Lecture 04: Convolutional Neural Networks, CNN for texts

MADE, Moscow
15.04.2020

Radoslav Neychev

Outline

- Convolutional Neural Networks
  - Intro/recap
  - Main definitions

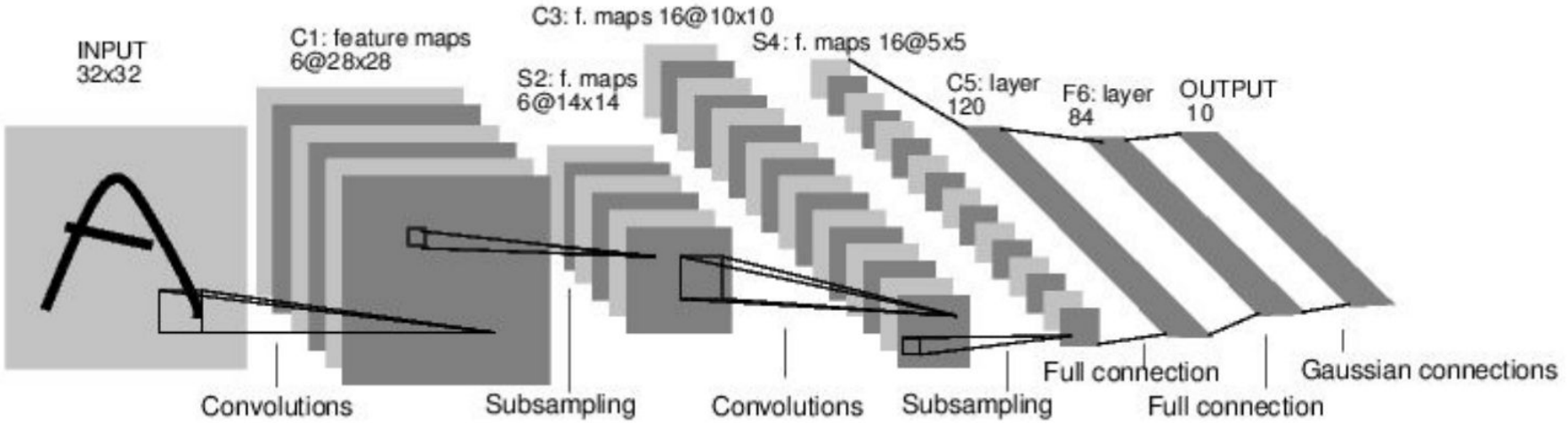
- RNN problems recap:
  - Vanishing gradient
  - Exploding gradient

- Potential solutions:
  - LSTM/GRU
  - Gradient clipping
  - Skip connections

- CNNs for text processing

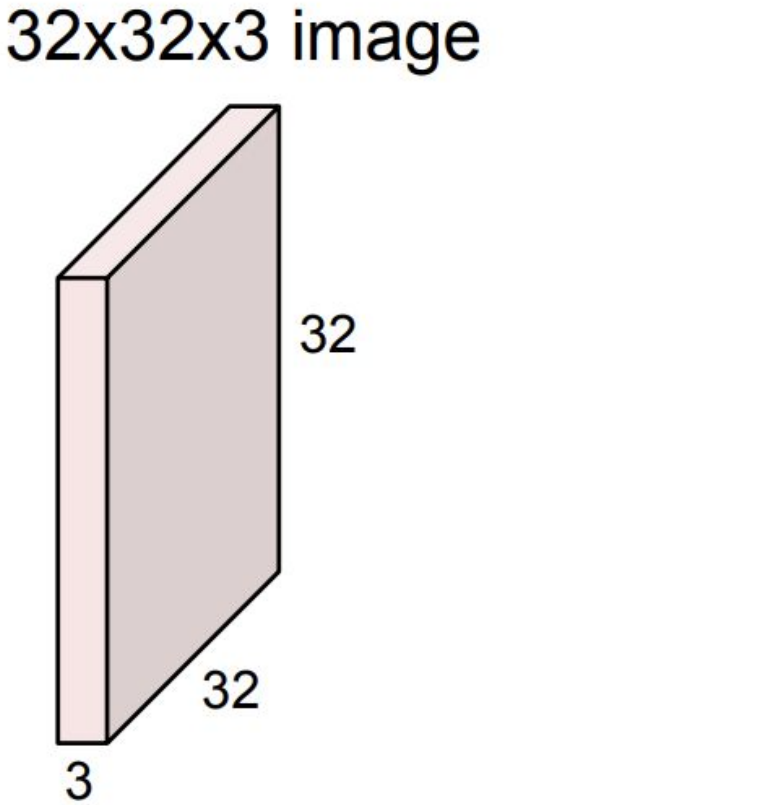
Convolutional Neural Networks: Intro or recap

CNN



[LeNet-5, LeCun 1998]

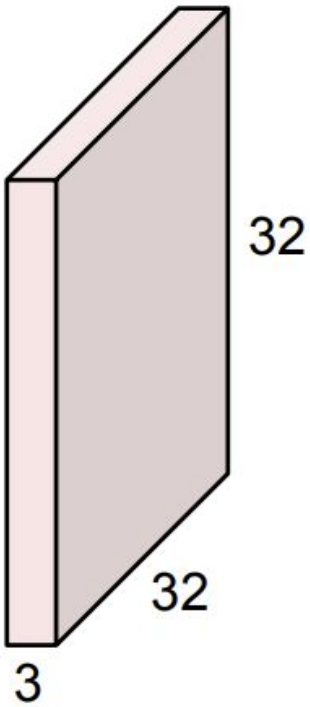
Convolutional layer



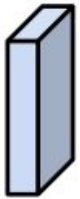
source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

Convolutional layer

32x32x3 image



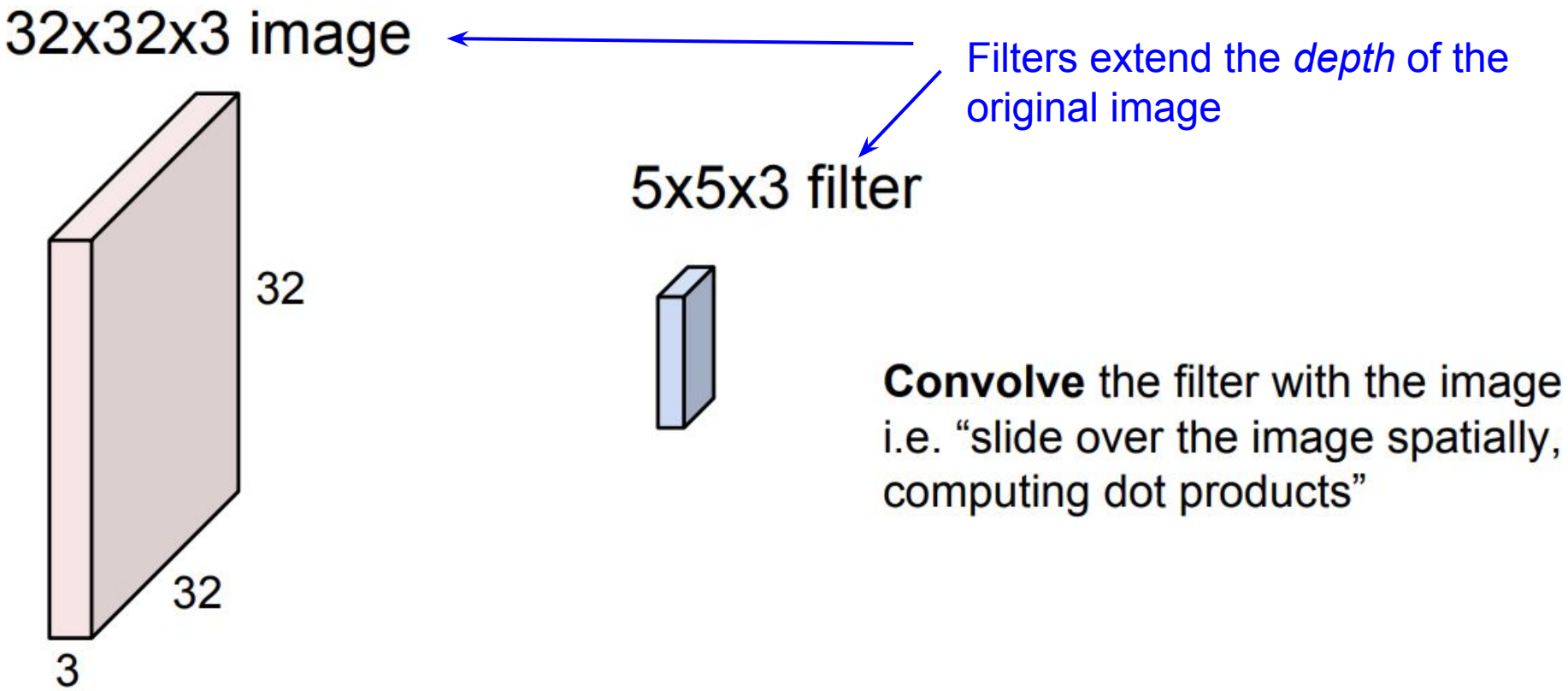
5x5x3 filter



Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

Convolutional layer



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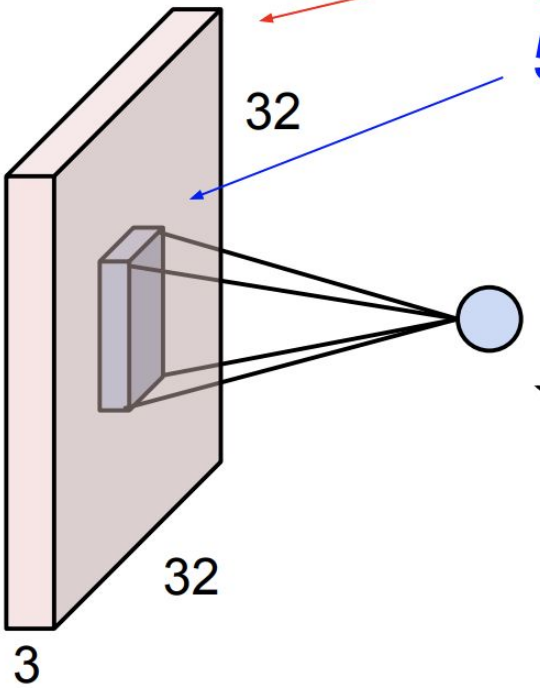
Convolutional layer



32x32x3 image

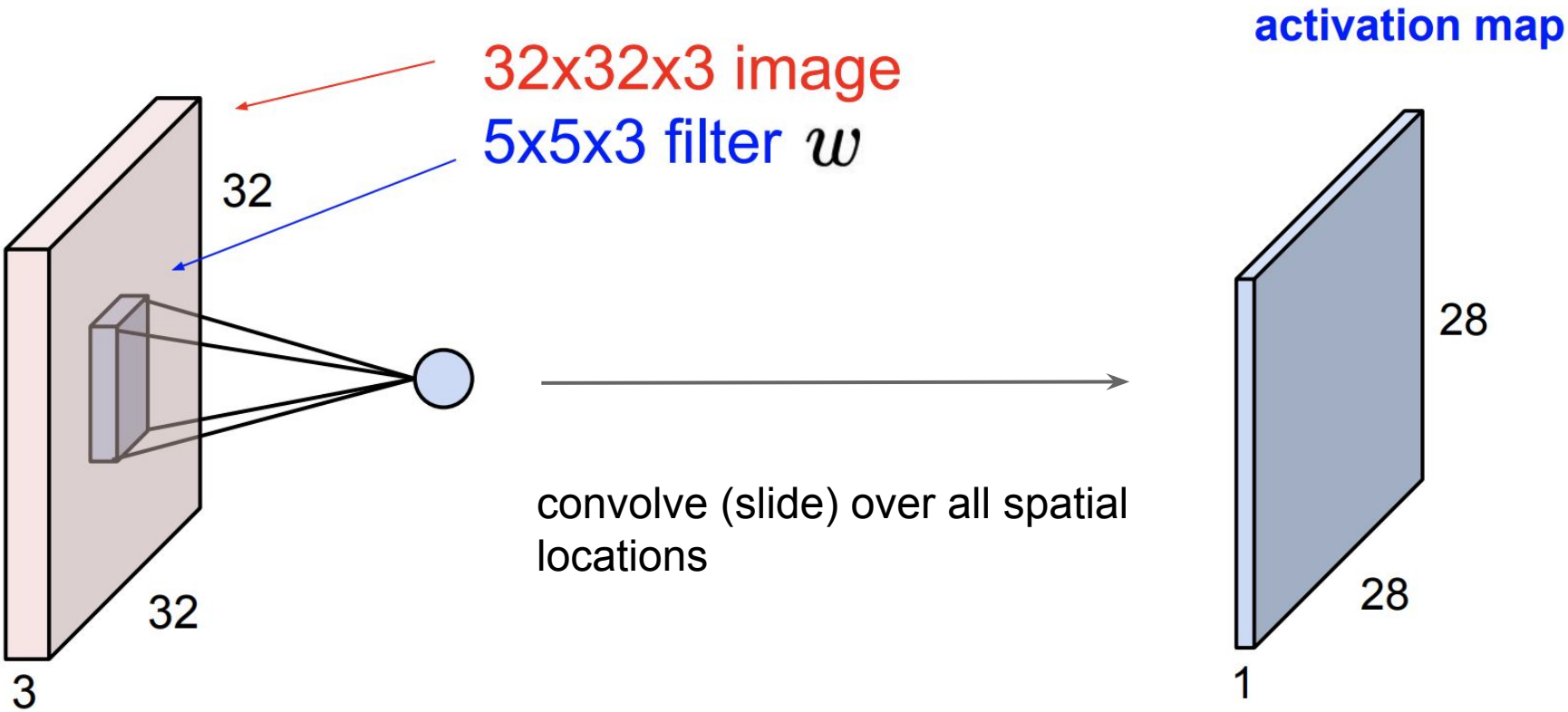
5x5x3 filter w

1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

Convolutional layer



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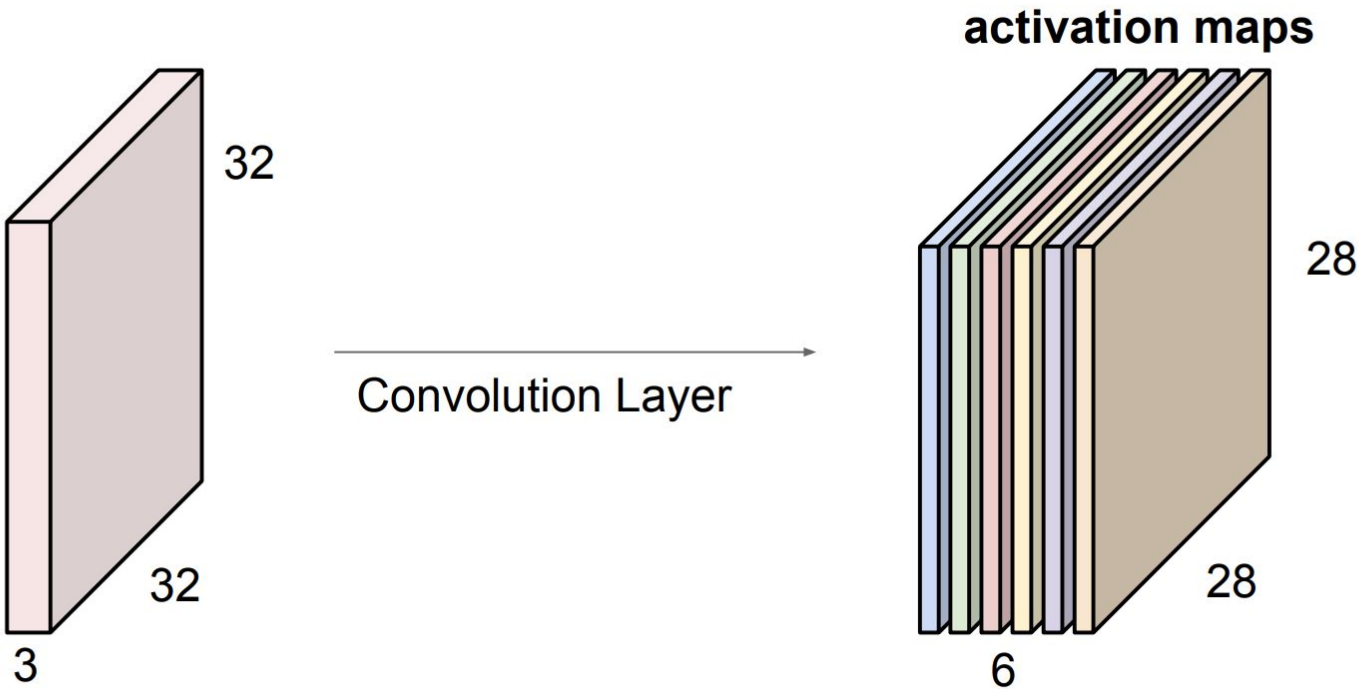
Convolutional layer

