Convolutional Neural Networks

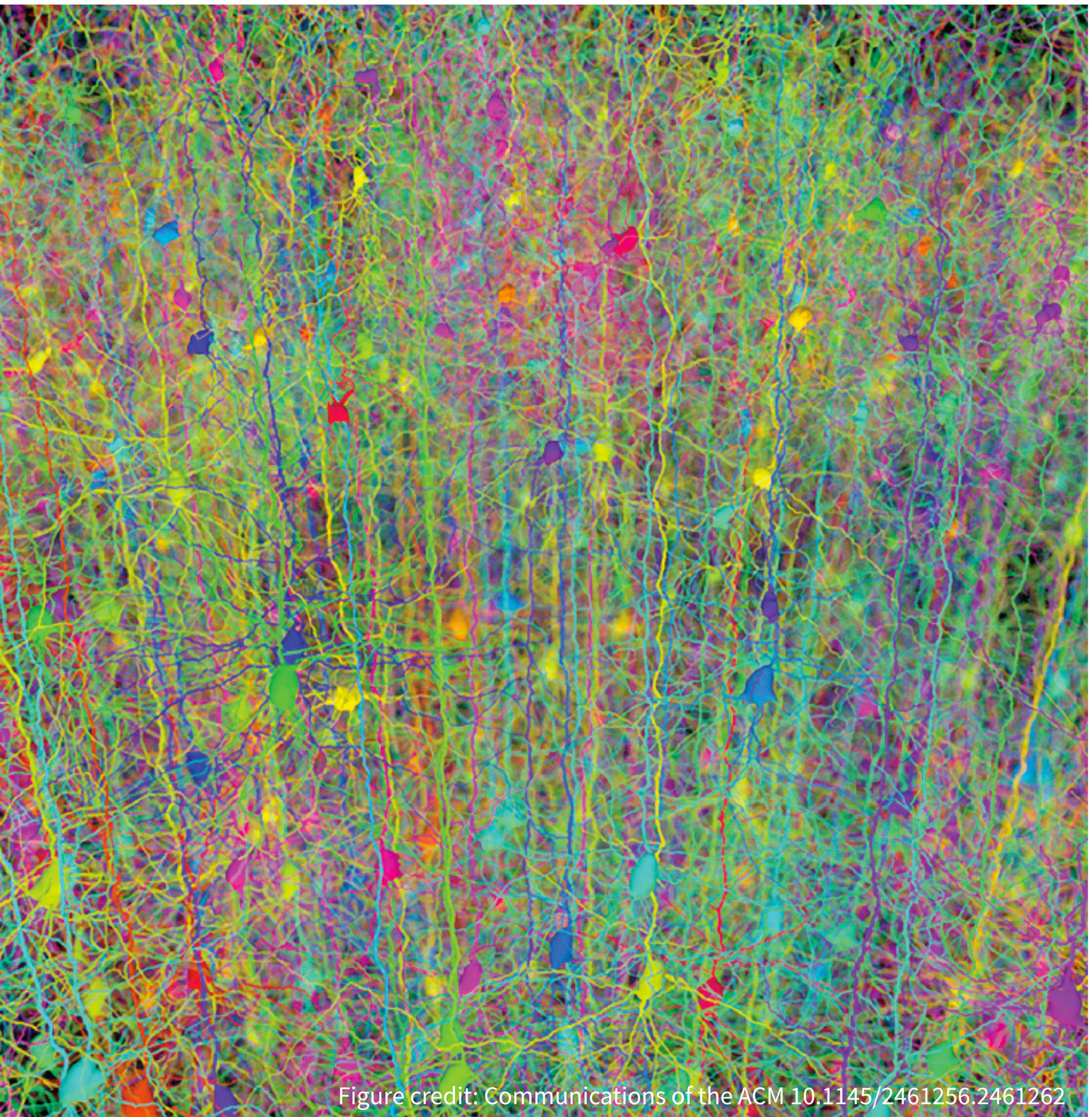

Figure credit: Communications of the ACM 10.1145/2461256.2461262

GRAHAM TAYLOR

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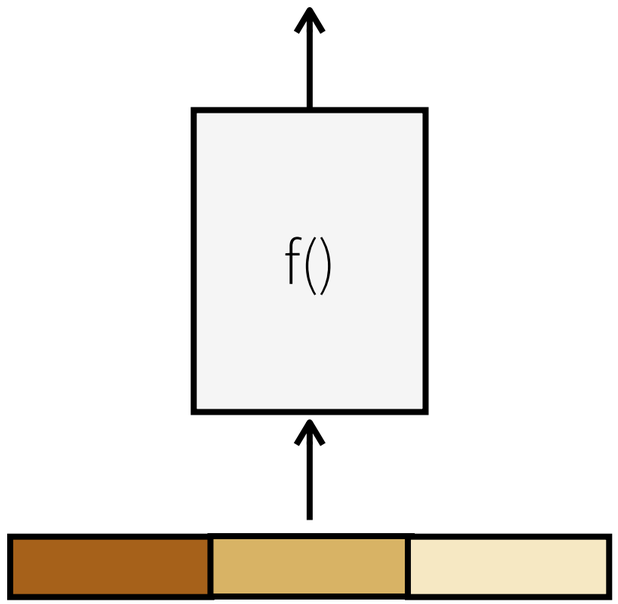
DNNs for Visual Recognition

- For a long time, images have been a common “testbed” for deep learning
- Computer vision and machine learning have been intimately linked, moreso in recent years
- The application of feedforward neural networks to image data has typically been patch-based, or on very tiny images, e.g.
  - MNIST (28 × 28)
  - CIFAR-10 (32 × 32)
  - SVHN (32 × 32)
  - etc…

Encoding Domain Knowledge

- We've so-far operated on vectors
  - Paying no heed to structured relationships among elements
- Images can also be processed as vectors
  - Ignoring that we are dealing with pixels
- But this ignores readily available domain knowledge about the structure of the problem



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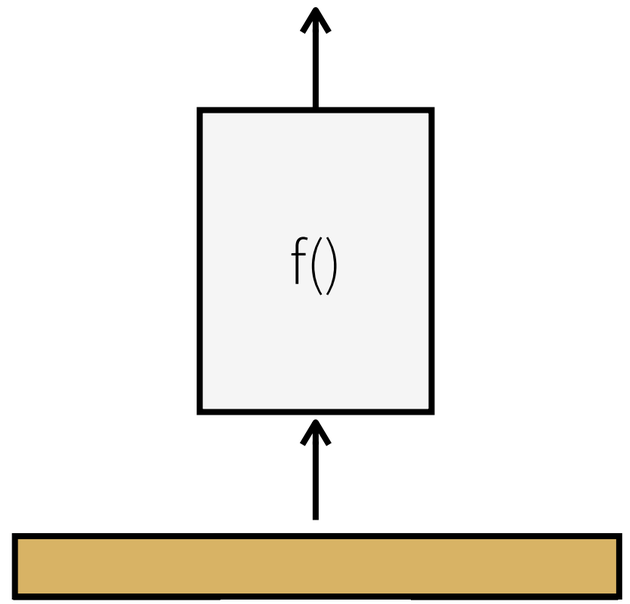

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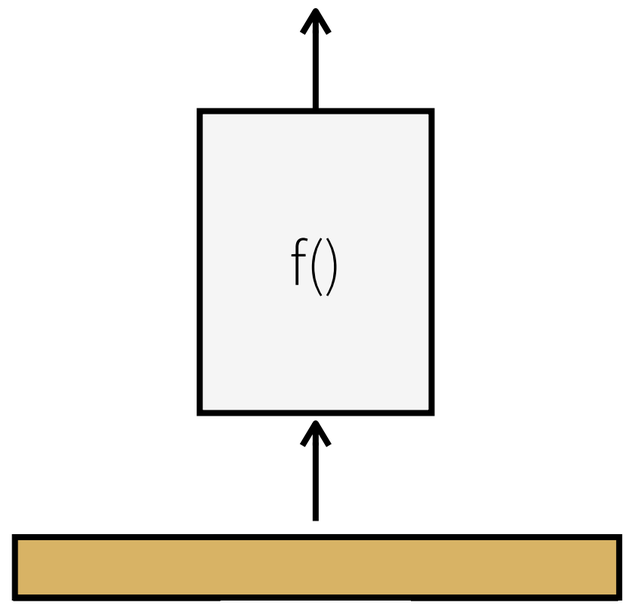

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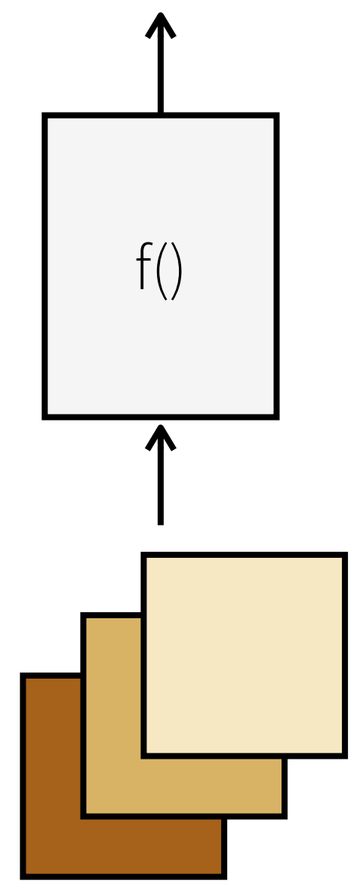
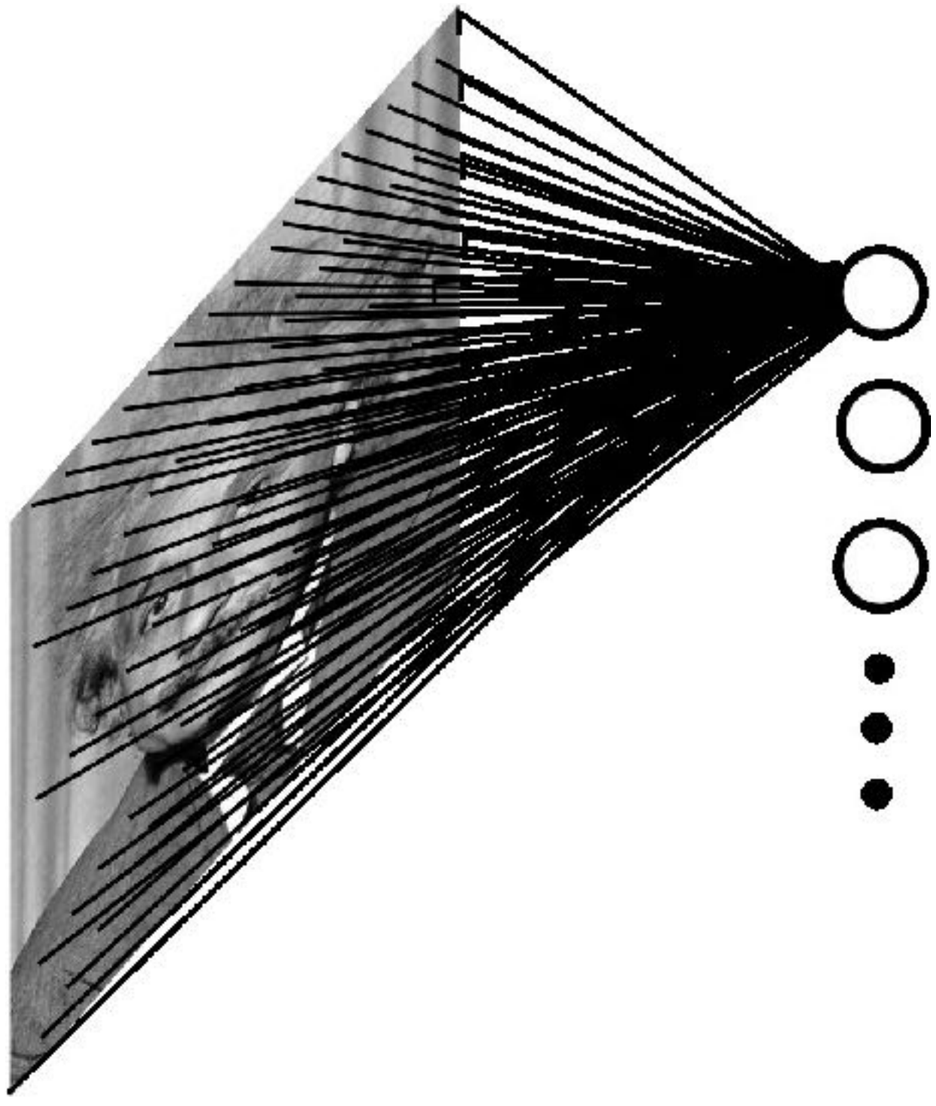


