Data Science

Lecture 7: Text Data Processing

University of Amsterdam

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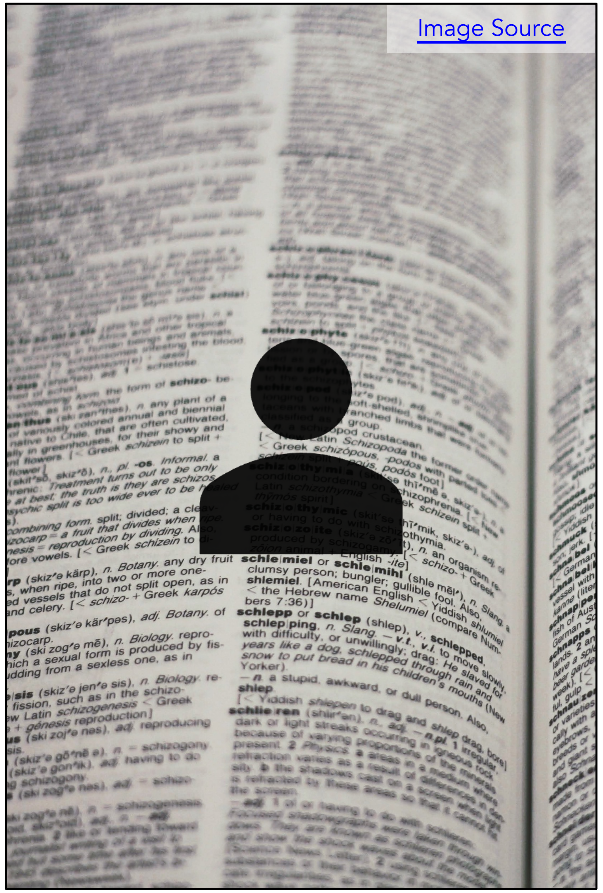
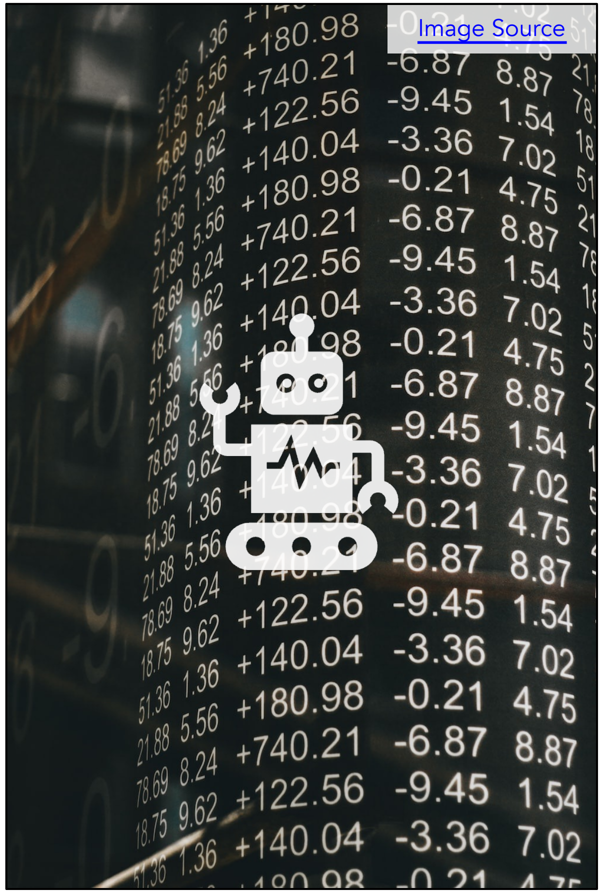
This lecture covers the pipeline of Natural Language Processing (NLP):

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

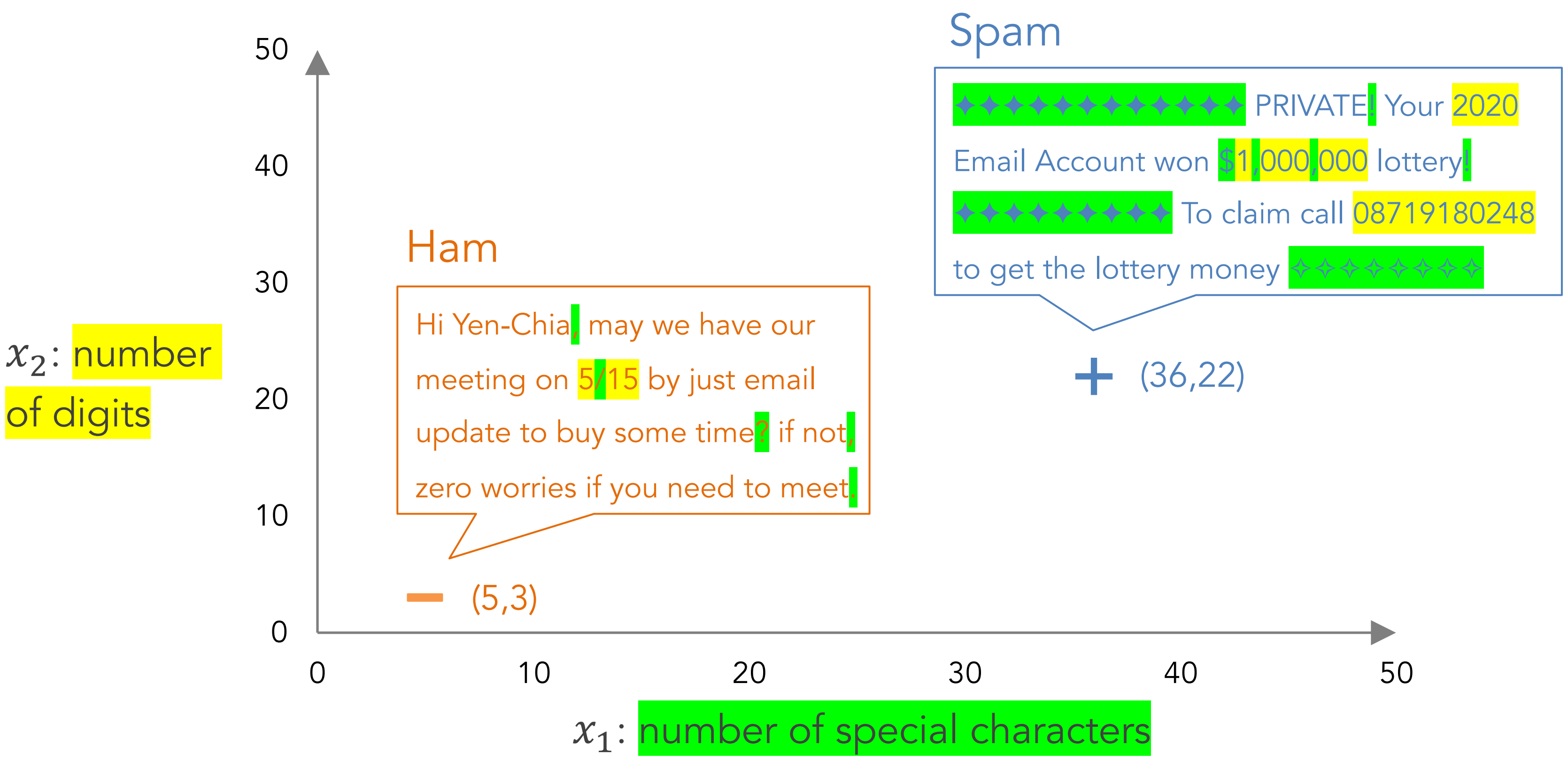
People can read text, but computers can only read numbers. So, we need to represent text as numbers in a way that computers can read, but how?



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']

```
>>> stemmer = nltk.stem.porter.PorterStemmer()
>>> clean_tokens = [stemmer.stem(t) for t in tokens]
```

['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']

```
>>> from nltk.corpus import wordnet
>>> lemmatizer = nltk.stem.WordNetLemmatizer()
>>> pos = [wordnet_pos(p) for p in nltk.pos_tag(tokens)]
>>> clean_tokens = [lemmatizer.lemmatize(t,p) for t, p in pos]
```

['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.

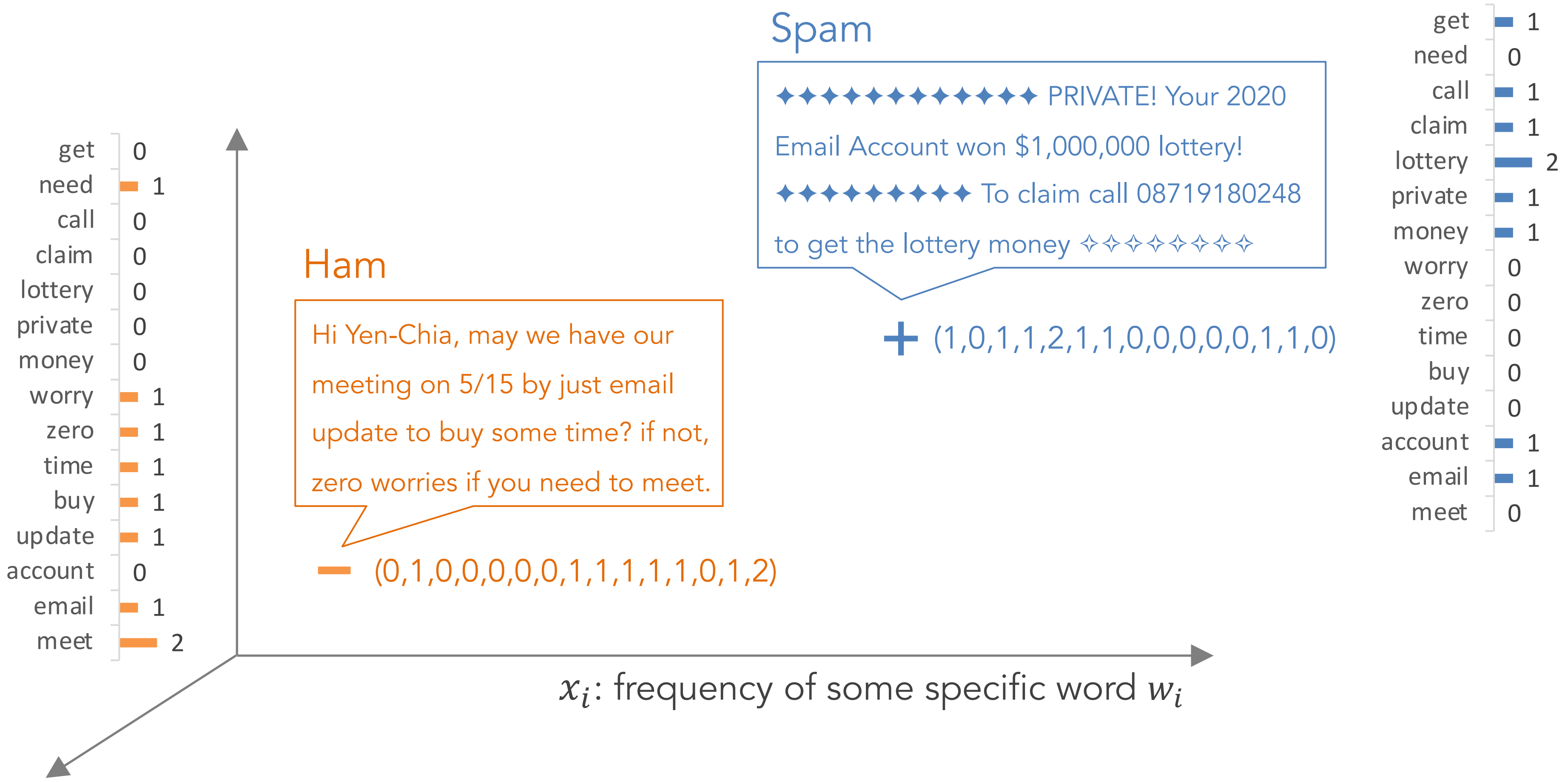
nsubj	p	vmod	prep	nn	pobj	p	num	nn	appos	p
Google	,	headquartered	in	Mountain	View	(	1600	Amphitheatre	Pkwy	,
NOUN	PUNCT	VERB	ADP	NOUN	NOUN	PUNCT	NUM	NOUN	NOUN	PUNCT

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

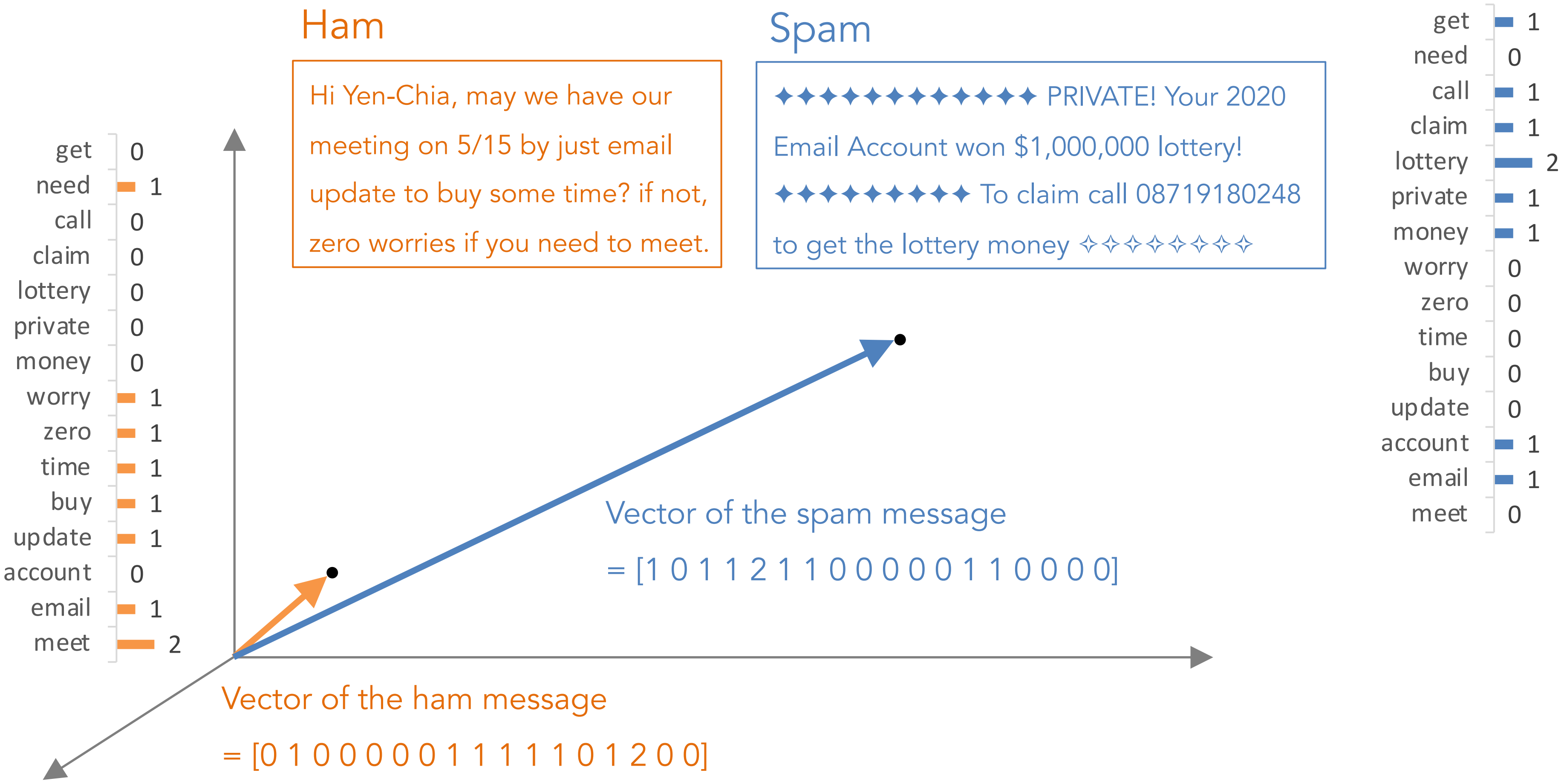
nn	nsubj	root	prep	poss	pobj	mark	nsubj	ccomp	poss	amod	nn	dobj
Sundar	Pichai	said	in	his	keynote	that	users	love	their	new	Android	phones
NOUN	NOUN	VERB	ADP	PRON	NOUN	ADP	NOUN	VERB	PRON	ADJ	NOUN	NOUN

```
>>> 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.

Final TF-IDF score for a term in a document

$$w_{t,d} = \underbrace{\mathrm{tf}(t, d)}_{\text{The more frequently a term appears in a given document...}} \times \underbrace{\mathrm{idf}(t, D)}_{\text{...and the fewer times it appears in other documents...}}$$

The higher its TF-IDF value.

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.

