Lab. – Classification

Convolutional Neural Networks (CNNs)

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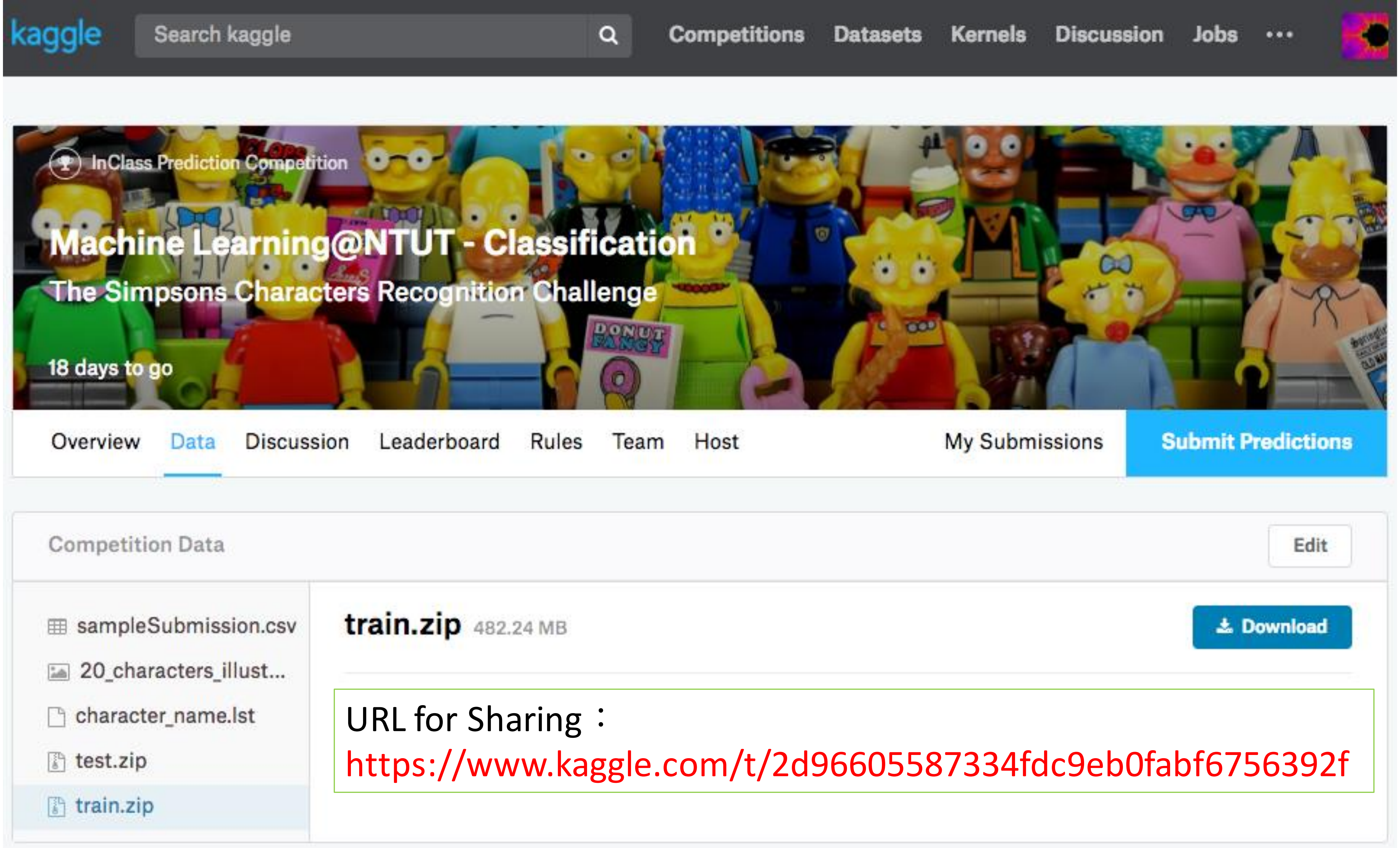
Kaggle Competition - The Simpsons Characters Recognition Challenge

https://www.kaggle.com/t/2d96605587334fdc9eb0fabf6756392f

- Images of 20 characters extracted from The Simpsons episodes
  - ✓ About 1000 images per character
  - ✓ Pictures are under various size, scenes
  - ✓ not necessarily centered in each image and could sometimes be with or cropped from other characters



URL for Sharing：
https://www.kaggle.com/t/2d96605587334fdc9eb0fabf6756392f

GitHub Classroom

Machine Learning@NTUT - 2017

MachineLearningNTUT

Classification

Individual assigment

Give this to your students

https://classroom.github.com/a/4JnaHLk8

20 Characters in The Simposons

abraham_grampa_simpson apu_nahasapeemapetilon bart_simpson charles_montgomery_burns chief_wiggum
comic_book_guy edna_krabappel homer_simpson kent_brockman krusty_the_clown

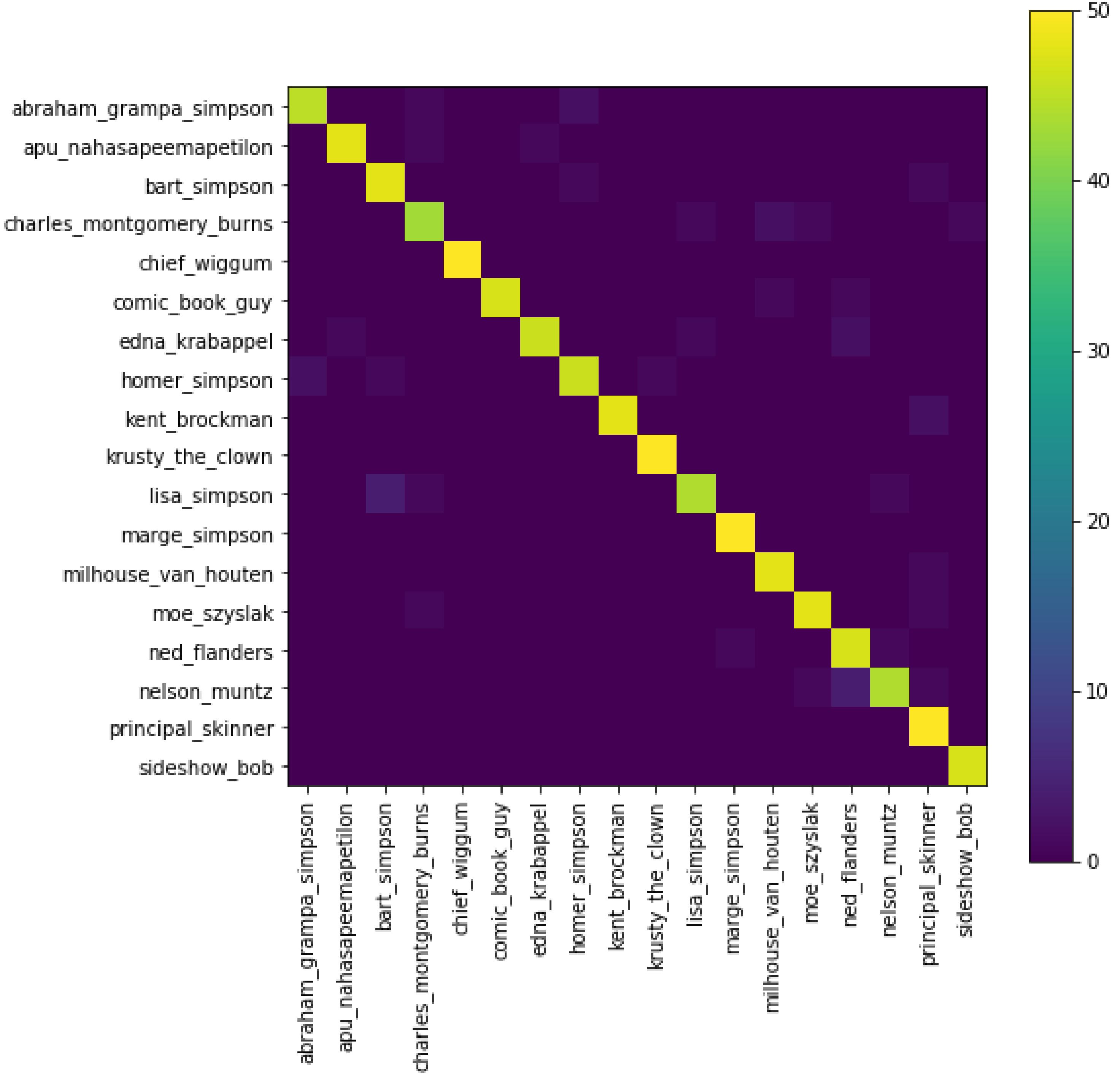
lenny_leonard lisa_simpson marge_simpson mayor_quimby milhouse_van_houten
moe_szyslakned_flanders nelson_muntz principal_skinner sideshow_bob

Demo

https://thumbs.gfycat.com/HarshCaringIndianpalmsquirrel-mobile.mp4 https://youtu.be/ta_hCXKZ_DM

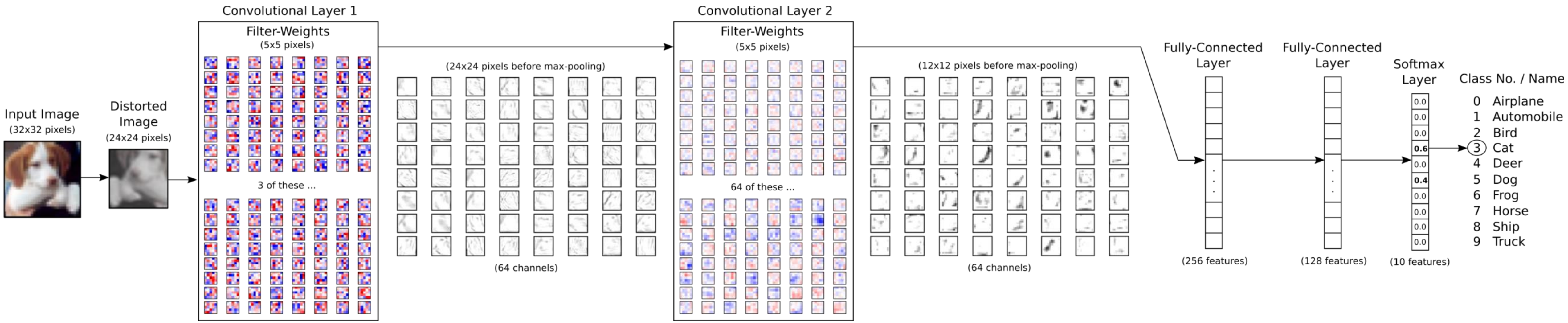
- # Task1
  - **Predict Simpsons Characters in all pictures**

