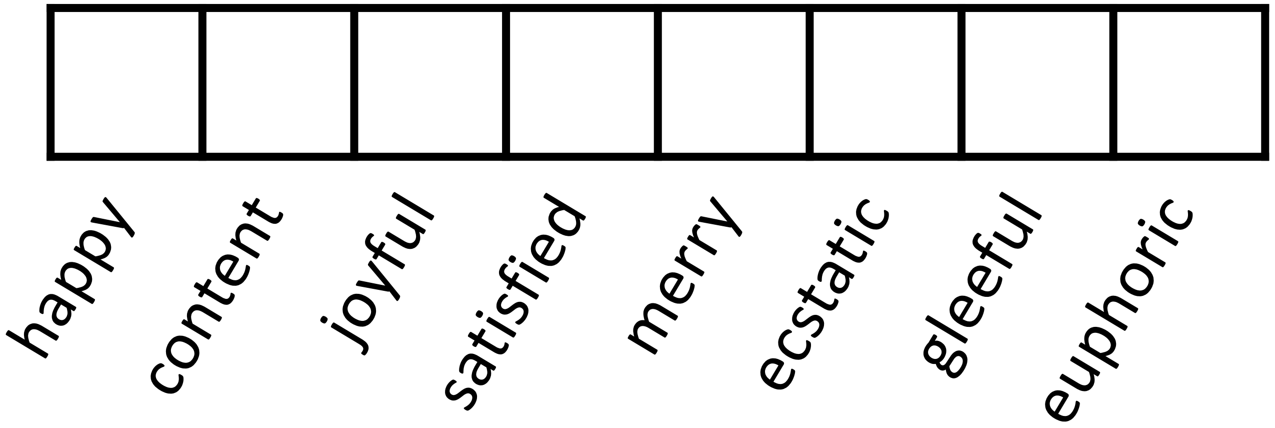
Word Embeddings and A Very Simple Word Embedding Based Model

MMCi Block 5

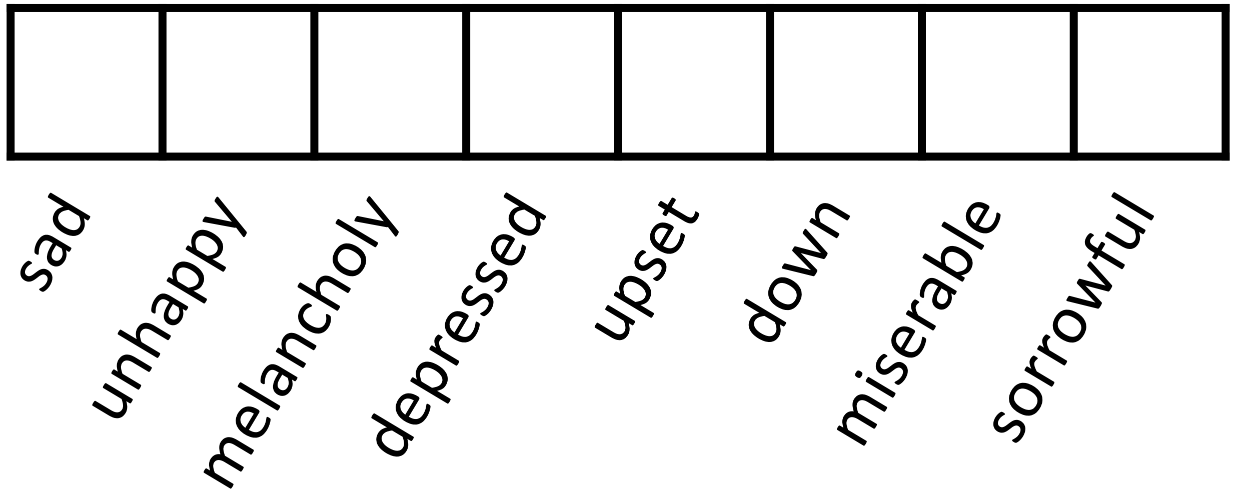
Matthew Engelhard

Problem: our model counts words, but has no understanding of their meaning



Goal: predict sentiment (positive/negative)

Problem: our model counts words, but has no understanding of their meaning

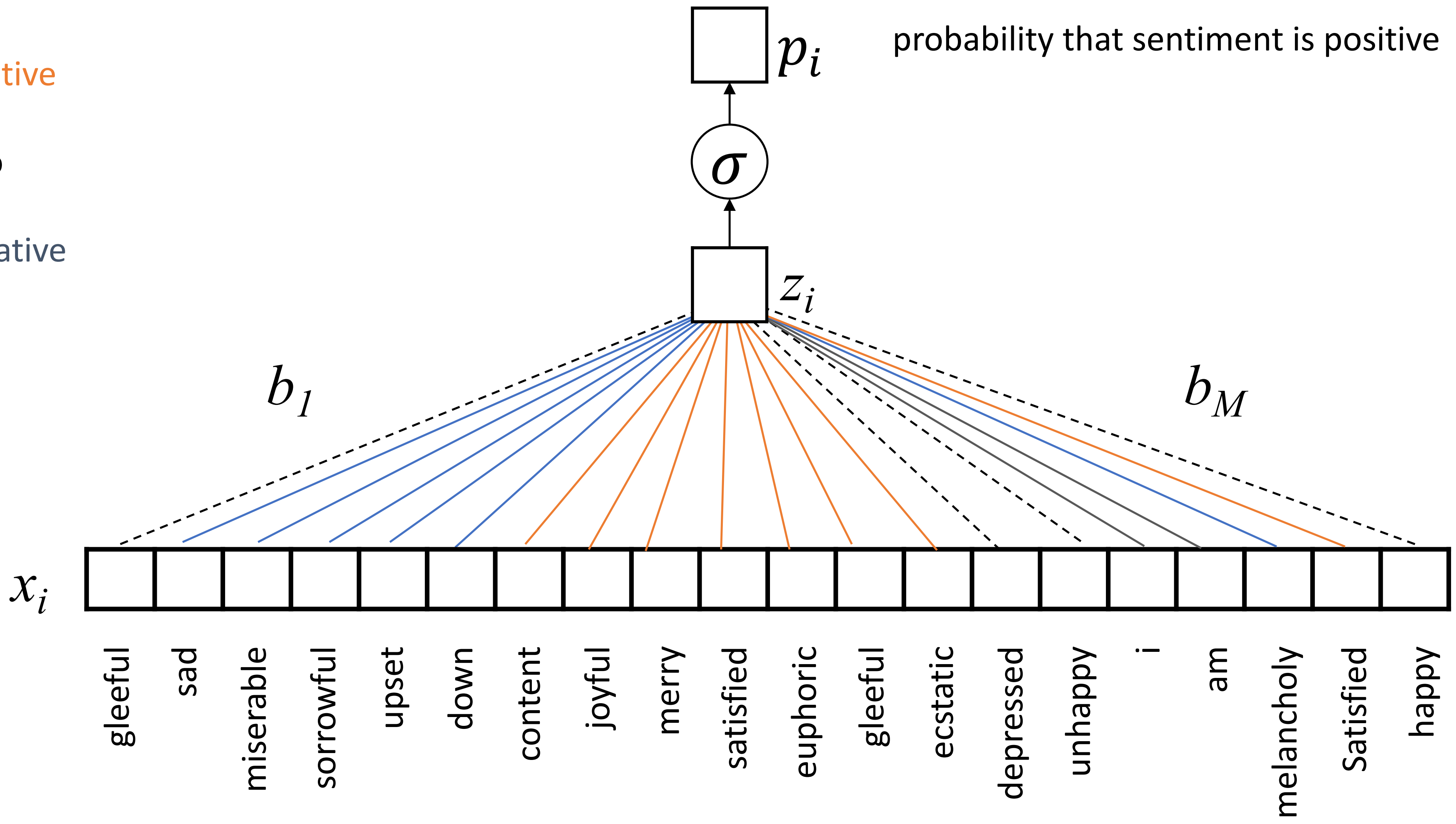


Goal: predict sentiment (positive/negative)

To effectively predict sentiment, it would be helpful to understand which words have similar meaning

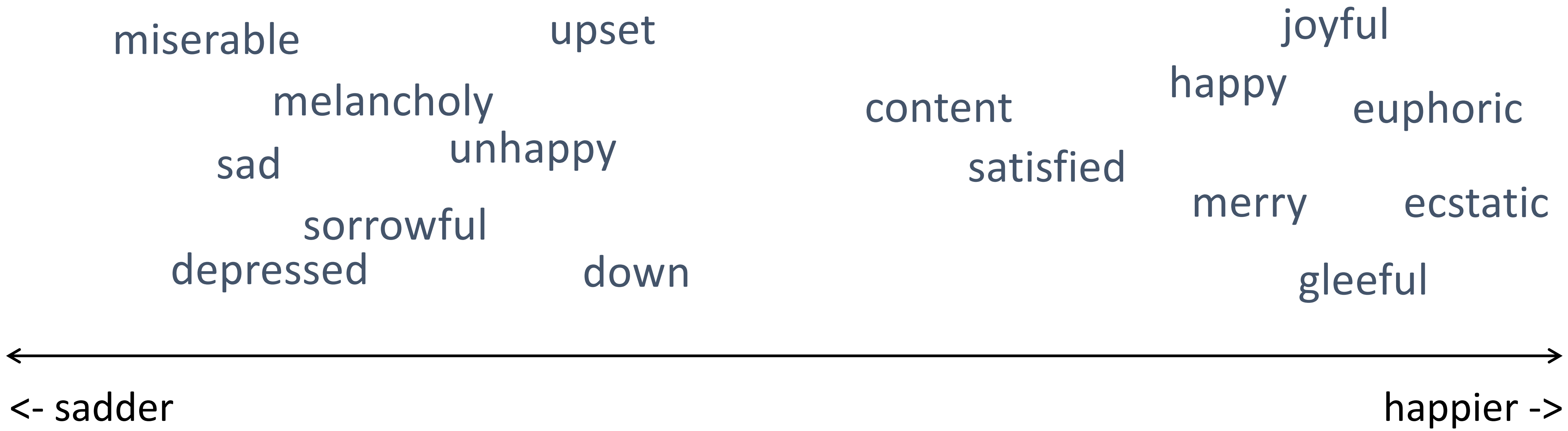
I am sad	☹	training set
I am miserable	☹	
I am sorrowful	☹	
I am upset	☹	
I am down	☹	
I am content	☺	
I am joyful	☺	
I am merry	☺	
I am satisfied	☺	
I am euphoric	☺	
I am depressed	?	test set
I am unhappy	?	
I am happy	?	
I am gleeful	?	

logistic regression: positive / negative sentiment



I passed out and Mom said I was shaking

We'd like a numeric representation of words that encodes their meaning



Numeric value indicating whether the word is happy or sad

Training a robot to buy groceries

Example from Anand Chowdhury, MMCi 2019

Grocery List

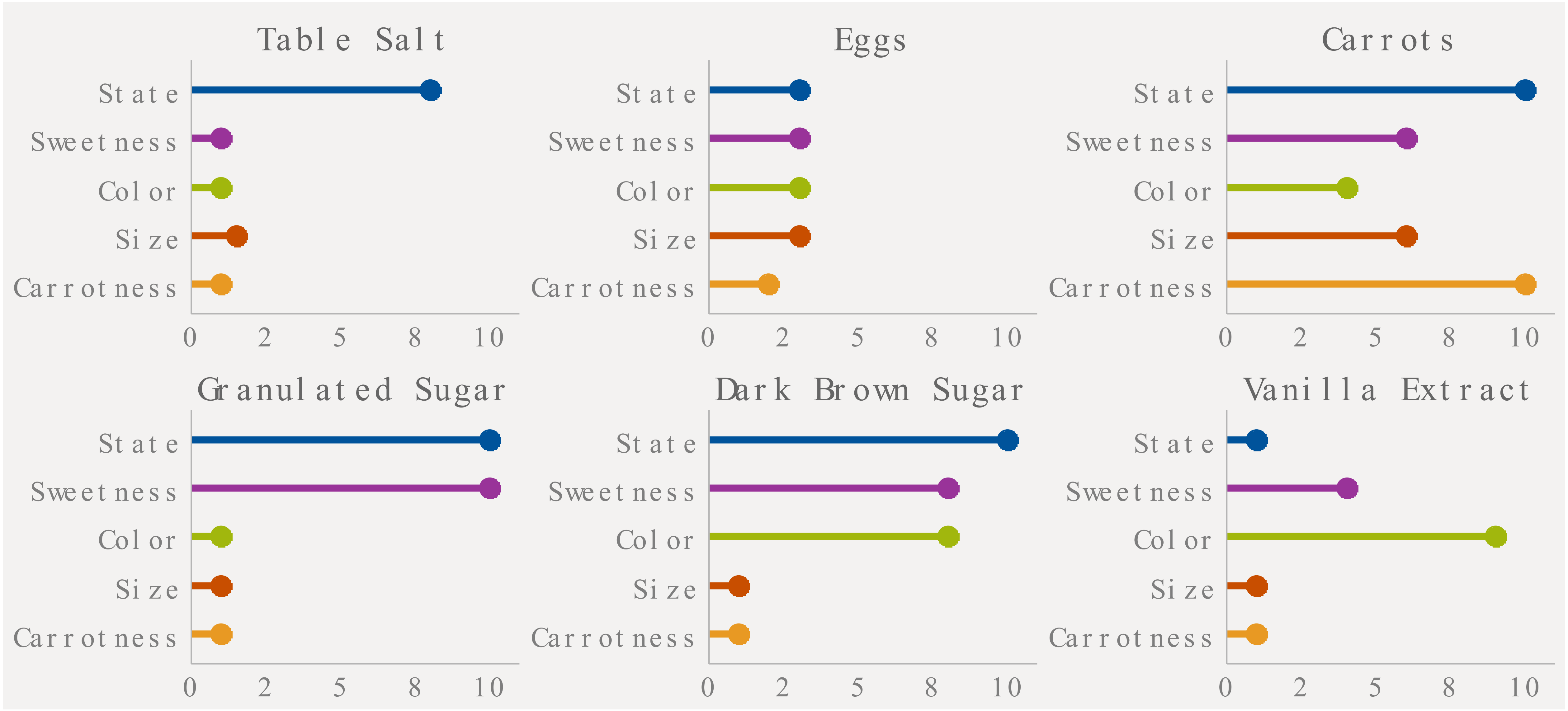
- ❑ granulated sugar
- ❑ vanilla extract
- ❑ dark brown sugar
- ❑ carrots
- ❑ table salt
- ❑ eggs

Characteristics/Dimensions

Dimension	1	10
State	Liquid	Solid
Sweetness	Bland	Sweet
Color	Light	Dark
Size	Small	Large
Carrotness	Not really	🥕

“Carrot Vegetables” icon by CHARIE Tristan from the Noun Project.

