Representation Learning for Text

Kevin Duh

Johns Hopkins University

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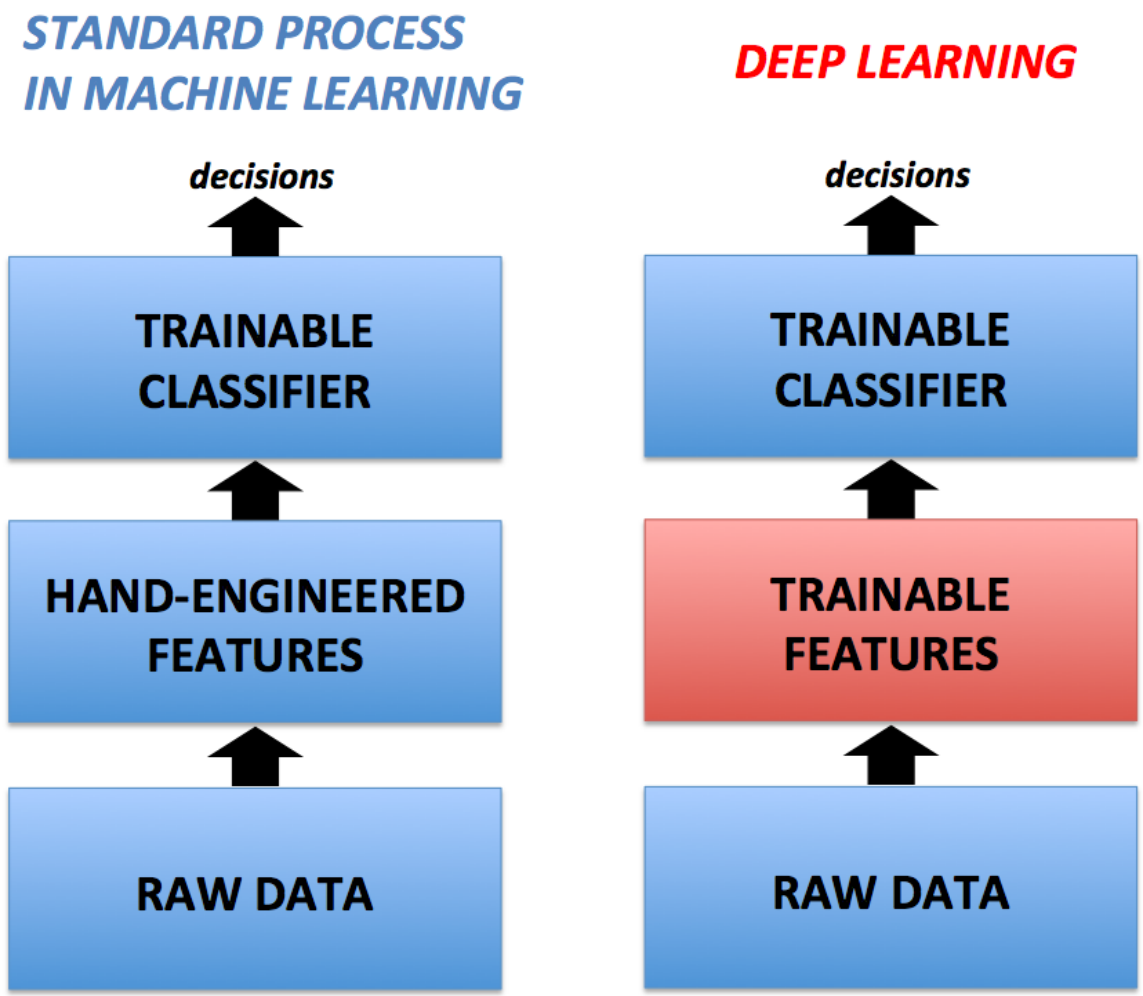
Terminology

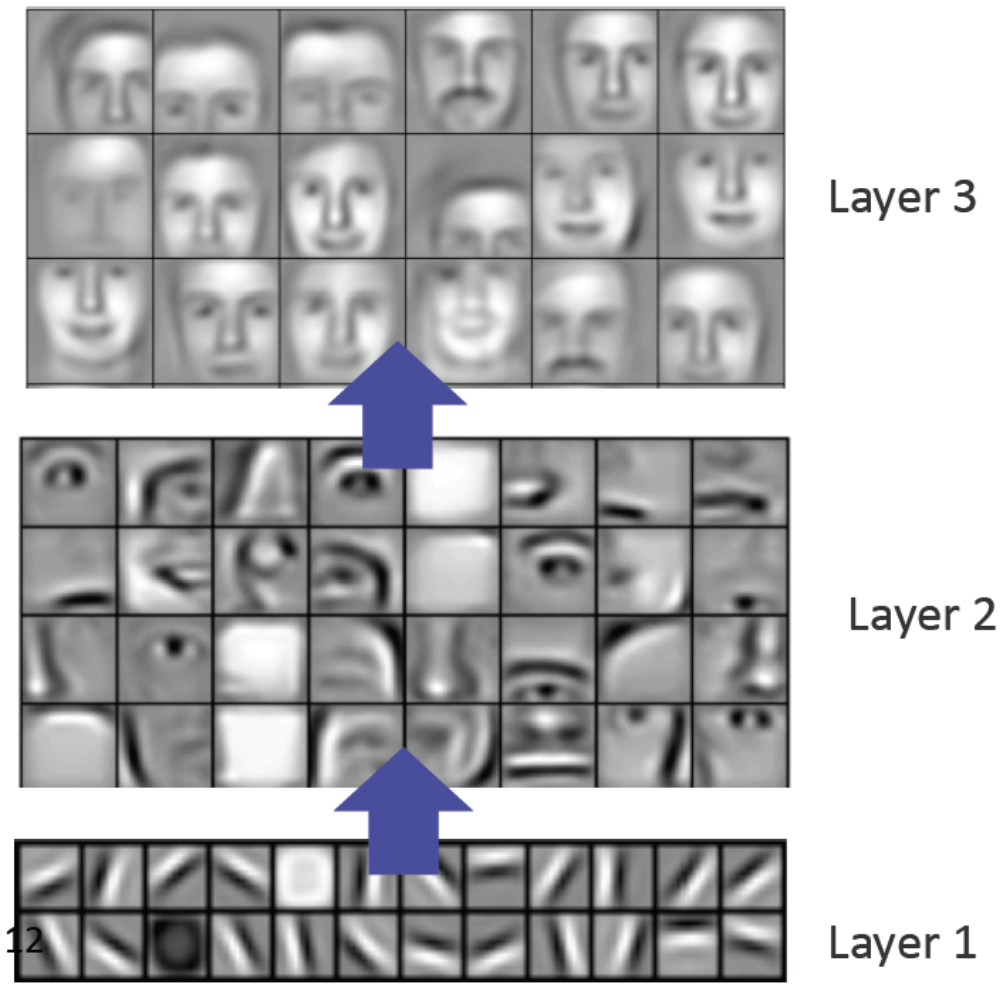
- Representation Learning is a problem statement
- Deep Learning is a solution technique
- Neural network is a way of implementing deep learning



Representation Learning in Images

Automatically trained features make sense! [Lee et al., 2009]

Input: Images (raw pixels)
$\rightarrow$ Output: Features of Edges, Body Parts, Full Faces



Outline

1. Word Embeddings
   - What should be encoded in a word representation?
   - Neural language model and word2vec
   - Multiview Learning

2. Sentence Embeddings
   - What should be encoded?
   - Handling variable length sequences

Outline

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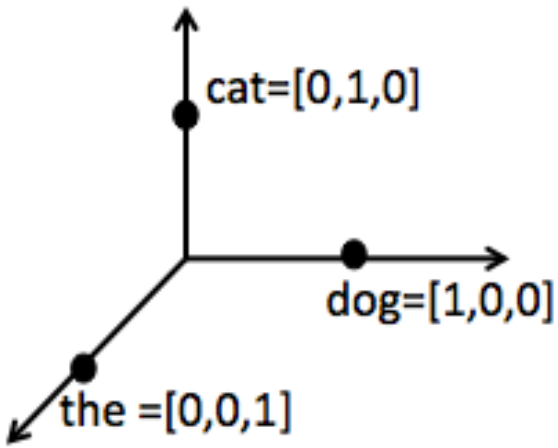
Representations of Words

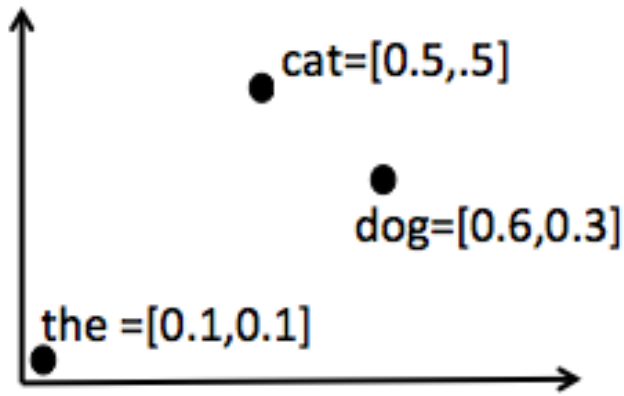
- Central question: How to computationally represent "words" in a natural language processing system?

