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 4
- Yes, you can audit the class, but project milestones won't be graded and can't guarantee access to resources

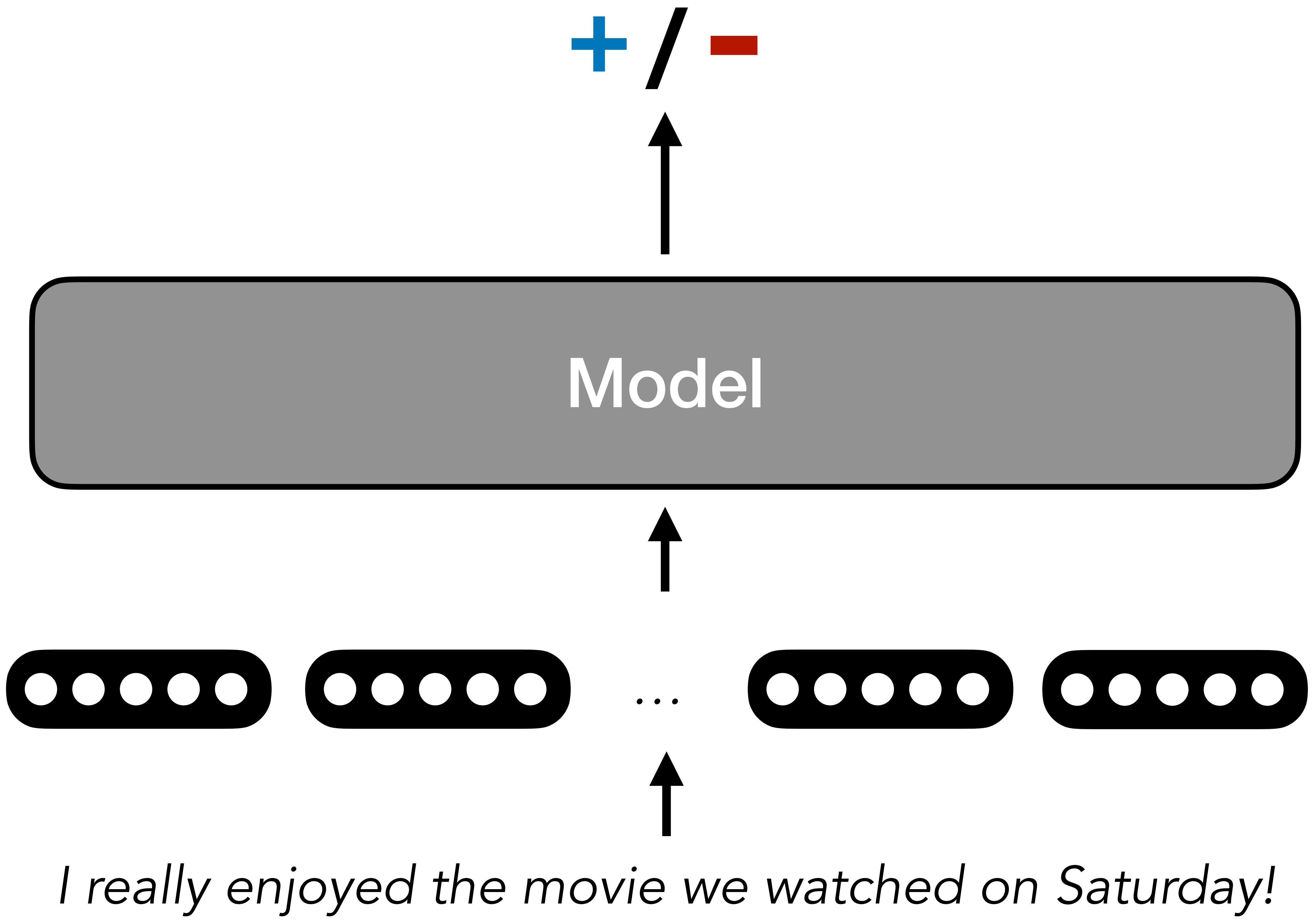
Today’s Outline

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

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**!

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 <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	$\longrightarrow$	[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 0]

Problem: **sparse embeddings**

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

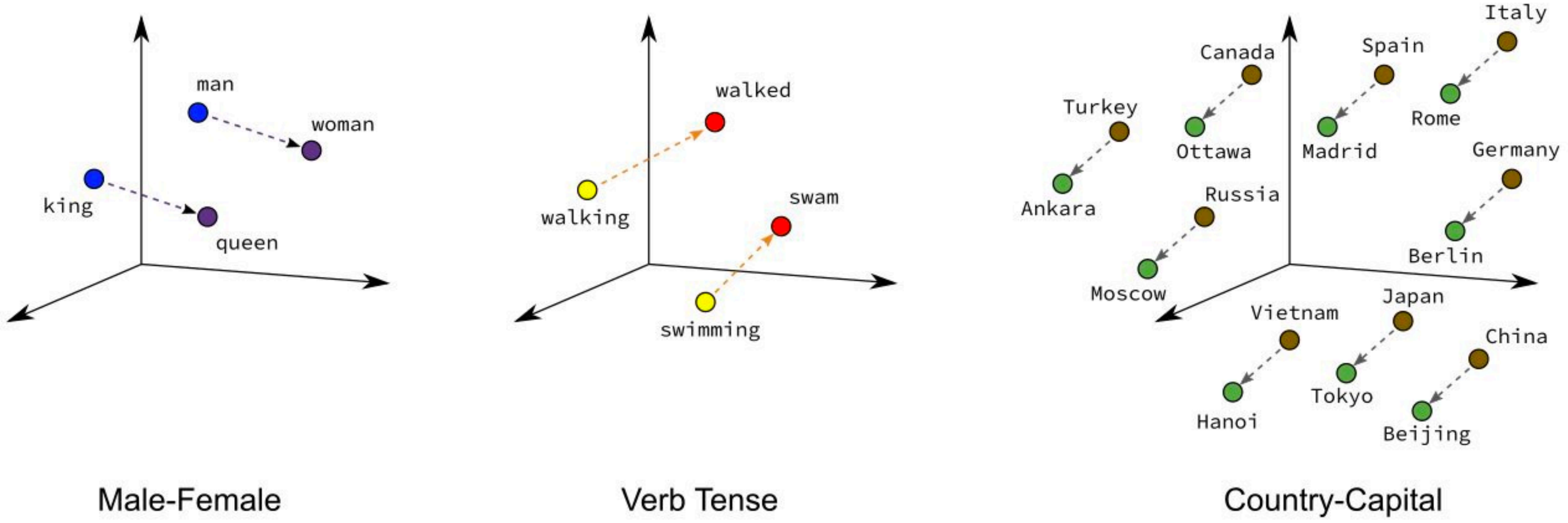
How do you learn learn similarity between words?

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

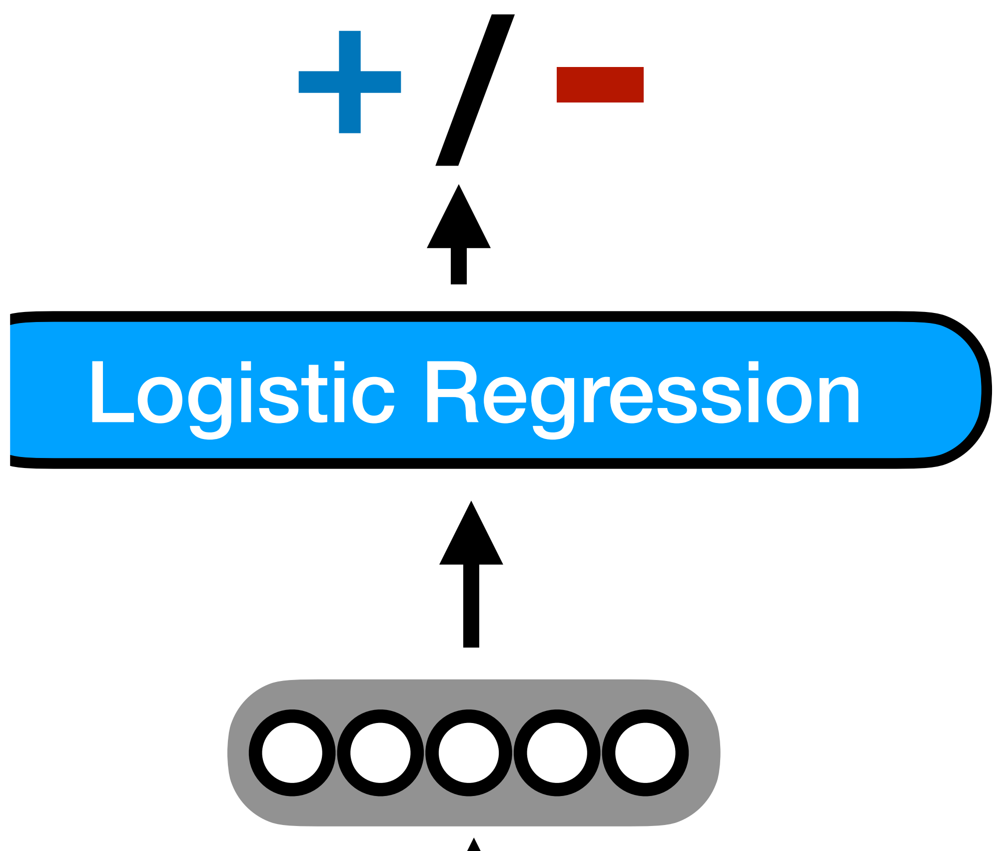
others...

