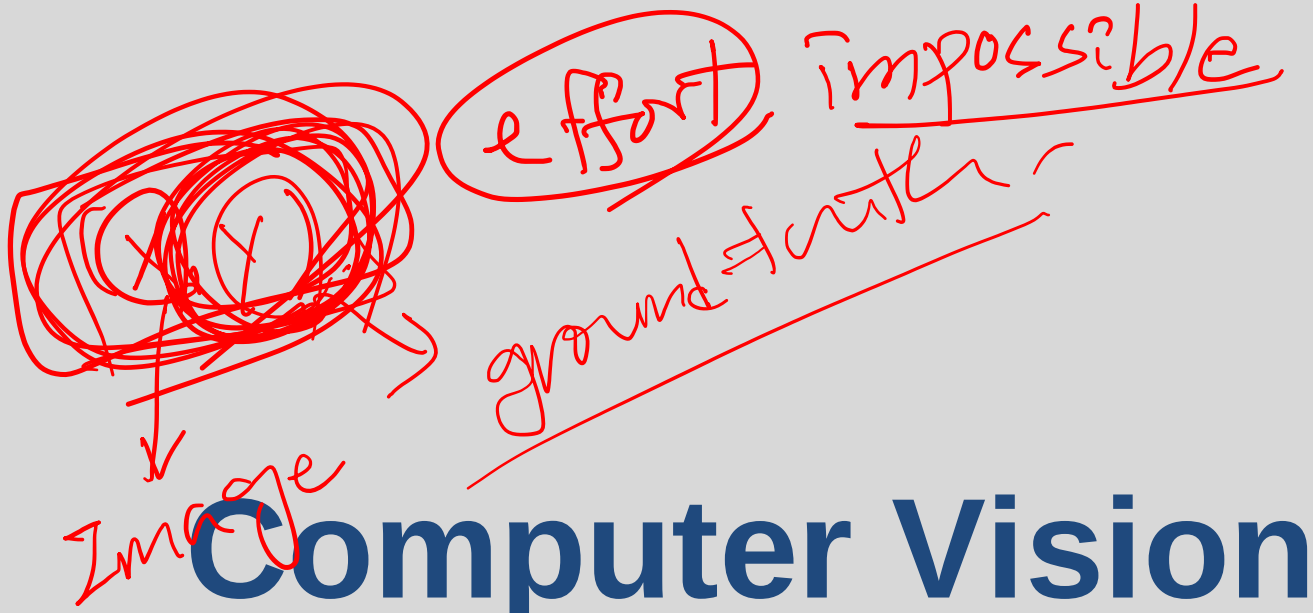
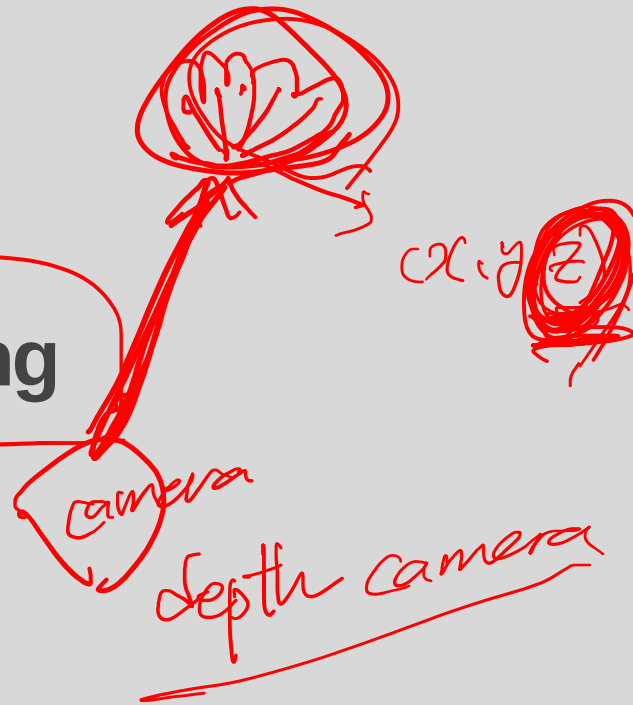


Computer Vision

Lecture 08: Data-efficient Training



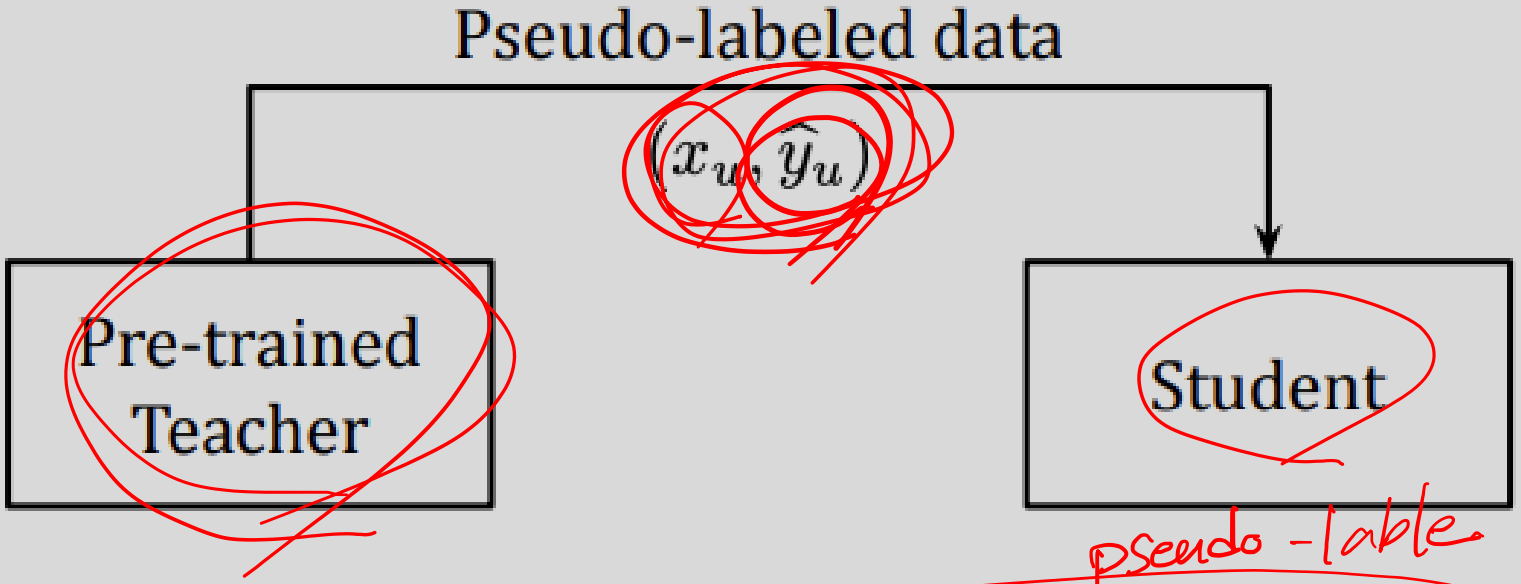
Pseudo labels

- Networks are trained in a supervised fashion jointly with labeled and unlabeled data.

- Pseudo-Labels are target classes for unlabeled data predicted from another network as if they were true labels.

Pseudo labels

self-training



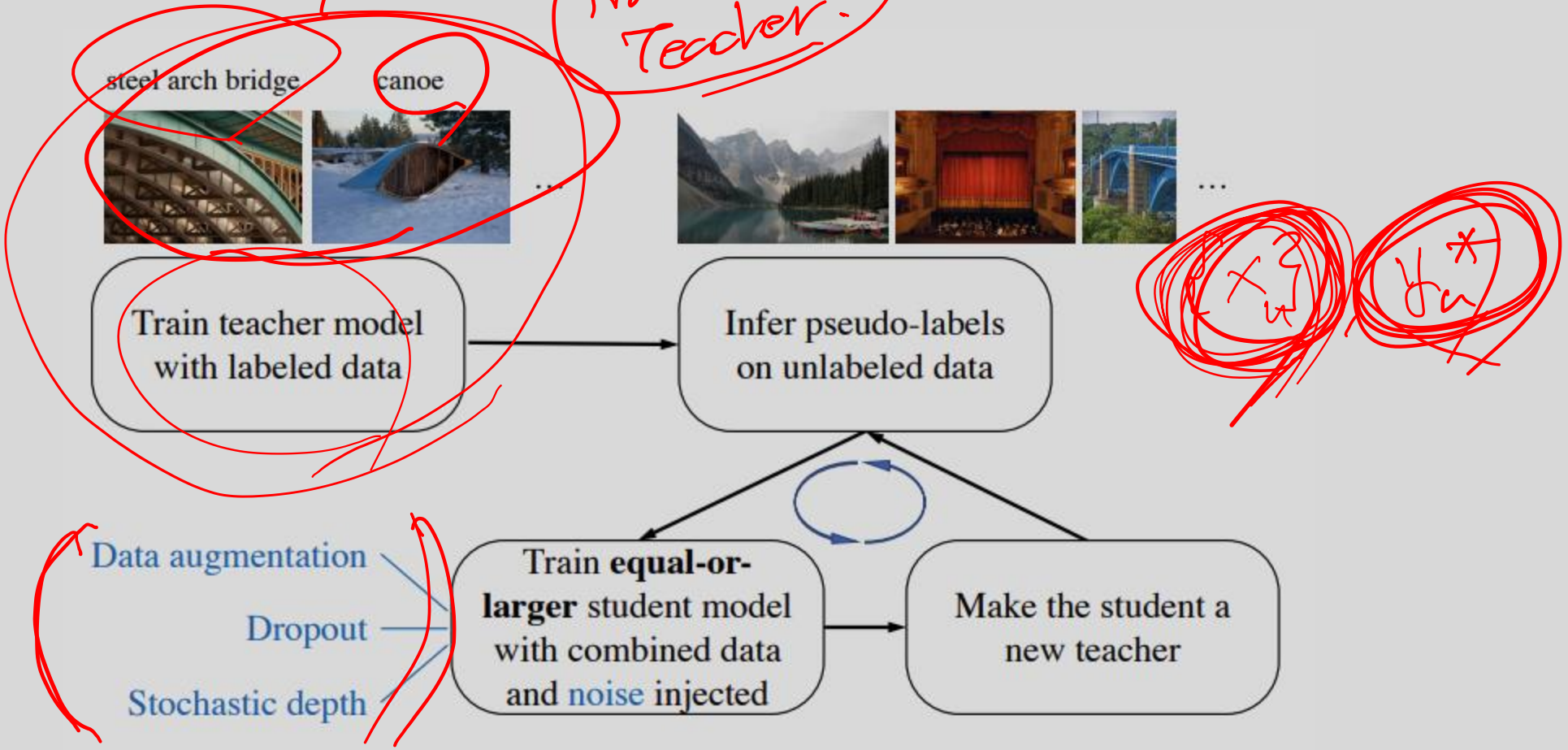
pseudo-label

S(·).

$$\theta_S^{\mathrm{PL}} = \underset{\theta_S}{\operatorname{argmin}} \; \mathbb{E}_{x_u}\Big[\mathrm{CE}\big(T(x_u;\theta_T), S(x_u;\theta_S)\big)\Big]$$

$$:= \mathcal{L}_u\left(\theta_T, \theta_S\right)$$

Self-training



Self-training with noisy student improves imagenet classification, CVPR'20.

Self-training

Require: Labeled images $\{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$ and unlabeled images $\{\tilde{x}_1, \tilde{x}_2, ..., \tilde{x}_m\}$.

1: Learn teacher model θ_*^t which minimizes the cross entropy loss on labeled images

$$\frac{1}{n}\sum_{i=1}^{n} \ell(y_i, f^{noised}(x_i, \theta^t))$$

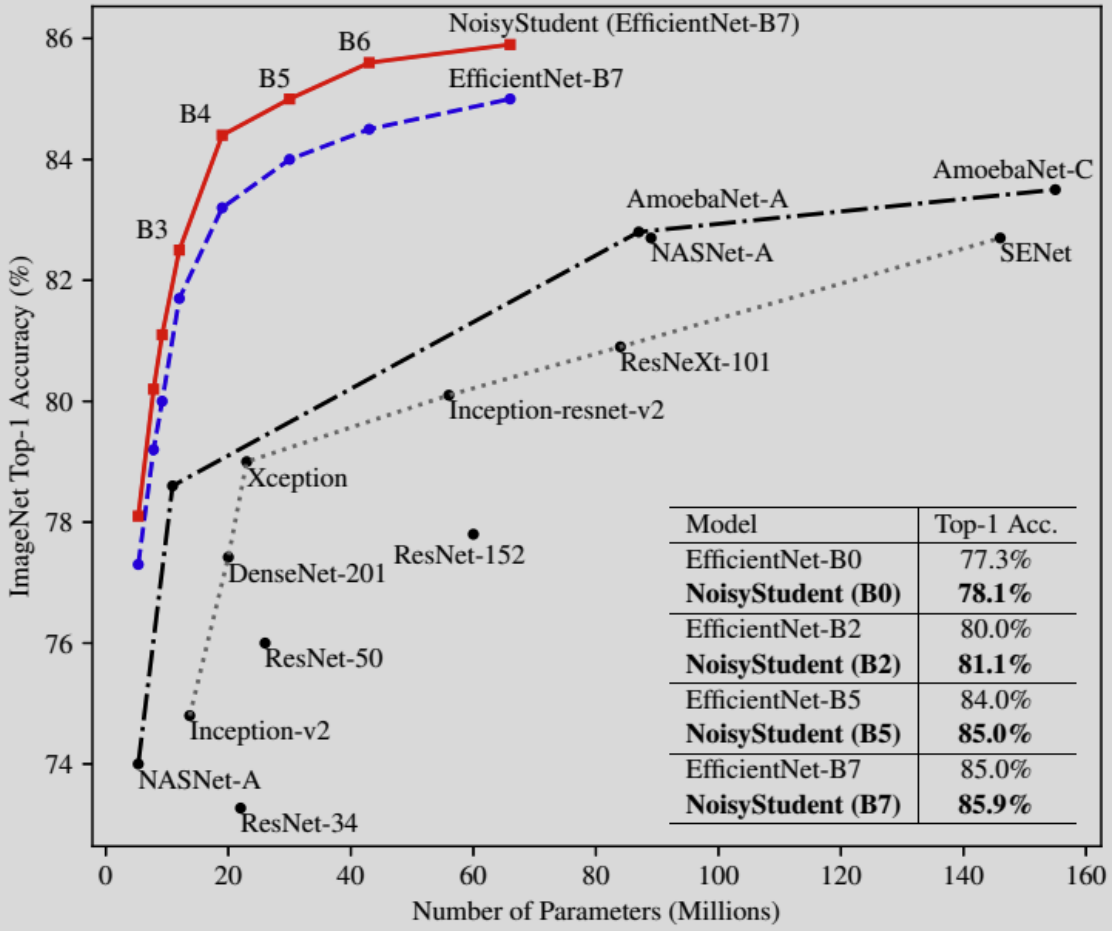
2: Use an unnoised teacher model to generate soft or hard pseudo labels for unlabeled images

$$\tilde{y}_i = f(\tilde{x}_i, \theta_*^t), \forall i = 1, \cdots, m$$

3: Learn an **equal-or-larger** student model θ_*^s which minimizes the cross entropy loss on labeled images and unlabeled images with **noise** added to the student model

