MDI 341 - Machine Learning avancé

Machine Learning for Natural Language Processing : Sequence modeling

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Outline

- Introduction: Language modeling
- N-gram Neural Language Model
- Reccurent Language Model and extensions
- Convolutional architectures in NLP
- NMT and Sequence-to-Sequence models
- References

A central task: Language Modeling

What is language modeling ?

$\rightarrow$ A Language Model (**LM**) can:

- Compute the probability of a sentence:

$$P(\text{What is language modeling ?}) = ?$$

- Compute the probability of a word, given previous ones (**context**):

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$\rightarrow$ Language models are mainly used to rank word and sentences probabilities for various tasks:

$$P(\text{What is language modeling ?}) > P(\text{What language modeling is ?})$$

$$P(\text{modeling}|\text{What is language}) \; > P(\text{learning}|\text{What is language})$$

A central task: Language Modeling

Applications ?

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$$P(\text{'recognize speech'}) > P(\text{'wreck a nice beach'})$$

- Speech Recognition

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- Information Retrieval
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- Question Answering
- ... and many other tasks (including anything that necessitate **Text Generation**)

Counting words

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But: There is too many possible sentences and not enough data !

$\rightarrow$ We use the simplifying **Markov assumption**:

$$(\text{Order 1}) \quad P(\text{modeling}|\text{What is language}) \approx \; P(\text{modeling}|\text{language})$$

$$\downarrow$$

$$(\text{Order m}) \quad P(w_i|w_1, ..., w_{i-1}) \approx \; P(w_i|w_{i-m}, ..., w_{i-1})$$

N-gram models

With the **Markov assumption** and the **chain rule**, we obtain simple language models:

$$\text{(Order 1: Unigram)} \qquad P(w_1, ..., w_n) \approx \prod_{i=1}^{n} P(w_i)$$

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$\rightarrow$ They can be extended to trigram, 4-gram, 5-gram LMs

- Because of long-term dependancies, this is in general insufficient to model language !
- However, n-gram models are still used in numerous applications

N-gram models: Estimating probabilities

$$P(\text{What is language modeling}) \approx P(\text{What}) \times P(\text{is} \mid \text{What})$$
$$\times P(\text{language} \mid \text{is}) \times P(\text{modeling} \mid \text{language})$$

Some practical advice:

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- Represent the beginning and end of sentences with special tokens:

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- Represent rare words with another special token:

$$\text{What is language}\ <\text{UNK}>\ ?$$

N-gram models: Evaluation

- **Extrinsic** evaluation:

  Apply the models that we want to compare on a a task, and use the related metric !

  $\rightarrow$ It's time consuming, and can vary a lot depending on tasks !

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- **Intrinsic** evaluation - **Perplexity**:

  A measure of *uncertainty*: how surprised is the model by the data ?

  $\rightarrow$ On test data, lower is better !

$$Perplexity(w_1, ..., w_n) = \sqrt[n]{\prod_{i=1}^{n} \frac{1}{P(w_i | w_{i-m}, ..., w_{i-1})}}$$

  - Can be interpreted as a *branching factor*
  - But is **tied to a particular vocabulary** $\mathcal{V}$
  - Is not great at tracking progress and measuring performance

N-gram models: Generalization

- **Zero probability n-grams**:
  In a corpus, occuring n-grams represent a very small part of the possible n-grams.
  $\rightarrow$ In Shakespeare's work (Example from Dan Jurafsky):
  - 884,647 tokens and a vocabulary of 29,066 words
  - 300K out of the 844M bigrams appear (0,04%) !

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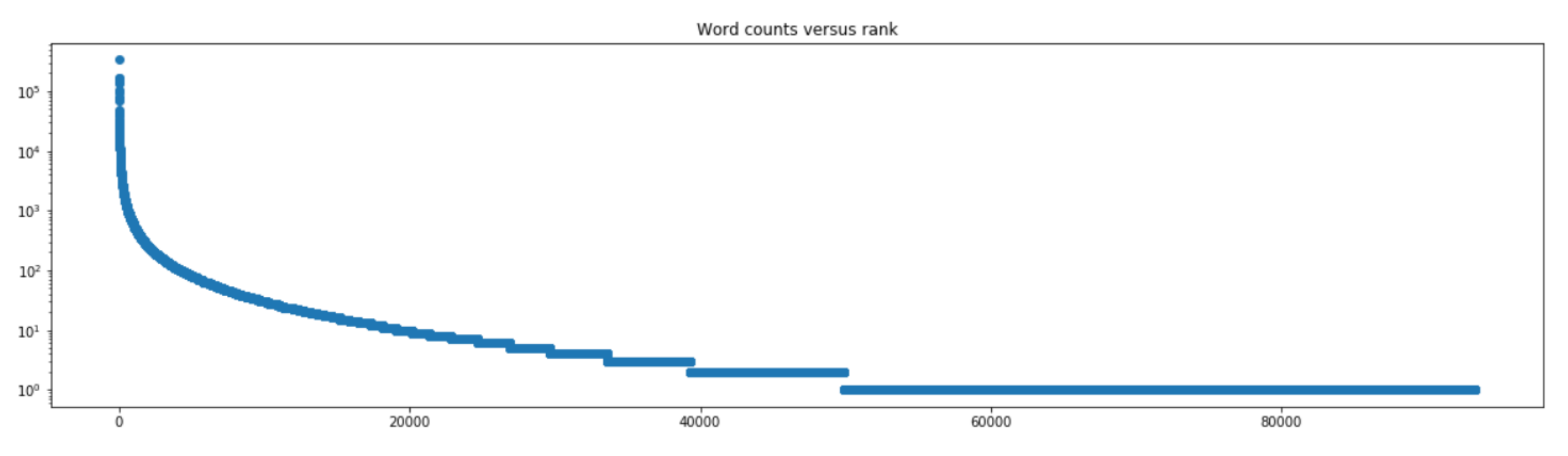
- Tied to **Zipf's Law**: $frequency \propto 1/rank$



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- **Kneyser-Ney smoothing**:
  Considers probabilities in relation to higher orders: we need to look at $P(\text{San Francisco})$ to correctly use $P(\text{francisco})$
  $\rightarrow$ Still widely used as fast and easy to train baseline !

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Applied to speech recognition *(Schwenk and Gauvain, 2002)* and machine translation.

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- **Continuous probability function**: The probability of the next word is expressed as a continuous function of the features of the word in the current context - using a feedforward neural network
- **Joint learning**: Both the parameters of the word representation and of the probability function are learnt jointly.

NPLM: Joint learning

Why should it work ?

$\rightarrow$ Continuity !

The probability function is smooth, implying that a small change in the feature vector will induce a small change in the probability.

Hence, the updates caused by having the following sentence:

$$\text{A dog was running in a room}$$

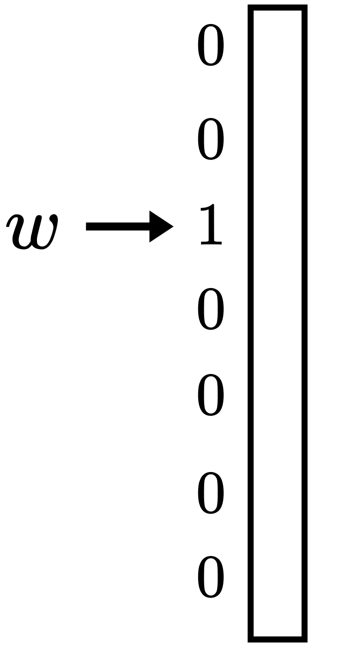
in the training data will increase the probability of all 'neighbor' sentences. Having also the following sentence:

$$\text{The cat was running in a room}$$

will make the features of the words (dog, cat) get close to each other.

NPLM: Projecting words

- The first layer is the **vocabulary** $\mathcal{V}$: the input is a one-hot vector.



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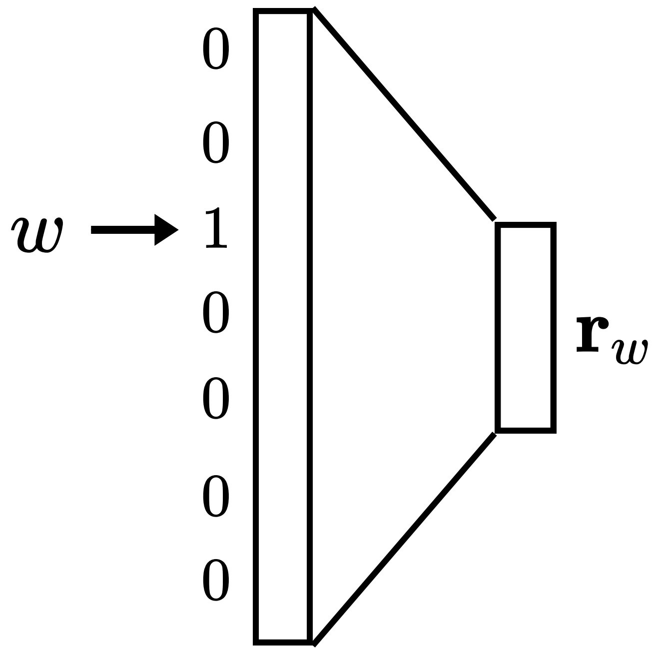

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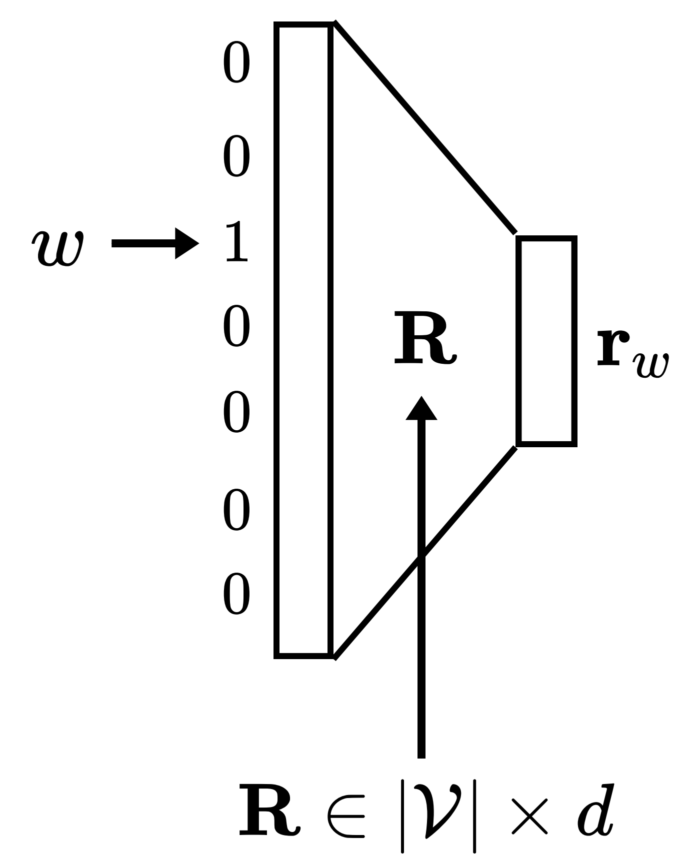

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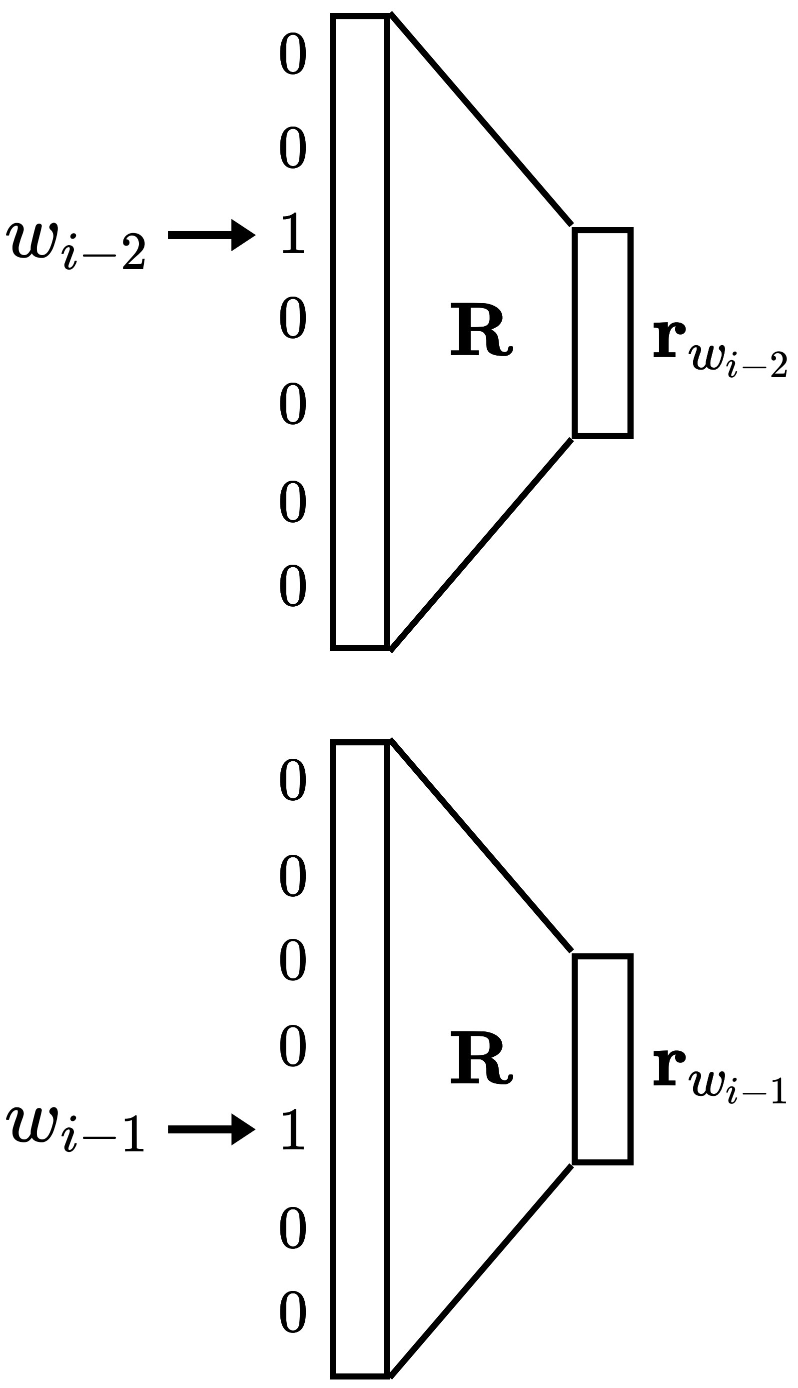

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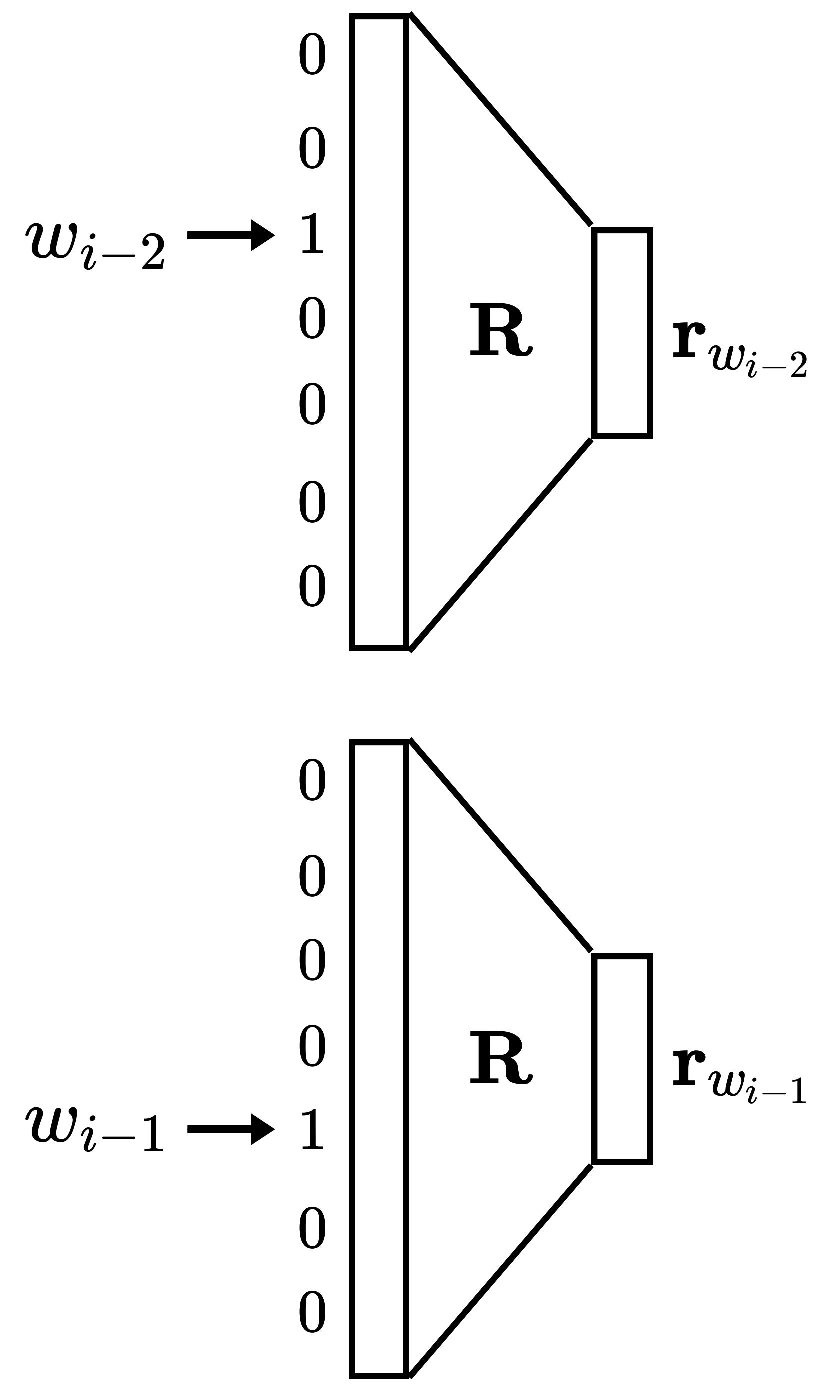

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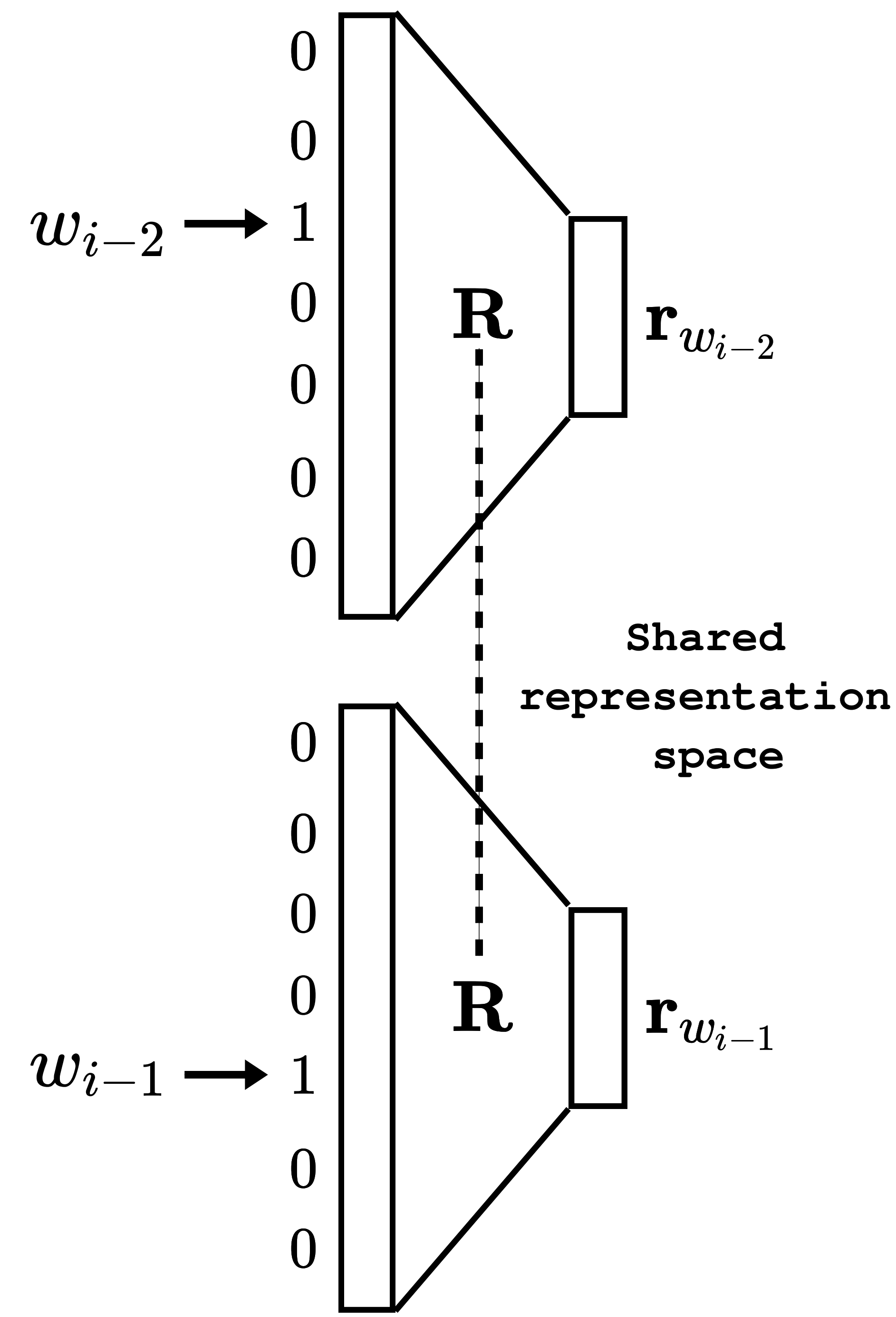

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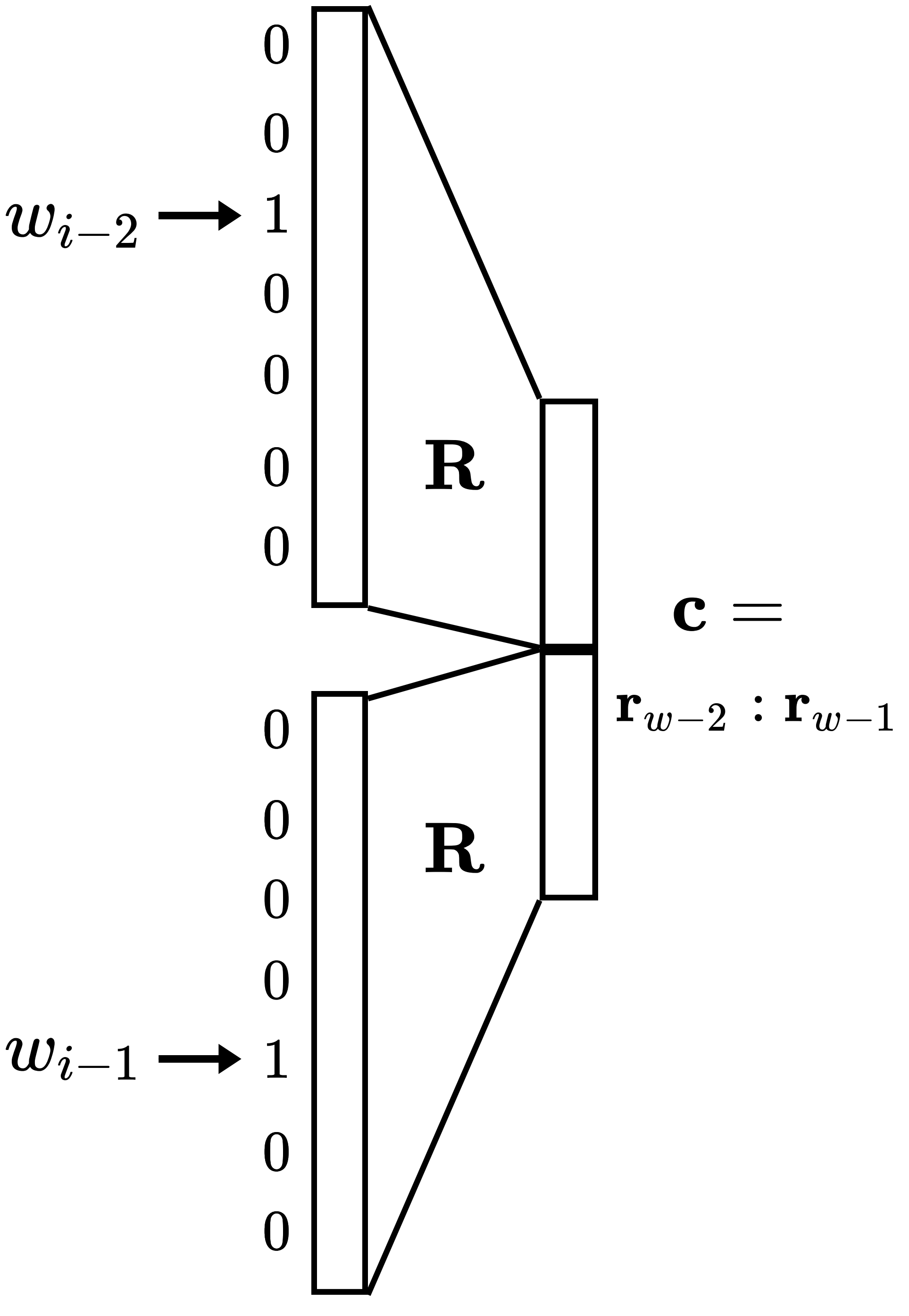
- For a trigram model, we project two words
- These are merged into a single vector $\mathbf{c}$ representing the context



