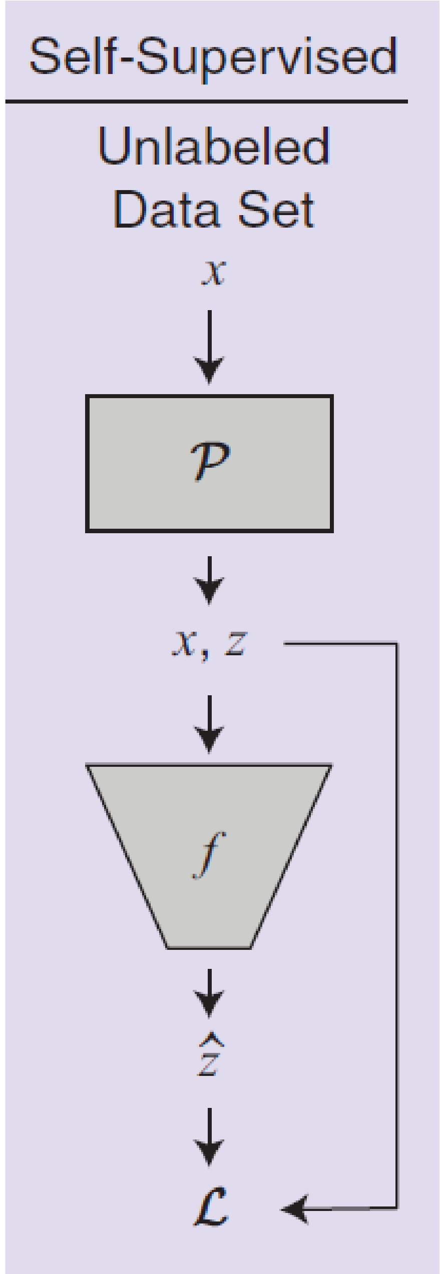
Pretext tasks
2. Relative Position

1 2	SELF-PREDICTION	INNATE RELATIONSHIP (Context-based)	1. ROTATION 2. RELATIVE POSITION	IMAGE
3	CONTRASTIVE LEARNING	INTER-SAMPLE CLASSIFICATION	1. Instance Discrimination 2. SimCLR [Contrastive Loss] 3. Theory – Guarantees / Bounds	IMAGE
4	CONTRASTIVE LEARNING	INTER-SAMPLE CLASSIFICATION	Contrastive Predictive Coding (CPC), [NCE, InfoNCE Loss]	AUDIO/ SPEECH
5	SELF-PREDICTION	GENERATIVE (VAE)	1. AE – Variational Bayes 2. VQ-VAE + AR	IMAGE AUDIO/ SPEECH
6	SELF-PREDICTION	GENERATIVE (AR)	1. AR-LM – GPT 2. Masked-LM – BERT	LANGUAGE
7	SELF-PREDICTION	MASKED-GEN (Masked LM for ASR)	1. Wav2Vec / 2.0 2. HuBERT	AUDIO/ SPEECH



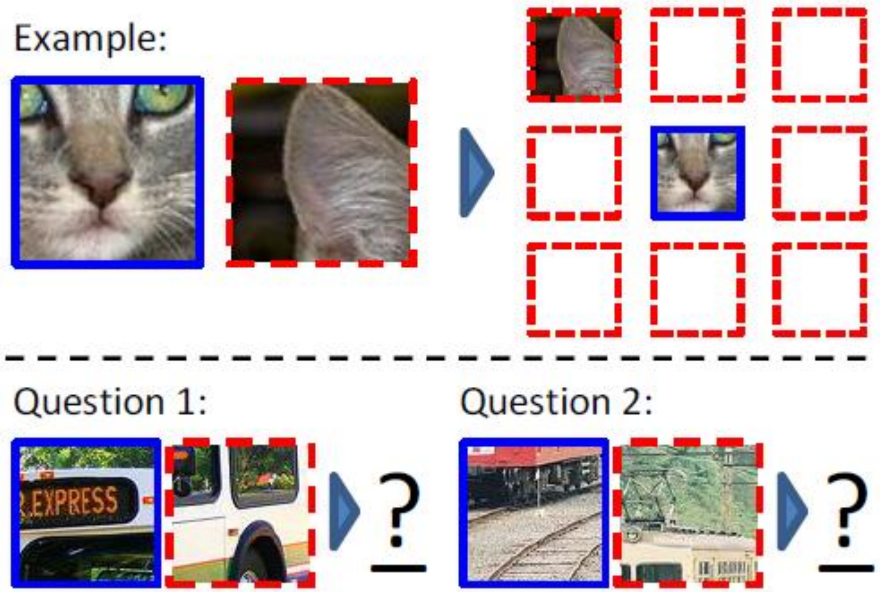
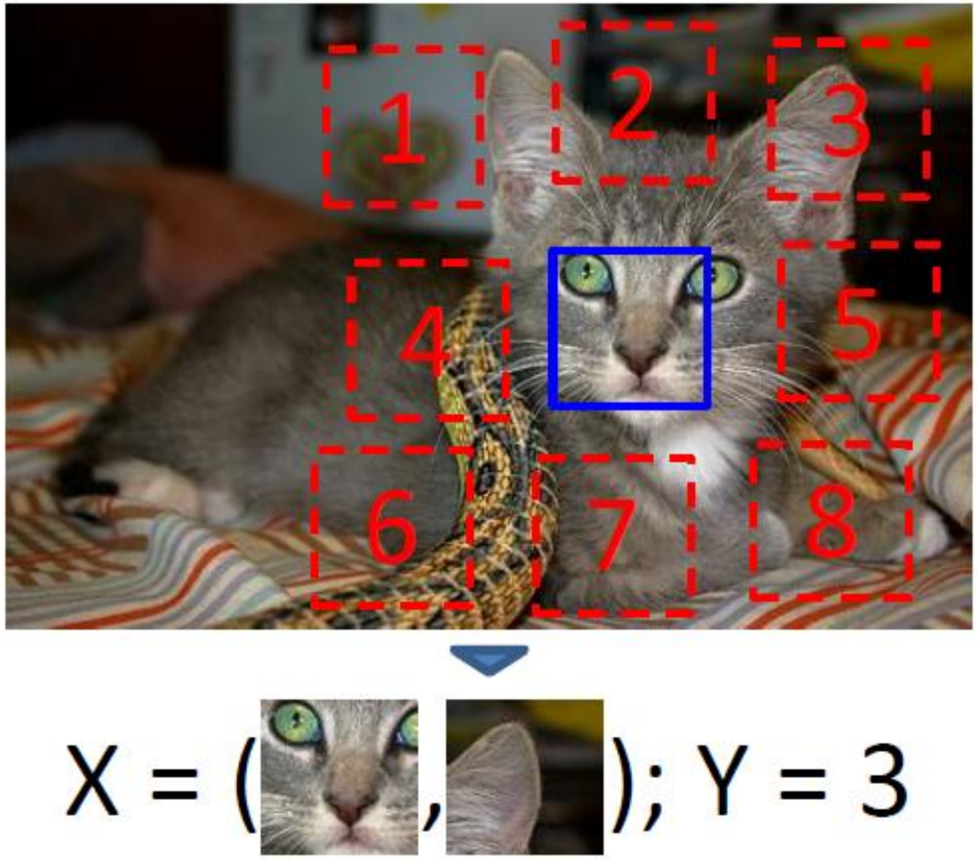


Figure 1. Our task for learning patch representations involves randomly sampling a patch (blue) and then one of eight possible neighbors (red). Can you guess the spatial configuration for the two pairs of patches? Note that the task is much easier once you have recognized the object!

Answer key: Q1: Bottom right Q2: Top center



Unsupervised Visual Representation Learning by Context Prediction

Carl Doersch[1,2] Abhinav Gupta[1] Alexei A. Efros[2]

[1] School of Computer Science
Carnegie Mellon University

[2] Dept. of Electrical Engineering and Computer Science
University of California, Berkeley

The ultimate goal is to learn a feature embedding for *individual* patches, such that patches which are visually similar (across different images) would be close in the embedding space.

