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Machine learning – Block 5

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Department of Statistics, Uppsala University

Autumn 2022

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This week's lectures

- Word embeddings
- Recurrent Neural Networks
- Attention and Transformers
- BERT models

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Practicalities

- Remember the project proposition deadline the 12th of December
- One lecture later this week on word embeddings (Väinö Yrjänäinen)
- We are behind on correcting assignments

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Assignment 4: Evaluation

- Minor comments

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Section 2

Word embeddings

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How do we represent words?

- One-hot encoding
  - A vector of length V (vocabulary size)

$$\text{Uppsala} = [0, ..., 1, ..., 0] = \mathbf{1}_i$$

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How do we represent words?

- One-hot encoding
  - A vector of length V (vocabulary size)

$$\text{Uppsala} = [0, ..., 1, ..., 0] = \mathbf{1}_i$$

- Word embeddings
  - A vector of length D (embedding dimension)

$$\text{Uppsala} = [-0.1231, ..., 1.9001, ..., 0.012]$$

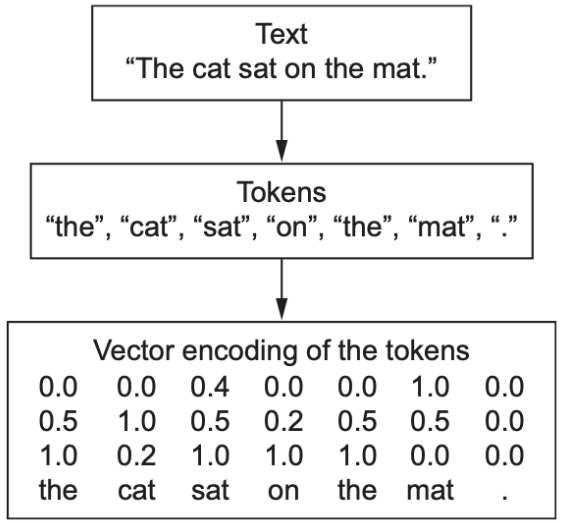

Figure: Representing words as word emnbeddings (Chollet and Allair, 2018, Fig. 6.1)

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Word embeddings vs. One-Hot

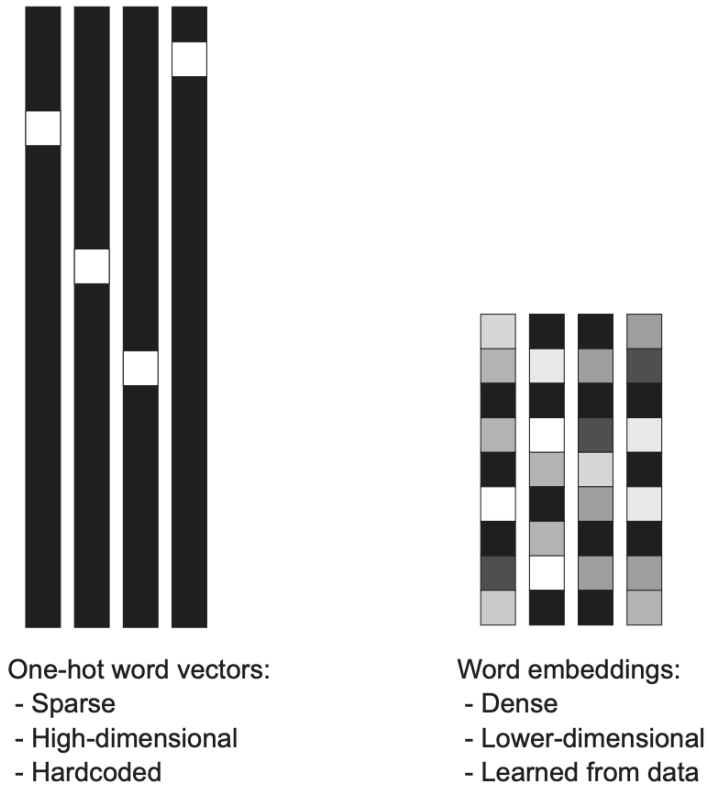

Figure: One-Hot vs. Word embeddings (Chollet and Allair, 2018, Fig. 6.2)

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Word embeddings

The quick brown fox jumps over the lazy dog.

- A word type represent meaning in a low-dimensional semantic space
- The distributional hypothesis:
  - Harris (1954) and Firth (1957):
    "A word is characterized by the company it keeps"
  - Semantics (broadly defined) is captured by context
- Lots of different embeddings:
  `word2vec`, GloVe, Probabilistic Embeddings

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Word embeddings

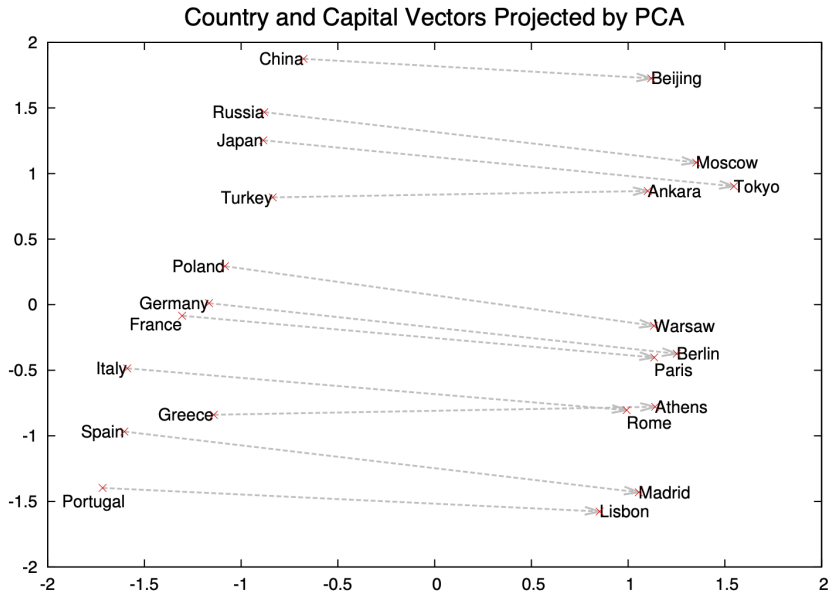

Figure: Word embedding properties (Mikolov et al, 2013)

$$\text{king} - \text{man} + \text{woman} \approx \text{queen}$$

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Word embeddings

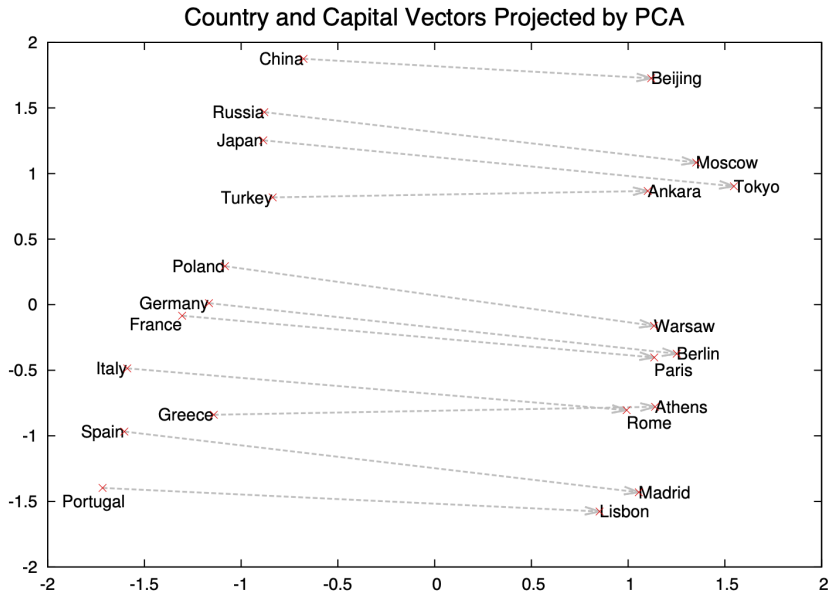

Figure: Word embedding properties (Mikolov et al, 2013)

$$\text{king} - \text{man} + \text{woman} \approx \text{queen}$$

But also (Bolukbasi et al., 2016):

$$\text{computer programmer} - \text{man} + \text{woman} \approx \text{homemaker}$$

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Context Matters!

Figure: Context matters (Alammar, 2020)

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Section 3

Recurrent Neural Networks

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Recurrent Neural Networks

- Recurrent Neural Networks, Recurrent Nets, RNN, ...
- Modeling of temporal data structures, such as
  - Time series data
  - Sequences of words (language models)

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Recurrent Neural Networks

- Recurrent Neural Networks, Recurrent Nets, RNN, ...
- Modeling of temporal data structures, such as
  - Time series data
  - Sequences of words (language models)
- Examples of applications:
  - Text classification
  - Sequence / word classification
  - Time series predictions
  - Audio data

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Recurrent Neural Networks

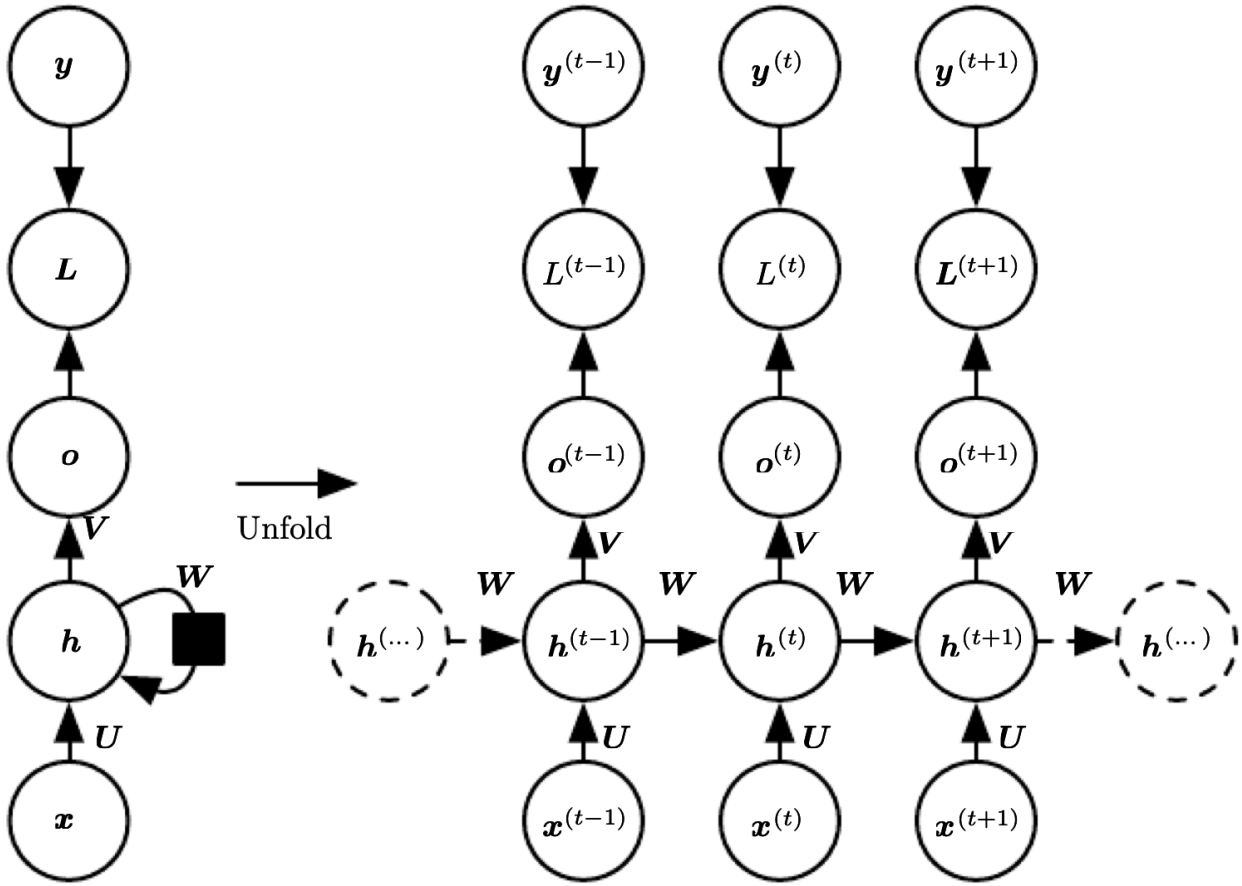

Figure: Recurrent Neural Network (Goodfellow et al, 2017, Fig. 10.3)

