Lecture 02: CNN for texts, embeddings for different languages

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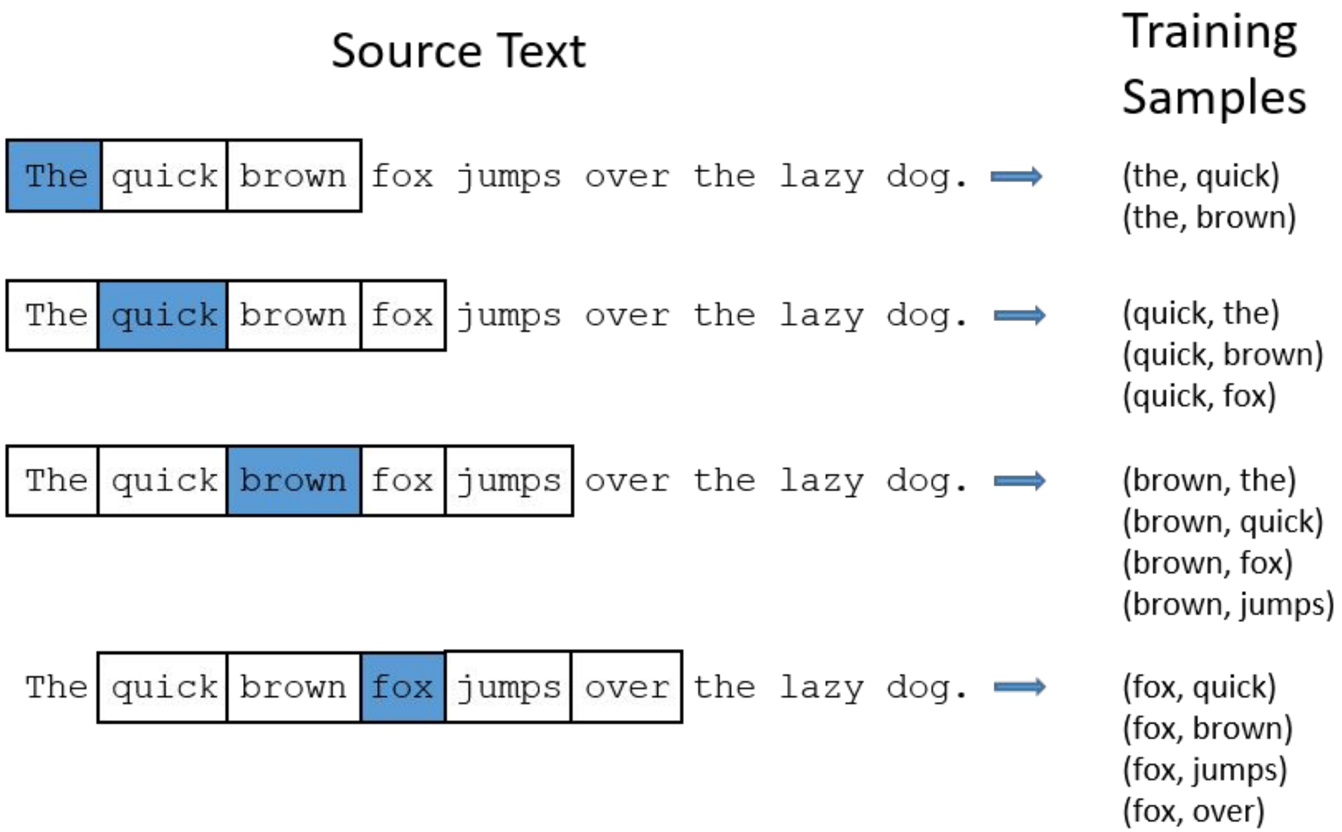
Outline

- Embeddings in the wild
  - Recap
  - Unsupervised translation

- RNNs recap:
  - Dealing with sequences
  - LSTM and GRU recap
  - Vanishing and exploding gradient recap

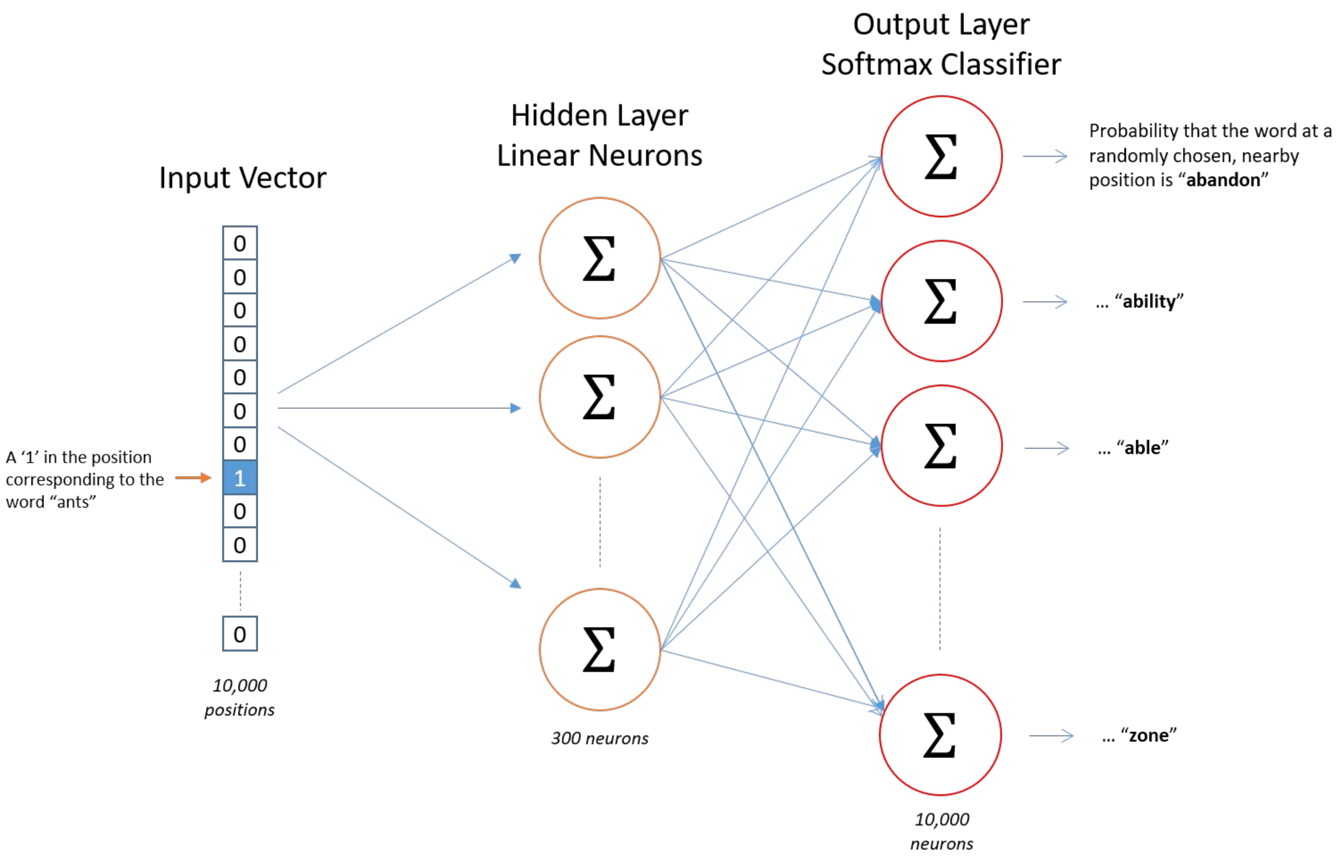
- CNNs for text processing

Embeddings: word2vec



Source: http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/

Embeddings: word2vec



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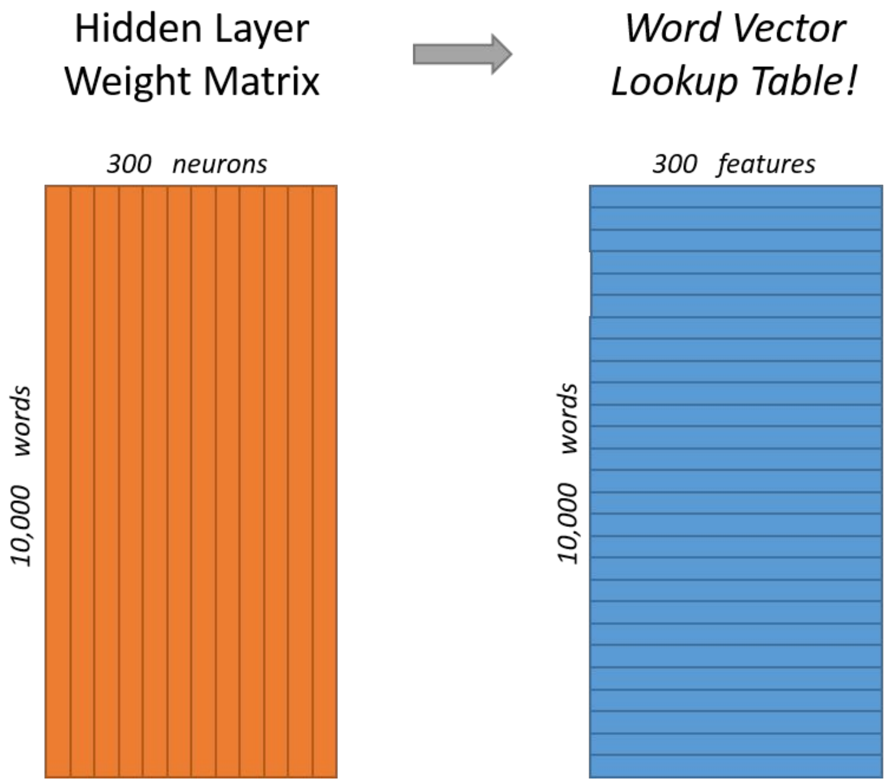
Embeddings: word2vec