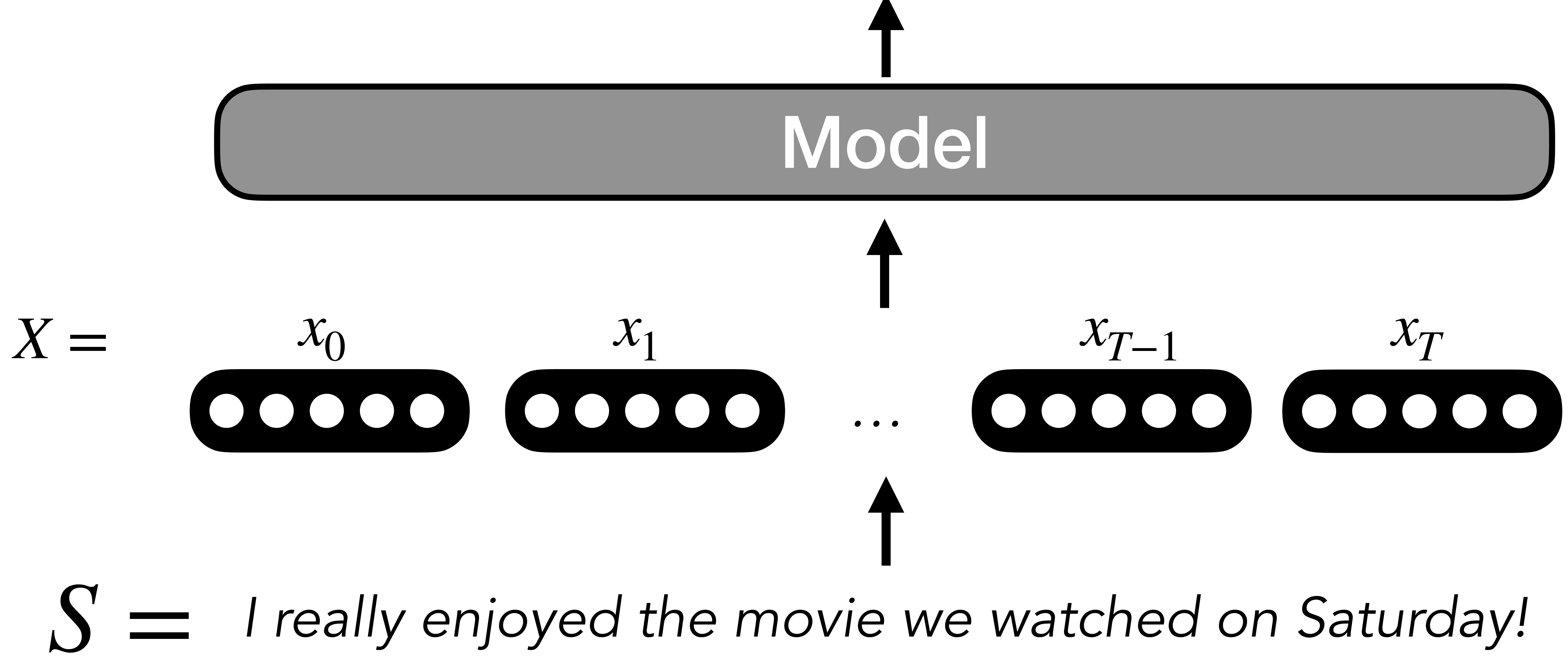
- Similarity of vectors represents similarity of meaning for particular words

Learn embeddings from the task!

What Does It Mean?

1. **"Learn using backpropagation"**
    - Backpropagation is the algorithm used to train neural networks. It updates the embeddings based on how well (or poorly) the model is performing.
2. **"Compute gradients of loss with respect to initial embeddings X"**
    - Initially, word embeddings X are **random** or **pre-trained** (e.g., Word2Vec, GloVe).
    - During training, the model computes the **loss** (how wrong the predictions are).
    - Then, it **calculates gradients** (small changes needed) to improve the embeddings.
    - These gradients tell the model how to slightly adjust the embeddings to minimize the loss.
3. **"Learn embeddings that allow you to do the task successfully!"**
    - The embeddings are **not fixed** but are **optimized** based on the specific task.
    - For example:
        - If the task is **sentiment analysis**, embeddings adjust so that "great" and "excellent" are closer to each other in vector space.
        - If the task is **machine translation**, embeddings adjust so that "dog" (English) and "chien" (French) have similar representations.





Step 1: Initialize embeddings randomly

- Suppose we start with **random** word embeddings for `"great"`, `"bad"`, and `"movie"`.

Step 2: Train the model using backpropagation

- We feed in labeled data (e.g., `"great movie" → Positive`, `"bad movie" → Negative`).
- The model makes predictions and computes **loss** (error).
- **Backpropagation** updates the embeddings to **improve classification**.

Step 3: Adjust embeddings

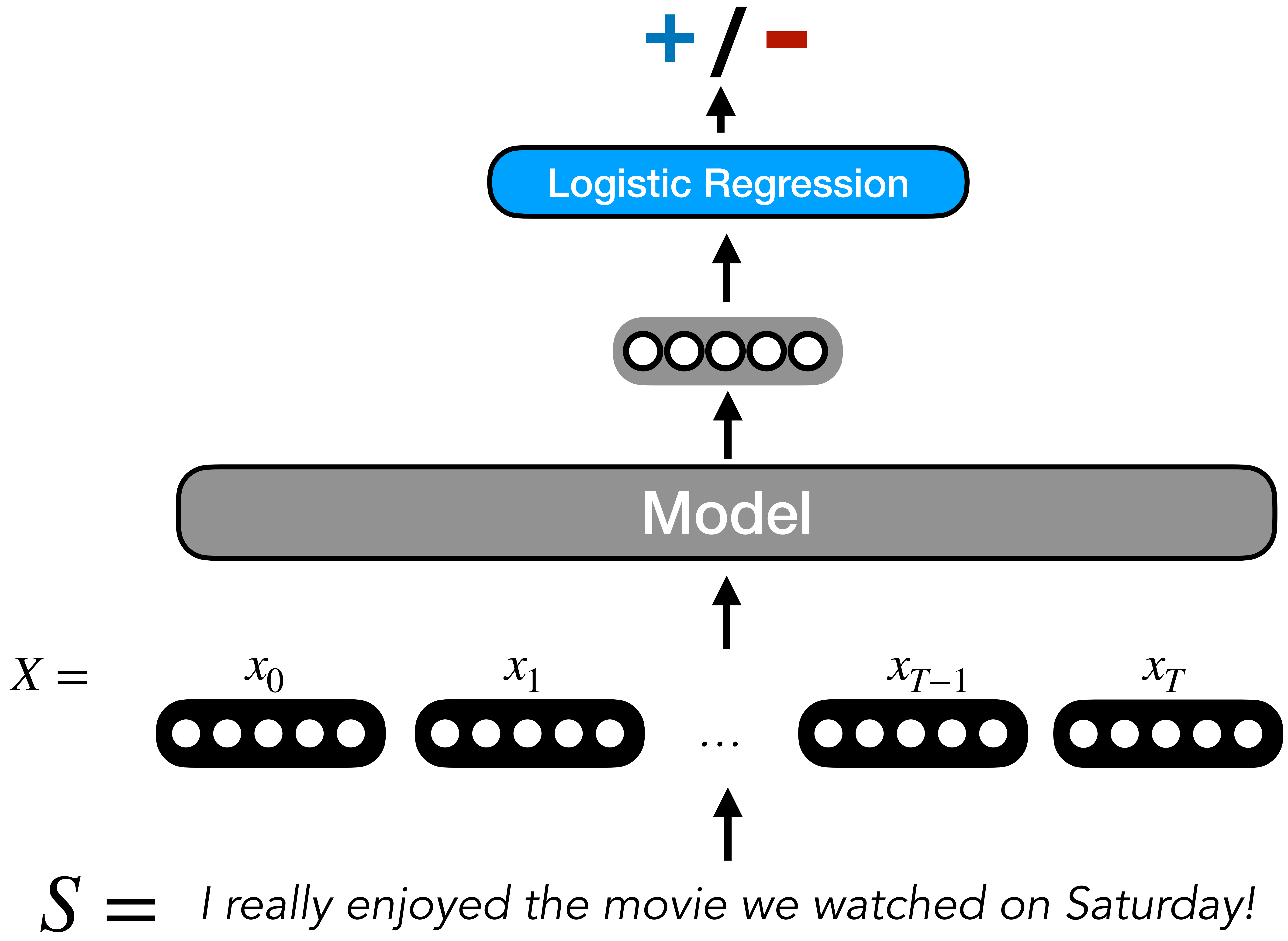
- After training, `"great"` and `"amazing"` will have **similar embeddings**, while `"bad"` and `"terrible"` will be **closer** in the vector space.

