Semantic search and similarity ranking

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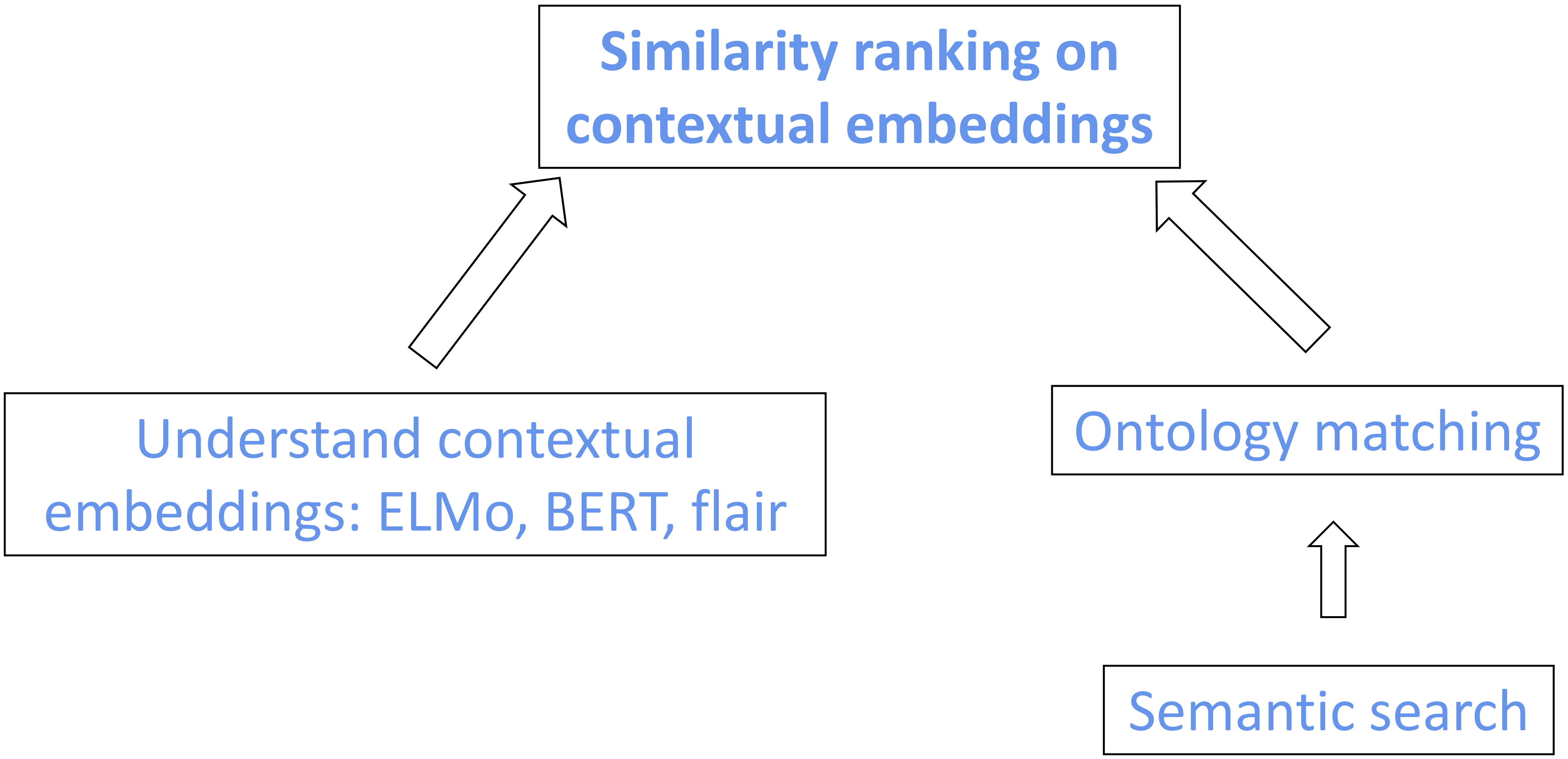
Similarity ranking on contextual embeddings
Understand contextual embeddings: ELMo, BERT, flair
Ontology matching
Semantic search

Why is this interesting?

- Contextual embeddings have achieved unprecedented results in many tasks
- But what are they, how do they work, how do they represent language?
- Do they follow (my) intuition on sentence similarity?
    - A invited B for lunch vs.
    - A did not invite B for lunch vs.
    - B invited A for lunch

Plan

Part 1: Semantic search

- Ontology matching

Part 2: Contextualized word embeddings

- ELMo
- BERT
- Flair

Part 3: Experiments

- Word order
- Lexical similarity
- Synonyms
- Out of vocab words

Part 4: Conclusion

1. Semantic search

- **Lexical** search: literal matches of the query words
  - Anthony Hopkins age → relevant results
  - How old is Anthony Hopkins? → not relevant results
- **Semantic** search: search with meaning, understand the intention of the user
  - Why is my laptop overheating?
  - How many continents are there in the world?

1.1. Ontology matching

The search engine has a huge knowledge graph / ontology with past searches

- Ontology: a representation of semantic relations between documents.

Pipeline:

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

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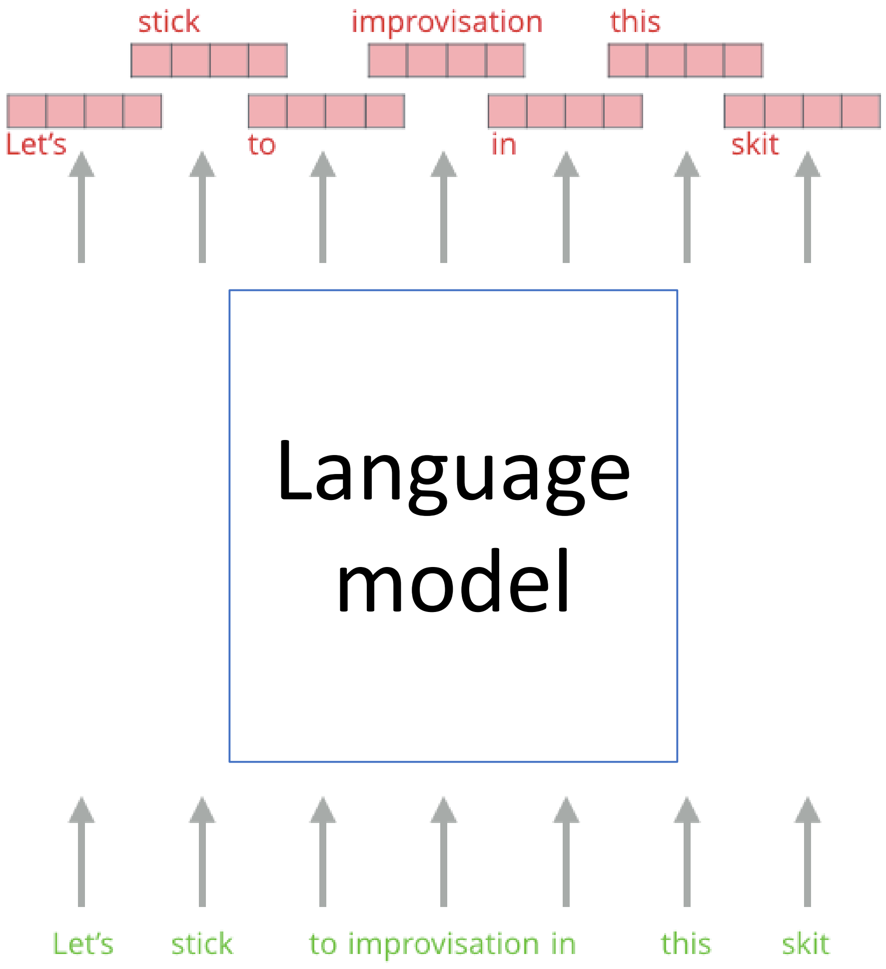
2. Contextualized word embeddings



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

2. Contextualized word embeddings

- **ELMo**: Embeddings from language models
- Approach to add contextual embeddings to word embeddings from **bidirectional language models**
  - LSTM used as LM
  - Using fLM + bLM has better performance than just fLM
  - The two LMs are trained separately but share some weights

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  - LSTM used as LM
  - Using fLM + bLM has better performance than just fLM
  - The two LMs are trained separately but share some weights
- Input for **ELMo**: sequences of words
- Output from **ELMo**: a single **context-sensitive** representation for each word

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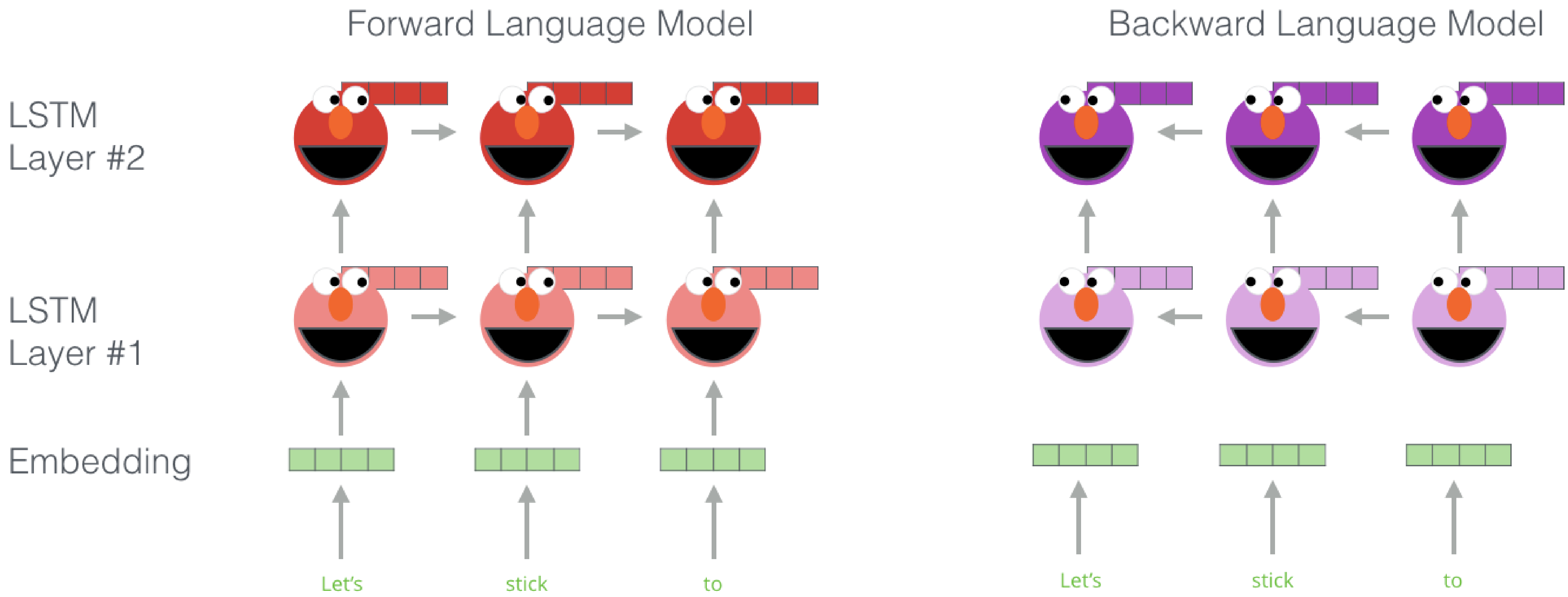
Embedding of ‘stick’ in ‘Let’s stick to’: step #1

