Deep Learning for NLP

The lecture starts at 14:15

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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

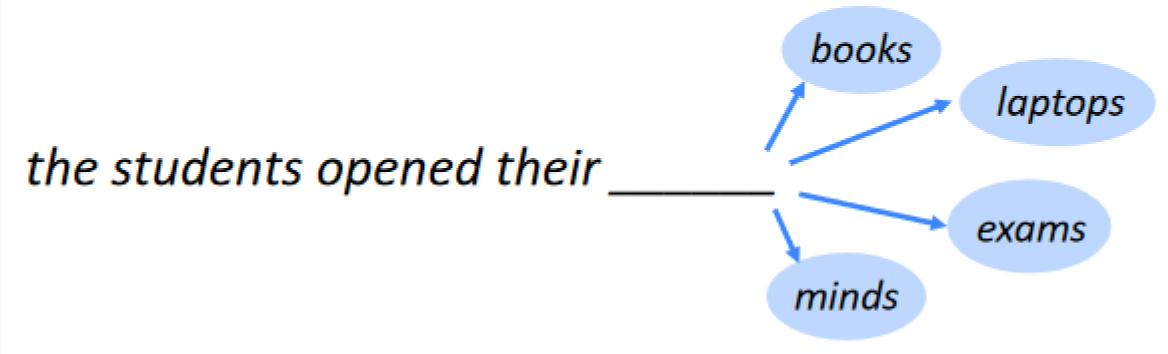
Neural Language Models

Relevant Literature

- Jurafsky & Martin, SLP, 3rd Edition: *Chapters 6, 7, 8, 9, 13*
  - (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 $P(w_n \mid w_1, w_2 \dots w_{n-1})$
- How did you compute P?
  - Count and divide
  - Markov Assumption

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

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

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

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

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

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

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

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

Language Model

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

Perplexity

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

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

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** f_θ

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"))

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

$$\begin{array}{rcccccccccc}
 & \text{a} & \text{hair} & & & & \text{cat} & & & & \text{zombie} \\
\text{vocabulary index:} & [\,1, & 2, & 3, & 4, & 5, & 6, & 7, & ...., & ..., & |V|\,] \\
 & [\,0, & 0, & 0, & 0, & 0, & 1, & 0, & ...., & ..., & 0\,]
\end{array}$$

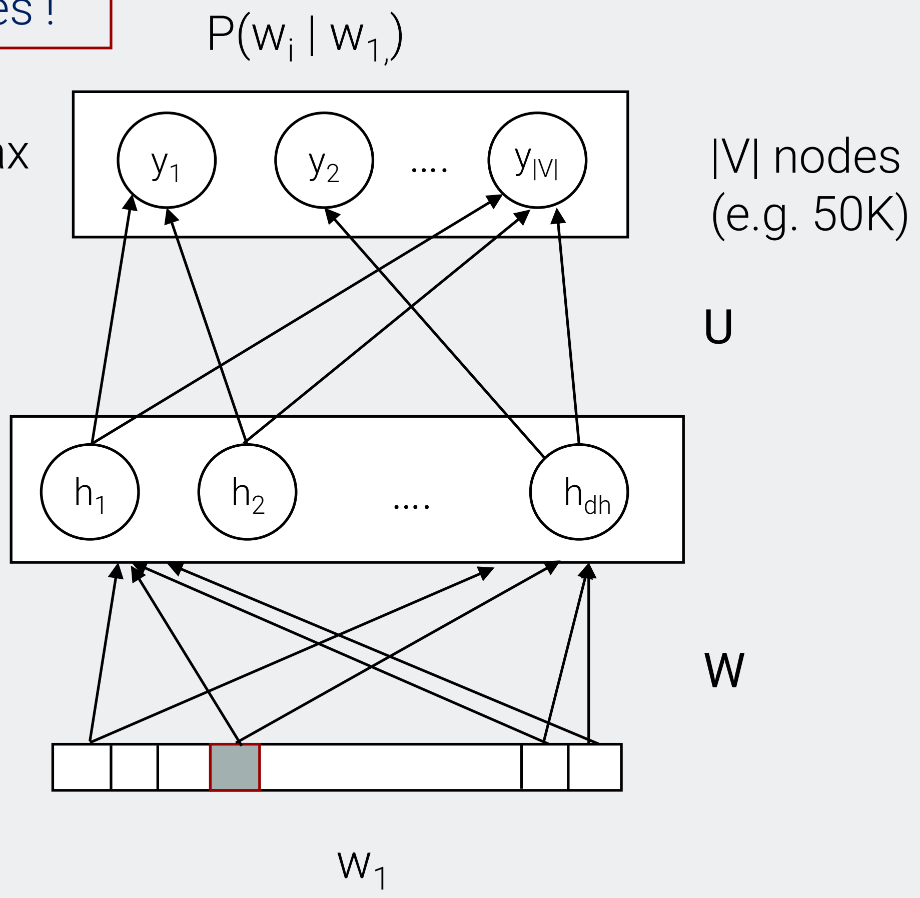
Neural Language Model with a Feed Forward Net - Execution

Multiple classes !

Output layer - softmax
$P(w \mid context)$

Hidden Layer

Input Layer
one-hot vectors



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

Neural Language Model for Bigrams, with a Feed Forward Net - Execution

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

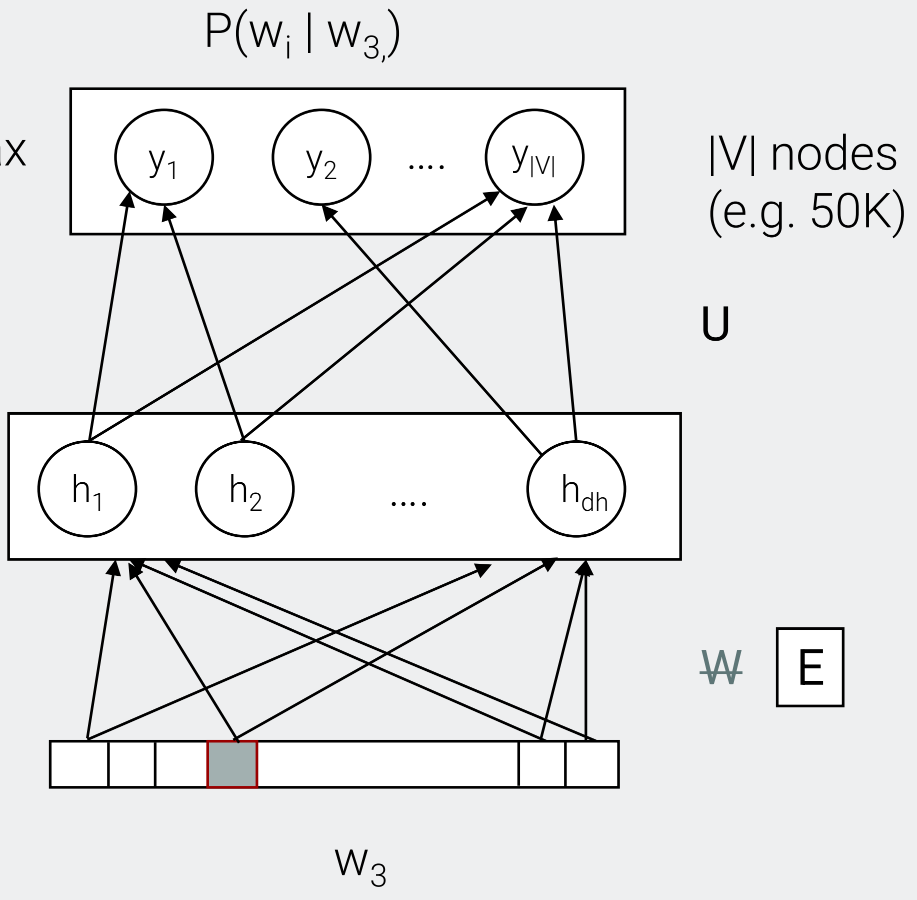
Negative samples ($w_{3,}$ w_{xx})
(metal heavy)
(metal towel)

[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

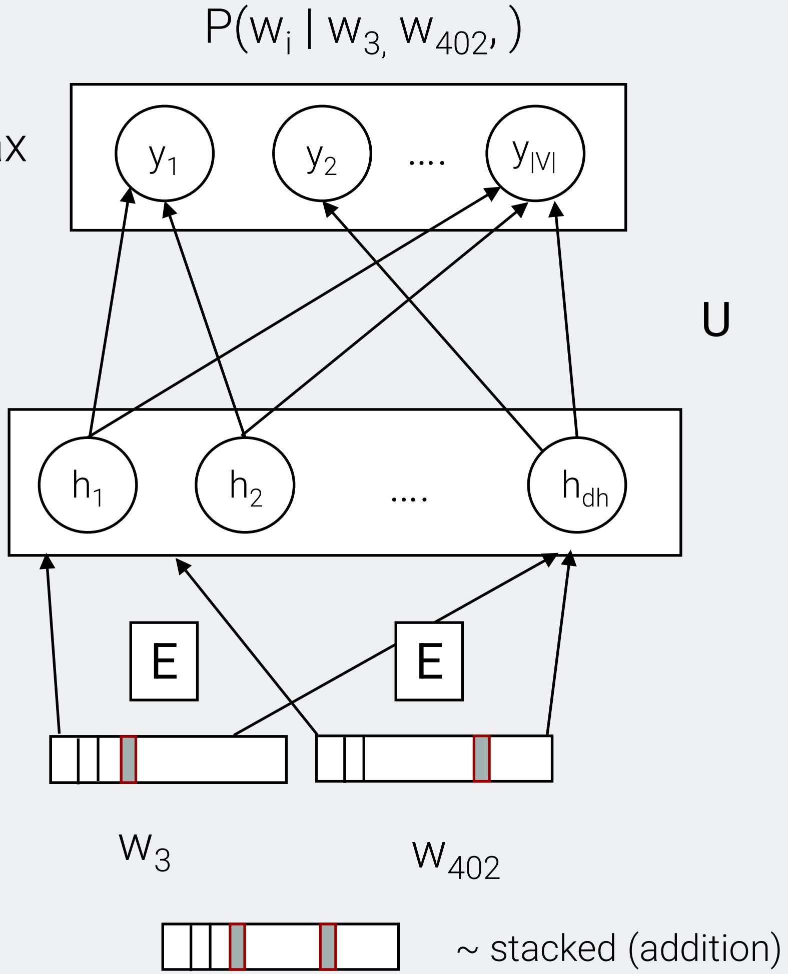


Neural Language Model for 3-grams, with a Feed Forward Net - Training

Output layer - softmax
P(w | context)

Hidden Layer

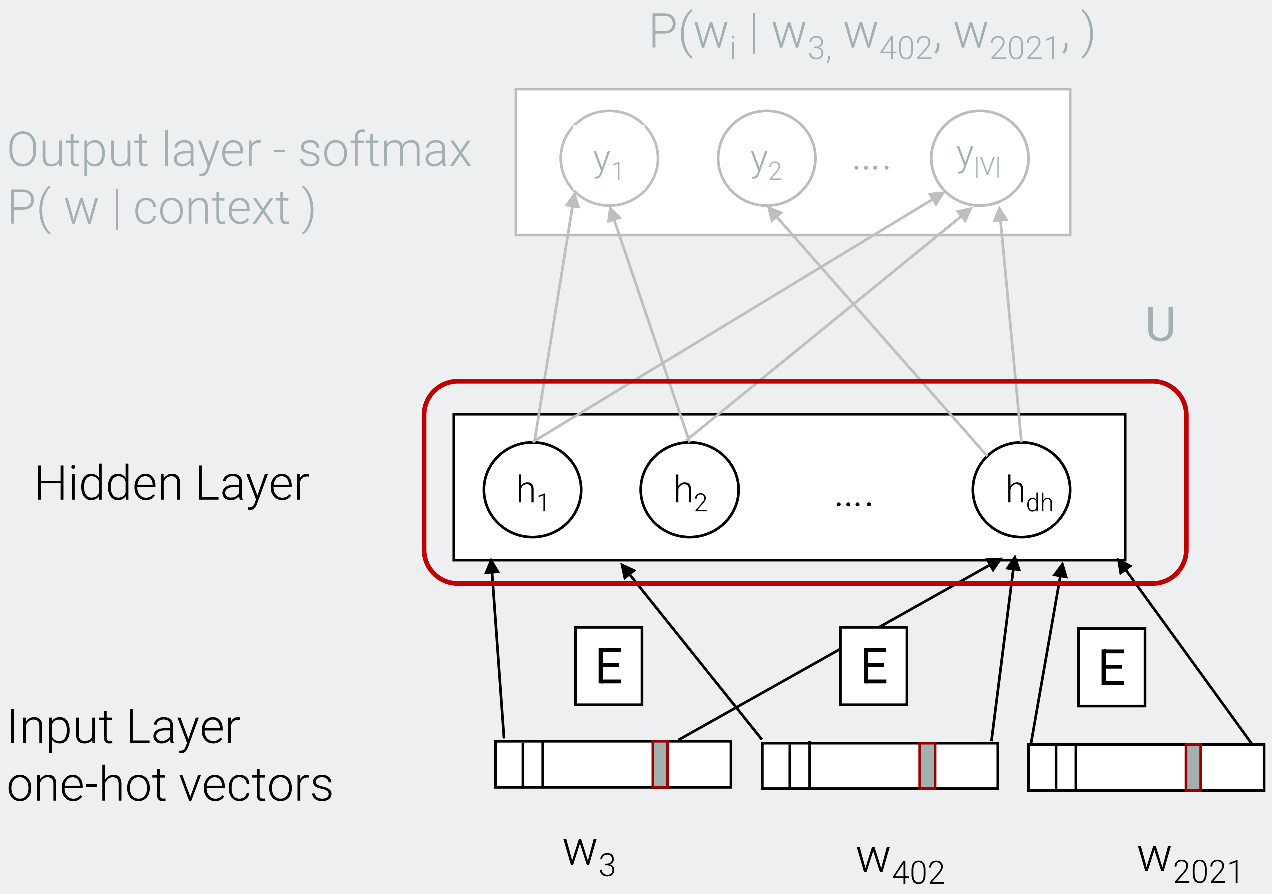
Input Layer
one-hot vectors



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

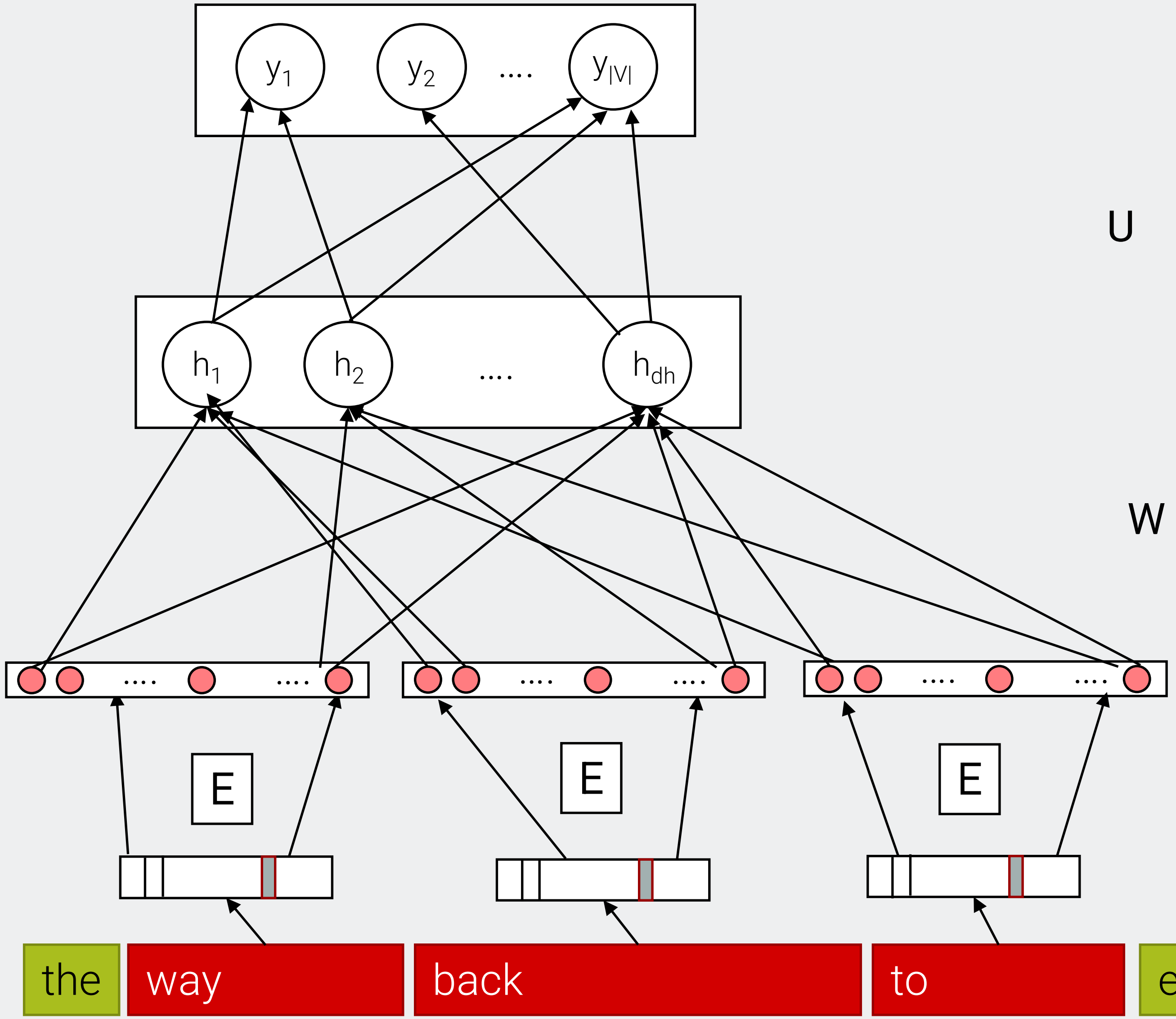
Negative samples ($w_{3,}$ w_{402}, w_{xx})
(metal skirt mouse)
(metal skirt towel)

Neural Language Model for n-grams, with a Feed Forward Net - Training



Projection layer

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



Output layer - softmax
P(w | context)

1 x |V|

U |V| x dh

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

$$z = Uh$$

1 x dh

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

Transformation layer

W dh x 3d

1 x 3d

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

(context vector!)

