Semantic search and similarity ranking

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LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN

Plan

Part 1: Semantic search
- Introduction
- Ontology matching

Part 2: Similarity ranking
- Word vectors
- Contextualized word embeddings
- ELMo
- BERT
- Flair

Part 3: Experiments
- A
- A

Part 4: Conclusion

1.1. Introduction

- **Lexical** search: literal matches of the query words.
  - Anthony Hopkins age → good
  - How old is Anthony Hopkins? → bad
- **Semantic** search: search with meaning, understand the query and the intention of the user
  - Why is my laptop overheating?
  - Why do bees follow me?
  - How many continents are there in the world?
    - Correct answer: 6

1.2. Ontology matching

The search engine has a huge knowledge graph / ontology with past searches, a representation of semantic relations between documents.

Pipeline:

1. New query arrives
2. Query broken into root terms: POS tagging removal, NER, error correction, conversion to embeddings, etc
3. Return the closest/more relevant/semantically most similar documents from the ontology (similarity ranking)

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2.1. Word vectors: history

"A word is characterized by the company it keeps" – Firth, 1958

How to quantify and categorize semantic similarities between linguistic items based on their distributional properties?

- 1980s, LSA: reduce the number of dimensions using singular value decomposition
- 2000, Bengio et al.: reduce the high dimensionality of words representations in contexts by learning a distributed representation for words
- 2013, Mikolov et al., word2vec: word embedding toolkit to train word vectors in NNs, faster than n-gram models
- Pre-trained word embeddings became the norm (word2vec, GloVe, FastText) as input to NNs

2.2. Contextualized word embeddings

- Word embeddings: each word gets an embedding vector
- Irrelevant of the context, part of speech, polysemy

- 2017, Peters et al.: **TagLM**: give the words an embedding vector based on its context, in order to:
  - capture word meaning in that context
  - capture other contextual information

Semi-supervised sequence tagging with bidirectional language models, Peters et al., 2017

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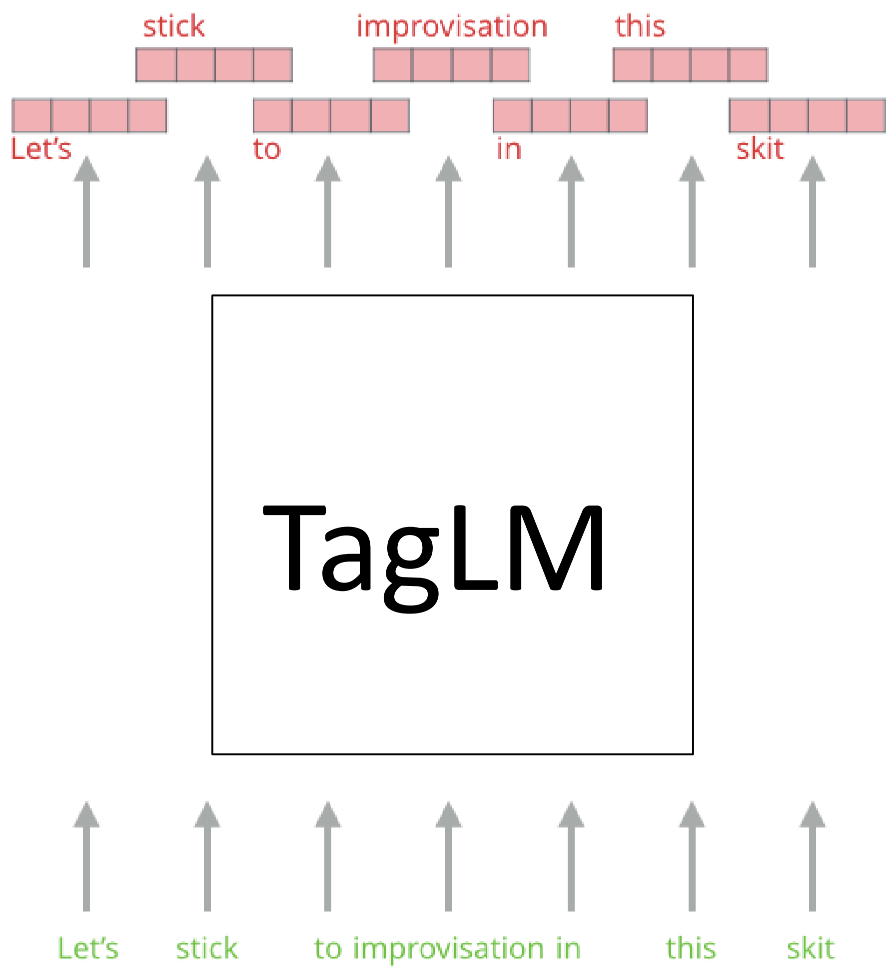

