Supplementary Materials

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Abstract

This material includes additional experimental results and architecture details of the Semi-Supervised Knowledge Transfer (SSKT).

1. SSKT with Multiple Tasks and Problem Domains

Prerequisite Learning based Knowledge Transfer (SSKT) supports a training procedure that enables transfer learning in a variety of scenarios using deep neural networks. SSKT has a structure that transfers pretrained knoweldge naturally, without compromising the training information of the pretrained network or requiring additional supervision in the target task training process. We achieved this goal using the soft label-based knowledge transfer techniques with auxiliary task learning through self-supervision, for the various domain of image recognition variants. Final formulation of SSKT as follows:

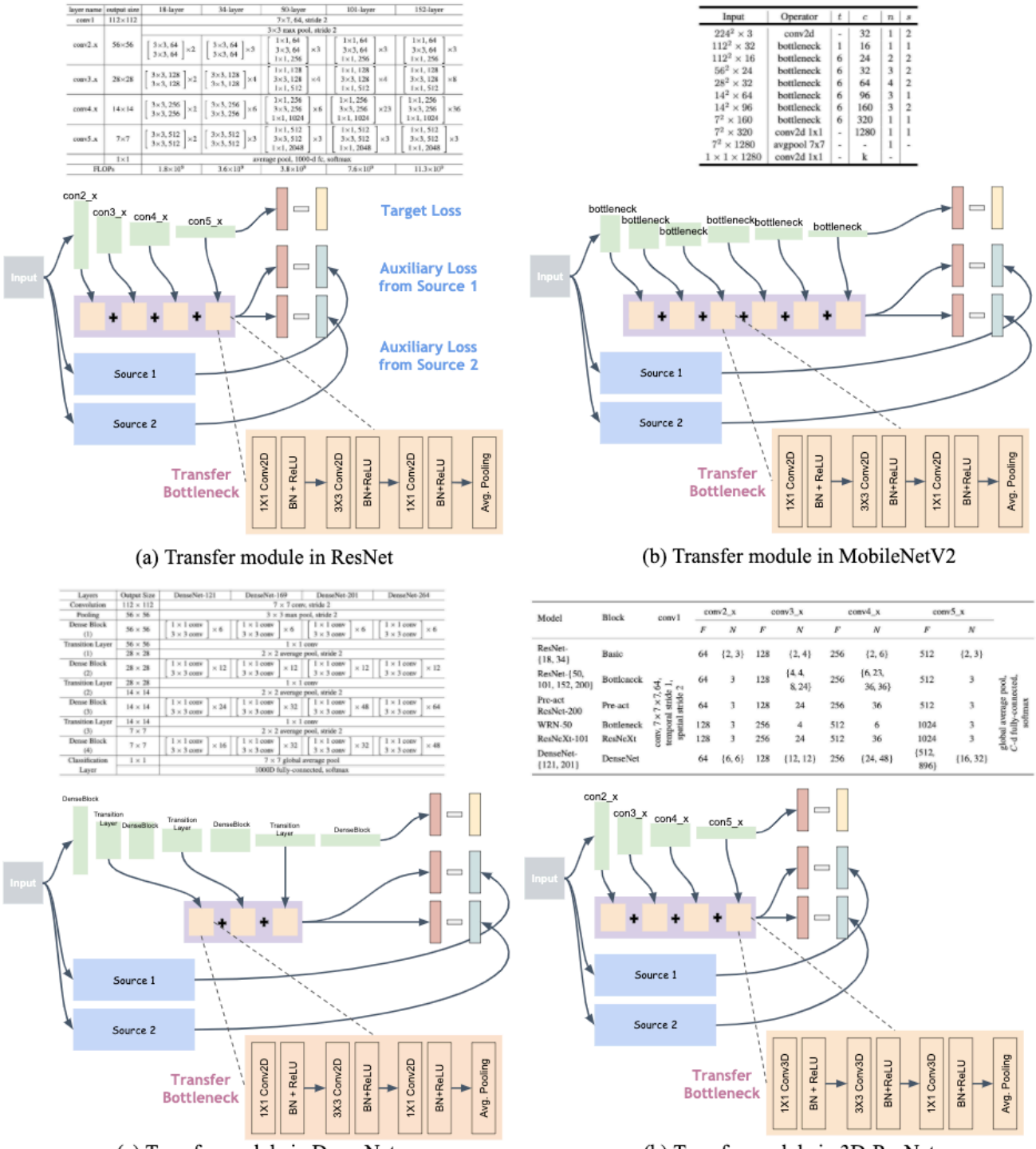
$$\begin{aligned}\underset{\theta_t}{\operatorname{argmin}} \Big(& L(h_t^{prim}(x_i;\theta_t.D_t,T_t),y_{t,i}^{prim}) \\ & +\alpha(L(h_t^{aux}(f_{s_1}(x_i);\theta_t.D_t,T_{s_1}),y_{s_1,i}^{aux}) \\ & +L(h_t^{aux}(f_{s_2}(x_i);\theta_t.D_t,T_{s_2}),y_{s_2,i}^{aux})+\dots \\ & +L(h_t^{aux}(f_{s_M}(x_i);\theta_t.D_t,T_{s_M}),y_{s_M,i}^{aux}))\Big). \end{aligned} \quad (1)$$

