Dynamically Sacrificing Accuracy for Reduced Computation: Cascaded Inference Based on Softmax Confidence

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Abstract

We study the tradeoff between computational effort and classification accuracy in a cascade of deep neural networks. During inference, the user sets the acceptable accuracy degradation which then automatically determines confidence thresholds for the intermediate classifiers. As soon as the confidence threshold is met, inference terminates immediately without having to compute the output of the complete network. Confidence levels are derived directly from the softmax outputs of intermediate classifiers, as we do not train special decision functions. We show that using a softmax output as a confidence measure in a cascade of deep neural networks leads to a reduction of 15% - 50% in the number of MAC operations while degrading the classification accuracy by roughly 1%. Our method can be easily incorporated into pre-trained non-cascaded architectures, as we exemplify on ResNet. Our main contribution is a method that dynamically adjusts the tradeoff between accuracy and computation without retraining the model.

1 Introduction

State-of-the-art Deep Neural Networks (DNNs) usually consist of hundreds of layers and millions of trainable weights. At inference time, this translates into billions of multiply-accumulate operations (MACs) for a single input [SCYE17]. The training process of models is a computationally intensive task that is performed once. After training is completed, the trained model is used for inference. Inference requires fewer computations than training, however, the inference is performed multiple times. Hence, reducing the amount of computation during the inference is an interesting ongoing goal [HLM⁺16]. Moreover, modern DNNs usually apply the same number of operations for every inputs, and the natural question that arises is whether this amount of computation is indeed required [PSR16].

In this paper, we focus on the computational effort spent on inference in DNNs. For simplicity, we measure the computational effort in the number of multiply-accumulate operations (MACs). Many claim that the computational effort required for classifying images should depend on the image [Gra16, FCZ⁺17, PSR16, TMK16]. We claim that the required computational effort for classification is an intrinsic yet hidden property of the inputs. Namely, some images are much easier to classify than others, but the required computational effort needed for classification is hard to predict before classification is completed.

The desire to spend the "right" computational effort in classification leads to the first goal in this work.

Goal 1.1. Given a model M, design a model M' in which the computational effort during the classification of an input x is proportional to the likelihood of misclassifying x using M.

Misclassification likelihood indicates and measures the hardness of an input. The question we pose is whether we can (almost) preserve accuracy while reducing the computational effort required to classify "easy" instances. The two extreme cases are: (1) Consider a distribution of inputs D for which the misclassification likelihood is very low (say 1%) in model M. We view D as a distribution of "easy" inputs, and would like the new model M' to classify $x \in D$ while spending a fraction of the computational effort compared to M. (2) Consider a distribution of inputs D' for which the misclassification likelihood is high (say, 25%) in model M. We view D' as a distribution of "hard" inputs, and would like the new model M' to classify inputs from D' almost as accurately as Mdoes. The computational effort of M' for inputs in D' is only slightly higher than that of M (c.f., an overhead of 1% in the computation). The principle behind our goal is that an efficient model should achieve a high classification accuracy faster for "easy" instances than for "harder" ones.

A motivation to reduce the computational effort during the inference can be exemplified by systems with non-constant power consumption or throughput. Examples of such settings are: (1) As the battery drains in a mobile device, one would like to enter a "power saving mode" in which less power is spent per classification. (2) If the input rate increases in a real-time system (e.g., due to a burst of inputs), then one must spend less time per input [CZC⁺10]. (3) Timely processing in a data center during spikes in query arrival rates may require reducing the computational effort per query [Bod10].

Dynamic changes in the computational effort or the throughput lead to the second goal in this work.

Goal 1.2. Introduce the ability to dynamically control the computational effort while sacrificing accuracy as little as possible. Such changes in the computational effort should not involve retraining of the DNN.

1.1 Contribution

We propose an architecture that is based on a cascade of DNNs [BWDS17] depicted in Figure 1. The cascade comprises multiple DNNs (e.g., three DNNs), called *component DNNs*. The cascade is organized sequentially so that the next component DNN is fed by the previous component. Hence previous computations are reused and further refined by the next component. Classification takes place by invoking the component DNNs one-by-one and stopping the computation as soon as the confidence level reaches the desired level. Our setting is applicable to general multiclass classification in general architectures that terminate with a softmax function.

