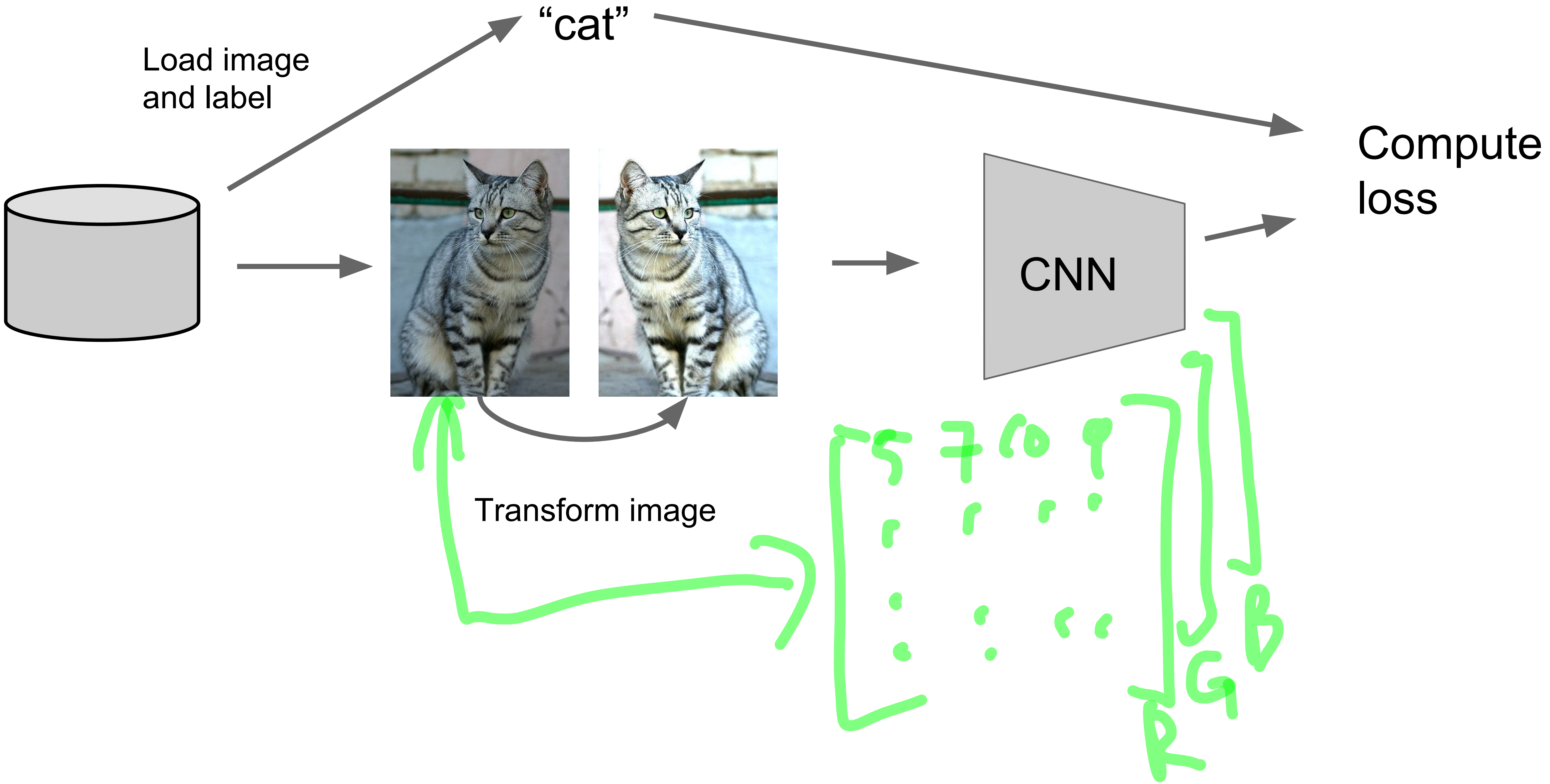
# Data Augmentation & Transfer Learning

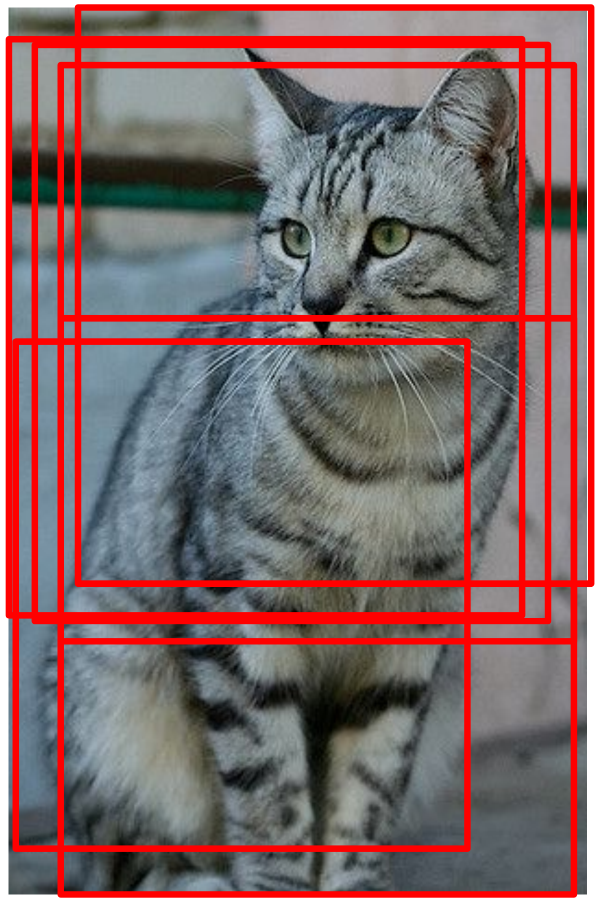
regularization methods specialized for CNN

- http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture7.pdf
- http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture13.pdf