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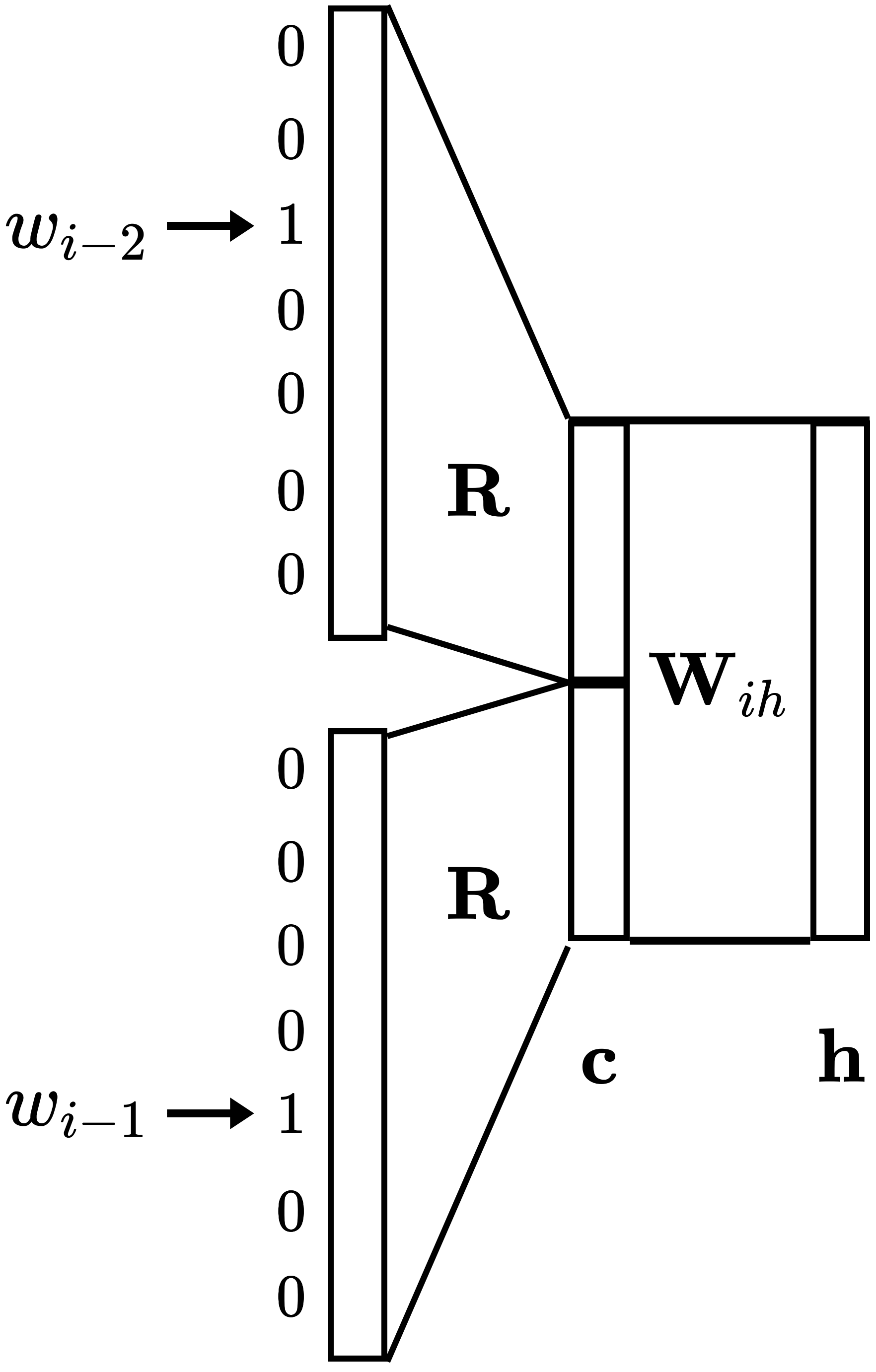
- Given the context representation $\mathbf{c}$, create a hidden representation:

$$\mathbf{h} = \phi(\mathbf{W}_{ih}\mathbf{c})$$



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- Then, estimate probabilities for all words in $\mathcal{V}$ given $\mathbf{h}$, with the softmax function:

$$\mathbf{o} = \mathbf{W}_{ho}\mathbf{h}$$

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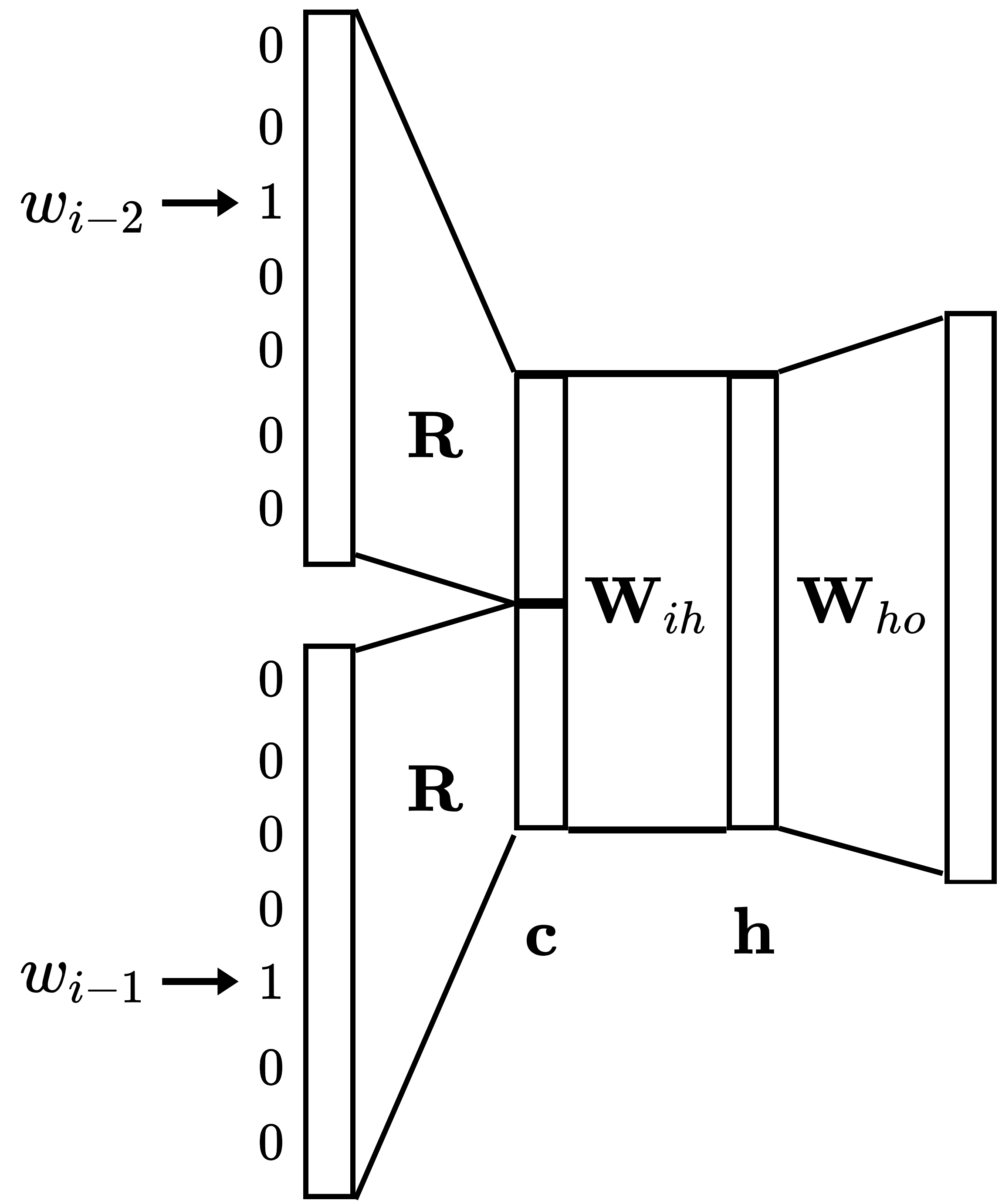

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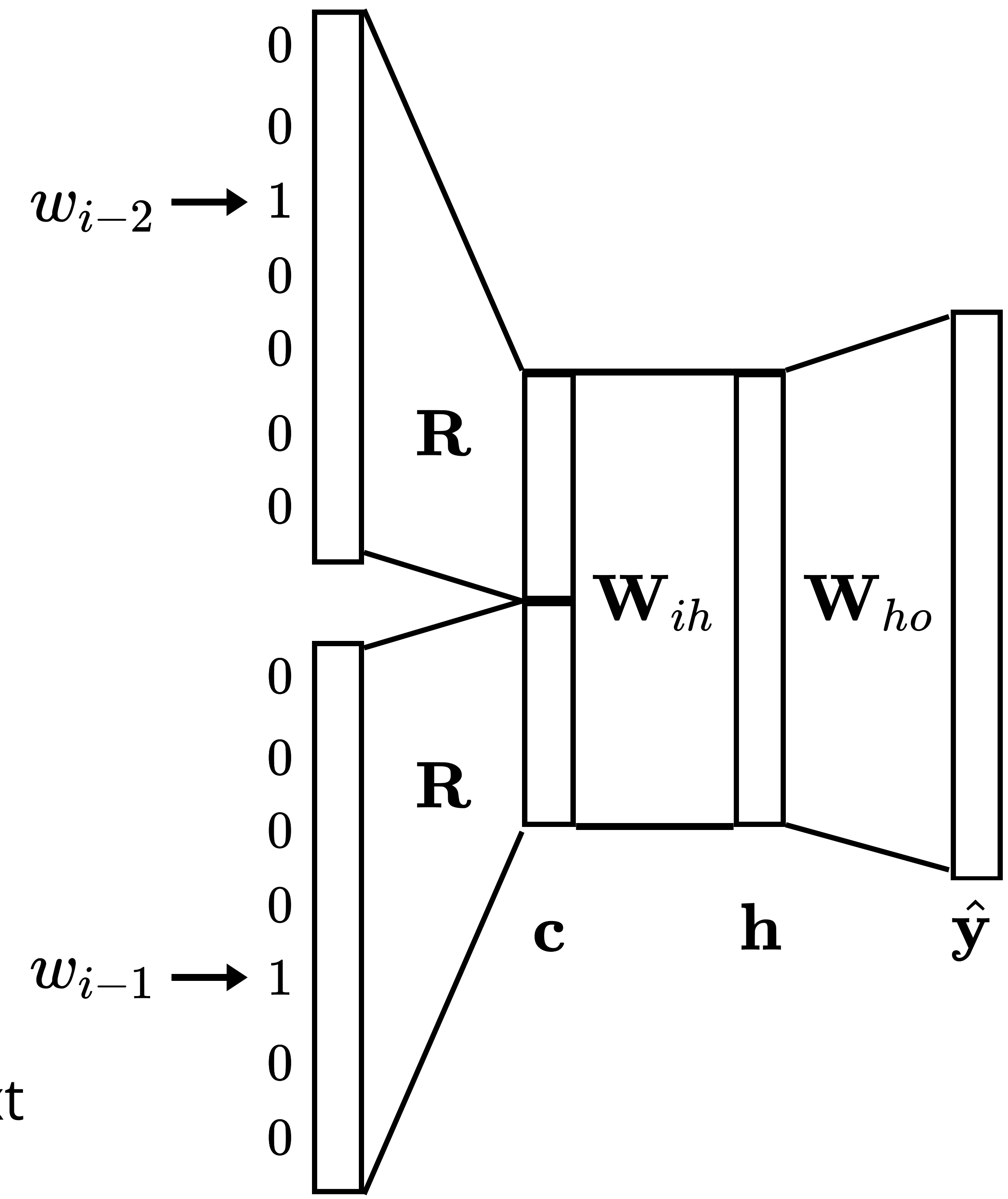
$$P(w|w_{i-1}, w_{i-2}) = \frac{\exp(\mathbf{o}_w)}{\sum_{w' \in \mathcal{V}} \exp(\mathbf{o}_{w'})}$$

- We note the predicted vector as $\hat{\mathbf{y}}$:

$$\hat{\mathbf{y}}_{i-1} = (P(w|w_{i-2}, w_{i-1}))_{w \in \mathcal{V}}$$

and use the *argmax* to choose the next word.



NPLM: Assessment

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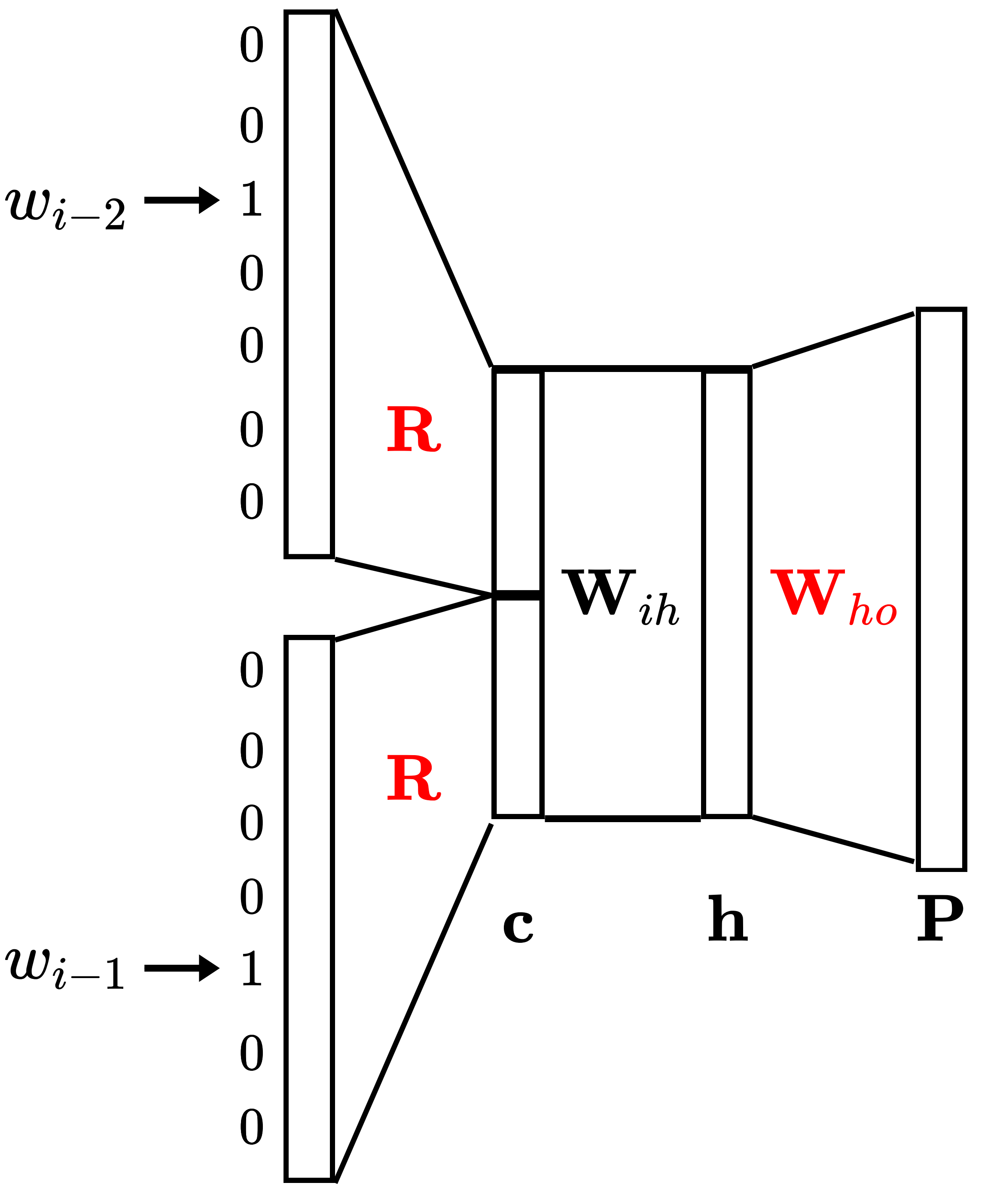

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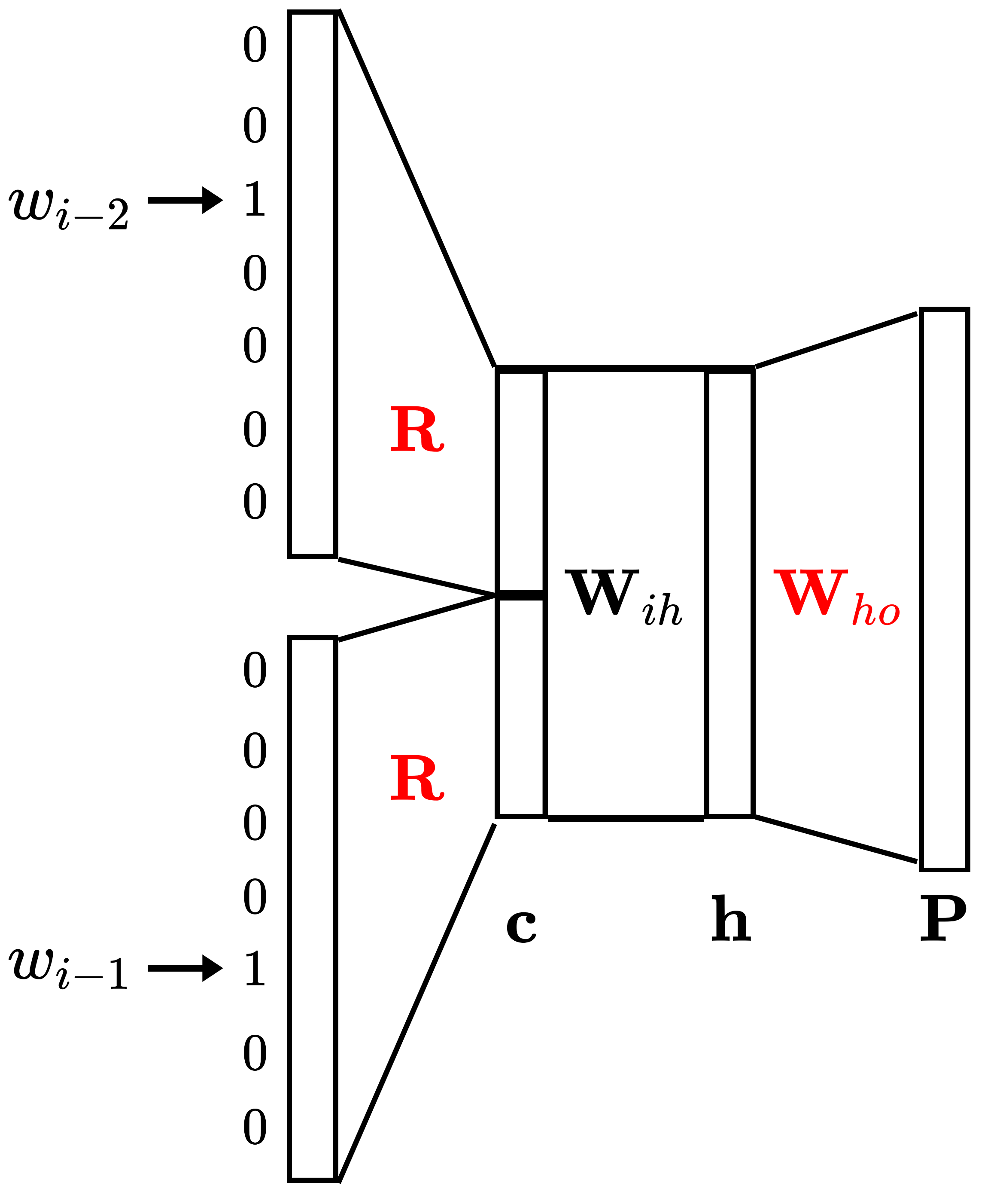

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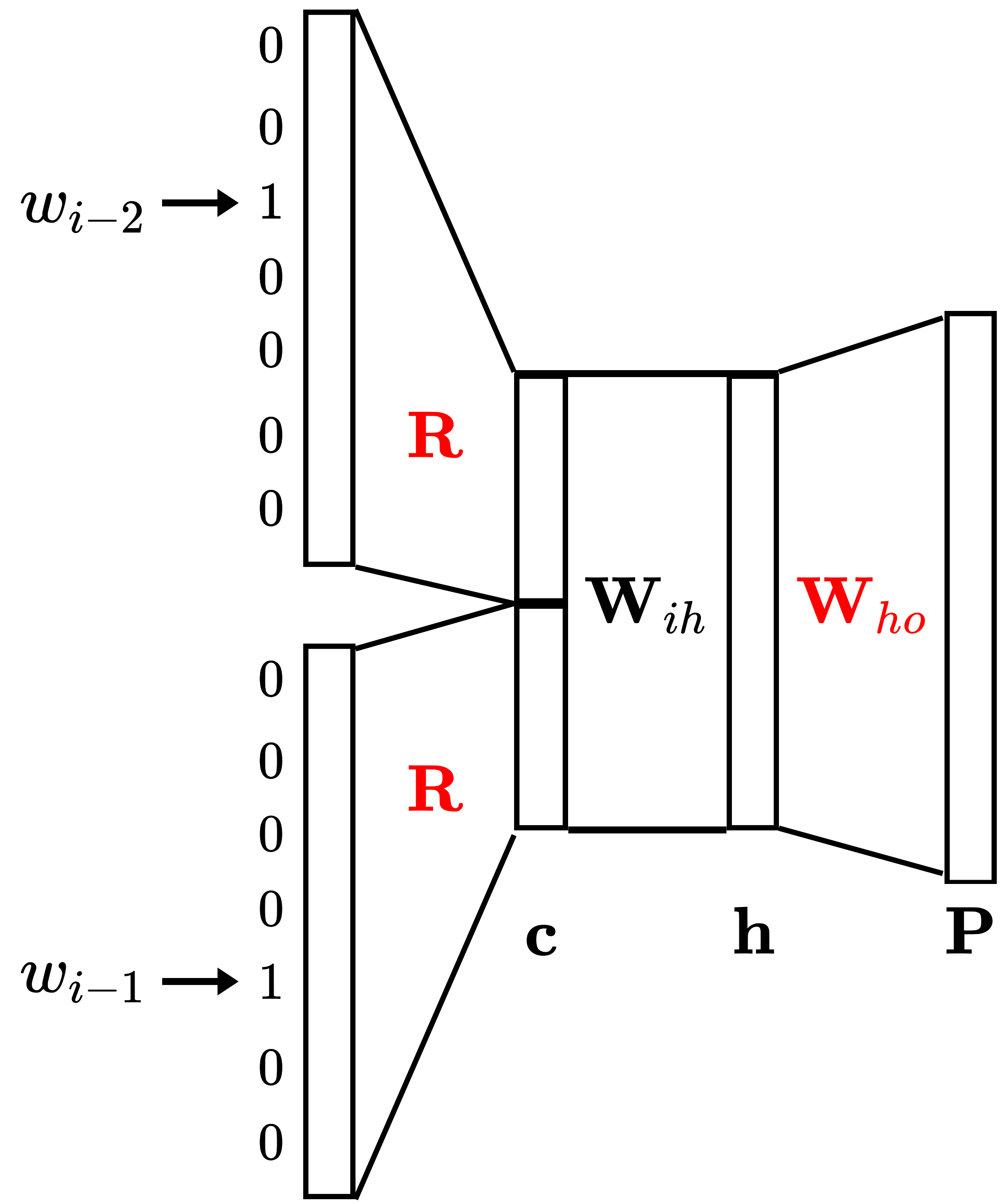

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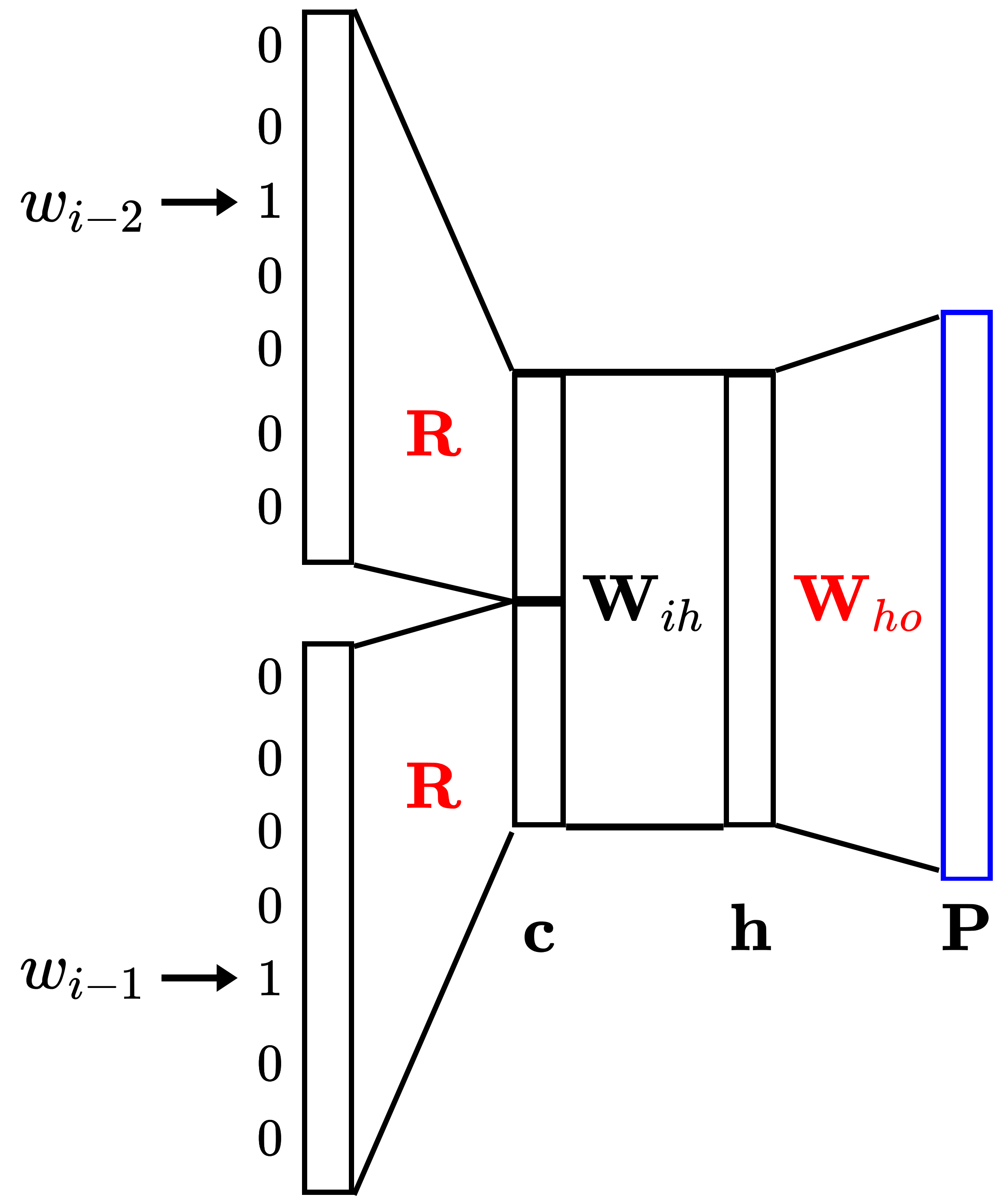
- The bottleneck is the **output vocabulary size** **!**



NPLM: Learning bottleneck

- The *projection* and *prediction* are learned jointly: $\theta = (\mathbf{R}, \mathbf{W}_{ih}, \mathbf{W}_{ho})$, the parameters of the model, are trained through the **MLE** objective, which equates minimizing the **negative log-likelihood** on $\mathcal{D} = (w_i)_{i=1}^{N}$:

$$NLL(\theta) = -\sum_{i=1}^{N} l(\hat{\mathbf{y}}_{i-1}|\theta, w_i) = -\sum_{i=1}^{N} \log P_\theta(w_i|w_{i-2}, w_{i-1})$$

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$\rightarrow$ The **softmax** causes this computational **bottleneck** !

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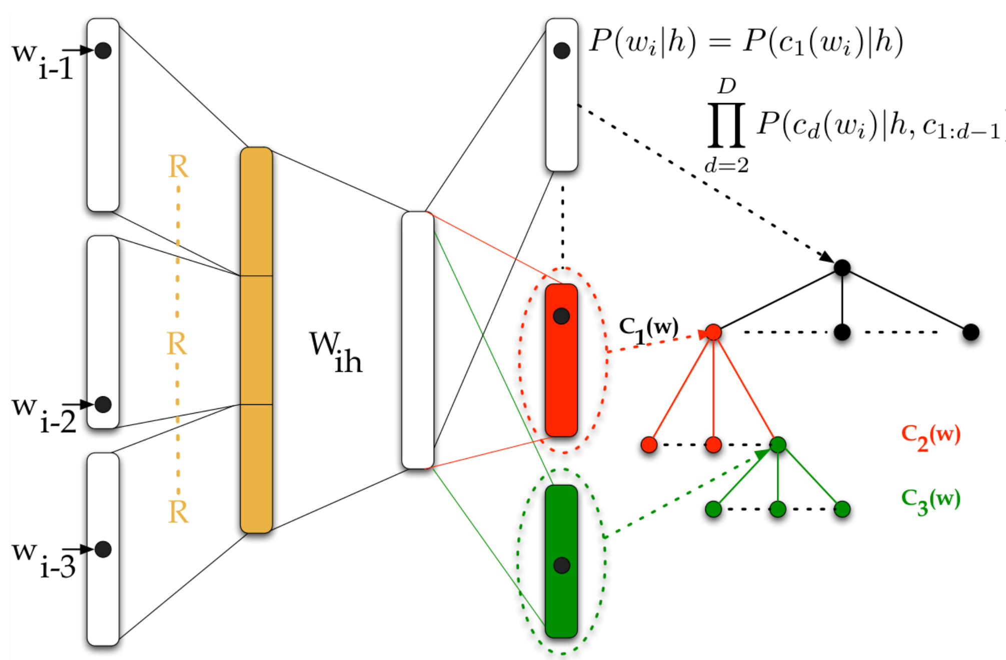

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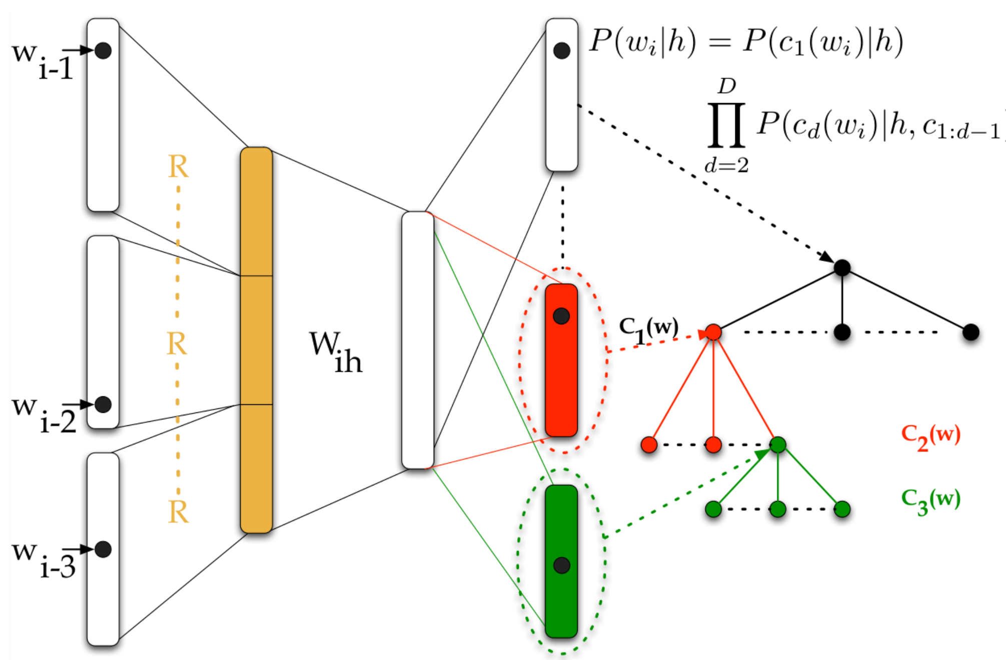

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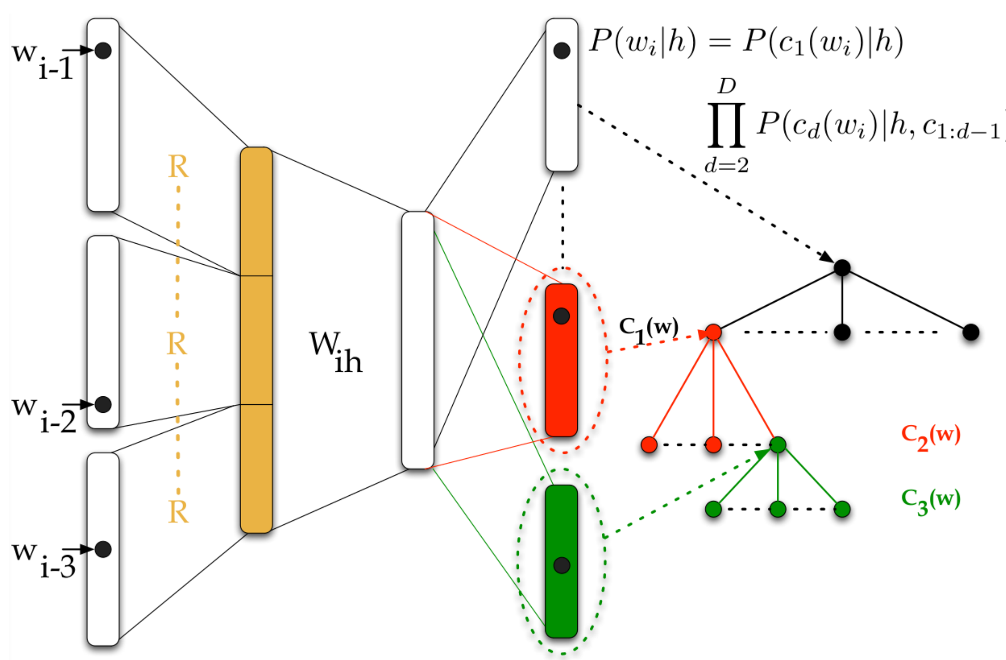
- Use **sampling-based** methods, aiming at replacing the sum over the vocabulary by k samples when computing the gradient ($k \ll |\mathcal{V}|$):
  $\rightarrow$ **Importance Sampling**, **Noise-Contrastive Estimation**, ...

