Deep Learning for NLP

The lecture starts at 13:15

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What we did last week

- Vector Semantics & Embeddings
    - Lexical and Vector Semantics
    - Words as Vectors
    - Measuring similarity & tf-idf
    - Word2Vec
- Neural Networks
    - Perceptron, units, activation functions
    - Feed forward
    - Training
- Neural Language Models

Contents

- Neural Language Models
- Recurrent Neural Networks
- LSTMs (Long Short-Term Memory Networks)

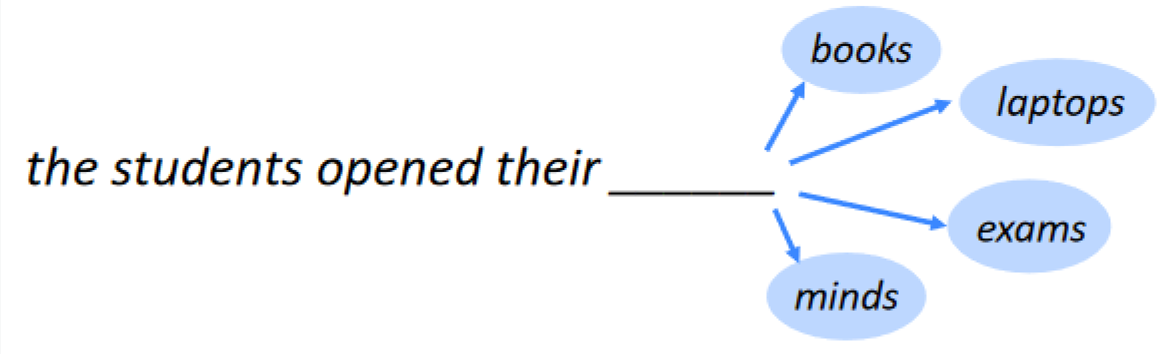
Neural Language Models

Relevant Literature

- Jurafsky & Martin, SLP, 3rd Edition: *Chapters 7, 9*
  - (including slides), references therein
- Cho, 2017, NLU with Distributional Representation, Chapters 4, 5
- Other material listed on individual slides

What is a “Language Model”?

- A model that predicts P(W) or $P(w_n \mid w_1,w_2 \ldots w_{n-1})$
- Probabilistic Language Models
  - Compare probabilities of sequences of words
  - Probability of upcoming word



What is a "Language Model"?

- A model that predicts P(W) or $P(w_n \mid w_1, w_2 \ldots w_{n-1})$

"A *language model* is a function that puts a probability measure on strings drawn from some vocabulary."

(Manning, Raghvan, Schütze – An Introduction to Information Retrieval, 2009, Cambridge UP)

Model M_1	
the	0.2
a	0.1
frog	0.01
toad	0.01
said	0.03
likes	0.02
that	0.04
dog	0.005
cat	0.003
monkey	0.001
...	...

$$\begin{aligned} P(\text{frog said that toad likes frog}) &= (0.01 \times 0.03 \times 0.04 \times 0.01 \times 0.02 \times 0.01) \\ &\quad \times (0.8 \times 0.8 \times 0.8 \times 0.8 \times 0.8 \times 0.8 \times 0.2) \\ &\approx 0.000000000001573 \end{aligned}$$

$$\sum_{t \in V} P(t) = 1$$

This is a unigram model, aka. "Bag of Words" model

What is a "Language Model"?

- A model that predicts P(W) or $P(w_n \mid w_1, w_2 \ldots w_{n-1})$
- How did you compute P?
  - Count and divide
  - Markov Assumption

$$P(\text{the} \mid \text{its water is so transparent that}) = \frac{Count(\text{its water is so transparent that the})}{Count(\text{its water is so transparent that})}$$

$P(\text{the} \mid \text{its water is so transparent that})$ » $P(\text{the} \mid \text{that})$

$P(\text{the} \mid \text{its water is so transparent that})$ » $P(\text{the} \mid \text{transparent that})$

- Unigrams: $P(w_n)$
- Bi-grams: $P(w_n \mid w_{n-1})$
- …
- N-grams: $P(w_n \mid w_1, w_2 \ldots w_{n-1})$

Language Model: A simple (bi-gram) example

$$P(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$

<s> I am Sam </s>

<s> Sam I am </s>

<s> I do not like green eggs and ham </s>

Symbols for the start and end of a sentence

$P(\texttt{I} \mid \texttt{<s>}) = \frac{2}{3} = .67$ $P(\texttt{Sam} \mid \texttt{<s>}) = \frac{1}{3} = .33$ $P(\texttt{am} \mid \texttt{I}) = \frac{2}{3} = .67$

$P(\texttt{</s>} \mid \texttt{Sam}) = \frac{1}{2} = 0.5$ $P(\texttt{Sam} \mid \texttt{am}) = \frac{1}{2} = .5$ $P(\texttt{do} \mid \texttt{I}) = \frac{1}{3} = .33$

$\boxed{P(\textbf{like} \mid \textbf{I}) = 0}$

Language Model

- A model that predicts $P(W)$ or $P(w_n \mid w_1,w_2 \ldots w_{n-1})$
- Many types of LMs
  - N-gram based
  - Grammar-based
  - Context-free grammars
  - …
- Less complex in IR (Information Retrieval)
- Performance measurement

Perplexity

$$\mathrm{PP}(W) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i|w_1 \ldots w_{i-1})}}$$

- Issues: zero probabilities, smoothing, interpolation

$$\boxed{P(\,\textbf{like} \mid \textbf{I}\,) = 0}$$

Neural Language Model

- No smoothing
- Longer histories (compared to the fixed N in ”N-gram”)
- Generalize over contexts
    - “chases a dog” vs. “chases a cat” vs. “chases a rabbit”

- Higher predictive accuracy!
- Further models are based on NLMs.

- Slower to train!

Neural Language Model - Definition

- Standard Feed-Forward Network
- Input: a representation of previous words (w_1, w_2, …)
- Output: probability distribution over possible next words.

$$P(w_n \mid w_1, w_2 \ldots w_{n-1}) = f_\theta^{w_n}(w_1, w_2 \ldots w_{n-1})$$

i.e.: find the function

Neural Language Model - Input

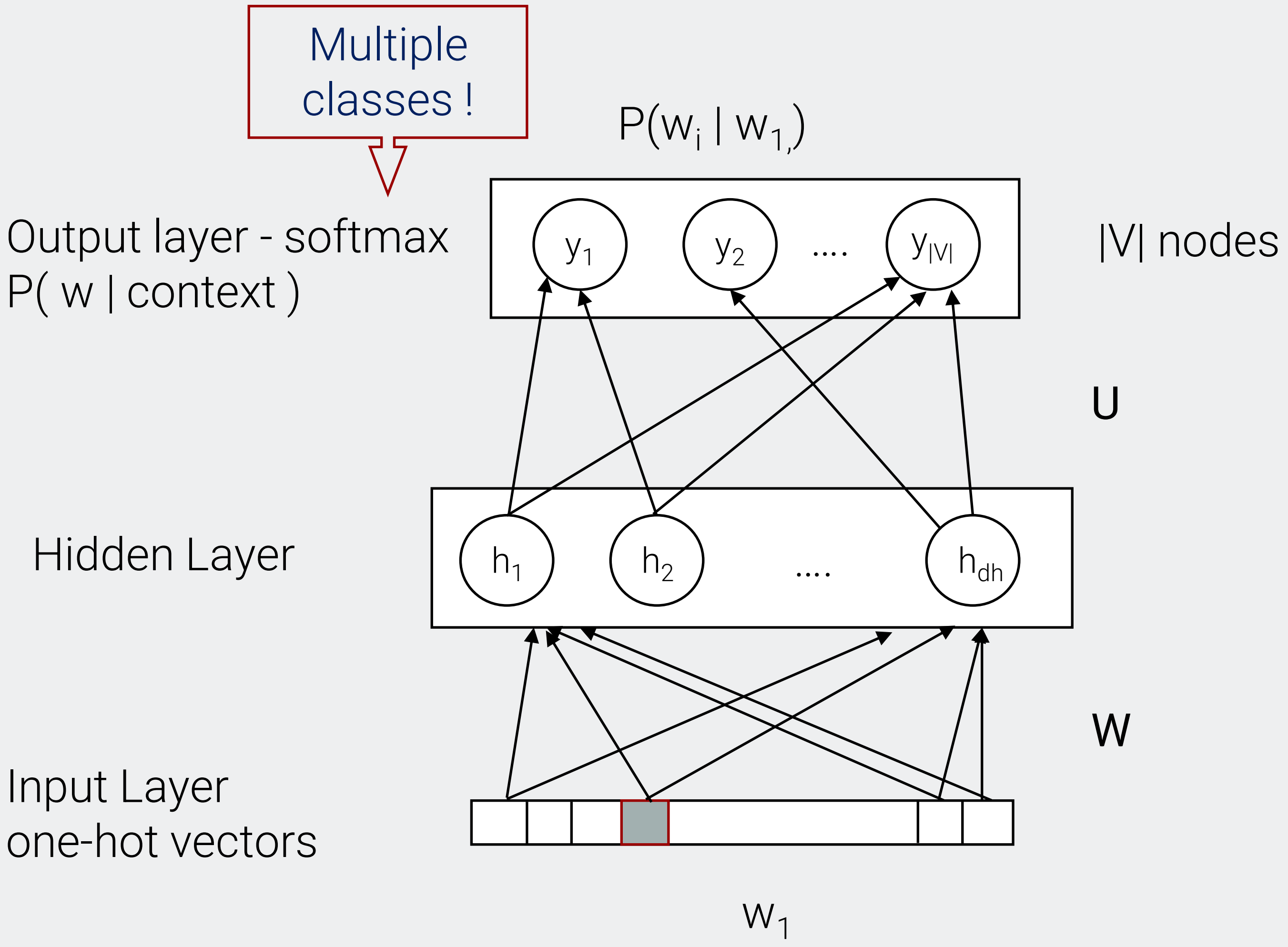
- Standard Feed-Forward Network
- **Input**: a representation of previous words (w_1, w_2, …)
- Output: probability distribution over possible next words.

- N-grams used exact words! (P("cat"))

- Equi-distance! (lowest prior knowledge)
- 1-of-N encoding (aka. one-hot vector)

	a	hair				cat				zombie
vocabulary index:	[1,	2,	3,	4,	5,	6,	7,	….,	…,	|V|]
	[0,	0,	0,	0,	0,	1,	0,	….,	…,	0]

Feed Forward Net - Execution



[1, 2, 3, 4, 5, 6, 7, ..., ..., | V |]
[0, 0, 0, 0, 0, 1, 0, ..., 0, 0 , 0]

Feed Forward Net - Training

Positive samples ($w_{3,}$ w_{402})
(metal jacket)

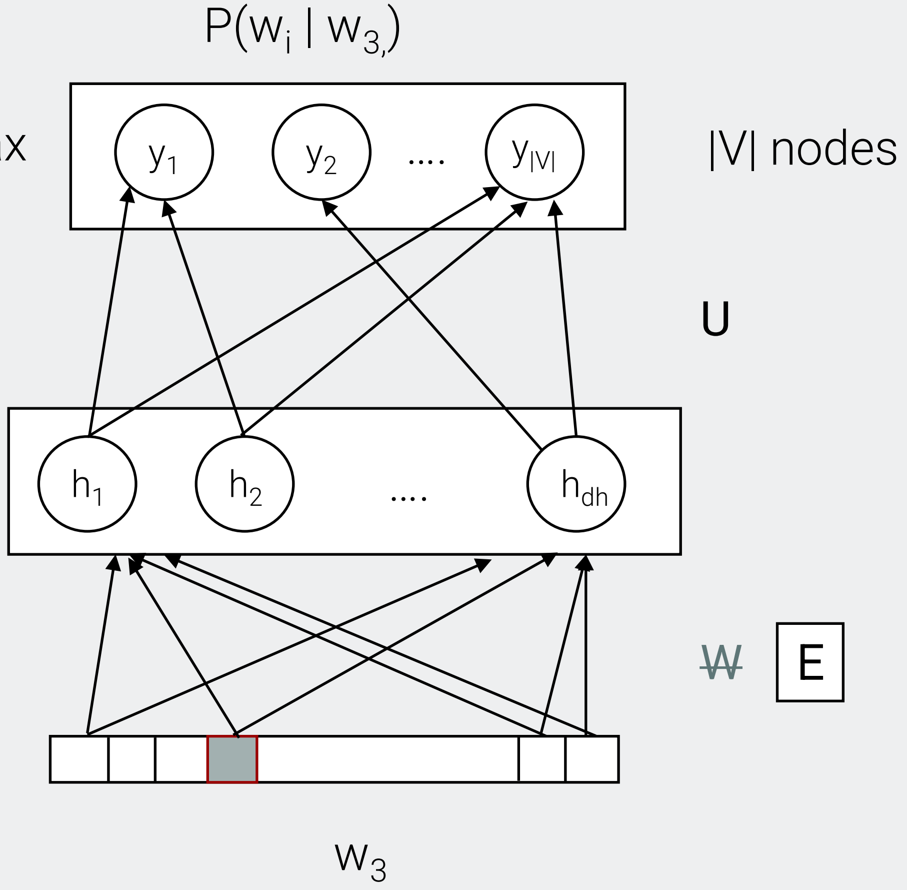
Negative samples ($w_{3,}$ w_{xx})
(metal heavy)
(metal towel)

[1, 2, 3, 4, 5, 6, 7, …., …, | V |]
[0, 0, 0, 0, 0, 1, 0, …., 0, 0 , 0]

Output layer - softmax
P(w | context)

Hidden Layer

Input Layer
one-hot vectors



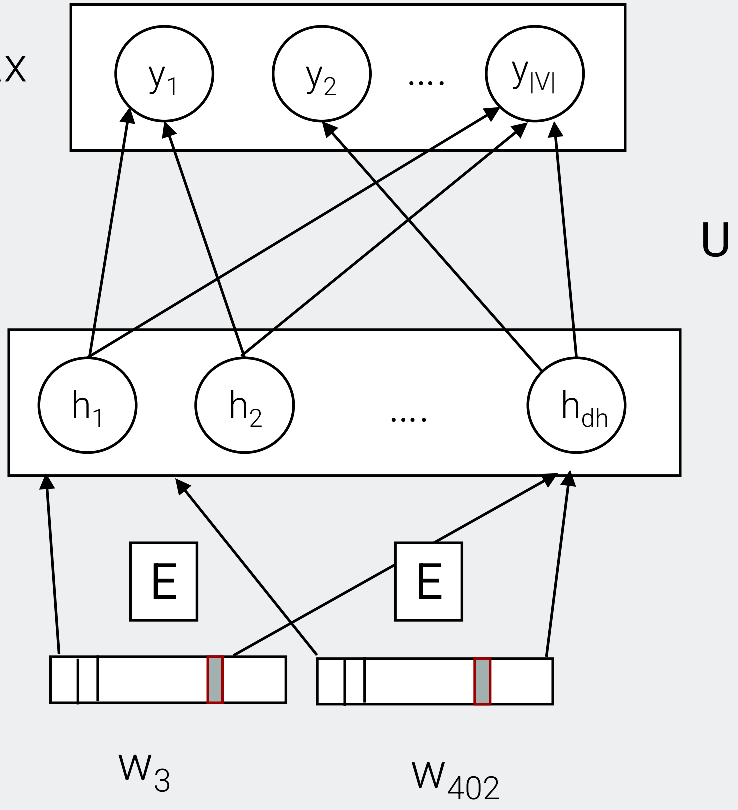
Feed Forward Net - Training

$P(w_i \mid w_{3,} w_{402},)$

Output layer - softmax
P(w | context)

Hidden Layer

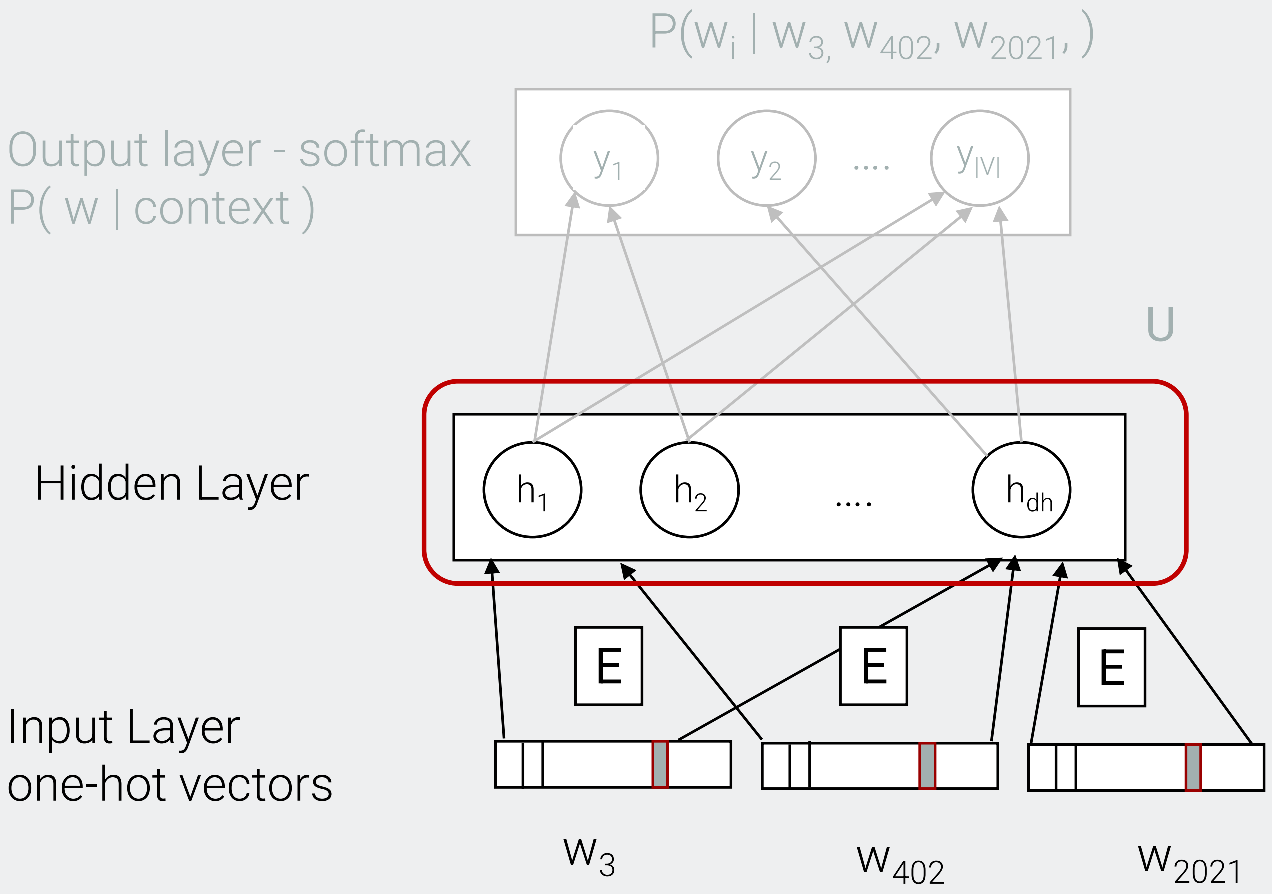
Input Layer
one-hot vectors



Positive samples ($w_{3,}$ w_{402}, w_{2021})
(**metal skirt hanger**)

