

Lecture 7: Tricks + Word Embeddings

Alan Ritter

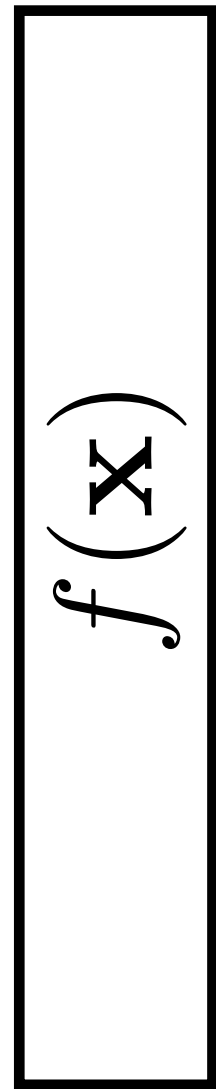
(many slides from Greg Durrett)

Recall: Feedforward NNs

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$

Recall: Feedforward NNs

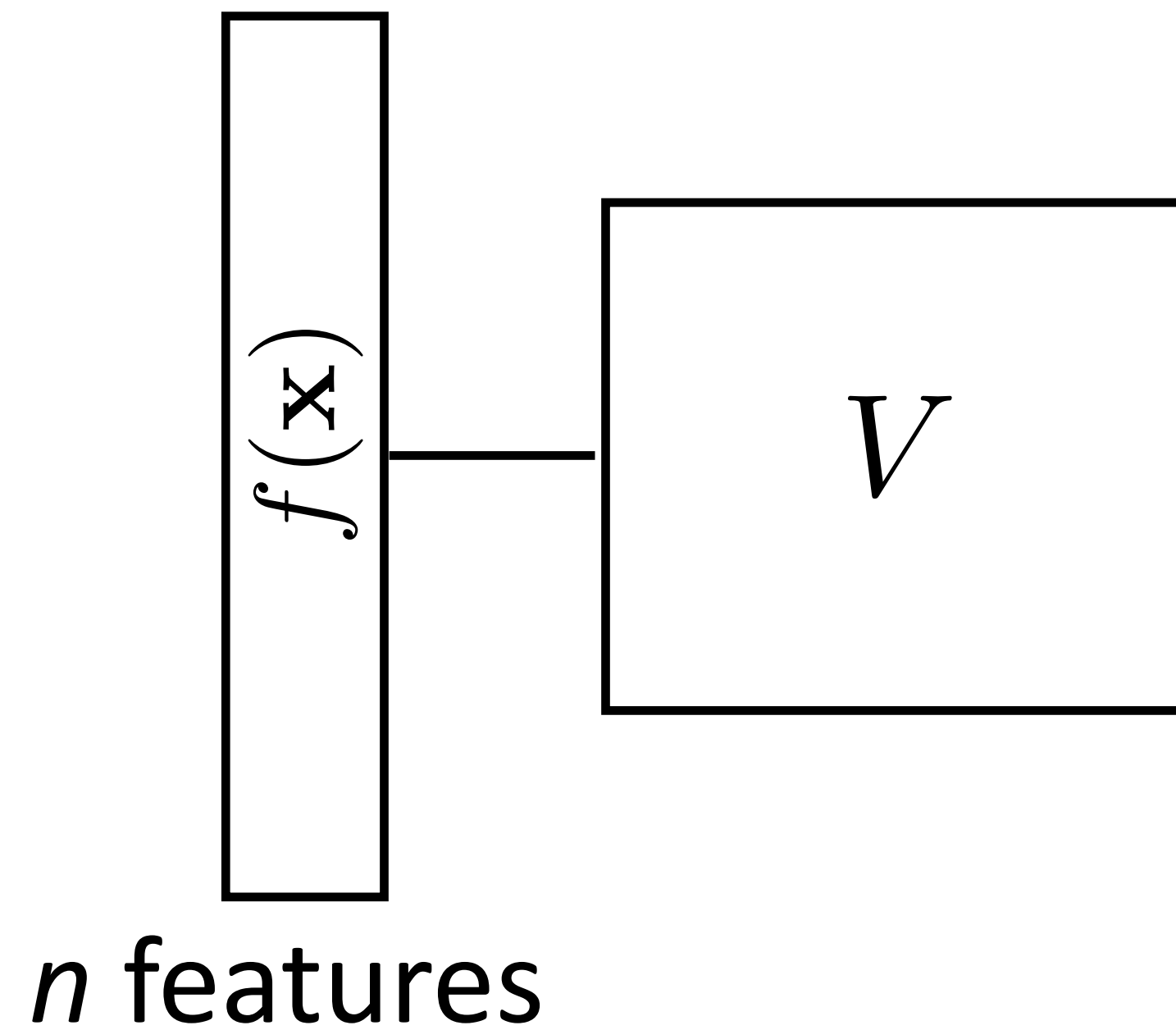
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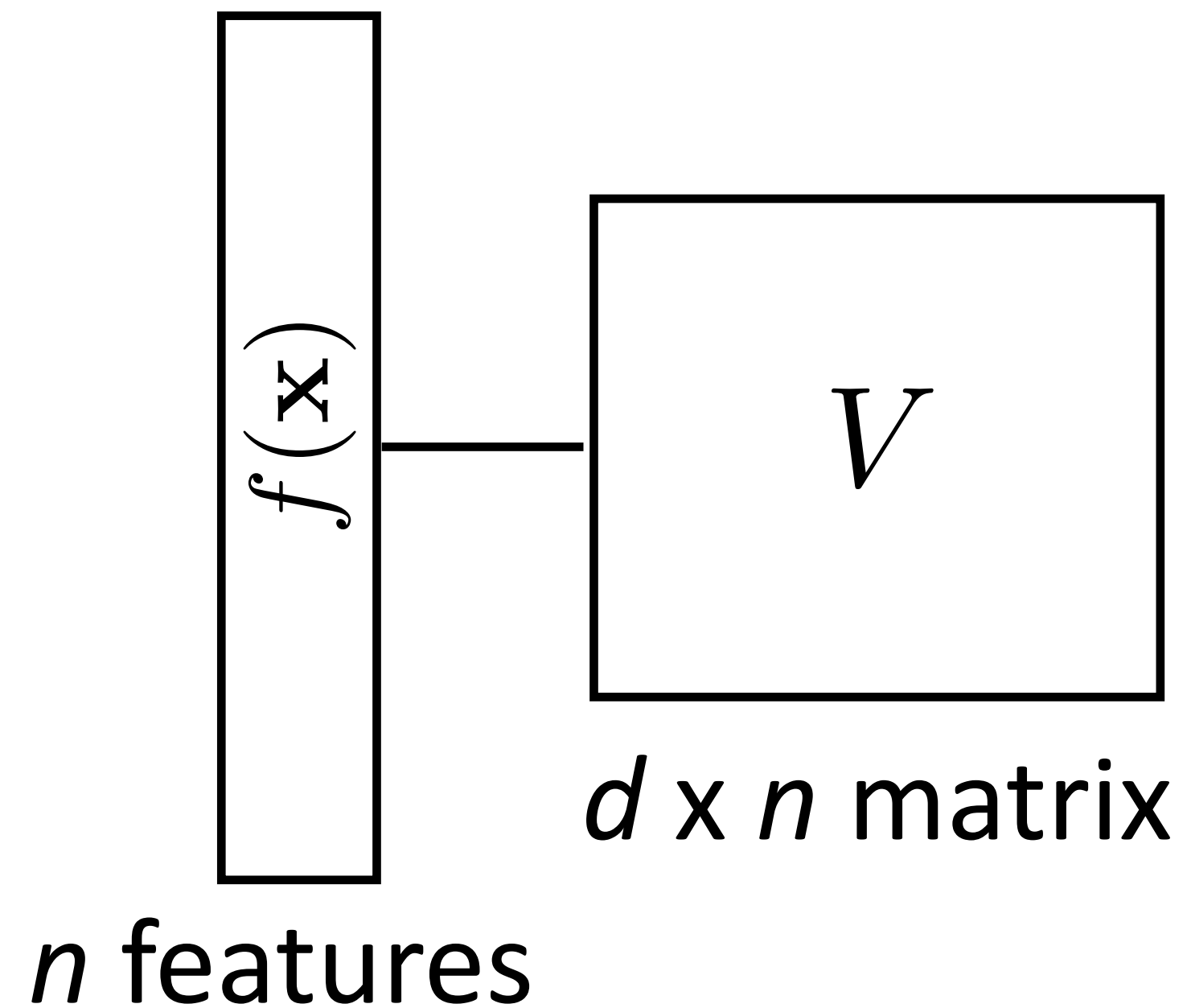
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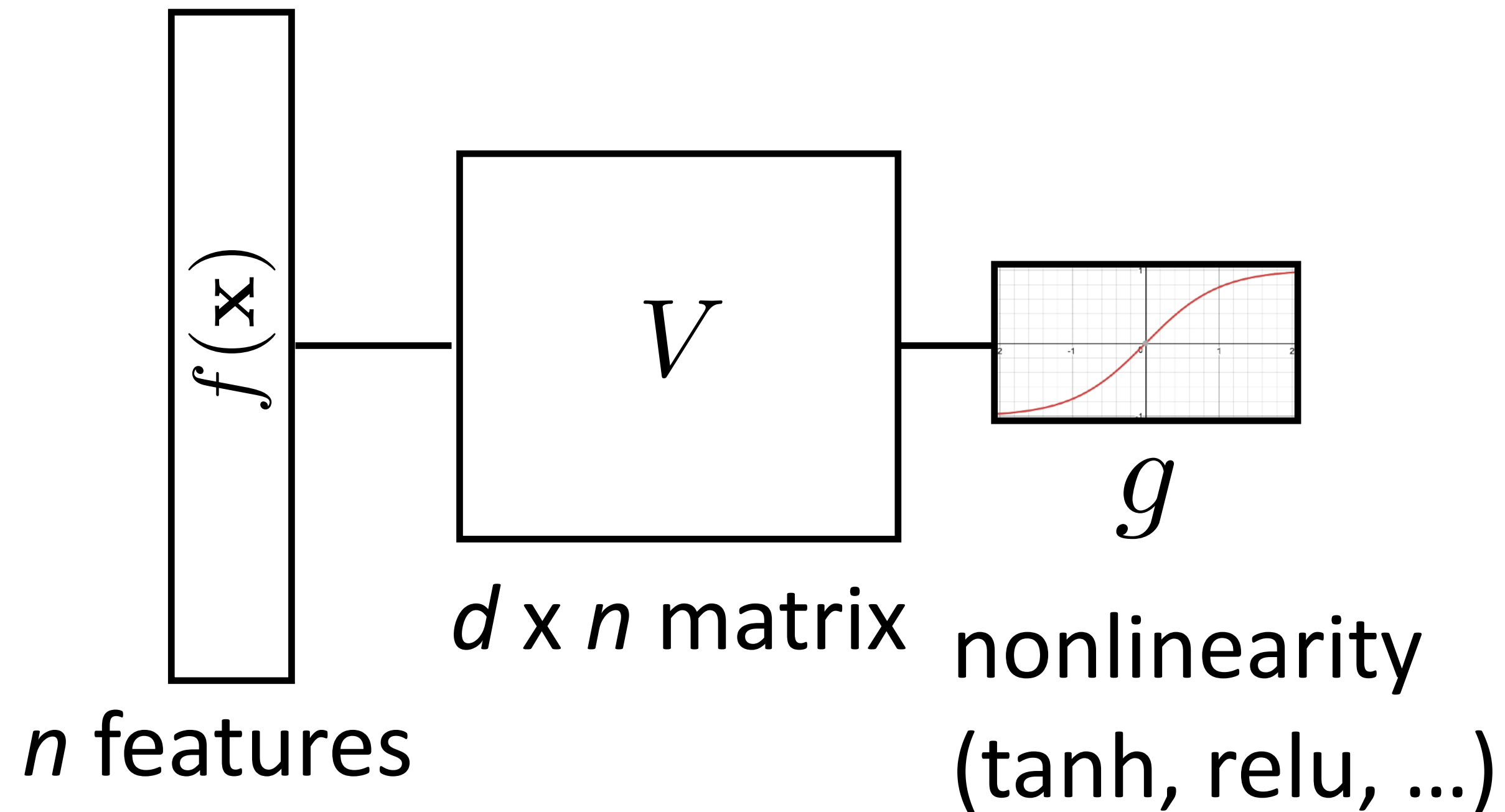
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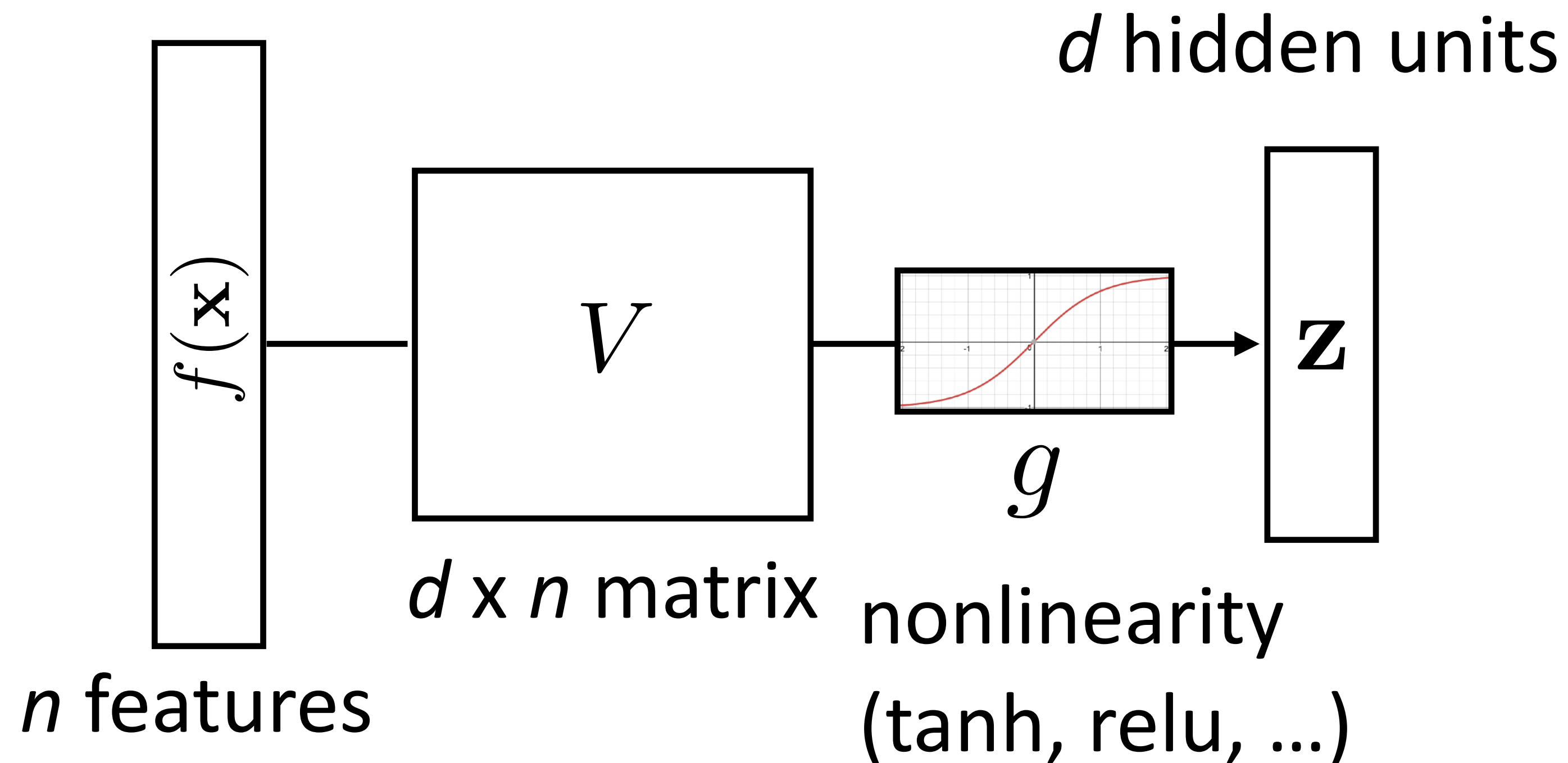
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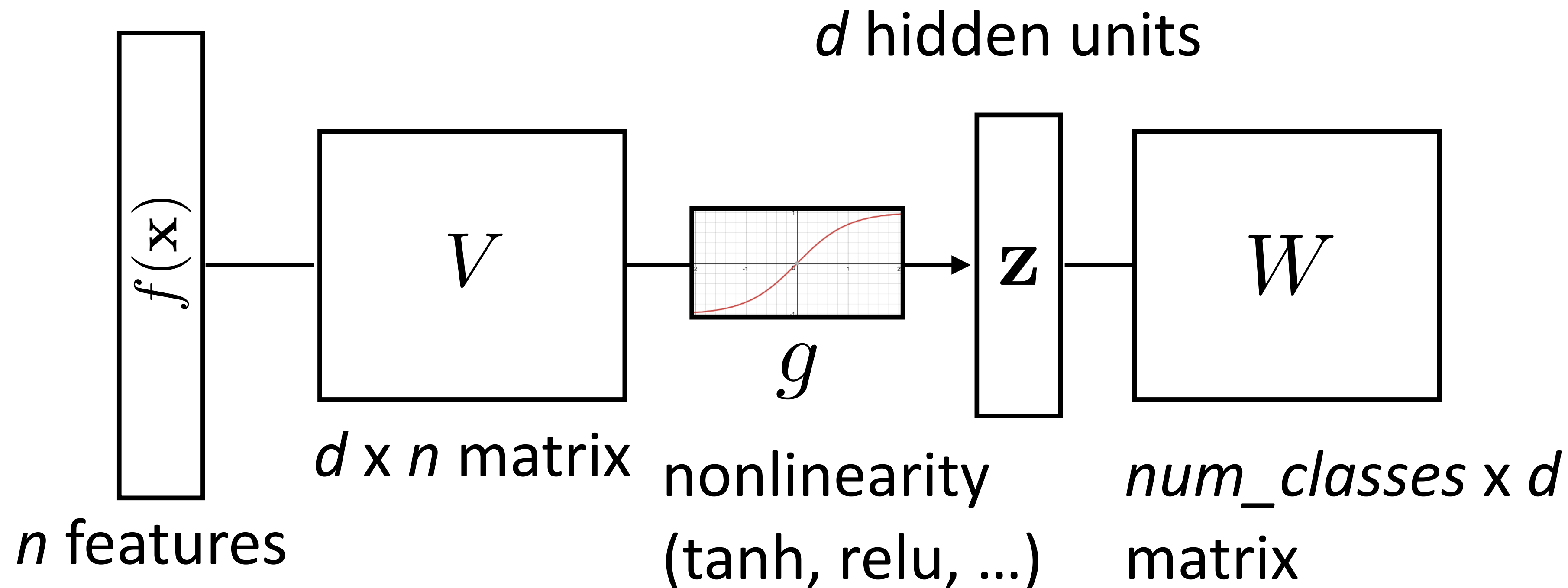
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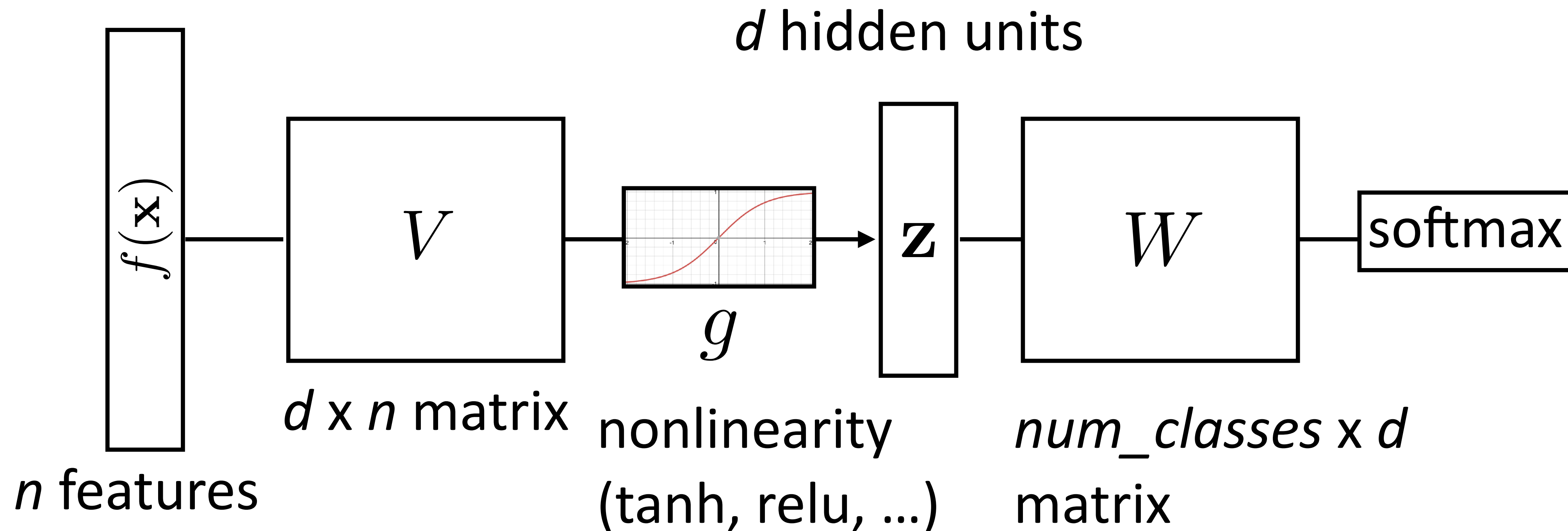
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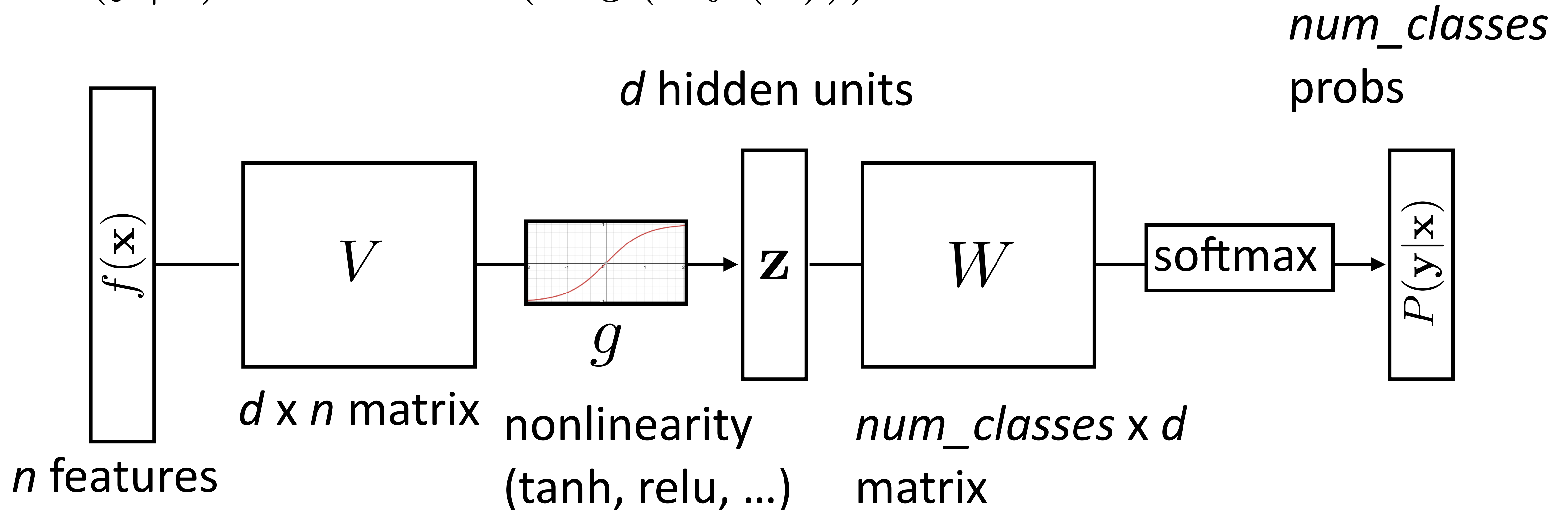
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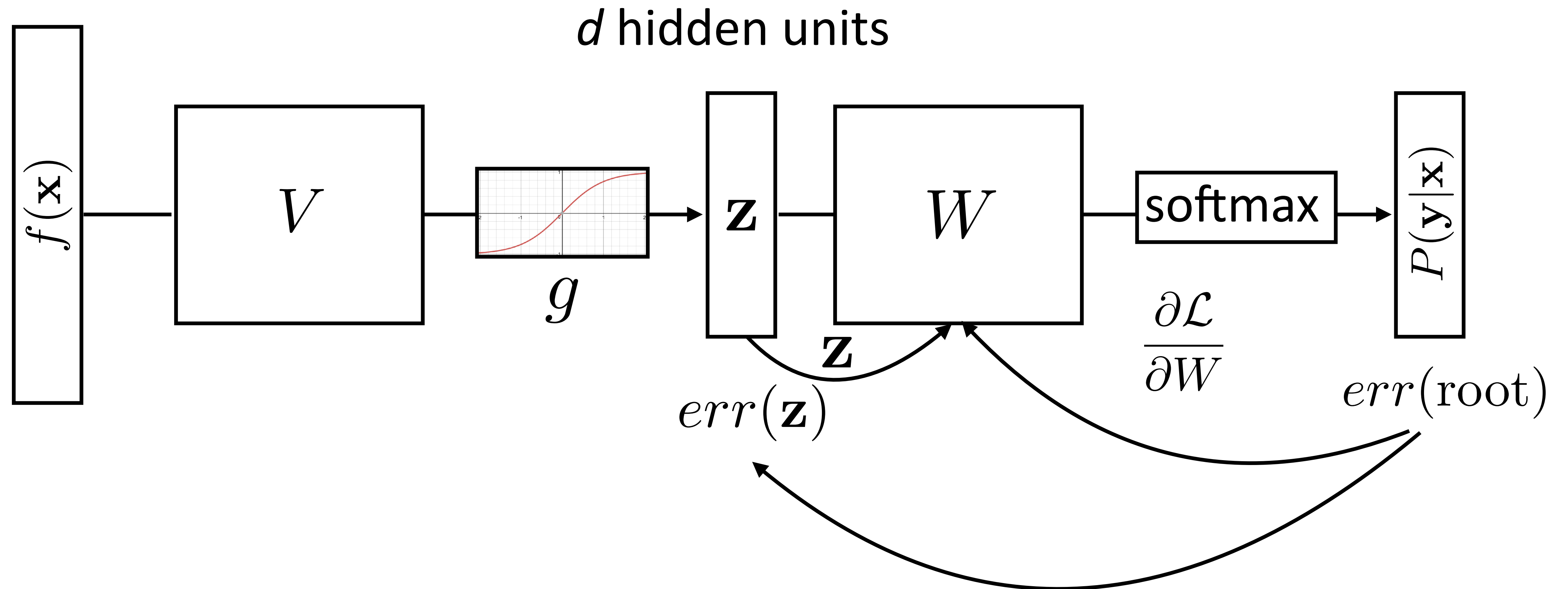
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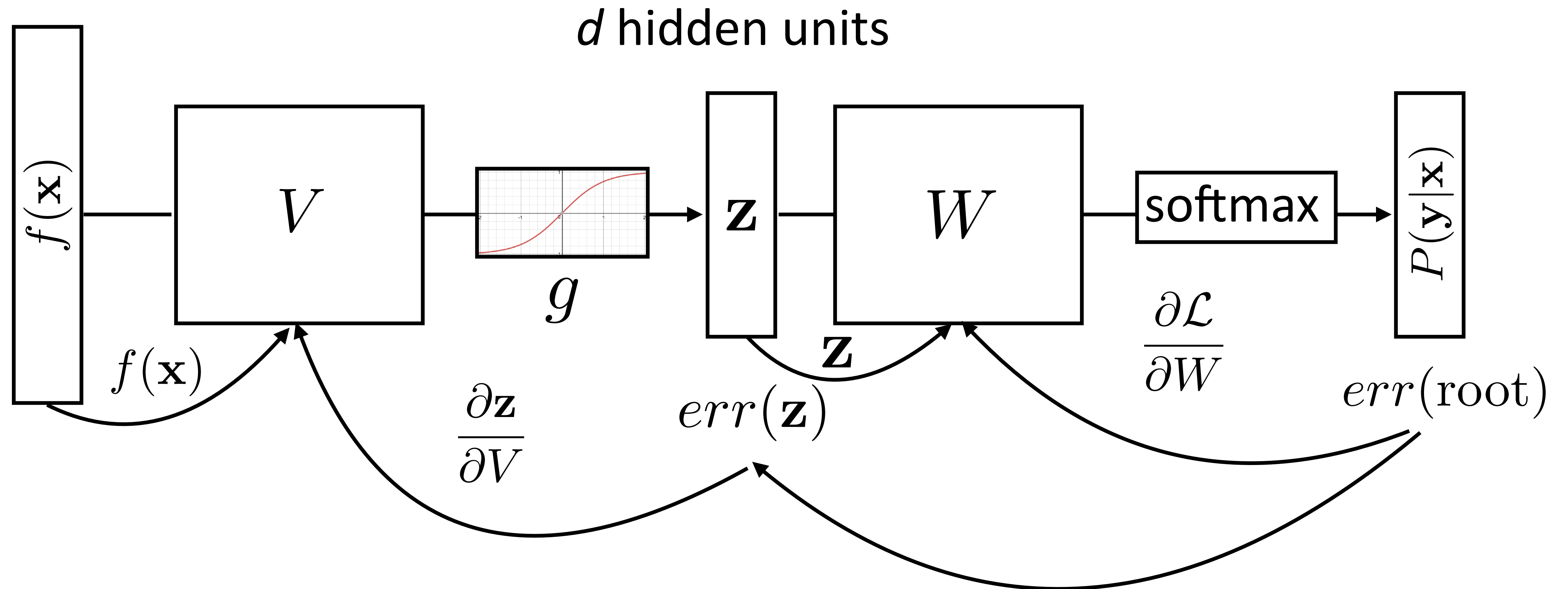
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This Lecture

- ▶ Training
- ▶ Word representations
- ▶ word2vec/GloVe
- ▶ Evaluating word embeddings

Training Tips

Training Basics

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- ▶ Basic formula: compute gradients on batch, use first-order opt. method

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- ▶ How to initialize? How to regularize? What optimizer to use?



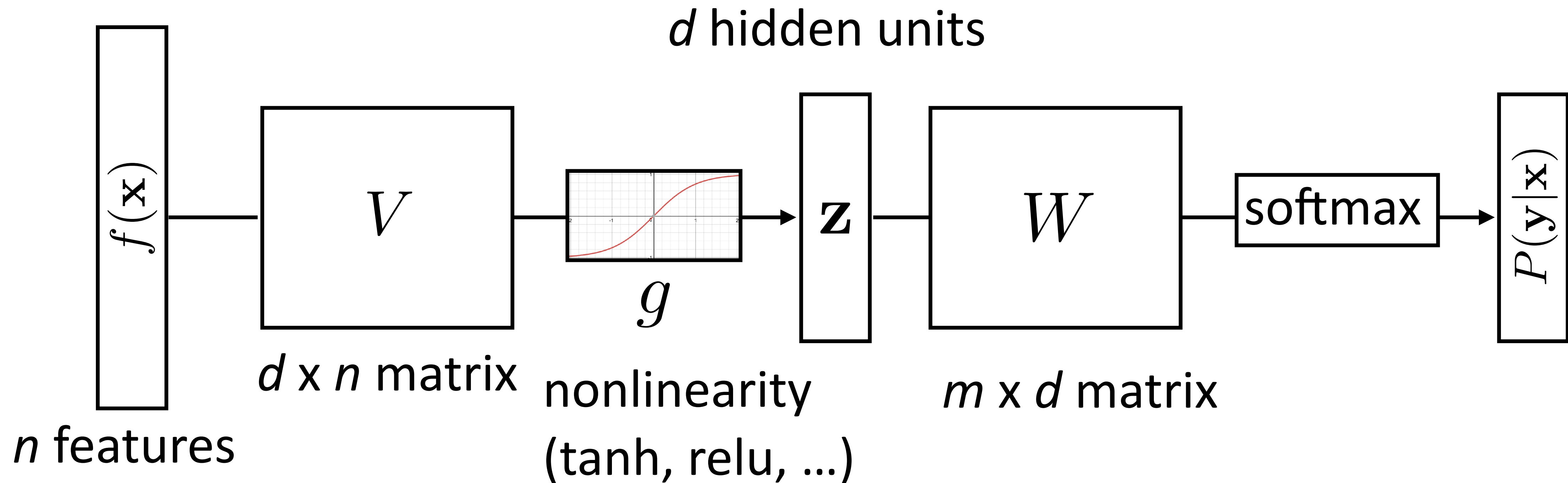
Training Basics

- ▶ Basic formula: compute gradients on batch, use first-order opt. method
- ▶ How to initialize? How to regularize? What optimizer to use?
- ▶ This lecture: some practical tricks. Take deep learning or optimization courses to understand this further



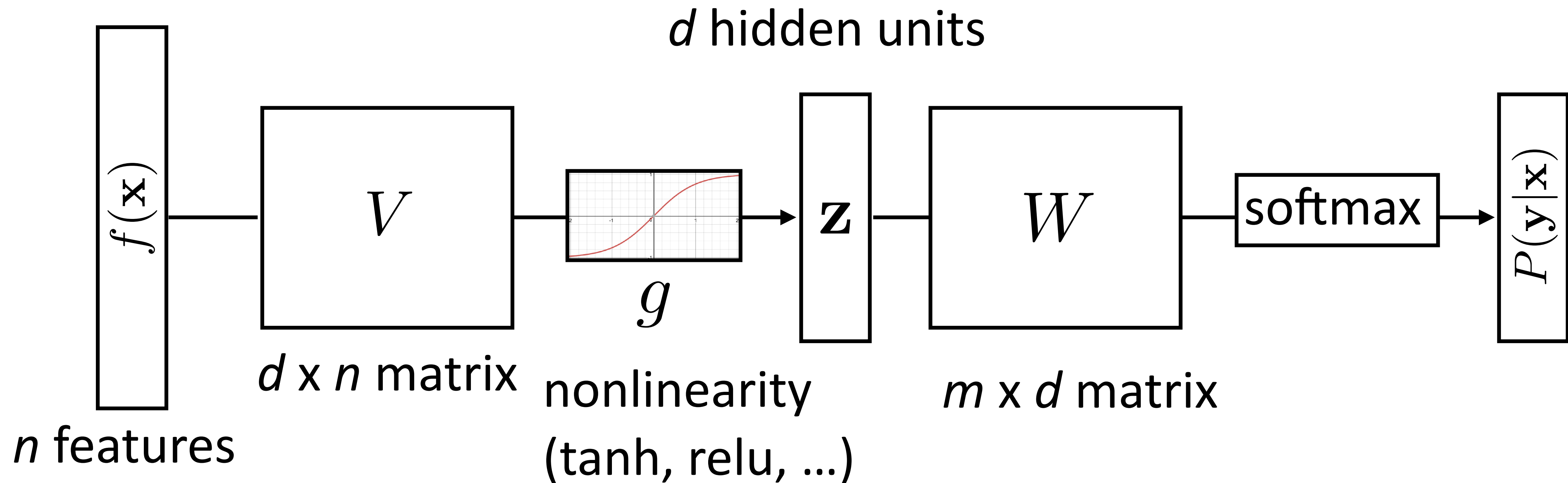
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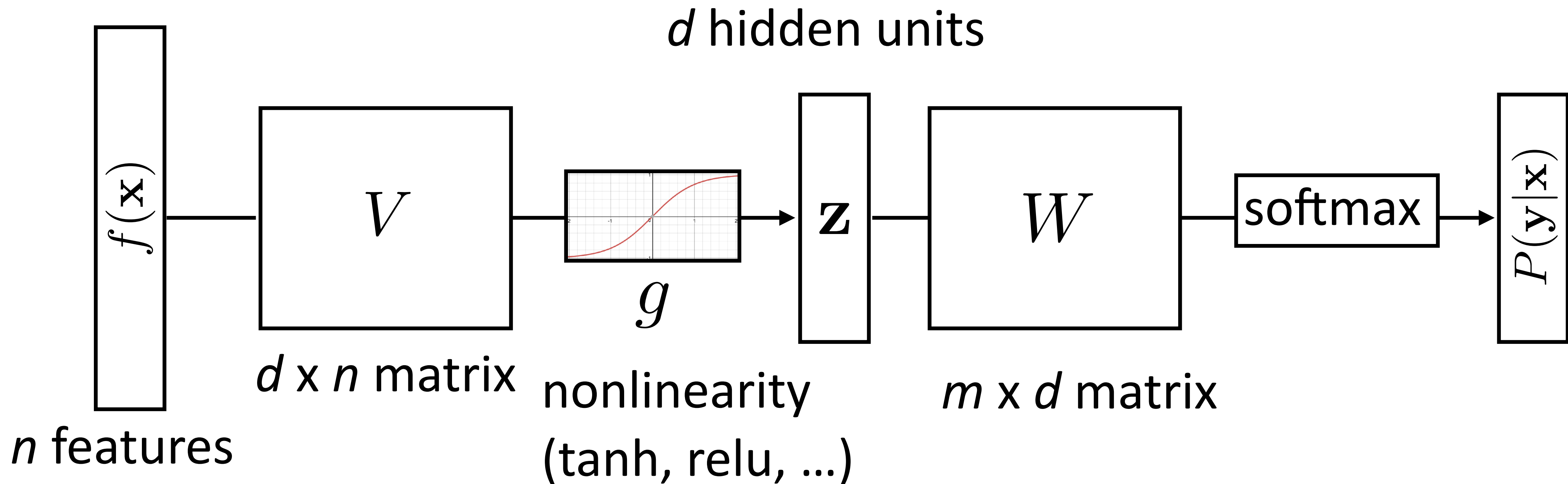
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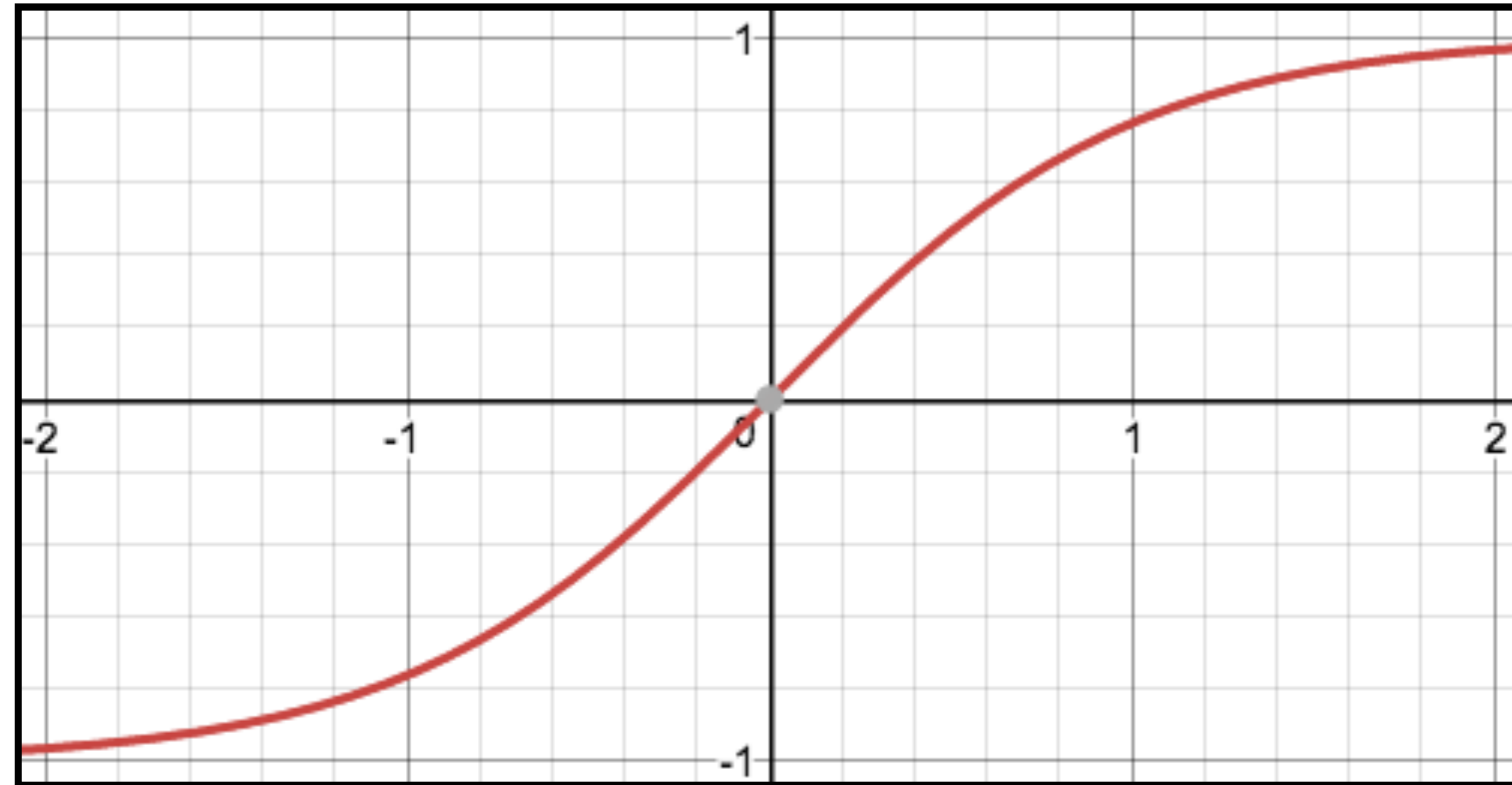
- ▶ How do we initialize V and W ? What consequences does this have?
- ▶ *Nonconvex* problem, so initialization matters!

How does initialization affect learning?

- ▶ Nonlinear model...how does this affect things?

