Advanced ML course

Lecture 5: Word representations and Recurrent Neural Networks

Neychev Radoslav
ML Instructor (MIPT, HSE, Harbour.Space, BigData Team)
Research Scientist, MIPT

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Outline

1. Classic word representations
2. Word embeddings
3. RNN intuitions
4. LSTM
5. Relations to CNN
6. Names generation from scratch
7. Q & A

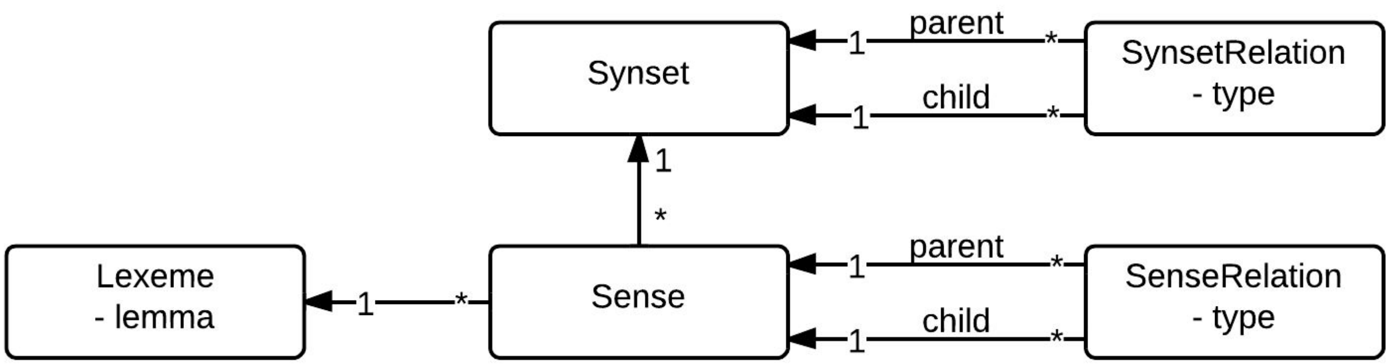
Optional: Small attention outro

Different layers

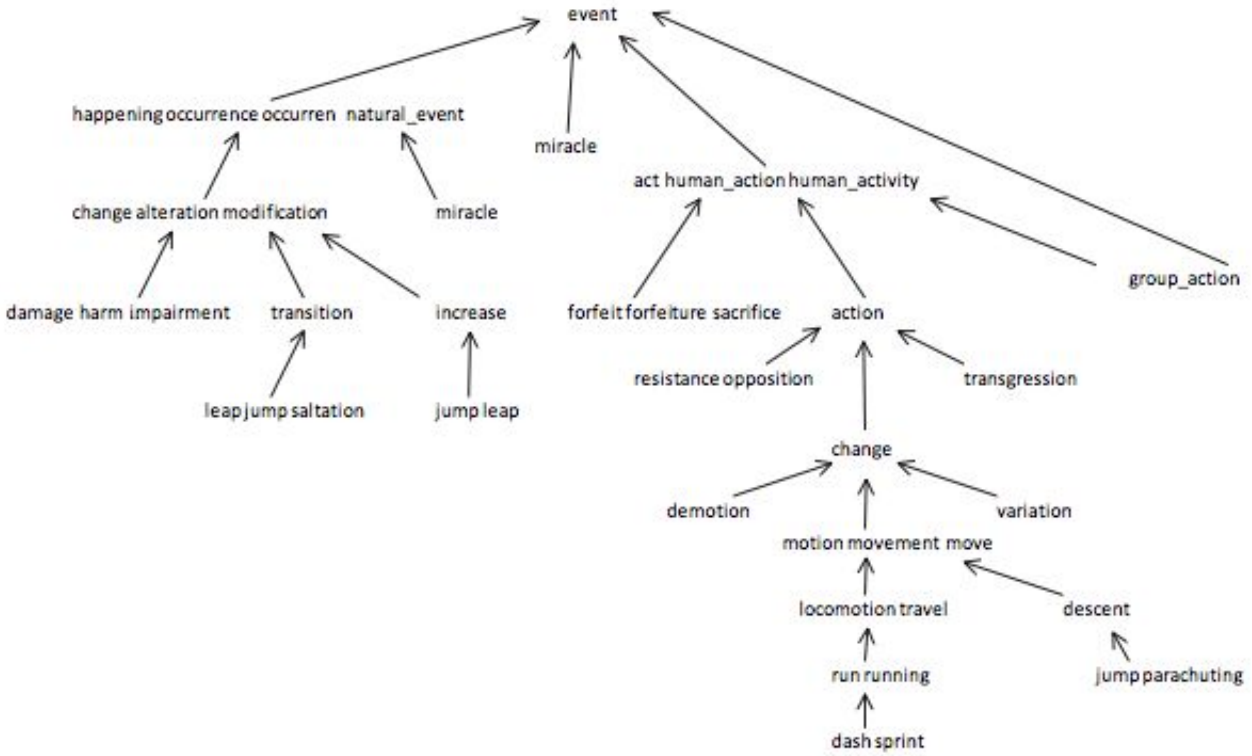
- Layers
  a. Dense layer *(done)*
  b. Convolutional layer *(next lecture)*
  c. Pooling layer *(next lecture)*
  d. Dropout layer *(done)*
  e. Batchnorm layer (batch normalization) *(done)*
  f. Embeddings (aka word2vec, GloVe) *(today)*
  g. Recurrent layer~~s~~ *(today)*

How to represent text in a computer?

Use a taxonomy like WordNet that has hypernyms (is-a) relationships and synonym sets



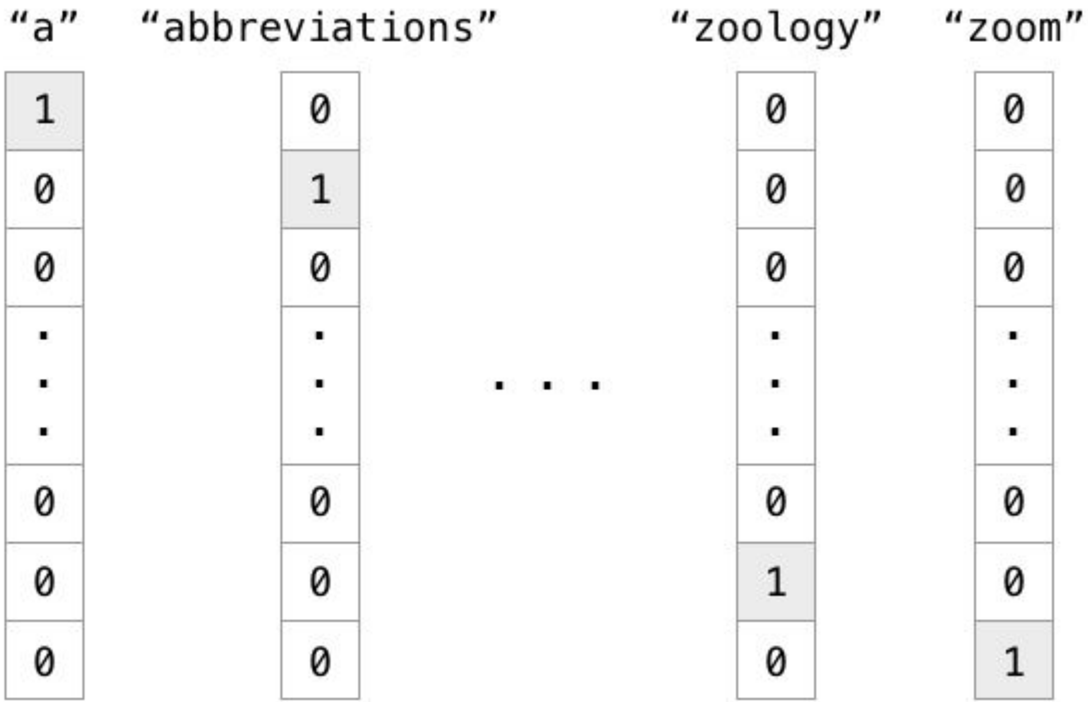
How to represent text in a computer: WordNet



Discrete representations: problems

- Missing new words
- Subjective
- Requires human labor to create and adapt
- Hard to compute accurate word similarity

Discrete representations: one-hot encoding



Making it better: TF-iDF

If word is repeated in the query, it's probably important

Repetitions of query words in the document ➔ good

Rare words more important

$$s(Q,D) = \sum_{w} tf_{w,Q} \cdot \underbrace{\frac{tf_{w,D}}{tf_{w,D} + \frac{k|D|}{avg|D|}}}_{\text{Repetitions of same word less important than different words. Except in very long documents}} \cdot \log \frac{|C|}{df_w}$$