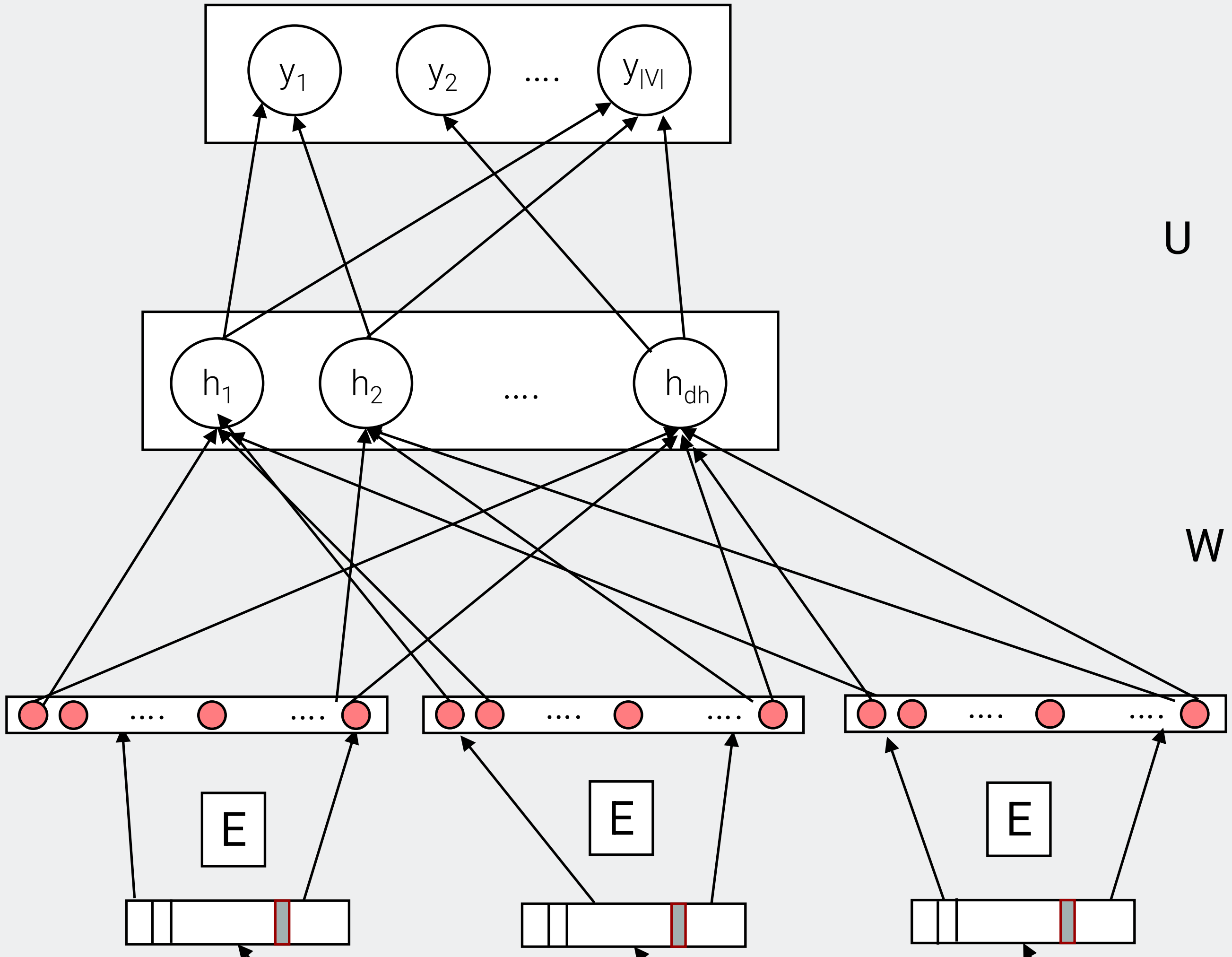
Negative samples ($w_{3,}$ w_{402}, w_{xx})
(metal skirt mouse)
(metal skirt towel)

Feed Forward Net - Training



Projection layer

E gives us at the end the word embeddings for this specific data set



1 x |V|

Output layer - softmax
P(w | context)

$$y = \text{softmax}(z)$$

U |V| x dh

$$z = Uh$$

1 x dh

$$h = \sigma(We+b)$$

W dh x 3d

1 x 3d

$$e = (Ex_1, Ex_2, \ldots, Ex)$$

(context vector!)

d x |V|

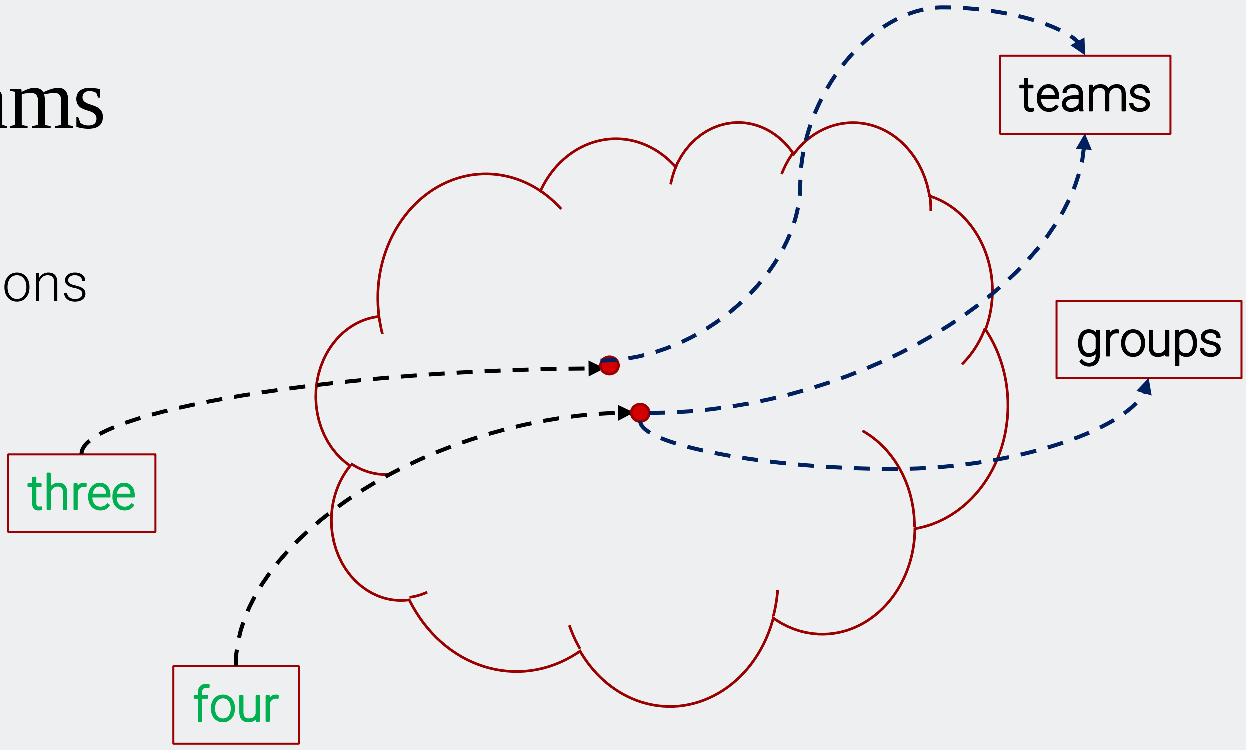
1 x |V|

Input Layer, one-hot vectors

the way back to embeddings ...

Generalization to Unseen n-grams

- There are three **teams** left for the qualifications
- four **teams** have passed the first round
- four **groups** are playing in the field



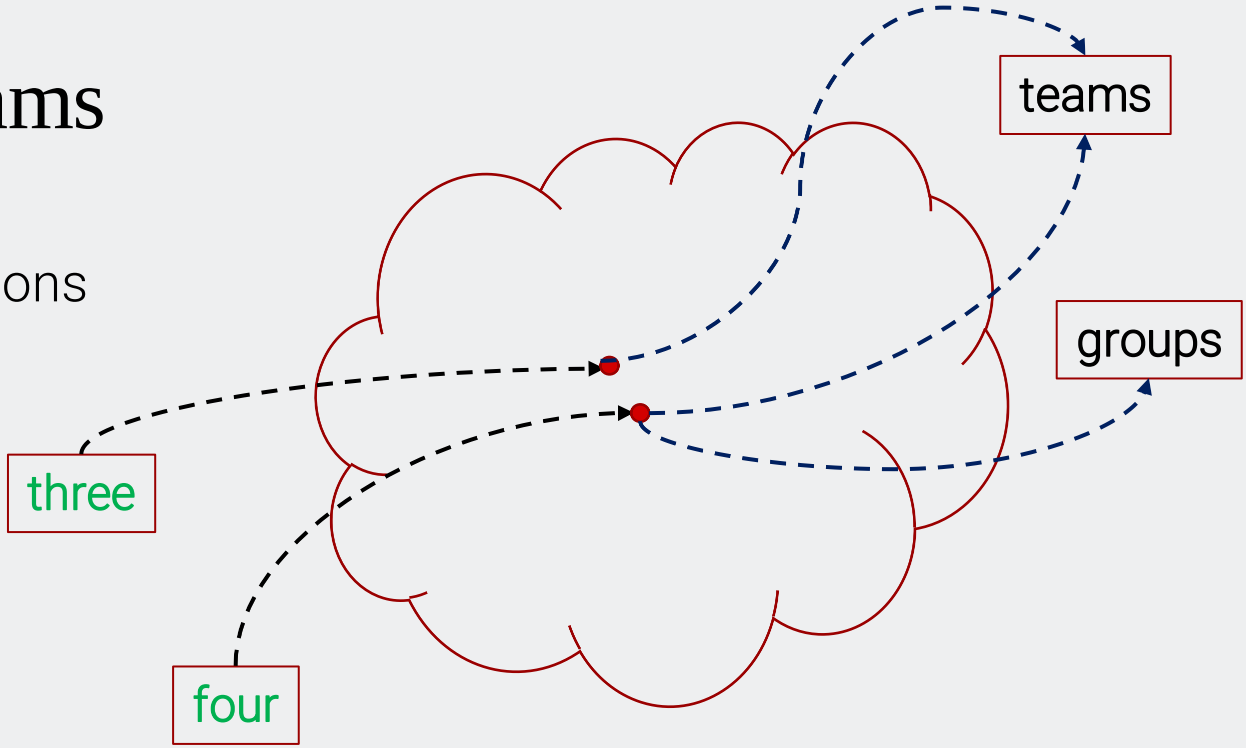
P(**teams** | four) ≈ P(**groups** | four)

- (during training)
- context

Generalization to Unseen n-grams

- There are three teams left for the qualifications
- four teams have passed the first round
- four groups are playing in the field

- Assign probability to “three groups”



P(teams | four) ≈ P(groups | four)

- (during inference)
- context

Neural Language Models – In a small nutshell

- pattern recognition problems
- Data-driven
- High performance in many problems
- No domain knowledge needed
- Generalization

- Data-hungry (bad for small data sets)
- Cannot handle symbols very well
- Computationally high costs

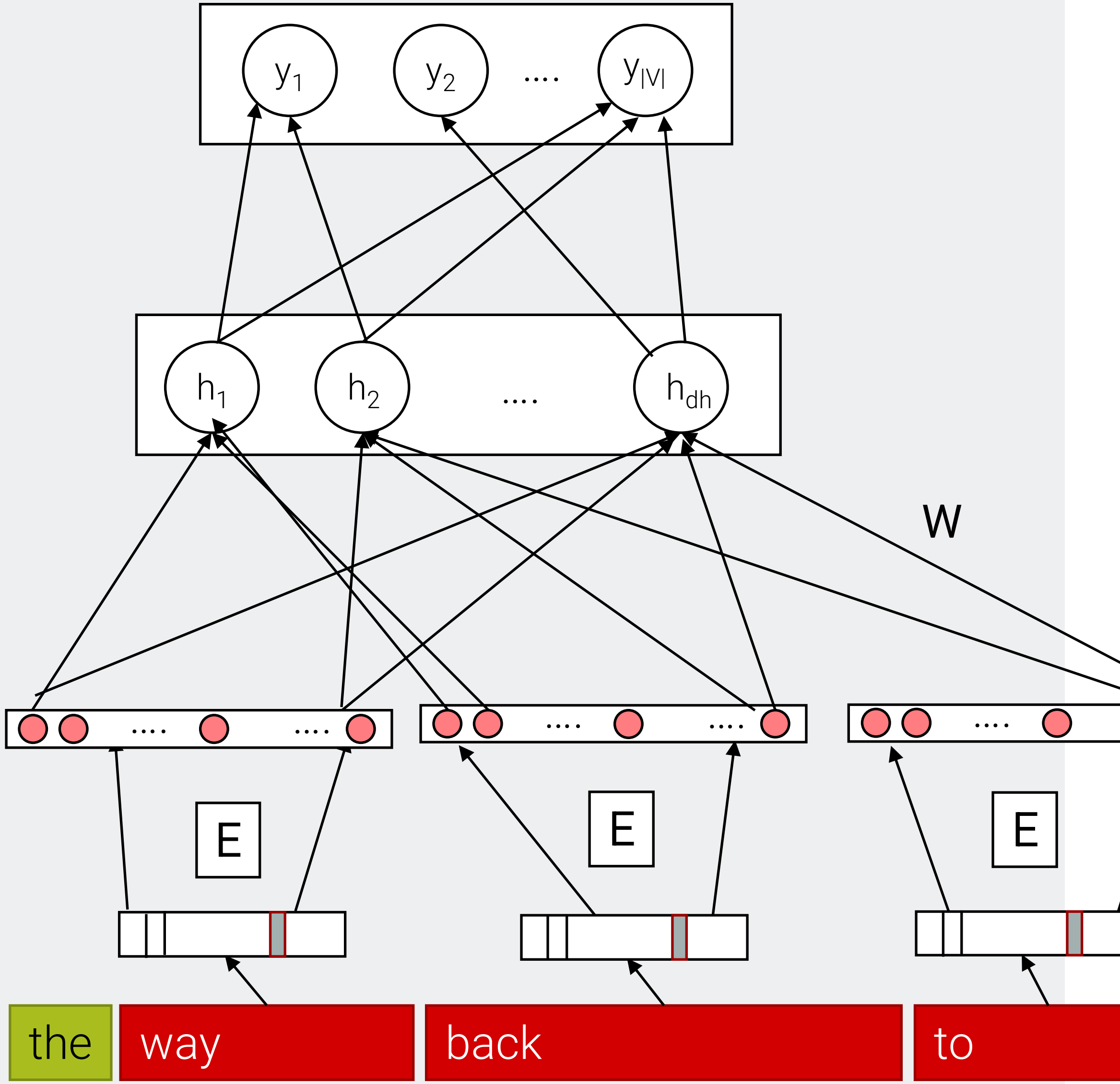
Content

- Neural Language Models
- Recurrent Neural Networks
- LSTMs (Long Short-Term Memory Networks)

(Simple) Neural Language Models

- Improvements over n-gram LM
  - No sparsity problem
  - Don't need to store all observed n-grams
- Remaining problems:
  - Fixed window is too small
  - Enlarging window enlarges W
  - Window can never be large enough!
  - (embedded) words are multiplied by completely different weights in W

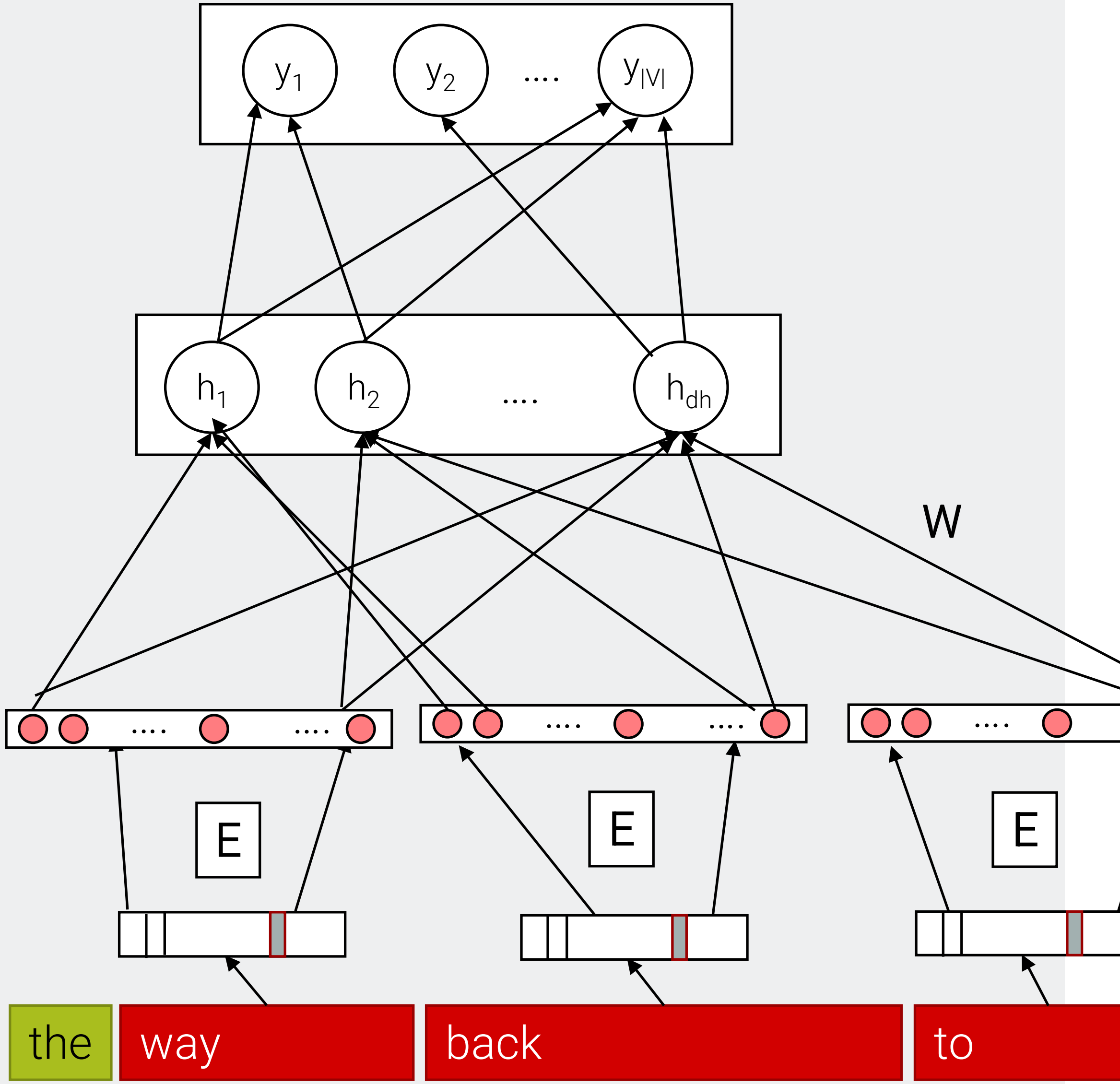
    (No symmetry in input processing)



(Simple) Neural Language Models

- How to deal with inputs of varying lengths (i.e. sequences)?