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Recurrent Neural Networks

$$
\begin{aligned}
a_t &= b + Wh_{t-1} + Ux_t \\
h_t &= \sigma_1(a_t) \\
o_t &= c + Vh_t \\
\hat{y}_t &= \sigma_{\text{output}}(o_t) = \text{softmax}(o_t)
\end{aligned}
$$

Think of h_t as the "state" at timepoint t

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Recurrent network with one output

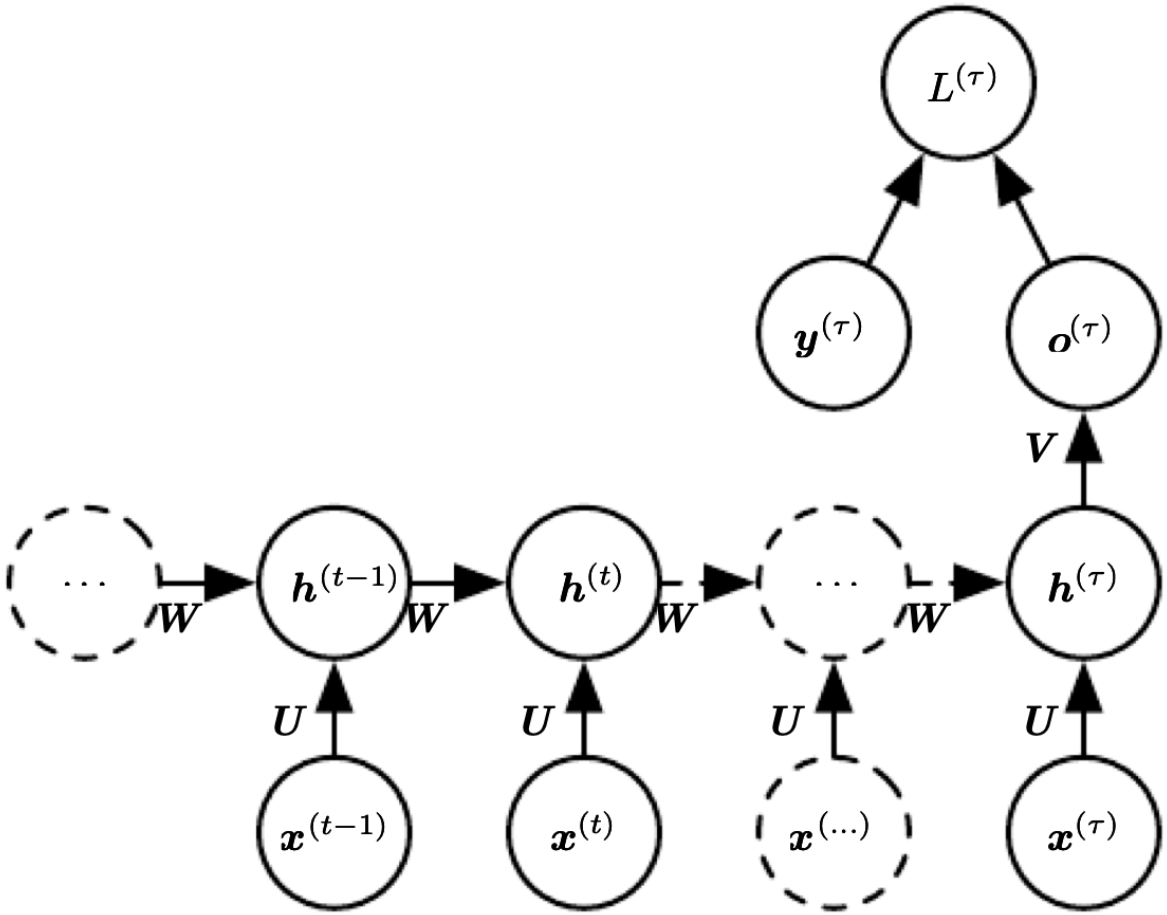

Figure: Recurrent Neural Network with one output (Goodfellow et al, 2017, Fig. 10.5)

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Sequence to Sequence: Encoder-Decoder

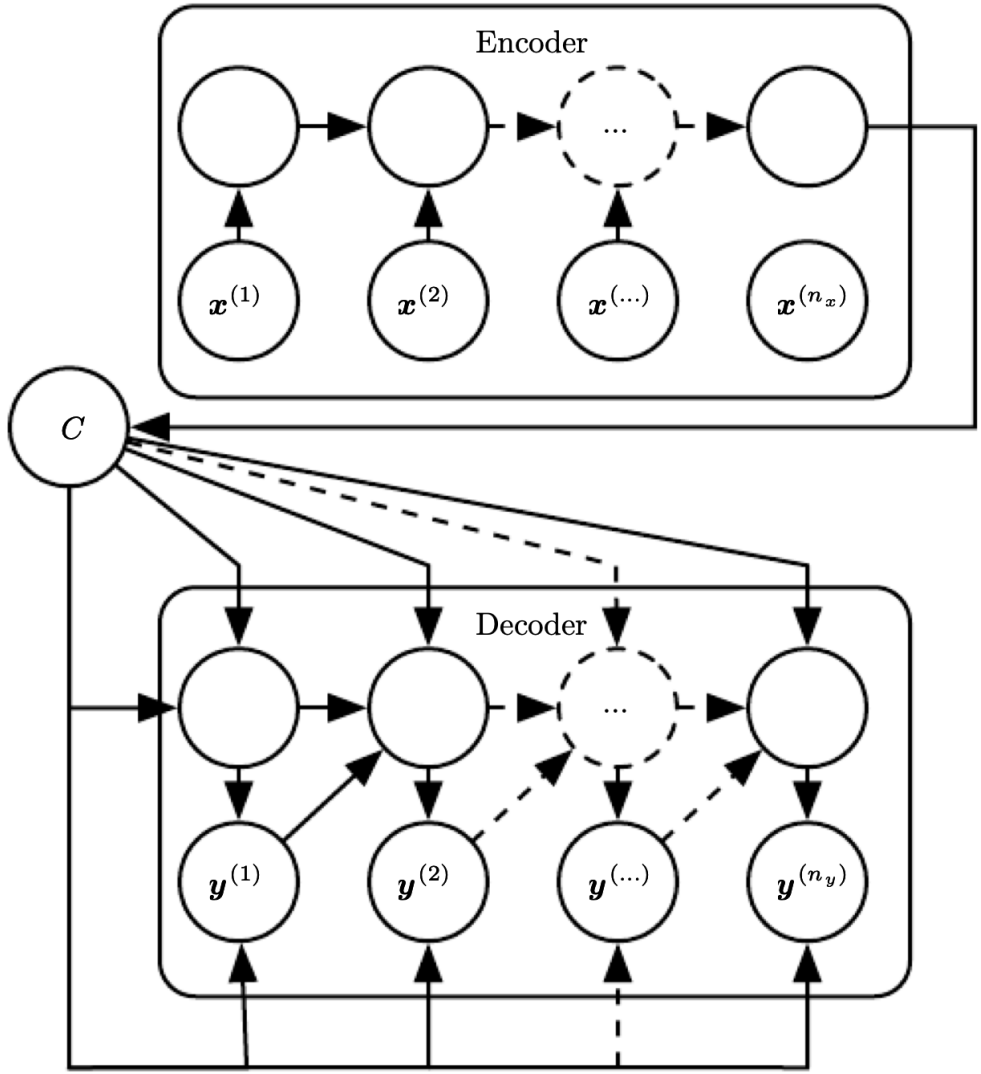

Figure: Encoder-Decoder Recurrent Networks (Goodfellow et al, 2017, Fig. 10.12)

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Problems with RNN

- Exploding and vanishing gradients
- Long-term dependencies

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Long Short-Term Memory (LSTM)

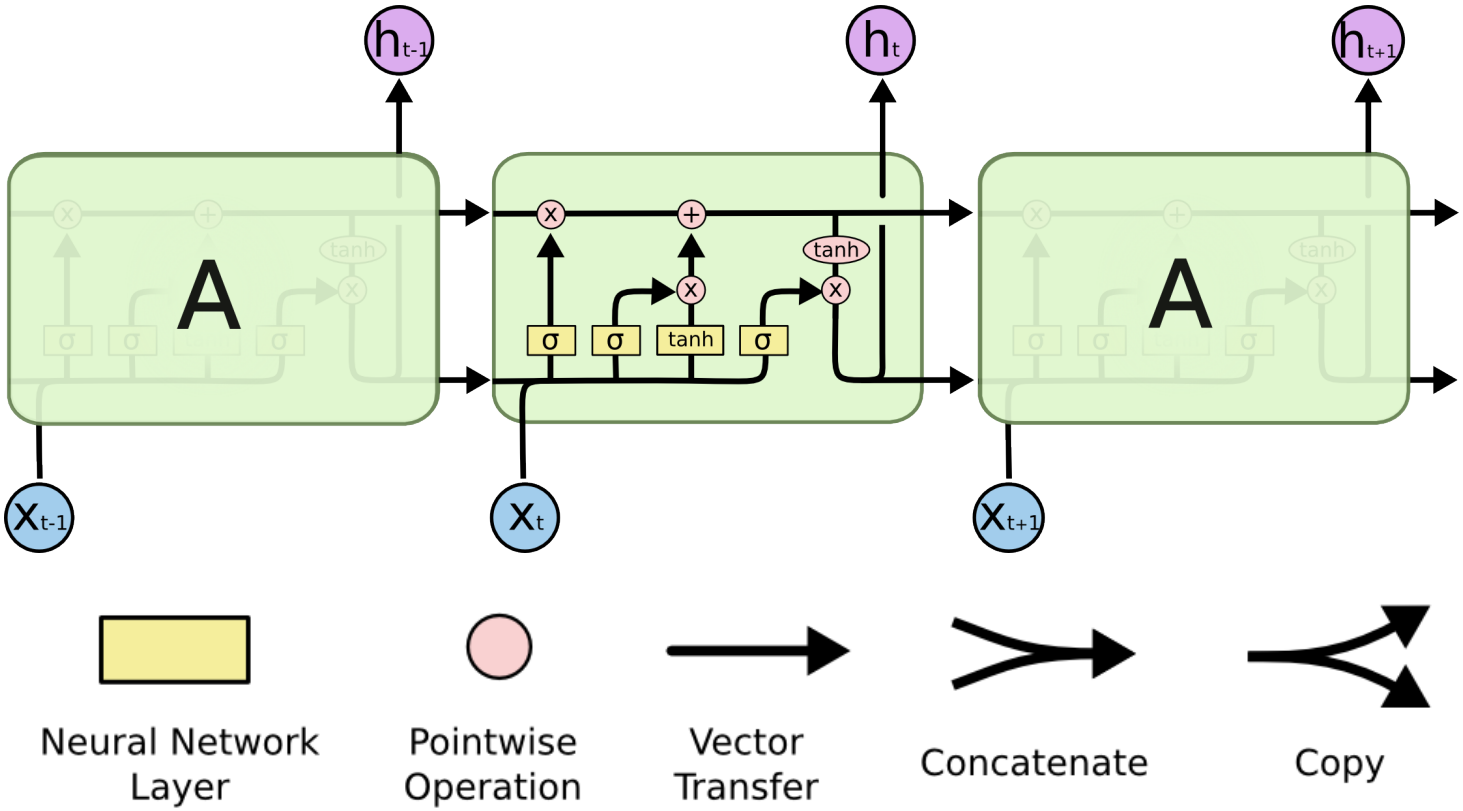

Figure: The LSTM (Olah, 2015)

