CENG501 – Deep Learning

Week 4

Fall 2024

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Per-parameter Methods: Adaptive Moments (Adam)

Previously on CENG501

- A variation of RMSprop + momentum
- Incorporates first & second order moments
- Bias correction needed to get rid of bias towards zero at initialization

Algorithm taken from:
Goodfellow et al., Deep Learning, 2016.

Algorithm 8.7 The Adam algorithm

Require: Step size ϵ (Suggested default: 0.001)
Require: Exponential decay rates for moment estimates, ρ_1 and ρ_2 in $[0, 1)$. (Suggested defaults: 0.9 and 0.999 respectively)
Require: Small constant δ used for numerical stabilization (Suggested default: 10^{-8})
Require: Initial parameters $\boldsymbol{\theta}$
Initialize 1st and 2nd moment variables $\boldsymbol{s} = \mathbf{0}$, $\boldsymbol{r} = \mathbf{0}$
Initialize time step $t = 0$
while stopping criterion not met **do**
Sample a minibatch of m examples from the training set $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ with corresponding targets $\boldsymbol{y}^{(i)}$.
Compute gradient: $\boldsymbol{g} \leftarrow \frac{1}{m} \nabla_{\boldsymbol{\theta}} \sum_i L(f(\boldsymbol{x}^{(i)}; \boldsymbol{\theta}), \boldsymbol{y}^{(i)})$
$t \leftarrow t + 1$
Update biased first moment estimate: $\boldsymbol{s} \leftarrow \rho_1 \boldsymbol{s} + (1 - \rho_1)\boldsymbol{g}$
Update biased second moment estimate: $\boldsymbol{r} \leftarrow \rho_2 \boldsymbol{r} + (1 - \rho_2)\boldsymbol{g} \odot \boldsymbol{g}$
Correct bias in first moment: $\hat{\boldsymbol{s}} \leftarrow \frac{\boldsymbol{s}}{1 - \rho_1^t}$
Correct bias in second moment: $\hat{\boldsymbol{r}} \leftarrow \frac{\boldsymbol{r}}{1 - \rho_2^t}$
Compute update: $\Delta\boldsymbol{\theta} = -\epsilon \frac{\hat{\boldsymbol{s}}}{\sqrt{\hat{\boldsymbol{r}}} + \delta}$ (operations applied element-wise)
Apply update: $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \Delta\boldsymbol{\theta}$
end while

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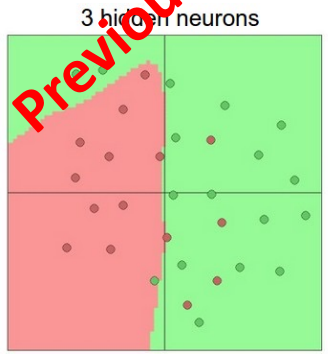
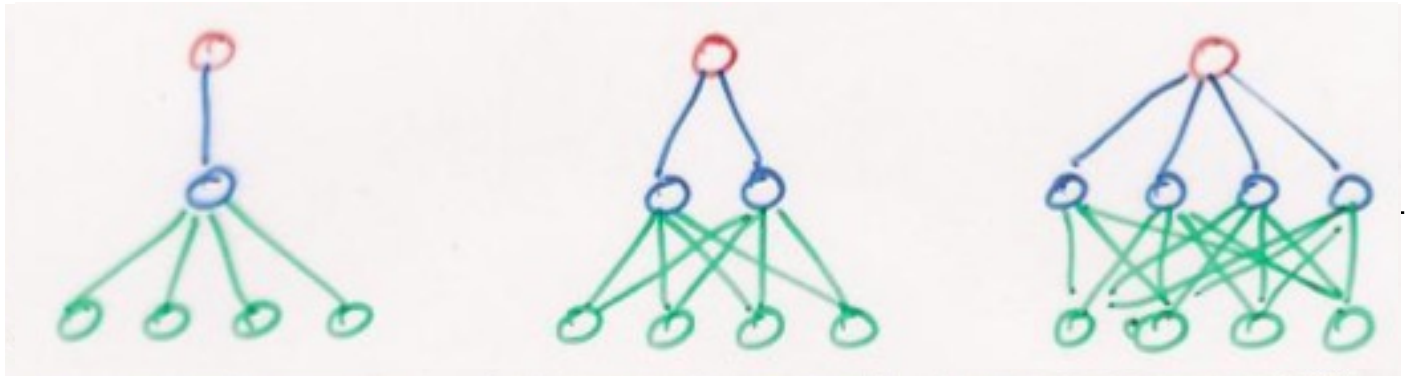
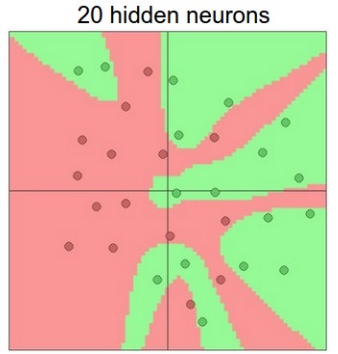
Model Complexity

- Models range in their flexibility to fit arbitrary data



https://cs231n.github.io/





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high bias model

low variance

small capacity may prevent it from representing all structure in data

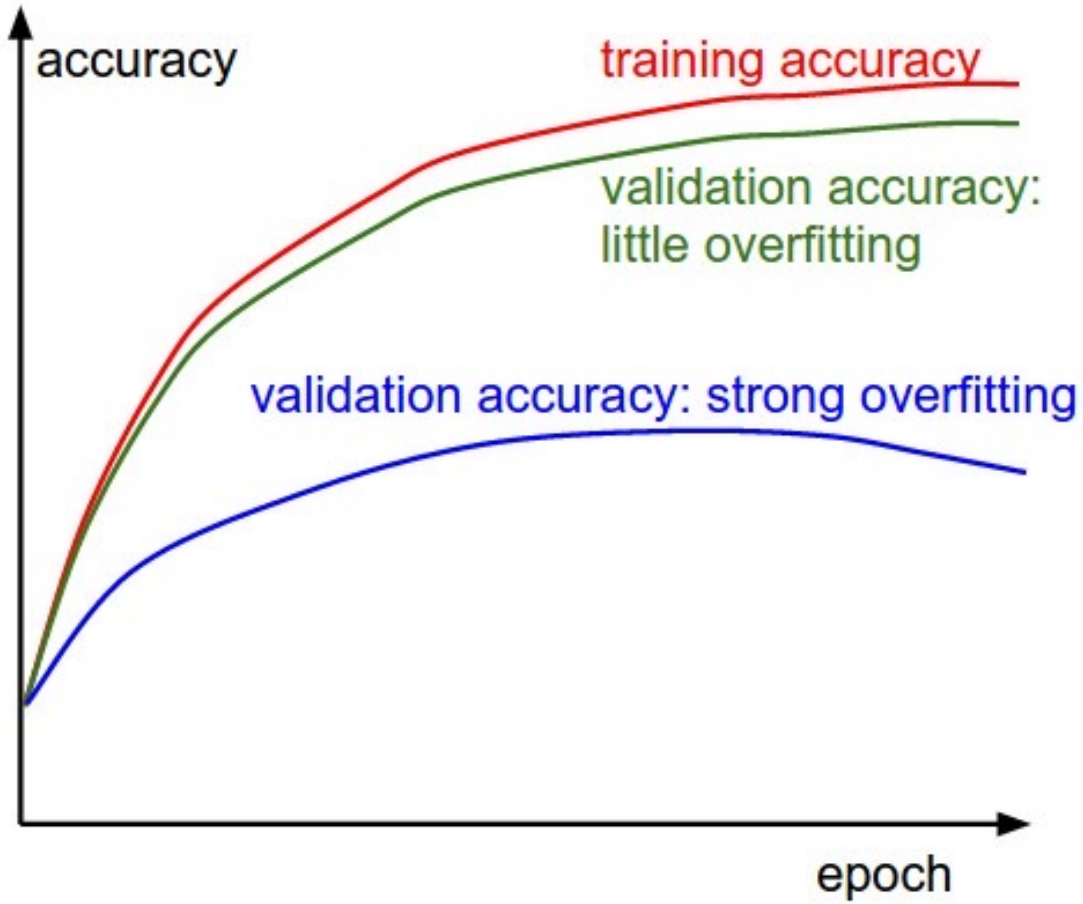
low bias model

high variance

large capacity may allow it to memorize data and fail to capture regularities

Slide Credit: Michael Mozer

How do you spot overfitting?



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Avoiding Overfitting

- Increase training set size
  - Make sure effective size is growing; redundancy doesn't help
- Incorporate domain-appropriate bias into model
  - Customize model to your problem
- Tune hyperparameters of model
  - number of layers, number of hidden units per layer, connectivity, etc.
- Regularization techniques

Slide Credit: Michael Mozer

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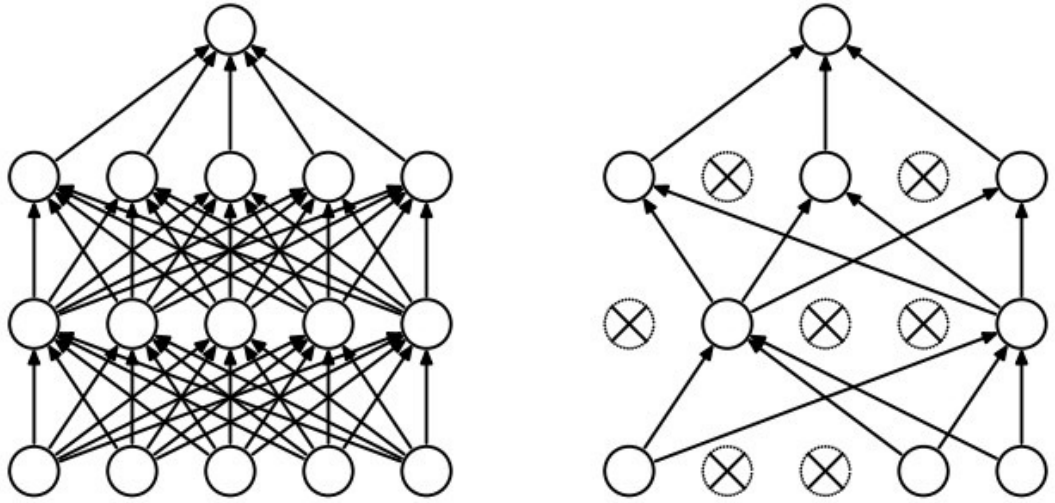
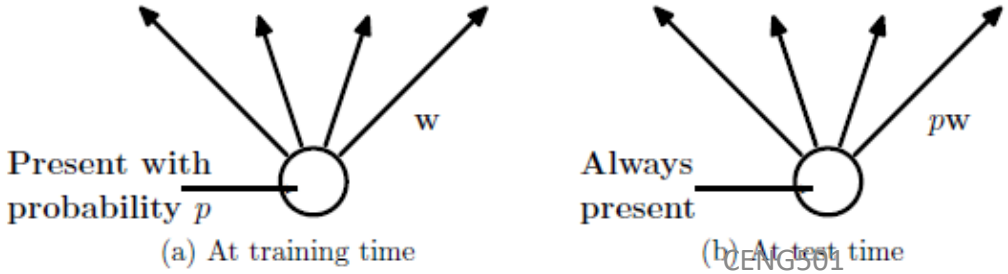
Regularization: Dropout

Fig: Srivastava et al., 2014



(a) Standard Neural Net (b) After applying dropout.

- Feed-forward only on active units
- Can be trained using SGD with mini-batch
  - Back propagate only “active” units.
- One issue:
  - Expected output x with dropout:
  - $E[x'] = \frac{1}{N}\sum_i (px_i + (1-p)0) = p\frac{1}{N}\sum_i x_i = pE[x]$
- To have the same scale at testing time (no dropout), multiply test-time activations with p.



(a) At training time (b) At test time

Fig: Srivastava et al., 2014

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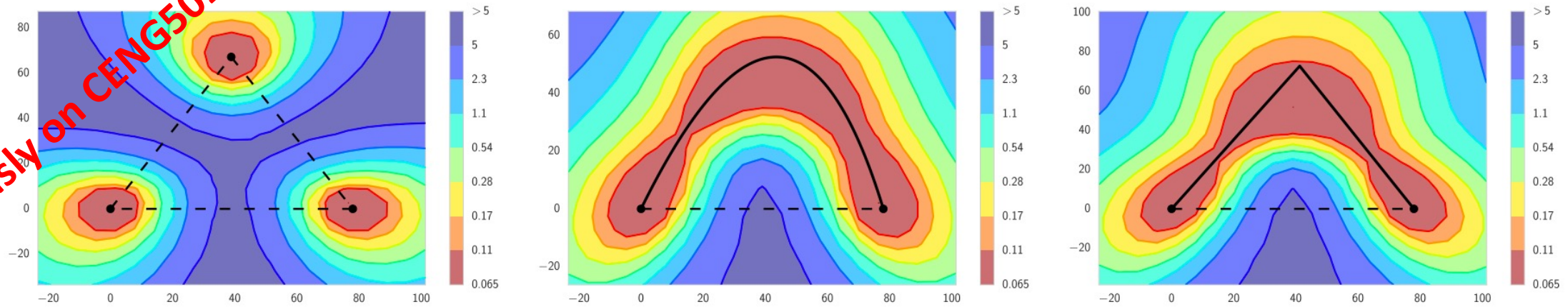

Figure 1: The ℓ_2-regularized cross-entropy train loss surface of a ResNet-164 on CIFAR-100, as a function of network weights in a two-dimensional subspace. In each panel, the horizontal axis is fixed and is attached to the optima of two independently trained networks. The vertical axis changes between panels as we change planes (defined in the main text). **Left:** Three optima for independently trained networks. **Middle** and **Right**: A quadratic Bezier curve, and a polygonal chain with one bend, connecting the lower two optima on the left panel along a path of near-constant loss. Notice that in each panel a direct linear path between each mode would incur high loss.

Garipov et al., “Loss Surfaces, Mode Connectivity, and Fast Ensembling of DNNs”, 2018.

See also: Kuditipudi et al., “Explaining Landscape Connectivity of Low-cost Solutions for Multilayer Nets”, 2020.
- Explains this with noise stability, dropout stability.

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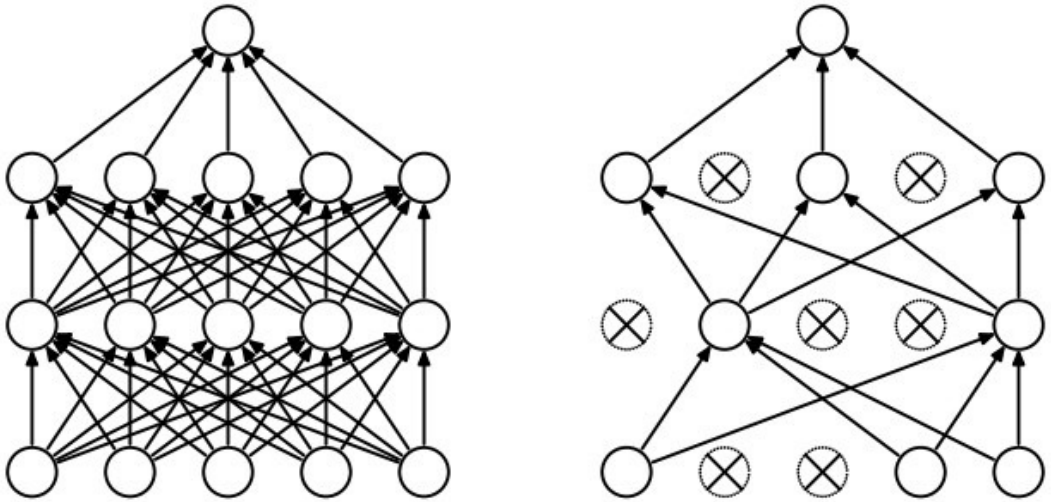
Dropout as Ensemble Training Method

"Dropout performs gradient descent on-line with respect to both the training examples and the ensemble of all possible subnetworks."

Fig: Srivastava et al., 2014



(a) Standard Neural Net

(b) After applying dropout.

Pierre Baldi and Peter J Sadowski. Understanding dropout. In Advances in neural information processing systems, pp. 2814–2822, 2013.

Data Augmentation

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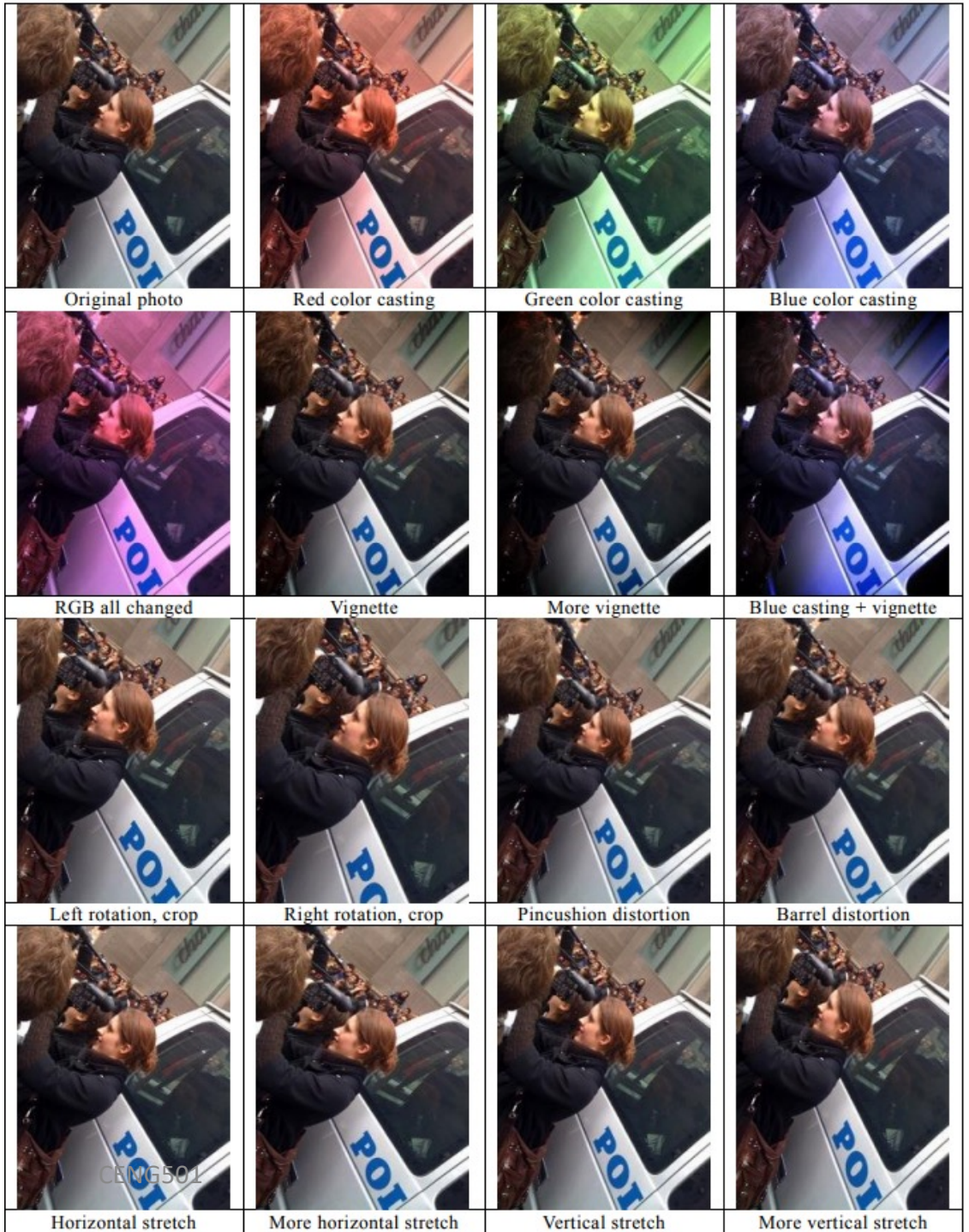

http://blcv.pl/static//2018/02/27/demystifying-face-recognition-v-data-augmentation/

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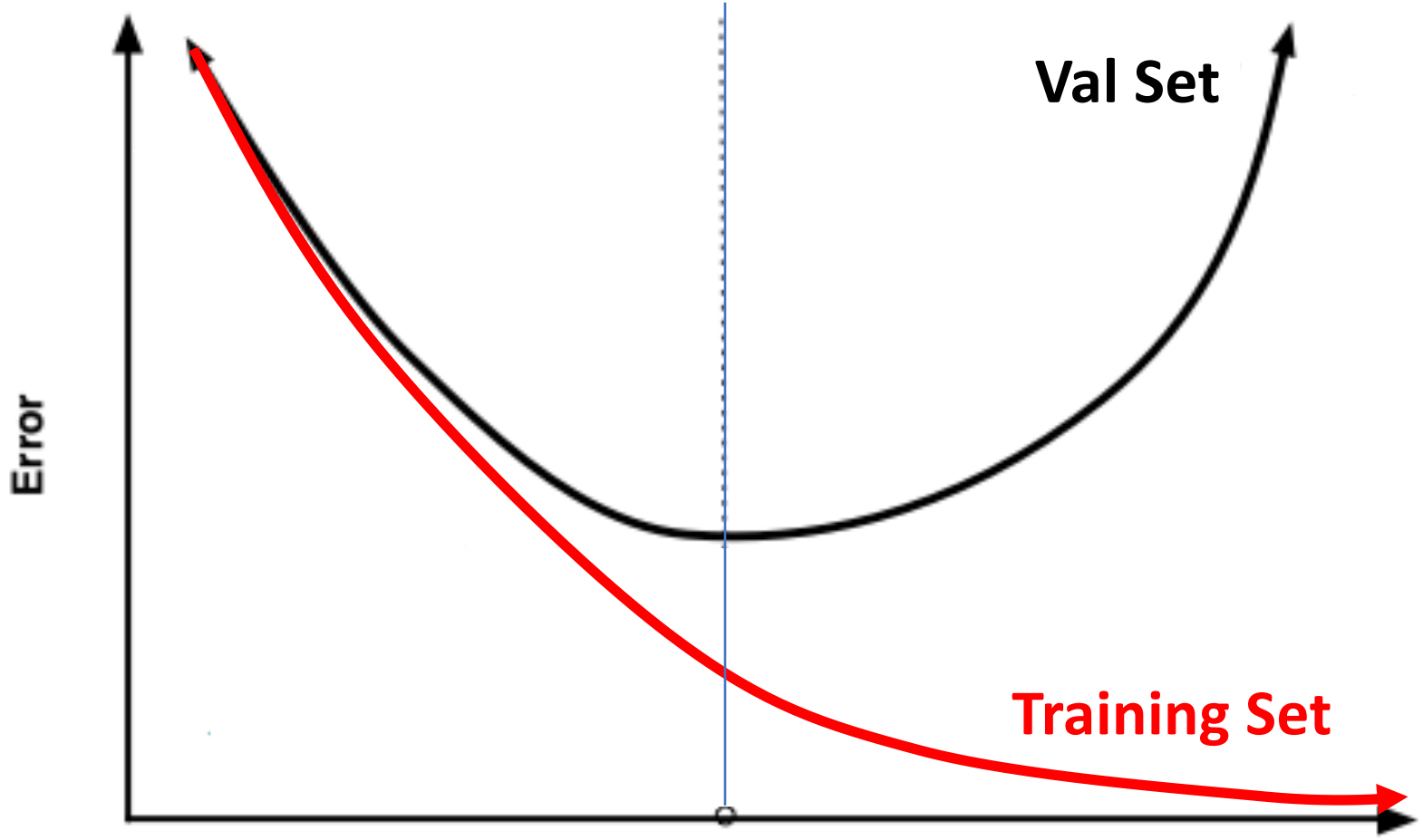
When to stop training



Slide Credit: Michael Mozer

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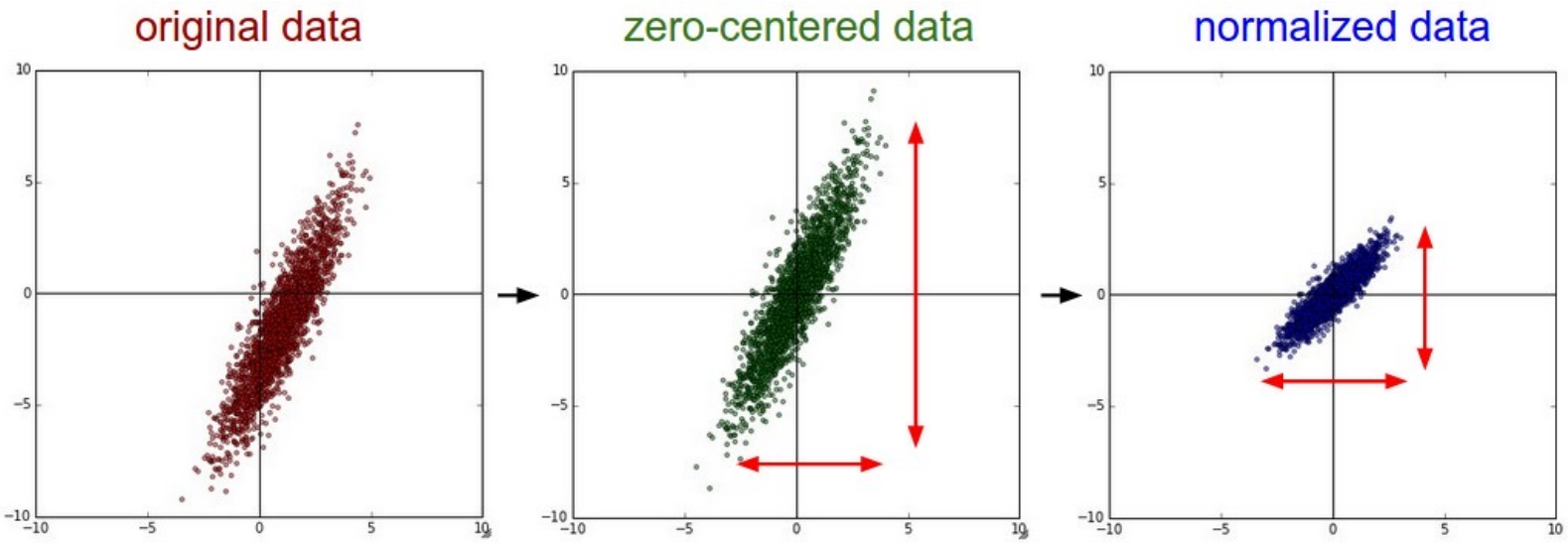
Data Preprocessing: Normalization (or conditioning)

- Necessary if you believe that your dimensions have different scales
  - Might need to reduce this to give equal importance to each dimension
- Normalize each dimension by its std. dev. after mean subtraction:

$$x'_{ji} = x_{ji} - \mu_i$$
$$x''_{ji} = x'_{ji} / \sigma_i$$

- Effect: Make the dimensions have the same scale



http://cs231n.github.io/neural-networks-2/

Initial Weight Normalization

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- Solution:
  - Get rid of n in $Var(s) = (n$ Var(w))Var(x)

- How?
  - Scale the initial weights by $\sqrt{n}$
  - Why? Because: $Var(aX) = a^2 Var(X)$

- Standard Initialization (top plots in Figure 6 & 7):

$$w_i \sim U\left[-\frac{1}{\sqrt{n}}, \frac{1}{\sqrt{n}}\right]$$

which yields $n\,Var(w) = \frac{1}{3}$

because variance of $U[-r, r]$ is $\frac{r^2}{3}$ [1].

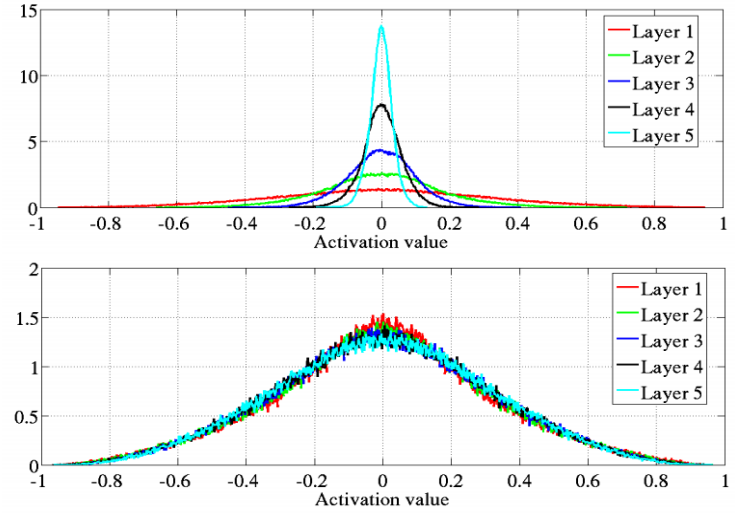

Figure 6: *Activation values normalized histograms with hyperbolic tangent activation, with standard (top) vs normalized initialization (bottom). Top: 0-peak increases for higher layers.*

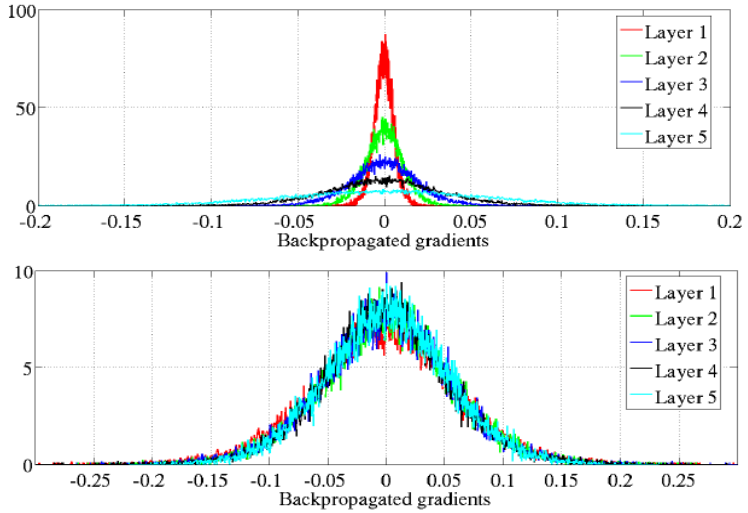

Figure 7: *Back-propagated gradients normalized histograms with hyperbolic tangent activation, with standard (top) vs normalized (bottom) initialization. Top: 0-peak decreases for higher layers.*

Figures: Glorot & Bengio, "Understanding the difficulty of training deep feedforward neural networks", 2010.

Xavier initialization for symmetric activation functions (Glorot & Bengio):

$$w_i \sim N\left(0, \frac{\sqrt{2}}{\sqrt{n_{in} + n_{out}}}\right)$$

With Uniform distribution:

$$w_i \sim U\left[-\frac{\sqrt{6}}{\sqrt{n_{in} + n_{out}}}, \frac{\sqrt{6}}{\sqrt{n_{in} + n_{out}}}\right]$$

[1] https://proofwiki.org/wiki/Variance_of_Continuous_Uniform_Distribution

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Alternative: Batch Normalization

- Normalization is differentiable
  - So, make it part of the model (not only at the beginning)
  - I.e., perform normalization during every step of processing
- More robust to initialization
- Shown to also regularize the network in some cases (dropping the need for dropout)
- Issue: How to normalize at test time?
  1. Store means and variances during training, or
  2. Calculate mean & variance over your test data
- PyTorch: use model.eval() in test time.

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Algorithm 1: Batch Normalizing Transform, applied to activation x over a mini-batch.

Ioffe & Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift", 2015.

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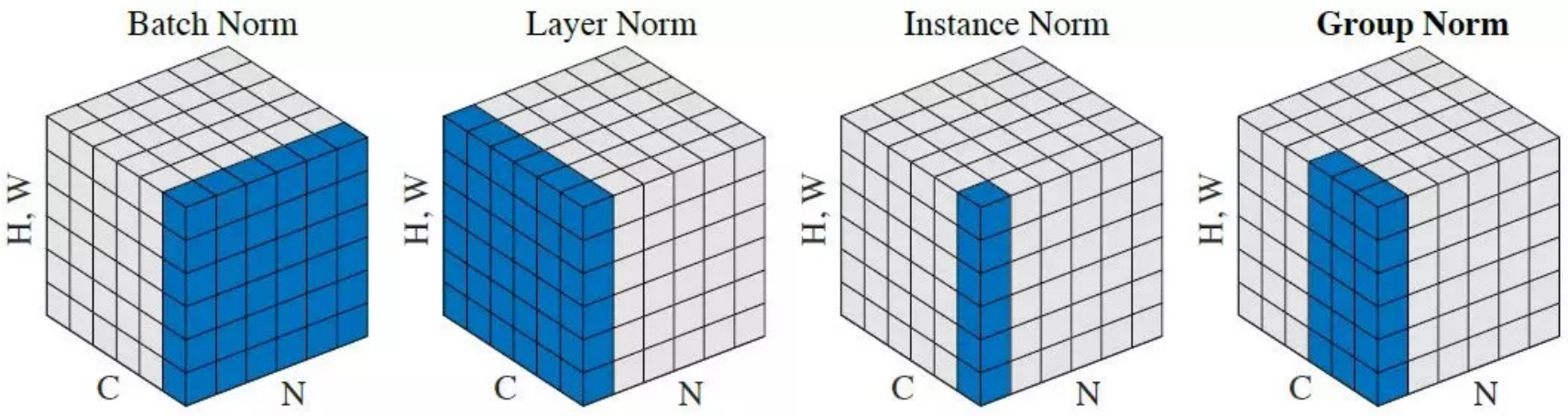
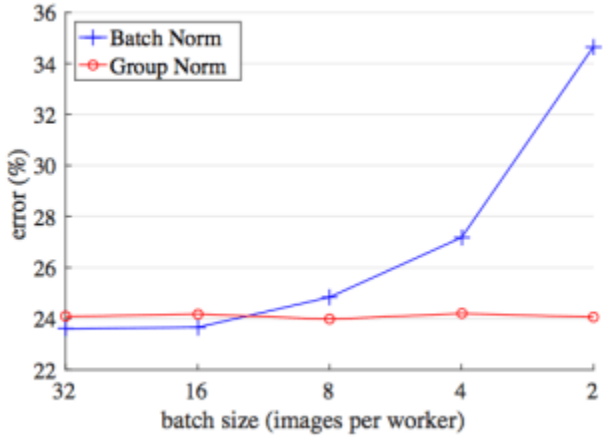
Alternative Normalizations





https://medium.com/syncedreview/facebook-ai-proposes-group-normalization-alternative-to-batch-normalization-fb0699bffae7

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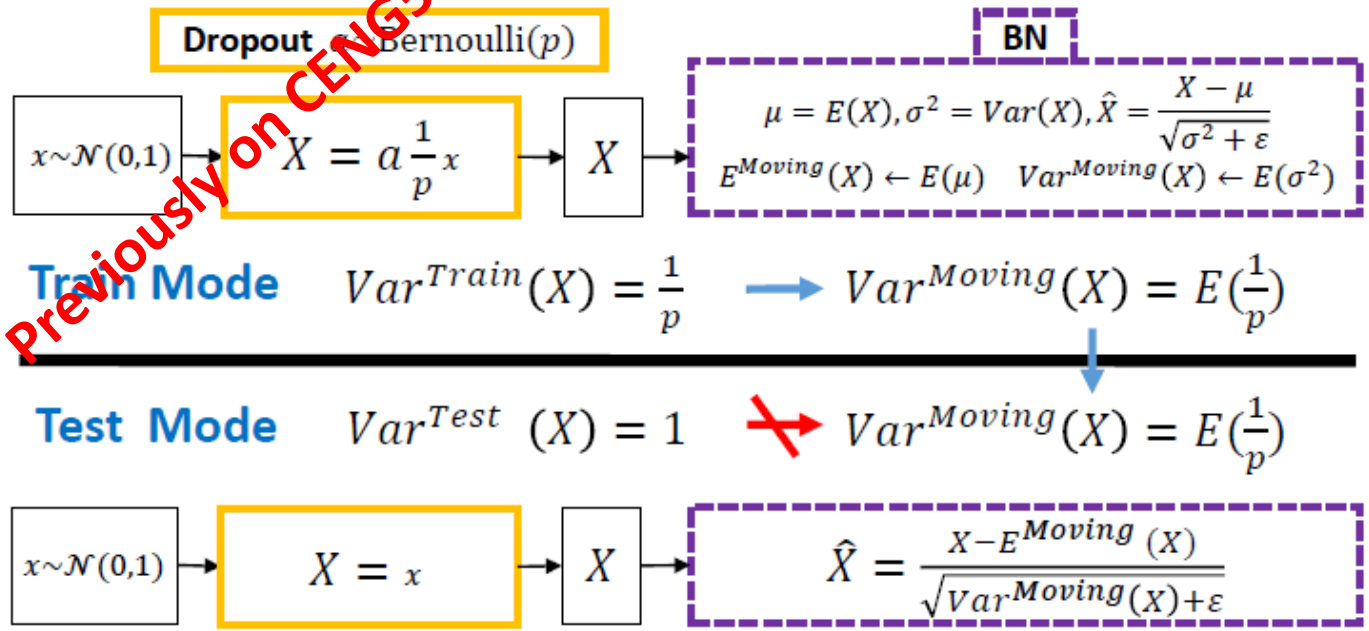

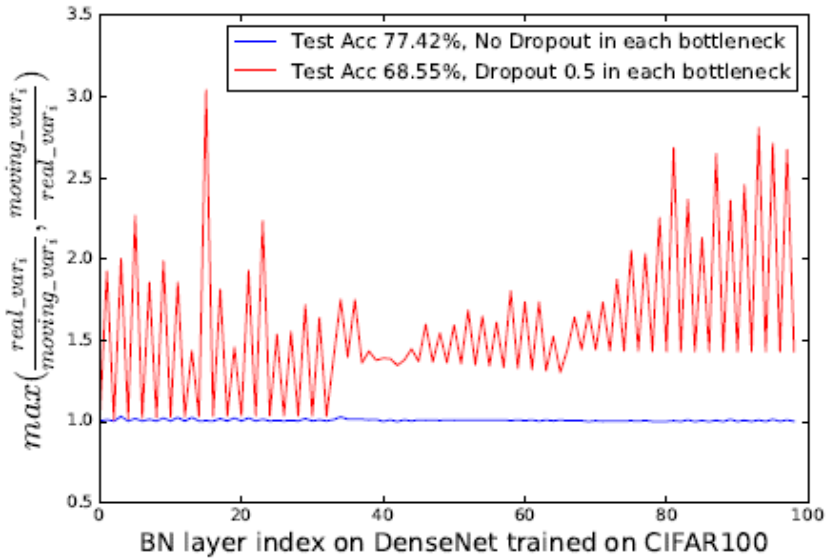

Understanding the Disharmony between Dropout and Batch Normalization by Variance Shift

Xiang Li [1] Shuo Chen [1] Xiaolin Hu [2] Jian Yang [1]

2018

Since we get a clear knowledge about the disharmony between Dropout and BN, we can easily develop several approaches to combine them together, to see whether an extra improvement could be obtained. In this section, we introduce two possible solutions in modifying Dropout. One is to avoid the scaling on feature-map before every BN layer, by only applying Dropout after the last BN block. Another is to slightly modify the formula of Dropout and make it less sensitive to variance, which can alleviate the shift problem and stabilize the numerical behaviors.

