QuEST: Quantized embedding space for transferring knowledge

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Abstract

Knowledge distillation refers to the process of training a compact student network to achieve better accuracy by learning from a high capacity teacher network. Most of the existing knowledge distillation methods direct the student to follow the teacher by matching the teacher’s output, feature maps or their distribution. In this work, we propose a novel way to achieve this goal: by distilling the knowledge through a quantized space. According to our method, the teacher’s feature maps are quantized to represent the main visual concepts encompassed in the feature maps. The student is then asked to predict the quantized representation, which thus forms the task that the student uses to learn from the teacher. Despite its simplicity, we show that our approach is able to yield results that improve the state of the art on knowledge distillation. To that end, we provide an extensive evaluation across several network architectures and most commonly used benchmark datasets.

1. Introduction

Deep neural networks excel in many vision tasks, owing to their high modeling capacity and enormous training data. But these high capacity models cannot be used for many real-world scenarios, when there are constraints in terms of computation resource, storage and power consumption as, for example, with autonomous vehicles or drones. To address this problem, many techniques for model compression have been explored like parameter pruning and sharing, low-rank factorization, transferred convolutional filters, and knowledge distillation.

Knowledge Distillation (KD) for deep networks was introduced by Hinton \textit{et al}. [9]. The main idea is to train a network using the output of another pre-trained network. Specifically, in the context of model compression, a low-capacity “student network” is trained to mimic the softened classification predictions of a higher capacity pre-trained “teacher network”. Hinton \textit{et al}. [9] demonstrated that adding such an auxiliary objective to the standard training loss of the student network, leads to learning a more accurate model. Furthermore, knowledge distillation has also been shown to be beneficial to transfer learning [15] and semi-supervised learning [22, 14] problems. For instance, Li and Hoiem [15] showed that the KD loss [9] can be employed for reducing the tendency of neural networks to “forget” prior tasks when trained in an incremental way. To that end, they add a distillation loss to the (student) network that is being trained at each step using as teacher the frozen network at the end of the previous step. Also, in the context of the semi-supervised learning, Laine and Aila [14] use a distillation-like loss for learning with extra unlabeled images, in which case the teacher is an ensemble of the same network but at different training snapshots.

Since KD, several other approaches have been proposed for knowledge distillation [20, 29, 18, 25, 6, 12, 16, 8, 4]. The key question is what type of information to transfer from the teacher to the student. Most approaches focus on transferring knowledge through intermediate features of the two networks [20, 29]. Broadly, these approaches differ by how they match the features of teacher and student networks. FitNets [20] uses a learned projection of student’s feature to regress features of teacher. Attention transfer [29] aggregates the feature maps to get an attention map which it then uses for knowledge transfer. While other methods transfer knowledge by matching the distributions of the feature maps of the two networks [10]. In general these methods force the student to regress aggregated or raw feature maps of the teacher network. However, although feature maps tend to encode useful semantic knowledge, the exact values/magnitudes of their feature activations might not be that semantically-important. Moreover, feature activations are sometimes sensitive to small perturbations on the input image and, due to different network architectures, might exhibit different behavior. Therefore, forcing the student to regress the feature activations of the teacher can be (a) a hard-to-solve problem that (b) needlessly spends the student’s capacity for transferring potentially unimportant aspects of the teacher network. On the other hand, aggregating the feature maps to a single-channel attention map might discard significant knowledge captured on individual feature map channels.

To circumvent the aforementioned drawback of transfer-
ring raw feature maps, we propose in this paper to achieve the knowledge transfer task in the context of a \emph{spatially dense quantization of the feature maps}. First, we learn a predefined vocabulary of the teacher deep features (which we call visual teacher-words). We then propose a novel approach for model distillation that is defined with respect to a spatially dense quantization of the teacher feature maps. Our distillation strategy aims at aligning the student network behavior with the teacher one, not using the feature prediction but their projections over the pre-computed teacher-word dictionary. The strength of the approach is that it encodes only the main visual concepts/words that the teacher learned during its training without being sensitive to perturbations of the teacher feature values.