[Semi-supervised sequence tagging with bidirectional language models](), Peters et al., 2017

2.3. TagLM (April 2017)

Formally described as: **semi-supervised** approach to add contextual embeddings to word embeddings from **bidirectional language models**

- **Language model** (LM): computes the probability of a token given a token sequence.
- Uses LSTM architecture, produces LM embeddings
  - Forward LM: Given the previous token sequence in a sentence, predict next token
  - Backward LM: Given the future token sequence, predict previous token
  - Bidirectional LM: forwLM and backLM trained separatedly and then concatenated to form the biLM embeddings
- **Semi-supervised** approach:
  - the biLM is trained on a large unlabelled corpus
  - the biLM embeddings are added as additional input to the NLP task

Semi-supervised sequence tagging with bidirectional language models, Peters et al., 2017

2.3. TagLM: paper remarks

- Applied to sequence labelling tasks: assigning a categorical label to each member of a sequence of words.
- Using both forwLM and backLM embeddings boosts performance over forwLM embeddings
- Transfer learning: the biLM embeddings trained in one domain can be transferred to another
- Inputs to **TagLM**:
  - Character representation model, CNN or RNN
  - Token embeddings, initialized using pre-trained word embeddings
  - Recurrent LM: LSTM model with multiple layers
- Output from **TagLM**: a single context-independent representation for each word, **the output layer of the LSTM**.

Semi-supervised sequence tagging with bidirectional language models, Peters et al., 2017

2.3. ELMo (February 2018)

- Why just the last layer of the LSTM? Use all layers

Deep contextualized word representations, Peters et al., 2018

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Deep contextualized word representations, Peters et al., 2018

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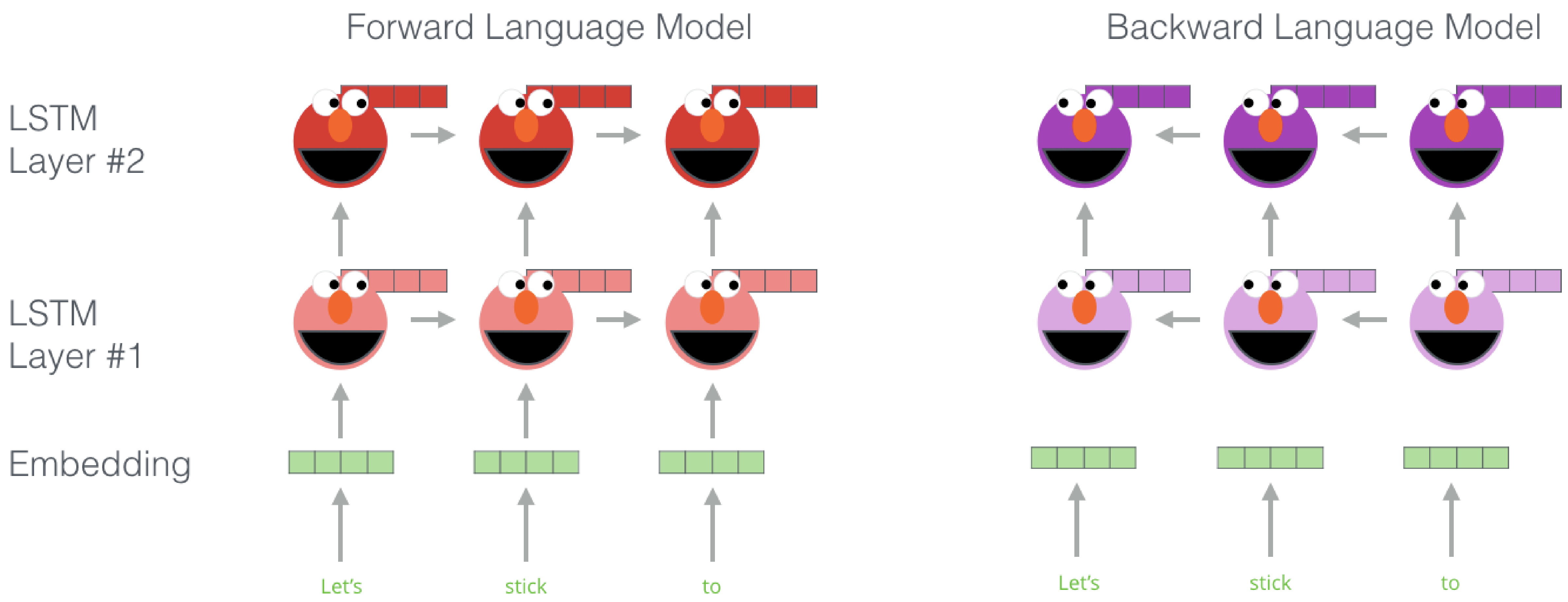
- Higher-level layers of the LSTM capture context-dependent aspects of word meaning
- Lower-level layers of the LSTM capture aspects of syntax and can be used for POS tagging
- ELMo is a **feature-based approach** for contextual embeddings: task-specific architectures that include the pre-trained representations as additional features
  - different architectures for different NLP tasks
  - The embeddings are added as additional inputs to the NLP task