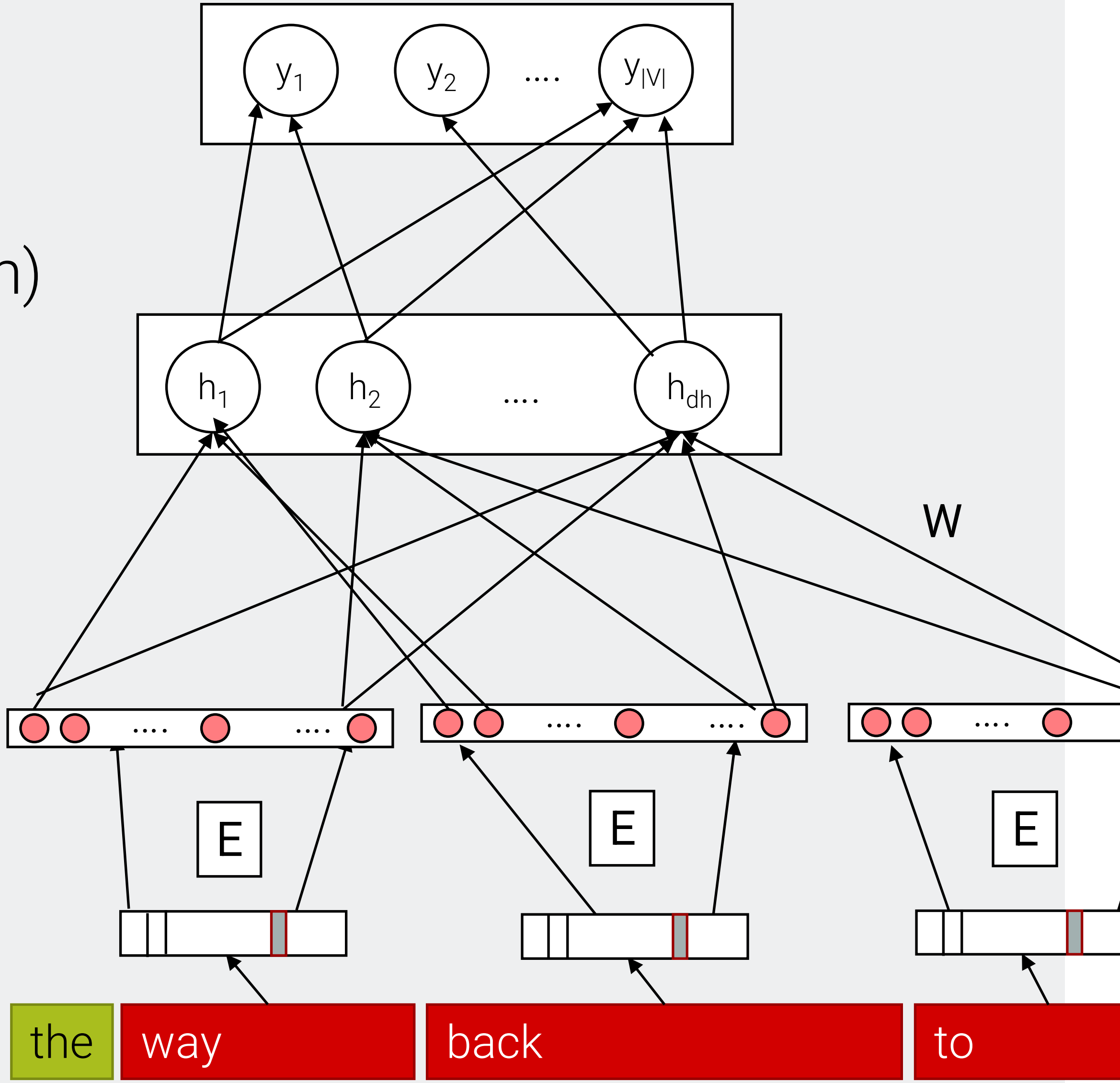
- Slide the input window
- Still, decision on one window does not influence decision on other window.
- Cannot learn systematic patterns (e.g. Constituency)



(Simple) Neural Language Models

- Language is temporal (continuous stream)
  - “Sequence that unfolds in time”
- Algorithms use this
  - Viterbi (see SLP3 book)

- Previous ML approaches have access to all input, simultaneously
- How to deal with *sequences of varying lengths*?



Sequences – Input of **Variable Lengths**

$$x^1 = (x^1_1, x^1_2, \ldots, x^1_{l^1})$$

- Each input has a variable number of elements:

- Simplification: binary elements (0 or 1 values)
- How many 1s in this sequence? How can we implement that?

- ADD1, Recursive function
- Call it for each element of the input.

Algorithm 1 A function ADD1

$\cancel{s \leftarrow 0}$

function ADD1(v,s)
  if $v = 0$ **then return** s
  else return $s + 1$
  end if
end function

Algorithm 2 A function ADD1

$s \leftarrow 0$
for $i \leftarrow 1, 2, \ldots, l$ **do** $s \leftarrow$ ADD1(x_i, s)
end for

Recursive Function for Natural Language Understanding

- ADD1 is hardcoded
- Parametrized recursive function

- Memory: $\mathbf{h} \in \mathbb{R}^{d_h}$

- Input x_1 and memory **h**, returns the new **h**
- Time index!

$$h_t = f(x_t, \mathbf{h}_{t-1})$$

$$f(x_t, \mathbf{h}_{t-1}) = g(\mathbf{W}\phi(x_t) + \mathbf{U}\mathbf{h}_{t-1}).$$

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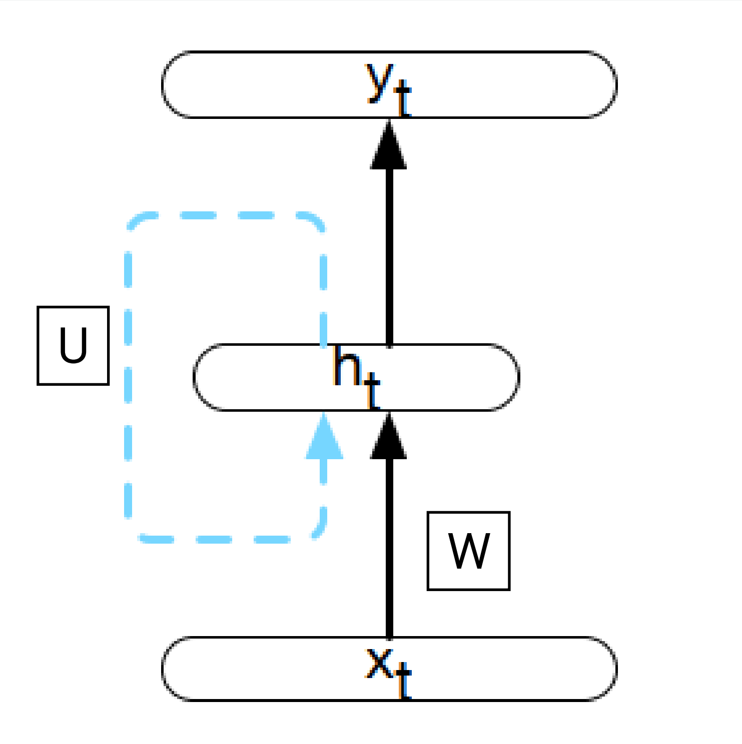
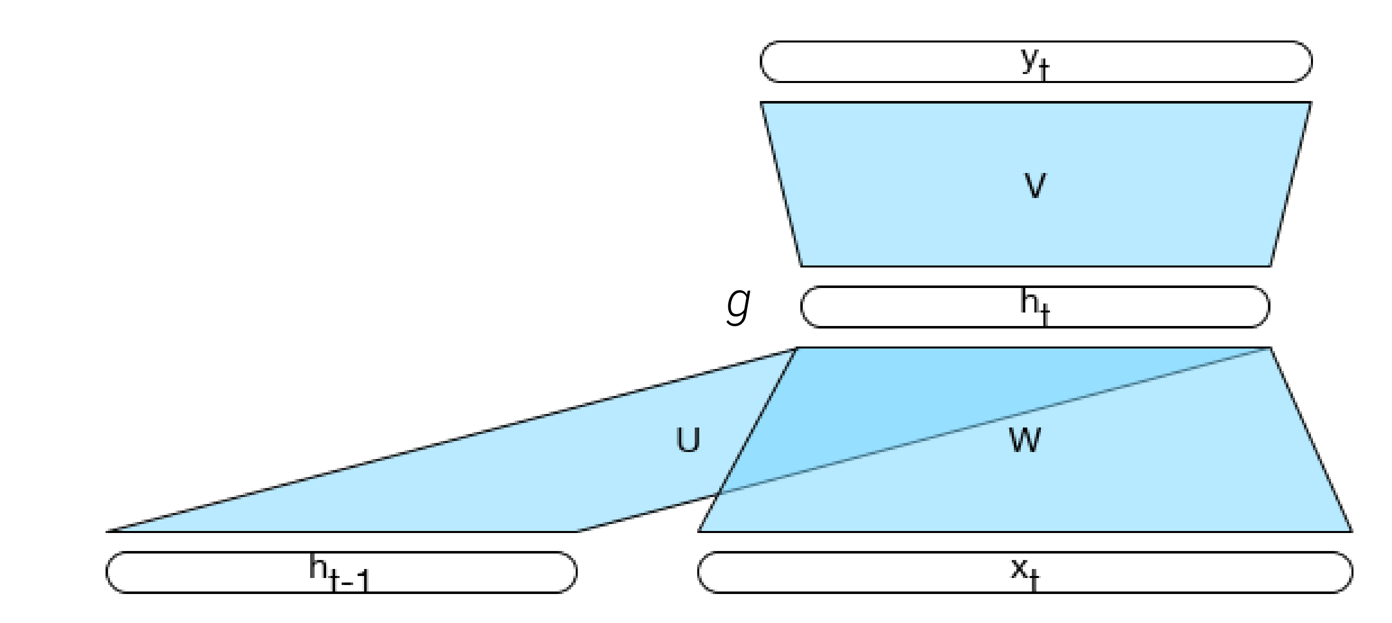


Recursive Neural Network – Unrolled

Inferencing:

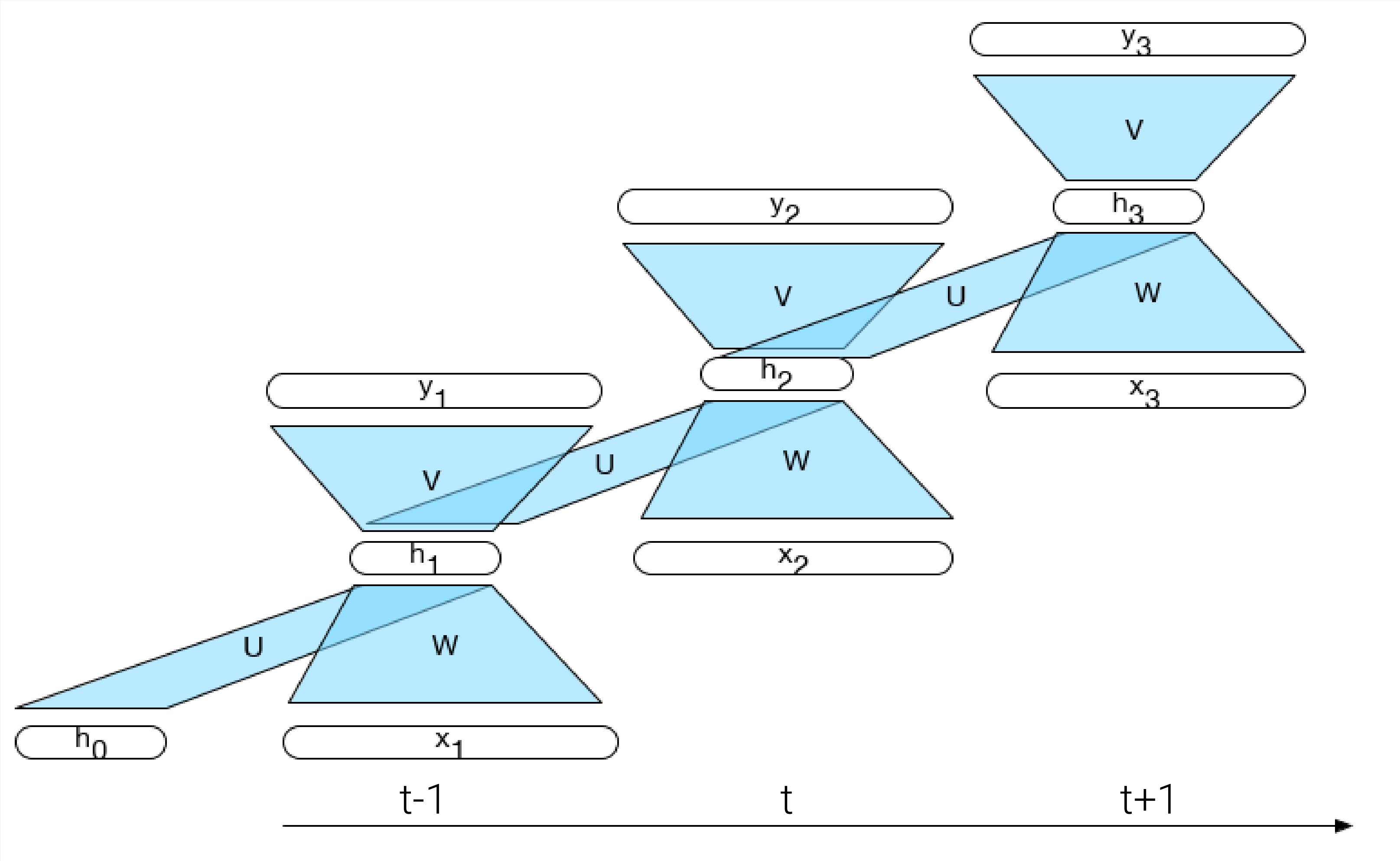
$$
\begin{aligned}
h_t &= g(Uh_{t-1} + Wx_t) \\
y_t &= f(Vh_t)
\end{aligned}
$$

$$y_t = softmax(Vh_t)$$



- Time dimension makes them look exotic (they aren't)
- Difference to FNN -> additional set of weights (U)

Recursive Neural Network – Unrolled

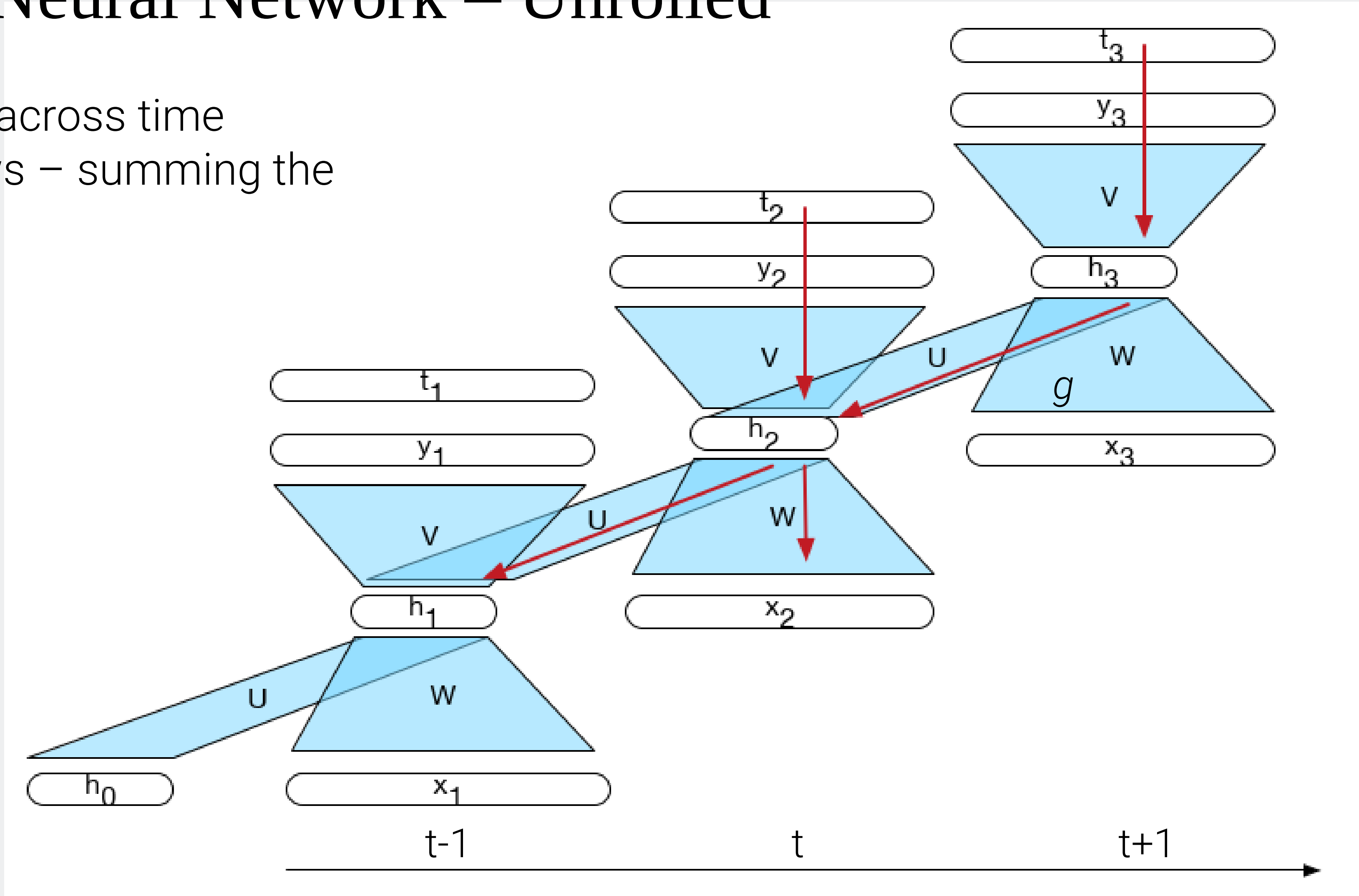


U, W, V – shared across time!

Recursive Neural Network – Unrolled

backpropagation – across time

two incoming arrows – summing the values /errors



RNN – Applications

- RNN Language Models
    - (Autoregressive) generation
- Sequence labelling
- Sequence classification
- …

RNN – Language Models

- N-gram and FF models
  - Fixed sliding window, i.e. fixed context.

$$P(w_n|w_1^{n-1})$$

  - Quality of prediction largely dependent on the size of the window
  - Constrained by the Markov assumption

$$P(w_n|w_1^{n-1}) \approx P(w_n|w_{n-N+1}^{n-1})$$

- Limitation is avoided in RNN!