For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:

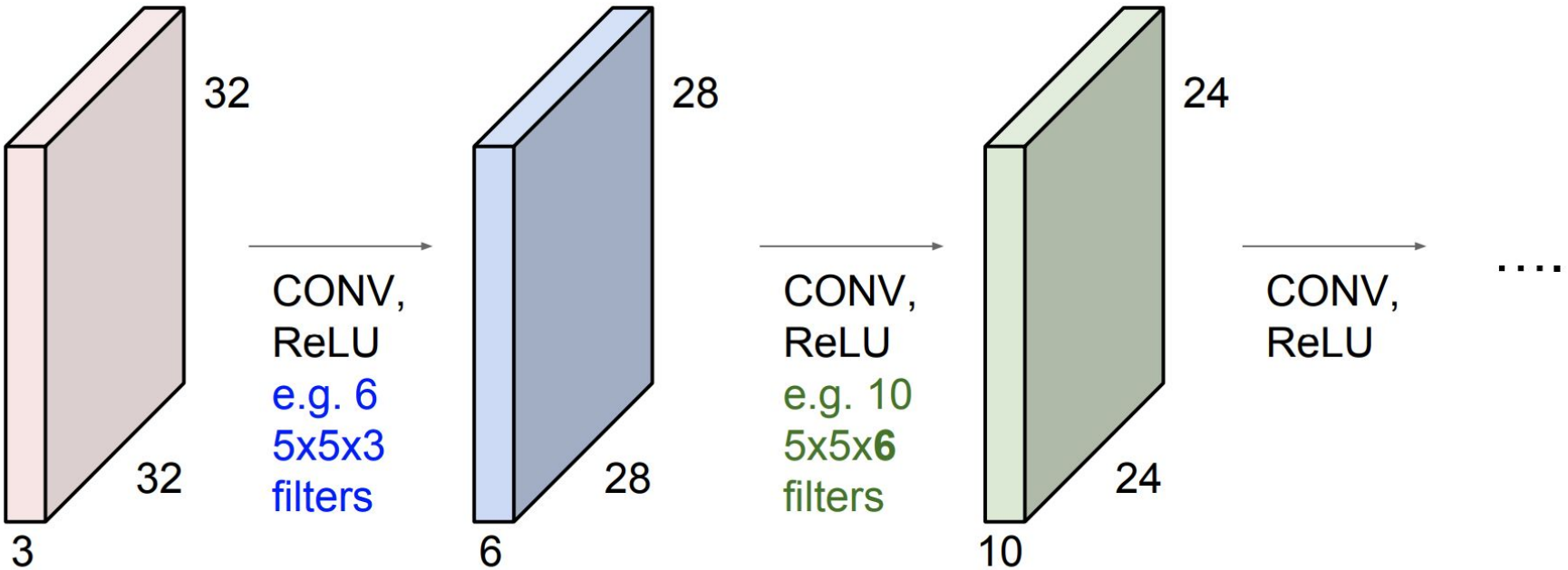


We stack these up to get a "new image" of size 28x28x6!

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

Convolutional layer

Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



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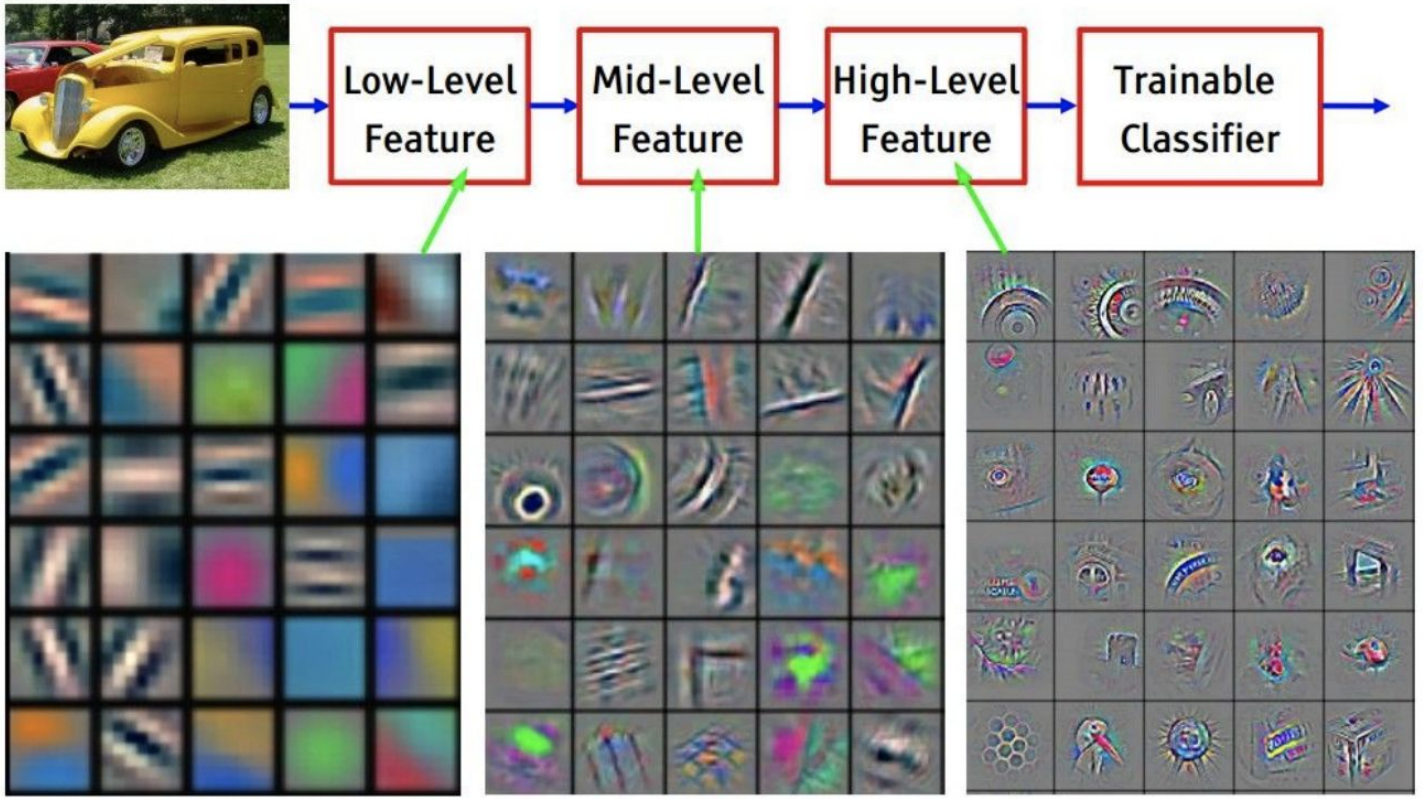
Convolutional layer

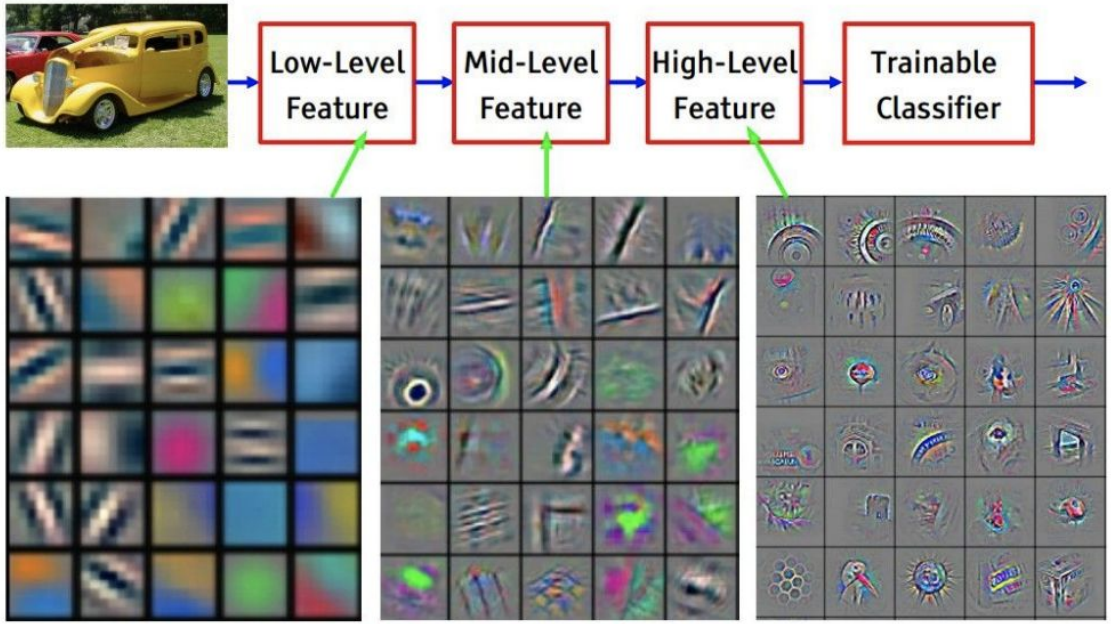


Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

[From Yann LeCun slides]

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

Convolutional layer and visual cortex



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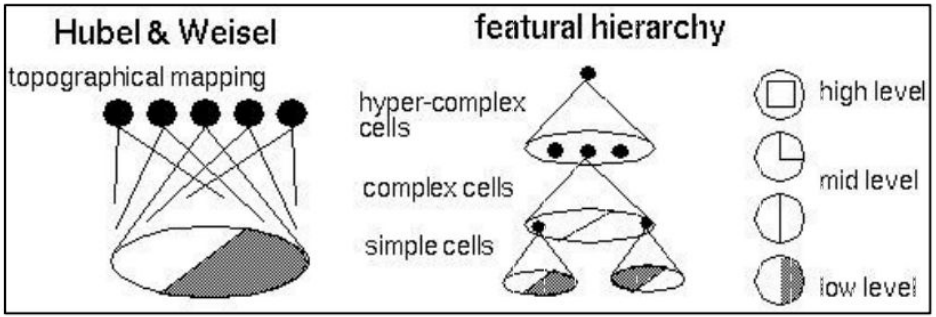

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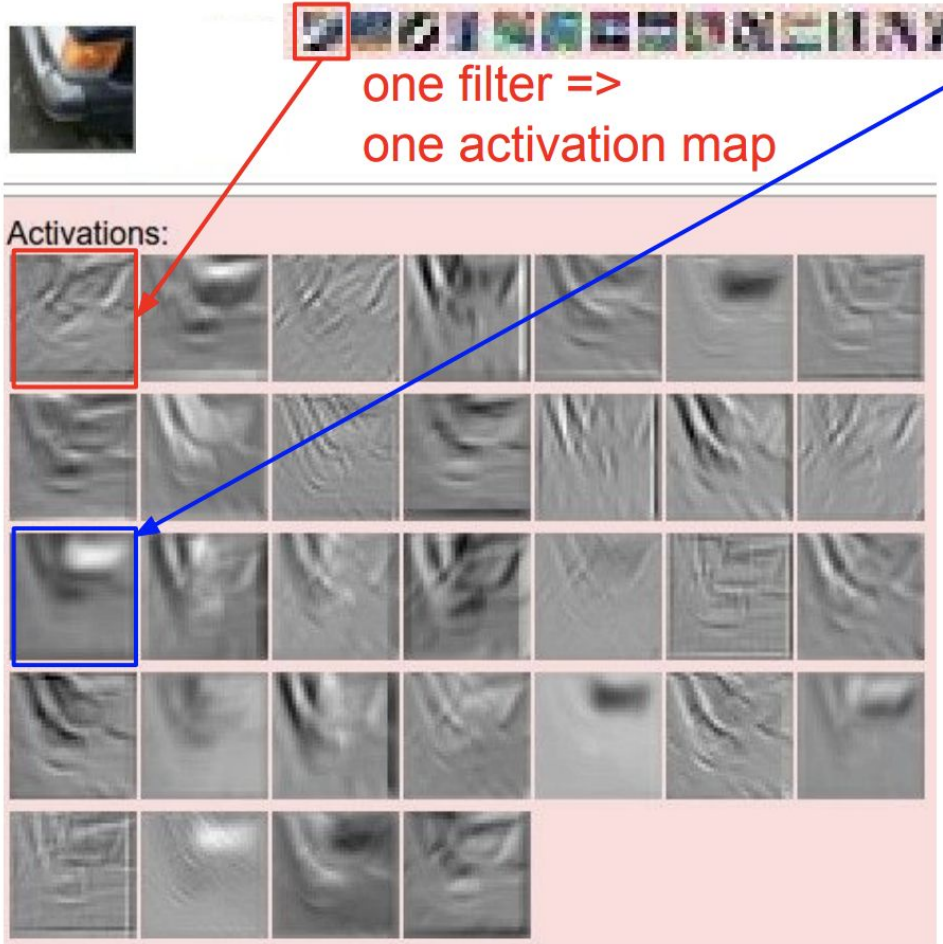


example 5x5 filters
(32 total)

