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Why can't we extend existing KD methods to MLKD?

Traditional KD

Logits-based methods	The sum of predicted probabilities = 1, so we can use KL divergence.	The prol canno
Feature-based methods	Only one object in a image, which makes the semantic information in the feature map very clear	Multi imag semar fea

Our proposed L2D framework



multi-label examples

Label-wise embeddings

Predicted probabilities

Class/Instance-aware Label-wise Embedding Distillation



Multi-Label Knowledge Distillation

MLKD

e sum of predicted babilities ≠ 1, so we ot use KL divergence.

iple semantics in one ge, which makes the ntic information in the ature map unclear

Instance-aware label-wise distillation



Take as an example.



Performance on MS-COCO

_	Table	e 1. Result	s on MS-C	COCO who	ere teacher	r and stude	ent models	are in the	same arc	chitectures				Table 2	2. Results of	on MS-CO	CO where	e teacher a	nd student	models ar	e in the d	ifferent a	architectur	es.	
Teacher	R	epVGG-A	A2	1	ResNet-10)1		WRN-10	1		Swin-S		Teacher	F	ResNet-10)1		Swin-T		F	ResNet-10)1		Swin-T	
Student	R	epVGG-A	40		ResNet-3	4		WRN-50			Swin-T		Student	R	epVGG-A	4 0		ResNet-3	4	M	lobileNet	v2	M	lobileNet	v2
Metrics	mAP	OF1	CF1	mAP	OF1	CF1	mAP	OF1	CF1	mAP	OF1	CF1	Metrics	mAP	OF1	CF1	mAP	OF1	CF1	mAP	OF1	CF1	mAP	OF1	CF1
Teacher	72.71	74.11	68.63	73.62	73.89	68.61	74.70	75.56	70.73	81.70	80.48	77.12	Teacher	73.62	73.89	68.61	79.43	78.77	75.07	73.62	73.89	68.61	79.43	78.77	75.07
Student	70.02	72.49	66.77	70.31	72.49	66.82	74.45	75.43	70.61	79.59	79.18	75.42	Student	70.02	72.49	66.77	70.31	72.49	66.82	71.85	73.59	68.26	71.85	73.59	68.26
RKD	70.08	72.39	66.73	70.13	72.44	66.78	74.70	75.71	70.84	79.63	79.19	75.57	RKD	70.08	72.35	66.72	70.00	72.34	66.64	71.76	73.68	68.40	71.74	73.68	68.37
PKT	70.11	72.47	66.80	70.43	72.64	66.68	74.54	75.47	70.58	79.64	79.09	75.39	PKT	69.99	72.35	66.56	70.26	72.39	66.82	71.88	73.60	68.35	71.84	73.76	68.37
ReviewKD	70.00	72.35	66.82	70.39	72.62	66.76	74.03	75.29	70.36	79.81	79.18	75.55	ReviewKD	70.00	72.33	66.62	70.29	72.39	66.58	71.92	73.73	68.48	71.73	73.71	68.36
MSE	70.26	72.54	66.99	70.54	72.75	66.85	74.53	75.60	70.71	79.67	79.20	75.52	MSE	70.07	72.50	66.85	70.33	72.57	66.72	71.91	73.68	68.28	71.80	73.74	68.38
PS	70.65	72.89	67.60	70.86	72.66	67.12	75.12	76.05	71.63	79.96	79.64	76.20	PS	70.30	72.61	67.10	70.94	72.93	67.57	72.11	73.89	68.42	72.42	74.14	68.94
MLD	70.74	72.81	67.46	70.68	72.69	67.19	74.92	75.75	71.21	80.11	79.68	76.44	MLD	70.48	72.77	67.10	71.14	72.99	67.63	72.17	73.84	68.52	72.35	74.10	68.91
L2D	72.81	74.59	69.49	72.87	74.45	69.43	76.61	77.08	72.79	81.59	81.03	77.86	L2D	72.14	74.08	68.78	73.42	74.97	70.20	73.24	74.85	69.72	74.21	75.72	70.87