- # Task2
  - **Compute the Confusion Matrix**



• Task3

- **Visualization and Understanding Convolutional Neural Networks**
  - 畫出每一層filter的權重
  - 畫出每一層的feature map

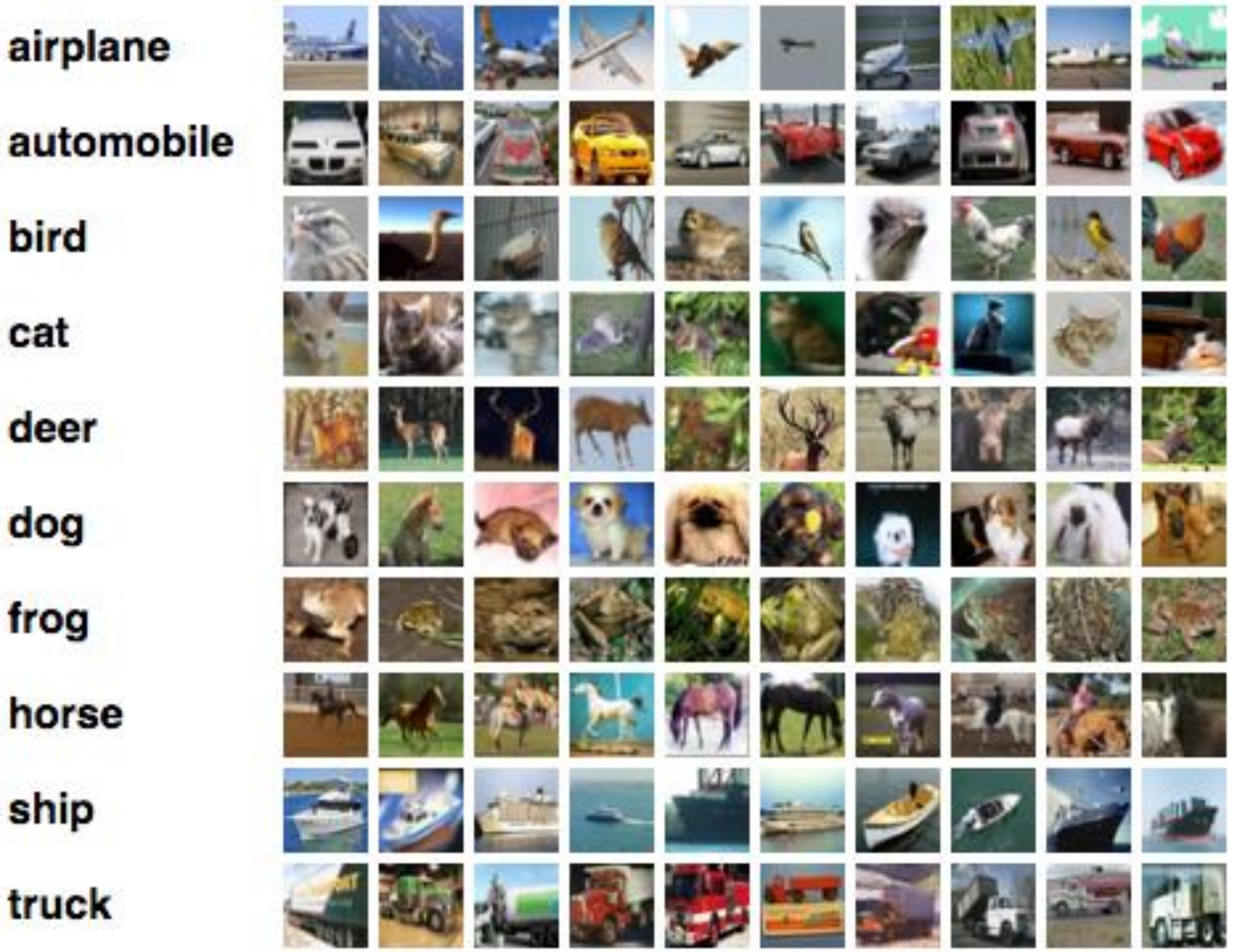


Example

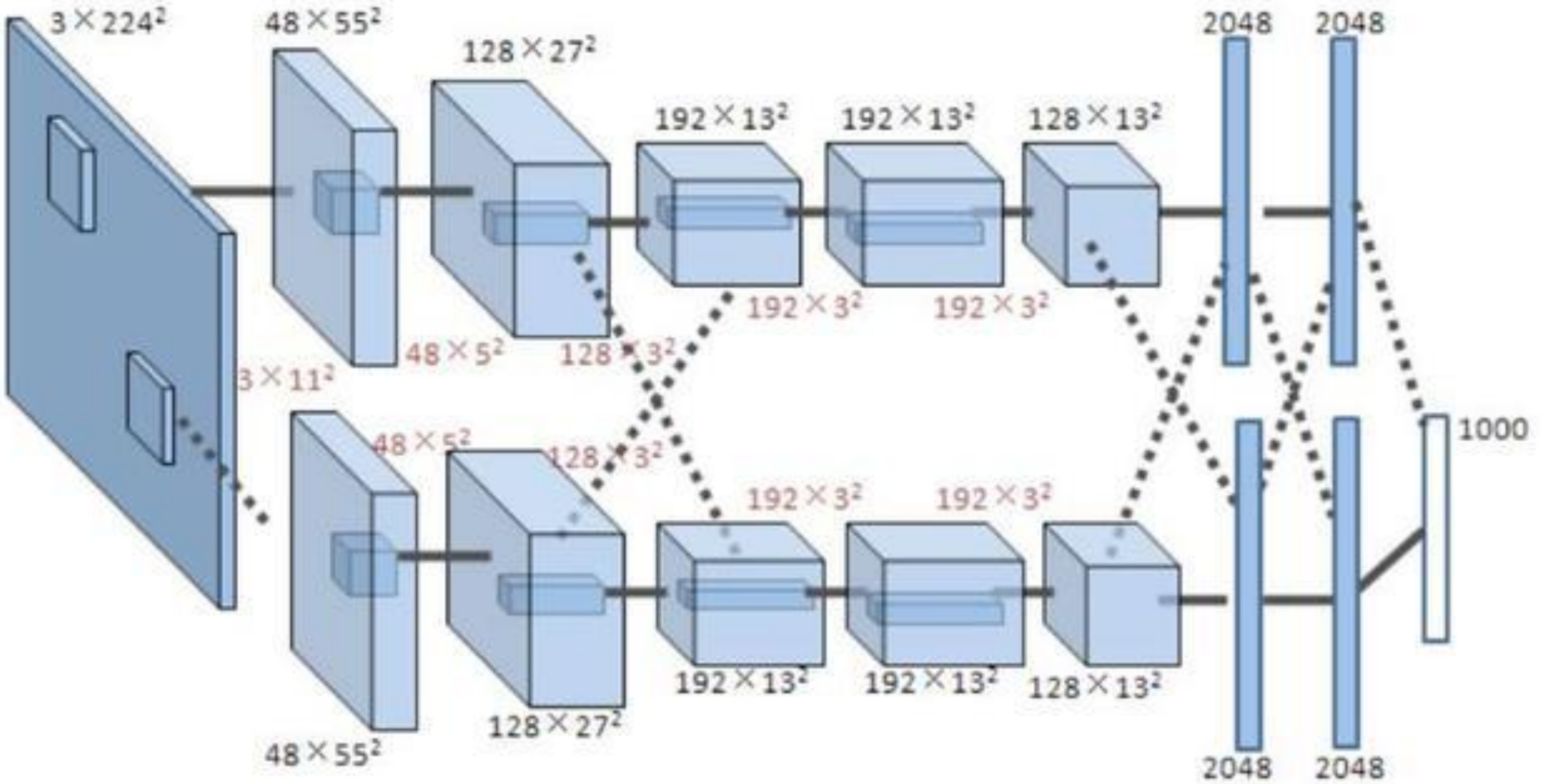
- Tensorflow Tutorial - Convolutional Neural Networks
  - https://www.tensorflow.org/versions/r0.11/tutorials/deep_cnn/index.html
  - The code for this tutorial resides in tensorflow/models/image/cifar10/
  - Accuracy on Test-Set: 79.3% (7932 / 10000)

CIFAR-10

- CIFAR-10 classification is a common benchmark problem in machine learning.
- The problem is to classify RGB 32x32 pixel images across 10 categories: airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck



AlexNet



3 × 224²
48 × 55²
128 × 27²
192 × 13²
192 × 13²
128 × 13²
2048
2048
3 × 11²
48 × 5²
128 × 3²
192 × 3²
192 × 3²
48 × 5²
128 × 3²
192 × 3²
192 × 3²
1000
192 × 13²
192 × 13²
128 × 13²
128 × 27²
48 × 55²
2048
2048