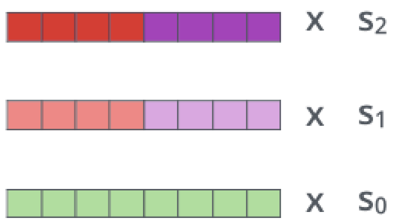


[The Illustrated BERT, ELMo, and co.,](#) Jay Alammar, 2018

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

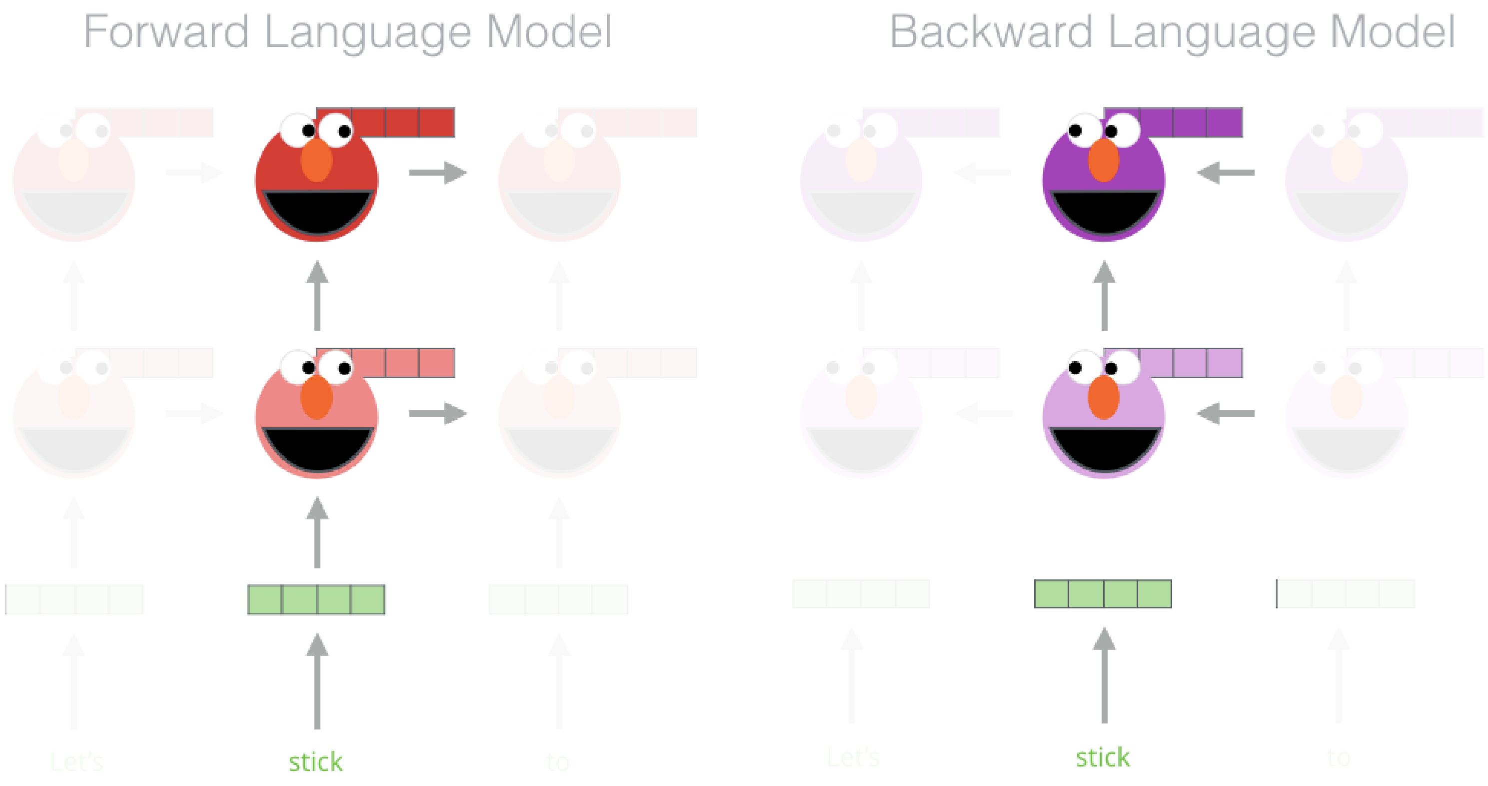
1- Concatenate hidden layers

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



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2.2. The Transformer vs LSTM

Attention Is All You Need, Vaswani et al., 2018
The illustrated Transformer, Jay Alammar, 2018
R-Transformer: recurrent neural network enhanced Transformer, Wang et al., 2019

2.2. The Transformer vs LSTM

- Problems with recurrent, sequential models such as LSTMs
  - can’t parallelize the computation procedure
  - can’t capture long-term dependencies

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- The Transformer
  - More parallelizable than LSTMs
  - Deals with long-term dependencies better than LSTMs
  - No sequence, based solely on **self-attention** mechanisms → no info about word order

Attention Is All You Need, Vaswani et al., 2018
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2.2. BERT: Bidirectional Embedding Representations from Transformers

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, Devlin et al., 2018
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- BERT jointly conditions on both left and right context in all layers (unlike ELMo)
- Input to BERT: sub-words after word tokenization
- BERT is a **fine-tuned** approach
  - to use it with a specific task, all pre-trained parameters are fine-tuned end-to-end

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- **Pre-trained BERT can be used to create contextualized embeddings**

