

Asymmetric metric learning for knowledge transfer

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asymmetric metric learning (AML)

- instance-level image retrieval
- **asymmetric testing**: database represented by large network, queries by lightweight network on device, no re-indexing
- **asymmetric metric learning**: use asymmetric representations at training in **teacher-student** setup
- applies to both symmetric and asymmetric testing
- combines of **knowledge transfer** with **supervised metric learning**

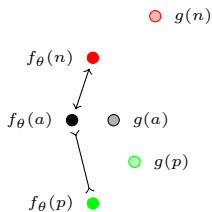
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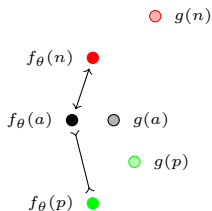
metric learning and knowledge transfer



symmetric

- labels used, teacher not used
- **positive** pairs of examples mutually **attracted** and **negative** pairs are **repulsed** in student space

metric learning and knowledge transfer

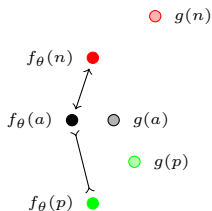


symmetric

- labels used, teacher not used (f_θ : student, g : teacher)
- **contrastive** $\ell_C(a; \theta)$: **independently**, positive examples p close to anchor a , negative n farther from a by margin m in student space

$$\sum_{n \in N(a)} [s_\theta(a, n) - m]_+ - \sum_{p \in P(a)} s_\theta(a, p)$$

metric learning and knowledge transfer

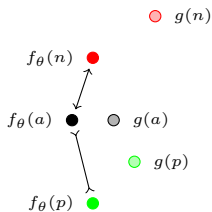


symmetric

- labels used, teacher not used (f_θ : student, g : teacher)
- triplet $\ell_T(a; \theta)$: positive examples p closer to the anchor a than negative n by margin m in student space

$$\sum_{(p,n) \in L(a)} [s_\theta(a, n) - s_\theta(a, p) + m]_+$$

metric learning and knowledge transfer

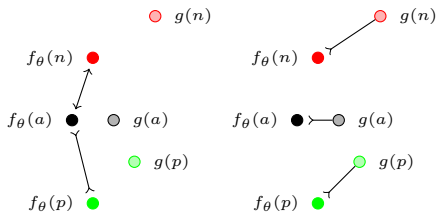


symmetric

- labels used, teacher not used (f_θ : student, g : teacher)
- **multi-similarity** $\ell_{\text{MS}}(a; \theta)$: positives p (negatives n) **farthest** from (**nearest to**) anchor a receive the **greatest** relative weight

$$\frac{1}{\alpha} \log \left(1 + \sum_{p \in P(a)} e^{-\alpha(s_\theta(a,p) - m)} \right) + \frac{1}{\beta} \log \left(1 + \sum_{n \in N(a)} e^{\beta(s_\theta(a,n) - m)} \right)$$

metric learning and knowledge transfer

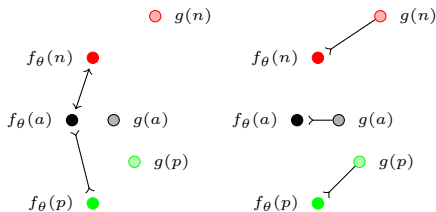


symmetric

regression

- labels not used, teacher used
- examples in **student space** attracted to corresponding examples in **teacher space**

metric learning and knowledge transfer



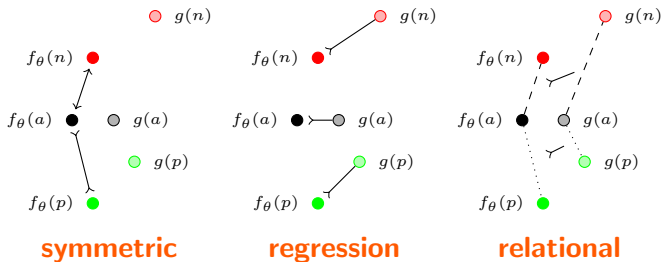
symmetric

regression

- labels not used, teacher used (f_θ : student, g : teacher)
- **regression** $\ell_R(a; \theta)$: representations of **same example** a by **two models** f_θ, g close to each other, where g is fixed