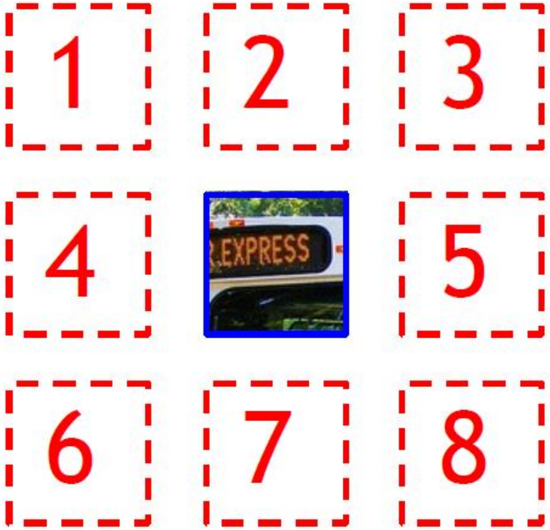
Abstract

This work explores the use of spatial context as a source of free and plentiful supervisory signal for training a rich visual representation. Given only a large, unlabeled image collection, we extract random pairs of patches from each image and train a convolutional neural net to predict the position of the second patch relative to the first. We argue that doing well on this task requires the model to learn to recognize objects and their parts. We demonstrate that the feature representation learned using this within-image context indeed captures visual similarity across images. For example, this representation allows us to perform unsupervised visual discovery of objects like cats, people, and even birds from the Pascal VOC 2011 detection dataset. Furthermore, we show that the learned ConvNet can be used in the R-CNN framework [21] and provides a significant boost over a randomly-initialized ConvNet, resulting in state-of-the-art performance among algorithms which use only Pascal-provided training set annotations.

Doersch et al. “Unsupervised Visual Representation Learning by Context Prediction”, ICCV 2015

A

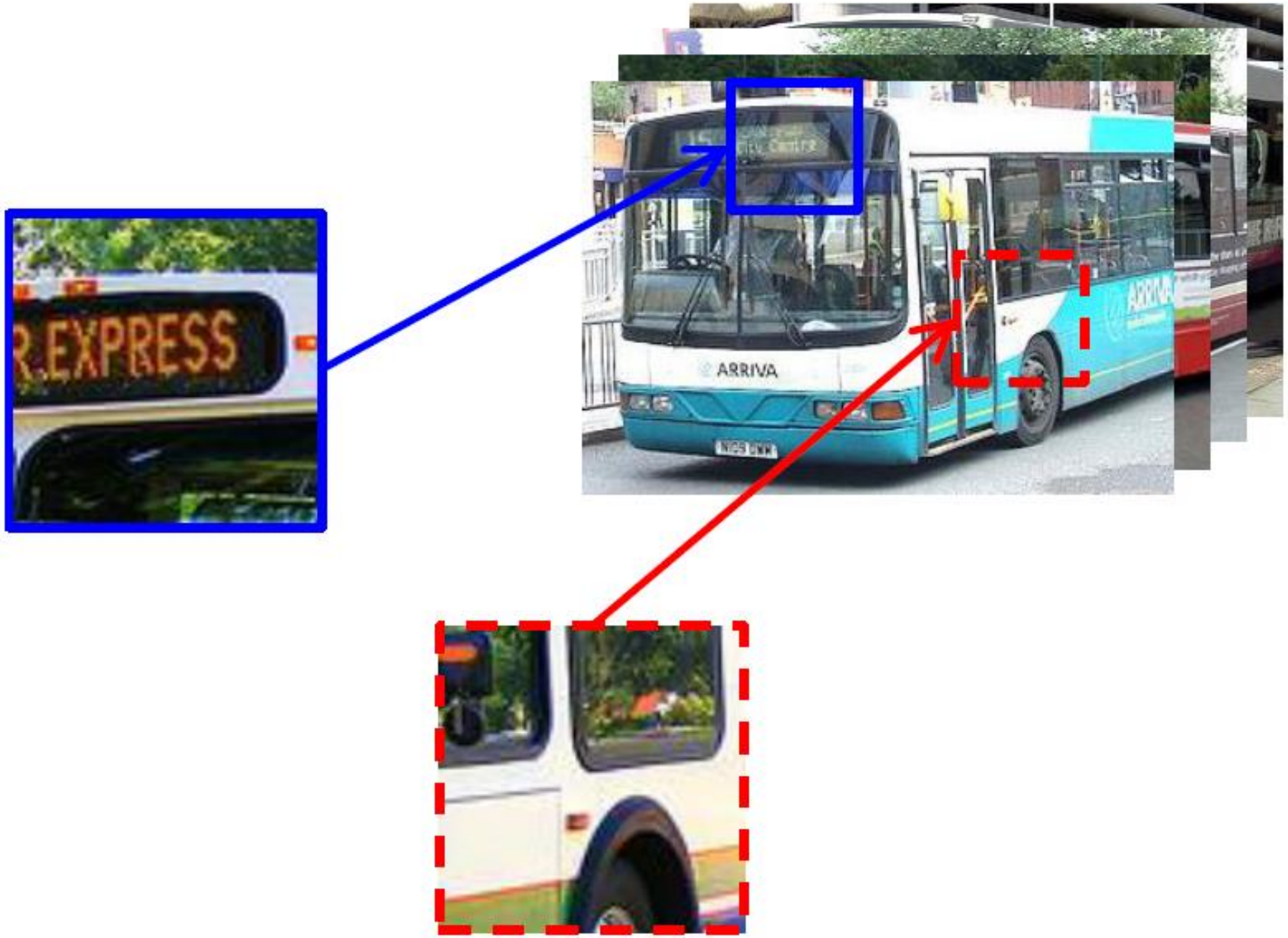
B



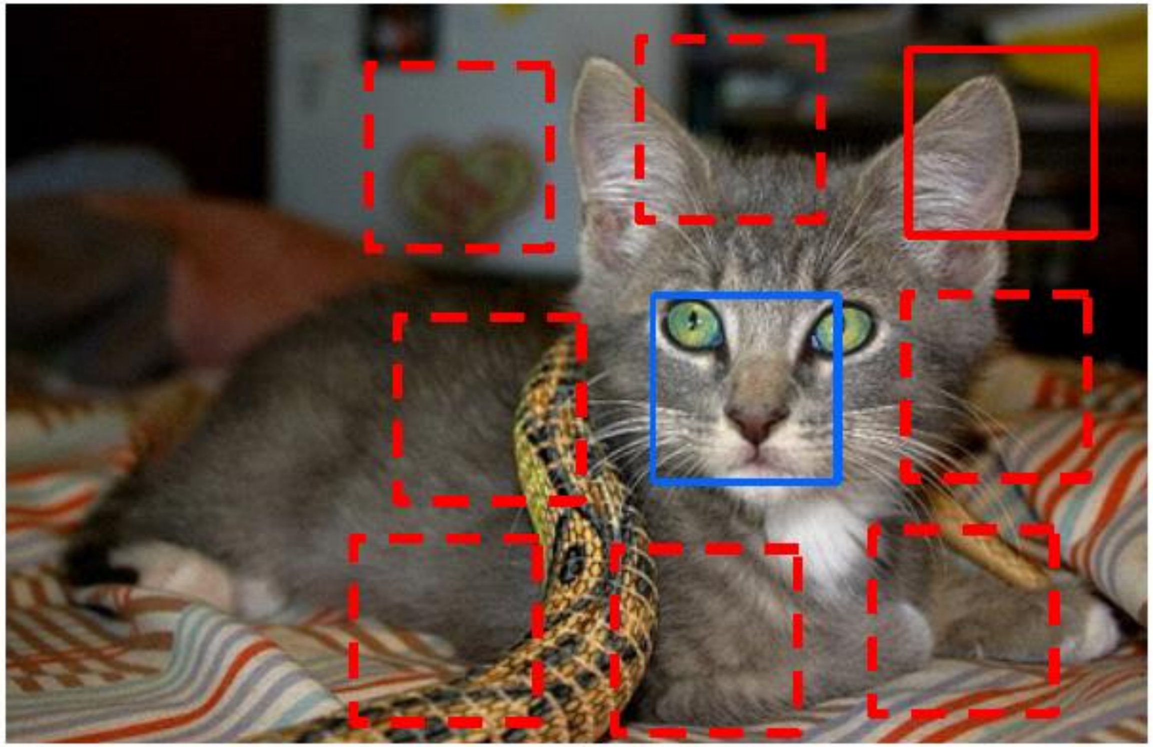
Can you tell where B goes relative to A?

