Language Models and Transfer Learning

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Slides adapted from various sources (see reference page)

What is a Language Model

- A statistical language model is a probability distribution over sequences of words
- Given such a sequence, say of length m, it assigns a probability to the whole sequence:

$$P(w_1, \ldots, w_m)$$

- Main problem: data sparsity

[Slide from https://en.wikipedia.org/wiki/Language_model.]

Unigram model: Bag of words

- General probability distribution:

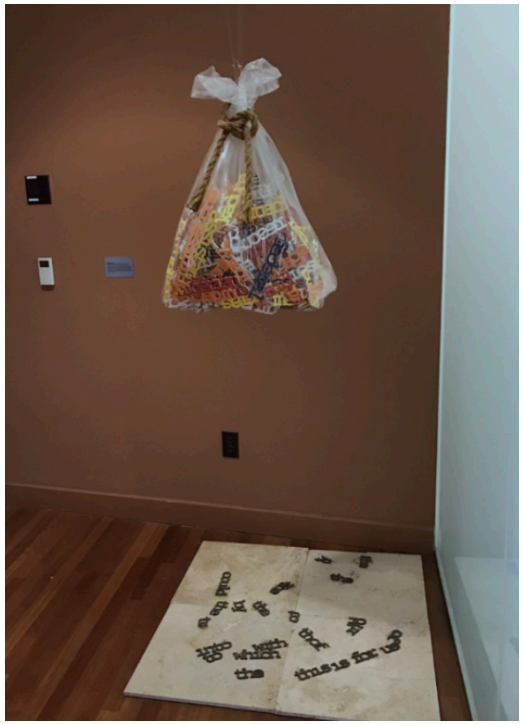
$$P(t_1 t_2 t_3) = P(t_1)P(t_2 \mid t_1)P(t_3 \mid t_1 t_2)$$

- Unigram model assumption:

$$P_{\text{uni}}(t_1 t_2 t_3) = P(t_1)P(t_2)P(t_3)$$

- Essentially, bag of words model
- Estimation of unigram params: count word frequency in the doc

Terms	Probability in doc
a	0.1
world	0.2
likes	0.05
we	0.05
share	0.3
...	...



[Slide from https://en.wikipedia.org/wiki/Language_model.]

n-gram model

- n-gram assumption:

$$P(w_1, \ldots, w_m) = \prod_{i=1}^{m} P(w_i \mid w_1, \ldots, w_{i-1}) \approx \prod_{i=1}^{m} P(w_i \mid w_{i-(n-1)}, \ldots, w_{i-1})$$

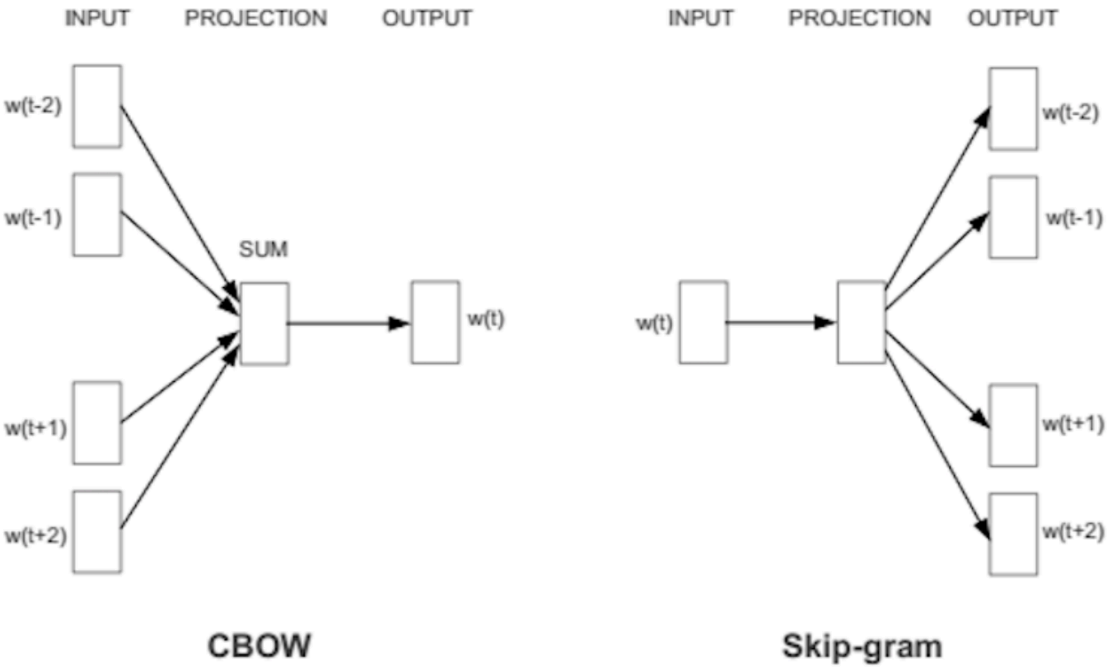
- Estimation of n-gram params:

$$P(w_i \mid w_{i-(n-1)}, \ldots, w_{i-1}) = \frac{\text{count}(w_{i-(n-1)}, \ldots, w_{i-1}, w_i)}{\text{count}(w_{i-(n-1)}, \ldots, w_{i-1})}$$

[Slide from https://en.wikipedia.org/wiki/Language_model.]