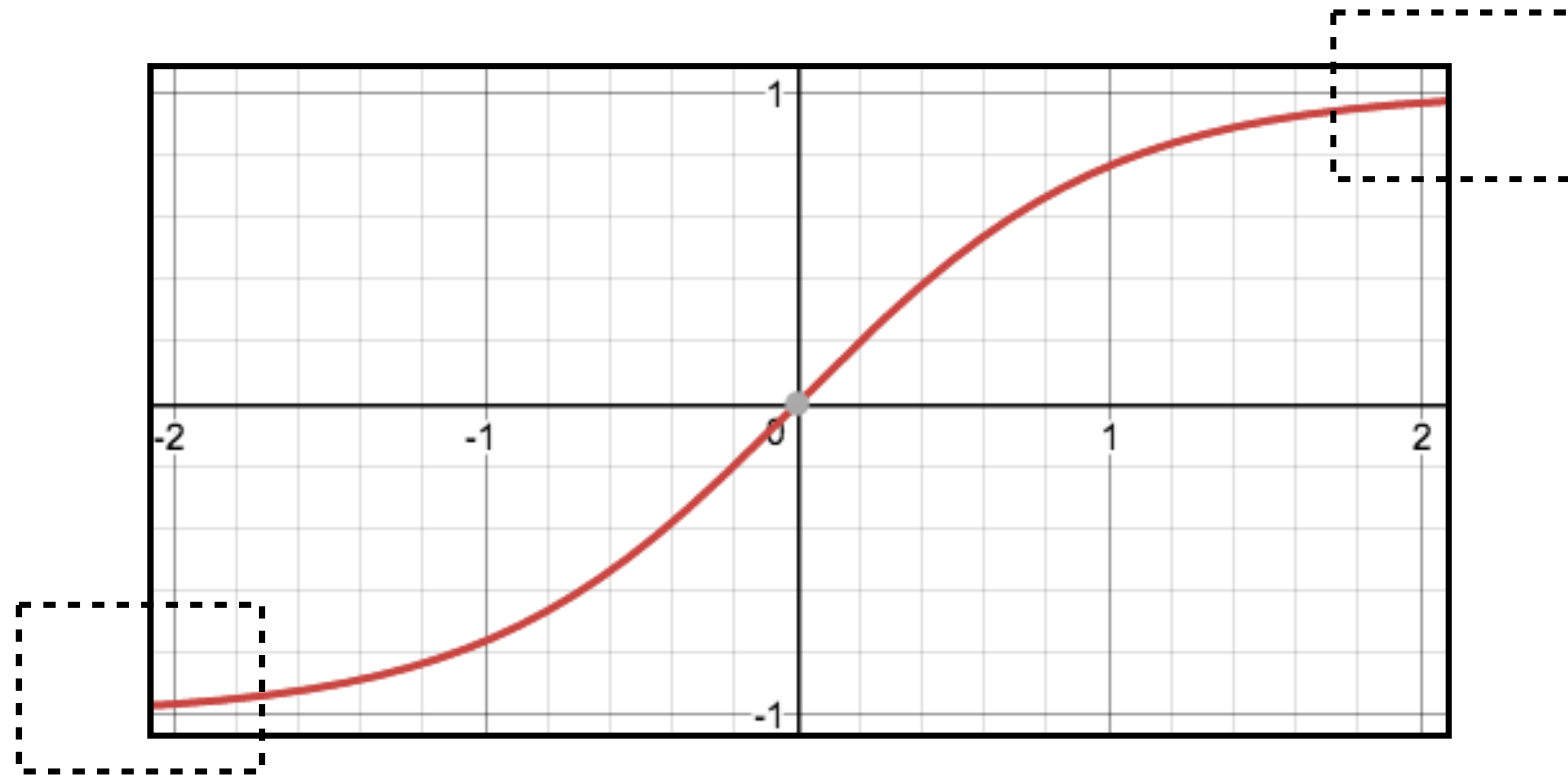
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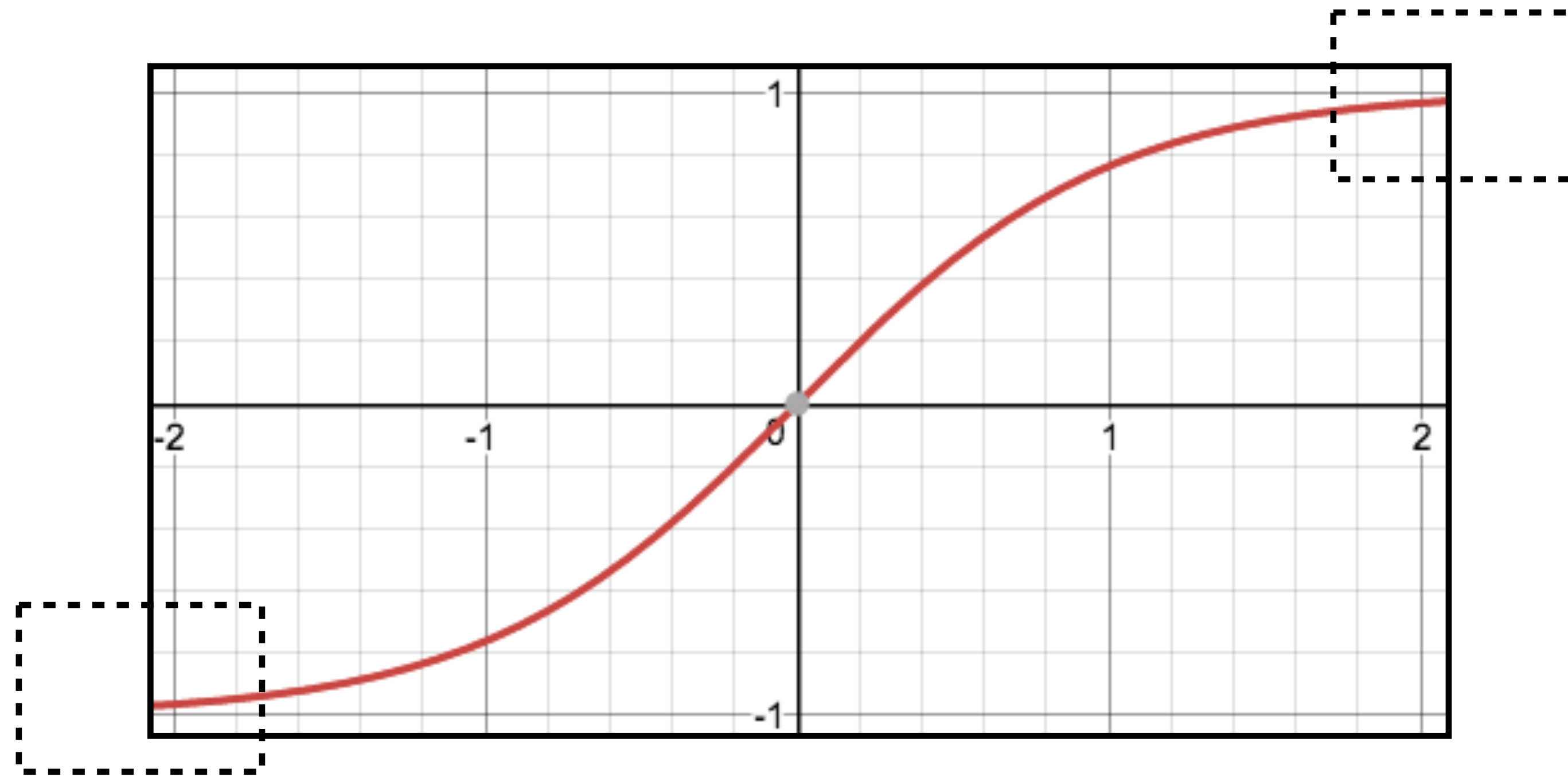
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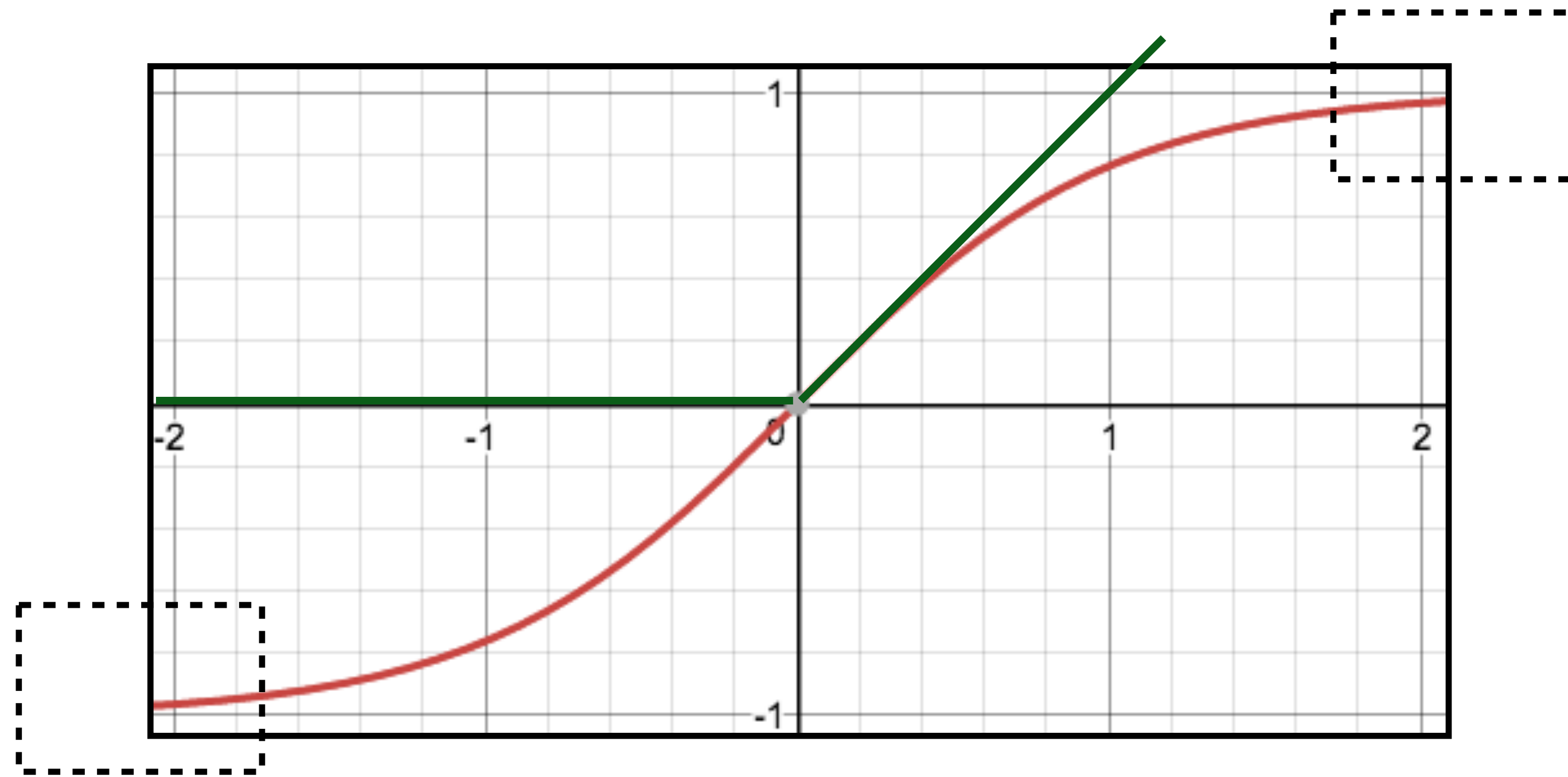
- ▶ Nonlinear model...how does this affect things?



- ▶ If cell activations are too large in absolute value, gradients are small

How does initialization affect learning?

- ▶ Nonlinear model...how does this affect things?



- ▶ If cell activations are too large in absolute value, gradients are small
- ▶ **ReLU**: larger dynamic range (all positive numbers), but can produce big values, can break down if everything is too negative

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► Xavier initializer: $U \left[-\sqrt{\frac{6}{\text{fan-in} + \text{fan-out}}}, +\sqrt{\frac{6}{\text{fan-in} + \text{fan-out}}} \right]$

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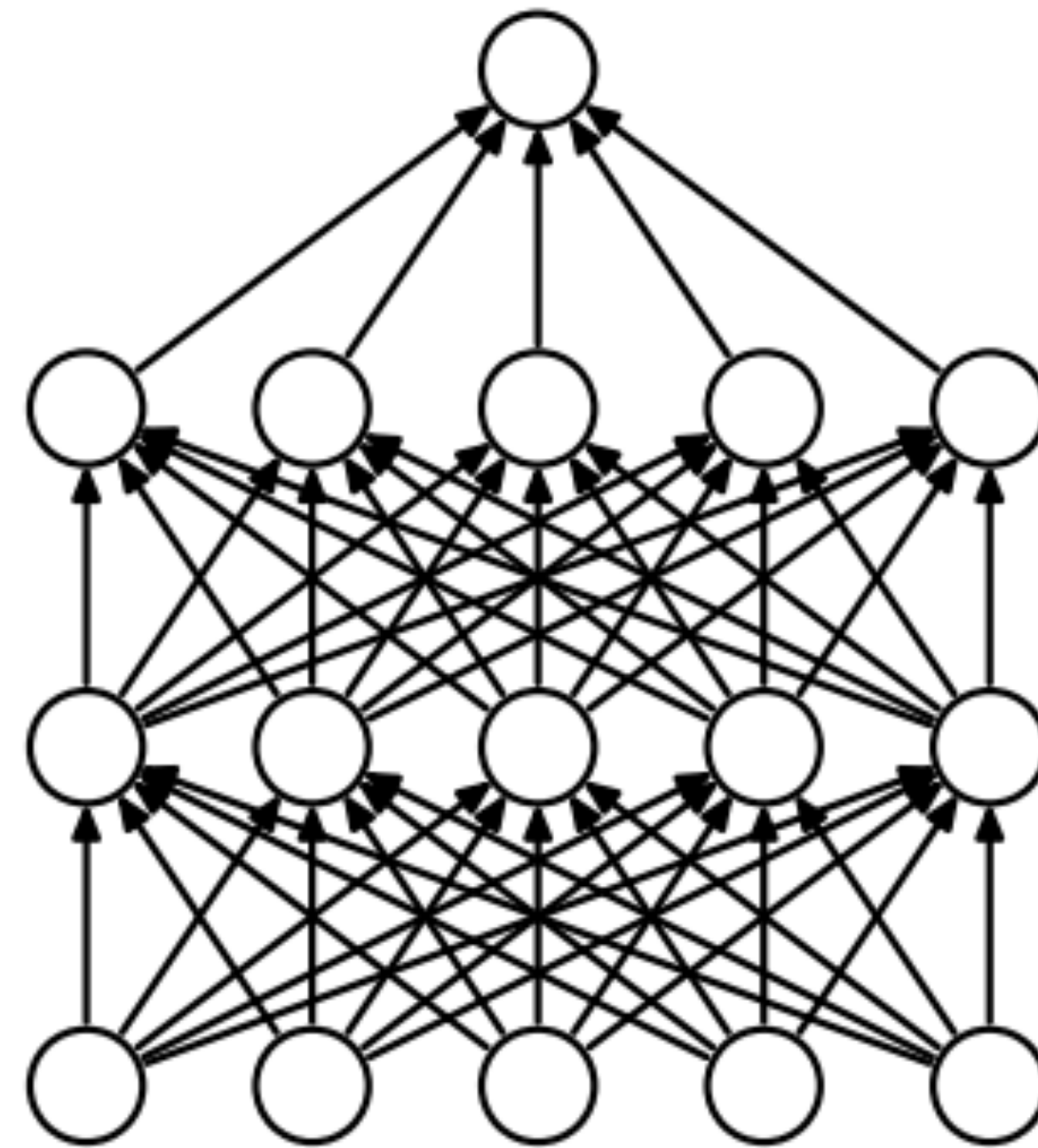
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Initialization

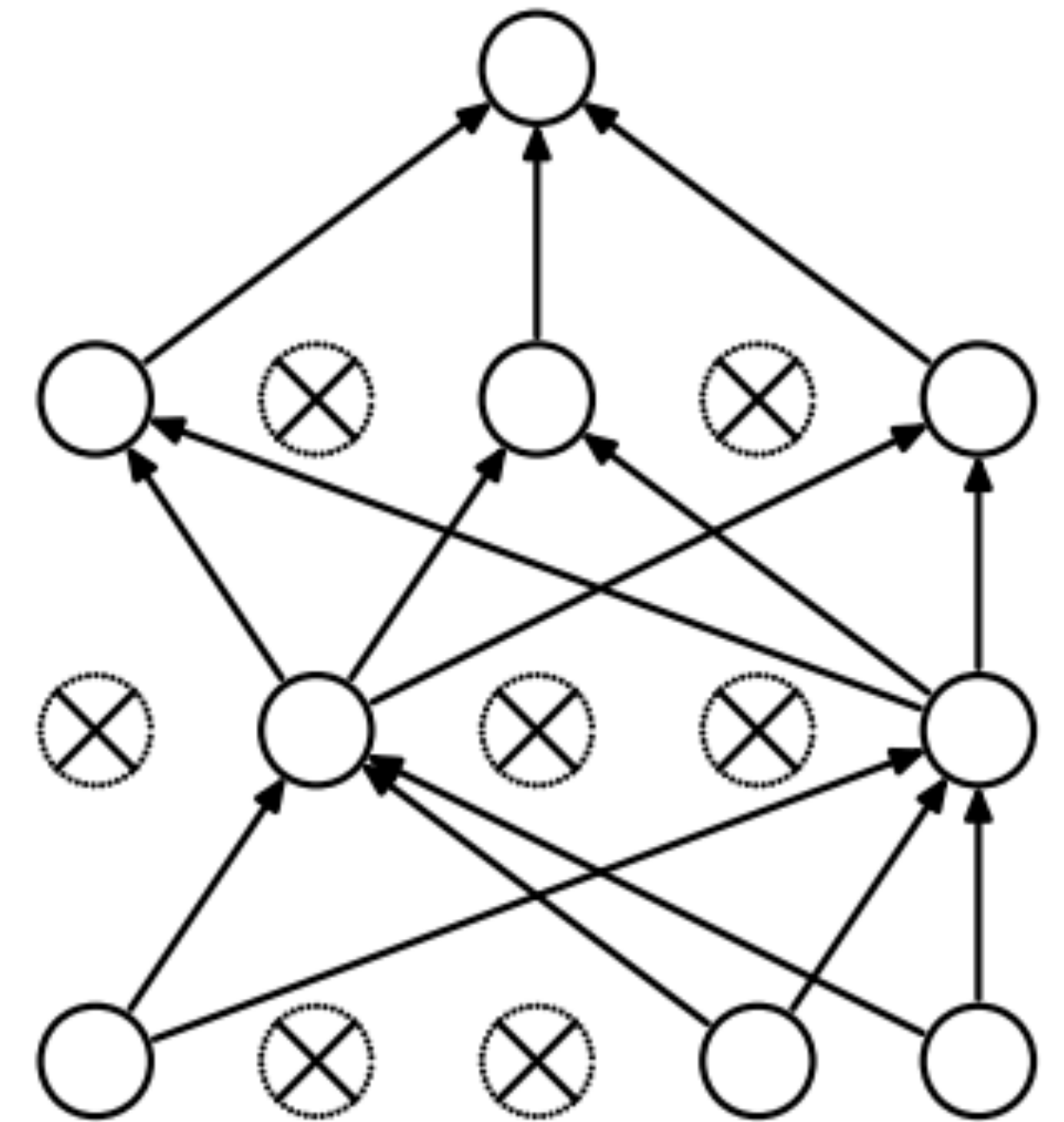
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 - ▶ Want variance of inputs and gradients for each layer to be the same
 - ▶ Batch normalization (Ioffe and Szegedy, 2015): periodically shift+rescale each layer to have mean 0 and variance 1 over a batch (useful if net is deep)

Dropout

- Probabilistically zero out parts of the network during training to prevent overfitting, use whole network at test time



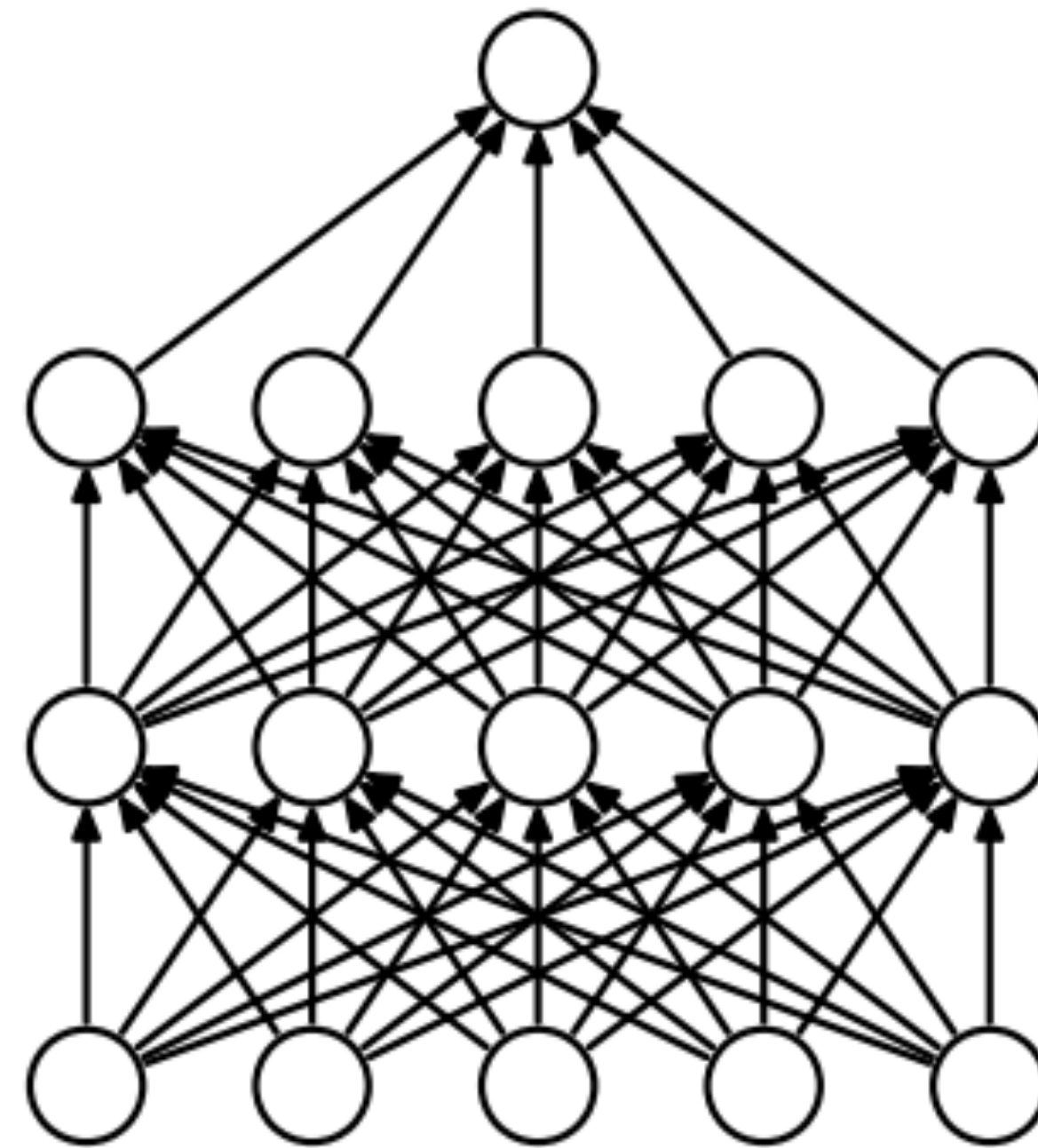
(a) Standard Neural Net



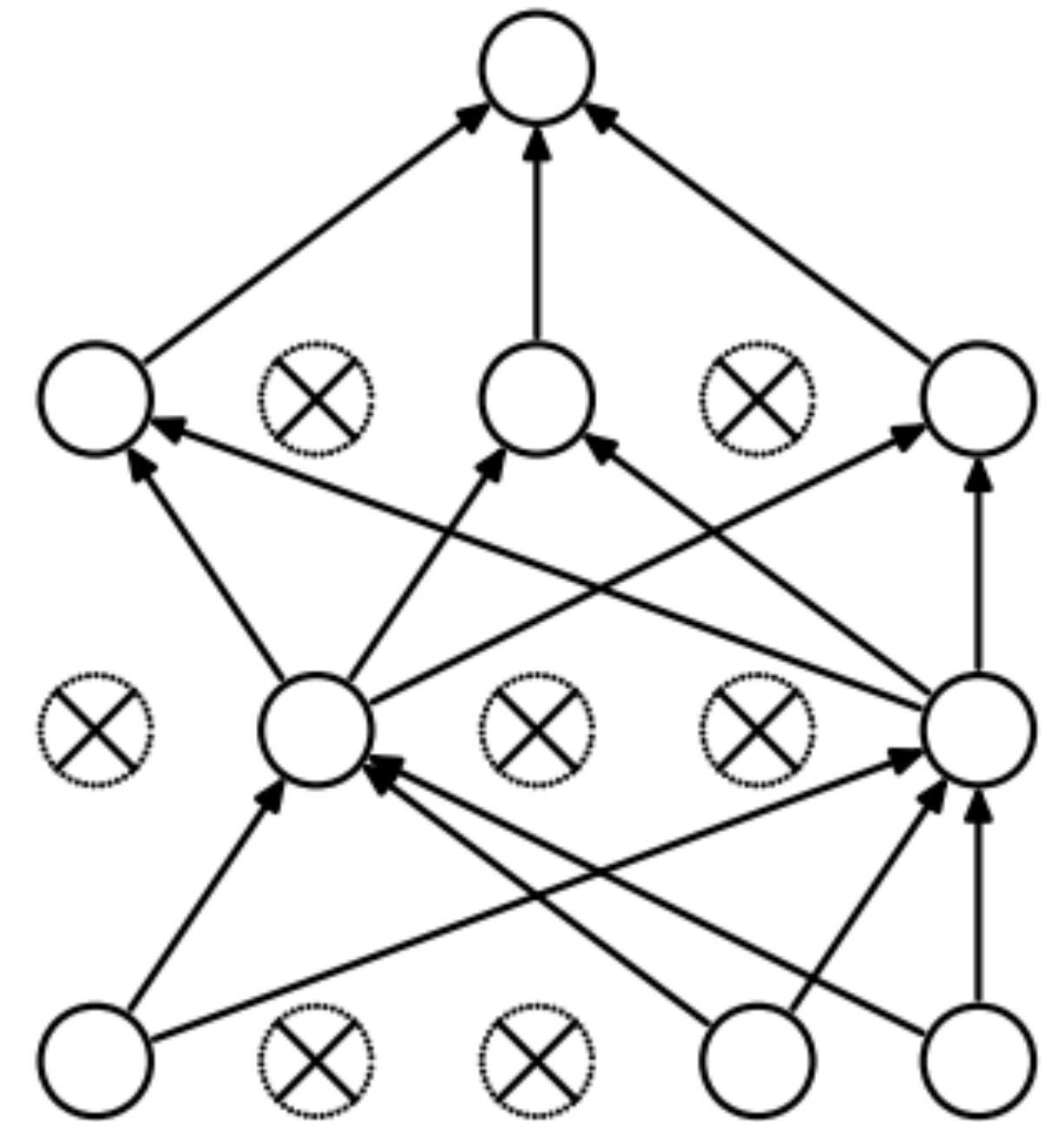
(b) After applying dropout.

Dropout

- ▶ Probabilistically zero out parts of the network during training to prevent overfitting, use whole network at test time
- ▶ Form of stochastic regularization



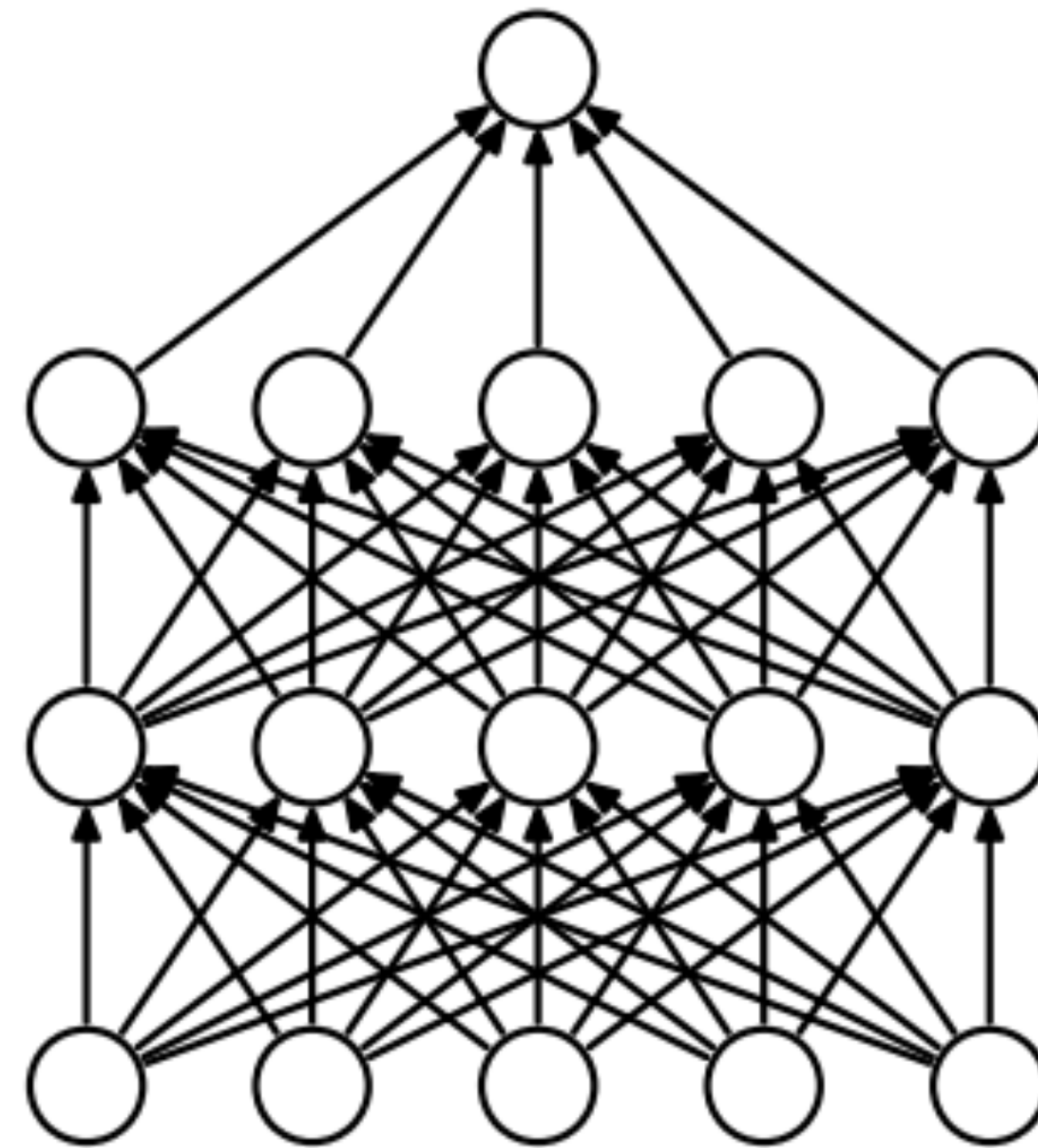
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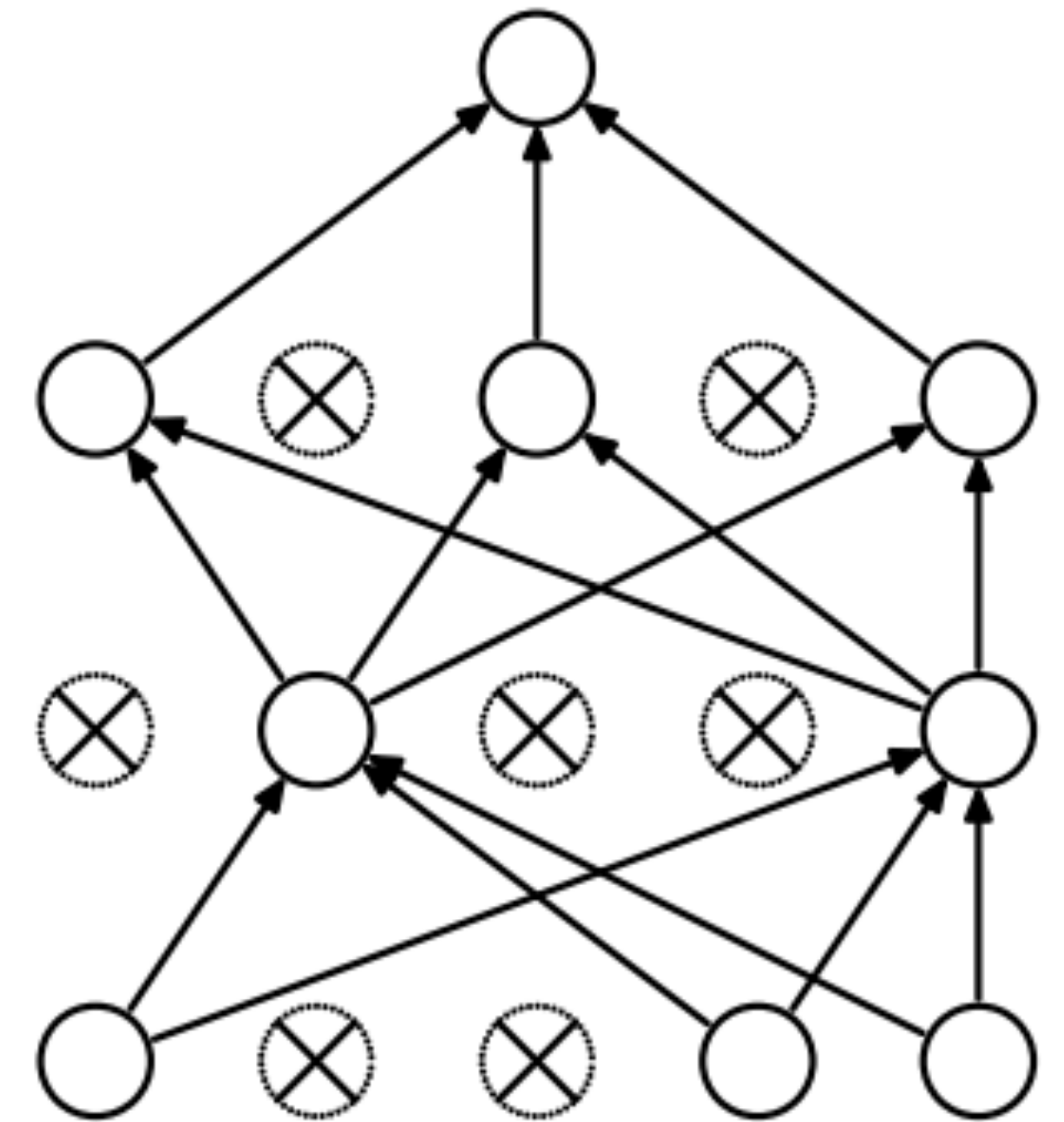
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Dropout

- ▶ Probabilistically zero out parts of the network during training to prevent overfitting, use whole network at test time
- ▶ Form of stochastic regularization
- ▶ Similar to benefits of ensembling: network needs to be robust to missing signals, so it has redundancy



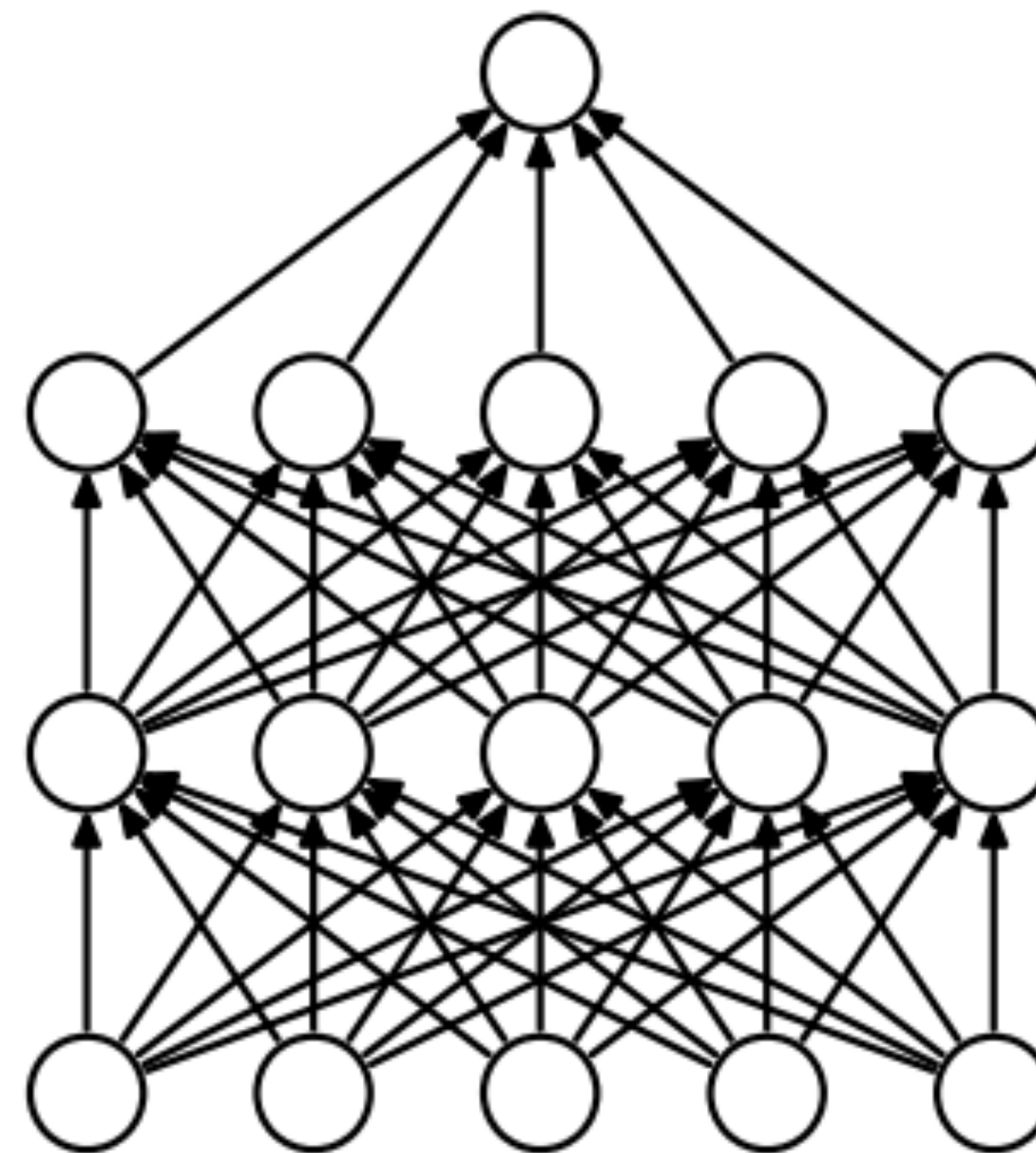
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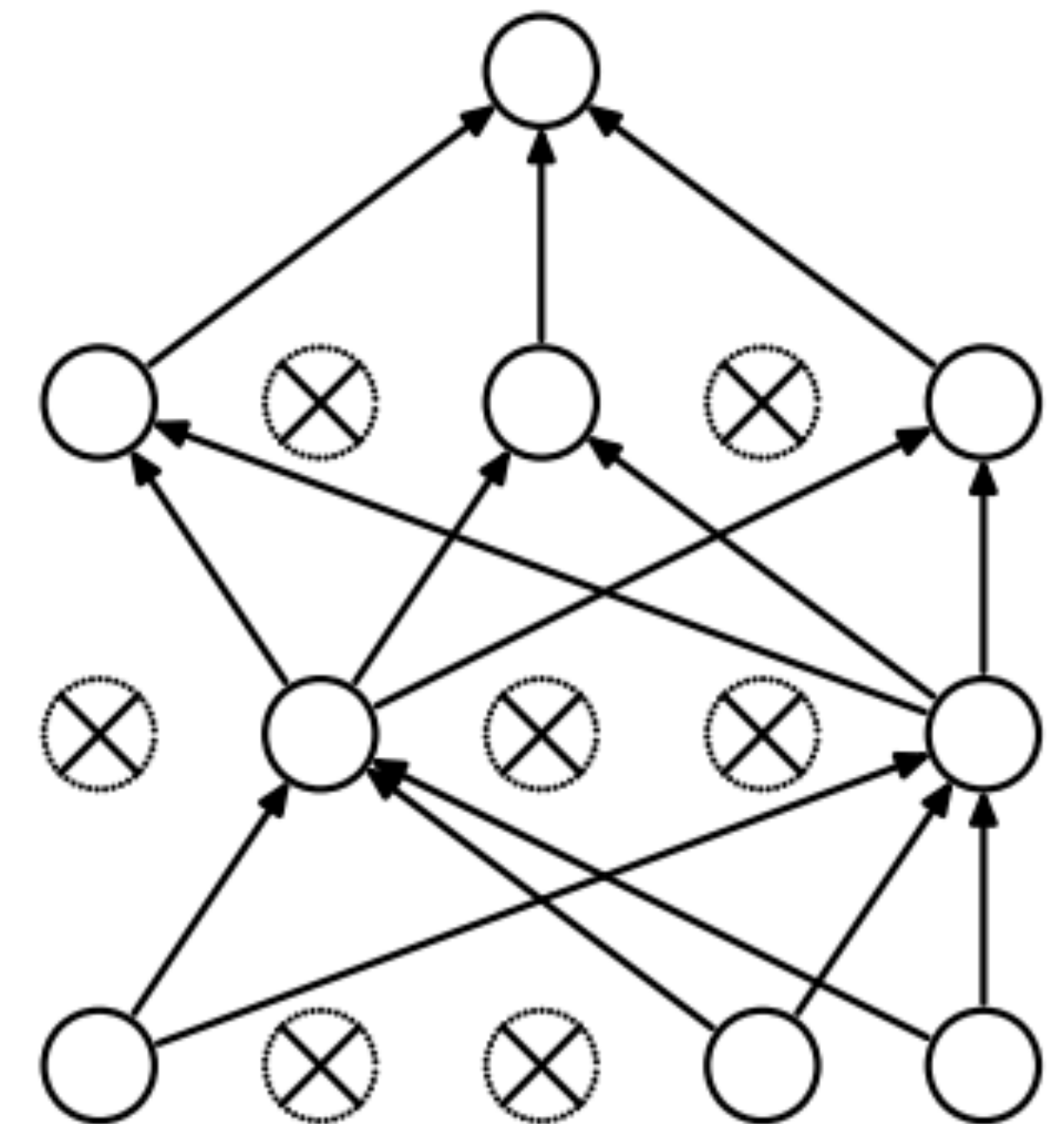
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- ▶ One line in Pytorch/Tensorflow



(a) Standard Neural Net



(b) After applying dropout.