Deep contextualized word representations, Peters et al., 2018

Embedding of ‘stick’ in ‘Let’s stick to’: step #1

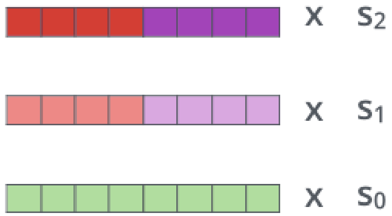


[The Illustrated BERT, ELMo, and co.,](#) Jay Alammar, 2018

Embedding of ‘stick’ in ‘Let’s stick to’: step #2

1- Concatenate hidden layers

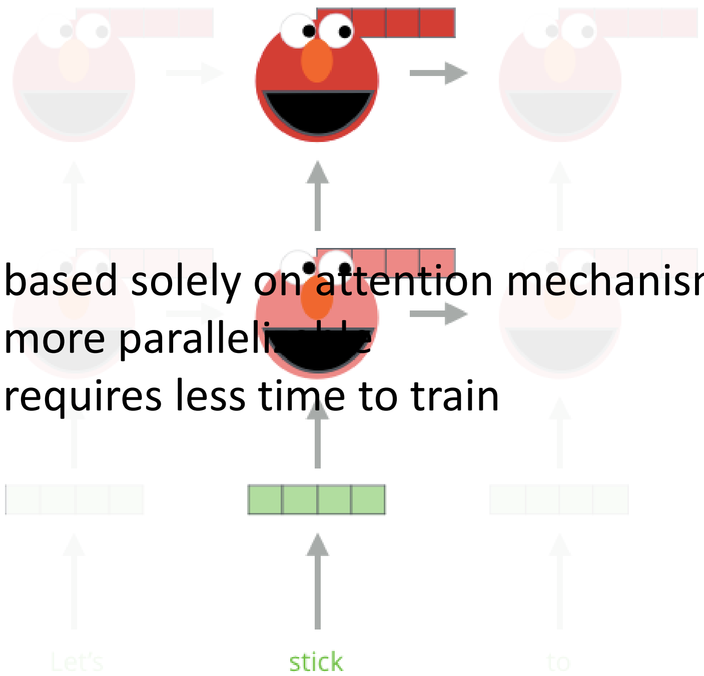
2- Multiply each vector by a weight based on the task



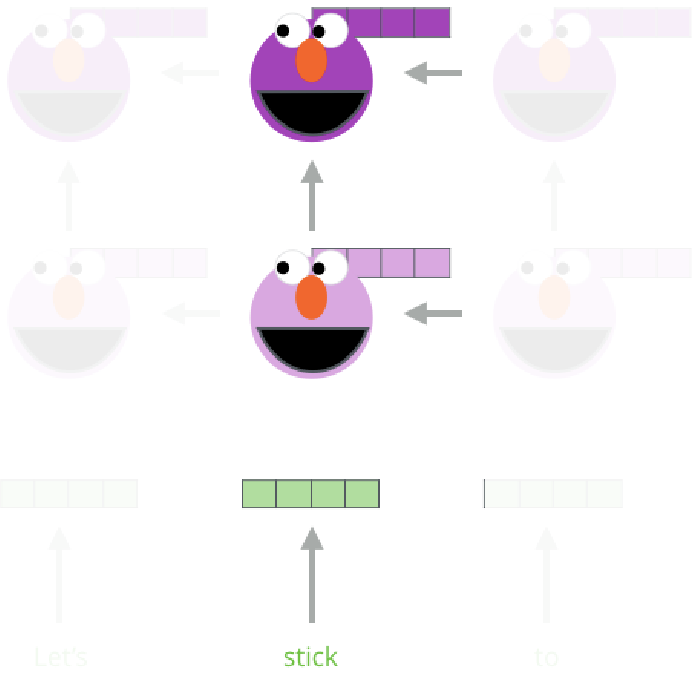
3- Sum the (now weighted) vectors

ELMo embedding of “stick” for this task in this context

Forward Language Model



Backward Language Model



based solely on attention mechanisms
more paralleli
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The Illustrated BERT, ELMo, and co., Jay Alammar, 2018

