Full paper (ArXiv)   Codes (Github)

Logit Standardization in Knowledge Distillation

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Introduction & Analysis

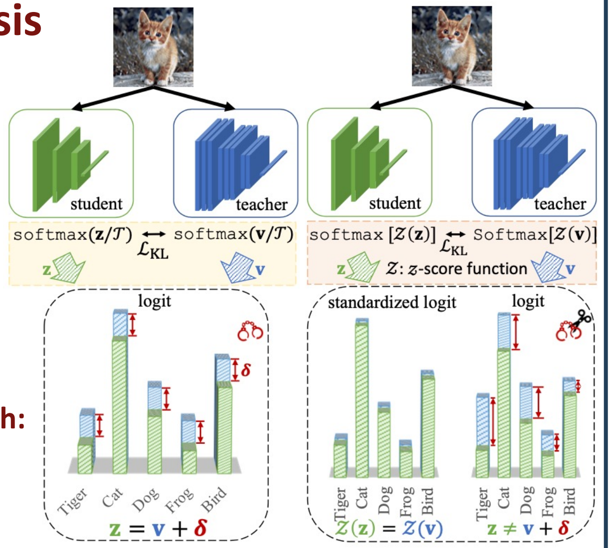
- Common KD assumes $\mathcal{T}_S = \mathcal{T}_T$ for all sample for simplicity
- But we find no explicit constraint on $\mathcal{T}_S$ and $\mathcal{T}_T$, based on the derivation of `softmax` in KD by the entropy-maximum principle
- We find **2** issues when $\mathcal{T}_S = \mathcal{T}_T$

ISSUE 1

An implicit mandatory logit match:

Given logit $\mathbf{z}$ for S and $\mathbf{v}$ for T

- $\mathbf{z} = \mathbf{v} + \mathbf{\Delta}$, where $\mathbf{\Delta} = \bar{\mathbf{z}} - \bar{\mathbf{v}}$
- $\mathrm{std}(\mathbf{z})/\mathrm{std}(\mathbf{v}) = \mathcal{T}_S/\mathcal{T}_T = 1$



(a) Vanilla KD (b) KD w/ our logit standardization

Toy Case

ISSUE 2

Conventional KD pipeline fails to reflect student performance

- Without ours:

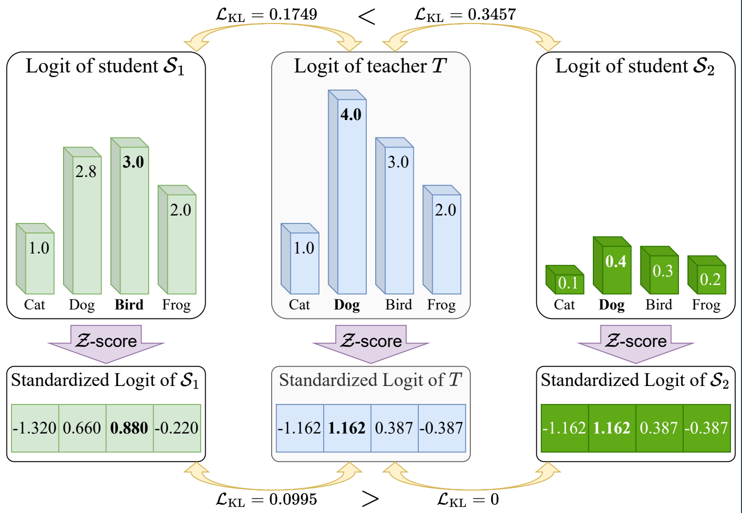
S_1 has **better** $\mathcal{L}_{KL}$ but **wrong** prediction

S_2 has **worse** $\mathcal{L}_{KL}$ but **correct** prediction

- With ours:

S_2 has **better** $\mathcal{L}_{KL}$ and **correct** prediction

Contradiction solved



(a) $\mathcal{S}_1$'s prediction: ~~Bird~~ (b) Teacher prediction: Dog (c) $\mathcal{S}_2$'s prediction: Dog✓

Proposed Method: Logit Standardization

- Determine Temperature adaptively based on a weighted $\mathcal{Z}$-score
- Serve as a beneficial pre-process for the existing logit-based KD

Algorithm 1: Weighted $\mathcal{Z}$-score function.

Input: Input vector $\mathbf{x}$ and Base temperature τ

Output: Standardized vector $\mathcal{Z}(\mathbf{x};\tau)$

1 $\bar{\mathbf{x}} \leftarrow \frac{1}{K}\sum_{k=1}^{K}\mathbf{x}^{(k)}$

2 $\sigma(\mathbf{x}) \leftarrow \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(\mathbf{x}^{(k)} - \bar{\mathbf{x}}\right)^2}$

3 **return** $(\mathbf{x} - \bar{\mathbf{x}})/\sigma(\mathbf{x})/\tau$

Algorithm 2: $\mathcal{Z}$-score logit standardization pre-process in knowledge distillation.