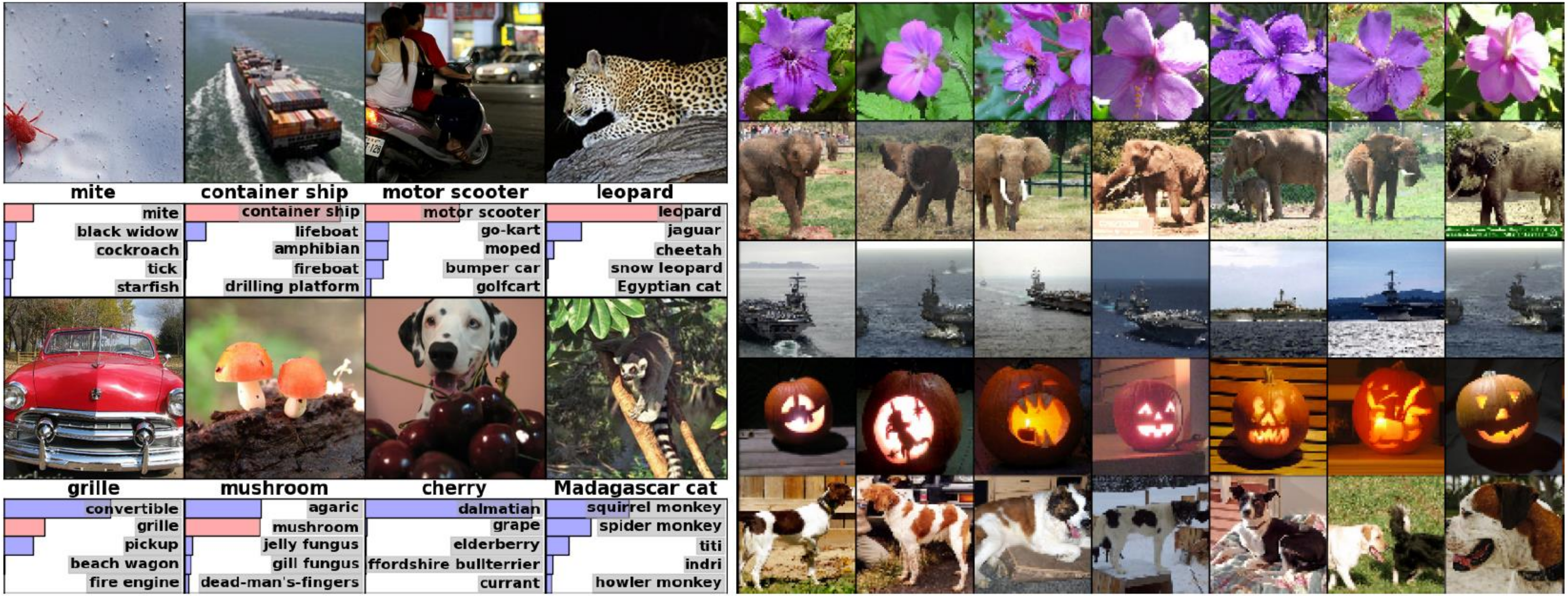


Figure 4: **(Left)** Eight ILSVRC-2010 test images and the five labels considered most probable by our model. The correct label is written under each image, and the probability assigned to the correct label is also shown with a red bar (if it happens to be in the top 5). **(Right)** Five ILSVRC-2010 test images in the first column. The remaining columns show the six training images that produce feature vectors in the last hidden layer with the smallest Euclidean distance from the feature vector for the test image.

References

- TensorFlow Tutorial CIFAR-10
  - https://www.youtube.com/watch?v=3BXfw_1_TF4
- TensorFlow CIFAR-10 tutorial, detailed step-by-step review
  - Part 1: http://www.aimechanic.com/2016/10/13/d242-tensorflow-cifar-10-tutorial-detailed-step-by-step-review-part-1/
  - Part 2: http://www.aimechanic.com/2016/10/17/d246-tensorflow-cifar-10-tutorial-detailed-review-part-2/
- TensorFlow-Tutorials/06_CIFAR-10.ipynb
  - https://github.com/Hvass-Labs/TensorFlow-Tutorials/blob/master/06_CIFAR-10.ipynb

ImageNet Classification with Deep Convolutional Neural Networks

Goa
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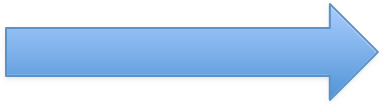
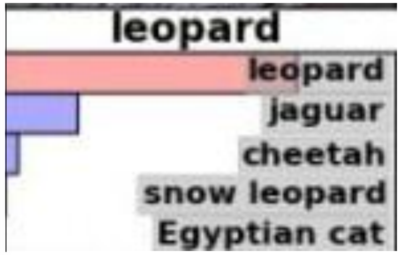
Classifica(on





ImageNe
t

- Over 15M labeled high resolution images
- Roughly 22K categories
- Collected from web and labeled by Amazon Mechanical Turk

h-p://image--net.org/

ILSVRC

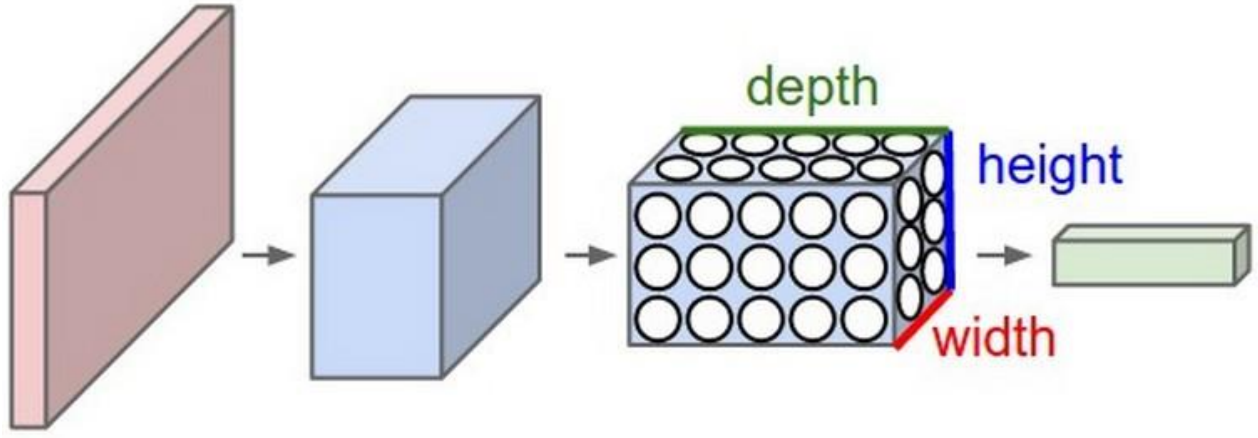
- Annual competition of image classification at large scale
- 1.2M images in 1K categories
- Classification: make 5 guesses about the image label

EntleBucher

Appenzeller

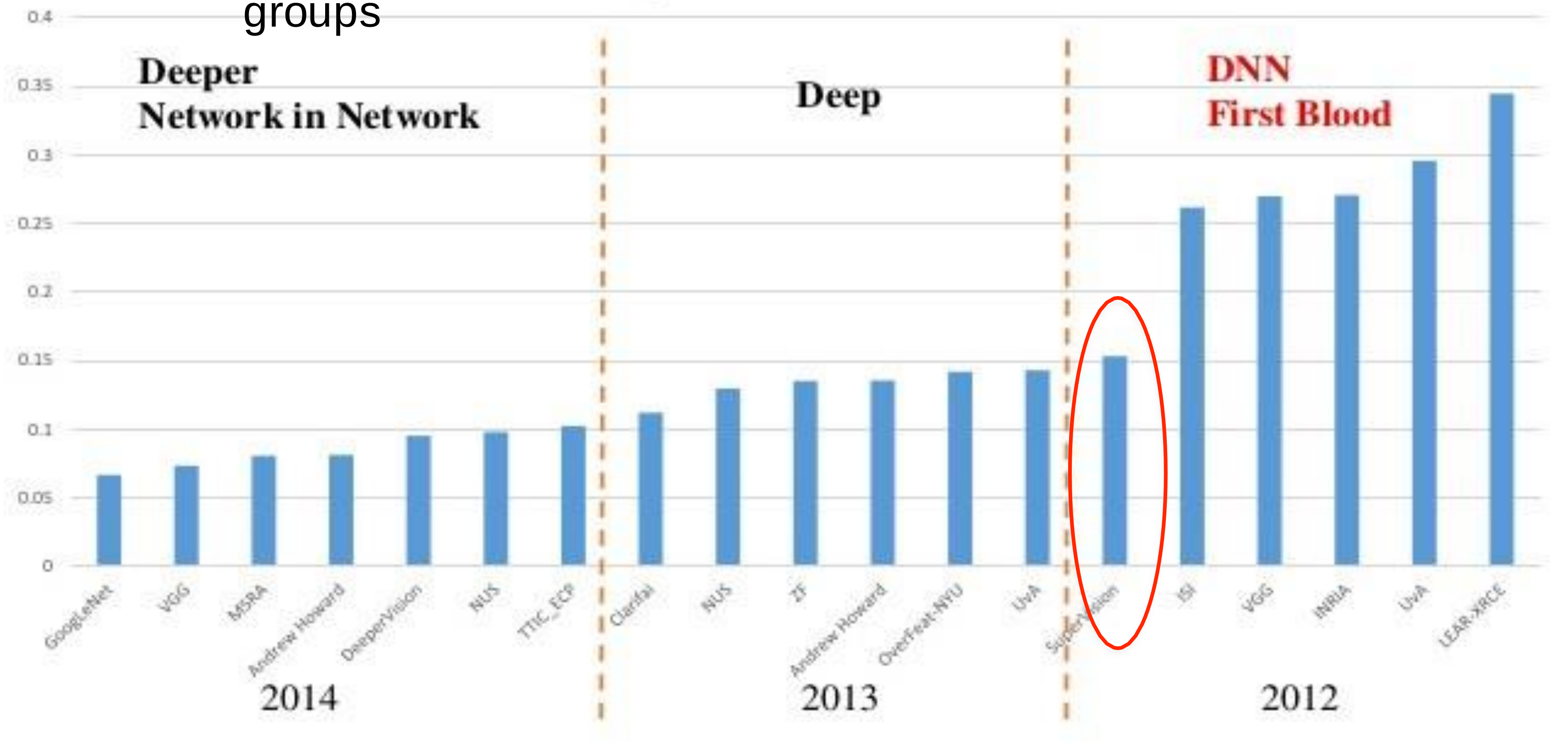
ConvolutionalNeural Networks

- Model with a large learning capacity
- Prior knowledge to compensate all data we do not have

