Lecture 02: CNN for texts, embeddings for different languages

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Outline

- Embeddings in the wild
  - Recap
  - Unsupervised translation

- RNNs recap:

- CNNs for text processing

Embeddings: word2vec

Source Text

Training Samples

The quick brown fox jumps over the lazy dog. →

(the, quick)
(the, brown)

The quick brown fox jumps over the lazy dog. →

(quick, the)
(quick, brown)
(quick, fox)

The quick brown fox jumps over the lazy dog. →

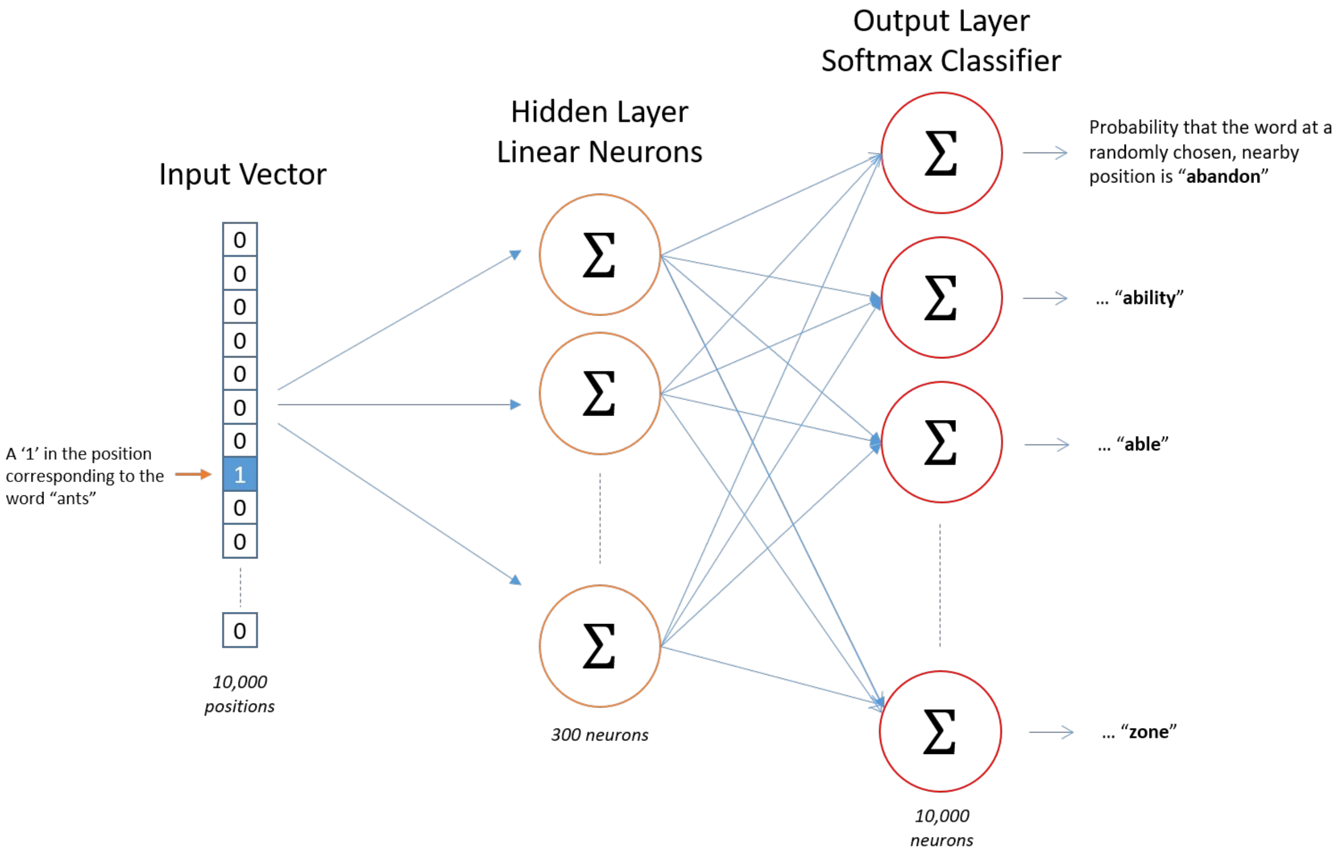
(brown, the)
(brown, quick)
(brown, fox)
(brown, jumps)

The quick brown fox jumps over the lazy dog. →

(fox, quick)
(fox, brown)
(fox, jumps)
(fox, over)

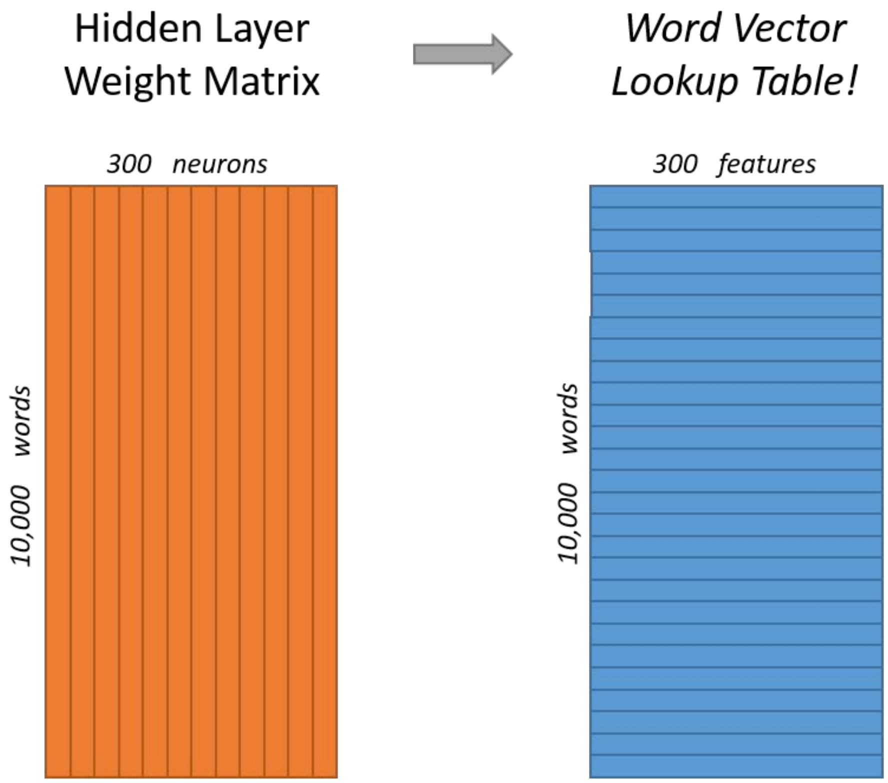
Source: http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/