The stopping decision is based on the softmax output of each component DNN. We define a simple confidence threshold, based on the softmax output, that allows for trading off (a small) decrease in accuracy for (a substantial) reduction in computational effort. The resulting approach has several advantages over the previous work [PSR16, BWDS17, SCP⁺18]. The main contribution of our work is:

Dynamically change the compromise between accuracy and computational effort without retraining the cascaded model.

In addition, we show how a cascaded architecture can be obtained from an ordinary feed-forward DNN while requiring only small fine-tuning (see section 6). We demonstrate the performance of our models on various image classification datasets: (i) A computation reduction of 34% that sacrifices 1.2% accuracy with respect to the CIFAR-10 test set. (ii) A computation reduction of 16% that sacrifices 0.7% accuracy with respect to the CIFAR-100 test set. (iii) A computation reduction of 54% that sacrifices 1.4% accuracy with respect to the SVHN test set. (iv) A computation reduction of 17% that sacrifices 1.3% accuracy with respect to the IMAGENET validation set.

Finally, our experimentation demonstrates a monotone relation between softmax values and classification accuracy in intermediate classifiers (see section 7.3).

2 Related work

The two principle techniques that we employ are *cascaded classification* and *confidence estimation*. We elaborate on the recent usage of these techniques hereinafter.

2.1 Cascaded classification

Cascaded classification is suggested in the seminal work of Viola and Jones [VJ01]. As opposed to voting or stacking ensembles in which classification is derived from the outputs of multiple experts (e.g., majority), the decision in a cascaded architecture is based on the last expert. A cascaded neural network architecture for computer vision is presented in [WLCS18]. In their work, as the complexity of the input increases, the evaluation is performed with increased resolution and increased number of component DNNs in the cascade. The works of Wang *et al.* [WYDG17, WSL⁺18] presents the skipping approach, where each input can take a path composed of a subset of layers of the original architecture. Skipping of layers requires training of switches that decide whether skipping of layers takes place. The work by Lerox *et al.* [LBDC⁺17] presented the idea of early stopping in a setting in which the cascaded DNNs are distributed among multiple devices.

Reinforcement learning is employed by Odena *et al.* [OLO17] in a cascade of meta-layers to train controllers that select computational modules per meta-layer. meta-layers to train controllers that select computational modules per meta-layer.

2.2 Confidence estimation

Uncertainty measures of classifiers are discussed in [CDTV95, DSV00]. These works address the issue of the degree of confidence that a classifier has about its output. The confidence of an assembly of algorithms is investigated by Fagin *et al.* [FLN03] in general setup. Fagin *et al.* define instance optimality and suggest to terminate the execution according to a criterion based on a threshold.

Rejection refers to the event that a classifier is not confident about its outcome, and hence, the output is rendered unreliable. Geifman and El-Yaniv [GEY17] describe a selective classification technique, in which a classifier and a rejection-function are trained together. The goal is to obtain coverage (i.e., at least one classifier does not reject) while controlling the risk via rejection functions. They proposed a softmax-response mechanism for deriving the rejection function and discussed how the true-risk of a classifier (i.e., the average loss of all the non-rejected samples) can be traded-off with its coverage (i.e., the mass of the non-rejected region in the input space). Our work adopts the usage of the softmax response as a confidence rate function, however, it differs in a way we apply the confidence threshold. Namely, we propose a cascade of classifiers that terminates as soon as the desired confidence threshold is reached.

The ability of the softmax output to reflect the true confidence of the classifier was investigated by Gu *et al.* [GPSW17]. The authors propose the temperature scaling technique in order to calibrate the softmax output, making it highly correlated with the expected accuracy.

2.3 Combined approach: cascaded inference with confidence estimation

The work of Cambazoglu *et al.* $[CZC^+10]$ presents an additive ensemble machine learning approach with early exits in a context of the web document ranking. In the additive approach, the sum of the outputs of a prefix of the classifiers provides the current output confidence.

