

Neural Word Embeddings

Antoine Bosselut

Announcements

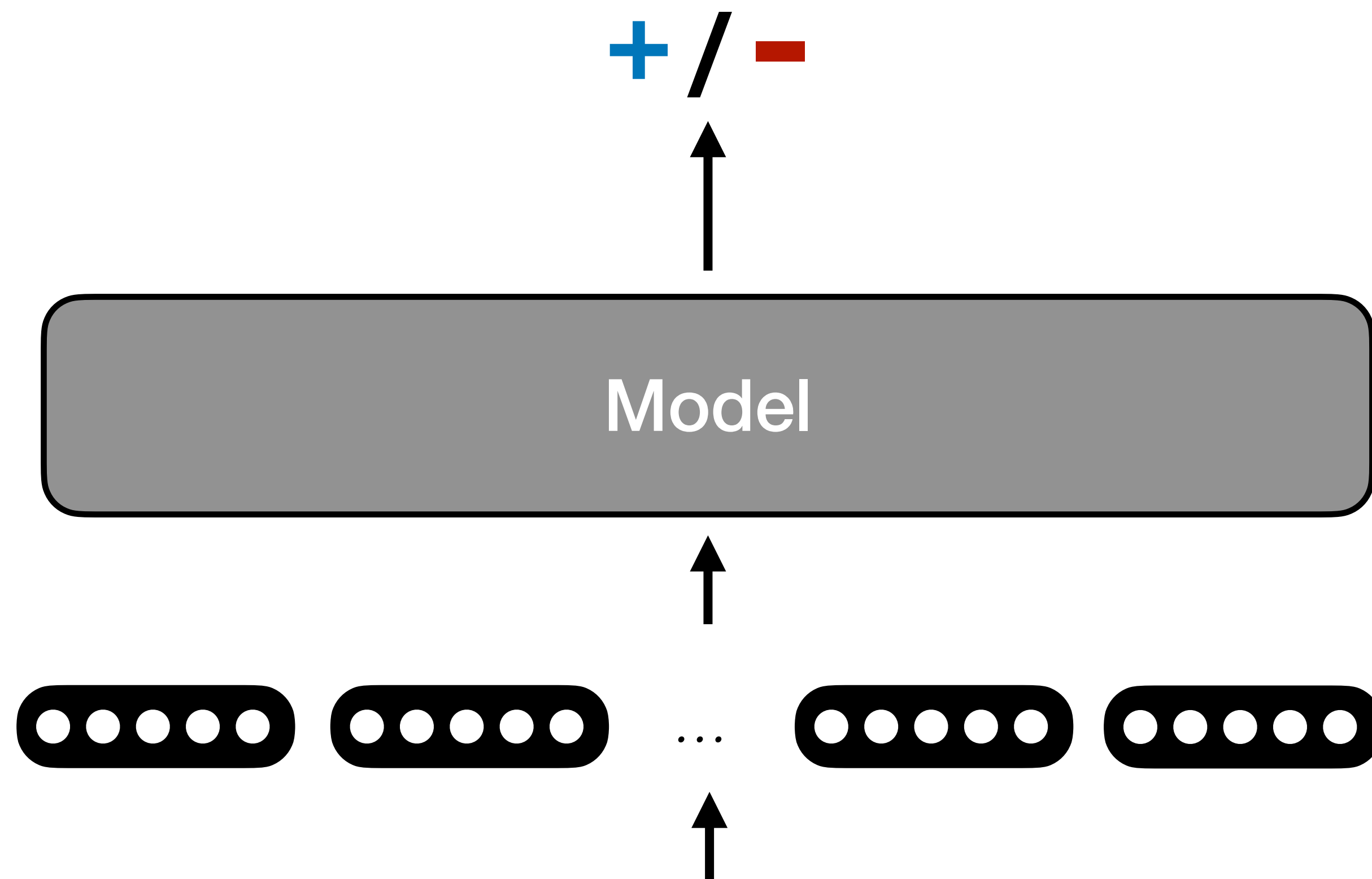
- Lectures are being recorded and MediaSpace channel will be posted to the course website
- Projects should be done in teams of 4
- Yes, you can audit the class, but project milestones won't be graded and can't guarantee access to resources

Today's Outline

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

Word Representations

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



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?
 - Week 11 - 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 $\langle \text{UNK} \rangle$ token (i.e., “unknown”).

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>I</i> | → | <i>[0 ... 0 0 0 1 ... 0 0]</i> |
| <i>really</i> | → | <i>[0 ... 1 ... 0 0 0 0 0]</i> |
| <i>enjoyed</i> | → | <i>[0 ... 0 0 0 1 0 ... 0]</i> |
| <i>the</i> | → | <i>[0 ... 0 1 0 0 0 ... 0]</i> |
| <i>movie</i> | → | <i>[0 ... 0 0 0 0 0 ... 1]</i> |
| <i>!</i> | → | <i>[1 ... 0 0 0 0 0 0 0 0]</i> |

Problem: sparse embeddings

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

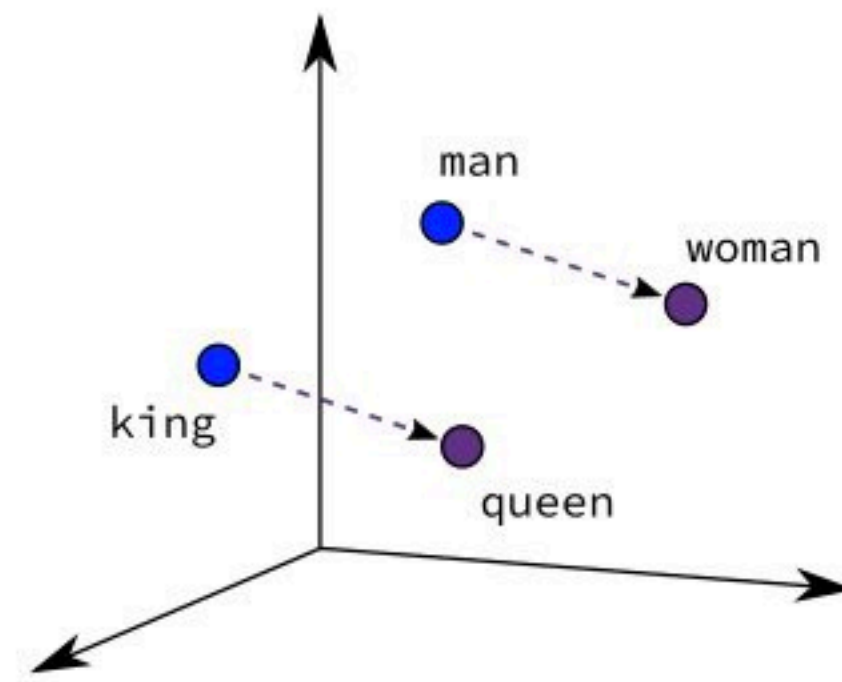
How do you learn similarity between words?

enjoyed \longrightarrow $[0 \dots 0 \ 0 \ 0 \ 1 \dots 0 \ 0]$

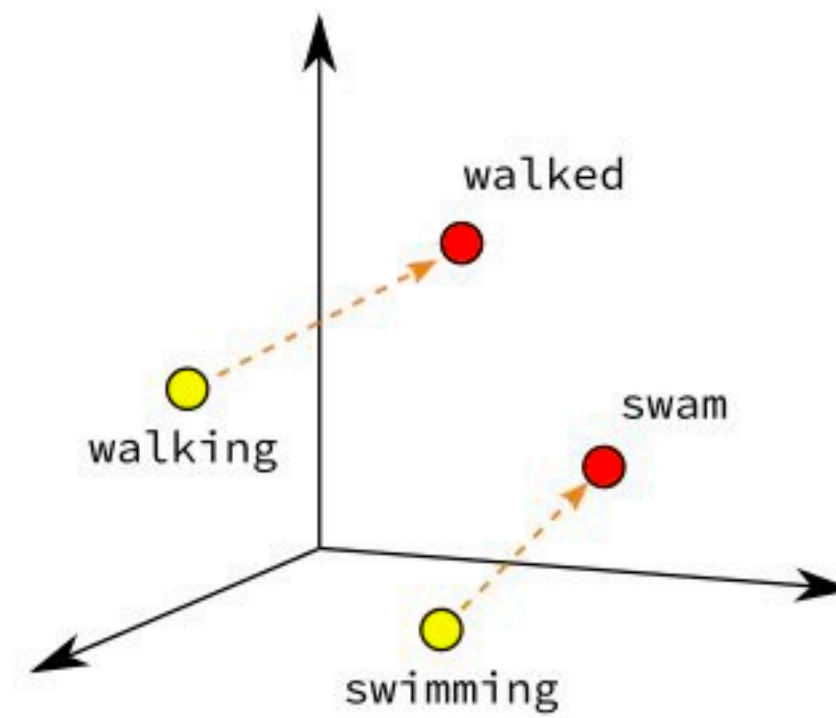
loved \longrightarrow $[0 \dots 1 \dots 0 \ 0 \ 0 \ 0 \ 0]$