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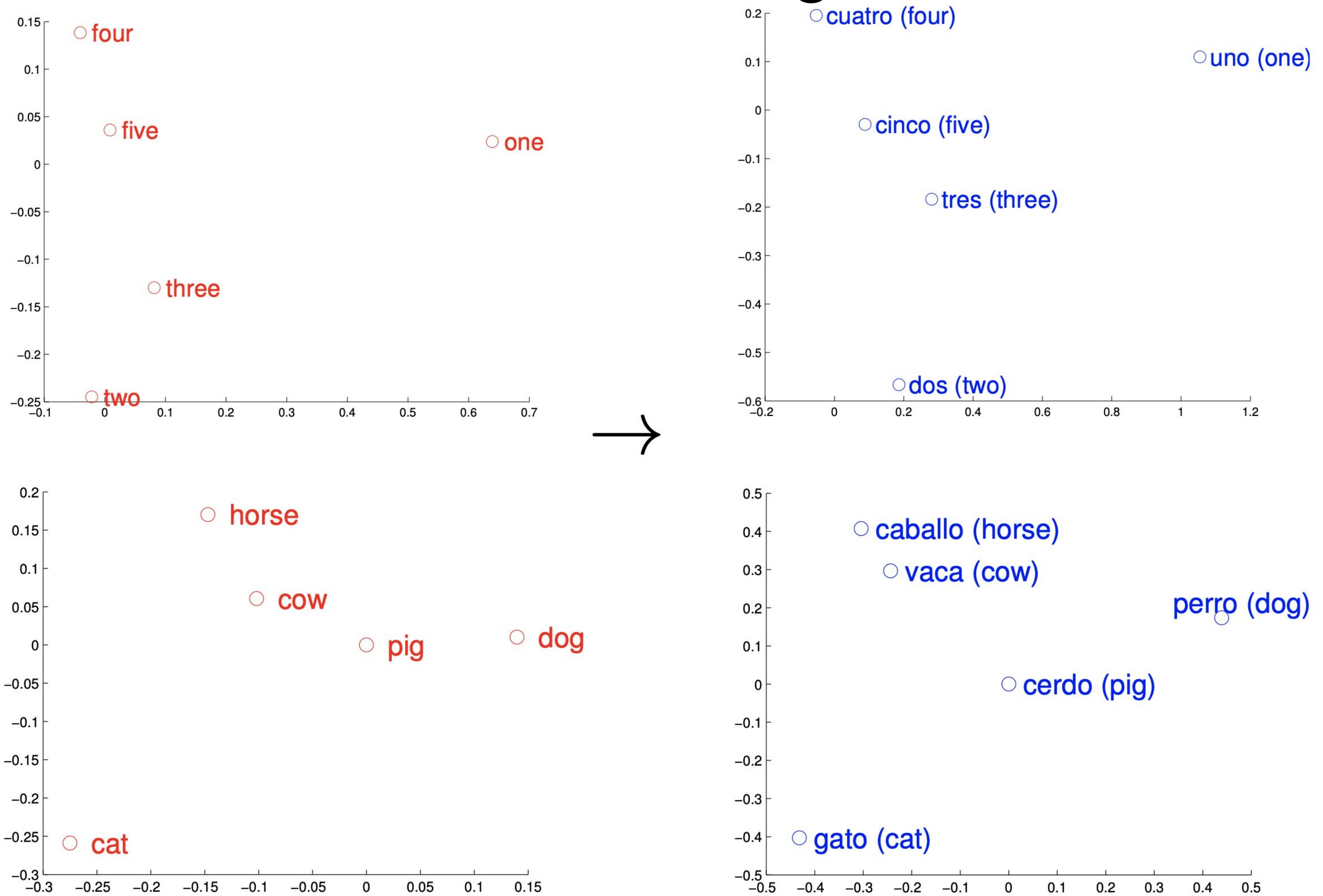
Word embeddings in different languages



Source: [Exploiting similarities among languages for machine translation, 2013]

Word embeddings in different languages

- Word embeddings are quite similar for different languages
- Assume there n = 5000 word-translation pairs $\{x_i, y_i\}_{i \in \{1,n\}}$
- Learn linear mapping between the source and target spaces

$$W^\star = \underset{W \in M_d(\mathbb{R})}{\operatorname{argmin}} \|WX - Y\|_\mathrm{F}$$

- The translation of source word is $t = \operatorname{argmax}_t \cos(Wx_s, y_t)$.

Sources: Exploiting similarities among languages for machine translation, 2013
Word translation without parallel data, ICLR 2018

Word embeddings in different languages

- Word embeddings are quite similar for different languages
- Assume there n = 5000 word-translation pairs $\{x_i, y_i\}_{i \in \{1,n\}}$
- Learn linear mapping between the source and target spaces

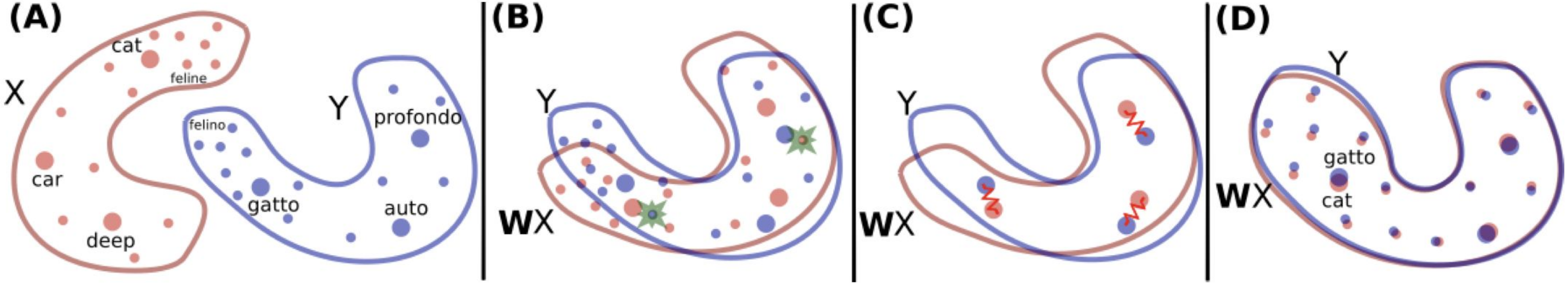
  enforcing an orthogonality constraint on W:

$$W^\star = \underset{W \in O_d(\mathbb{R})}{\text{argmin}} \|WX - Y\|_{\mathrm{F}} = UV^T, \text{with } U\Sigma V^T = \mathrm{SVD}(YX^T).$$

- The translation of source word is $t = \text{argmax}_t \cos(Wx_s, y_t)$.

Sources: Normalized word embedding and orthogonal transform for bilingual word translation, NAACL 2015
Word translation without parallel data, ICLR 2018

Word embeddings in different languages



Comment: mapping between two languages can be done completely in unsupervised manner with GANs.

We will meet later.

More info available in the mentioned paper:

Source: [Word translation without parallel data, ICLR 2018]

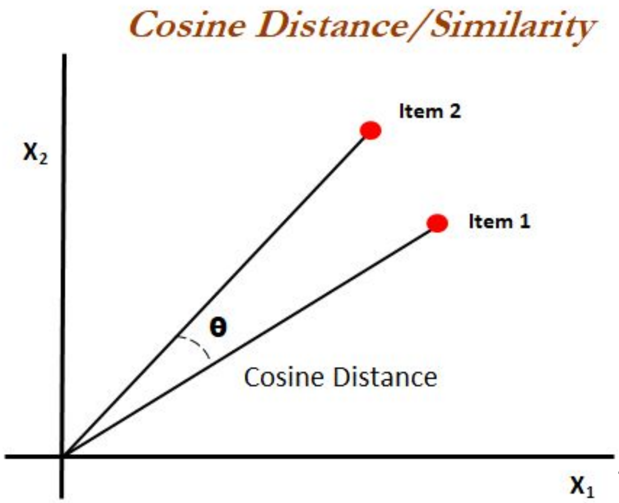
Why cosine distance/similarity?