The work of Teerapittayanon *et al.* [TMK16] presents the BranchyNet approach, in which a neural network architecture has multiple branches, each branch consists of a few convolutional layers terminated by a classifier and a softmax function. The approach in [TMK16] does not help to reduce the amount of computation that takes place outside the "main path". The confidence of an output vector y in BranchyNet is derived from the entropy function *entropy* $(y) = -\sum_{c} y_{c} \log y_{c}$. Finally, in [TMK16], automatic setting of threshold levels is not developed, and the gains of their approach were not examined on large datasets.

Cascaded classification with dedicated linear confidence estimations (rather than softmax) appears in the Conditional Deep Learning (CDL) of [PSR16], however, this approach was not examined on large datasets and did not discuss an automatic setting of confidence thresholds. Cascaded classification with confidence estimation appears also in the SACT mechanism [FCZ⁺17], an extension of the prior work by Graves [Gra16] that deals with recurrent neural networks. Confidence estimation is based on the summation of the halting scores. Computation is terminated as soon the cumulative halting score reaches a threshold. An interesting aspect of SACT architecture is the feature of spatial adaptivity. Namely, different computational efforts are spent on different regions of the input image. Recently, Bolukbasi *et al.* [BWDS17] proposed an adaptive-early-exit cascaded classification architecture. The computation may terminate after each convolutional layer. For every convolutional layer k, a special decision function γ_k is trained to whether an exit should be chosen. One of the drawbacks of this approach is that the decision functions must be re-trained per value of the acceptable accuracy degradation.

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3 Cascaded Inference (CI)

Table 1 lists the parameters and notations introduced in this chapter.

Notation	Table Domain	Table 1: Notations and definitions used in this papernSemantics		
n_e	N	Number of training epochs		
D	N	Number of component DNNs in the cascade		
C	\mathbb{N}	Number of classes in the classification task		
n	\mathbb{N}	Number of ResNet-blocks in a ResNet-module		
T		Labeled training set, containing pairs of inputs and corresponding labels		
M		Set of component DNNs that form a cascade $(M = D)$		
M_m		The m^{th} component in the cascade, $m \in \{0,, D-1\}$		
θ_{conv_m}		Weights and biases of the convolutional layers in component M_m		
Θ_{conv}		Weights and biases of the convolutional layers in the cascade		
Θ_{fc}		Weights and biases of the fully connected layers of the cascade		
$ heta_{fc_m}$		Weights and biases of the fully connected layers of component M_m		
$out_m(x)$	$\{0,, C-1\}$	Class predicted by component M_m for input x		
$\delta_m(x)$	[0,1]	Confidence output by component M_m for input x		
$\hat{\delta}_m$	[0,1]	Confidence threshold of component m		

Note: throughout the paper, we use the terms "classifier" and "component DNN" interchangeably.

3.1 Cascaded architecture

A cascade of DNNs is a chain of convolutional layers with branching between layers to a classifier (see Figure 1). Early termination in cascaded DNN components means that intermediate feature maps are evaluated by classifiers. These classifiers attempt to classify the feature map and output a confidence measurement of their classification. If the confidence level is above a threshold, then execution terminates, and the classification of the intermediate feature map is output. See Figure 1 for an example of a cascaded architecture based on three convolutional layers. Each component in a cascaded architecture consists of convolutional layers followed by a branching that leads to (1) a classifier, and (2) the next component.

In our experimentation, we employ ResNet block layers [HZRS16a] as component DNNs in our cascade. Moreover, in section 6 we show how a large pre-trained model (ResNet-50-v2) can be quickly transformed into a cascaded architecture.

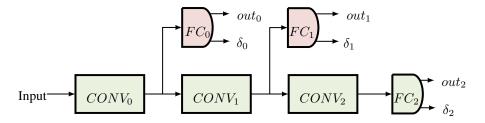


Figure 1: An example of a cascaded architecture of three component DNNs with early termination. A cascade of convolutional layers $(CONV_0, \ldots, CONV_2)$ ends with a classifier clf_2 . Early termination is enabled by introducing the classifiers clf_i after convolutional layers. Each classifier outputs a classification out_i and a its confidence δ_i .