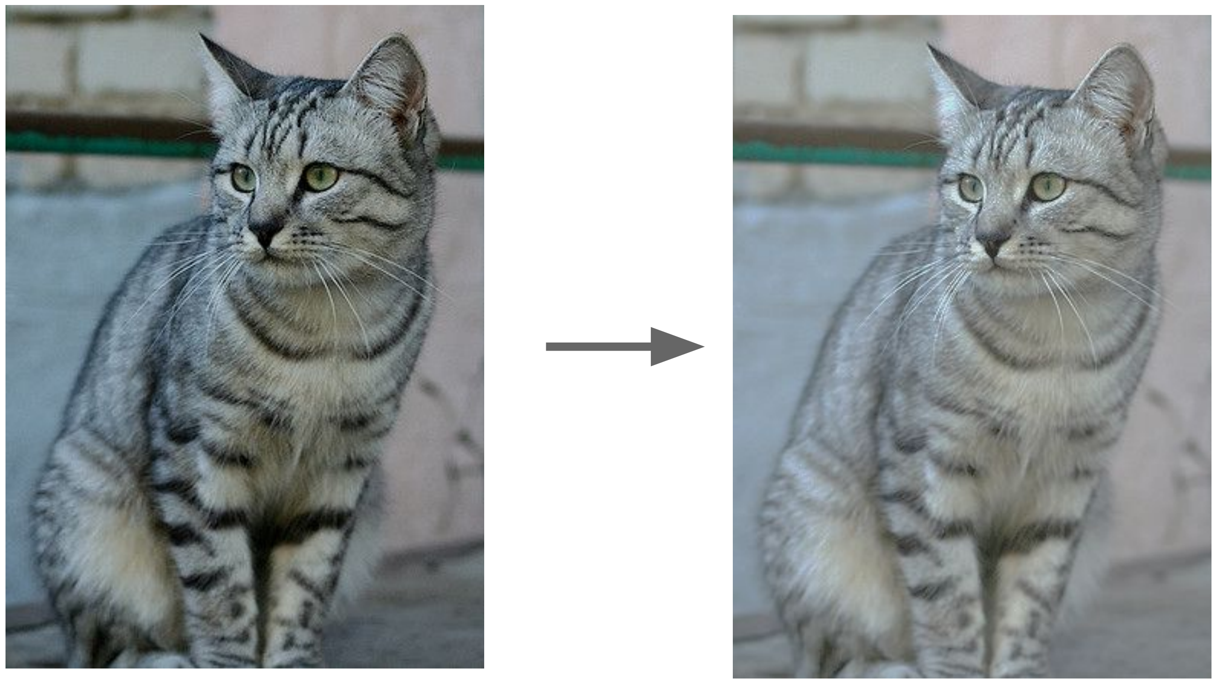
# Data Augmentation



# Data Augmentation



**crop/scale**



**color jitter**

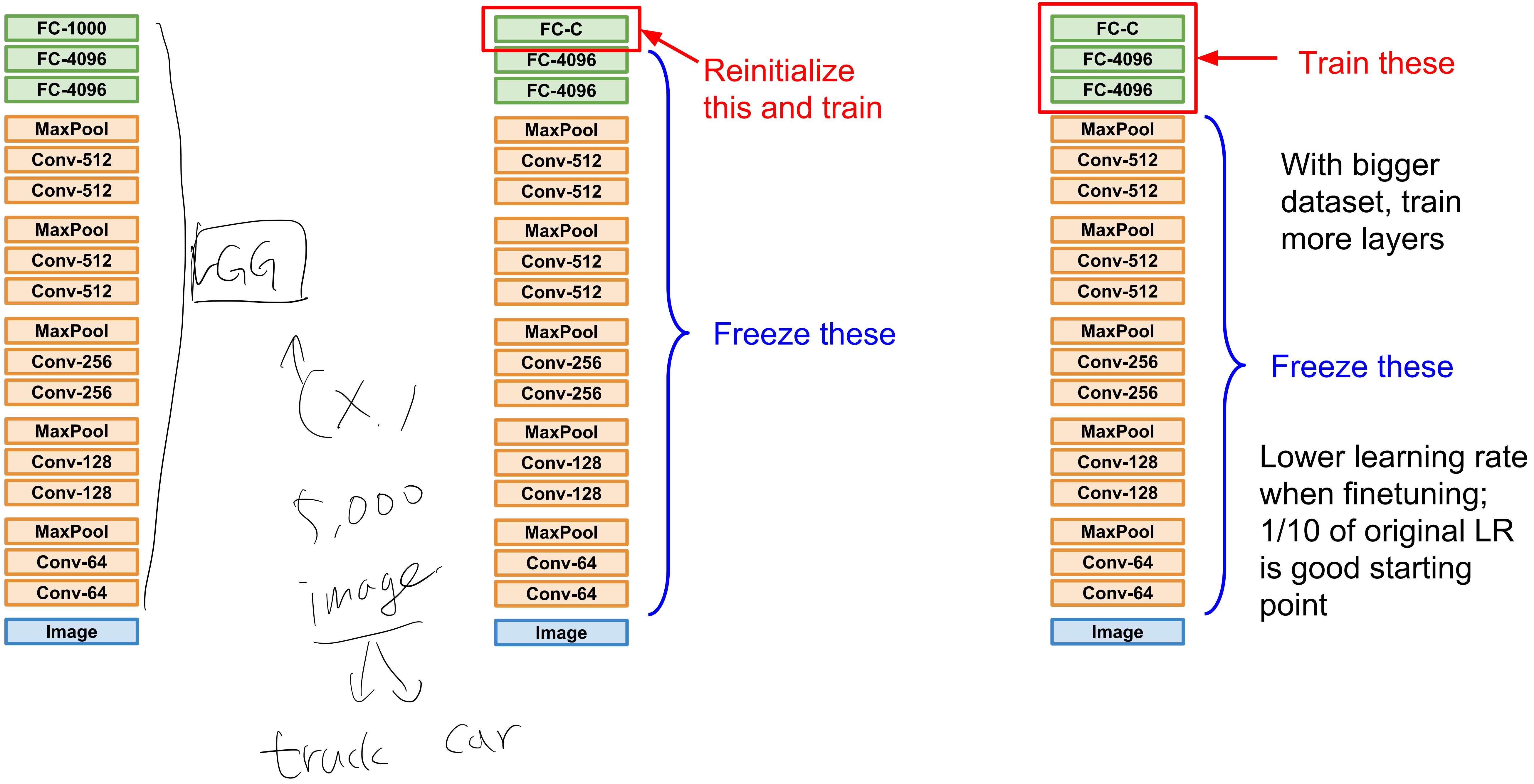
# Transfer Learning with CNNs

Donahue et al, “DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition”, ICML 2014
Razavian et al, “CNN Features Off-the-Shelf: An Astounding Baseline for Recognition”, CVPR Workshops 2014

