Data Science

Lecture 7: Text Data Processing

University of Amsterdam

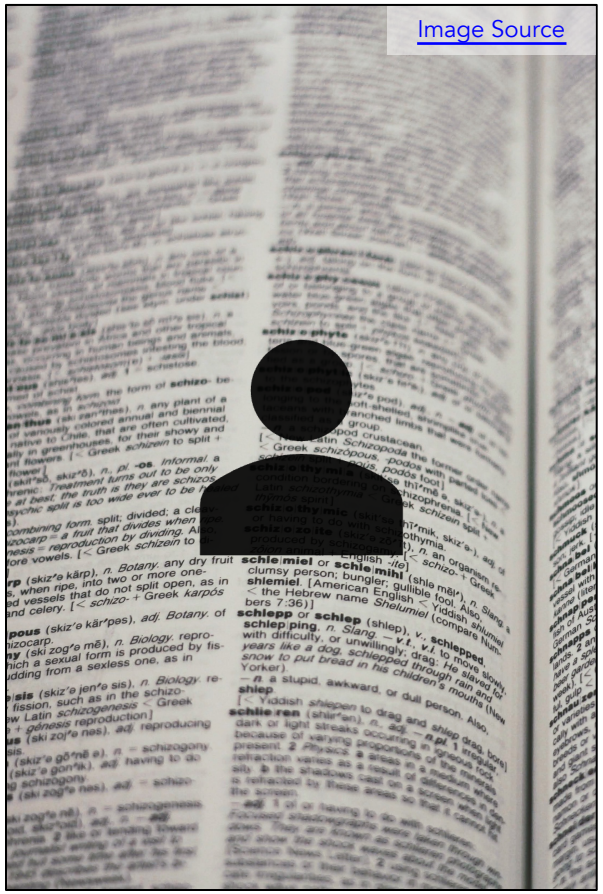
Lecturer: Yen-Chia Hsu

Date: Feb 2026

This lecture covers the pipeline of Natural Language Processing (NLP):

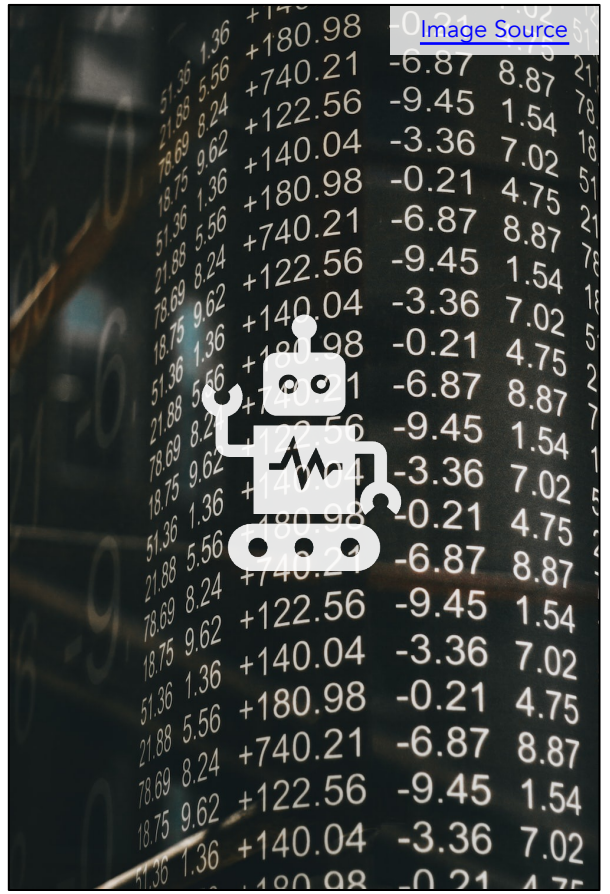
- Text preprocessing
- Bag of words and TF-IDF
- Topic modeling
- Word embeddings and Word2Vec
- Sentence/document representations
- Attention mechanism

People can read text, but computers can only read numbers. So, we need to represent text as numbers in a way that computers can read, but how?

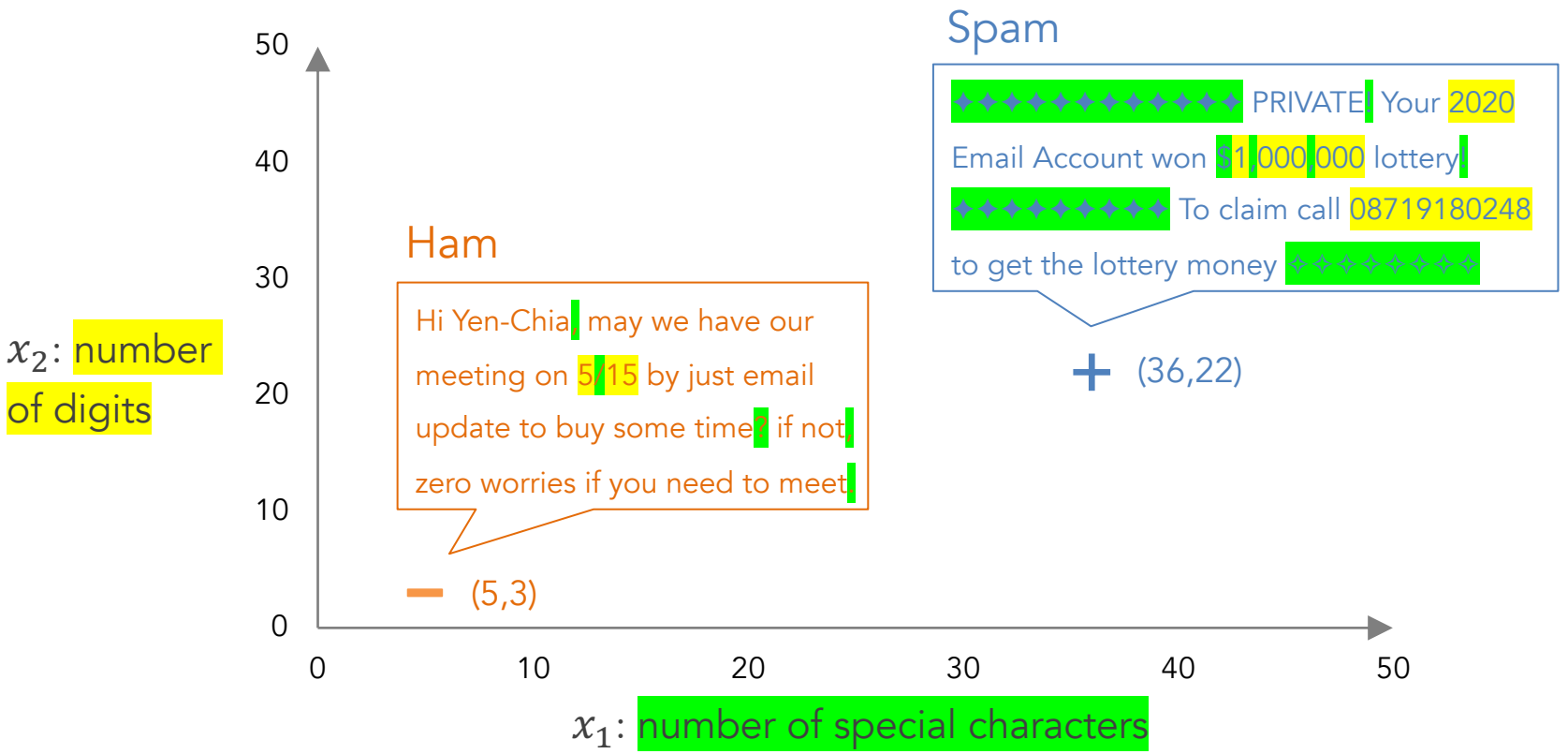


?

Text → Numbers



Previously, we have learned the spam classification example about how to represent messages as data points on a 2-dimensional space, using some hand-crafted features.



Typically, before the deep learning era, we need to preprocess text using tokenization (i.e., separating words) and normalization (i.e., standardizing the word format).

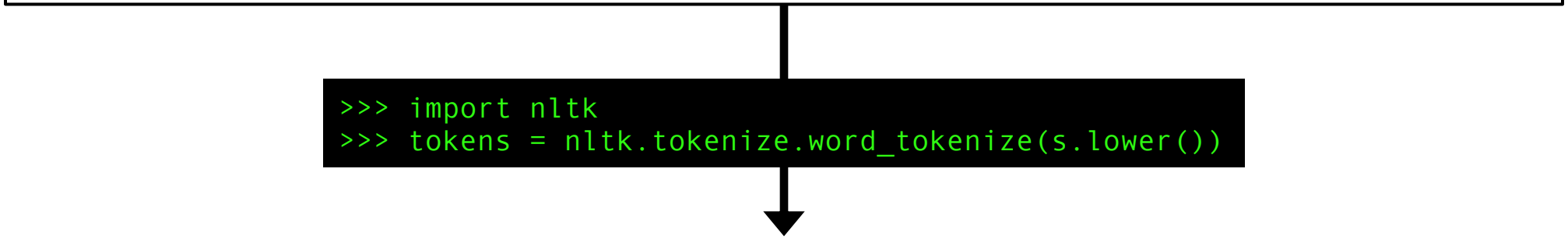
> Google, headquartered in Mountain View (1600 Amphitheatre Pkwy, Mountain View, CA 940430), unveiled the new Android phone for $799 at the Consumer Electronic Show. Sundar Pichai said in his keynote that users love their new Android phones.

['google', 'headquarter', 'mountain', 'view', 'amphitheatre', 'pkwy', 'mountain', 'view', 'ca', 'unveil', 'new', 'android', 'phone', 'consumer', 'electronic', 'show', 'sundar', 'pichai', 'say', 'keynote', 'user', 'love', 'new', 'android', 'phone']

The tokenization step separates a sentence into word fragments (i.e., an array of words).

We can lower the cases first before tokenization.

Google, headquartered in Mountain View (1600 Amphitheatre Pkwy, Mountain View, CA 940430), unveiled the new Android phone for $799 at the Consumer Electronic Show. Sundar Pichai said in his keynote that users love their new Android phones.



```
>>> import nltk
>>> tokens = nltk.tokenize.word_tokenize(s.lower())
```

['google', ',', 'headquartered', 'in', 'mountain', 'view', '(', '1600', 'amphitheatre', 'pkwy', ',', 'mountain', 'view', ',', 'ca', '940430', ')', ',', 'unveiled', 'the', 'new', 'android', 'phone', 'for', '$', '799', 'at', 'the', 'consumer', 'electronic', 'show', '.', 'sundar', 'pichai', 'said', 'in', 'his', 'keynote', 'that', 'users', 'love', 'their', 'new', 'android', 'phones', '.']

During tokenization, we can also remove unwanted tokens, such as punctuations, digits, symbols, emojis, stop words (i.e., high frequency words, like “the”), etc.

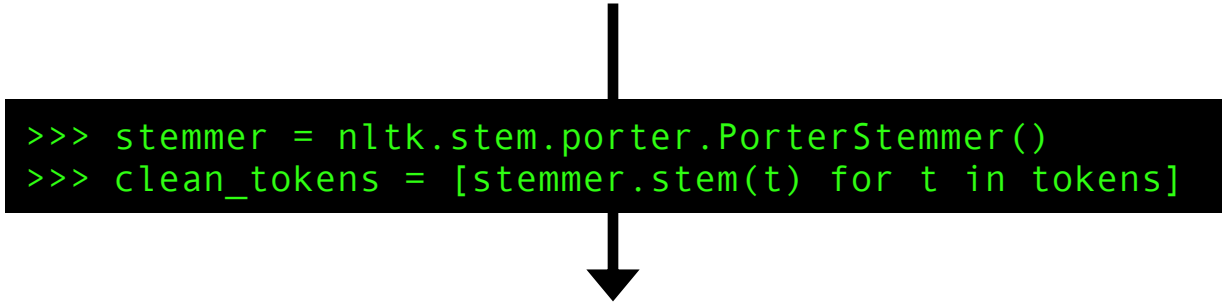
['google', ',', 'headquartered', 'in', 'mountain', 'view', '(', '1600', 'amphitheatre', 'pkwy', ',', 'mountain', 'view', ',', 'ca', '940430', ')', ',', 'unveiled', 'the', 'new', 'android', 'phone', 'for', '$', '799', 'at', 'the', 'consumer', 'electronic', 'show', '.', 'sundar', 'pichai', 'said', 'in', 'his', 'keynote', 'that', 'users', 'love', 'their', 'new', 'android', 'phones', '.']

```
>>> stws = nltk.corpus.stopwords.words('english')
>>> tokens = [t for t in tokens if t.isalpha() and t not in stws]
```

['google', 'headquartered', 'mountain', 'view', 'amphitheatre', 'pkwy', 'mountain', 'view', 'ca', 'unveiled', 'new', 'android', 'phone', 'consumer', 'electronic', 'show', 'sundar', 'pichai', 'said', 'keynote', 'users', 'love', 'new', 'android', 'phones']

One way to perform normalization is stemming, which chops or replaces word tails (e.g., removing “s”) with the goal of approximate the word’s original form.

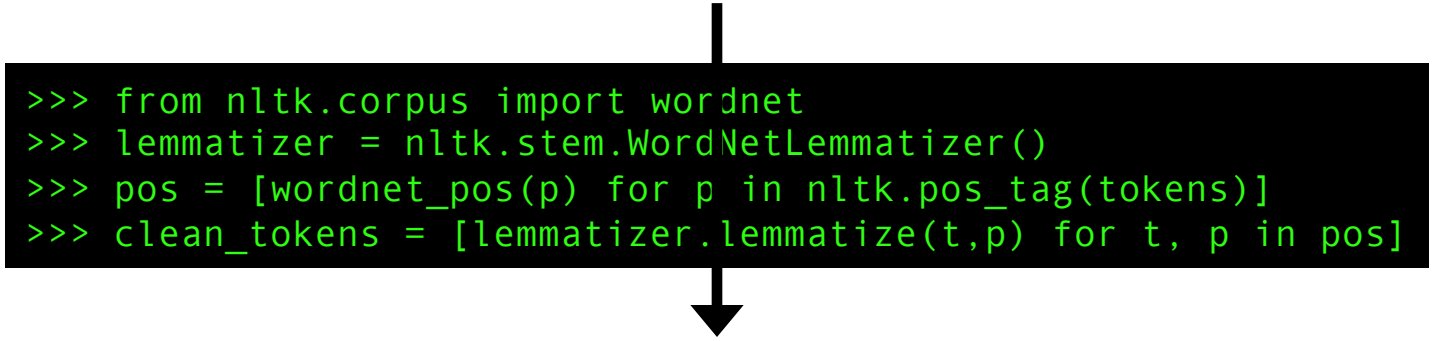
['google', 'headquartered', 'mountain', 'view', 'amphitheatre', 'pkwy', 'mountain', 'view', 'ca', 'unveiled', 'new', 'android', 'phone', 'consumer', 'electronic', 'show', 'sundar', 'pichai', 'said', 'keynote', 'users', 'love', 'new', 'android', 'phones']



['googl', 'headquart', 'mountain', 'view', 'amphitheatr', 'pkwi', 'mountain', 'view', 'ca', 'unveil', 'new', 'android', 'phone', 'consum', 'electron', 'show', 'sundar', 'pichai', 'said', 'keynot', 'user', 'love', 'new', 'android', 'phone']

Another way to perform normalization is lemmatization, which uses dictionaries and full morphological analysis to correctly identify the lemma (i.e., base form) for each word.

['google', 'headquartered', 'mountain', 'view', 'amphitheatre', 'pkwy', 'mountain', 'view', 'ca', 'unveiled', 'new', 'android', 'phone', 'consumer', 'electronic', 'show', 'sundar', 'pichai', 'said', 'keynote', 'users', 'love', 'new', 'android', 'phones']



['google', 'headquarter', 'mountain', 'view', 'amphitheatre', 'pkwy', 'mountain', 'view', 'ca', 'unveil', 'new', 'android', 'phone', 'consumer', 'electronic', 'show', 'sundar', 'pichai', 'say', 'keynote', 'user', 'love', 'new', 'android', 'phone']

To perform lemmatization appropriately, we need POS (Part Of Speech) tagging, which means labeling the role of each word in a particular part of speech.

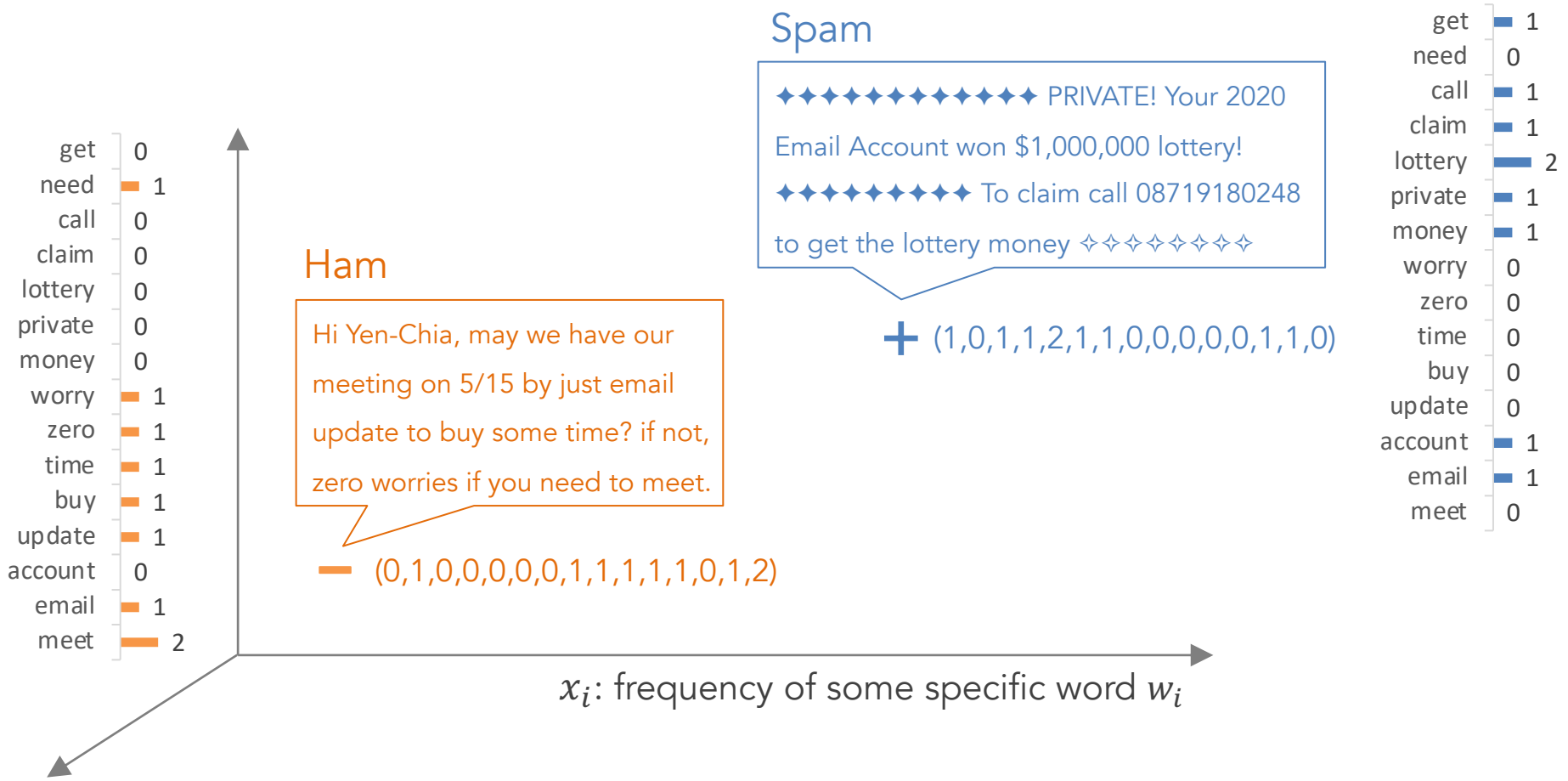
nsubj	p	vmod	prep	nn	pobj	p	num	nn	appos	p
Google	,	headquartered	in	Mountain	View	(	1600	Amphitheatre	Pkwy	,
NOUN	PUNCT	VERB	ADP	NOUN	NOUN	PUNCT	NUM	NOUN	NOUN	PUNCT

nn	appos	p	appos	num	p	p	root	det	amod	nn	dobj	prep	pobj	prep	det	nn	nn	pobj	p
Mountain	View	,	CA	940430	)	,	unveiled	the	new	Android	phone	for	$799	at	the	Consumer	Electronic	Show	.
NOUN	NOUN	PUNCT	NOUN	NUM	PUNCT	PUNCT	VERB	DET	ADJ	NOUN	NOUN	ADP	NUM	ADP	DET	NOUN	NOUN	NOUN	PUNCT

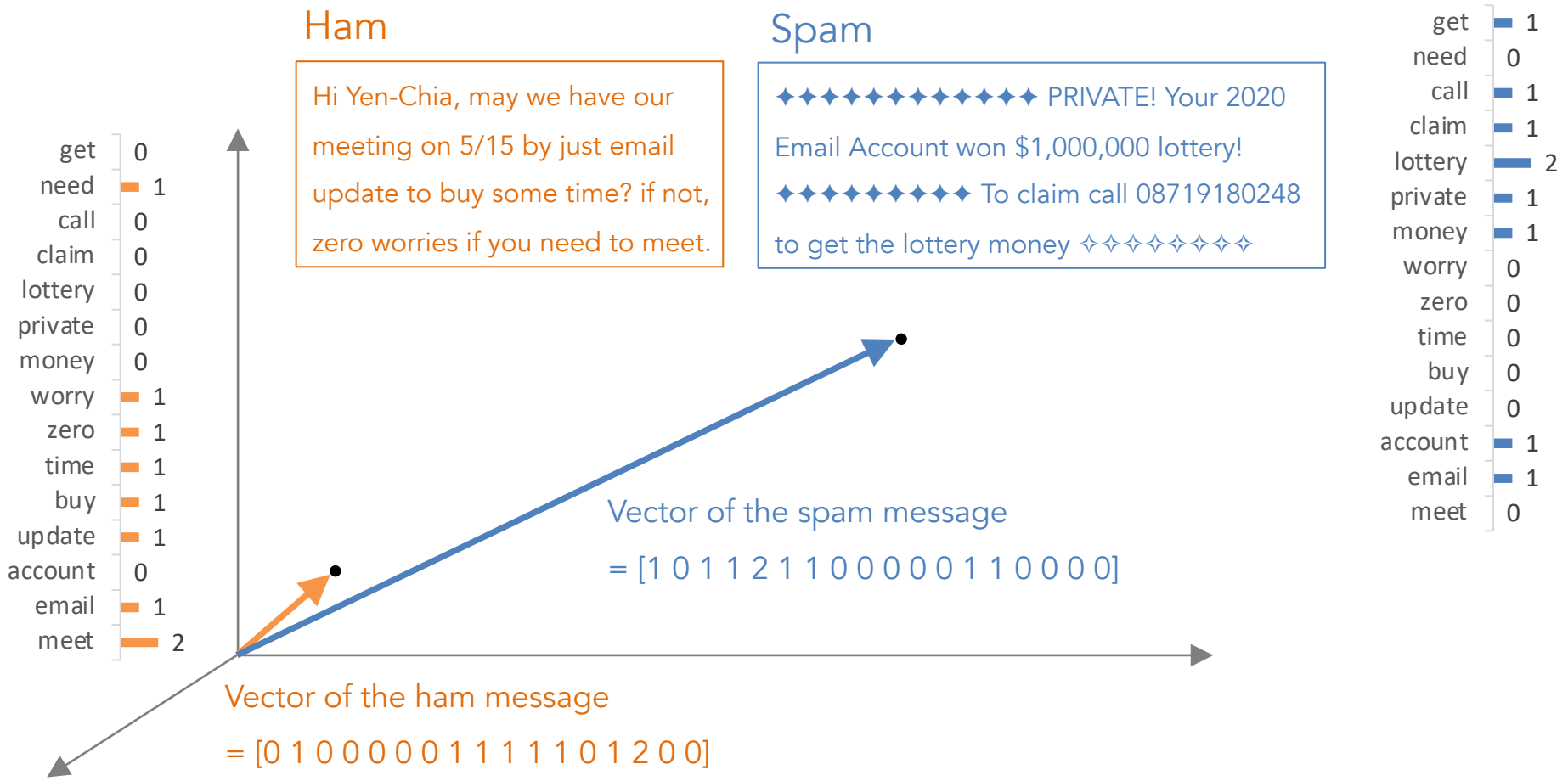
nn	nsubj	root	prep	poss	pobj	mark	nsubj	ccomp	poss	amod	nn	dobj
Sundar	Pichai	said	in	his	keynote	that	users	love	their	new	Android	phones
NOUN	NOUN	VERB	ADP	PRON	NOUN	ADP	NOUN	VERB	PRON	ADJ	NOUN	NOUN

```
>>> from nltk.corpus import wordnet
>>> def wordnet_pos(nltk_pos):
...   if nltk_pos[1].startswith('V'): return (nltk_pos[0], wordnet.VERB)
...   if nltk_pos[1].startswith('J'): return (nltk_pos[0], wordnet.ADJ)
...   if nltk_pos[1].startswith('R'): return (nltk_pos[0], wordnet.ADV)
...   else: return (nltk_pos[0], wordnet.NOUN)
```

Now we have the cleaned tokens that represent a sentence. We need to transform them to data points in some high-dimensional space. One example is Bag of Words.