RNN – Language Models

- Limitation is avoided in RNN!

$$P(w_n|w_1^{n-1}) = y_n$$
$$= softmax(Vh_n)$$

$$P(w_1^n) = \prod_{k=1}^{n} P(w_k|w_1^{k-1})$$
$$= \prod_{k=1}^{n} y_k$$

At each step:

- get embedding for w_n
- combine with previous steps (hidden layer)
- pass through *softmax* (probability distribution over all vocabulary)

- Probability of the complete sequence is product of probabilities

RNN – Language Models

- Limitation is avoided in RNN!

$$\begin{aligned} P(w_n|w_1^{n-1}) &= y_n \\ &= softmax(Vh_n) \end{aligned}$$

$$\begin{aligned} P(w_1^n) &= \prod_{k=1}^{n} P(w_k|w_1^{k-1}) \\ &= \prod_{k=1}^{n} y_k \end{aligned}$$

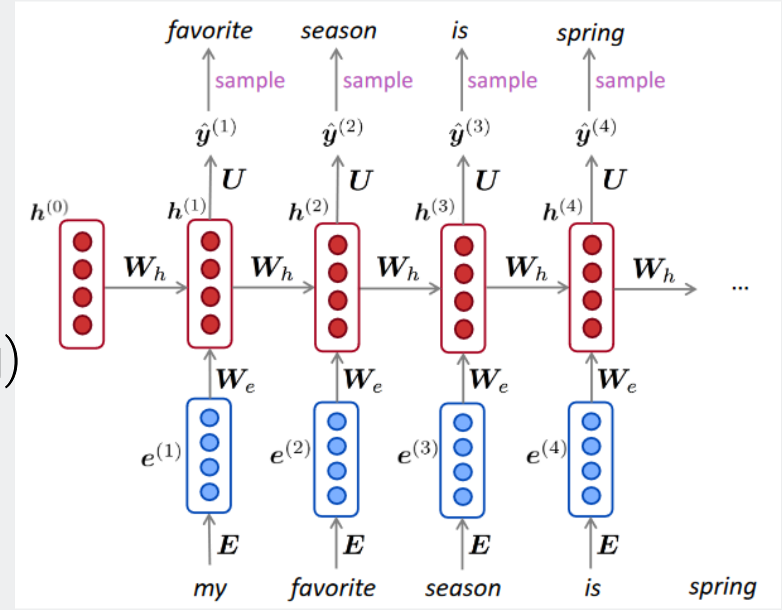
- Cross-entropy function for training

$$\begin{aligned} L_{CE}(\hat{y}, y) &= -\log \hat{y}_i \\ &= -\log \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \end{aligned}$$

- Perplexity for evaluation

$$\text{PP}(W) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i|w_{i-1})}}$$

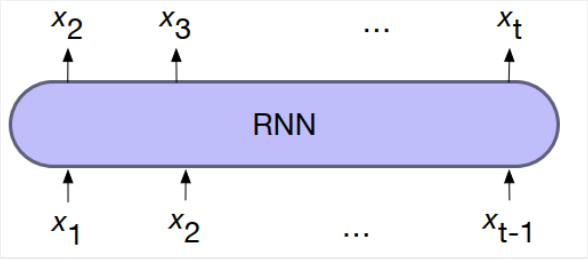
RNN – Language Models



- Generate text by repeated sampling (during training)

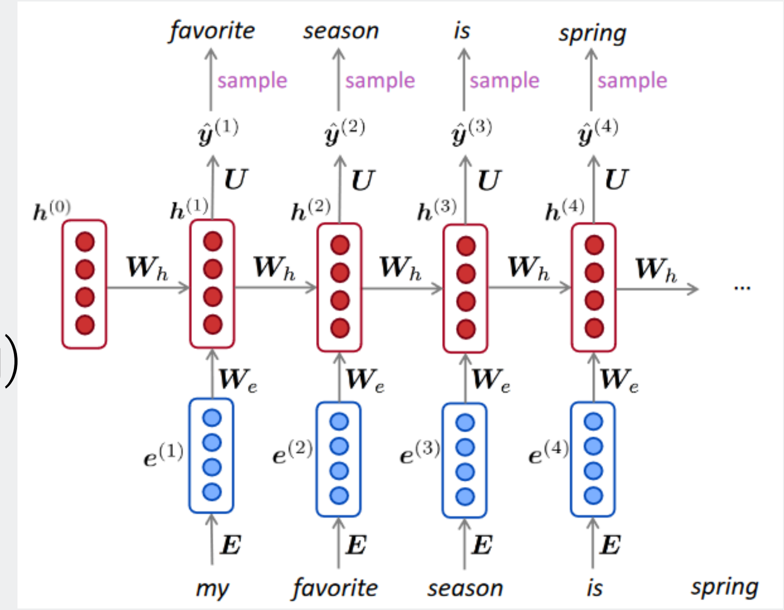
    - RNN-LM trained on Obama speeches

The United States will step up to the cost of a new challenges of the American people that will share the fact that we created the problem. They were attacked and so that they have to say that all the task of the final days of war that I will not be able to get this done.

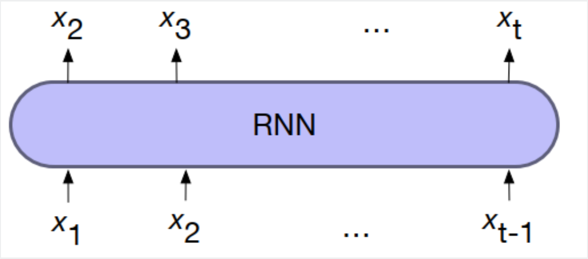


https://medium.com/@samim/obama-rnn-machine-generated-political-speeches-c8abd18a2ea0

RNN – Language Models



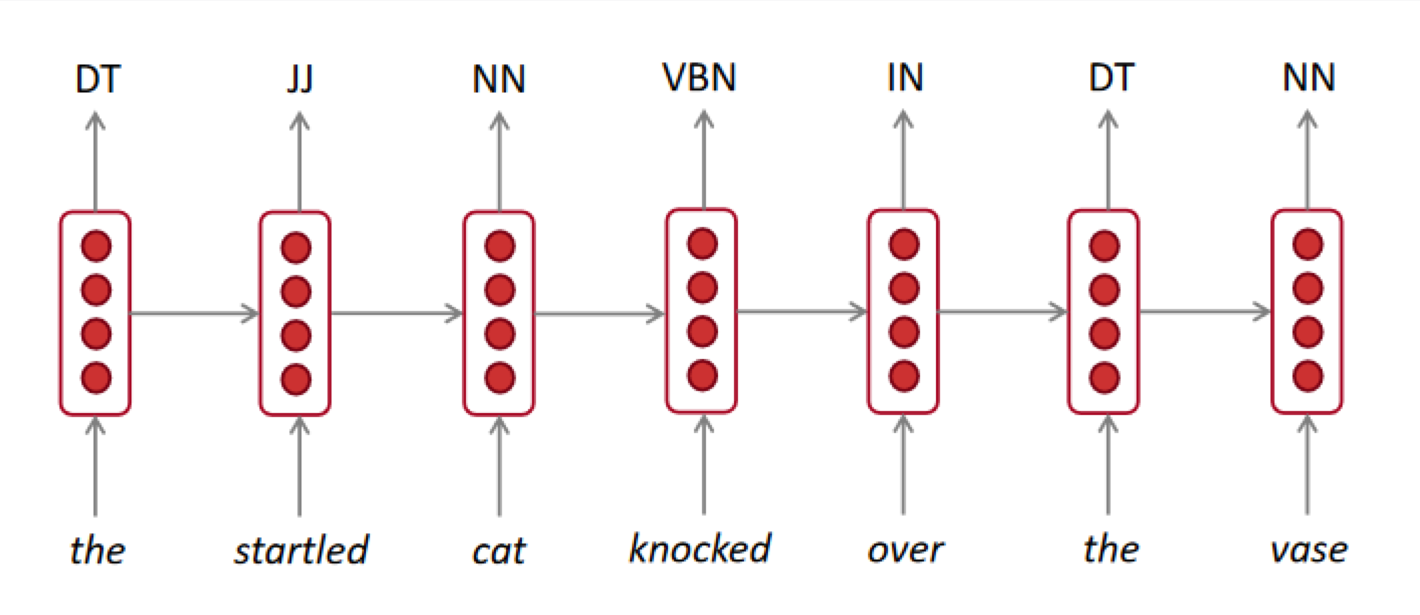
- Generate text by repeated sampling (during training)
    - On any kind of text!
    - Character level example

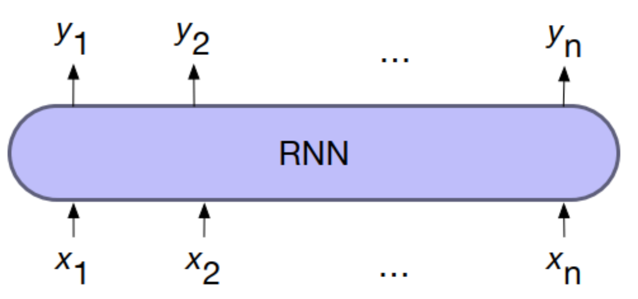


http://aiweirdness.com/post/160776374467/new-paint-colors-invented-by-neural-network

RNN – Applications

- Tagging (POS, named entity recognition, IOB encoding etc.)
- (sequence labelling)

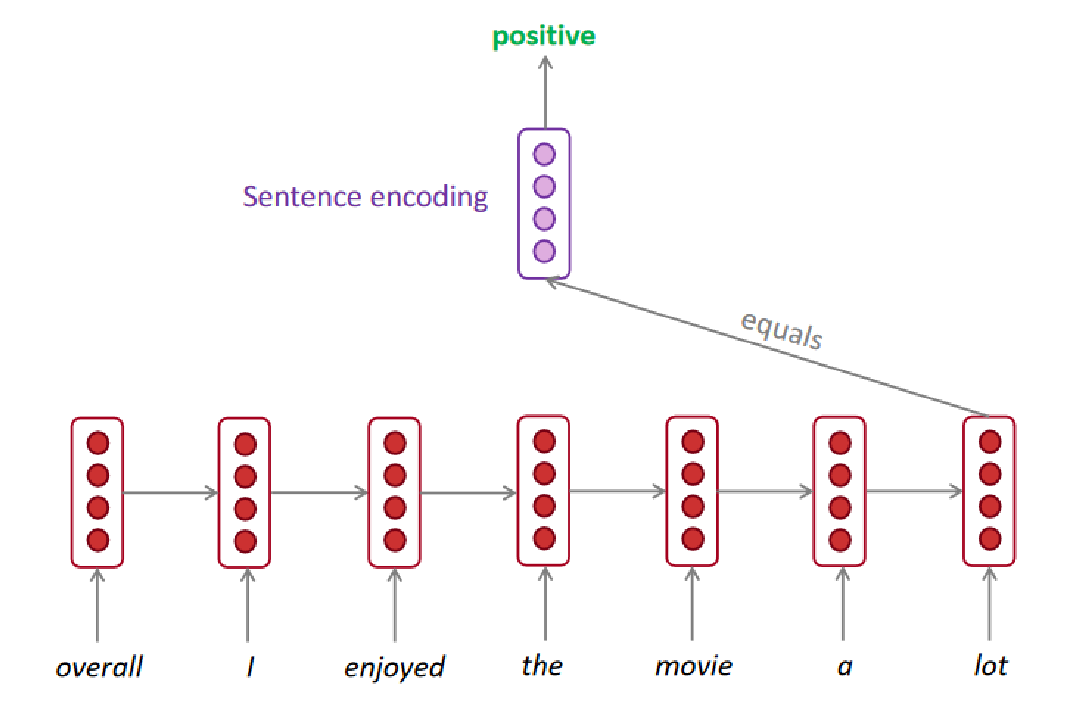


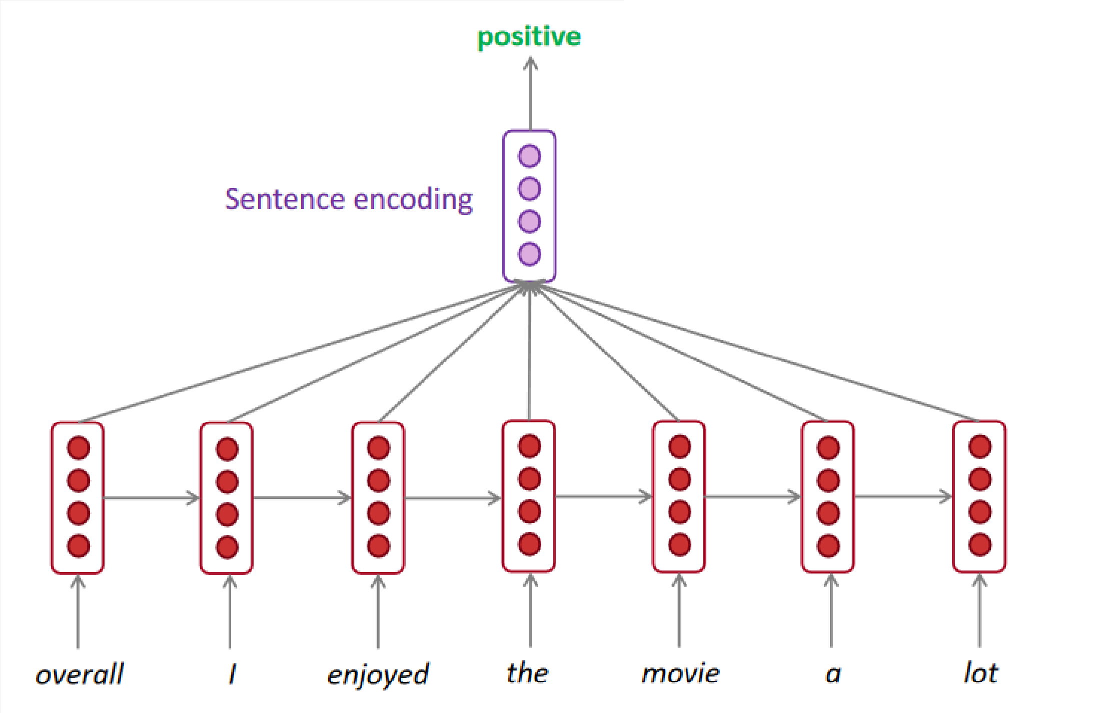


Jurafsky & Martin, SLP, 3rd Edition: *Chapter 8*

RNN – Applications

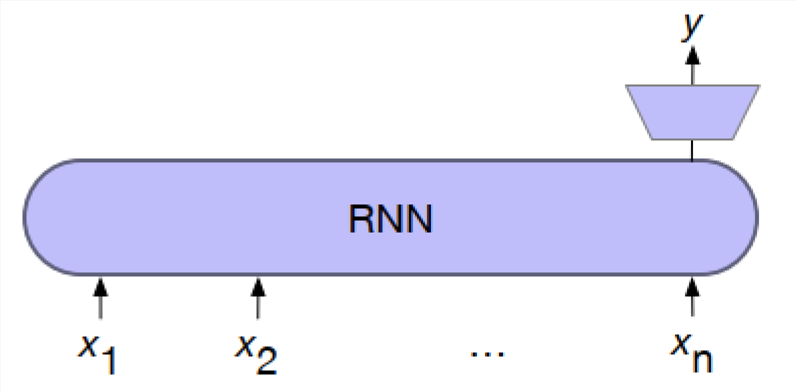
- Sentence (sequence) Classification





RNN – Deep Networks: Stacked and Bidirectional

- Sequence Classification
  - Usually RNN combined with a FF
- end-to-end training