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

Learn embeddings that allow you to do the task successfully!

✔ **Embeddings are not static; they are learned based on the task.**
✔ **Backpropagation adjusts embeddings to minimize loss and improve performance.**
✔ **Final embeddings encode task-specific relationships between words.**

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

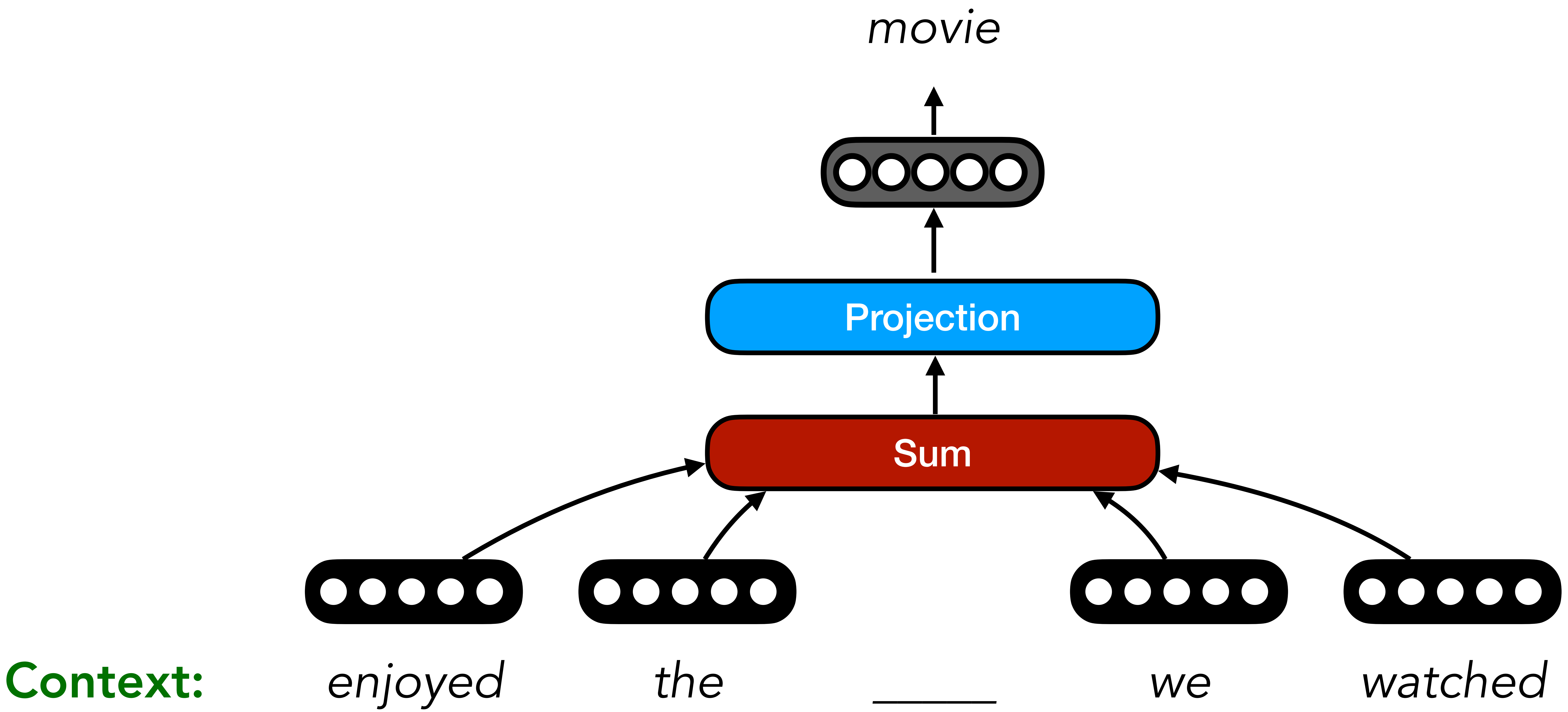
Learning Word Embeddings

- 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

(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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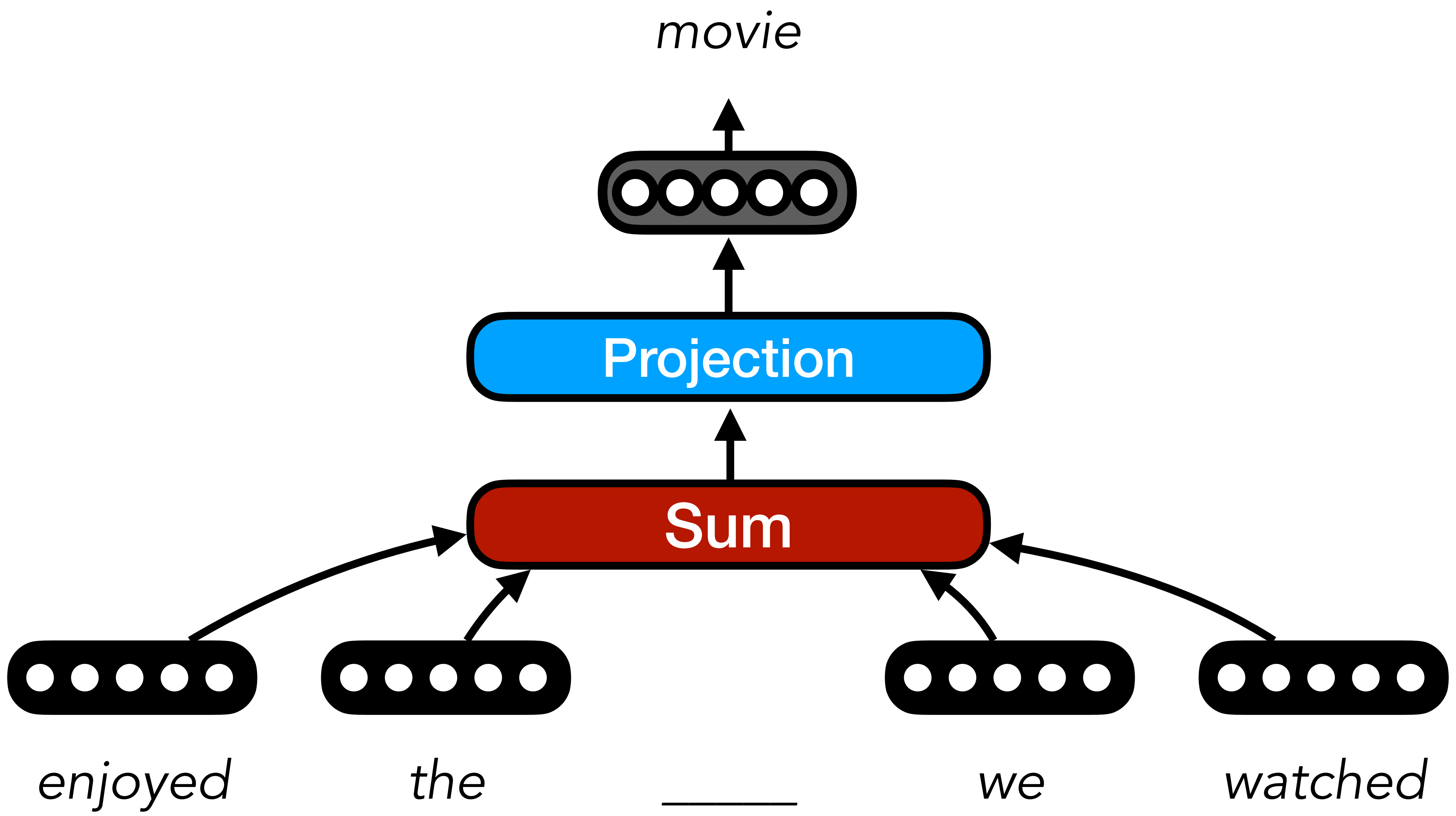

$$\max P(movie \mid enjoyed, the, we, watched)$$

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

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

(Mikolov et al., 2013a)

Continuous Bag of Words (CBOW)