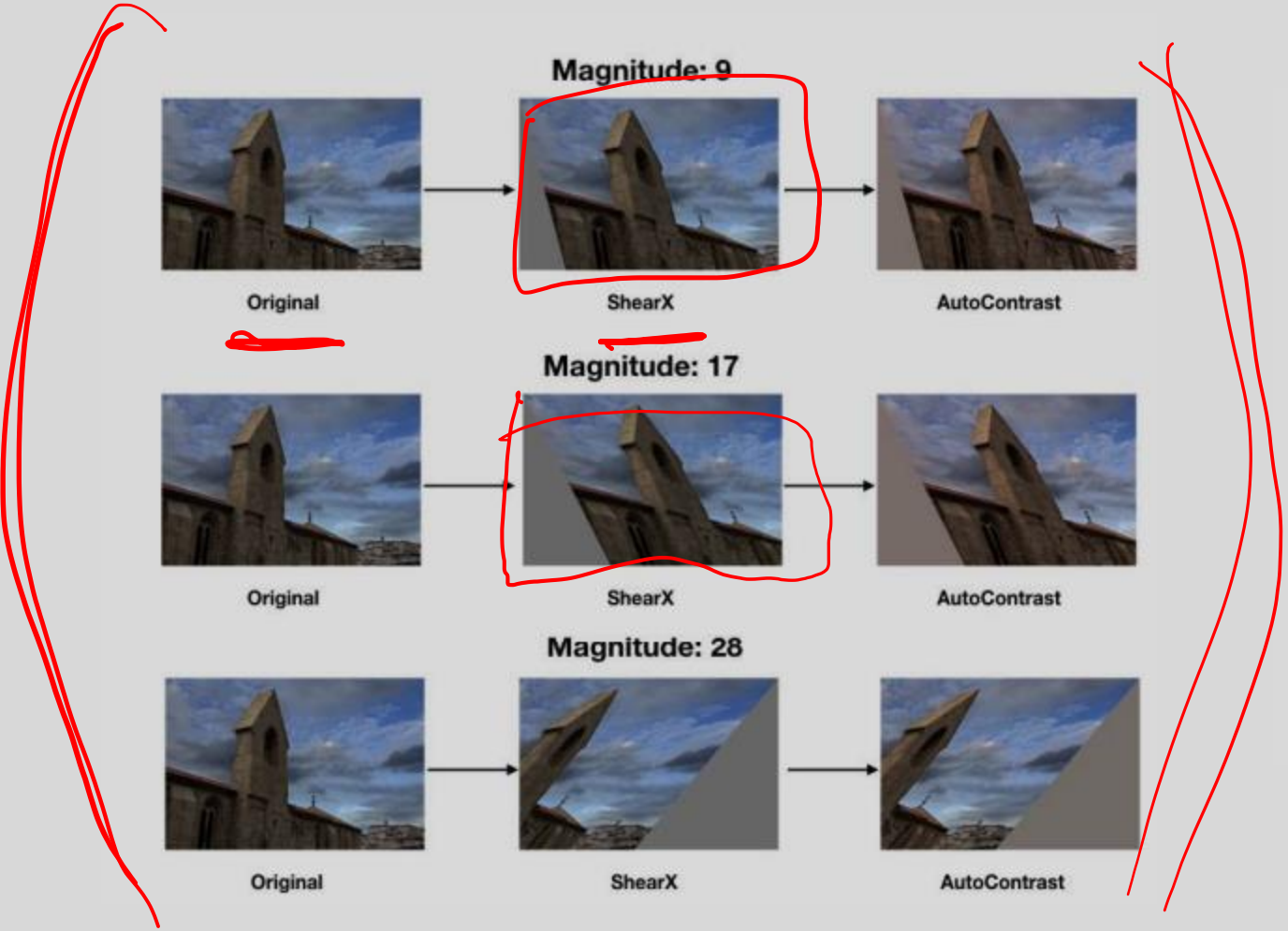
$$\frac{1}{n}\sum_{i=1}^{n} \ell(y_i, f^{noised}(x_i, \theta^s)) + \frac{1}{m}\sum_{i=1}^{m} \ell(\tilde{y}_i, f^{noised}(\tilde{x}_i, \theta^s))$$

4: Iterative training: Use the student as a teacher and go back to step 2.



Model	Top-1 Acc.
EfficientNet-B0	77.3%
NoisyStudent (B0)	**78.1%**
EfficientNet-B2	80.0%
NoisyStudent (B2)	**81.1%**
EfficientNet-B5	84.0%
NoisyStudent (B5)	**85.0%**
EfficientNet-B7	85.0%
NoisyStudent (B7)	**85.9%**

Self-training (Noise)



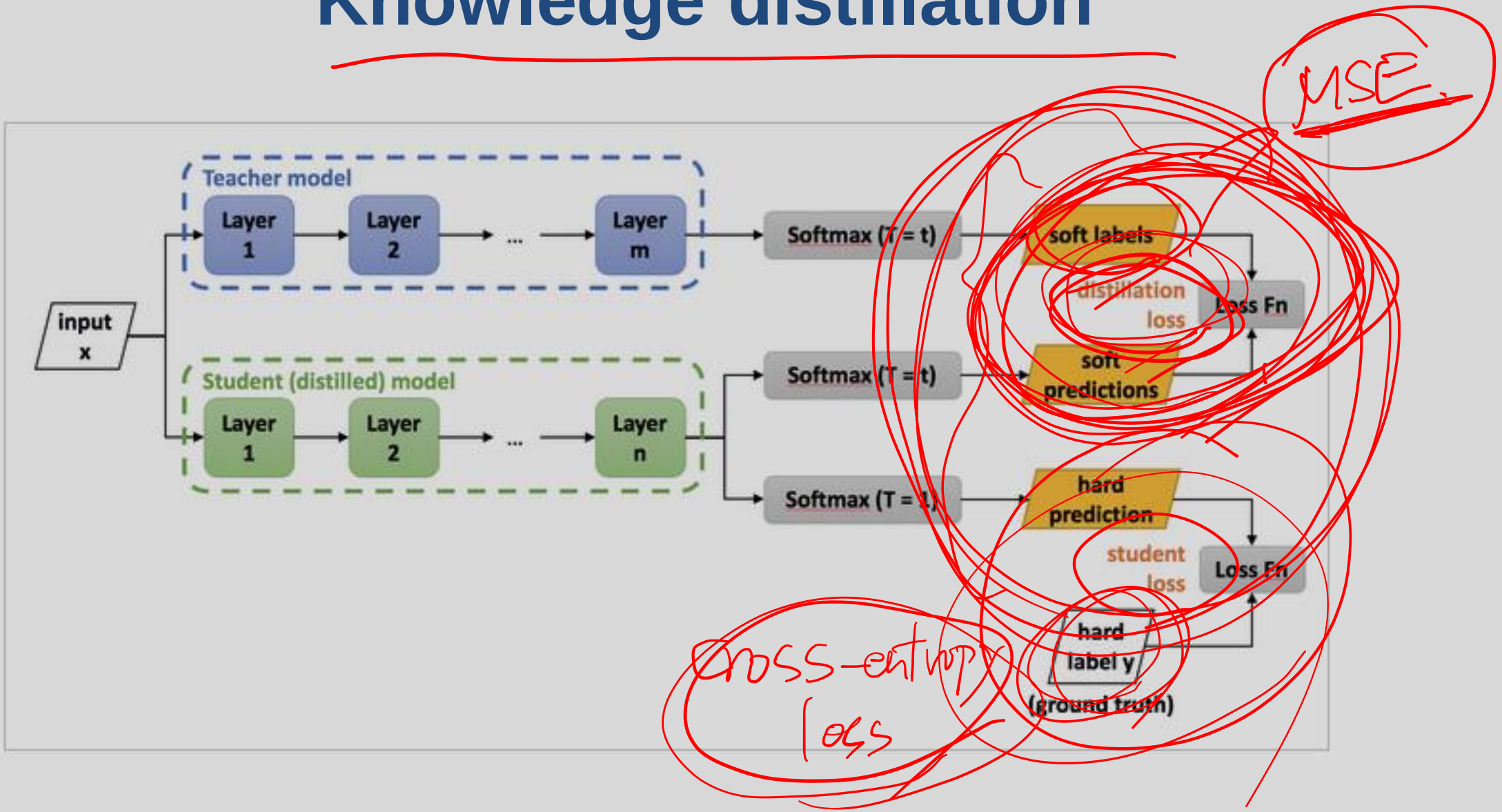

```
transforms = [
'Identity', 'AutoContrast', 'Equalize', 'Rotate',
    'Solarize', 'Color',
'Posterize', 'Contrast', 'Brightness', 'Sharpness',
    'ShearX', 'ShearY',
'TranslateX', 'TranslateY']

def randaugment(N, M):
"""Generate a set of distortions.

  Args:
    N: Number of augmentation transformations to apply
        sequentially.
    M: Magnitude for all the transformations.
"""

  sampled_ops = np.random.choice(transforms, N)
  return [(op, M) for op in sampled_ops]
```

Knowledge distillation (KD)

- The teacher network provides a richer supervisory signal than the data supervision.

- KD guides the training of a student network by encouraging it to mimic some aspect of a teacher network.

Knowledge distillation



Knowledge distillation

cow	dog	cat	car
0	1	0	0

hard label.

cow	dog	cat	car
10^{-6}	.9	.1	10^{-9}

`Dark knowledge'

Which classes the teacher found more similar to the predicted class.

cow	dog	cat	car
.05	.3	.2	.005

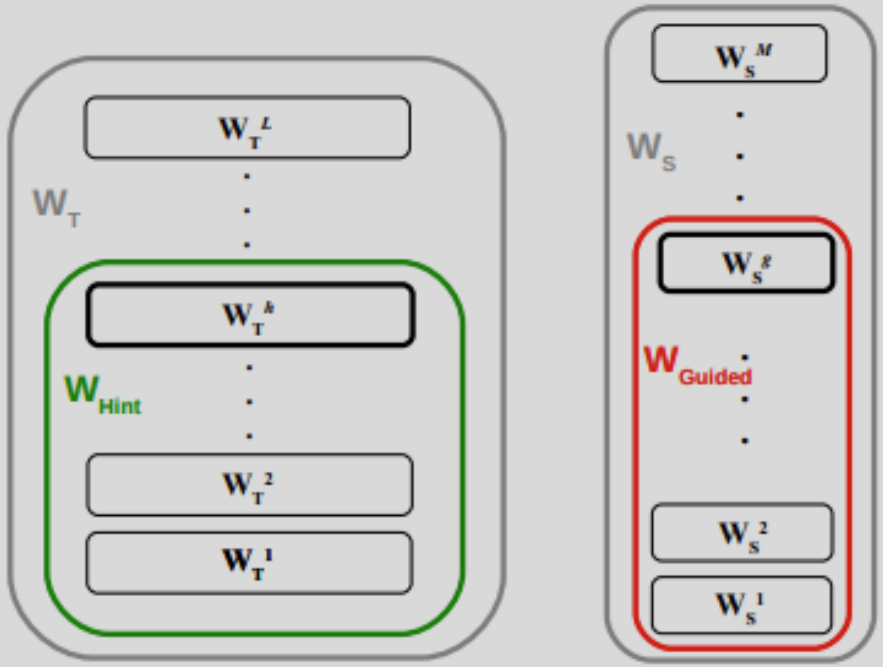
soft label. (prob.)

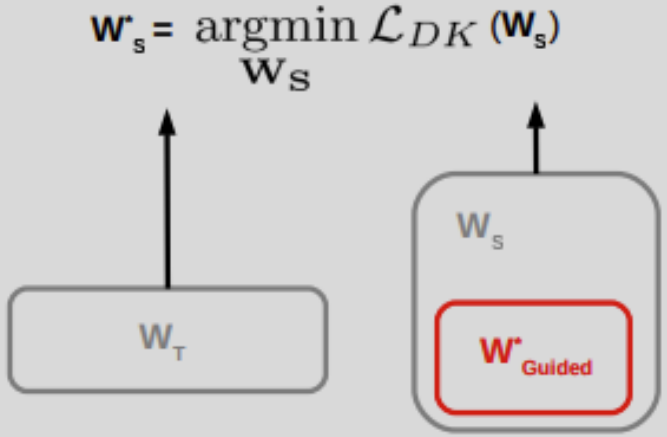
$$q_i = \frac{exp(z_i/T)}{\sum_j exp(z_j/T)}$$

q : probability
T : temperature

Softmax.

Knowledge distillation





$$\mathrm{P}_{\mathrm{T}}^{\tau} = \mathrm{softmax}\left(\frac{\mathbf{a}_T}{\tau}\right), \quad \mathrm{P}_{\mathrm{S}}^{\tau} = \mathrm{softmax}\left(\frac{\mathbf{a}_S}{\tau}\right) \quad \mathcal{L}_{KD}(\mathbf{W_S}) = \mathcal{H}(\mathbf{y_{true}}, \mathrm{P_S}) + \lambda \mathcal{H}(\mathrm{P}_{\mathrm{T}}^{\tau}, \mathrm{P}_{\mathrm{S}}^{\tau})$$

CE

KD Loss.