Answer:

Semantics from a non-semantic task

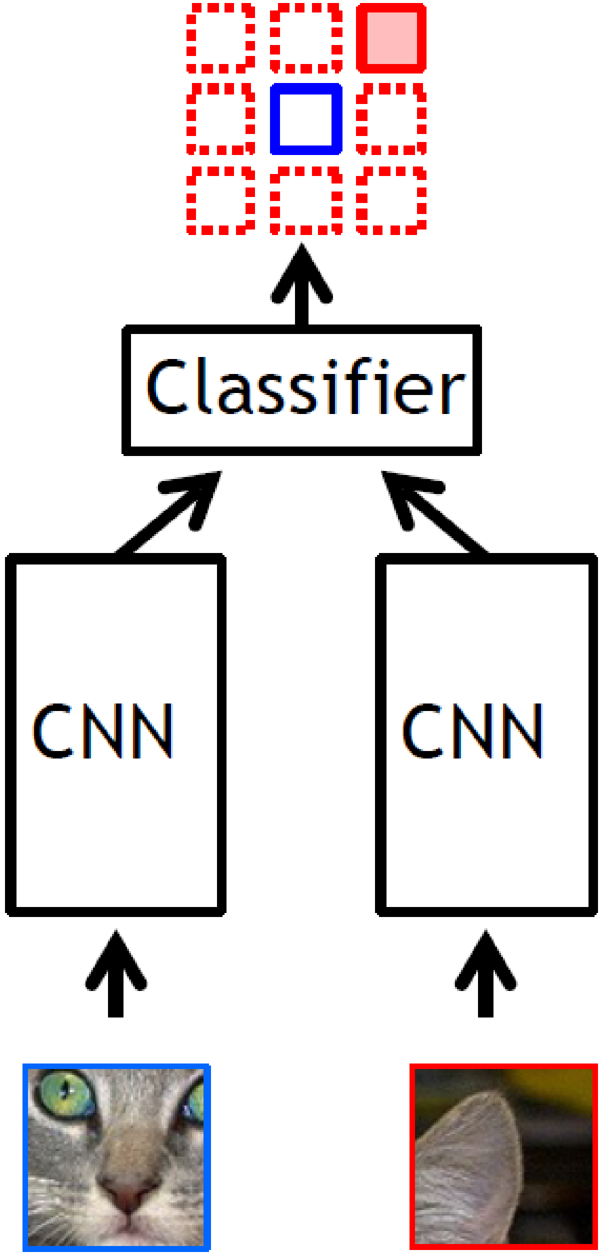


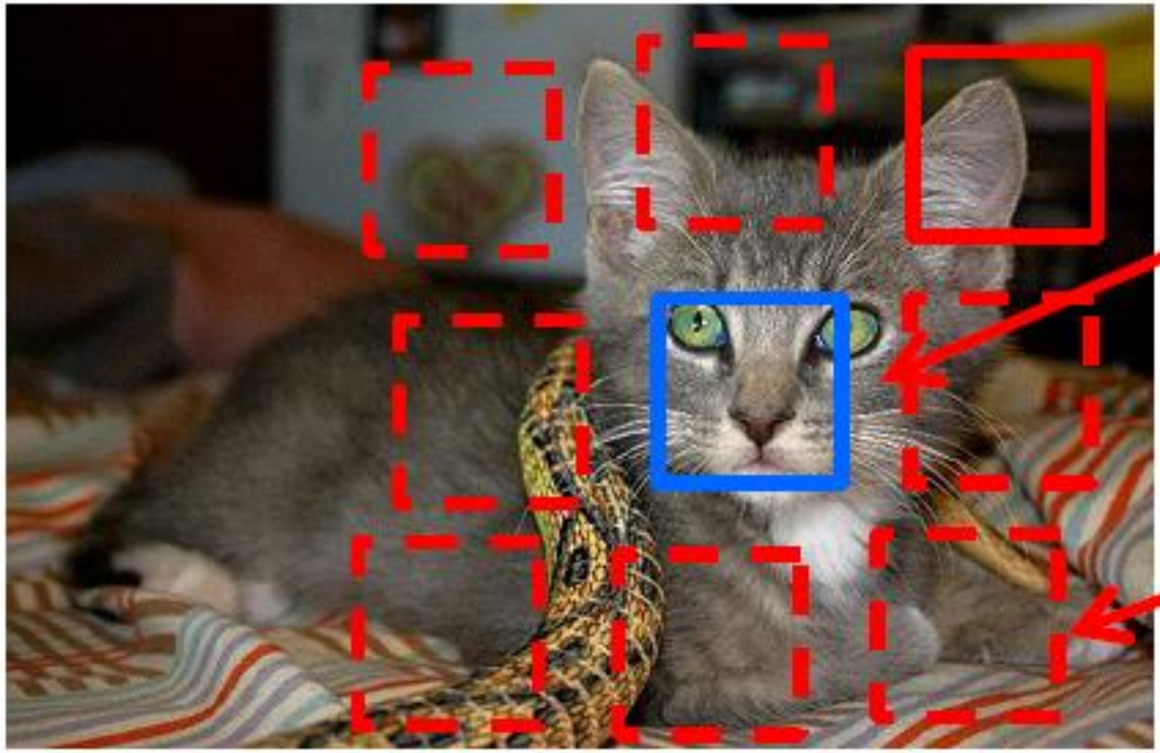
Unlabeled training image



Randomly Sample Patch

Sample Second Patch





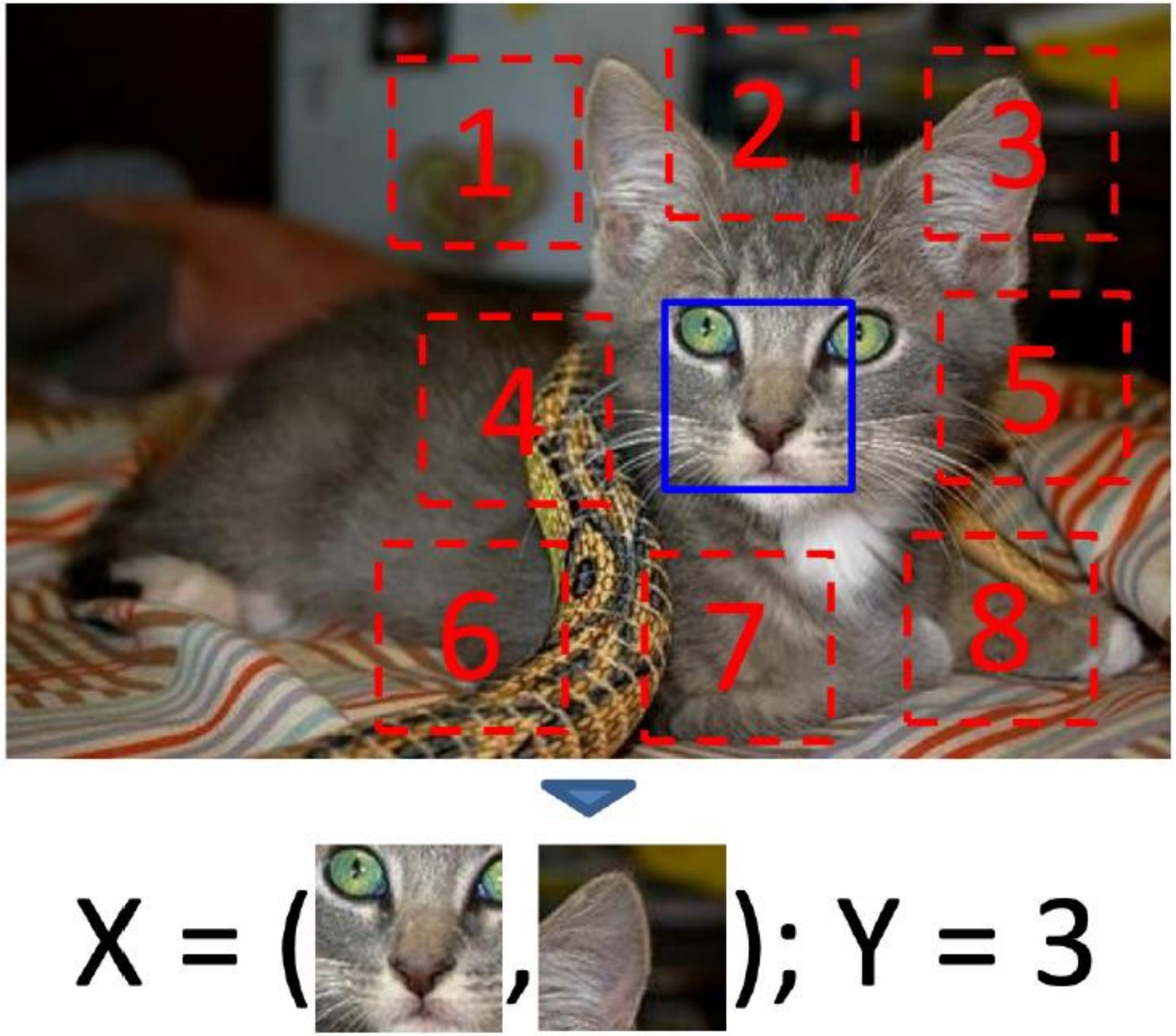
Include a gap

Jitter the patch locations

Context Prediction

Model predicts relative location of two patches from the same image.
Discriminative pretraining task

