EFFICIENT ONLINE SUBCLASS KNOWLEDGE DISTILLATION FOR IMAGE CLASSIFICATION

Maria Tzelepi, Nikolaos Passalis and Anastasios Tefas
Department of Informatics, Aristotle University of Thessaloniki (Greece)
email: mtzelepi@csd.auth.gr, passalis@csd.auth.gr, tefas@csd.auth.gr

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ARISTOTLE UNIVERSITY OF THESSALONIKI

Introduction

- Knowledge Distillation (KD) has been established as a highly promising approach for **training compact and faster models** by **transferring knowledge** from powerful models
- However, KD in its conventional version constitutes an enduring, computationally and memory demanding process
- Thus, many **online KD** approaches have recently been proposed
- **Online KD** describes the process where the teacher and student networks are trained **simultaneously**, without requiring a separate stage for pre-training the teacher network
- Current online KD works propose to train multiple models mutually from each other, or to create ensembles of multiple identical branches of a target network in order to build a strong teacher and distill the knowledge to the target network

Motivation

- In conventional KD methods it is manifested that it is advantageous for each sample to **maintain the similarities with the other classes**, instead of merely training with the hard labels
- In this work, we considered that inside each class there is also a set of **sub-classes** that **share semantic similarities** (e.g., blue cars, inflatable boats, etc.)
- The sub-classes inside each class are unknown and thus, we proposed to **estimate** them using the **neighborhood** of each sample
- We assume that the **nearest neighbors** of each sample inside a class belong to the **same sub-class**
- The model is trained **synchronously** both with the conventional supervised loss (hard labels) and the **soft labels** so as to **maintain these sub-class similarities**

Proposed method

- We proposed **Online Subclass Knowledge Distillation** (OSKD) method, that distills additional knowledge **online** from the **model itself** throughout the network's training
- We introduced an additional **distillation objective** which encourages the data representations to come closer to the nearest representations of the same class and concurrently to move further away from the nearest representations of the other classes
- Considering an input vector $\mathbf{y}_i$, a neural network $\varphi(\cdot,W)$ with a set of parameters W, and the output vector of $\mathbf{y}_i$ given the network φ $\varphi(\mathbf{y}_i,W)$ the additional distillation objective is formulated as follows:

$$\min_{\mathcal{W}} \mathcal{J}_1 = \min_{\mathcal{W}} \sum_{\boldsymbol{y}_i,\boldsymbol{y}_j \in \mathcal{R}^i} \|\phi(\boldsymbol{y}_i;\mathcal{W}) - \phi(\boldsymbol{y}_j;\mathcal{W})\|_2^2 \quad \max_{\mathcal{W}} \mathcal{J}_2 = \max_{\mathcal{W}} \sum_{\boldsymbol{y}_i,\boldsymbol{y}_l \in \mathcal{V}^i} \|\phi(\boldsymbol{y}_i;\mathcal{W}) - \phi(\boldsymbol{y}_l;\mathcal{W})\|_2^2.$$

- The above equations can also be formulated as follows:

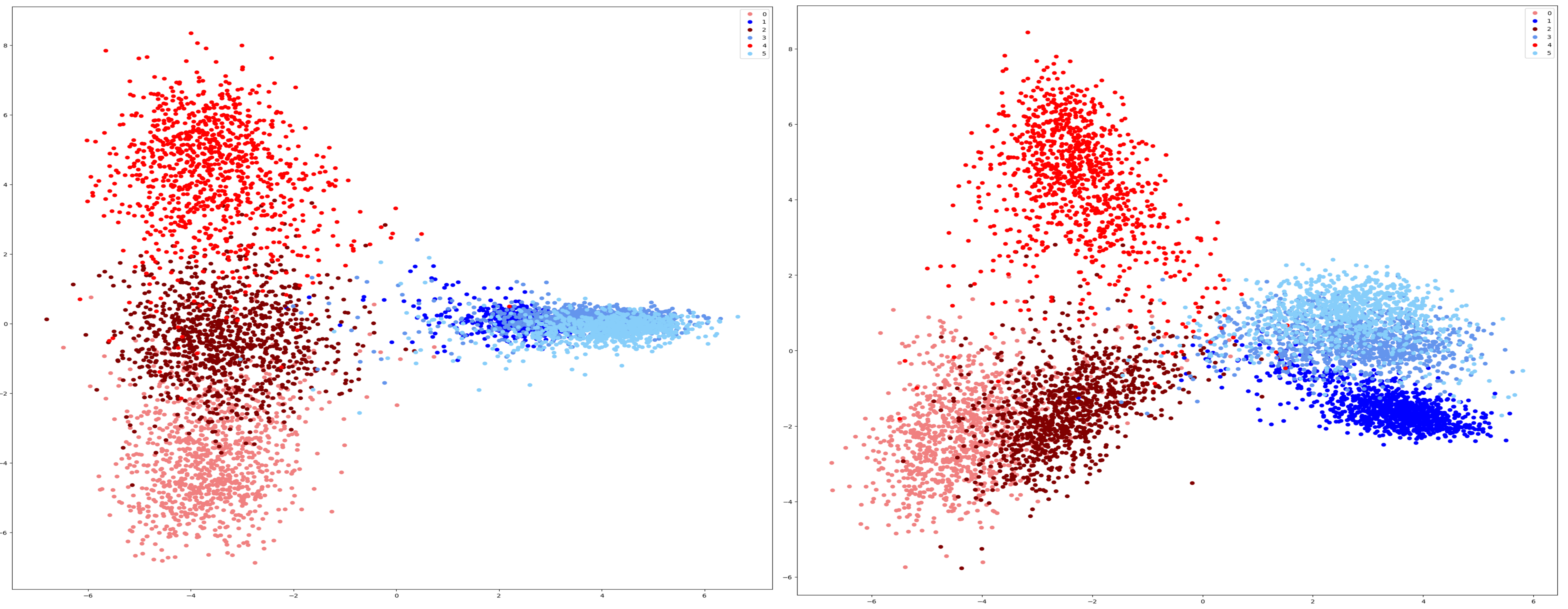
$$\min_{\mathcal{W}} \mathcal{J}_1 = \min_{\mathcal{W}} \sum_{\boldsymbol{y}_i \in \mathcal{R}^i} \|\phi(\boldsymbol{y}_i;\mathcal{W}) - \boldsymbol{\mu}_r^i\|_2^2, \quad \max_{\mathcal{W}} \mathcal{J}_2 = \max_{\mathcal{W}} \sum_{\boldsymbol{y}_i \in \mathcal{V}^i} \|\phi(\boldsymbol{y}_i;\mathcal{W}) - \boldsymbol{\mu}_v^i\|_2^2$$