Fully-Connected Layer



Example: 200 ×200 image

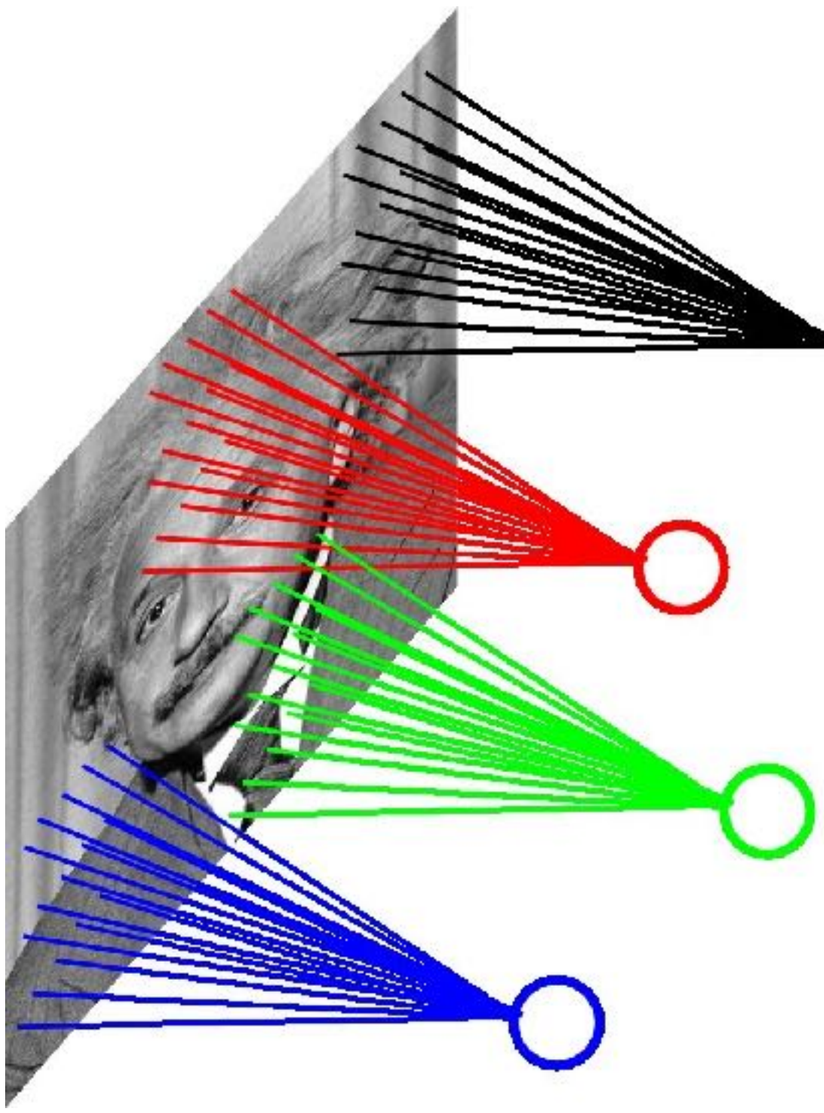
40k hidden units

➡ ~2B parameters!

- Spatial correlation is local
- Waste of resources
- We don’t have enough training examples to fit!

Credit: Marc’Aurelio Ranzato

Locally-Connected Layer



Example: 200 × 200 image

40k hidden units

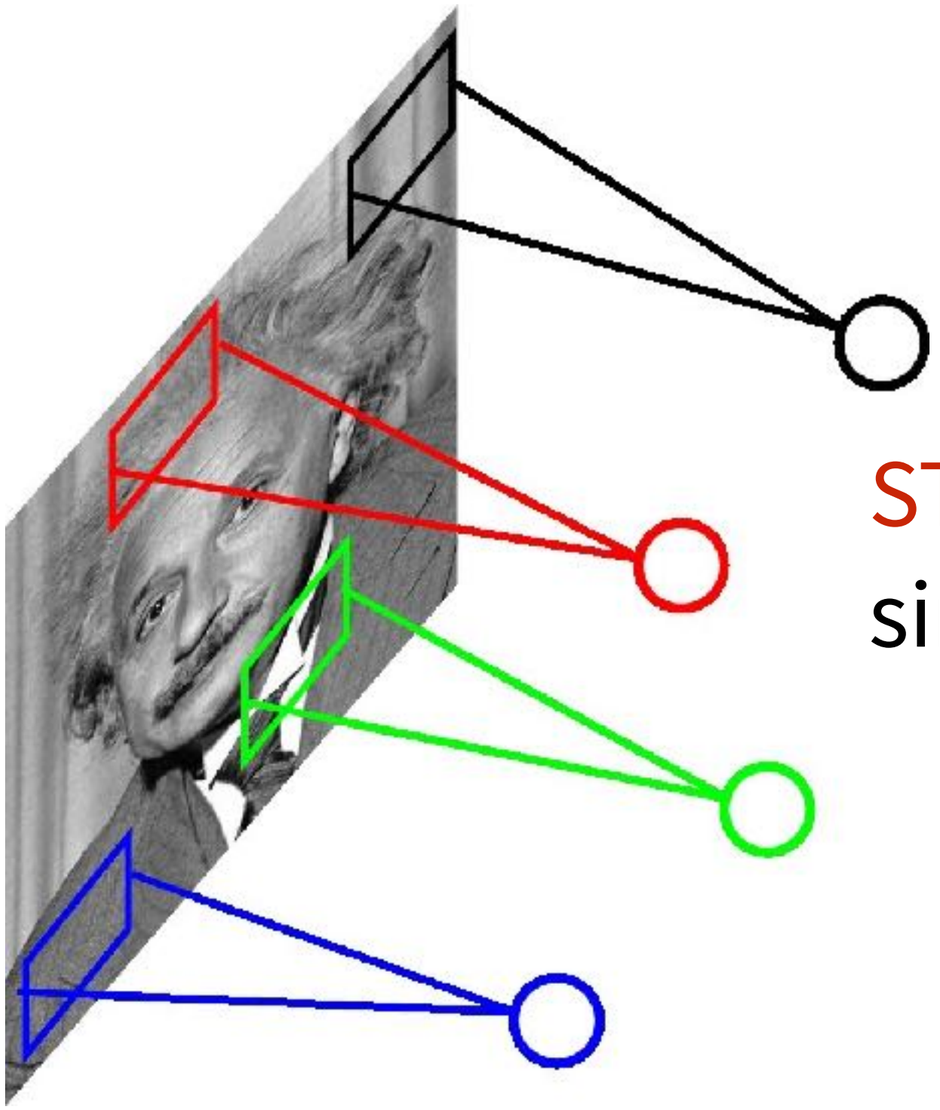
Filter size: 10 × 10

4M parameters

Note: this parameterization is good when the input images are registered (e.g. face recognition)

Credit: Marc'Aurelio Ranzato

Locally-Connected Layer



Example: 200 × 200 image

40k hidden units

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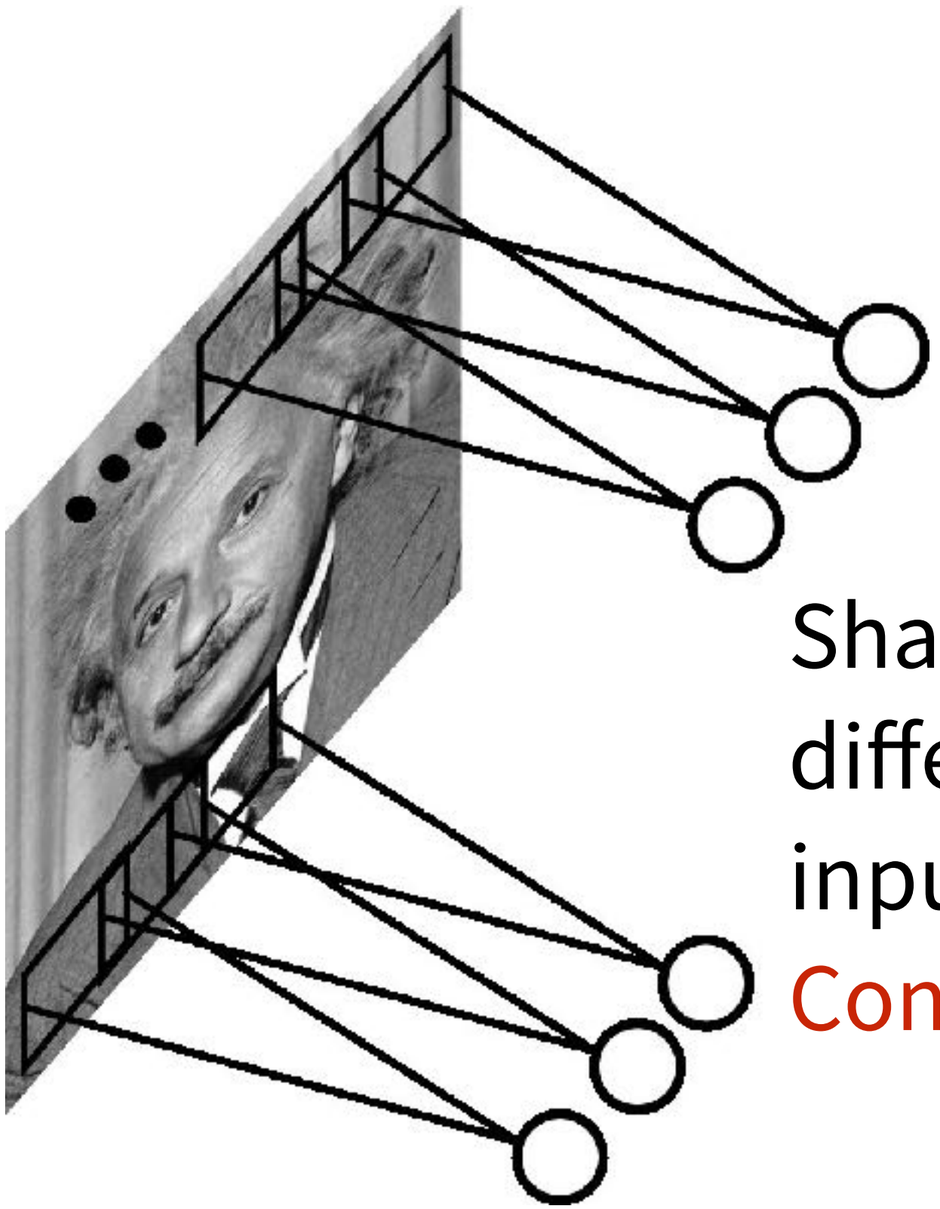
4M parameters

STATIONARITY? Statistics are similar at different locations.

