Neural Word Embeddings

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Announcements

- Lectures are being recorded and MediaSpace channel is posted to the course website.
  - Make sure to see lectures marked [2026]
  - First lectures should be online by next week
- You can audit the class, but you can't take the midterm and project milestones won't be graded. We also can't guarantee access to resources

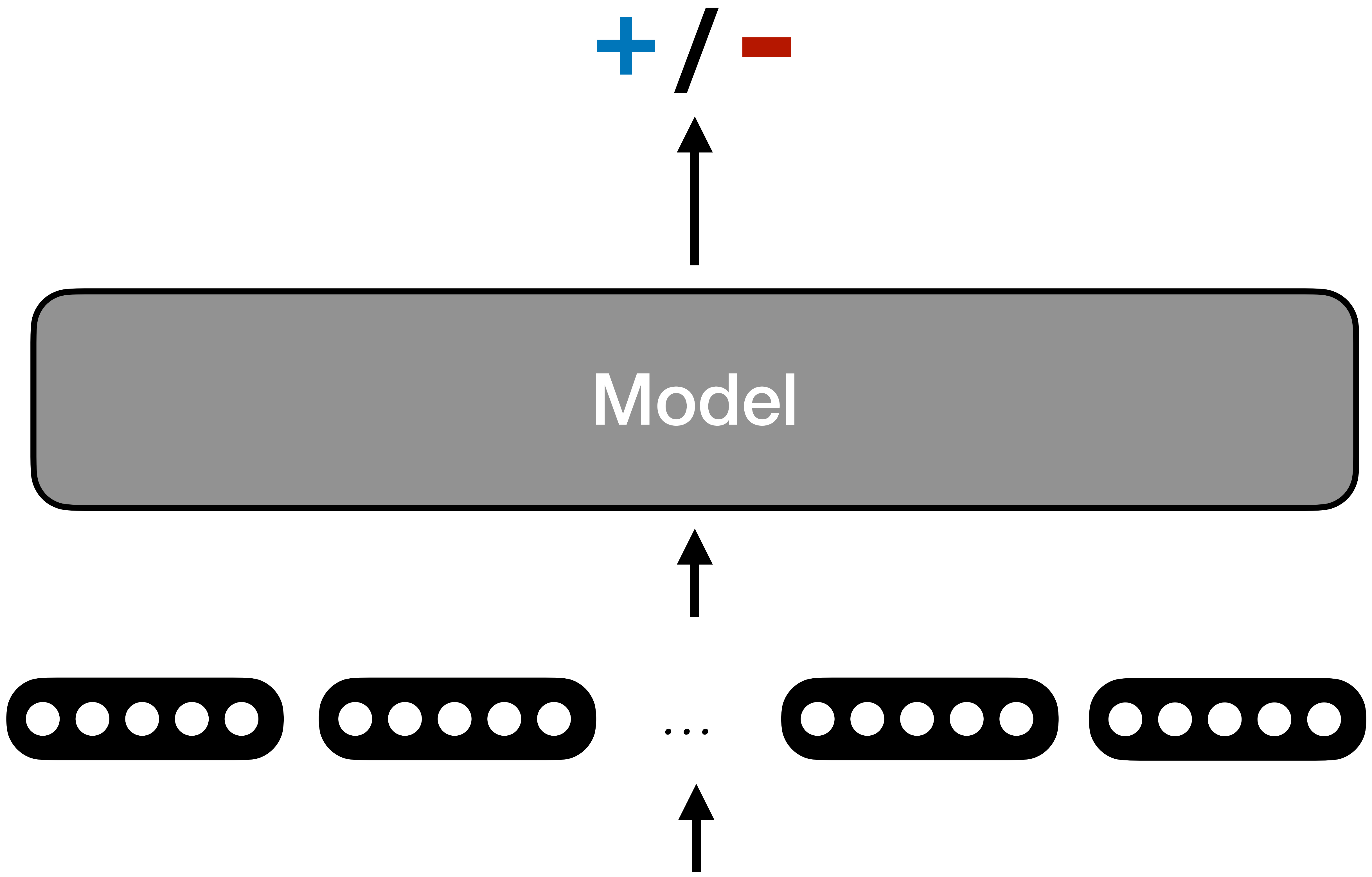
Today’s Outline

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

Some slides adapted from Mohit Iyyer

Word Representations

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



I really enjoyed the movie we watched on Saturday!

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

Three Parts in our System

- **Embeddings:** how do we represent sequences of discrete words ?
- **Model:** how do we compose these embeddings to get sequence-level meaning representations?
- **Prediction:** how do we map our model's representation of a sequence to a task-relevant prediction?

Today, let's talk about embeddings in more detail !

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?
  - Next week - 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 (i.e., “unknown”).

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

How to represent words: **sparse embeddings**

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

- 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	⟶	[0 … 0 0 0 1 … 0 0]
really	⟶	[0 … 1 … 0 0 0 0 0]
enjoyed	⟶	[0 … 0 0 0 1 0 … 0]
the	⟶	[0 … 0 1 0 0 0 … 0]
movie	⟶	[0 … 0 0 0 0 0 … 1]
!	⟶	[1 … 0 0 0 0 0 0 0 0]

Problem: **sparse embeddings**

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

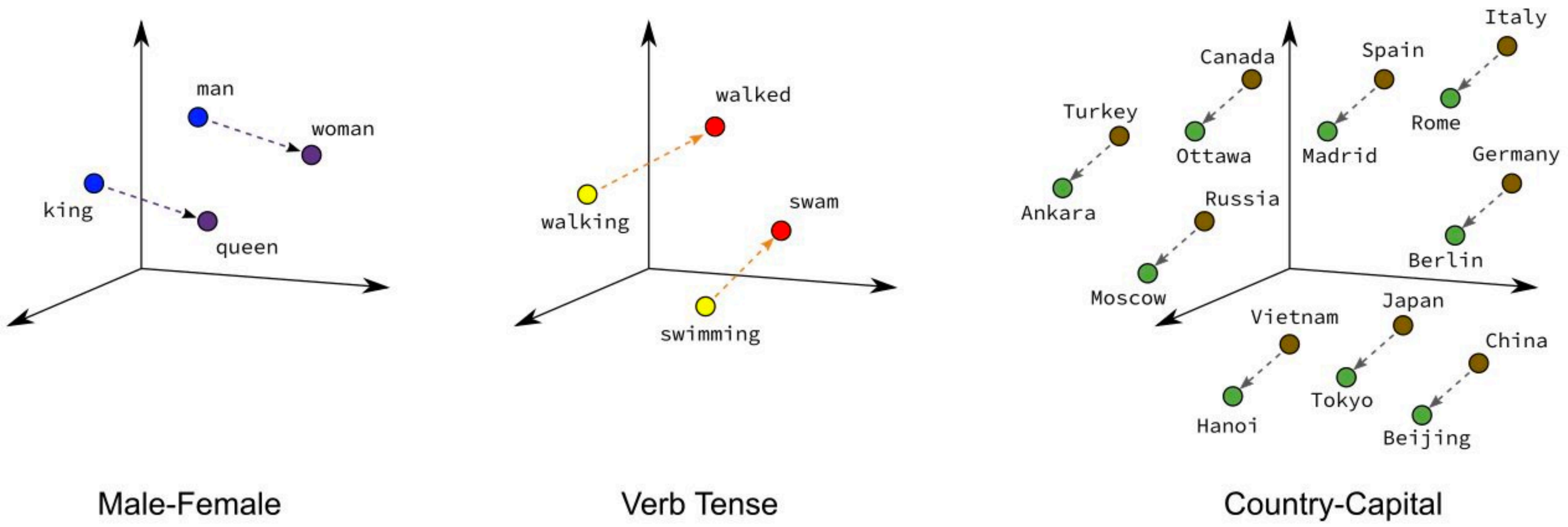
How do you learn learn similarity between words?

enjoyed ⟶ [0 … 0 0 0 1 … 0 0]

loved ⟶ [0 … 1 … 0 0 0 0 0]

sim(*enjoyed*, *loved*) = **0**

Embeddings Goal



How do we train semantics-encoding embeddings of words?

