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Machine learning – Block 5

- Practicalities
- Word embeddings
- Recurrent Neural Networks
 - LSTM
- Transformers
 - Attention
 - Multi-Head Attention
 - Positional encoding
 - Add and Normalize
- BERT
 - Training BERT
 - Using BERT

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Autumn 2022



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



Practicalities

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 - Training BERT
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- 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



Assignment 4: Evaluation

- **Practicalities**
- Word embeddings
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- **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)

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



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How do we represent words?

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

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

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

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

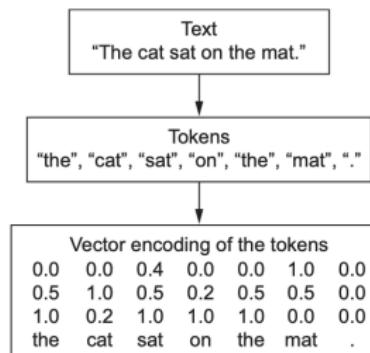
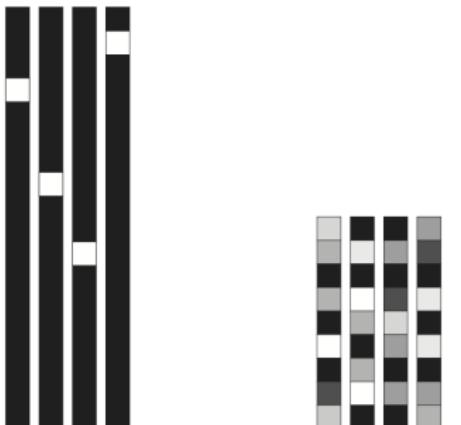


Figure: Representing words as word emnbeddings (Chollet and Allair, 2018, Fig. 6.1)



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- One-hot word vectors:
- Sparse
 - High-dimensional
 - Hardcoded

- Word embeddings:
- Dense
 - Lower-dimensional
 - Learned from data

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

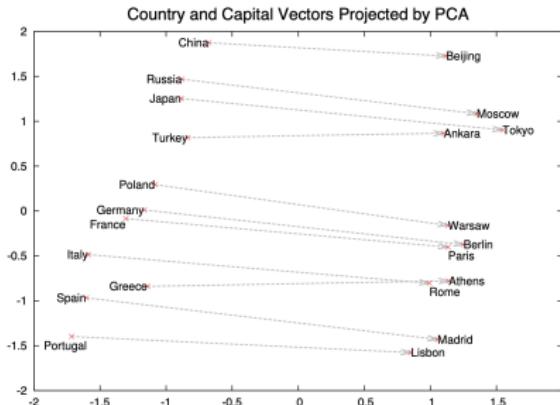


Figure: Word embedding properties (Mikolov et al, 2013)

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



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Word embeddings

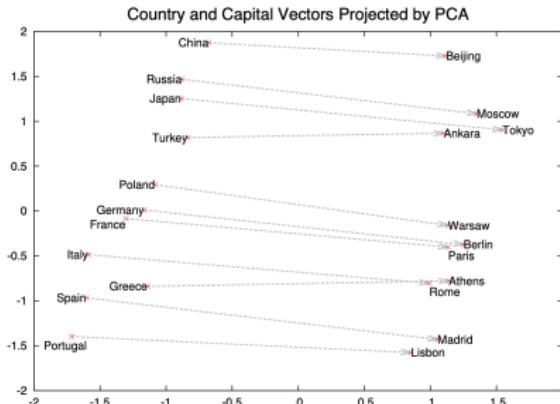


Figure: Word embedding properties (Mikolov et al, 2013)

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

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



Recurrent Neural Networks

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 - Training BERT
 - Using BERT
- 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

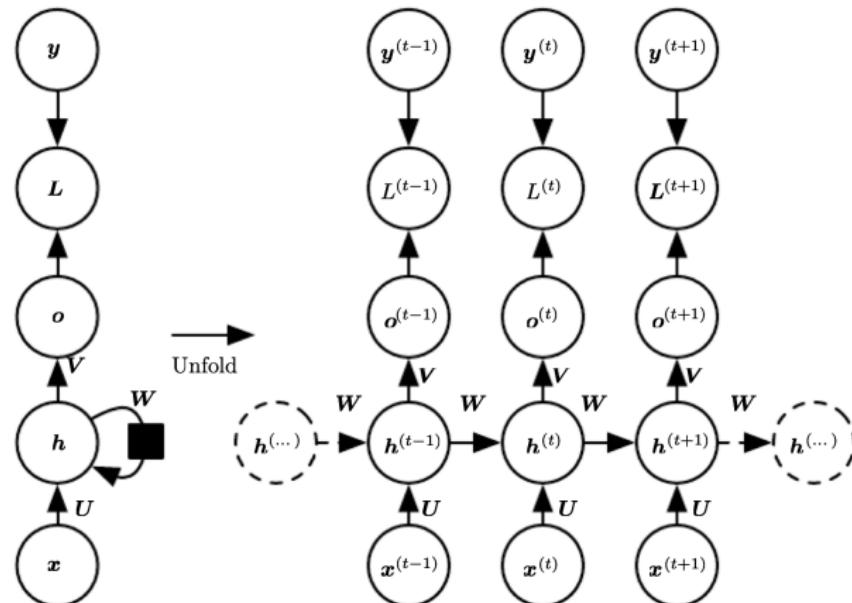


Figure: Recurrent Neural Network (Goodfellow et al, 2017, Fig. 10.3)



Recurrent Neural Networks

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$$a_t = b + Wh_{t-1} + Ux_t$$

$$h_t = \sigma_1(a_t)$$

$$o_t = c + Vh_t$$

$$\hat{y}_t = \sigma_{\text{output}}(o_t) = \text{softmax}(o_t)$$

Think of h_t as the "state" at timepoint t



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Recurrent network with one output