Credit: Marc'Aurelio Ranzato

Weight Sharing



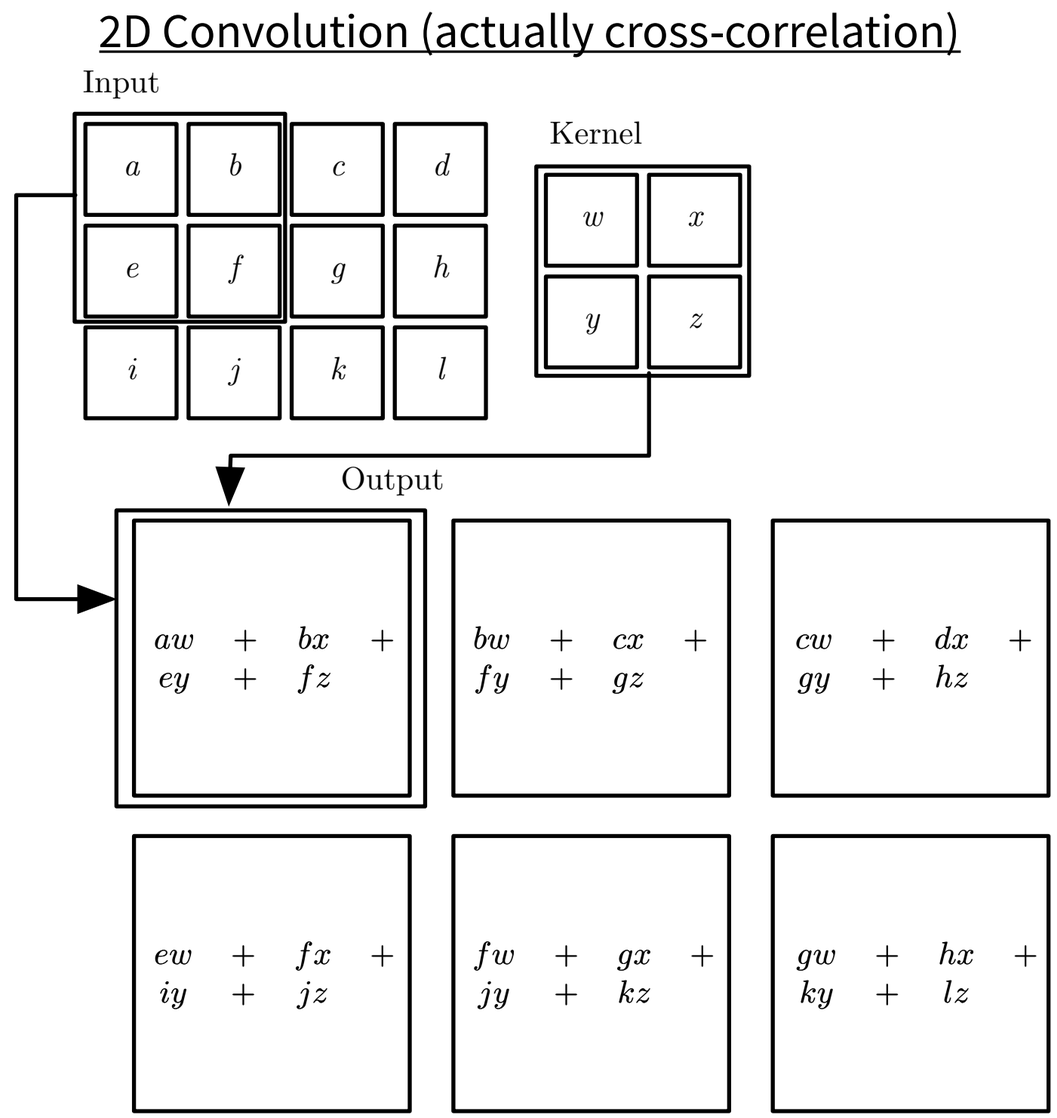
Share the same parameters across different locations (assuming input is stationary)

Convolutions with learned kernels

Credit: Marc'Aurelio Ranzato

What is Convolution?

- Convolution is a specialized kind of linear operation
- Can think of it as a weighted averaging operation in time or space
- For vision, we “convolve” two-dimensional convolution kernels with two-dimensional images:



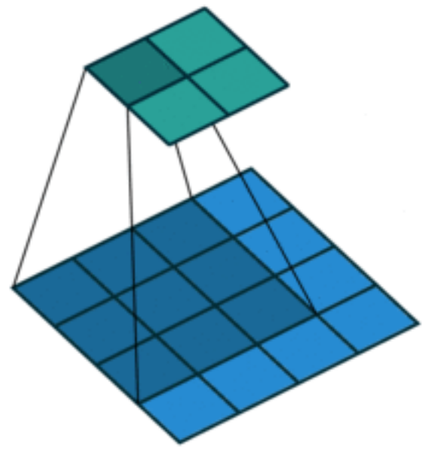
$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(m,n)K(i-m, j-n)$$

Reproduced from Goodfellow et al.

Convolution (Animation)

- Note: hidden units are spatially organized into a “feature map”

- Each hidden unit only receives input from a local region of the input, its “receptive field”



Animation from Vincent Dumoulin
https://github.com/vdumoulin/conv_arithmetic

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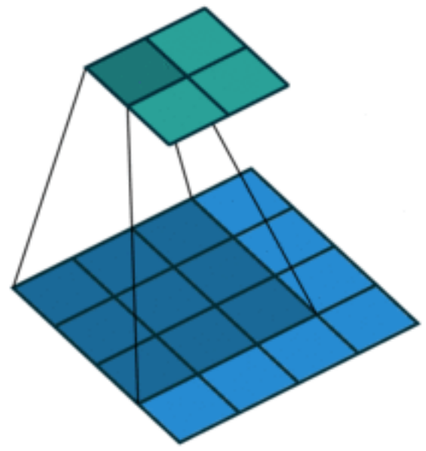

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Convolutional Layer

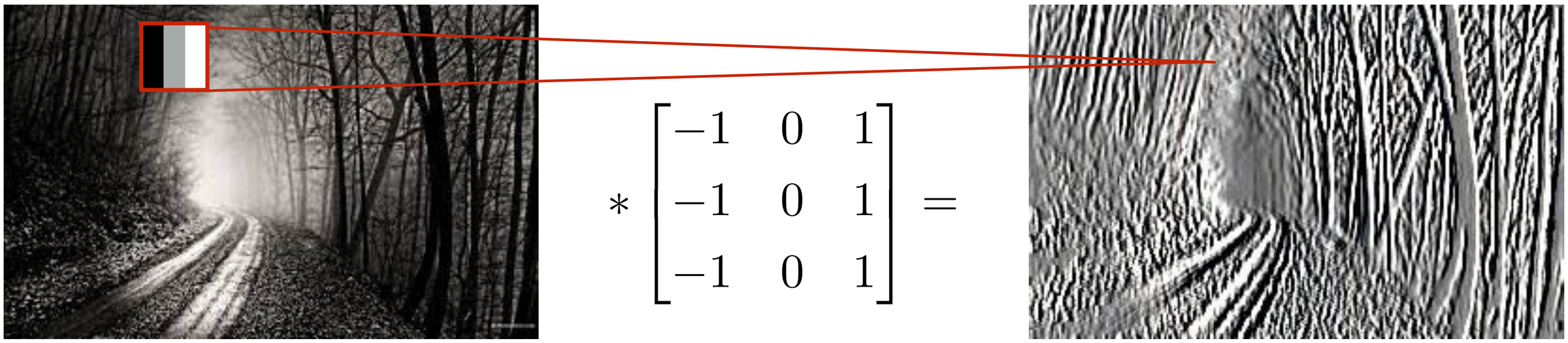


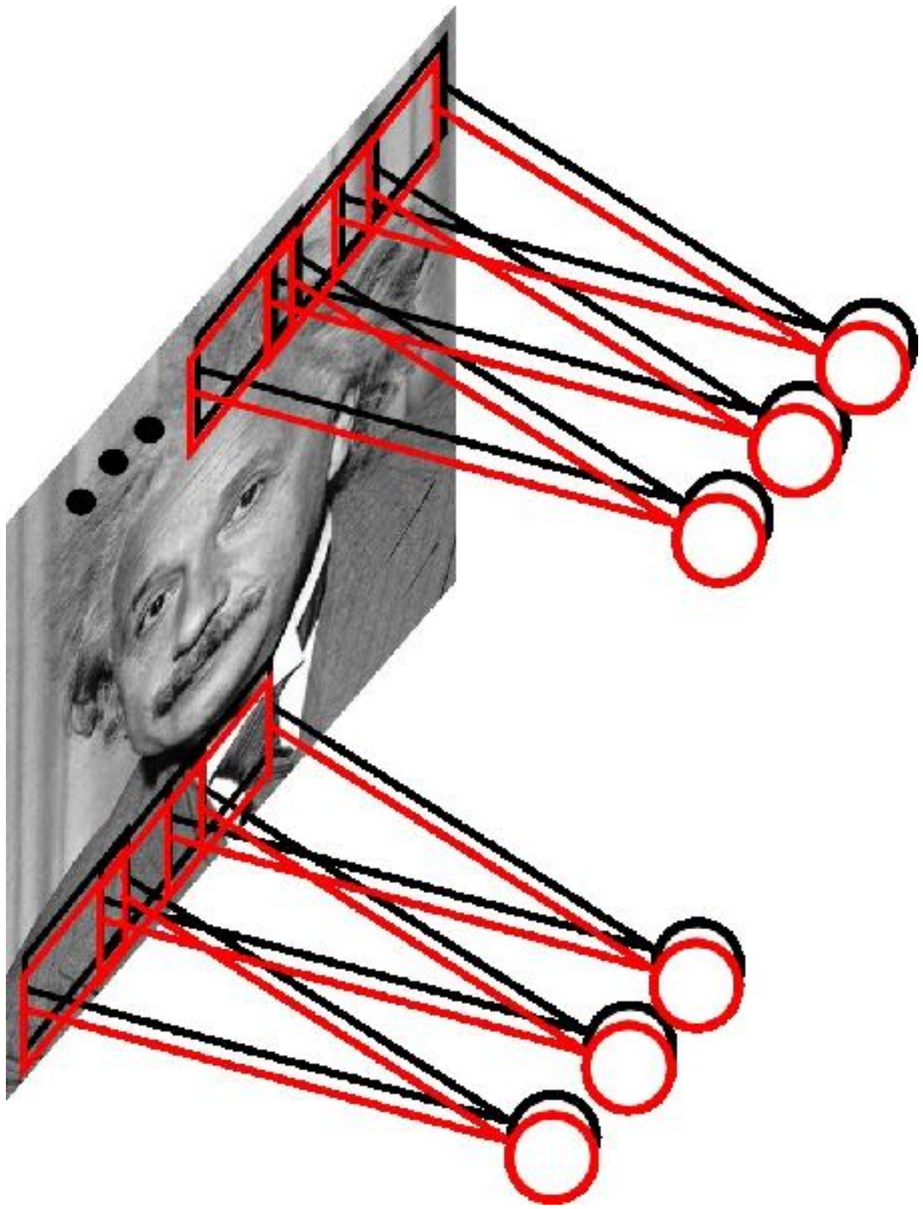
image (input)

convolution kernel

“feature map” (output)

Credit: Marc’Aurelio Ranzato

Convolutional Layer



Learn multiple filters.