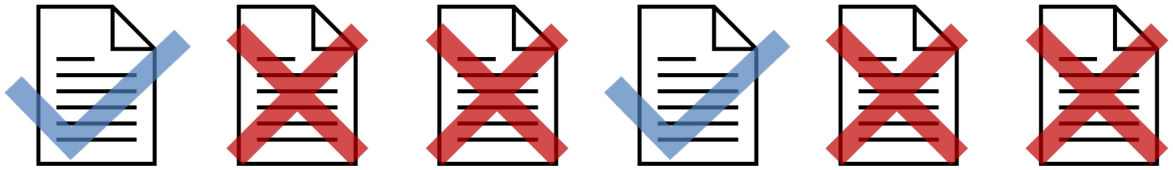


These data points are also called vectors, which means arrays of numbers that encode both the direction and length information.



More about vectors -- https://www.3blue1brown.com/lessons/vectors

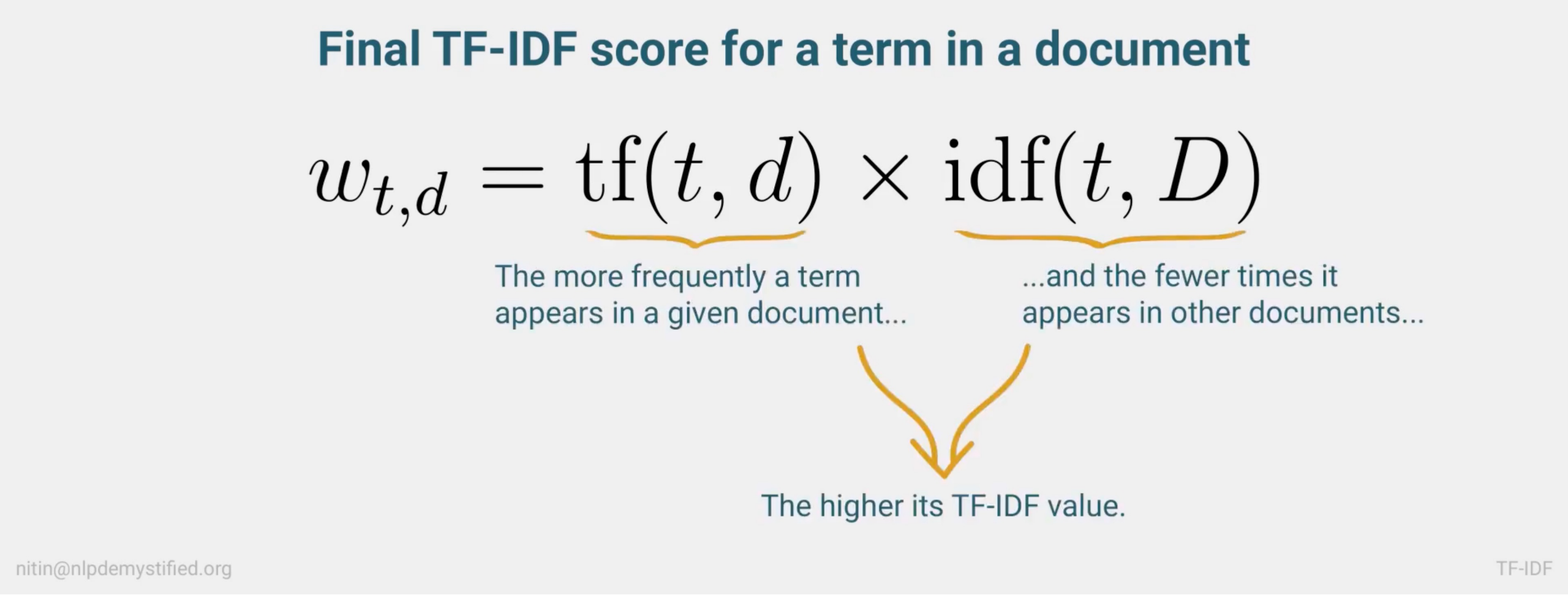
The Bag of Words approach can be problematic since it weights all words equally, even after removing stop words. For example, "play" can appear many times in sports news.



If a word appears in only a few documents (and frequently in these documents), it contains more information and should be more important.

If a word appears in almost all documents, it should be less important, since seeing this word does not give us much information.

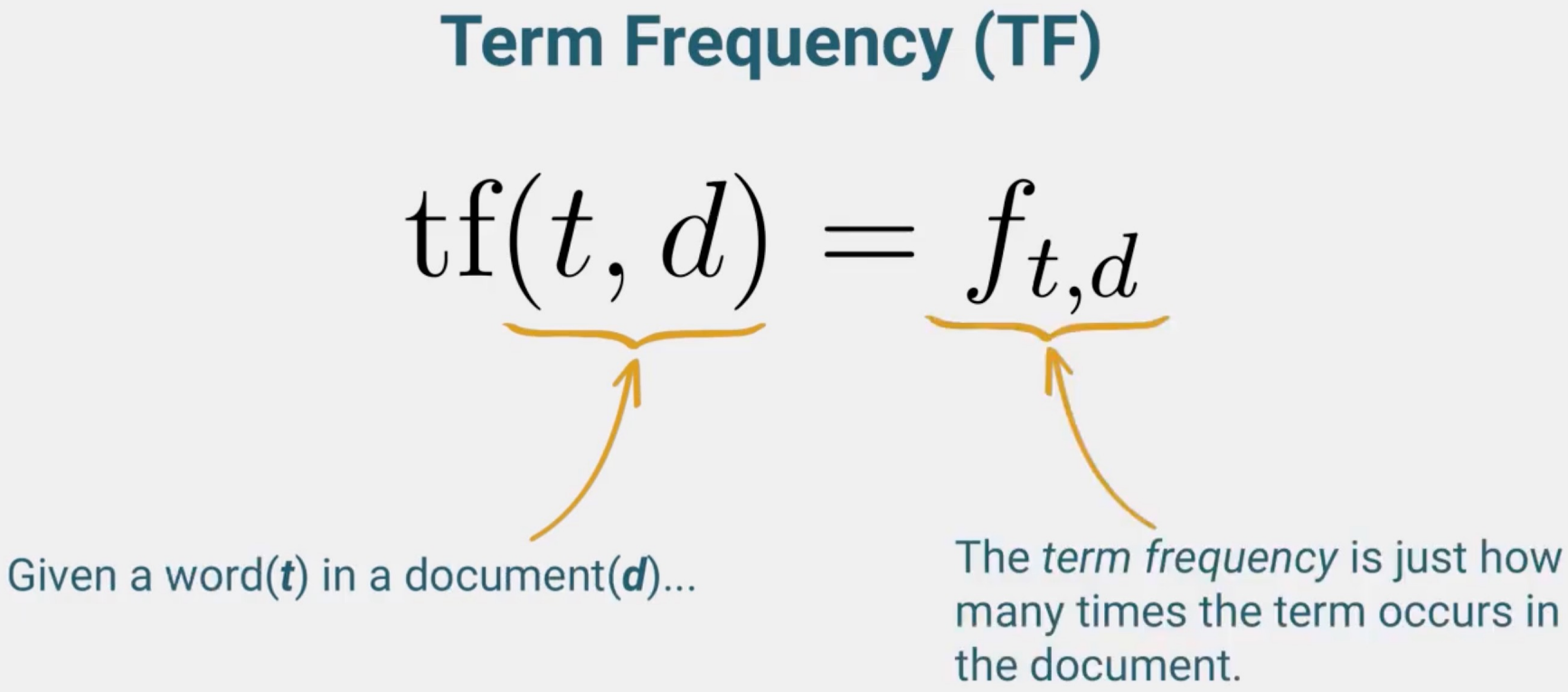
So, we can use TF-IDF (term frequency-inverse document frequency) to transform sentences or documents into vectors. Intuitively, TF-IDF means weighted Bag of Words.



Source -- https://www.nlpdemystified.org/course/tf-idf

Term Frequency (TF) measures how frequently a term (word) appears in a document.

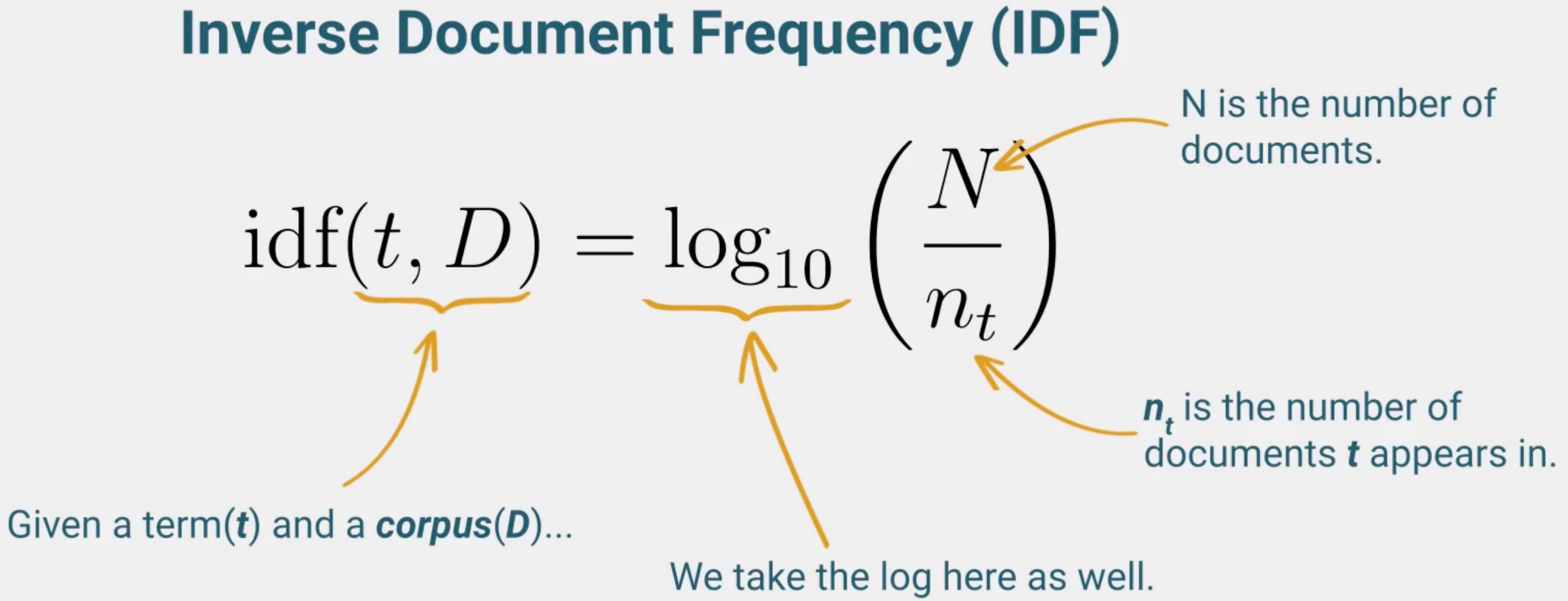
There are different implementations, such as using a log function to scale it down.



Alternative Implementation: $\mathrm{tf}(t, d) = \log_{10}(f_{t,d} + 1)$

Source -- https://www.nlpdemystified.org/course/tf-idf

Inverse Document Frequency (IDF) weights each word by considering how frequently it shows in different documents. IDF is higher when the term appears in fewer documents.



Source -- https://www.nlpdemystified.org/course/tf-idf

Exercise 7.1: Given the following term frequency table for four words ("apple", "bike", "spaceship", "tea") in four documents (i.e., document set D), which word is the most representative for the first document (with Document ID $doc1$) according to TF-IDF?

ID	TF for "apple"	TF for "bike"	TF for "spaceship"	TF for "tea"
doc1	8	0	4	8
doc2	3	2	3	0
doc3	2	3	0	1
doc4	4	0	0	0

$tf(apple, doc1) = ?$ $idf(apple, D) = ?$

$tf(bike, doc1) = ?$ $idf(bike, D) = ?$

$tf(spaceship, doc1) = ?$ $idf(spaceship, D) = ?$

$tf(tea, doc1) = ?$ $idf(tea, D) = ?$

$$\mathrm{tf}(t, d) = f_{t,d}$$

Given a word(***t***) in a document(***d***)...

The *term frequency* is just how many times the term occurs in the document.

$$\mathrm{idf}(t, D) = \log_{10}\left(\frac{N}{n_t}\right)$$

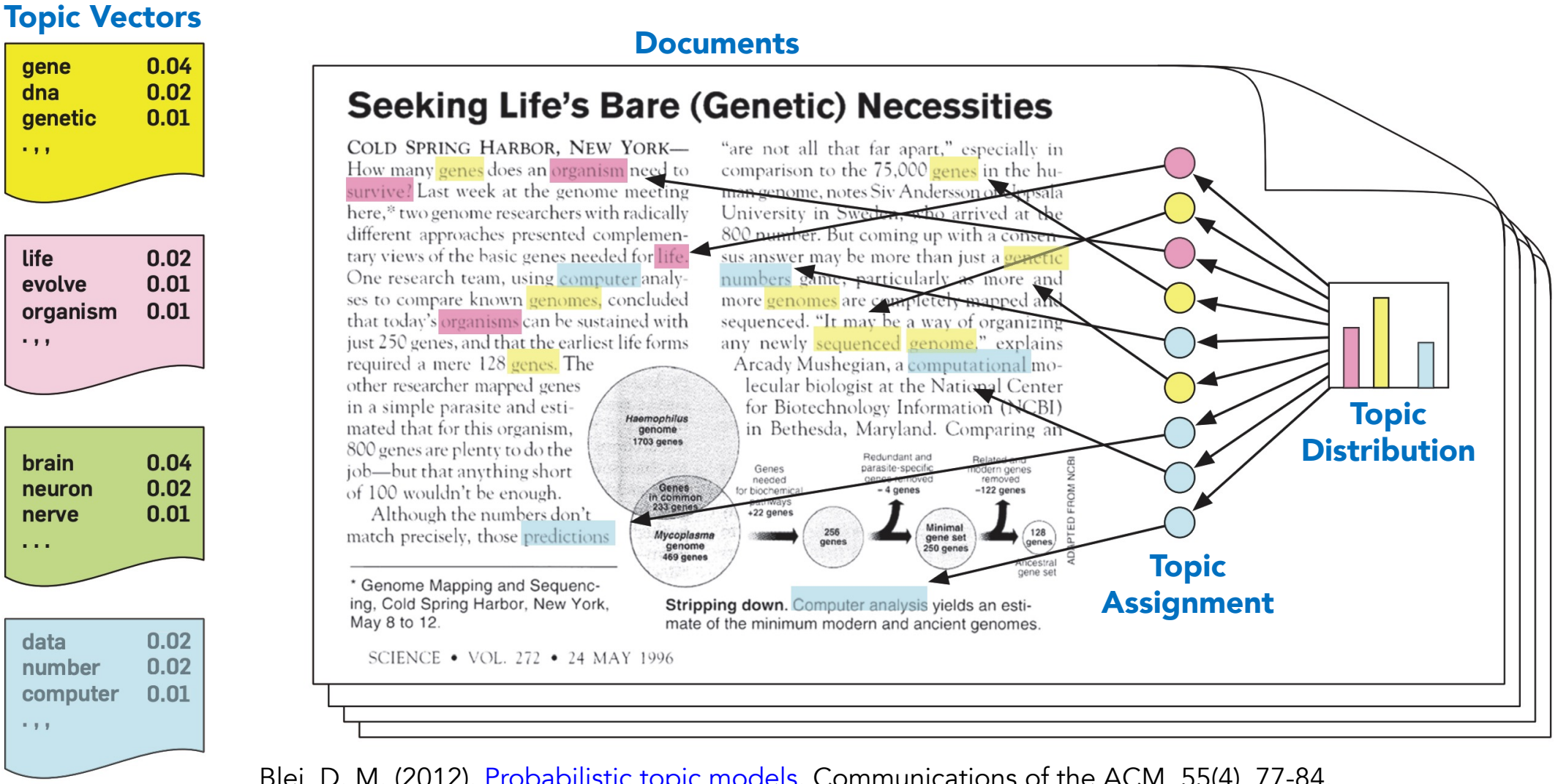
N is the number of documents.

n_t is the number of documents ***t*** appears in.

Given a term(***t***) and a ***corpus***(***D***)...

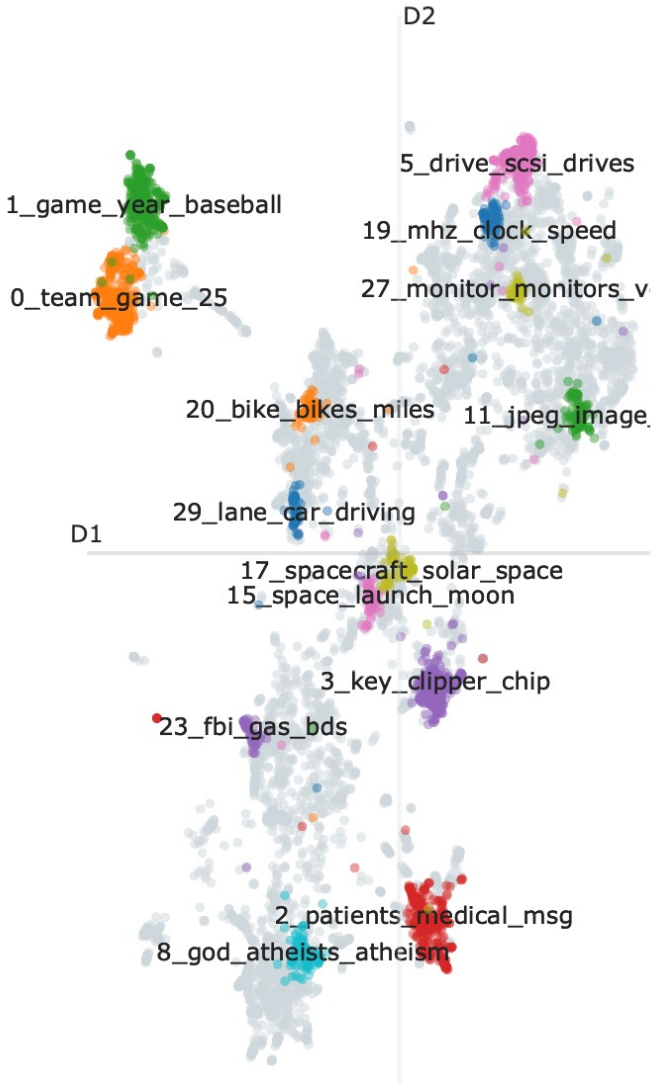
We take the log here as well.

We can also use topic modeling to encode a sentence/document into a distribution of topics. Below is an intuition of how the Latent Dirichlet Allocation method works.



Blei, D. M. (2012). Probabilistic topic models. Communications of the ACM, 55(4), 77-84.

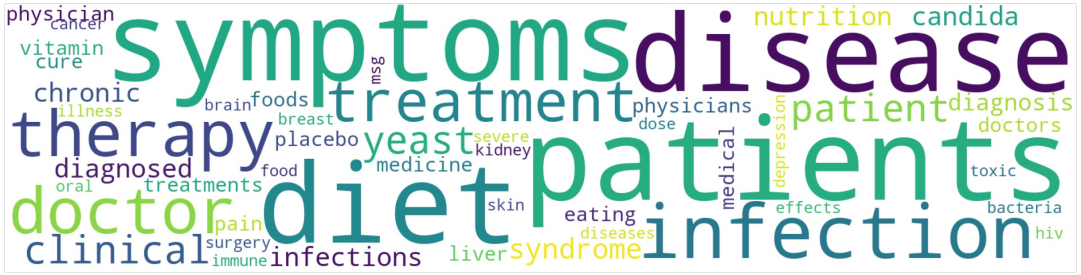
Each topic vector is represented by a list of words with different weights.



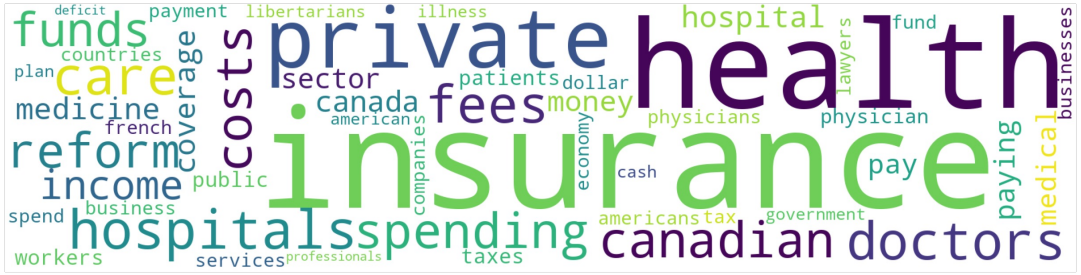
Source -- https://maartengr.github.io/BERTopic/getting_started/visualization/visualization.html

Each topic vector is represented by a list of words with different weights.