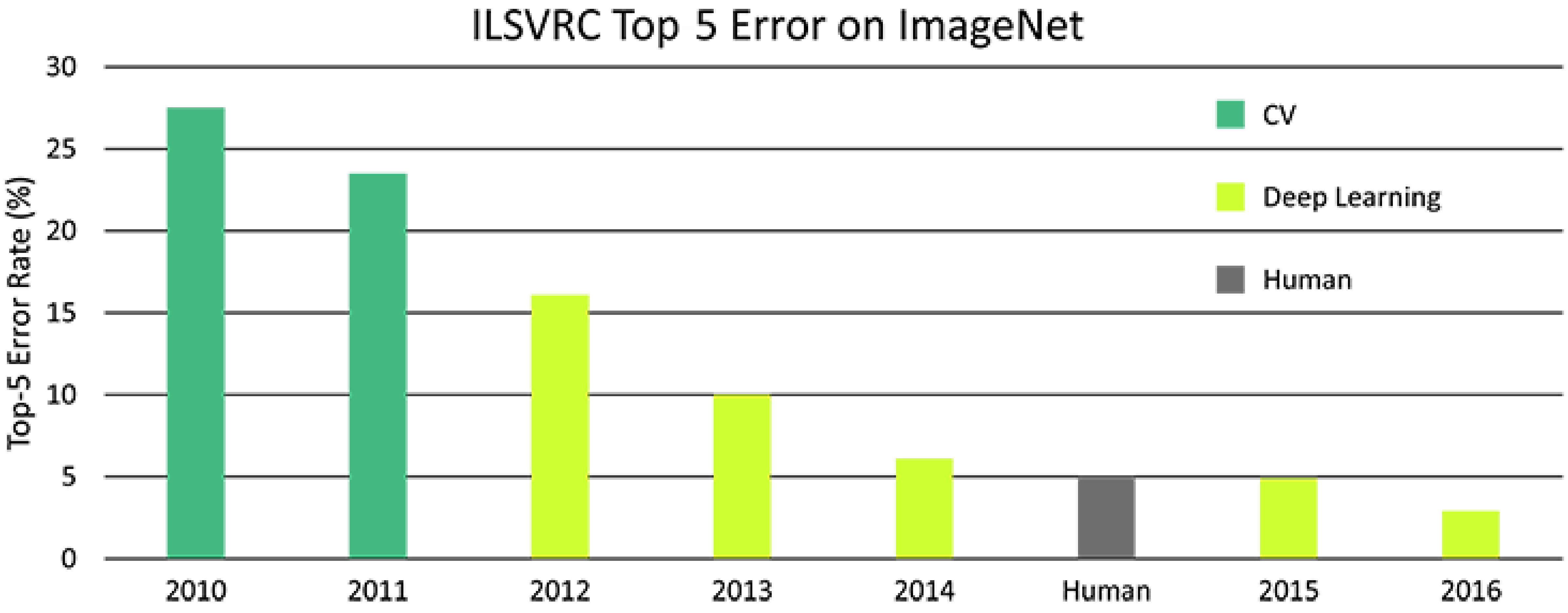


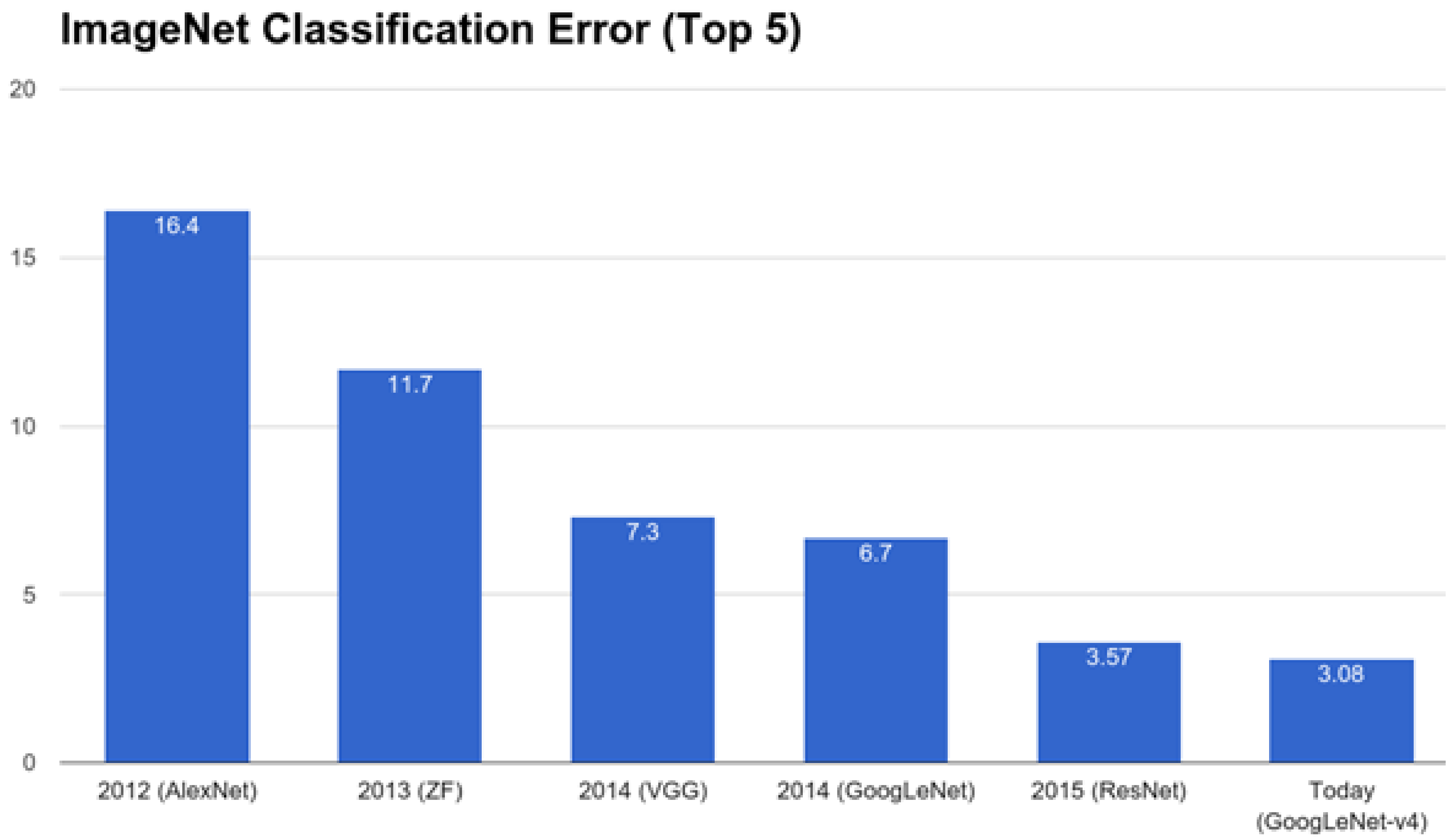
ILSVRC

ImageNet Classification error throughout years and groups



Li Fei-Fei: ImageNet Large Scale Visual Recognition Challenge, 2014 http://image-net.org/


ILSVRC Top 5 Error on ImageNet
30
25
20
15
10
5
0
Top-5 Error Rate (%)
CV
Deep Learning
Human
2010
2011
2012
2013
2014
Human
2015
2016


ImageNet Classification Error (Top 5)
20
15
10
5
0
16.4
11.7
7.3
6.7
3.57
3.08
2012 (AlexNet)
2013 (ZF)
2014 (VGG)
2014 (GoogLeNet)
2015 (ResNet)
Today (GoogLeNet-v4)

SuperVision (SV)

Image classification with deep convolutional neural networks

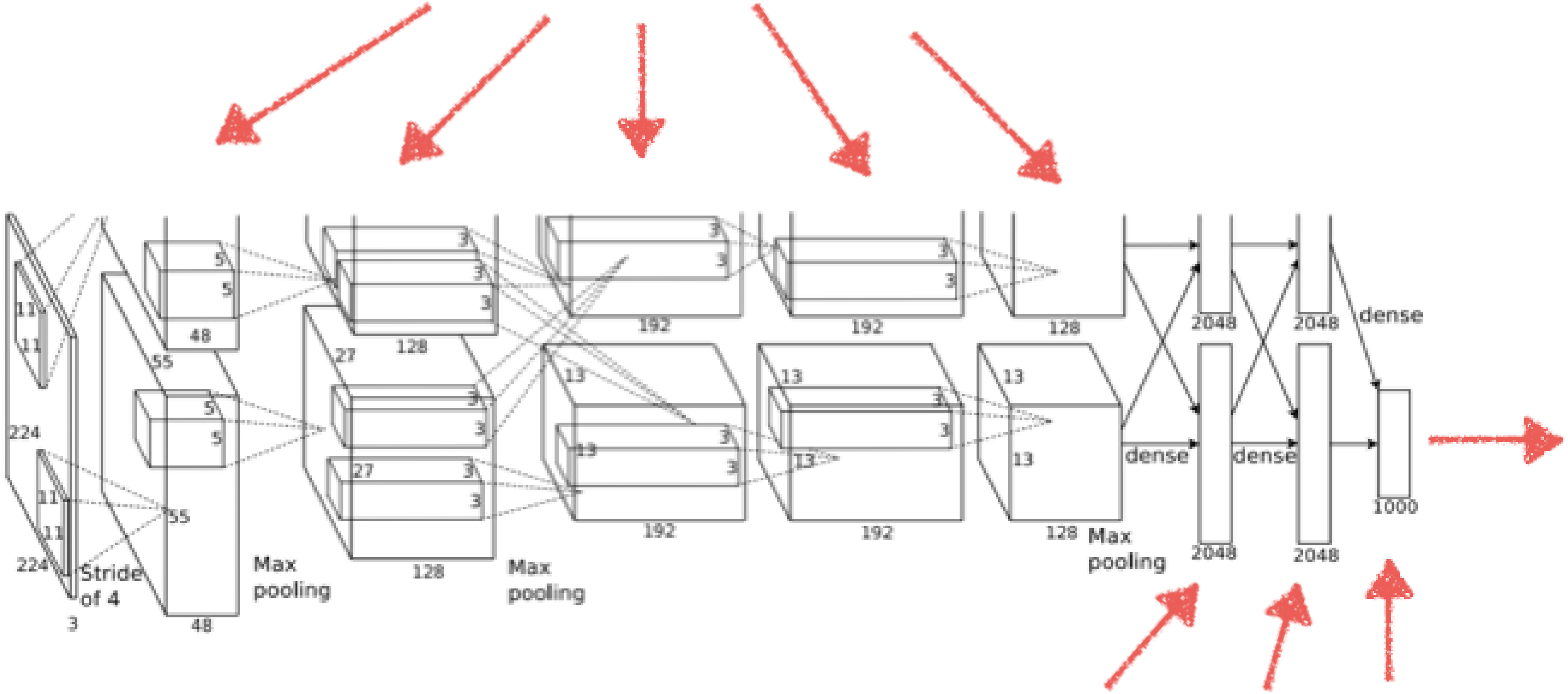
- 7 hidden “weight” layers
- 650K neurons
- 60M parameters
- 630M connections