It is tempting to adjust the aforementioned topology of the cascade for even higher computational reuse. For example, the out_i output of the classifier can be fed to the following component (namely to the $CONV_{i+1}$). Such an adjustment, however, is not applicable in the case when the CONV layers are pre-trained in a non-cascaded setup, losing a major advantage of the method we propose.

3.2 Early termination based on confidence threshold

The usage of the threshold for determining early termination in the cascade is listed as Algorithm 1. The algorithm applies the component DNNs one by one and stops as soon as the confidence measure reaches the confidence threshold of this component. This approach differs from previous cascaded architectures in which a combination (e.g., sum) of the confidence measures of the components is used to control the execution [FCZ⁺17, CZC⁺10].

Instead of having D per-component thresholds, one could suggest using a single global threshold for the whole cascade. Another alternative is to set $D \cdot C$ thresholds for every (component, class) pair. We empirically compared the three aforementioned approaches and found the first one (per component thresholds) to be the most effective, which therefore became the approach of our choice.

Algorithm 1 CI (M, δ, x) - Cascaded Inference. Early termination takes place as soon as the confidence level reaches the confidence threshold.

1: Input: cascaded model M, thresholds $\hat{\delta}$, input x2: for m = 0 to D - 1 do 3: $(out_m(x), \delta_m(x)) \leftarrow M_m(x)$ 4: if $\delta_m(x) \ge \hat{\delta}_m$ then 5: return $out_m(x)$ 6: end if 7: end for 8: return $out_{D-1}(x)$

3.3 Softmax confidence

Every component DNN is terminated by a classifier with one or more FC layers followed by a softmax function. Let $z_m \in \mathbb{R}^C$ denote the input to the softmax function in the *m*'th component of the cascade. Let $s_m \in [0,1]^C$ denote the softmax vector in the *m*'th component. The softmax vector is defined as follows.

Definition 3.1 (softmax). $s_m[i] = \frac{e^{z_m[i]}}{\sum_{c=0}^{C-1} e^{z_m[c]}}$.

Definition 3.2 (confidence measure). The confidence measure $\delta_m \in [0,1]$ is defined by $\delta_m \triangleq \max_c \{s_m[c] \mid 0 \le c \le C-1\}$.

Definition 3.3 (predicted class). The predicted class $out_m \in \{0, ..., C-1\}$ is defined to be the class c such that $s_m[c] = \delta_m$.

4 Training procedure

In this section we present the training procedure of the component DNNs.

Consider a cascaded architecture with D components. We denote this cascade by $M = (M_0, \ldots, M_{D-1})$, where M_m denotes the *m*'th component in the cascade. Let $\Theta_{conv} = \{\theta_{conv_0}, \ldots, \theta_{conv_{D-1}}\}$ denote the weights and biases of the convolutional layers of the component DNNs (M_1, \ldots, M_{D-1}) . Let $\Theta_{clf} = \{\theta_{clf_0}, \ldots, \theta_{clf_{D-1}}\}$ denote the weights and biases of the classifiers of the component DNNs (M_1, \ldots, M_{D-1}) .

Let $L_M(out_m, T)$ denote a loss function of the cascade M with respect to the output of the m'th component, averaged over the labeled dataset T. In order to train the cascade M, we propose a backtrack-training (Algorithm 2) BT(M, T). We emphasize that the training procedure first optimizes all the convolutional weights together with the weights of the last classifier. Only then, do we optimize the weights of the classifiers clf_i , for $0 \le i \le D - 2$ (i.e., classifiers of intermediate components). Our approach differs from previous training procedures [TMK16, WYDG17] in

which the loss functions associated with all the classifiers were *jointly optimized*. This difference has two following advantages: (1) the longest computational path of the cascade is trained independently of the intermediate loss functions, hence the maximum achievable accuracy of the model is not compromised. (2) A pre-trained, non-cascaded, architecture can be transformed into a cascade and then trained according to lines 4-7 of the BT(M, T) algorithm to fine-tune only the intermediate classifiers.