Embeddings: word2vec



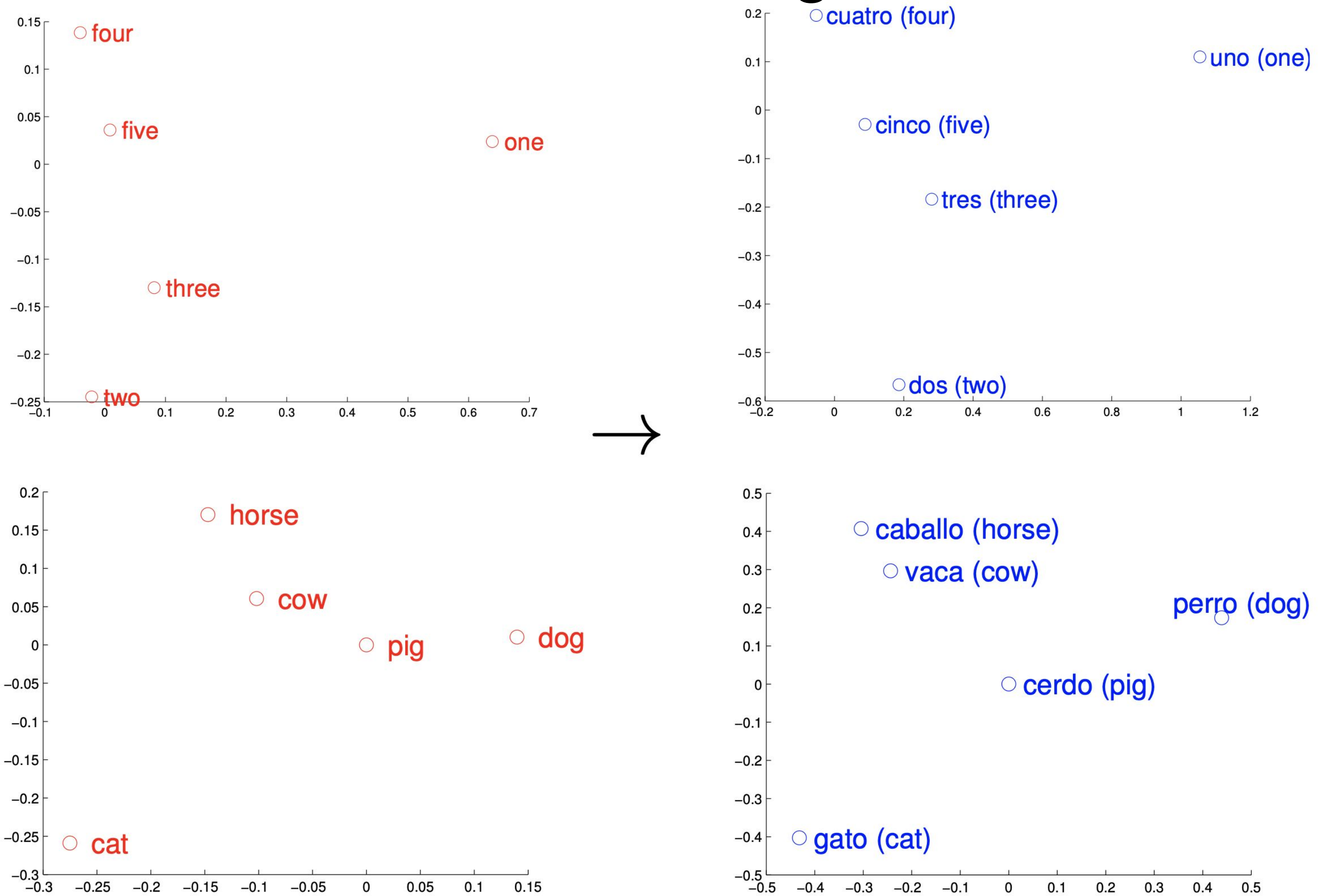
Source: http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/

Embeddings: word2vec



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

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

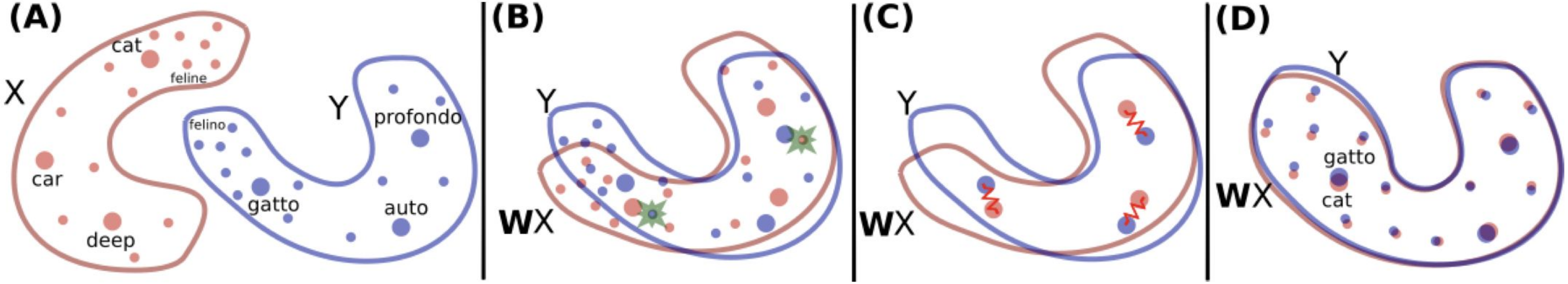
- Word embeddings are quite similar for different languages
- Assume there n = 5000 word-translation pairs $\{x_i, y_i\}_{i \in \{1,n\}}$
- Learn linear mapping between the source and target spaces **enforcing an orthogonality constraint** on W:

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

- 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]

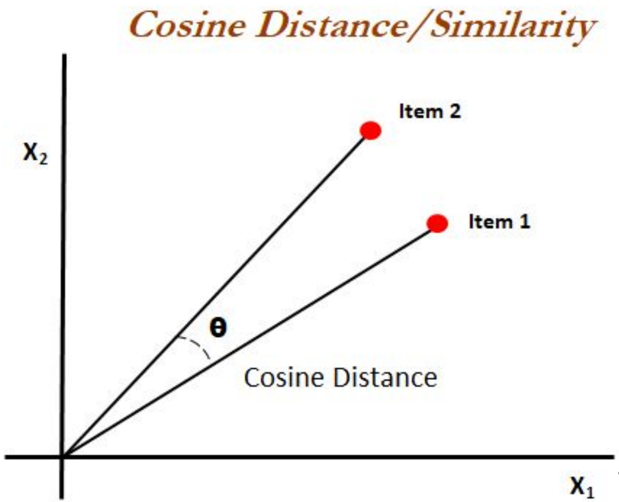
Why cosine distance/similarity?

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

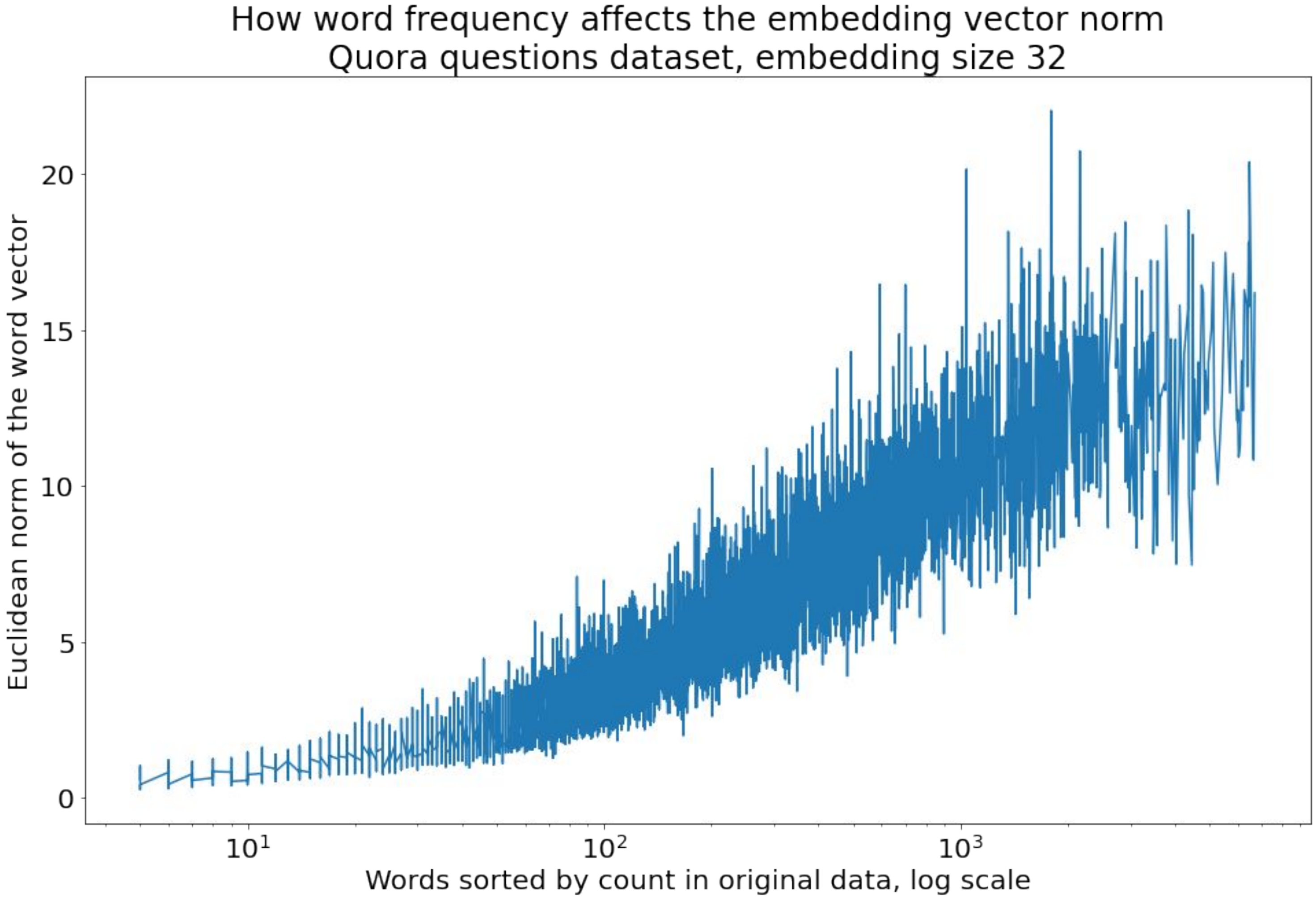
Cosine distance focuses on angle between the vectors.

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

With word embeddings it is useful as well.