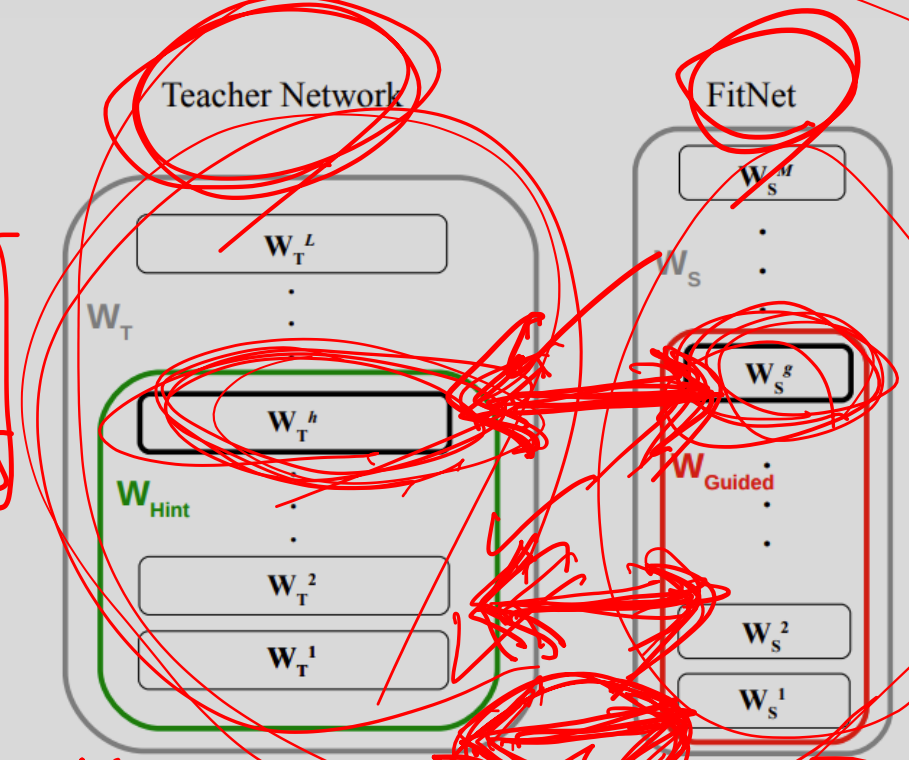
Distilling the Knowledge in a Neural Network, NeurIPS'14

Hints

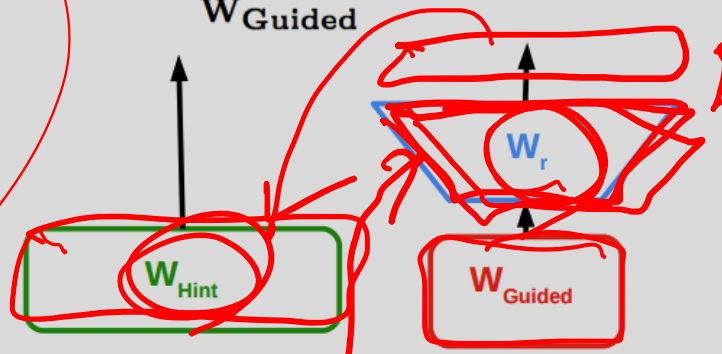
- KD fails when the depth of the student network getting deeper.

- *Hint* is defined as the output of a teacher's hidden layer.

Learning hints



$$W^*_{Guided} = \underset{W_{Guided}}{\operatorname{argmin}} \mathcal{L}_{HT}(W_{Guided}, W_r)$$



$$\mathcal{L}_{HT}(\mathbf{W_{Guided}}, \mathbf{W_r}) = \frac{1}{2}||u_h(\mathbf{x}; \mathbf{W_{Hint}}) - r(u_g(\mathbf{x}; \mathbf{W_{Guided}}); \mathbf{W_r})||^2$$

# of object

FitNets: hints for thin deep nets, ICLR'15.

Learning hints

Input: $\mathbf{W_S}, \mathbf{W_T}, g, h$
Output: $\mathbf{W_S^*}$

1: $\mathbf{W_{Hint}} \leftarrow \{\mathbf{W_T}^1, \ldots, \mathbf{W_T}^h\}$
2: $\mathbf{W_{Guided}} \leftarrow \{\mathbf{W_S}^1, \ldots, \mathbf{W_S}^g\}$
3: Intialize $\mathbf{W_r}$ to small random values
4: $\mathbf{W^*_{Guided}} \leftarrow \underset{\mathbf{W_{Guided}}}{\text{argmin}}\ \mathcal{L}_{HT}(\mathbf{W_{Guided}}, \mathbf{W_r})$
5: $\{\mathbf{W_S}^1, \ldots, \mathbf{W_S}^g\} \leftarrow \{\mathbf{W_{Guided}}^{*1}, \ldots, \mathbf{W_{Guided}}^{*g}\}$
6: $\mathbf{W_S^*} \leftarrow \underset{\mathbf{W_S}}{\text{argmin}}\, \mathcal{L}_{KD}(\mathbf{W_S})$

Intermediate representation

Algorithm	# params	Accuracy
Compression		
FitNet	~2.5M	**91.61%**
Teacher	~9M	90.18%
Mimic single	~54M	84.6%
Mimic single	~70M	84.9%
Mimic ensemble	~70M	85.8%
State-of-the-art methods		
Maxout		90.65%
Network in Network		91.2%
Deeply-Supervised Networks		**91.78%**
Deeply-Supervised Networks (19)		88.2%

Table 1: Accuracy on CIFAR-10

Algorithm	# params	Accuracy
Compression		
FitNet	~2.5M	**64.96%**
Teacher	~9M	63.54%
State-of-the-art methods		
Maxout		61.43%
Network in Network		64.32%
Deeply-Supervised Networks		**65.43%**

Table 2: Accuracy on CIFAR-100

Intermediate representation

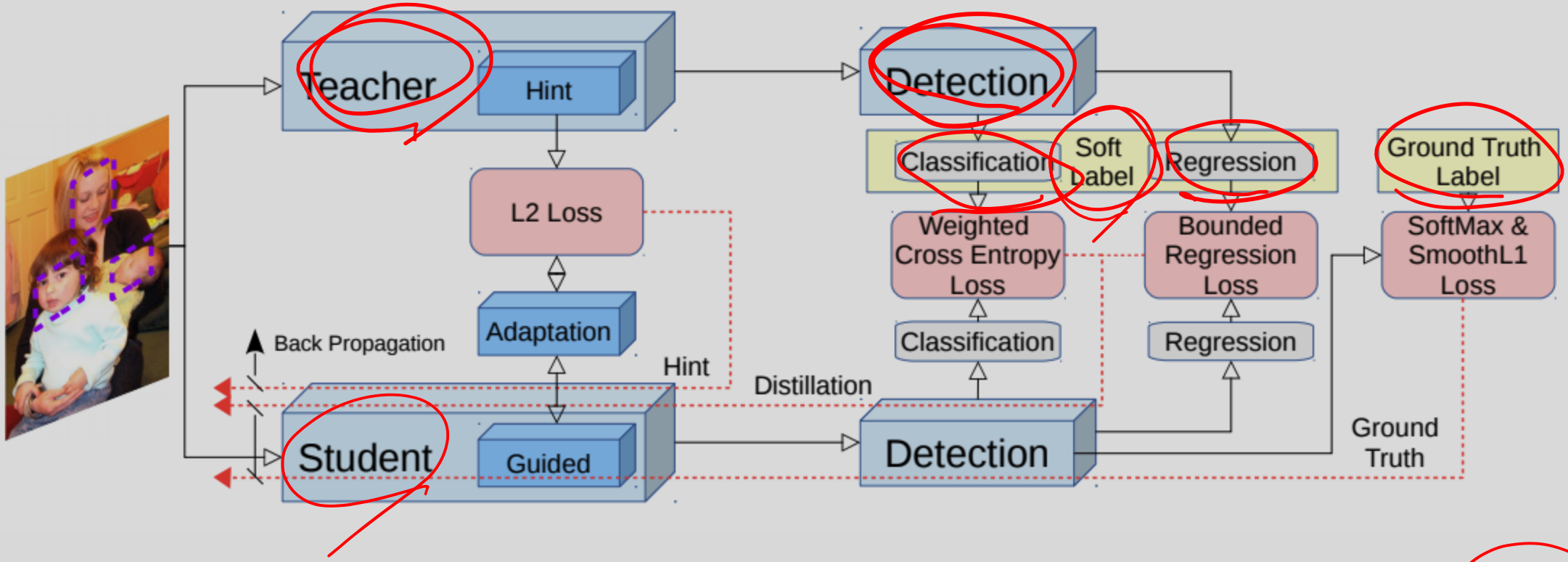
Algorithm	# params	Misclass
Compression		
FitNet	~1.5M	2.42%
Teacher	~4.9M	**2.38%**
State-of-the-art methods		
Maxout		2.47%
Network in Network		2.35%
Deeply-Supervised Networks		**1.92%**

Table 3: SVHN error

Algorithm	# params	Misclass
Compression		
Teacher	~361K	0.55%
Standard backprop	~30K	1.9%
KD	~30K	0.65%
FitNet	~30K	**0.51%**
State-of-the-art methods		
Maxout		0.45%
Network in Network		0.47%
Deeply-Supervised Networks		**0.39%**

Table 4: MNIST error

KD for object detection



Learning Efficient Object Detection Models with Knowledge Distillation, NIPS'17.

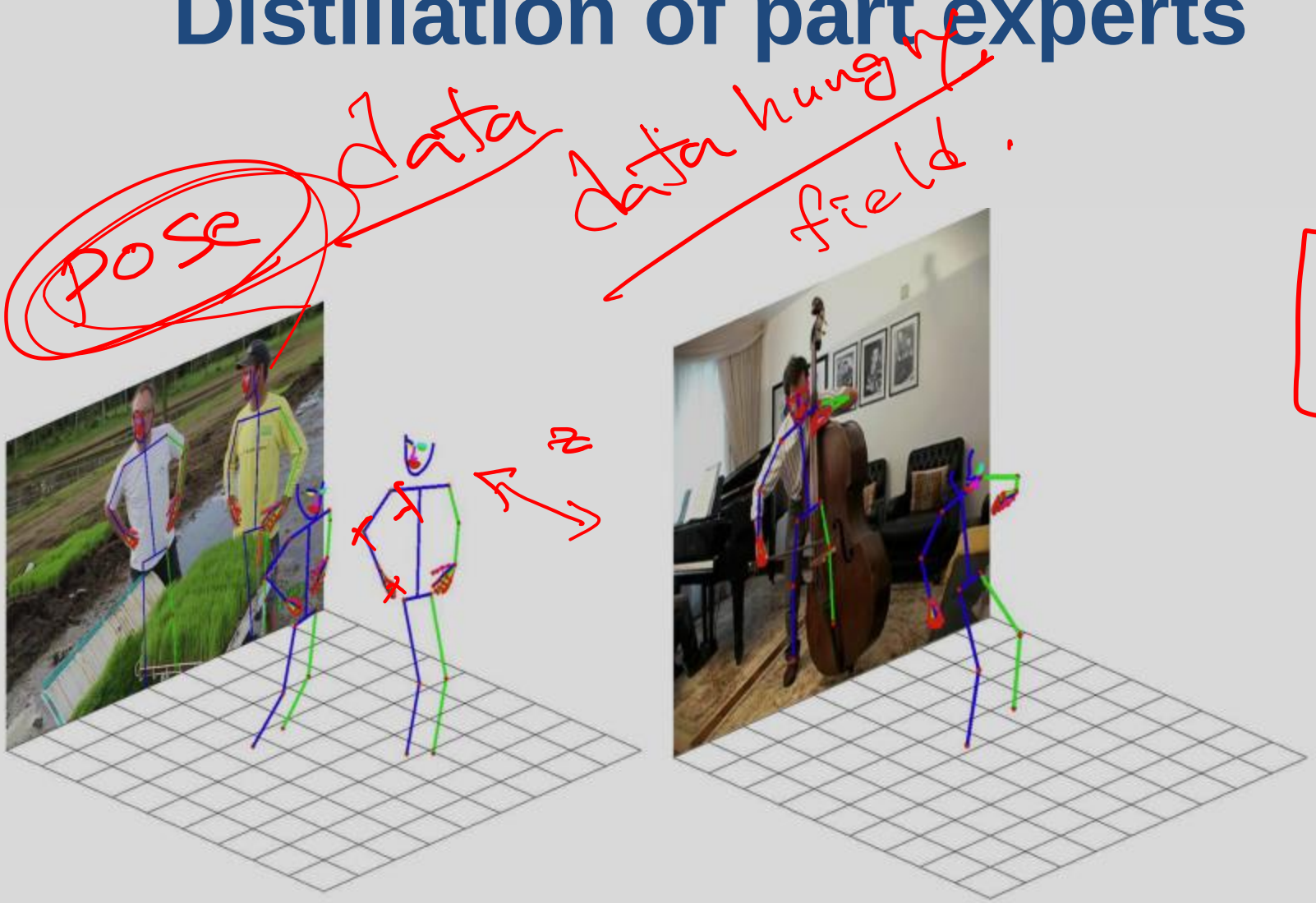
KD for object detection

		Baseline	Distillation	Hint	Distillation + Hint
PASCAL	Trainval	79.6	78.3	80.9	83.5
	Test	54.7	58.4	58	59.4
COCO	Train	45.3	45.4	47.1	49.6
	Val	25.4	26.1	27.8	28.3

learning on different datasets with Tucker and VGG16 pair.