NPLM: Dealing with that bottleneck ?

- Use a class-based language model, making **hierarchical** predictions:
  $\rightarrow$ Replace complexity in $O(|\mathcal{V}|)$ by $O(\log|\mathcal{V}|)$



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  $\rightarrow$ **Importance Sampling**, **Noise-Contrastive Estimation**, ...
- More recently: implement a class-based softmax, based on word frequencies, and attribute more parameters to frequent words
  $\rightarrow$ **Adaptive softmax**

Applying window-based Neural models to sequential tasks

Natural language processing (almost) from scratch (Collobert et al, 2011)

- Four standard NLP tasks, for which the state-of-the-art depend on task-specific features:

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  - **Part-of-speech** tagging (POS)

I	ate	the	spaghetti	with	meatballs	.
Pro	V	Det	N	Prep	N	PUN

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[NP I] [VP ate] [NP the spaghetti] [PP with] [NP meatballs]

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(Agent Patient Source Destination Instrument)

John	drove	Mary	from	Austin	to	Dallas	in	his	DS Citroën
A		P		S		D			I

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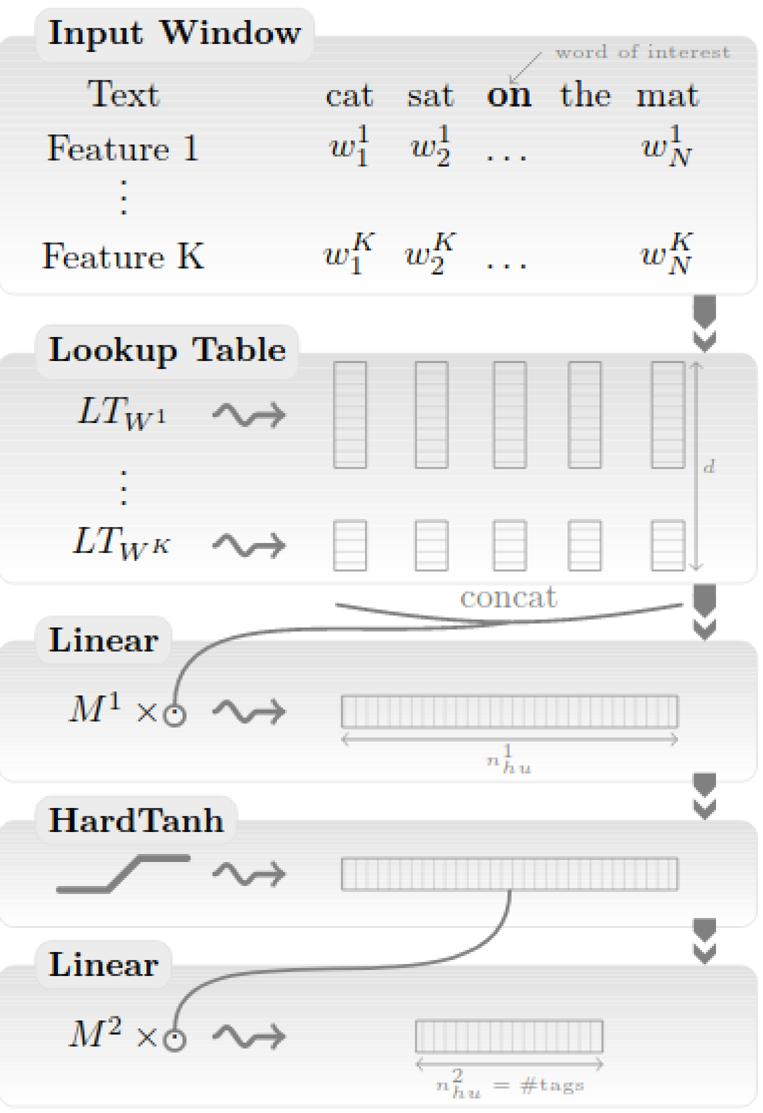
$\rightarrow$ A **task-independent** approach is better because no single task can provide a complete representation of a text

Applying window-based Neural models to sequential tasks

Natural language processing (almost) from scratch (Collobert et al, 2011)

- First approach: **window-based**
- Language-modeling like training, **to rank unlabelled sentences**, brings results above the state-of-the-art for the three first tasks
- However, for SRL, the correct tag for a word may easily depend on a word outside of the current window



Towards RNN Language Models

With n-gram neural language model, *sparsity* is not an issue anymore, but we still can not deal with **long distance dependancies** between words:

- While we can increase the size of the input window, it is not practical (and actually stops improving results quite fast)
- Input words are processed differently depending on their position

$\rightarrow$ We need an architecture that can process **inputs of any lengths**, using the **same weights** for every input word.

RNN Language Models

Extensions of recurrent neural network language model, (Mikolov et al, 2011)

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w_1 w_2 w_3 w_4

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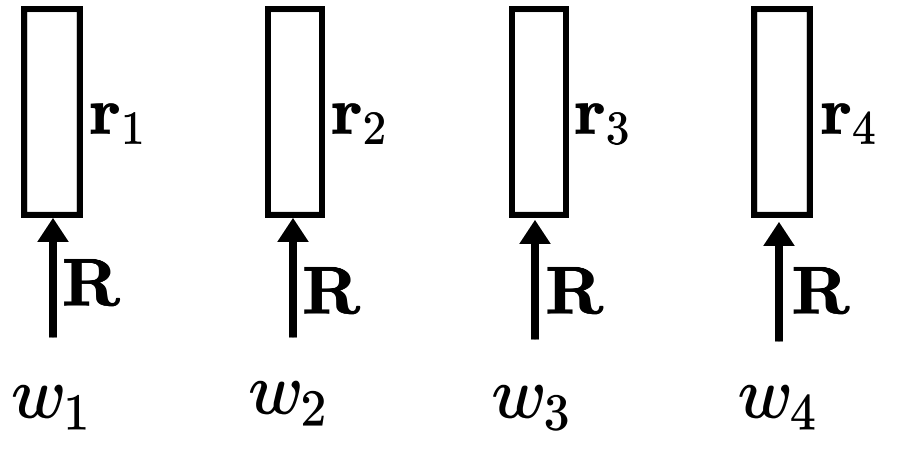

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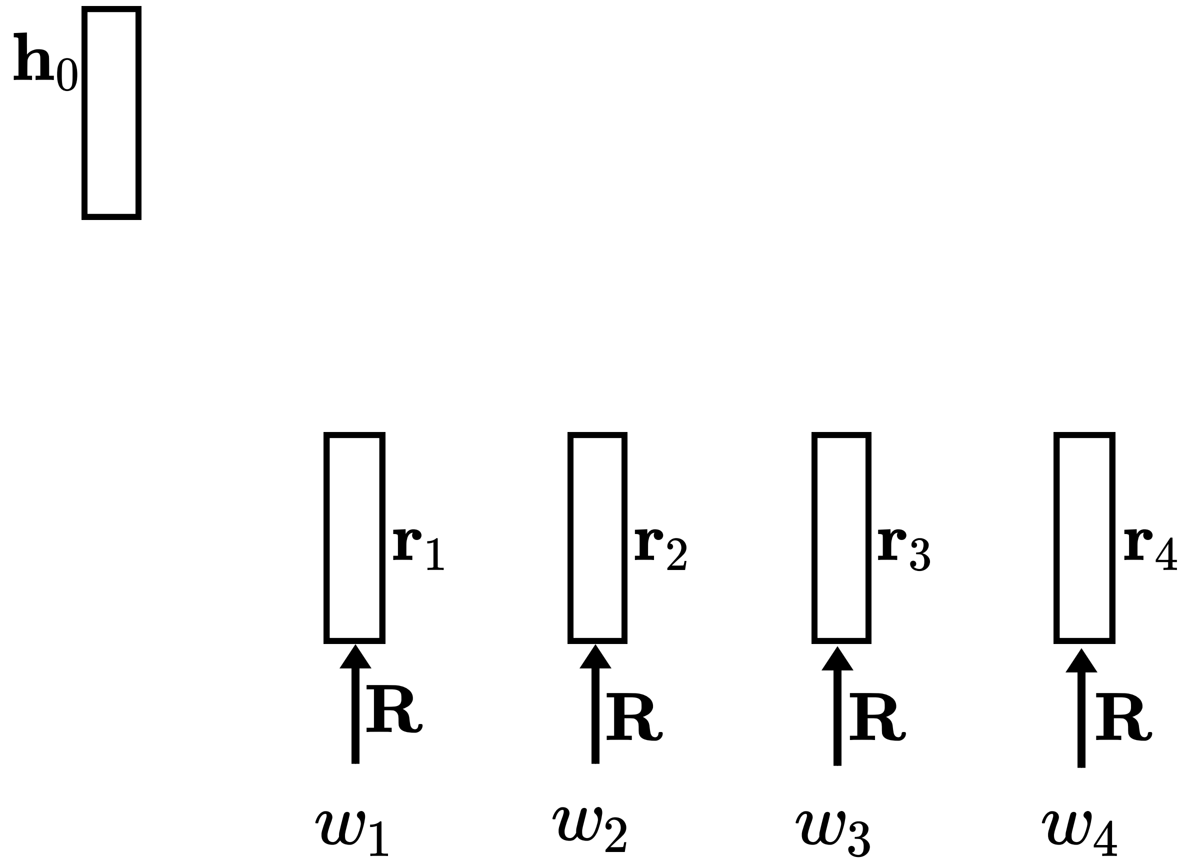

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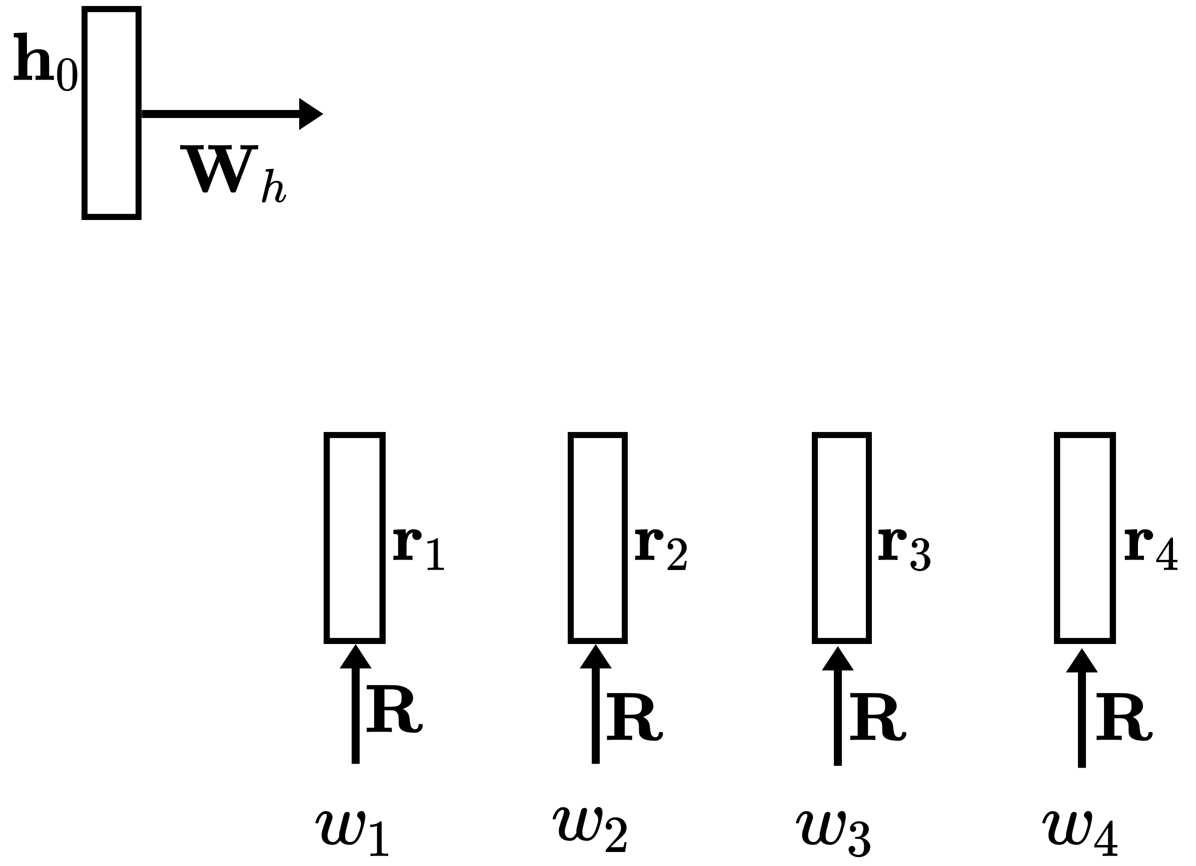

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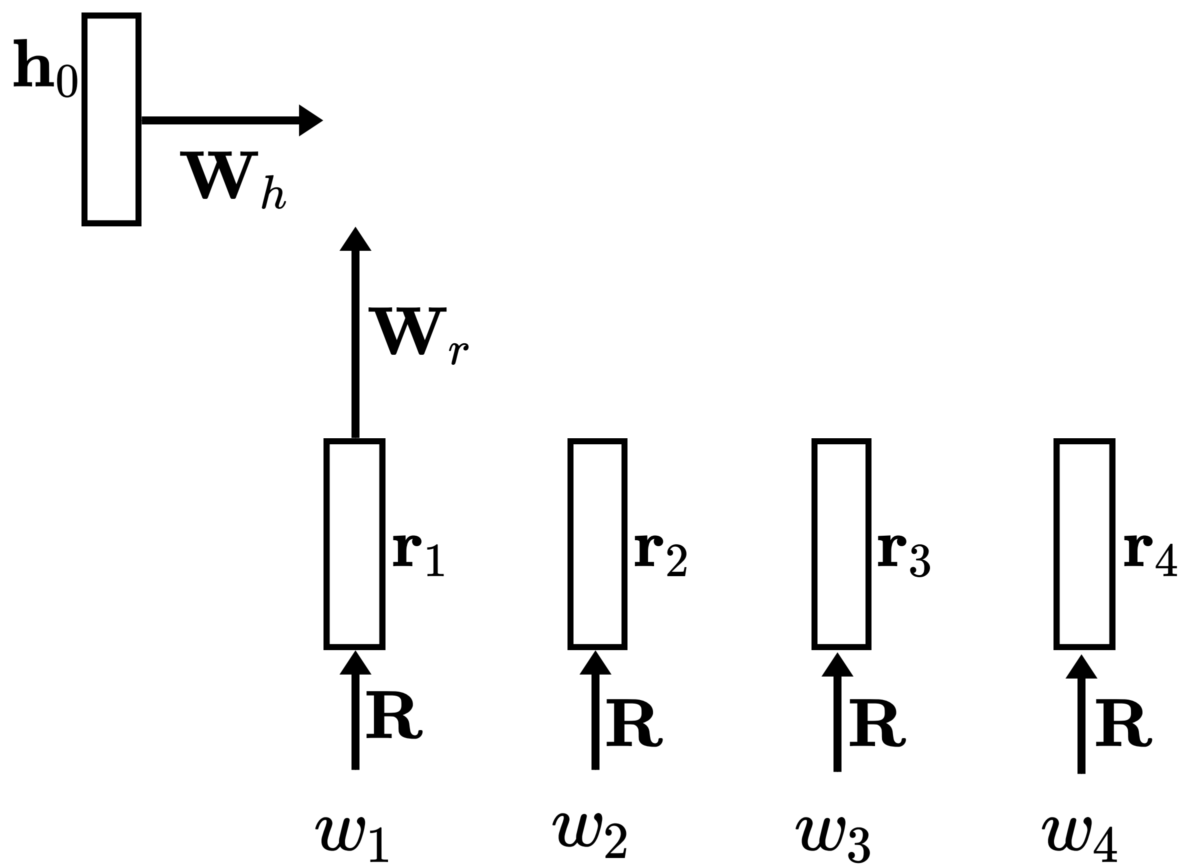

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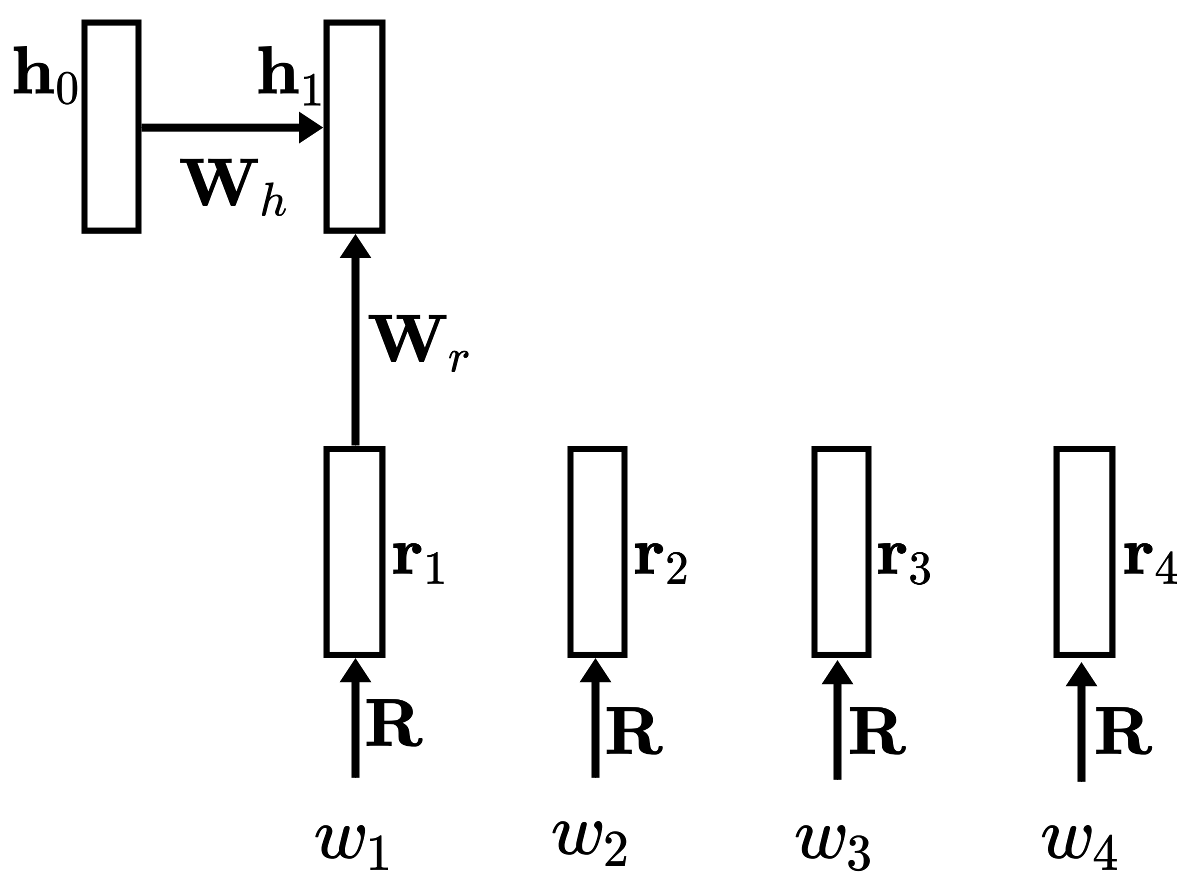

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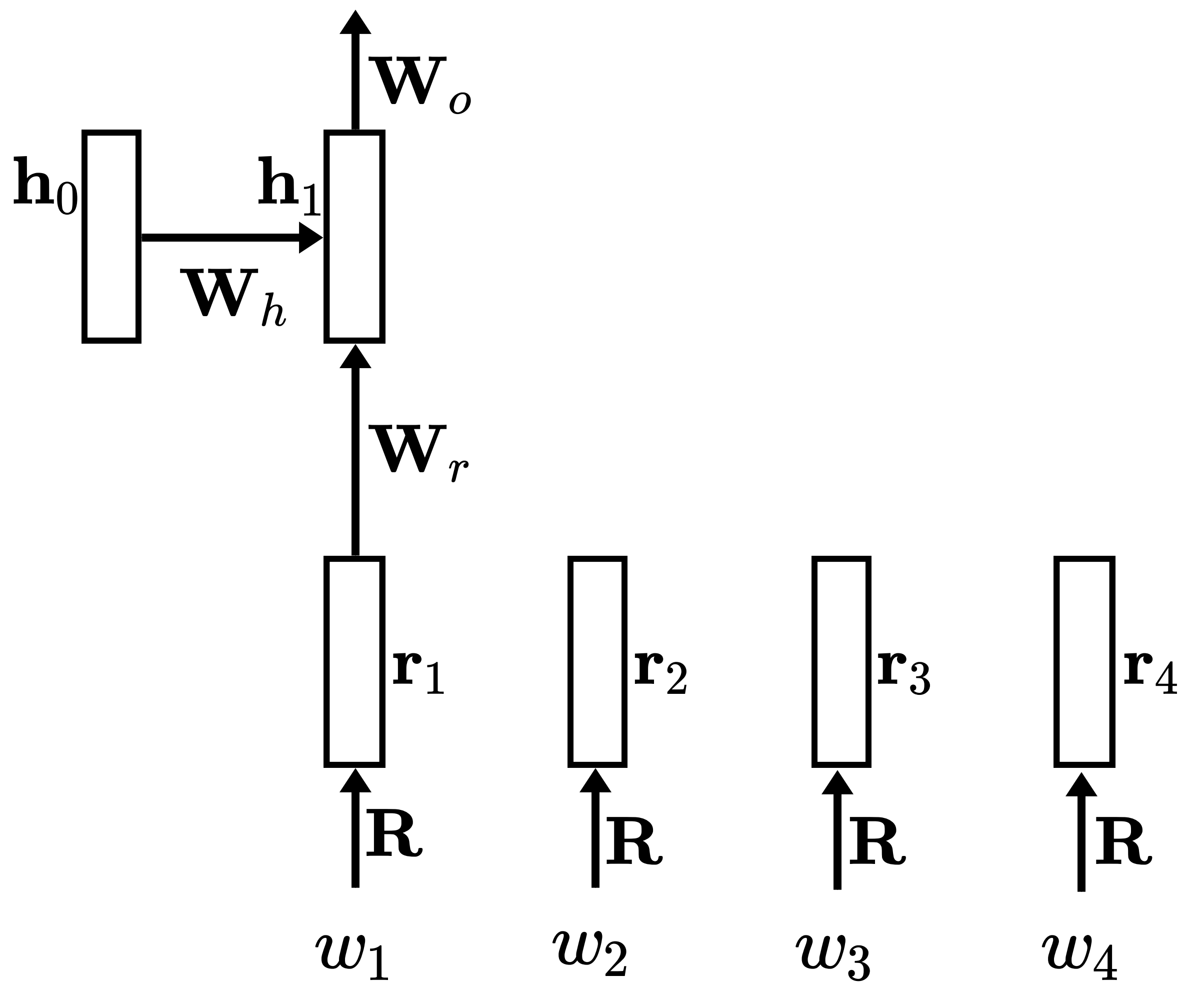

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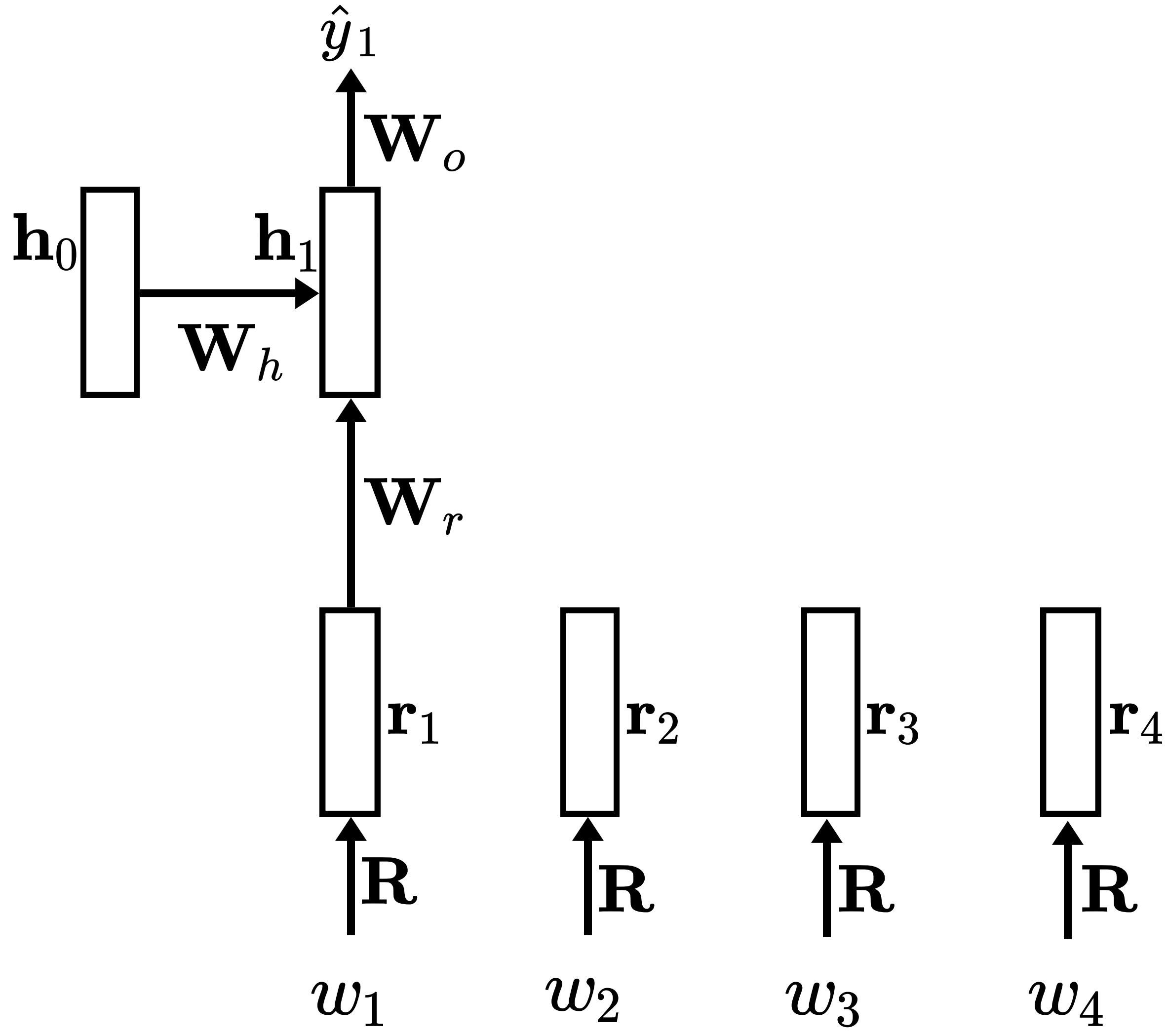