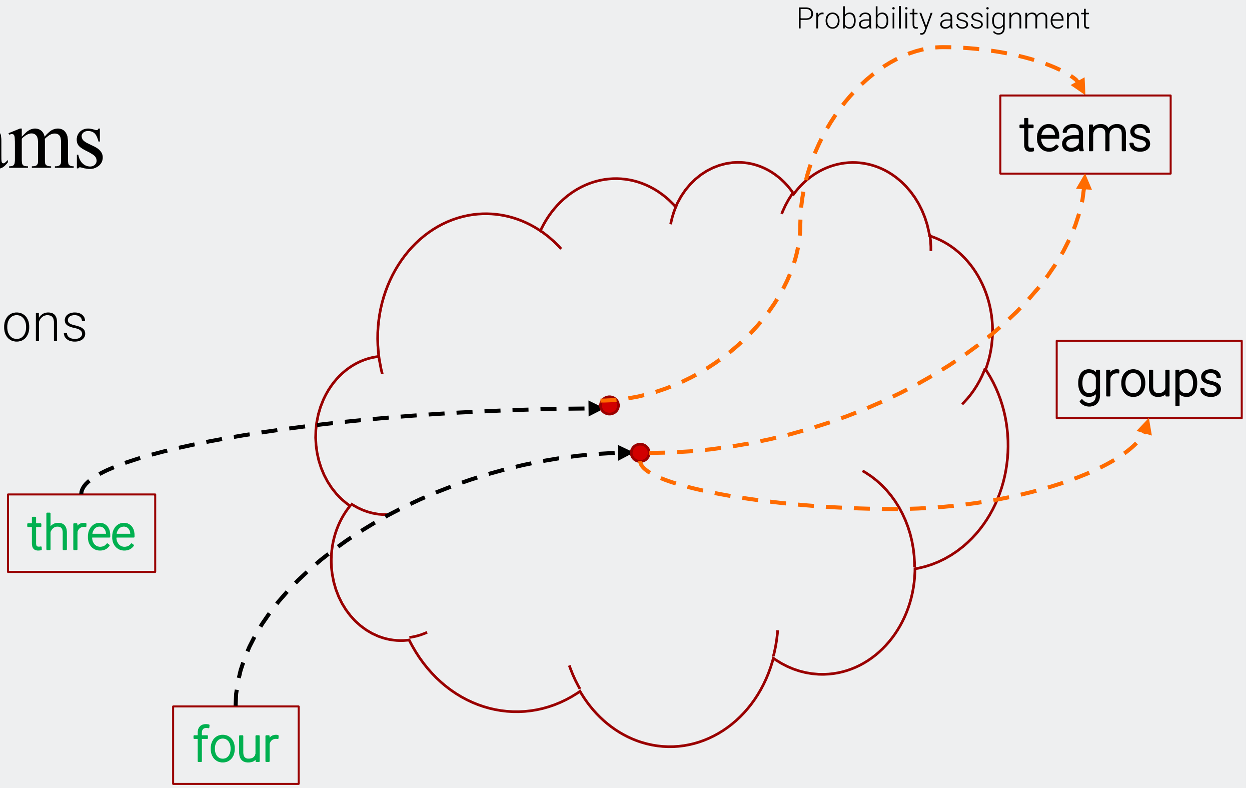
d x |V|

1 x |V|

Input Layer, one-hot vectors

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)

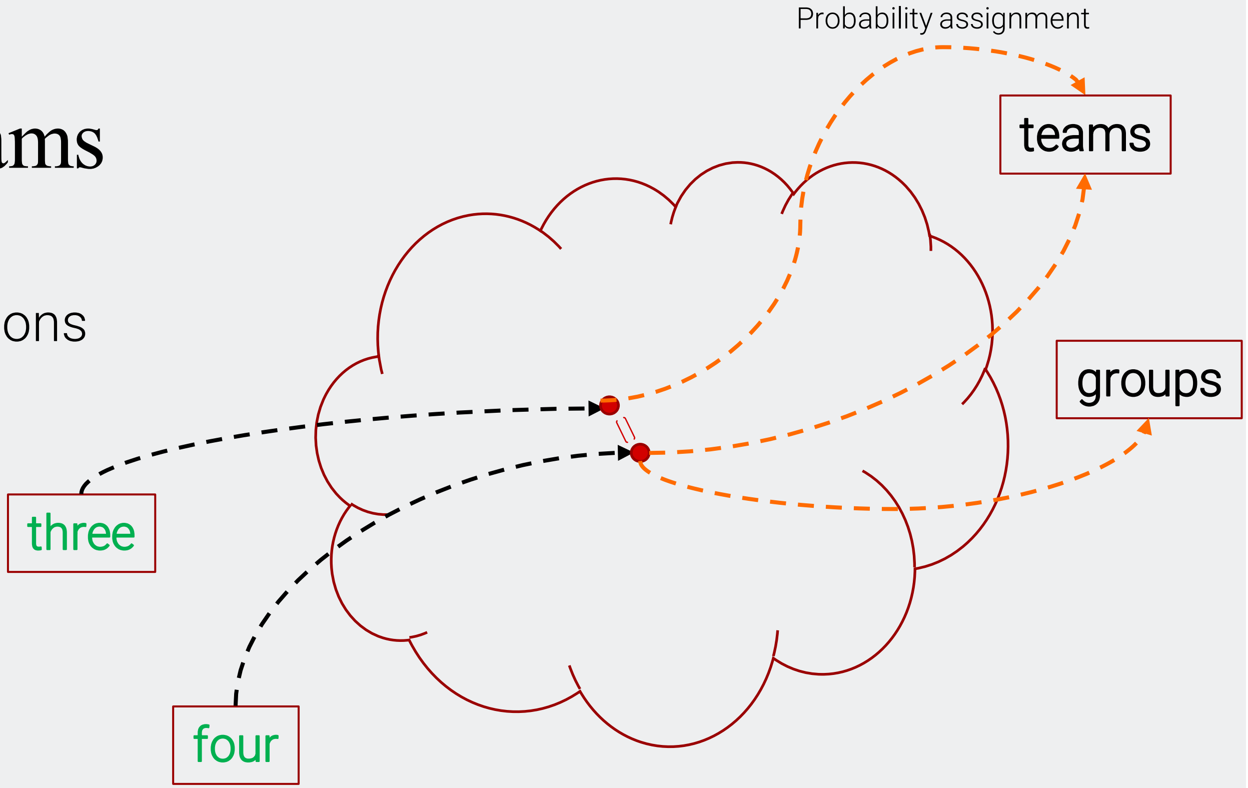
- (during training)
- context

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"

  context vectors of "three" and "four" are close to each-other → model will assign a high probability to "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)
- Basic Encoder – Decoder Architecture

Intermezzo – Large LM biases

- Availability bias – data that is already there
- Confirmation bias – questions/prompts are formulated st. replies fall into own view set
- Selection bias – training data is not representative (only Western data)
- Group attribution bias – extrapolate from anecdotical / insufficient evidence
- Linguistic bias – style, vocabularies, terms favoured over other cultural nuances
- Anchoring bias – rely on initial info
- Automation bias – tendency to trust AI output blindly

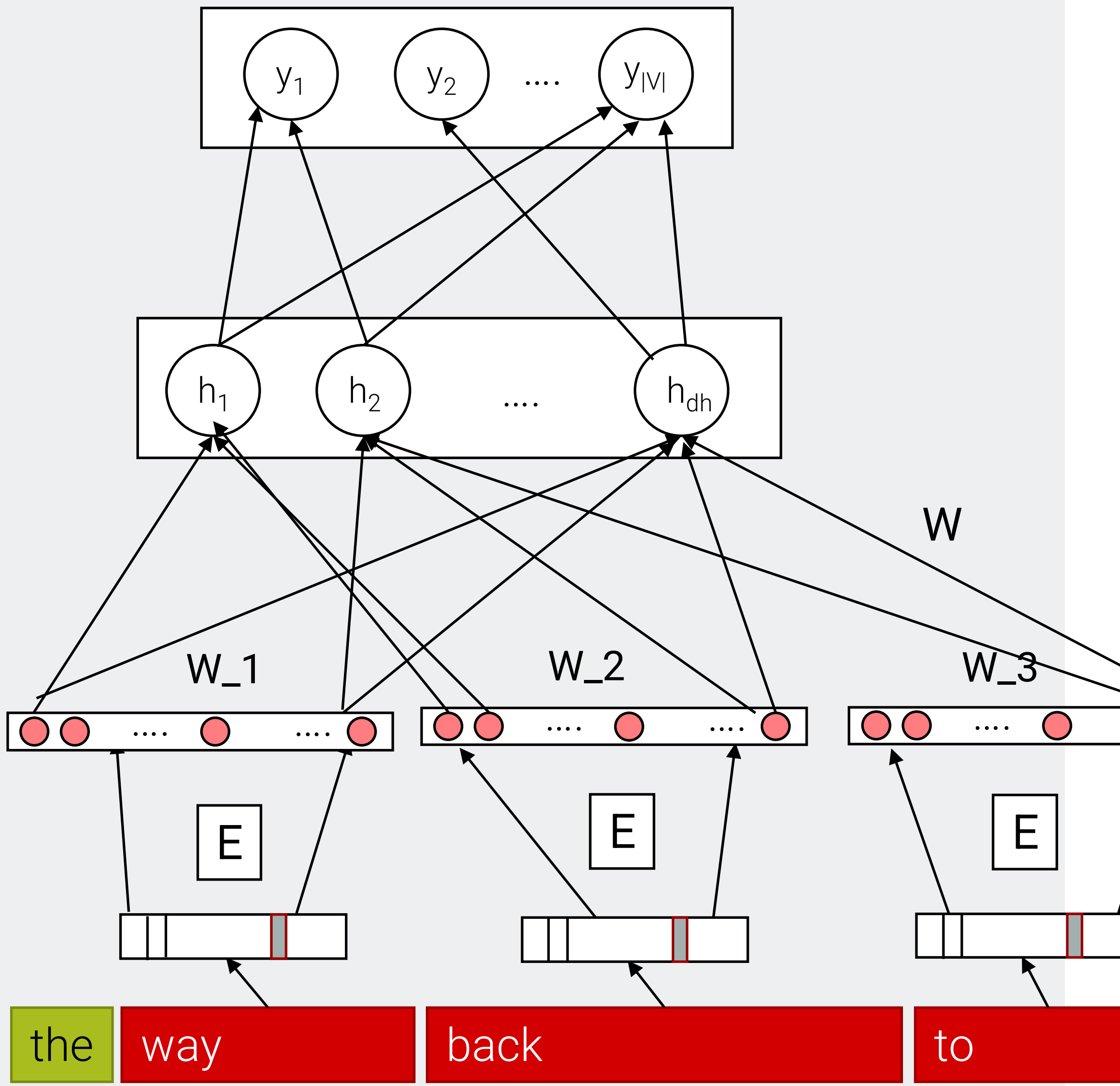
Content

- Neural Language Models
- Recurrent Neural Networks
- LSTMs (Long Short-Term Memory Networks)
- Basic Encoder – Decoder Architecture

(Simple) Neural Language Models

- Improvements over n-gram LM
  - No sparsity problem
  - Don't need to store all observed n-grams and their probabilities
- 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

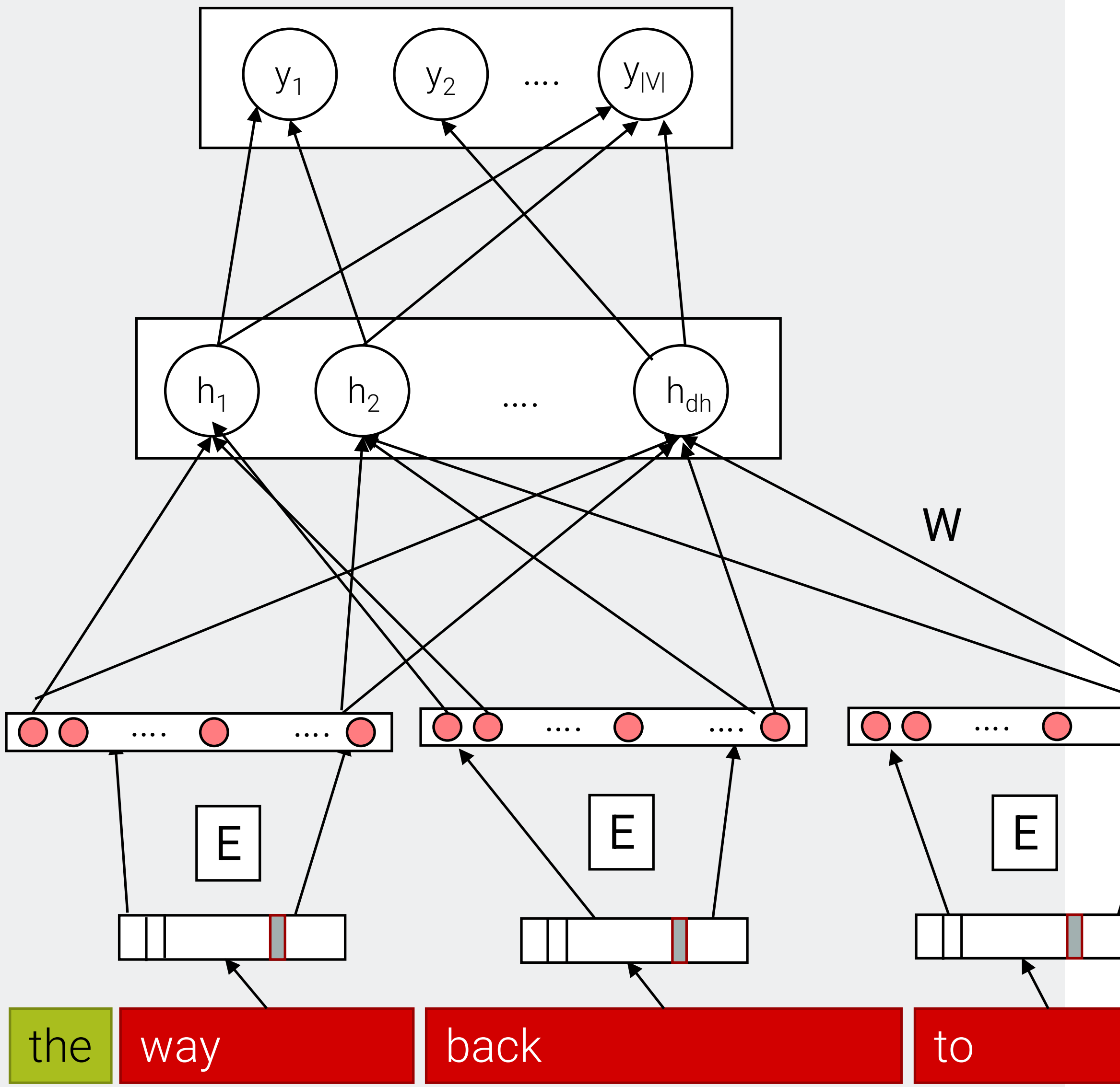
    (No symmetry in input processing)



(Simple) Neural Language Models

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

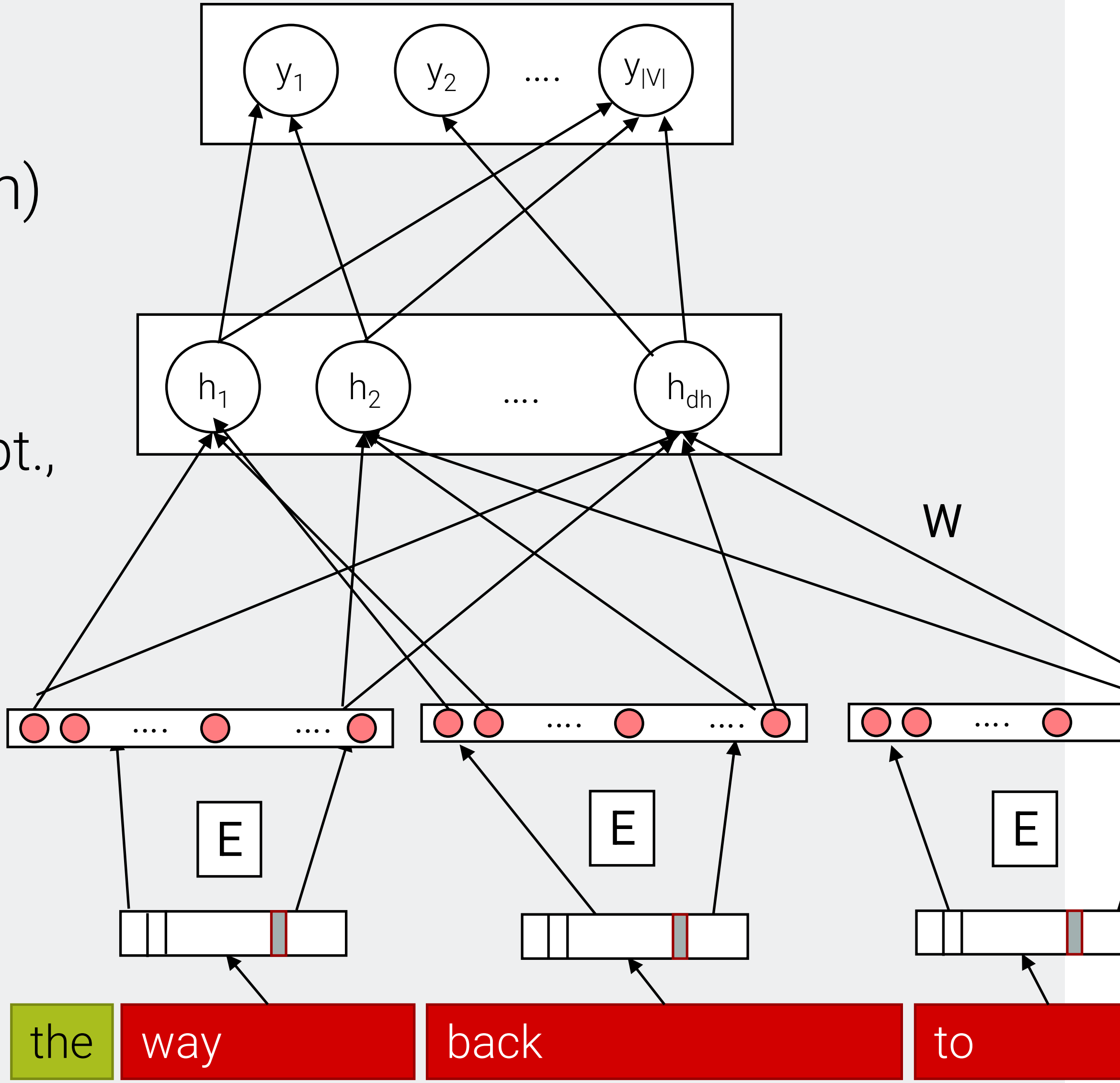
- Slide the input window
- Still, decision on one window does not influence decision on other window.
- Cannot learn systematic patterns (e.g. Constituency)



(Simple) Neural Language Models

- Language is temporal (continuous stream)
  - "Sequence that unfolds in time"
- Algorithms use this
  - Viterbi (probabilistic word similarity compt., 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**

- Each input has a variable number of elements:

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

- 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 ADD1 function definition

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

Algorithm 2 ADD1 function call

$s \leftarrow 0$
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
- We want: Parametrized recursive function