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

Dense Embeddings

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

word vectors

word embeddings

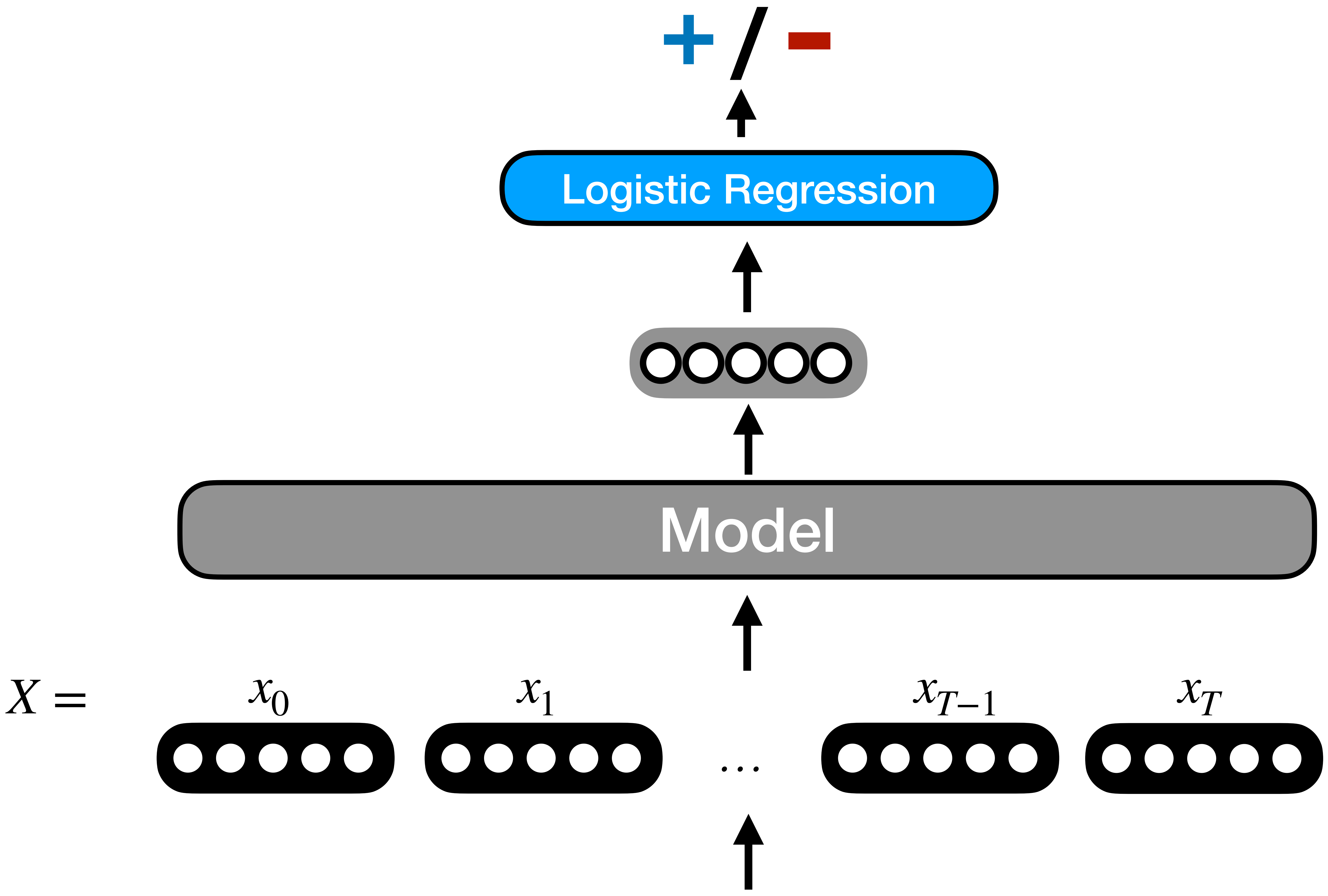
neural embeddings

dense embeddings

others...

- Similarity of vectors represents similarity of meaning for particular words

Learn embeddings from the task!

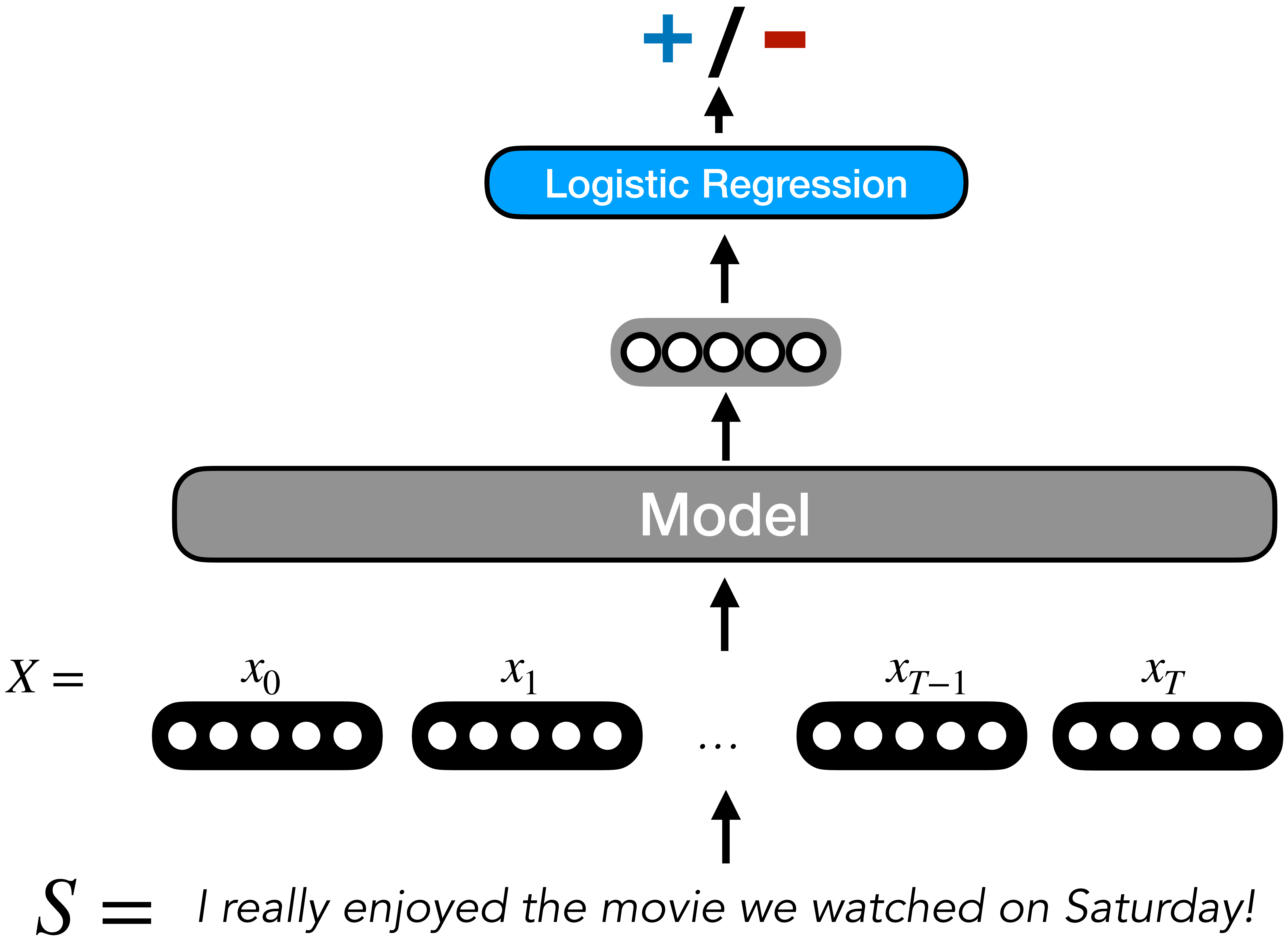


$S =$ *I really enjoyed the movie we watched on Saturday!*

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

Learn embeddings that allow you to do the task successfully!

Learn embeddings from the task!