2.4. The transformer (june 2017) vs LSTM

- Recurrent, sequential models can't parallelize, which become critical at longer sequence lengths
- The transformer:
  - No sequence, based solely on attention mechanisms
  - Deals with long-term dependencies better than LSTMs
  - More parallelizable
  - Requires less time to train
  - first transduction model relying entirely on **self-attention** to compute representations of its input and output without using sequence-aligned RNNs or convolutions

Attention Is All You Need, Vaswani et al., 2018
The illustrated Transformer, Jay Alammar, 2018

2.4. BERT

Expectation

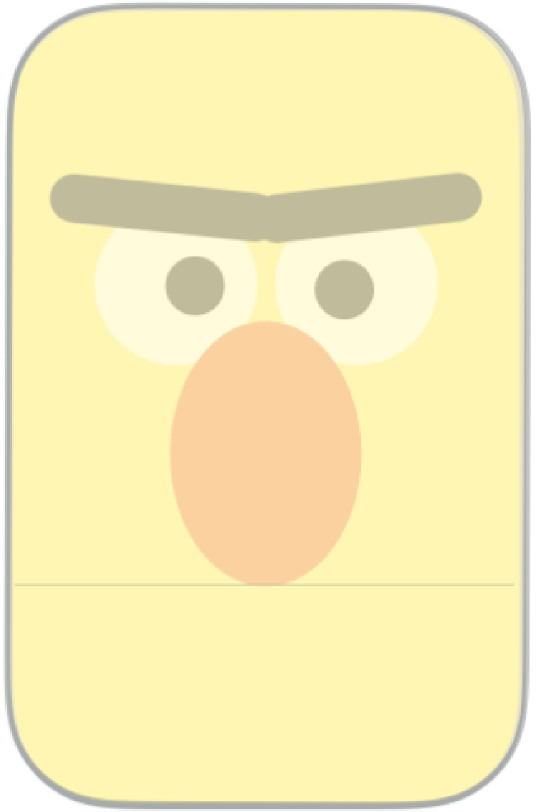
2.4. BERT

Expectation

Reality

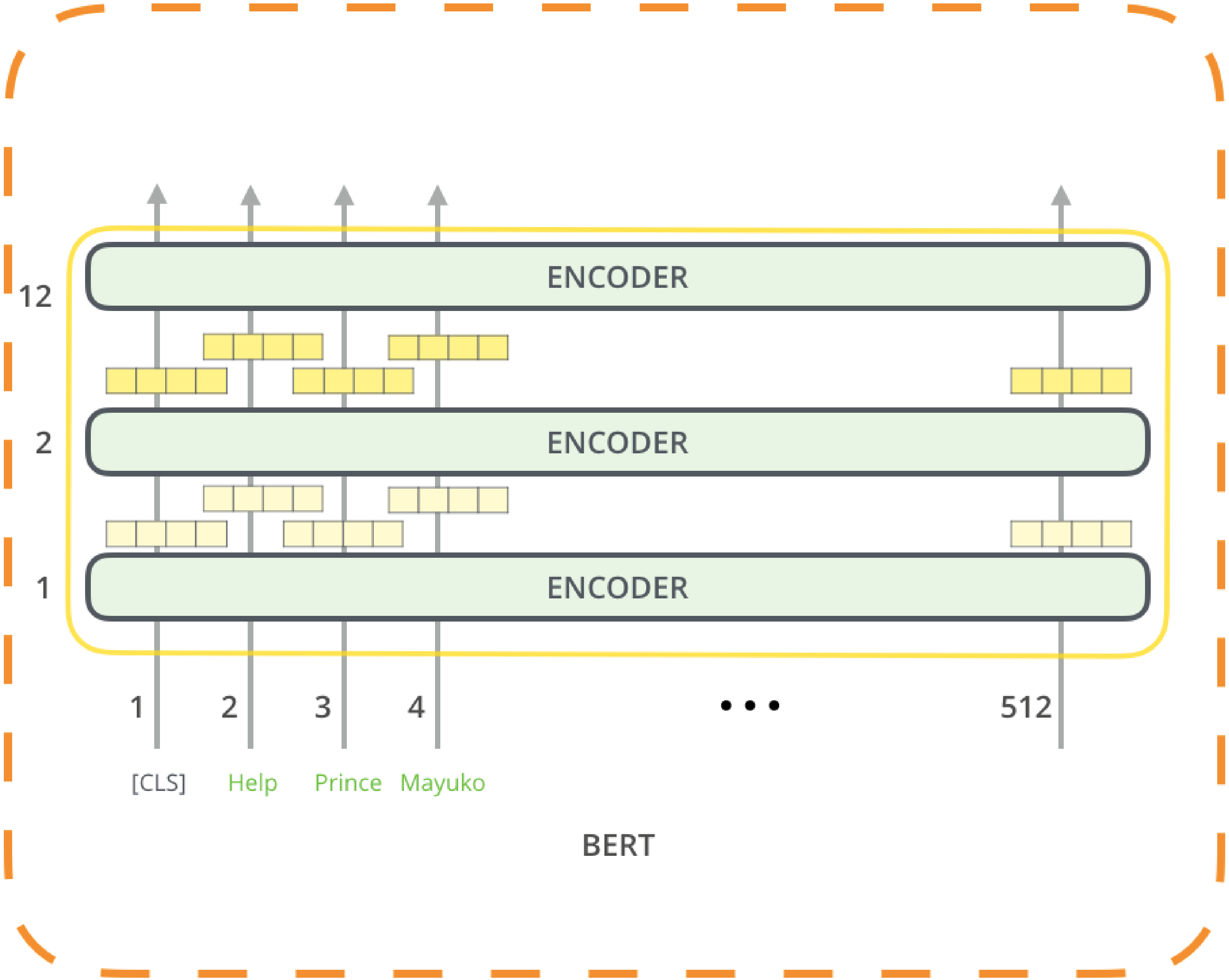
2.4. BERT: Bidirectional Embedding Representations from Transformers (October 2018)