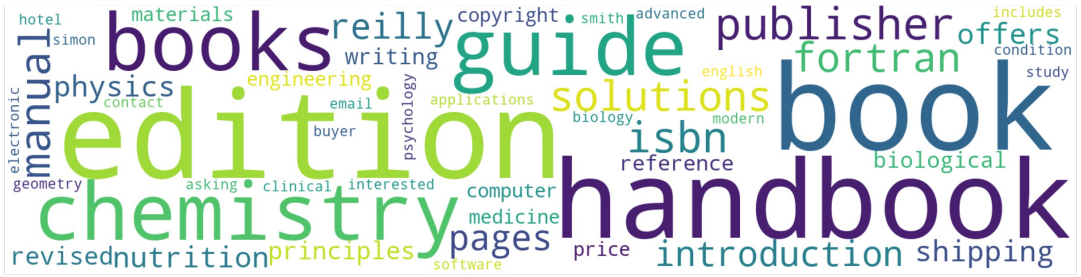
Topic 21



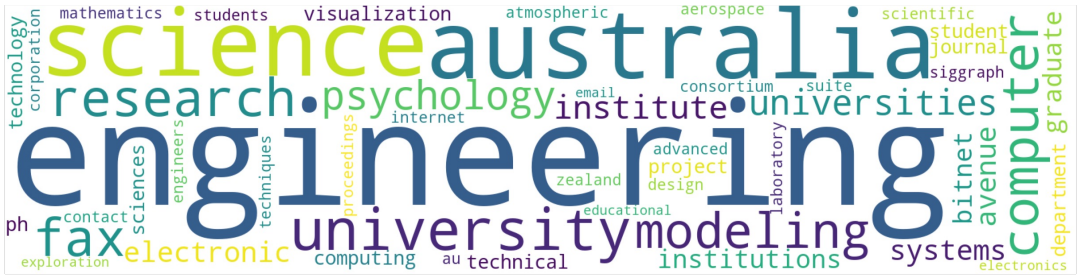
Topic 29



Topic 9

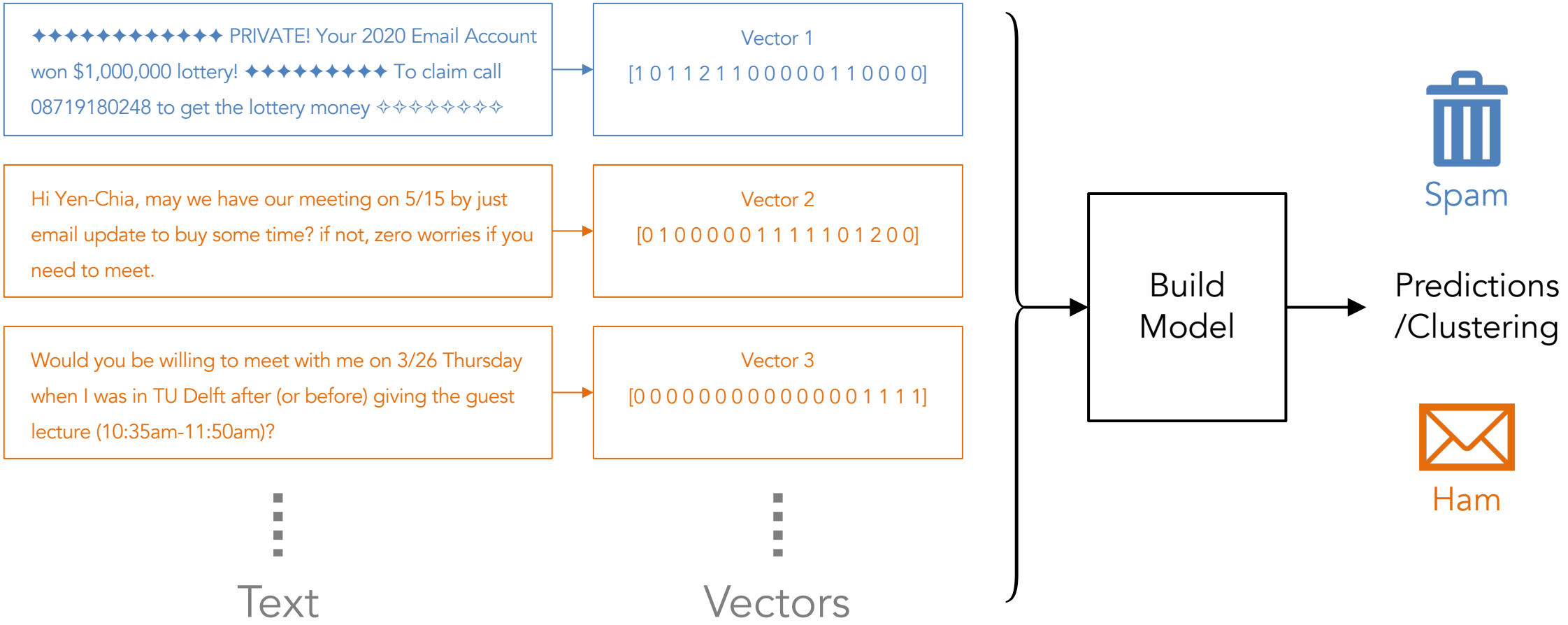


Topic 61

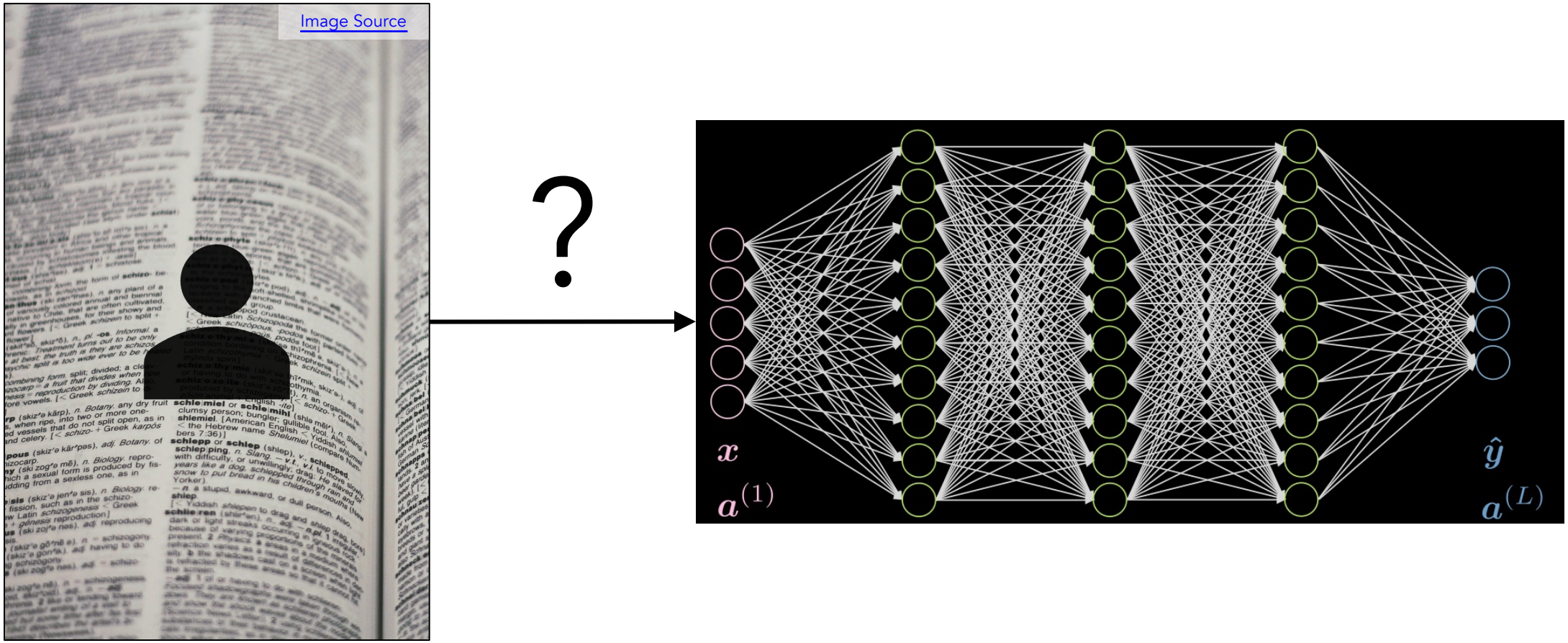


Source -- https://github.com/ddangelov/Top2Vec

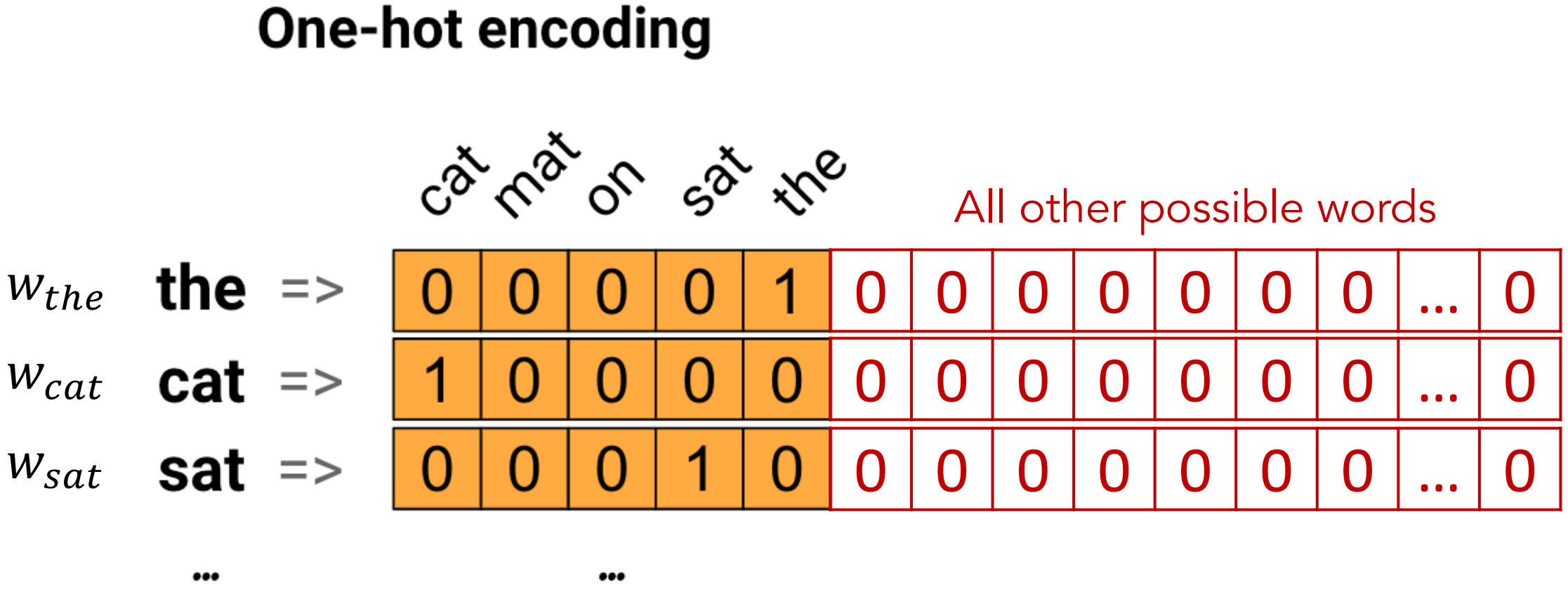
After transforming text into vectors, we can use these vectors for national language processing tasks, such as sentence/document classification (or clustering).



We have seen the approach of crafting features manually. But we can use deep learning to automate feature engineering. What should be the input vectors in this case?



We can use one-hot encoding. But this approach is inefficient (in terms of computation) because it creates long vectors with many zeros, which uses a lot of computer memory.



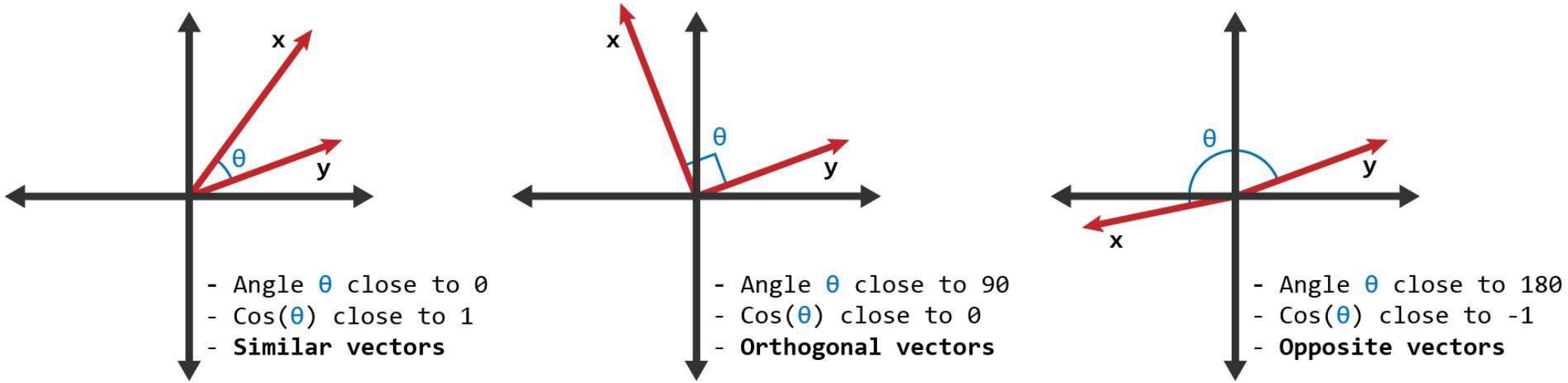
Word Embeddings -- https://www.tensorflow.org/text/guide/word_embeddings

Another problem of one-hot encoding is that it does not encode similarity. For example, the cosine similarity between two one-hot encoded vectors are always zero.

$$\text{CosineSimilarity}(w_{cat}, w_{sat}) = \cos(\theta) = \frac{< w_{cat} \cdot w_{sat} >}{\|w_{cat}\| \|w_{sat}\|} = \begin{bmatrix} w_{cat}^T \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} w_{sat} \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} = 0$$

dot product = $w_{cat}^T w_{sat}$

length of w_{cat}

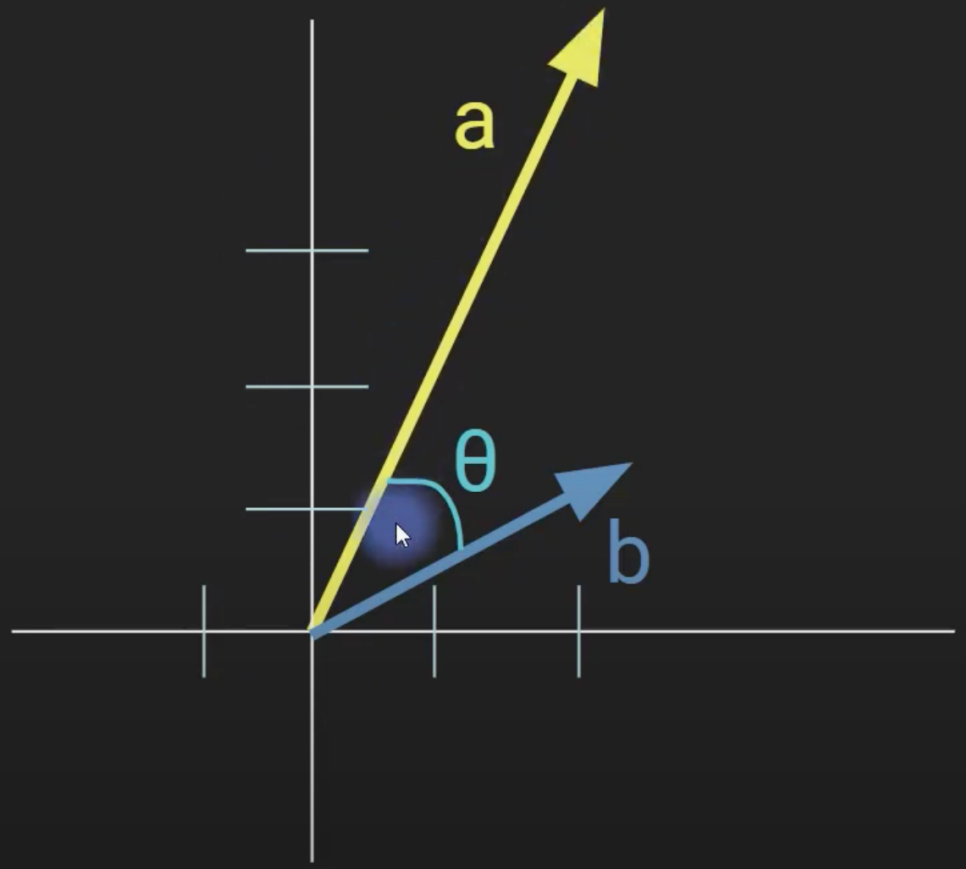


Cosine Similarity -- https://www.learndatasci.com/glossary/cosine-similarity/

The dot product of two vectors can also be used to measure similarity, which considers both the angle and the vector lengths. Cosine similarity is a normalized dot product.

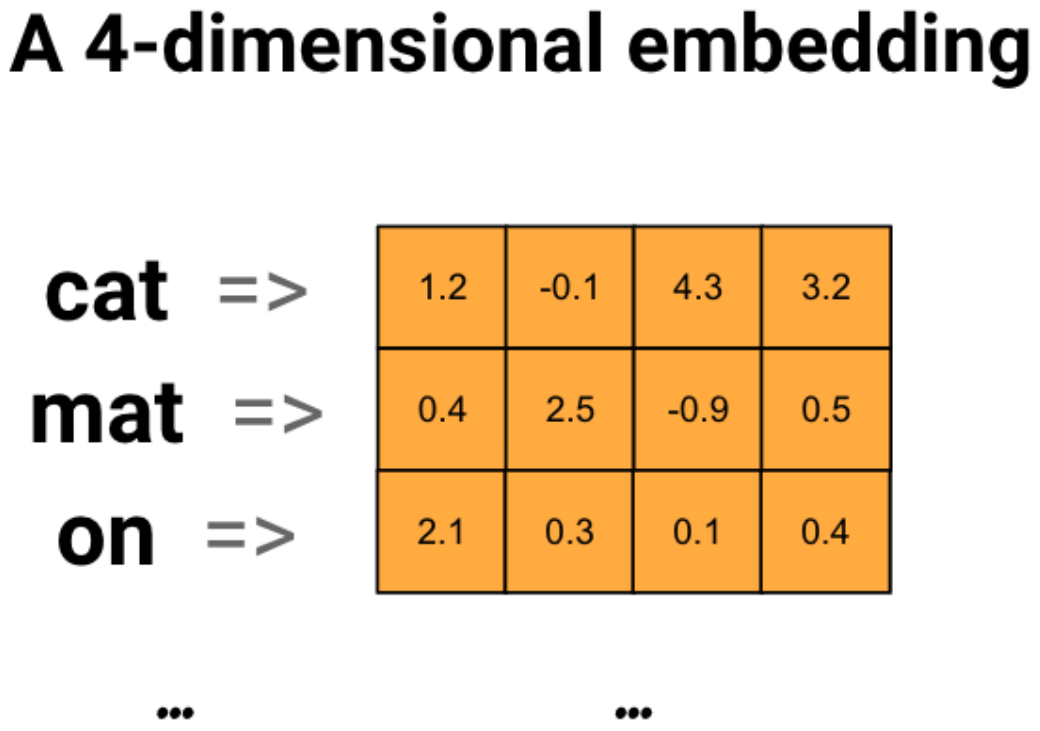
Magnitudes of vectors
scaled by angle between them

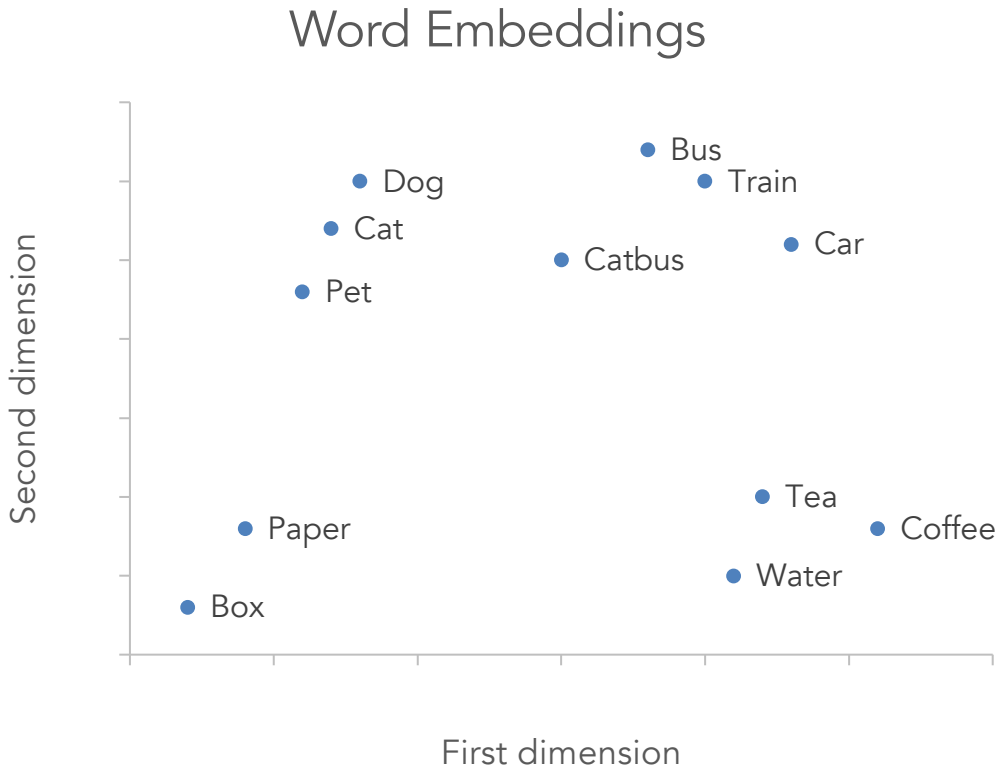
$$\alpha = |a||b|\cos(\theta_{ab})$$



Source of the graph and more information about the dot product -- https://www.youtube.com/watch?v=C0sPtQ3wX9o

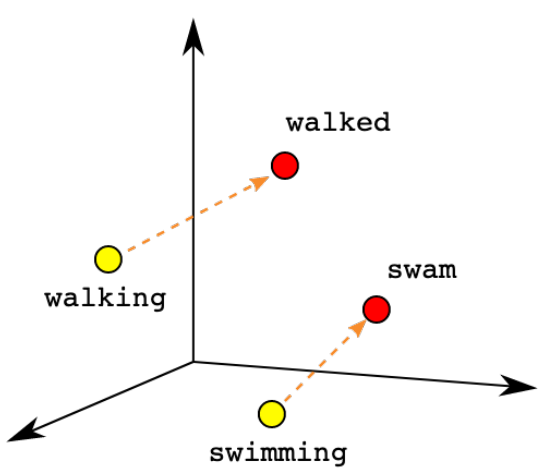
We can use word embeddings to efficiently represent text as vectors, in which similar words have a similar encoding in a high-dimensional space.



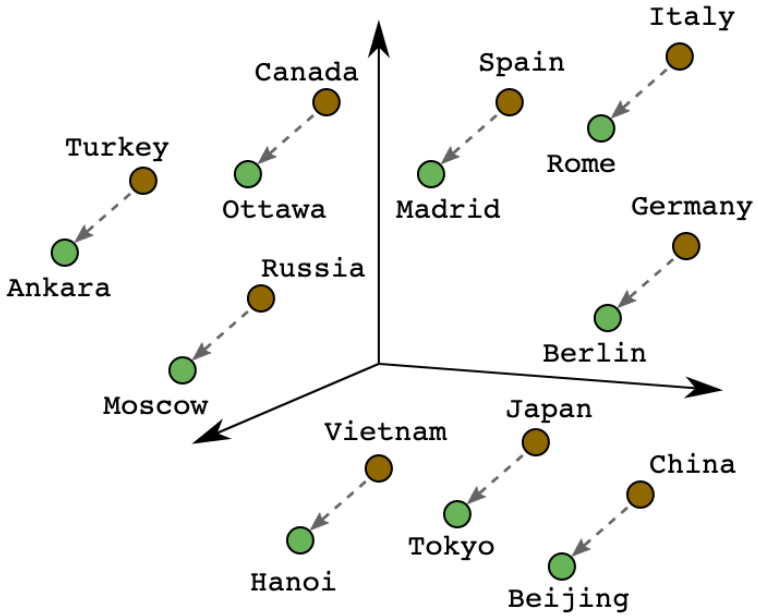


Word Embeddings -- https://www.tensorflow.org/text/guide/word_embeddings

Position (e.g., distance and direction) in the word embedding vector space can encode semantic relations, such as the relation between a country and its capital.



Verb Tense



Country-Capital

Source -- https://developers.google.com/machine-learning/crash-course/embeddings/translating-to-a-lower-dimensional-space

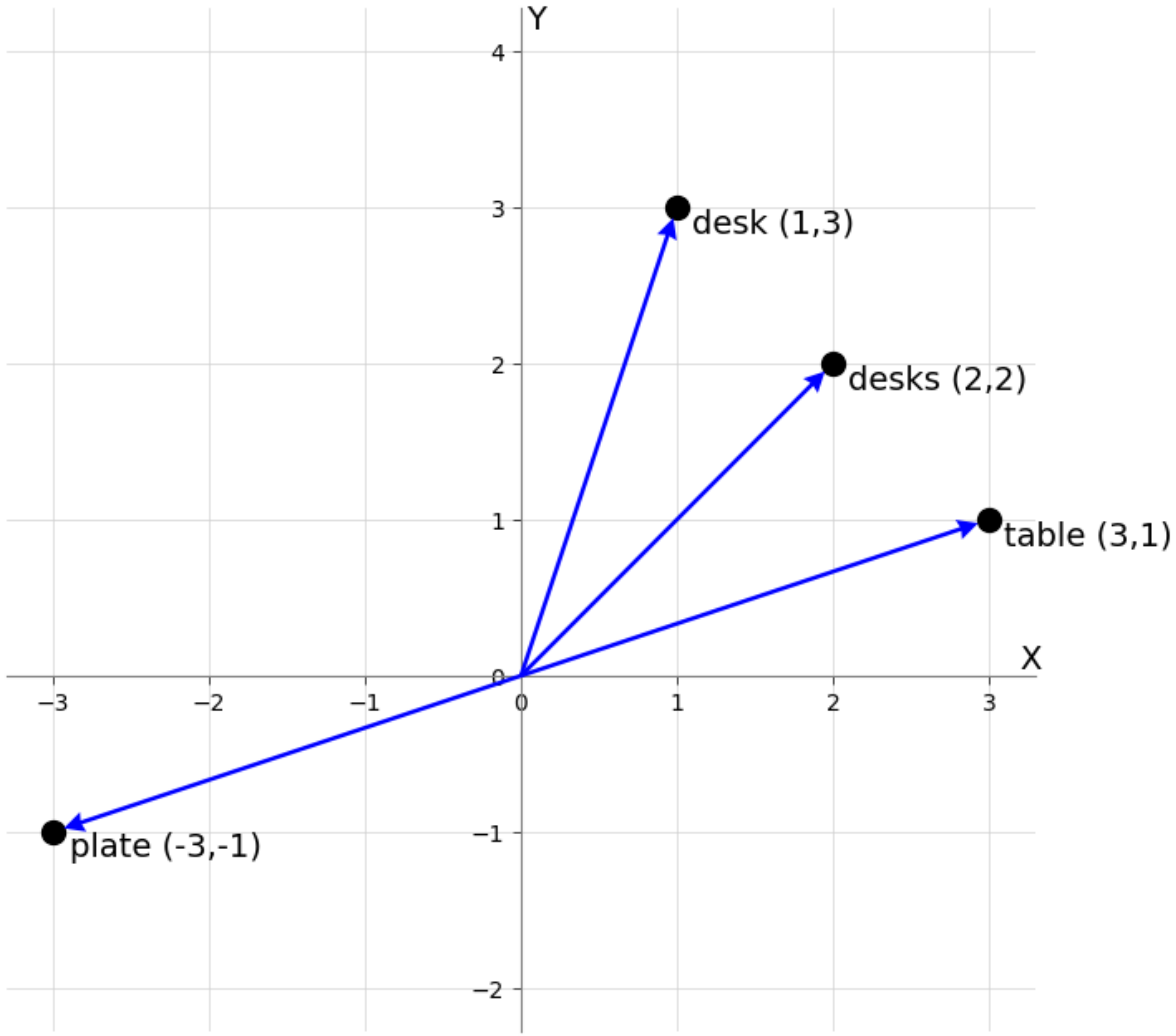
Exercise 7.2: Given the following word embeddings, compute the cosine similarity between “desk” and “table”, as well as between “desk” and “desks”.