Algorithm 2 BT(M,T) - An algorithm for a backtrack training of the cascade $M = \{M_0, \ldots, M_{D-1}\}$. The output is the trained weights of the cascade M

1: Input: cascaded model M, training set T2: Let $\Theta_{deep} = \Theta_{conv} \cup \theta_{clf_{D-1}}$ 3: $\Theta_{deep} = \arg \min_{\Theta_{deep}} \{L_M(out_{D-1}, T)\}.$ 4: for m = 0 to D - 2 do 5: $\theta_{clf_m} = \arg \min_{\theta_{clf_m}} \{L_M(out_m, T)\}.$ 6: end for 7: return $\Theta_{conv} \cup \Theta_{clf}$

5 Setting of confidence thresholds

In this section, we present an automatic methodology for setting the confidence threshold $\hat{\delta}_m$ for every component M_m given an acceptable accuracy degradation ϵ . We note that the hyper-parameter ϵ is a single parameter for the whole cascade, and the automatic methodology we present determines an individual confidence threshold for every component in the cascade. The important attribute of the automatic setting of the confidence thresholds is that one can change them on the fly during the inference stage.

Let $T_m(\delta) \subseteq T$ denote the subset of inputs for which the confidence measure of the *m*th component is at least δ .

$$T_m(\delta) \triangleq \{(x, y) \mid \delta_m(x) \ge \delta\}.$$

Let $\gamma_m(\delta)$ denote the number of times the classification output by component M_m is correct for inputs in $T_m(\delta)$.

$$\gamma_m(\delta) \triangleq \sum_{(x,y) \in T_m(\delta)} \mathbbm{1}\{out_m(x) = y\}.$$

Let $\alpha_m(\delta)$ denote the accuracy of component M_m with respect to $T_m(\delta)$.

$$\alpha_m(\delta) \triangleq \begin{cases} \frac{\gamma_m(\delta)}{|T_m(\delta)|} \text{ if } |T_m(\delta)| > 0\\ 0 \text{ otherwise} \end{cases}$$

Let α_m^* denote the maximum accuracy for component M_m .

$$\alpha_m^* \triangleq \max_{\delta \in [0,1]} \alpha_m(\delta).$$

For an acceptable accuracy degradation $\epsilon > 0$, we define the confidence threshold $\delta_m(\epsilon)$ by

$$\delta_m(\epsilon) \triangleq \min\left\{\delta \mid \alpha_m(\delta) \ge \alpha_m^* - \epsilon\right\}$$

When a cascaded inference is performed using $CI(M, \hat{\delta}, x)$ (Algorithm 1), the confidence threshold vector $\hat{\delta}$ is set as follows. Choose an $\epsilon \in [0, 1]$, and set $\hat{\delta}_m \leftarrow \delta_m(\epsilon)$, for every m. We remark that

(i) the threshold for the last component should be zero, and (ii) one could use separate datasets for training the weights and setting the confidence threshold.

In some applications, the desired accuracy metric is "top-K", meaning that a prediction is regarded as correct if the top K most confident predictions of a classifier contain the ground truth class. To choose appropriate thresholds for the top-K metric, the only change to the methodology above is to set $\delta_m(x)$ to be the sum over the top K elements in the softmax vector.

6 Experimental Setup

In order to examine the usefulness of cascaded inference we performed experiments on CIFAR-10, CIFAR-100 and SVHN datasets using ResNet-110 architecture and on IMAGENET dataset using ResNet-50-v2 architecture. The transformation of the ResNet architecture into a cascade was done by dividing it into three stages; the choice of the layers after which a new stage begins was based on the structure of the architecture (i.e., between distinct layer blocks, differently color-coded in Figure 3 of [HZRS16a]). In the resulting cascade, each component DNN consists of a stage and a classifier, as depicted in Figure 2c. The analysis of the overhead introduced by our transformation is depicted in Table 2. According to this analysis, the increase in the number of MACs, caused by the transformation of the ResNet into a cascade of 3 component DNNs, is less than 0.2%.