Term Frequency (TF)

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

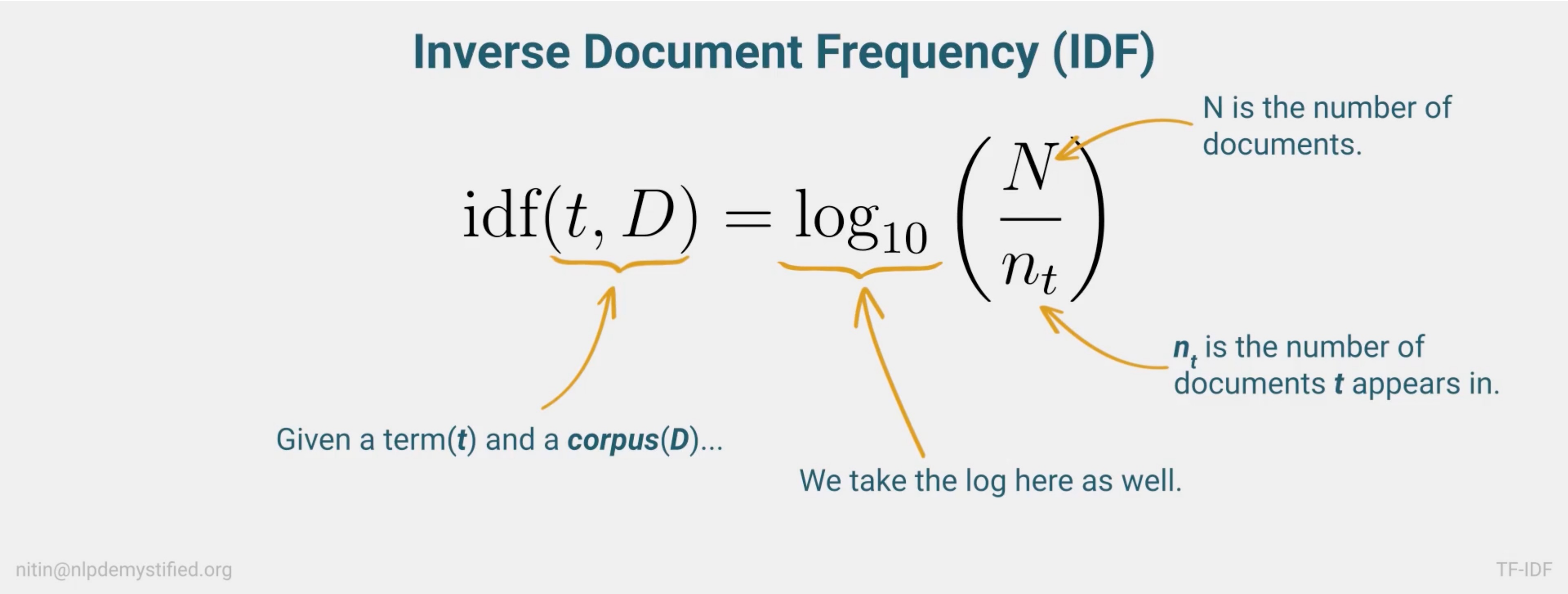
Given a word(***t***) in a document(***d***)...

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

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

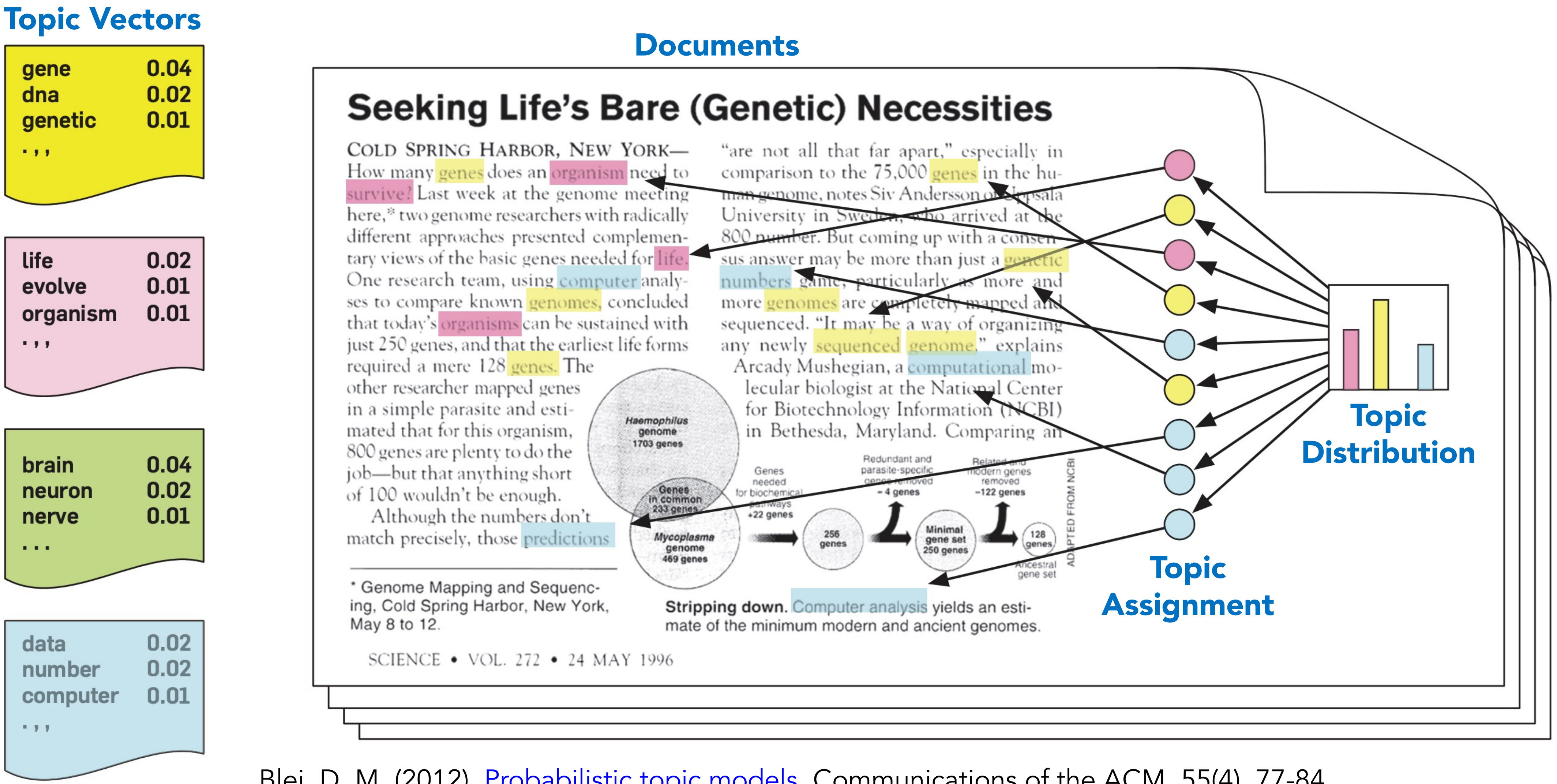
Source -- https://www.nlpdemystified.org/course/tf-idf

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.



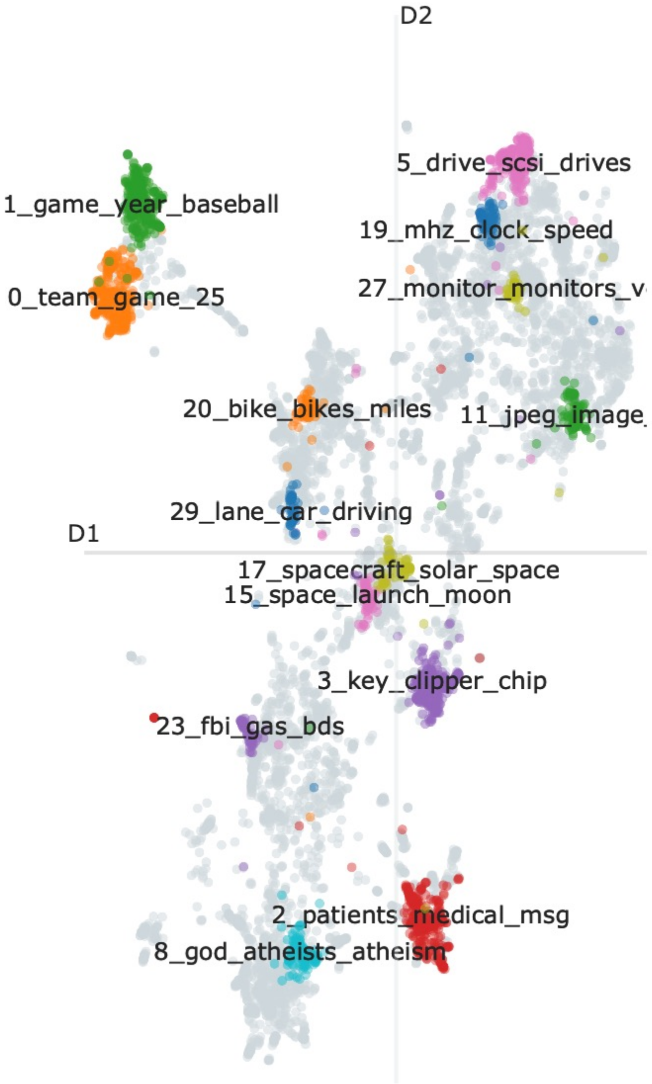
Source -- https://www.nlpdemystified.org/course/tf-idf

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.

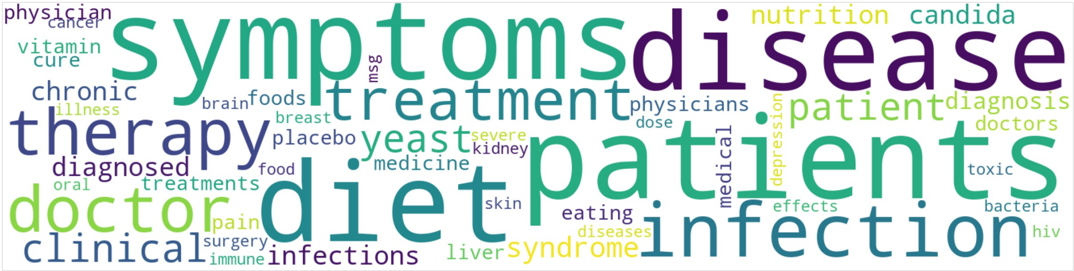
Each topic vector is represented by a list of words with different weights.



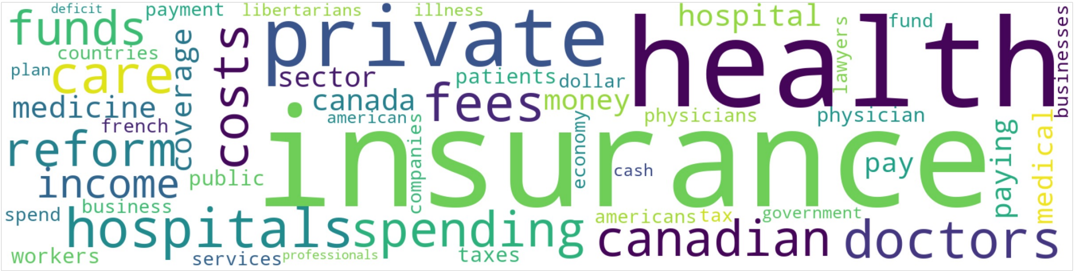
Source -- https://maartengr.github.io/BERTopic/getting_started/visualization/visualization.html

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

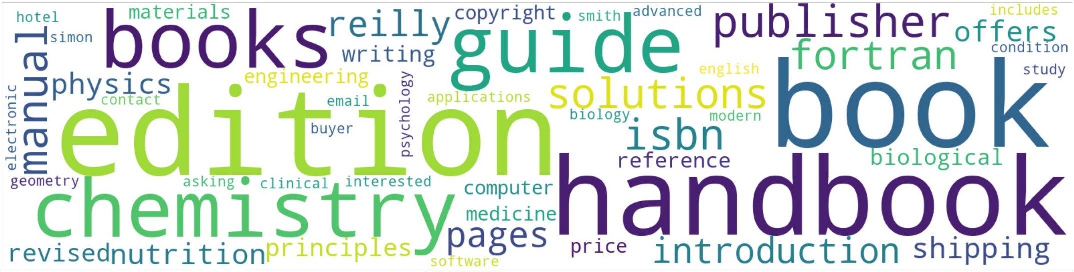
Topic 21



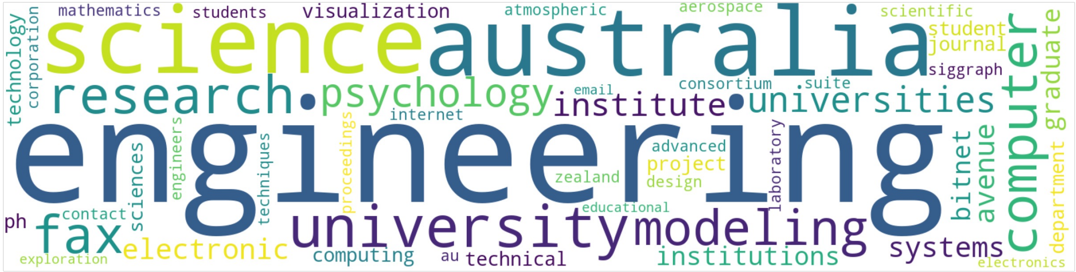
Topic 29



Topic 9

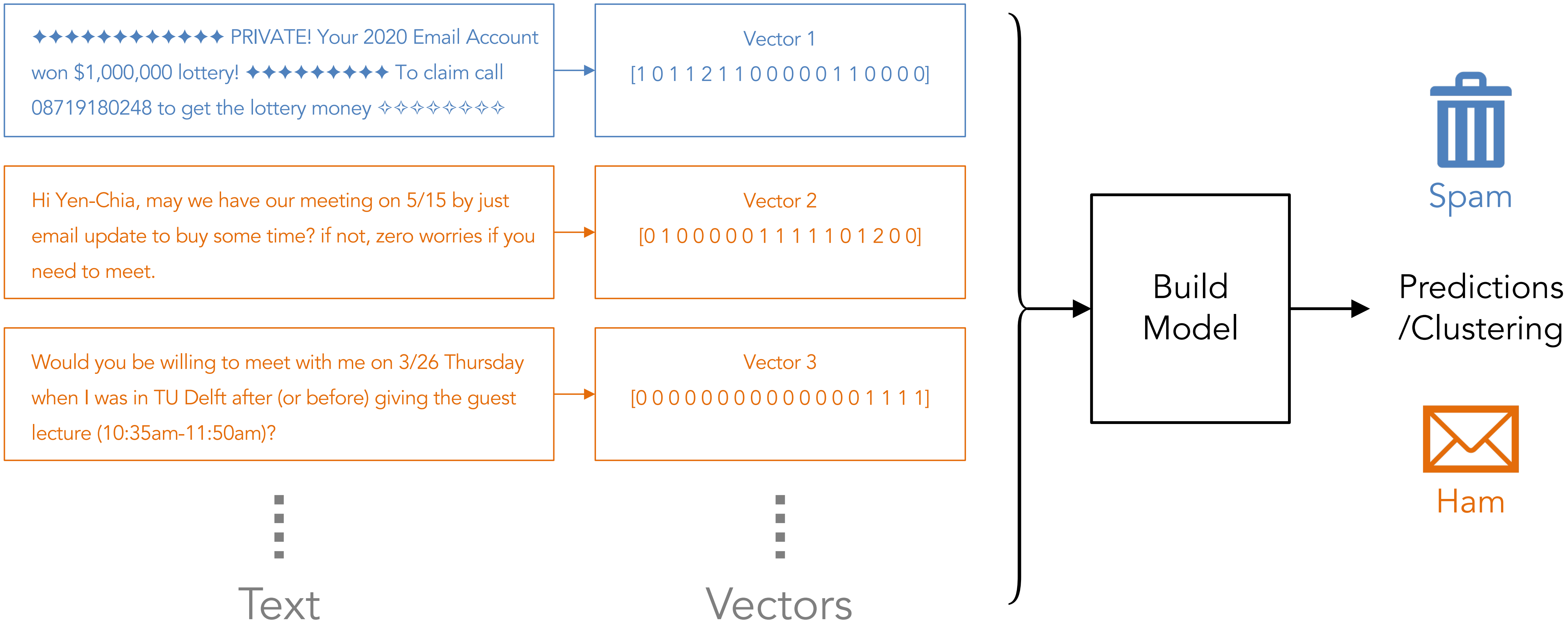


Topic 61

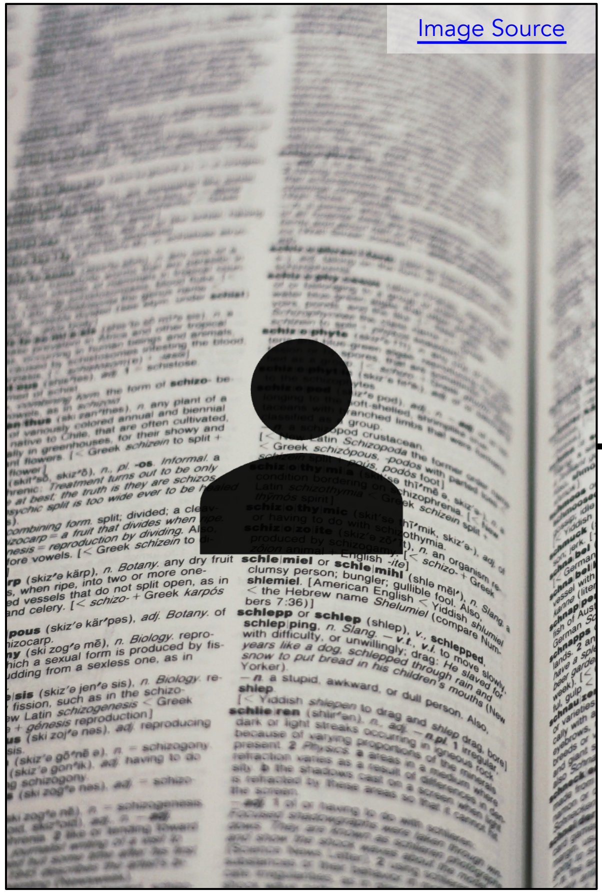


Source -- https://github.com/ddangelov/Top2Vec

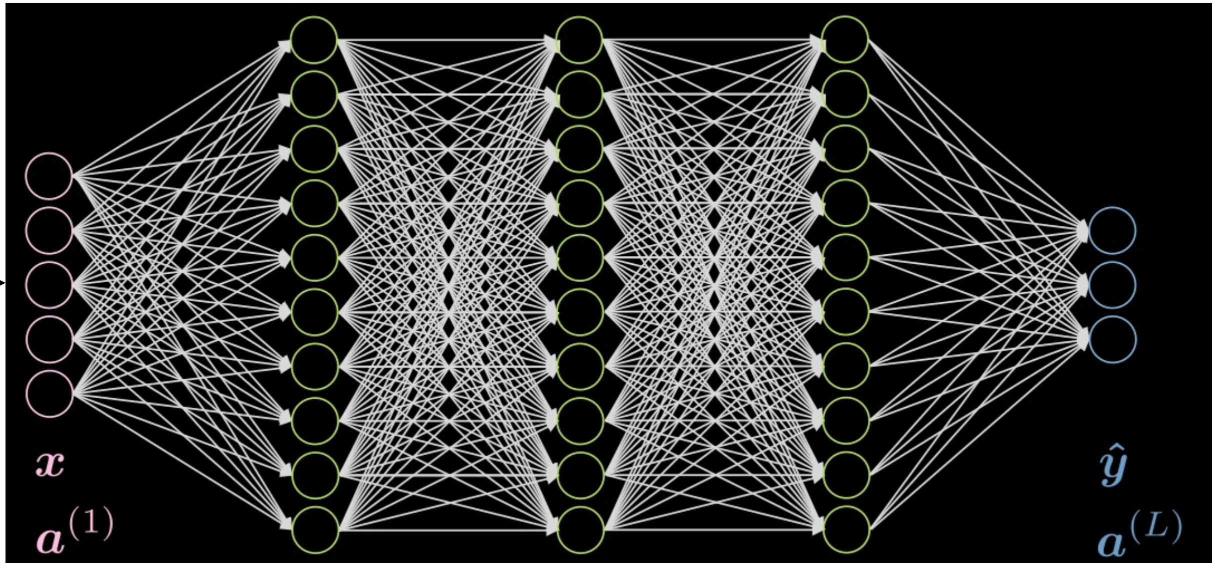
After transforming text into vectors, we can use these vectors for national language processing tasks, such as sentence/document classification (or clustering).