Source: [question]

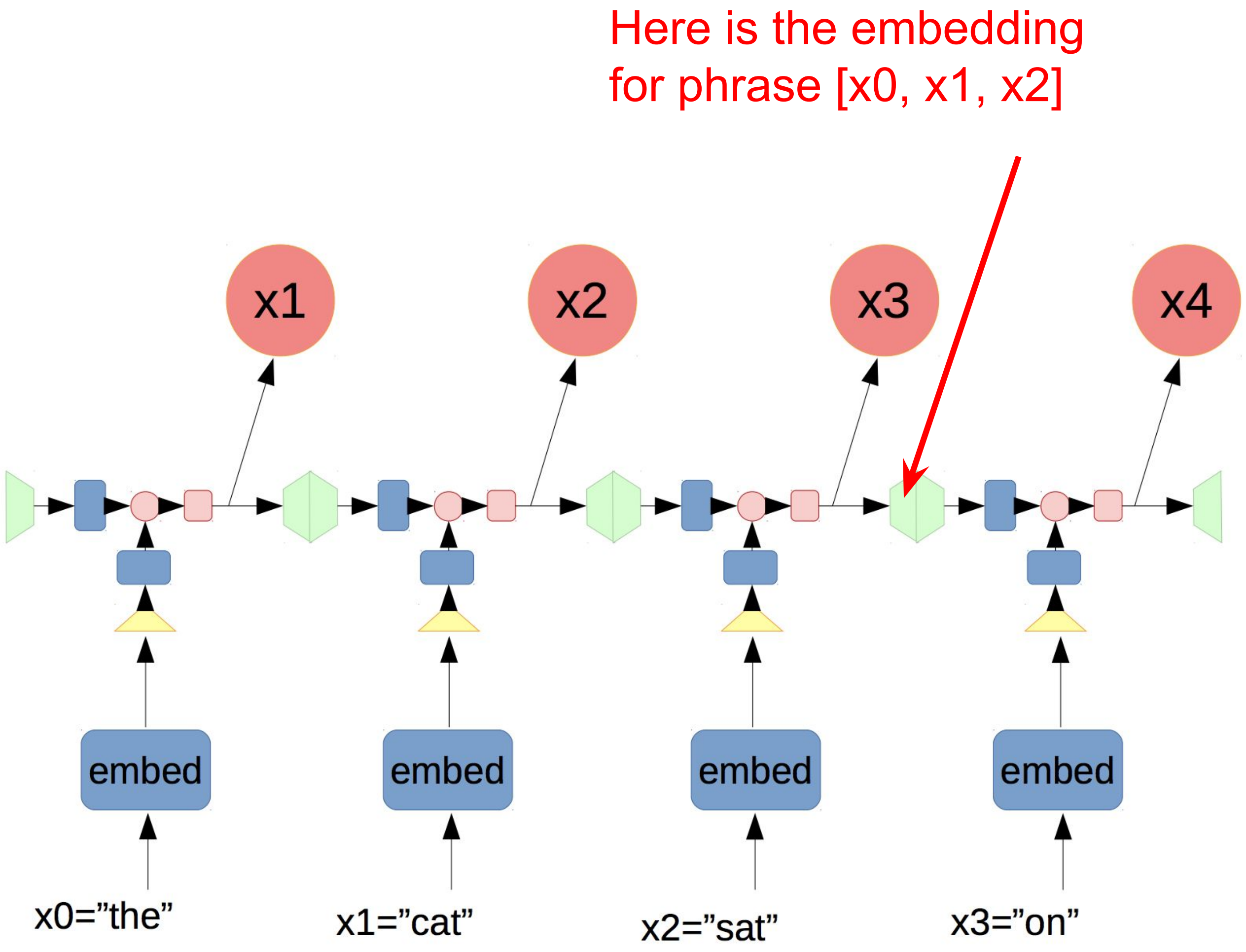

How word frequency affects the embedding vector norm
Quora questions dataset, embedding size 32
Euclidean norm of the word vector
0
5
10
15
20
10^1
10^2
10^3
Words sorted by count in original data, log scale

Vector norms for words with no specific context

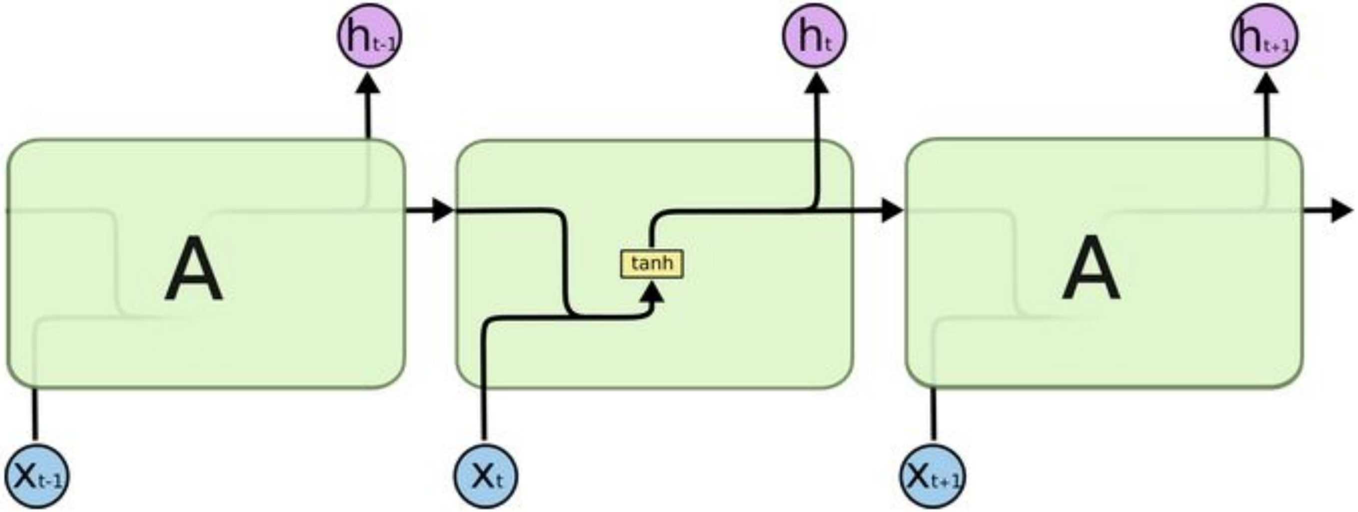
word	count	vector norm
overheat	11	0.81233
enormous	12	0.807057
dog	1212	11.2591
cat	1545	10.3738
laptop	1906	14.5192
phone	4124	15.7901
a	155726	11.4656
the	252068	8.47355

How to deal with texts?