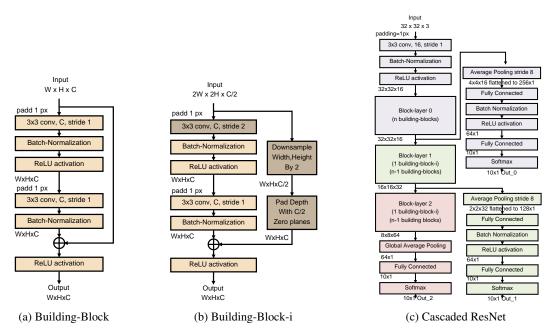


Figure 2: (a) - building-block. (b) - first building-block in each block-layer performs a sub-sampling using stride 2. (c) - the cascaded version of ResNet architecture, parameterized by n such that the number of layers in it is 2 + 6n. For instance, setting n = 18 yields the structure denoted ResNet 110 in the literature.

	ResNet-110	ResNet-50-v2
non-Cascaded	253,953,214	4,037,883,817
Cascade - total component DNN 0 component DNN 1 component DNN 2	$\begin{array}{c} 253,978,670\\ 86,000,922\\ 84,068,170\\ 83,909,578 \end{array}$	$\begin{array}{c} 4,044,633,979\\ 1,817,092,009\\ 1,467,571,177\\ 759,970,793 \end{array}$
Computation increase	0.01%	0.17%

Table 2: Number of MAC operations required for a single inference in ordinary ResNet models and in their cascaded counterparts.

We trained the cascaded ResNet-110 from scratch with respect to algorithm 2. Simple data augmentation was employed only for CIFAR models as in [HZRS16a]. The optimization of every classifier was performed with Stochastic Gradient Descent (SGD) for 160 epochs in CIFAR datasets and for 50 epochs for SVHN dataset. Learning rate was scheduled as described in [HZRS16a]. For the IMAGENET dataset we chose the ResNet-50-v2 [HZRS16b] architecture, which requires roughly 4 Giga-MAC operations per inference and achieves a classification accuracy of roughly 76.51%¹. Deeper models such as ResNet-152 and ResNet-200 require more computation. One could argue that these deeper architectures contain a great deal of redundant computation without sacrificing accuracy.

For the IMAGENET experiments, we transformed the official pre-trained Tensorflow [AAB⁺15] ResNet-50-v2 model into a 3-stage cascaded architecture by introducing additional classifiers after every layer block. We then followed lines 4-7 of the BT(M, T) algorithm (Algorithm 2) to train the two new classifiers, each of which has 2 FC layers, while freezing all the pre-trained weights. Source code, for reproducing our IMAGENET results, is publicly available². This fine tuning of the pre-trained model took less than 20 hours per classifier using 4 GPUs.

7 Results

7.1 Confidence threshold effect

We trained the cascaded versions of ResNet-110 and ResNet-50-v2 models as described in Section 6. We evaluated the performance using various ϵ values. The tradeoff between the test-accuracy and the number of MACs required for a single inference is shown in Figure 3. The MAC counts were obtained analytically by summing up the linear operations in the convolutional layers and the FC layers, excluding activations and batch normalization. Quantitative results that appear in Table 3 demonstrate the ability of the cascaded architectures to trade as little as 1.3% of accuracy for a reduction of 16% - 53% of the computational effort. Note the reduced effect on accuracy for IMAGENET when accuracy is measured with respect to the top-5 classifications compared to the top-1 classification (see last two lines in Table 3).

Table 3: Accuracy-computation tradeoffs. - Column 1 lists the tested datasets. Columns 2-4 list the accuracy of classifier clf_i , for $i \in \{0, 1, 2\}$, with respect to the complete test set. Columns 5-10 list the accuracy of our cascaded architecture for different values of ϵ - the acceptable accuracy degradation (see Sec. 6 for the details of which network was used for each dataset). Computational reduction by the cascade for each ϵ is relative to the computational effort of the non-cascaded architecture $M_{0,1,2}$ and is defined by $1 - \frac{\#MAC_Count(Cascade(\epsilon))}{\#MAC_Count(M_{0,1,2})}$.