The more query words we match, the better. Σ over the vocabulary

TF - term frequency

iDF - Inversed Document Frequency

TF-iDF: an example

$$\mathrm{tf}(''\mathsf{this}'', d_1) = \frac{1}{5} = 0.2$$

$$\mathrm{tf}(''\mathsf{this}'', d_2) = \frac{1}{7} \approx 0.14$$

$$\mathrm{idf}(''\mathsf{this}'', D) = \log\left(\frac{2}{2}\right) = 0$$

$$\mathrm{tfidf}(''\mathsf{this}'', d_1, D) = 0.2 \times 0 = 0$$

$$\mathrm{tfidf}(''\mathsf{this}'', d_2, D) = 0.14 \times 0 = 0$$

Document 1

Term	Term Count
this	1
is	1
a	2
sample	1

Document 2

Term	Term Count
this	1
is	1
another	2
example	3

Word ‘this’ is not very informative

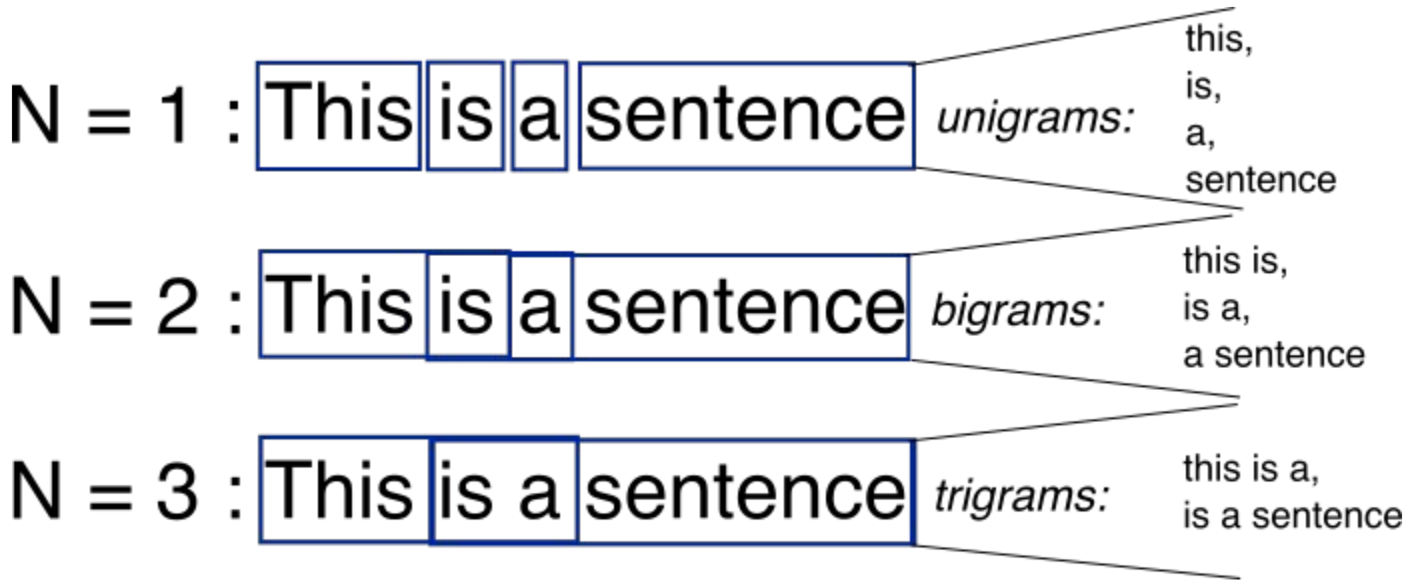
Words cooccurrences

One of the most successful ideas of statistical NLP:

"You shall know a word by the company it keeps"

(J. R. Firth 1957: 11)

Words cooccurrences: n-gramms



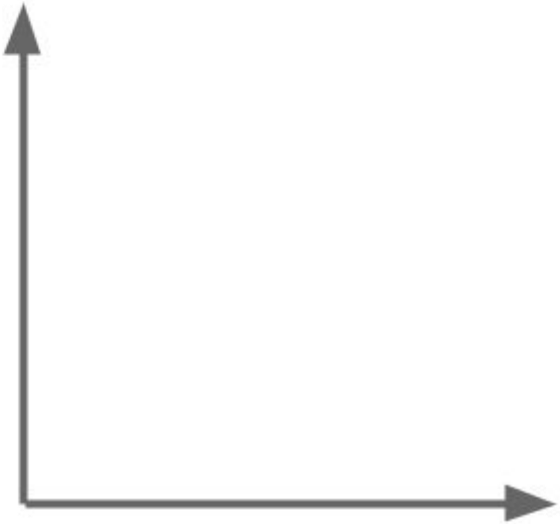
N-gramm approach problems

- Increase in size with vocabulary
- Very high dimensional: require a lot of storage
- Subsequent classification models have sparsity issues

Models are less robust

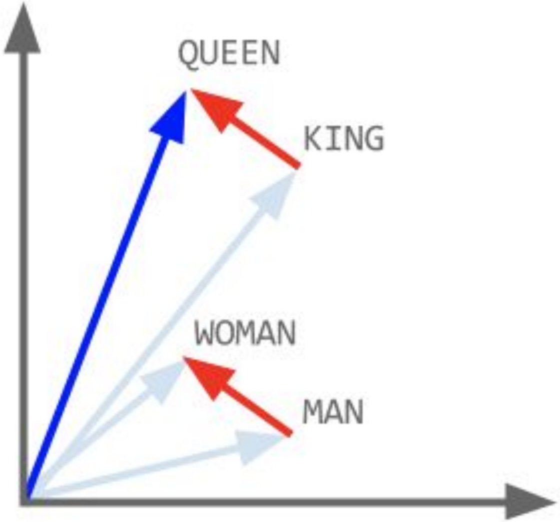
Embeddings: intuition

What is `king` - `man` + `woman`?



Embeddings: intuition

So king - man + woman = queen!

