the training may be compression-augmented / compression-aware, e.g., by introducing JPEG [15] or HVEC [10] as a non-trainable layer, and using several quality configurations as a form of regularization.

Instead of introducing an extraneous compressor, many split architectures choose a learned neural-network compressor/decompressor (i.e., an auto-encoder) that can be trained seamlessly with the rest of the network [10, 15, 16, 18, 22, 27, 28, 30, 29, 32, 33]. In addition to such conceptual attractiveness, learned compressors have been shown to outperform, in terms of bandwidth savings, classical compression [5]. The challenge is making those full-neural schemes configurable. Existing schemes (e.g., [18]) often focus on optimizing data transmission for different bandwidth regimens, but require different sets of weights. One exception is the work of Choi et al. [12], which allows selecting a subset of channels on the same encoder, but needs different decoders (with different weights) for the reconstruction. At the time of this writing, we are not aware of any full-neural architecture configurable on both the encoder and the decoder.

In comparison to bandwidth, computational configurability has not yet been explored by the literature, even though non-configurable options have tackled the impact of computation for split classification models [15, 22, 32, 33]. Theoretical results on information bottlenecks [37, 1], suggesting that the actual information content of deep representations decreases the further we advance layer-wise, motivated the idea of a computation–communication trade-off: the client may save communication by advancing to further layers and obtaining more compressible representations. That compromise may be exploited to obtain optimal split-points, but so far, the proposed solutions require different trained weights for each choice of split-point.

In a more applied direction, the seminal work of slimmable networks [43], in which the network is trained si-
multaneously with different subsets of the channels, as well as follow-up models [6, 40, 42], provided a mechanism to achieve configurability on deep networks without requiring multiple split points. As far as we know, our work is the first to employ that family of techniques on split networks.

2.2. Other directions

We mention, for the sake of curiosity, interesting directions taken by recent works, which include multiple split points and multiple representations at the split point [2, 14], allocation policies for split computing [7], resilience to network packet loss [24], and inference-time privacy [4]. We mention, in particular, collaborative intelligence under additive white Gaussian noise channels [22, 32, 33], which optimize learning, compression, and coding all at once, and strive to minimize on-device computation and create a standardized comparison, even if current works are limited to the setting of 32×32 images of CIFAR.

3. Proposed split design

As seen in the previous section, split deep-learning models appear as a promising solution for implementing costly inference on mobile devices, but introduce a communication bottleneck between the local encoder and the remote decoder that must adapt to a varying bandwidth availability. For object detection, the split happens before the branching of the network, and on full-neural solutions, we introduce a network block at the end of the encoder to compress the representation and a corresponding reconstruction block in front of the decoder (Figure 2).

The main novelty of the proposed architecture (Figure 3) is its reconfigurability, in the sense explained in Section 2.1. All models we introduced are bandwidth-reconfigurable, and several are computation-reconfigurable (in the encoder) as well. Another novelty was the use of the high-performance EfficientDet [35] as foundation for the architecture, which entailed the need for a compressor compatible with those innovations. We discuss each of those innovations below.

Configurability. Existing works achieve bandwidth flexibility either by introducing non-differentiable operations into the neural network or by reloading a set of network weights trained for each transmitted representation size. The advantage of a full-neural solution is that the compression adapts to the data, since it is integrated seamlessly into the model. However, existing full-neural models require a different set of weights for each bandwidth configuration, creating a compromise between flexibility (configuration points) and training/space cost (number of weight-sets). Even worse, those models introduce a disrupting latency during reconfiguration, each time a weight-set must be loaded to memory.

In contrast, our solution makes the model adaptive with a single set of weights. Bandwidth reconfiguration becomes extremely flexible because increasing the number of points does not require adding more weight-sets. Changing operational constraints does not require reloading weights: it is achieved by dynamically selecting $\alpha$, the fraction of active channels in the convolutional layers (Fig. 3).