Vector Representation of Words (word embeddings)

- Embed word in vector space, such that nearby words are syntactically or semantically similar
- Neural nets can be used to learn these vectors from raw text [Collobert et al., 2011, Chen et al., 2013]

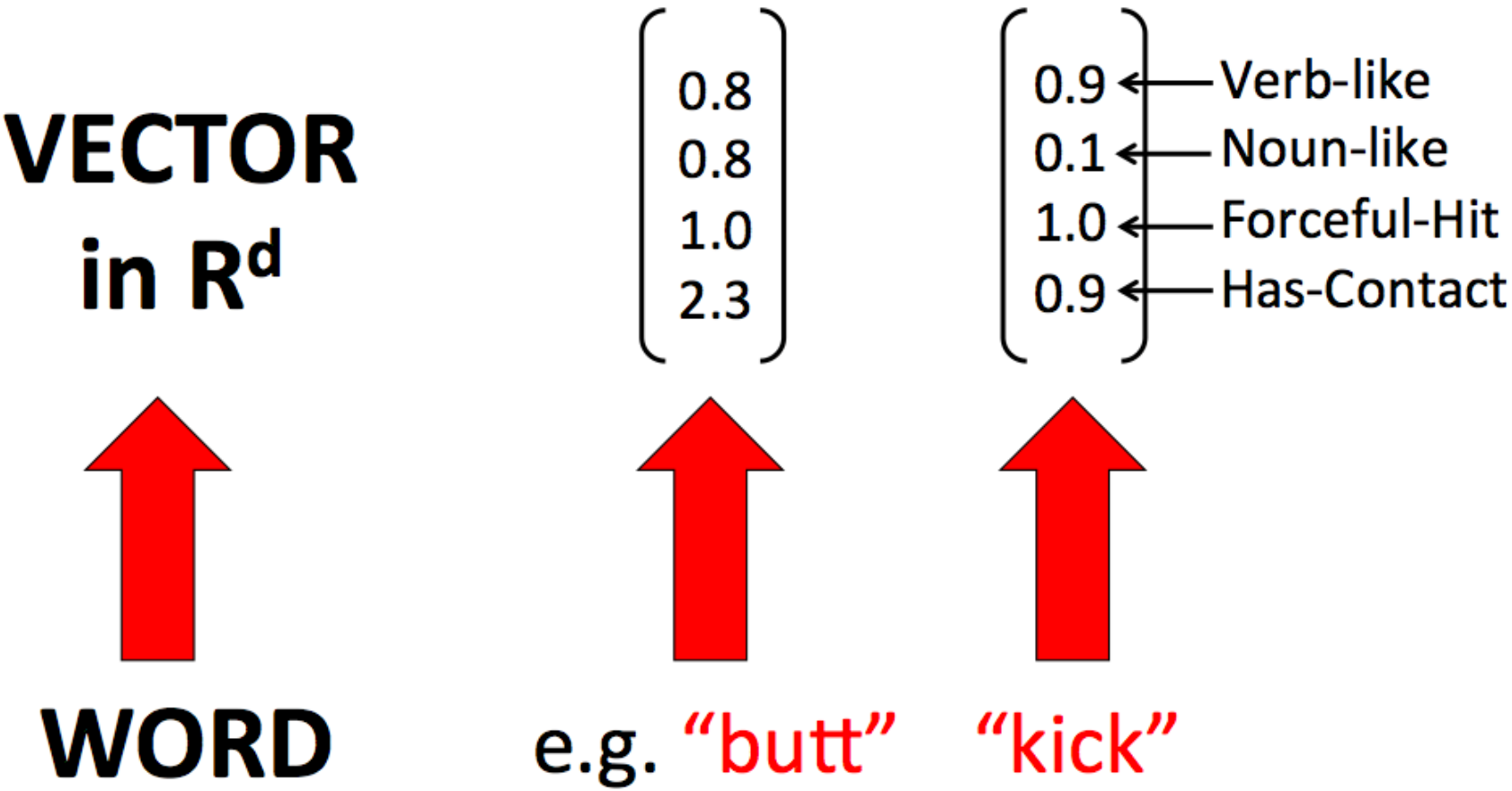


One-Hot Representation:
Word as discrete atomic feature



Distributed Representation:
Word as vectors

Vector Representations of Words (Word Embeddings)



Vector Representations of Words (Word Embeddings)

Vector representation:

$$\text{similarity}(\text{butt}=\begin{pmatrix}0.8\\0.3\\1.0\\2.3\end{pmatrix},\text{kick}=\begin{pmatrix}0.9\\0.1\\1.0\\0.9\end{pmatrix}) > 0$$

Suppose "butt" is a rare word

One-hot representation:

$$\text{similarity}(\text{butt}=\begin{pmatrix}0\\0\\\dots\\1\\0\end{pmatrix},\text{kick}=\begin{pmatrix}0\\0\\\dots\\0\\1\end{pmatrix}) = 0$$

What information is needed for a good representation?

You shall know a word by the company it keeps. – J. R. Firth (linguist)

- Distributional Semantics: a word's meaning is based on its positional distribution in text

Distributional Semantics

Large Text Dataset

Your pet dog is so cute

Your pet cat is so cute

The dog ate my homework

The cat ate my homework

→ dog is-similar-to cats (in usage & meaning)

Example: "Bar-ba-loots"

- Do you know what is a bar-ba-loot?

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  - $P(\mathbf{w_t} = \textit{fruits} \mid \mathbf{w_{t-1}} = \textit{like}, \mathbf{w_{t-2}} = \textit{Bar-ba-loots})$
  - $P(\mathbf{w_t} = \textit{looting} \mid \mathbf{w_{t-1}} = \textit{like}, \mathbf{w_{t-2}} = \textit{Bar-ba-loots})$

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- Purpose of word embedding: Improve generalization

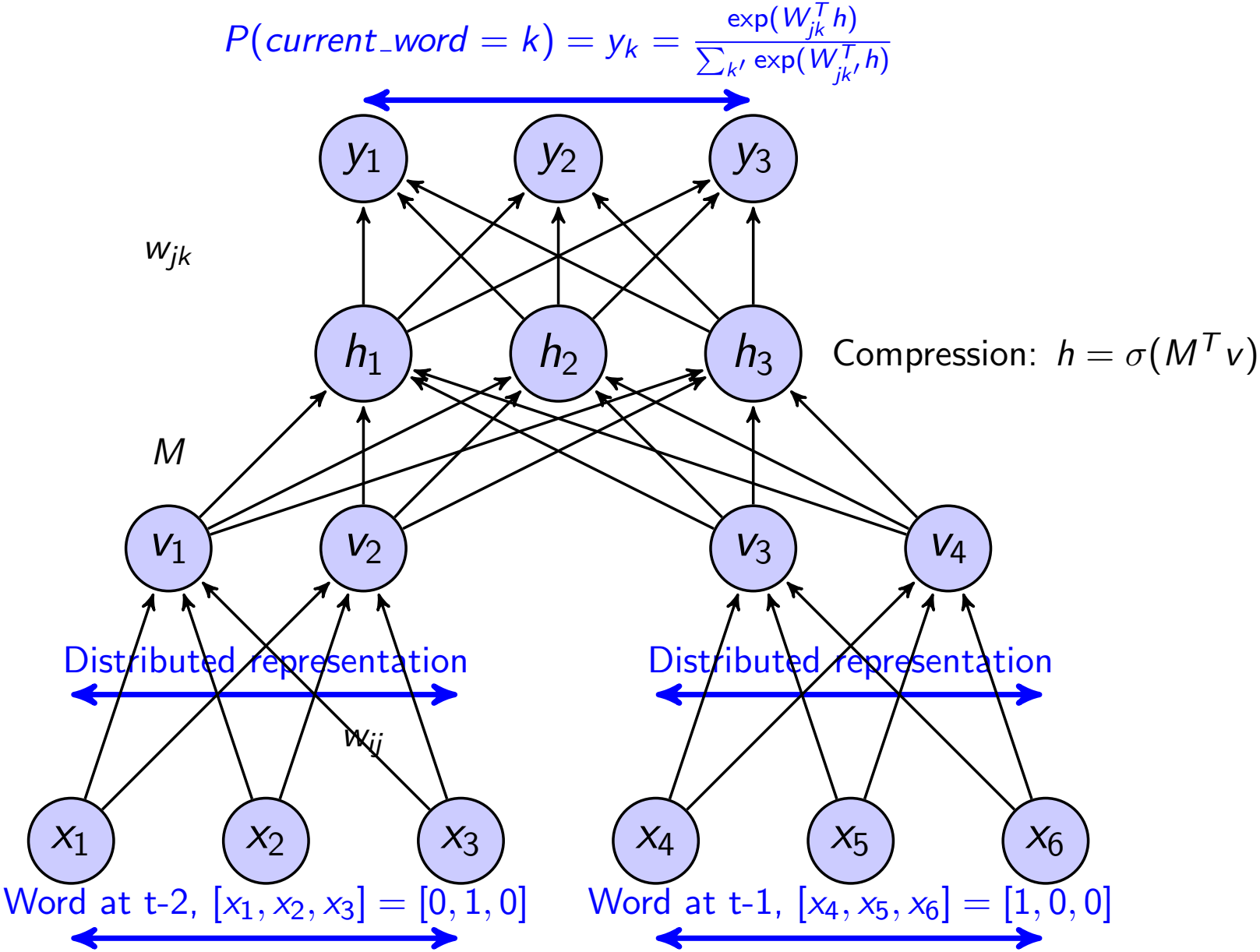
Outline

Neural language model and word2vec

- Feed-forward neural language model
  - Model $P(\mathbf{w_t} = \textit{looting} \mid \mathbf{w_{t-1}} = \textit{like}, \mathbf{w_{t-2}} = \textit{Bar-ba-loots})$ with a feed-forward neural LM
  - Can be used a LM inside machine translation / speech recognition systems
  - Or, can extract first layer as word embedding
- word2vec
  - If we only want word embeddings and don't need a probability distribution over next words, we can save on training time

Word embeddings from Neural LM, one method

[Bengio et al., 2003]



Training a Neural LM

- Find parameters θ that maximizes likelihood $P_\theta(\mathbf{w_t} \mid \mathbf{w_{t-1}}, \mathbf{w_{t-2}})$ on training data
  - For each input $\mathbf{x_t} = (\mathbf{w_{t-1}}, \mathbf{w_{t-2}})$ and output $\mathbf{w_t}$ pair, forward compute $P_\theta(\cdot)$ and then back-prop

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- $P_\theta(\mathbf{w_t} \mid \mathbf{x_t}) = \mathit{softmax}(\mathit{score}(\mathbf{w_t}, \mathbf{x_t})) = \frac{\exp(\mathit{score}(\mathbf{w_t}, \mathbf{h_t}))}{\sum_{\mathbf{w'} \in \mathit{Vocabulary}} \exp(\mathit{score}(\mathbf{w'}, \mathbf{x_t}))}$
- max-likelihood objective:
  $\log P_\theta(\mathbf{w_t} \mid \mathbf{x_t}) = \mathit{score}(\mathbf{w_t}, \mathbf{x_t}) - \log \sum_{\mathbf{w'} \in \mathit{Vocabulary}} \exp(\mathit{score}(\mathbf{w'}, \mathbf{x_t}))$
  - challenge: sum over all vocabulary for each gradient step may be expensive.

word2vec [Mikolov et al., 2013]