Recap: RNN


Here is the embedding
for phrase [x0, x1, x2]
x1
x2
x3
x4
embed
embed
embed
embed
x0="the"
x1="cat"
x2="sat"
x3="on"

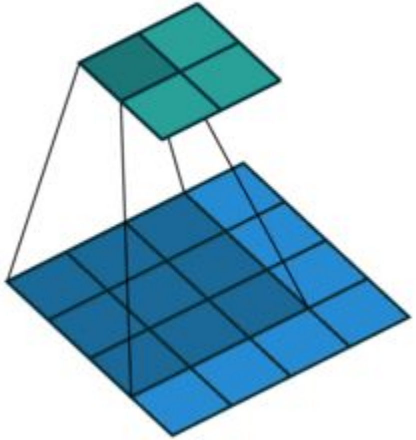
Recap: Vanilla RNN



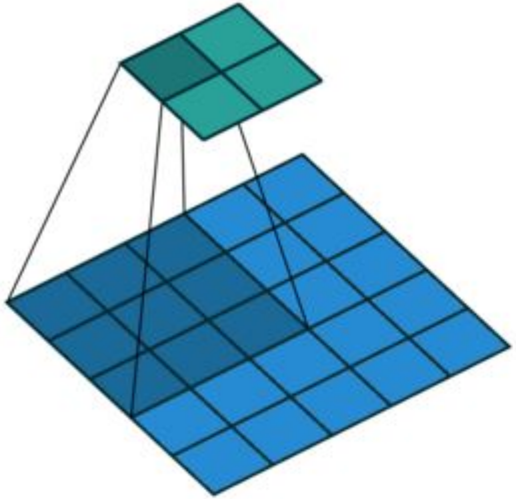
Source: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Applying CNNs to texts