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Disadvantages of MLPs: Dimensionality

- The number of parameters in an MLP is high for practical problems
  - e.g., for grayscale images with 1000x1000 resolution, a fully-connected layer with 1000 neurons requires 10^9 parameters.
- The number of parameters in an MLP increases quadratically with an increase in input dimensionality
- For example, for a fully-connected layer with n_{in} input neurons and n_{out} output neurons:
  - Number of parameters: $n_{in} \times n_{out}$
  - Assuming proportional decrease in layer size, e.g. $n_{out} = n_{in}/10$, gives: $n_{in} \times n_{out} = n_{in}^2/10$
  - Increasing n_{in} by d yields a change of $\mathcal{O}(d^2)$.
- This is a problem because:
  - More parameters => larger model size & more computational complexity.
- Teaser for CNNs:
  - Input size does not affect model size (in general)

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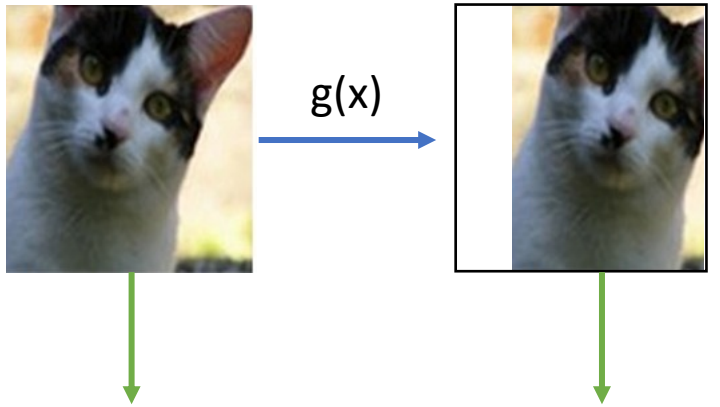
Equivariance vs. Invariance

- Equivariant problem: image segmentation.
  - f(g(x)) = g(f(x))

https://www.mathworks.com/discovery/image-segmentation.html

- Invariant problem: object recognition.
  - f(g(x)) = f(x)



- Pooling provides invariance, convolution provides equivariance.

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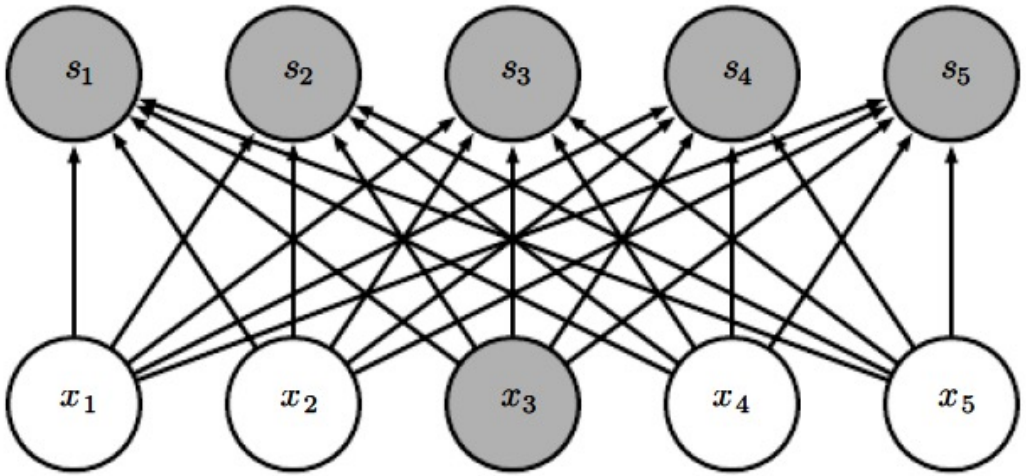
CNNs: Underlying Principle



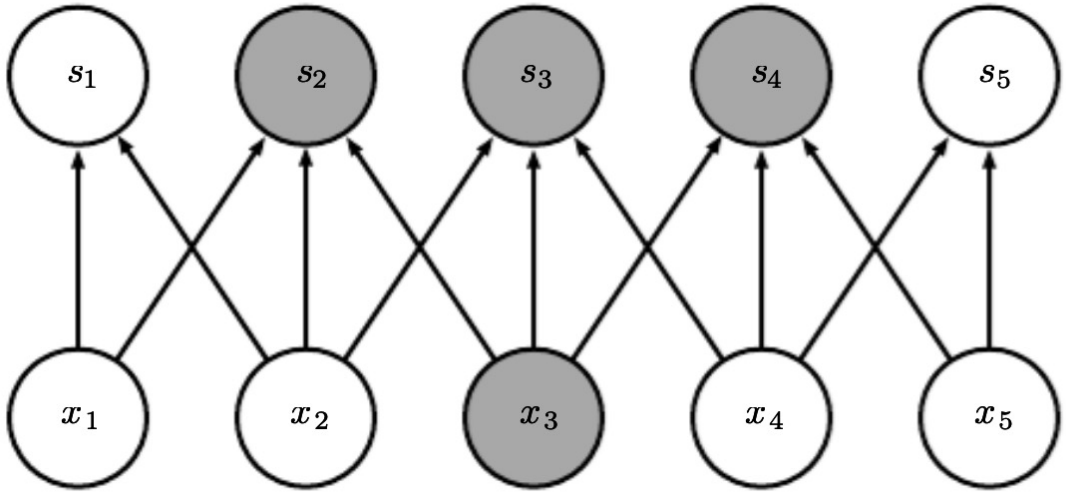


Figure: Goodfellow et al., "Deep Learning", MIT Press, 2016.

CNNs vs. MLPs: Curse of Dimensionality

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- A fully-connected network has too many parameters
  - On CIFAR-10:
    - Images have size 32x32x3 ➔ one neuron in hidden layer has 3072 weights!
  - With images of size 1024x1024x3 ➔ one neuron in hidden layer has 3,145,728 weights!
  - This explodes quickly if you increase the number of neurons & layers.
- Alternative: enforce local connectivity!

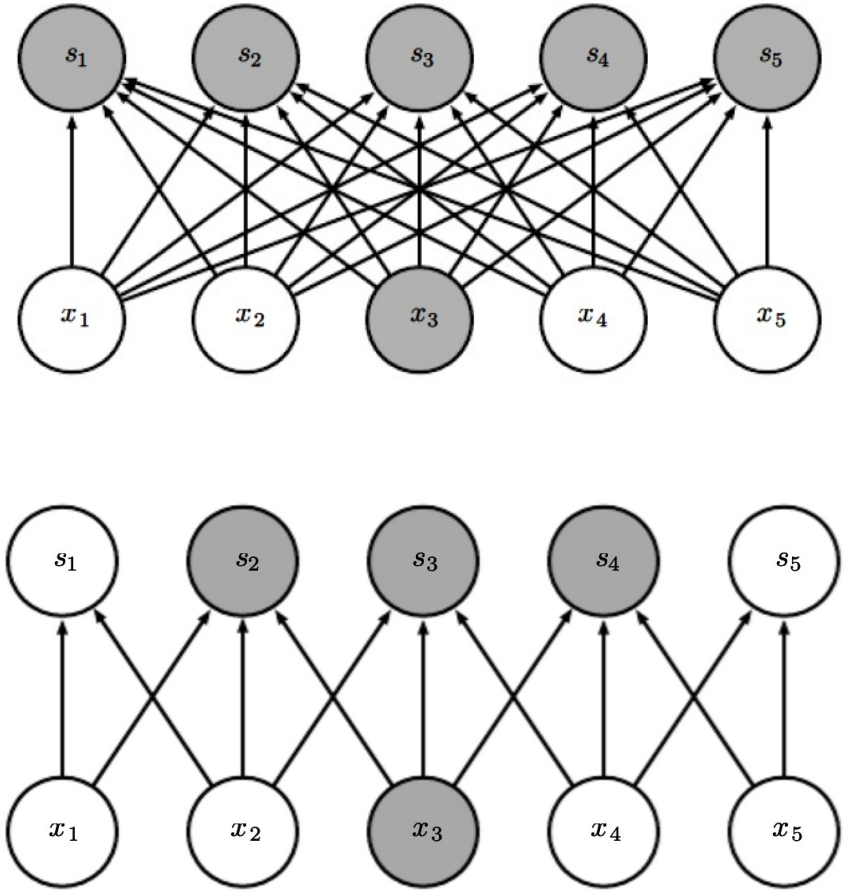

Figure: Goodfellow et al., "Deep Learning", MIT Press, 2016.

CNNs vs. MLPs: Curse of Dimensionality

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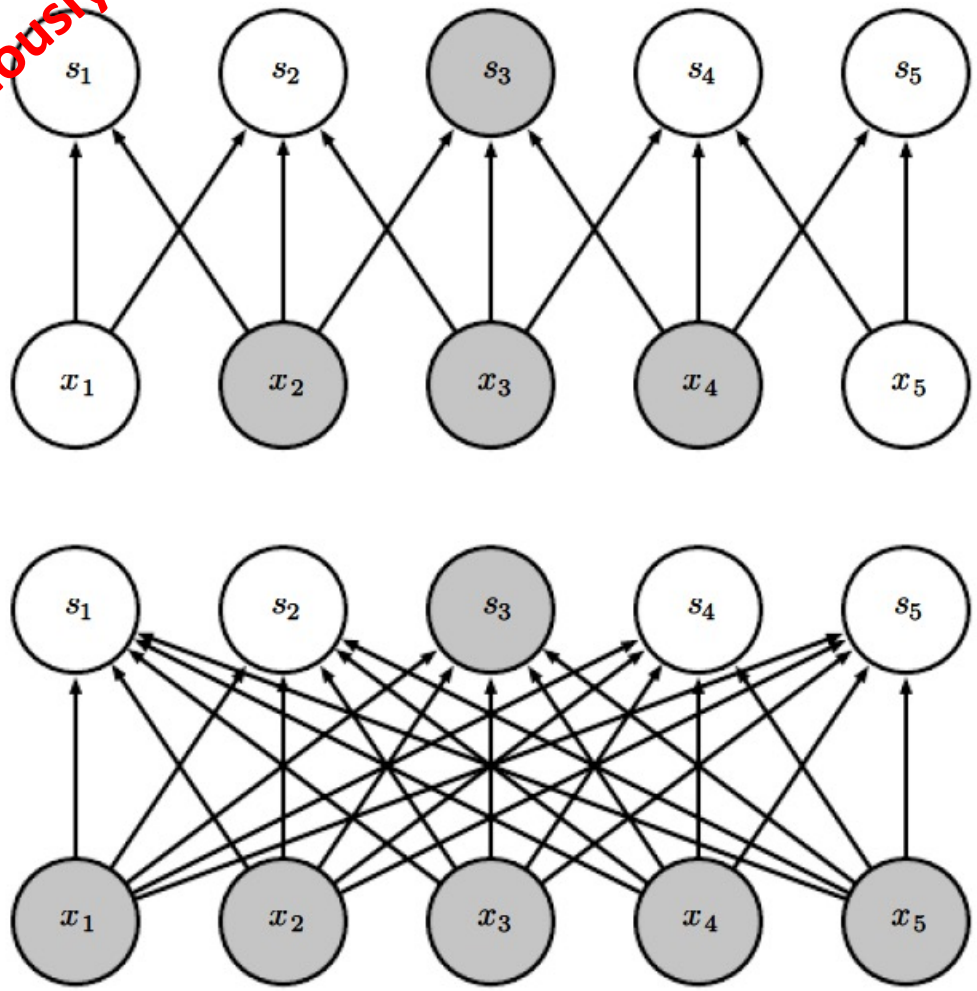

When things go deep, an output may depend on all or most of the input:

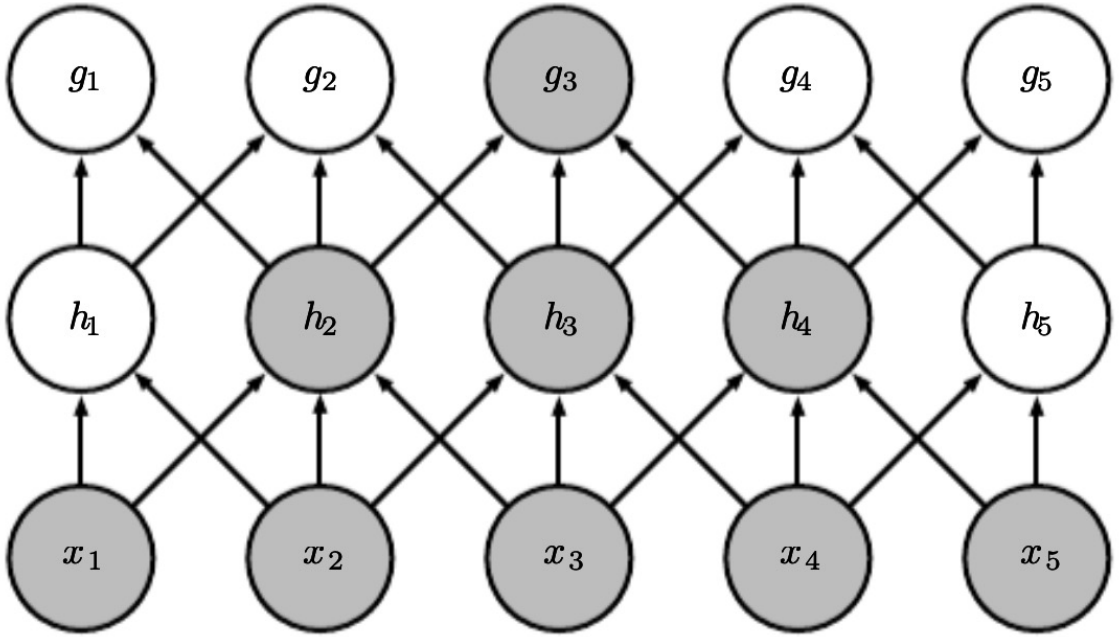

Figure: Goodfellow et al., “Deep Learning”, MIT Press, 2016.

Previously on CENG501

How Many Samples are Needed to Learn a Convolutional Neural Network?

Simon S. Du*[1], Yining Wang*[1], Xiyu Zhai[2], Sivaraman Balakrishnan[3], Ruslan Salakhutdinov[1], and Aarti Singh[1]

[1]Machine Learning Department, Carnegie Mellon University
[2]University of Cambridge
[3]Department of Statistics, Carnegie Mellon University

May 22, 2018

Abstract

A widespread folklore for explaining the success of convolutional neural network (CNN) is that CNN is a more compact representation than the fully connected neural network (FNN) and thus requires fewer samples for learning. We initiate the study of rigorously characterizing the sample complexity of learning convolutional neural networks. We show that for learning an m-dimensional convolutional filter with linear activation acting on a d-dimensional input, the sample complexity of achieving population prediction error of ϵ is $\widetilde{O}(m/\epsilon^2)$[1], whereas its FNN counterpart needs at least $\Omega(d/\epsilon^2)$ samples. Since $m \ll d$, this result demonstrates the advantage of using CNN. We further consider the sample complexity of learning a one-hidden-layer CNN with linear activation where both the m-dimensional convolutional filter and the r-dimensional output weights are unknown. For this model, we show the sample complexity is $\widetilde{O}\left((m+r)/\epsilon^2\right)$ when the ratio between the stride size and the filter size is a constant. For both models, we also present lower bounds showing our sample complexities are tight up to logarithmic factors. Our main tools for deriving these results are localized empirical process and a new lemma characterizing the convolutional structure. We believe these tools may inspire further developments in understanding CNN.

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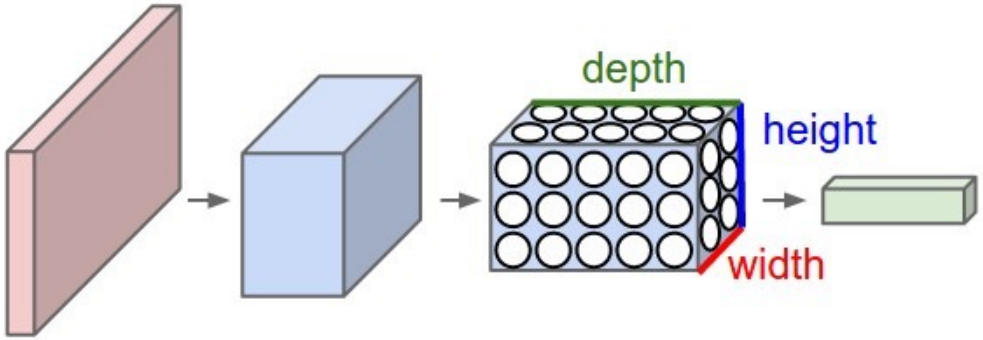
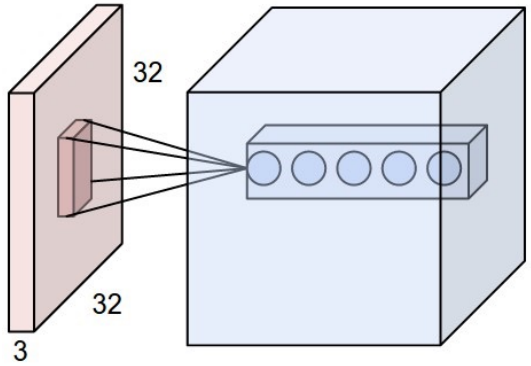
Connectivity in CNN

- Local: The behavior of a neuron does not change other than being restricted to a subspace of the input.
- Each neuron is connected to slice of the previous layer
- A layer is actually a volume having a certain width x height and depth (or channel)
- A neuron is connected to a subspace of width x height but to all channels (depth)
- Example: CIFAR-10
  - Input: 32 x 32 x 3 (3 for RGB channels)
  - A neuron in the next layer with receptive field size 5x5 has input from a volume of 5x5x3.





http://cs231n.github.io/convolutional-networks/

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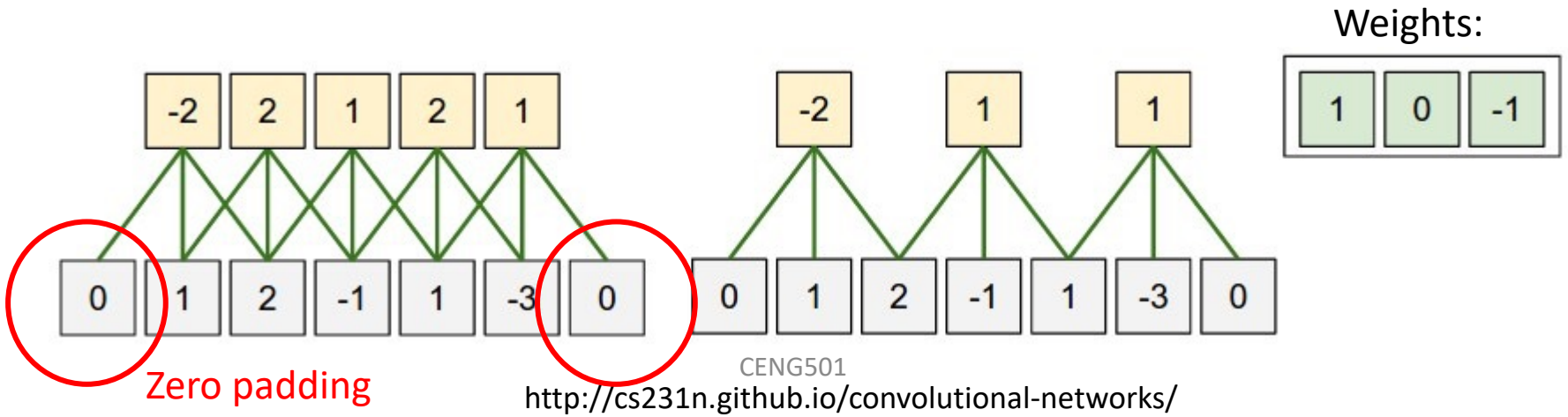
Size of the next layer

- Along a dimension:
  - W: Size of the input
  - F: Size of the receptive field
  - S: Stride
  - P: Amount of zero-padding
- Then: the number of neurons as the output of a convolution layer:

$$\frac{W - F + 2P}{S} + 1$$

- If this number is not an integer, your strides are incorrect and your neurons cannot tile nicely to cover the input volume



http://cs231n.github.io/convolutional-networks/

Today

- Continue with CNNs
  - Different types of convolution in CNNs

Administrative Notes

- Paper Selection

Types of Convolution: Unshared convolution

- In some cases, sharing the weights does not make sense
  - When?
- Different parts of the input might require different types of processing/features
- In such a case, we just have a network with local connectivity
- E.g., a face.
  - Features are not repeated across the space.

Types of Convolution: Dilated (Atrous) Convolution

Purpose: Increase effective receptive field size without increasing parameters.

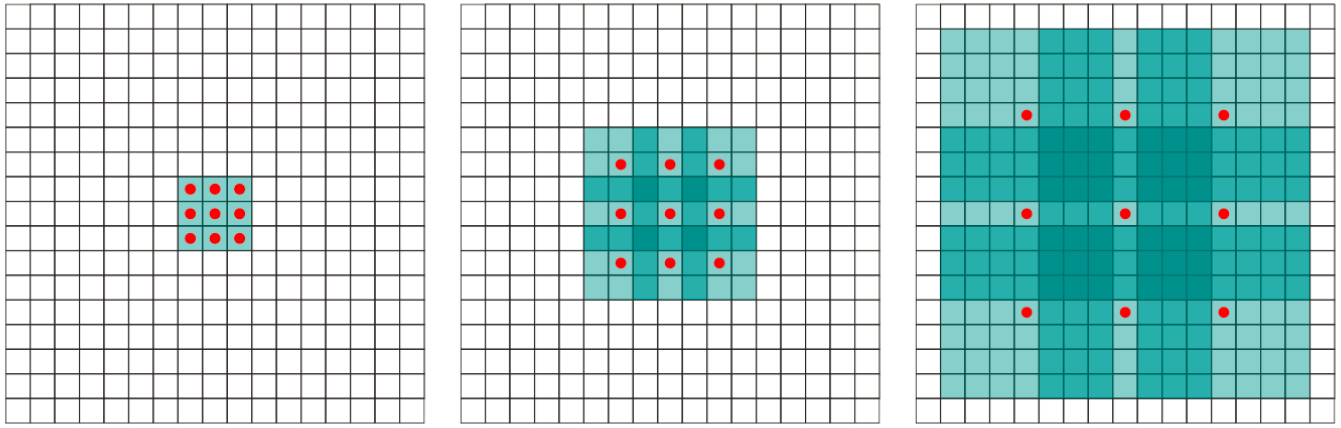


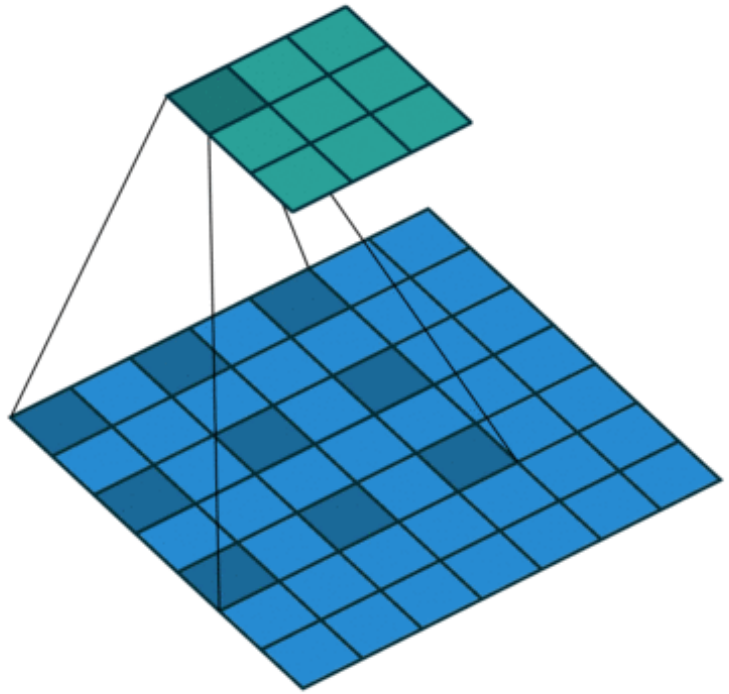
Figure 1: Systematic dilation supports exponential expansion of the receptive field without loss of resolution or coverage. (a) F_1 is produced from F_0 by a 1-dilated convolution; each element in F_1 has a receptive field of 3×3. (b) F_2 is produced from F_1 by a 2-dilated convolution; each element in F_2 has a receptive field of 7×7. (c) F_3 is produced from F_2 by a 4-dilated convolution; each element in F_3 has a receptive field of 15×15. The number of parameters associated with each layer is identical. The receptive field grows exponentially while the number of parameters grows linearly.

Published as a conference paper at ICLR 2016

MULTI-SCALE CONTEXT AGGREGATION BY DILATED CONVOLUTIONS

Fisher Yu
Princeton University

Vladlen Koltun
Intel Labs



https://github.com/vdumoulin/conv_arithmetic

Types of Convolution: Transposed Convolution

Purpose: Increasing layer width+height (upsampling).

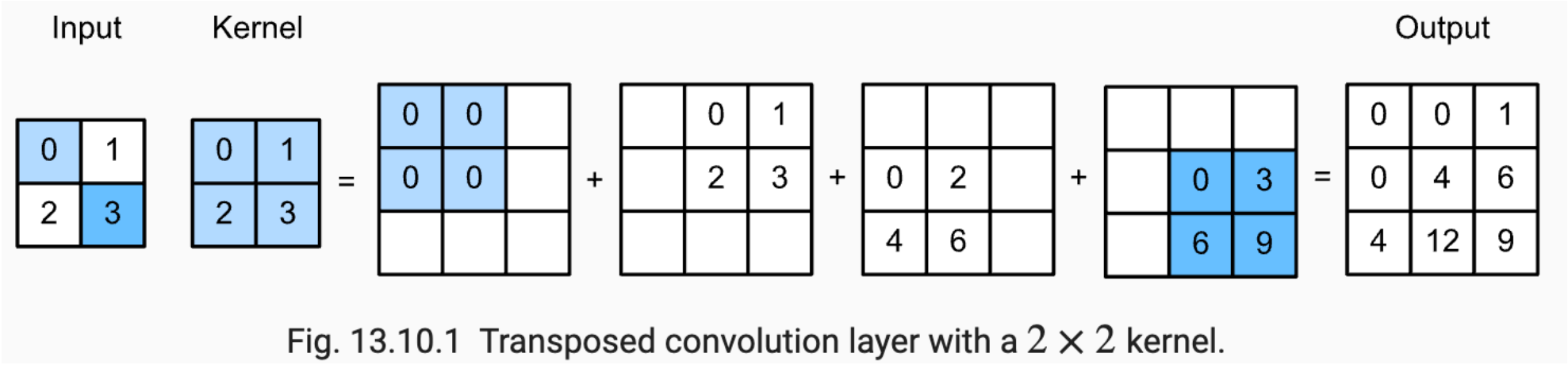


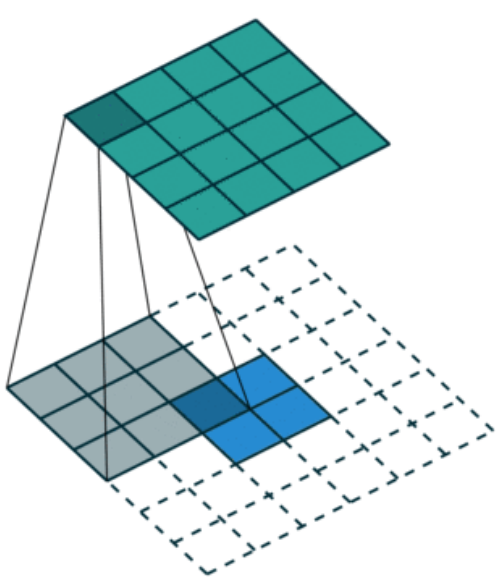
Fig. 13.10.1 Transposed convolution layer with a 2×2 kernel.

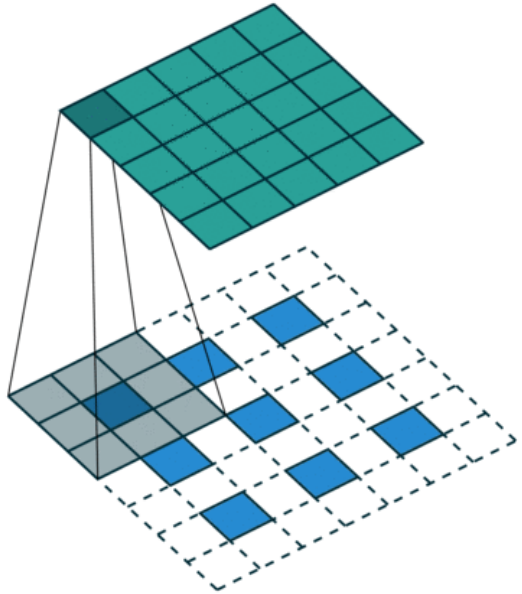
Figure: https://d2l.ai/chapter_computer-vision/transposed-conv.html

The size of the output:

- Regular convolution: $O = \frac{W-F+2\times P}{S} + 1$
- Transpose convolution: $W = (O-1)\times S + F - 2\times P$

Types of Convolution:
Upsampling with Padding or Dilation

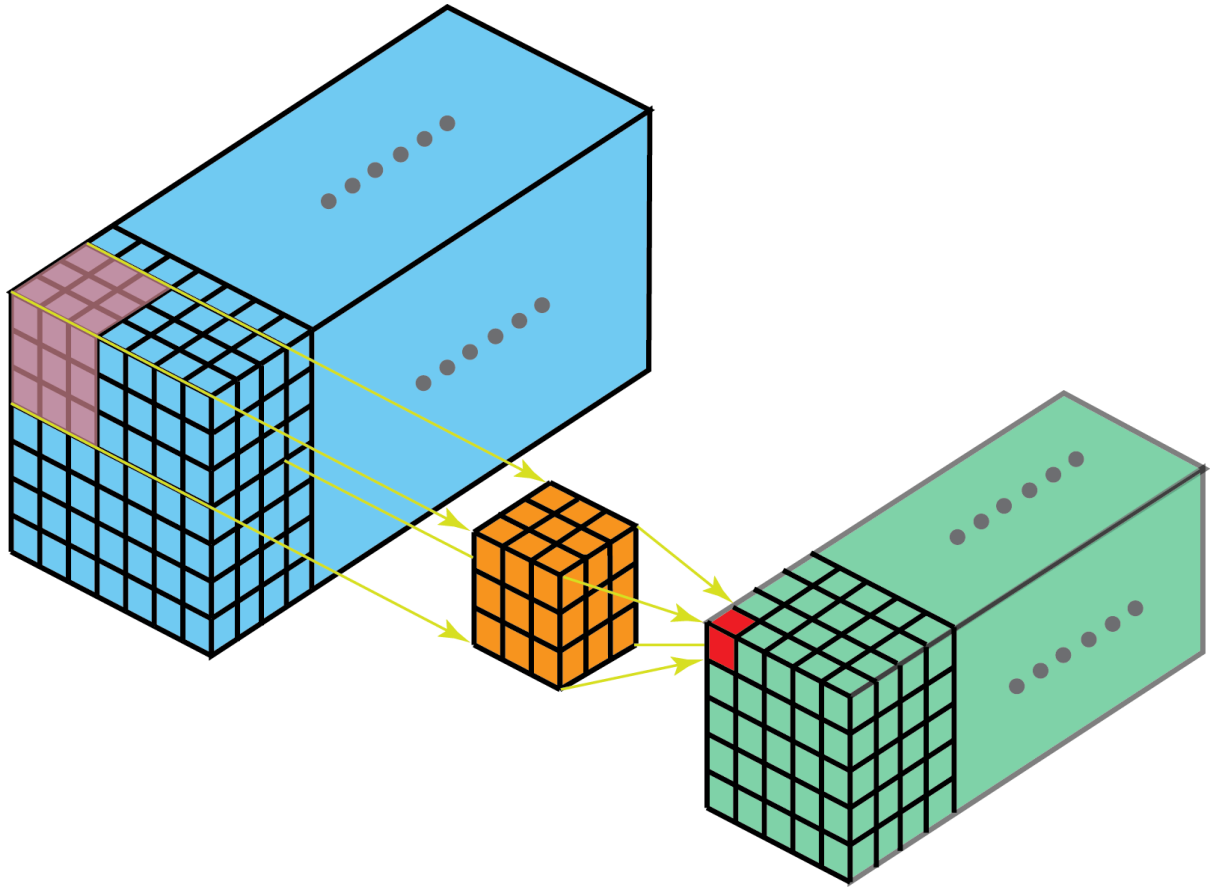




https://github.com/vdumoulin/conv_arithmetic

Types of Convolution: 3D Convolution

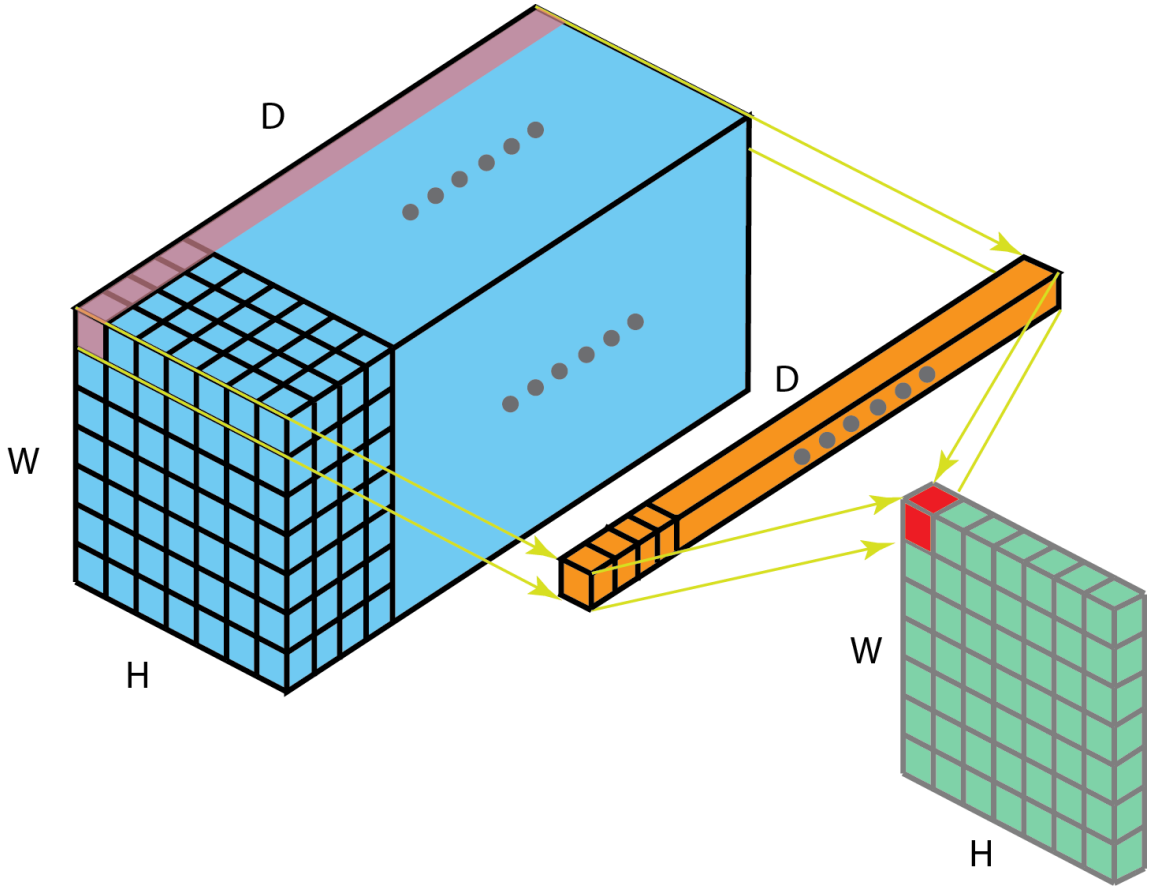
Purpose: Work with 3D data, e.g. learn spatial + temporal representations for videos.



https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

Types of Convolution: 1x1 Convolution

Purpose: Reduce number of channels.

