ConvNet Case Study I: Alexnet

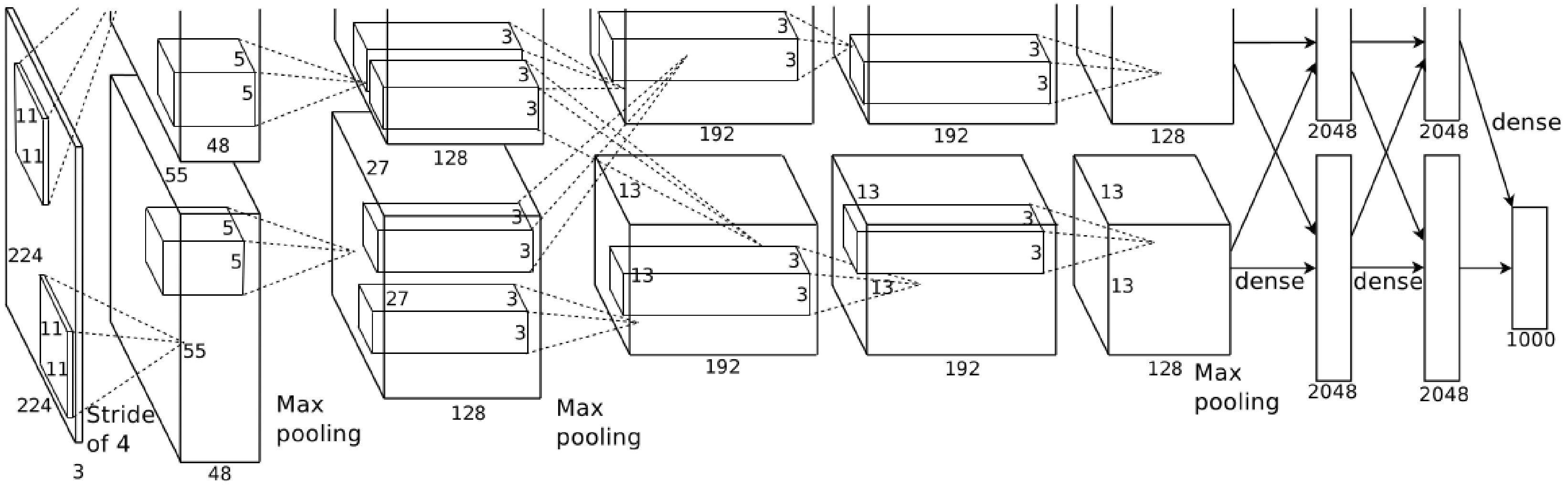