Intuition: Requires understanding objects and their parts



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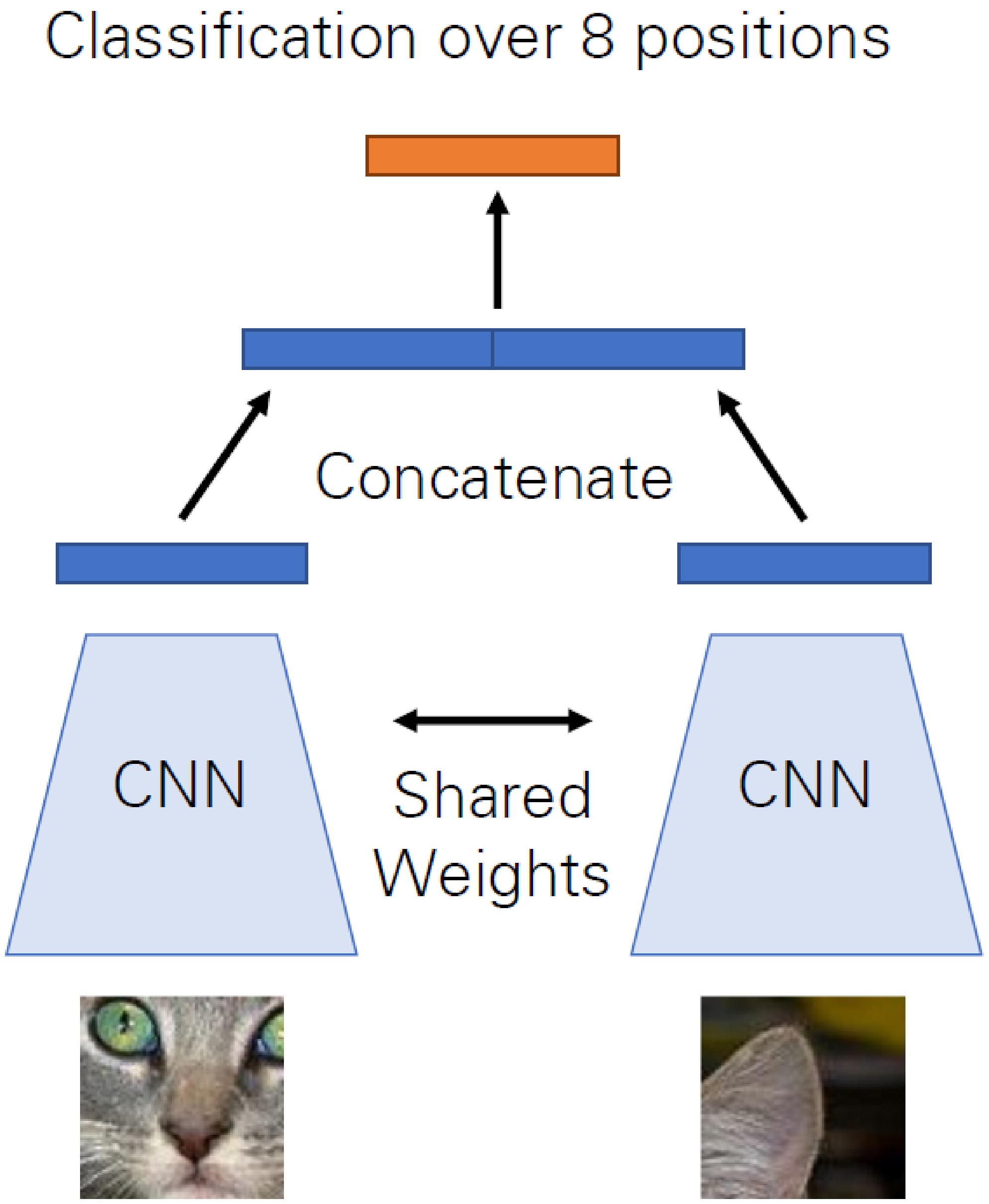
Two networks with shared weights sometimes called a "Siamese network"



"For experiments, we use a ConvNet trained on a K40 GPU for approximately four weeks."