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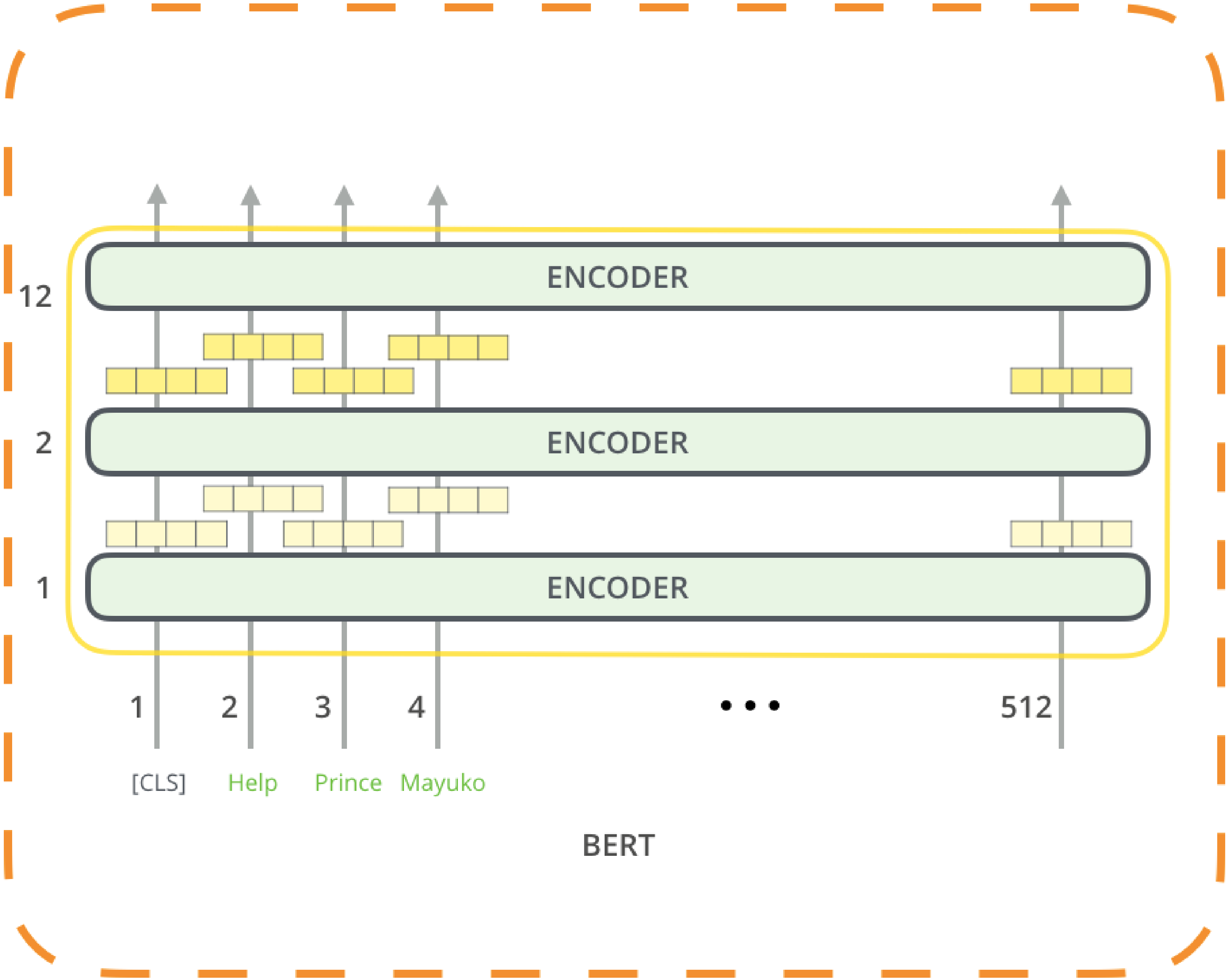
Generate Contexualized Embeddings



