Neural Word Embeddings

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Announcements

- Lectures are being recorded and MediaSpace channel will be posted to the course website
- Projects should be done in teams of 3
- Yes, you can audit the class, but assignments won't be graded and can't guarantee access to resources

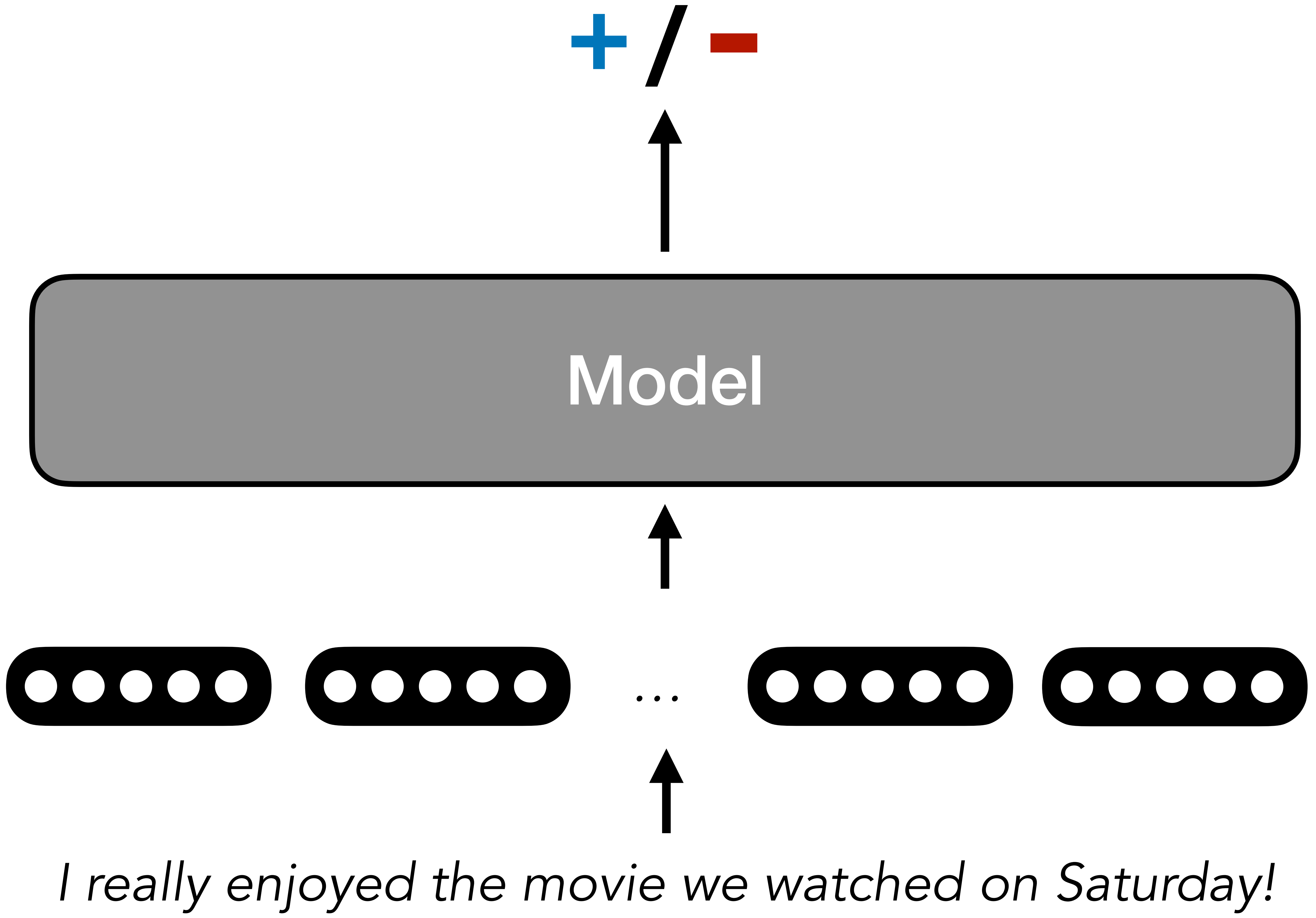
Today's Outline

- **Recap**: Words are vectors!
- **New:** Dense vector representations - CBOW, Skipgram, GloVe, fastText

Some slides adapted from Mohit Iyyer

Word Representations

- How do we represent natural language sequences for NLP problems?



In neural natural language processing, **words** are **vectors**!

Choosing a vocabulary

- Language contains many words (e.g., ~600,000 in English)
  - **What about other tokens**: Capitalisation? Accents ? Typos!? Words in other languages!? In other scripts!? Emojis !? Unicode !?
  - **Millions of potential unique tokens!** Most rarely appear in our training data (Zipfian distribution)
  - Model has limited capacity
- How should we select which tokens we want our model to process?
  - Week 13 - tokenisation!
  - For now, initialize a vocabulary *V* of tokens that we can represent as a vector
  - Any token not in this vocabulary *V* is mapped to a special <UNK> token (e.g., unknown).

https://en.wikipedia.org/wiki/List_of_dictionaries_by_number_of_words

One upon a time: **sparse word representations**

$$x_i \in \{0,1\}^V$$

- Define a vocabulary *V*
- Each word in the vocabulary is represented by a sparse *vector*
- Dimensionality of sparse vector is size of vocabulary (e.g., thousands, possibly millions)

I	$\longrightarrow$	[0 … 0 0 0 1 … 0 0]
really	$\longrightarrow$	[0 … 1 … 0 0 0 0 0]
enjoyed	$\longrightarrow$	[0 … 0 0 0 1 0 … 0]
the	$\longrightarrow$	[0 … 0 1 0 0 0 … 0]
movie	$\longrightarrow$	[0 … 0 0 0 0 0 … 1]
!	$\longrightarrow$	[1 … 0 0 0 0 0 0 0 0]

Problem

With sparse vectors, similarity is a function of common words!

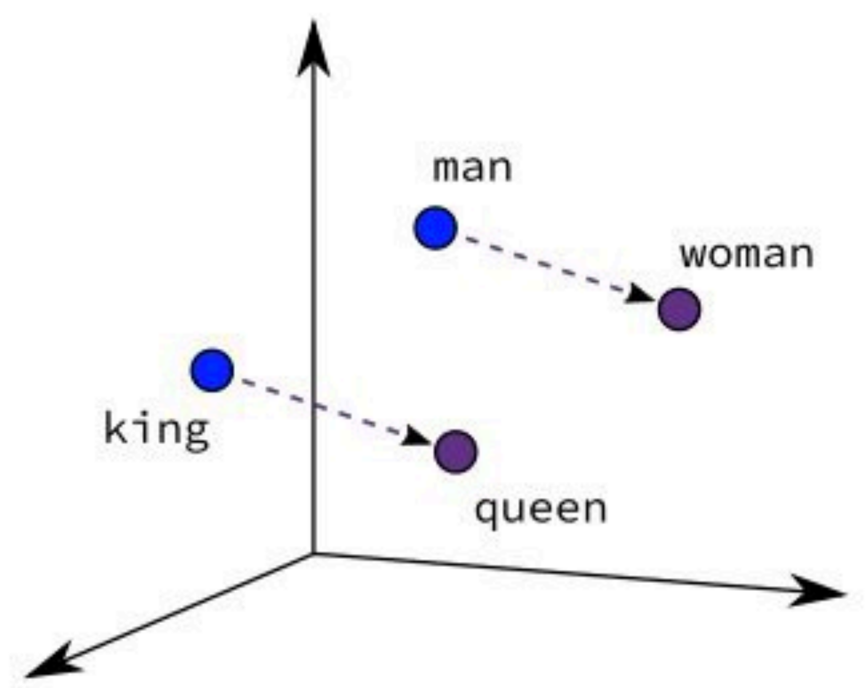
How do you learn learn similarity between words?

$$\textit{enjoyed} \longrightarrow [\,0 \ldots 0\;0\;0\;1 \ldots 0\;0\,]$$

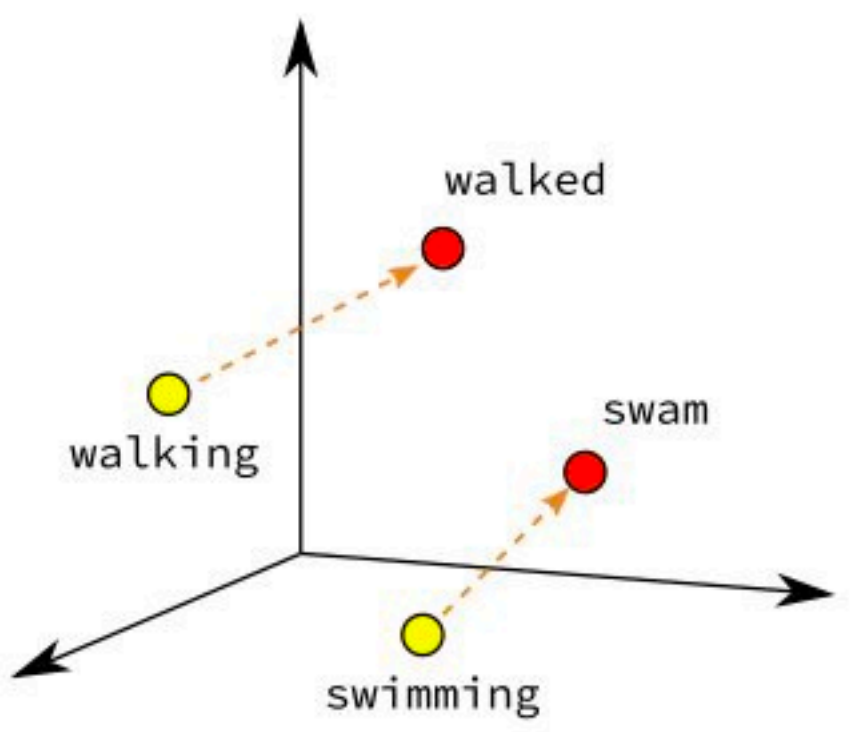
$$\textit{loved} \longrightarrow [\,0 \ldots 1 \ldots 0\;0\;0\;0\;0\,]$$