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LSTM cell state

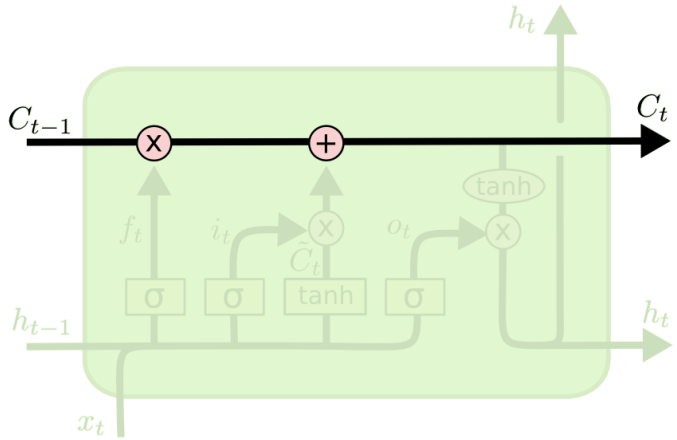

Figure: LSTM cell state, i.e. "carrybelt" (Olah, 2015)

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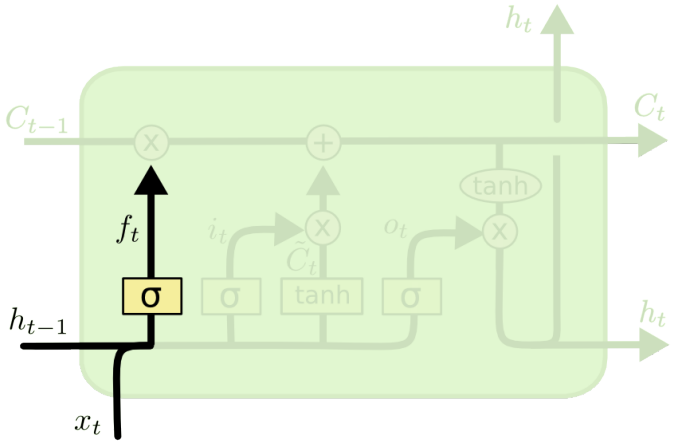
LSTM forget gate



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

Figure: LSTM forget gate (Olah, 2015)

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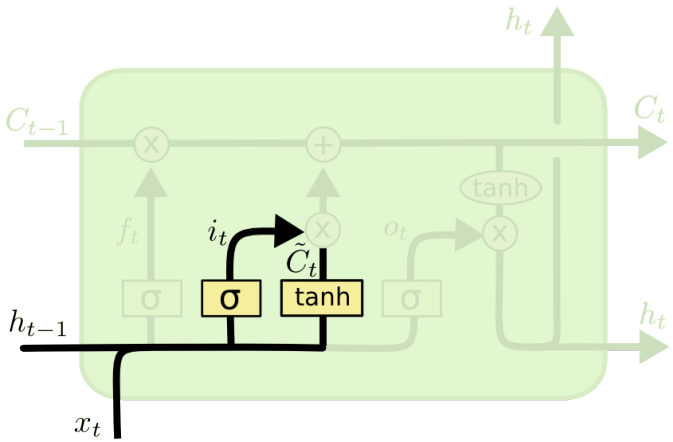
LSTM input gate



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

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

Figure: LSTM input gate (Olah, 2015)

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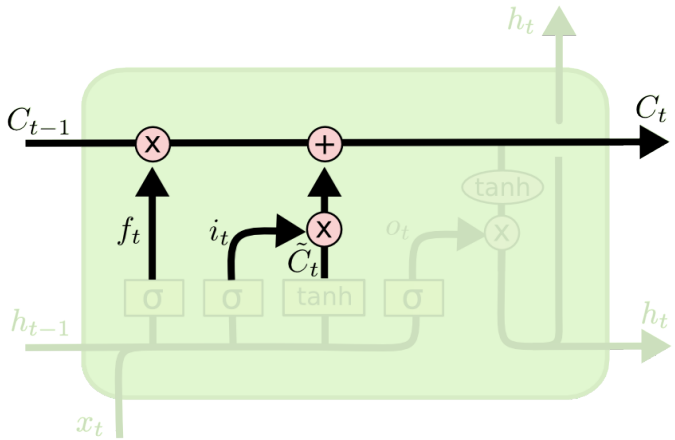
LSTM cell state update



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

Figure: Update cell state (Olah, 2015)

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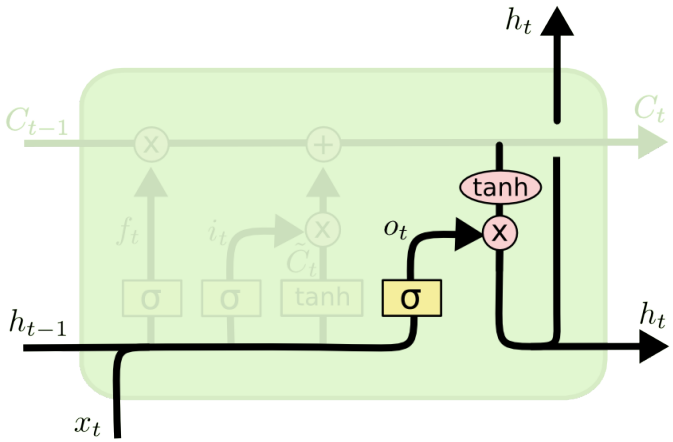
LSTM output gate



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

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

Figure: LSTM output gate (Olah, 2015)

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Problems

- Still a recurrent structure, (vanishing and exploding gradients)
- Long-term dependencies still difficult
- Hard to do transfer learning

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Section 4

Transformers

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The Transformer

- Introduced in 2017 in Vaswani et al. (2017)
- Behind the recent progress in NLP: BERT, GPT-2, GPT-3, etc.

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The Transformer

- Introduced in 2017 in Vaswani et al. (2017)
- Behind the recent progress in NLP: BERT, GPT-2, GPT-3, etc.
- Becoming de-facto standard in industry and academia

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The Transformer

- Introduced in 2017 in Vaswani et al. (2017)
- Behind the recent progress in NLP: BERT, GPT-2, GPT-3, etc.
- Becoming de-facto standard in industry and academia
- Four benefits:
  - Enables more parallelism
  - Better handling of long-range dependencies
  - Brings transfer learning to text data
  - Enables deeper networks

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A Sequence-to-Sequence Model

Figure: Attention (Allamar, 2018)

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Stacked Encoder-Decoder Structure

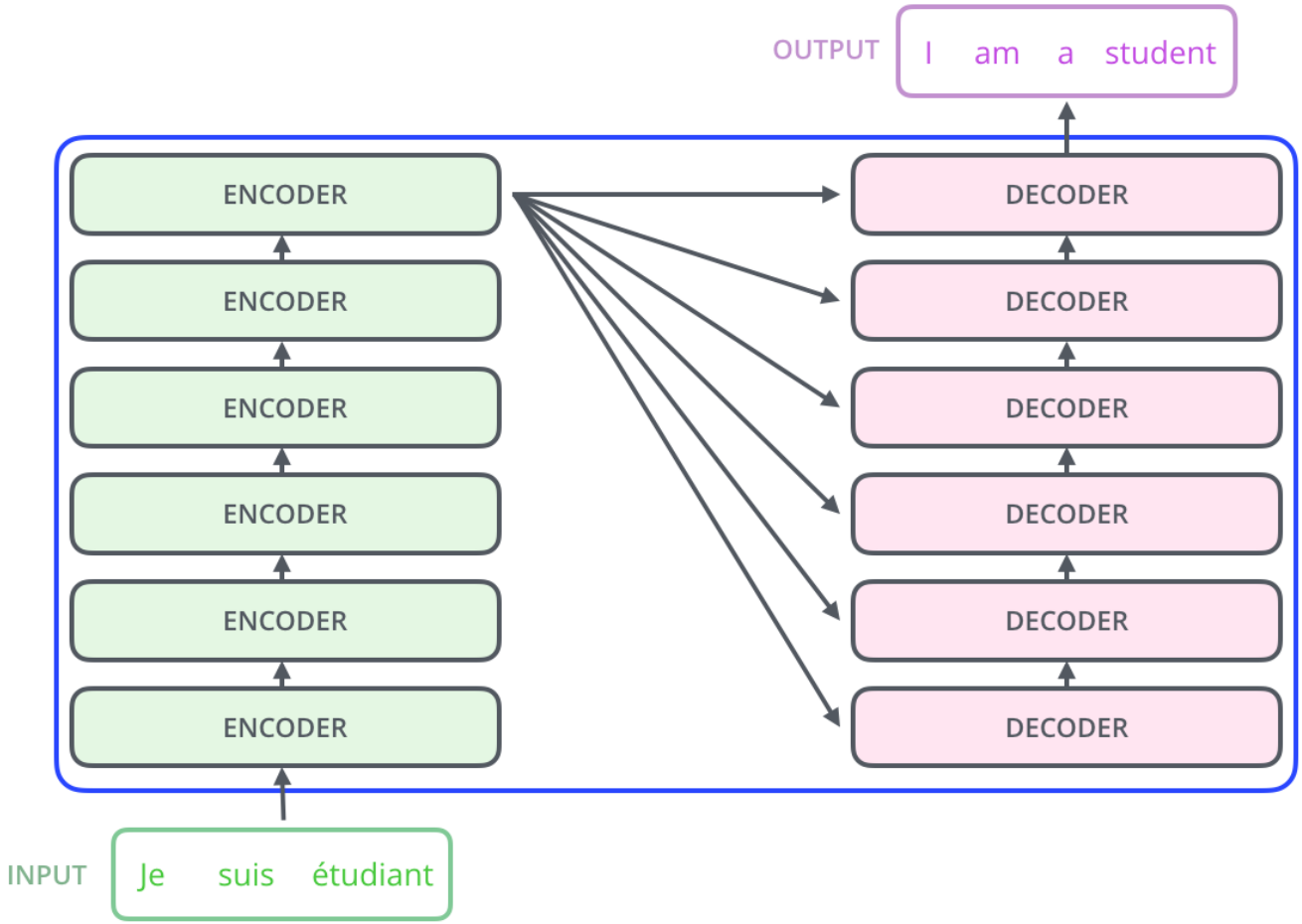

Figure: Attention (Allamar, 2018)

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Transformer

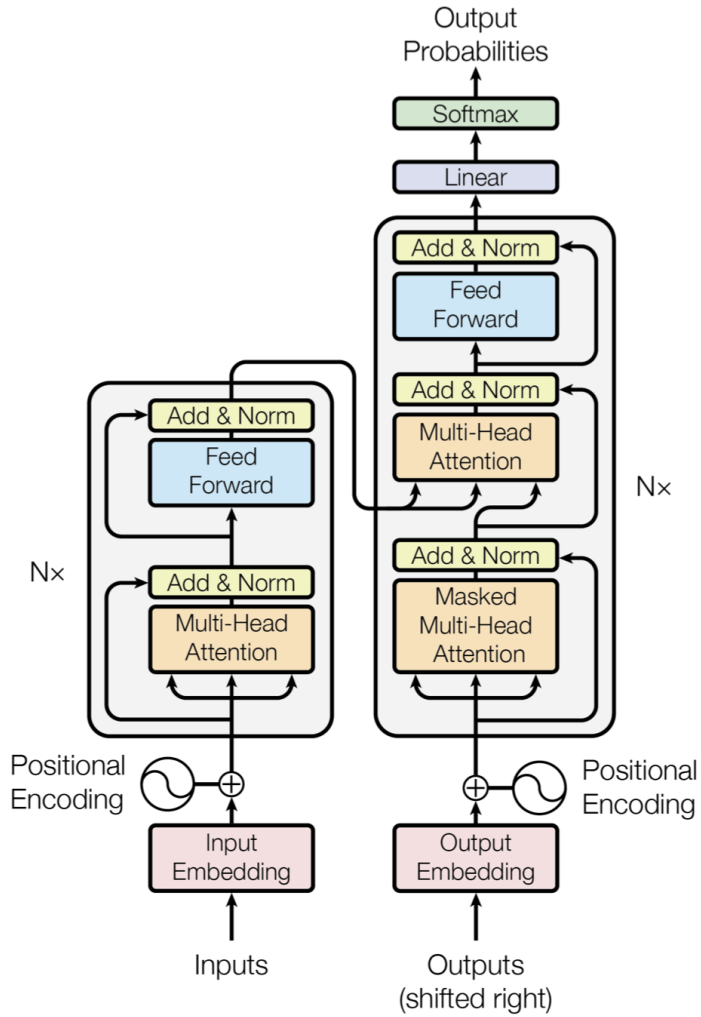

Figure: The Transformer Architecture (Vaswani et al., 2017)