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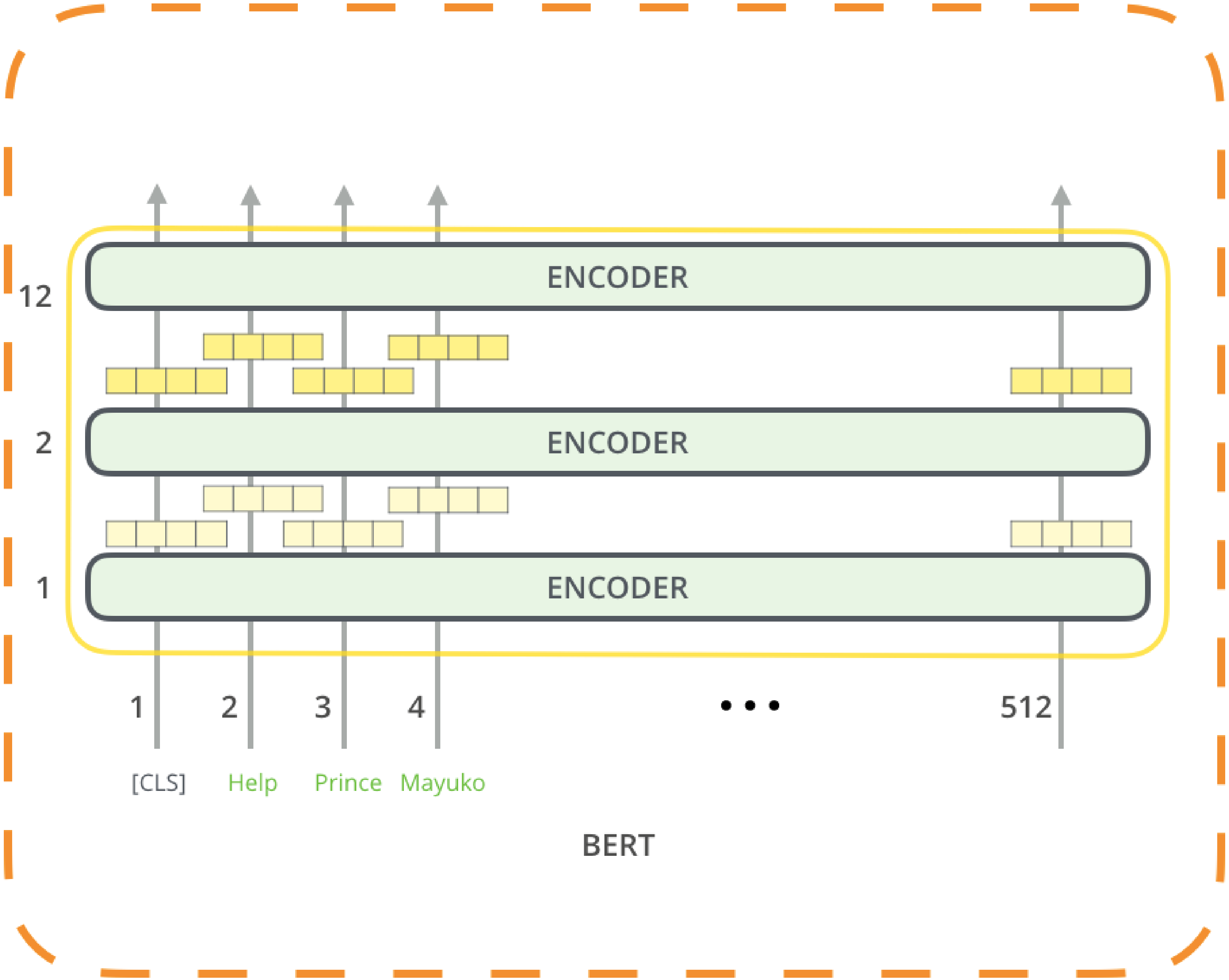
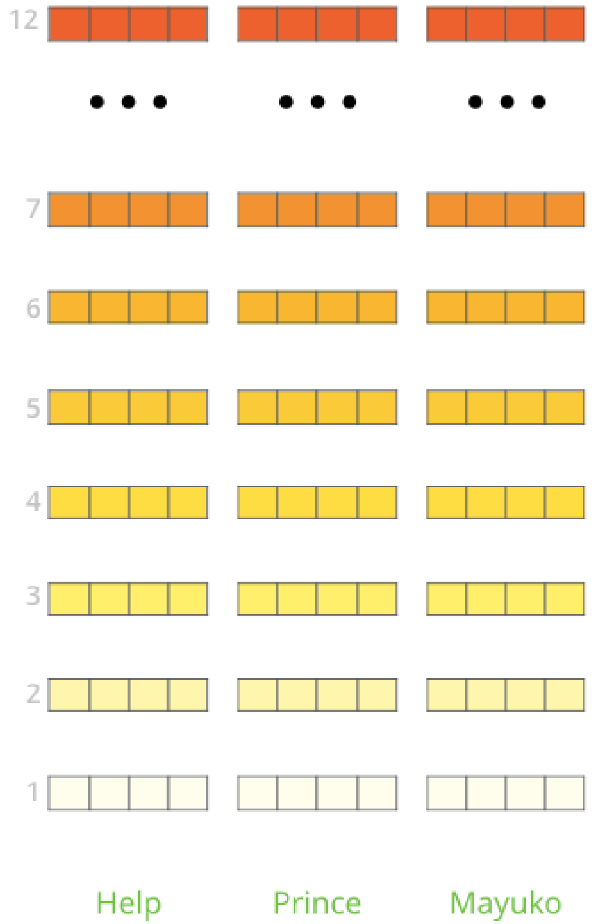