We define a multi-tast network $h_t(x;\theta_t,D_t,T_t)$, where x is the input, θ_t is a parameter of the target network, D_t is a target dataset, and T_t is the task to be trained. θ_t is updated simultaneously through target loss and auxiliary loss during training to solve the primary task. $h_s(x;\theta_s,D_s,T_s)$ describes a source network that receives the input x and delivers knowledge to the target network. θ_s denotes a parameter trained by the source task T_s for the source data set D_s. θ_s is not updated during the target task training. i is the i^{th} batch of the training data, α is balanced parameter for total loss, and $y_{s,i}^{aux}=h_s(x_i;\theta_s,D_s,T_s)$ is the softmax output from the pretrained source network and conveys the dark knowledge of the pretrained dataset by soft labels. The data transformation function f_s converts the data type to match the source task to infer the recognition information to the task of the source domain. For example, if T_t is an action recognition problem using 3D-CNN, the input $x^{w\times h\times d}\in D_t$ is defined as a three-dimensional tensor. In this case, if a pretrained network for transfer learning is obtained through the image recognition problem T_s using 2D-CNN, $f_s: x^{w\times h\times d}\rightarrow \hat{x}^{w\times h}$ should be defined as a function that maps a three-dimensional tensor to a two-dimensional matrix into which h_s can be input. Up to M number of different type of transformation functions could be defined.

Transfer Modules Depending on CNN Architecture. To encourage predicting $y_{s,i}^{aux}$ by h_t, we design bottleneck structure based transfer module supporting auxiliary task using feature output from each convolutional block. Figure 1 shows configuration of transfer modules depending on each CNN architecture for its problem domain. We applied the transfer module to four different CNN architectures such as ResNet (He et al. 2016), DenseNet (Huang et al. 2017), MobileNet (Sandler et al. 2018), and 3D-ResNet (Hara, Kataoka, and Satoh 2018) for each problem domain.

2. Experiments Results

We provide performance for all experimental conditions for each dataset, in addition to the results contained in the paper. For fair comparison of SSKT, the experimental conditions consist of a combination of the type of source and target network, the presence or absence of a transfer module, and a loss function. For model architecture and hyperparameters configuration for training (See Table 1 of the paper). Same as the experiment results of the paper, the datasets of the source task are ImageNet (Deng et al. 2009) and Places365 (Zhou et al. 2018), and the datasets of the target task are CIFAR10/100 (Krizhevsky 2009), STL10 (Coates, Lee, and Ng 2011), ImageNet, Places365, PASCAL VOC (Everingham et al. 2015), UCF101 (Soomro, Zamir, and Shah 2012), and HMDB51 (Kuehne et al. 2011). Tables 1 to 6 provide performance according to the experimental conditions of each dataset. At the same time, we



(a) Transfer module in ResNet

(b) Transfer module in MobileNetV2

(a) Transfer module in DenseNet

(b) Transfer module in 3D-ResNet

Figure 1. **Schematic of the transfer modules for efficient SSKT with different CNN architectures.** The transfer module used in the SSKT consists of summation of feature output of bottleneck layers from each convolutional block. Schematic shows and example of the transfer module with different CNN architectures for SSKT using multiple sources.

included all experimental results for hyperparameter optimization. Figure 2 shows the performance changes of the hyperparameters for loss in the STL10 and PASCAL VOC datasets, the structure of the source and target network, and

Table 1. SSKT-based transfer learning performance change for CIFAR10 dataset compared to the training from scratch. All experiments evaluated test performance 3 times from the same random seed for the model. TM stands for Transfer Module and R[depth] stands for ResNet structure. The best performance of each network architecture highlighted in **bold**.