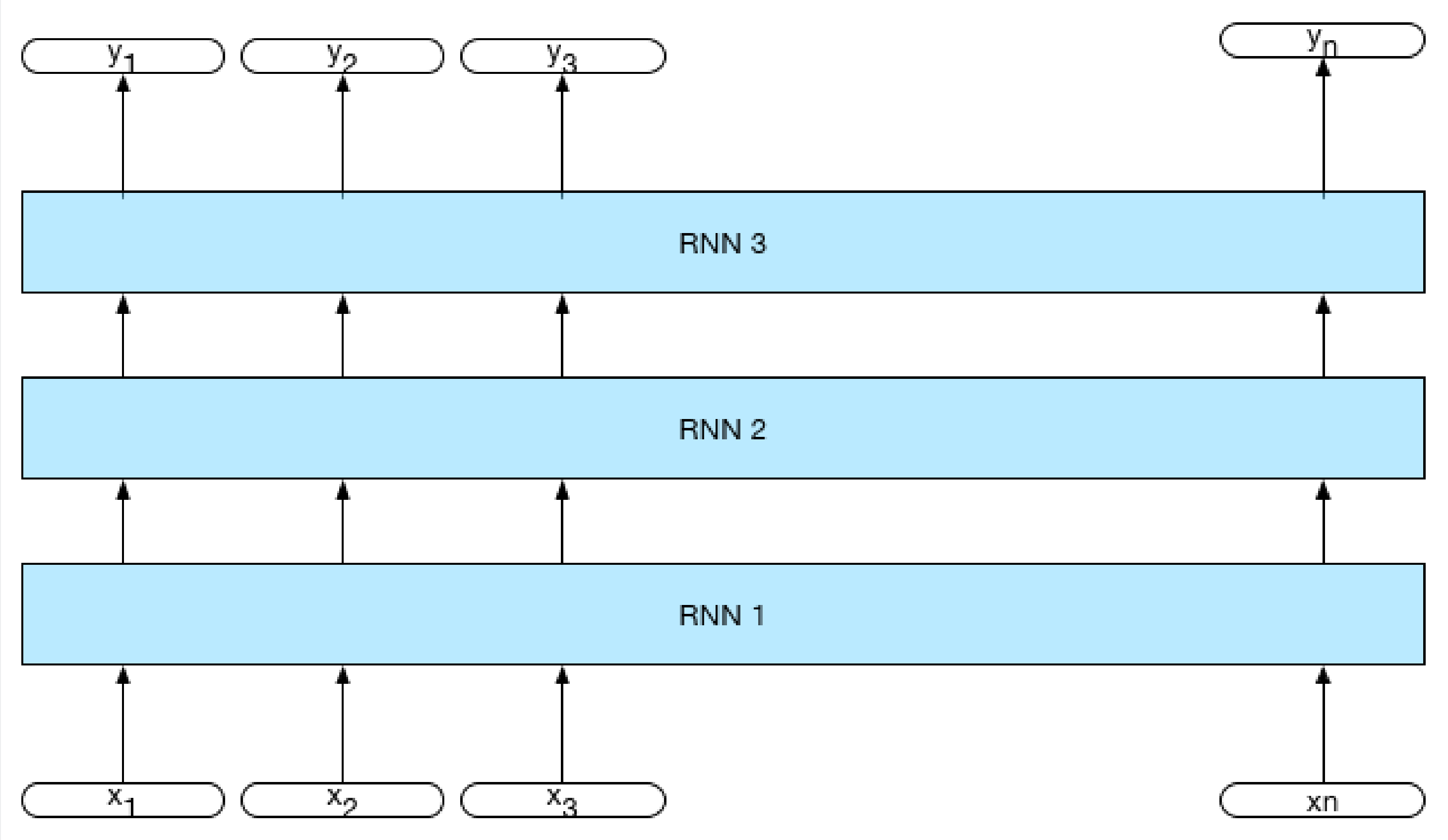
1ST Deep Neural Network

RNN – Deep Networks: Stacked

- Stacked

- Outperform single-layer
- Induce representations

- High training costs



RNN – Deep Networks: Bidirectional

- RNN$_{\text{forward}}$

$$h_t^f = RNN_{forward}(x_1^t)$$

- We have access to the entire input sequence

- RNN$_{\text{backward}}$

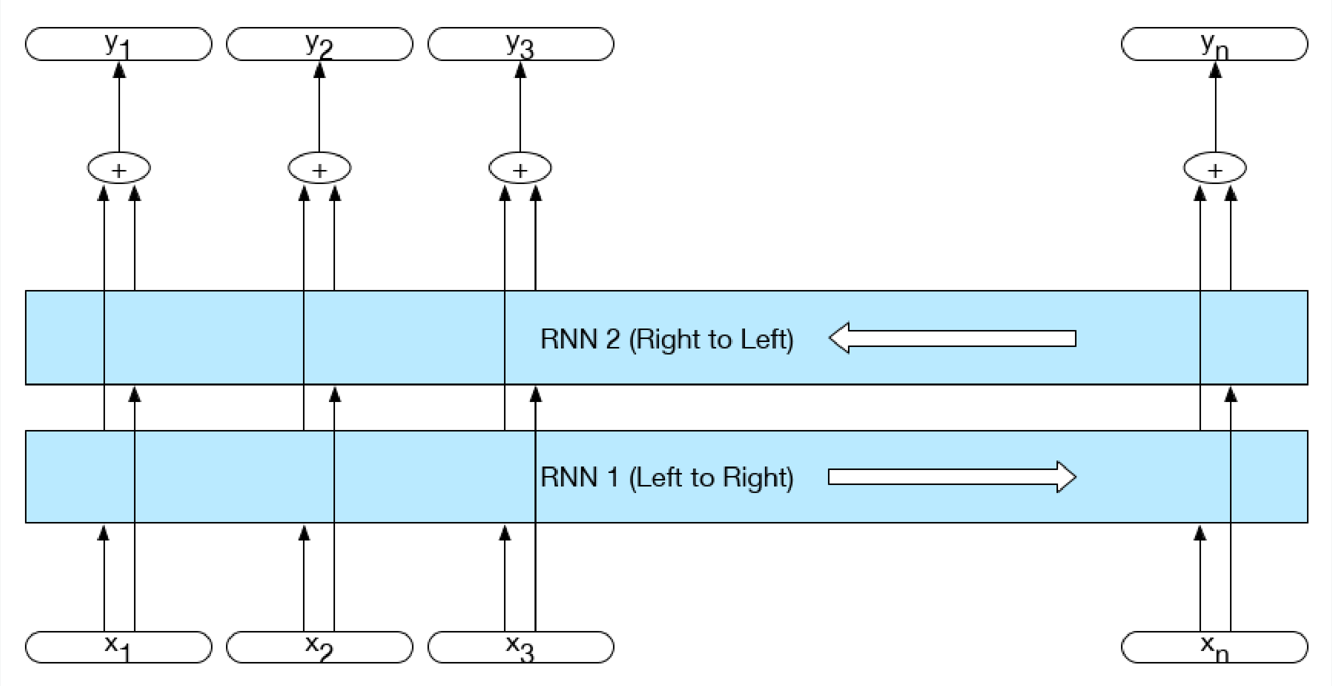
$$h_t^b = RNN_{backward}(x_t^n)$$

- Combine them -> Bi-RNN

$$h_t = h_t^f \oplus h_t^b$$

RNN – Deep Networks: Bidirectional

- Bi-RNN combines $h_t = h_t^f \oplus h_t^b$

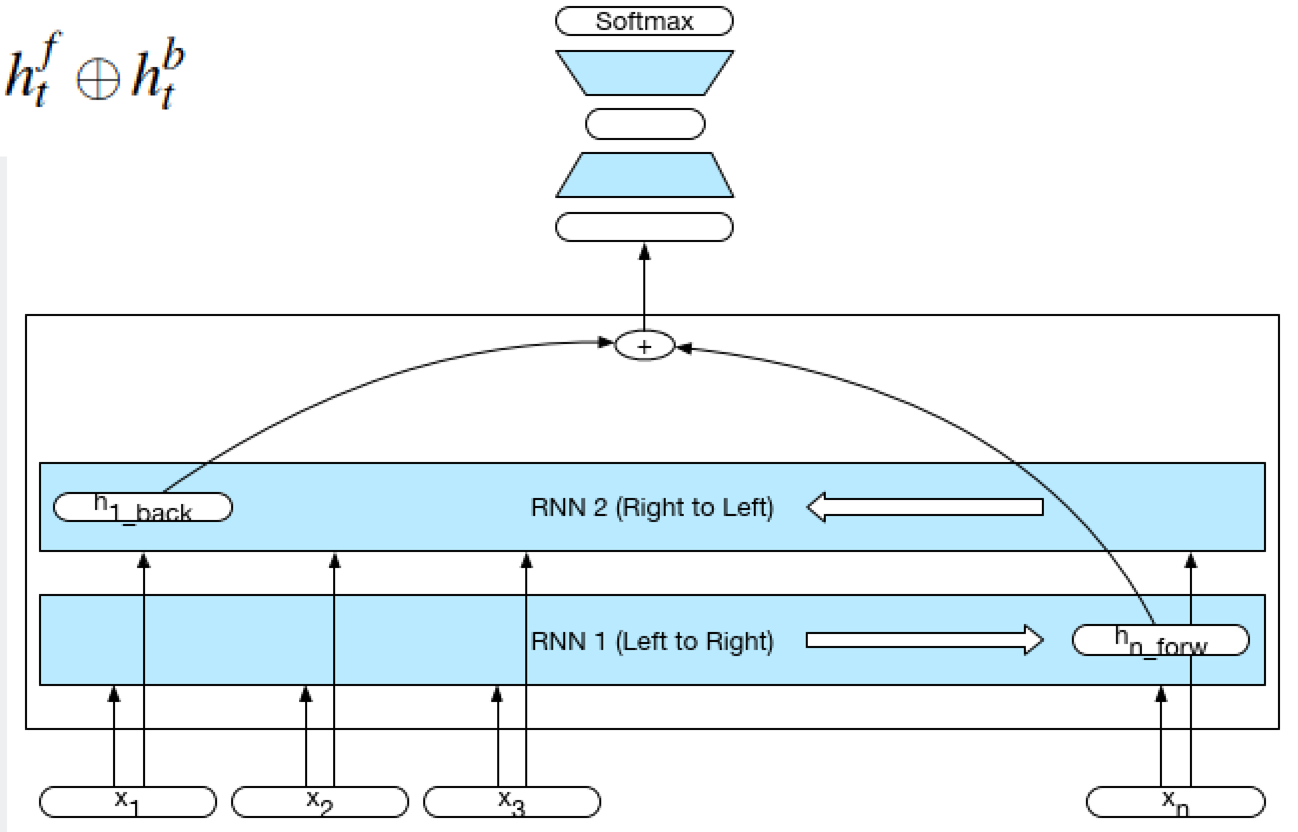


RNN – Deep Networks: Bidirectional

- Bi-RNN combines

$$h_t = h_t^f \oplus h_t^b$$

- Sequence classification



Content

- Neural Language Models
- Recurrent Neural Networks
- LSTMs (Long Short-Term Memory Networks)

Quick Recap

- Simple RNNs process sequences naturally one element at a time
- Neural unit output at time *t* is based both on the current input and value of the hidden layer from the previous *t*-s
- RNNs trained backpropagation through time (BPTT – extension of the usual BP)
- Common language-based applications include:
  - – Probabilistic language modelling (assigns a probabilities to sequences or to the next element of a sequence)
  - – Auto-regressive generation using a trained language model.
  - – Sequence labelling
  - – Sequence classification (e.g. spam detection, sentiment analysis).

Long Short-Term Memory Networks

RNN Shortcomings

- Cannot use information distant from the current time
- Information encoded in the current hidden layer is local

The flights the airline was cancelling were full.

  - Hidden layers and weights:
    - useful information for ***current*** decision
    - Update information for ***future*** decisions

P(was | airline) – OK
P(were | flights) – ?

- Vanishing gradients

RNN Shortcomings

- How to maintain relevant context over time?

The flights the airline was cancelling were full.

- Learn to forget
- Learn what to keep

P(was | airline) – OK
P(were | flights) – ?

Recursive Function for Natural Language Understanding

- ADD1 is hardcoded
- Parametrized recursive function
- Memory: $\boxed{\mathbf{h} \in \mathbb{R}^{d_h}}$
- Input x_1 and memory **h**, returns the new **h**
- Time index!

Remember this?

$$h_t = f(x_t, \mathbf{h}_{t-1})$$

$$f(x_t, \mathbf{h}_{t-1}) = g(\mathbf{W}\phi(x_t) + \mathbf{U}\mathbf{h}_{t-1})$$

Algorithm 1 A function ADD1

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  end if
end function

Algorithm 2 A function ADD1

$s \leftarrow 0$
for $i \leftarrow 1, 2, \ldots, l$ **do** $s \leftarrow$ ADD1(x_i, s)
end for

Long Short-Term Memory Networks (LSTMs)

- Memory (aka. context): $\boxed{\mathbf{h} \in \mathbb{R}^{d_h}}$

- Want: divide context management into:
  - Forgetting (old/unnecessary information)
  - memorizing (new information/context)

- If possible <u>**without**</u> **hard-coding into the architecture**!

- Solution:
  - add an explicit context layer
  - gates to control the forgetting/memorizing

Long Short

gates

context ≈ memory

U is W and W is U

We have a sequence of inputs $x^{(t)}$, and we will compute a sequence of hidden states $h^{(t)}$ and cell states $c^{(t)}$. On timestep t:

Sigmoid function: all gate values are between 0 and 1

Forget gate: controls what is kept vs forgotten, from previous cell state

$$\boldsymbol{f}^{(t)} = \sigma\left(\boldsymbol{W}_f \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_f \boldsymbol{x}^{(t)} + \boldsymbol{b}_f\right)$$

Input gate: controls what parts of the new cell content are written to cell

$$\boldsymbol{i}^{(t)} = \sigma\left(\boldsymbol{W}_i \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_i \boldsymbol{x}^{(t)} + \boldsymbol{b}_i\right)$$

Output gate: controls what parts of cell are output to hidden state

$$\boldsymbol{o}^{(t)} = \sigma\left(\boldsymbol{W}_o \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_o \boldsymbol{x}^{(t)} + \boldsymbol{b}_o\right)$$

New cell content: this is the new content to be written to the cell

$$\tilde{\boldsymbol{c}}^{(t)} = \tanh\left(\boldsymbol{W}_c \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_c \boldsymbol{x}^{(t)} + \boldsymbol{b}_c\right)$$

Cell state: erase ("forget") some content from last cell state, and write ("input") some new cell content

$$\boldsymbol{c}^{(t)} = \boldsymbol{f}^{(t)} \circ \boldsymbol{c}^{(t-1)} + \boldsymbol{i}^{(t)} \circ \tilde{\boldsymbol{c}}^{(t)}$$

Hidden state: read ("output") some content from the cell

$$\boldsymbol{h}^{(t)} = \boldsymbol{o}^{(t)} \circ \tanh \boldsymbol{c}^{(t)}$$

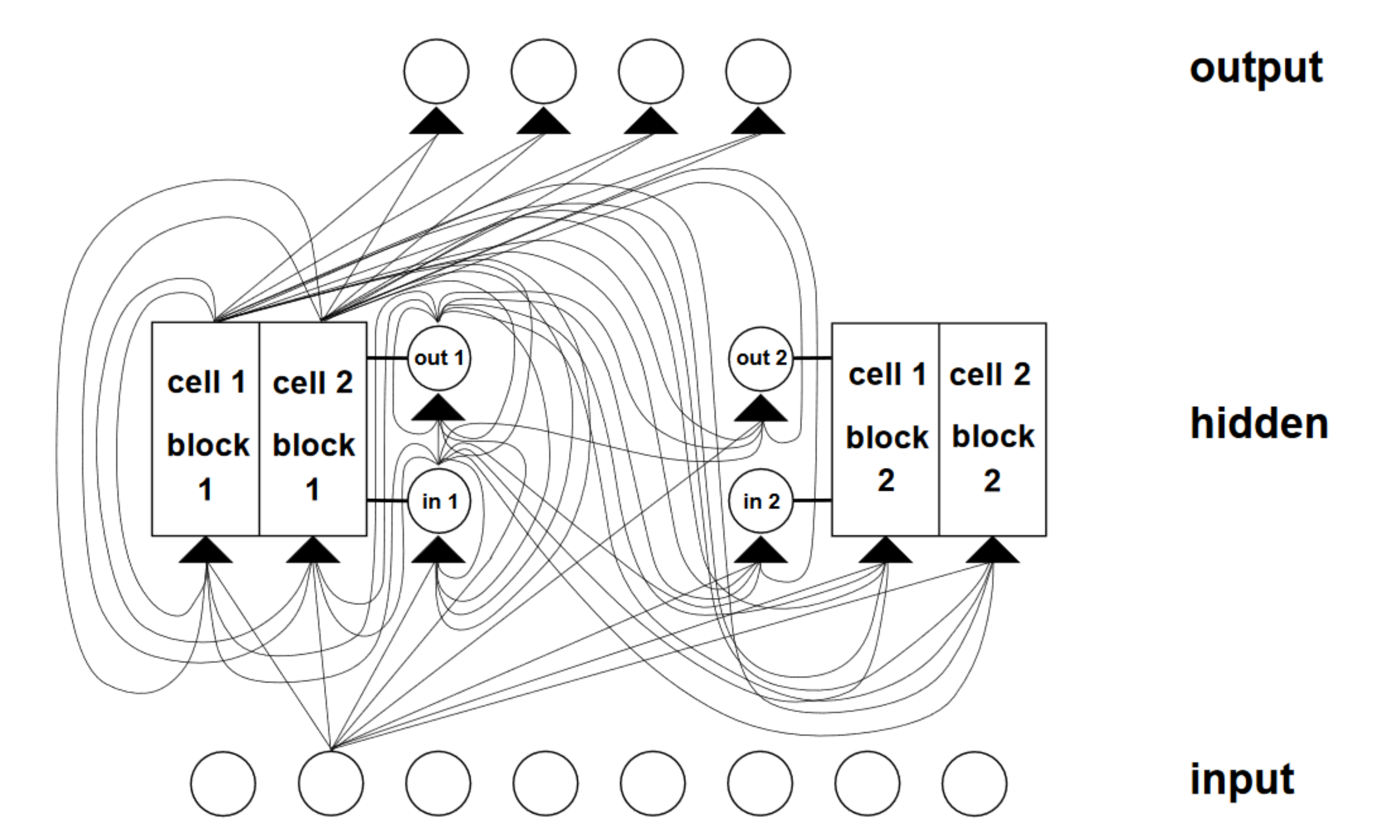
Gates are applied using element-wise product

All these are vectors of same length n

TU WIEN Informatics

https://web.stanford.edu/class/cs224n/slides/cs224n-2020-lecture07-fancy-rnn.pdf

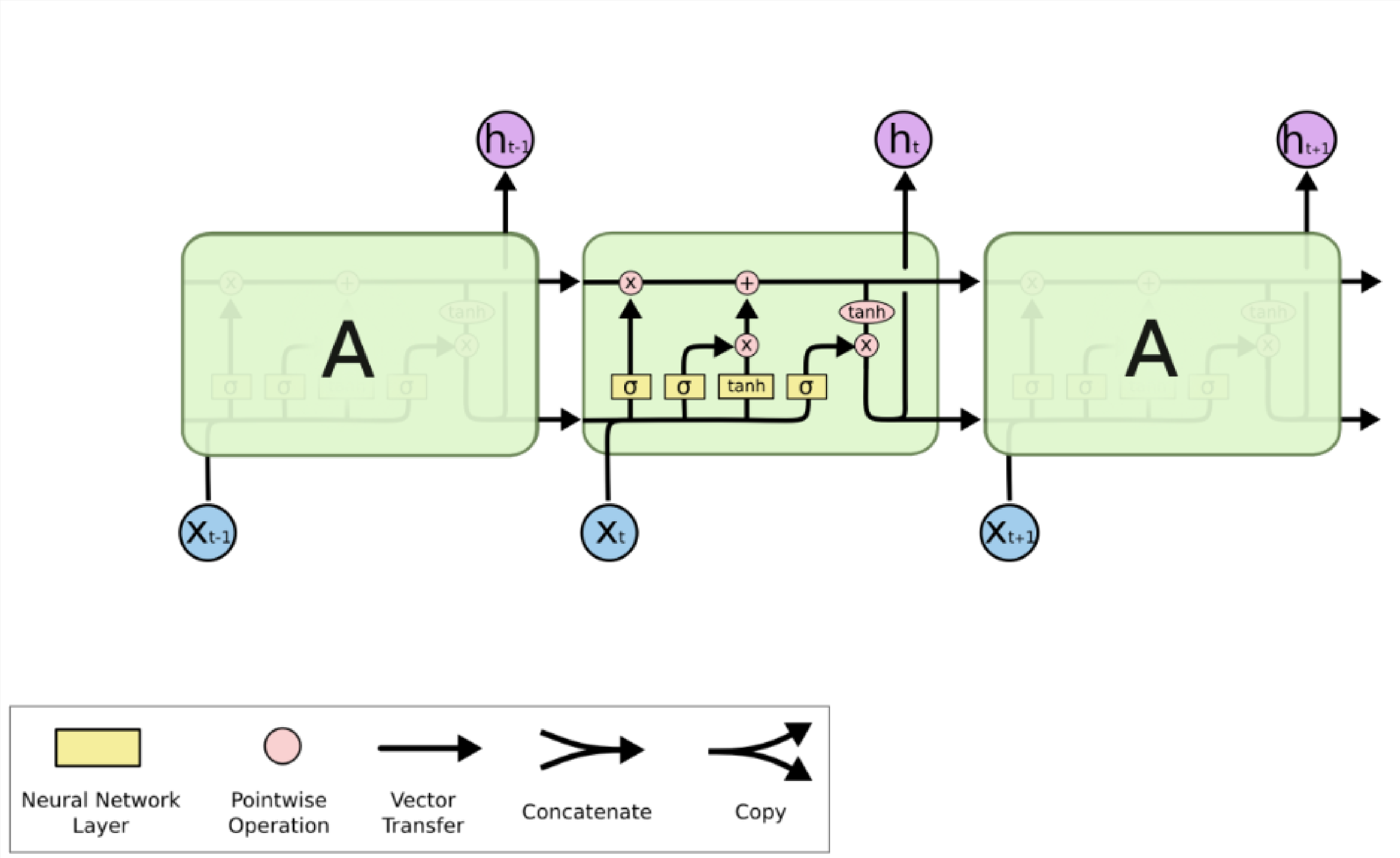
Long Short-Term Memory Networks (LSTMs)



TU WIEN Informatics

(Hochreiter, Schmidhuber, 1997) https://www.bioinf.jku.at/publications/older/2604.pdf

Long Short-Term Memory Networks (LSTMs)



Informatics

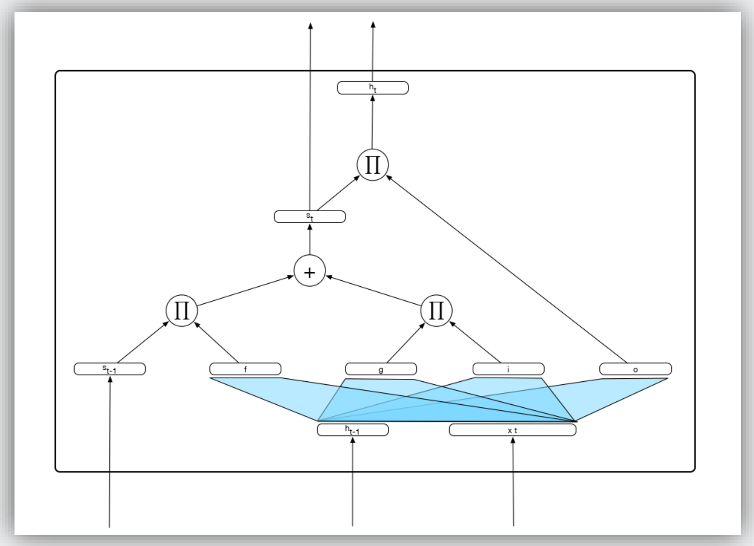
http://colah.github.io/posts/2015-08-Understanding-LSTMs/

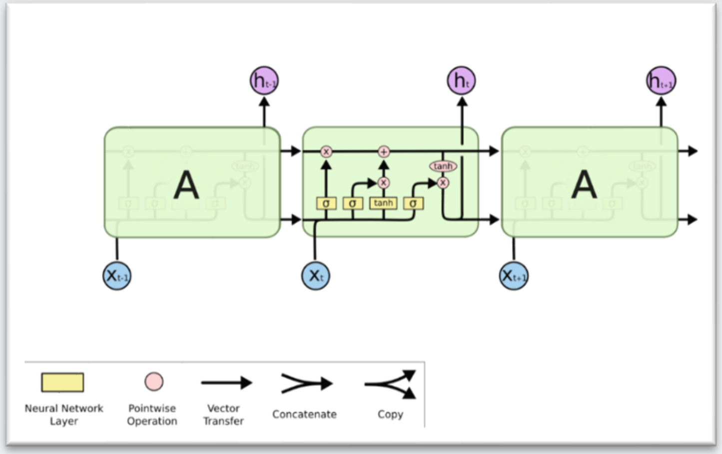
LSTMs – recap

At each step:

- Hidden state *h*
- Cell state *c*
- Gates to control the cell state *c* (read, write, erase)
  - Forgetting (unnecessary info)
  - Memorizing (new information)
  - Dynamic! (we didn’t hard code them)

- But lots of new parameters → higher training costs
- Learning 8 weight matrixes!