The output of each encoder layer along each token's path can be used as a feature representing that token.



But which one should we use?

Which contextualized embedding do we take for ‘Help’ in this context?

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

- Higher-level layers of the LM capture context-dependent aspects of word meaning
- Lower-level layers of the LM capture aspects of syntax

- For NER CoNLLTask 2003:

Which contextualized embedding do we take for ‘Help’ in this context?

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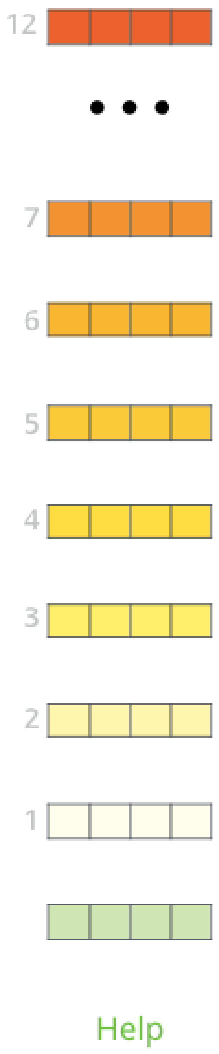

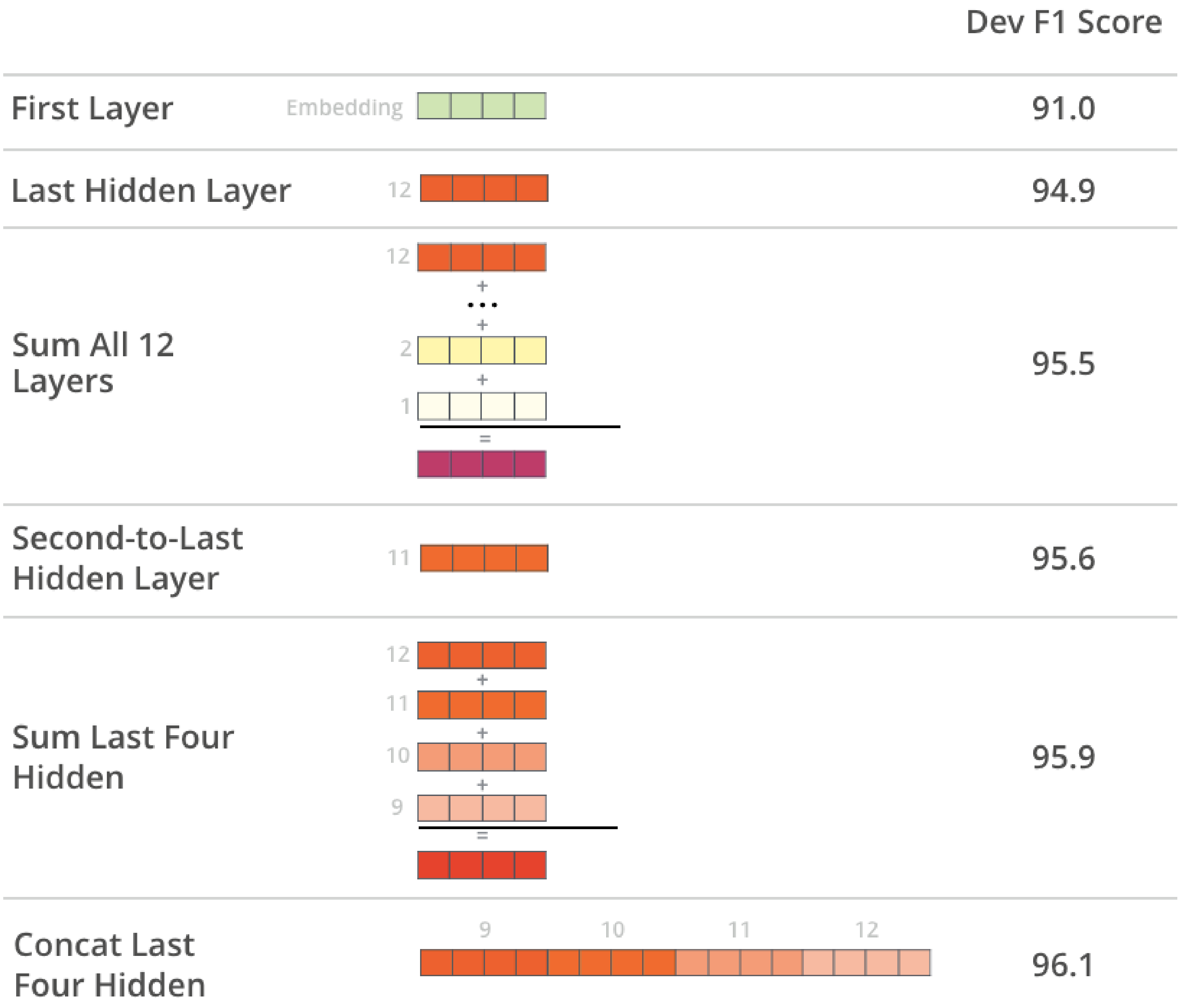

2.3. flair

- Another type of contextual string embeddings, **trained without an explicit notion of what a word is**
  - Models words as sequences of characters
  - The same word has different embeddings depending on its context
- Inputs to flair: characters
- Character-level LM is independent of tokenization and has a fixed vocabulary
- Deal with typos, rare and out of vocabulary words better

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

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3. Experiments

	Input text type	Vocabulary size
ELMo	word	700k words
BERT	subword	30k tokens
BERT multilingual	subword	120k tokens in total for 104 languages
flair	character	~256 characters (depending on the language)

3. Experiments

- Import ELMo, BERT-cased, BERT-uncased, and flair embeddings
  - BERT-uncased: text is lowercased before tokenisation and strips out accent markers
  - BERT paper: “uncased is typically better unless you know that case information is relevant to your task”
- For each experiment, create a reference sentence and several (dis-)similar sentences and rank them based on intuitive similarity
- Obtain contextual embeddings for each embedding type
- Calculate similarity between embedding(reference) and embedding(similar_sentence)
- Visualizations

3.1. Does word order matter?

the doctor invited the patient for lunch	Change
0. the patient invited the doctor for lunch	Switch subject and object ('opposite' sentence)
1. the lunch invited the doctor for the patient	Change semantic role
2. for invited patient the doctor the lunch	Random ordering

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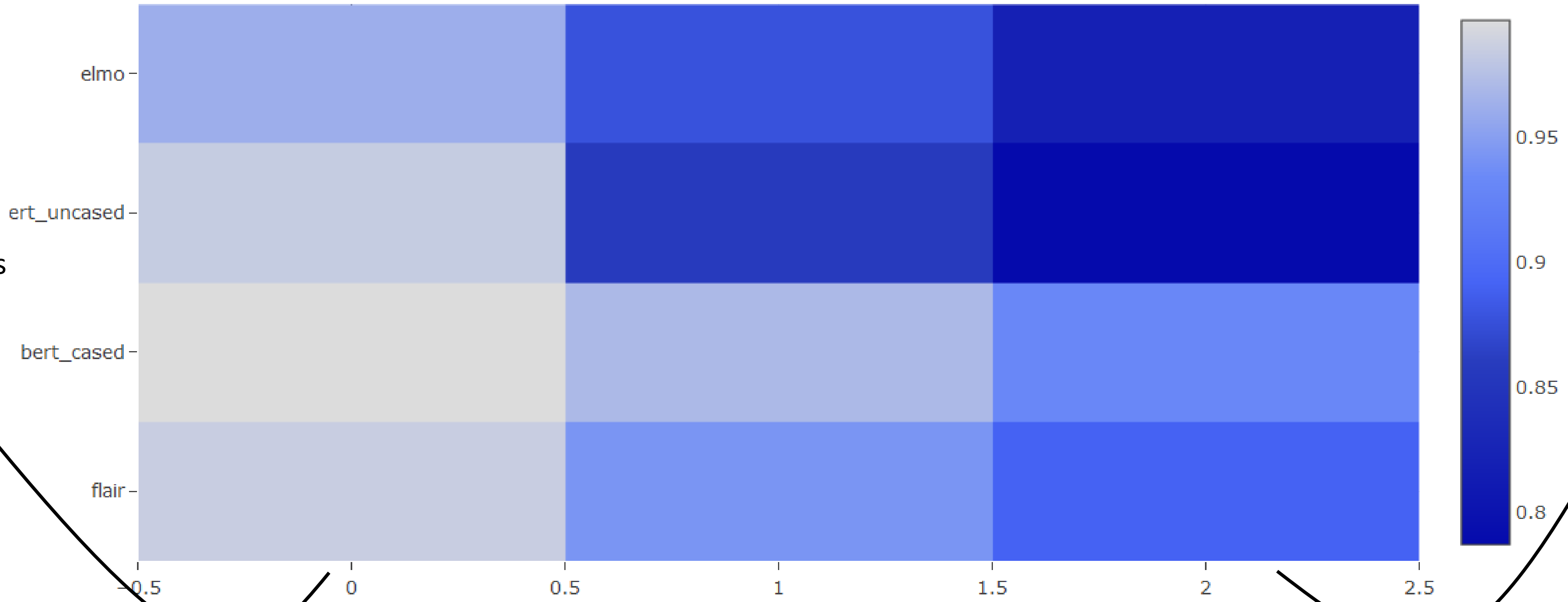
'opposite' sentence has very high similarity