Performance on VOC

	Table 3. R	esults on l	Pascal VO	C 2007 va	lidation te	acher and	student me	odels are i	n the sam	e architec	tures.		Table	e 4. Result	s on Pascal	1 VOC 200)7 validatio	on where t	eacher and	l student n	nodels are	in the dif	ferent arc	chitectures	\$.
Teacher	R	epVGG-A	12		ResNet-50)		WRN-101	l		Swin-S		Teacher		ResNet-50	0		Swin-T			ResNet-50)		Swin-T	
Student	R	epVGG-A	A 0		ResNet-1	3		WRN-50			Swin-T		Student	R	epVGG-A	40		ResNet-1	8	M	lobileNet	v2	M	obileNet	v2
Metrics	mAP	OF1	CF1	mAP	OF1	CF1	mAP	OF1	CF1	mAP	OF1	CF1	Metrics	mAP	OF1	CF1	mAP	OF1	CF1	mAP	OF1	CF1	mAP	OF1	CF1
Teacher	86.20	85.63	82.62	86.73	84.92	81.21	88.00	87.03	83.72	92.75	91.05	88.82	Teacher	86.73	84.92	81.21	91.43	89.81	87.63	86.73	84.92	81.21	91.43	89.81	87.63
Student	83.79	83.36	79.83	84.01	83.60	79.42	88.52	87.21	84.08	91.31	89.98	88.00	Student	83.79	83.36	79.83	84.01	83.60	79.42	86.12	85.01	81.76	86.12	85.01	81.76
RKD	83.75	83.41	79.85	84.48	83.54	79.83	88.21	87.33	84.55	91.52	90.44	88.51	RKD	84.26	84.29	80.70	83.27	83.05	79.55	86.22	84.97	81.76	85.68	85.31	81.57
PKT	83.63	83.53	80.04	84.12	83.10	79.31	87.69	87.07	84.14	91.28	90.17	88.03	PKT	83.93	83.79	80.03	83.45	83.25	79.64	86.10	84.84	81.66	85.67	85.22	81.68
ReviewKD	83.87	83.98	80.54	83.71	83.01	79.25	88.23	87.13	84.20	91.45	90.17	88.06	ReviewKD	84.07	83.62	80.34	83.37	83.08	78.93	85.87	85.04	81.73	85.69	85.10	81.56
MSE	84.02	83.67	79.94	84.23	83.16	79.29	88.04	86.49	83.57	91.06	89.99	87.66	MSE	84.01	84.05	80.52	83.60	83.06	79.46	86.20	84.94	81.84	85.80	85.51	81.98
PS	83.77	83.74	80.28	84.44	83.78	79.95	88.30	86.92	83.91	91.21	90.25	88.12	PS	84.80	84.46	81.13	83.97	83.75	79.86	86.26	85.47	82.06	86.07	85.73	82.39
MLD	83.65	83.66	80.02	84.48	84.07	80.29	88.29	87.16	84.25	91.43	90.72	88.81	MLD	85.07	84.91	81.55	84.61	84.26	80.78	86.38	85.67	82.43	86.11	85.98	82.55
L2D	84.56	84.37	80.82	85.71	85.70	82.11	89.52	88.25	85.69	91.92	91.34	89.58	L2D	86.26	85.85	82.55	85.87	85.67	82.17	87.32	86.48	83.26	87.37	86.88	83.68