1. Different objective (negative sampling): discriminate target word from a few (k) noise words sampled from distribution q:
   - $\log p(D = 1 \mid \mathbf{w_t}, \mathbf{x_t}) + k\mathbb{E}_{w' \sim q} \log p(D = 0 \mid \mathbf{w}', \mathbf{x_t})$
   - binary classifier discriminates true and noise samples:
     $p(D = 1 \mid \mathbf{w_t}, \mathbf{x_t}) = \frac{score(\mathbf{w_t}, \mathbf{x_t})}{score(\mathbf{w_t}, \mathbf{x_t})+1}$; $p(D = 0 \mid \mathbf{w_t}, \mathbf{x_t}) = \frac{1}{score(\mathbf{w_t}, \mathbf{x_t})+1}$

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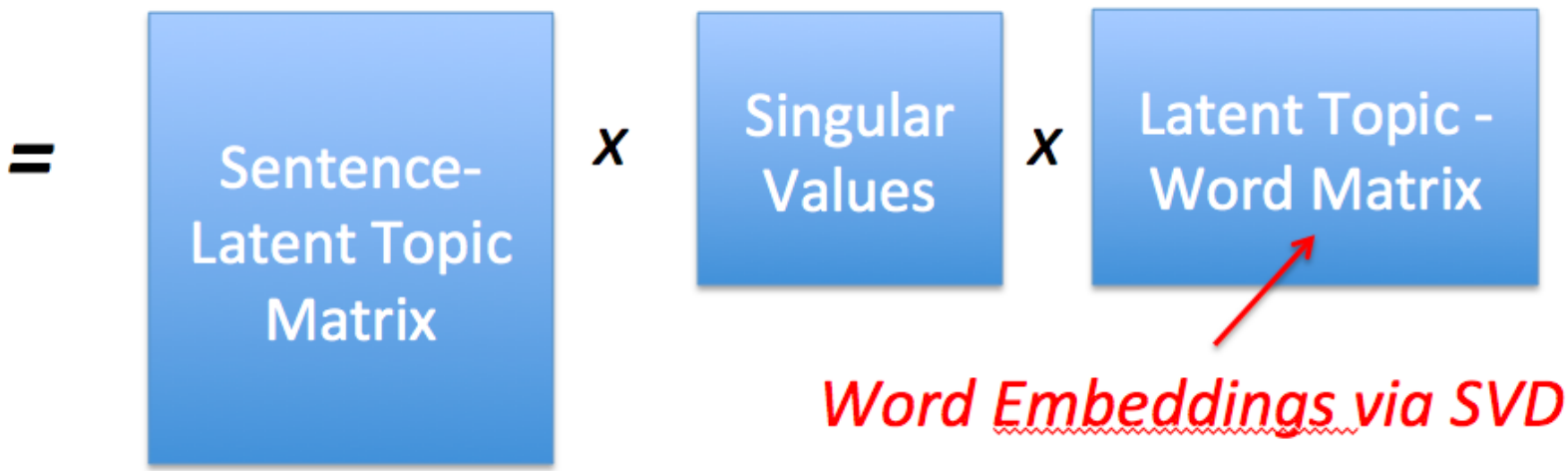
2. Simplified architecture:
   - $score(\mathbf{w_t}, \mathbf{x_t}) = \exp(\mathbf{vec}(\mathbf{w_t})^T \cdot \mathbf{vec}(\mathbf{x_t}))$
   - skip-gram variant: $\mathbf{x_t}$ is input, predict left/right neighbors
   - note: input/output embeddings may differ

Learning Distributional Semantics via SVD

Sentence-Term Matrix

	pet	dog	is	cat	the	ate
S1	1	1	1	0	0	0
S2	1	0	1	1	0	0
S3	0	1	0	0	1	1
S4	0	0	0	1	1	1

S1: ... *pet dog is* ...
S2: ... *pet cat is* ...
S3: *The dog ate* ...
S4: *The cat ate* ...



Outline

From single-view to multi-view

- What are other "definitions" of word meaning, besides distributional semantics?
- Can we include them in the encoding of word representations?

View 2: Relational Semantics

dog is-a-kind-of canine

poodle is-a-kind-of dog

dog has-a tail

dog barking sounds-like woof-woof!

- Many such relational knowledge have been created in e.g. WordNet [Miller, 1995], Freebase [Bollacker et al., 2008]
- [Faruqui et al., 2014, Fried and Duh, 2014] incorporate both relational and distributional objectives in embeddings

View 3: Bilingual information

- The translation y of a word x provides an additional view (different form, same meaning)
- Method 1: Assume word translation pairs [Faruqui and Dyer, 2014]:
  - $v, w = CCA(x, y) = \arg\max_{v,w} \rho(xv, yw)$

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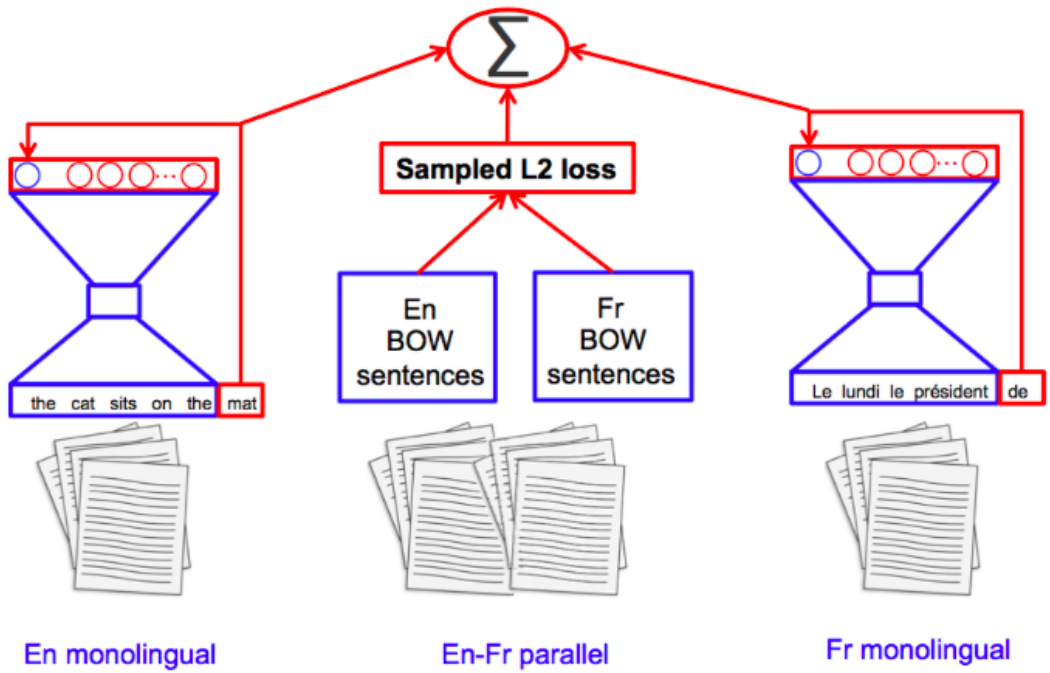
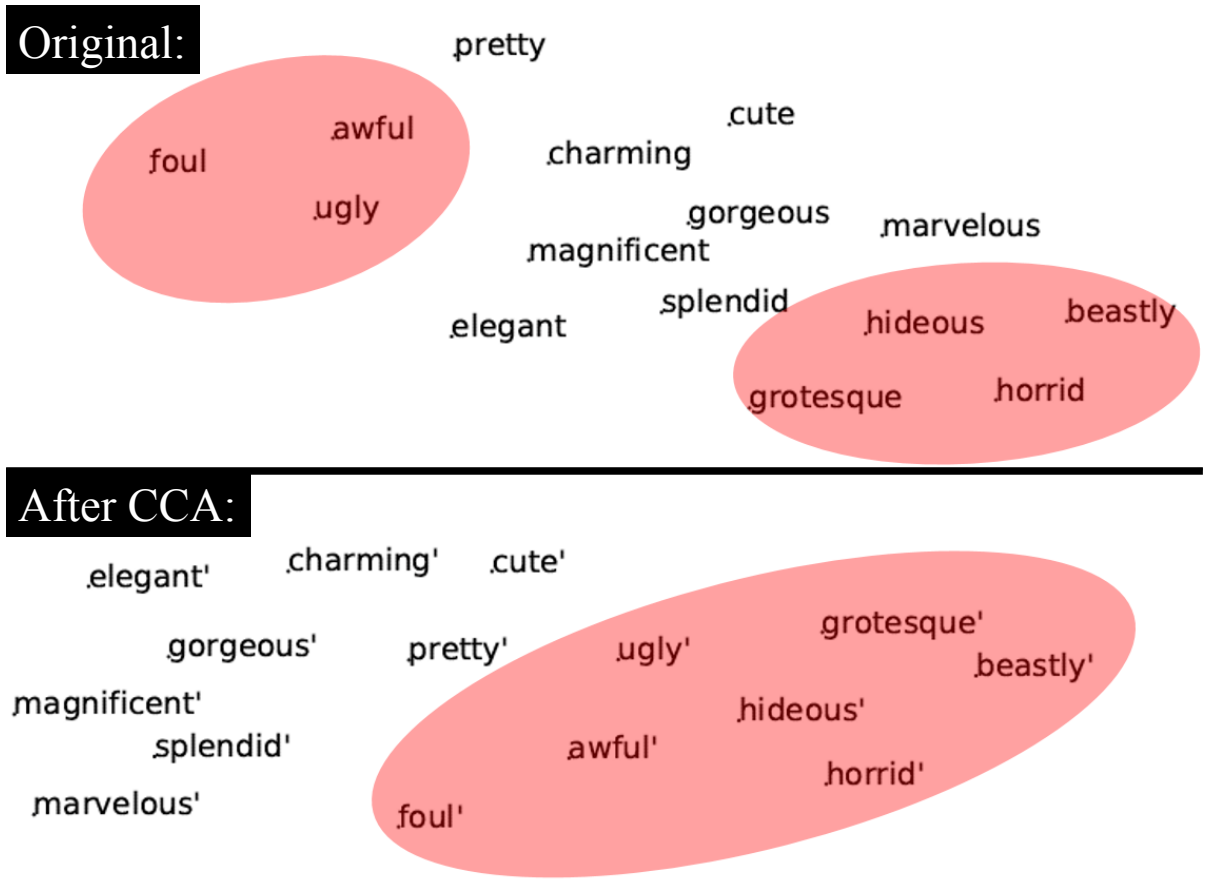
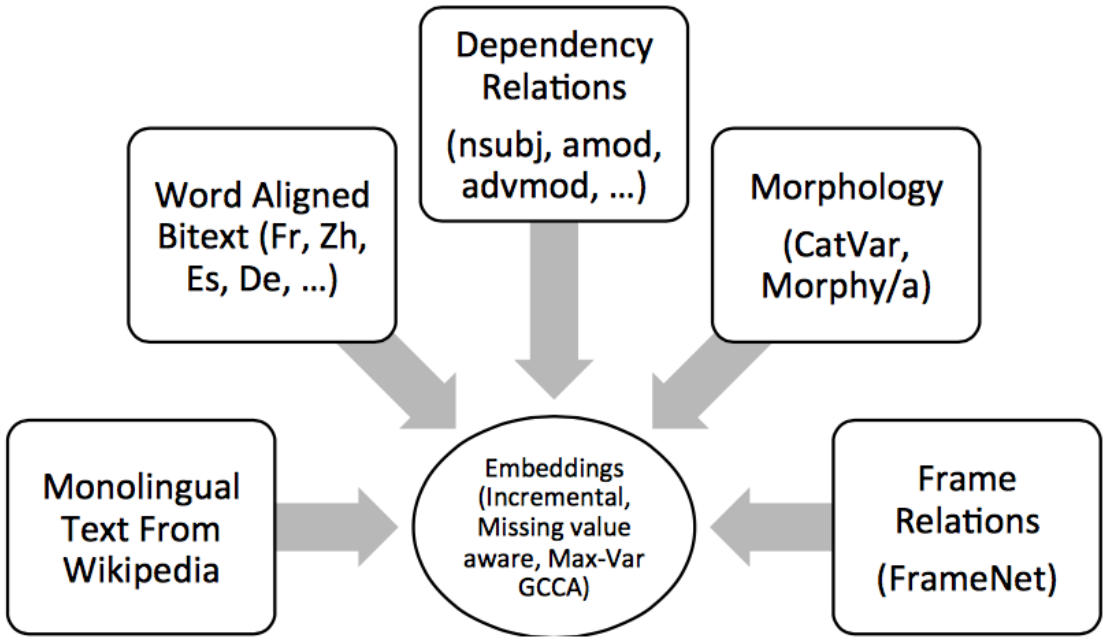