We extensively evaluate the proposed method with various teacher-student architectures and across a variety of commonly used datasets (CIFAR-10, CIFAR-100, and ImageNet), and demonstrate that our simple but effective approach manages to achieve state-of-the-art results.

In the remainder of the paper, we discuss related work in Section 2, describe our distillation methodology in Section 3, and provide experimental results in Section 4. Finally, we conclude in Section 5.

2. Related work

The aim of knowledge distillation is to transfer knowledge from a trained teacher network to a student network. To carry out the knowledge transfer, in knowledge distillation methods, the student tries to imitate some facets of the teacher network. In the context of model compression, Bulucu \etal\ [2] proposed the idea of training a model as an approximator of a large ensemble of networks by predicting the output of the network ensemble. Hinton \etal\ [9] proposed to distill the knowledge from a teacher network by using the softened prediction (with a temperature value greater than one in softmax function) of the teacher as the target for student network.

The teacher and the student are deep networks, hence have a sequential structure that is known to learn hierarchical representations of increasing abstraction. Inspired by this, some methods propose to match the intermediate activation or feature maps of the teacher as the distillation task for the student. This encourages the student to follow the intermediate solutions produced by the teacher. FitNets [20] proposes to train the student with an additional layer to regress the feature maps of the teacher. While AT [29] builds “attention maps” by aggregating feature maps, and $\ell_2$ error between normalized attention maps of student and teacher is used as distillation loss. In FSP [26], the difference between Gram matrices of feature maps of the two networks is minimized for distillation. AB [8] proposes to match binarized activation of the teacher and the student to do knowledge transfer.

Another line of works on knowledge distillation focus on matching distributions of feature maps rather than feature maps themselves. In NST [10], maximum mean discrepancy (MMD) between the distributions of feature maps of teacher and student is minimized. The authors show three variants of their method based on three different kernel functions in the MMD loss. For the linear and polynomial kernel, they show its equivalence to matching attention maps (AT) and matching Gram matrices (FSP) respectively. VID [1] and CRD [23] consider maximizing mutual information between the two networks as the knowledge distillation task. Mutual information is maximized by maximizing variational lower bound (VID) or contrastive loss (CRD).

SP [24] departs from matching feature maps or their distributions. This relieves the student network from the demanding task of copying the teacher network, which could be too ambitious given the difference in their capacity and architecture. SP proposes a similarity preserving constraint by using difference in pairwise similarity, computed on a mini-batch, as distillation loss. Similar methods are proposed in other recent works RKD [17] and CC [19].

In our work, similar to SP, we propose a different space for distillation than feature space. We propose to use a quantized space where the teacher’s feature maps are encoded by quantization with learned visual words. These visual words are learned by k-means clustering on the feature maps of the teacher thus, they represent useful semantic concepts. With the proposed quantized space we concentrate more on the important semantic concepts and their spatial correlation for knowledge distillation.

Similar to ours, AB [8] can be seen as employing quantized space for knowledge transfer but the two approaches are significantly different. AB quantizes the activations into binary values while we use learned visual words, representing semantic concepts, to quantize the feature maps.

3. Approach

3.1. Preliminaries

Here we briefly explain the learning setting of knowledge distillation methods. Let $S$ be a student network that we want to train using a dataset of $(x, y)$ examples, where $x$ is the image and $y$ is the label. In the standard supervised learning setting the teacher $T$ is trained to minimise for each example $(x, y)$ the classification loss $L_{CLS}(S) = L_{CE}(y, \sigma(z_S))$, where $L_{CE}$ is the cross-entropy loss, $z_S = S(x)$ are the classification logits predicted from $S$ for the image $x$, and $\sigma(\cdot)$ is the softmax function. Knowledge distillation methods assume that there is available a pre-trained teacher network $T$, which has higher capacity than that of the student $S$. The goal is to exploit the pre-trained knowledge of teacher $T$ for training a better (i.e., more accurate) student $S$ than the standard supervised