- Rectified Linear Units, overlapping pooling, dropout trick
- Randomly extracted 224x224 patches for more data

h-p://image--net.org/challenges/LSVRC/2012/supervision.pdf

Architectur
e

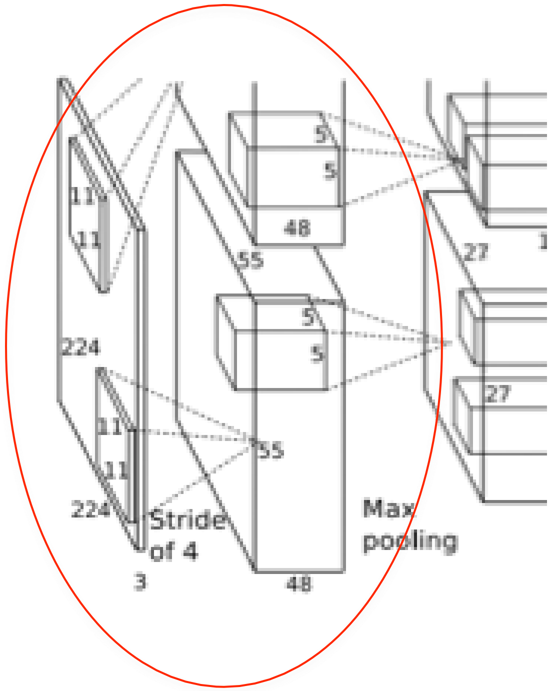
5 Convolu(onal Layers



1000-way
soLmax

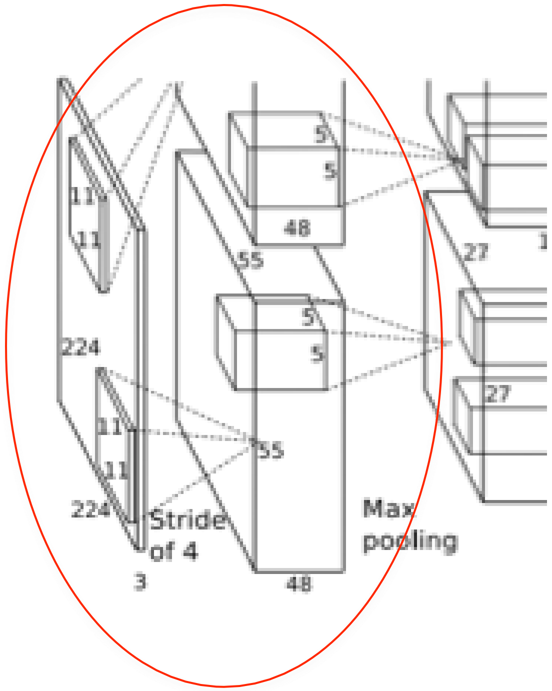
3 Fully Connected Layers

Layer 1 (Convolutional)



- Images: 227x227x3
- F (receptive field size): 11
- S (stride) = 4
- Conv layer output: 55x55x96

Layer 1 (Convolutional)



- 55*55*96 = 290,400 neurons
- each has 11*11*3 = 363 weights and 1 bias
- 290400 * 364 = 105,705,600 paramaters on the first layer of the AlexNet alone!

Architectur
e

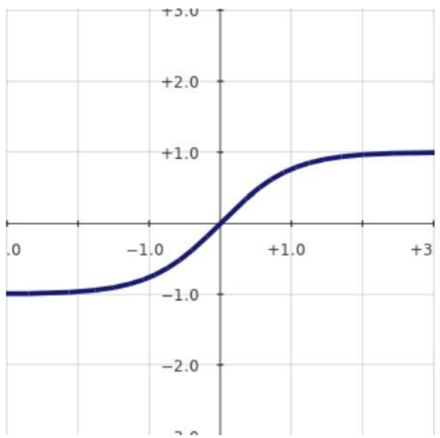
RELU Nonlinearity

- Standard way to model a neuron

$$f(x) = \tanh(x) \quad \text{or} \quad f(x) = (1 + e^{-x})^{-1}$$

Very slow to train

f(x) = tanh(x)

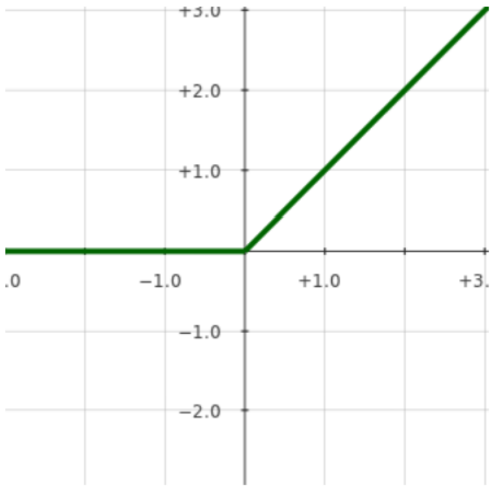


- Non-saturating nonlinearity (RELU)

$$f(x) = max(0, x)$$

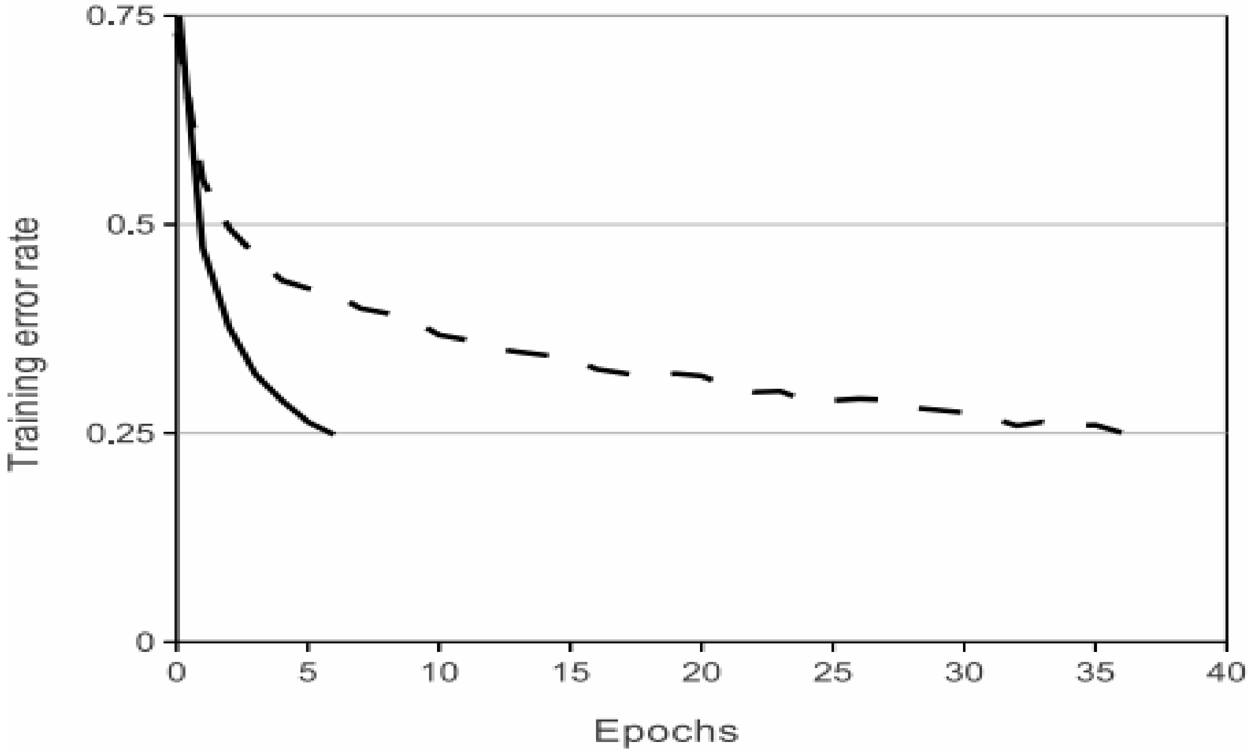
Quick to train

f(x) = max(0, x)



Architecture

RELU Nonlinearity



A 4 layer CNN with ReLUs (solid line) converges six times faster than an equivalent network with tanh neurons (dashed line) on CIFAR-10 dataset

Architectur
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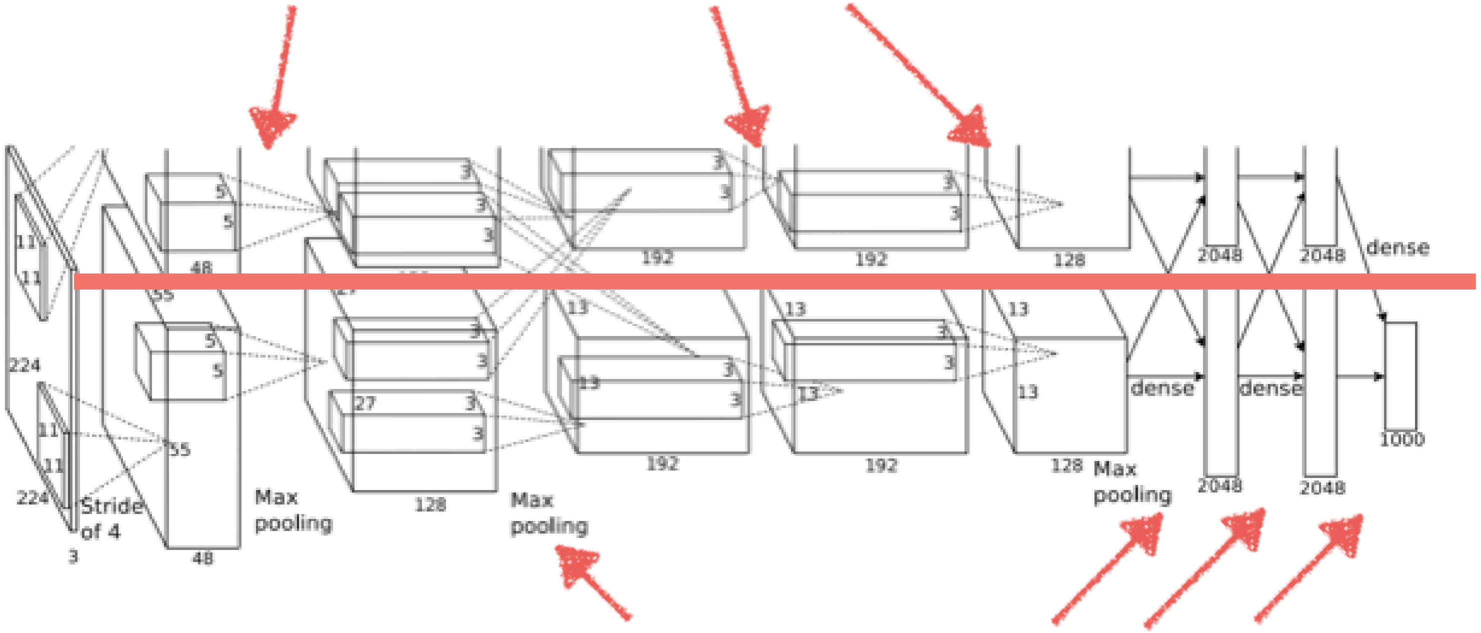
Training on Multiple GPUs