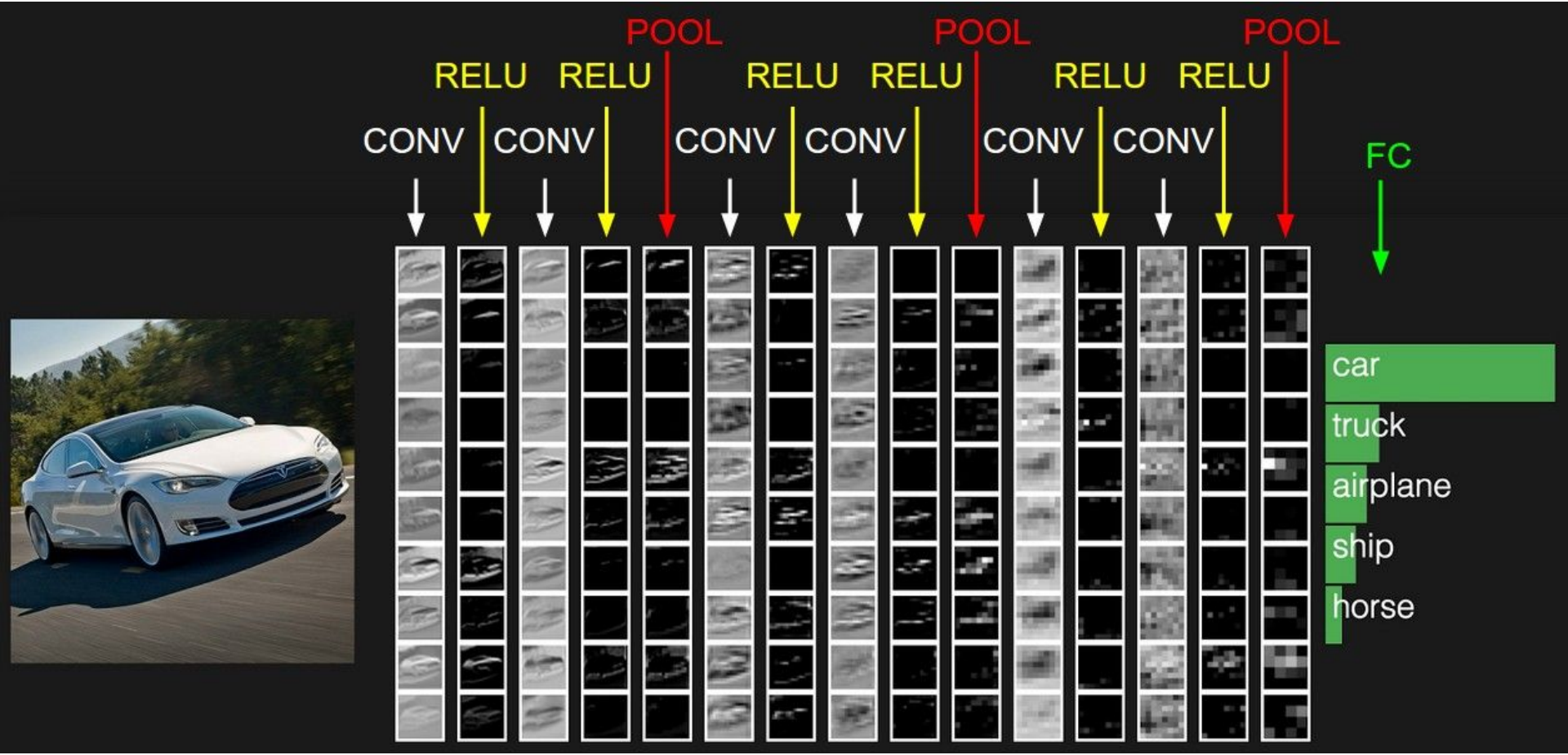
We call the layer convolutional because it is related to convolution of two signals:

$$f[x,y] * g[x,y] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} f[n_1,n_2] \cdot g[x-n_1, y-n_2]$$

elementwise multiplication and sum of a filter and the signal (image)

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

CIFAR-10 online demo:
https://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html



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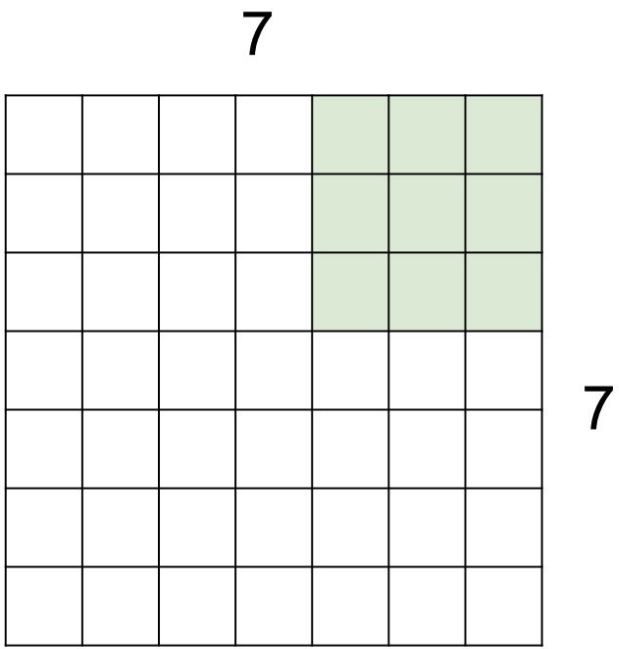
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

=> 5x5 output

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

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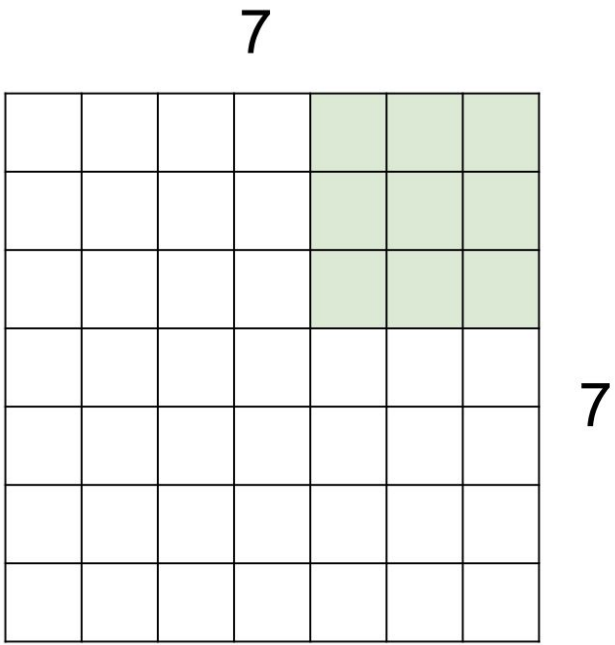
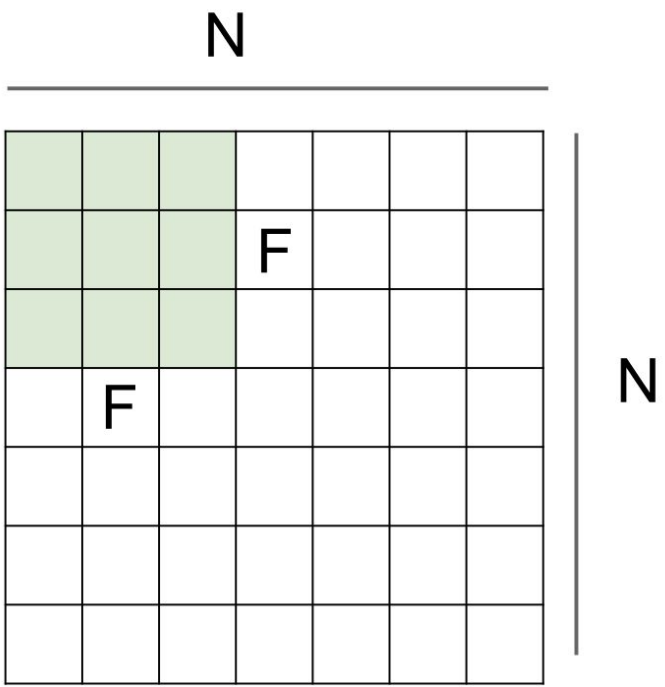


7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

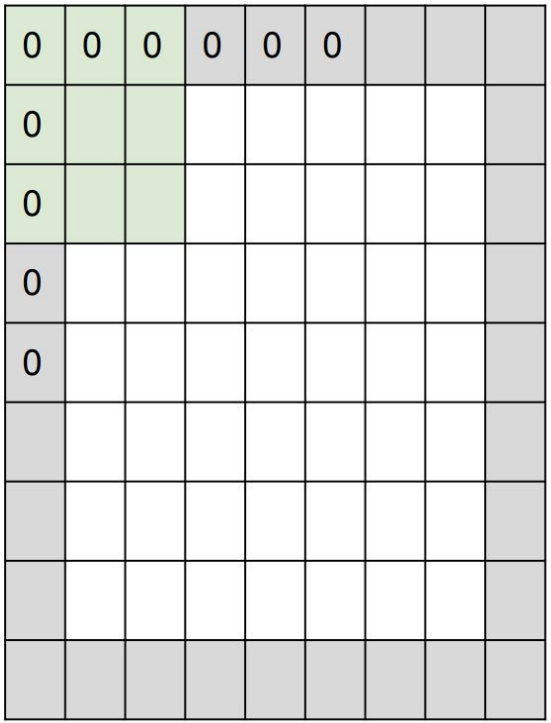


Output size:
(N - F) / stride + 1

e.g. N = 7, F = 3:
stride 1 => (7 - 3)/1 + 1 = 5
stride 2 => (7 - 3)/2 + 1 = 3
stride 3 => (7 - 3)/3 + 1 = 2.33 :\

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

In practice: Common to zero pad the border



e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

7x7 output!
in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
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F = 7 => zero pad with 3

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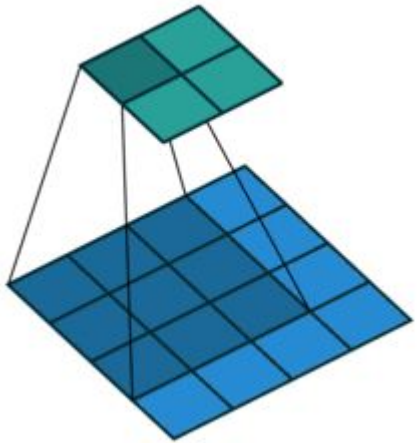
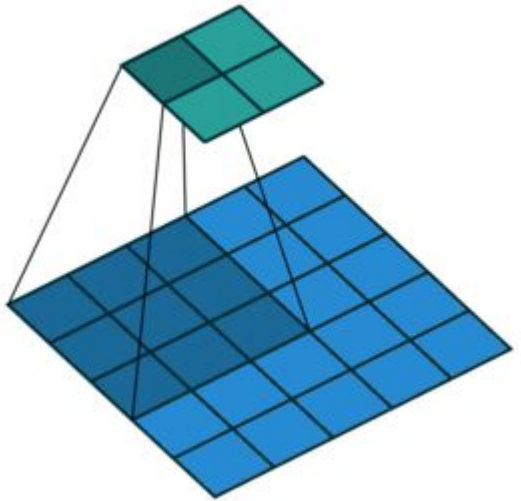
Strides, padding in convolutional layer



No padding,
no strides



No padding,
with strides

Image source: https://github.com/vdumoulin/conv_arithmetic

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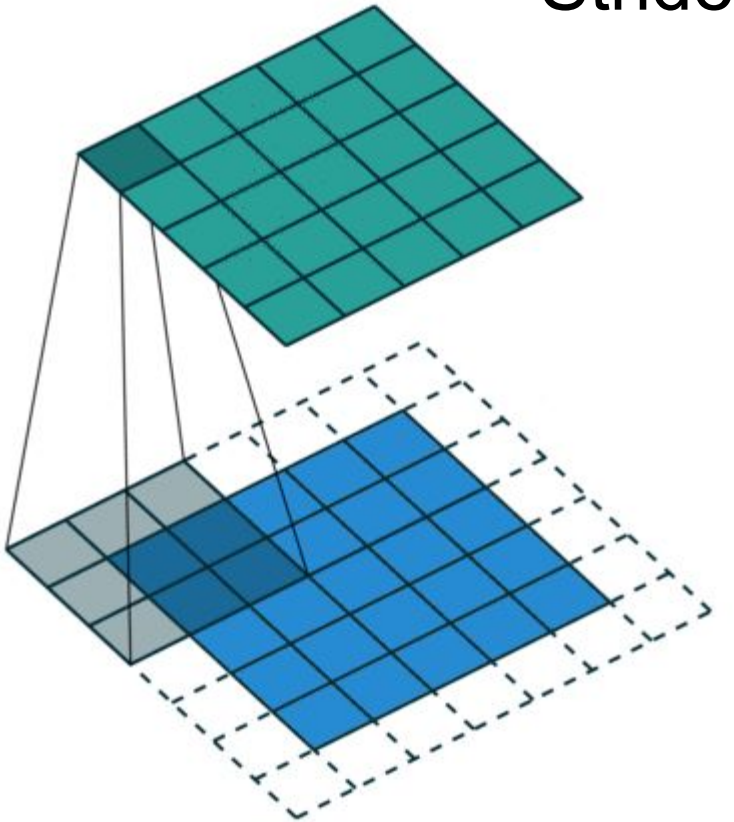
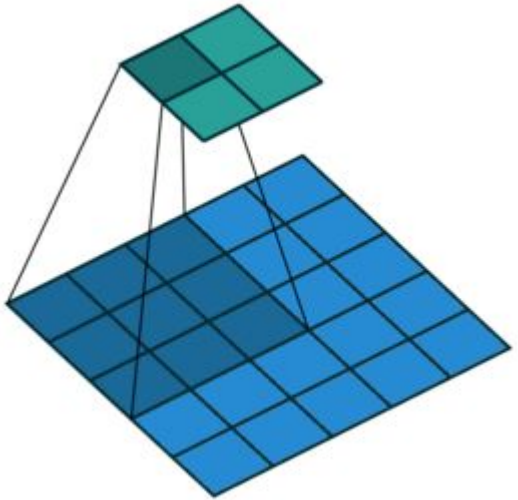


With padding,
no strides



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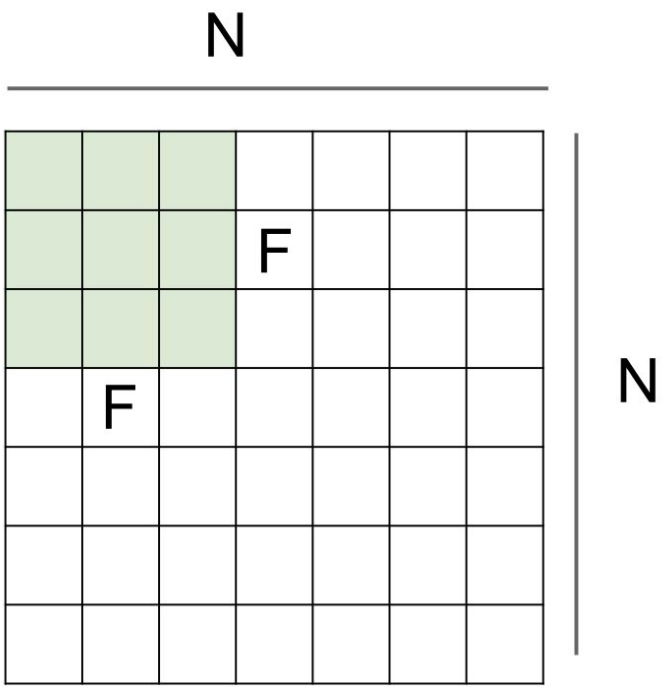

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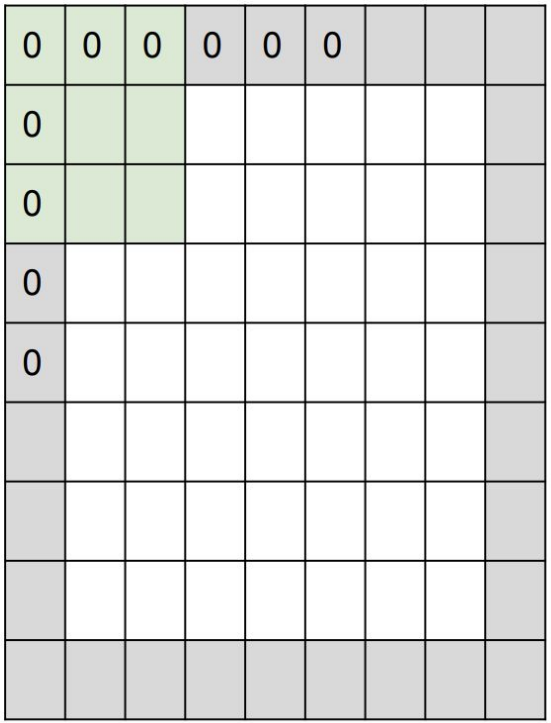

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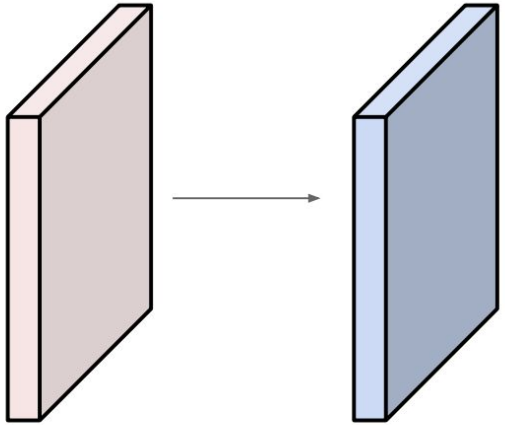
Examples time:



Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

Output volume size: ?