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.

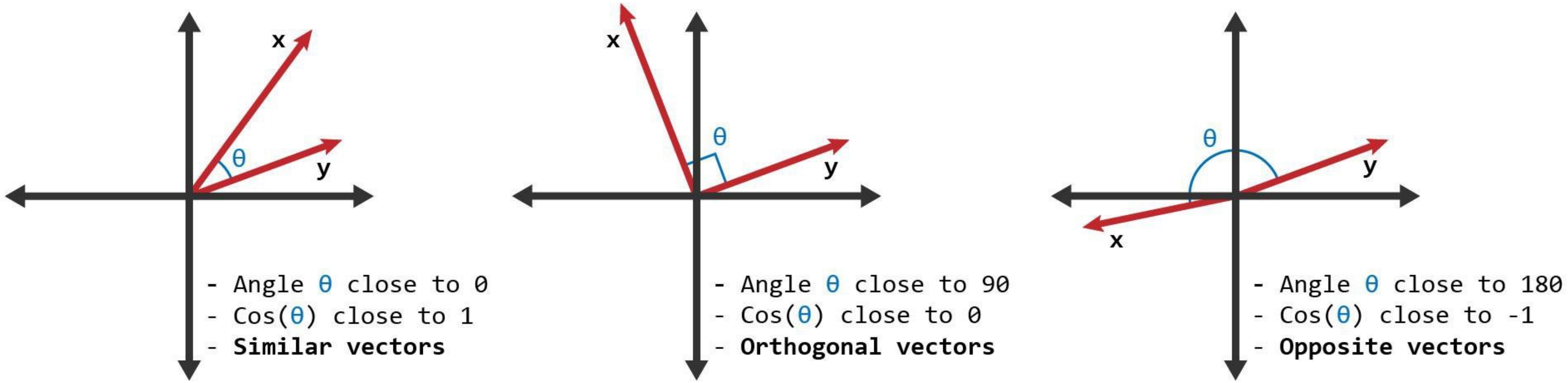
One-hot encoding

			cat	mat	on	sat	the	All other possible words								
w_{the}	**the**	=>	0	0	0	0	1	0	0	0	0	0	0	0	...	0
w_{cat}	**cat**	=>	1	0	0	0	0	0	0	0	0	0	0	0	...	0
w_{sat}	**sat**	=>	0	0	0	1	0	0	0	0	0	0	0	0	...	0
	...				...											

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

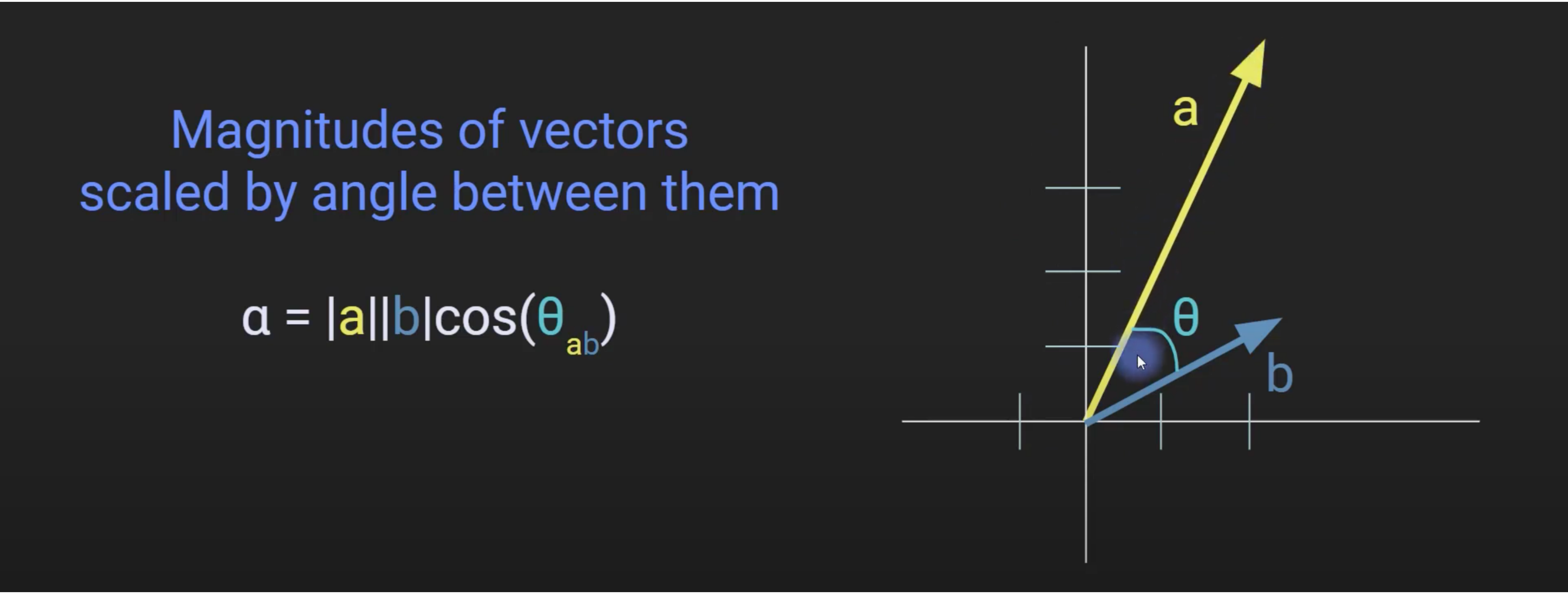
Another problem of one-hot encoding is that it does not encode similarity. For example, the cosine similarity between two one-hot encoded vectors are always zero.

$$\text{CosineSimilarity}(w_{cat}, w_{sat}) = \cos(\theta) = \frac{\overbrace{\boxed{< w_{cat} \cdot w_{sat} >}}^{\text{dot product} = w_{cat}^T w_{sat}}}{\underbrace{\boxed{\|w_{cat}\|}}_{\text{length of } w_{cat}}\|w_{sat}\|} = \overbrace{[1 \quad 0 \quad 0 \quad 0 \quad 0]}^{w_{cat}^T} \cdot \overbrace{\begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}}^{w_{sat}} = 0$$



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.



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

Exercise 7.1: Given the following word embeddings, compute the cosine similarity between "desk" and "table", as well as between "desk" and "desks".

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

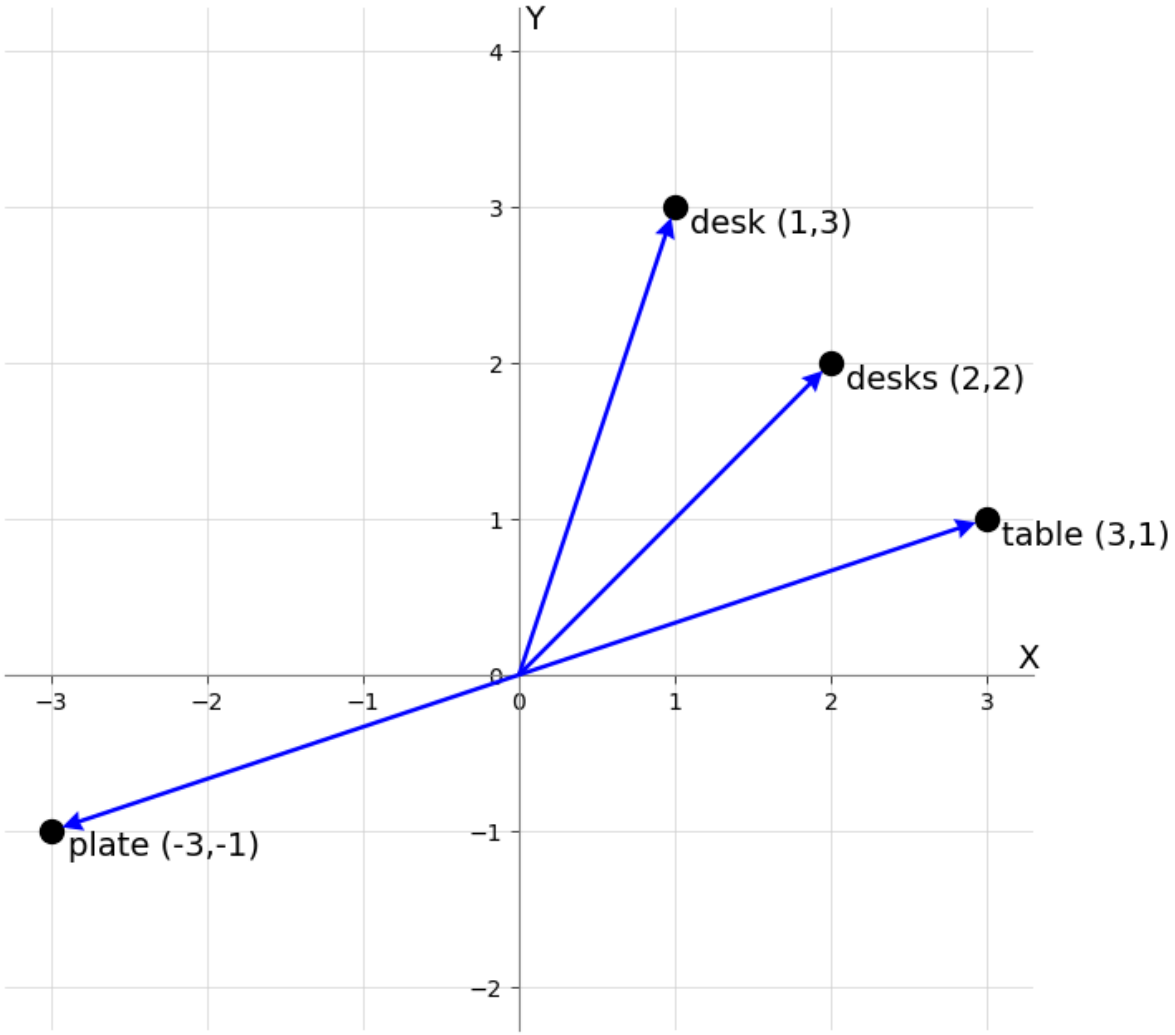
$$= \frac{\boxed{< p_1 \cdot p_2 >}}{\|p_1\| \|p_2\|}$$ dot product

$$= \frac{\boxed{[x_1 \quad y_1] \cdot \begin{bmatrix} x_2 \\ y_2 \end{bmatrix}}}{\|p_1\| \|p_2\|}$$

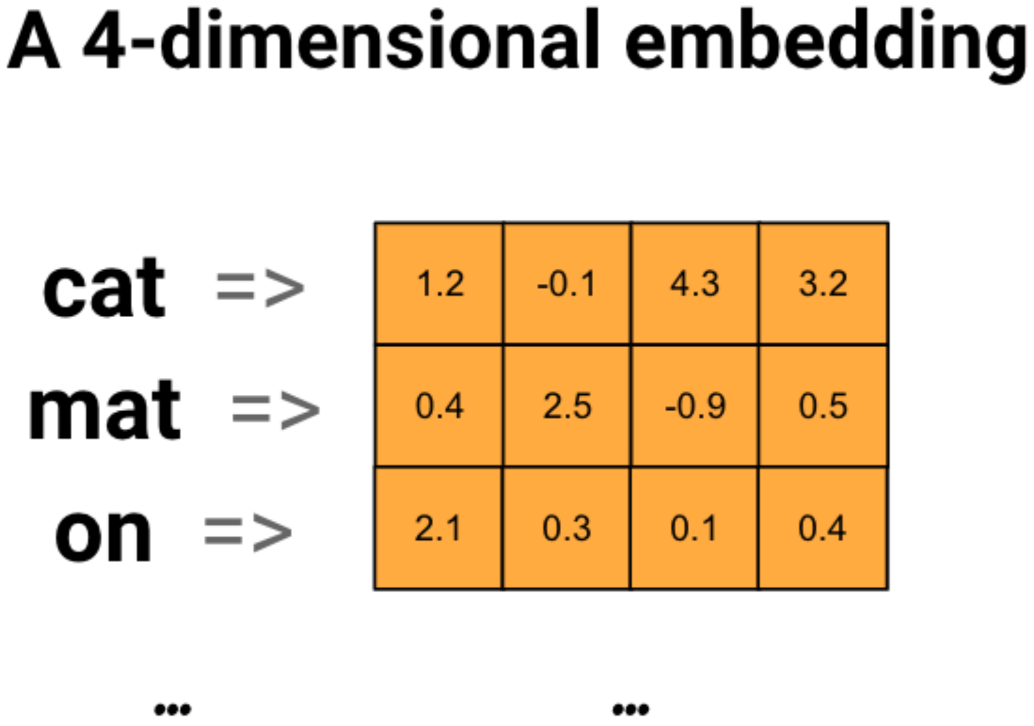
$p_1 = (x_1, y_1)$

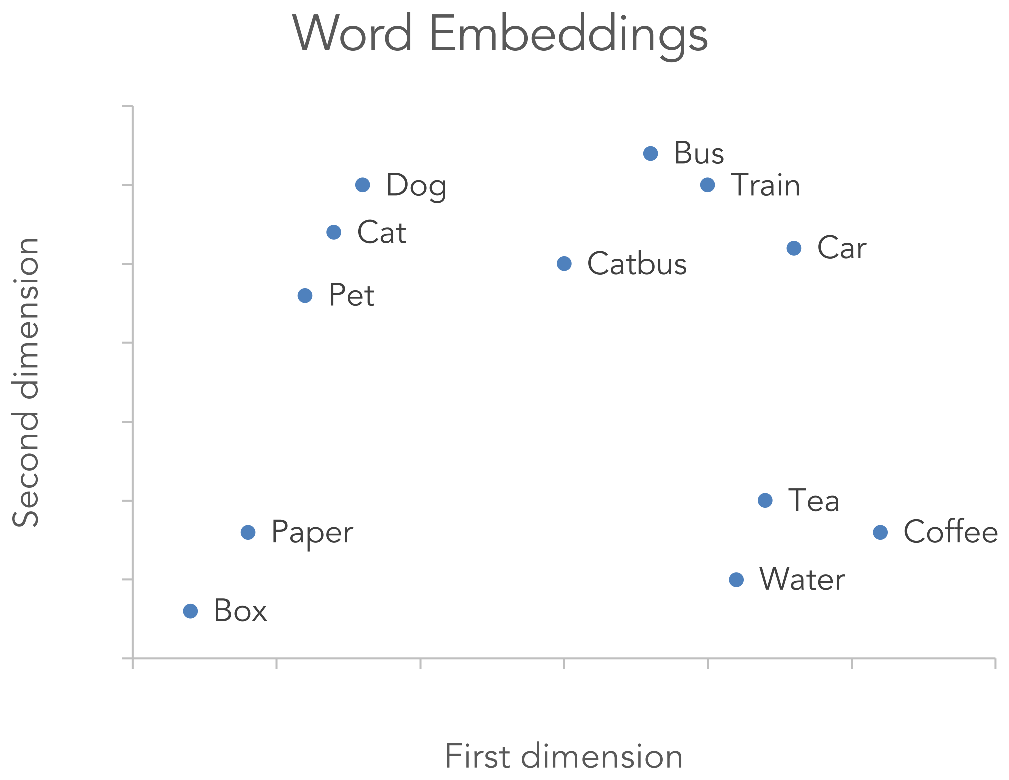
$p_2 = (x_2, y_2)$

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



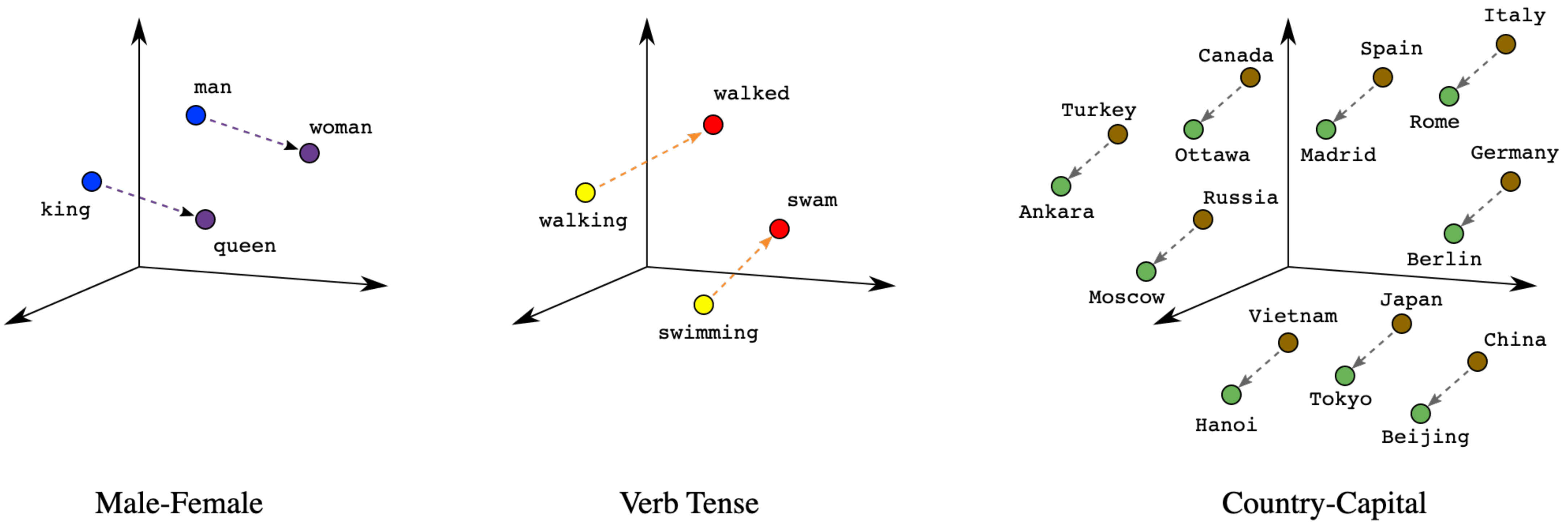
We can use word embeddings to efficiently represent text as vectors, in which similar words have a similar encoding in a high-dimensional space.