Example: 200 × 200 image

100 filters

Filter size: 10 × 10

10k parameters

Credit: Marc'Aurelio Ranzato

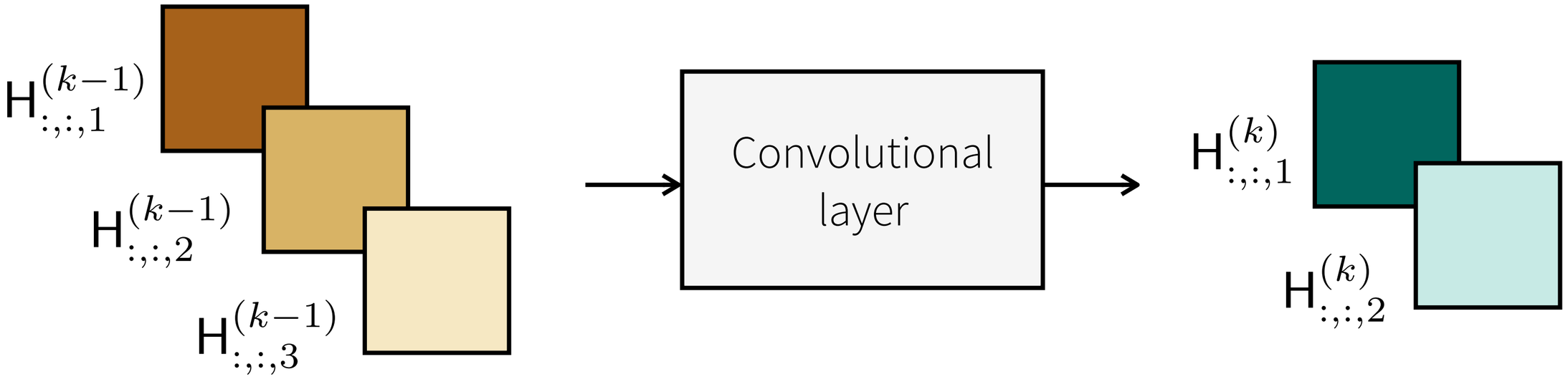
Convolutional Layer

$$\mathrm{H}^{(k)}_{:,:,i} = g\left(\sum_j \mathrm{H}^{(k-1)}_{:,:,j} * \mathrm{W}^{(k)}_{:,:,i,j}\right)$$

output feature map

input feature map

kernel



k indexes layers

i, j index maps (features)

Convolutional Layer

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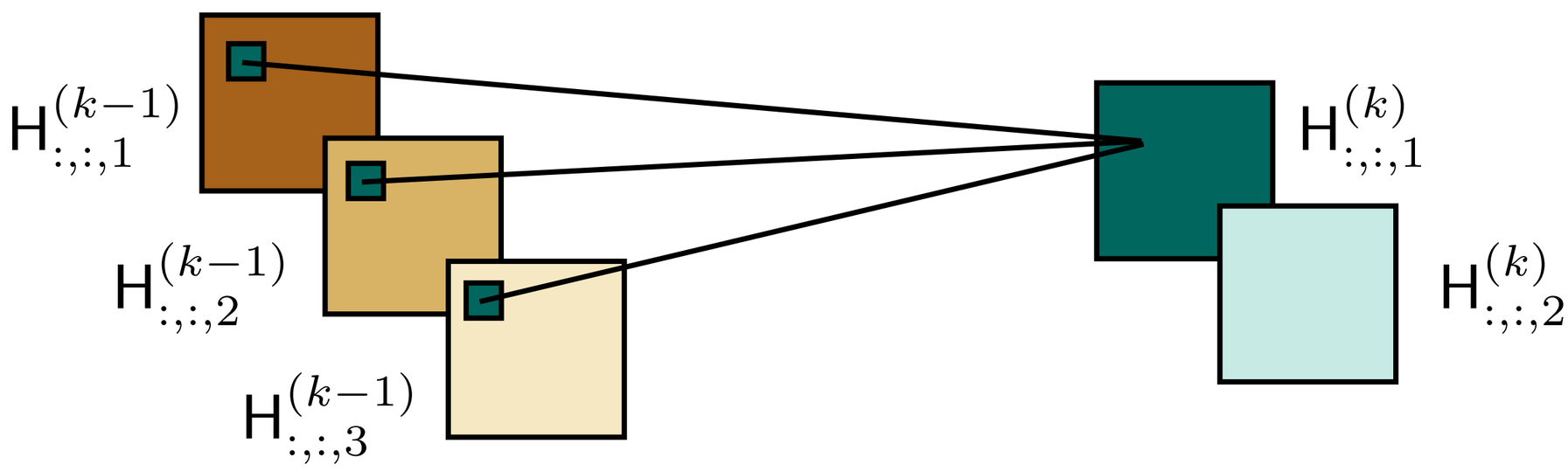

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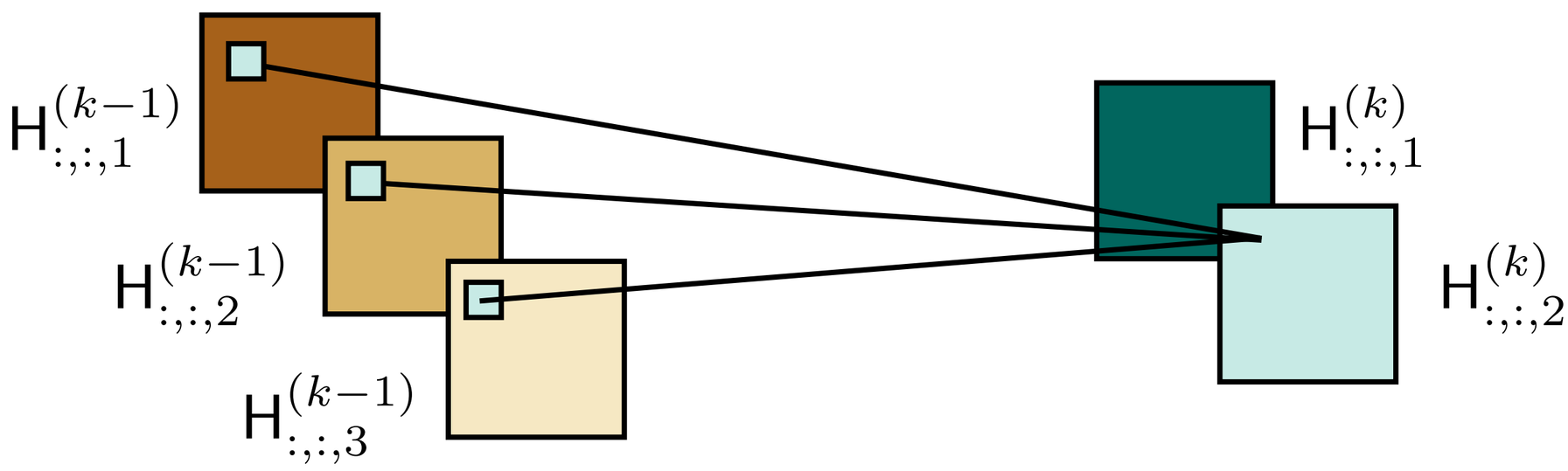
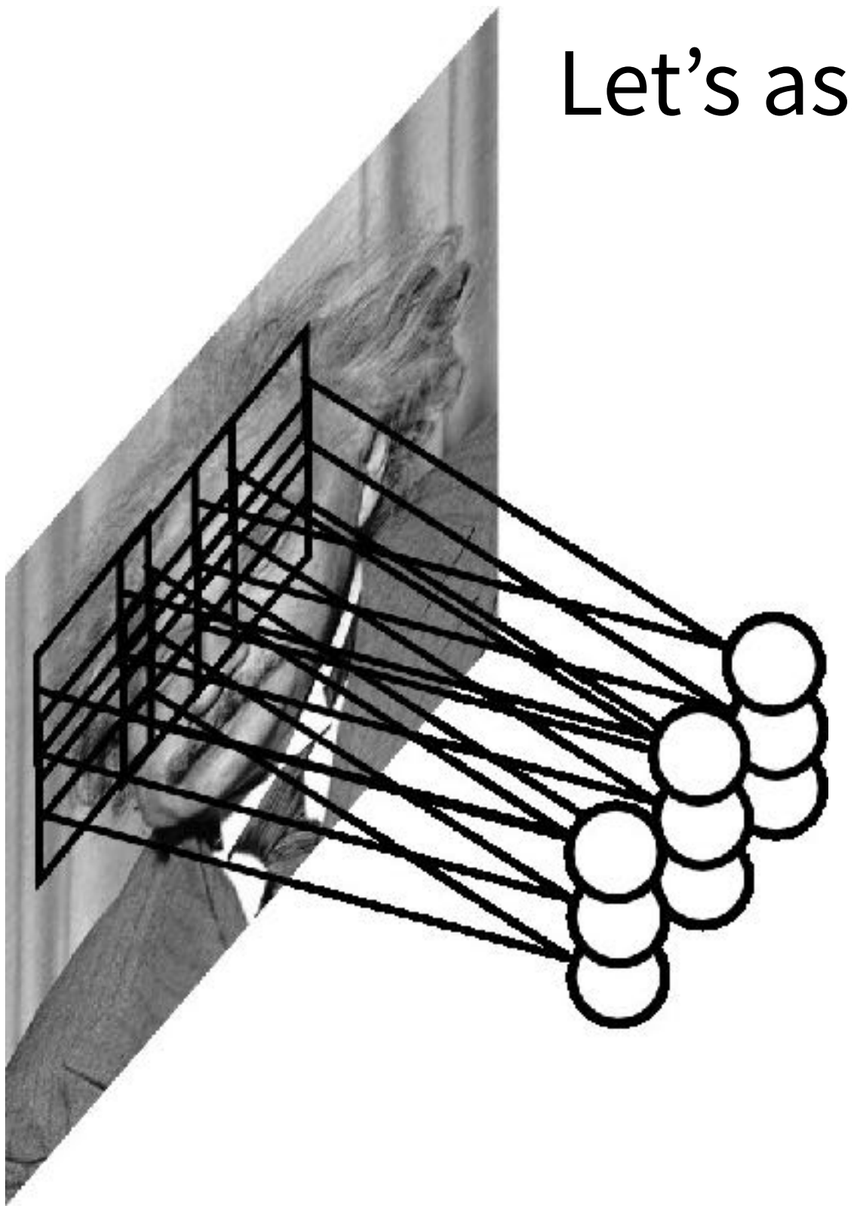