- 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

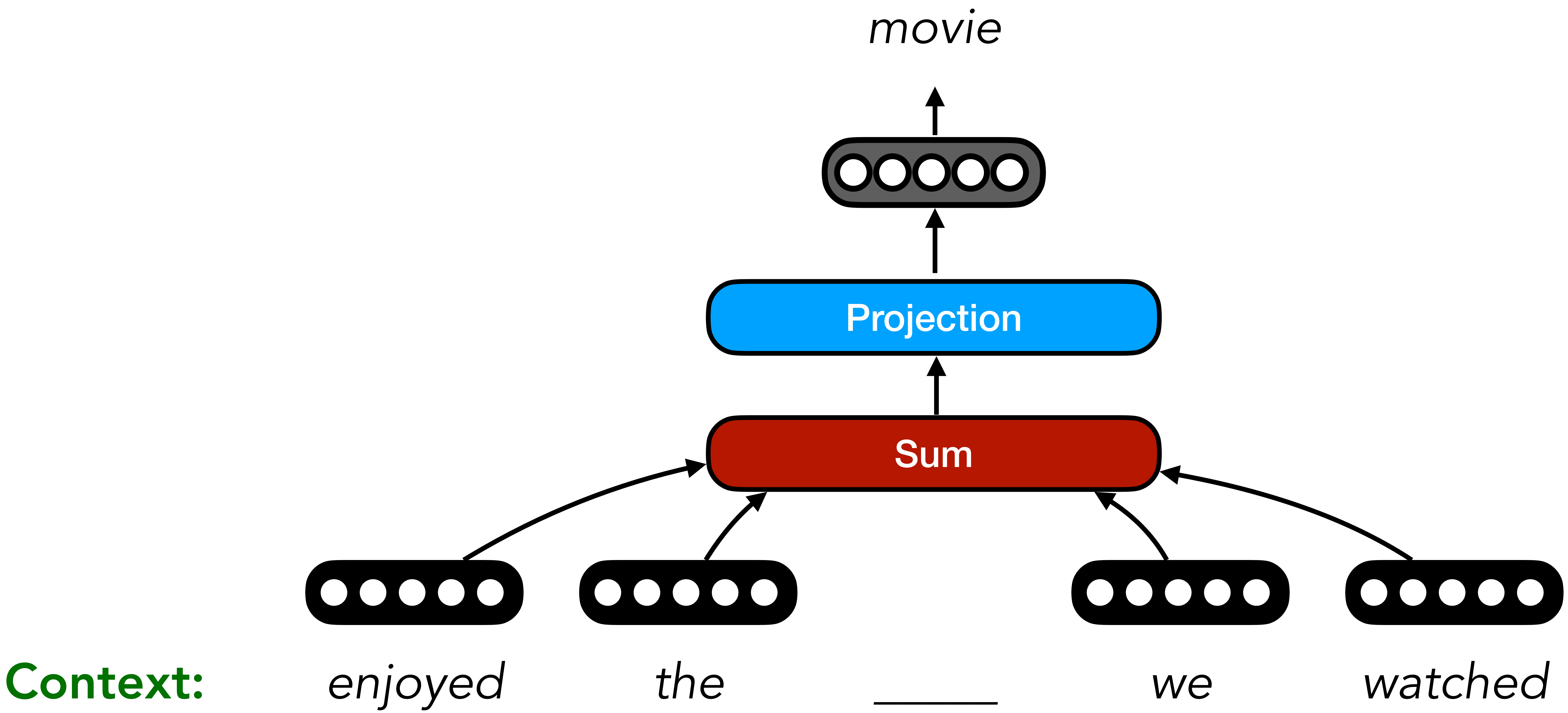
Learning Word Embeddings

- 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**
  - Learn to predict global co-occurrence statistics

(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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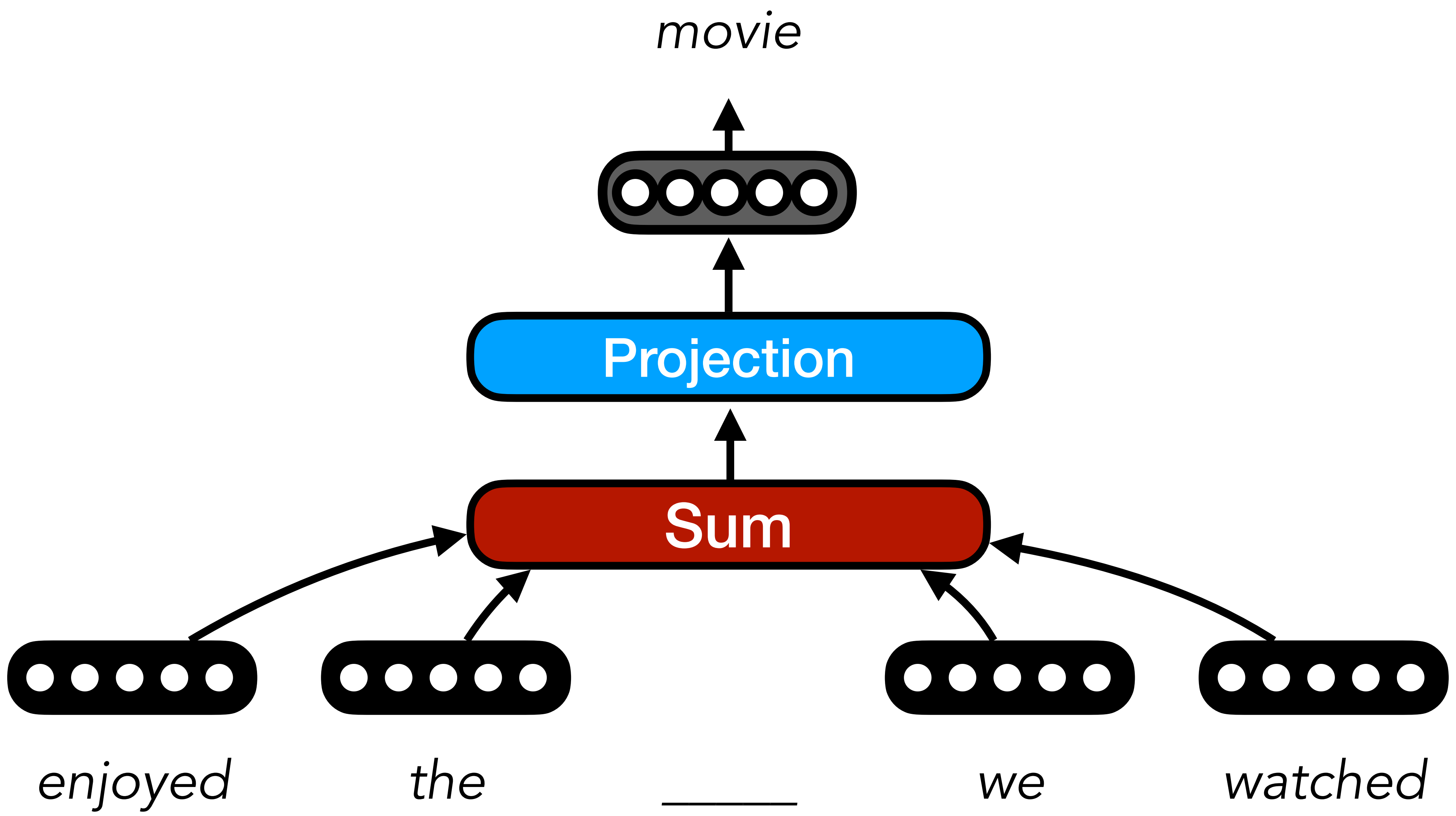

$$\max P(movie \mid enjoyed, the, we, watched)$$

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

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

(Mikolov et al., 2013a)

Continuous Bag of Words (CBOW)