1. Train on Imagenet

2. Small Dataset (C classes)

3. Bigger dataset



Reinitialize this and train

Freeze these

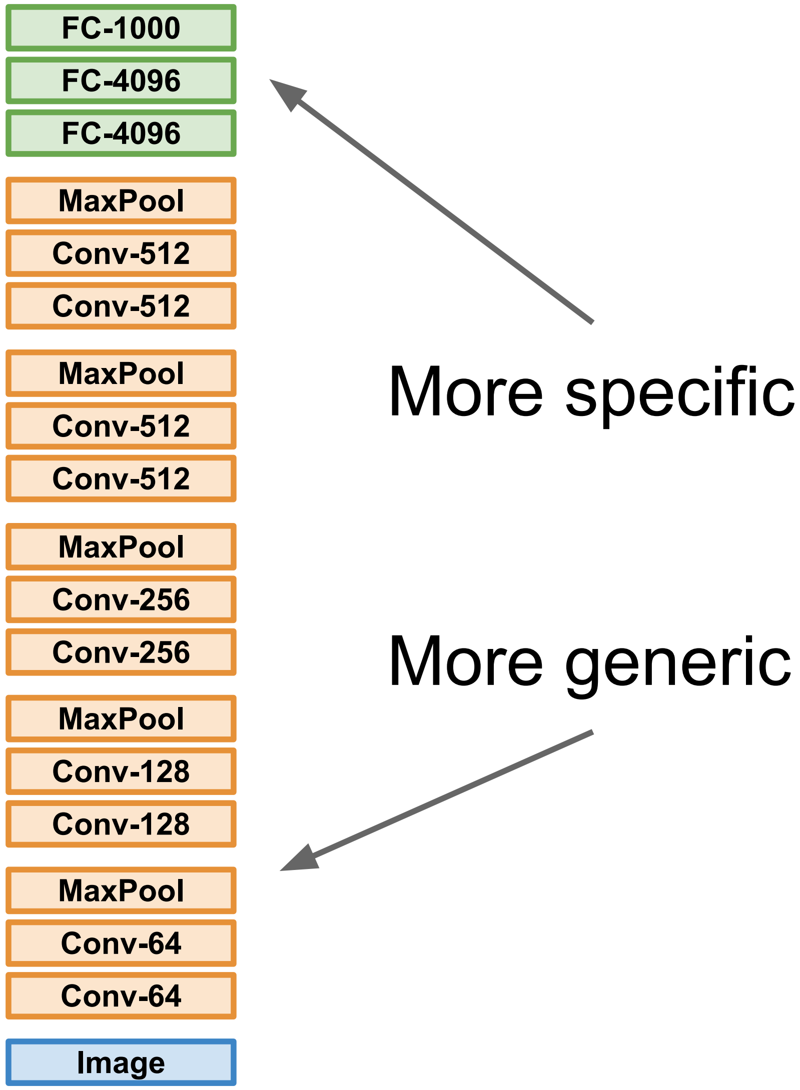
Train these

With bigger dataset, train more layers

Freeze these

Lower learning rate when finetuning; 1/10 of original LR is good starting point

# Transfer Learning

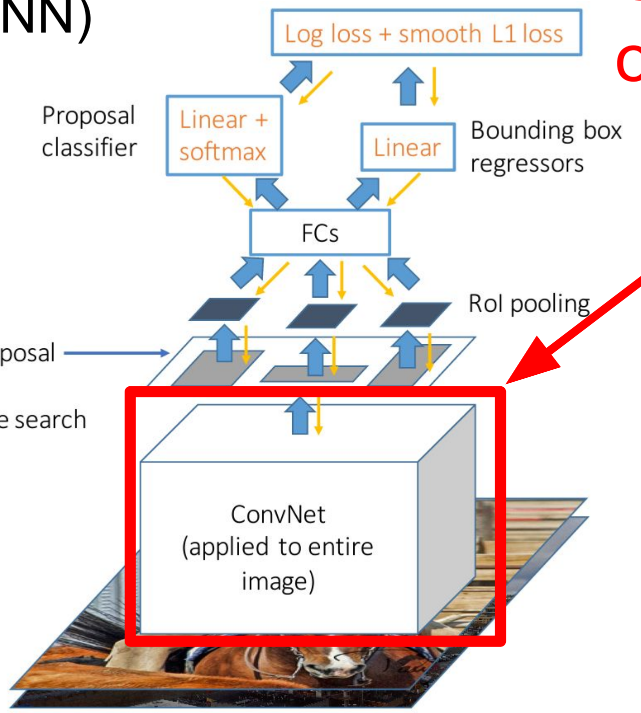


| | **very similar dataset** | **very different dataset** |
|---|---|---|
| **very little data** | Use Linear Classifier on top layer | You're in trouble… Try linear classifier from different stages |
| **quite a lot of data** | Finetune a few layers | Finetune a larger number of layers |

# Transfer Learning

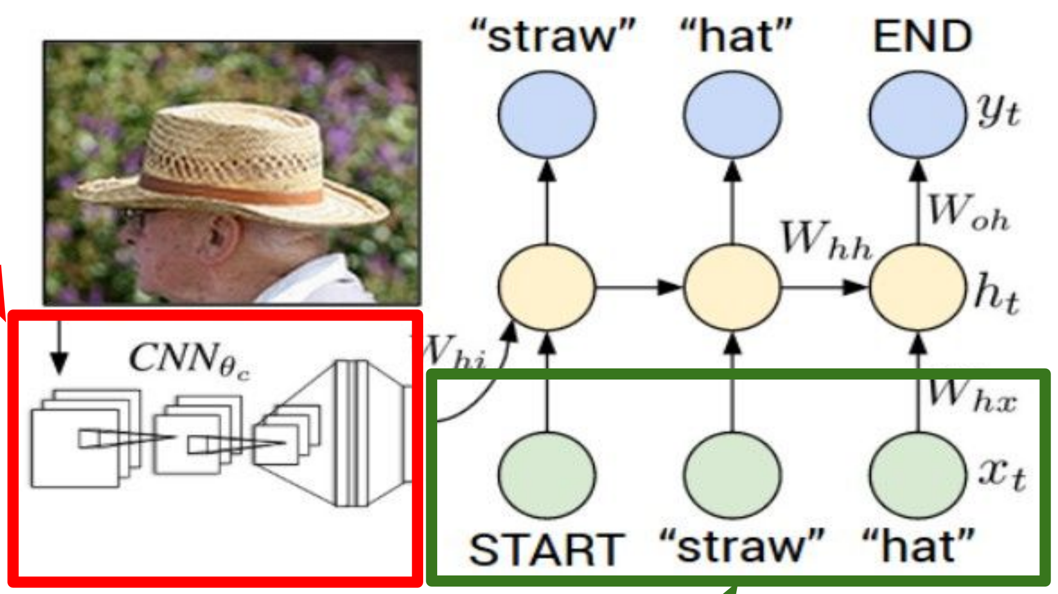
Transfer learning with CNNs is pervasive…
(it's the norm, not an exception)