$$\mathrm{sim}(\textit{enjoyed}, \textit{loved}) = \mathbf{0}$$

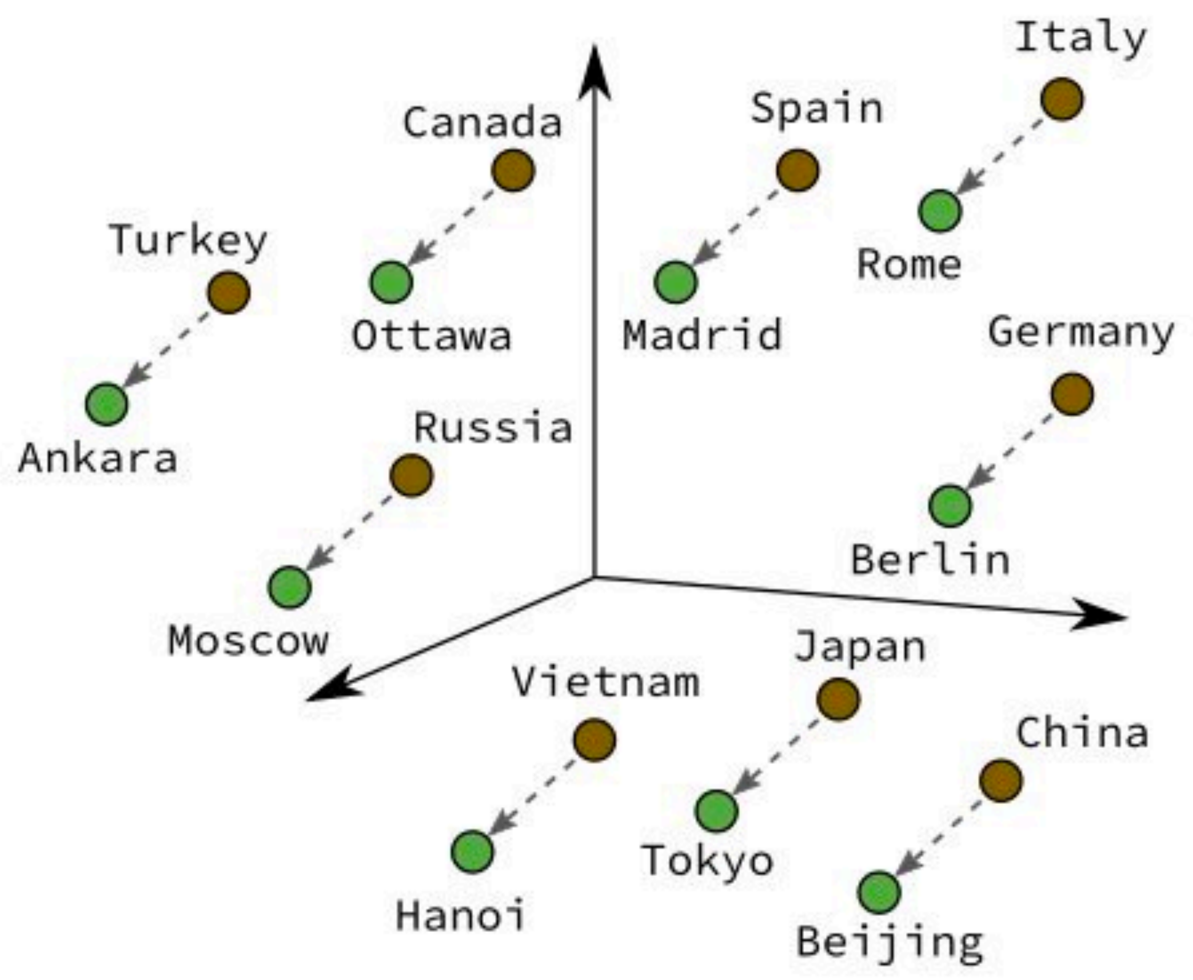
Embeddings Goal



Male-Female



Verb Tense



Country-Capital

How do we train semantics-encoding embeddings of words?

Image Credit: https://towardsdatascience.com/legal-applications-of-neural-word-embeddings-556b7515012f

Dense Word Vectors

- Represent each word as a high-dimensional*, **real-valued** vector
  - *Low-dimensional compared to V-dimension sparse representations, but still usually O(10^2 - 10^3)

I	$\longrightarrow$	[0.113 -0.782 1.893 0.984 6.349 ...]
really	$\longrightarrow$	[0.906 0.661 -0.214 -0.894 -0.880 ...]
enjoyed	$\longrightarrow$	[-0.842 0.647 -0.882 0.045 0.029 ...]
the	$\longrightarrow$	[0.100 0.765 -0.333 -0.538 -0.150 ...]
movie	$\longrightarrow$	[0.104 -0.054 -0.268 -0.877 0.005 ...]
!	$\longrightarrow$	[0.439 -0.577 -0.727 0.261 0.699 ...]

word vectors

word embeddings

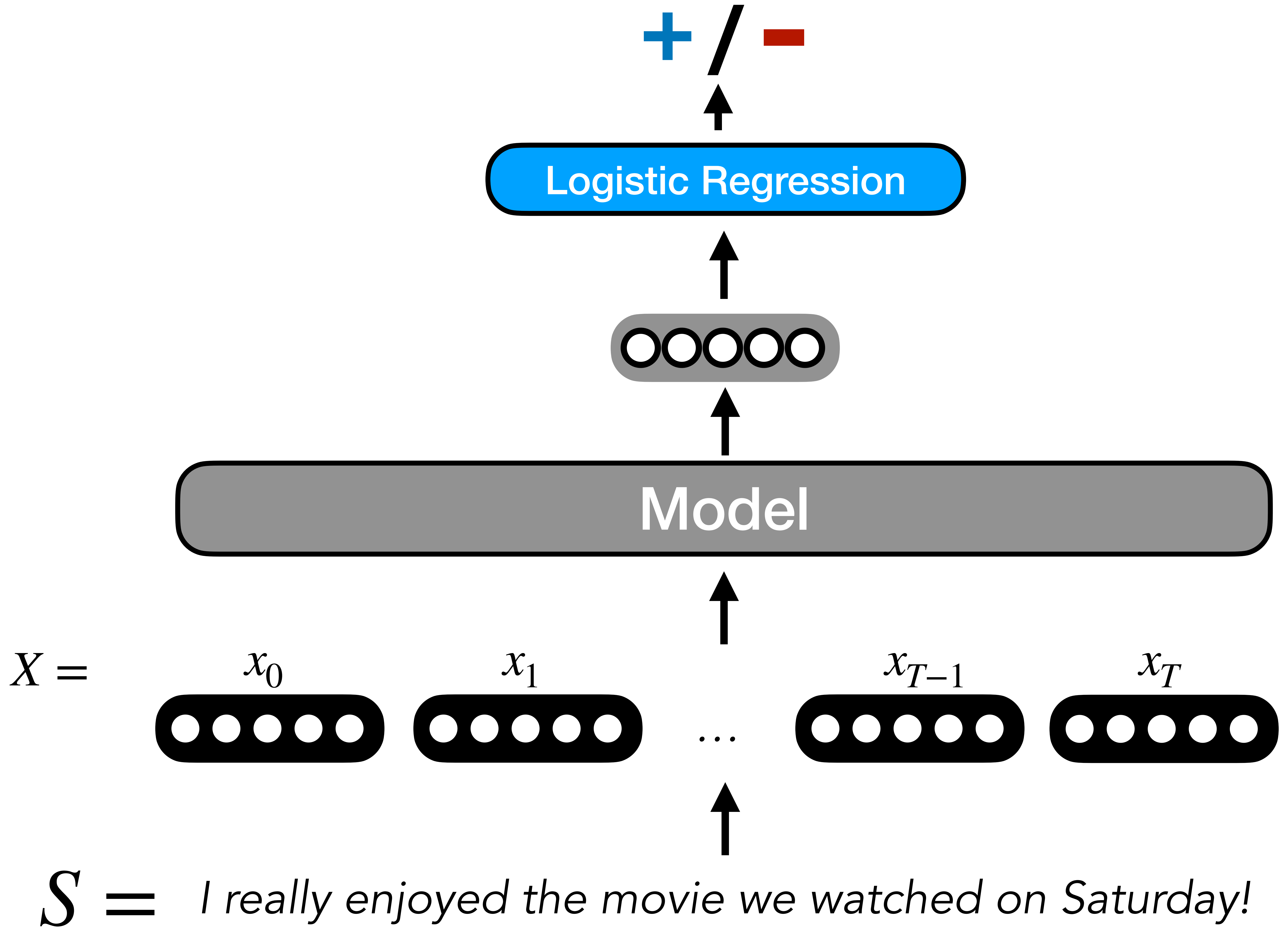
neural embeddings

dense embeddings

others...

- Similarity of vectors represents similarity of meaning for particular words

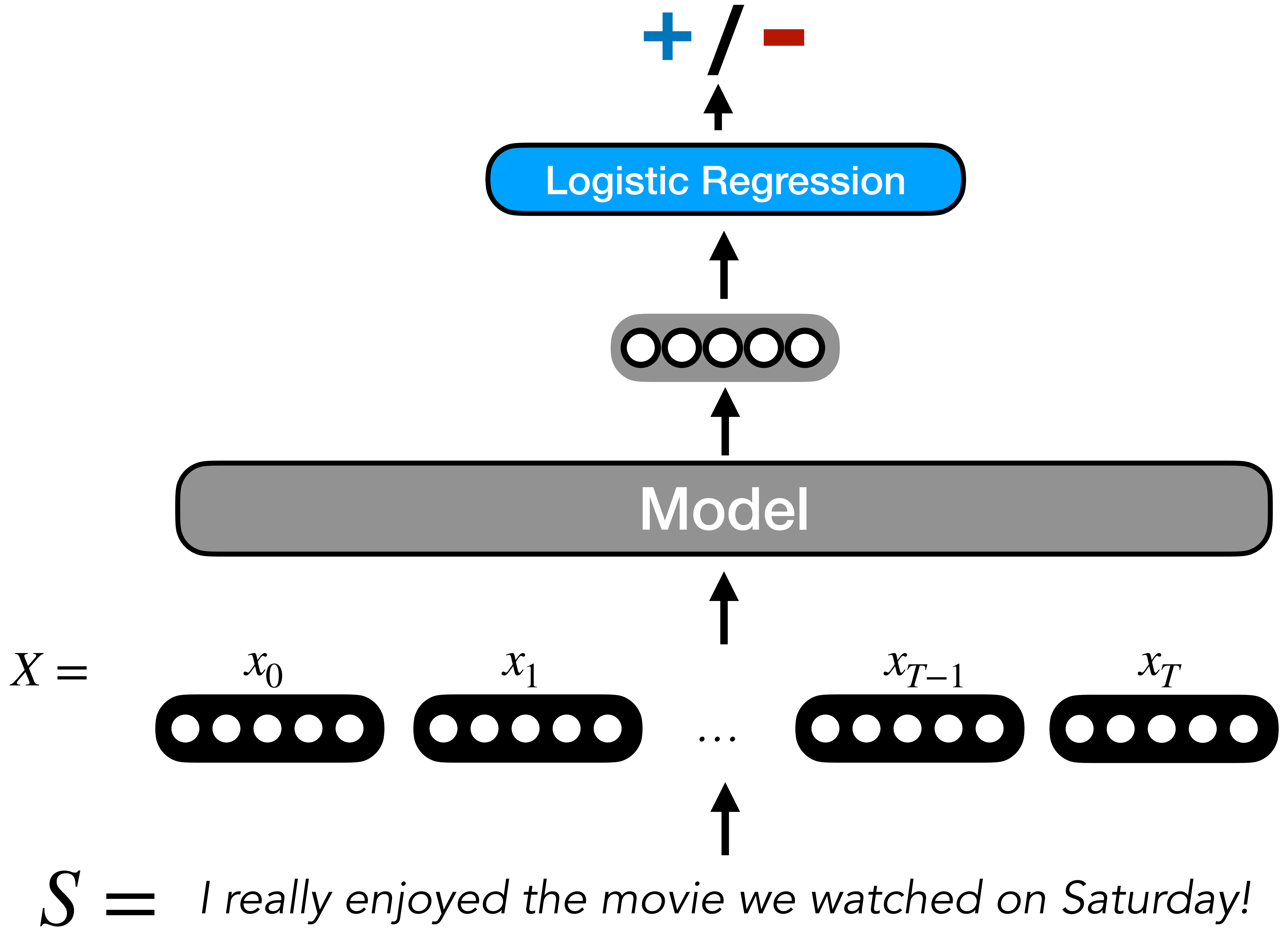
Learn embeddings from the task!



Learn using **backpropagation:** compute gradients of loss with respect to initial embeddings X

Learn embeddings that allow you to do the task successfully!