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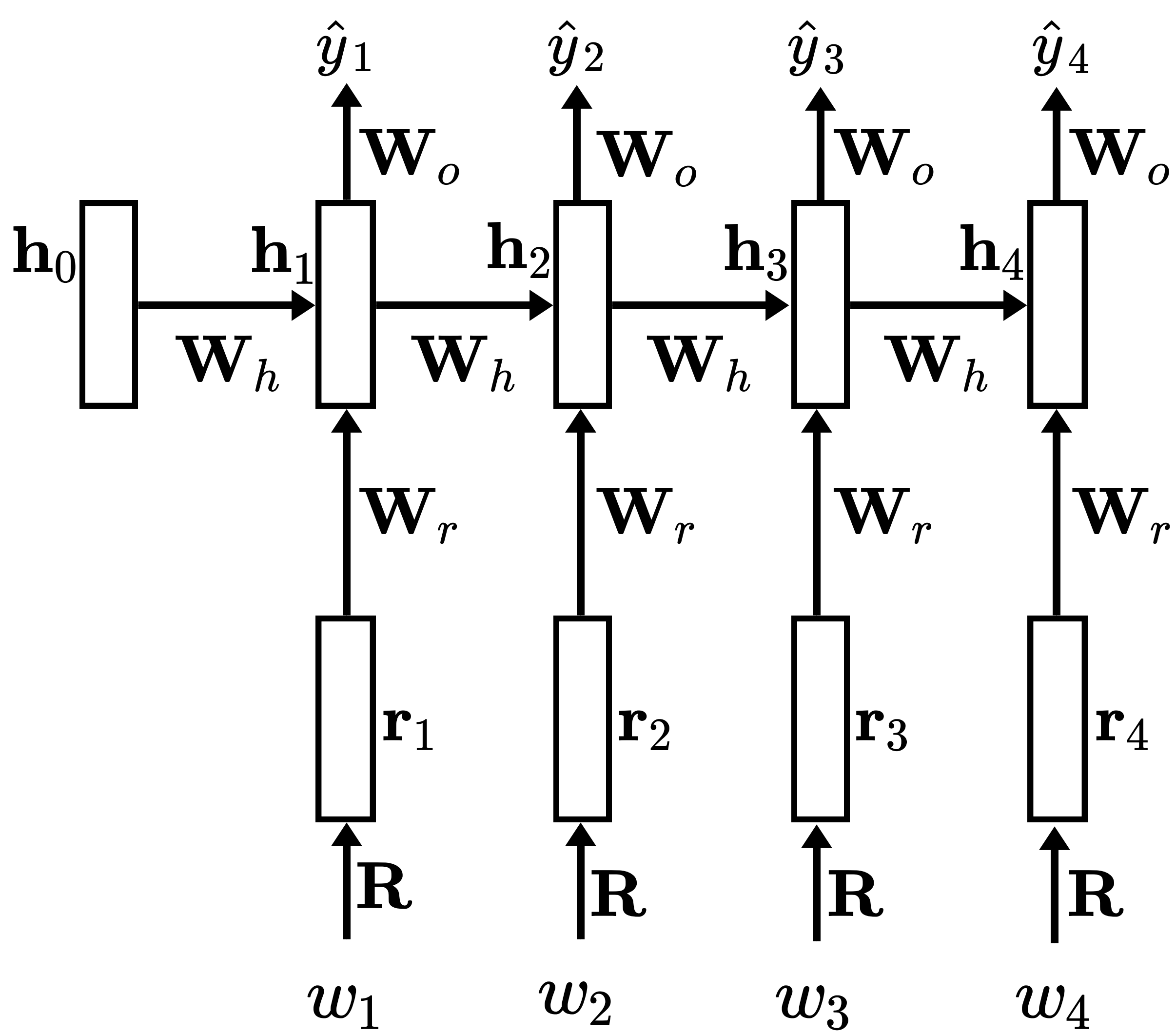

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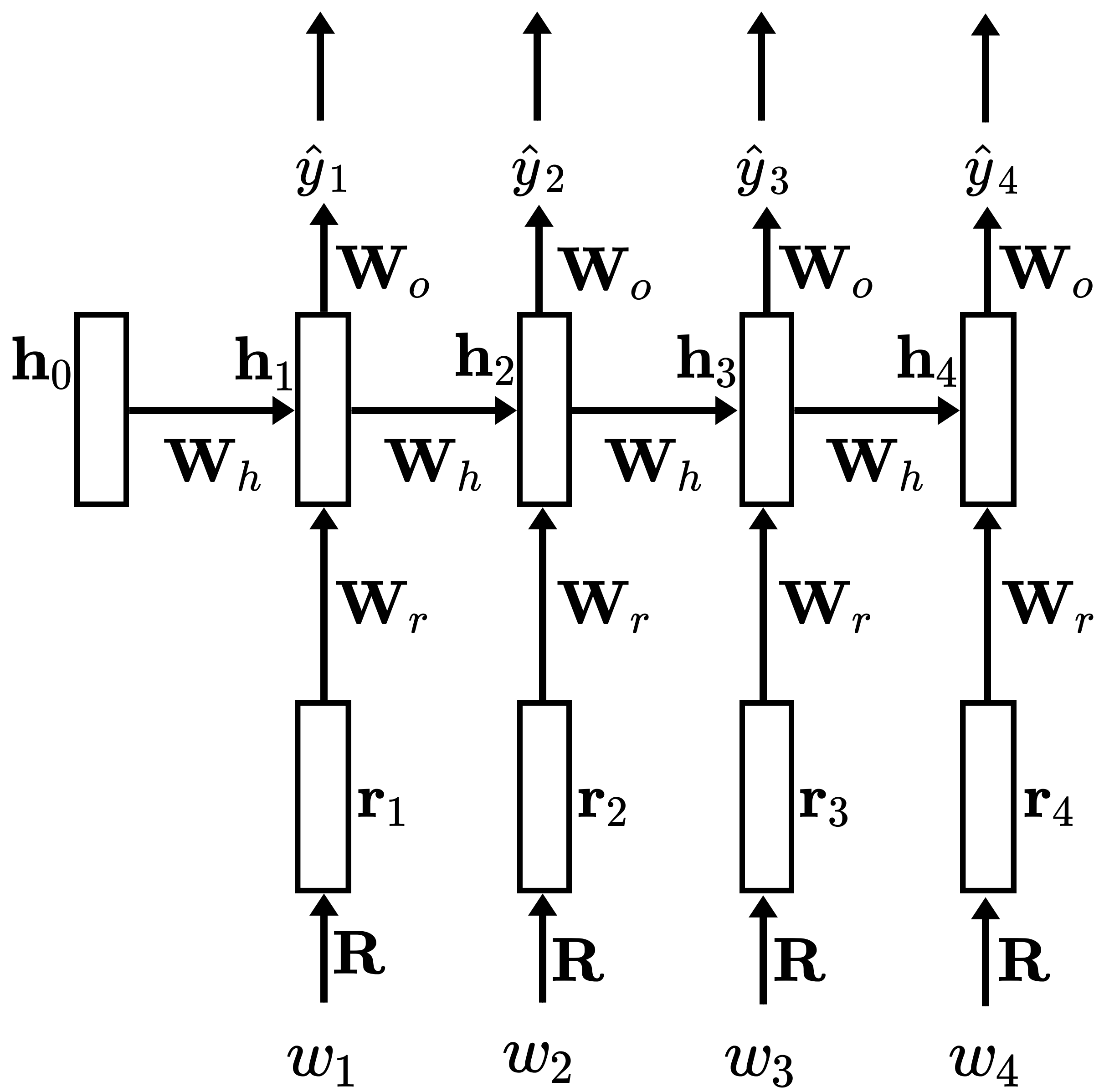

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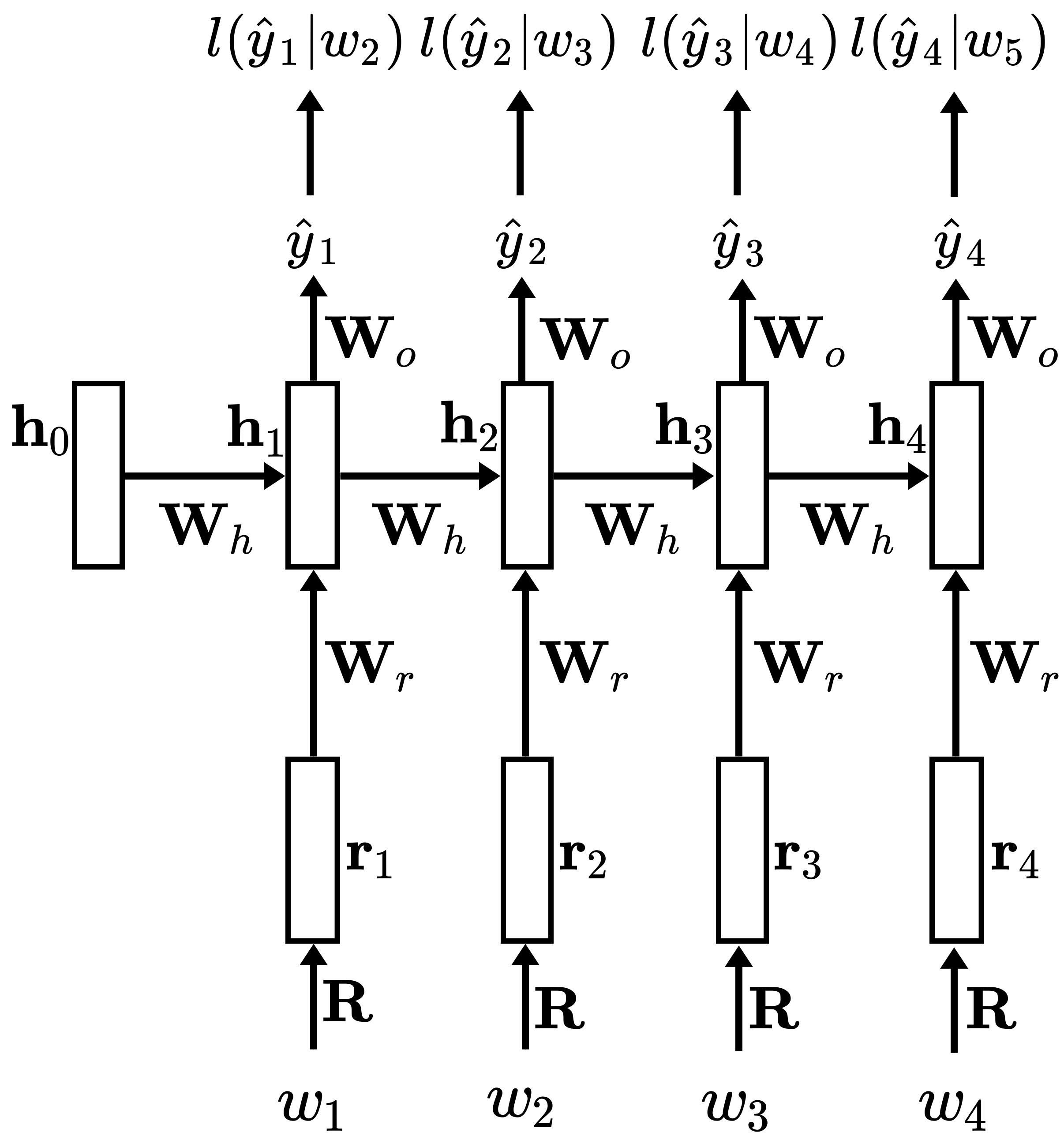

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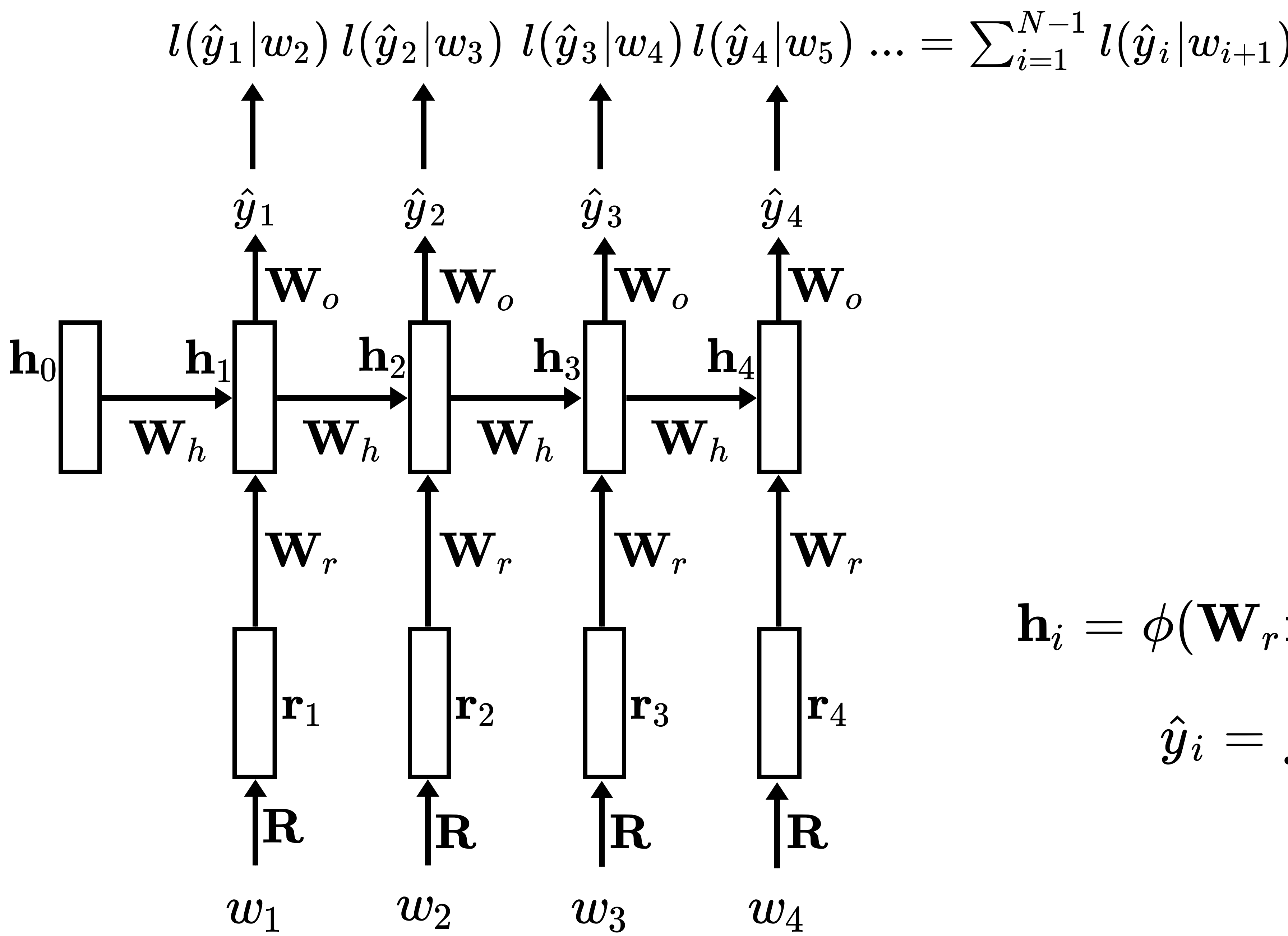

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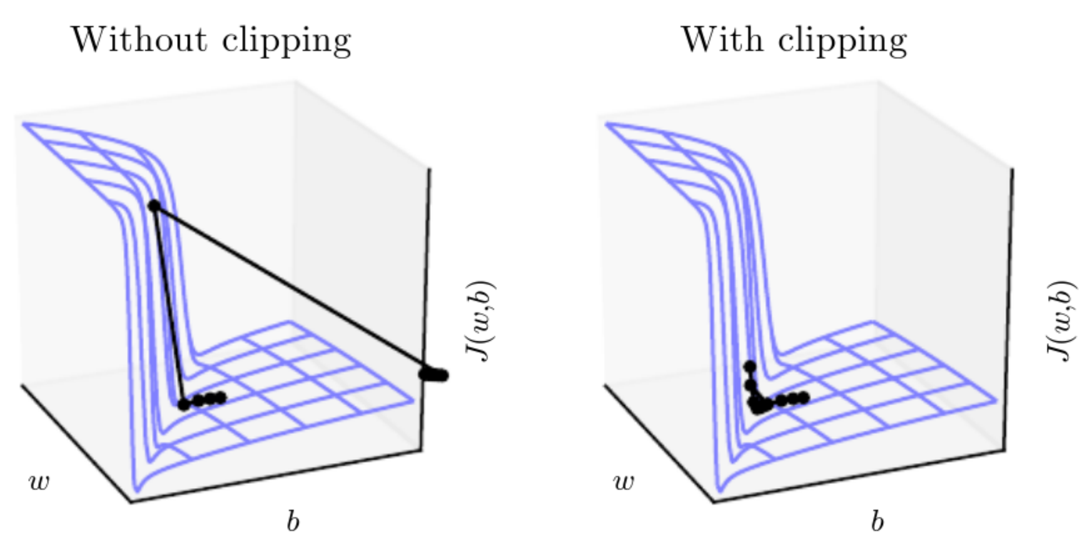

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- **Long term memory**:
  $\rightarrow$ bidirectional architectures !

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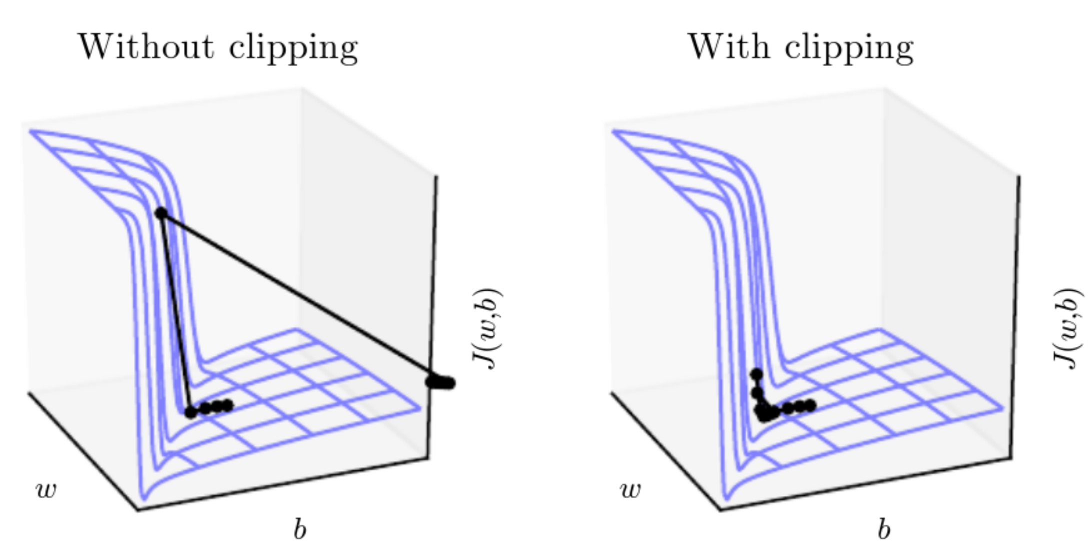
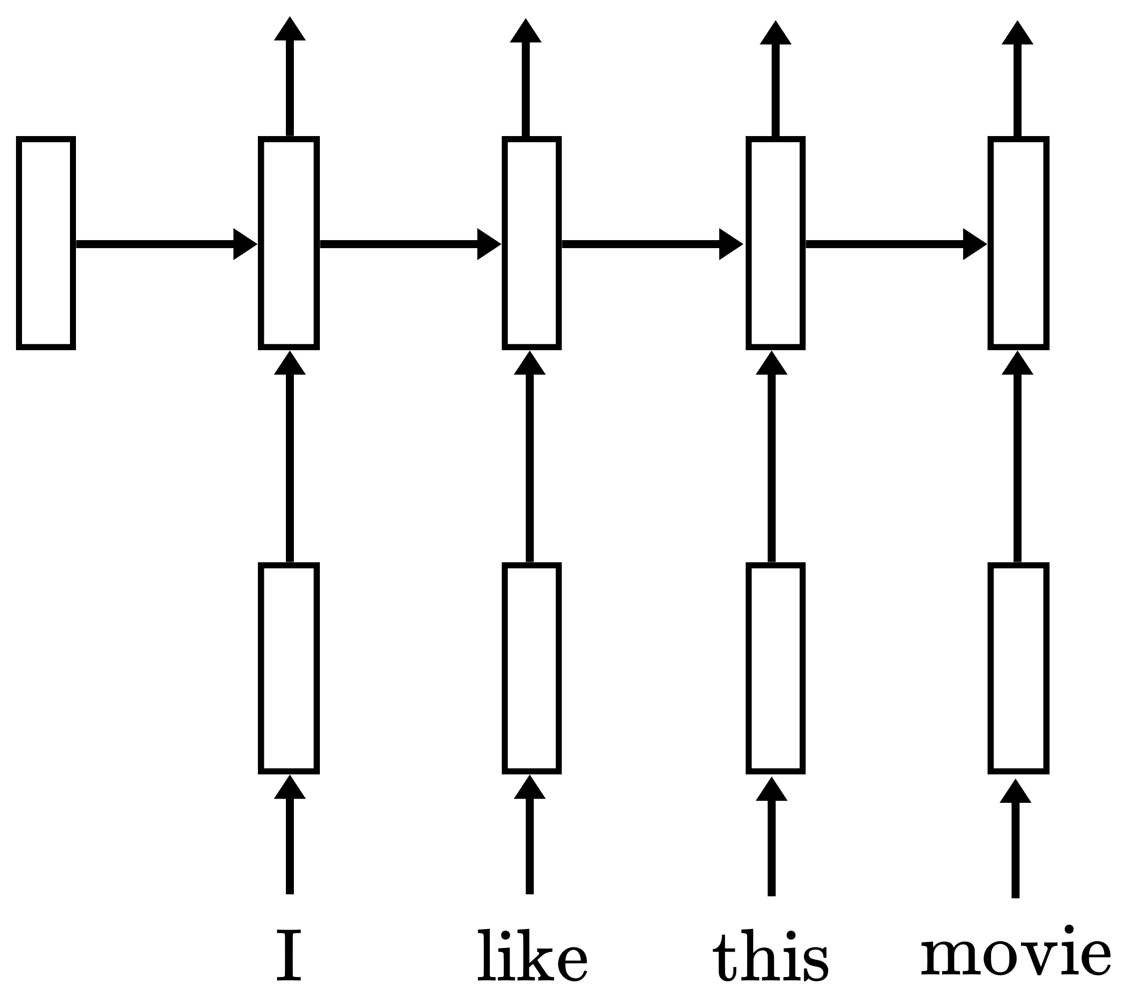
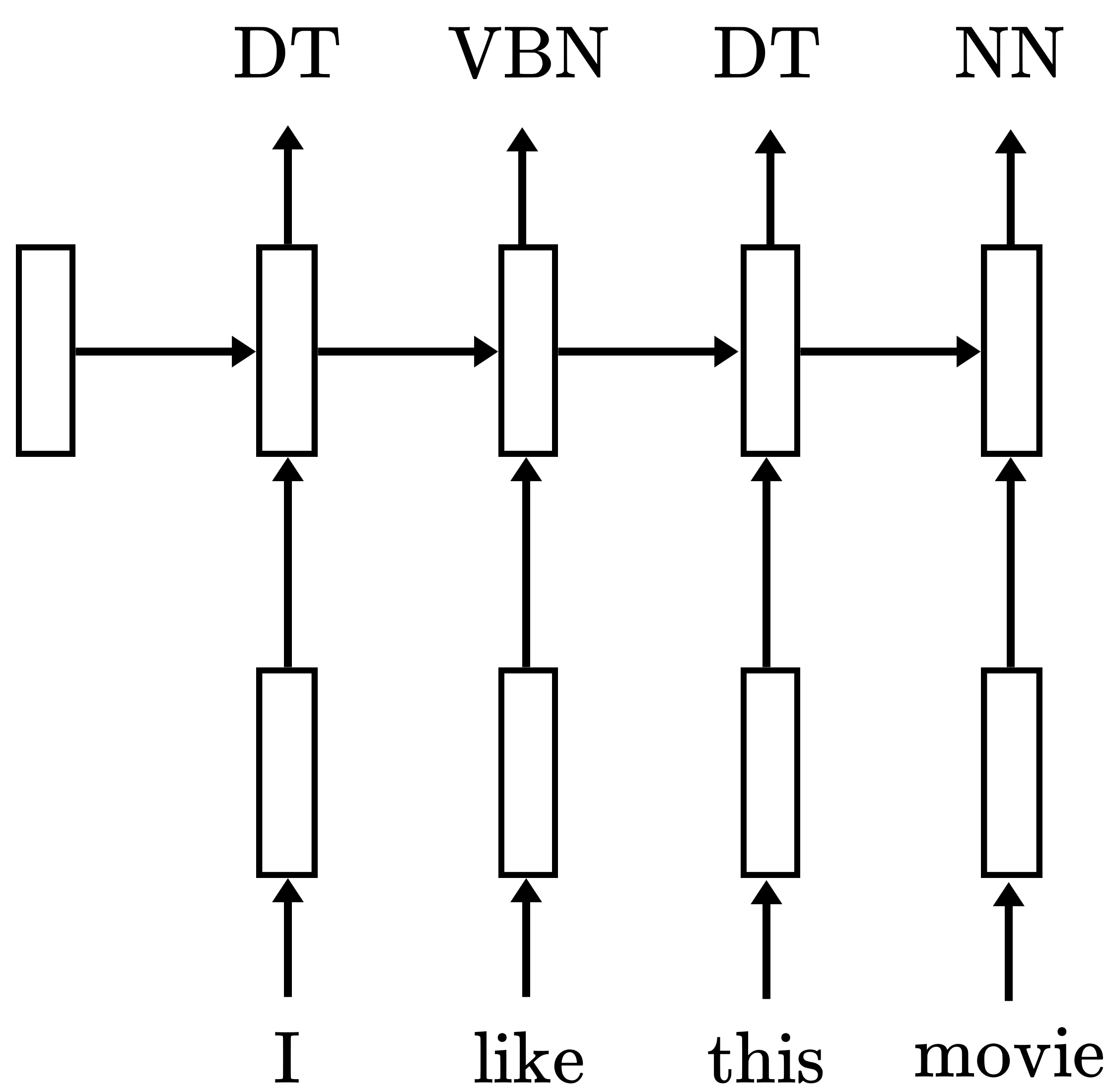


