Neural Nets, Deep-Learning and applications (NLP)

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Outline

1. Advanced Architectures with NLP applications
   - n-gram language model
   - Sequence representation
   - Character based model for sequence tagging

2. Conclusion

Outline

A case study : language model

The n-gram model

Applications

Automatic Speech Recognition, Machine Translation, OCR, ...

The goal

Estimate the (non-zero) probability of a word sequence for a given vocabulary

n-gram assumption

$$P(w_1^L) = \prod_{i=1}^{L} P(w_i | w_{i-n+1}^{i-1}), \quad \forall i, w_i \in \mathcal{V}$$

Discrete n-gram model (conventional)

A word given its context

$n = 4$:

$\underbrace{\text{time goes by}}_{\text{context}} \quad \rightarrow \quad ?$

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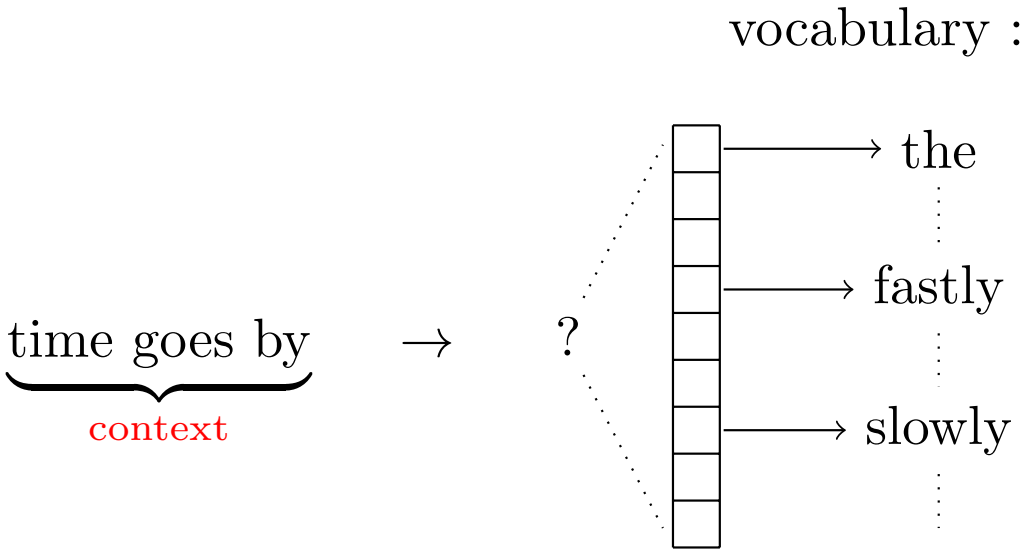

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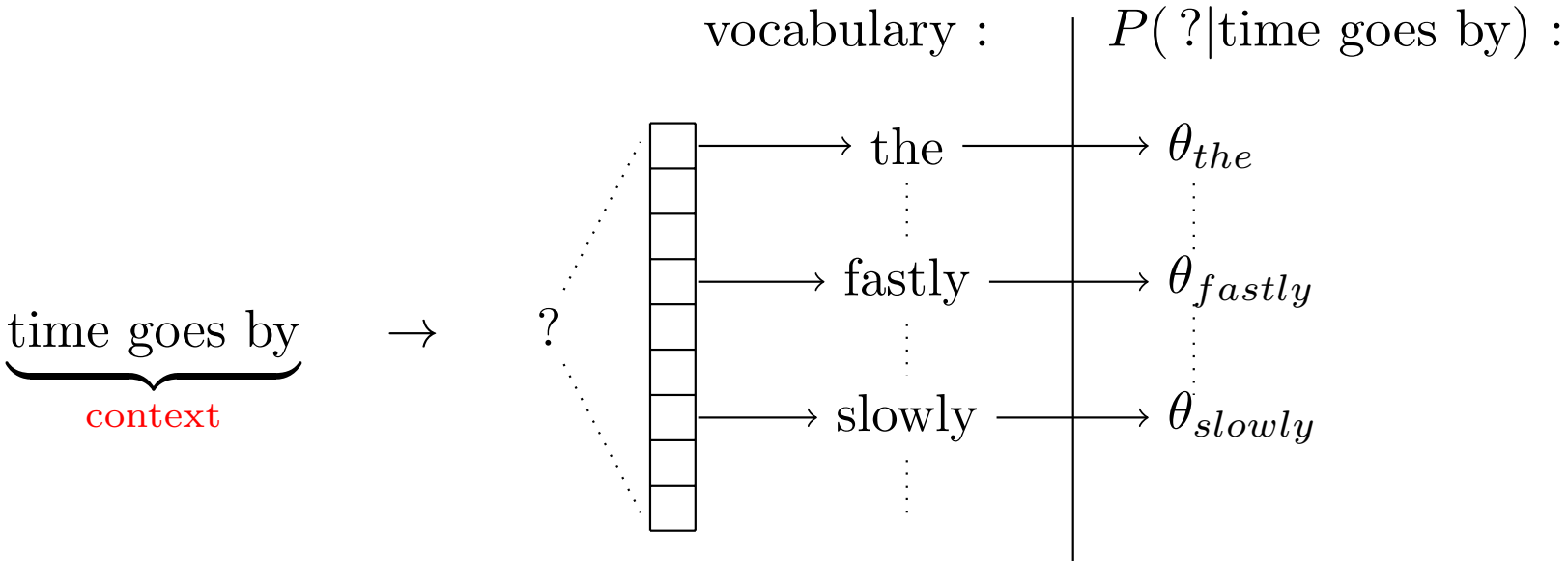

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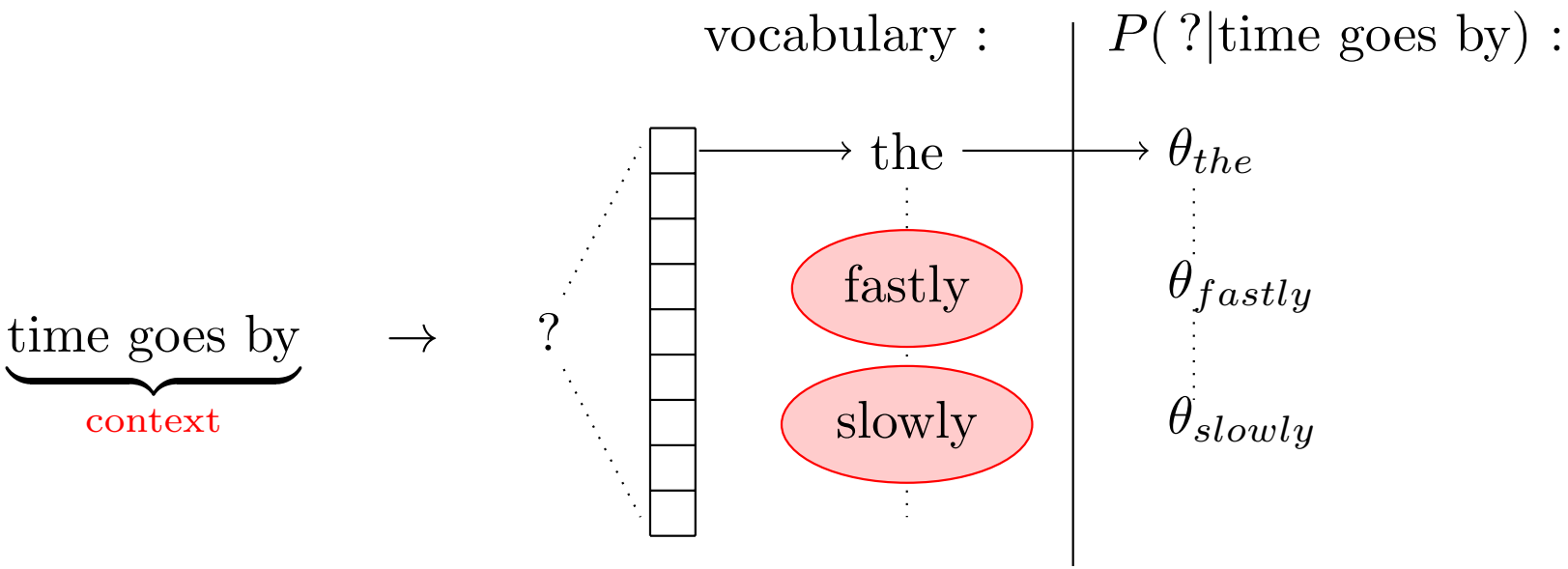

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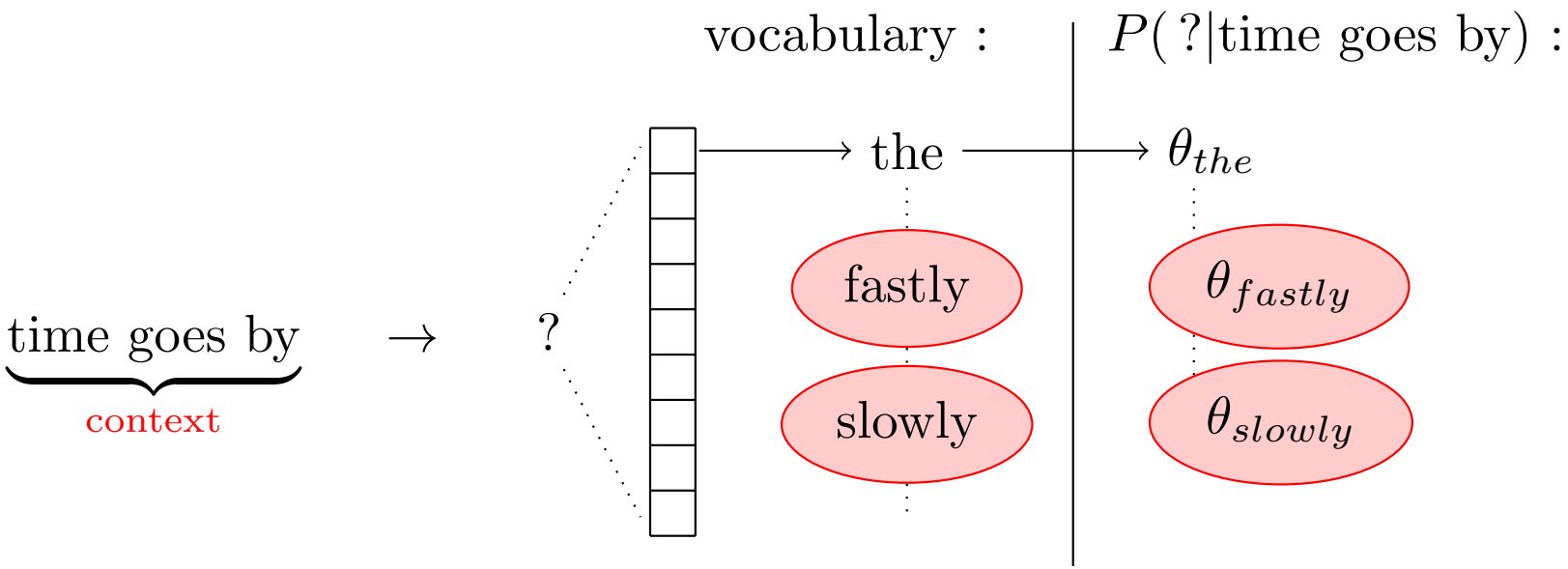

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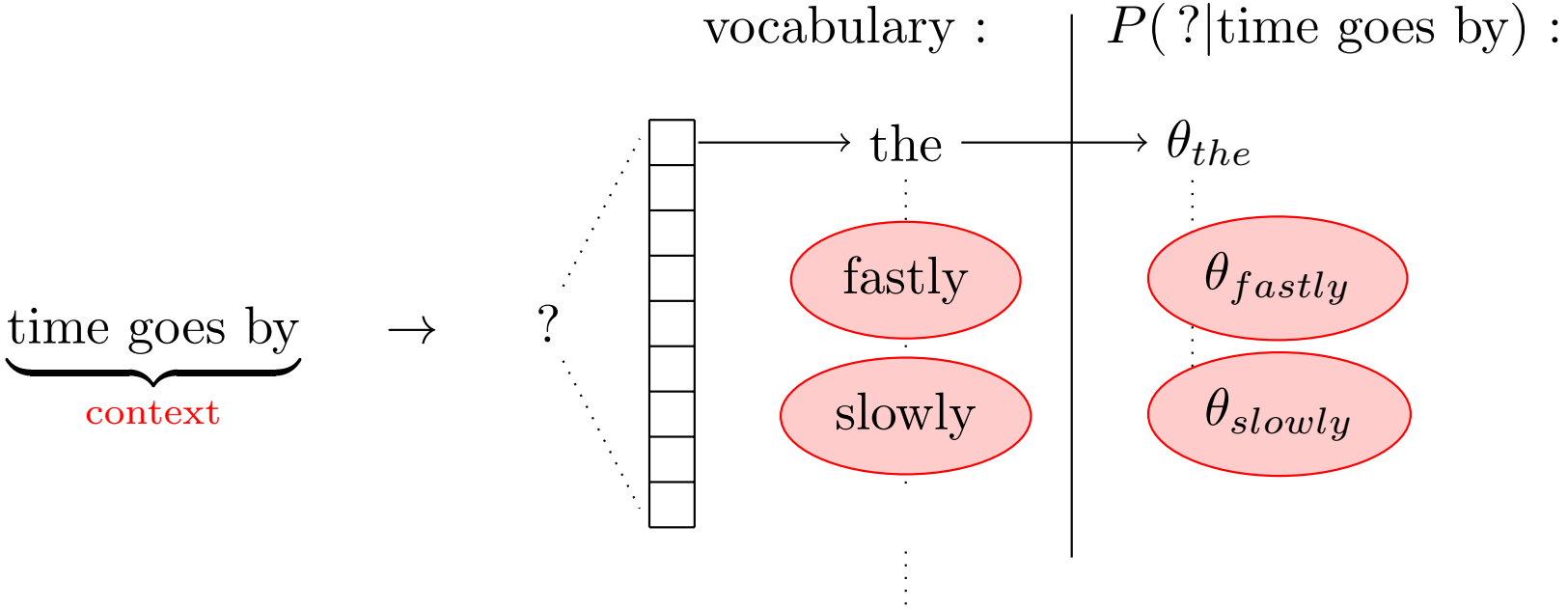