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$

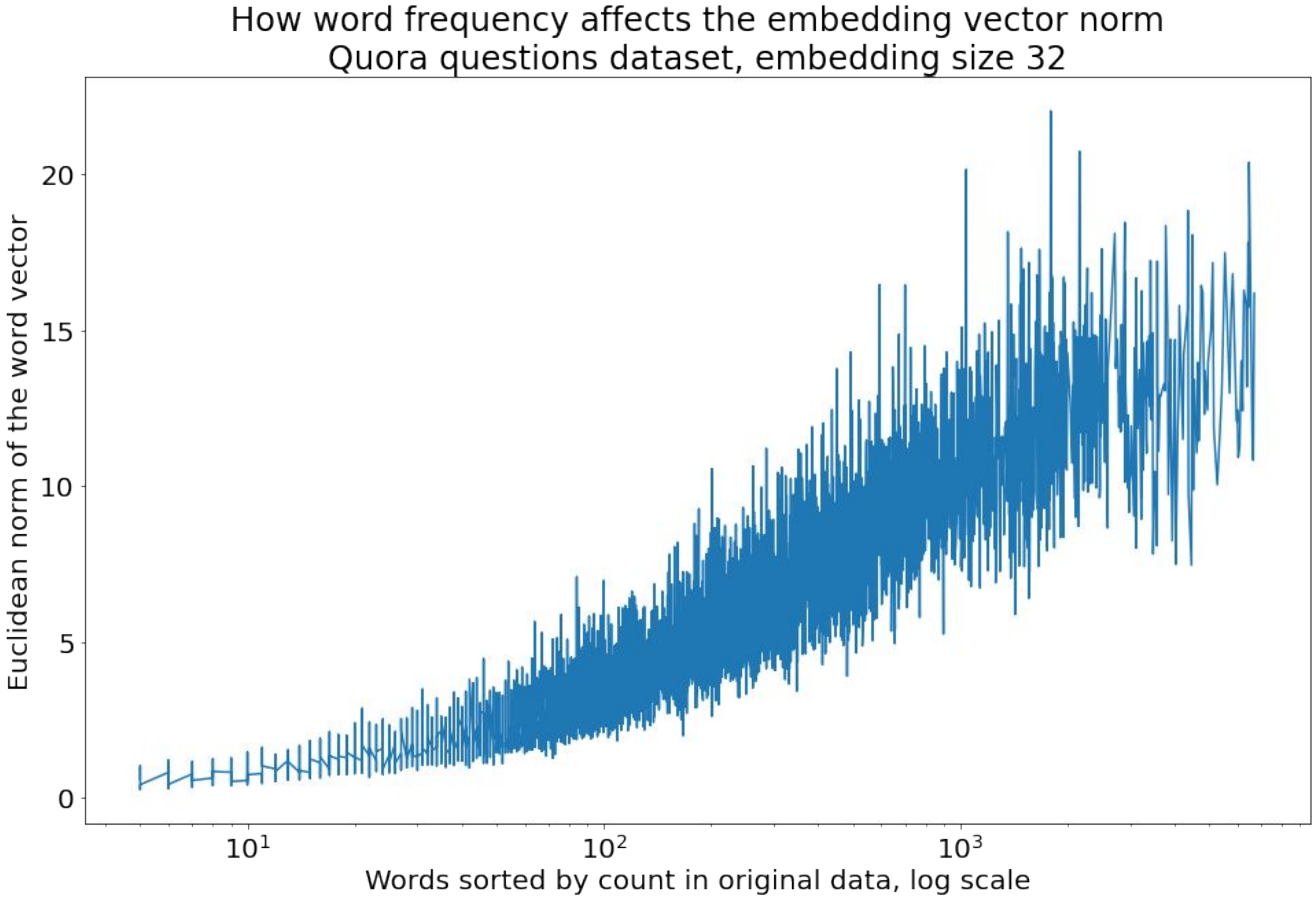
Cosine distance focuses on angle between the vectors.

With count-based approaches (e.g. BOW) it is really useful.

With word embeddings it is useful as well.



Source: [question]


How word frequency affects the embedding vector norm
Quora questions dataset, embedding size 32
Euclidean norm of the word vector
0
5
10
15
20
10^1
10^2
10^3
Words sorted by count in original data, log scale

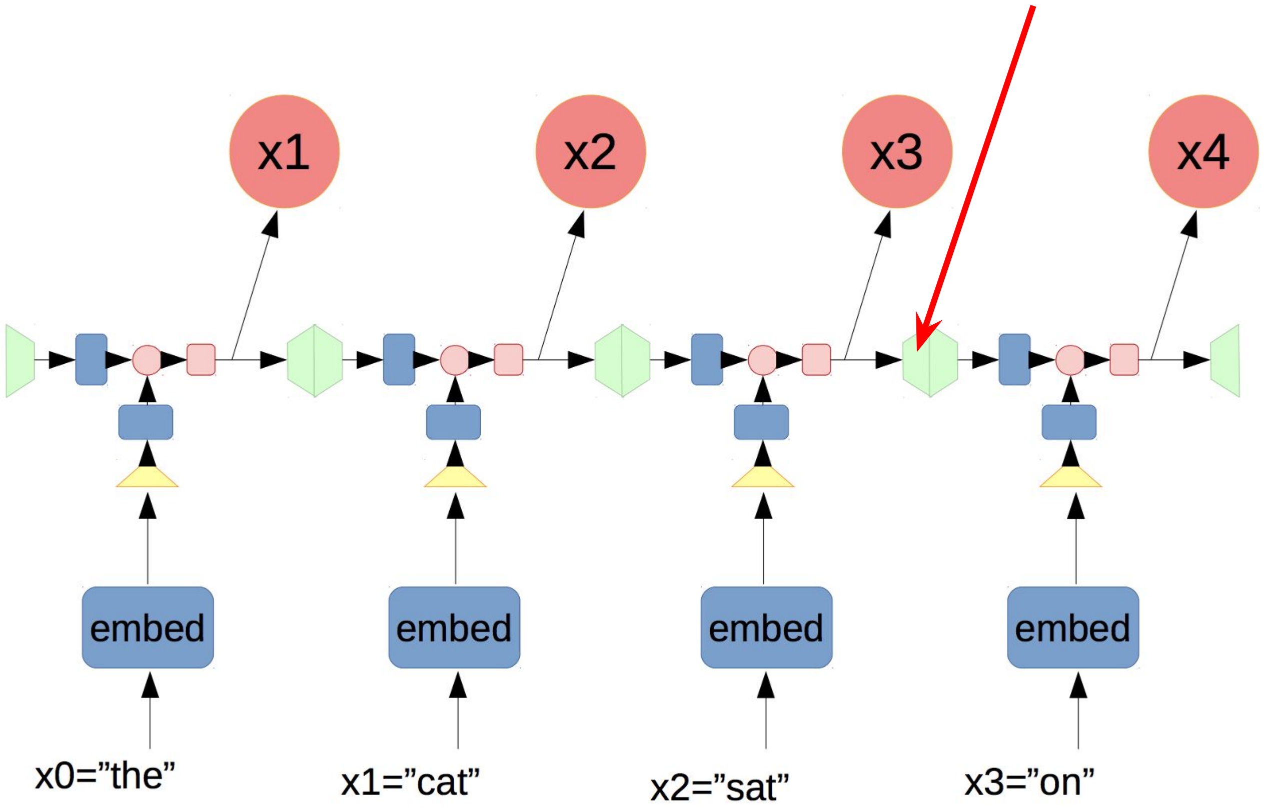
Vector norms for words with no specific context

word	count	vector norm
overheat	11	0.81233
enormous	12	0.807057
dog	1212	11.2591
cat	1545	10.3738
laptop	1906	14.5192
phone	4124	15.7901
a	155726	11.4656
the	252068	8.47355

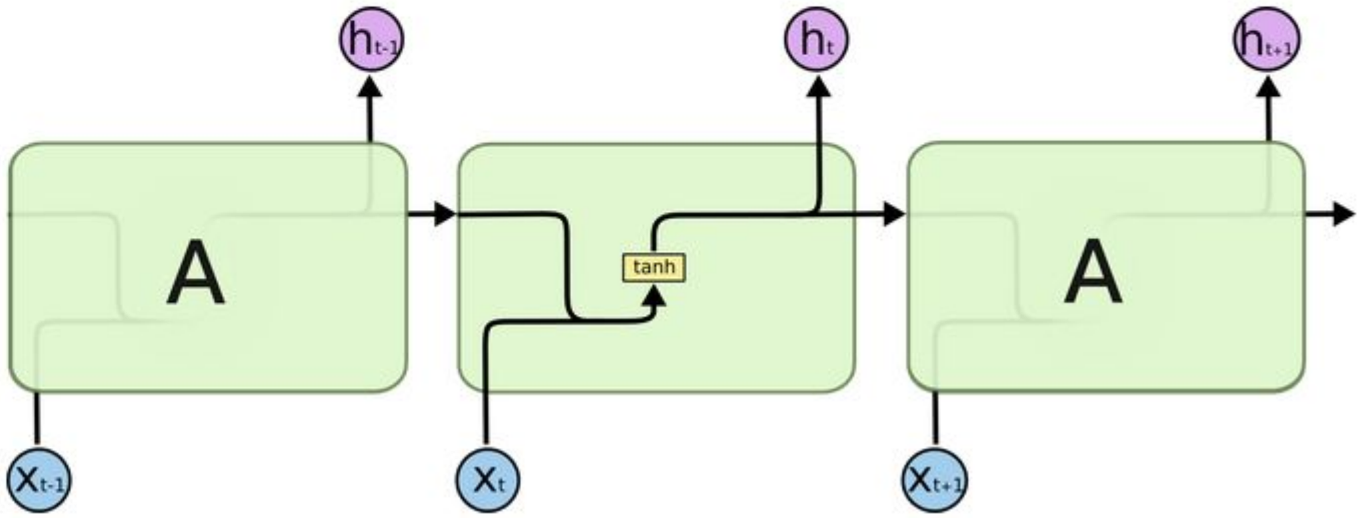
How to deal with texts?