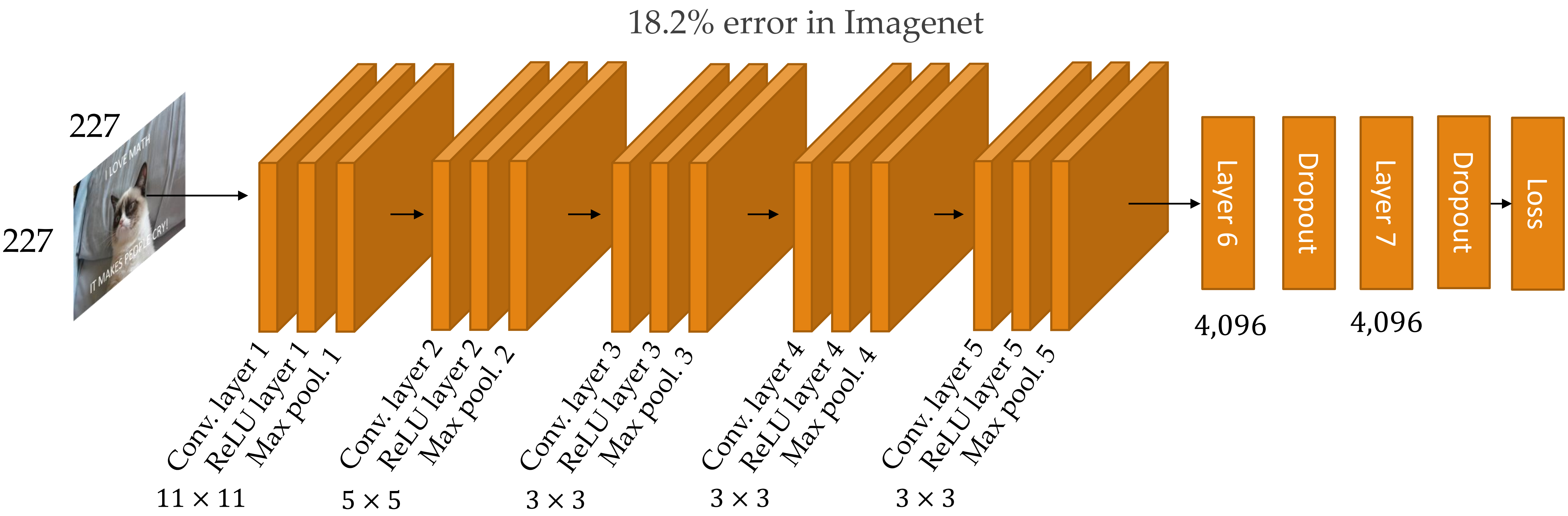
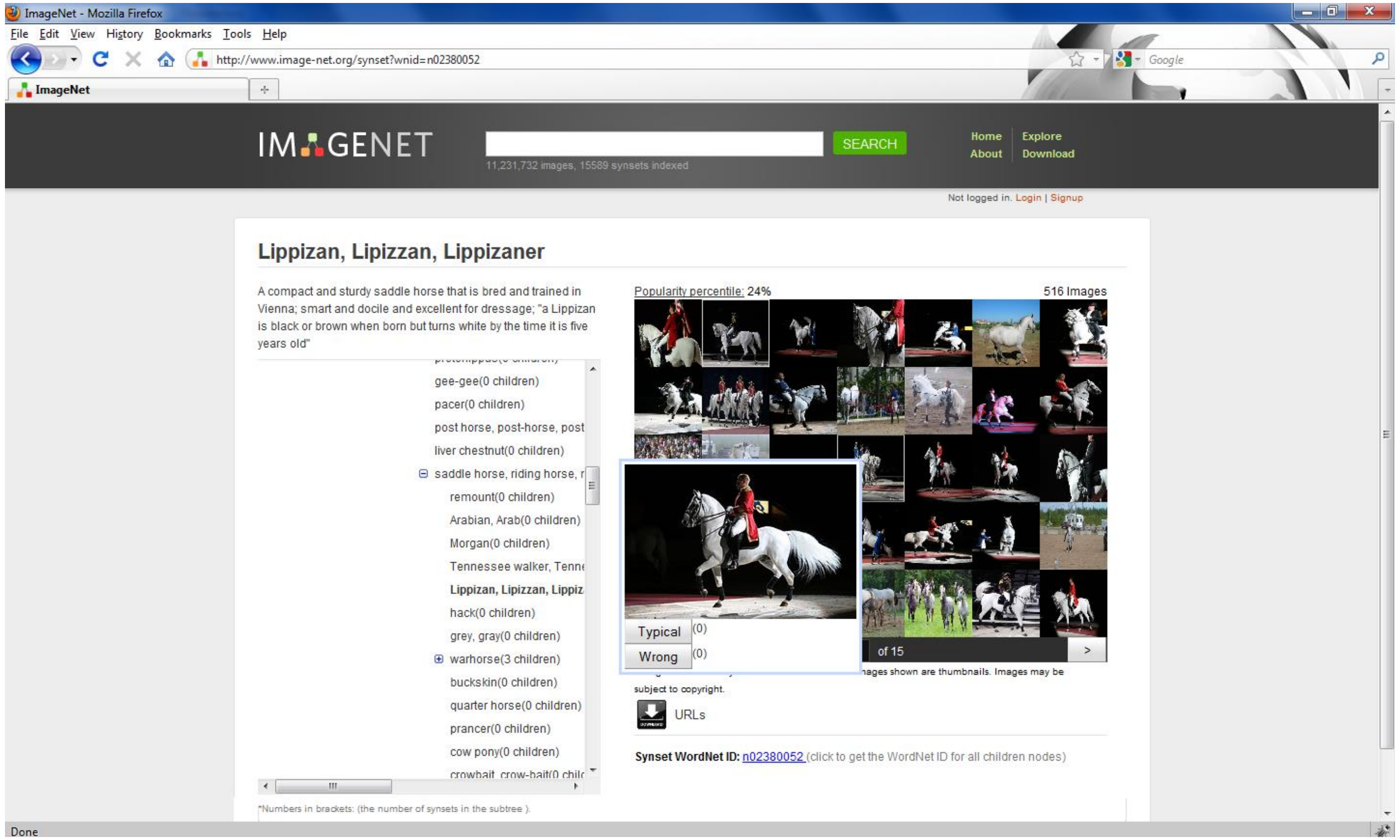