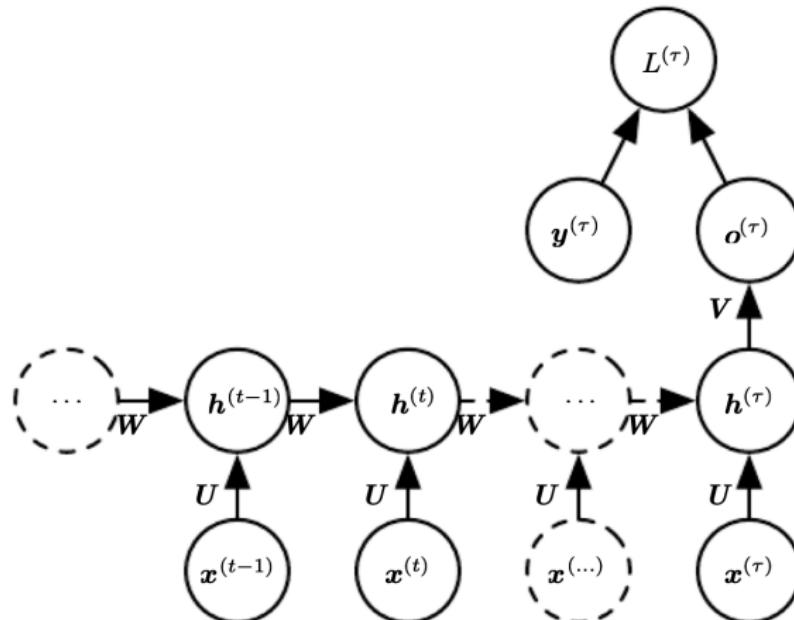


Figure: Recurrent Neural Network with one output (Goodfellow et al., 2017, Fig. 10.5)



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Sequence to Sequence: Encoder-Decoder

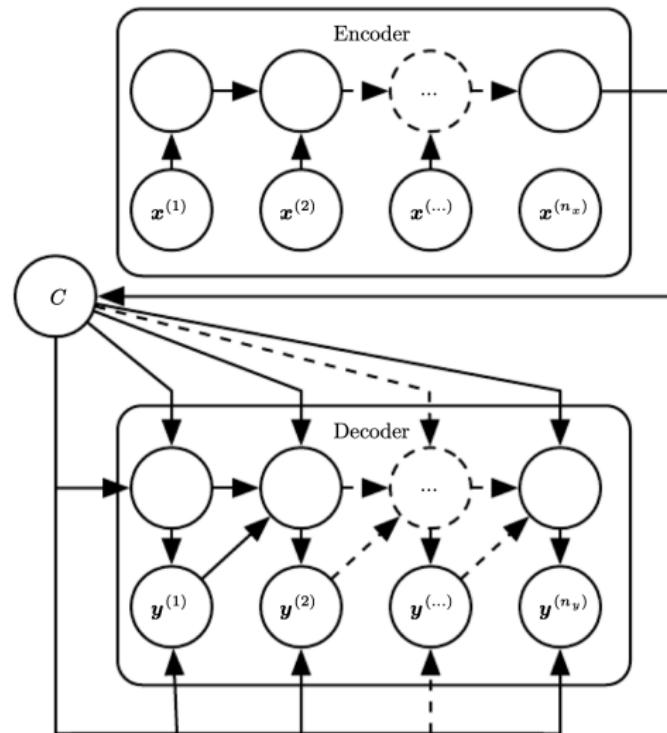


Figure: Encoder-Decoder Recurrent Networks (Goodfellow et al, 2017, Fig. 10.12)



Problems with RNN

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 - Using BERT
- Exploding and vanishing gradients
 - Long-term dependencies



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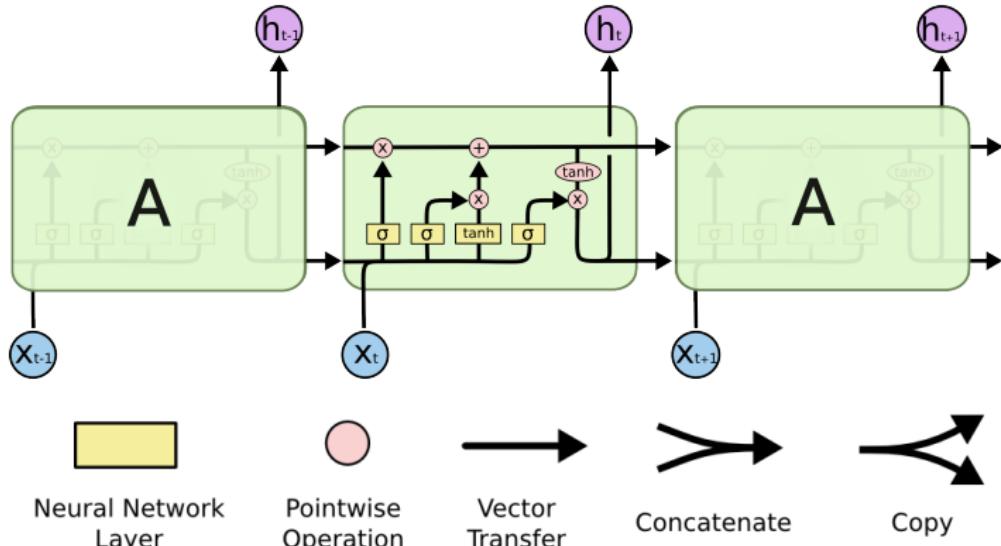


Figure: The LSTM (Olah, 2015)



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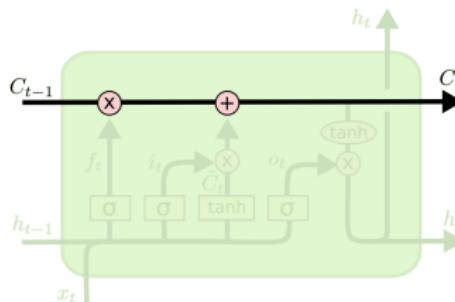