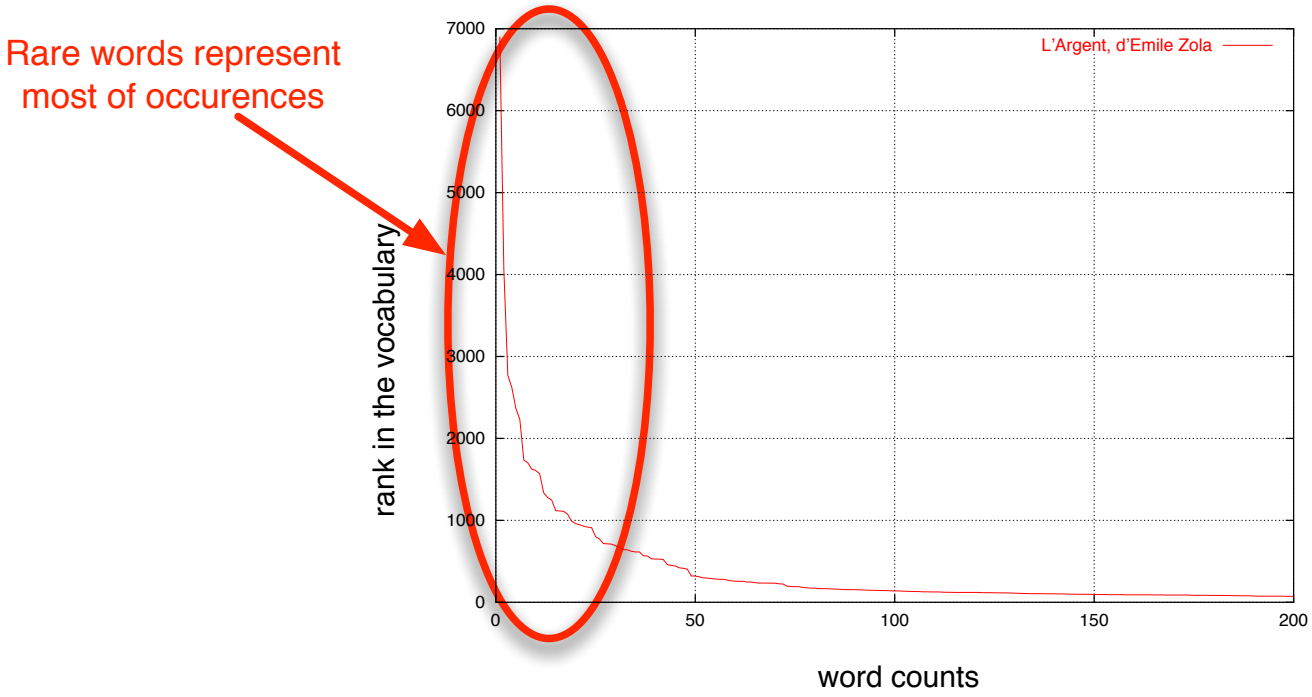
- For each context, a multinomial distribution
- A word in its context = one parameter to learn
- No parameter tying within words

$\Rightarrow$ No knowledge sharing

Practical issues

Data sparsity

- The Zipf law



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Restricted context

- The number of parameters grows drastically with n

$\Rightarrow$ The curse of dimensionality.

$\Rightarrow$ In practice $n \leq 5$

Illustration

With 6 billions of running words (English texts) and a vocabulary of 500 000 words :

- $500\ 000^4 \approx 6 \times 10^{22}$ possible 4-grams,
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For a better generalization :

- Learn shared representations for words

$\Rightarrow$ Continuous space language models
i.e neural network language models

Estimate n-gram probabilities in a continuous space

Introduced in (Bengio and Ducharme2001; Bengio et al.2003) and applied to speech recognition and machine translation in (Schwenk and Gauvain2002).

In a nutshell

1. associate each word with a continuous feature vector
2. express the probability function of a word sequence in terms of the feature vectors of these words
3. learn simultaneously the feature vectors and the parameters of that probability function.

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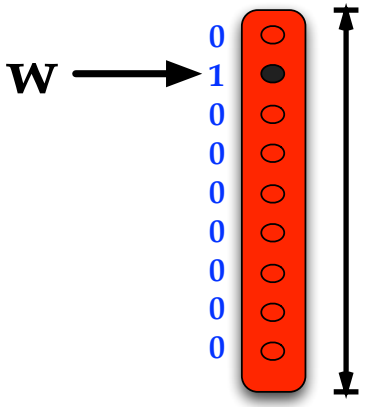
Why should it work ?

- "similar" words are expected to have a similar feature vectors
- the probability function is a smooth function of these feature values

$\Rightarrow$ a small change in the features will induce a small change in the probability

Project a word sequence in a continuous space

- The vocabulary is a neuron layer.

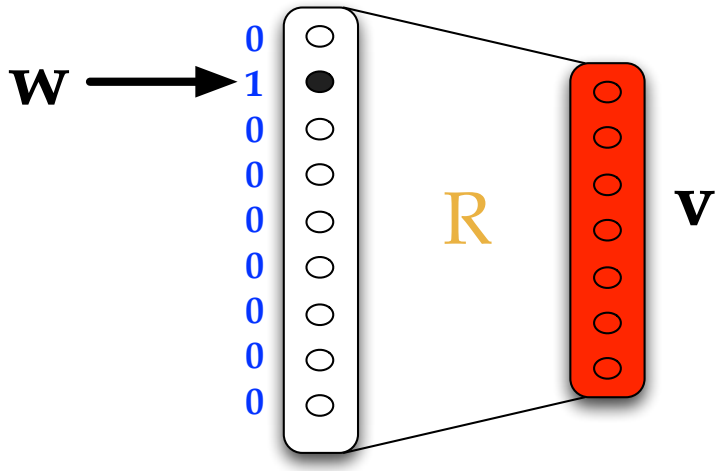


|V|: vocabulary size

- A neuron layer represents a vector of values,
- one neuron per value

Project a word sequence in a continuous space

- The vocabulary is a neuron layer.
- Project the word in the continuous space : add a second layer fully connected.



- The connection between two layers is a matrix operation
- The matrix $\mathbf{R}$ contains all the connection weights
- $\mathbf{v}$ is a continuous vector

Project a word sequence in a continuous space

- The vocabulary is a neuron layer.
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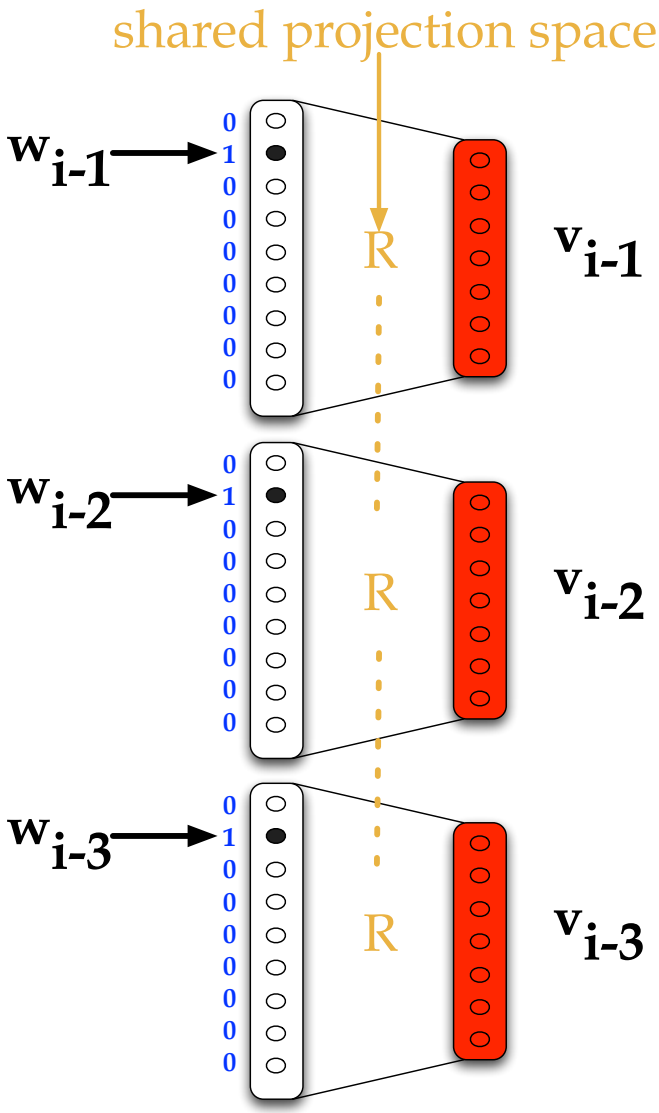
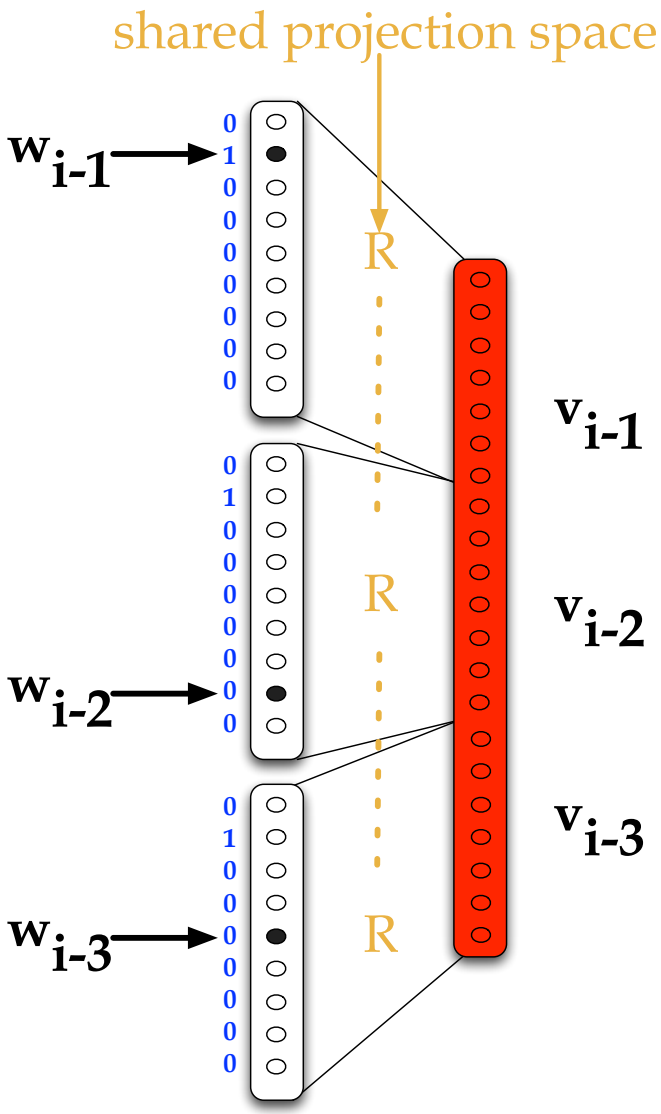
- For a 4-gram, the history is a sequence of 3 words.



Project a word sequence in a continuous space

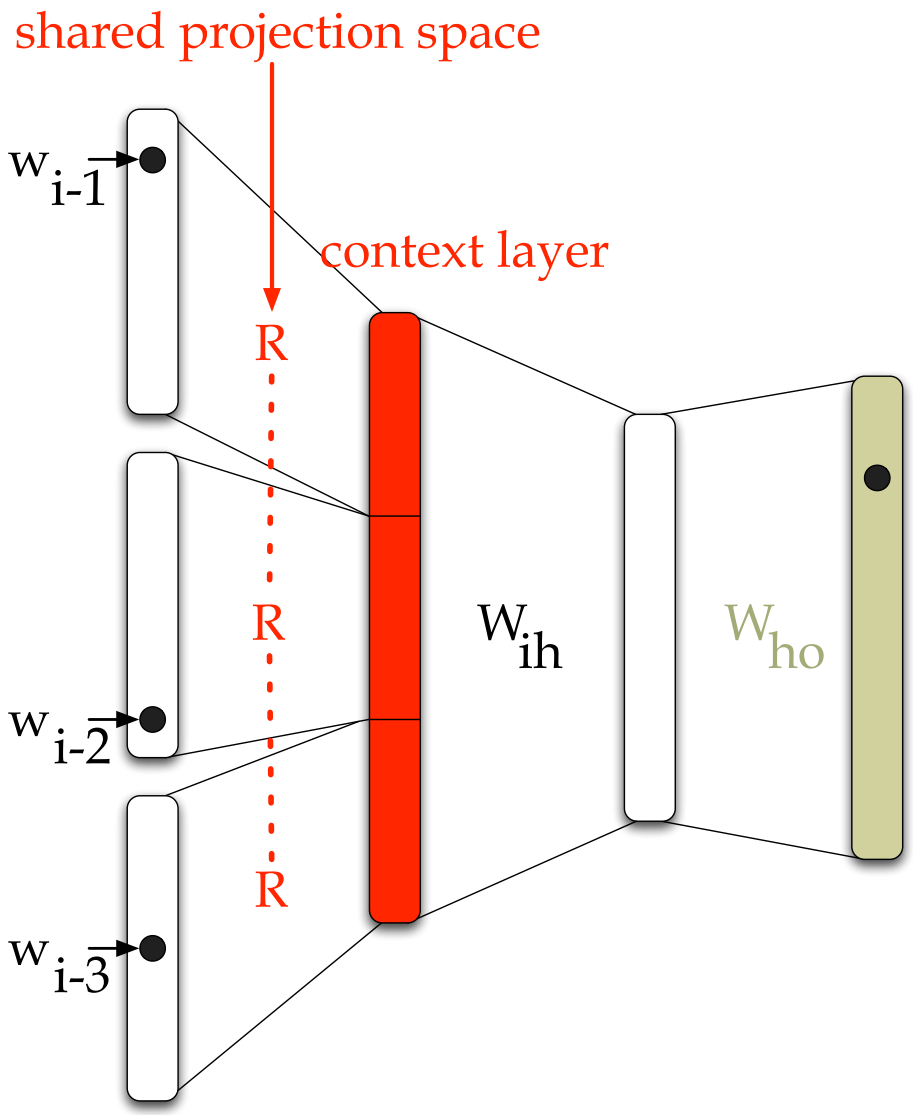
- The vocabulary is a neuron layer.
- Project the word in the continuous space : add a second layer fully connected.
- For a 4-gram, the history is a sequence of 3 words.
- Merge these three vectors to derive a single vector for the history



Estimate the n-gram probability

The program

- Given the history expressed as a feature vector.