T_s	T_t	Model	Method	TM	Loss	acc.
-	C10	R20	scratch	-	CE	92.19±0.09
P		R20	SSKT	x	CE+CE	92.21±0.06
		R20	SSKT	x	CE+KD	92.24±0.14
		R20	SSKT	o	CE+CE	92.23±0.04
		R20	SSKT	o	CE+KD	92.25±0.04
I		R20	SSKT	x	CE+CE	92.28±0.07
		R20	SSKT	x	CE+KD	92.34±0.07
		R20	SSKT	o	CE+CE	92.44±0.05
		R20	SSKT	o	CE+KD	92.29±0.0
P+I		R20	SSKT	x	CE+CE	91.9±0.1
		R20	SSKT	x	CE+KD	**92.46±0.15**
		R20	SSKT	o	CE+CE	92.42±0.07
		R20	SSKT	o	CE+KD	92.22±0.17
-		R32	scratch	-	CE	93.21±0.09
P		R32	SSKT	x	CE+CE	92.77±0.14
		R32	SSKT	x	CE+KD	92.87±0.31
		R32	SSKT	o	CE+CE	92.65±0.26
		R32	SSKT	o	CE+KD	92.59±0.22
I		R32	SSKT	x	CE+CE	93.26±0.08
		R32	SSKT	x	CE+KD	92.78±0.2
		R32	SSKT	o	CE+CE	93.25±0.12
		R32	SSKT	o	CE+KD	92.88±0.07
P+I		R32	SSKT	x	CE+CE	92.88±0.15
		R32	SSKT	x	CE+KD	93.07±0.09
		R32	SSKT	o	CE+CE	**93.38±0.02**
		R32	SSKT	o	CE+KD	93.1±0.22

the presence or absence of a transfer module. The abbreviations for the datasets and model architectures listed in all experimental tables are as follows:

Datasets: ImageNet (I), Places365 (P), CIFAR10 (C10), CIFAR100 (C100), STL10 (S10), PASCAL VOC (VOC), UCF101 (U101), and HMDB51 (H51).

Model architectures: ResNet (R), DenseNet (D), MobileNetV2 (MV2), and 3D-ResNet (3DR).

Finally, we included the results according to the experimental configuration for further experiments for SSKT analysis. Table 7 shows the experimental results for DenseNet121 and MoblieNetV2, and Table 8 shows the evaluation results for each experimental setting with fine-tuning scenario.

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Table 2. SSKT-based transfer learning performance change for CIFAR100 dataset compared to the training from scratch.

T_s	T_t	Model	Method	TM	Loss	acc.
-	C100	R20	scratch	-	CE	68.26±0.36
P		R20	SSKT	x	CE+CE	67.65±0.21
		R20	SSKT	x	CE+KD	68.01±0.42
		R20	SSKT	o	CE+CE	67.96±0.27
		R20	SSKT	o	CE+KD	67.83±0.34
I		R20	SSKT	x	CE+CE	68.3±0.17
		R20	SSKT	x	CE+KD	68.37±0.23
		R20	SSKT	o	CE+CE	**68.63±0.12**
		R20	SSKT	o	CE+KD	68.35±0.1
P+I		R20	SSKT	x	CE+CE	67.87±0.17
		R20	SSKT	x	CE+KD	68.13±0.05
		R20	SSKT	o	CE+CE	68.56±0.23
		R20	SSKT	o	CE+KD	67.84±0.28
-		R32	scratch	-	CE	70.33±0.19
P		R32	SSKT	x	CE+CE	69.97±0.16
		R32	SSKT	x	CE+KD	69.93±0.21
		R32	SSKT	o	CE+CE	69.69±0.19
		R32	SSKT	o	CE+KD	69.92±0.31
I		R32	SSKT	x	CE+CE	70.6±0.05
		R32	SSKT	x	CE+KD	70.17±0.14
		R32	SSKT	o	CE+CE	70.75±0.06
		R32	SSKT	o	CE+KD	70.0±0.11
P+I		R32	SSKT	x	CE+CE	69.25±0.58
		R32	SSKT	x	CE+KD	69.22±0.43
		R32	SSKT	o	CE+CE	**70.94±0.36**
		R32	SSKT	o	CE+KD	69.44±0.01

Table 3. SSKT-based transfer learning performance change for STL10 dataset compared to the training from scratch.