Word2Vec

- Word2Vec: Learns distributed representations of words
- Continuous bag-of-words (CBOW)
  - Predicts current word from a window of surrounding context words
- **Continuous skip-gram**
  - Uses current word to predict surrounding window of context words
  - Slower but does a better job for infrequent words

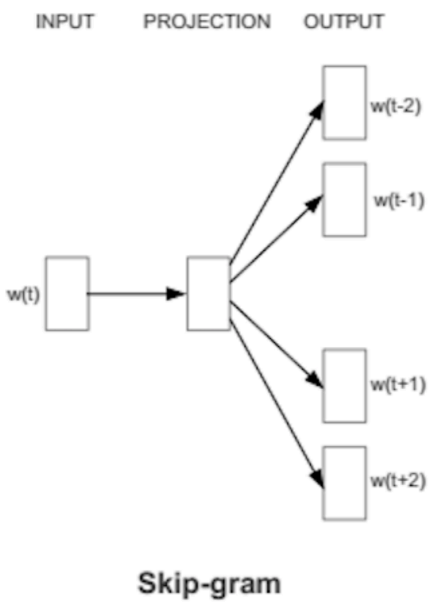


[Slide from https://www.tensorflow.org/tutorials/representation/word2vec.]

Skip-gram Word2Vec

- All words: $\mathcal{G}$
- Parameters of skip-gram word2vec model
  - Word embedding for each word: $\mathcal{E} = \{\mathbf{e}_g \in \mathbb{R}^n\}_{g \in \mathcal{G}}$
  - Context embedding for each word: $\mathcal{V} = \{\mathbf{v}_g \in \mathbb{R}^n\}_{g \in \mathcal{G}}$
- Assumption:

$$\Pr\left(c \in \text{Context}(g) \mid g\right) = \frac{\exp\left(\mathbf{e}_g^\intercal \mathbf{v}_c\right)}{\sum_{c' \in \mathcal{G}} \exp\left(\mathbf{e}_g^\intercal \mathbf{v}_{c'}\right)}$$

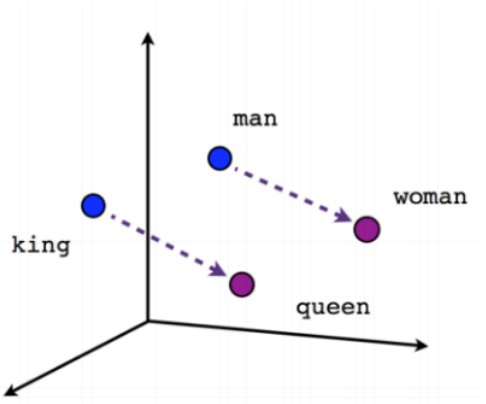


Skip-gram

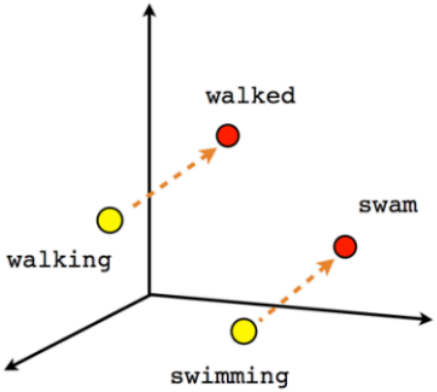
[Slide from https://www.tensorflow.org/tutorials/representation/word2vec.]

Distributed Representations of Words

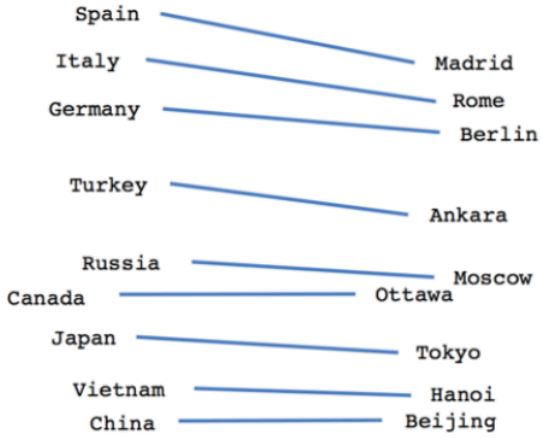
- The trained parameters of words in skip-gram word2vec model
- Semantics and embedding space



