Lecture 7: Tricks + Word Embeddings

Alan Ritter

(many slides from Greg Durrett)

Recall: Feedforward NNs

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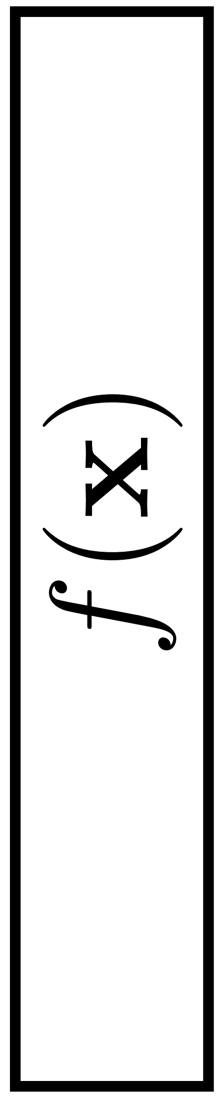

n features

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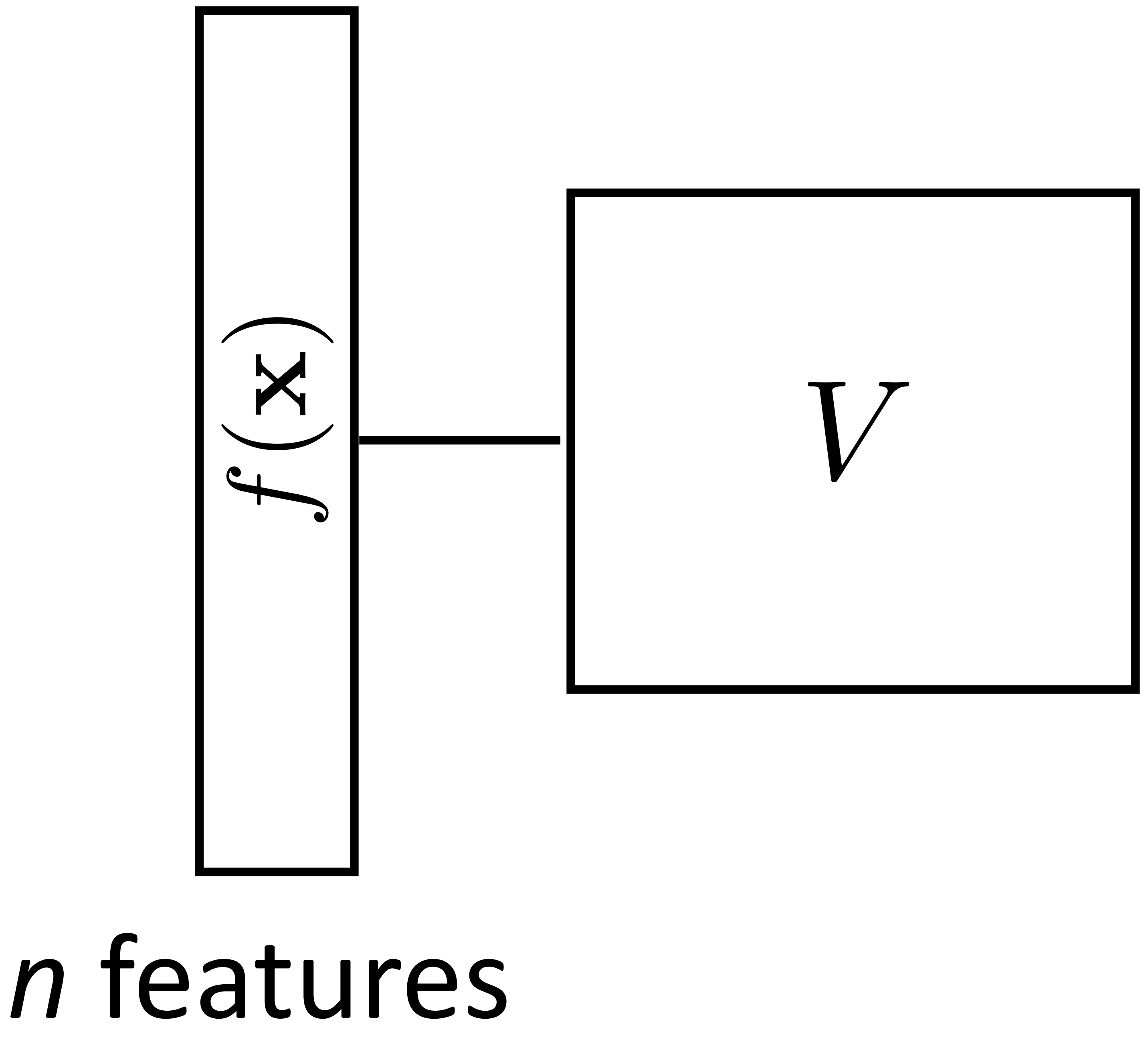

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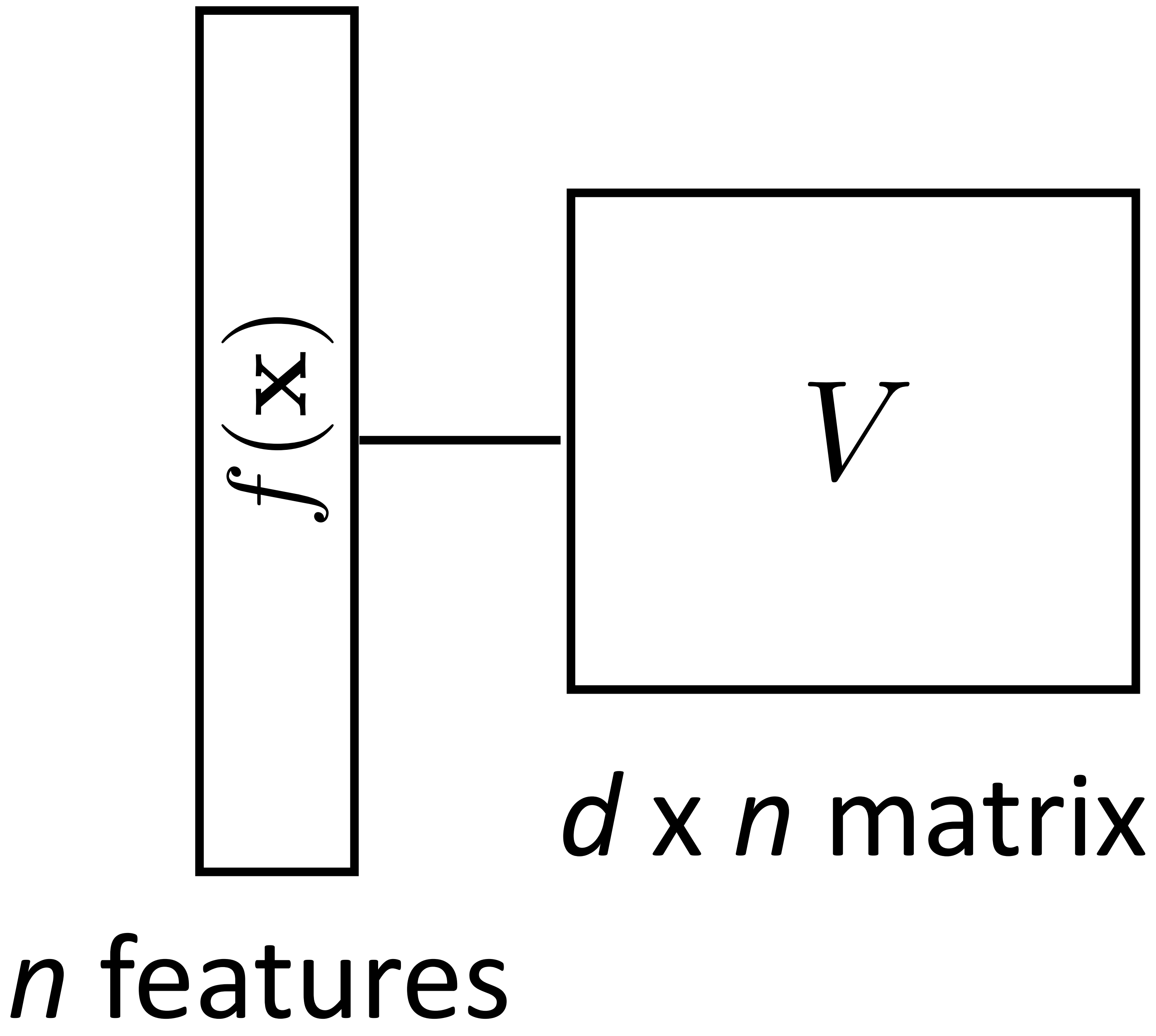