RNN: Other sequential tasks



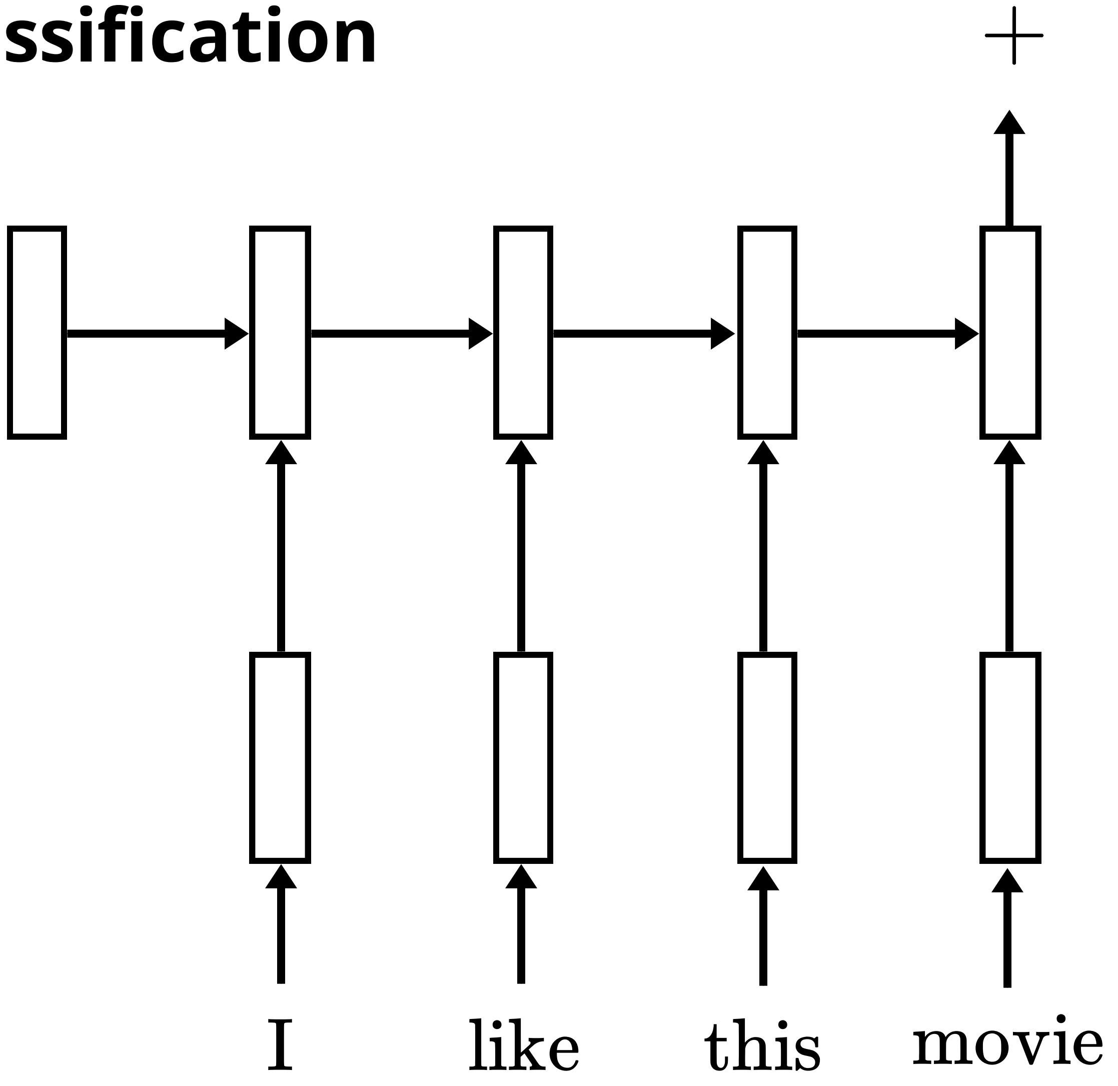
RNN: Other sequential tasks

POS Tagging



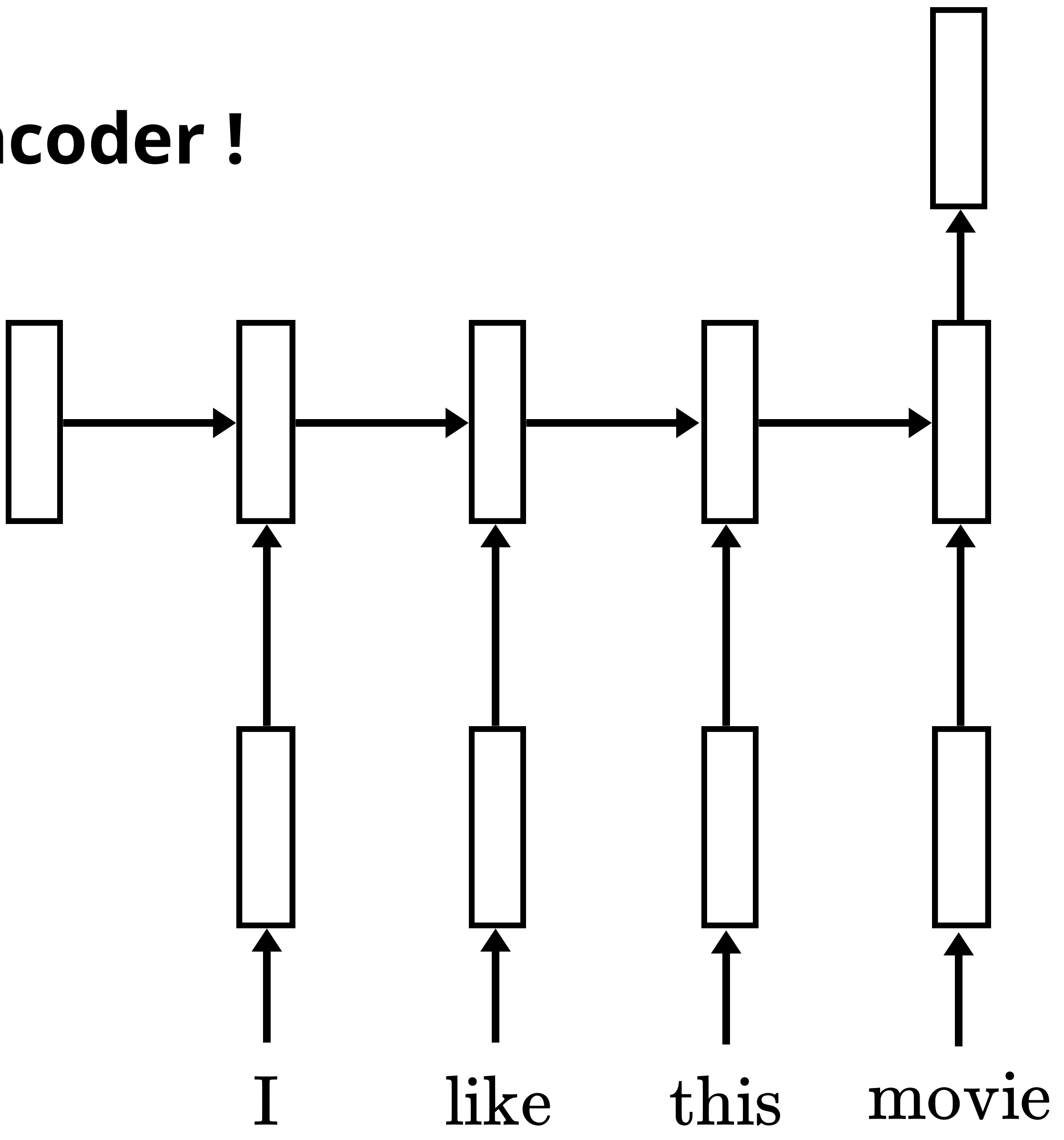
RNN: Other sequential tasks

Sentiment Classification



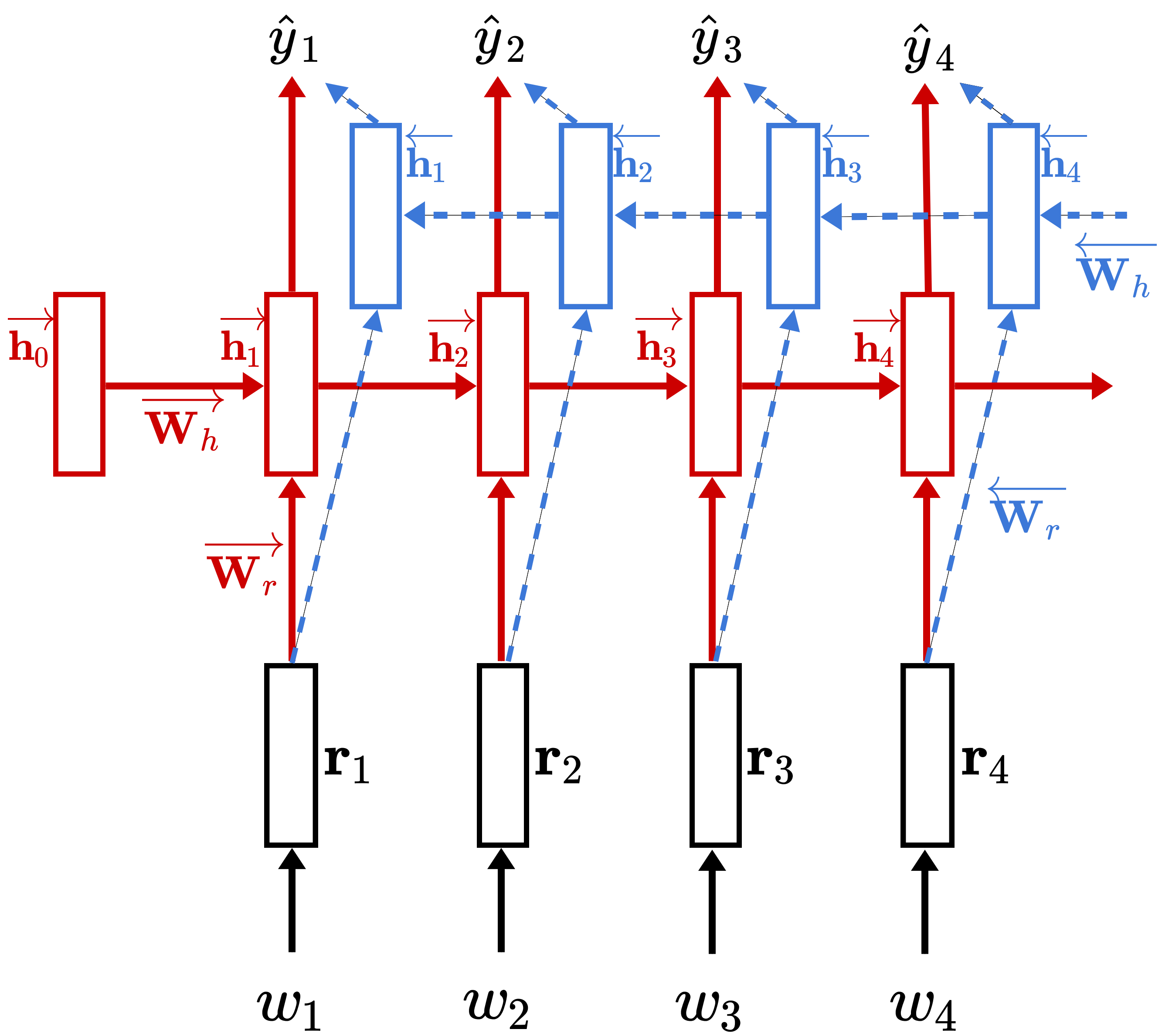
RNN: Other sequential tasks

Any kind of encoder !



Bidirectional Architectures

Bidirectional LSTMnetworks for improved phoneme classification and recognition (Graves et al, 2005)



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$$\hat{y}_i = f(\mathbf{W}_o[\overrightarrow{\mathbf{h}}_i : \overleftarrow{\mathbf{h}}_i])$$

- $[\overrightarrow{\mathbf{h}}_i : \overleftarrow{\mathbf{h}}_i]$ represents w_i using both contexts !
- Powerful, but you need the **entire input sequence** $\rightarrow$ It can not be used for language modeling…

Before RNNs: Sentence-based approach

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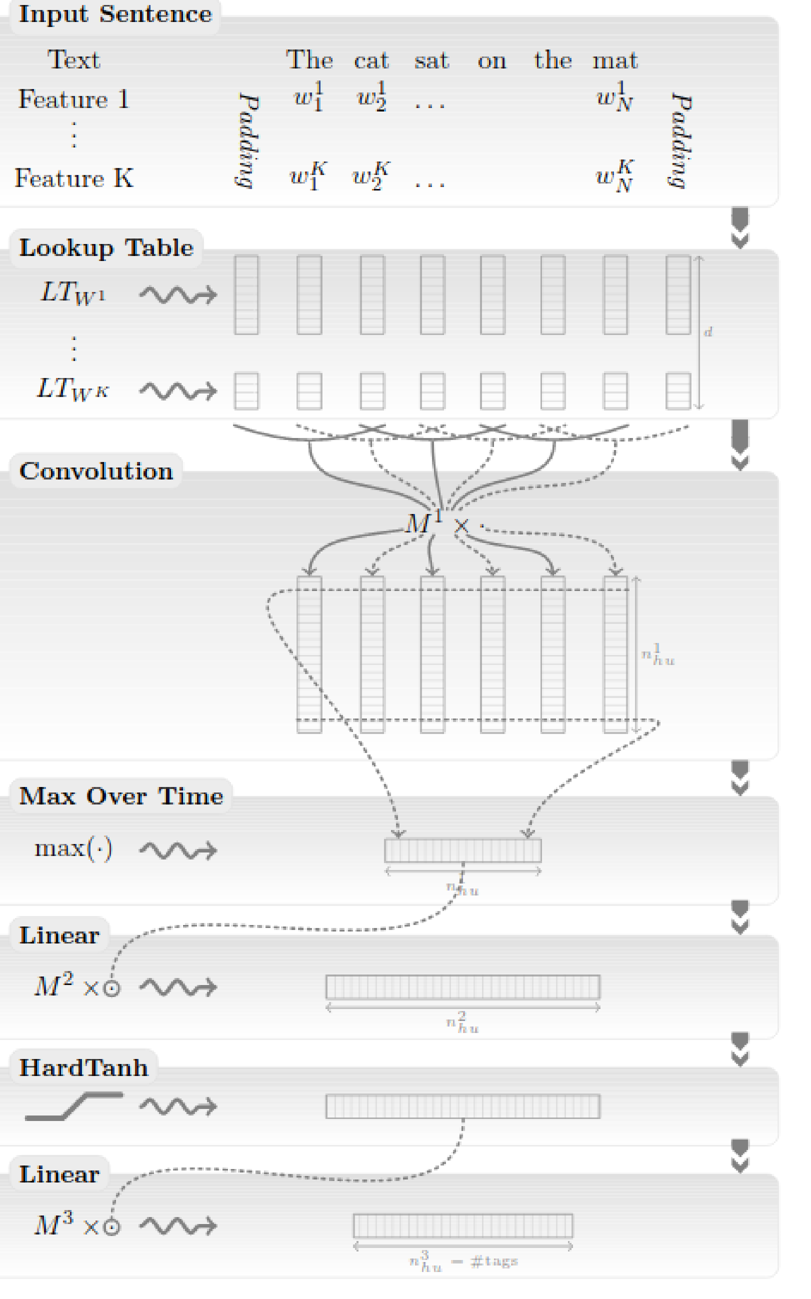

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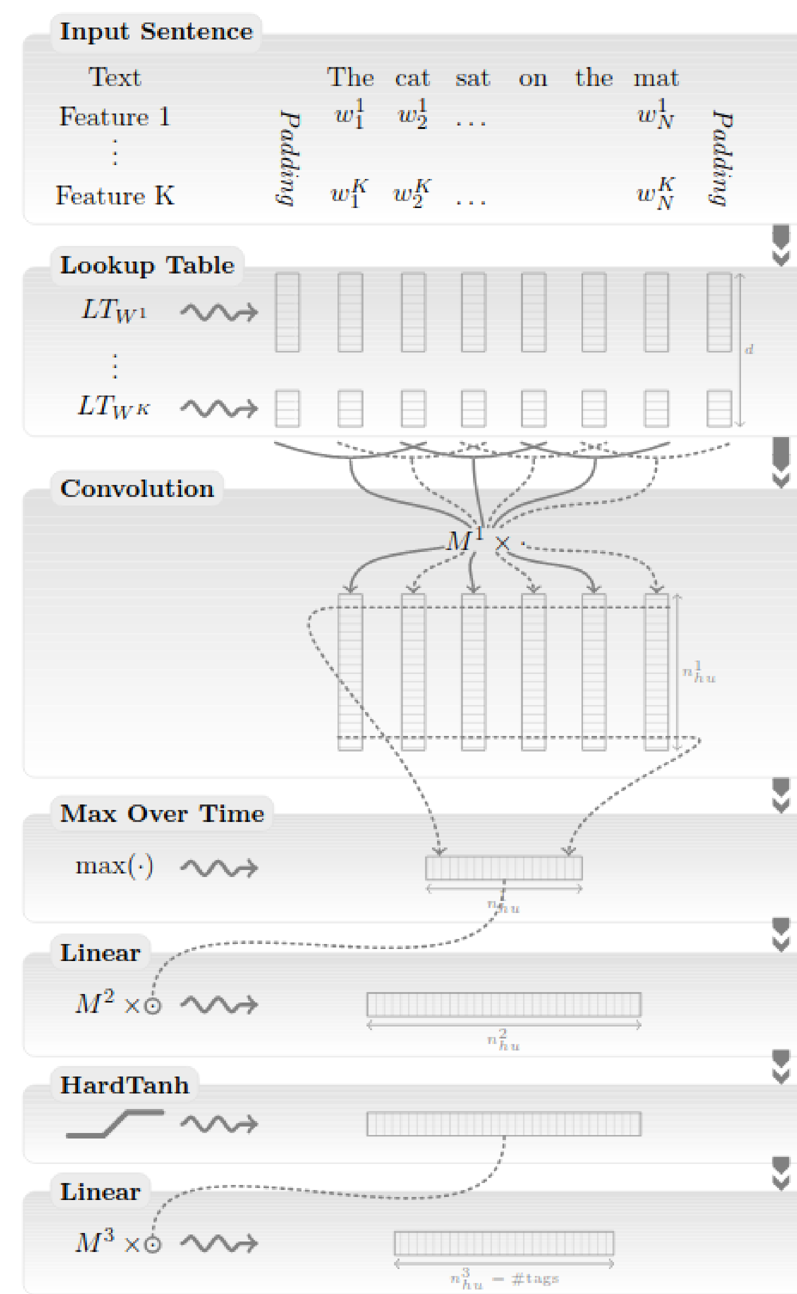

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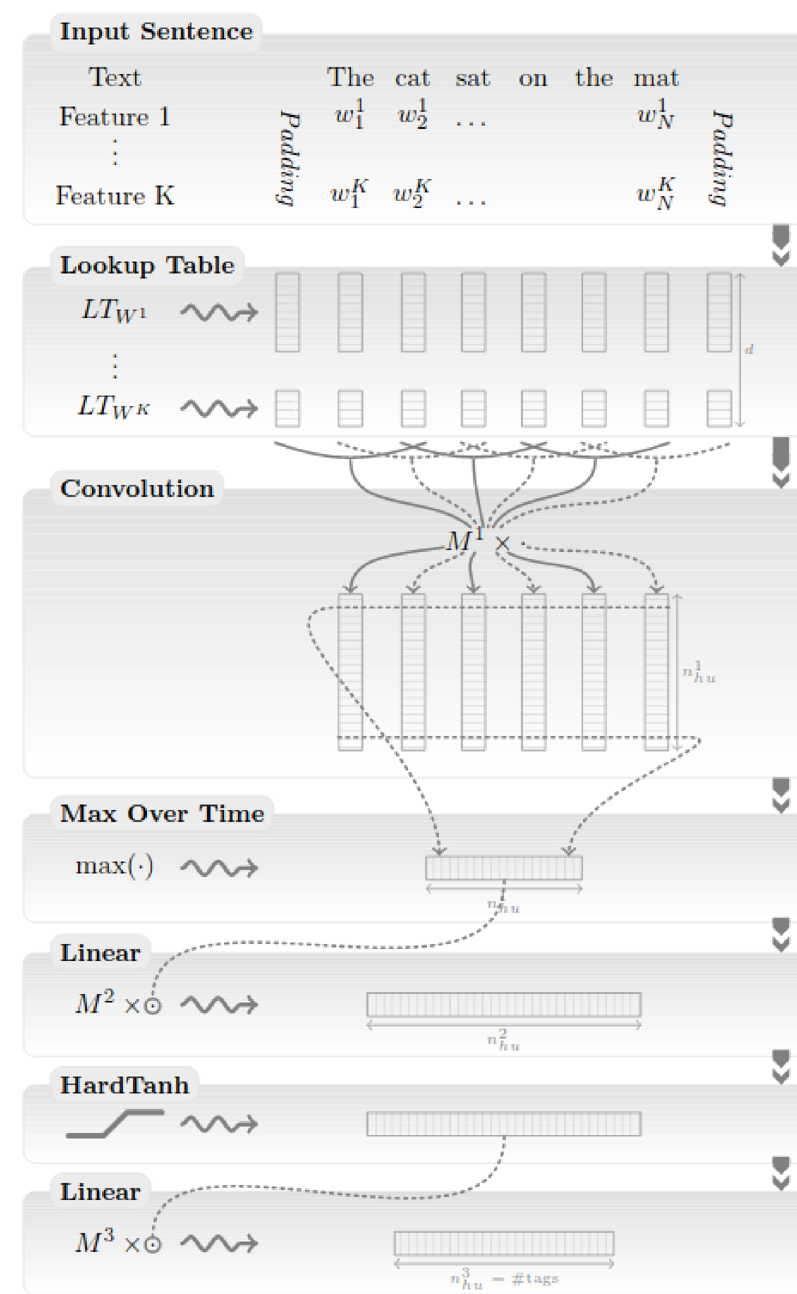
- A **structured training objective** (taking in accounts dependancies between predicted tags) helps improving results



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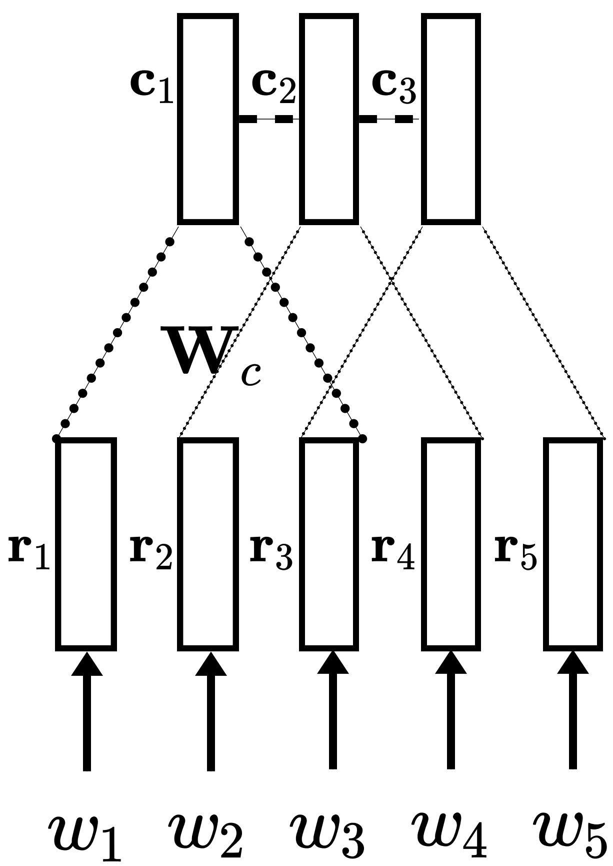
Convolutional networks for NLP



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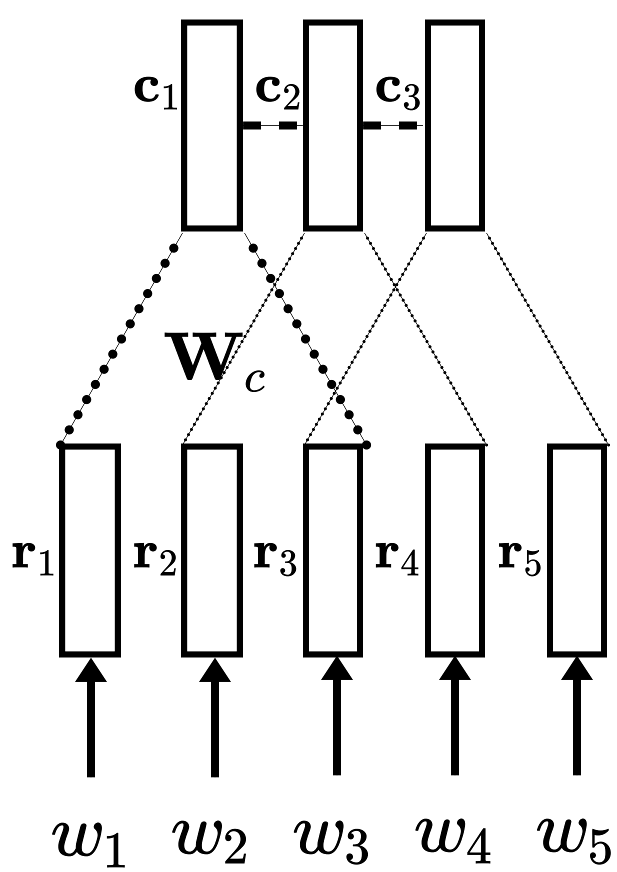

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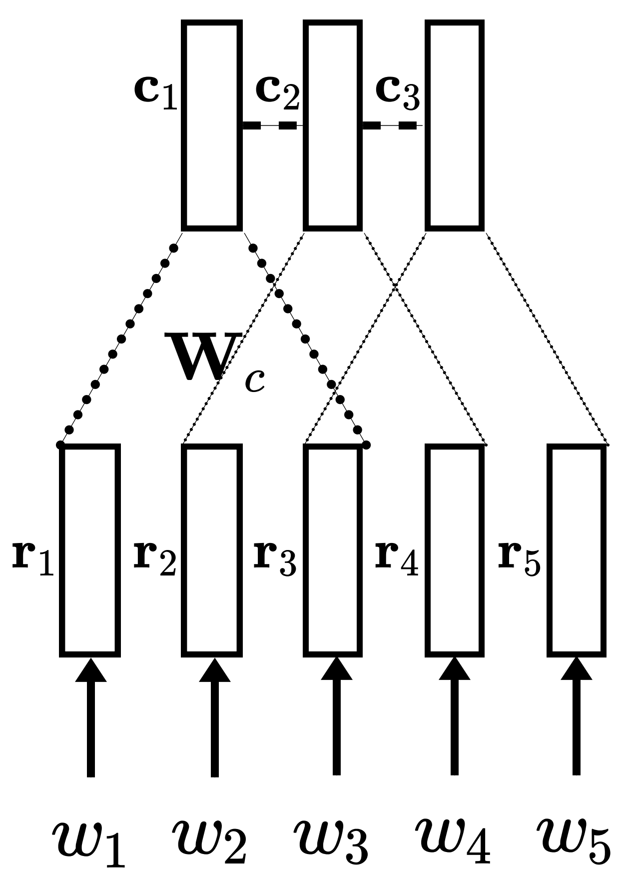

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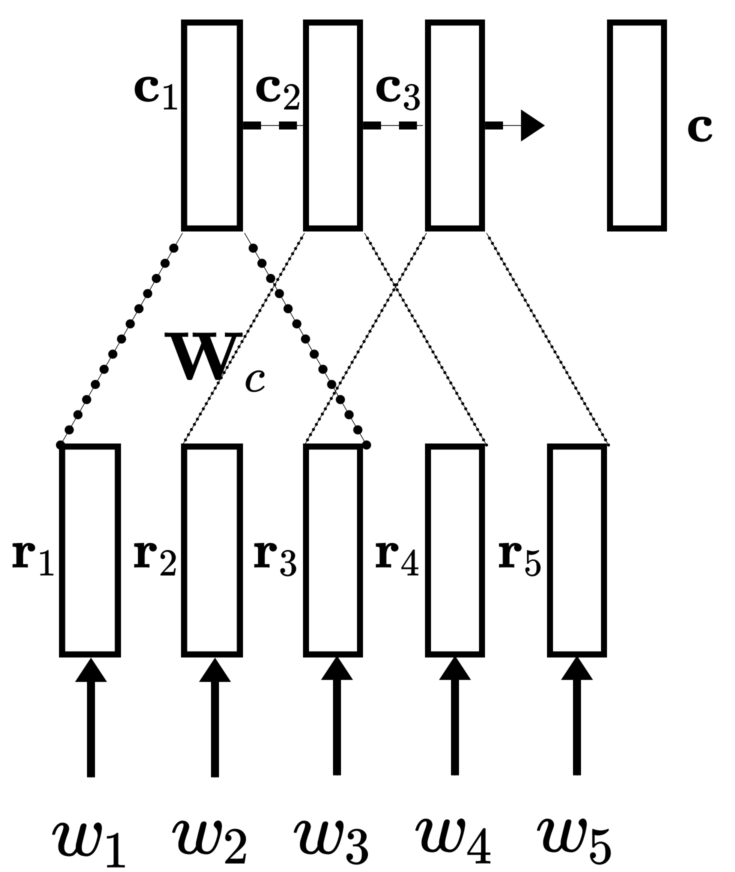

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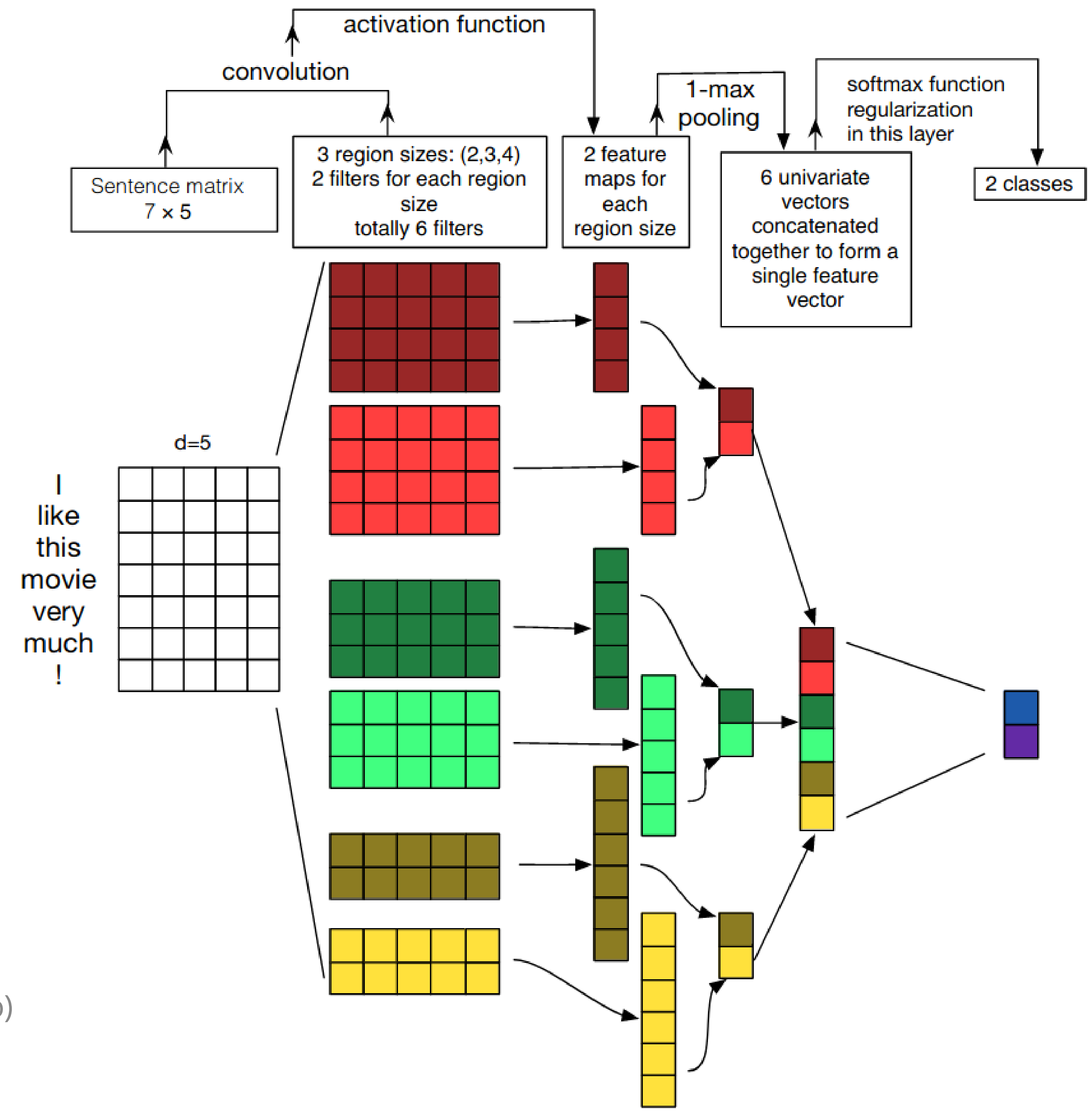
- With max-pooling, the idea is to capture the most important activation over time:
$$\mathbf{c} = max(\{\mathbf{c}_i\}_{i=1}^{n-t})$$

CNN for NLP: Applications

- Convolutional networks are lighter, faster - and we can apply filters on **windows of various** sizes !