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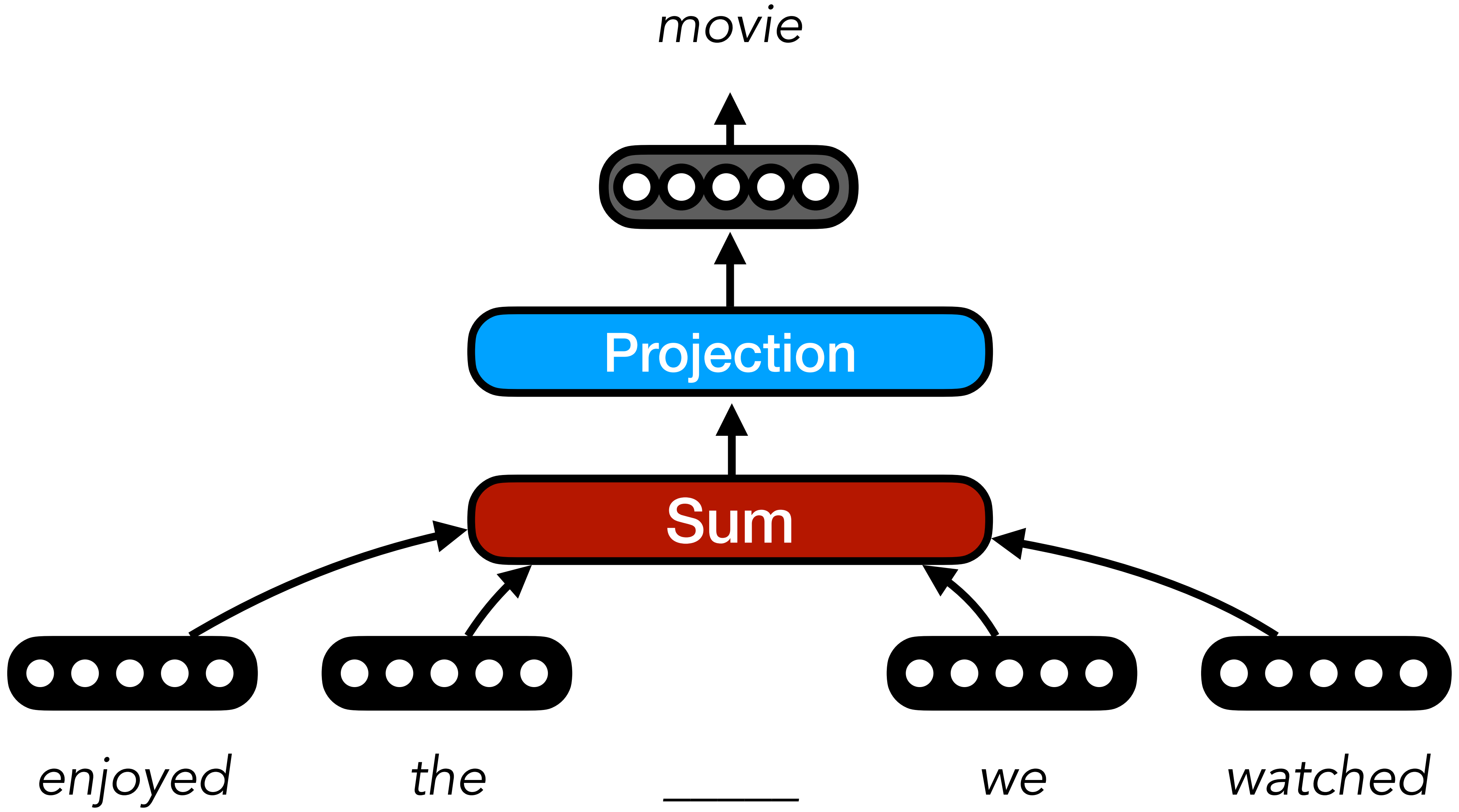
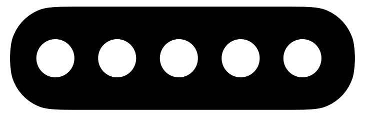


$$P(x_t \mid \{x_s\}_{s=t-2}^{s=t+2}) = \textbf{softmax}\left(\mathbf{U} \sum_{\substack{s=t-2 \\ s \neq t}}^{t+2} \mathbf{x}_s\right)$$

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



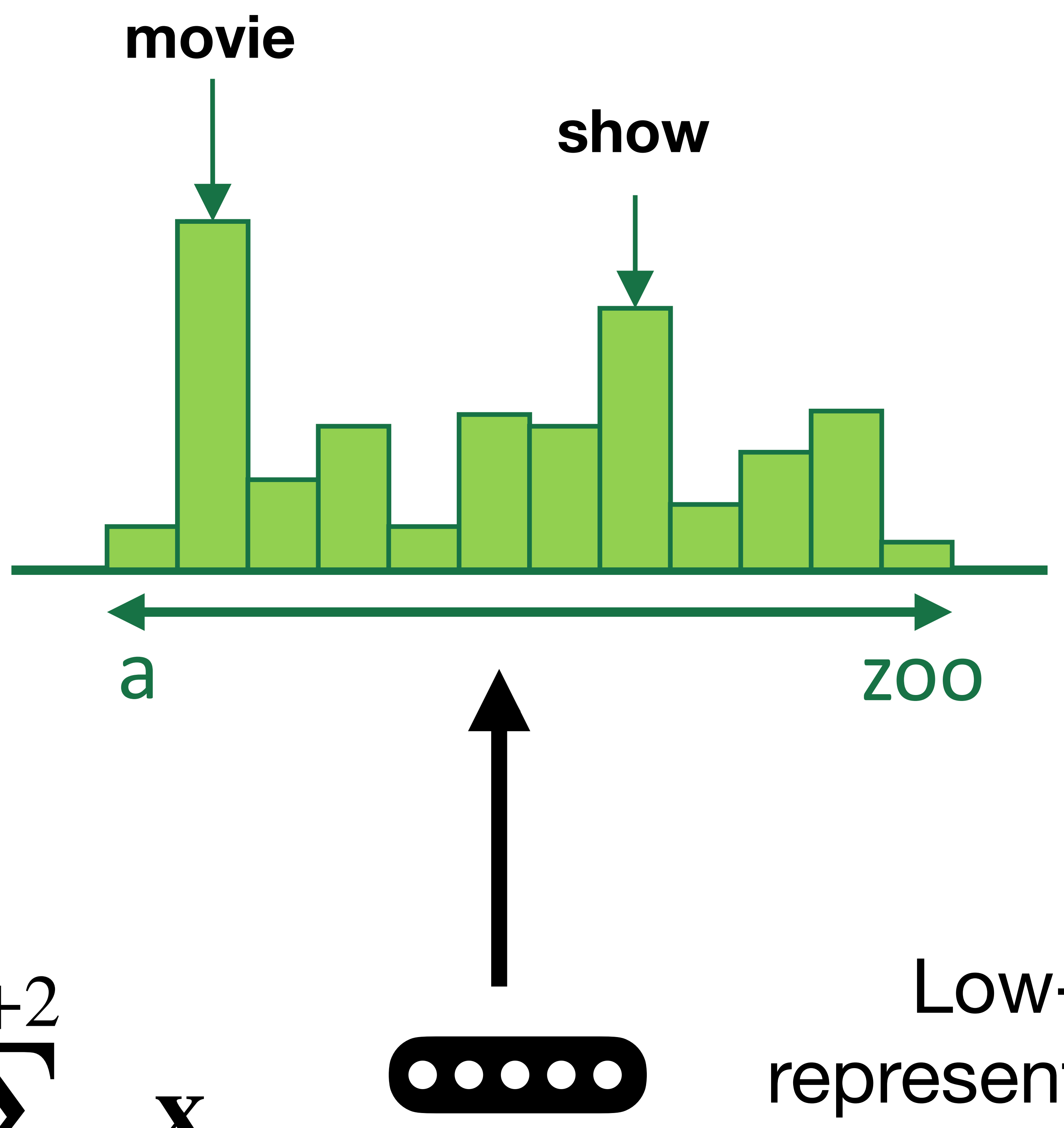
$\mathbf{U} \in \mathbb{R}^{d \times V}$

(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”.

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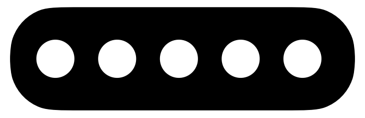


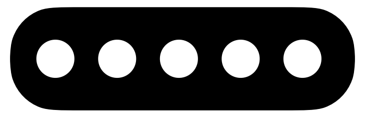
Low-dimensional representation of context: “enjoyed the we watched”

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”.

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

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

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

Here’s an example 3-d prefix vector

How do we get there?