Five dimensions



Make Sense of Items not Seen Before

Item	State	Sweetness	Color	Size	Carrotness
???	0	8	7	6	0
???	0	0	10	6	0
???	8	9	8	3	0
???	0	5	3	4	10

Make Sense of Items not Seen Before

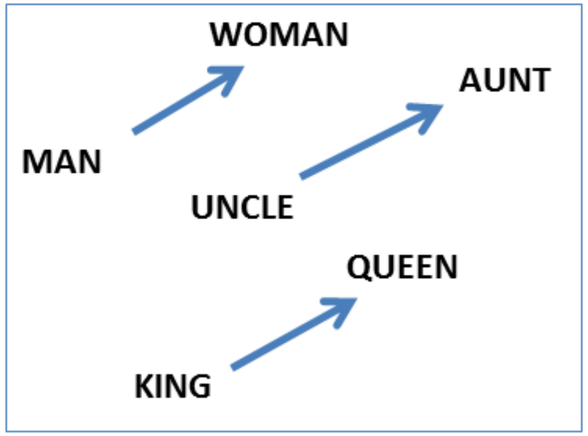
Item	State	Sweetness	Color	Size	Carrotness
Soda / Sweet Tea	0	8	7	6	0
Black Coffee	0	0	10	6	0
Chocolate	8	9	8	3	0
Carrot Juice	0	5	3	4	10

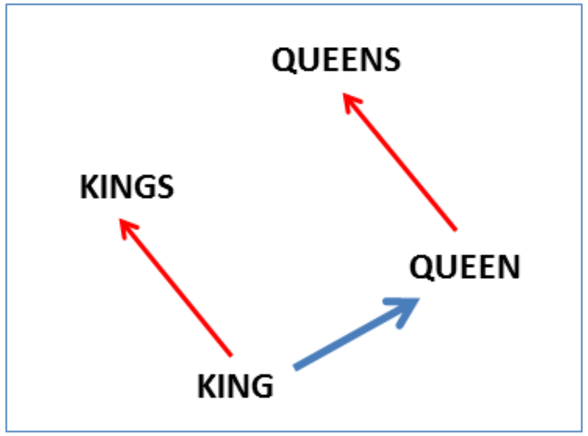
Recipe

Dark Brown Sugar – Granulated Sugar + Carrots

	Item	State	Sweetness	Color	Size	Carrotness
	Dark Brown Sugar	10	8	8	1	1
-	Granulated Sugar	10	10	1	1	1
+	Carrots	10	6	4	6	10
=	???	10	4	11	6	10

Word Embeddings: Assign Each Word in our Vocabulary to a Numeric Vector (of characteristics)



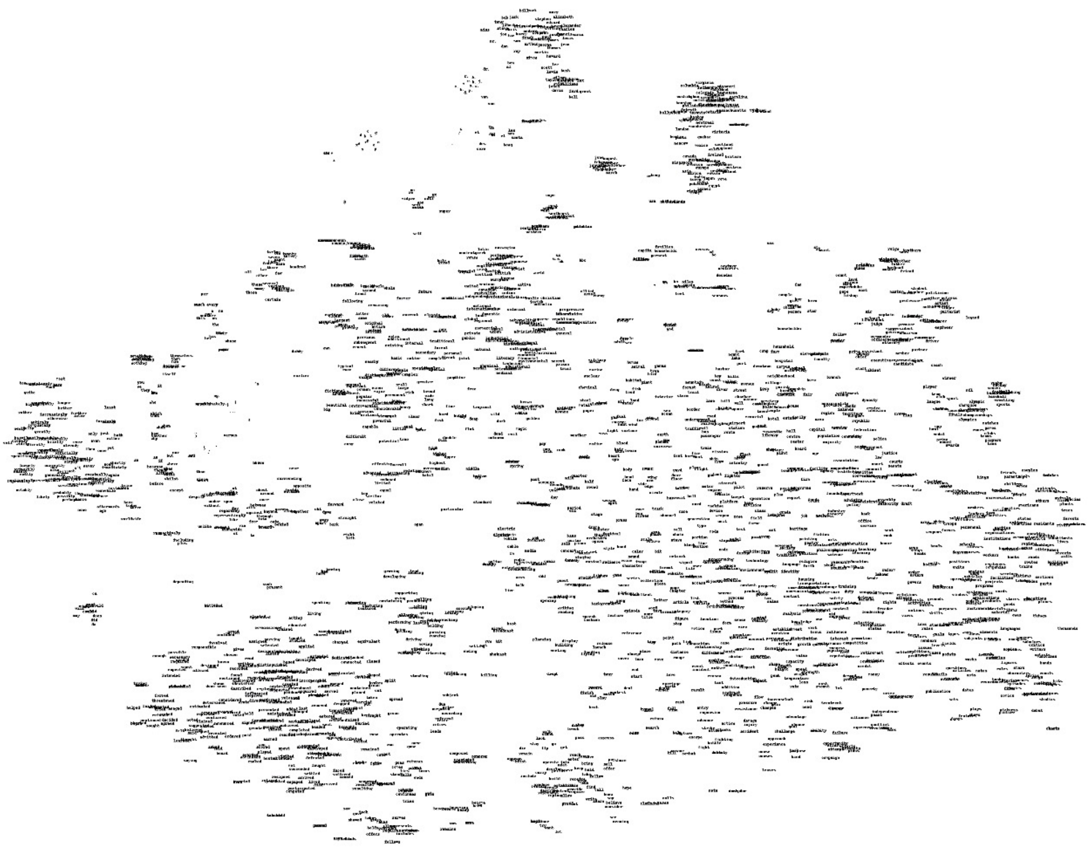


Dimension	1	10
Gender	Male	Female
Class	Commoner	Royalty
Plural	One	Many

Visualizing Word Embeddings

Here we show the learned numeric representations (limited here to 2 dimensions) of many different vocabulary words

Too many words here to see! Let's zoom in on a smaller section.

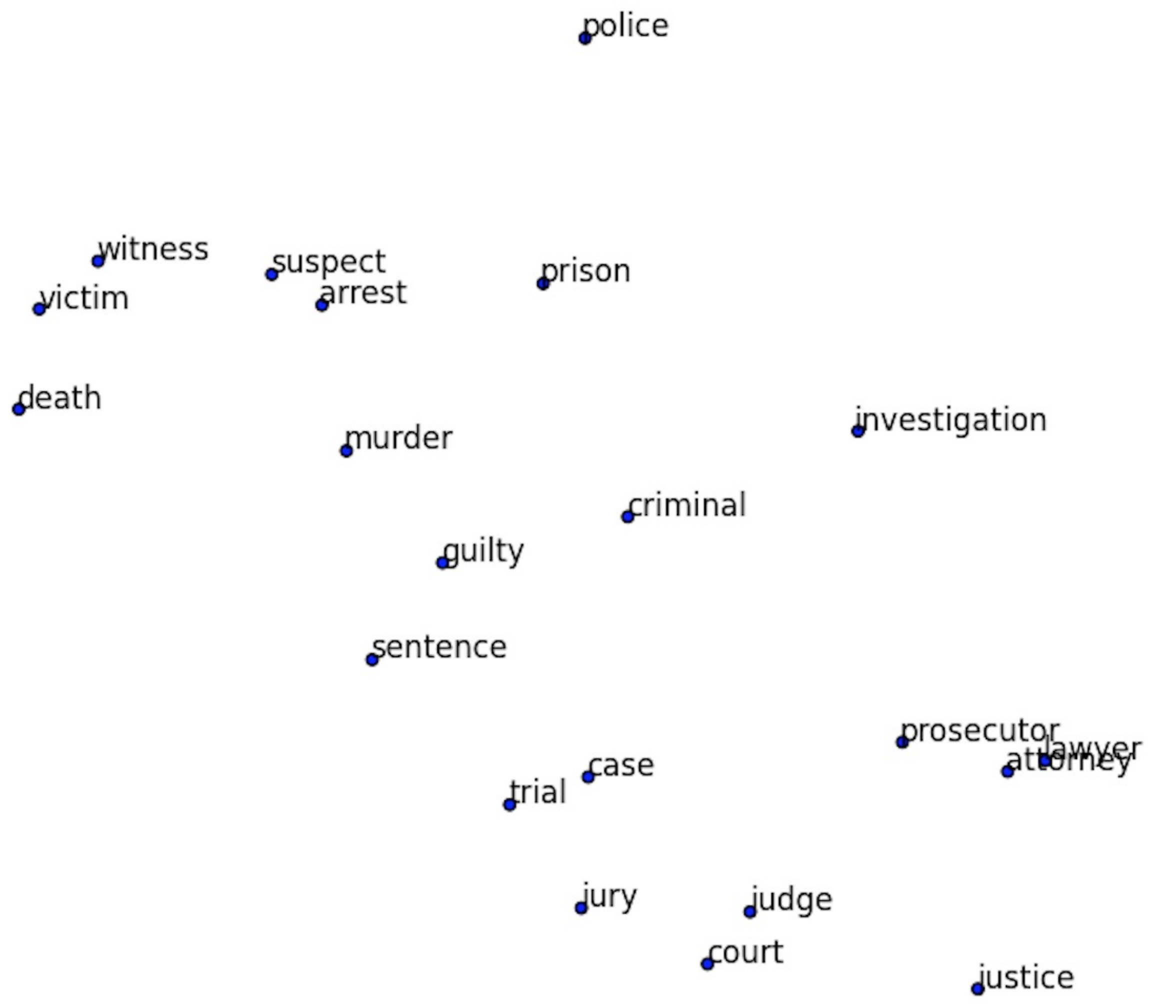


Visualizing Word Embeddings

If we zoom in on a small region of our word map, it's all related words.

Note the similarity of all the words as a whole, but also of the individual neighbors.

"Lawyer" and "attorney" are right next to each other – they have almost identical characteristics!

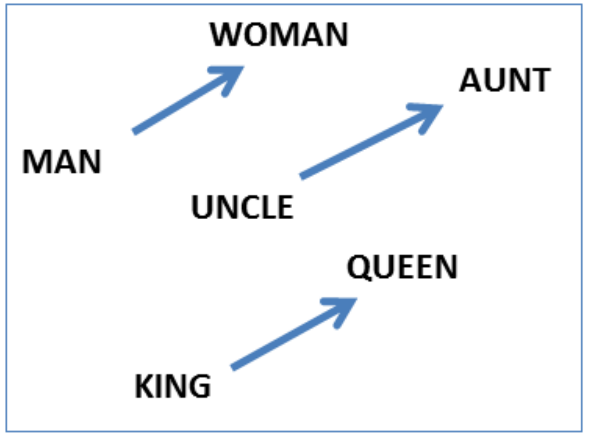


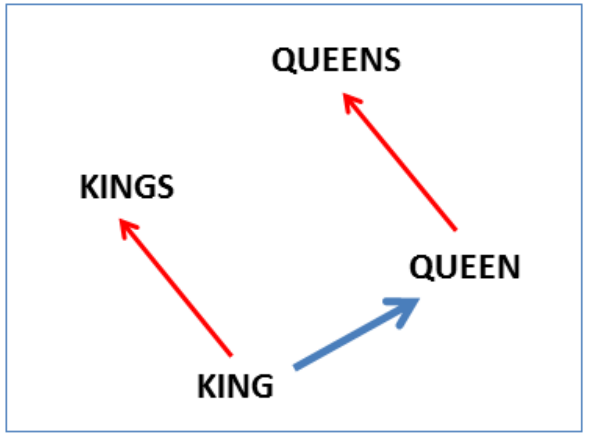
Word Recipes

The relationship between words can be maintained, we can do mathematical operations on these word vectors.

Add the same vector distance between man and woman will convert uncle to aunt and king to queen.