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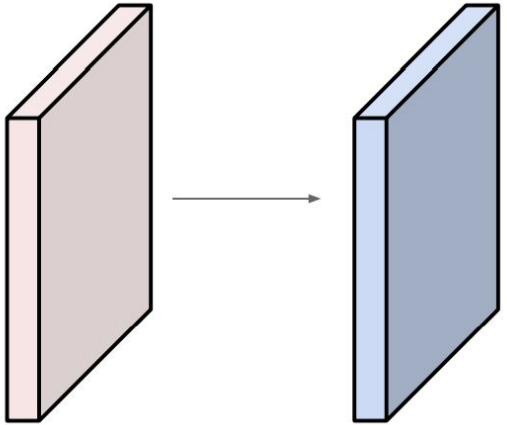
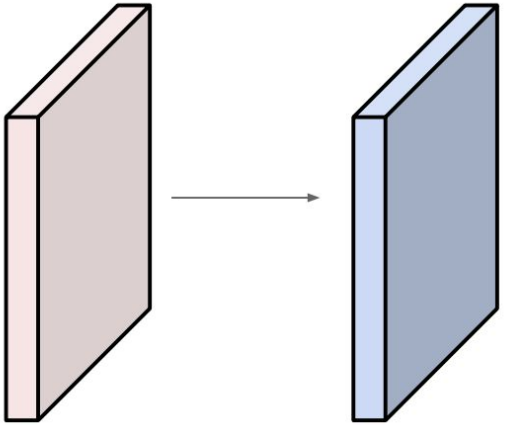


Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

Output volume size:
(32+2*2-5)/1+1 = 32 spatially, so
32x32x10

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

Examples time:



Input volume: **32x32x3**
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Number of parameters in this layer?

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

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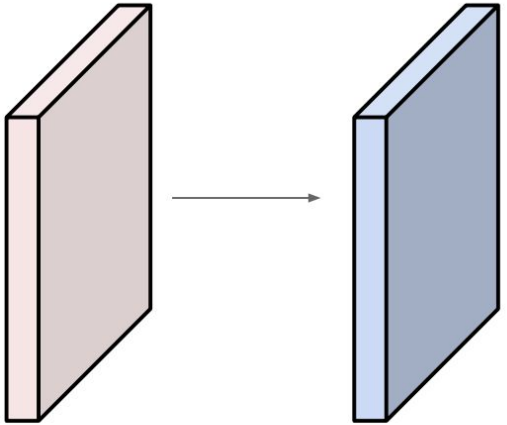
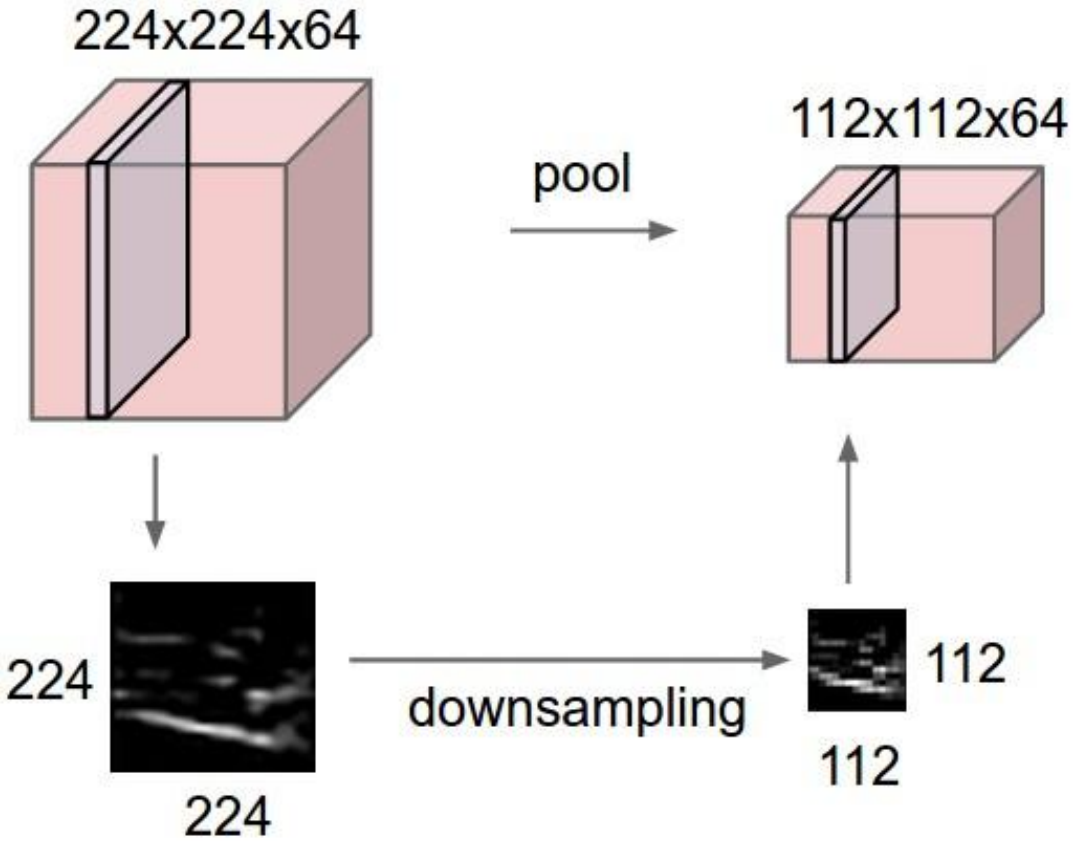


Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

Number of parameters in this layer?
each filter has 5*5*3 + 1 = 76 params (+1 for bias)
=> 76*10 = **760**

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

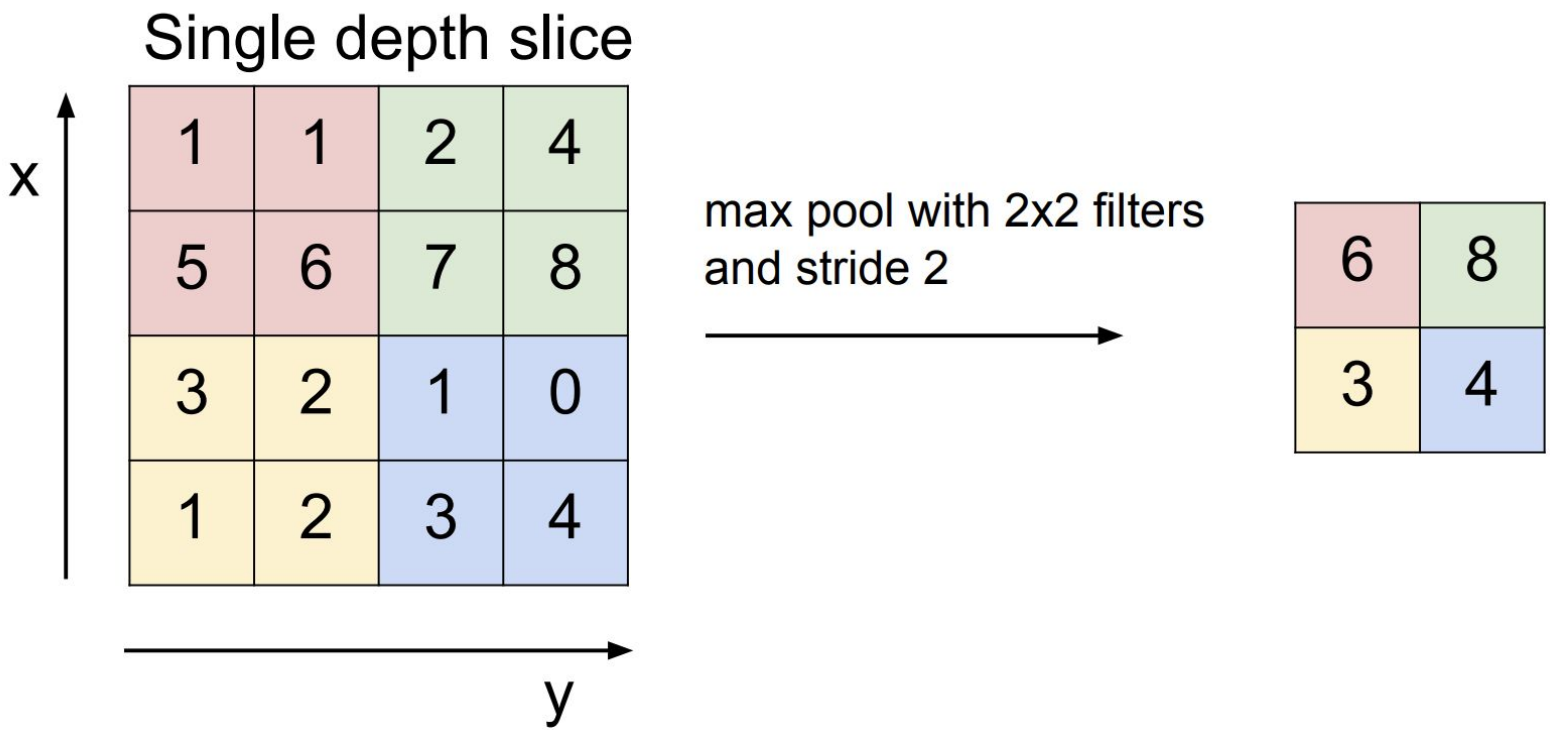
Pooling layer



- Makes the representations smaller and more manageable
- Operates over each activation map independently

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

Max pooling



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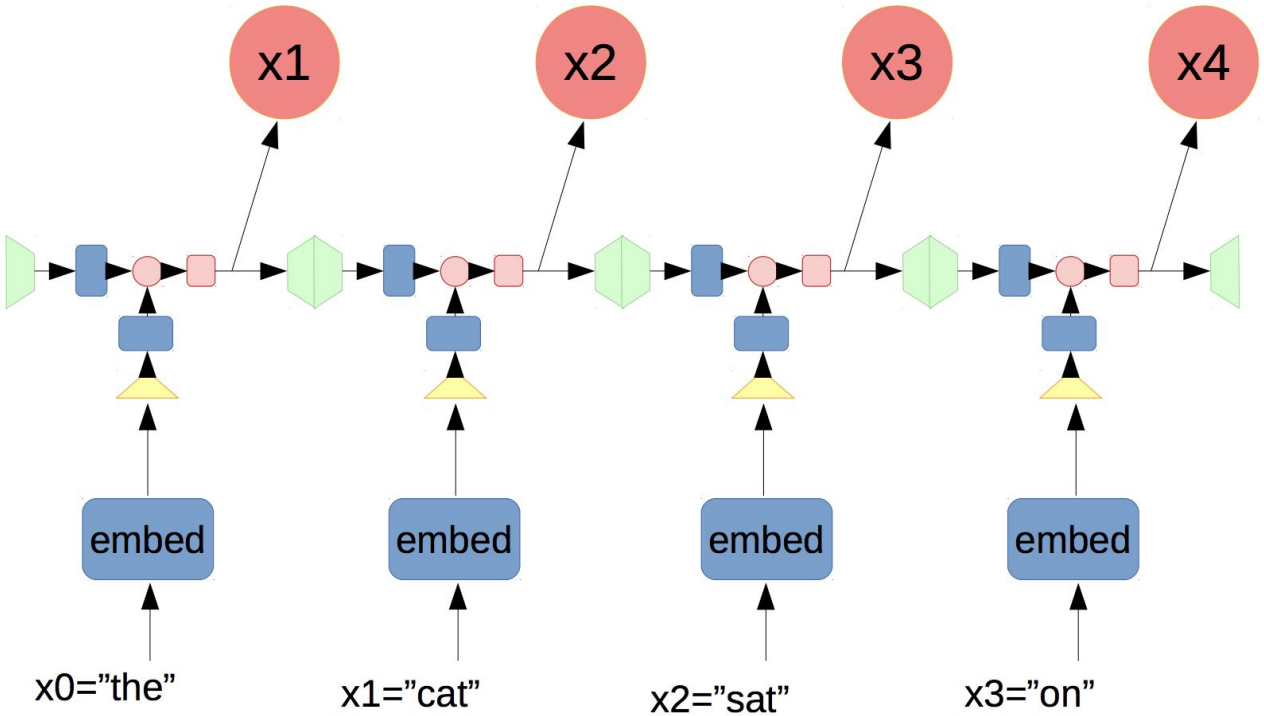
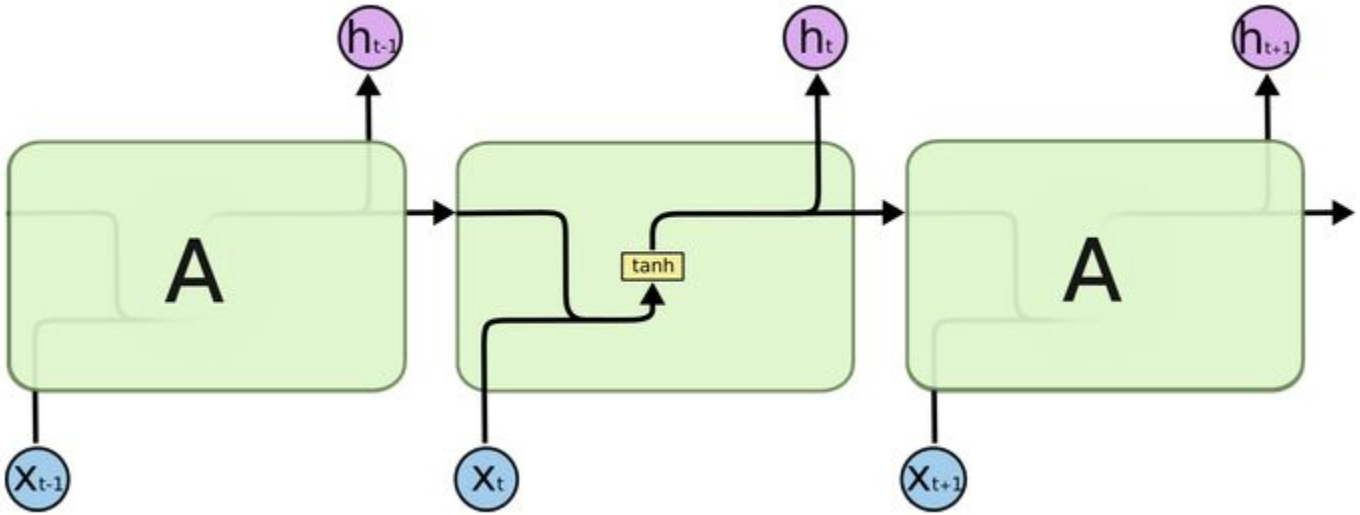
Back to texts