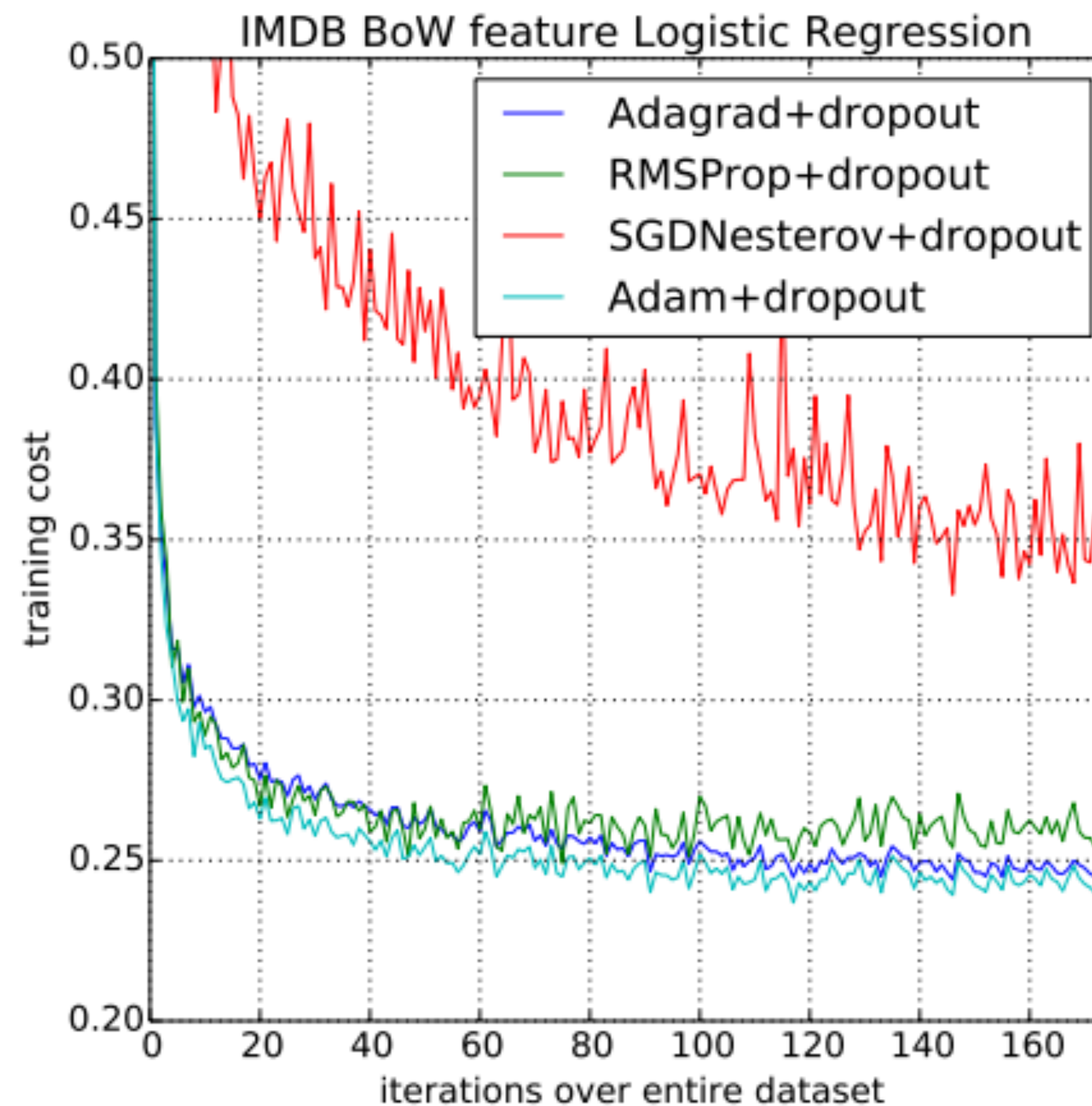
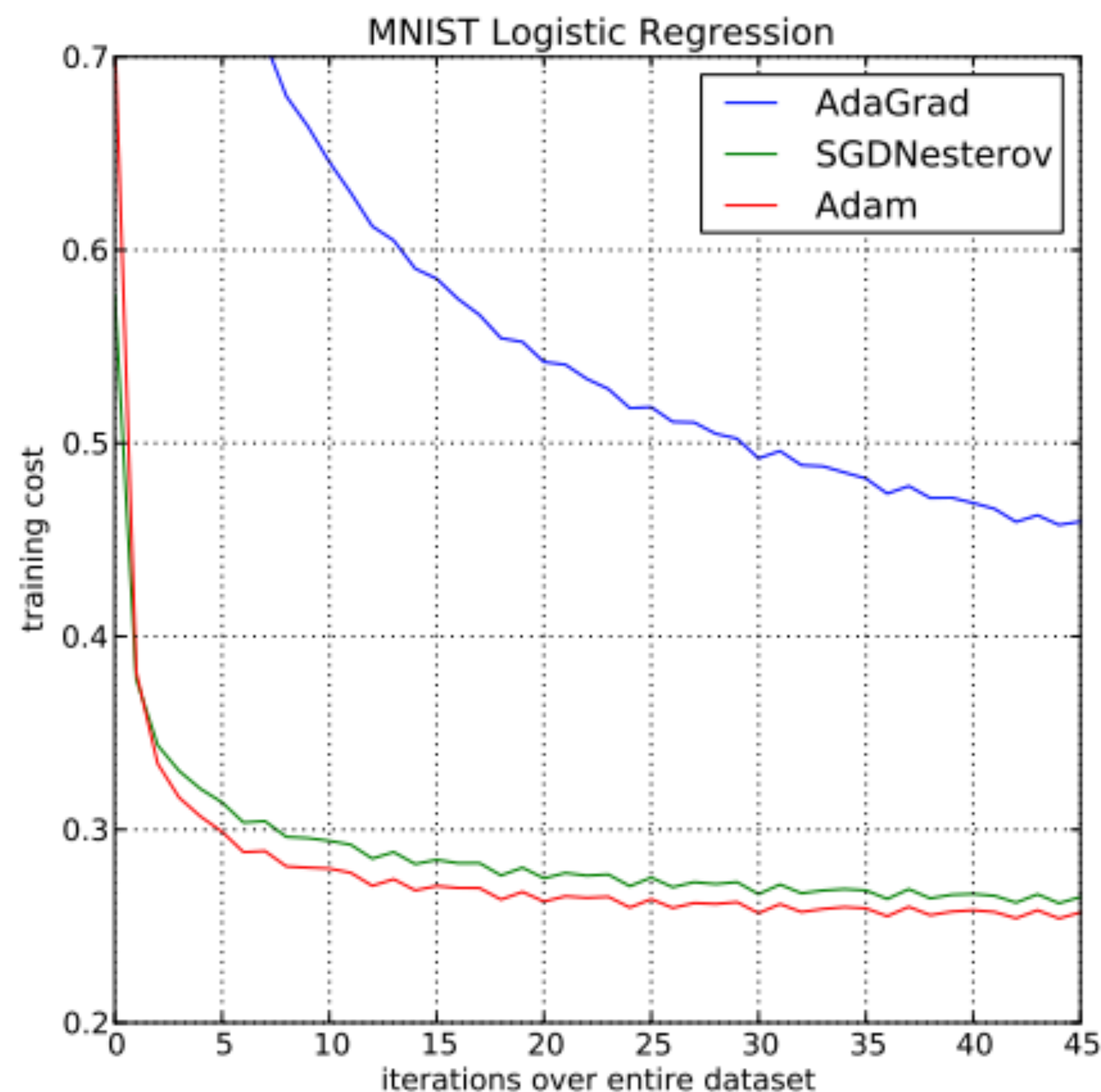
Srivastava et al. (2014)

Optimizer

- ▶ Adam (Kingma and Ba, ICLR 2015) is very widely used
- ▶ Adaptive step size like Adagrad, incorporates momentum

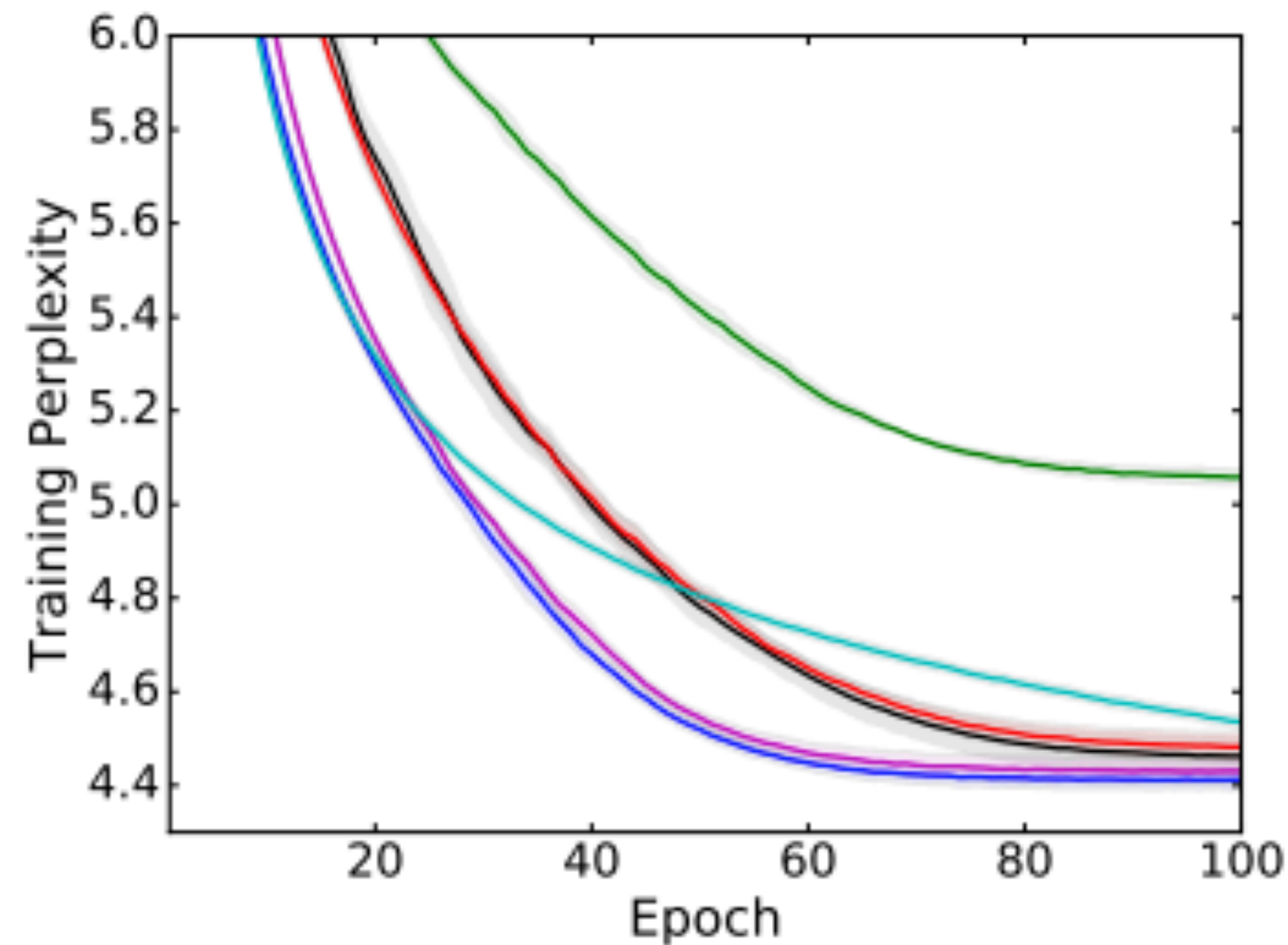
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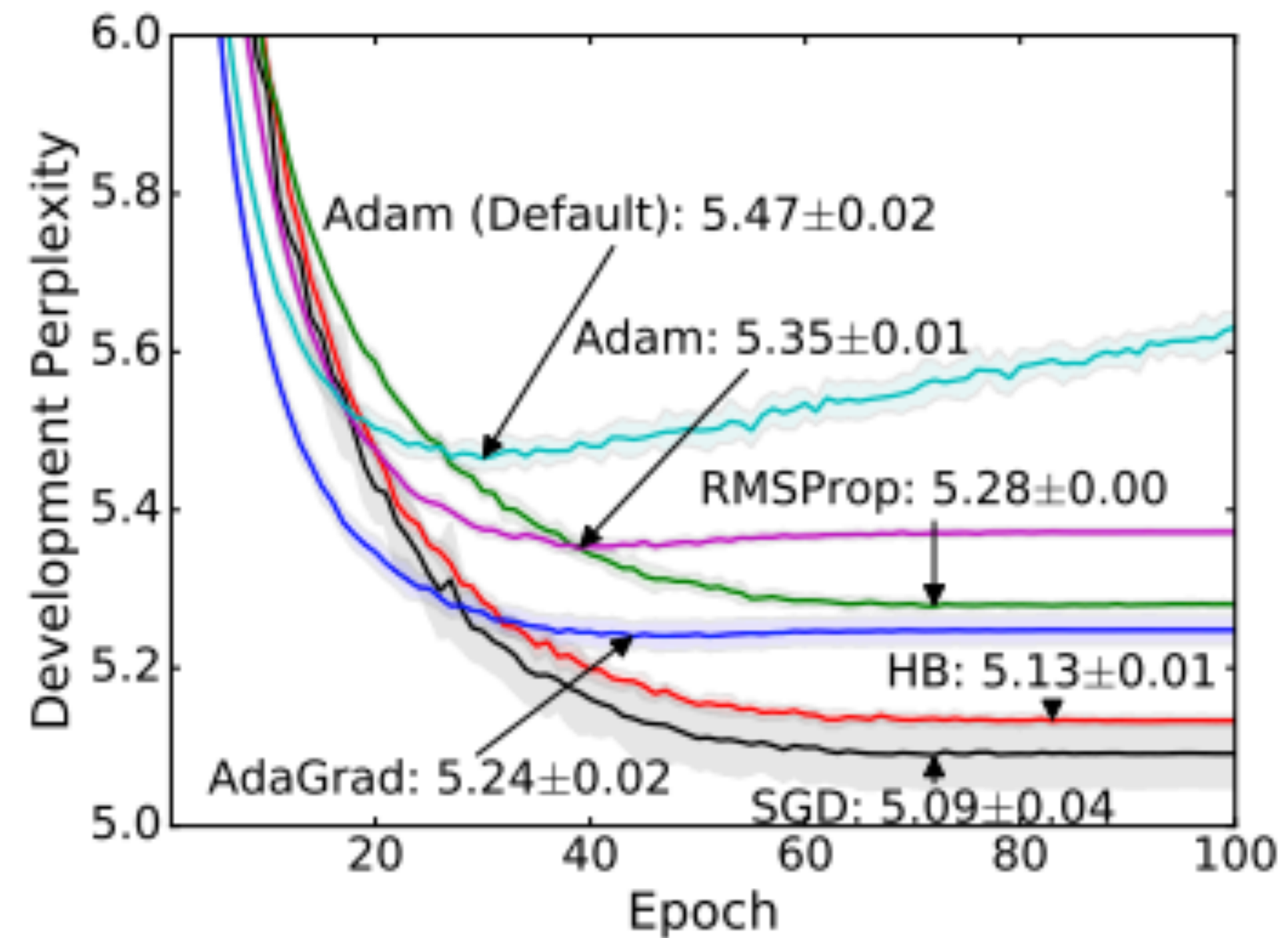


Optimizer

- Wilson et al. NIPS 2017: adaptive methods can actually perform badly at test time (Adam is in pink, SGD in black)



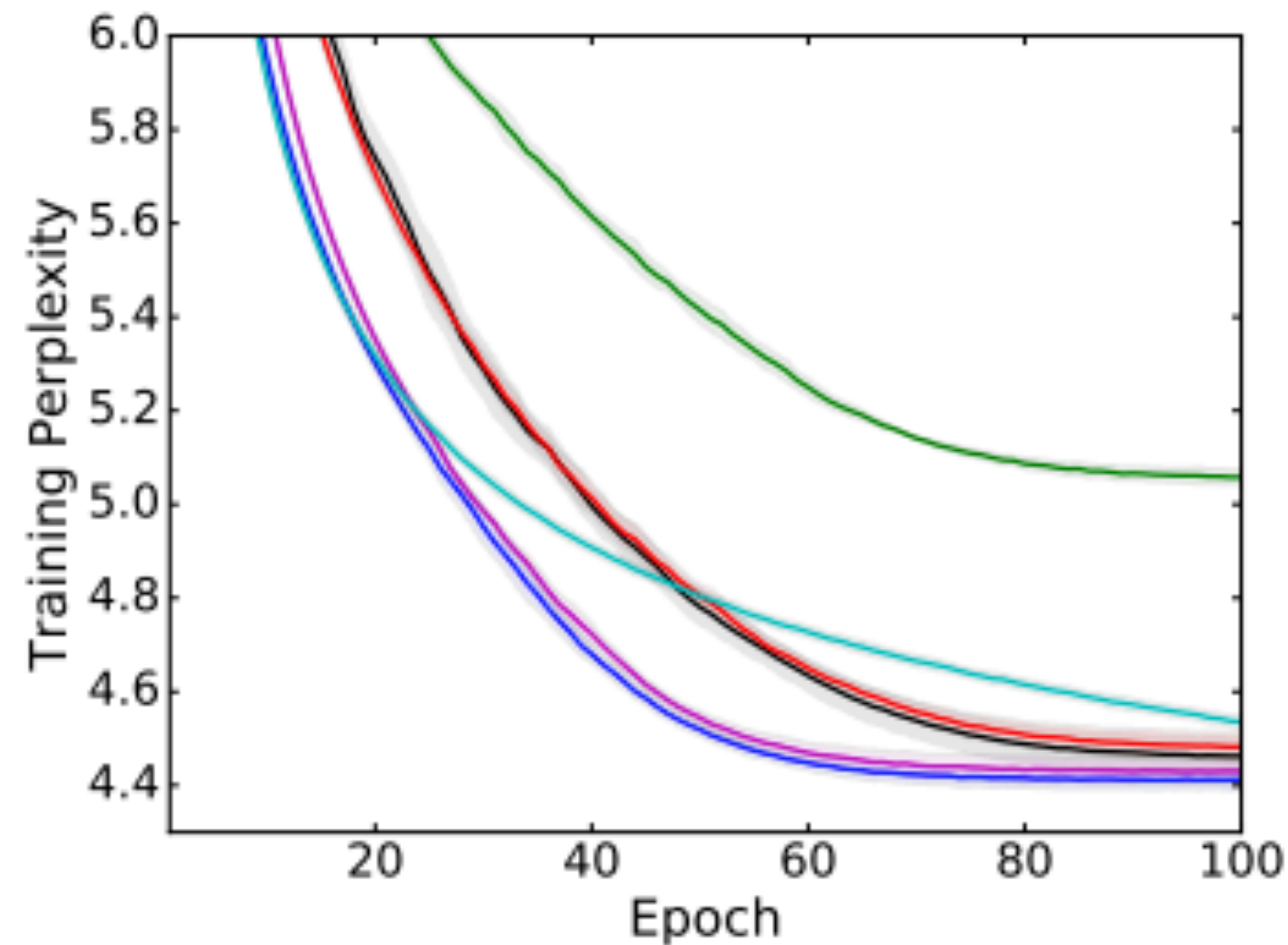
(e) Generative Parsing (Training Set)



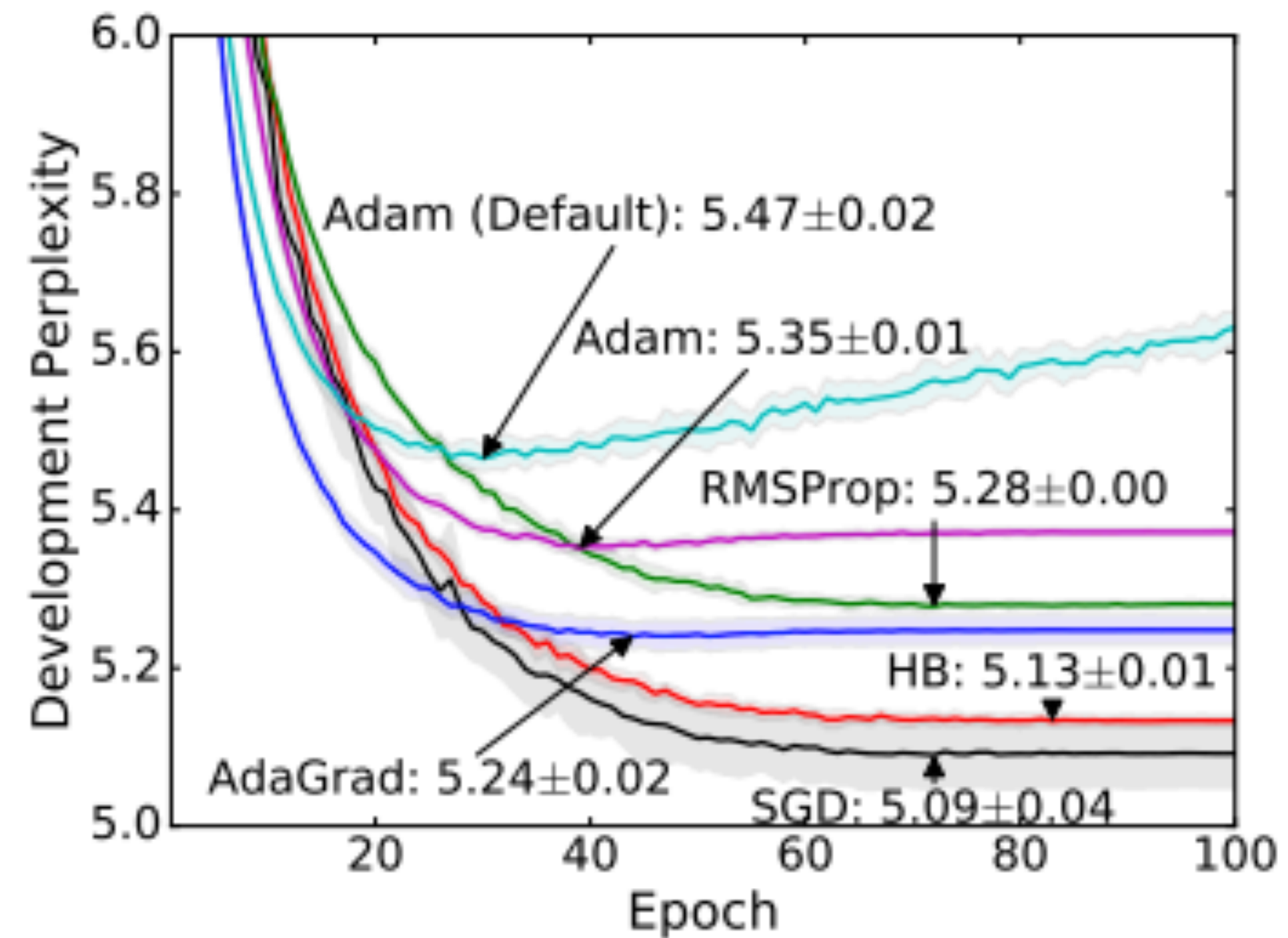
(f) Generative Parsing (Development Set)

Optimizer

- ▶ Wilson et al. NIPS 2017: adaptive methods can actually perform badly at test time (Adam is in pink, SGD in black)
- ▶ Check dev set periodically, decrease learning rate if not making progress



(e) Generative Parsing (Training Set)



(f) Generative Parsing (Development Set)

Elements of Machine Learning

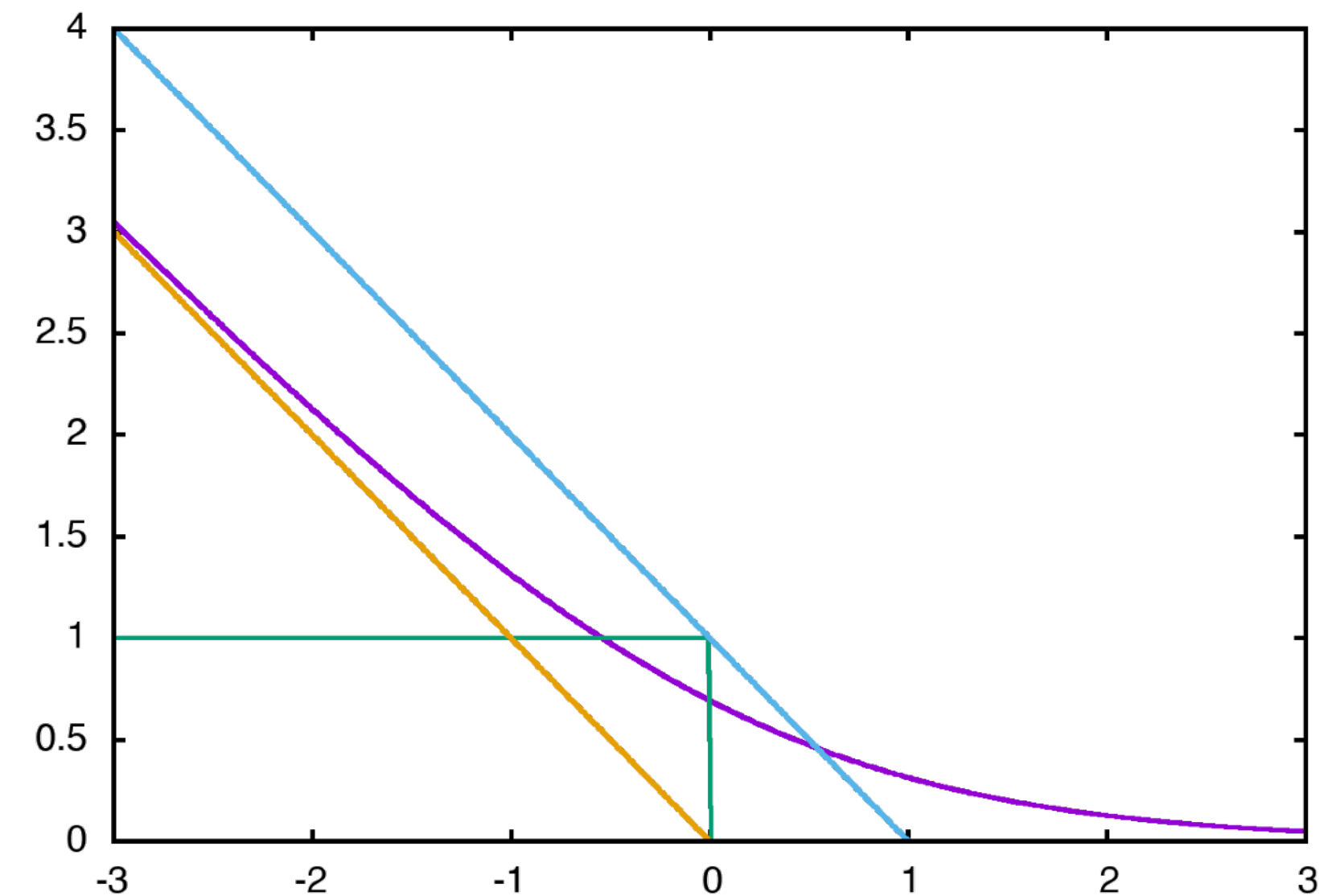
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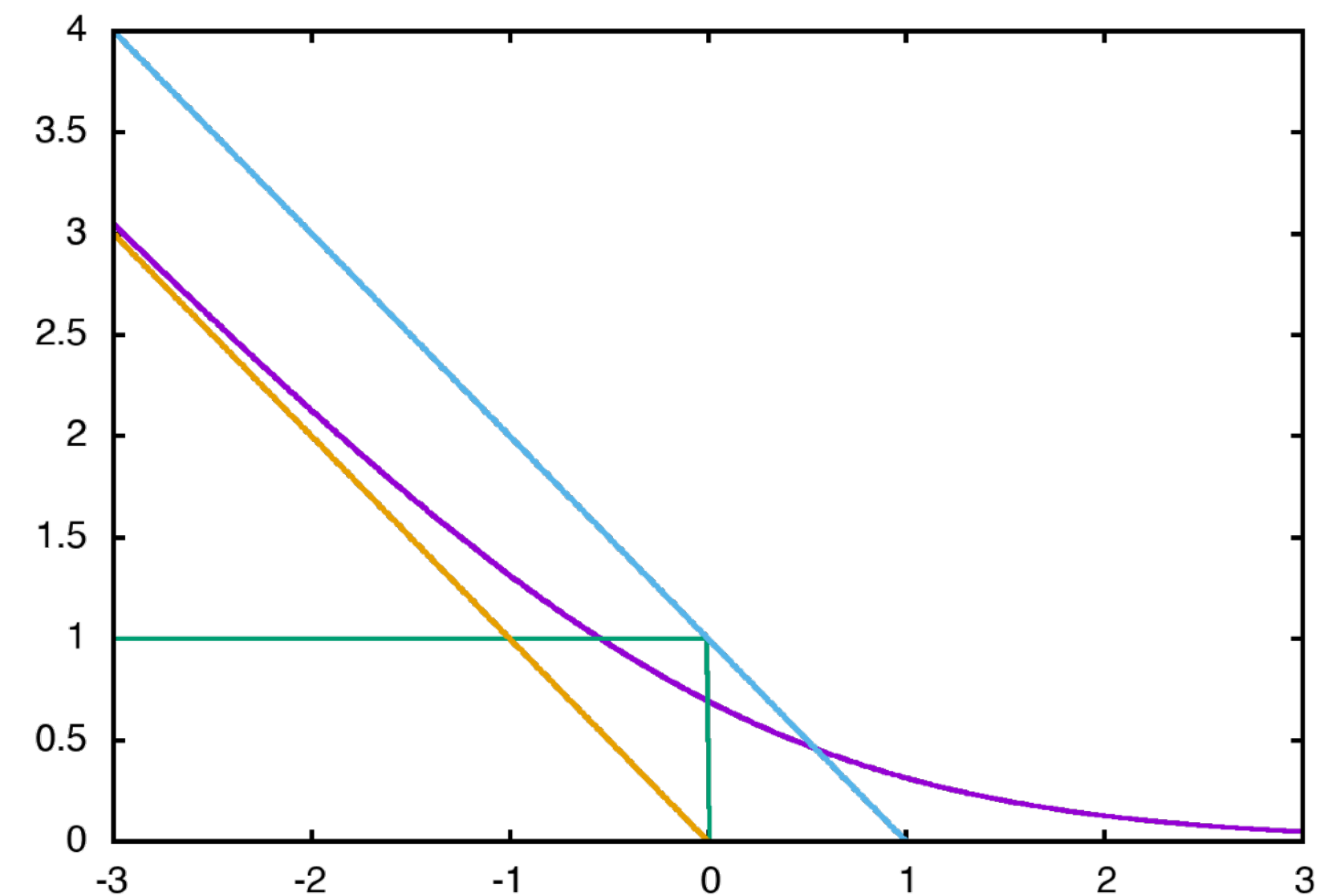
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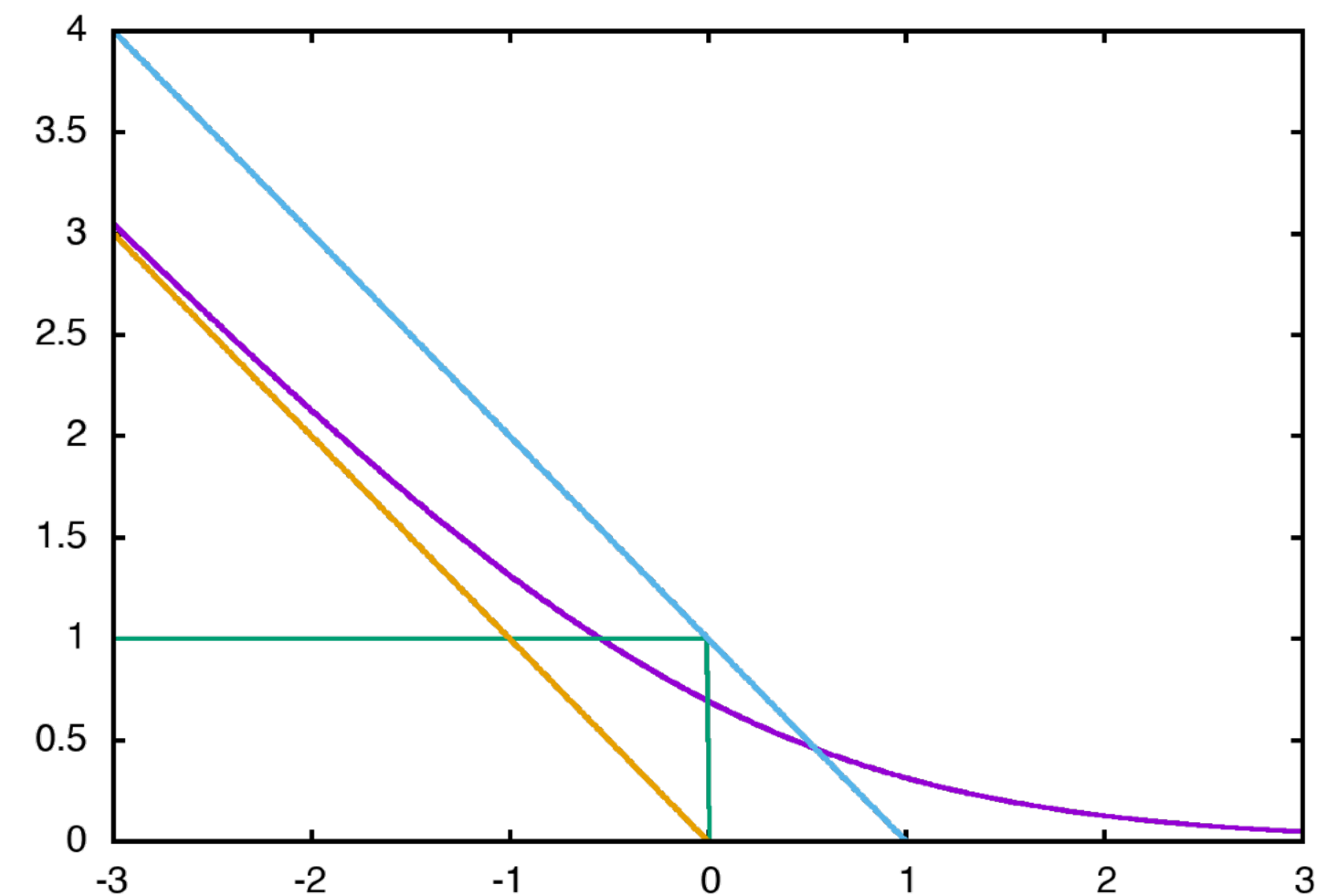
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- ▶ Training: lots of choices for optimization/hyperparameters



Word Representations

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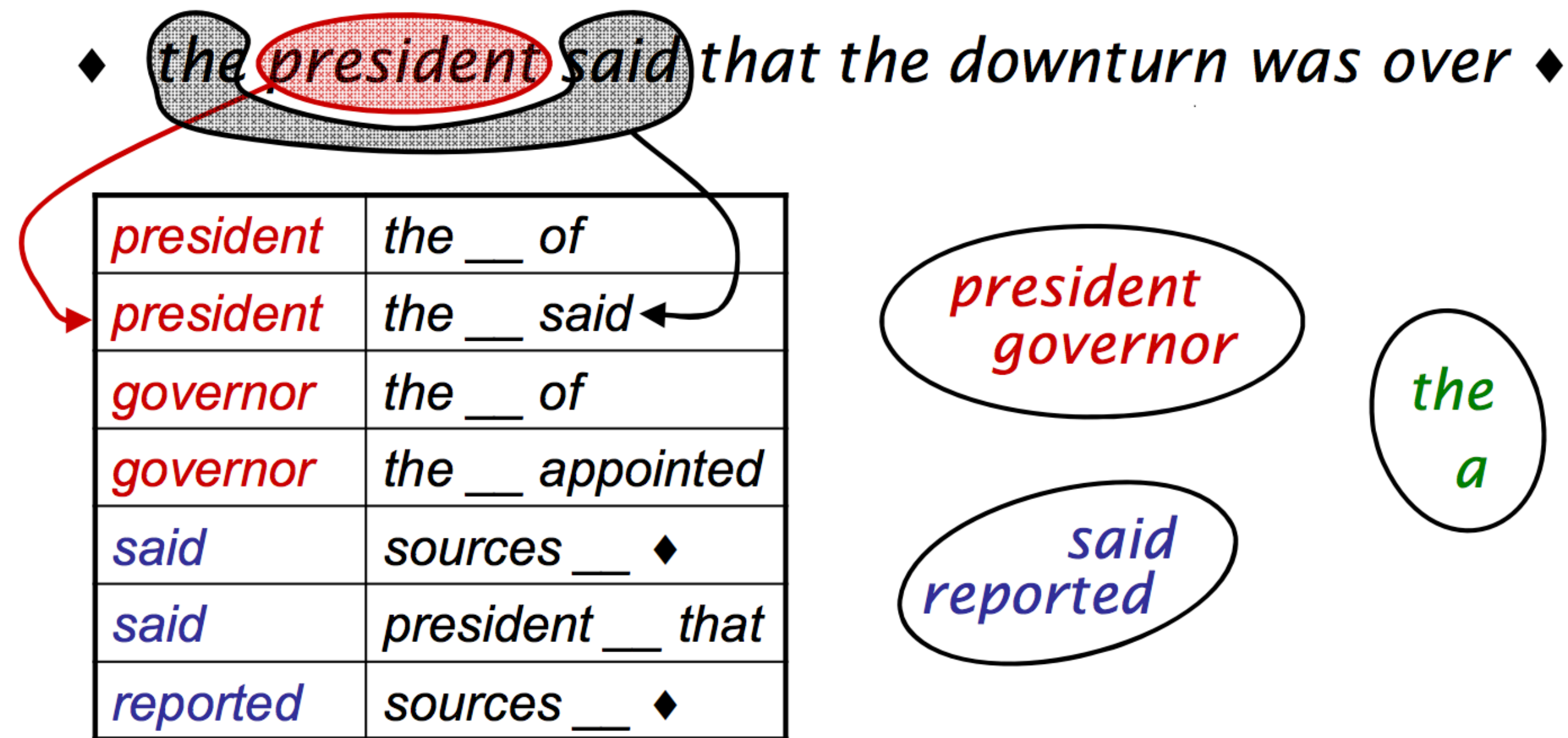
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- ▶ Continuous model \leftrightarrow expects continuous semantics from input
- ▶ “You shall know a word by the company it keeps” Firth (1957)



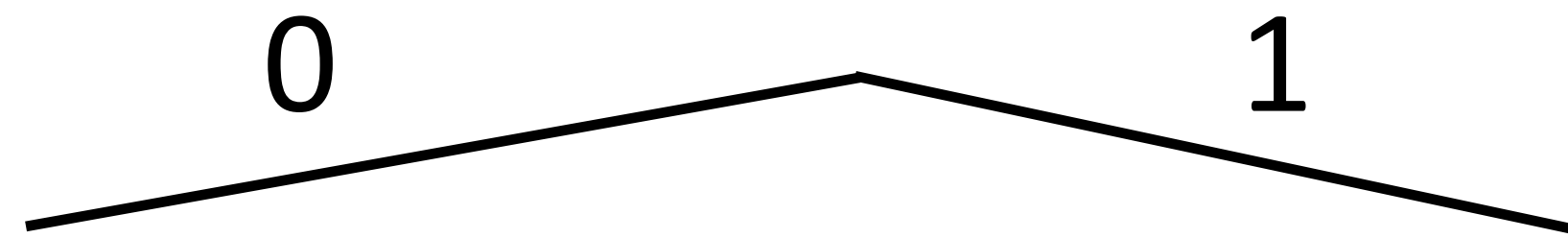
Discrete Word Representations

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- ▶ Brown clusters: hierarchical agglomerative *hard* clustering (each word has one cluster, not some posterior distribution like in mixture models)