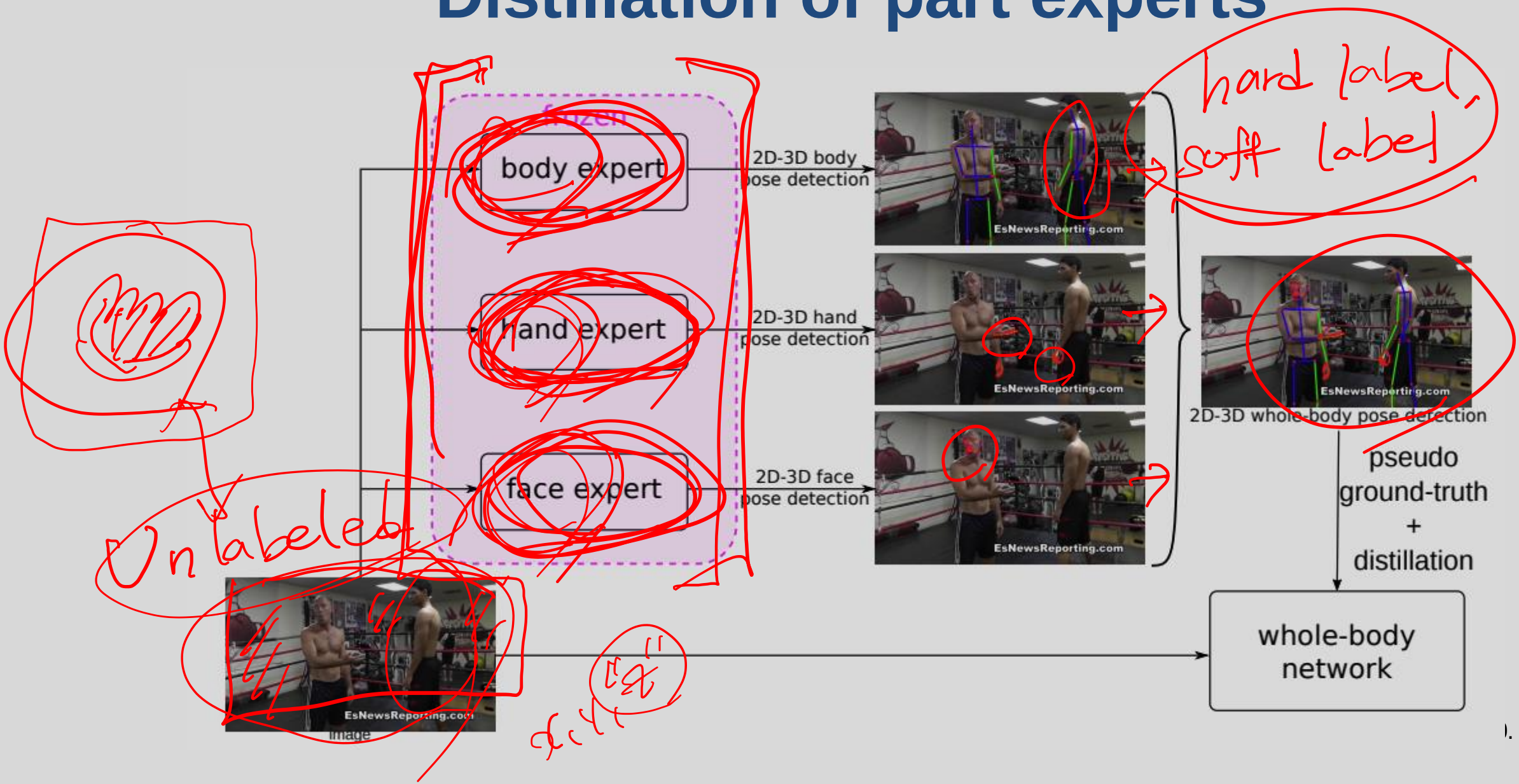
Learning Efficient Object Detection Models with Knowledge Distillation, NIPS'17.

Distillation of part experts



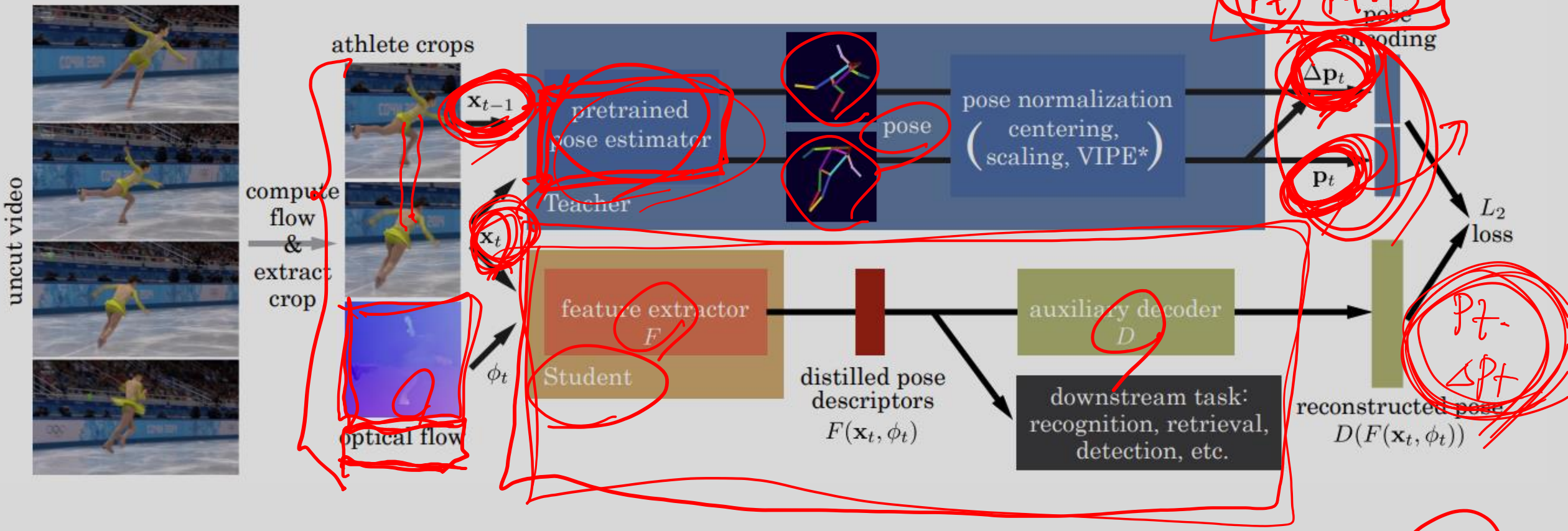
DOPE: Distillation Of Part Experts for whole-body 3D pose estimation in the wild, ECCV'20.

Distillation of part experts



Distillation of part experts

Video pose distillation



Video Pose Distillation for Few-Shot, Fine-Grained Sports Action Recognition, ICCV'21.

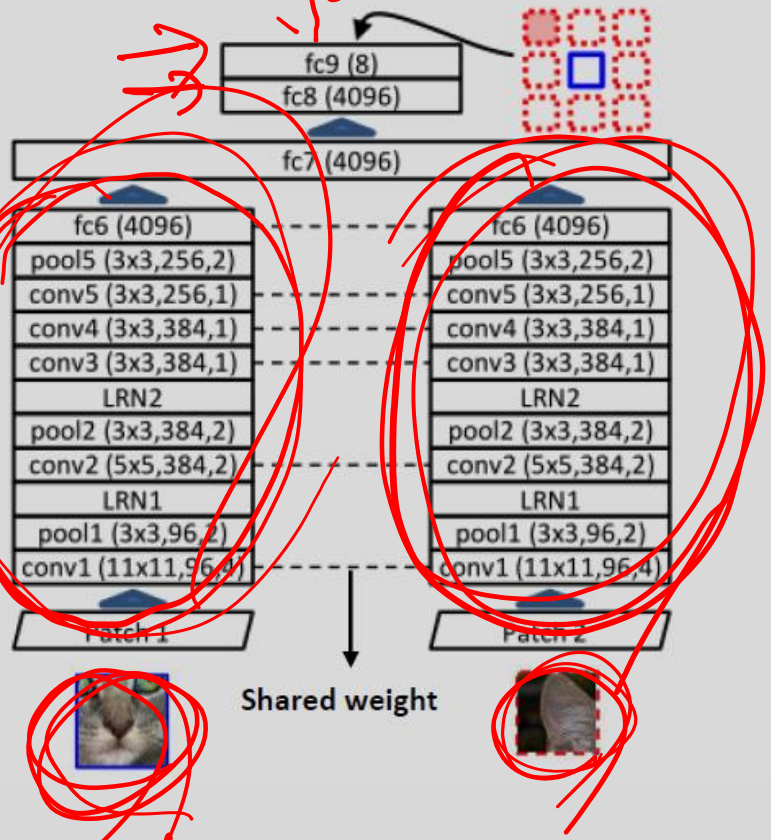
Video pose distillation

$$\Delta \mathbf{p}_t := \mathbf{p}_t - \mathbf{p}_{t-1}$$

$$\underset{F,D}{\text{minimize}} \sum_{t=1}^{N} \left\| D(F(\mathbf{x}_t, \phi_t)) - \begin{bmatrix} \mathbf{p}_t \\ \Delta \mathbf{p}_t \end{bmatrix} \right\|_2^2$$

Video Pose Distillation for Few-Shot, Fine-Grained Sports Action Recognition, ICCV'21.

Self-supervised learning



Unsupervised Visual Representation Learning by Context Prediction, *ICCV 2015*

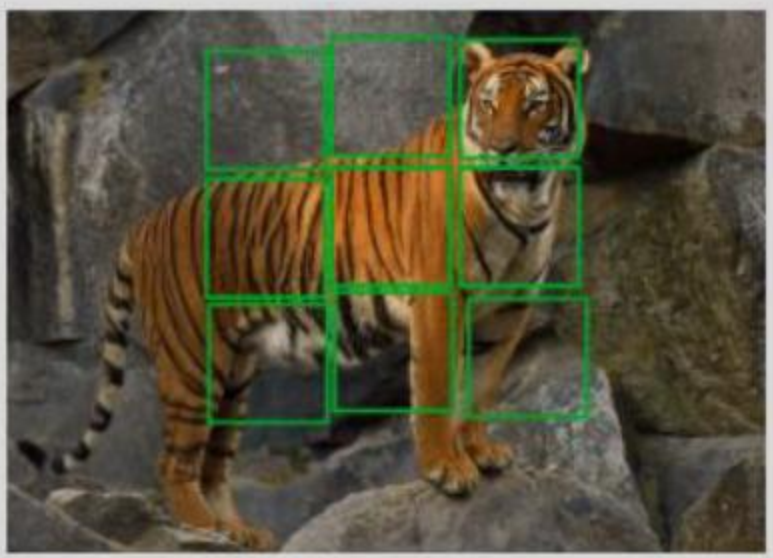
Self-supervised learning

Context Prediction: Predict relative positions of patches

- You have to understand the object to solve this problem!
- Be aware of trivial solution! CNN is especially good at it

Unsupervised Visual Representation Learning by Context Prediction. *ICCV 2015*

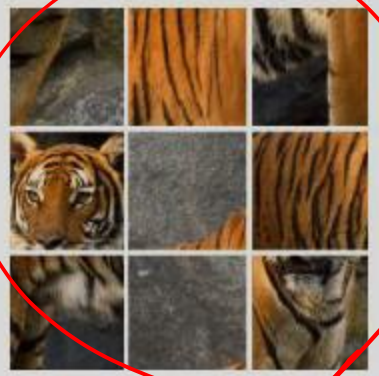
Self-supervised learning



Sample image

Extract 9 patches

Permutation
9, 5, 8, 3, 2, 4, 7, 1, 6



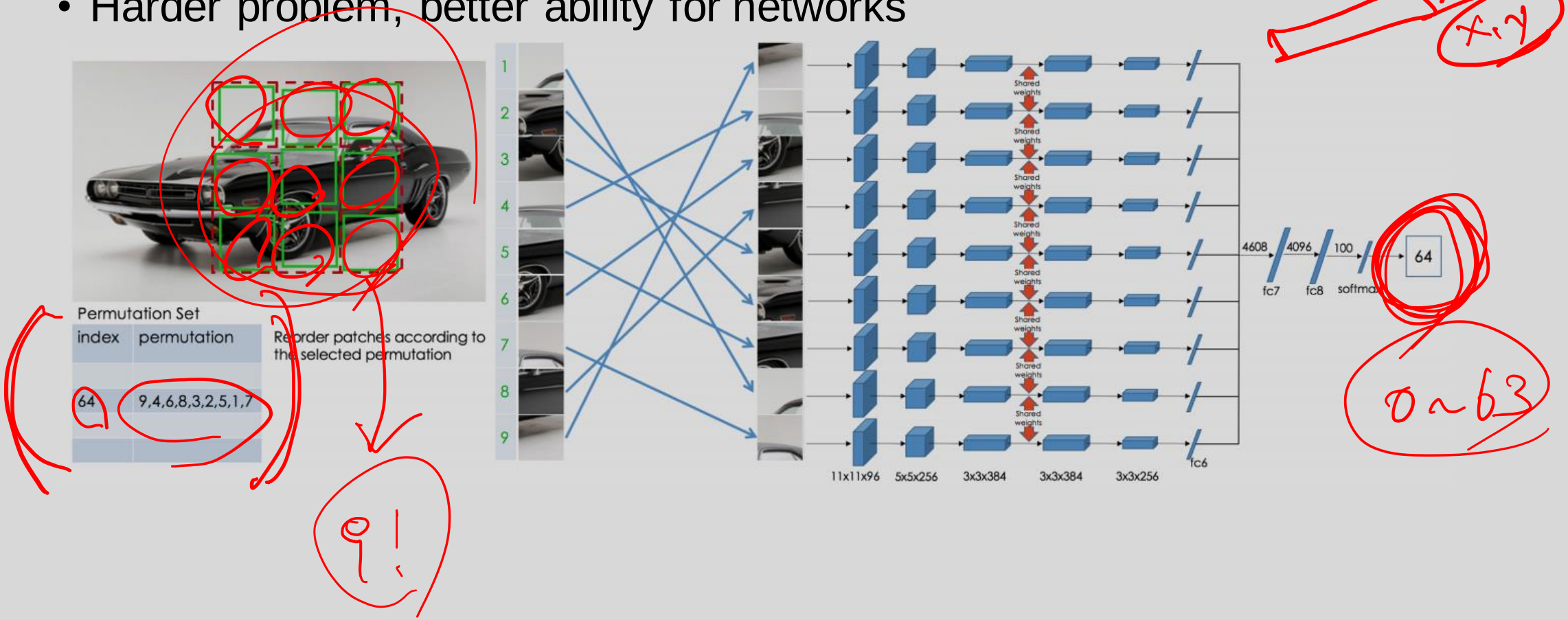
Permutate 9 patches

Unsupervised learning of visual representations by solving jigsaw puzzles. In *ECCV 2016*.