Recap: RNN

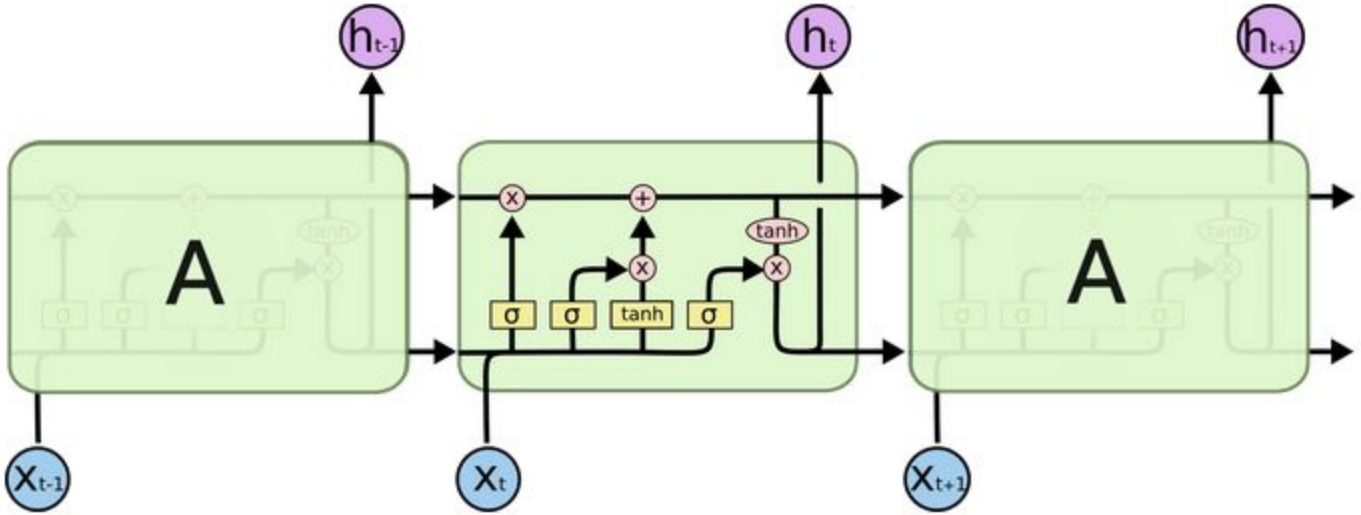


Recap: Vanilla RNN



Source: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Recap: LSTM



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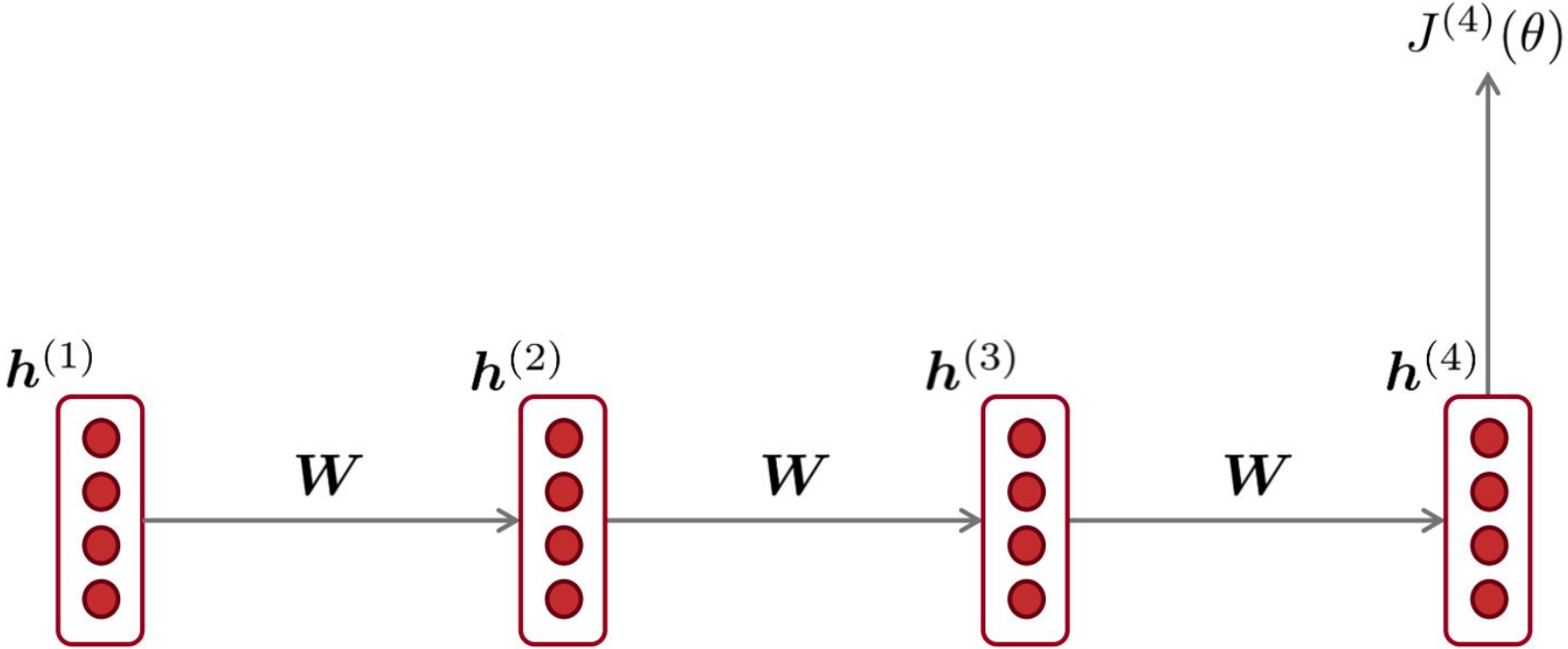
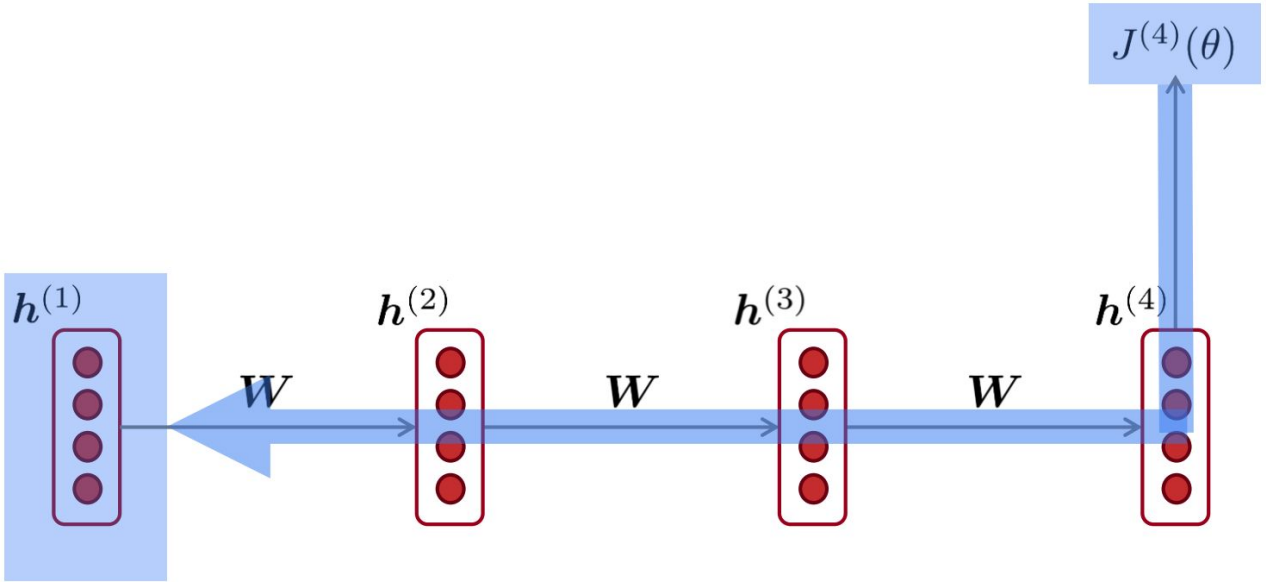
Vanishing gradient problem



Based on: Lecture by Abigail See, CS224n Lecture 7

Vanishing gradient problem



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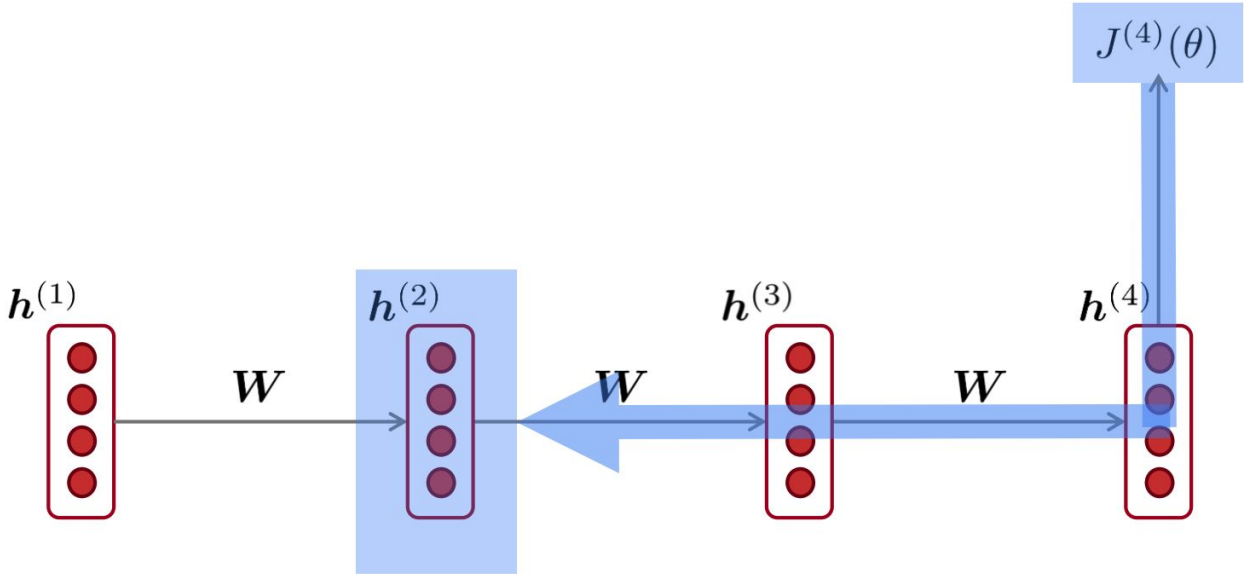
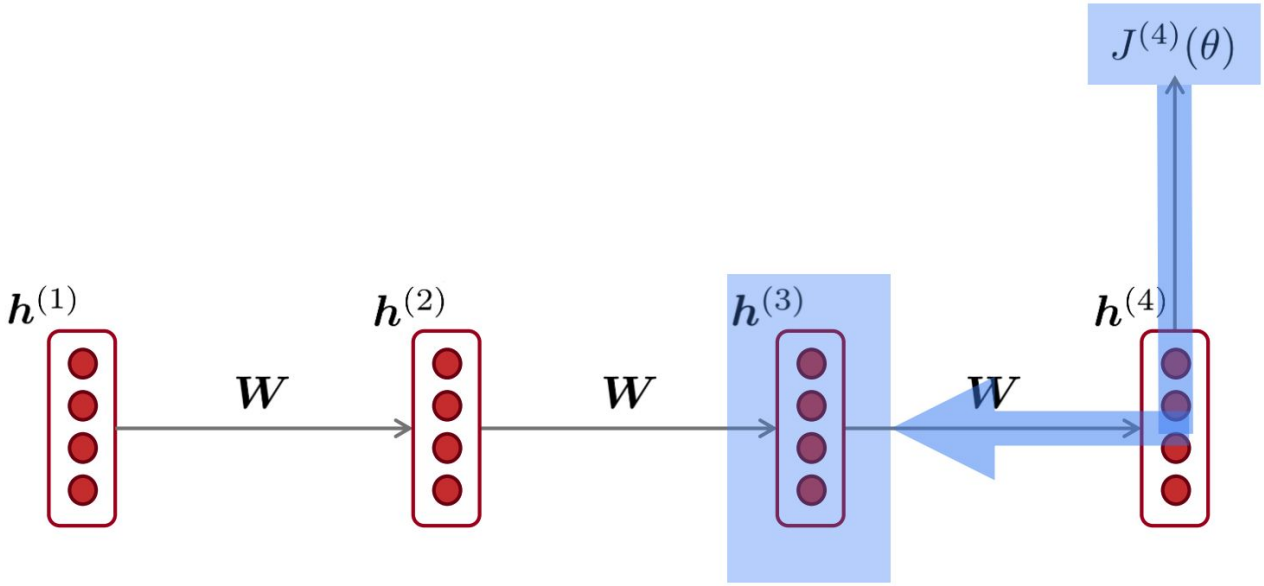


$$\frac{\partial J^{(4)}}{\partial \boldsymbol{h}^{(1)}} = \frac{\partial \boldsymbol{h}^{(2)}}{\partial \boldsymbol{h}^{(1)}} \times \frac{\partial J^{(4)}}{\partial \boldsymbol{h}^{(2)}}$$

chain rule!