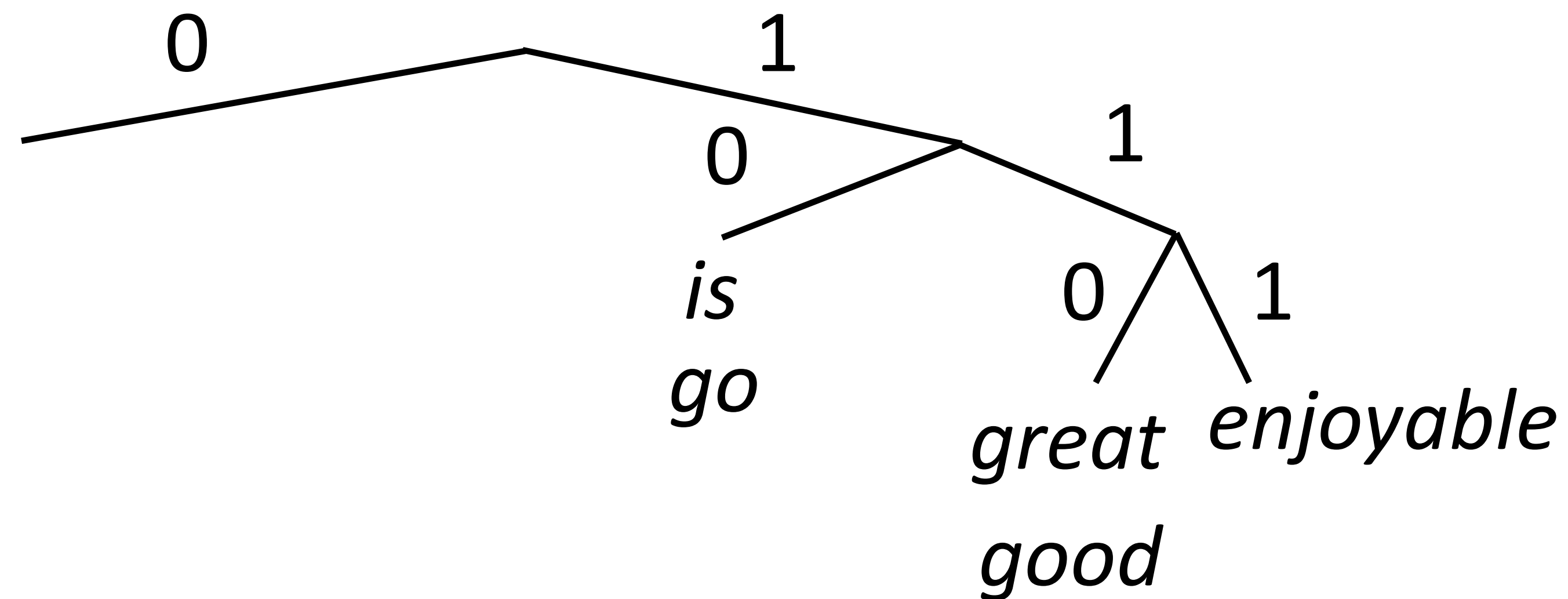
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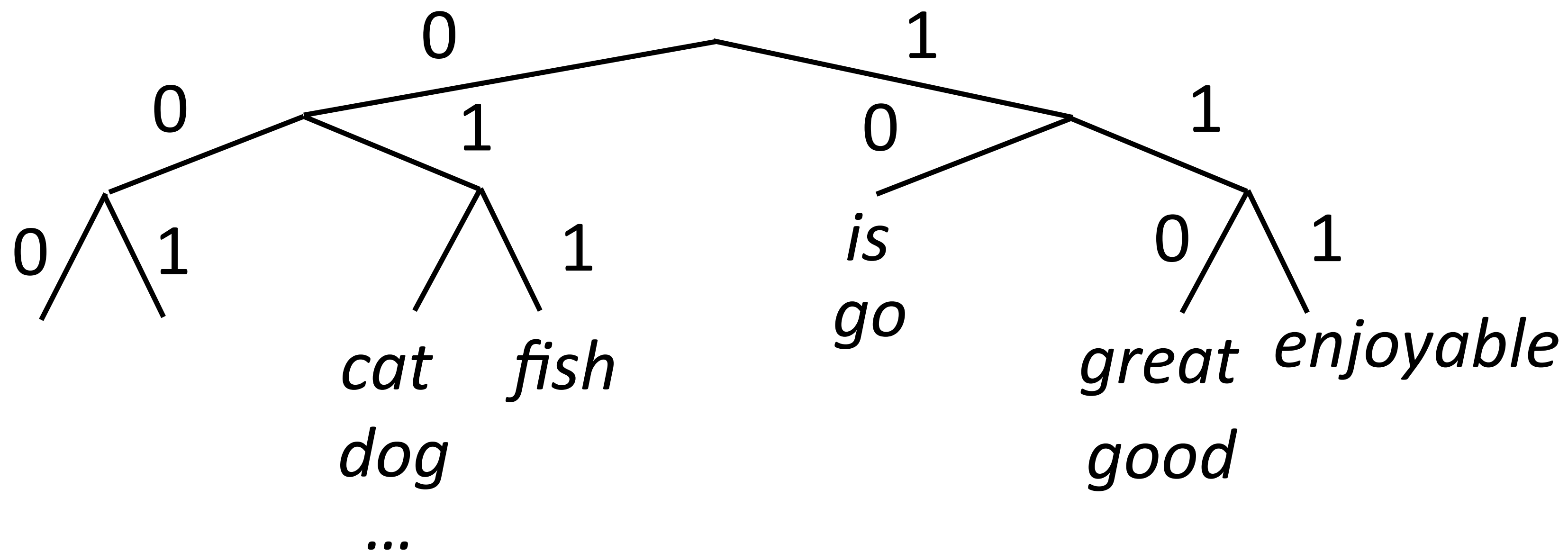
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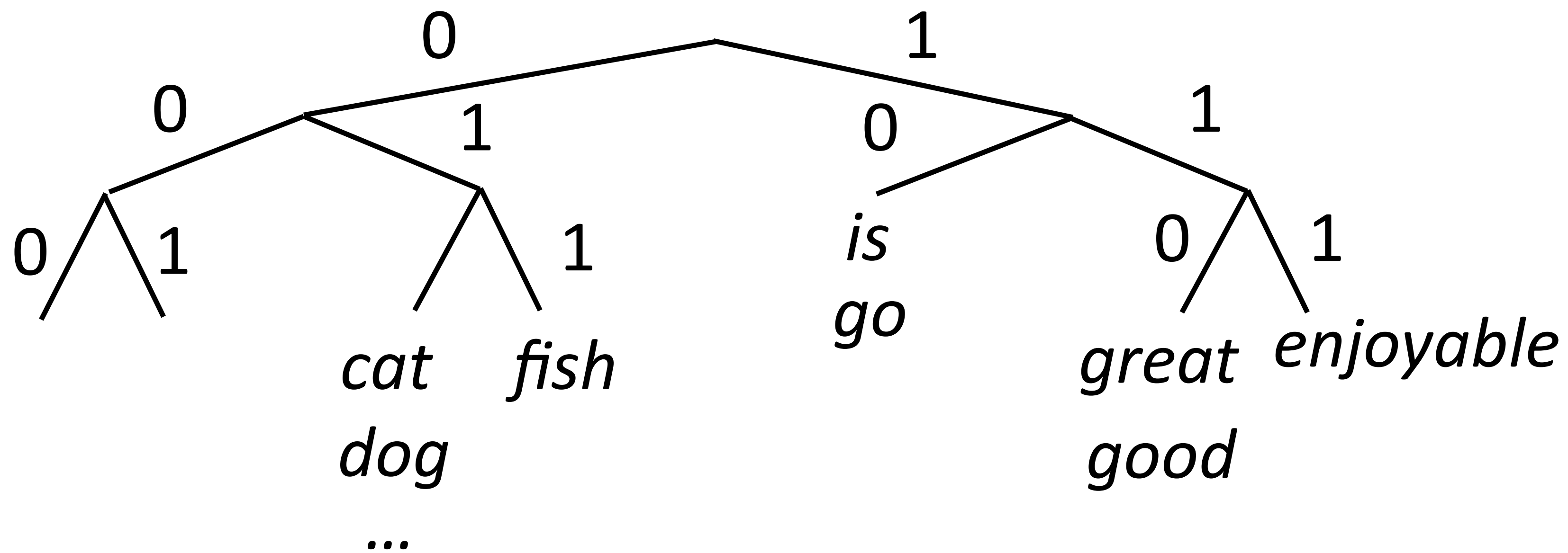
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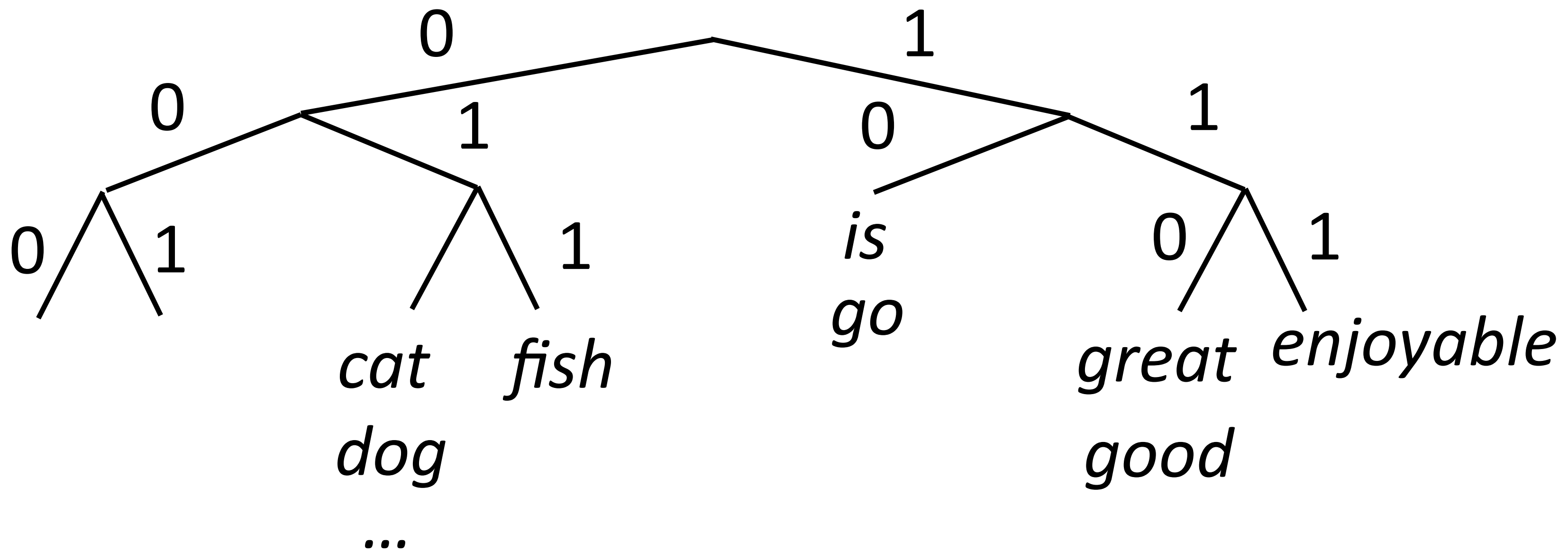
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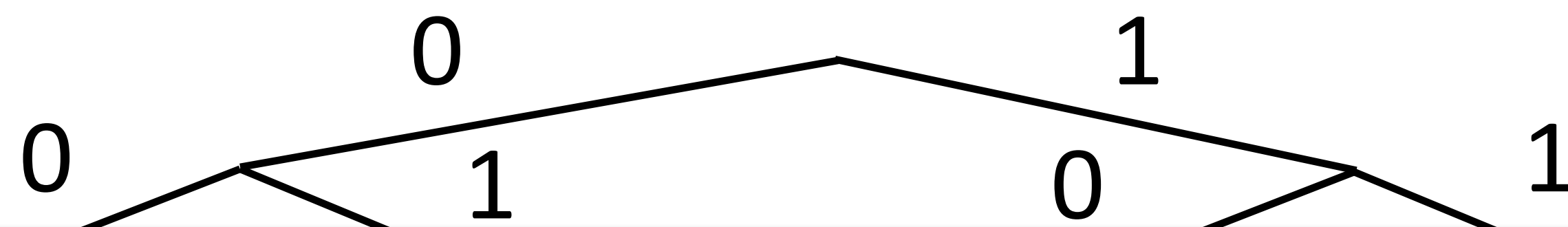
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- Brown et al. (1992)

Discrete Word Representations

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Sample Brown Clusters:

- https://raw.githubusercontent.com/aritter/5525_perceptron_tagger/master/60K_clusters.bits.txt

cat fish good great enjoyable
dog good
...

- ▶ Maximize $P(w_i|w_{i-1}) = P(c_i|c_{i-1})P(w_i|c_i)$
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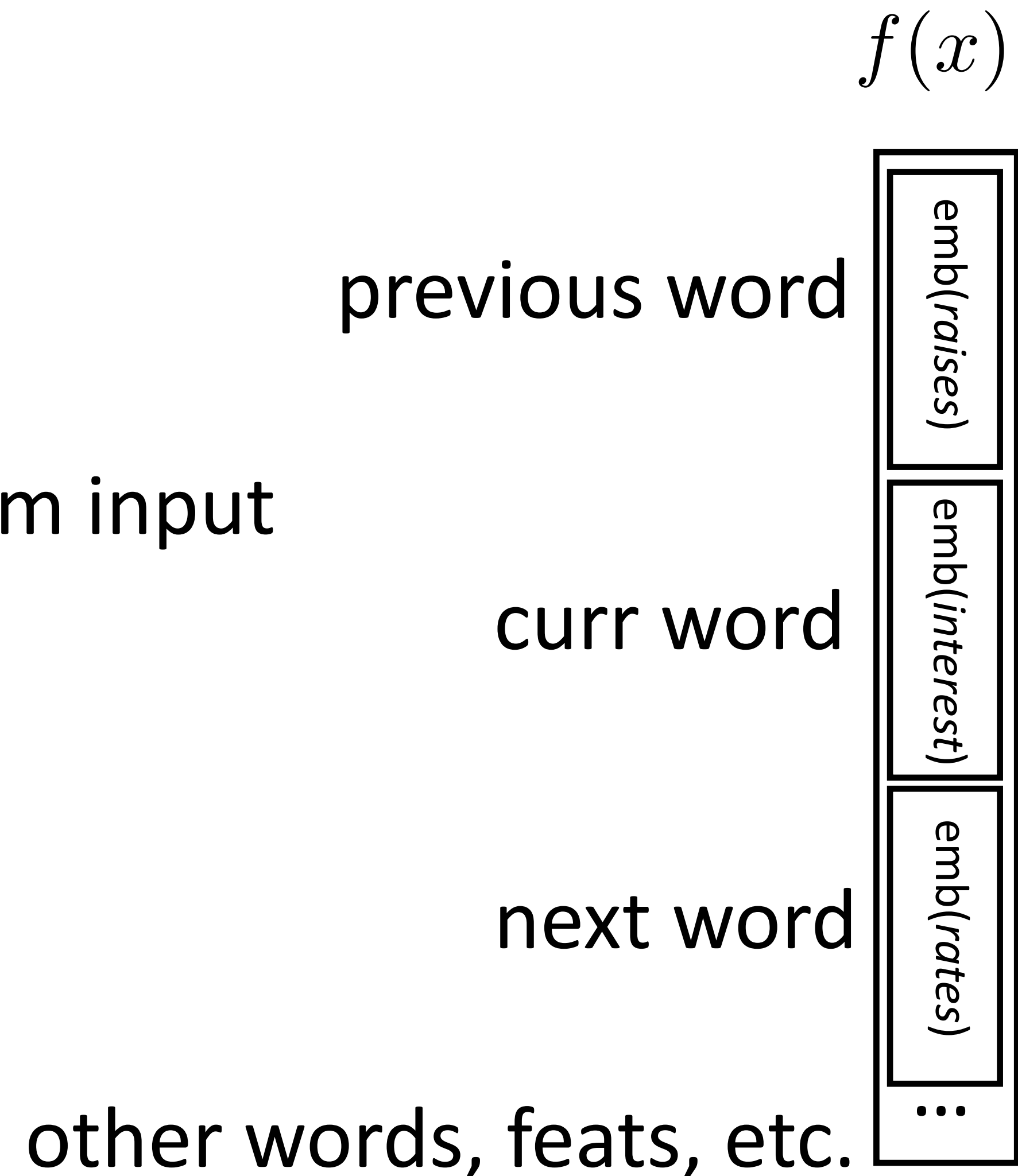
Word Embeddings

- Part-of-speech tagging with FFNNs

??

*Fed raises **interest** rates in order to ...*

- Word embeddings for each word form input



Botha et al. (2017)

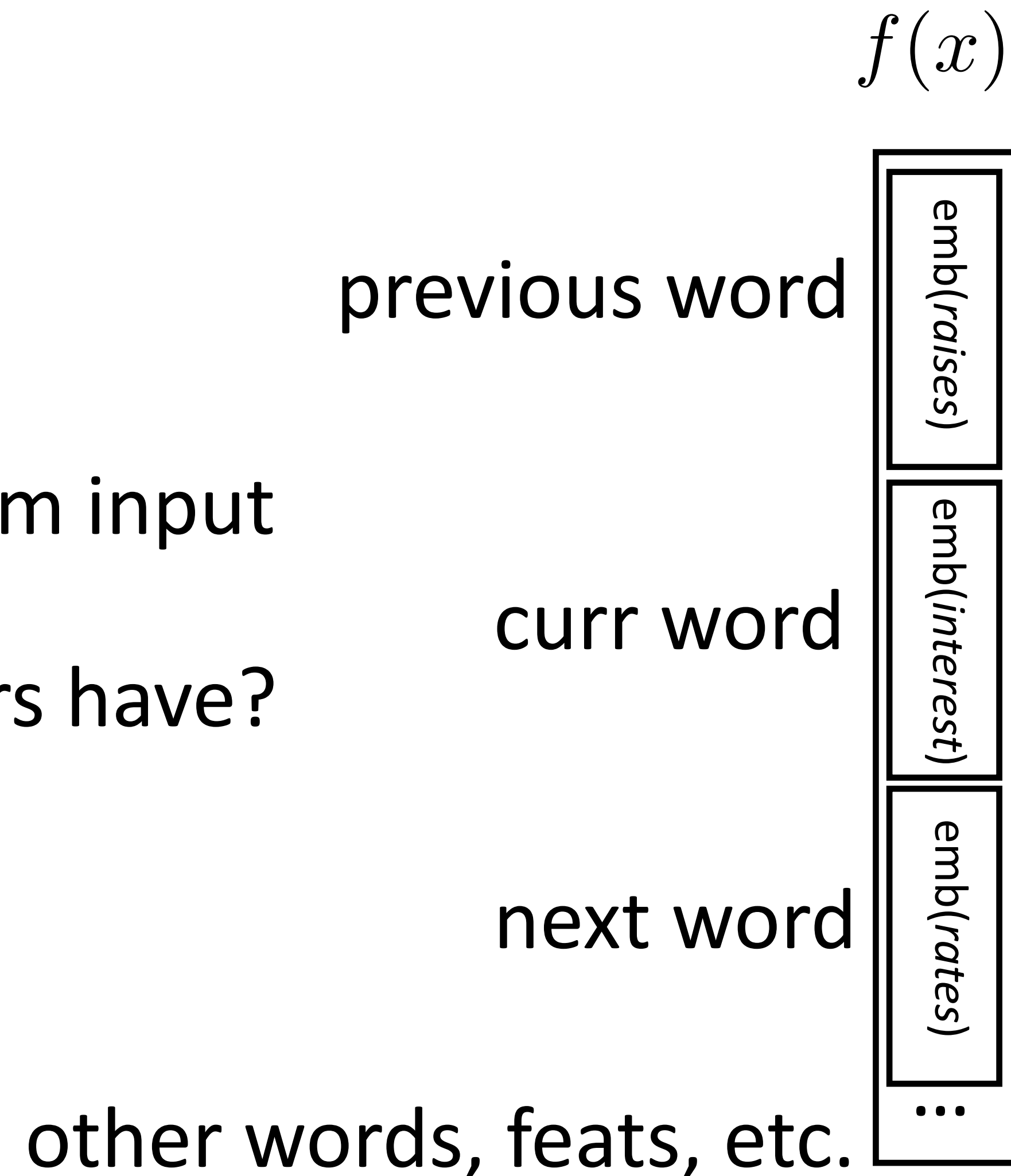
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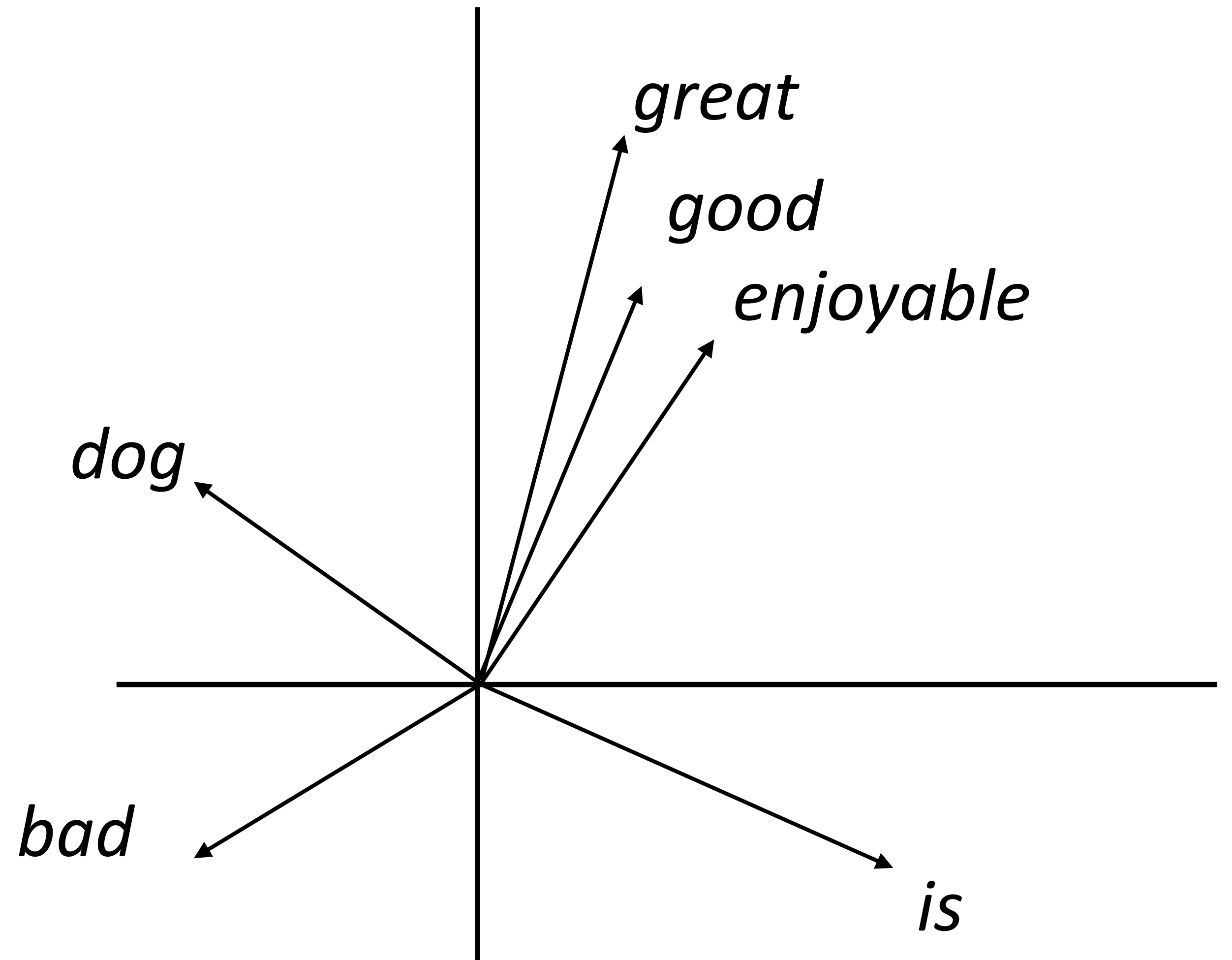
- Word embeddings for each word form input
- What properties should these vectors have?



Botha et al. (2017)

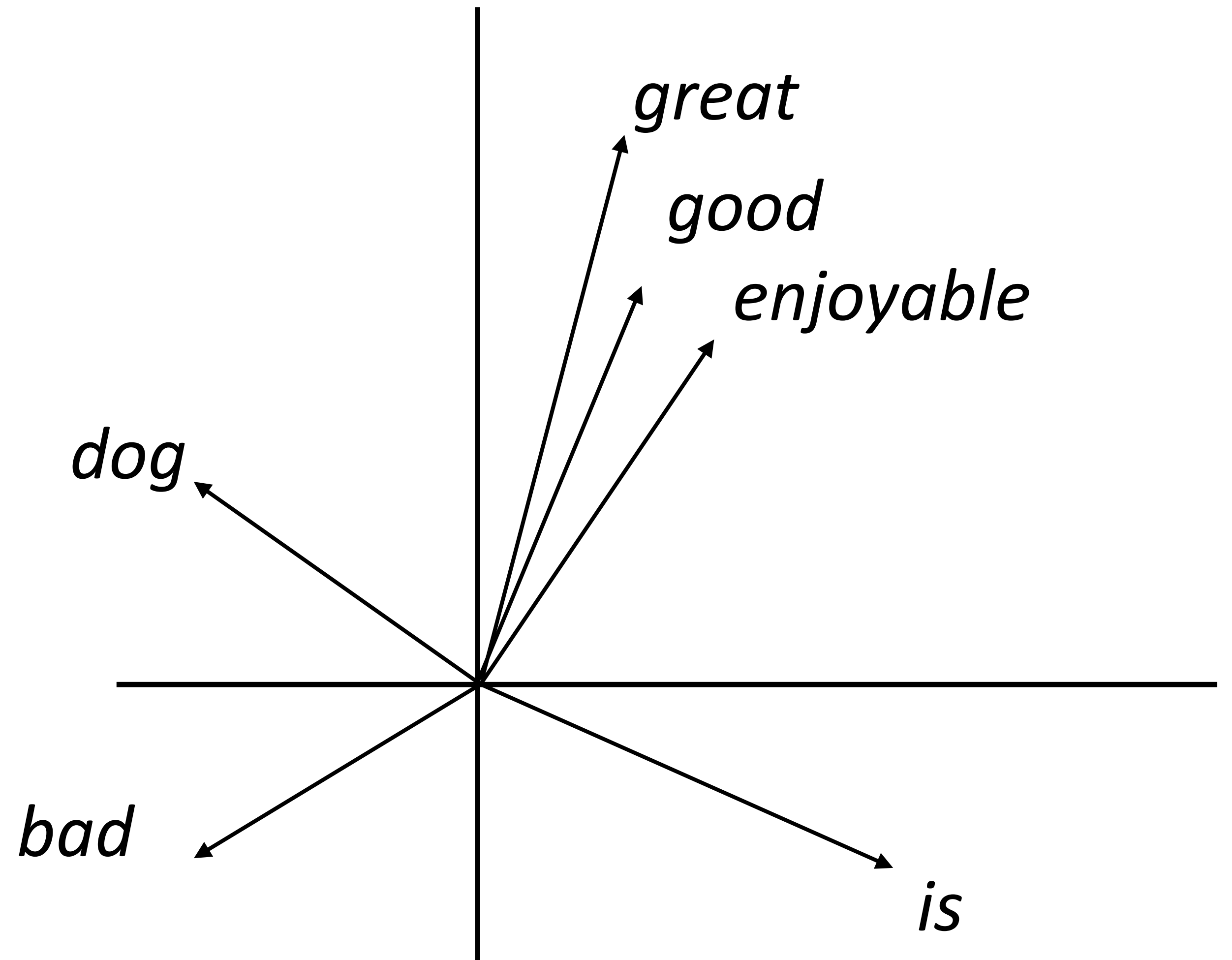
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Word Embeddings

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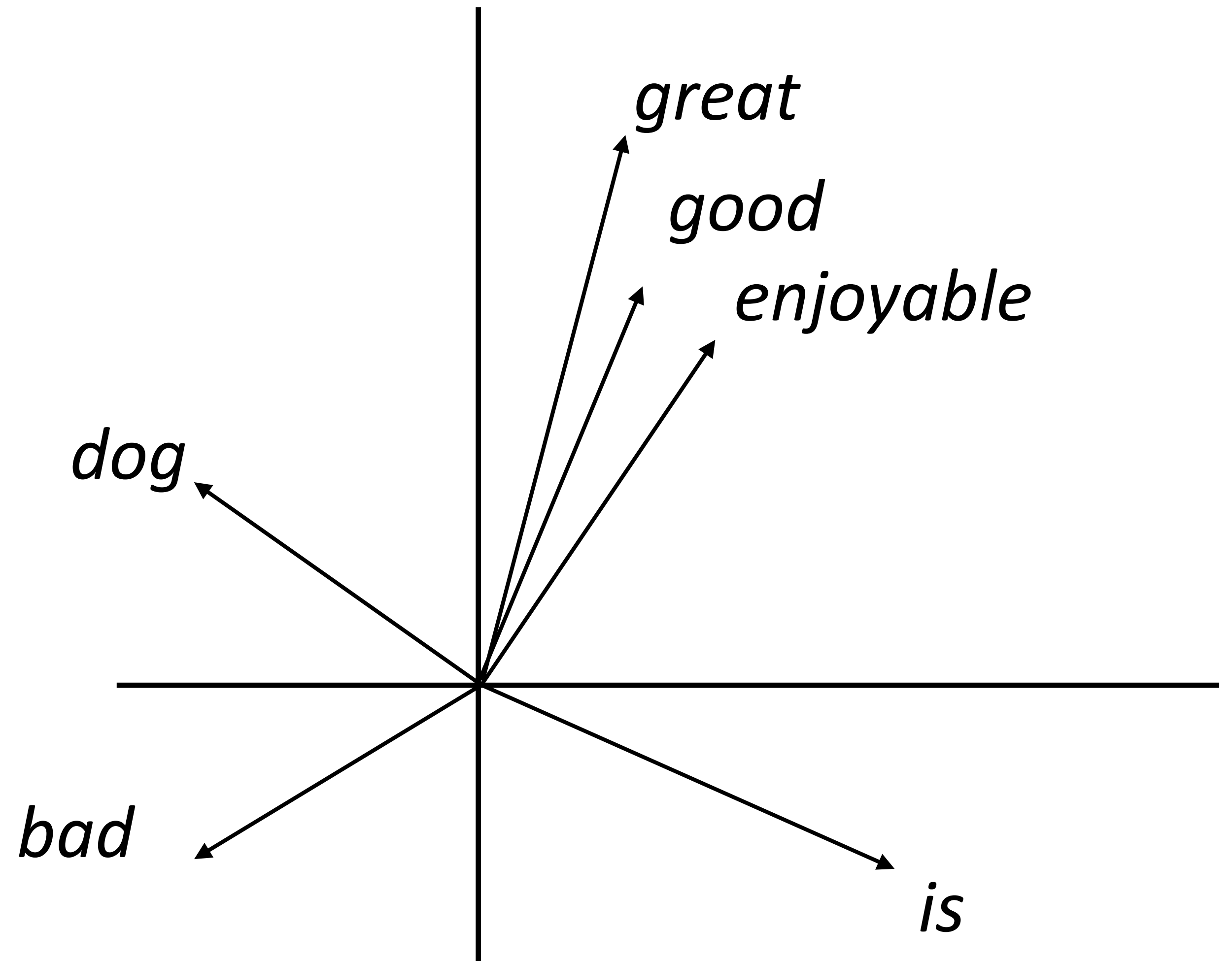
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Word Embeddings

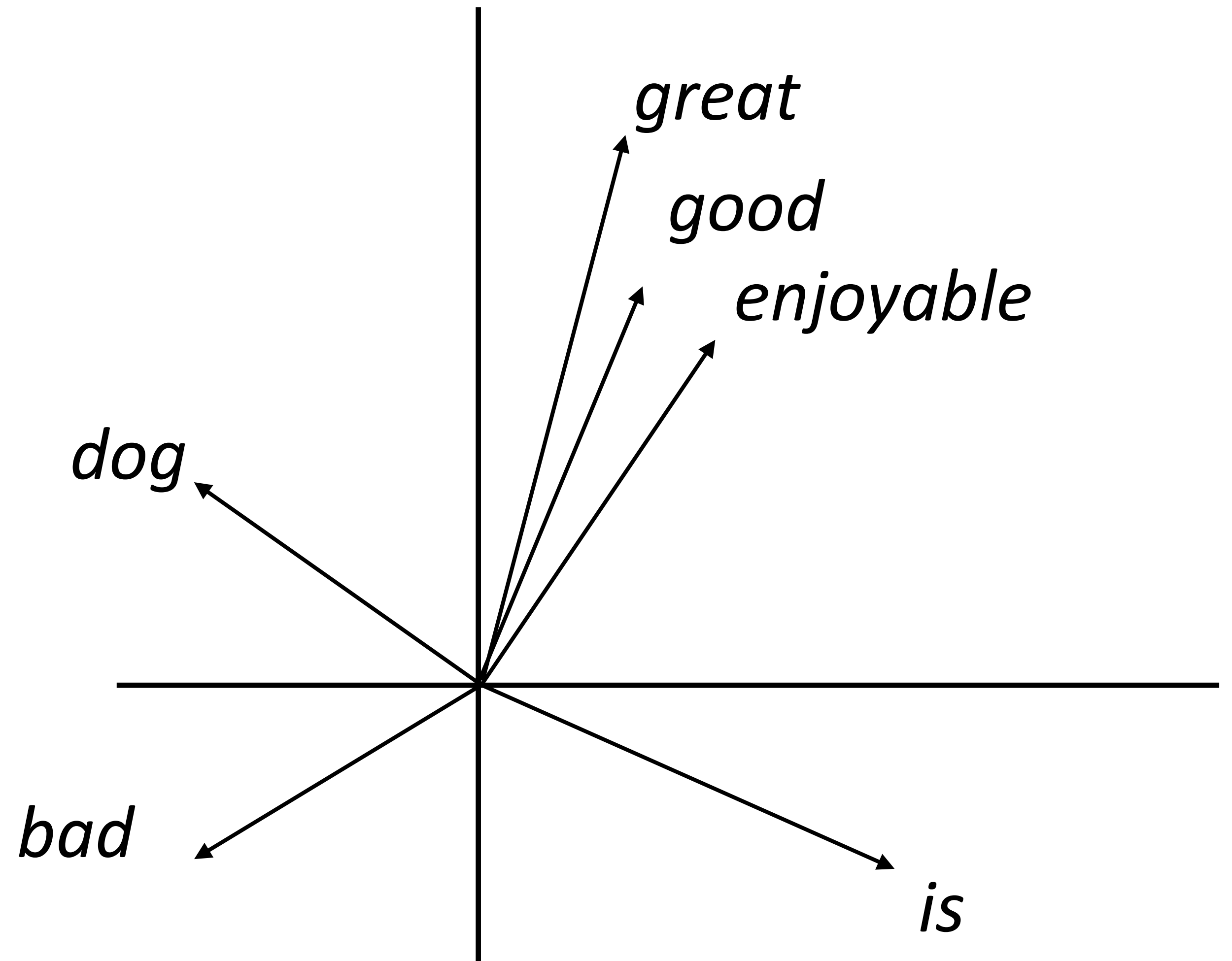
- ▶ Want a vector space where similar words have similar embeddings

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- ▶ Goal: come up with a way to produce these embeddings



word2vec/GloVe

Continuous Bag-of-Words

- ▶ Predict word from context

the dog bit the man





Continuous Bag-of-Words

- Predict word from context

the dog bit the man

The sentence "the dog bit the man" is shown in an italicized font. The word "bit" is highlighted with a solid blue square. A dashed black rectangle encloses the words "the dog bit the", indicating the context used for prediction.

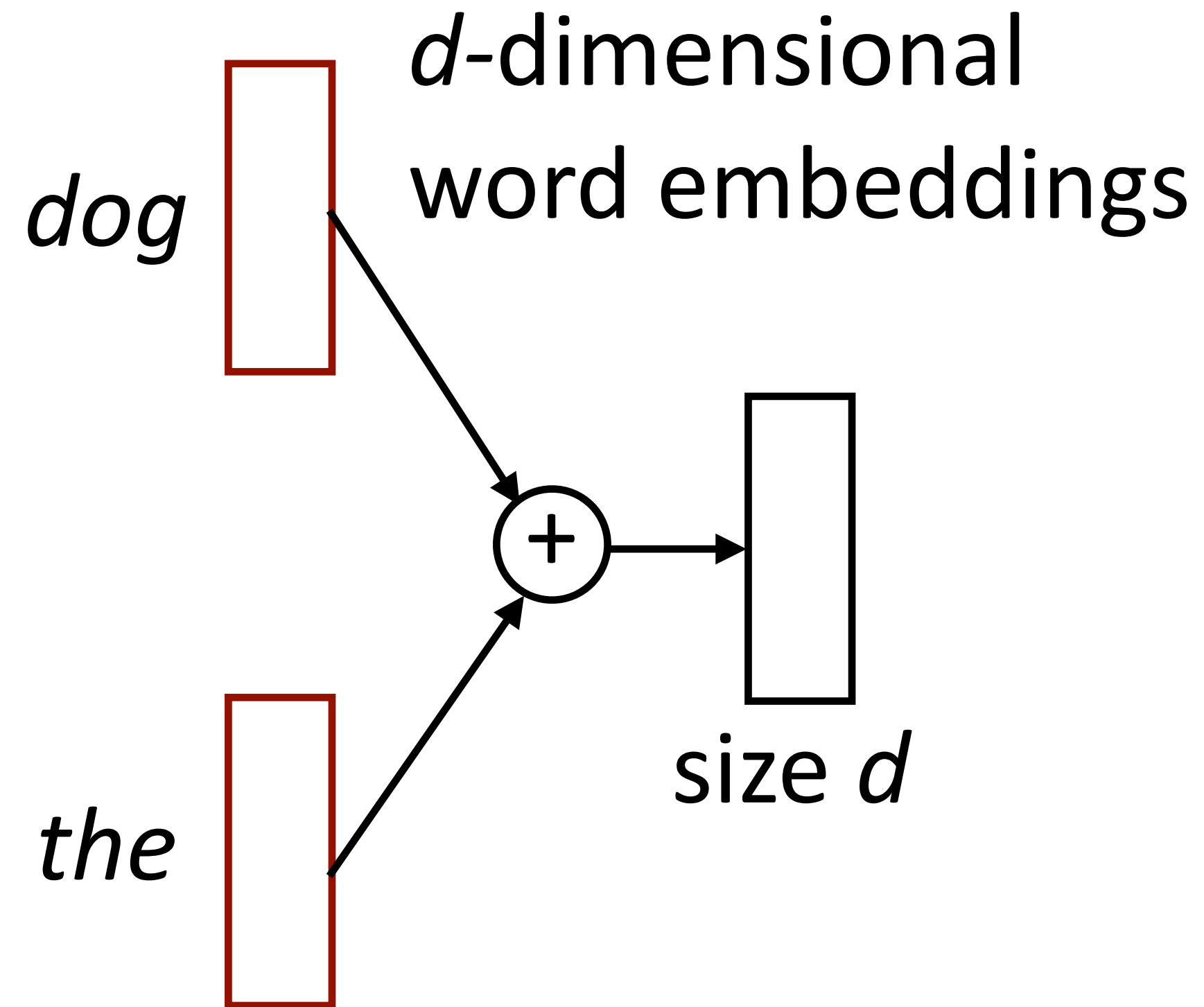
dog  d -dimensional
word embeddings

the 

Continuous Bag-of-Words

- Predict word from context

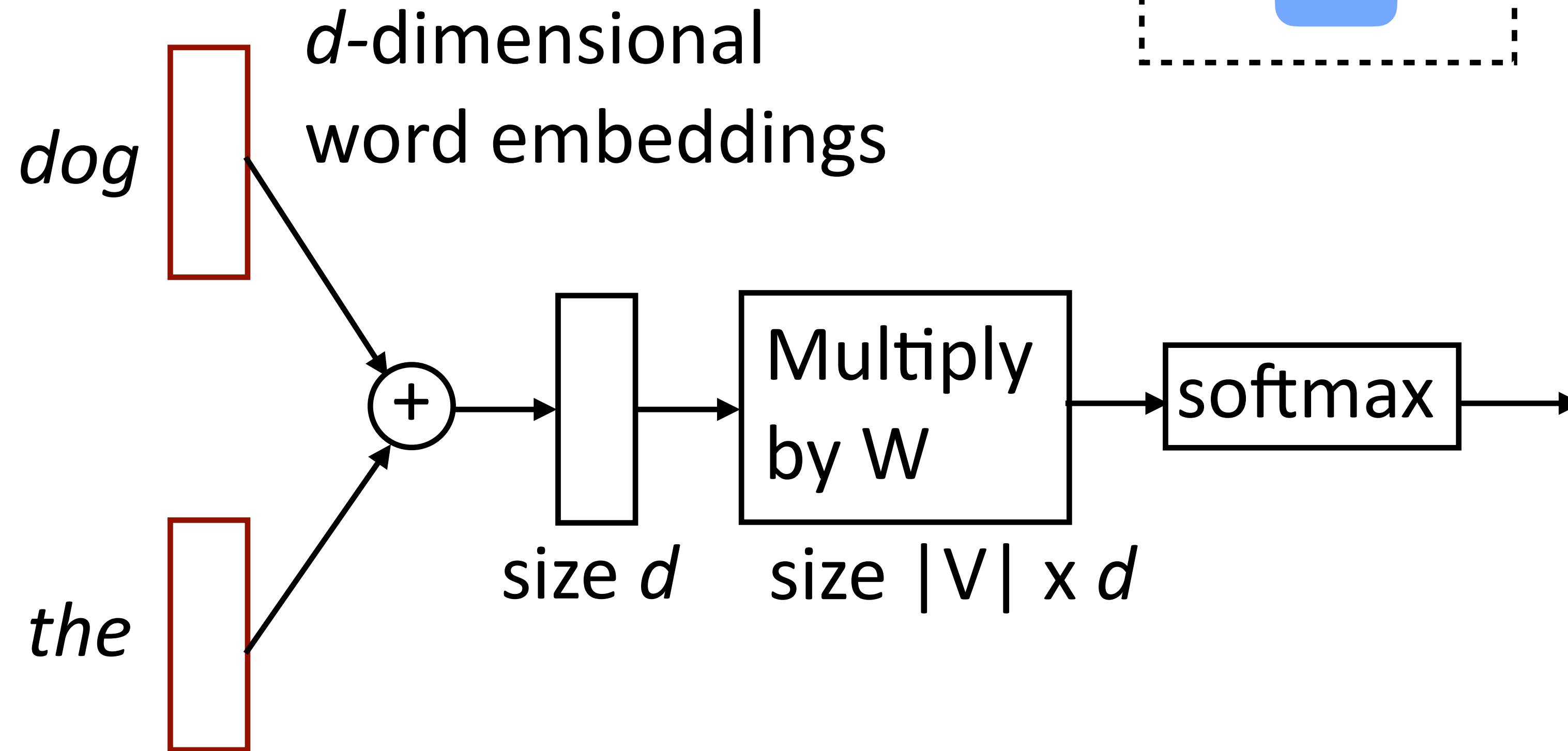
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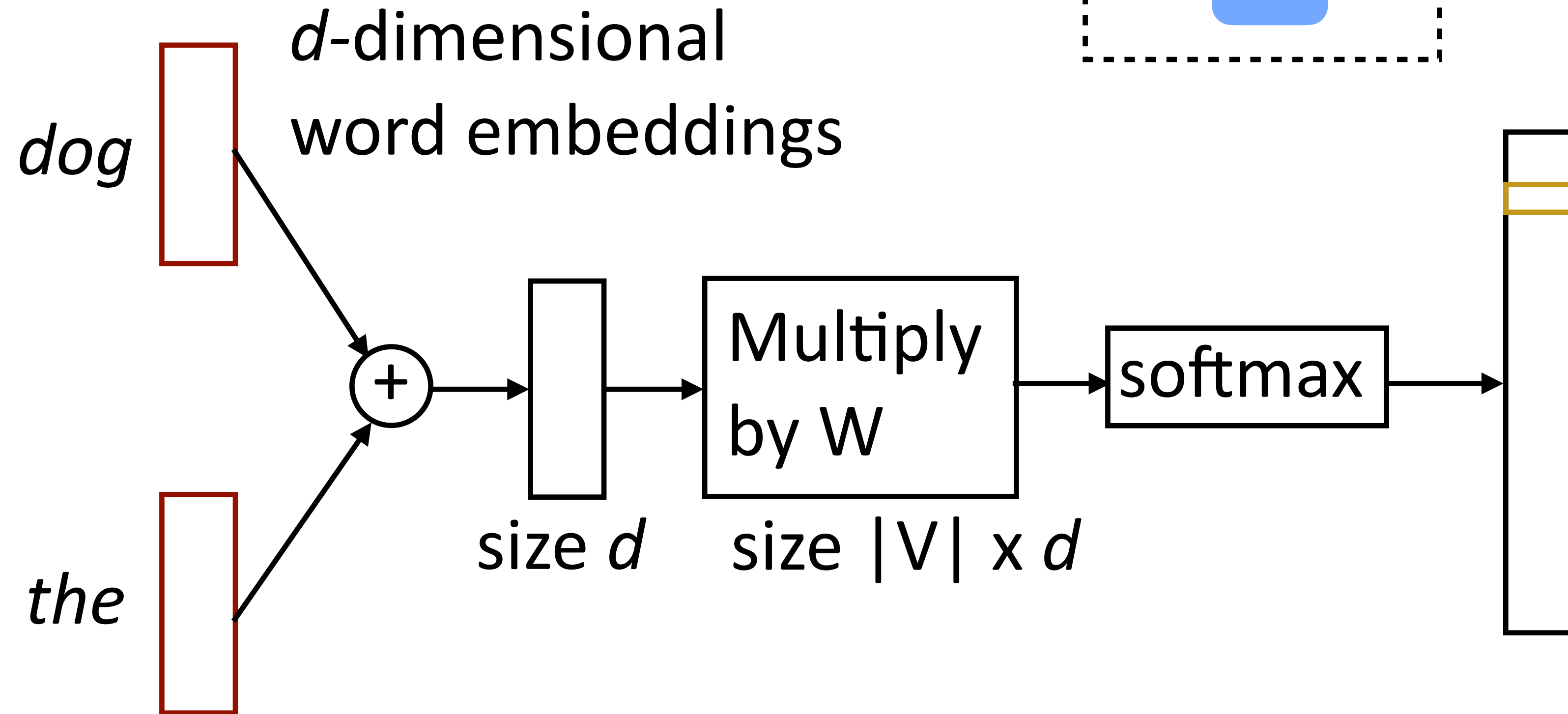
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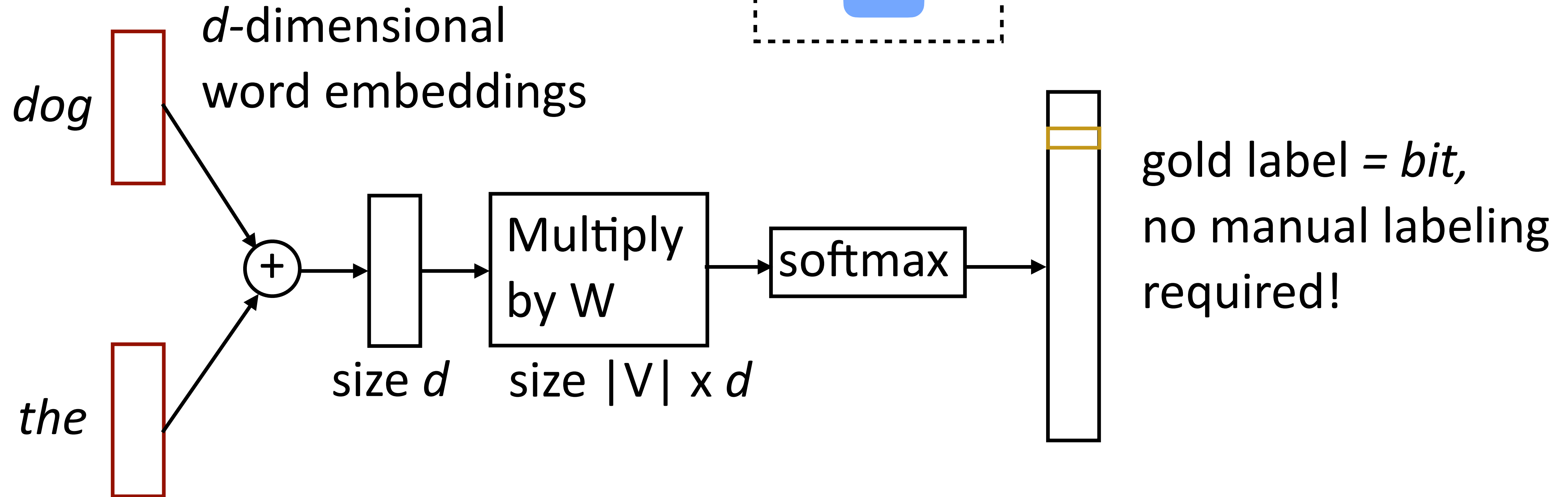
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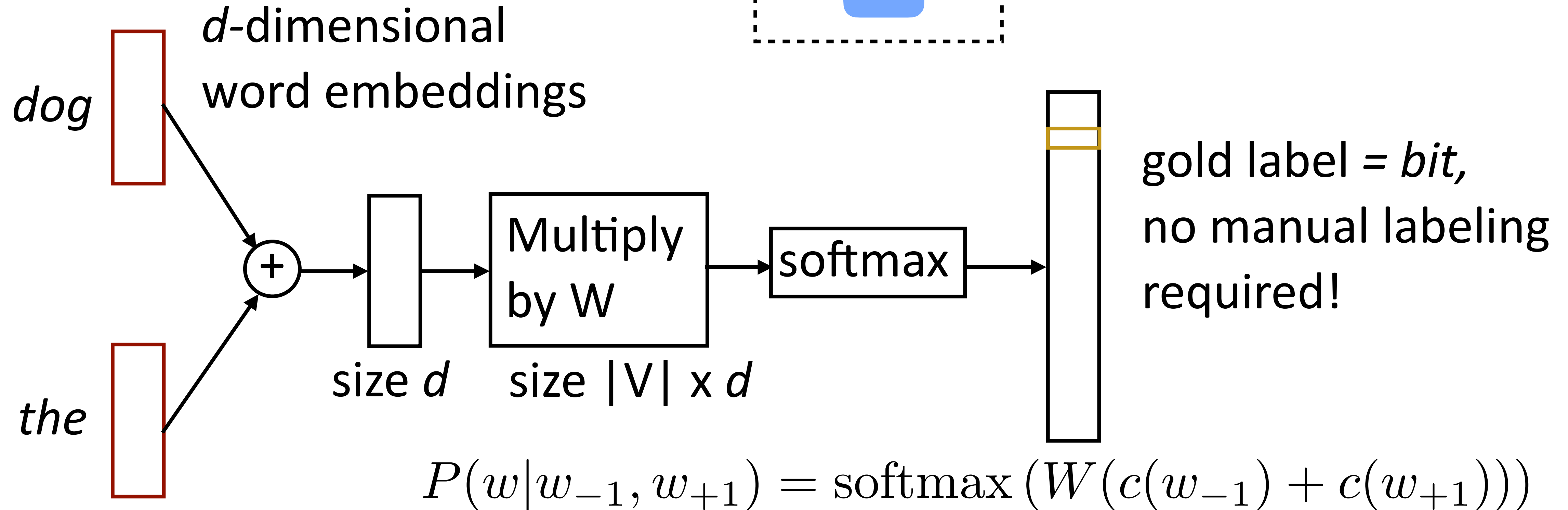
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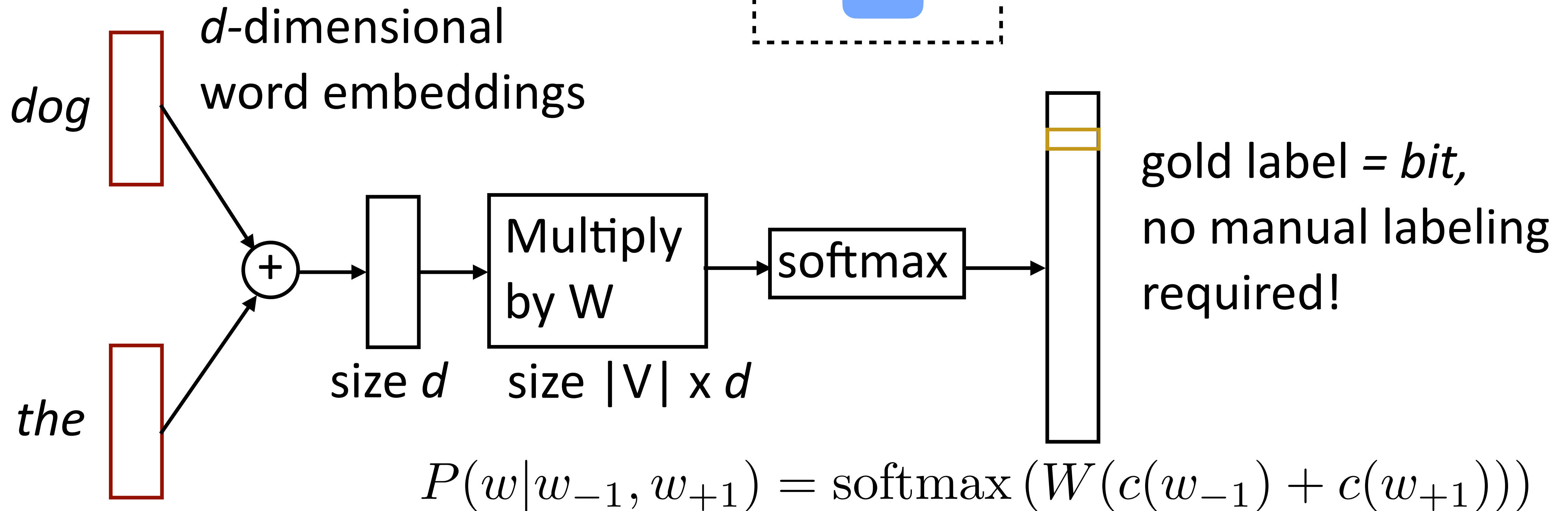
*the dog **bit** the man*