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

- Input x_1 and memory **h**, returns the new **h**
- Time index, t! $h_t = f(x_t, \mathbf{h}_{t-1})$

- What kinds of f do we know of?
  - Transformation layer function:

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

Algorithm 1 ADD1 function definition

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function ADD1(v,s)
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end function

Algorithm 2 ADD1 function call

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

W, U – weight matrixes,
φ(x) – projection layer (i.e. embeddings)
g – non-linear activation function

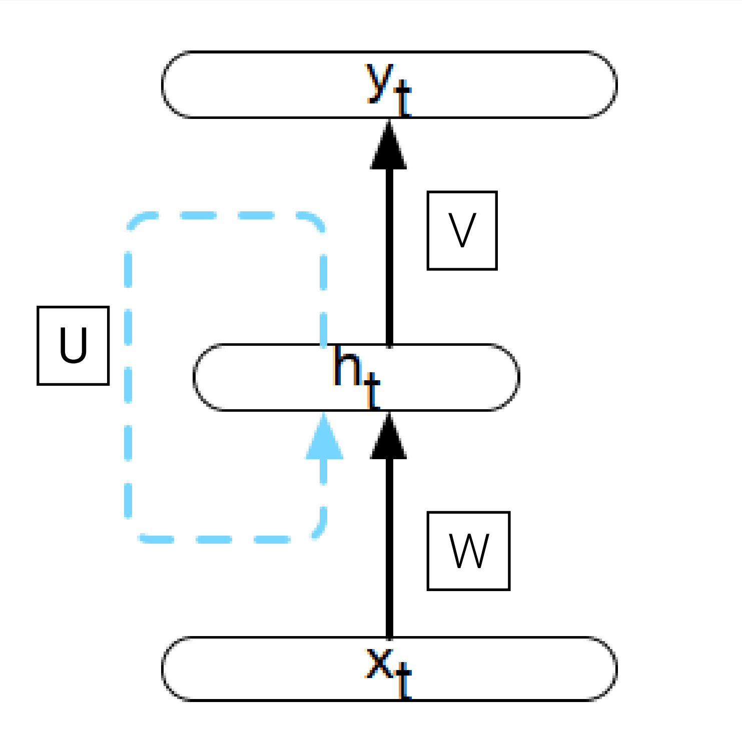
Recursive Function for Natural Language Understanding

$\mathbf{h} \in \mathbb{R}^{d_h}$

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

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

Elman network



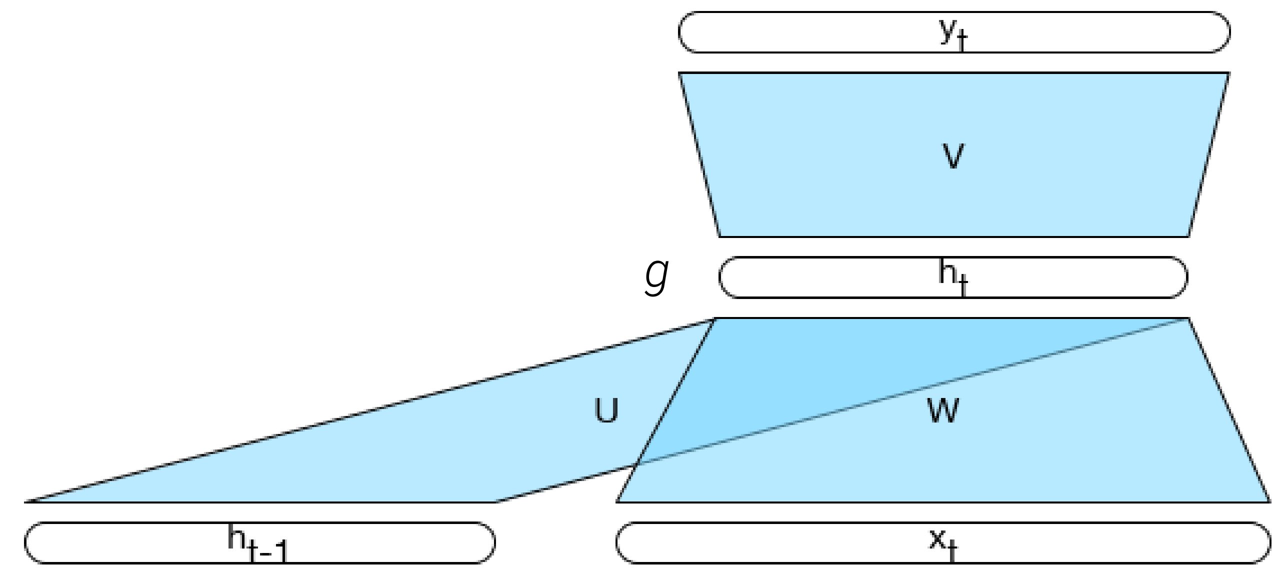
Input sequence: one element at a time
(no restriction on input length!)

Recursive Neural Network – Unrolled

Inferencing:

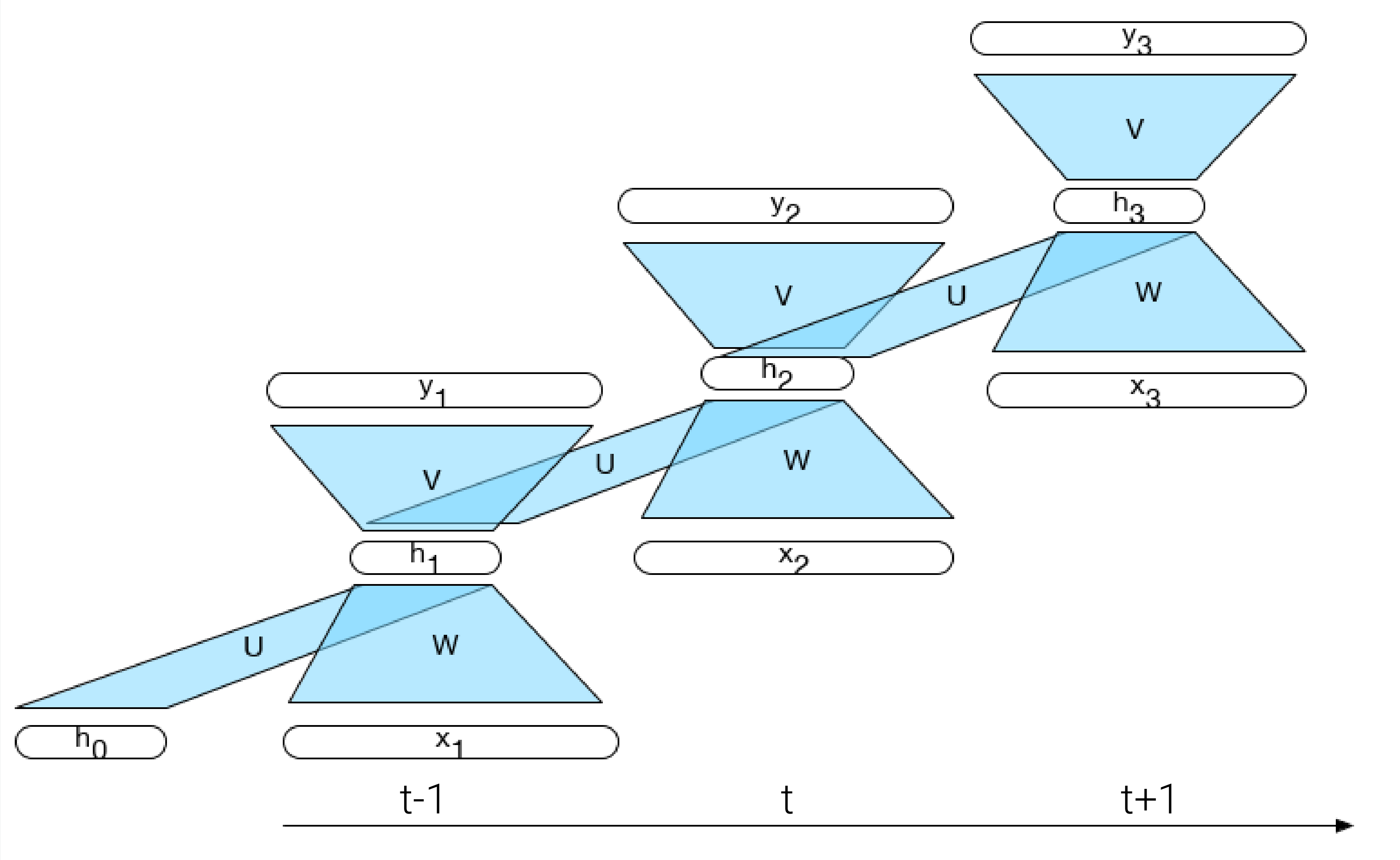
$$
\begin{aligned}
h_t &= g(Uh_{t-1} + Wx_t) \\
y_t &= f(Vh_t)
\end{aligned}
$$

$$y_t = softmax(Vh_t)$$



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

Recursive Neural Network – Unrolled

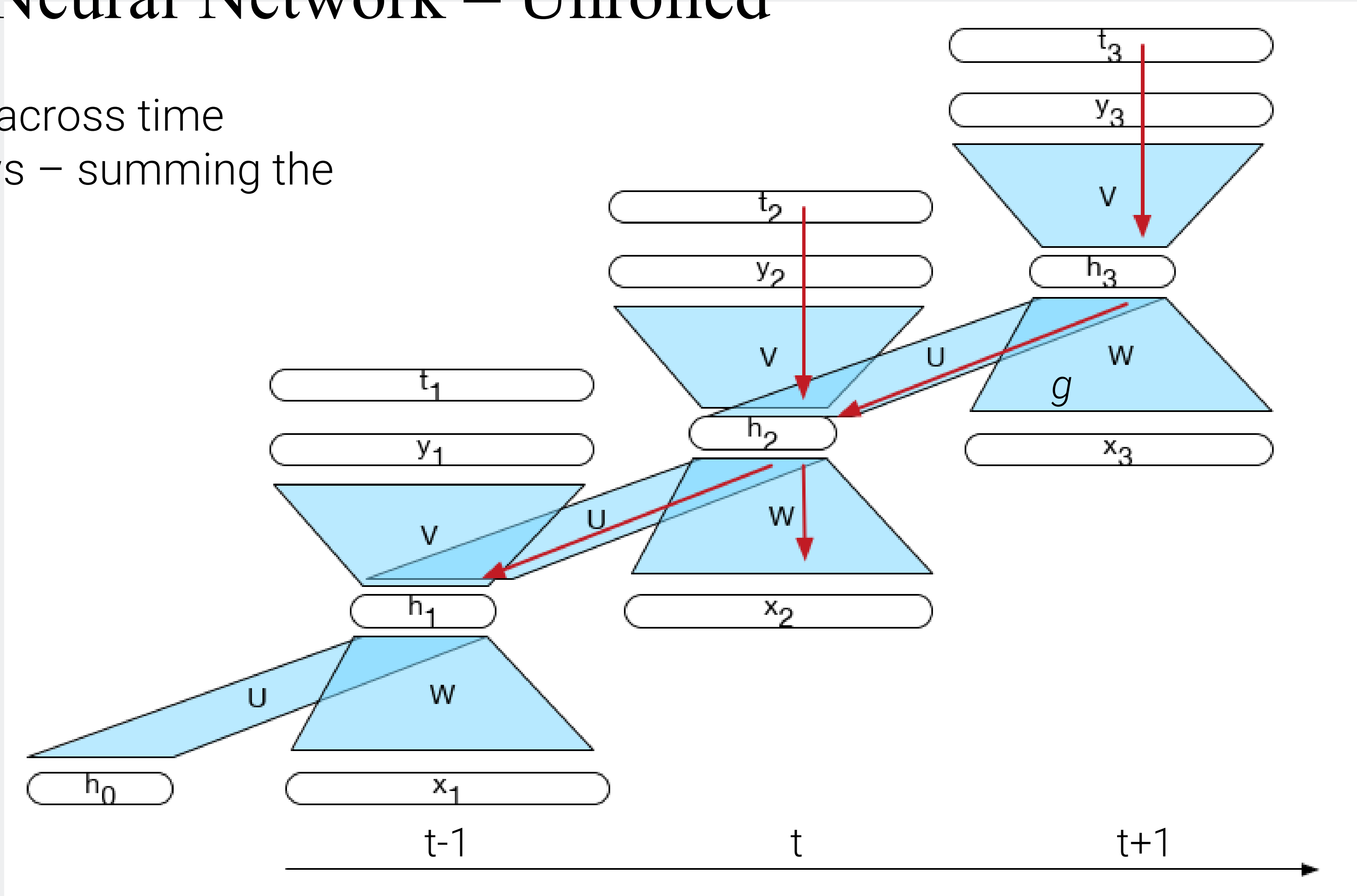


U, W, V – shared across time!

i.e. during inferencing the matrices are the same across all sequence tokens (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
  (a) Fixed sliding window, i.e. fixed context.
    - Quality of prediction largely dependent on the size of the window

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

  (b) 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!

(a) Length of the input sequence not fixed
(b) Hidden state embodies info in the preceding sequence words

RNN – Language Models: Execution/Inference

- 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, each including prior word information

RNN – Language Models: Training

- 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

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

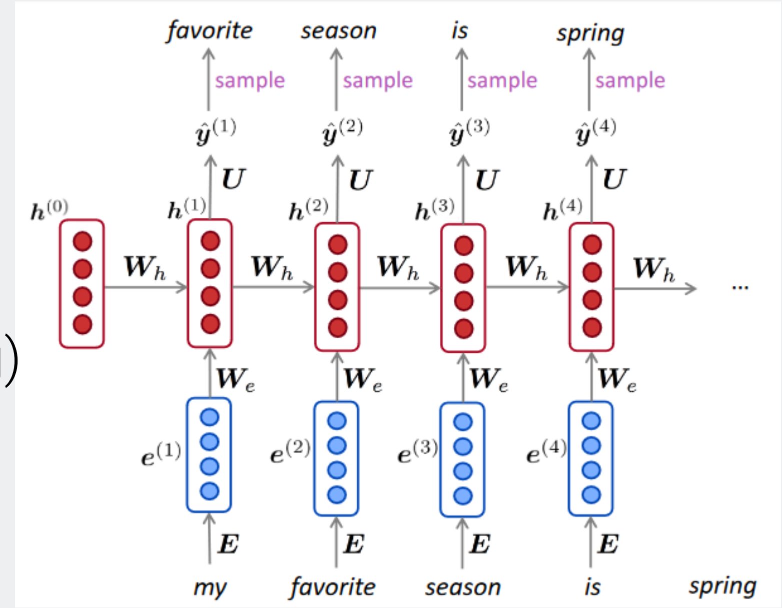
- Perplexity for evaluation

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

- Gradient descent f. weight adjustment

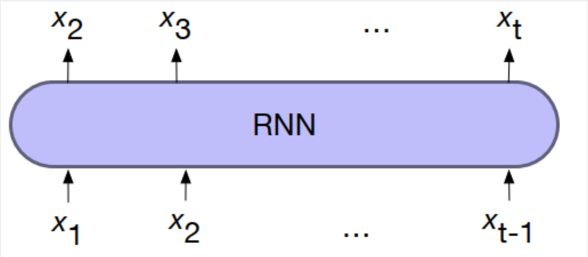
RNN – Language Models

- 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.

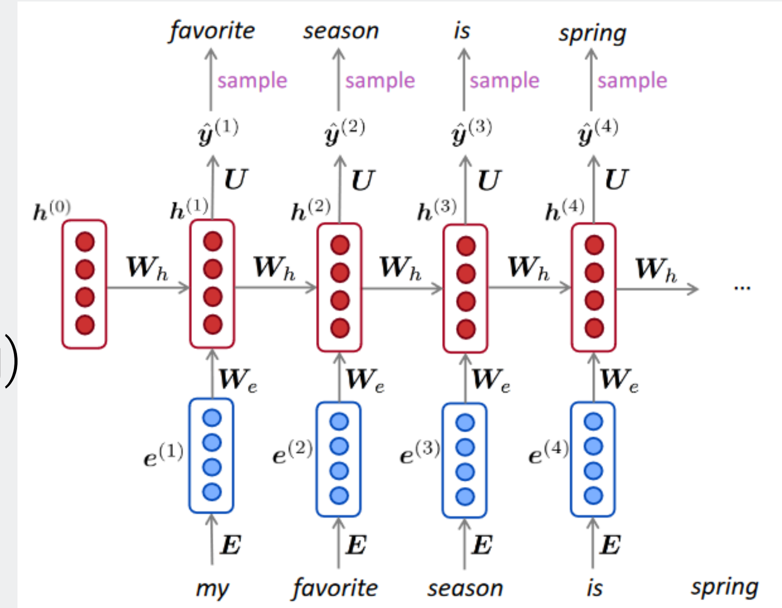


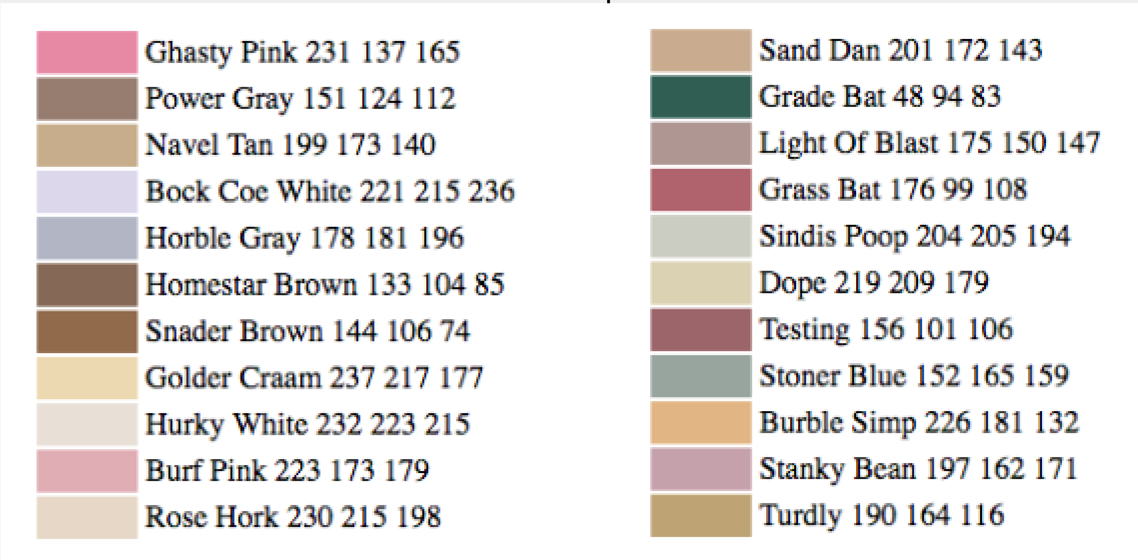
https://medium.com/@samim/obama-rnn-machine-generated-political-speeches-c8abd18a2ea0