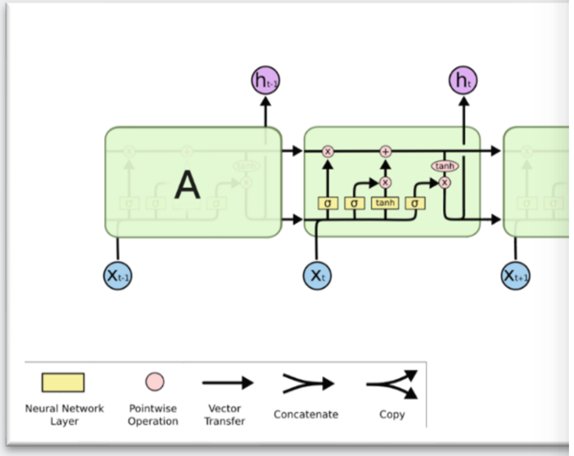


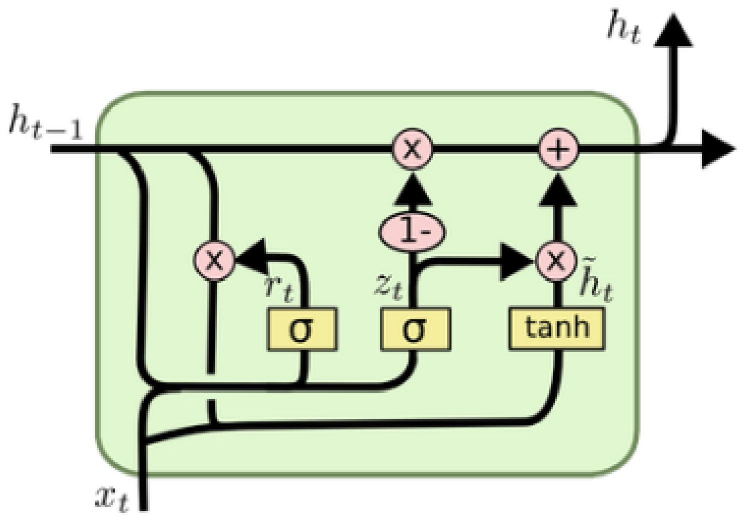


http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Gated Recurrent Unit

- Uses only two gates: “reset”, *r*, and “update”, *z*
- Collapse “forget” and “input” gates into the “update” gate z
- (less training effort)





$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

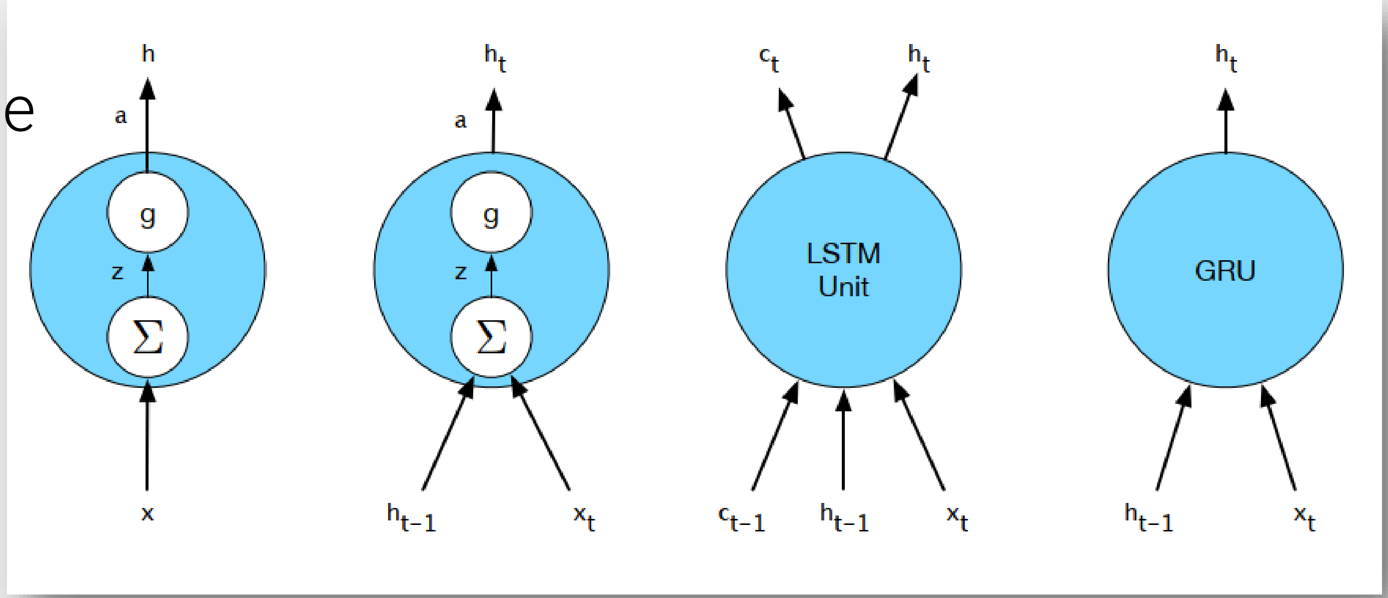
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Cho et al., 2014, http://arxiv.org/pdf/1406.1078v3.pdf
http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Neural Units

- Complexity encapsulated in basic processing units
- Easy modularity maintenance
- “wild” architectures easy to understand



Unrolling!

Content

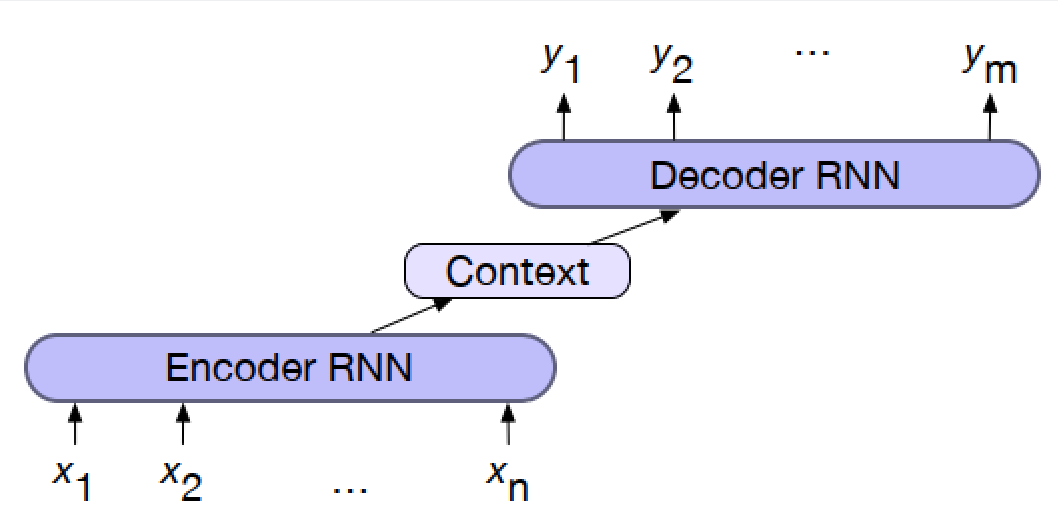
- Neural Language Models
- Recurrent Neural Networks
- LSTMs (Long Short-Term Memory Networks)

- Encoder-Decoder
- Attention

- Very active research area – not all details are included

Machine Translation

(sequence-to-sequence processing)



Sequence-to-Sequence aka. Encoder-decoder Models

- Neural Machine Translation

- **Source** sentence X in source language
- **Target** sentence Y in target language

$$X = (x_1, x_2, \ldots, x_{T_x})$$
$$Y = (y_1, y_2, \ldots, y_{T_y})$$

- Translation: function application:

$$f : V_x^+ \rightarrow C_{|V_y|-1}^+$$

- More than one correct translation

$$P(Y|X)$$

$$C_k = \left\{ (t_0, \ldots, t_k) \in \mathbb{R}^{k+1} \middle| \sum_{i=1}^{k} t_k = 1 \text{ a} \ldots \text{or all } i \right\}$$

Following slides based on Cho, 2017, NLU with Distributional Representation, Chapter 6

Neural Machine Translation

- Conditional language modelling!

$$X = (x_1, x_2, \ldots, x_{T_x})$$
$$Y = (y_1, y_2, \ldots, y_{T_y})$$

$$f : V_x^+ \to C_{|V_y|-1}^+$$

$$P(Y|X) = \underbrace{\prod_{t=1}^{T_y} P(y_t|y_1, \ldots, y_{t-1}, \underbrace{X}_{\text{conditional}})}_{\text{language modelling}}$$

$$C_k = \left\{ (t_0, \ldots, t_k) \in \mathbb{R}^{k+1} \,\middle|\, \sum_{i=1}^{k} t_k = 1 \text{ and } t_i \geq 0 \text{ for all } i \right\}$$

- Use what we learned to compute these!
  - N-grams
  - Embeddings
  - …

Neural Machine Translation

- Conditional language modelling!

$$X = (x_1, x_2, \ldots, x_{T_x})$$

$$Y = (y_1, y_2, \ldots, y_{T_y})$$

$$P(Y|X) = \prod_{t=1}^{T_y} \underbrace{P(y_t|y_1, \ldots, y_{t-1}, \underbrace{X}_{\text{conditional}})}_{\text{language modelling}}$$

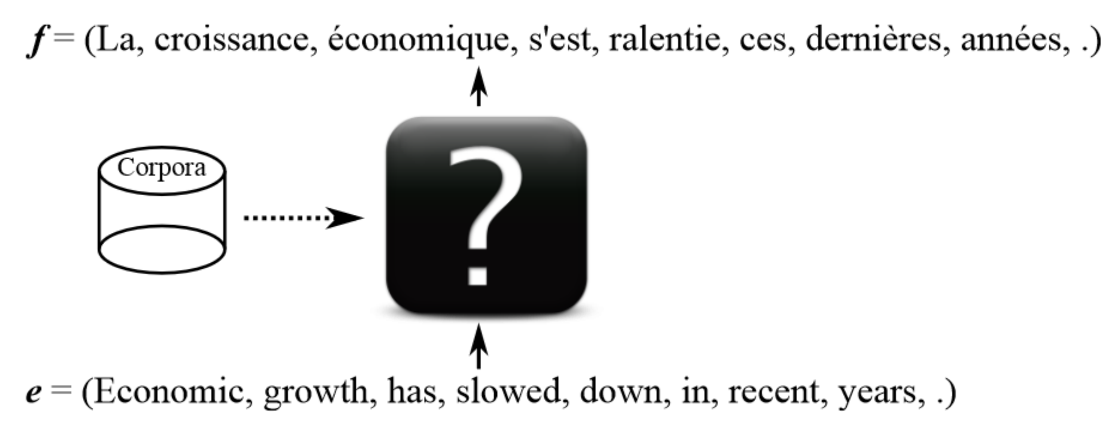
- Training:
  - Maximizing the log-likelihood cost function for a given training set

$$-\frac{1}{N}\sum_{n=1}^{N}\sum_{t=1}^{T_y} \log p(y_t^n | y_{<t}^n, X^n)$$

$$\{(X^1, Y^1), (X^2, Y^2), \ldots, (X^N, Y^N)\}$$

Neural Machine Translation

- The big picture:



1) Assign probabilities to sentences
2) Handle variable length sequences (RNNs)
3) Train with costs functions & gradient descent

? Training data

? Evaluating MT

Training Data for Machine Translation

- Sequence-to-sequence
- Sentence pairs (source_language, target_language)

- *parallel- corpus*
  - where to get it?

- International news agencies (AFP)
- Books published in multiple lanugages
- Ebay/Amazon/… (product descriptions)

Copyright issues!

Training Data for Machine Translation

- Sequence-to-sequence
- Sentence pairs (source_language, target_language)

- *parallel- corpus*
    - where to get it?

- proceedings from the Canadian parliament (Brown et al, 1990)
    - French – English, curated (professional translators)
- EU parliament - more than 20 languages

Brown et al, 1990, A statistical approach to machine translation
http://www.isi.edu/natural-language/download/hansard/
http://www.statmt.org/europarl/

Training Data for Machine Translation

- translated subtitle of the TED talks, (WIT, https://wit3.fbk.eu/)
  - 104 languages
- Russian-English: Yandex (https://translate.yandex.ru/corpus?lang=en)
- SWRC English-Korean multilingual corpus: 60,000 sentence pairs
- https://github.com/jungyeul/korean-parallel-corpora (~94K sentence pairs)

- Crawl the internet for pairs of pages (but check the small print!)
  - Wikipedia
- Common Crawl Parallel Corpus (Smith et. Al, 2013)
  - http://www.statmt.org/wmt13/training-parallel-commoncrawl.tgz

Smith et al, 2013, Dirt cheap web-scale parallel text from the common crawl, ACL

Evaluating Machine Translation

- There may be many correct translations for one sentence
  - It is a guide to action that ensures that the military will forever heed Party commands.
  - It is the guiding principle which guarantees the military forces always being under the command of the Party.
  - It is the practical guide for the army always to heed the directions of the party.
- Quality is not success or failure

Smith et al, 2013, Dirt cheap web-scale parallel text from the common crawl, ACL

Evaluating Machine Translation

- Quality is not success or failure:
  - French: “J’aime un llama, qui est un animal mignon qui vit en Amérique du Sud”
  - “I like a llama which is a cute animal living in South America”. 100
  - “I like a llama, a cute animal that lives in South America”. 90
  - “I like a llama from South America”? 50
  - “I do not like a llama which is an animal from South America”?

- We want automated evaluation!

Evaluating Machine Translation – BLEU score

- geometric mean of the modified N-gram precision scores multiplied by brevity penalty.
  - N-gram precision:

$$p_n = \frac{\sum_{S \in C} \sum_{\text{ngram} \in S} \hat{c}(\text{ngram})}{\sum_{S \in C} \sum_{\text{ngram} \in S} c(\text{ngram})}$$

$$\hat{c}(\text{ngram}) = \min(c(\text{ngram}), c_{\text{ref}}(\text{ngram})).$$

  - Geometric mean

$$P_1^4 = \exp\left(\frac{1}{4}\sum_{n=1}^{4} \log p_n\right)$$

  - But: “cute animal that lives” P = 1
  - Brevity Penalty (BP)

$$\boxed{\text{BP} = \begin{cases} 1 & \text{, if } l \geq r \\ \exp\left(1 - \frac{r}{l}\right) & \text{, if } l < r \end{cases}}$$

Papineni et al. “Bleu: a method for automatic evaluation of machine translation.”

Evaluating Machine Translation – BLEU score

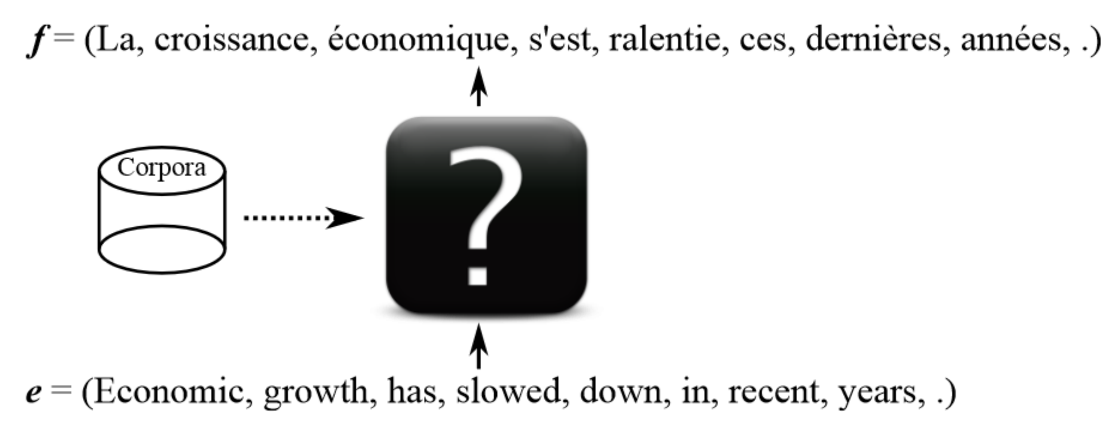
- The BLEU was shown to correlate well with human judgements
- But not perfect automatic evaluation metric

- METEOR (M. Denkowski and A. Lavie, 2014)
- TER (Translation Edit Rate, M. Snover, 2006)

Papineni et al. “Bleu: a method for automatic evaluation of machine translation.”

Neural Machine Translation

- The big picture:



1) Assign probabilities to sentences
2) Handle variable length sequences (RNNs)
3) Train with costs functions & gradient descent

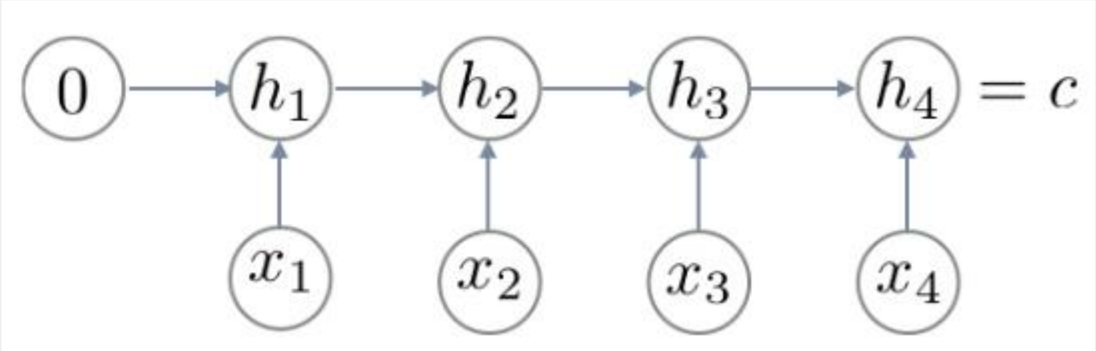
✓ Training data
✓ Evaluating MT

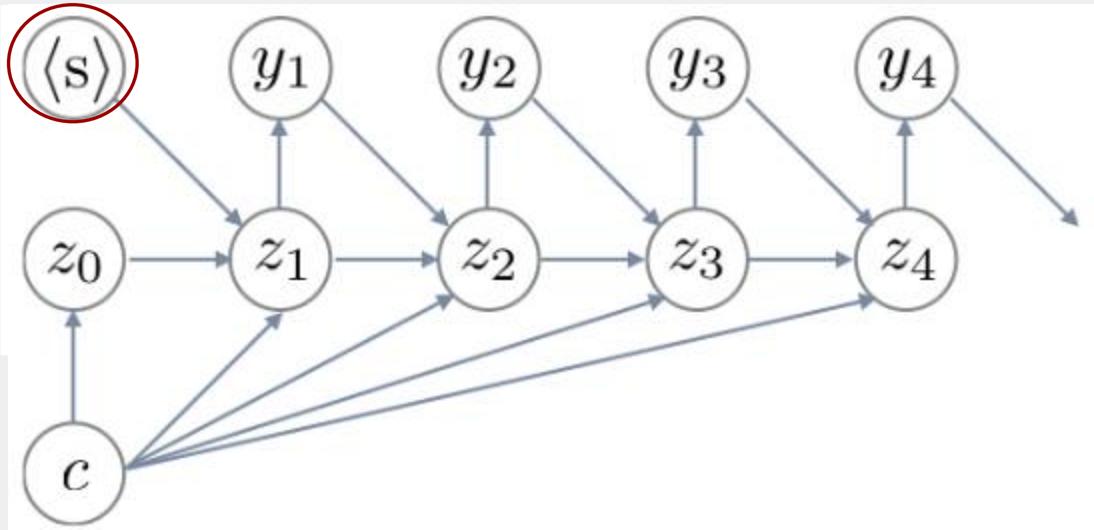
Neural Machine Translation: Encoder-Decoder Model