CNN simple recap



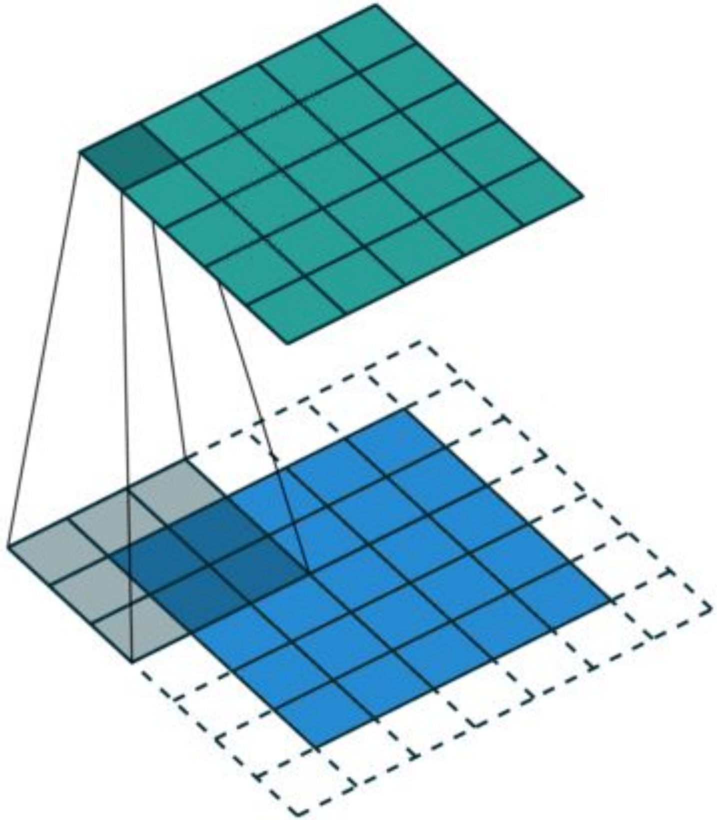
No padding,
no strides



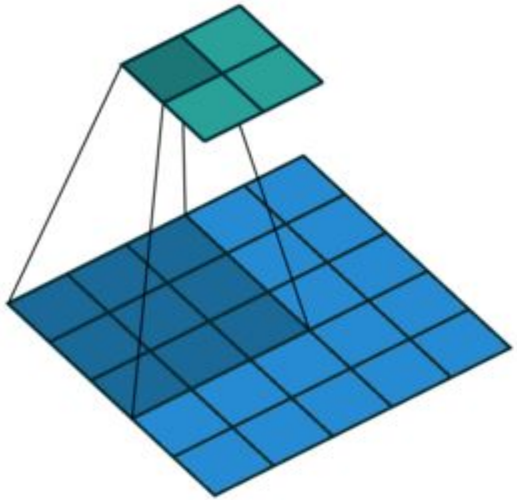
No padding,
with strides

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

CNN simple recap



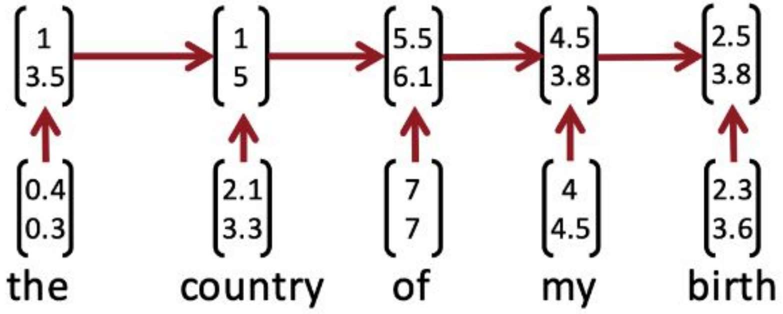
With padding,
no strides



No padding,
with strides

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

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

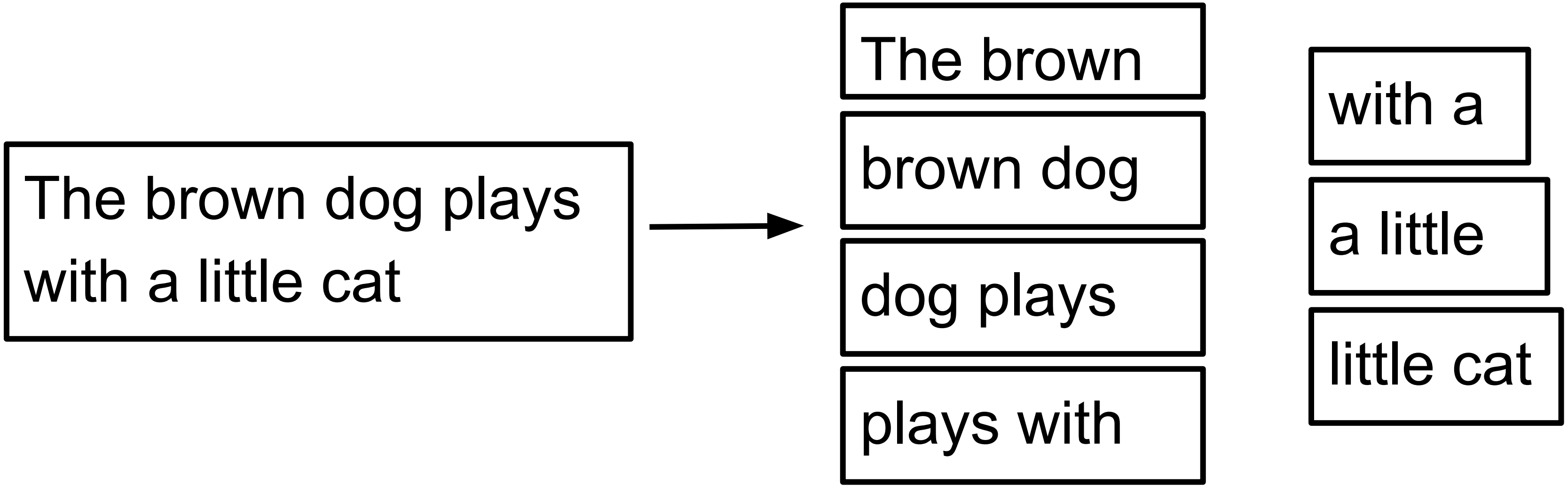
- RNN: Get compositional vectors for grammatical phrases only

- 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

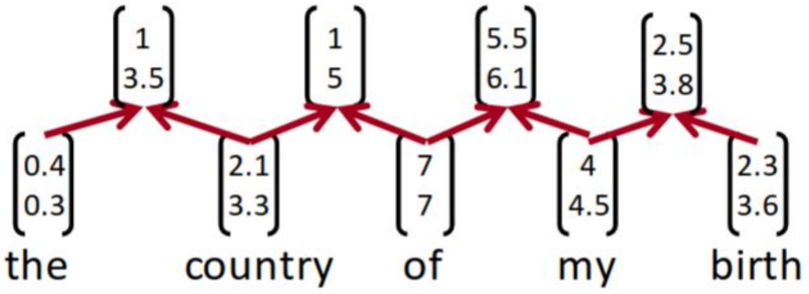
Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

Recap: n-gramms



From RNN to CNN

- Imagine using only bigrams



- Same operation as in RNN, but for every pair

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

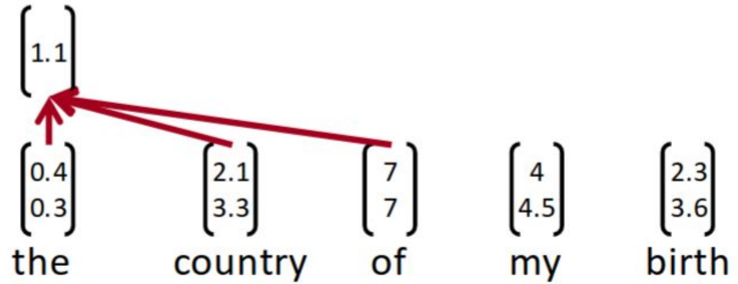
- Can be interpreted as convolution over the word vectors

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

One layer CNN

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

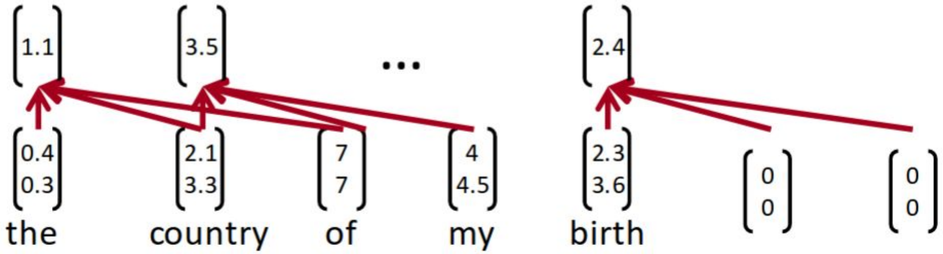
- Simple convolution + pooling
- Window size may be different (2 or more)
- The feature map based on bigrams:



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

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:

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

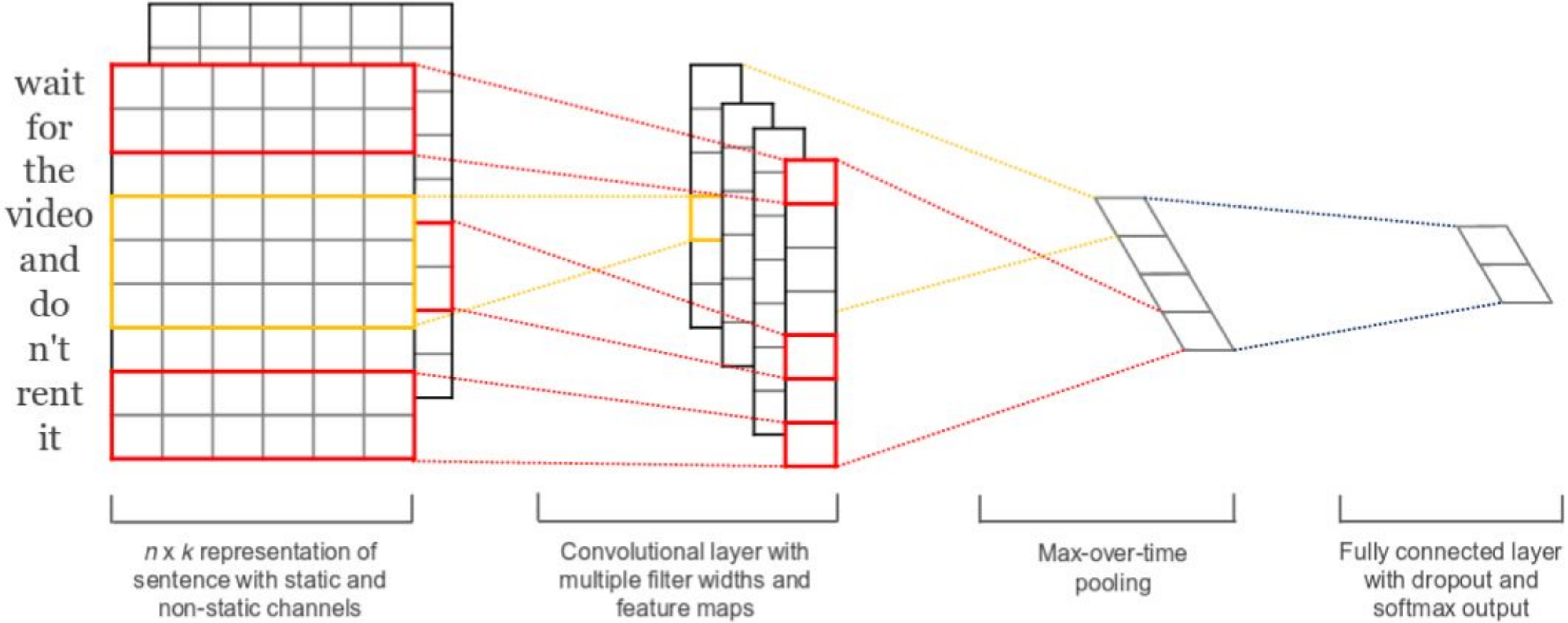
- Let's use pooling:

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

- 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



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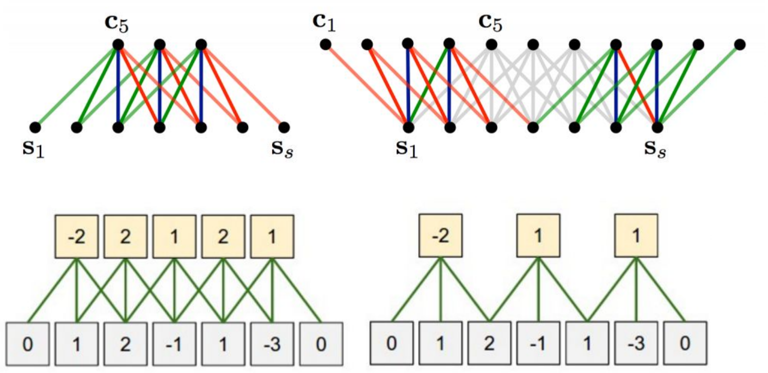
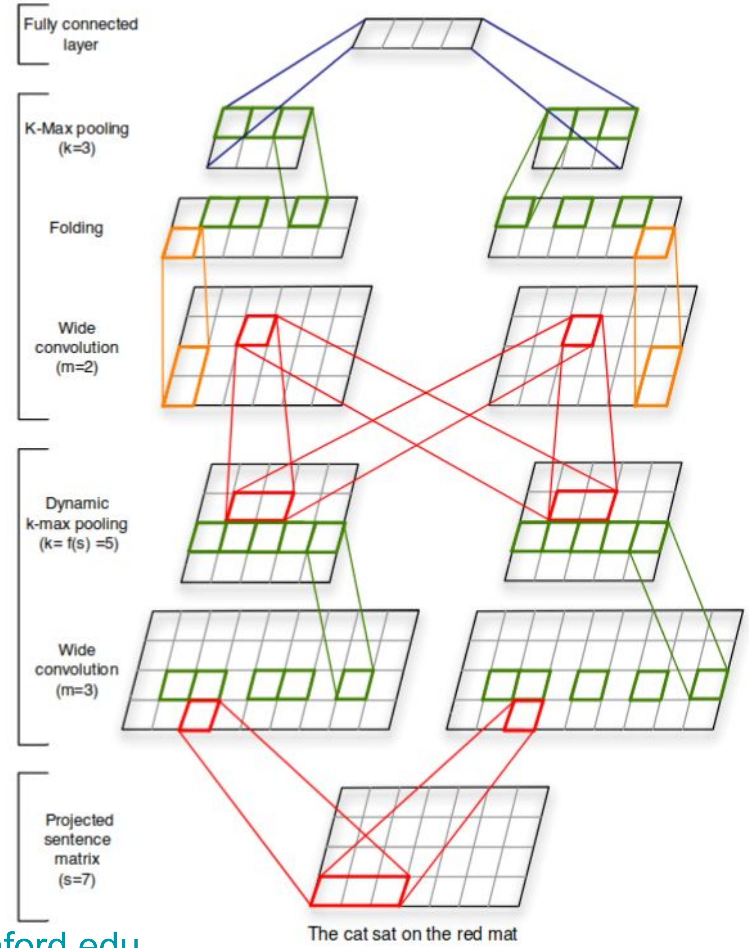
More about CNN