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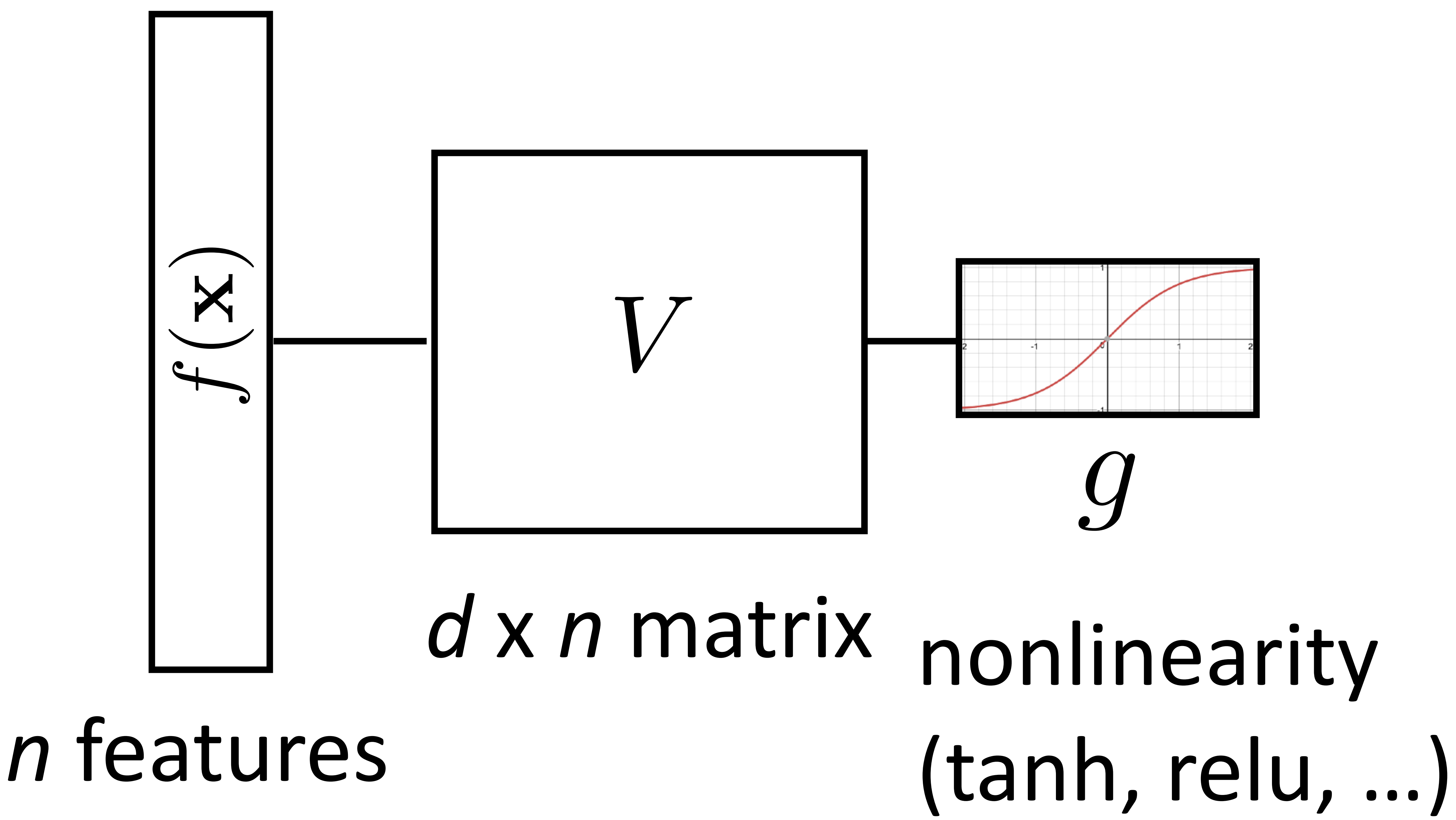

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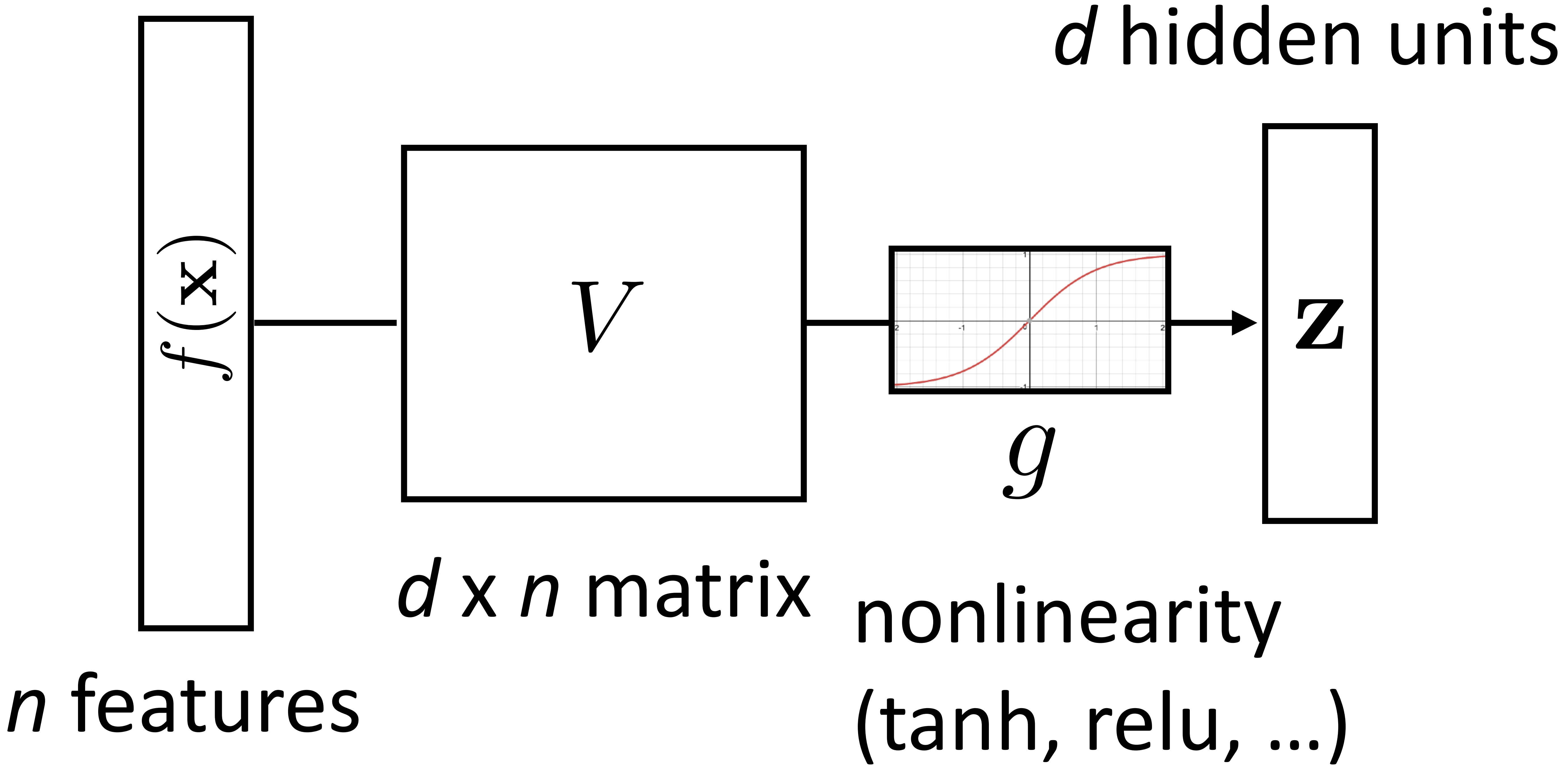