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The encoder vs. the decoder

- Encoder:
  - Input: words (embeddings)
  - Output: contextualized embeddings
- Decoder:
  - Input: contextualized embeddings and previous words (embeddings)
  - Output: words (embeddings)

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The Transformer Layer (Encoder layer)

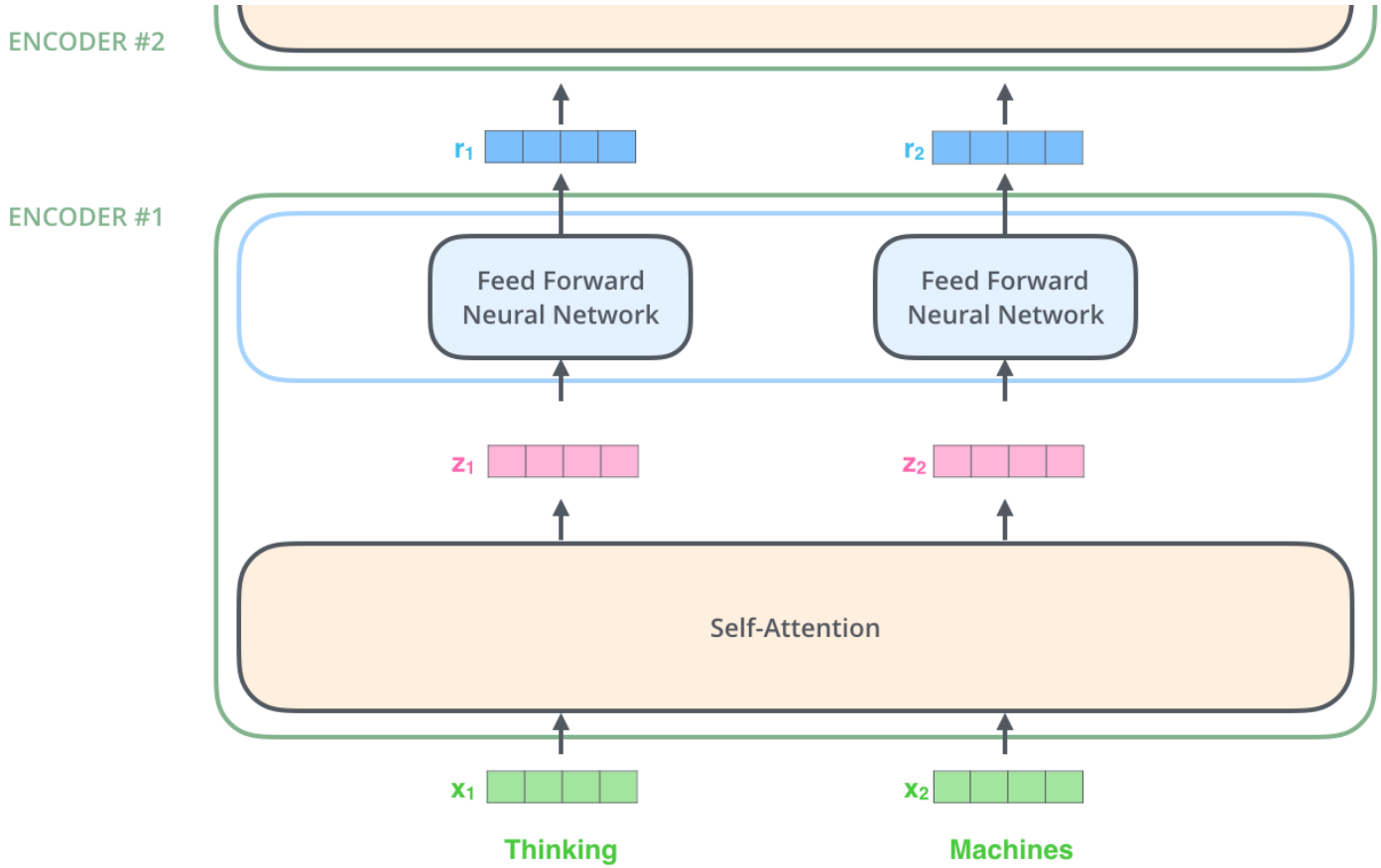

Figure: The Encoder Layer (Alammar, 2018)

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Scaled Dot-Product Attention

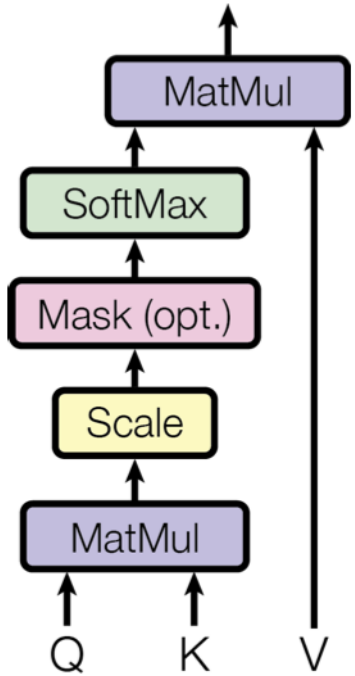

Figure: Scaled Dot-Product Attention (Vaswani et al., 2017)

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right)\mathbf{V}$$

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Attention components

- (Q)uery: Word i query other words
- (K)ey: The other words return their key to i
- (V)alue: The value of the other words to i

Computing Q, V and K

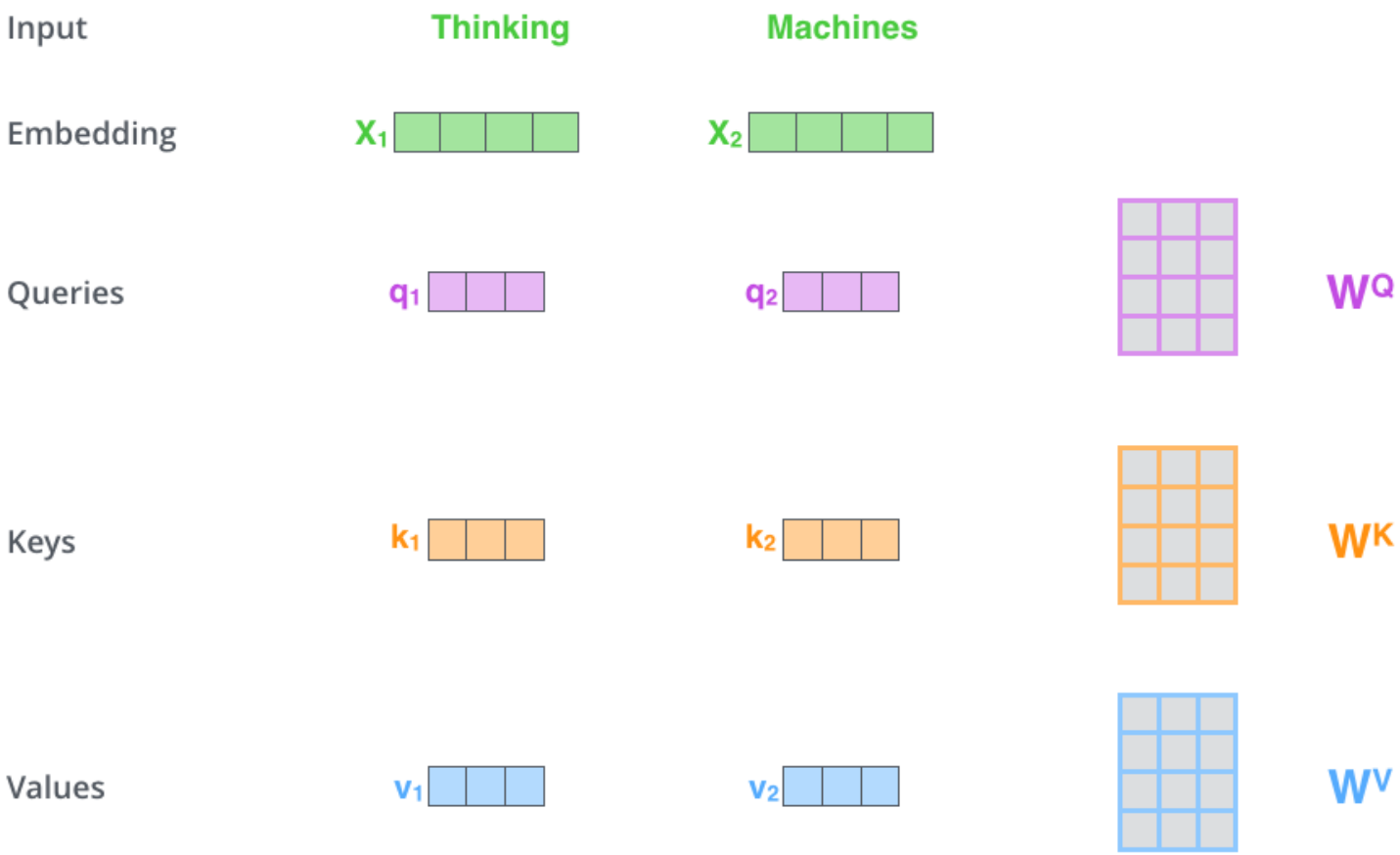

Figure: Attention heads (Alammar, 2018)