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.



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

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

...government debt problems turning into ***banking*** *crises as happened in 2009...*

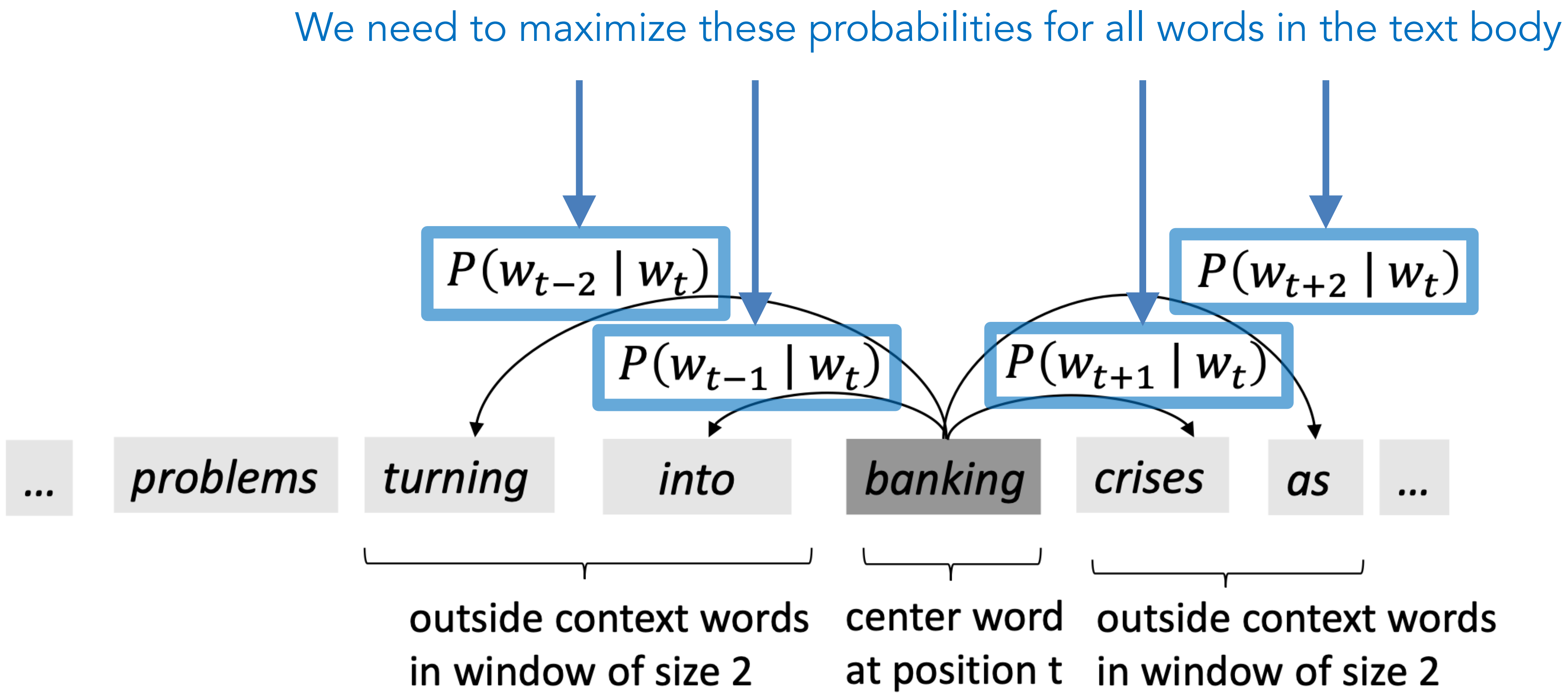
...saying that Europe needs unified ***banking*** *regulation to replace the hodgepodge...*

...India has just given its ***banking*** *system a shot in the arm...*

These context words will be used to represent the word: "banking"

Source -- https://web.stanford.edu/class/cs224n/slides/cs224n-2023-lecture01-wordvecs1.pdf

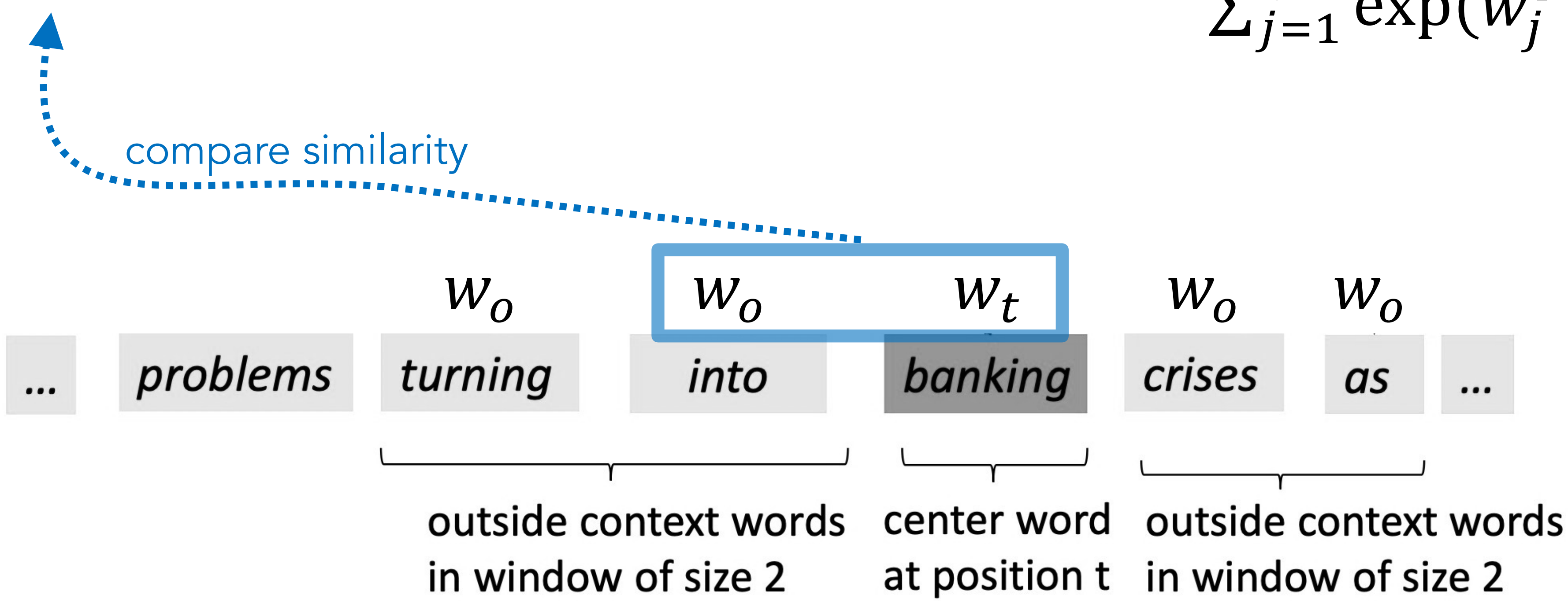
Word2Vec is a method to train word embeddings by context. The goal is to use the center word to predict nearby words as accurate as possible, based on probabilities.



Source -- https://web.stanford.edu/class/cs224n/slides/cs224n-2023-lecture01-wordvecs1.pdf

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

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



Source -- https://web.stanford.edu/class/cs224n/slides/cs224n-2023-lecture01-wordvecs1.pdf

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

Larger dot product means larger probability

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

The entire denominator is just for normalization

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

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

Source -- https://web.stanford.edu/class/cs224n/slides/cs224n-2023-lecture01-wordvecs1.pdf

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

$$\begin{bmatrix}2\\1\\0.1\end{bmatrix} \rightarrow \begin{matrix} \dfrac{\exp(2)}{\exp(2)+\exp(1)+\exp(0.1)} \\[2ex] \dfrac{\exp(1)}{\exp(2)+\exp(1)+\exp(0.1)} \\[2ex] \dfrac{\exp(0.1)}{\exp(2)+\exp(1)+\exp(0.1)} \end{matrix} \rightarrow \begin{bmatrix}0.66\\0.24\\0.10\end{bmatrix}$$

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

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 $t = 1, \dots, T$ with window size m, we can adjust the word vectors (θ) to maximize the likelihood function, based on the probability that we calculated.

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

θ is all variables to be optimized

		w_{t-2}	w_{t-1}	w_t	w_{t+1}	w_{t+2}	
...	*problems*	*turning*	*into*	*banking*	*crises*	*as*	...

$\underbrace{\textit{turning} \quad \textit{into}}_{\text{outside context words in window of size 2}}$ $\underbrace{\textit{banking}}_{\text{center word at position t}}$ $\underbrace{\textit{crises} \quad \textit{as}}_{\text{outside context words in window of size 2}}$

outside context words in window of size 2

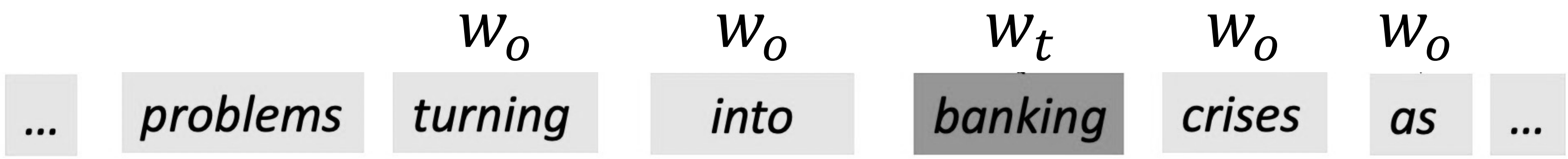
center word at position t

outside context words in window of size 2

More about Maximum Likelihood Estimation -- https://www.youtube.com/watch?v=Dn6b9fClUpM

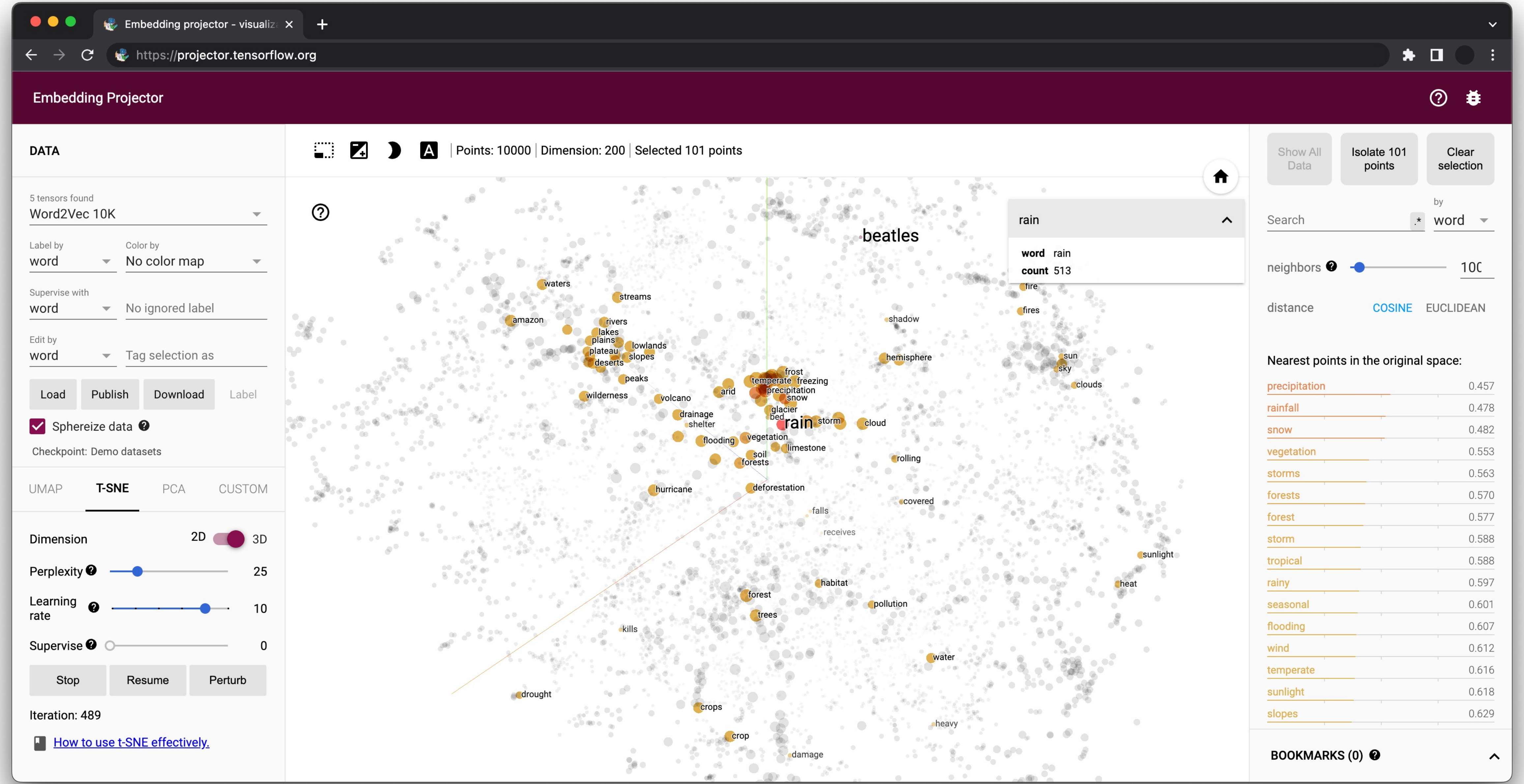
To sum up, below are the high-level ideas for training word embeddings:

- We have a large text corpus (i.e., text body) with a long list of words
- Every word is represented by a vector w
- For each position t in the text, determine the center word w_t and the context words w_o (i.e., the words that are nearby w_t)



- For each word w_t, compute the probability of $P(w_o|w_t)$ using the dot product similarity of word vectors w_o and w_t
- Keep adjusting the word vectors to maximize this probability

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?