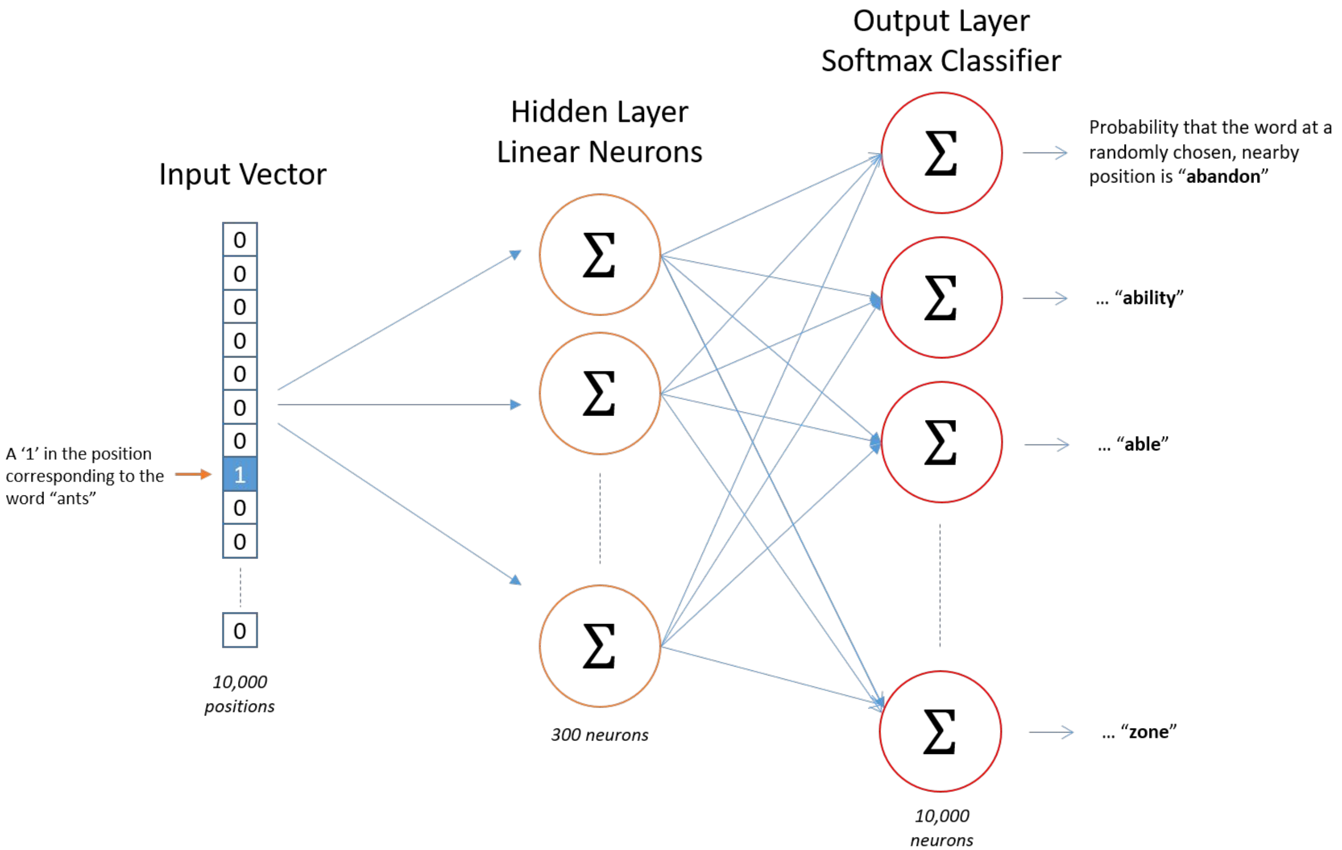


Embeddings: word2vec

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



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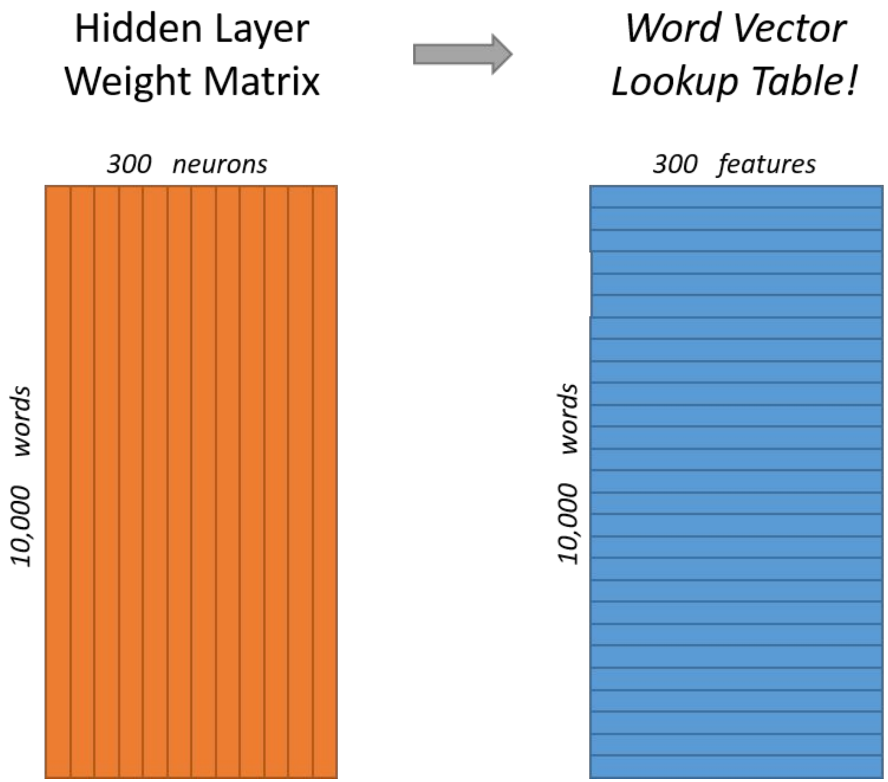
Embeddings: word2vec



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Embeddings: word2vec

- Word vectors with 300 components
- Vocabulary of 10,000 words.
- Weight matrix with 300 x 10,000 = 3 million weights each!

Training is too long and computationally expensive

How to fix this?

Embeddings: word2vec

Basic approaches:

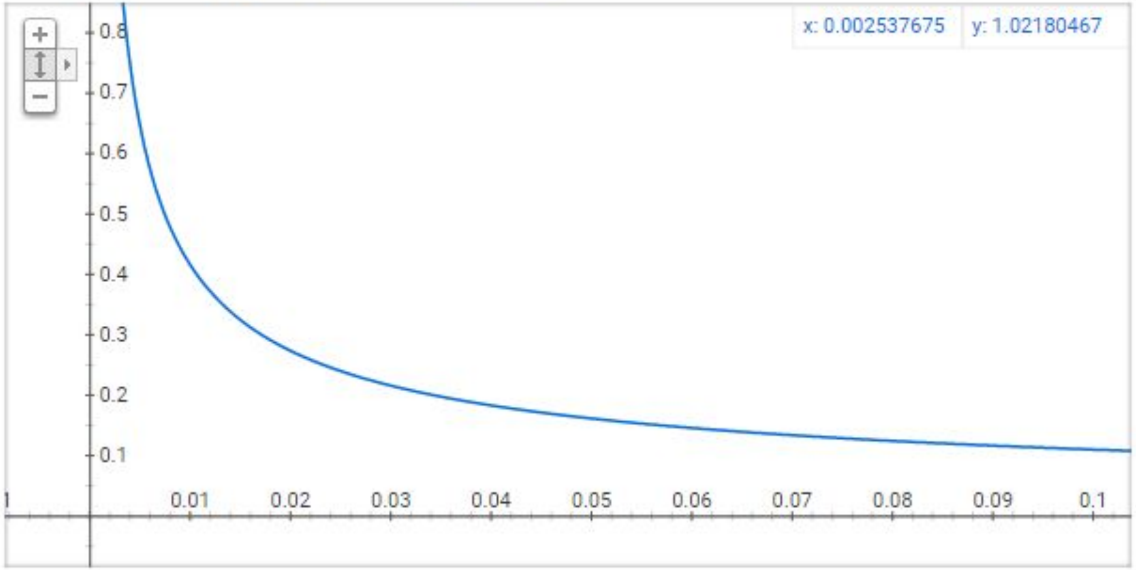
1. Treating common word pairs or phrases as single “words” in their model.
2. Subsampling frequent words to decrease the number of training examples.
3. Modifying the optimization objective with a technique they called “Negative Sampling”, which causes each training sample to update only a small percentage of the model’s weights.

Embeddings: word2vec

Subsampling frequent words.

w_i is the word, $z(w_i)$ is the fraction of this word in the whole text,

Graph for (sqrt(x/0.001)+1)*0.001/x



$P(w_i)$ is the probability of *keeping* the word:

$$P(w_i) = \left(\sqrt{\frac{z(w_i)}{0.001}} + 1\right) \cdot \frac{0.001}{z(w_i)}$$

Source: http://mccormickml.com/2017/01/11/word2vec-tutorial-part-2-negative-sampling/

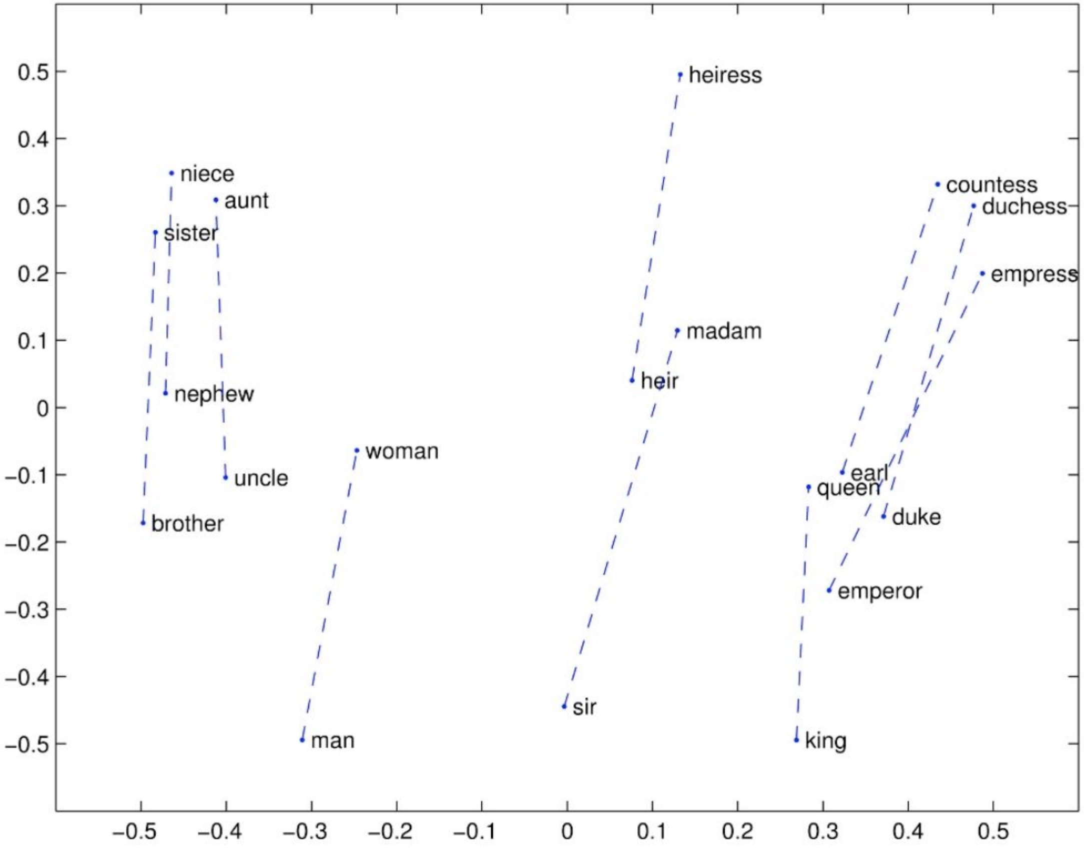
Embeddings: negative sampling

Negative Sampling idea: only few words error is computed. All other words has zero error, so no updates by the backprop mechanism.