Supervised Learning



- Supervised learning with a task-specific objective
  - Learn word embeddings that help complete the task

- **Q: Downsides of learning embeddings this way?**
  - Data scarcity (clean labeled data is expensive to collect)
  - Embeddings are optimised for this task — maybe not others!

Question

What could be a better way to learn word embeddings?

Self-supervised learning

"You shall know a word by the company it keeps"

–J.R. Firth, 1957

Context Representations

Solution:

Rely on the context in which words occur to learn their meaning

Context is the **set of words** that occur **nearby**

I really enjoyed the ____ we watched on Saturday!

The ___ growled at me, making me run away.

I need to go to the ____ to pick up some dinner.

Foundation of distributional semantics

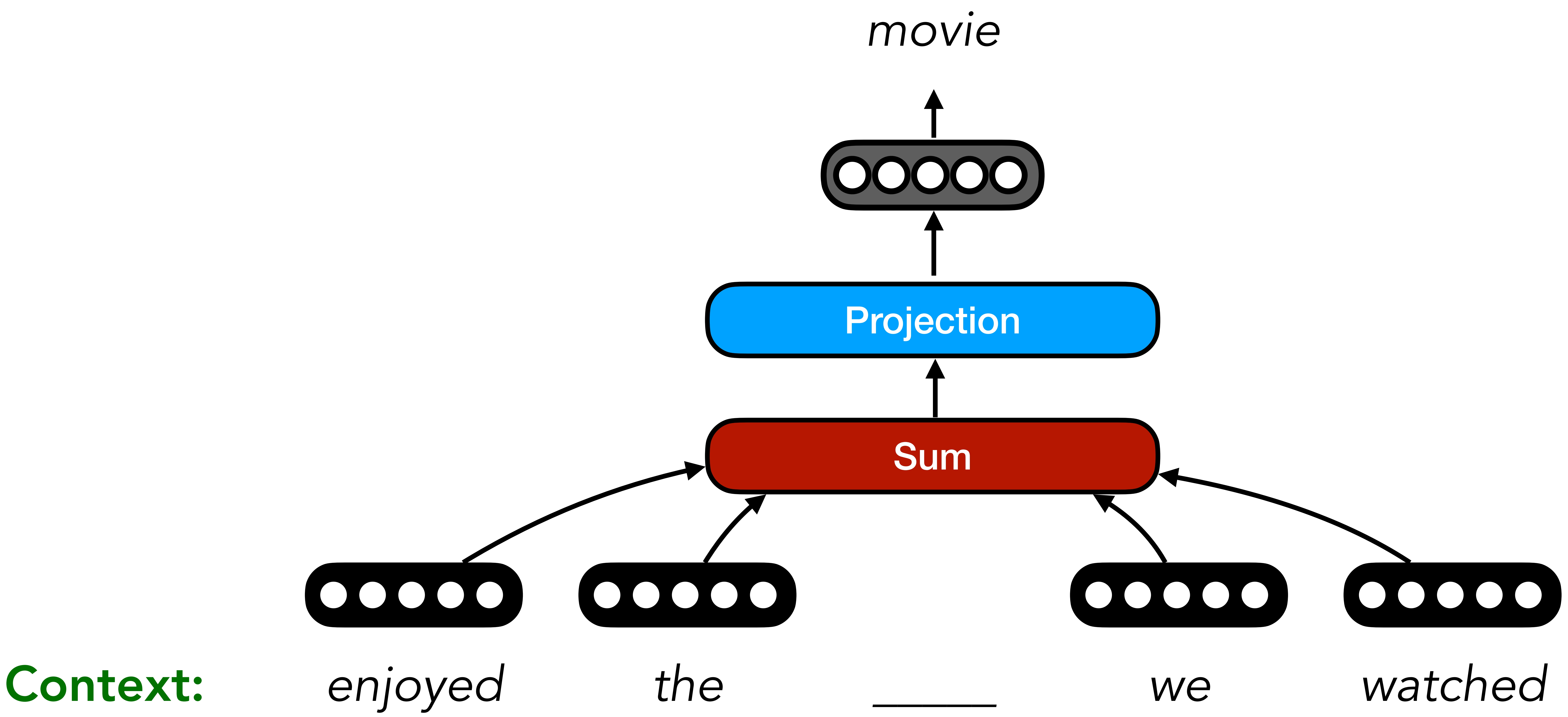
Learning Word Embeddings

- Many options, huge area of research, but three standard approaches
- **Word2vec - Continuous Bag of Words (CBOW)**
  - Learn to predict missing word from surrounding window of words
- **Word2vec - Skip-gram**
  - Learn to predict surrounding window of words from given word
- **GloVe**
  - Not covered today

(Mikolov et al., 2013a; 2013b; Pennington et al., 2014)

Continuous Bag of Words (CBOW)

- Predict the missing word from a window of surrounding words



(Mikolov et al., 2013a)

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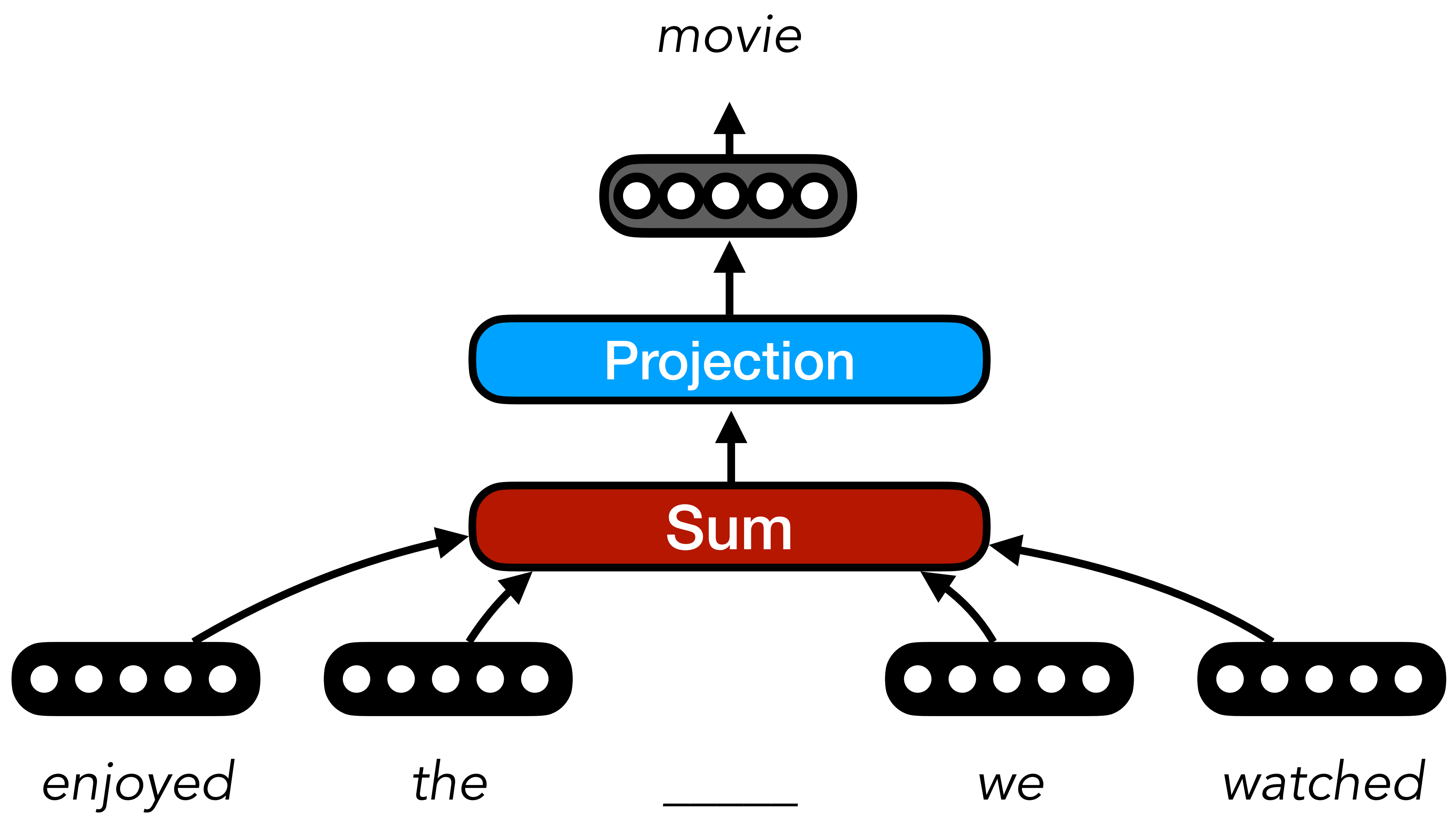

$$\max P(movie \mid enjoyed, the, we, watched)$$

$$\max P(x_t \mid x_{t-2}, x_{t-1}, x_{t+1}, x_{t+2})$$

$$\max P(x_t \mid \{x_s\}_{s=t-2}^{s=t+2})$$

(Mikolov et al., 2013a)

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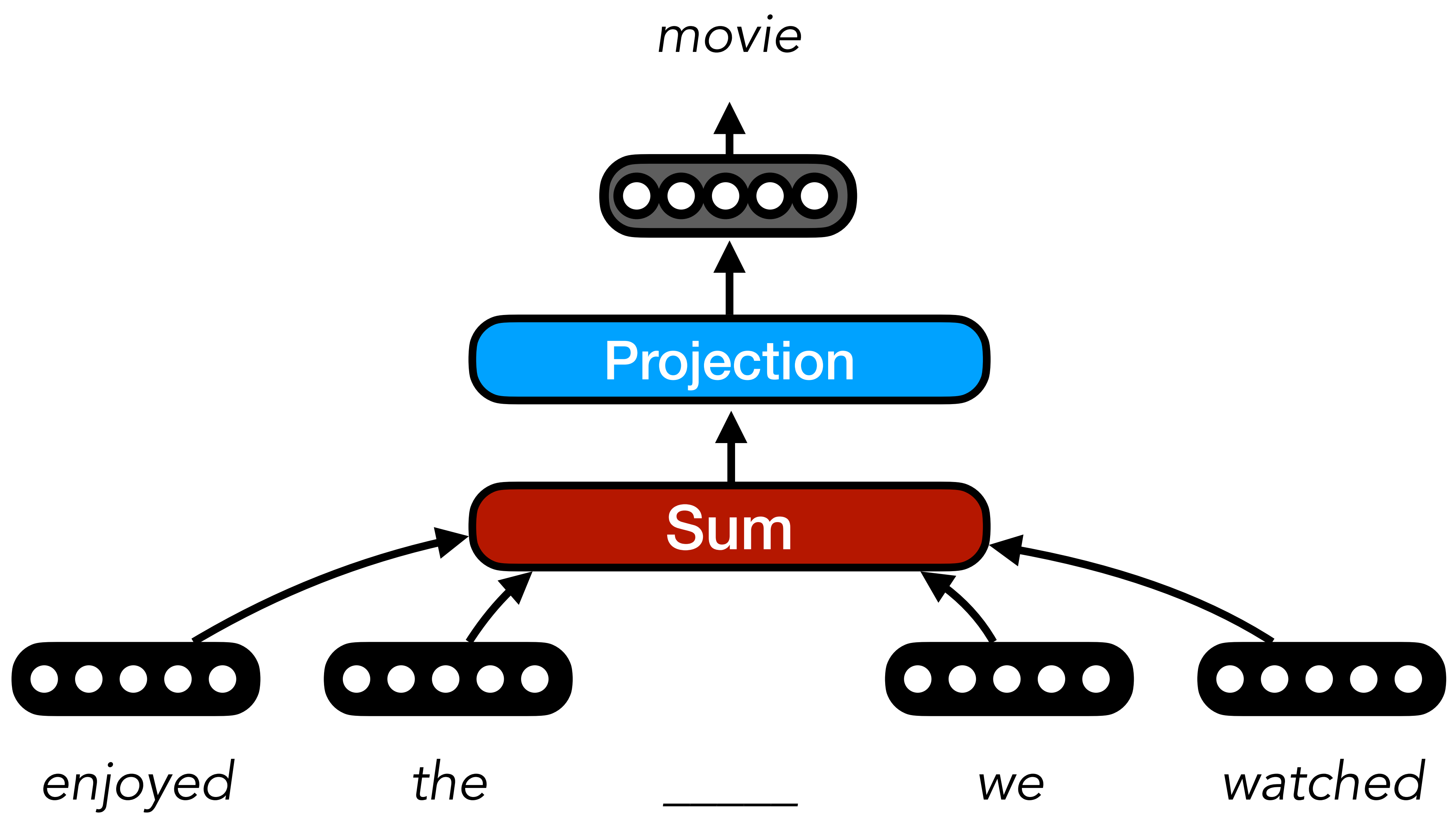
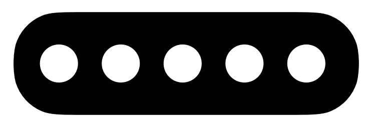