Male-Female



Verb tense

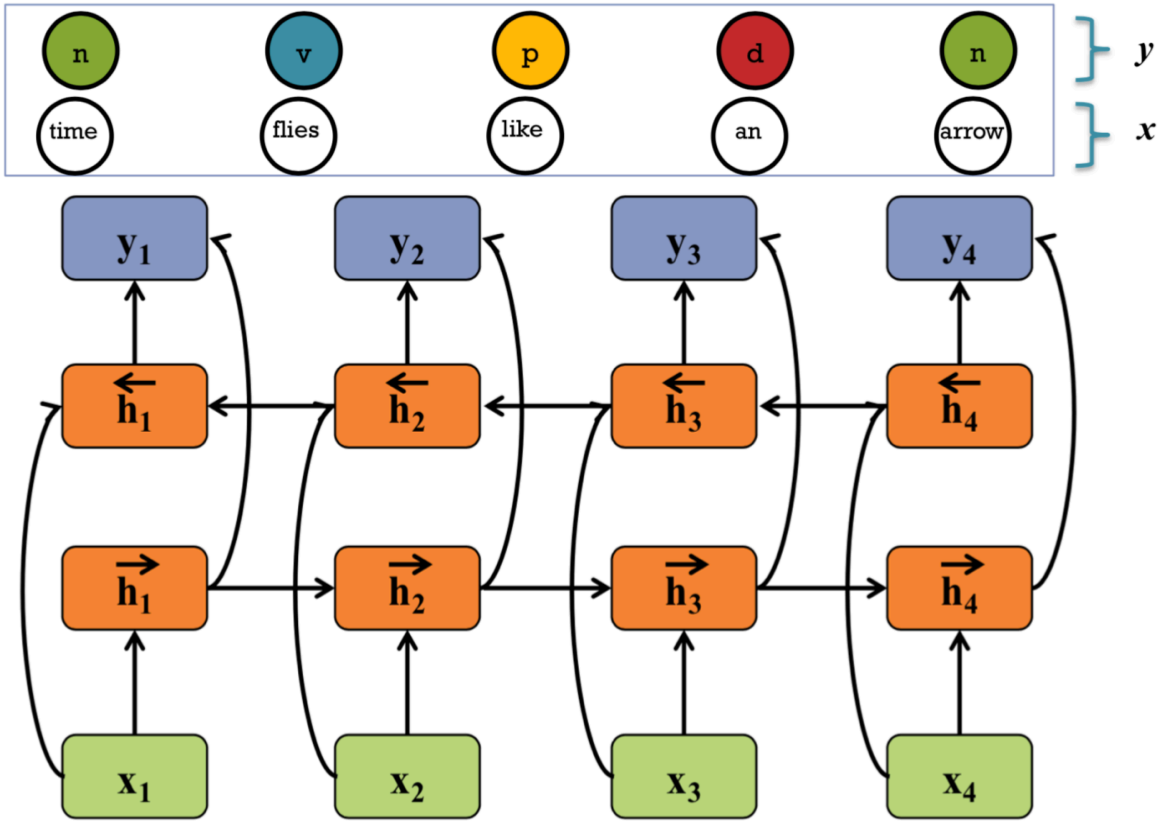


Country-Capital

[Slide from https://www.tensorflow.org/tutorials/representation/word2vec.]

Word Embeddings in Transfer Learning

- Transfer learning:
  - Labeled data are limited
  - Unlabeled text corpus enormous
  - Pretrained word embeddings can be transferred to other supervised tasks. E.g., POS, NER, QA, MT, Sentiment classification



[Slide from Matt Gormley.]

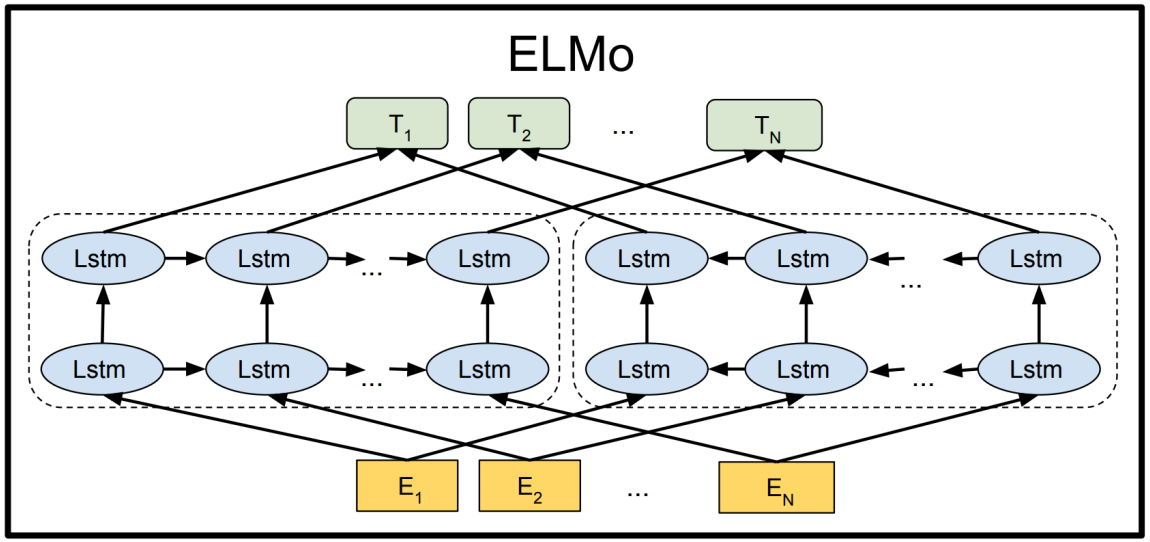
SOTA Language Models: ELMo

- Embeddings from Language Models: ELMo
  - Fits full conditional probability in forward direction:

$$p(t_1, t_2, \ldots, t_N) = \prod_{k=1}^{N} p(t_k \mid t_1, t_2, \ldots, t_{k-1}).$$