T_s	T_t	Model	Method	TM	Loss	acc.
-	STL10	R20	scratch	-	CE	81.15±0.34
P		R20	SSKT	x	CE+CE	81.56±0.32
		R20	SSKT	x	CE+KD	80.88±0.19
		R20	SSKT	o	CE+CE	82.76±0.05
		R20	SSKT	o	CE+KD	81.06±0.2
I		R20	SSKT	x	CE+CE	82.2±0.17
		R20	SSKT	x	CE+KD	80.82±0.14
		R20	SSKT	o	CE+CE	83.45±0.07
		R20	SSKT	o	CE+KD	81.3±0.39
P+I		R20	SSKT	x	CE+CE	82.46±0.24
		R20	SSKT	x	CE+KD	81.47±0.22
		R20	SSKT	o	CE+CE	**84.56±0.35**
		R20	SSKT	o	CE+KD	81.33±0.11
-		R32	scratch	-	CE	81.19±0.17
P		R32	SSKT	x	CE+CE	82.1±0.14
		R32	SSKT	x	CE+KD	81.29±0.22
		R32	SSKT	o	CE+CE	83.06±0.27
		R32	SSKT	o	CE+KD	81.19±0.12
I		R32	SSKT	x	CE+CE	82.88±0.33
		R32	SSKT	x	CE+KD	81.4±0.23
		R32	SSKT	o	CE+CE	83.68±0.28
		R32	SSKT	o	CE+KD	81.76±0.18
P+I		R32	SSKT	x	CE+CE	82.39±0.15
		R32	SSKT	x	CE+KD	79.8±0.47
		R32	SSKT	o	CE+CE	**83.4±0.2**
		R32	SSKT	o	CE+KD	80.05±1.06