Recap: RNN

Here is the embedding
for phrase [x0, x1, x2]

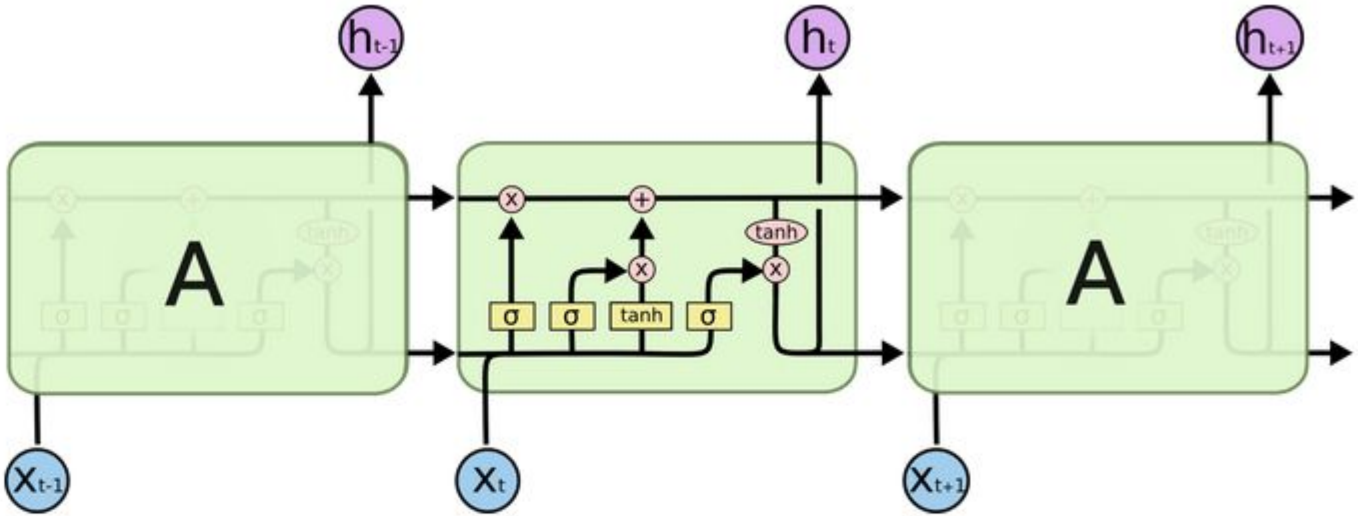


Recap: Vanilla RNN



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

Recap: LSTM



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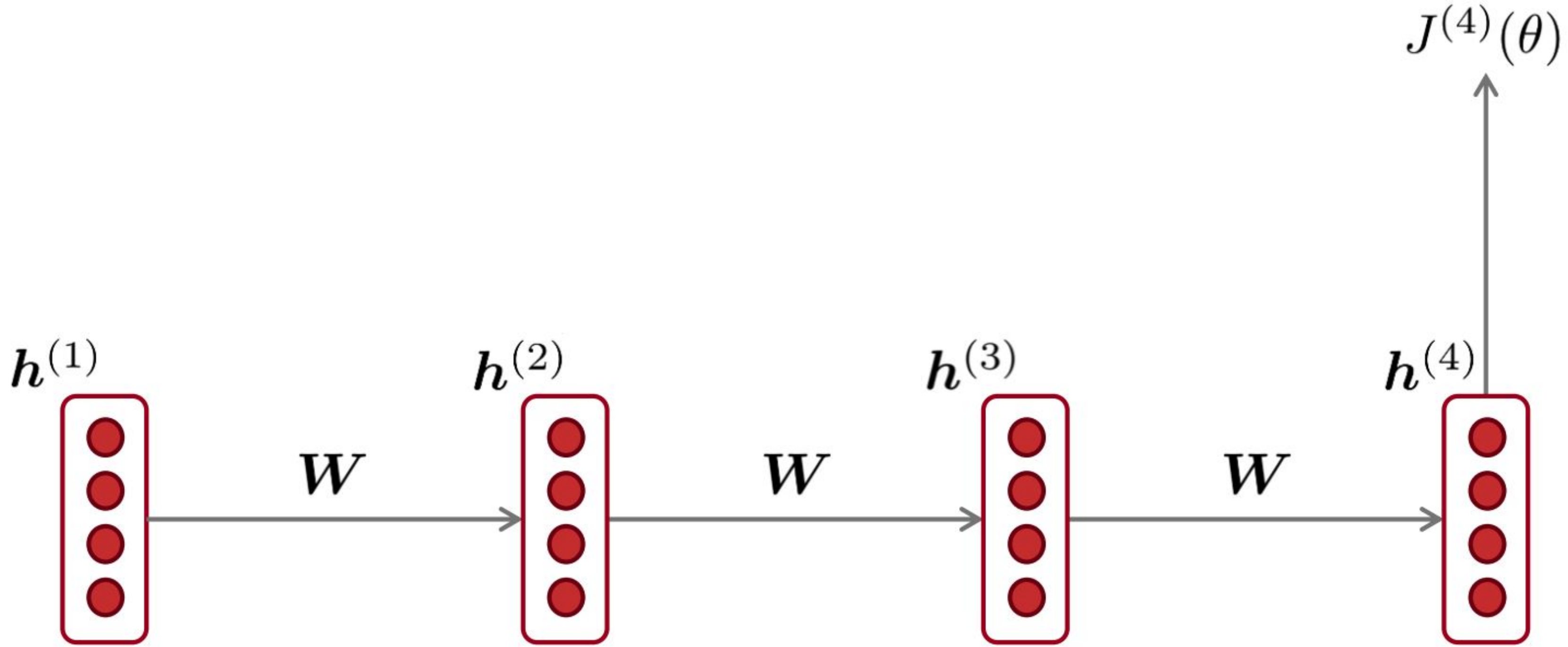
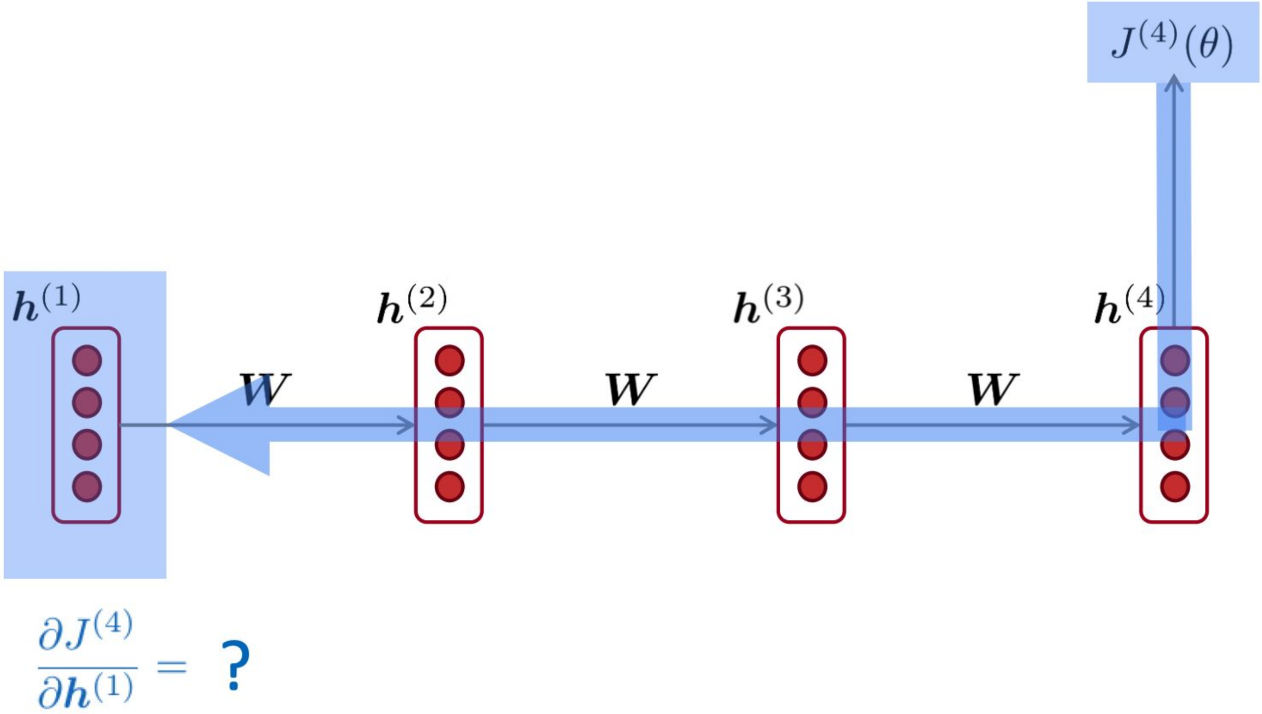
Vanishing gradient problem



Based on: Lecture by Abigail See, [CS224n Lecture 7]

Vanishing gradient problem



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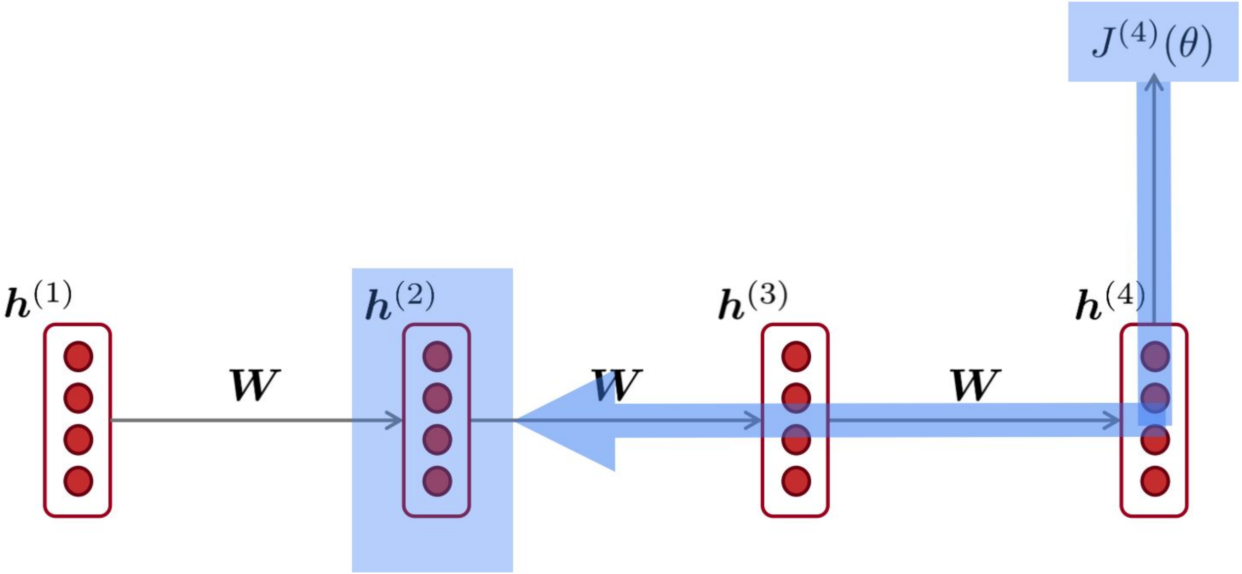
Vanishing gradient problem