$$\text{CosineSimilarity}(p_1, p_2)$$

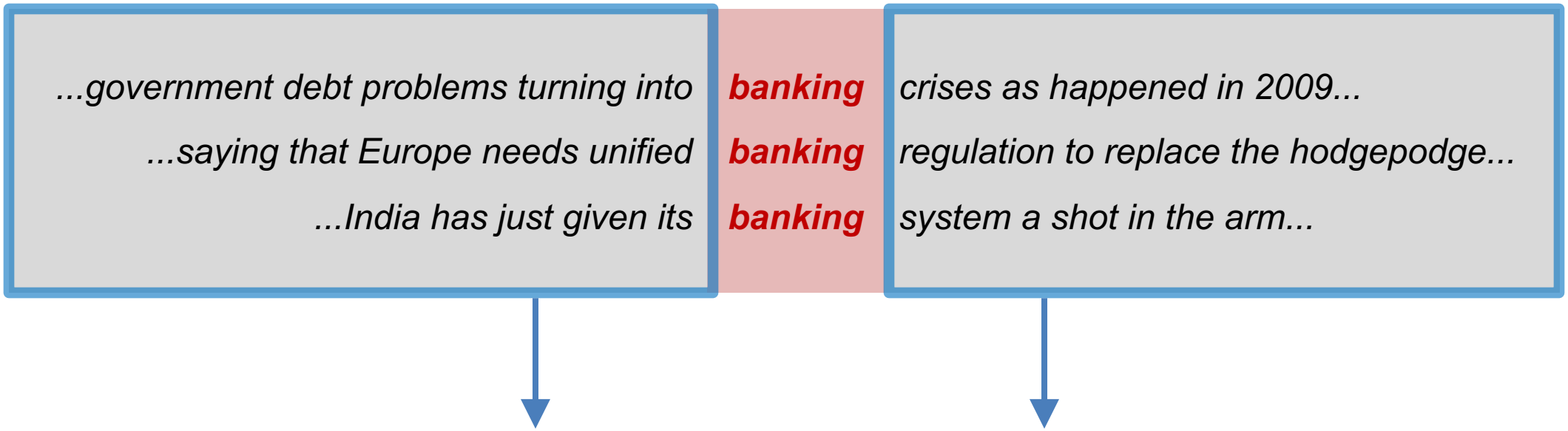
$$= \frac{< p_1 \cdot p_2 >}{\|p_1\|\|p_2\|}$$ dot product

$$= \frac{\begin{bmatrix} x_1 & y_1 \end{bmatrix} \cdot \begin{bmatrix} x_2 \\ y_2 \end{bmatrix}}{\|p_1\|\|p_2\|}$$ $p_1 = (x_1, y_1)$ $p_2 = (x_2, y_2)$

$$= \frac{x_1 x_2 + y_1 y_2}{\sqrt{x_1^2 + y_1^2} \cdot \sqrt{x_2^2 + y_2^2}}$$

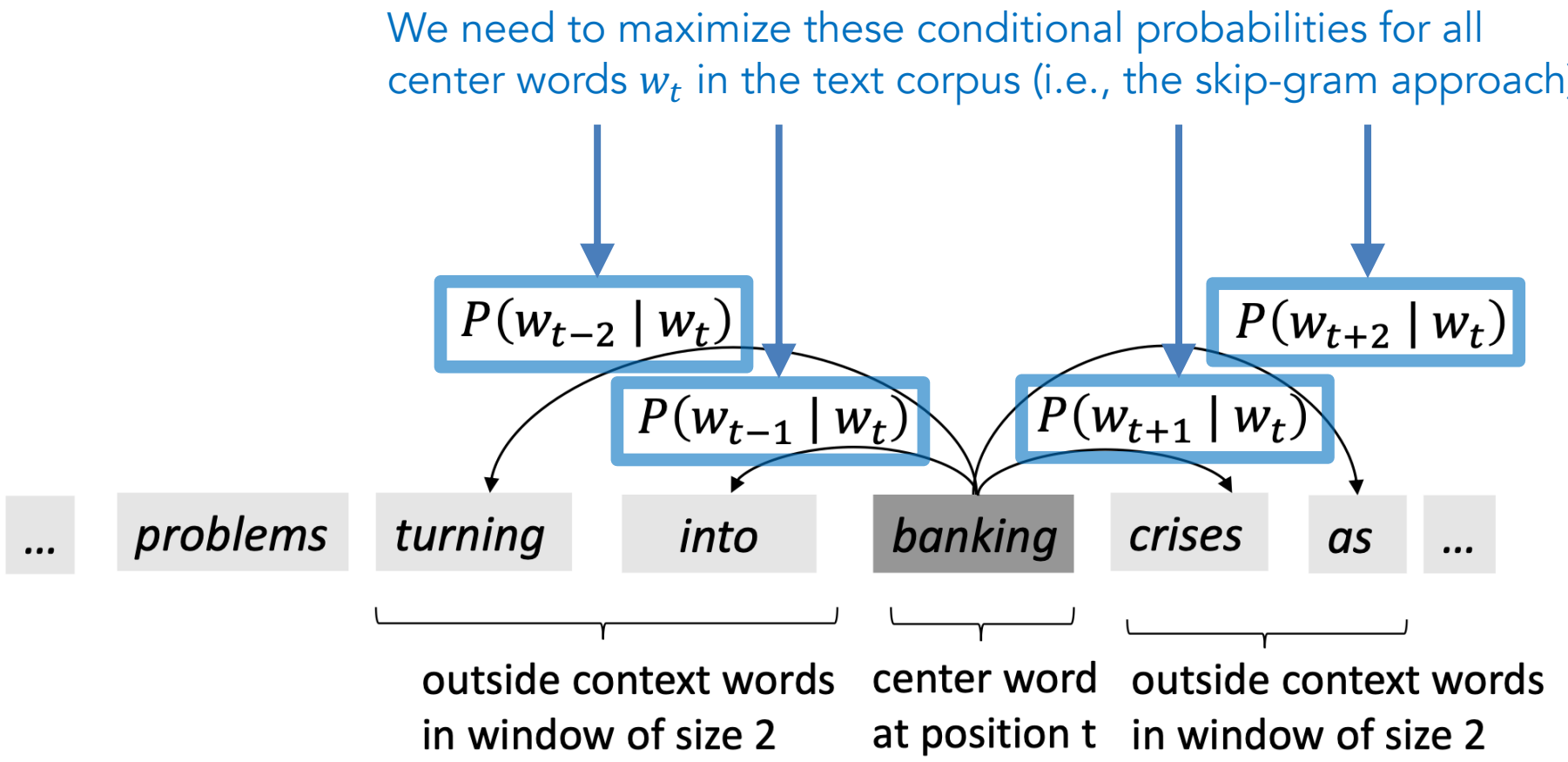


But how can we train the word embeddings (i.e., word vectors)? Intuitively, we can represent words by their context (i.e., the nearby words within a fixed-size window).



Source -- https://web.stanford.edu/class/cs224n/

Word2Vec is a method to train word embeddings by context. The goal is to use the center word to predict nearby words as accurate as possible, based on probabilities.



Source -- https://web.stanford.edu/class/cs224n/

To prepare the training data, we need to build a set of center-context word pairs from a large text corpus (for maximizing the conditional probabilities of these pairs).

Window Size	Text	Skip-grams
2	[The **wide** road shimmered] in the hot sun.	wide, the wide, road wide, shimmered
	The [wide road **shimmered** in the] hot sun.	shimmered, wide shimmered, road shimmered, in shimmered, the
	The wide road shimmered in [the hot **sun**].	sun, the sun, hot

Source -- https://www.tensorflow.org/text/tutorials/word2vec

Conditional probability describes the probability of an event occurring given that another event has already occurred.

$P(W,T)$: joint probability distribution

Temperature (T)	Weather (W)	Probability (P)
hot	sunny	0.4
hot	rainy	0.1
cold	sunny	0.2
cold	rainy	0.3

To calculate conditional probability:

$$P(A|B) = \frac{P(A,B)}{P(B)}$$

$$P(sunny|hot) = \frac{P(sunny,hot)}{P(hot)} = \frac{0.4}{0.5} = 0.8$$

$P(W|T)$: conditional probability distribution

$P(W|T = hot)$

Weather (W)	Conditional Probability (P)
sunny	0.8
rainy	0.2

$P(W|T = cold)$

Weather (W)	Conditional Probability (P)
sunny	0.4
rainy	0.6

More about conditional probability -- https://www.youtube.com/watch?v=_IgyaD7vOOA

Why do we need to model the conditional probability, such as $P(w_{t+1}|w_t)$, rather than just construct the joint probability table $P(w_{t+1}, w_t)$ and then calculate $P(w_{t+1}|w_t)$?

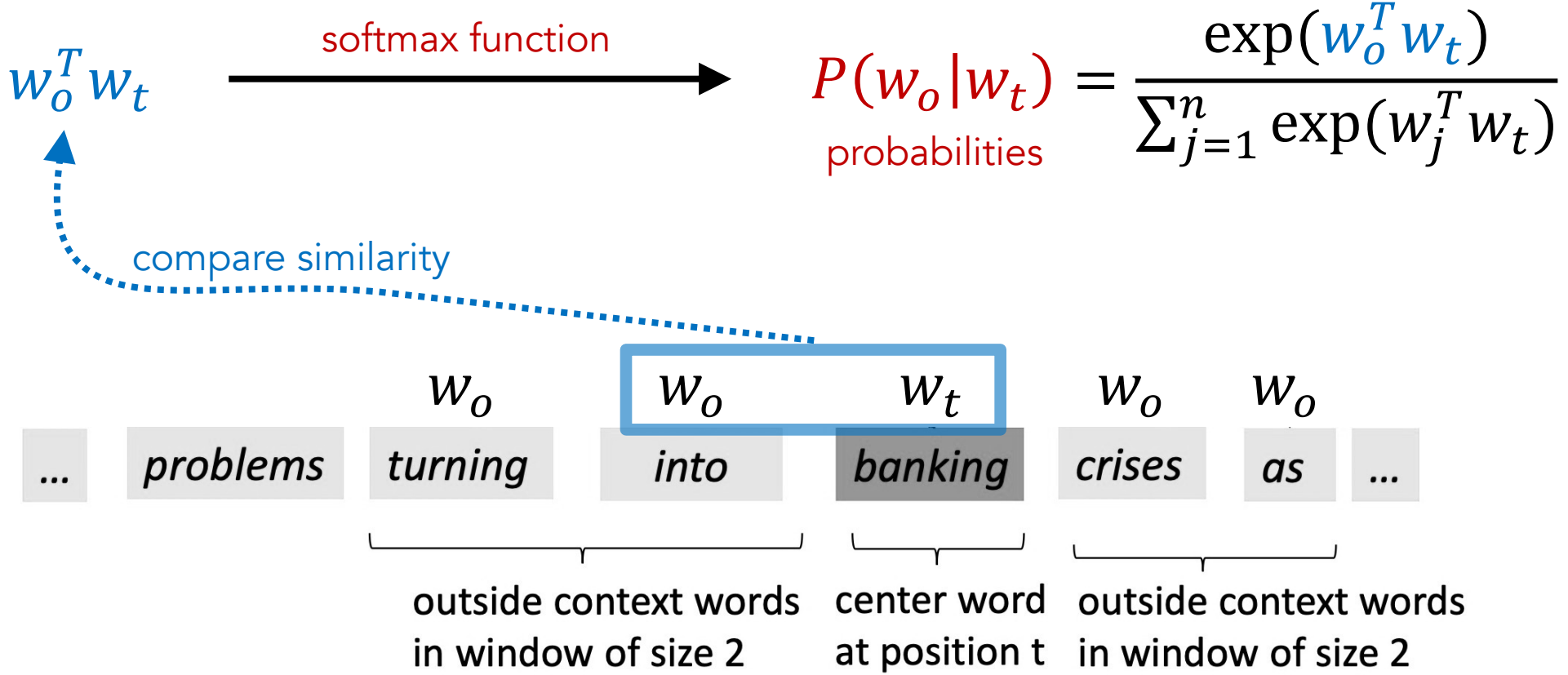
$P(w_{t+1}, w_t)$: joint probability distribution

w_{t+1}	w_t	Occurrence
crisis	banking	10
house	banking	0
account	banking	21
apple	banking	0
information	banking	6
news	banking	4
…	…	…
regulations	government	15
orange	government	0
capybara	government	0
policy	government	8
…	…	…

Think about the following:

- What is the actual task that we want to do in the context of Word2Vec?
- How large can the table be? What impact would such a table cause during calculation?
- What if we have assumptions about what the probability distribution should look like?

How is probability related to word vectors? We use the dot product similarity of word vectors to calculate the conditional probabilities, with the help of the softmax function.



Source -- https://web.stanford.edu/class/cs224n/

The softmax function maps any arbitrary values to a probability distribution.

Larger dot product means larger probability

$w_o^T w_t$ → softmax function → $P(w_o|w_t) = \frac{\exp(w_o^T w_t)}{\sum_{j=1}^{n} \exp(w_j^T w_t)}$

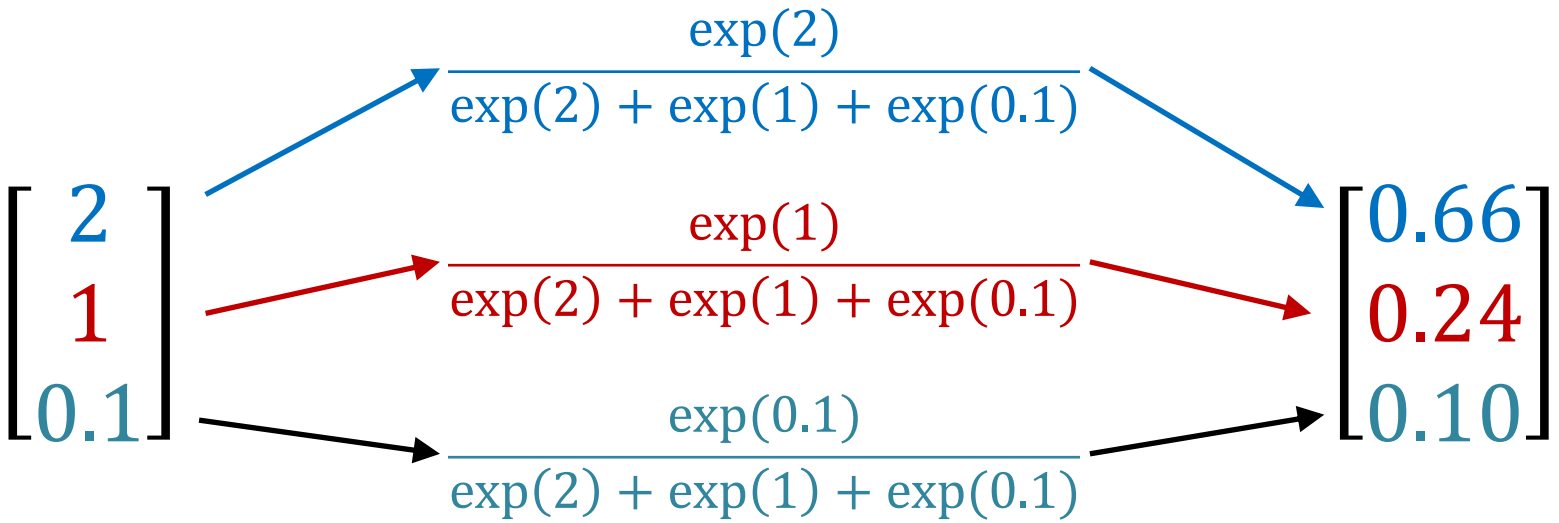
The entire denominator is just for normalization
(n is the number of words in the entire vocabulary list)

x_i → softmax function → $P(x_i) = \frac{\exp(x_i)}{\sum_{j=1}^{n} \exp(x_j)}$

The exponential function makes things positive: $\exp(x) = e^x$

Source -- https://web.stanford.edu/class/cs224n/

Below is an example of how the softmax function maps numbers to probabilities.



$$x_i \xrightarrow{\text{softmax function}} P(x_i) = \frac{\exp(x_i)}{\sum_{j=1}^{n} \exp(x_j)}$$

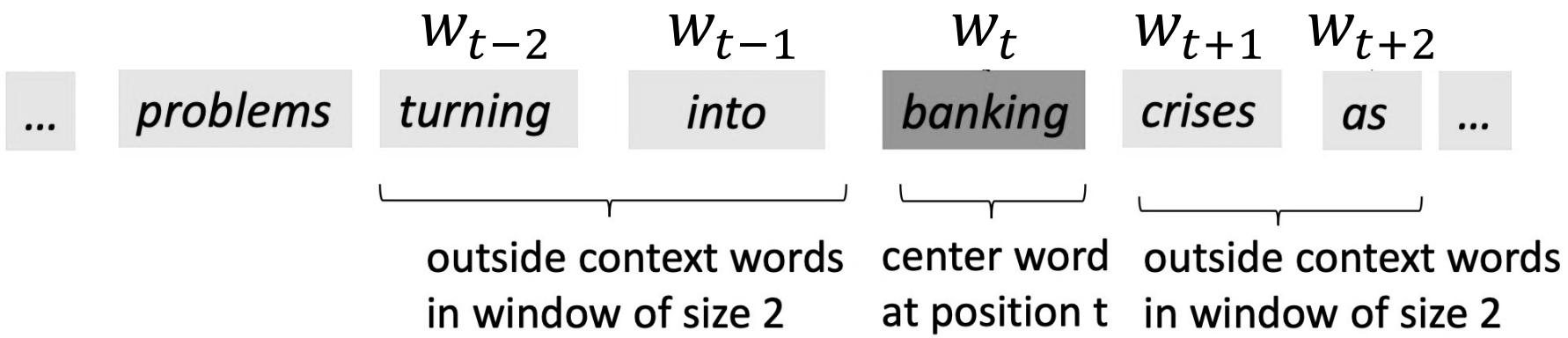
Remember that the denominator is just for normalization

More about the softmax function -- https://developers.google.com/machine-learning/crash-course/multi-class-neural-networks/softmax

For each word position $t = 1, \ldots, T$ with window size m, we can adjust the word vectors (θ) to maximize the likelihood function, based on the conditional probabilities.

$$\text{Likelihood} = L(\theta) = \prod_{t=1}^{T} \prod_{\substack{-m \le j \le m \\ j \neq 0}} P(w_{t+j} \mid w_t; \theta)$$

θ is all variables to be optimized

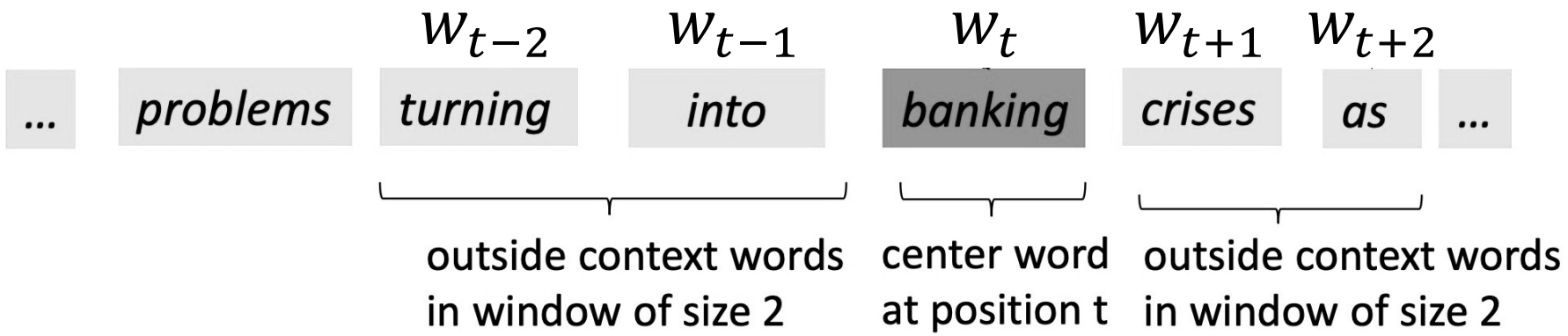


The likelihood function is a product of probabilities of individual data points. In this case, it is the product of the probabilities of context words given the center words.

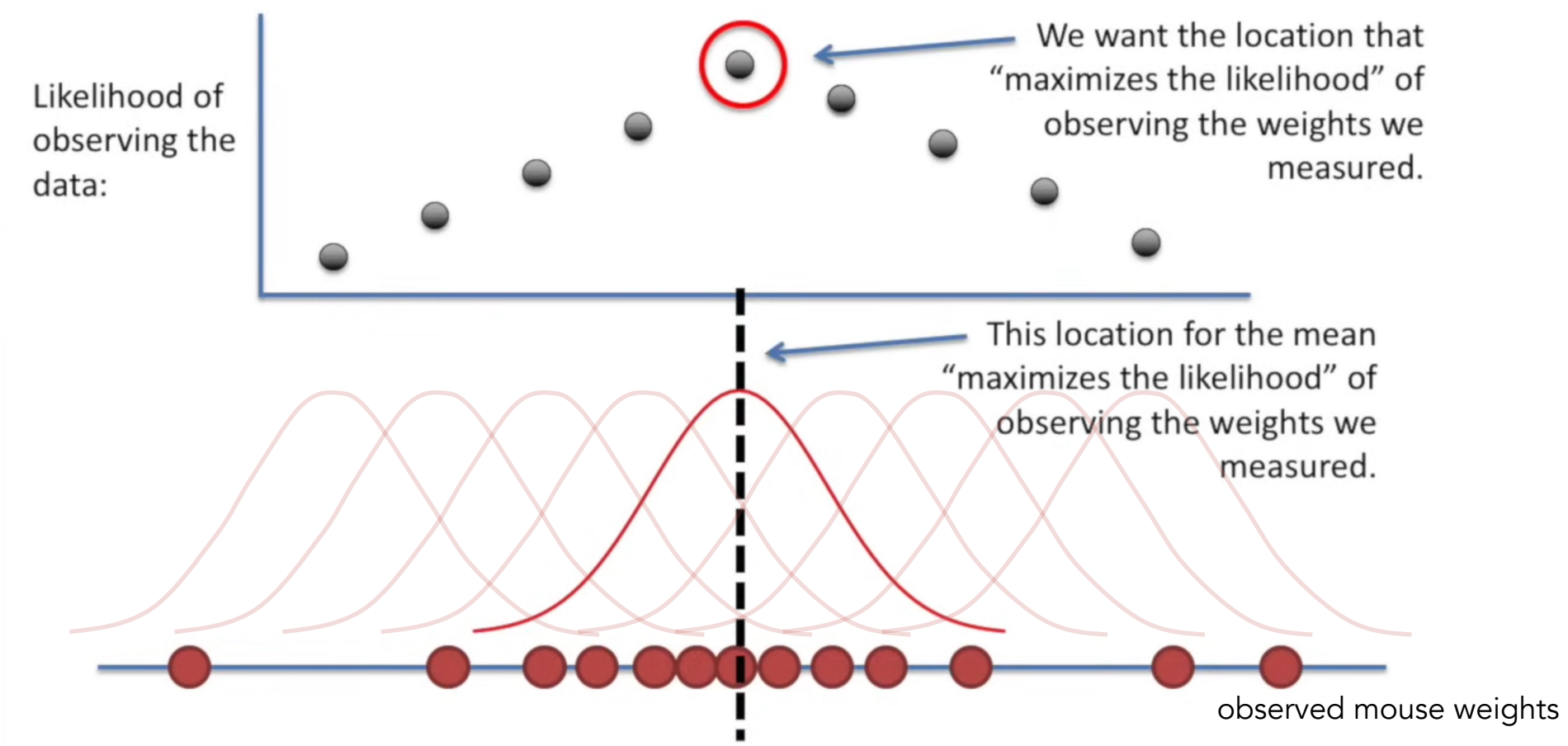
$$\text{Likelihood} = L(\theta) = \prod_{t=1}^{T} P(w_{t-2}|w_t)P(w_{t-1}|w_t)\,P(w_{t+1}|w_t)\,P(w_{t+2}|w_t)$$

θ is all variables to be optimized

Assume that we use a window size of 2



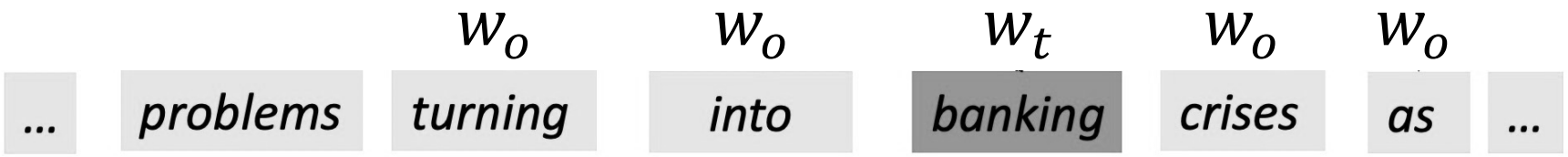
Maximum Likelihood Estimation (MLE) finds the optimal way to fit a distribution to the observed data. In this example, we fit a Gaussian distribution.



