

# Visual Representaion 1



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Aug. 10th, 2021



# Unsupervised Visual Representation Learning by Context Prediction [C. Doersch et al., 2015] (1/4)

## ■ Introduction

### ➤ Unsupervised learning

- Limitation of supervised learning

- Human annotation required

### ➤ Self-supervised learning

- Text domain

- Context : powerful source of automatic supervision
- Corpus  $\longrightarrow$  Feature vector  $\longrightarrow$  Predict words
- Convert unsupervised problem into self-supervised one

### ➤ Self-supervised learning for image

- Process

- Sample random pairs of patches
- Provide two patches to network
- Train to guess the position of the patches

- Contribution

- Good for object detection & unsupervised object discovery / visual data mining
- Generalizes across images
- Instance-level supervision

Example:



Question 1:



Question 2:



Types of object detection



# Unsupervised Visual Representation Learning by Context Prediction [C. Doersch et al., 2015] (2/4)

## Learning visual context prediction

### ➤ Architecture

#### • Late-fusion architecture

- A pair of conv net that process separately
- Must predict relative position of patches
- Feed two input patches through conv layers
- Produce output that assigns a probability
- Feature embedding for individual patches
- Semantic reasoning

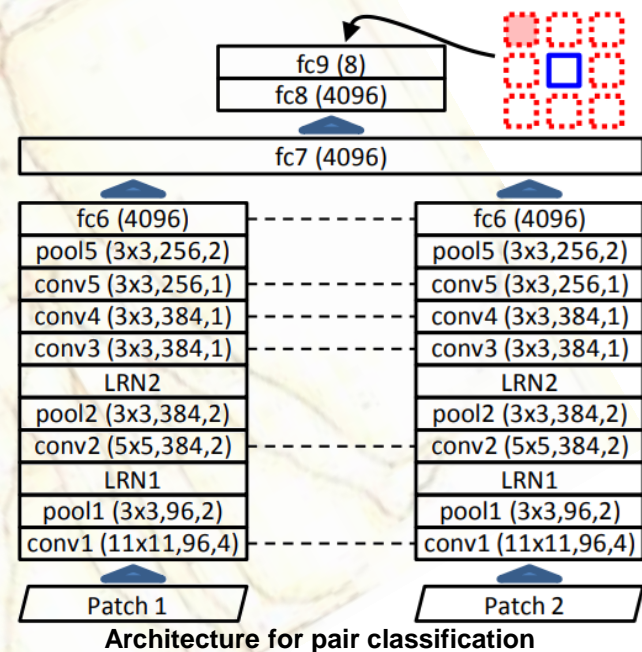
## Avoiding trivial solutions

### ➤ Extract the desired information

- Use high-level semantic not texture or boundary
- Include gap between patches
- Randomly jitter each patch location

### ➤ Chromatic aberration

- Lens focuses light at different wavelengths
  - Detecting the separation between green and magenta
  - Projection
  - Color dropping
- Conv net can learn to localize a patch relative to the lens itself
  - Detecting the separation between green and magenta
  - Projection
  - Color dropping







# Unsupervised Visual Representation Learning by Context Prediction [C. Doersch et al., 2015] (3/4)

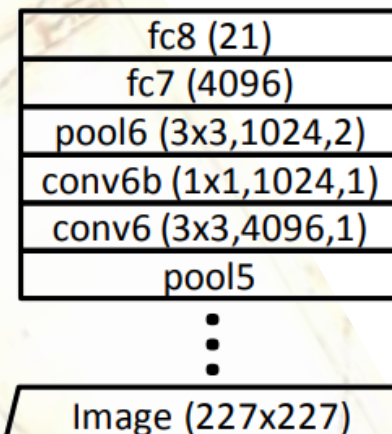
## Experiments

### ➤ Nearest neighbors

- Use normalized correlation
- Repeat the experiment using fc7 & fc6
  - Fc7: feature from AlexNet trained on ImageNet
  - Fc6: feature from authors' architecture without training
- In a few cases, untrained ConvNet does reasonably well

### ➤ Object detection

- None of unsupervised pre-training provide such a performance boost
- Adopt R-CNN pipeline
- Use only one stack
- Resize the conv layer 227x227
- Reduce dimensionality to 1024
- 5% better than training from scratch
- 8% below label supervision



Architecture for Pascal VOC detection

Results on VOC-2007

VOC-2007 Test	person	plant	sheep	sofa	train	tv	mAP
DPM-v5[17]	43.2	12.0	21.1	36.1	46.0	43.5	33.7
[8] w/o context	29.9	20.0	41.1	36.4	48.6	53.2	38.5
Regionlets[55]	43.4	16.4	36.6	37.7	<b>59.4</b>	52.3	41.7
Scratch-R-CNN[2]	47.5	28.0	42.3	28.6	51.2	50.0	40.7
Scratch-Ours	46.5	25.6	42.4	23.5	50.0	50.6	39.8
Ours-projection	49.4	<b>29.0</b>	<b>47.5</b>	28.4	54.7	56.8	45.7
Ours-color-dropping	<b>50.0</b>	28.1	46.7	<b>42.6</b>	54.8	<b>58.6</b>	<b>46.3</b>
Ours-Yahoo100m	48.7	28.4	45.1	33.6	49.0	55.5	44.2
Ours-VGG	54.1	26.1	43.9	55.9	69.8	50.9	53.0
ImageNet-R-CNN[19]	54.2	31.5	52.8	48.9	57.9	64.7	54.2



# Unsupervised Visual Representation Learning by Context Prediction [C. Doersch et al., 2015] (4/4)

## Visual data mining

### ➤ Definition

- Collect images that depict the same semantic objects
- Dataset visualization, image search
- Connect visual data to unstructured data

### ➤ Method

- Sample four adjacent patches from an image
- Find the top 100 images
- Use geometric verification
- Rank the different constellations

## Accuracy on the relative prediction task

### ➤ Improve the representation

- Analyze classification performance on pretext task
  - Sample 500 random images from Pascal VOC
- Accuracy of 38.4%
- Pretext task is difficult
  - Large fraction of patches within each image
  - The task is almost impossible



Object cluster discovered by algorithm