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learning setting. To that end, they define for each training example \((x, y)\) an additional loss term \(L_{DIST}(S; T)\) based on the pre-trained teacher \(T\). For instance, in the seminal work of Hinton et al. [9], the additional distillation loss is the cross entropy of the two network output softmax distributions for the same training example \((x, y)\):

\[
L_{DIST}(S; T) = \rho^2 L_{CE}(\sigma(z_T/\rho), \sigma(z_S/\rho)),
\]

where \(z_T = T(x)\) are the logits produced from \(T\) for the image \(x\), and \(\rho > 0\) is a temperature that softens (i.e., lowers the peakiness) of the two softmax distributions; essentially, through this loss, the student learns from the teacher by mimicking the teacher’s output on the training data. Therefore, the final objective that the student \(S\) has to minimize per training example \((x, y)\) is:

\[
L = \alpha L_{CLS}(S) + \beta L_{DIST}(S; T),
\]

where \(\alpha\) and \(\beta\) are the weights of the two loss terms.

In the next subsection we explain the distillation loss \(L_{DIST}(S; T)\) that we propose in our work.

### 3.2. Distilling quantized representations

An overview of our approach is provided in Figure 1. The proposed distillation task first quantizes the teacher feature maps (§3.2.1) and then trains the student to predict this quantization from its own feature maps (§3.2.2).

#### 3.2.1 Quantizing the teacher feature maps

Given an image \(x\), let \(f_T \in \mathbb{R}^{C_T \times H_T \times W_T}\) be the feature map (with \(C_T\) channels and \(H_T \times W_T\) spatial dimensions) that \(T\) generates at one of its hidden layers, and \(f_T^{(h,w)} \in \mathbb{R}^{C_T}\) be the feature vector at the location \((h, w)\) of this feature map. Unless stated otherwise, we use as feature maps those of the last hidden layer. We quantize \(f_T\) in a spatially dense way using a predefined vocabulary \(V = \{v_k\}_{k=1}^{K}\) of \(K C_T\)-dimensional visual word embeddings. Specifically, we first compute for each location \((w,h)\) the squared Euclidean distances between the feature vector \(f_T^{(h,w)}\) and the \(K\) visual words:

\[
d^{(h,w)} = \left[ \left\| v_k - f_T^{(h,w)} \right\|_2^2 \right]_{k=1}^{K}.
\]

Then, using \(d^{(h,w)}\) we compute the \(K\)-dimensional soft-assignment vector \(p_T^{(h,w)}\), which lies on a \(K\)-dimensional probability simplex, as:

\[
p_T^{(h,w)} = \sigma(-d^{(h,w)}/\tau),
\]
where $\tau > 0$ is a temperature value used for controlling the softness of the assignment. The quantization vocabulary $V$ is learned off-line by k-means clustering feature vectors $f_T^{(h,w)}$ extracted from the available training dataset. Hence, $p_T^{(h,w)}$ essentially encodes which semantic concepts (defined by the vocabulary $V$) the feature vector $f_T^{(h,w)}$ adheres to.

Soft-quantization vs. hard-quantization. In our experiments we noticed that the optimal $\tau$ value produces very peaky soft-quantizations, e.g., the softmax probability for the closest visual word is on average around 0.995, which is very close to hard quantization. However, it still leads to slightly better students, which can be attributed to either (a) the fact that the remaining probability mass of the soft-quantization carries useful teacher knowledge, or (b) soft-assignments regularize the quantization prediction task that the student has to perform [27].

3.2.2 Predicting the teacher’s quantized feature maps

The distillation task that we propose is to train the student $S$ to predict the teacher soft-assignment map $p_T$ based on its own feature map $f_S \in \mathbb{R}^{C_S \times H_S \times W_S}$. As $p_T$ encodes semantic information with spatial structure, we posit that, to predict $p_T$, the student must build an understanding of semantics similar to the teacher. For now, we assume for simplicity that the student feature map $f_S$ has the same spatial size as the teacher one, i.e., $H_S = H_T$ and $W_S = W_T$. We also note that we impose no constraint on the number of student feature channels $C_S$. Therefore, to predict $p_T$, we use an assignment predictor $A$, which consists of one cosine-similarity-based convolutional layer with $1 \times 1$ kernel size followed by a learnable scaling factor and a softmax function. Specifically, at each location $(h,w)$, the student predicts the $K$-dimensional soft-assignment vector $p_S^{(h,w)}$ from its feature vector $f_S^{(h,w)}$, as:

$$p_S^{(h,w)} = A(f_S^{(h,w)}) = \sigma \left( \sum_{i=1}^{K} \frac{\langle W_i, f_S^{(h,w)} \rangle}{\|W_i\| \|f_S^{(h,w)}\|} \right),$$

where $\gamma$ is the learnable scaling factor, $W \in \mathbb{R}^{C_S \times K}$ are the parameters of the convolutional layer, and $W_i$ is the $i$-th column of $W$. Hence, $W$ plays essentially the role of a new student vocabulary, and soft assignment is done according to cosine similarity (instead of Euclidean distance).

Finally, we define our distillation loss $L_{DIST}(S; T)$ (for a training example) as the summation over all the locations $(h,w)$ of the KL-divergence $D_{KL}$ of the predicted soft-assignment distribution $p_S^{(h,w)}$ from the target distribution $p_T^{(h,w)}$:

$$L_{DIST}(S; T) = \sum_{h,w} D_{KL}(p_T^{(h,w)} \| p_S^{(h,w)}) ,$$

where $D_{KL}(p_T^{(h,w)} \| p_S^{(h,w)})$ consists of the cross-entropy of $p_T^{(h,w)}$ and $p_S^{(h,w)}$, and the entropy of $p_T^{(h,w)}$. The latter is independent to the student and thus does not actually affect the training. We minimize the total loss $L = \alpha L_{CLS}(S) + \beta L_{DIST}(S; T)$ of the student network over $W$, $\gamma$, and the parameters of $S$. In our experiments both loss weights $\alpha$ and $\beta$ are set to 1.0.

We should note at this point that in our work we use as distillation loss only that of the quantization prediction task. Many prior methods combine their proposed distillation loss with the KD loss proposed by Hinton et al. [9]. In our case however, we empirically observed that adding the KD loss to our method is not required as it does not offer any significant performance improvement, which verifies the effectiveness of our method.

Aligning the feature maps of two networks. By minimizing the KL-divergence between the predicted quantizations $p_S$ and the teacher quantized feature maps $p_T$, we essentially quantize the student feature maps according to the quantization at the teacher side. The difference is that in the student case, the visual vocabulary is implicitly defined by the parameters $W$ of the assignment predictor $A$, and the assignment is done via cosine similarity instead of Euclidean distance (see equation (5)). Hence, the student feature maps must learn to discriminate (i.e., to cluster together) the same image patterns (represented by the visual words) as the teacher feature maps. Thus, the student learns to spatially and semantically align its feature maps with those of the teacher network, but without constraining it to regress the exact feature activations of its teacher.

Feature maps $f_S$ and $f_T$ of different spatial sizes. So far we have assumed that the teacher $f_T$ and student $f_S$ feature maps have the same spatial size. However, this might not be always the case, since the teacher and the student networks might have different architecture designs. In this case, we follow the simple solution of down-sampling the biggest feature map to the smaller one with an (adaptive) average pooling layer. We stress out that the down-sampling operation is applied only in the context of the quantization encoding/prediction network components and does not alter in any way the remaining architecture of either the teacher or the student networks.

4. Experiments

In this section we experimentally evaluate our proposed approach (QuEST) and compare it with several state-of-the
art knowledge distillation methods. In the remainder of this section, we first compare our approach against prior art in Section 4.1, and then, in Section 4.2, we analyse and discuss the impact of various hyper-parameters and design choices of our algorithm.

4.1. Comparison with prior work

We extensively evaluate our approach on three different datasets: ImageNet [5], CIFAR-100 [13] and CIFAR-10. In the following three sub-sections we discuss the experimental results for each dataset. We start with ImageNet (§4.1.1), as this is the most challenging and interesting dataset among the three. Then, we move to CIFAR-100 (§4.1.2) where we conduct an extensive evaluation on many network architectures and compare against several state-of-the-art methods. Finally, we conclude with the CIFAR-10 (§4.1.3).

