Neural Networks for Natural Language Processing

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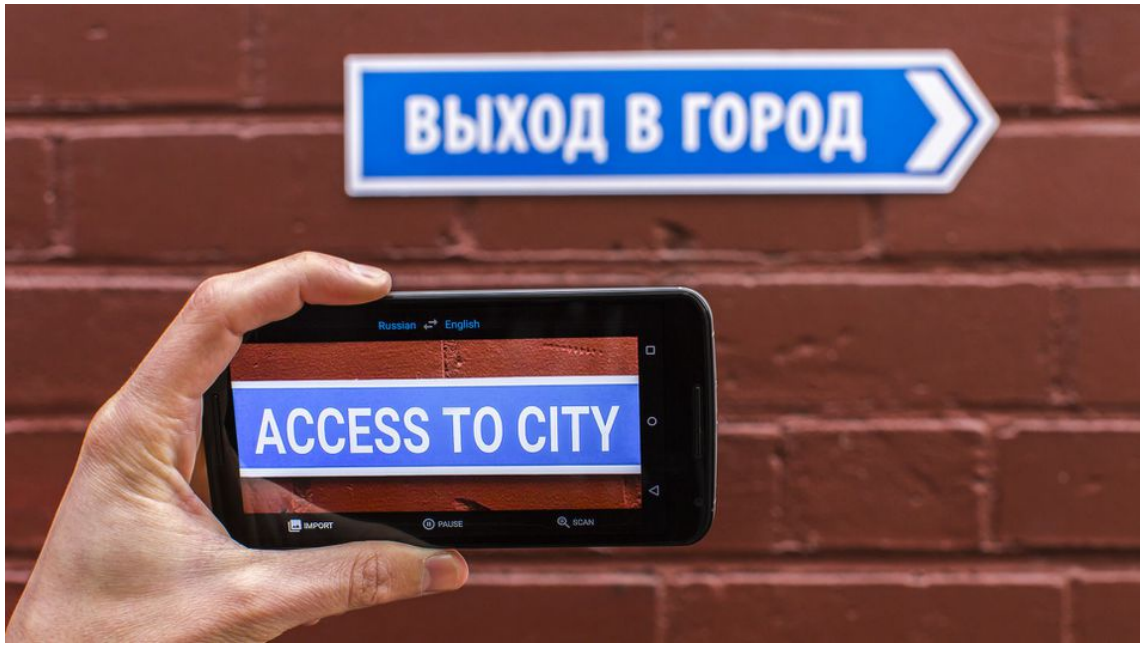
19/01/2017

Outline

“Successful” applications of Natural Language Processing (NLP)



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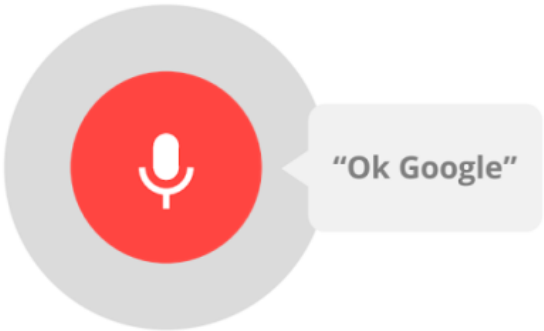

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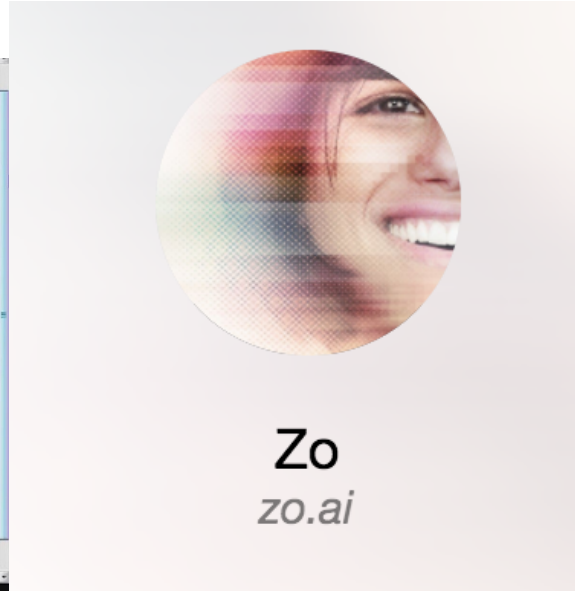


Some NLP tasks

Machine Translation

第13届上海国际电影节开幕...

The 13th Shanghai Film festival ...

Word Sense Disambiguation

I need new batteries for my **mouse**

Paraphrase

XYZ acquired ABC yesterday

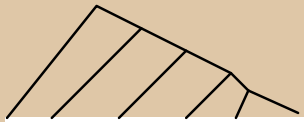
ABC has been taken over by XYZ

Spam detection

Let's go to Agra!

Buy V1AGRA ...

Syntactic Parsing



I see him with a telescope

Summarization

The Dow Jones is up

The S&P 500 jumped

Housing price rose

Economy is good

Part of Speech (POS) tagging

ADJ	ADJ	NOUN	VERB	ADV
Colorless	green	ideas	sleep	furiously

Coreference resolution

Carter told Mubarak **he** shouldn't run again

Dialog / Question Answering

Where is a Bug's life playing ?

Sept Parnassien at 7:30

Ambiguous, noisy and with great variability

Why NLP is so hard ?

Named entities and Idioms

- Where is A Bug's Life playing (...)
- Let It Be was recorded (...)
- Push the daisies
- lose face

Non-canonical language

Great job `@justinbieber`! Were SOO PROUD of what youve done!

U taught us 2 #neversaynever & you yourself should never give up either

Neologism

- unfriend, retweet,
- bromance, +1, ...

World knowledge

- Mary and Sue are sisters
- Mary and Sue are mothers

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Hospitals are Sued by 7 Foot Doctors
Kids Make Nutritious Snacks
Iraqi Head Seeks Arms

Statistical NLP

A very successful approach, indeed

From Peter Norvig (`http://norvig.com/chomsky.html`)

- **Search engines**: 100% of major players are trained and probabilistic.
- **Speech recognition**: 100% of major systems ...
- **Machine translation**: 100% of top competitors ...
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Statistical NLP ?

Using statistical techniques to **infer structures** from text based on **statistical language modeling**.

Statistical NLP - a (very) brief history

1970 -1983: Early success in speech reocgnition

- Hidden Markov models for acoustic modeling
- The first notion of language modeling as a Makov Chain

1983 - : Dominance of empiricism and statistical methods

- Incorporate probabilities for most language processing
- Use large corpora for training and evaluation

2003 - : Neural networks

- As a component at the beginning ...
- to end-to-end systems today

NLP: Statistical issues

Data sparsity in high dimension

For most of NLP tasks:

- model structured data
- with very peculiar and sparse distributions
- with a large set of possible outcomes

Ambiguity and variability

- The *context* is essential.
- Language is difficult to "interpret", even for human

→ Learning to efficiently represent language data
→ Neural networks have renewed the research perspectives

Is it so important ?

It is decisive !

Machine translation issue :

Opinion mining and Stock prediction

A. Hathaway *vs* Berkshire Hathaway

Outline

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n-gram language 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

$$n = 4\text{: } P(w_i = ? | \underbrace{w_{i-3}, w_{i-2}, w_{i-1}}_{\text{context}})$$

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

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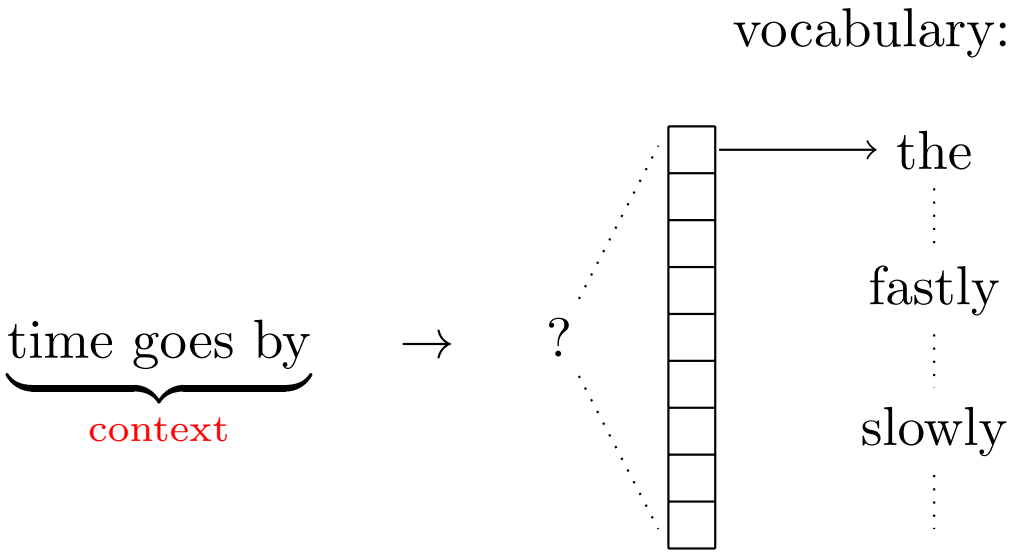

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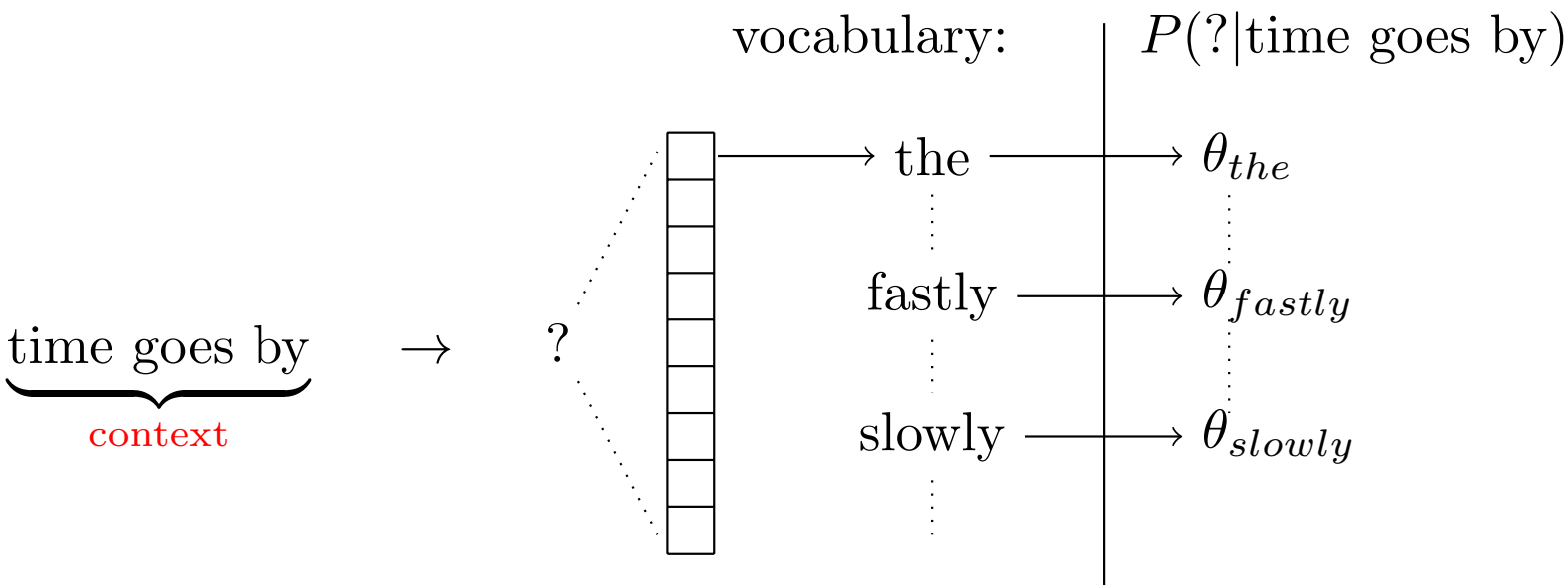