Continuous Bag-of-Words

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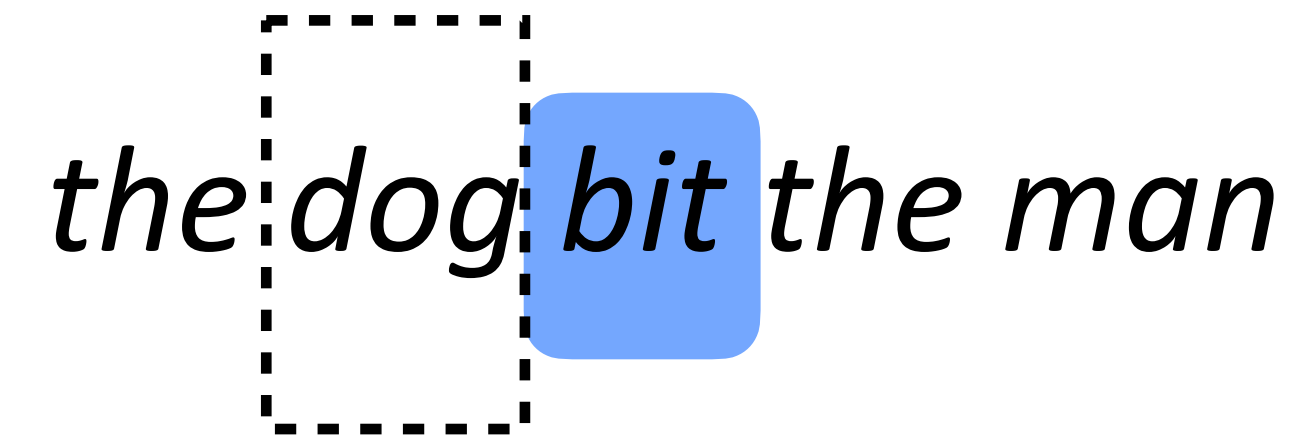
- Parameters: $d \times |V|$ (one d -length **vector per voc word**),
 $|V| \times d$ output parameters (W)

Mikolov et al. (2013)

Skip-Gram

- Predict one word of context from word

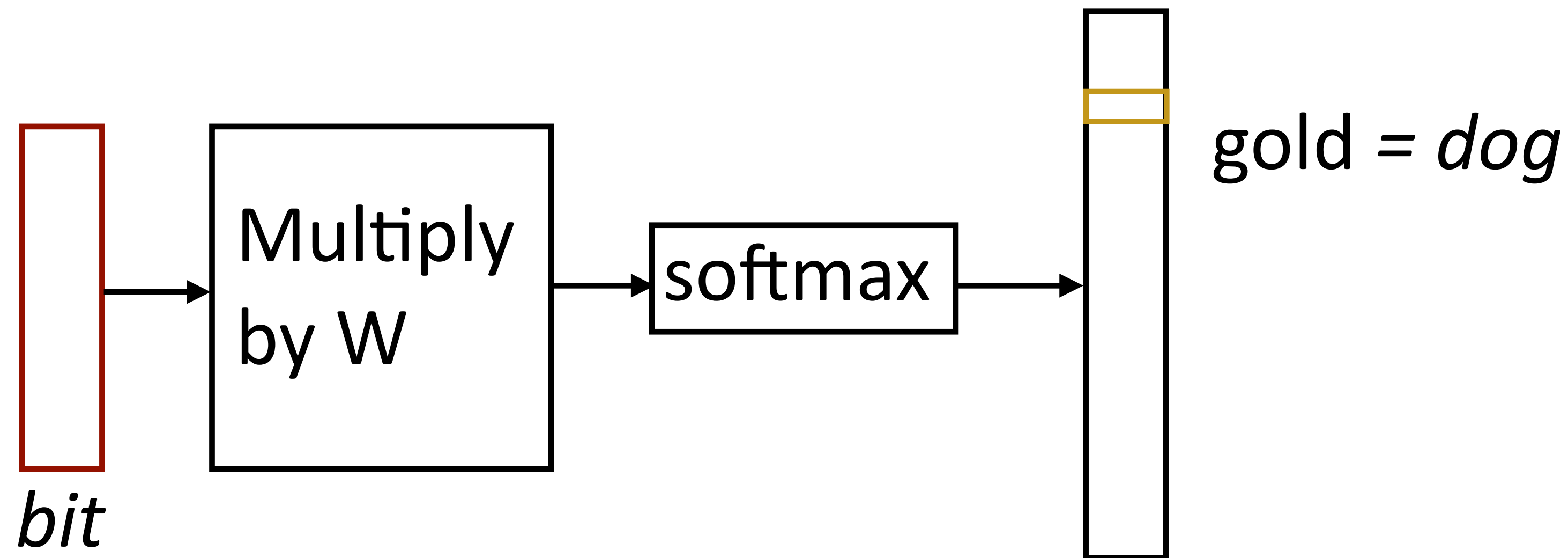
the dog bit the man



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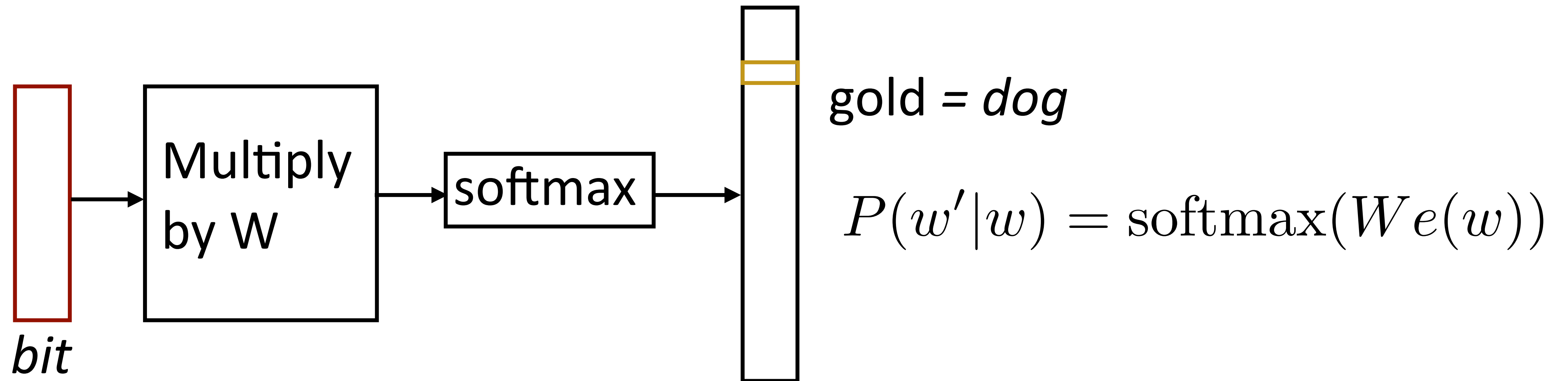
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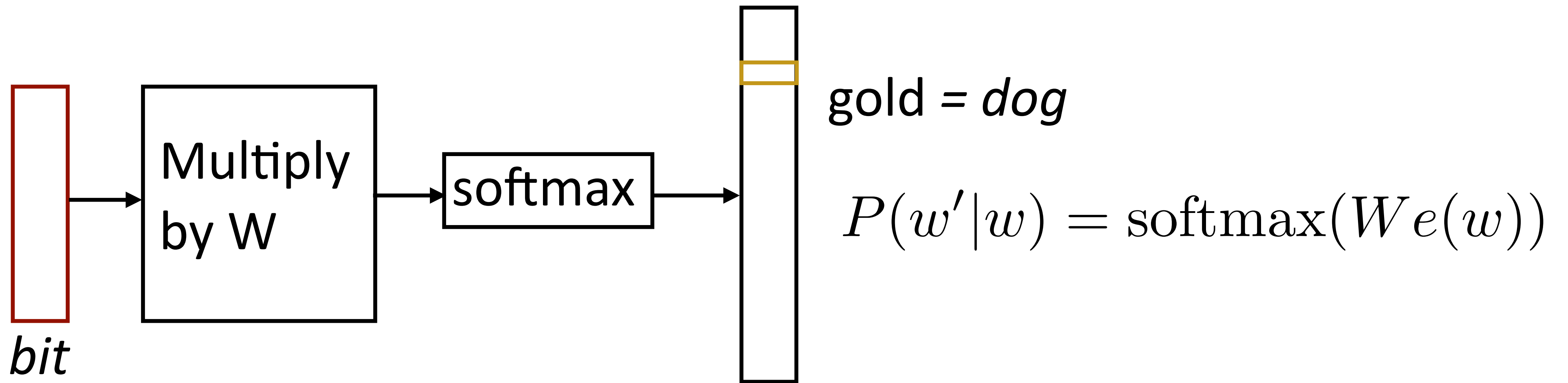
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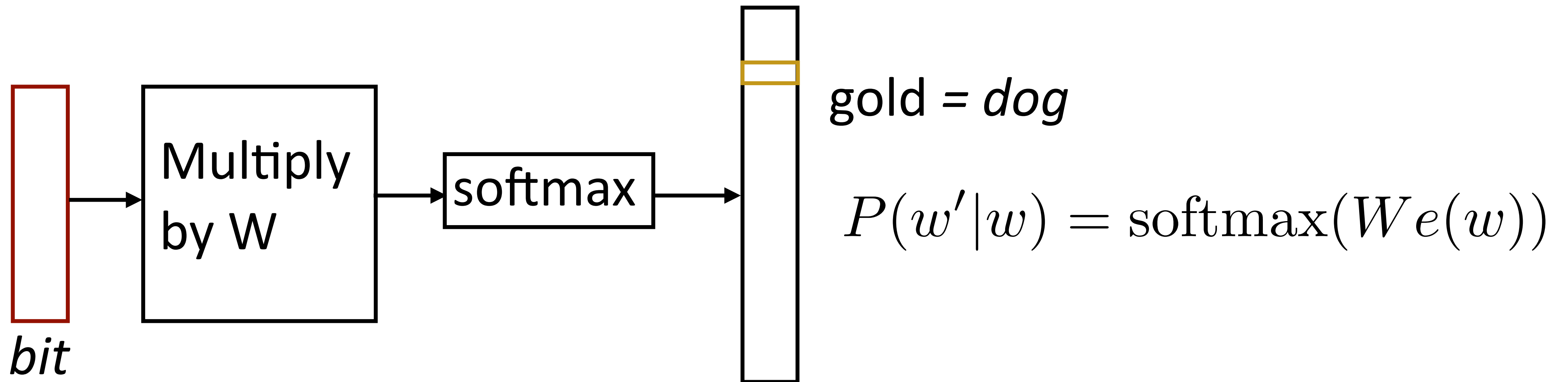


- Another training example: *bit* -> *the*

Skip-Gram

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- Another training example: *bit* -> *the*
- Parameters: $d \times |V|$ **vectors**, $|V| \times d$ output parameters (W) (also usable as vectors!)

Hierarchical Softmax

$$P(w|w_{-1}, w_{+1}) = \text{softmax}(W(c(w_{-1}) + c(w_{+1}))) \quad P(w'|w) = \text{softmax}(We(w))$$

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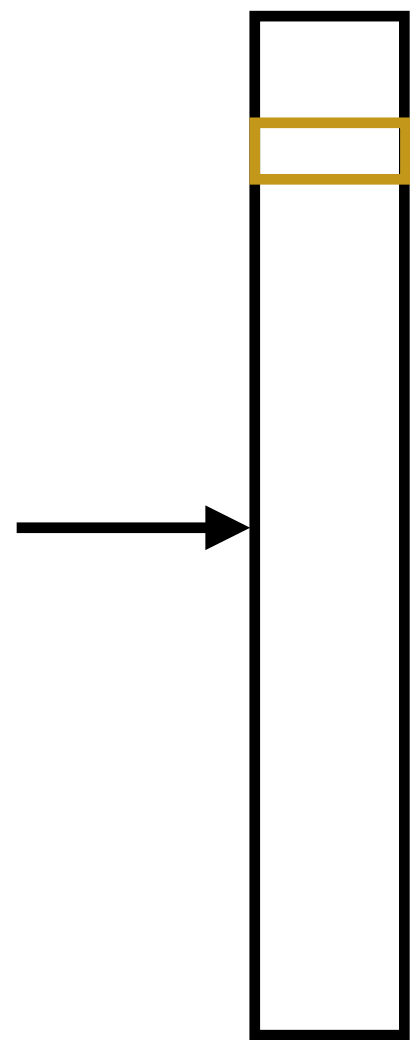
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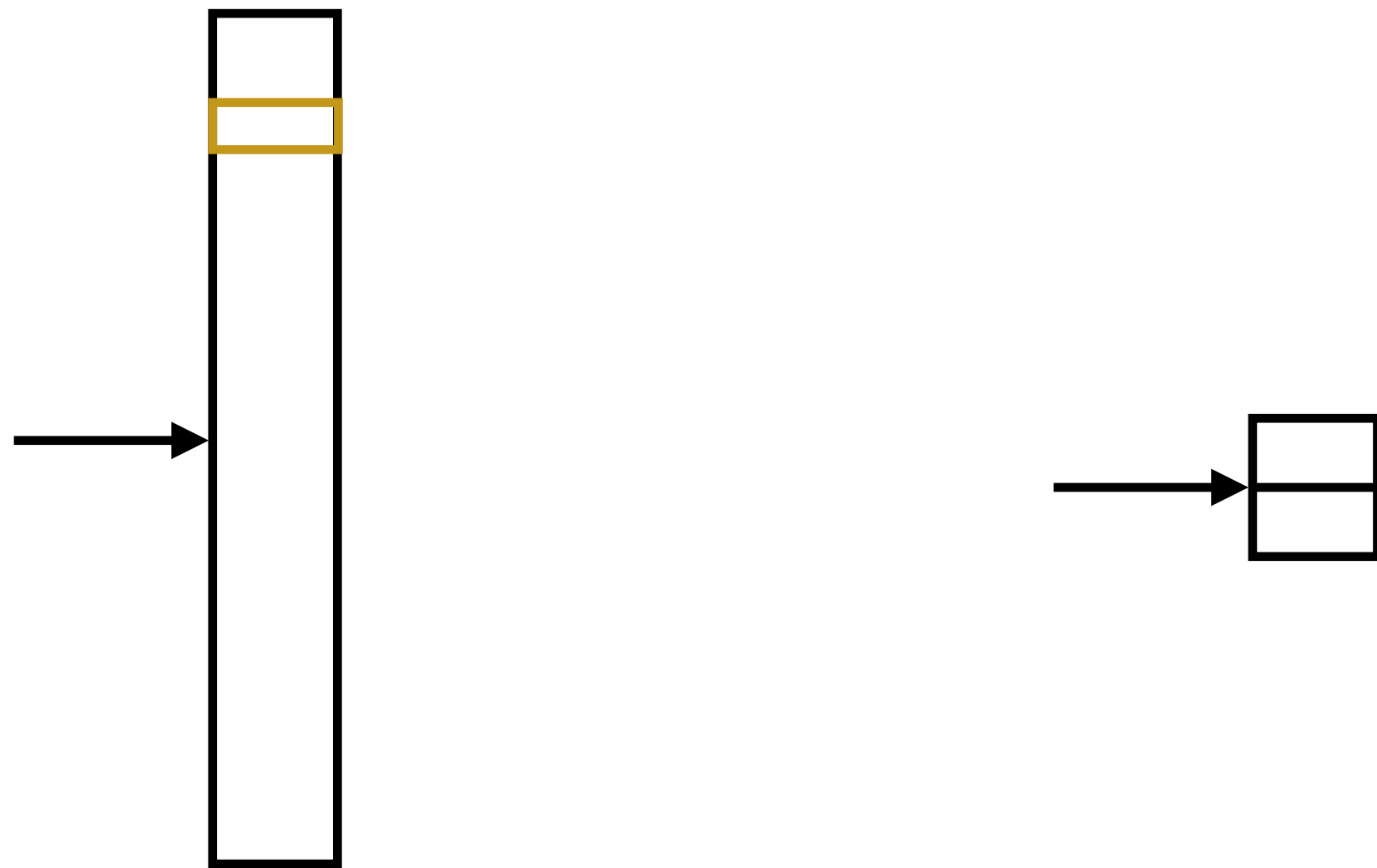


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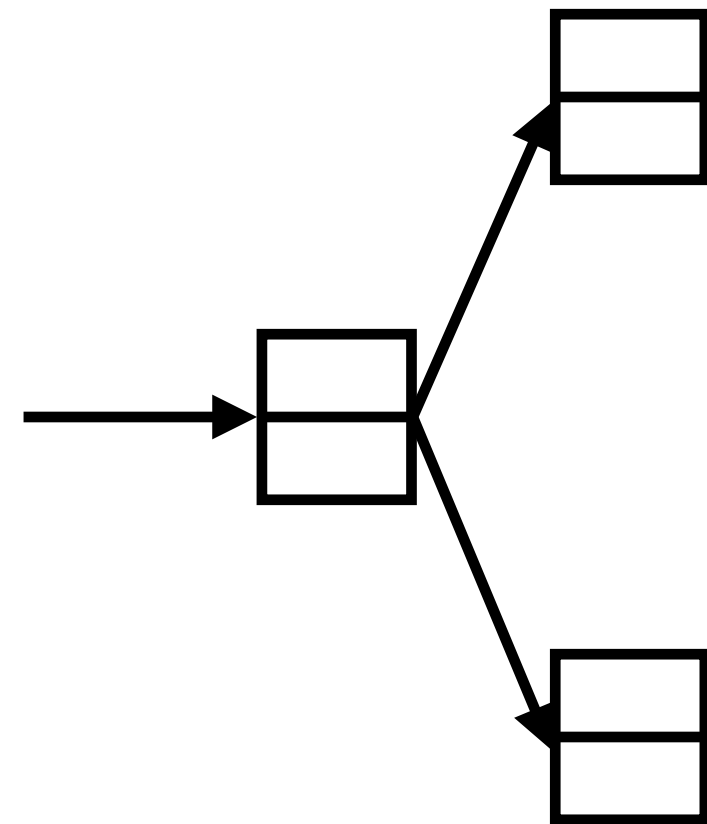
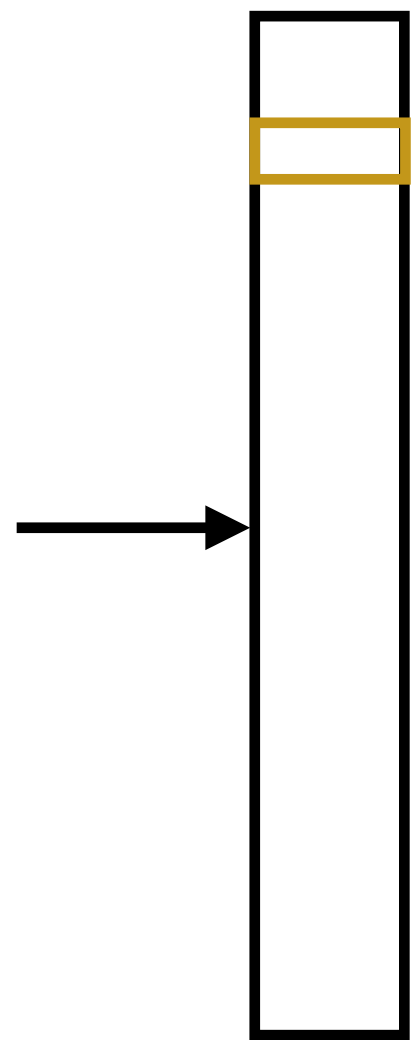


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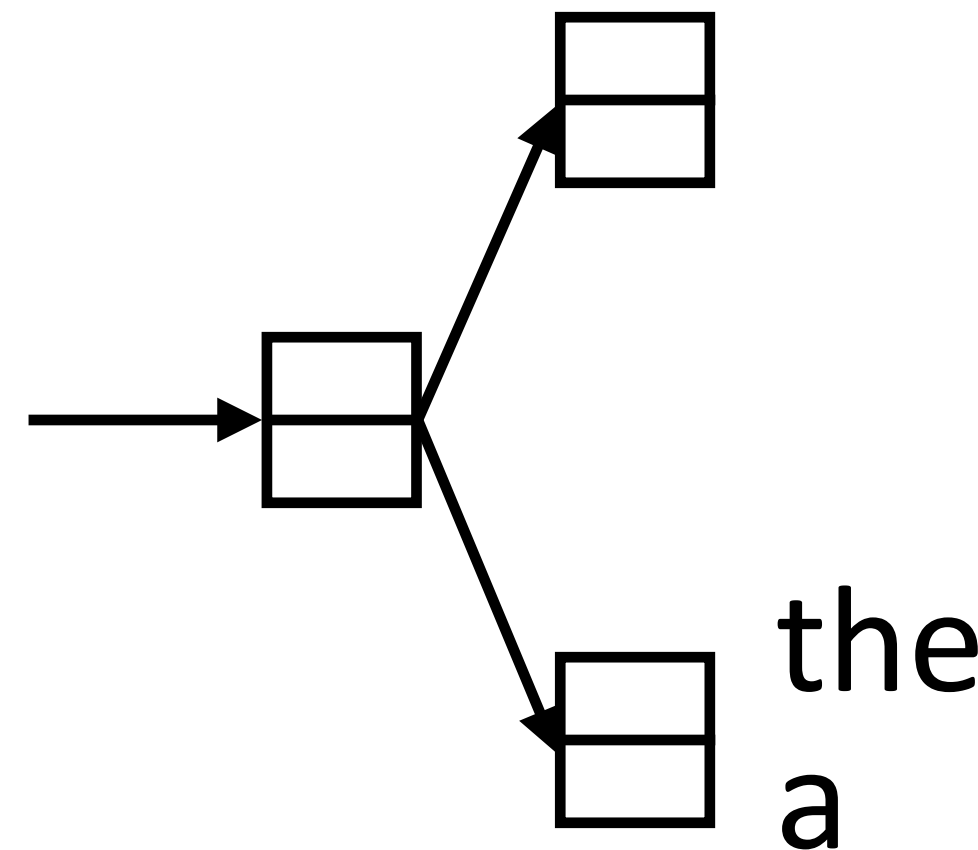
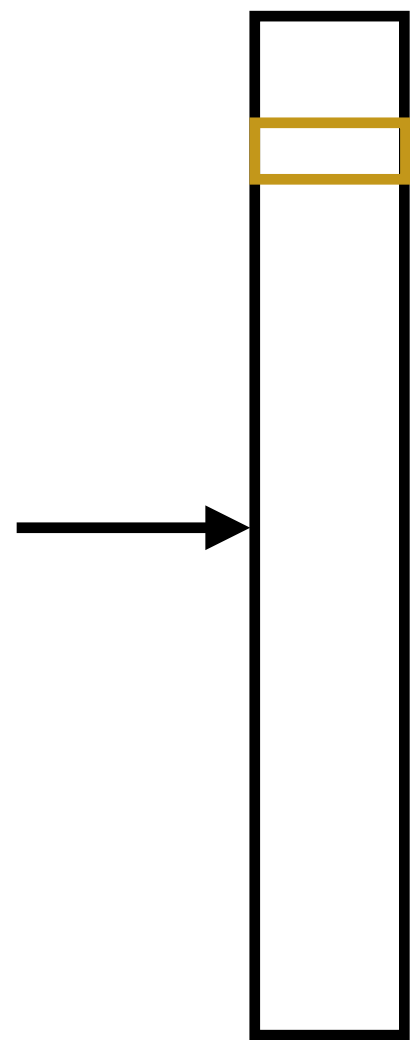


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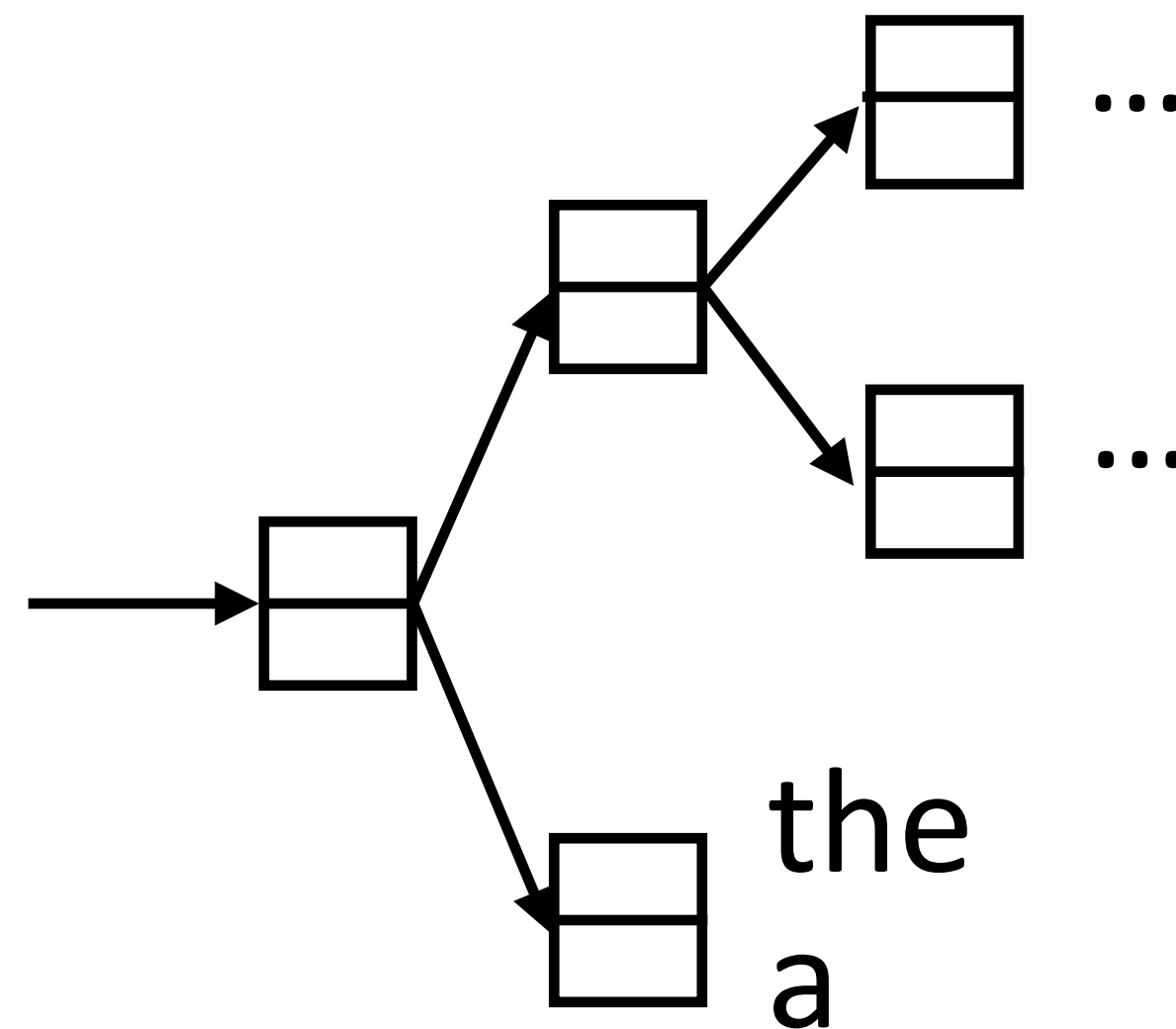
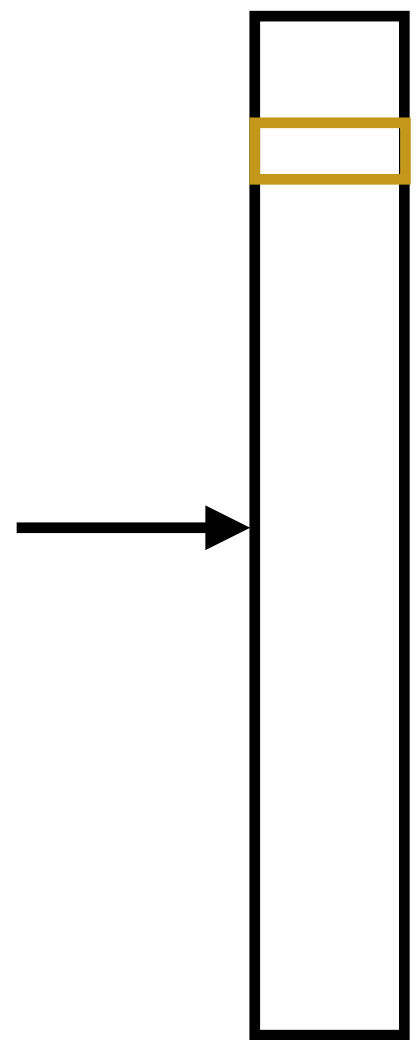


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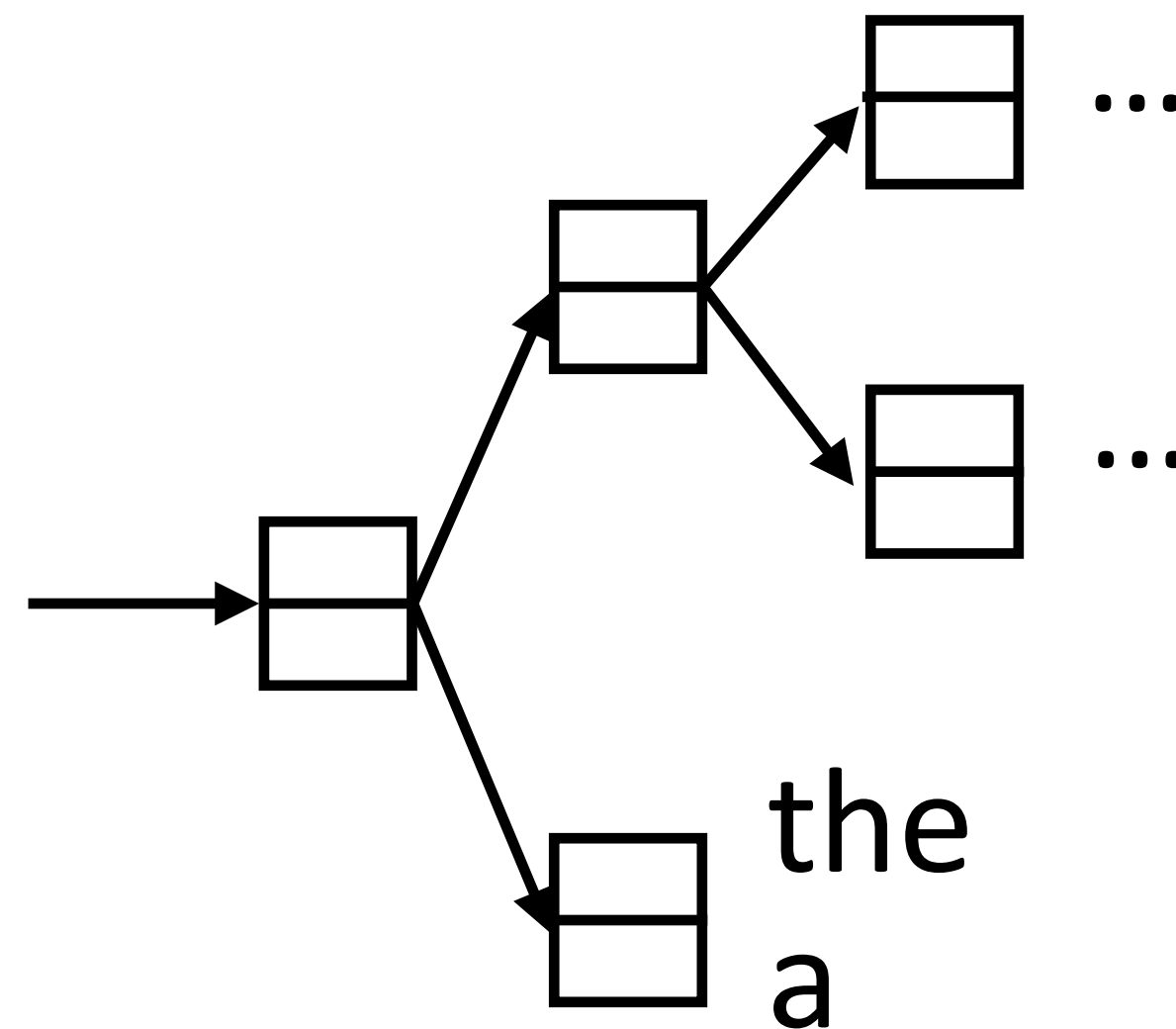
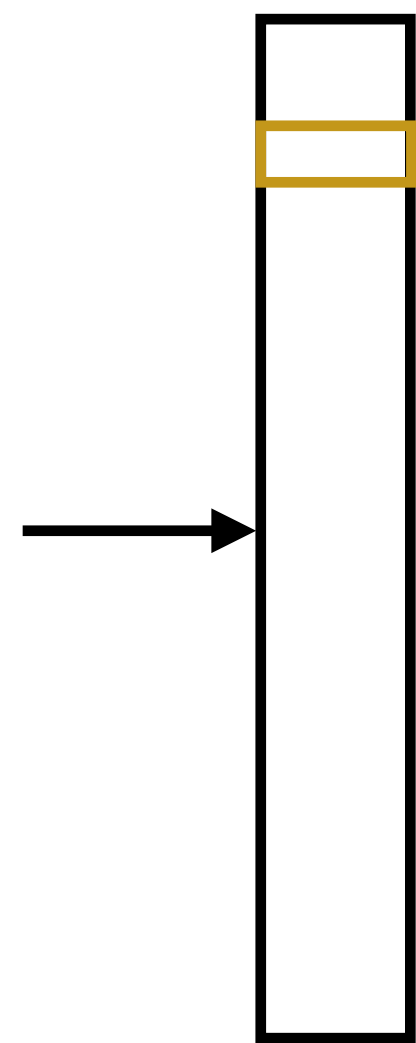