Convolutional Net - Recap

- A fully-connected neural network applied to images
  - scales quadratically with the size of the input
  - does not leverage stationarity
- Solution
  - connect each hidden to a small patch of input
  - share the weights across space
- This is called a convolutional layer
- A network with convolutional layers is called a convolutional net

Credit: Marc'Aurelio Ranzato

Pooling Layer

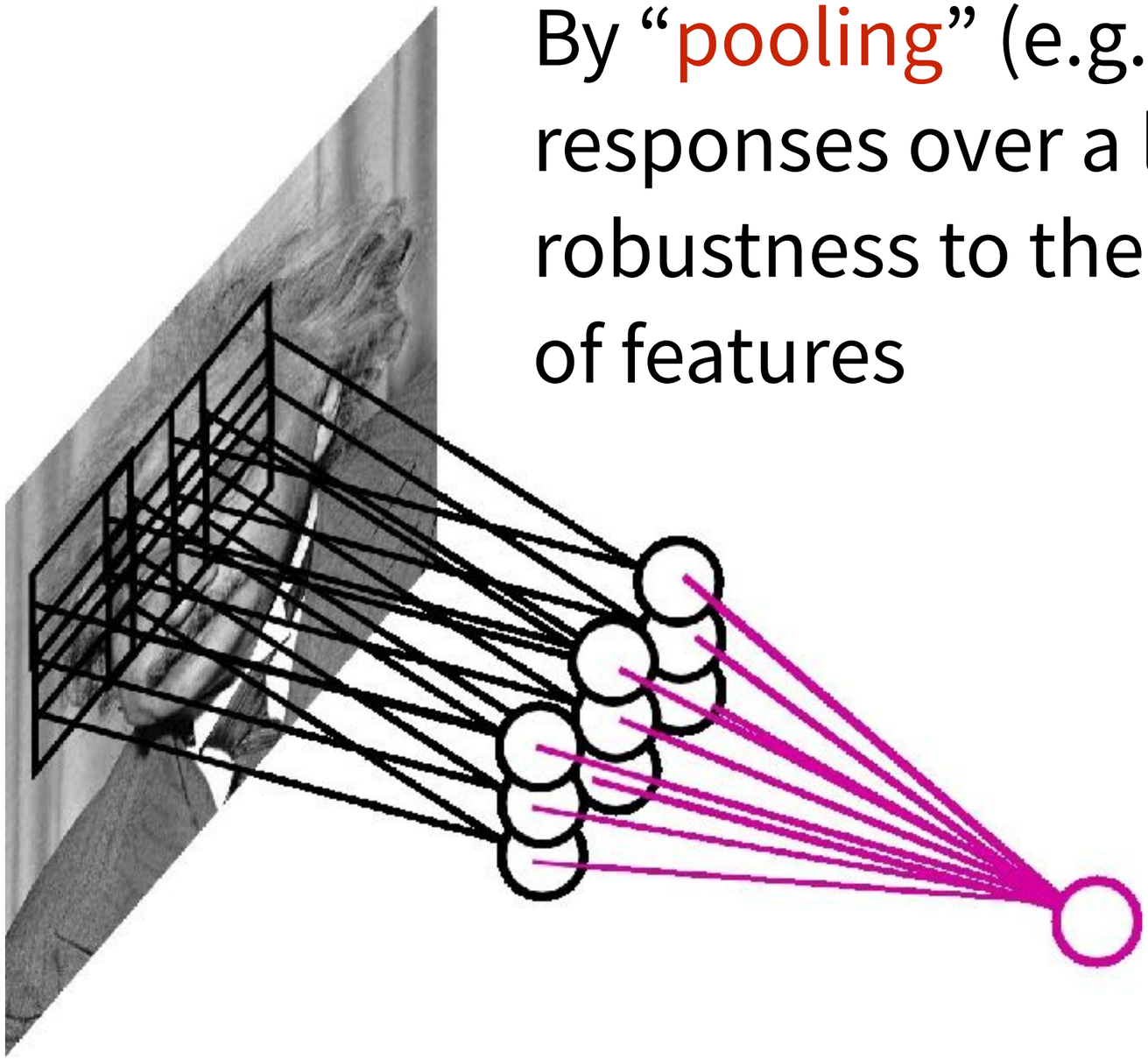


Let’s assume the filter is an “eye” detector

How can we make the detection robust to the exact location of the eye?

Credit: Marc’Aurelio Ranzato

Pooling Layer



By “pooling” (e.g. taking max) the filter responses over a local region we gain robustness to the exact spatial location of features

“Shift invariance”

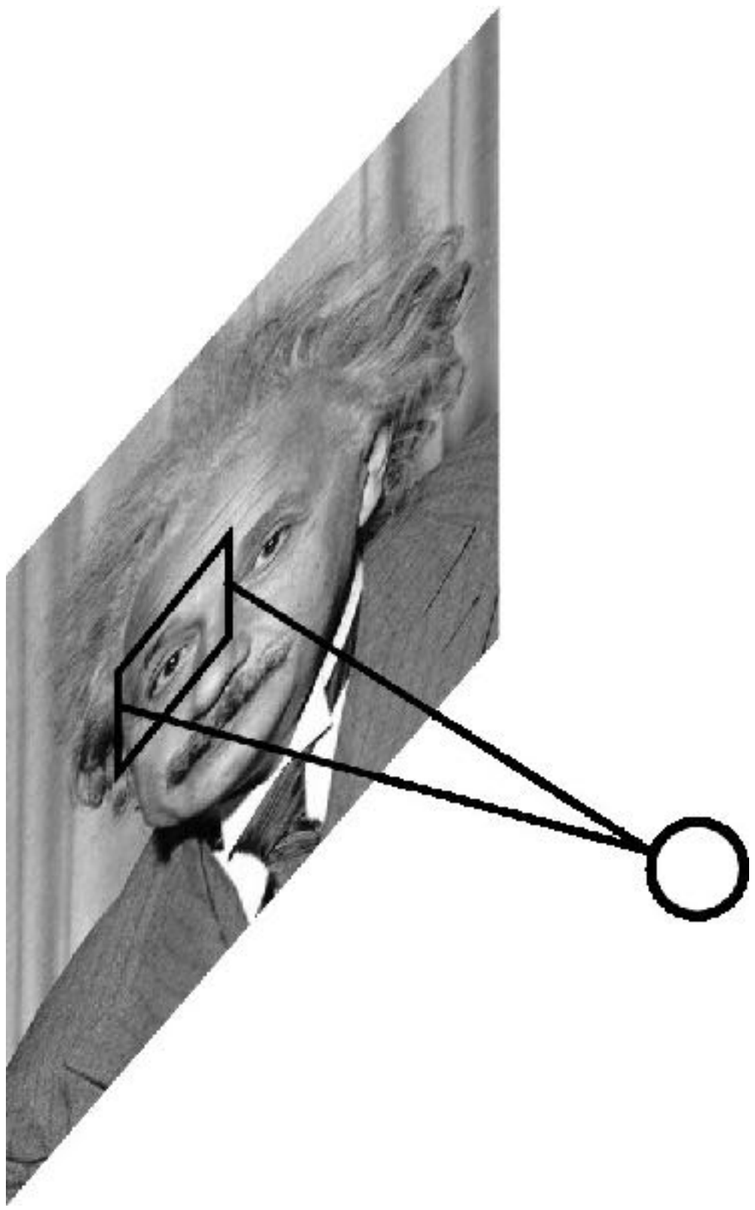
Credit: Marc’Aurelio Ranzato

Types of Pooling

Max-Pooling	$\mathsf{H}^{(k)}_{m,n,i} = \max_{m' \in \mathbb{N}(m), n' \in \mathbb{N}(n)} \mathsf{H}^{(k-1)}_{m',n',i}$
Average-Pooling	$\mathsf{H}^{(k)}_{m,n,i} = \frac{1}{\lvert\mathbb{N}(m)\rvert\lvert\mathbb{N}(n)\rvert} \sum_{m' \in \mathbb{N}(m), n' \in \mathbb{N}(n)} \mathsf{H}^{(k-1)}_{m',n',i}$
L2-Pooling	$\mathsf{H}^{(k)}_{m,n,i} = \sqrt{\sum_{m' \in \mathbb{N}(m), n' \in \mathbb{N}(n)} \left(\mathsf{H}^{(k-1)}_{m',n',i}\right)^2}$
L2-Pooling Over Features	$\mathsf{H}^{(k)}_{m,n,i} = \sqrt{\sum_{j \in \mathbb{N}(i)} \left(\mathsf{H}^{(k-1)}_{m,n,j}\right)^2}$

Credit: Marc'Aurelio Ranzato

Local Contrast Normalization



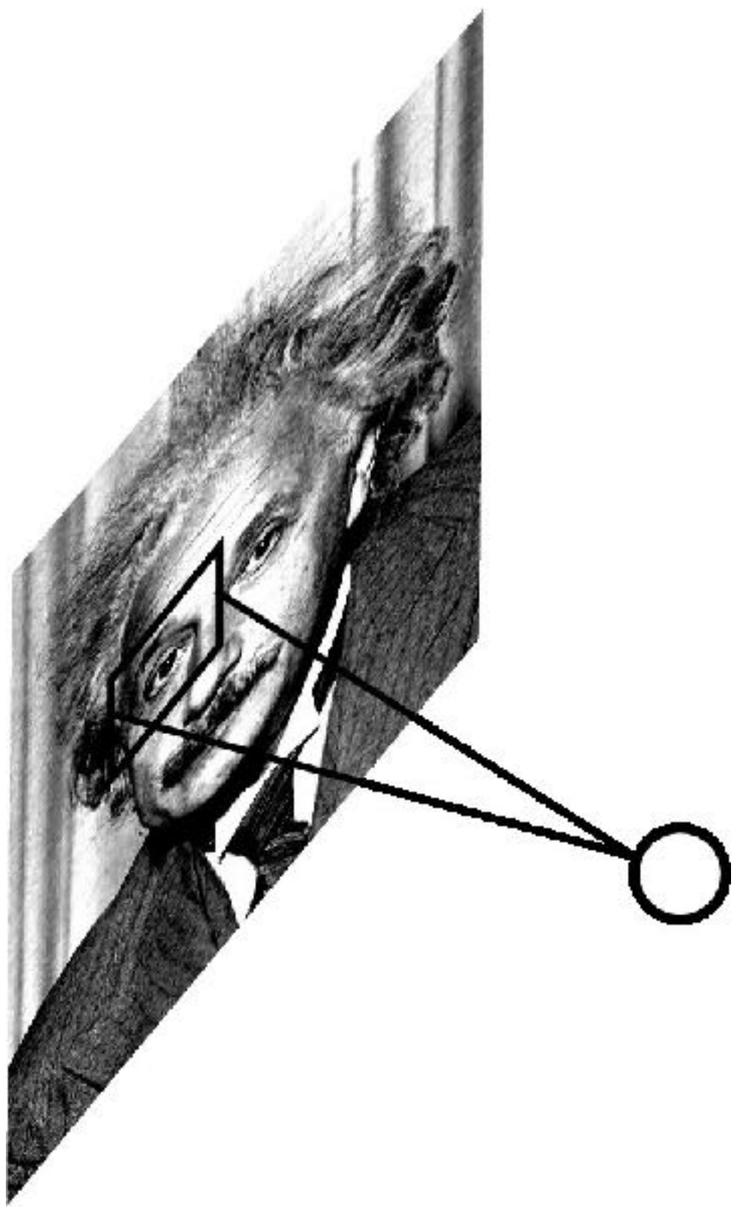
$$\mathsf{H}^{(k)}_{m,n,i} = \frac{\mathsf{H}^{(k-1)}_{m,n,i} - \mathsf{M}^{(k-1)}_{m,n,i}}{\mathsf{S}^{(k-1)}_{m,n,i}}$$