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

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

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

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

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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1.2 * -2.3
+ -0.3 * 0.9
+ 0.9 * 5.4

h_t = <-2.3, 0.9, 5.4>

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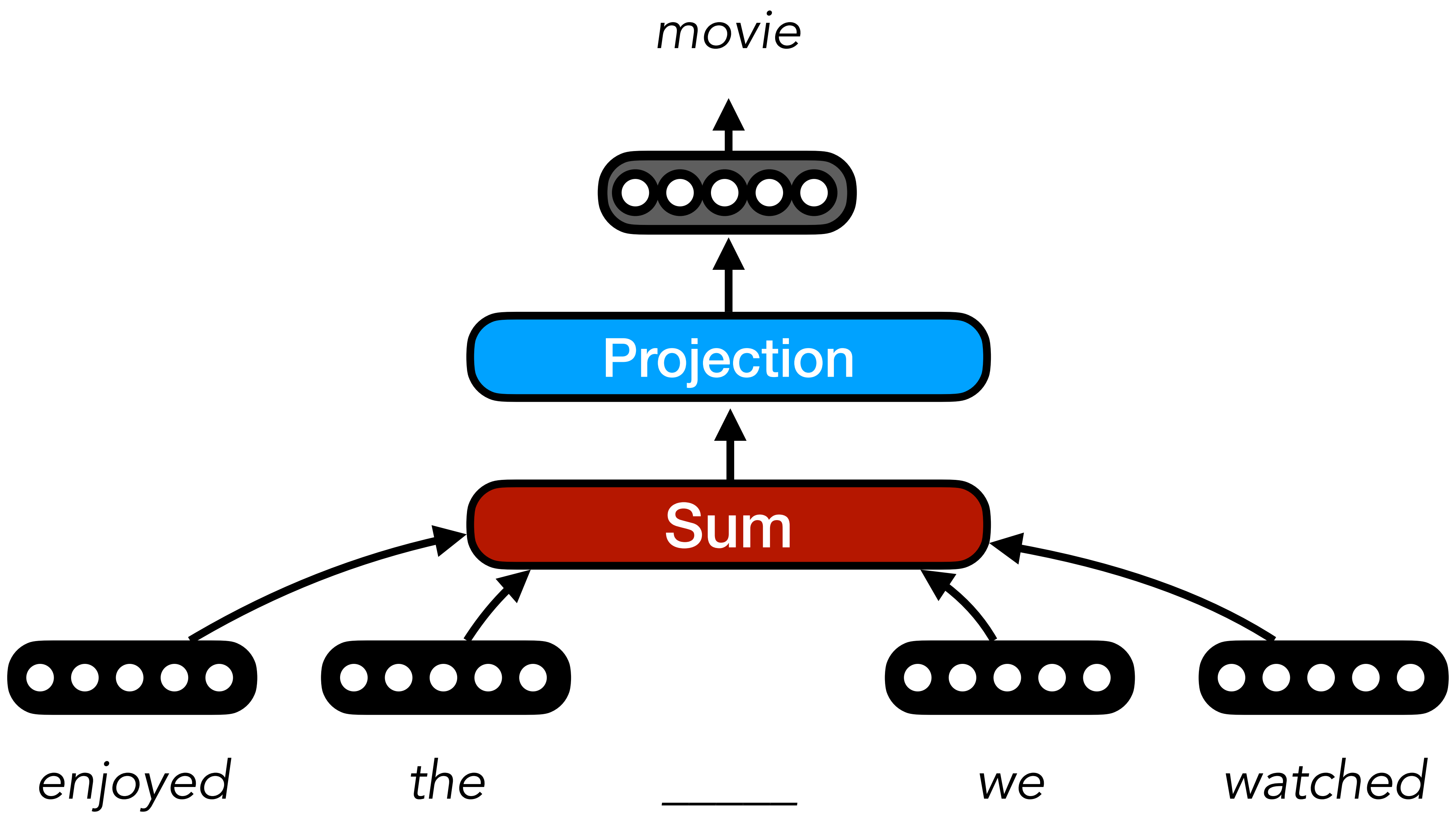
$\mathbf{U}h_t$ = <1.8, -1.9, 2.9, -0.9>

$\textbf{softmax}(\mathbf{U}h_t)$ = <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



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

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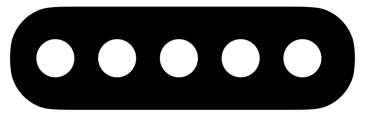

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(Mikolov et al., 2013a)

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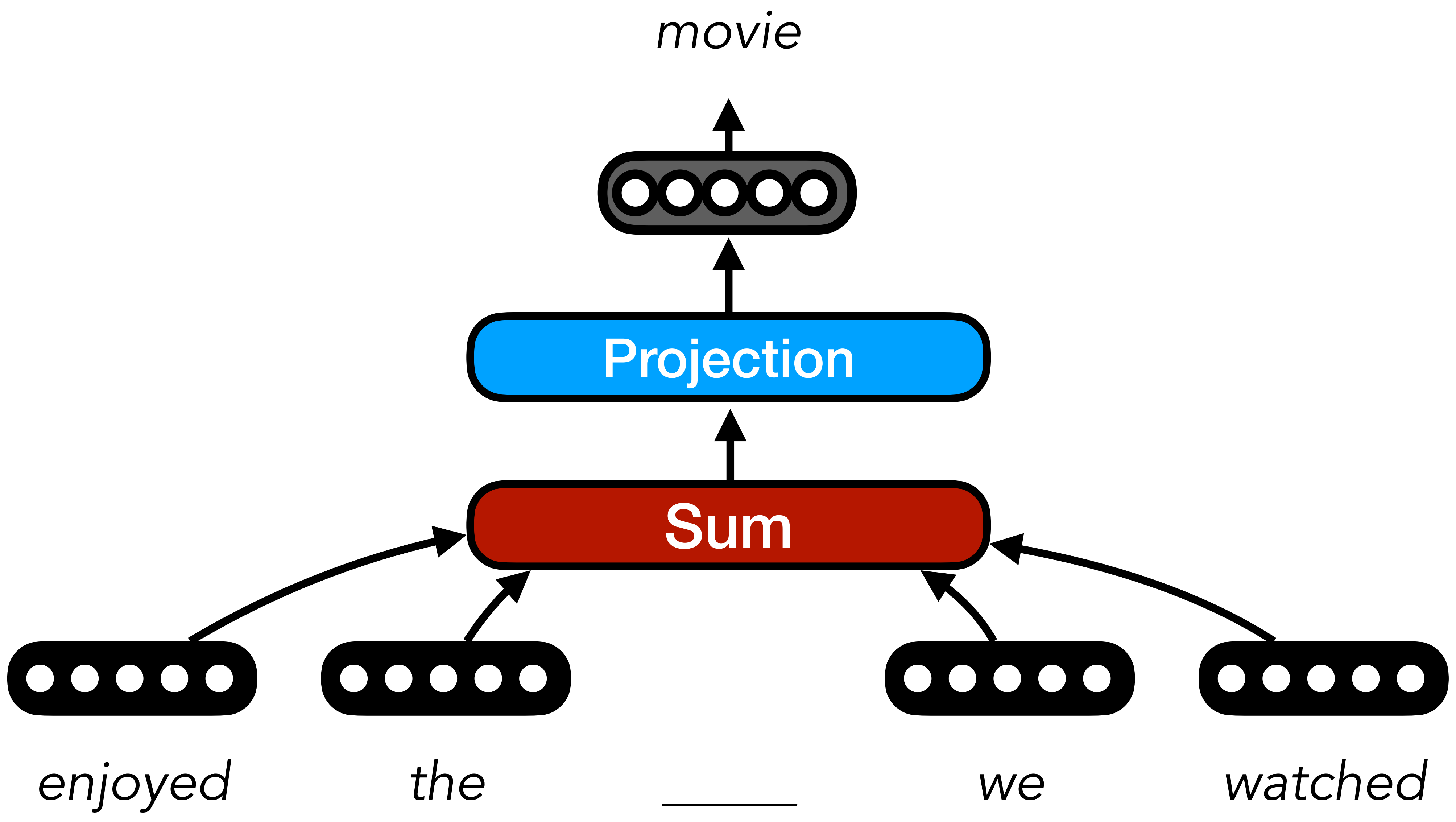
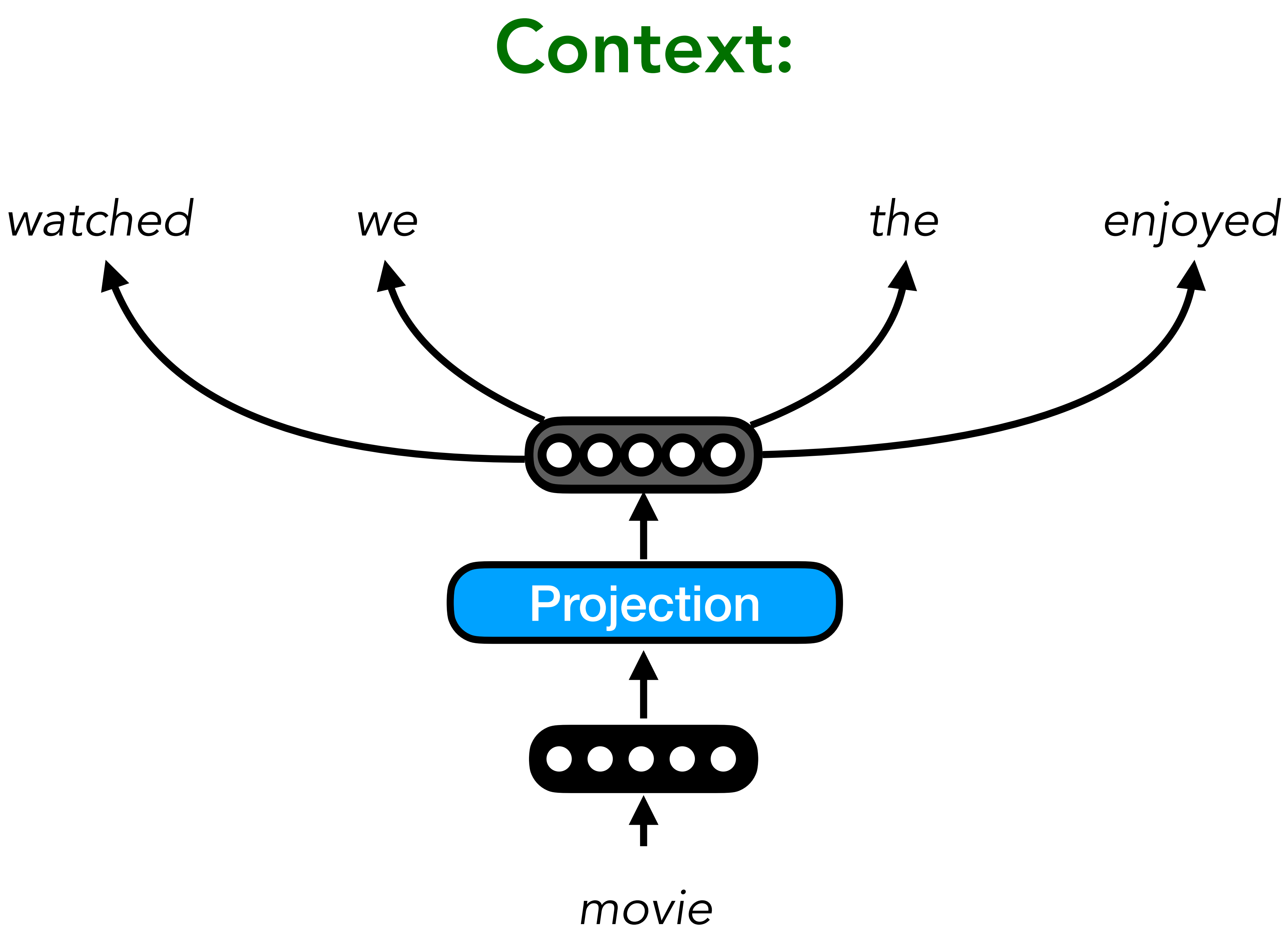