$$P(x_t \mid \{x_s\}_{s=t-2}^{s=t+2}) = \textbf{softmax}\left(\mathbf{U} \sum_{\substack{s=t-2 \\ s \neq t}}^{t+2} \mathbf{x}_s\right)$$

$\mathbf{x}_s \in \mathbb{R}^{1\times d}$



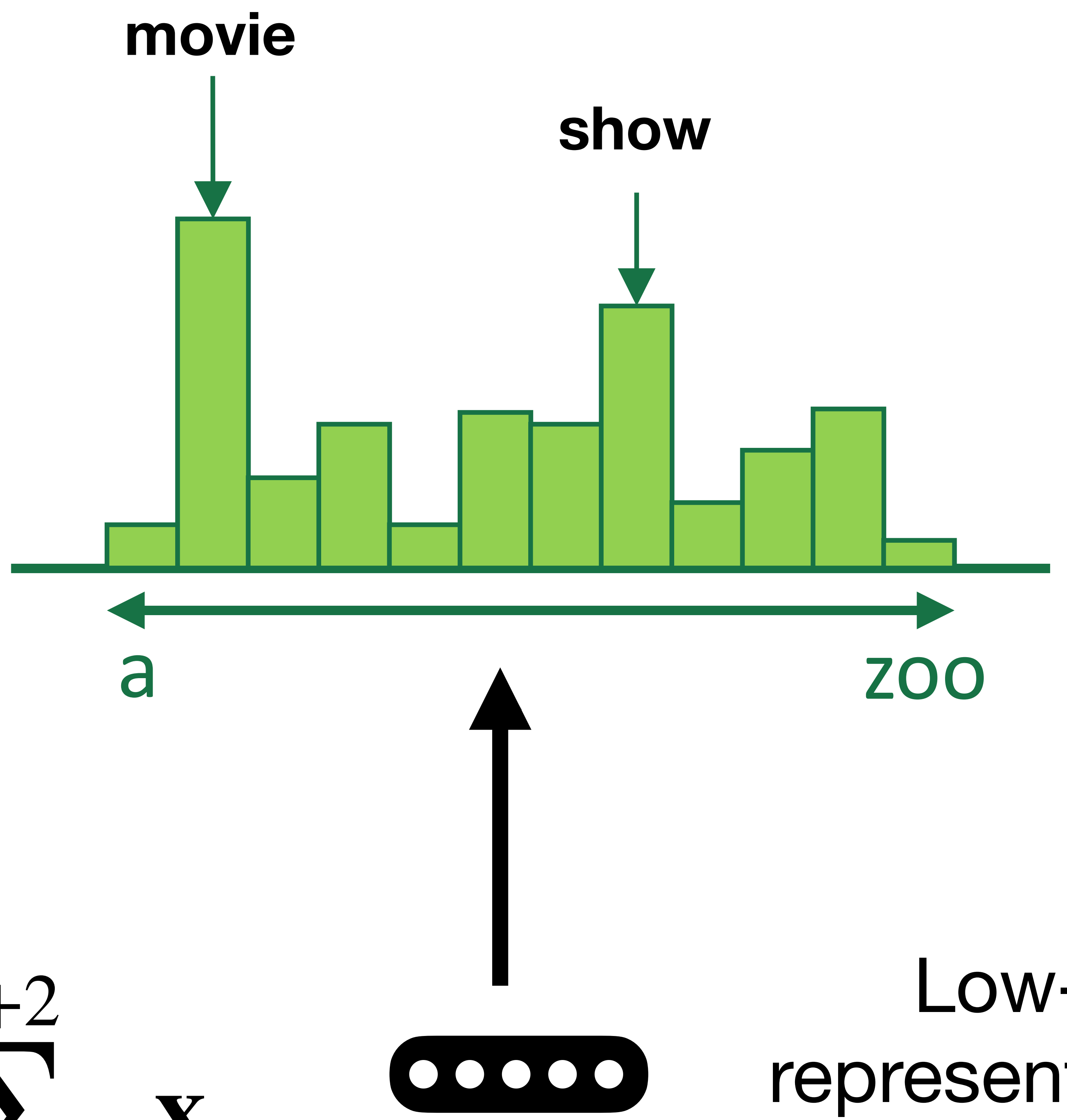
$\mathbf{U} \in \mathbb{R}^{d\times V}$

(Mikolov et al., 2013a)

Vocabulary Space Projection

$P(w_i \mid \text{vector for "enjoyed the we watched"})$

Probability distribution over the entire vocabulary

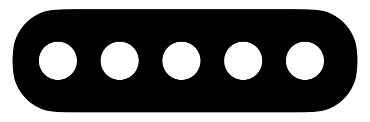


$$h_t = \sum_{\substack{s = t-2 \\ s \neq t}}^{t+2} \mathbf{x}_s$$

Low-dimensional representation of context: “enjoyed the we watched”

Let’s say our output vocabulary consists of just four words: “movie”, “show”, “book”, and “shelf”.

$$h_t = \sum_{\substack{s = t-2 \\ s \neq t}}^{t+2} \mathbf{x}_s$$

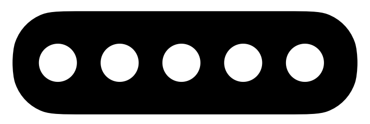


Low-dimensional representation of context: “enjoyed the we watched”

Let’s say our output vocabulary consists of just four words: “movie”, “show”, “book”, and “shelf”.

movie	show	book	shelf
<0.6,	0.2,	0.1,	0.1>

We want to get a probability distribution over these four words



Low-dimensional representation of context: “enjoyed the we watched”

Let’s say our output vocabulary consists of just four words: “movie”, “show”, “book”, and “shelf”.

$$\mathbf{U} = \left\{ \begin{array}{ccc} 1.2, & -0.3, & 0.9 \\ 0.2, & 0.4, & -2.2 \\ 8.9, & -1.9, & 6.5 \\ 4.5, & 2.2, & -0.1 \end{array} \right\}$$

first, we’ll project our 3-d context representation to 4-d with a matrix-vector product

$$h_t = \langle -2.3, 0.9, 5.4 \rangle$$

Here’s an example 3-d prefix vector

How do we get there?

$$\mathbf{U} = \left\{ \begin{matrix} 1.2, & -0.3, & 0.9 \\ 0.2, & 0.4, & -2.2 \\ 8.9, & -1.9, & 6.5 \\ 4.5, & 2.2, & -0.1 \end{matrix} \right\}$$

$h_t =$ <-2.3, 0.9, 5.4>

intuition: each dimension of h_t corresponds to a *feature* of the context

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$$\mathbf{U} = \left\{\begin{array}{lll|l} 1.2, & -0.3, & 0.9 & \text{movie} \\ 0.2, & 0.4, & -2.2 & \text{show} \\ 8.9, & -1.9, & 6.5 & \text{book} \\ 4.5, & 2.2, & -0.1 & \text{shelf} \end{array}\right\}$$

intuition: each row of **U** contains *feature weights* for a corresponding word in the vocabulary

$h_t = \langle -2.3, 0.9, 5.4 \rangle$

intuition: each dimension of h_t corresponds to a *feature* of the context

$\mathbf{U}h_t$ = <1.8, -11.9, 12.9, -8.9>

How did we compute this? It's just the dot product of each row of **U** with h_t

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$$\begin{array}{l} 1.2 * -2.3 \\ + -0.3 * 0.9 \\ + 0.9 * 5.4 \end{array}$$

$$h_t = \langle -2.3,\ 0.9,\ 5.4 \rangle$$

Softmax

- The **softmax** function generates a probability distribution from the elements of the vector it is given

$$\textbf{softmax}(\mathbf{a})_i = \frac{e^{a_i}}{\sum_{j=1}^{|\mathbf{a}|} e^{a_j}}$$

- **a** is a vector
- a_i is dimension *i* of **a**
- each dimension *i* of the softmaxed output represents the probability of class *i*

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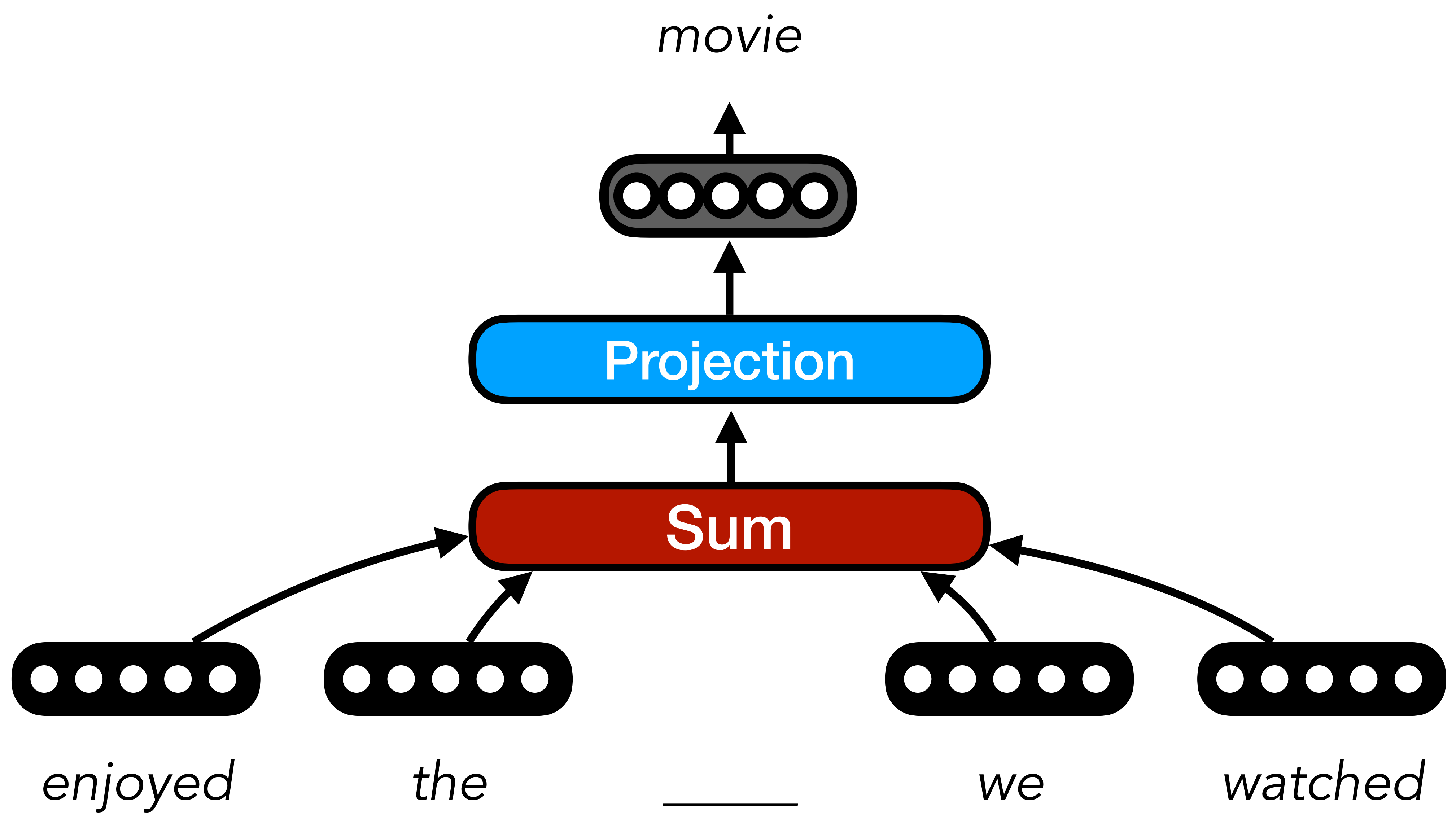
$\mathbf{U}h_t$ = <1.8, -1.9, 2.9, -0.9>