where $\boldsymbol{\mu}_r$ and $\boldsymbol{\mu}_u$ correspond to the mean vectors of the nearest representations of the same class and the nearest representations of the other classes, respectively.

- Thus the overall distillation loss is formulated as: $J_{oskd} = J_1 + (1-J_2)$
- Therefore, in the proposed distillation training process we seek for the parameters W* that minimize the overall loss of cross entropy, J_{ce}, and distillation, J_{oskd}:

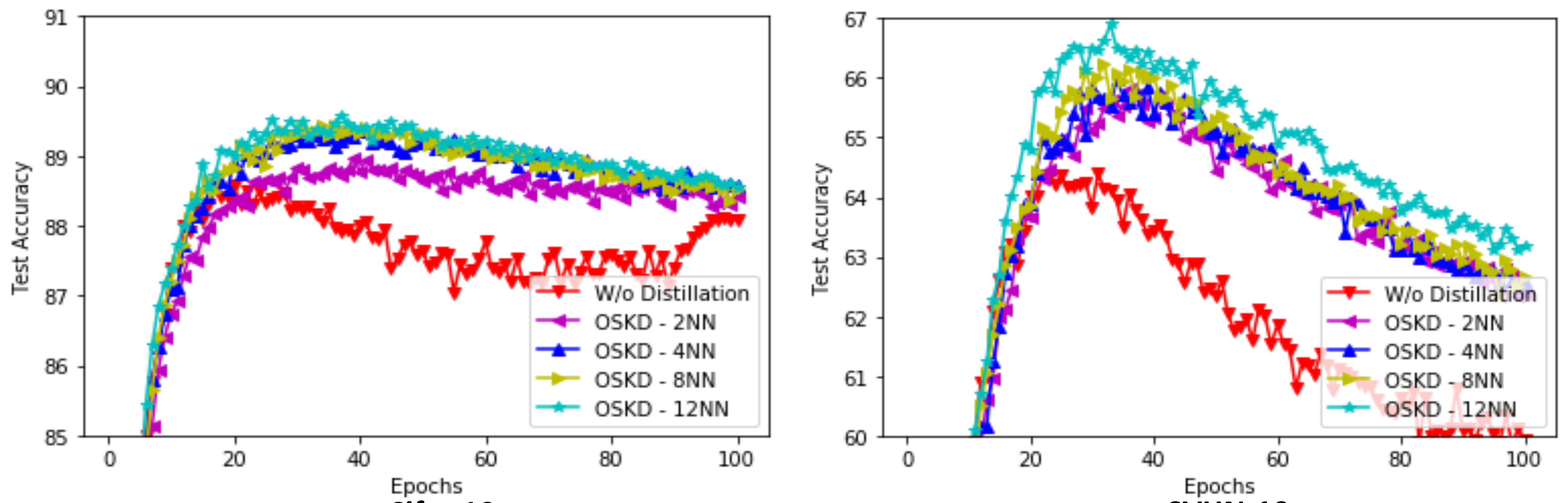
$$\mathcal{W}^* = \arg\min_{\mathcal{W}} \sum_{i=1}^{N} [J_{ce}(c_i, \phi(\boldsymbol{y}_i;\mathcal{W})) + \lambda J_{oskd}(\boldsymbol{\mu}_r^i, \boldsymbol{\mu}_v^i, \phi(\boldsymbol{y}_i;\mathcal{W}))]$$

Experimental Results



W/o Distillation OSKD

MNIST (odd vs even digits with 3 subclasses per class): LDA Visualization



Cifar-10 SVHN-10

Test accuracy for different numbers of nearest neighbors inside each class

Test Accuracy for different numbers of nearest neighbors on Cifar-10 and SVHN-10 datasets

Method	Cifar-10	SVHN-10
W/o Distillation	64.83% ± 0.57%	88.82% ± 0.21%
OSKD - 2NN	66.16% ± 0.76%	89.00% ± 0.14%
OSKD - 4NN	66.39% ± 0.77%	89.52% ± 0.23%
OSKD - 8NN	66.59% ± 0.78%	89.61% ± 0.29%
OSKD - 12NN	**67.36% ± 0.82%**	**89.67% ± 0.28%**

Comparisons against existing online distillation methods using WRN 16-2

Method	Test Accuracy
WRN 16-2	93.55% ± 0.11%
ONE	93.76%± 0.16%
FFL-S	93.79% ± 0.12%
ONE-E	93.84%± 0.20%
FFL	93.86% ± 0.11%
OSKD	**93.96% ± 0.13%**

Acknowledgments

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