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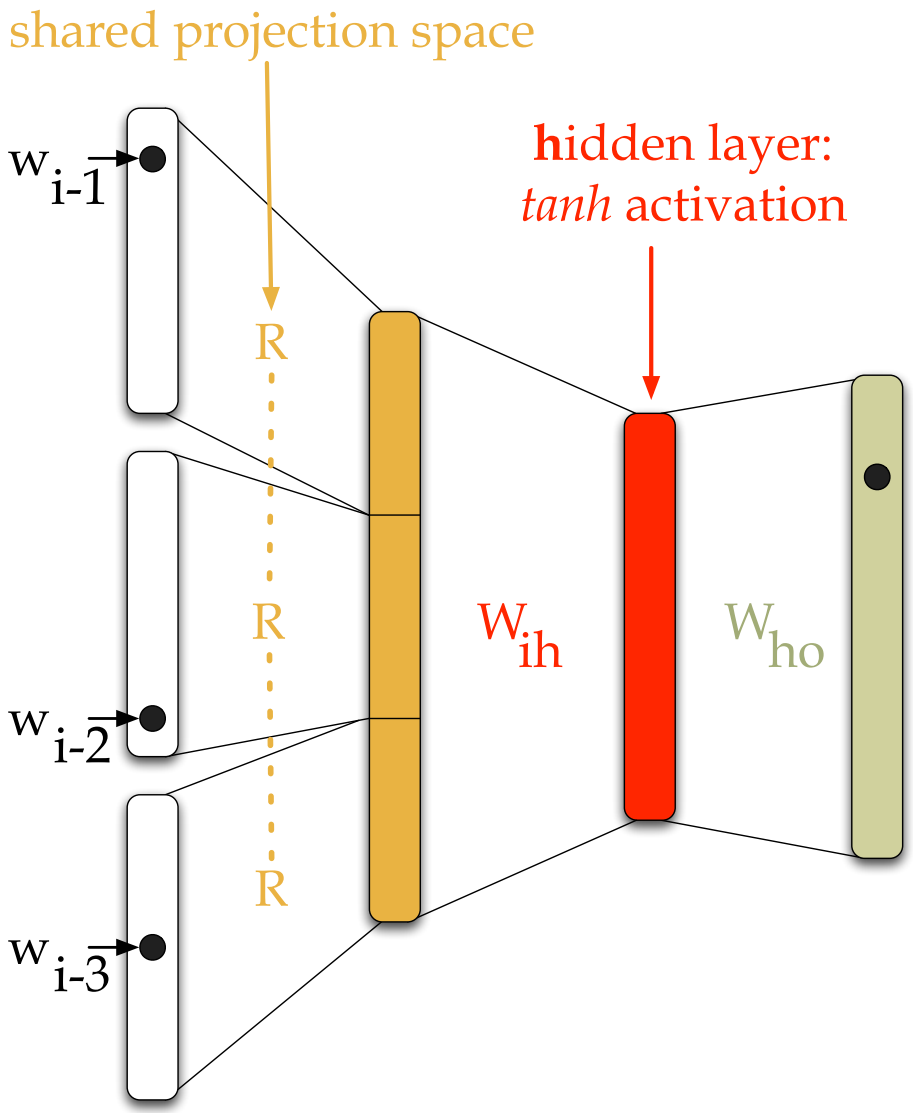
- Create a feature vector for the word to be predicted in the **prediction space**.



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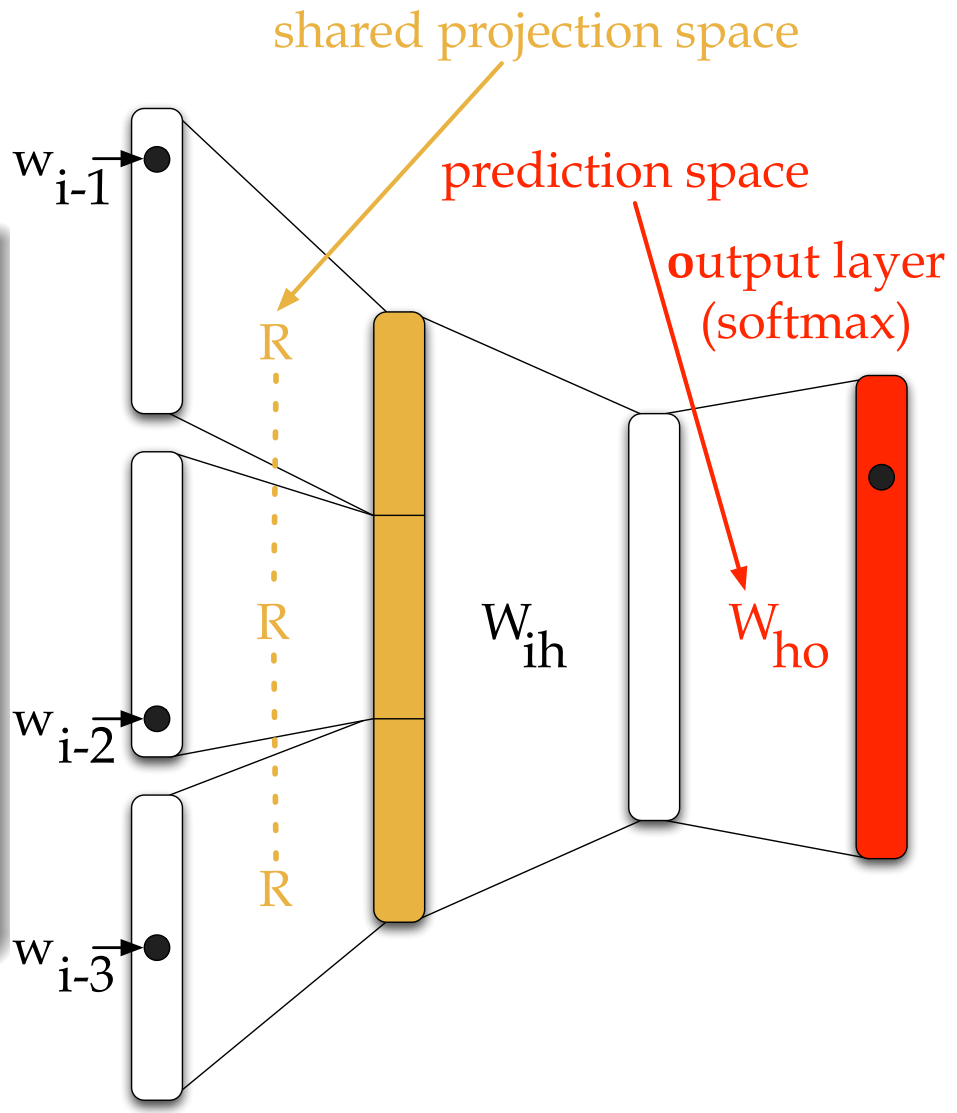

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- Create a feature vector for the word to be predicted in the **prediction space**.
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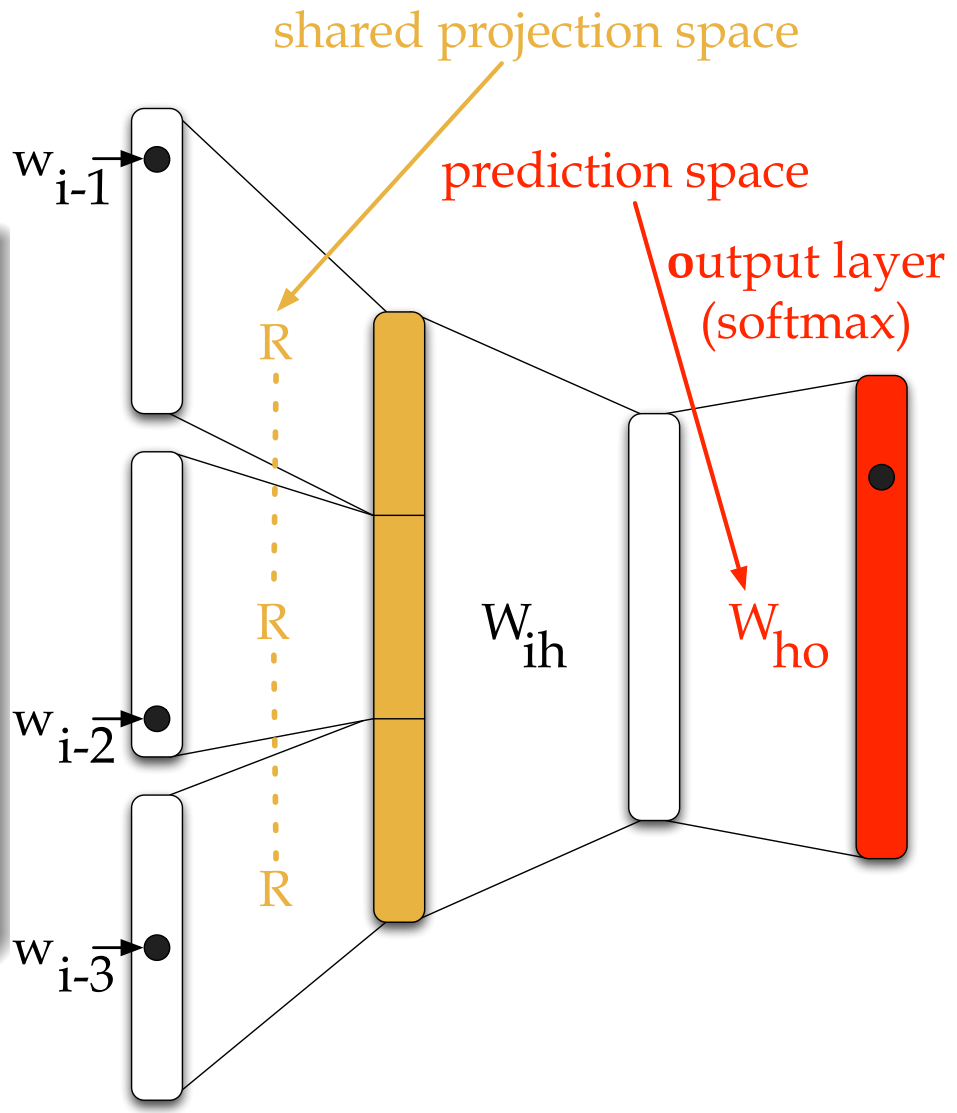
- All the parameters must be learnt $(\mathbf{R}, \mathbf{W_{ih}}, \mathbf{W_{ho}})$.



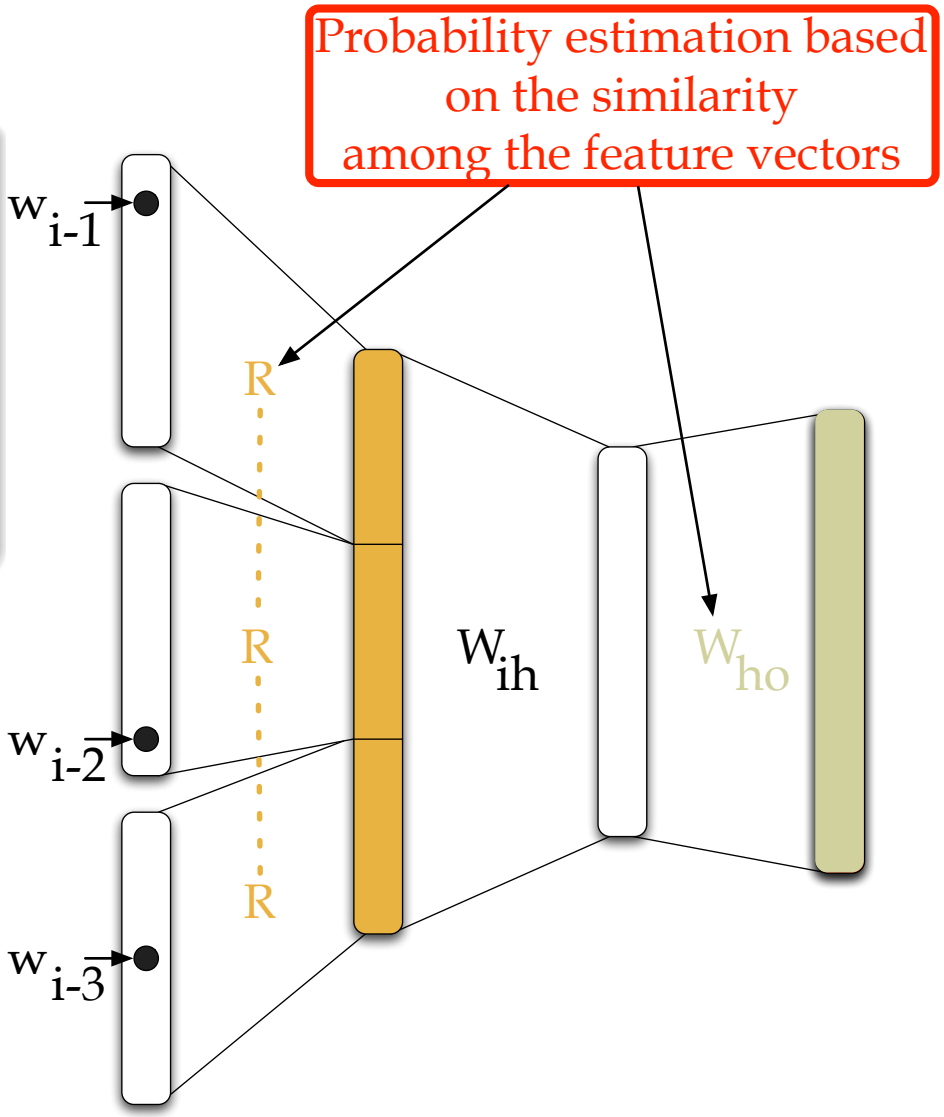
Early assessment

Key points

- The projection **in continuous spaces**

→ reduces the sparsity issues

- Learn simultaneously the projection and the prediction



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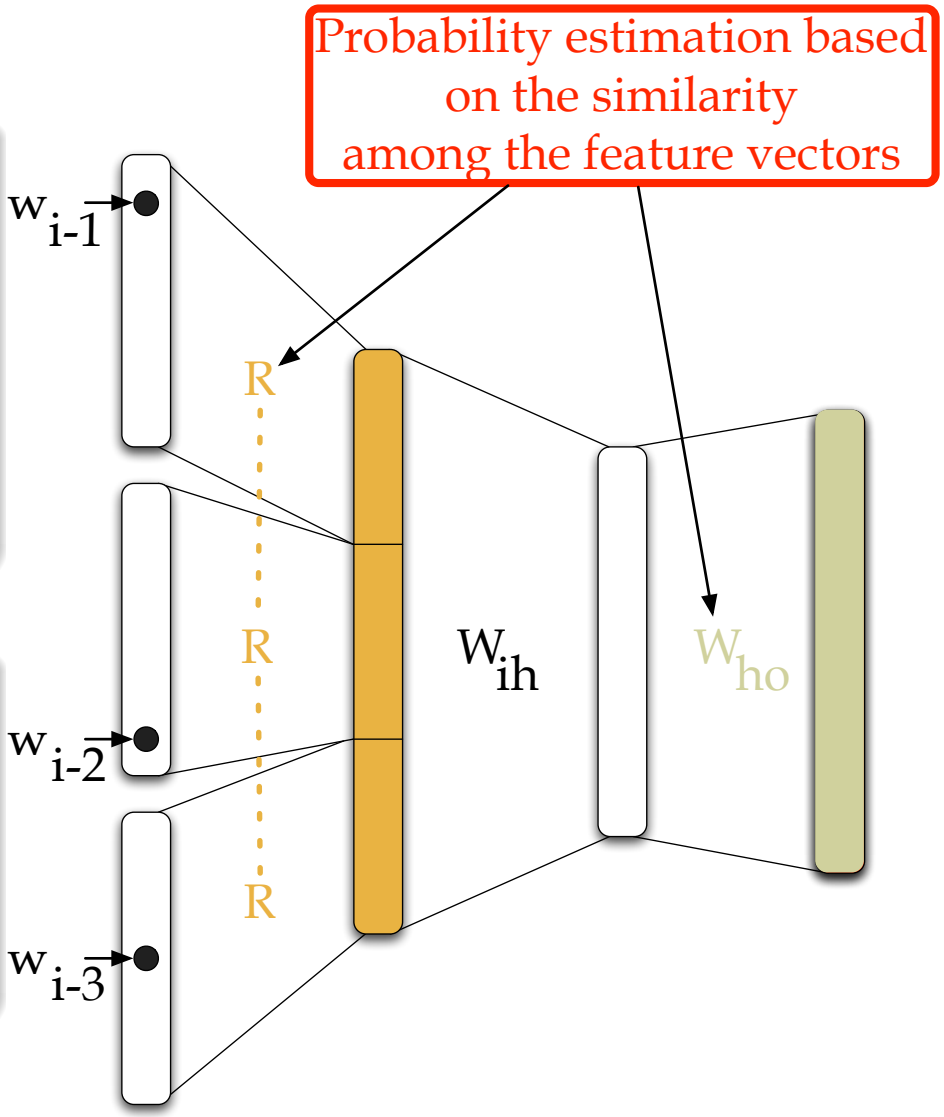
In practice