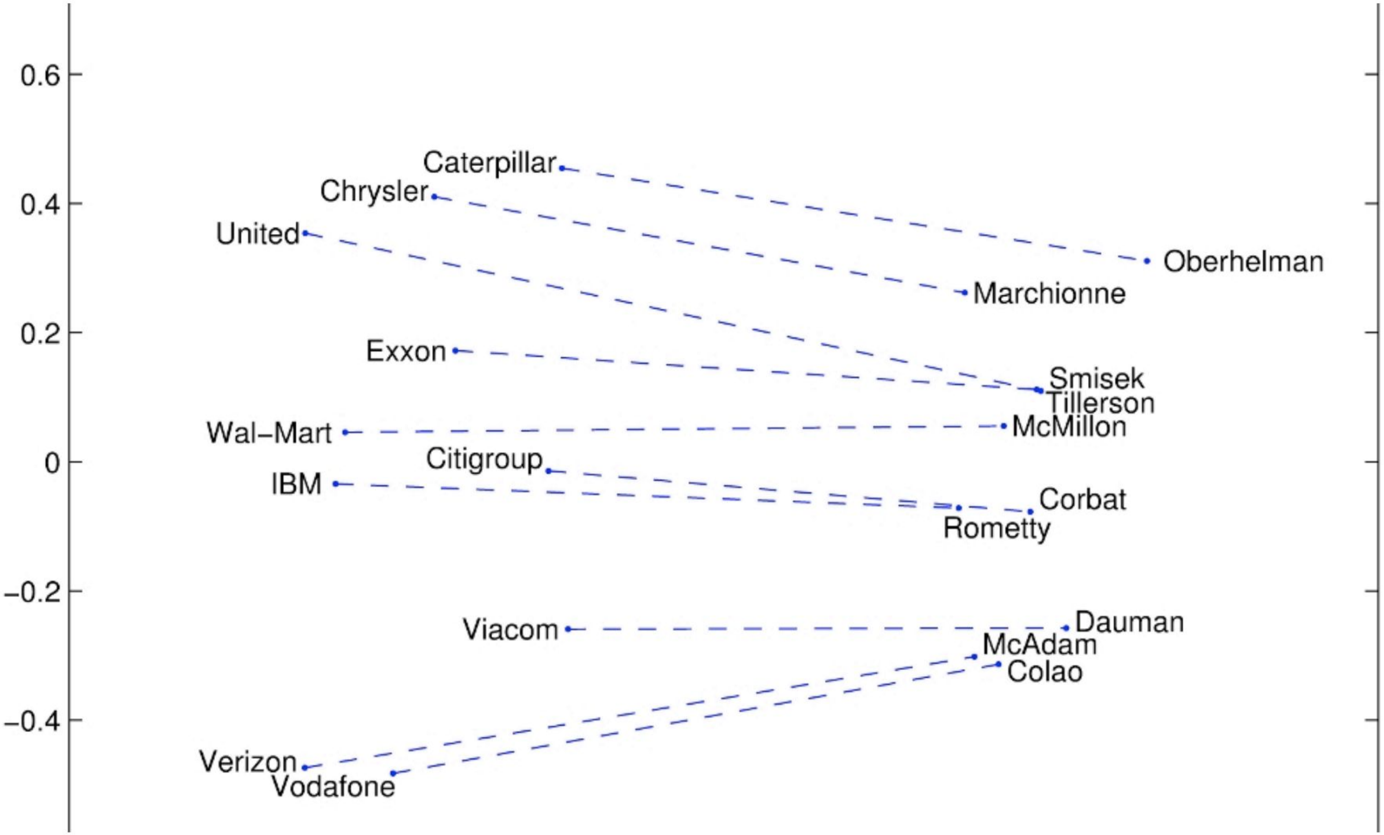
More frequent words are selected to be negative samples more often.The probability for a selecting a word is just it’s weight divided by the sum of weights for all words.

$$P(w_i) = \frac{f(w_i)^{3/4}}{\sum_{j=0}^{n} \left(f(w_j)^{3/4}\right)}$$

GloVe Visualizations



GloVe Visualizations: Company - CEO



Small outro about word representations

Word vectors are simply vectors of numbers that represent the meaning of a word

Approaches:

- One-hot encoding
- Bag-of-words models
- Counts of word / context co-occurrences
- TF-IDF
- Predictions of context given word (skip-gram neural network models, e.g. word2vec)

RNNs generating...

Shakespeare

PANDARUS:
Alas, I think he shall be come approached and the day
When little srain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

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VIOLA:
I'll drink it.

Algebraic Geometry (Latex)

Proof. Omitted. □

Lemma 0.1. *Let $\mathcal{C}$ be a set of the construction.*

Let $\mathcal{C}$ be a gerber covering. Let $\mathcal{F}$ be a quasi-coherent sheaves of $\mathcal{O}$-modules. We have to show that

$$\mathcal{O}_{\mathcal{O}_X} = \mathcal{O}_X(\mathcal{L})$$

.

Proof. This is an algebraic space with the composition of sheaves $\mathcal{F}$ on $X_{étale}$ we have

$$\mathcal{O}_X(\mathcal{F}) = \{morph_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$$

where $\mathcal{G}$ defines an isomorphism $\mathcal{F} \to \mathcal{F}$ of $\mathcal{O}$-modules. □

Lemma 0.2. *This is an integer $\mathcal{Z}$ is injective.*

Proof. See Spaces, Lemma ??. □

Lemma 0.3. *Let S be a scheme. Let X be a scheme and X is an affine open covering. Let $\mathcal{U} \subset \mathcal{X}$ be a canonical and locally of finite type. Let X be a scheme. Let X be a scheme which is equal to the formal complex.*

The following to the construction of the lemma follows.

Let X be a scheme. Let X be a scheme covering. Let

$$b : X \to Y' \to Y \to Y \to Y' \times_X Y \to X.$$

be a morphism of algebraic spaces over S and Y.

Proof. Let X be a nonzero scheme of X. Let X be an algebraic space. Let $\mathcal{F}$ be a quasi-coherent sheaf of $\mathcal{O}_X$-modules. The following are equivalent

(1) $\mathcal{F}$ is an algebraic space over S.
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Consider a common structure on X and X the functor $\mathcal{O}_X(U)$ which is locally of finite type. □

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  unsigned long flags;
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  buf[0] = 0xFFFFFFFF & (bit << 4);
  min(inc, slist->bytes);
  printk(KERN_WARNING "Memory allocated %02x/%02x, "
    "original MLL instead\n"),
    min(min(multi_run - s->len, max) * num_data_in),
    frame_pos, sz + first_seg);
  div_u64_w(val, inb_p);
  spin_unlock(&disk->queue_lock);
  mutex_unlock(&s->sock->mutex);
  mutex_unlock(&func->mutex);
  return disassemble(info->pending_bh);
}
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http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Proof. Omitted. ☐

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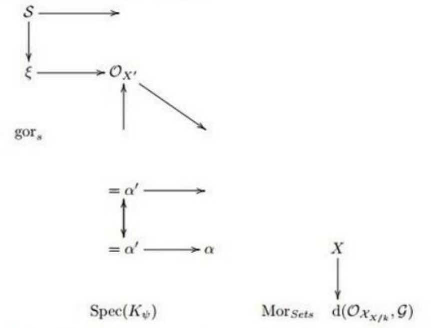
This since $\mathcal{F} \in \mathcal{F}$ and $x \in \mathcal{G}$ the diagram



is a limit. Then $\mathcal{G}$ is a finite type and assume S is a flat and $\mathcal{F}$ and $\mathcal{G}$ is a finite type f_*. This is of finite type diagrams, and

- the composition of $\mathcal{G}$ is a regular sequence,
- $\mathcal{O}_{X'}$ is a sheaf of rings.

☐

Proof. We have see that $X = \mathrm{Spec}(R)$ and $\mathcal{F}$ is a finite type representable by algebraic space. The property $\mathcal{F}$ is a finite morphism of algebraic stacks. Then the cohomology of X is an open neighbourhood of U. ☐

Proof. This is clear that $\mathcal{G}$ is a finite presentation, see Lemmas ??.
A *reduced above* we conclude that U is an open covering of $\mathcal{C}$. The functor $\mathcal{F}$ is a "field

$$\mathcal{O}_{X,x} \longrightarrow \mathcal{F}_{\overline{x}} \ \text{-}1(\mathcal{O}_{X_{\acute{e}tale}}) \longrightarrow \mathcal{O}_{X_\ell}^{-1}\mathcal{O}_{X_\lambda}(\mathcal{O}_{X_\eta}^{\overline{v}})$$

is an isomorphism of covering of $\mathcal{O}_{X_i}$. If $\mathcal{F}$ is the unique element of $\mathcal{F}$ such that X is an isomorphism.
The property $\mathcal{F}$ is a disjoint union of Proposition ?? and we can filtered set of presentations of a scheme $\mathcal{O}_X$-algebra with $\mathcal{F}$ are opens of finite type over S.
If $\mathcal{F}$ is a scheme theoretic image points. ☐

If $\mathcal{F}$ is a finite direct sum $\mathcal{O}_{X_\lambda}$ is a closed immersion, see Lemma ??. This is a sequence of $\mathcal{F}$ is a similar morphism.

http://karpathy.github.io/2015/05/21/rnn-effectiveness/

```
#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system_info.h>
#include <asm/setew.h>
#include <asm/pgproto.h>

#define REG_PG    vesa_slot_addr_pack
#define PFM_NOCOMP  AFSR(0, load)
#define STACK_DDR(type)     (func)

#define SWAP_ALLOCATE(nr)     (e)
#define emulate_sigs()  arch_get_unaligned_child()
#define access_rw(TST)  asm volatile("movd %%esp, %0, %3" : : "r" (0));   \
  if (__type & DO_READ)

static void stat_PC_SEC __read_mostly offsetof(struct seq_argsqueue, \
          pC>[1]);

static void
os_prefix(unsigned long sys)
{
#ifdef CONFIG_PREEMPT
  PUT_PARAM_RAID(2, sel) = get_state_state();
  set_pid_sum((unsigned long)state, current_state_str(),
           (unsigned long)-1->lr_full; low;
}
```