Object Detection
(Fast R-CNN)



CNN pretrained on ImageNet

Image Captioning: CNN + RNN



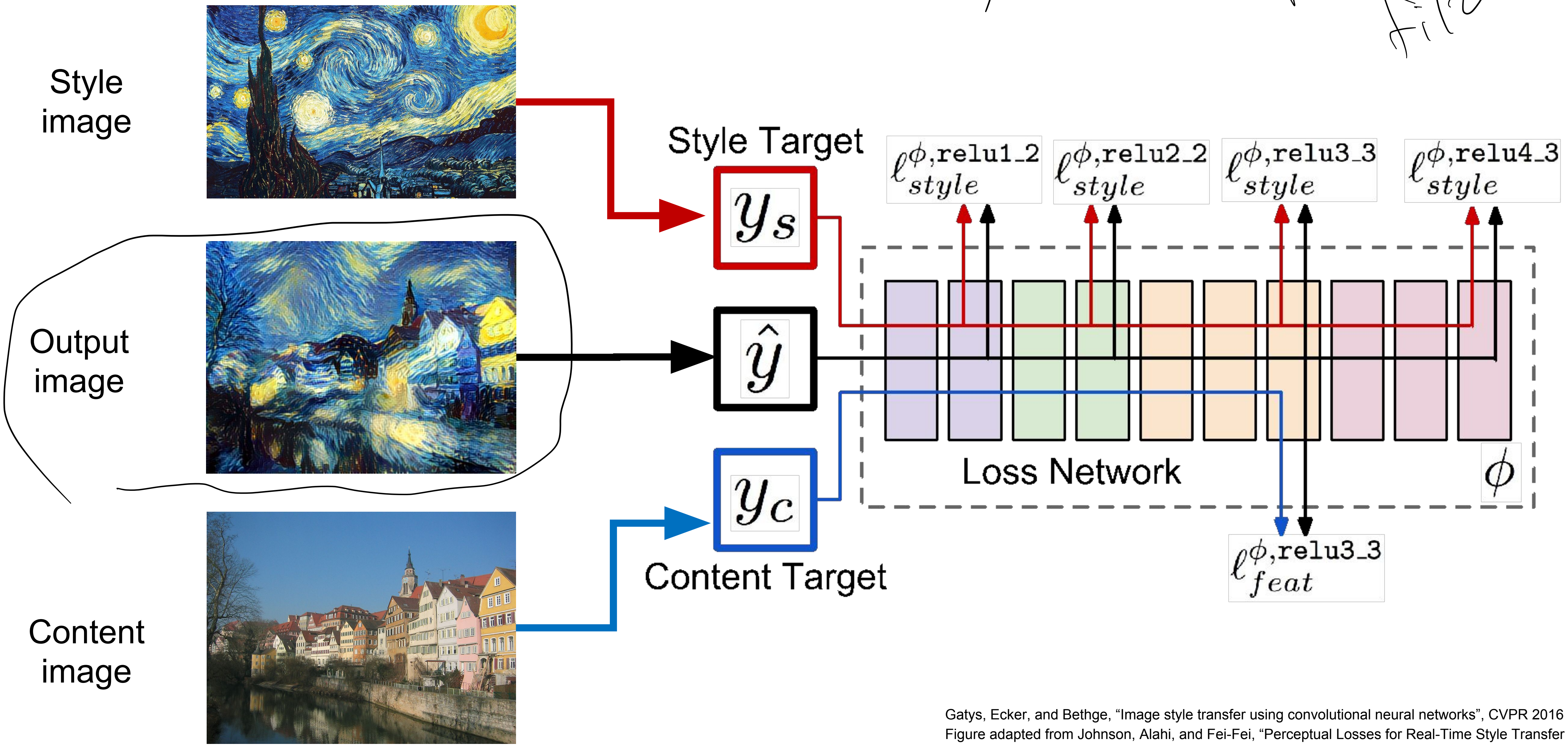
Word vectors pretrained with word2vec

Girshick, "Fast R-CNN", ICCV 2015
Figure copyright Ross Girshick, 2015. Reproduced with permission.

Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015
Figure copyright IEEE, 2015. Reproduced for educational purposes.

# Style Transfer

style information correlation matrix of filters.

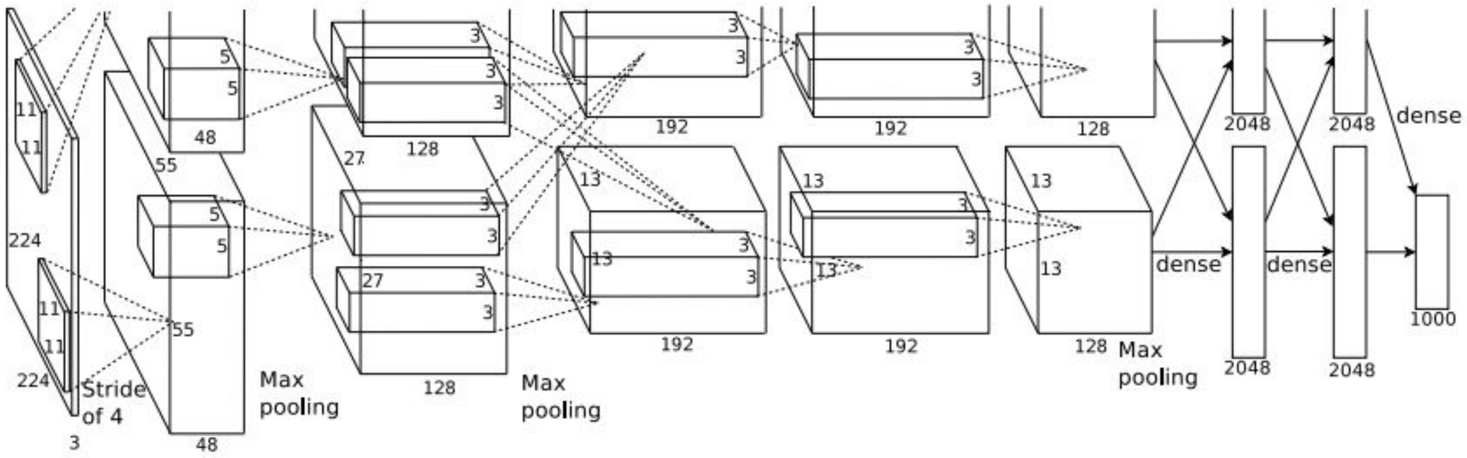

Style image
Output image
Content image
Style Target
$y_s$
$\hat{y}$
$y_c$
Content Target
$\ell_{style}^{\phi,relu1\_2}$
$\ell_{style}^{\phi,relu2\_2}$
$\ell_{style}^{\phi,relu3\_3}$
$\ell_{style}^{\phi,relu4\_3}$
Loss Network
$\phi$
$\ell_{feat}^{\phi,relu3\_3}$

Gatys, Ecker, and Bethge, "Image style transfer using convolutional neural networks", CVPR 2016
Figure adapted from Johnson, Alahi, and Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution", ECCV 2016. Copyright Springer, 2016. Reproduced for educational purposes.