Self-supervised learning

Solving the Jigsaw

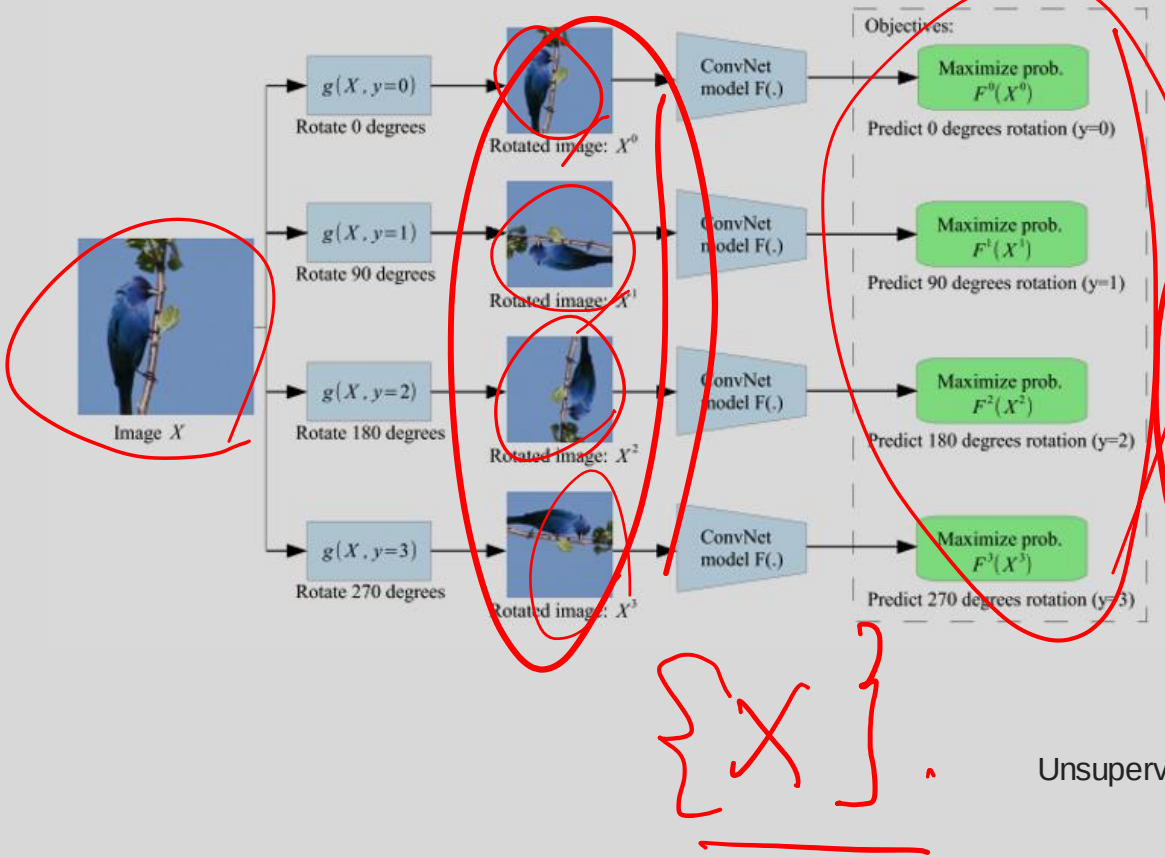
- Use stronger supervision, solve the real jigsaw problem
- Harder problem, better ability for networks



Self-supervised learning

Predicting the rotations

- Predict the 4 types of rotation angles.



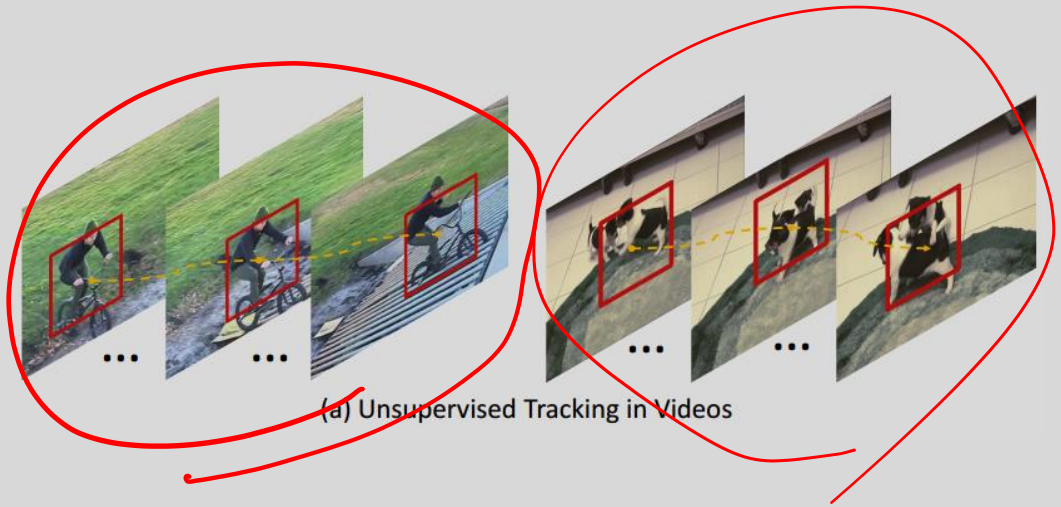
Method	Conv1	Conv2	Conv3	Conv4	Conv5
ImageNet labels	19.3	36.3	44.2	48.3	50.5
Random	11.6	17.1	16.9	16.3	14.1
Random rescaled Krähenbühl et al. (2015)	17.5	23.0	24.5	23.2	20.6
Context (Doersch et al., 2015)	16.2	23.3	30.2	31.7	29.6
Context Encoders (Pathak et al., 2016b)	14.1	20.7	21.0	19.8	15.5
Colorization (Zhang et al., 2016a)	12.5	24.5	30.4	31.5	30.3
Jigsaw Puzzles (Noroozi & Favaro, 2016)	18.2	28.8	34.0	33.9	27.1
BIGAN (Donahue et al., 2016)	17.7	24.5	31.0	29.9	28.0
Split-Brain (Zhang et al., 2016b)	17.7	29.3	35.4	35.2	32.8
Counting (Noroozi et al., 2017)	18.0	30.6	34.3	32.5	25.7
(Ours) RotNet	**18.8**	**31.7**	**38.7**	**38.2**	**36.5**

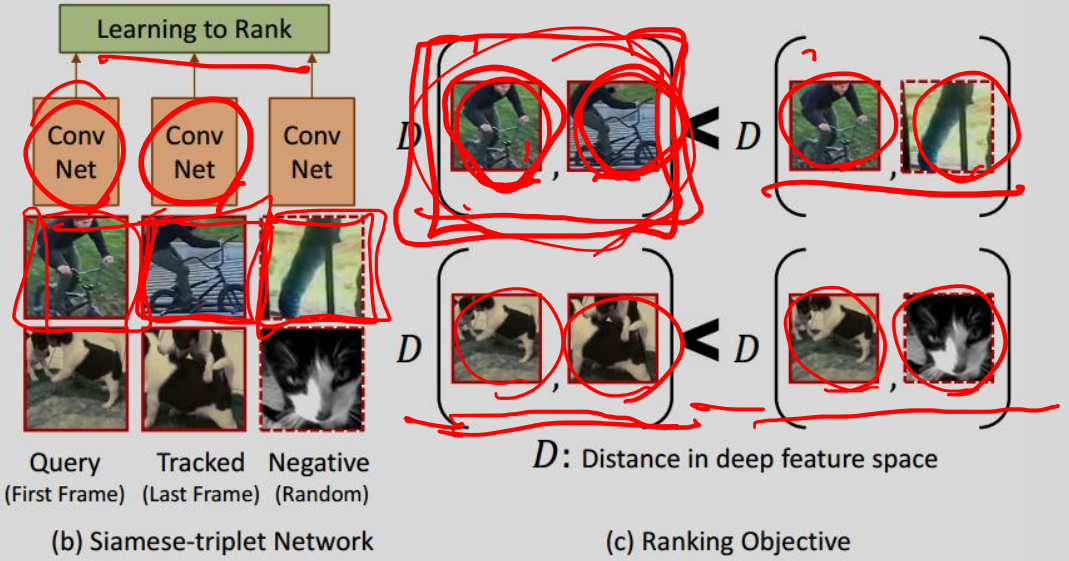
ImageNet classification top-1 accuracy

Unsupervised representation learning by predicting image rotations. In *ICLR 2018*.

Self-supervision for video

Find corresponding pairs using visual tracking



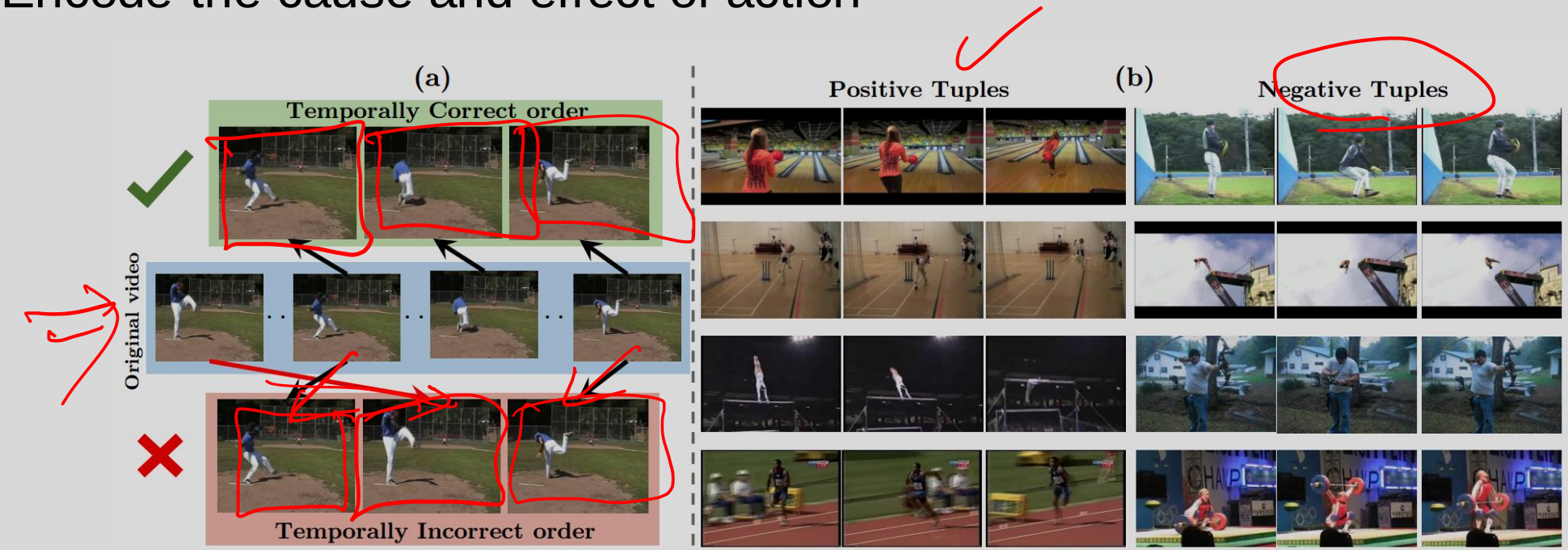


Wang, X., & Gupta, A. (2015). Unsupervised learning of visual representations using videos. In *ICCV2015*

Self-supervision for video

Is the temporal order of a video correct?

- Encode the cause and effect of action

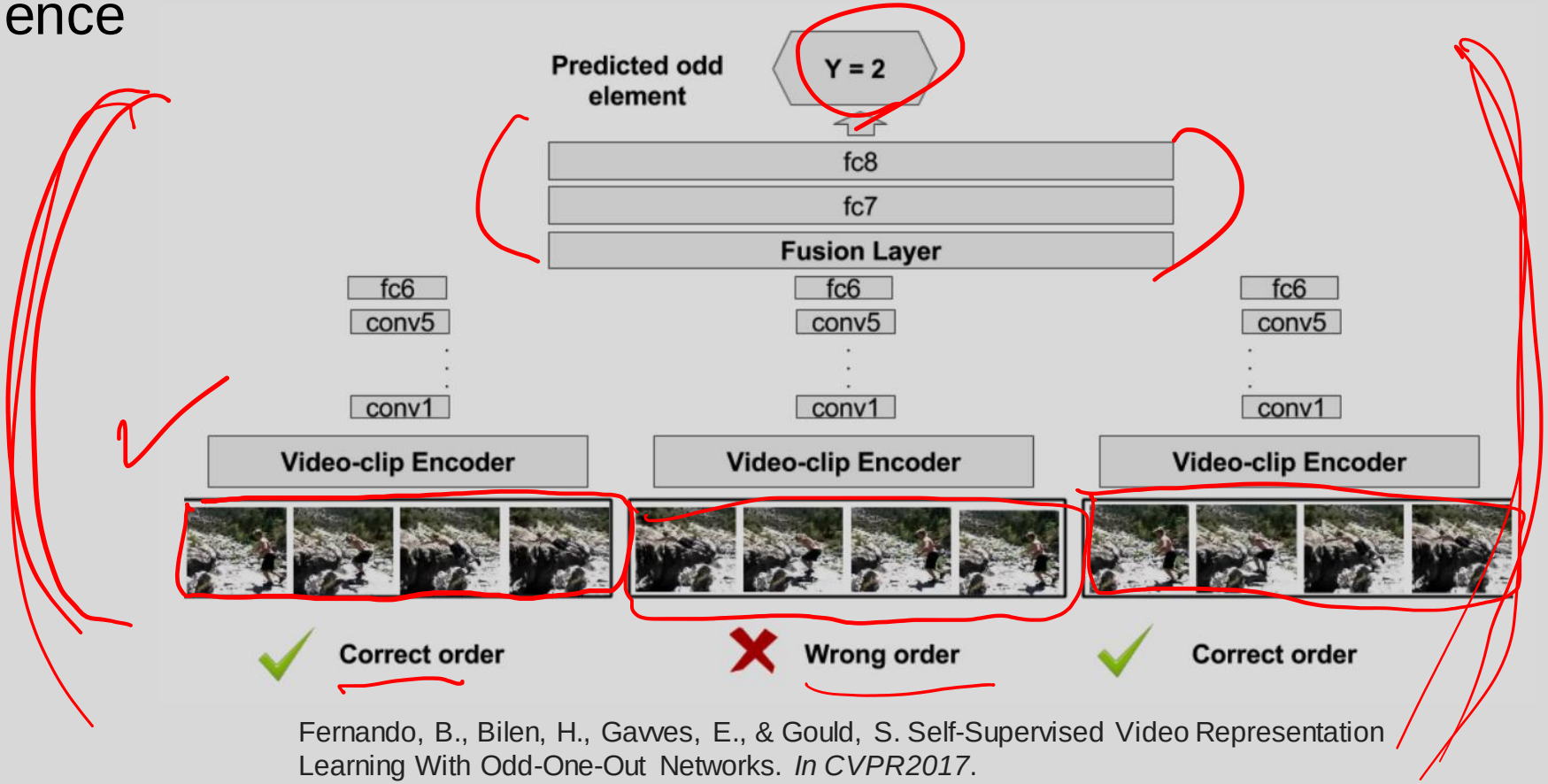


Misra, I., Zitnick, C. L., & Hebert, M. Shuffle and learn: unsupervised learning using temporal order verification. In *ECCV 2016*.