- BERT pretrains deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers. (unlike ELMo)
  - ELMo uses shallow concatenation of independently trained forward and backward LMs
- BERT is fine-tuned: minimal task-specific parameters. trained on NLP tasks by simply fine-tuning **all** pre-trained parameters end-to-end. Compared to pre-training, fine-tuning is relatively inexpensive
- BERT uses a masked LM, randomly masking some tokens in the sentence and training to predict the masked token. MLM enables the representation to fuse the left and right context
- **Pre-trained BERT can be used to create contextualized word embeddings**

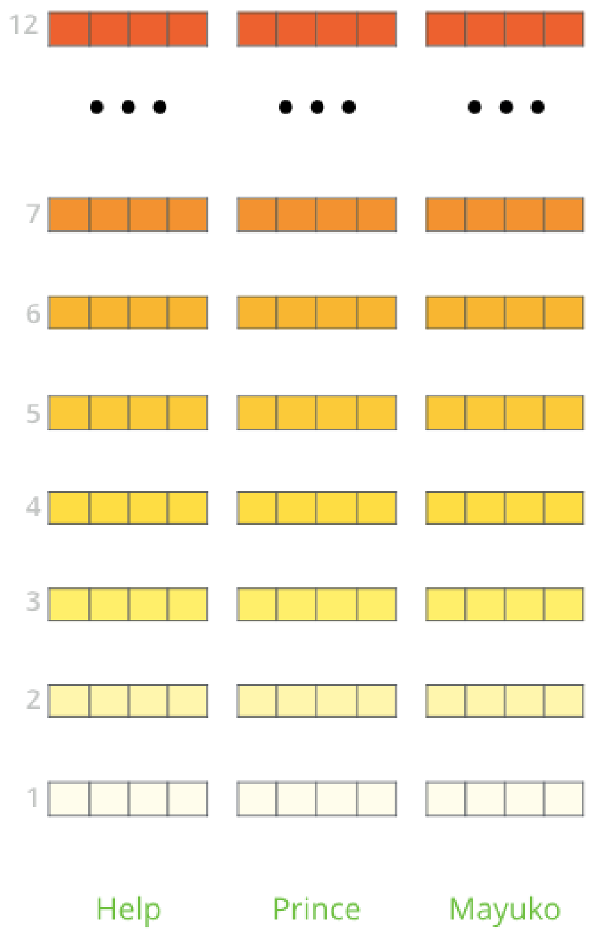


BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, Devlin et al., 2018
The Illustrated BERT, ELMo, and co., Jay Alammar, 2018