# What’s going on inside ConvNets?

This image is CC0 public domain

Input Image:
3 x 224 x 224

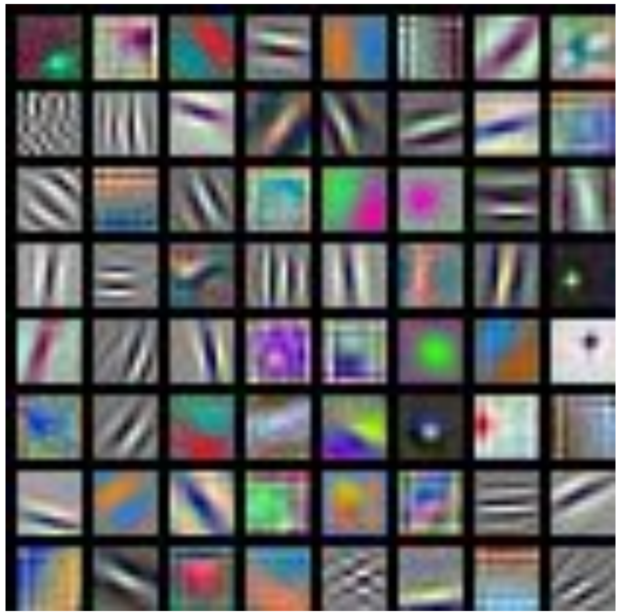


Class Scores:
1000 numbers

What are the intermediate features looking for?