That flexibility is gained thanks to slimmable networks [43], a set of training methods in which a single set of weights learns to perform well for multiple channel-widths (values of $\alpha$). As base (teacher) architectures, we test Mask RCNN and the Faster RCNN, for the sake of comparison with Matsubara et al. [30, 29], and introduce EfficientDet. For each architecture, we must choose the slimmable layers (discussed below) and the layers to use on the distillation loss: we used the outputs of blocks 1–4 on Faster RCNN and Mask RCNN, and blocks 3–5 on EfficientDet, chosen because they are the branching points of the network. We present the training procedure in detail in Section 3.1.

Computation-configurability. Depending on the choice of the slimmable layers, we may achieve both bandwidth and computation configurability, or only the former (Figure 5).

For bandwidth-only configurability, we only have to make the compressor and decompressor slimmable (technically, there will be some impact in computation, but too small to be of practical use). For configurability in both criteria, we may elect to make all convolutions in the encoder slimmable. Because both computation and communication are critical resources in mobile devices, those designs may be unavoidable to regulate energy and thermal constraints.

While the impact of varying a single convolutional layer is small, when $\alpha$ (explained above) is applied to neighboring layers, it accumulates quadratically, affecting both the output of one layer, and the input of the next:

$$MAC = k^2 \cdot c_{in} \cdot c_{out} = k^2 \cdot \alpha^2 \cdot c_{in} \cdot c_{out}$$ (1)

where, for a given layer, $MAC$ is the number of multiply-accumulate arithmetic operations, $k$ is the kernel width, $c_{in}$ is the number of input channels, and $c_{out}$ is the number of output channels.

Base network. In this work we introduced EfficientDet [35] as base architectures, motivated not only by its performance in COCO-2017 but also by its reduced encoder size and compact tensor output at the end of each block. Compared to the Mask RCNN employed by Matsubara et al. [29] (7.8 GMAC, GMAC = $10^9$ multiply-accumulate operations), or the YOLO-v3 employed by Cohen et al. [13] (10.4 GMAC), EfficientDet (with scaling parameter $D = 2$) has better mAP@50:95 on COCO-2017, with a much more economic encoder (2.4 GMAC). A silhouette comparison
Figure 2. Three split architectures for object detection: (a) one of ours, based on EfficientDet-D2, (b) one by Cohen et al. [13] based on YOLO-v3—Darknet, (c) one by Matsubara et al. [29] based on Mask RCNN—ResNet. The encoder is to run on the mobile client, and the decoder, on a remote server. Those models require a compressor/decompressor (in red), and their bandwidth is the size of the feature that leaves the compressor. The mAP@50-95 of the full (teacher) networks on COCO-2017 validation set was (a) 42.2, (b) 37.9 and (c) 38.0.

Choice of compressor. The compressive autoencoder inserted at the split point is what allows a full-neural architecture. Many alternatives appear in existing split networks, mainly with feed-forward convolutional layers (without skip connections), and ReLU activation [15, 16, 29], sigmoid activation [32], pointwise convolutions for channel reduction [15, 16], and PReLU + Generalized Divisive Normalization (GDN) [22].

The feedforward autoencoders implemented in Mask RCNN and Faster RCNN by Matsubara et al. [29] were unfeasible for our model, because, by themselves, they spent a great deal of computation (more than 6 GMAC), which is more than twice our entire encoder.

Experimental work (which we showcase in our experiments) shows a certain latitude in compressor choice. We tested a compressor inspired by Bottlenet [15], but without the non-differentiable JPEG layer, for we aimed at a full-neural solution: compressor and decompressor had a spatial reduction unit and a channel-wise reduction unit (both explained in their paper). In another scheme, we simply duplicated the last layer of EfficientDet twice (once as a compressor, once as a decompressor), changing only the size of the bottleneck representation $C$. We also tested a variation of the latter without the compressor layer, connecting the encoder’s output (again changing the size of the output bottleneck representation) directly on the decompressor. We tested different values for $C$, but contrarily to the freely configurable $\alpha$, changing $C$ requires retraining the model.