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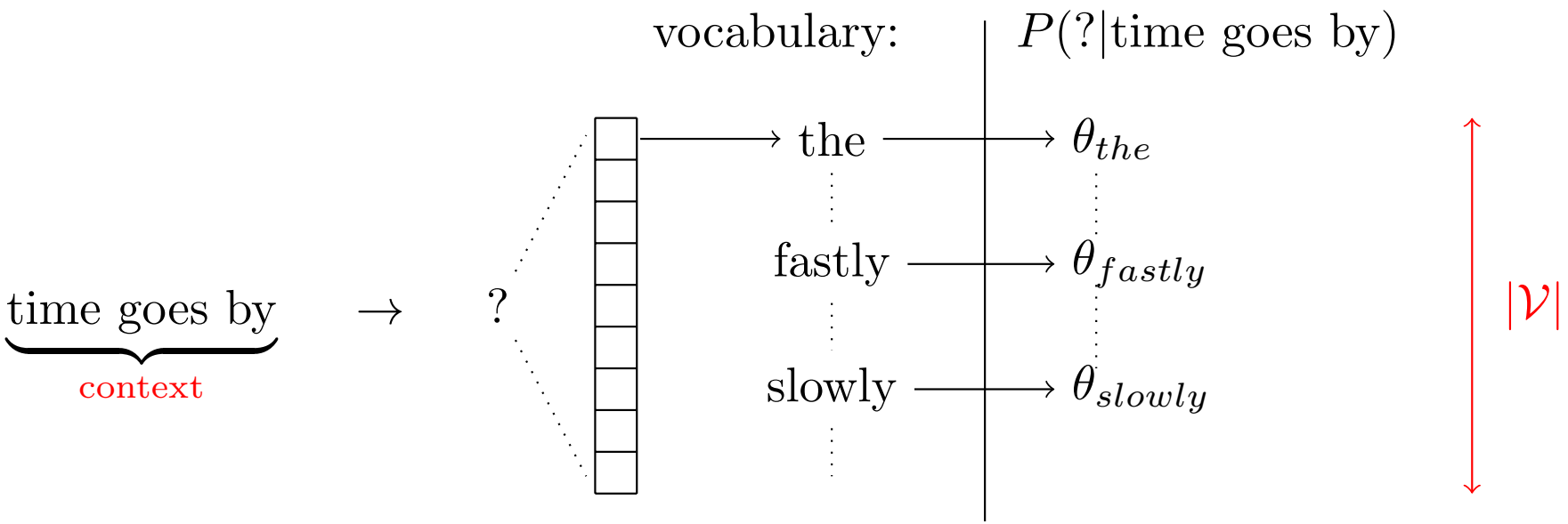

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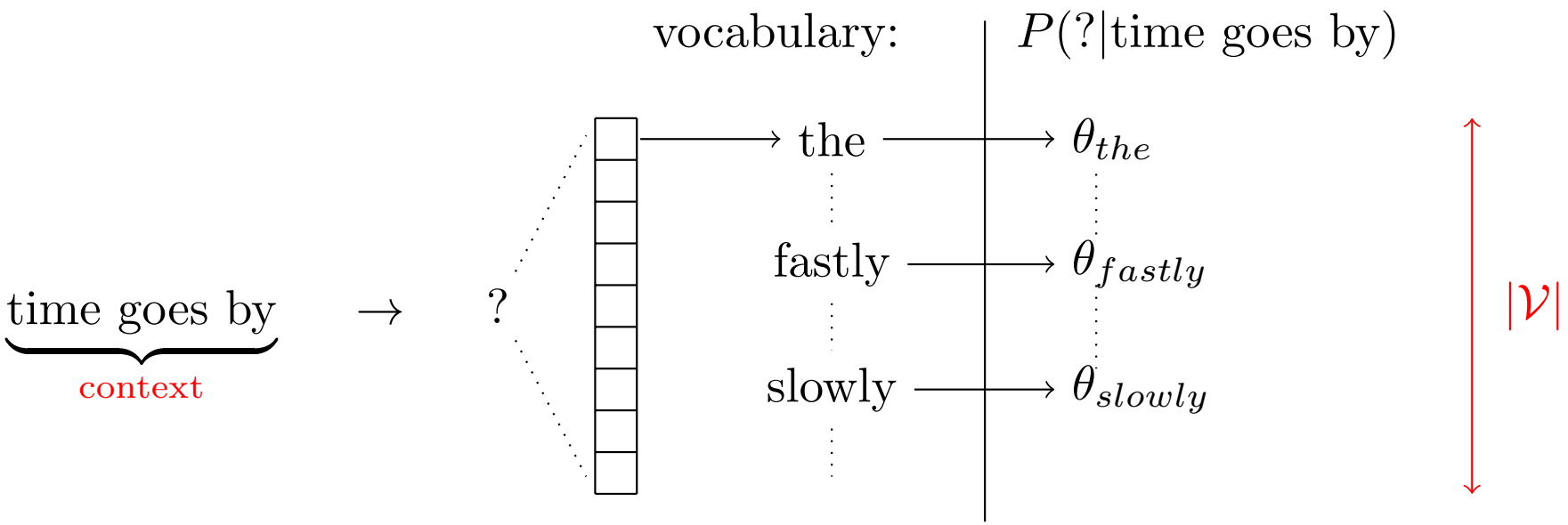
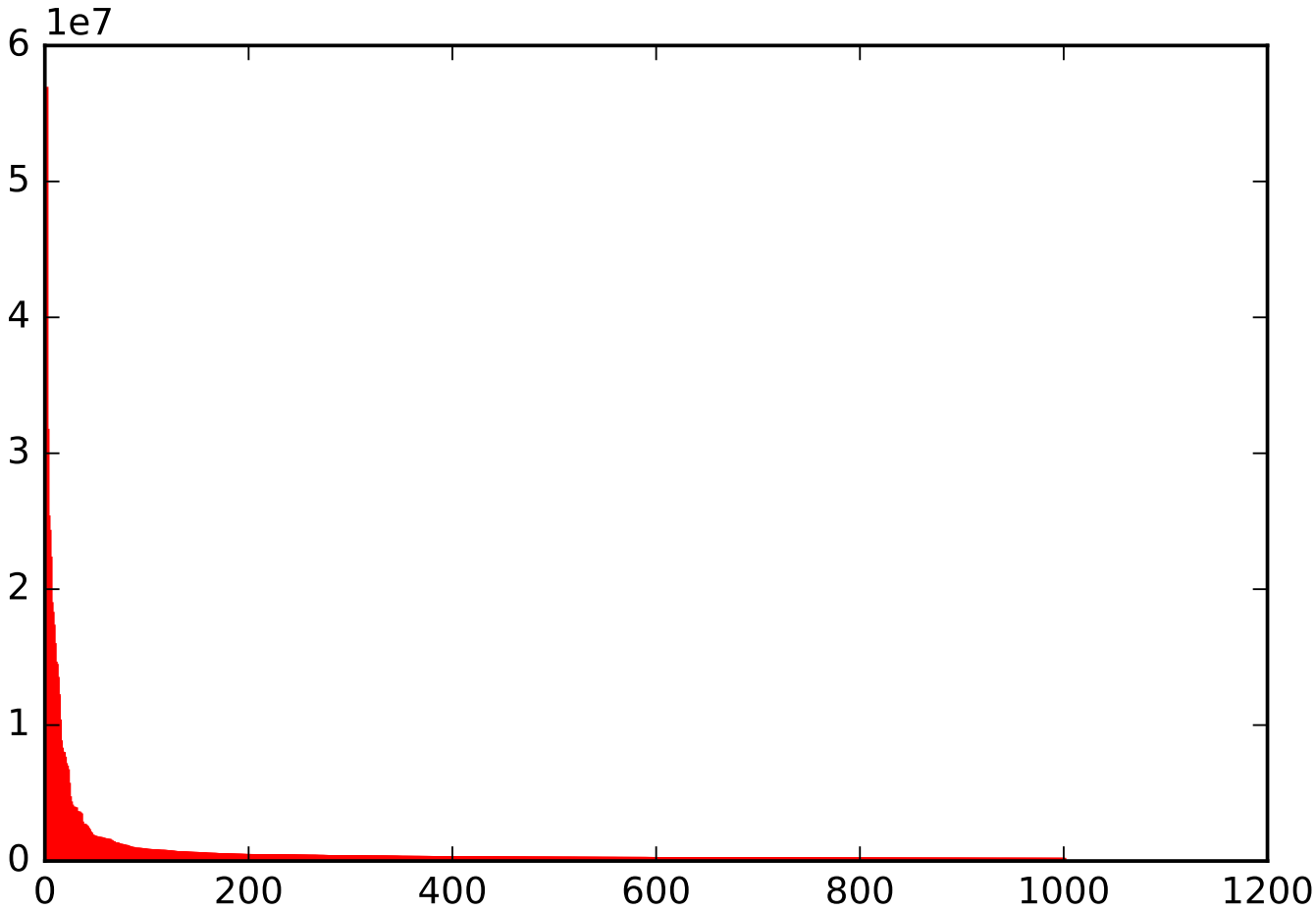


$|\mathcal{V}|^4$ parameters, Maximum Likelihood Estimate

The Zipf law (for French)

$$frequency \propto 1/rank$$



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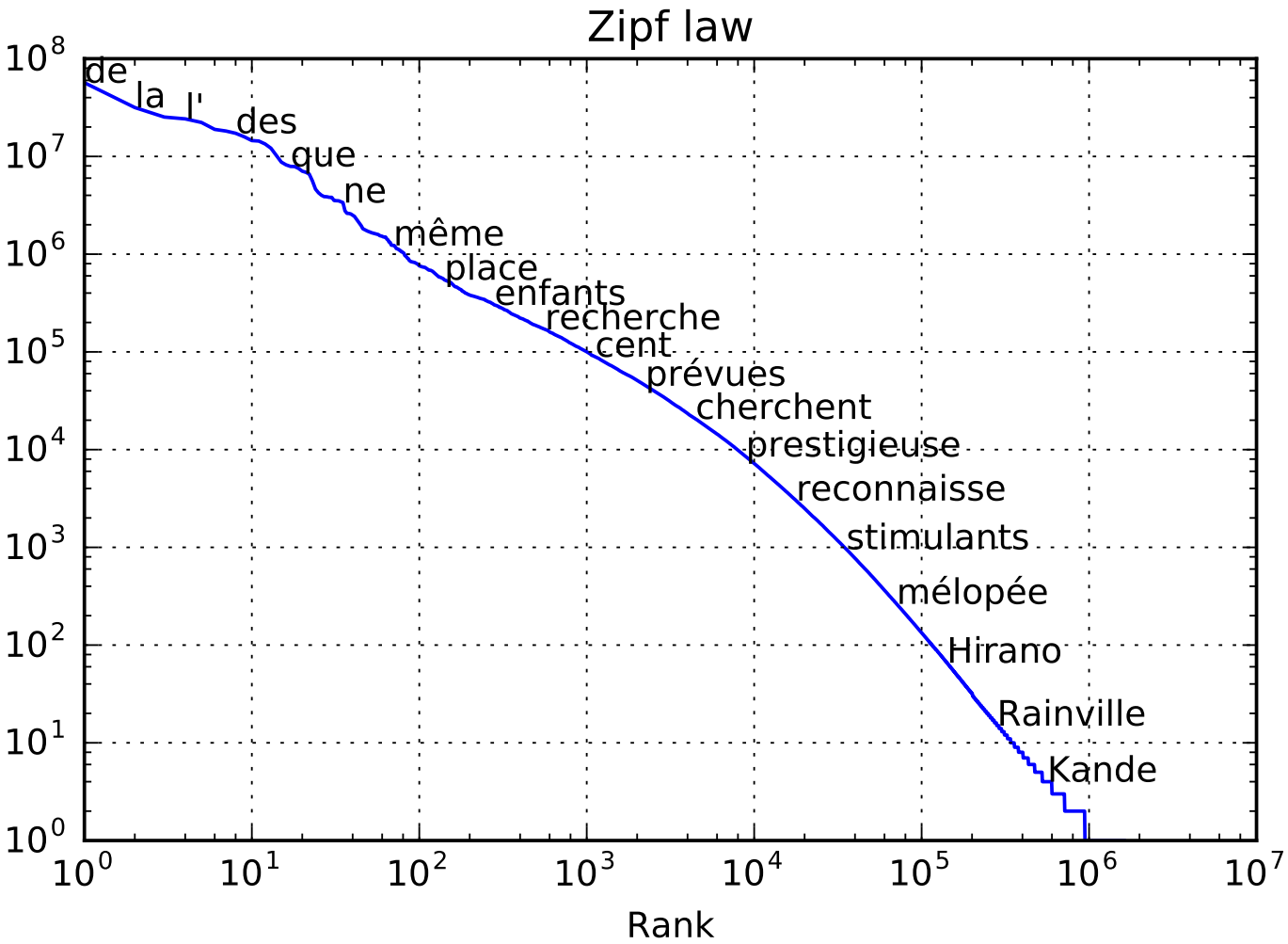