Example [Faruqui and Dyer, 2014]



Antonyms are mixed up when relying only on one language's distributional semantics (view 1), but is nicely teased apart with multilingual views.

2+ views [Rastogi et al., 2015]



$$\arg\min_{G,U_j} \sum_{j=1}^{J} \left\| G - X_j U_j \right\|_F^2$$

$$\text{subject to } G^\top G = I.$$

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Challenges

1. What to encode in the representation?
2. How to handle variable length sequences?

What should be encoded? (1) Semantic equivalence

- "Bob gave Jane a book on her birthday"
  $\rightarrow$ vector $\mathbf{s_1}$
- "Jane's birthday present from Bob was a book"
  $\rightarrow$ vector $\mathbf{s_2}$
- Hopefully $\mathbf{s_1} = \mathbf{s_2}$

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- "Bob gave Jane a book on her birthday"
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- "Bob gab Jane ein Buch an ihren Geburstag"
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What should be encoded? (2) Entailment, Relatedness, and Inference

- s1: A sea turtle is hunting for fish
- s2: A sea turtle is hunting for food
- s3: The turtle is following the fish
- s4: The turtle is following the red fish

Does s1 entail s2? Are they semantically equivalent?

Does s1 entail s3? Or can you infer s3 is likely true given s1?

What should be encoded? (2) Entailment, Relatedness, and Inference

- s5: The first settlements on the site of Jakarta were established at the mouth of the Ciliwung, perhaps as early as the 5th century AD.
- s6: The first settlements on the site of Jakarta were established as early as the 5th century AD.
- s7: The first settlements on the site of Jakarta were established as late as the 4th century AD.

s6 summarizes s5. How should the vectors relate mathematically?

s6 and s7 are syntactically similar, but contradictory. What should be their vectors?

What should be encoded? (2) Entailment, Relatedness, and Inference

- s7: Tom was accidentally shot by his teammate in the Army
- s8: Tom dies
- s9: Tom is bleeding

s8 is a possible consequence of s7 by inference. How should the vectors relate?

s9 is an even more likely consequence of s7 by inference. How do the three vectors relate?

The cynic

Does it even make sense to represent one sentence as one vector?

One possible work-around: attention

- Representation is $\sum_i \alpha_i v_i$ where $0 \leq \alpha_i \leq 1, v_i \in \mathbb{R}^d$
- Integrate representation in an end-to-end system, and α_i is adaptively re-computed based on some state

Attention in machine translation [Bahdanau et al., 2014]

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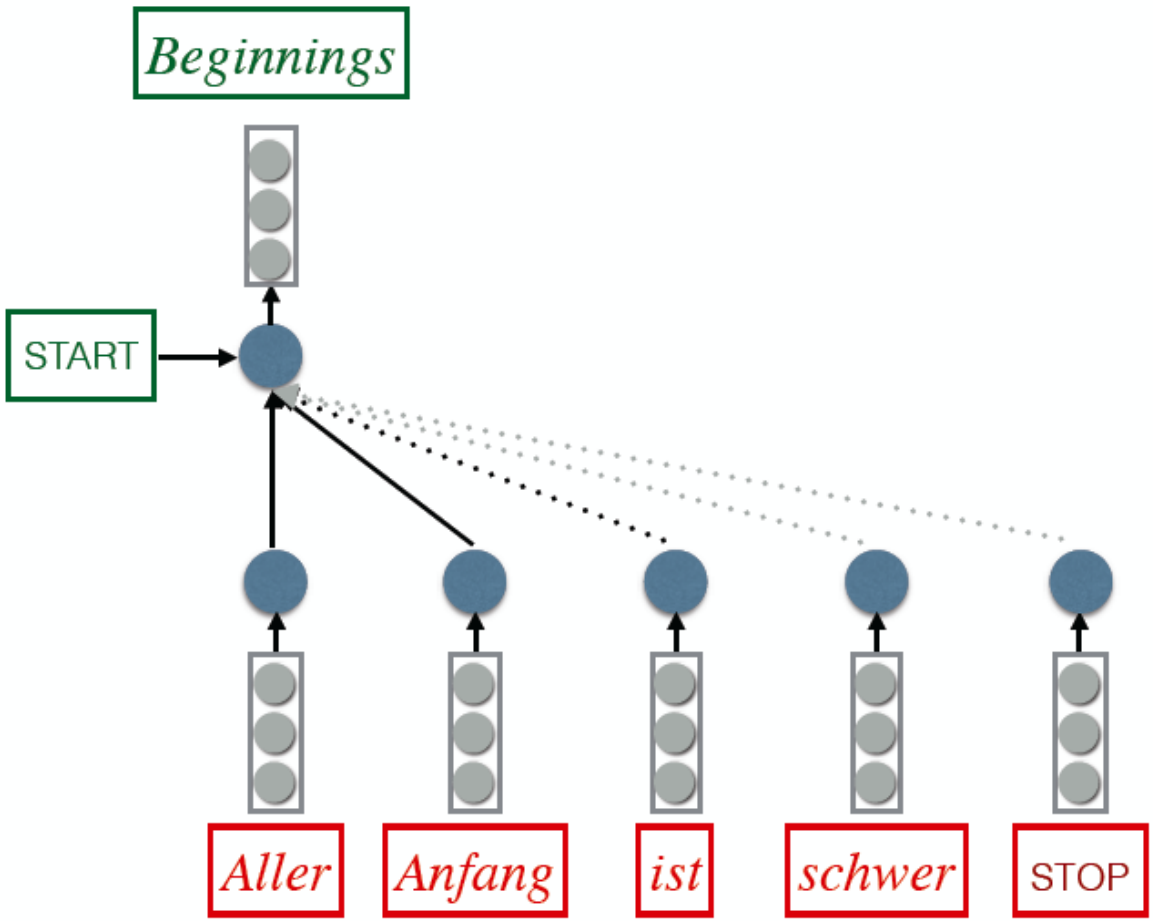

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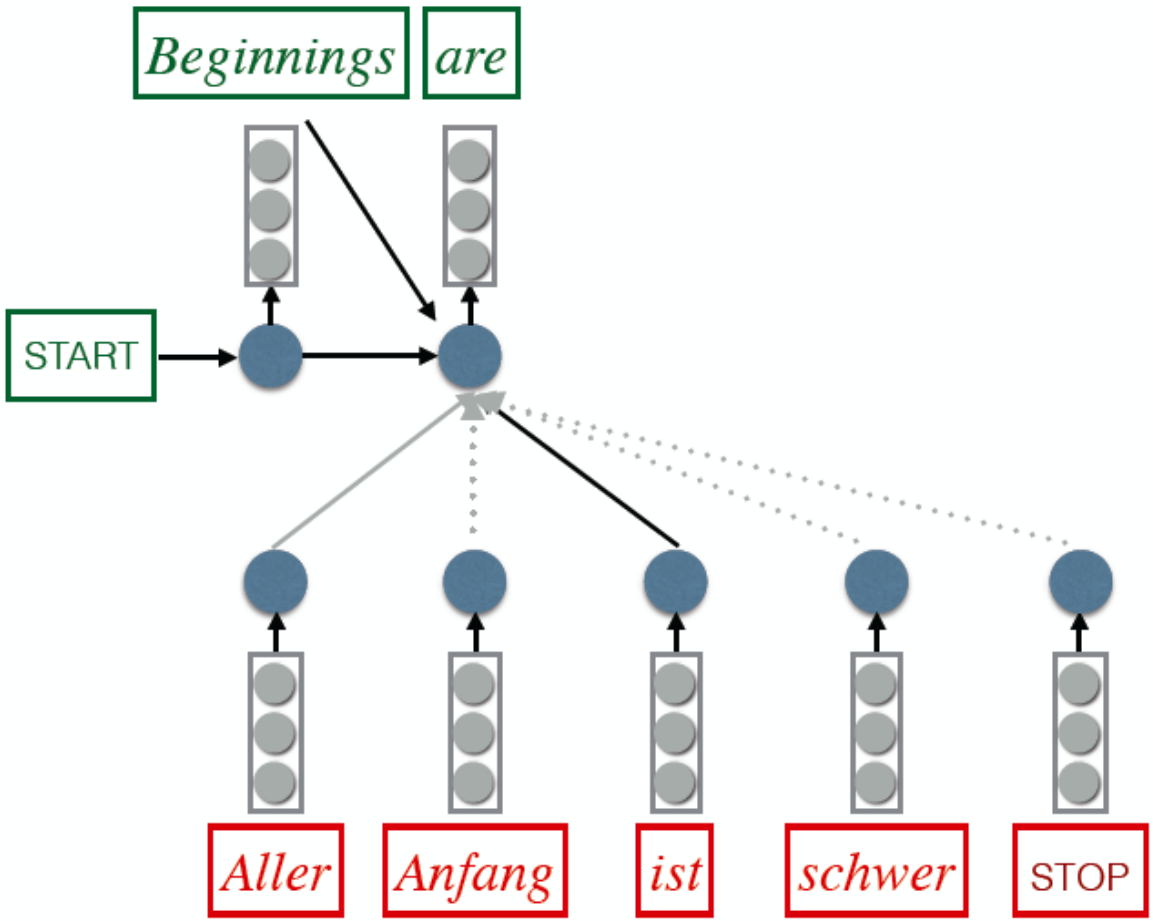