$\mathsf{M}^{(k)}_{m,n,i}$ mean of a local neighbourhood around pixels m, n

$\mathsf{S}^{(k)}_{m,n,i}$ standard deviation of a local neighbourhood around pixels m, n

Credit: Marc'Aurelio Ranzato

Local Contrast Normalization



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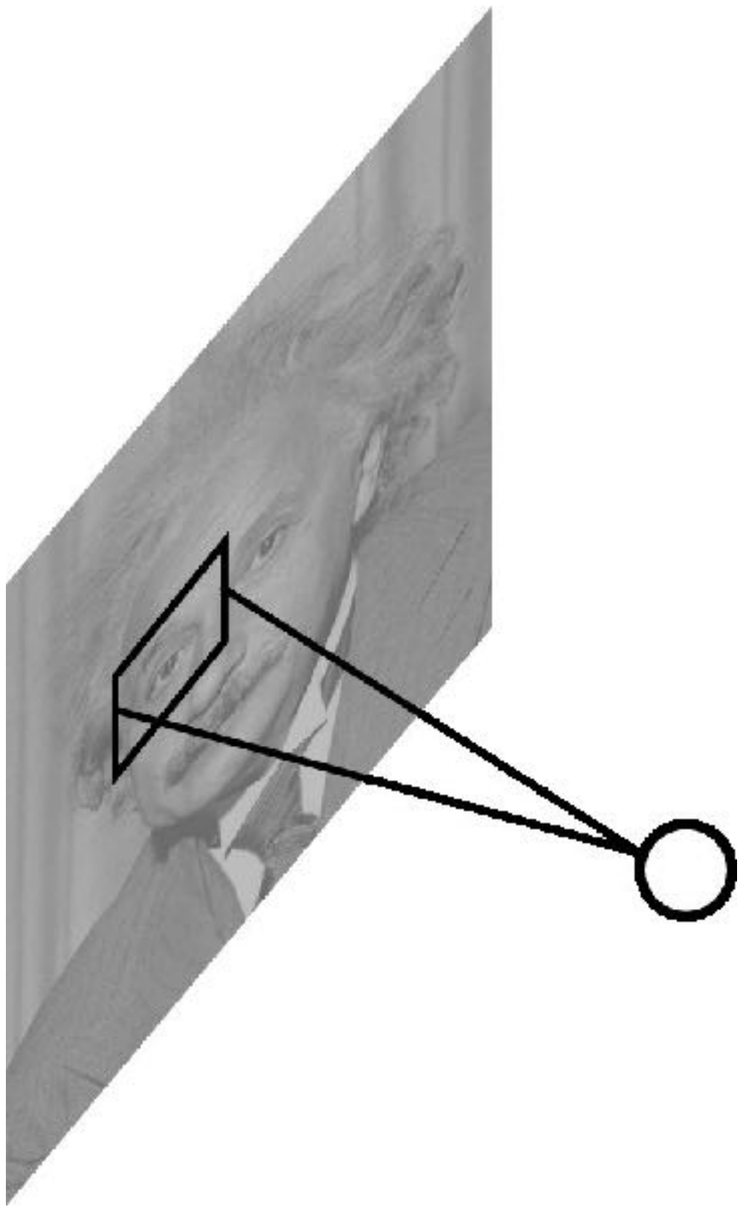
Controls the dynamic range of each feature map.

Credit: Marc'Aurelio Ranzato

Local Contrast Normalization



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Performed also across features and in the higher layers…
Effects:

- improves invariance
- improves optimization
- increases sparsity

Note: computational cost is negligible compared to convolutional layer.

Credit: Marc'Aurelio Ranzato

Convnets: Single Stage

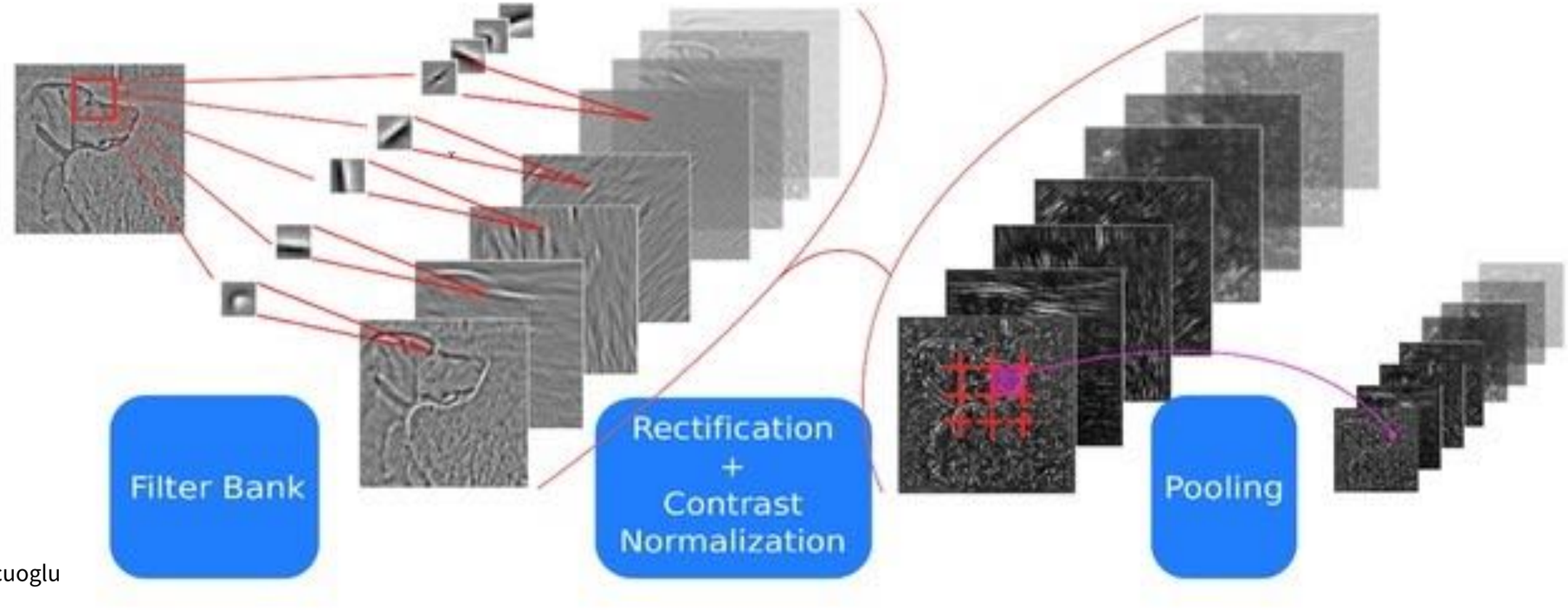


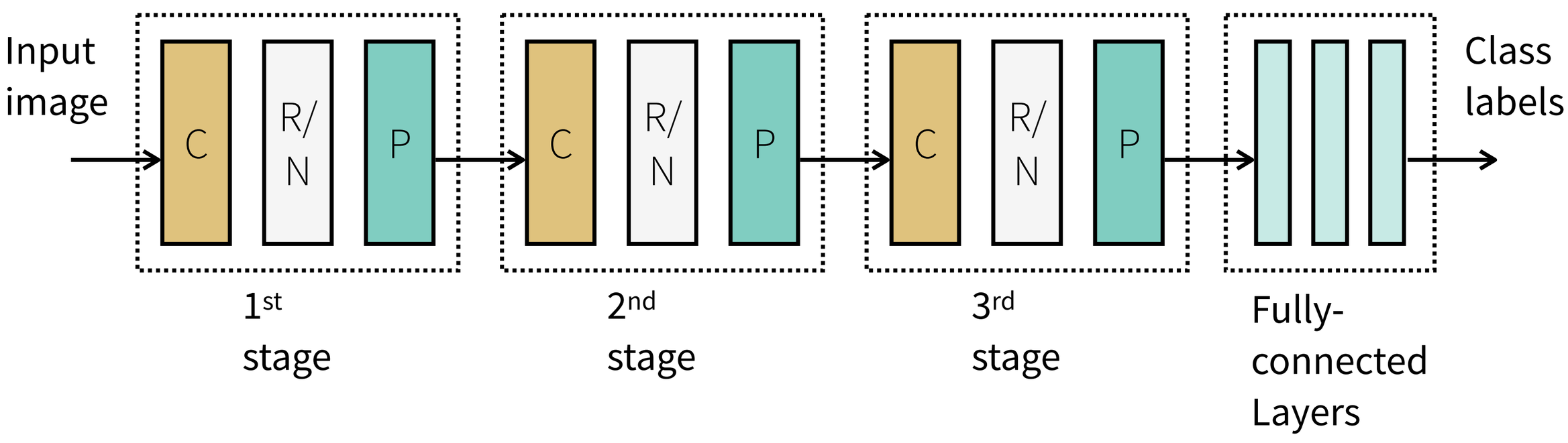
Image credit: Koray Kavukcuoglu

Credit: Marc'Aurelio Ranzato

Convnets: Typical Architecture

Single stage

Whole system



Credit: Marc'Aurelio Ranzato

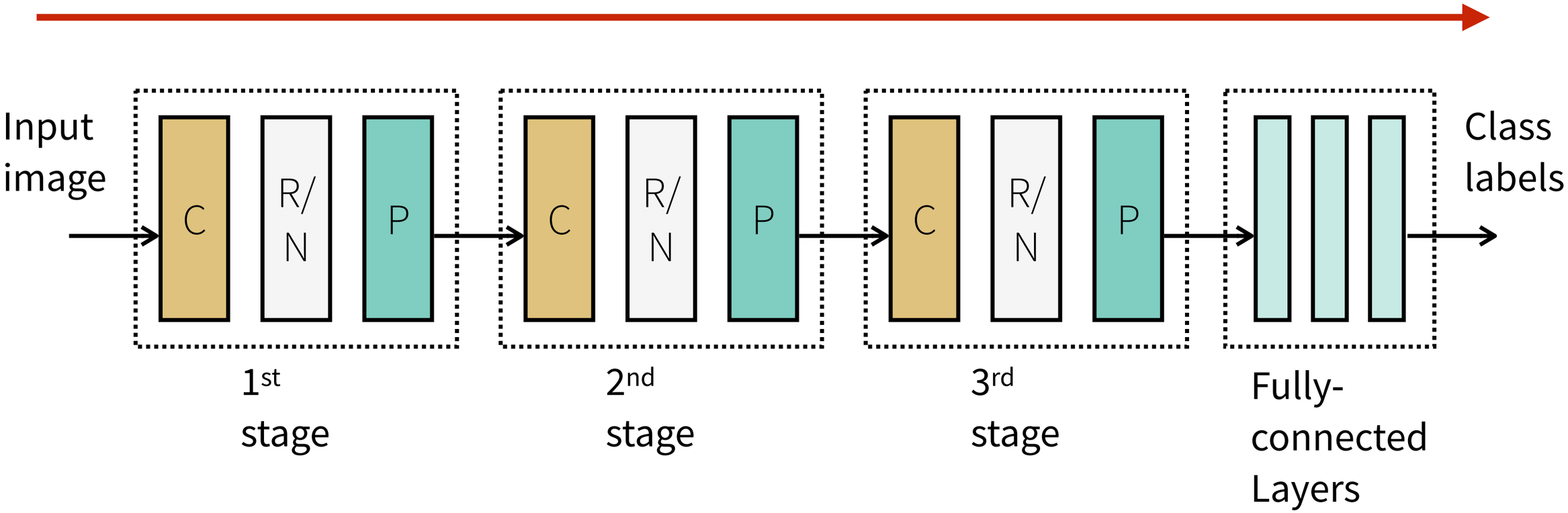
Convnets: Training

- All layers are differentiable
- We can use standard back-propagation
- Algorithm:
  - Given a small mini-batch:
    - F-Prop
    - B-Prop
    - Parameter updates

Credit: Marc'Aurelio Ranzato

Convnets: Testing

At test time, only run forward propagation



Convnets can naturally process larger images at little cost.
Traditional methods use inefficient sliding windows.