- The architecture became popular for NLP tasks with *Convolutional Neural Networks for Sentence Classification* (Kim, 2014)



From "A Sensitivity Analysis of (and Practitioners' Guide to) Convolutional Neural Networks for Sentence Classification" (Ye Zhang, Byron Wallace, 2015)

Supplementary innovations used in NLP

- **Gating/Skipping**, similar to LSTM/GRU, but vertically:

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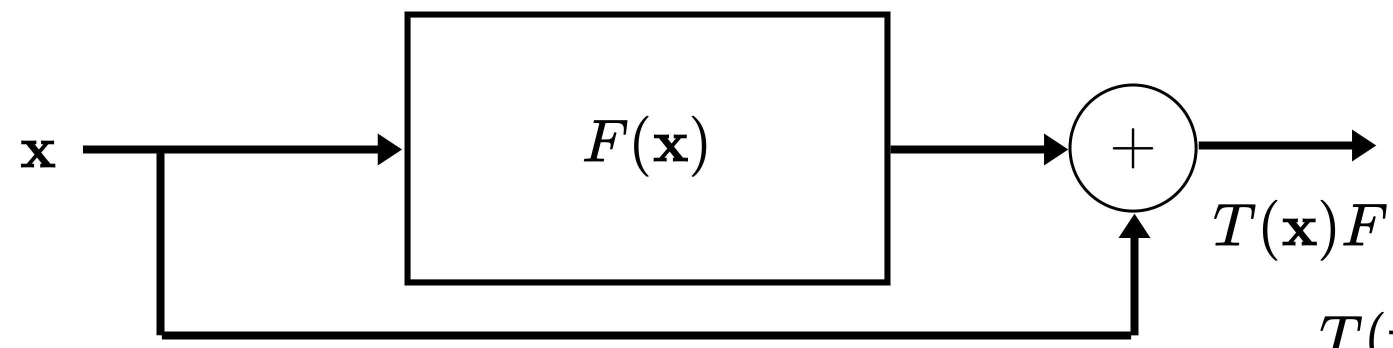

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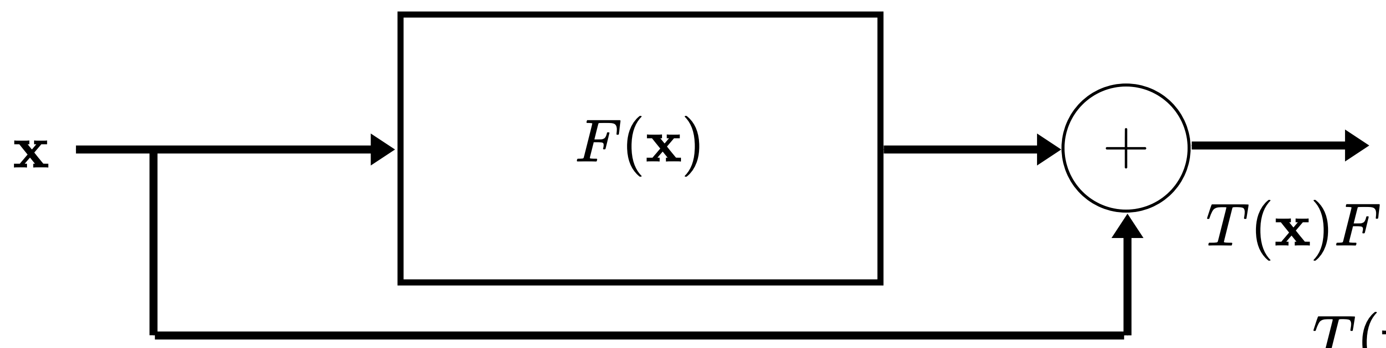

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- **Batch Normalization**: Scaling the output of the activation function to have zero mean and unit variance - *Batch normalization: Accelerating deep network training by reducing internal covariate shift* (Ioffe et al, 2015)
  - Make models less sensible to parameter initialization
  - Reduce the difficulty with learning rate tuning

Subwords models

- Common issues with word-based models:
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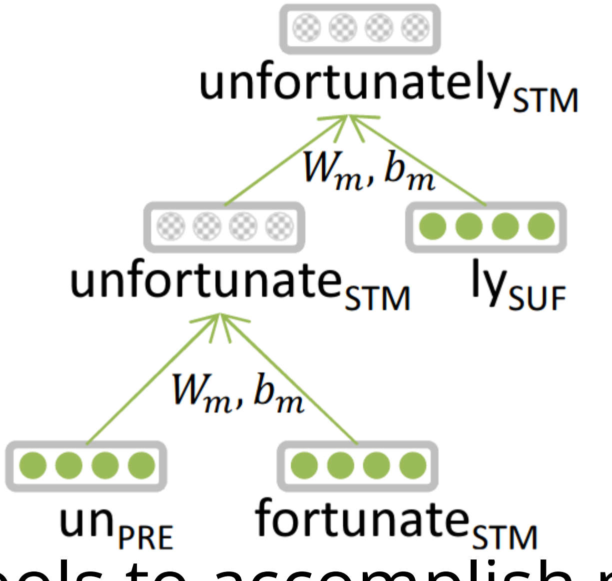
- Common issues with word-based models:
  - The vocabulary is **closed -** especially an issue when **spelling varies**
  - We are missing a lot of information **linking words**
- Linguistically motivated decomposition:
  - **Phonemes** (Distinctive features in audio), **morphemes** (smallest semantic unit)

    Better Word Representations with Recursive Neural Networks forMorphology, (Luong et al, 2013)



$\rightarrow$ While there exist tools to accomplish morphological decomposition, it remains **costly** to obtain

Subwords models

- The goal here is to obtain better word representation **from subwords**
  $\rightarrow$ An easier alternative is to use character n-grams !

$$\text{Unfortunately}$$

$$\downarrow$$

$$\overbrace{\text{Unf}}, \overbrace{\text{nfo}}, \ldots, \overbrace{\text{tel}}, \overbrace{\text{ely}}$$

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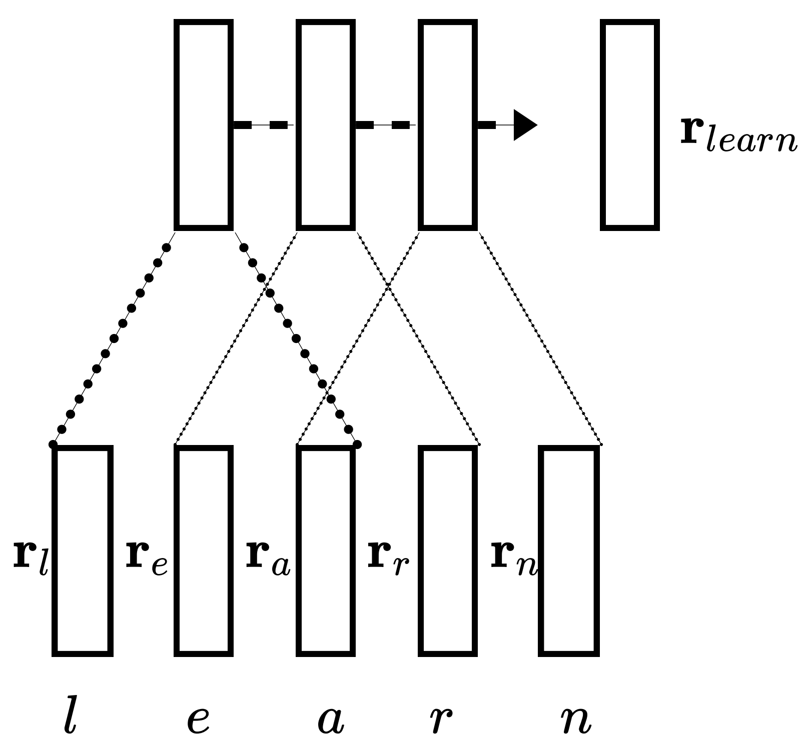
$$\overbrace{\text{Unf}}, \overbrace{\text{nfo}}, \ldots, \overbrace{\text{tel}}, \overbrace{\text{ely}}$$

- We can obtain word representations with a convolution, or a Bi-LSTM:



Compare the different architectures:

From Characters to Words to in Between: Do We Capture Morphology ? (Vania et al, 2017)

Subwords models : Applications

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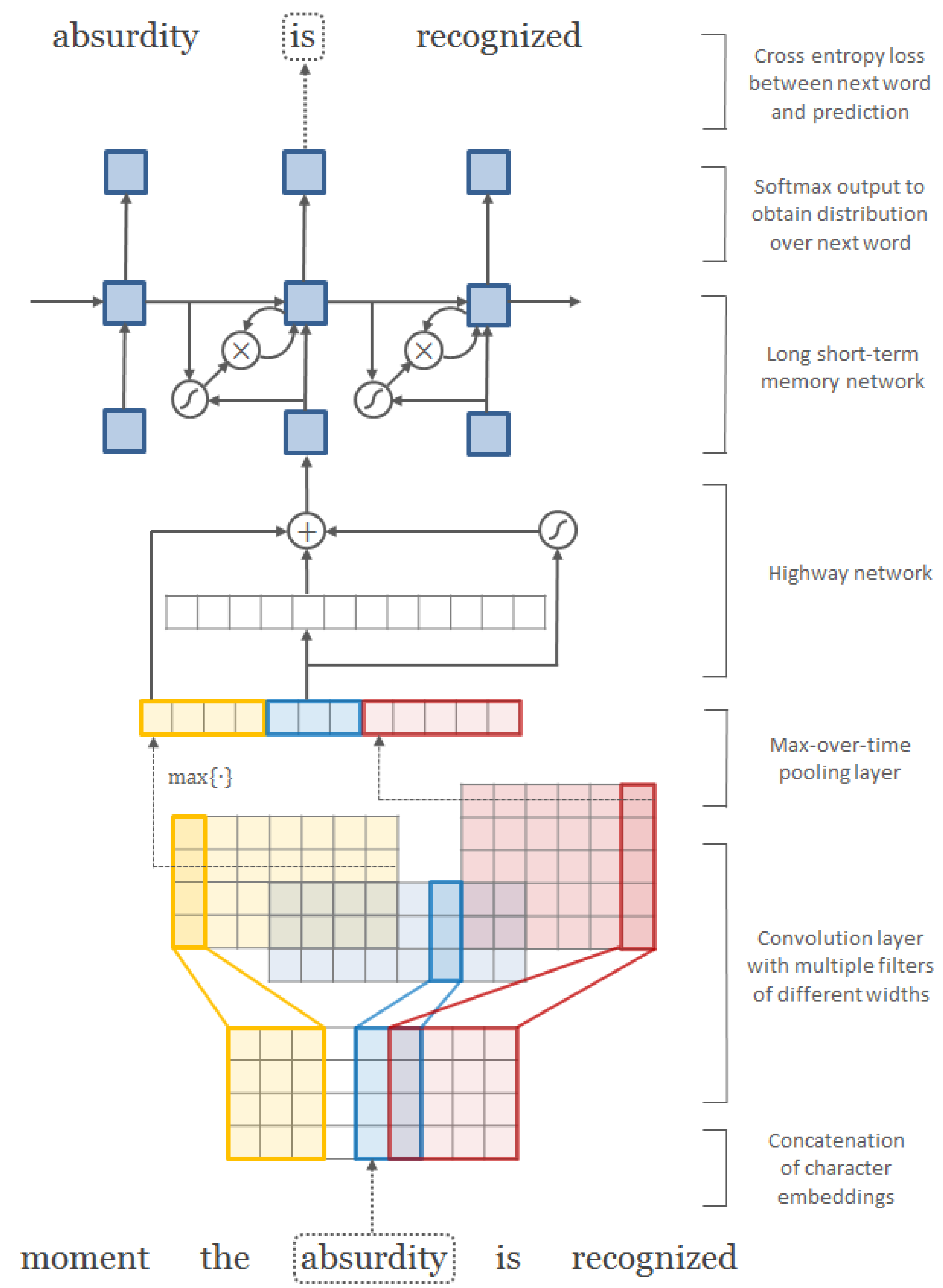

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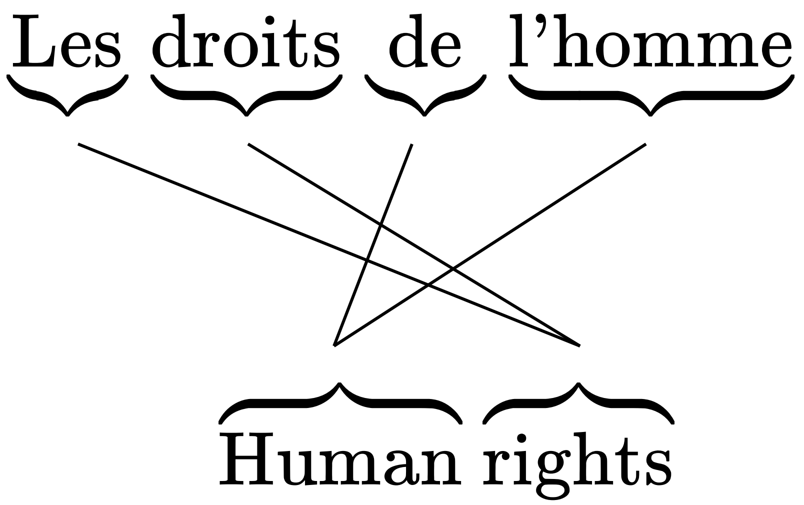

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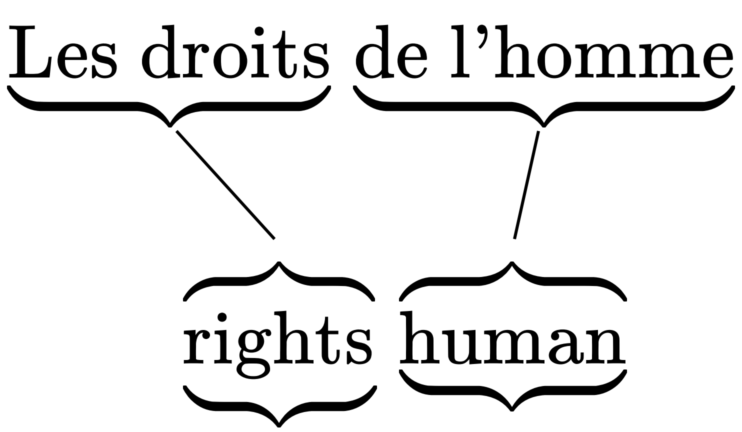

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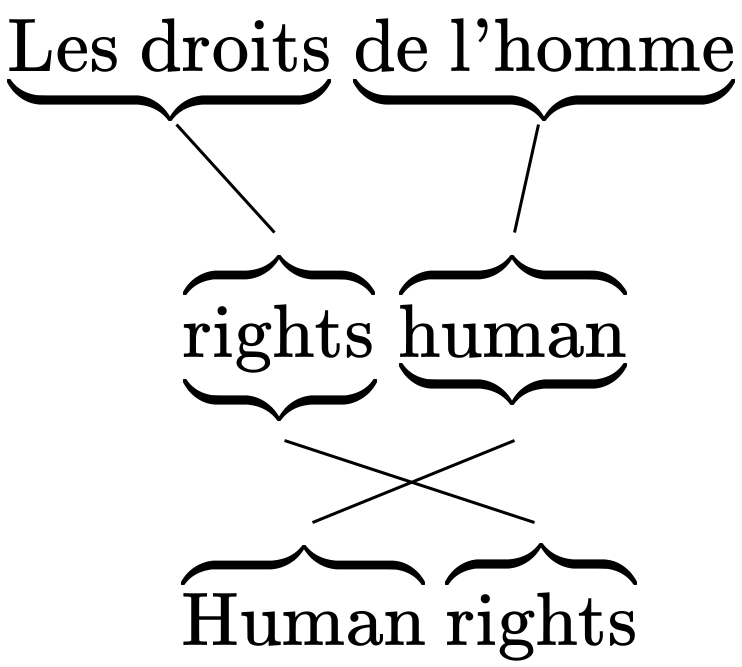

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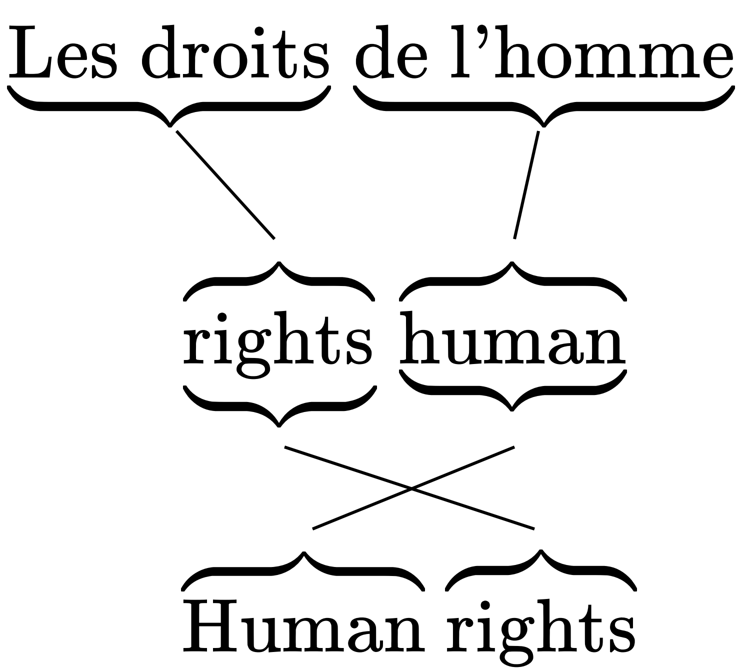


$\rightarrow$ Each of these (and others) steps implies many complex design choices !

Besides, *feature engineering*, supplementary *linguistic resources*, systems to maintain and update... *for every different language pair* !

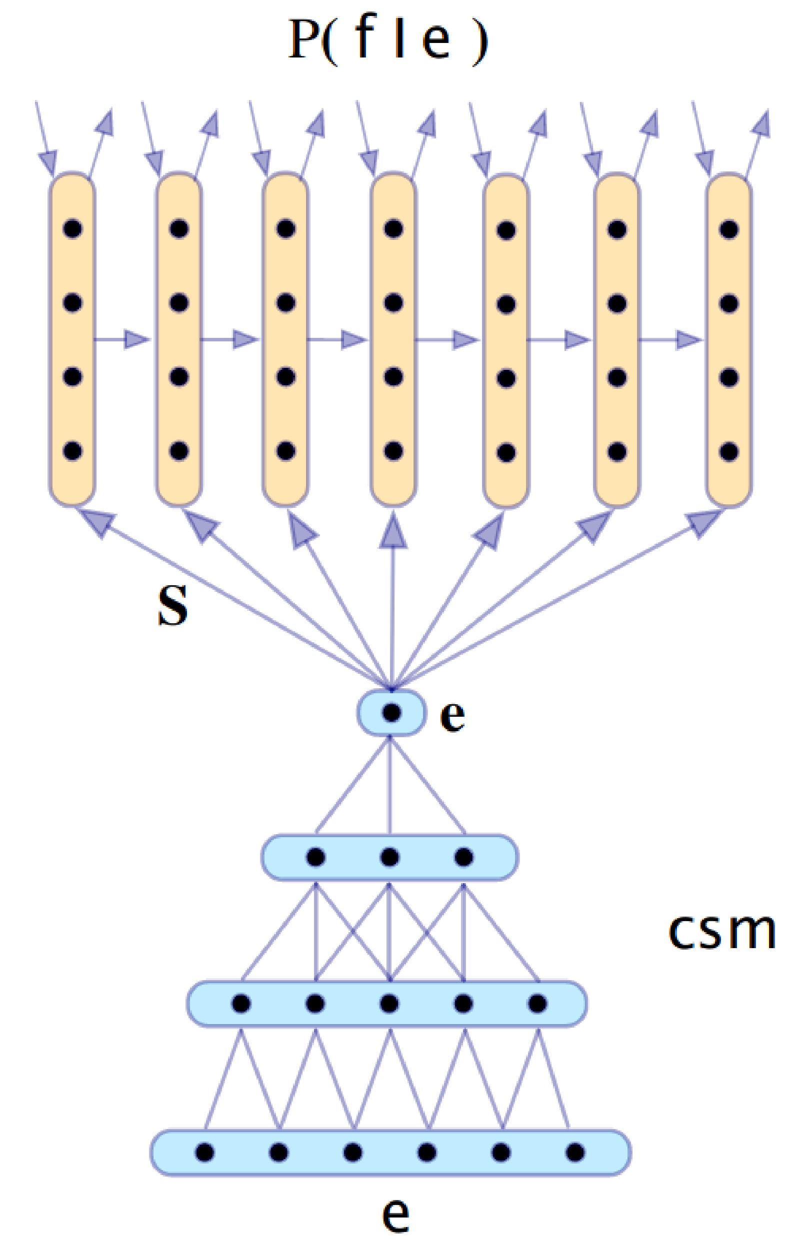
$\rightarrow$ Many other difficulties: using context, long-range dependancies, ...

Towards Sequence-to-sequence models

Recurrent Continuous Translation Models (Kalchbrenner et al, 2013)

One of the first neural model **for end-to-end machine translation**:

- The input sentence is encoded into **one global representation** via convolution
- The representation is decoded into the target sentence with a RNN



Sequence-to-sequence models for NMT

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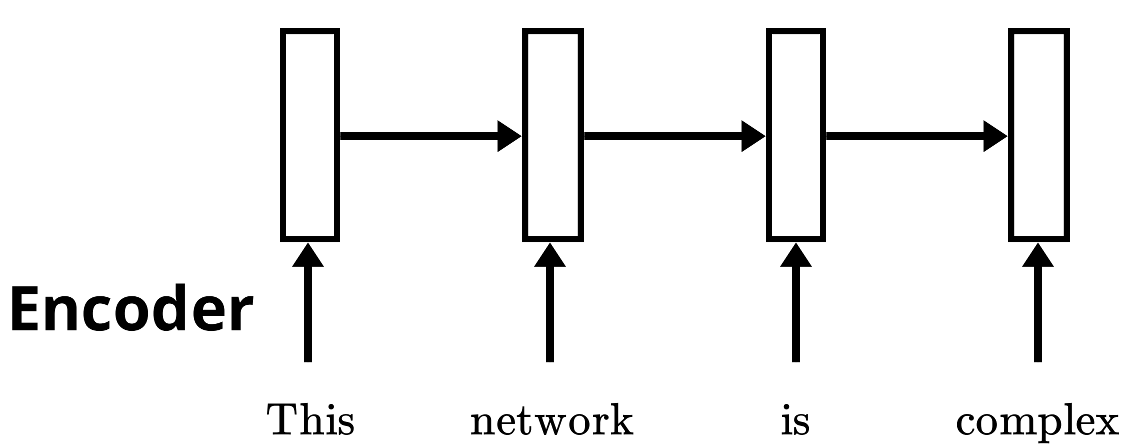

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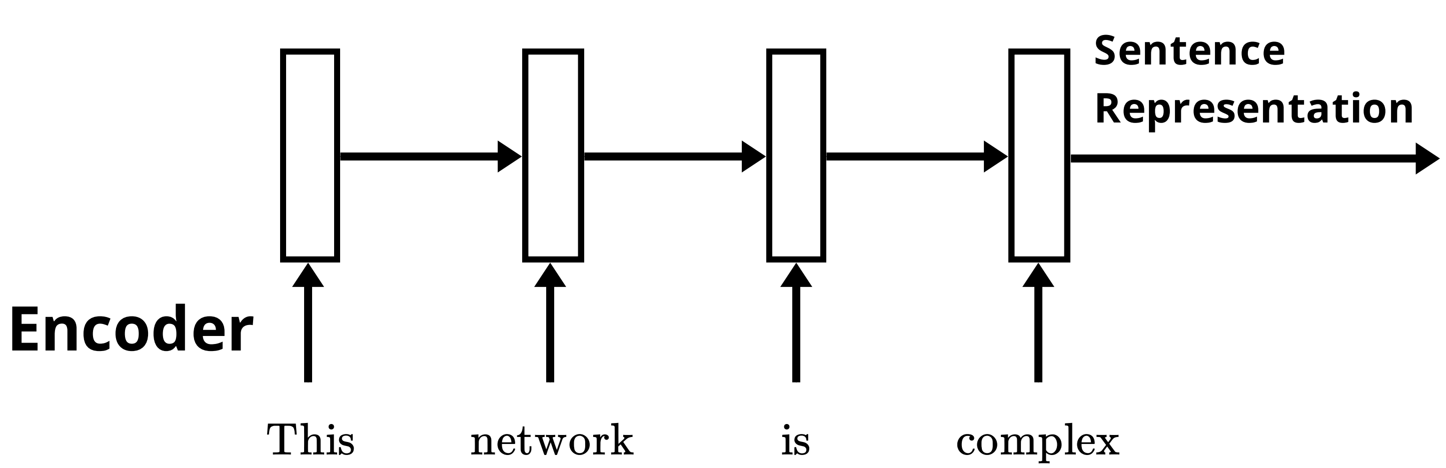

