

10707

Deep Learning

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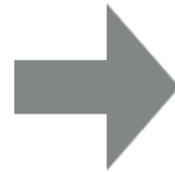
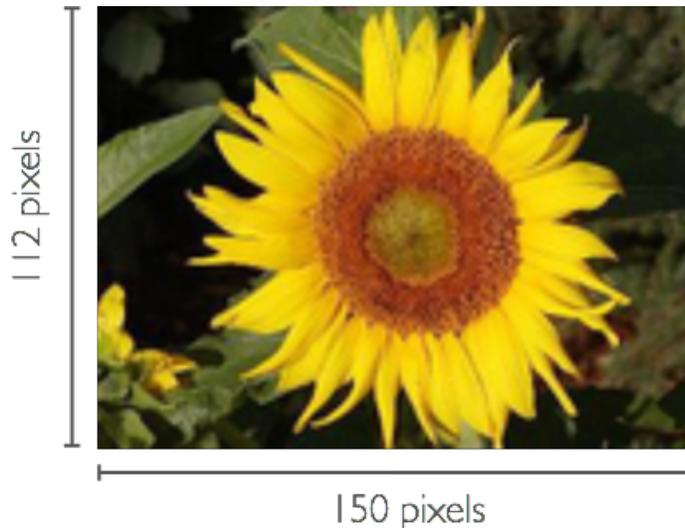
Convolutional Networks I

Used Resources

- **Disclaimer:** Much of the material in this lecture was borrowed from Hugo Larochelle's class on Neural Networks:
<https://sites.google.com/site/deeplearningsummerschool2016/>
- Some tutorial slides were borrowed from Rob Fergus' CIFAR tutorial on ConvNets:
<https://sites.google.com/site/deeplearningsummerschool2016/speakers>
- Some slides were borrowed from Marc'Aurelio Ranzato's CVPR 2014 tutorial on Convolutional Nets
<https://sites.google.com/site/lsvrtutorialcvpr14/home/deeplearning>

Computer Vision

- Design algorithms that can process visual data to accomplish a given task:
 - For example, **object recognition**: Given an input image, identify which object it contains



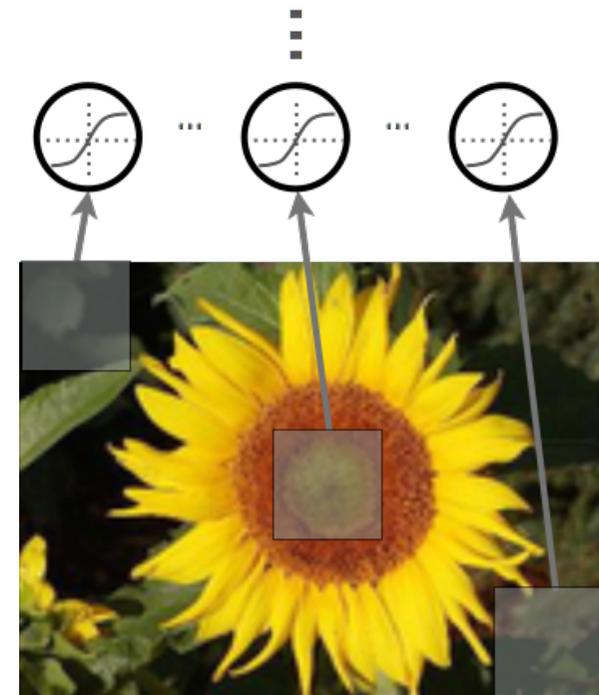
"sun flower"

Computer Vision

- Our goal is to design neural networks that are specifically adapted for such problems
 - Must deal with very **high-dimensional inputs**: 150 x 150 pixels = 22500 inputs, or 3 x 22500 if RGB pixels
 - Can exploit the **2D topology** of pixels (or 3D for video data)
 - Can build in **invariance** to certain variations: translation, illumination, etc.
- **Convolutional networks** leverage these ideas
 - Local connectivity
 - Parameter sharing
 - Convolution
 - Pooling / subsampling hidden units

Local Connectivity

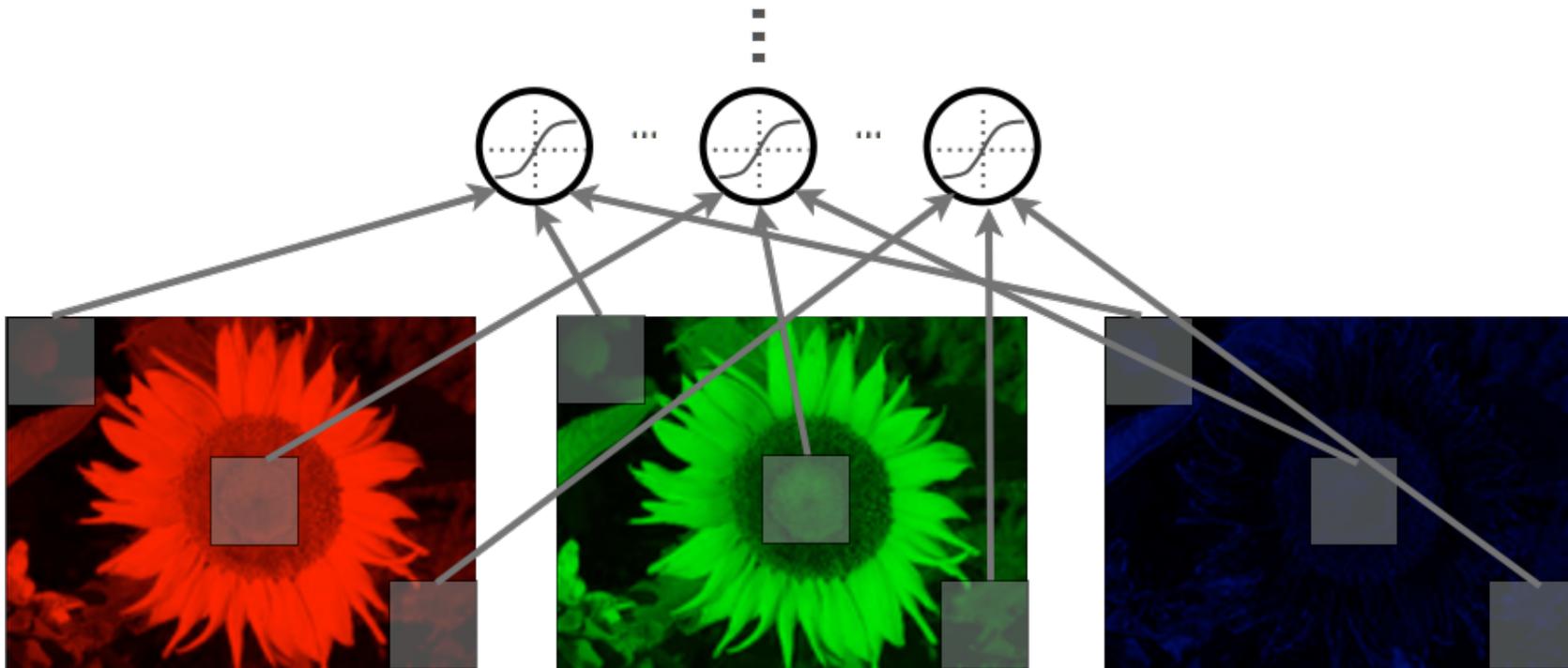
- Use a **local connectivity** of hidden units
 - Each hidden unit is connected only to a sub-region (patch) of the input image
 - It is connected to all channels: 1 if grayscale, 3 (R, G, B) if color image
- Why local connectivity?
 - Fully connected layer has **a lot of parameters** to fit, requires a lot of data
 - Spatial correlation is local



r  = receptive field

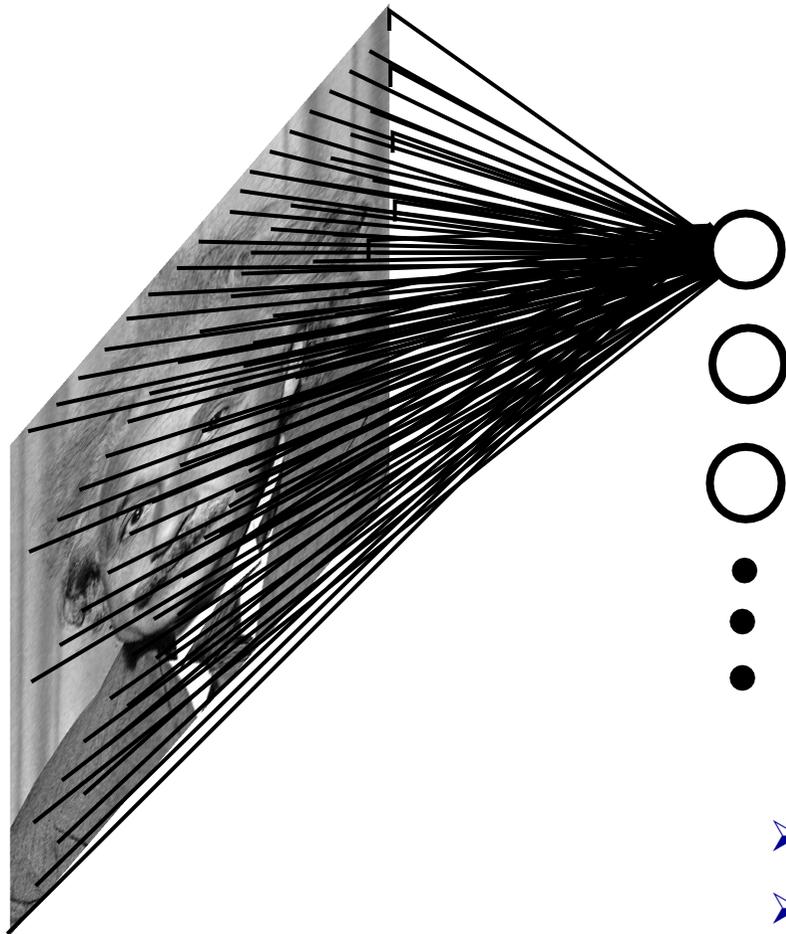
Local Connectivity

- Units are connected to all channels:
 - 1 channel if grayscale image,
 - 3 channels (R, G, B) if color image