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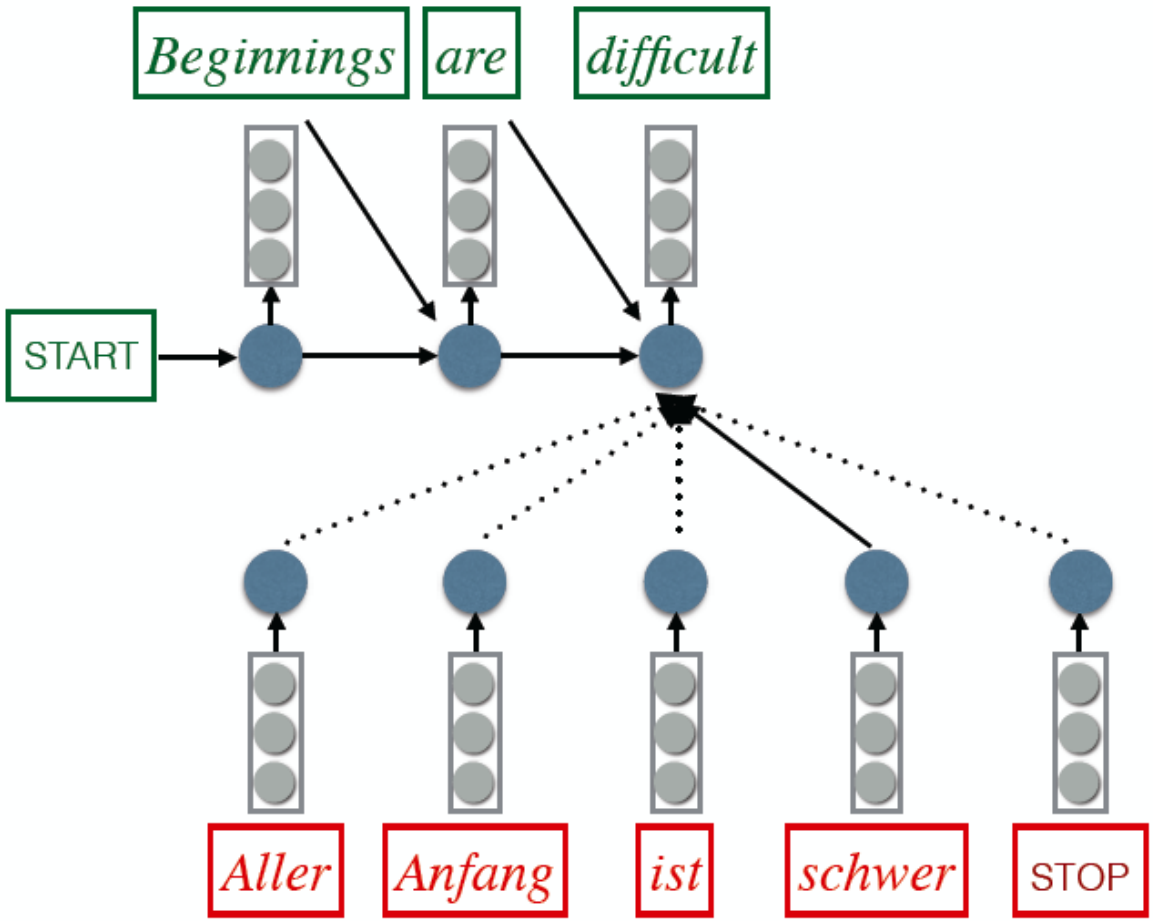

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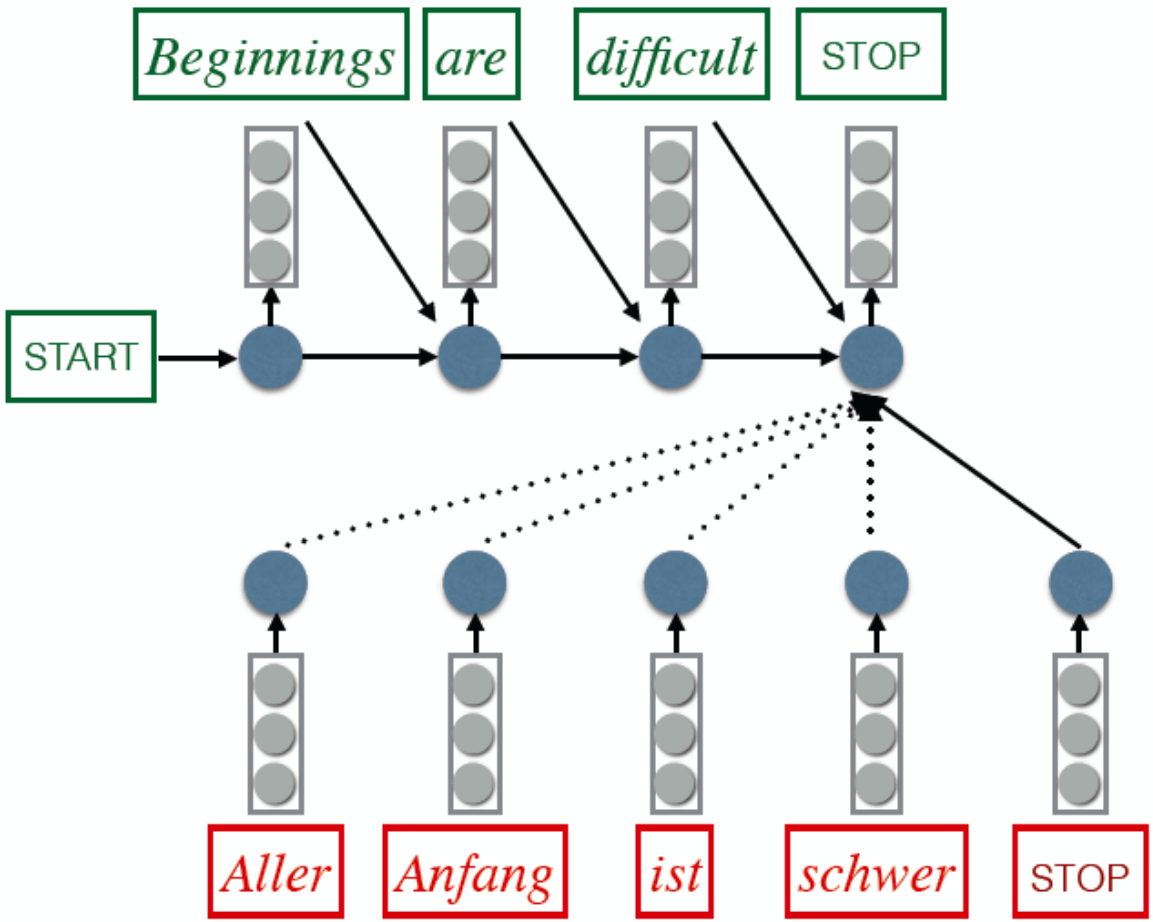

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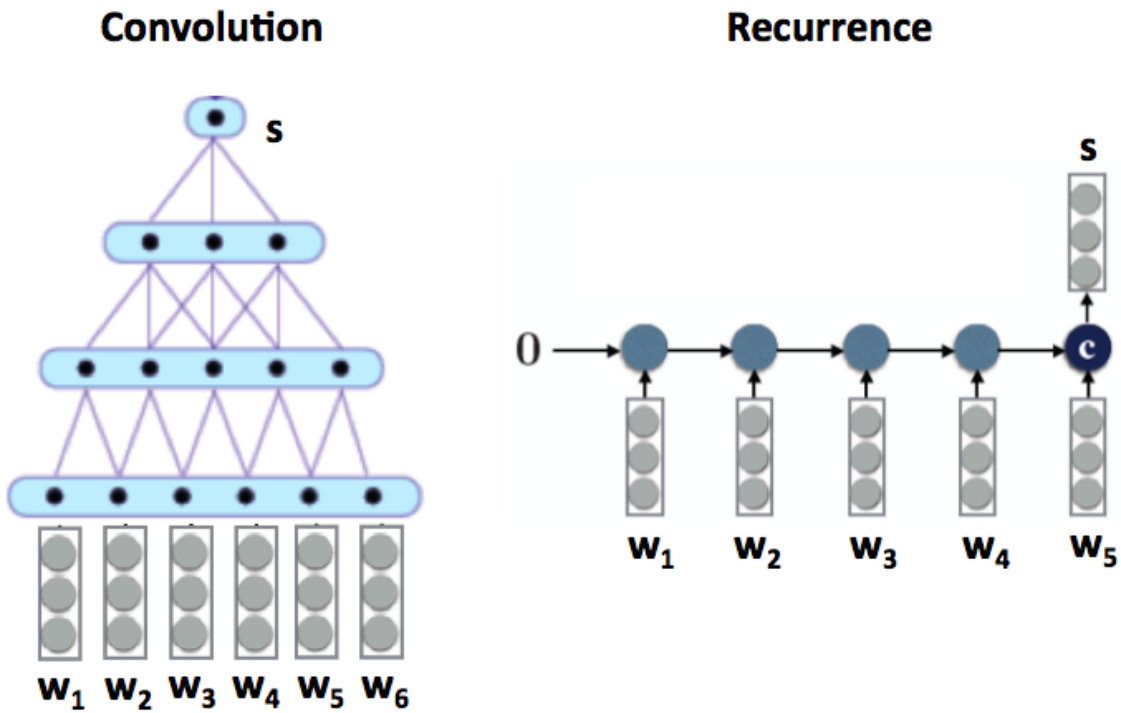
Approach 1: Bag of words

- Sentence vector = sum of word vectors
- $\mathbf{s} = w(Bob) + w(gave) + w(Jane) + w(a) + w(book) + w(on) + w(her) + w(birthday)$
- Variants: product, weighted sum, bag of bigrams, ...