Accuracy of $M_{0,\ldots,m-1}$				Accuracy(top), computation reduction(bottom)					
Dataset	M_0	$M_{0,1}$	$M_{0,1,2}$	$\epsilon = 0\%$	$\epsilon = 1\%$	$\epsilon=2\%$	$\epsilon = 4\%$	$\epsilon=7\%$	$\epsilon=8\%$
CIFAR-10	77.50%	81.40%	93.10%	$93.10\%\ 6\%$	$92.70\%\ 27\%$	91.90 % 34 %	91.10% 42%	$87.32\%\ 50\%$	$rac{86.35\%}{52\%}$
CIFAR-100	48.10%	50.00%	70.50%	70.50% 1%	70.65% 4%	$70.50\% \\ 7\%$	$70.30\%\ 10\%$	$69.94\%\ 15\%$	69.78% 16%
SVHN	89.80%	85.20%	97.03%	$97.03\%\ 0\%$	$95.60\%\ 54\%$	$94.00\%\ 59\%$	$91.30\%\ 64\%$	$89.76\%\ 66\%$	$89.80\%\ 66\%$
				$\epsilon = 0\%$	$\epsilon = 1\%$	$\epsilon=2\%$	$\epsilon=5\%$	$\epsilon=6\%$	$\epsilon=7\%$
IMAGENET top-1	46.69%	62.76%	76.51%	$76.51\%\ 0\%$	$76.51\%\ 3\%$	$76.50\% \\ 7\%$	$75.90\%\ 14\%$	$75.56\%\ 15\%$	$75.19\%\ 17\%$
IMAGENET top-5	70.22%	84.31%	93.21%	$93.21\%\ 0\%$	$92.84\%\ 11\%$	92.02% 17%	$\frac{88.54\%}{28\%}$	$87.30\%\ 31\%$	$rac{86.13\%}{33\%}$

7.2 Comparison with Bolukbasi et al.

Figure 3e and Table 4 compare the top-5 accuracy-to-computation tradeoffs of our cascaded inference against adaptive cascaded inference over ResNet-50 with early exits [BWDS17]. We translated

¹https://github.com/tensorflow/models/tree/master/official/resnet

 $^{{}^{2} \}tt{https://github.com/AnonymousConferenceCode/Cascaded_Inference.}$

the speedups presented in [BWDS17] from time to MAC-count speedups for the purpose of comparison to our work (to exclude the impact of software and hardware environments differences). Our model demonstrates higher accuracy for any given computational effort, in addition to being able to dynamically adjust to different accuracy-to-computation tradeoffs.

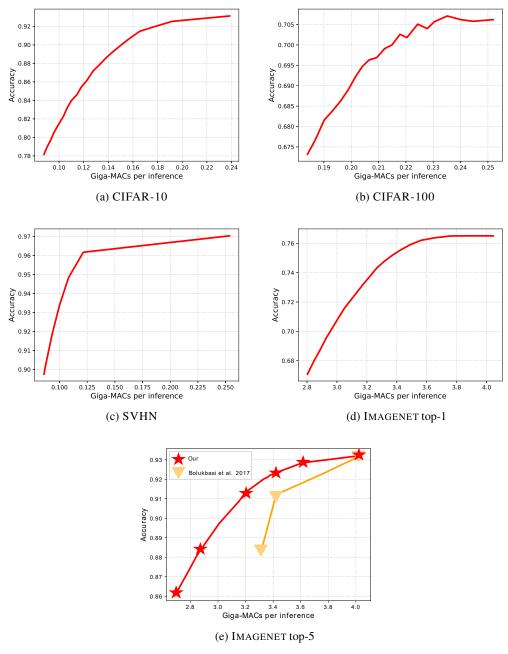


Figure 3: Cascaded inference with early termination test accuracy vs. average number of MAC operations per inference. The measured points on the curves are obtained by considering variable values of $\epsilon \in \{20\%, \dots, 1\%, 0\%\}$.