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

Architectural details



IMAGENET



http://www.image-net.org

Constructing ImageNet

Step 1:
Collect candidate images
via the Internet

Step 2:
Clean up the candidate
Images by humans

YAHOO! picsearch flickr Live Search Google Image Search

amazon mechanical turk
Artificial Artificial Intelligence

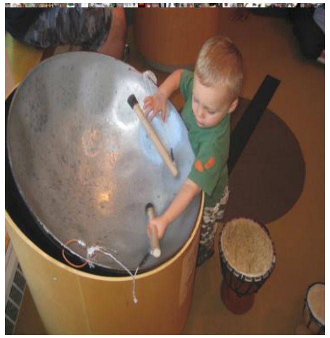
Some statistics

- July 2008: 0 images
- Dec 2008: 3 million images, 6K+ synsets
- April 2010: 11 million images, 15K+ synsets
- Currently: 14 million images, 21K synsets indexed

ImageNet Large Scale Visual Recognition Challenge

- Ran from 2010 to 2017
  - Today a Kaggle competition

- Main task: image classification
  - Automatically label 1.4M images with 1K objects
  - Measure top-5 classification error



Output		**Output**	
Scale		Scale	
T-shirt		T-shirt	
Steel drum	✓	Giant panda	✗
Drumstick		Drumstick	
Mud turtle		Mud turtle	

Deep learning at ImageNet classification challenge

CNN based, non-CNN based

2012 Teams	%error
Supervision (Toronto)	15.3
ISI (Tokyo)	26.1
VGG (Oxford)	26.9
XRCE/INRIA	27.0
UvA (Amsterdam)	29.6
INRIA/LEAR	33.4

Figures from Y. LeCun’s CVPR 2015 plenary talk

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2013 Teams	%error
Clarifai (NYU spinoff)	11.7
NUS (singapore)	12.9
Zeiler-Fergus (NYU)	13.5
A. Howard	13.5
OverFeat (NYU)	14.1
UvA (Amsterdam)	14.2
Adobe	15.2
VGG (Oxford)	15.2
VGG (Oxford)	23.0