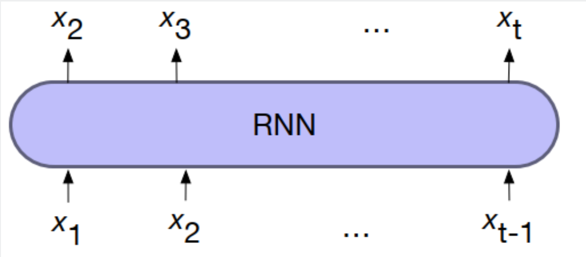
RNN – Language Models

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

  - Character level example



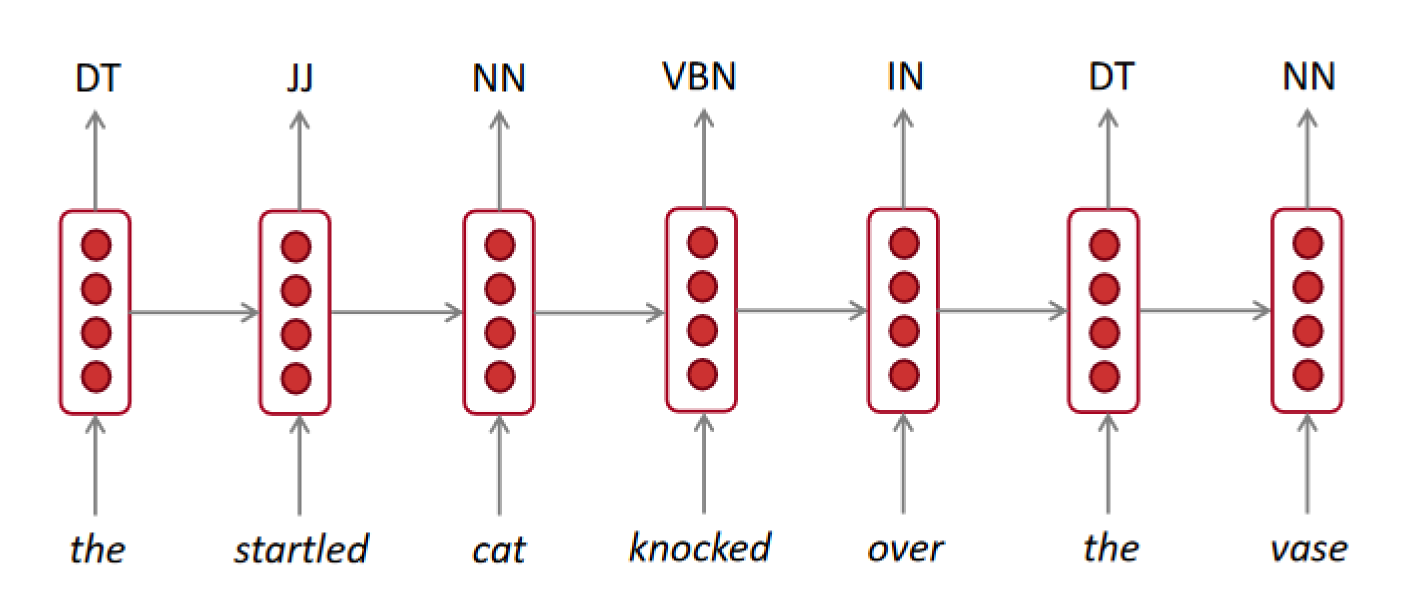


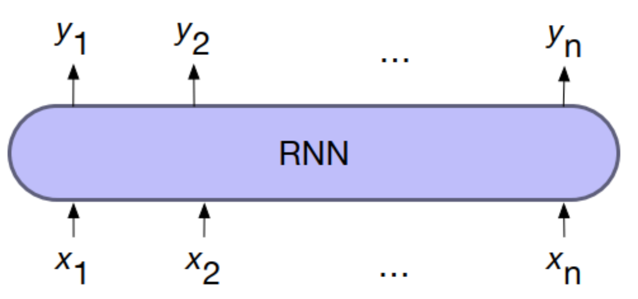


http://aiweirdness.com/post/160776374467/new-paint-colors-invented-by-neural-network

RNN – Applications

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

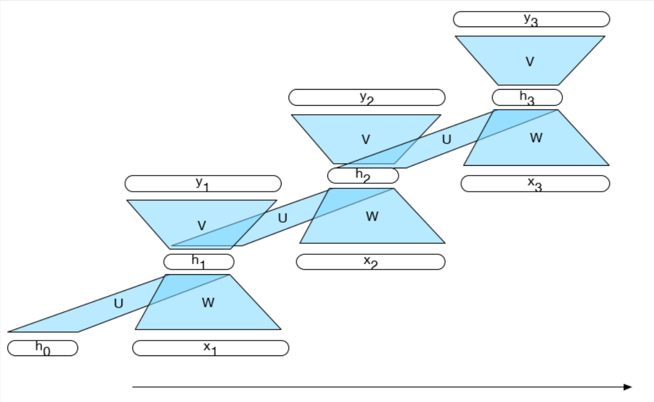


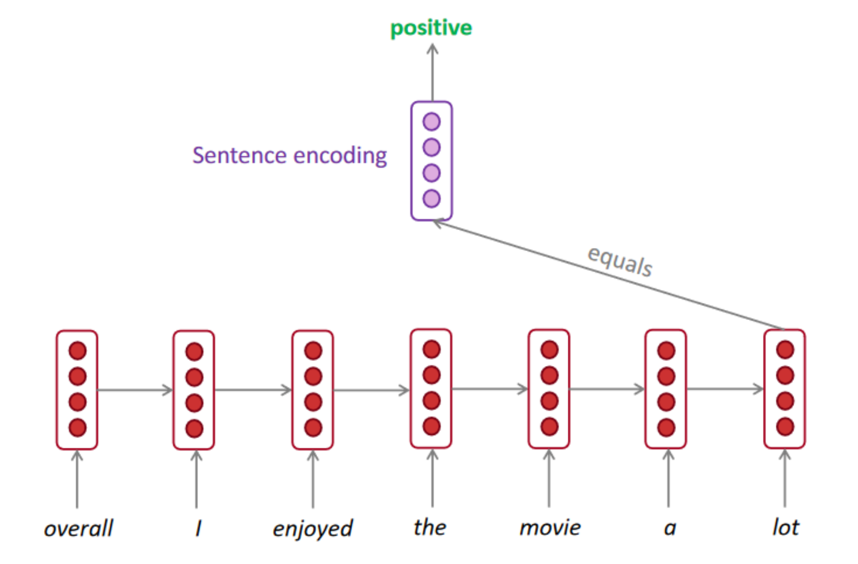


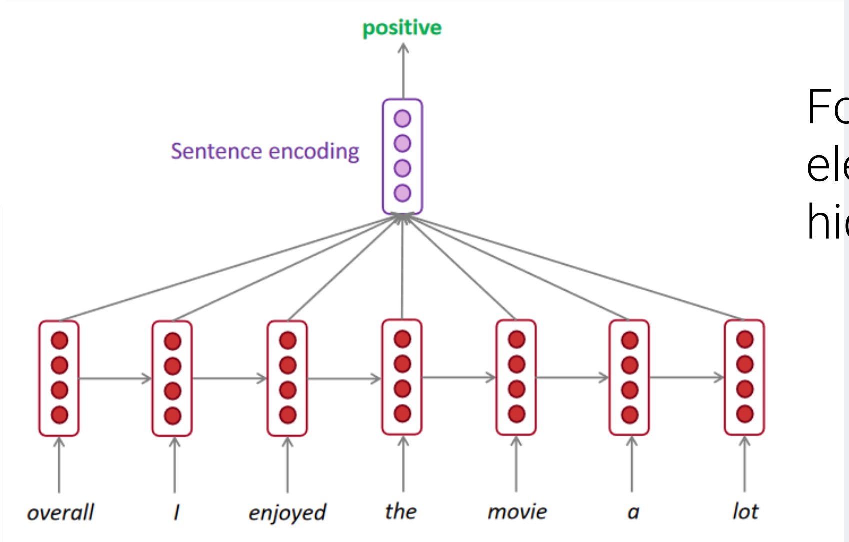
Jurafsky & Martin, SLP, 3rd Edition: *Chapter 13*

RNN – Applications

- Sentence (sequence) Classification



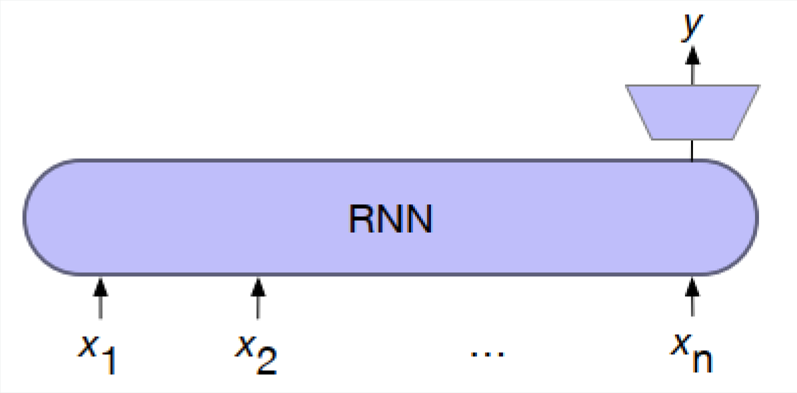




For sentence encoding take element-wise max of all hidden states (works better)

RNN – Deep Networks: Stacked and Bidirectional

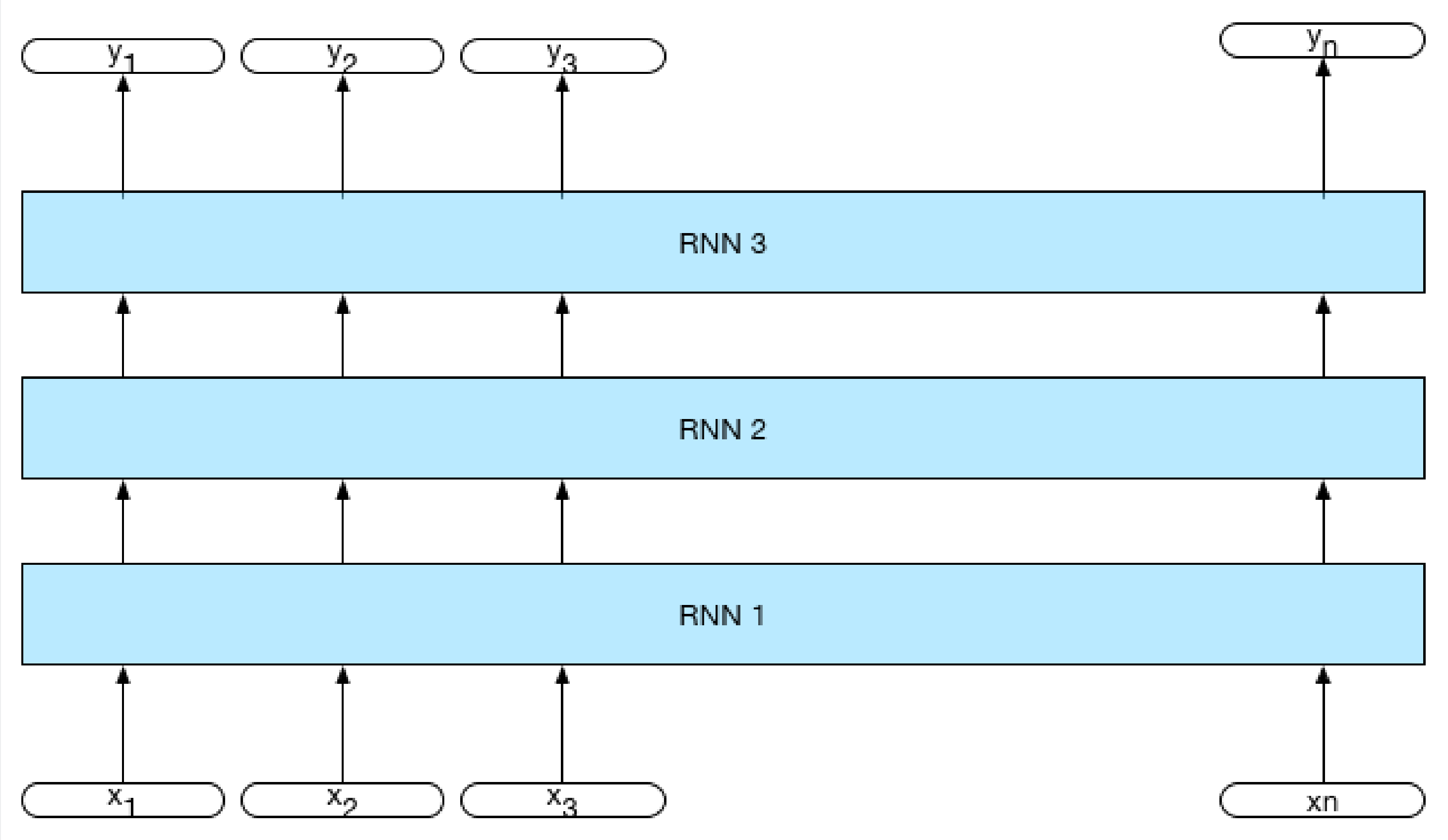
- Sequence Classification
  - Usually RNN combined with a FF
- end-to-end training



1ST Deep Neural Network

RNN – Deep Networks: Stacked

- Stacked
- Outperform single-layer
- Induce representations
- High training costs



RNN – Deep Networks: Bidirectional

- We have access to the entire input sequence, take advantage of it!

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

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

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

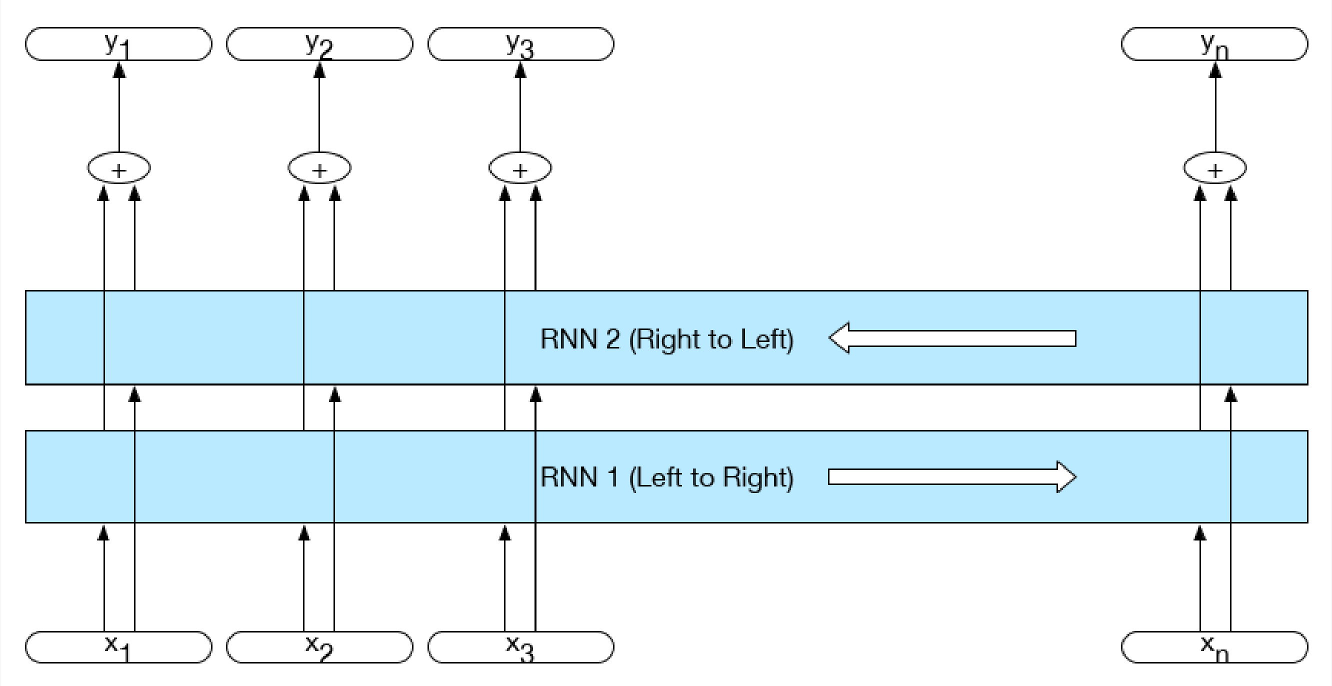
$$h_t^b = RNN_{backward}(x_t^n)$$

- Combine them -> Bi-RNN

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

RNN – Deep Networks: Bidirectional

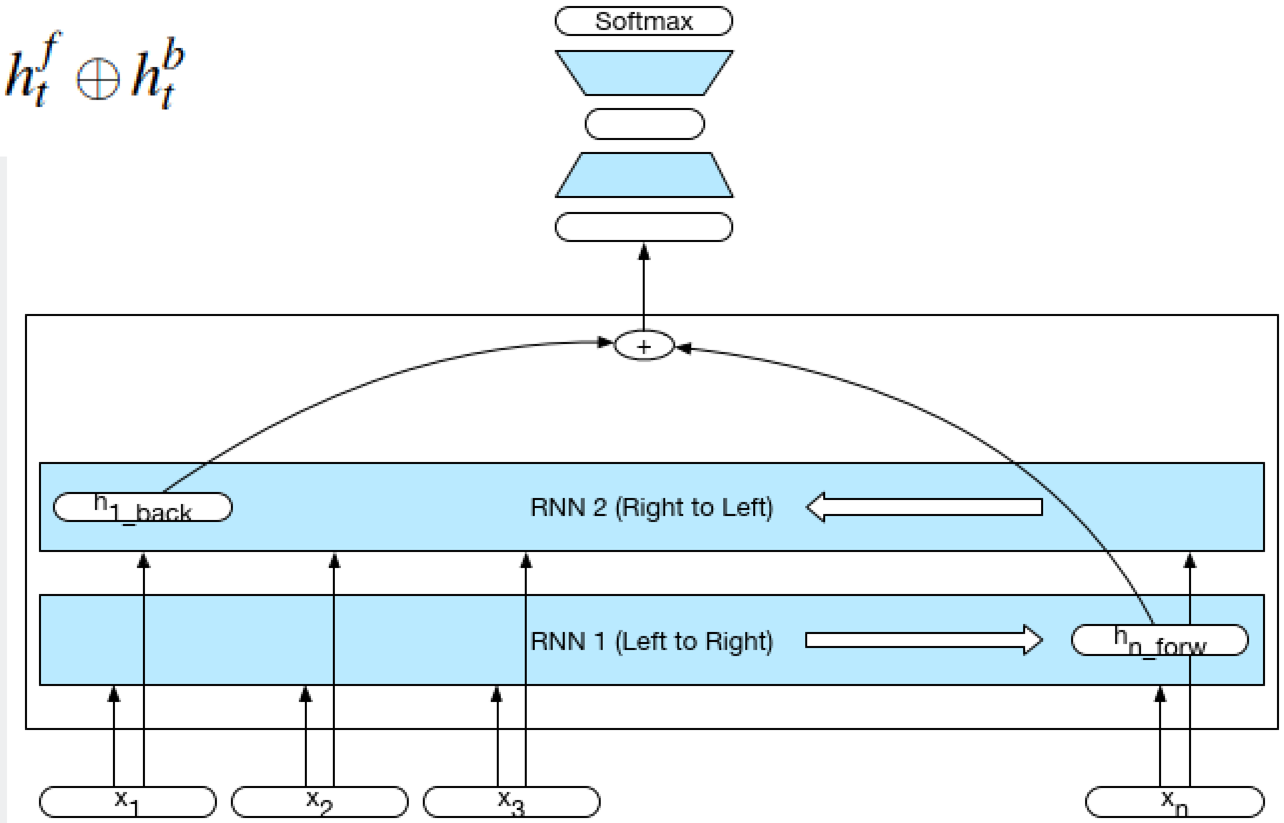
- Bi-RNN combines $h_t = h_t^f \oplus h_t^b$



RNN – Deep Networks: Bidirectional

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

- Sequence classification
  - The RNN computes a sentence representation
  - The FFN does the 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 (matrix multiplication along several time-steps)

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
- We want: Parametrized recursive function

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

- Input x_1 and memory **h**, returns the new **h**
- Time index, t! $h_t = f(x_t, \mathbf{h}_{t-1})$

- What kinds of f do we know of?
  - Transformation layer function:

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

Remember this?