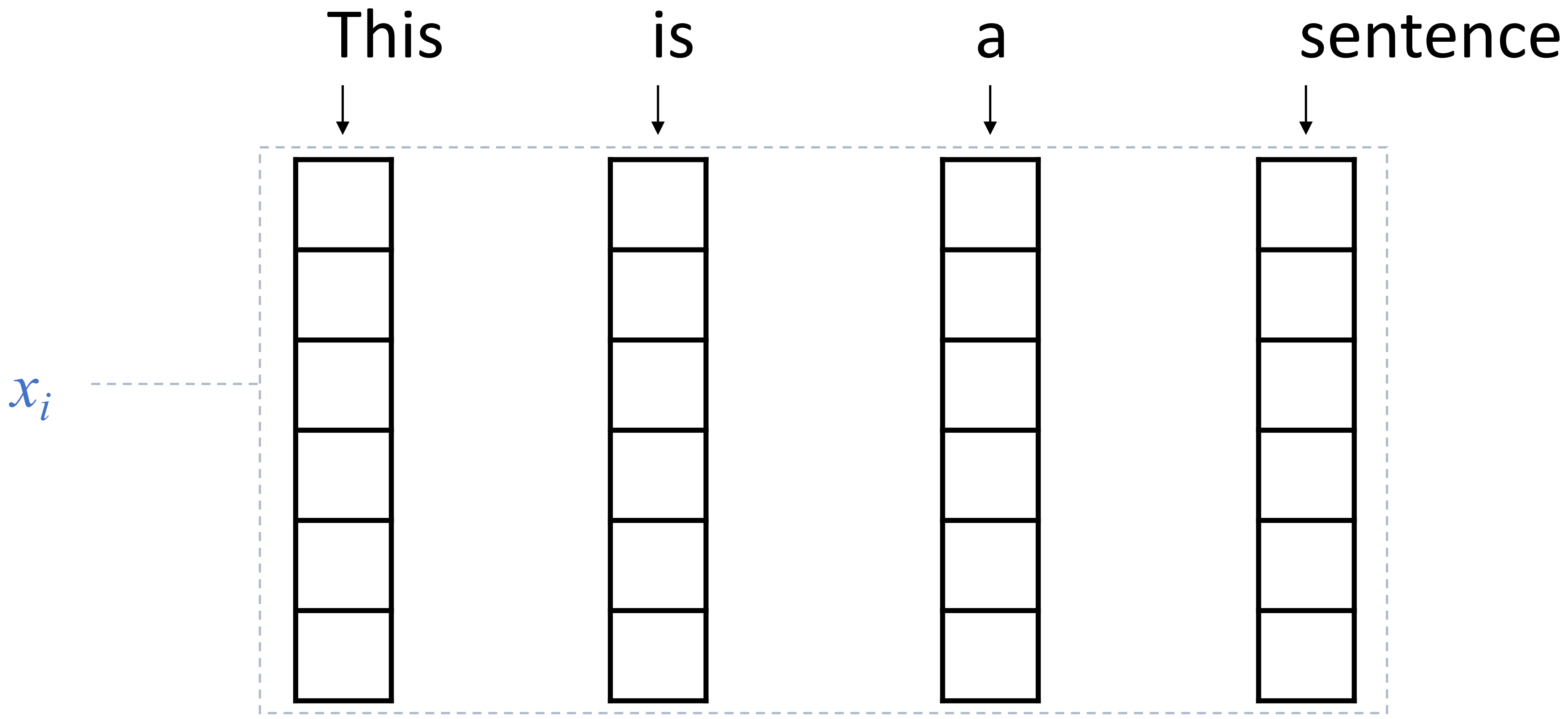
Plural relationships are also maintained.





What happens when we embed all words in a sentence?

- Look up words individually to obtain their vectors
- Construct a sequence of vectors



A brief note on how word embeddings are learned…

KEY IDEA: words are *defined* by the context in which they appear

A man strolls down the street

A woman strolls down the street

A child strolls down the street

A crocodile strolls down the street

A banana strolls down the street

A concept strolls down the street

KEY IDEA: words are *defined* by the context in which they appear

-> if words are always exchangeable, they must have very similar meaning

learn word meaning like an adult:
explicit definitions

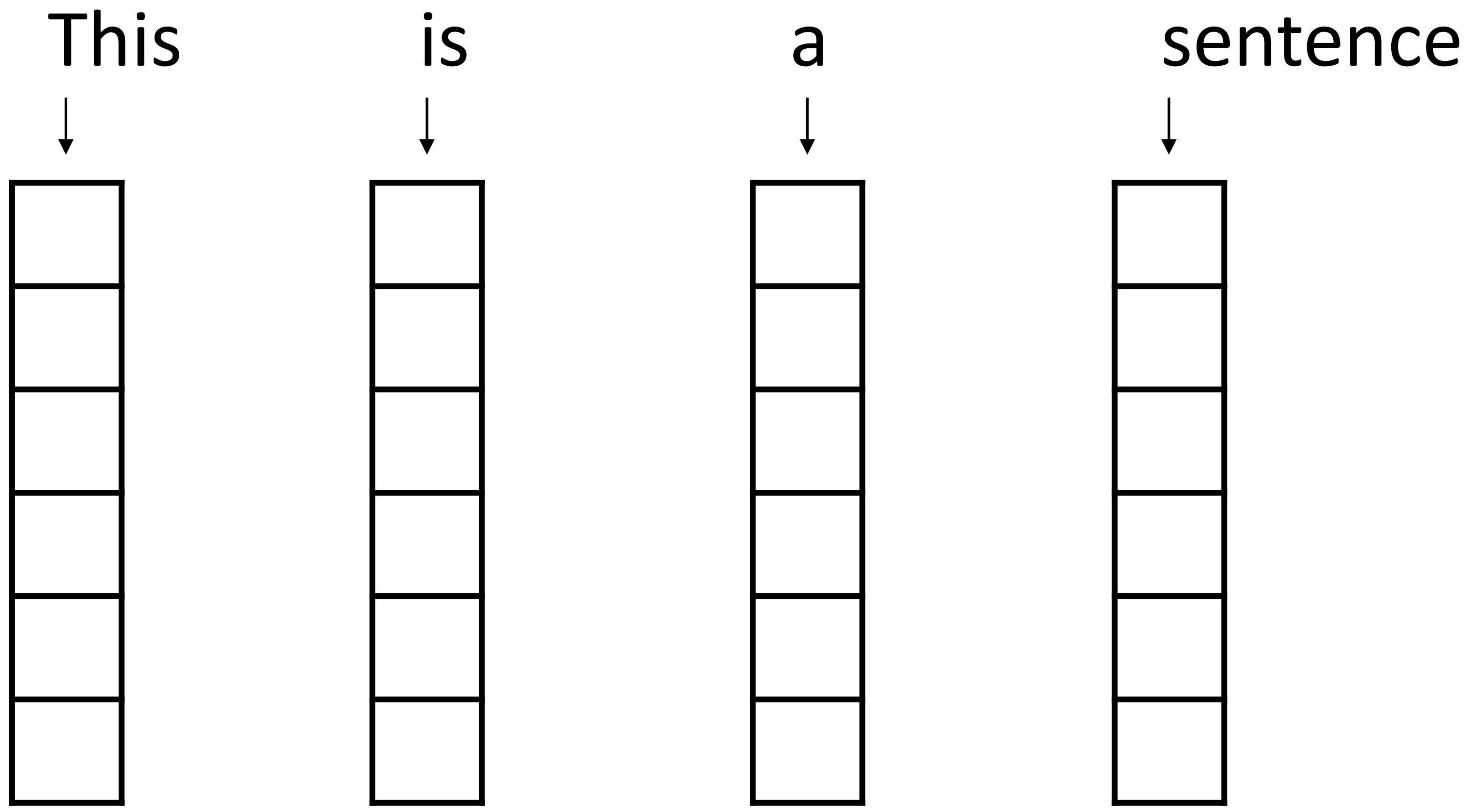
https://www.parenting.com/activities/baby/teach-baby-to-talk/

learn word meaning like an child:
implicit definitions from context

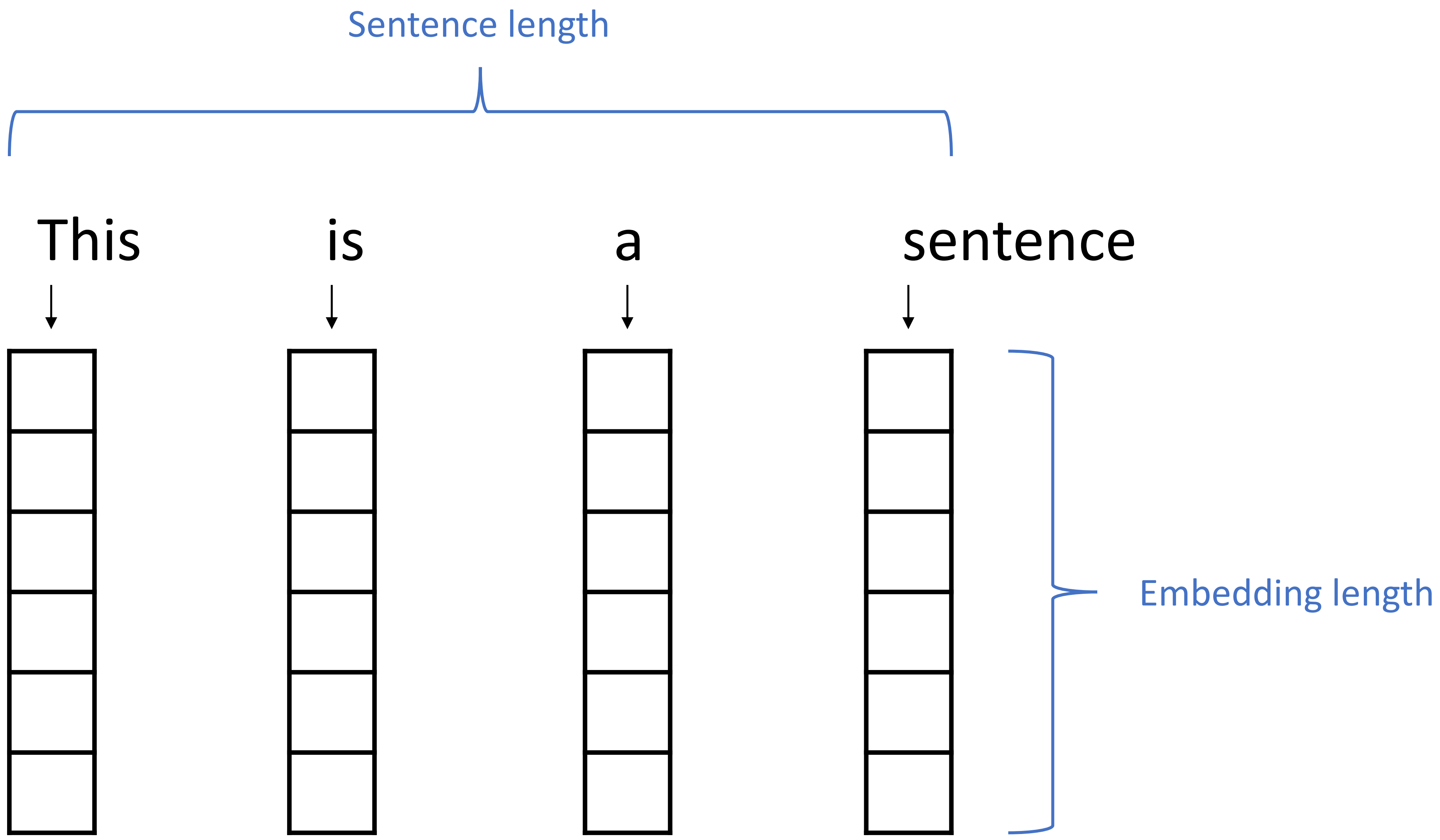
A Very Simple Word Embedding-Based Model

VSWEM Step 1: Convert sentence to vectors

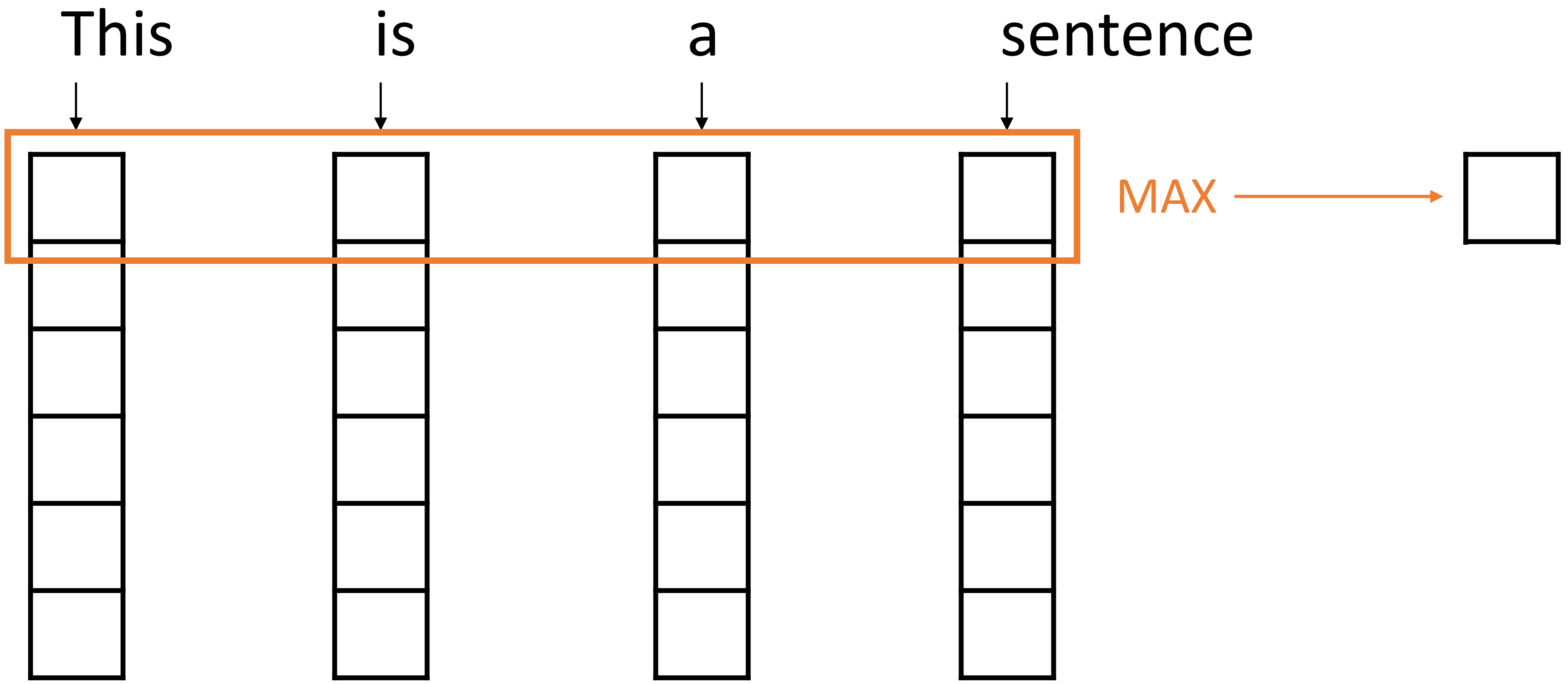
- Look up words individually to obtain their vectors
- Construct a <u>sequence</u> of vectors