- Input: $Y = (y_1, \ldots, y_{t-1})$ $X = (x_1, \ldots, x_{T_x})$

$$P(Y|X) = \prod_{t=1}^{T_y} \underbrace{P(y_t | y_1, \ldots, y_{t-1}, \underbrace{X}_{\text{conditional}})}_{\text{language modelling}}$$

- Start with *X*, how to handle it?
  - Variable-length sequence (RNN)
  - No explicit output/target → only the summary (vector)
  - RNN ~ *encoder*





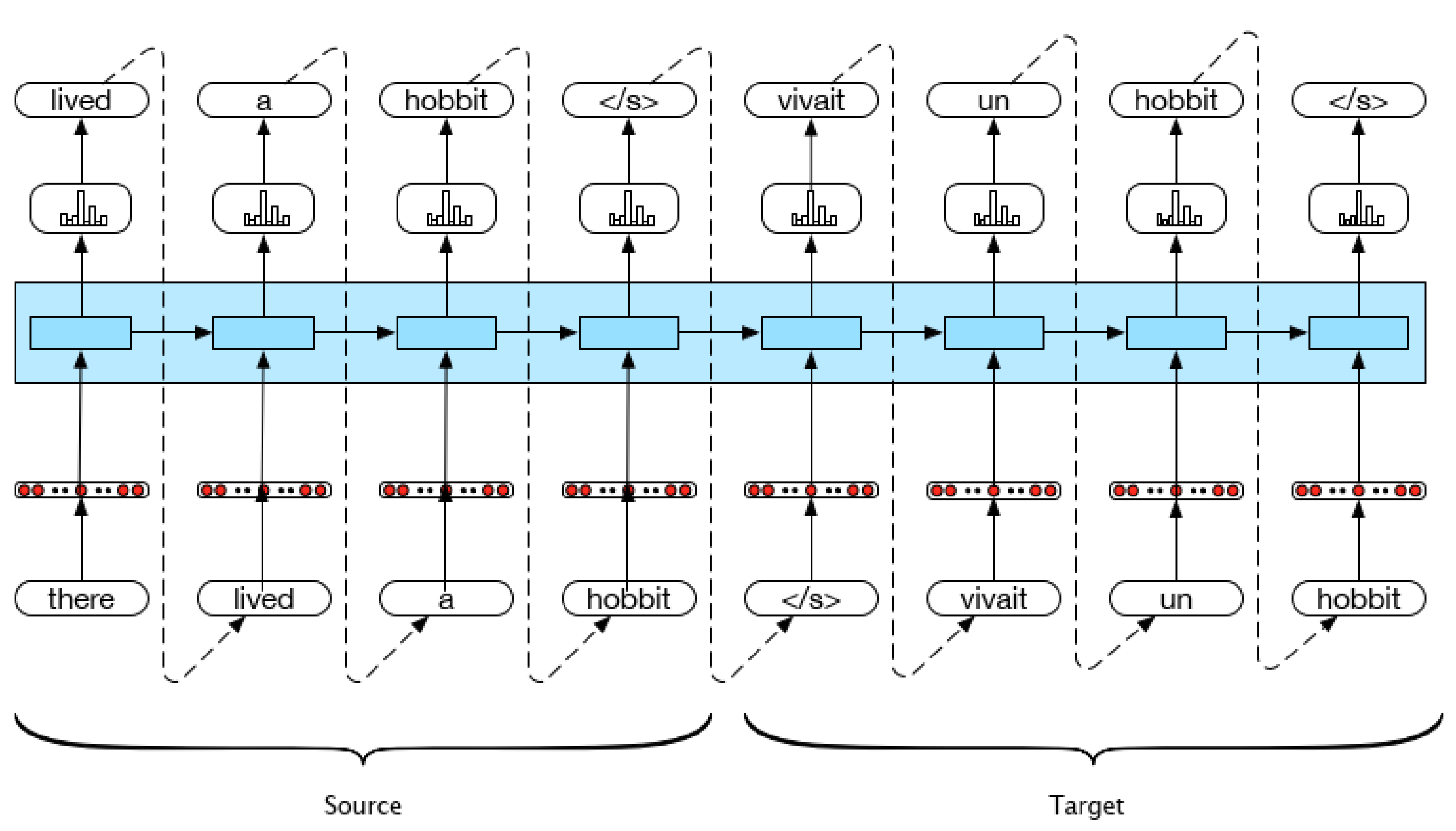
Neural Machine Translation: Encoder-Decoder Model

- Task: automatically translate from one language to another
- Source language/sentence/sequence
- Target language/sentence/sequence
- Parallel Corpus or **bitexts**

- Language Models & Autoregressive Generation extended to Machine Translation
  - End-of-sentence marker between **bitexts** (source</s>target)
  - Use them as training data (RNN-based LM)
  - Predict next word in the sentence

Neural Machine Translation: Encoder-Decoder Model

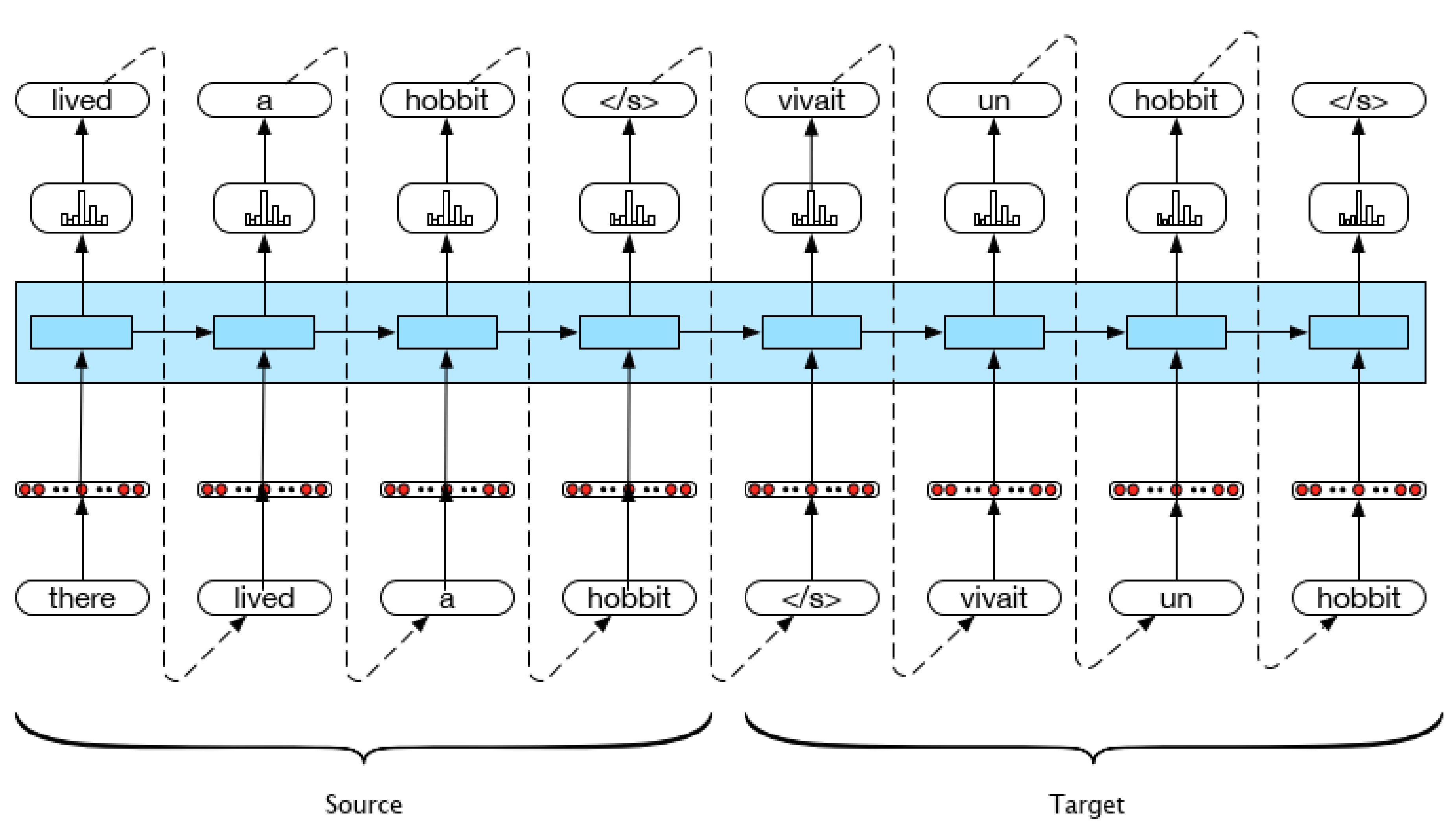
Simple RNN,
LSTM, GRU, …



Encoder-Decoders
(aka. Sequence-to-sequence Models)

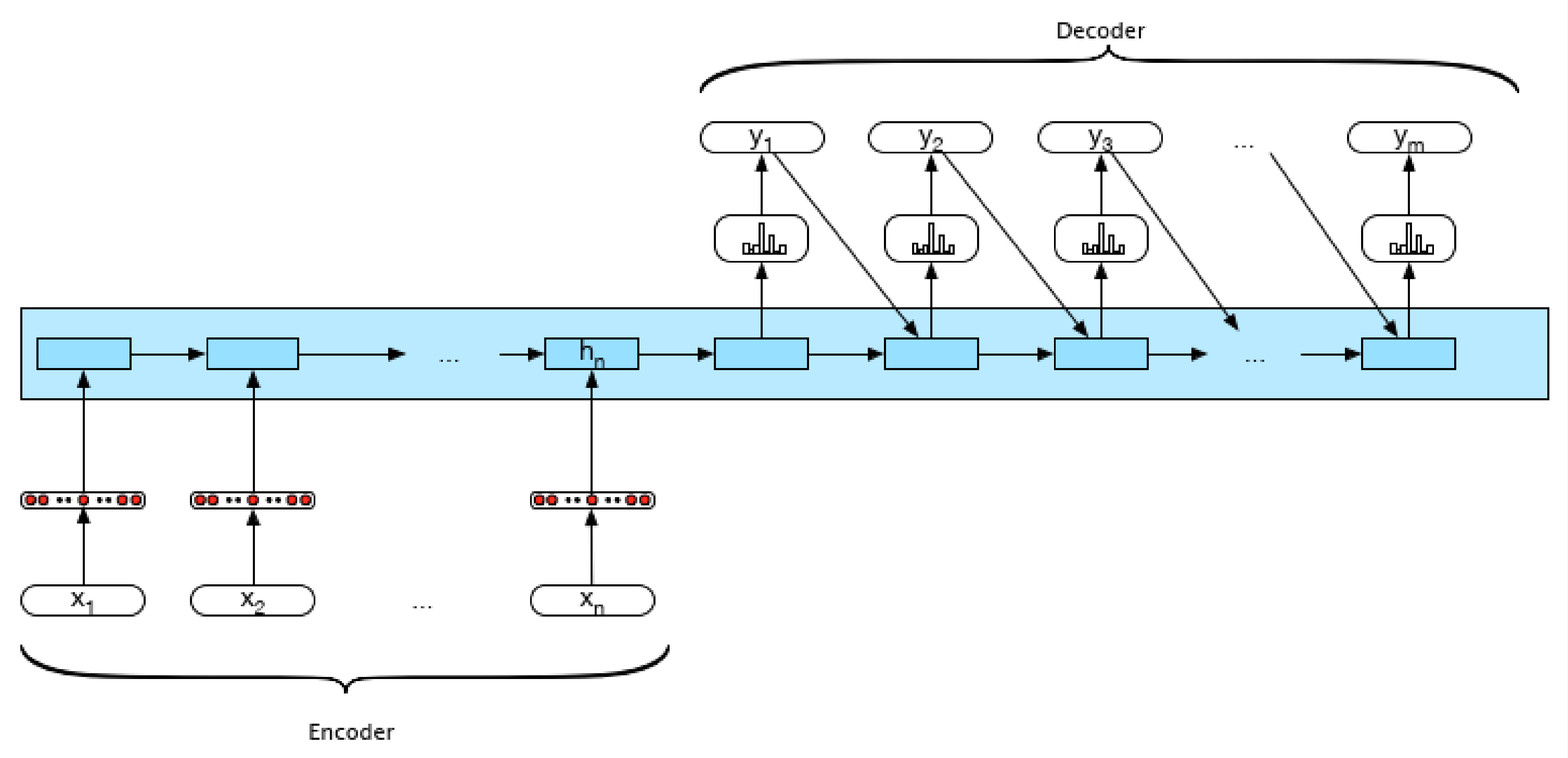
Neural Machine Translation: Encoder-Decoder Model

Simple RNN,
LSTM, GRU, …



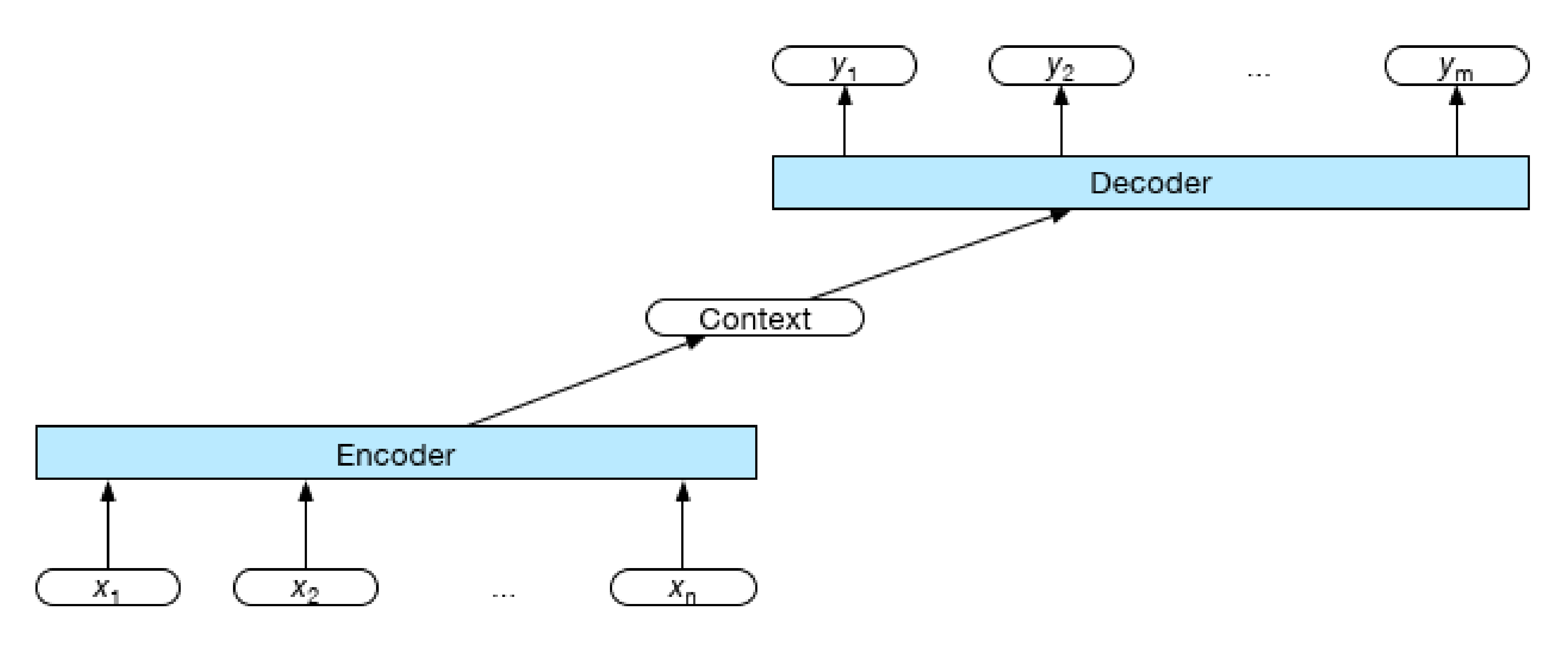
Neural Machine Translation: Encoder-Decoder Model

Simple RNN,
LSTM, GRU, ..



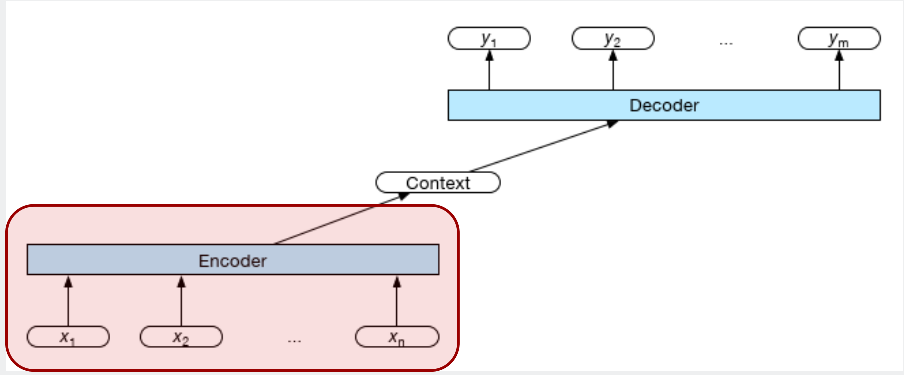
Neural Machine Translation: Encoder-Decoder Model

- Three main components:
  - Encoder
  - Context vector
  - decoder

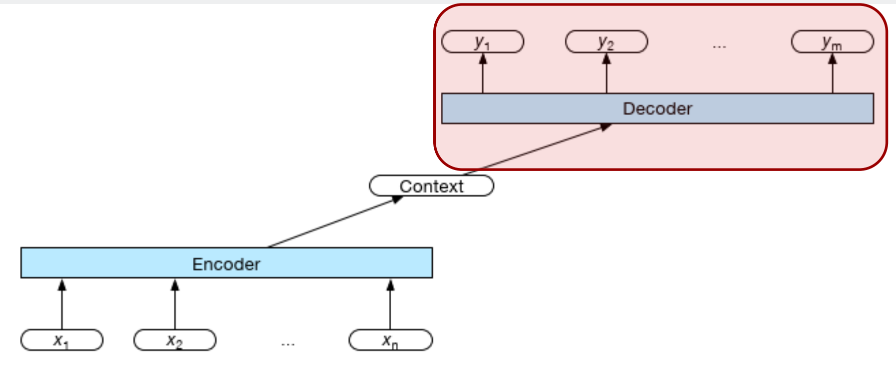


Encoder

- Simple RNNs, LSTM, GRU
- Stacked
- Bi-LSTMs are the norm



Decoder



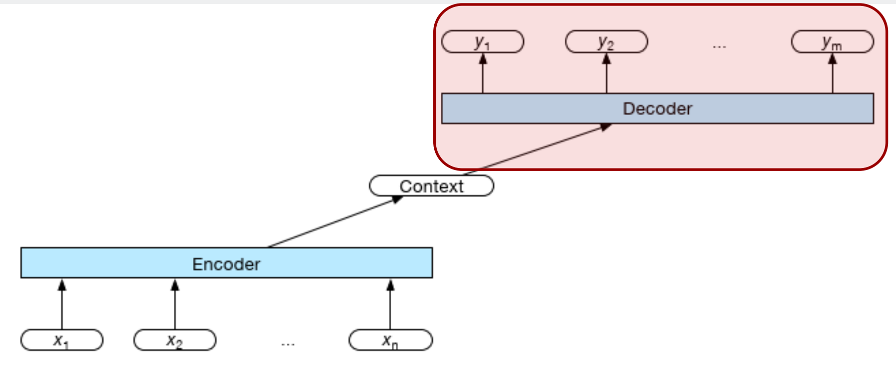
- Autoregressive generation
- Until </s> is generated
- LSTM, GRU

$$
\begin{aligned}
c &= h_n^e \\
h_0^d &= c
\end{aligned}
$$

$$
\begin{aligned}
h_t^d &= g(\hat{y}_{t-1}, h_{t-1}^d) \\
z_t &= f(h_t^d) \\
y_t &= \text{softmax}(z_t)
\end{aligned}
$$