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

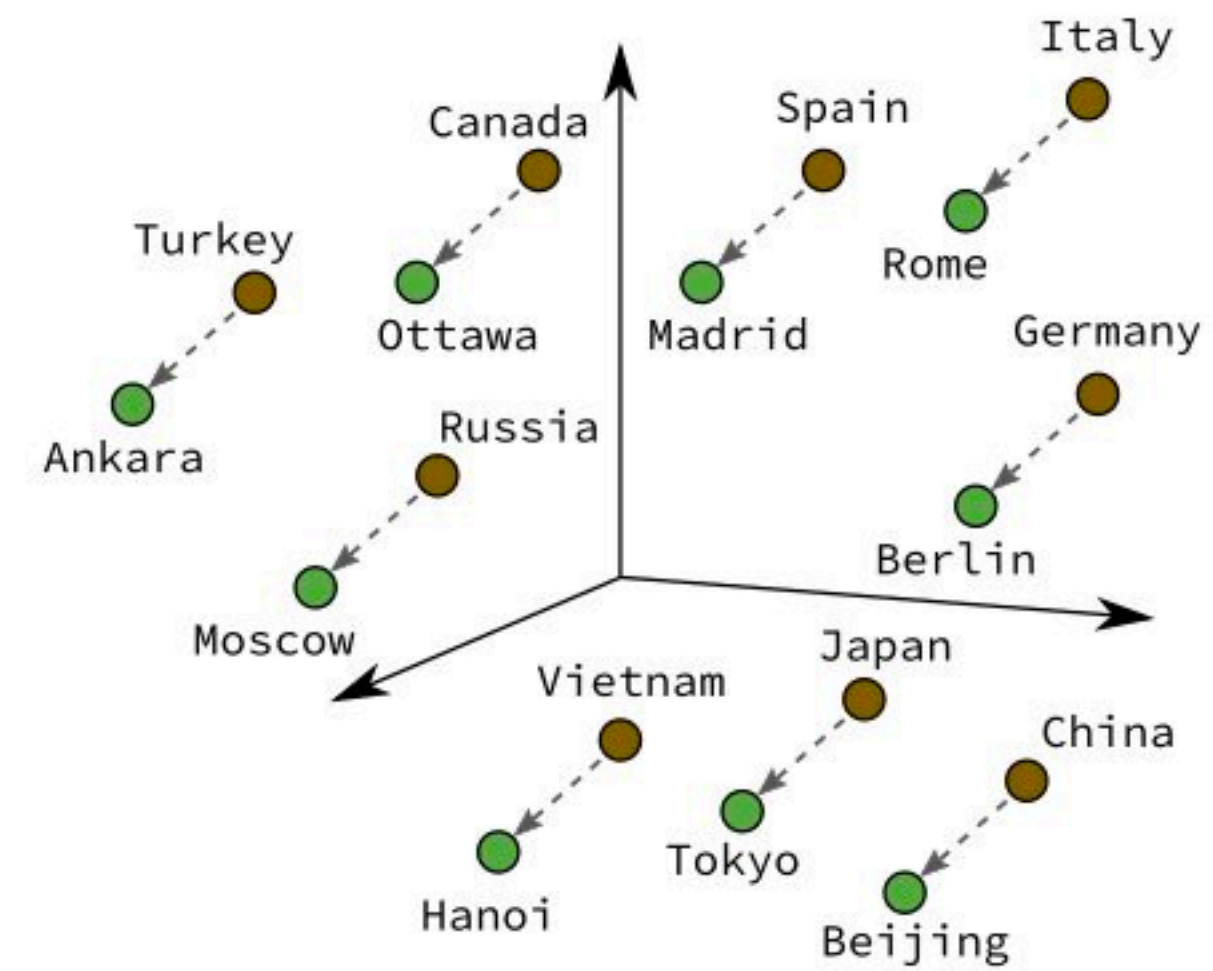
Embeddings Goal



Male-Female



Verb Tense



Country-Capital

How do we train semantics-encoding embeddings of words?

Dense Embeddings

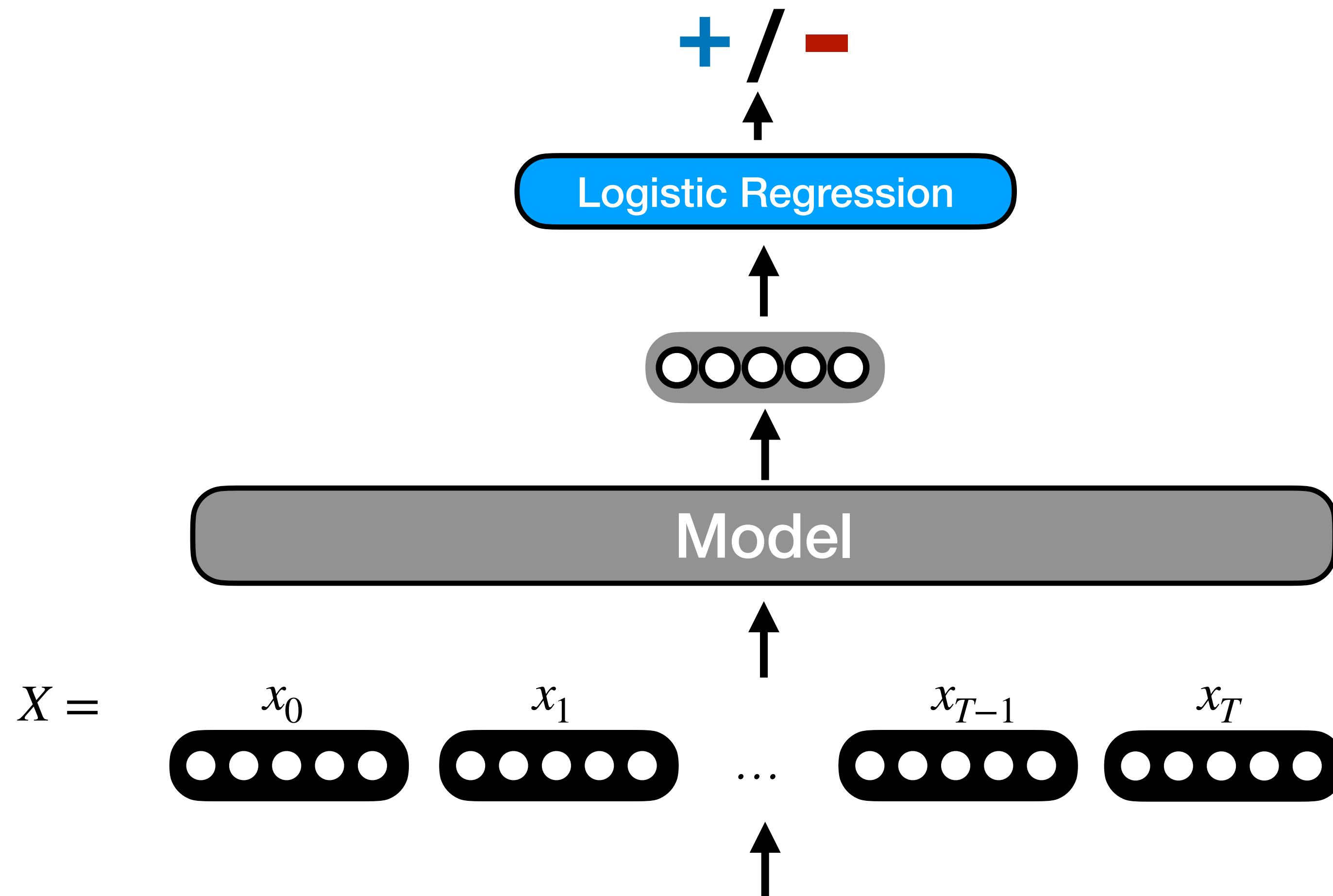
- Represent each word as a high-dimensional*, **real-valued** vector
 - *Low-dimensional compared to V-dimension sparse representations, but still usually $O(10^2 - 10^3)$

| | | |
|---------|---|--|
| 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!