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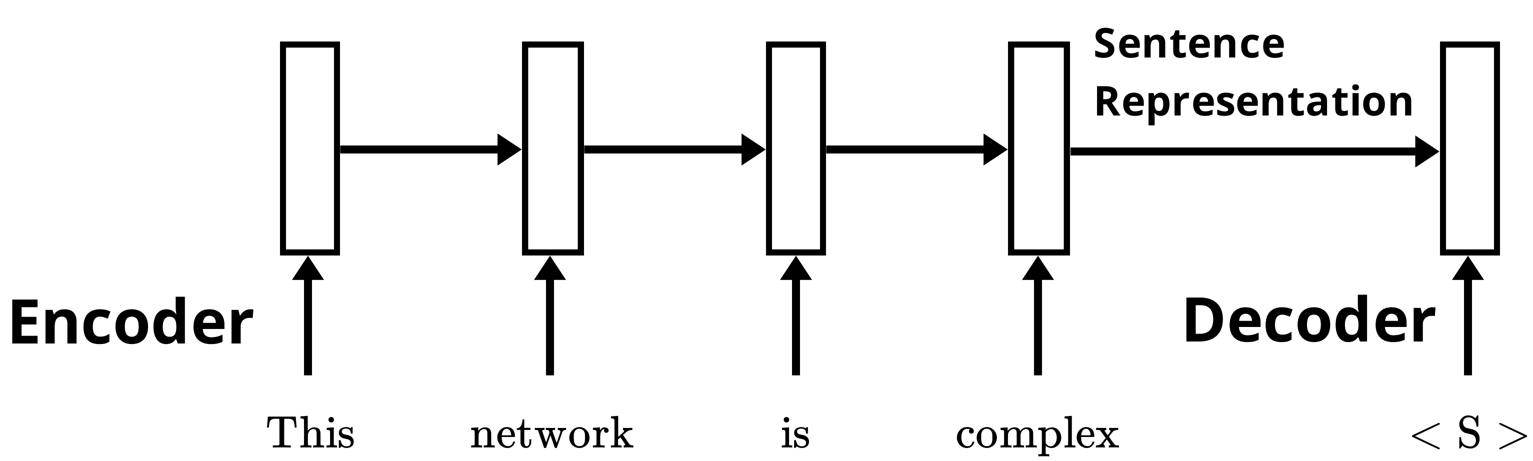

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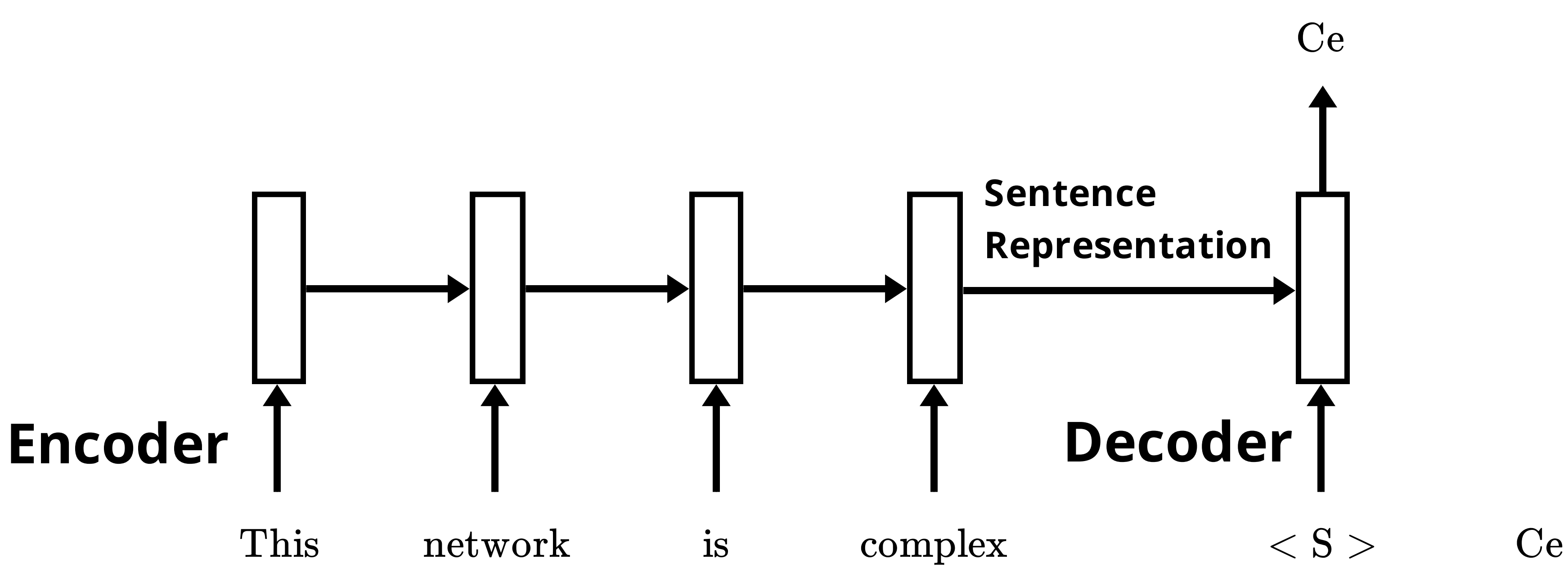

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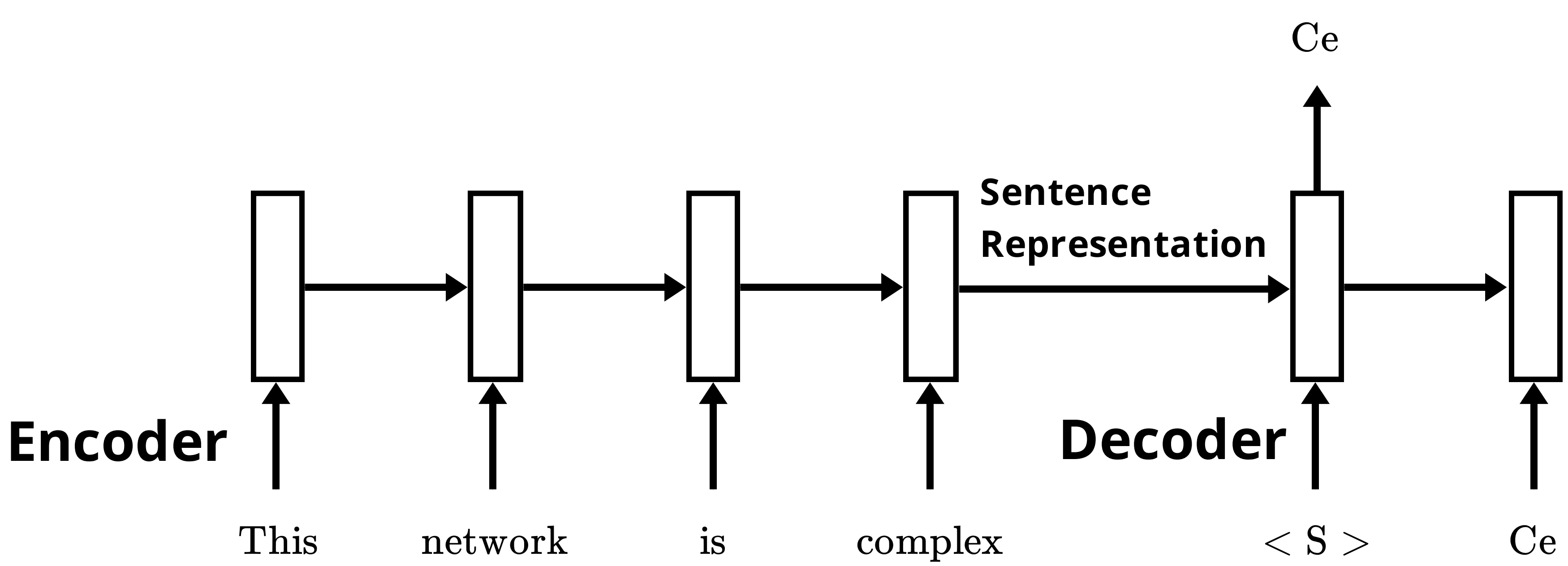

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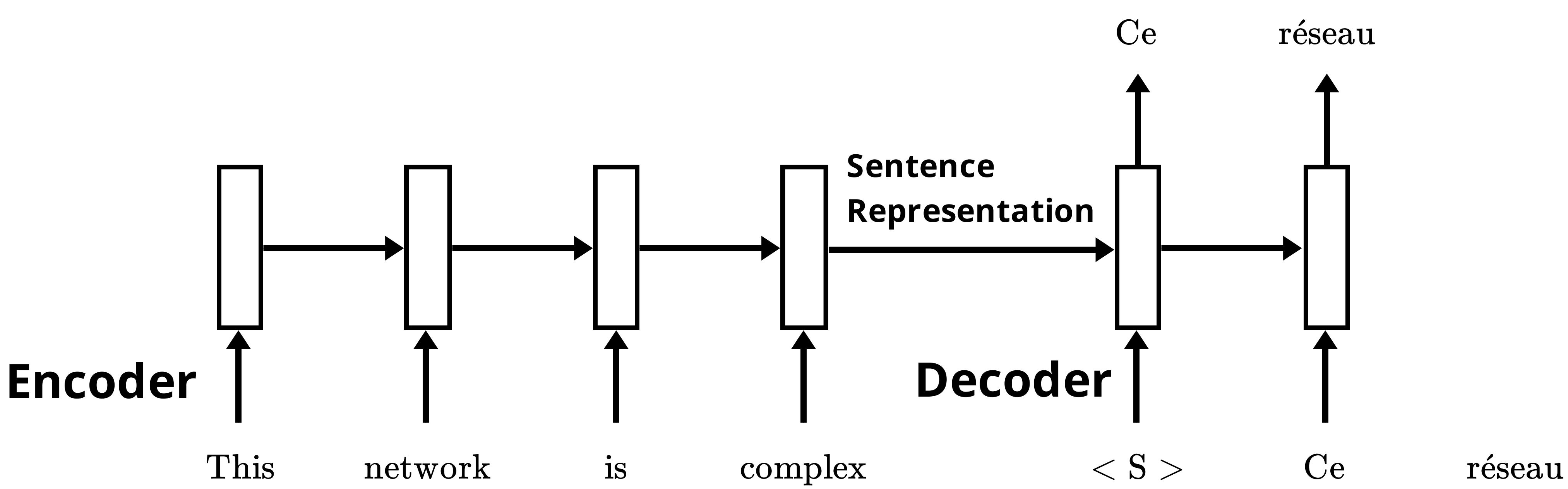

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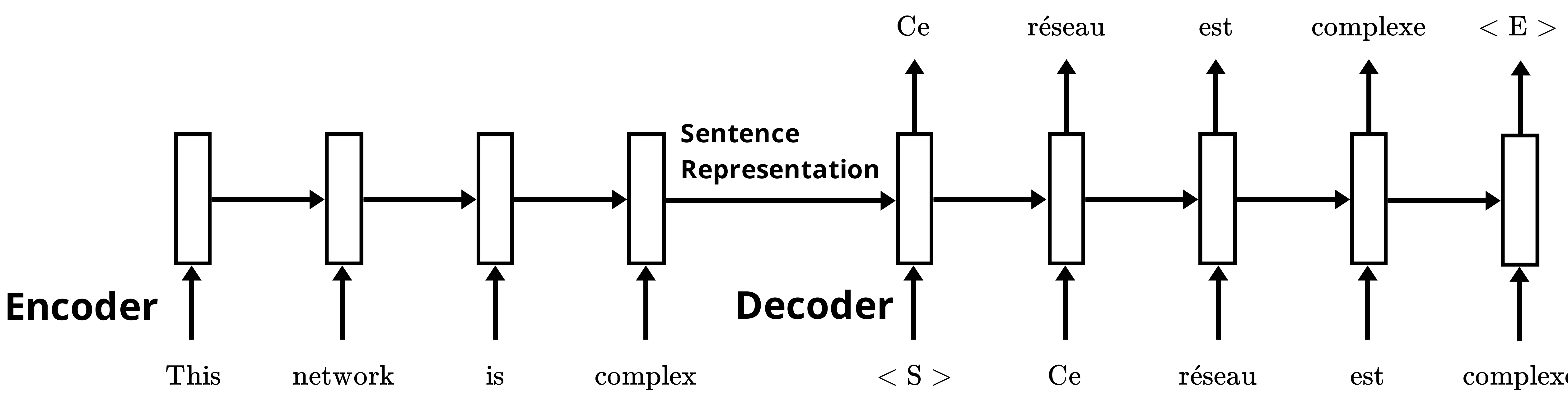
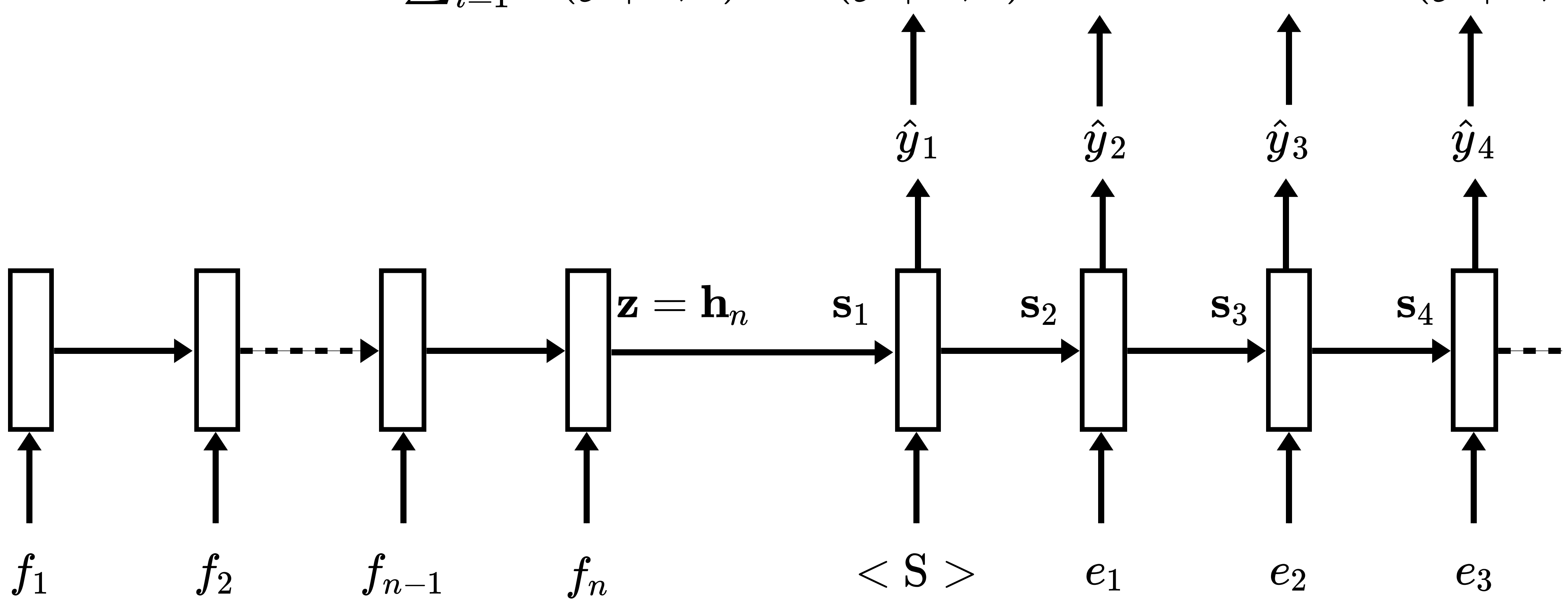


Training Seq2seq models for NMT

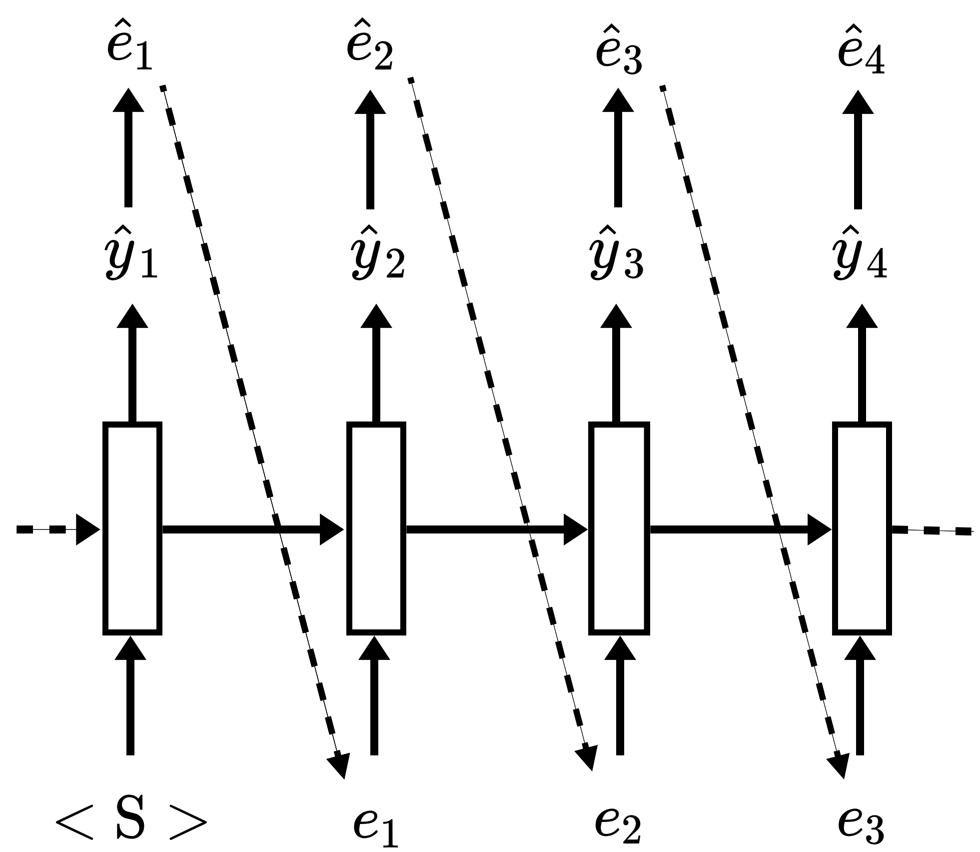
$$\sum_{i=1}^{N-1} l(\hat{y}_i | e_i, \mathbf{z}) = \; l(\hat{y}_1|e_1,\mathbf{z}) + ... \quad + \quad ... \quad + l(\hat{y}_4|e_1,..,e_4,\mathbf{z}) + ...$$



This NMT model can be seen as a conditional language model: we optimize $P(e|f) = P(e_1|f)P(e_2|e_1,f)...$

- As usual, we minimize the **negative log-likelihood**
- The model is optimized **end-to-end** with backpropagation
- During training, we give the model the **true inputs** (target sentence)

Greedy decoding of Seq2seq models



Greedy decoding:

$\rightarrow$ Taking the argmax at each step of the decoder and use it as next input, until the end symbol $<\mathrm{E}>$ is generated

- It does not take the **structure** of the target sentence into account
- If there is a **mistake** during decoding, impossible to go back
- But it is impossible to keep track of all possibilities ($|\mathcal{V}|$ is very large !)

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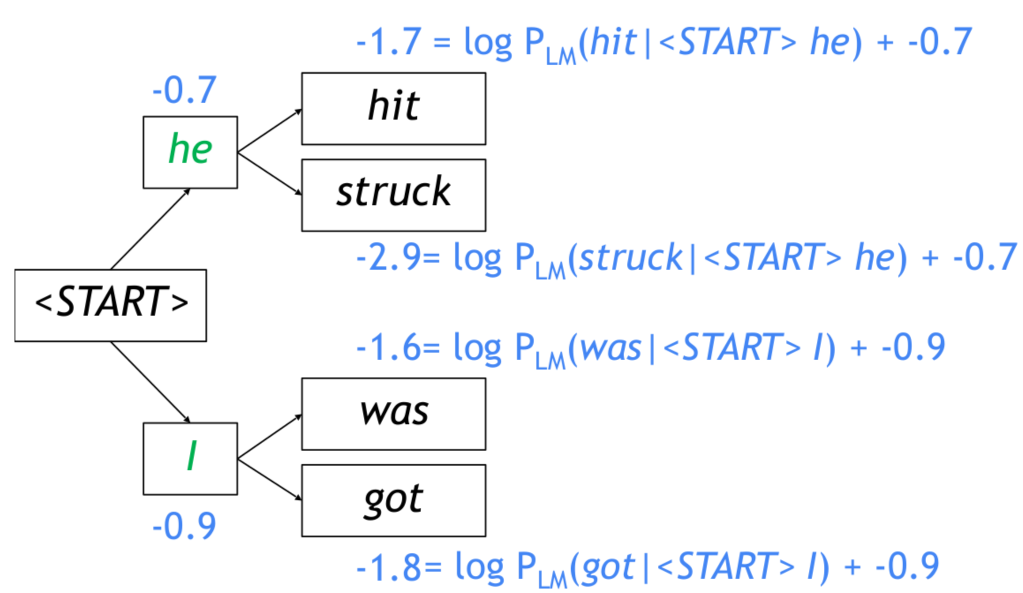

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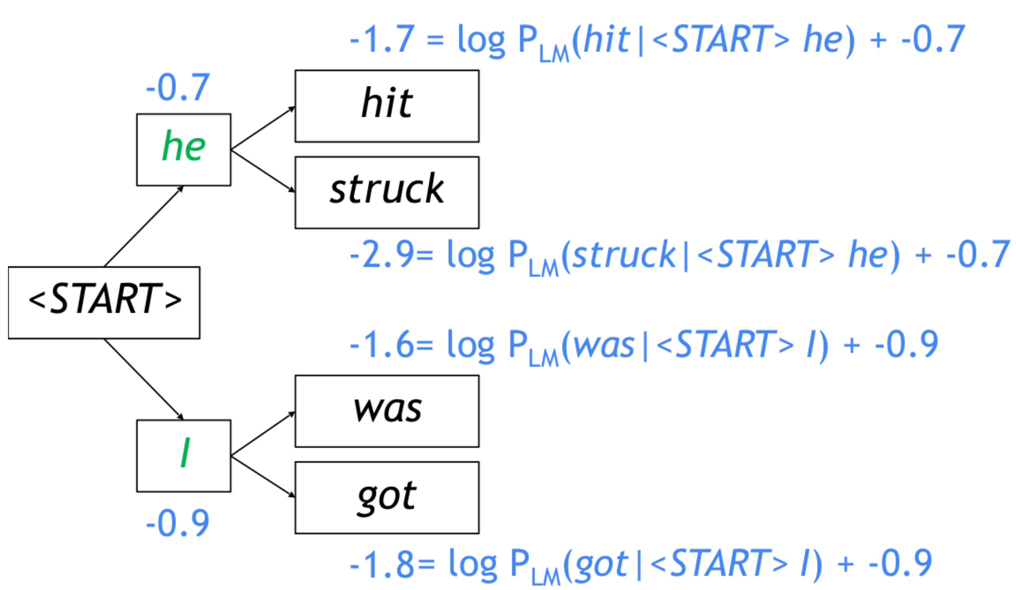

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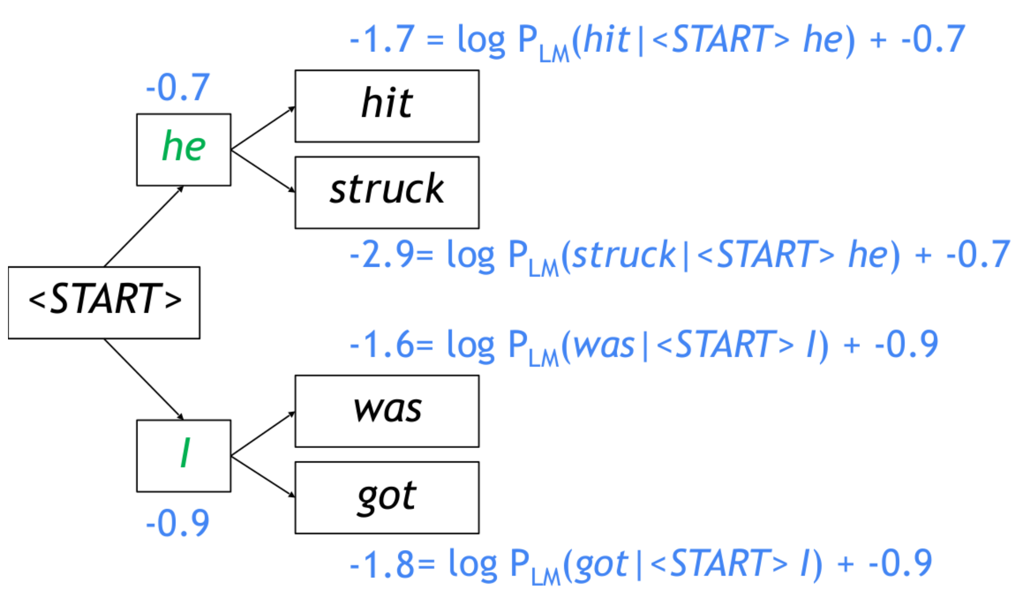

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- The search is not optimal, but it is very efficient !
- We may decode until we reach a limit length, or until we generate a limit number of completed sequences

Seq2seq models: Assesment

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- However, as often with neural models, NMT is less interpretable and difficult to control.
- Besides, some problems are still there:
  - The large ($\rightarrow$ slow training) and closed **output vocabulary**
  - **Long-term dependencies**
  - It does not work well on **low-resource** language pairs

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Neural Machine Translation of Rare Words with Subword Units, (Seinrich et al, 2016)

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- Variant: **wordpiece/sentencepiece** - Tokenize in order to greedily reduce perplexity

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Difficulty: encode a sentence in a fixed-sized vector ? Besides, long-term dependencies are not well considered during decoding...