Architecture

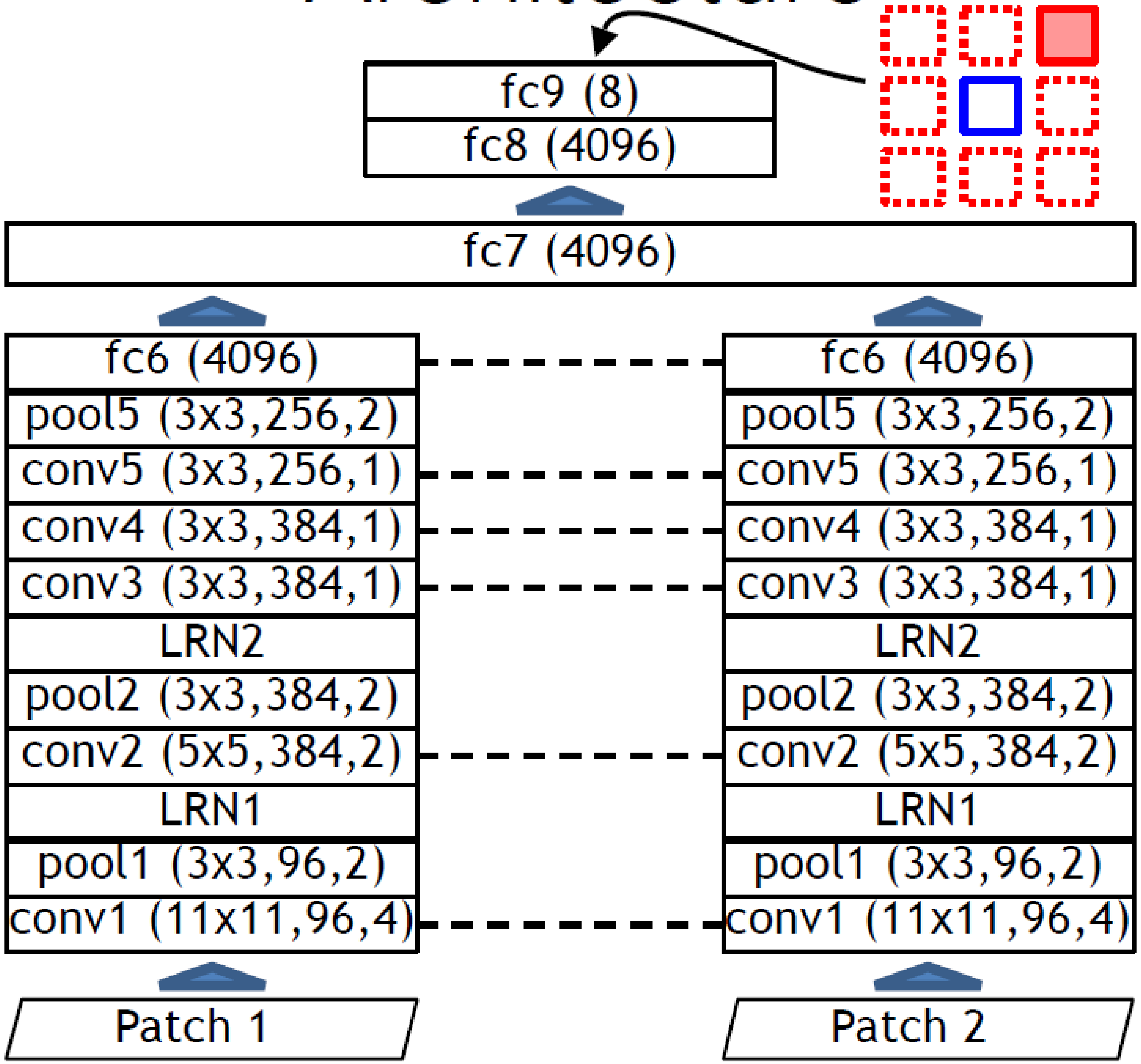
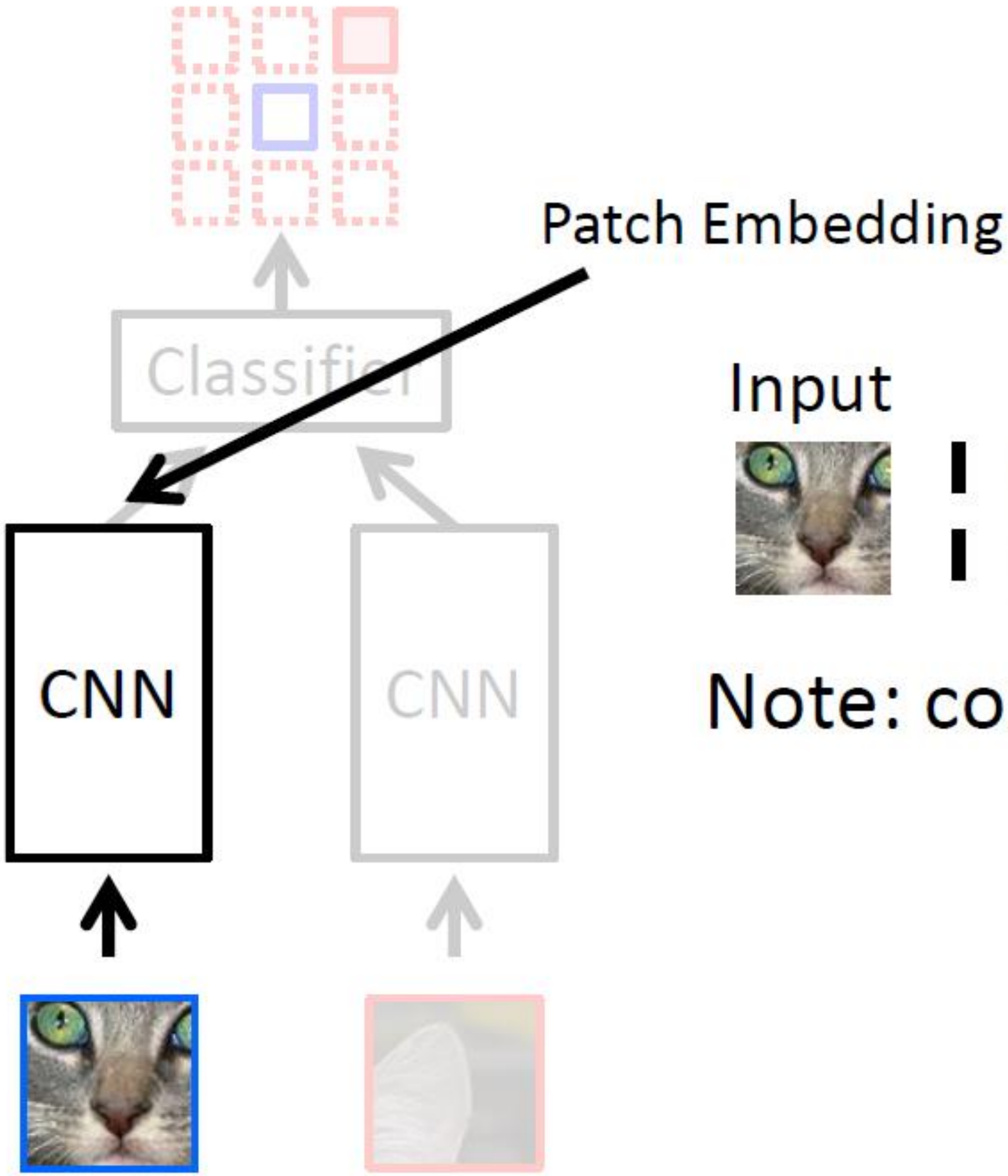
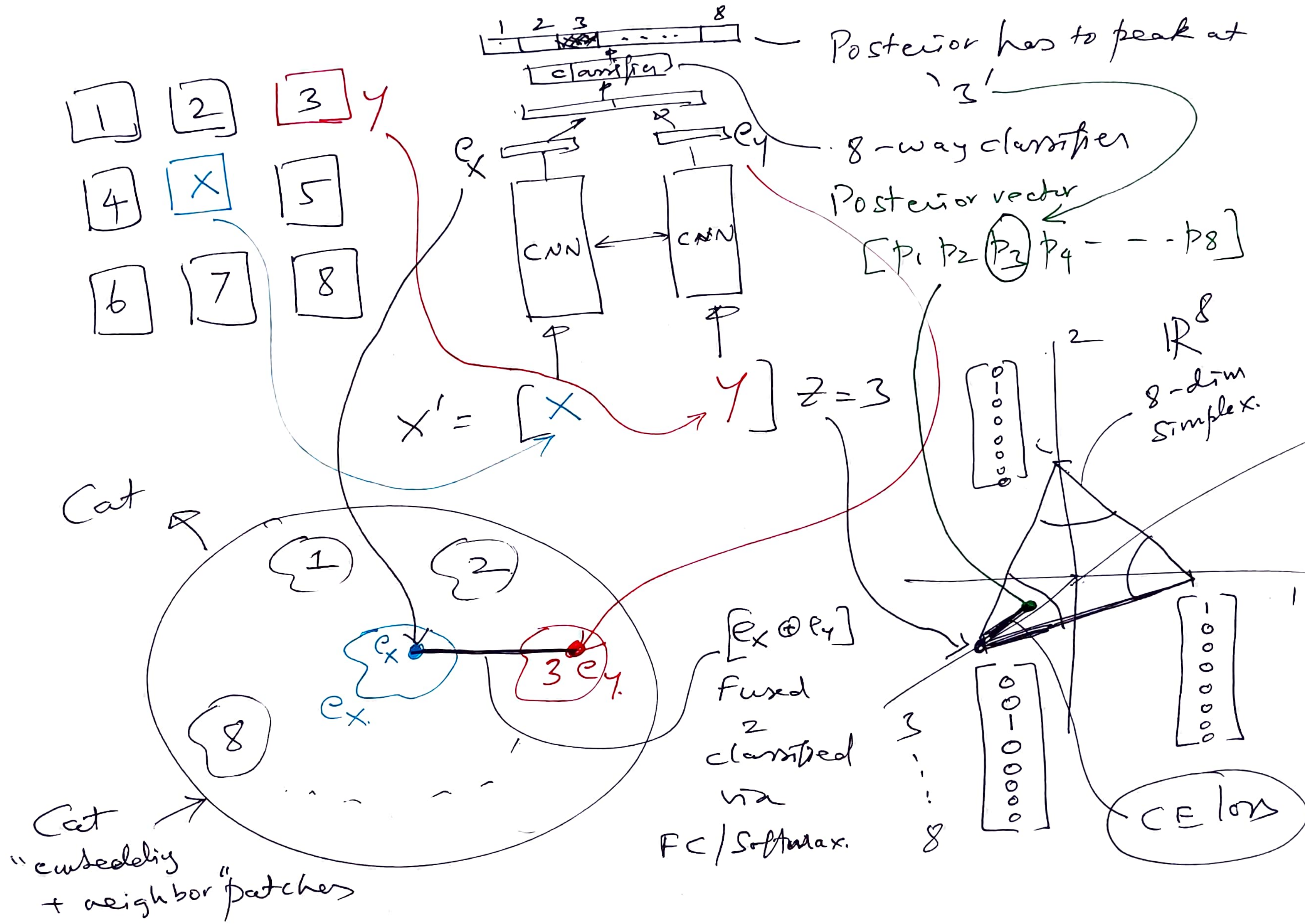


Figure 3. Our architecture for pair classification. Dotted lines indicate shared weights. 'conv' stands for a convolution layer, 'fc' stands for a fully-connected one, 'pool' is a max-pooling layer, and 'LRN' is a local response normalization layer. Numbers in parentheses are kernel size, number of outputs, and stride (fc layers have only a number of outputs). The LRN parameters follow [32]. All conv and fc layers are followed by ReLU nonlinearities, except fc9 which feeds into a softmax classifier.



Note: connects ***across*** instances!