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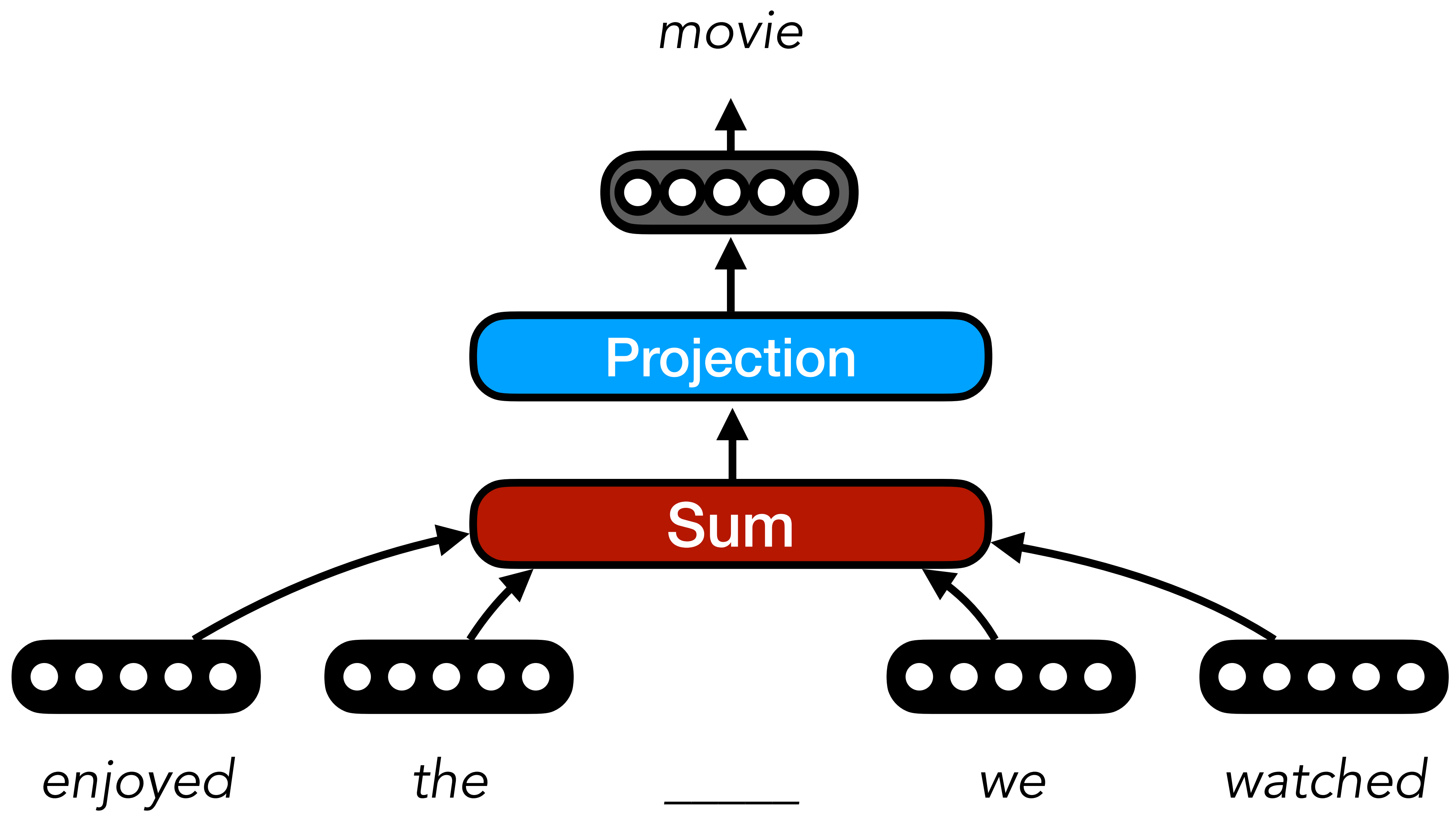
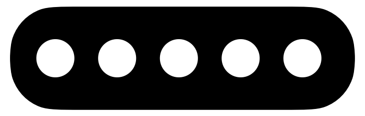


$$P(x_t \mid \{x_s\}_{s=t-2}^{s=t+2}) = \textbf{softmax}\left(\mathbf{U} \sum_{\substack{s=t-2 \\ s \neq t}}^{t+2} \mathbf{x}_s\right)$$

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



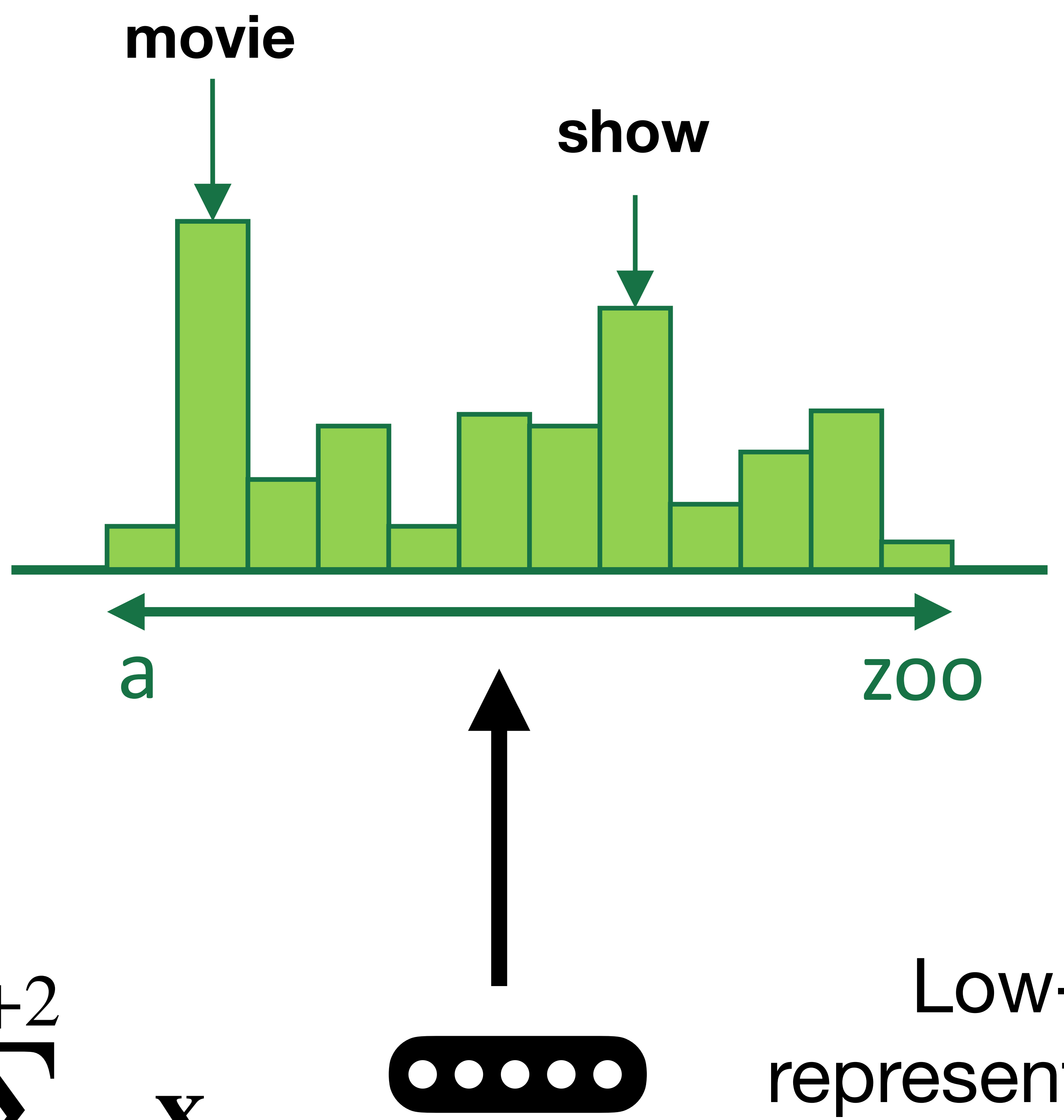
$$\mathbf{U} \in \mathbb{R}^{d \times V}$$

(Mikolov et al., 2013a)

Vocabulary Space Projection

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

Probability distribution over the entire vocabulary

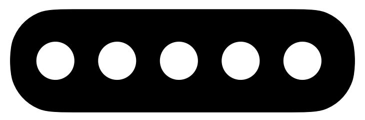


$$h_t = \sum_{\substack{s = t-2 \\ s \neq t}}^{t+2} \mathbf{x}_s$$

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”.