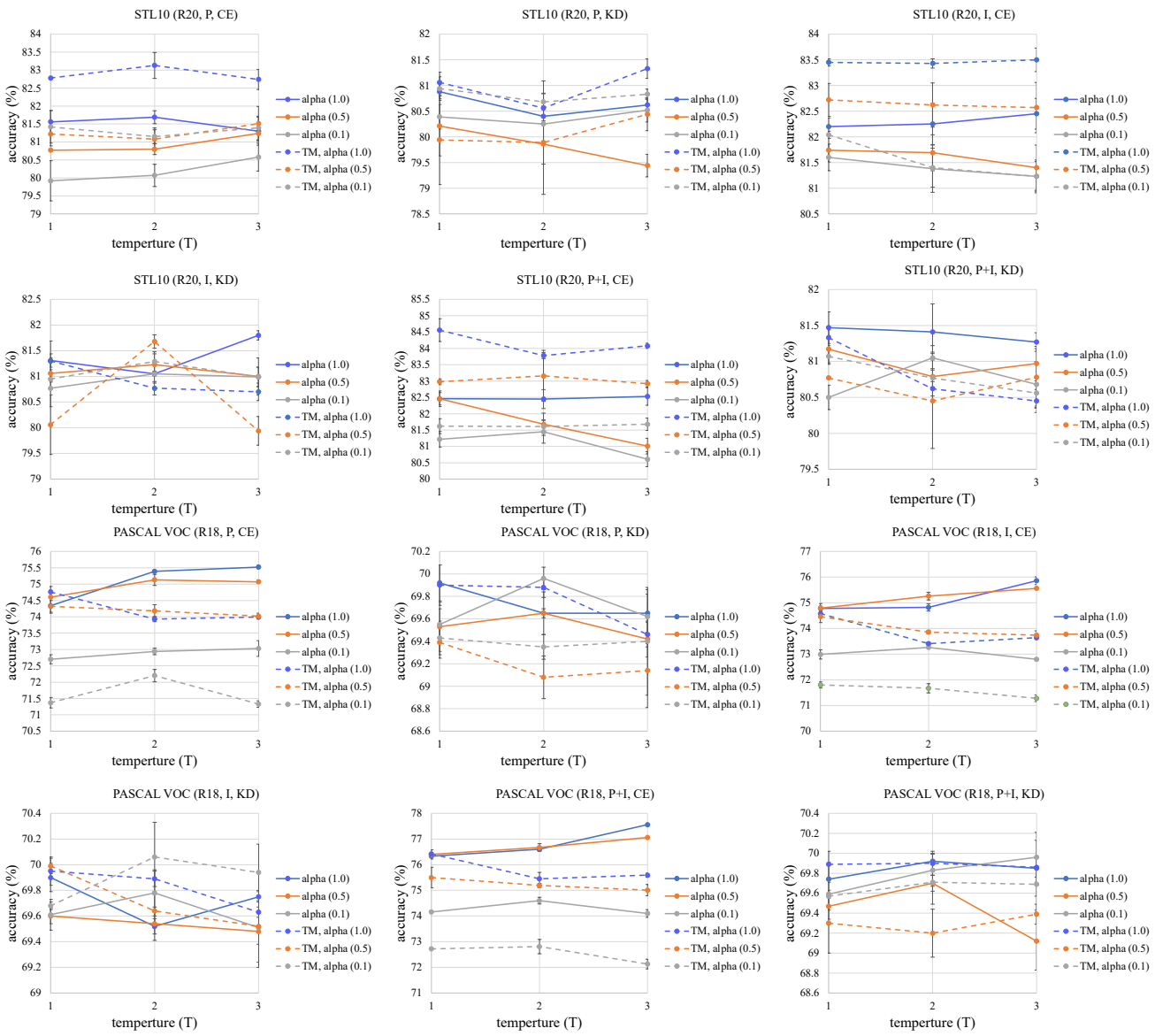

Figure 2. **Graph visualization for parameter optimization of SSKT.** The title of each graph is composed of D_t (target model, T_s, auxiliary loss). T is the temparture parameter of each auxiliary loss, and α is the balance parameter of the total loss.

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Table 4. SSKT-based transfer learning performance change for ImageNet and Places365 compared to the training from scratch.

T_s	T_t	Model	Method	TM	Loss	acc.
-	P	R18	scratch	-	CE	50.92
P		R18	SSKT	x	CE+CE	54.41
		R18	SSKT	x	CE+KD	53.42
		R18	SSKT	o	CE+CE	54.5
		R18	SSKT	o	CE+KD	54.11
I		R18	SSKT	x	CE+CE	53.47
		R18	SSKT	x	CE+KD	53.51
		R18	SSKT	o	CE+CE	53.67
		R18	SSKT	o	CE+KD	53.44
P+I		R18	SSKT	x	CE+CE	**54.78**
		R18	SSKT	x	CE+KD	54.5
		R18	SSKT	o	CE+CE	54.62
		R18	SSKT	o	CE+KD	54.5
-	I	R18	scratch	-	CE	64.14
P		R18	SSKT	x	CE+CE	64.18
		R18	SSKT	x	CE+KD	64.21
		R18	SSKT	o	CE+CE	64.99
		R18	SSKT	o	CE+KD	63.53
I		R18	SSKT	x	CE+CE	67.79
		R18	SSKT	x	CE+KD	66.0
		R18	SSKT	o	CE+CE	67.46
		R18	SSKT	o	CE+KD	65.65
P+I		R18	SSKT	x	CE+CE	**70.57**
		R18	SSKT	x	CE+KD	67.42
		R18	SSKT	o	CE+CE	67.64
		R18	SSKT	o	CE+KD	66.81

Table 5. SSKT-based transfer learning performance change for PASCAL VOC compared to the training from scratch.