Posterior has to peak at '3'
classifier
8-way classifier
Posterior vector
[p1 p2 p3 p4 - - - p8]
CNN
CNN
ex
ey
x' = [x y] z = 3
R^8
8-dim simplex.
Cat
Cat "embedding + neighbor" patches
ex.
3 ey.
[ex ⊕ ey]
Fused classified via FC/Softmax.
CE loss

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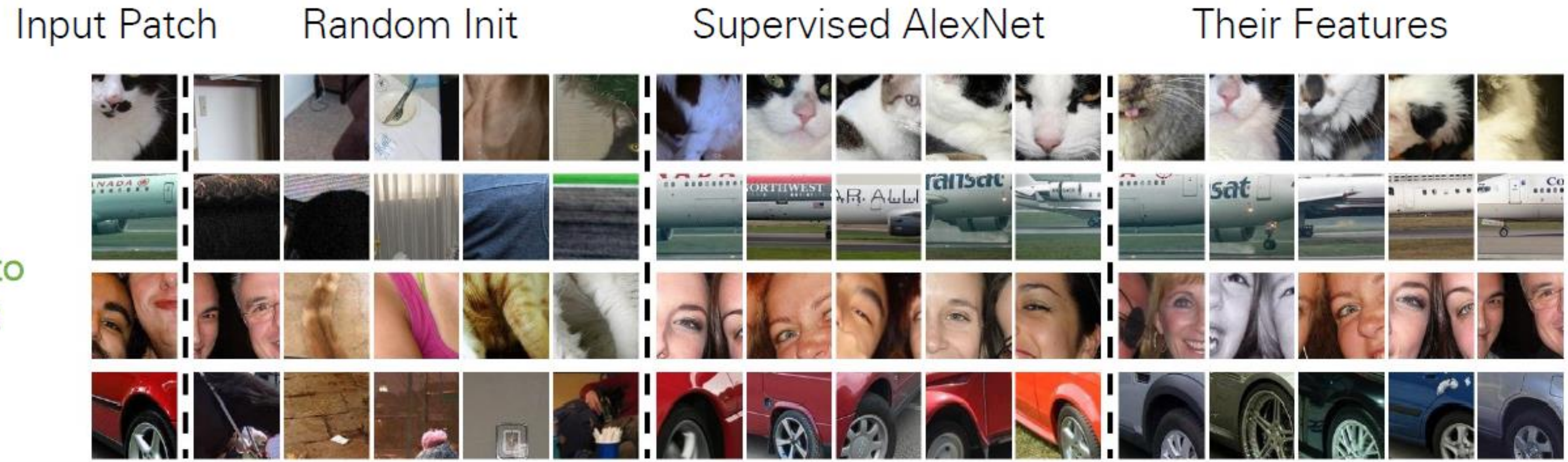
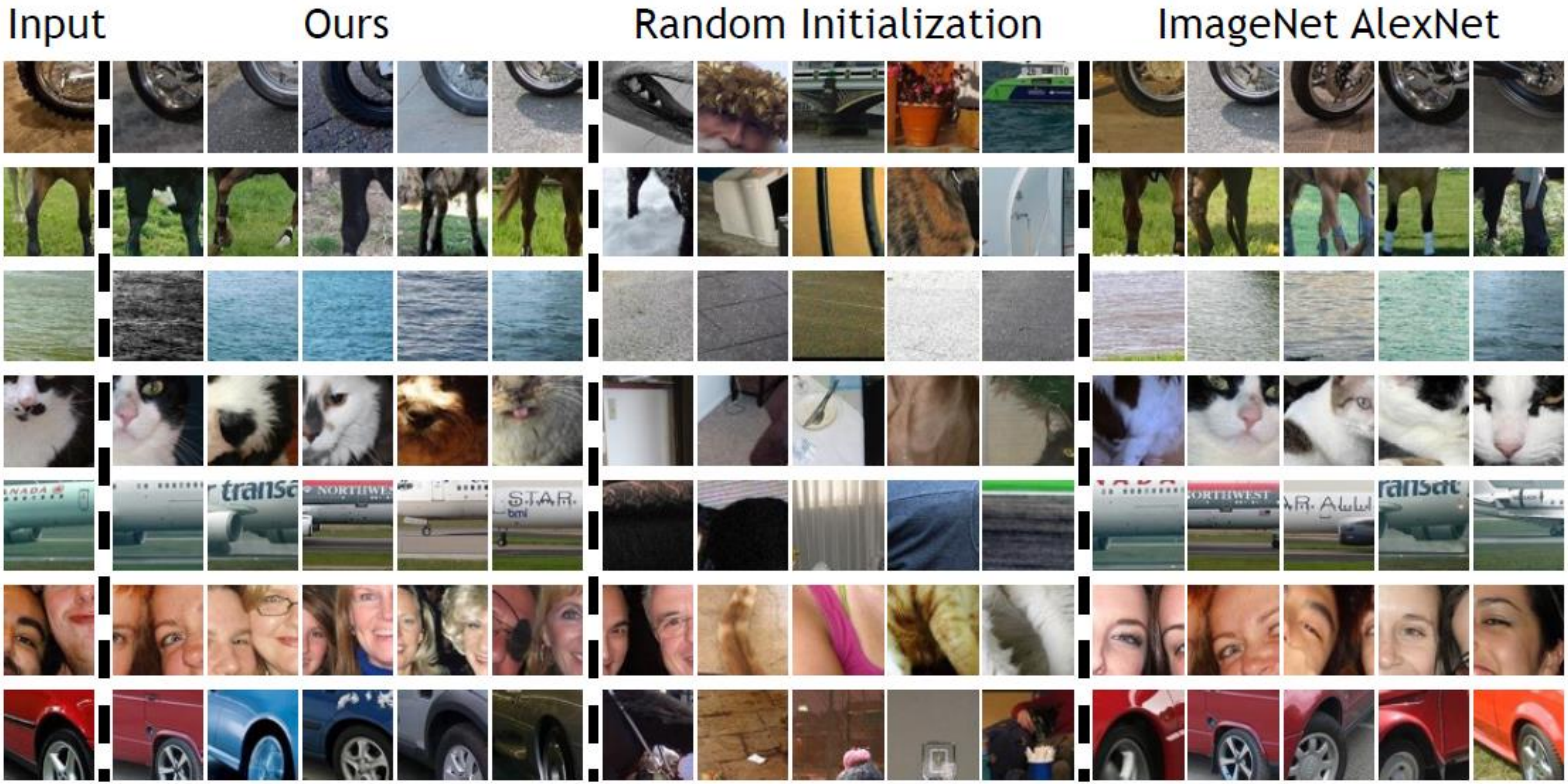
Context Prediction: Nearest Neighbors in Feature Space