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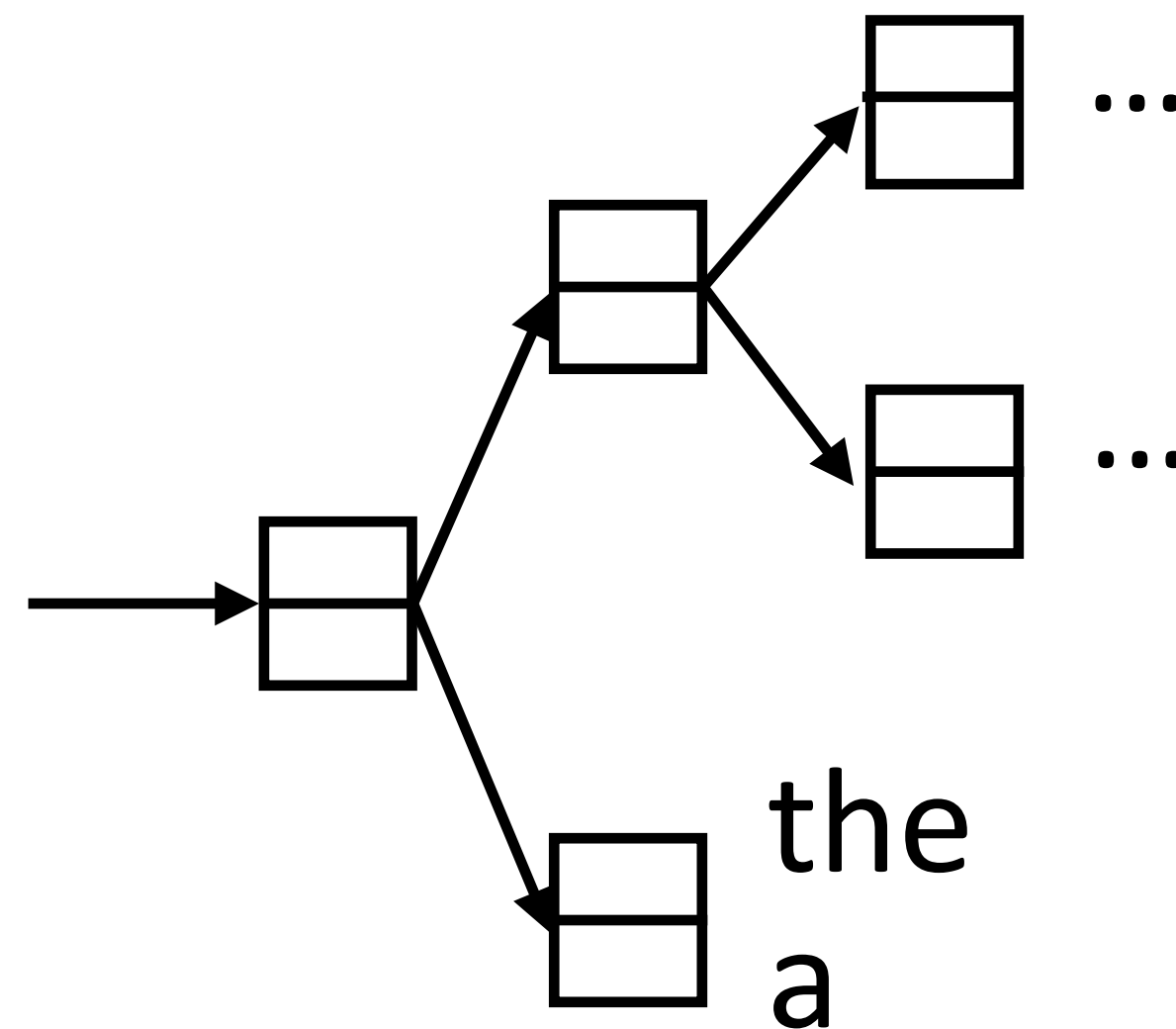
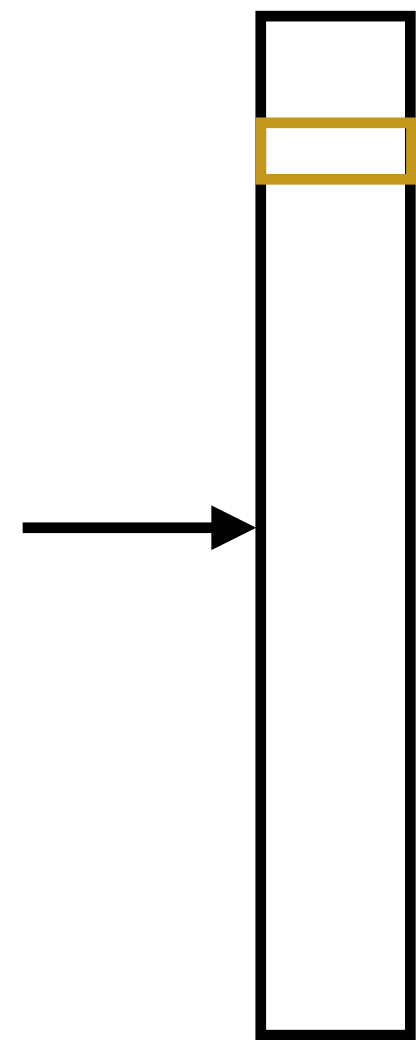
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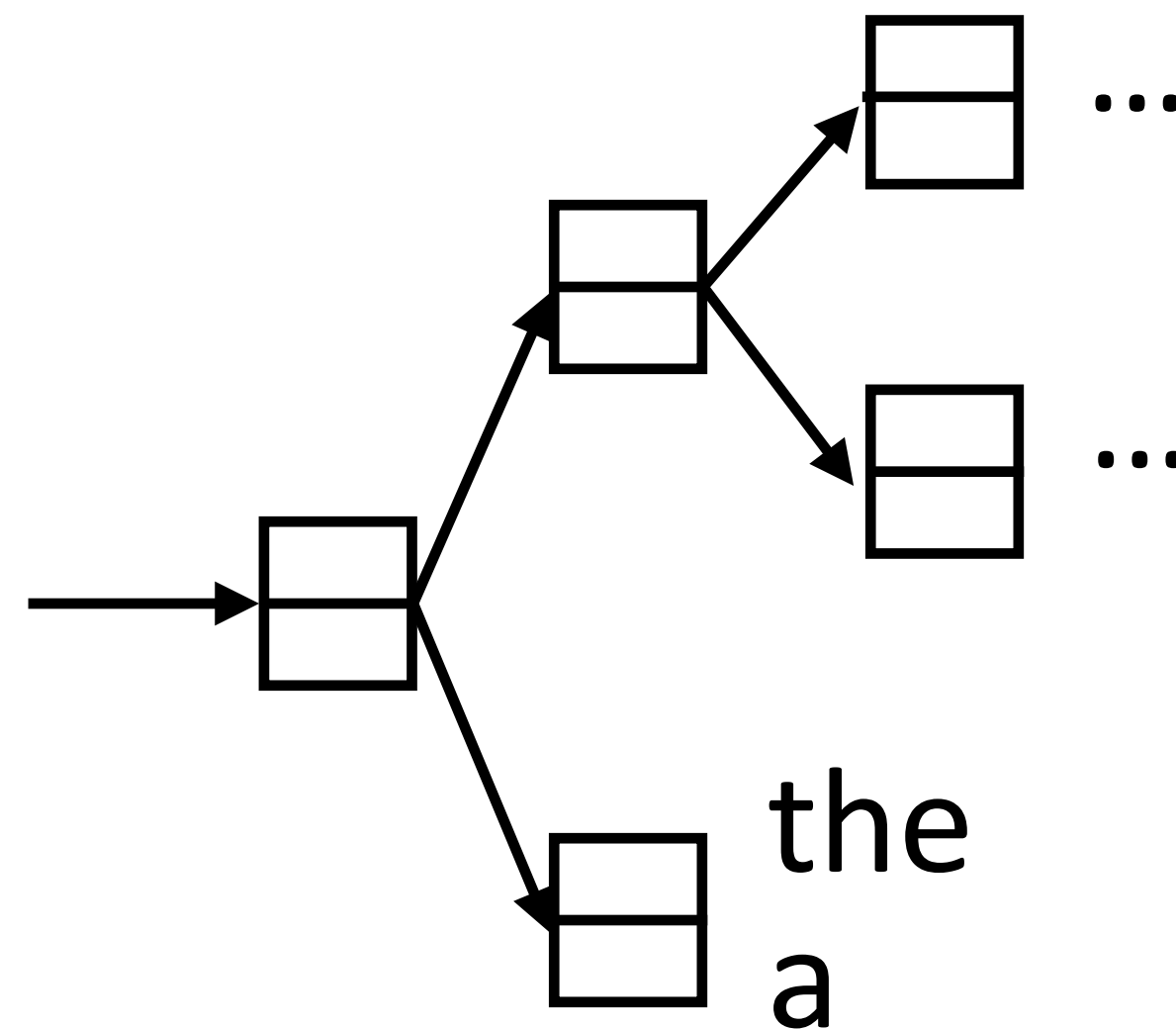
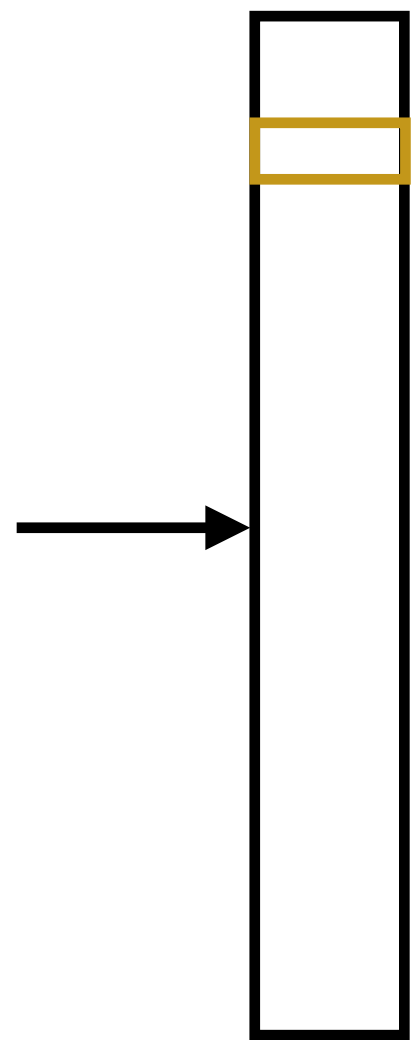


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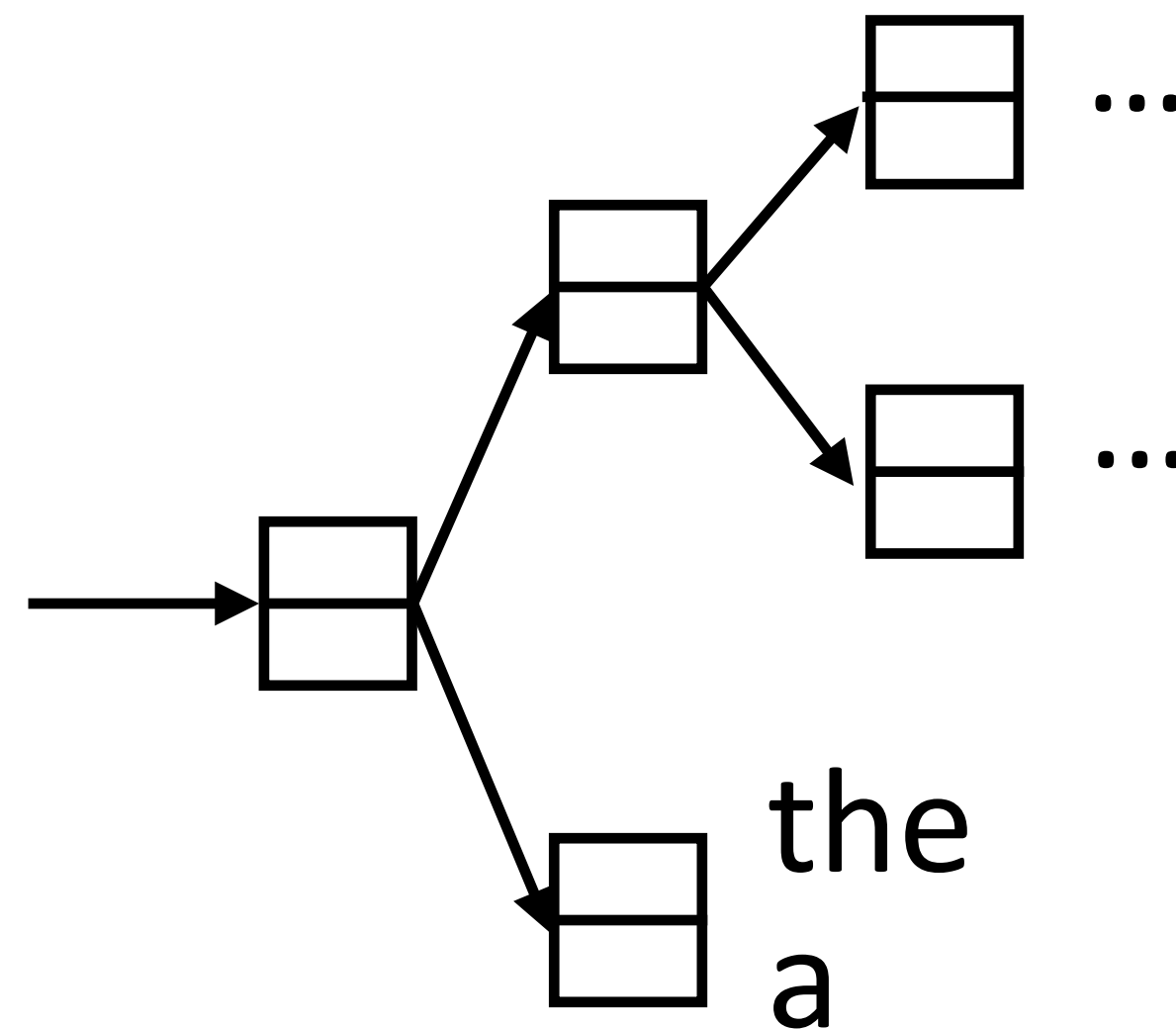
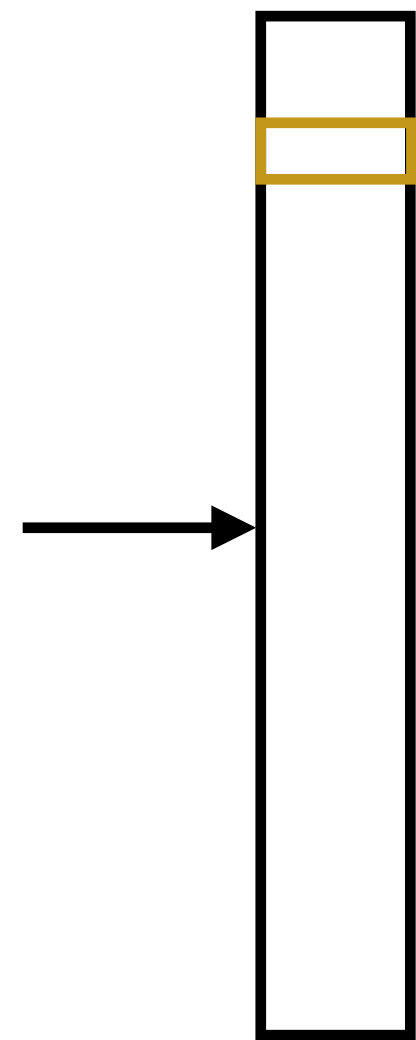
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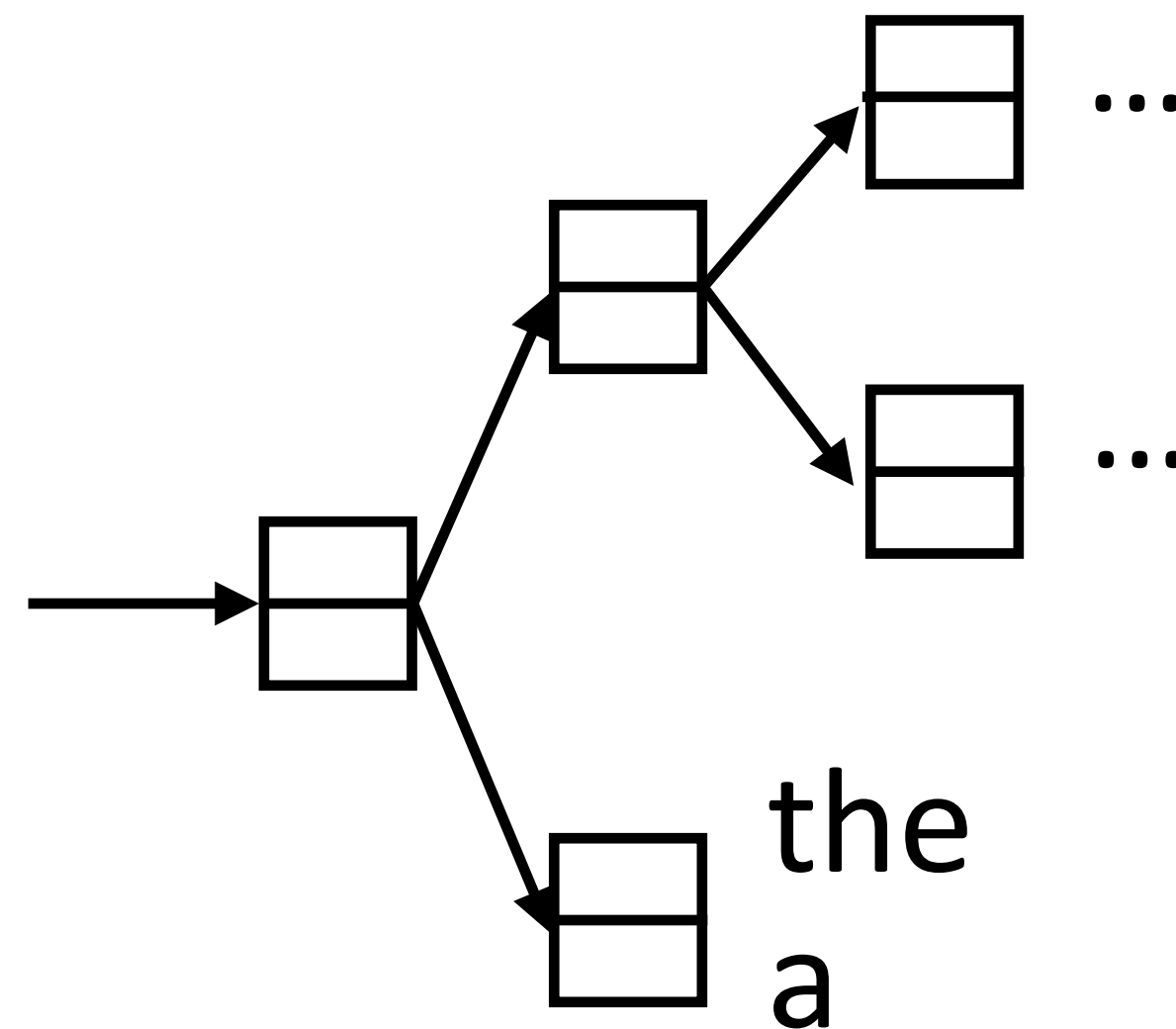
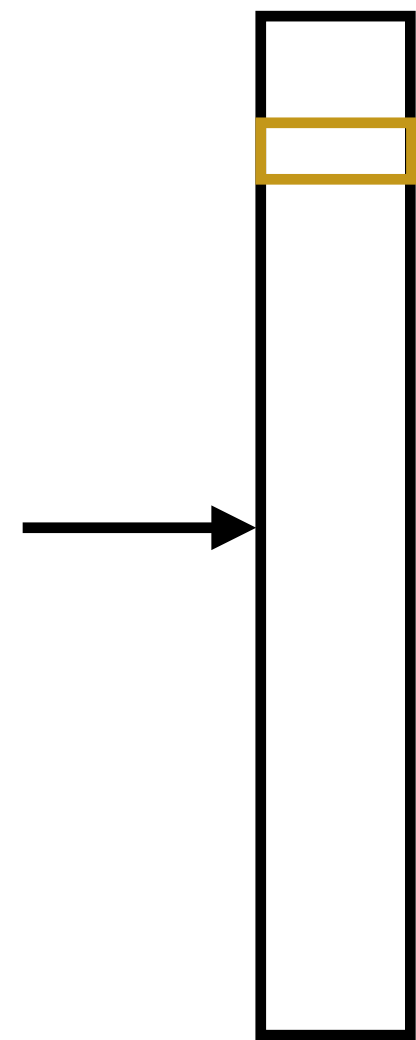
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Mikolov et al. (2013)

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sampld

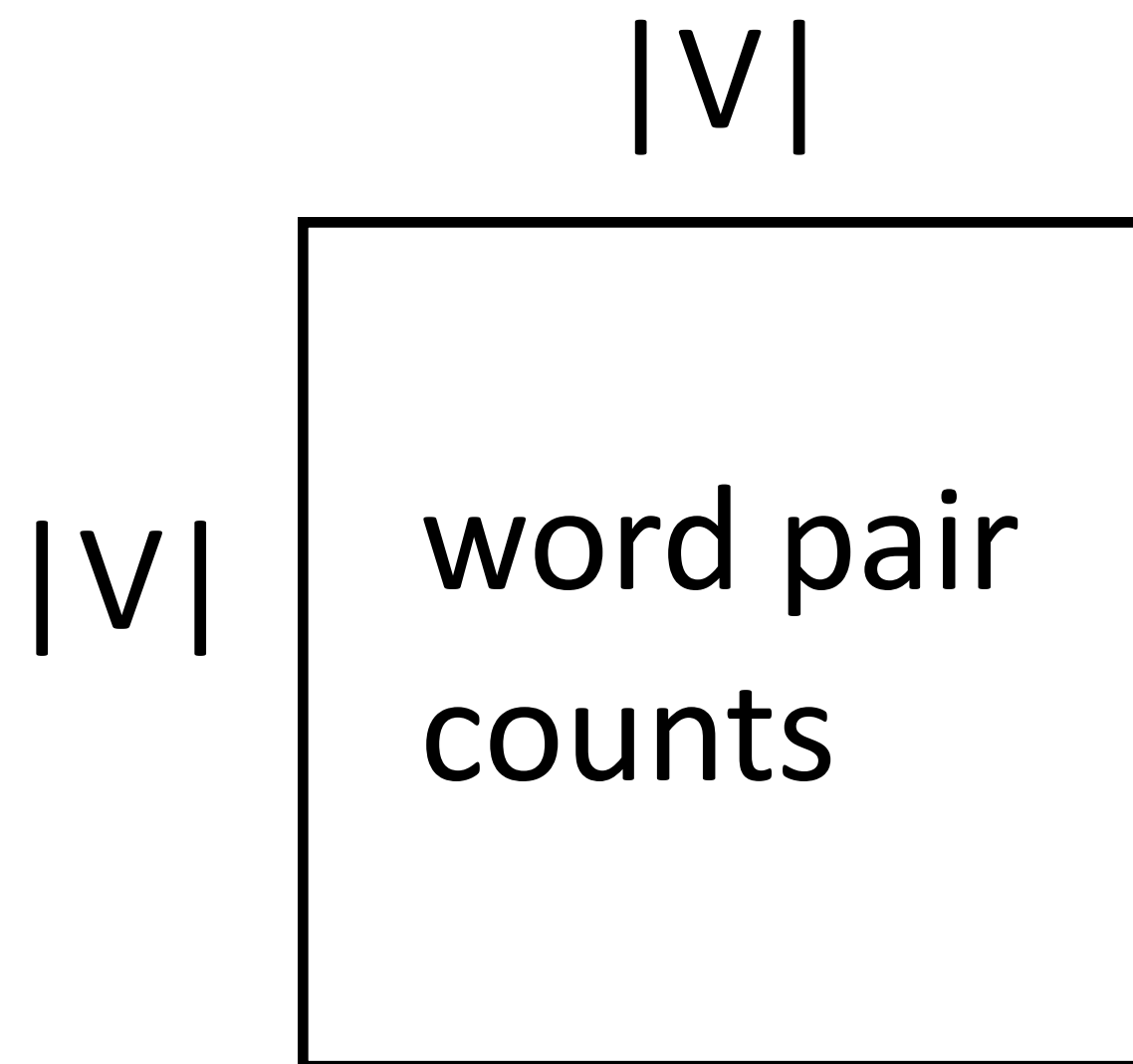
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Connections with Matrix Factorization

- ▶ Skip-gram model looks at word-word co-occurrences and produces two types of vectors

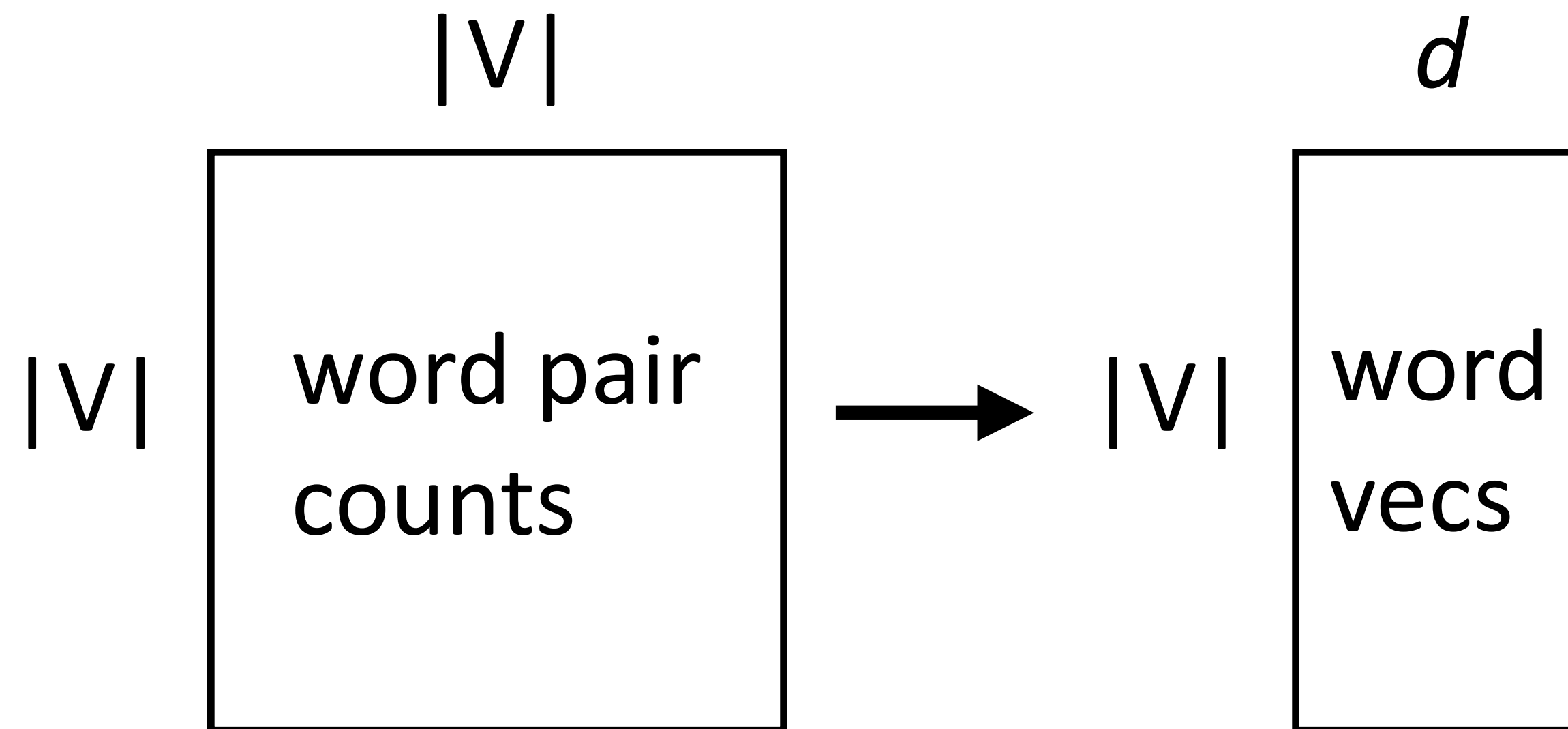
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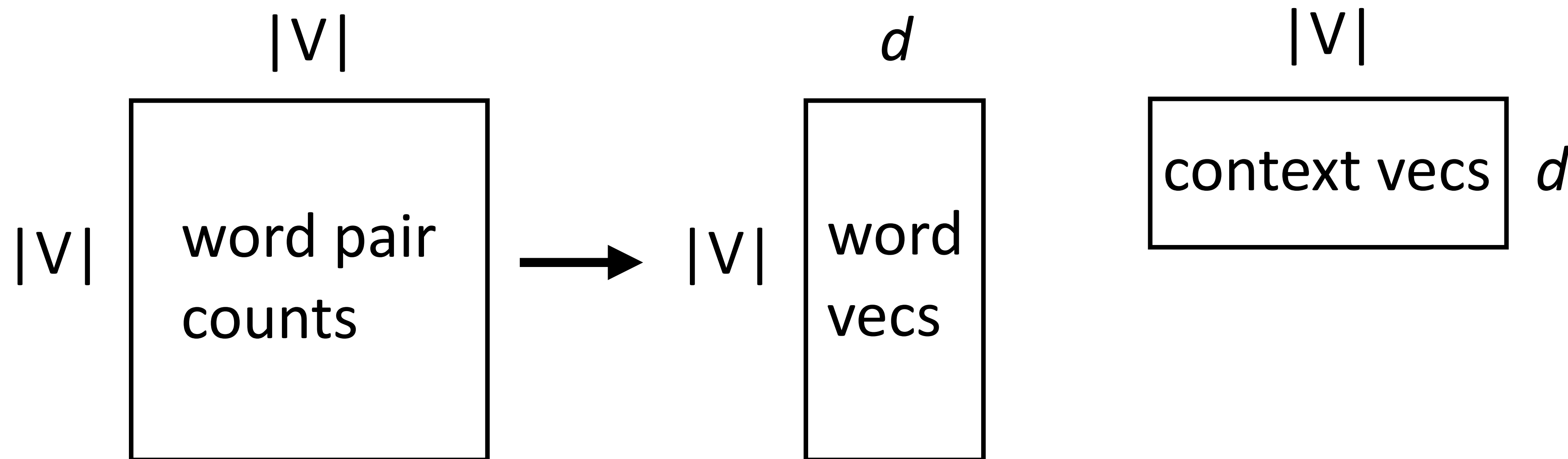
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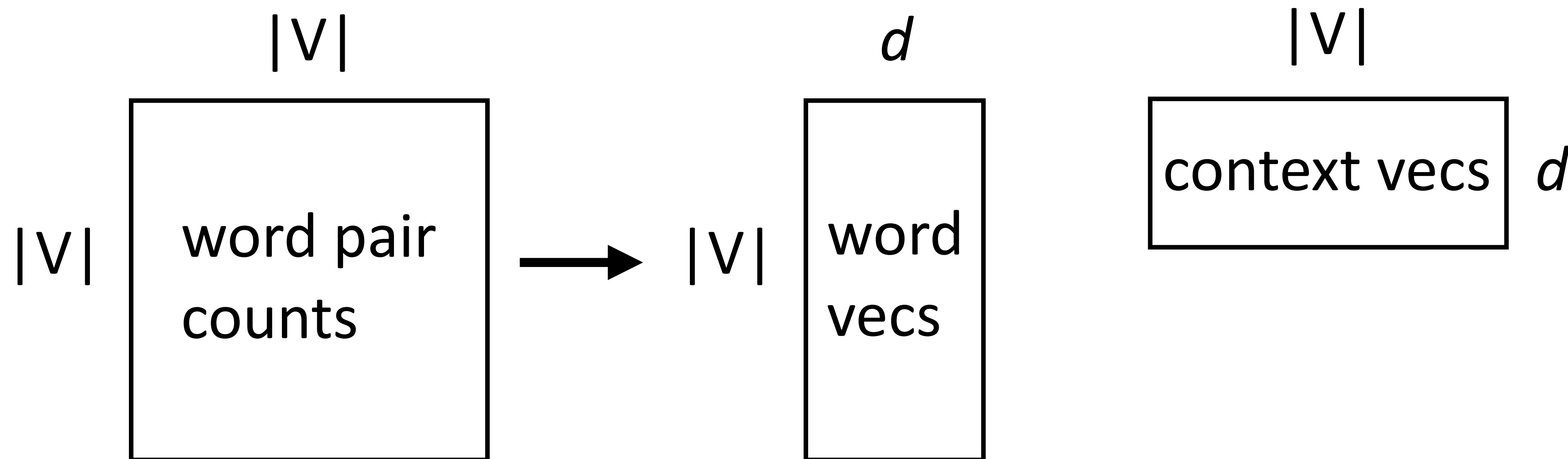
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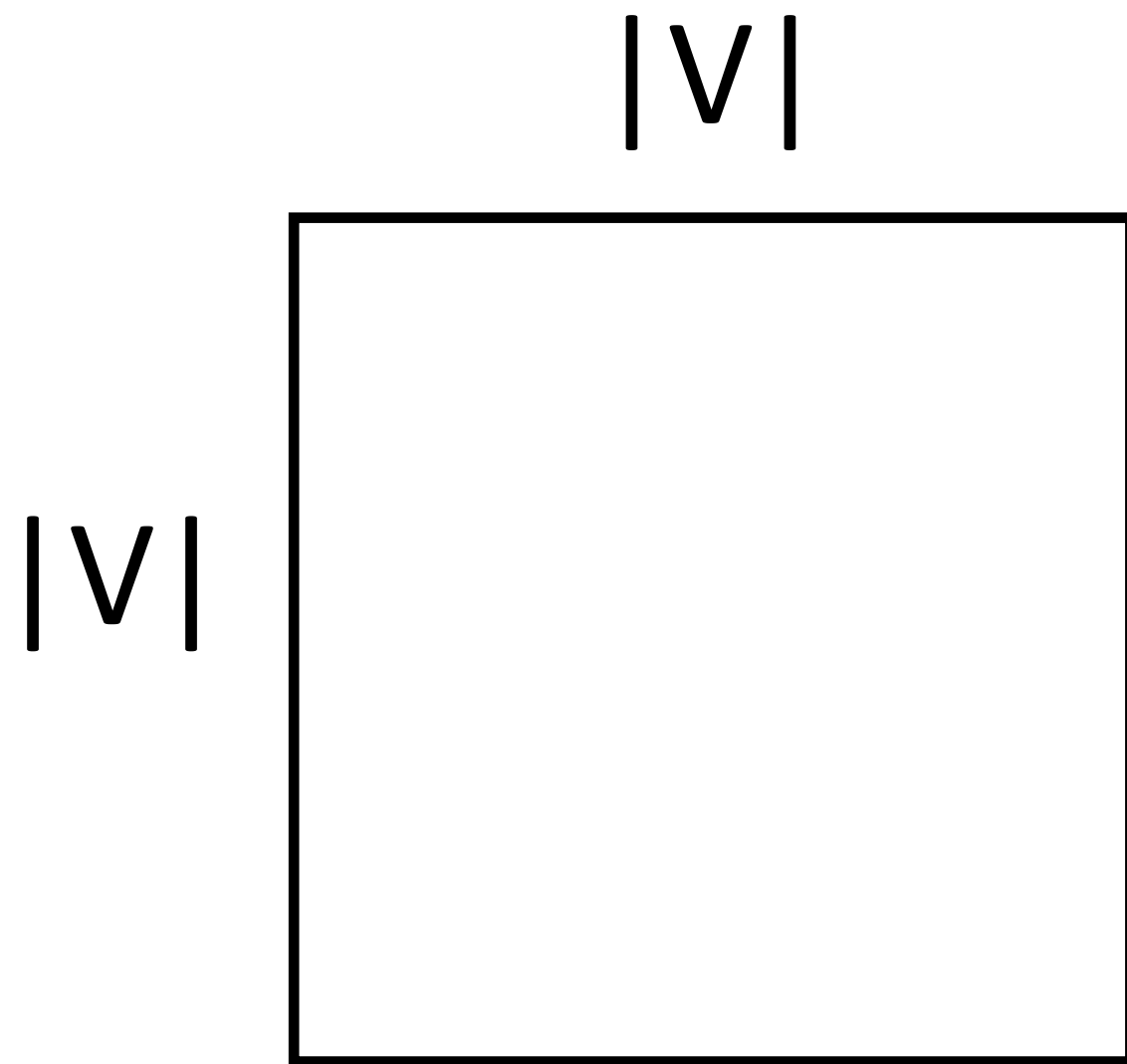
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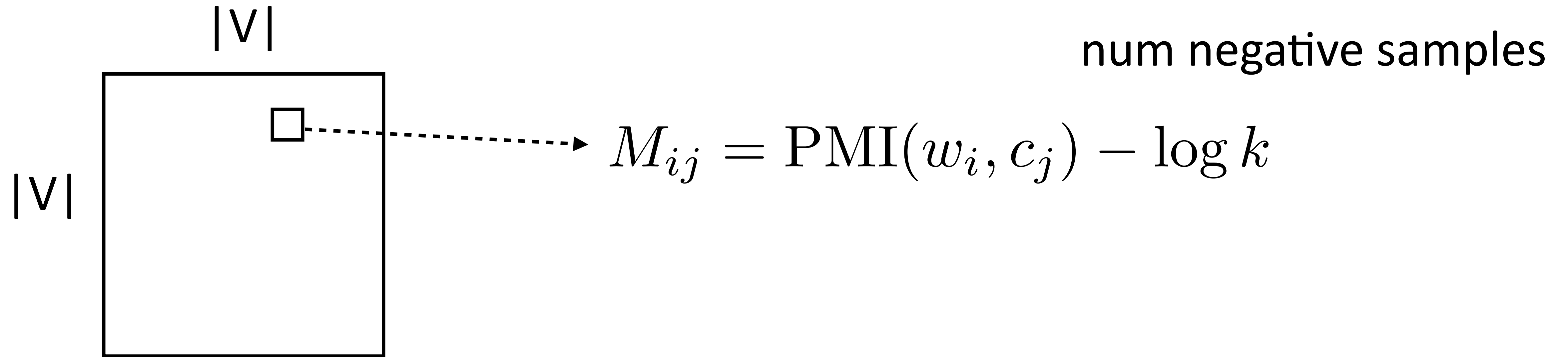


- ▶ Looks almost like a matrix factorization...can we interpret it this way?

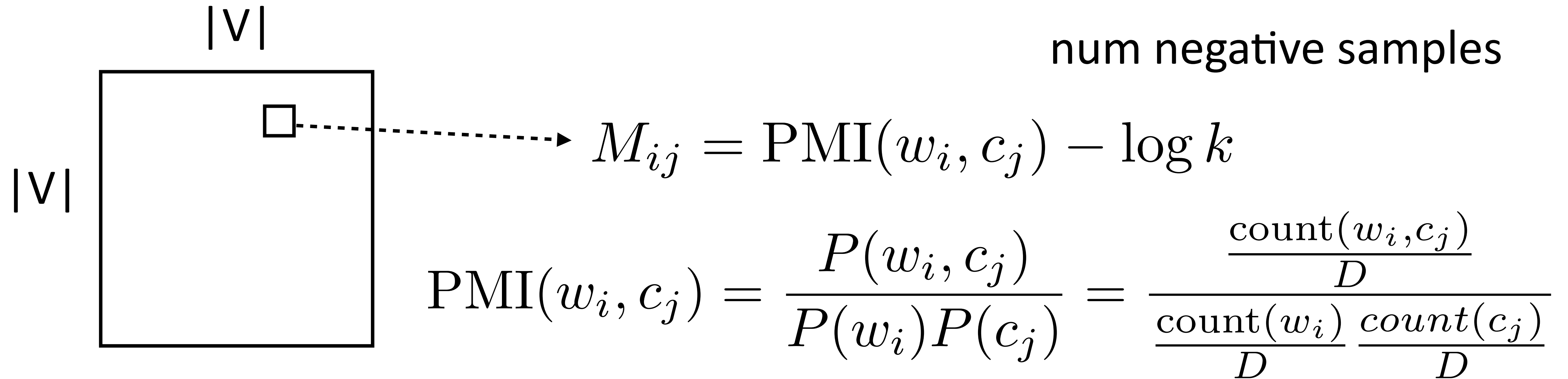
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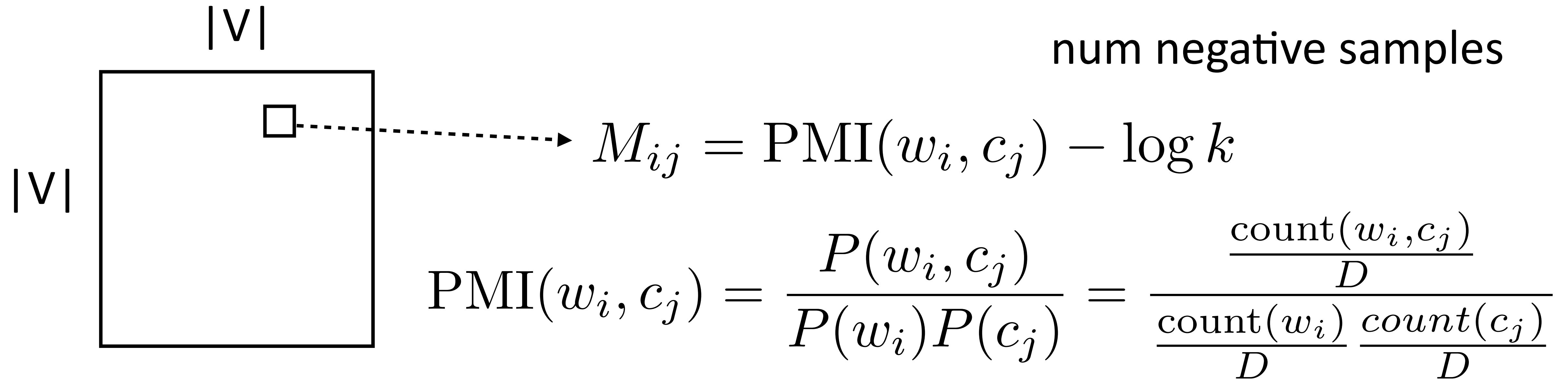
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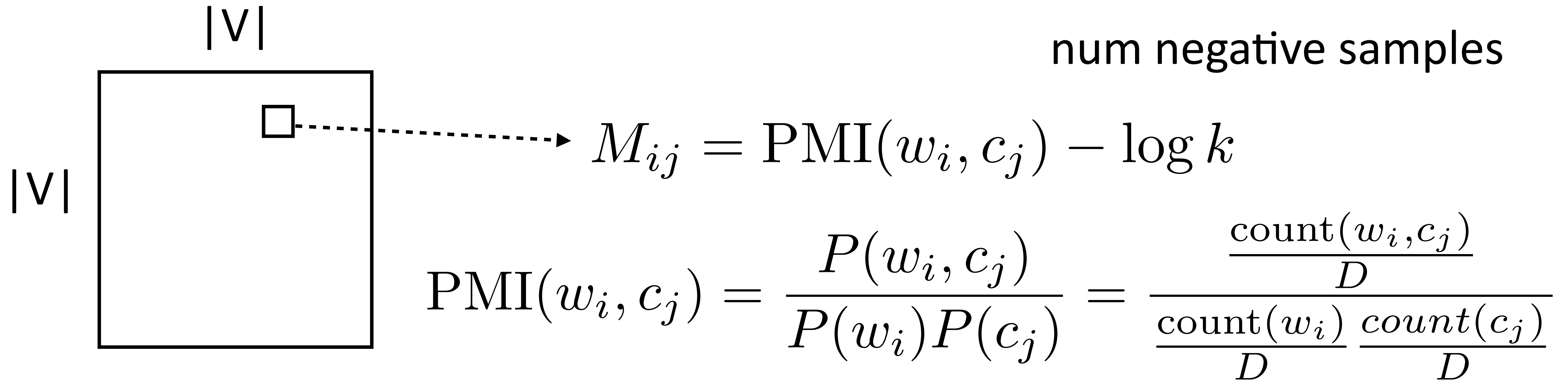


Skip-Gram as Matrix Factorization



Skip-gram objective *exactly* corresponds to factoring this matrix:

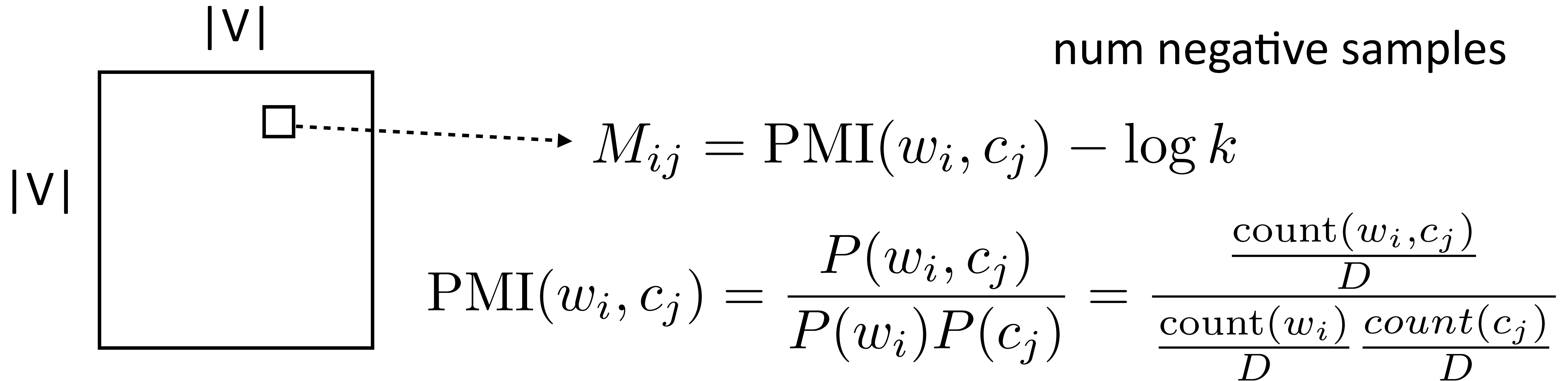
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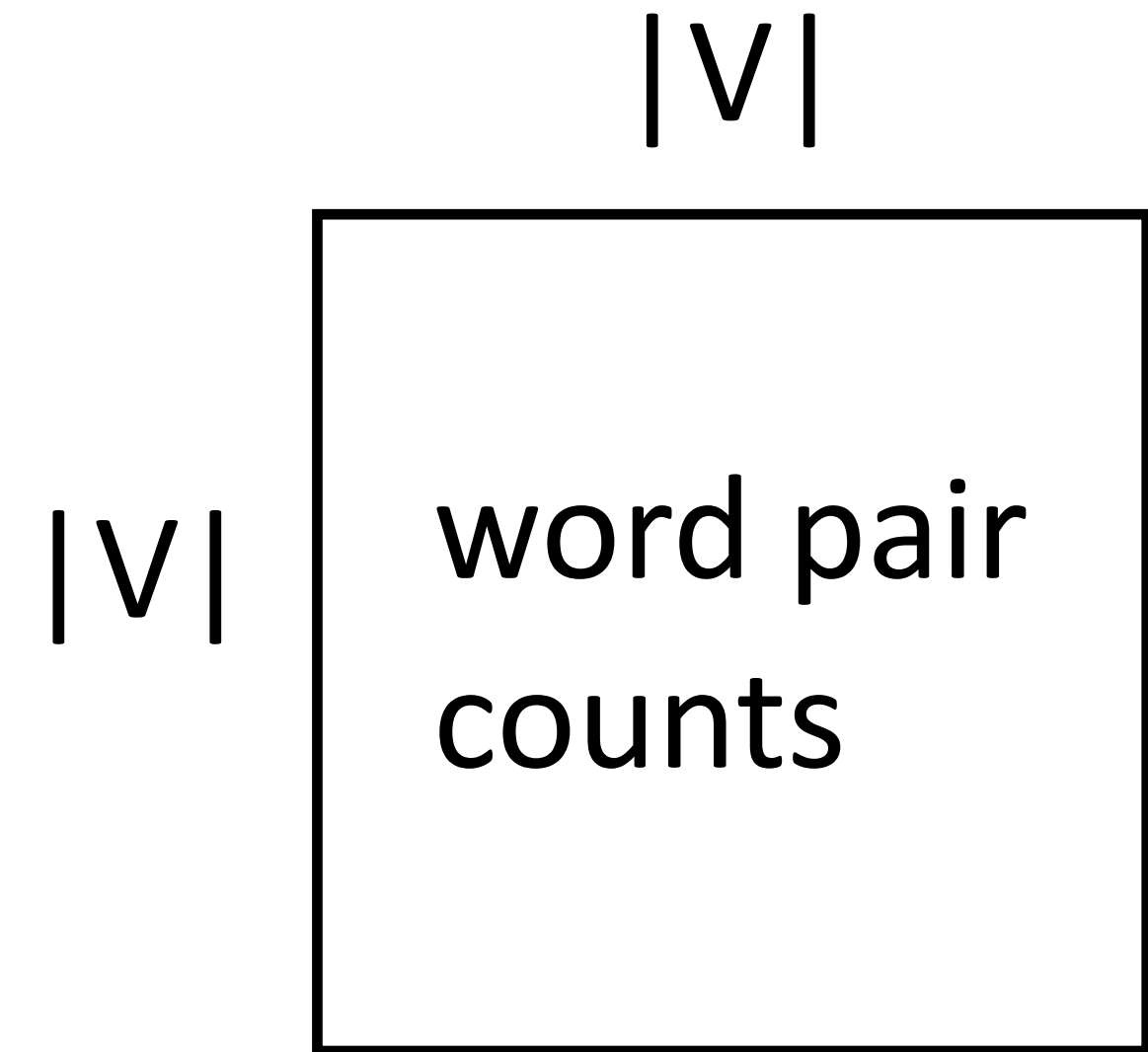


Skip-gram objective *exactly* corresponds to factoring this matrix:

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- ▶ ...and it's a *weighted* factorization problem (weighted by word freq)

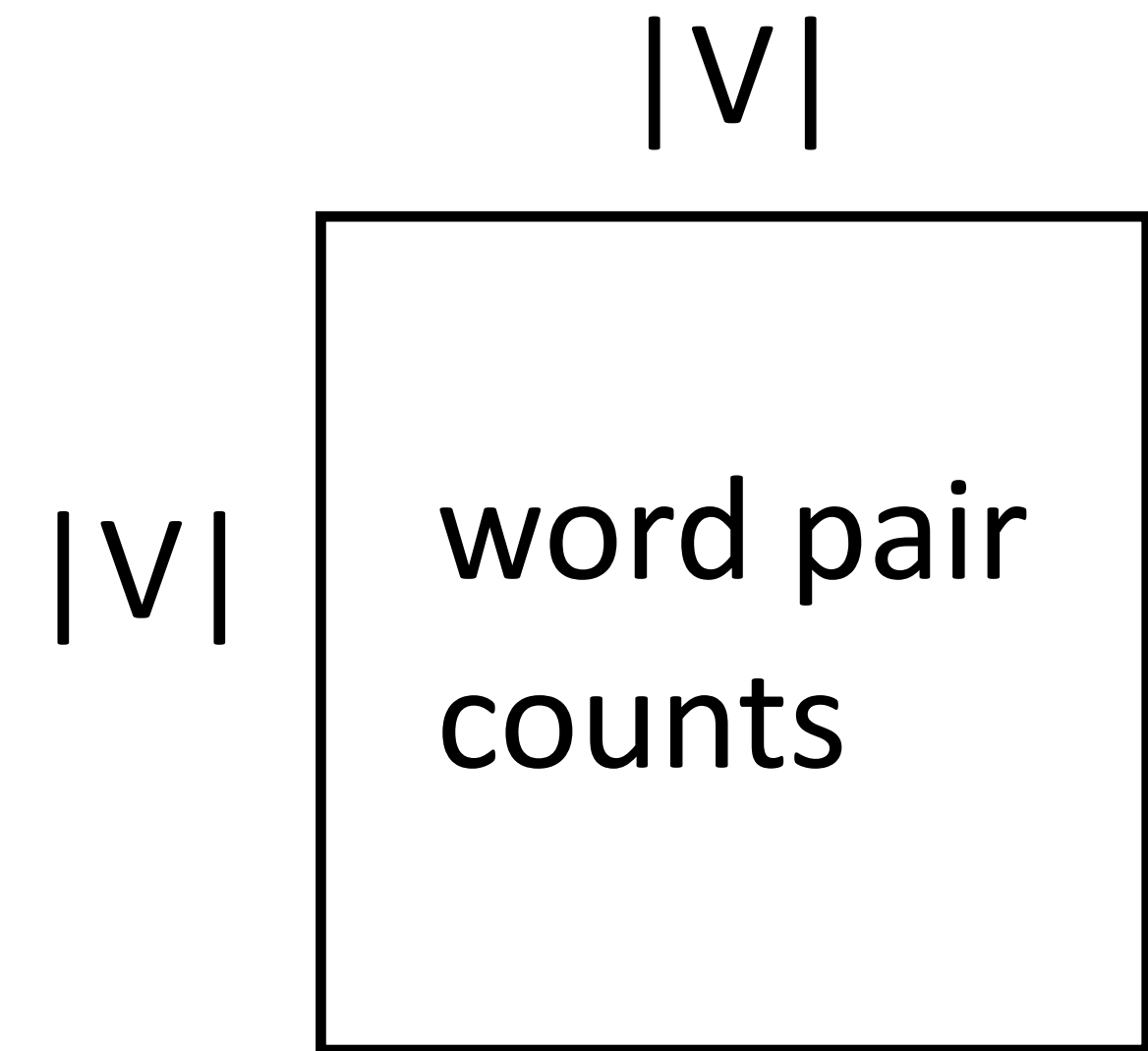
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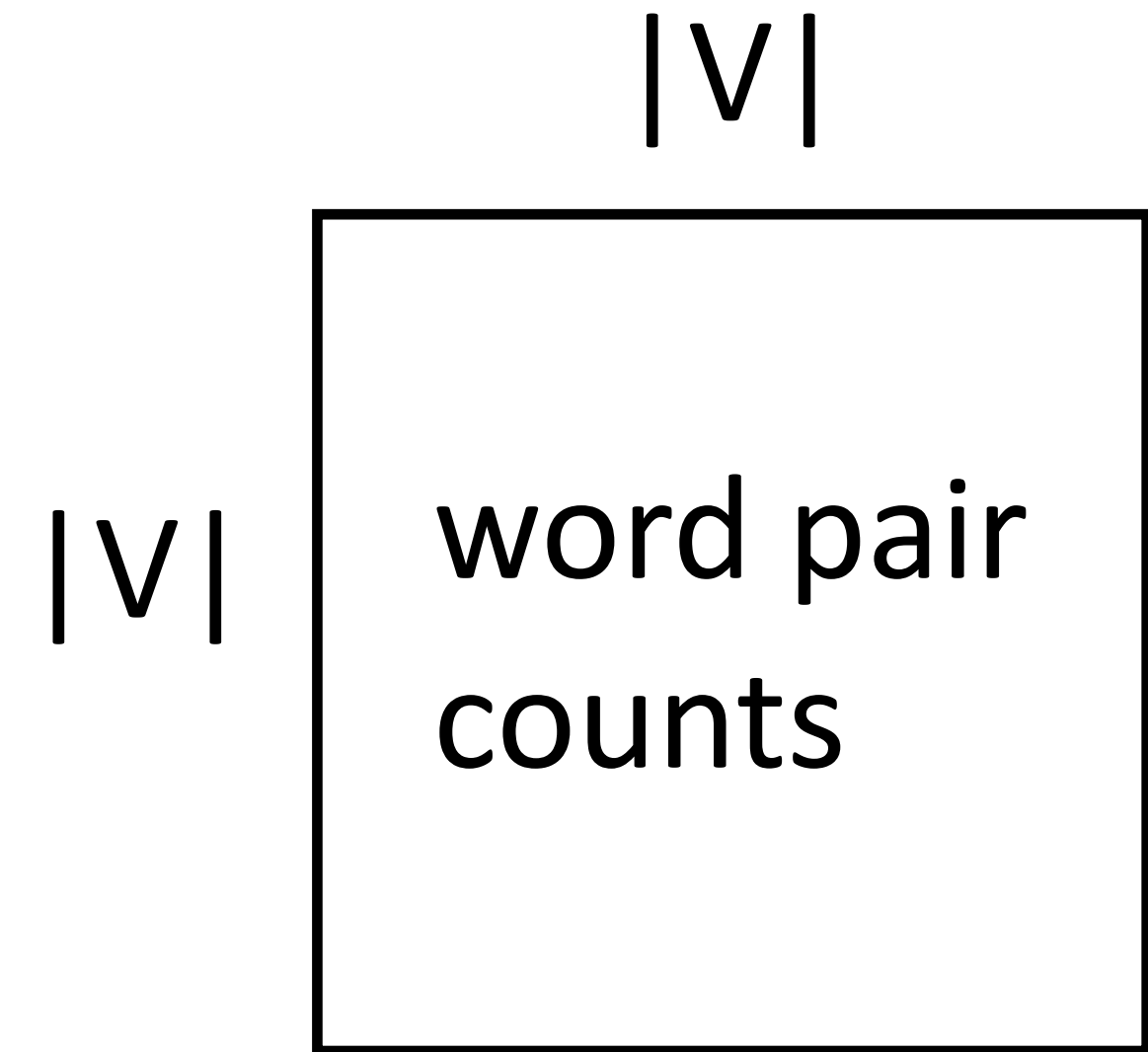
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- ▶ Loss
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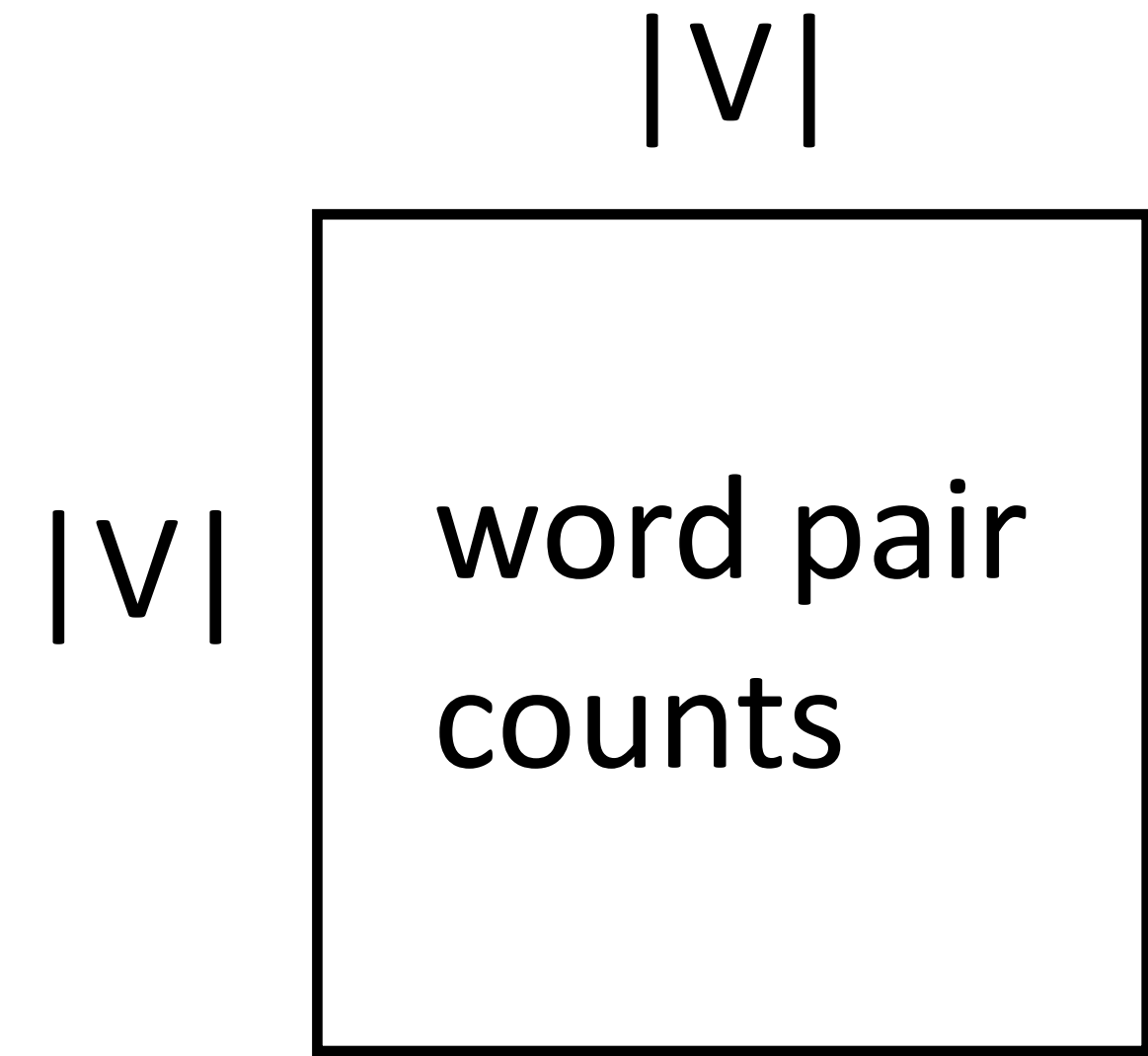
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- ▶ By far the most common (uncontextualized) word vectors used today (20,000+ citations)

Pennington et al. (2014)

Preview: Context-dependent Embeddings

- ▶ How to handle different word senses? One vector for *balls*

they dance at balls

they hit the balls

Preview: Context-dependent Embeddings

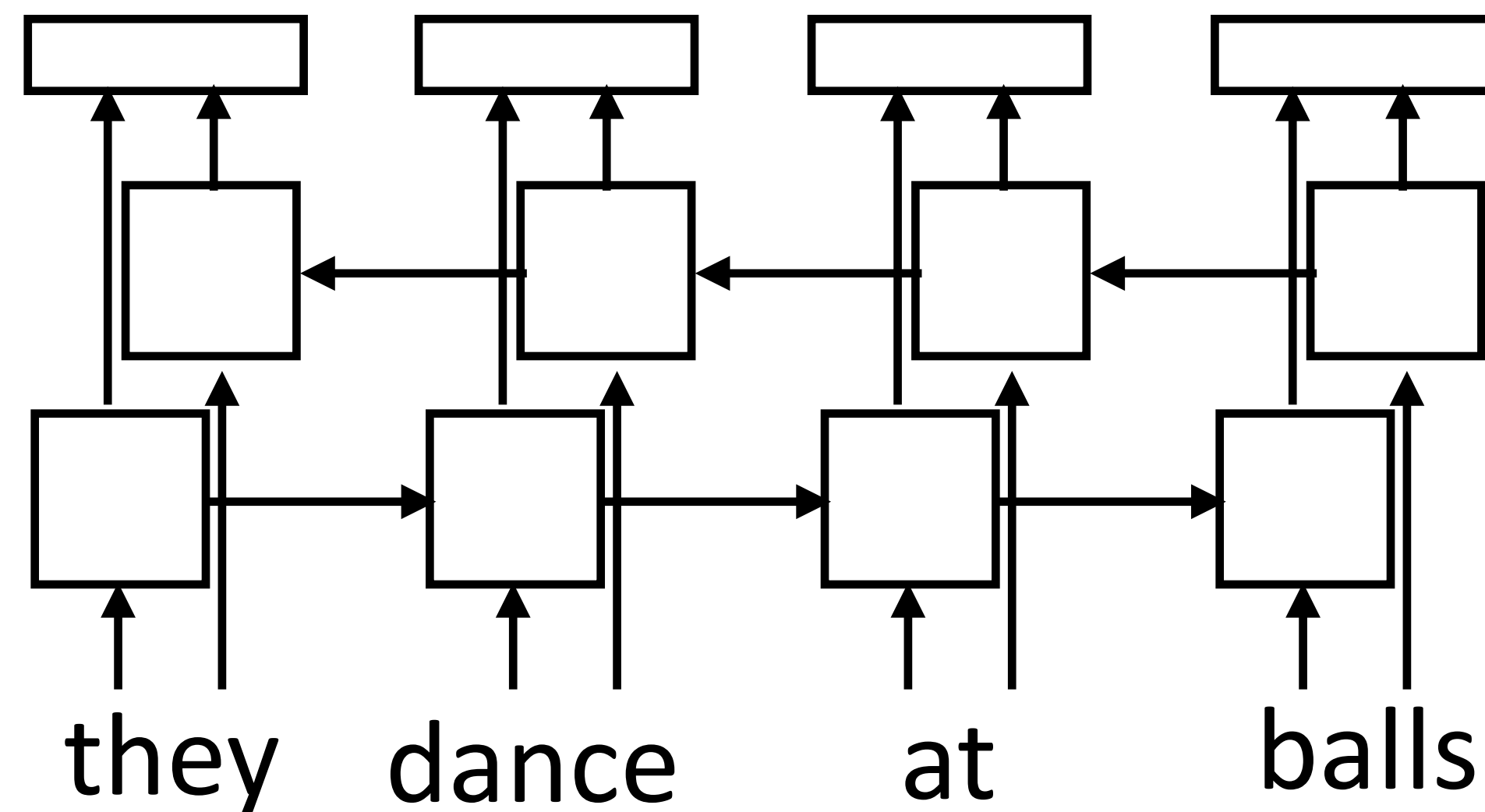
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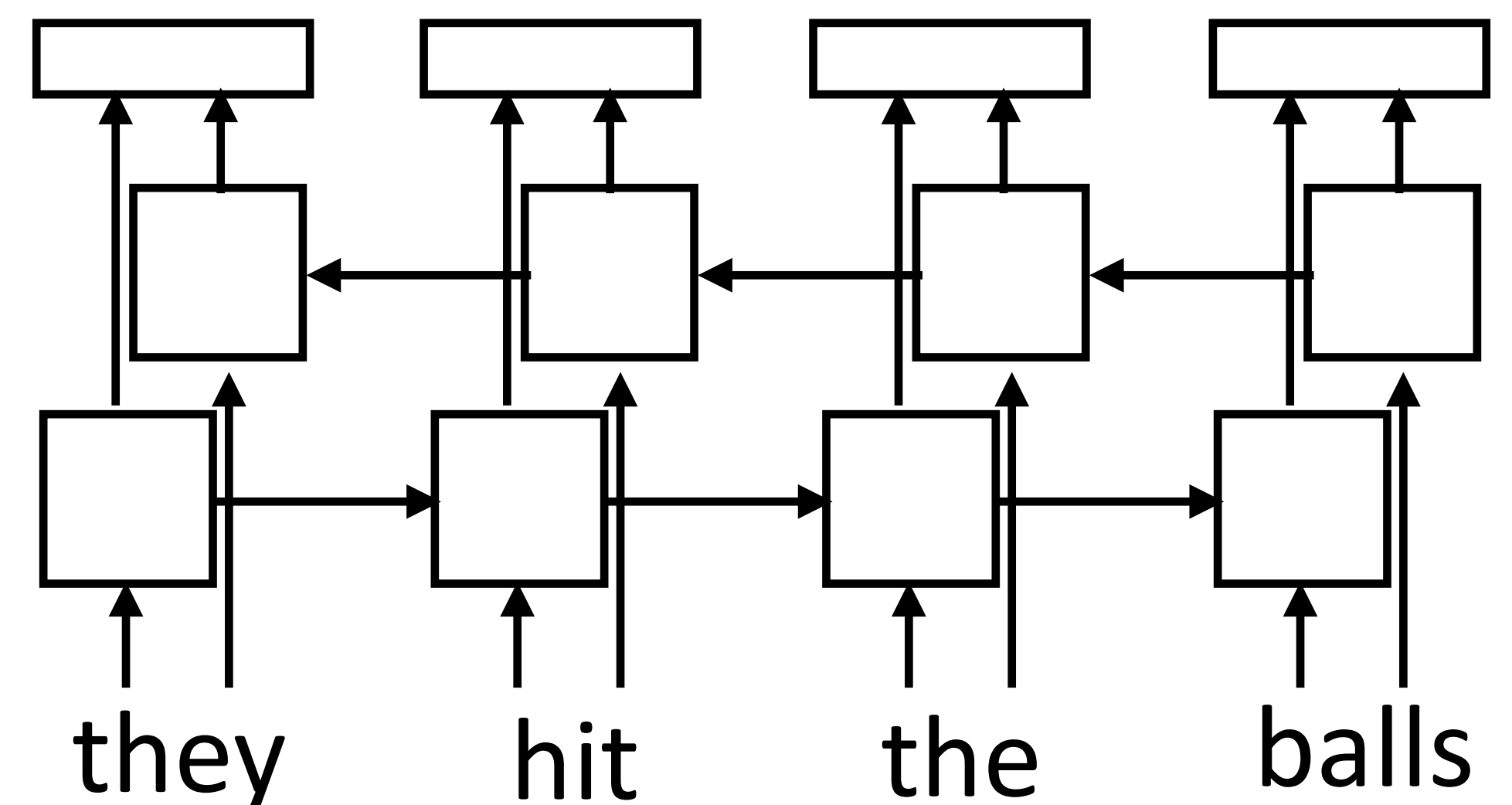
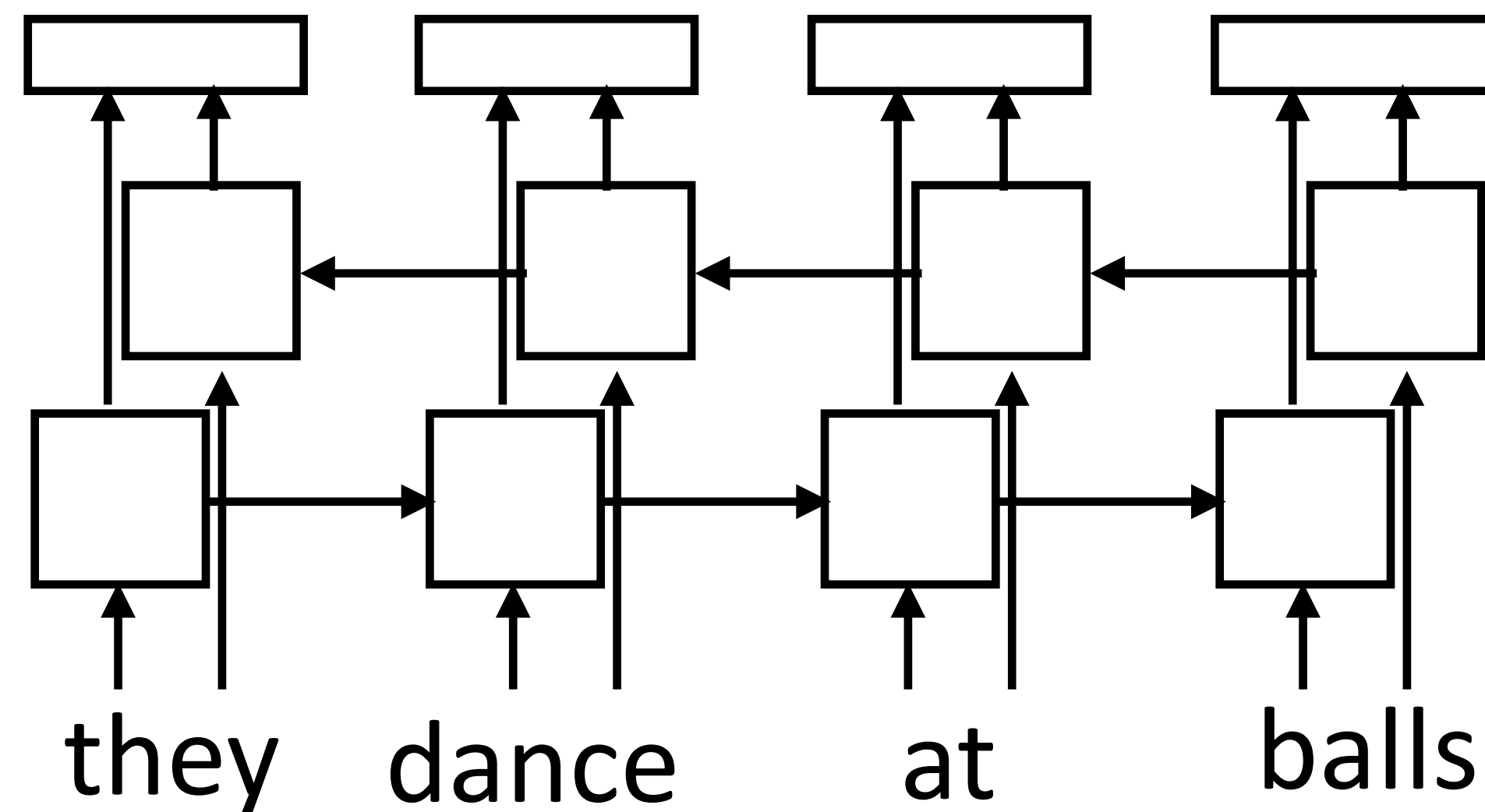


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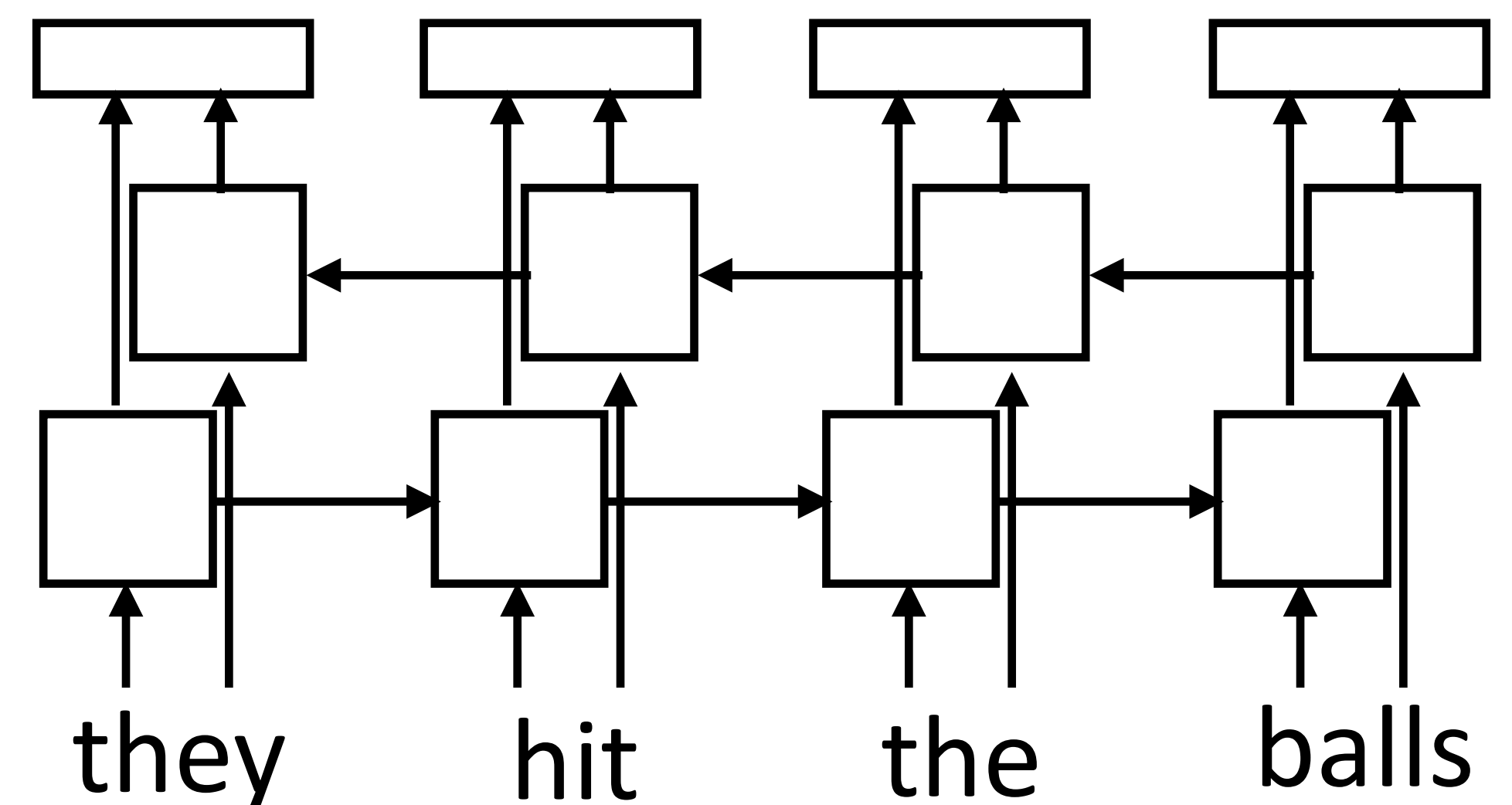
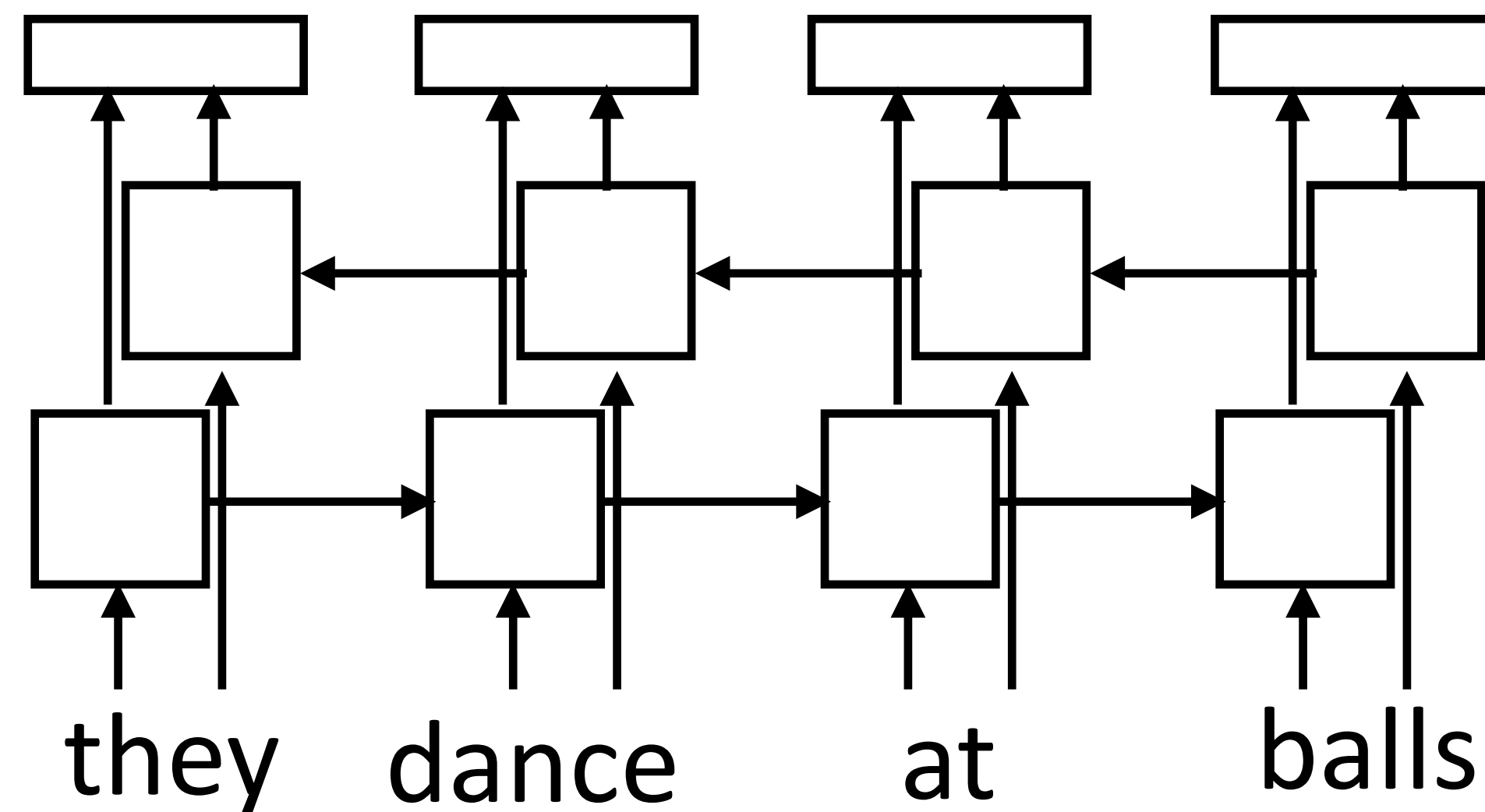
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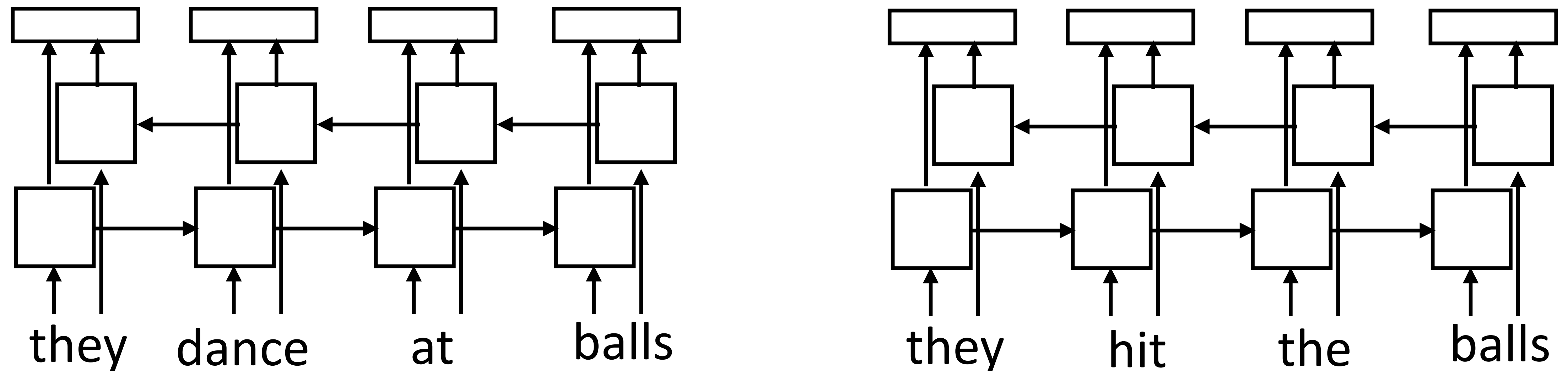
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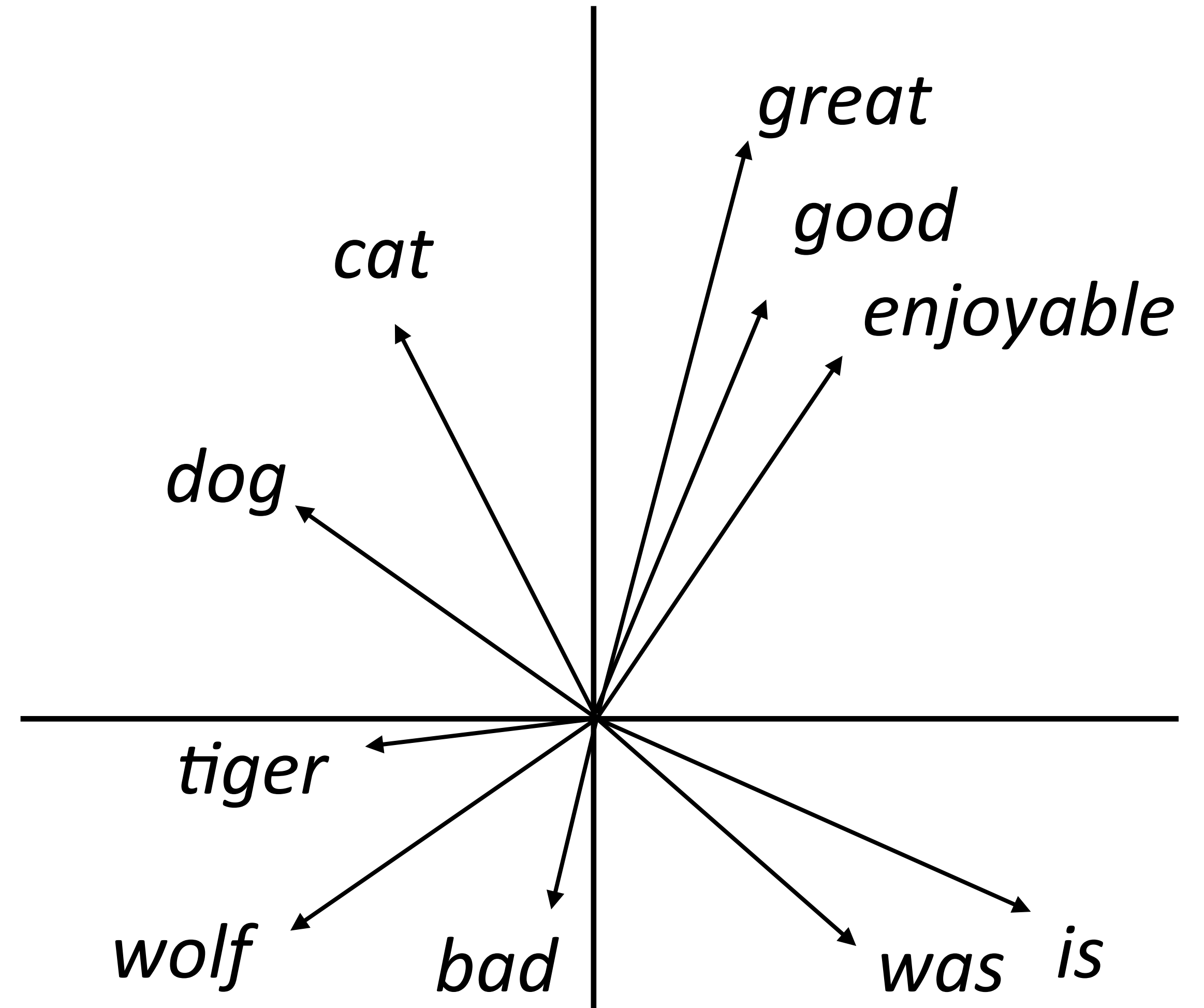
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- ▶ *Context-sensitive* word embeddings: depend on rest of the sentence
- ▶ *Huge* improvements across nearly all NLP tasks over GloVe

Peters et al. (2018)