- Significant and systematic improvements
- In machine translation and speech recognition tasks



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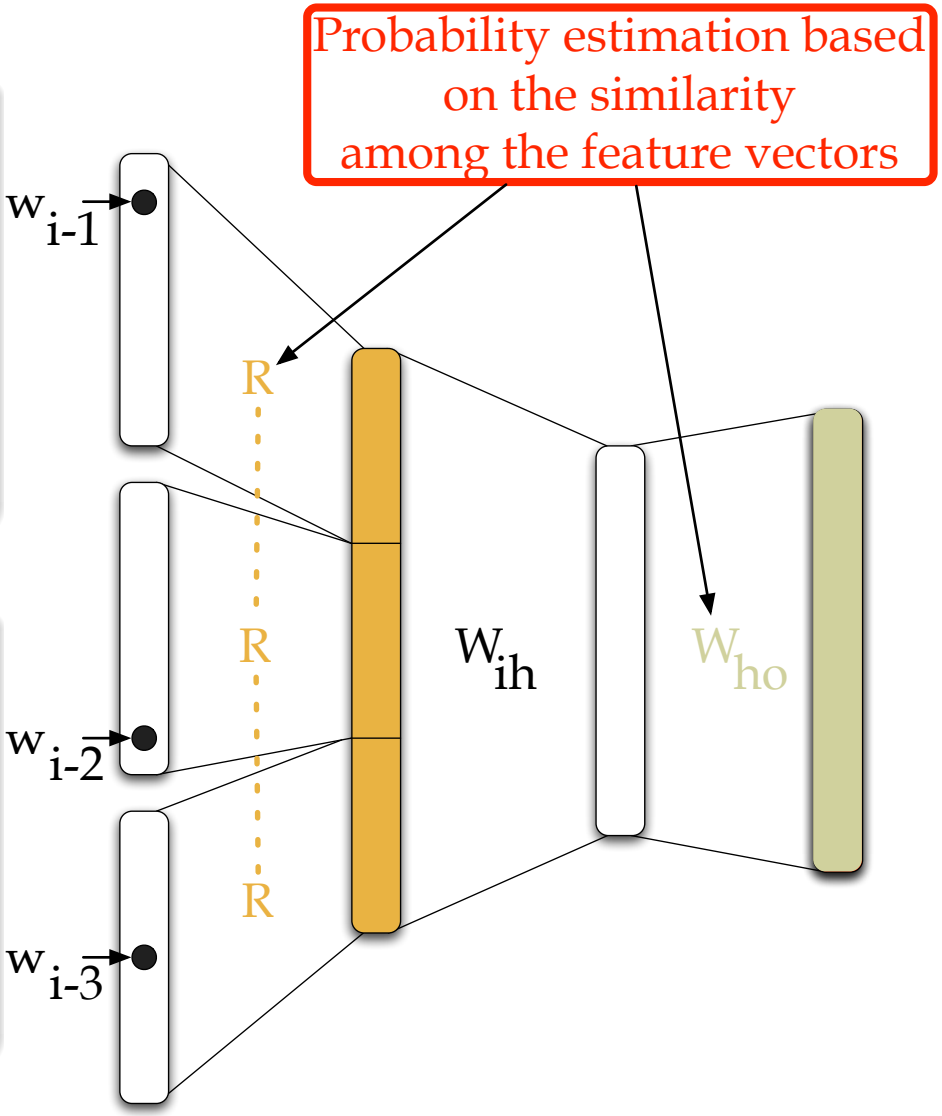
☺ **Everybody should use it !**



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☹ **Learning and inference time**

With a small training set

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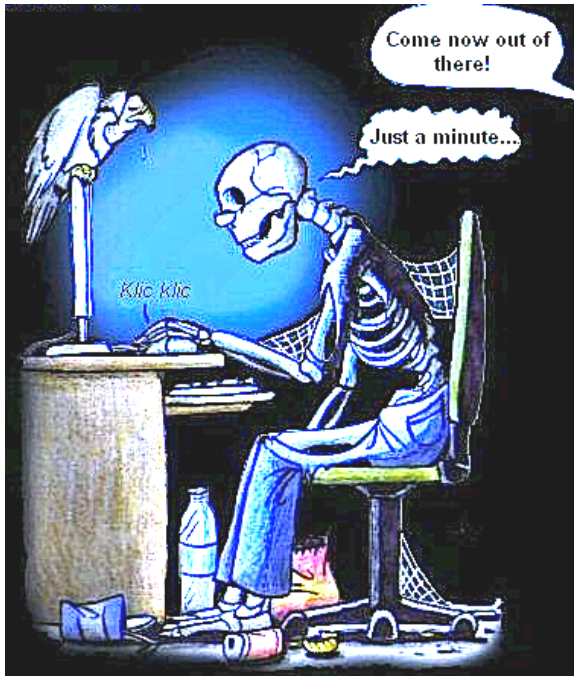
☹ **Learning and inference time**

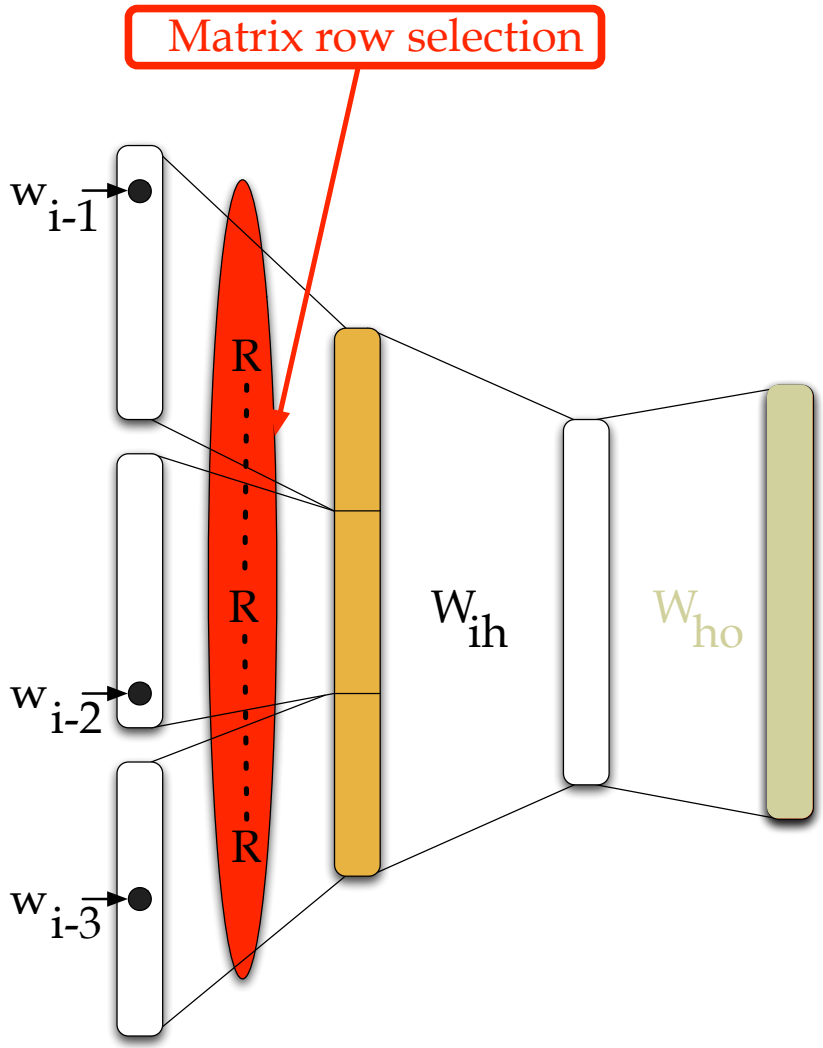
With a large training set



Why it is so long ? - Inference

Forward propagation of the history

- The projection : select a row in $\mathbf{R}$



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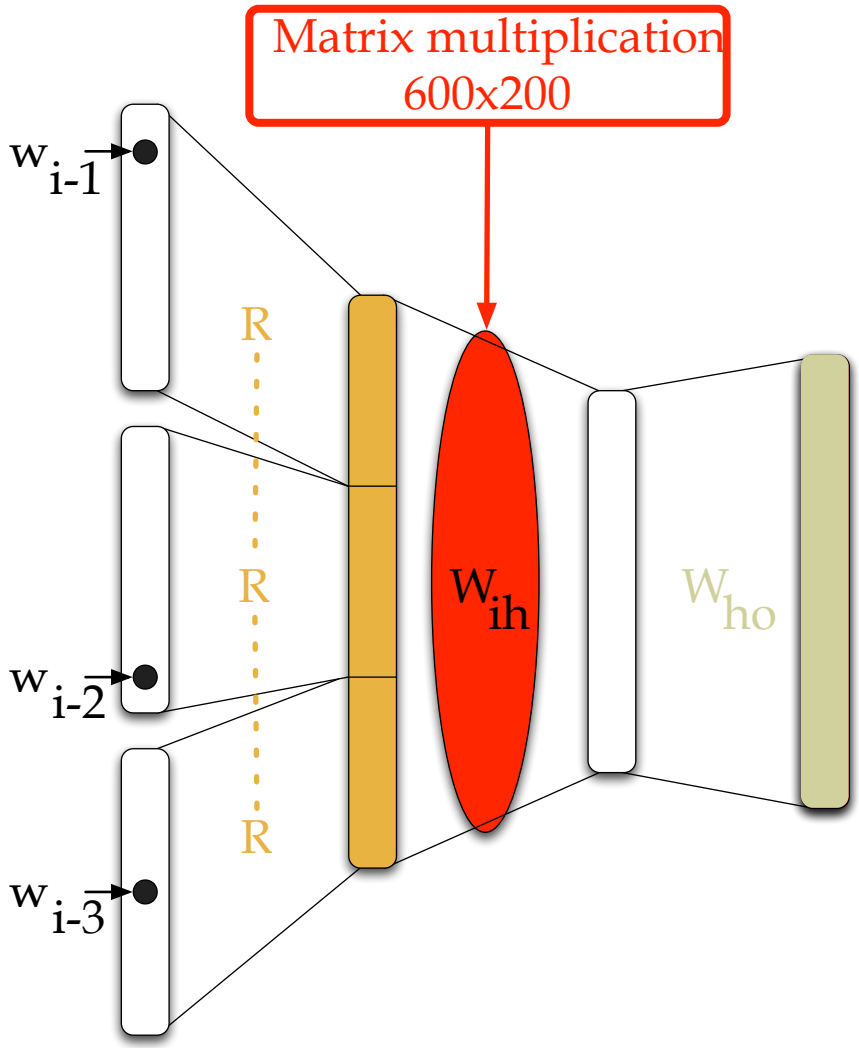

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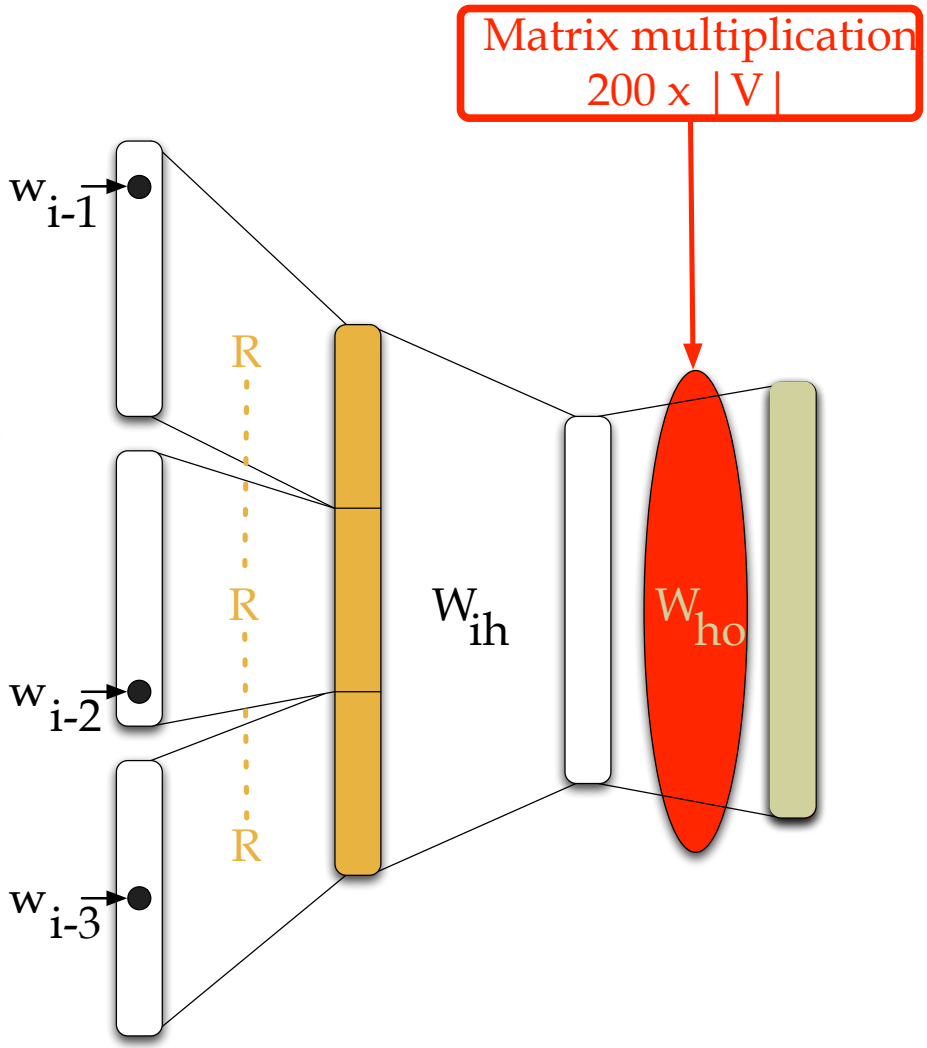