$\textbf{softmax}(\mathbf{U}h_t)$ = <0.24, 0.006, 0.73, 0.02>

Softmax will keep popping up, so be sure to understand it!

Continuous Bag of Words (CBOW)

- Predict the missing word from a window of surrounding words



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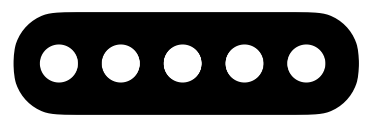

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(Mikolov et al., 2013a)

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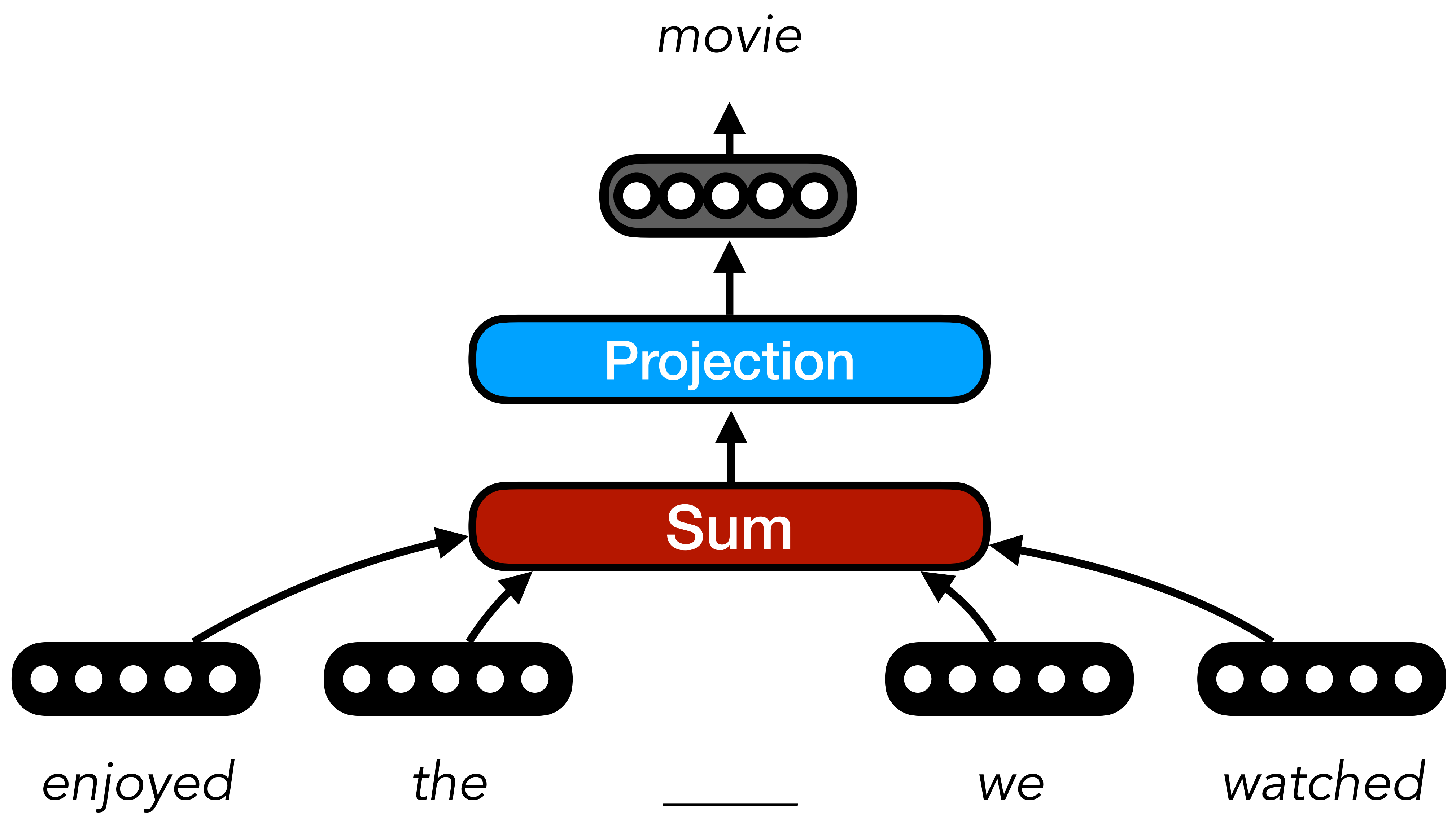
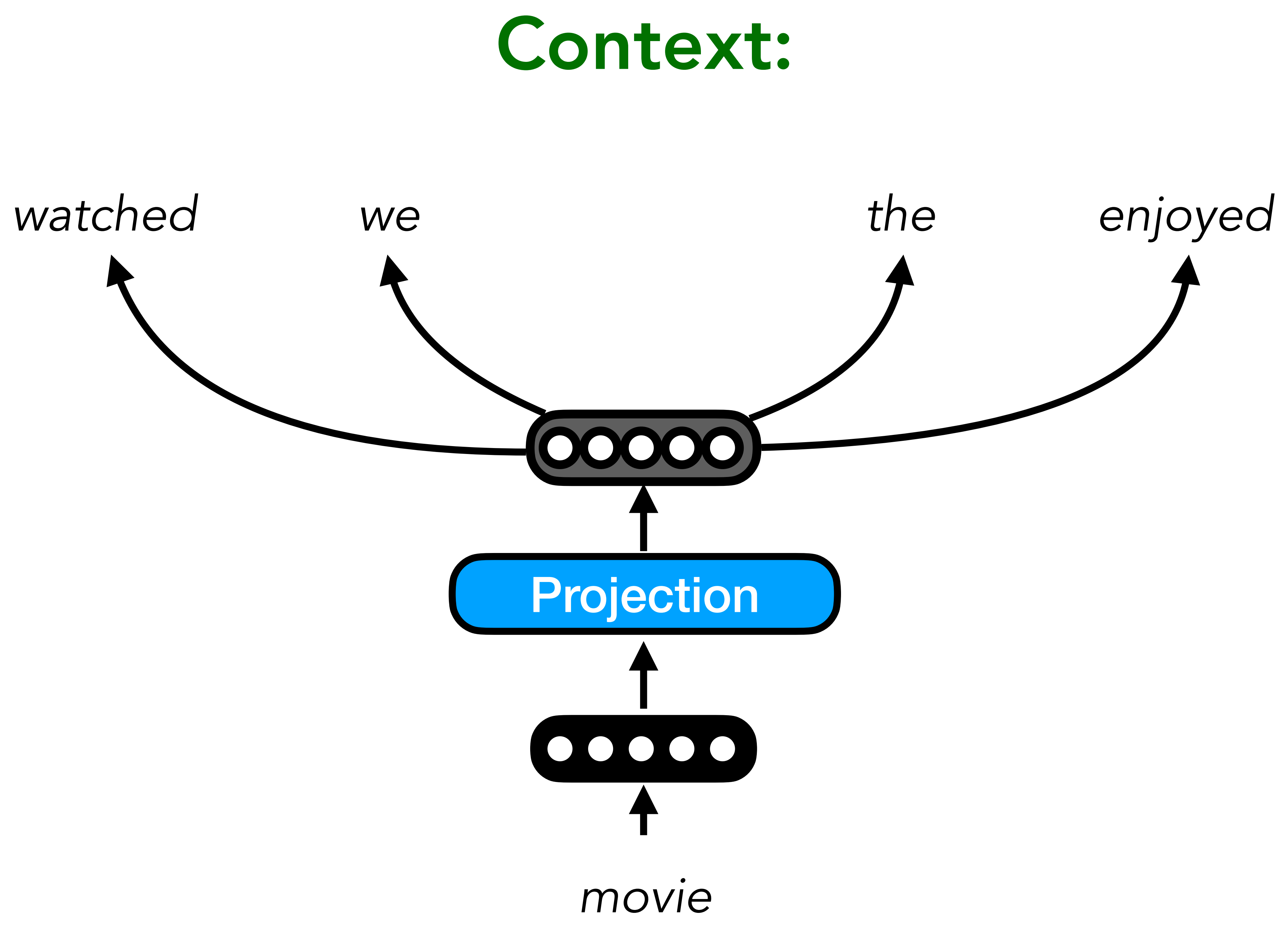


- Model is trained to **maximise** the **probability** of the missing word
  - For computational reasons, the model is typically trained to **minimise** the **negative log probability** of the missing word
- Here, we use a window of **N=2**, but the window size is a **hyperparameter**
- For computational reasons, a **hierarchical softmax** used to compute distribution (Eisenstein, 14.5.3)

(Mikolov et al., 2013a)

Skip-gram

- We can also learn embeddings by predicting the surrounding context from a single word



$$\max P(enjoyed, the, we, watched \mid movie)$$

$$\max P(x_{t-2}, x_{t-1}, x_{t+1}, x_{t+2} \mid x_t)$$

(Mikolov et al., 2013b)