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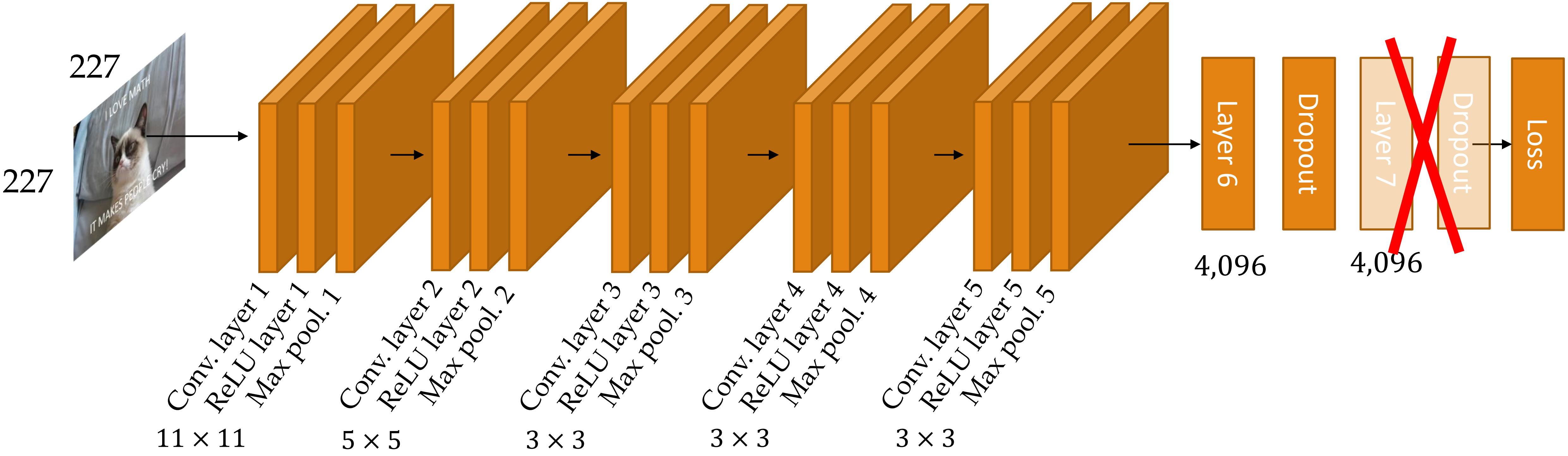
VGG (Oxford)	15.2
VGG (Oxford)	23.0

2014 Teams	%error
GoogLeNet	6.6
VGG (Oxford)	7.3
MSRA	8.0
A. Howard	8.1
DeeperVision	9.5
NUS-BST	9.7
TTIC-ECP	10.2
XYZ	11.2
UvA	12.1