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



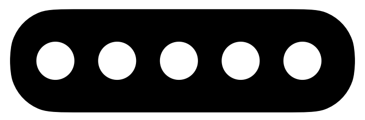
Low-dimensional representation of context: “enjoyed the we watched”

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



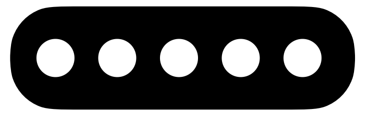
Low-dimensional representation of context: “enjoyed the we watched”

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

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

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?

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

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

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

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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

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

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

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

1.2 * -2.3
+ -0.3 * 0.9
+ 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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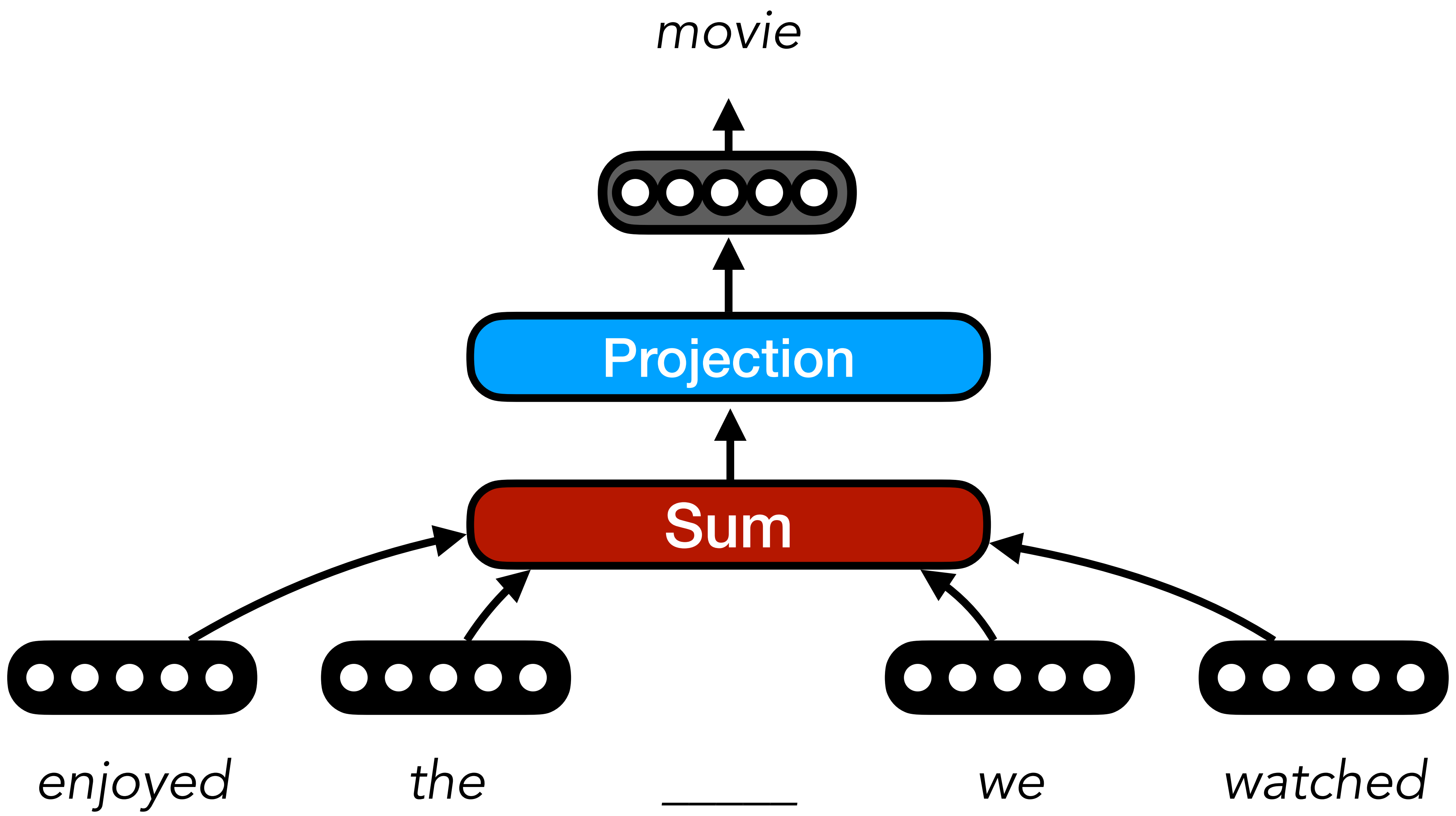
$\mathbf{U}h_t$ = <1.8, -1.9, 2.9, -0.9>

softmax(Uh_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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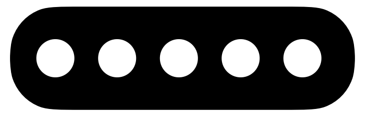

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(Mikolov et al., 2013a)

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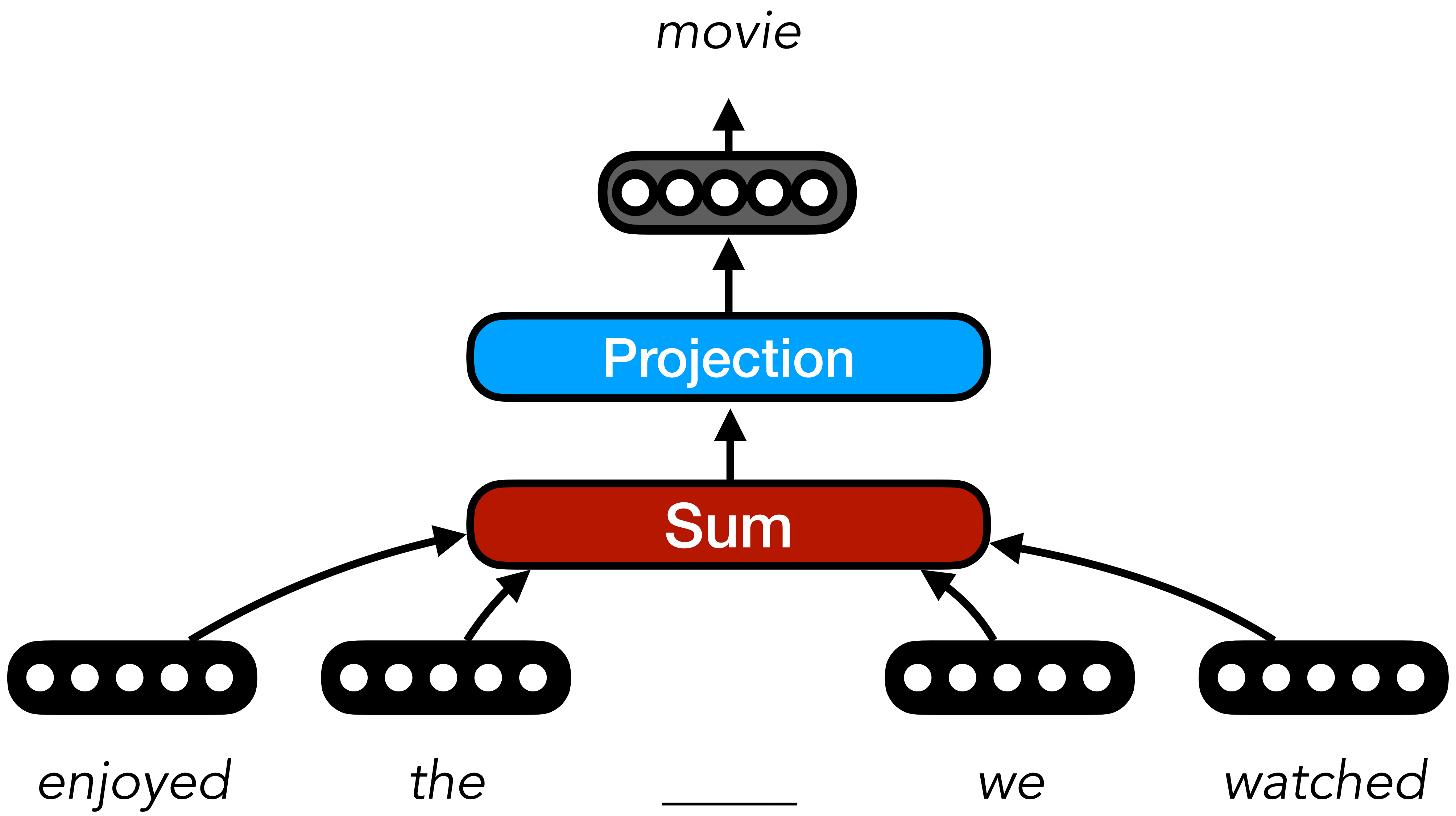