Skip-gram

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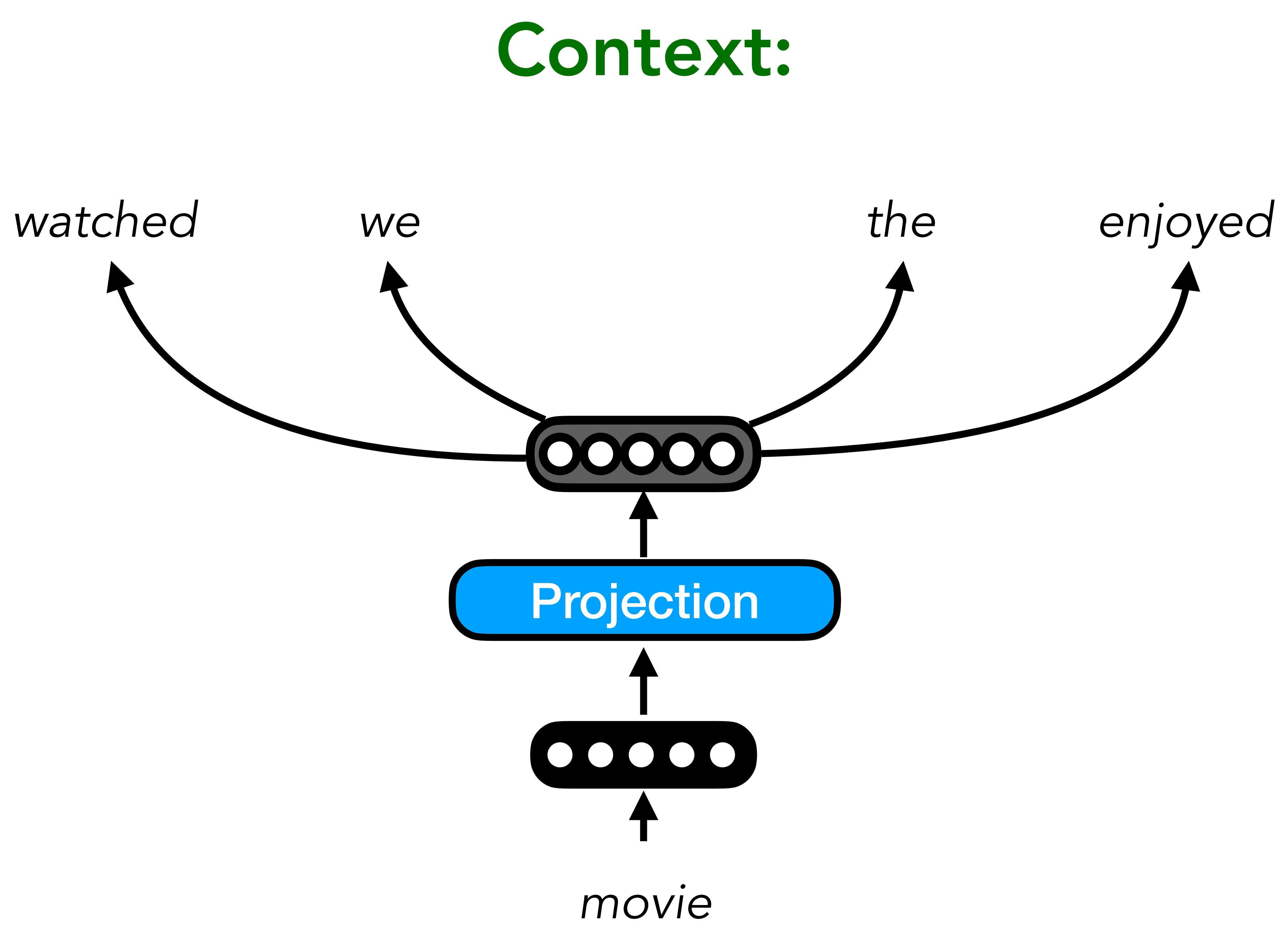

$$\max P(enjoyed, the, we, watched \mid movie)$$

$$= \max P(x_{t-2}, x_{t-1}, x_{t+1}, x_{t+2} \mid x_t)$$

$$= \max \log P(x_{t-2}, x_{t-1}, x_{t+1}, x_{t+2} \mid x_t)$$

$$= \max \Big(\log P(x_{t-2} \mid x_t) + \log P(x_{t-1} \mid x_t)$$

$$+ \log P(x_{t+1} \mid x_t) + \log P(x_{t+2} \mid x_t) \Big)$$

(Mikolov et al., 2013b)

Skip-gram

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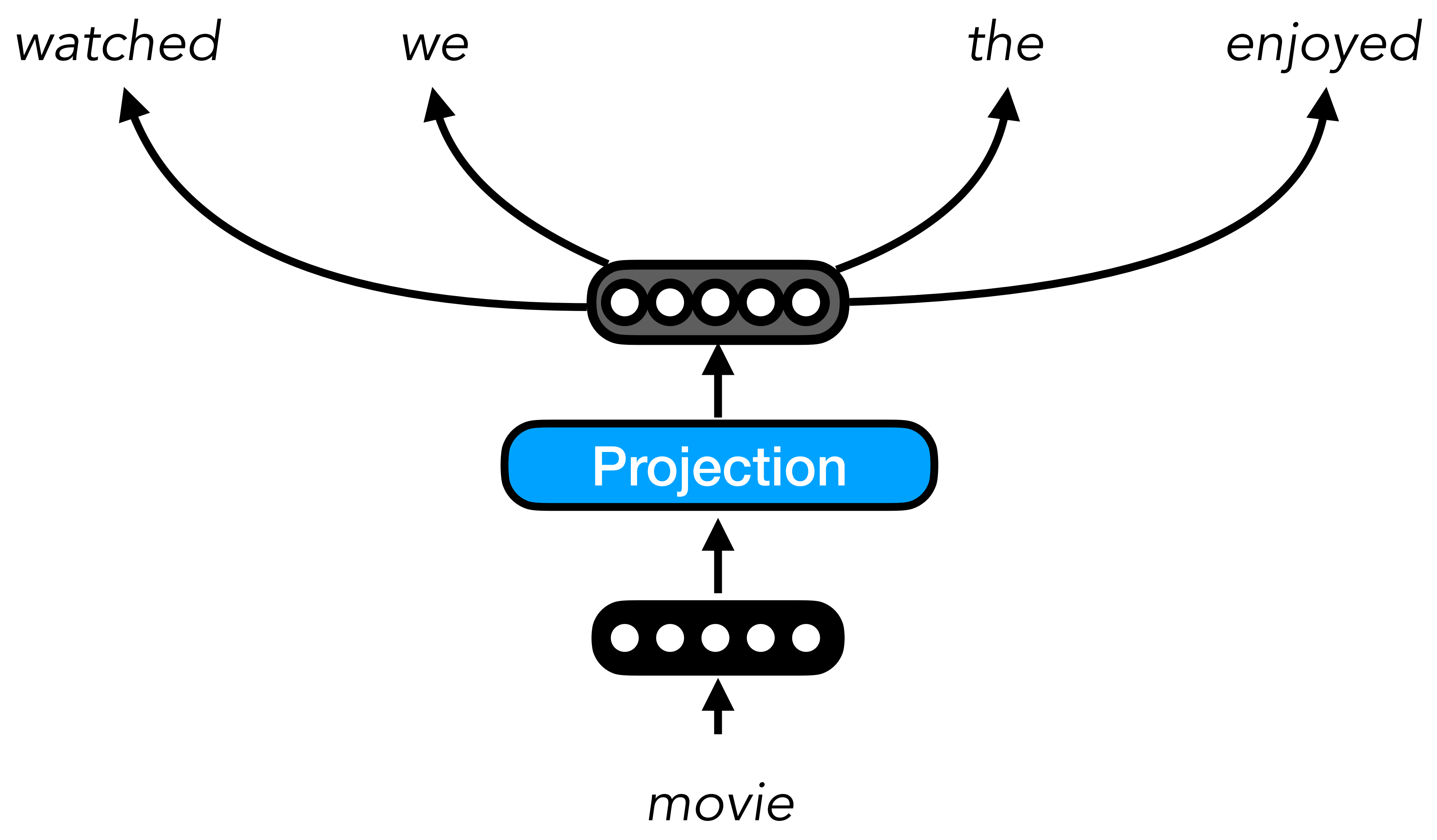
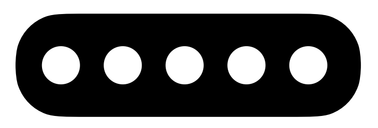
Context:



$$P(x_s \mid x_t) = \textbf{softmax}(\mathbf{U}\mathbf{x}_t)$$

$\mathbf{x}_t \in \mathbb{R}^{1 \times d}$

$\mathbf{U} \in \mathbb{R}^{d \times V}$



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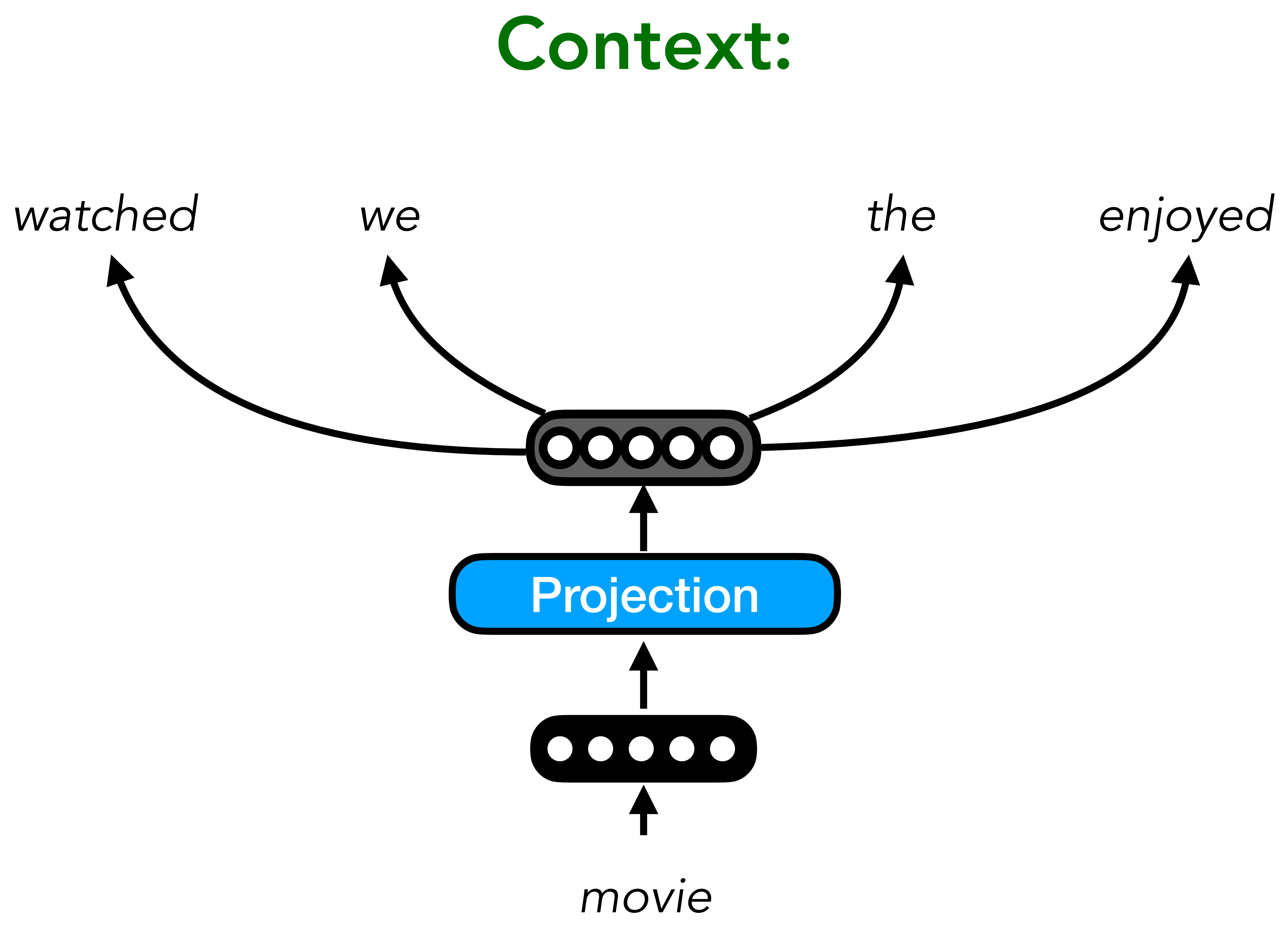