# Example: First layer

## First Layer: Visualize Filters

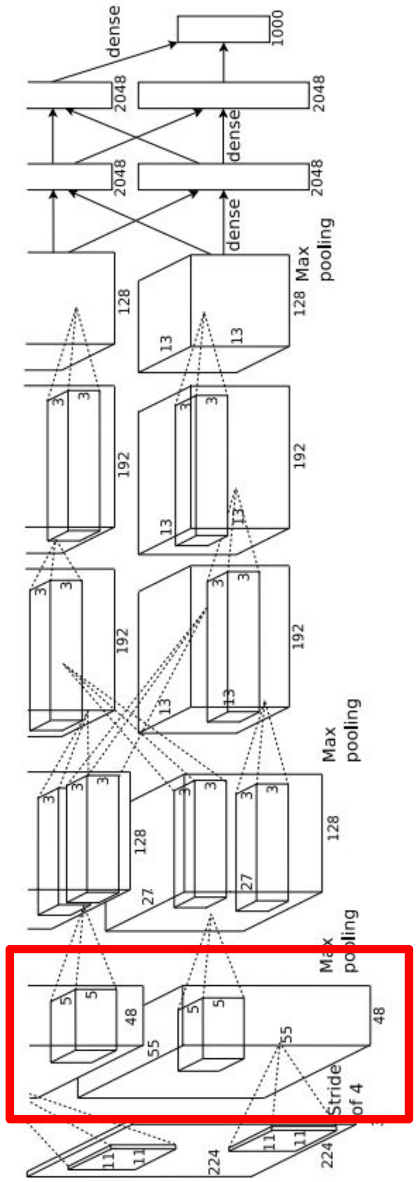


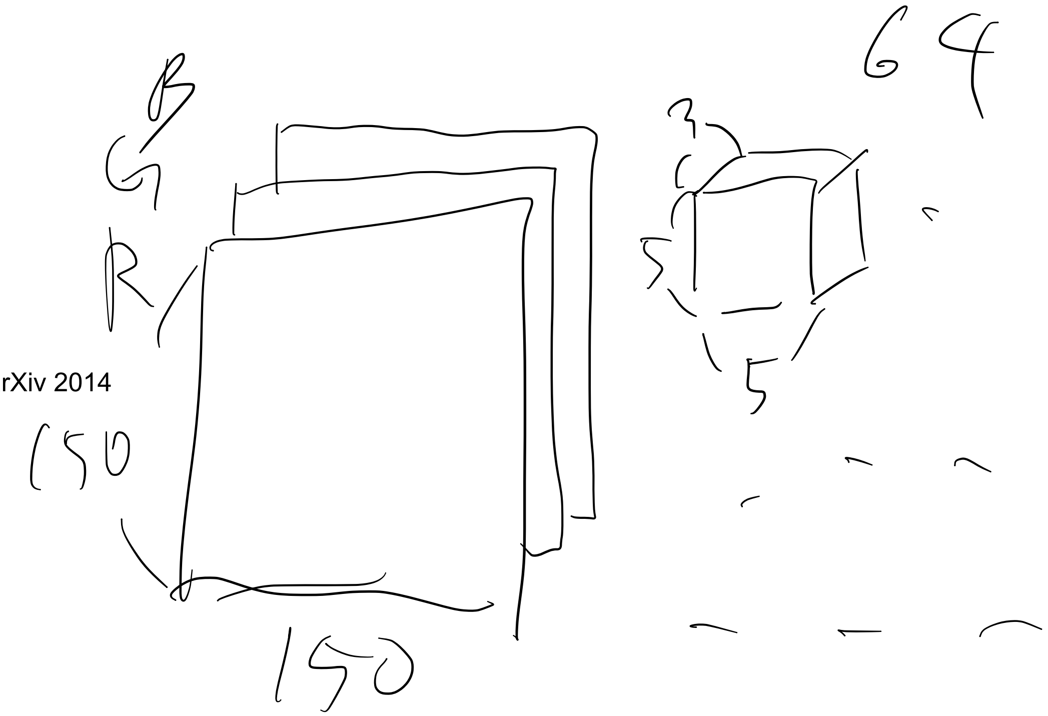
AlexNet:
64 x 3 x 11 x 11

ResNet-18:
64 x 3 x 7 x 7

ResNet-101:
64 x 3 x 7 x 7

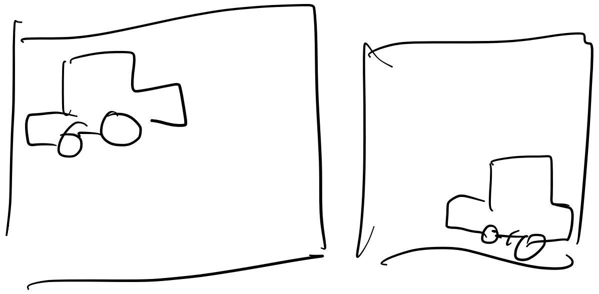
DenseNet-121:
64 x 3 x 7 x 7





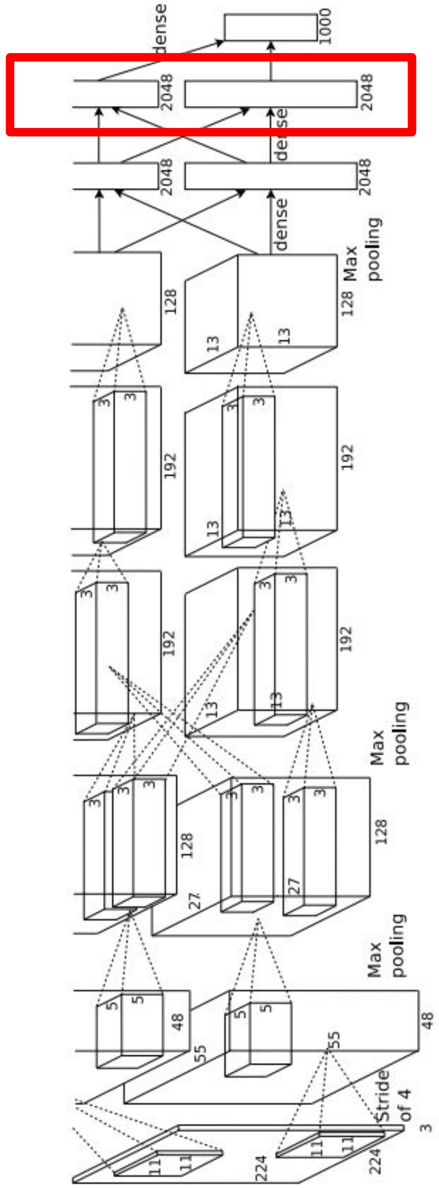
Krizhevsky, “One weird trick for parallelizing convolutional neural networks”, arXiv 2014
He et al, “Deep Residual Learning for Image Recognition”, CVPR 2016
Huang et al, “Densely Connected Convolutional Networks”, CVPR 2017