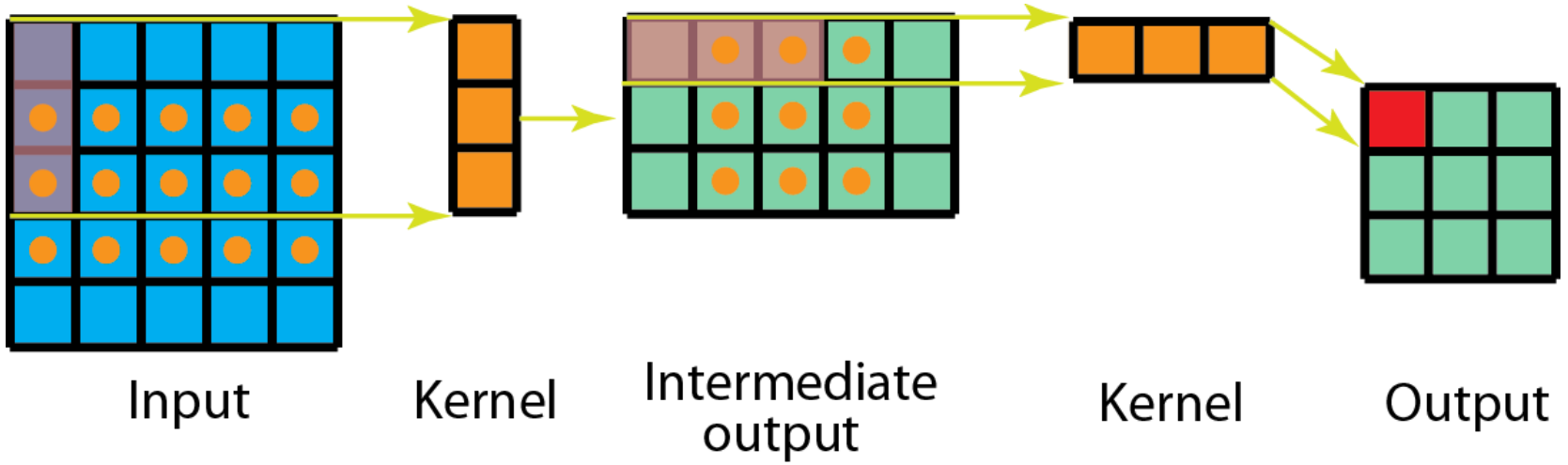


https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

Types of Convolution: Separable Convolution

Purpose: Reduce number of parameters and multiplications.

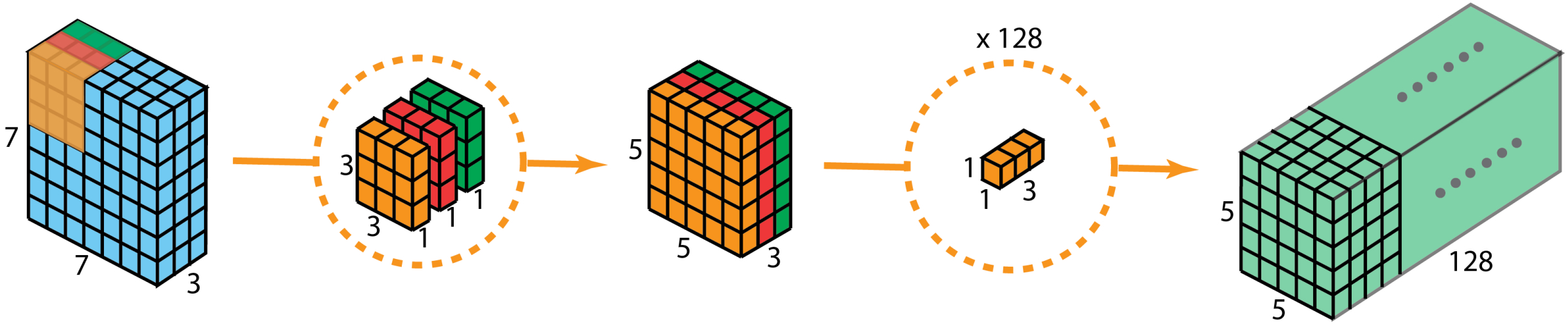
$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \times \begin{bmatrix} -1 & 0 & 1 \end{bmatrix}$$



https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

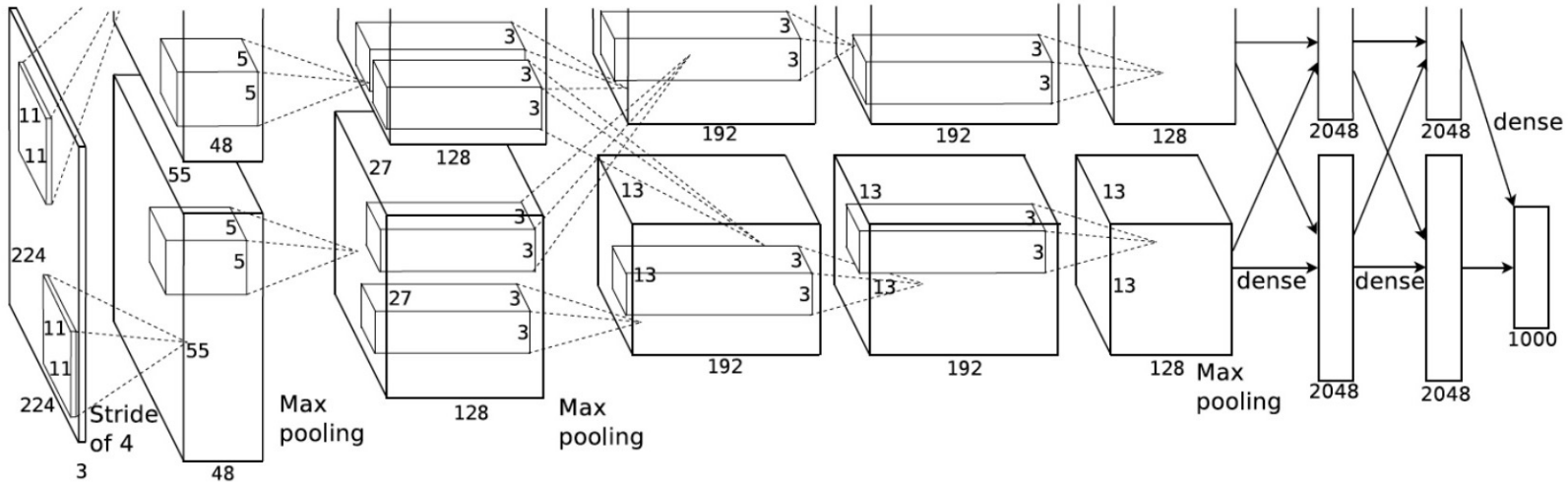
Types of Convolution: Depth-wise Separable Convolution

Purpose: Reduce number of parameters and multiplications.

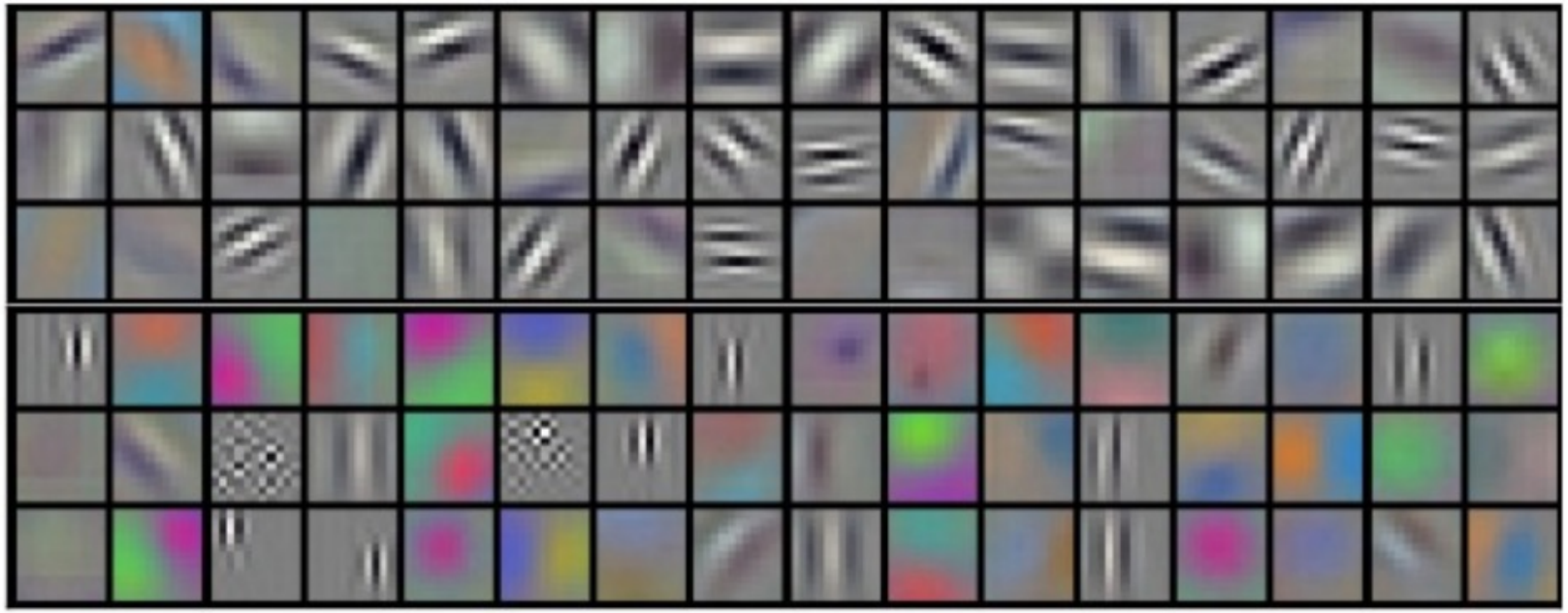


https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

Types of Convolution: Group Convolution

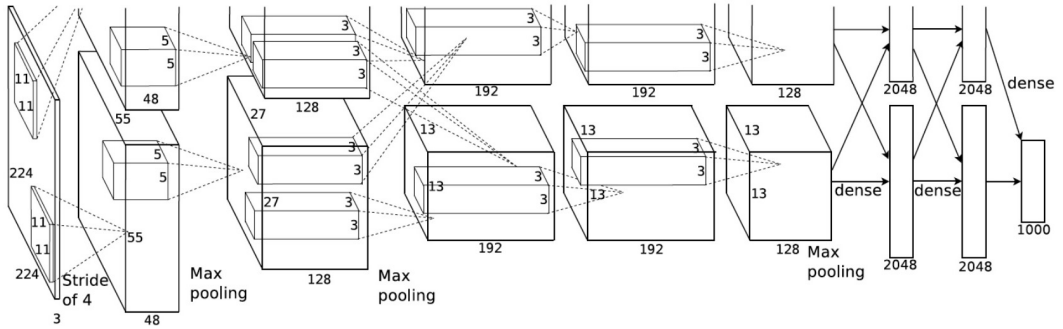


AlexNet (Krizhevsky et al.)

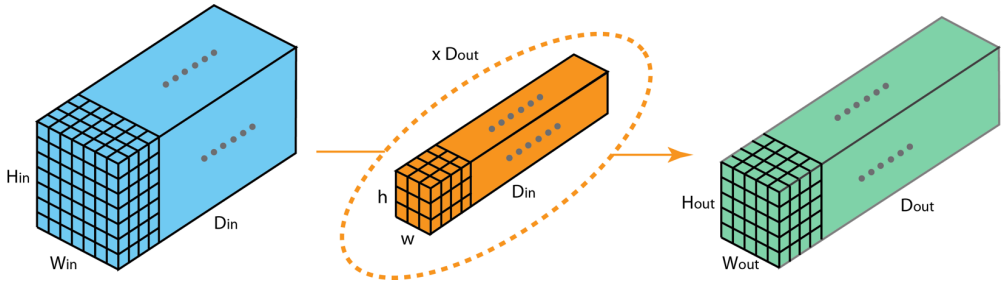


Types of Convolution: Group Convolution

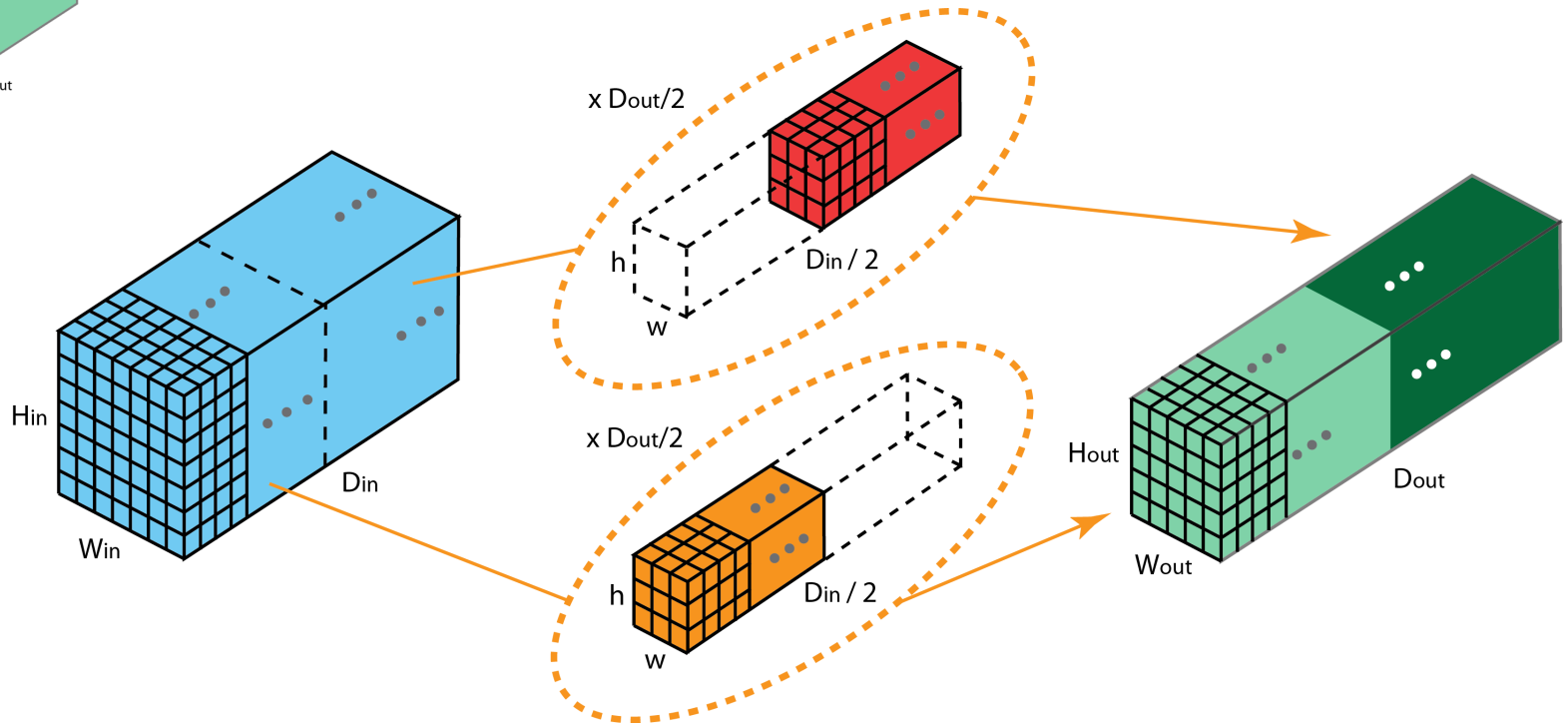
Purpose: Reduce number of parameters and multiplications.



AlexNet



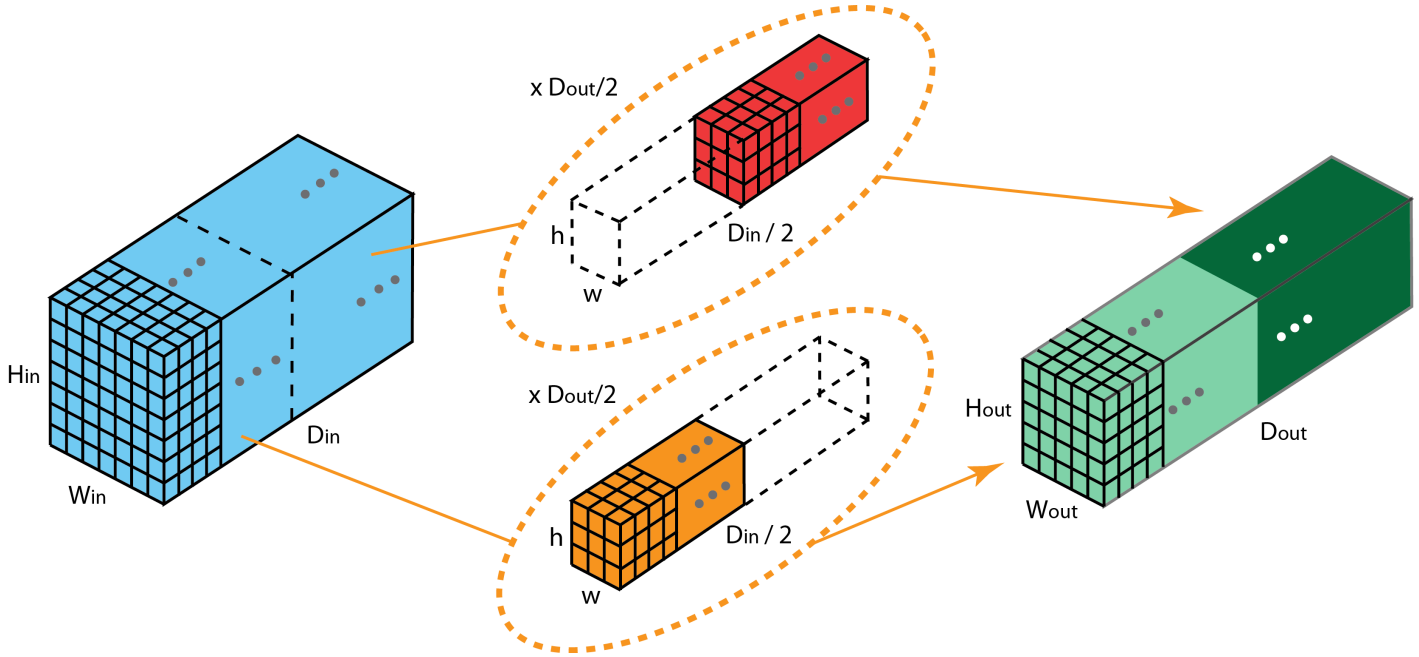
Normal Convolution



https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

Types of Convolution
Group Convolution

- Benefits:
  - Efficiency in training (distribute groups to different GPUs)
  - Decrease in # of parameters as the # of groups increases
  - Better performance?



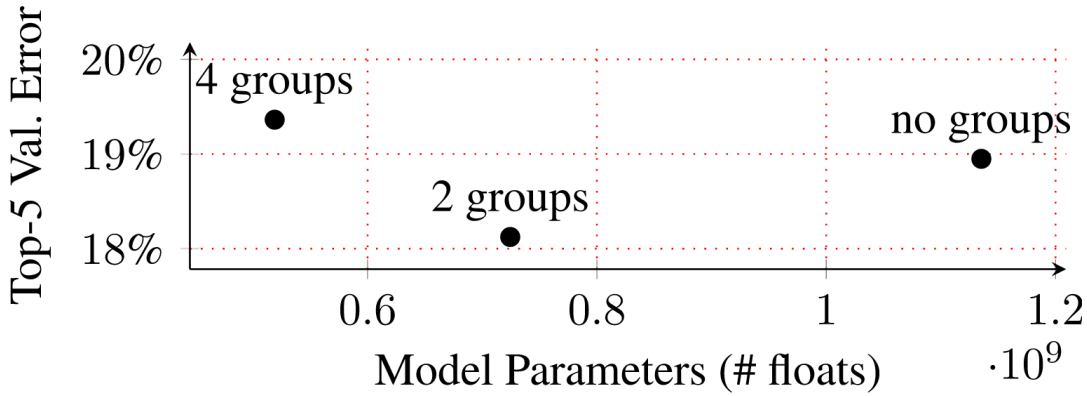


Figure: https://blog.yani.ai/filter-group-tutorial/

https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

Types of Convolution: Deformable Convolution

Dai, J., Qi, H., Xiong, Y., Li, Y., Zhang, G., Hu, H., & Wei, Y. (2017). Deformable convolutional networks. ICCV.

Purpose: Flexible receptive field.

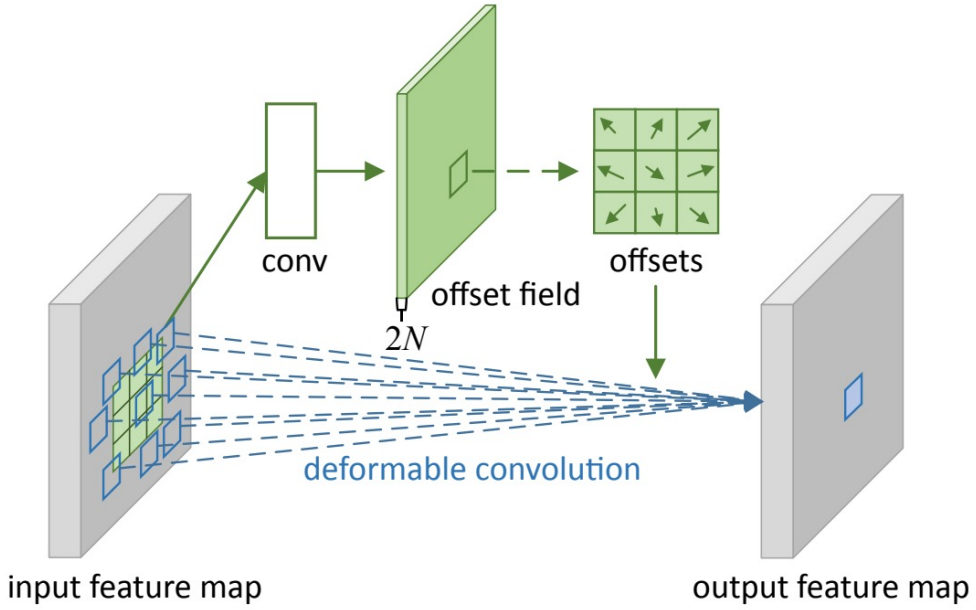


Figure 2: Illustration of 3×3 deformable convolution.

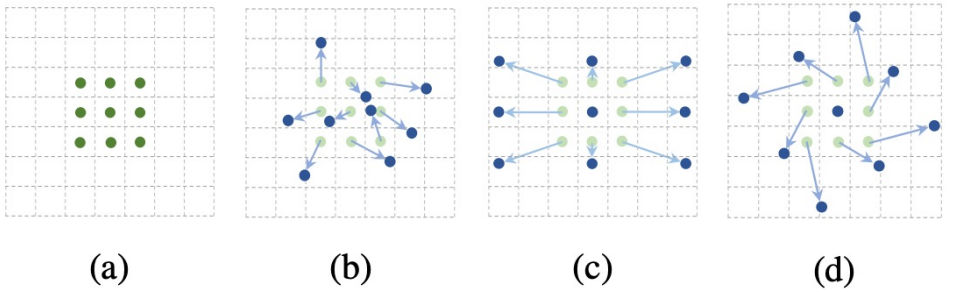
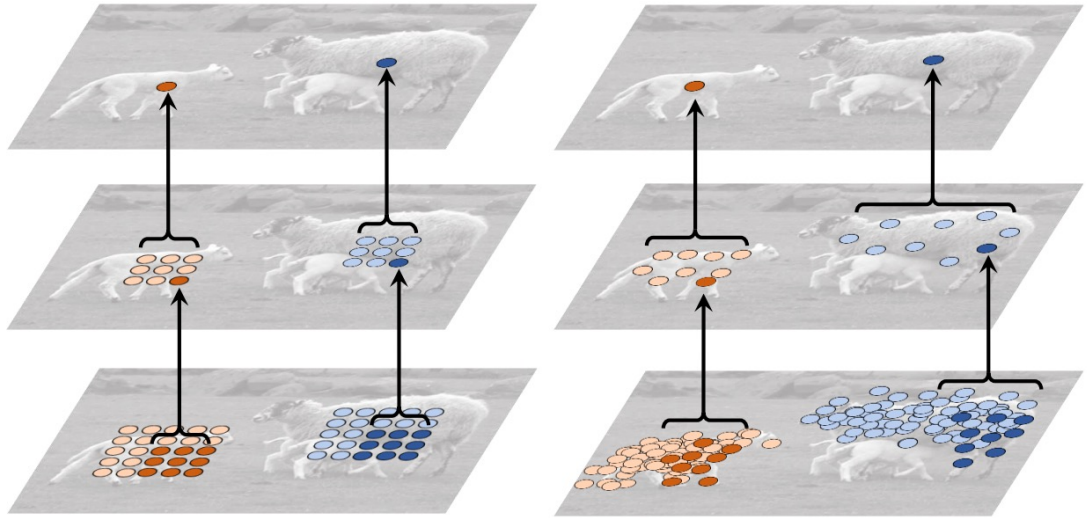


Figure 1: Illustration of the sampling locations in 3×3 standard and deformable convolutions. (a) regular sampling grid (green points) of standard convolution. (b) deformed sampling locations (dark blue points) with augmented offsets (light blue arrows) in deformable convolution. (c)(d) are special cases of (b), showing that the deformable convolution generalizes various transformations for scale, (anisotropic) aspect ratio and rotation.



(a) standard convolution (b) deformable convolution

Types of Convolution: Deformable Convolution

Dai, J., Qi, H., Xiong, Y., Li, Y., Zhang, G., Hu, H., & Wei, Y. (2017). Deformable convolutional networks. ICCV.

Bilinear interpolation for x(p).

$$\mathcal{R} = \{(-1,-1),(-1,0),\ldots,(0,1),(1,1)\}$$

defines a 3×3 kernel with dilation 1.

For each location $\mathbf{p}_0$ on the output feature map $\mathbf{y}$, we have

$$\mathbf{y}(\mathbf{p}_0) = \sum_{\mathbf{p}_n \in \mathcal{R}} \mathbf{w}(\mathbf{p}_n) \cdot \mathbf{x}(\mathbf{p}_0 + \mathbf{p}_n), \quad (1)$$

where $\mathbf{p}_n$ enumerates the locations in $\mathcal{R}$.

In deformable convolution, the regular grid $\mathcal{R}$ is augmented with offsets $\{\Delta\mathbf{p}_n | n = 1, ..., N\}$, where $N = |\mathcal{R}|$. Eq. (1) becomes

$$\mathbf{y}(\mathbf{p}_0) = \sum_{\mathbf{p}_n \in \mathcal{R}} \mathbf{w}(\mathbf{p}_n) \cdot \mathbf{x}(\mathbf{p}_0 + \mathbf{p}_n + \Delta\mathbf{p}_n). \quad (2)$$

Now, the sampling is on the irregular and offset locations $\mathbf{p}_n + \Delta\mathbf{p}_n$. As the offset $\Delta\mathbf{p}_n$ is typically fractional, Eq. (2) is implemented via bilinear interpolation as

$$\mathbf{x}(\mathbf{p}) = \sum_{\mathbf{q}} G(\mathbf{q}, \mathbf{p}) \cdot \mathbf{x}(\mathbf{q}), \quad (3)$$

where $\mathbf{p}$ denotes an arbitrary (fractional) location ($\mathbf{p} = \mathbf{p}_0 + \mathbf{p}_n + \Delta\mathbf{p}_n$ for Eq. (2)), $\mathbf{q}$ enumerates all integral spatial locations in the feature map $\mathbf{x}$, and $G(\cdot,\cdot)$ is the bilinear interpolation kernel. Note that G is two dimensional. It is separated into two one dimensional kernels as

$$G(\mathbf{q}, \mathbf{p}) = g(q_x, p_x) \cdot g(q_y, p_y), \quad (4)$$

where $g(a,b) = max(0, 1 - |a - b|)$. Eq. (3) is fast to compute as $G(\mathbf{q}, \mathbf{p})$ is non-zero only for a few $\mathbf{q}$s.

In the deformable convolution Eq. (2), the gradient w.r.t. the offset $\Delta\mathbf{p}_n$ is computed as

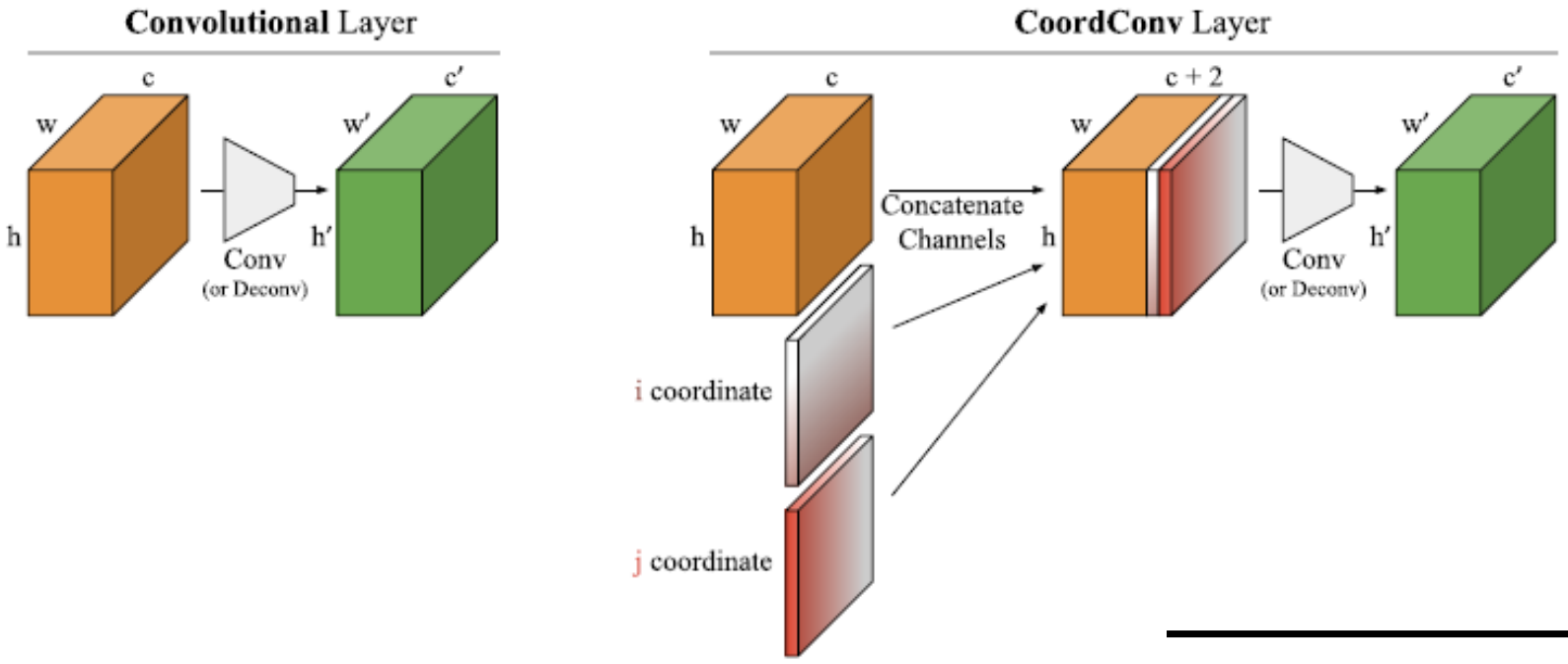
$$\frac{\partial \mathbf{y}(\mathbf{p}_0)}{\partial \Delta\mathbf{p}_n} = \sum_{\mathbf{p}_n \in \mathcal{R}} \mathbf{w}(\mathbf{p}_n) \cdot \frac{\partial \mathbf{x}(\mathbf{p}_0 + \mathbf{p}_n + \Delta\mathbf{p}_n)}{\partial \Delta\mathbf{p}_n}$$

$$= \sum_{\mathbf{p}_n \in \mathcal{R}} \left[\mathbf{w}(\mathbf{p}_n) \cdot \sum_{\mathbf{q}} \frac{\partial G(\mathbf{q}, \mathbf{p}_0 + \mathbf{p}_n + \Delta\mathbf{p}_n)}{\partial \Delta\mathbf{p}_n} \mathbf{x}(\mathbf{q}) \right], \quad (7)$$

where the term $\frac{\partial G(\mathbf{q}, \mathbf{p}_0 + \mathbf{p}_n + \Delta\mathbf{p}_n)}{\partial \Delta\mathbf{p}_n}$ can be derived from Eq. (4). Note that the offset $\Delta\mathbf{p}_n$ is 2D and we use $\partial\Delta\mathbf{p}_n$ to denote $\partial\Delta p_n^x$ and $\partial\Delta p_n^y$ for simplicity.

Types of Convolution: Position-sensitive convolution

- Learn to use position information when necessary



An intriguing failing of convolutional neural networks and the CoordConv solution 2018

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Convolution demos & tutorials

- https://github.com/vdumoulin/conv_arithmetic
- http://cs231n.github.io/assets/conv-demo/index.html
- https://ezyang.github.io/convolution-visualizer/index.html
- https://ikhlestov.github.io/pages/machine-learning/convolutions-types/
- https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

OPERATIONS IN A CNN: Pooling

Pooling

Remember the motivation for CNNs:
S (simple) cells: local feature extraction.
C (complex) cells: provide tolerance to deformation, e.g. shift.