Figure: LSTM cell state, i.e. "carrybelt" (Olah, 2015)



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LSTM forget gate

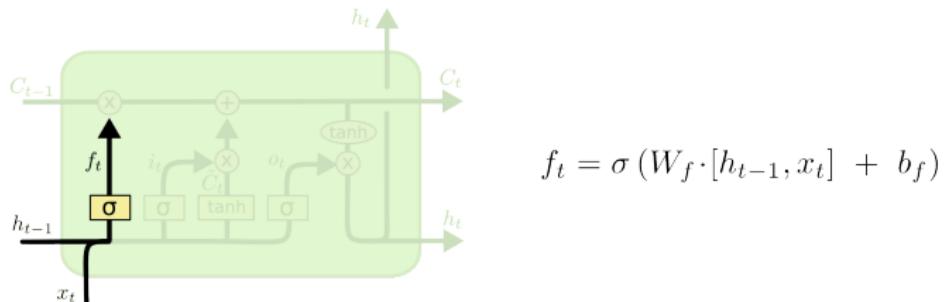


Figure: LSTM forget gate (Olah, 2015)



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LSTM input gate

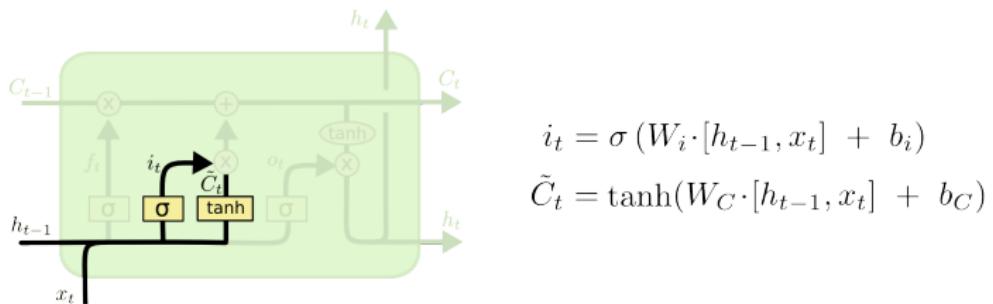


Figure: LSTM input gate (Olah, 2015)



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LSTM cell state update

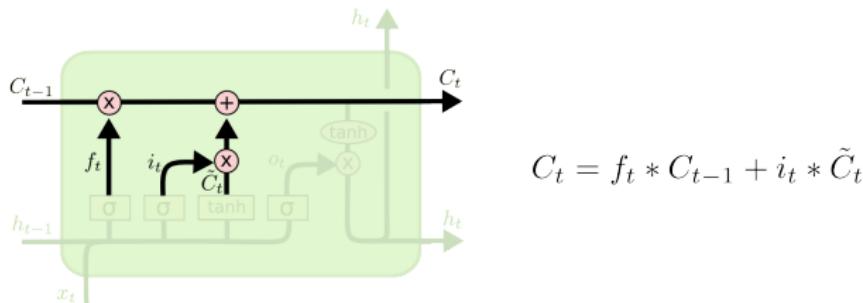
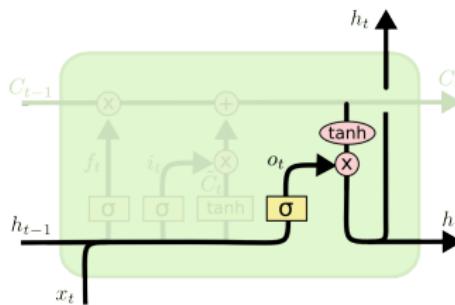


Figure: Update cell state (Olah, 2015)



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LSTM output gate



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

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

Figure: LSTM output gate (Olah, 2015)



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-
- 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



The Transformer

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





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- 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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- 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

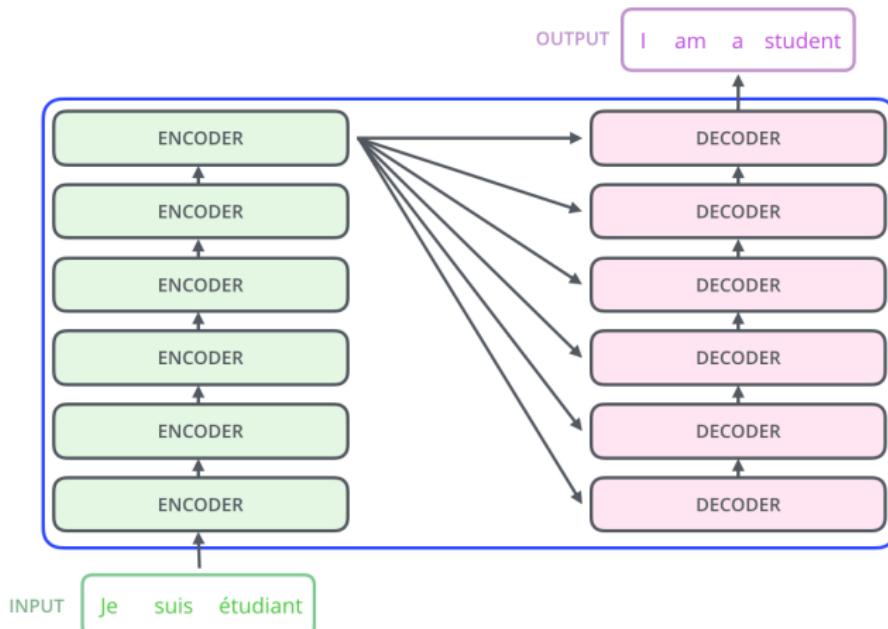


Figure: Attention (Allamar, 2018)