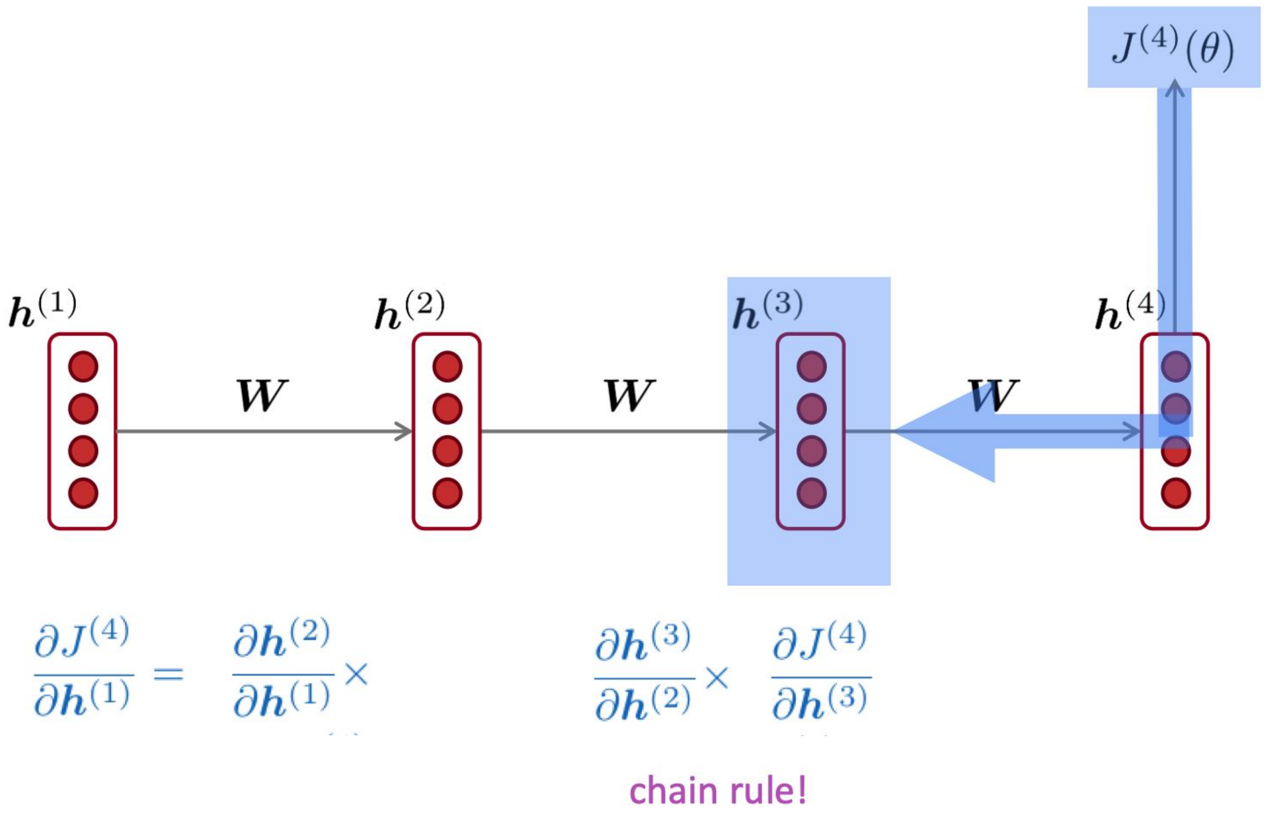


$$\frac{\partial J^{(4)}}{\partial \boldsymbol{h}^{(1)}} = \frac{\partial \boldsymbol{h}^{(2)}}{\partial \boldsymbol{h}^{(1)}} \times \frac{\partial J^{(4)}}{\partial \boldsymbol{h}^{(2)}}$$

chain rule!

Based on: Lecture by Abigail See, CS224n Lecture 7

Vanishing gradient problem



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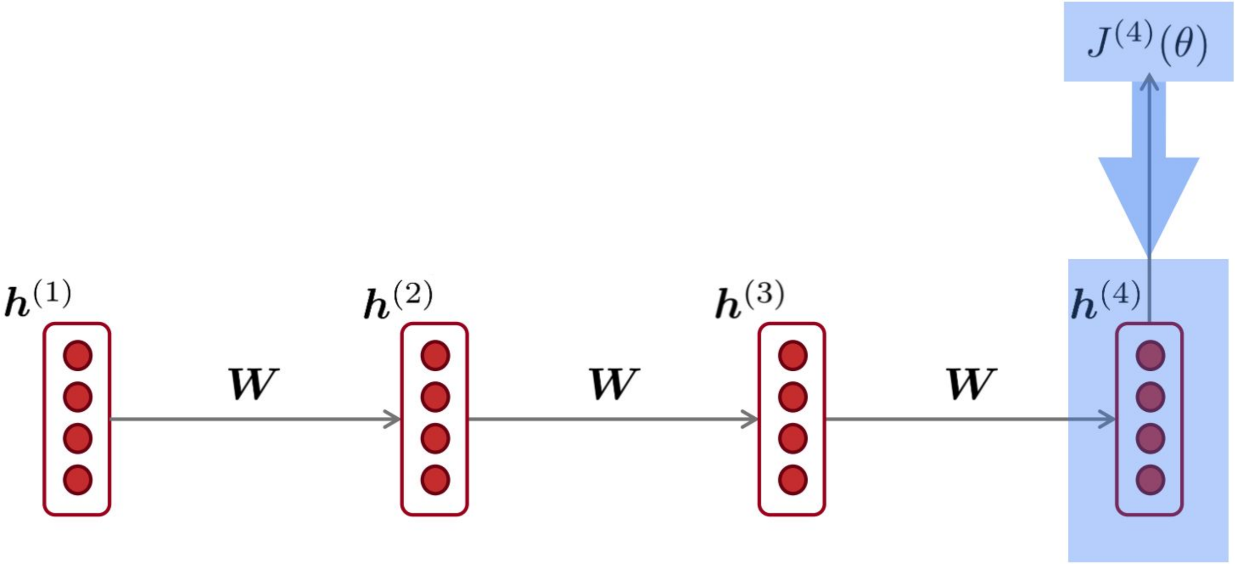
Vanishing gradient problem



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

chain rule!

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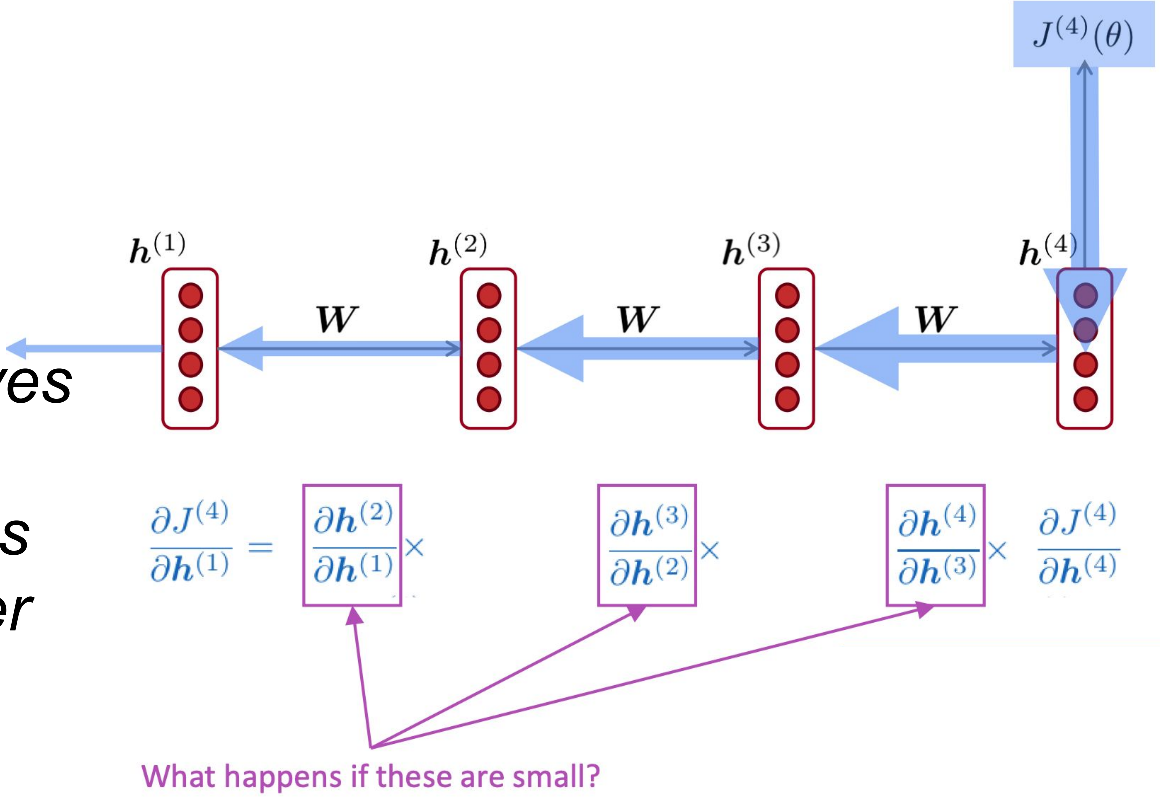
Vanishing gradient problem