Self-supervision for video

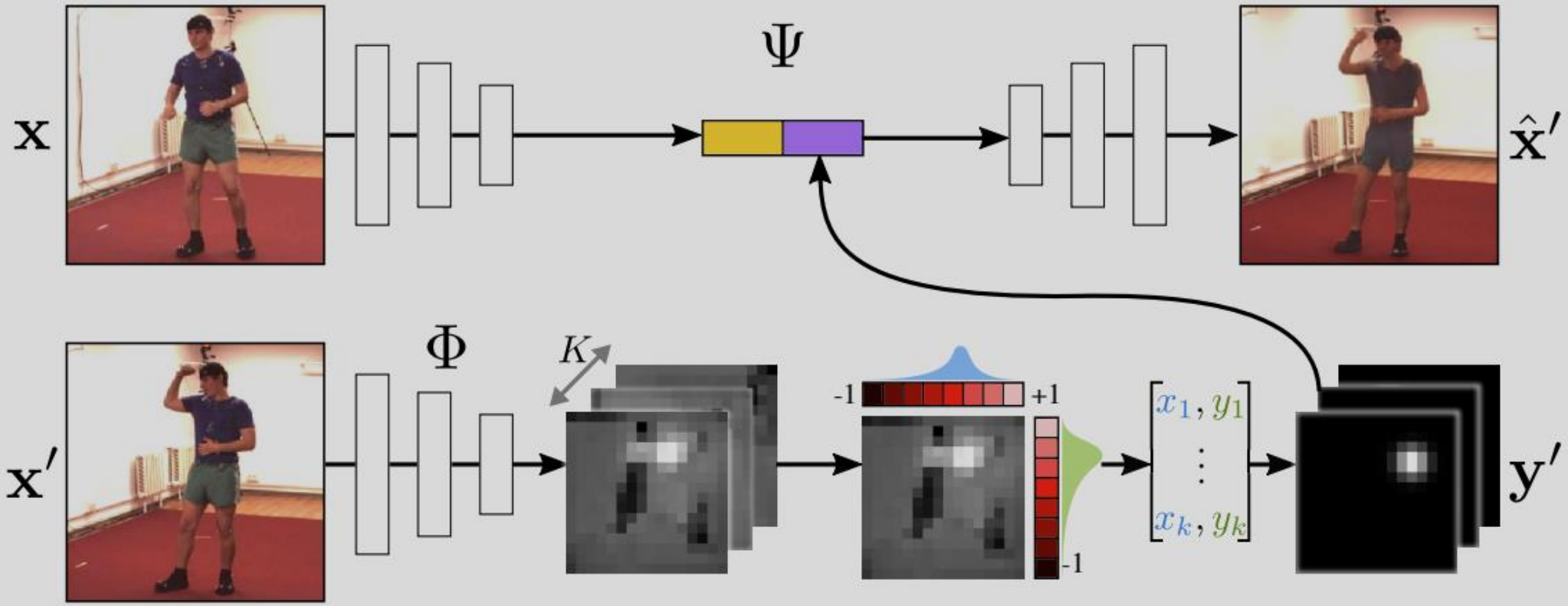
Is the temporal order of a video correct?

- Find the odd sequence



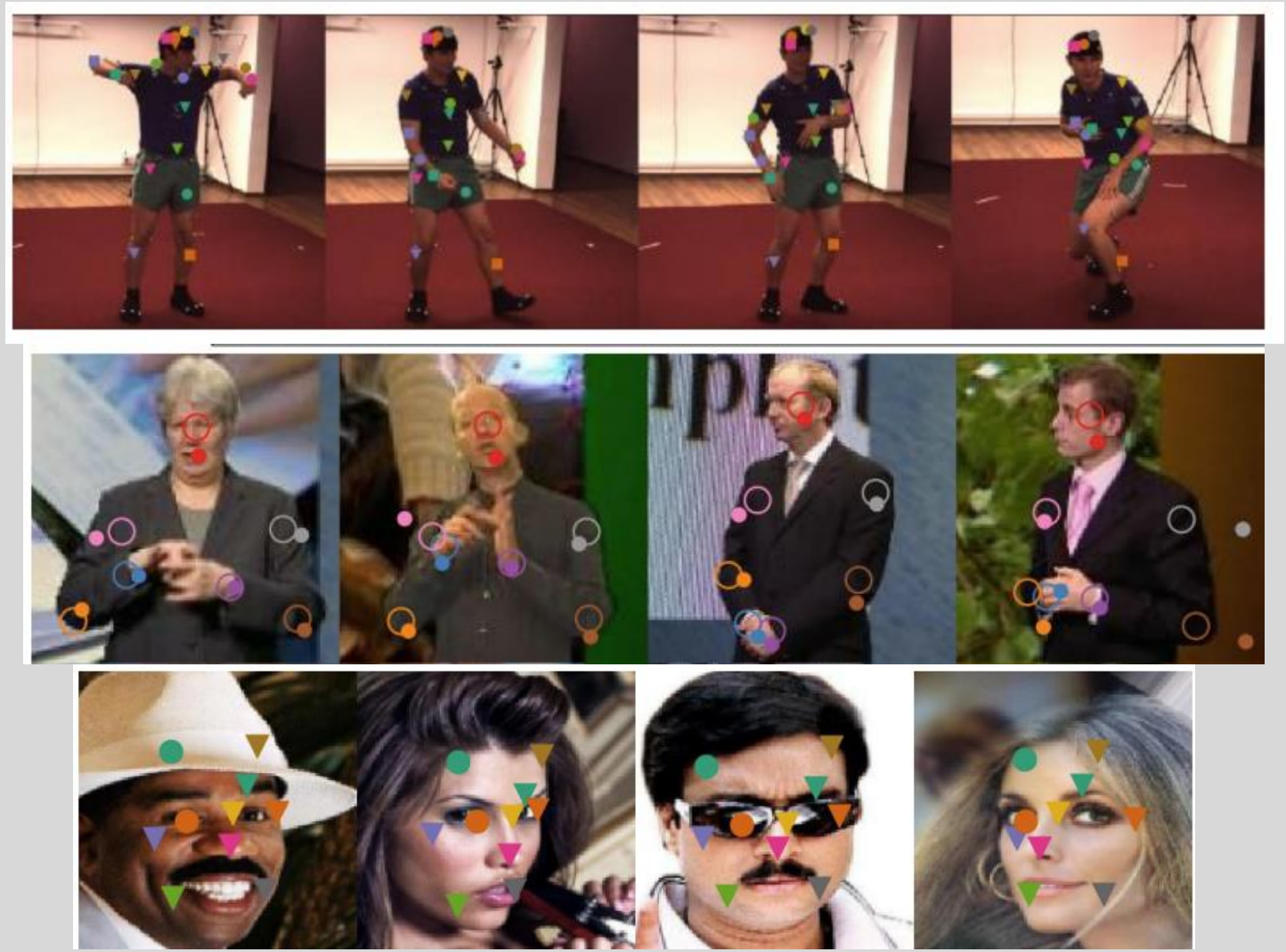
Fernando, B., Bilen, H., Gavves, E., & Gould, S. Self-Supervised Video Representation Learning With Odd-One-Out Networks. *In CVPR2017*.

Self-supervision for pose



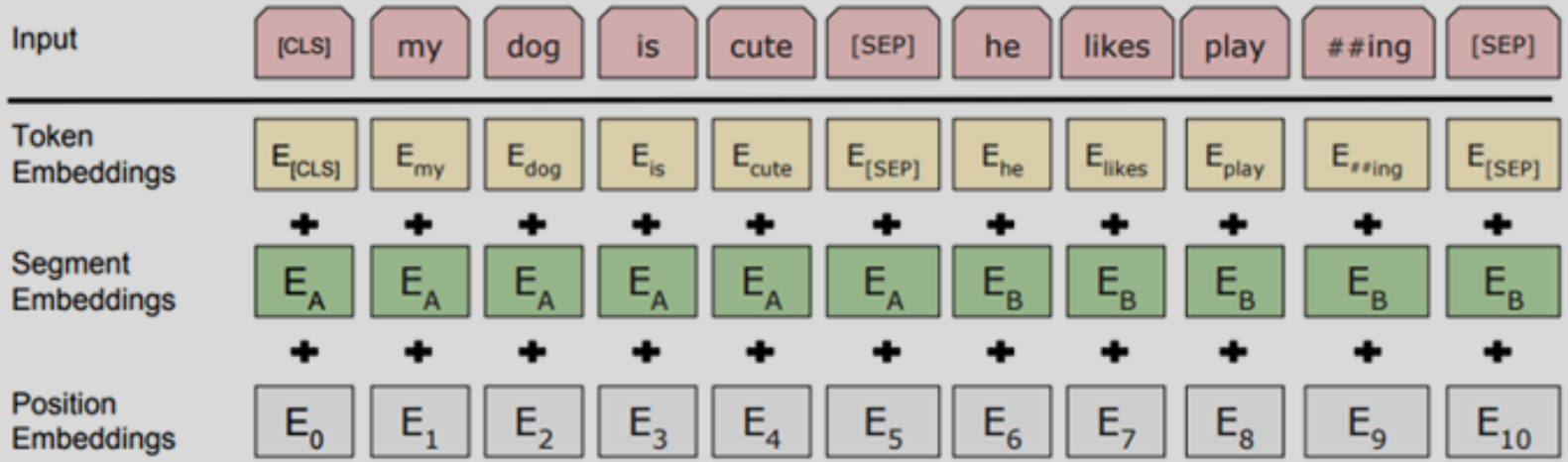
Unsupervised Learning of Object Landmarks through Conditional Image Generation, NeurIPS'18.

Self-supervision for pose

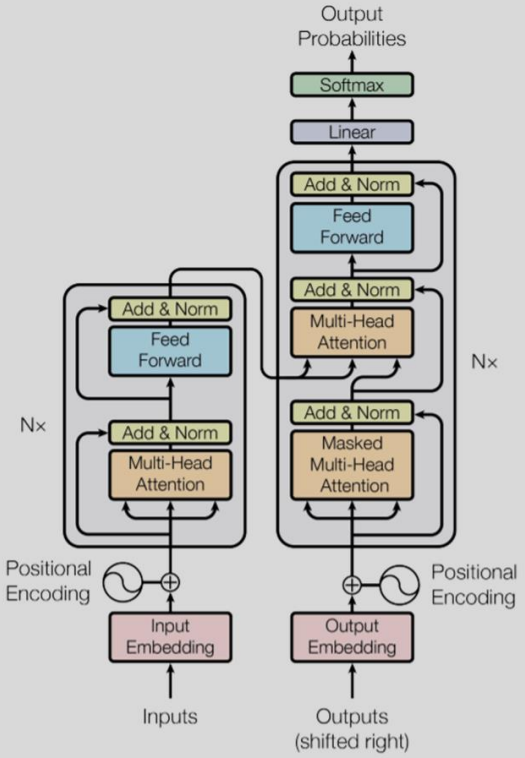


Self-supervised learning

- Self-supervision: Learning without tagged data.
- The method could be applied to any inputs.
  - Speech, image, video, text and etc.