T_s	T_t	Model	Method	TM	Loss	acc.
-	VOC	R18	scratch	-	BCE	67.28±0.25
P		R18	SSKT	x	BCE+CE	74.34±0.23
		R18	SSKT	x	BCE+KD	69.92±0.16
		R18	SSKT	o	BCE+CE	74.76±0.17
		R18	SSKT	o	BCE+KD	69.9±0.18
I		R18	SSKT	x	BCE+CE	74.78±0.09
		R18	SSKT	x	BCE+KD	69.9±0.35
		R18	SSKT	o	BCE+CE	74.58±0.11
		R18	SSKT	o	BCE+KD	69.95±0.19
P+I		R18	SSKT	x	BCE+CE	76.33±0.0
		R18	SSKT	x	BCE+KD	69.74±0.17
		R18	SSKT	o	BCE+CE	**76.42±0.06**
		R18	SSKT	o	BCE+KD	69.89±0.13
-		R34	scratch	-	BCE	66.0±0.49
P		R34	SSKT	x	BCE+CE	73.83±0.38
		R34	SSKT	x	BCE+KD	69.93±0.03
		R34	SSKT	o	BCE+CE	75.65±0.12
		R34	SSKT	o	BCE+KD	69.51±0.13
I		R34	SSKT	x	BCE+CE	74.25±0.12
		R34	SSKT	x	BCE+KD	70.05±0.14
		R34	SSKT	o	BCE+CE	75.14±0.14
		R34	SSKT	o	BCE+KD	70.18±0.11
P+I		R34	SSKT	x	BCE+CE	75.88±0.1
		R34	SSKT	x	BCE+KD	70.15±0.09
		R34	SSKT	o	BCE+CE	**77.02±0.02**
		R34	SSKT	o	BCE+KD	70.58±0.35
-		R50	scratch	-	BCE	61.16±0.34
P		R50	SSKT	x	BCE+CE	63.29±1.43
		R50	SSKT	x	BCE+KD	65.5±0.2
		R50	SSKT	o	BCE+CE	74.44±0.06
		R50	SSKT	o	BCE+KD	65.94±0.09
I		R50	SSKT	x	BCE+CE	63.96±2.74
		R50	SSKT	x	BCE+KD	66.11±0.32
		R50	SSKT	o	BCE+CE	74.24±0.05
		R50	SSKT	o	BCE+KD	65.77±0.13
P+I		R50	SSKT	x	BCE+CE	69.27±0.21
		R50	SSKT	x	BCE+KD	66.0±0.29
		R50	SSKT	o	BCE+CE	**77.1±0.14**
		R50	SSKT	o	BCE+KD	66.22±0.23

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Table 6. SSKT-based transfer learning performance change for UCF101 and HMDB51 compared to the training from scratch.

T_s	T_t	Model	Method	TM	Loss	acc.
-	U101	3DR18	scratch	-	CE	43.28
P		3DR18	SSKT	x	CE+CE	44.1
		3DR18	SSKT	x	CE+KD	44.79
		3DR18	SSKT	o	CE+CE	45.35
		3DR18	SSKT	o	CE+KD	43.95
I		3DR18	SSKT	x	CE+CE	46.62
		3DR18	SSKT	x	CE+KD	40.35
		3DR18	SSKT	o	CE+CE	44.26
		3DR18	SSKT	o	CE+KD	38.95
P+I		3DR18	SSKT	x	CE+CE	**52.19**
		3DR18	SSKT	x	CE+KD	43.68
		3DR18	SSKT	o	CE+CE	47.09
		3DR18	SSKT	o	CE+KD	45.0
-	H51	3DR18	scratch	-	CE	17.14
P		3DR18	SSKT	x	CE+CE	18.18
		3DR18	SSKT	x	CE+KD	17.33
		3DR18	SSKT	o	CE+CE	18.77
		3DR18	SSKT	o	CE+KD	17.59
I		3DR18	SSKT	x	CE+CE	18.64
		3DR18	SSKT	x	CE+KD	18.12
		3DR18	SSKT	o	CE+CE	18.38
		3DR18	SSKT	o	CE+KD	18.77
P+I		3DR18	SSKT	x	CE+CE	19.75
		3DR18	SSKT	x	CE+KD	18.38
		3DR18	SSKT	o	CE+CE	**20.54**
		3DR18	SSKT	o	CE+KD	17.99

Table 7. SSKT-based transfer learning performance change for UCF101 and HMDB51 compared to the training from scratch with MobileNet V2 (MV2) and DenseNet121 (D121).