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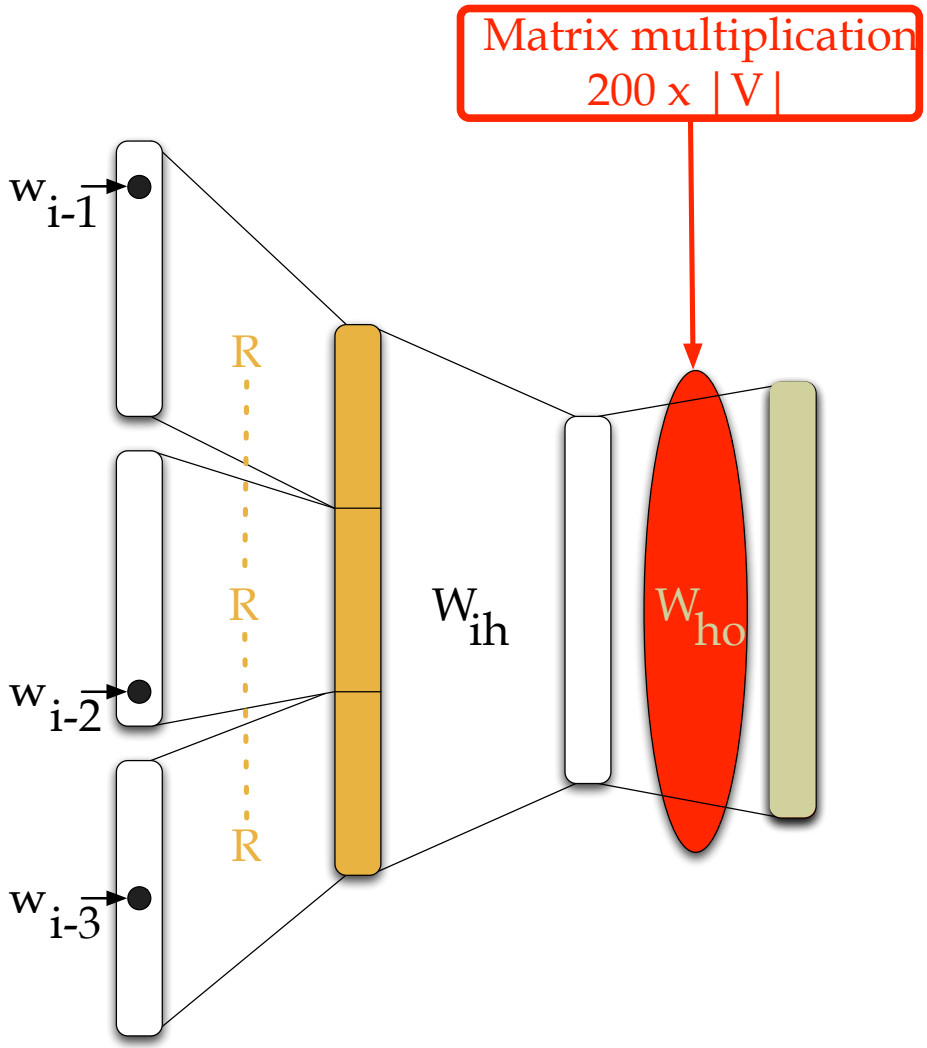
Complexity issues

- The input vocabulary can be as large as we want.
- Increasing the order of n does not increase the complexity.
- **The problem is the output vocabulary size.**



Usual tricks to speed-up training (and inference)

Re-sampling and batch training

- For each epoch : down-sampling of the training data
- Forward and Back-propagation for a group of n-grams

Reduce the output vocabulary

- Use the Neural network to predict only the K most frequent words.
- For a tractable model : $K = 6,000$ to $20,000$.
- Requires the normalization of the distribution for the whole vocabulary.

$\Rightarrow$ use the standard n-gram LM.

A solution : class-based language model

Main ideas

As proposed by (Mnih and Hinton2008) :

- Represent the vocabulary as a clustering tree (Brown et al.1992).
- Predict the path in this clustering tree.

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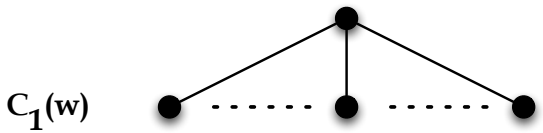
- Put each word w with a single root class $c_1(w)$
- Split these word classes in sub-classes $(c_2(w))$ and so on.



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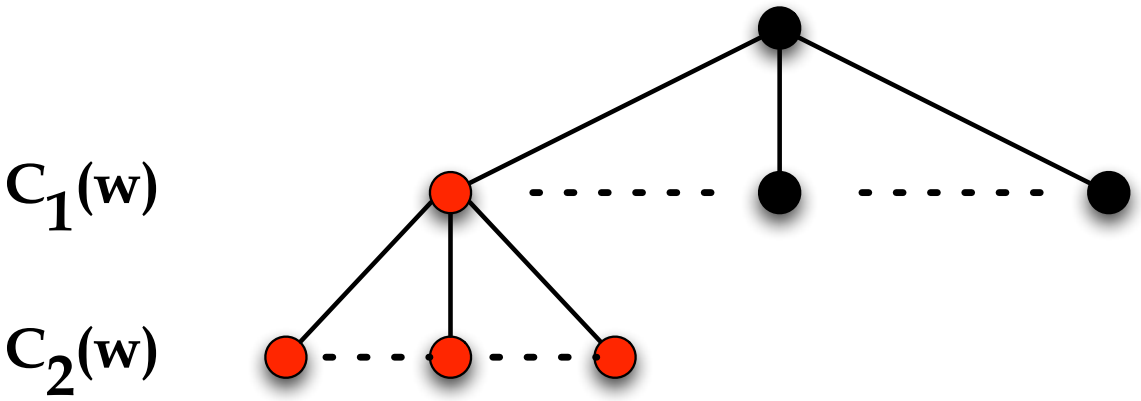

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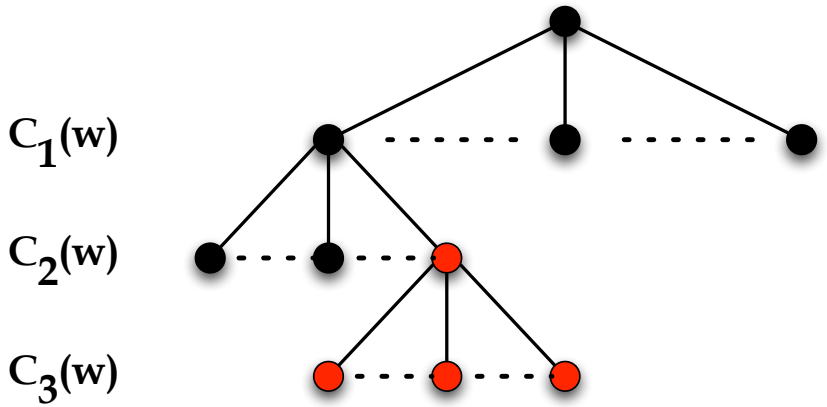
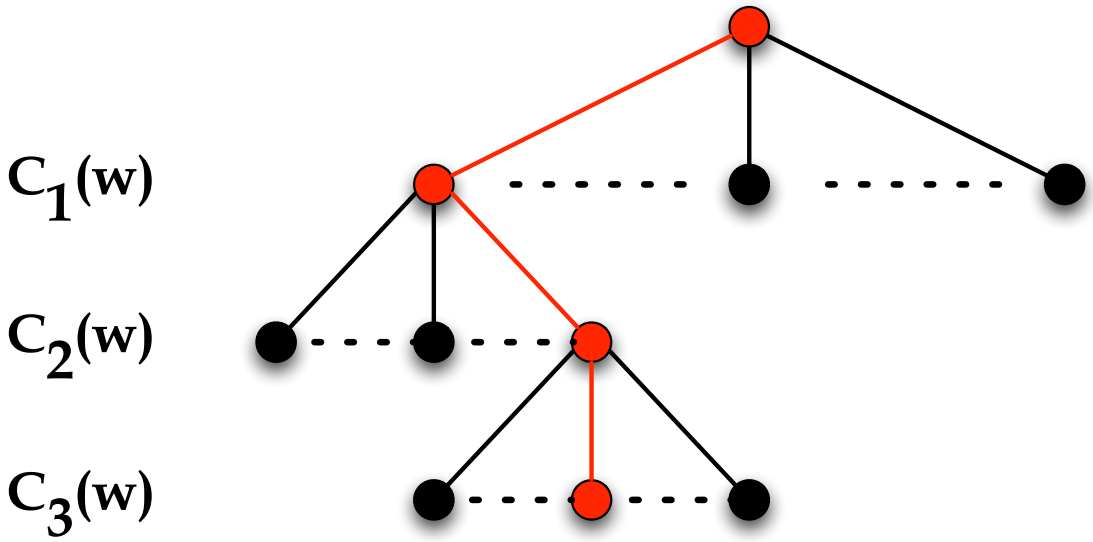


Word probabilities

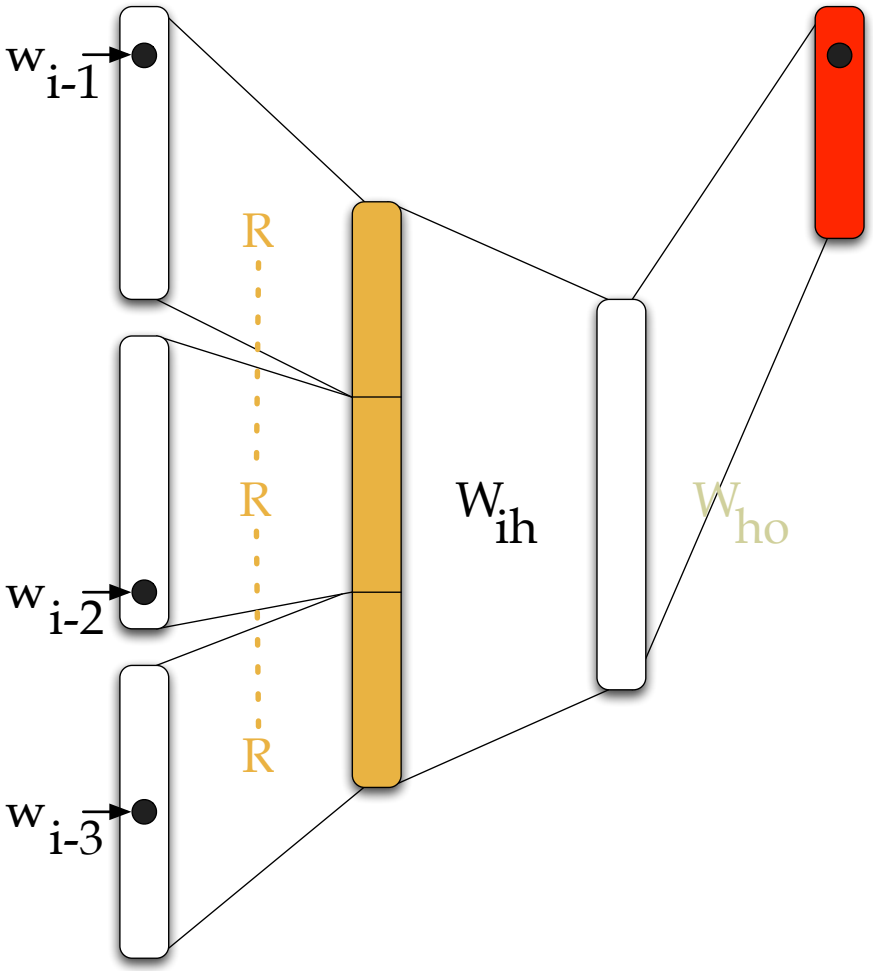


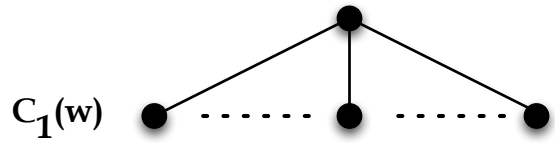
$$P(w_i|h) = P(c_1(w_i)|h) \prod_{d=2}^{D} P(c_d(w_i)|h, c_{1:d-1})$$

- $c_{1:D}(w_i) = c_1, \ldots, c_D$: path for the word w_i in the clustering tree,
- D : depth of the tree,
- $c_d(w_i)$: (sub-)class,
- $c_D(w_i)$: leaf.

The SOUL language model

(Le et al.2011)





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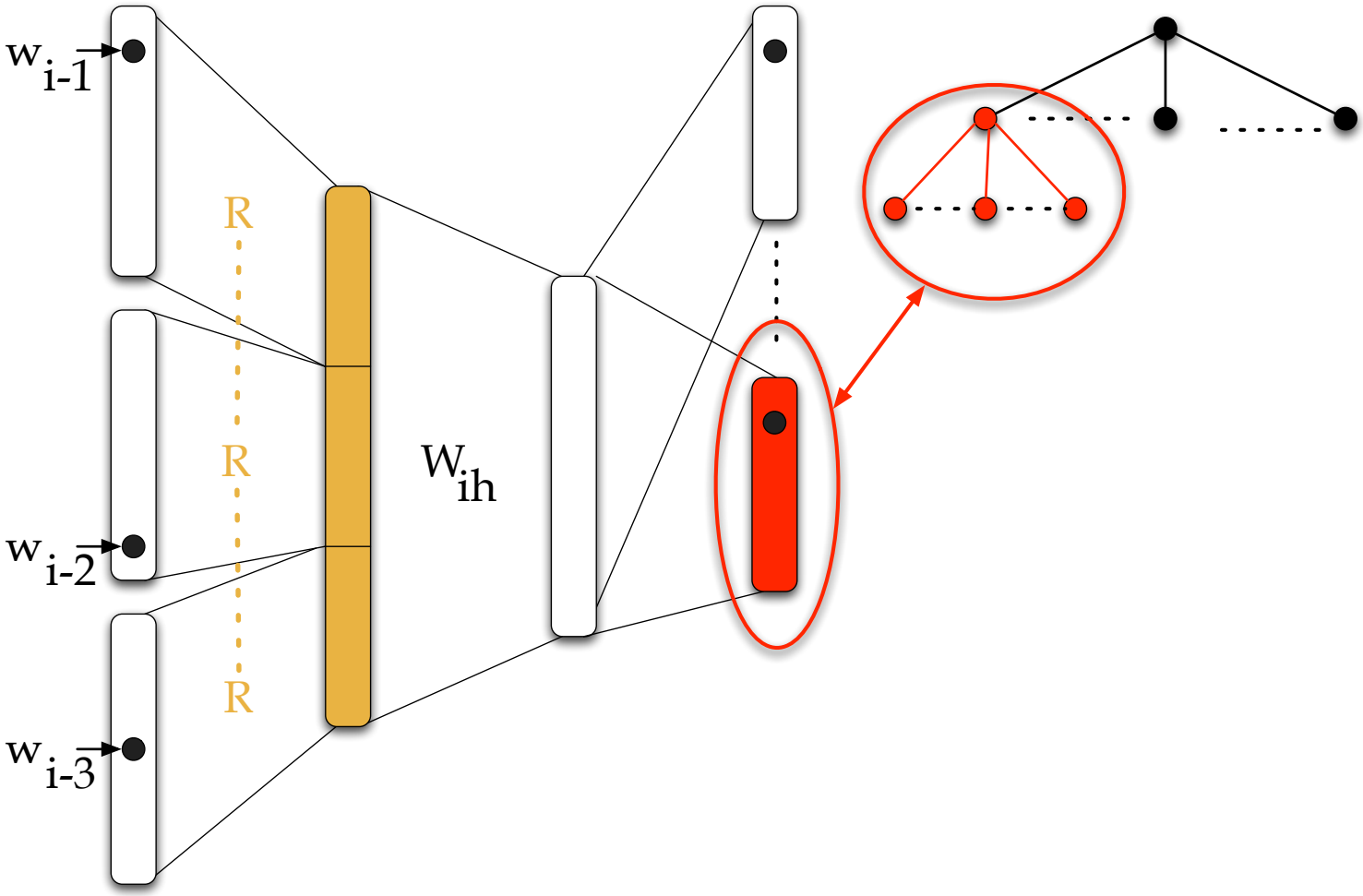