Figures from Y. LeCun’s CVPR 2015 plenary talk

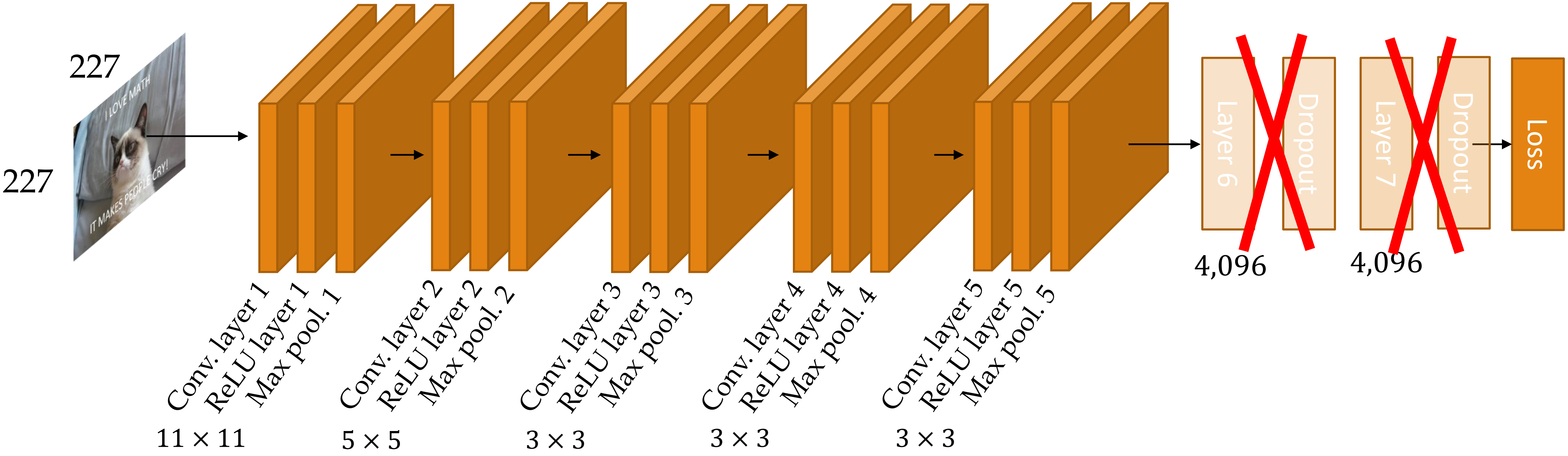
Removing layer 7

1.1% drop in performance, 16 million less parameters



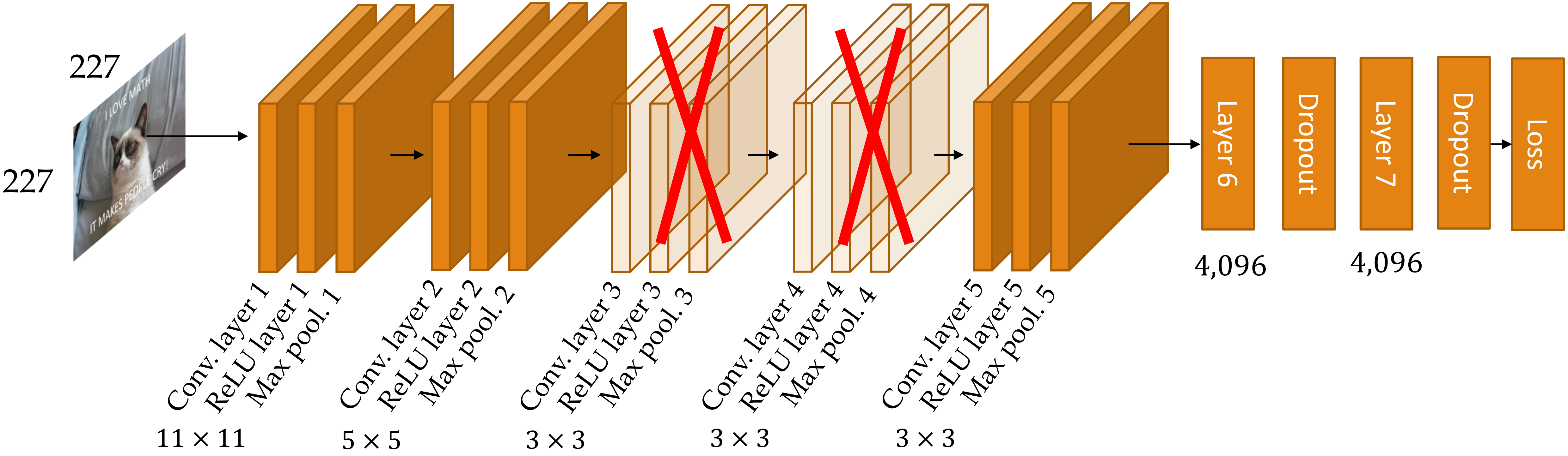