- Apply an operation on the "detector" results to combine or to summarize the answers of a set of units.
  - Applied to **each channel (depth slice) independently**
  - The operation has to be differentiable of course.
- Alternatives:
  - Maximum
  - Sum
  - Average
  - Weighted average with distance from the value of the center pixel
  - L2 norm
  - Second-order statistics?
  - …
- Different problems may perform better with different pooling methods
- Pooling can be overlapping or non-overlapping

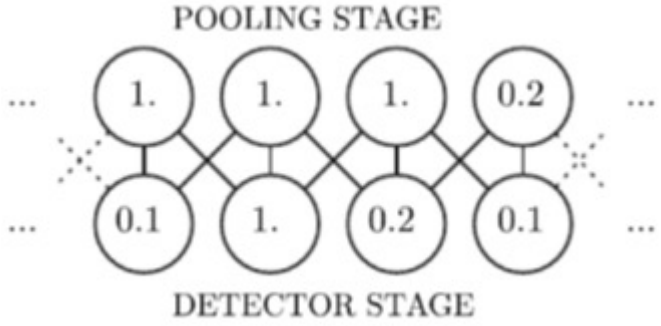


Figure: Goodfellow et al., "Deep Learning", MIT Press, 2016.

http://cs231n.github.io/convolutional-networks/

Pooling

- Example
  - Pooling layer with filters of size 2x2
  - With stride = 2
  - Discards 75% of the activations
  - Depth dimension remains unchanged
- Max pooling with F=3, S=2 or F=2, S=2 are quite common.
  - Pooling with bigger receptive field sizes can be destructive
- Avg pooling is an obsolete choice. Max pooling is shown to work better in practice.

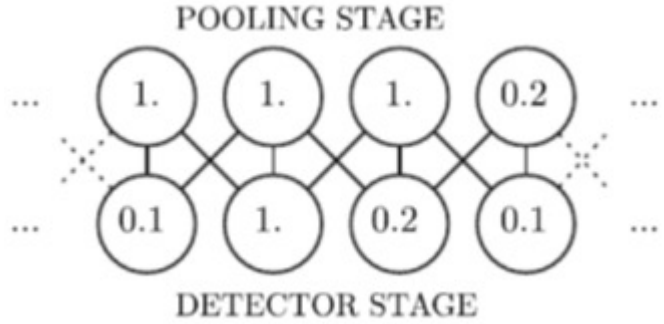
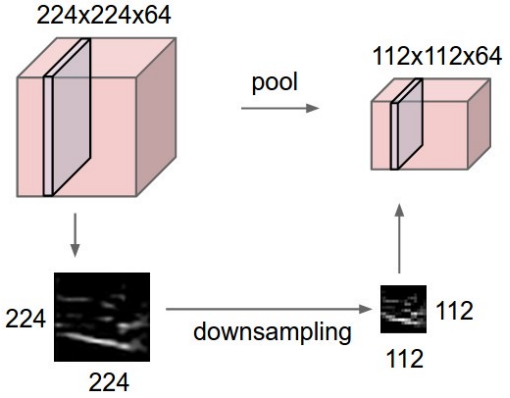
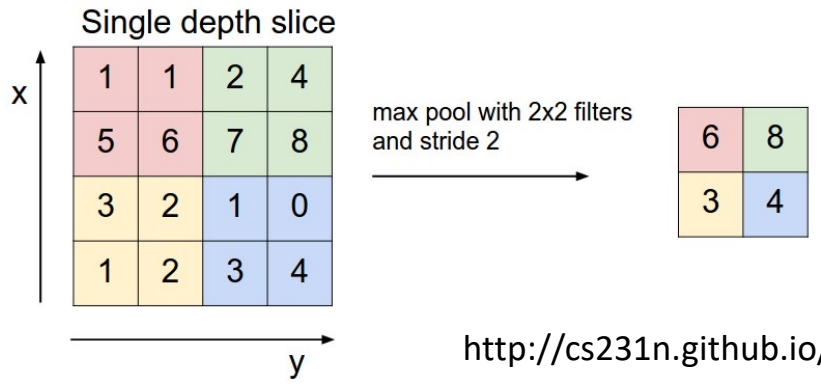


Figure: Goodfellow et al., "Deep Learning", MIT Press, 2016.

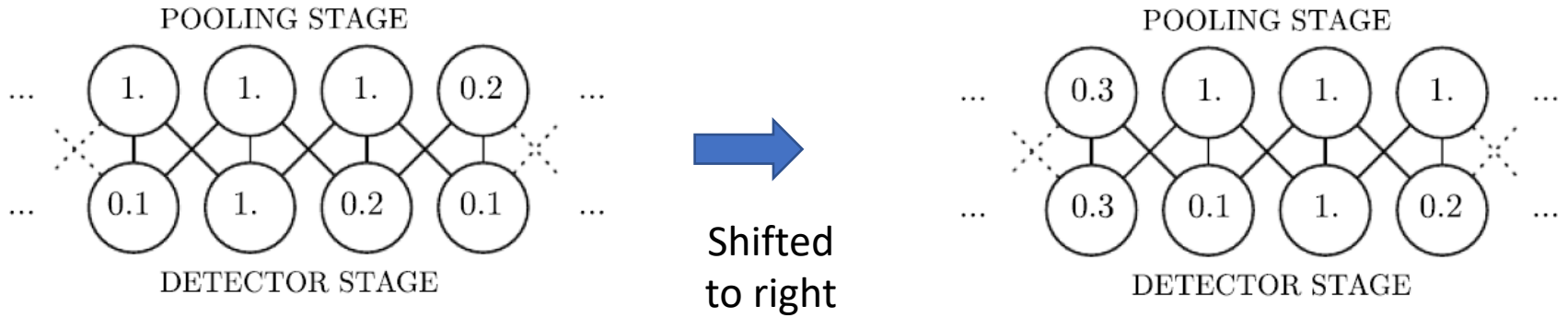




http://cs231n.github.io/convolutional-networks/

Pooling

- Pooling provides invariance to small translation.



Figures: Goodfellow et al., "Deep Learning", MIT Press, 2016.

- If you pool over different convolution operators, you can gain invariance to different transformations.

Pooling can downsample

- Especially needed when to produce an output with fixed-length on varying length input.

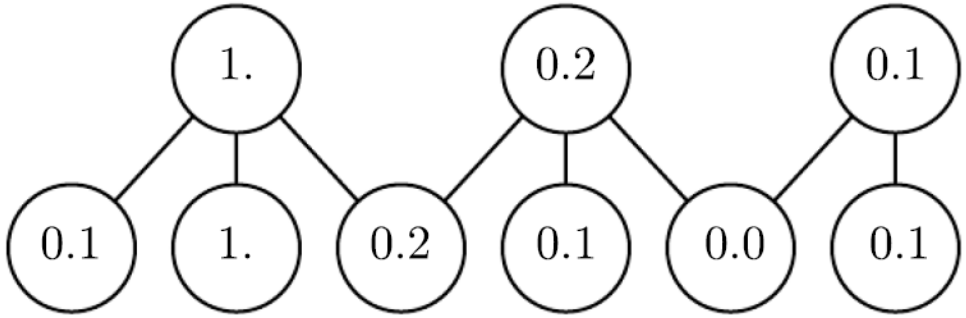


Figure: Goodfellow et al., “Deep Learning”, MIT Press, 2016.

- If you want to use the network on images of varying size, you can arrange this with pooling (with the help of convolutional layers)

CNNs without pooling

- *"Striving for Simplicity: The All Convolutional Net proposes to discard the pooling layer in favor of architecture that only consists of repeated CONV layers. To reduce the size of the representation they suggest using larger stride in CONV layer once in a while."*

CIFAR-10 classification error

Model	Error (%)	# parameters
without data augmentation		
Model A	12.47%	≈ 0.9 M
Strided-CNN-A	13.46%	≈ 0.9 M
ConvPool-CNN-A	**10.21%**	≈ 1.28 M
ALL-CNN-A	10.30%	≈ 1.28 M
Model B	10.20%	≈ 1 M
Strided-CNN-B	10.98%	≈ 1 M
ConvPool-CNN-B	9.33%	≈ 1.35 M
ALL-CNN-B	**9.10%**	≈ 1.35 M
Model C	9.74%	≈ 1.3 M
Strided-CNN-C	10.19%	≈ 1.3 M
ConvPool-CNN-C	9.31%	≈ 1.4 M
ALL-CNN-C	**9.08%**	≈ 1.4 M

(ALL-CNN: No pooling)

https://arxiv.org/pdf/1412.6806.pdf

http://cs231n.github.io/convolutional-networks/

Summary: Convolution & pooling

- Provide strong bias on the model and the solution
- They directly affect the overall performance of the system

OPERATIONS IN A CNN: nonlinearity

Non-linearity

- Sigmoid
- Tanh
- ReLU and its variants
  - The common choice
  - Faster
  - Easier (in backpropagation etc.)
  - Avoids saturation issues
- …

OPERATIONS IN A CNN: normalization

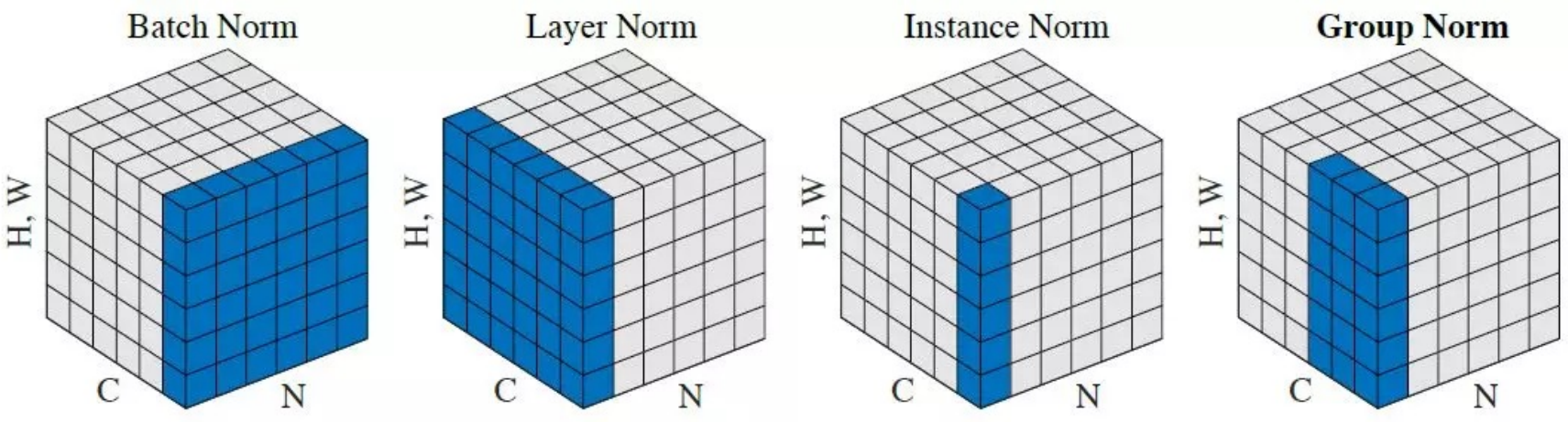
- From Krizhevsky et al. (2012):

generalization. Denoting by $a^i_{x,y}$ the activity of a neuron computed by applying kernel i at position (x, y) and then applying the ReLU nonlinearity, the response-normalized activity $b^i_{x,y}$ is given by the expression

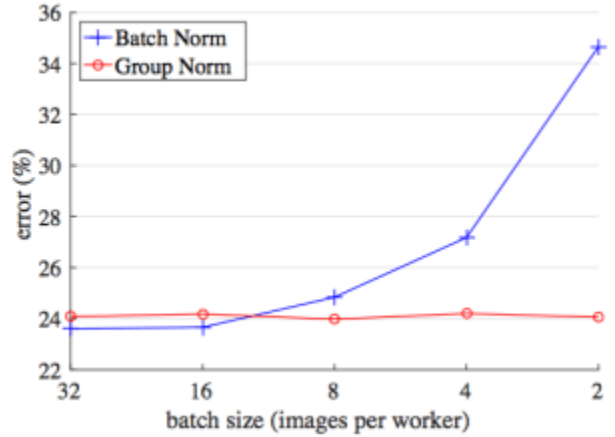
$$b^i_{x,y} = a^i_{x,y} / \left(k + \alpha \sum_{j=\max(0,i-n/2)}^{\min(N-1,i+n/2)} (a^j_{x,y})^2 \right)^\beta$$

where the sum runs over n "adjacent" kernel maps at the same spatial position, and N is the total number of kernels in the layer. The ordering of the kernel maps is of course arbitrary and determined before training begins. This sort of response normalization implements a form of lateral inhibition inspired by the type found in real neurons, creating competition for big activities amongst neuron outputs computed using different kernels. The constants k, n, α, and β are hyper-parameters whose values are determined using a validation set; we used $k = 2$, $n = 5$, $\alpha = 10^{-4}$, and $\beta = 0.75$. We

Normalization



For each channel independently.

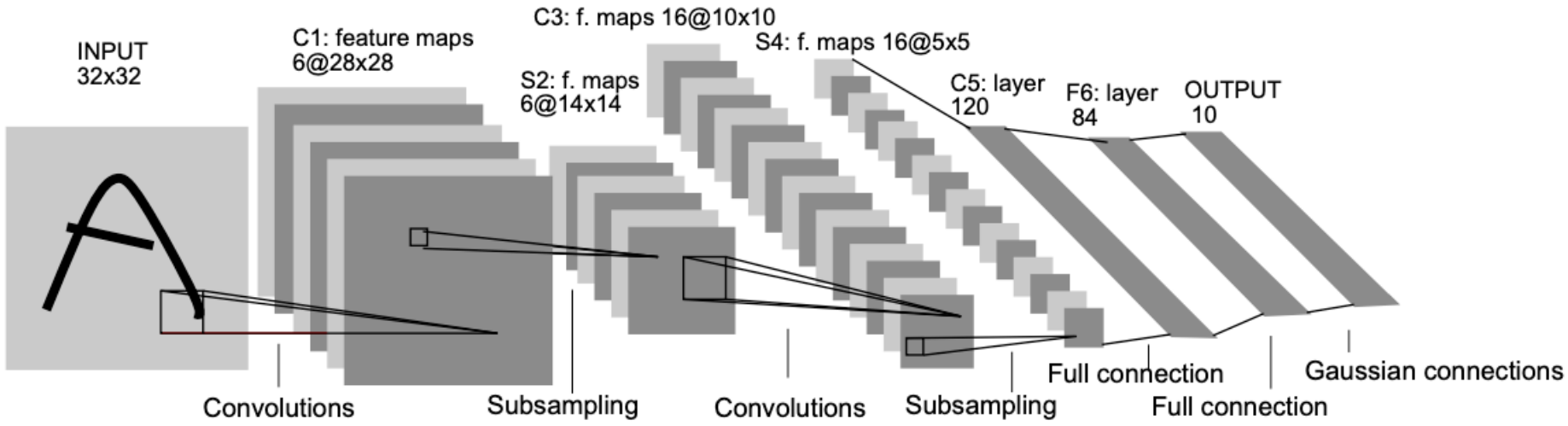


https://medium.com/syncedreview/facebook-ai-proposes-group-normalization-alternative-to-batch-normalization-fb0699bffae7

OPERATIONS IN A CNN: fully connected layer

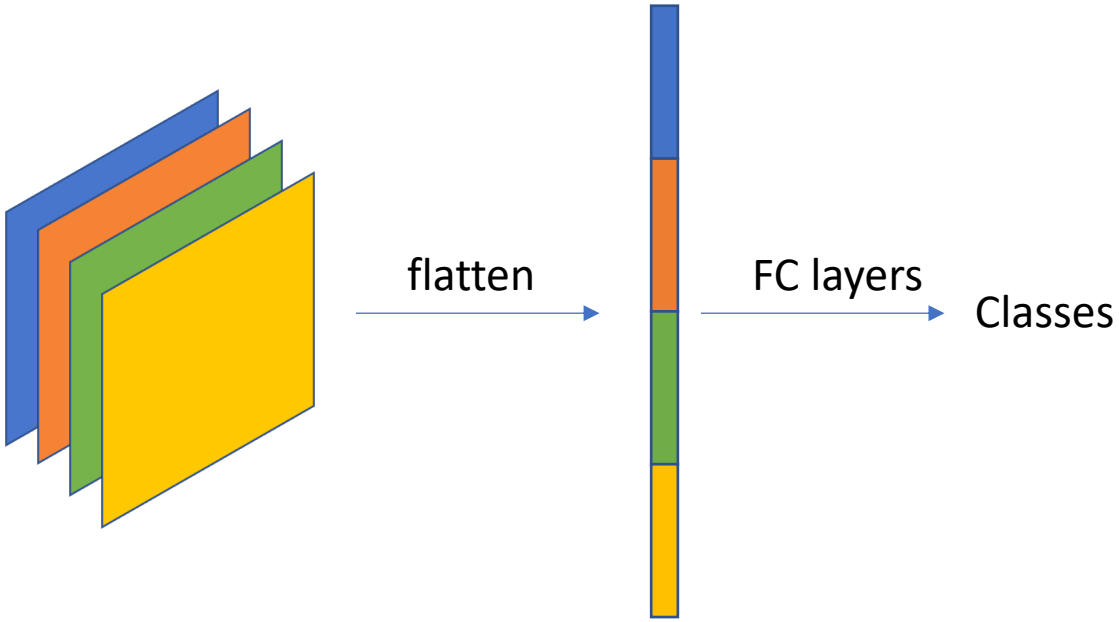
Fully-connected layer

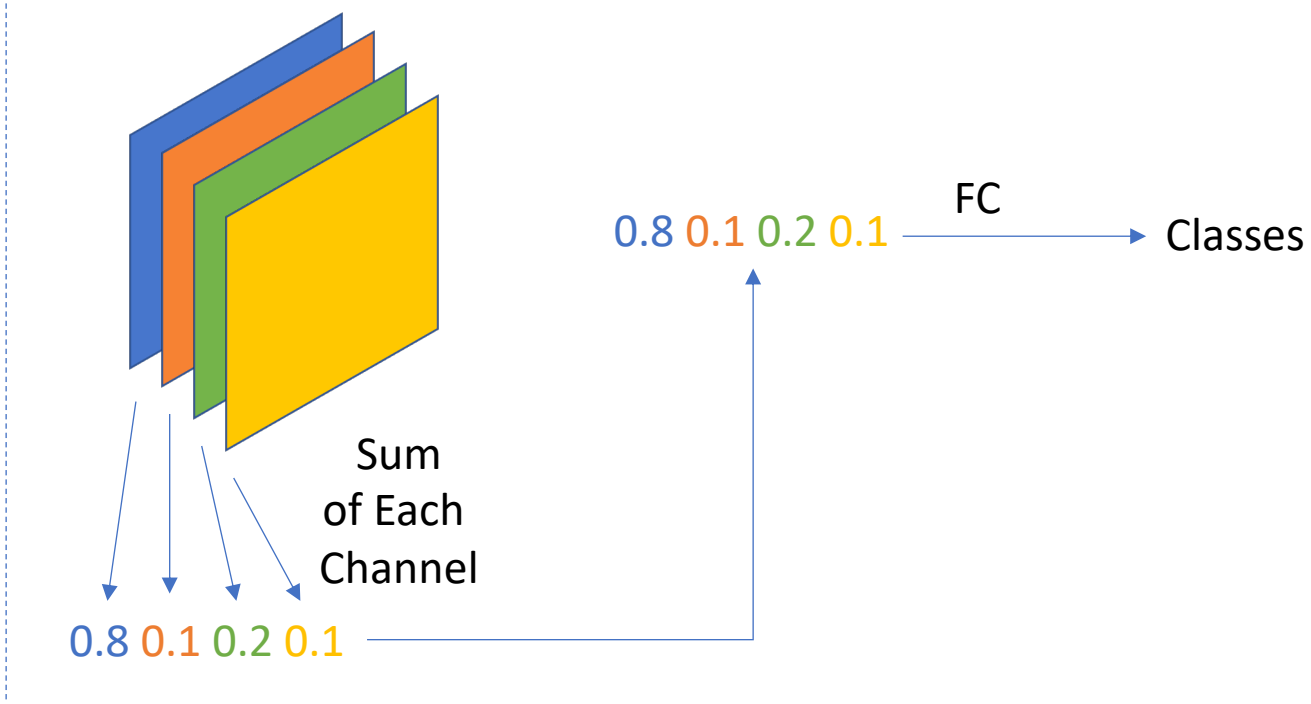
- At the top of the network for mapping the feature responses to output labels
- Full connectivity
- Can be many layers
- Various activation functions can be used



Alternative to FC: Global Average Pooling

"Network In Network", https://arxiv.org/pdf/1312.4400.pdf





Alternative to FC: Global Average Pooling

"Network In Network", https://arxiv.org/pdf/1312.4400.pdf

- We have n feature maps:

  $f_1, \ldots, f_n$.

- Global average pooling is then:

$$\bar{f}_i = \sum_{x,y} f_i(x, y)$$

- Classification scores are obtained by:

$$S_c = \sum_i w_i^c \bar{f}_i$$

- Advantages:
  - No parameters, hence significant improvement in terms of overfitting problem.
  - Forces the feature maps to capture confidence maps.
  - It is more suitable to the nature of CNNs.
  - Provides invariance to spatial transformations.

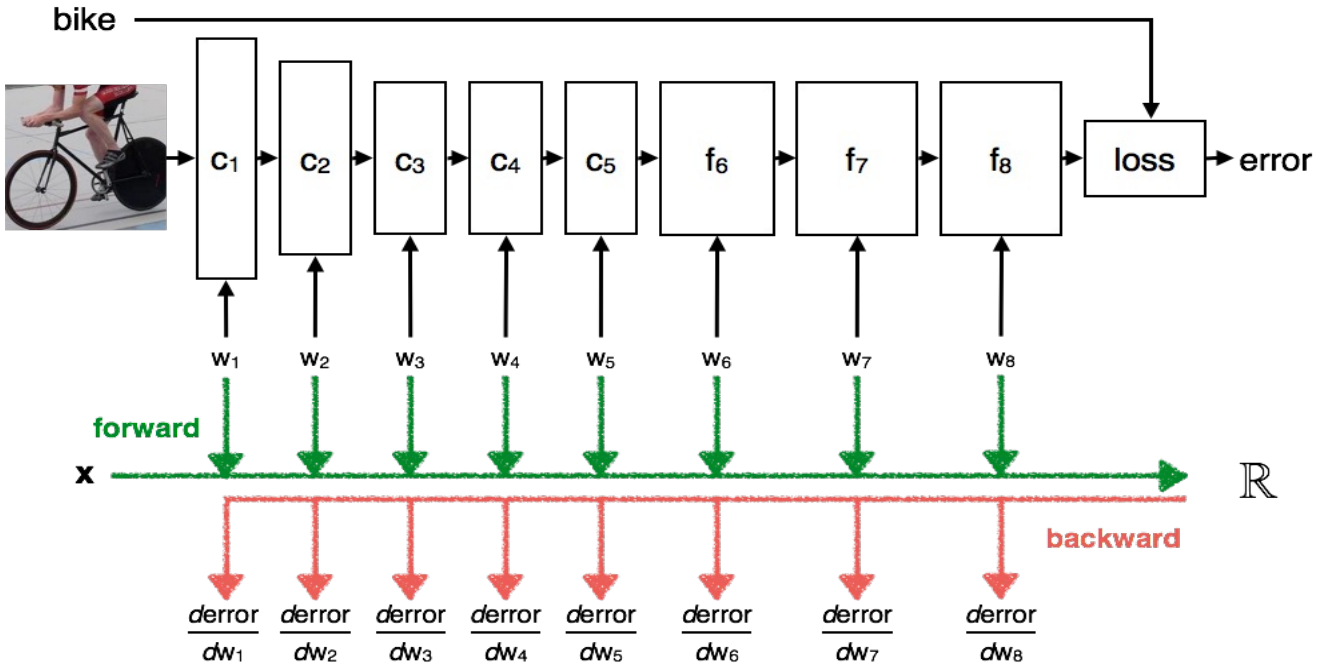
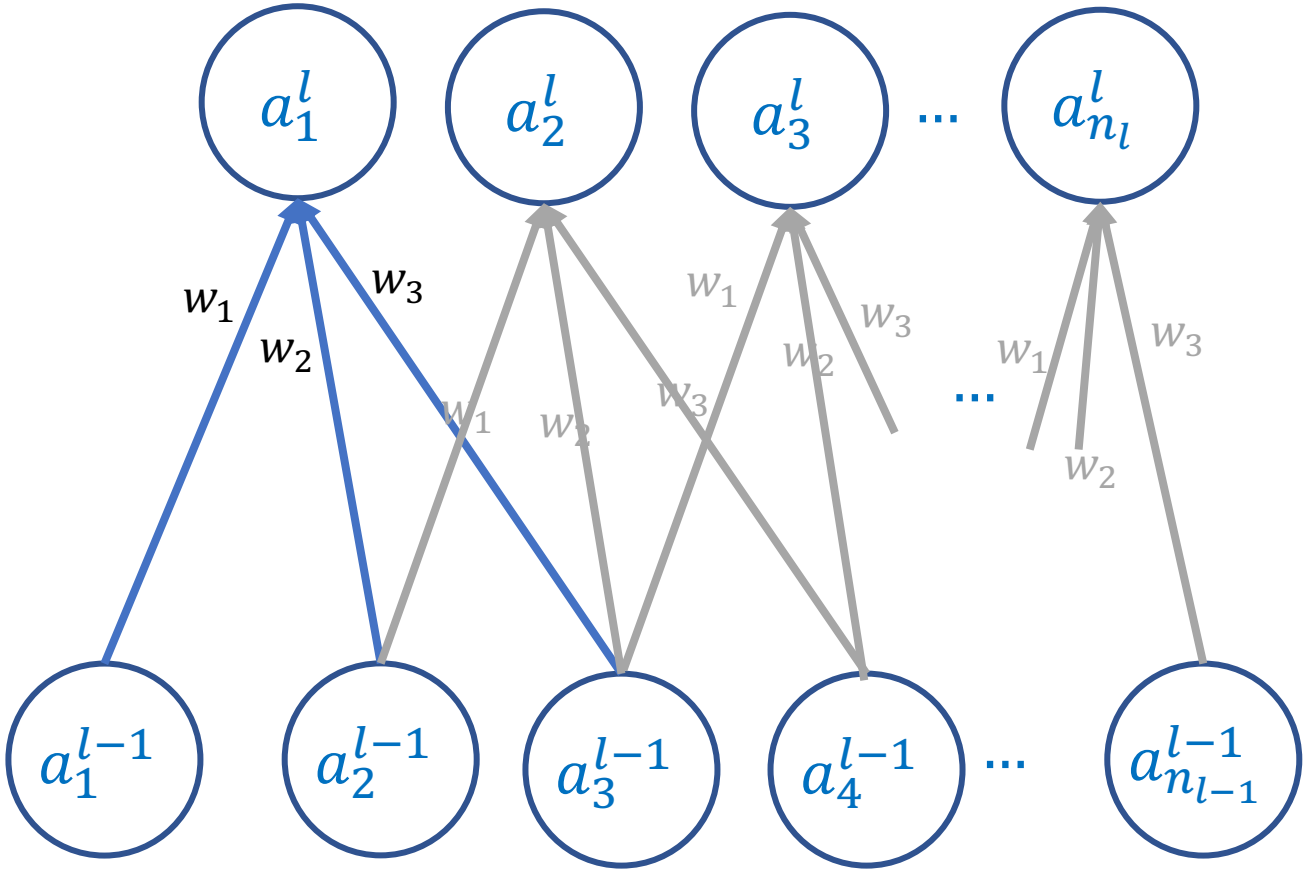


Fig: http://www.robots.ox.ac.uk/~vgg/practicals/cnn/

Training a CNN

Feed-forward through convolution



$$a_i^l = \sigma\left(net_i^l\right)$$

$$net_i^l = \sum_{j=1}^{F} w_j \cdot a_{i+j-1}^{l-1}$$

For example:

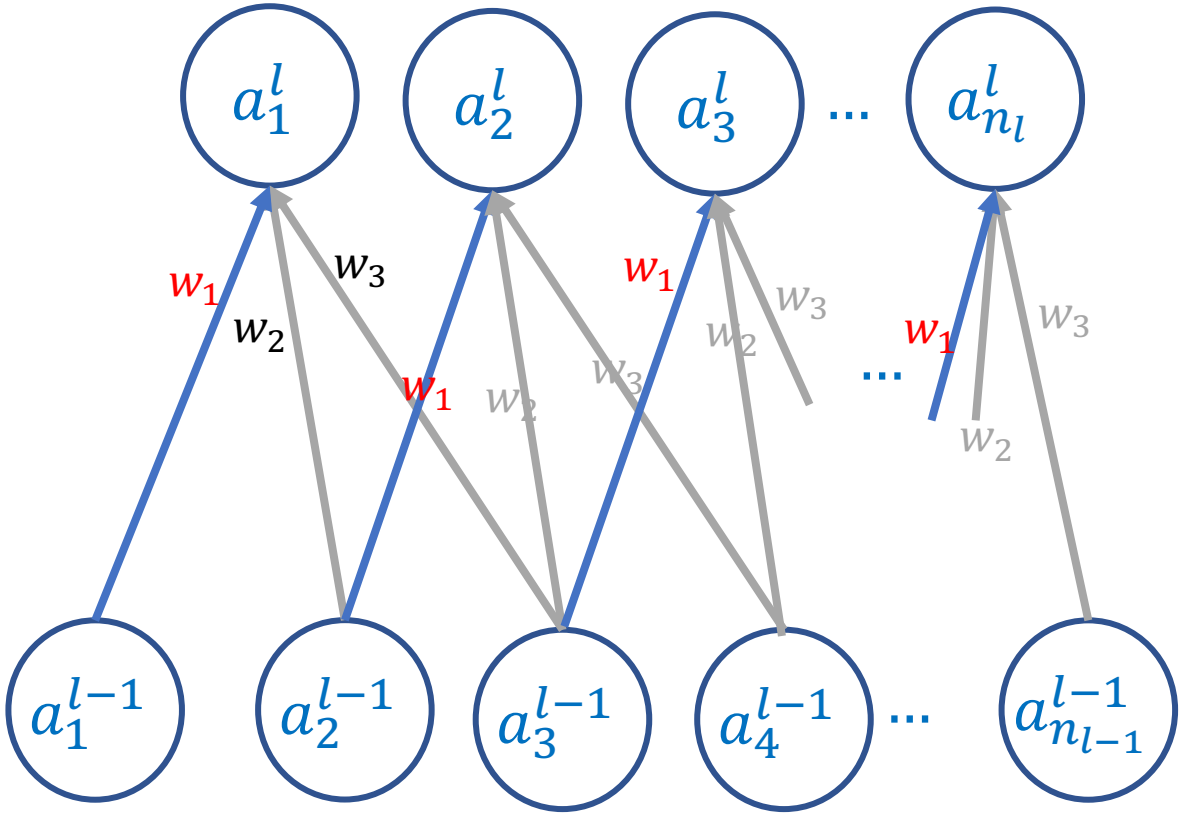
$$net_1^l = w_1 a_1^{l-1} + w_2 a_2^{l-1} + w_3 a_3^{l-1}$$

Backpropagation through convolution

Feedforward:

$$a_i^l = \sigma(net_i^l)$$

$$net_i^l = \sum_{j=1}^{F} w_j \cdot a_{i+j-1}^{l-1}$$



Gradient wrt. weights:

$$\frac{\partial L}{\partial w_k} = ?$$

$$= \frac{\partial L}{\partial a_1^l}\frac{\partial a_1^l}{\partial w_k} + \frac{\partial L}{\partial a_2^l}\frac{\partial a_2^l}{\partial w_k} \dots$$

$$= \sum_i \frac{\partial L}{\partial a_i^l}\frac{\partial a_i^l}{\partial w_k}$$

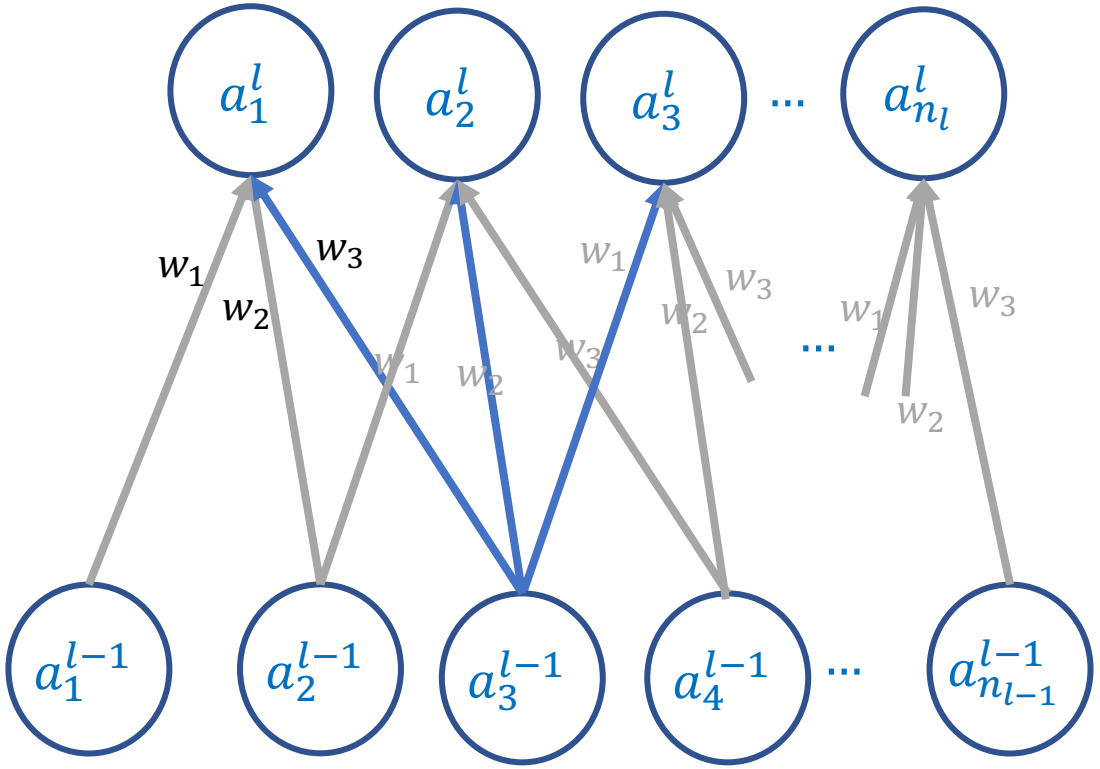
$$= \sum_i \frac{\partial L}{\partial a_i^l}\frac{\partial a_i^l}{\partial net_i^l}\frac{\partial net_i^l}{\partial w_k}$$

Backpropagation through convolution

Feedforward:

$$a_i^l = \sigma(net_i^l)$$

$$net_i^l = \sum_{j=1}^{F} w_j \cdot a_{i+j-1}^{l-1}$$



Gradient wrt. input layer:

$$\frac{\partial L}{\partial a_3^{l-1}} = ?$$

$$= \frac{\partial L}{\partial a_1^l}\frac{\partial a_1^l}{\partial net_1^l}\frac{\partial net_1^l}{\partial a_3^{l-1}} + \frac{\partial L}{\partial a_2^l}\frac{\partial a_2^l}{\partial net_2^l}\frac{\partial net_2^l}{\partial a_3^{l-1}} + \frac{\partial L}{\partial a_2^l}\frac{\partial a_2^l}{\partial net_2^l}\frac{\partial net_2^l}{\partial a_3^{l-1}}$$

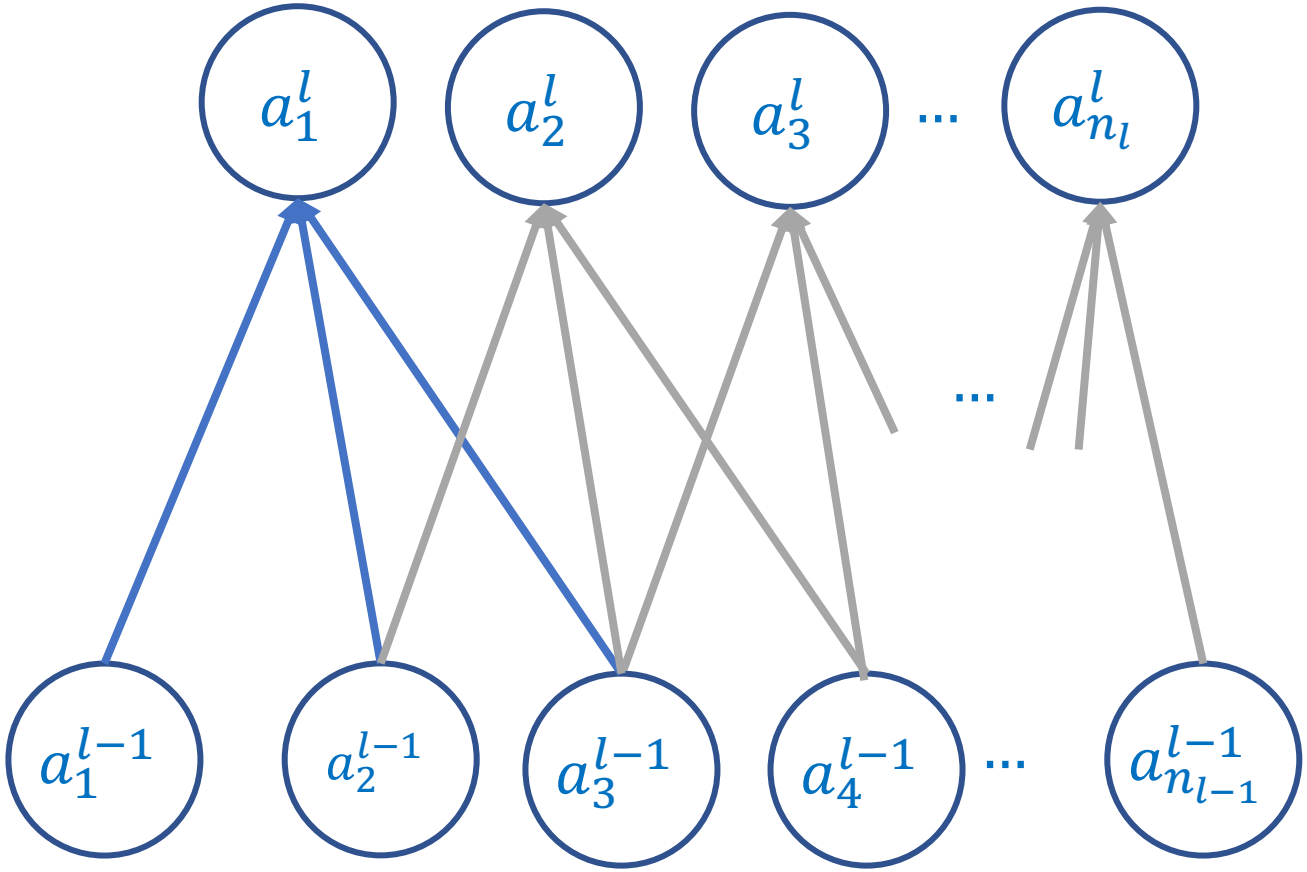
$$= \frac{\partial L}{\partial net_1^l} w_3 + \frac{\partial L}{\partial net_2^l} w_2 + \frac{\partial L}{\partial net_3^l} w_1$$

This is also convolution!