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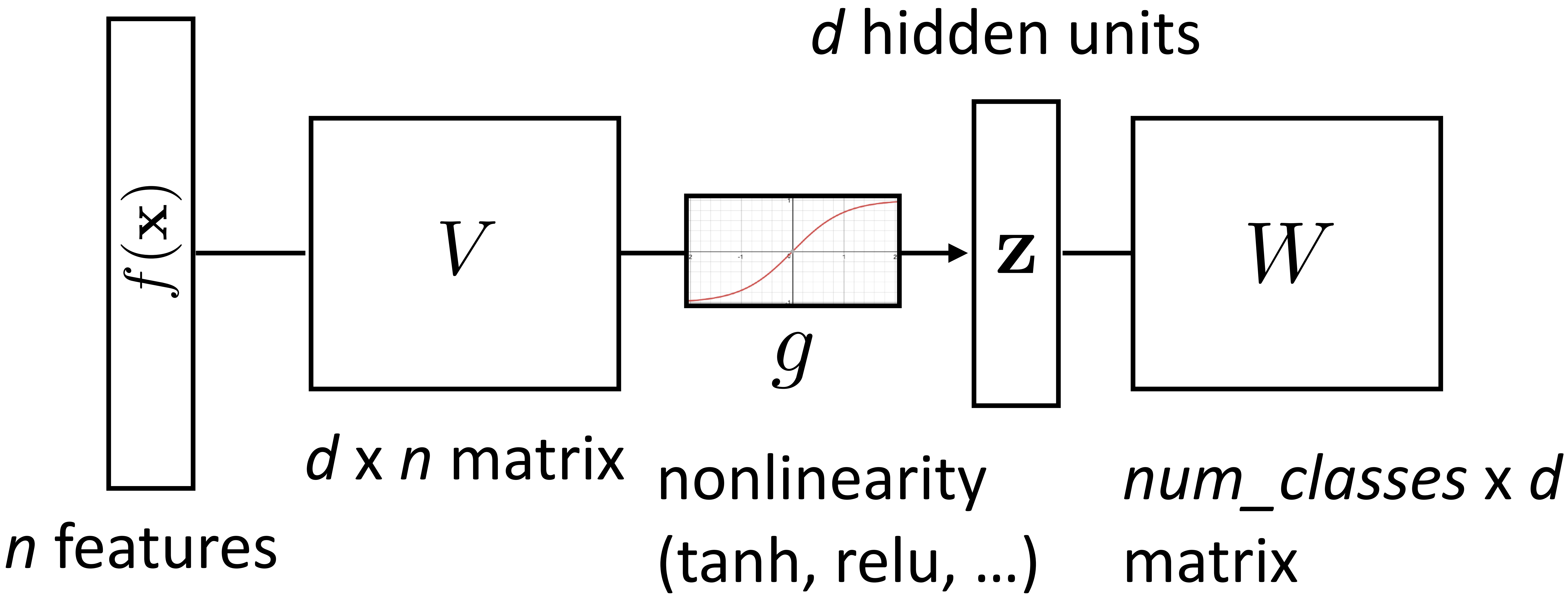

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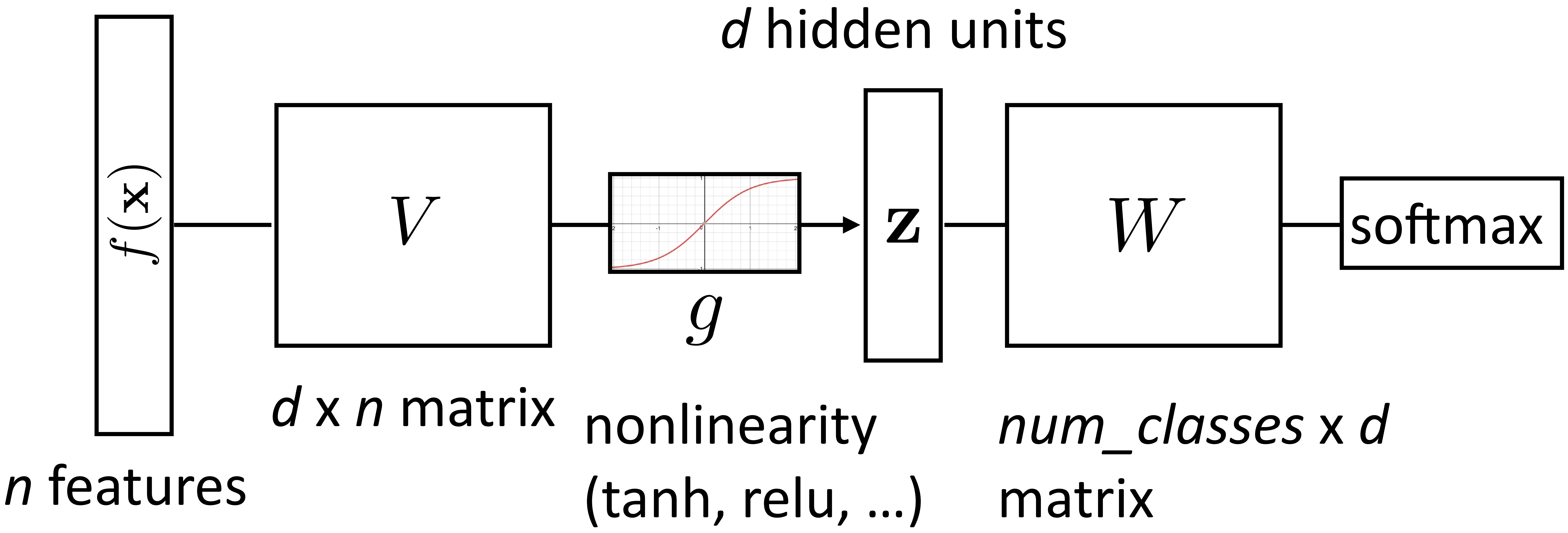

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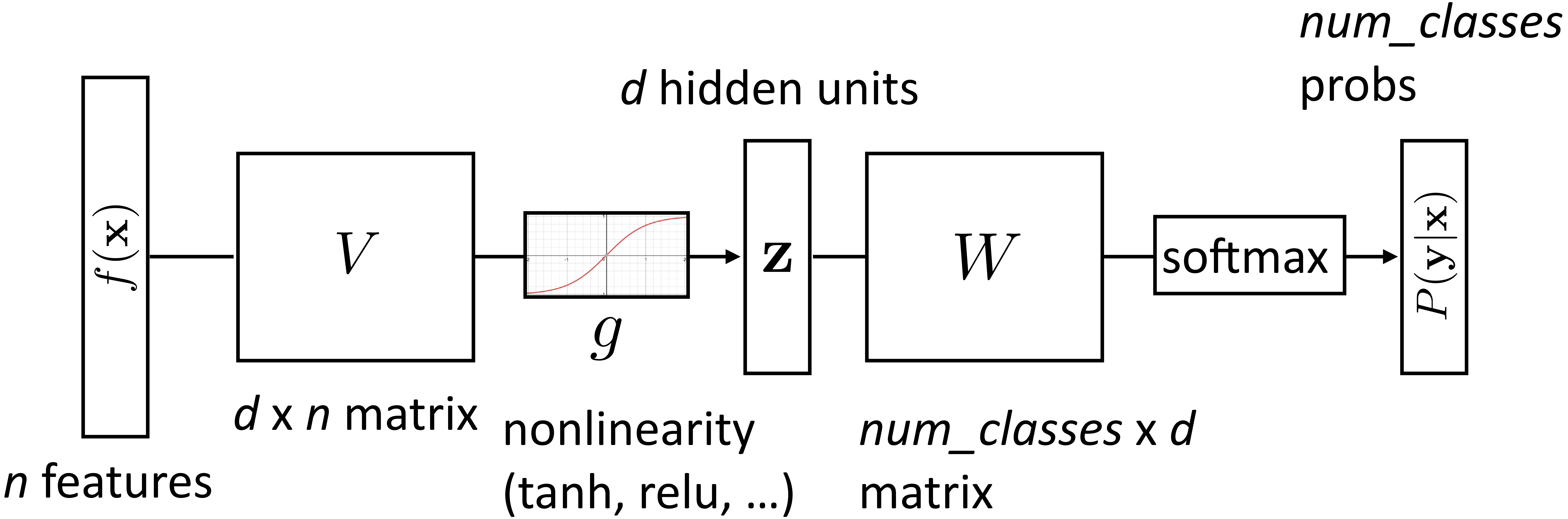