GPU #1

intra--GPU connec(ons

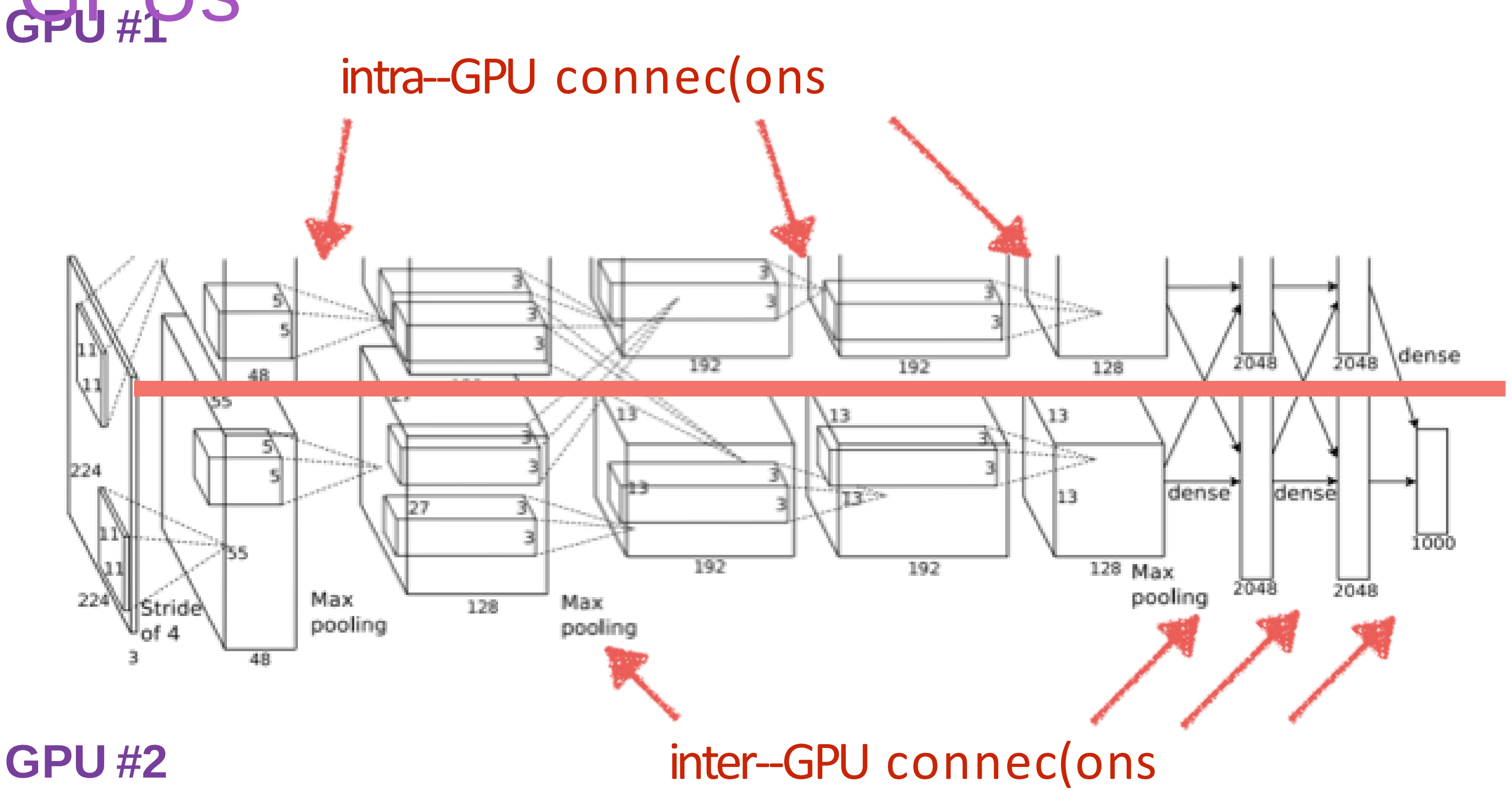


GPU #2

inter--GPU connec(ons

Architecture

Training on Multiple GPUs

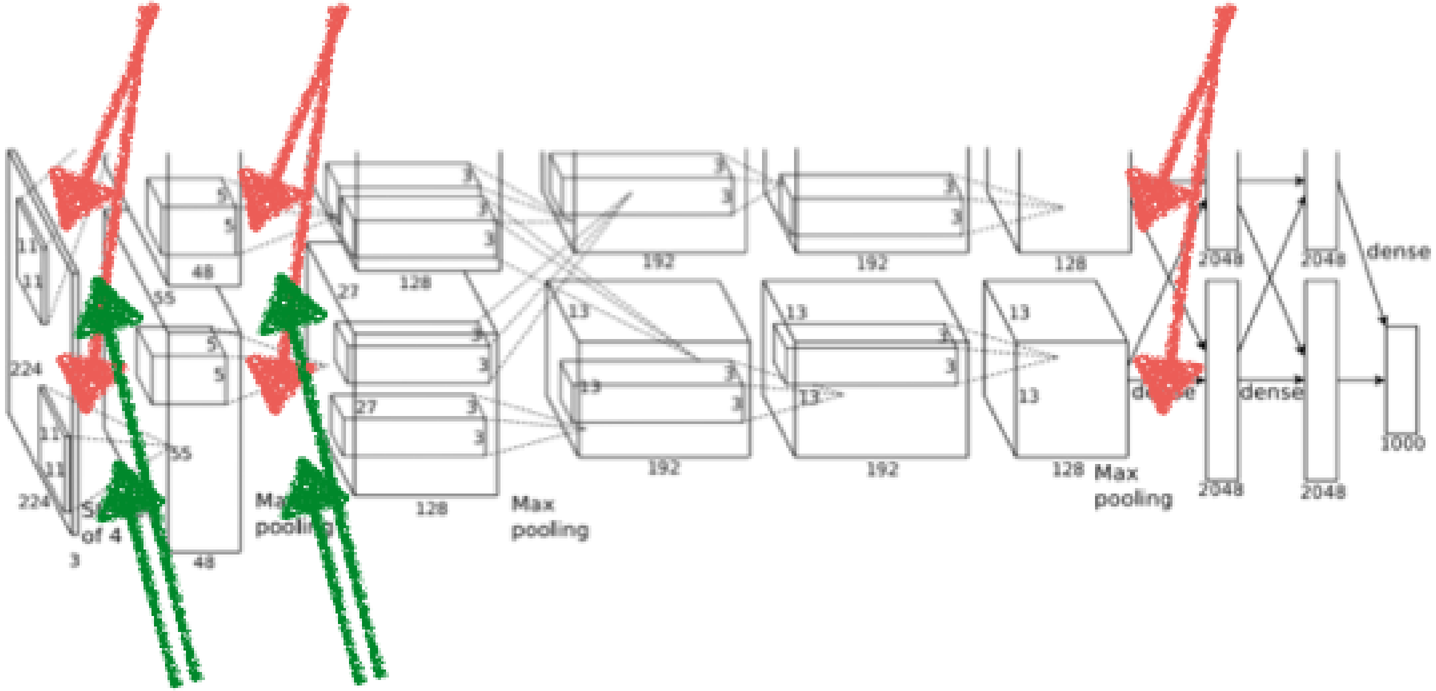


Top-1 and Top-5 error rates decreases by 1.7% & 1.2% respectively, comparing to the net trained with one GPU and half neurons!!

Architecture

Overlaping Pooling

Max-pooling layers



Response normalization layers

Architectur
e

Local Response Normalization

- No need to input normalization with ReLUs.
- But still the following local normalization scheme helps generalization.

$$b^i_{x,y} = a^i_{x,y} \Big/ \left(k + \alpha \sum_{j=\max(0,i-n/2)}^{\min(N-1,i+n/2)} (a^j_{x,y})^2 \right)^\beta$$

Response–normalized ac(vity

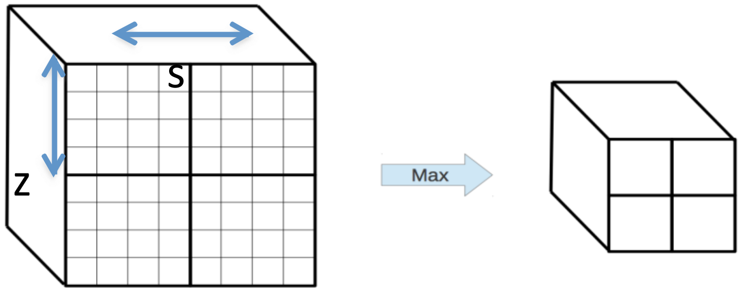
Ac(vity of a neuron computed by applying kernel I at posi(on (x,y) and then applying the ReLU nonlinearity

- Response normalization reduces top-1 and top-5 error rates by 1.4% and 1.2% , respectively.