Based on: Lecture by Abigail See, CS224n Lecture 7

Vanishing gradient problem



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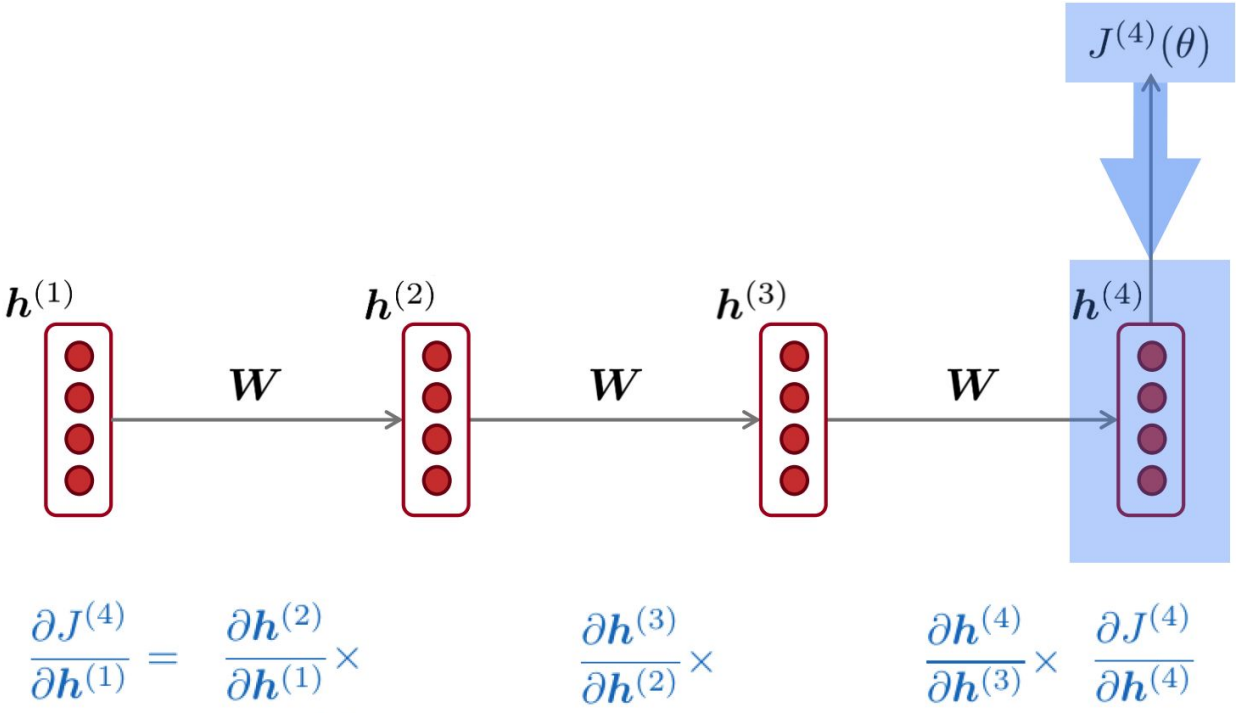

$$\frac{\partial J^{(4)}}{\partial h^{(1)}} = \frac{\partial h^{(2)}}{\partial h^{(1)}} \times \frac{\partial h^{(3)}}{\partial h^{(2)}} \times \frac{\partial h^{(4)}}{\partial h^{(3)}} \times \frac{\partial J^{(4)}}{\partial h^{(4)}}$$

chain rule!

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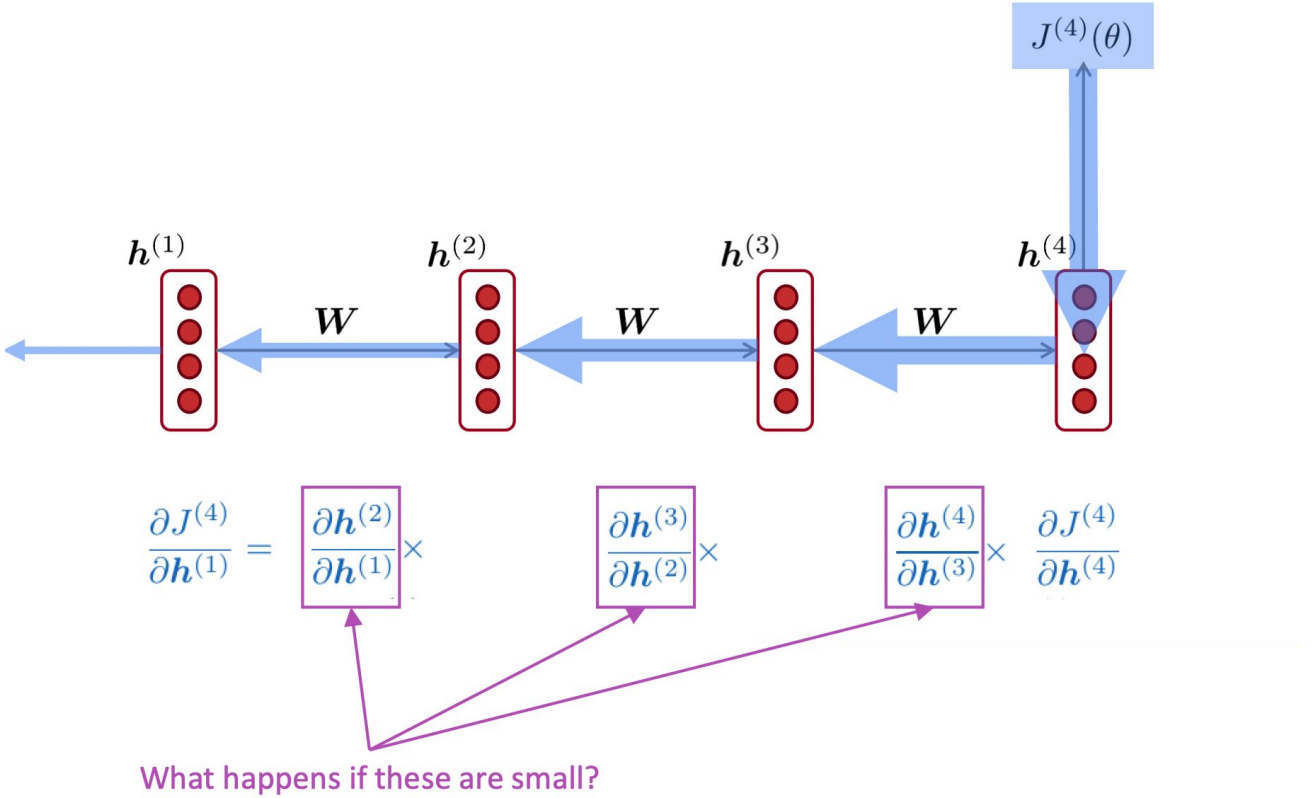
Vanishing gradient problem

Vanishing gradient problem:

When the derivatives are small, the gradient signal gets smaller and smaller as it backpropagates further

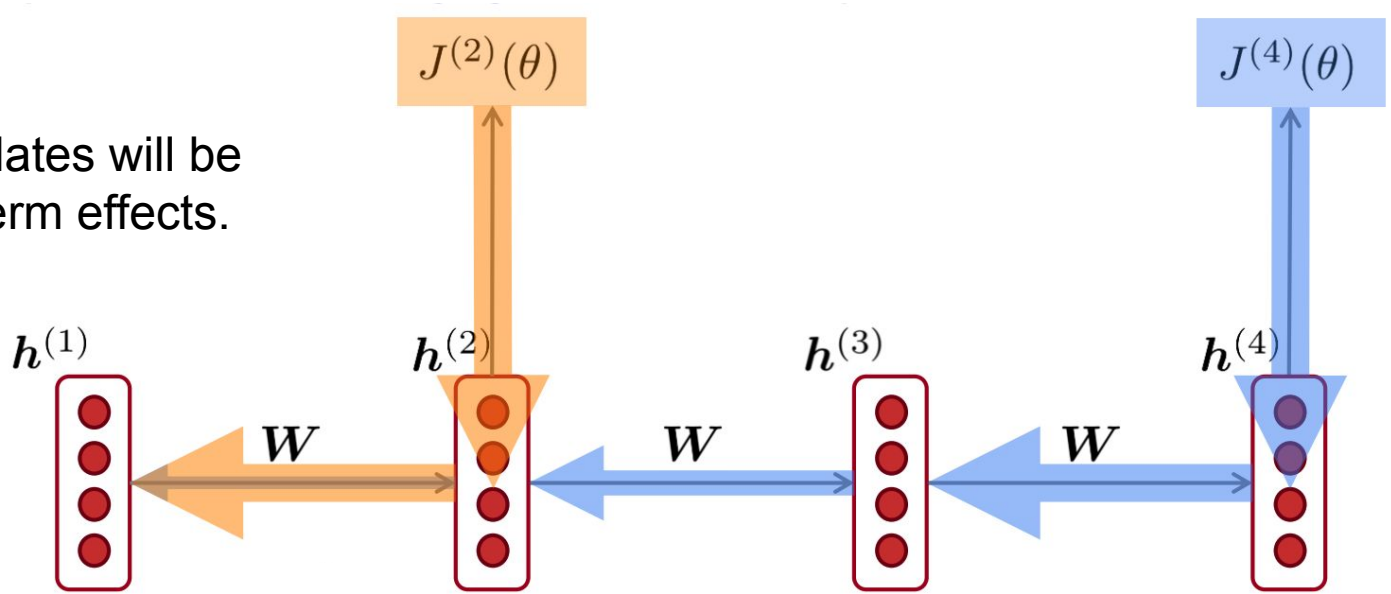


More info: "On the difficulty of training recurrent neural networks", Pascanu et al, 2013
http://proceedings.mlr.press/v28/pascanu13.pdf

Vanishing gradient problem

Gradient signal from far away is lost because it's much smaller than from close-by.

So model weights updates will be based only on short-term effects.



Based on: Lecture by Abigail See, CS224n Lecture 7

Exploding gradient problem

- If the gradient becomes too big, then the SGD update step becomes too big:

$$\theta^{new} = \theta^{old} - \underbrace{\alpha}_{\text{learning rate}} \underbrace{\nabla_\theta J(\theta)}_{\text{gradient}}$$

- This can cause bad updates: we take too large a step and reach a bad parameter configuration (with large loss)

- In the worst case, this will result in Inf or NaN in your network (then you have to restart training from an earlier checkpoint)

Based on: Lecture by Abigail See, CS224n Lecture 7

Exploding gradient solution

- Gradient clipping: if the norm of the gradient is greater than some threshold, scale it down before applying SGD update

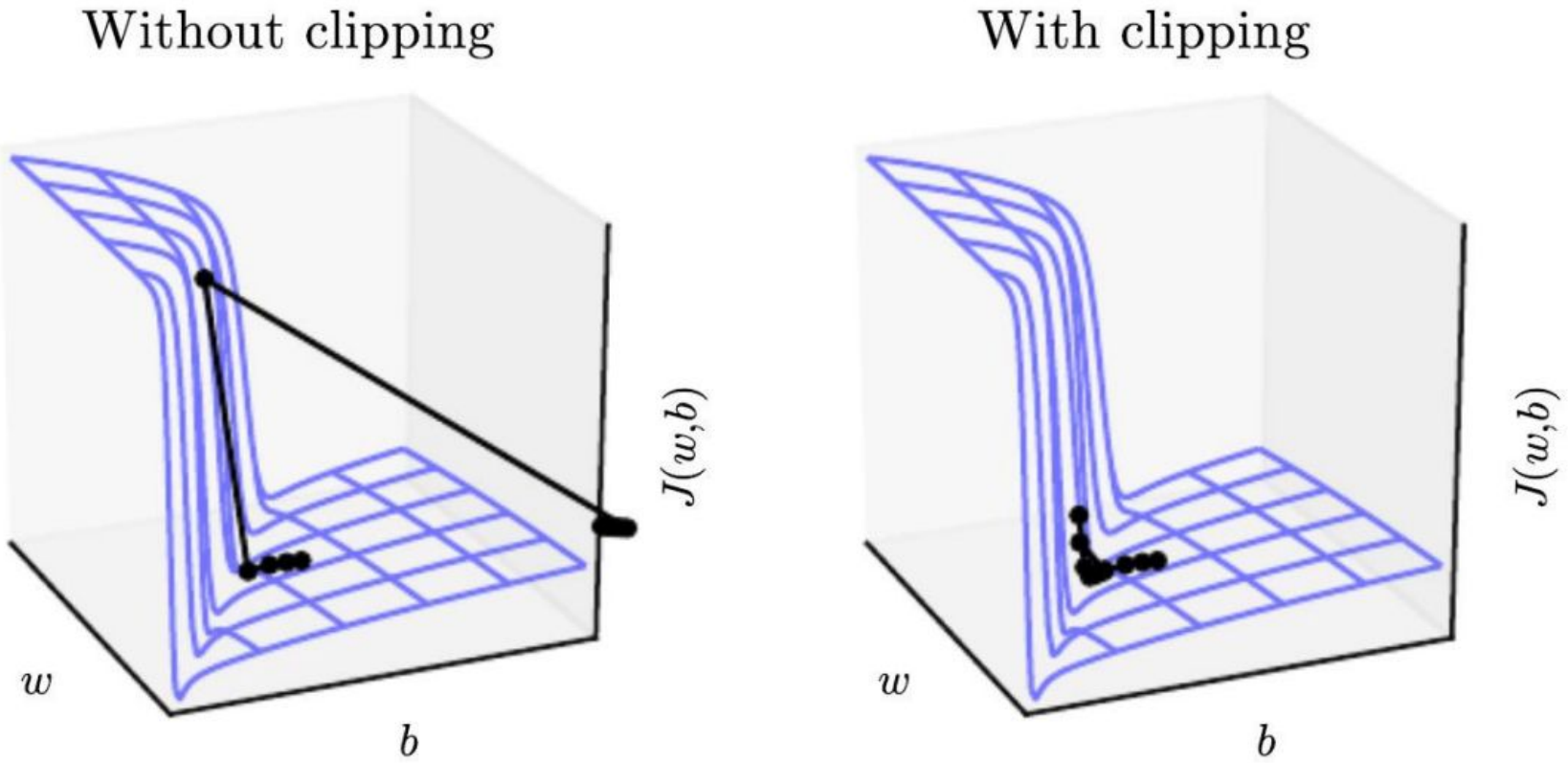
Algorithm 1 Pseudo-code for norm clipping

$\hat{\mathbf{g}} \leftarrow \frac{\partial \mathcal{E}}{\partial \theta}$
if $\|\hat{\mathbf{g}}\| \geq threshold$ **then**
  $\hat{\mathbf{g}} \leftarrow \frac{threshold}{\|\hat{\mathbf{g}}\|}\hat{\mathbf{g}}$
end if

- Intuition: take a step in the same direction, but a smaller step

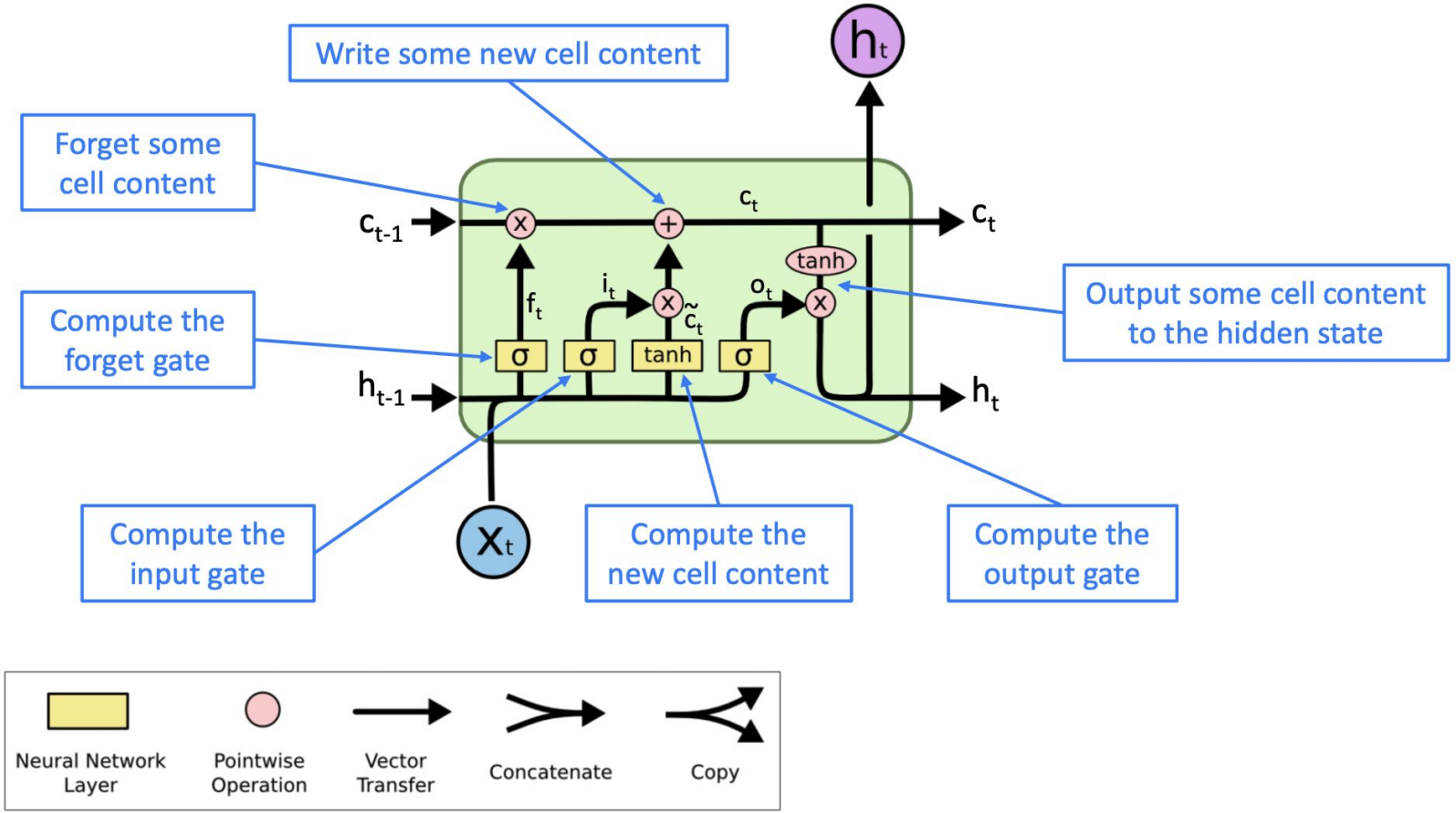
Based on: Lecture by Abigail See, CS224n Lecture 7