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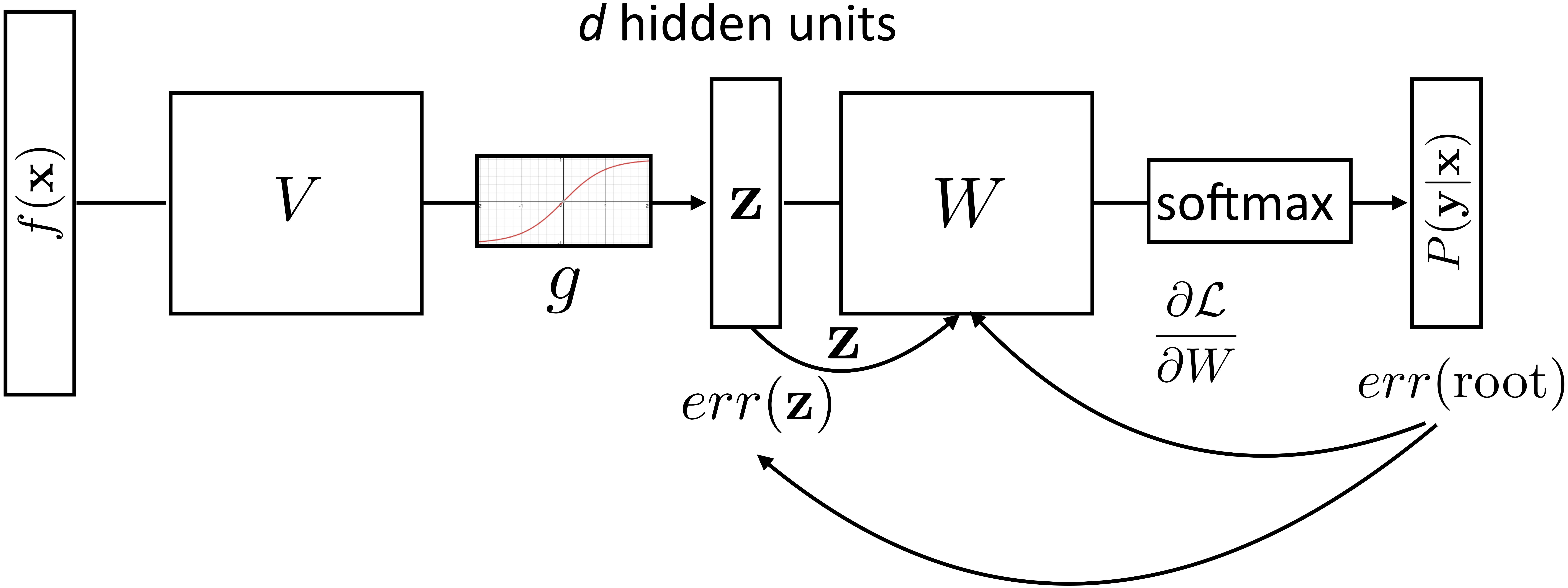

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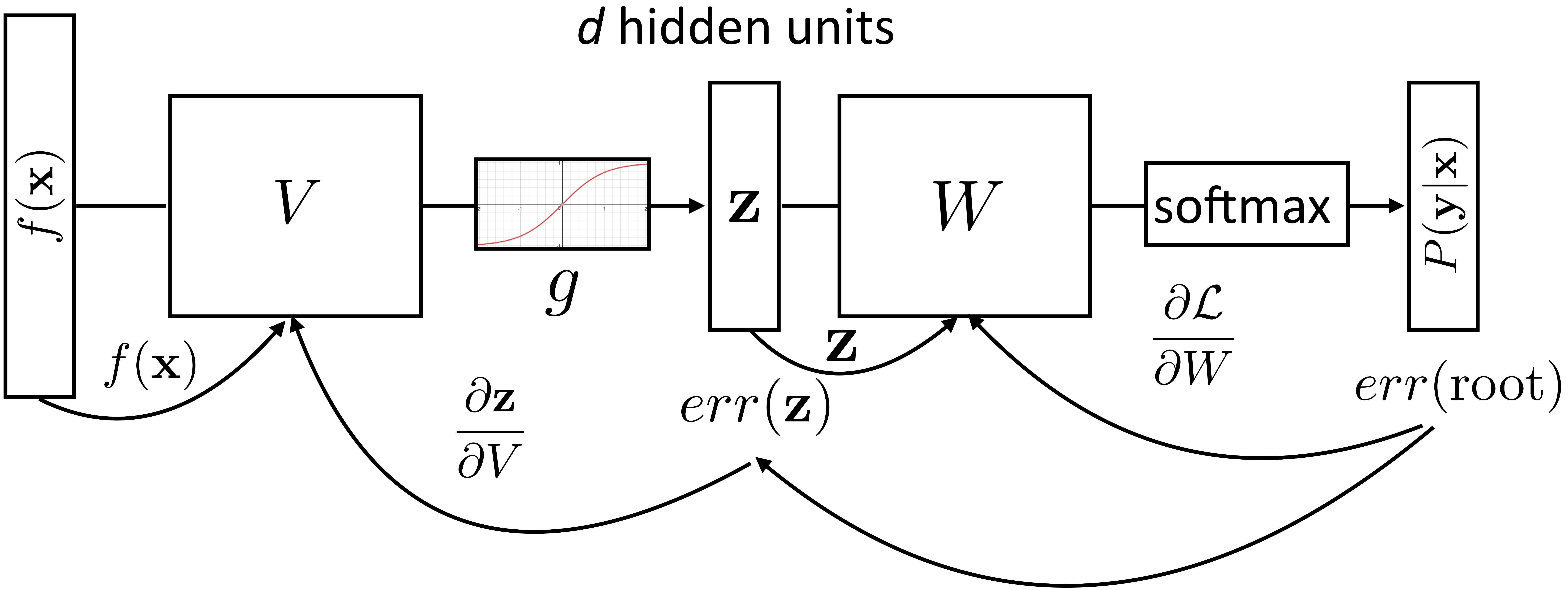

This Lecture

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

Training Tips

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- 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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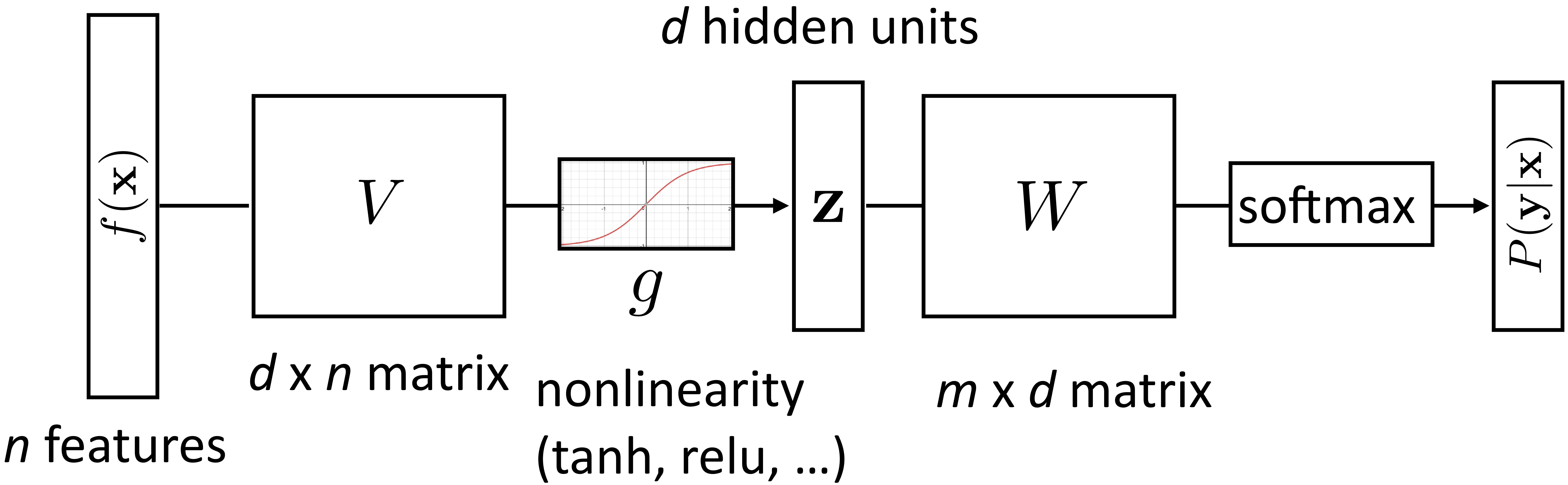

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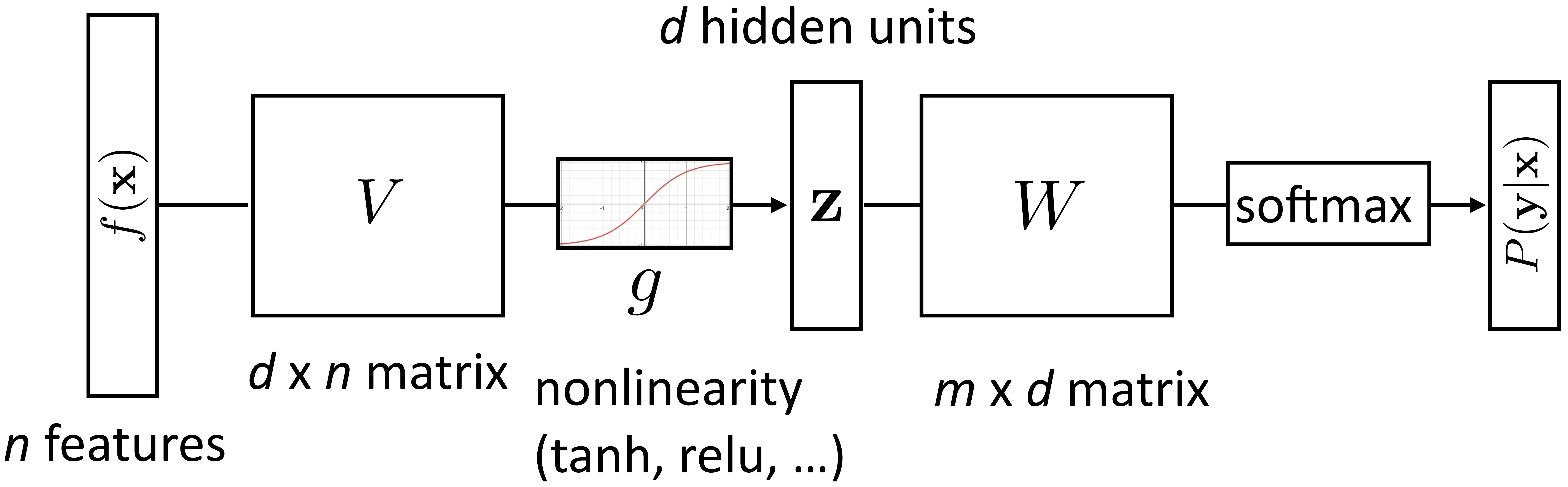