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Transformer

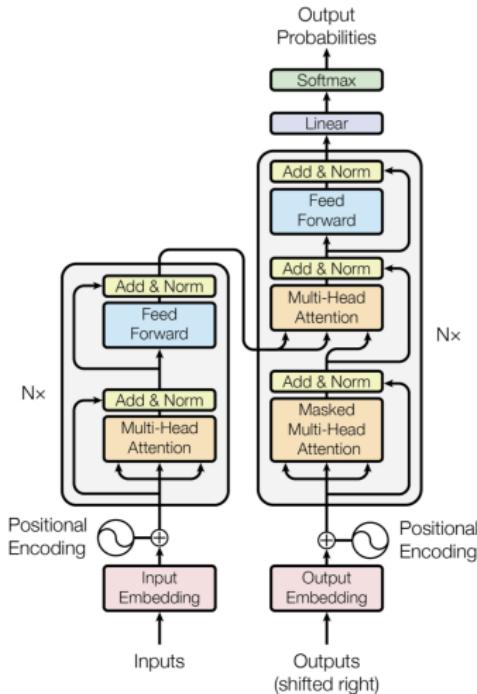


Figure: The Transformer Architecture (Vaswani et al., 2017)



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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)

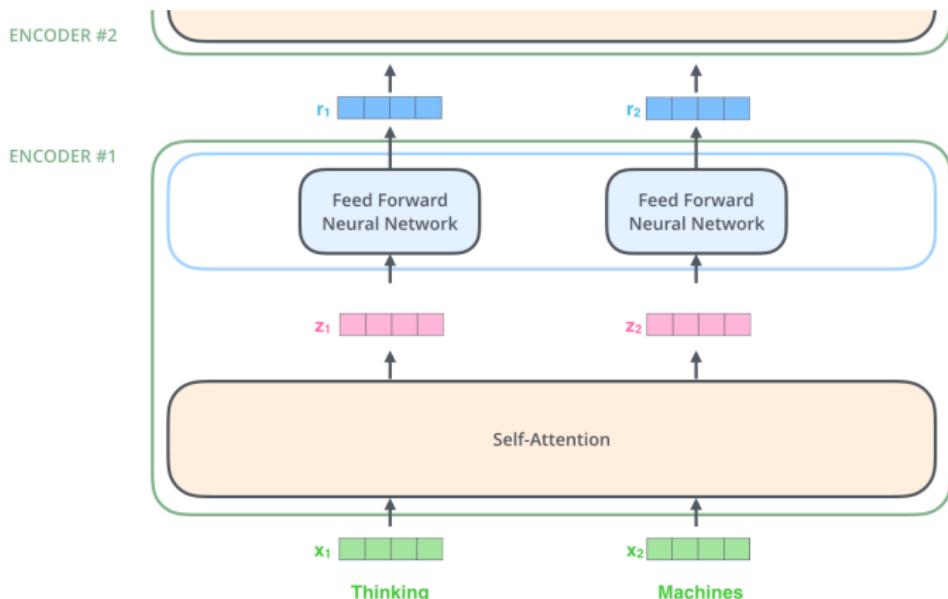


Figure: The Encoder Layer (Alammar, 2018)



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Scaled Dot-Product Attention

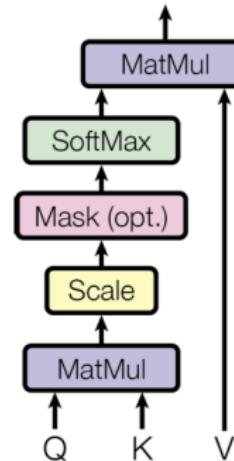


Figure: Scaled Dot-Product Attention (Vaswani et al., 2017)



The encoder vs. the decoder

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- (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



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Computing Q, V and K

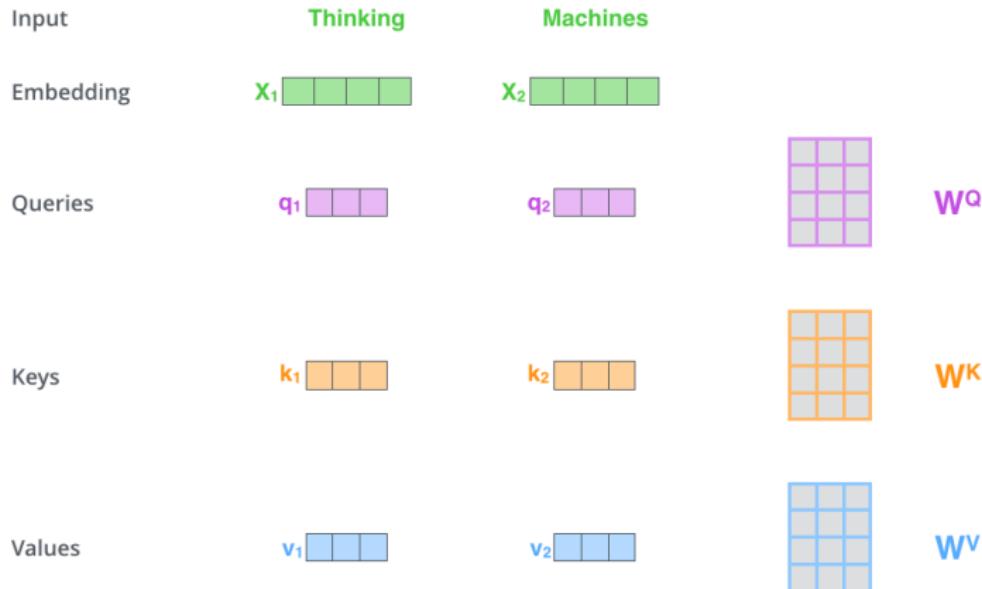


Figure: Attention heads (Alammar, 2018)