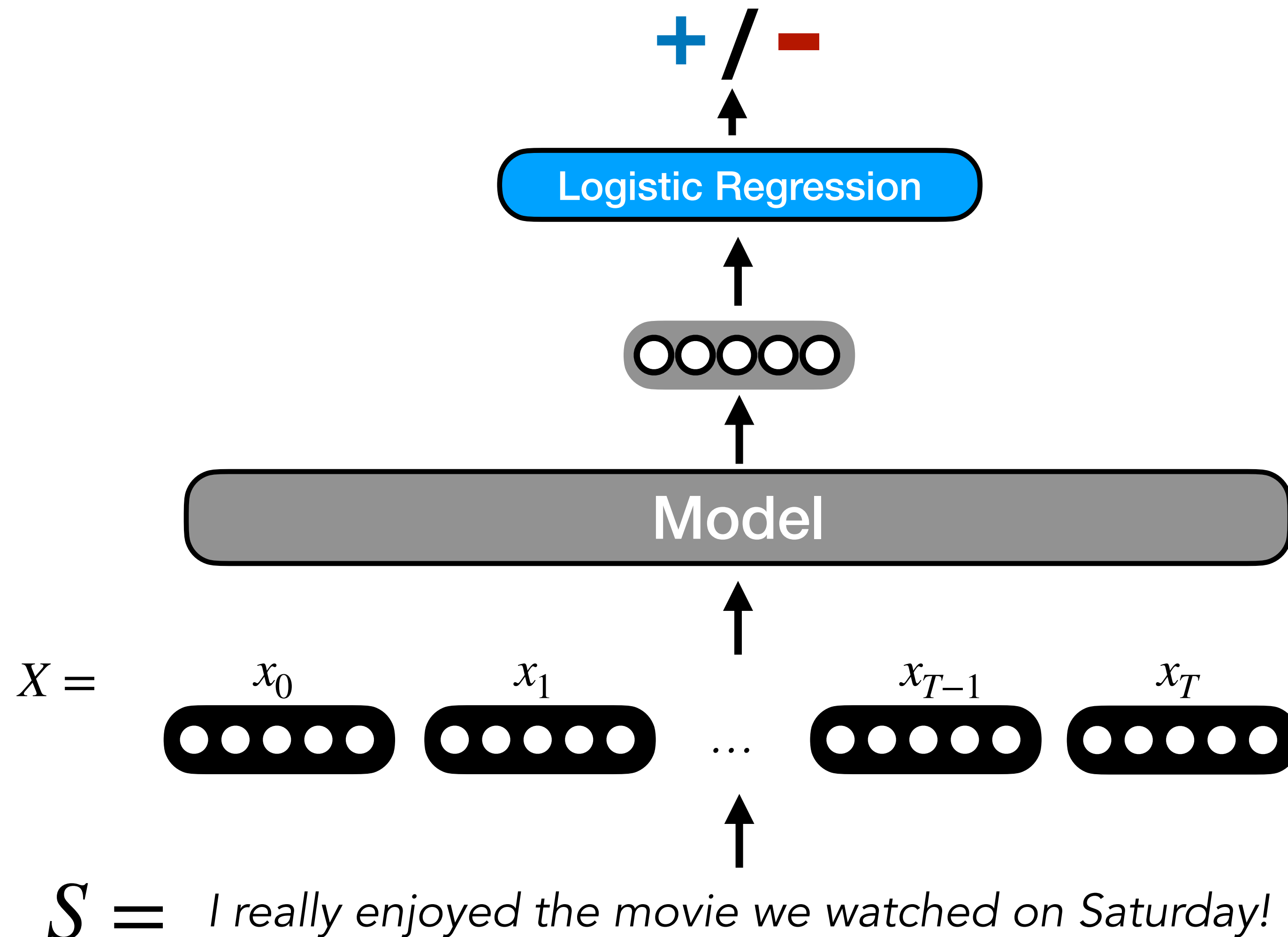


Learn using **backpropagation**:
compute gradients of loss with
respect to initial embeddings X

Learn embeddings that allow you
to do the task successfully!

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

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.

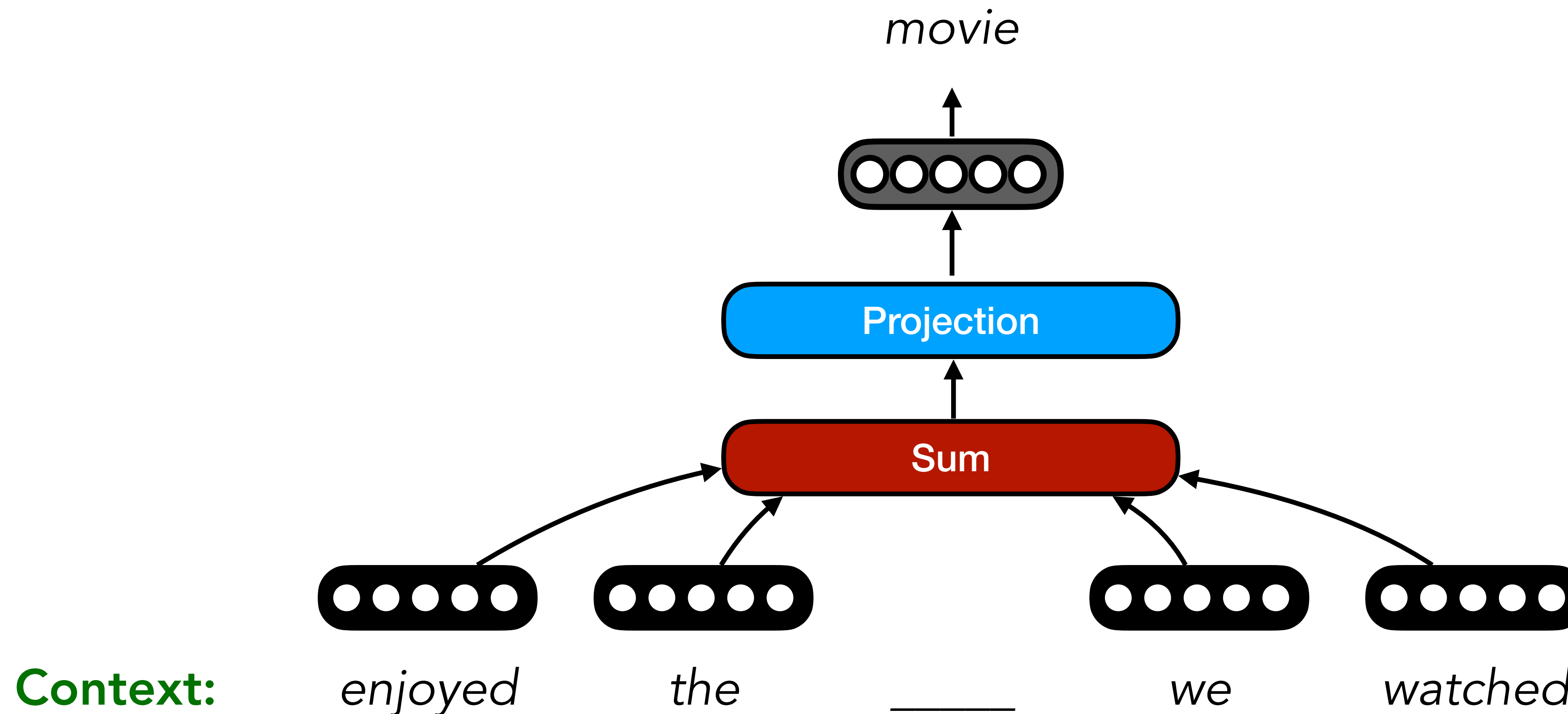
Foundation of **distributional semantics**

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**
 - Not covered today

Continuous Bag of Words (CBOW)