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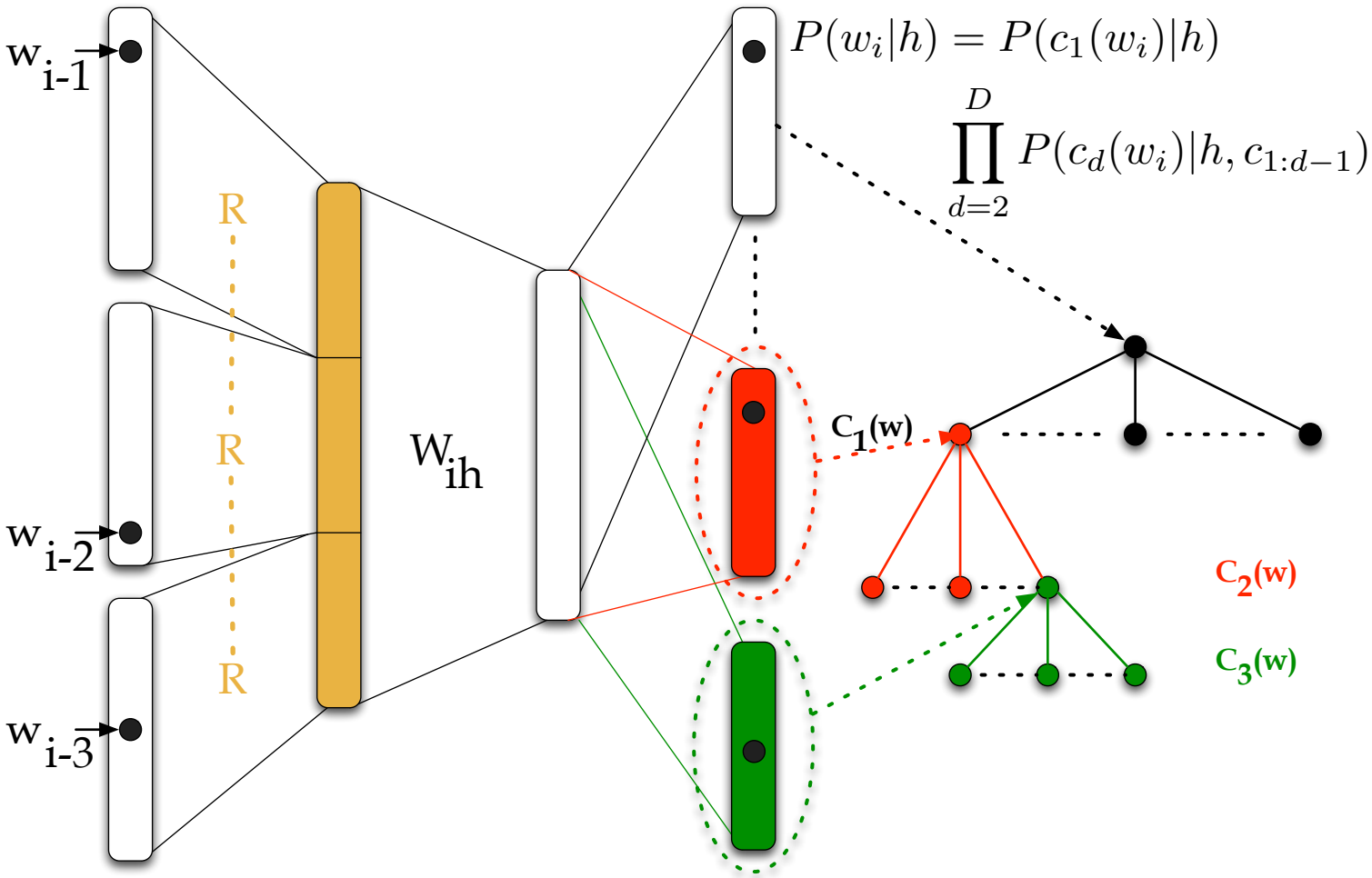

The SOUL language model

Overview

- A class-based language model
- Estimated in a continuous space with neural networks
- The class introduction $\Rightarrow$ many small output layers instead of a single but big layer.

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- The class introduction $\Rightarrow$ many small output layers instead of a single but big layer.

In practice

- The first level : The 8k most frequent words + 4k word classes
- The depth is between 3 and 4.

Another solution : self-normalized model

Gradient computation

For a word w in its context h, the model provides $P^h(w)$ and the gradient is :

$$\frac{\partial l(\boldsymbol{\theta}, w, h)}{\partial \boldsymbol{\theta}} = \frac{\partial a^h_{\boldsymbol{\theta}}(w)}{\partial \boldsymbol{\theta}} - E_{P^h_{\boldsymbol{\theta}}}\left[\frac{\partial a^h_{\boldsymbol{\theta}}}{\partial \boldsymbol{\theta}}\right]$$

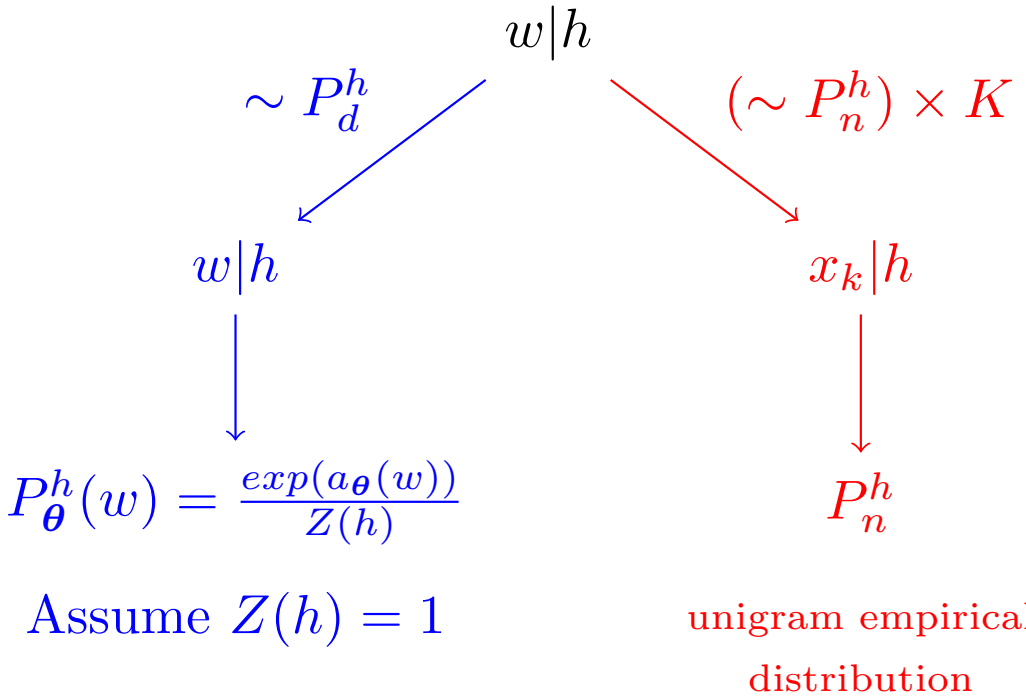
with $a^h_{\boldsymbol{\theta}}(w)$ the pre-activation associated to the word w.

How to approximate the second term

- Important sampling (Bengio and Sénécal2003) is not efficient

$\Rightarrow$ Noise Contrastive Estimation, introduced in (Gutmann and Hyvärinen2010) and applied to language model in (Mnih and Teh2012).

Noise Contrastive Estimation (NCE)



$$J^h(\theta) = E_{P_d^h}\left[log\frac{P_\theta^h(w)}{P_\theta^h(w) + kP_n^h(w)}\right] + kE_{P_n^h}\left[log\frac{kP_n^h(w)}{P_\theta^h(w) + kP_n^h(w)}\right]$$

Why does it work ?

The gradient of the NCE objective function

The gradient can be written as follows :

$$\sum_{w \in V} \frac{k P_n^h(w)}{P_\theta^h(w) + k P_n^h(w)} \times (P_d^h(w) - P_\theta^h(w)) \frac{\partial \log P_\theta^h(w)}{\partial \theta}$$

- The noise distribution must be non-zero wherever the data distribution is.
- It onverges to the maximum likelihood gradient when $k \longrightarrow \infty$

Inference

- The model converge to an approximately normalized model

$\Rightarrow$ During inference, just need to compute $a_{\boldsymbol{\theta}}^h(w)$

Summary for large vocabulary application

The size of the output layer has a great impact on the computational cost.

Structured output

- Replace one large softmax by several smaller ones,
- with a hierarchical softmax (Morin and Bengio2005).
- See the work of (Mnih and Hinton2008; Le et al.2011; Mikolov et al.2011).

Un-normalized model

- Preserve the conventional output structure
- A simplified version : Negative Sampling (Mikolov et al.2013)
- Variant : include the normalizer in the objective function (Devlin et al.2014)

Outline

Sentence level representation

The goal

- To derive a continuous representation of a sentence (or a document).
- Not a bag of words !

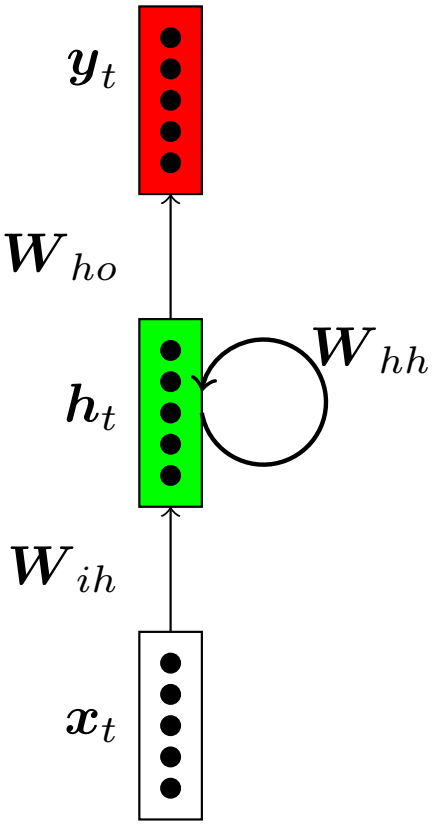
"Deep Net" Solutions

There are two ways to deal with sequences of arbitrary size.

- Recurrent network (Mikolov et al.2011)
- Convolutional network + pooling (Kalchbrenner and Blunsom2013; Kalchbrenner et al.2014)

Recurrent network

Interlude introducing new architectures



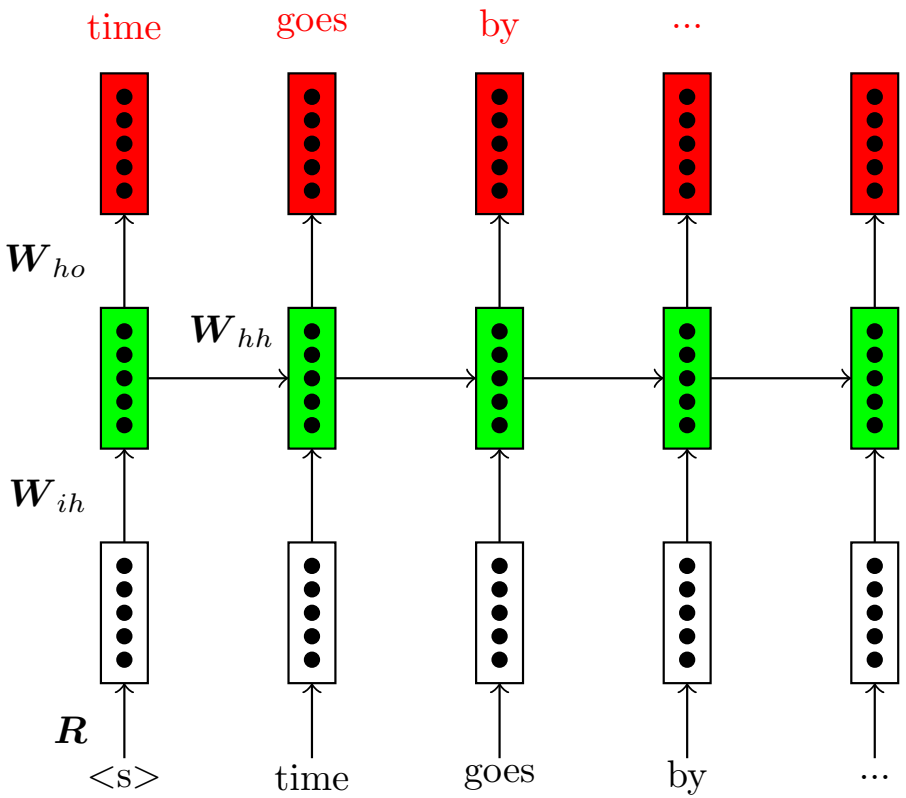
A dynamic system, at time t :

- maintains a hidden representation, the internal state : $\boldsymbol{h}_t$
- Updated with the observation of $\boldsymbol{x}_t$ and the previous state $\boldsymbol{h}_{t-1}$
- The prediction $\boldsymbol{y}_t$ depends on the internal state ($\boldsymbol{h}_t$)
- For a language model, $\boldsymbol{x}_t$ comes from word embeddings

The same parameter set is shared across time steps

Recurrent network language model

Unfolding the structure : a deep-network



At each step t

- Read the word $w_t \rightarrow \boldsymbol{x}_t$ from $\boldsymbol{R}$
- Update the hidden state $\boldsymbol{h}_t = f(\boldsymbol{W}_{ih}\boldsymbol{x}_t + \boldsymbol{W}_{\boldsymbol{hh}}\boldsymbol{h}_{\boldsymbol{t-1}})$
- The word at $t+1$ can be predicted from $\boldsymbol{h}_t$:

$$\boldsymbol{y}_t = g(\boldsymbol{W}_{ho}\boldsymbol{h}_t)$$

- g is the softmax function over the vocabulary

Training recurrent language model

Training algorithm

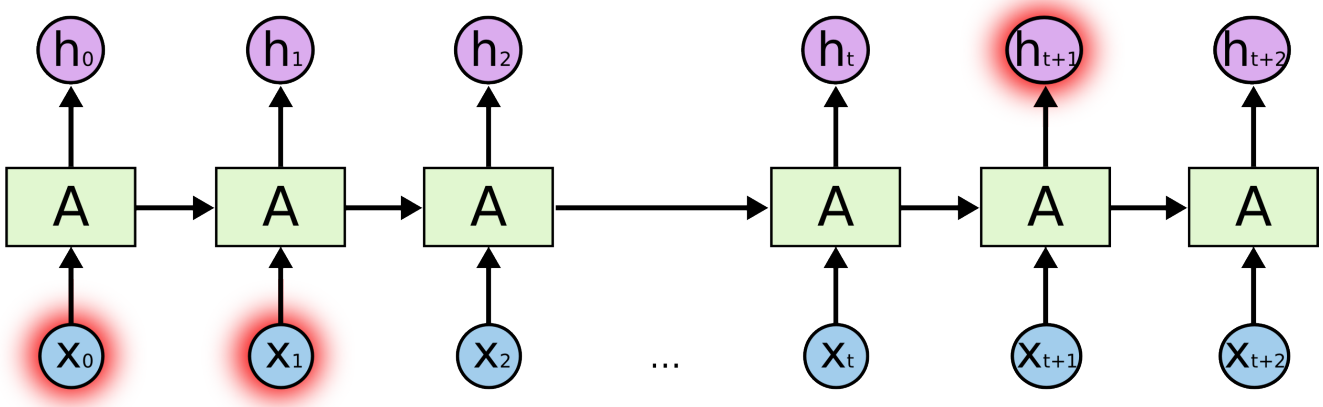
Back-Propagation through time or BPTT (Rumelhart et al.1986; Mikolov et al.2011) :