4.1.1 ImageNet results

In Table 1 we provide results for the ImageNet dataset. The dataset contains 1.28M images for training and 50K images for testing. It has 1000 semantic classes. ImageNet is a much more challenging and realistic dataset than CIFAR-100 and CIRAR-10, which makes it a much more interesting and true benchmark for evaluating distillation methods.

Implementation details. Similar to [29] and [23], for training on ImageNet we do 100 epochs with batch size of 256. The initial learning rate is set to 0.1 which is reduced every 30 epochs with a decay rate of 0.1. For the hyper-parameters of our distillation method we use $\alpha = 1$, $\beta = 1$, $\tau = 0.2$, and $K = 4096$.

Comparison with prior work. We observe that our distillation method manages to reduce the Top-1 error of the student from 30.24% to 28.33%, which sets the new state-of-the-art on this challenging dataset. The next best performing method is CRD+KD that has around 0.30 higher error than ours. We note that due to the time-consuming nature of the ImageNet experiments we did not try to tune the hyper-parameters of our method in this case (instead we reused the ones chosen for CIFAR-100). As a result, a further reduction of the error rates of the student might very well be possible by a more proper adjustment of the hyper-parameters.

4.1.2 CIFAR-100 results

The CIFAR-100 dataset is one of the most commonly used dataset for evaluating knowledge distillation methods. It consists of small $32 \times 32$ resolution images and 100 semantic classes. It has 50K images in the training set and 10K in the test set. The train and test sets are evenly distributed across the semantic classes.

In Tables 2 and 3 we provide an exhaustive evaluation of our method QUEST under many different network architectures. Also, we compare our method against KD [9], feature matching-based FitNet [20] and AT [29], similarity preserving SP [24], and distribution matching-based VID [1] and CRD [23].

Implementation details. For all the experiments here, we follow the protocol of [23] for training the student networks. Specifically, in all cases we train the student for 240 epochs with batch size of 64 and an initial learning rate of 0.05, which we drop by factor of 0.1 after 150, 180, and 210 epochs. The only exception is MobileNetV2 and ShuffleNetV1/V2, where the learning rate is initialized to 0.01. The hyper-parameters of our method are $\beta = 1$, $\tau = 0.2$, and $K = 4096$.

Knowledge transfer between networks with the same architecture design. In Table 2, we compare knowledge distillation methods with teacher and student networks that have the same architecture design but different depth or width (by width we mean the number of channels per layer). For the network architectures, we evaluate the knowledge distillation between WideResNet [28], ResNet [7] and VGG [21] networks.

Our method outperforms all the other methods on all the different teacher-student combinations except for the VGG13 to VGG8 case where we are second only to CRD [23], which is a contemporary method to ours. On average we improve by an absolute 2.97% over students without distillation, which is relatively 16.9% more than CRD (2.54% over student) and 7.6% more than CRD+KD (2.76%). Moreover, in some cases our students achieve accuracy that is either very close to that of the teacher (cases ResNet56 to ResNet20 and ResNet110 to ResNet32), or even exceeds it (case WRN-40-2 to WRN-40-1), which further demonstrates the efficacy of our method.

Knowledge transfer between networks with different architecture designs. In Table 3, we evaluate the efficacy of our approach for knowledge distillation between different network architectures. All of them but one have different spatial dimensions between feature maps of student and teacher. For example, MobileNetV2 at the penultimate layer has $2 \times 2$ feature maps while the teachers, VGG13 and ResNet50, have $4 \times 4$. Similarly, ShuffleNetV1/V2 have $4 \times 4$ while ResNet32x4 and WRN-40-2 have $8 \times 8$. As the quantized representations $p_T$ and $p_S$ should have the same spatial dimension to apply our distillation loss, we do average pooling on the feature maps of teacher before quantization, as explained in section §3.2.2.