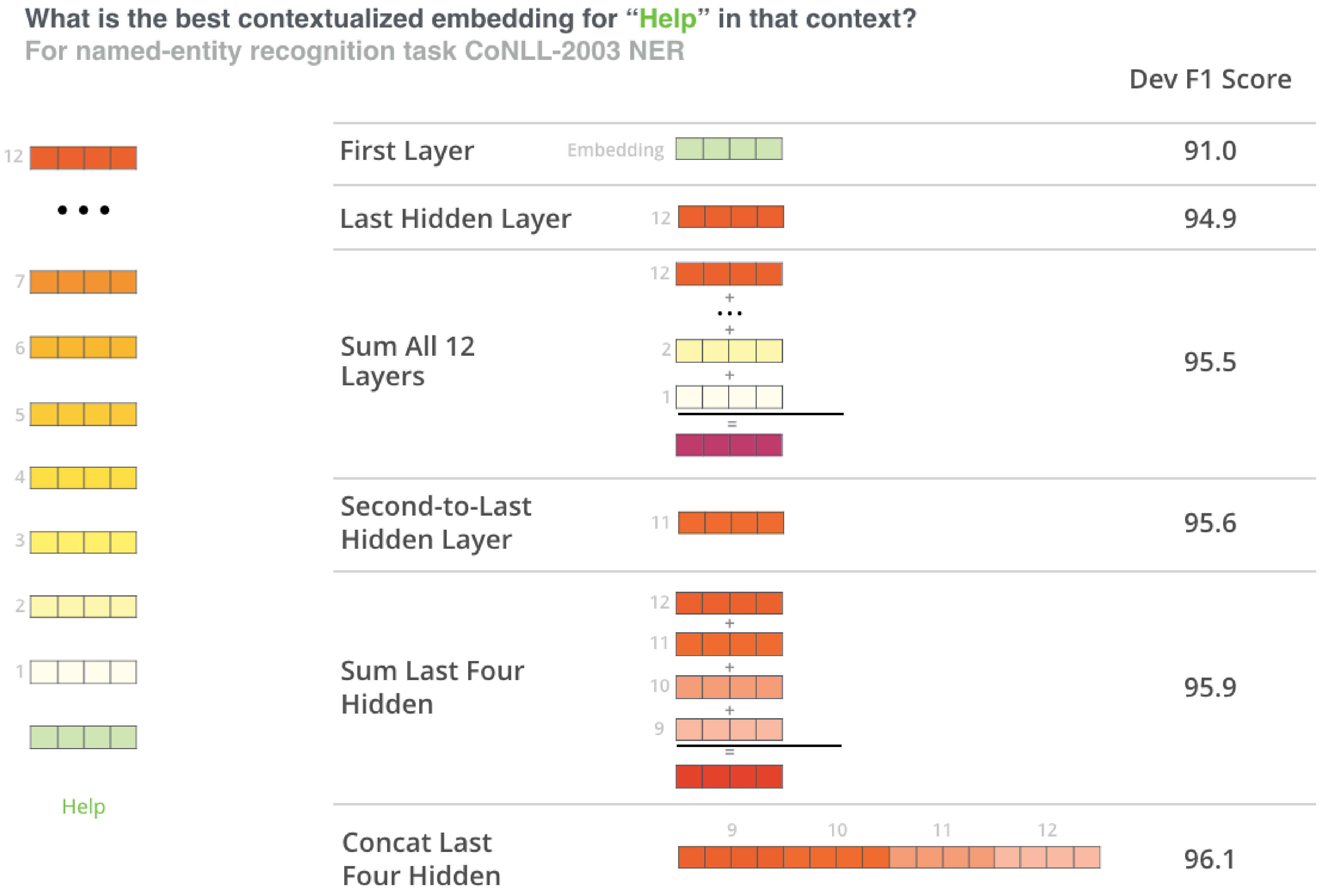
Generate Contexualized Embeddings



The output of each encoder layer along each token's path can be used as a feature representing that token.



But which one should we use?



The layer(s) to use depend on the NLP task

Some tasks look at similarities between sentences, others care more about syntax and POS tagging

2.5. flair

- (didn't read paper yet)

Contextual String Embeddings for Sequence Labeling, Akbik et al., 2018

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3.1. Experiments

- *Awesome explanation about the results*

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4. Conclusion

- *Awesome conclusion*

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