



Deep Adversarial Metric Learning

*Yueqi Duan, Wenzhao Zheng, Xudong Lin,
Jiwen Lu, and Jie Zhou*

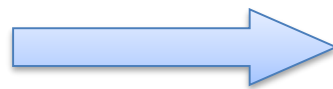
Department of Automation, Tsinghua University, China

http://ivg.au.tsinghua.edu.cn/people/Yueqi_Duan/

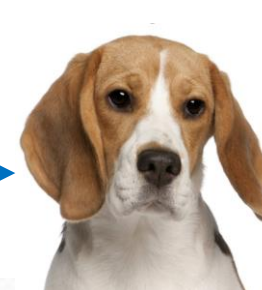
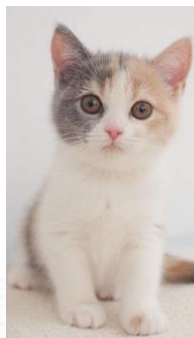
Metric Learning



Original Space



Learned Space



Sampling Matters

- Objective functions

- Contrastive loss: $L_{\text{cont}}(x_i, x_j; \theta) = \mathbf{1}\{y_i = y_j\} D_{ij}^2 + \mathbf{1}\{y_i \neq y_j\} [\alpha - D_{ij}]_+^2$

- Triplet loss: $L_{\text{tri}}(x_a, x_p, x_n; \theta) = [D_{ap}^2 - D_{an}^2 + \alpha]_+$

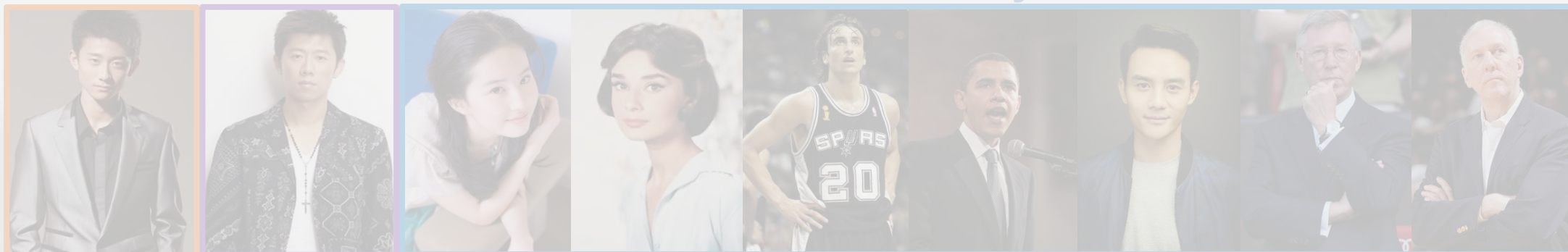
Easy negatives account for the vast majority.

Are easy negatives really useless?

Anchor

Hard

Easy



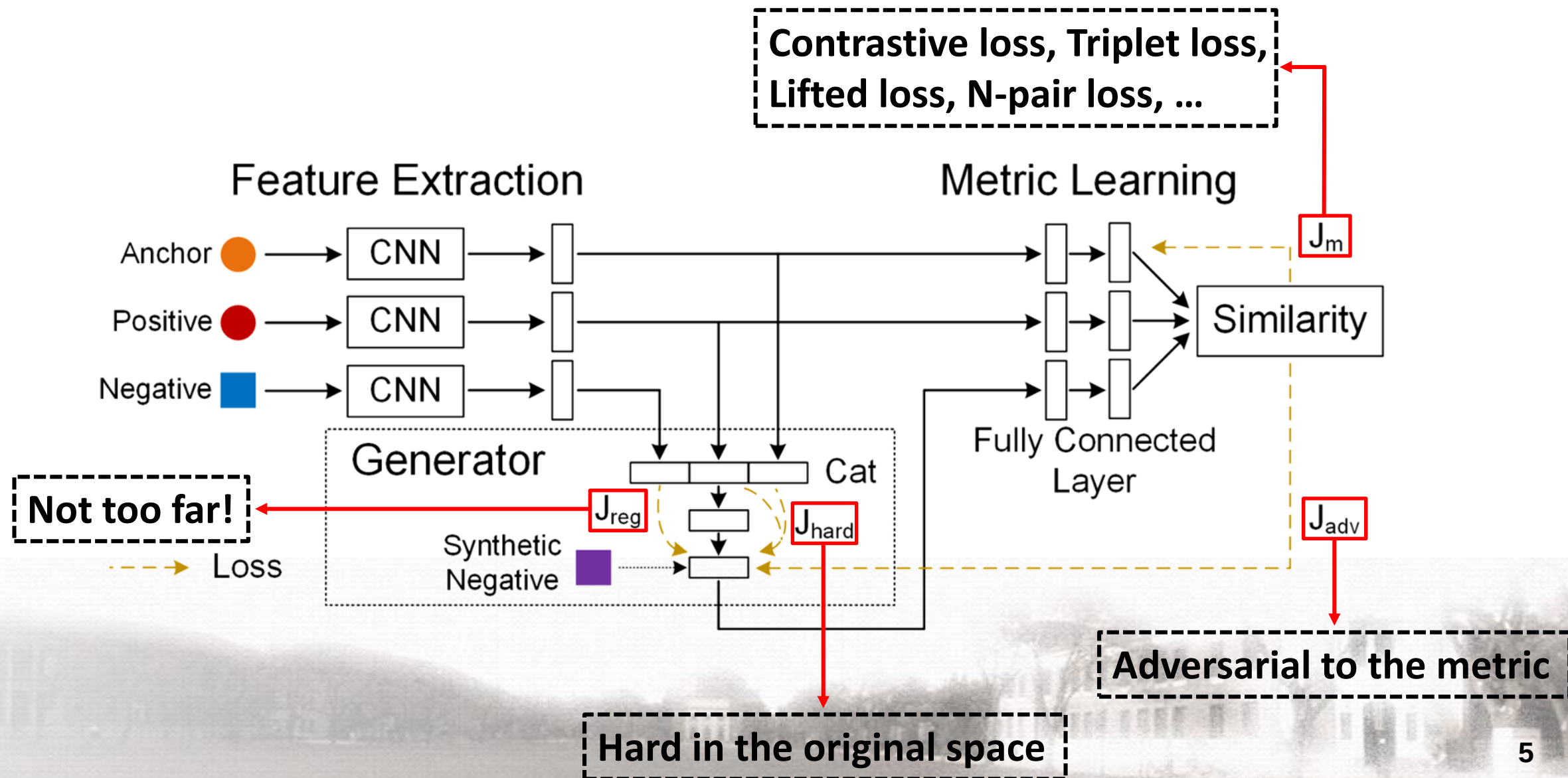
Hard Negative Mining!