  - Fits full conditional probability in both directions using LSTM:

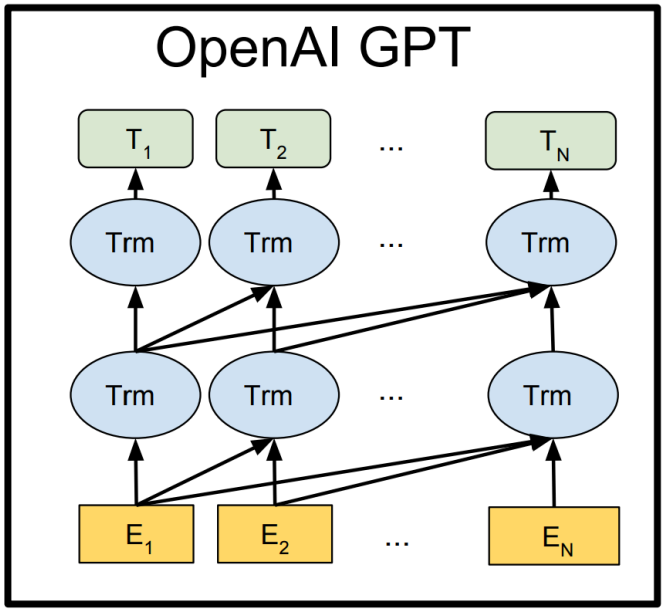
$$\sum_{k=1}^{N} (\log p(t_k \mid t_1, \ldots, t_{k-1}; \Theta_x, \overrightarrow{\Theta}_{LSTM}, \Theta_s) + \log p(t_k \mid t_{k+1}, \ldots, t_N; \Theta_x, \overleftarrow{\Theta}_{LSTM}, \Theta_s))$$

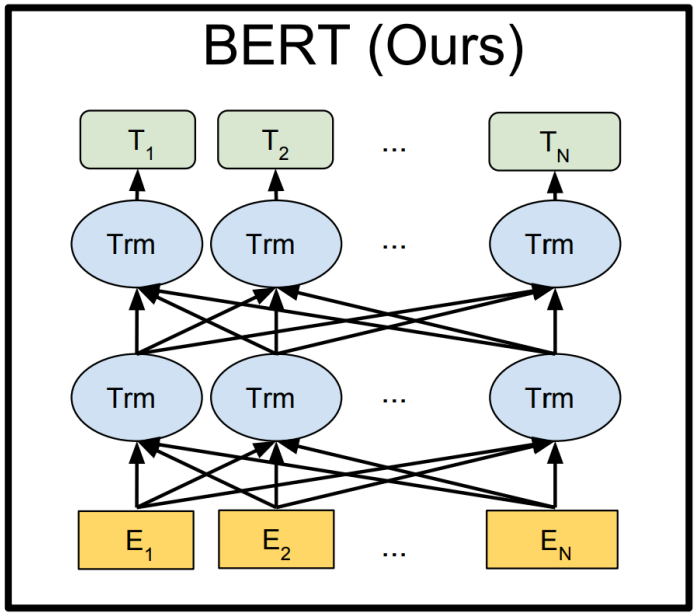


[Slide from https://arxiv.org/pdf/1802.05365.pdf and https://arxiv.org/abs/1810.04805.]

SOTA Language Models: OpenAI GPT & BERT

- Uses transformer other than LSTM to model language
  - OpenAI GPT: single direction
  - BERT: bi-direction