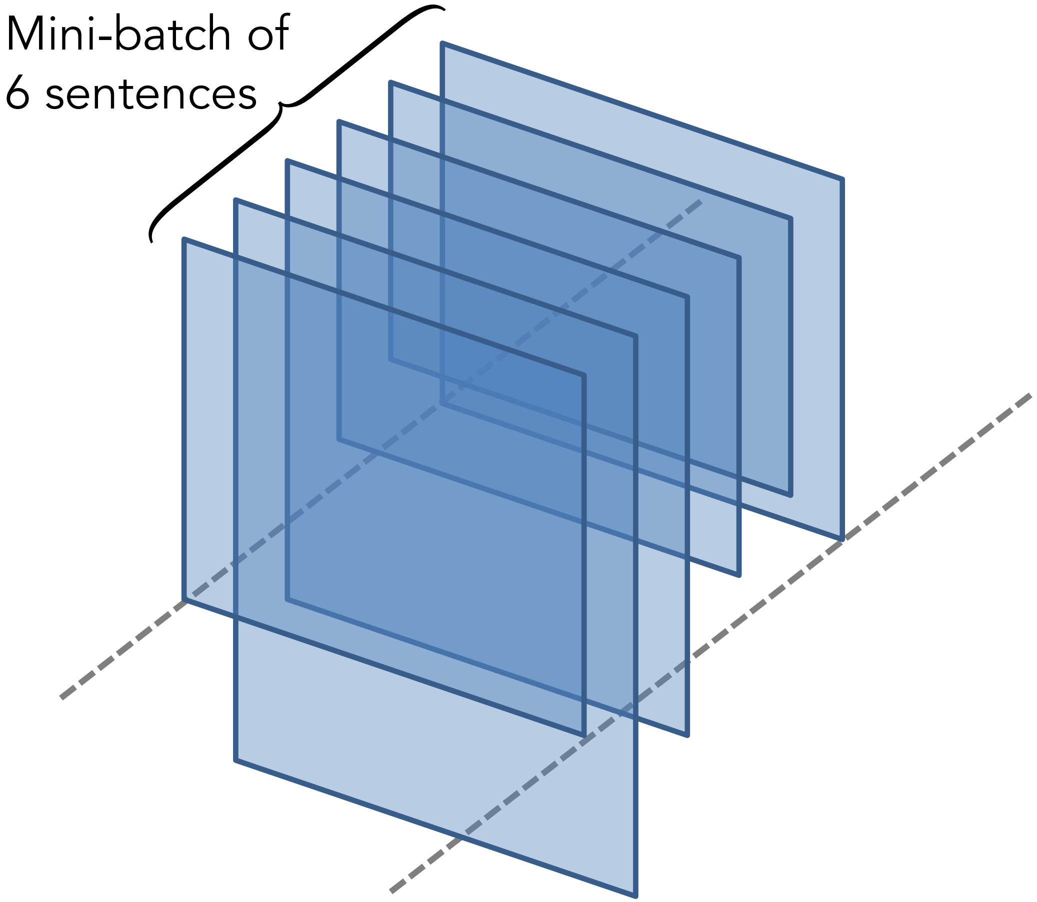
We can stack all the word vectors into a matrix, where each column means a dimension of the word vector, and the number of rows means sentence length.

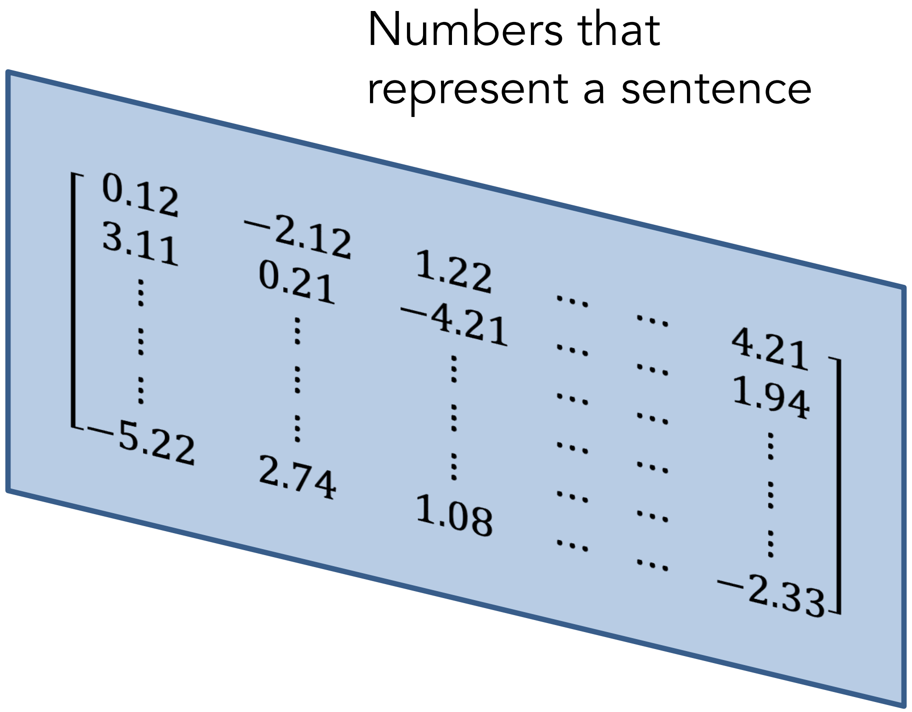
['google', 'headquarter', 'mountain', 'view', 'amphitheatre', 'pkwy', 'mountain', 'view', 'ca', 'unveil', 'new', 'android', 'phone', 'consumer', 'electronic', 'show', 'sundar', 'pichai', 'say', 'keynote', 'user', 'love', 'new', 'android', 'phone']

First dimension of word vector

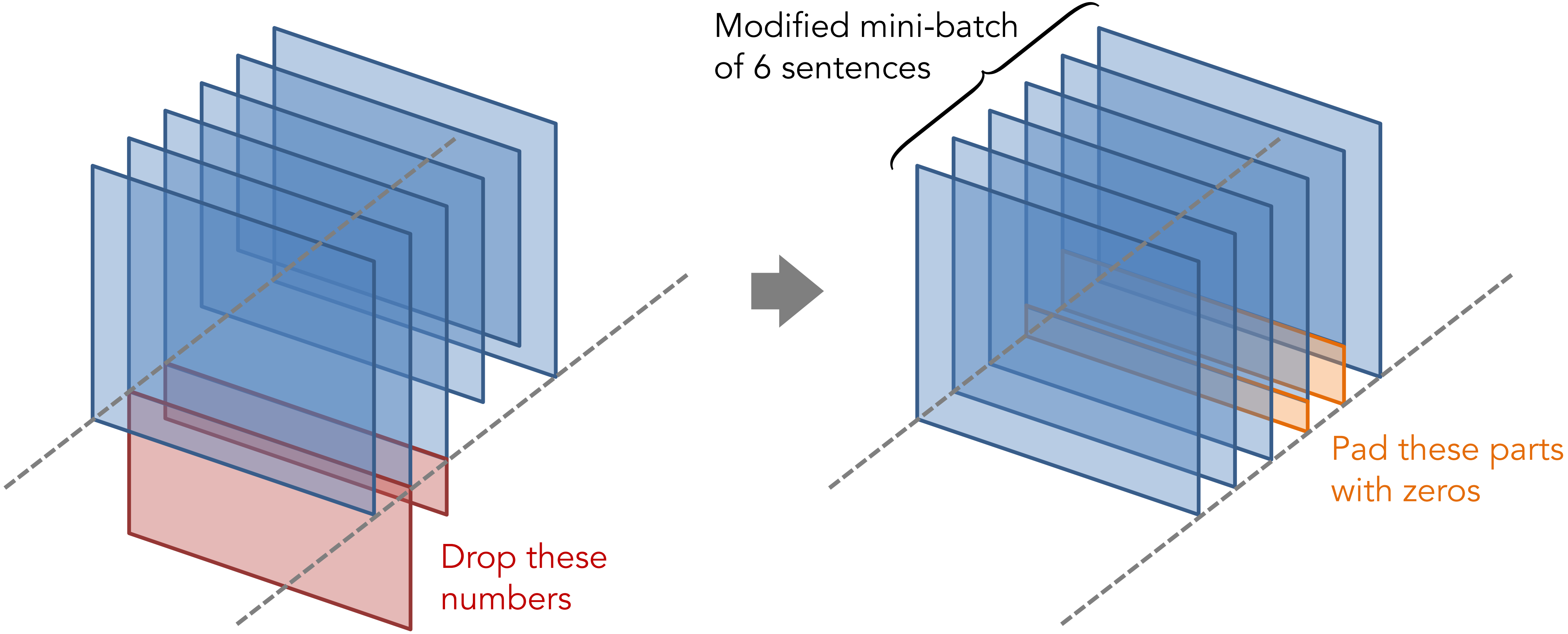
$$\begin{array}{cl} \begin{bmatrix} 0.12 & -2.12 & 1.22 & \cdots & \cdots & 4.21 \\ 3.11 & 0.21 & -4.21 & \cdots & \cdots & 1.94 \\ \vdots & \vdots & \vdots & \cdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & \cdots & \vdots \\ -5.22 & 2.74 & 1.08 & \cdots & \cdots & -2.33 \end{bmatrix} & \begin{array}{l} \text{google} \\ \text{headquarter} \\ \\ \\ \\ \text{phone} \end{array} \end{array}$$

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?

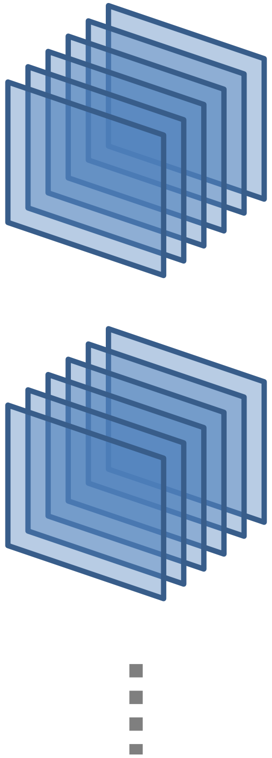




We can drop the parts that are too long and pad the parts that are too short with zeros.



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

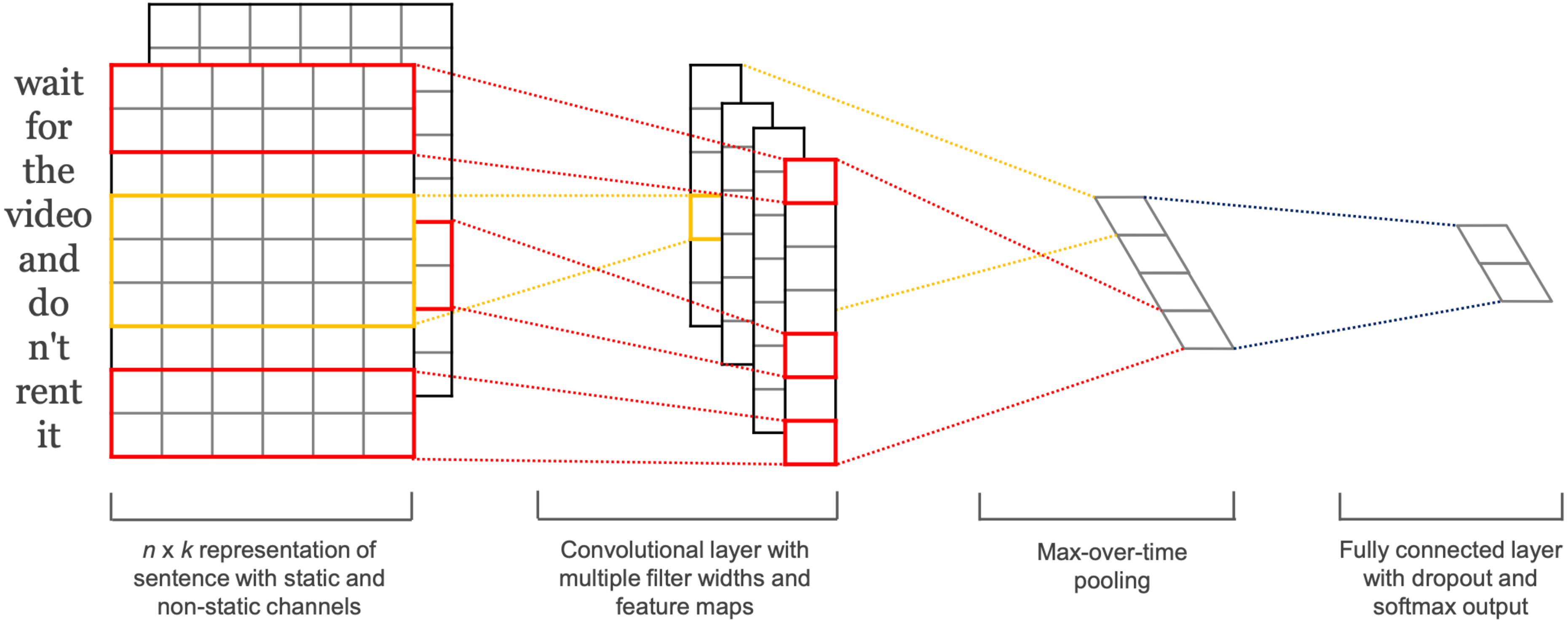
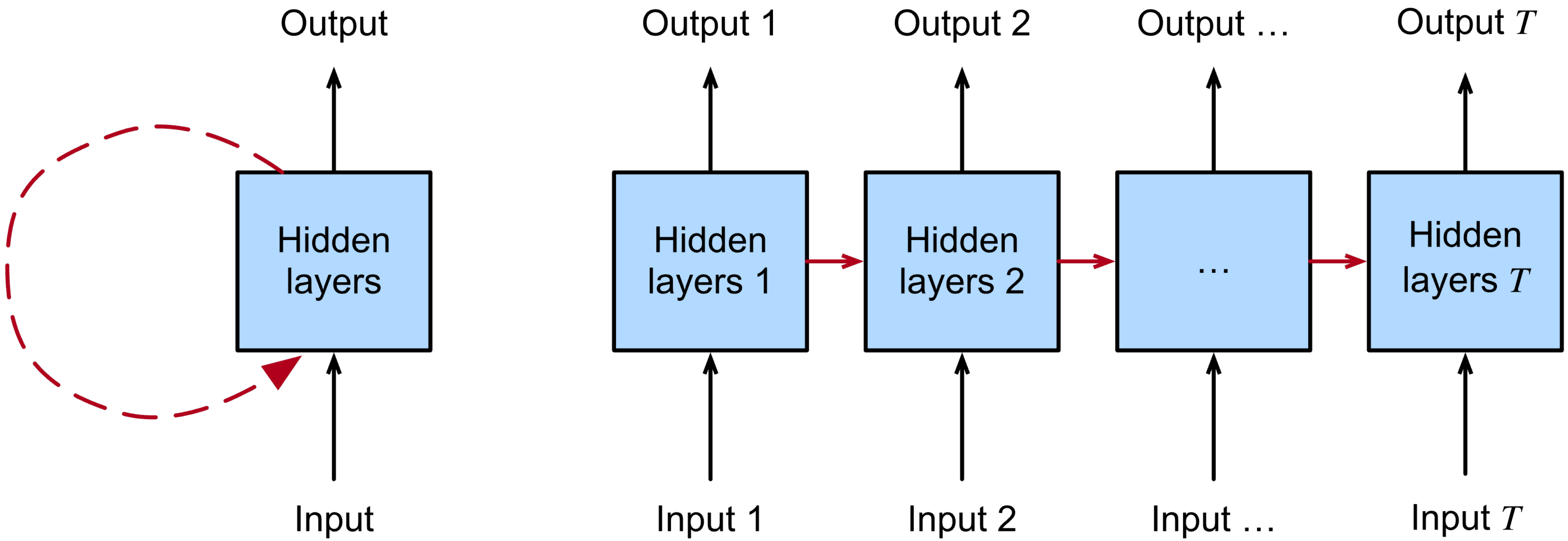


Figure 1: Model architecture with two channels for an example sentence.

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

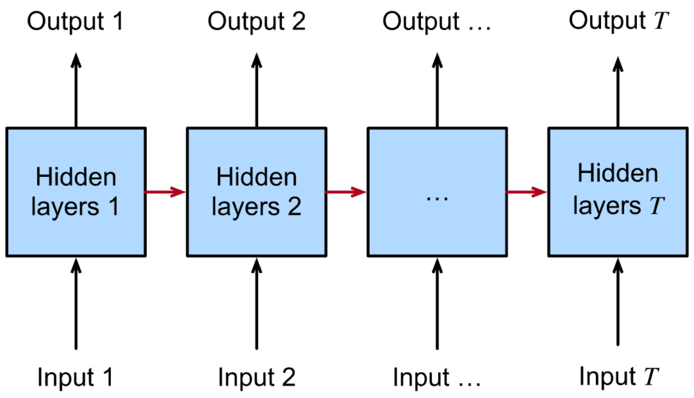
We can also use the recurrent neural network (RNN) to takes inputs with various lengths.

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.