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Computing Self-Attention

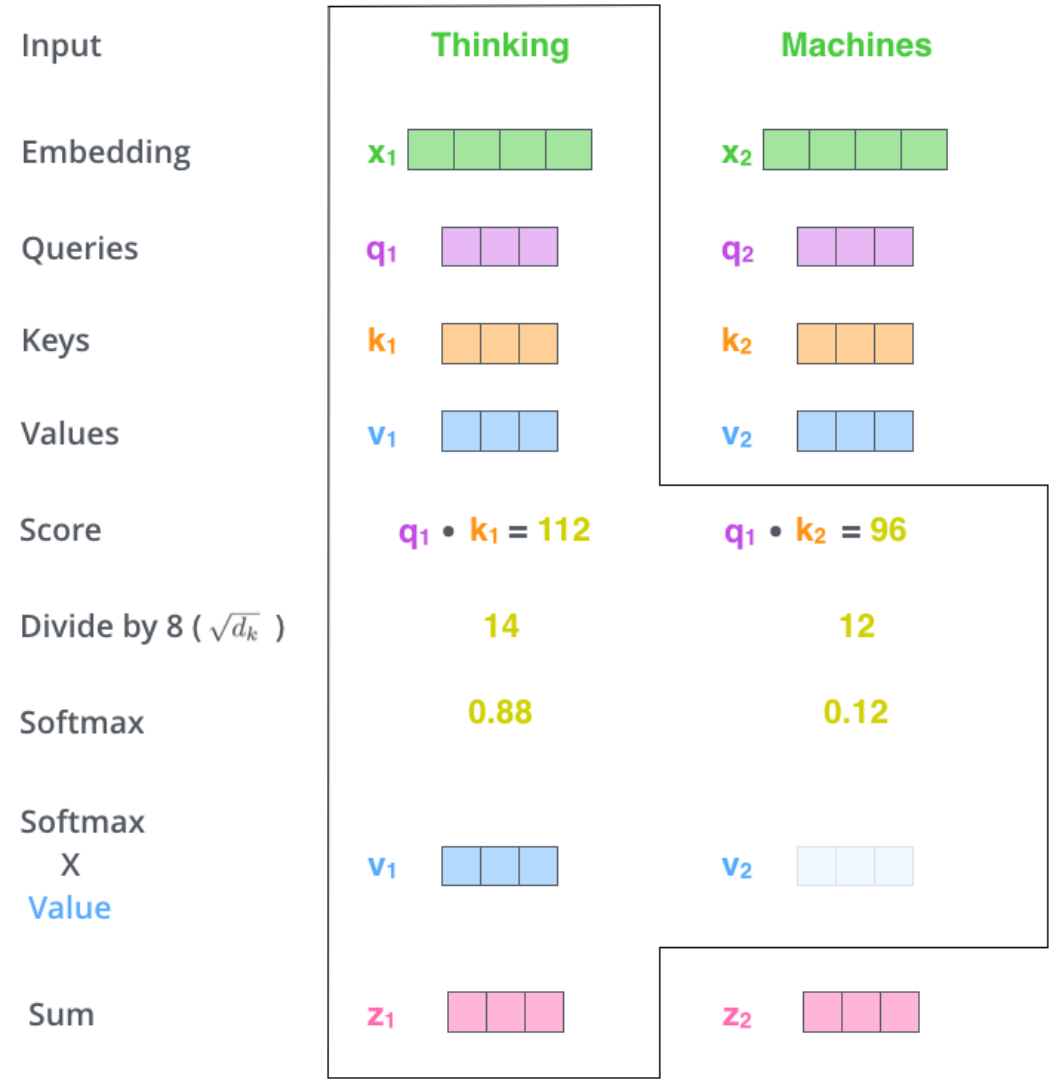

Figure: Attention (Alammar, 2018)

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Multi-Head Attention

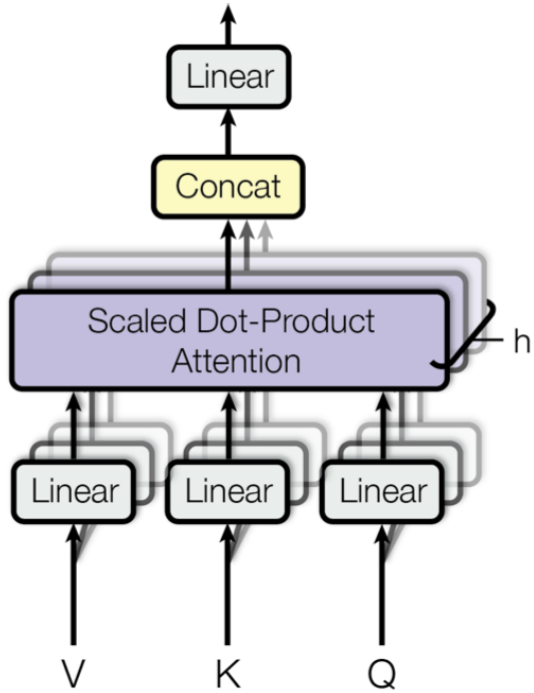

Figure: Scaled Dot-Product Attention (Vaswani et al., 2017)

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Attentions Heads

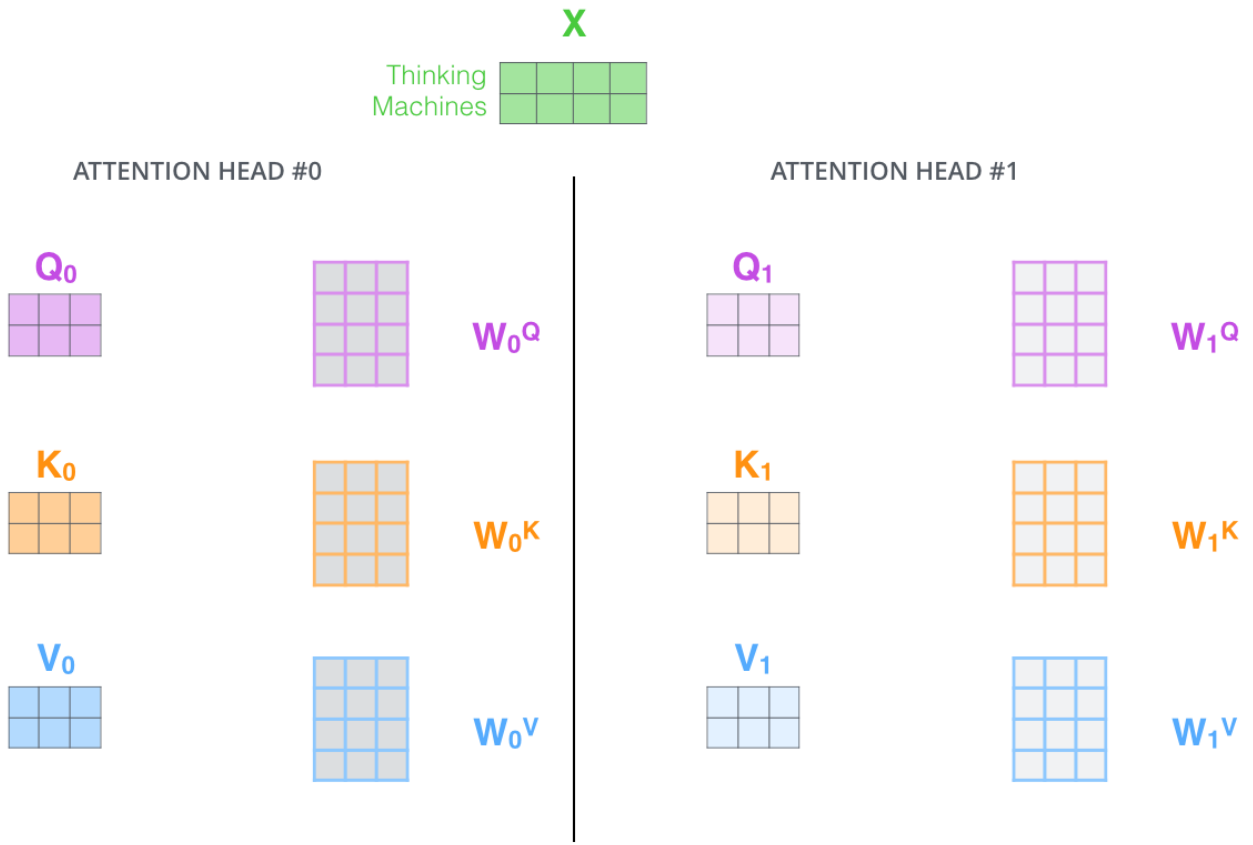

Figure: Attention heads (Alammar, 2018)

Multi-head attention

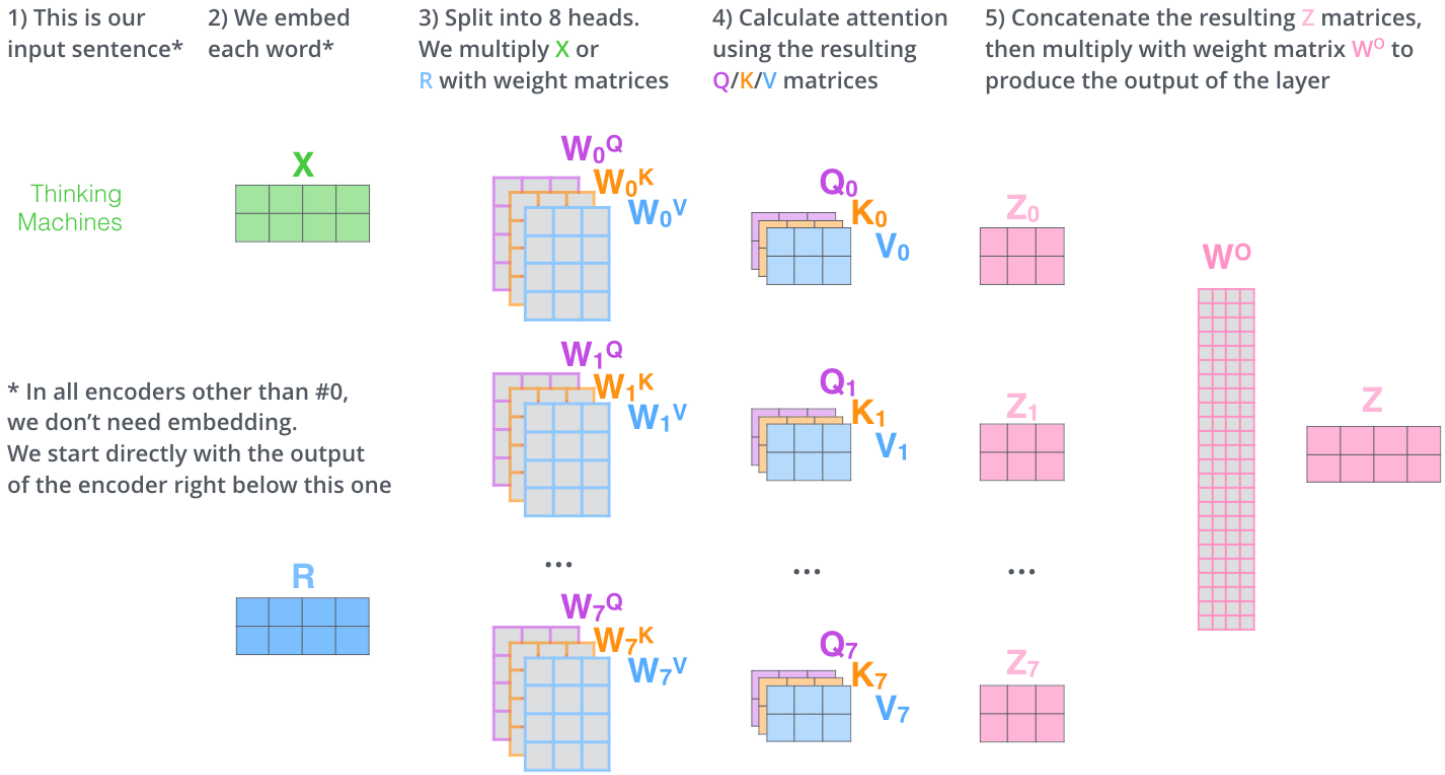

Figure: Attention heads (Alammar, 2018)

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Multi-Head Attention example