Works well! Similar to AlexNet

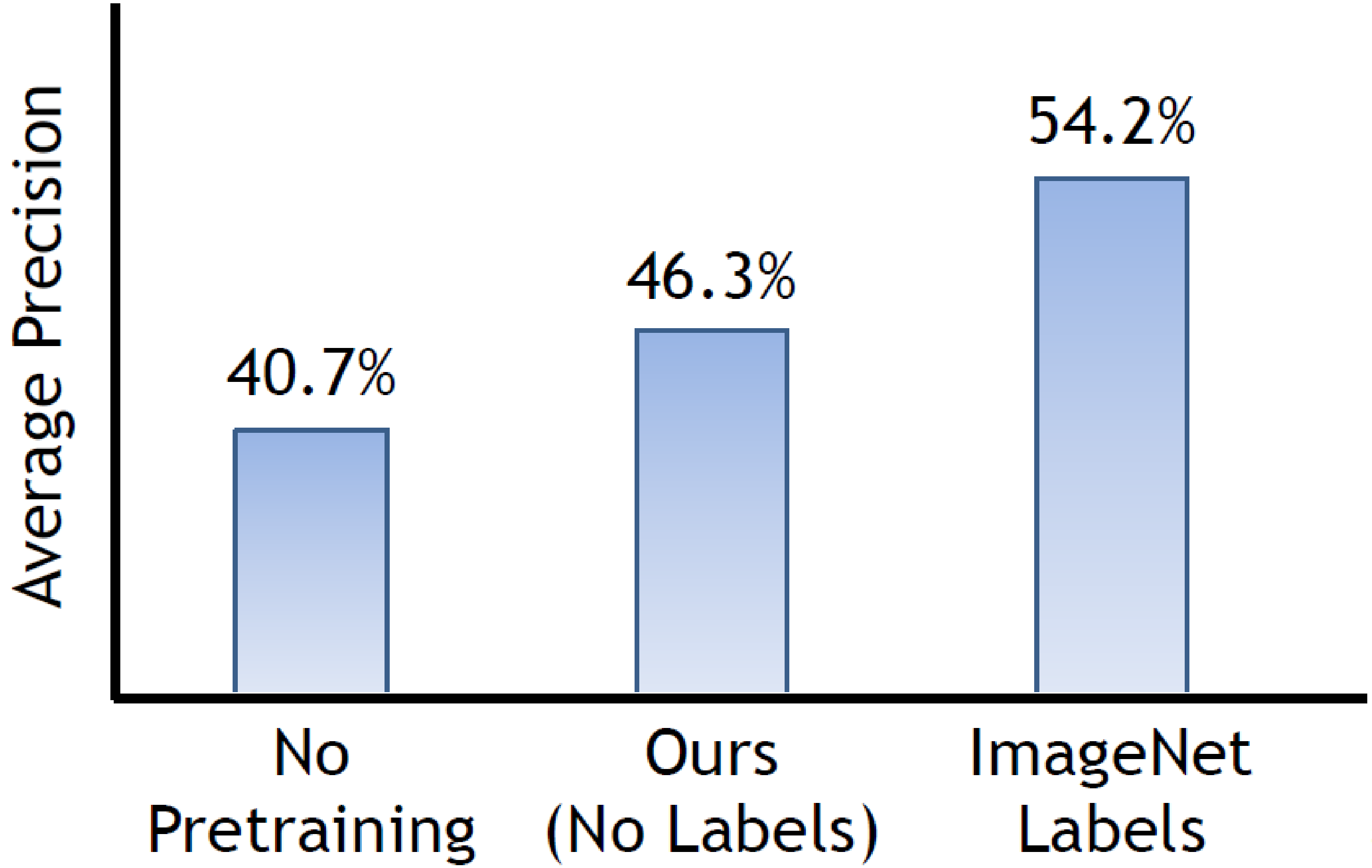

Input
Ours
Random Initialization
ImageNet AlexNet

VOC-2007 Test	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mAP
DPM-v5[17]	33.2	60.3	10.2	16.1	27.3	54.3	58.2	23.0	20.0	24.1	26.7	12.7	58.1	48.2	43.2	12.0	21.1	36.1	46.0	43.5	33.7
[8] w/o context	52.6	52.6	19.2	25.4	18.7	47.3	56.9	42.1	16.6	41.4	41.9	27.7	47.9	51.5	29.9	20.0	41.1	36.4	48.6	53.2	38.5
Regionlets[58]	54.2	52.0	20.3	24.0	20.1	55.5	68.7	42.6	19.2	44.2	49.1	26.6	57.0	54.5	43.4	16.4	36.6	37.7	59.4	52.3	41.7
Scratch-R-CNN[2]	49.9	60.6	24.7	23.7	20.3	52.5	64.8	32.9	20.4	43.5	34.2	29.9	49.0	60.4	47.5	28.0	42.3	28.6	51.2	50.0	40.7
Scratch-Ours	52.6	60.5	23.8	24.3	18.1	50.6	65.9	29.2	19.5	43.5	35.2	27.6	46.5	59.4	46.5	25.6	42.4	23.5	50.0	50.6	39.8
Ours-projection	58.4	62.8	33.5	27.7	24.4	58.5	68.5	41.2	26.3	49.5	42.6	37.3	55.7	62.5	49.4	29.0	47.5	28.4	54.7	56.8	45.7
Ours-color-dropping	60.5	66.5	29.6	28.5	26.3	56.1	70.4	44.8	24.6	45.5	45.4	35.1	52.2	60.2	50.0	28.1	46.7	42.6	54.8	58.6	46.3
Ours-Yahoo100m	56.2	63.9	29.8	27.8	23.9	57.4	69.8	35.6	23.7	47.4	43.0	29.5	52.9	62.0	48.7	28.4	45.1	33.6	49.0	55.5	44.2
ImageNet-R-CNN[21]	64.2	69.7	50	41.9	32.0	62.6	71.0	60.7	32.7	58.5	46.5	56.1	60.6	66.8	54.2	31.5	52.8	48.9	57.9	64.7	54.2
K-means-rescale [31]	55.7	60.9	27.9	30.9	12.0	59.1	63.7	47.0	21.4	45.2	55.8	40.3	67.5	61.2	48.3	21.9	32.8	46.9	61.6	51.7	45.6
Ours-rescale [31]	61.9	63.3	35.8	32.6	17.2	68.0	67.9	54.8	29.6	52.4	62.9	51.3	67.1	64.3	50.5	24.4	43.7	54.9	67.1	52.7	51.1
ImageNet-rescale [31]	64.0	69.6	53.2	44.4	24.9	65.7	69.6	69.2	28.9	63.6	62.8	63.9	73.3	64.6	55.8	25.7	50.5	55.4	69.3	56.4	56.5
VGG-K-means-rescale	56.1	58.6	23.3	25.7	12.8	57.8	61.2	45.2	21.4	47.1	39.5	35.6	60.1	61.4	44.9	17.3	37.7	33.2	57.9	51.2	42.4
VGG-Ours-rescale	71.1	72.4	54.1	48.2	29.9	75.2	78.0	71.9	38.3	60.5	62.3	68.1	74.3	74.2	64.8	32.6	56.5	66.4	74.0	60.3	61.7
VGG-ImageNet-rescale	76.6	79.6	68.5	57.4	40.8	79.9	78.4	85.4	41.7	77.0	69.3	80.1	78.6	74.6	70.1	37.5	66.0	67.5	77.4	64.9	68.6

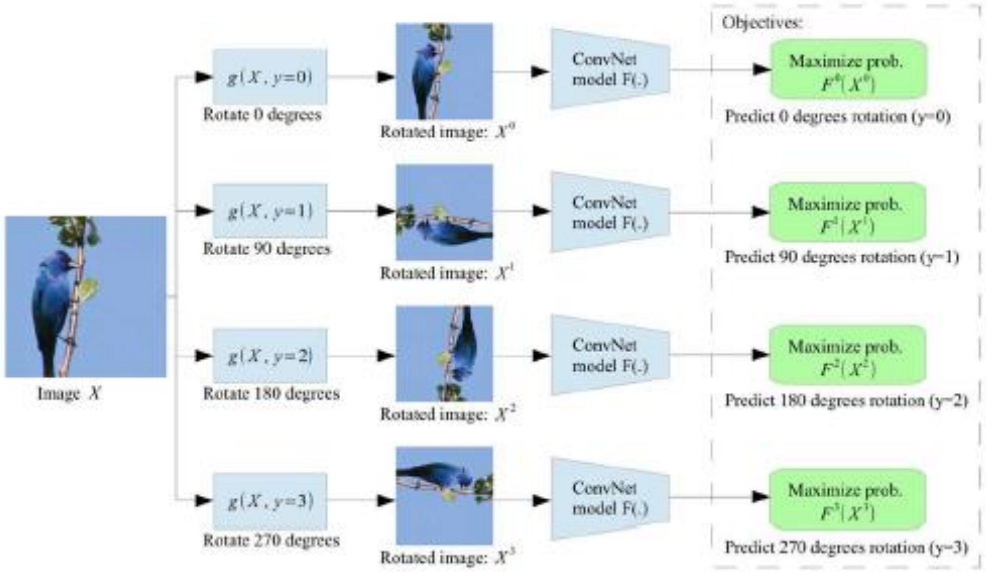
Table 1. Mean Average Precision on VOC-2007.