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Computing Self-Attention

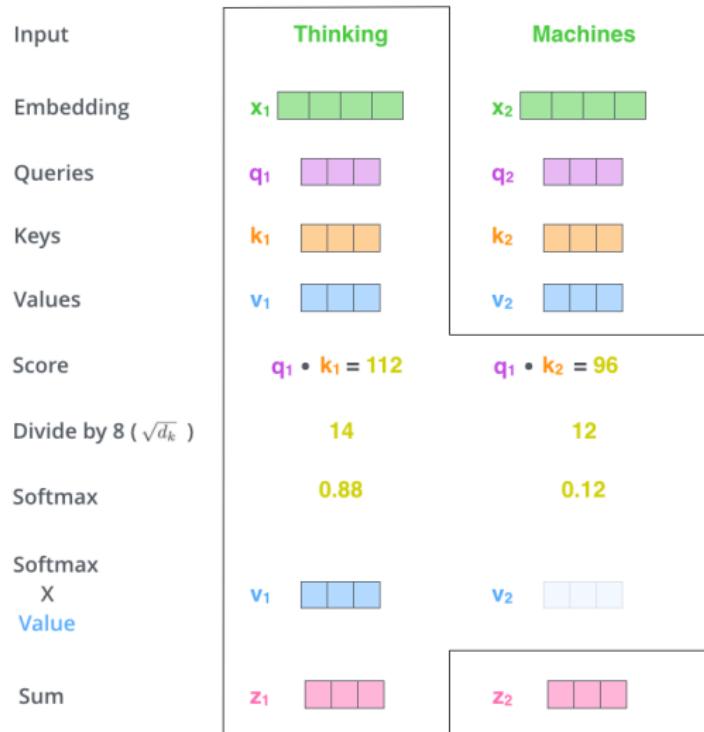


Figure: Attention (Alammar, 2018)



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Multi-Head Attention

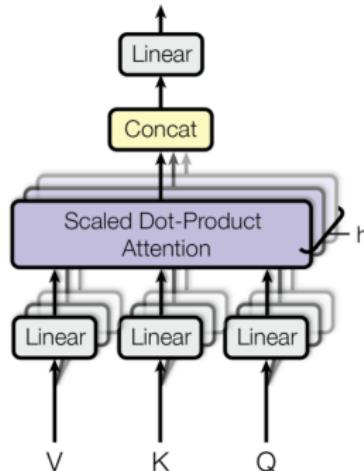


Figure: Scaled Dot-Product Attention (Vaswani et al., 2017)



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Attentions Heads

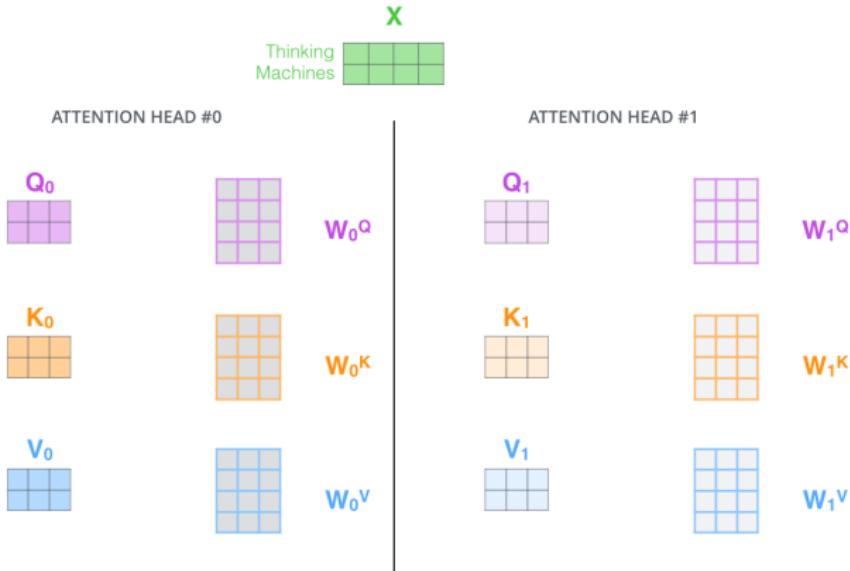


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Multi-head attention

- 1) This is our input sentence*
- 2) We embed each word*
- 3) Split into 8 heads. We multiply X or R with weight matrices
- 4) Calculate attention using the resulting $Q/K/V$ matrices
- 5) Concatenate the resulting Z matrices, then multiply with weight matrix W^O to produce the output of the layer

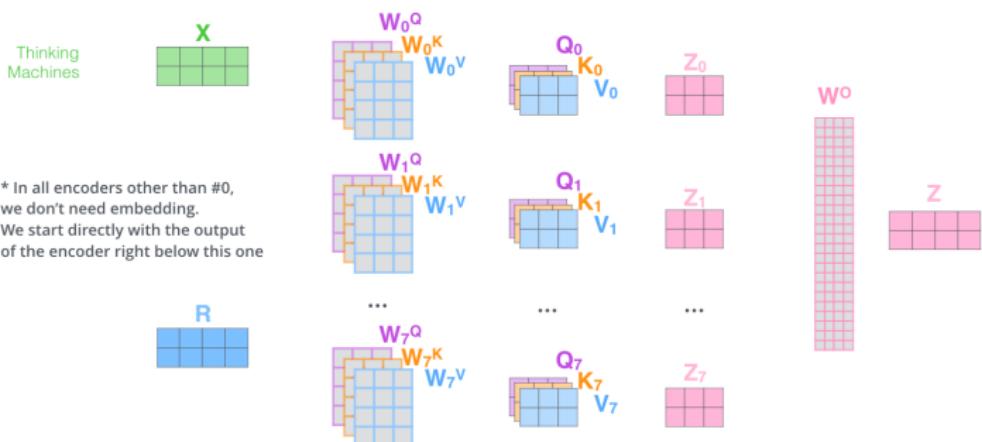


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Multi-Head Attention example