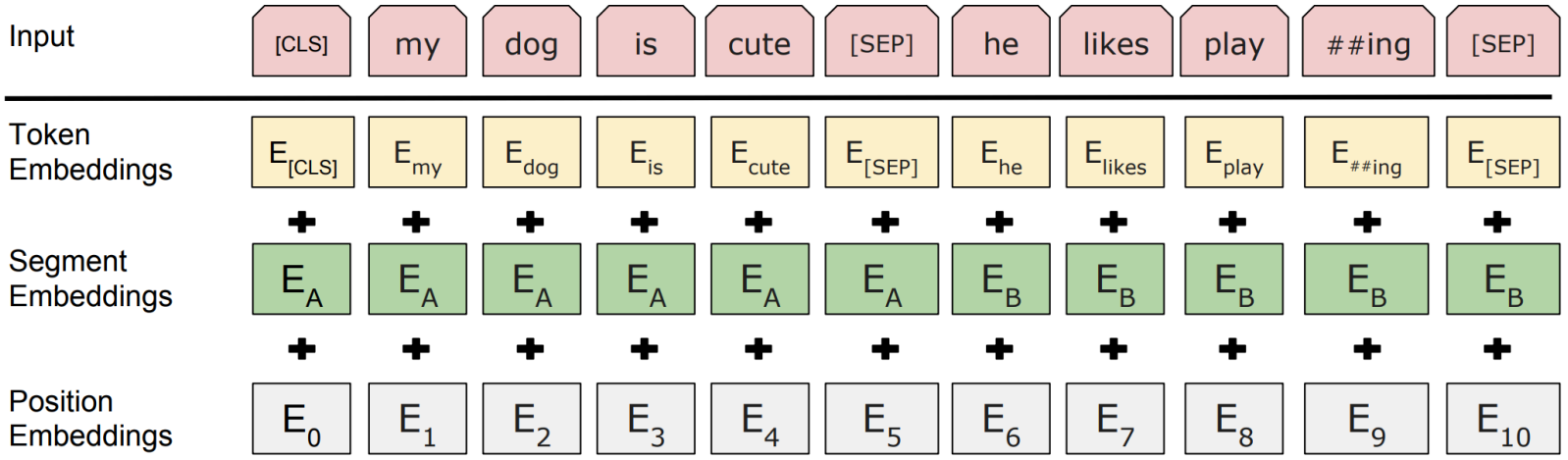




[Slide from https://arxiv.org/abs/1810.04805.]

SOTA Language Models: BERT

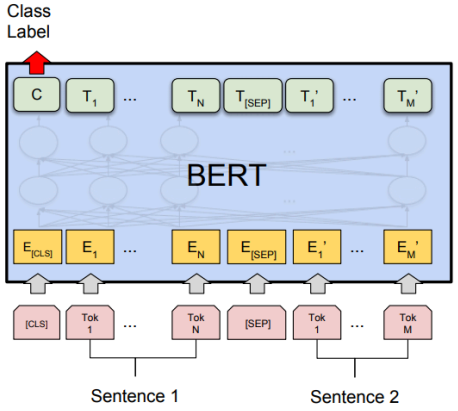
- Additional language modeling task: predict whether sentences come from same paragraph.



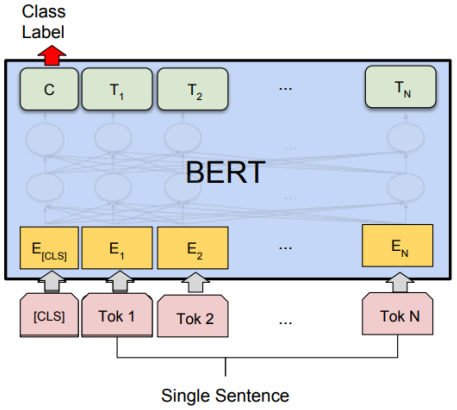
[Slide from https://arxiv.org/abs/1810.04805.]

SOTA Language Models: BERT

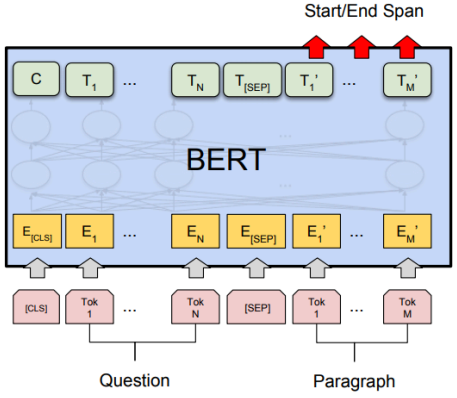
- Instead of extract embeddings and hidden layer outputs, can be fine-tuned to specific supervised learning tasks.



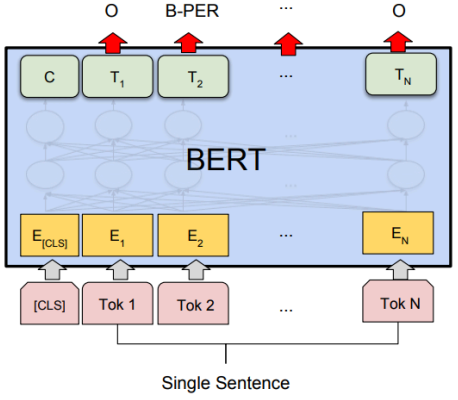
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