Architectur e

Overlaping Pooling

- Traditional pooling (s = z)



- s < z ➔ overlapping pooling
- top-1 and top-5 error rates decrease by 0.4% and 0.3%, respectively, compared to the non-overlapping scheme s = 2, z = 2

Architectur
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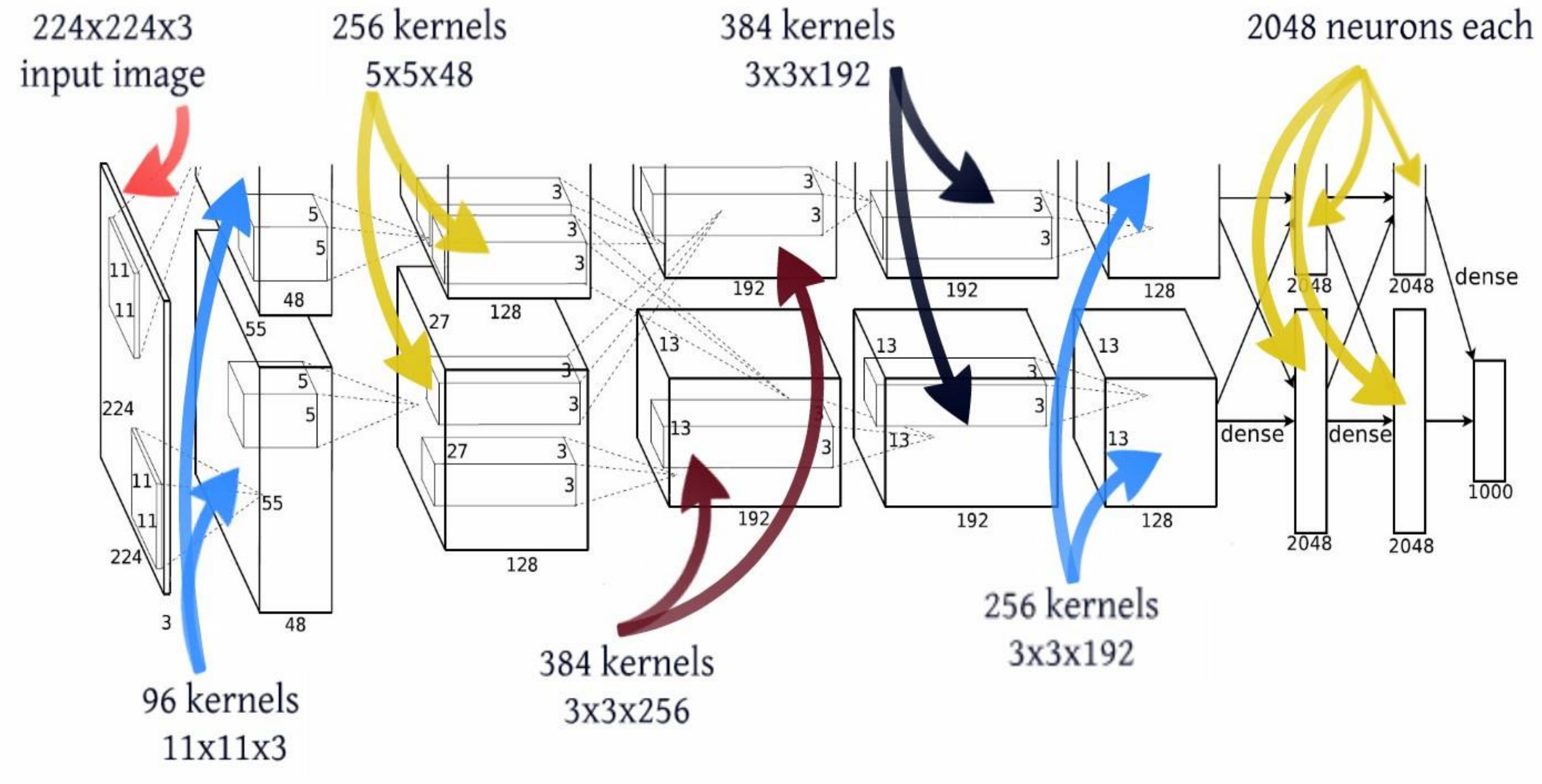
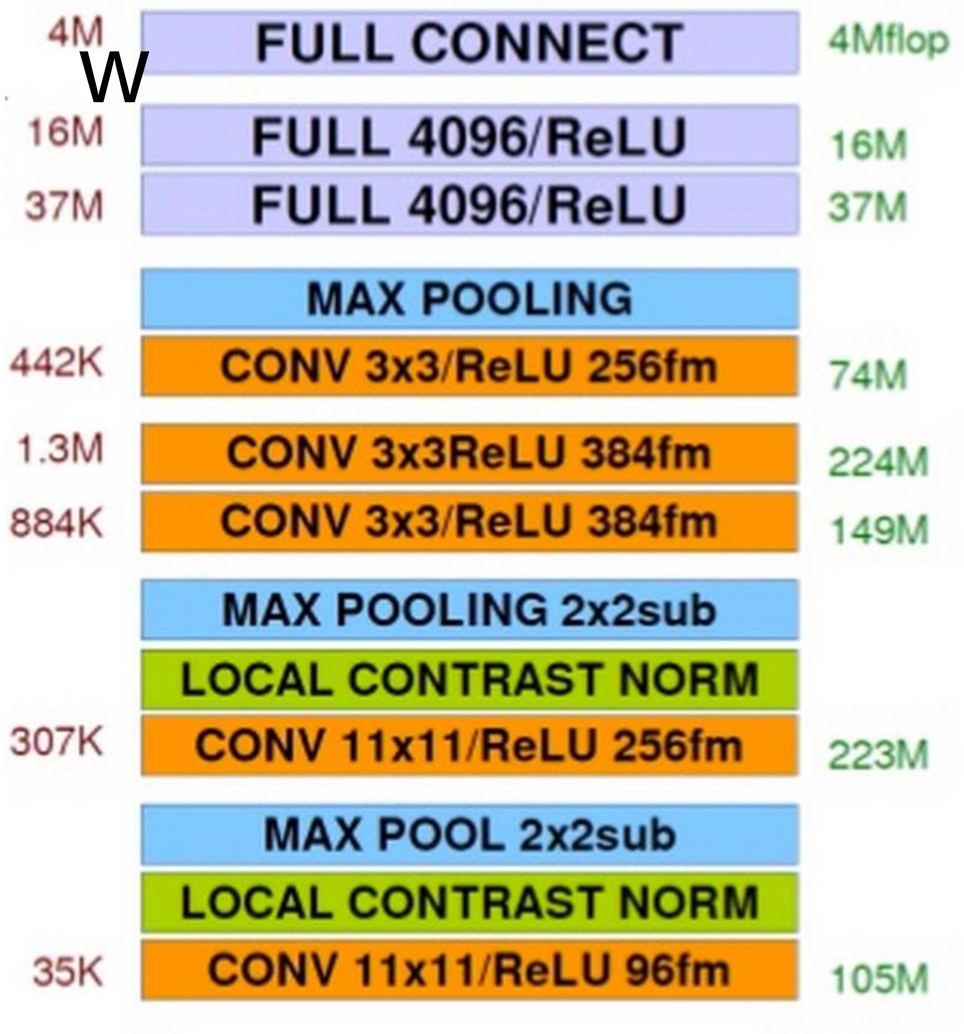


Architecture Overview



Reducing Overfitting

Data Augmentation

- 60 million parameters, 650,000 neurons

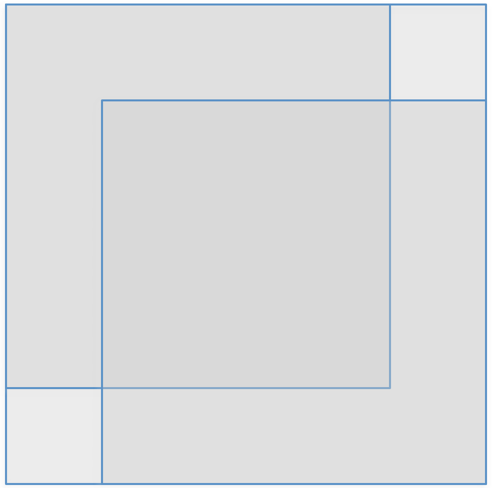
  → Overfits a lot.

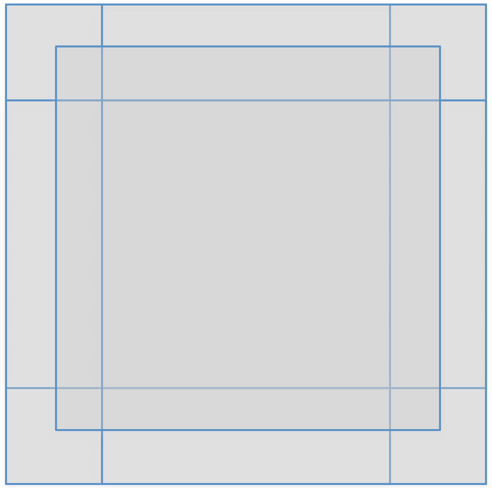
- Crop 224x224 patches (and their horizontal reflections.)

Reducing Overfitting

Data Augmentation

- At test time, average the predictions on the 10 patches.





Reducing

- Softmax

$$L = \frac{1}{N}\sum_i -\log\left(\boxed{\frac{e^{f_{y_j}}}{\sum_j e^{f_j}}}\right) + \lambda \sum_k \sum_l W_{k,l}^2$$

$j = 1\ldots1000$

$\boxed{P(y_i \mid x_i; W)}$ Likelihood

- No need to calibrate to average the predictions over 10 patches.

cf. SVM

$$L = \frac{1}{N}\sum_i \sum_{j \neq y_i}\left[\max(0, f(x_i;W)_j - f(x_i;W)_{y_i} + \Delta) + \lambda \sum_k \sum_l W_{k,l}^2\right]$$

Slide credit from [Stanford CS231N Lecture 3]