VOC 2007 Performance

(pretraining for R-CNN)



Self-supervision from (spatial) context



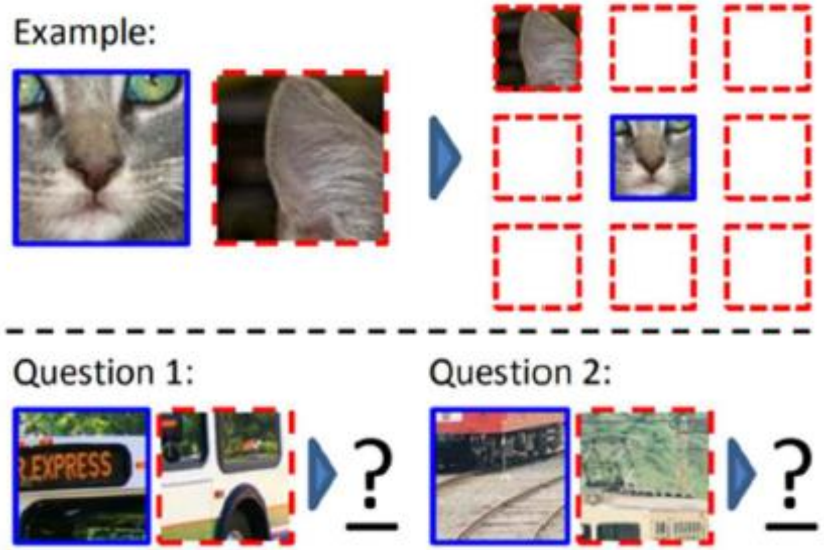


Figure 1. Our task for learning patch representations involves randomly sampling a patch (blue) and then one of eight possible neighbors (red). Can you guess the spatial configuration for the two pairs of patches? Note that the task is much easier once you have recognized the object!

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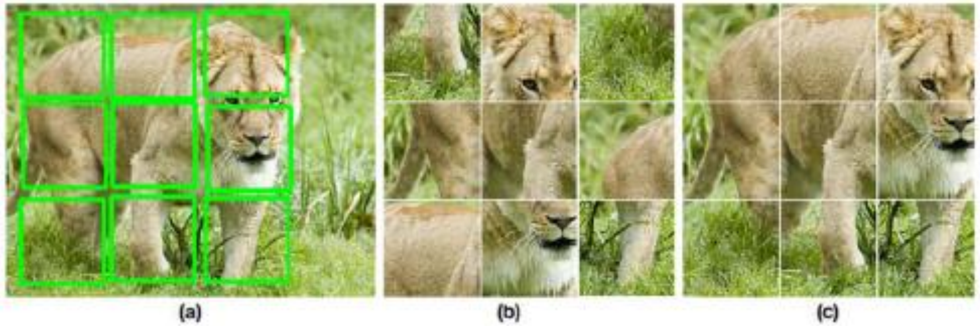

S. Gidaris, P. Singh, and N. Komodakis, "Unsupervised representation learning by predicting image rotations" in ICLR 2018.
Doersch et al. "Unsupervised Visual Representation Learning by Context Prediction", ICCV 2015
M. Noroozi and P. Favaro, "Unsupervised learning of visual representions by solving jigsaw puzzles", ECCV 2016.

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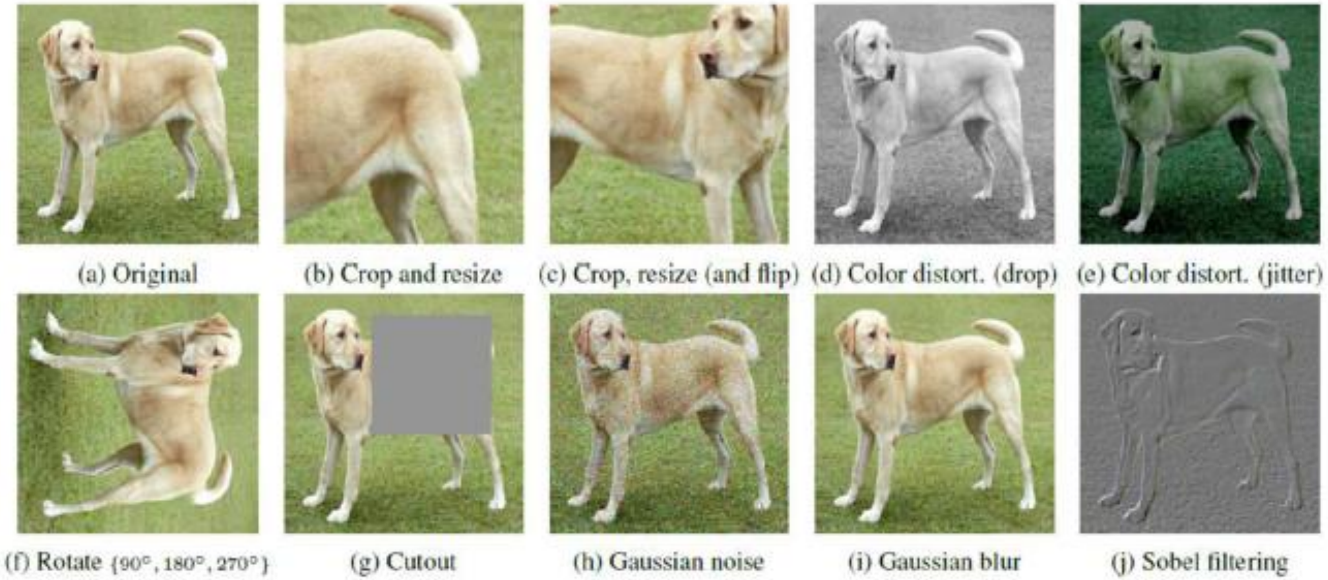
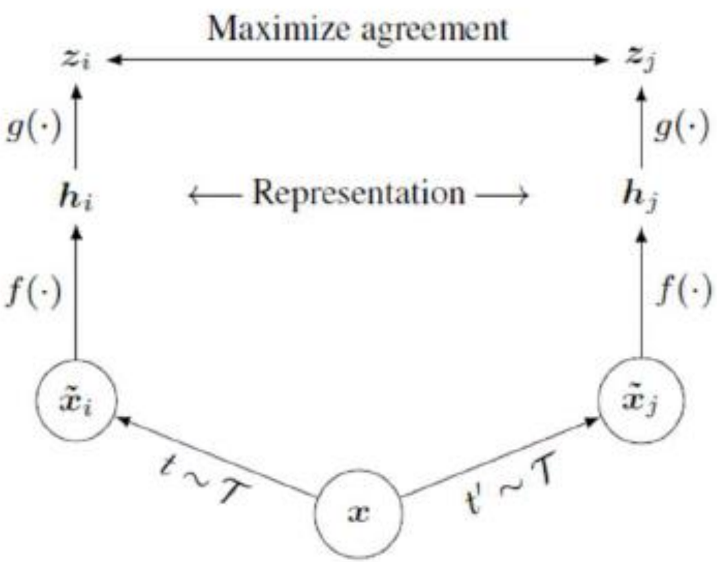
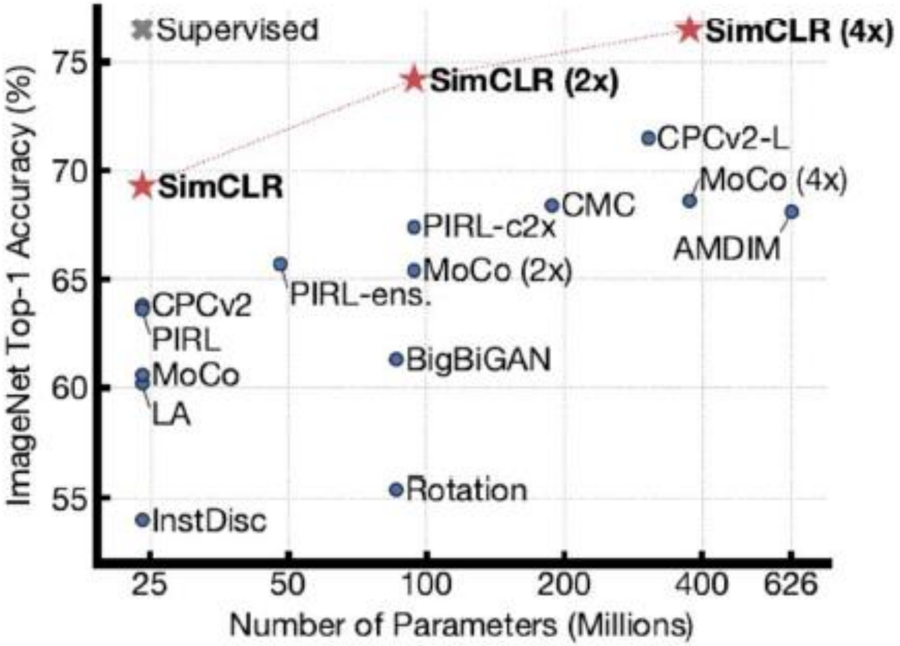
Self-supervision by contrastive learning

State-of-the-art self-supervised methods **are closing the gap** with respect to the supervised couterpart in some tasks.







Ting Chen et al. , "A Simple Framework for Contrastive Learning of Visual Representations", https://arxiv.org/abs/2002.05709

Thank you !!