(b) Single Sentence Classification Tasks: SST-2, CoLA



(c) Question Answering Tasks: SQuAD v1.1

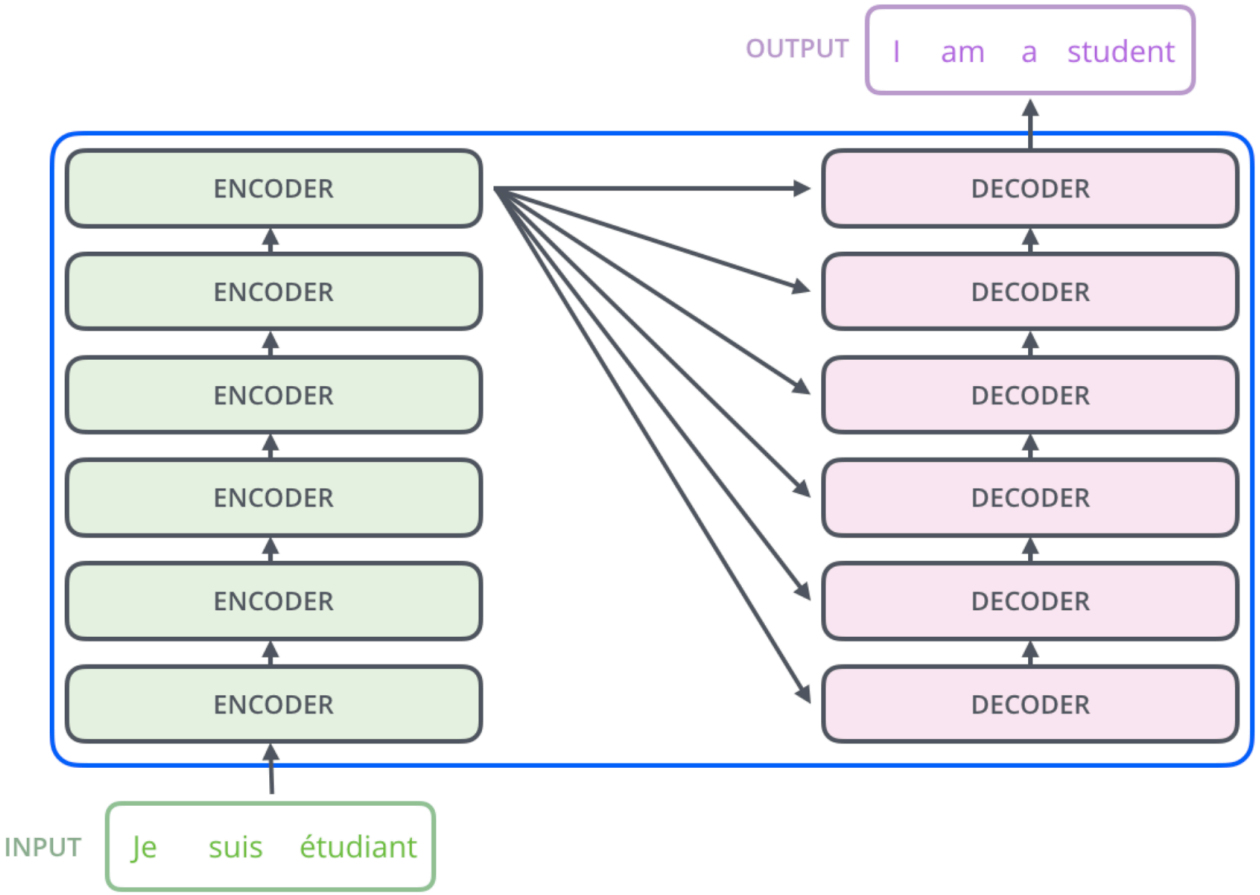


(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

[Slide from https://arxiv.org/abs/1810.04805.]

The Transformer and Attention Mechanism

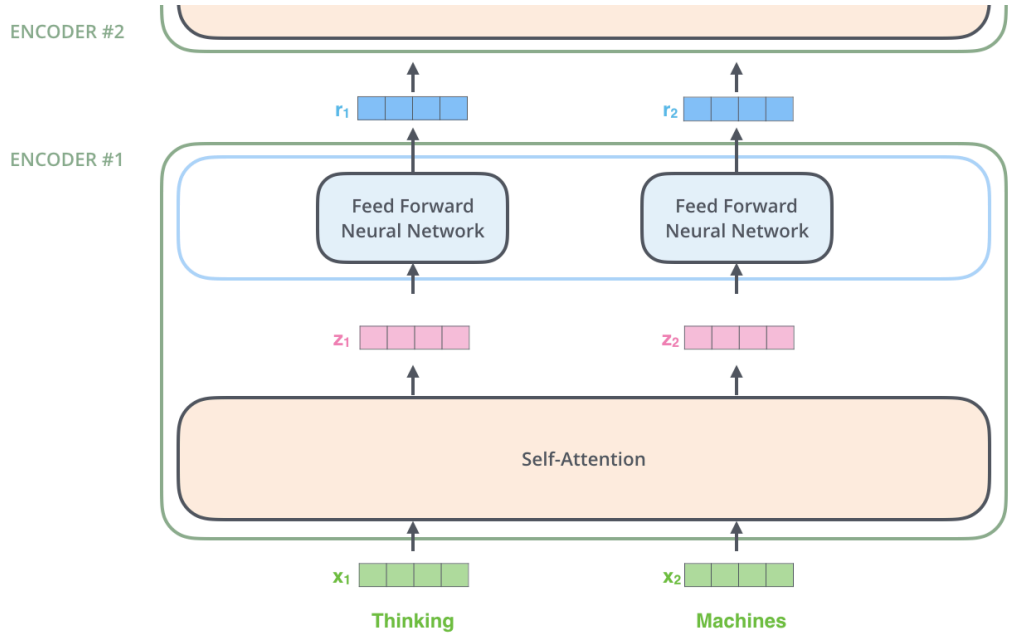
- An encoder-decoder structure
- Our focus: encoder and attention mechanism