- for each step t
  - compute the loss gradient
  - Back-Propagation through the unfolded structure

Inference

- Cannot be easily integrated to conventional approaches (ASR, SMT, ...)
- A powerful device for end-to-end system

The Problem of Long-Term Dependencies



ex : "I grew up in France... I speak fluent French"

- Recent observations hide the older ones (Bengio et al.1994)
- The vanishing (exploding) gradient is a real issue (Pascanu et al.2013)

Solutions

Improved optimization

- Gradient clipping (Pascanu et al.2013)
- Hessian-Free optimzation (Martens and Sutskever2012) or natural gradient (Desjardins et al.2013; Ollivier2015)

Modified unit

A recurrent network should be able to mitigate the observations *vs* its internal state :

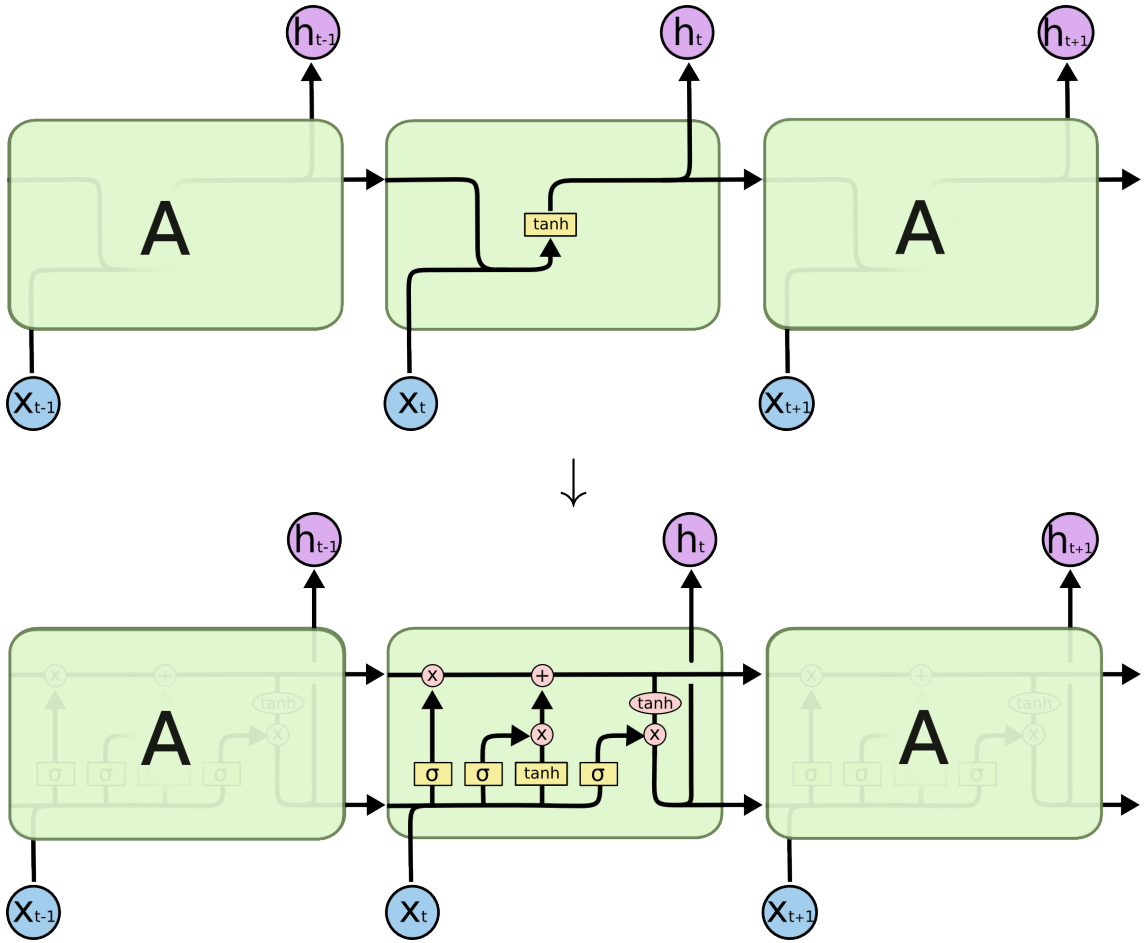
- LSTM or Long-Short-Term-Memory cell (Hochreiter and Schmidhuber1997; Graves and Schmidhuber2009)
- Gated Recurrent Unit or GRU (Cho et al.2014)

Introduction to LSTM

Based on http://colah.github.io/posts/2015-08-Understanding-LSTMs/

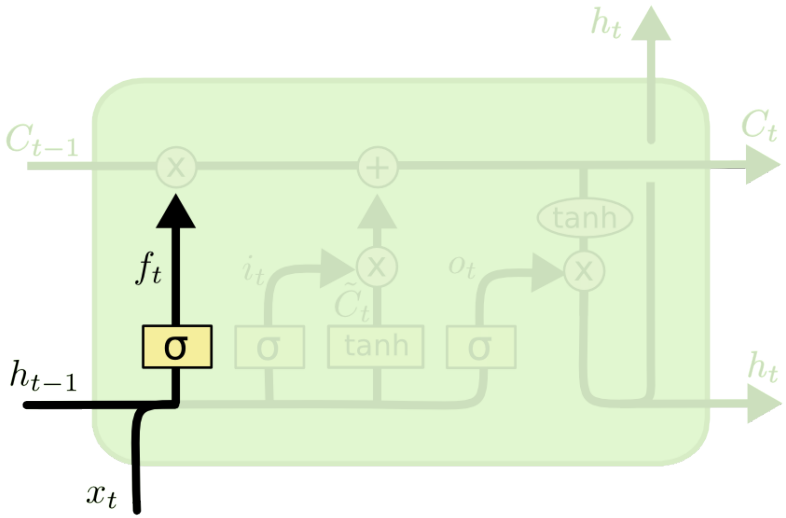
Instead of having a single neural network layer, there are four, interacting in a very special way.

- Lines carry a vector
- A recurrent net transmits its hidden states
- LSTM introduces a second channel : the cell state
- It acts as a memory
- Gates control the memory



LSTM : Control flow - 1

What should be forgotten from the previous cell state ?



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

Action

The sigmoid (forget gate) answers for each component :

- 1 : to keep it,
- 0 to forget it, or
- a value in-between to mitigate its influence

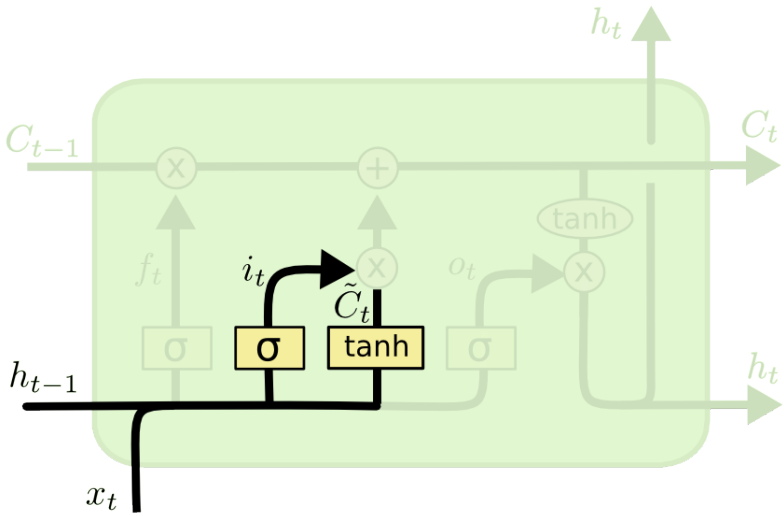
Intuition for language modeling

The cell state might embed the gender of the present subject :

- keep it to predict the correct pronouns,
- or forget it, when a new subject appears

LSTM : Control flow - 2

What should be taken into account ?



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

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

Actions

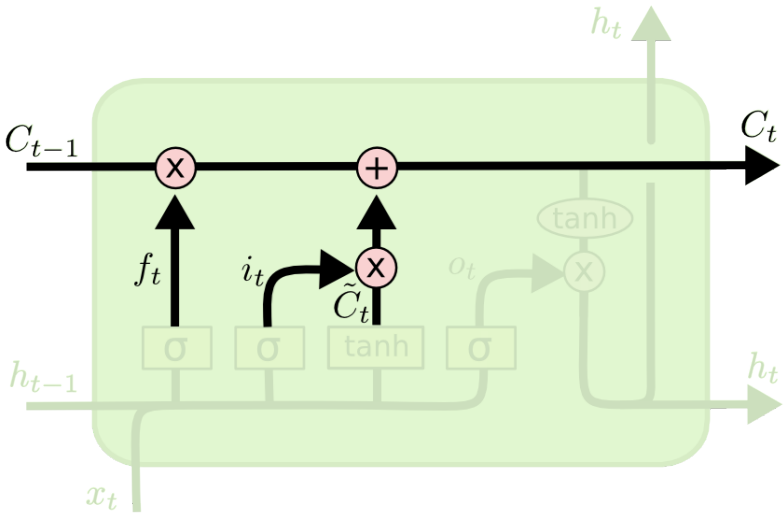
- Create the update $\tilde{C}_t$ of the cell state
- and its contribution i_t (the input gate with a sigmoid activation)

Intuition

- Add the gender of the new subject to the cell state,
- to replace the old one we're forgetting.

LSTM : Control flow - 3

Write the new state



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

Actions

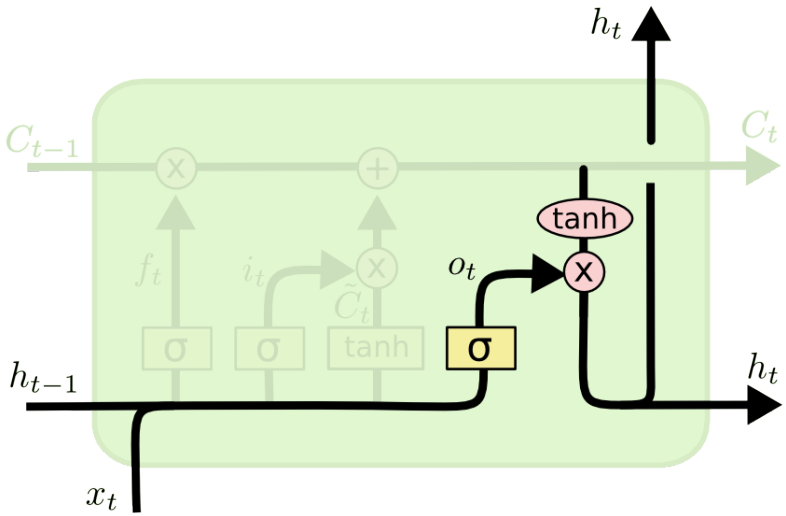
- Merge the old cell state modified by the forget gate
- with the new input

Intuition for language modeling

- Decide to drop the information about the old subject
- Refresh the memory

LSTM : Control flow - 4

Write the new hidden state



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

$$h_t = o_t * \tanh\left(C_t\right)$$

Actions

- Decide what parts of the (filtered) cell state to output o_t
- Compute the hidden state

Intuition for language modeling

- Since we just saw a subject,
- output the relevant information for the future (gender, number)

LSTM summary

A special kind of recurrent architecture

The internal cell state allows the model to :

- keep information in memory
- select the relevant outputs
- to reset or mitigate the long-term memory

Consequences

- An efficient model of sequences
- Overcome the vanishing gradient issue
- Very promising results in generation

Variants

- Gated recurrent units (GRU) (Cho et al.2014) or a more complicated one (Gers and Schmidhuber2000)
- Some recent comparisons (Józefowicz et al.2015; Greff et al.2015)

Outline

Motivations

For morphologically-rich and non-canonical languages

- Very productive word formation processes

$\Rightarrow$ generate a proliferation of word forms.

Freundschaftsbezeigungen, görüntülenebilir $\leftrightarrow$ *MYL, AFAIK, cul8r*

Consequences

- Morphologically-rich and under-resourced language processing
- Social Media implies fast change in the language use

$\rightarrow$ An evolving vocabulary with new compound tokens, abbreviations, ...

Tokens decipherment/encoding

Ex : German POS-Tagging

The Task

The TIGER corpus defines a POS-tagging task with very rich tagset (around 600 tags)

State of the art results (Mueller et al.2013)

- A second order CRF
- with an intensive feature engineering to describe the morphology

Deep Net approach

- A lot of information about words can be leveraged from subword features.

$\Rightarrow$ Learn to infer a word representation from the character level

$\Rightarrow$ Make these representations aware of the context (sentence level)

A training example

Sentence	POS-tags
Er	PPER-case=nom|@gender=masc|number=sg|person=3
fürchtet	VVFIN-mood=ind|number=sg|person=3|tense=pres
noch	ADV
Schlimmeres	NN-case=acc|gender=neut|number=sg
.	$.

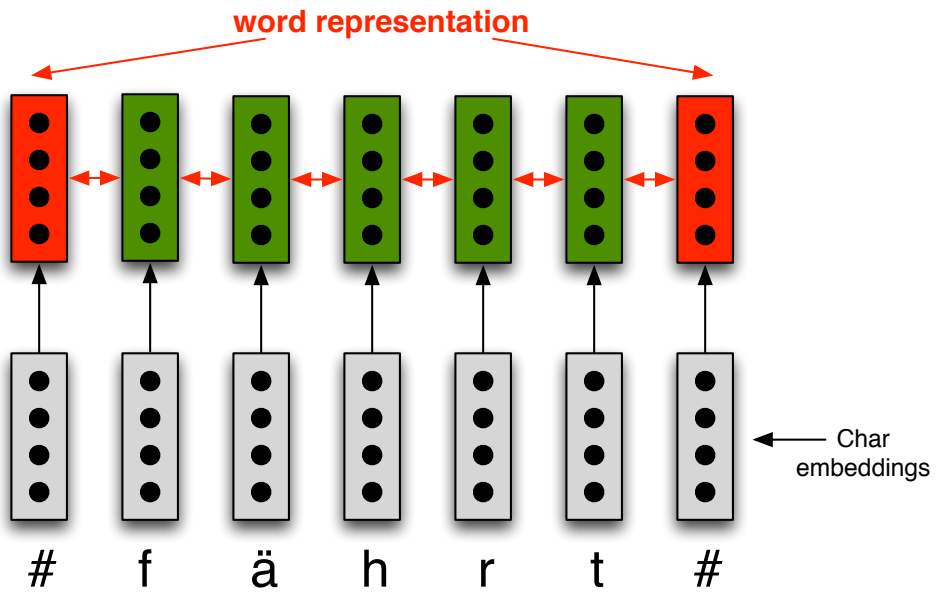
From characters to word representation

A word is a sequence of characters !