Approach 2: Convolution and Recurrent units

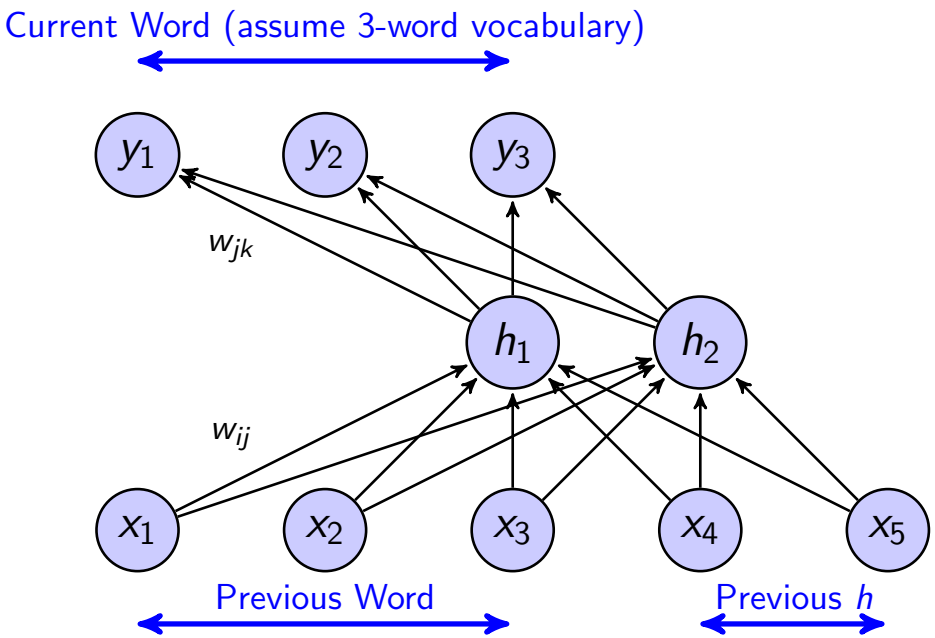
- Encode variable-length sequence into fix-length vector



- Examples in sentence translation
  [Kalchbrenner and Blunsom, 2013, Sutskever et al., 2014]

Recurrent Neural Net Language Models

Model $p(\textit{current\_word}|\textit{previous\_words})$ with a recurrent hidden layer [Mikolov et al., 2010]

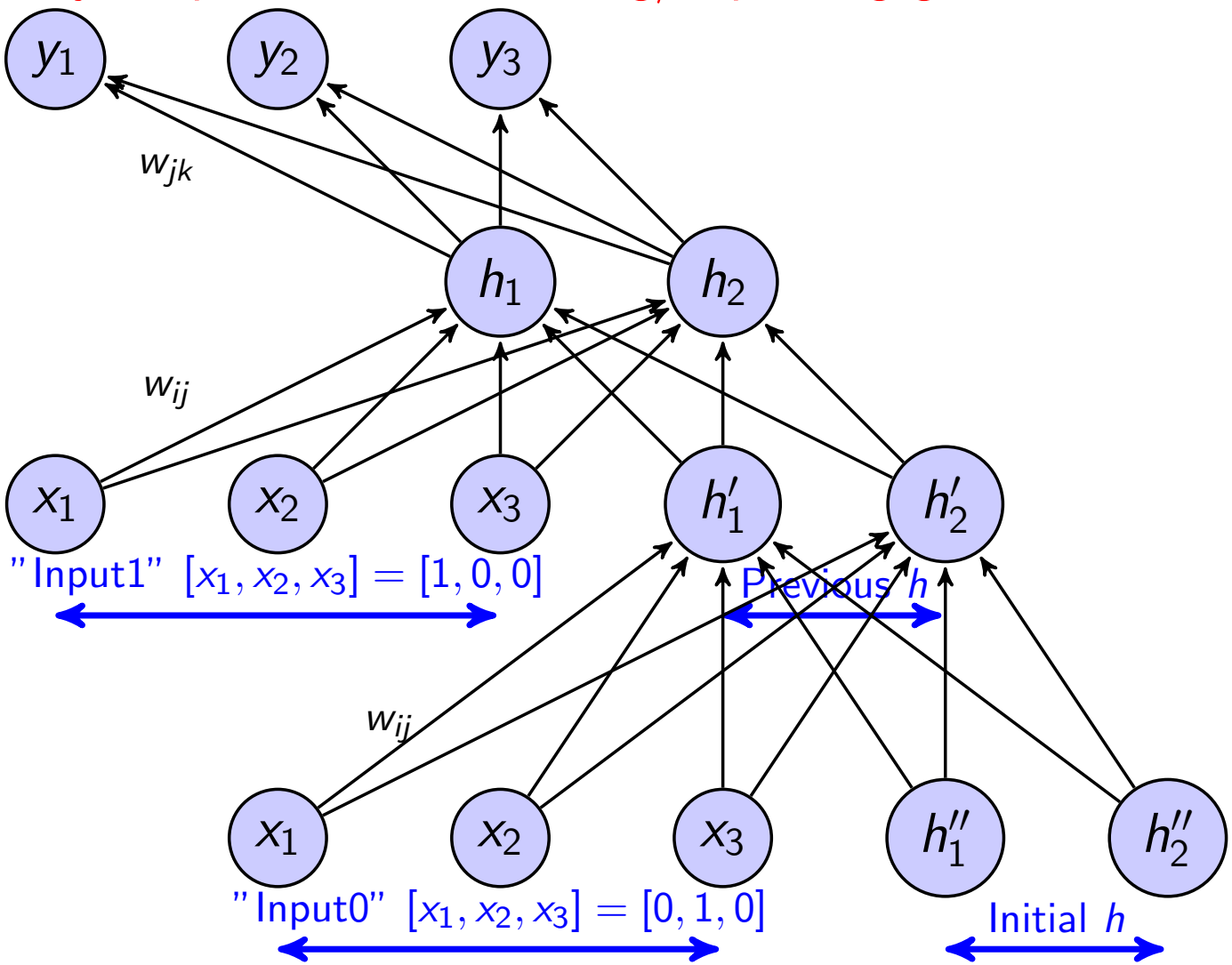


- Probability of word: $y_k = \frac{\exp(W_{jk}^T h)}{\sum_{k'} \exp(W_{jk'}^T h)}$
- $[x_4, x_5]$ is a copy of $[h_1, h_2]$ from the previous time-step
- $h_j = \sigma(W_{ij}^T x_i)$ is hidden state of partial sentence
- Arbitrarily-long history is (theoretically) kept through recurrence

Training: Backpropagation through Time

Unroll the hidden states for a few time-steps, then backprop.

Very deep network: vanishing/exploding gradients!



A popular recurrent unit: LSTM

Long Short-term Memory (LSTM):

- Idea: Shouldn't need to back-prop to beginning of history. Just keep a memory of important bits.

*Nice explanation of LSTM and variants here:
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Long Short-term Memory (LSTM):

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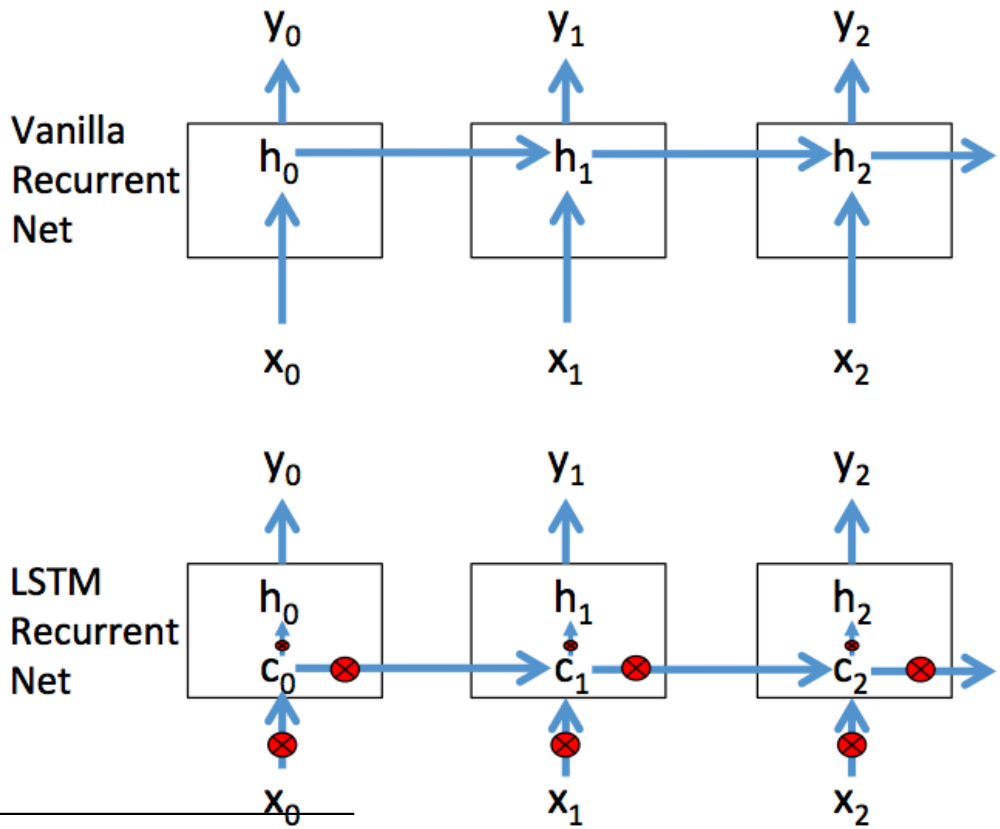
- Introduces memory cell (c_t), with input/output/forget gates to keep track of what to remember and when