- Model is trained to **minimise** the **negative log probability** of the surrounding words
- Here, we use a window of **N=2**, but the window size is a **hyperparameter.**
    - Larger window = more information about related words in embedding
- Typically, set large window **(N=10),** but randomly select $i \in [1, N]$ as dynamic window size so that closer words contribute more to learning

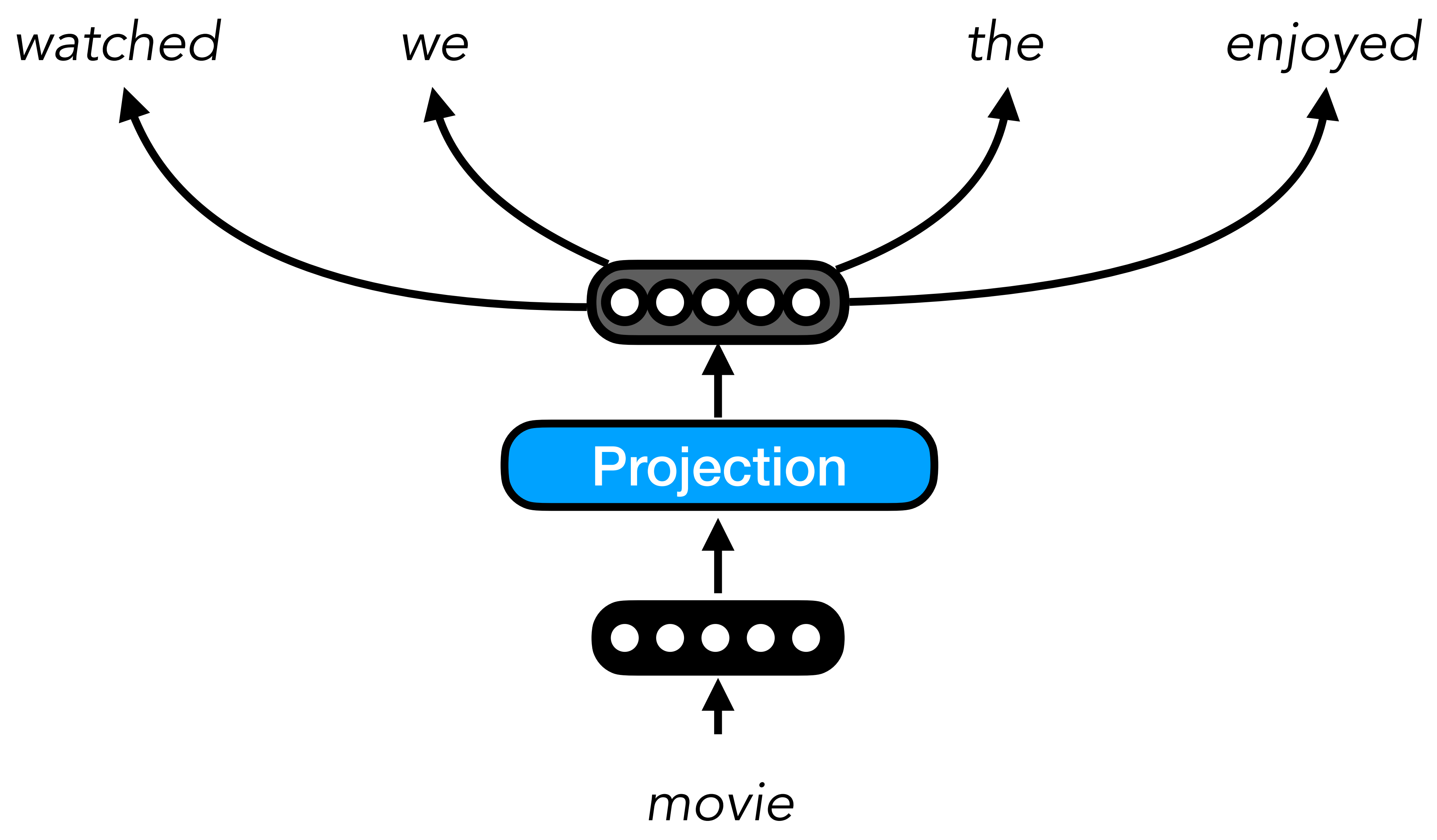
(Mikolov et al., 2013b)

Question

What is the major conceptual difference between the CBOW and Skipgram methods for training word embeddings?

Skip-gram vs. CBOW

- **Question:** Do you expect a difference between what is learned by CBOW and Skipgram methods?



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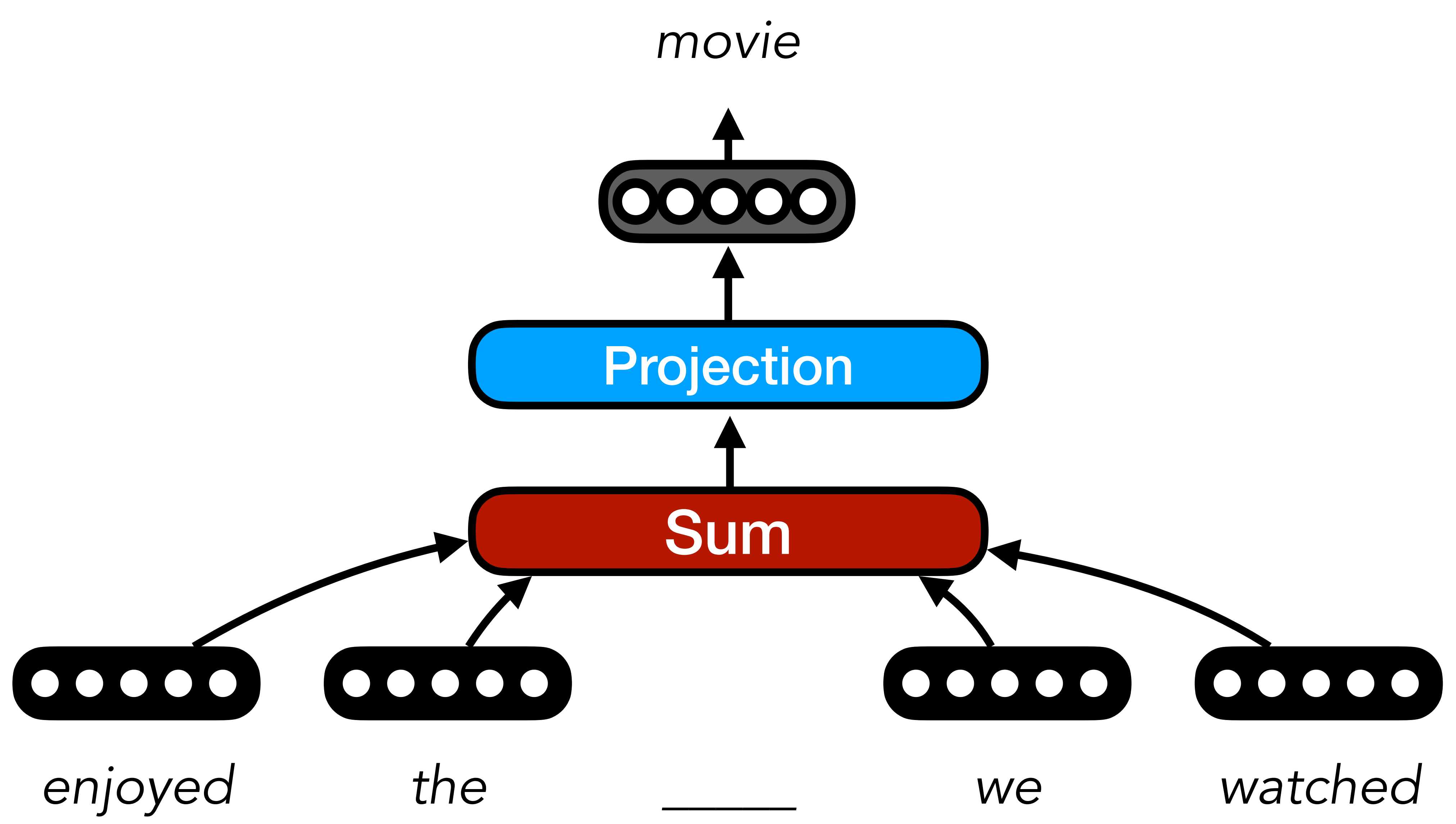
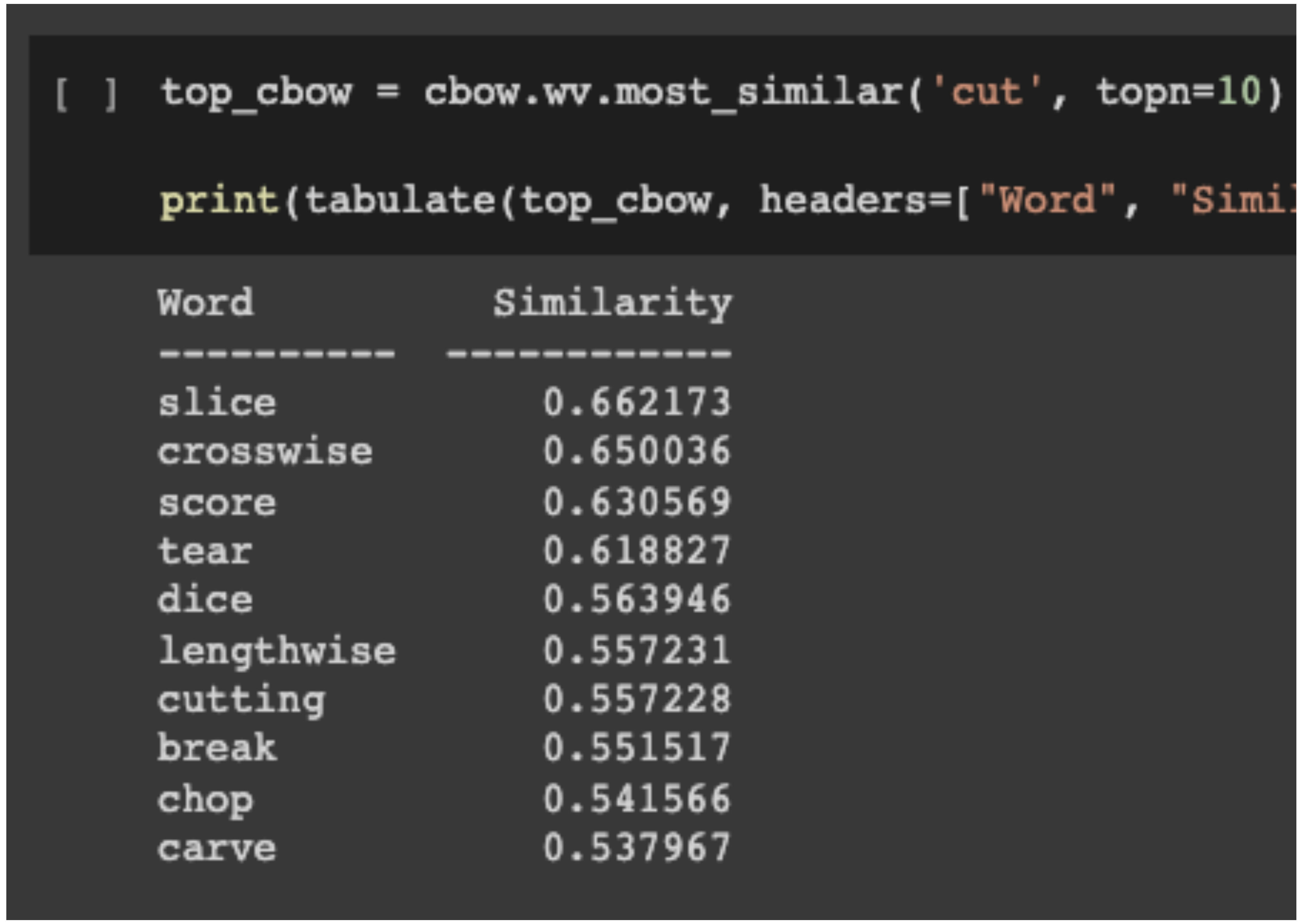