Self-supervised learning



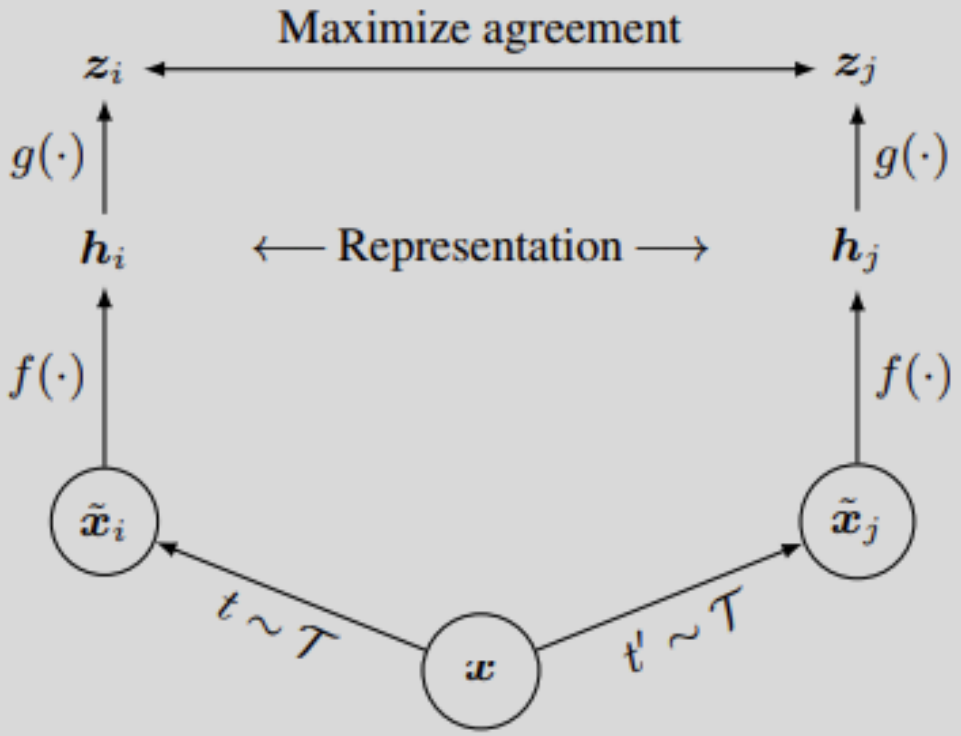
$$\text{Input} = \texttt{[CLS] the man went to [MASK] store [SEP]}$$
$$\texttt{he bought a gallon [MASK] milk [SEP]}$$
$$\text{Label} = \texttt{IsNext}$$

$$\text{Input} = \texttt{[CLS] the man [MASK] to the store [SEP]}$$
$$\texttt{penguin [MASK] are flight ##less birds [SEP]}$$
$$\text{Label} = \texttt{NotNext}$$

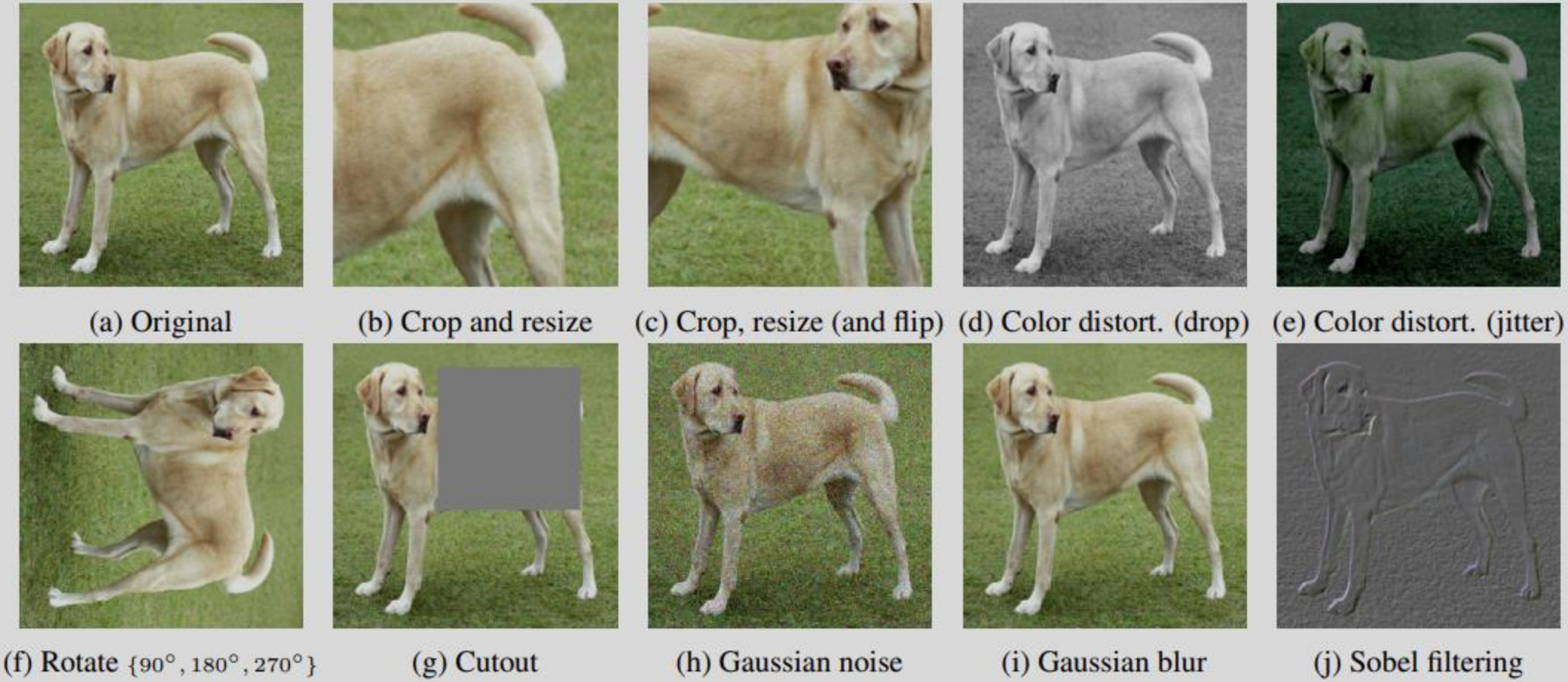
Transformer architecture is trained by 1) Masked language model, 2) Next sentence prediction

Contrastive learning

$$\ell_{i,j} = -\log \frac{\exp(\text{sim}(\boldsymbol{z}_i, \boldsymbol{z}_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(\text{sim}(\boldsymbol{z}_i, \boldsymbol{z}_k)/\tau)}$$



Contrastive learning



(a) Original (b) Crop and resize (c) Crop, resize (and flip) (d) Color distort. (drop) (e) Color distort. (jitter)

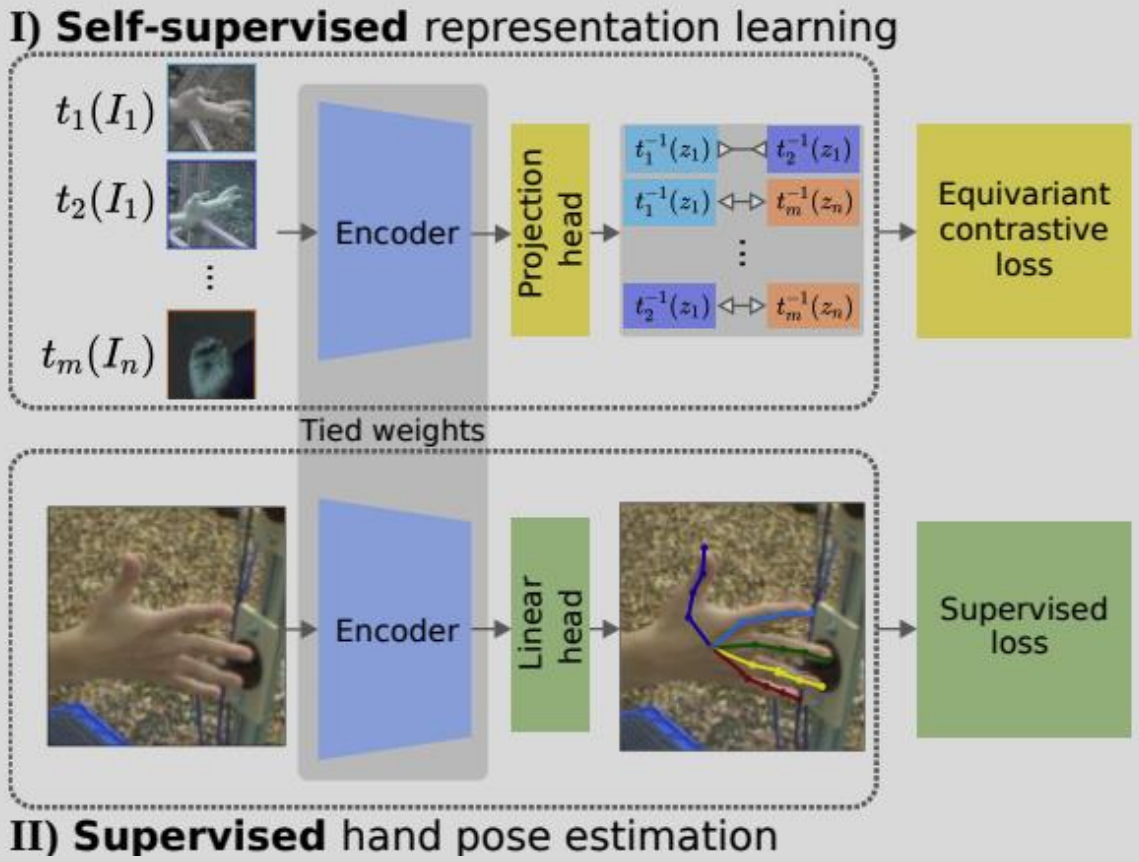
(f) Rotate $\{90°, 180°, 270°\}$ (g) Cutout (h) Gaussian noise (i) Gaussian blur (j) Sobel filtering

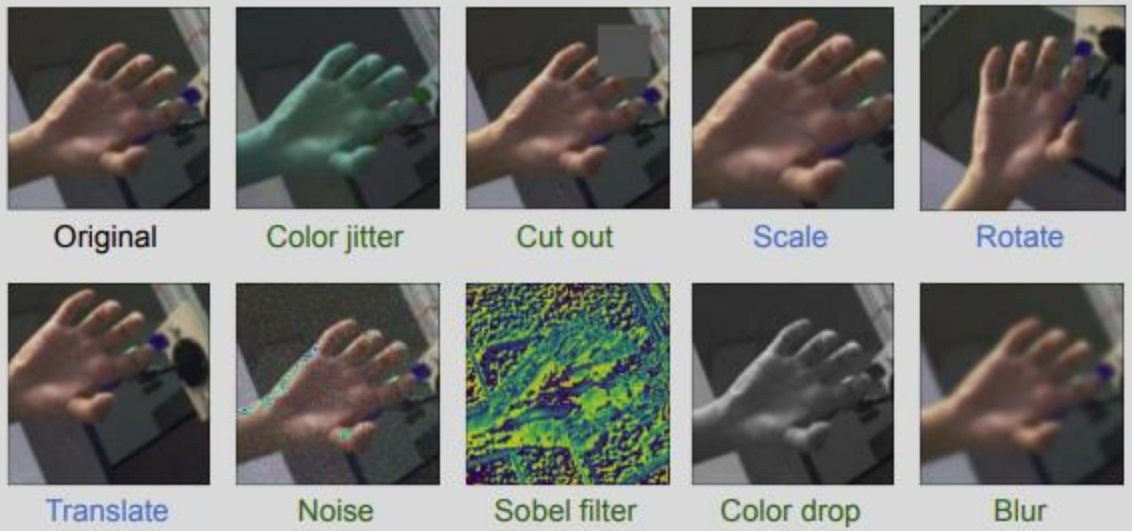
Contrastive learning

	Food	CIFAR10	CIFAR100	Birdsnap	SUN397	Cars	Aircraft	VOC2007	DTD	Pets	Caltech-101	Flowers
Linear evaluation:												
SimCLR (ours)	**76.9**	**95.3**	80.2	48.4	**65.9**	60.0	61.2	**84.2**	**78.9**	89.2	**93.9**	**95.0**
Supervised	75.2	**95.7**	**81.2**	**56.4**	64.9	**68.8**	**63.8**	83.8	**78.7**	**92.3**	**94.1**	94.2
Fine-tuned:												
SimCLR (ours)	**89.4**	**98.6**	**89.0**	**78.2**	**68.1**	**92.1**	**87.0**	**86.6**	**77.8**	92.1	**94.1**	97.6
Supervised	88.7	98.3	**88.7**	**77.8**	67.0	91.4	**88.0**	86.5	**78.8**	**93.2**	**94.2**	**98.0**
Random init	88.3	96.0	81.9	**77.0**	53.7	91.3	84.8	69.4	64.1	82.7	72.5	92.5

A Simple Framework for Contrastive Learning of Visual Representations, ICLR'20

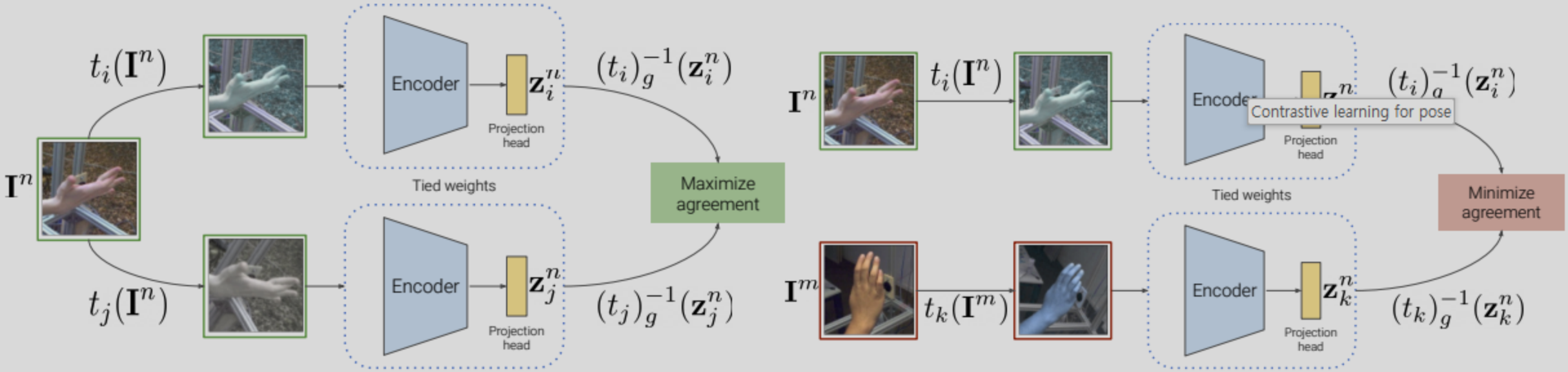
Contrastive learning for pose





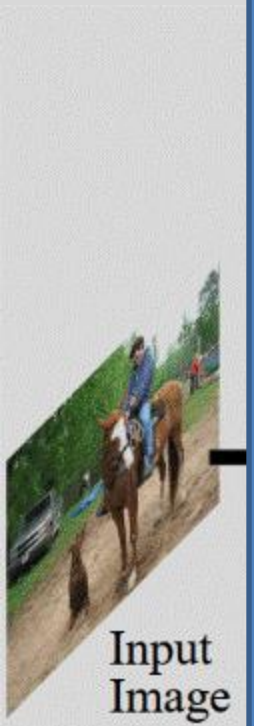
Self-Supervised 3D Hand Pose Estimation from monocular RGB via Contrastive Learning, ICCV'21

Contrastive learning for pose



The agreement between projections from the same input image is maximized (left) and agreements amongst projections from different input images are minimized (right)