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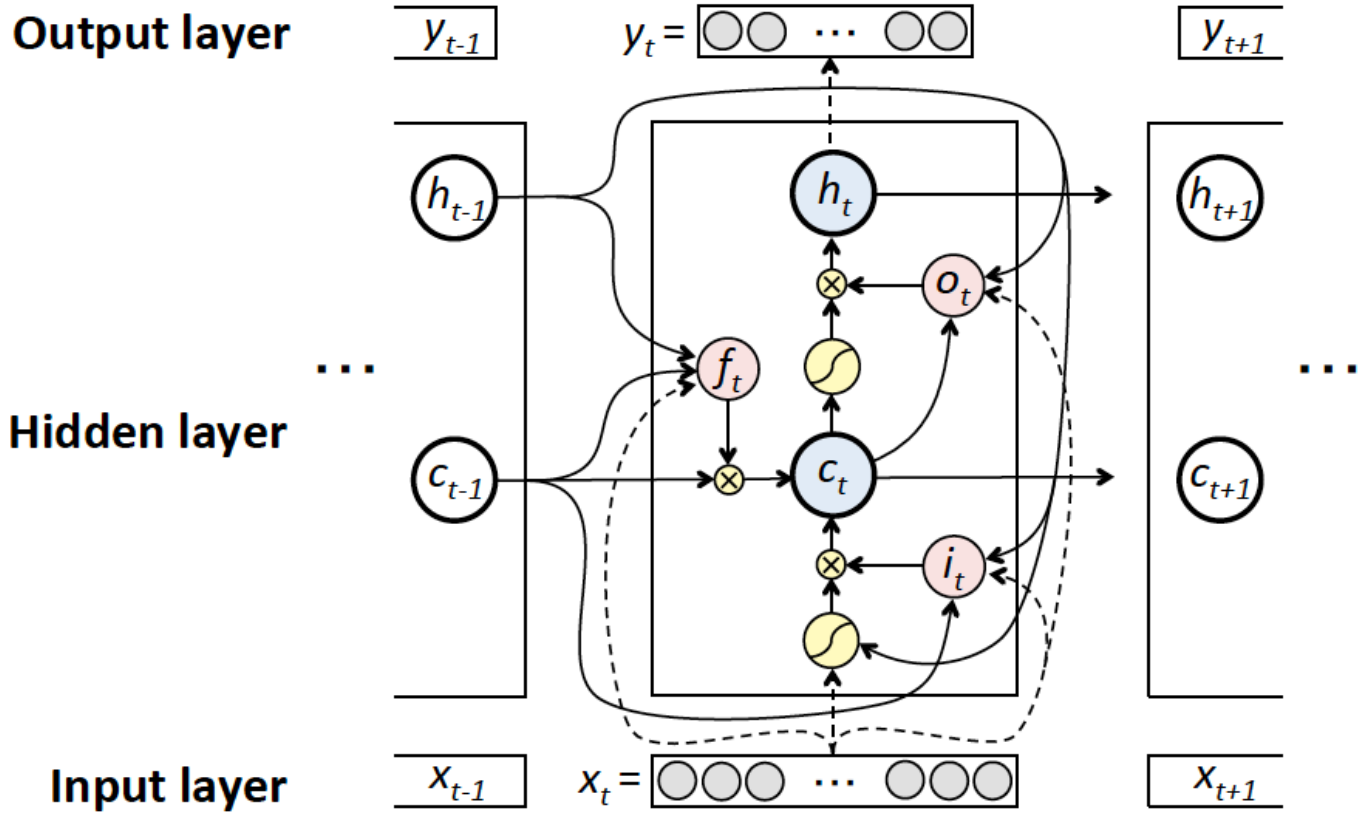
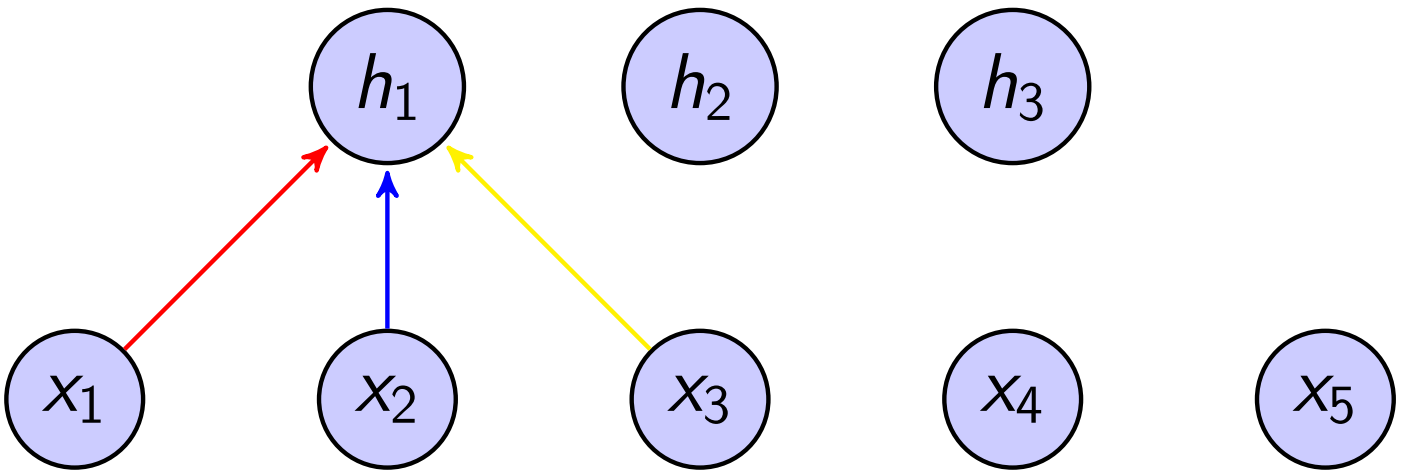
LSTM in detail [Gers et al., 2002]



$$
\begin{aligned}
i_t &= \sigma(W_{xi}x_t + W_{ci}c_{t-1} + W_{hi}h_{t-1}) \\
f_t &= \sigma(W_{xf}x_t + W_{cf}c_{t-1} + W_{hf}h_{t-1}) \\
c_t &= f_t c_{t-1} + i_t \ tanh(W_{xc}x_t + W_{hc}h_{t-1}) \\
o_t &= \sigma(W_{xo}x_t + W_{co}c_t + W_{ho}h_{t-1}) \\
h_t &= o_t \tanh(c_t), \quad y_t = softmax(W_{hy}h_t)
\end{aligned}
$$

Figure courtesy of Adhi Kuncoro & Yuichiro Sawai

Convolution



Sliding window of shared weights: $h_j = \sum_{\tau=0}^{2} w_\tau x_{j+\tau}$

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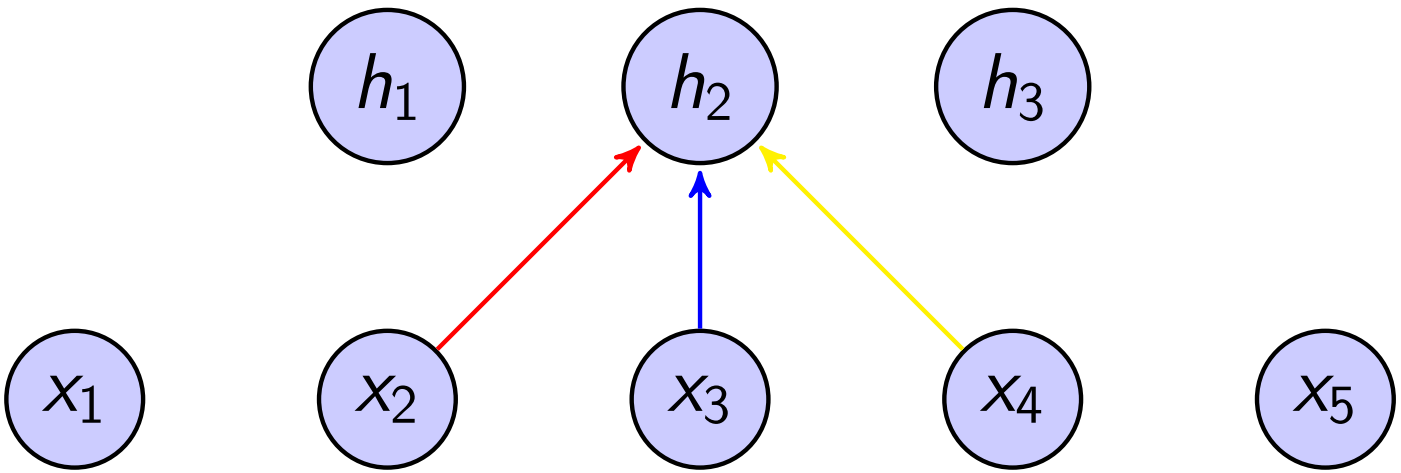

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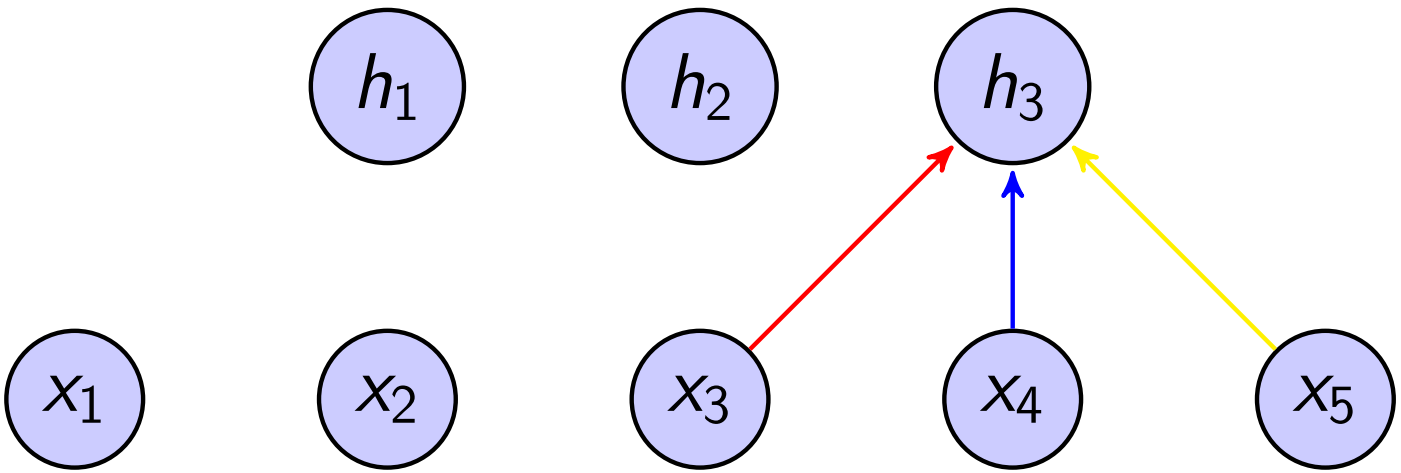