VSWEM Step 1: Convert sentence to vectors



VSWEM Step 2: Take the MAX over the sentence for each embedding dimension



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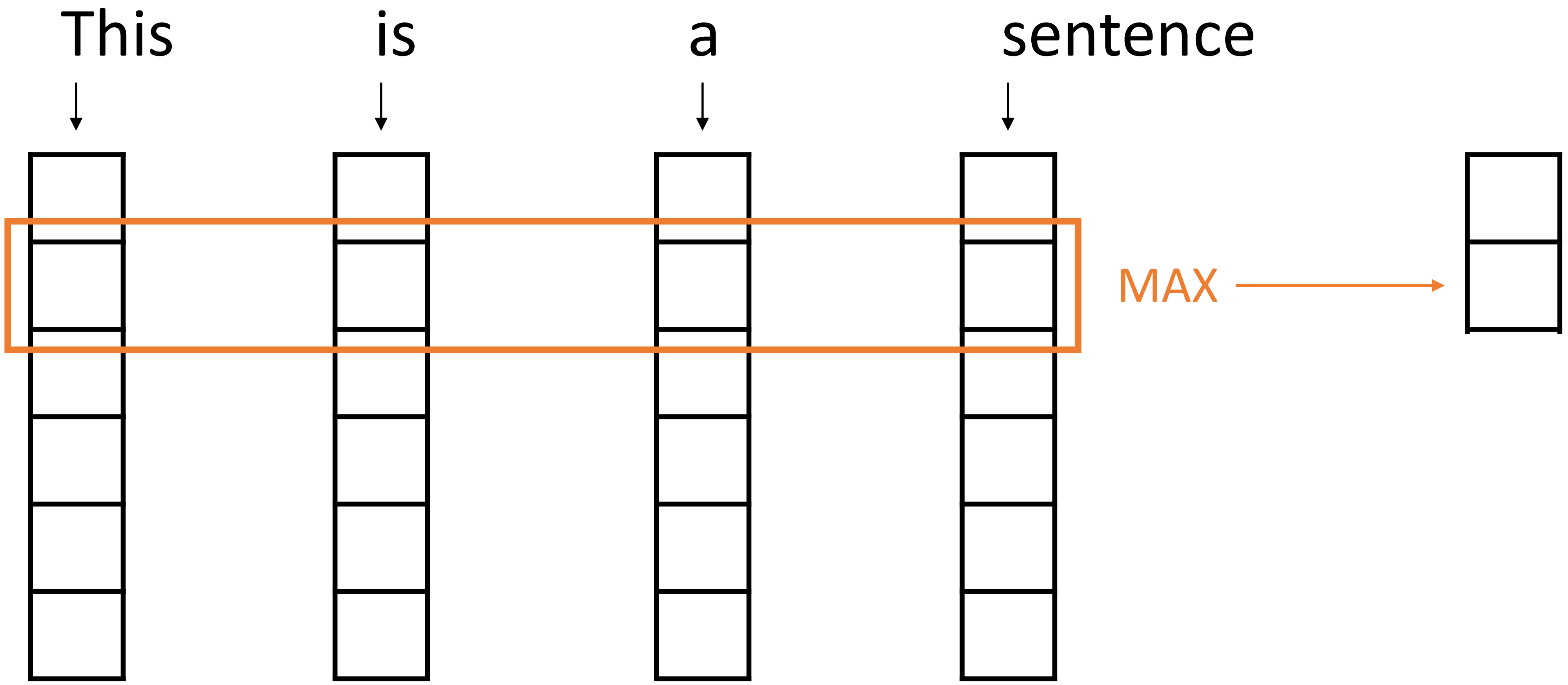

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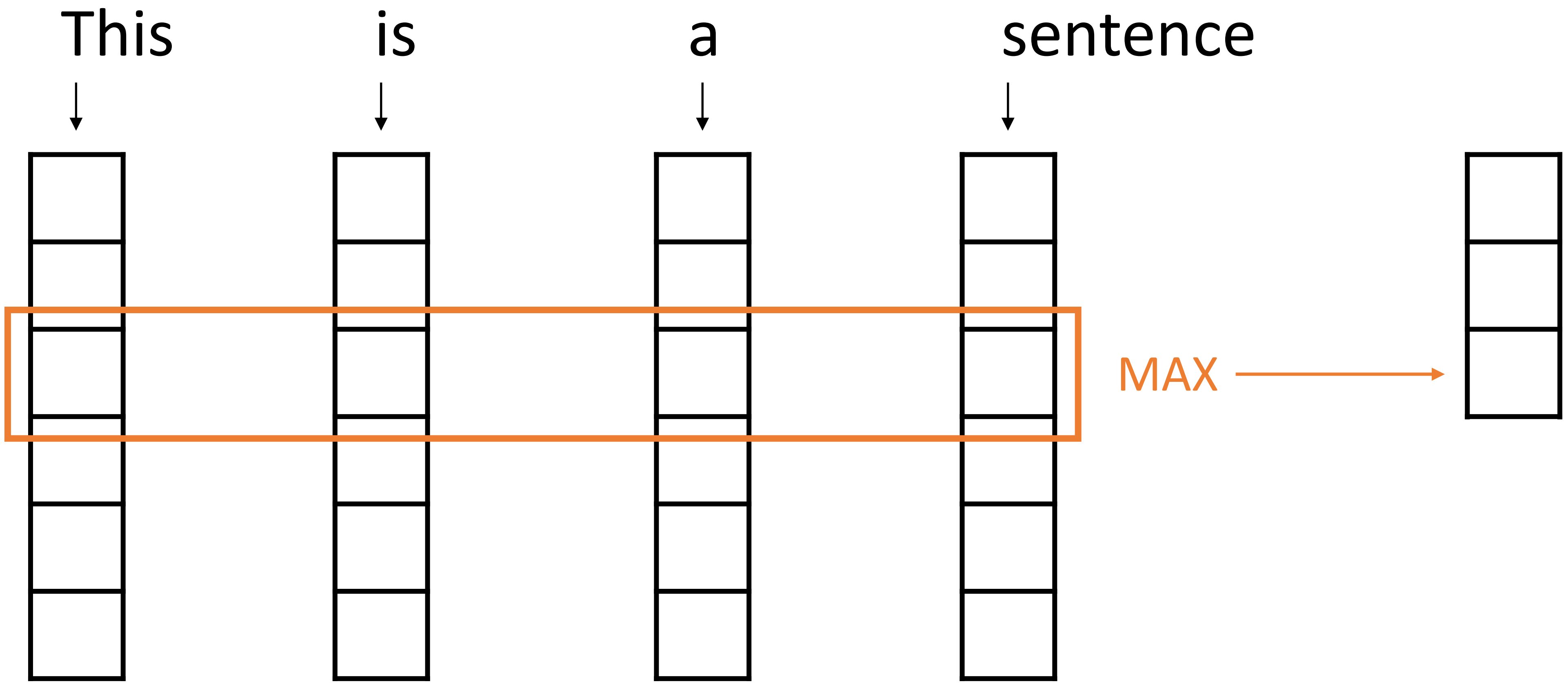

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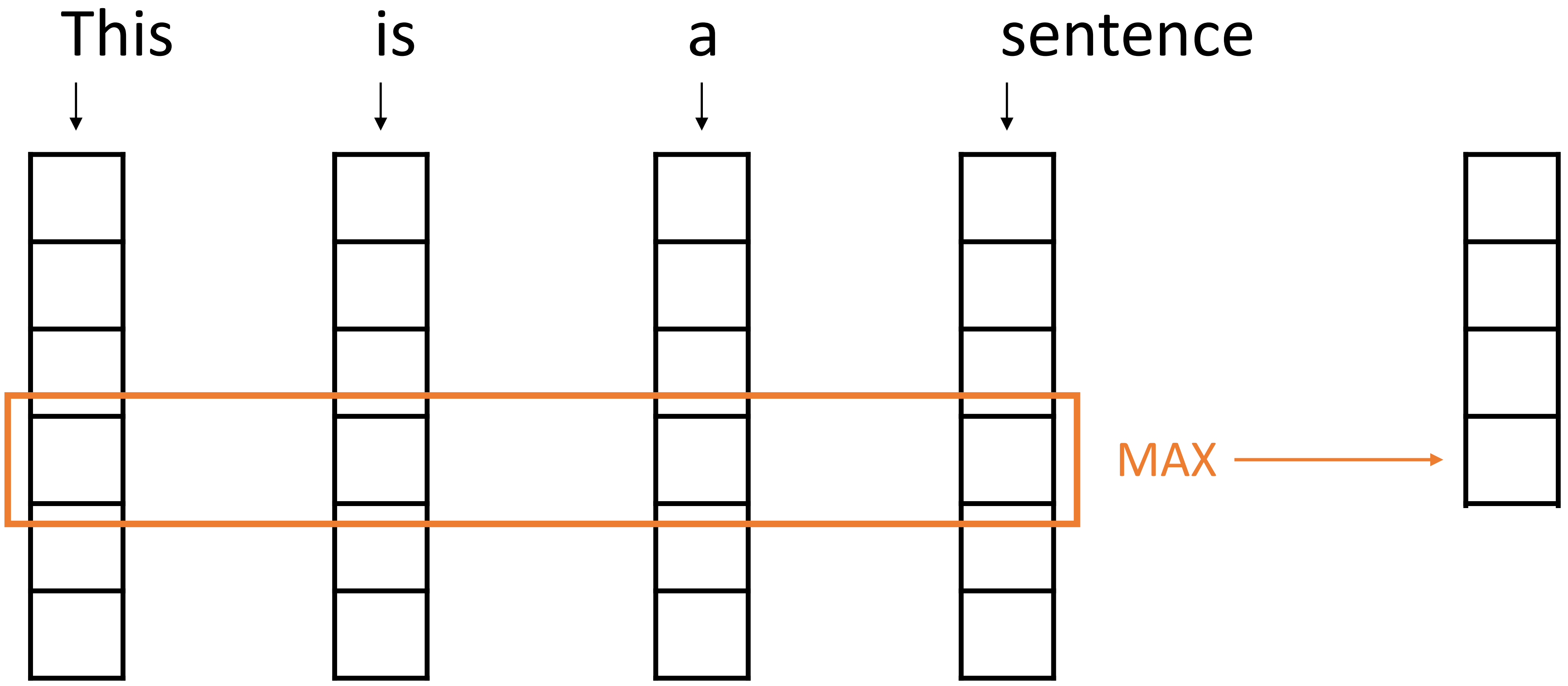

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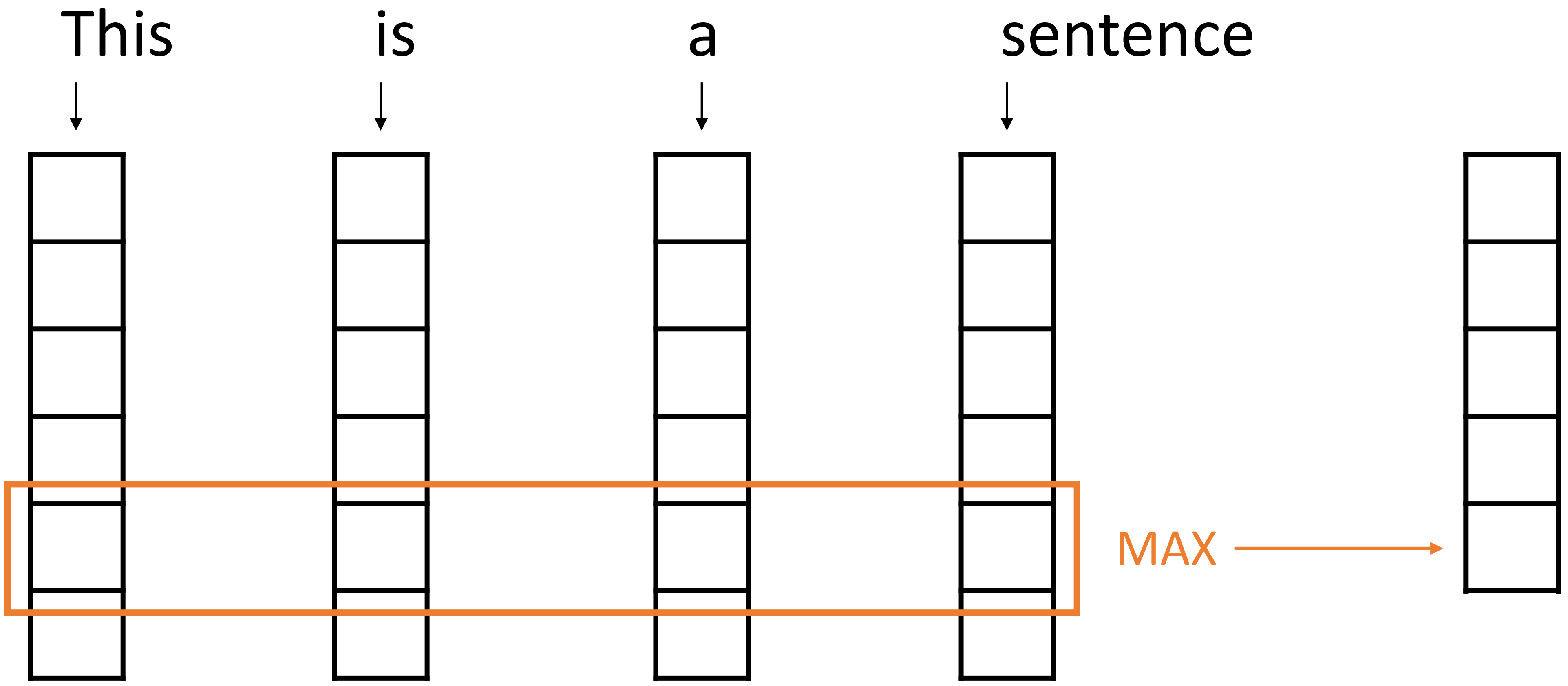