# Example: Last layer

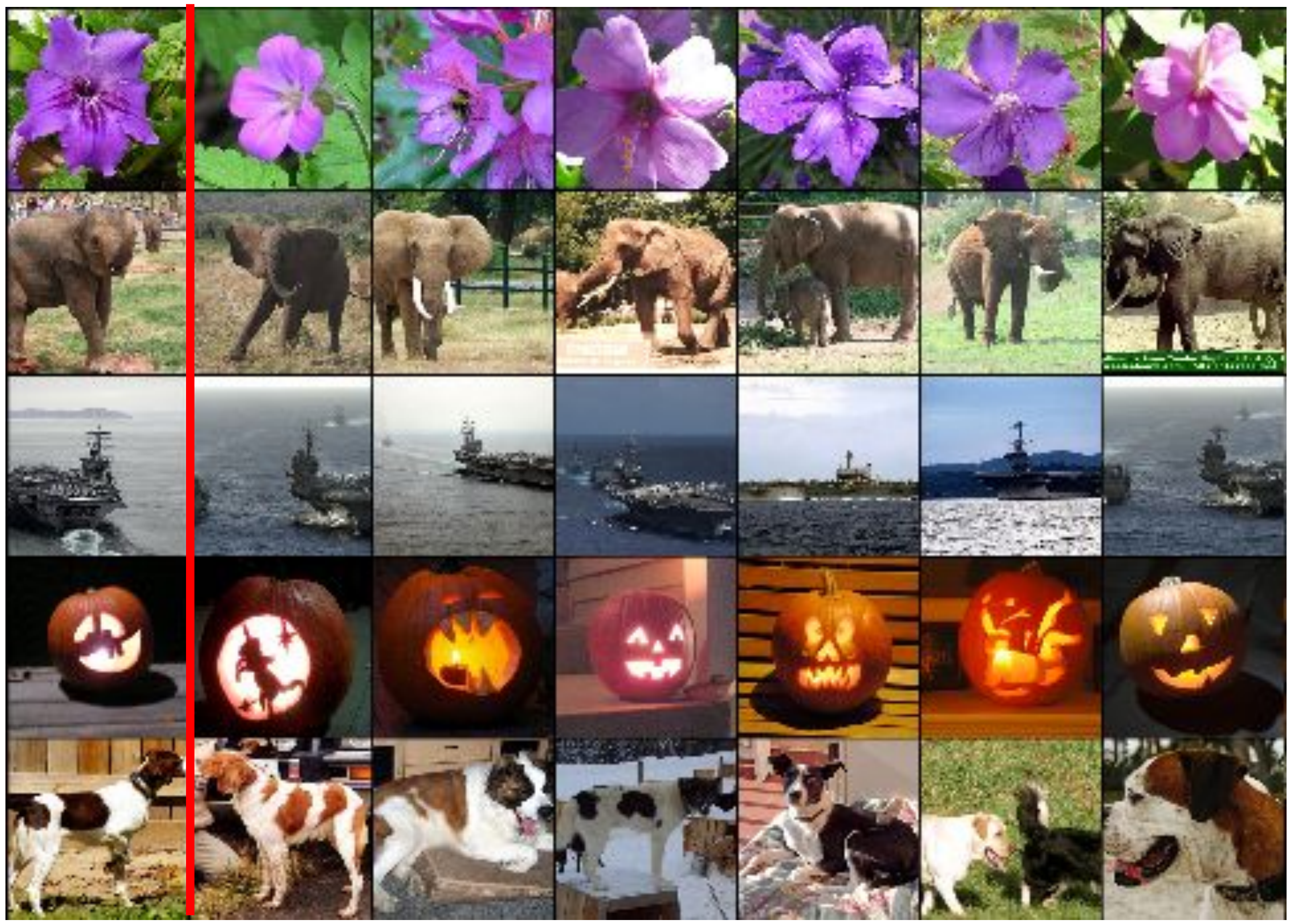


## Last Layer: Nearest Neighbors

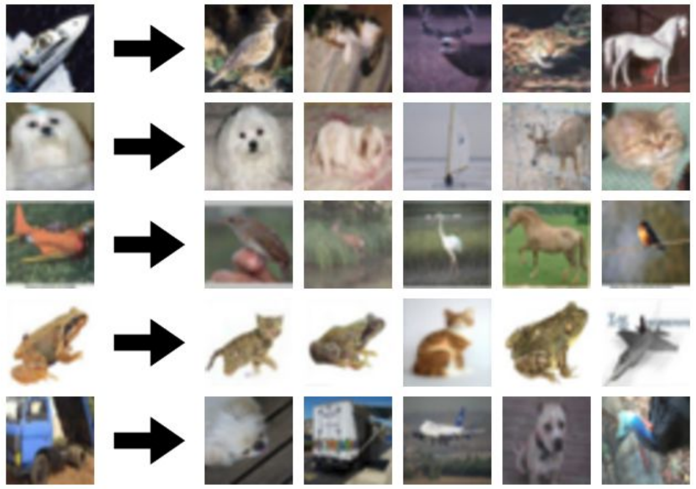
4096-dim vector



Test image L2 Nearest neighbors in feature space



**Recall**: Nearest neighbors in pixel space



Krizhevsky et al, “ImageNet Classification with Deep Convolutional Neural Networks”, NIPS 2012.
Figures reproduced with permission.