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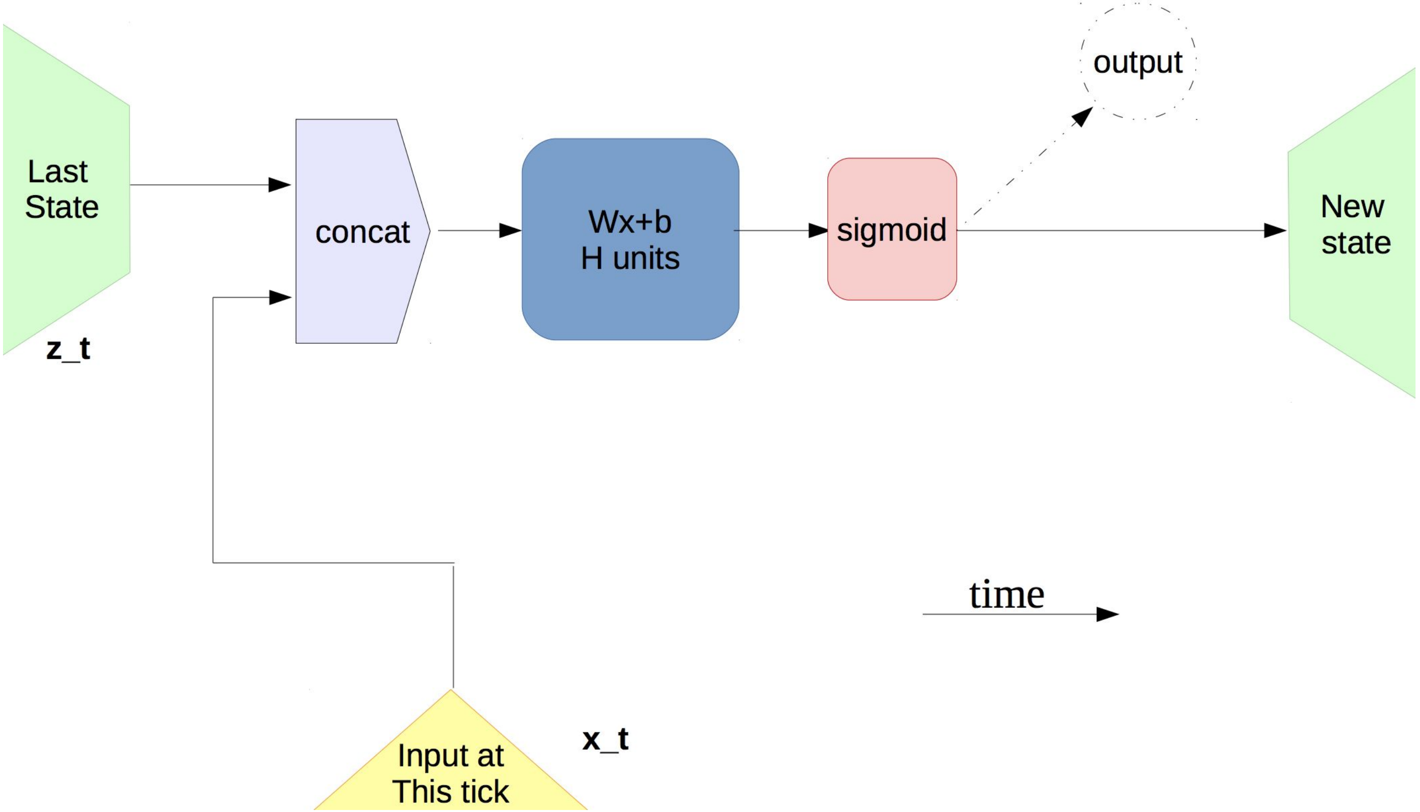
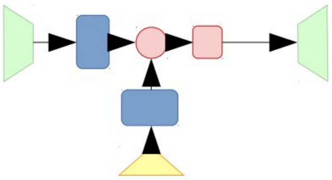
Recurrent neural network

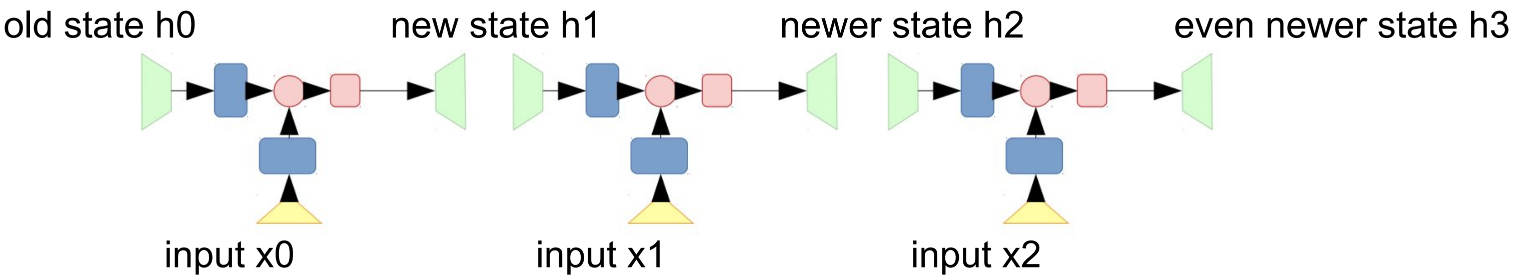


Recurrent neural network

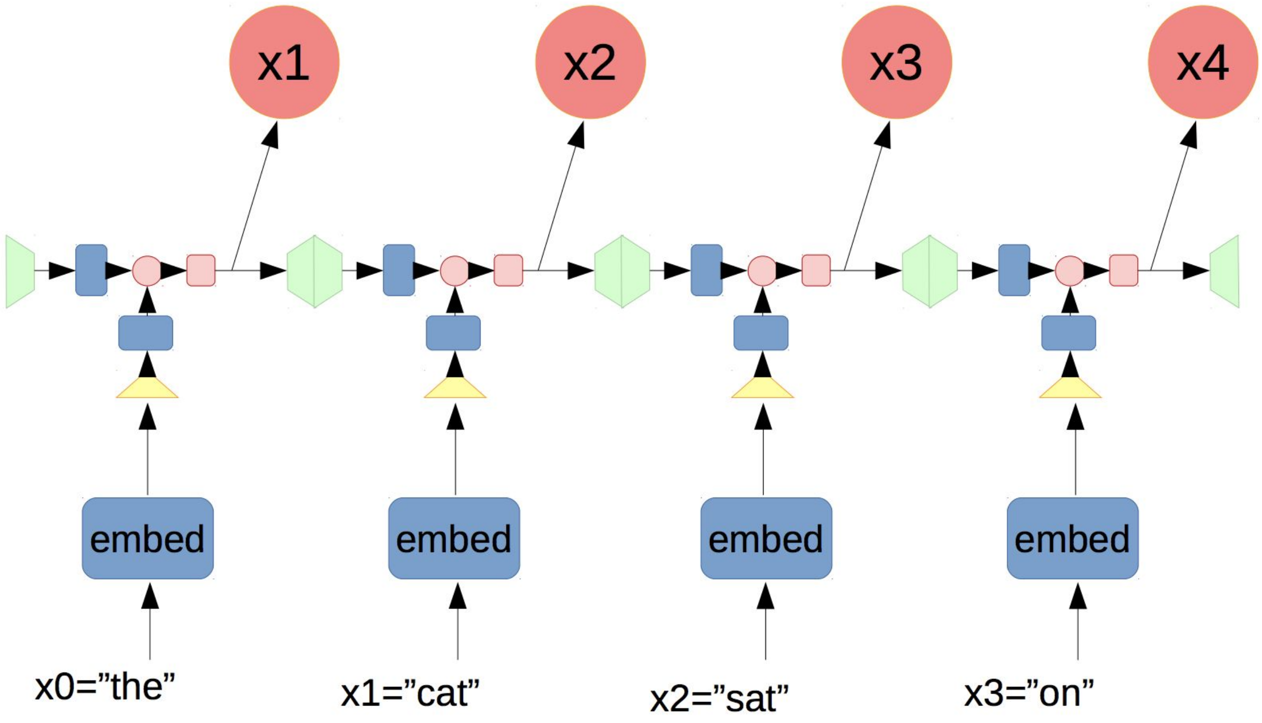


Recurrent neural network

We use same weight matrices for all steps



Recurrent neural network



Recurrent neural network

Now with formulas

$$h_0 = \bar{0}$$

$$h_1 = \sigma\Big(\langle W_{\text{hid}}[h_0, x_0]\rangle + b\Big)$$

$$h_2 = \sigma\Big(\langle W_{\text{hid}}[h_1, x_1]\rangle + b\Big) = \sigma\Big(\langle W_{\text{hid}}[\sigma\Big(\langle W_{\text{hid}}[h_0, x_0]\rangle + b, x_1]\rangle + b\Big)$$

$$h_{i+1} = \sigma\Big(\langle W_{\text{hid}}[h_i, x_i]\rangle + b\Big)$$

$$P(x_{i+1}) = \text{softmax}\Big(\langle W_{\text{out}}, h_i\rangle + b_{\text{out}}\Big)$$

RNNs generating...