Exploding gradient solution



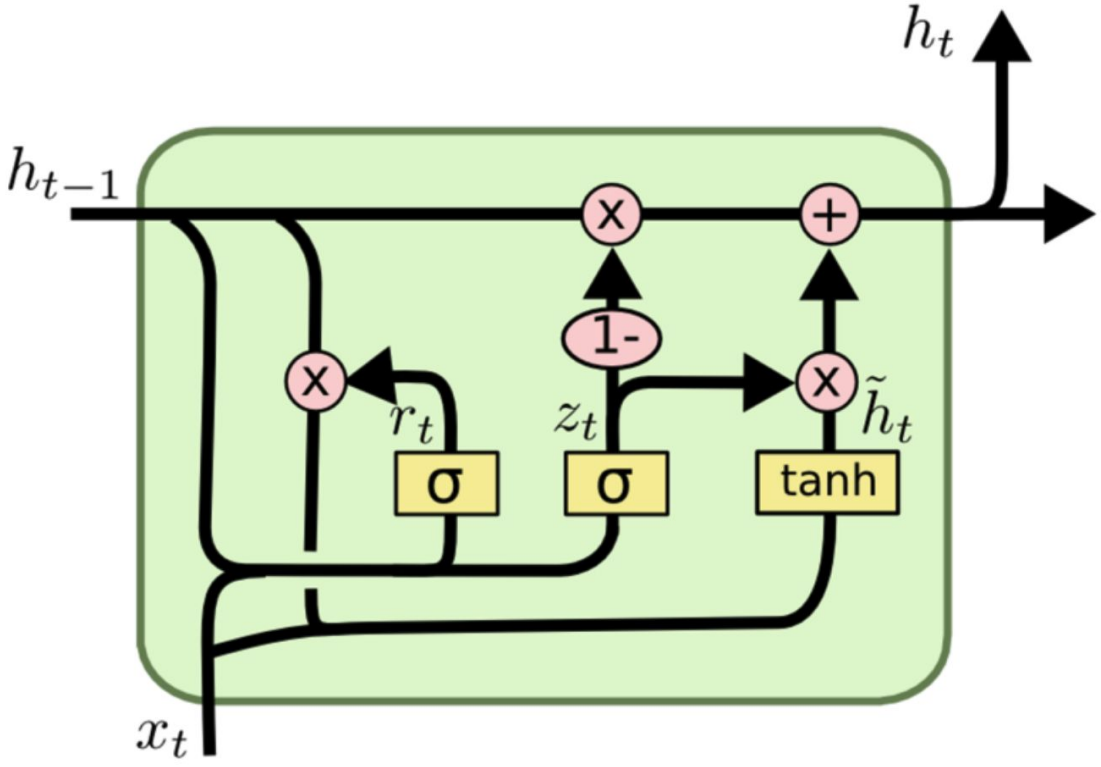
Based on: Lecture by Abigail See, CS224n Lecture 7

Vanishing gradient: LSTM



Based on: Lecture by Abigail See, CS224n Lecture 7

Vanishing gradient: GRU



Vanishing gradient: LSTM vs GRU

- LSTM and GRU are both great
  - GRU is quicker to compute and has fewer parameters than LSTM
  - There is no conclusive evidence that one consistently performs better than the other
  - LSTM is a good default choice (especially if your data has particularly long dependencies, or you have lots of training data)

Rule of thumb: start with LSTM, but switch to GRU if you want something more efficient

Vanishing gradient in non-RNN

Vanishing gradient is present in **all** deep neural network architectures.

- Due to chain rule / choice of nonlinearity function, gradient can become vanishingly small during backpropagation
- Lower levels are hard to train and are trained slower
- **Potential solution**: direct (or skip-) connections (just like in ResNet)

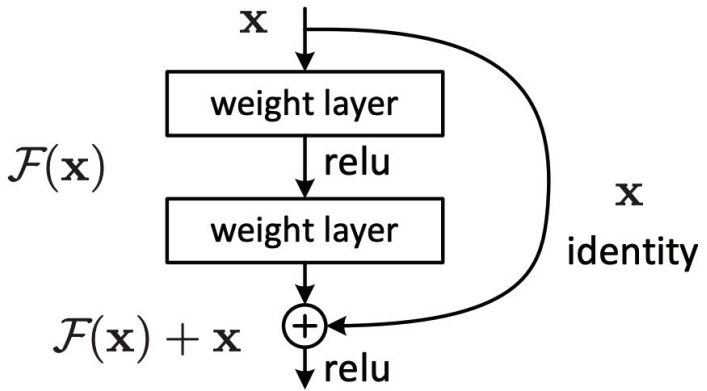


Figure 2. Residual learning: a building block.

Source: "Deep Residual Learning for Image Recognition", He et al, 2015. https://arxiv.org/pdf/1512.03385.pdf

Vanishing gradient in non-RNN

Vanishing gradient is present in **all** deep neural network architectures.

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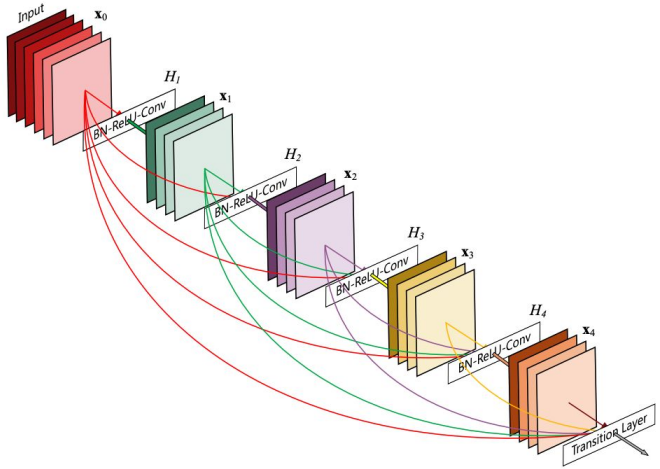
- **Potential solution**: dense connections (just like in DenseNet)



Source: ”Densely Connected Convolutional Networks", Huang et al, 2017 https://arxiv.org/pdf/1608.06993.pdf

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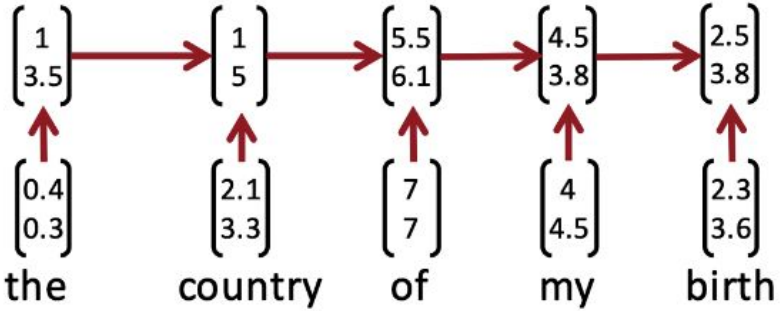
Conclusion:

Though vanishing/exploding gradients are a general problem, RNNs are particularly unstable due to the repeated multiplication by the same weight matrix [Bengio et al, 1994]

Source: ”Learning Long-Term Dependencies with Gradient Descent is Difficult", Bengio et al. 1994, http://ai.dinfo.unifi.it/paolo//ps/tnn-94-gradient.pdf

Applying CNNs to texts

From RNN to CNN



- Recurrent neural nets can not capture phrases without prefix context and often capture too much of last words in final vector

Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

From RNN to CNN

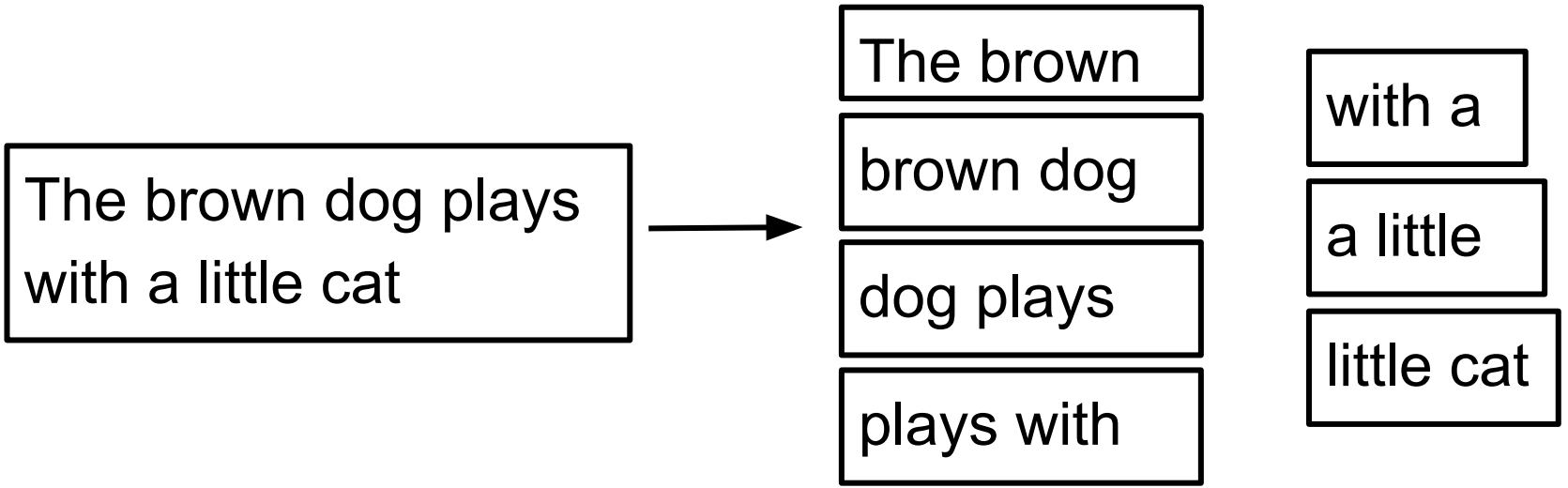
- RNN: Get compositional vectors for grammatical phrases only

- CNN: What if we compute vectors for every possible phrase?
  - Example: *“the country of my birth”* computes vectors for:
    - *the country, country of, of my, my birth, the country of, country of my, of my birth, the country of my, country of my birth*

- Regardless of whether it is grammatical
- Wouldn’t need parser
- Not very linguistically or cognitively plausible

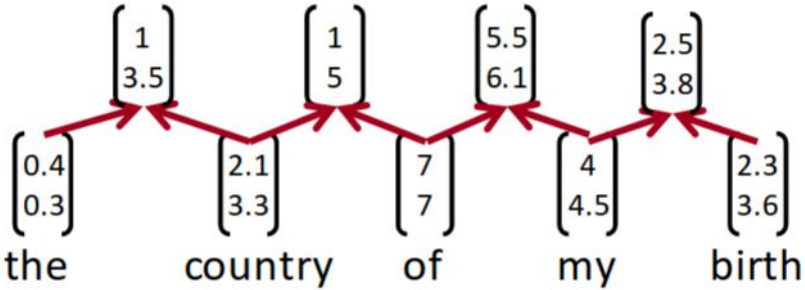
Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

Recap: n-gramms



From RNN to CNN

- Imagine using only bigrams



- Same operation as in RNN, but for every pair

$$p = \tanh\left(W \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right)$$

- Can be interpreted as convolution over the word vectors

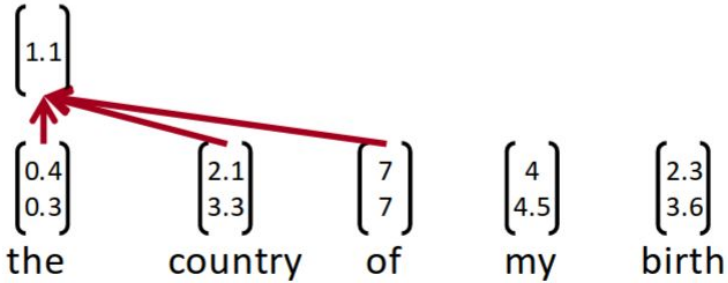
Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

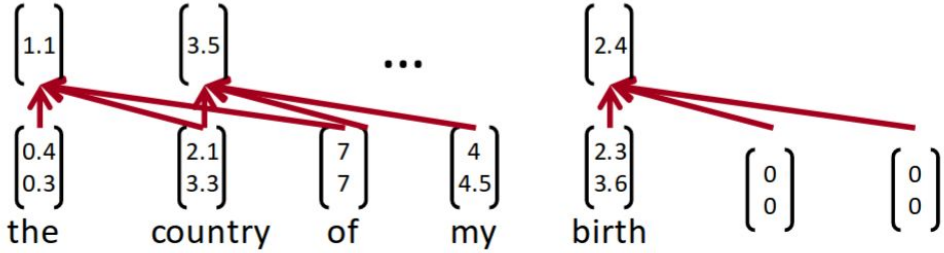
One layer CNN

- Simple convolution + pooling
- Window size may be different (2 or more)
- The feature map based on bigrams:

$$c_i = f(\mathbf{w}^T \mathbf{x}_{i:i+h-1} + b)$$

$$\mathbf{c} = [c_1, c_2, \ldots, c_{n-h+1}] \in \mathbb{R}^{n-h+1}$$





Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

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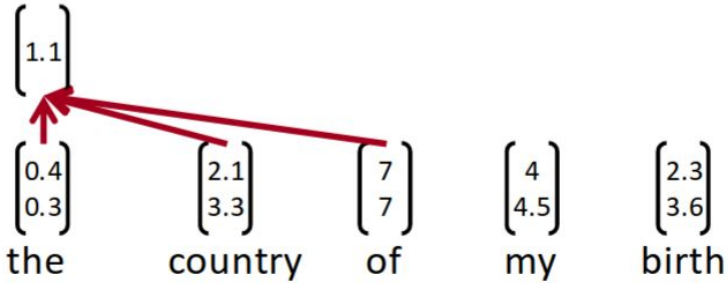
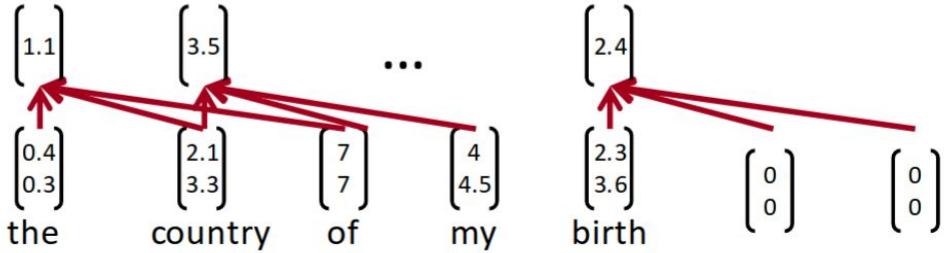


$$\mathbf{c} = [c_1, c_2, \ldots, c_{n-h+1}] \in \mathbb{R}^{n-h+1}$$

What's next?