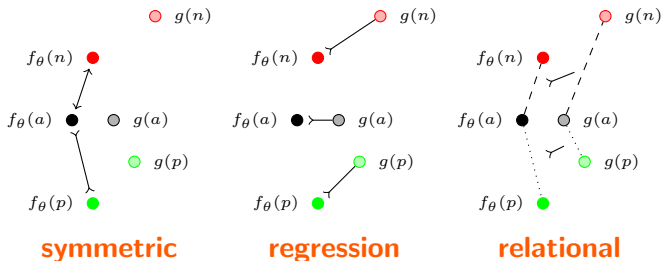
$$-s_\theta^{\text{asym}}(a, a) = -\text{sim}(f_\theta(a), g(a))$$

metric learning and knowledge transfer



- labels not used, teacher used
- pairwise / groupwise relations like **distances**, **angles** or **ranks** encouraged to be **compatible in both spaces**

metric learning and knowledge transfer

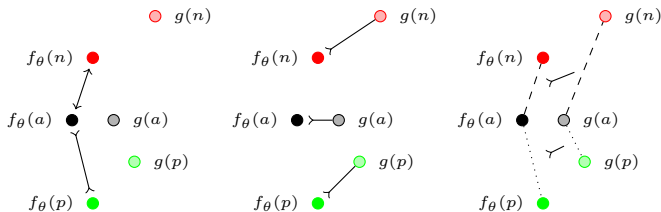


- labels not used, teacher used (f_θ : student, g : teacher)
- **relational distillation** $\ell_{\text{RKD}}(a; \theta)$: measurements $\psi(\mathbf{a}, \mathbf{x}, \dots)$ of **same examples** (a, x, \dots) by **two models** f_θ, g close to each other

$$\sum_{(x, \dots) \in U(a)^n} -\text{sim}(\psi(f_\theta(a), f_\theta(x), \dots), \psi(g(a), g(x), \dots)))$$

e.g. **distance** $\|\mathbf{a} - \mathbf{x}\|$, **angle** $\text{sim}(\mathbf{a} - \mathbf{x}, \mathbf{a} - \mathbf{y})$; **regression** $\psi(\mathbf{a}) := \mathbf{a}$

metric learning and knowledge transfer



symmetric

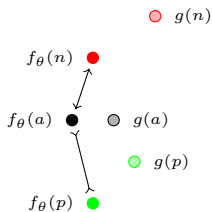
regression

relational

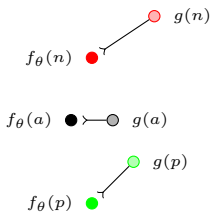
- labels not used, teacher used (f_θ : student, g : teacher)
- **DarkRank** $\ell_{DR}(a; \theta)$: examples $y \in V(a, x)$ mapped **farther from anchor a than x in teacher space** do the same in **student space**:

$$- \sum_{x \in U(a)} \left(s_\theta^{\text{sym}}(a, x) - \log \sum_{y \in V(a, x)} e^{s_\theta^{\text{sym}}(a, y)} \right)$$

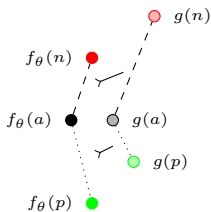
metric learning and knowledge transfer



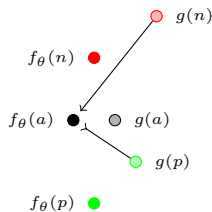
symmetric



regression



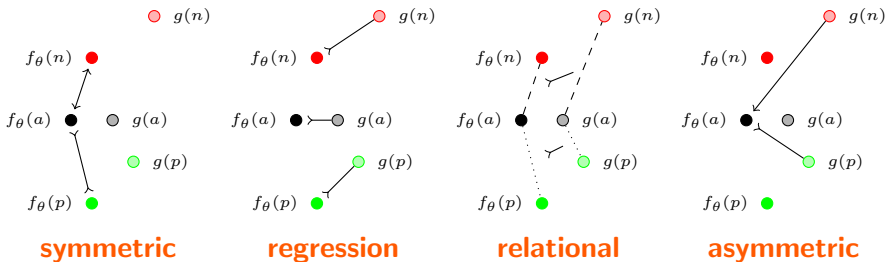
relational



asymmetric

- both labels and teacher used
- anchors in student space attracted to positives and repulsed from negatives in teacher space