7.3 Softmax as a confidence measure

For the cascaded ResNet models, we analyzed the accuracy $\alpha_m(\delta)$ (see definition in Section 5) of each classifier independently. The accuracy $\alpha_m(\delta)$ was measured for $\delta \in [0, 1]$ using the test-set

Table 4: **Comparison of cascaded inference to [BWDS17]** on IMAGENET top-5 metric. Column 1 lists the accuracy lost relative to the original ResNet-50 model. Columns 2 and 3 list the speedups of the work by Bolukbasi *et al.* and of our cascaded inference with respect to the full ResNet-50 model. Speedup is $\frac{old_{MACs}}{max_{MACs}} - 1$.

Accuracy reduction	Bolukbasi et al. 2017 speedup	Our Cascade speedup
1%	8%	20%
2%	18%	27%
5%	22%	41%

rather than to the training set. The plots in Figure 4 show how the choice of the threshold provides control over the test accuracy. Note that the range of $\alpha_m(\delta)$ starts with the accuracy of clf_m and ends with the accuracy that corresponds to the highest confidence measure. The almost linear behavior of $\alpha_m(\delta)$ as a function of δ justifies basing the confidence threshold on the softmax output. We note that these results were obtained without applying softmax calibration techniques.

In addition, we examined the frequency of the different confidence levels observed at the output of each classifier in a cascade. This observation is presented in the form of a bar-plot distribution in Figure 4. The distribution of the first two components of the cascade is relatively uniform. Whereas the distribution of the confidences of the last classifier has no importance since in our inference approach the confidence threshold of the last classifier is set to $\delta_{D-1} = 0$.

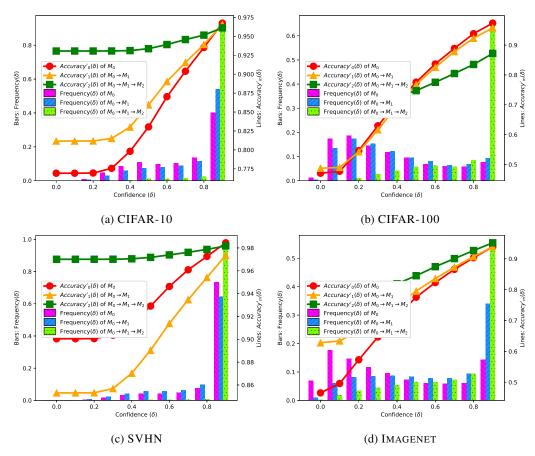


Figure 4: **Softmax as a confidence measure**. The line plots show the accuracy $\alpha_m(\delta)$ of each classifier in the cascade independently. The bar plot presents the frequency of the different confidence levels sampled over the test set. All plots were obtained by separately testing the three component DNNs of the cascaded ResNet.

8 Discussion and future work

As further research, cascading can be applied to RNNs or alternatively, the impact of depth of feedforward DNNs on the confidence estimation can be investigated. A gap between the allowed accuracy degradation (ϵ) and the actual test accuracy degradation was especially evident in the CIFAR-100 dataset. This gap can be bridged by performing softmax-calibration, which can serve as a practical extension of our study.

9 Conclusions

We showed that using a softmax output as a confidence measure in a cascade of DNNs can provide a reduction of 15% - 50% in the number of MAC operations while degrading the classification accuracy by roughly 1%. This approach allows to dynamically change the acceptable accuracy degradation (ϵ) without retraining because the confidence thresholds are automatically derived from ϵ . This achieves the second goal of our work.

Secondly, our approach is easily adoptable, since the transformation of the trained non-cascaded DNN into a cascade of component DNNs requires only training of the auxiliary classifiers, which are small relative to the original network. In other words, non-cascaded state-of-the-art models can be transformed into a cascade of component DNNs with very little training involved. Once the transformation is complete, these models will benefit from less computation during inference.

Finally, we observed a monotone, almost linear, relation between the softmax function and the test accuracy. This implies that the softmax output is a good estimate of the neural network confidence. Our approach explicitly demands lower computational effort for inputs that indicate higher confidence. This achieves the first goal of this work.

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