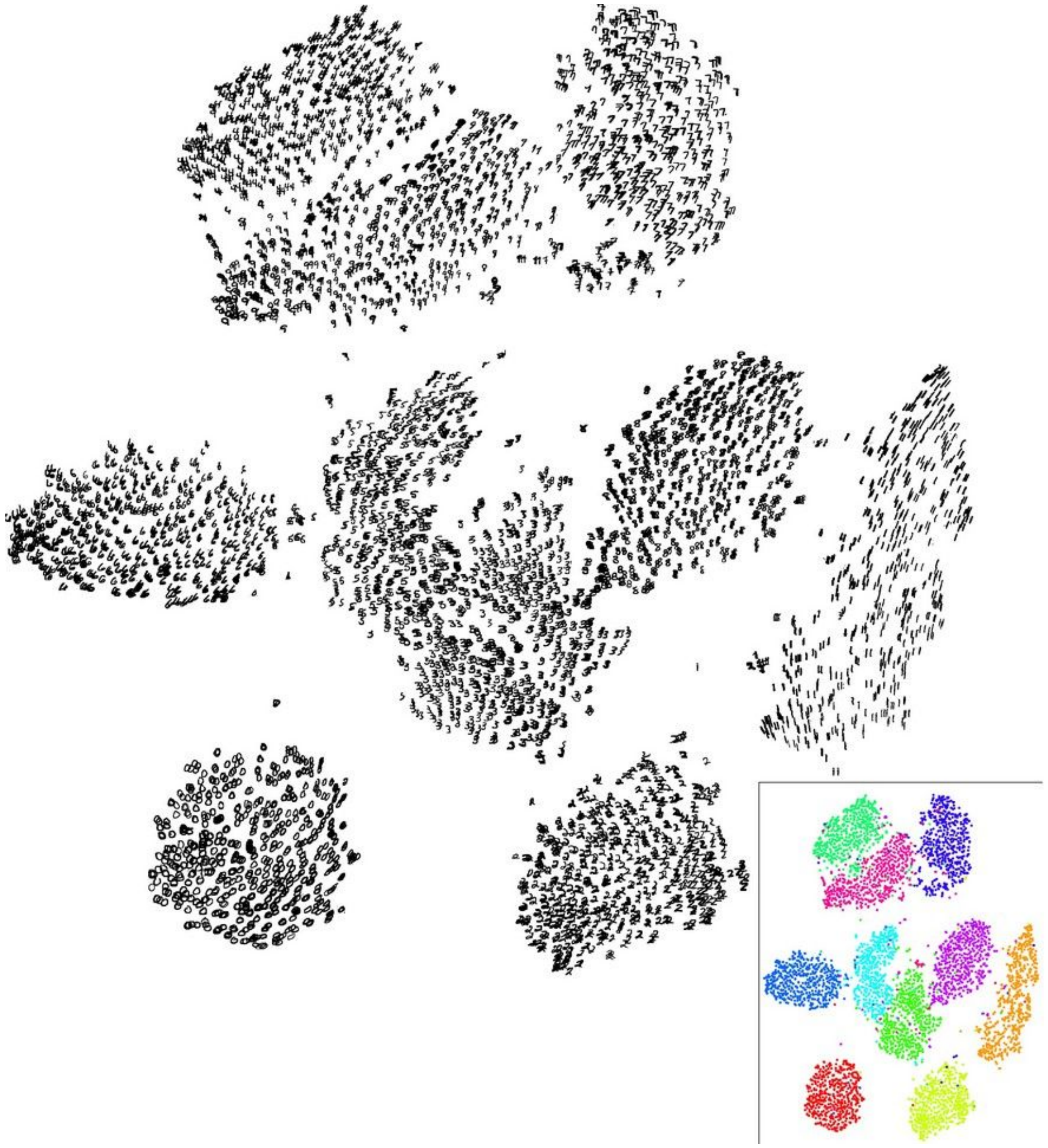
# Example: Last Layer

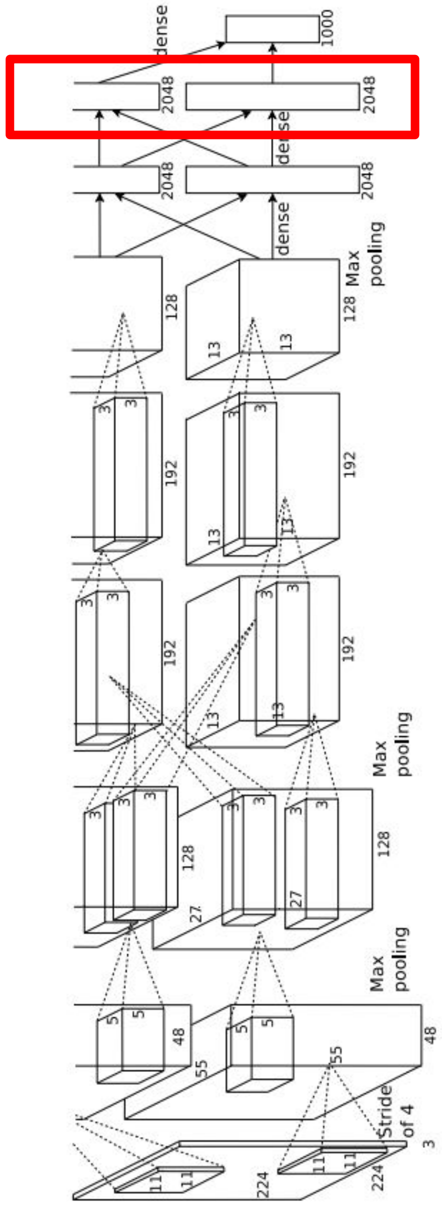
## Last Layer: Dimensionality Reduction

Visualize the "space" of FC7 feature vectors by reducing dimensionality of vectors from 4096 to 2 dimensions

Simple algorithm: Principal Component Analysis (PCA)

More complex: **t-SNE**

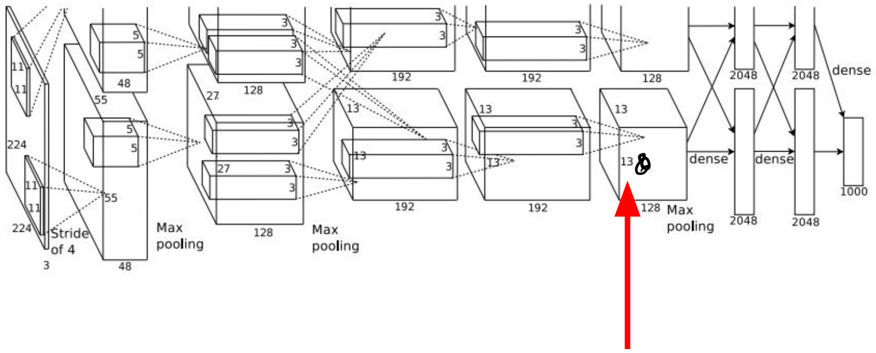




Van der Maaten and Hinton, "Visualizing Data using t-SNE", JMLR 2008
Figure copyright Laurens van der Maaten and Geoff Hinton, 2008. Reproduced with permission.

# Neurons?

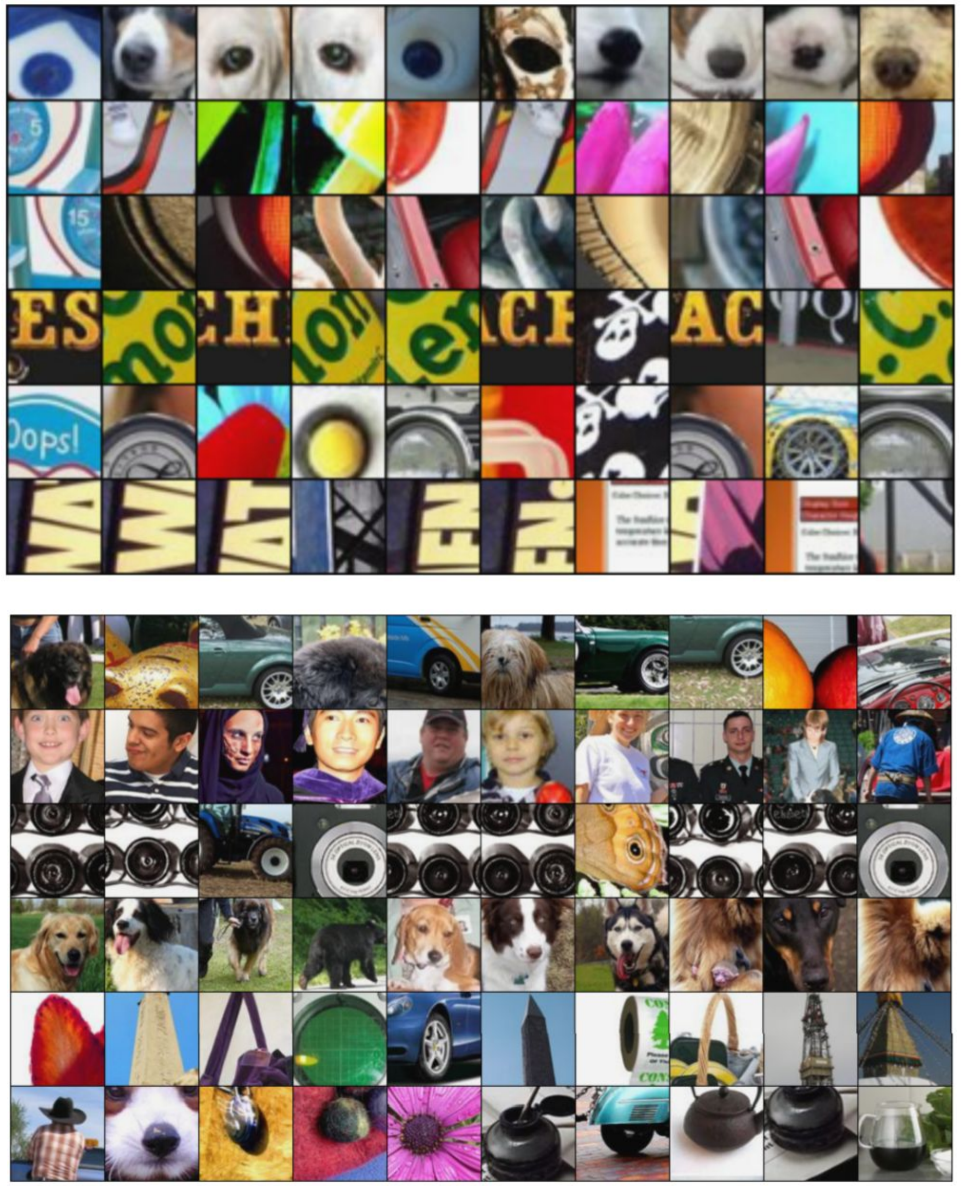
## Maximally Activating Patches



Pick a layer and a channel; e.g. conv5 is 128 x 13 x 13, pick channel 17/128

Run many images through the network, record values of chosen channel

Visualize image patches that correspond to maximal activations



Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015
Figure copyright Jost Tobias Springenberg, Alexey Dosovitskiy, Thomas Brox, Martin Riedmiller, 2015; reproduced with permission.