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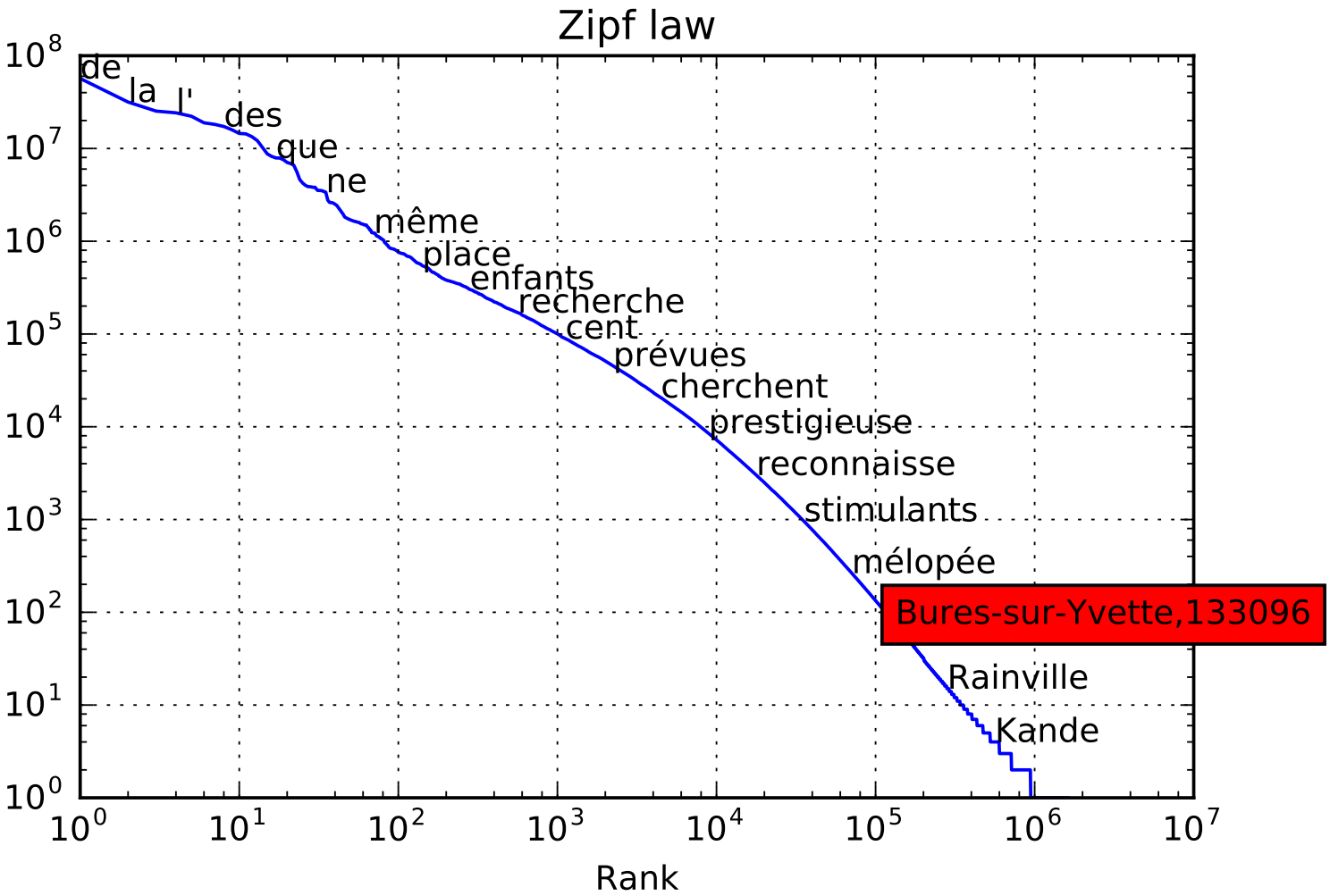
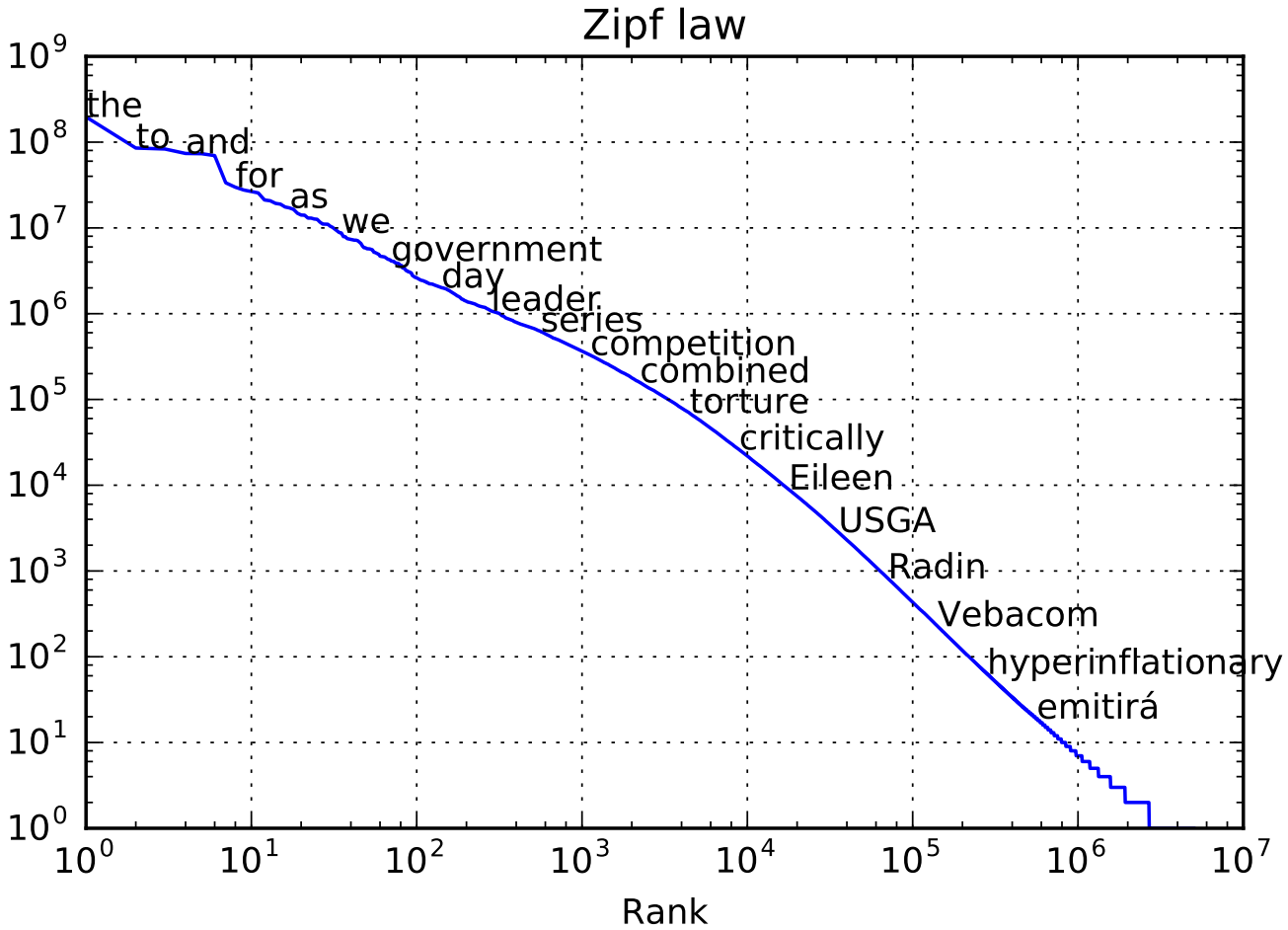


The Zipf law (for English)



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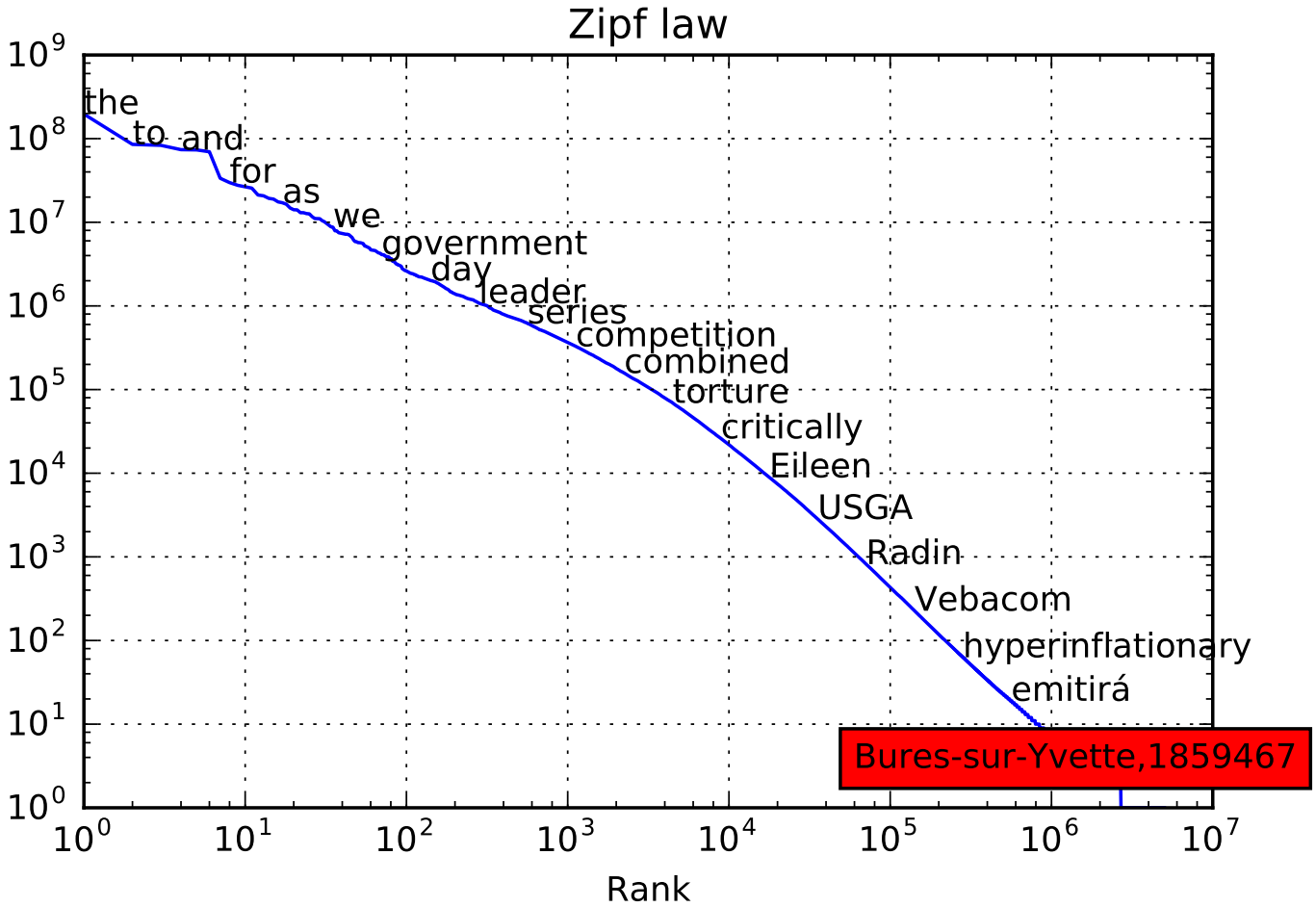


Consequences

Large vocabulary

- For many applications, $|\mathcal{V}| \propto 10^5$ or 10^6
- but most of the words quite never occur.