(Mikolov et al., 2013a)

Example

CBOW

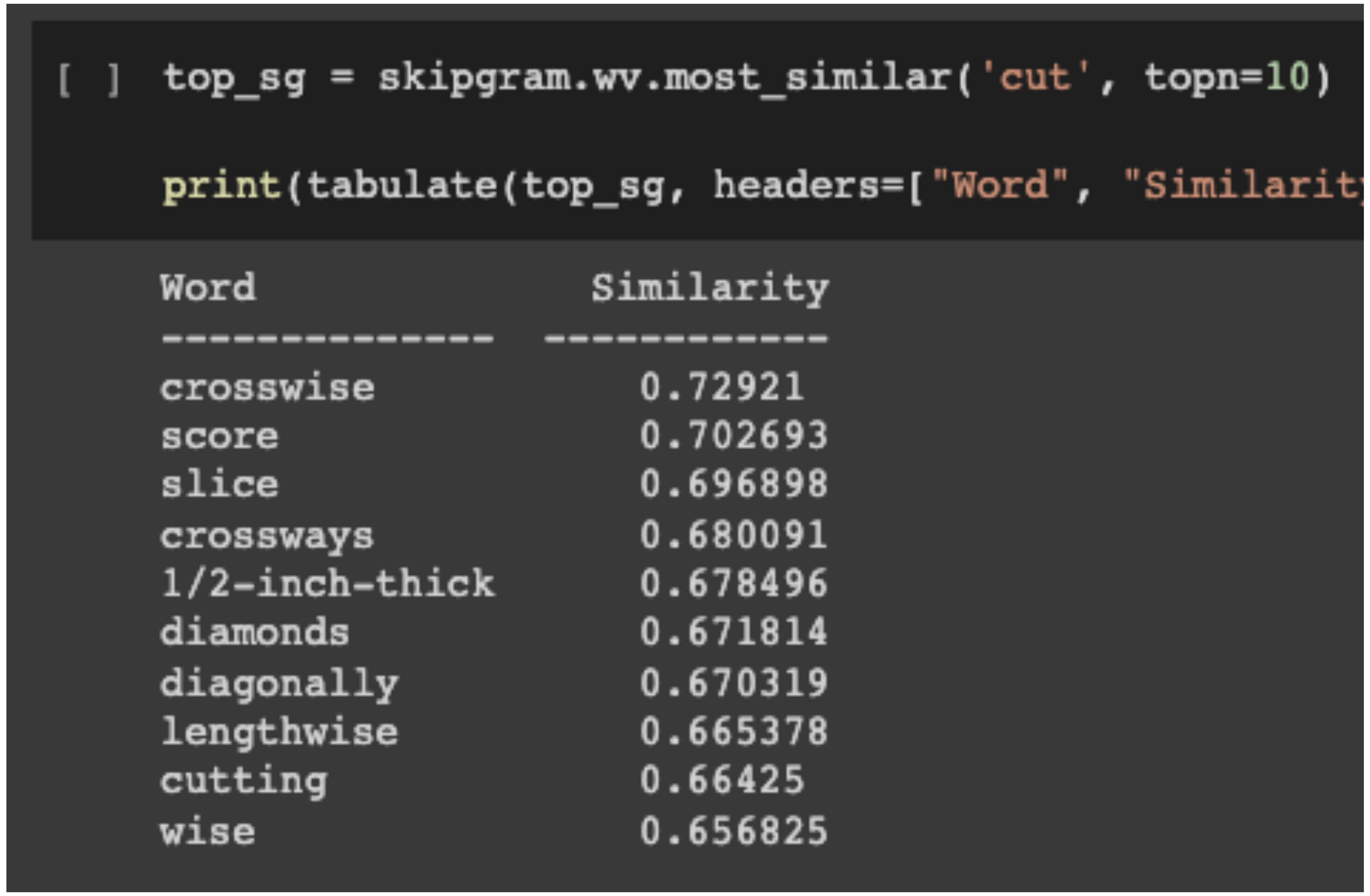


```
[ ]  top_cbow = cbow.wv.most_similar('cut', topn=10)

     print(tabulate(top_cbow, headers=["Word", "Simi

     Word          Similarity
     ----------  ------------
     slice           0.662173
     crosswise       0.650036
     score           0.630569
     tear            0.618827
     dice            0.563946
     lengthwise      0.557231
     cutting         0.557228
     break           0.551517
     chop            0.541566
     carve           0.537967
```

Skip-gram



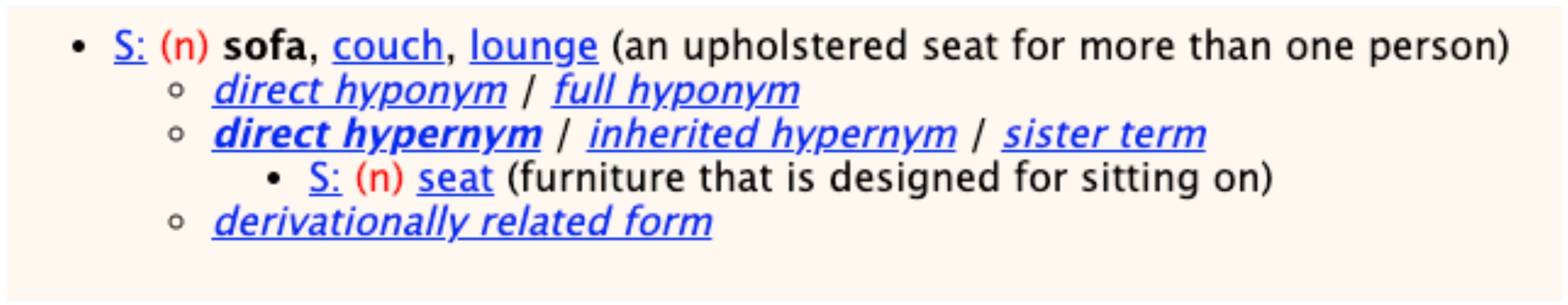
```
[ ]  top_sg = skipgram.wv.most_similar('cut', topn=10)

     print(tabulate(top_sg, headers=["Word", "Similarit

     Word              Similarity
     --------------  ------------
     crosswise            0.72921
     score                0.702693
     slice                0.696898
     crossways            0.680091
     1/2-inch-thick       0.678496
     diamonds             0.671814
     diagonally           0.670319
     lengthwise           0.665378
     cutting              0.66425
     wise                 0.656825
```

Other Resources of Interest

- **GloVe** Embeddings (Pennington et al., 2014)
  - Use co-occurrence statistics to speed up training of skip-gram-like embeddings
  - Word pairs are training examples, rather than windows in a textual training corpus
- **FastText** Embeddings (Bojanowski et al., 2017; Mikolov et al., 2018)
  - Enhancement of Skip-gram model that handles morphology
  - Divide words into character n-grams of size *n* — <where> = <*wh*, *whe*, *her*, *ere*, *re*>
- Retrofitting word vectors to semantic lexicons (Faruqui et al., 2014)
  - Training word vectors to encode relationships (e.g., synonymy) from high-level semantic resources: WordNet, PPDB, and FrameNet



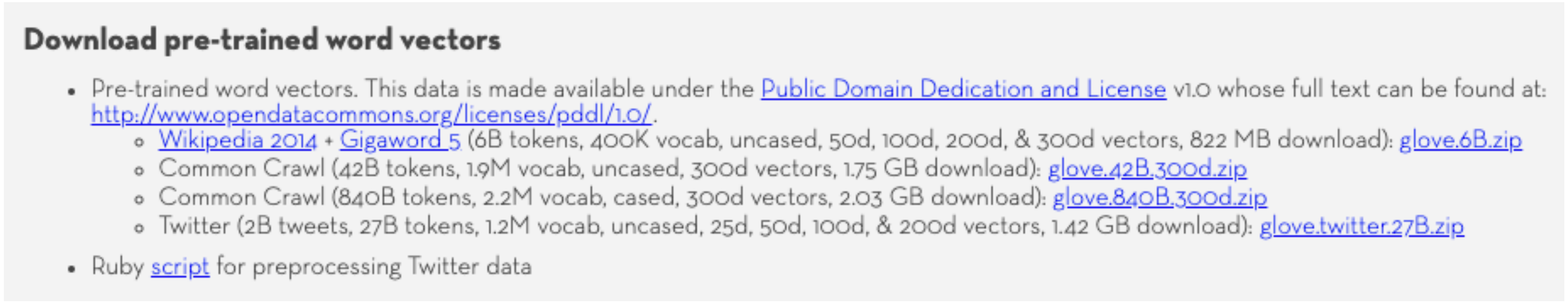
- S: (n) **sofa**, couch, lounge (an upholstered seat for more than one person)
  - *direct hyponym* / *full hyponym*
  - ***direct hypernym*** / *inherited hypernym* / *sister term*
    - S: (n) seat (furniture that is designed for sitting on)
  - *derivationally related form*

Recap

- **Problem:** Learning word embeddings from scratch using labeled for a task is data-inefficient!
- **Solution:** Word embeddings can be learned in a self-supervised manner from large quantities of raw text
- **Three main algorithms:** Continuous Bag of Words (CBOW), Skip-gram, and GloVe

Resources

- **word2vec**: https://code.google.com/archive/p/word2vec/
- **GloVe**: https://nlp.stanford.edu/projects/glove/
- **FastText**: https://fasttext.cc/
- **Gensim:** https://radimrehurek.com/gensim/



Download pre-trained word vectors

- Pre-trained word vectors. This data is made available under the Public Domain Dedication and License v1.0 whose full text can be found at: http://www.opendatacommons.org/licenses/pddl/1.0/.
  - Wikipedia 2014 + Gigaword 5 (6B tokens, 400K vocab, uncased, 50d, 100d, 200d, & 300d vectors, 822 MB download): glove.6B.zip
  - Common Crawl (42B tokens, 1.9M vocab, uncased, 300d vectors, 1.75 GB download): glove.42B.300d.zip
  - Common Crawl (840B tokens, 2.2M vocab, cased, 300d vectors, 2.03 GB download): glove.840B.300d.zip
  - Twitter (2B tweets, 27B tokens, 1.2M vocab, uncased, 25d, 50d, 100d, & 200d vectors, 1.42 GB download): glove.twitter.27B.zip
- Ruby script for preprocessing Twitter data

References

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