- Predict the missing word from a window of surrounding words



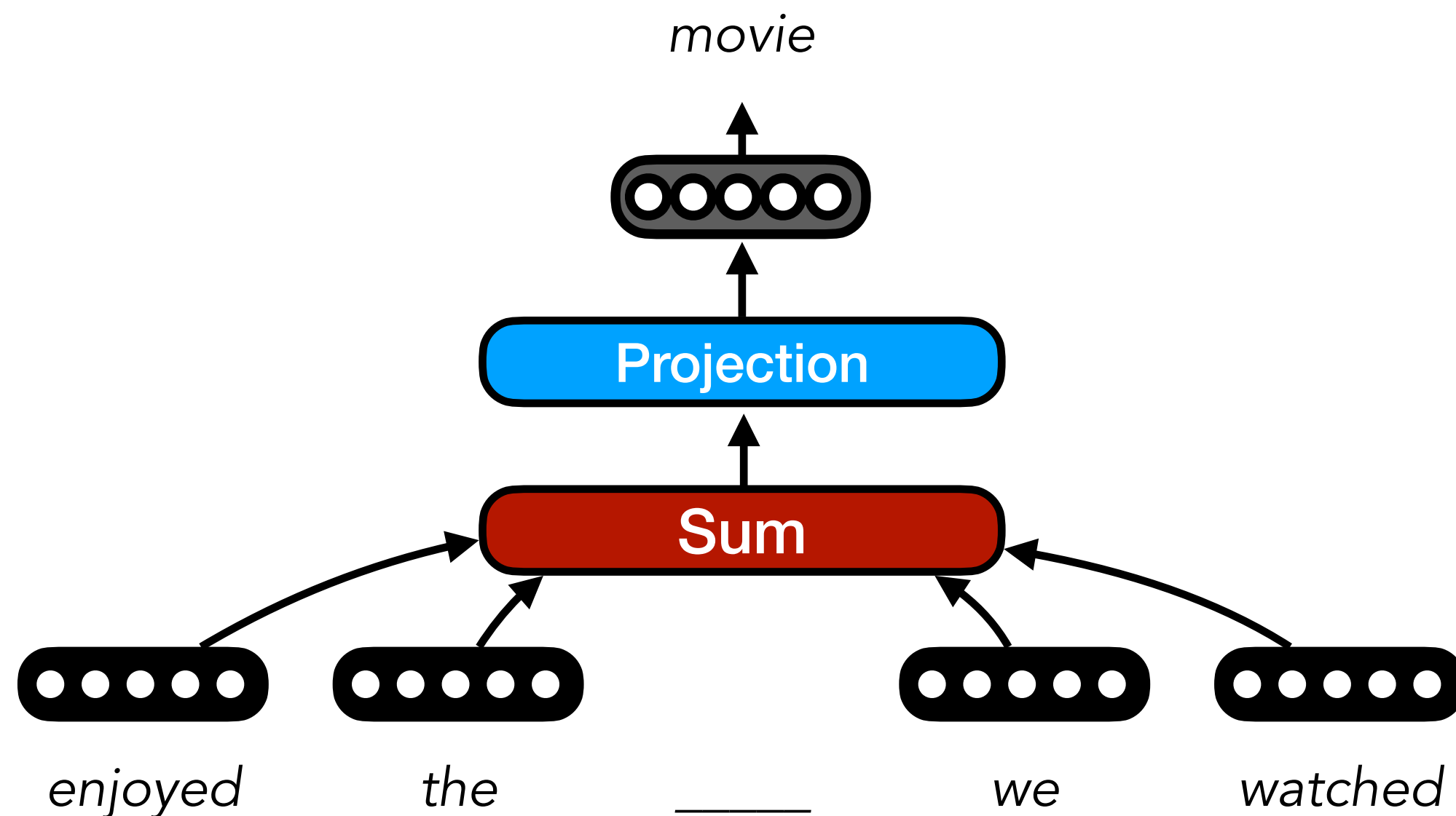
Continuous Bag of Words (CBOW)

- Predict the missing word from a window of surrounding words

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

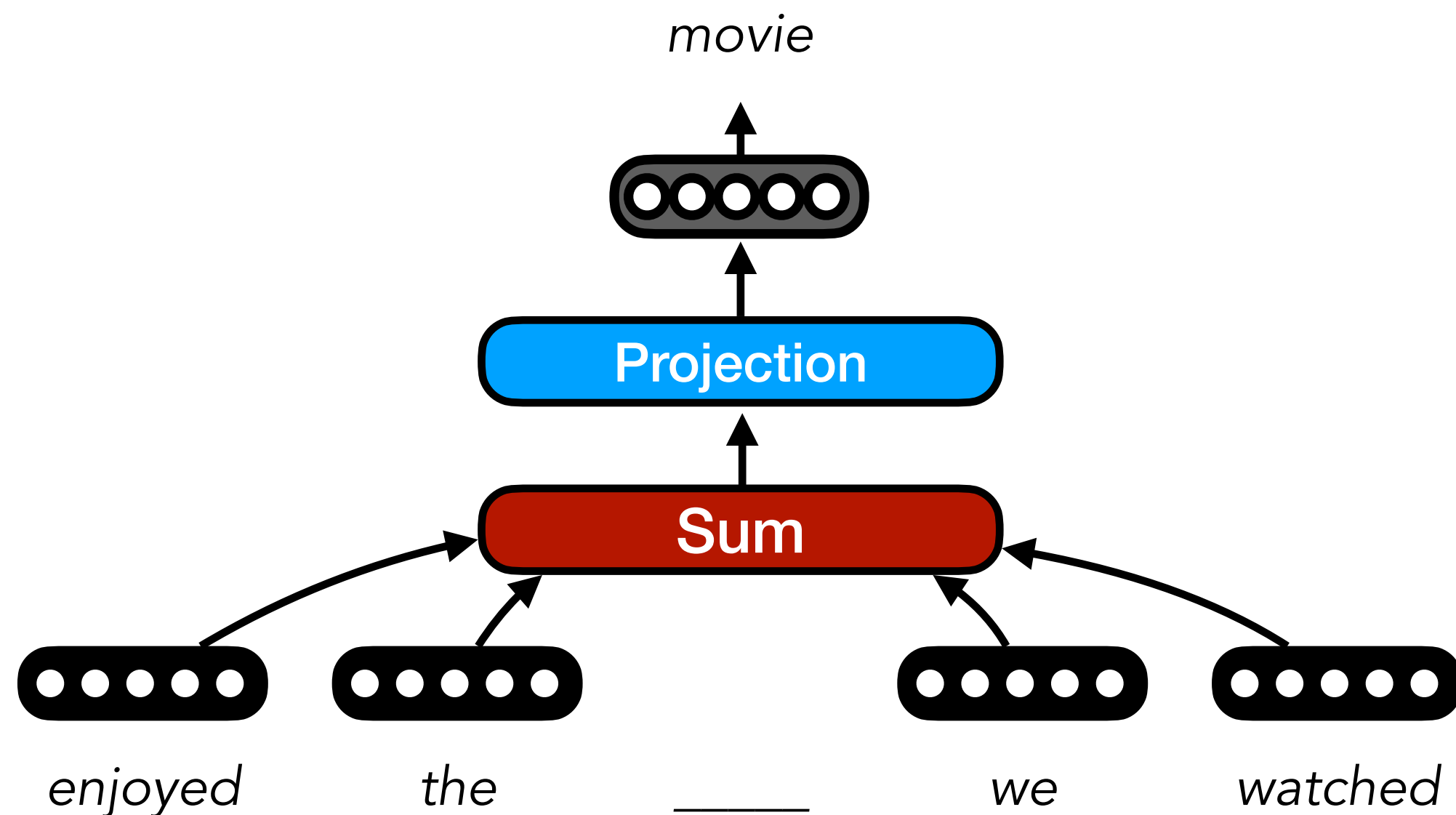
$$\max P(x_t \mid x_{t-2}, x_{t-1}, x_{t+1}, x_{t+2})$$

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



Continuous Bag of Words (CBOW)