For n-gram model, it is even worse

- Most of n-grams never occur.

$\Rightarrow$ a restricted context ($n = 4, 5$ at most)

With 7 billions of running English words and $|\mathcal{V}| = 200\ 000$:

- $200\ 000^4 \approx 1.6 \times 10^{21}$ possible 4-grams,
- Hardly 1 billion observed
- Most of them just once

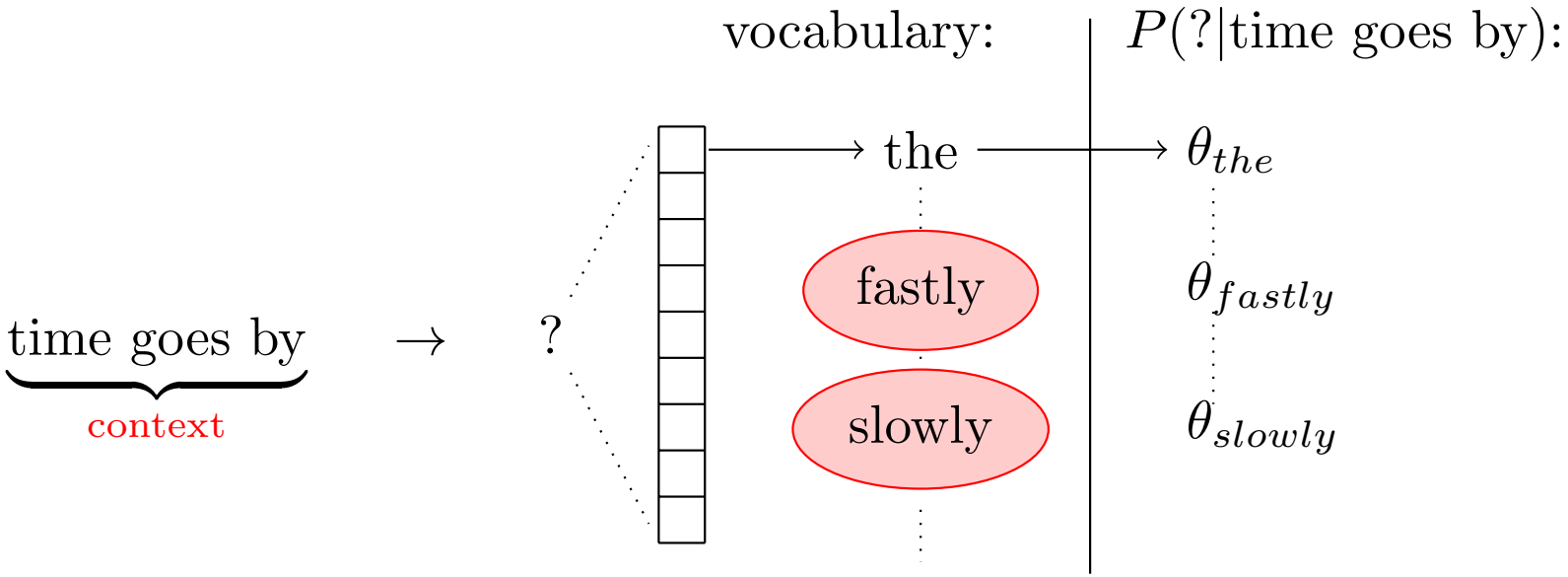
Some conventional remedies

- Increase the amount of data
- Smoothing methods (Chen and Goodman1998)

Lack of generalization - 1

A word given its context

$n = 4$:



- For each context, a multinomial distribution
- A word in its context = one parameter to learn

Lack of generalization - 1

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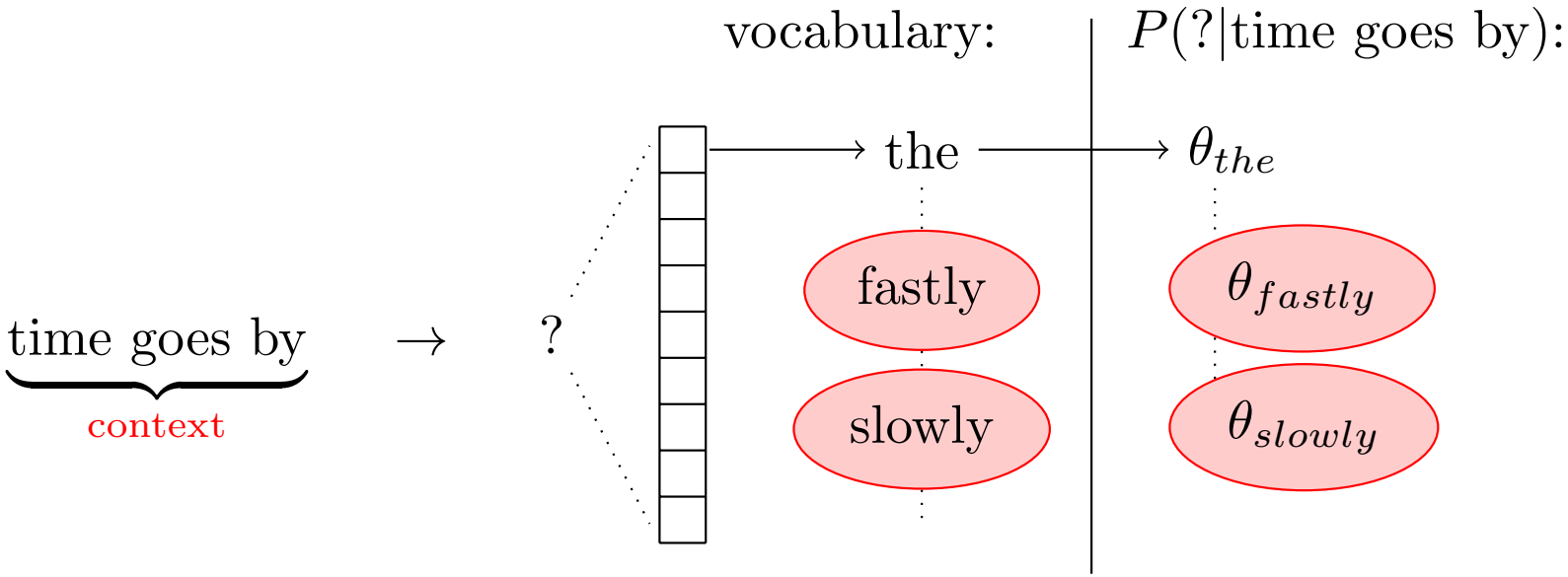
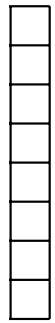


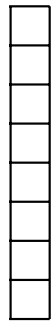
- For each context, a multinomial distribution
- A word in its context = one parameter to learn
- No parameter tying between words

$\Rightarrow$ No knowledge sharing

Lack of generalization - 2

and for different contexts

time goes by $\longrightarrow \boldsymbol{\theta}^{\text{time goes by}} =$ 

train goes by $\longrightarrow \boldsymbol{\theta}^{\text{train goes by}} =$ 

Each distribution is independant of the others

Sequence tagging

$$\mathbf{w} = w_1^L = w_1, w_2, ..., w_L$$
$$\mathbf{t} = t_1^L = t_1, t_2, ..., t_L$$

Example : Part-of-Speech (POS) tagging

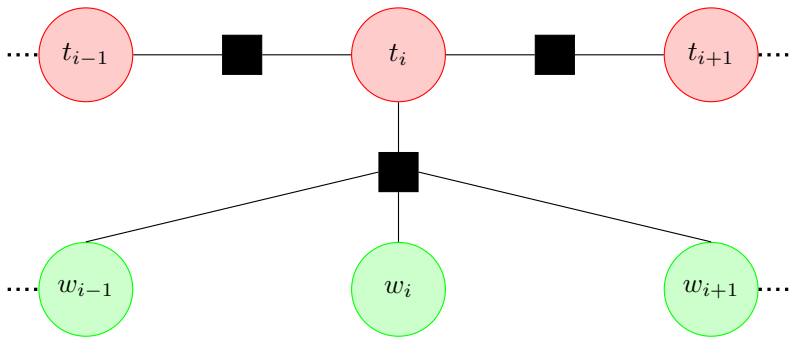
Sentence	POS-tags
Er	PPER-case=nom|@gender=masc|number=sg|person=3
fürchtet	VVFIN-mood=ind|number=sg|person=3|tense=pres
noch	ADV
Schlimmeres	NN-case=acc|gender=neut|number=sg
.	$.

Conditional Random Fields (CRF)

Linear chain

$$P(\mathbf{t}|\mathbf{w}) = \frac{1}{Z(\mathbf{w})} \prod_{i=1}^{L} \exp\Big(\langle \boldsymbol{\theta}, \boldsymbol{\phi}(t_i, t_{i-1}, \mathbf{w}) \rangle \Big)$$

$$= \frac{1}{Z(\mathbf{w})} \prod_{i=1}^{L} \exp\Big(\langle \boldsymbol{\theta}_u, \boldsymbol{\phi}_u(t_i, \mathbf{w}) \rangle + \langle \boldsymbol{\theta}_b, \boldsymbol{\phi}_b(t_i, t_{i-1}, \mathbf{w}) \rangle \Big)$$



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The basic feature template with binary indicators:

- $\boldsymbol{\phi}_u(t_i, \mathbf{w}) = \boldsymbol{\phi}_u(t_i, w_i) = \mathbb{I}\big(w_i \wedge t_i\big)$
- $\boldsymbol{\phi}_b(t_i, t_{i-1}, \mathbf{w}) = \boldsymbol{\phi}_b(t_i, t_{i-1}) = \mathbb{I}\big(t_{i-1} \wedge t_i\big)$
- ...

A hand-crafted word representation :

$$\boldsymbol{\theta}_u \longleftrightarrow \boldsymbol{\phi}_u(t_i, w_i)$$

$$\boldsymbol{\theta}_{u,t_i} \longleftrightarrow \boldsymbol{\phi}_{u,t_i}(w_i)$$

Word representation in CRF

Word representation may include:

- surface form

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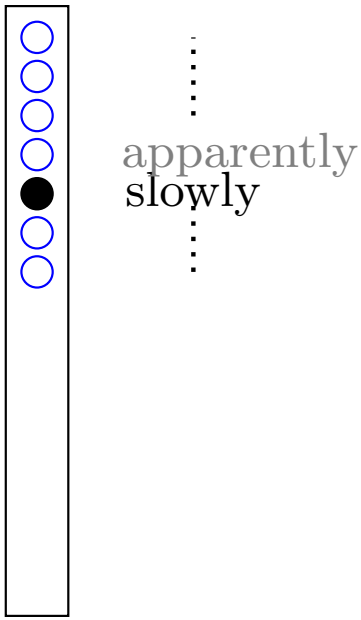
$w_i \rightarrow \mathbf{x}_i =$

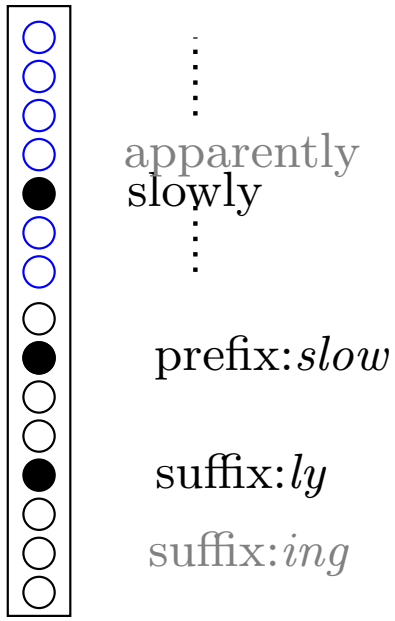


Word representation in CRF

Word representation may include:

- surface form
- prefix
- suffix
- ...