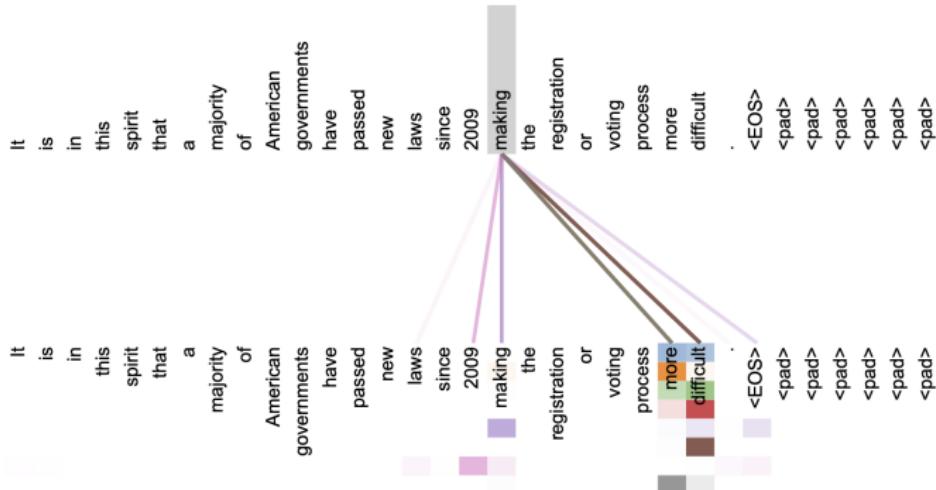


Figure 3: An example of the attention mechanism following long-distance dependencies in the encoder self-attention in layer 5 of 6. Many of the attention heads attend to a distant dependency of the verb ‘making’, completing the phrase ‘making...more difficult’. Attentions here shown only for the word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

Figure: Attention (Vaswani et al., 2017)



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Positional Encoding

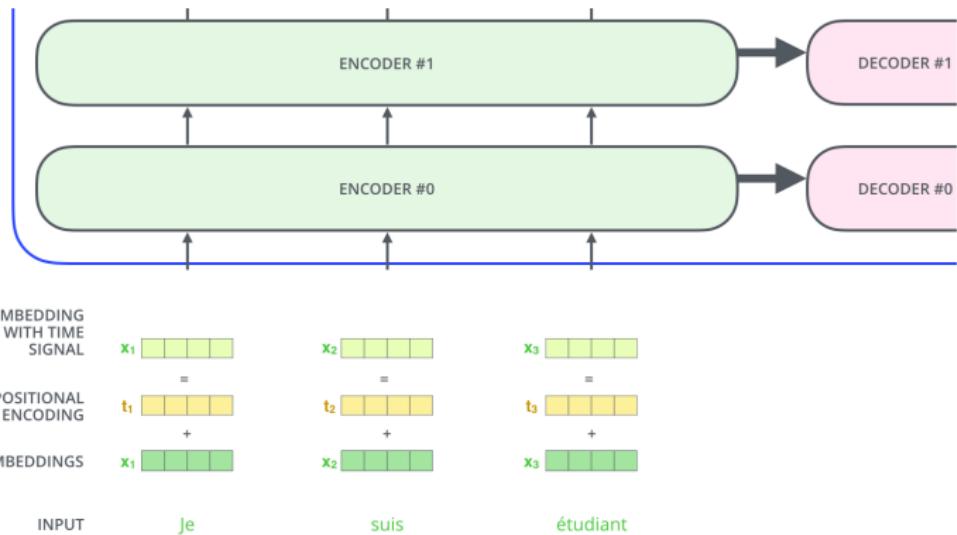


Figure: Attention heads (Alammar, 2018)



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Positional Encoding



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



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Add and Normalize

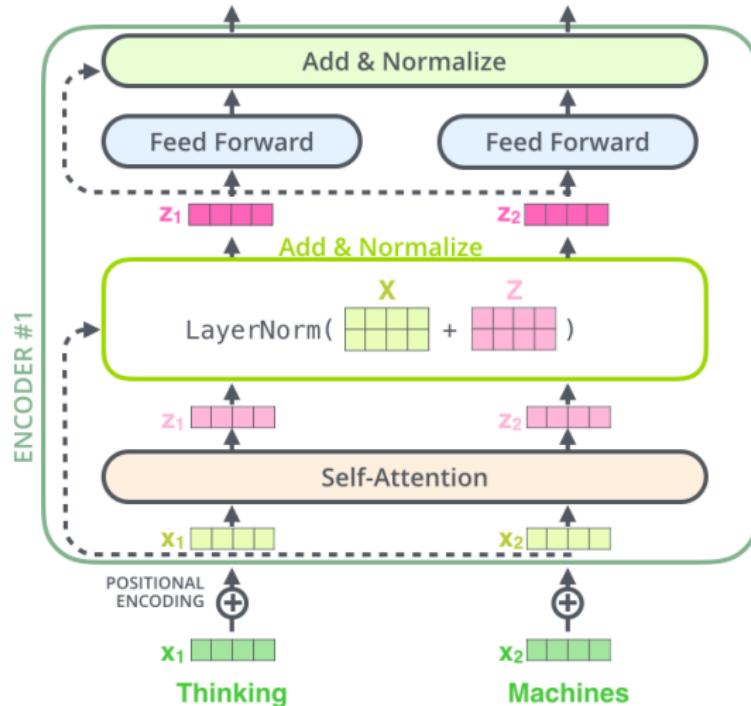


Figure: Add and Normalize (Alammar, 2018)