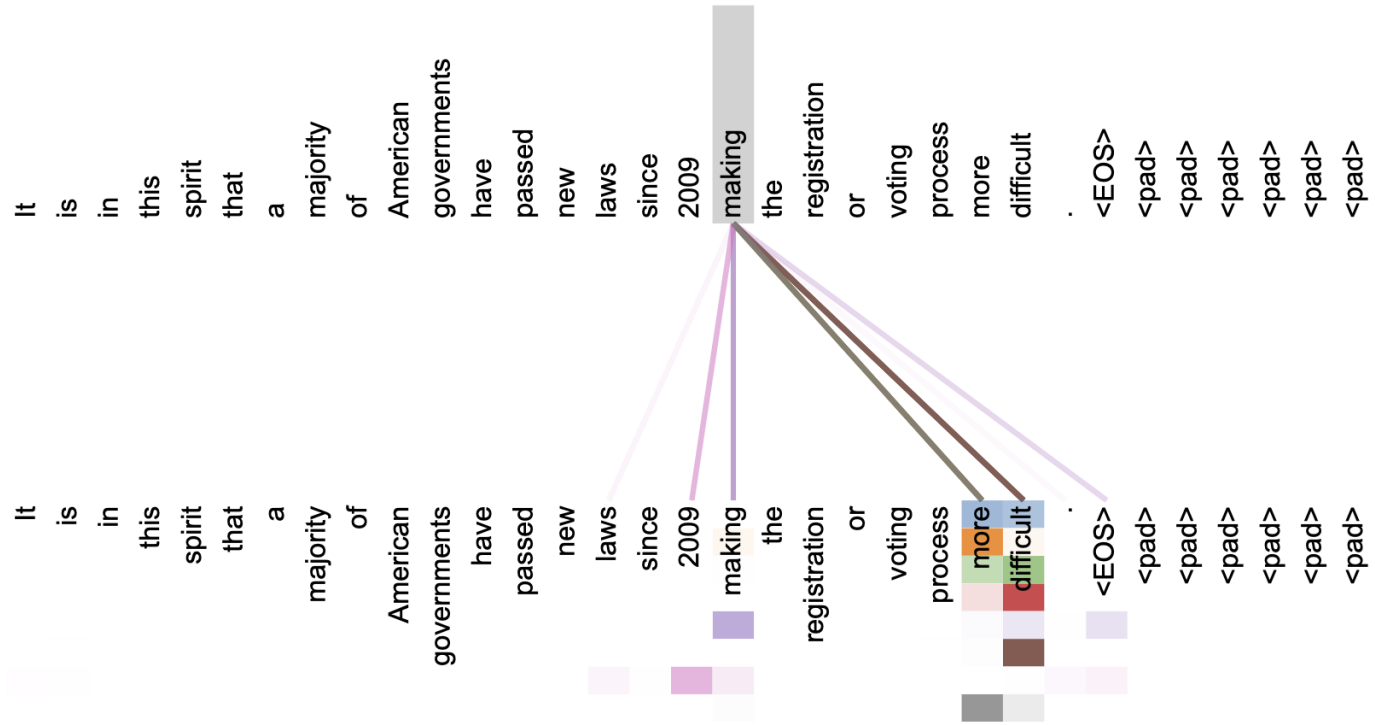

Figure 3: An example of the attention mechanism following long-distance dependencies in the encoder self-attention in layer 5 of 6. Many of the attention heads attend to a distant dependency of the verb 'making', completing the phrase 'making...more difficult'. Attentions here shown only for the word 'making'. Different colors represent different heads. Best viewed in color.

Figure: Attention (Vaswani et al., 2017)

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Positional Encoding

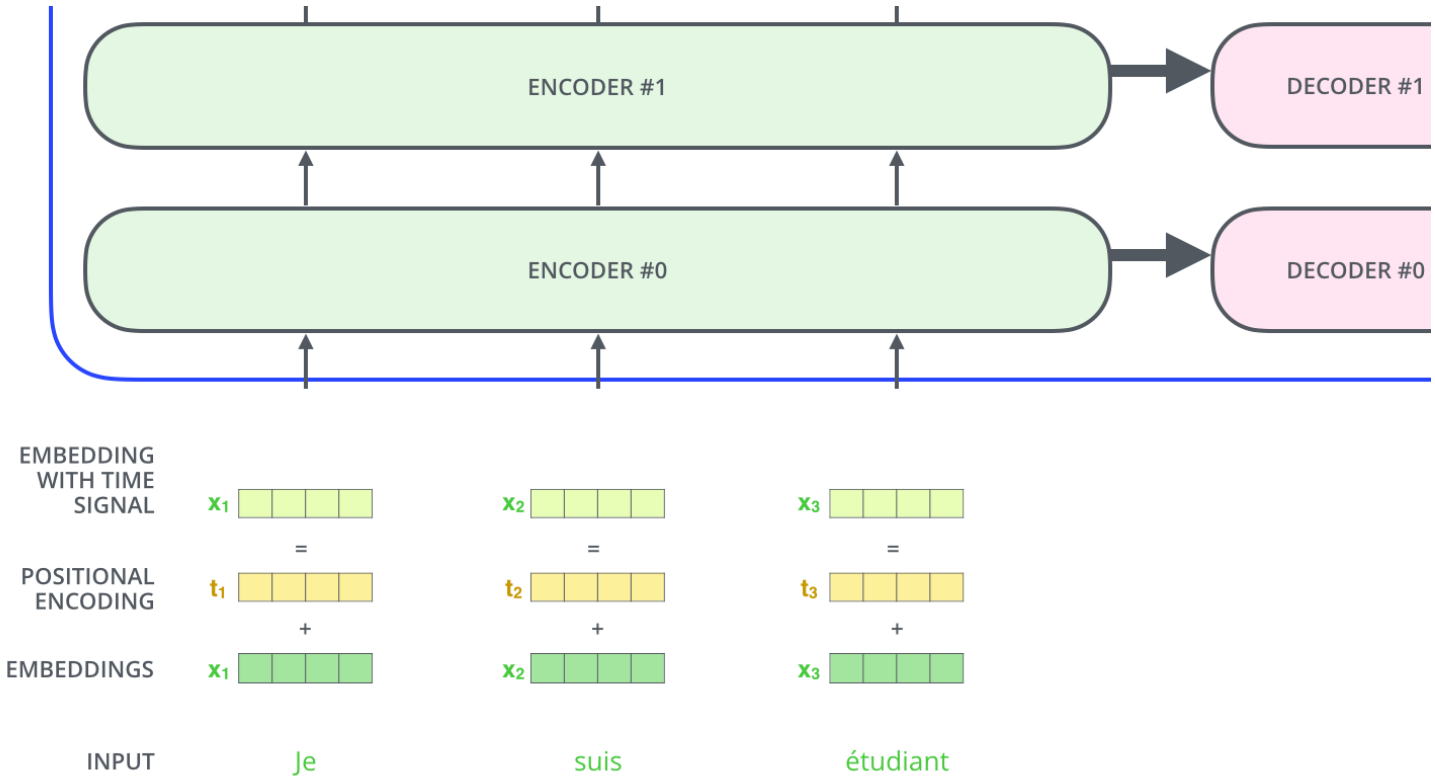

Figure: Attention heads (Alammar, 2018)

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Positional Encoding

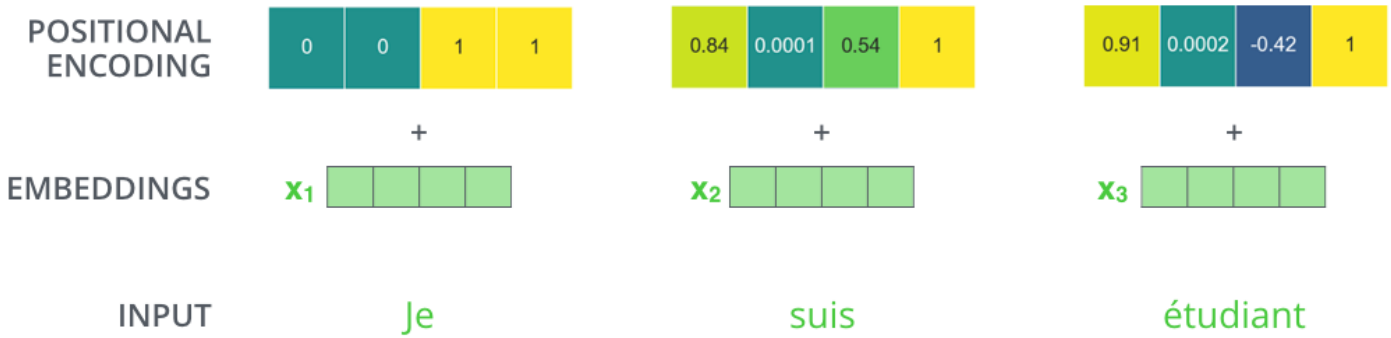

Figure: Adding positional encodings to embeddings (Alammar, 2018)

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Add and Normalize

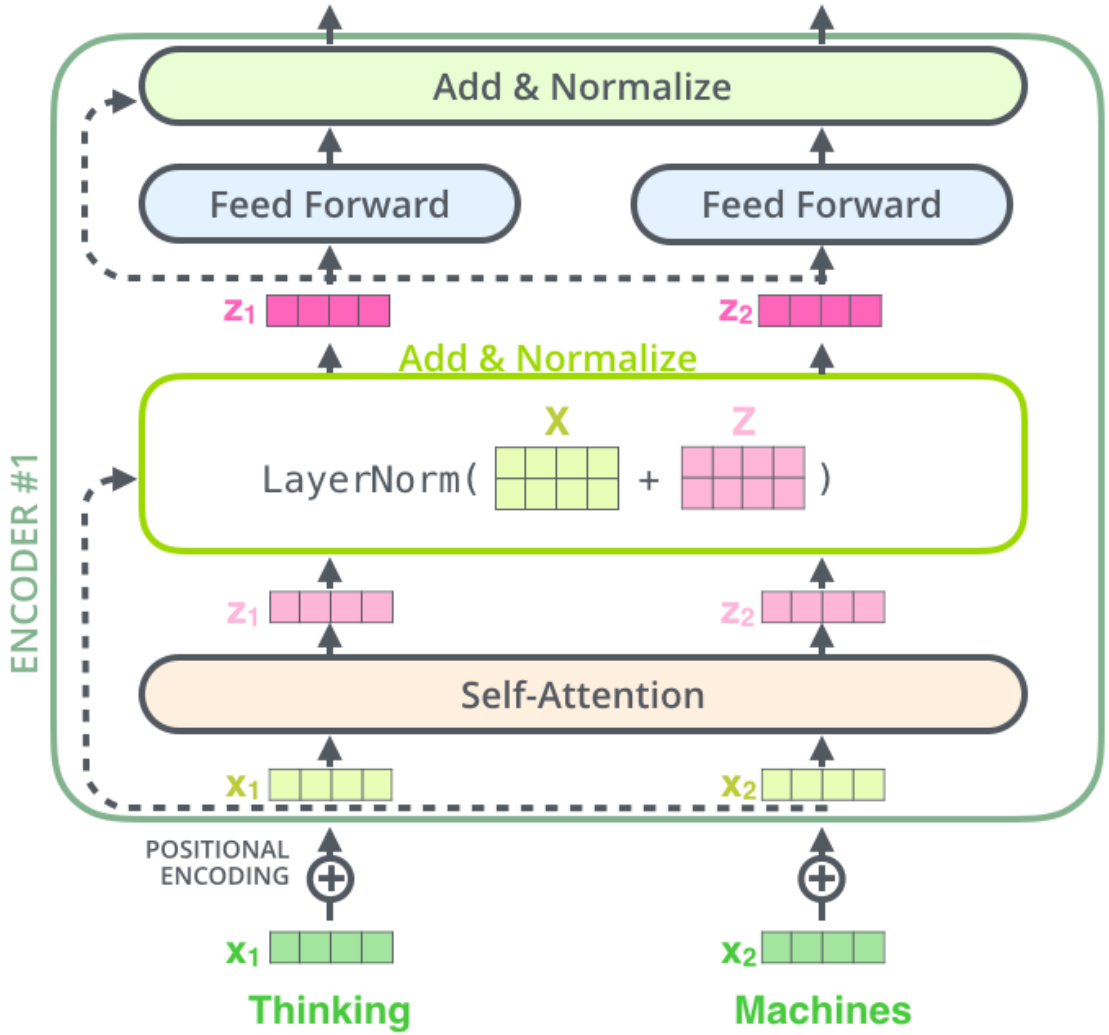

Figure: Add and Normalize (Alammar, 2018)