In general:

$$\frac{\partial L}{\partial a_i^{l-1}} = \sum_{j=1} \frac{\partial L}{\partial net_{i-j+1}^l} w_j$$

Feed-forward through pooling



$$a_i^l = \max \left\{ a_{i+j-1}^{l-1} \right\}_{j=1}^{F}$$

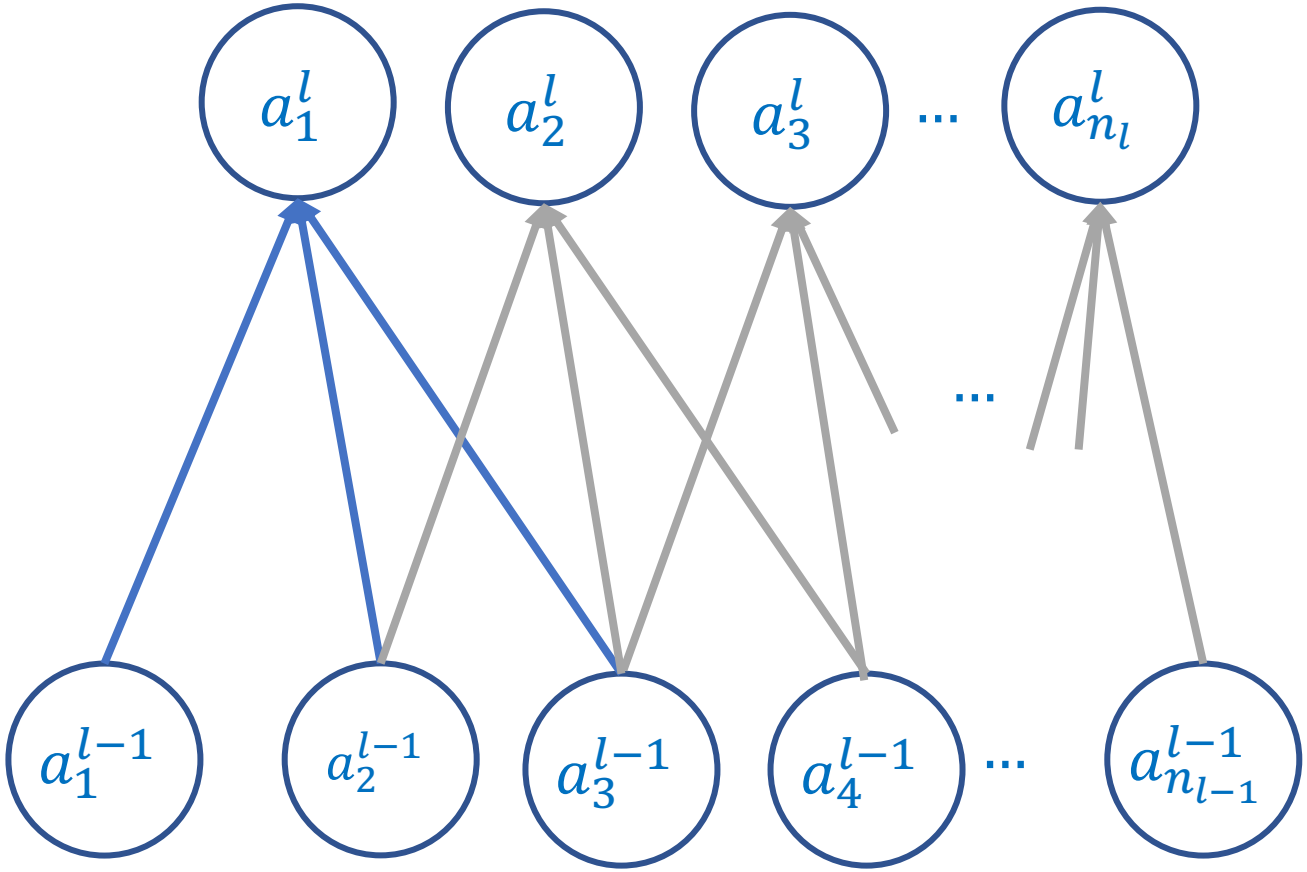
For example:

$$net_1^l = \max \left\{ a_1^{l-1}, a_2^{l-1}, a_3^{l-1} \right\}$$

Backpropagation through pooling

Feedforward:

$$a_i^l = \max\{a_{i+j-1}^{l-1}\}_{j=1}^{F}$$



Using derivative of max:

$$\frac{\partial L}{\partial a_i^{l-1}} = \frac{\partial L}{\partial net_k^l}\frac{\partial net_k^l}{\partial a_i^{l-1}}$$

$$= \begin{cases} \dfrac{\partial L}{\partial net_k^l}, & a_i^{l-1} \text{ is max} \\ 0, & \text{otherwise} \end{cases}$$

This requires that we save the index of the max activation (sometimes also called *the switches*) so that gradient "routing" is handled efficiently during backpropagation.

Backpropagation

- Backpropagation through fully-connected layers are as we discussed gradient through MLPs
- Backpropagation through non-linearity is straight-forward

Designing CNN Architectures

A Blueprint for CNNs

`INPUT -> [[CONV -> RELU]*N -> POOL?]*M -> [FC -> RELU]*K -> FC`

where the `*` indicates repetition, and the `POOL?` indicates an optional pooling layer. Moreover, `N >= 0` (and usually `N <= 3`), `M >= 0`, `K >= 0` (and usually `K < 3`). For example, here are some common ConvNet architectures you may see that follow this pattern:

- `INPUT -> FC`, implements a linear classifier. Here `N = M = K = 0`.
- `INPUT -> CONV -> RELU -> FC`
- `INPUT -> [CONV -> RELU -> POOL]*2 -> FC -> RELU -> FC`. Here we see that there is a single CONV layer between every POOL layer.
- `INPUT -> [CONV -> RELU -> CONV -> RELU -> POOL]*3 -> [FC -> RELU]*2 -> FC` Here we see two CONV layers stacked before every POOL layer. This is generally a good idea for larger and deeper networks, because multiple stacked CONV layers can develop more complex features of the input volume before the destructive pooling operation.

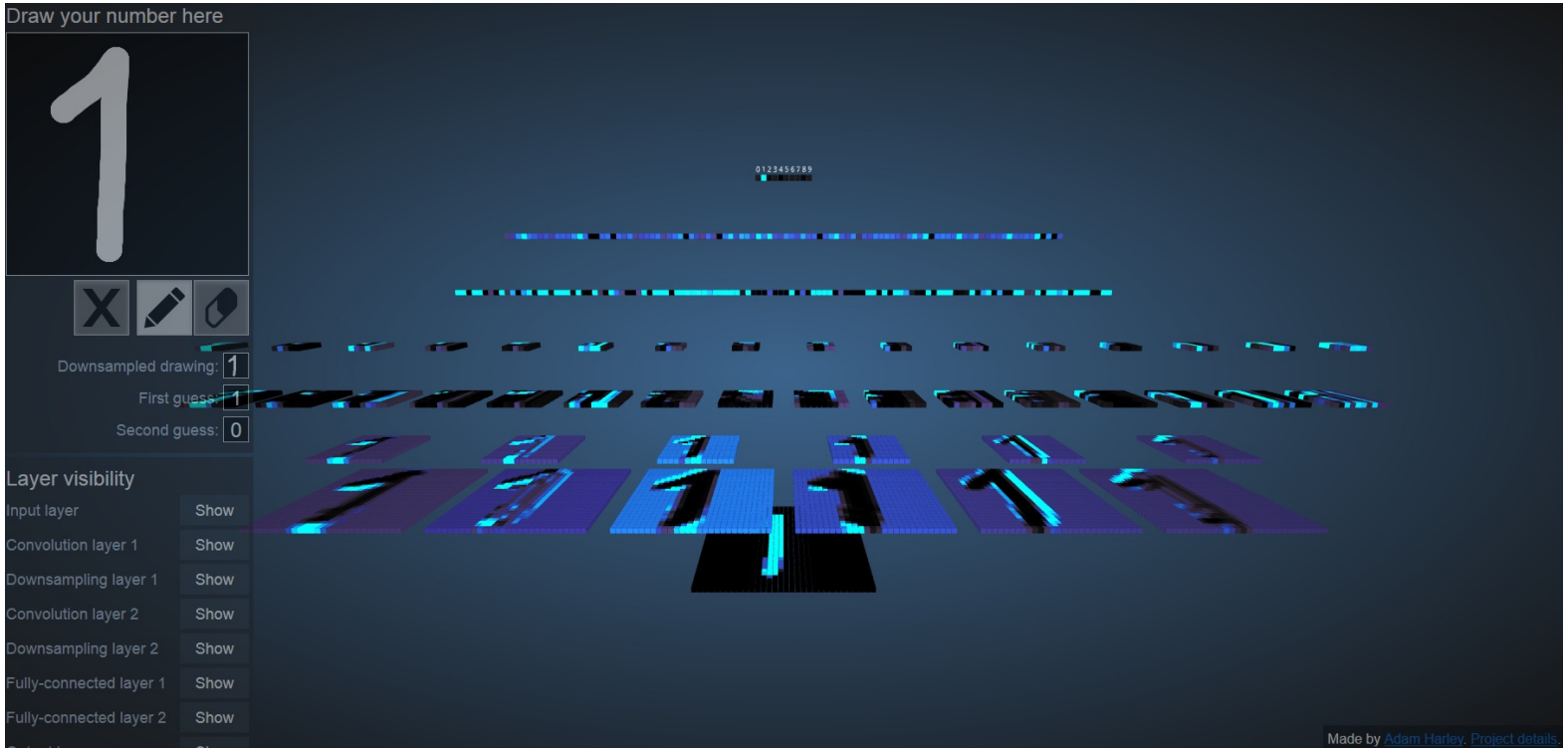
http://cs231n.github.io/convolutional-networks/

Demo

https://poloclub.github.io/cnn-explainer/

The following doesn't work, try cnn-explainer instead

http://scs.ryerson.ca/~aharley/vis/conv/



Fully Convolutional Networks (FCNs)

Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional networks for semantic segmentation. CVPR.

- Fully-connected layers limit the input size
- Use convolution, especially 1x1 convolution to reduce channels and layer size

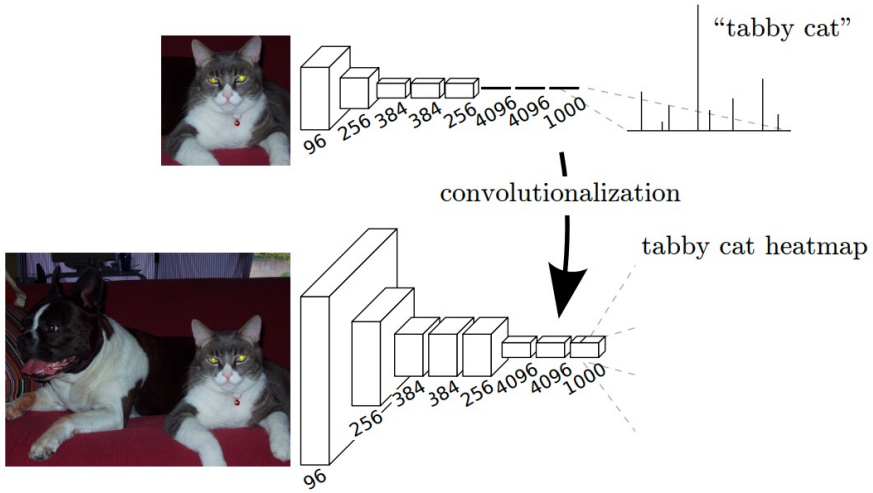


Figure 2. Transforming fully connected layers into convolution layers enables a classification net to output a heatmap. Adding layers and a spatial loss (as in Figure 1) produces an efficient machine for end-to-end dense learning.

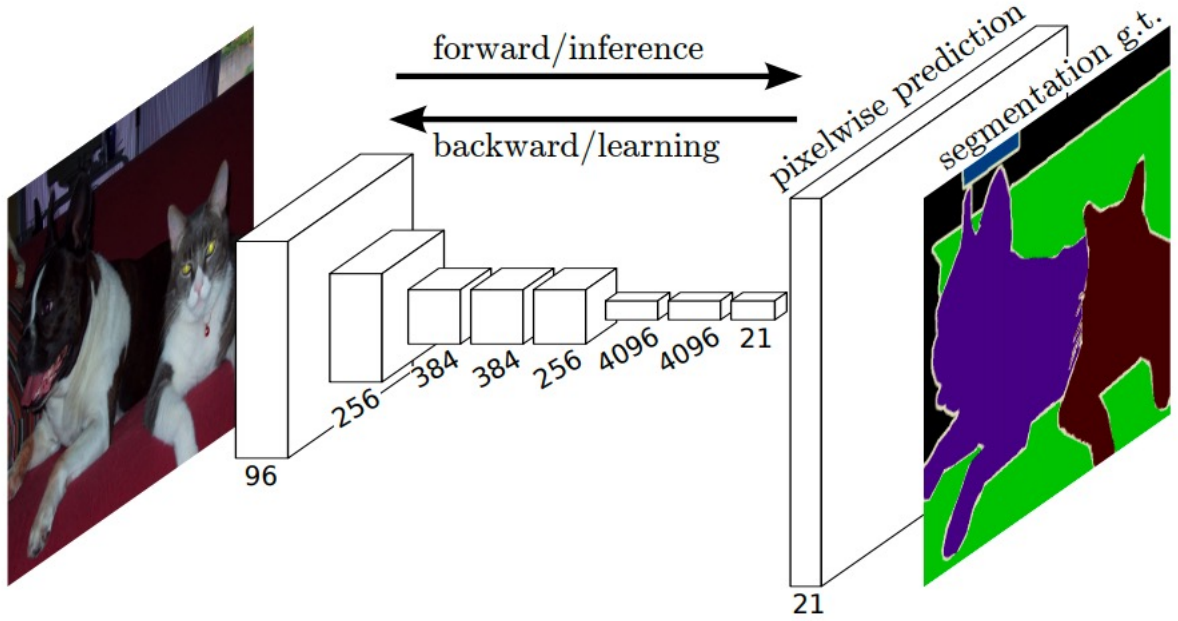


Figure 1. Fully convolutional networks can efficiently learn to make dense predictions for per-pixel tasks like semantic segmentation.

General rules of thumb: The input layer

- The size of the input layer should be divisible by 2 many times
  - Hopefully a power of 2
- E.g.,
  - 32 (e.g. CIFAR-10),
  - 64,
  - 96 (e.g. STL-10), or
  - 224 (e.g. common ImageNet ConvNets),
  - 384, and 512 etc.

General rules of thumb: The conv layer

- Small filters with stride 1
- Usually zero-padding applied to keep the input size unchanged
- In general, for a certain F, if you choose

$$P = (F - 1)/2,$$

the input size is preserved (for S=1):

$$\frac{W - F + 2P}{S} + 1$$

- Number of filters:
  - A convolution channel is more expensive compared to fully-connected layer.
  - We should keep this as small as possible.

General rules of thumb: The pooling layer

- Commonly,
  - F=2 with S=2
  - Or: F=3 with S=2

- Bigger F or S is very destructive

Taking care of downsampling

- At some point(s) in the network, we need to reduce the size
- If conv layers do not downsize, then only pooling layers take care of downsampling
- If conv layers also downsize, you need to be careful about strides etc. so that
  - (i) the dimension requirements of all layers are satisfied and
  - (ii) all layers tile up properly.
- S=1 seems to work well in practice
- However, for bigger input volumes, you may try bigger strides

Trade-offs in architecture

- Between filter size and number of layers (depth)
  - Keep the layer widths fixed.
  - *"When the time complexity is roughly the same, the deeper networks with smaller filters show better results than the shallower networks with larger filters."*
- Between layer width and number of layers (depth)
  - Keep the size of the filters fixed.
  - *"We find that increasing the depth leads to considerable gains, even the width needs to be properly reduced."*
- Between filter size and layer width
  - Keep the number of layers (depth) fixed.
  - No significant difference

Convolutional Neural Networks at Constrained Time Cost

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4.4. Is Deeper Always Better?

The above results have shown the priority of depth for improving accuracy. With the above trade-offs, we can have a much deeper model if we further decrease width/filter sizes and increase depth. However, in experiments we find that the accuracy is stagnant or even reduced in some of our very deep attempts. There are two possible explanations: (1) the width/filter sizes are reduced overly and may harm the accuracy, or (2) overly increasing the depth will degrade the accuracy even if the other factors are not traded. To understand the main reason, *in this subsection we do not constrain the time complexity* but solely increase the depth without other changes.

Memory

Main sources of memory load:

- Activation maps:
  - Training: They need to be kept during training so that backpropagation can be performed
  - Testing: No need to keep the activations of earlier layers
- Parameters:
  - The weights, their gradients and also another copy if momentum is used
- Data:
  - The originals + their augmentations
- If all these don’t fit into memory,
  - Load your data batch by batch from disk
  - Decrease the size of your batches

Memory constraints

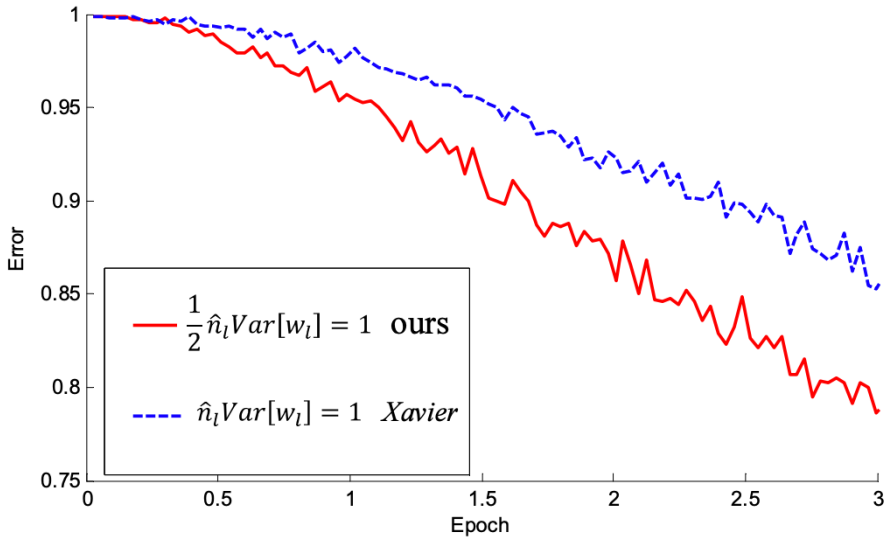
- Using smaller RFs with more layers means more memory since you need to store more activation maps

- In such memory-scarce cases,
  - the first layer may use bigger RFs with S>1
  - information loss from the input volume may be less critical than the following layers

- E.g., AlexNet uses RFs of 11x11 and S = 4 for the first layer.

How to initialize the weights?

- Option 1: randomly
  - E.g. using He initialization (check Week 8 slides)
  - This has been shown to work nicely in the literature
- Option 2:
  - Train/obtain the “filters” elsewhere and use them as the weights
  - Unsupervised pre-training using image patches (windows)
  - Avoids full feedforward and backward pass, allows the search to start from a better position
  - You may even skip training the convolutional layers



He et al., “Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification”, 2015.

CONVOLUTIONAL CLUSTERING FOR UNSUPERVISED LEARNING

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Table 3: Classification error on MNIST.

(a) Algorithms that learn the filters unsupervised.

Algorithm	600	1000	3000	All
Zhao et al. (2015) (auto-encoder)	8.4%	6.40%	4.76%	-
Rifai et al. (2011) (constractive auto-encoder)	6.3%	4.77%	3.22%	1.14%
This work (2 layers + multi dict.)	2.8%	2.5%	1.4%	0.5%

(b) Supervised and semi-supervised algorithms.

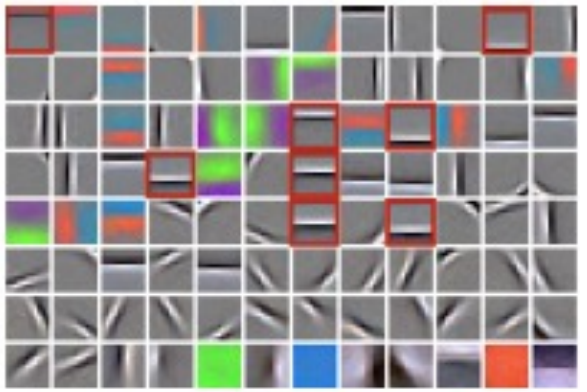
Algorithm	600	1000	3000	All
LeCun et al. (1998) (convnet)	7.68%	6.45%	3.35%	
Lee (2013) (psuedo-label)	5.03%	3.46%	2.69%	-
Zhao et al. (2015) (semi-supervised auto-encoder)	3.31%	2.83%	2.10%	0.71%
Kingma et al. (2014) (generative models)	2.59%	2.40%	2.18%	0.96%
Rasmus et al. (2015) (semi-supervised ladder)	-	1.0%	-	-

3.1 LEARNING FILTERS WITH K-MEANS

Our method for learning filters is based on the k-means algorithm. The classic k-means algorithm finds cluster centroids that minimize the distance between points in the Euclidean space. In this context, the points are randomly extracted image patches and the centroids are the filters that will be used to encode images. From this perspective, k-means algorithm learns a dictionary $D \in \mathbb{R}^{n \times k}$ from the data vector $w^{(i)} \in \mathbb{R}^n$ for $i = 1, 2, ..., m$. The algorithm finds the dictionary as follows:

$$\begin{aligned} s_j^{(i)} &:= \begin{cases} {D^{(j)}}^T w^{(i)} & \text{if } j = \underset{l}{\operatorname{argmax}} \left| {D^{(l)}}^T w^{(i)} \right|, \\ 0 & \text{otherwise,} \end{cases} \\ D &:= W S^T + D, \\ D^{(j)} &:= \frac{D^{(j)}}{||D^{(j)}||_2}, \end{aligned} \tag{1}$$

where $s^{(i)} \in \mathbb{R}^k$ is the code vector associated with the input $w^{(i)}$, and $D^{(j)}$ is the j'th column of the dictionary D. The matrices $W \in \mathbb{R}^{n \times m}$ and $S \in \mathbb{R}^{k \times m}$ have the columns $w^{(i)}$ and $s^{(i)}$, respectively. $w^{(i)}$'s are randomly extracted patches from input images that have the same dimension as the dictionary vectors, $D^{(j)}$.



(a) k-means

(b) convolutional k-means

Transfer learning:
using a trained CNN & fine-tuning

Using trained CNN

- Also called transfer learning
  - Rare to design and train a CNN from scratch!
- Take a trained CNN, e.g., AlexNet
  - Use a trained CNN as a feature detector:
    - Remove the last fully-connected layer
    - The activations of the remaining layer are called CNN codes
    - This yields a 4096 dimensional feature vector for AlexNet
    - Now, add a fully-connected layer for your problem and train a linear classifier on your dataset.
  - Alternatively, fine-tune the whole network with your new layer and outputs
    - You may limit updating only to the last layers because earlier layers are generic, and quite dataset independent
- Pre-trained CNNs

CNN Features off-the-shelf: an Astounding Baseline for Recognition

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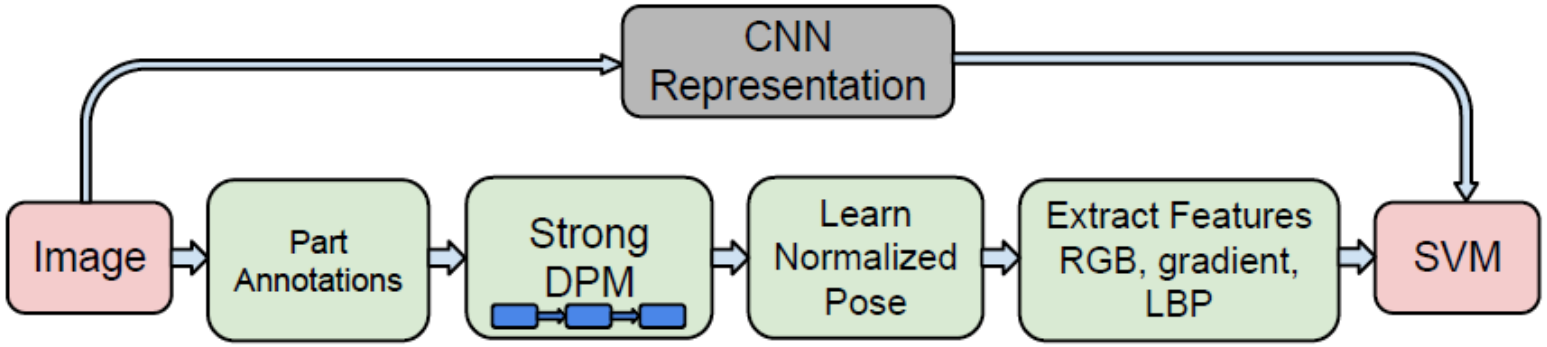
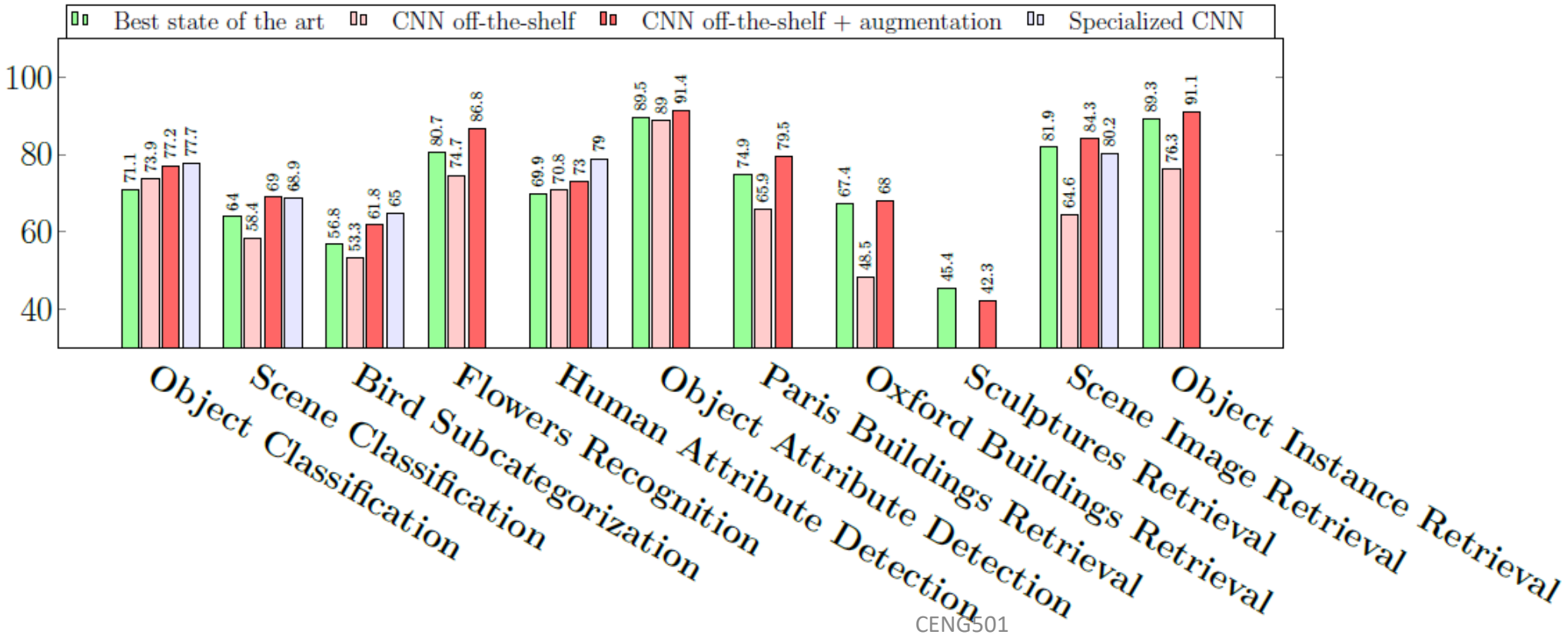
2014





Finetuning

1.If the new dataset is small and similar to the original dataset used to train the CNN:

- Finetuning the whole network may lead to overfitting
- Just train the newly added layer

2.If the new dataset is big and similar to the original dataset:

- The more, the merrier: go ahead and train the whole network

3.If the new dataset is small and different from the original dataset:

- Not a good idea to train the whole network
- However, add your new layer not to the top of the network, since those parts are very dataset (problem) specific
- Add your layer to earlier parts of the network

4.If the new dataset is big and different from the original dataset:

- We can "finetune" the whole network
- This amounts to a new training problem by initializing the weights with those of another network

More on finetuning

- You cannot change the architecture of the trained network (e.g., remove layers) arbitrarily

- The sizes of the layers can be varied
  - For convolution & pooling layers, this is straightforward
  - For the fully-connected layers: you can convert the fully-connected layers to convolution layers, which makes it size-independent.

- You should use small learning rates while fine-tuning

See also:

Preprint release. Full citation: Yosinski J, Clune J, Bengio Y, and Lipson H. *How transferable are features in deep neural networks?* In Advances in Neural Information Processing Systems 27 (NIPS '14), NIPS Foundation, 2014.

How transferable are features in deep neural networks?

Jason Yosinski,[1] Jeff Clune,[2] Yoshua Bengio,[3] and Hod Lipson[4]
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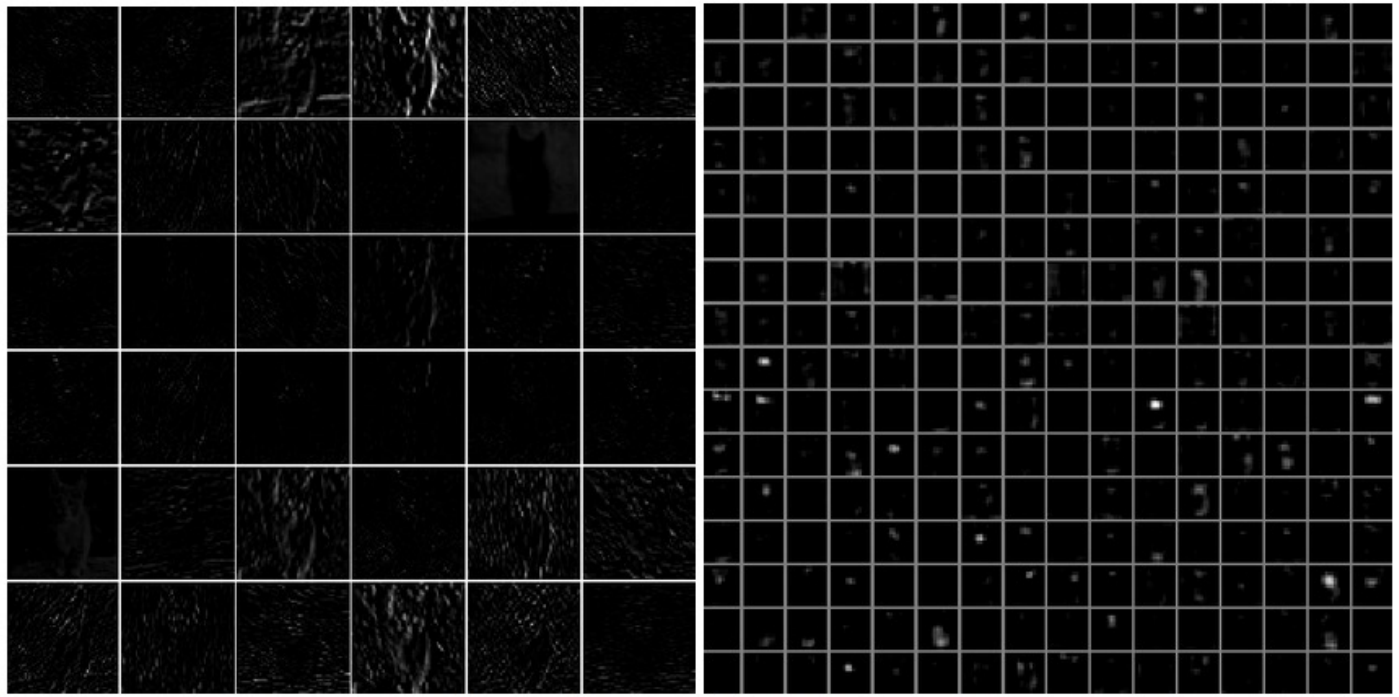
Visualizing and Understanding CNNs

Many different mechanisms

- Visualize layer activations
- Visualize the weights (i.e., filters)
- Visualize examples that maximally activate a neuron
- Visualize a 2D embedding of the inputs based on their CNN codes
- Occlude parts of the window and see how the prediction is affected
- Data gradients

Visualize activations during training

- Activations are dense at the beginning.
  - They should get sparser during training.
- If some activation maps are all zero for many inputs, dying neuron problem => high learning rate in the case of ReLUs.