We observe that our approach outperforms every other method on all but one experiment. In the cases of the
Table 1: Evaluation on ImageNet dataset. Top-1 and Top-5 error rate of student network on ImageNet validation set. ResNet-34 is used as the teacher and ResNet-18 as the student network. The results for other methods are taken from [23].

| Model          | KD | AT+KD | SP | CC | Online KD[30] | CRD | CRD+KD | QUEST |
|----------------|----|-------|----|----|---------------|-----|--------|-------|
| Top-1          | 26.69 | 30.25 | 29.34 | 30.04 | 29.45 | 28.83 | 28.62 | 28.33 |
| Top-5          | 8.58  | 10.93 | 10.12 | 10.20 | 10.83 | 10.41 | 9.87  | 9.33  |

Table 2: Experiments on CIFAR-100. Top-1 test accuracy of student networks for various student-teacher combinations and knowledge distillation methods. The pre-trained teacher models are taken from [23] and for all methods except ours we use the results reported in [23] for a fair comparison. We report average over 5 runs as in [23].

| Teacher          | Student          | KD | FitNet | AT | SP | VID | AB | CRD | CRD+KD | QUEST |
|------------------|------------------|----|--------|----|----|-----|----|-----|--------|-------|
| WRN-40-2         | WRN-16-2         | 74.92 | 73.58 | 74.08 | 73.83 | 71.11 | 72.50 | 75.48 | 75.64 | 76.10 |
| WRN-40-2         | WRN-40-1         | 73.54 | 72.24 | 72.77 | 72.43 | 73.30 | 72.38 | 74.14 | 74.38 | 74.58 |
| ResNet56         | ResNet20         | 70.66 | 69.21 | 70.55 | 69.67 | 70.38 | 69.47 | 71.16 | 71.63 | 71.84 |
| ResNet110        | ResNet20         | 70.67 | 68.99 | 70.22 | 70.04 | 70.16 | 69.53 | 71.46 | 71.56 | 71.89 |
| ResNet110        | ResNet32         | 73.08 | 71.06 | 72.31 | 72.69 | 72.61 | 70.98 | 73.48 | 73.75 | 74.08 |
| ResNet32x4       | ResNet8x4        | 73.33 | 73.5  | 73.44 | 72.94 | 73.09 | 73.17 | 75.51 | 75.46 | 75.88 |
| VGG13            | VGG8             | 72.98 | 71.02 | 71.43 | 72.68 | 71.23 | 70.94 | 73.94 | 74.29 | 73.81 |

ResNet32x4 teacher, we notice an improvement of more than 1% against the other methods. Overall, the proposed approach improves by an average of 5.25% on the student without distillation. While the most competitive CRD and CRD+KD bring respectively an improvement of 4.59% and 4.85%. Note that, in terms of average gain over the student without distillation, we get a relative improvement of 14.29% and 8.21% compared to CRD and CRD+KD respectively.

4.1.3 CIFAR-10 results

The CIFAR-10 dataset is similar to CIFAR-100 with the only difference that there are now 10 semantic classes instead of 100.

Implementation details. For the CIFAR-10 experiments we follow the protocol of [24] and train the student for 200 epochs with a batch size of 128. The initial learning rate is set to 0.1 which decays by a factor of 0.2 at 60th, 120th, 160th epoch. For the hyper-parameters of our distillation method we use $\alpha = 1$, $\beta = 1$, $\tau = 0.005$ and $K = 256$.

Comparison with prior work. In Table 4, we compare our approach with KD, AT, and SP in terms of error rate on CIFAR-10 test set. We consider distillation between WideResNet student and teacher with different depth and/or width. Again, our method achieves state-of-the-art results on CIFAR-10. Specifically, we outperform the other methods on two settings (WRN-40-1 to WRN-16-1 and WRN-16-8 to WRN-16-2), while we achieve almost the same results on the other three settings with statistically negligible difference of less than 0.04%. Our approach achieves an average reduction in error rate of 0.82% compared to the student without distillation, while the most competitive SP method gets 0.75% followed by AT with 0.48%.

4.2. Further analysis

In this subsection we analyse several aspects of our distillation method.