- Model is trained to **maximise** the **probability** of the missing word
    - For computational reasons, the model is typically trained to **minimise** the **negative log probability** of the missing word
- Here, we use a window of **N=2**, but the window size is a **hyperparameter**
- For computational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

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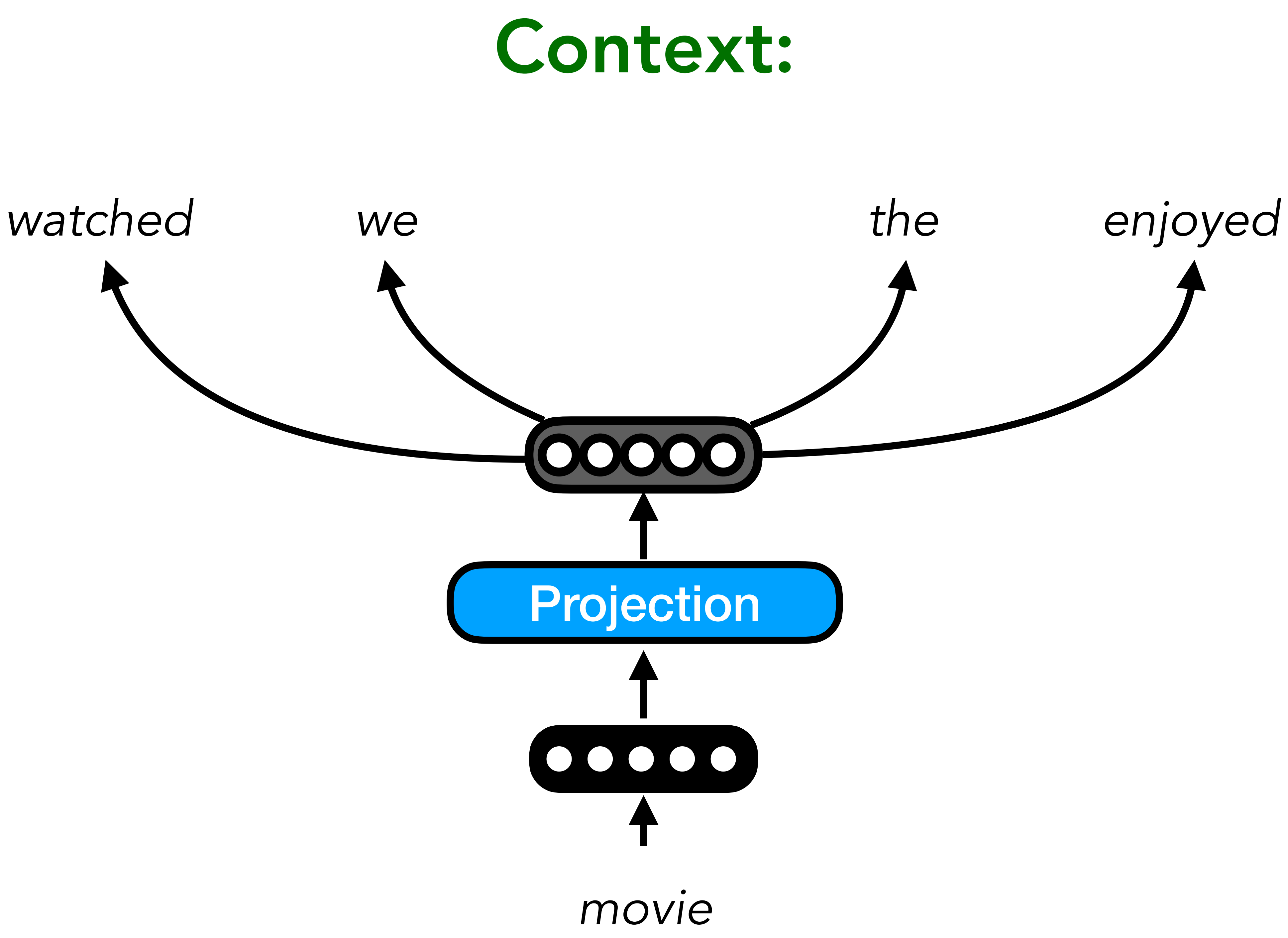

$$\max P(enjoyed, the, we, watched \mid movie)$$

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

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

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

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

(Mikolov et al., 2013b)