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```
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When little srain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
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Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

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  buf[0] = 0xFFFFFFFF & (bit << 4);
  min(inc, slist->bytes);
  printk(KERN_WARNING "Memory allocated %02x/%02x, "
    "original MLL instead\n"),
    min(min(multi_run - s->len, max) * num_data_in),
    frame_pos, sz + first_seg);
  div_u64_w(val, inb_p);
  spin_unlock(&disk->queue_lock);
  mutex_unlock(&s->sock->mutex);
  mutex_unlock(&func->mutex);
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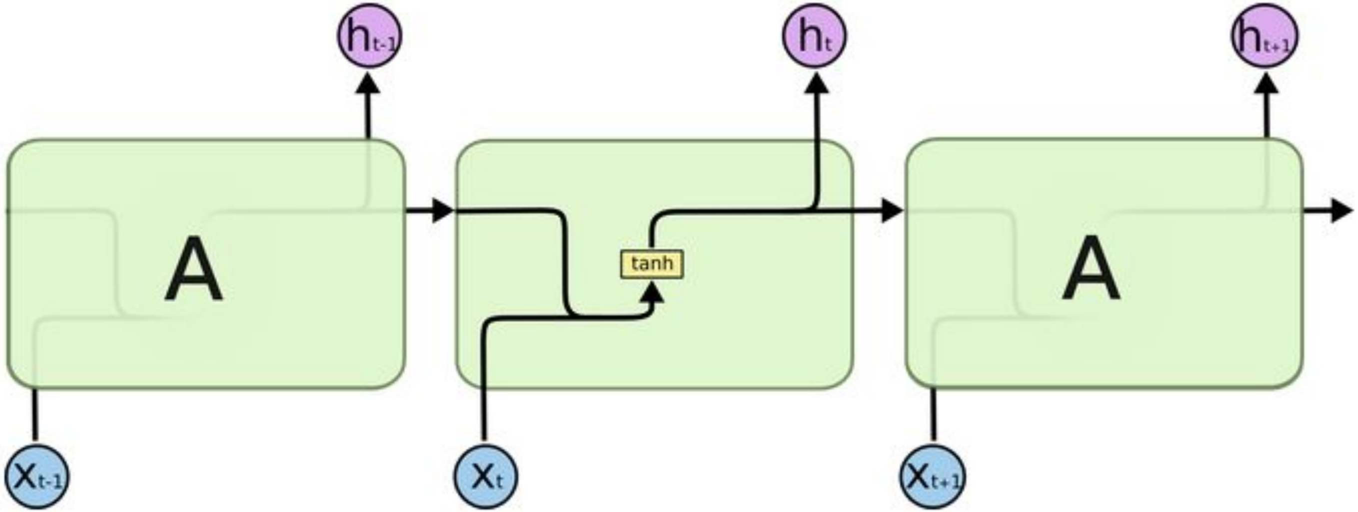
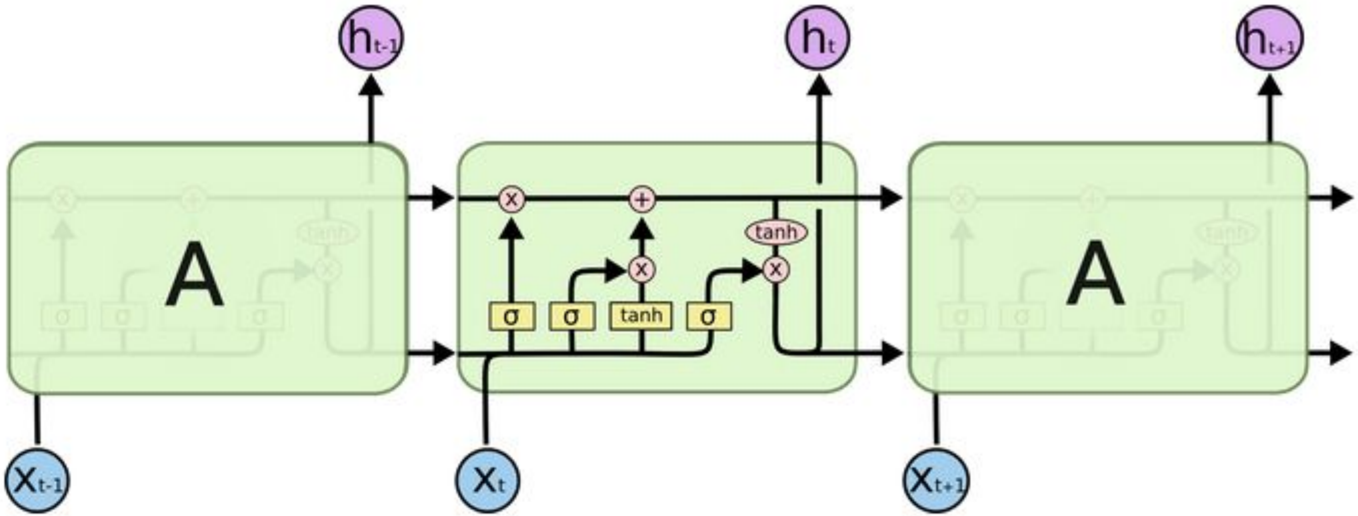
Vanilla RNN



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

LSTM



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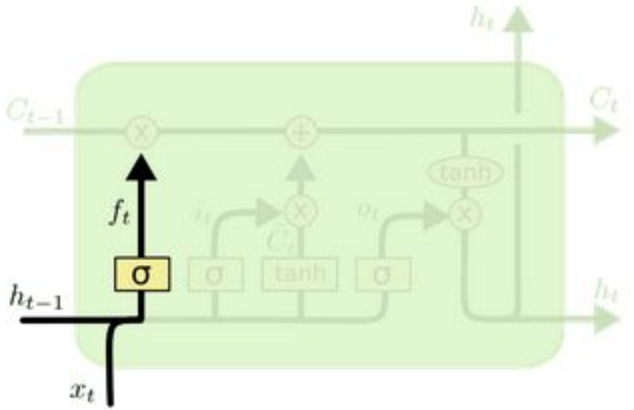
LSTM: quick overview



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

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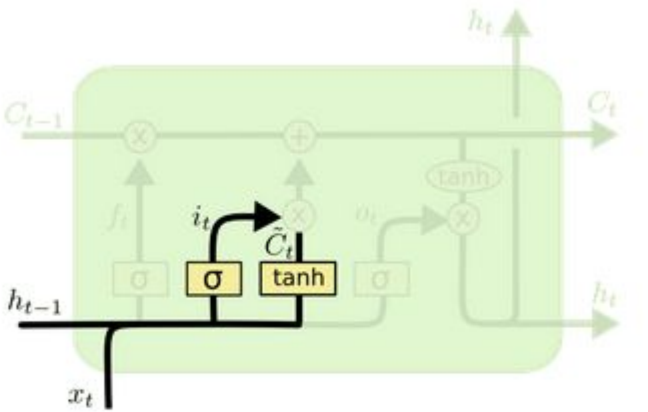
LSTM: quick overview



$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

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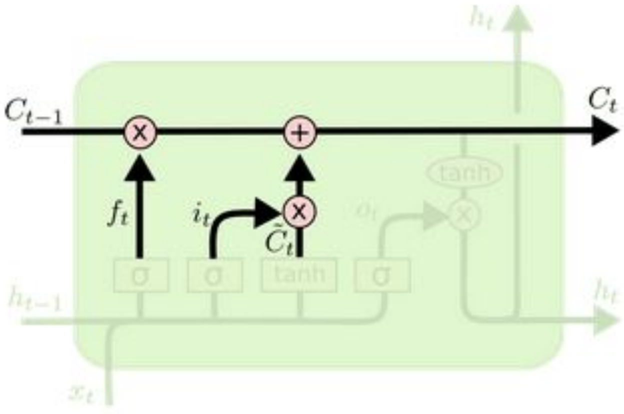
LSTM: quick overview



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

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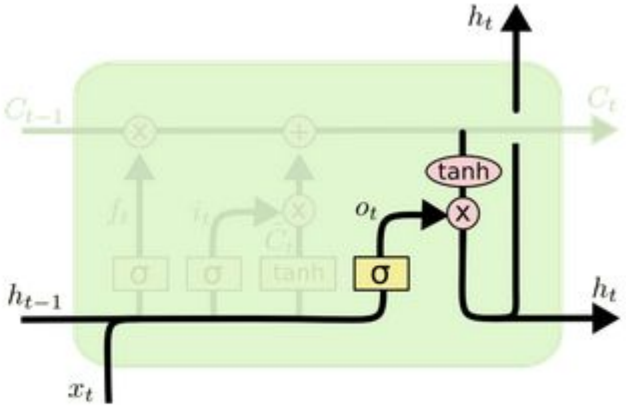
LSTM: quick overview



$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$
$$h_t = o_t * \tanh\left(C_t\right)$$

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

Tips

- Do not forget about dropout. It really rocks.
- Other regularization approaches are welcome as well (see previous lectures).
- Combining RNN and CNN worlds? *Coming soon*