observation at time T: $x^{(T)}$

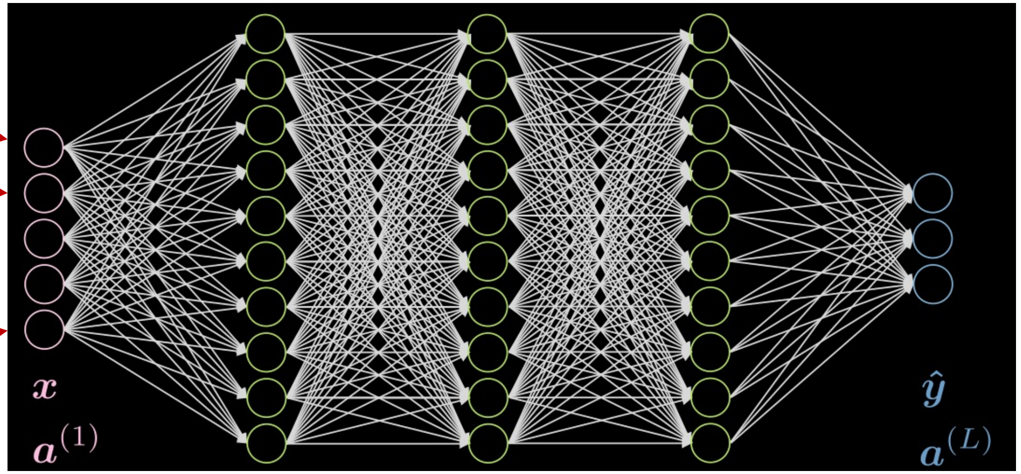
$$X^T = \begin{bmatrix} x_1^{(1)} & x_1^{(2)} & \cdots & \cdots & x_1^{(T)} \\ x_2^{(1)} & x_2^{(2)} & \cdots & \cdots & x_2^{(T)} \\ \vdots & \vdots & \cdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \cdots & \vdots \\ x_p^{(1)} & x_p^{(2)} & \cdots & \cdots & x_p^{(T)} \end{bmatrix}$$

['google', 'headquarter', … 'phones']

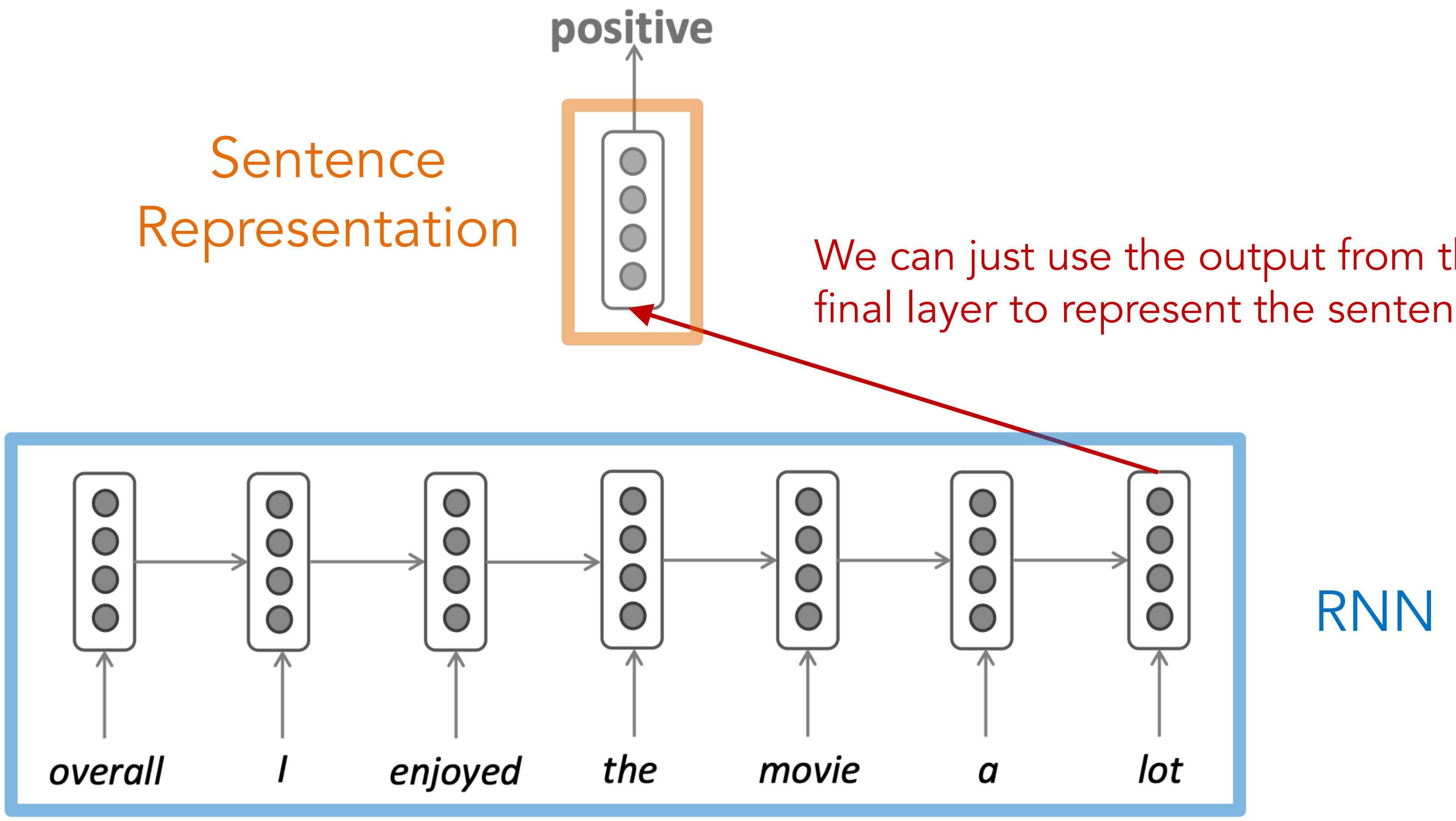
feature: x_p

An example for natural language processing:

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

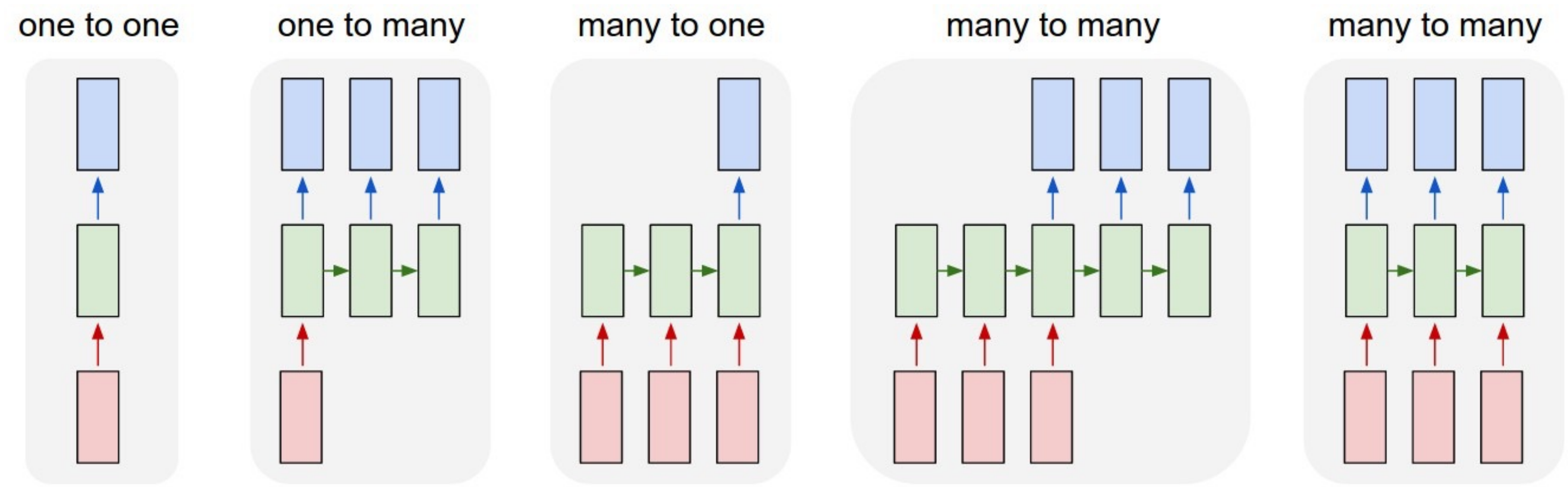


We can combine RNNs into a sequence-to-sequence (Seq2Seq) model for sentence classification or sentiment analysis. In this case, the output sequence has only one label.



Source -- https://web.stanford.edu/class/cs224n/slides/cs224n-2023-lecture05-rnnlm.pdf

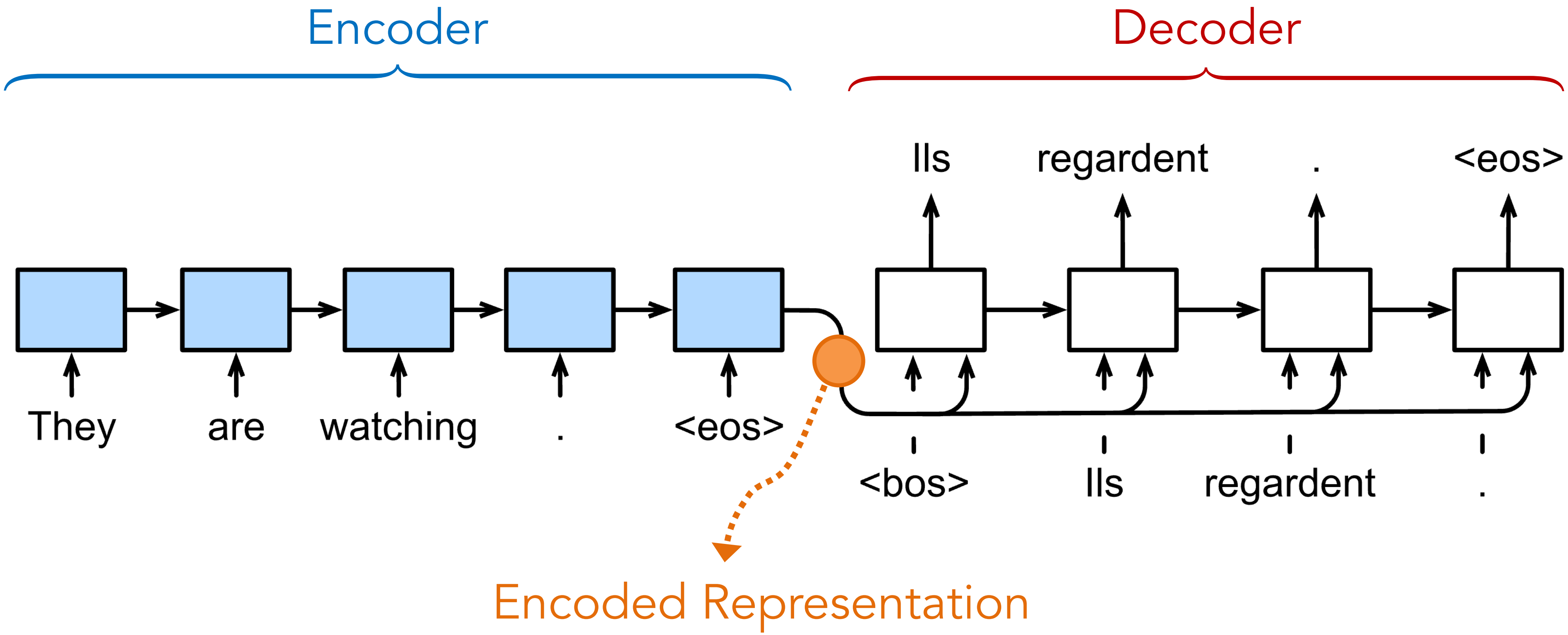
Seq2Seq models are flexible in the input and output sizes. The rectangles in the graph below mean vectors, red rectangles mean inputs, and blue rectangles mean outputs.



e.g., image classification | e.g., image captioning | e.g., sentence classification | e.g., machine translation | e.g., video frame classification

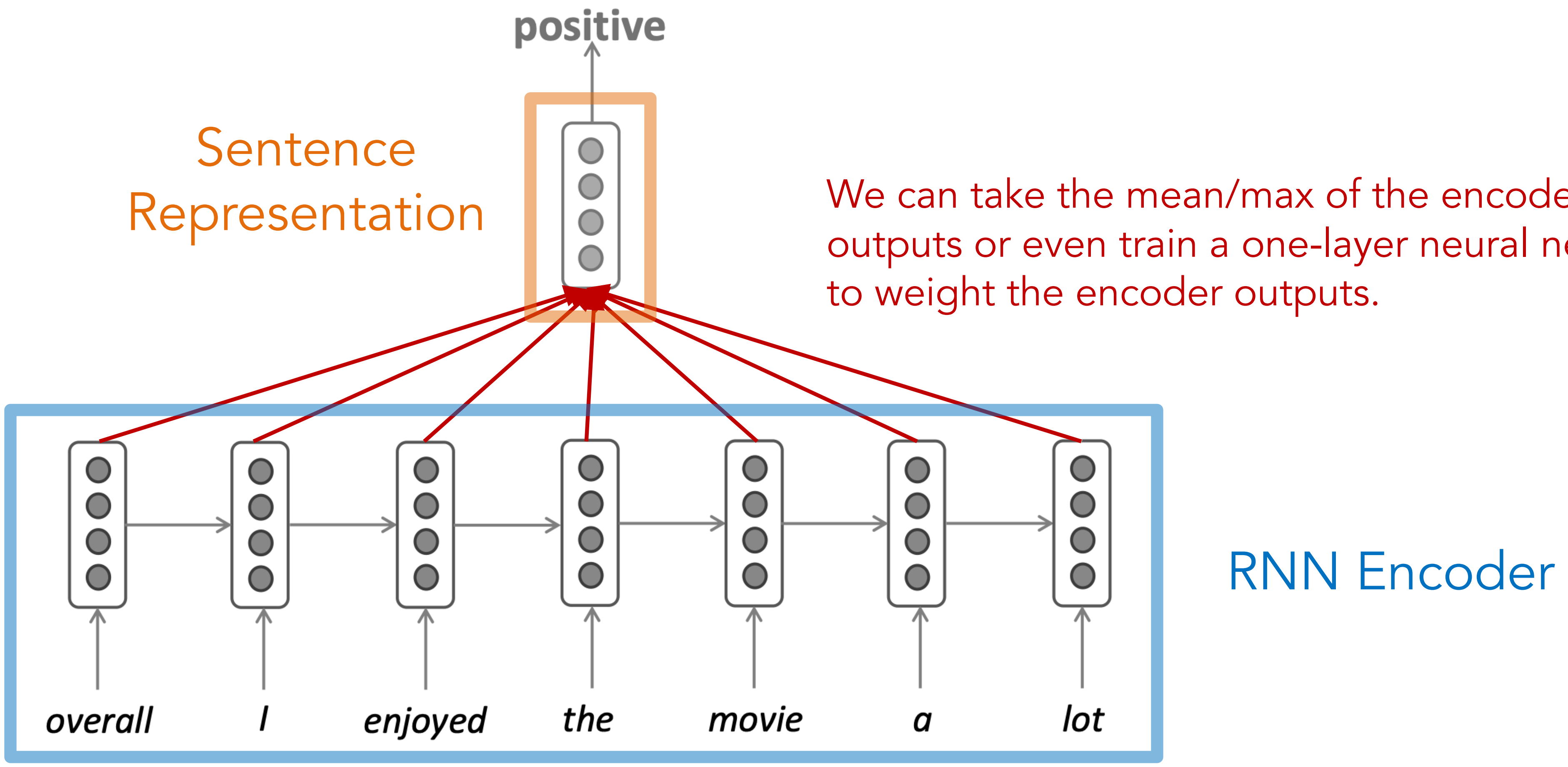
Source -- http://karpathy.github.io/2015/05/21/rnn-effectiveness/

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



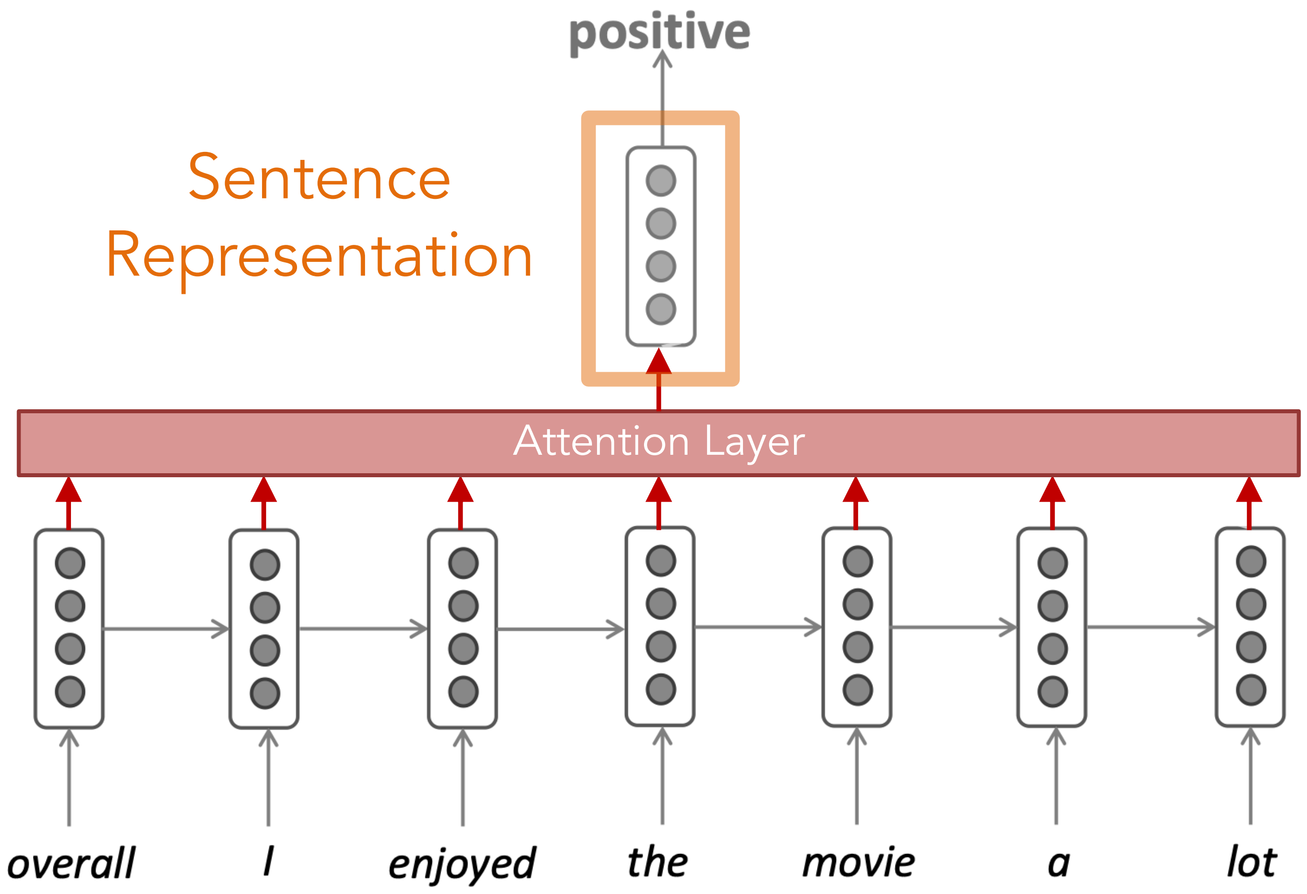
Source -- https://d2l.ai/chapter_recurrent-modern/seq2seq.html

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 considers all outputs.