$w_i \rightarrow \mathbf{x}_i =$



Word vectors

A word is described by a feature vector: its representation or embedding

The goal

- address the sparsity issue
- a better generalization

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Drawbacks

- "expertise" is required and dedicated to the task, the language, the domain, ...
- in practice, relies on linguistic resources

Outline

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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In a nutshell

1. associate each word with a continuous feature vector
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3. learn simultaneously the feature vectors and the parameters of that probability function.

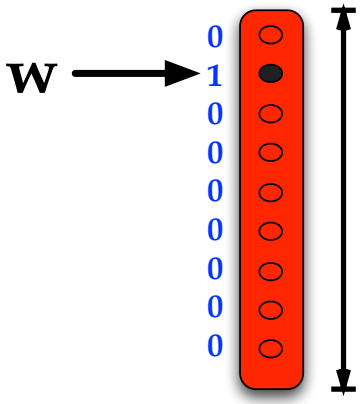
Why should it work ?

- "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 words into a continuous space

- The vocabulary is a neural network layer

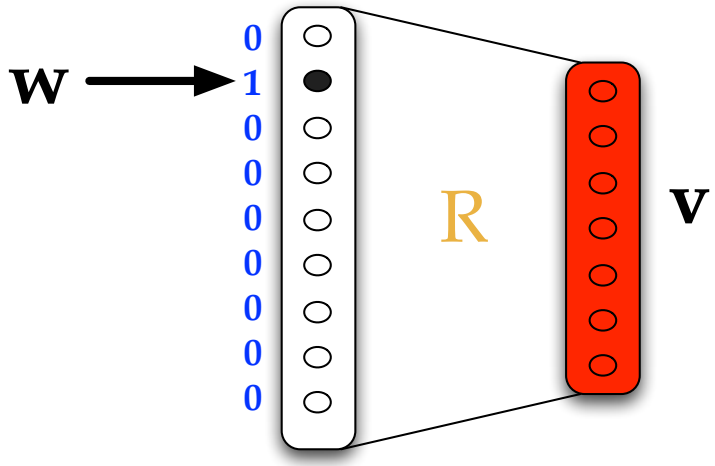


|V|: vocabulary size

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

Project a words into a continuous space

- The vocabulary is a neural network layer
- Word continuous representation:
  add a second layer fully connected



- The connection between two layers is a matrix operation
- The matrix **R** contains all the connection weights
- **v** is a continuous vector

Project a words into a continuous space

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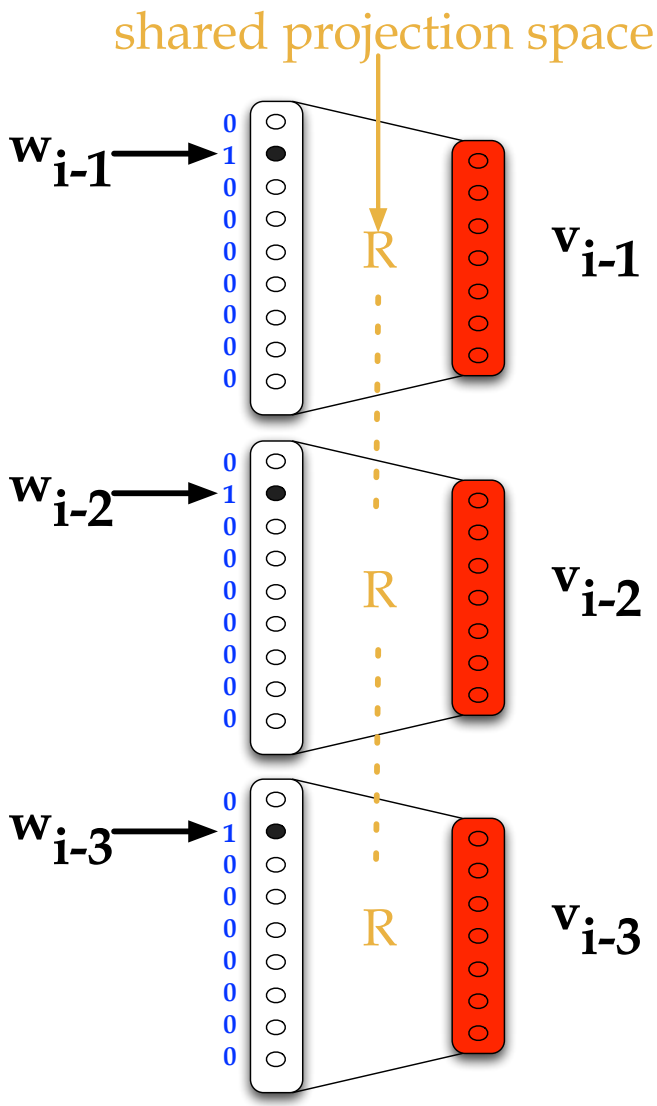
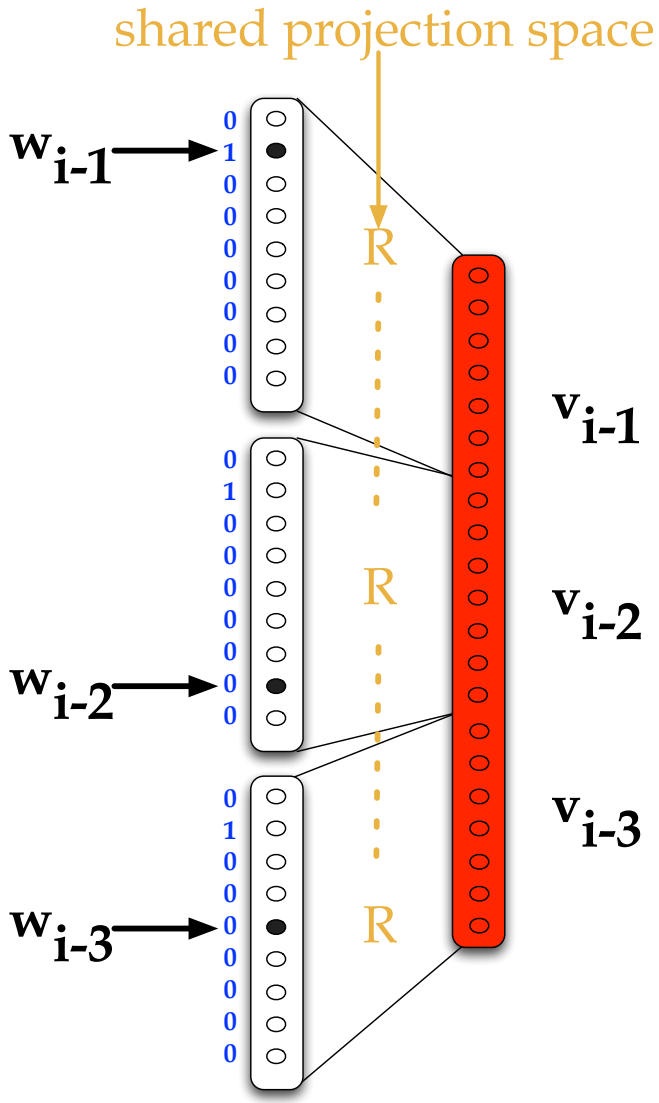
- For a 4-gram, the history is a sequence of
  3 words



Project a words into a continuous space

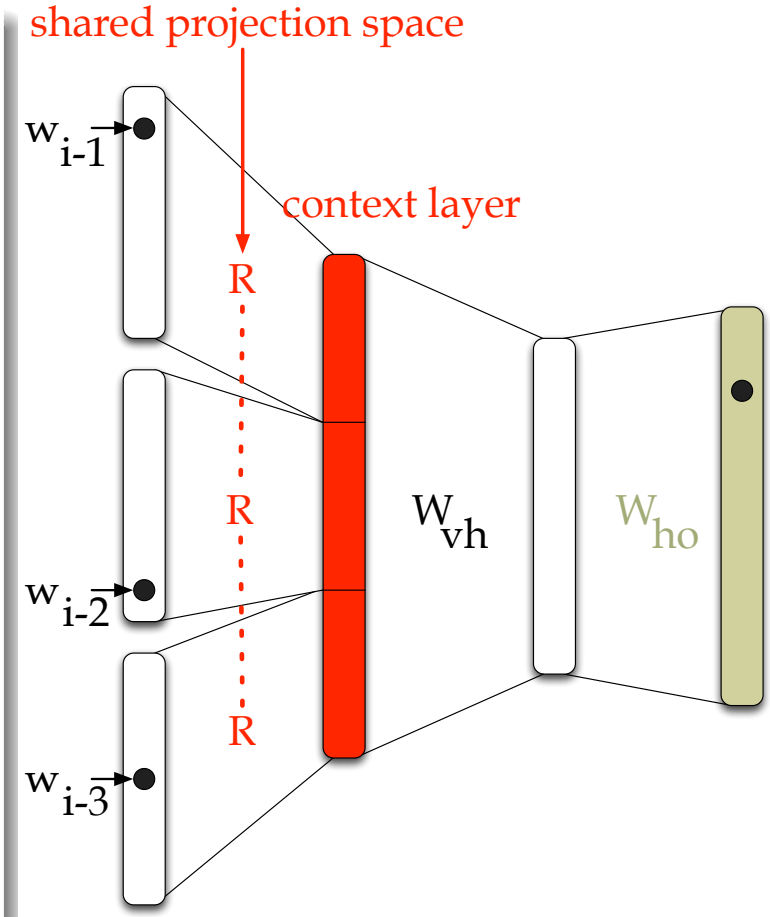
- The vocabulary is a neural network layer
- Word continuous representation: add a second layer fully connected
- For a 4-gram, the history is a sequence of 3 words
- Merge these three vectors to derive a single vector for the history



Estimate the n-gram probability

The program

- Given the history expressed as a feature vector : $\mathbf{v}$



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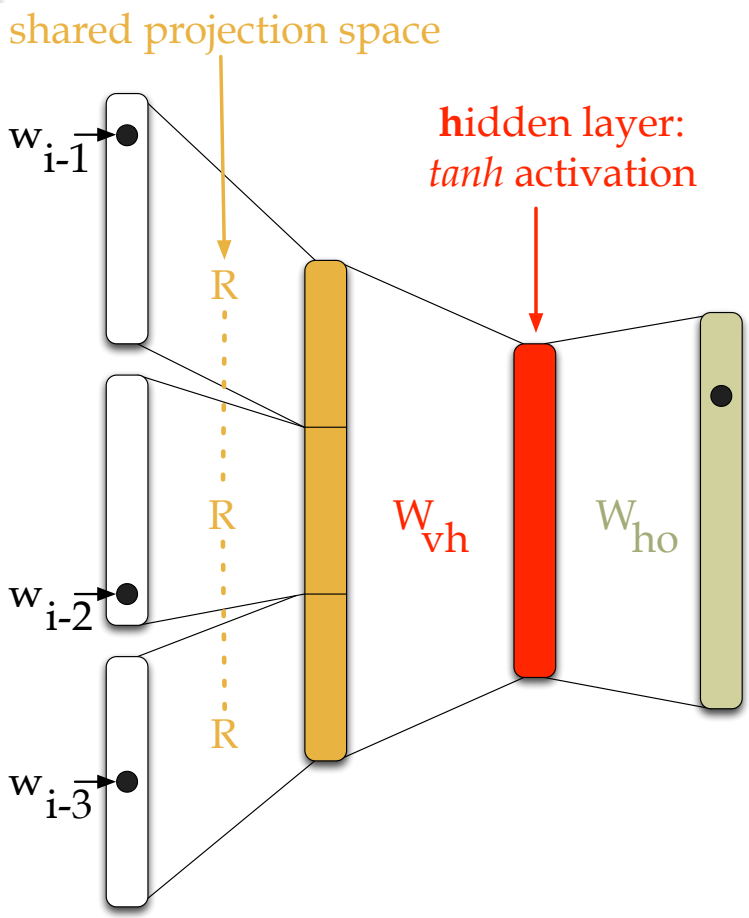
$$\mathbf{h} = f(\mathbf{W}_{vh}\mathbf{v})$$