Removing layer 6, 7

5.7% drop in performance, 50 million less parameters

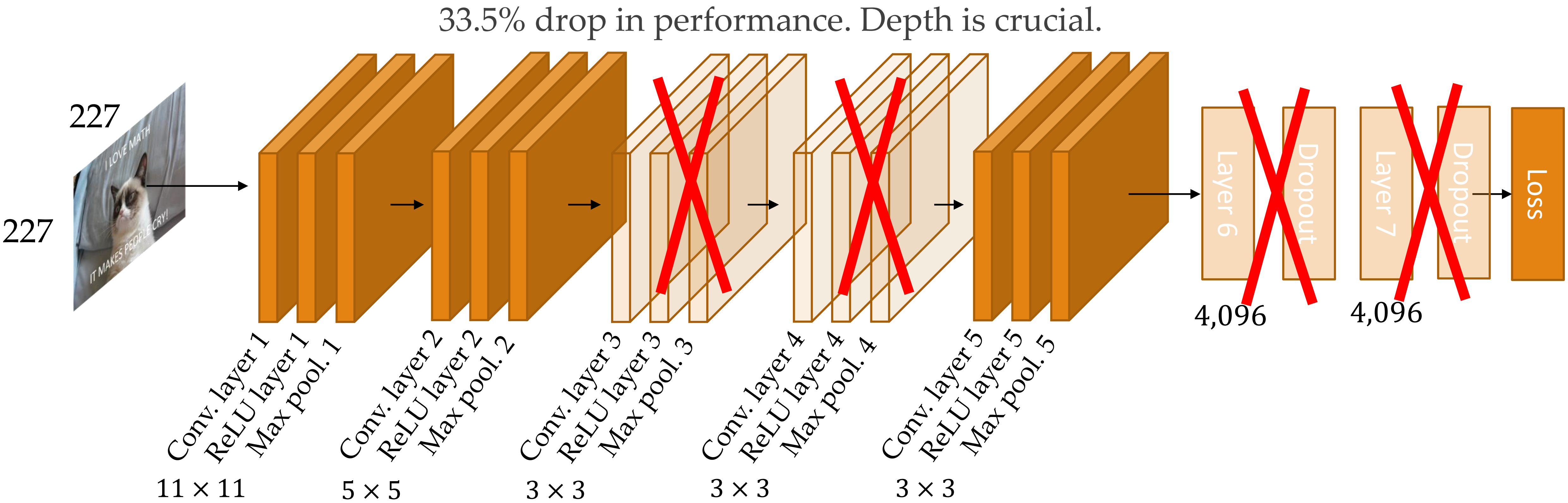


Removing layer 3, 4

3.0% drop in performance, 1 million less parameters. Why?