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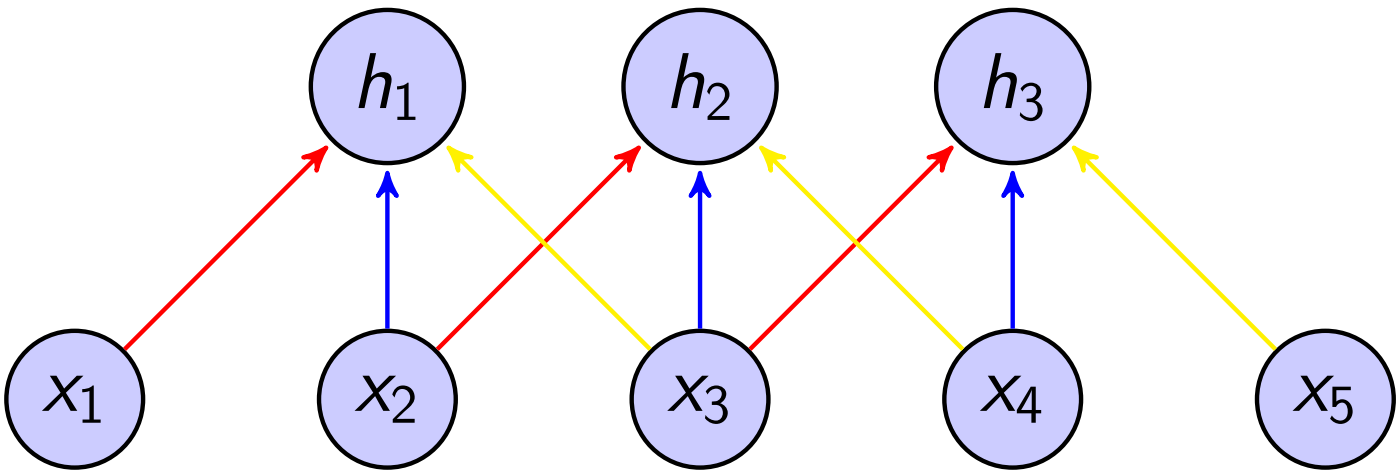
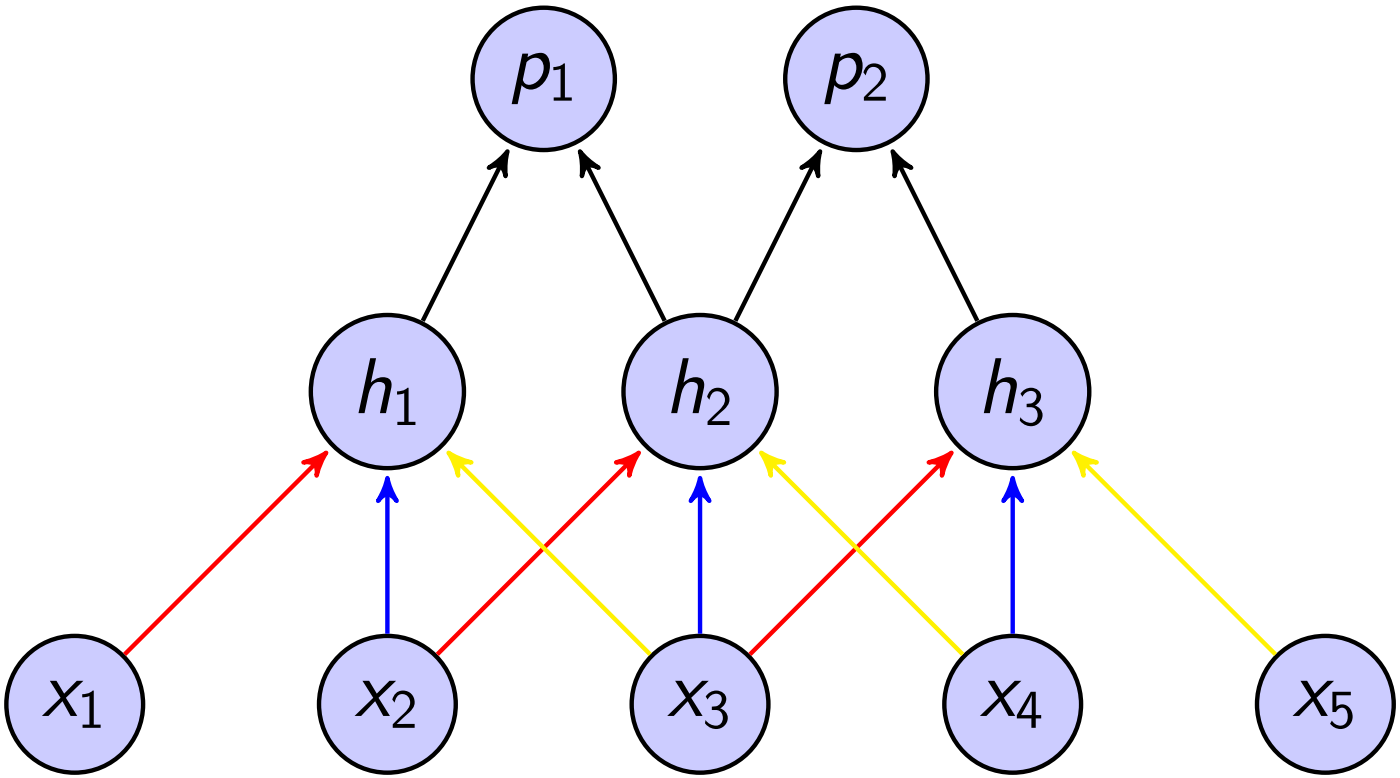


Sliding window of shared weights: $h_j = \sum_{\tau=0}^{2} w_\tau x_{j+\tau}$

Pooling



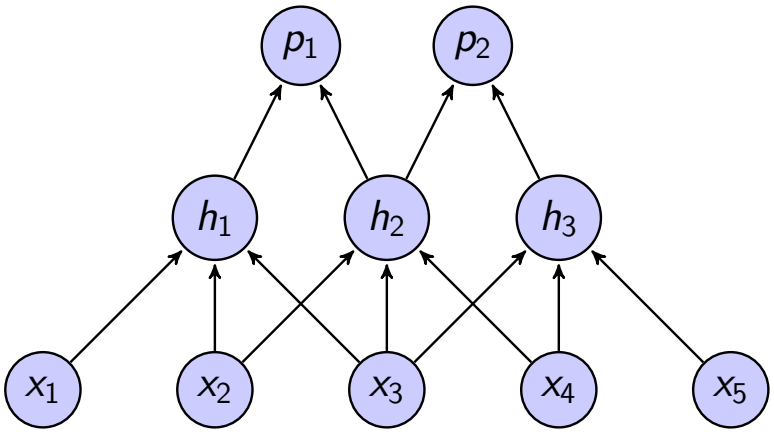
Max-Pooling

nodes: $p_1 = max(h_1, h_2)$, $p_2 = max(h_2, h_3)$

Advantages of Convolution + Pooling:

1. Fewer weights
2. Shift invariance

Convolutional Nets in vision [LeCun et al., 1998]



Receptive Field (RF): each h_j only connects to small input region via convolution.

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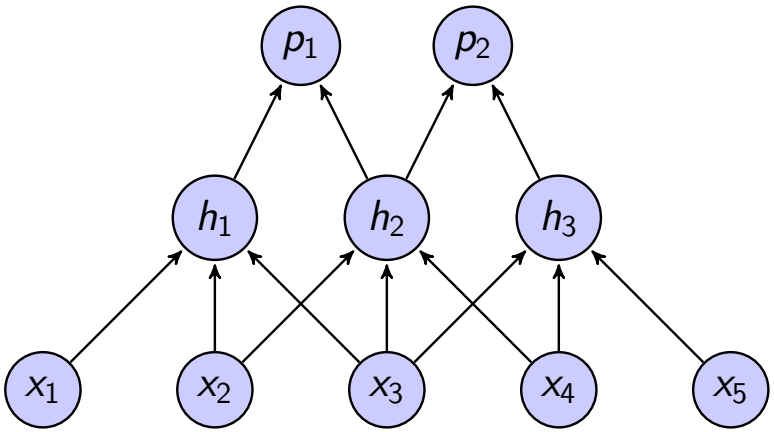

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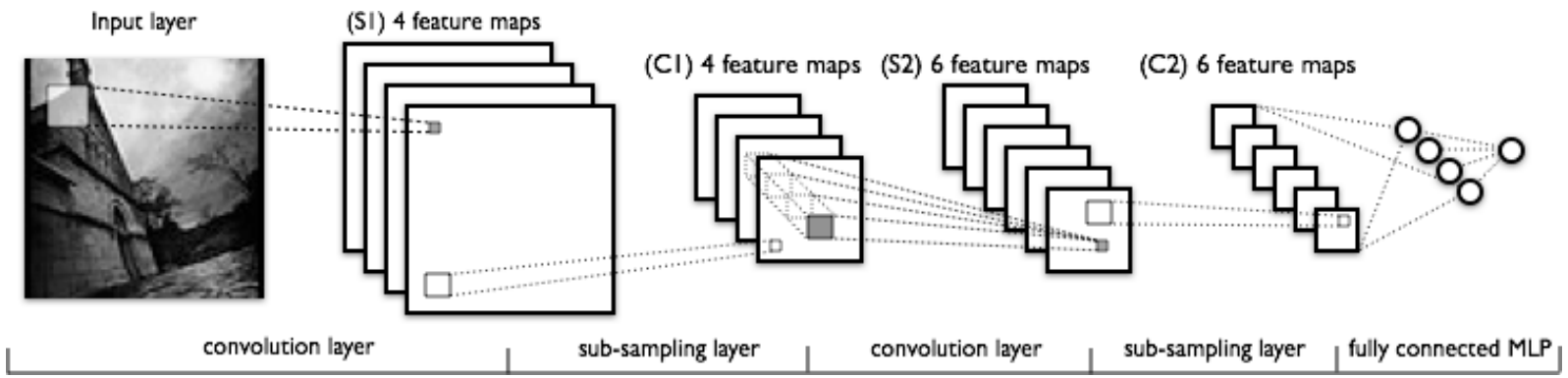

(Figure from `http://deeplearning.net/tutorial/lenet.html`)

Summary and Thoughts

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   - Feed-forward neural language models and word2vec

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   - What is the verdict on end-to-end learning vs. pre-trained word/sentence embeddings?

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