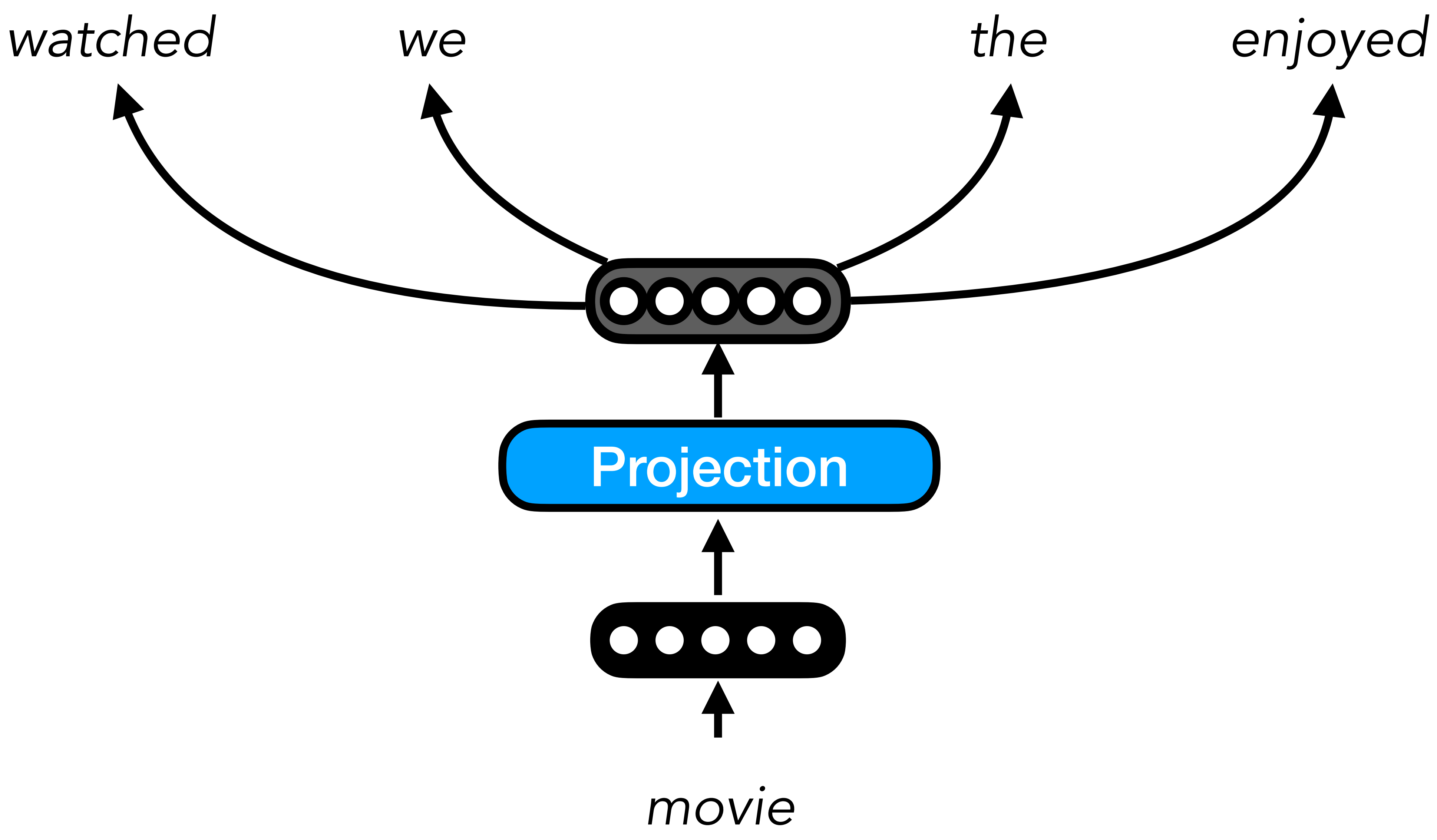
- Model is trained to **maximise** the **probability** of the missing word
  - For computational reasons, the model is typically trained to **minimise** the **negative log probability** of the missing word
- Here, we use a window of **N=2**, but the window size is a **hyperparameter**
- For computational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

Context:



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

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

(Mikolov et al., 2013b)

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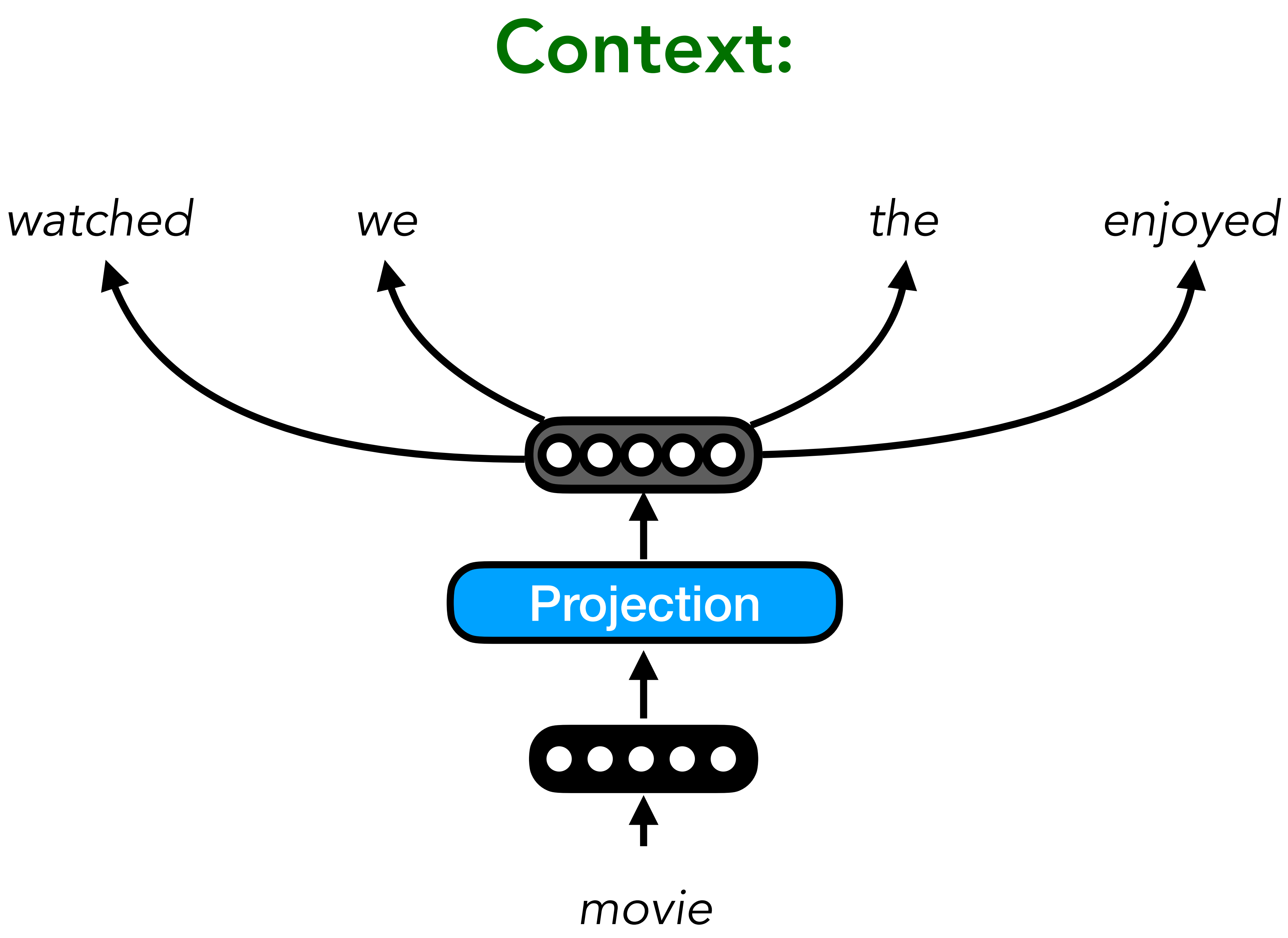

$$\max P(enjoyed, the, we, watched \,|\, movie)$$

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

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

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

(Mikolov et al., 2013b)