Input: Transfer set $\mathcal{D}$ with image-label sample pair $\{\mathbf{x}_n, y_n\}_{n=1}^{N}$, Base temperature τ, Teacher f_T, Student f_S, Loss $\mathcal{L}_{\mathrm{KD}}$ (e.g., $\mathcal{L}_{\mathrm{KL}}$), loss weight λ, and $\mathcal{Z}$-score function $\mathcal{Z}$ in Algo. 1

Output: Trained student model f_S

1 **foreach** $(\mathbf{x}_n, y_n)$ *in* $\mathcal{D}$ **do**

2 $\quad \mathbf{v}_n \leftarrow f_T(\mathbf{x}_n)$, $\mathbf{z}_n \leftarrow f_S(\mathbf{x}_n)$

3 $\quad q(\mathbf{v}_n) \leftarrow \mathtt{softmax}[\mathcal{Z}(\mathbf{v}_n;\tau)]$

4 $\quad q(\mathbf{z}_n) \leftarrow \mathtt{softmax}[\mathcal{Z}(\mathbf{z}_n;\tau)]$

5 $\quad q'(\mathbf{z}_n) \leftarrow \mathtt{softmax}(\mathbf{z}_n)$

6 $\quad$ Update f_S towards minimizing $\lambda_{\mathrm{CE}}\mathcal{L}_{\mathrm{CE}}(y_n, q'(\mathbf{z}_n)) + \lambda_{\mathrm{KD}}\tau^2\mathcal{L}(q(\mathbf{v}_n), q(\mathbf{z}_n))$

7 **end**

- Four Beneficial properties of standardized logit:
  1. Zero mean
  2. Finite std.=1
  3. Monotonicity
  4. Boundedness within $\pm\frac{\sqrt{K-1}}{\tau}$

Experiments

Distillation on CIFAR-100

Part of Table for Different Structures | Part of Table for Identical Structures

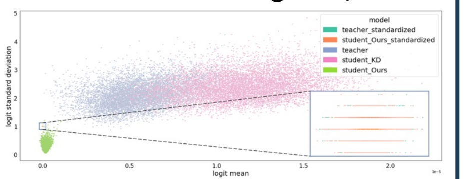
Type	Teacher / Student	ResNet32×4 79.42 / SHN-V2 71.82	ResNet32×4 79.42 / WRN-16-2 73.26	ResNet32×4 79.42 / WRN-40-2 75.61	WRN-40-2 75.61 / WRN-16-2 73.26	ResNet56 72.34 / ResNet20 69.06	ResNet110 74.31 / ResNet32 71.14	ResNet110 74.31 / ResNet20 69.06
Feature	FitNet [31]	73.54	74.70	77.69	73.58	69.21	71.06	68.99
	AT [46]	72.73	73.91	77.43	74.08	70.55	72.31	70.65
	RKD [29]	73.21	74.86	77.82	73.35	69.61	71.82	69.25
	CRD [37]	75.65	75.65	78.15	75.48	71.16	73.48	71.46
	OFD [12]	76.82	76.17	79.25	75.24	70.98	73.23	71.29
	ReviewKD [5]	77.78	76.11	78.96	76.12	71.89	73.89	71.34
	SimKD [4]	78.39	77.17	79.29	75.53	71.05	73.92	71.06
	CAT-KD [10]	78.41	76.97	78.59	75.60	71.62	73.62	71.37
Logit	KD [13]	74.45	74.90	77.70	74.92	70.66	73.08	70.67
	KD+Ours	75.56	75.26	77.92	76.11	71.43	74.17	71.48
	Δ	1.11	0.36	0.22	1.19	0.77	1.09	0.81
	CTKD [24]	75.37	74.57	77.66	75.45	71.19	73.52	70.99
	CTKD+Ours	76.18	75.16	77.99	76.08	71.34	74.01	71.39
	Δ	0.81	0.59	0.33	0.63	0.15	0.49	0.40
	DKD [50]	77.07	75.70	78.46	76.24	71.97	74.11	71.06
	DKD+Ours	77.37	76.19	78.95	76.39	72.32	74.29	71.85
	Δ	0.30	0.49	0.49	0.15	0.35	0.18	0.79
	MLKD [17]	78.44	76.52	79.26	76.63	72.19	74.11	71.89
	MLKD+Ours	**78.76**	**77.53**	**79.66**	**76.95**	**72.33**	**74.32**	**72.27**
	Δ	0.32	1.01	0.40	0.32	0.14	0.21	0.38

Distillation on ImageNet

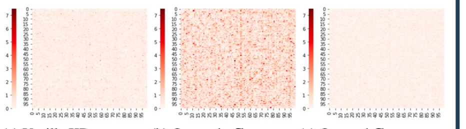
Teacher/Student	ResNet34/ResNet18		ResNet50/MN-V1	
Accuracy	top-1	top-5	top-1	top-5
Teacher	73.31	91.42	76.16	92.86
Student	69.75	89.07	68.87	88.76
AT [46]	70.69	90.01	69.56	89.33
OFD [12]	70.81	89.98	71.25	90.34
CRD [37]	71.17	90.13	71.37	90.41
ReviewKD [5]	71.61	90.51	72.56	91.00
SimKD [4]	71.59	90.48	72.25	90.86
CAT-KD [10]	71.26	90.45	72.24	91.13
KD [13]	71.03	90.05	70.50	89.80
KD+Ours	71.42 +0.39	90.29 +0.24	72.18 +1.68	90.80 +1.00
KD+CTKD [24]	71.38	90.27	71.16	90.11
KD+CTKD+Ours	71.81 +0.43	90.46 +0.19	72.92 +1.76	91.25 +1.14
DKD [50]	71.70	90.41	72.05	91.05
DKD+Ours	71.88 +0.18	90.58 +0.17	72.85 +0.80	91.23 +0.18
MLKD [17]	71.90	90.55	73.01	91.42
MLKD+Ours	**72.08** +0.18	**90.74** +0.19	**73.22** +0.21	**91.59** +0.17

Visualization

- No restriction in mean and std.
- Better match of logits w/ ours



Bivariate histogram of logit mean and std.



(a) Vanilla KD Mean: 0.27, Max: 3.03. (b) Ours w/o $\mathcal{Z}$-score Mean: 0.94, Max: 7.36. (c) Ours w/ $\mathcal{Z}$-score Mean: 0.18, Max:1.18.

Heatmap of avg. logit diff. between T & S