3.1. Training

Our training procedure (Figure 4) merges the best advantages of Generalized Head Network Distillation [30] and of MutualNet [40].

From the latter, we employ the slimmable training [42] using several versions of the same set of weights, at $N$ widths at a time, choosing for each training step the lowest, the highest, and $N - 2$ randomly chosen intermediate widths among all desired configuration widths for the network [42]. Yu et al. call that procedure “sandwich rule”. The $N$ versions are used in a round-robin loop to compute...
Figure 4. Training of the proposed split slimmable architecture. First the reference teacher architecture (non-split, non-slimmable) is trained and frozen. Then the slimmable architecture is learned by distillation: $N$ “copies” of the model (all sharing a single set of weights) are trained concurrently, for varying number of active channels.

Figure 5. Encoder design: depending on the choice of the slimmable layers, we may achieve bandwidth-only configurability (left), or both bandwidth and computation configurability (right). In the latter, at each internal convolutional layer, $\alpha$ has a quadratic effect on computation, by reducing both input and output.

the gradients from the loss and, ultimately, to update the single weight-set (see Algorithm 1 in [42]).

From the former, we adopt the loss based upon minimizing an $\ell_2$ norm between the features extracted by student and teacher at several points of the decoder, including the point where the network splits. That procedure changes from MutualNet (and from Yu et al.’s), which is based on a KL-divergence loss over the model outputs.

As hinted above, one important parameter during training is the set of widths for which the network should learn to operate, e.g., $\alpha = 0.25, 0.33, 0.5, 0.66, 1.0$. The number of widths may be larger than $N$, as different values will be chosen at random by the sandwich rule. In our experiments, we found out that $\alpha_{\min}$, the minimum value in the set, dominates the impact on performance.

Post-training batch normalization statistics. A fine but crucial point in moving from Faster RCNN and Mask RCNN toward EfficientDet was removing the post-training batchnorm statistics used by Yu & Huang [42], since in our setting they considerably hindered the model.

4. Experiments and results

4.1. Materials and methods

We performed all experiments on the COCO-2017 dataset [23], measuring the outcomes on the validation split with the mAP@50:95 metric, the primary metric for the COCO challenge, which corresponds to the mean average precision, averaged for all region IoU thresholds between 50 and 95%, with a 5% step. We used the official COCO API to compute the metric.

We used the Faster RCNN and Mask RCNN models of Matsubara et al. [30], including the public trained weights, as non-configurable baselines. We contrast those models with the performance of four bandwidth-configurable models (Faster RCNN, Mask RCNN, EfficientDet-D1, and EfficientDet-D2) and two computation- and bandwidth-configurable models (EfficientDet-D2 and Faster RCNN).

We trained (distilled) all models for 12 epochs, using the largest batch size possible for each model (6 for non-configurable, 8 for configurable models). We hand-optimized the learning rates and schedulers of all models, setting learning rates to decrease by half every 3 epochs for non-configurable and bandwidth-configurable models, and every 2 epochs for full-configurable models. For inference, we quantized at 8 bits the output of the compressor for
Figure 6. Comparison between models that are only bandwidth-configurable (BW-Conf) with models that are also computation-configurable (CP-Conf), showcasing local computation expenditure (multiply-accumulate operations on encoder) in the data points’ sizes and labels. Remark that some configurations may present a similar compromise of bandwidth vs. mAP but vastly different computation cost.

Our results (half-filled dots) show that it is possible to make Mask RCNN and Faster RCNN configurable without impacting their performance. However, EfficientDet-D1 and, especially, EfficientDet-D2 present much better mAP vs. bandwidth compromises — although there is some performance penalty in making them configurable. The penalty is constant and relatively small up to a certain bandwidth threshold, and then it grows steeply. Still, a single architecture (EfficientNet-D2) with a single set of weights is able to dominate a large area of the configuration space, essentially everything above the yellow dotted line.