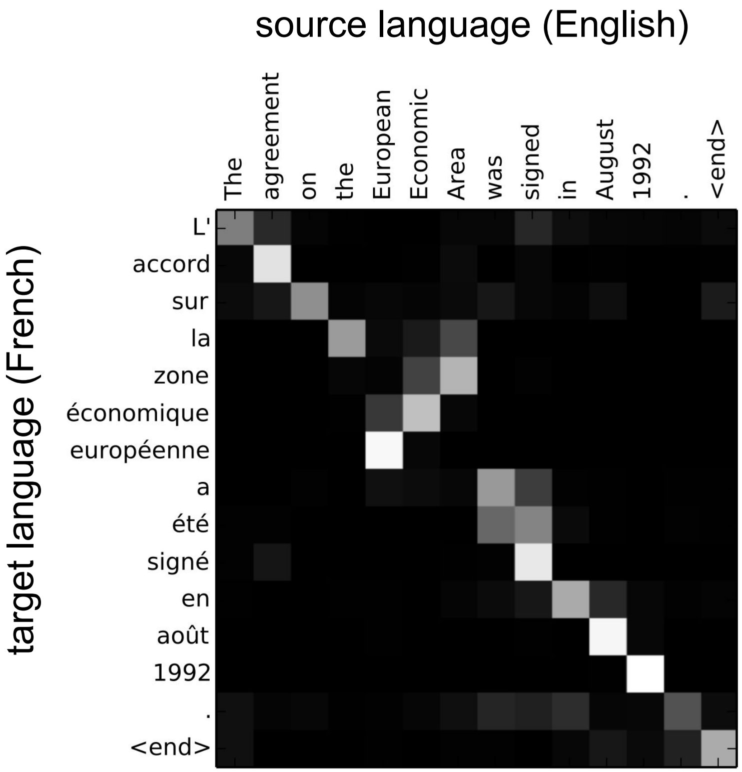
Q & A

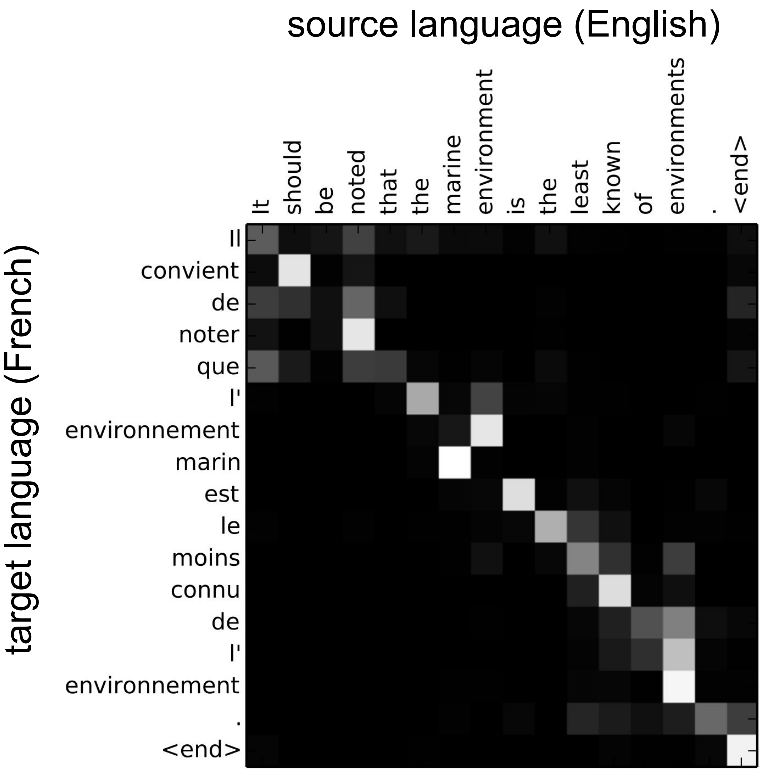
That’s all. Feel free to ask any questions.

RNNs, we are coming. Time to generate some names!

Backlog

Attention maps in translation





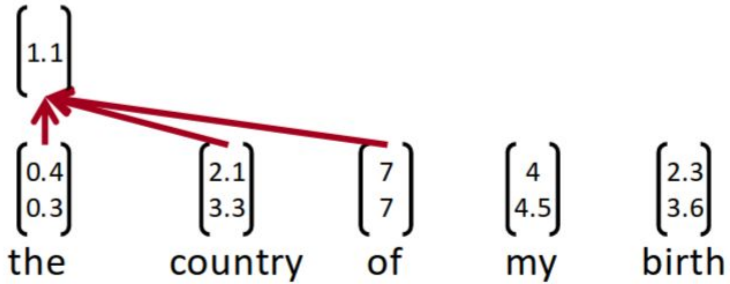
Bahdanau et al. "Neural Machine Translation by Jointly Learning to Align and Translate", 2014

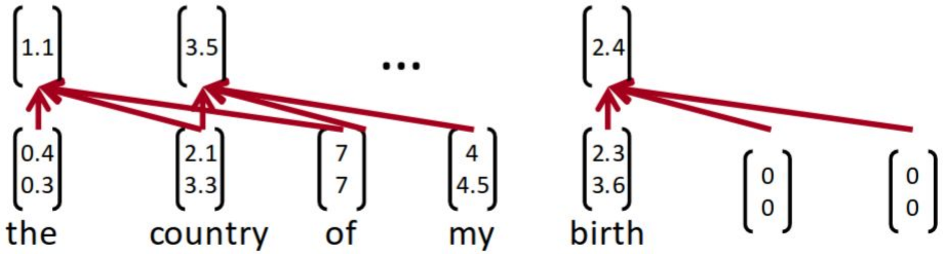
One layer CNN

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

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

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





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

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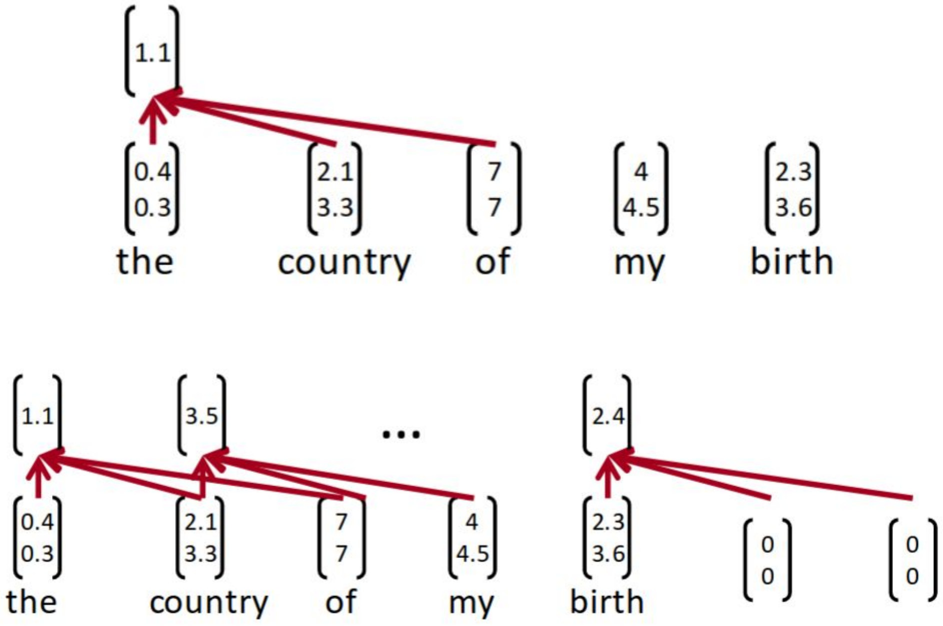

What's next?

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One layer CNN

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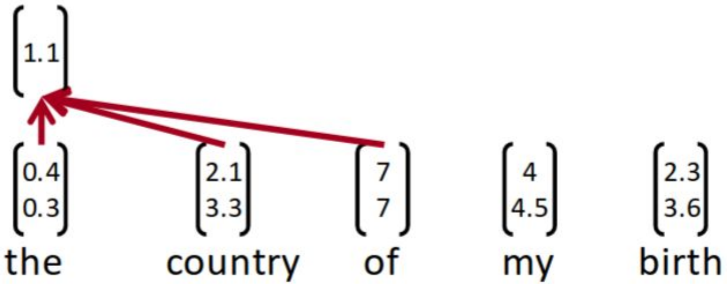
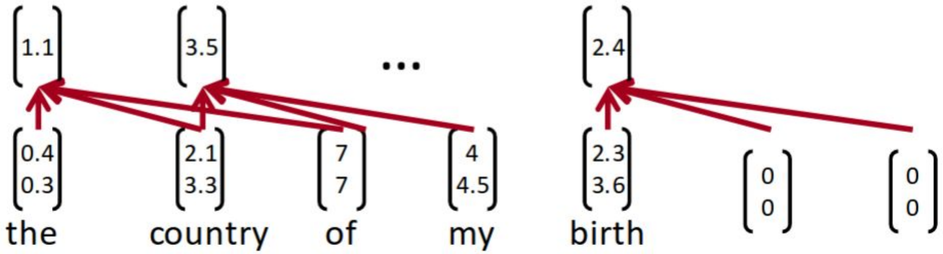


What's next?

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.