Source -- https://web.stanford.edu/class/cs224n/slides/cs224n-2023-lecture05-rnnlm.pdf

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.

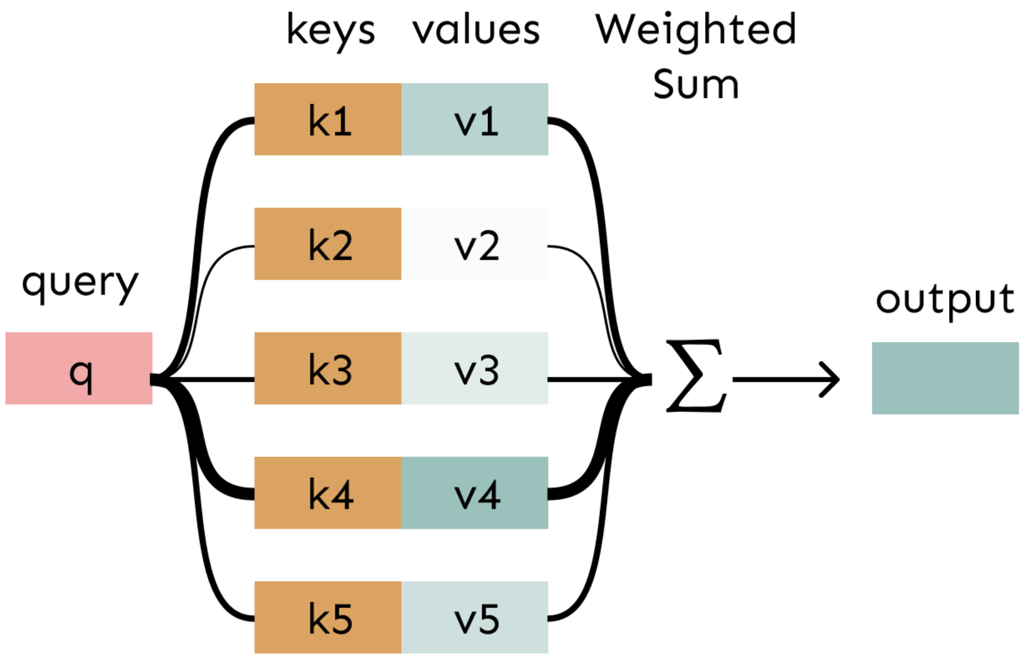


Yang, Z., et al. (2016, June). Hierarchical attention networks for document classification. NAACL conference.

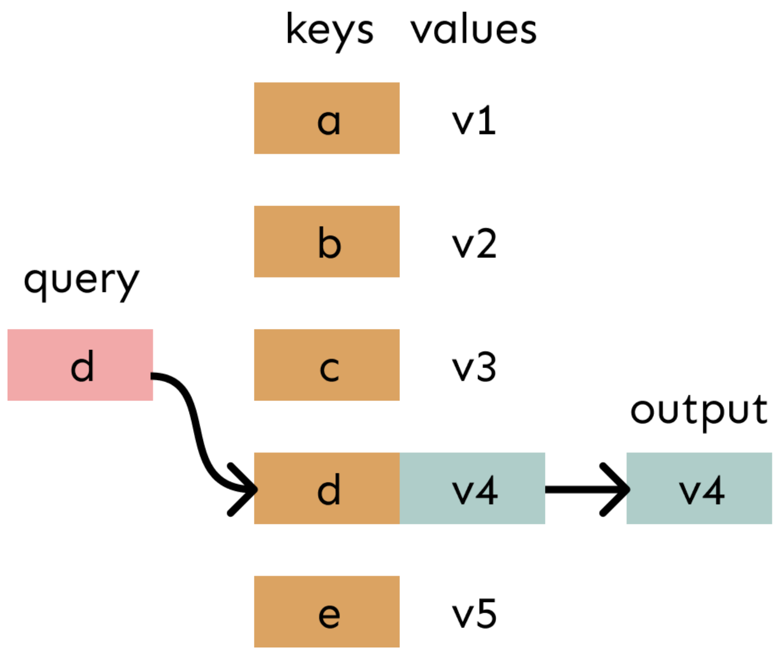
Attention is *weighted* averaging, which lets you do lookups!

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

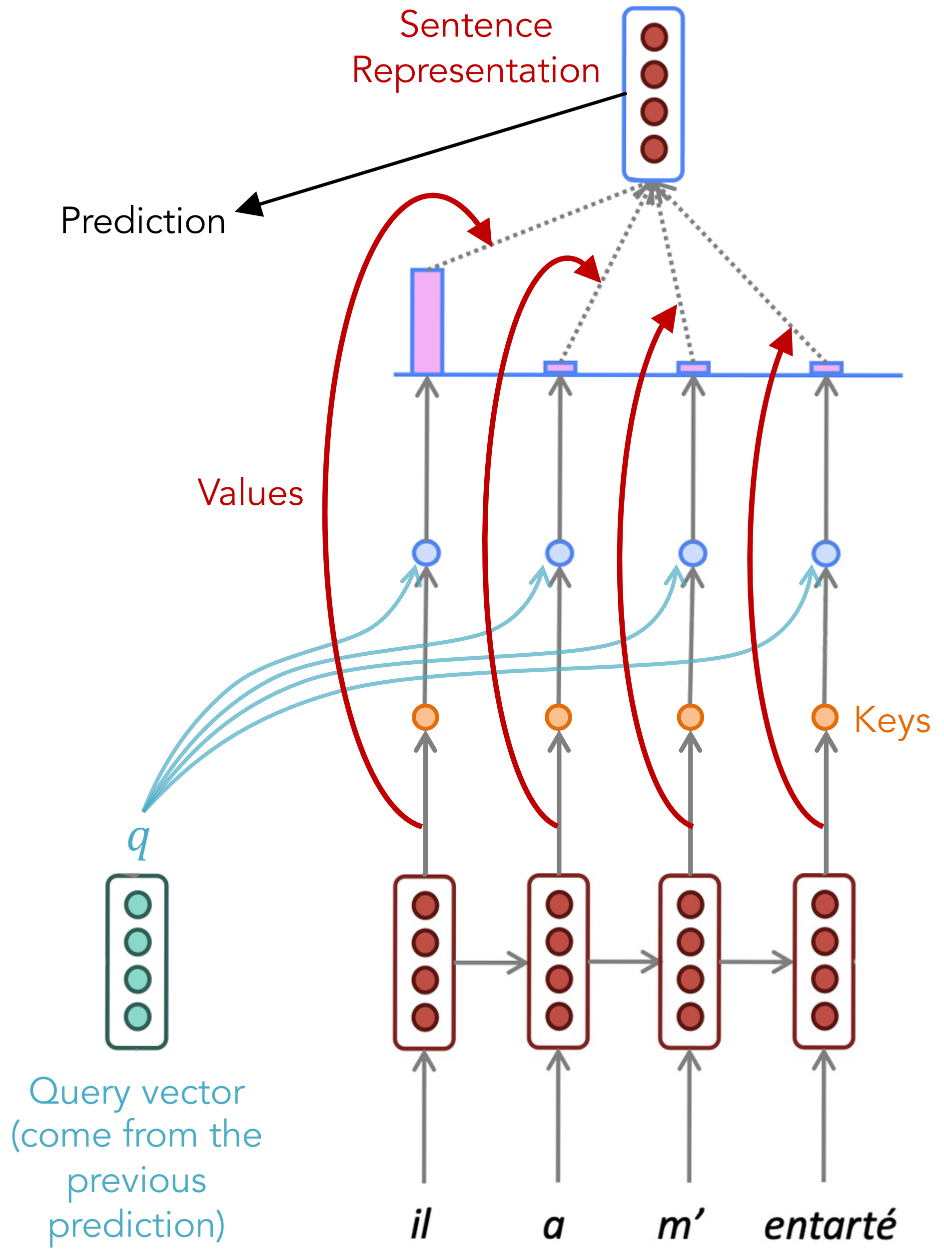
In **attention**, the query matches all keys *softly*, to a weight between 0 and 1. The keys' values are multiplied by the weights and summed.



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



The figure is from the Stanford CS224N course -- https://web.stanford.edu/class/cs224n/slides/cs224n-2024-lecture08-transformers.pdf



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

- $\sum_{t=1}^{T} a_t h_t$

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):

- $e_t = q^T u_t$ — q is trainable

Step 2: Transform encoder outputs (dimension reduction):

- $u_t = \tanh(W h_t)$ — W is trainable

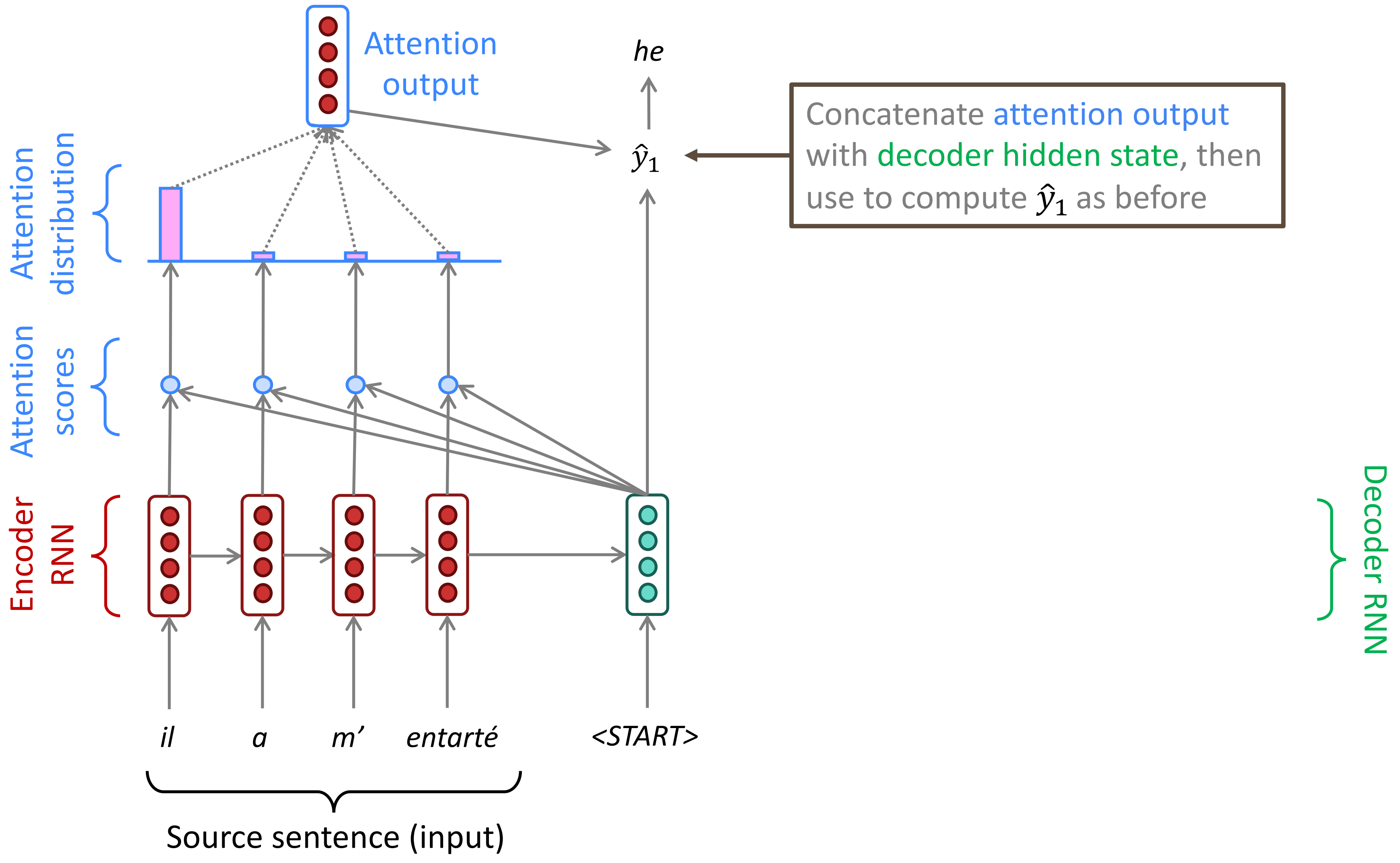
Step 1: Get the encoder output values (from the RNN):

- h_t

There are many ways of doing step 2 and 3

Source -- https://web.stanford.edu/class/cs224n/slides/cs224n-2023-lecture07-final-project.pdf