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Transformer

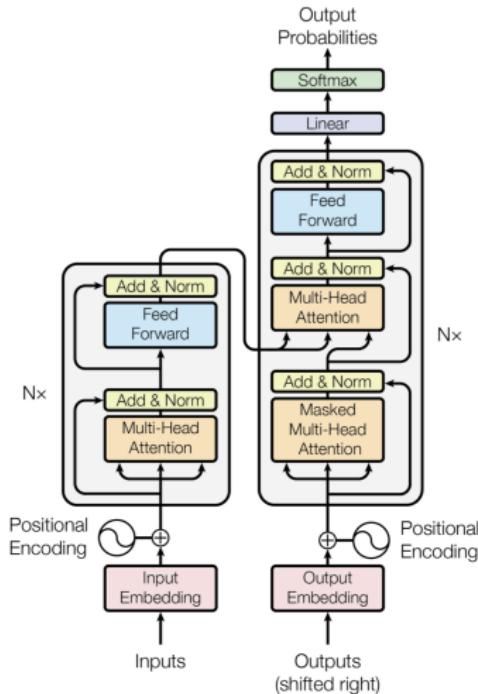


Figure: The Transformer Architecture (Vaswani et al., 2017)



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



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- Bidirectional Encoder Representations from Transformers
- Introduced in 2018/2019 in Devlin et al. (2017)
- **State-of-the-Art** in many text prediction tasks, such as
 - Question-Answering
 - Named-Entity Recognition
 - Text Classification



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- Introduced in 2018/2019 in Devlin et al. (2017)
- **State-of-the-Art** in many text prediction tasks, such as
 - Question-Answering
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 - Text Classification
- Becoming the de facto new standard in industry and NLP



- Practicalities
- Word embeddings
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- Transformers
 - Attention
 - Multi-Head Attention
 - Positional encoding
 - Add and Normalize
- **BERT**
 - Training BERT
 - Using BERT

BERT

- Bidirectional Encoder Representations from Transformers
- Introduced in 2018/2019 in Devlin et al. (2017)
- **State-of-the-Art** in many text prediction tasks, such as
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 - Named-Entity Recognition
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- Many new versions has come out RoBERTa, DistillBERT, ALBERT etc.



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

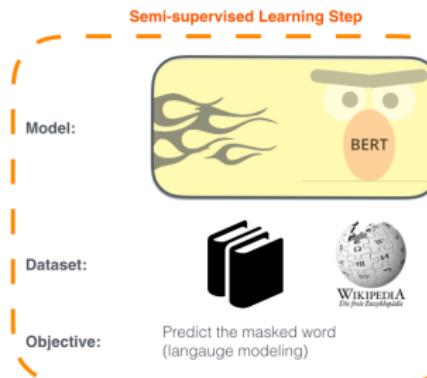


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BERT and transfer learning

1 - Semi-supervised training on large amounts of text (books, wikipedia..etc).

The model is trained on a certain task that enables it to grasp patterns in language. By the end of the training process, BERT has language-processing abilities capable of empowering many models we later need to build and train in a supervised way.



2 - Supervised training on a specific task with a labeled dataset.

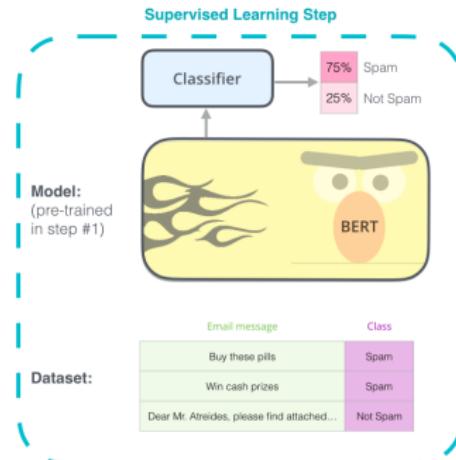


Figure: Using BERT for Transfer Learning (Alammar, 2019)



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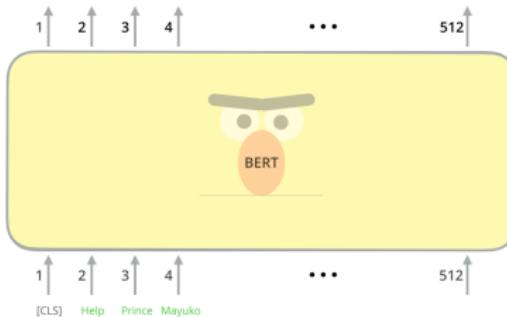


Figure: The BERT model (Alammar, 2019)



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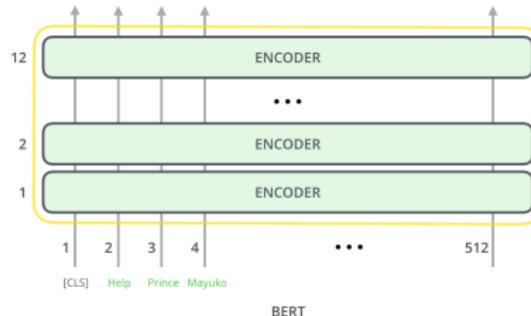


Figure: Opening up BERT (Vaswani et al., 2017)

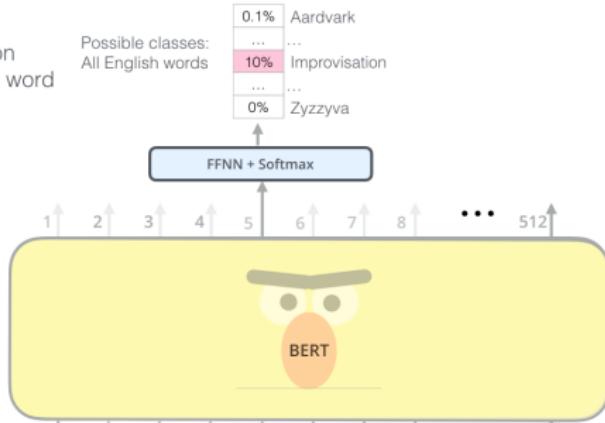


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Task 1: Masked Language Model

Use the output of the masked word's position to predict the masked word

Possible classes:
All English words



Randomly mask 15% of tokens

Input



Figure: Masked Language Modeling (Alammar, 2019)