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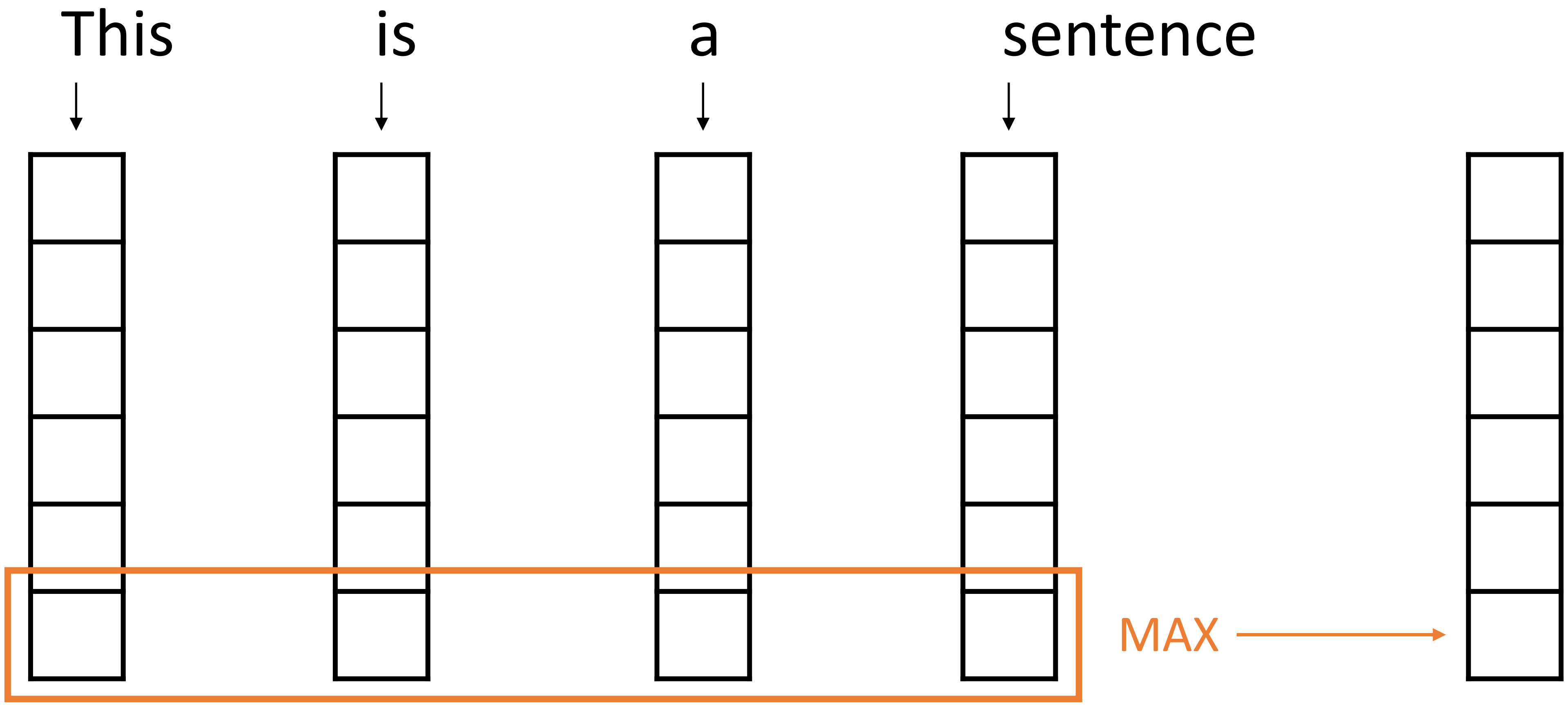
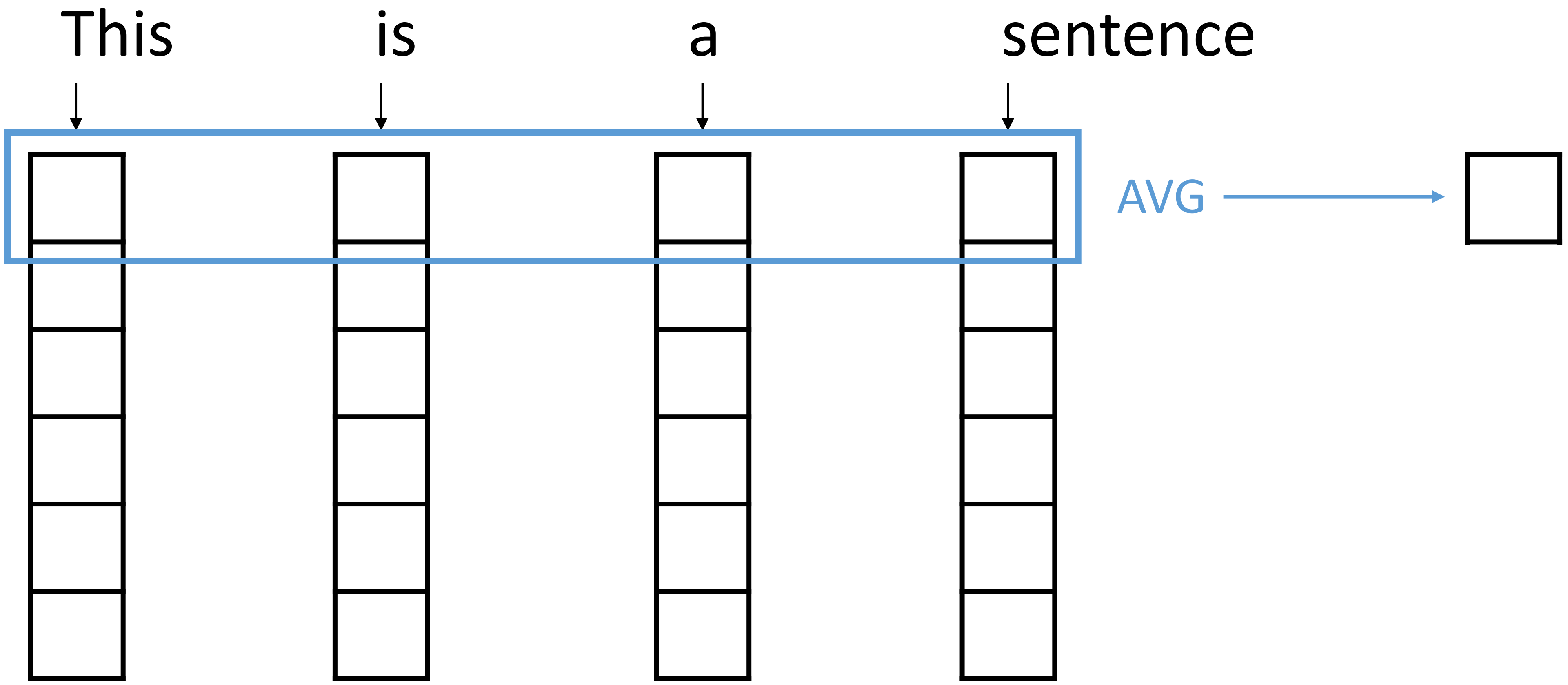


VSWEM Step 3: Take the AVERAGE over the sentence for each embedding dimension



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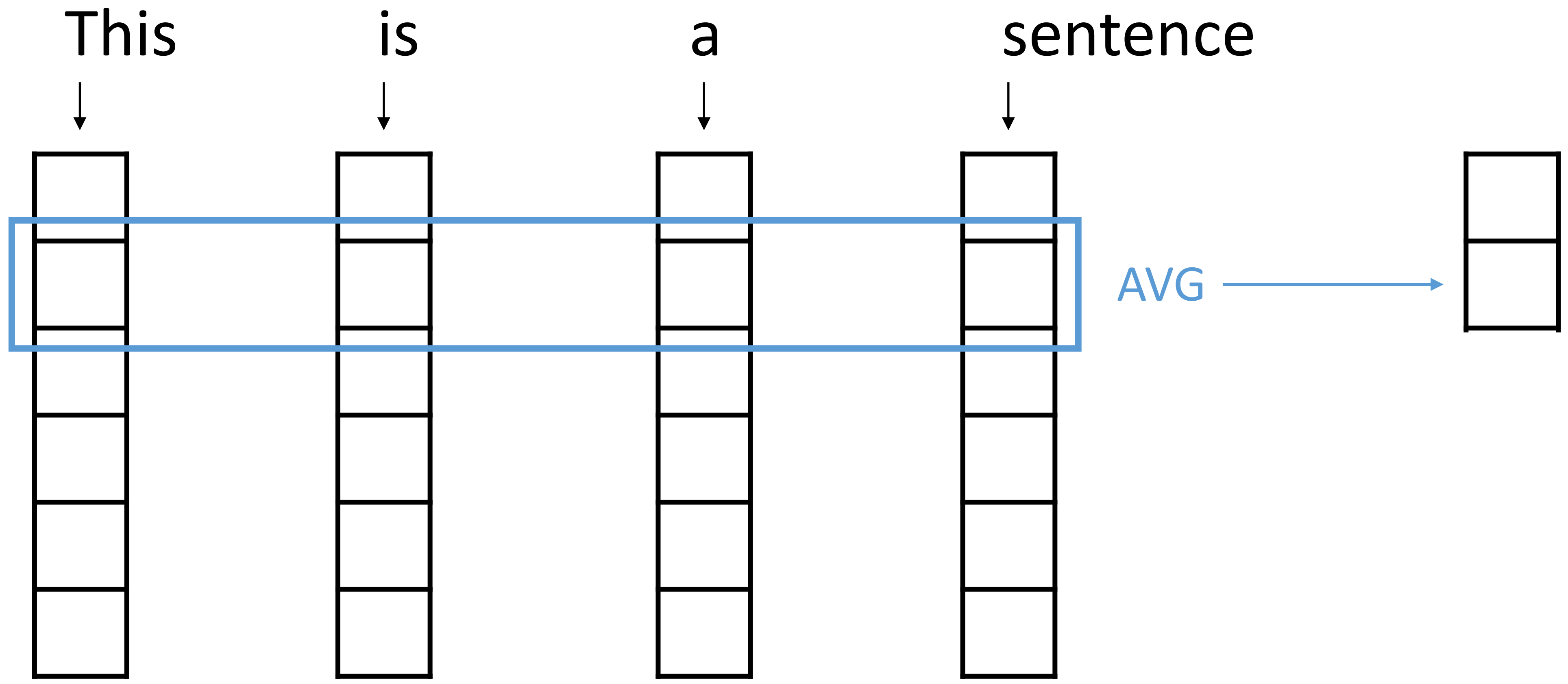

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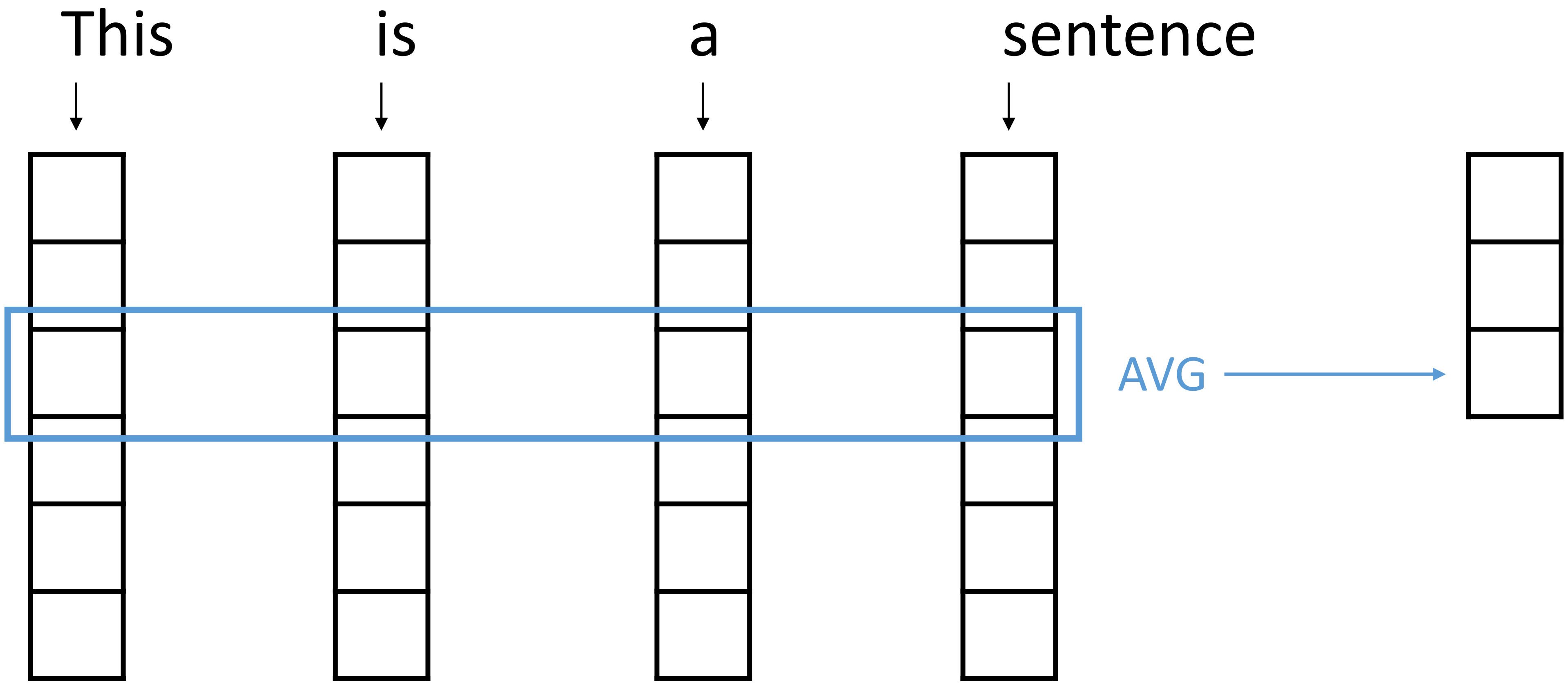