Reducing Overfitting

Data Augmentation

- Change the intensity of RGB channels
-

$$I_{xy} = [I_{xy}, \quad I^{G}_{xy}, \quad I^{BR}_{xy}]^{T}$$

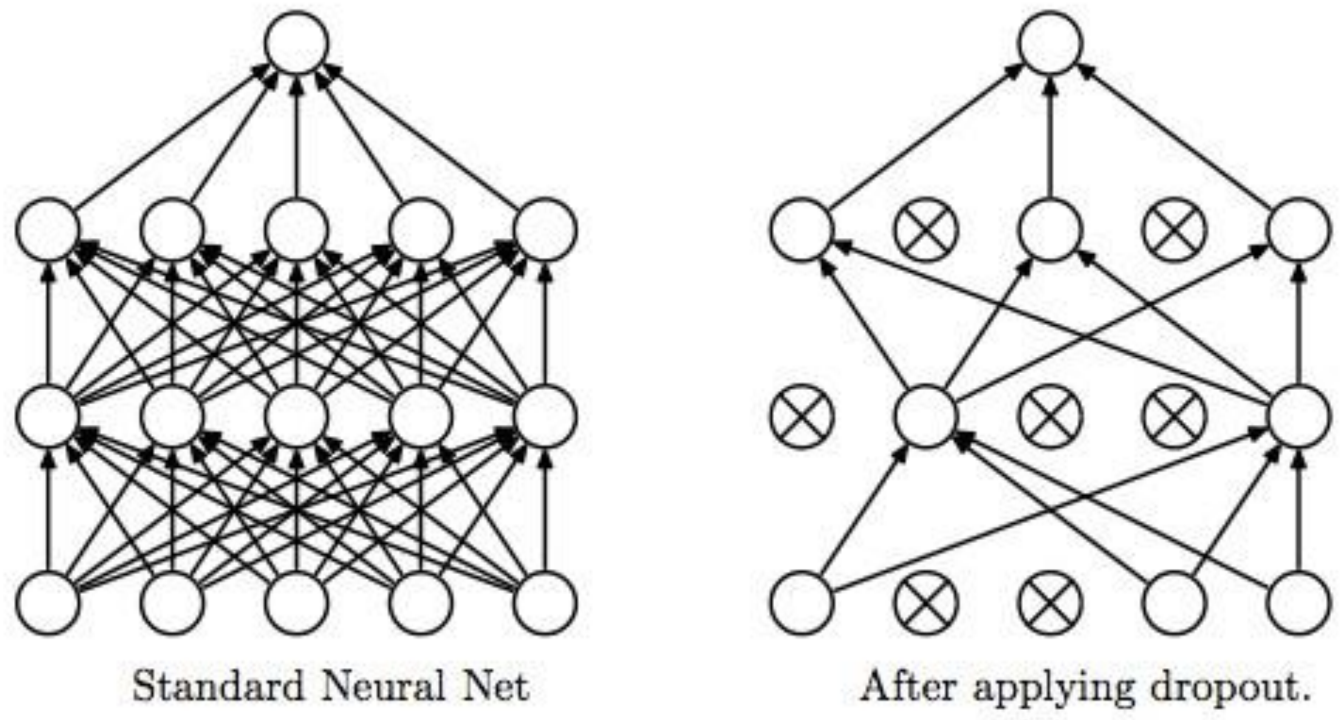
add multiples of principle components

$$[\mathbf{p}_1, \mathbf{p}_2, \mathbf{p}_3][\alpha_1\lambda_1, \alpha_2\lambda_2, \alpha_3\lambda_3]^T$$

$$\langle_{i} \sim N(0, \quad 0.1)$$

Reducing Overfitting

Dropou



- With probability 0.5
- last two 4096 fully-connected layers.

Figure credit from [Srivastava et al.]

Stochastic Gradient Descent Learning

Momentum Update

momentum(damping parameter)

Learning rate (ini(alized at 0.01)

$$v_{i+1} := \underline{0.9} \cdot v_i - 0.0005 \cdot \epsilon \cdot w_i - \underline{\epsilon} \cdot \underline{\left\langle \frac{\partial L}{\partial w}\Big|_{w_i} \right\rangle_{D_i}}$$

$$w_{i+1} := w_i + v_{i+1}$$

weight decay

Gradient of Loss
w.r.t weight
Averaged over batch

Batch size: 128

- • The training took 5 to 6 days on two NVIDIA GTX 580 3GB GPUs.

Results: ILSVRC-2010

Model	**Top-1**	**Top-5**
Sparse coding [2]	*47.1%*	*28.2%*
SIFT + FVs [24]	*45.7%*	*25.7%*
CNN	**37.5%**	**17.0%**

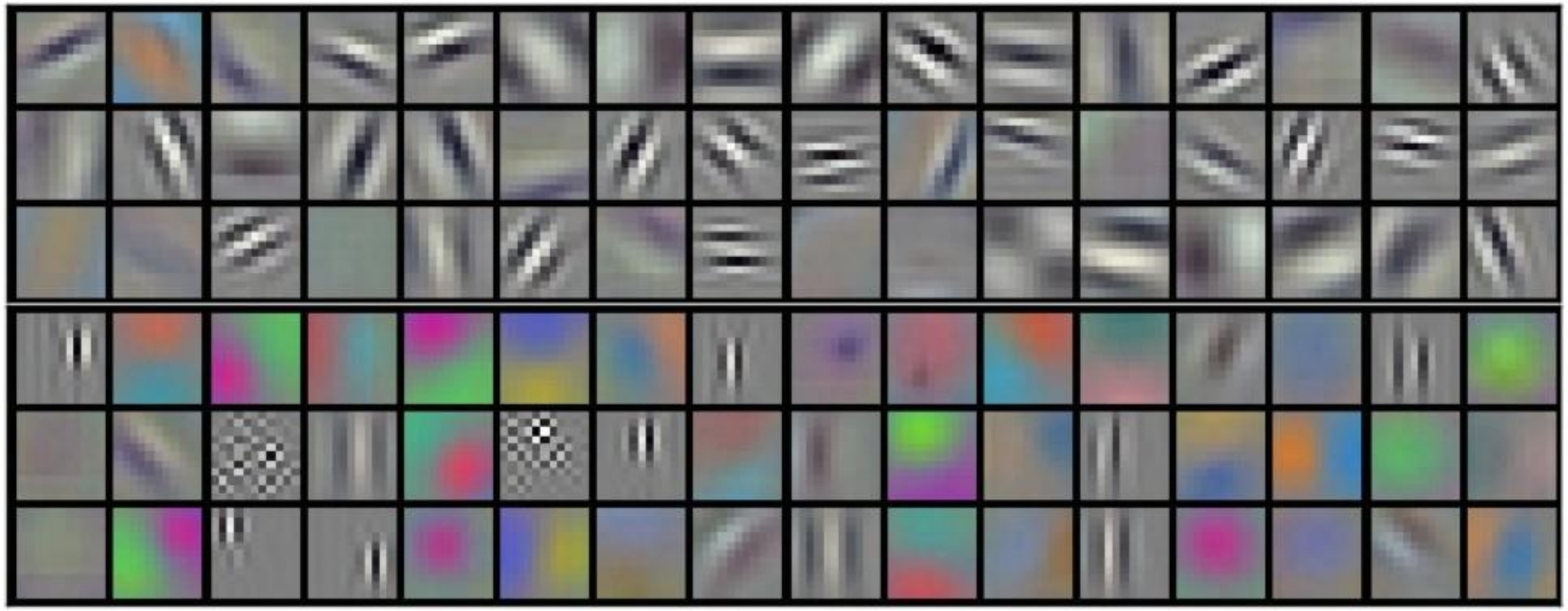
Table 1: Comparison of results on ILSVRC-2010 test set. In *italics* are best results achieved by others.

Results: ILSVRC-2012

Model	**Top-1 (val)**	**Top-5 (val)**	**Top-5 (test)**
SIFT + FVs [7]	—	—	*26.2%*
1 CNN	40.7%	18.2%	—
5 CNNs	38.1%	16.4%	**16.4%**
1 CNN*	39.0%	16.6%	—
7 CNNs*	36.7%	15.4%	**15.3%**

Table 2: Comparison of error rates on ILSVRC-2012 validation and test sets. In *italics* are best results achieved by others. Models with an asterisk* were "pre-trained" to classify the entire ImageNet 2011 Fall release. See Section 6 for details.

96 Convolutional Kernels

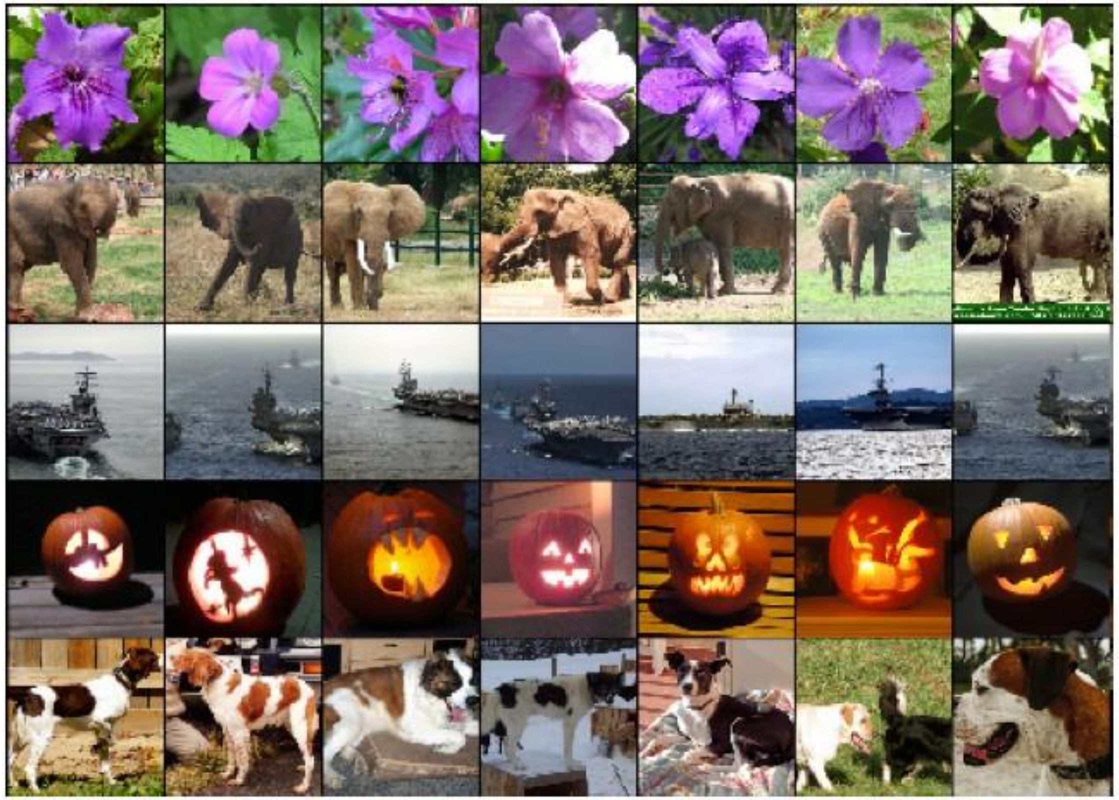


- 11 x 11 x 3 size kernels.
- top 48 kernels on GPU 1 : color-agnostic
- bottom 48 kernels on GPU 2 : color-specific.

Why?

Eight ILSVRC-2010test images

Five ILSVRC-2010 test images



The output from the last 4096 fully-connected layer

: 4096 dimensional feature.

Discussion

- Depth is really important.

removing a single convolutional layer degrades the performance.

K. Simonyan, A. Zisserman. Very Deep Convolutional Networks for Large-Scale Image Recognition. Technical report, 2014.

→16-layer model, 19-layer model. 7.3% top-5 test error on ILSVRC-2012