- Predict the missing word from a window of surrounding words



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

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

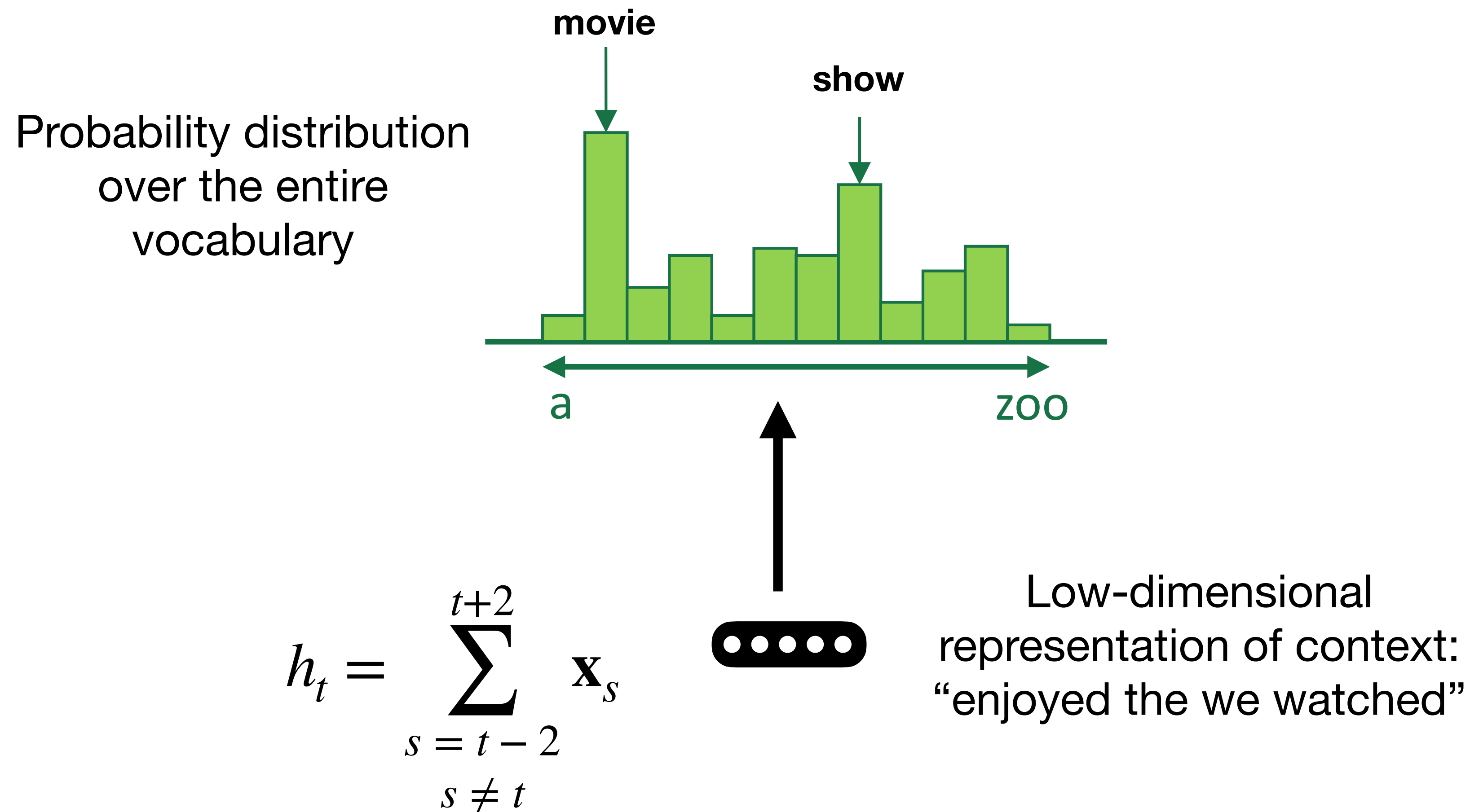


$$\mathbf{U} \in \mathbb{R}^{d \times V}$$

Projection

Vocabulary Space Projection

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



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



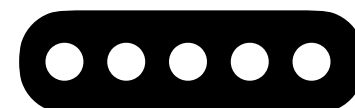
Low-dimensional representation of context:
"enjoyed the we watched"

Let's say our output vocabulary consists of just four words: "movie", "show", "book", and "shelf".

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

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?

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

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

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

How do we get there?

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

intuition: each row of \mathbf{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

$$\mathbf{U}h_t = \langle 1.8, -11.9, 12.9, -8.9 \rangle$$

How did we compute this?
It's just the dot product of
each row of \mathbf{U} with h_t

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

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

$$\mathbf{U}h_t = \langle 1.8, -11.9, 12.9, -8.9 \rangle$$

How did we compute this?
It's just the dot product of
each row of \mathbf{U} with h_t

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

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

$$\mathbf{U}h_t = \langle 1.8, -11.9, 12.9, -8.9 \rangle$$

How did we compute this?
It's just the dot product of
each row of \mathbf{U} with h_t

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

$$\begin{aligned} &1.2 * -2.3 \\ &+ -0.3 * 0.9 \\ &+ 0.9 * 5.4 \end{aligned}$$

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

Softmax

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

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

- \mathbf{a} is a vector
- a_i is dimension i of \mathbf{a}
- each dimension i of the softmaxed output represents the probability of class i

Softmax

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

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

- \mathbf{a} is a vector
- a_i is dimension i of \mathbf{a}
- each dimension i of the softmaxed output represents the probability of class i

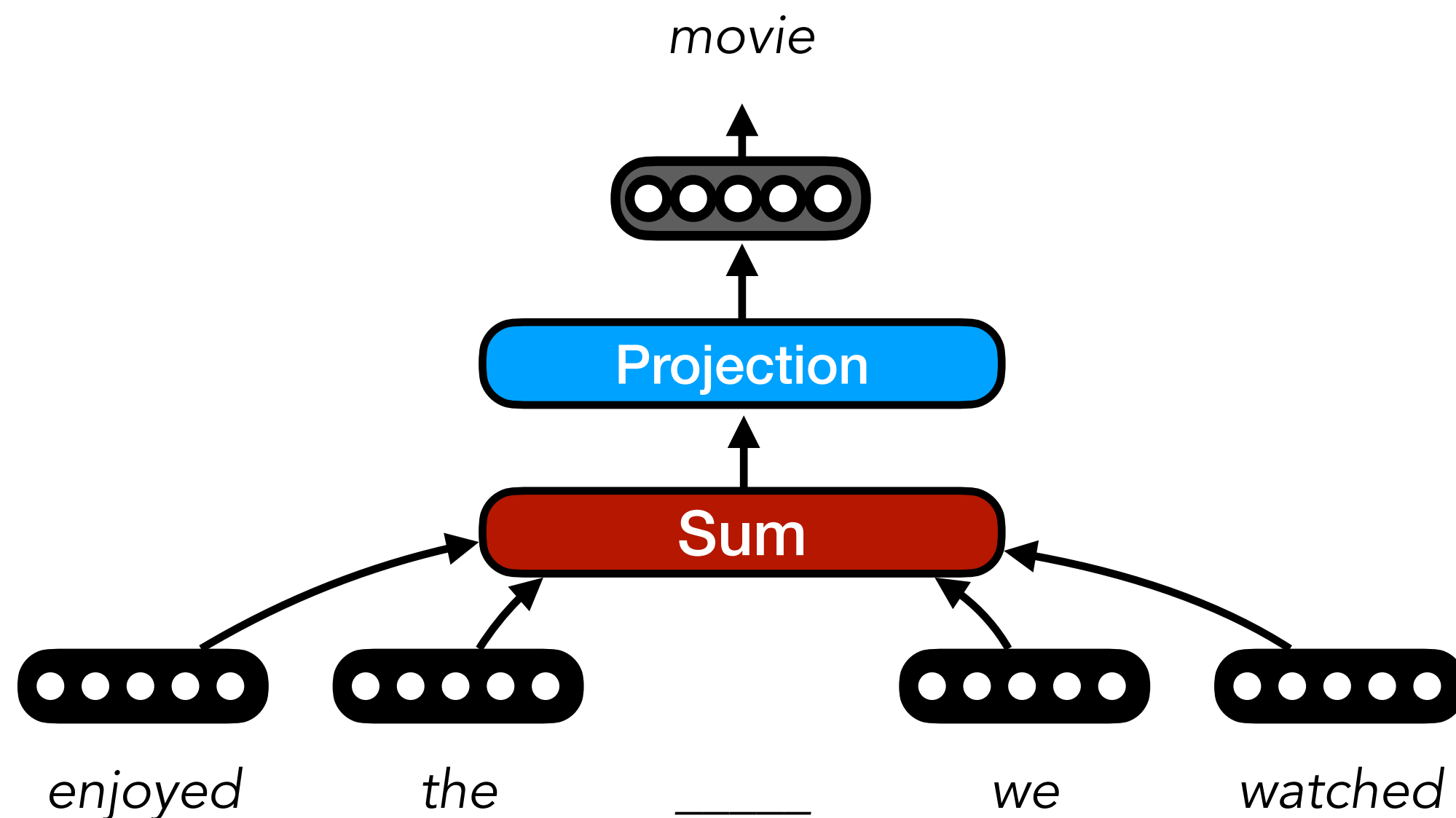
$$\mathbf{U}h_t = \langle 1.8, -1.9, 2.9, -0.9 \rangle$$

$$\mathbf{softmax}(\mathbf{U}h_t) = \langle 0.24, 0.006, 0.73, 0.02 \rangle$$

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



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

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

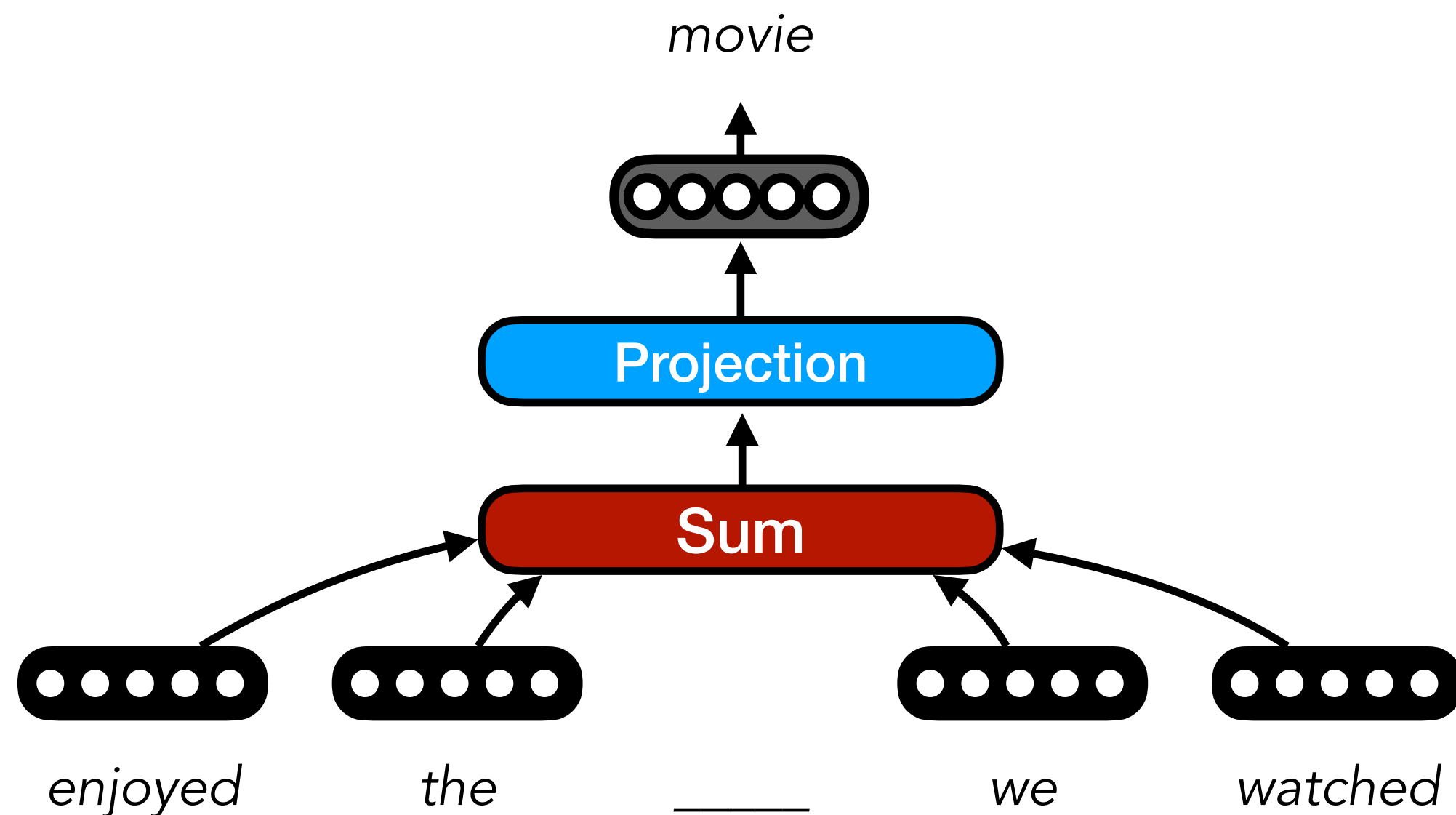
A single word vector representation, depicted as a black capsule containing five white dots.