Weakly-supervised learning

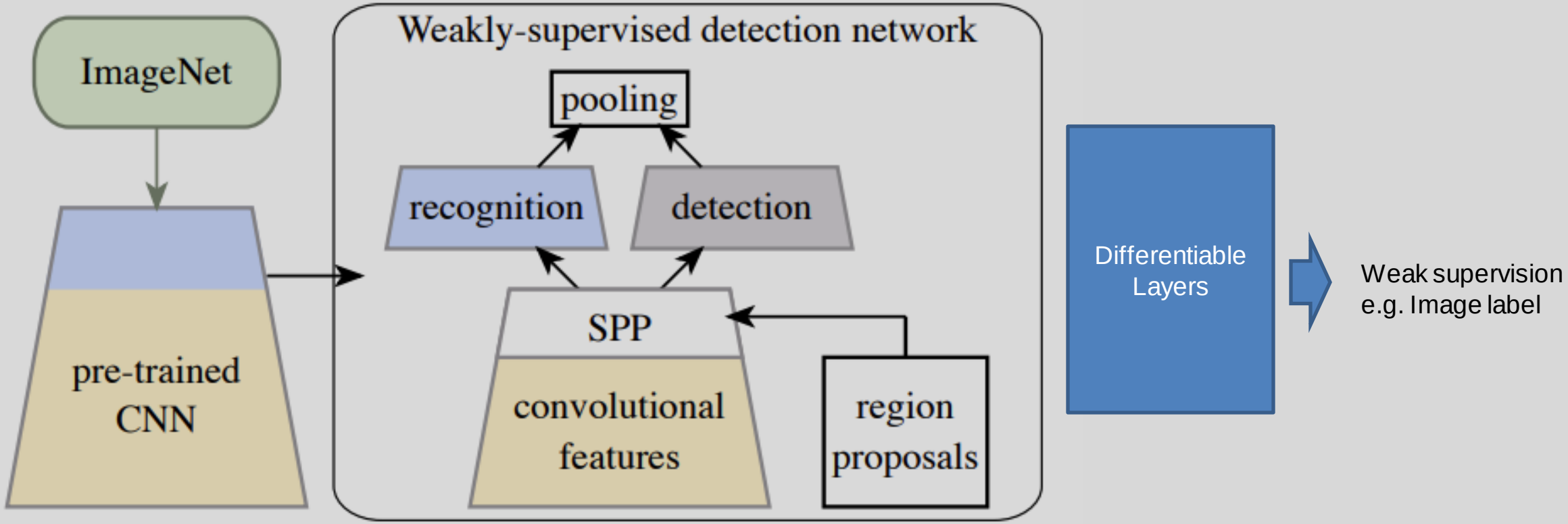


Target Network

Differentiable Layers

Weak supervision
e.g. Image label

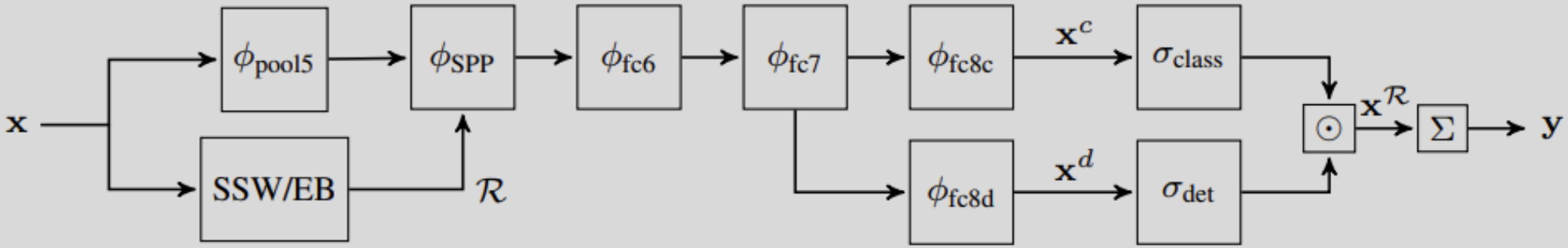
Weakly-supervised object detection



Weakly Supervised Deep Detection Networks, CVPR'16

Weakly-supervised object detection

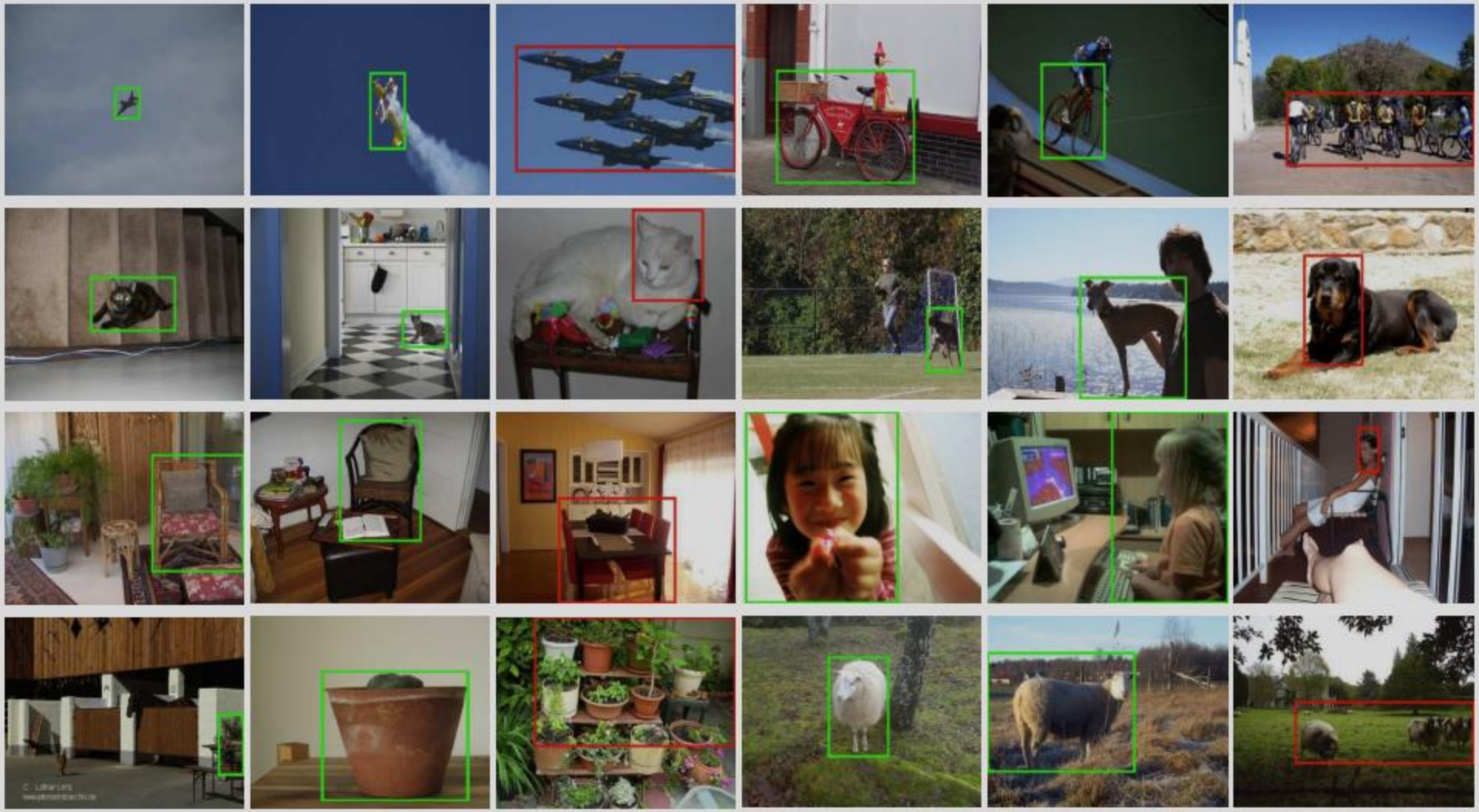
$$[\sigma_{\text{class}}(\mathbf{x}^c)]_{ij} = \frac{e^{x^c_{ij}}}{\sum_{k=1}^{C} e^{x^c_{kj}}}$$



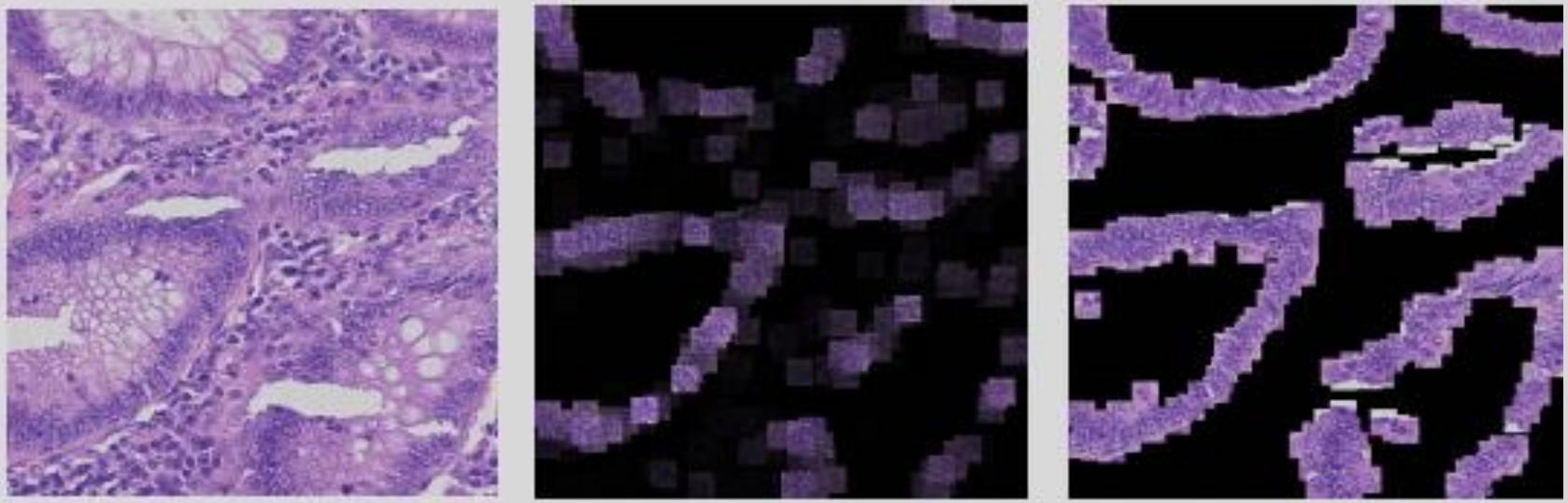
$$y_c = \sum_{r=1}^{|\mathcal{R}|} x^{\mathcal{R}}_{cr}$$

$$[\sigma_{\text{det}}(\mathbf{x}^d)]_{ij} = \frac{e^{x^d_{ij}}}{\sum_{k=1}^{|\mathcal{R}|} e^{x^d_{ik}}}$$

Weakly-supervised object detection



Weakly-supervised segmentation



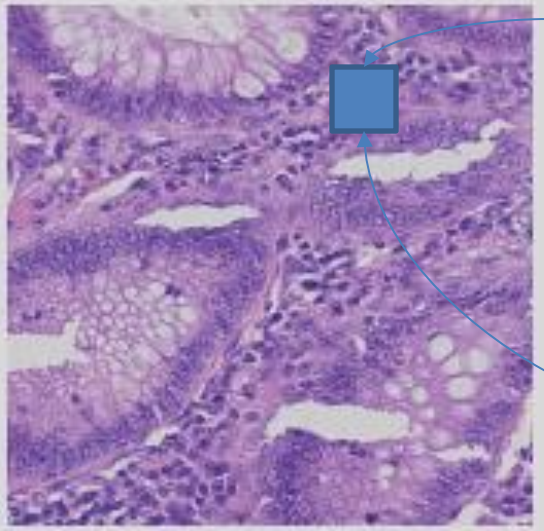
Original image | Predicted patch weights | Ground-truth patches

Attention-based Deep Multiple Instance Learning, ICML'18

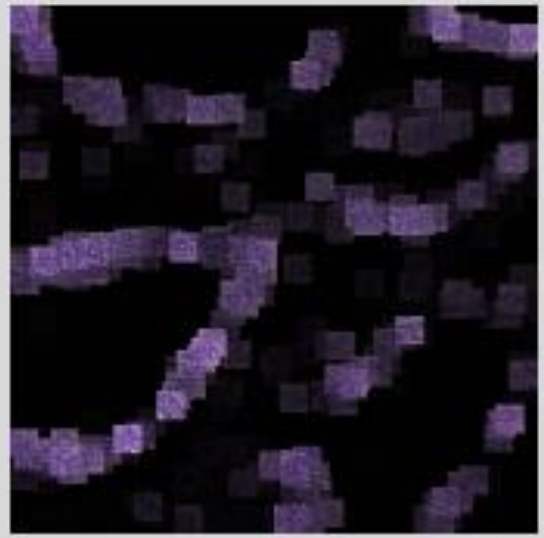
Weakly-supervised segmentation

$$\mathbf{z} = \sum_{k=1}^{K} a_k \mathbf{h}_k$$

$$a_k = \frac{\exp\{\mathbf{w}^\top \tanh\left(\mathbf{V}\mathbf{h}_k^\top\right)\}}{\sum_{j=1}^{K} \exp\{\mathbf{w}^\top \tanh\left(\mathbf{V}\mathbf{h}_j^\top\right)\}}$$



Original image



Predicted patch weights

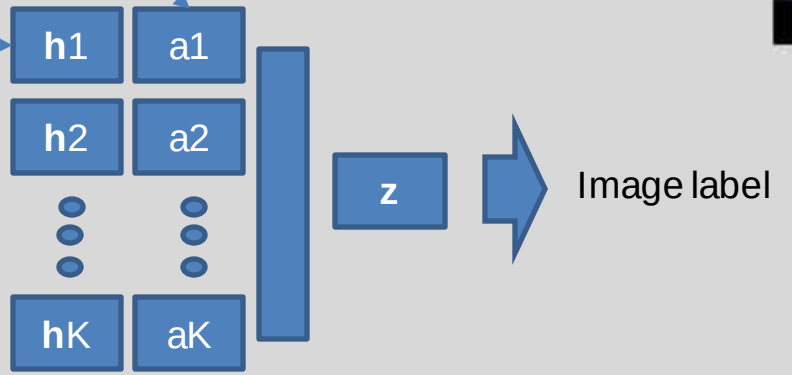


Image label


Thank you!
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