Algorithm 1 ADD1 function definition

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

Algorithm 2 ADD1 function call

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

W, U – weight matrixes,
φ(x) – projection layer (i.e. embeddings)
g – non-linear activation function

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 (***c*** on next slides)
  - gates to control the forgetting/memorizing (***f*** and ***i*** on next slides)

Long Short

Gates: activation functions of FF layers + sigmoid

~ binary masks

Each gate has its own weight matrix

context ≈ memory

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

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

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

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

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

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

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

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

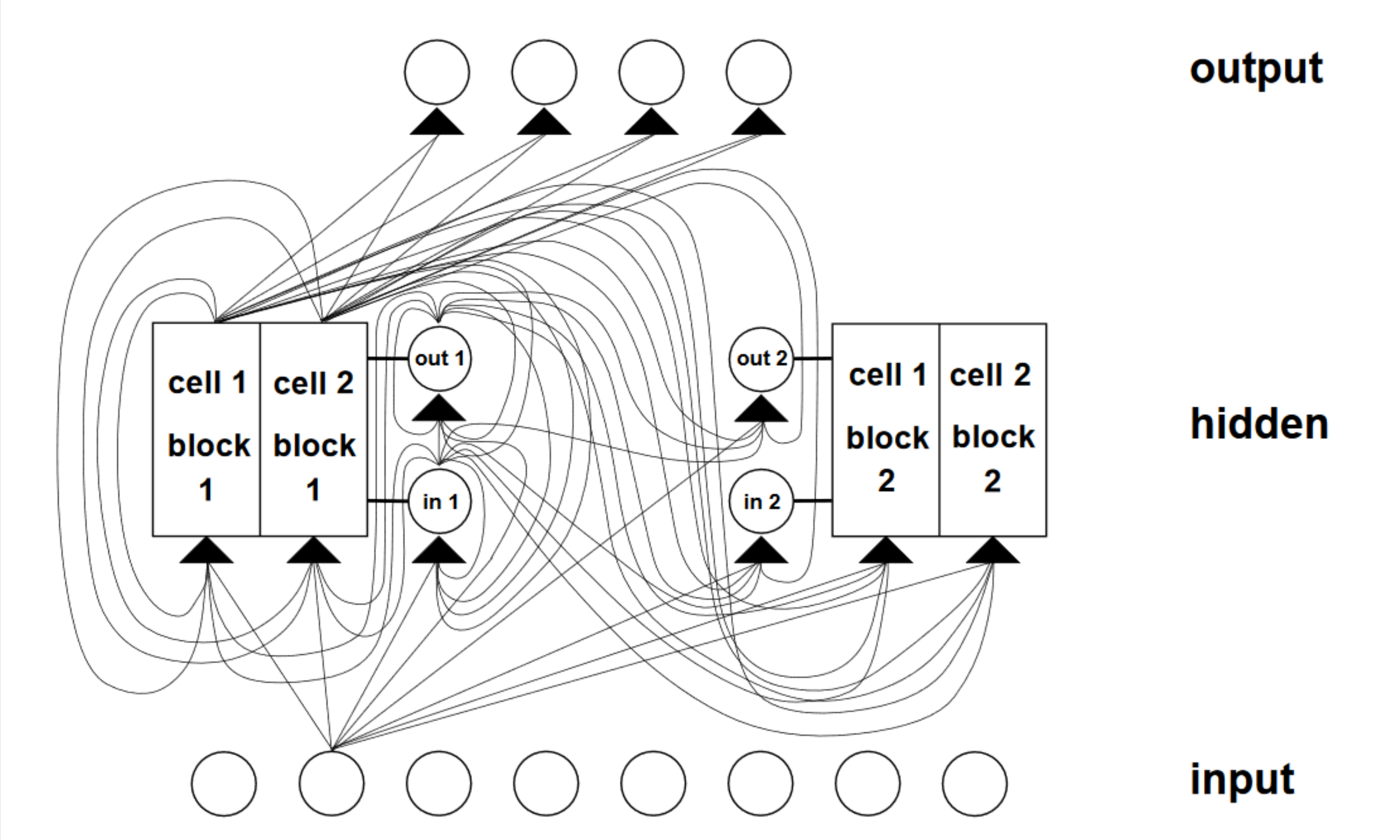
All these are vectors of same length n

Gates are applied using element-wise product

U is W and W is U

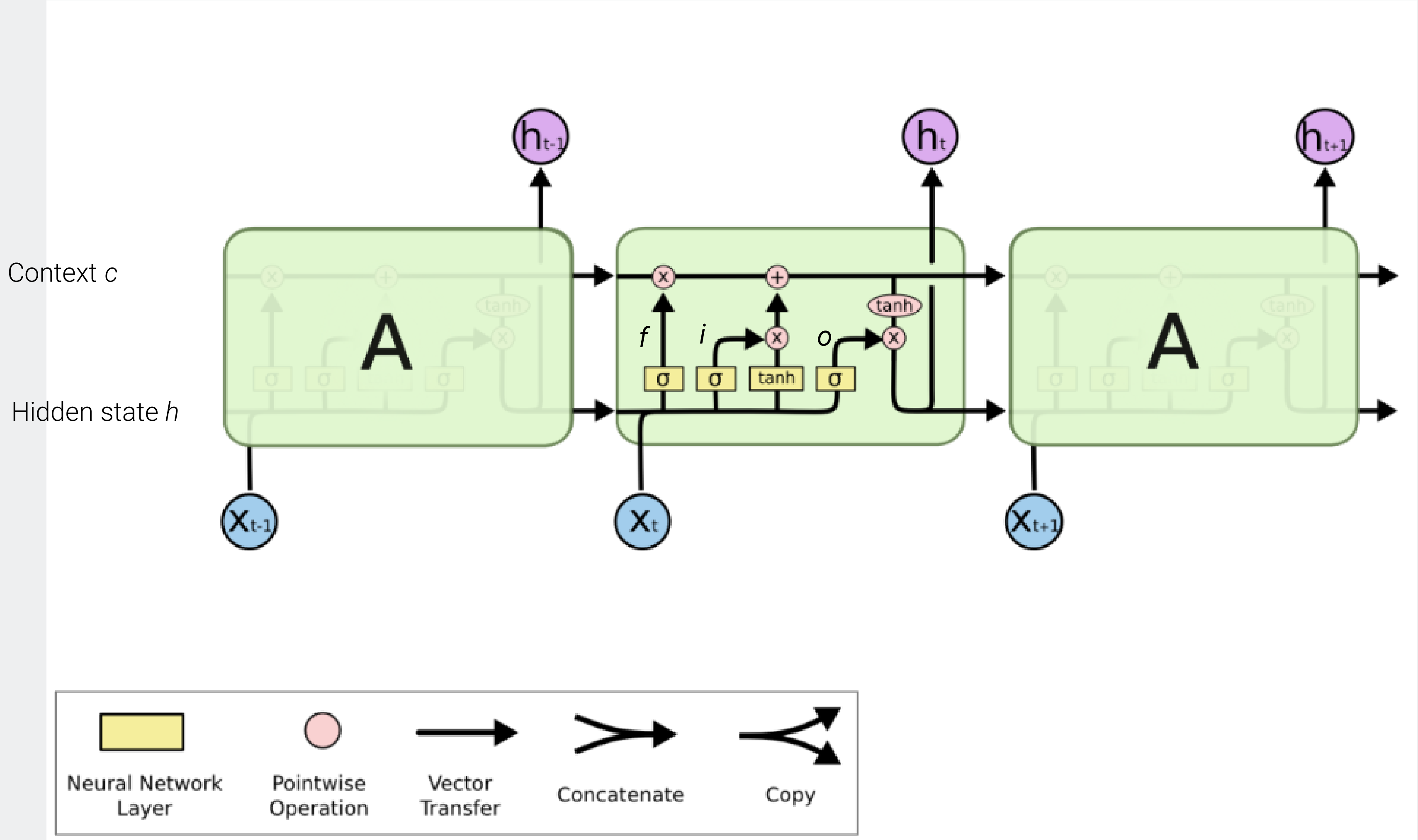
https://web.stanford.edu/class/cs224n/slides/cs224n-2020-lecture07-fancy-rnn.pdf

Long Short-Term Memory Networks (LSTMs)



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

Long Short-Term Memory Networks (LSTMs)



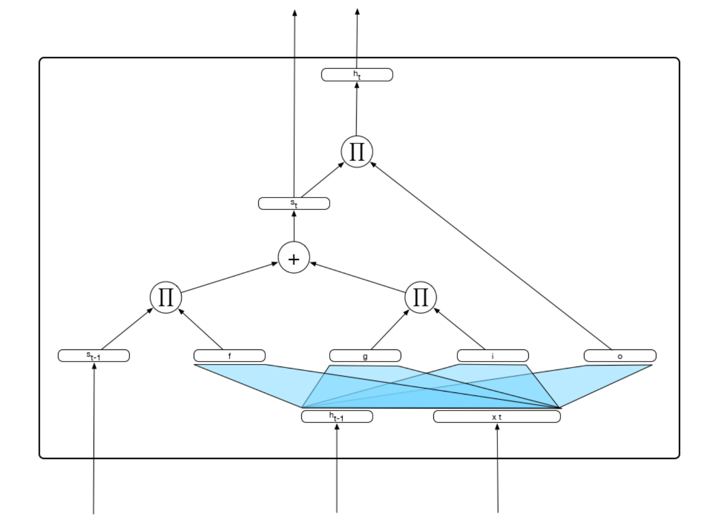
http://colah.github.io/posts/2015-08-Understanding-LSTMs/

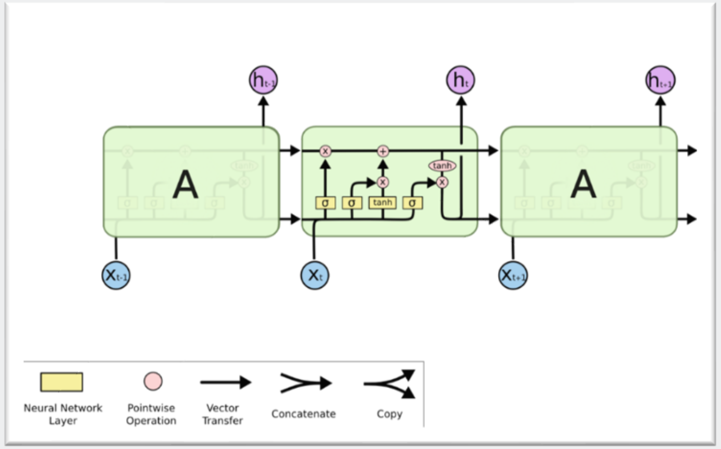
LSTMs – recap

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!

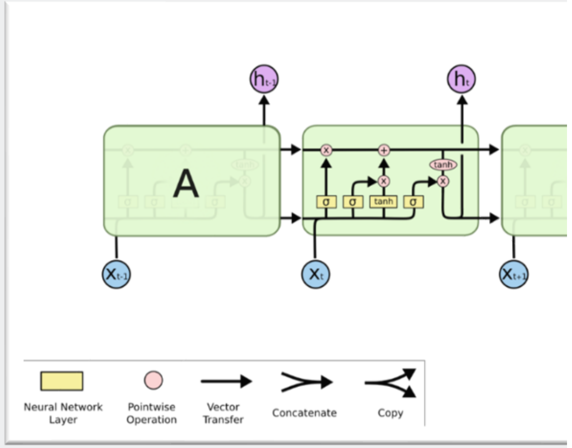


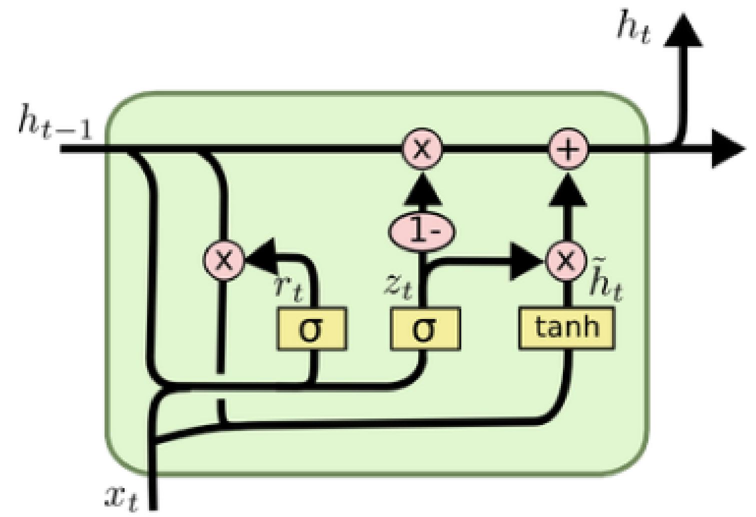


http://colah.github.io/posts/2015-08-Understanding-LSTMs/

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)





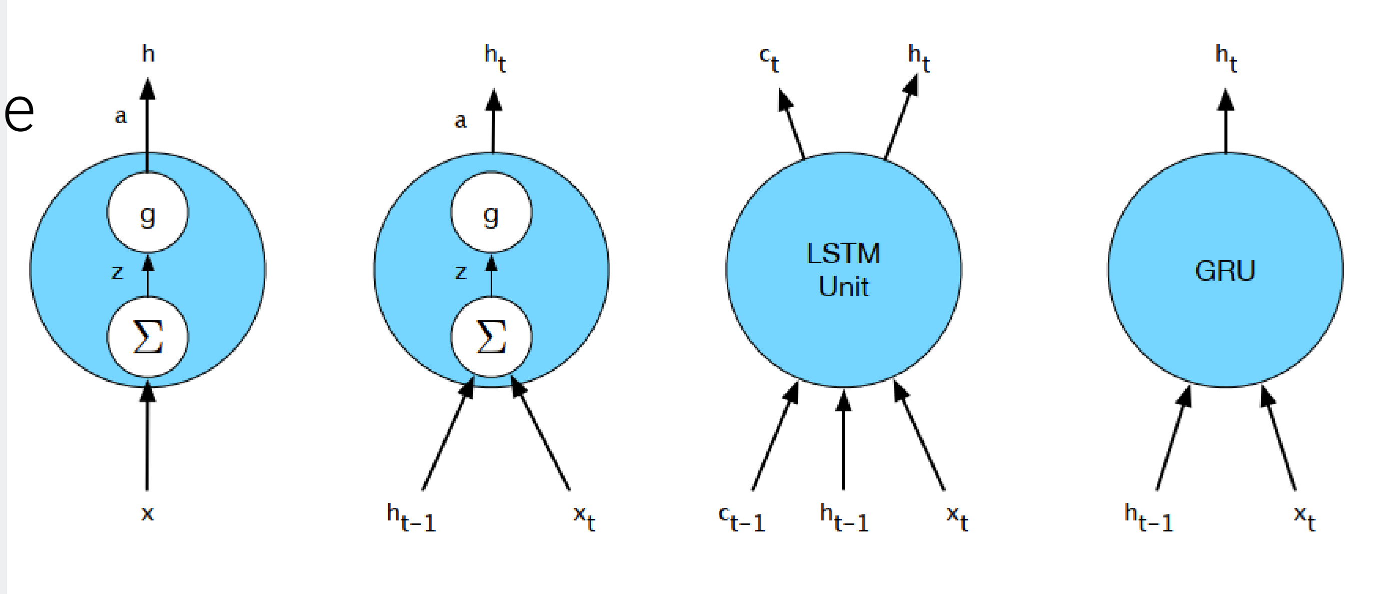
$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

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

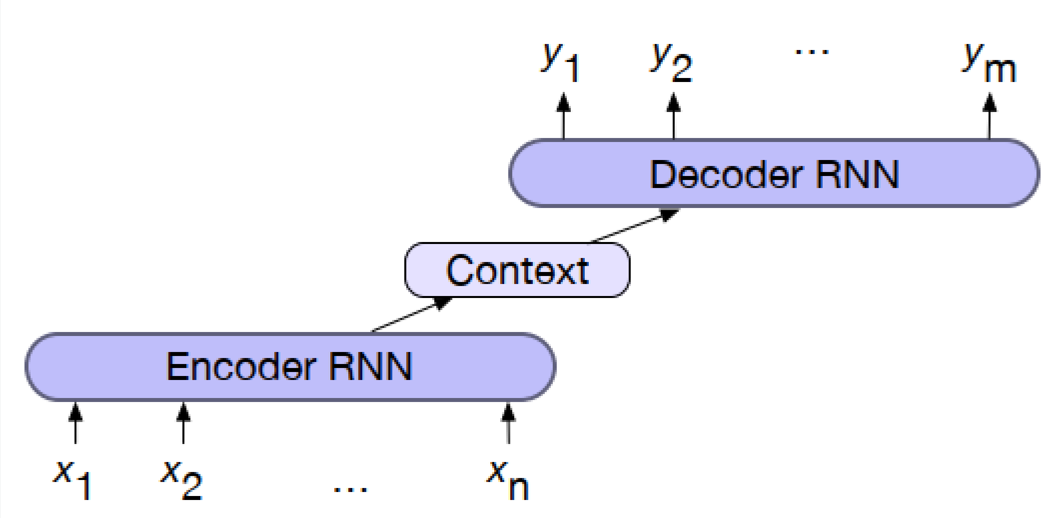
- Neural Language Models
- Recurrent Neural Networks
- LSTMs (Long Short-Term Memory Networks)

- Encoder-Decoder
- Attention

- Very active research area – not all details are included

Machine Translation

(sequence-to-sequence processing)



TU WIEN Informatics

Sequence-to-Sequence aka. Encoder-decoder Models

Problem statement: Neural Machine Translation

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

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

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

- Translation: function application:

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

- More than one correct translation

$$\boxed{P(Y|X)}$$

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

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

Neural Machine Translation – Problem statement

- Conditional language modelling!