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

Projection

Continuous Bag of Words (CBOW)

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

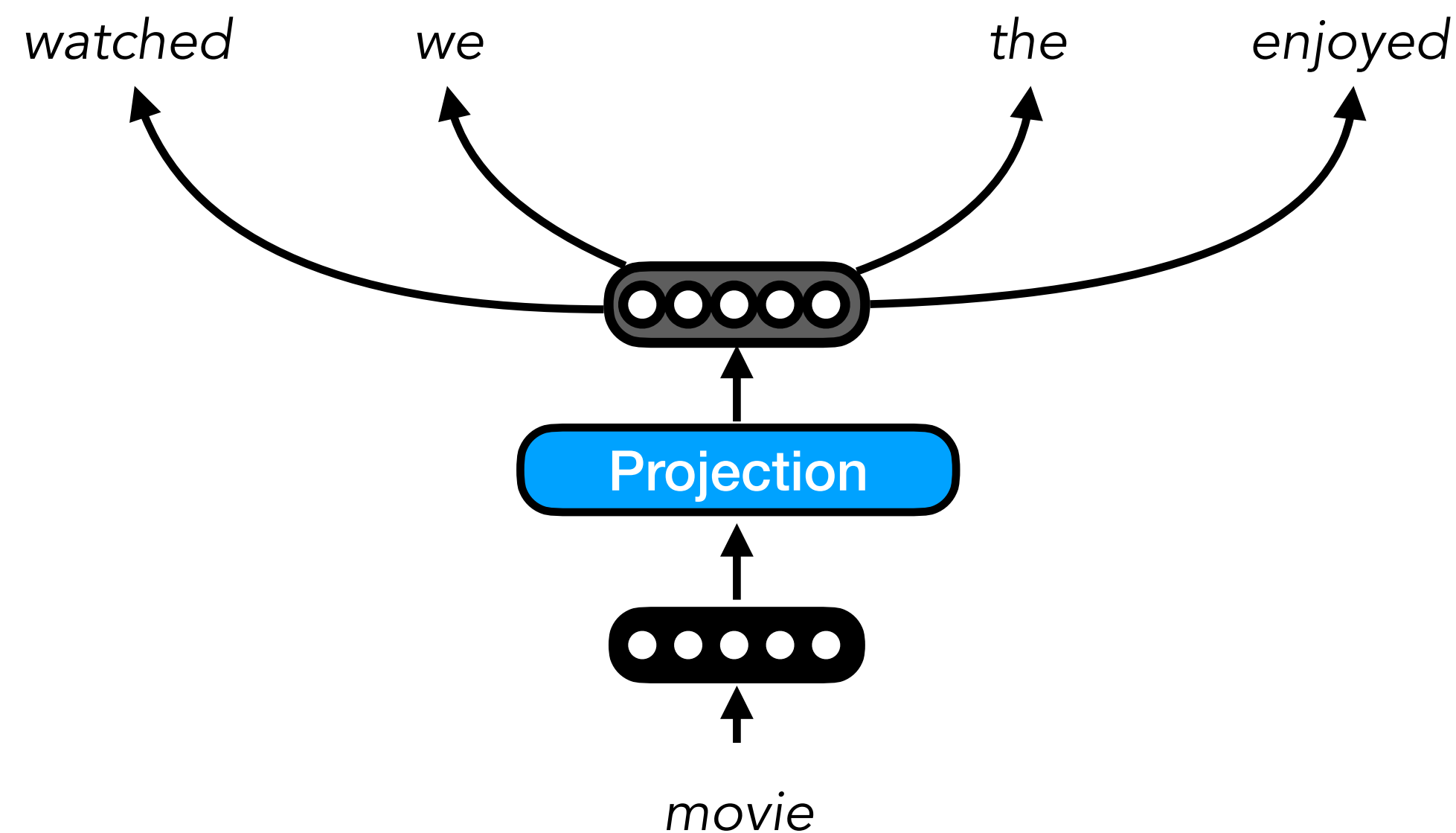


- Model is trained to **maximise** the **probability** of the missing word
 - For computational reasons, the model is typically trained to **minimise** the **negative log probability** of the missing word
- Here, we use a window of **N=2**, but the window size is a **hyperparameter**
- For computational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

Skip-gram

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

Context:



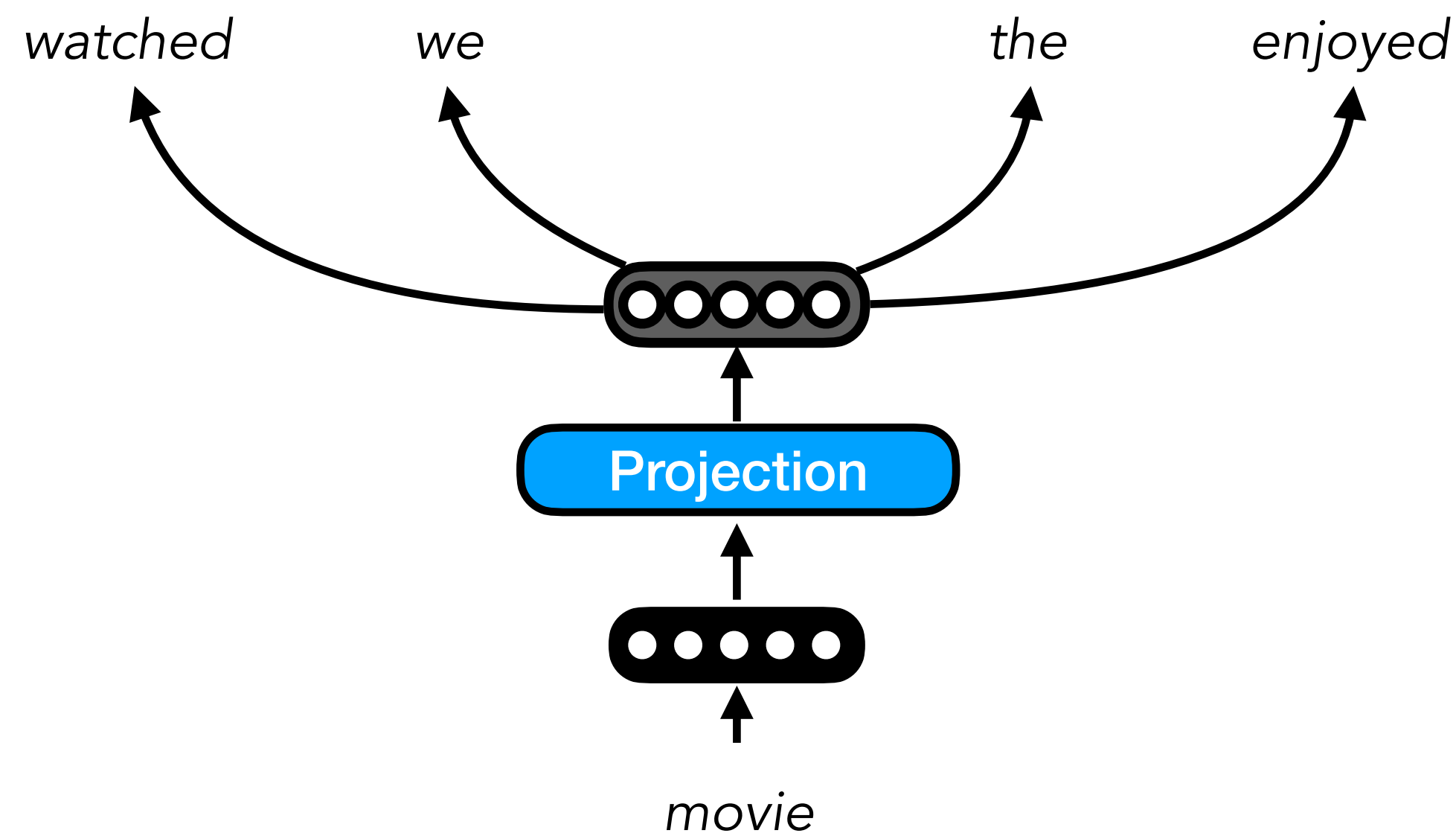
$$\max P(\textit{enjoyed}, \textit{the}, \textit{we}, \textit{watched} \mid \textit{movie})$$