Vanishing gradient problem:

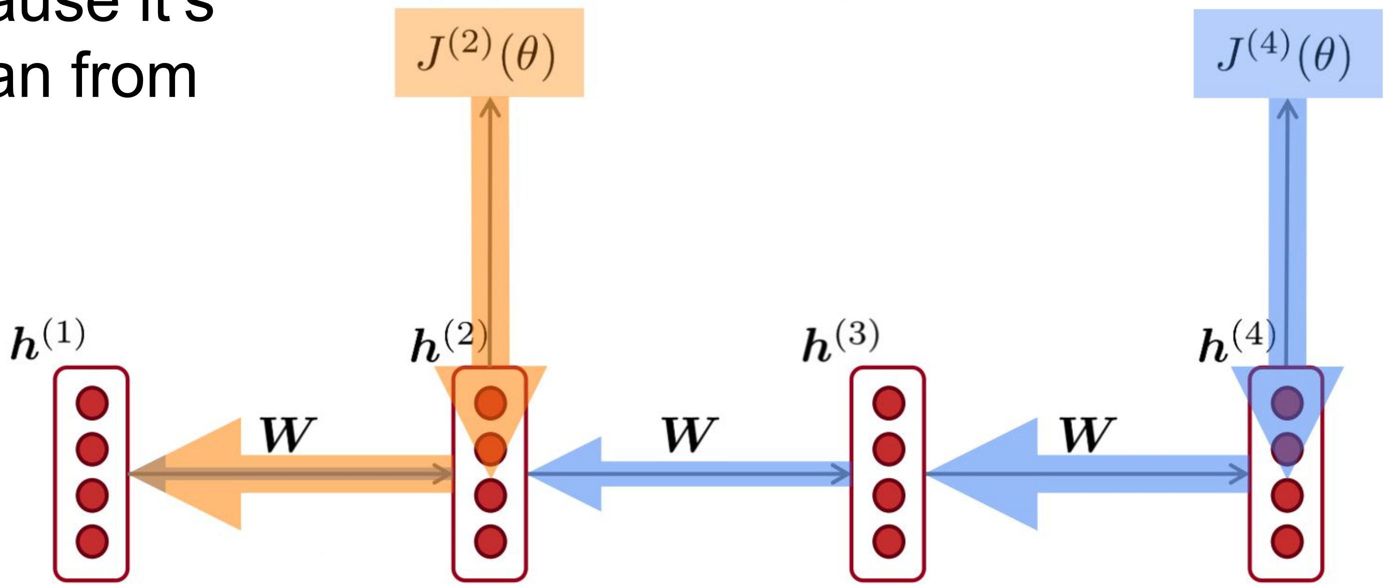
When the derivatives are small, the gradient signal gets smaller and smaller as it propagates further



More info: [On the difficulty of training recurrent neural networks, Pascanu et al, 2013]

Vanishing gradient problem

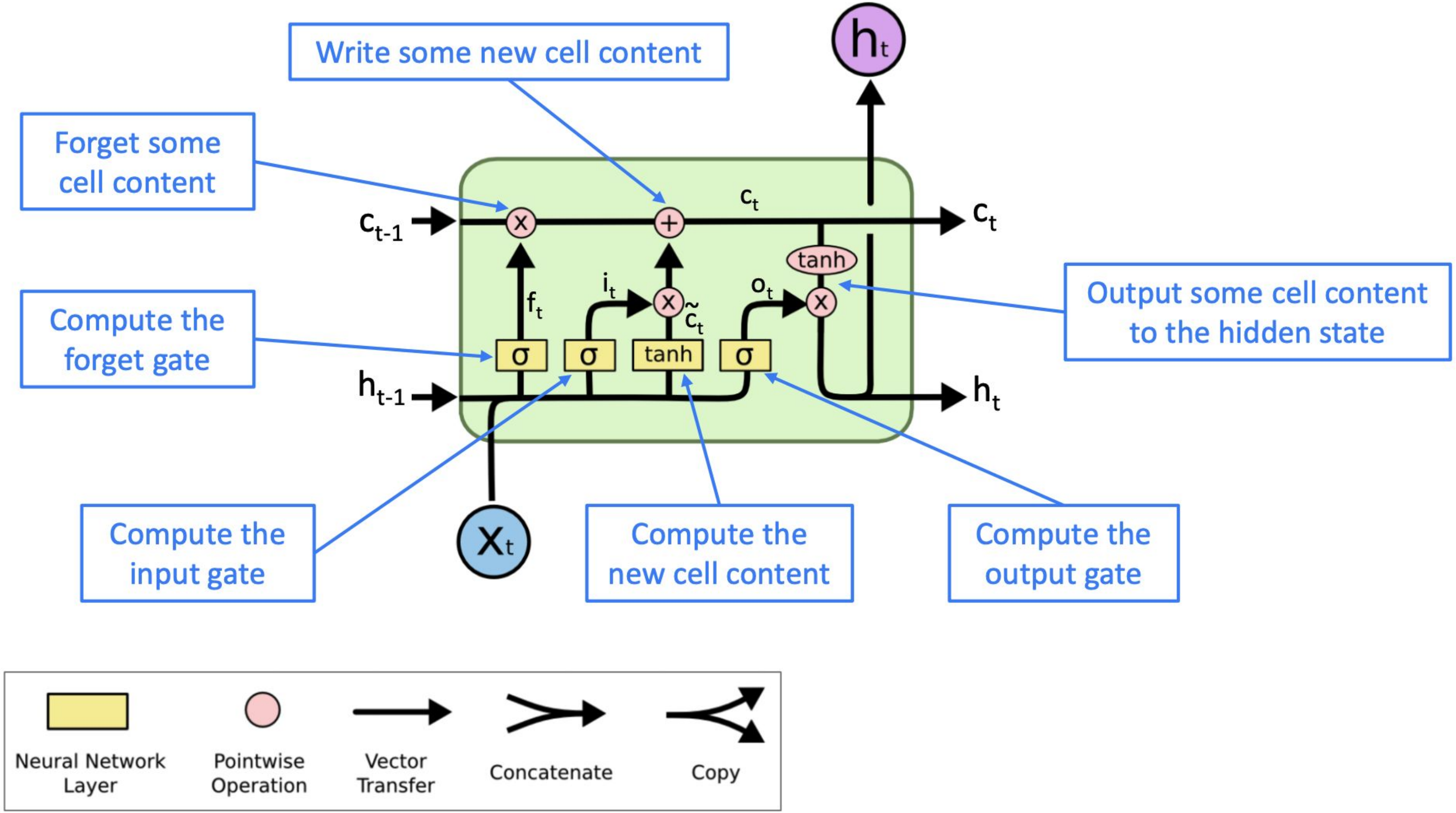
Gradient signal from far away is lost because it's much smaller than from close-by



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

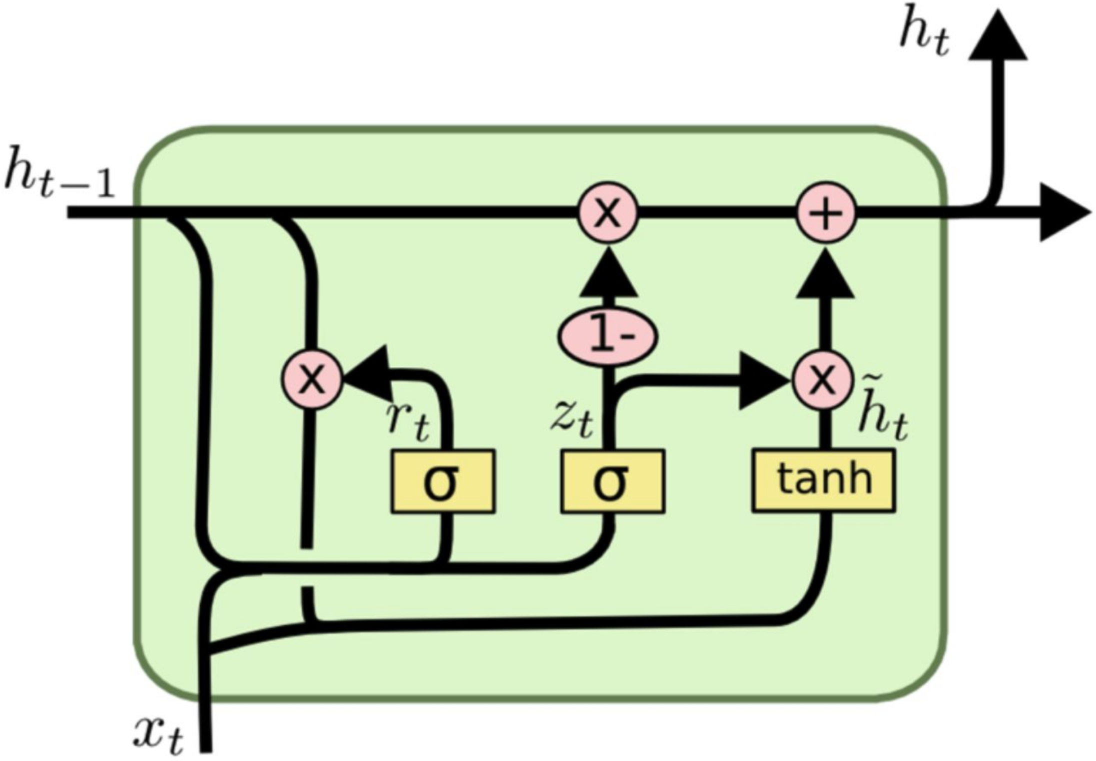
Based on: Lecture by Abigail See, [CS224n Lecture 7]