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Transformer

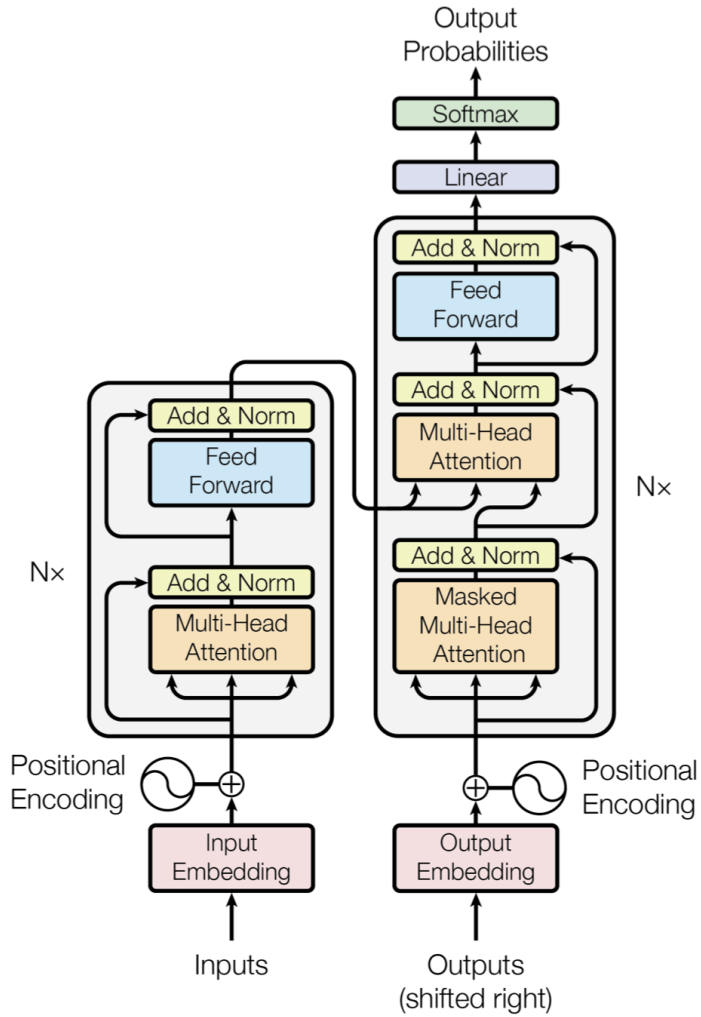

Figure: The Transformer Architecture (Vaswani et al., 2017)

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BERT

- Bidirectional Encoder Representations from Transformers
- Introduced in 2018/2019 in Devlin et al. (2017)

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- State-of-the-Art in many text prediction tasks, such as
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  - Named-Entity Recognition
  - Text Classification

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- Pre-trained on a large number of books
- Available both in English and Swedish (The National Library)

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BERT and transfer learning

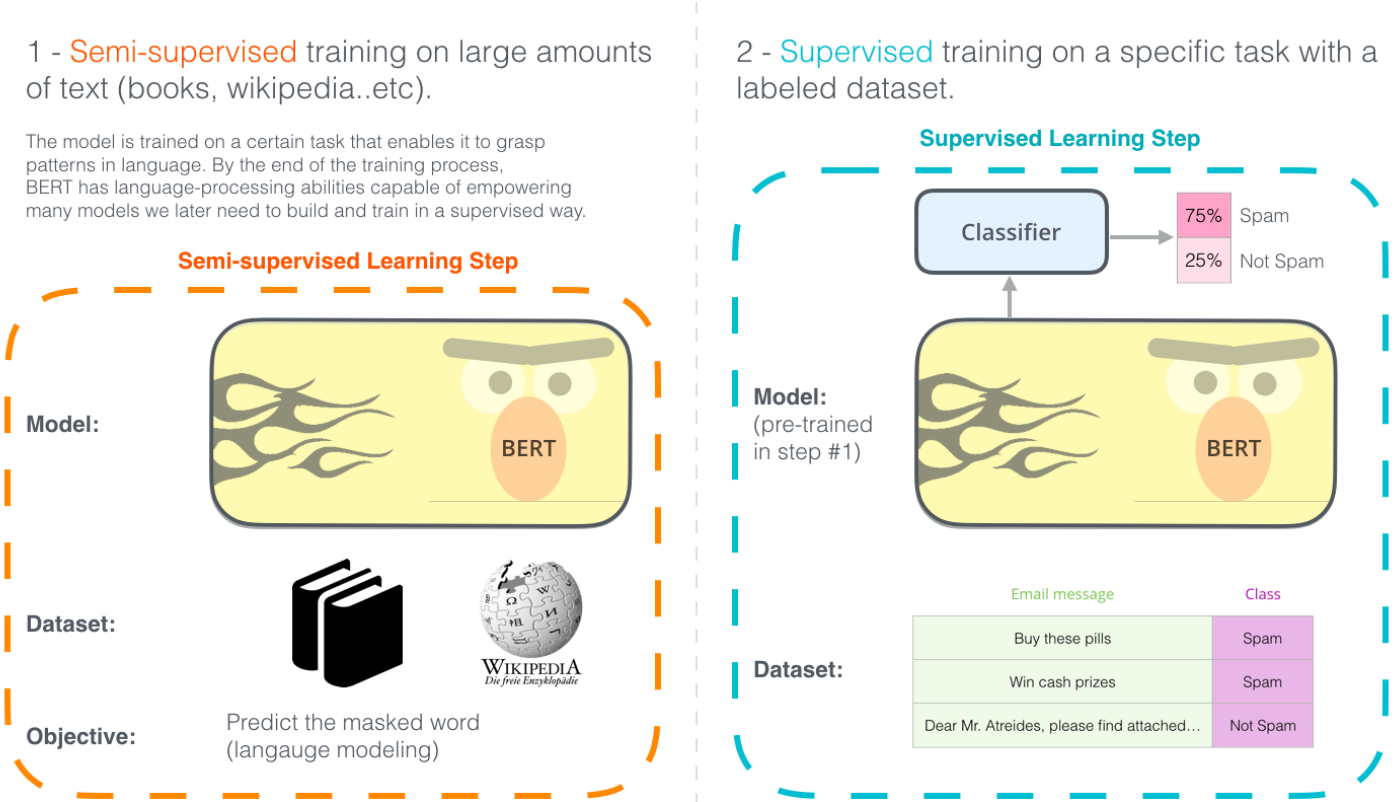

Figure: Using BERT for Transfer Learning (Alammar, 2019)

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The BERT model

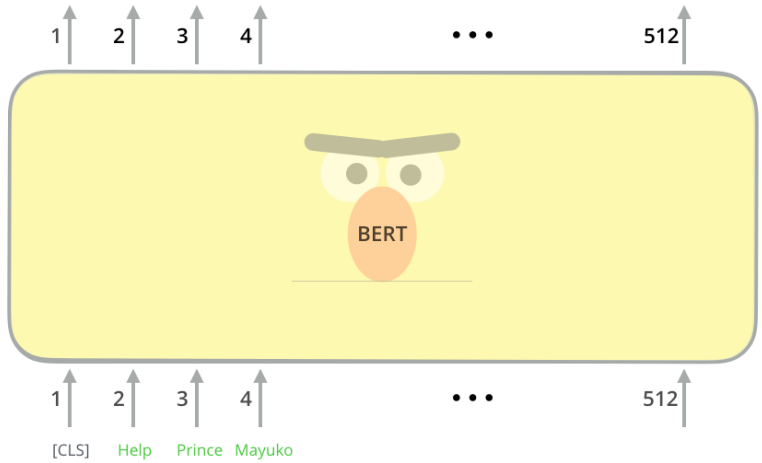

Figure: The BERT model (Alammar, 2019)

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BERT Architecture

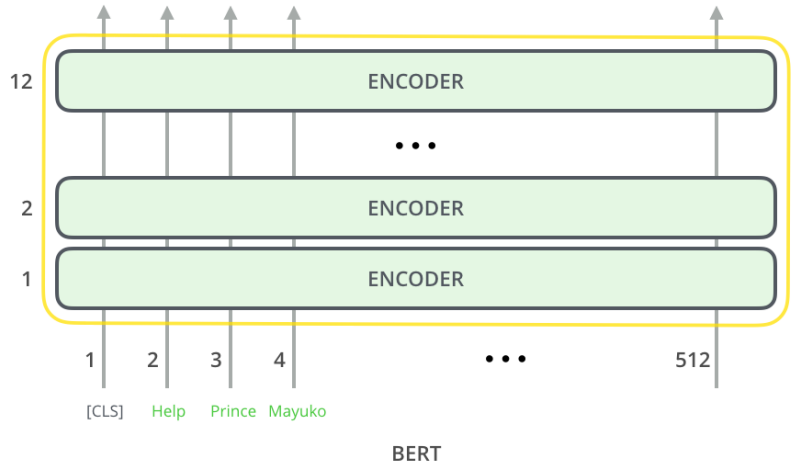

Figure: Opening up BERT (Vaswani et al., 2017)

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Task 1: Masked Language Model

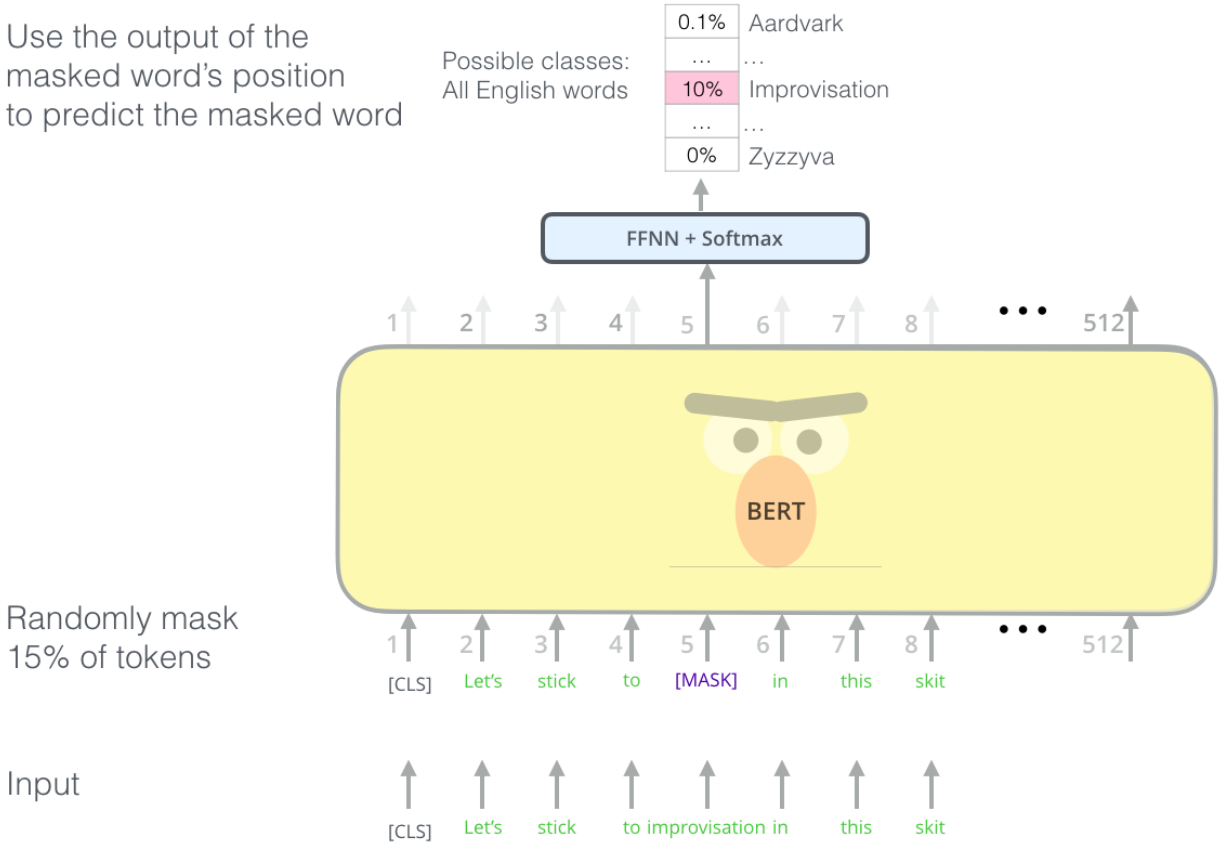

Figure: Masked Language Modeling (Alammar, 2019)