We need more features!



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One layer CNN

- Feature representation is based on some applied filter:

$$\mathbf{c} = [c_1, c_2, \ldots, c_{n-h+1}] \in \mathbb{R}^{n-h+1}$$

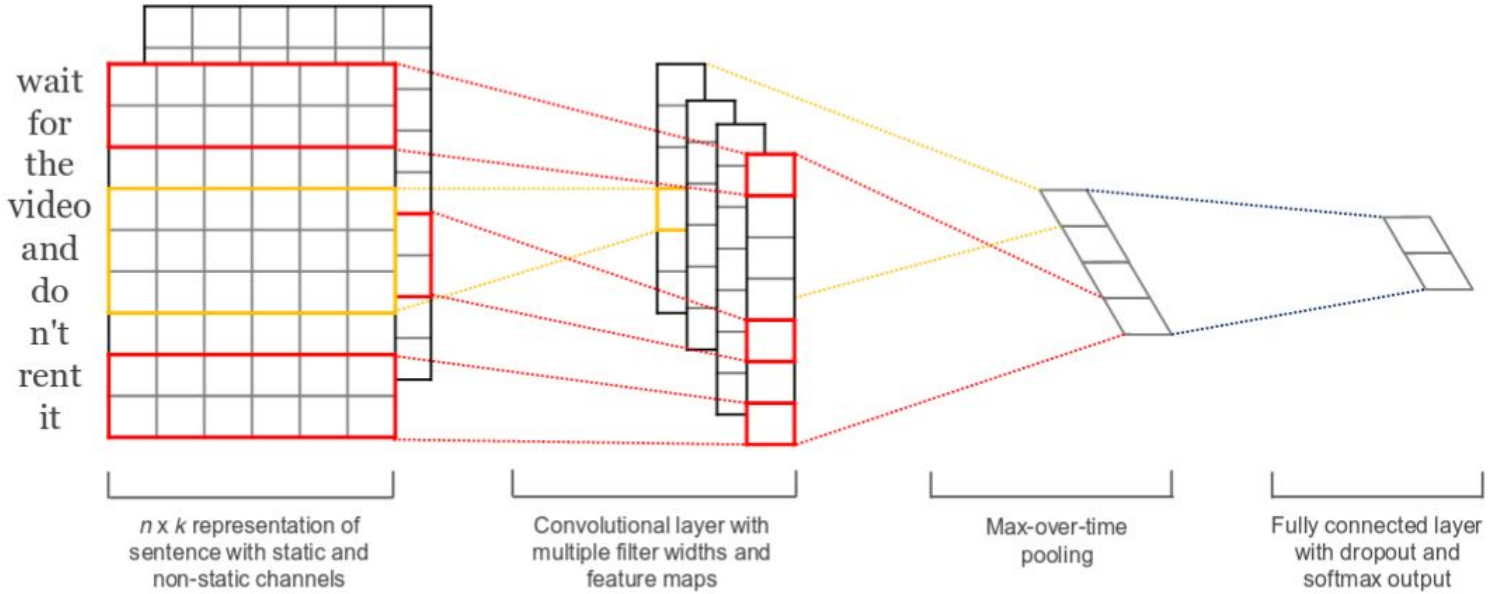
- Let's use pooling: $\hat{c} = \max\{\mathbf{c}\}$

- Now the length of **c** is irrelevant!

- So we can use filters based on unigrams, bigrams, tri-grams, 4-grams, etc.

Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

Another example from Kim (2014) paper



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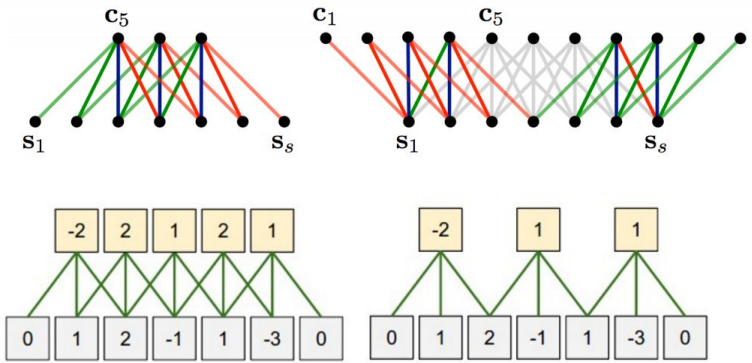
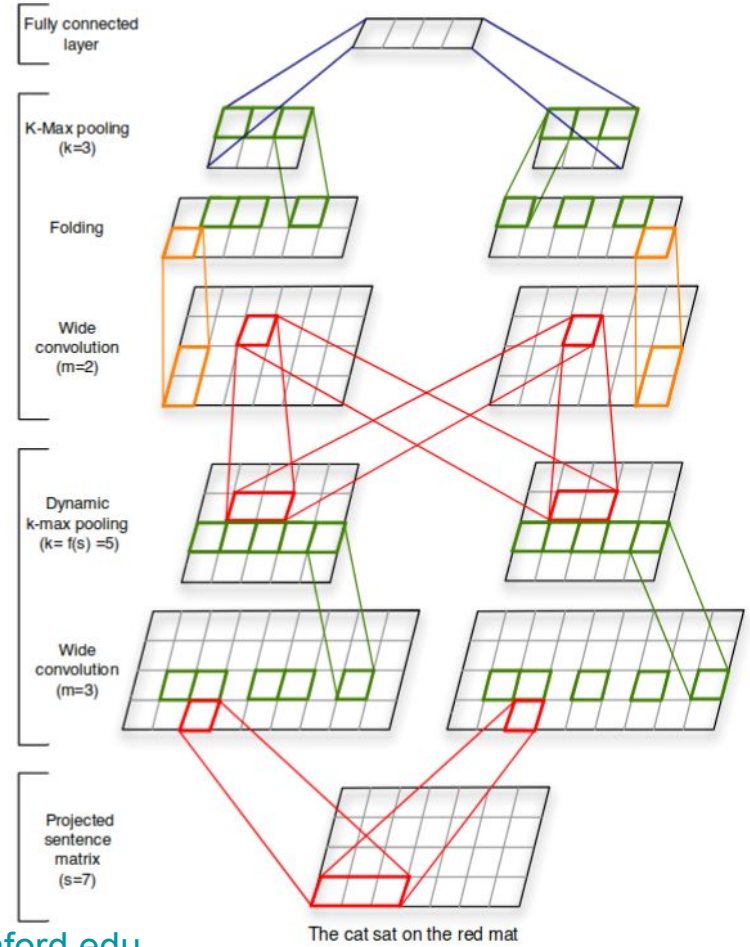
More about CNN

- Narrow vs wide convolution (stride and zero-padding)



- Complex pooling schemes over sequences
- Great readings (e.g. Kalchbrenner et. al. 2014)



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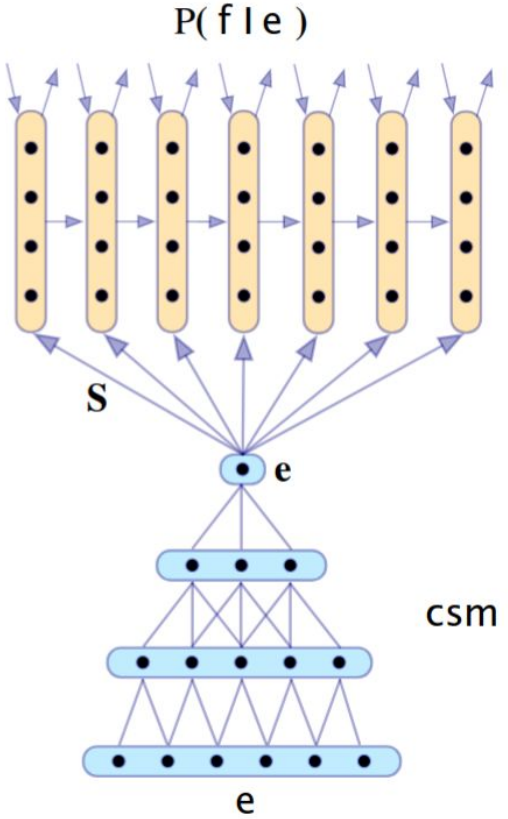
CNN applications

- Neural machine translation: CNN as encoder, RNN as decoder
- Kalchbrenner and Blunsom (2013) “Recurrent Continuous Translation Models”
- One of the first neural machine translation efforts



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Approaches comparison

Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-rand	76.1	45.0	82.7	89.6	91.2	79.8	83.4
CNN-static	81.0	45.5	86.8	93.0	92.8	84.7	**89.6**
CNN-non-static	**81.5**	48.0	87.2	93.4	93.6	84.3	89.5
CNN-multichannel	81.1	47.4	**88.1**	93.2	92.2	**85.0**	89.4
RAE (Socher et al., 2011)	77.7	43.2	82.4	–	–	–	86.4
MV-RNN (Socher et al., 2012)	79.0	44.4	82.9	–	–	–	–
RNTN (Socher et al., 2013)	–	45.7	85.4	–	–	–	–
DCNN (Kalchbrenner et al., 2014)	–	48.5	86.8	–	93.0	–	–
Paragraph-Vec (Le and Mikolov, 2014)	–	**48.7**	87.8	–	–	–	–
CCAE (Hermann and Blunsom, 2013)	77.8	–	–	–	–	–	87.2
Sent-Parser (Dong et al., 2014)	79.5	–	–	–	–	–	86.3
NBSVM (Wang and Manning, 2012)	79.4	–	–	93.2	–	81.8	86.3
MNB (Wang and Manning, 2012)	79.0	–	–	**93.6**	–	80.0	86.3
G-Dropout (Wang and Manning, 2013)	79.0	–	–	93.4	–	82.1	86.1
F-Dropout (Wang and Manning, 2013)	79.1	–	–	**93.6**	–	81.9	86.3
Tree-CRF (Nakagawa et al., 2010)	77.3	–	–	–	–	81.4	86.1
CRF-PR (Yang and Cardie, 2014)	–	–	–	–	–	82.7	–
SVM_S (Silva et al., 2011)	–	–	–	–	**95.0**	–	–

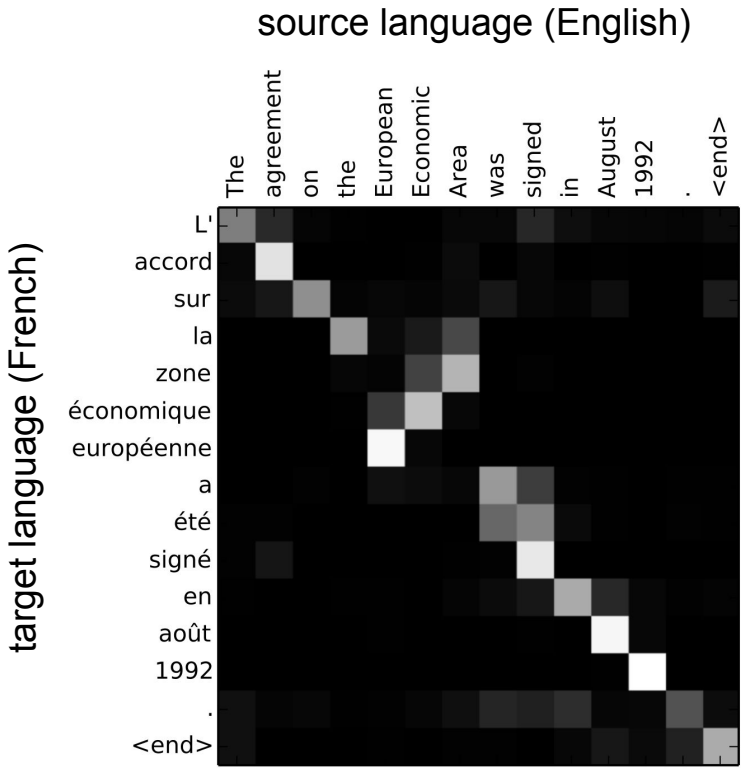
Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

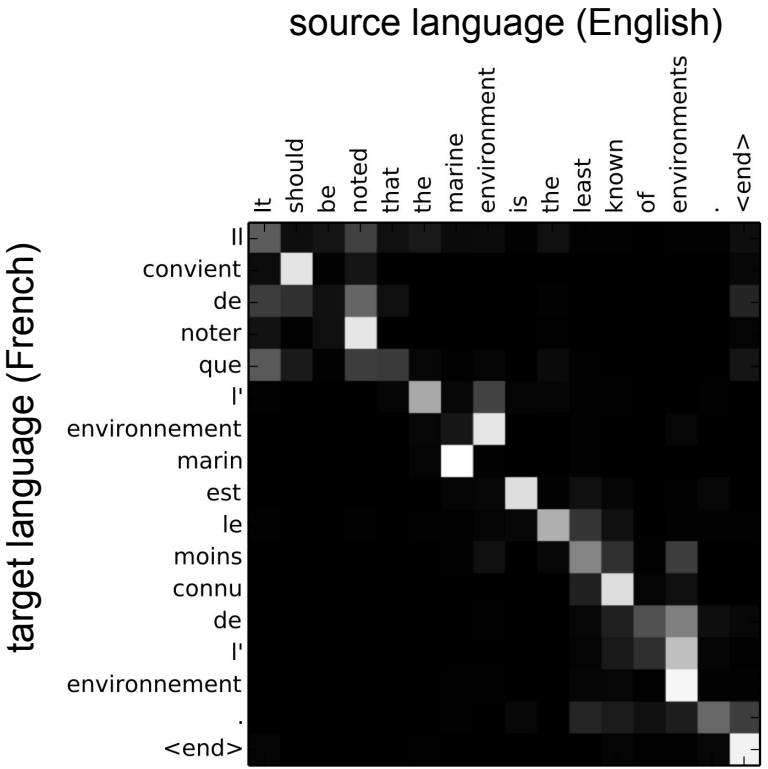
Outro and Q & A

- Vanishing gradient is present not only in RNNs
  - Use some kind of memory or skip-connections
- LSTM and GRU are both great
  - GRU is quicker, LSTM catch more complex dependencies
- Rule of thumb: start with LSTM, but switch to GRU if you want something more efficient
- Clip your gradients
- Combining RNN and CNN worlds? Why not ;)

That’s all. Feel free to ask any questions.

Attention outro





Bahdanau et al. "Neural Machine Translation by Jointly Learning to Align and Translate", 2014