Credit: Marc'Aurelio Ranzato

Convnets: today

- Until 2012, the common wisdom was that training didn't work because we would "get stuck in local minima"
- Local minima are all similar, there are long plateaus, and it can take a long time to break symmetries
- Optimization is not the real problem, when:
  - the dataset is large
  - units do not saturate much
  - we use normalization layers

Credit: Marc'Aurelio Ranzato

Scalability

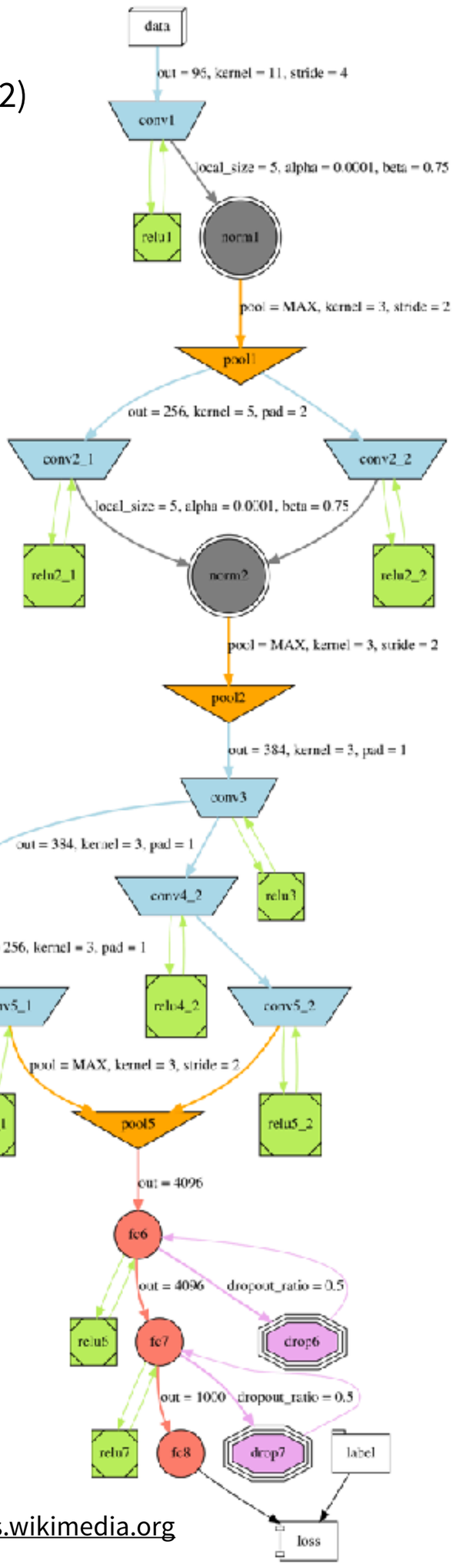
- The real challenges are:
  - Generalization
    - How many training examples to fit 1B params?
    - How many parameters/samples to model spaces with 1M dimensions?
  - Scalability

Credit: Marc'Aurelio Ranzato

Profile: AlexNet

(Krizhevsky et al. 2012)

- First work to popularize DNNs in vision
- Astonishing result on ILSVRC 2012 (16% top-5 error compared to 26% for runner-up)
- Similar to early LeNet architectures but deeper, bigger, and stacked convolutional layers (without pooling)
- Uses dropout regularization
- Optimized for 2 GPUs



via commons.wikimedia.org

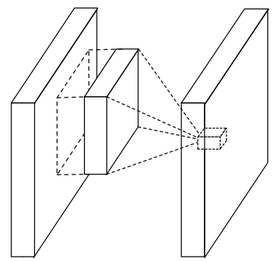
(Lin et al. 2013)

Profile: Network-in-Network

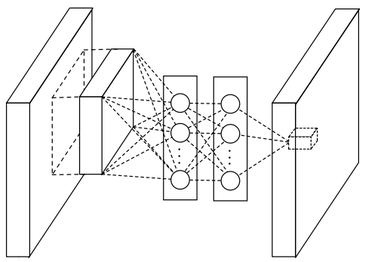
Not an ILSVRC competitor, this paper proposed a number of novel ideas which were utilized by later architectures:

- Replaces linear convolution layer with a “micro network” structure which is a general nonlinear operation
- Noting that fully connected layers are prone to overfitting, proposed “Global Average Pooling”

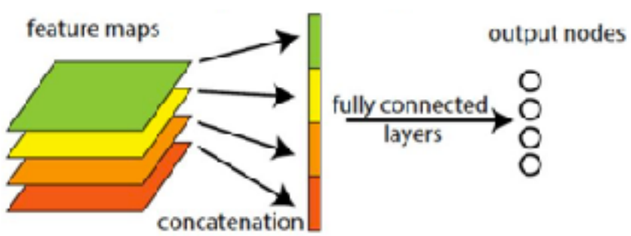
Linear convolution layer



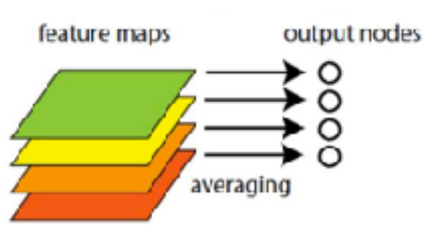
Mlpconv layer



CNN



GAP

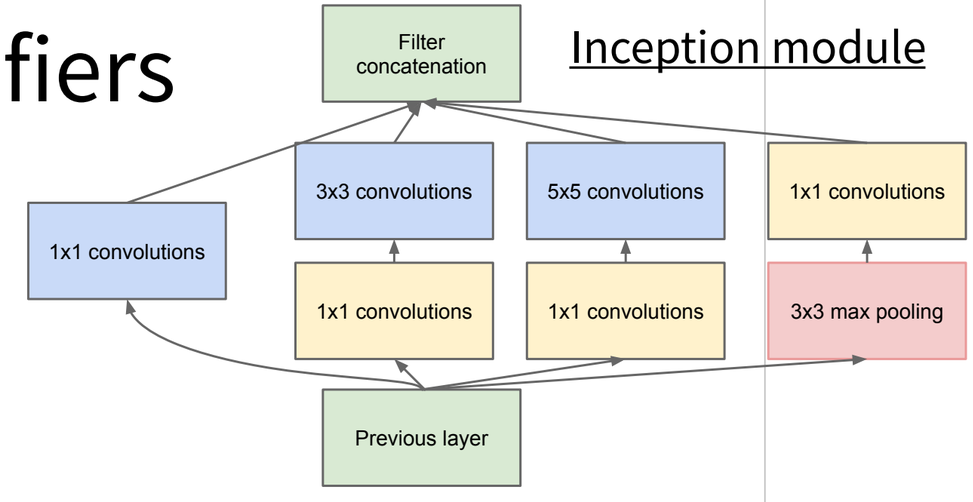


via Lin et al., caffecn.cn

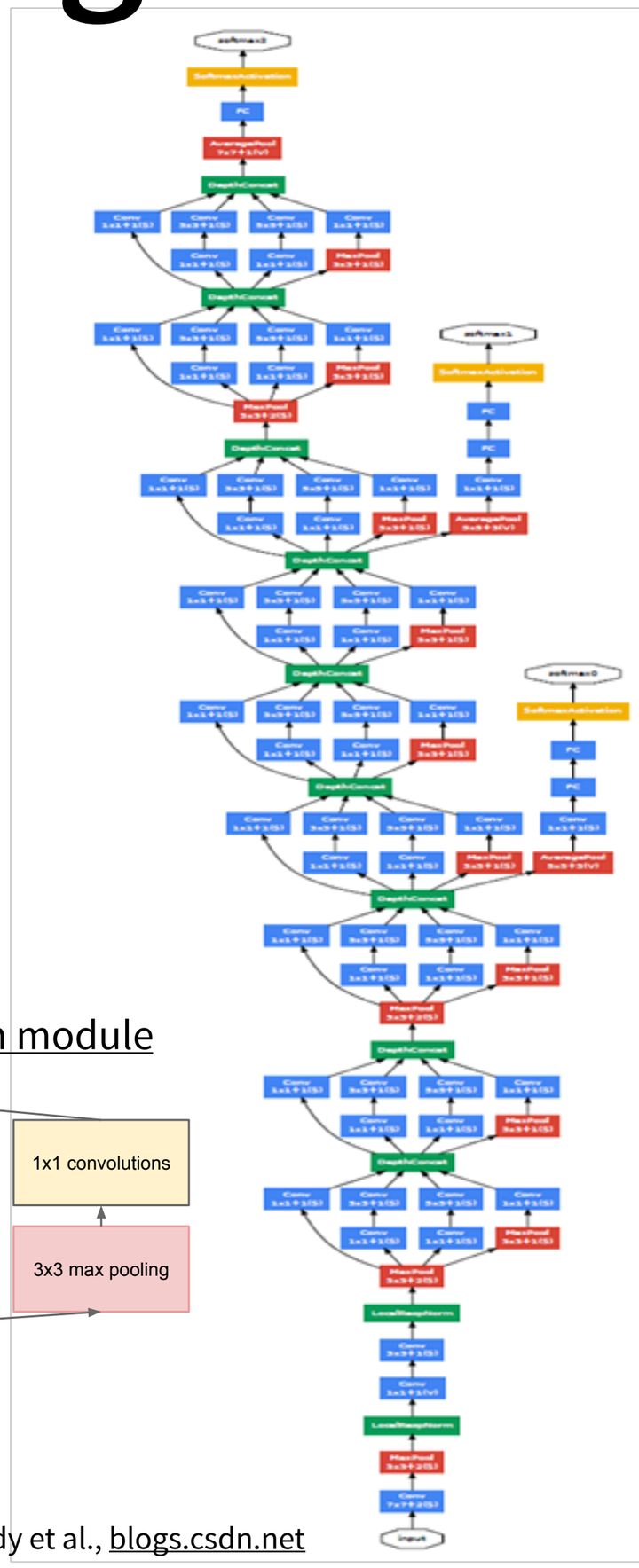
(Szegedy et al. 2015)