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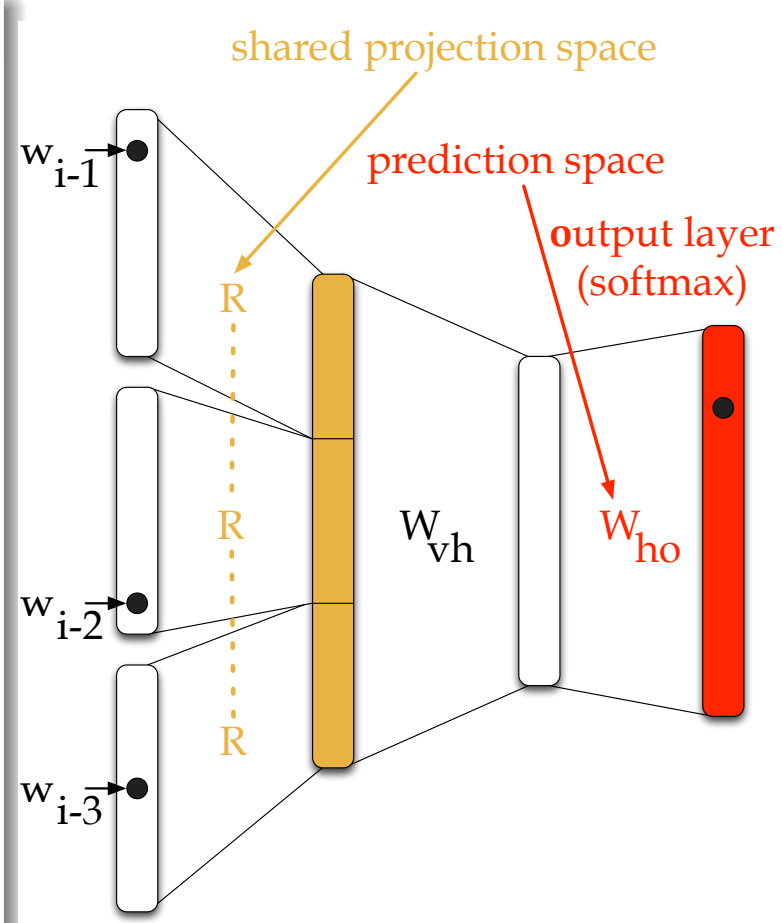
- Estimate probabilities for all words given the history:

$$\mathbf{o} = f(\mathbf{W}_{ho}\mathbf{h})$$

$$P(w|w_{i-n+1:i-1}) = \frac{\exp(o_{w_i})}{\sum_{w \in \mathcal{V}} \exp(o_{w_i})}$$



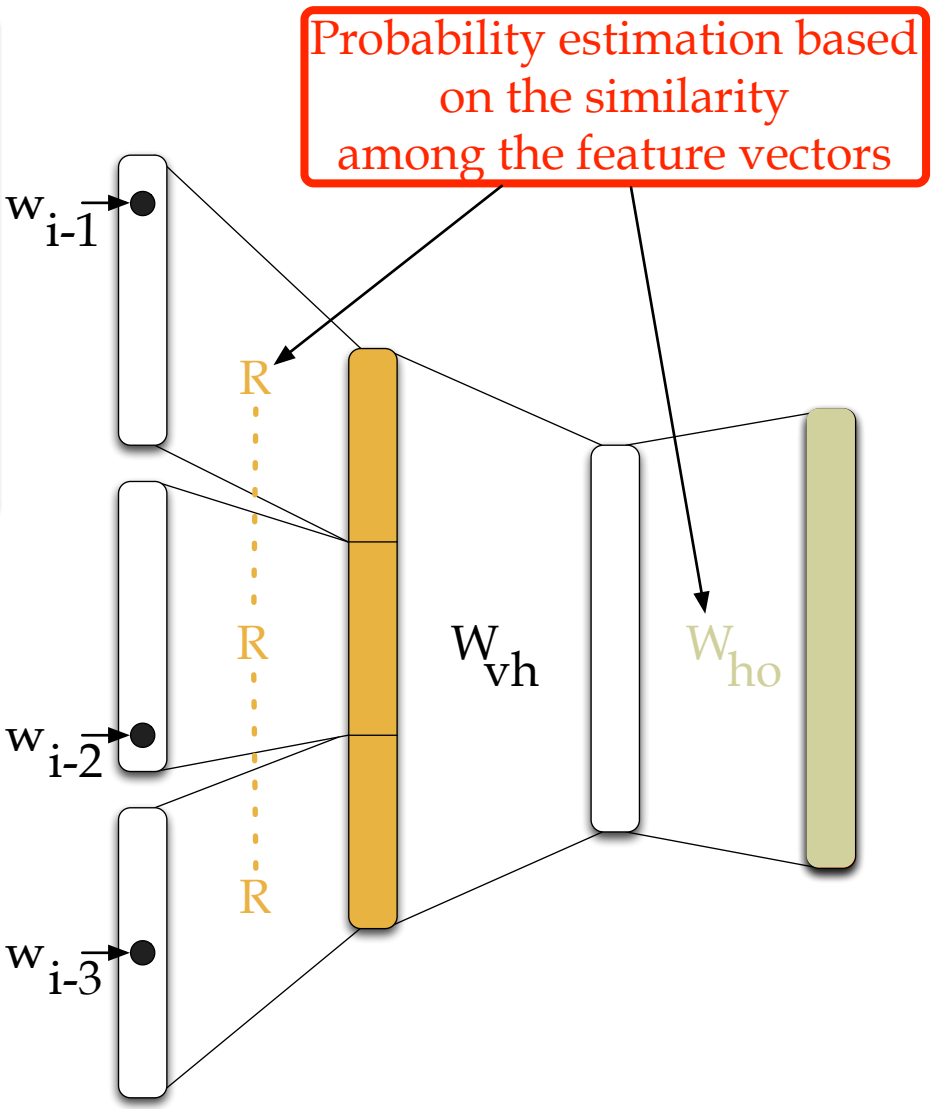
Early assessment

Key points

- The projection **in continuous spaces**

→ reduces the sparsity issues

- Learn simultaneously the projection and the prediction: $(\mathbf{R}, \mathbf{W_{vh}}, \mathbf{W_{ho}})$



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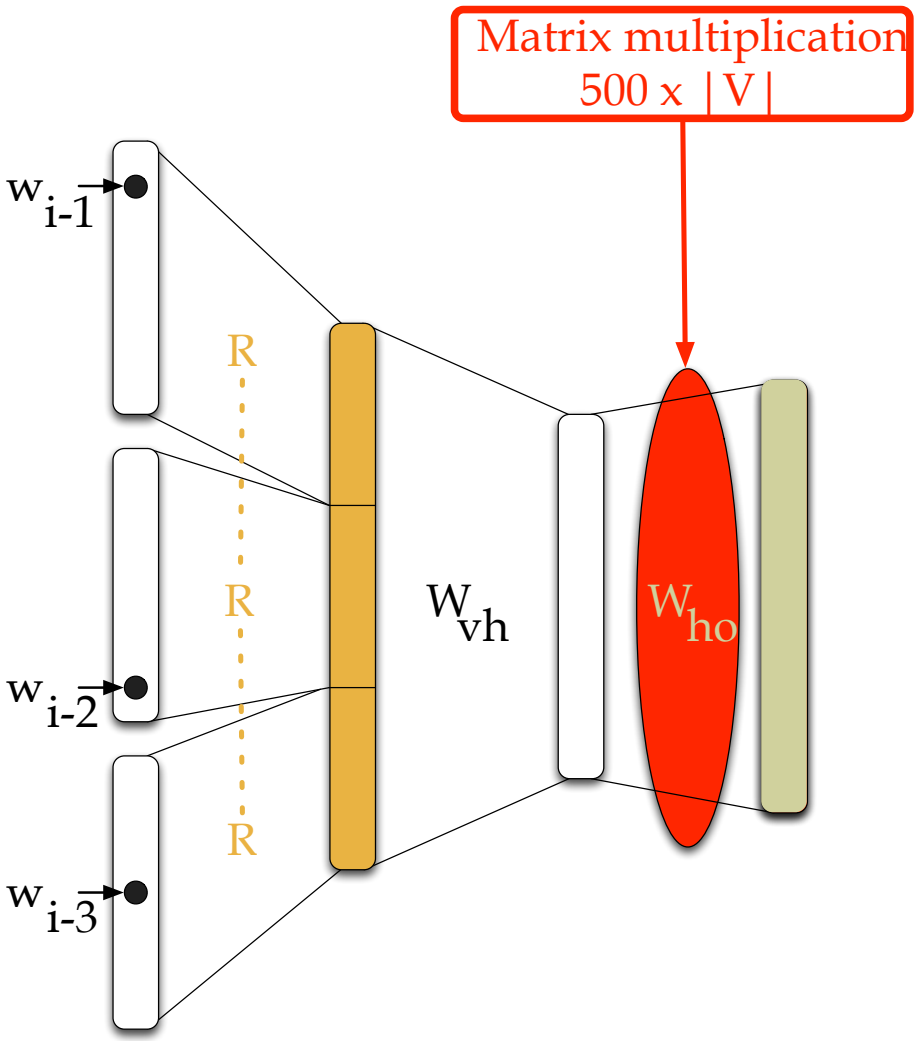
Complexity issues

- 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.**



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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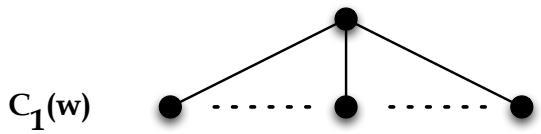
- Split these word classes in sub-classes $(c_2(w))$ and so on.



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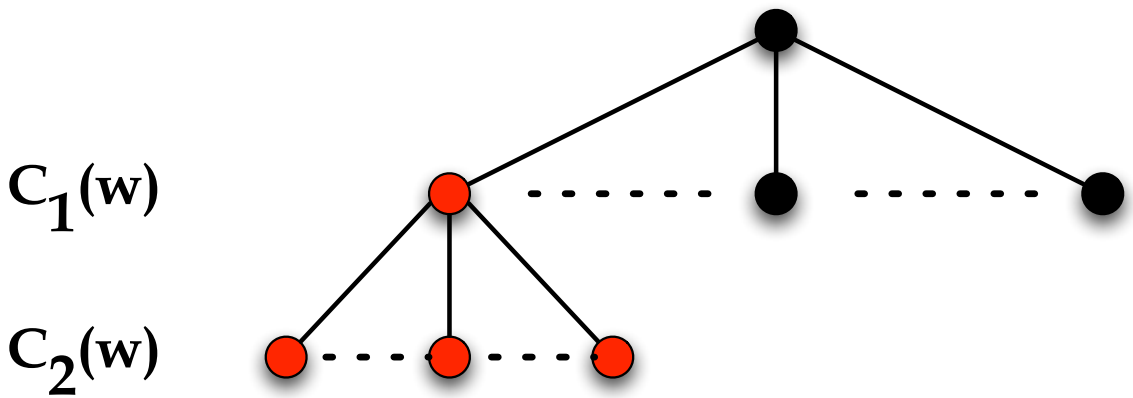


A solution : class-based language model

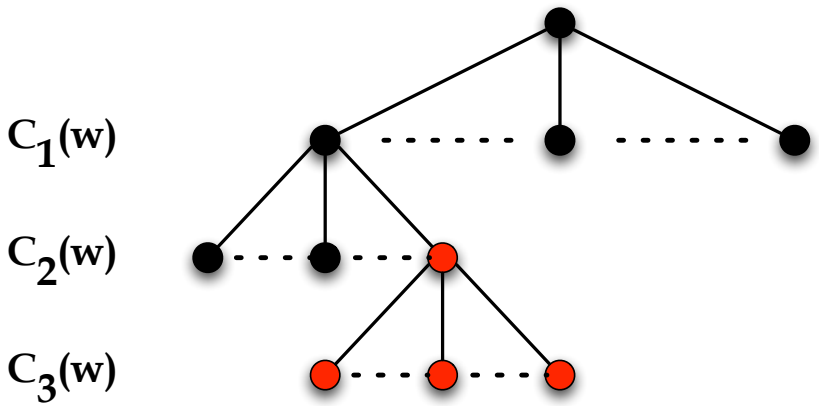
Main ideas

As proposed by (Mnih and Hinton2008):