Evaluation

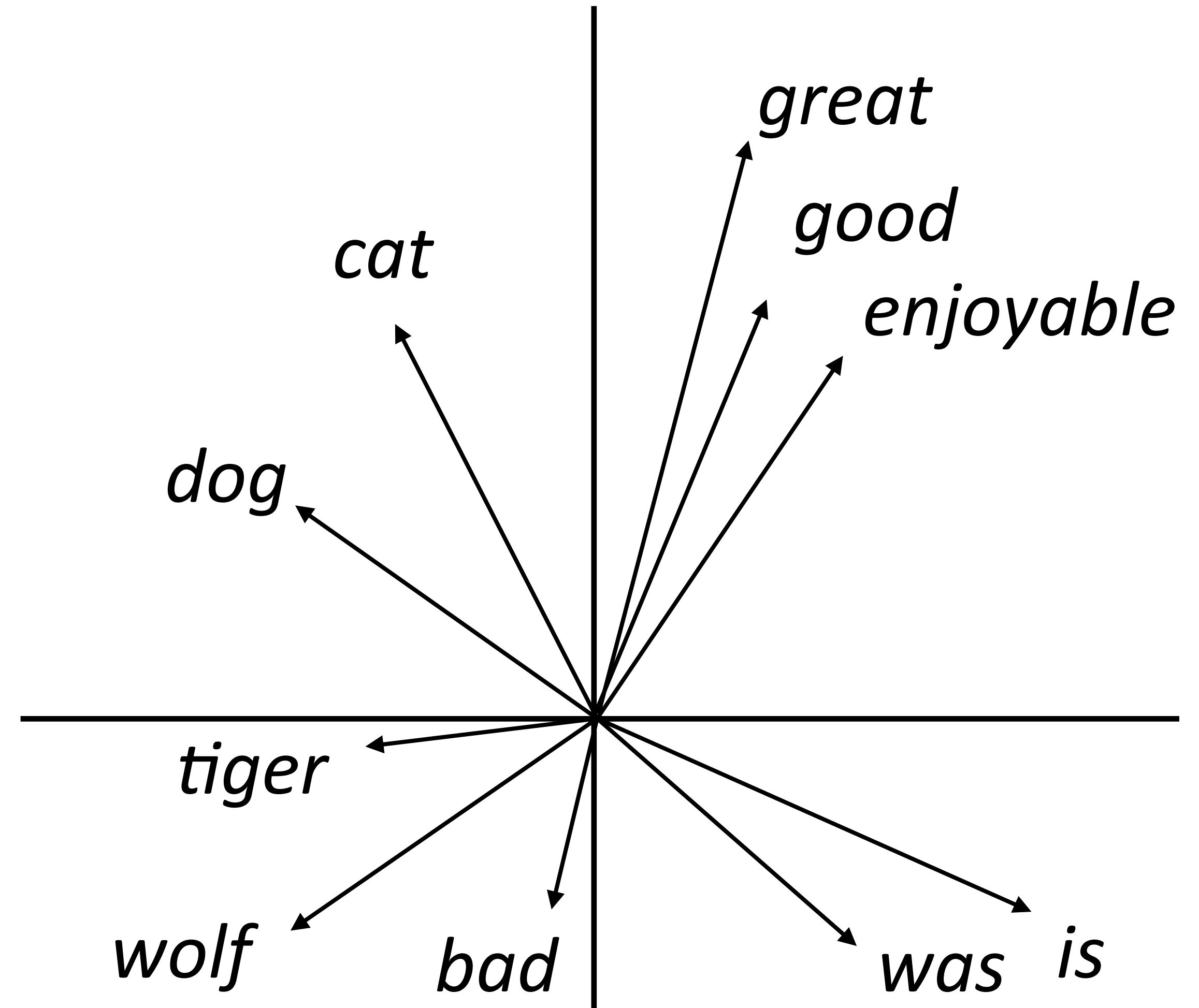
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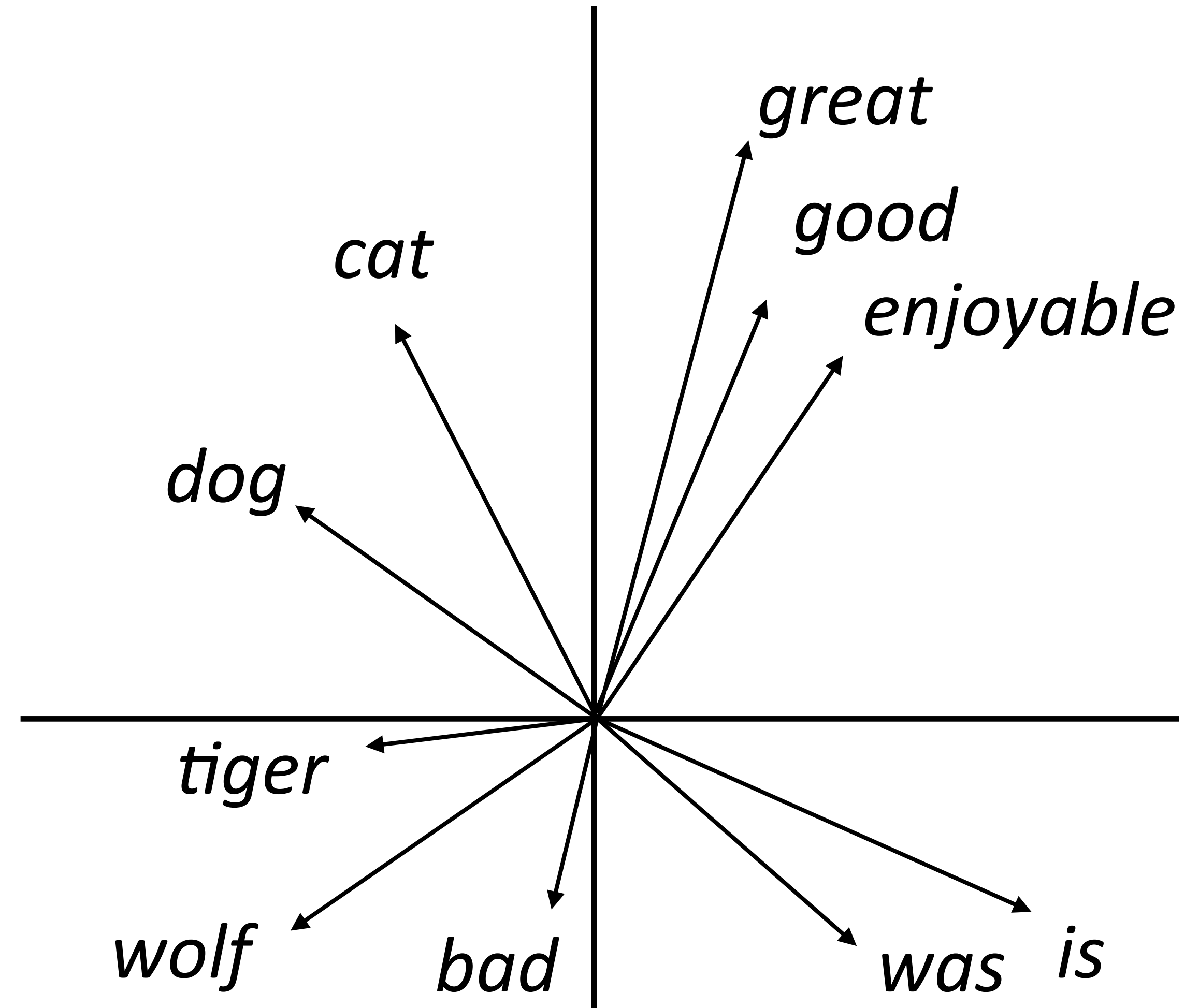


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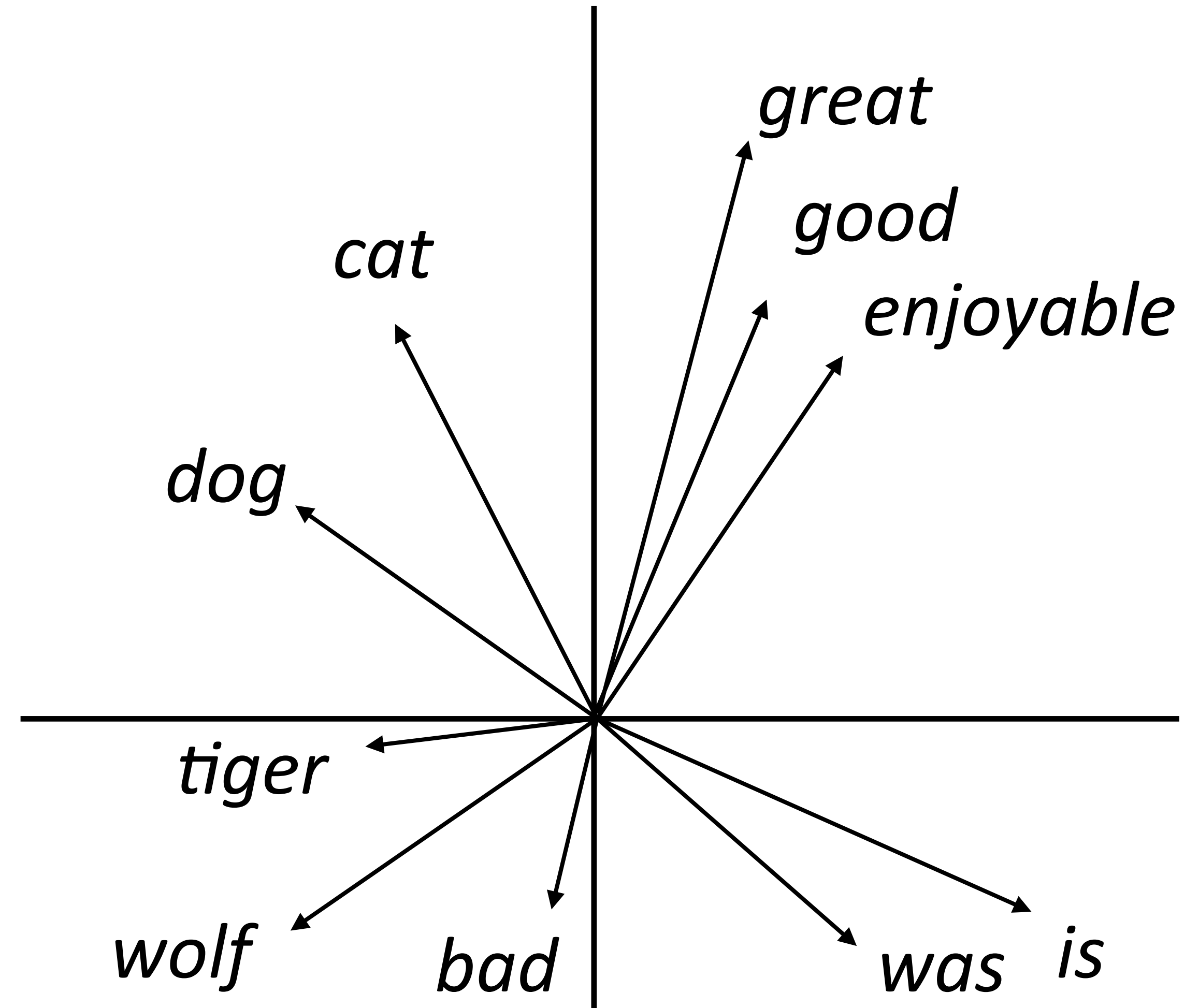


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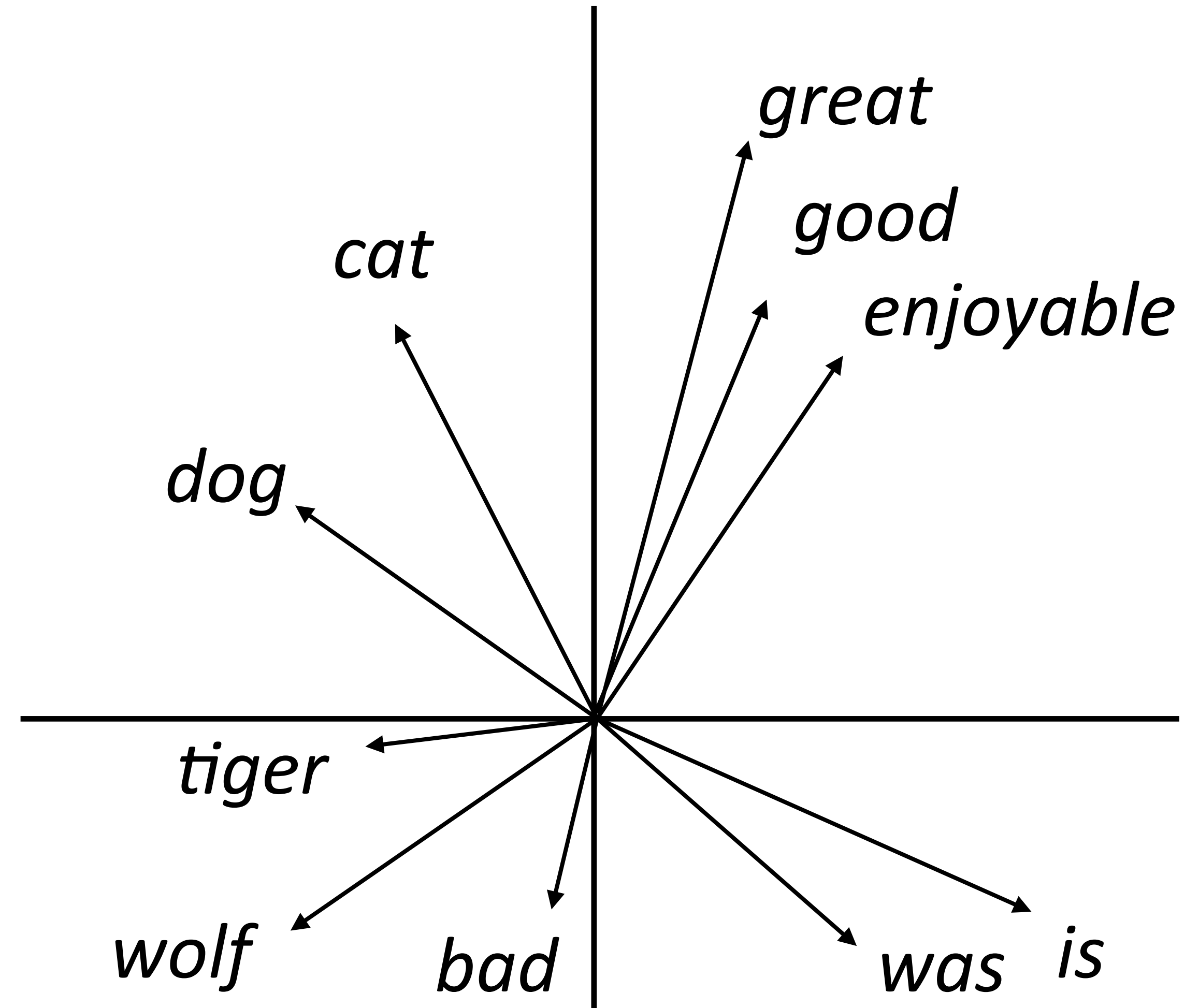
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Similarity

| Method | WordSim Similarity | WordSim Relatedness | Bruni et al. MEN | Radinsky et al. M. Turk | Luong et al. Rare Words | Hill et al. SimLex |
|--------|-----------------------|------------------------|---------------------|----------------------------|----------------------------|-----------------------|
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- ▶ SVD = singular value decomposition on PMI matrix
- ▶ GloVe does not appear to be the best when experiments are carefully controlled, but it depends on hyperparameters + these distinctions don't matter in practice

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| GE + KL | 52.0 | 39.4 | 23.7 | 54.4 | 25.9 |
| DIVE + C· Δ S | 57.2 | 36.6 | 32.0 | 60.9 | 32.7 |

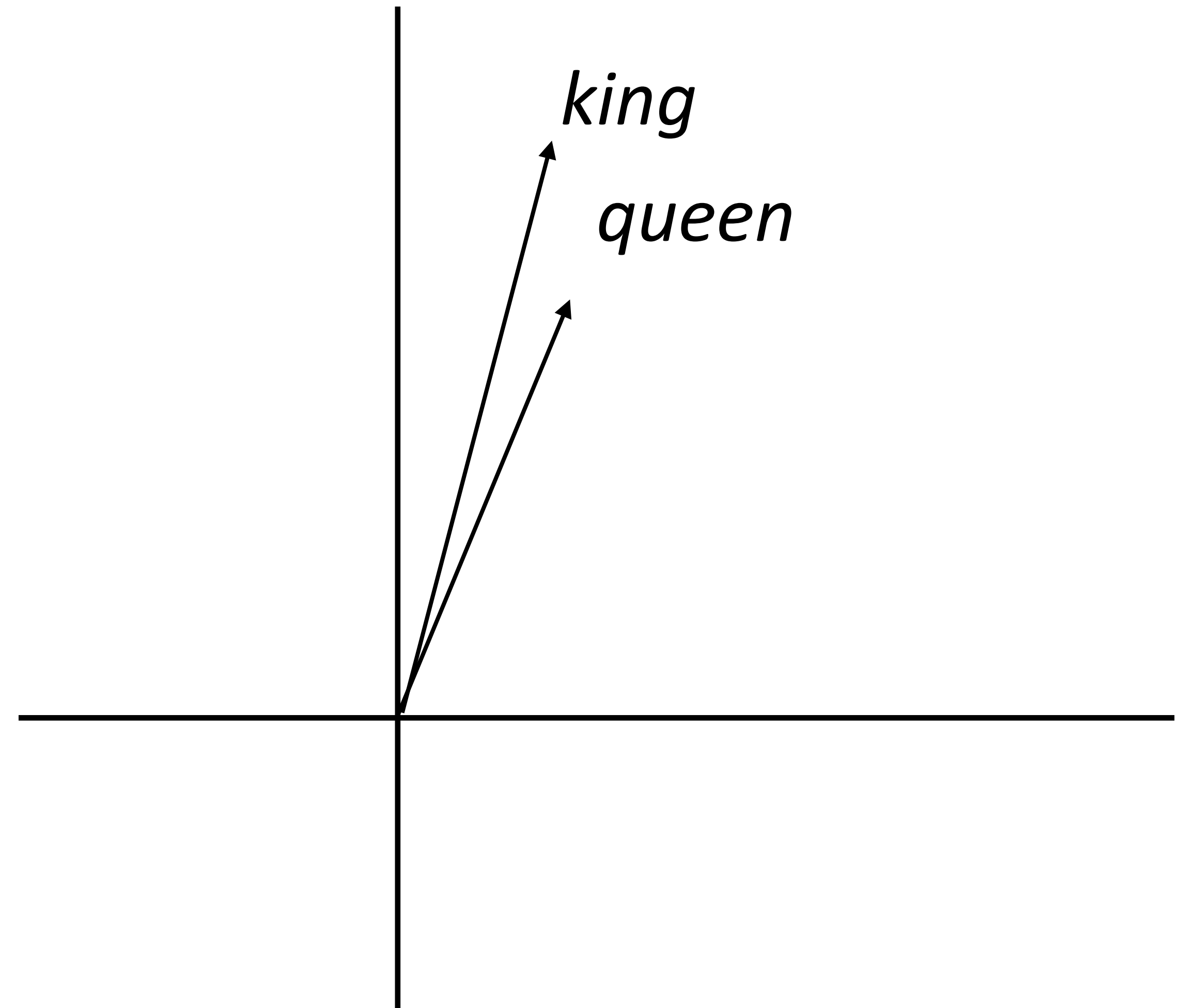
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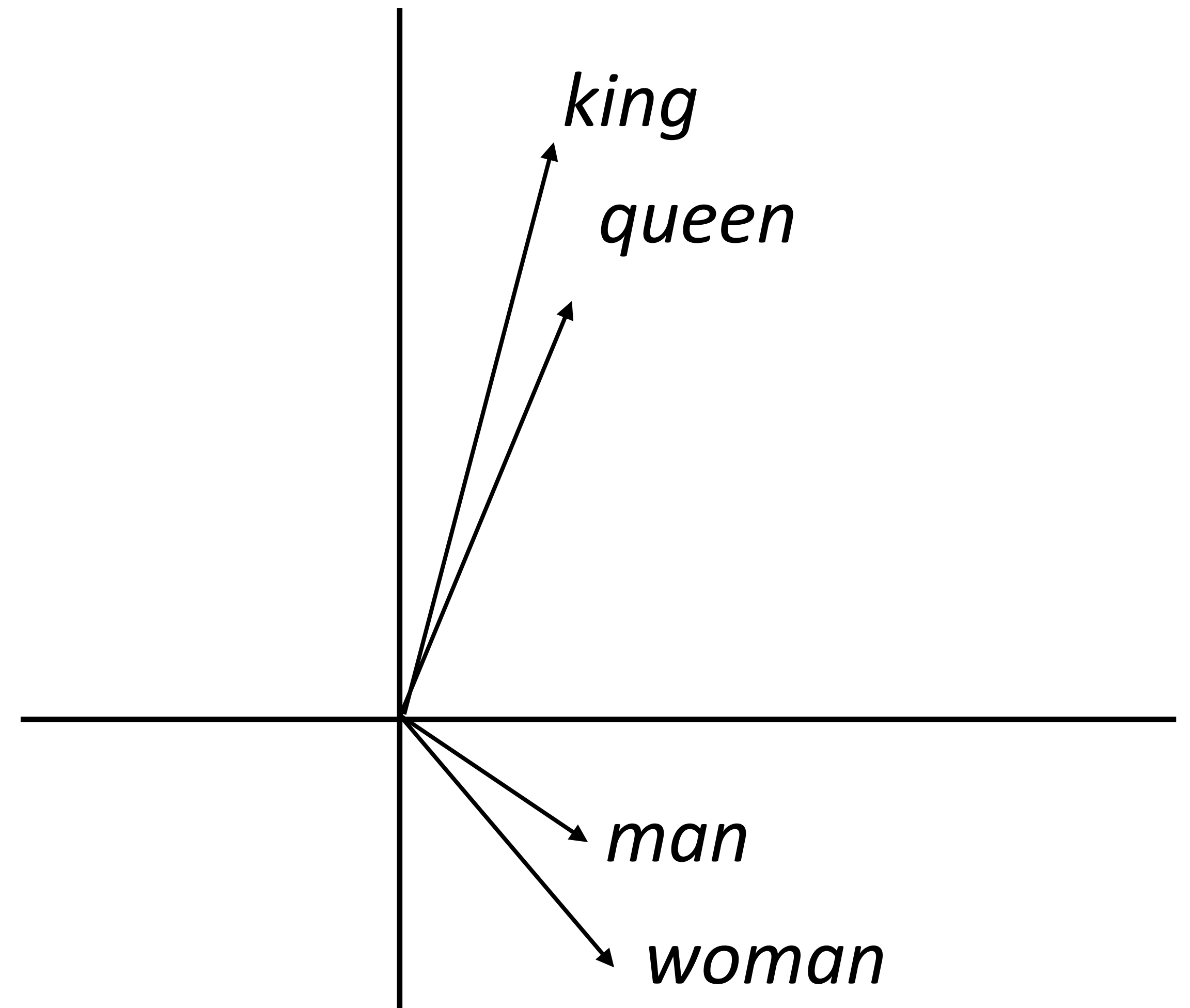
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- ▶ word2vec (SGNS) works barely better than random guessing here

Analogies

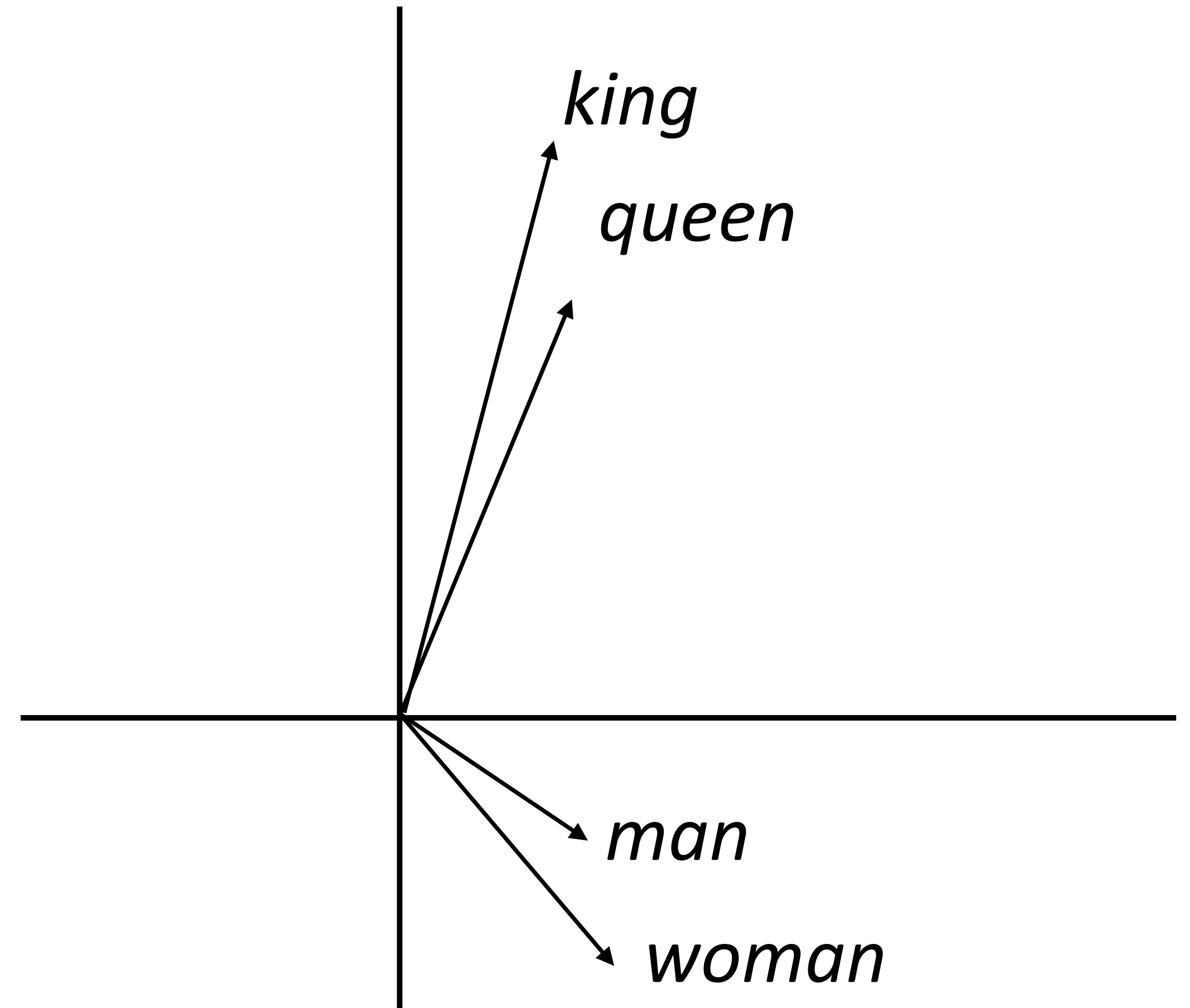


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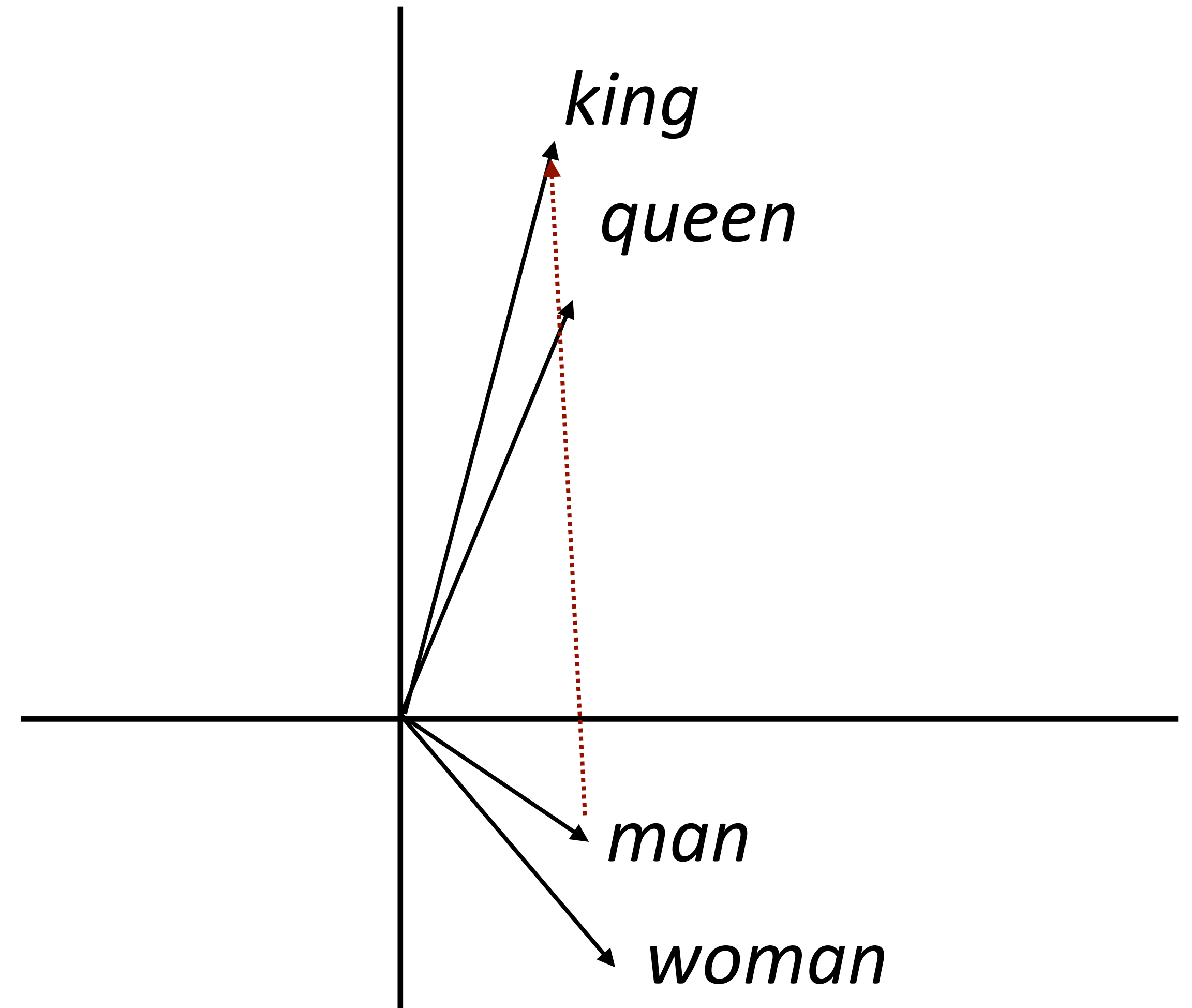
Analogies

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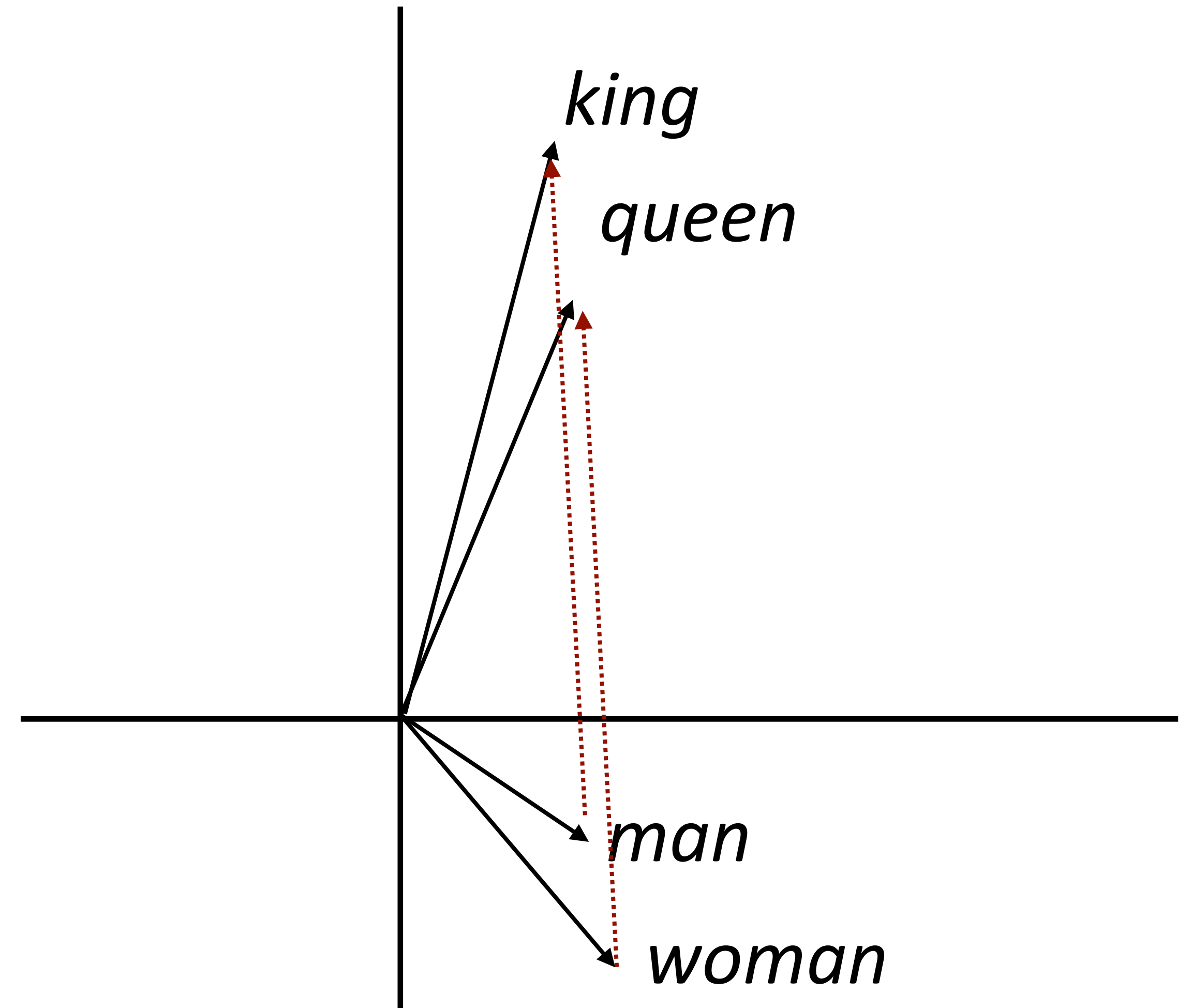
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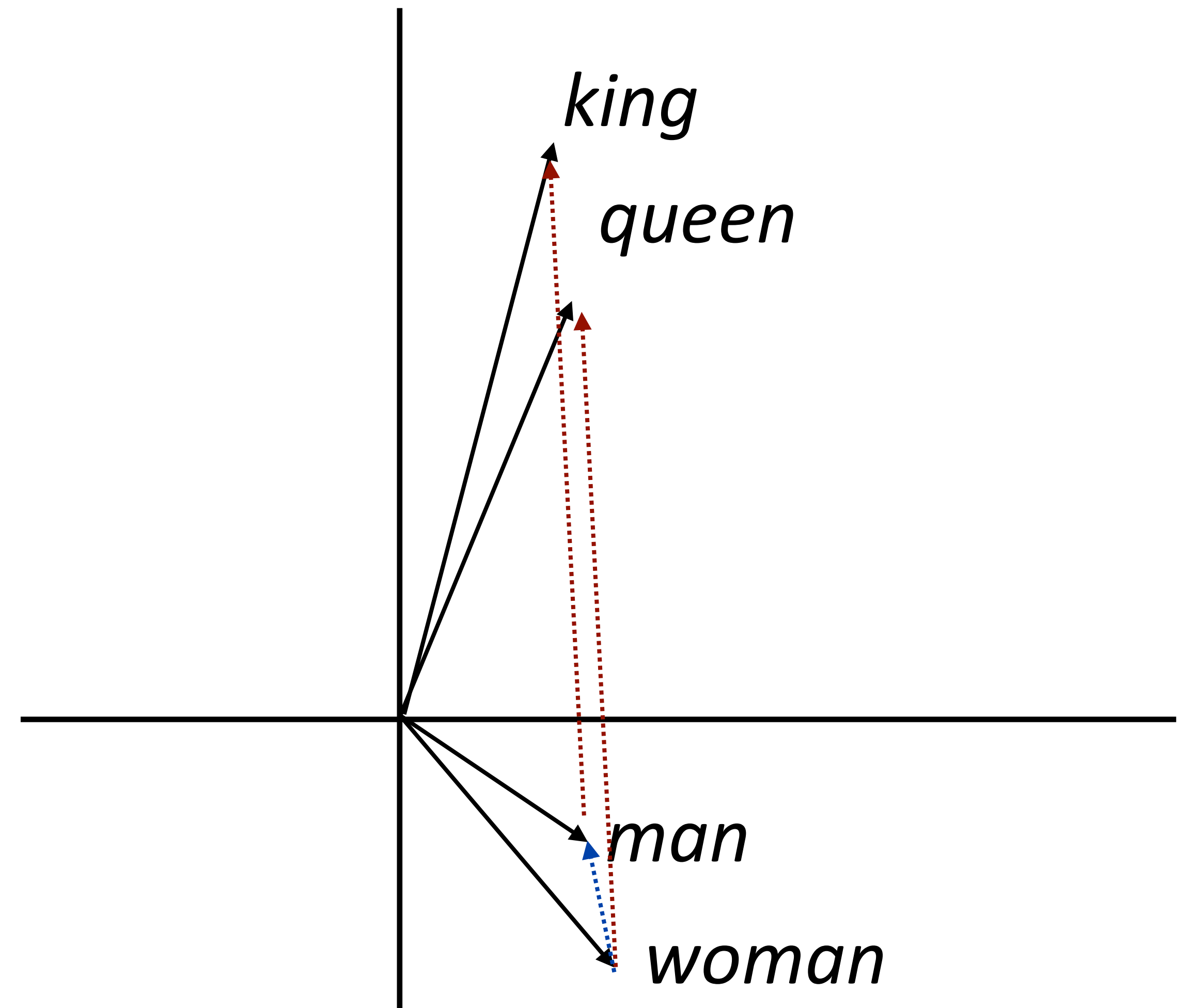


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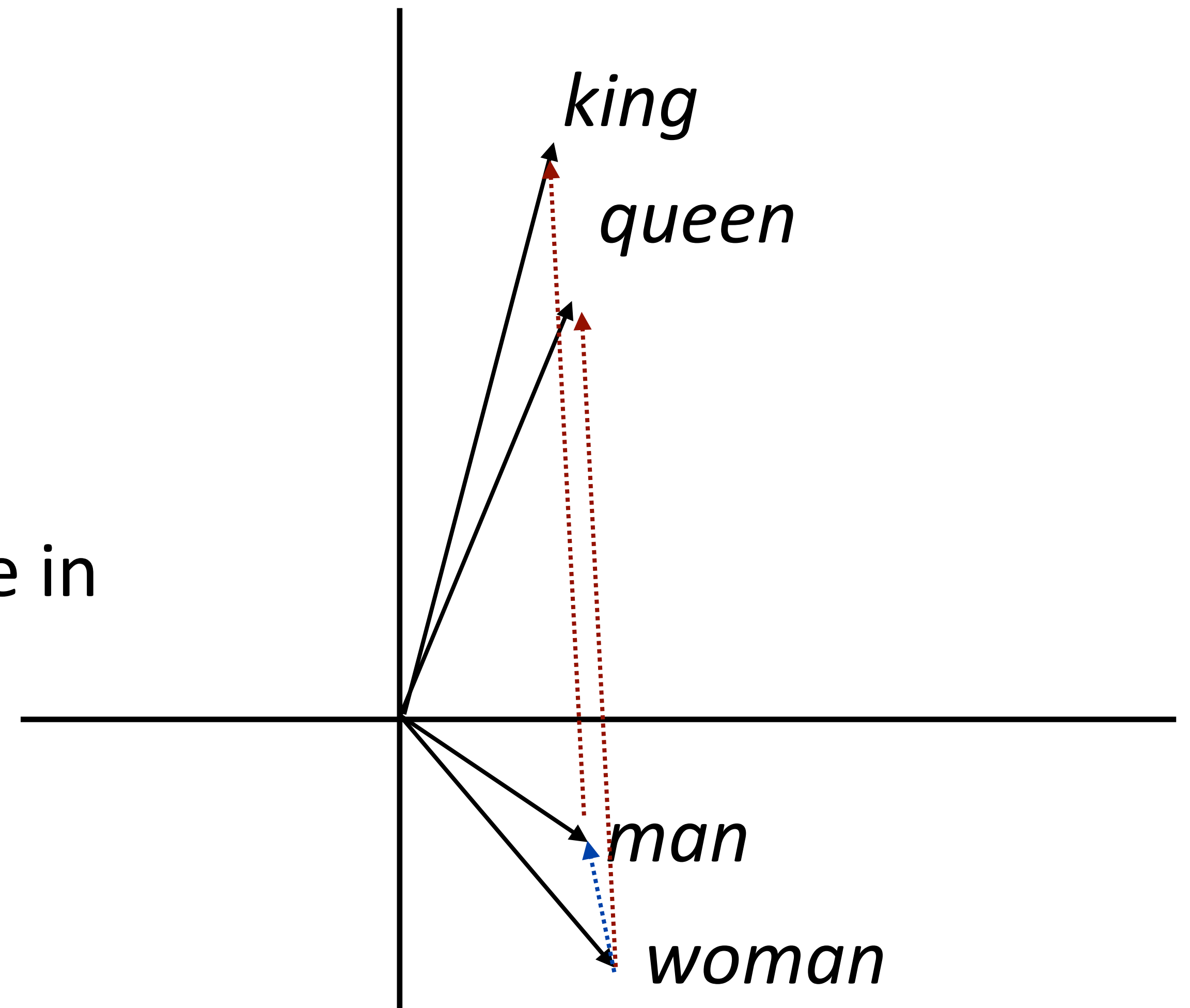


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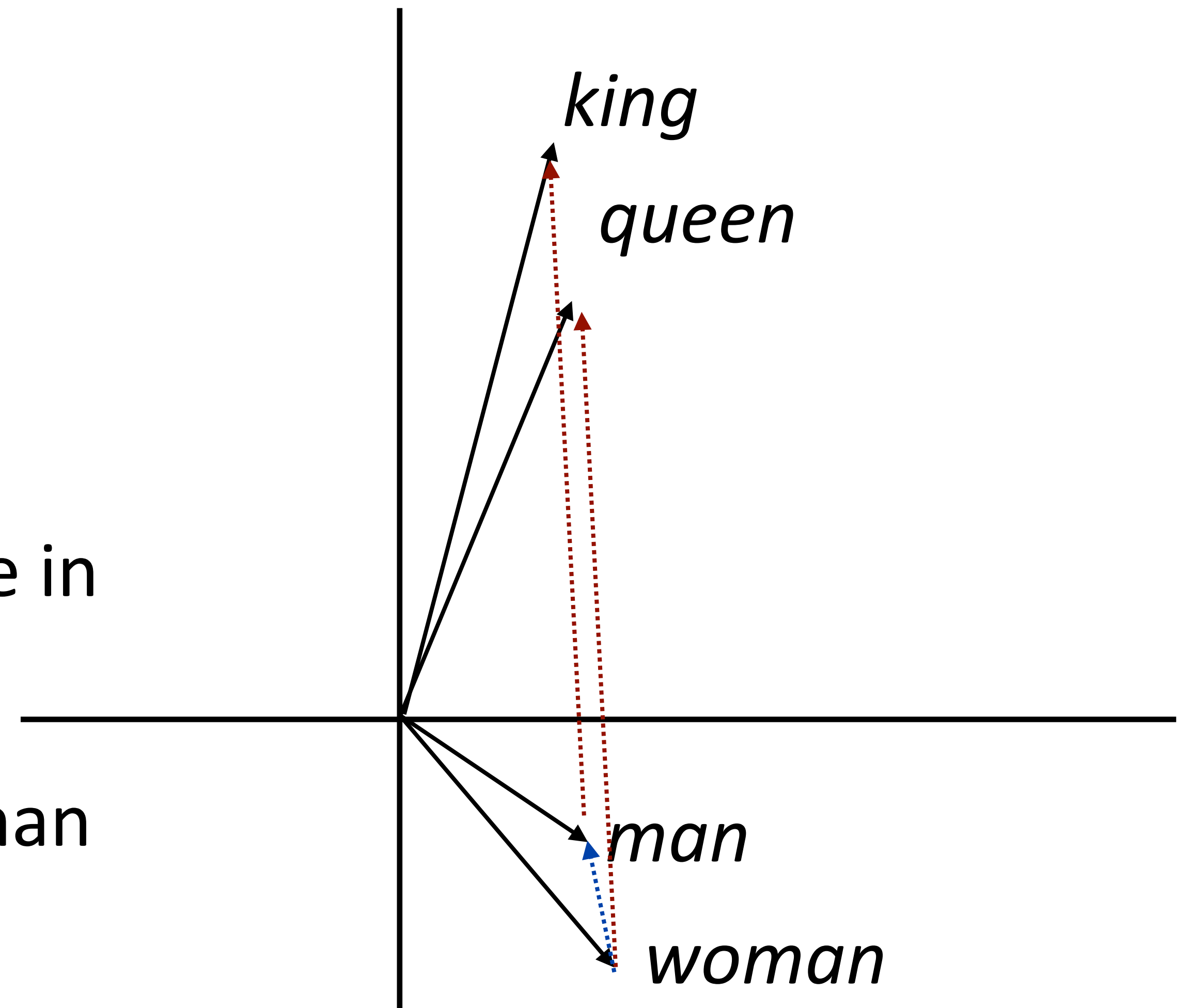


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$king + (woman - man) = queen$

- ▶ Why would this be?
- ▶ woman - man captures the difference in the contexts that these occur in
- ▶ Dominant change: more “he” with man and “she” with woman — similar to difference between king and queen



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$$\text{Maximizing for } b: \text{Add} = \cos(b, a_2 - a_1 + b_1) \quad \text{Mul} = \frac{\cos(b_2, a_2) \cos(b_2, b_1)}{\cos(b_2, a_1) + \epsilon}$$

Levy et al. (2015)

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 - ▶ Faster because no need to update these parameters
- ▶ Approach 3: initialize using GloVe, fine-tune
 - ▶ Works best for some tasks, but not used for ELMo

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- ▶ Will return to this in a few weeks

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- ▶ Next time: RNNs and CNNs