Maximum Likelihood Estimation -- https://www.youtube.com/watch?v=XepXtl9YKwc , https://www.youtube.com/watch?v=Dn6b9fCIUpM

Below are high-level steps for training word embeddings using Word2Vec skip-gram:

- Build a vocabulary list from a large text corpus
- Initialize each word with a random embedding vector w
- For each word w_t in the text corpus, select the context words w_o (i.e., the words that are nearby w_t) with a fixed window size

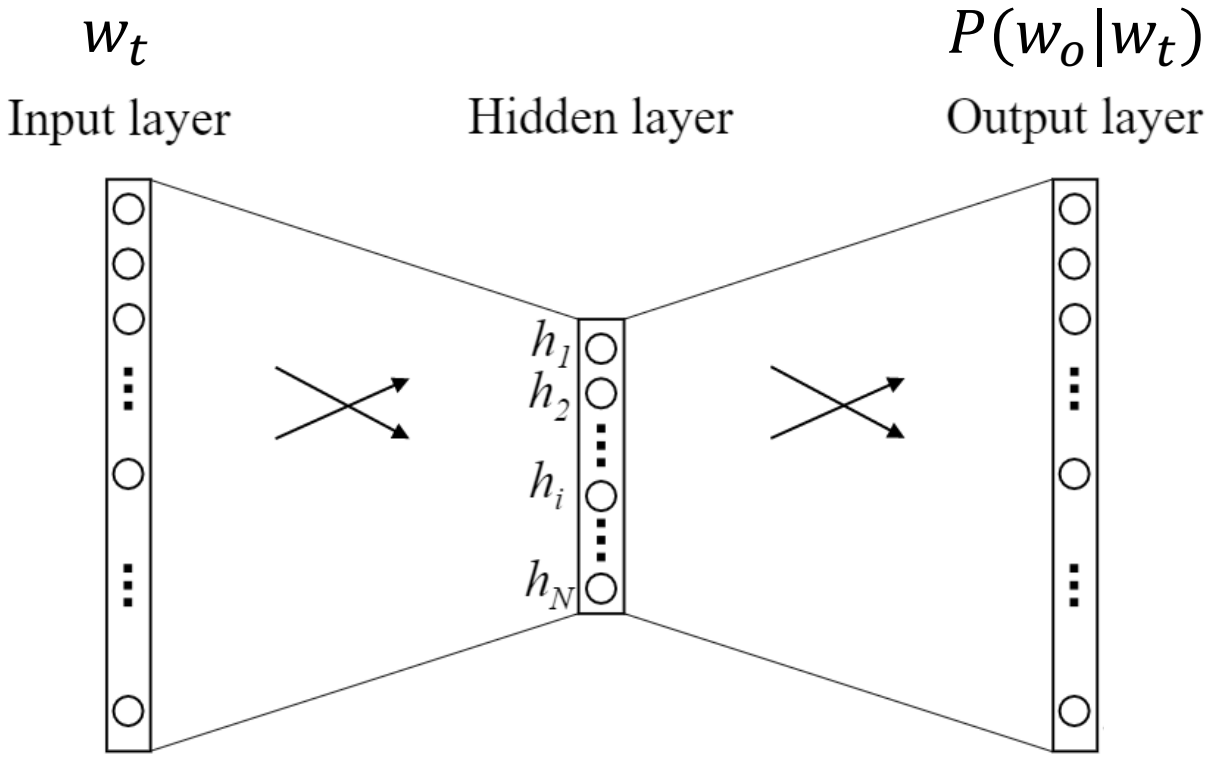


- For each pair w_t and w_o, compute the conditional probability $P(w_o|w_t)$
- Use gradient descent to update the word vectors to maximize the likelihood function (equivalent to minimizing the cross-entropy loss)

Mikolov, T., et al. (2013). Distributed Representations of Words and Phrases and their Compositionality. arXiv preprint arXiv:1310.4546.

How to implement the Word2Vec model using a neural network?

- How many layers?
- What is the format of the input?
- What is the format of the output?
- What is the format of the ground truth?
- Where are the embedding vectors?



		w_o	w_o	w_t	w_o	w_o	
...	problems	turning	into	banking	crises	as	...

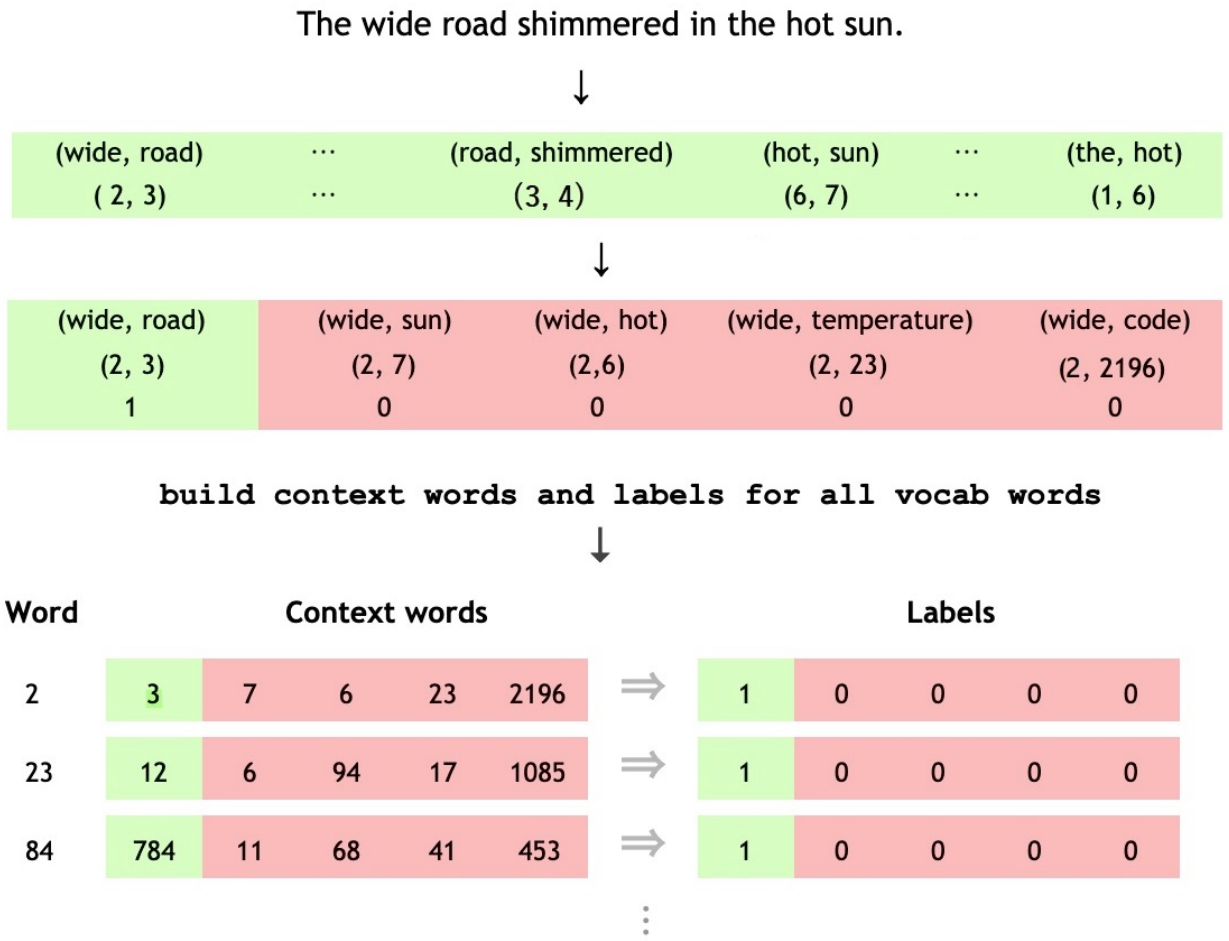
Rong, X. (2014). word2vec parameter learning explained. arXiv preprint arXiv:1411.2738.

In practice, computing the conditional probability $P(w_o|w_t)$ using the softmax function is expensive (why?). One alternative is to use negative sampling to approximate it.

$$P(w_o|w_t) = \frac{\exp(w_o^T w_t)}{\sum_{j=1}^{n} \exp(w_j^T w_t)}$$

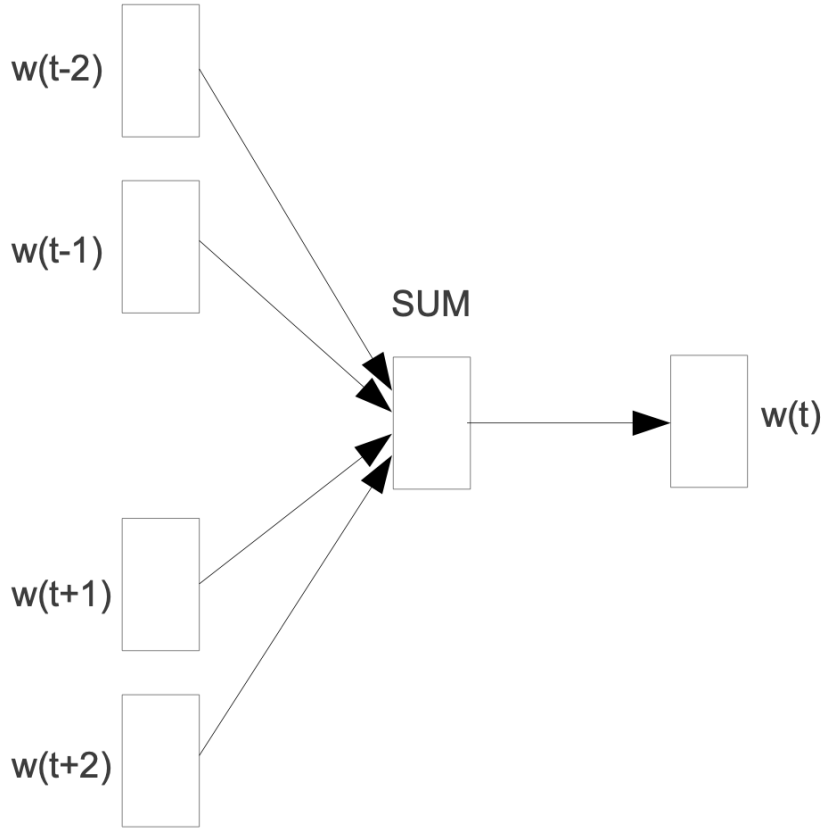
Original softmax: "Given a center word w_t, what is the probability distribution over all words given the context word?"

Negative sampling: "Given a center word w_t and a context word w_o, is the pair real or fake (randomly sampled)?"

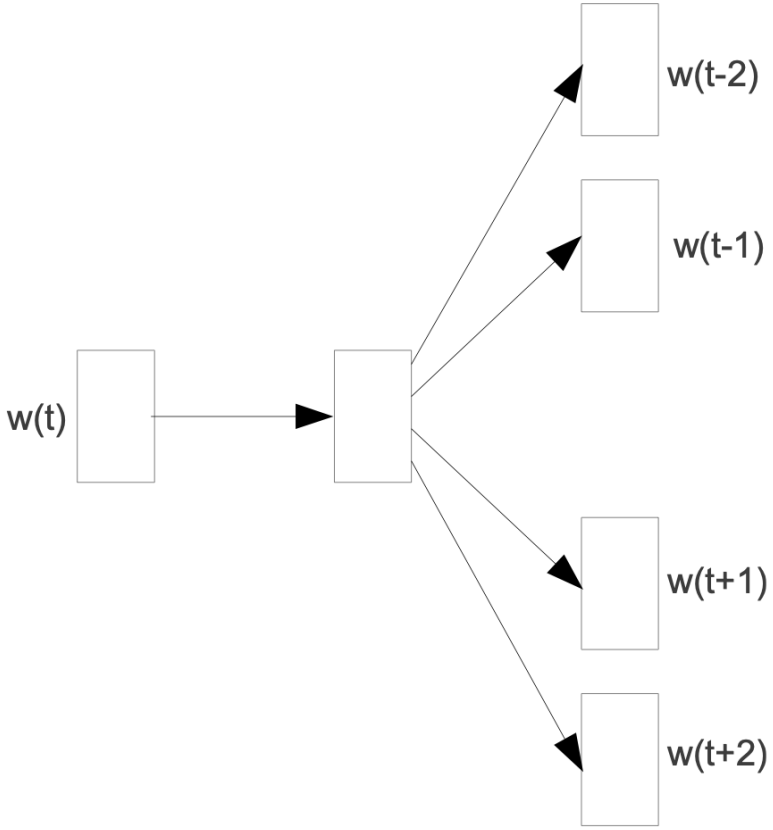


Source -- https://www.tensorflow.org/text/tutorials/word2vec

Besides the skip-gram approach, we can also use the CBOW (Continuous Bag of Words Model) approach. We will skip the math for CBOW (check the paper below for details).

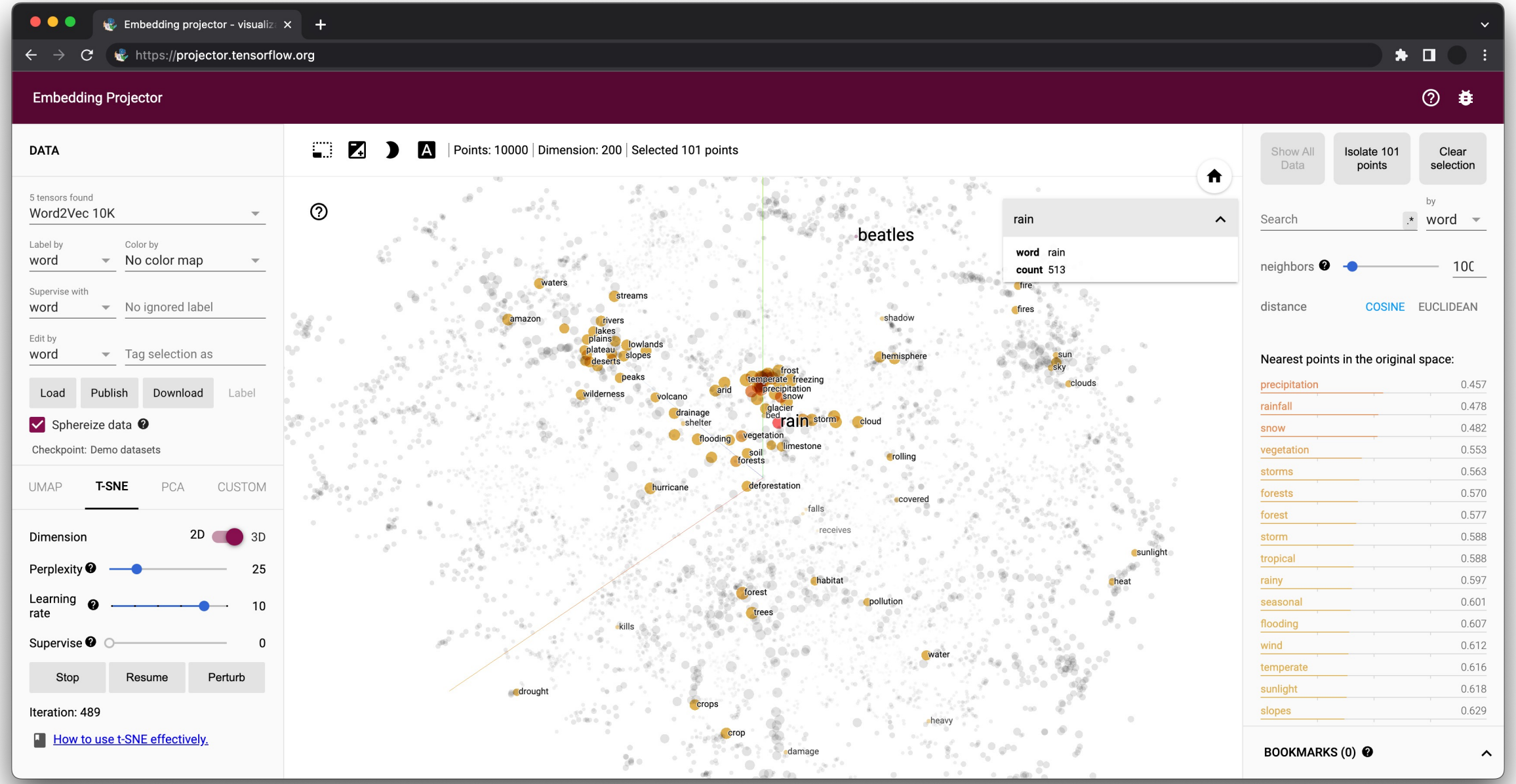


CBOW



Skip-gram

Mikolov, T., et al. (2013). Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781.



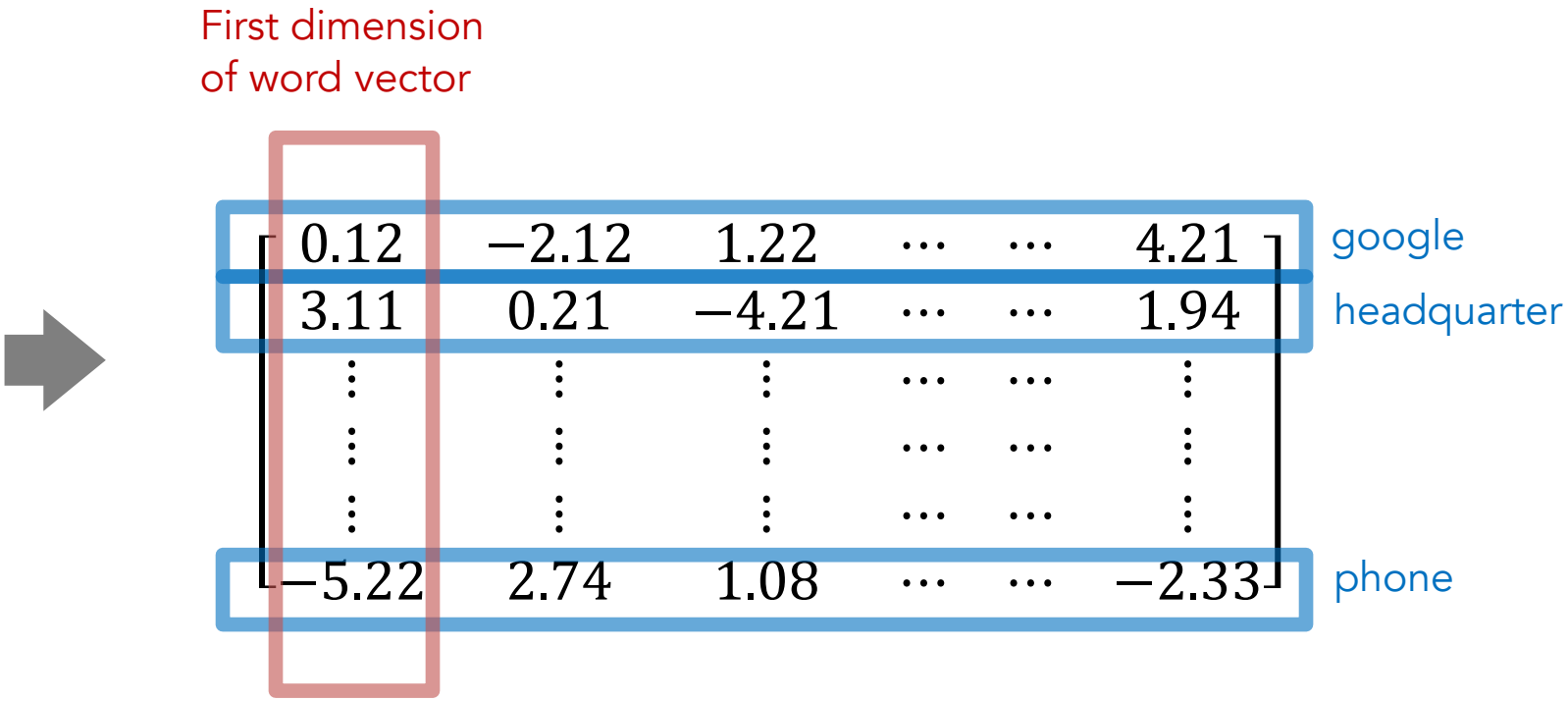
Playground for word embeddings -- http://projector.tensorflow.org/

Word embeddings represent words in vectors.

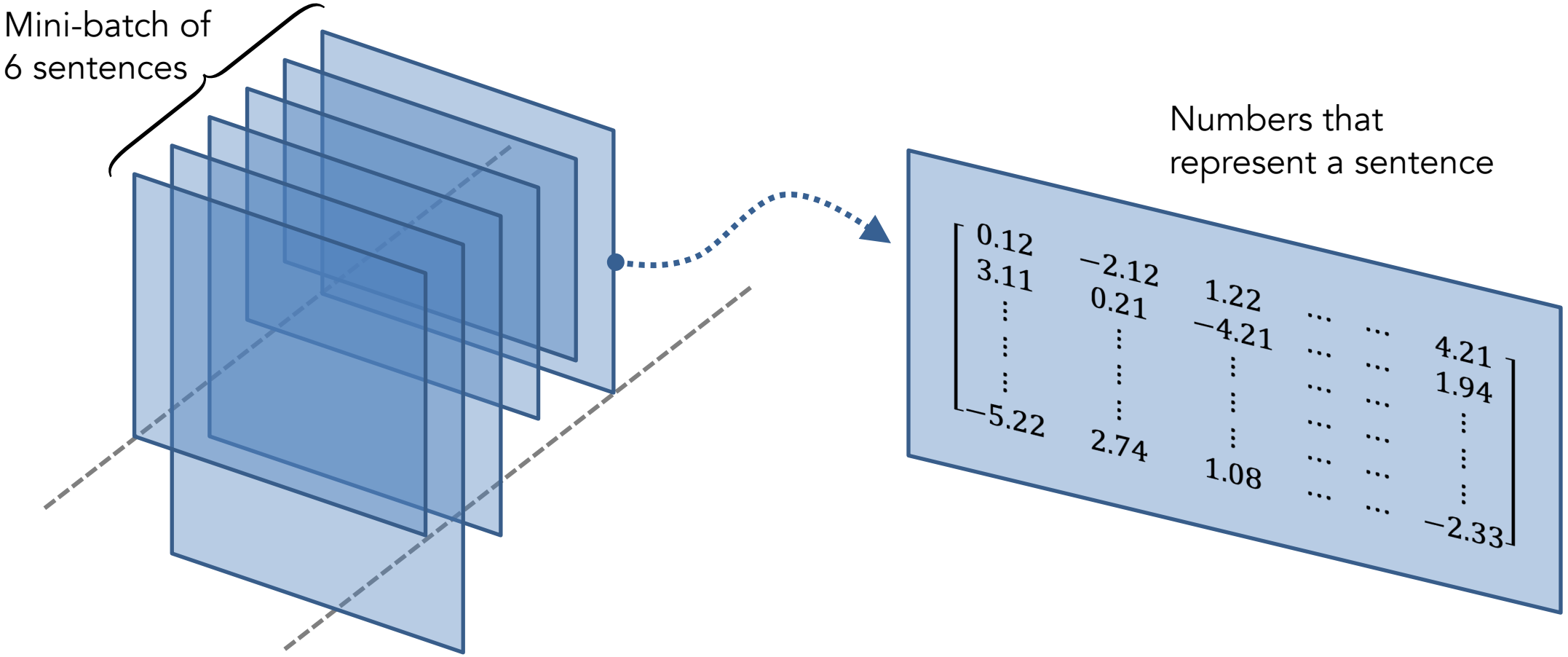
But how to represent sentences in vectors?

We can stack all the word vectors into a matrix, where each column means a dimension of the word vector, and the number of rows means sentence length.