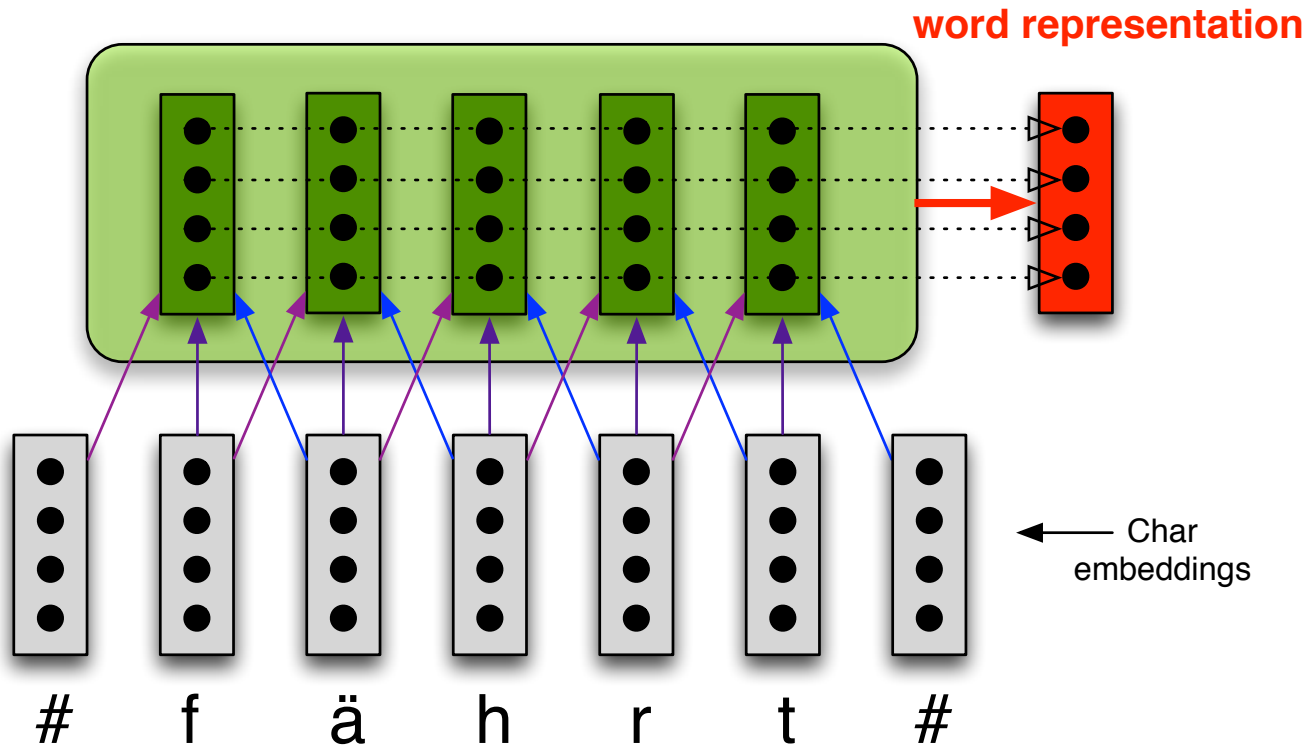
Sequence representation

- Recurrent network (Elman1990; Mikolov et al.2011)
- Convolutional network + pooling (Kalchbrenner et al.2014; Santos and Zadrozny2014)

The "recurrent" way

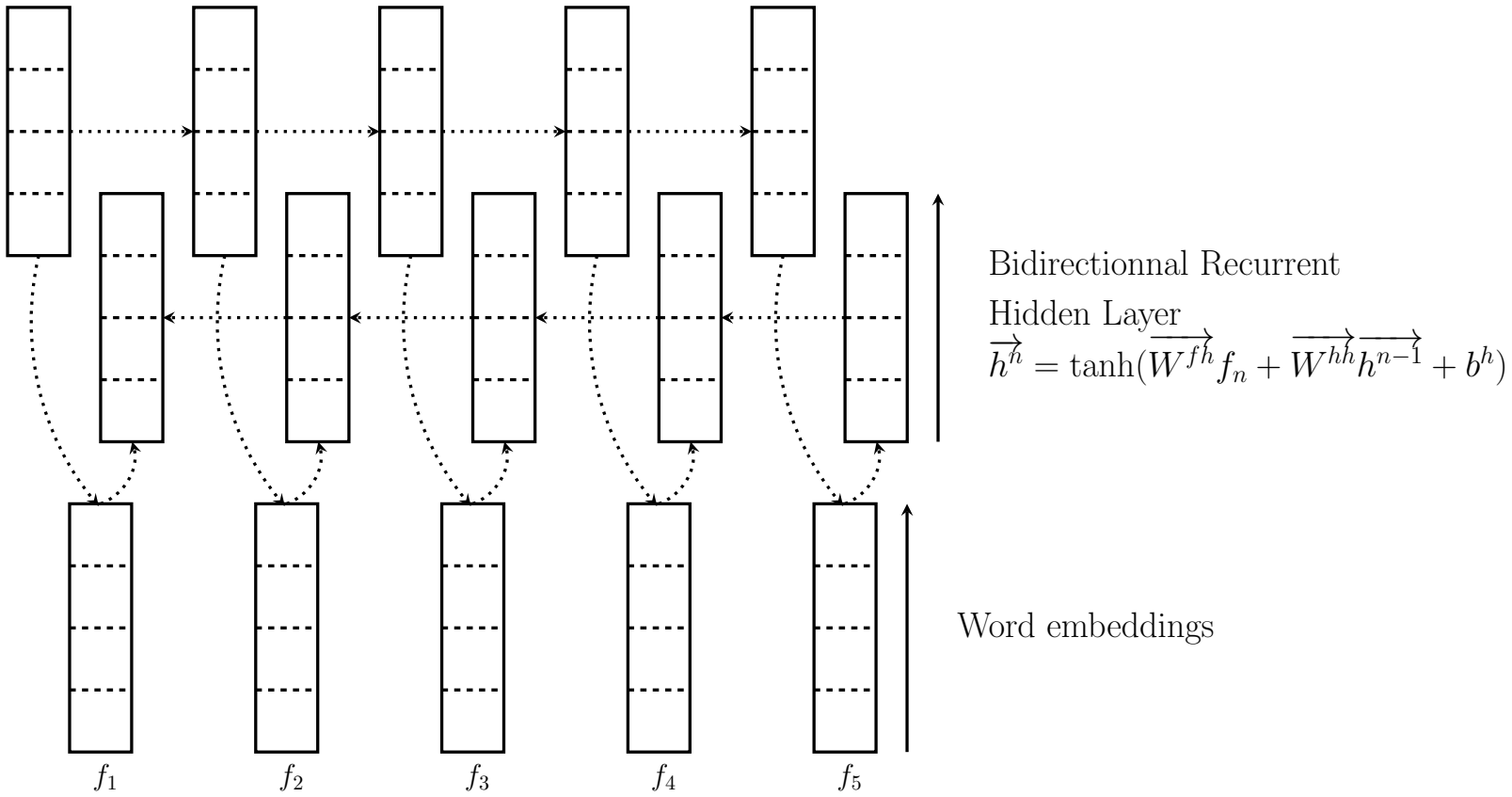


Convolutional net and pooling



- A convolution net is applied at each position
- In 1-D, it mixes the inputs within a window (represent the local context)
- Max-pooling reduces this sequence in one vector

From word to a contextual representation



For each word, derive a new representation, sentence dependant

From sequence to prediction

Simple prediction : position by position

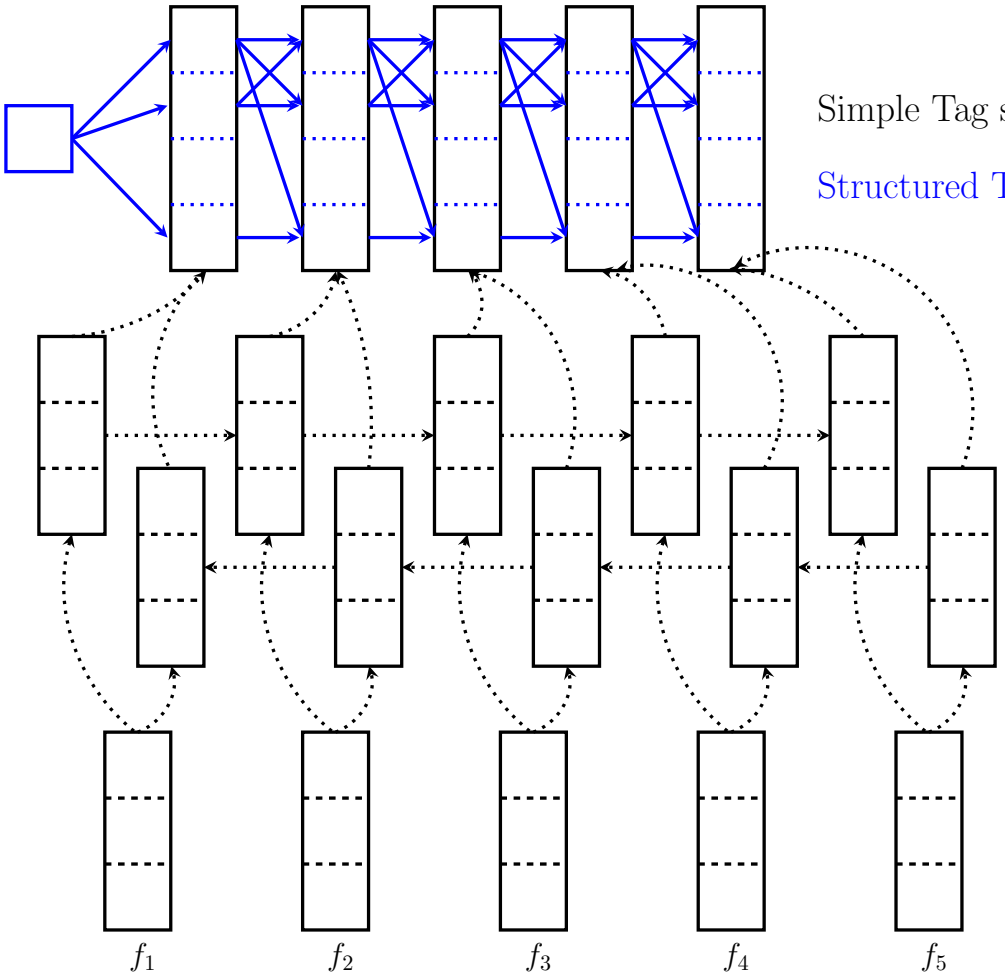
$$s_n = W^o(\overrightarrow{h^n} : \overleftarrow{h^n}) + b^o.$$

Sequence prediction (Collobert2011; Santos and Zadrozny2014)

Add a transition matrix W^{trans} and compute with the Viterbi algorithm, the best tag sequence $\{t_1, \ldots, t_{|s|}\}$ *wrt* :

$$s(\{t\}_1^{|s|}, \{w\}_1^{|s|}) = \sum_{1 \leq n \leq |s|} \left(W^{trans}_{t_{n-1}, t_n} + [s_n]_{t_n} \right)$$

Sequence prediction



Simple Tag scoring : $s_n = W^o(\overrightarrow{h^h} : \overleftarrow{h^n}) + b^o$

Structured Tag prediction (Viterbi inference)

Bidirectionnal Recurrent Hidden Layer

$\overrightarrow{h^h} = \tanh(\overrightarrow{W^{fh}} f_n + \overrightarrow{W^{hh}} \overrightarrow{h^{n-1}} + b^h)$

Word embeddings

Putting all together

(Labeau et al.2015)

A unified model that can

- Infer word representation from the character level
- which takes sentence level information into account
- Make sequence prediction

Training

- Maximize the conditional log-likelihood of the tag sequence given the word sequence
- Optimization with AdaGrad (Duchi et al.2011)

Results

- This model achieves state of the art performance
- without any feature engineering

Summary

The basics : the Feedforward architecture

- Basically matrix operation and a specific terminology
- Training : Back-propagation and SGD
- Regularization : weight decay and dropout

For structured i/o

- Recurrent network and LSTM
- Convolutional Net and pooling

Conclusion

Deep Networks learn higher levels of abstraction

Higher-level abstractions disentangle the factors of variation :

$\Rightarrow$ Hierarchical layers of representation

$\Rightarrow$ Allows the model a much easier generalization and transfer

Why today ?

- After a long and intensive experimental exploration,
- efficient recipies and tools are available
- but Training Deep Nets is not so "simple"

In practice

- Often very simple matrix derivatives (backprop) for training and matrix multiplications for inference
- Fast inference and well suited for multicore CPUs/GPUs and parallelization across machines

Conclusion - 2

A success story

Many state of the art results on a variety of language and vision tasks

For natural language processing

Continuous representation of words, sentences, ... opens perspectives

- Sequence tagging (Collobert et al.2011), Parsing (Vinyals et al.2015), question answering (Weston et al.2015), **Semantics** (Socher et al.2013; Baroni et al.2014), ...
- Machine Translation (a special issue in Computer Speech and Language)

Warning :
This is not magical and this won't solve all the problems.

> "Natural language processing (NLP) has not been revolutionized by deep learning, though there has been huge progress during the last years."
>
> (Y. Bengio @ DL-workshop, ICML2015)

Future work

In NLP

- Under-resourced, non-canonical, and morphologically-rich languages
- Transfer learning
- A unified framework for joint tasks, *e.g* speech-to-speech translation

Unsupervised and semi-supervised learning

There is a huge amount of unlabeled data!

- Unsupervised learning (RBM, Auto-Encoder, ...) strikes back (Larochelle et al.2009)
- Semi-supervised learning (Kingma et al.2014; Rasmus et al.2015)
- Multi-task learning (sharing parameters across scarce tasks) (Collobert et al.2011)

Toolkits

Theano : http://deeplearning.net/software/theano/

- in python, works on CPU and GPU and several wrappers
- http://lasagne.readthedocs.org/
- http://keras.io/
- https://www.cs.cmu.edu/~ymiao/pdnntk.html
- http://deeplearning.net/software/pylearn2/
- http://blocks.readthedocs.org/

Torch7 : http://torch.ch/

Lua interface to C/CUDA

TensorFlow https://www.tensorflow.org

API in C++ and Python

Further reading

- *Deep Learning Book* by Yoshua Bengio, Ian Goodfellow and Aaron Courville (`http://www.iro.umontreal.ca/~bengioy/dlbook/`)
- *Deep Learning for Natural Language Processing* by Stanford University `http://cs224d.stanford.edu/`
- *Deep Learning - Methods and Applications* by Li Deng and Dong Yu `http://research.microsoft.com/pubs/219984/BOOK2014.pdf`
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