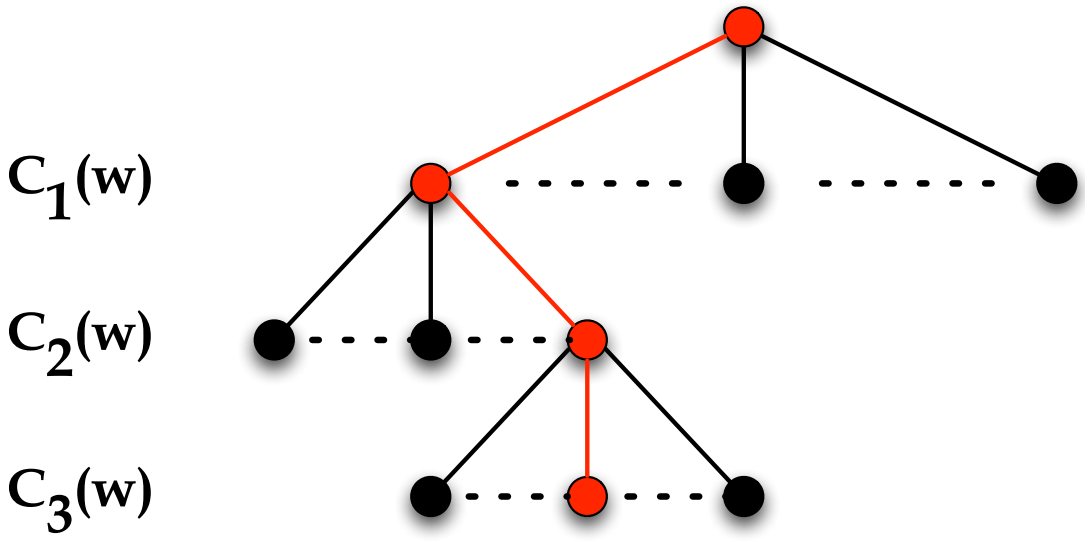
- Represent the vocabulary as a clustering tree (Brown et al.1992).
- Predict the path in this clustering tree.

Word clustering

- 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.



Word probabilities

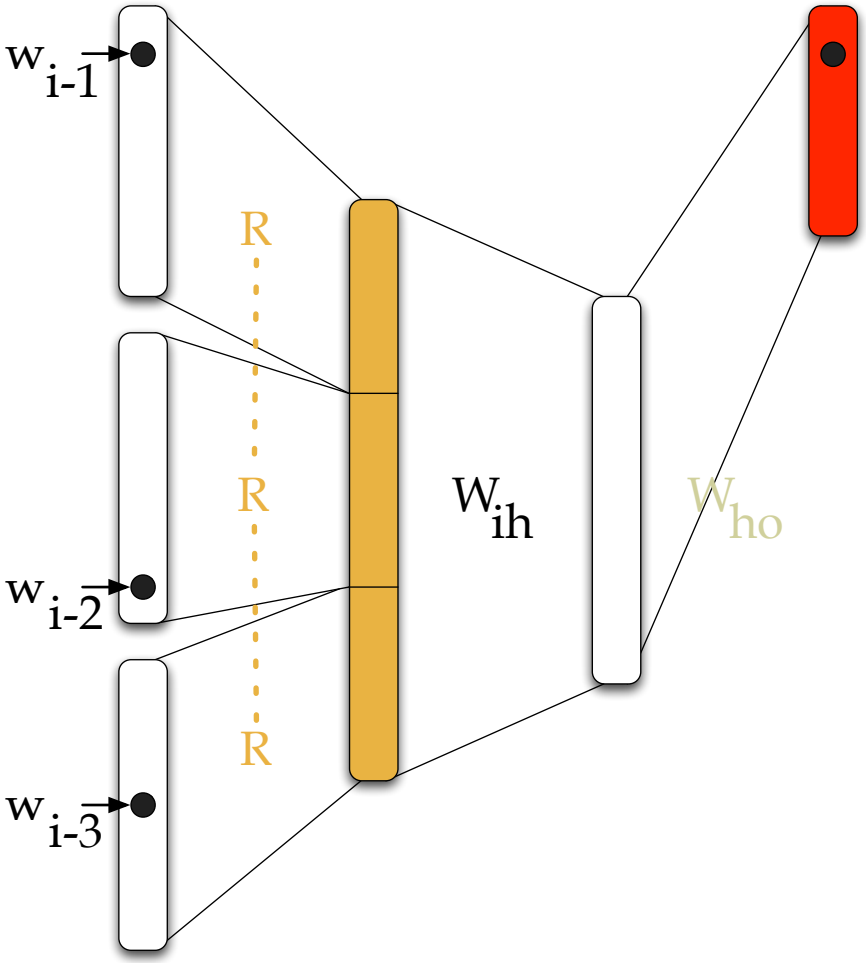


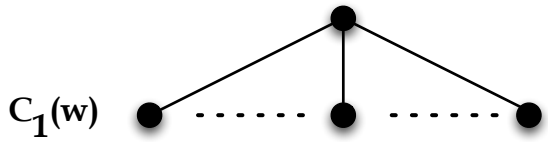
$$P(w_i|h) = P(c_1(w_i)|h) \prod_{d=2}^{D} P(c_d(w_i)|h, c_{1:d-1})$$

- $c_{1:D}(w_i) = c_1, \ldots, c_D$: 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

A solution for large vocabulary NLP tasks (Le et al.2011)





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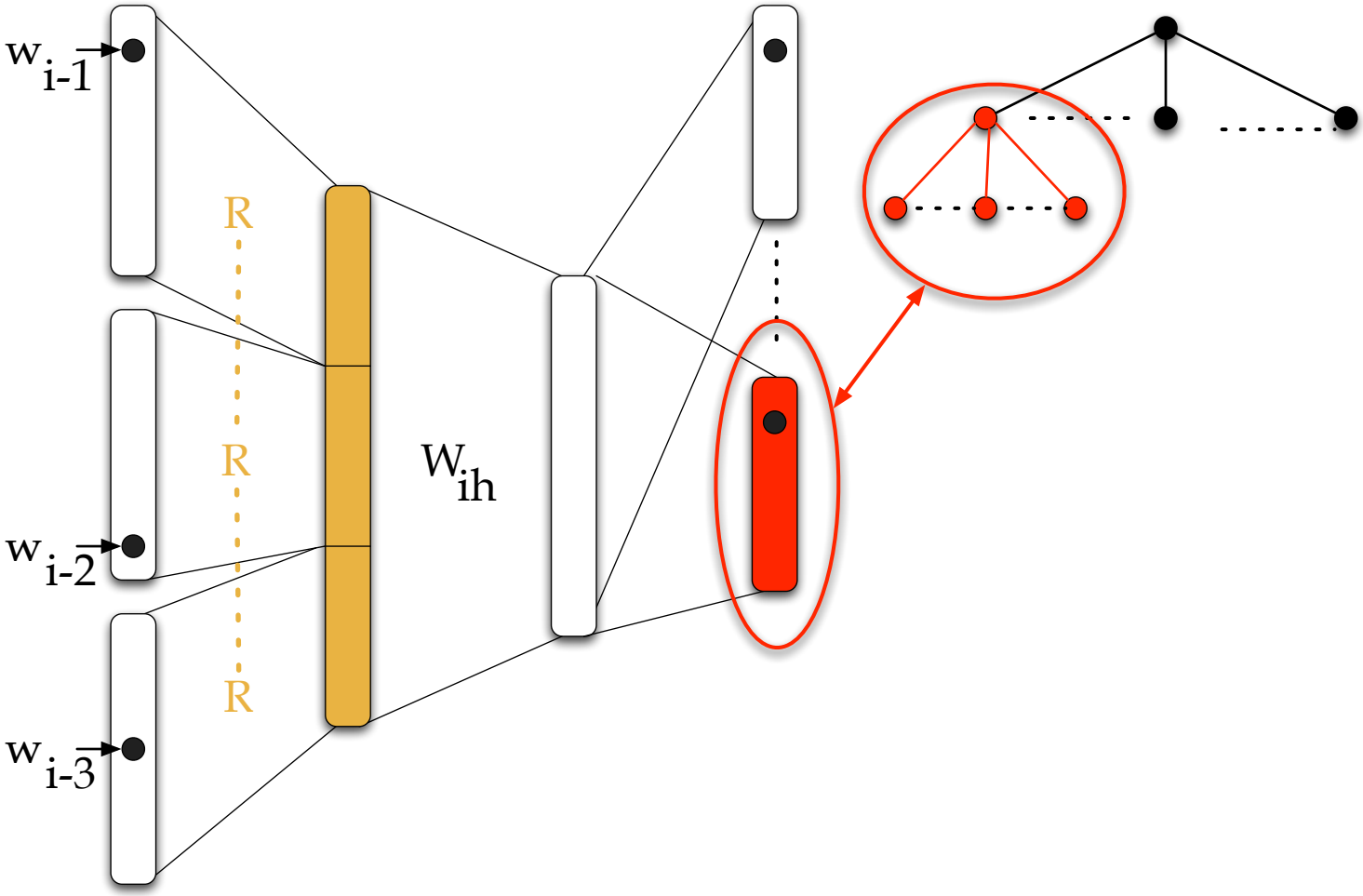

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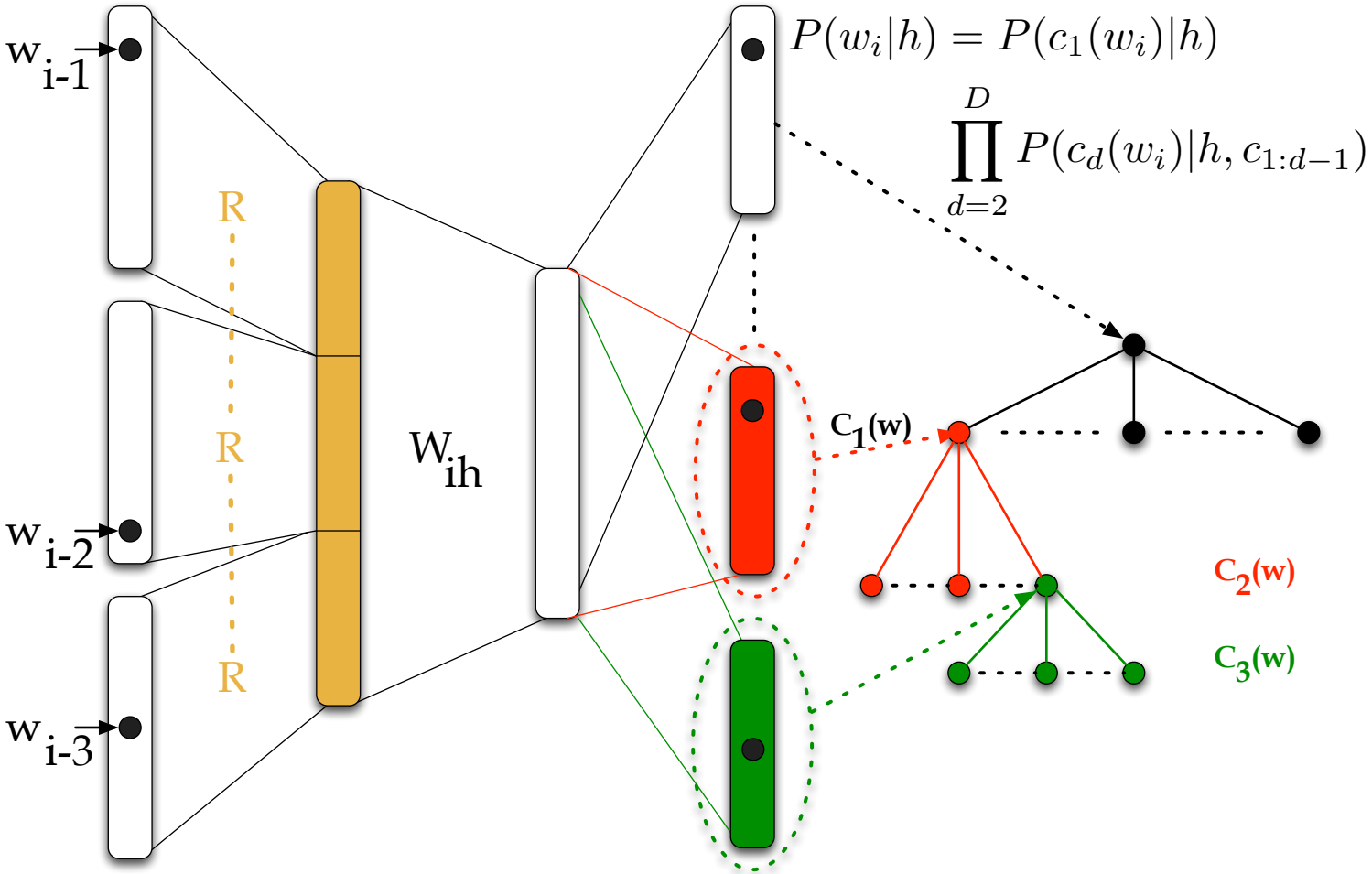


Experimental results

For automatic speech recognition

- On Mandarin Chinese and Arabic data (GALE)
- Significant improvements over state of the art systems.