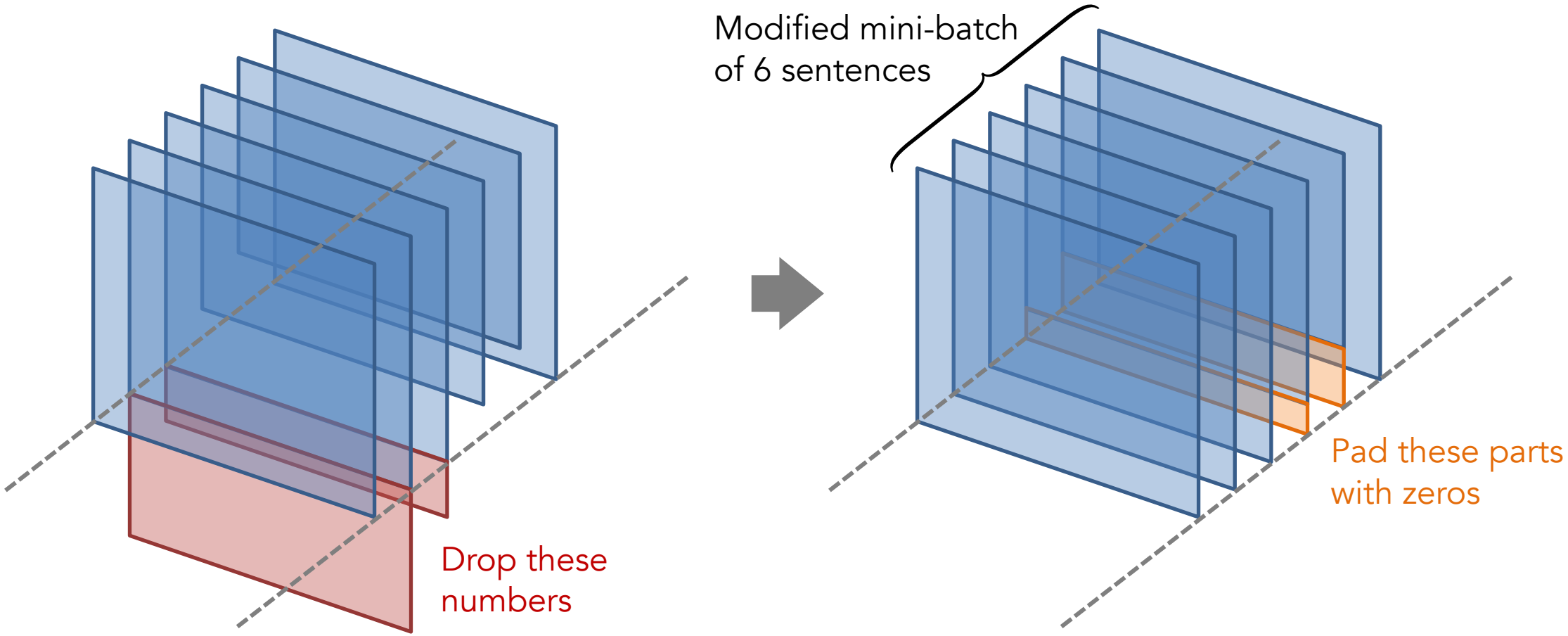
['google', 'headquarter',
'mountain', 'view',
'amphitheatre', 'pkwy',
'mountain', 'view', 'ca', 'unveil',
'new', 'android', 'phone',
'consumer', 'electronic', 'show',
'sundar', 'pichai', 'say',
'keynote', 'user', 'love', 'new',
'android', 'phone']



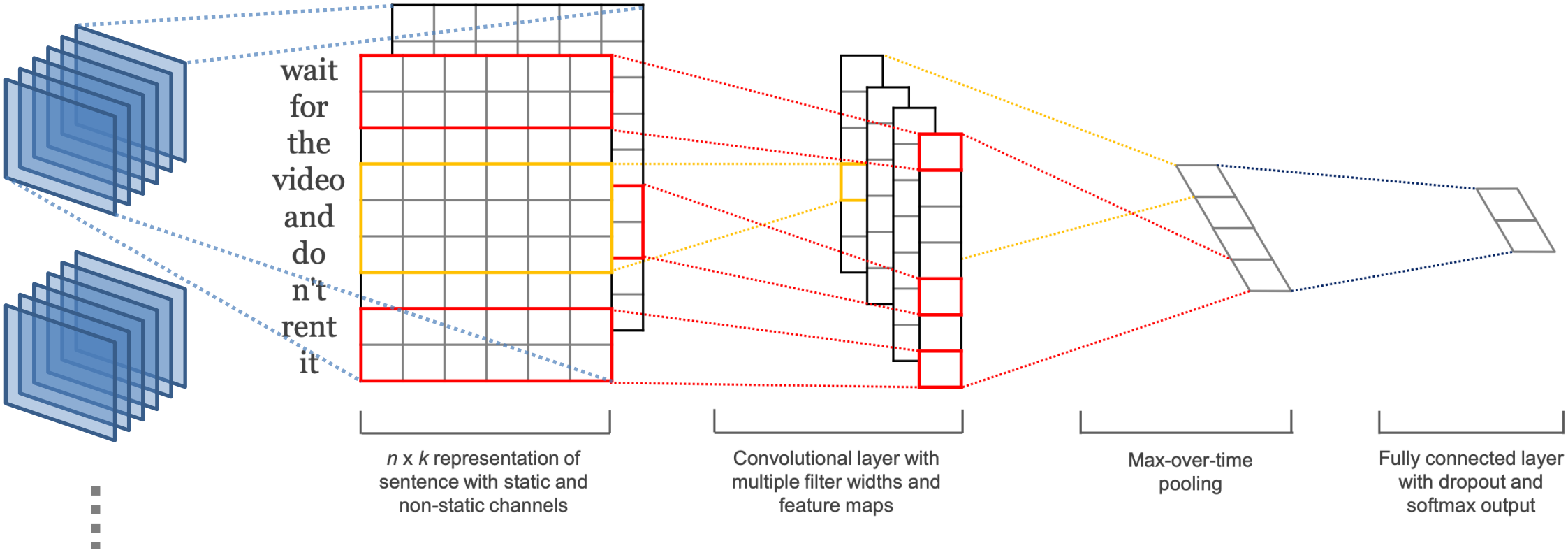
For a deep feedforward network (or convolutional neural network), all inputs need to have the same size. But sentences can have different length. So, what should we do?



We can drop the parts that are too long and pad the parts that are too short with zeros.



After we make sure that all input data have the same size, we can put them into deep neural networks for different tasks, such as sentence/document classification.

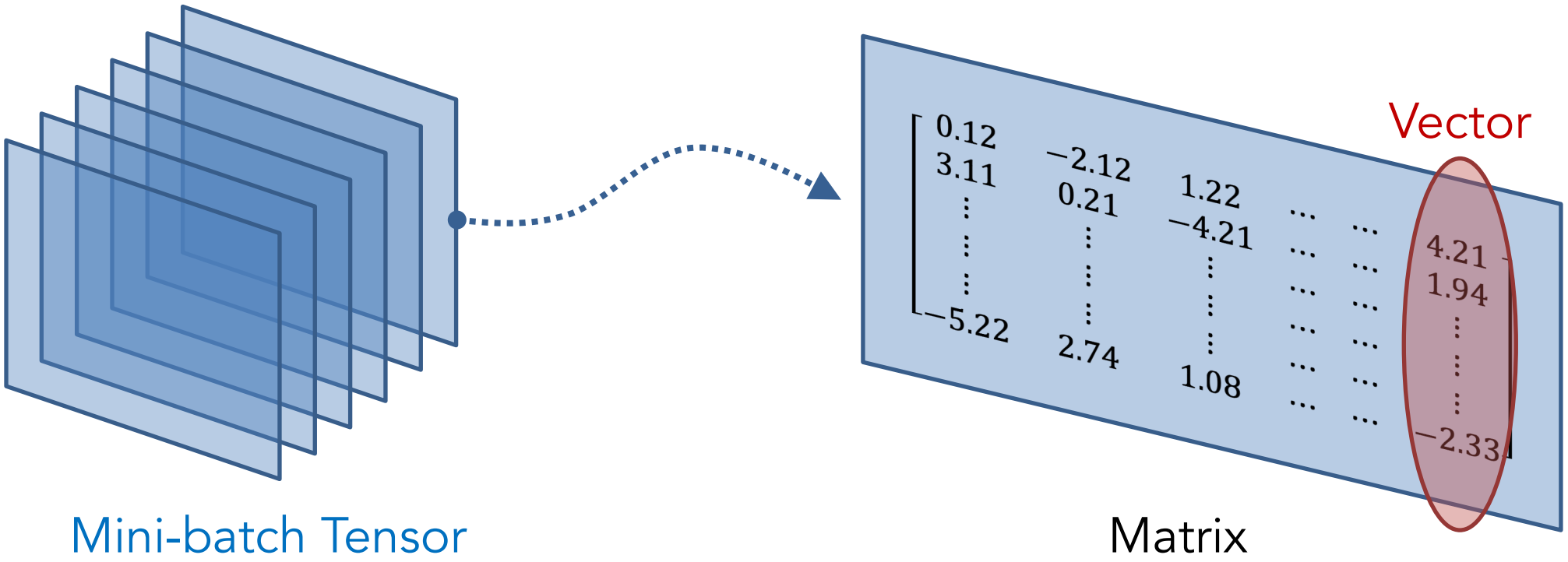


Mini-batches

Figure 1: Model architecture with two channels for an example sentence.

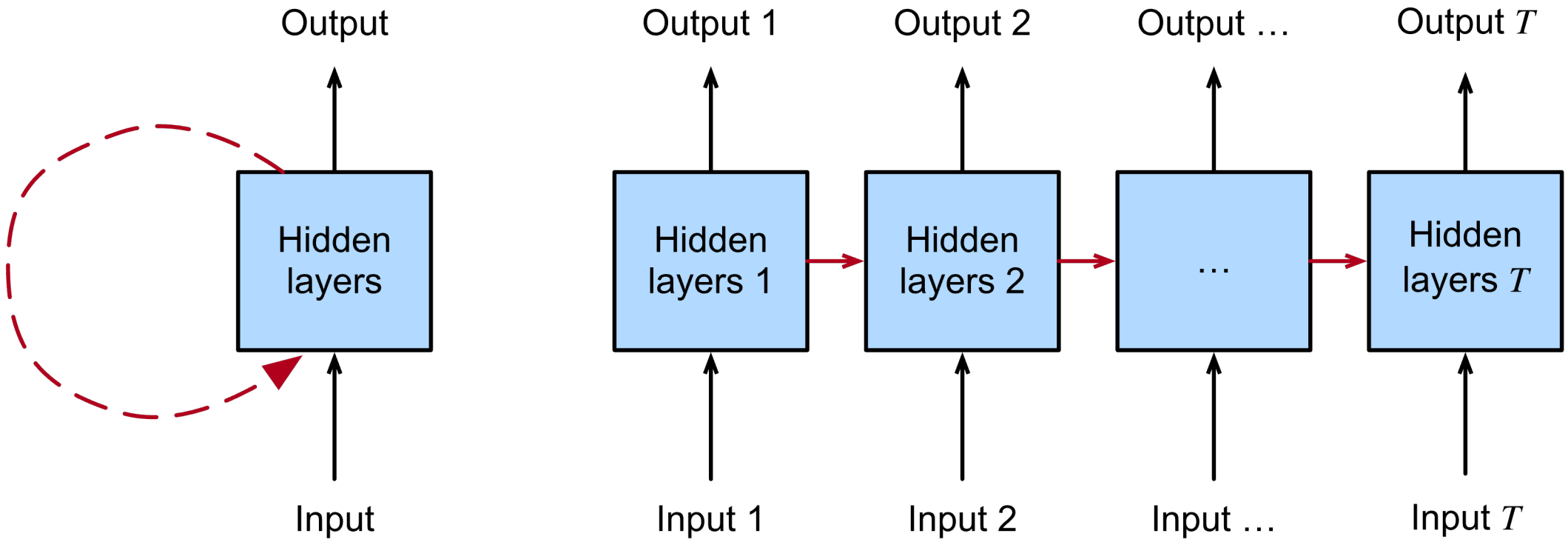
Kim, Y. (2014). Convolutional neural networks for sentence classification. EMNLP.

Each mini-batch is stored in a tensor object when doing computation, which is a multidimensional array (i.e., a generalization of scalar, vector, and matrix).



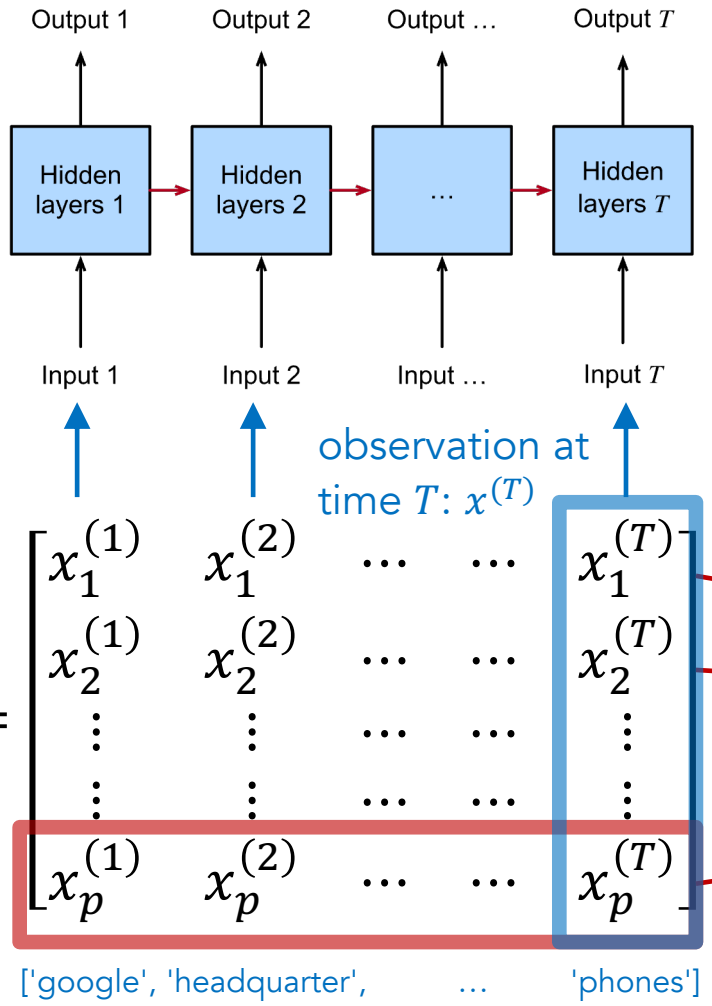
We can also use the recurrent neural network (RNN) to takes inputs with various lengths.

Recurrent connections are shown in the red cyclic edges (and unfolded into red arrows).



Source -- https://d2l.ai/chapter_recurrent-neural-networks/index.html

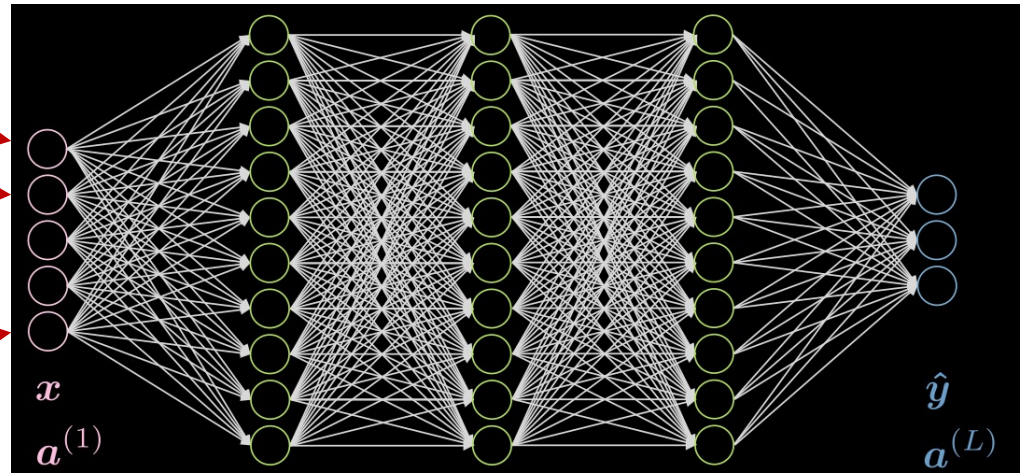
Typically, we feed features to the deep neural net, but we feed observations (for each time step) to the recurrent neural net. Notice that the input X below is transposed.



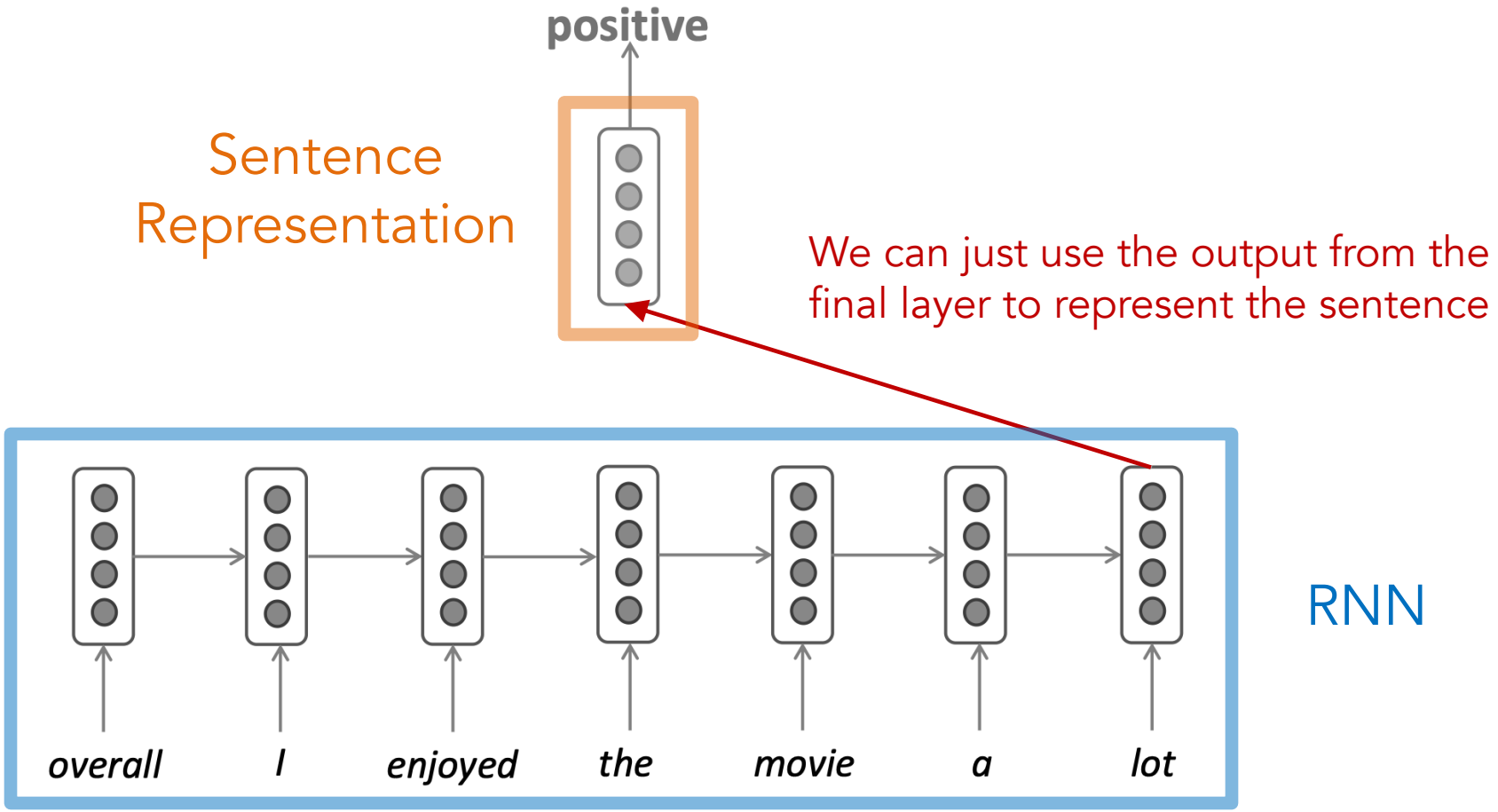
feature: x_p

An example for natural language processing:

- Feature: the word embedding dimensions
- Observation: the word at position T in a sentence

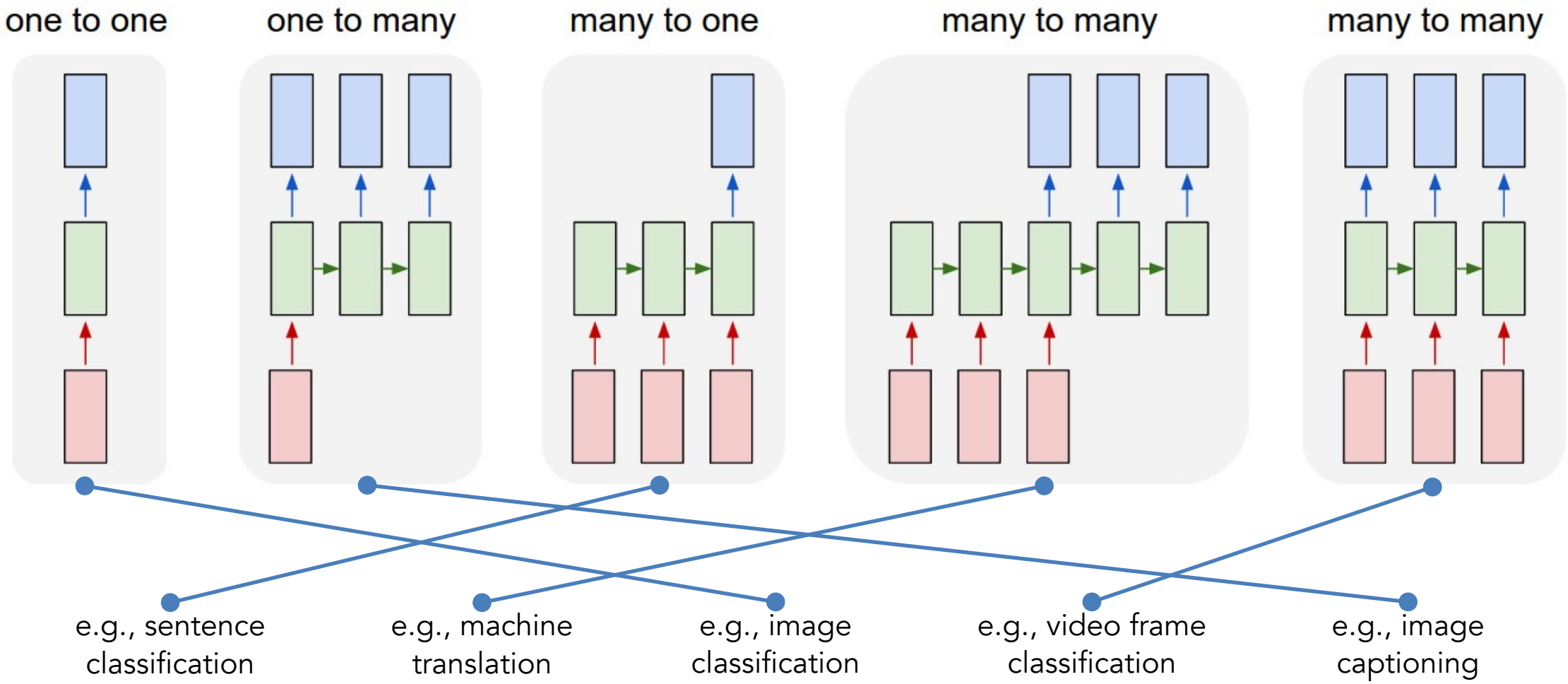


We can combine RNNs into a sequence-to-sequence (Seq2Seq) model for sentence classification or sentiment analysis. In this case, the output sequence has only one label.



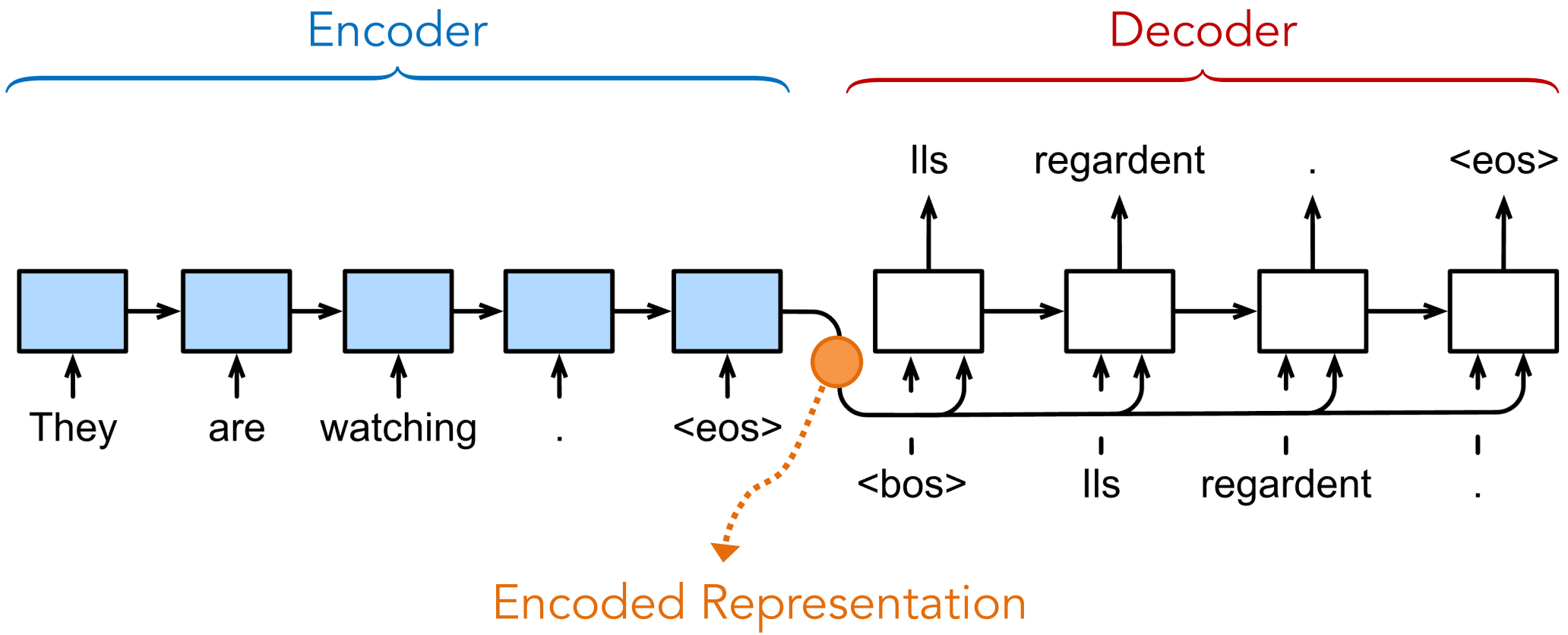
Source -- https://web.stanford.edu/class/cs224n/

Seq2Seq models are flexible in the input and output sizes. The rectangles in the graph below mean vectors, red rectangles mean inputs, and blue rectangles mean outputs.