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

Skip-gram

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

Context:



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

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

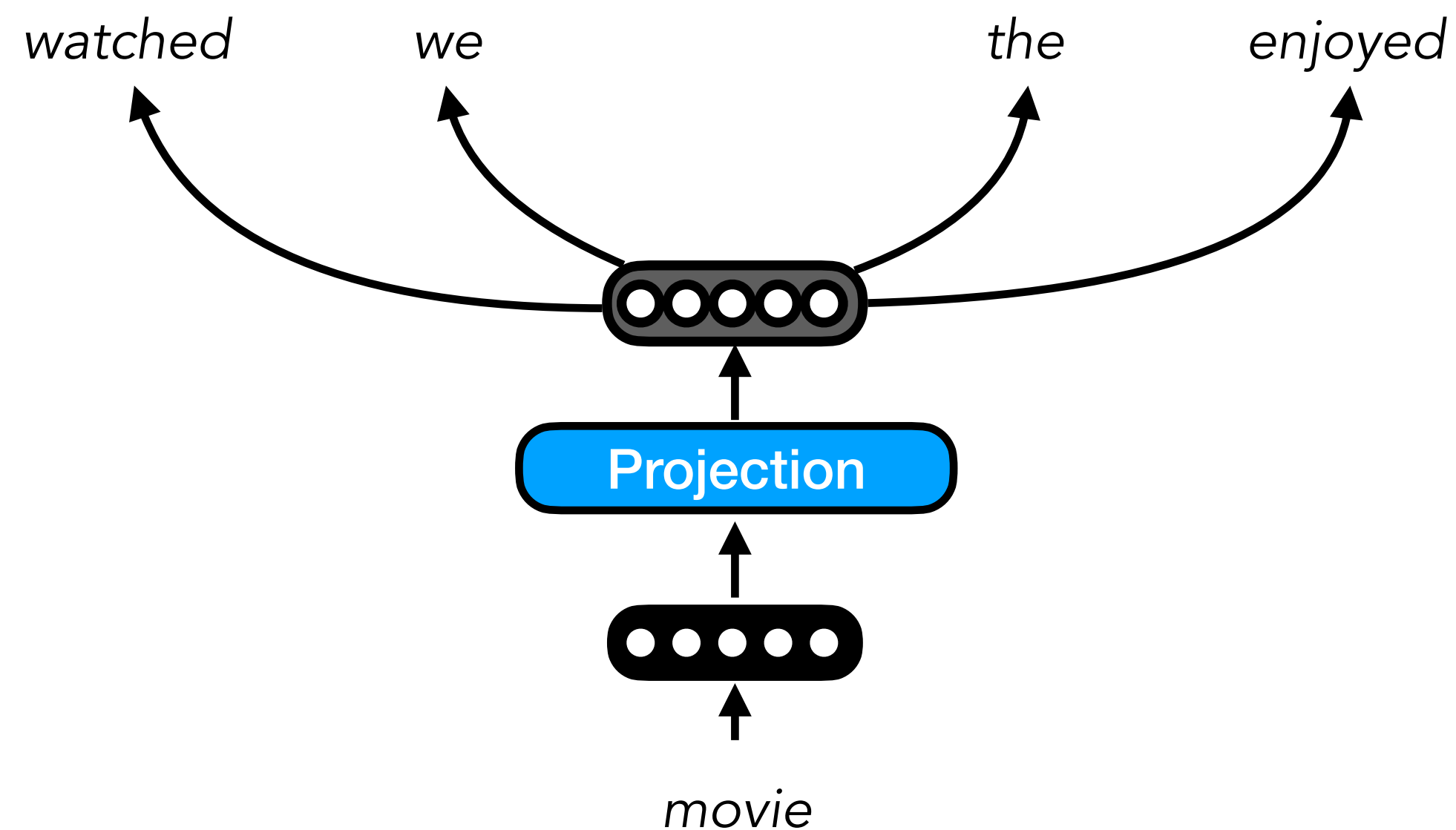
$$= \max \log P(x_{t-2}, x_{t-1}, x_{t+1}, x_{t+2} \mid x_t)$$

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

Skip-gram

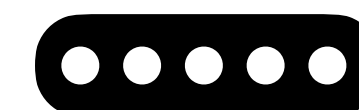
- We can also learn embeddings by predicting the surrounding context from a single word

Context:



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

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



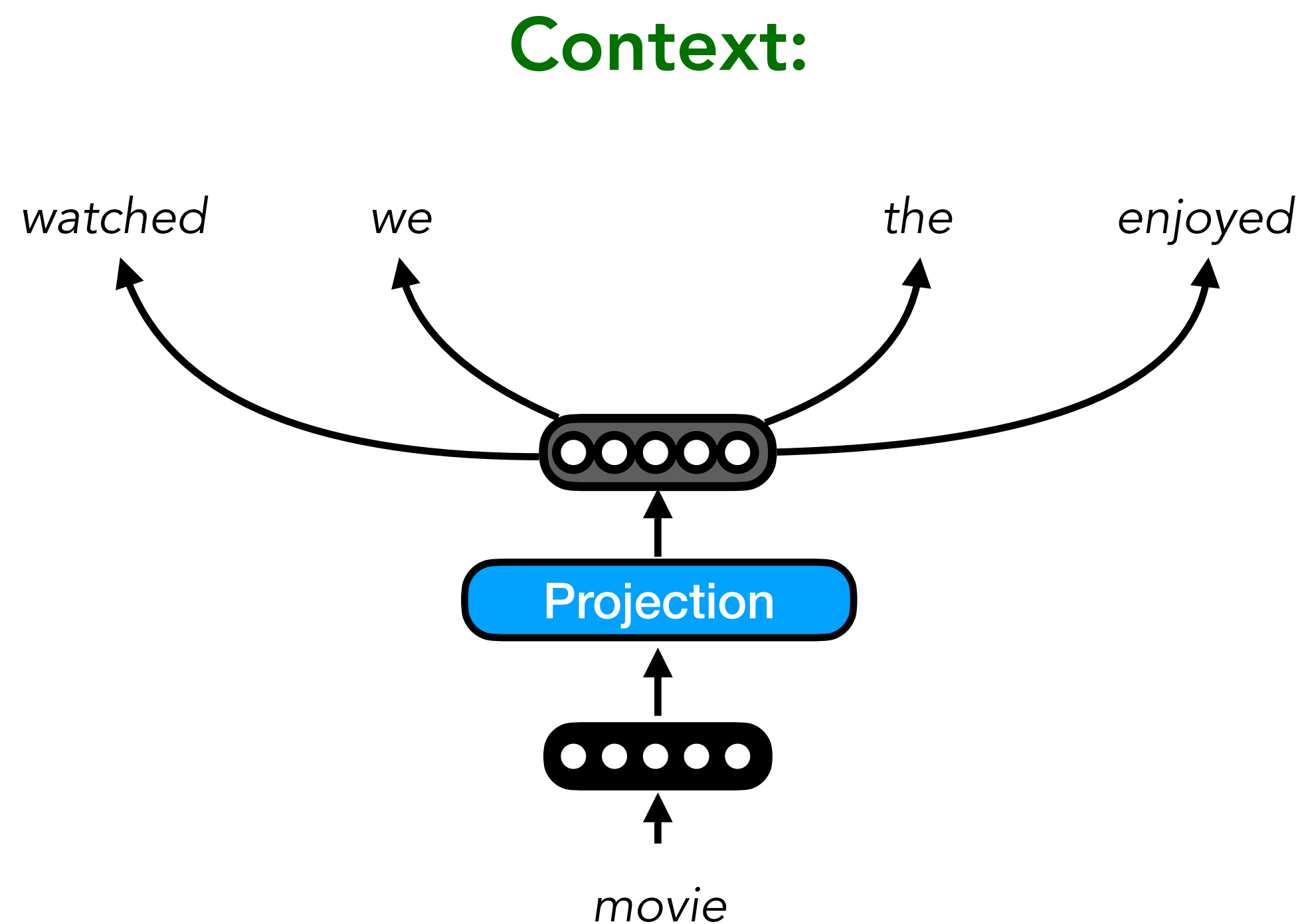
$$\mathbf{U} \in \mathbb{R}^{d \times V}$$