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

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

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

$$\boxed{P(Y|X)}$$

Rewrite to

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

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

Neural Machine Translation – Training

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

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

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

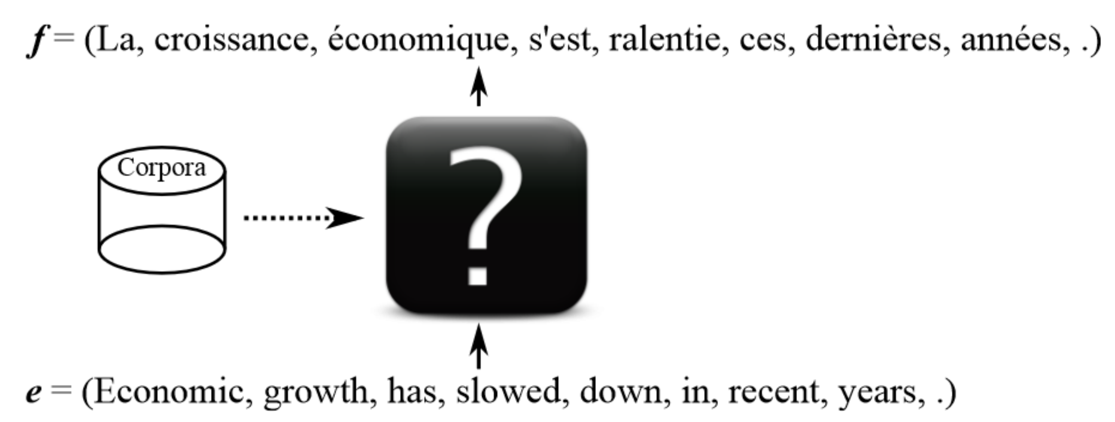
$$P(Y|X) = \underbrace{\prod_{t=1}^{T_y} P(y_t|y_1, \ldots, y_{t-1}, \underbrace{X}_{\text{conditional}})}_{\text{language modelling}}$$

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

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

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)

Small scale

- 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
- And and and …

Large scale

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

- Ratio of n-gram overlaps between a reference text and the translation text
- 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

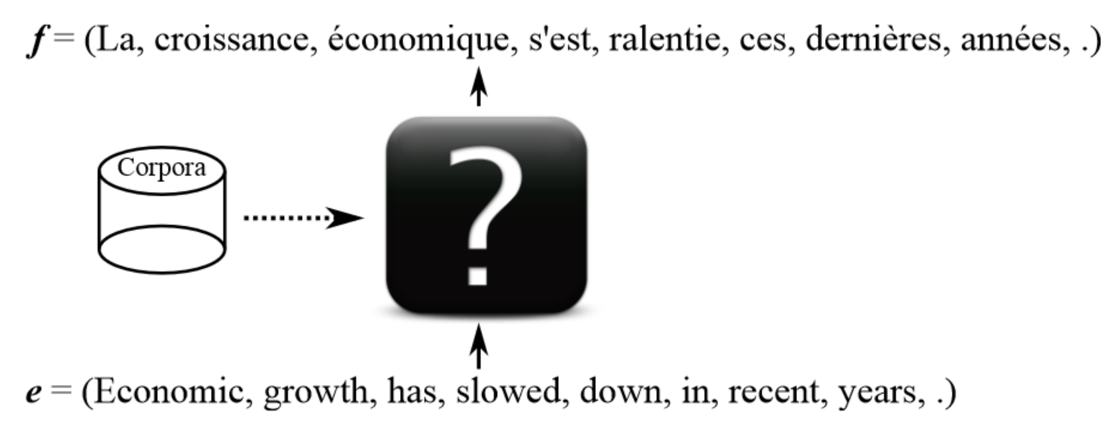
- The BLEU was shown to correlate well with human judgements
- But not perfect automatic evaluation metric

- 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

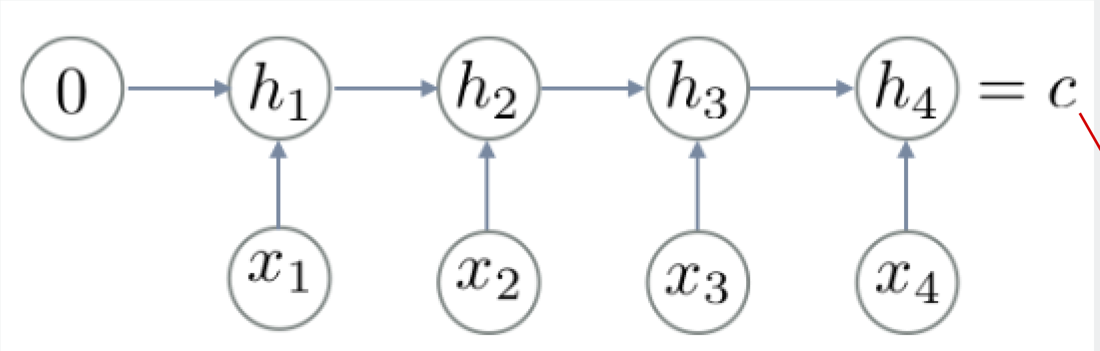
✓ Training data
✓ Evaluating MT (Bleu score, read about Rouge, Rouge-n, etc.)

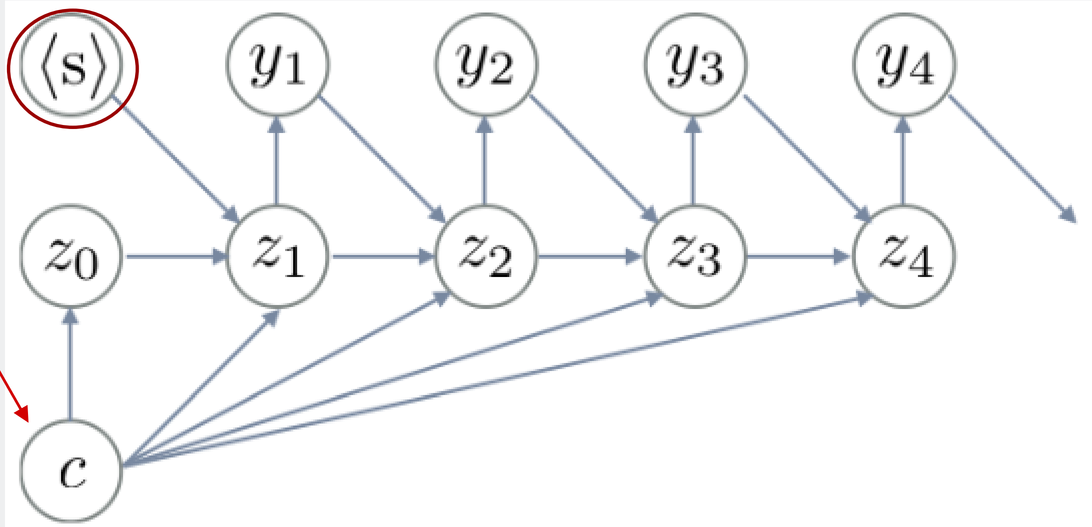
Neural Machine Translation: Encoder-Decoder Model

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

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

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





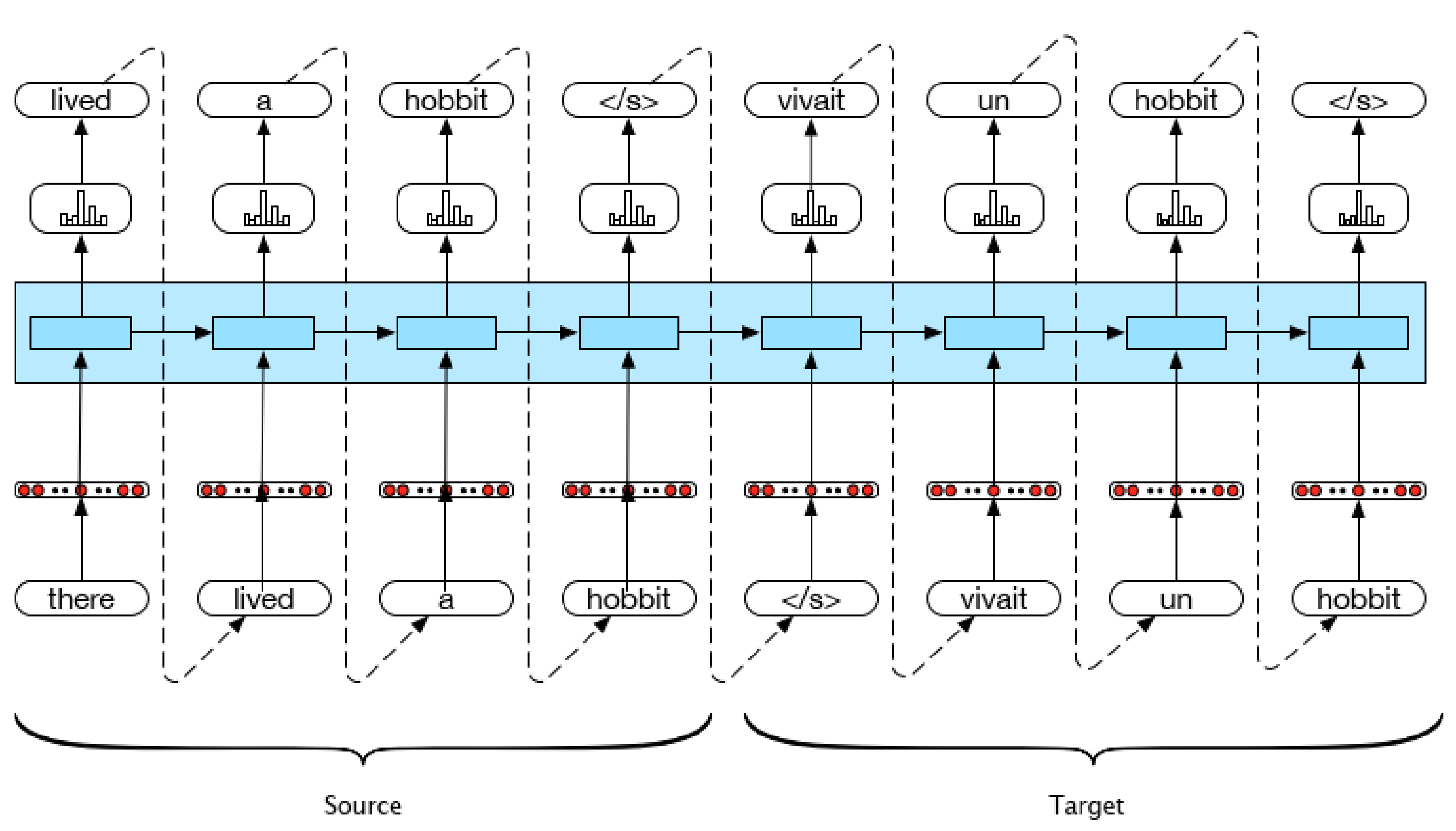
Neural Machine Translation: Encoder-Decoder Model