Profile: Inception/GoogLeNet

- Winner of ILSVRC 2014
- Main contribution is the “Inception Module” that dramatically reduced the number of parameters in the network (4M compared to 60M for AlexNet)
- Uses auxillary classifiers



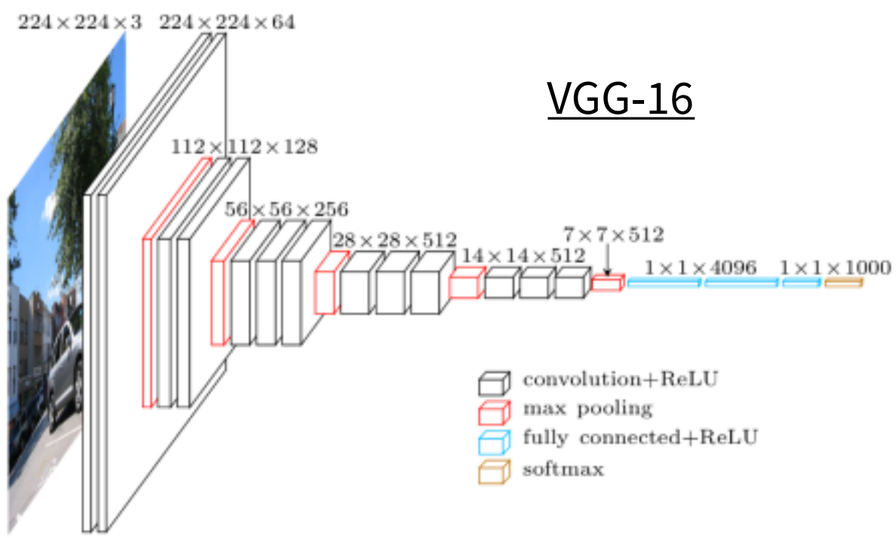
Inception module



via Szegedy et al., blogs.csdn.net

Profile: VGGNet (Simonyan and Zisserman 2014)

- Runner-up to ILSVRC 2014
- Main contribution: showing that depth of the network is a critical component for good performance (16 CONV/FC layers)
- Extremely homogeneous architecture that only performs 3x3 convolutions and 2x2 pooling from beginning to end
- Expensive to evaluate, uses a lot of memory and has 140M parameters



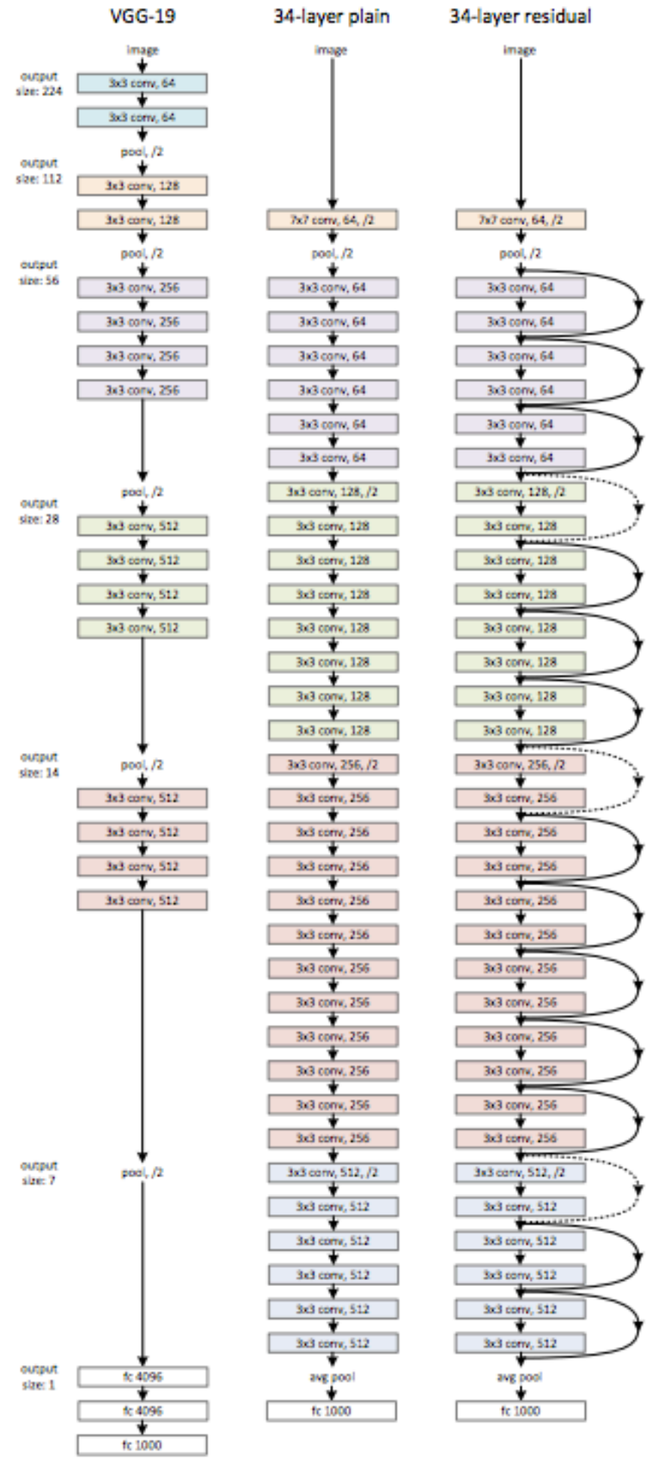
VGG-16

via Alexis Cook

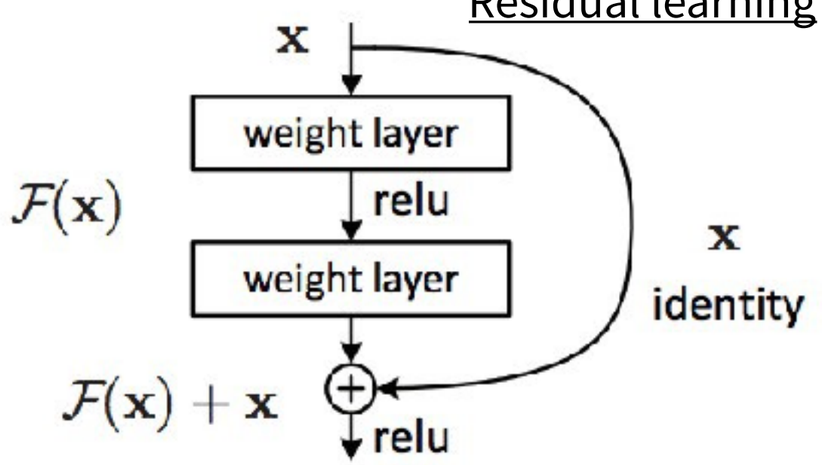
Profile: ResNet

(He et al. 2015)

- Winner of ILSVRC 2015
- It features special skip connections and heavy use of batch normalization
- The architecture is also missing fully connected layers at the end of the network (note use of GAP)
- Winning network had 152 layers; 1000-layer models have been trained

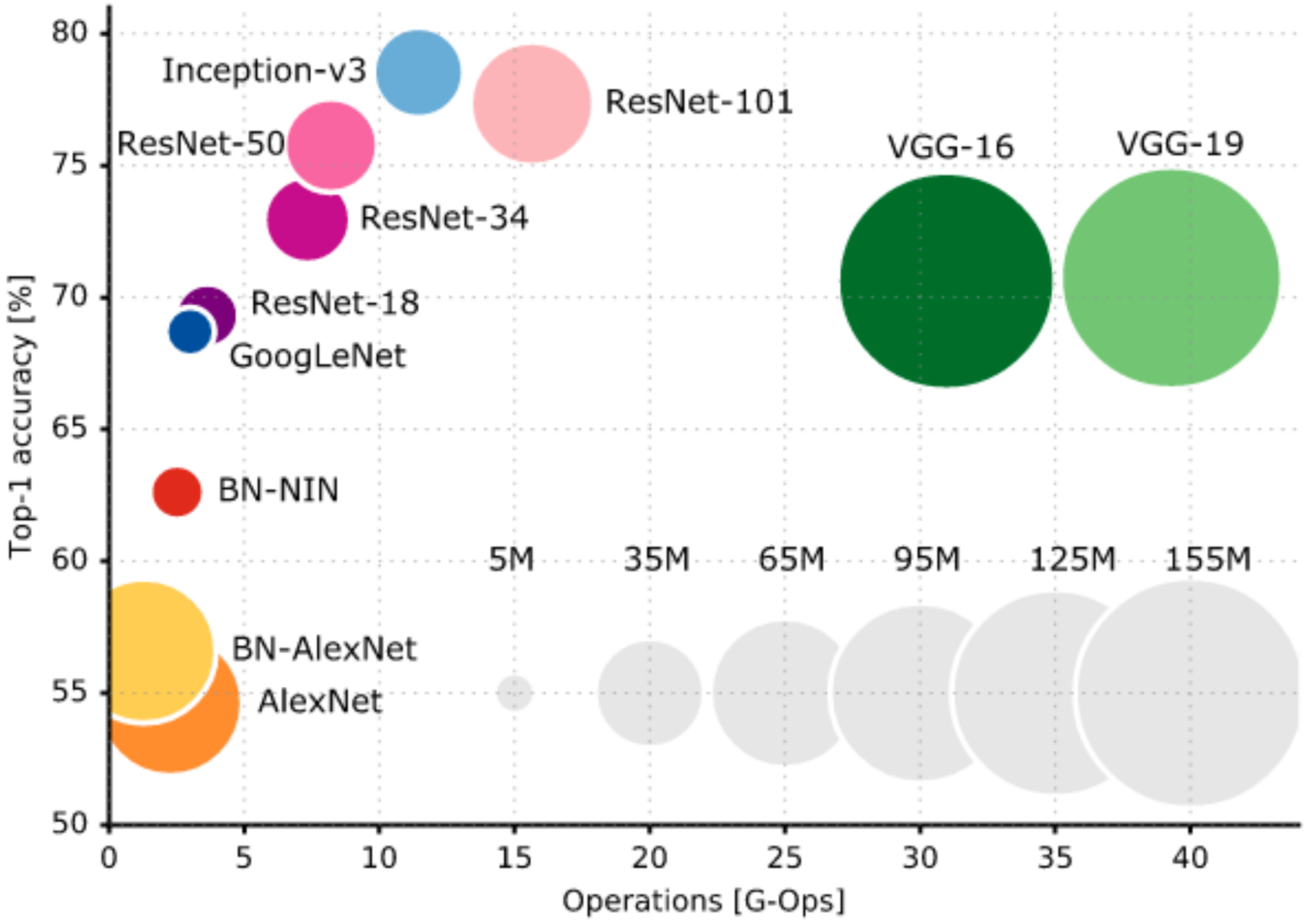


Residual learning



via He et al.

Modern Architectures



Eugenio Culurciello's blog:
https://culurciello.github.io/tech/2016/06/04/nets.html