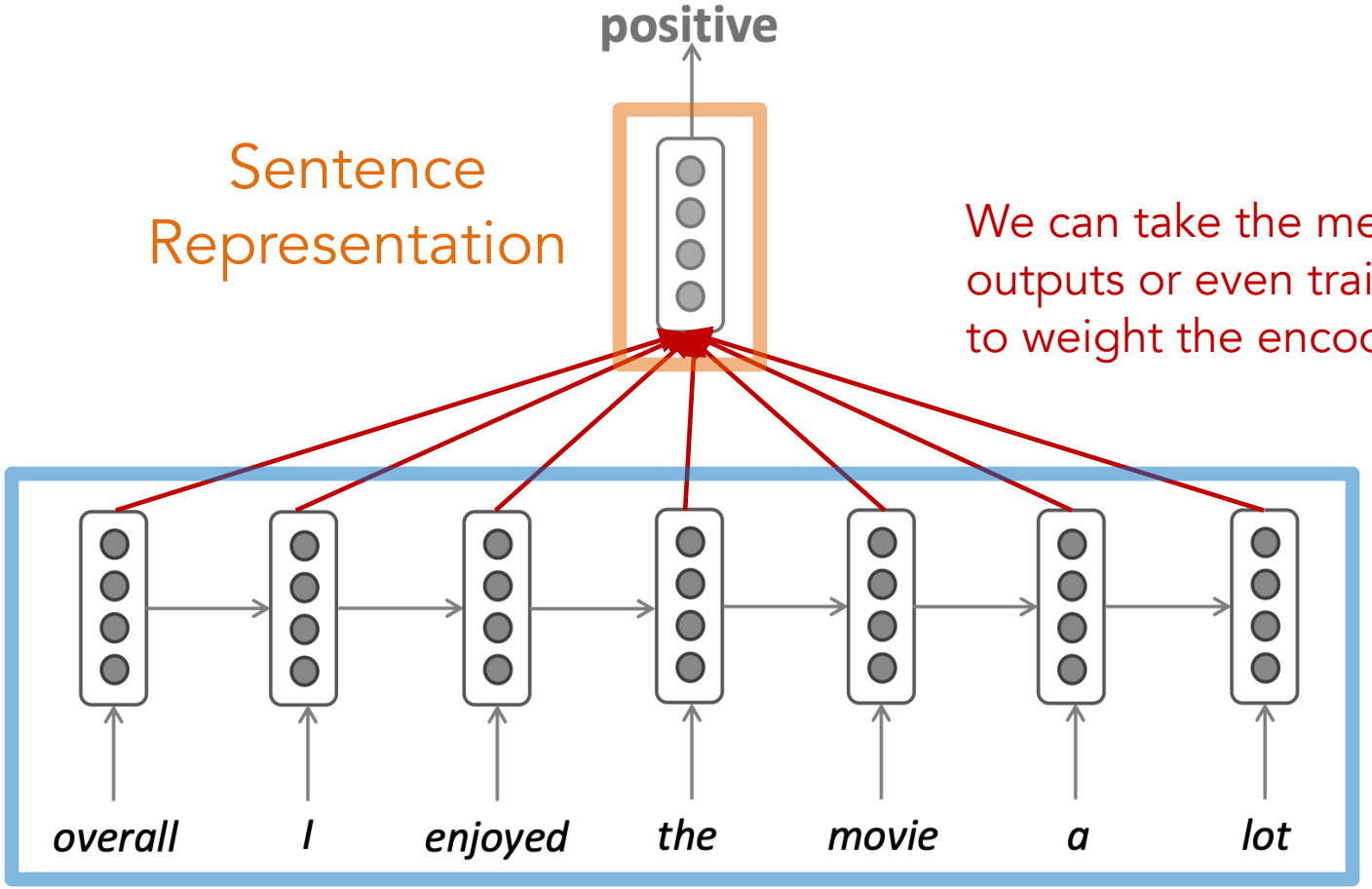
Source -- http://karpathy.github.io/2015/05/21/rnn-effectiveness/

We can generalize the Seq2Seq model further to the encoder-decoder structure, where the encoder produces an encoded representation of the entire input sequence.



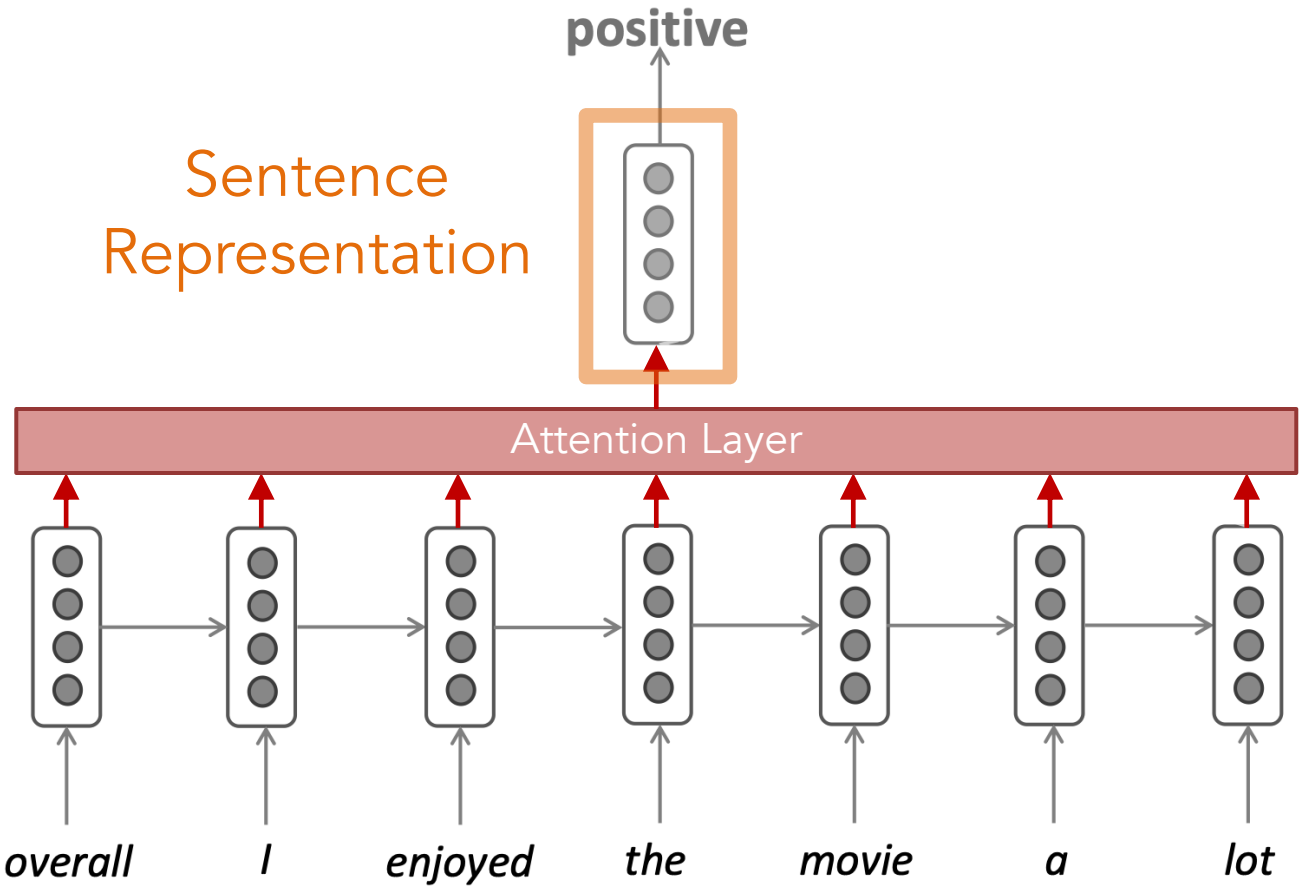
Source -- https://d2l.ai/chapter_recurrent-modern/seq2seq.html

The problem of using only the final encoder output is that it is hard for the model to remember previous information. Instead, we can have the model consider all outputs.



Source -- https://web.stanford.edu/class/cs224n/

But, using the same weights may be insufficient, as we may want the weights to change according to different inputs. We can use the attention mechanism to achieve this.

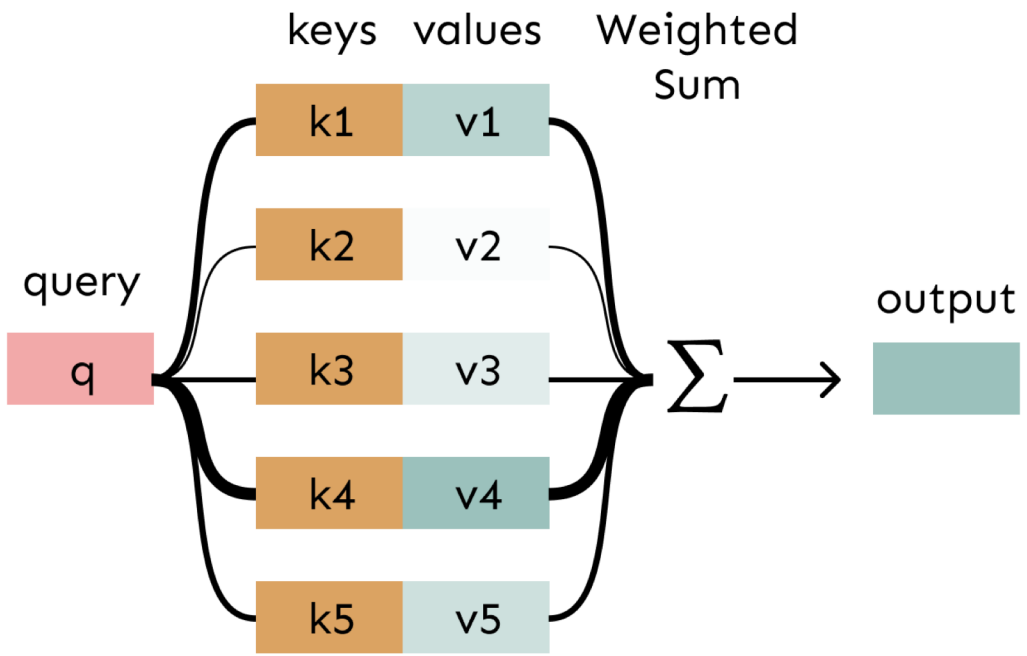


Yang, Z., et al. (2016, June). Hierarchical attention networks for document classification. NAACL conference.

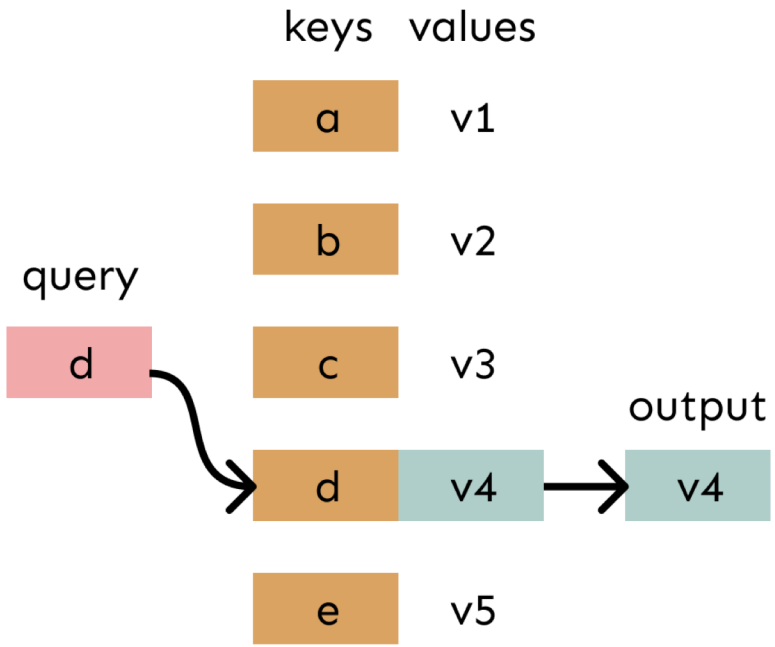
Attention is *weighted* averaging, which lets you do lookups!

Attention is just a **weighted** average – this is very powerful if the weights are learned!

In **attention**, the query matches all keys *softly*, to a weight between 0 and 1. The keys' values are multiplied by the weights and summed.



In a **lookup table**, we have a table of keys that map to values. The query matches one of the keys, returning its value.



Source -- https://web.stanford.edu/class/cs224n/

Step 5: Compute attention-weighted sum of encoder output:

$$\sum_{t=1}^{T} a_t v_t$$

Step 4: Compute the attention distribution using softmax:

$$[a_1 \ a_2 \ \dots \ a_T] = \text{softmax}([e_1 \ e_2 \ \dots \ e_T])$$

Step 3: Compute attention scores (dot product similarity):

$$e_t = score(q, k_t) = q^T k_t$$

W_k is trainable

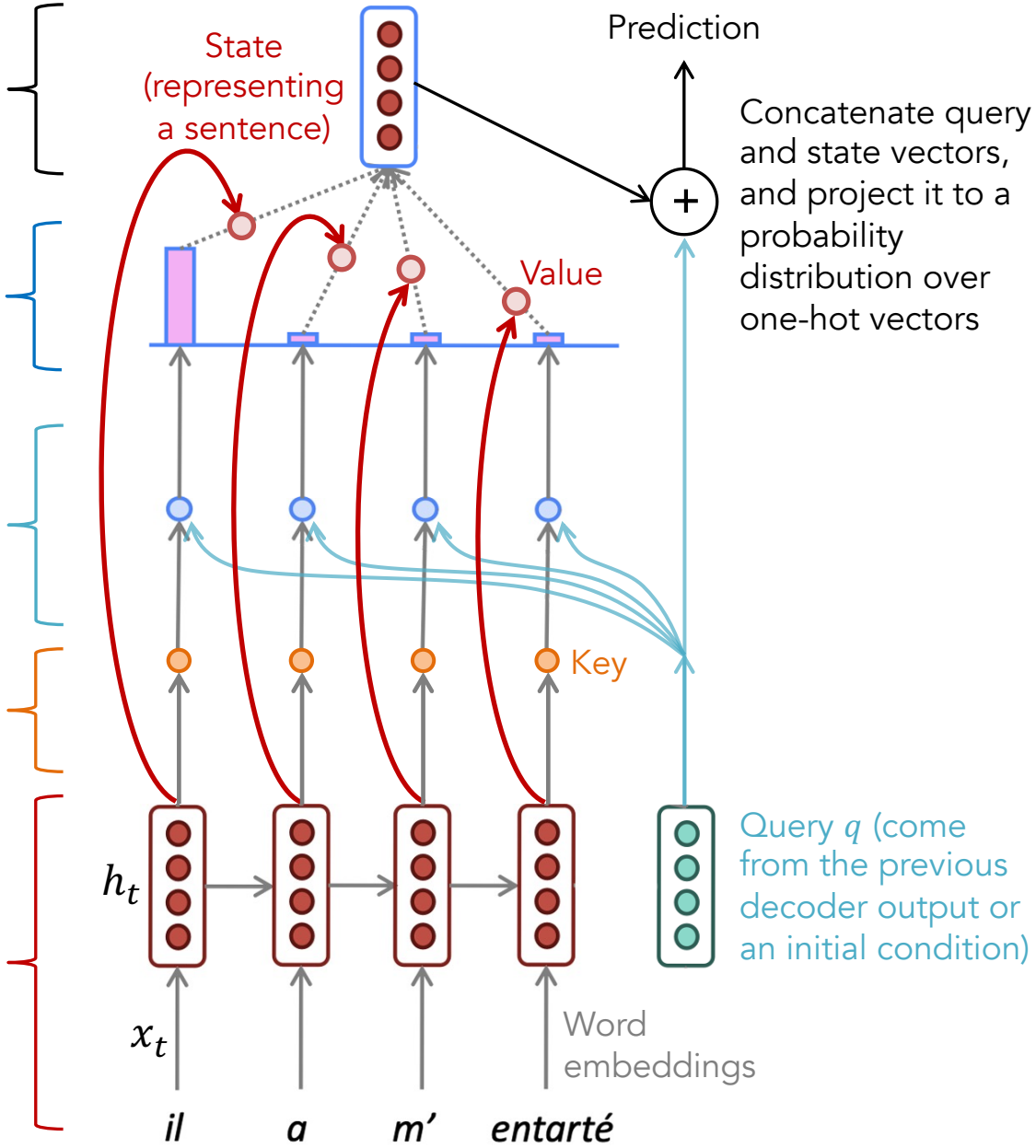
Step 2: Transform encoder outputs (dimension reduction):

$$k_t = \tanh(W_k h_t)$$

Step 1: Get the encoder output values (from the RNN):

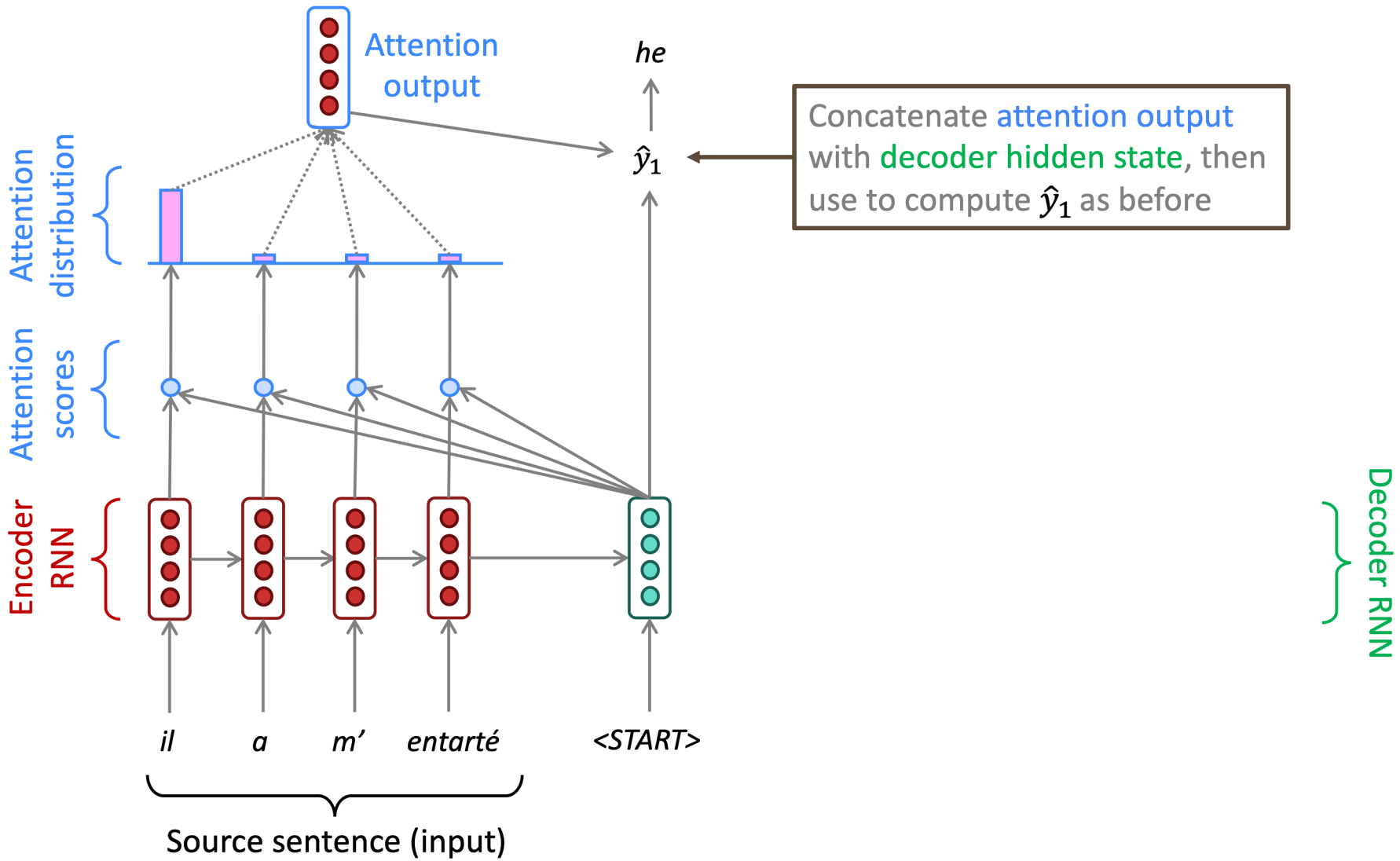
$$v_t = h_t = h(x_t)$$

There are many ways of doing step 2 and 3



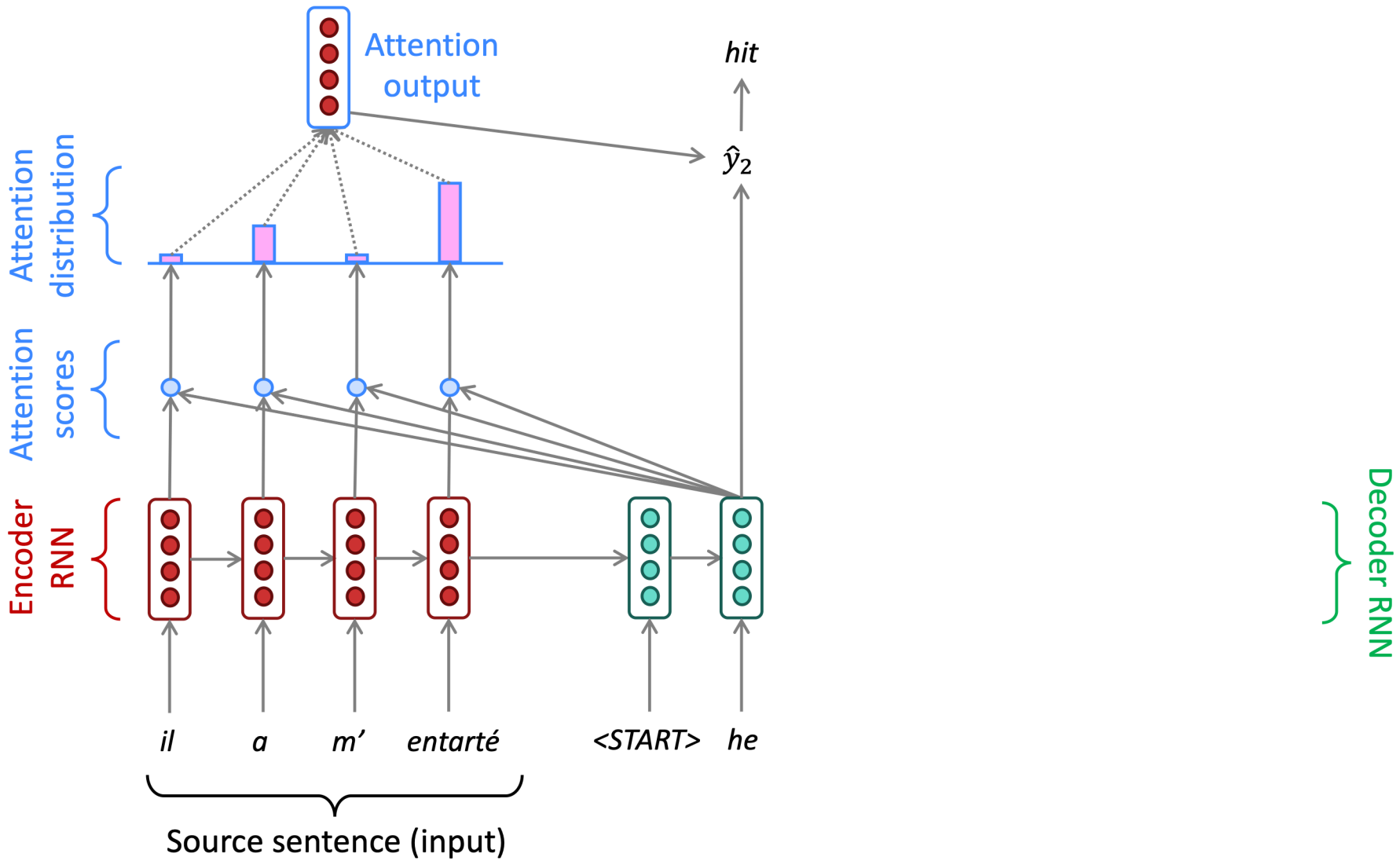
Source -- https://web.stanford.edu/class/cs224n/