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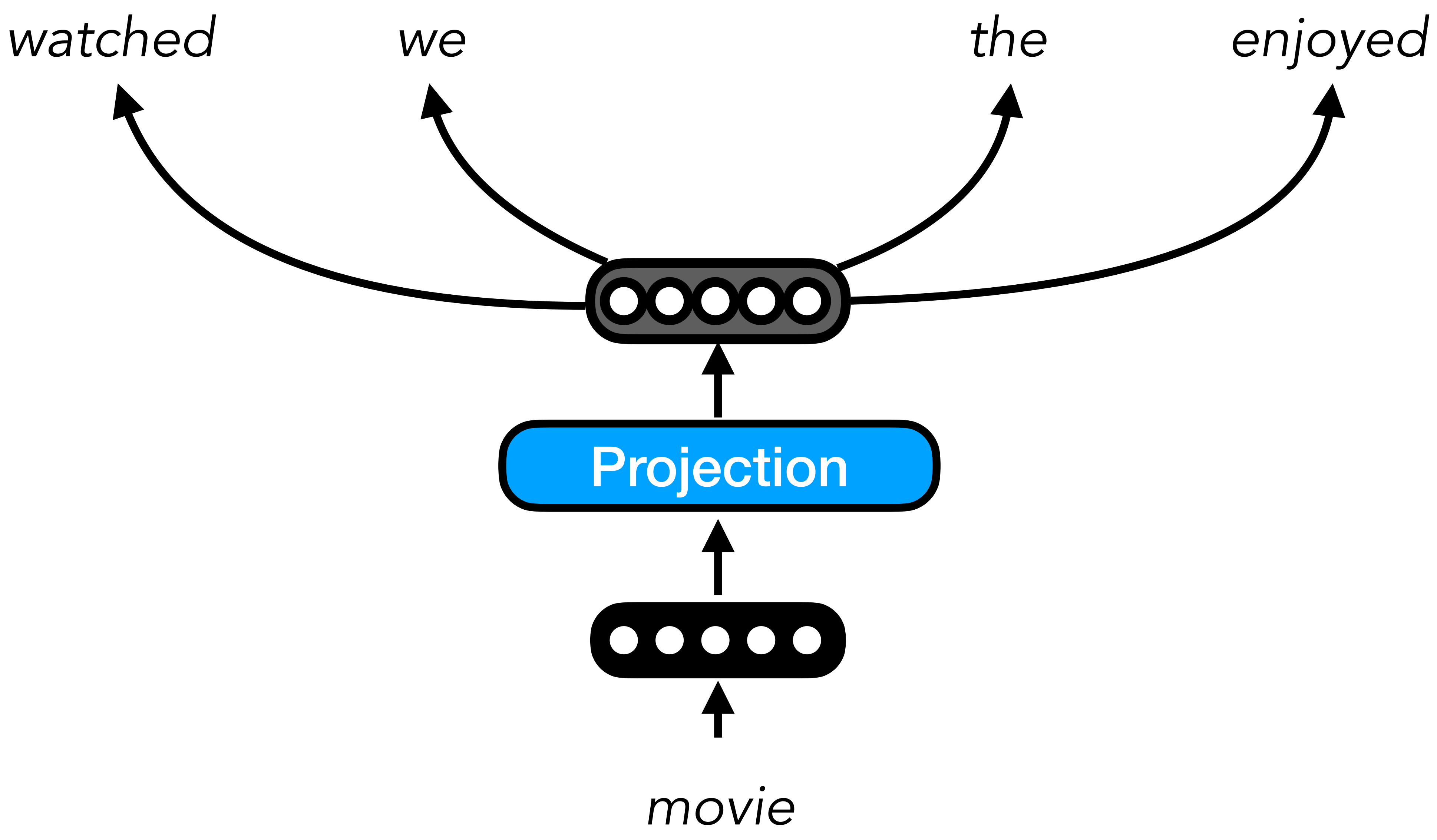

$$P(x_s \mid x_t) = \textbf{softmax}\left(\mathbf{U}\mathbf{x}_t\right)$$

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

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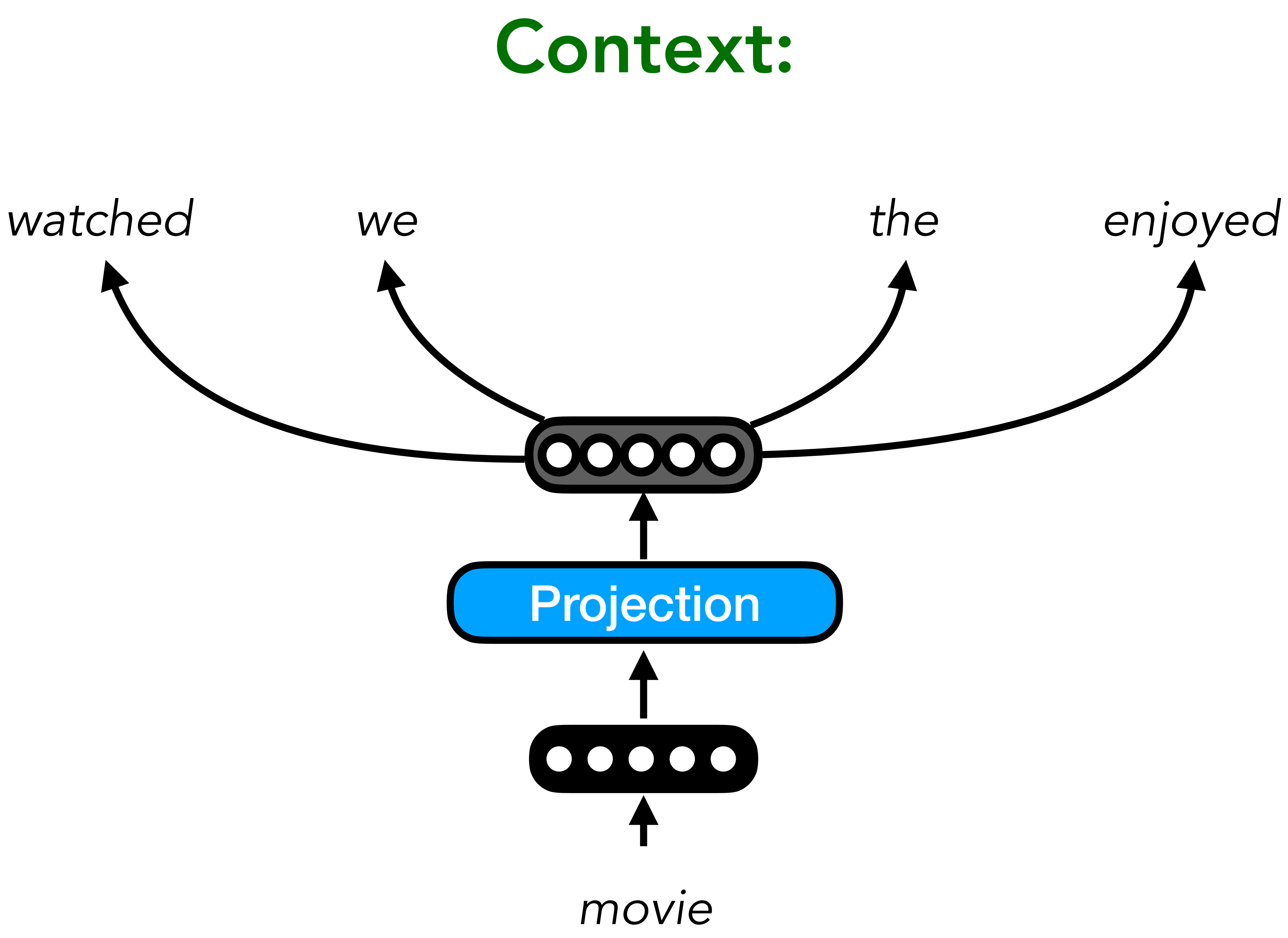


- Model is trained to **minimise** the **negative log probability** of the surrounding words
- Here, we use a window of **N=2**, but the window size is a **hyperparameter.**
  - Larger window = more information about related words in embedding
- Typically, set large window **(N=10),** but randomly select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