Projection



Skip-gram

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



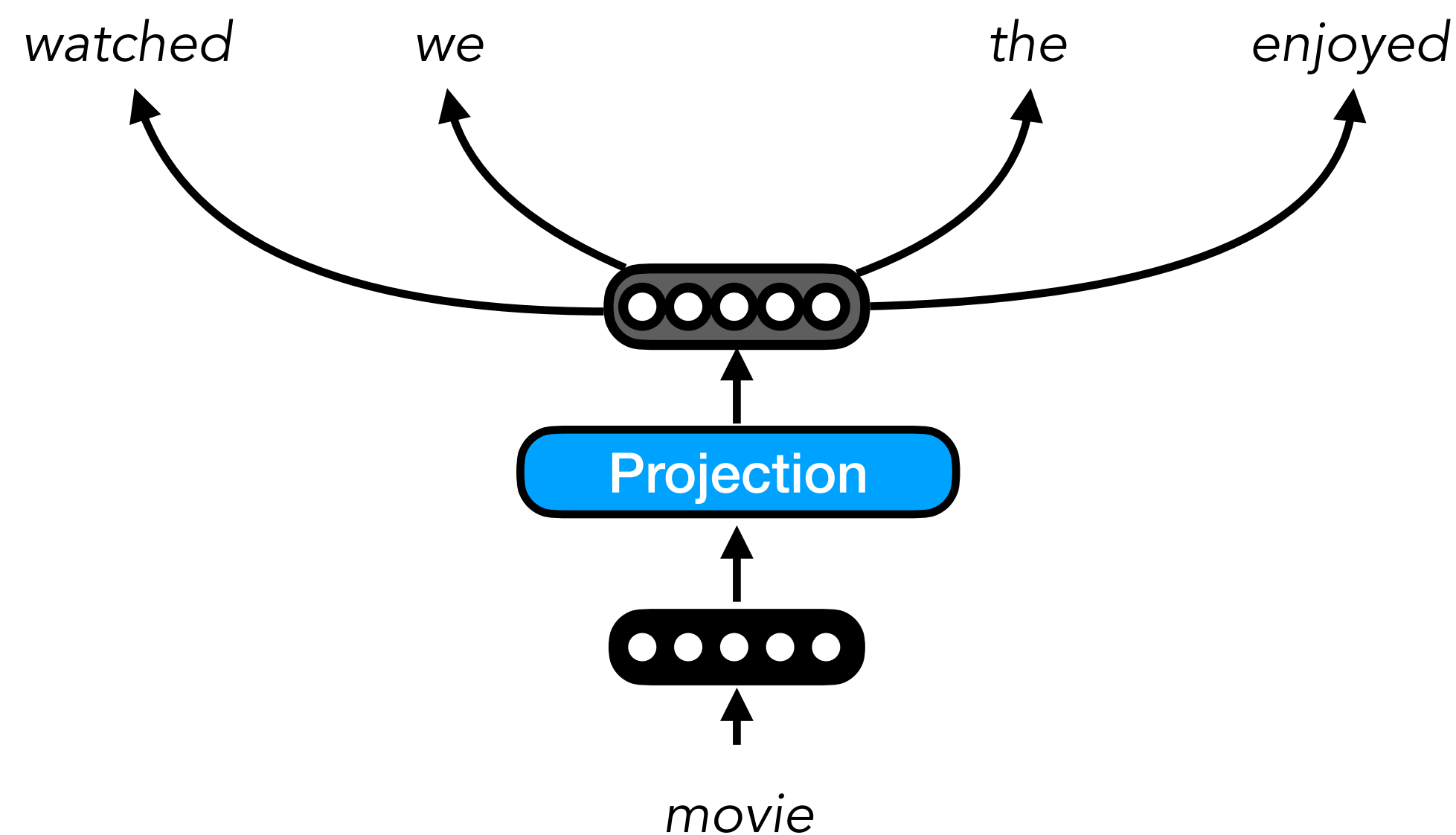
- Model is trained to **minimise** the **negative log probability** of the surrounding words
- Here, we use a window of **N=2**, but the window size is a **hyperparameter**.
 - Larger window = more information about related words in embedding
- Typically, set large window (**N=10**), but randomly select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

Question

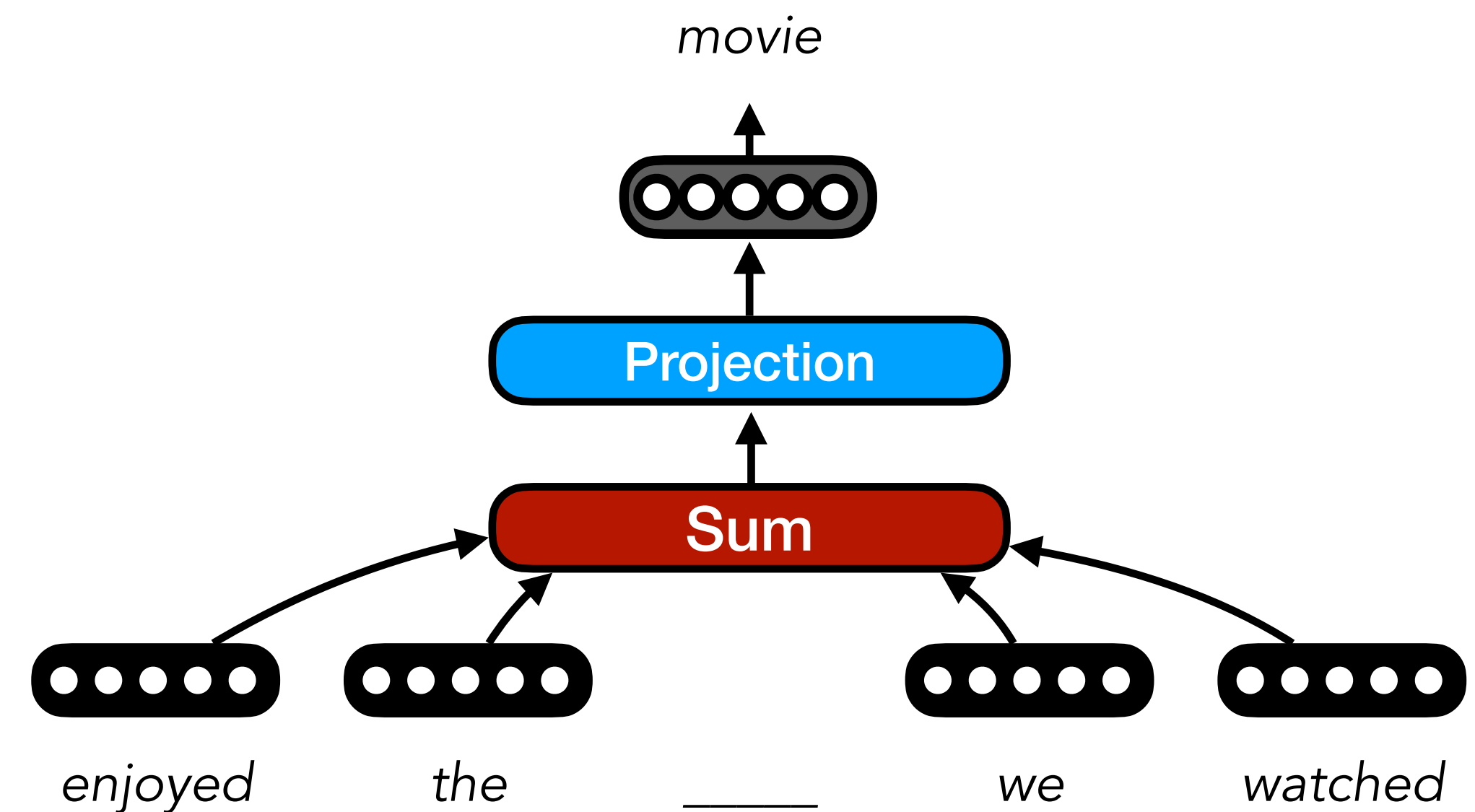
What is the major conceptual difference between the CBOW and Skipgram methods for training word embeddings?

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", "Similarity"])
```

| 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", "Similarity"])
```

| 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 — $\langle \text{where} \rangle = \langle \text{wh}, \text{whe}, \text{her}, \text{ere}, \text{re} \rangle$
- 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](http://www.opendatacommons.org/licenses/pddl/1.0/) 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., Puhersch, C., & Joulin, A. (2018). Advances in pre-training distributed word representations. *International Conference on Language Resources and Evaluation*.