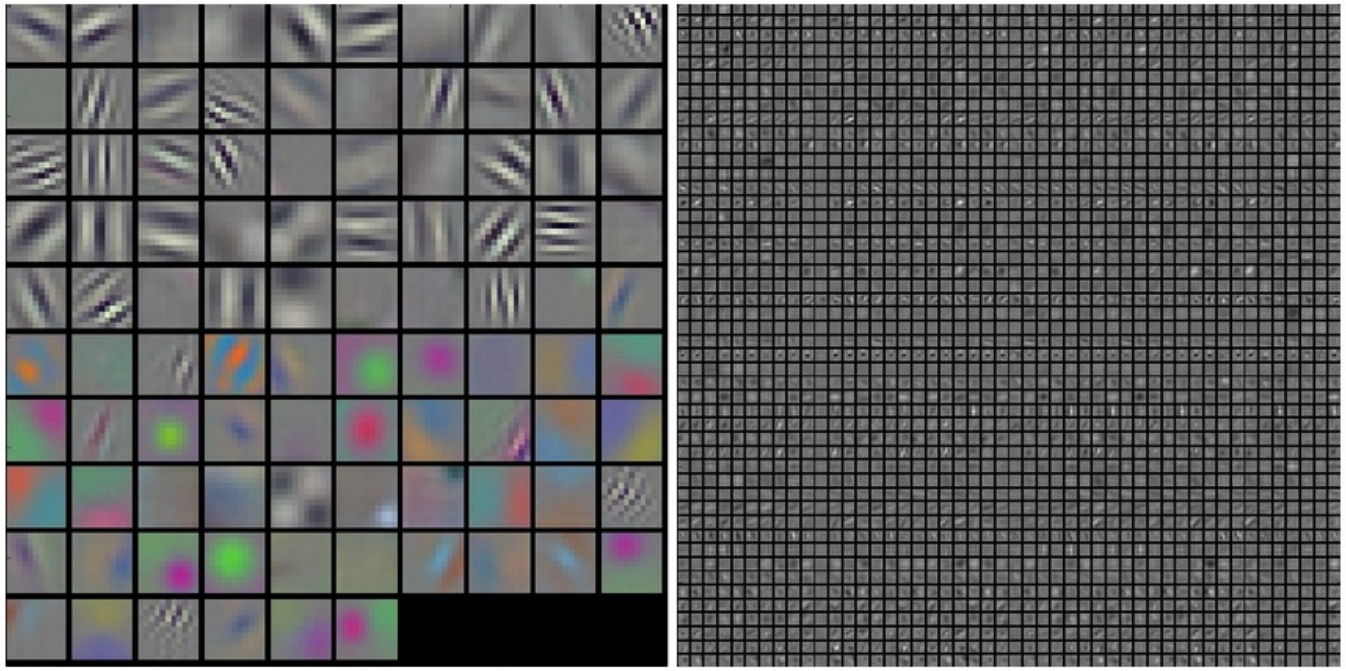


Typical-looking activations on the first CONV layer (left), and the 5th CONV layer (right) of a trained AlexNet looking at a picture of a cat. Every box shows an activation map corresponding to some filter. Notice that the activations are sparse (most values are zero, in this visualization shown in black) and mostly local.

http://cs231n.github.io/convolutional-networks/

Visualize the weights

- We can directly look at the filters of all layers
- First layer is easier to interpret
- Filters shouldn’t look noisy



Typical-looking filters on the first CONV layer (left), and the 2nd CONV layer (right) of a trained AlexNet. Notice that the first-layer weights are very nice and smooth, indicating nicely converged network. The color/grayscale features are clustered because the AlexNet contains two separate streams of processing, and an apparent consequence of this architecture is that one stream develops high-frequency grayscale features and the other low-frequency color features. The 2nd CONV layer weights are not as interpretable, but it is apparent that they are still smooth, well-formed, and absent of noisy patterns.

http://cs231n.github.io/convolutional-networks/

Visualize the inputs that maximally activate a neuron

- Keep track of which images activate a neuron most

Rich feature hierarchies for accurate object detection and semantic segmentation
Tech report (v5)

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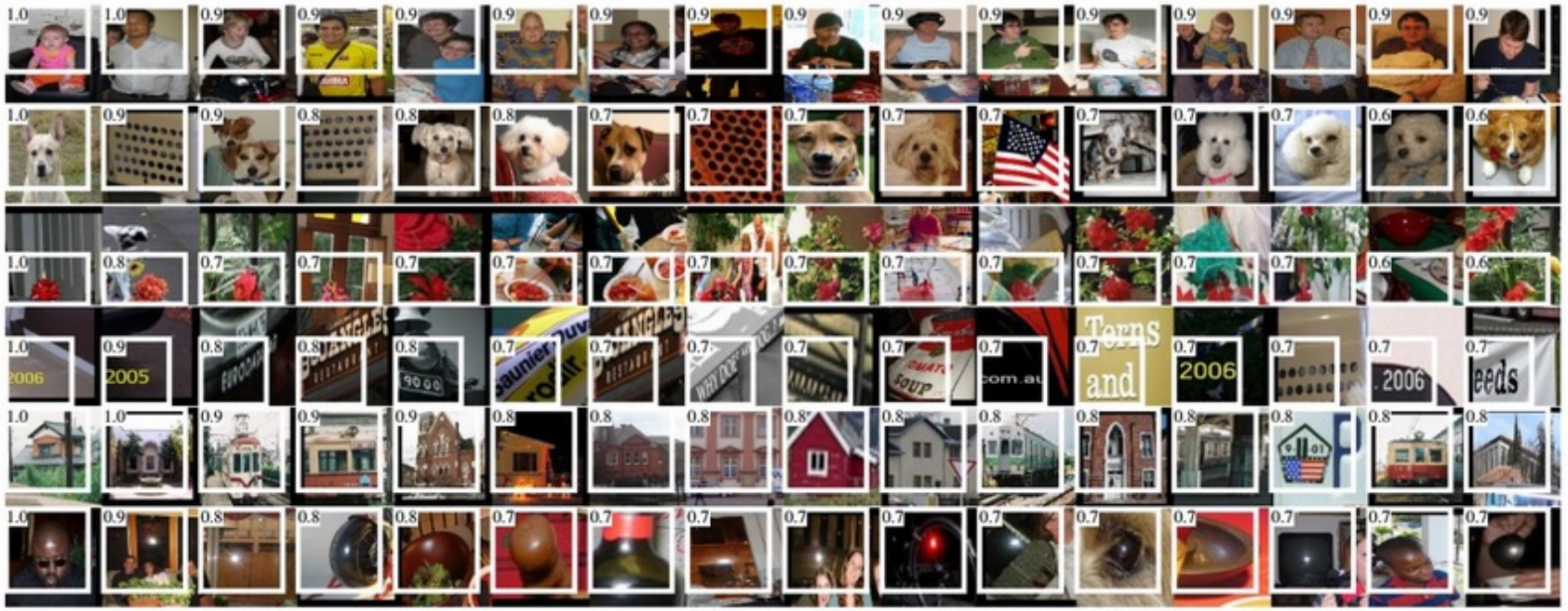
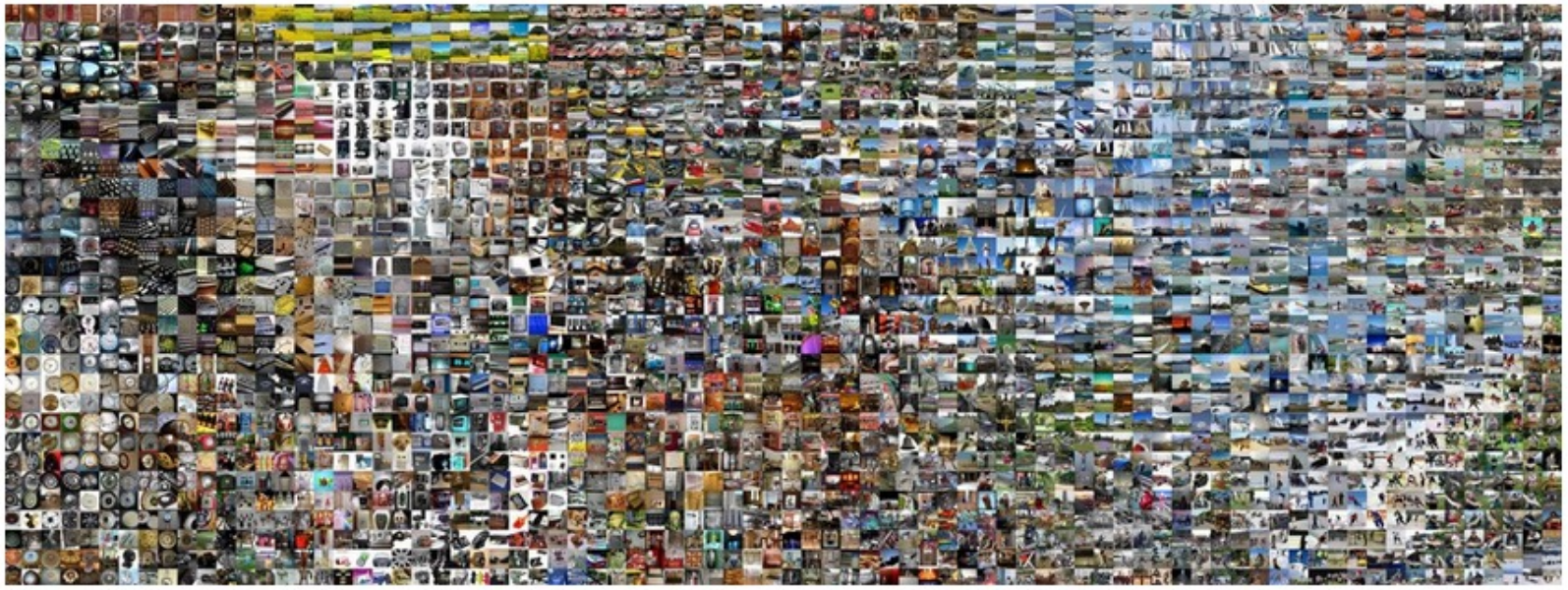


Maximally activating images for some POOL5 (5th pool layer) neurons of an AlexNet. The activation values and the receptive field of the particular neuron are shown in white. (In particular, note that the POOL5 neurons are a function of a relatively large portion of the input image!) It can be seen that some neurons are responsive to upper bodies, text, or specular highlights.

http://cs231n.github.io/convolutional-networks/

Embed the codes in a lower-dimensional space

- Place images into a 2D space such that images which produce similar CNN codes are placed close.
- You can use, e.g., t-Distributed Stochastic Neighbor Embedding (t-SNE)



t-SNE embedding of a set of images based on their CNN codes. Images that are nearby each other are also close in the CNN representation space, which implies that the CNN "sees" them as being very similar. Notice that the similarities are more often class-based and semantic rather than pixel and color-based. For more details on how this visualization was produced the associated code, and more related visualizations at different scales refer to t-SNE visualization of CNN codes.

http://cs231n.github.io/convolutional-networks/

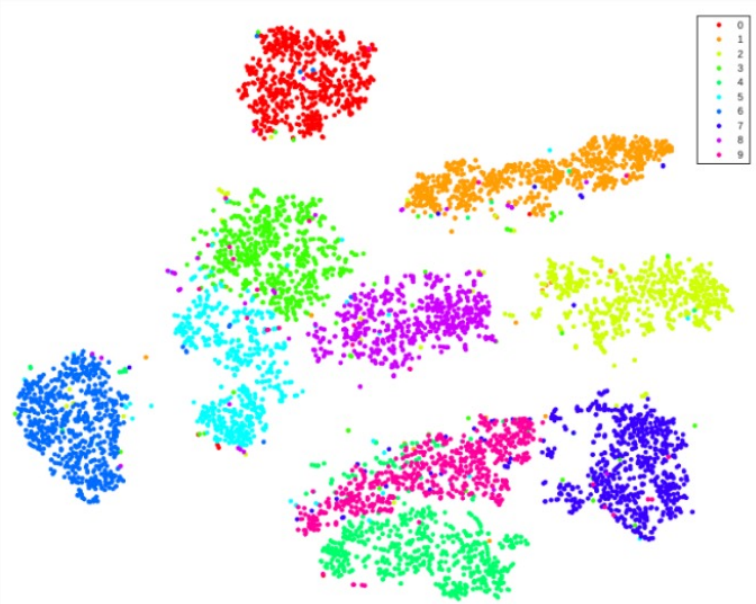
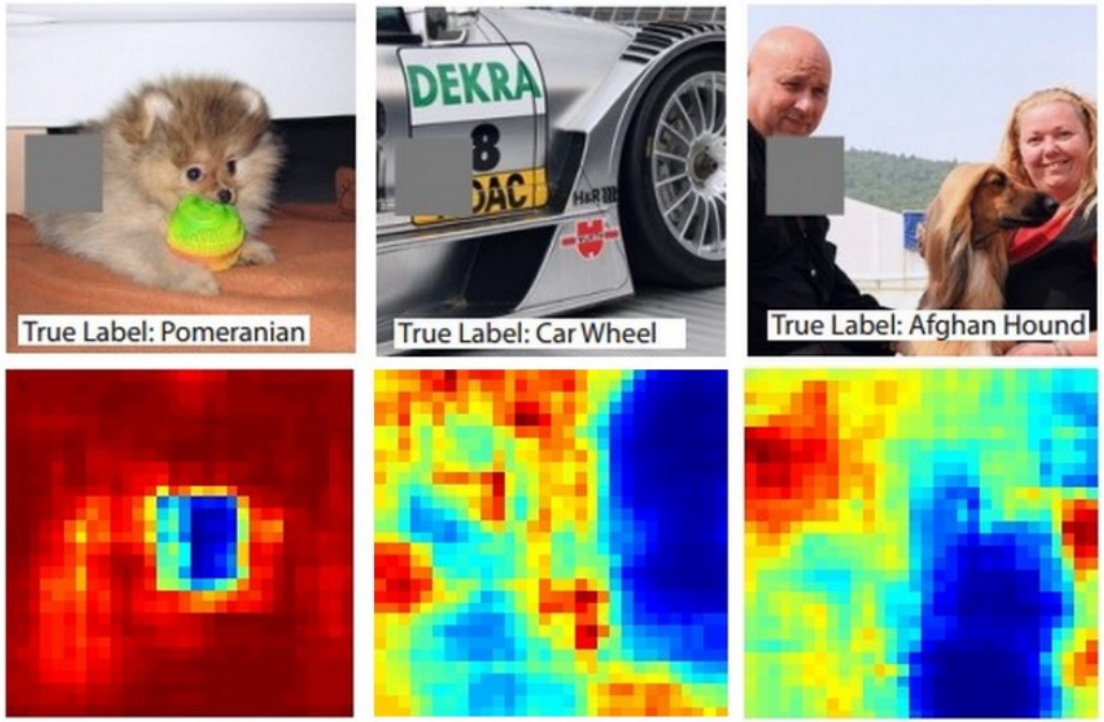


Figure 1 : Illustration of t-SNE on MNIST dataset

Figure: Laurens van der Maaten and Geoffrey Hinton

Occlude parts of the image

- Slide an “occlusion window” over the image
- For each occluded image, determine the class prediction confidence/probability.



Three input images (top). Notice that the occluder region is shown in grey. As we slide the occluder over the image we record the probability of the correct class and then visualize it as a heatmap (shown below each image). For instance, in the left-most image we see that the probability of Pomeranian plummets when the occluder covers the face of the dog, giving us some level of confidence that the dog's face is primarily responsible for the high classification score. Conversely, zeroing out other parts of the image is seen to have relatively negligible impact.

http://cs231n.github.io/convolutional-networks/

Data gradients

- Generate an image that maximizes the class score.

More formally, let $S_c(I)$ be the score of the class c, computed by the classification layer of the ConvNet for an image I. We would like to find an L_2-regularised image, such that the score S_c is high:

$$\arg\max_I S_c(I) - \lambda\|I\|_2^2, \quad (1)$$

where λ is the regularisation parameter. A locally-optimal I can be found by the back-propagation

- Use: Gradient ascent!

Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps

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2014

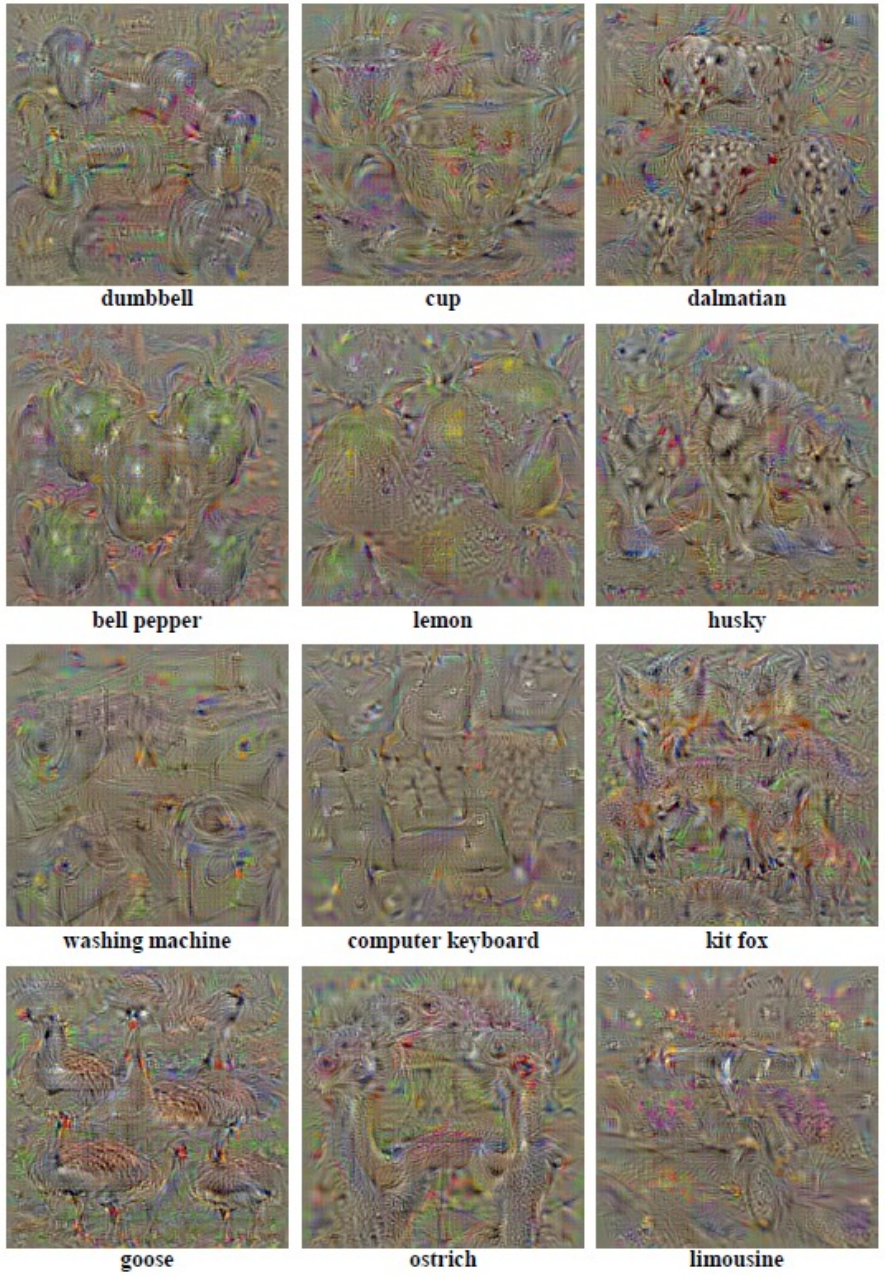

Figure 1: **Numerically computed images, illustrating the class appearance models, learnt by a ConvNet, trained on ILSVRC-2013.** Note how different aspects of class appearance are captured in a single image. Better viewed in colour.

Data gradients

- The gradient with respect to the input is high for pixels which are on the object

We start with a motivational example. Consider the linear score model for the class c:

$$S_c(I) = w_c^T I + b_c, \tag{2}$$

where the image I is represented in the vectorised (one-dimensional) form, and w_c and b_c are respectively the weight vector and the bias of the model. In this case, it is easy to see that the magnitude of elements of w defines the importance of the corresponding pixels of I for the class c.

In the case of deep ConvNets, the class score $S_c(I)$ is a highly non-linear function of I, so the reasoning of the previous paragraph can not be immediately applied. However, given an image I_0, we can approximate $S_c(I)$ with a linear function in the neighbourhood of I_0 by computing the first-order Taylor expansion:

$$S_c(I) \approx w^T I + b, \tag{3}$$

where w is the derivative of S_c with respect to the image I at the point (image) I_0:

$$w = \left.\frac{\partial S_c}{\partial I}\right|_{I_0}. \tag{4}$$

Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps

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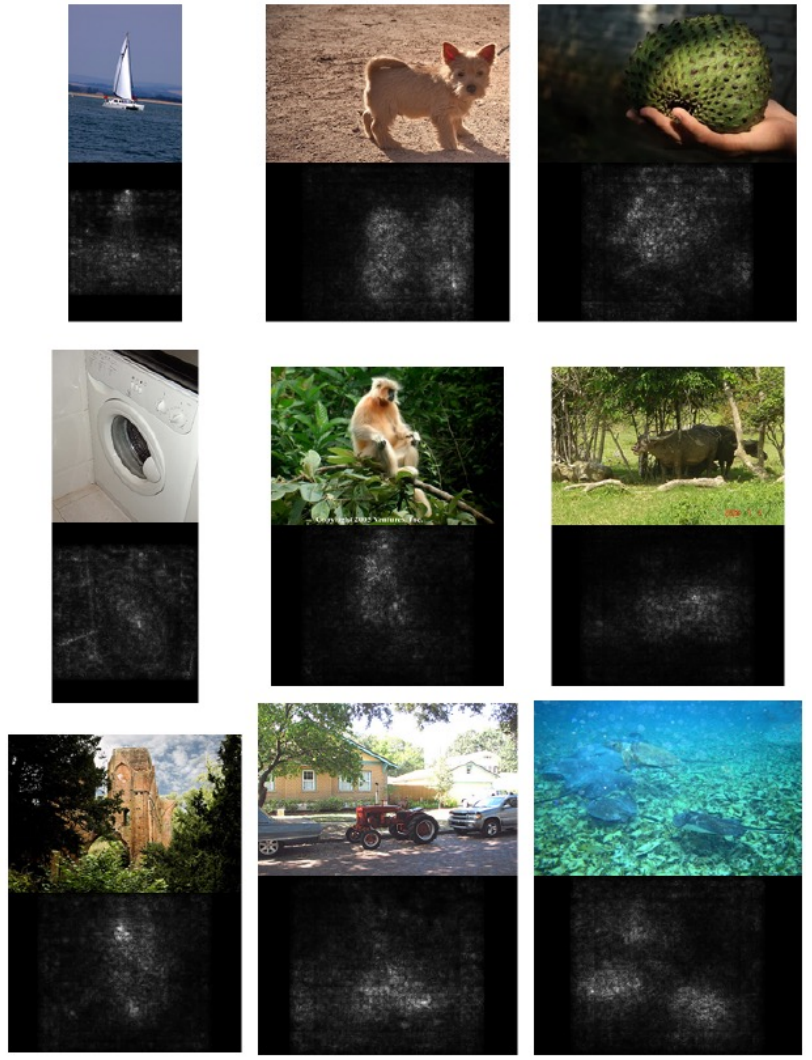
2014



Class Activation Maps

- Weighted combination of the feature maps before GAP:

$$M(x,y) = \sum_k w_k^c f_k(x,y)$$

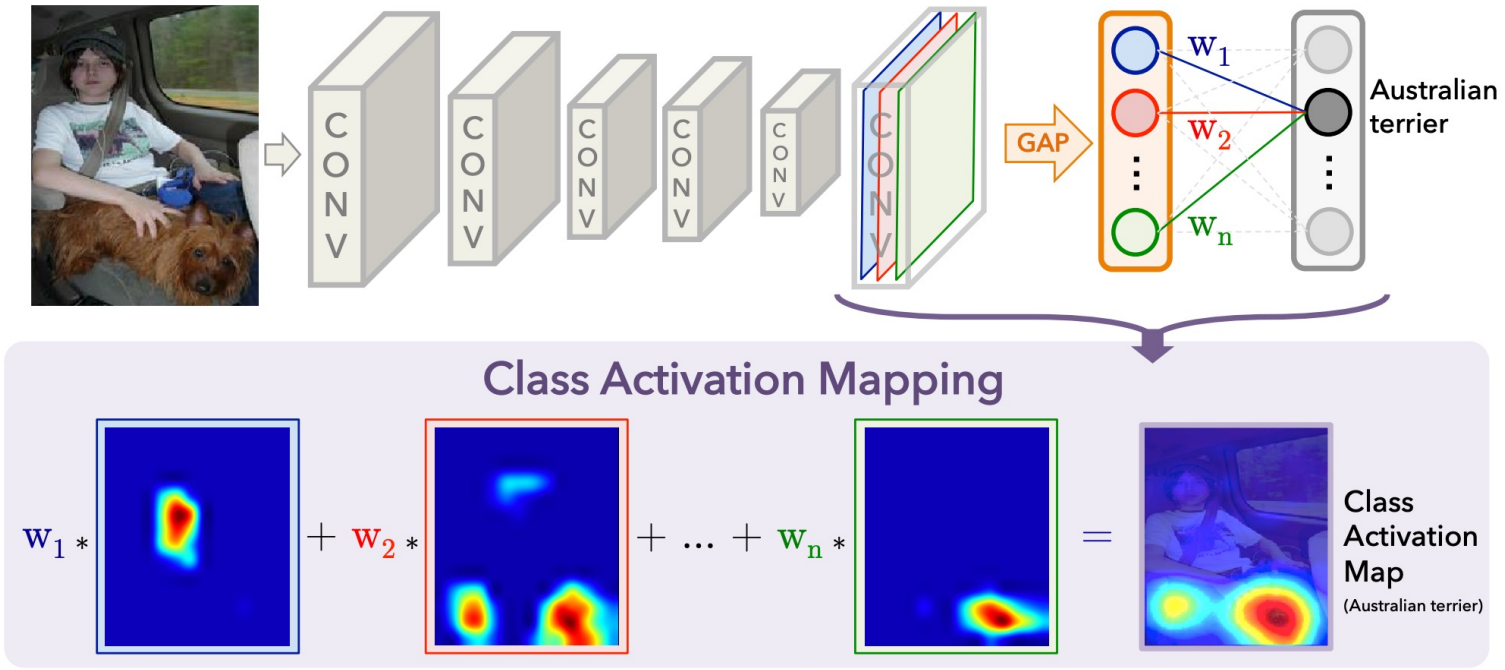


Figure 2. Class Activation Mapping: the predicted class score is mapped back to the previous convolutional layer to generate the class activation maps (CAMs). The CAM highlights the class-specific discriminative regions.

B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba, "Learning deep features for discriminative localization," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 2921–2929.

Class Activation Maps

- GradCAM:

$$\alpha_k^c = \sum_{x,y} \frac{\partial S_c}{\partial f_k(x,y)}$$

$$M^c(x,y) = ReLU\left(\sum_k \alpha_k^c f_k(x,y)\right)$$

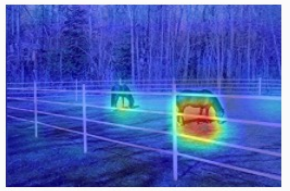
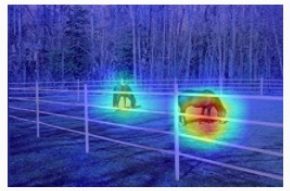
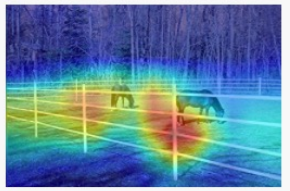
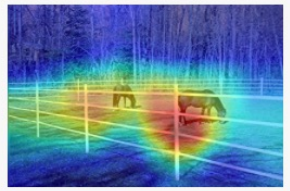
Network	Image	GradCAM	GradCAM++
VGG16			
Resnet50			

Figure: https://pypi.org/project/grad-cam/

R. R. Selvaraju, A. Das, R. Vedantam, M. Cogswell, D. Parikh, and D. Batra, "Grad-cam: Why did you say that? visual explanations from deep networks via gradient-based localization," arXiv preprint arXiv:1610.02391, 2016.

Chattopadhay, A., Sarkar, A., Howlader, P., & Balasubramanian, V. N. (2018, March). Grad-cam++: Generalized gradient-based visual explanations for deep convolutional networks. In *2018 IEEE Winter Conference on Applications of Computer Vision (WACV)* (pp. 839-847). IEEE.

Feature inversion

- Learns to reconstruct an image from its representation

This section introduces our method to compute an approximate inverse of an image representation. This is formulated as the problem of finding an image whose representation best matches the one given [34]. Formally, given a representation function $\Phi : \mathbb{R}^{H\times W\times C} \to \mathbb{R}^d$ and a representation $\Phi_0 = \Phi(\mathbf{x}_0)$ to be inverted, reconstruction finds the image $\mathbf{x} \in \mathbb{R}^{H\times W\times C}$ that minimizes the objective:

$$\mathbf{x}^* = \underset{\mathbf{x}\in\mathbb{R}^{H\times W\times C}}{\operatorname{argmin}} \ \ell(\Phi(\mathbf{x}), \Phi_0) + \lambda\mathcal{R}(\mathbf{x}) \qquad (1)$$

where the loss ℓ compares the image representation $\Phi(\mathbf{x})$ to the target one Φ_0 and $\mathcal{R} : \mathbb{R}^{H\times W\times C} \to \mathbb{R}$ is a regulariser capturing a *natural image prior*.

- Regularization term here is the key factor, e.g. a combination of the two terms:

$$\mathcal{R}_\alpha(\mathbf{x}) = \|\mathbf{x}\|_\alpha^\alpha \qquad \mathcal{R}_{V^\beta}(\mathbf{x}) = \sum_{i,j}\left((x_{i,j+1} - x_{ij})^2 + (x_{i+1,j} - x_{ij})^2\right)^{\frac{\beta}{2}}$$

Understanding Deep Image Representations by Inverting Them

Aravindh Mahendran
University of Oxford

Andrea Vedaldi
University of Oxford

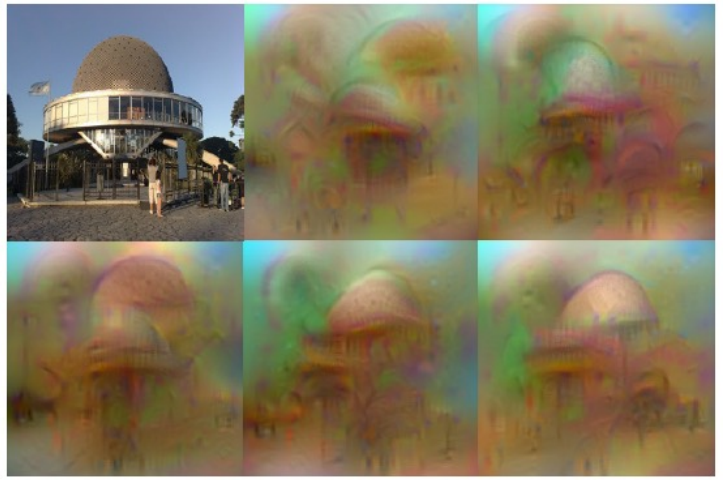


Figure 1. **What is encoded by a CNN?** The figure shows five possible reconstructions of the reference image obtained from the 1,000-dimensional code extracted at the penultimate layer of a reference CNN[13] (before the softmax is applied) trained on the ImageNet data. From the viewpoint of the model, all these images are practically equivalent. This image is best viewed in color/screen.

Feature inversion with perceptual losses

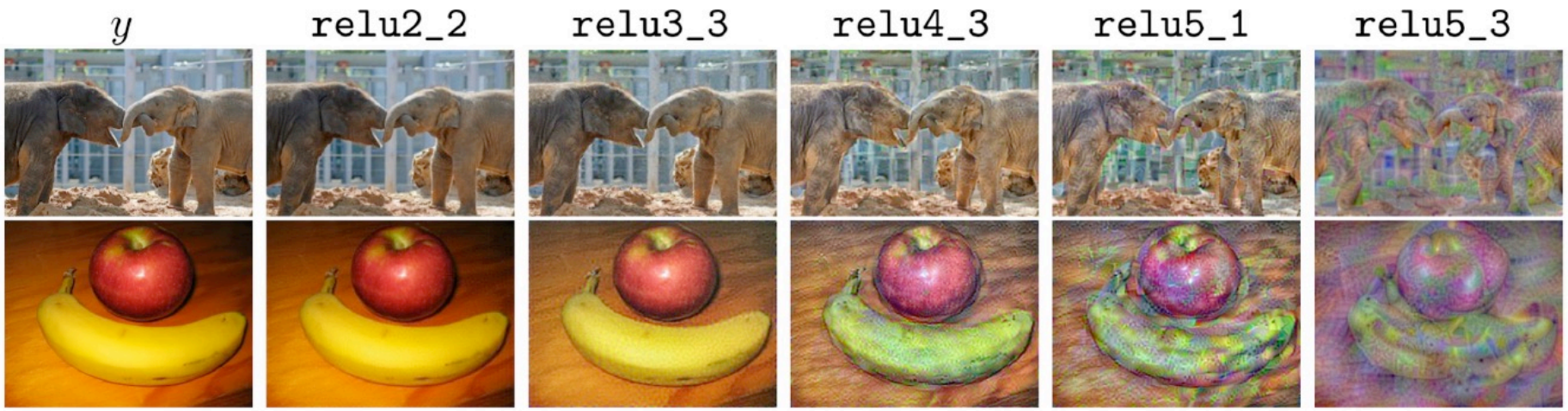


Figure from Johnson, Alahi, and Fei-Fei, “Perceptual Losses for Real-Time Style Transfer and Super-Resolution”, ECCV 2016.

Visualization distill.pub

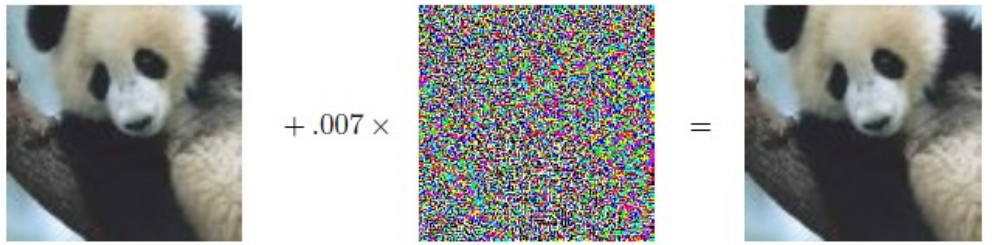
https://distill.pub/2017/feature-visualization/

https://distill.pub/2018/building-blocks/

Fooling ConvNets

- Given an image I labeled as l_1, find minimum "r" (noise) such that $I + r$ is classified as a different label, l_2.
- I.e., minimize:

$$\arg\min_r loss(I + r, l_2) + c|r|$$



Published as a conference paper at ICLR 2015

EXPLAINING AND HARNESSING ADVERSARIAL EXAMPLES

Ian J. Goodfellow, Jonathon Shlens & Christian Szegedy
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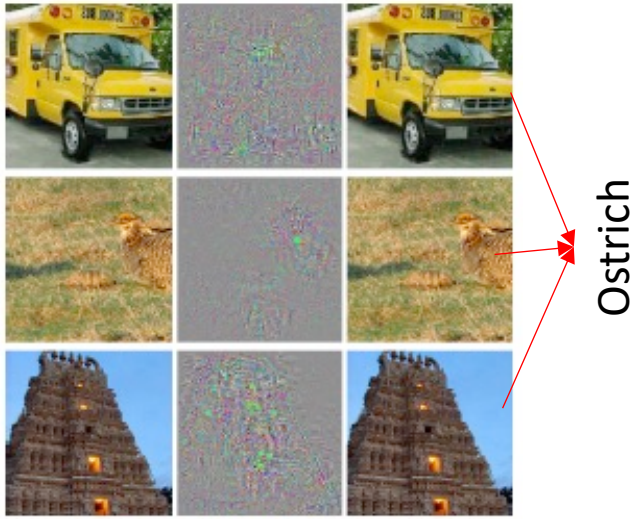
Intriguing properties of neural networks

Christian Szegedy Google Inc.
Wojciech Zaremba New York University
Ilya Sutskever Google Inc.
Joan Bruna New York University
Dumitru Erhan Google Inc.
Ian Goodfellow University of Montreal
Rob Fergus New York University
Facebook Inc.



More on adversarial examples

- How to classify adversarial examples correctly?
  - You need to train your network against them!
  - That is very expensive and training against all kinds of adversarial examples is not possible
  - However, training against adversarial examples increases accuracy on non-adversarial examples as well.
- They are still an unsolved issue in neural networks
- Adversarial examples are problems of any learning method
- See I. Goodfellow for more on adversarial examples:
  - http://www.kdnuggets.com/2015/07/deep-learning-adversarial-examples-misconceptions.html

There Is No Free Lunch In Adversarial Robustness (But There Are Unexpected Benefits)

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2018

- "We provide a new understanding of the fundamental nature of adversarially robust classifiers and how they differ from standard models. In particular, we show that there provably exists a trade-off between the standard accuracy of a model and its robustness to adversarial perturbations. We demonstrate an intriguing phenomenon at the root of this tension: a certain dichotomy between "robust" and "non-robust" features. We show that while robustness comes at a price, it also has some surprising benefits. Robust models turn out to have interpretable gradients and feature representations that align unusually well with salient data characteristics. In fact, they yield striking feature interpolations that have thus far been possible to obtain only using generative models such as GANs."