Skip-gram

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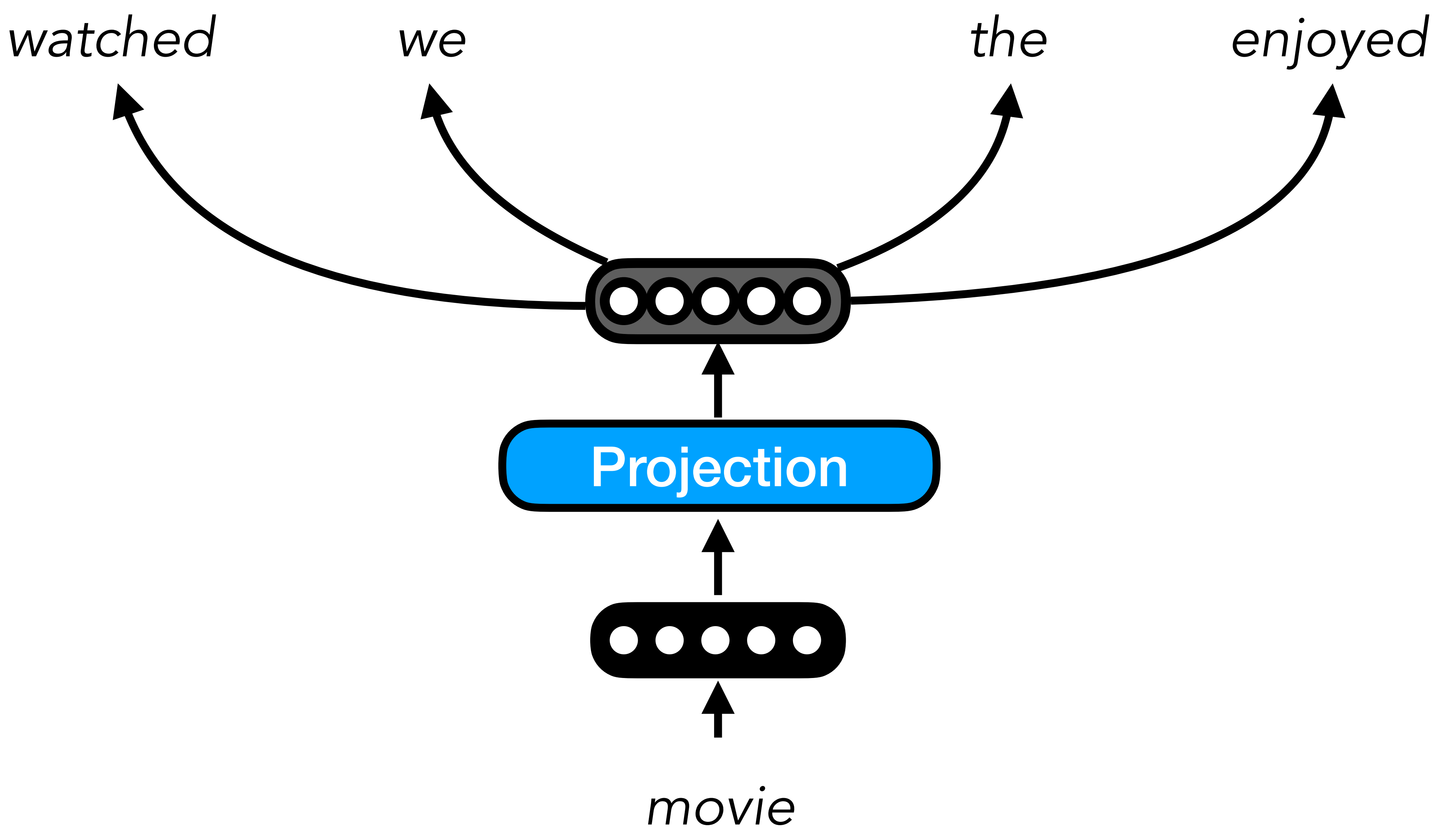
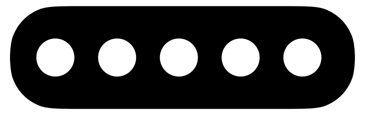
Context:



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

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

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

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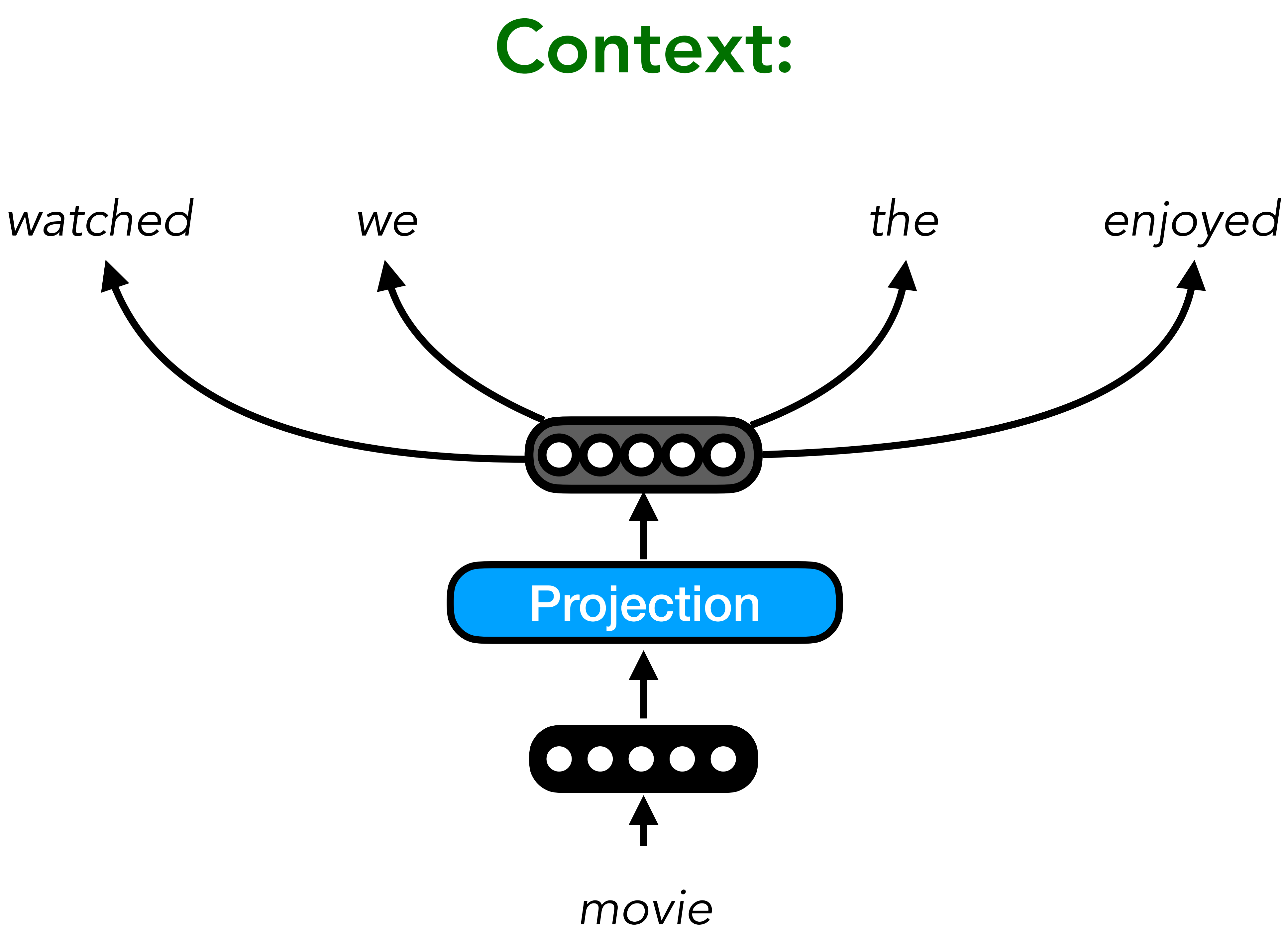


- Model is trained to **minimise** the **negative log probability** of the surrounding words
- Here, we use a window of **N=2**, but the window size is a **hyperparameter.**
  - Larger window = more information about related words in embedding
- Typically, set large window **(N=10),** but randomly select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