Impact of temperature value $\tau$. In Figure 2 we plot how the temperature value $\tau$ of the soft-quantization of the teacher feature maps (see equation (4)) affects the performance of our distillation method. Specifically, we provide results for two teacher-student network configurations, (1) WRN-40-2 teacher to WRN-16-2 student, and (2) WRN-40-2 teacher to ShuffleNetV1 student, and 5 different $\tau$ values, 0.1, 0.2, 0.5, 1.0, and 2.0. We also provide results for the hard-assignment case, which we denote with the $\tau = 0$ in the plot. We observe that choosing a small $\tau$ value, which means a more peaky soft-assignment (i.e., closer to hard-assignment), leads to better distillation performance. How-
Table 3: **Distillation between different architectures.** Top-1 test accuracy on CIFAR100 dataset of the student networks. The student models are learned with knowledge distillation from a teacher with different architecture. The table compares various distillation methods. Similar to Table 2, we use the pre-trained teacher networks provide by [23] and the results for other methods are also taken from [23]. Following the protocol of [23], we report average over 3 runs.

| Model     | KD | FitNet | AT | SP | VID | AB | CRD | CRD+KD | QUEST | teacher | student |
|-----------|----|--------|----|----|-----|----|-----|--------|-------|---------|---------|
| VGG13     | 67.37 | 64.14 | 59.4 | 66.3 | 65.56 | 66.06 | 69.73 | **69.94** | 68.79 | 74.64 | 64.6 |
| MobileNetV2 | 67.35 | 63.16 | 58.58 | 68.08 | 67.57 | 70.65 | 74.3 | 74.58 | **75.17** | 79.34 | 70.36 |
| ResNet50  | 73.81 | 70.69 | 71.84 | 73.34 | 70.3 | 70.65 | 74.3 | 74.58 | **75.17** | 79.34 | 70.36 |
| MobileNetV2 | 74.07 | 73.59 | 71.73 | 73.48 | 73.38 | 73.55 | 75.11 | 75.12 | **76.28** | 79.42 | 70.50 |
| ResNet50  | 74.45 | 73.54 | 72.73 | 74.56 | 73.4 | 74.31 | 75.65 | 76.05 | **77.09** | 79.42 | 71.82 |
| MobileNetV2 | 74.83 | 73.73 | 73.32 | 74.52 | 73.61 | 73.34 | 76.05 | 76.27 | **76.75** | 75.61 | 75.0 |

Table 4: **Experiments of CIFAR-10.** Top-1 error on CIFAR-10 of the student networks. We use the results reported in [24] and following it we use median of 5 runs.

| CIFAR-100 | CIFAR-10 |
|-----------|----------|
| WRN-40-2 → WRN-16-2 | WRN-40-1 → WRN-16-1 |
| Block $L - 1$ | 74.16 |
| Block $L$ | **76.10** |
| Block $L - 1$ | 8.36 |
| Block $L$ | **8.02** |

Table 5: **Distillation at different layers.** Comparing student networks with the proposed approach when applied at different layers. Block $L$ corresponds to the penultimate layer (before classification layer) while Block $L - 1$ refers to the layer at a block before Block $L$. For CIFAR-100 Top-1 accuracy and for CIFAR-10 error rate are reported. Our approach performs better with distillation at the penultimate layer.

ever, going to the extreme case of hard-assignment (i.e., $\tau = 0$) drops the distillation performance. Hence, very peaky soft-assignment achieves better knowledge transfer than the hard-assignment case.

**Impact of vocabulary size $K$.** In Figure 3 we plot the distillation performance of our method as a function of the vocabulary size $K$ in CIFAR-100. We get the best results for size $K = 4096$. Also, for $K \geq 2048$ the distillation performance of our method is relatively stable w.r.t. the vocabulary size $K$ in CIFAR-100. Figure 4 shows a similar plot on CIFAR-10 dataset with error rate on the $y$-axis (lower is better). In general, the range of “good” values for the vocabulary size $K$ is lower than that of CIFAR-100. In our experiments $K = 256$ comes out as a good choice. This indicates that the choice for the hyper-parameter $K$ depends on the complexity of the task at hand, i.e., 100-way classification in CIFAR-100 vs. 10-way classification in CIFAR-10.