Popular CNN models

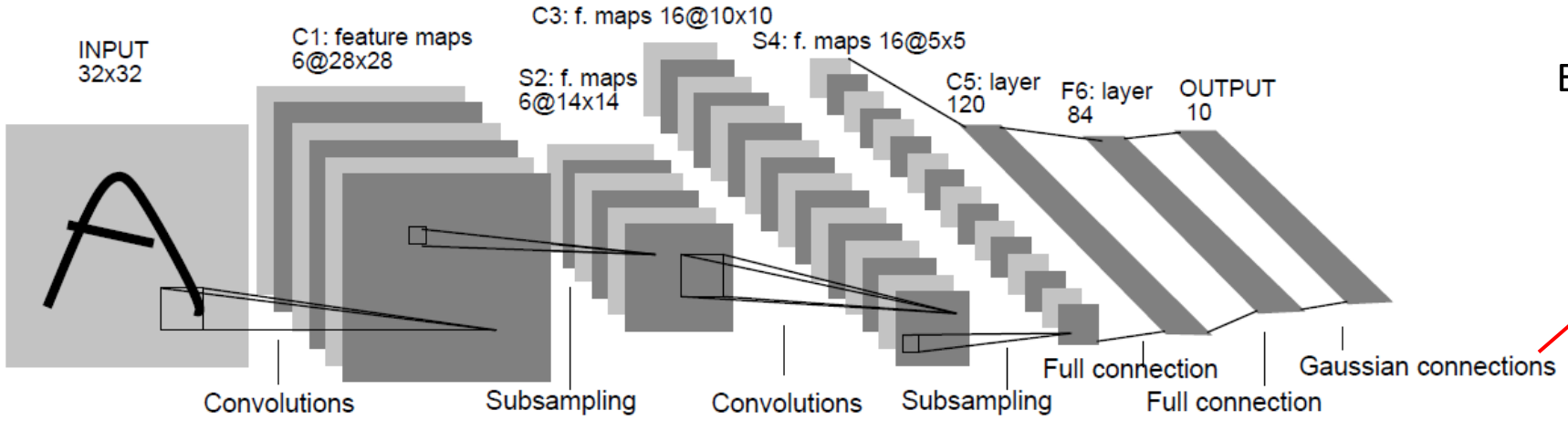
PROC. OF THE IEEE, NOVEMBER 1998

LeNet (1998)

Gradient-Based Learning Applied to Document Recognition

Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner

- For reading zip codes and digits



Euclidean RBF:

$$y_i = \sum_j (x_j - w_{ij})^2.$$

F=5x5
S=1
P=0

F=2x2
S=2
sigm($\alpha \times avg + b$)
α & b: trainable

F=5x5
S=1
P=0

F=2x2
S=2
sigm($\alpha \times avg + b$)
α & b: trainable

F=5x5
S=1
P=0

AlexNet (2012)

ImageNet Classification with Deep Convolutional Neural Networks

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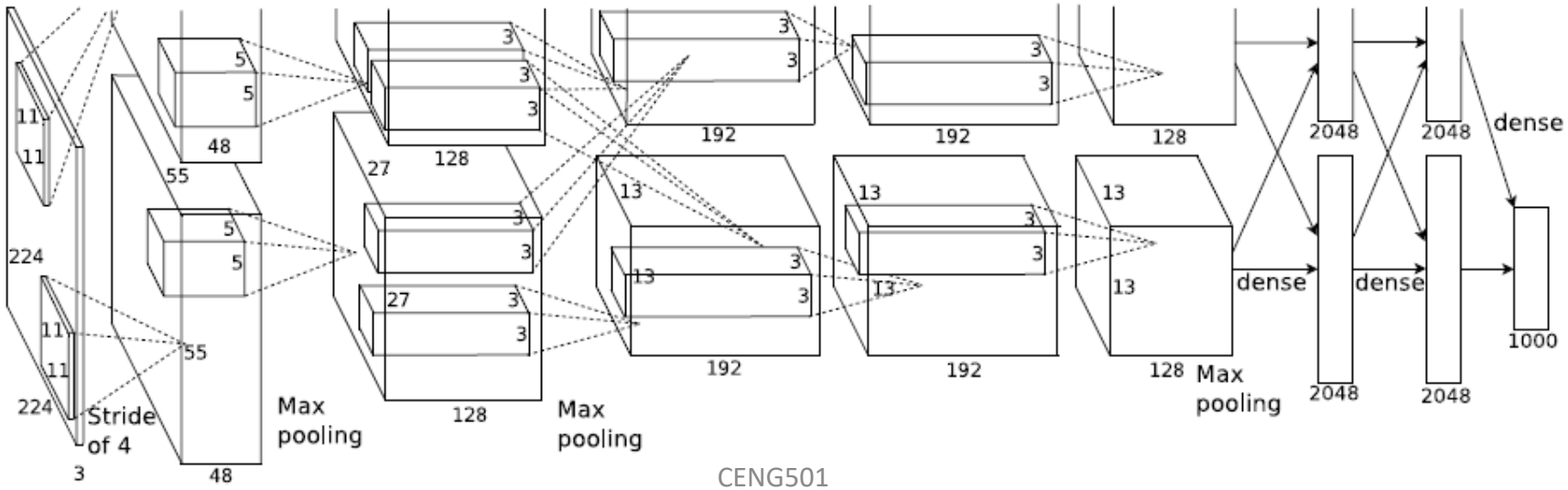
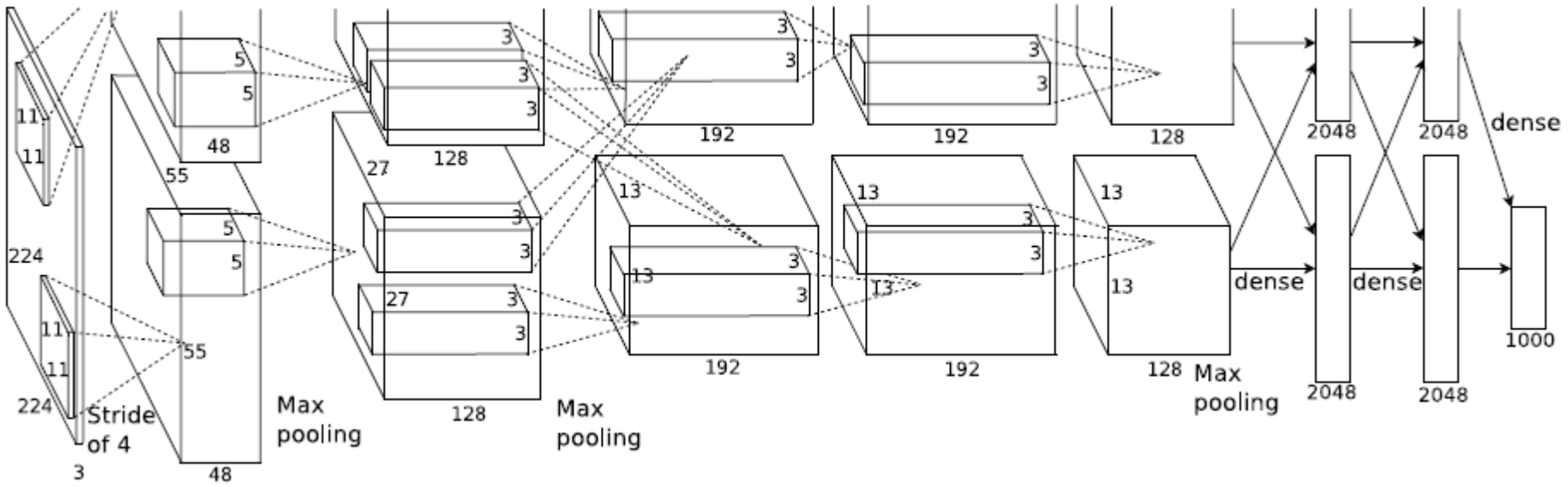
Geoffrey E. Hinton University of Toronto hinton@cs.utoronto.ca

- Popularized CNN in computer vision & pattern recognition
- ImageNet ILSVRC challenge 2012 winner
- Similar to LeNet
  - Deeper & bigger
  - Many CONV layers on top of each other (rather than adding immediately a pooling layer after a CONV layer)
  - Uses GPU
- 650K neurons. 60M parameters. Trained on 2 GPUs for a week.

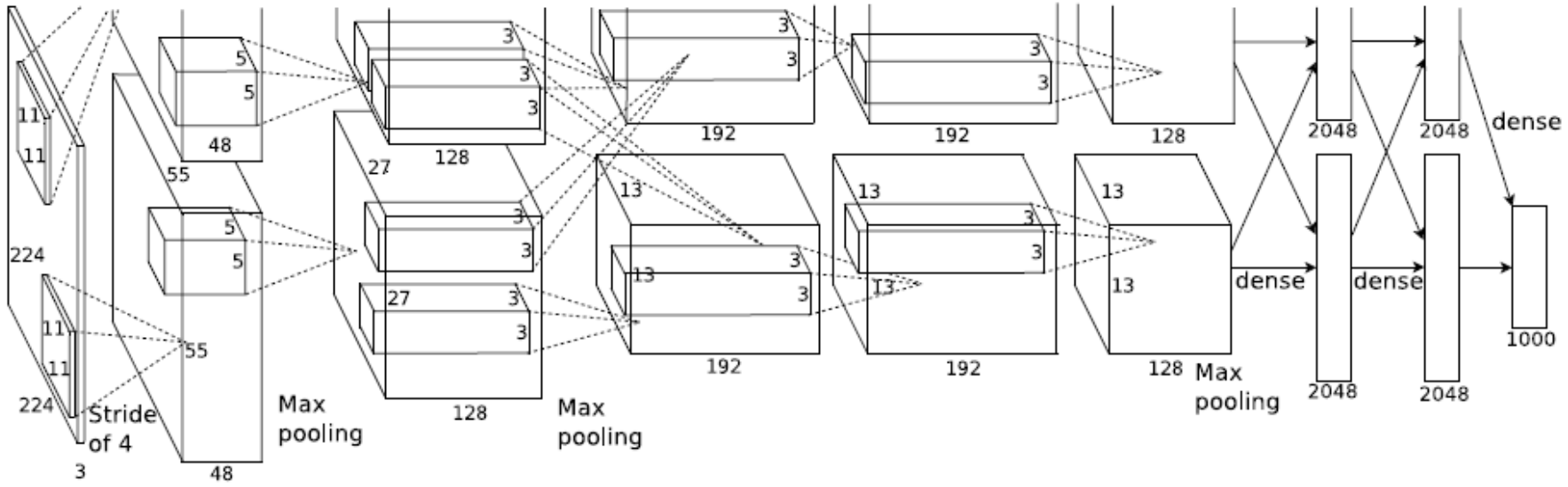


AlexNet (2012) Details



- Since the network is too big to fit in on GPU, it is divided into two.
- Note the cross connections between the “pathways”.
- Uses ReLU as non-linearity after every convolutional and fully-connected layer.
- Normalization layer is placed after the first & the second convolutional layers.
- Max-pooling layer is placed only after the normalization layers & the fifth convolutional layer.
- Last layer is a soft-max.

AlexNet (2012) Training



- Data augmentation & dropout are used during training to avoid overfitting.
- Stochastic Gradient Descent with a batchsize of 128 examples is used.
- Momentum with coefficient 0.9 is employed.
- Weight decay (L2 regularization cost) with factor 0.0005 is also used in the loss function.
- Weights are initialized from a zero-mean Gaussian distribution with 0.01 std.
- Learning rate started with 0.01 and manually divided by 10 when the validation error rate stopped improving.
- Trained on 1.2 million images, which took 5-6 days on two GPUs.

AlexNet (2012): The learned filters

Do you notice anything strange with the filters?

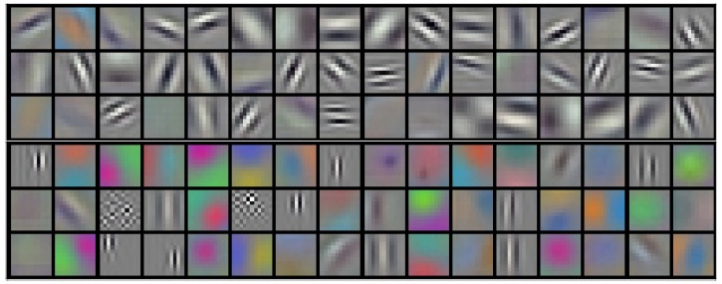


Figure 3: 96 convolutional kernels of size $11 \times 11 \times 3$ learned by the first convolutional layer on the $224 \times 224 \times 3$ input images. The top 48 kernels were learned on GPU 1 while the bottom 48 kernels were learned on GPU 2. See Section 6.1 for details.

Figure 3 shows the convolutional kernels learned by the network's two data-connected layers. The network has learned a variety of frequency- and orientation-selective kernels, as well as various colored blobs. Notice the specialization exhibited by the two GPUs, a result of the restricted connectivity described in Section 3.5. The kernels on GPU 1 are largely color-agnostic, while the kernels on on GPU 2 are largely color-specific. This kind of specialization occurs during every run and is independent of any particular random weight initialization (modulo a renumbering of the GPUs).

GoogleNet (2014)

Going deeper with convolutions

Christian Szegedy
Google Inc.

Wei Liu
University of North Carolina, Chapel Hill

Yangqing Jia
Google Inc.

Pierre Sermanet
Google Inc.

Scott Reed
University of Michigan

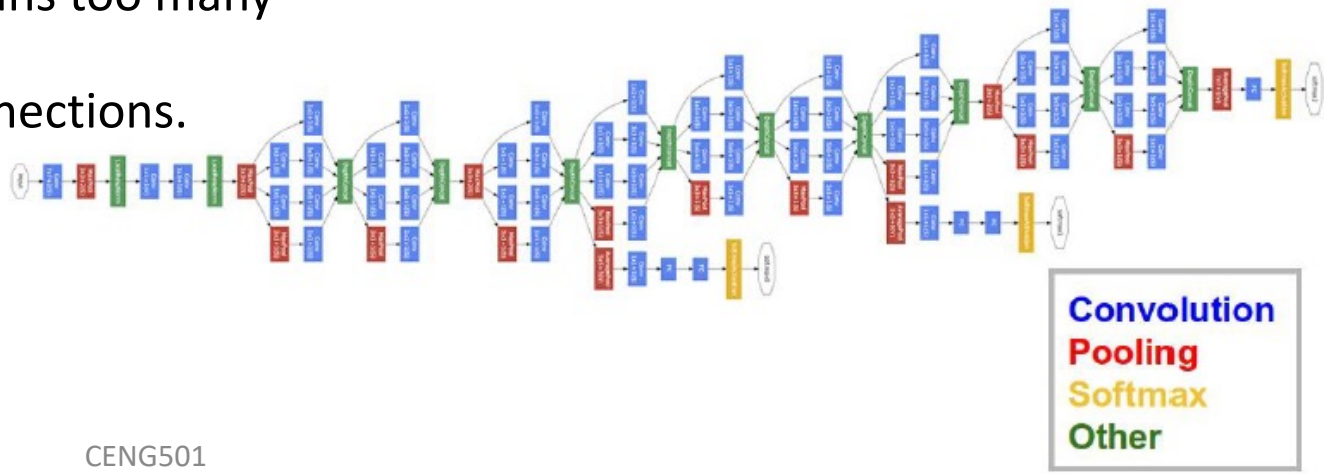
Dragomir Anguelov
Google Inc.

Dumitru Erhan
Google Inc.

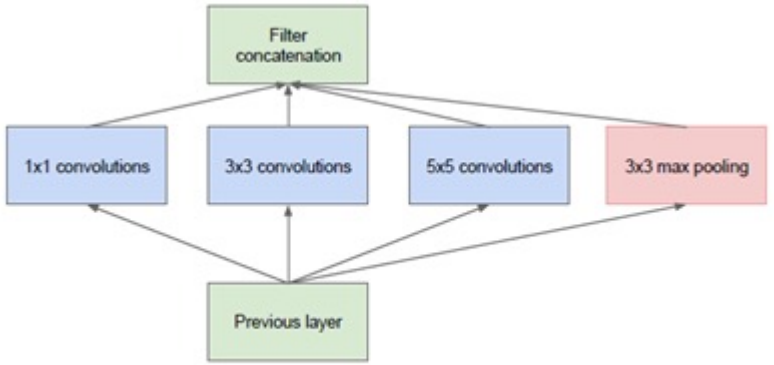
Vincent Vanhoucke
Google Inc.

Andrew Rabinovich
Google Inc.

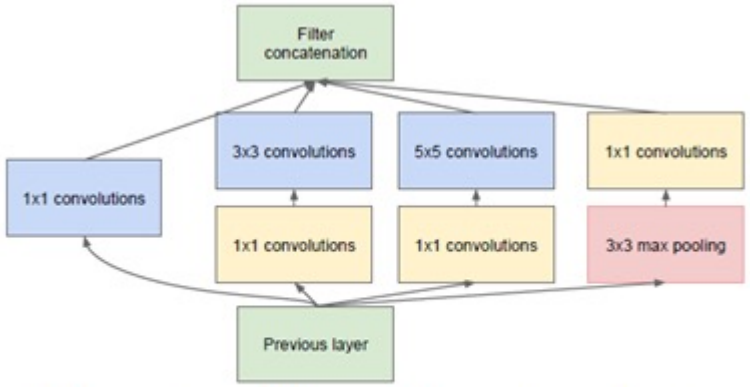
- ImageNet 2014 winner
- Contributions:
  - Inception module
    - Dramatically reduced parameters (from 60M in AlexNet to 4M)
  - Avg Pooling at the top, instead of fully-connected layer ➔ Reduced number of parameters
- Motivation:
  - Going bigger (in depth or width) means too many parameters.
  - Go bigger by maintaining sparse connections.



Inception module: "network in network" (inspired from Lin et al., 2013)

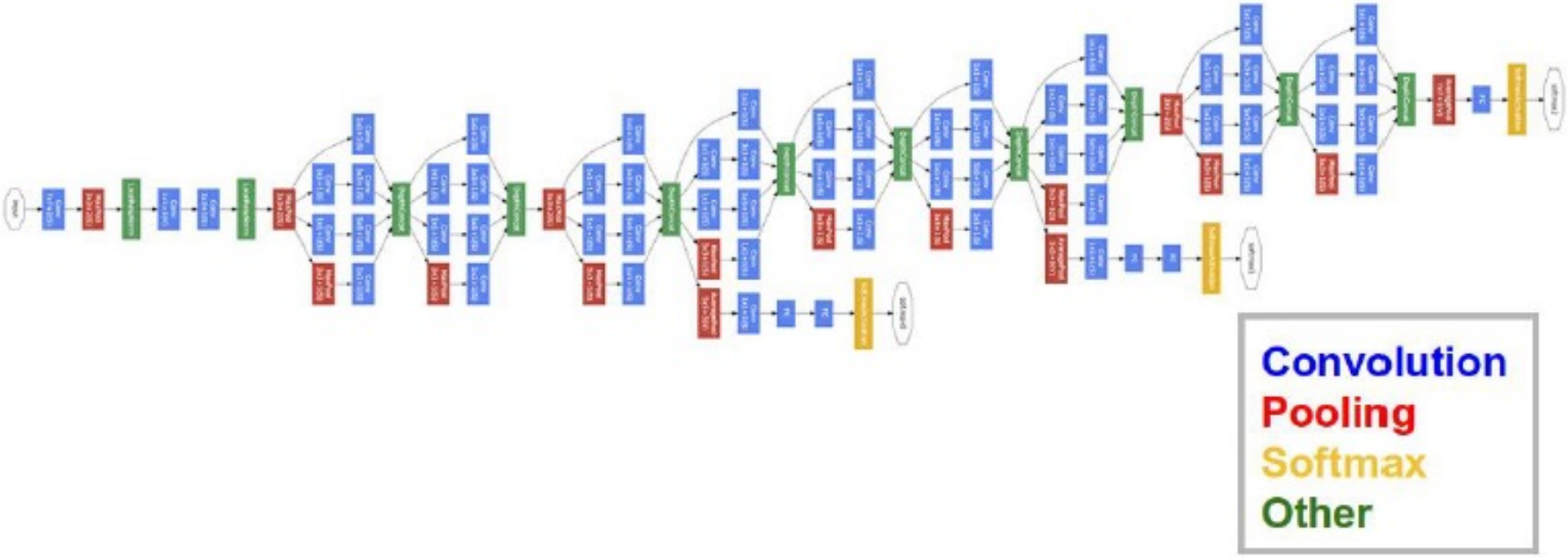


(a) Inception module, naïve version



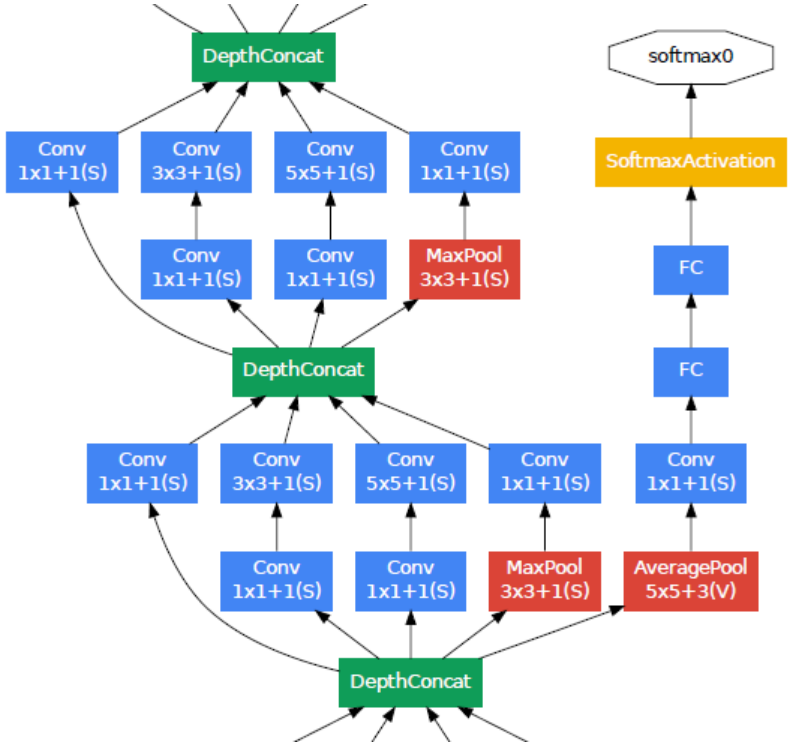
(b) Inception module with dimension reductions

- Concatenation is performed along the "columns" (depth).
  - The output of inception layers must have the same size.
- The naïve version has a tendency to blow up in number of channels.
  - Why? Max-pooling does not change the number of channels. When concatenated with other filter responses, number of channels increase with every layer.
  - Solution: Do 1x1 convolution to decrease the number of channels.
    - Also called "bottleneck".
- In order to decrease the computational complexity of 3x3 and 5x5 pooling, they are also preceded by 1x1 convolution (i.e., the number of channels are reduced).



One of the main beneficial aspects of this architecture is that it allows for increasing the number of units at each stage significantly without an uncontrolled blow-up in computational complexity. The ubiquitous use of dimension reduction allows for shielding the large number of input filters of the last stage to the next layer, first reducing their dimension before convolving over them with a large patch size. Another practically useful aspect of this design is that it aligns with the intuition that visual information should be processed at various scales and then aggregated so that the next stage can abstract features from different scales simultaneously.

- Since the intermediate layers learn to discriminate features specific to a class, we can directly link them to the loss term.
  - Encourages these layers to become more discriminative
  - Increases propagation of gradient signal to earlier stages



GoogleNet: More Details

- ReLU after all layers
- Max pooling in inception modules as well as a whole layer occasionally
- Avg pooling instead of fully-connected layers
  - Only a minor change in the accuracy (0.6%)
  - However, less number of parameters
- Other usual tricks (e.g., dropout, augmentation etc.) are used.
- Trained on CPUs using a distributed machine learning system.
- SGD with momentum (0.9).
- Fixed learning rate scheme with 4% decrease every 8 epochs
- They trained many different models with different initializations and parameters. They combined these models using different methods and tricks. There is no single training method that yields the results they achieved.

VGGNet (2014)

- ImageNet runner up in 2014
- Contribution:
  - Use small RFs & increase depth as much as possible
  - 16 CONV/FC layers.
  - 3x3 CONVs and 2x2 pooling from beginning to the end
- Although performs slightly worse than GoogleNet in image classification, VGGNet may perform better at other tasks (such as transfer learning problems).
- Downside: Needs a lot of memory & parameters (140M)

Table 1: **ConvNet configurations** (shown in columns). The depth of the configurations increases from the left (A) to the right (E), as more layers are added (the added layers are shown in bold). The convolutional layer parameters are denoted as "conv⟨receptive field size⟩-⟨number of channels⟩". The ReLU activation function is not shown for brevity.

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Table 2: **Number of parameters** (in millions).

Network	A,A-LRN	B	C	D	E
Number of parameters	133	133	134	138	144

ResNet (2015)

Deep Residual Learning for Image Recognition

Kaiming He Xiangyu Zhang Shaoqing Ren Jian Sun
Microsoft Research
{kahe, v-xiangz, v-shren, jiansun}@microsoft.com

- Increasing the depth naively may not give you better performance after a number of depths
  - Why?
    - This is shown to be not due to overfitting (since training error also gets worse) or vanishing gradients (suitable non-linearities used)
    - Accuracy is somehow saturated. Though reported in several studies.
- Solution: Make shortcut connections

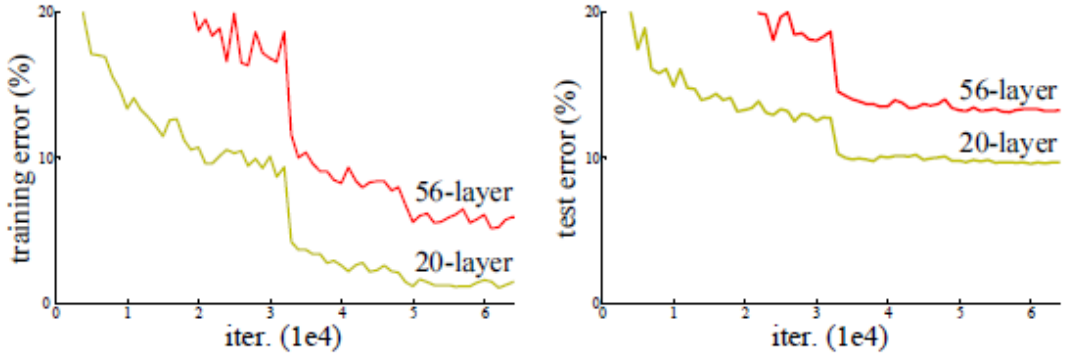


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

ResNet (2015)

Residual (shortcut) connections

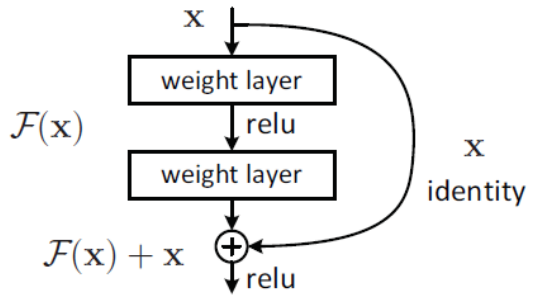


Figure 2. Residual learning: a building block.

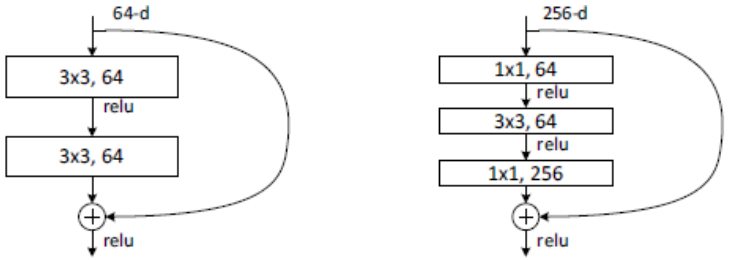
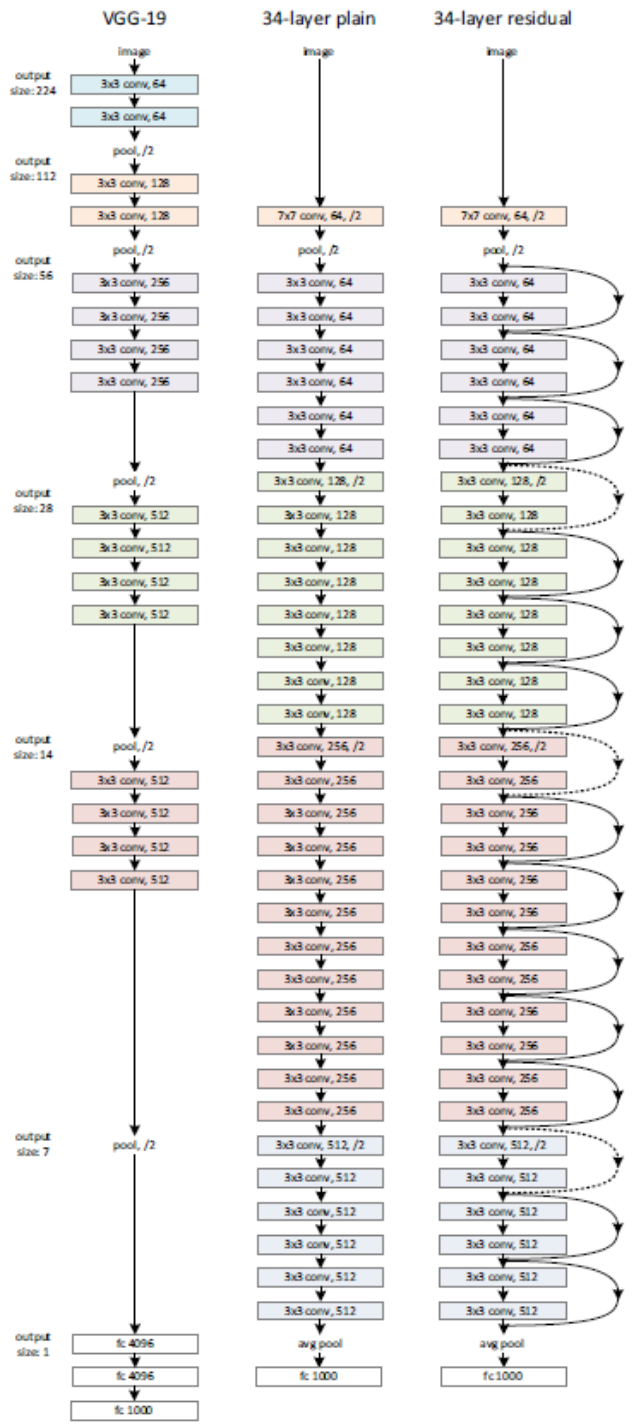


Figure 5. A deeper residual function $\mathcal{F}$ for ImageNet. Left: a building block (on 56×56 feature maps) as in Fig. 3 for ResNet-34. Right: a "bottleneck" building block for ResNet-50/101/152.



ResNet (2015)

Residual (shortcut) connections

method	top-1 err.	top-5 err.
VGG [41] (ILSVRC'14)	-	8.43†
GoogLeNet [44] (ILSVRC'14)	-	7.89
VGG [41] (v5)	24.4	7.1
PReLU-net [13]	21.59	5.71
BN-inception [16]	21.99	5.81
ResNet-34 B	21.84	5.71
ResNet-34 C	21.53	5.60
ResNet-50	20.74	5.25
ResNet-101	19.87	4.60
ResNet-152	**19.38**	**4.49**

Table 4. Error rates (%) of **single-model** results on the ImageNet validation set (except † reported on the test set).

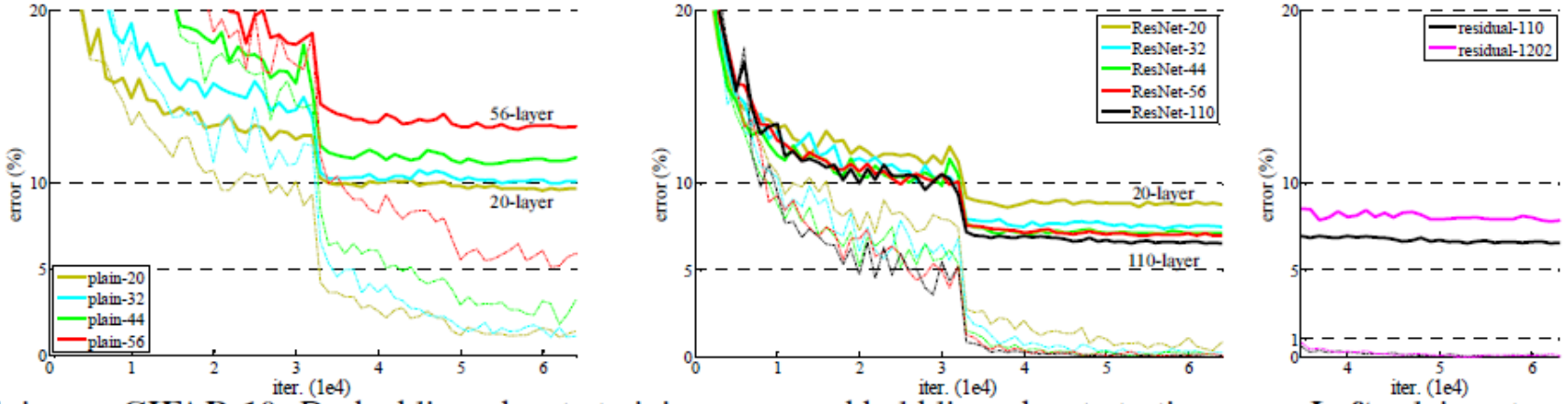
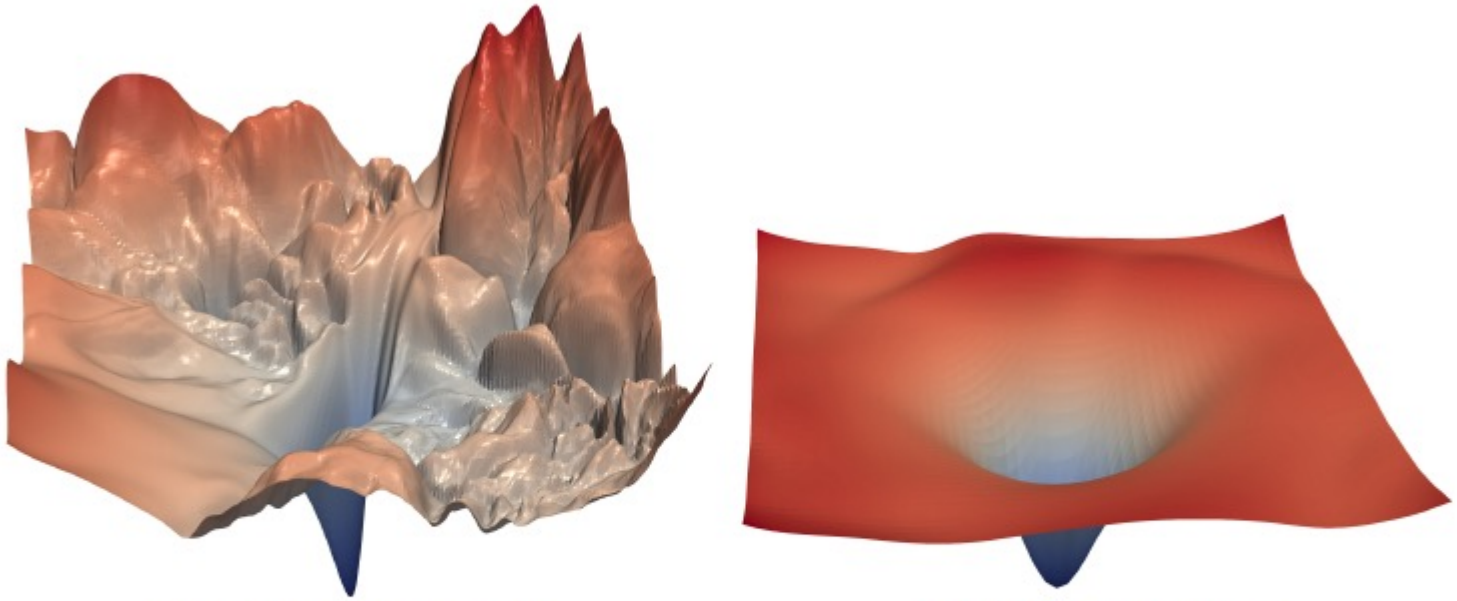


Figure 6. Training on **CIFAR-10**. Dashed lines denote training error, and bold lines denote testing error. **Left**: plain networks. The error of plain-110 is higher than 60% and not displayed. **Middle**: ResNets. **Right**: ResNets with 110 and 1202 layers.