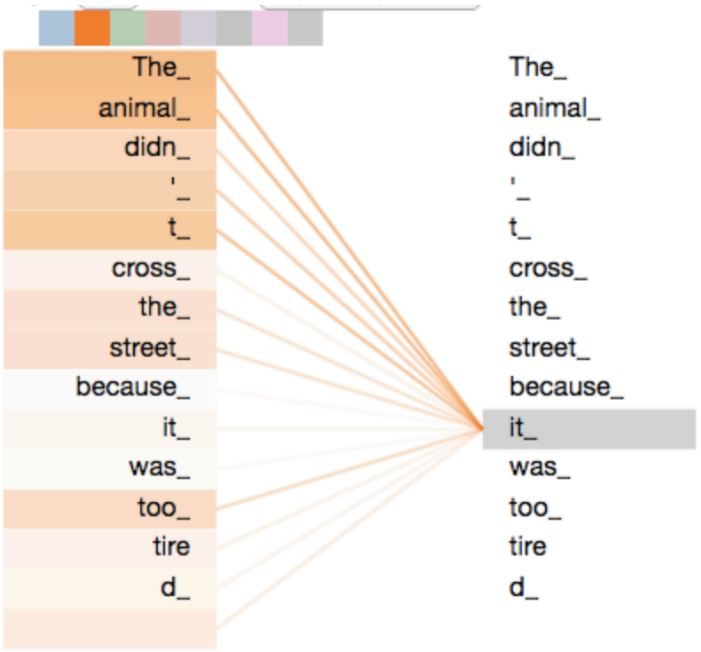


[Slide from https://jalammar.github.io/illustrated-transformer/.]

The Transformer and Attention Mechanism

- Self-attention
  - Ignores positions of words, assign weights globally.
  - Can be parallelized, in contrast to LSTM.
- E.g., the attention weights related to word “it_”:





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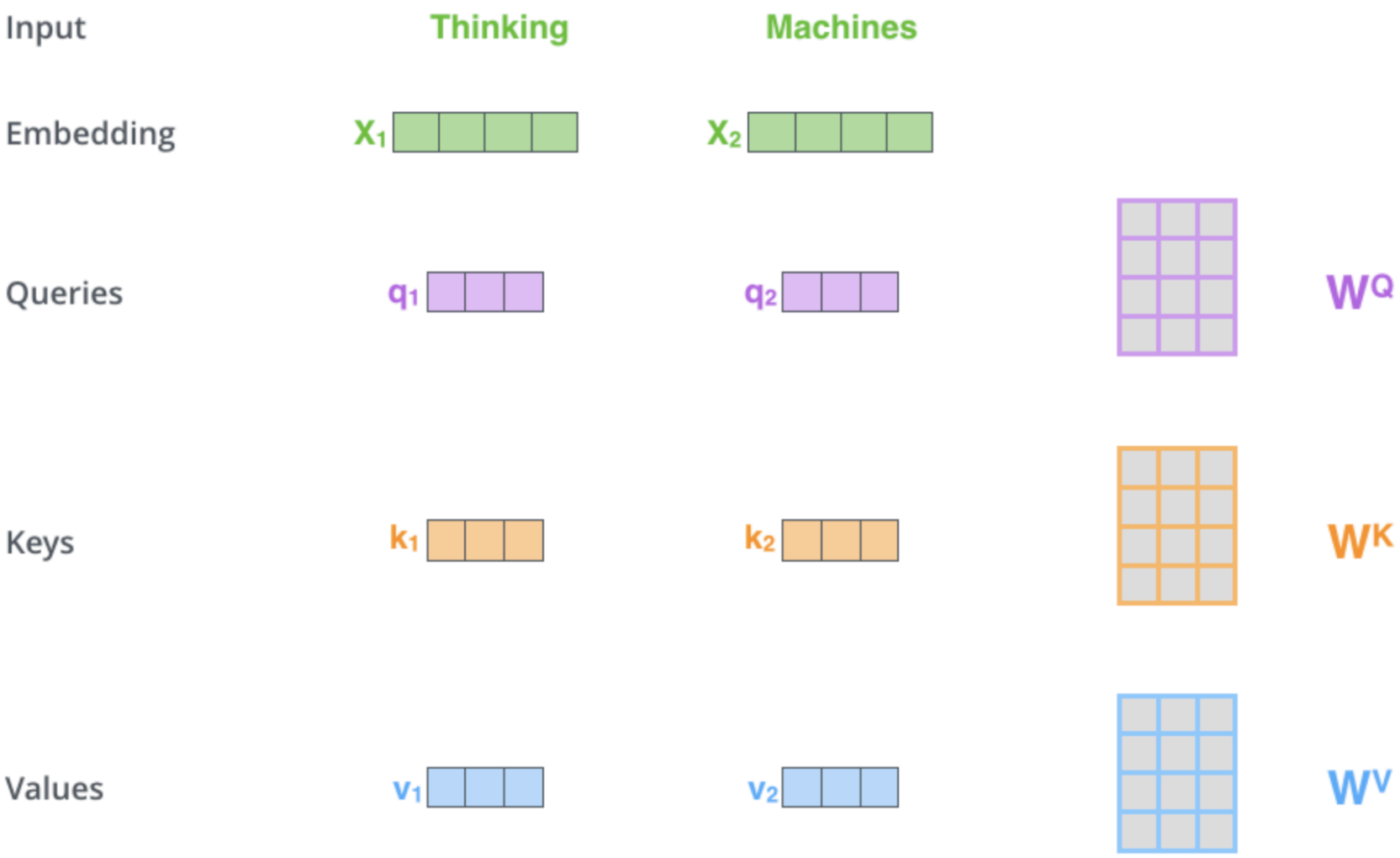
Self-attention Mechanism