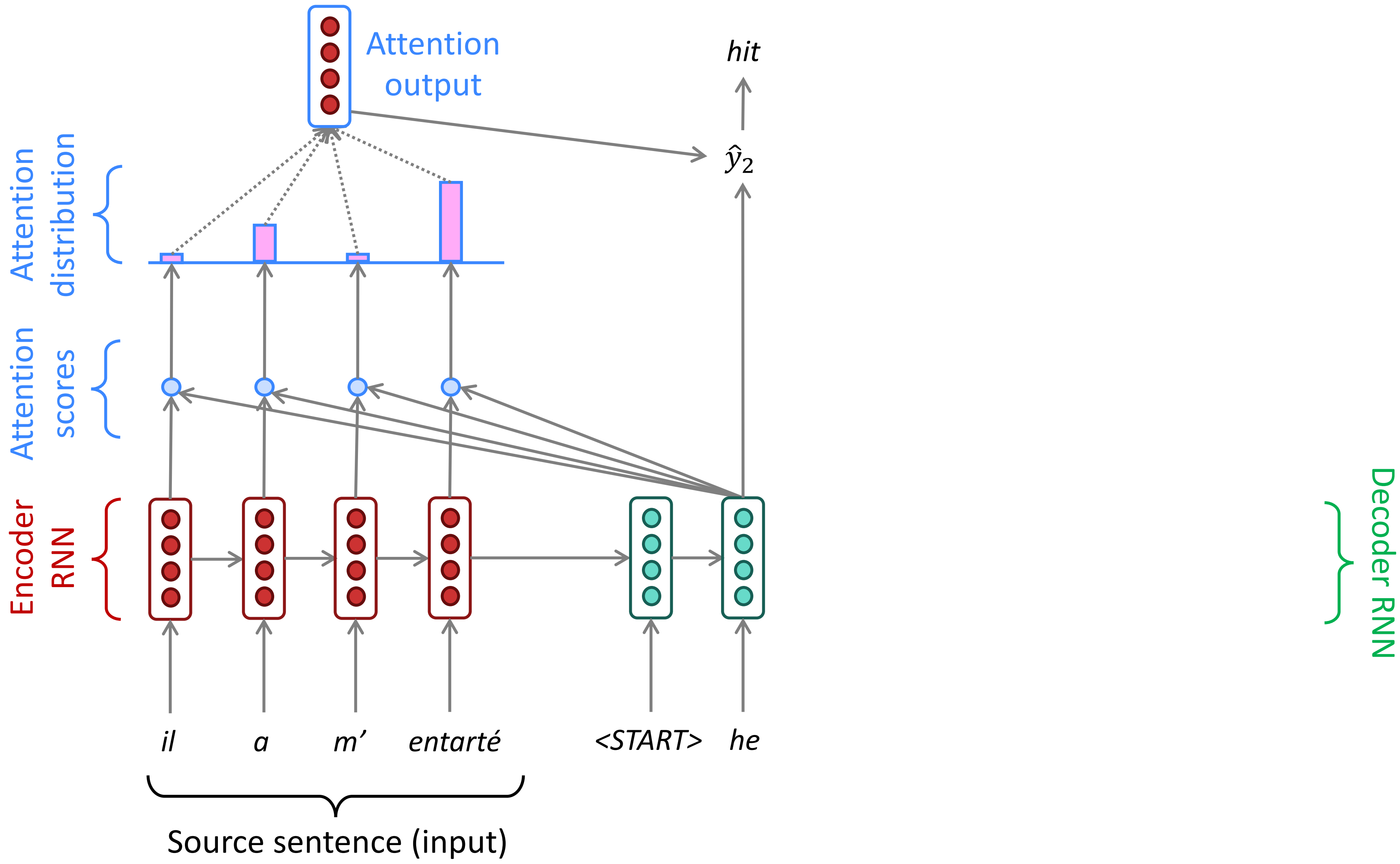
Sequence-to-sequence with attention



Concatenate attention output with decoder hidden state, then use to compute $\hat{y}_1$ as before

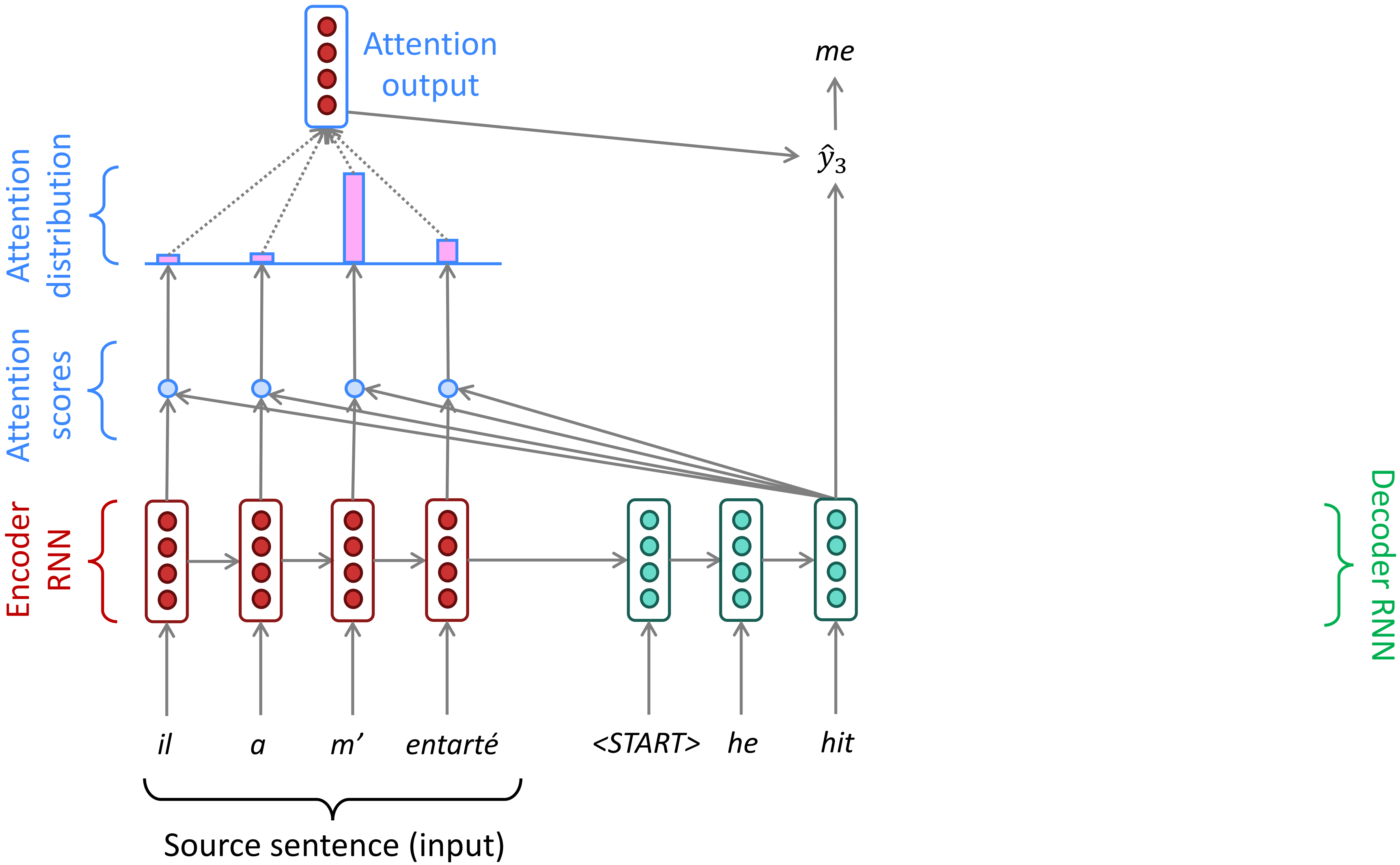
The figure is from the Stanford CS224N course -- https://web.stanford.edu/class/cs224n/slides/cs224n-2024-lecture08-transformers.pdf

Sequence-to-sequence with attention



The figure is from the Stanford CS224N course -- https://web.stanford.edu/class/cs224n/slides/cs224n-2024-lecture08-transformers.pdf

Sequence-to-sequence with attention



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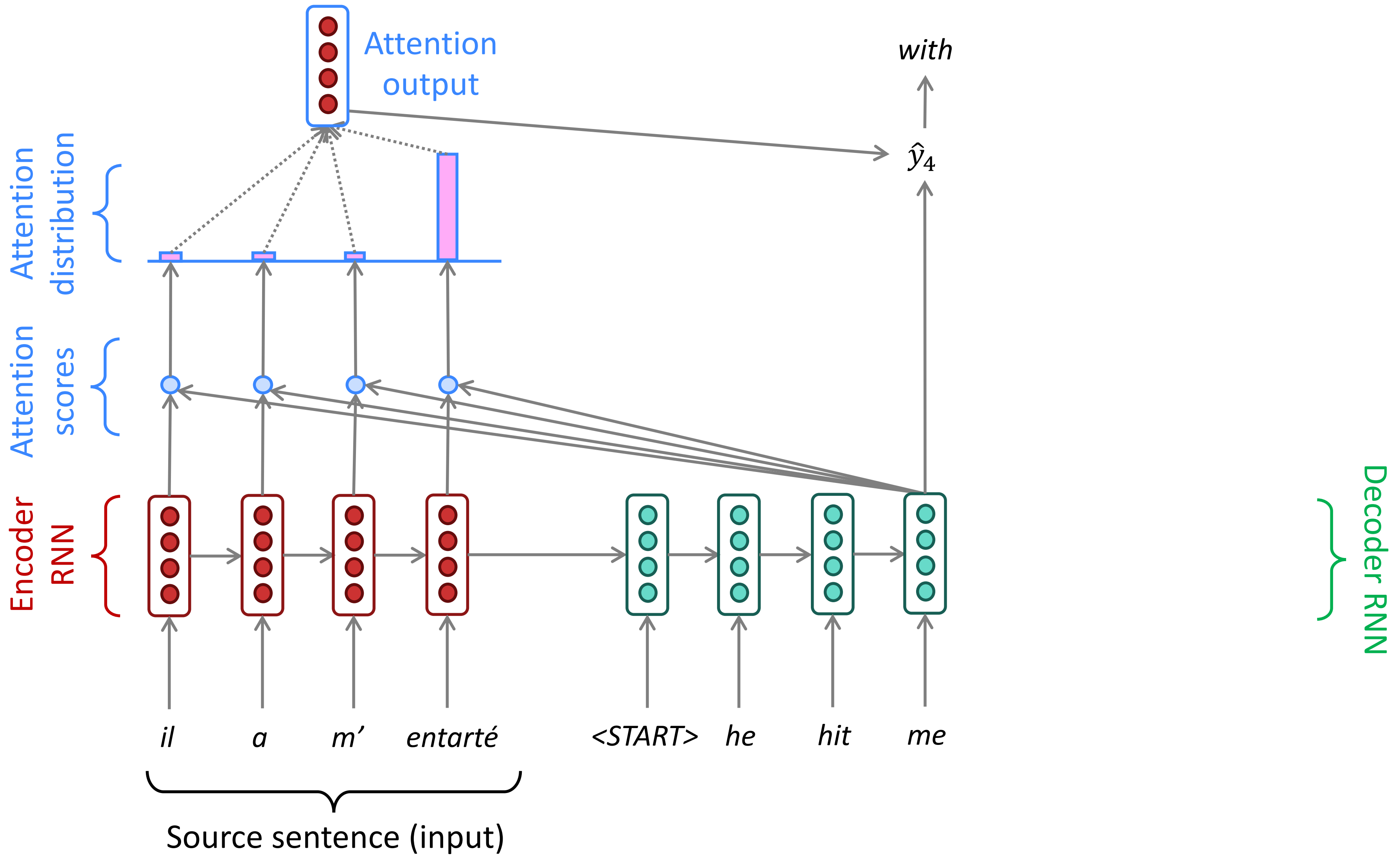

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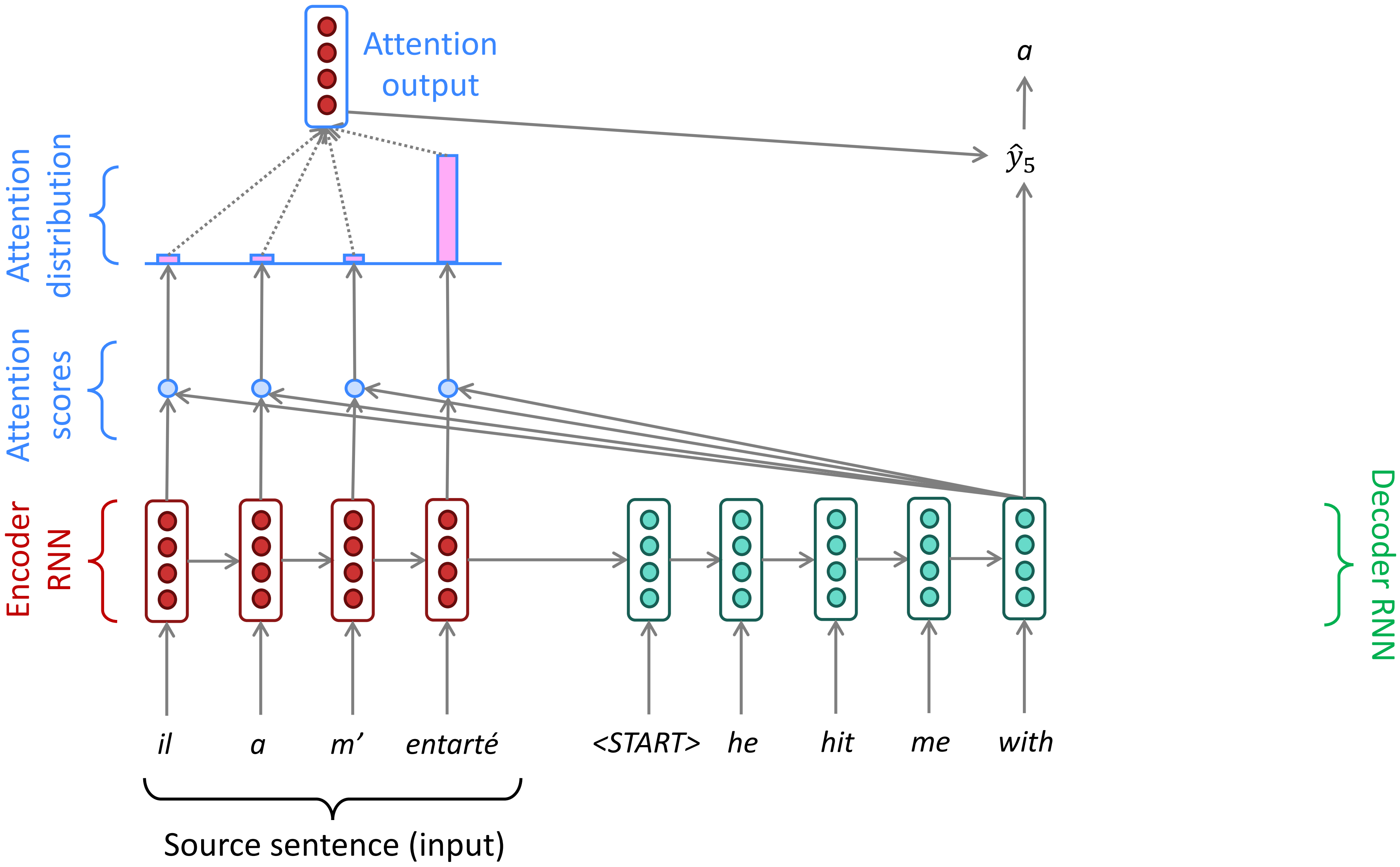
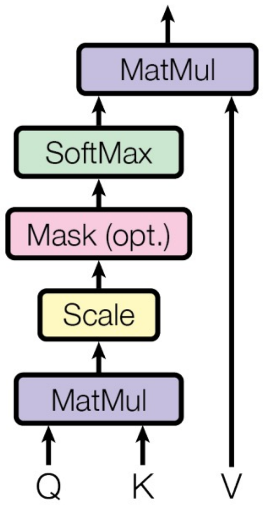
Sequence-to-sequence with attention



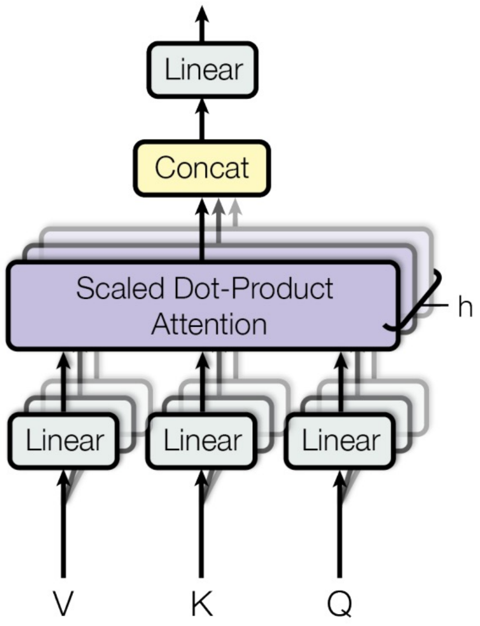
The figure is from the Stanford CS224N course -- https://web.stanford.edu/class/cs224n/slides/cs224n-2024-lecture08-transformers.pdf

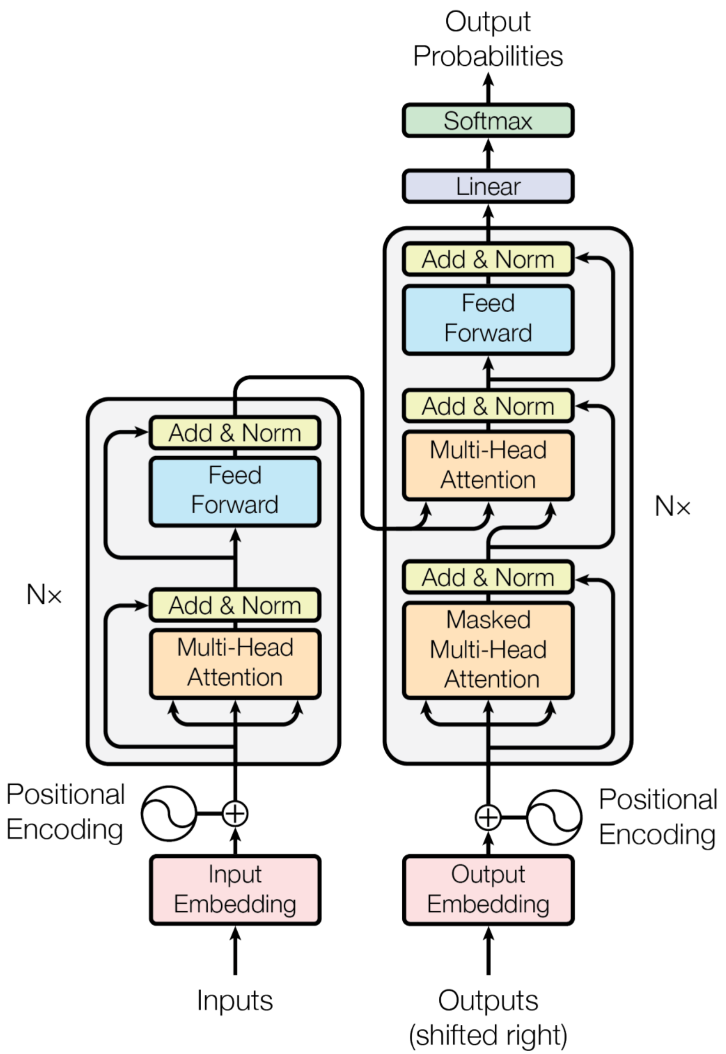
There is a more complicated attention mechanism, "multi-head self attention", which is the building block of the Transformer network architecture.

Scaled Dot-Product Attention



Multi-Head Attention





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

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?