Decoder

- Context available only once.
- How to choose, from the output space the right “next” decoded sequence element?
  - Large search space!
  - Algorithm: Beam Search



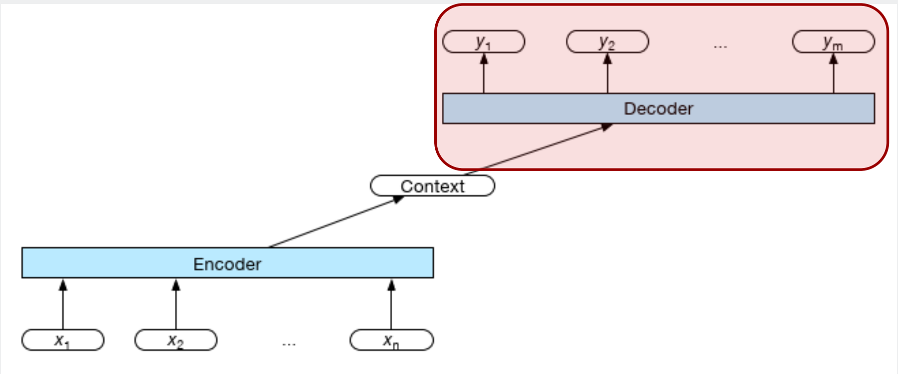
$$
\begin{aligned}
c &= h_n^e \\
h_0^d &= c \\
h_t^d &= g(\hat{y}_{t-1}, h_{t-1}^d) \\
z_t &= f(h_t^d) \\
y_t &= \text{softmax}(z_t)
\end{aligned}
$$

$$h_t^d = g(\hat{y}_{t-1}, h_{t-1}^d, c)$$

$$y_t = \text{softmax}(\hat{y}_{t-1}, z_t, c)$$

$$\hat{y} = \text{argmax} P(y_i | y_< i)$$

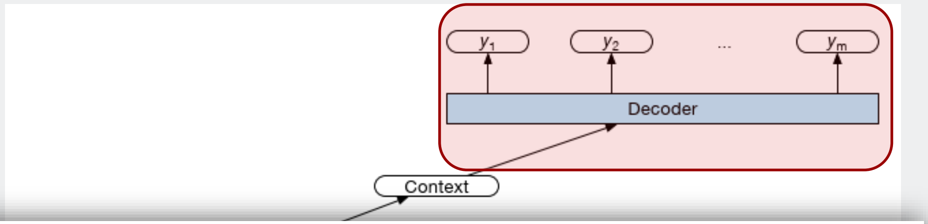
Beam Search



- Large search space
- Alternative: heuristic method, systematic exploration
- By controlling the exponential growth of the search space

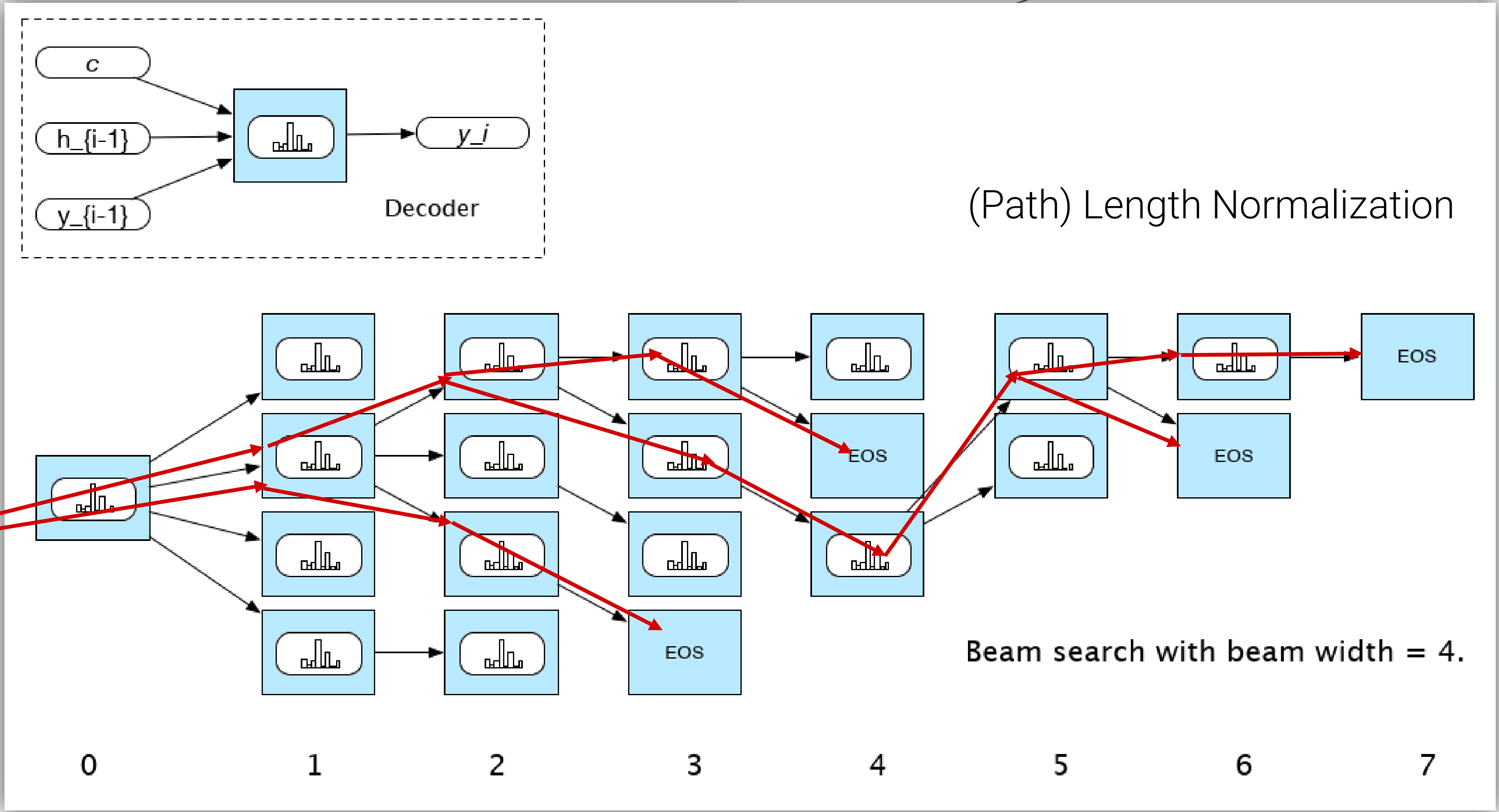
- How: combine breadth first with a heuristic filter
  - Score the options
  - Prune the search space

Beam Search



Scoring:

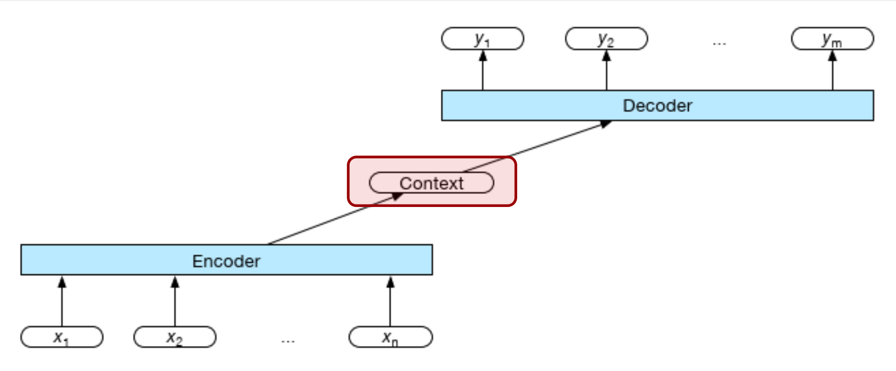
$$P(y_i|y_{<i})$$



hypotheses

Search Frontier

Context



- Context available only once.
- Function of the hidden encoder states

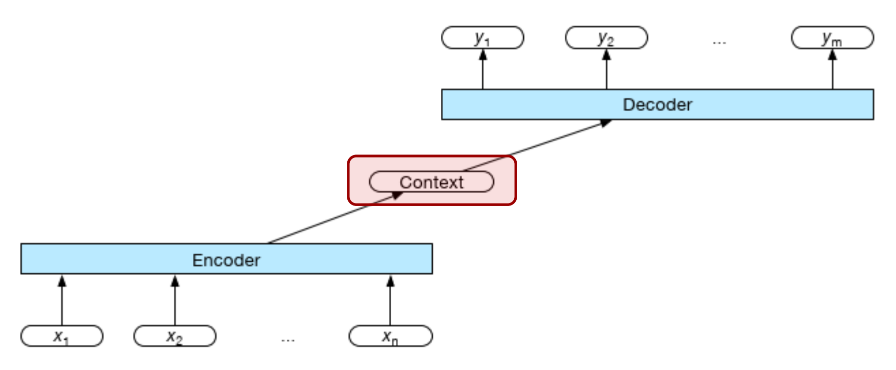
$$c = f(h_1^n)$$

- Variable number of hidden states!

- Bi-RNNs (end states of forward & backward passes, separate or concatenated)
- Average over encoder hidden states

Attention

Attention



- Take all encoder context
- Dynamically update during decoding -> c_i
- Function of the hidden encoder states
- Condition the decoding on the dynamic context
    - Relevance of **encoder** hidden states to the current decoder state
    - Use softmax to normalize these scores
        - Vector of weights

$$h_i^d = g(\hat{y}_{i-1}, h_{i-1}^d, c_i)$$

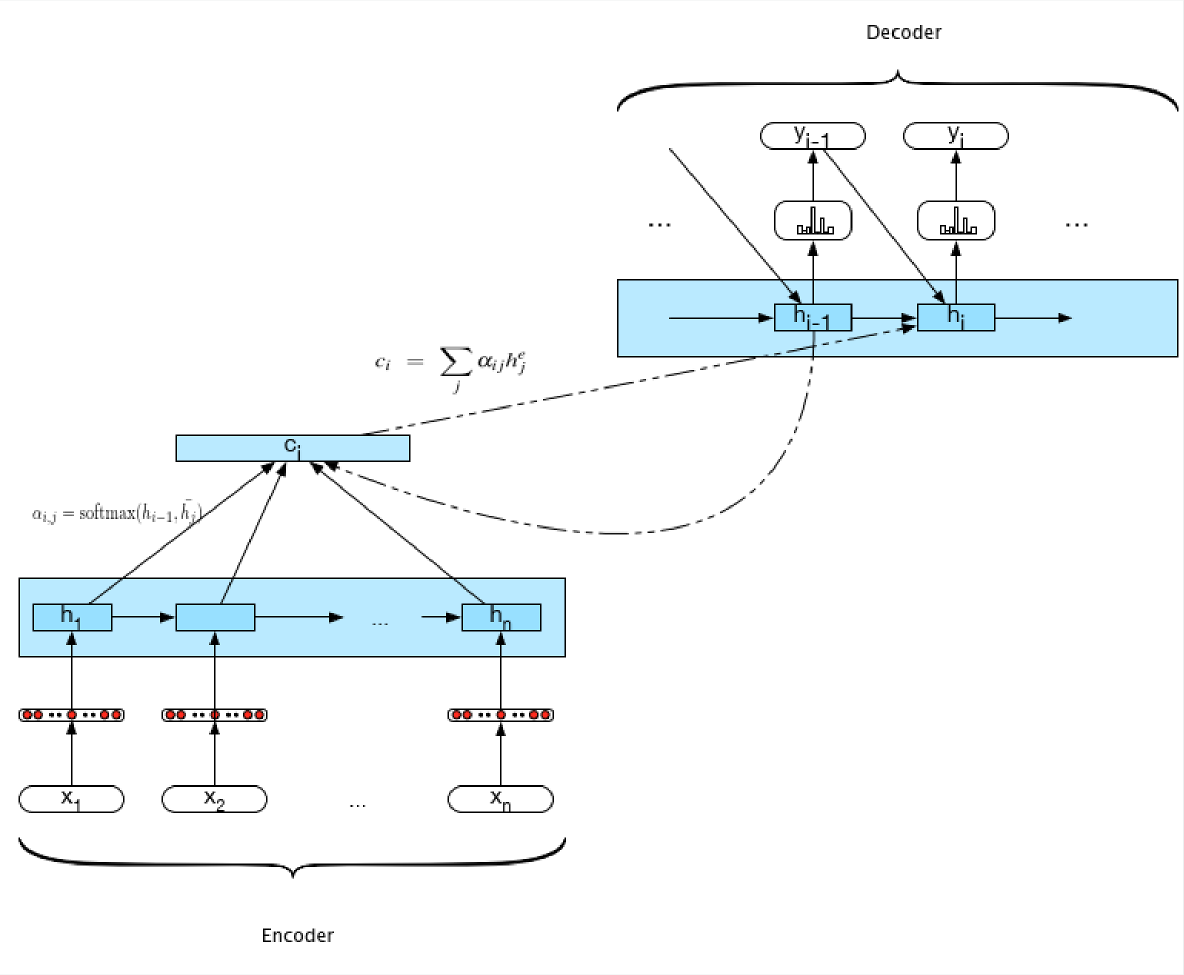
$$score(h_{i-1}^d, h_j^e) = h_{i-1}^d \cdot h_j^e$$

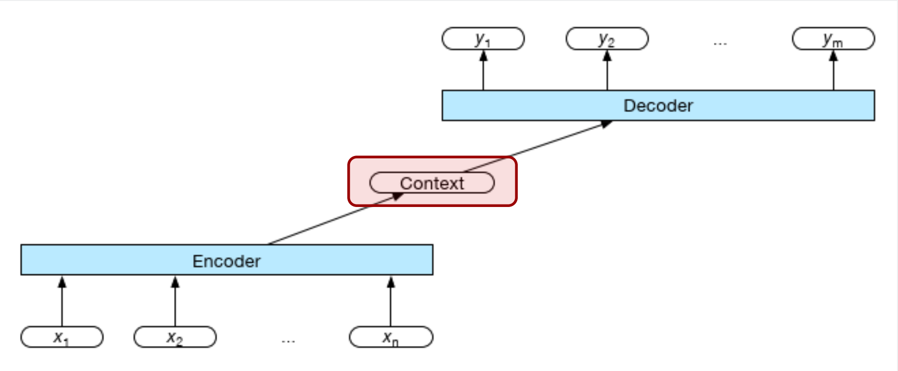
$$score(h_{i-1}^d, h_j^e) = h_{t-1}^d W_s h_j^e$$

$$\alpha_{ij} = \text{softmax}(score(h_{i-1}^d, h_j^e) \ \forall j \in e)$$

$$c_i = \sum_j \alpha_{ij} h_j^e$$

Attention





$$h_i^d = g(\hat{y}_{i-1}, h_{i-1}^d, c_i)$$

$$score(h_{i-1}^d, h_j^e) = h_{i-1}^d \cdot h_j^e$$

$$score(h_{i-1}^d, h_j^e) = h_{t-1}^d W_s h_j^e$$

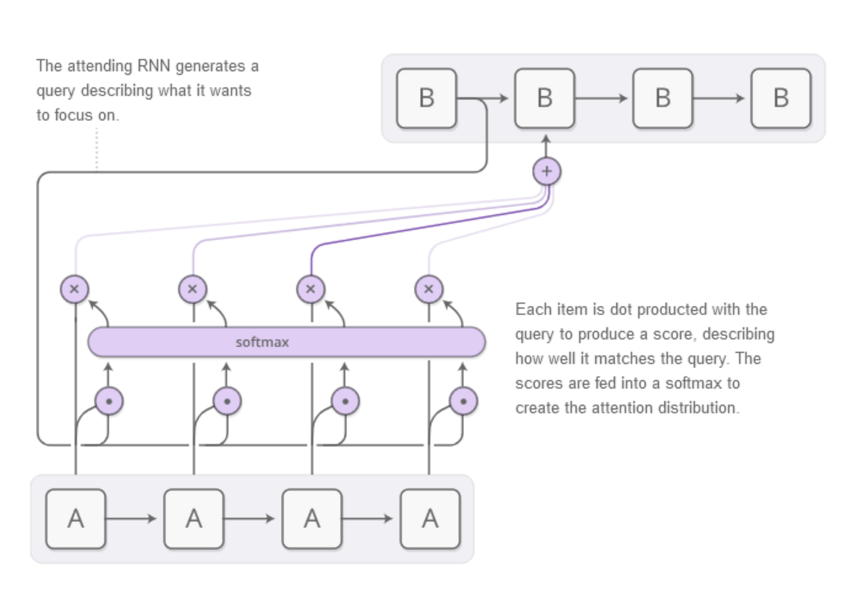
$$\alpha_{ij} = \mathrm{softmax}(score(h_{i-1}^d, h_j^e) \ \forall j \in e)$$

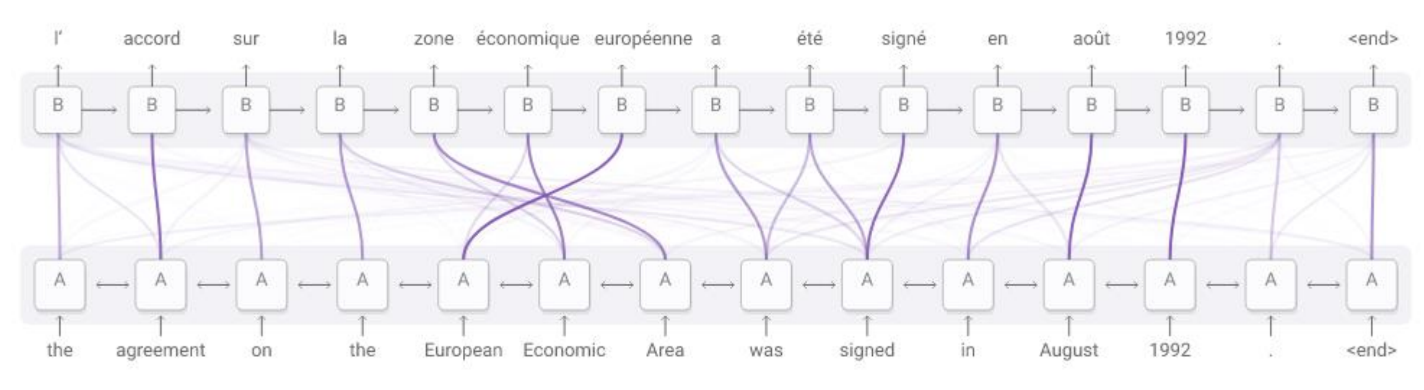
$$c_i = \sum_j \alpha_{ij} h_j^e$$

Attention

https://distill.pub/2016/augmented-rnns/

Live tool to observe which words in the input sequence affect which part of the output sequence





Content

- Sequence-to-sequence (Encoder-Decoder)
- Attention

"Attention is All You Need" https://arxiv.org/pdf/1706.03762.pdf

https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

https://www.analyticsvidhya.com/blog/2019/06/understanding-transformers-nlp-state-of-the-art-models/

https://mlexplained.com/2017/12/29/attention-is-all-you-need-explained/