- **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

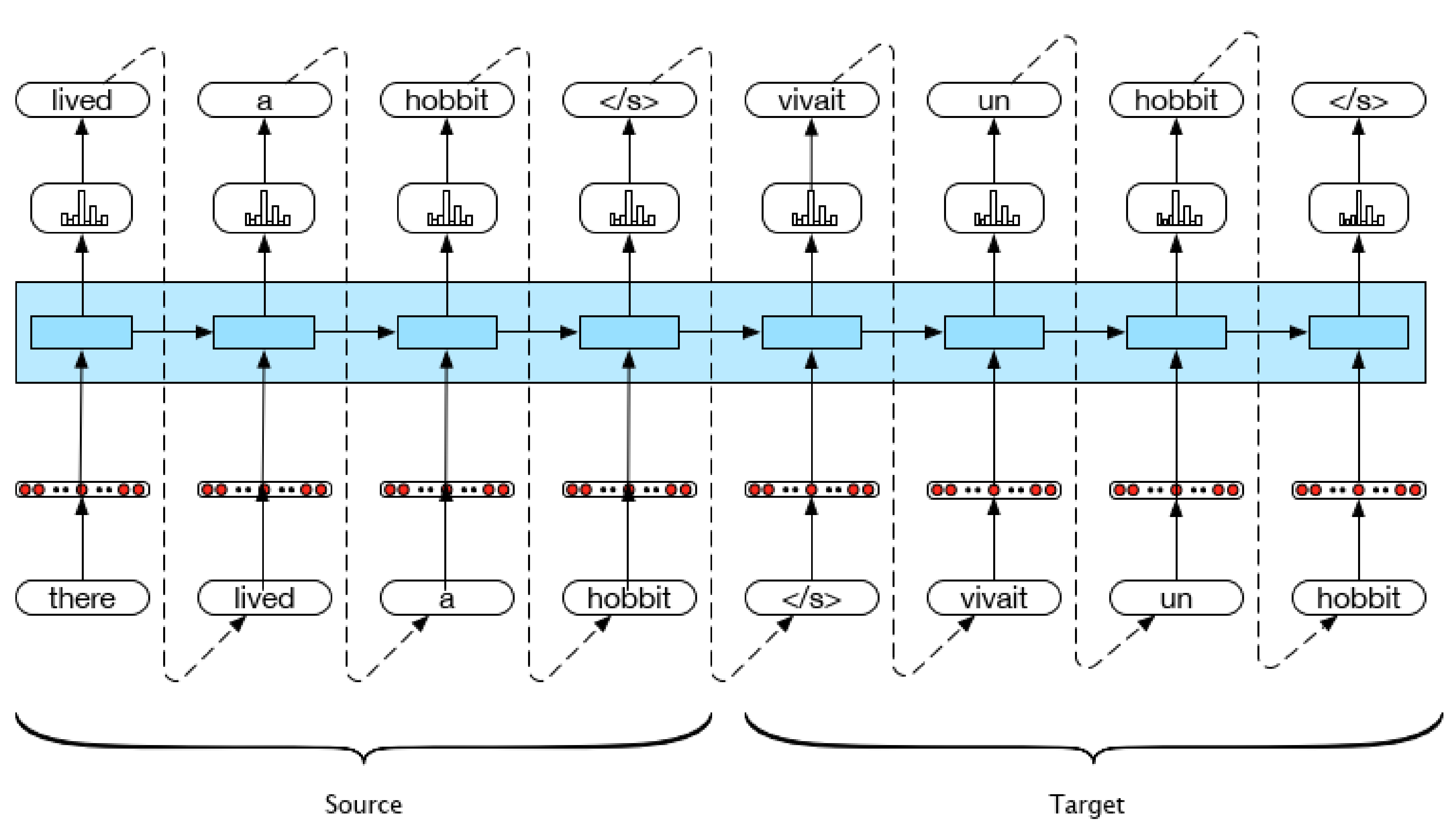
Simple RNN, LSTM, GRU, …



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

Neural Machine Translation: Encoder-Decoder Model

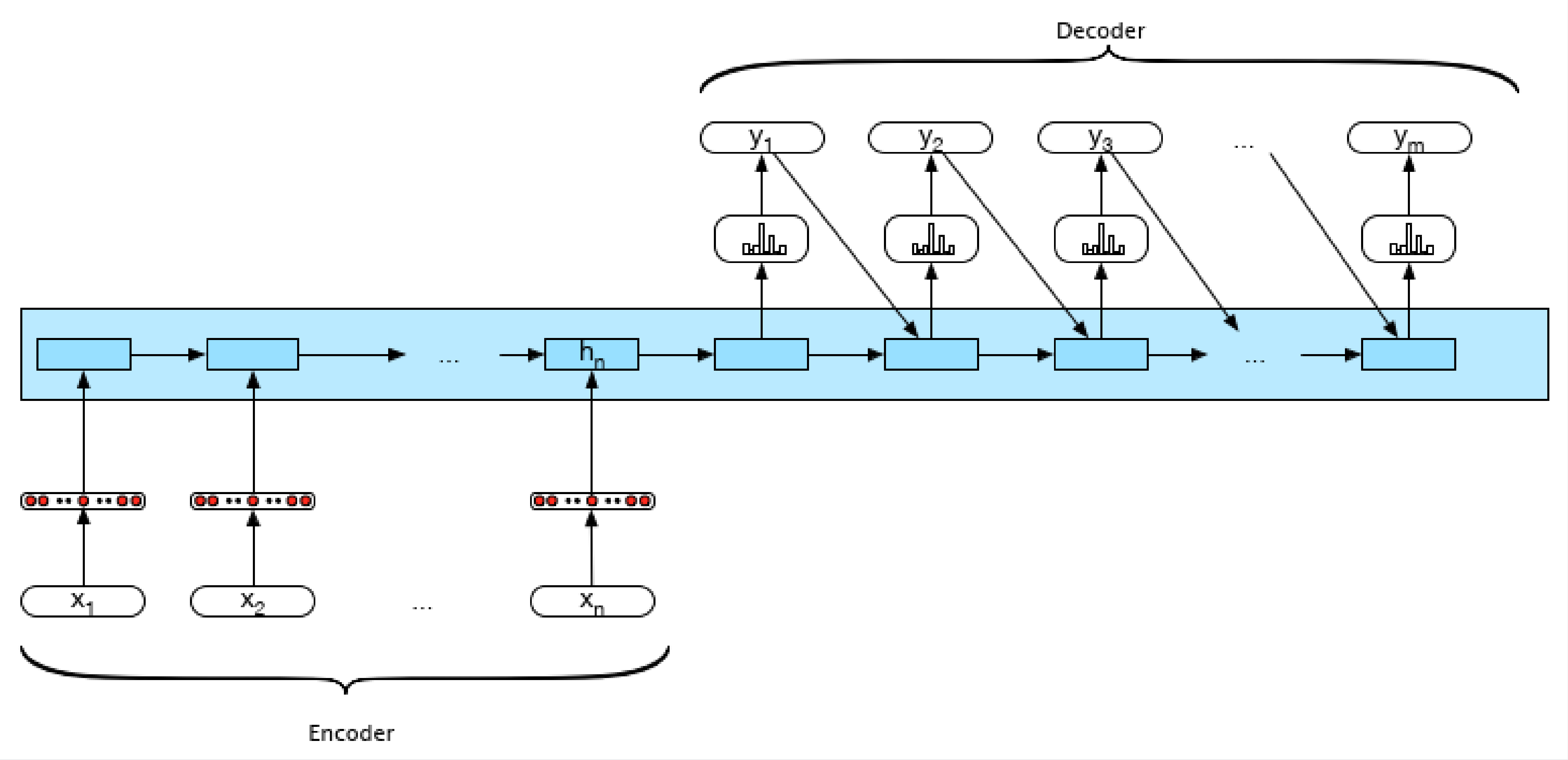
Simple RNN,
LSTM, GRU, …



Neural Machine Translation: Encoder-Decoder Model

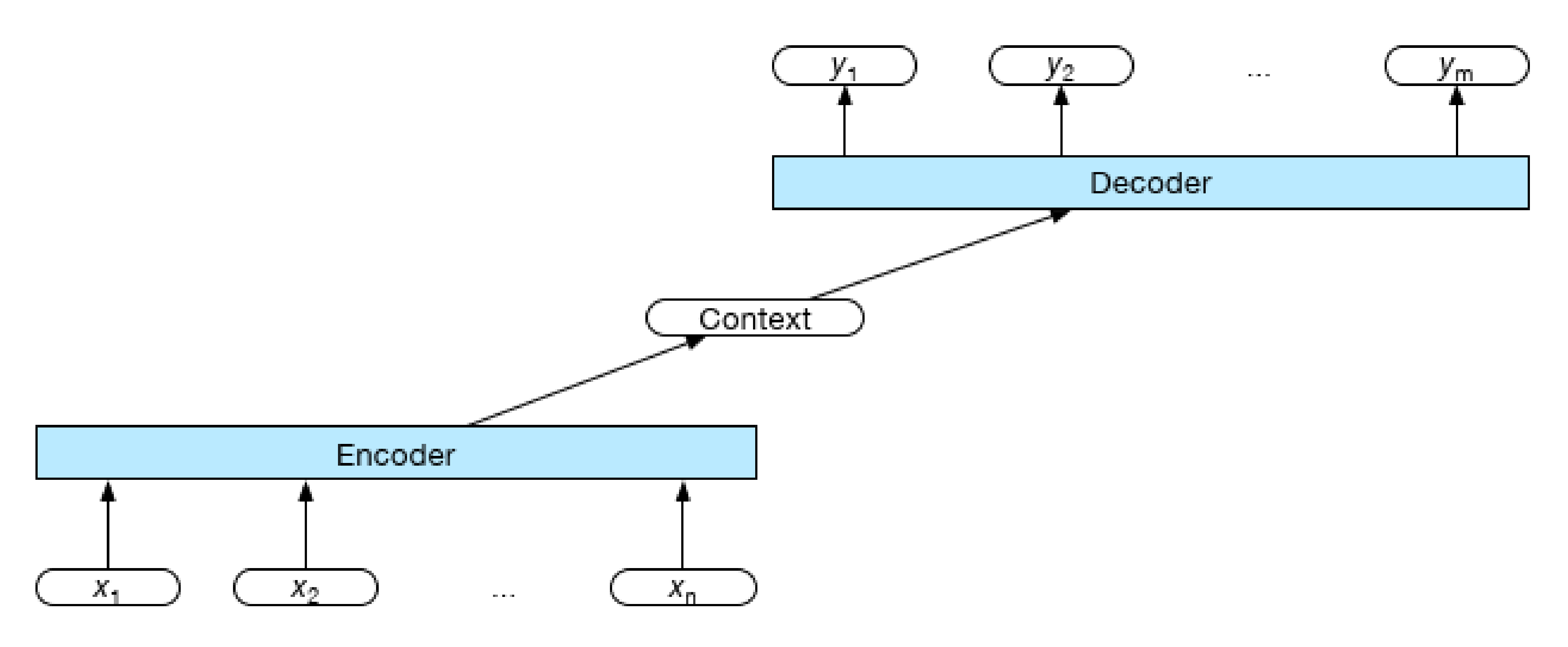
Simple RNN,

LSTM, GRU, ..



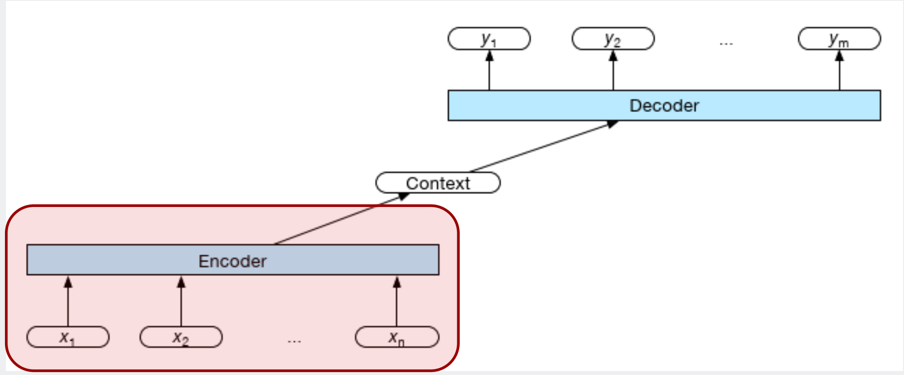
Neural Machine Translation: Encoder-Decoder Model

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



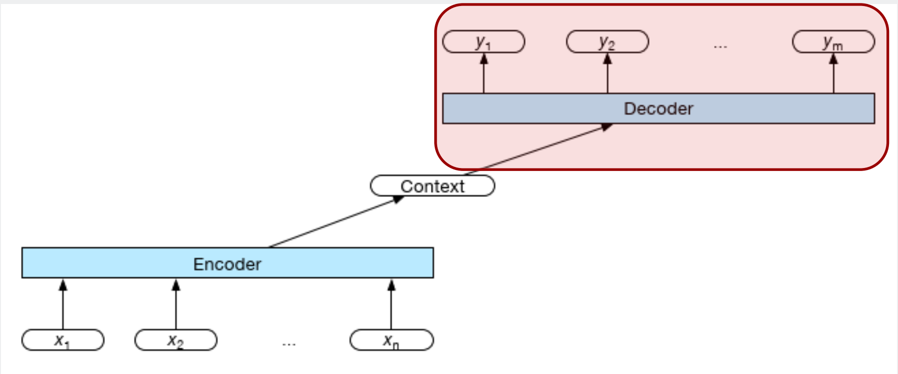
Encoder

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



Decoder

- Autoregressive generation
- Until </s> is generated
- LSTM, GRU
- *f* is a function of the hidden states

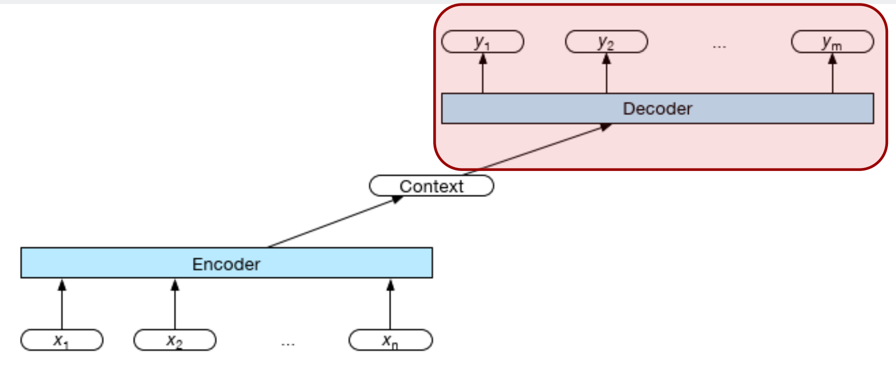


$$
\begin{aligned}
c &= h_n^e \\
h_0^d &= c \\
\\
h_t^d &= g(\hat{y}_{t-1}, h_{t-1}^d) \\
z_t &= f(h_t^d) \\
y_t &= \mathrm{softmax}(z_t)
\end{aligned}
$$

Notation:

- c – the context vector, h – hidden states
- Superscripts: *e* – encoder, *d* – decoder
- Subscripts: 0, t, t-1, n – time stamps
- y – input sequence, y-hat – output sequence

Decoder



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

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

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

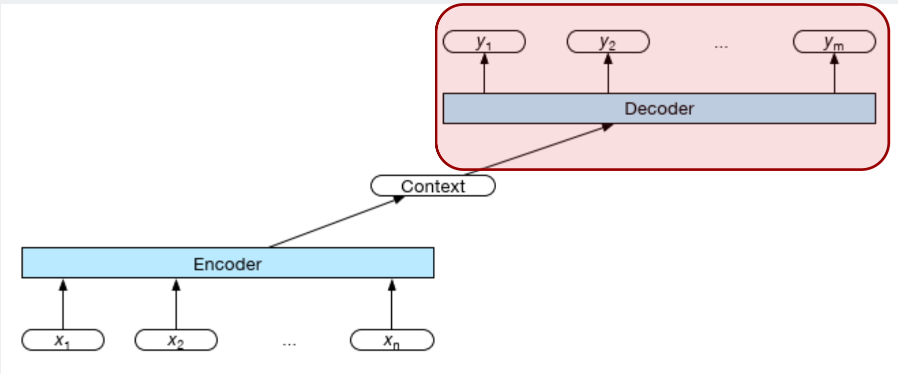
$$y_t = \text{softmax}(\hat{y}_{t-1}, z_t, c)$$

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

Notation:

- c – the context vector, h – hidden states
- Superscripts: *e* – encoder, *d* – decoder
- Subscripts: 0, t, t-1, n – time stamps
- y – input sequence, y-hat – output sequence

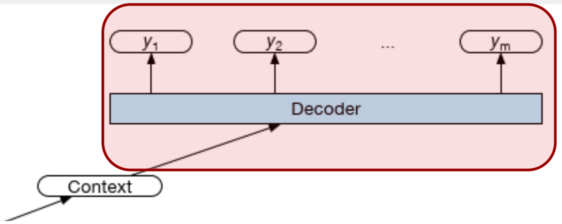
Beam Search



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

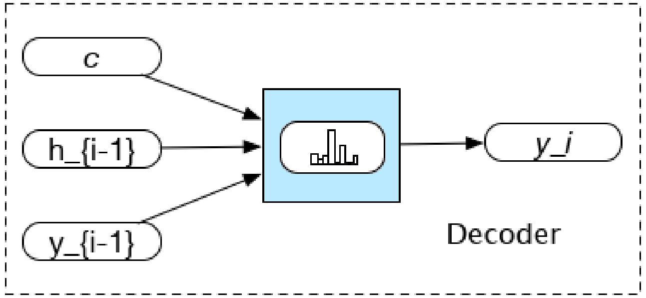
- How: combine breadth first with a heuristic filter
  - Score the options
  - Prune the search space

Beam Search



Scoring:

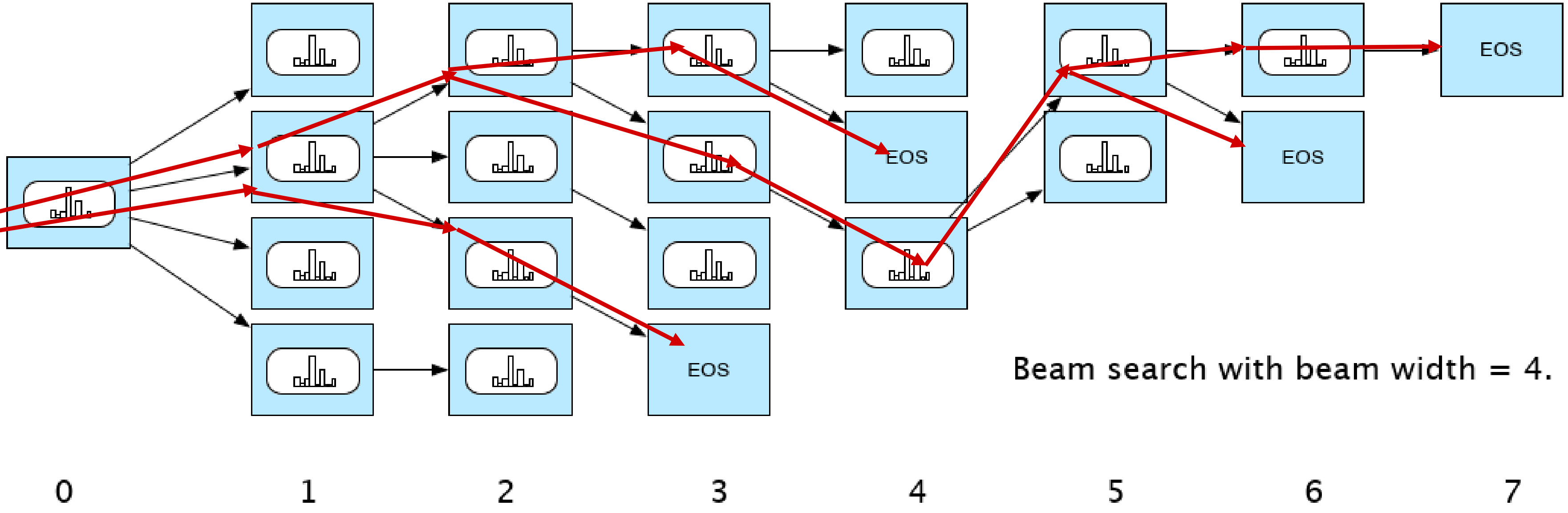
$$P(y_i | y_{<i})$$



(Path) Length Normalization

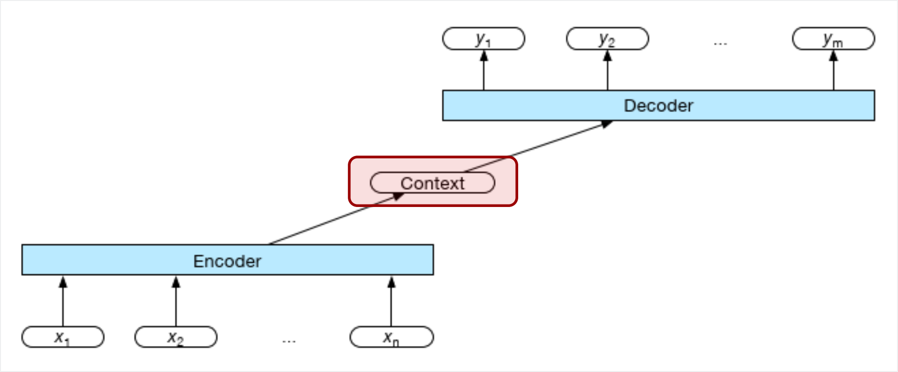
hypotheses

Search Frontier



Beam search with beam width = 4.

Context



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

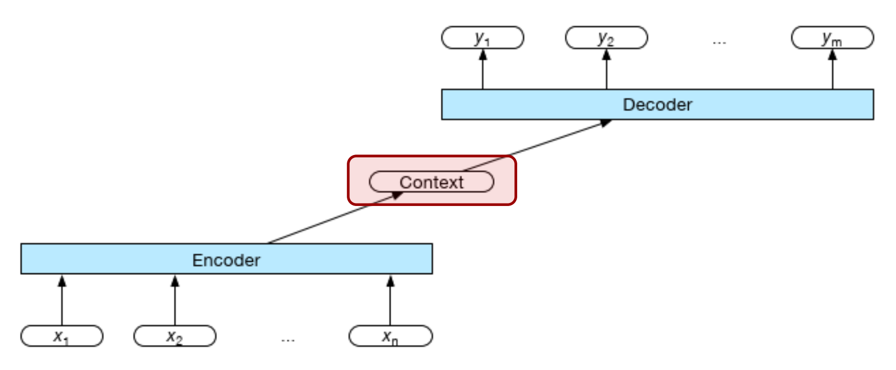
$$c = f(h_1^n)$$

- 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

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

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

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

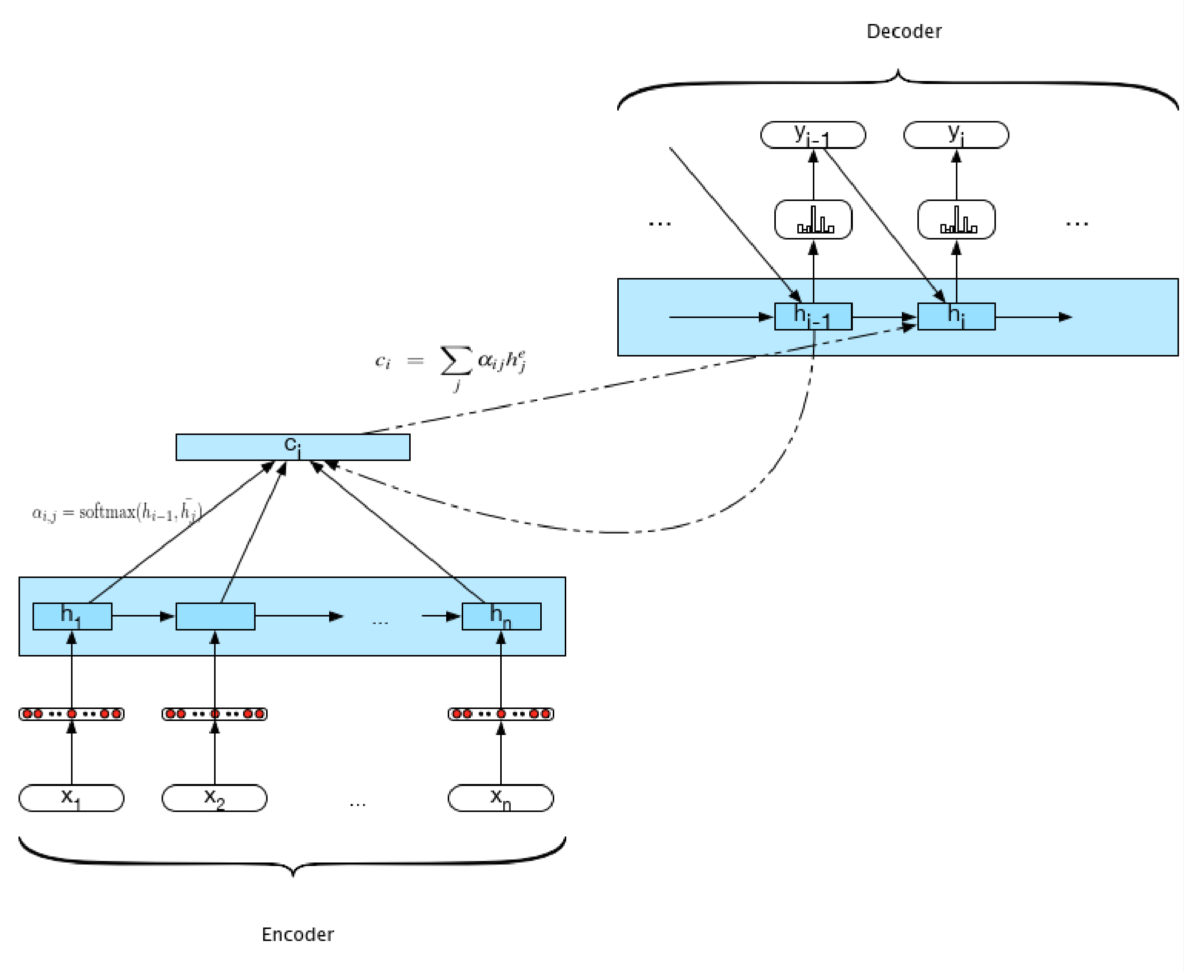
$$\alpha_{ij} = \mathrm{softmax}(score(h_{i-1}^d, h_j^e)\ \forall j \in e)$$