Sequence-to-sequence with attention



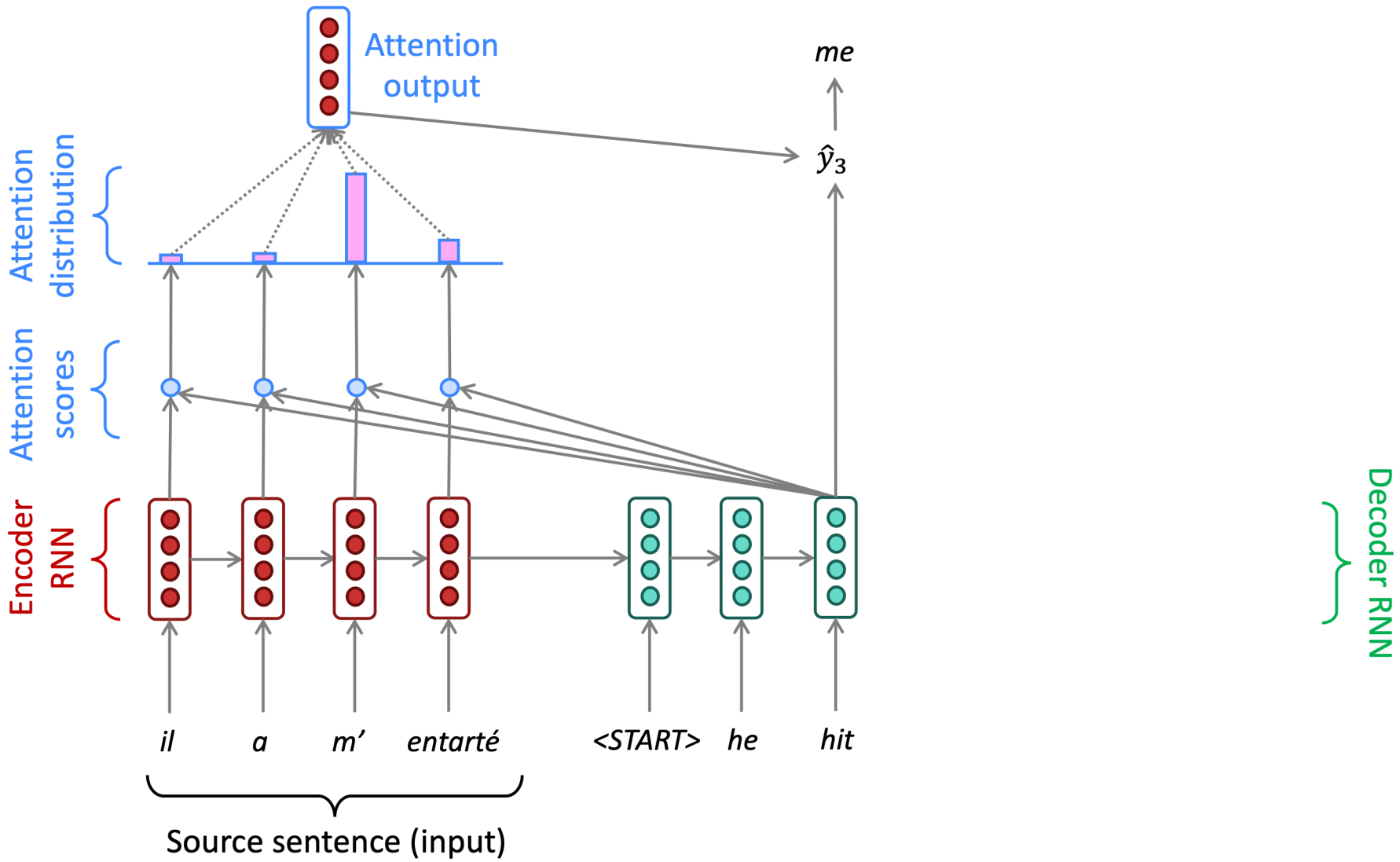
Source -- https://web.stanford.edu/class/cs224n/

Sequence-to-sequence with attention



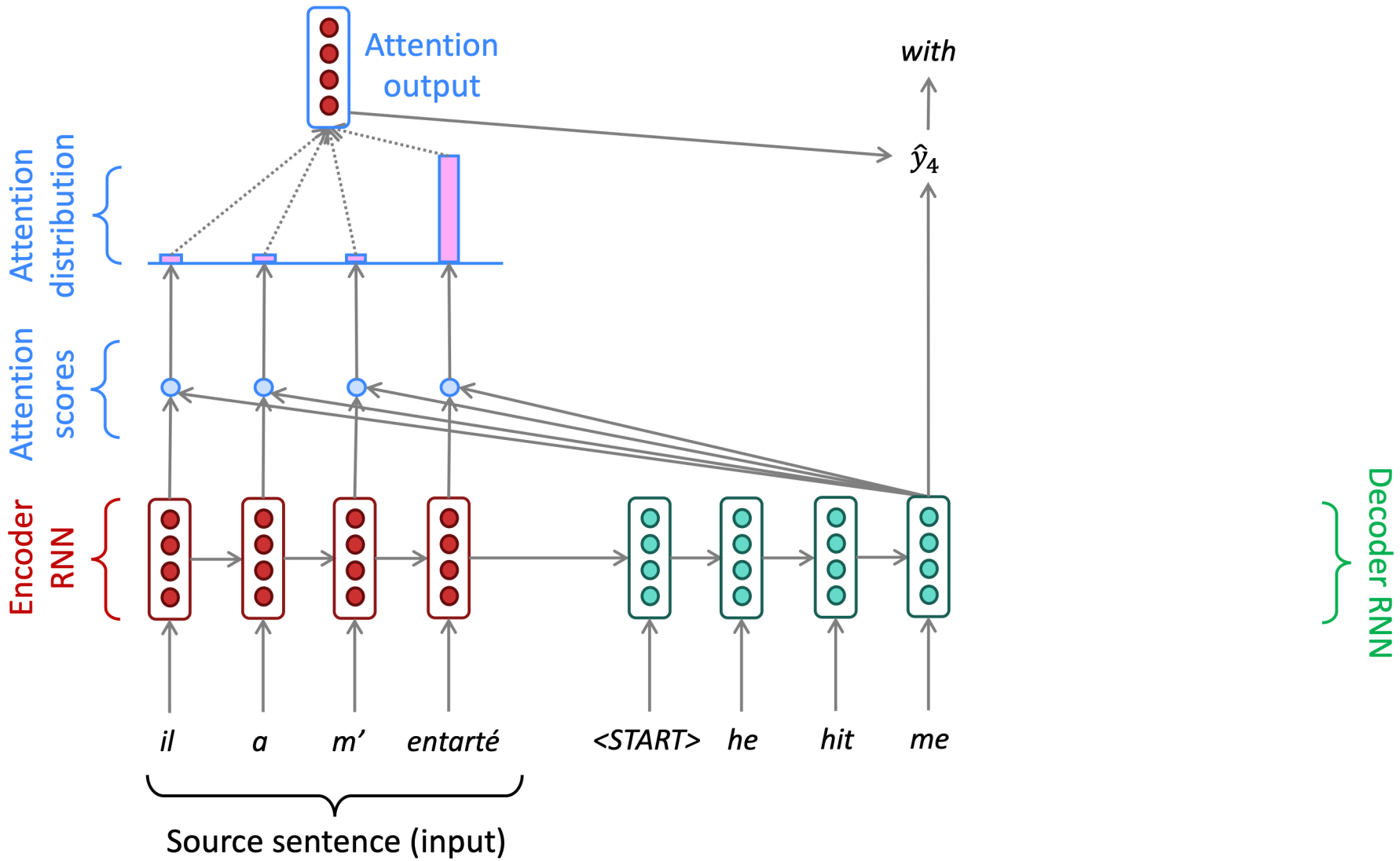
Source -- https://web.stanford.edu/class/cs224n/

Sequence-to-sequence with attention



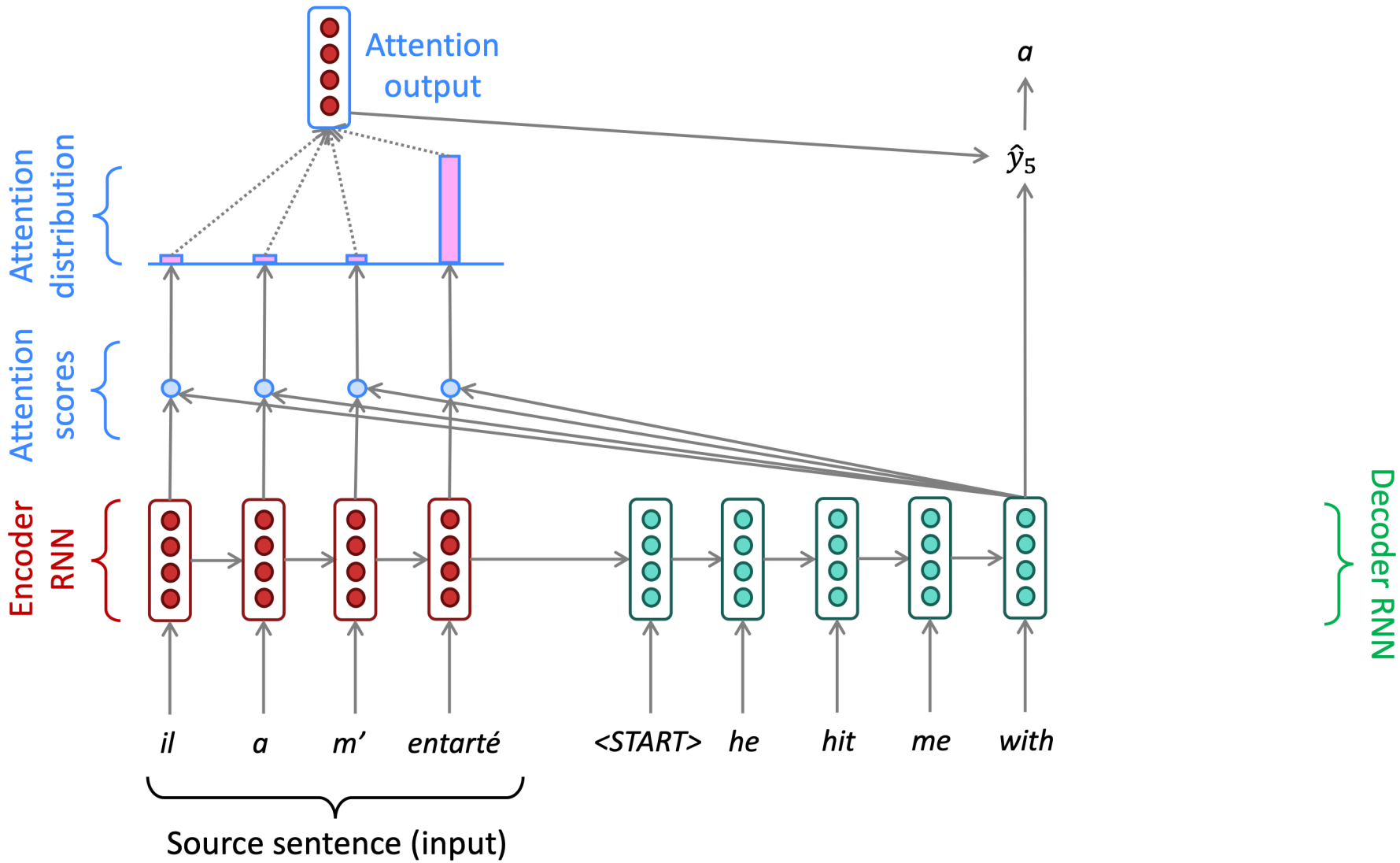
Source -- https://web.stanford.edu/class/cs224n/

Sequence-to-sequence with attention



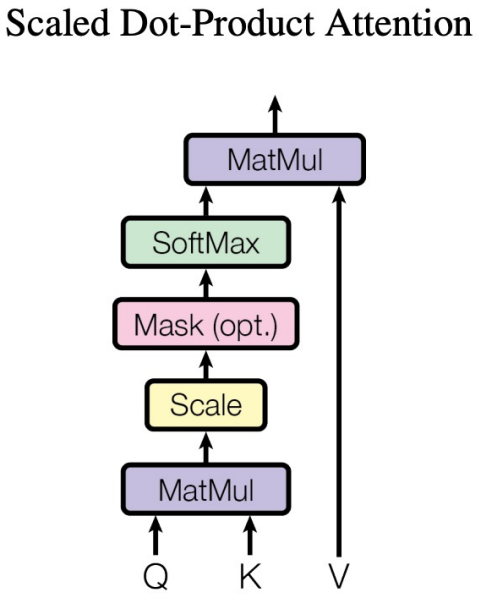
Source -- https://web.stanford.edu/class/cs224n/

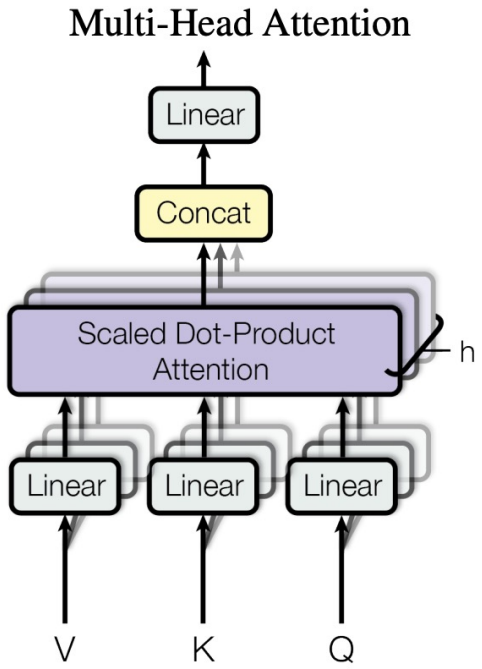
Sequence-to-sequence with attention

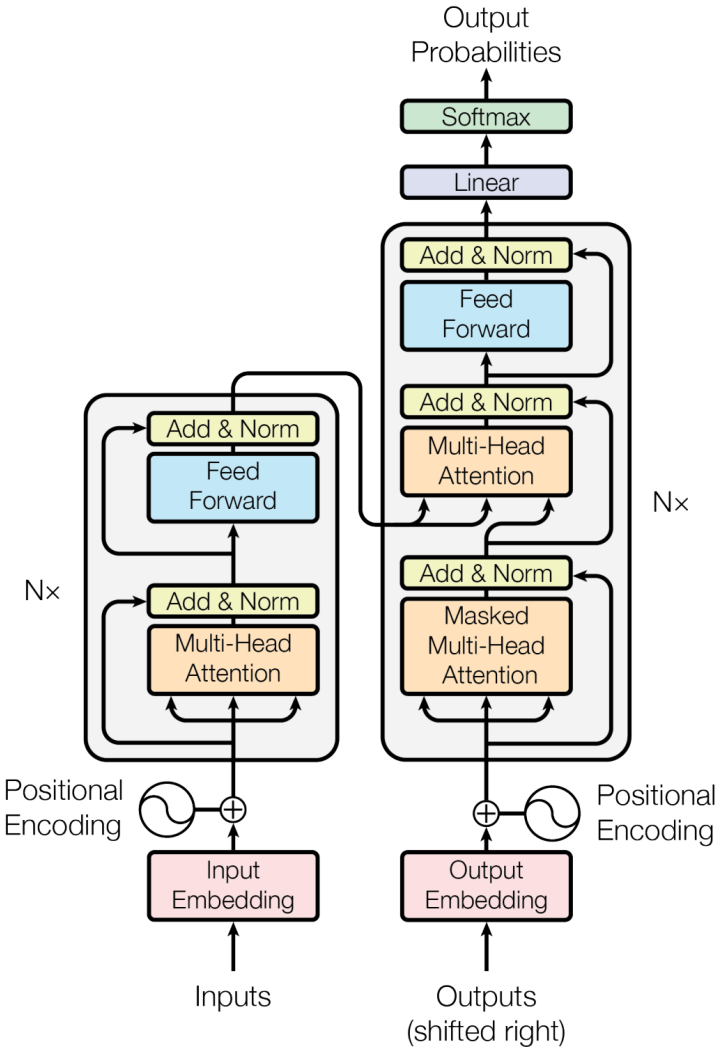


Source -- https://web.stanford.edu/class/cs224n/

There is a more complicated attention mechanism, “self-attention”, which is the building block of the Transformer network architecture.





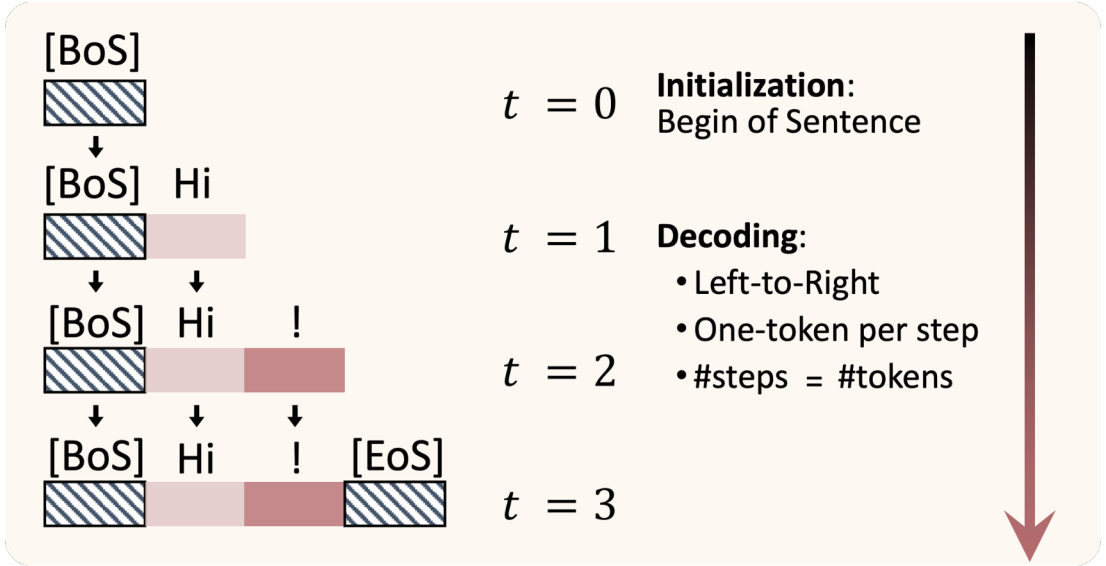


Vaswani, A., Shazeer, et al. (2017). Attention is all you need. Advances in neural information processing systems.

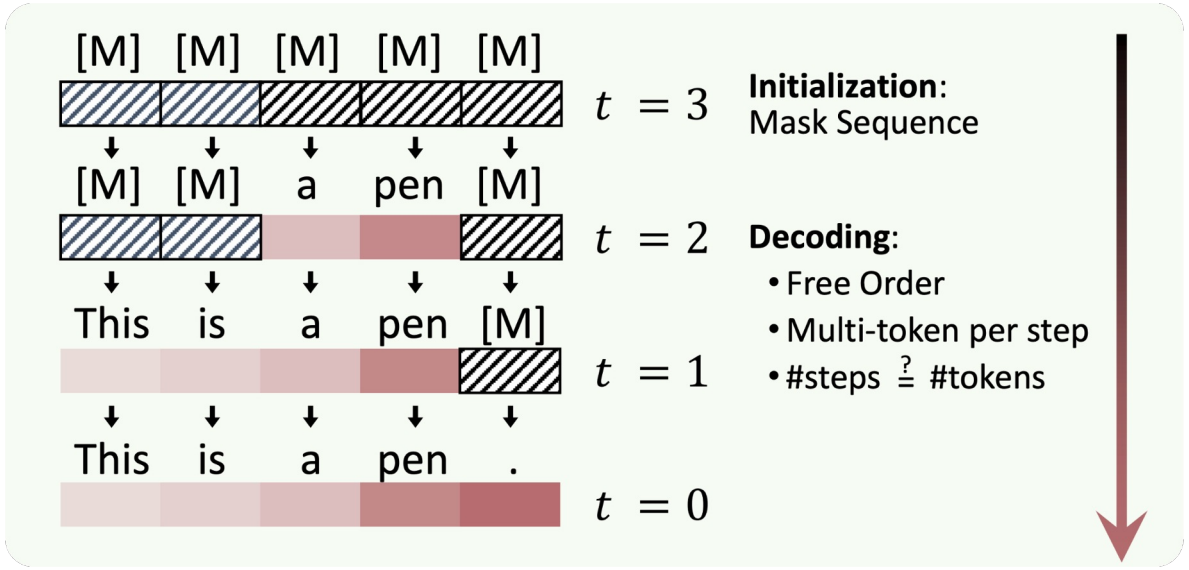
We have explained the autoregressive approach that generates words one by one.

There is another diffusion approach that can generate a sequence simultaneously.

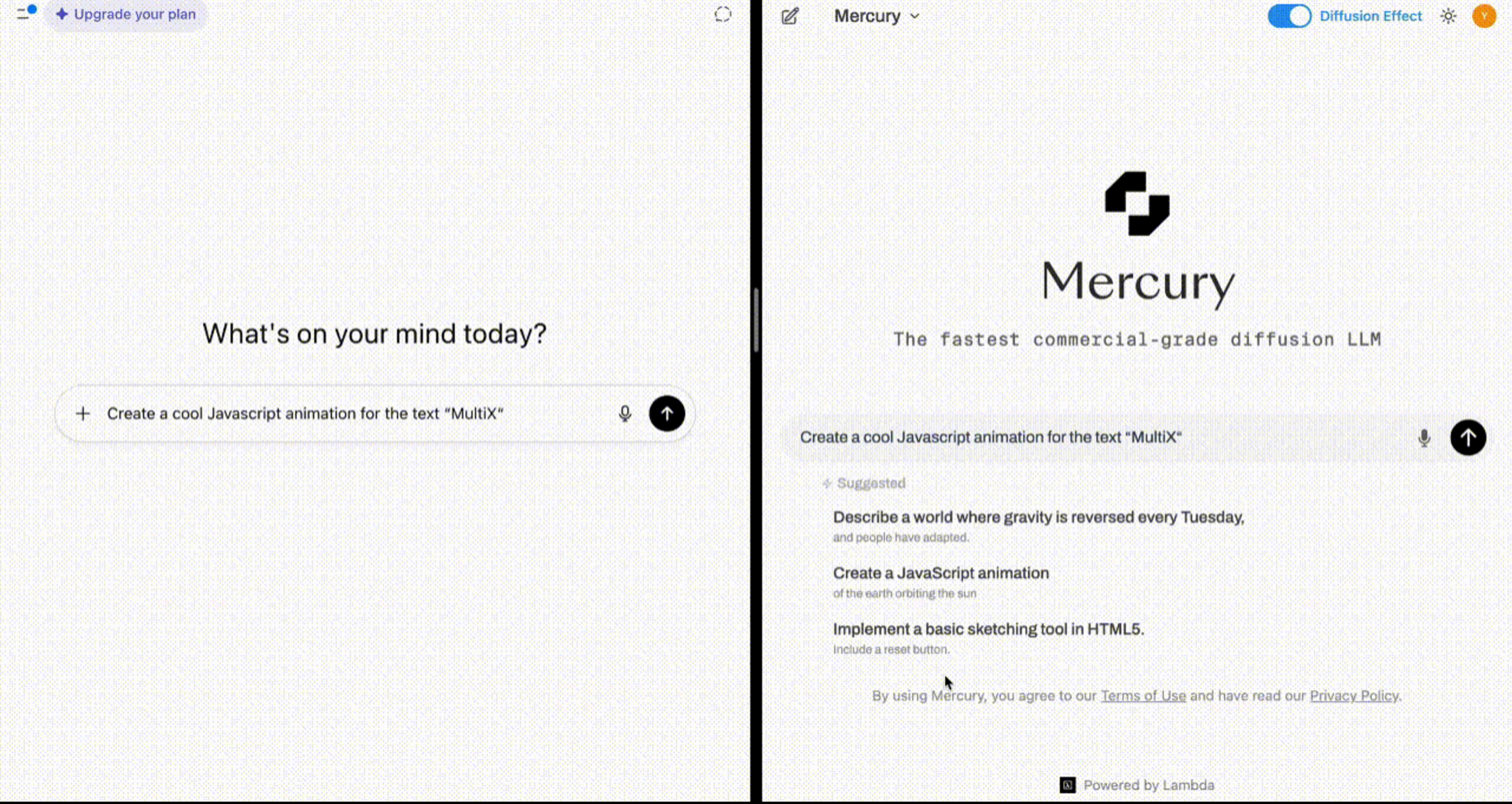
Autoregressive



Diffusion



Yu, R., Li, Q., & Wang, X. (2025). Discrete Diffusion in Large Language and Multimodal Models: A Survey. arXiv:2506.13759.



This video is created by Yijia Zheng in the MultiX research group at UvA.

Take-Away Messages

- We need to represent text as numbers for Natural Language Processing tasks.
- We can train word embeddings (vectors) to map words into data points in a high dimensional space.
- One way to train word embeddings is to use the context (e.g., nearby words) to represent a word.
- Word embeddings also encode semantics, which means similar words are close to each other.
- Cosine similarity and dot product can be used to measure how vectors are close to each other.
- Softmax is a commonly used function in deep learning to map arbitrary values to probabilities.
- Recurrent Neural Network can take inputs with various lengths (e.g., sentences).
- Attention helps the model learn information from the past and focus on a certain part of the source.

Questions?