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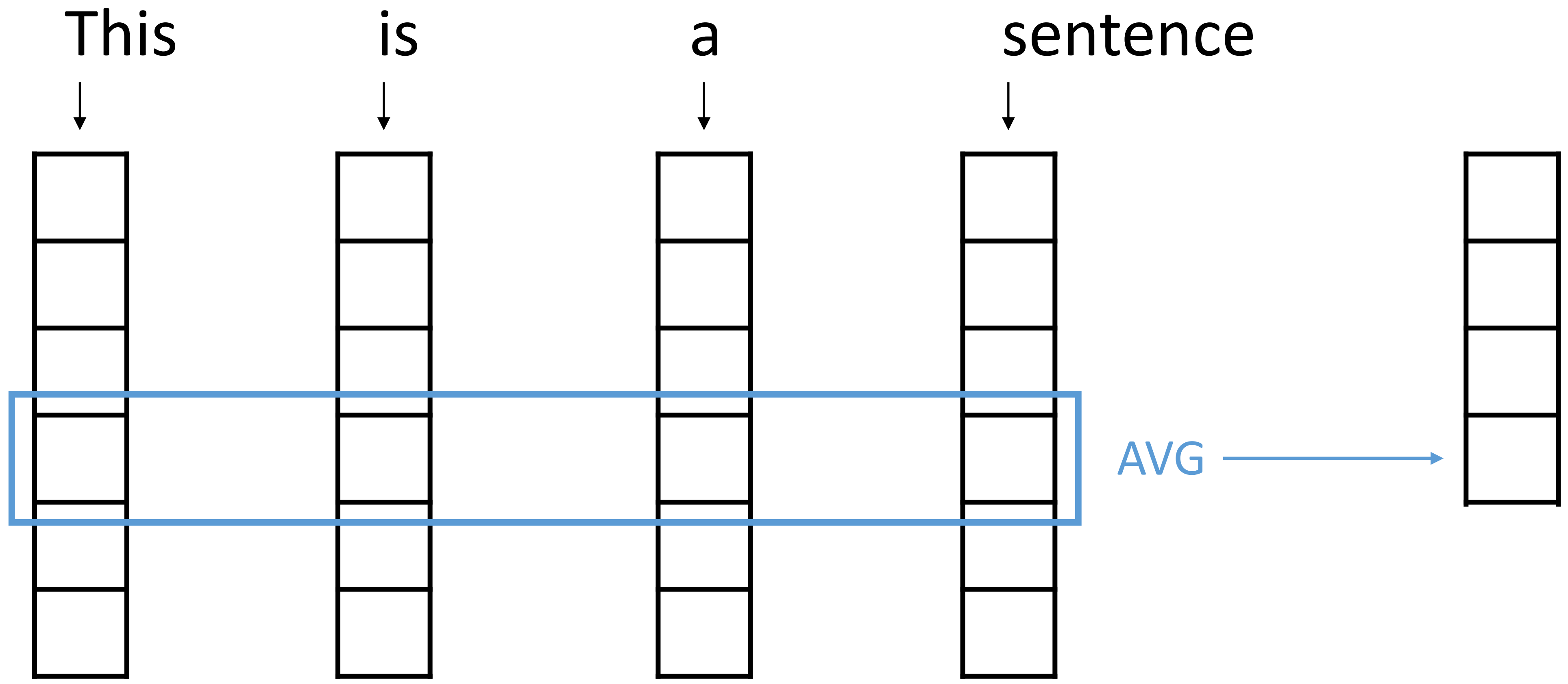

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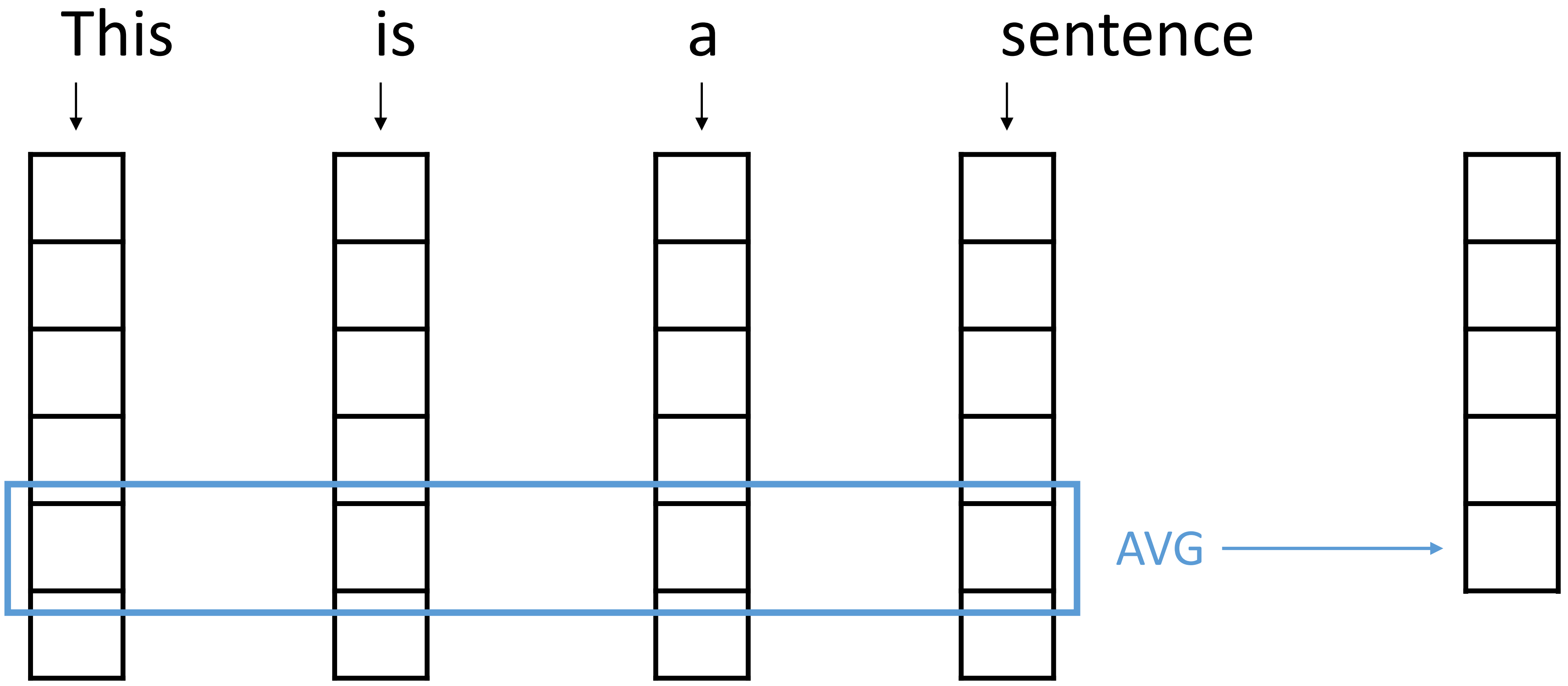

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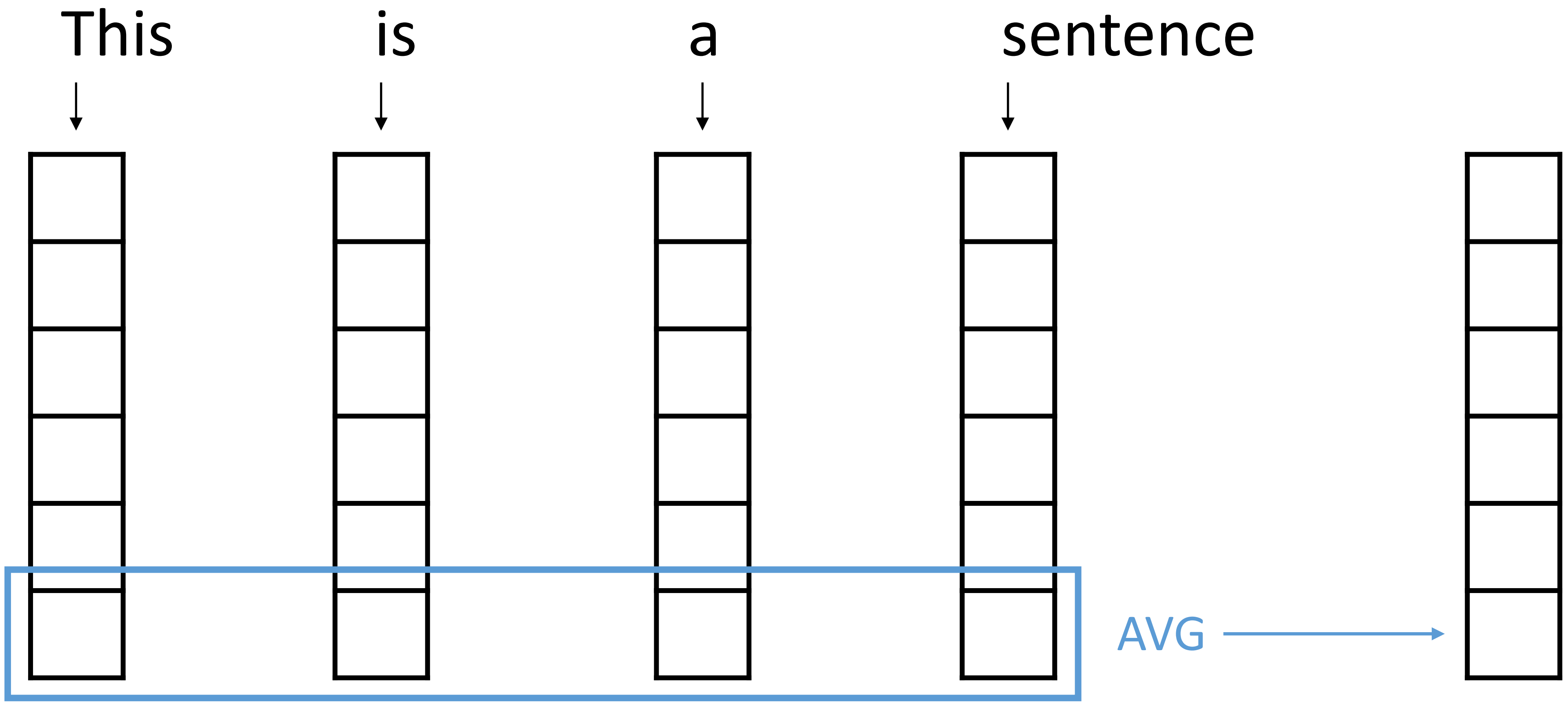
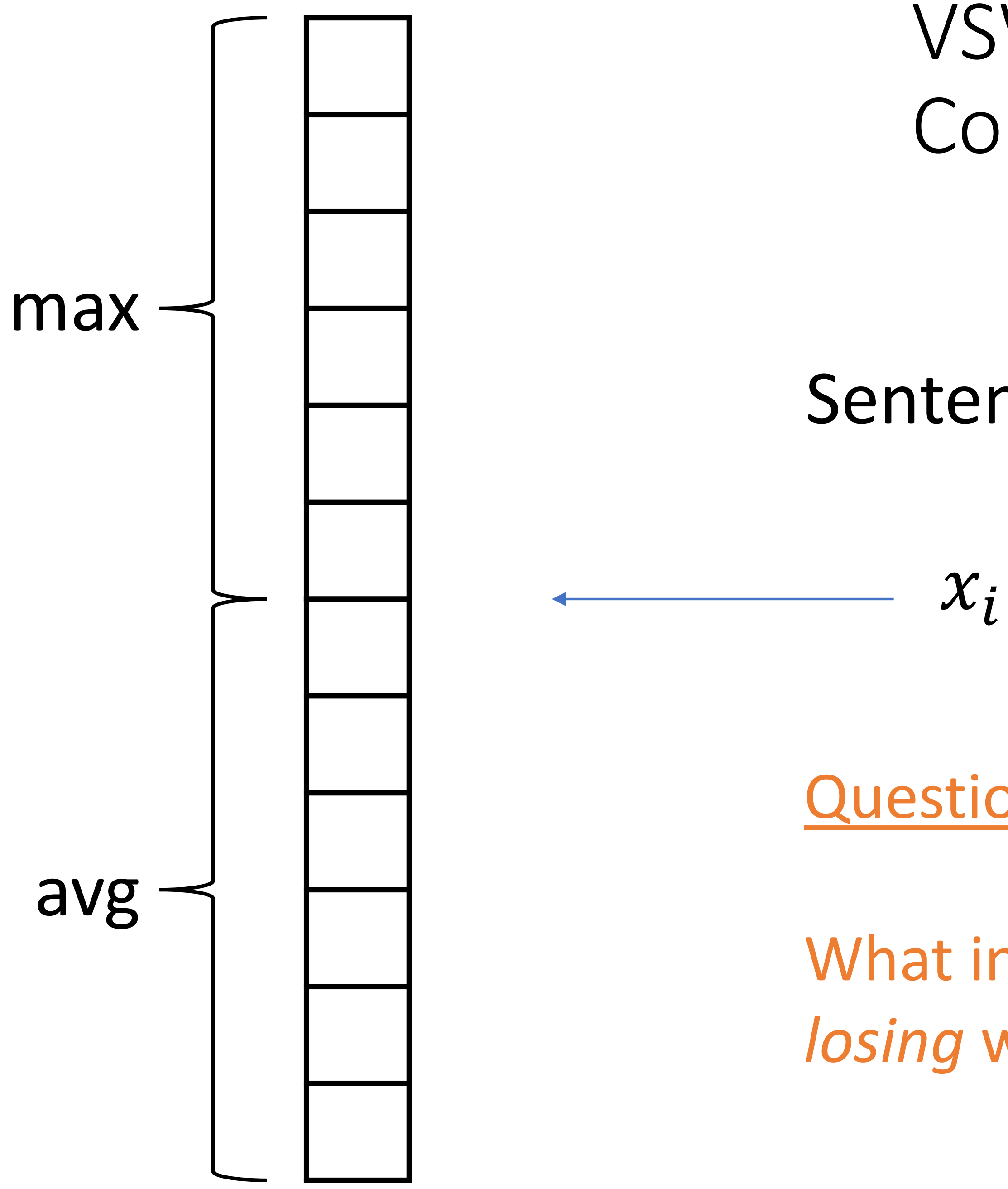