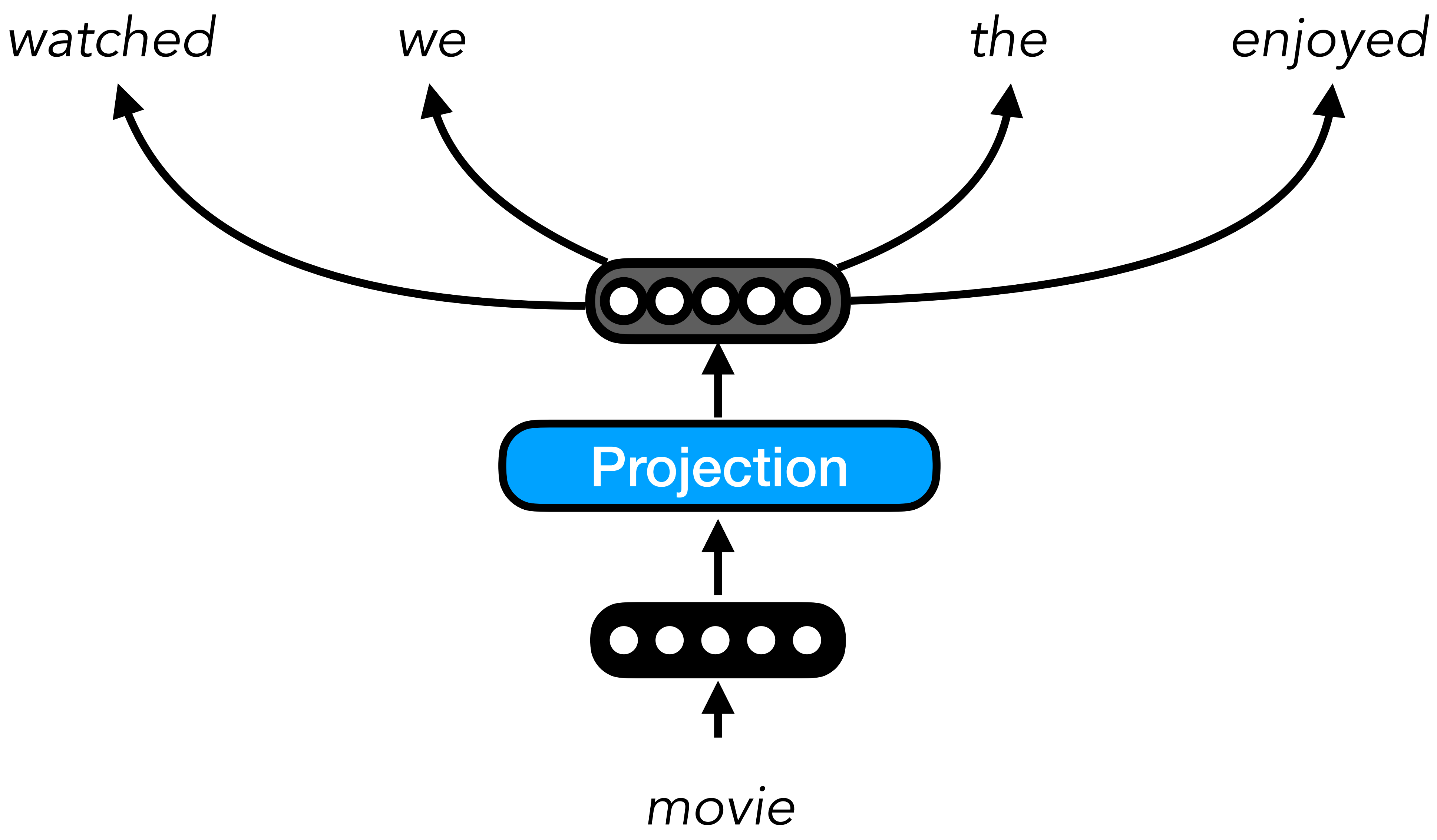
(Mikolov et al., 2013b)

Question

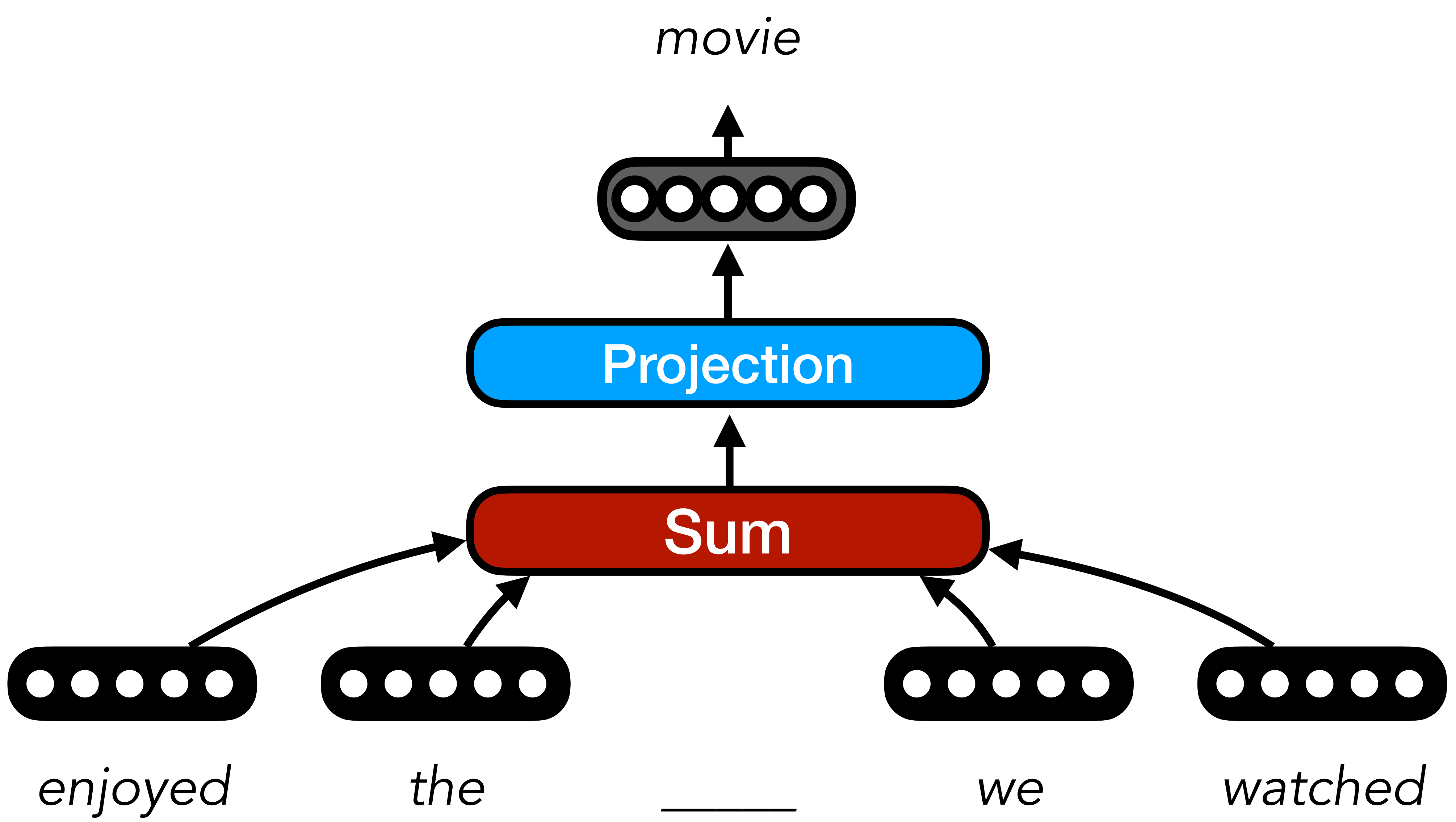
What is the major conceptual difference between the CBOW and Skipgram methods for training word embeddings?

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

Feature	CBOW	Skip-gram
Focus	Frequent words, general meanings	Rare words, detailed meanings
Word Relationships	More general, broad similarities	More specific, nuanced similarities
Similarity Scores	More balanced, spread out	More extreme, focused

Why Does Skip-gram Have Higher Similarity Scores?

- **More precise word relationships**
  - Since Skip-gram learns to predict words **near the target word**, it builds embeddings that reflect **specific word associations**, making words like "crosswise" and "cut" more strongly related.
- **Handles rare words better**
  - Skip-gram learns **detailed representations** for uncommon words, leading to more meaningful embeddings and **higher similarity scores** for relevant words.
- **CBOW is more smoothed and general**
  - CBOW tends to produce **less extreme** similarity scores since it generalizes word meanings over common contexts.

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
```

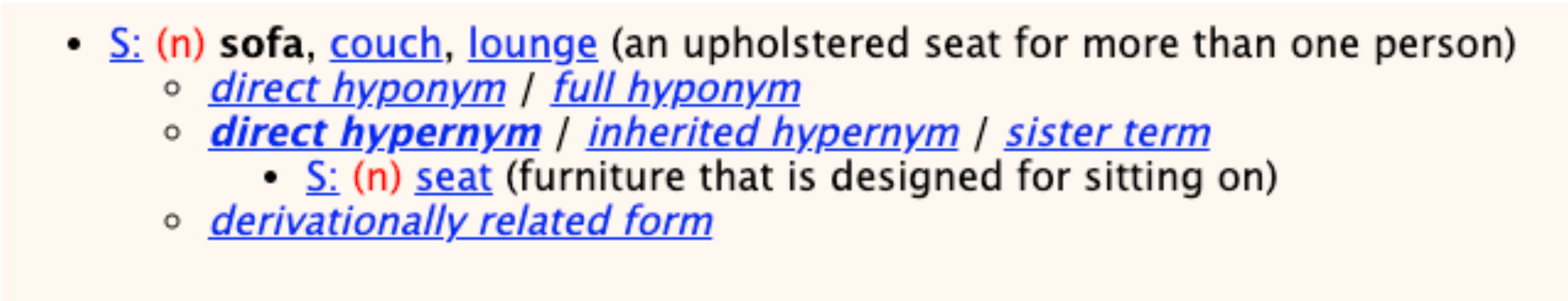
- If you want embeddings that generalize well → Use CBOW
- If you want embeddings with fine-grained, rare-word relationships → Use Skip-gram

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



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

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