metric learning and knowledge transfer



- both labels and teacher used (f_θ : student, g : teacher)
- **Asymmetric Metric Learning (AML)**: simply use

$$s_\theta^{\text{asym}}(a, x) := \text{sim}(f_\theta(a), g(x))$$

with **any** supervised metric learning loss like ℓ_C , ℓ_T , ℓ_{MS}

best loss functions

- regression (Reg)

$$\ell_R(a; \theta) := -s_{\theta}^{\text{asym}}(a, a) = -\text{sim}(f_{\theta}(a), g(a))$$

- asymmetric contrastive (Contr)

$$\ell_C(a; \theta) := \sum_{n \in N(a)} [s_{\theta}(a, n) - m]_+ - \sum_{p \in P(a)} s_{\theta}(a, p)$$

- asymmetric contrastive + regression (Contr⁺)

$$\ell_{C^+}(a; \theta) := \sum_{n \in N(a)} [s_{\theta}(a, n) - m]_+ - \sum_{p \in P(a)} s_{\theta}(a, p) - s_{\theta}(a, a)$$

test set: revisited Oxford and Paris



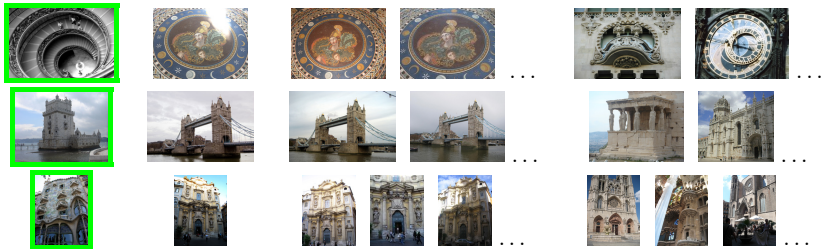
- 11 + 11 landmarks, 70 + 70 queries, 5k + 6k images, easy/hard
- 1M distractor images
- performance measured by mAP: positive ranked first

training set: SfM120k (positives)



- camera position (closest to query)
- number of inliers (co-observed 3D points with query)
- according to SIFT descriptors

training set: SfM120k (negatives)



- k -nearest neighbors from non-matching clusters
- at most one image per cluster
- according to learned descriptors

network models

NETWORK	TEACHER	d	GFLOPS	PARAM(M)
ResNet101		2048	42.85	42.50
EfficientNet-B3		1536	5.36	10.70
	ResNet101	2048	6.26	13.84

- **teacher**: ResNet101 (**RN101**)
- **student**: EfficientNet-B3 (**EN-B3**), dimensions d adapted to teacher
- 7 \times less FLOPS
- 3 \times less parameters

symmetric testing

STU	d	TEA	LAB	MINING	ASYM	LOSS	MEDIUM		HARD	
							ROxf	RPar	ROxf	RPar
RN101	2048		✓	hard		Contr	65.4	76.7	40.1	55.2
EN-B3	512		✓	hard		Contr	53.8	70.9	26.2	46.0
	2048		✓	hard		Contr	59.6	75.1	33.3	51.9
EN-B3	2048	RN101	✓	hard	✓	Contr ⁺	66.8	77.1	42.5	55.5
			✓	hard	✓	Contr	66.3	77.4	41.3	55.5
			✓	hard	✓	Triplet	39.5	69.4	11.6	45.8
			✓	hard	✓	MS	39.9	69.7	11.7	46.2
			–		✓	Reg	64.9	74.4	40.5	52.4
			random			RKD	56.3	73.0	30.5	50.4
			random		DR	40.3	69.9	11.8	46.4	

- Contr, Contr⁺: student beats teacher
- Reg: second best, slightly below teacher
- everything else fails (worse than student alone)

symmetric testing

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Mateusz



Yannis

paper

<https://arxiv.org/abs/2006.16331>

code

https://github.com/budnikm/asymmetric_metric_learning

more

<https://avrithis.net>