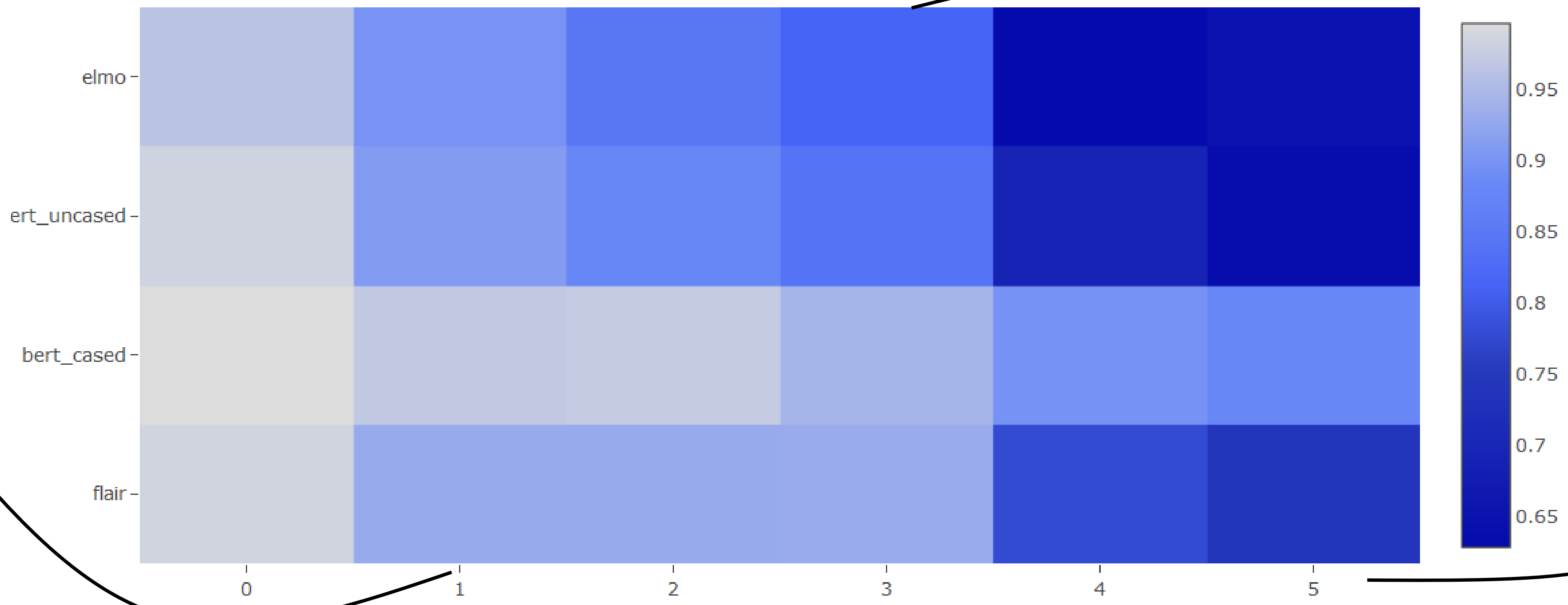


random ordering has lower similarity but still high

3.2. What is the impact of lexical similarity?

the doctor invited the patient for lunch	Change		Change
0. the patient invited the doctor for lunch	'opposite' sentence	*3. the doctor killed the patient after lunch*	Subj. and obj. overlap
1. the doctor did not invite the patient for lunch	negation	*4. that is a matter between the doctor and the patient*	Subj. and obj. overlap
2. the child invited the grandfather for lunch	Subj. and obj. change	*5. I wish I got invited for lunch*	Invite, lunch overlap

negation sentence has very high similarity



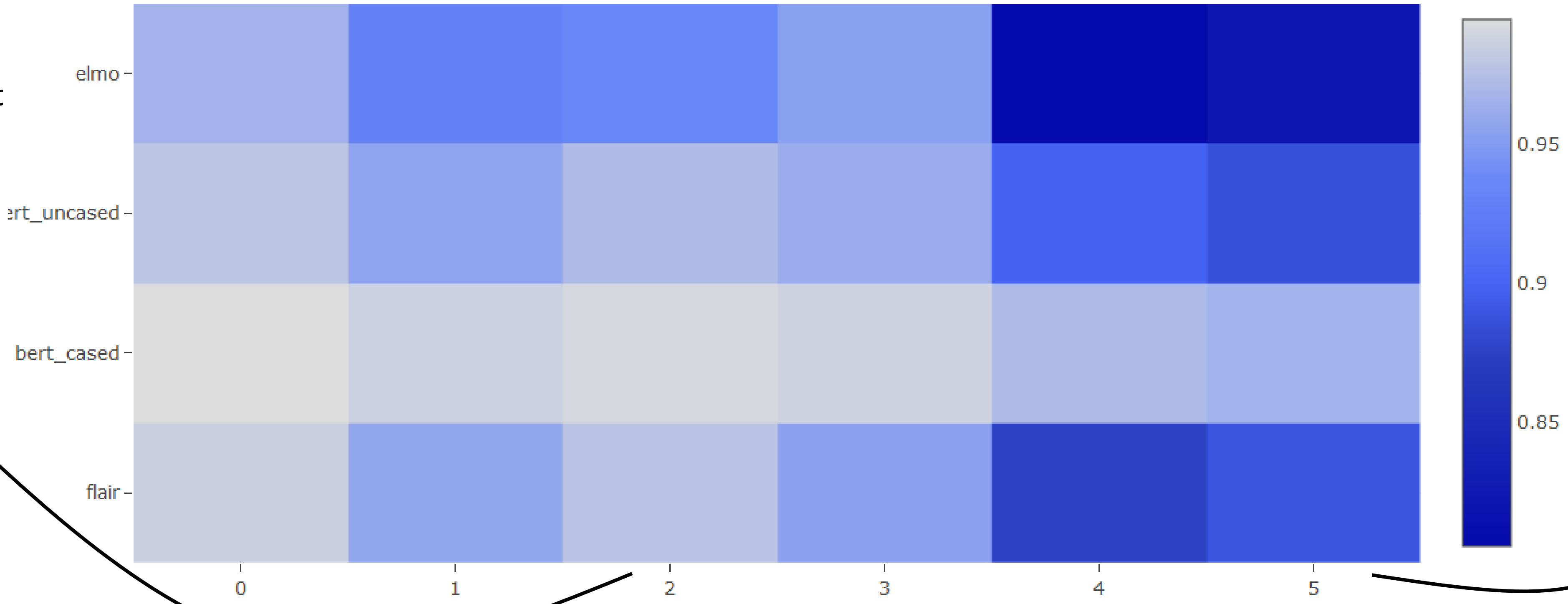
despite overlap, meaning of sentence is greatly changed