Recap: LSTM



Based on: Lecture by Abigail See, [CS224n Lecture 7]

Recap: 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 networks

- 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)

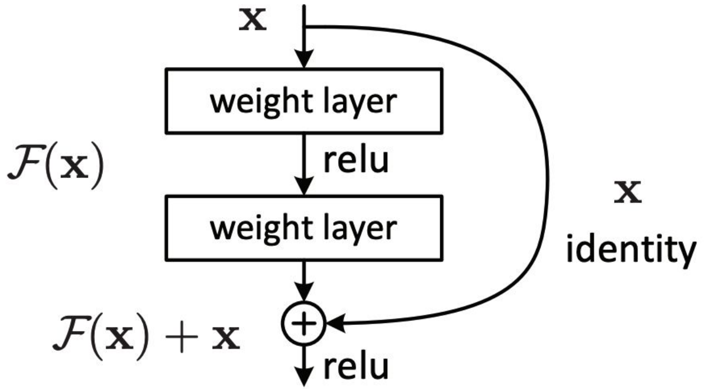


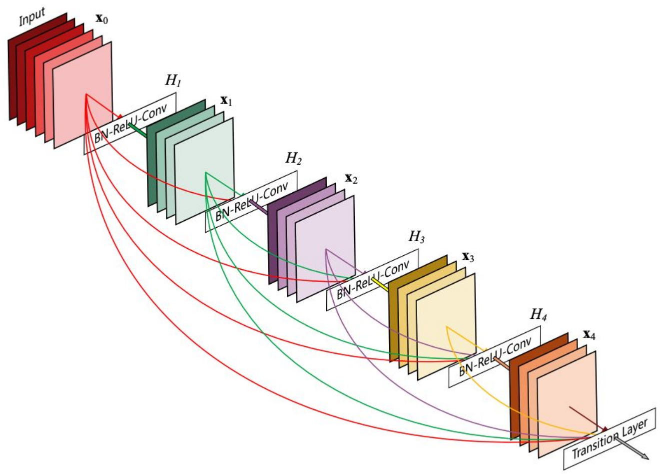
Figure 2. Residual learning: a building block.

Source: [Deep Residual Learning for Image Recognition, He et al, 2015]

Vanishing gradient in non-RNN

Vanishing gradient is present in **all** deep neural networks

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



Source: [Densely Connected Convolutional Networks, Huang et al, 2017]

Vanishing gradient in non-RNN

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- Lower levels are hard to train and are trained slower

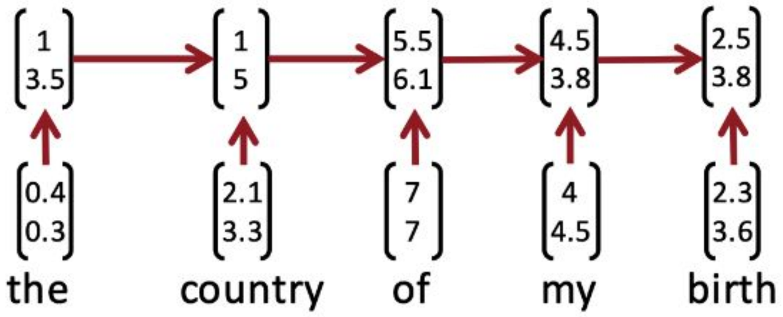
Conclusion:

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]

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

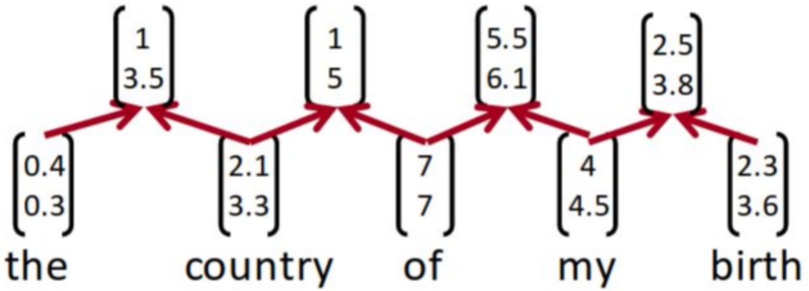
The brown dog plays with a little cat

→

- The brown
- brown dog
- dog plays
- plays with
- with a
- a little
- little cat

From RNN to CNN

- Imagine using only bigrams



- Same operation as in RNN, but for every pair

$$p = \tanh\left(W \left[\begin{array}{c} c_1 \\ c_2 \end{array} \right] + b\right)$$

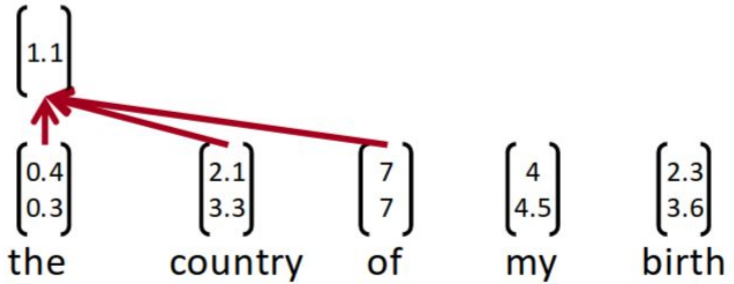
- Can be interpreted as convolution over the word vectors

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:

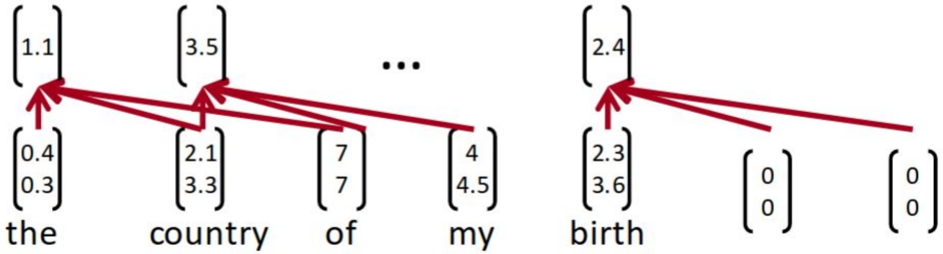
$$c_i = f(\mathbf{w}^T \mathbf{x}_{i:i+h-1} + b)$$



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

What's next?

We need more features!



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

One layer CNN

- Feature representation is based on some applied filter:

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

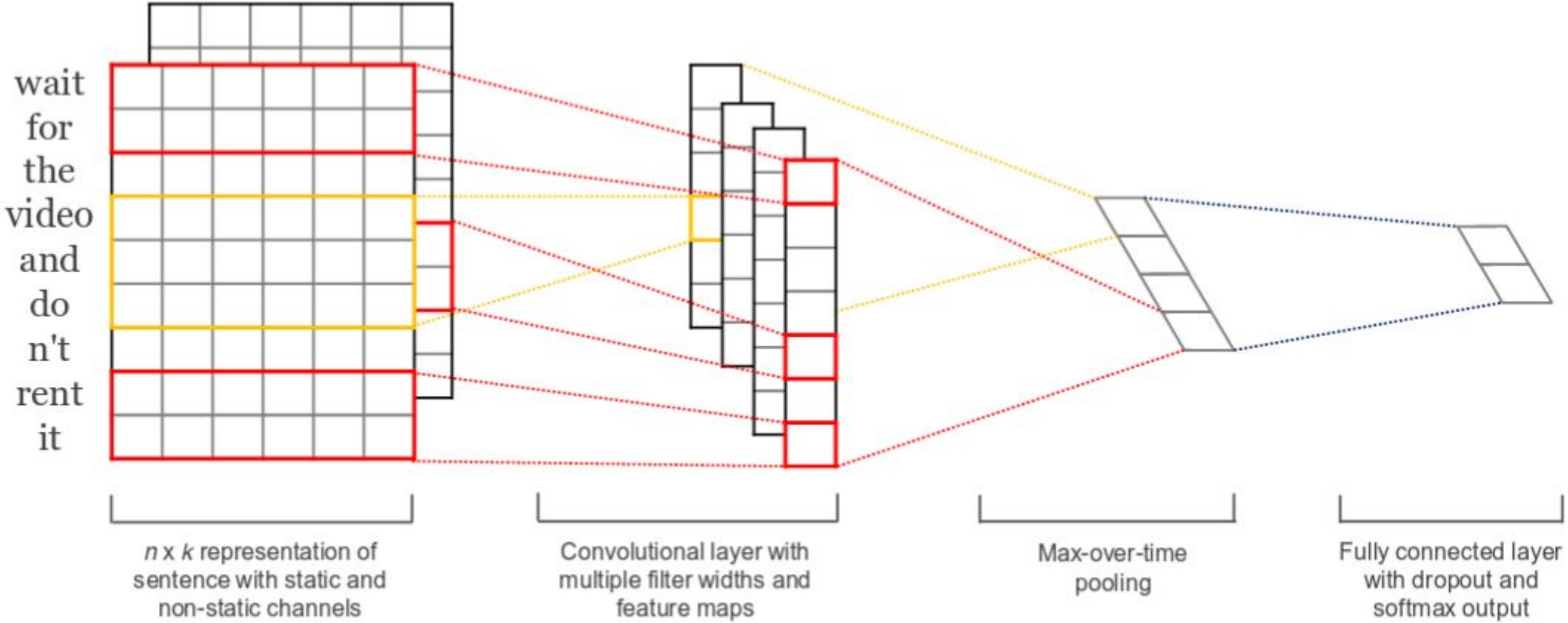
- Let's use pooling:

$$\hat{c} = \max\{\mathbf{c}\}$$

- 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

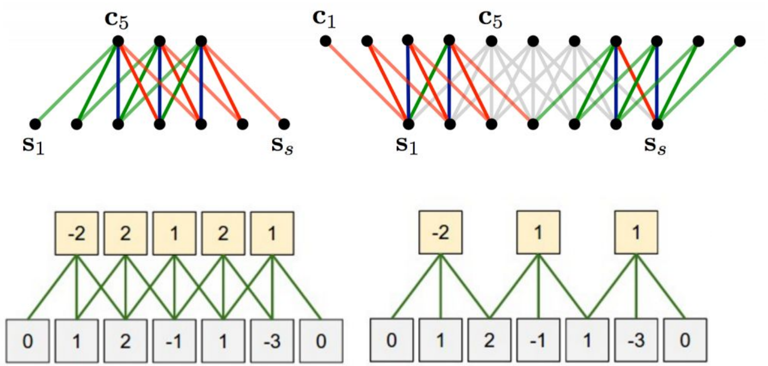
Another example from Kim (2014) paper



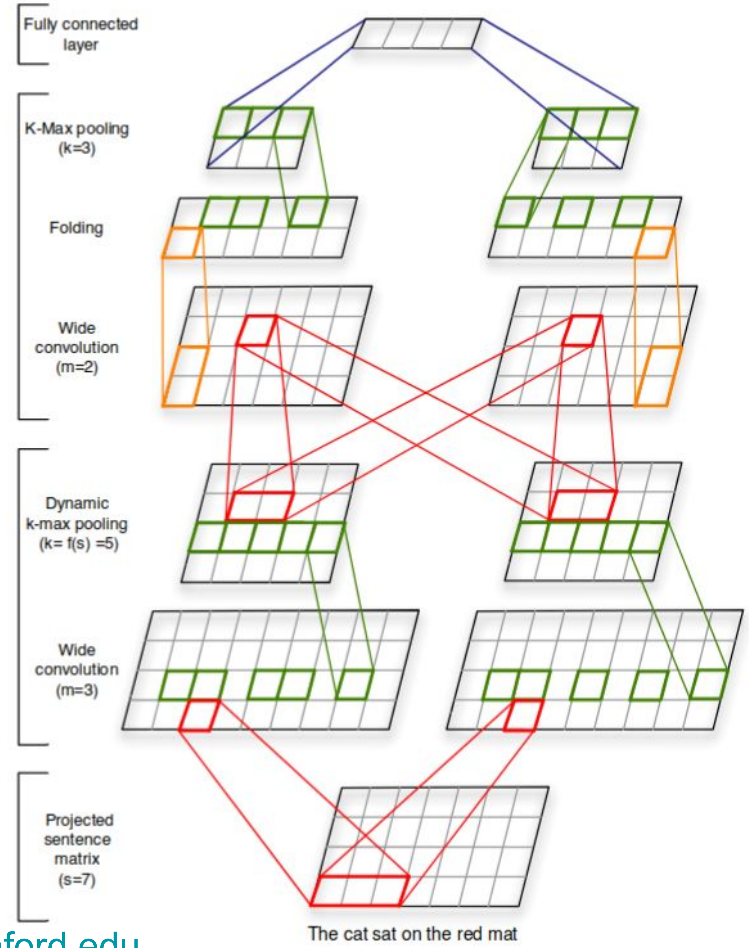
Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

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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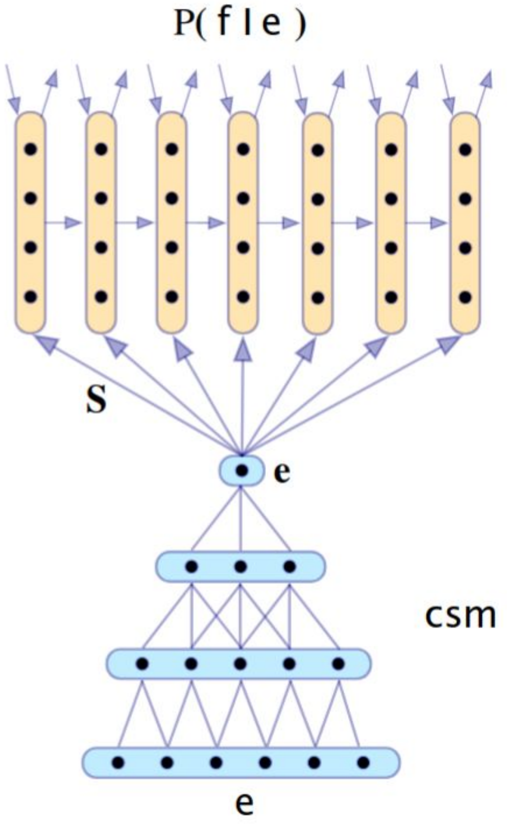
CNN applications

- Neural machine translation: CNN as encoder, RNN as decoder
- One of the first neural machine translation efforts
- Paper: [Recurrent Continuous Translation Models, Kalchbrenner and Blunsom, 2013]



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

Approaches comparison

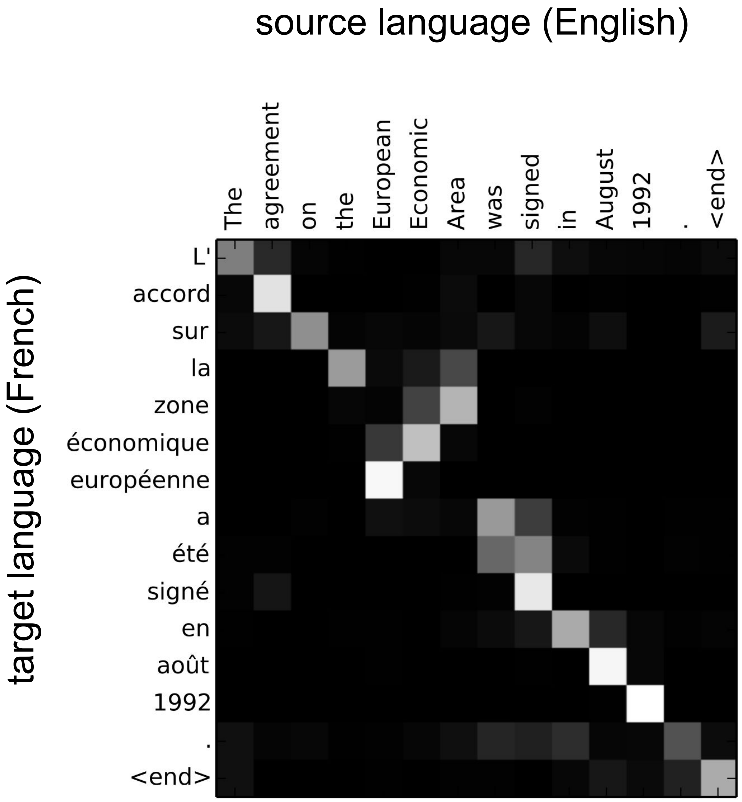
Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-rand	76.1	45.0	82.7	89.6	91.2	79.8	83.4
CNN-static	81.0	45.5	86.8	93.0	92.8	84.7	**89.6**
CNN-non-static	**81.5**	48.0	87.2	93.4	93.6	84.3	89.5
CNN-multichannel	81.1	47.4	**88.1**	93.2	92.2	**85.0**	89.4
RAE (Socher et al., 2011)	77.7	43.2	82.4	–	–	–	86.4
MV-RNN (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**	–	–

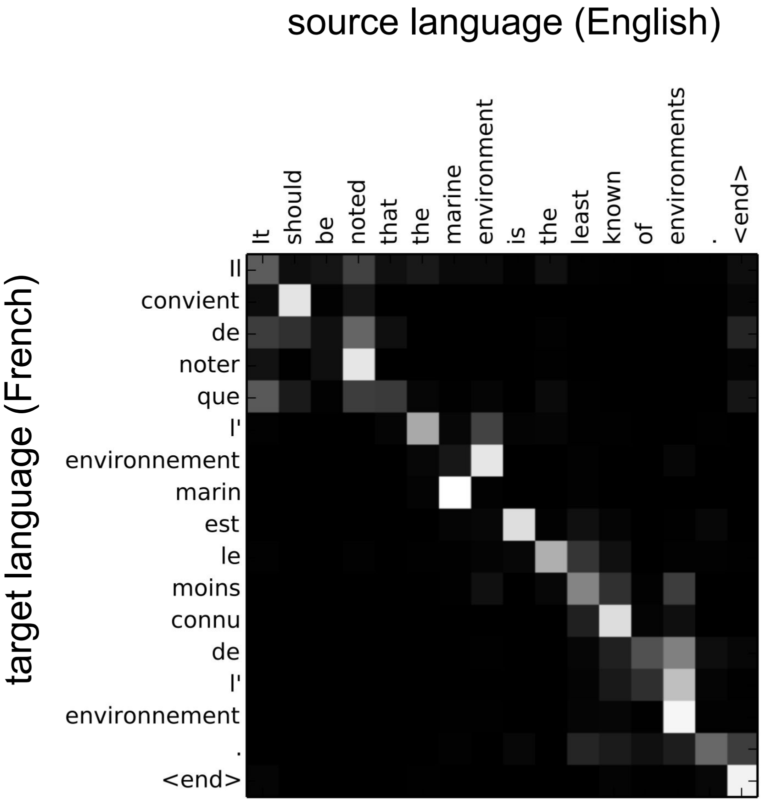
Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

Outro and Tips

- 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
- Clip your gradients
- Using CNNs for texts is similar to n-gramm trick
- CNNs are more effective in case of massive computations
- Combining RNN and CNN worlds? Why not

Attention outro





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

Problems?

Word2vec embeddings capture only **local** context