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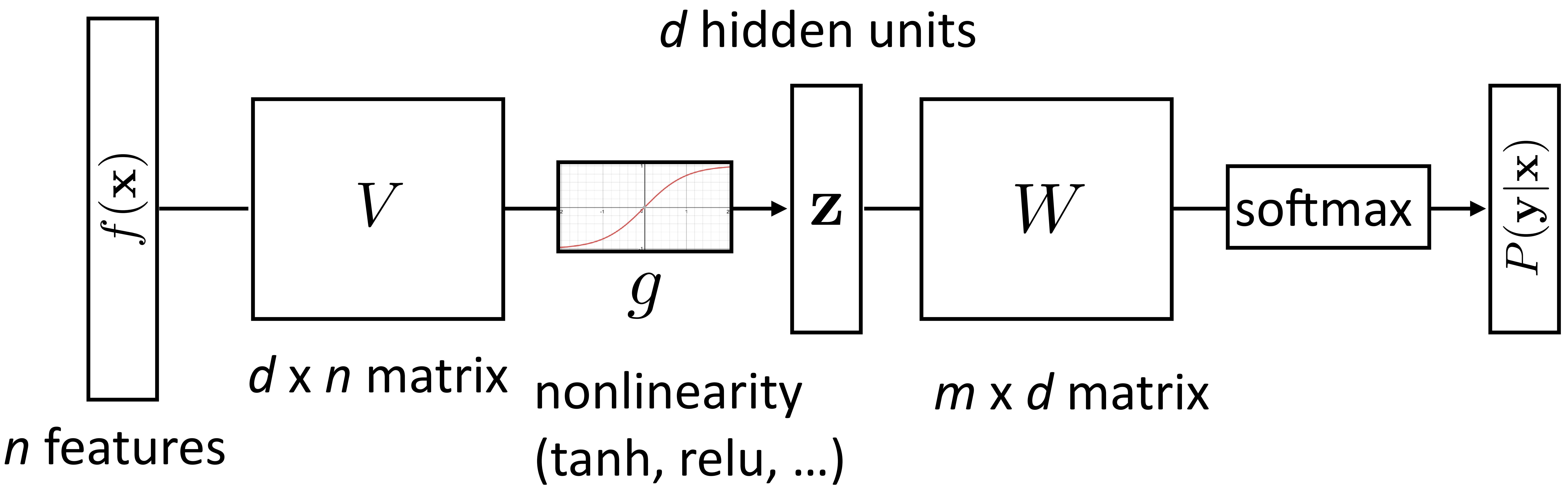

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- *Nonconvex* problem, so initialization matters!

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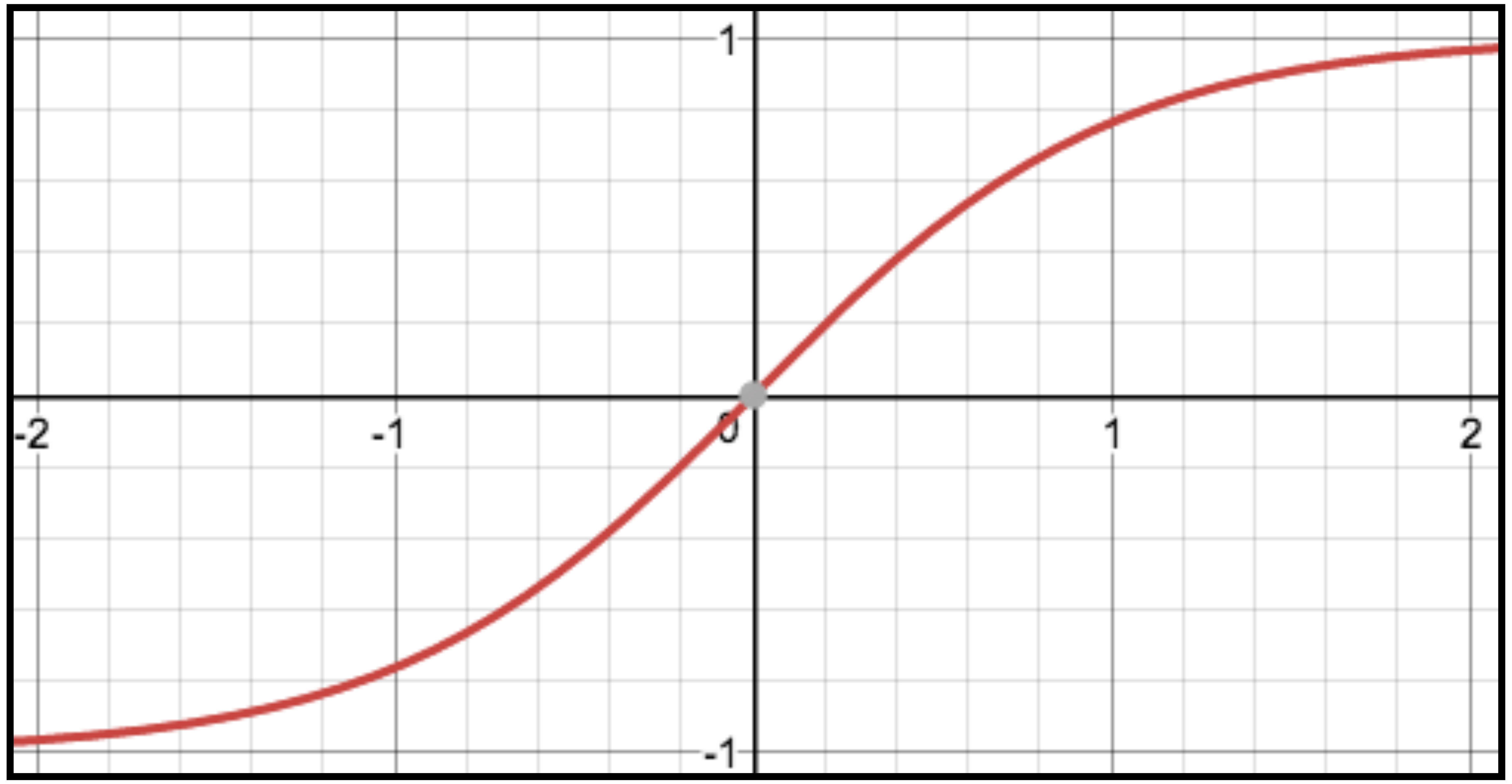