VSWEM Step 4: Concatenate MAX and AVG



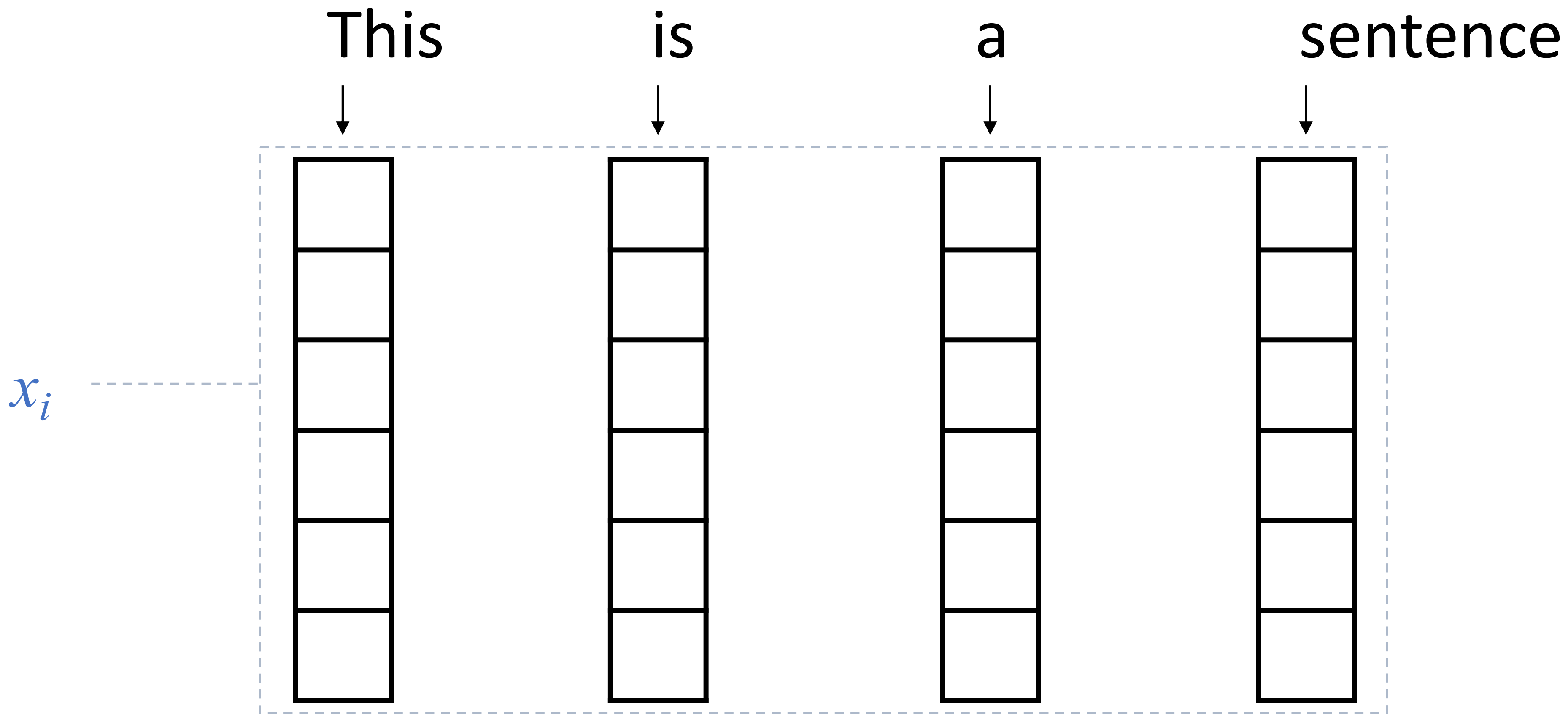
Sentence i → This is a sentence

Question:

What information are we *losing* when we do this?

Much more complex models…

- Look up words individually to obtain their vectors
- Construct a sequence of vectors
- Then, apply an NN-based model designed for sequences (e.g. transformer, RNN)



State of the art NLP models have *billions* of parameters (up to 1T).

SYSTEM PROMPT (HUMAN-WRITTEN)

A train carriage containing controlled nuclear materials was stolen in Cincinnati today. Its whereabouts are unknown.

MODEL COMPLETION (MACHINE-WRITTEN, FIRST TRY)

The incident occurred on the downtown train line, which runs from Covington and Ashland stations.

In an email to Ohio news outlets, the U.S. Department of Energy said it is working with the Federal Railroad Administration to find the thief.

“The theft of this nuclear material will have significant negative consequences on public and environmental health, our workforce and the economy of our nation,” said Tom Hicks, the U.S. Energy Secretary, in a statement. “Our top priority is to secure the theft and ensure it doesn’t happen again.”

The stolen material was taken from the University of Cincinnati’s Research Triangle Park nuclear research site, according to a news release from Department officials.
The Nuclear Regulatory Commission did not immediately release any information.

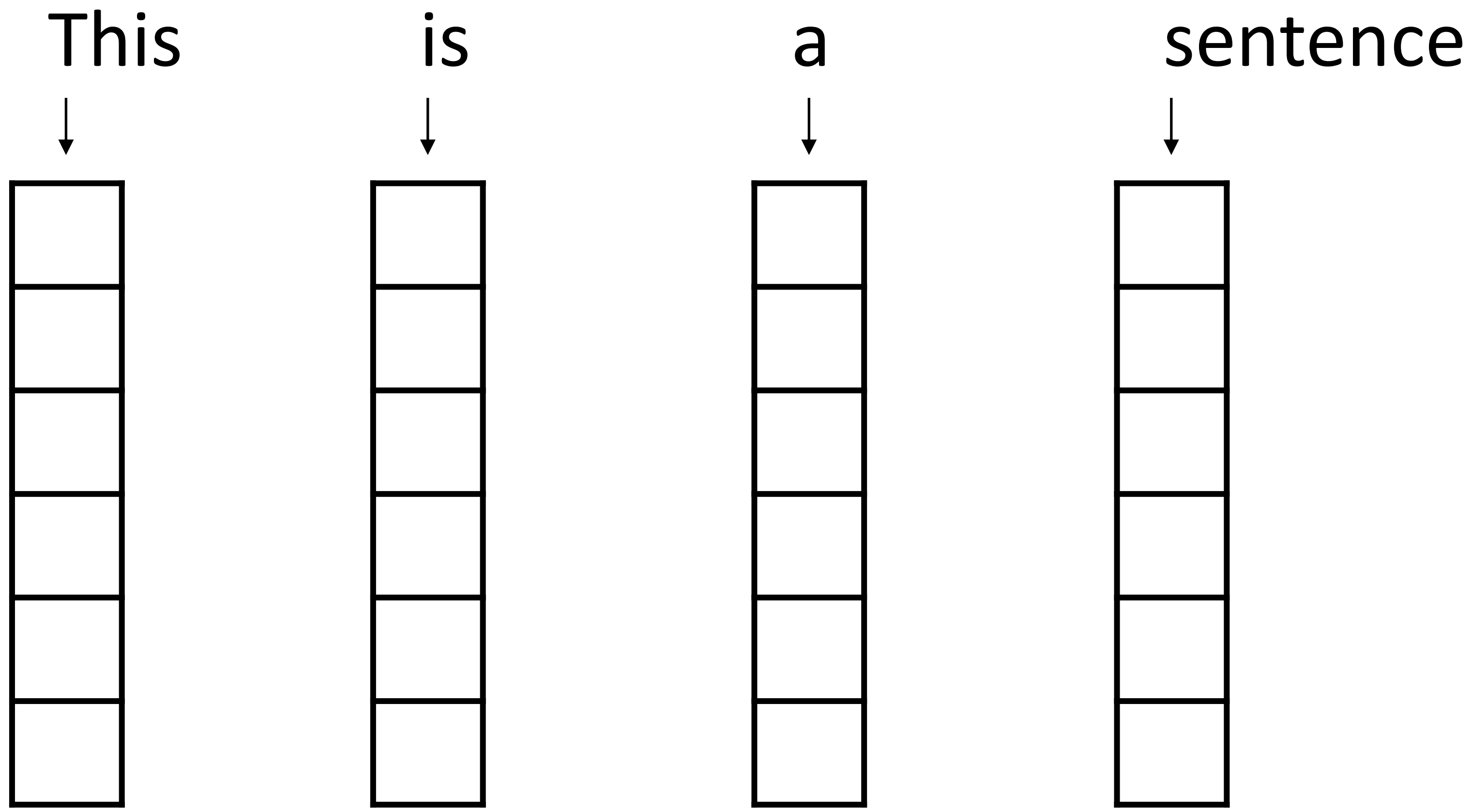
According to the release, the U.S. Department of Energy’s Office of Nuclear Material Safety and Security is leading that team’s investigation.

“The safety of people, the environment and the nation’s nuclear stockpile is our highest priority,” Hicks said. “We will get to the bottom of this and make no excuses.

“Better Language Models and Their Implications”
2/14/19
OPENAI

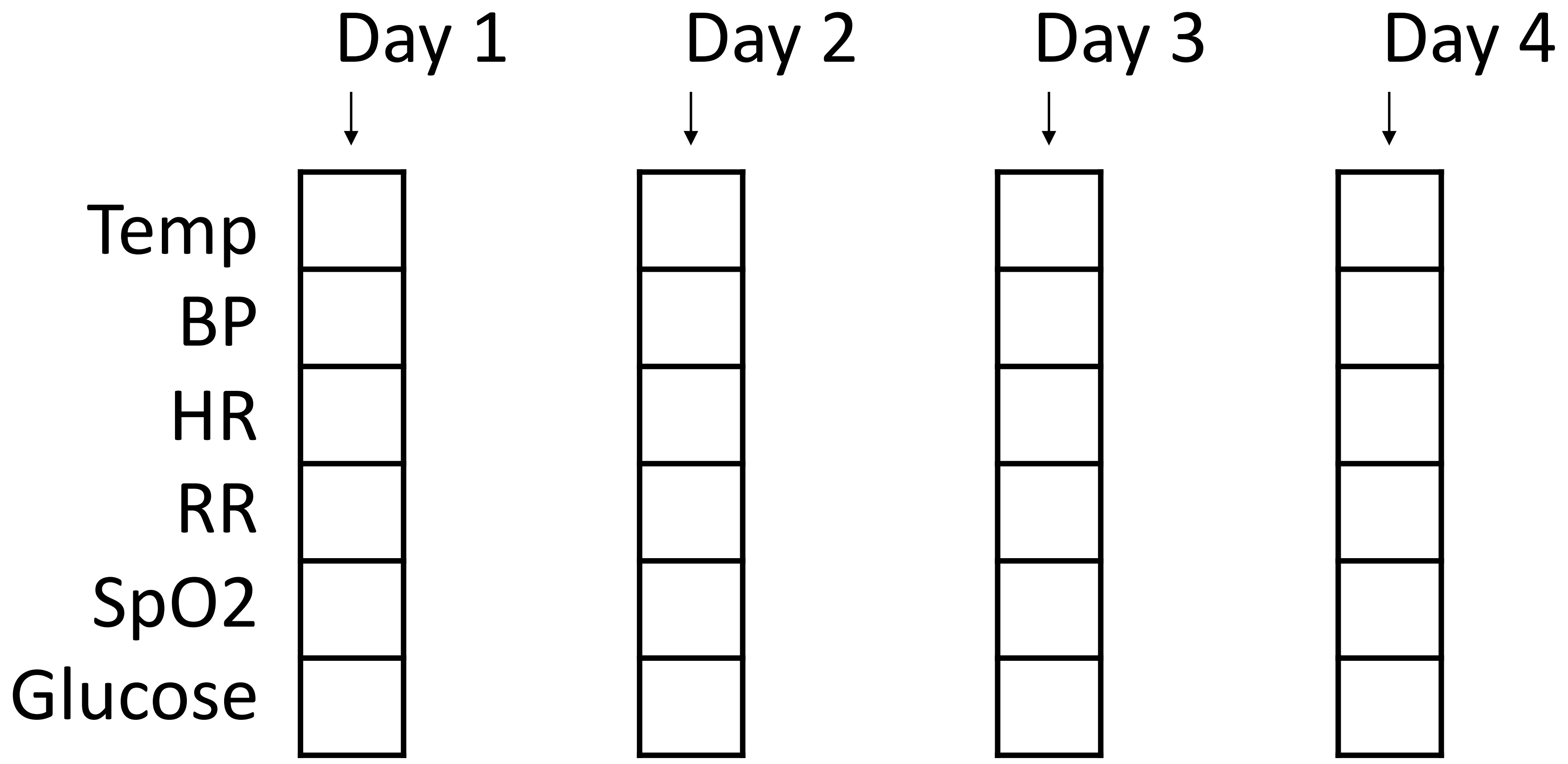
With word vectors, methods for text vs sequences are similar:

A sequence of word vectors…

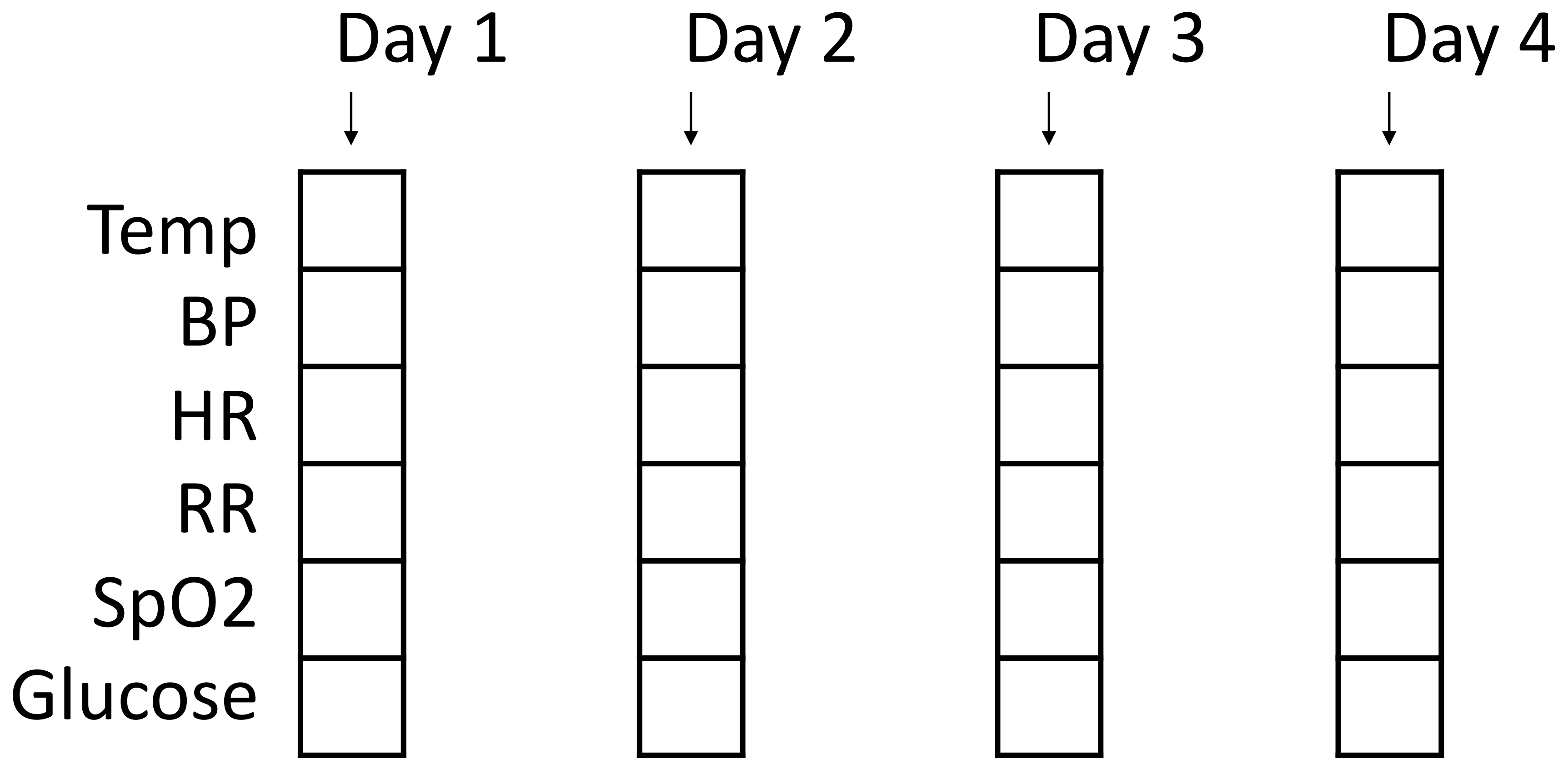


With word vectors, methods for text vs sequences are similar:

…now looks just like a sequence of measurements.

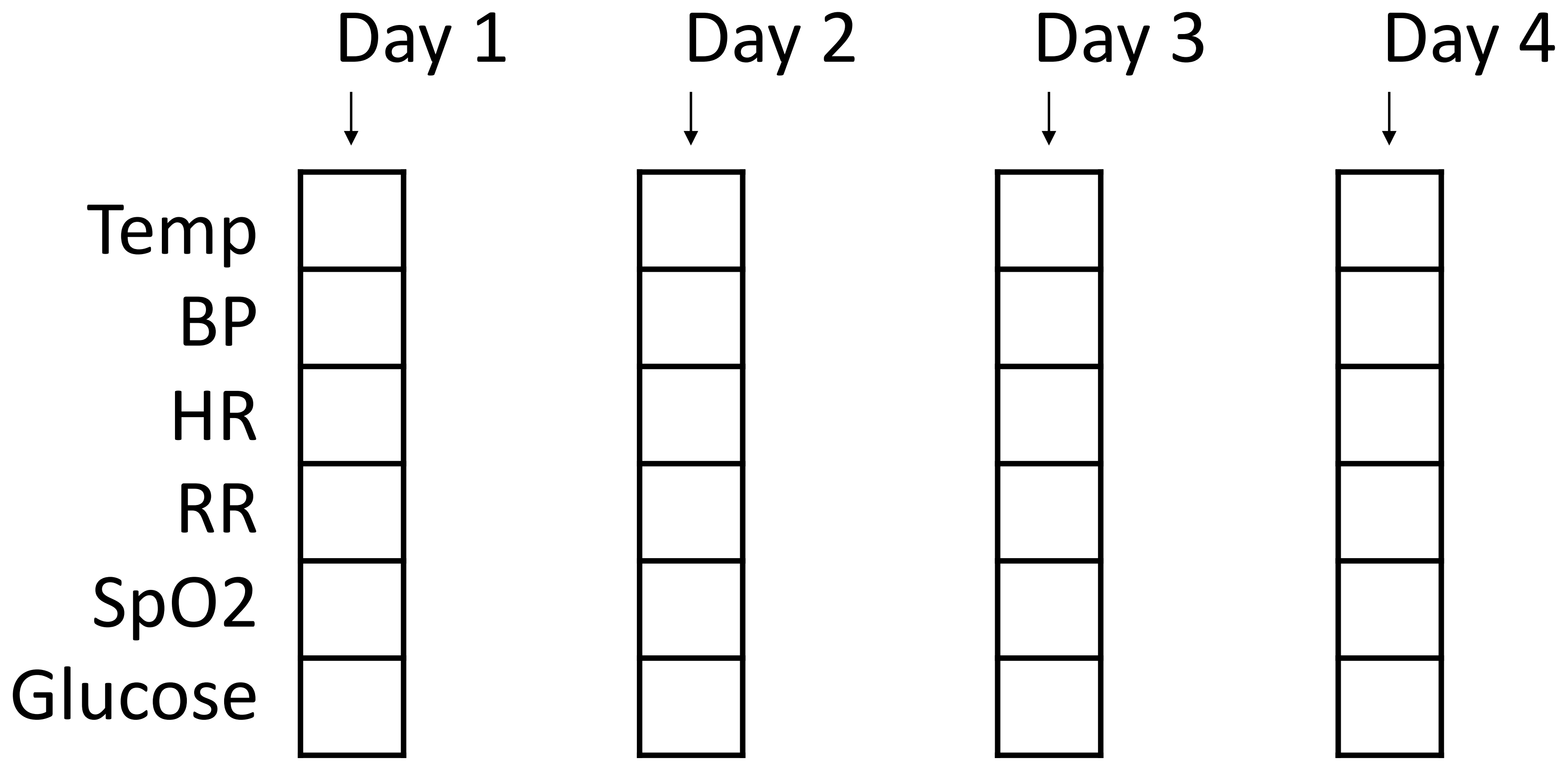


In this case, too, we can get a single numeric vector for our predictive models by taking a max and average (or any other summary statistics we'd like)



But when we do this, we lose information about *order*.

- Next time, we'll talk about ways to overcome this limitation



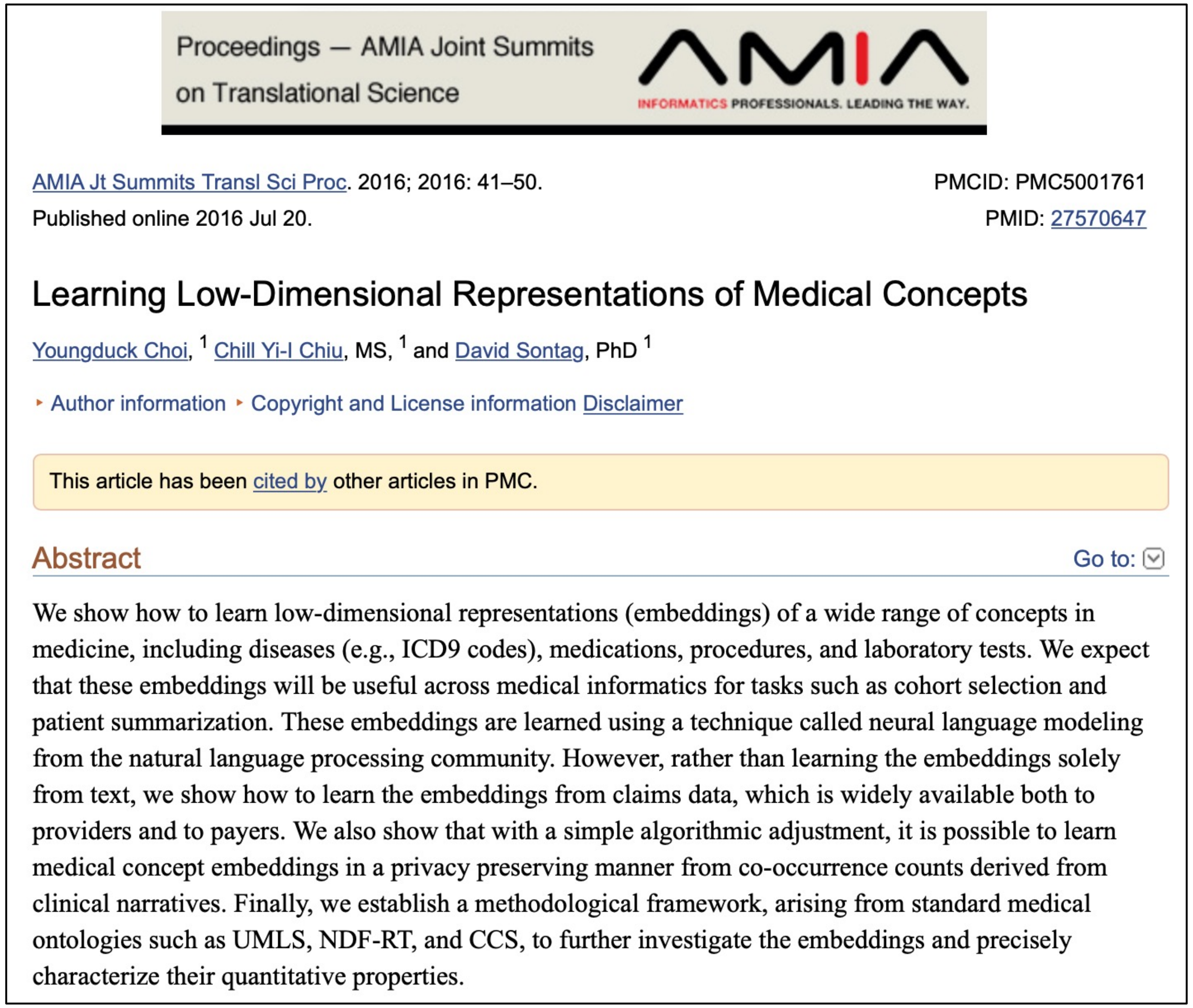
Conclusions

- NLP is approaching human performance on benchmark tasks like question answering
- Text data are central to clinical medicine, so the potential for NLP impact is high (but *not yet realized*)
- We can use word counts to turn text samples into vectors that we already know how to work with. This is the key to modern NLP.
- The techniques we have discussed already go beyond the majority of "NLP" found in the medical literature.
- Similar to image processing, we can take advantage of huge state of the art models by repurposing them for a specific clinical task via fine-tuning of parameters.

Bonus: we can also do this with categorical variables!

- Locations (city/state)
- Dx and procedure codes
- Medical concepts

- *What attributes could be used to encode the meaning of medical concepts?*



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Learning Low-Dimensional Representations of Medical Concepts

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Abstract

Go to:

We show how to learn low-dimensional representations (embeddings) of a wide range of concepts in medicine, including diseases (e.g., ICD9 codes), medications, procedures, and laboratory tests. We expect that these embeddings will be useful across medical informatics for tasks such as cohort selection and patient summarization. These embeddings are learned using a technique called neural language modeling from the natural language processing community. However, rather than learning the embeddings solely from text, we show how to learn the embeddings from claims data, which is widely available both to providers and to payers. We also show that with a simple algorithmic adjustment, it is possible to learn medical concept embeddings in a privacy preserving manner from co-occurrence counts derived from clinical narratives. Finally, we establish a methodological framework, arising from standard medical ontologies such as UMLS, NDF-RT, and CCS, to further investigate the embeddings and precisely characterize their quantitative properties.