For machine translation

WMT International evaluation campaign on european language pairs

best results for French-English in 2010 and 2011.

Extension to translation modeling (Le et al.2012)

Best results for French-English in 2012, 2013 and 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 (Santos and Zadrozny2014)

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

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

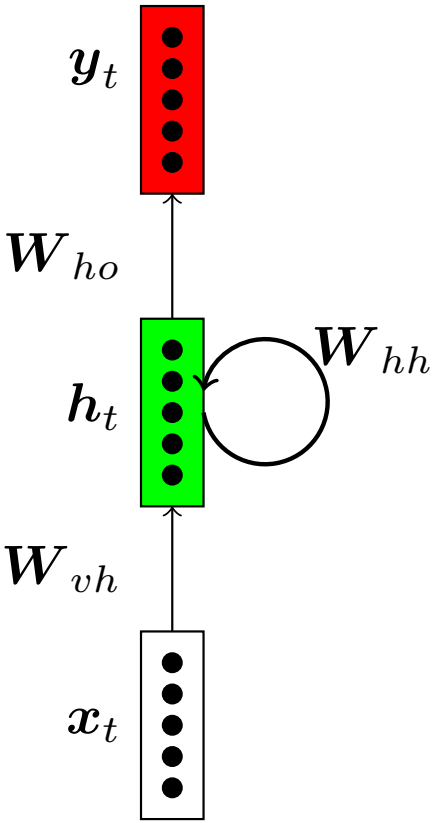
$\Rightarrow$ Make these representations aware of the context (sentence level)

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
.	$.

Recurrent network

Interlude



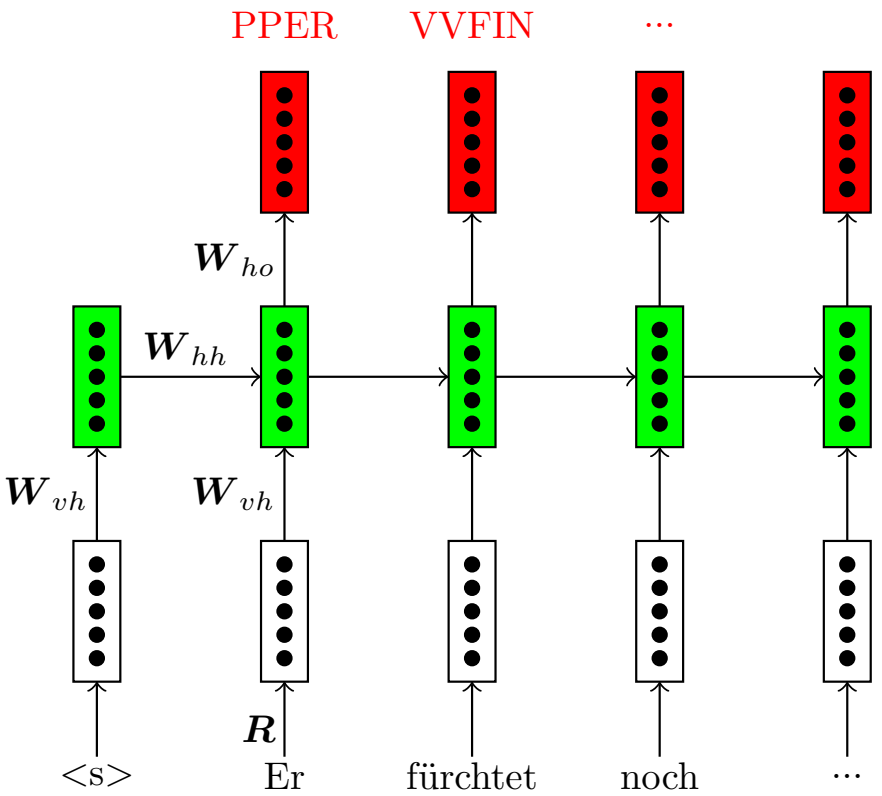
A dynamic system, at time t:

- 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 ($\boldsymbol{h}_t$)
- $\boldsymbol{x}_t$ comes from word embeddings

The same parameter set is shared across time steps

Recurrent network

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 $\boldsymbol{h}_t = f(\boldsymbol{W}_{vh}\boldsymbol{x}_t + \boldsymbol{W}_{\boldsymbol{hh}}\boldsymbol{h}_{\boldsymbol{t-1}})$
- The tag at t can be predicted from $\boldsymbol{h}_t$:

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

- g is the softmax function over the tagset

Training recurrent model

Training algorithm

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

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

Inference

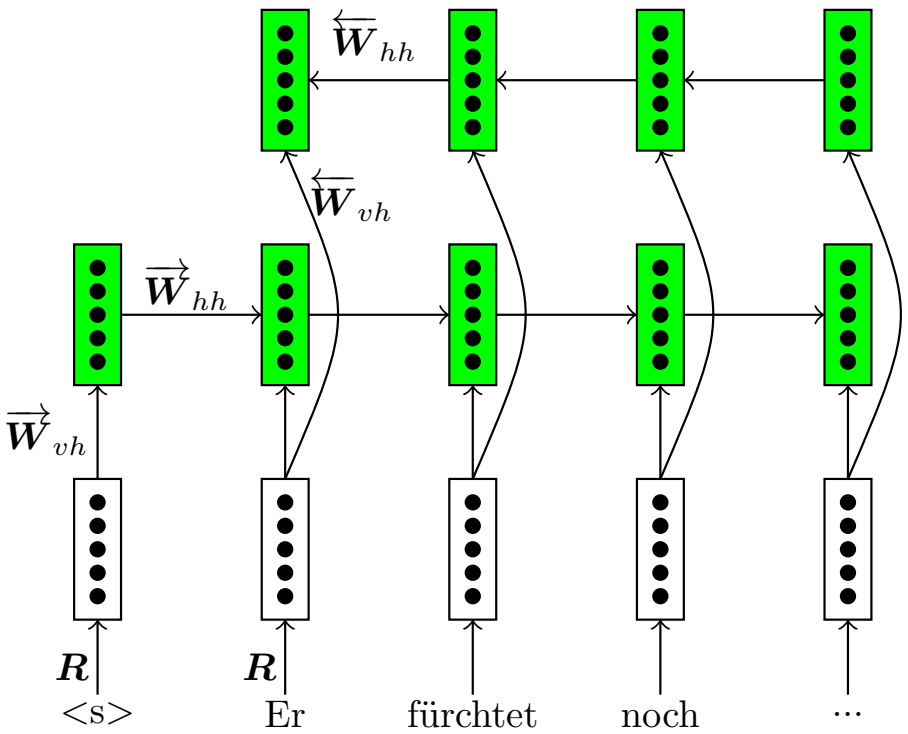
- Cannot be easily integrated to conventional approaches (ASR, SMT, ...)
- Well suited for sequence tagging
- $\boldsymbol{h}_t$ represent the word w_t in its left context
- A powerful device for end-to-end system

Known issues

- Vanishing gradient $\rightarrow$ LSTM
- Long-term memory $\rightarrow$ Bi-recurrent network

Bi-recurrent network

Unfolding the structure: a deep-network



At each step t, from left to right

- $w_t \rightarrow \boldsymbol{x}_t$
- $\overrightarrow{\boldsymbol{h}}_t = f(\overrightarrow{\boldsymbol{W}}_{vh}\boldsymbol{x}_t + \overrightarrow{\boldsymbol{W}}_{hh}\overrightarrow{\boldsymbol{h}}_{t-1})$

At each step t, from right to left

- $w_t \rightarrow \boldsymbol{x}_t$
- $\overleftarrow{\boldsymbol{h}}_t = f(\overleftarrow{\boldsymbol{W}}_{vh}\boldsymbol{x}_t + \overleftarrow{\boldsymbol{W}}_{hh}\overleftarrow{\boldsymbol{h}}_{t-1})$

For the prediction :

$$\boldsymbol{y}_t = g(\boldsymbol{W}_{ho}[\overrightarrow{\boldsymbol{h}}_t; \overleftarrow{\boldsymbol{h}}_t])$$

$[\overrightarrow{\boldsymbol{h}}_t; \overleftarrow{\boldsymbol{h}}_t]$ is a contextual representation of w_t

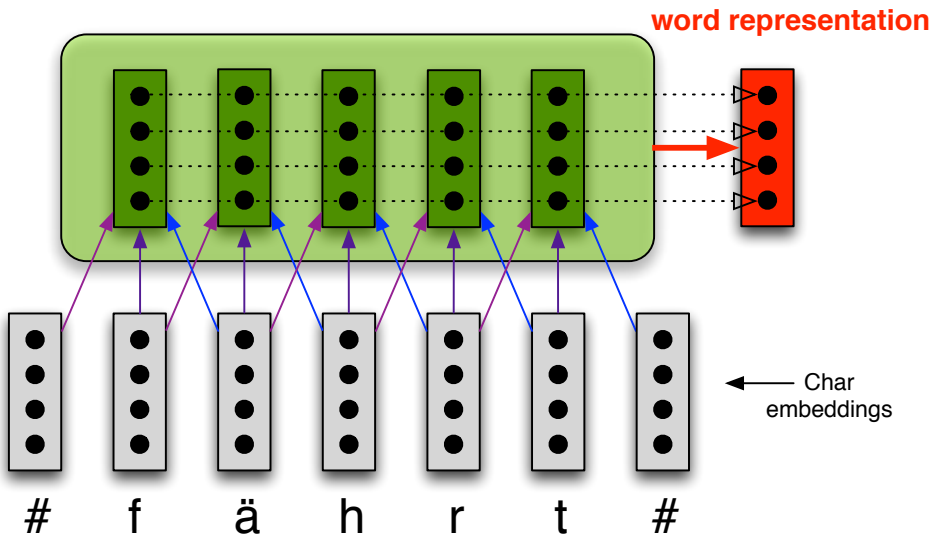
From characters to word representation

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)

Convolutional net + 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

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

Outline

Summary

Neural Networks : how to efficiently represent language data

- To address the sparsity issue
- To deal with large (output) vocabulary
- To handle different kinds of contexts

Ongoing work

End-to-end neural system for complexe tasks:

- Automatic speech recognition
- Machine translation
- Summarization, ...

World Wide NLP

Everyone does not speak like the Wall Street Journal

All the other languages

- Access to resources is very uneven and patchy:

→ under-resourced languages

→ different morphological, syntactical and semantical properties

Freundschaftsbezeigungen, görüntülenebilir

Cultural heritage and digital humanities

- Allow users to communicate in their native language
- Preserve the language diversity
- Language studies

User generated content

User generated content

URaQT ;-) I<3U BFF CUL8R 4evER !!!

- Social Media implies fast change in the language use and writting style
- Spontaneous and noisy

→ An evolving vocabulary with new compound tokens, abbreviations, ...

Challenges

- Learning to decipher new texts
- NLP is not "context free"
- Linked-data processing (image, video, speech and sounds)

Thank you for your attention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