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Next Sentence Prediction

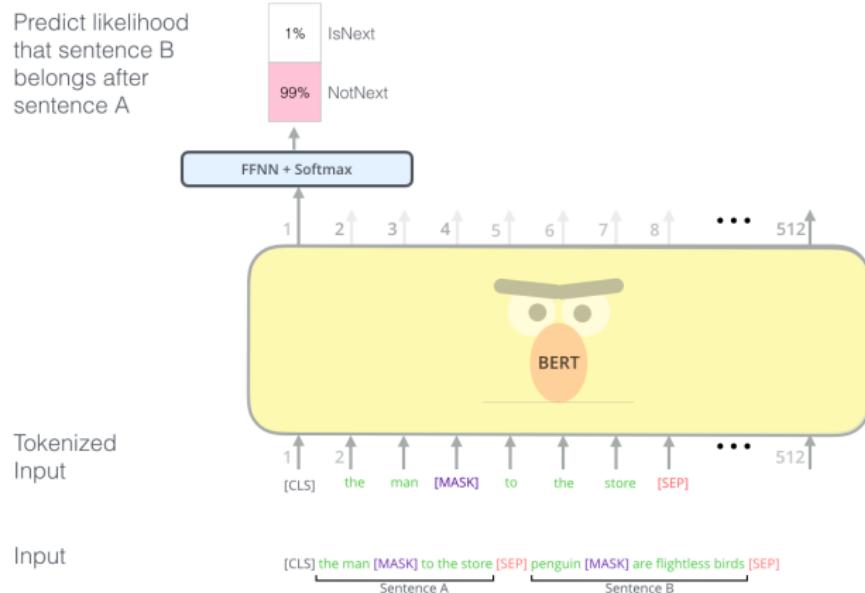


Figure: Next Sentence Prediction (Alammar, 2019)



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Using BERT for Classification

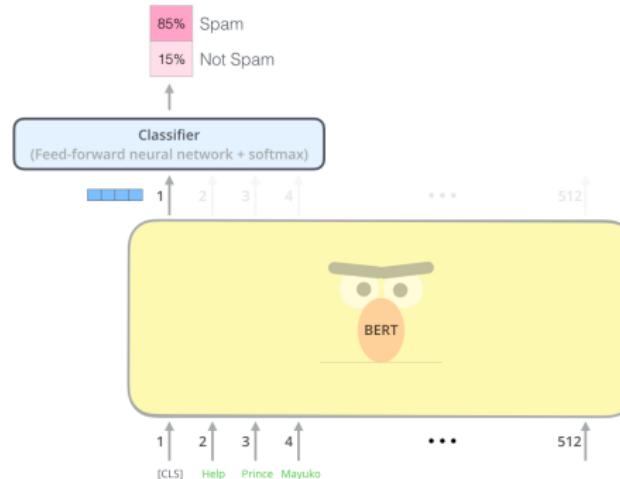


Figure: Using BERT for classification (Alammar, 2019)



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BERT and Contextualized embeddings

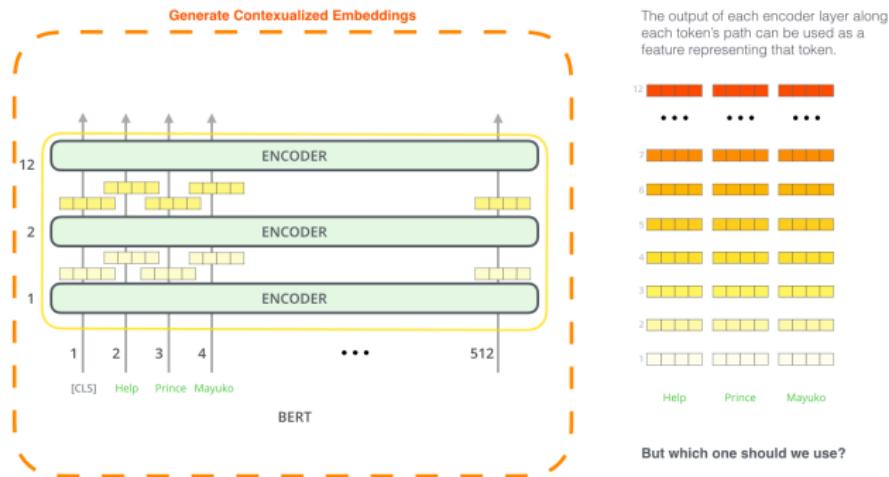


Figure: Contextualized Embeddings (Alammar, 2019)



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Using Contextualized Embeddings

What is the best contextualized embedding for "Help" in that context?
For named-entity recognition task CoNLL-2003 NER

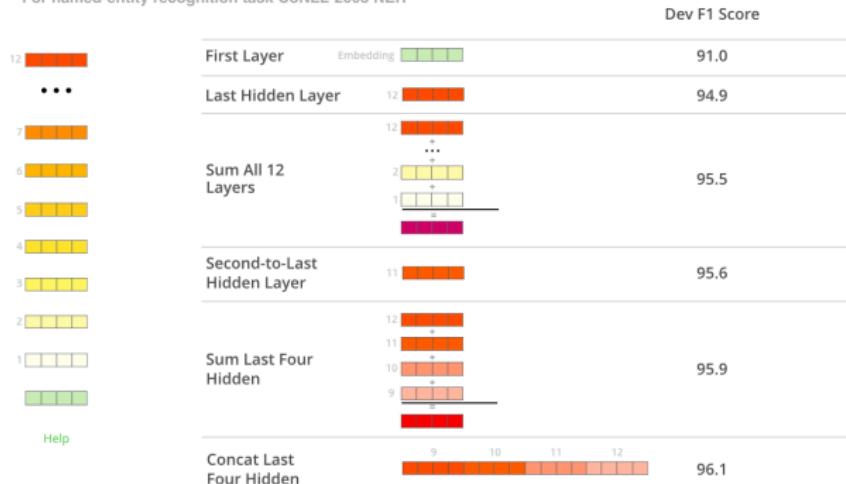


Figure: Using Contextualized Embeddings (Alammar, 2019)