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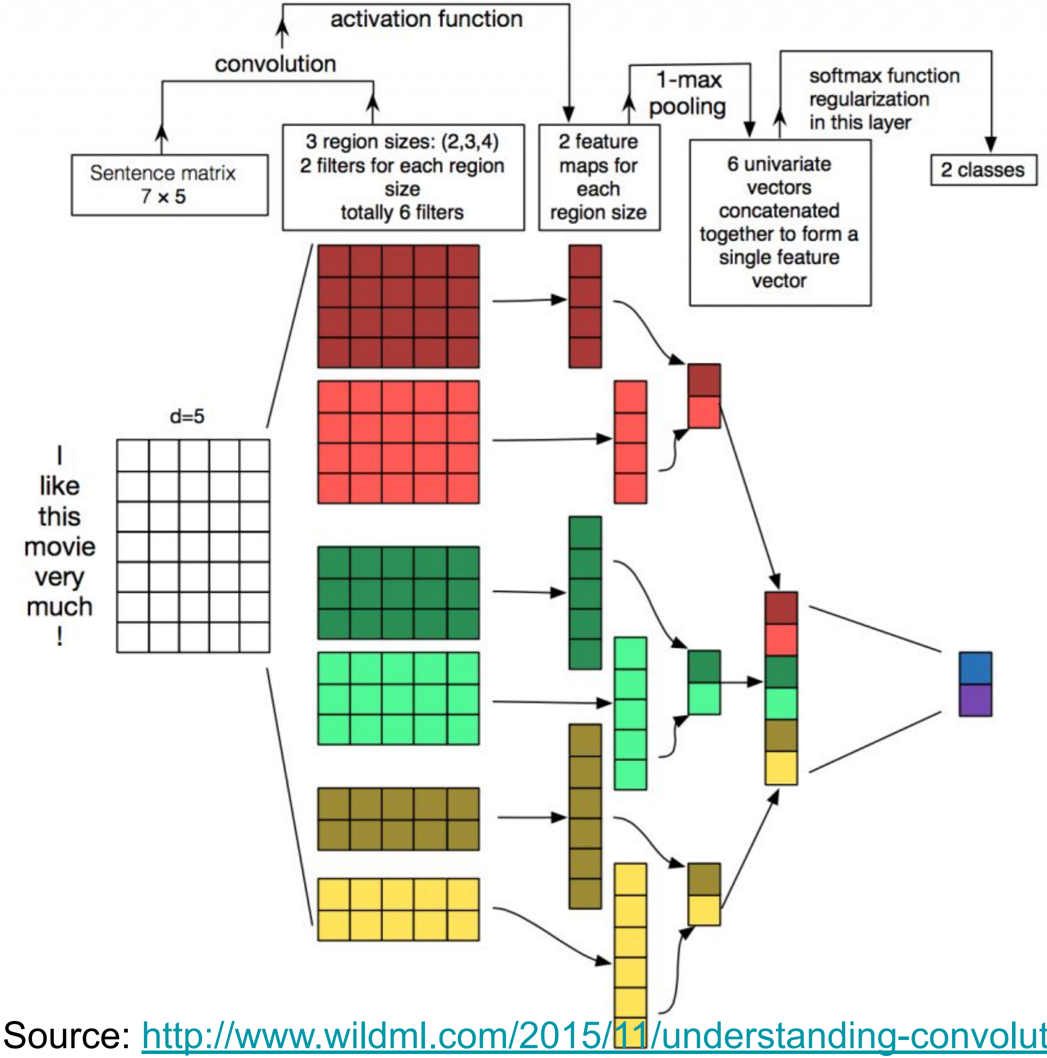
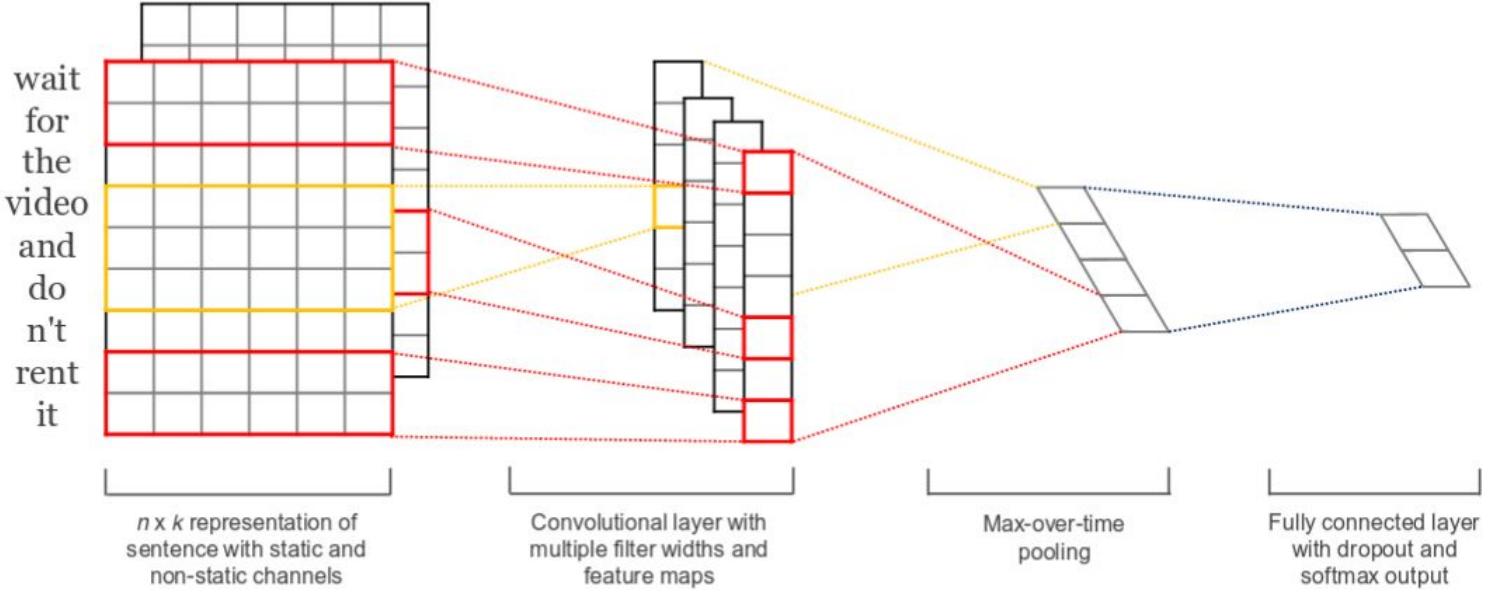
Example CNN structure



Source: http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-nlp/

Another example from Kim (2014) paper



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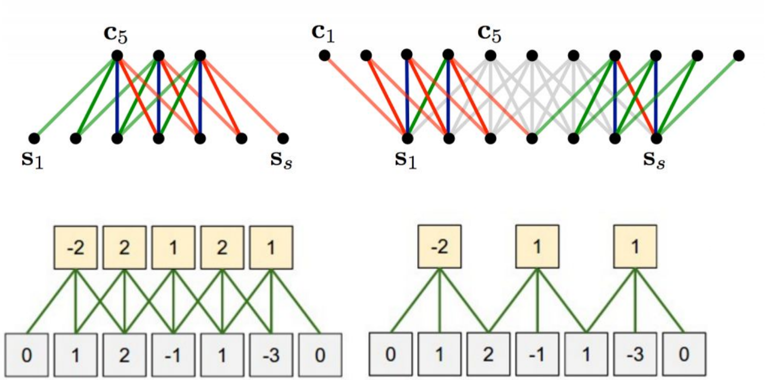
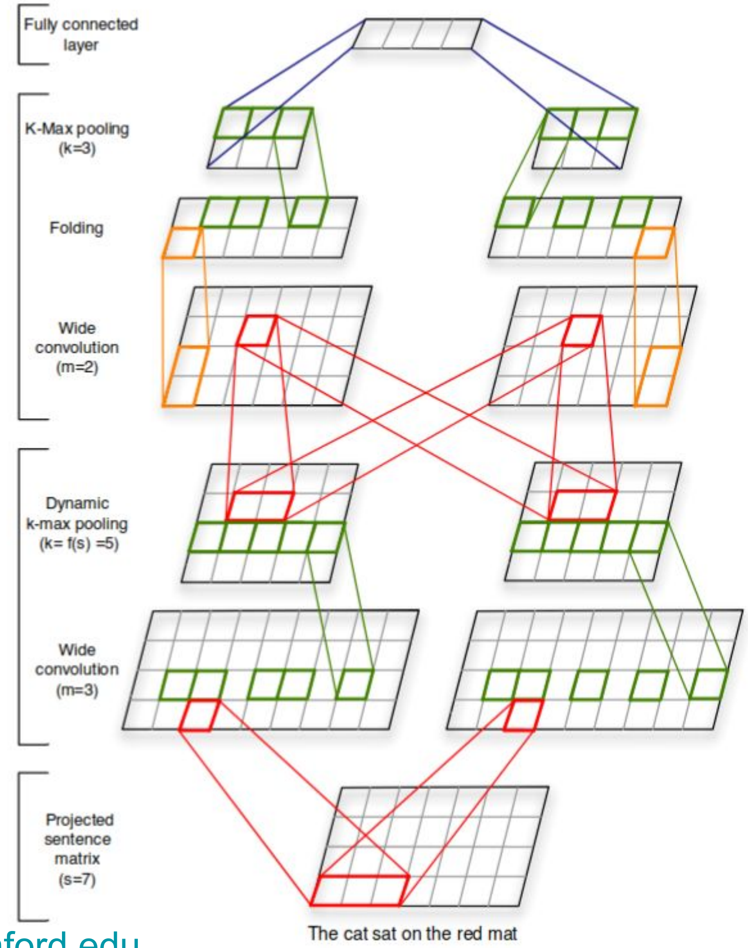
More about CNN

- 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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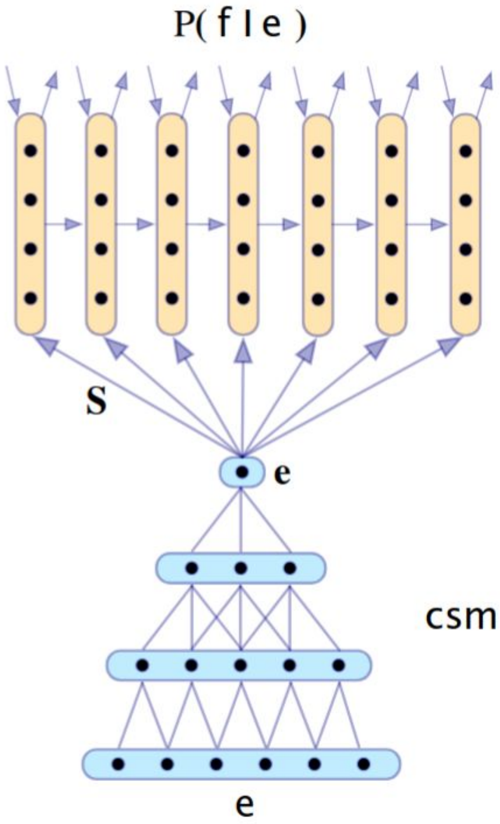
CNN applications



- 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