Local Connectivity

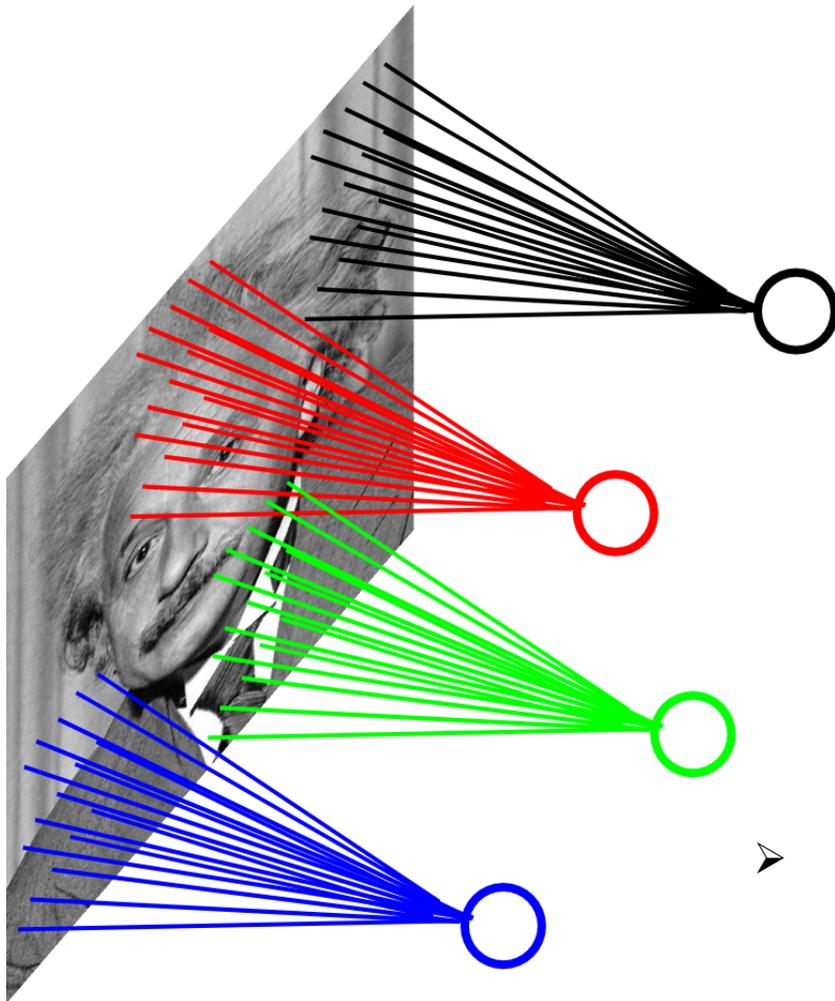
- Example: 200x200 image, 40K hidden units, **~2B parameters!**



- Spatial correlation is local
- Too many parameters, will require a lot of training data!

Local Connectivity

- **Example:** 200x200 image, 40K hidden units, filter size 10x10, 4M parameters!



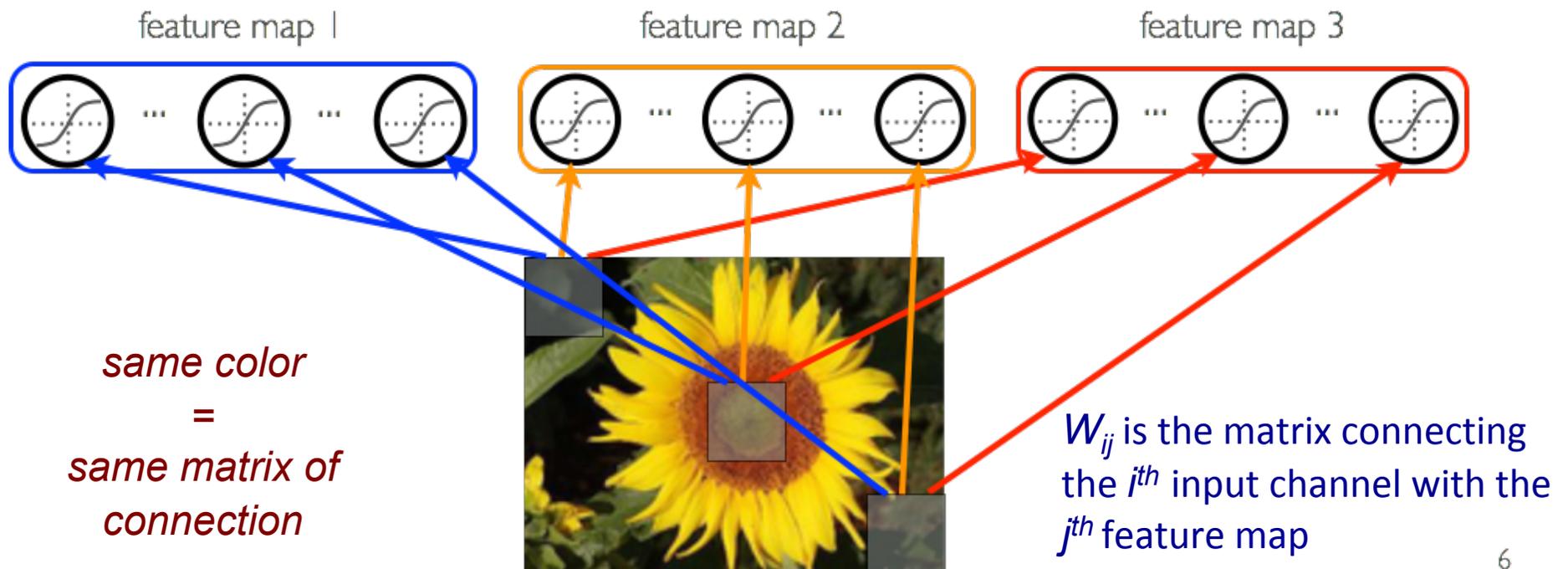
➤ This parameterization is good when input **image is registered**

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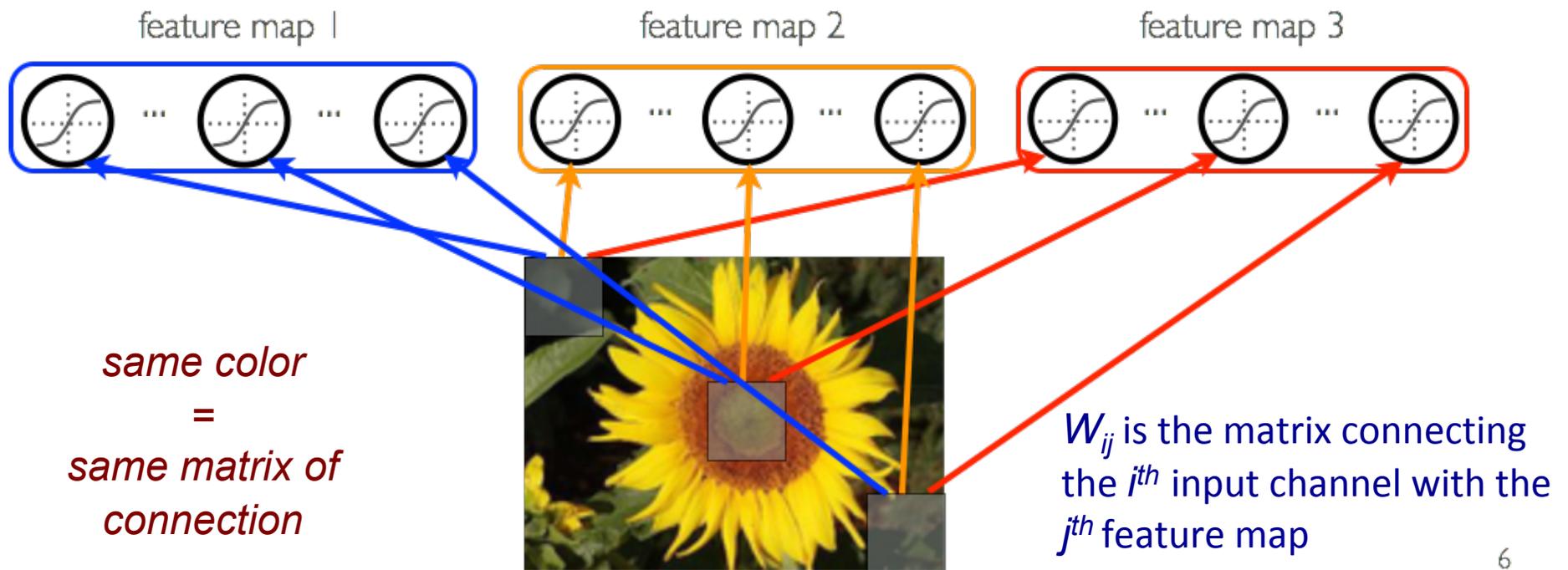
Parameter Sharing

- Share matrix of parameters across some units
 - Units that are organized into the ‘feature map’ share parameters
 - Hidden units within a feature map cover different positions in the image



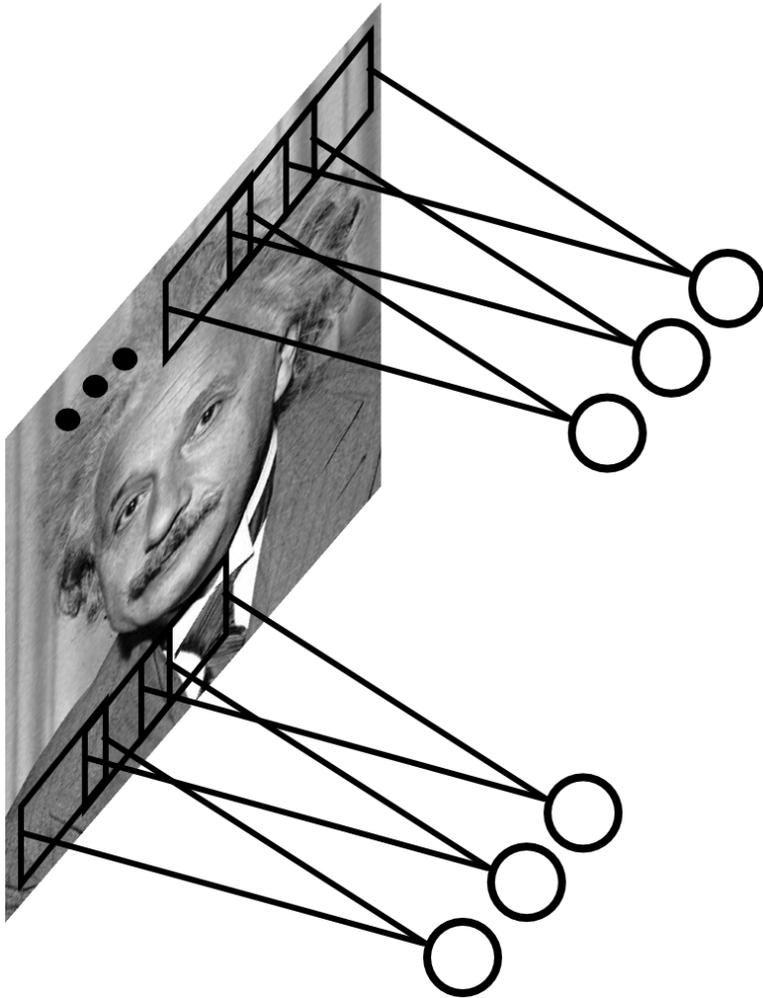
Parameter Sharing

- Why parameter sharing?
 - Reduces even more the number of parameters
 - Will extract the same features at every position (features are “equivariant”)