Performance on NUS-WIDE

Teacher	F	ResNet-10	1		Swin-T		ResNet34 \rightarrow ResNet101						
Student]	ResNet-34	4	M	obileNet	v2							
Metrics	mAP	OF1	CF1	mAP	OF1	CF1	Metrics	mAP	OF1	CF1			
Teacher	55.32	75.56	61.31	59.73	77.30	65.44	Teacher	70.19	72.30	66.50			
Student	53.41	75.10	60.08	54.49	75.72	61.74	Student	73.98 (+3.79)	75.01 (+2.71)	70.12 (+3.62)			
RKD	53.62	75.20	59.91	54.76	75.69	61.74	RKD	74.03 (+3.84)	74.96 (+2.66)	70.01 (+3.51)			
PKT	53.55	75.08	60.35	54.59	75.69	61.74	PKT	73.95 (+3.76)	74.94 (+2.64)	69.98 (+3.48)			
ReviewKD	53.52	75.23	60.44	54.85	75.84	61.75	ReviewKD	74.02 (+3.83)	74.96 (+2.66)	70.07 (+3.57)			
MSE	53.52	75.13	59.94	54.86	75.80	61.69	MSE	74.21 (+4.02)	75.12 (+2.82)	70.18 (+3.68)			
PS	54.14	75.43	60.79	55.18	75.91	62.35	PS	74.70 (+4.51)	75.78 (+3.48)	71.08 (+4.58)			
MLD	54.44	75.36	60.73	55.36	76.00	62.52	MLD	74.64 (+4.45)	75.78 (+3.48)	71.10 (+4.60)			
L2D	55.31	76.17	62.79	56.91	76.92	63.89	L2D	75.51(+5.32)	76.25(+3.95)	71.75(+5.25)			

Per-Class Performance on VOC

Comparison results of the comparing methods on VOC in terms of AP and mAP (%), where the backbones of teacher and student model are respectively ResNet-50 and ResNet-18. The best performance is highlighted in red, and second best performance is highlighted in blue.

Methods	bottle	plant	chair	sofa	table	cow	tv	bus	sheep	mbike	dog	bird	bike	cat	boat	car	horse	person	train	aero	mAP
Vanilla	57.18	67.43	70.35	73.17	76.14	82.65	82.30	85.53	84.16	88.38	90.18	90.65	91.40	90.67	92.54	92.72	94.22	95.73	96.09	97.27	84.01
RKD	59.01	67.01	71.31	72.86	76.90	81.11	81.70	84.79	84.77	88.8 6	90.03	91.65	91.53	91.86	92.53	92.06	93.97	95.88	97.08	97.00	84.18
PKT	57.29	66.16	71.16	73.22	76.89	81.75	81.95	85.06	83.66	88.73	90.10	91.31	91.77	91.83	92.35	92.07	93.12	95.80	96.99	97.09	83.86
MSE	58.26	68.02	70.68	72.06	77.93	81.06	82.36	86.03	83.72	88.30	90.46	90.60	91.58	91.07	91.64	92.01	94.05	95.69	97.13	97.10	84.23
MLD	58.32	68.88	71.12	73.77	78.65	84.60	82.42	86.41	83.77	88.58	90.78	91.02	91.92	91.63	92.25	92.34	94.53	96.04	96.97	97.30	84.48
L2D	59.71	70.52	74.77	75.01	78.93	83.87	84.13	85.45	85.67	89.83	90.60	91.48	91.90	92.14	92.57	93.40	94.67	96.46	96.81	97.39	85.71

Class-aware label-wise distillation

Take class **car** as an example.



Performance on Reversed KD



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	- 0.1
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Performance on Image Retrieval

Query



Book, Person, Remote





















Distilling Inter-class Correlations

Vanilla

ReviewKD

Μ	LD
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L2D

Visualization of Attention Maps

	Vanilla	ReviewKD	L2D	raw	Vanilla	ReviewKD	L2D
				handbag			
				tie			
				berson			
,	Vanilla	ReviewKD	L2D	raw	Vanilla	ReviewKD	L2D
	Vanilla	ReviewKD	L2D	raw	Vanilla	ReviewKD	L2D
	VanillaStatisticaStatisticaStatisticaStatistica	<image/>	<image/>	Pickel airblane Image: Second Seco	VanillaImage: Image: Ima	ReviewKD	L2D

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