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Next Sentence Prediction

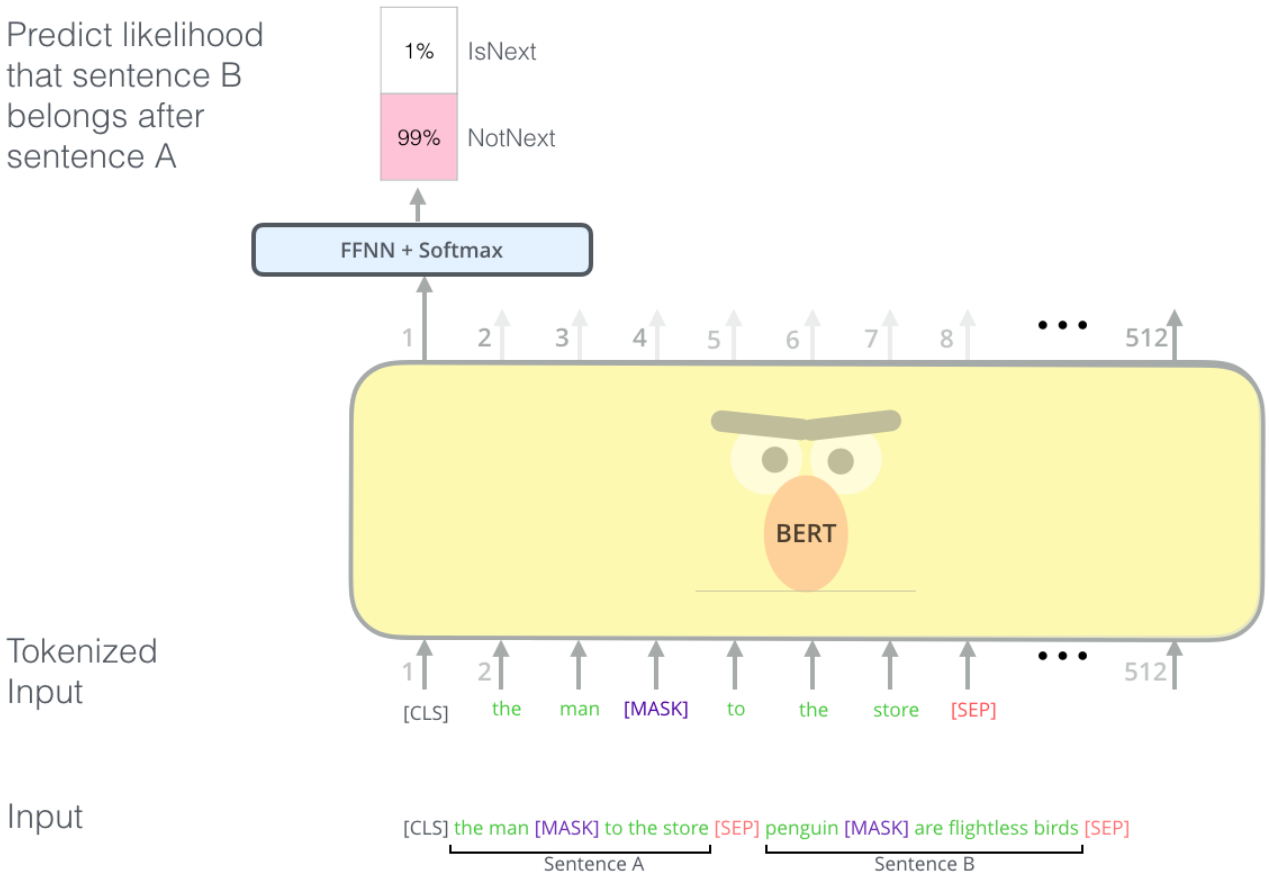

Figure: Next Sentence Prediction (Alammar, 2019)

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Using BERT for Classification

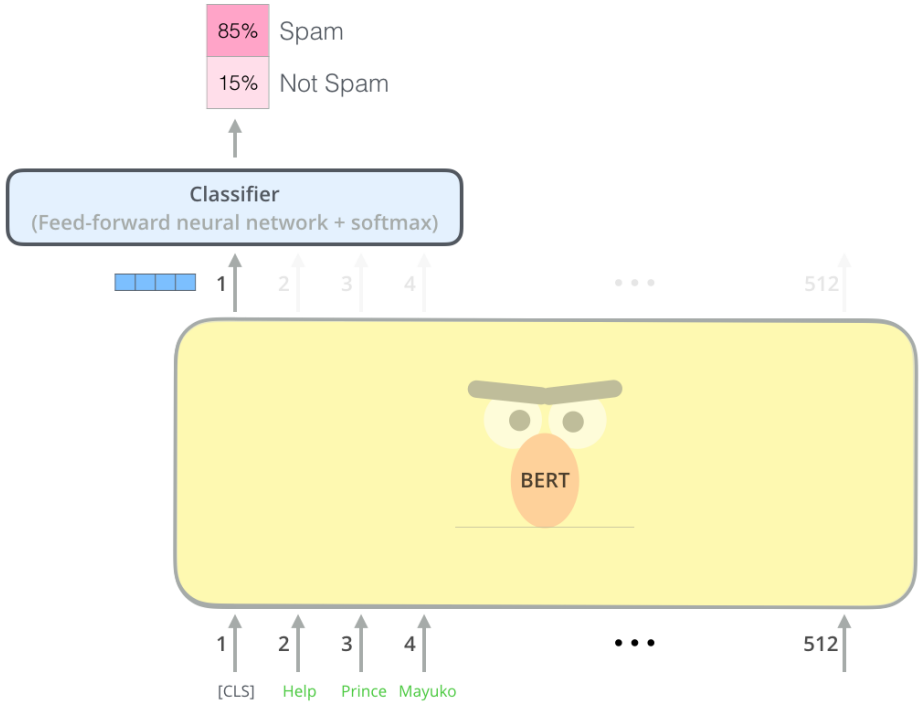

Figure: Using BERT for classification (Alammar, 2019)

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BERT and Contextualized embeddings

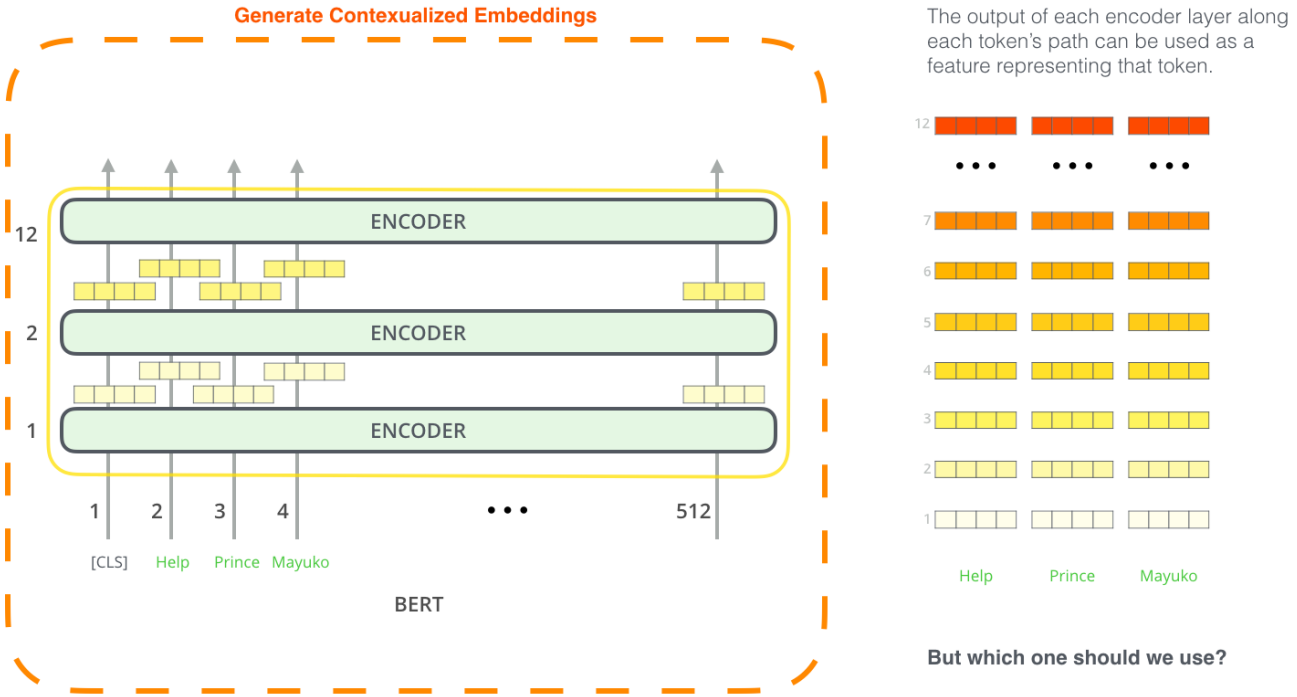

Figure: Contextualized Embeddings (Alammar, 2019)

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Using Contextualized Embeddings

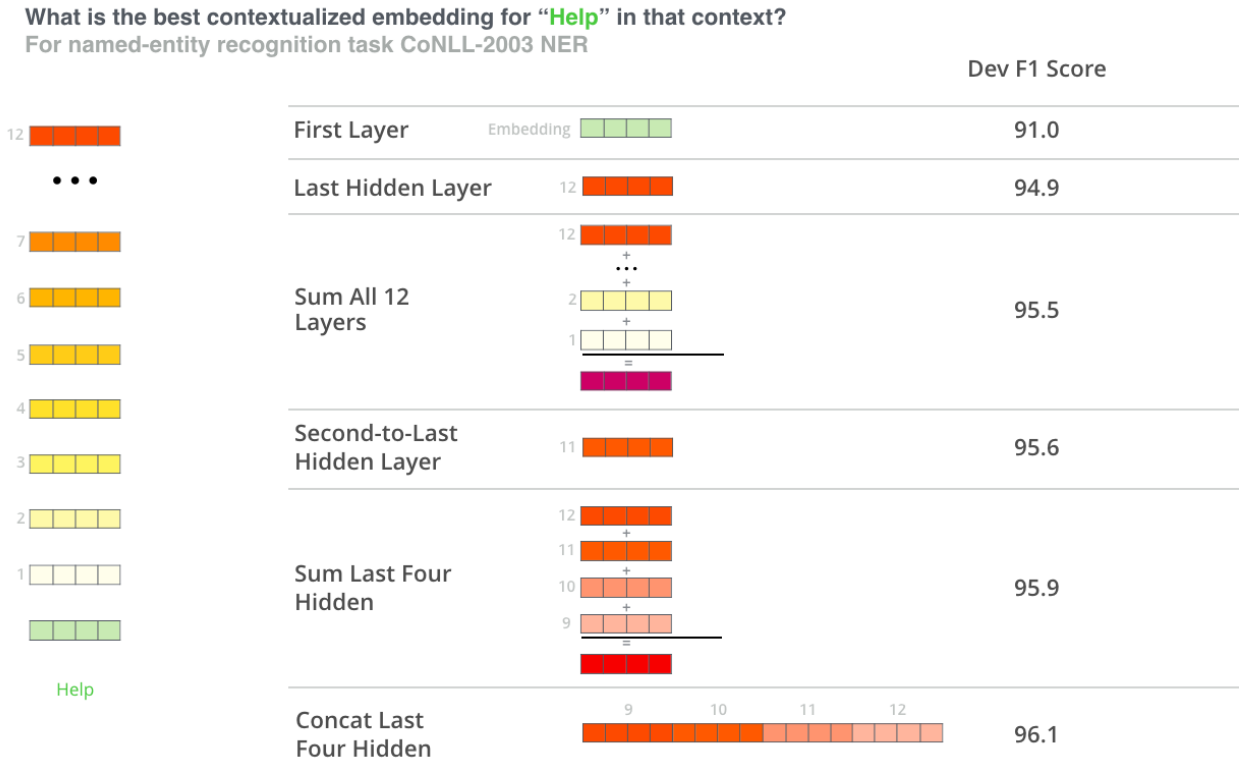

Figure: Using Contextualized Embeddings (Alammar, 2019)