Parameter Sharing

- Share matrix of parameters across certain units



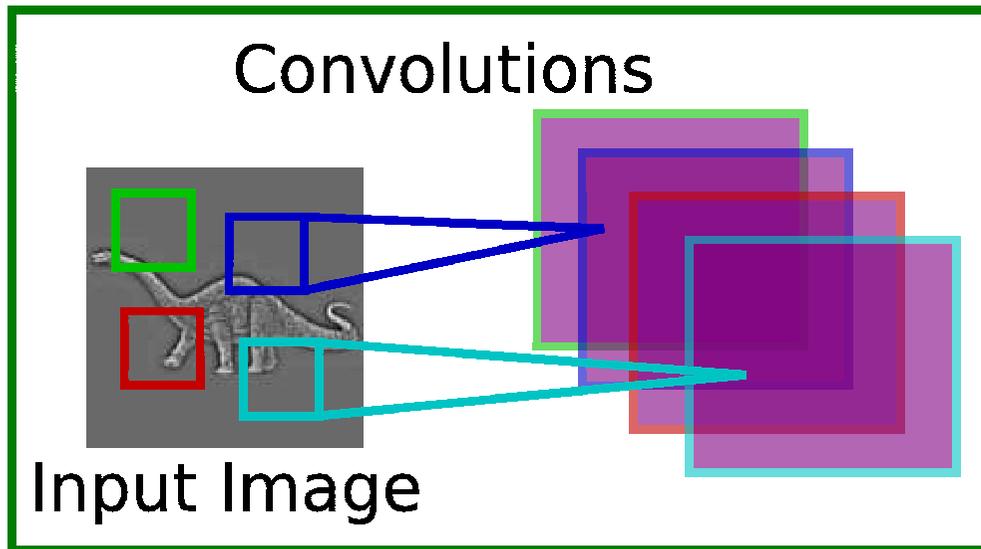
➤ **Convolutions** with certain kernels

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Parameter Sharing

- Each feature map forms a 2D grid of features
 - can be computed with a discrete convolution ($*$) of a **kernel matrix** k_{ij} which is the hidden weights matrix W_{ij} with its rows and columns flipped



Jarret et al. 2009

$$y_j = g_j \tanh\left(\sum_i k_{ij} * x_i\right)$$

- x_i is the i^{th} channel of input
- k_{ij} is the convolution kernel
- g_j is a learned scaling factor
- g_j is the hidden layer

can add bias

Discrete Convolution

- The convolution of an image x with a kernel k is computed as follows:

$$(x * k)_{ij} = \sum_{pq} x_{i+p, j+q} k_{r-p, r-q}$$

- Example:

0	80	40
20	40	0
0	0	40

x

*

0	0,25
0,5	1

k

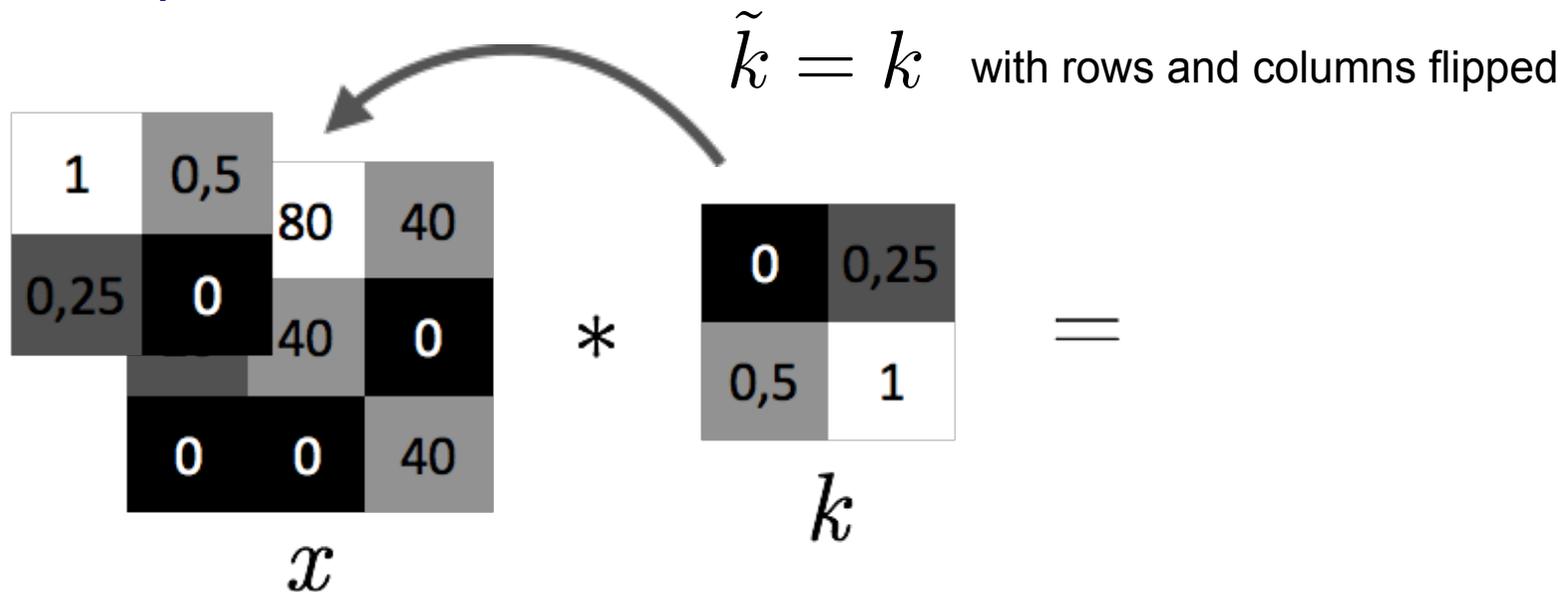
=

Discrete Convolution

- The convolution of an image x with a kernel k is computed as follows:

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- Example:

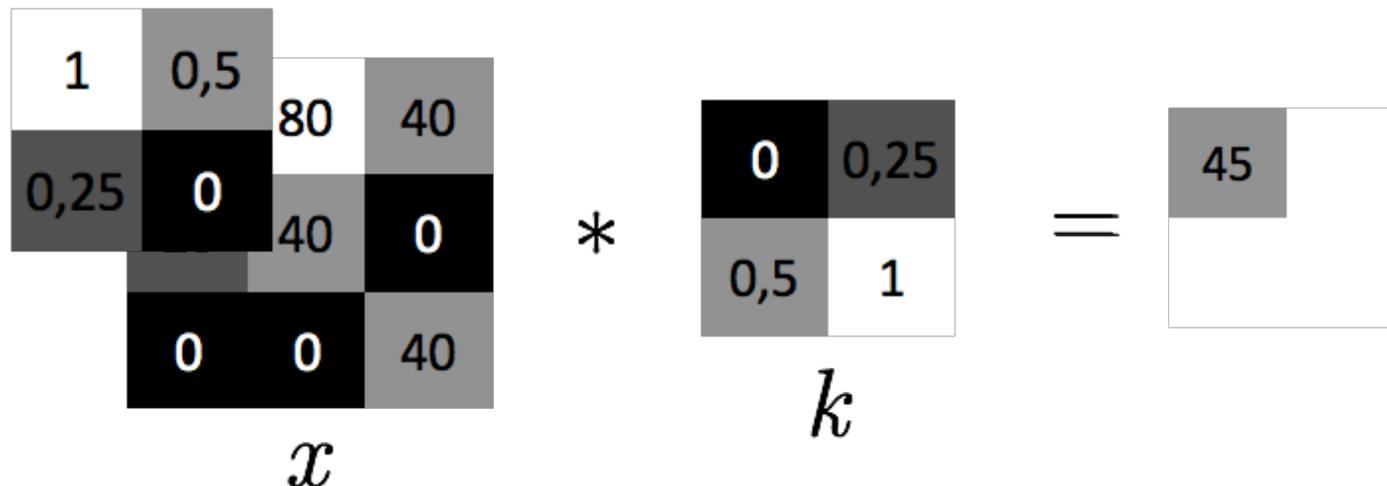


Discrete Convolution

- The convolution of an image x with a kernel k is computed as follows:

$$(x * k)_{ij} = \sum_{pq} x_{i+p, j+q} k_{r-p, r-q}$$

- Example:** $1 \times 0 + 0.5 \times 80 + 0.25 \times 20 + 0 \times 40 = 45$

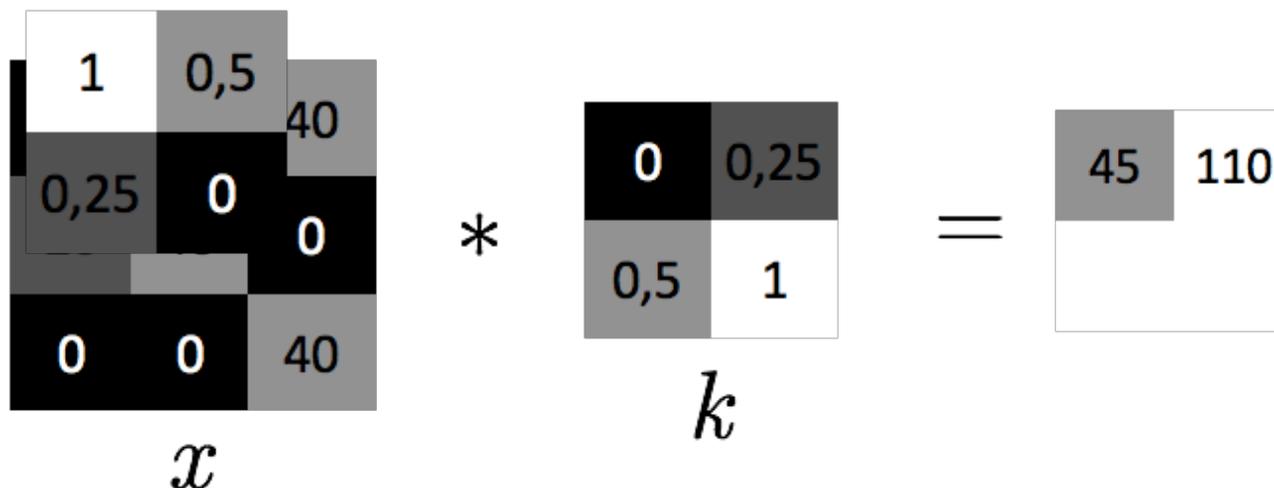


Discrete Convolution

- The convolution of an image x with a kernel k is computed as follows:

$$(x * k)_{ij} = \sum_{pq} x_{i+p, j+q} k_{r-p, r-q}$$

- Example:** $1 \times 80 + 0.5 \times 40 + 0.25 \times 40 + 0 \times 0 = 110$

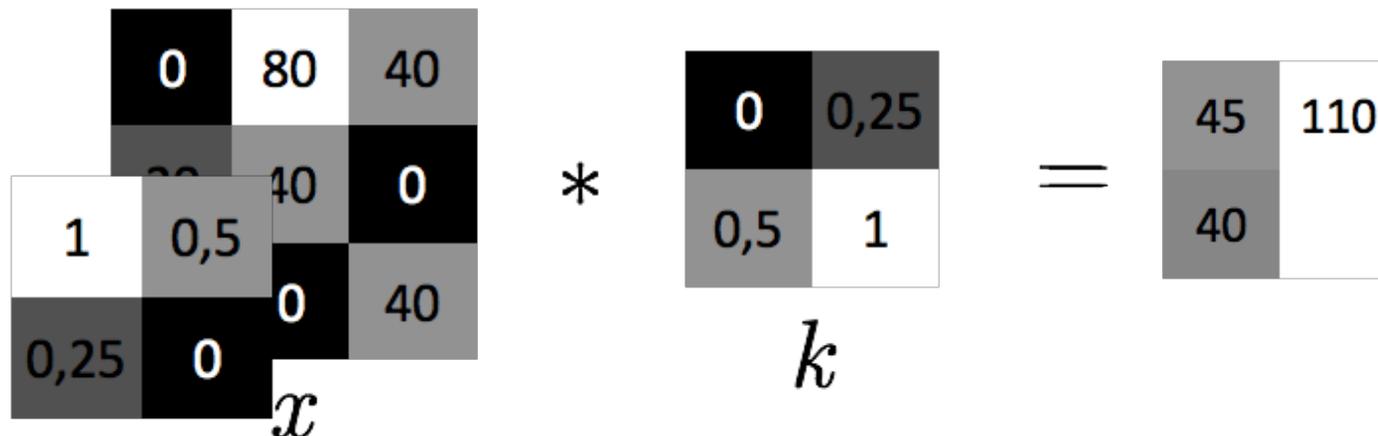


Discrete Convolution

- The convolution of an image x with a kernel k is computed as follows:

$$(x * k)_{ij} = \sum_{pq} x_{i+p, j+q} k_{r-p, r-q}$$

- Example:** $1 \times 20 + 0.5 \times 40 + 0.25 \times 0 + 0 \times 0 = 40$

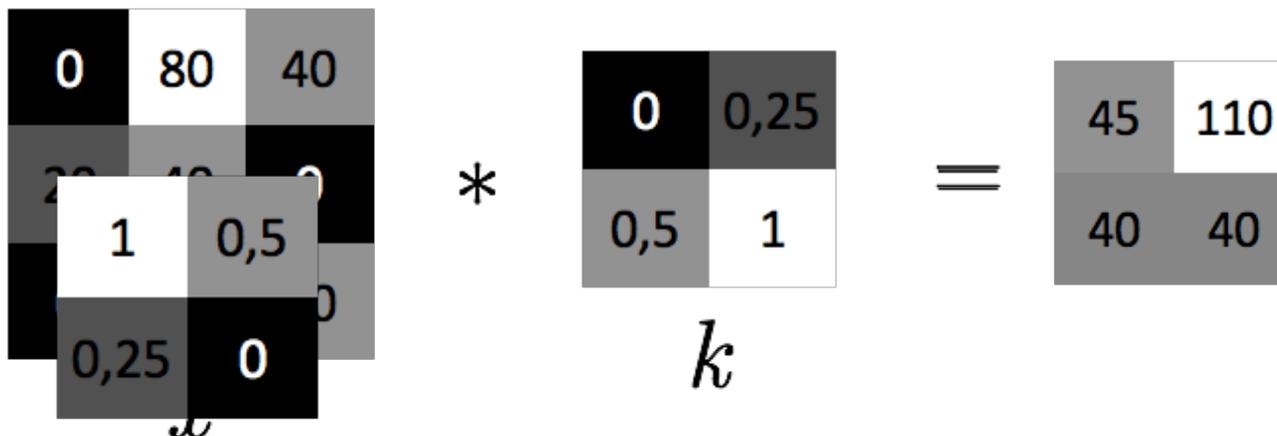


Discrete Convolution

- The convolution of an image x with a kernel k is computed as follows:

$$(x * k)_{ij} = \sum_{pq} x_{i+p, j+q} k_{r-p, r-q}$$

- Example:** $1 \times 40 + 0.5 \times 0 + 0.25 \times 0 + 0 \times 40 = 40$



Discrete Convolution

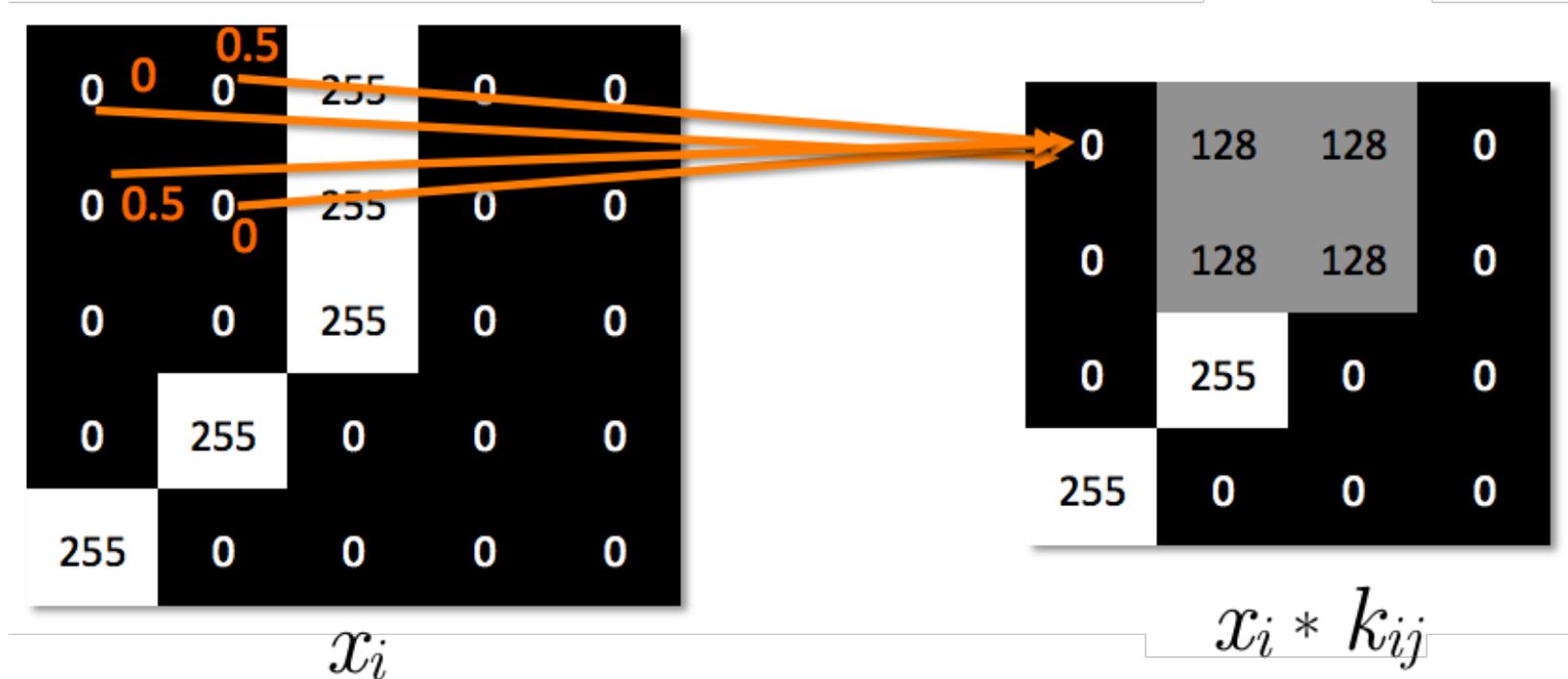
- **Pre-activations** from channel x_i into feature map y_j can be computed by:
 - getting the convolution kernel where $k_{ij} = \tilde{W}_{ij}$ from the connection matrix W_{ij}
 - applying the convolution $x_i * k_{ij}$
- This is equivalent to computing the **discrete correlation** of x_i with W_{ij}

Example

- Illustration:

$$x * k_{ij}, \quad \text{where } W_{ij} = \tilde{W}_{ij}$$

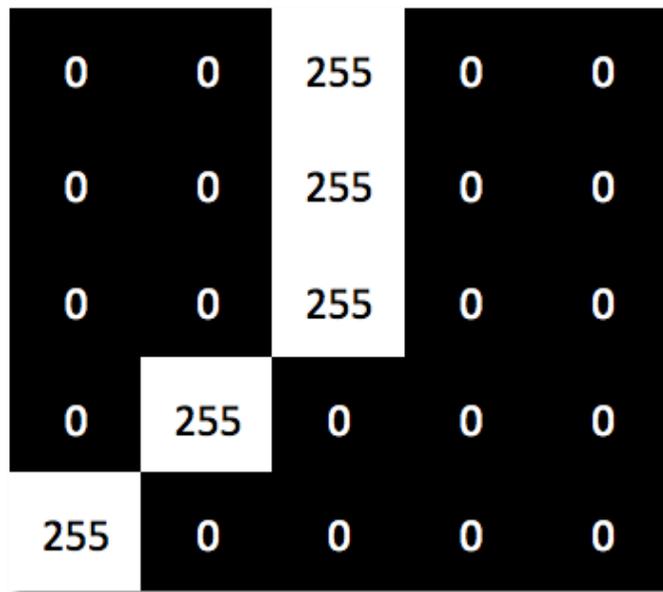
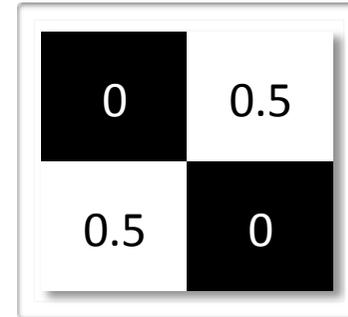
0	0.5
0.5	0