3/7 lexical overlap but much lower similarity

3.3. What is the impact of synonyms?

the doctor invited the patient for lunch	Change		Change
0. the surgeon invited the patient for lunch	Synonym of subj.	*3. the doctor invited the patient for a meal*	More general word
1. the doctor invited the sick person for lunch	More general synonym of obj.	*4. the doctor took the patient out for tea*	More general expression
2. the professor invited the patient for lunch	Synonym in different context	*5. the doctor paid for the patient's lunch*	Implicit action

unexpected result, aren't contextual embeddings supposed to generalize well to context?



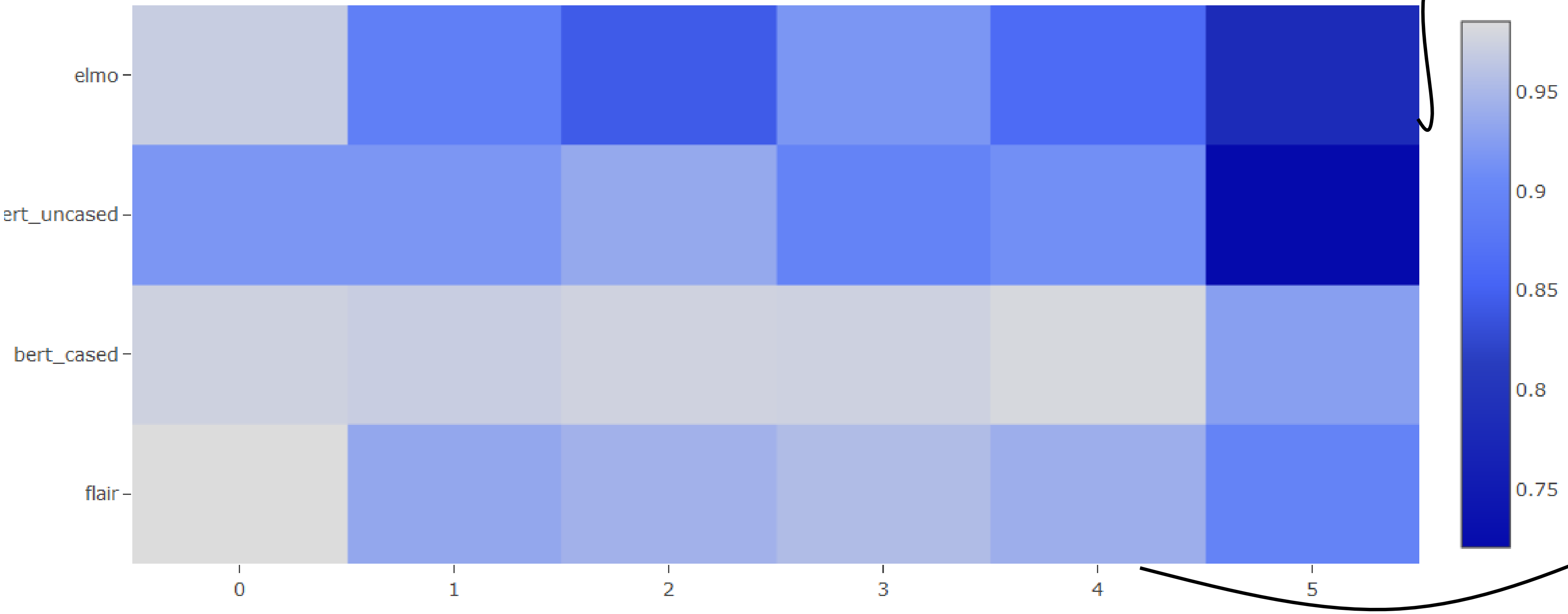
2 synonyms at the same is the possible cause

The implicit action sentence doesn't have bad results

3.4. What is the impact of out of vocabulary words?

the doctor invited the patient for lunch	Change		Change
0. the doctor invitted the patient for lunch	Typo	*3. the doctor invited the patient for sushi*	Specific food
1. the doctor kartoffeled the patient for lunch	Wrong word	*4. the doctor invited the patent for lunch*	Typo / different word
2. Stefan invited the patient for lunch	Proper name	*5.* the doctor invited the patent for linch	Typo / different word

slightly less similarity than the first one, but still high!



seems more logical

shouldn’t this be lower?

3. Experiment summary

- BERT overall shows extremely high similarities
  - Mystery: especially **bert_cased**: lowest achieved was 85% with random sentences
- Word order is not very relevant
- Sentences in the same semantic space are evaluated as similar, even negation or opposite sentences
- A lexical overlap of 50% can raise similarity to 90%
  - Mystery: **ELMo** (word-based) shows much lower similarities than **flair** (character-based)
- With synonyms that change context, similarities are still high (‘professor invited patient’)
- Typos and oov words don’t have much of an impact

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4. Conclusion

- Semantic search → ontology matching → experiments on similarity ranking with contextual embeddings
- In my specific examples:
  - word order doesn't seem to be relevant
  - sentences with very different meaning are evaluated as very similar
  - typos don't have much impact
- Future work
  - research extreme high similarities of **bert_cased**
  - research cause of similarity differences in **bert_cased** and **bert_uncased**
  - research impact of word ordering and lexical overlap
  - research difference between **word-based embeddings** vs **character-based embeddings**
  - try more phenomena/examples
  - Visualization: T-SNE

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