Effect of residual connections



(a) without skip connections (b) with skip connections

Figure 1: The loss surfaces of ResNet-56 with/without skip connections. The vertical axis is logarithmic to show dynamic range. The proposed filter normalization scheme is used to enable comparisons of sharpness/flatness between the two figures.

VISUALIZING THE LOSS LANDSCAPE OF NEURAL NETS

2018

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ResNet: Ensemble of Shallow Networks

Residual Networks Behave Like Ensembles of Relatively Shallow Networks

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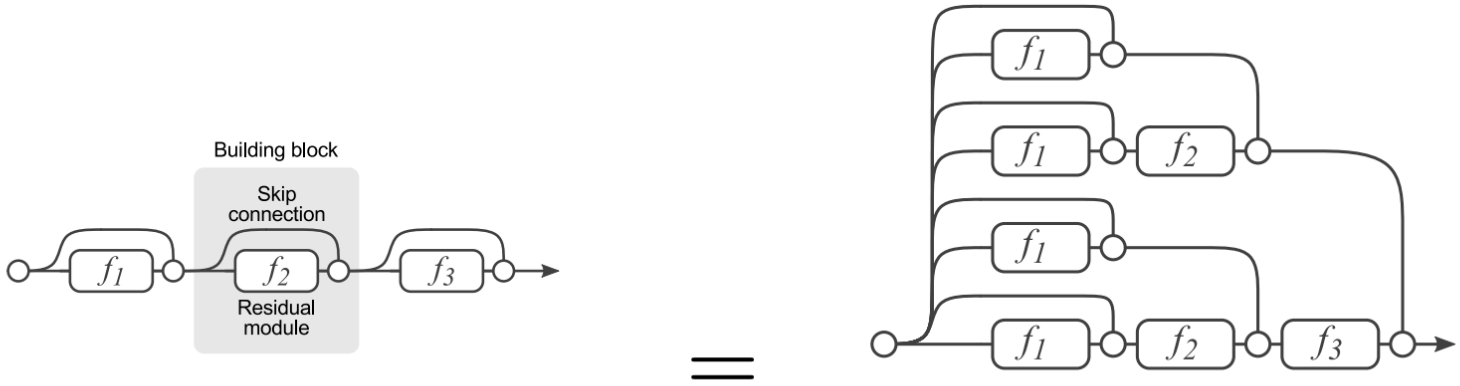
2016



(a) Conventional 3-block residual network (b) Unraveled view of (a)

Figure 1: Residual Networks are conventionally shown as (a), which is a natural representation of Equation (1). When we expand this formulation to Equation (6), we obtain an *unraveled view* of a 3-block residual network (b). Circular nodes represent additions. From this view, it is apparent that residual networks have $O(2^n)$ implicit paths connecting input and output and that adding a block doubles the number of paths.

Dynamical Isometry and a Mean Field Theory of CNNs: How to Train 10,000-Layer Vanilla Convolutional Neural Networks

Lechao Xiao [1 2] Yasaman Bahri [1 2] Jascha Sohl-Dickstein [1] Samuel S. Schoenholz [1] Jeffrey Pennington [1]

Abstract

In recent years, state-of-the-art methods in computer vision have utilized increasingly deep convolutional neural network architectures (CNNs), with some of the most successful models employing hundreds or even thousands of layers. A variety of pathologies such as vanishing/exploding gradients make training such deep networks challenging. While residual connections and batch normalization do enable training at these depths, it has remained unclear whether such specialized architecture designs are truly necessary to train deep CNNs. In this work, we demonstrate that it is possible to train vanilla CNNs with ten thousand layers or more simply by using an appropriate initialization scheme. We derive this initialization scheme theoretically by developing a mean field theory for signal propagation and by characterizing the conditions for *dynamical isometry*, the equilibration of singular values of the input-output Jacobian matrix. These conditions require that the convolution operator be an orthogonal transformation in the sense that it is norm-preserving. We present an algorithm for generating such random initial orthogonal convolution kernels and demonstrate empirically that they enable efficient training of extremely deep architectures.

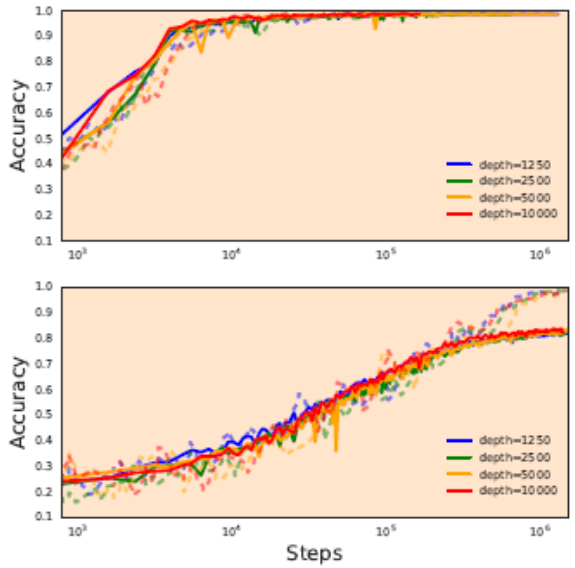


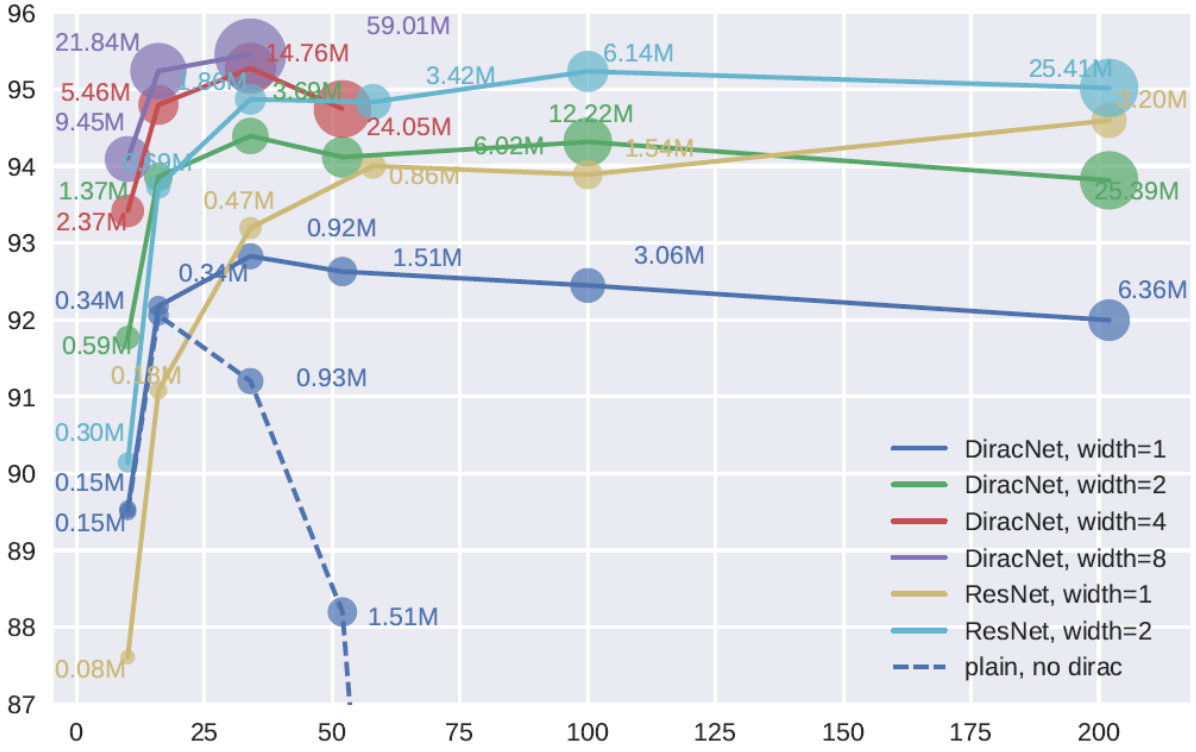
Figure 1. Extremely deep CNNs can be trained without the use of batch normalization or residual connections simply by using a Delta-Orthogonal initialization with critical weight and bias variance and appropriate (in this case, tanh) nonlinearity. Test (solid) and training (dashed) curves on MNIST (top) and CIFAR-10 (bottom) for depths 1,250, 2,500, 5,000, and 10, 000.

Kim, 2014), and recently even the board game Go (Silver et al., 2016; 2017).

The performance of deep convolutional networks has improved as these networks have been made ever deeper

"Our initial results suggest that past a certain depth, on the order of tens or hundreds of layers, the test performance for vanilla convolutional architecture saturates. These observations suggest that architectural features such as residual connections and batch normalization are likely to play an important role in defining a good model class, rather than simply enabling efficient training."

DiracNets



DiracNets: Training Very Deep Neural Networks Without Skip-Connections

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Abstract

Deep neural networks with skip-connections, such as ResNet, show excellent performance in various image classification benchmarks. It is though observed that the initial motivation behind them - training deeper networks - does not actually hold true, and the benefits come from increased capacity, rather than from depth. Motivated by this, and inspired from ResNet, we propose a simple Dirac weight parameterization, which allows us to train very deep plain networks without skip-connections, and achieve nearly the same performance. This parameterization has a minor computational cost at training time and no cost at all at inference. We're able to achieve 95.5% accuracy on CIFAR-10 with 34-layer deep plain network, surpassing 1001-layer deep ResNet, and approaching Wide ResNet. Our parameterization also mostly eliminates the need of careful initialization in residual and non-residual networks. The code and models for our experiments are available at https://github.com/szagoruyko/diracnets

ResNext

Aggregated Residual Transformations for Deep Neural Networks

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2017

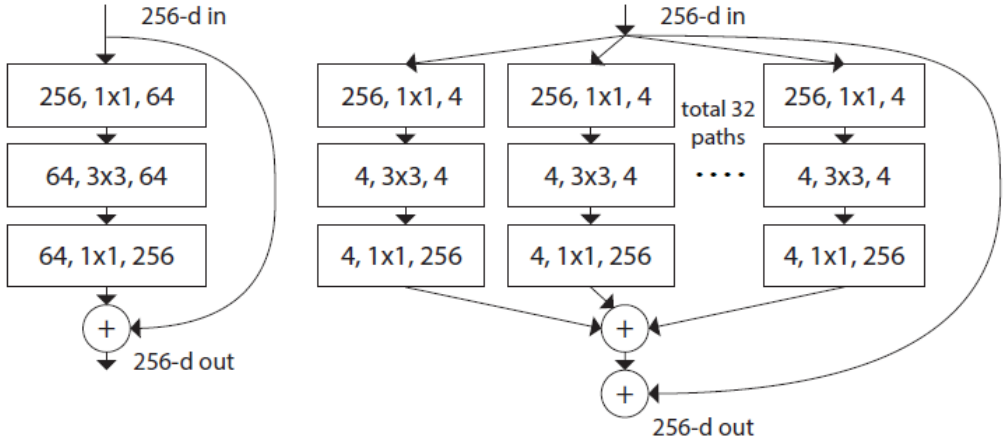

Figure 1. **Left**: A block of ResNet [14]. **Right**: A block of ResNeXt with cardinality = 32, with roughly the same complexity. A layer is shown as (# in channels, filter size, # out channels).

	setting	top-1 err (%)	top-5 err (%)
1× complexity references:			
ResNet-101	1 × 64d	22.0	6.0
ResNeXt-101	32 × 4d	21.2	5.6
2× complexity models follow:			
ResNet-**200** [15]	1 × 64d	21.7	5.8
ResNet-101, wider	1 × **100**d	21.3	5.7
ResNeXt-101	**2** × 64d	20.7	5.5
ResNeXt-101	**64** × 4d	**20.4**	**5.3**

DenseNet

Densely Connected Convolutional Networks

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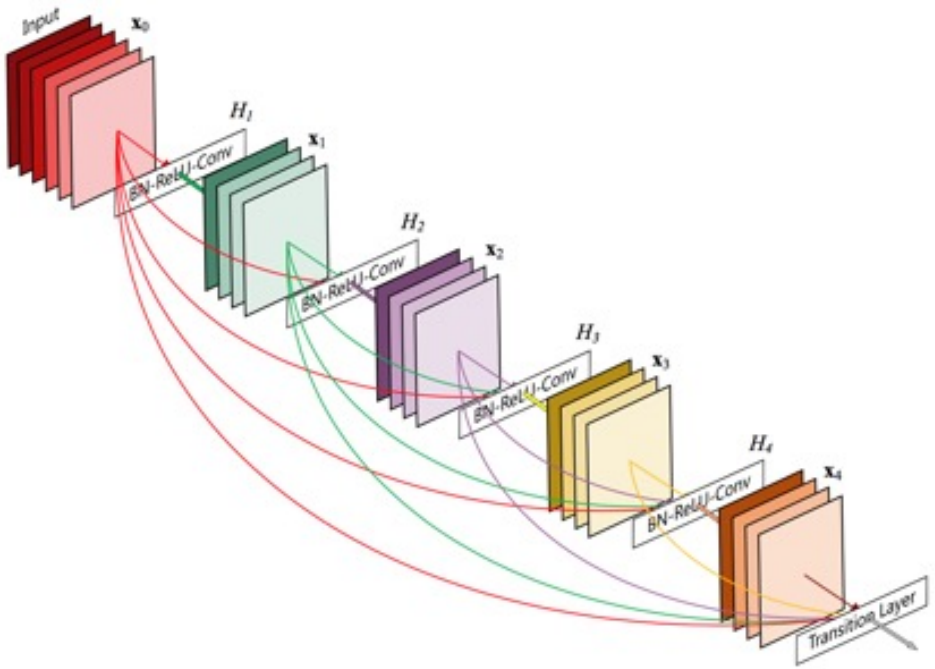
2016;2018



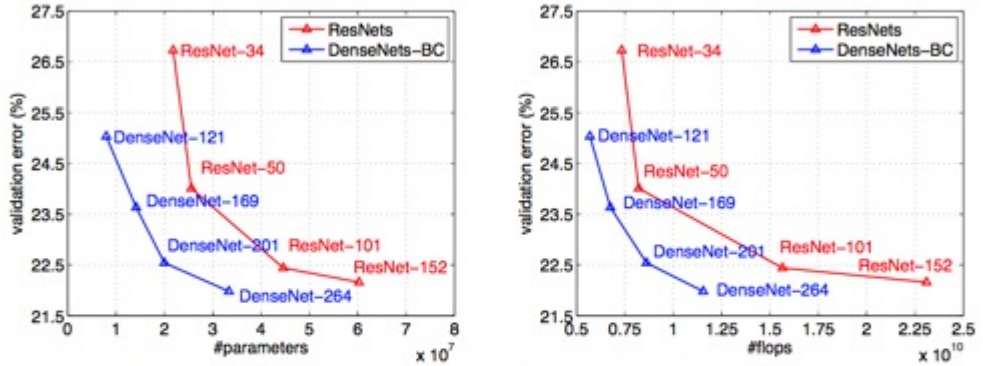


Figure 3: Comparison of the DenseNets and ResNets top-1 error rates (single-crop testing) on the ImageNet validation dataset as a function of learned parameters (*left*) and FLOPs during test-time (*right*).

Highway networks

- This is a regular MLP with gated units.

Highway Networks

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$$\mathbf{y} = H(\mathbf{x}, \mathbf{W_H}). \quad (1)$$

H is usually an affine transform followed by a non-linear activation function, but in general it may take other forms.

For a highway network, we additionally define two non-linear transforms $T(\mathbf{x}, \mathbf{W_T})$ and $C(\mathbf{x}, \mathbf{W_C})$ such that

$$\mathbf{y} = H(\mathbf{x}, \mathbf{W_H}) \cdot T(\mathbf{x}, \mathbf{W_T}) + \mathbf{x} \cdot C(\mathbf{x}, \mathbf{W_C}). \quad (2)$$

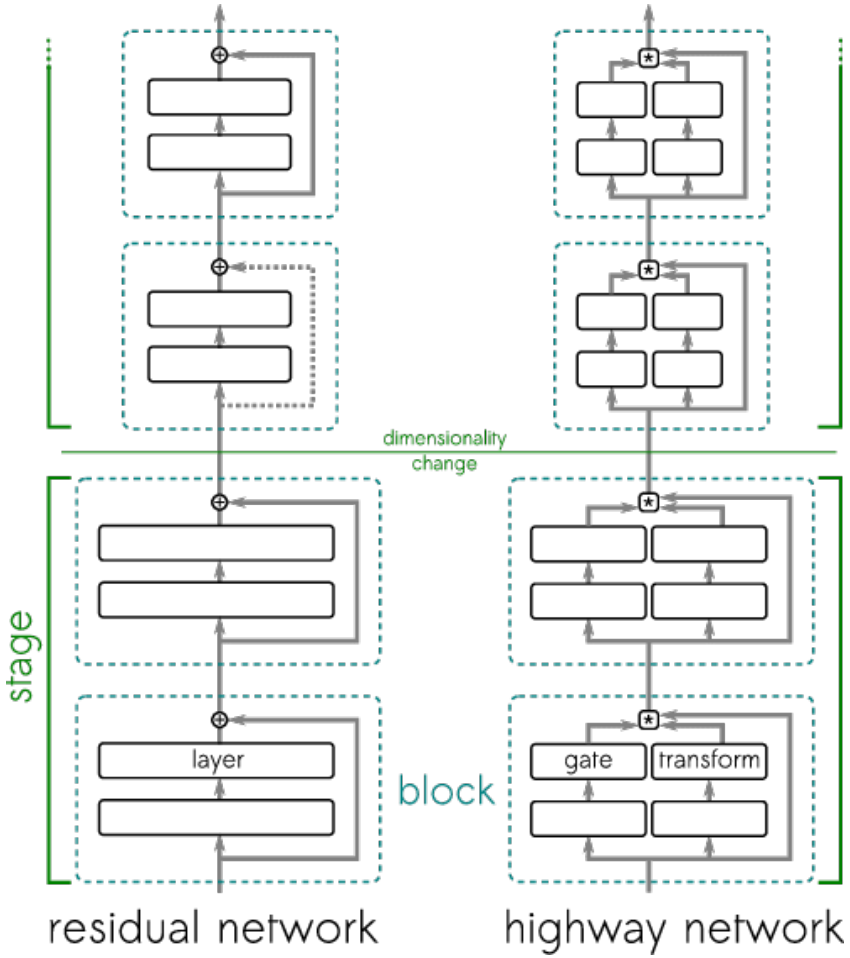
We refer to T as the *transform* gate and C as the *carry* gate, since they express how much of the output is produced by transforming the input and carrying it, respectively. For simplicity, in this paper we set $C = 1 - T$, giving

$$\mathbf{y} = H(\mathbf{x}, \mathbf{W_H}) \cdot T(\mathbf{x}, \mathbf{W_T}) + \mathbf{x} \cdot (1 - T(\mathbf{x}, \mathbf{W_T})). \quad (3)$$

The dimensionality of $\mathbf{x}, \mathbf{y}, H(\mathbf{x}, \mathbf{W_H})$ and $T(\mathbf{x}, \mathbf{W_T})$ must be the same for Equation (3) to be valid. Note that this re-parametrization of the layer transformation is much more flexible than Equation (1). In particular, observe that

$$\mathbf{y} = \begin{cases} \mathbf{x}, & \text{if } T(\mathbf{x}, \mathbf{W_T}) = \mathbf{0}, \\ H(\mathbf{x}, \mathbf{W_H}), & \text{if } T(\mathbf{x}, \mathbf{W_T}) = \mathbf{1}. \end{cases} \quad (4)$$

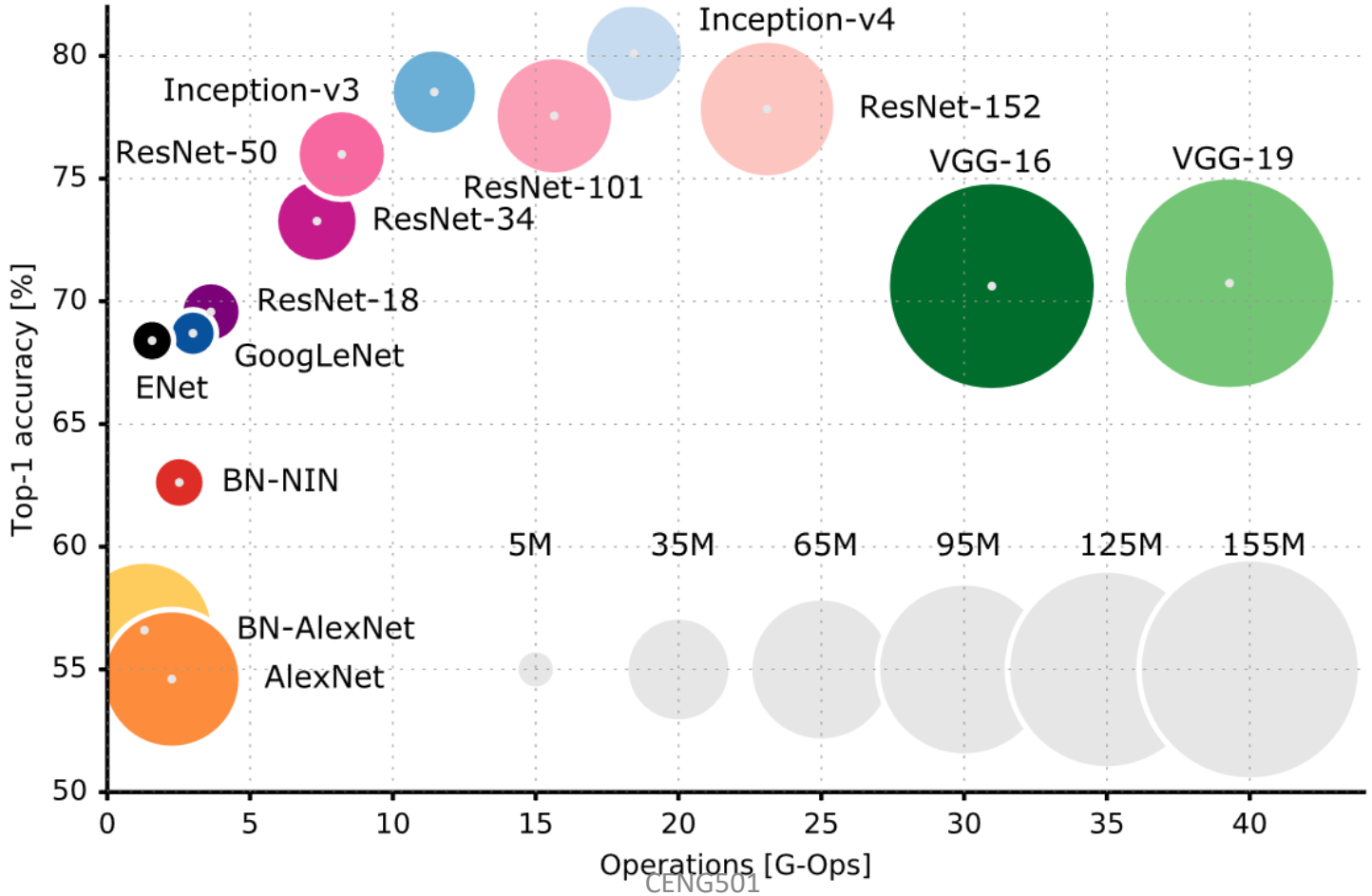
Highway Networks



https://www.researchgate.net/publication/311842587_Highway_and_Residual_Networks_learn_Unrolled_Iterative_Estimation

Comparison:

https://arxiv.org/pdf/1605.07678.pdf



Comparison:

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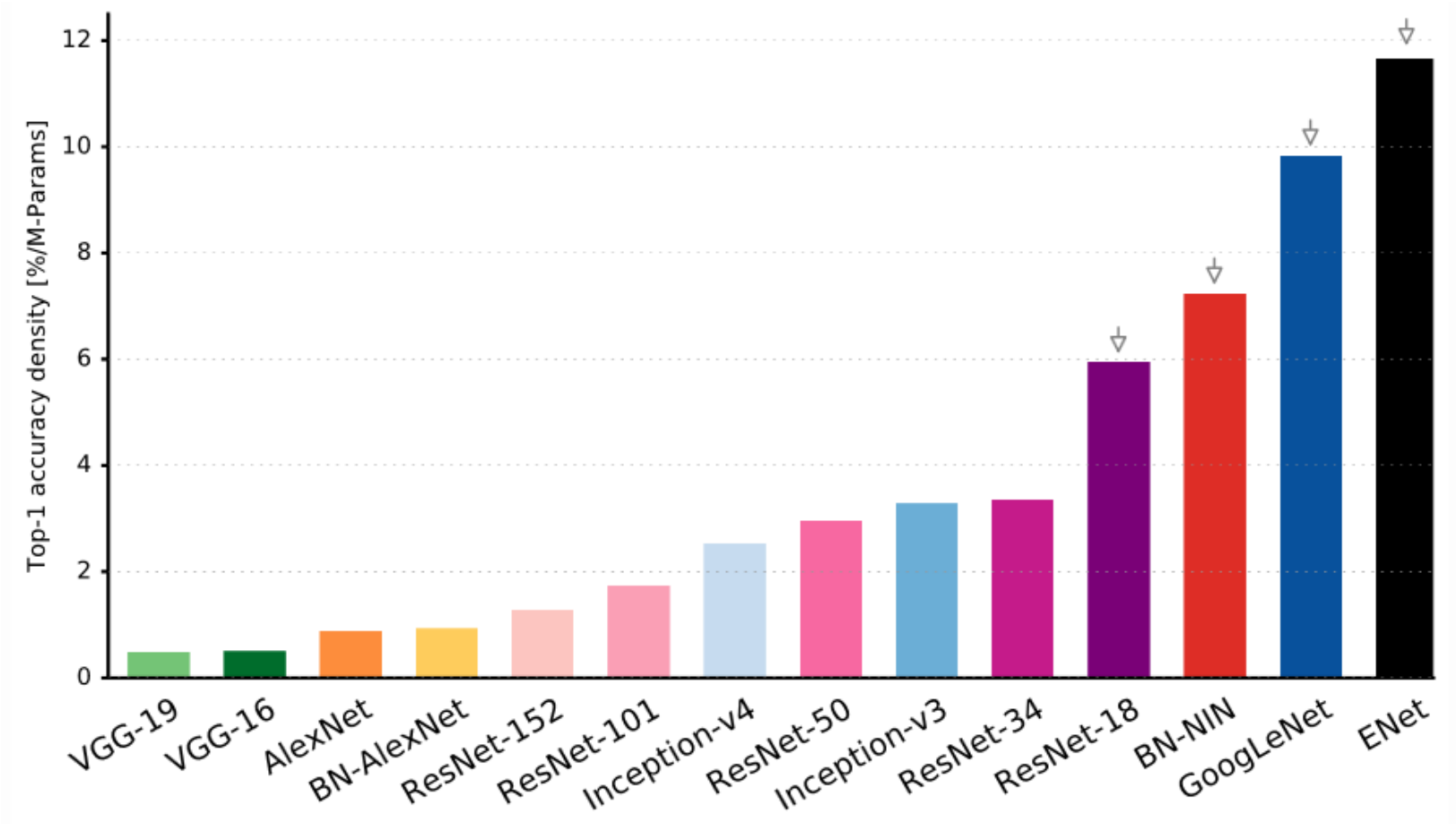

Going deep may not be the only answer

Shallow Networks for High-Accuracy Road Object-Detection

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Abstract

The ability to automatically detect other vehicles on the road is vital to the safety of partially-autonomous and fully-autonomous vehicles. Most of the high-accuracy techniques for this task are based on R-CNN or one of its faster variants. In the research community, much emphasis has been applied to using 3D vision or complex R-CNN variants to achieve higher accuracy. However, are there more straightforward modifications that could deliver higher accuracy? Yes. We show that increasing input image resolution (i.e. upsampling) offers up to 12 percentage-points higher accuracy compared to an off-the-shelf baseline. We also find situations where earlier/shallower layers of CNN provide higher accuracy than later/deeper layers. We further show that shallow models and upsampled images yield competitive accuracy. Our findings contrast with the current trend towards deeper and larger models to achieve high accuracy in domain specific detection tasks.

Recent work

"**Towards Principled Design of Deep Convolutional Networks: Introducing SimpNet"**

- Major winning Convolutional Neural Networks (CNNs), such as VGGNet, ResNet, DenseNet, \etc, include tens to hundreds of millions of parameters, which impose considerable computation and memory overheads. This limits their practical usage in training and optimizing for real-world applications. On the contrary, light-weight architectures, such as SqueezeNet, are being proposed to address this issue. However, they mainly suffer from low accuracy, as they have compromised between the processing power and efficiency. These inefficiencies mostly stem from following an ad-hoc designing procedure. In this work, we discuss and propose several crucial design principles for an efficient architecture design and elaborate intuitions concerning different aspects of the design procedure. Furthermore, we introduce a new layer called {\it SAF-pooling} to improve the generalization power of the network while keeping it simple by choosing best features. Based on such principles, we propose a simple architecture called {\it SimpNet}. We empirically show that SimpNet provides a good trade-off between the computation/memory efficiency and the accuracy solely based on these primitive but crucial principles. SimpNet outperforms the deeper and more complex architectures such as VGGNet, ResNet, WideResidualNet \etc, on several well-known benchmarks, while having 2 to 25 times fewer number of parameters and operations. We obtain state-of-the-art results (in terms of a balance between the accuracy and the number of involved parameters) on standard datasets, such as CIFAR10, CIFAR100, MNIST and SVHN. The implementations are available at \href{url}{this https URL}.

https://arxiv.org/abs/1802.06205

Binary networks

XNOR-Net: ImageNet Classification Using Binary Convolutional Neural Networks

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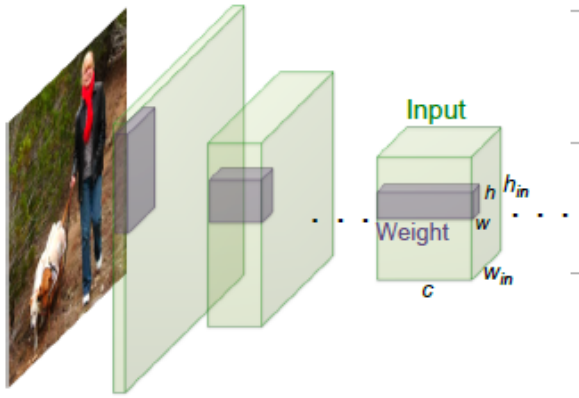
Abstract. We propose two efficient approximations to standard convolutional neural networks: Binary-Weight-Networks and XNOR-Networks. In Binary-Weight-Networks, the filters are approximated with binary values resulting in 32× memory saving. In XNOR-Networks, both the filters and the input to convolutional layers are binary. XNOR-Networks approximate convolutions using primarily binary operations. This results in 58× faster convolutional operations and 32× memory savings. XNOR-Nets offer the possibility of running state-of-the-art networks on CPUs (rather than GPUs) in real-time. Our binary networks are simple, accurate, efficient, and work on challenging visual tasks. We evaluate our approach on the ImageNet classification task. The classification accuracy with a Binary-Weight-Network version of AlexNet is only 2.9% less than the full-precision AlexNet (in top-1 measure). We compare our method with recent network binarization methods, BinaryConnect and BinaryNets, and outperform these methods by large margins on ImageNet, more than 16% in top-1 accuracy.

Binary networks



	Network Variations	Operations used in Convolution	Memory Saving (Inference)	Time Saving on CPU (Inference)	Accuracy on ImageNet (AlexNet)
Standard Convolution	Real-Value Inputs: 0.11 -0.21 ... -0.34 / -0.25 0.61 ... 0.52; Real-Value Weights: 0.12 -1.2 ... 0.41 / -0.2 0.5 ... 0.68	+ , − , ×	1x	1x	%56.7
Binary Weight	Real-Value Inputs: 0.11 -0.21 ... -0.34 / -0.25 0.61 ... 0.52; Binary Weights: 1 -1 ... 1 / -1 1 ... 1	+ , −	~32x	~2x	%53.8
BinaryWeight Binary Input **(XNOR-Net)**	Binary Inputs: 1 -1 ... -1 / -1 1 ... 1; Binary Weights: 1 -1 ... 1 / -1 1 ... 1	XNOR , bitcount	~32x	~58x	%44.2

Fig. 1: We propose two efficient variations of convolutional neural networks. **Binary-Weight-Networks**, when the weight filters contains binary values. **XNOR-Networks**, when both weigh and input have binary values. These networks are very efficient in terms of memory and computation, while being very accurate in natural image classification. This offers the possibility of using accurate vision techniques in portable devices with limited resources.

Exploring Randomly Wired Neural Networks for Image Recognition

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Facebook AI Research (FAIR)

Abstract

Neural networks for image recognition have evolved through extensive manual design from simple chain-like models to structures with multiple wiring paths. The success of ResNets [11] and DenseNets [16] is due in large part to their innovative wiring plans. Now, neural architecture search (NAS) studies are exploring the joint optimization of wiring and operation types, however, the space of possible wirings is constrained and still driven by manual design despite being searched. In this paper, we explore a more diverse set of connectivity patterns through the lens of randomly wired neural networks. *To do this, we first define the concept of a* stochastic network generator *that encapsulates the entire network generation process. Encapsulation provides a unified view of NAS and randomly wired networks. Then, we use three classical random graph models to generate randomly wired graphs for networks. The results are surprising: several variants of these random generators yield network instances that have competitive accuracy on the ImageNet benchmark. These results suggest that new efforts focusing on designing better network generators may lead to new breakthroughs by exploring less constrained search spaces with more room for novel design.*

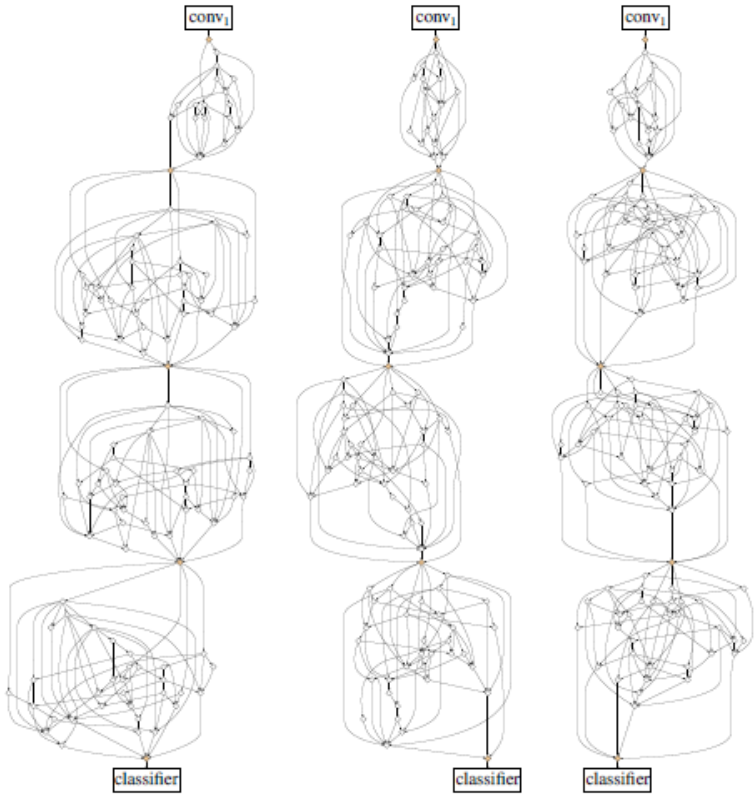

Figure 1. **Randomly wired neural networks** generated by the classical Watts-Strogatz (WS) [50] model: these three instances of random networks achieve (left-to-right) 79.1%, 79.1%, 79.0% classification accuracy on ImageNet under a similar computational budget to ResNet-50, which has 77.1% accuracy.

1. Introduction

CNNs:
summary & future directions

- Less parameters
- Allows going deeper
- High flexibility
  - In operations
  - In organization of layers
  - In the overall architecture etc.
- Future directions:
  - Understanding them better
  - Making them deeper, faster and more efficient
  - Compressing a big network into a smaller & cheaper one.
  - …