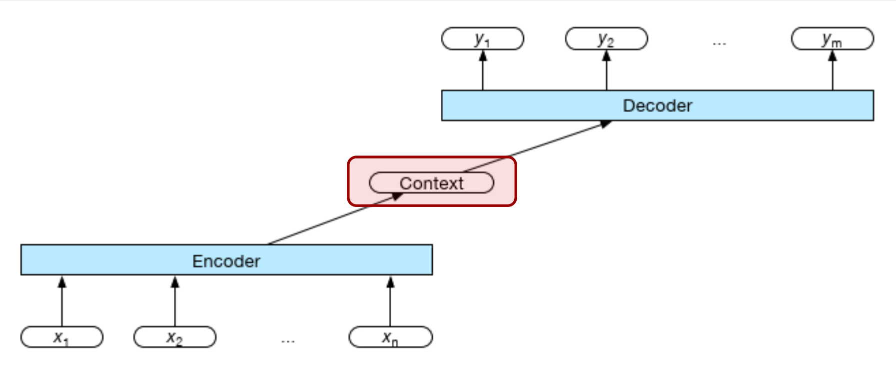
$$c_i = \sum_j \alpha_{ij} h_j^e$$

Notation:

- c – the context vector, h – hidden states
- Superscripts: *e* – encoder, *d* – decoder
- Subscripts: 0, t, t-1, n – time stamps
- y – input sequence, y-hat – output sequence

Attention





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

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

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

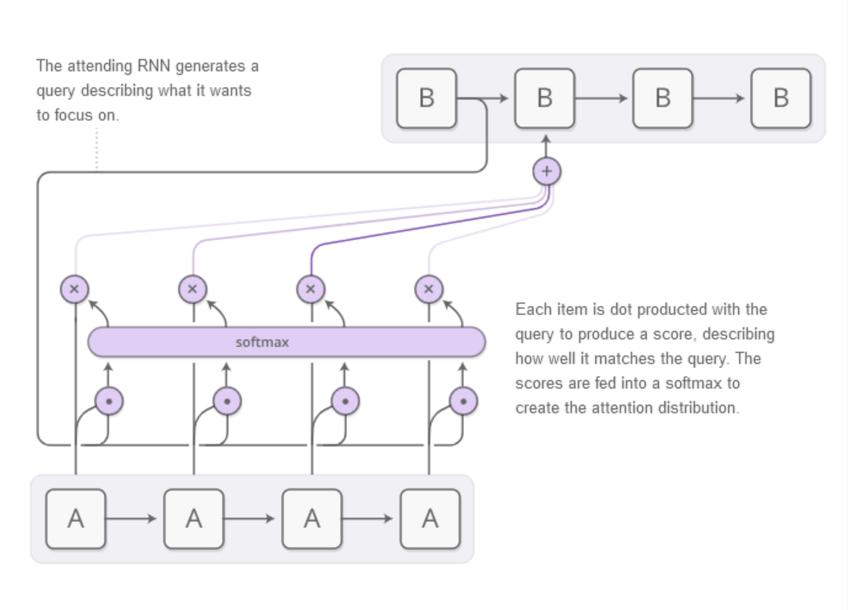
$$\alpha_{ij} = \mathrm{softmax}(score(h_{i-1}^d, h_j^e)\ \forall j \in e)$$

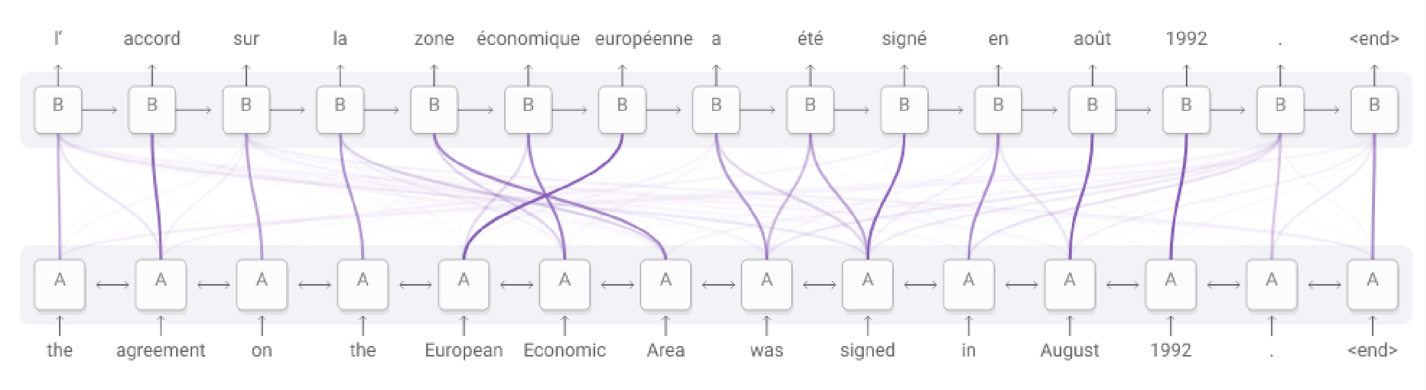
$$c_i = \sum_j \alpha_{ij} h_j^e$$

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://theaisummer.com/attention/

LLMs: Efficiency and Ethics

Resources

- Electricity (to power on)
- Water (to cool) – drinking water use

- Larger models (more CO2) not proportional accuracy gains
- NeurIPS requires a disclosure of resources used – very difficult to compute
- Green Software Foundation, the Software Carbon Intensity (SCI)
    - Energy used by your system (GPU power, monitors, etc) – kWh
    - Location-based carbon emission for the grid (how far you are from the data center) (gCO2eq/kWh)
    - Embodied carbon – carbon emitted for the production of the hardware and software
    - Functional unit (i.e. the training process)

- 103,000 kWh for one training session
- 400 – 800 kWh per year for a top-freezer fridge

- Similar consumption rates for inferencing or prompting

6 Billion Parameter Transformer. We tracked the energy consumption of training a large language model comprising over 6.1 billion parameters during 8 days on 256 NVIDIA A100s. The total energy amounted to a staggering 13.8 MWh. This model was not trained to completion, but only until 13%; a full training run would take 60 days. Thus, we estimate the total energy consumption to train this model to completion would be approximately $(60/8) * 13.8 = 103.5$ MWh, or 103,500 kWh — almost 2800 times more than training the BERT-small model!

Dodge, J. *et al.* Measuring the Carbon Intensity of AI in Cloud Instances. in *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency* 1877–1894 (Association for Computing Machinery, New York, NY, USA, 2022). doi:10.1145/3531146.3533234.

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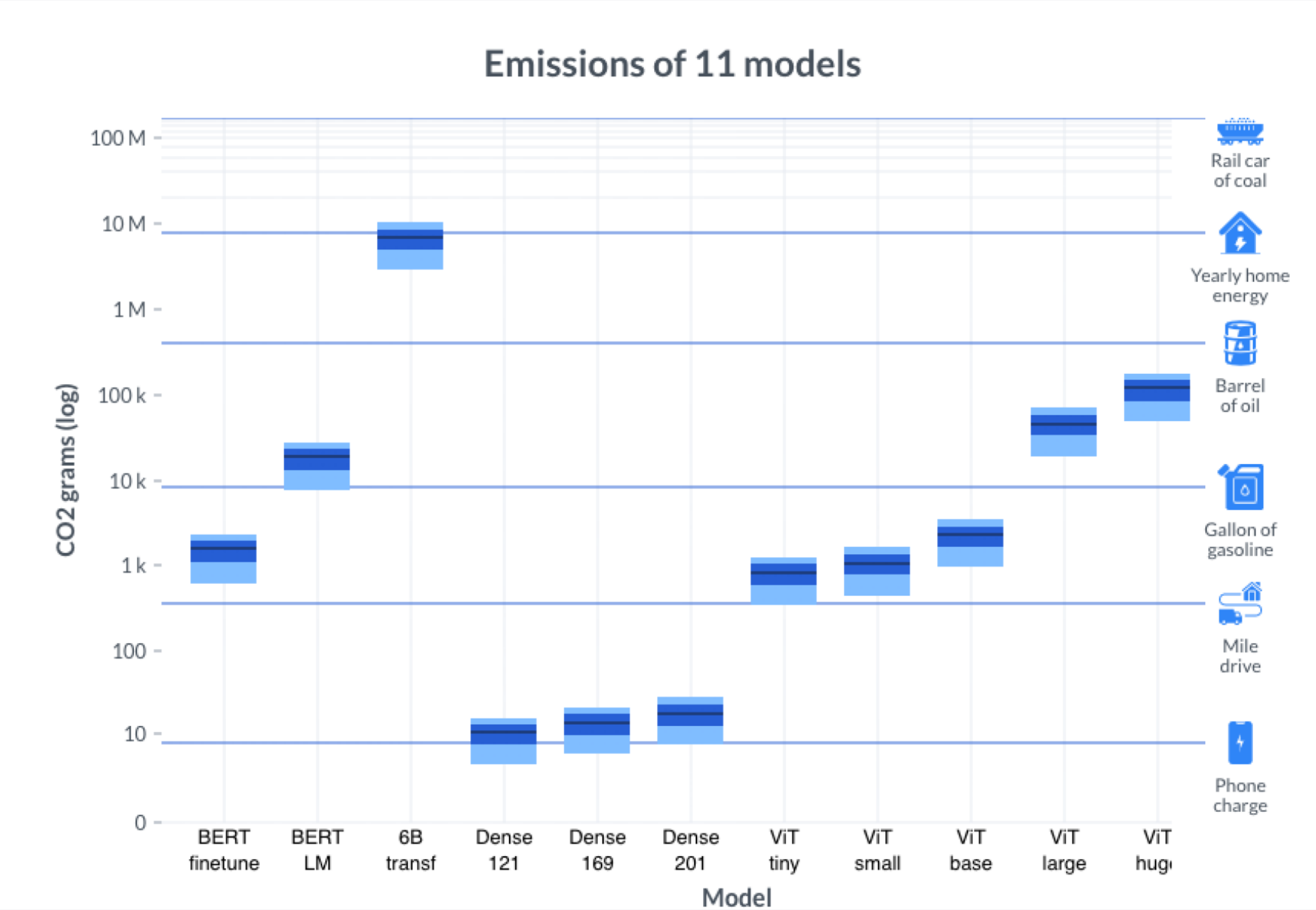


TU WIEN Informatics

Dodge, J. *et al.* Measuring the Carbon Intensity of AI in Cloud Instances. in *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency* 1877–1894 (Association for Computing Machinery, New York, NY, USA, 2022). doi:10.1145/3531146.3533234.

Resources

- Electricity (to power on)
- Water (to cool) – drinking water use

- Tools to check your CO2 footprint emerge

	Carbon Tracker	**Green Algorithms**	**Experiment Impact Tracker**	**ML CO2 Impact**	**energy usage**	**Cumulator**
	(Anthony et al., 2020)	(Lannelongue et al., 2021)	(Henderson et al., 2020)	(Lacoste et al., 2019)	(Lottick et al., 2019)	(Tristan Trebaol and Ghadikolaei, 2020)

Resources

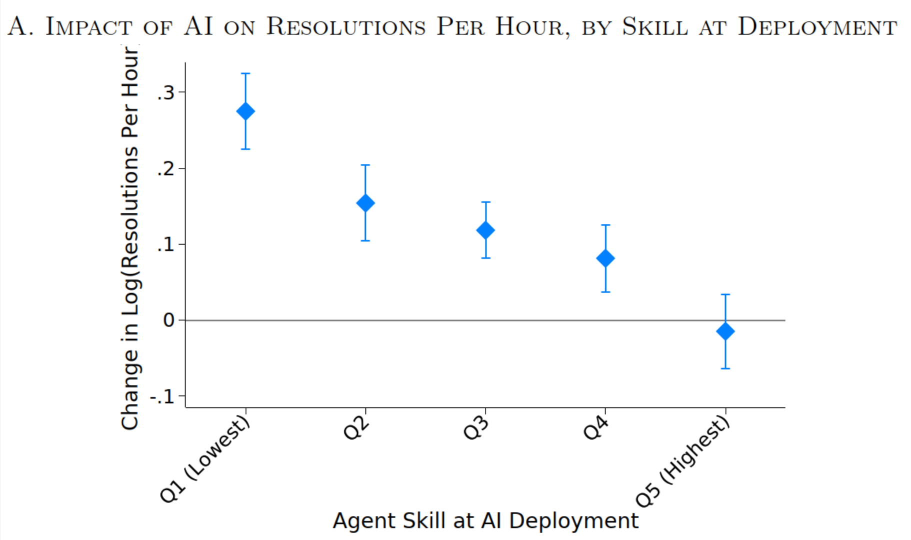
- Electricity (to power on)
- Water (to cool) – drinking water use

- ML.Energy Board:
  https://ml.energy/leaderboard/

Model	Parameters (Billions)	GPU model	Energy per response (Joules)
Gemma 2 2B	2	A100-SXM4-40GB	40.42
Mistral 7B	7	A100-SXM4-40GB	43.76
Phi 3 Small	7	A100-SXM4-40GB	44.89
Llama 3.1 8B	8	A100-SXM4-40GB	51.12
Phi 3 Mini	4	A100-SXM4-40GB	54.59
Mistral Nemo	12	A100-SXM4-40GB	66.71
Gemma 2 9B	9	A100-SXM4-40GB	68.24
Phi 3 Medium	14	A100-SXM4-40GB	96.26
Mixtral 8x7B	47	A100-SXM4-40GB	121.49
Gemma 2 27B	27	A100-SXM4-40GB	192.55
Llama 3.1 70B	70	A100-SXM4-40GB	512.84
Mistral Large	123	A100-SXM4-40GB	869.17
Mixtral 8x22B	141	A100-SXM4-40GB	1161.61

Social Impact

- Who profits?
  - Lower qualified employees
  - New / less experienced employees
- Who doesn't profit?
  - Experienced employees / experts
  - Highly qualified employees
- That is: highly qualified employees (expensive) will be replaced with less qualified ones (cheaper)
- However --> Competencies will be lost.



- Effectiveness
  - Those using AI-assistants are LESS effective and accurate than those who rely on AI tools (GenAI tools are bullshiters)
  - Unless, tools are tailored for the task, to REALLY assist humans

E. Brynjolfsson, D. Li, and L. R. Raymond, "Generative AI at Work," Apr. 2023, *National Bureau of Economic Research*: 31161. doi: 10.3386/w31161.

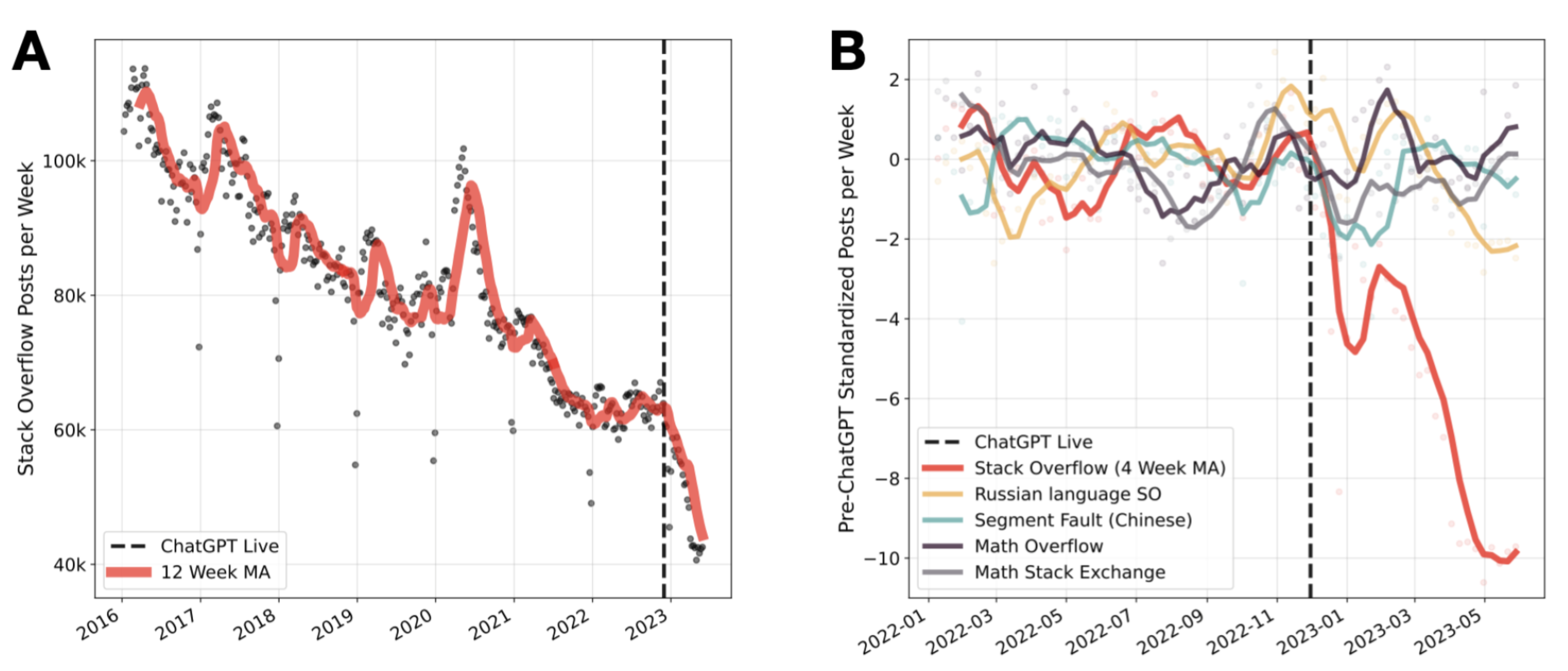
Social Impact

- Wisdom of the crowd – case of the stackoverflow
  - No user feedback anymore
  - No advancement, no information exchange
  - Parroting back existing solutions (scraped for training)

- Long-term effects:
  - Less diversity
  - No inclusion (because no diversity)
  - No community
  - Technical debt

https://montrealethics.ai/are-large-language-models-a-threat-to-digital-public-goods-evidence-from-activity-on-stack-overflow/

Social Impact



M. del Rio-Chanona, N. Laurentsyeva, and J. Wachs, “Are Large Language Models a Threat to Digital Public Goods? Evidence from Activity on Stack Overflow,” Jul. 14, 2023, *arXiv*: arXiv:2307.07367. doi: [10.48550/arXiv.2307.07367](https://doi.org/10.48550/arXiv.2307.07367).

What do do?

- Know about the pitfalls
- Educate yourself, become an expert independent of the AI-tools
- GenAI is a good tool (for speed-ups) when you’re already an expert
- RAGs and Fact-checking algorithms (IR plays an important role)
- …

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