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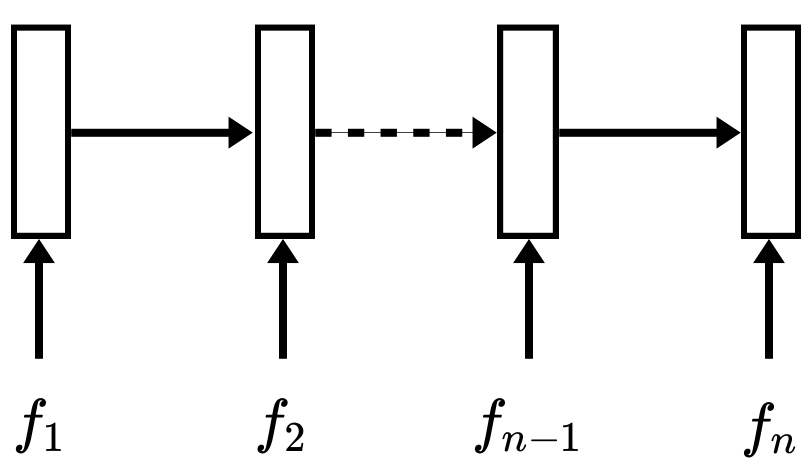

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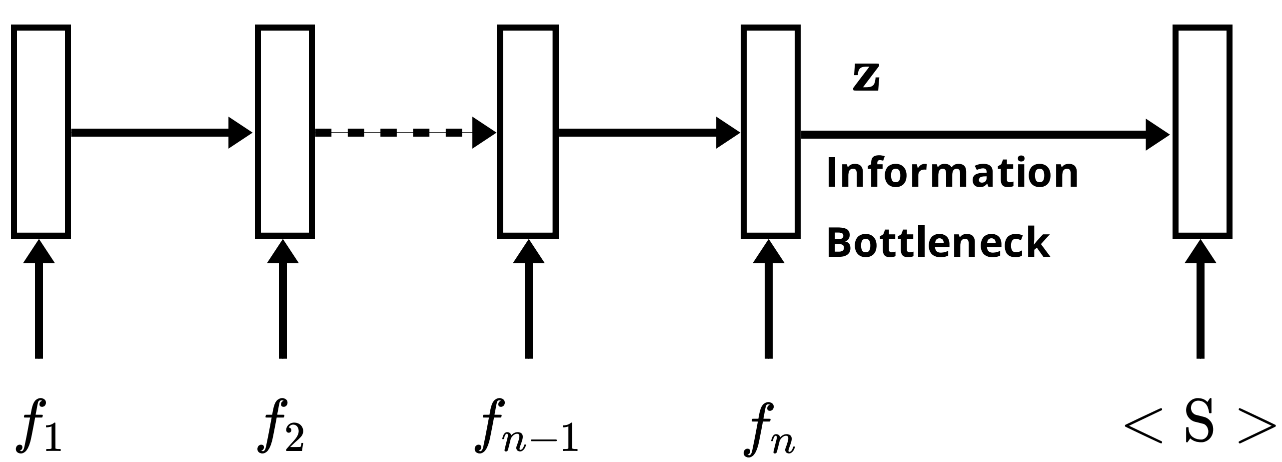

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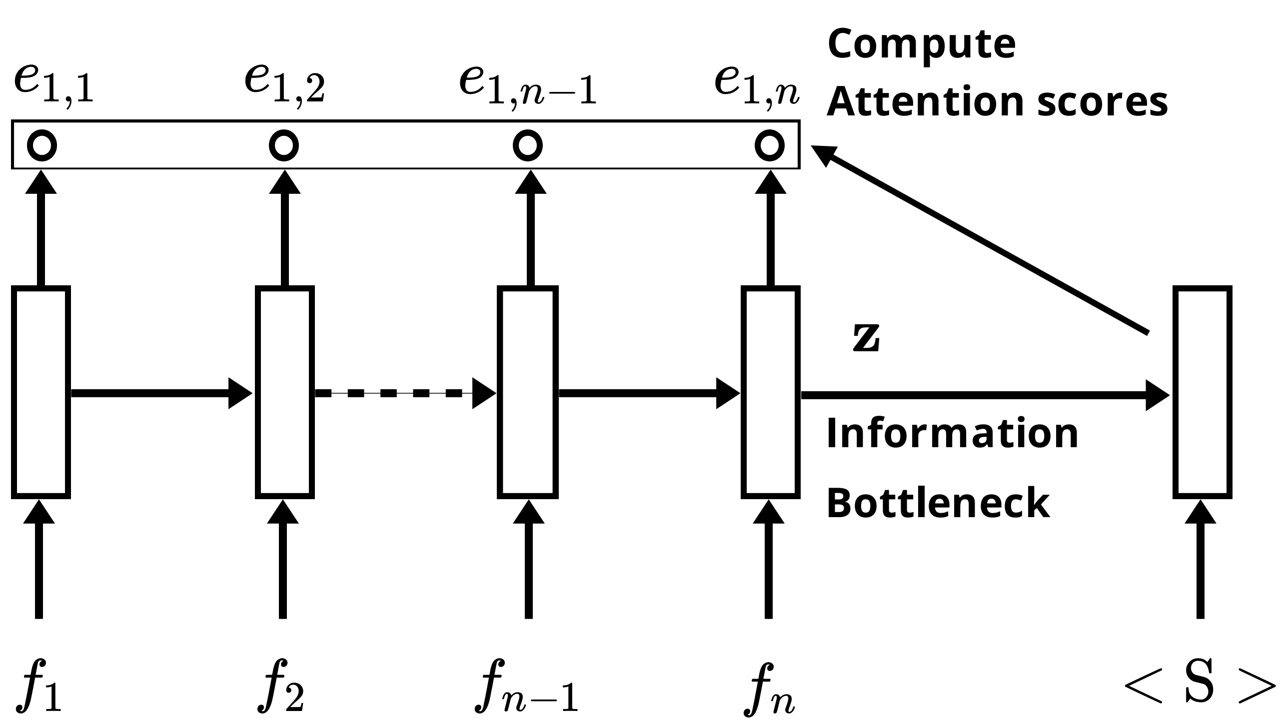

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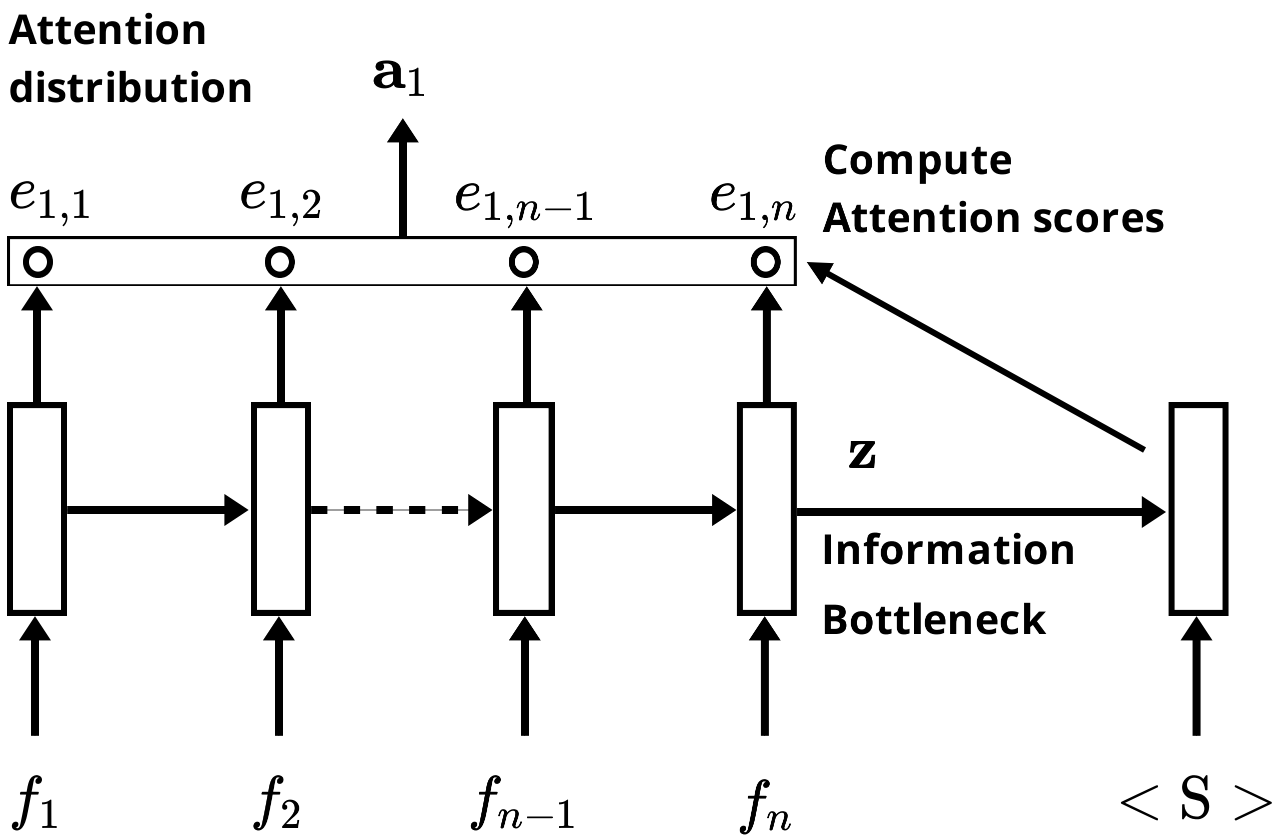

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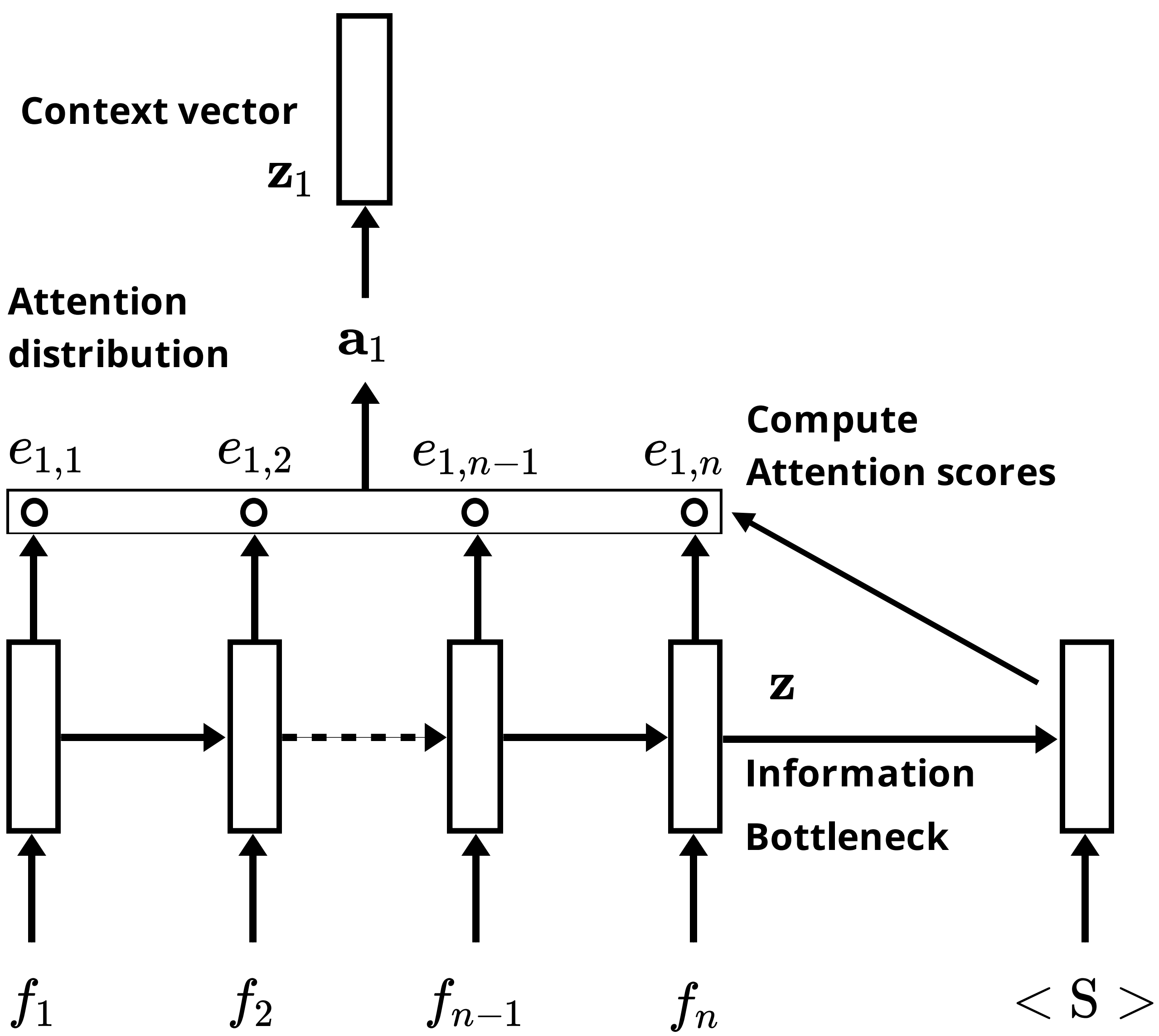

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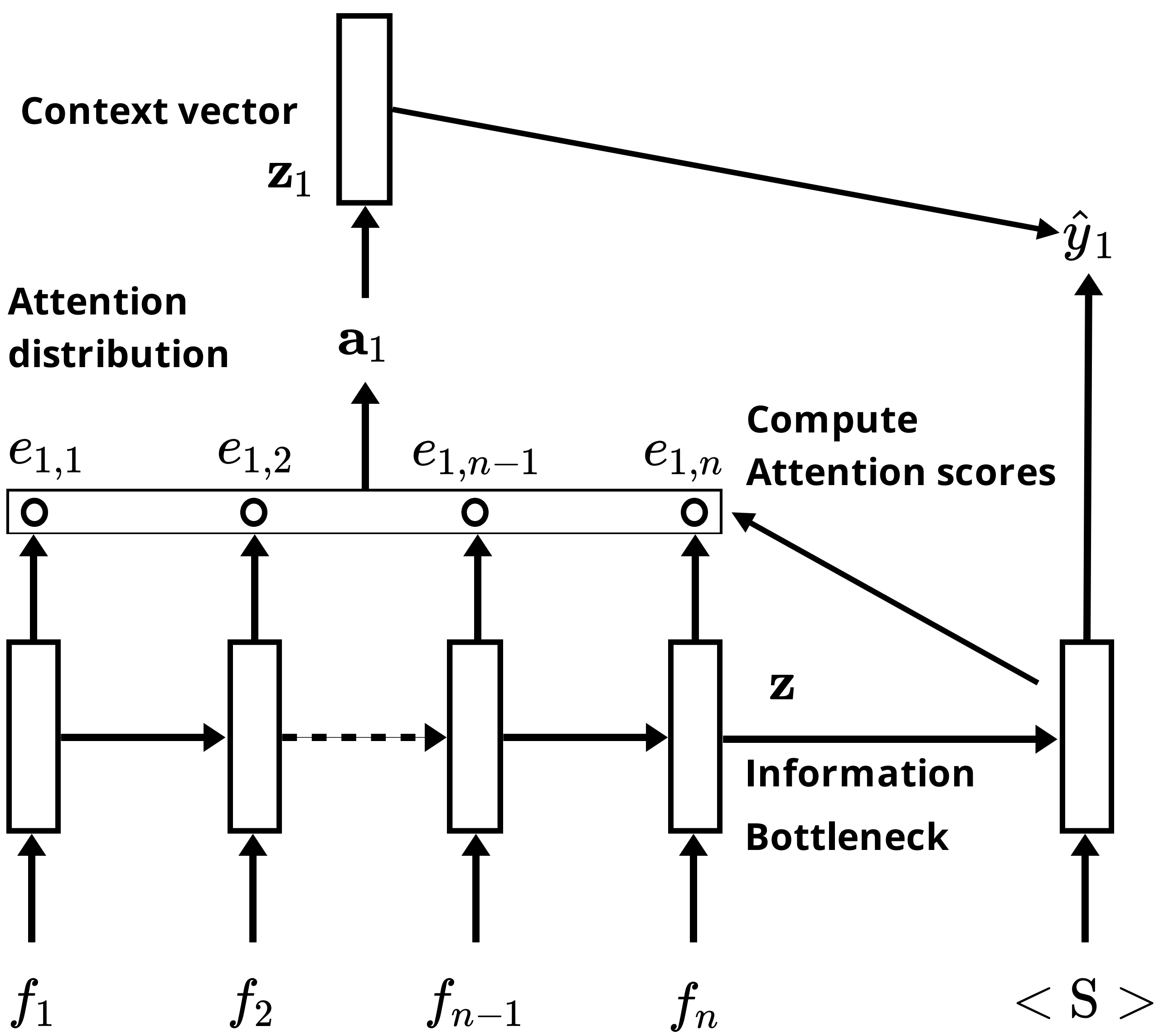

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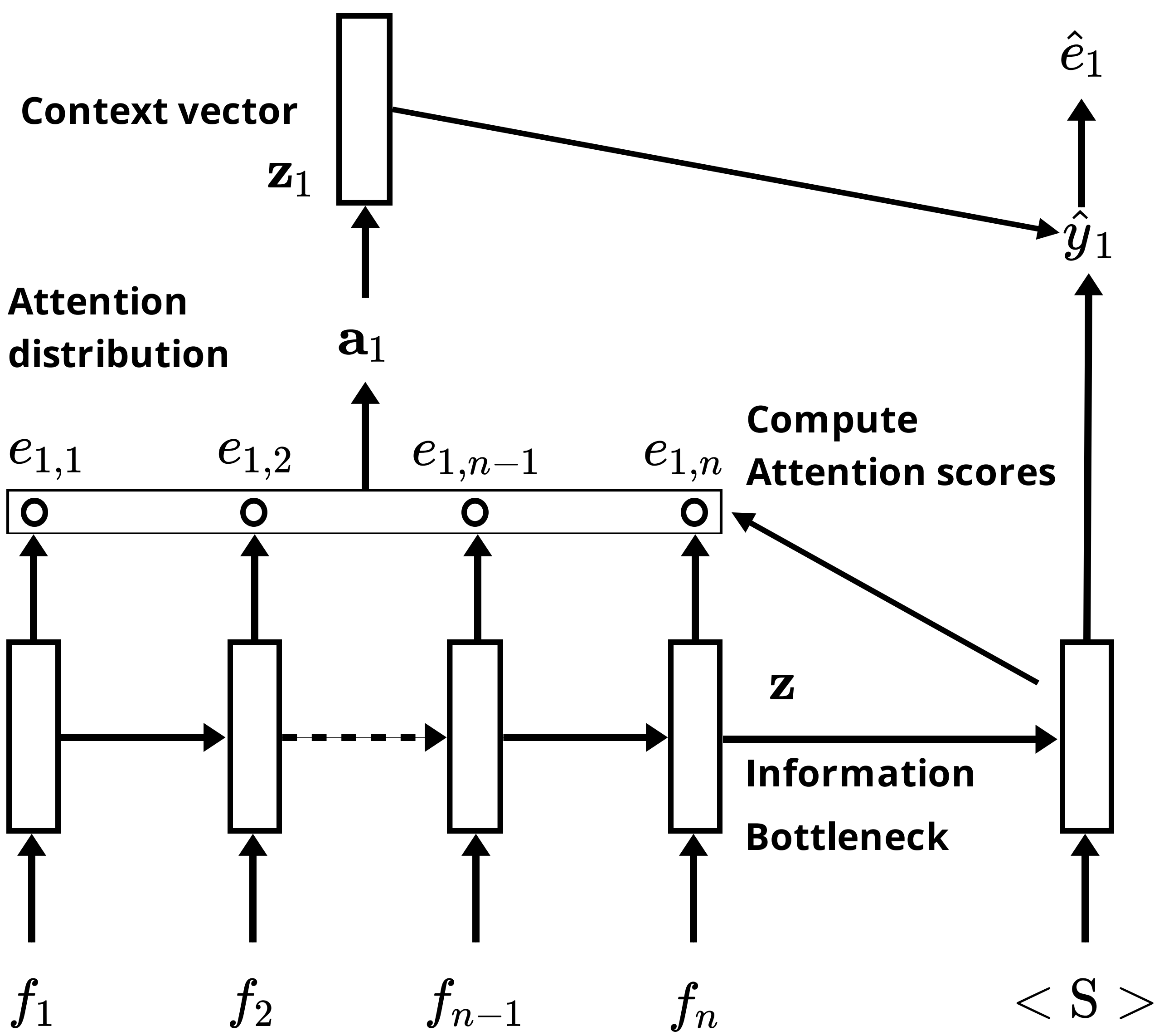

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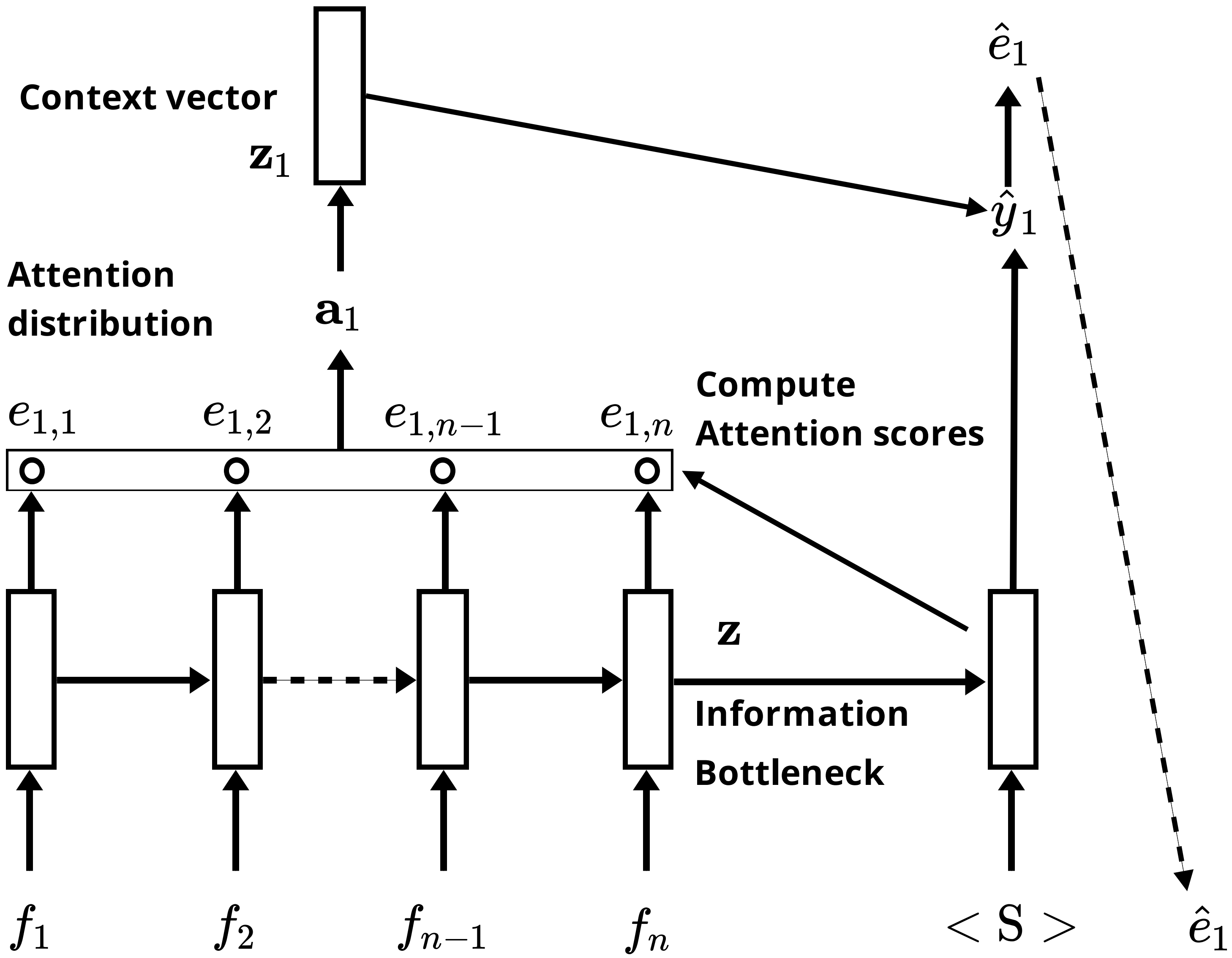

$\rightarrow$ **Attention** mechanism !

- Scores are computed with an alignement function f:
$$s_{i,j} = f(\mathbf{s}_i, \mathbf{h}_j)$$
- These scores give the attention weights:
$$\mathbf{a}_i = softmax(\mathbf{s}_i)$$
- The context vector is the combination of hidden states:
$$\mathbf{z}_i = \sum_{j=1}^{n} a_{i,j} \mathbf{h}_j$$

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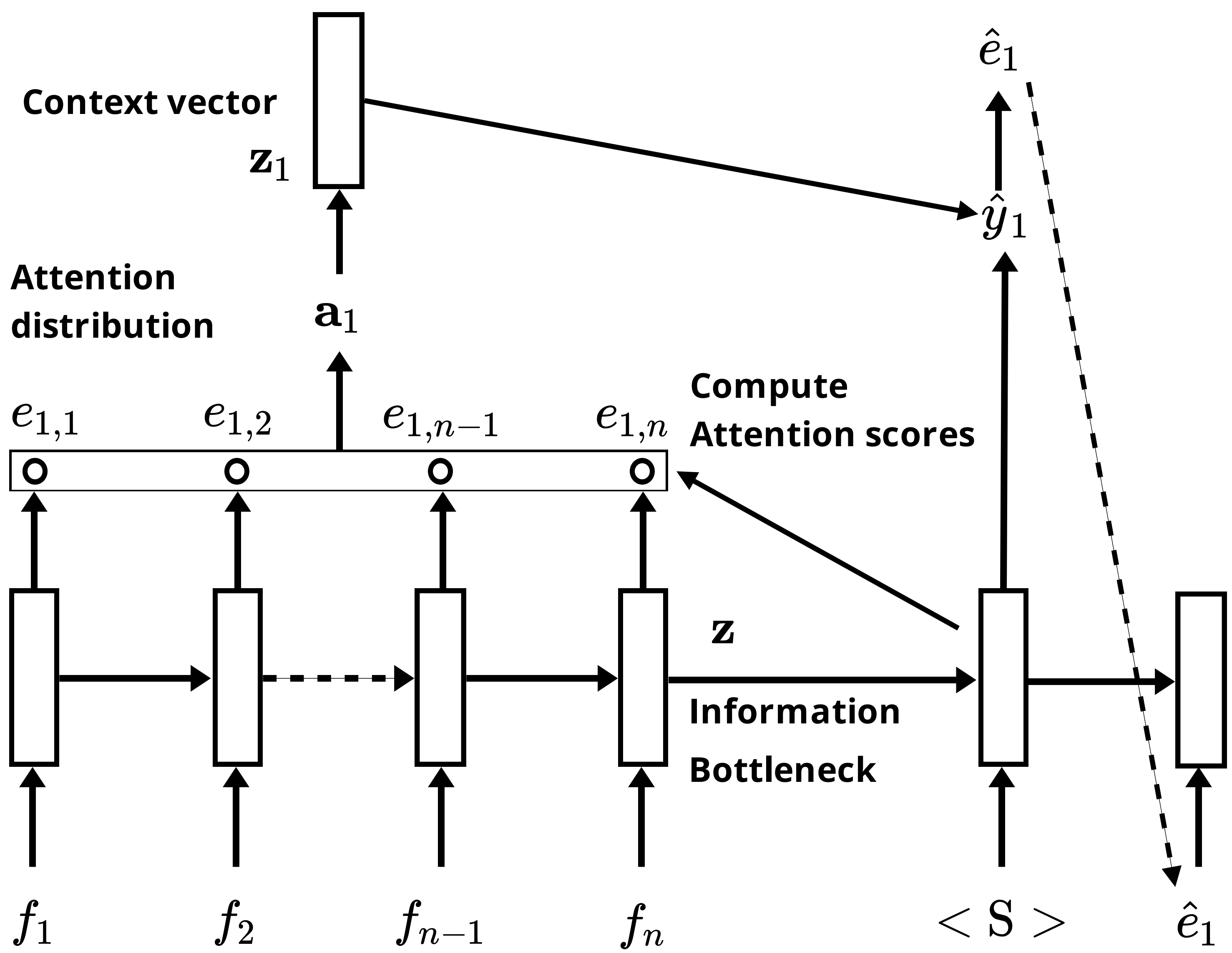

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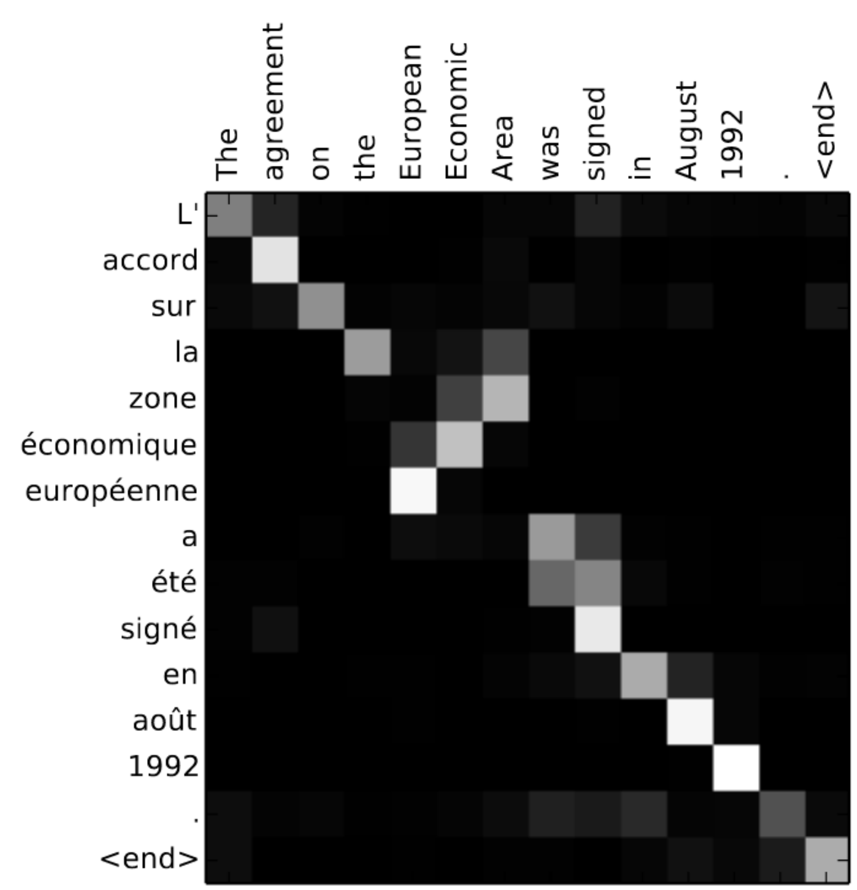
- Attention gives **soft alignement** on generated translations:



NMT as Catalyst

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- Similarly, **Attention** is a general technique, that can be applied within other models and to many other tasks, allowing to obtain a *fixed sized* representation from an *arbitrary number* of representations

$\rightarrow$ Neural Machine Translation has been a **catalyst** for the devellopment of deep learning techniques for NLP - and Seq2seq/Attention have been applied to many other tasks:

- Summarization (Document → Summary)
- Dialogue (Previous utterances → Next utterance)
- Parsing (Input text → Output parse sequence)
- ....

$\rightarrow$ Many other improvements have been made these last years, - some of these tasks are now catalysts themselves.

Acknowledgements & References

From slides by **Alexandre Allauzen** and the **CS224N** Stanford class

Some references:

- *The Deep Learning Book*, Chapters 9, 10 and 12.4

- *Speech and Language Processing*, Chapters 7,9 and 10 - but look at the rest !
- Section 1:
  - *A Bit of Progress in Language Modeling, (J. Goodman, 2001)*
  - *Improved backing-off for n-gram language modeling (Kneser et al, 1995)*
- Section 2:
  - *Strategies for training large vocab-ulary neural language models (Chen et al, 2016)*
  - *Efficient softmax approximation for gpus (Grave et al, 2016)*
- Section 3:
  - *On the difficulty of training Recurrent Neural Networks, (Pascanu et al, 2013)*
  - *Understanding LSTM Networks*
  - *An empirical exploration of recurrent network architectures (Jozefowicz et al, 2015)*