- Easy negatives may have **potential** to become hard negatives



- Ignore easy negatives?
- **DAML**: Exploit easy negatives through **adversarial hard negative generation**

Deep Adversarial Metric Learning





Objective Function

- Overall:

$$\min_{\theta_g, \theta_f} J = J_{\text{gen}} + \lambda J_{\text{m}}$$

- Hard negative generator:

$$\begin{aligned} \min_{\theta_g} J_{\text{gen}} &= J_{\text{hard}} + \lambda_1 J_{\text{reg}} + \lambda_2 J_{\text{adv}} \\ &= \sum_{i=1}^N (||\tilde{\mathbf{x}}_i^- - \mathbf{x}_i||_2^2 + \lambda_1 ||\tilde{\mathbf{x}}_i^- - \mathbf{x}_i^-||_2^2 \\ &\quad + \lambda_2 [D(\tilde{\mathbf{x}}_i^-, \mathbf{x}_i)^2 - D(\mathbf{x}_i^+, \mathbf{x}_i)^2 - \alpha]_+) \end{aligned}$$



Datasets

- CUB-200-2011 includes 11,788 images of 200 bird species.
- Cars196 contains 16,185 images of 196 cars models.
- Stanford Online Products has 120,053 images of 22,634 products from eBay.com.



Experiments on CUB-200-2011



Method	NMI	F ₁	R@1	R@2	R@4	R@8
DDML	47.3	13.1	31.2	41.6	54.7	67.1
Triplet+N-pair	54.1	20.0	42.8	54.9	66.2	77.6
Angular	61.0	30.2	53.6	65.0	75.3	83.7
Contrastive	47.2	12.5	27.2	36.3	49.8	62.1
DAML (cont)	49.1	16.2	35.7	48.4	60.8	73.6
Triplet	49.8	15.0	35.9	47.7	59.1	70.0
DAML (tri)	51.3	17.6	37.6	49.3	61.3	74.4
Lifted	56.4	22.6	46.9	59.8	71.2	81.5
DAML (lifted)	59.5	26.6	49.0	62.2	73.7	83.3
N-pair	60.2	28.2	51.9	64.3	74.9	83.2
DAML (N-pair)	61.3	29.5	52.7	65.4	75.5	84.3

Experiments on Cars196



Method	NMI	F ₁	R@1	R@2	R@4	R@8
DDML	41.7	10.9	32.7	43.9	56.5	68.8
Triplet+N-pair	54.3	19.6	46.3	59.9	71.4	81.3
Angular	62.4	31.8	71.3	80.7	87.0	91.8
Contrastive	42.3	10.5	27.6	38.3	51.0	63.9
DAML (cont)	42.6	11.4	37.2	49.6	61.8	73.3
Triplet	52.9	17.9	45.1	57.4	69.7	79.2
DAML (tri)	56.5	22.9	60.6	72.5	82.5	89.9
Lifted	57.8	25.1	59.9	70.4	79.6	87.0
DAML (lifted)	63.1	31.9	72.5	82.1	88.5	92.9
N-pair	62.7	31.8	68.9	78.9	85.8	90.9
DAML (N-pair)	66.0	36.4	75.1	83.8	89.7	93.5

Experiments on Stanford Online Products



Method	NMI	F ₁	R@1	R@10	R@100
DDML	83.4	10.7	42.1	57.8	73.7
Triplet+N-pair	86.4	21.0	58.1	76.0	89.1
Angular	87.8	26.5	67.9	83.2	92.2
Contrastive	82.4	10.1	37.5	53.9	71.0
DAML (cont)	83.5	10.9	41.7	57.5	73.5
Triplet	86.3	20.2	53.9	72.1	85.7
DAML (tri)	87.1	22.3	58.1	75.0	88.0
Lifted	87.2	25.3	62.6	80.9	91.2
DAML (lifted)	89.1	31.7	66.3	82.8	92.5
N-pair	87.9	27.1	66.4	82.9	92.1
DAML (N-pair)	89.4	32.4	68.4	83.5	92.3



Summary

- Hard negative mining ignores large numbers of easy negatives
- DAML taps their potential through adversarial hard negative generation
- The synthetic hard negatives provide essential complements for effective metric learning