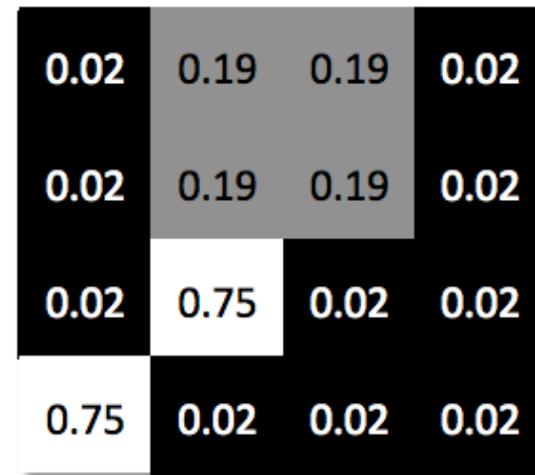
Example

- **With a non-linearity**, we get a detector of a feature at any position in the image:

$$x * k_{ij}, \quad \text{where } W_{ij} = \tilde{W}_{ij}$$



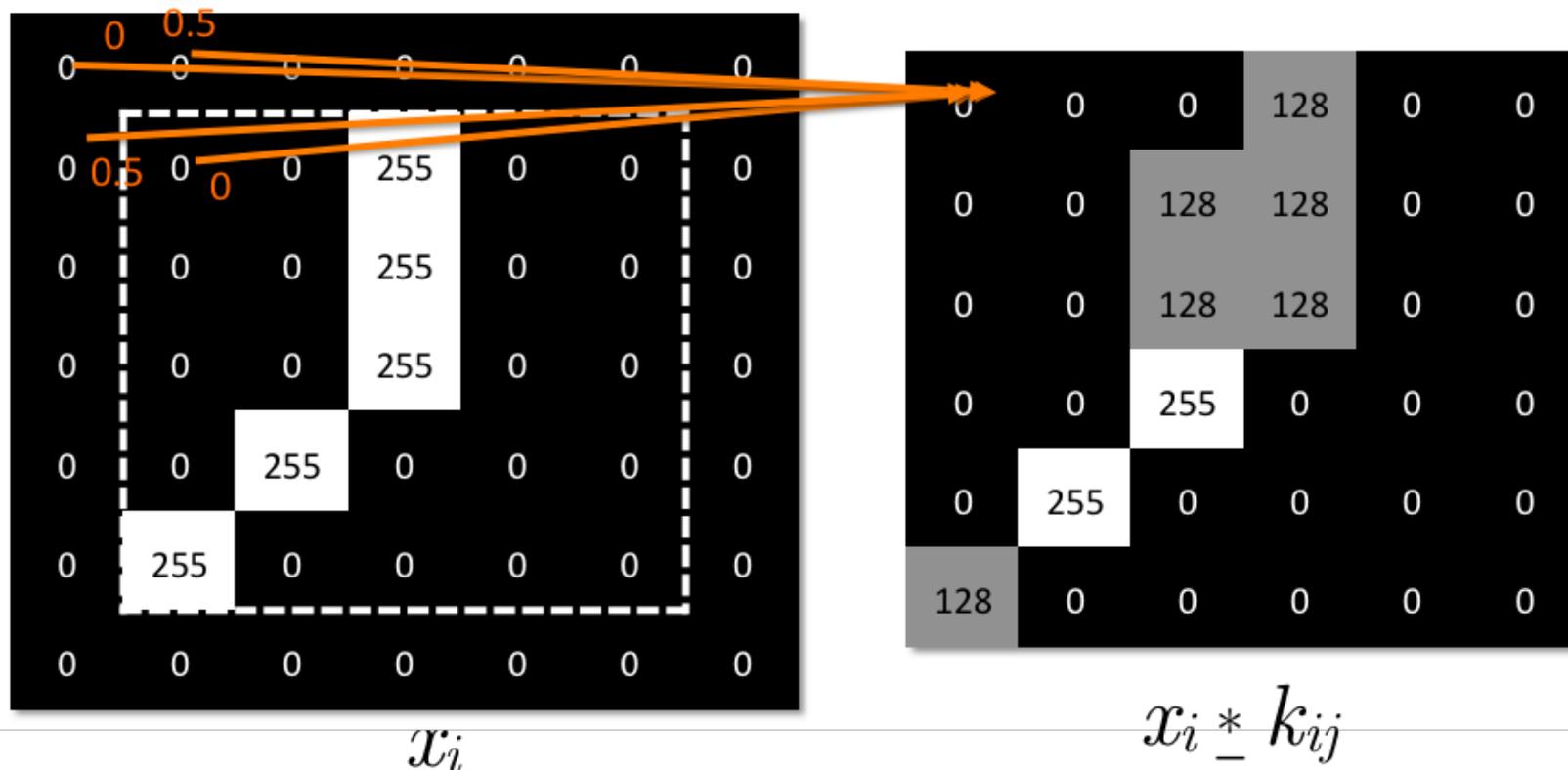
x_i



$$\text{sigm}(0.02 x_i * k_{ij} - 4)$$

Example

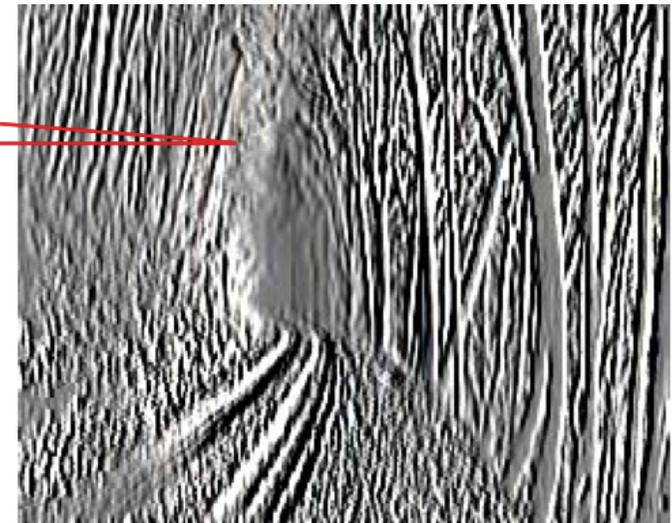
- Can use “zero padding” to allow going over the borders (*)



Example

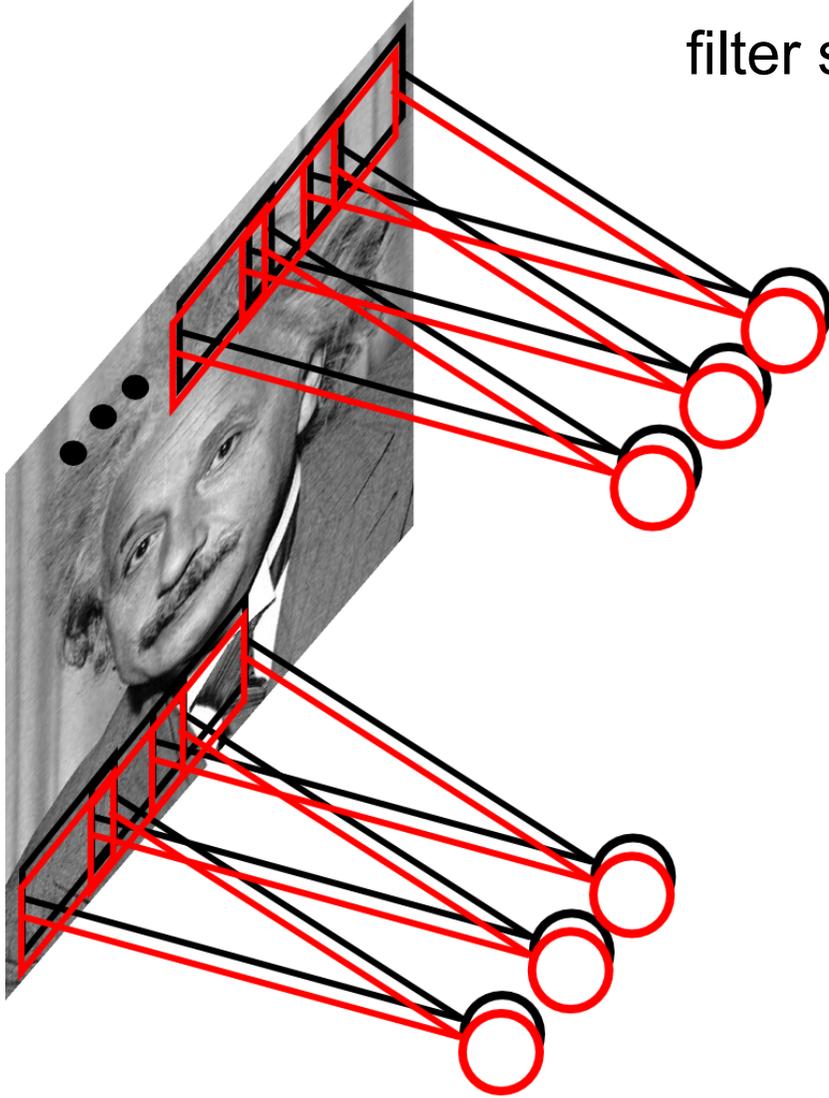


$$* \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} =$$



Multiple Feature Maps

- **Example:** 200x200 image, 100 filters, filter size 10x10, 10K parameters



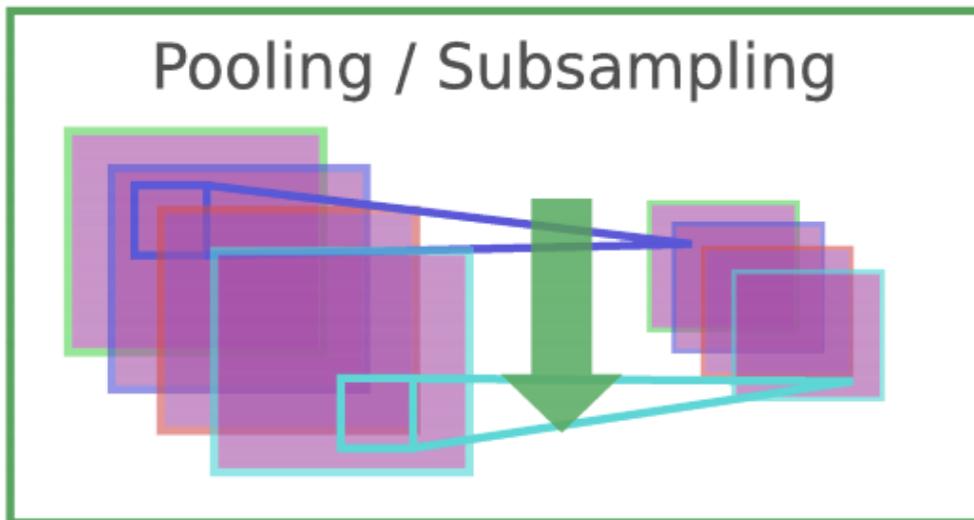
Computer Vision

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Pooling

- Pool hidden units in same neighborhood
 - **pooling** is performed in non-overlapping neighborhoods (subsampling)

$$y_{ijk} = \max_{p,q} x_{i,j+p,k+q}$$



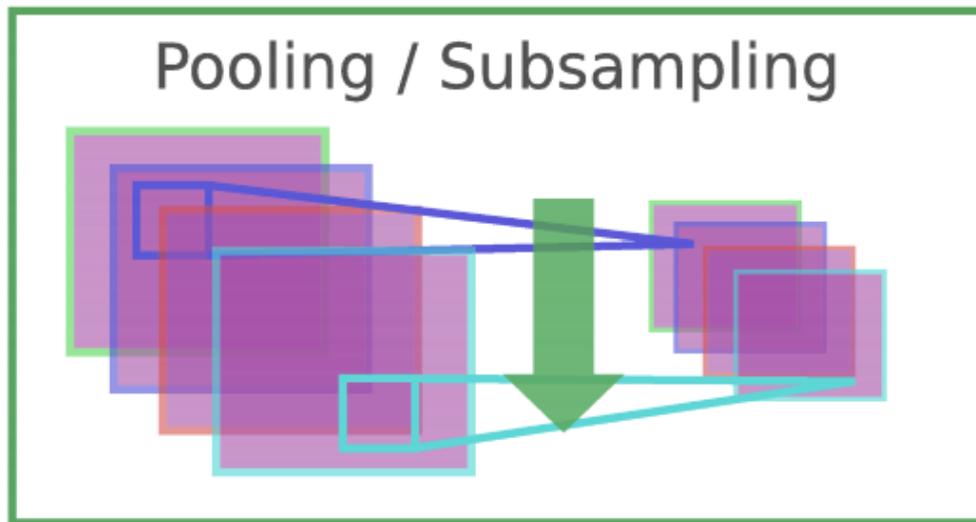
Jarret et al. 2009

- x_i is the i^{th} channel of input
- $x_{i,j,k}$ is value of the i^{th} feature map at position j,k
- p is vertical index in local neighborhood
- q is horizontal index in local neighborhood
- y_{ijk} is pooled / subsampled layer