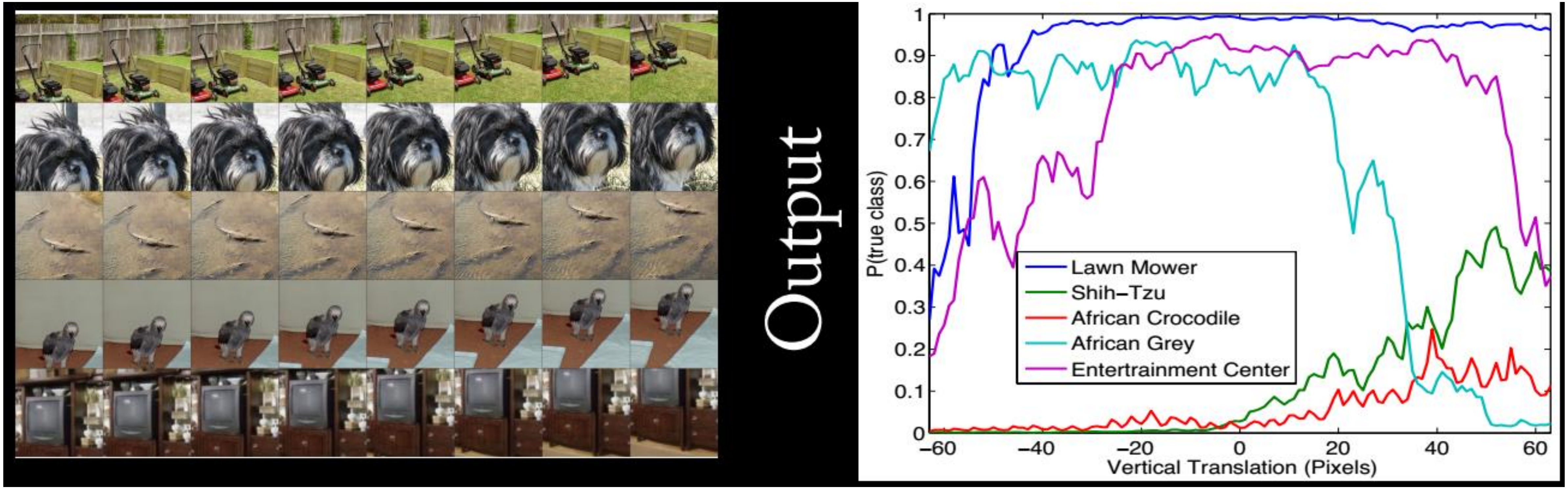


Removing layer 3, 4, 6, 7



Translation invariance

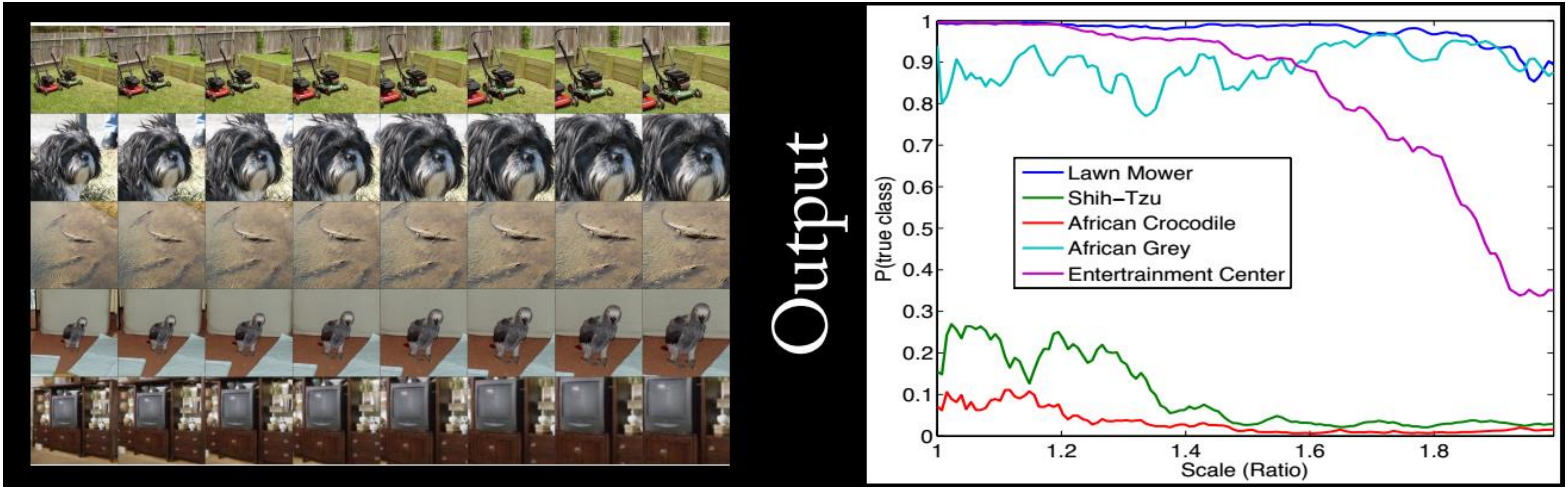
- CNNs are translation invariant



Credit: R. Fergus slides in Deep Learning Summer School 2016

Scale invariance

- CNNs are scale invariant to some degree
  - The standard convolutional filters not scale invariant
  - Scale invariance learnt depends on scale variations present in data



Rotation invariance

- CNNs are not rotation invariant
  - The standard convolutional filters not rotation invariant
  - And only few rotated examples in the training set. Augmentation can help