A finer-grained comparison of some of the models appears in Figure 6, where we added full-configurable (computation and bandwidth) techniques. The small labels inside the dots indicate the computation spent in the encoder, in tenths of GMAC = 10^8 multiply-accumulate operations. The areas of the dots also indicate, visually, that number. Here, the same bandwidth-only-configurable Faster RCNN and EfficientDet-D2 of Figure 1 appear as baselines (continuous lines). To reduce clutter, we only labeled the first and last dots in those essentially computation-constant models. In the other series, we plot the results by varying the size of the bottleneck C and the minimum value for α (see Figures 3 and 4). Figure 6 shows that full-configuration is achievable, with considerable reduction in computation, and modest impact on mAP, except, again, below a certain threshold. Achieving full configuration, however, is less straightforward than bandwidth configuration. Contrarily to the bandwidth-only-configurable Efficient-D2, a single full-configurable version cannot be stretched over extended regimens of bandwidth and computation without suffering large penalties: notice how the left tail of the (C = 48, α_{min} = 0.25) series drops sharply in mAP. Still, if covering such an extended range of configurations is necessary, it is possible to do it advantageously with just two sets of weights, instead of several.

4.1.2 Other analyses

Since simple feature quantization is so cheap, it is interesting to analyze how it compares with our technique. As shown in Figure 7, in terms of bandwidth, the effect of simple quantization is highly predictable, and may be computed deterministically (e.g., the bandwidth of a 4-bit-quantized compressor is exactly half that of 8-bit-quantized compressor). In terms of mAP, the results are not deterministic, but it is well known that deep networks are surprisingly robust to strong levels of quantization [8, 11]. The results in the plot show that pure quantization does not always provide the best operational compromise, but that adding quantization to the mix may greatly improve the configurability of the model.

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1https://github.com/jsiloto/adaptive-cob  
2https://github.com/zyl0117/Yet-Another-EfficientDet-Pytorch  
3https://github.com/JiahuiYu/slimmable_networks  
4https://github.com/yoshitomo-matsubara/hnd-ghnd-object-detectors  
5https://github.com/sovrasov/flops-counter.pytorch  
6https://github.com/pjreddie/darknet/issues/1039
Many implementation choices proved to be more or less indifferent, demonstrating a certain robustness of the design. For example, several compressor choices resulted in very similar mAPs on EfficientDet (Table 2). For the sake of uniformity, we opted for the design based on the last layer of EfficientDet for both the compressor and decompressor, but it is interesting to note that the design with only the decompressor has very slightly lower performance. Other choices that had little impact were the use of a pretrained encoder vs. random weights (Table 3) or enabling vs. disabling stochastic depth [19] (Table 4).

Other implementation "details" had considerable impact. The post-train statistics for batch normalization introduced by Yu & Huang [42], with a positive effect on Mask RCNN and Faster RCNN, has a negative effect on EfficientDet, as illustrated in Figure 8.

5. Discussion

In order to reach large-scale deployment to consumers, deep learning models will have to adapt on-the-fly to many severe operational constraints. This work is a step in that direction, by allowing configurability of object detection for two operational constraints with a single weight-set. The experiments show that our design works for three very different base architectures (Mask RCNN, Faster RCNN, and EfficientDet), with robustness to small implementation details, like the choice of compressor.

For simplicity of the concept, in this work we pick a single slimming factor $\alpha$ for the entire encoder. In future works, we intend to explore whether two or more factors may be advantageous — in particular, decoupling the choices of computation and bandwidth. In our current model, the choice of quantization may help to decouple those dimensions, but several slimming factors may further enhance that decoupling.

Another simplifying decision was keeping a single set of weights for both encoder and decoder, but having more than one model on the remote decoder, which runs on a large server, may be feasible, and possibly advantageous. On the other direction, bandwidth and computation configurability may be relevant on the server in high-throughput situations to avoid queuing. Analyzing how client and server may interact on-the-fly to maintain optimal quality-of-service is a fascinating frontier for deep computer vision.
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