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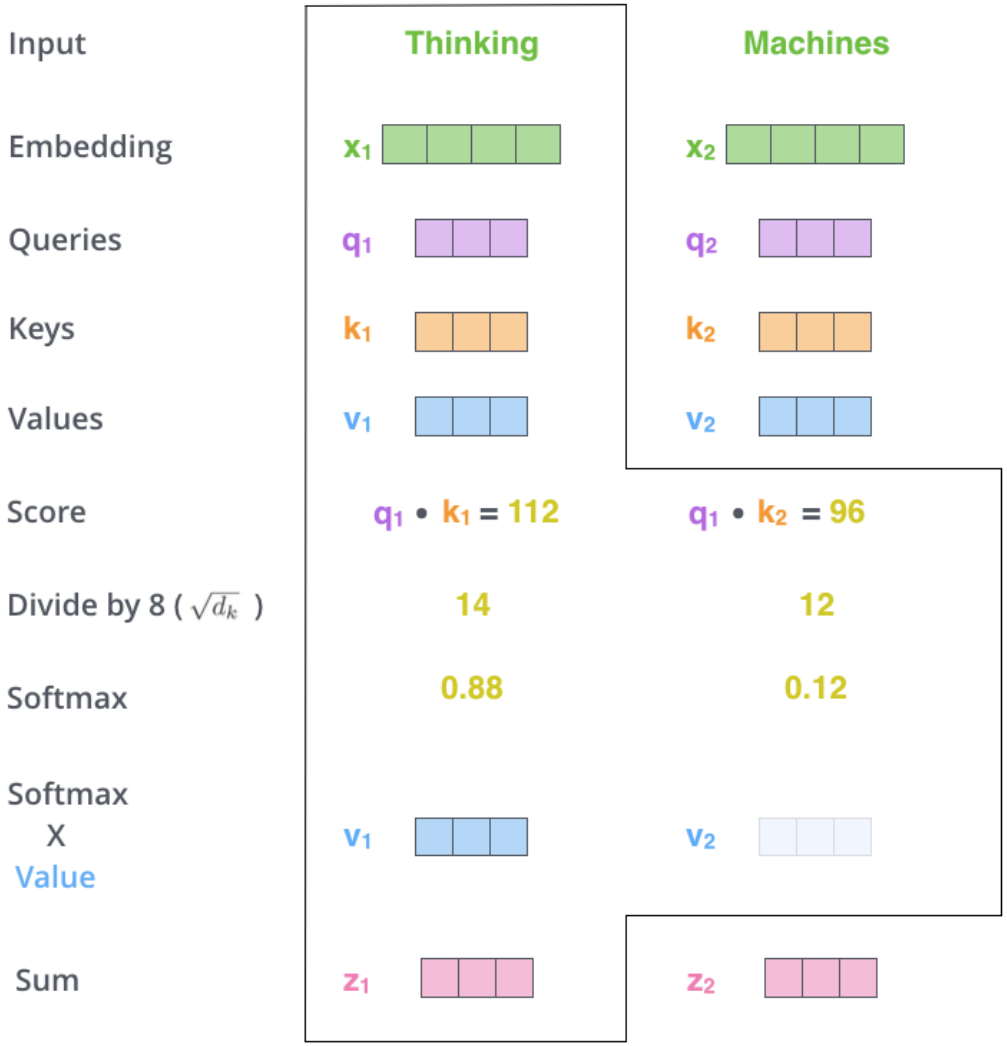
Self-attention Mechanism



- More…
- https://jalammar.github.io/illustrated-transformer/

[Slide from https://jalammar.github.io/illustrated-transformer/.]

Take home message

- Language models suffer from data sparsity
- Word2vec portrays language probability using distributed word embedding parameters
- ELMo, OpenAI GPT, BERT model language using deep neural networks
- Pre-trained language models or their parameters can be transferred to supervised learning problems in NLP
- Self-attention has the advantage over LSTM that it can be parallelized and consider interactions across the whole sentence

References

- Wikipedia: https://en.wikipedia.org/wiki/Language_model
- Tensorflow. Vector Representations of Words: https://www.tensorflow.org/tutorials/representation/word2vec
- Matt Gormley. 10601 Introduction to Machine Learning: http://www.cs.cmu.edu/~mgormley/courses/10601/index.html
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- Jay Alammar. The Illustrated Transformer: https://jalammar.github.io/illustrated-transformer/