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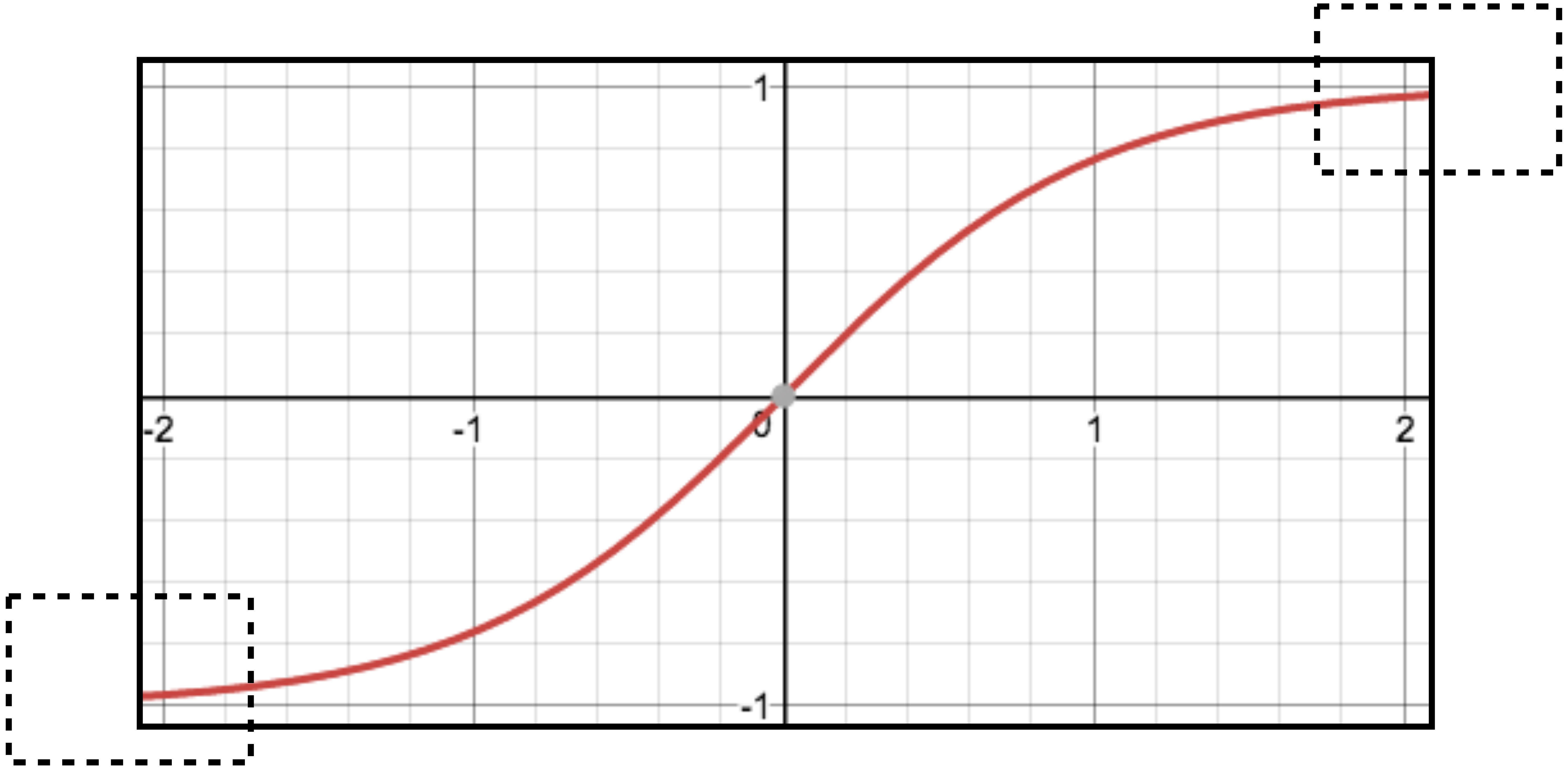

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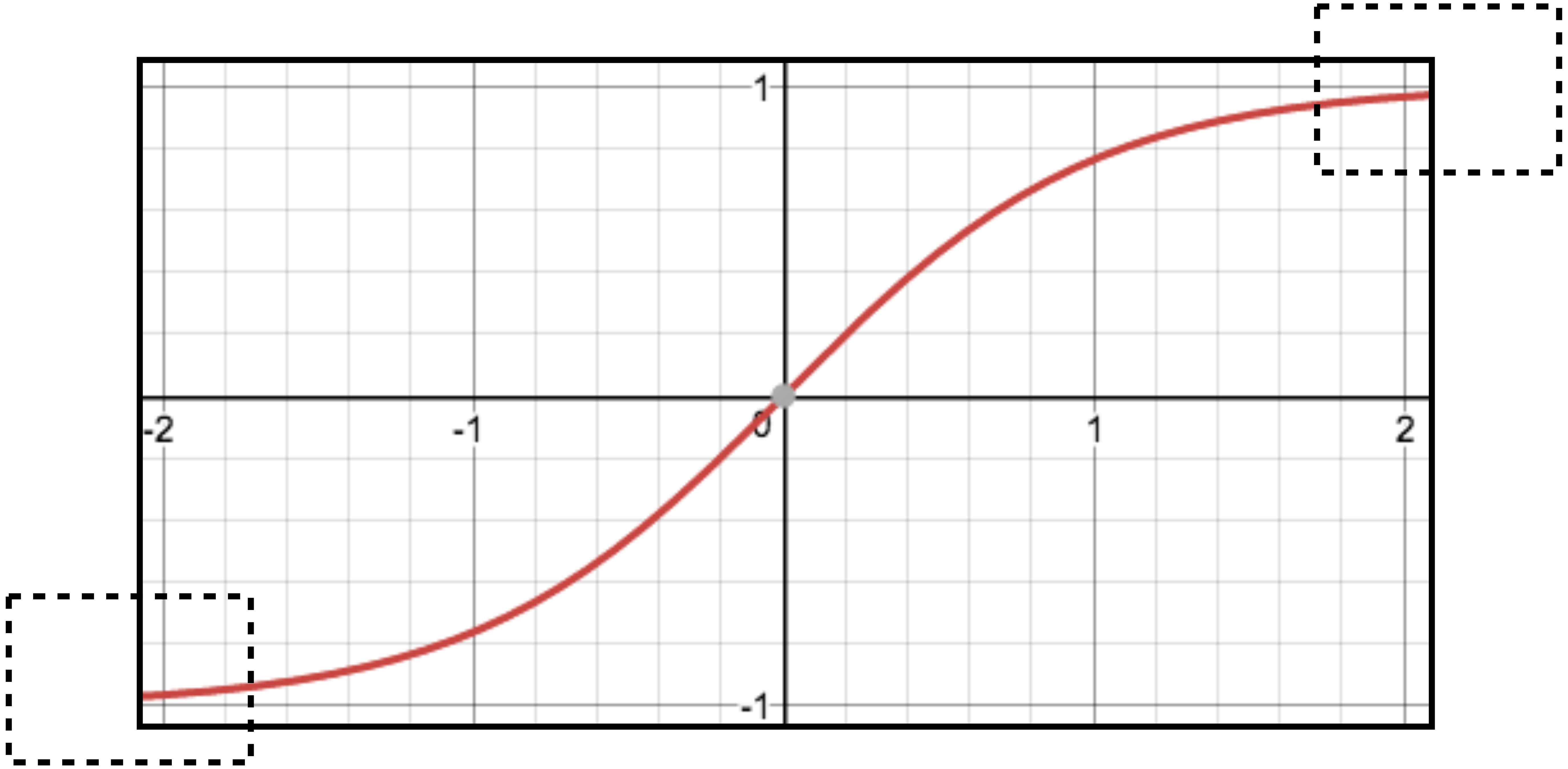

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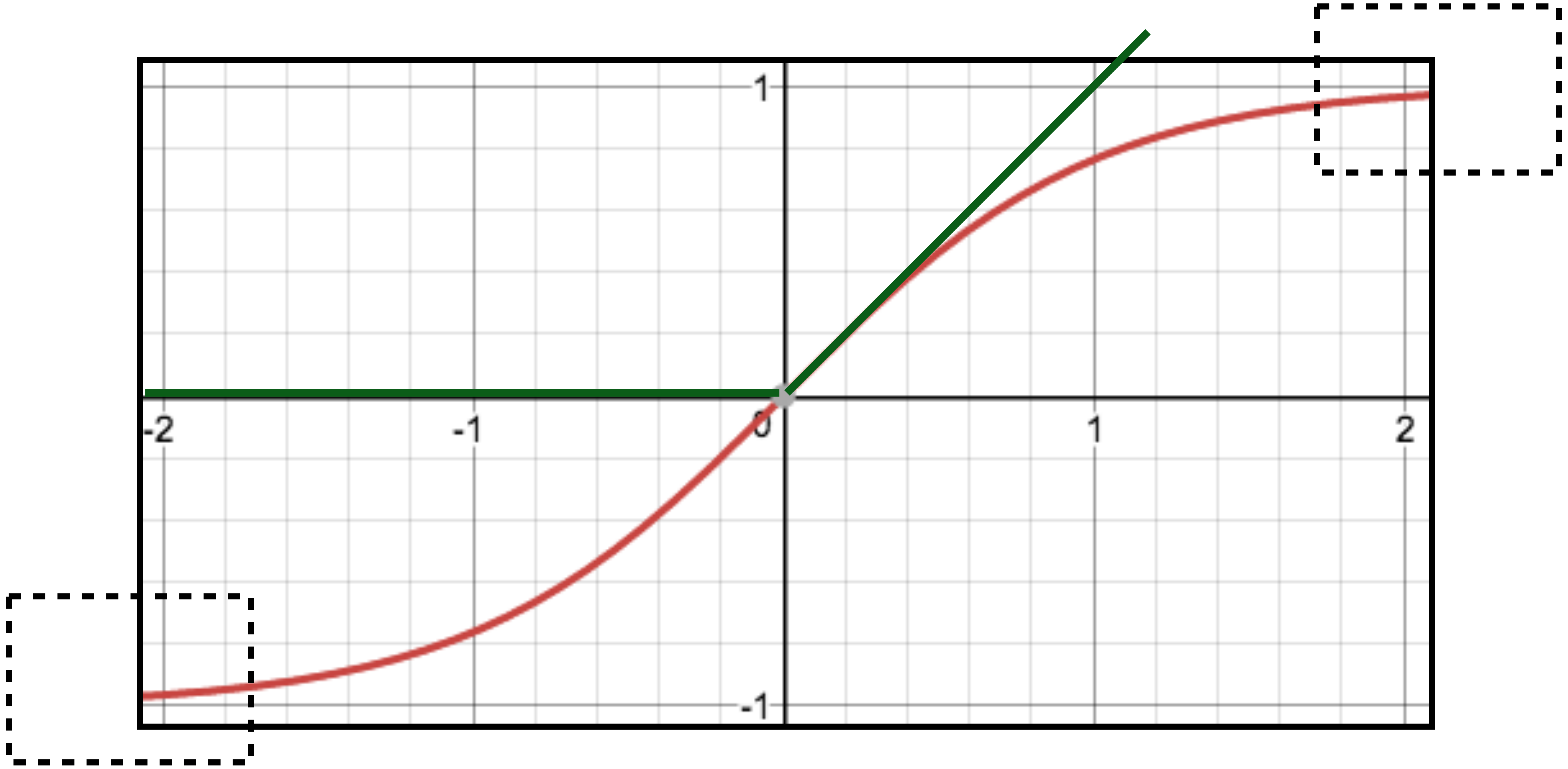