**At which feature level to apply the distillation loss?** In Table 5 we measure the performance of our method when the distillation loss is applied (1) to the last feature level of the teacher-student networks (which is what we have used
Figure 2: **Effect of temperature** $\tau$. The figure shows Top-1 accuracy vs. temperature $\tau$ plots for two teacher-student combinations on CIFAR-100. The students are trained with proposed distillation loss with WRN-40-2 as the teacher with different temperature $\tau$ for computing soft-assignment of $f_T^{(h,w)}$. For reference, the accuracy of the students without distillation is plotted with a straight dashed line. SNv1 refers to ShuffleNetV1.

Figure 3: **Effect of varying** $K$. Top-1 accuracy on CIFAR-100 with WRN-16-2 and ShuffleNetv1 as the student networks. The students are trained with the proposed distillation loss with varying number of visual words $K$ and WRN-40-2 as the teacher network.

Figure 4: **Effect of varying** $K$. Error rate vs. $K$ on CIFAR-10 with WRN-16-1 as the student networks. The students are trained on the proposed distillation loss with WRN-40-1 as the teacher with varying number of visual words $K$.

for all other experiments in the paper), and (2) to the feature level of the previous down-sampling stage (i.e., the output of the 2nd residual block in WRN-40-2/WRN-16-2 or WRN-40-1/WRN-16-1). We report results on CIFAR-100 and CIFAR-10. In all cases, switching to the feature maps of the previous down-sampling stage leads to a drop in performance. Therefore, our proposed distillation loss appears to perform best with the last feature level.

5. **Conclusions**

Knowledge distillation is an interesting learning problem with many practical applications. The goal is to improve the accuracy of a student network via exploiting the learned knowledge of a higher-capacity teacher network. In our work, we follow the common paradigm of transferring the knowledge encoded on the learned teacher features. However, instead of performing the distillation task in the context of the initial feature space of the teacher network, we transform it to a new quantized space that is more robust to the feature perturbations.

Specifically, our distillation method first quantizes the teacher feature maps in a spatially dense way and then trains the student to predict this quantization based on its own feature maps. By solving this task the student is forced to align its feature maps with those of the teacher, thus facilitating knowledge transfer between the two networks. We exhaustively evaluate our distillation method on the ImageNet, CIFAR-100 and CIFAR-10 datasets and across a variety of deep network architectures, showing that it exhibits state-of-the-art performance.

As future work, we believe that the simple and effective nature of our knowledge distillation method would make it a potentially good candidate for transfer learning scenarios, such as incremental learning or transfer learning to small datasets, which are also problems of great practical importance.
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A. Image retrieval in quantized space

As we claim in §3.2.2, our distillation loss enforces a quantization of the student feature space that is in accor-
Figure 5: Image retrieval in the quantized embedding spaces. For the query image we used the quantized features of a WRN-40-2 teacher network and for the database images we used the predicted quantized features of a WRN-16-2 student network trained with our distillation method. As database we used the 10K images of CIFAR-100 test set, and as queries we used randomly sampled images from this database. The figure shows the query on the left most column and top 10 retrieved images (in that order) next to the query. We see that as top results we always retrieve the query itself (framed with red box) as well as other semantically and structurally similar images. This indicates that the two quantized embedding spaces are well aligned.

B. Implementation details: k-means algorithm

In our quantization-based distillation method we use k-means to learn the quantization vocabulary $V$. Here we provide implementation details regarding how we apply the k-means clustering algorithm.

**k-means implementations.** For k-means, we use the implementation provided by the publicly available FAISS [11] library.

**Applying k-means on ImageNet.** The training set of ImageNet is quite large (i.e., it has around 1.28M images). Therefore, when we evaluate our distillation method on ImageNet, to efficiently learn the quantization vocabulary $V$, we apply k-means only to a randomly sampled subset of 0.2M images from the training set.