T_s	T_t	Model	Method	TM	Loss	acc.
-	S10	MV2	scratch	-	CE	72.26±0.83
P		MV2	SSKT	x	CE+CE	75.79±0.19
		MV2	SSKT	x	CE+KD	74.0±0.35
		MV2	SSKT	o	CE+CE	75.28±0.49
		MV2	SSKT	o	CE+KD	73.37±1.8
I		MV2	SSKT	x	CE+CE	76.08±0.63
		MV2	SSKT	x	CE+KD	74.39±0.82
		MV2	SSKT	o	CE+CE	75.35±0.61
		MV2	SSKT	o	CE+KD	72.6±0.67
P+I		MV2	SSKT	x	CE+CE	76.69±0.18
		MV2	SSKT	x	CE+KD	73.29±0.89
		MV2	SSKT	o	CE+CE	**76.96±0.39**
		MV2	SSKT	o	CE+KD	73.35±0.99
-		D121	scratch	-	CE	72.02±0.48
P		D121	SSKT	x	CE+CE	76.17±0.35
		D121	SSKT	x	CE+KD	74.83±0.59
		D121	SSKT	o	CE+CE	73.46±0.62
		D121	SSKT	o	CE+KD	72.55±0.43
I		D121	SSKT	x	CE+CE	76.0±0.33
		D121	SSKT	x	CE+KD	73.7±0.22
		D121	SSKT	o	CE+CE	74.35±0.3
		D121	SSKT	o	CE+KD	71.13±0.59
P+I		D121	SSKT	x	CE+CE	**77.03±0.17**
		D121	SSKT	x	CE+KD	73.76±0.84
		D121	SSKT	o	CE+CE	76.09±0.26
		D121	SSKT	o	CE+KD	70.94±1.14

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Table 8. SSKT results using pretrained weights. *ft* stands for fine-tuning and K stands for Kinetics-400 dataset (Kay et al. 2017).

T_s	T_t	Model	Method	TM	Loss	acc.
-	VOC	R18	*ft* (I)	-	CE	90.52±0.11
P		R18	SSKT	x	CE+CE	89.3±0.04
		R18	SSKT	x	CE+KD	**92.28±0.06**
		R18	SSKT	o	CE+CE	90.83±0.04
		R18	SSKT	o	CE+KD	92.21±0.05
I		R18	SSKT	x	CE+CE	91.29±0.03
		R18	SSKT	x	CE+KD	92.26±0.07
		R18	SSKT	o	CE+CE	91.58±0.15
		R18	SSKT	o	CE+KD	92.19±0.09
P+I		R18	SSKT	x	CE+CE	91.28±0.05
		R18	SSKT	x	CE+KD	92.19±0.07
		R18	SSKT	o	CE+CE	91.25±0.08
		R18	SSKT	o	CE+KD	92.25±0.07
-	U101	3DR18	*ft* (K)	-	CE	83.95
P		3DR18	SSKT	x	CE+CE	84.53
		3DR18	SSKT	x	CE+KD	**84.58**
		3DR18	SSKT	o	CE+CE	83.87
		3DR18	SSKT	o	CE+KD	83.98
I		3DR18	SSKT	x	CE+CE	81.99
		3DR18	SSKT	x	CE+KD	83.42
		3DR18	SSKT	o	CE+CE	84.29
		3DR18	SSKT	o	CE+KD	84.37
P+I		3DR18	SSKT	x	CE+CE	78.56
		3DR18	SSKT	x	CE+KD	84.14
		3DR18	SSKT	o	CE+CE	82.81
		3DR18	SSKT	o	CE+KD	84.19
-	H51	3DR18	*ft* (K)	-	CE	56.64
P		3DR18	SSKT	x	CE+CE	56.77
		3DR18	SSKT	x	CE+KD	56.77
		3DR18	SSKT	o	CE+CE	57.75
		3DR18	SSKT	o	CE+KD	**57.82**
I		3DR18	SSKT	x	CE+CE	56.18
		3DR18	SSKT	x	CE+KD	56.9
		3DR18	SSKT	o	CE+CE	53.3
		3DR18	SSKT	o	CE+KD	57.75
P+I		3DR18	SSKT	x	CE+CE	54.48
		3DR18	SSKT	x	CE+KD	56.05
		3DR18	SSKT	o	CE+CE	57.29
		3DR18	SSKT	o	CE+KD	57.1

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