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- ReLU: larger dynamic range (all positive numbers), but can produce big values, can break down if everything is too negative

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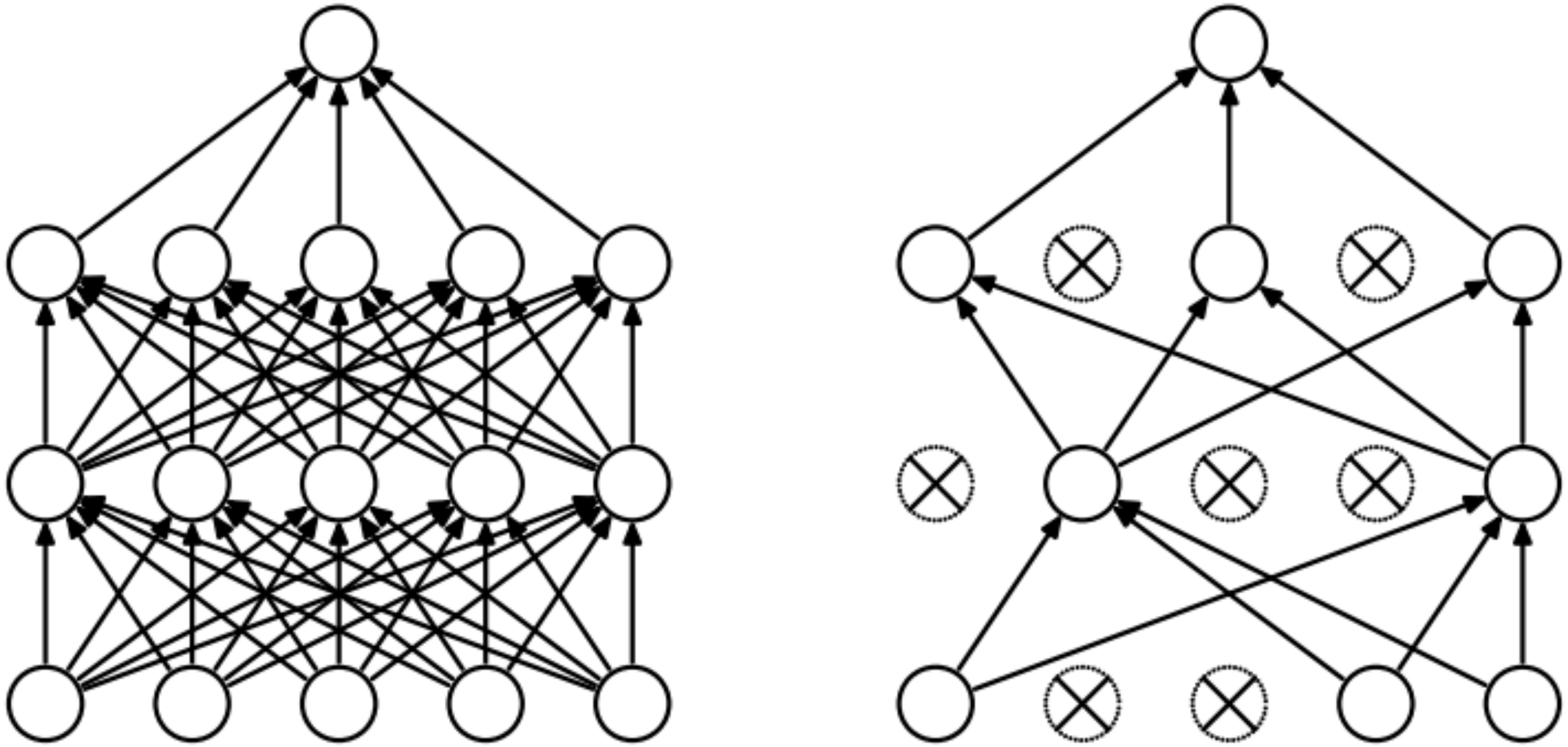
  - Want variance of inputs and gradients for each layer to be the same
- Batch normalization (Ioffe and Szegedy, 2015): periodically shift+rescale each layer to have mean 0 and variance 1 over a batch (useful if net is deep)

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.

Srivastava et al. (2014)

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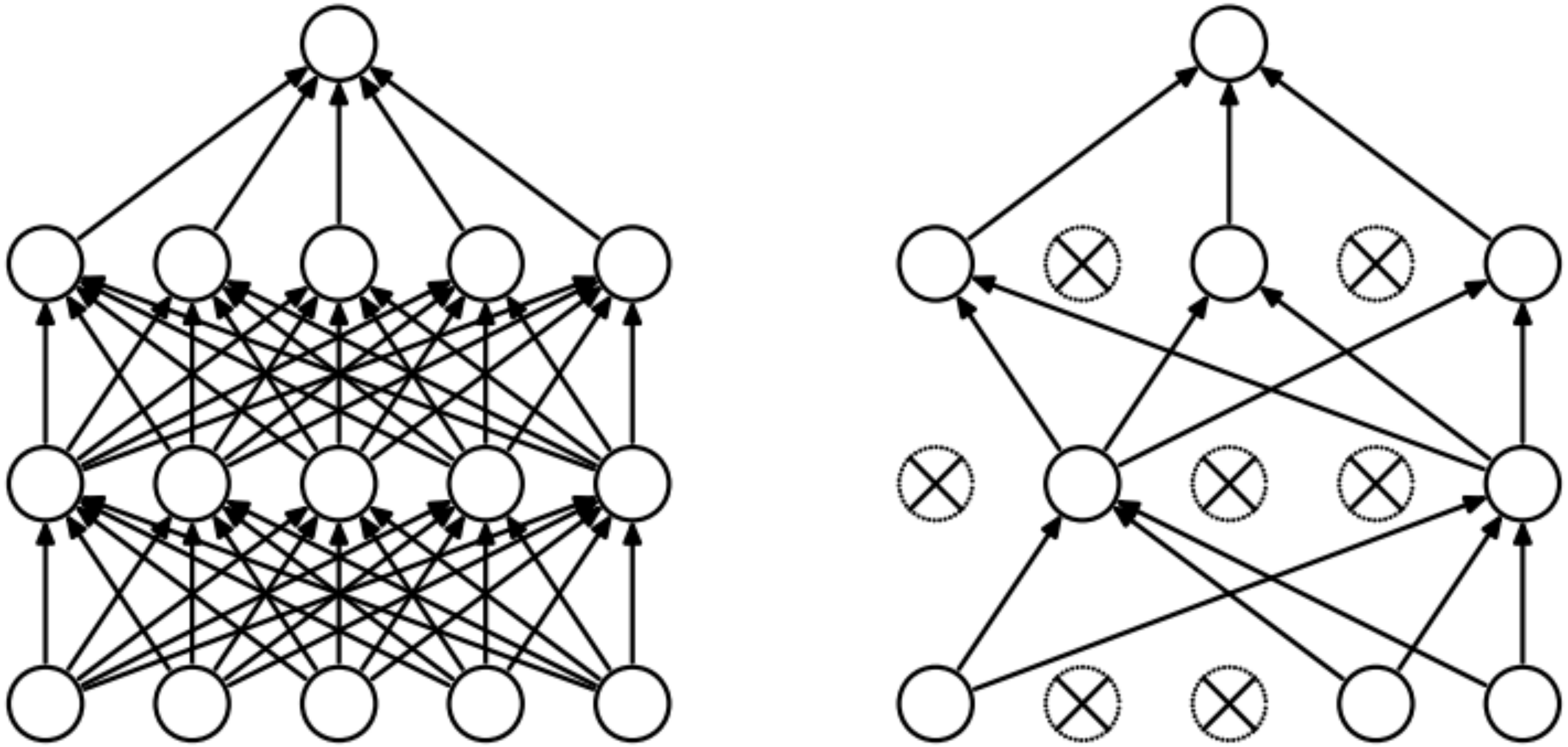