Pooling

- Pool hidden units in same neighborhood
 - an alternative to “max” pooling is “average” pooling

$$y_{ijk} = \frac{1}{m^2} \sum_{p,q} x_{i,j+p,k+q}$$

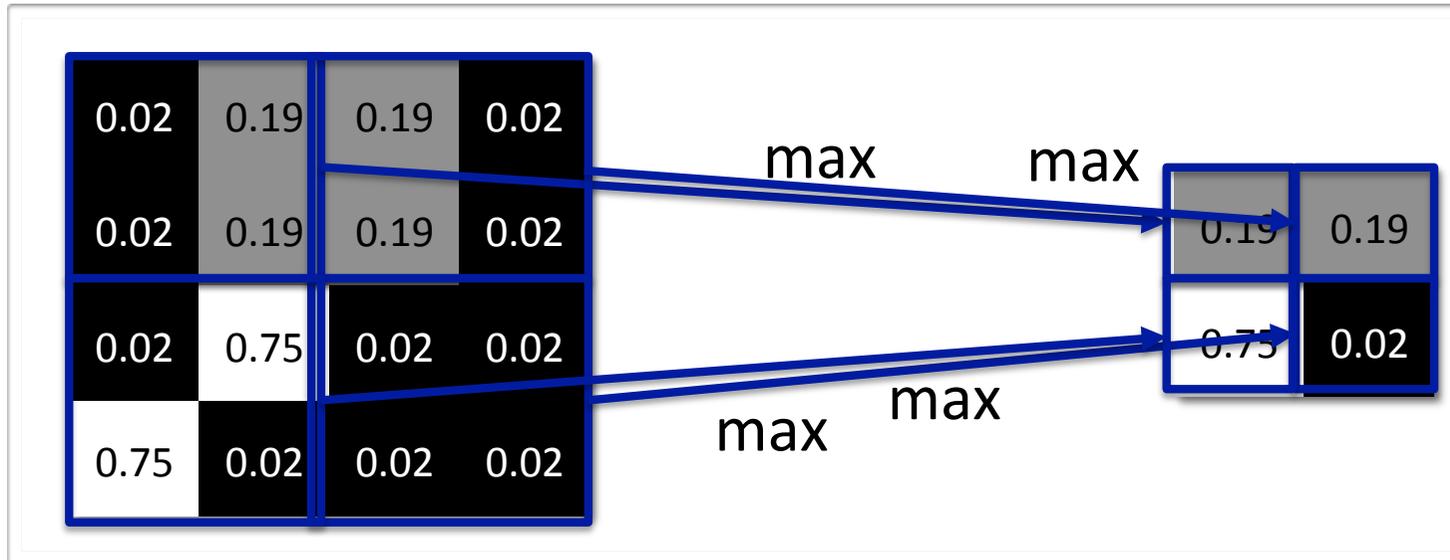


Jarret et al. 2009

- x_i is the i^{th} channel of input
- $x_{i,j,k}$ is value of the i^{th} feature map at position j,k
- p is vertical index in local neighborhood
- q is horizontal index in local neighborhood
- y_{ijk} is pooled / subsampled layer
- m is the neighborhood height/width

Example: Pooling

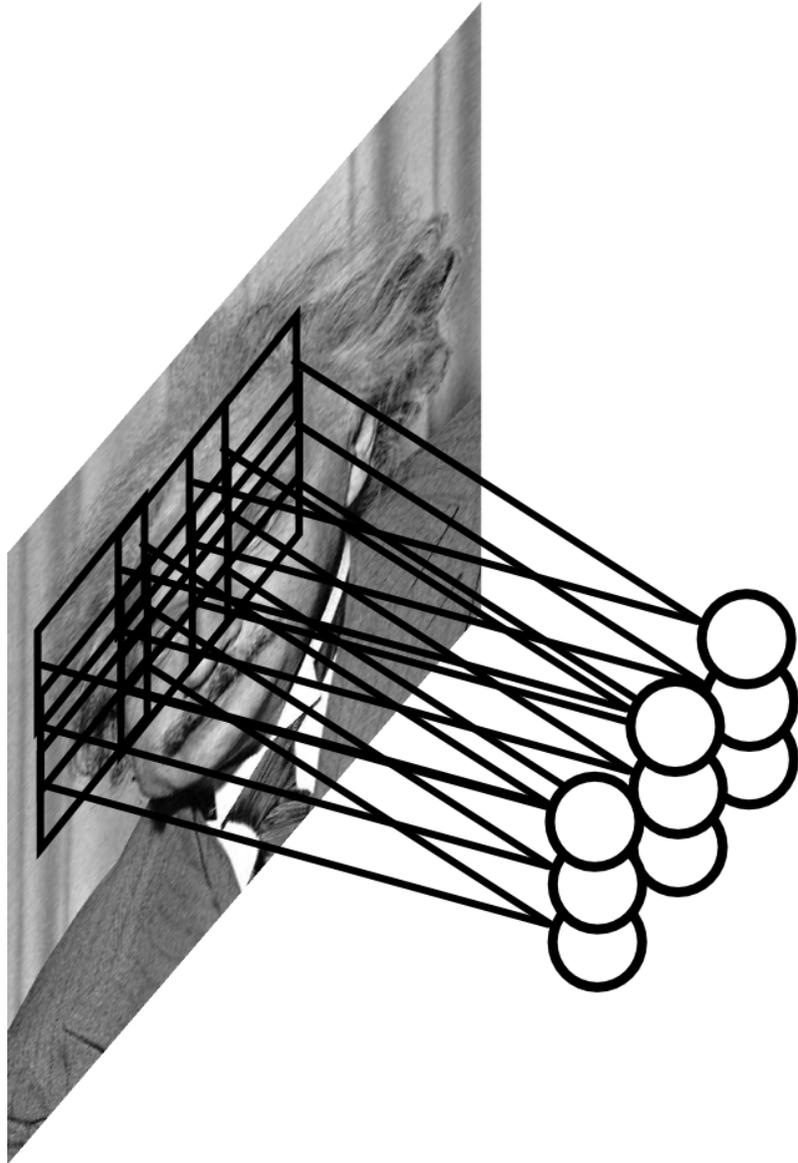
- Illustration of pooling/subsampling operation



- **Why pooling?**

- Introduces invariance to **local translations**
- Reduces the number of hidden units in hidden layer