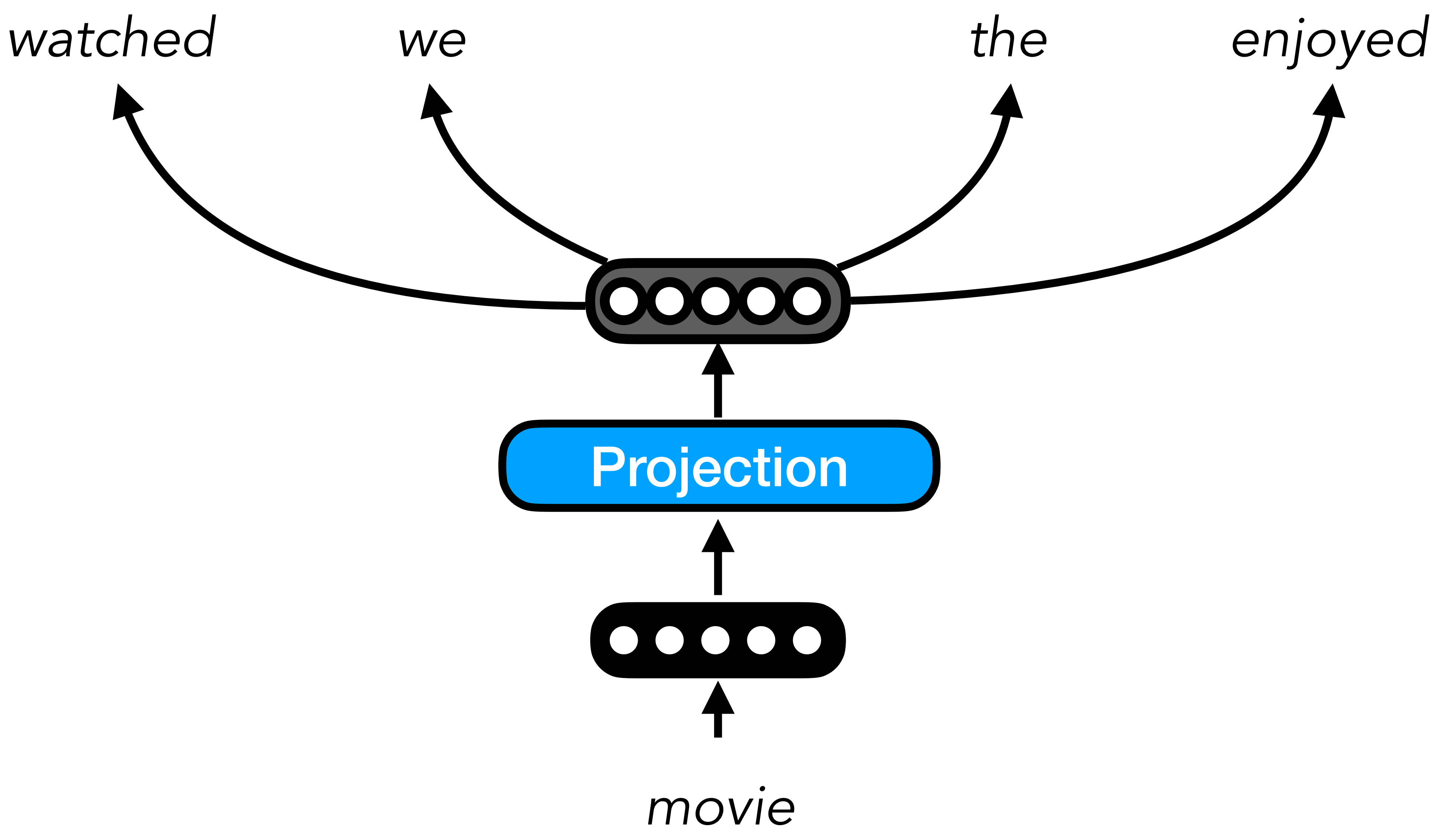
(Mikolov et al., 2013b)

Question

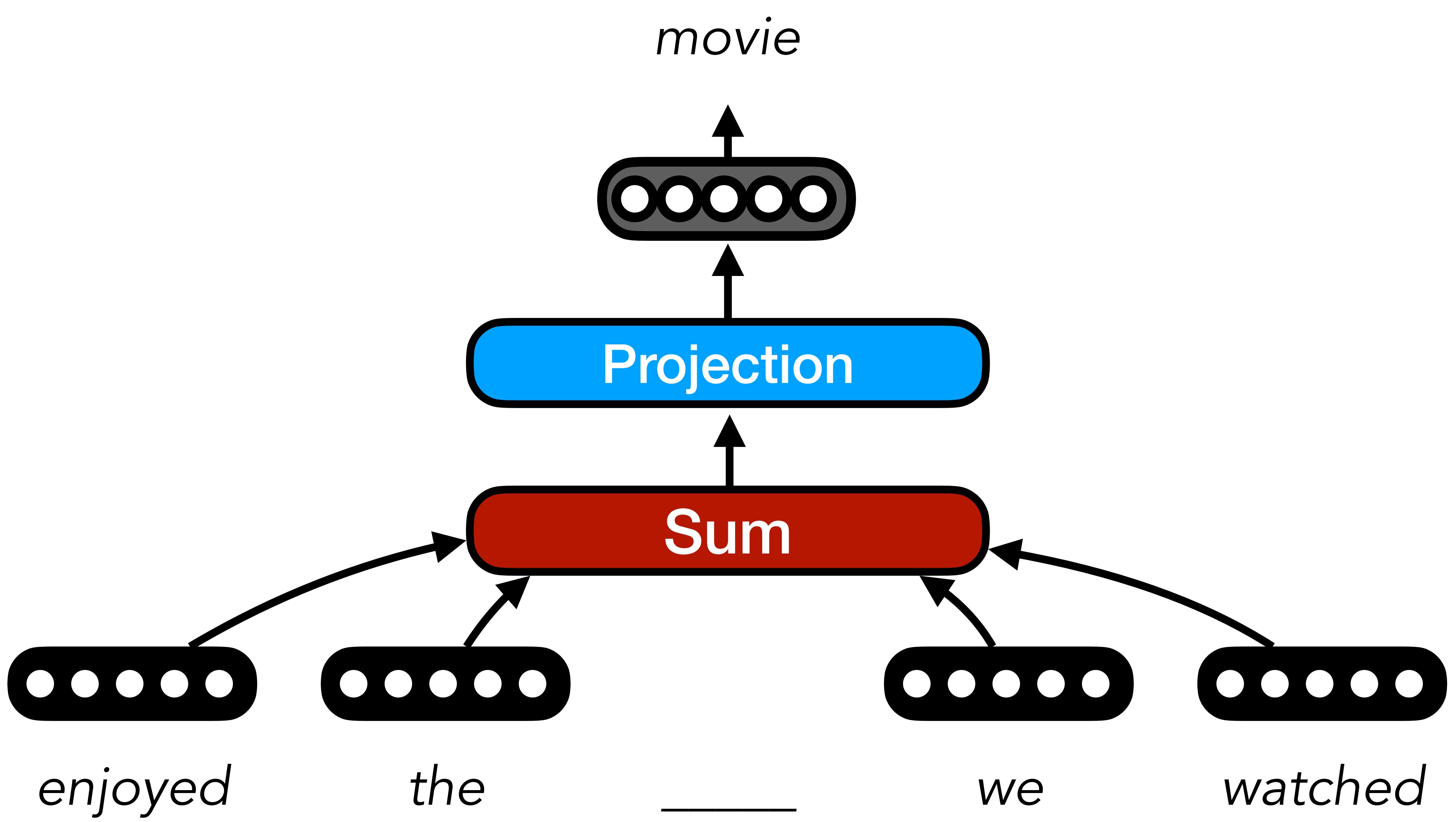
What is the major conceptual difference between the CBOW and Skipgram methods for training word embeddings?

Skip-gram vs. CBOW

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



(Mikolov et al., 2013b)



(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

Question

What do Skipgram and CBOW have in common ?

They both learn word representations from predicting *many* local context windows around those words.

Can we do something else?

GloVe: **Glo**bal **Ve**ctors

- **Problem:** Skip-gram and CBOW optimize local prediction objective and never explicitly model global corpus co-occurrence statistics.

- **Solution:** Build a global word–context co-occurrence matrix $\mathbf{X} \in \mathbb{R}^{V \times V}$ and learn embeddings that approximate log co-occurrence counts.

$$min \sum_{i,j} f(X_{i,j}) \left(w_i^T w_j + b_i + b_j - \log \mathbf{X}_{ij} \right)^2$$

In GloVe, embeddings are learned s.t. their dot products approximate log co-occurrence counts.

—> Embedding differences encode probability ratios, which capture semantic distinctions (Firth)

Other Resources of Interest

- **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 data 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

- Firth, J.R. (1957). A Synopsis of Linguistic Theory, 1930-1955.
- Mikolov, T., Chen, K., Corrado, G.S., & Dean, J. (2013a). Efficient Estimation of Word Representations in Vector Space. *International Conference on Learning Representations.*
- Mikolov, T., Sutskever, I., Chen, K., Corrado, G.S., & Dean, J. (2013b). Distributed Representations of Words and Phrases and their Compositionality. *ArXiv, abs/1310.4546.*
- Pennington, J., Socher, R., & Manning, C.D. (2014). GloVe: Global Vectors for Word Representation. *Conference on Empirical Methods in Natural Language Processing.*
- Bojanowski, P., Grave, E., Joulin, A., & Mikolov, T. (2017). Enriching word vectors with subword information. *Transactions of the association for computational linguistics.*
- Mikolov, T., Grave, E., Bojanowski, P., Puhrsch, C., & Joulin, A. (2018). Advances in pre-training distributed word representations. *International Conference on Language Resources and Evaluation.*