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



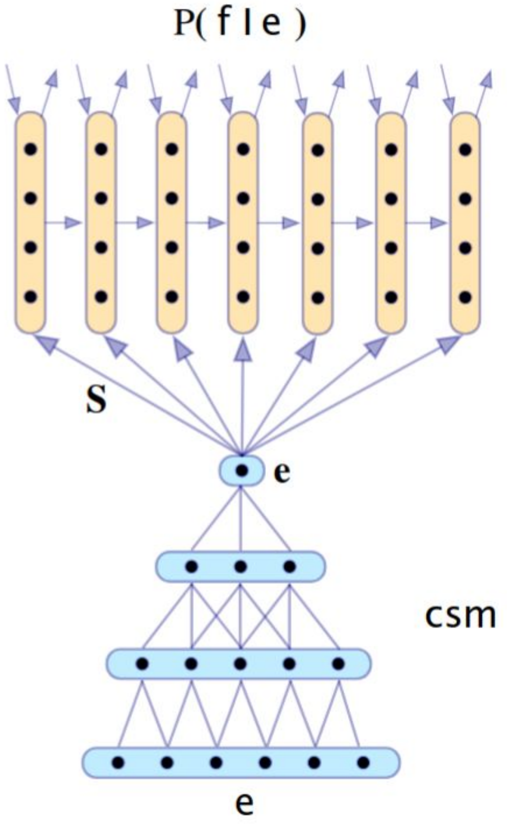
- Complex pooling schemes over sequences
- Great readings (e.g. Kalchbrenner et. al. 2014)



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

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]



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Approaches comparison

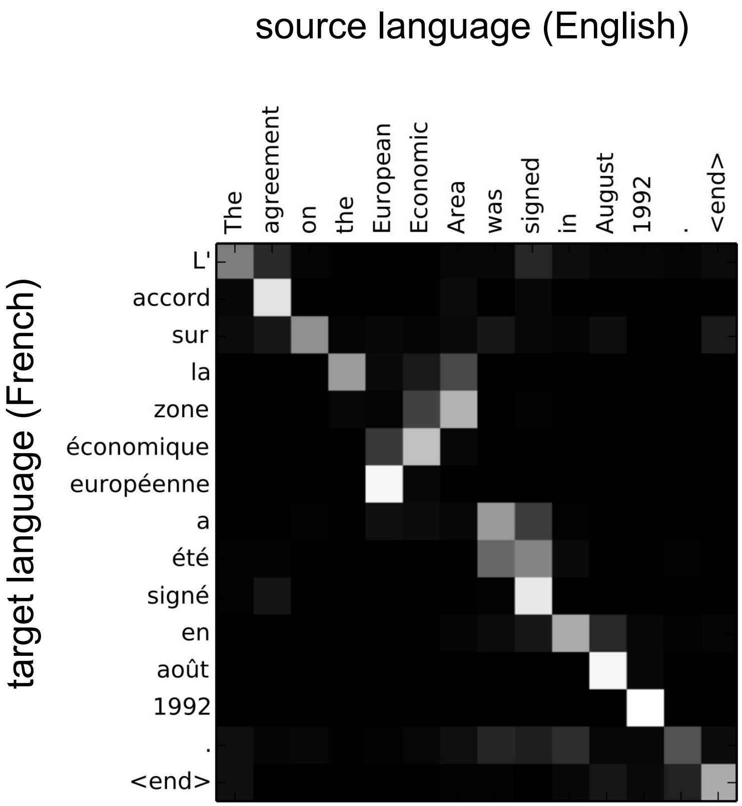
Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-rand	76.1	45.0	82.7	89.6	91.2	79.8	83.4
CNN-static	81.0	45.5	86.8	93.0	92.8	84.7	**89.6**
CNN-non-static	**81.5**	48.0	87.2	93.4	93.6	84.3	89.5
CNN-multichannel	81.1	47.4	**88.1**	93.2	92.2	**85.0**	89.4
RAE (Socher et al., 2011)	77.7	43.2	82.4	–	–	–	86.4
MV-RNN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

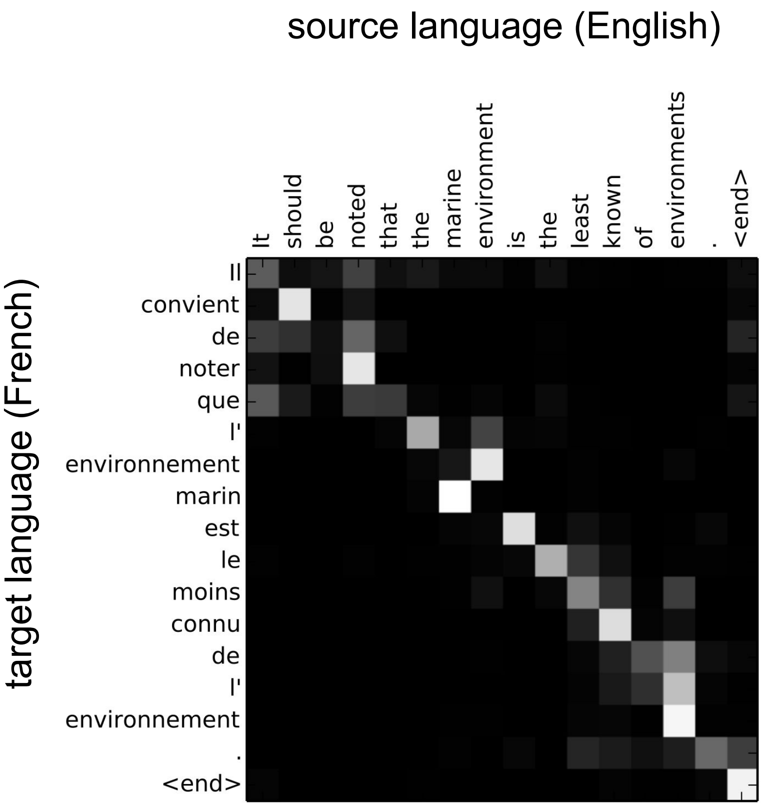
Based on: Lecture by Richard Socher 5/12/16, http://cs224d.stanford.edu

Outro and 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