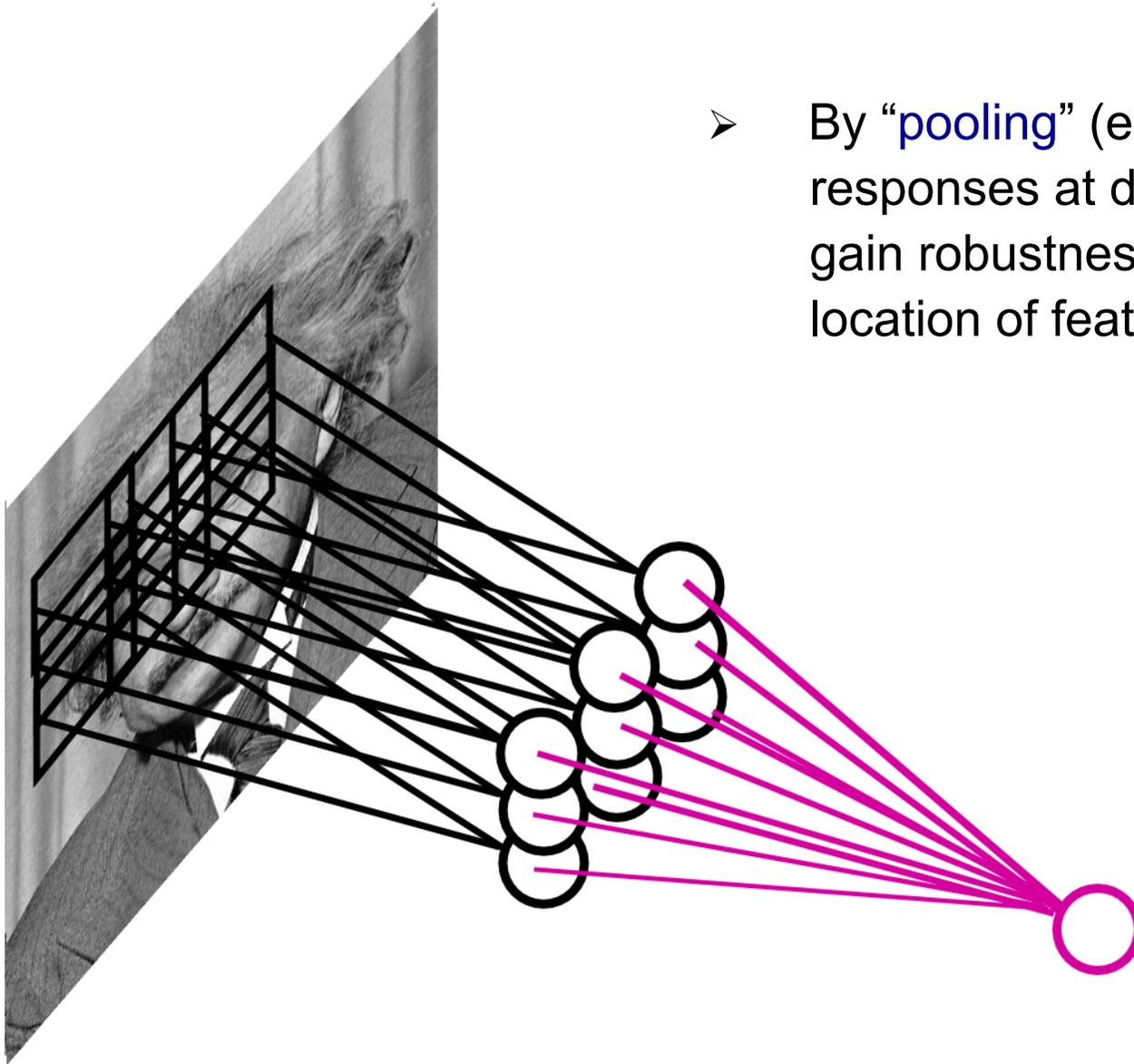
Example: Pooling



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

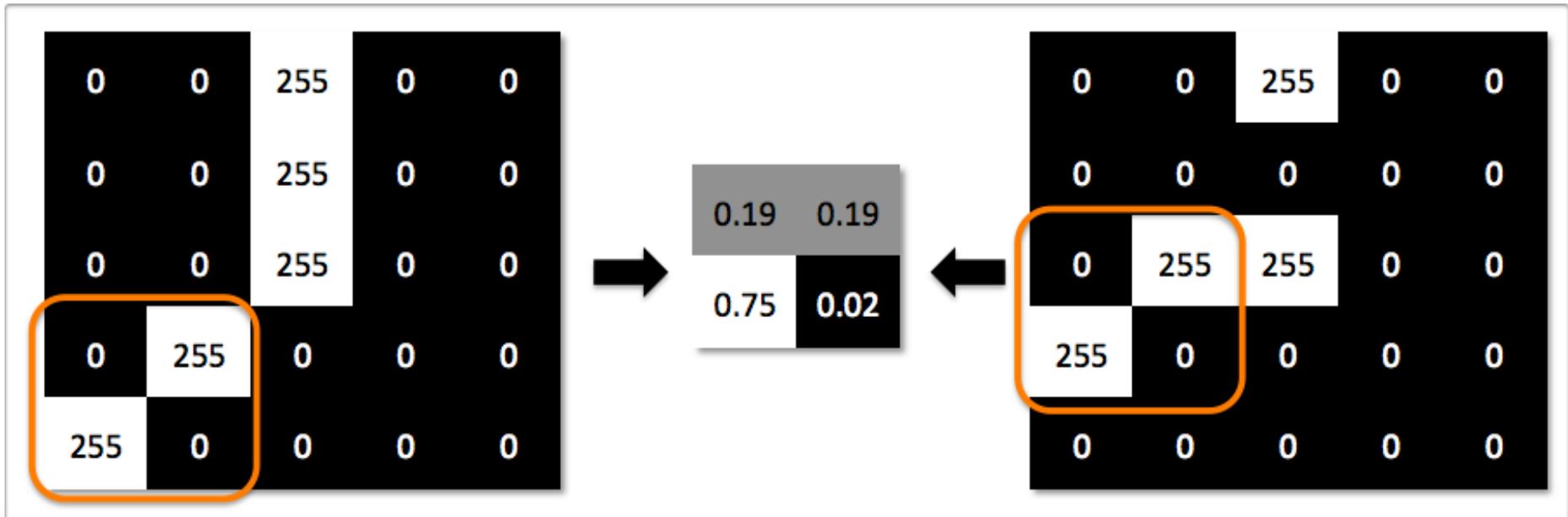
Example: Pooling

- By “pooling” (e.g., taking max) filter responses at different locations we gain robustness to the exact spatial location of features.



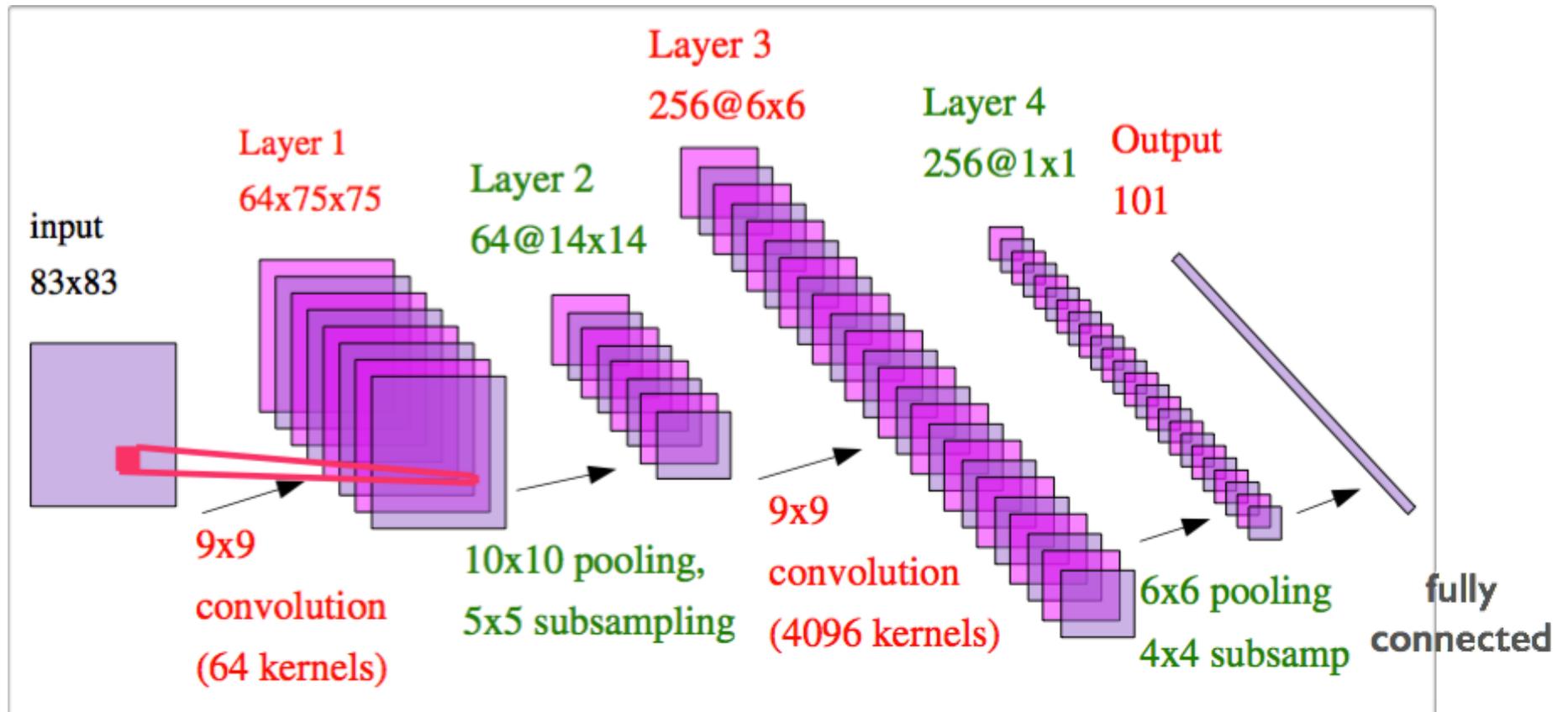
Translation Invariance

- Illustration of **local translation invariance**
 - both images result in the same feature map after pooling/
subsampling



Convolutional Network

- Convolutional neural network alternates between the convolutional and pooling layers



From Yann LeCun's slides

Convolutional Network

- For **classification**: Output layer is a regular, fully connected layer with softmax non-linearity
 - Output provides an estimate of the conditional probability of each class
- The network is trained by **stochastic gradient descent**
 - Backpropagation is used similarly as in a fully connected network
 - We have seen how to pass gradients through element-wise activation function
 - We also need to pass gradients through the convolution operation and the pooling operation

Gradient of Convolutional Layer

- Let l be the **loss function**

- For **max pooling** operation $y_{ijk} = \max_{p,q} x_{i,j+p,k+q}$, the gradient for x_{ijk} is

$$\nabla_{x_{ijk}} l = 0, \text{ except for } \nabla_{x_{i,j+p',k+q'}} l = \nabla_{y_{ijk}} l$$

where $p', q' = \operatorname{argmax}_{i,j+p,k+q} x_{i,j+p,k+q}$

- In other words, only the “**winning**” units in layer x get the gradient from the pooled layer

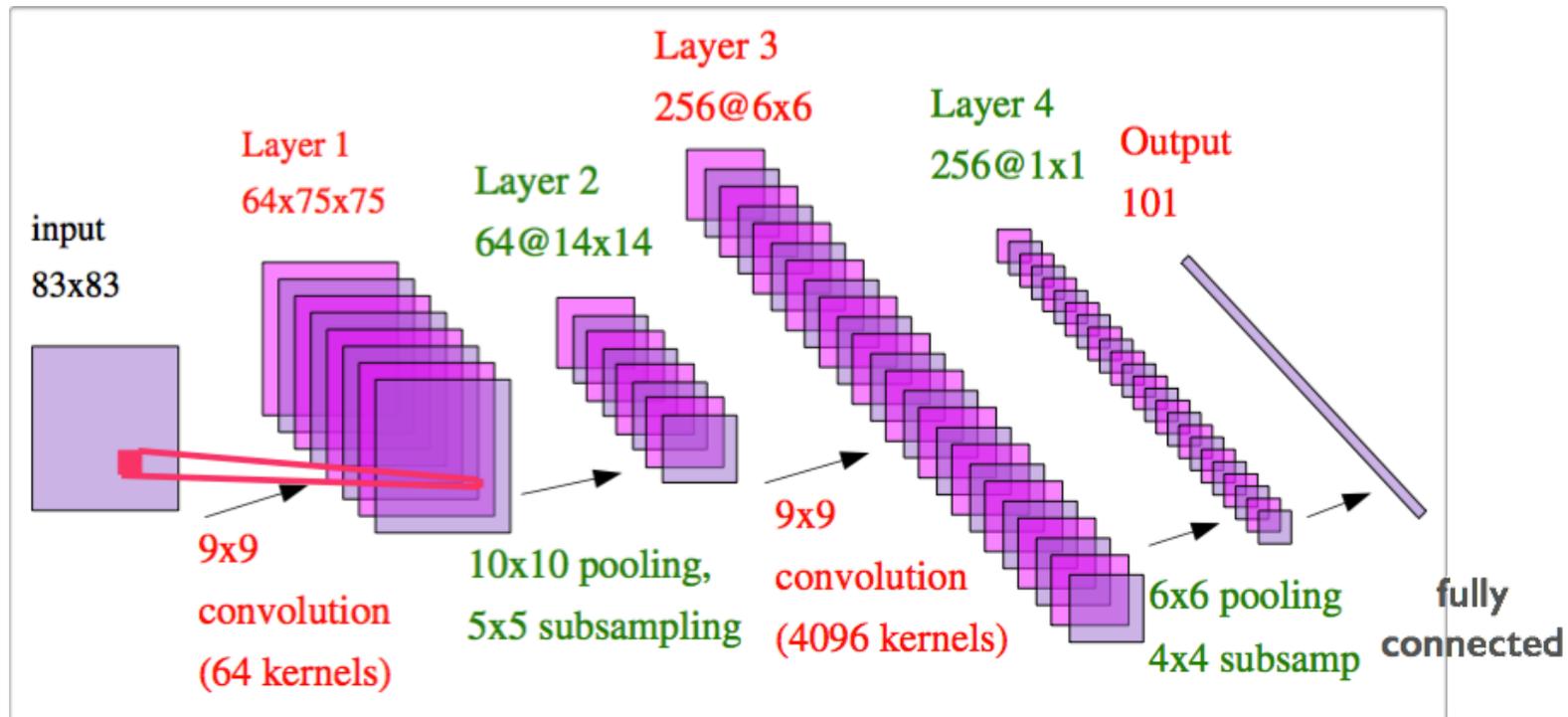
- For the **average** operation $y_{ijk} = \frac{1}{m^2} \sum_{p,q} x_{i,j+p,k+q}$, the gradient for x_{ijk} is

$$\nabla_x l = \frac{1}{m^2} \operatorname{upsample}(\nabla_y l)$$

where **upsample** inverts subsampling

Convolutional Network

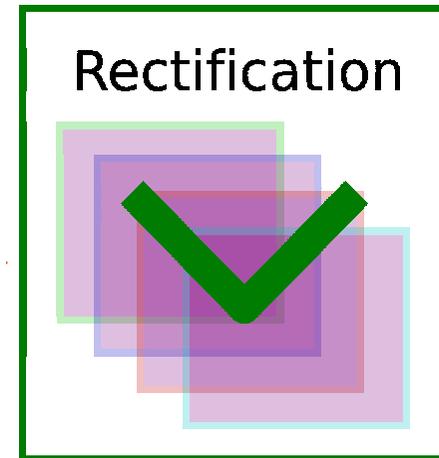
- Convolutional neural network alternates between the convolutional and pooling layers



- Need to introduce **other operations** that can improve object recognition.

Rectification

- **Rectification layer:** $y_{ijk} = |x_{ijk}|$
 - introduces invariance to the sign of the unit in the previous layer
 - for instance, loss of information of whether an edge is black-to-white or white-to-black



Local Contrast Normalization

- Perform local contrast normalization

$$v_{ijk} = x_{ijk} - \sum_{ipq} w_{pq} x_{i,j+p,k+q}$$

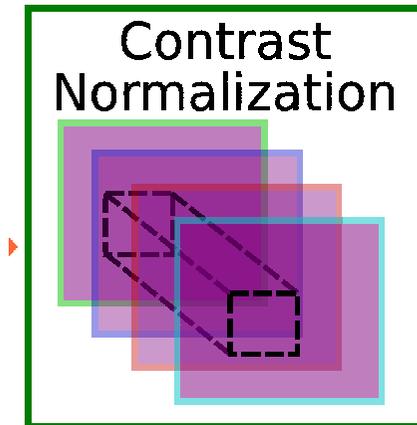
Local average

$$y_{ijk} = v_{ijk} / \max(c, \sigma_{jk})$$

$$\sigma_{jk} = \left(\sum_{ipq} w_{pq} v_{i,j+p,k+q}^2 \right)^{1/2}$$

Local stdev

$$\sum_{pq} w_{pq} = 1$$



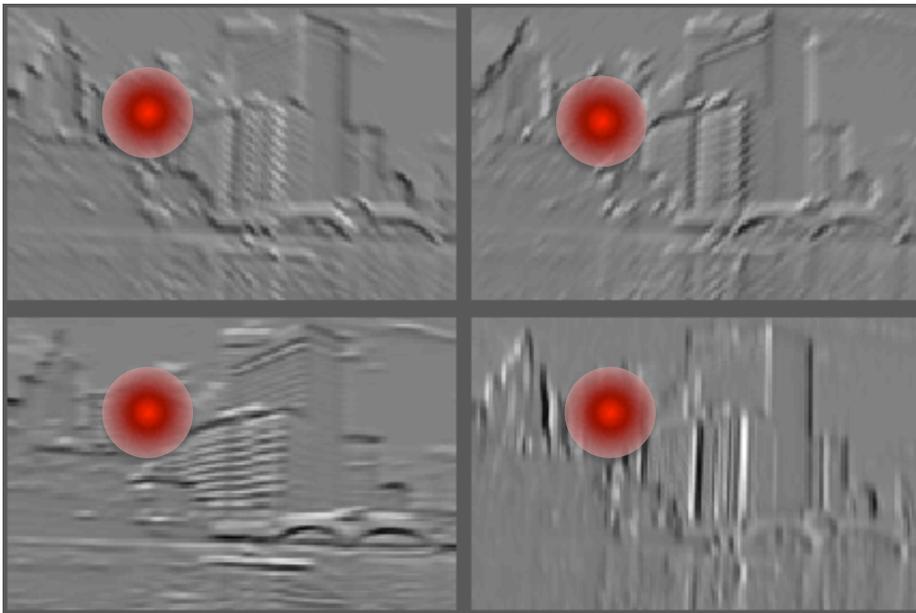
where c is a small constant to prevent division by 0

- reduces unit's activation if neighbors are also active
- creates competition between feature maps
- scales activations at each layer better for learning

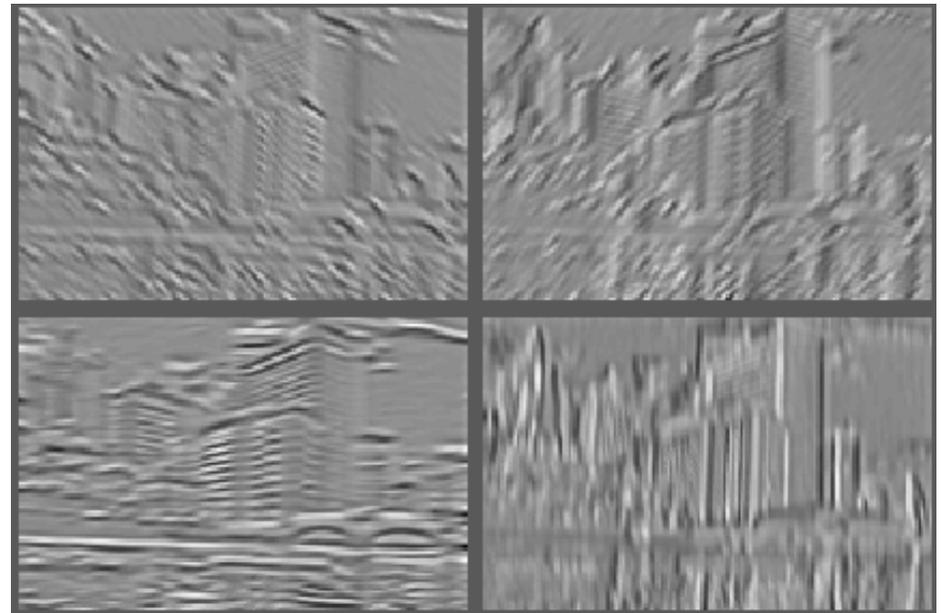
Local Contrast Normalization

- Perform local contrast normalization
 - Local mean=0, Local std. = 1, “Local” is 7x7 Gaussian

Feature Maps

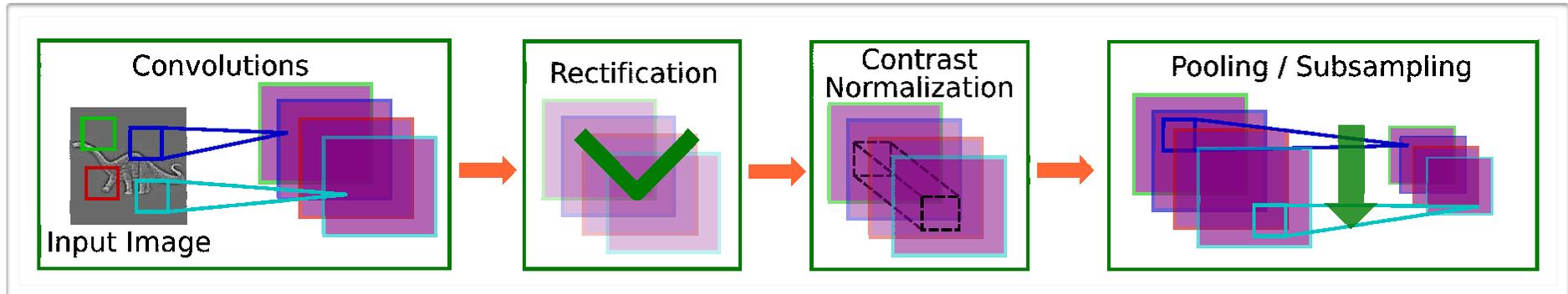


Feature Maps after
Contrast Normalization

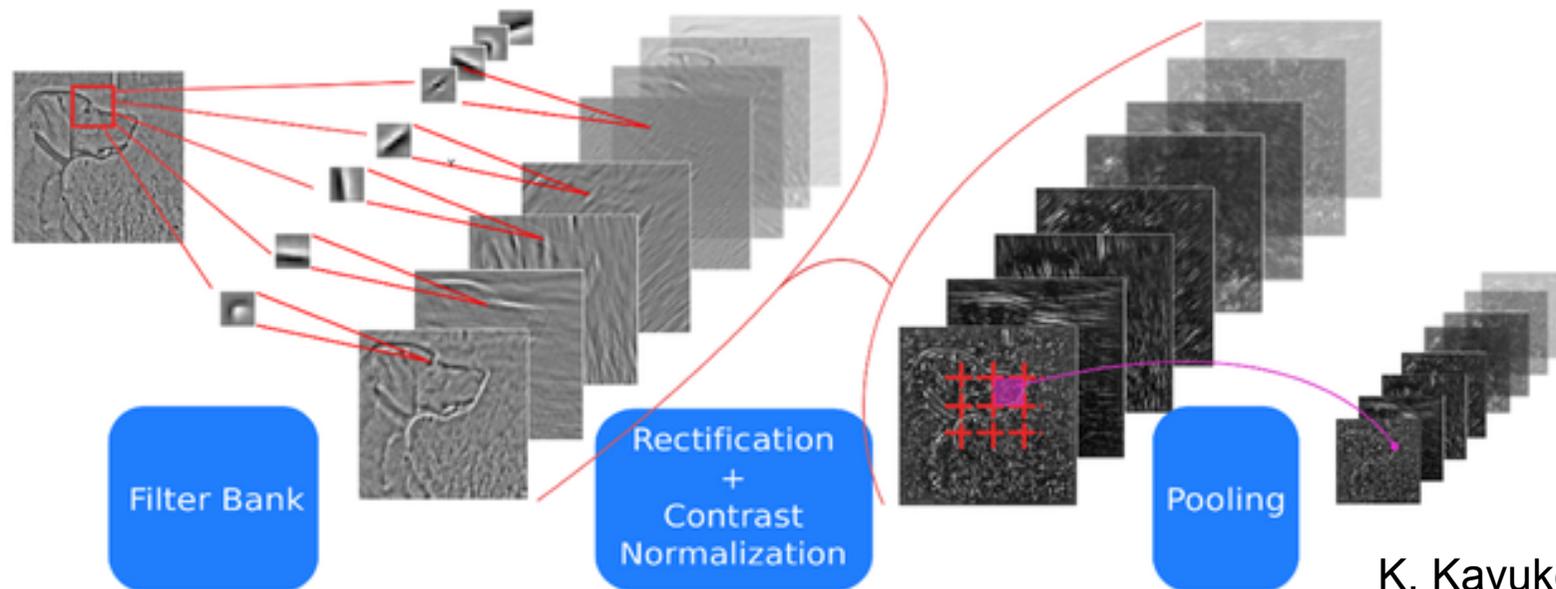


Convolutional Network

- These operations are inserted after the convolutions and before the pooling



Jarret et al. 2009



K. Kavukcuoglu

Remember Batch Normalization

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1\dots m}\}$;

Parameters to be learned: γ, β

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

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

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

$$\hat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \quad // \text{ normalize}$$

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

Learned linear transformation to adapt to non-linear activation function (γ and β are trained)