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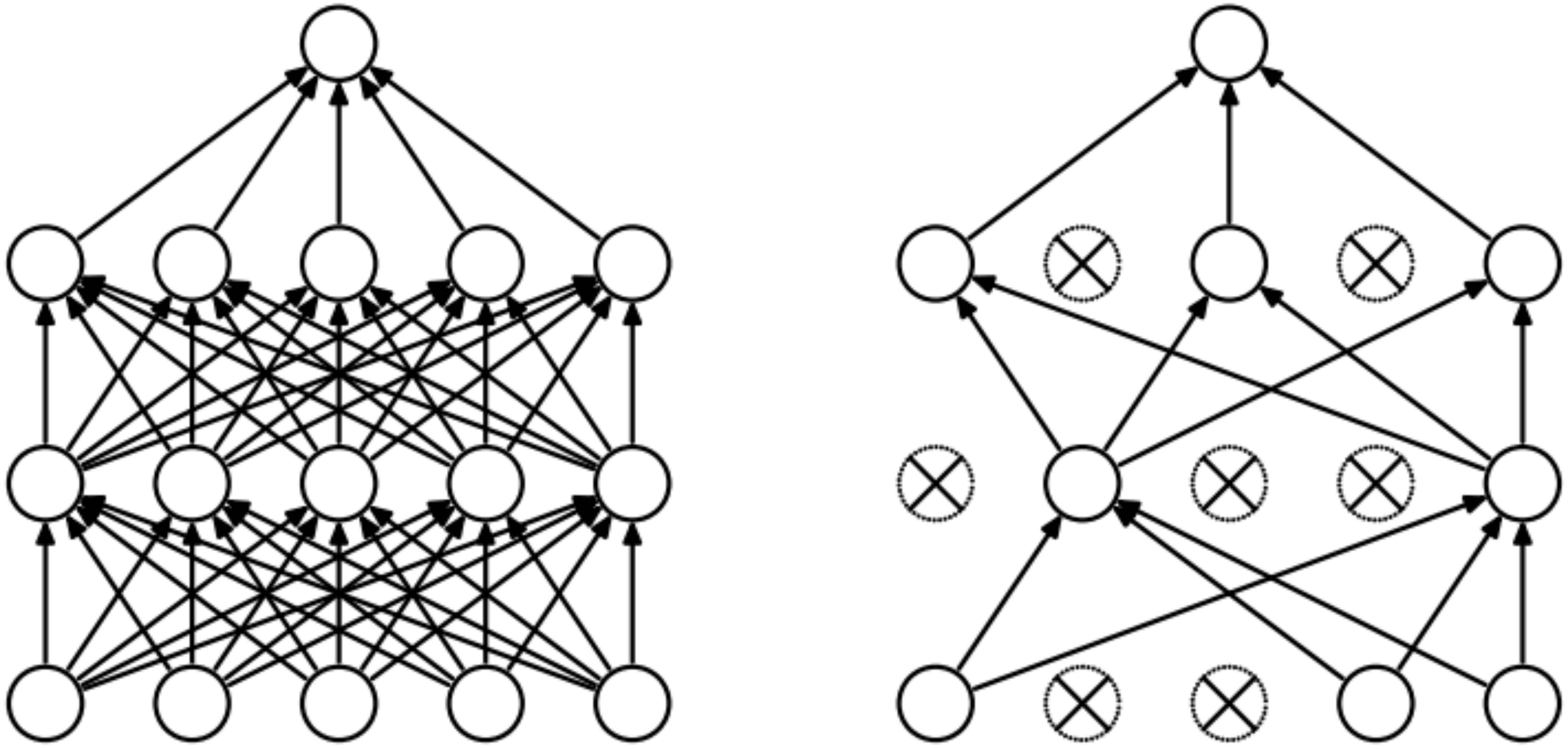

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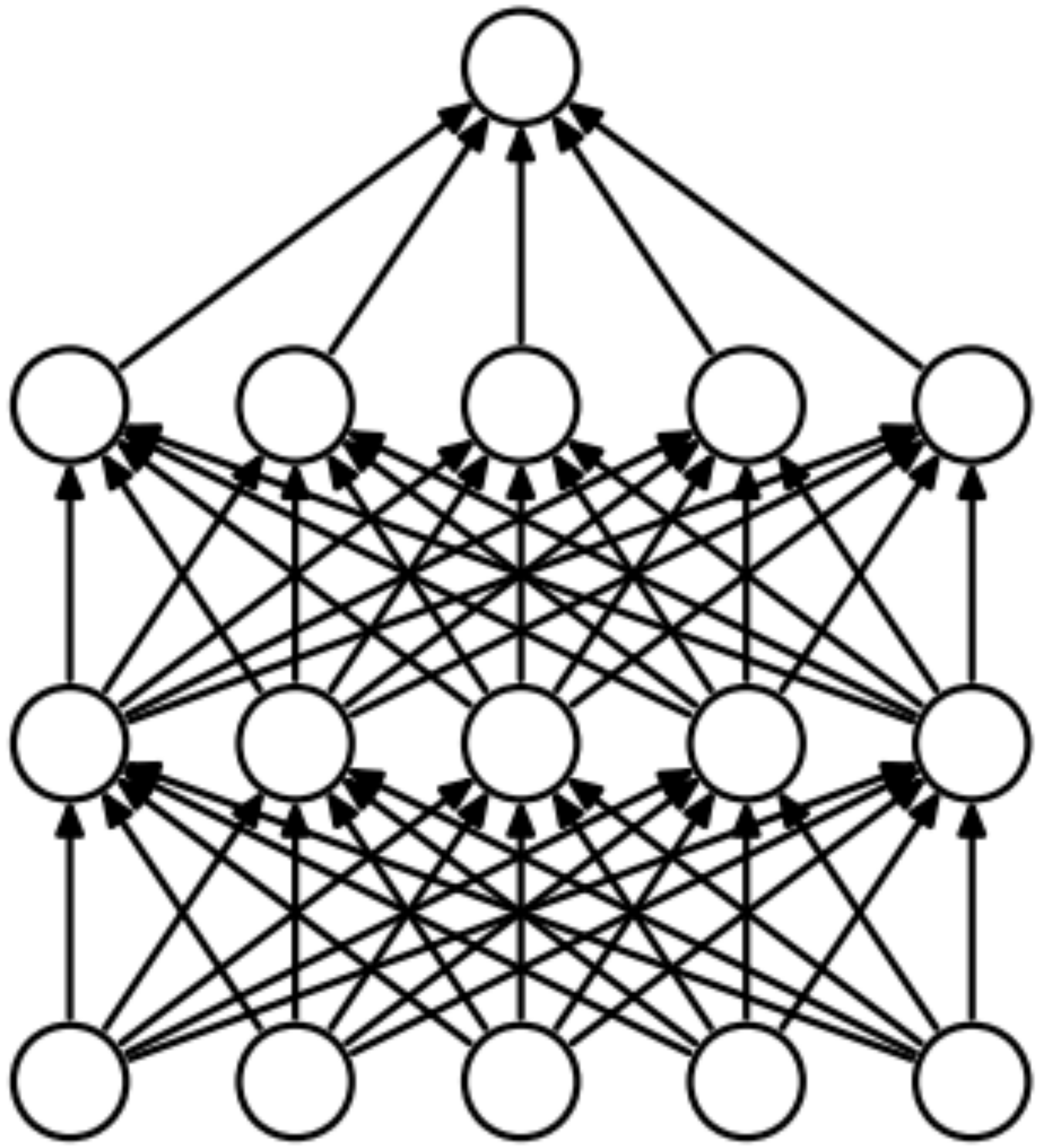

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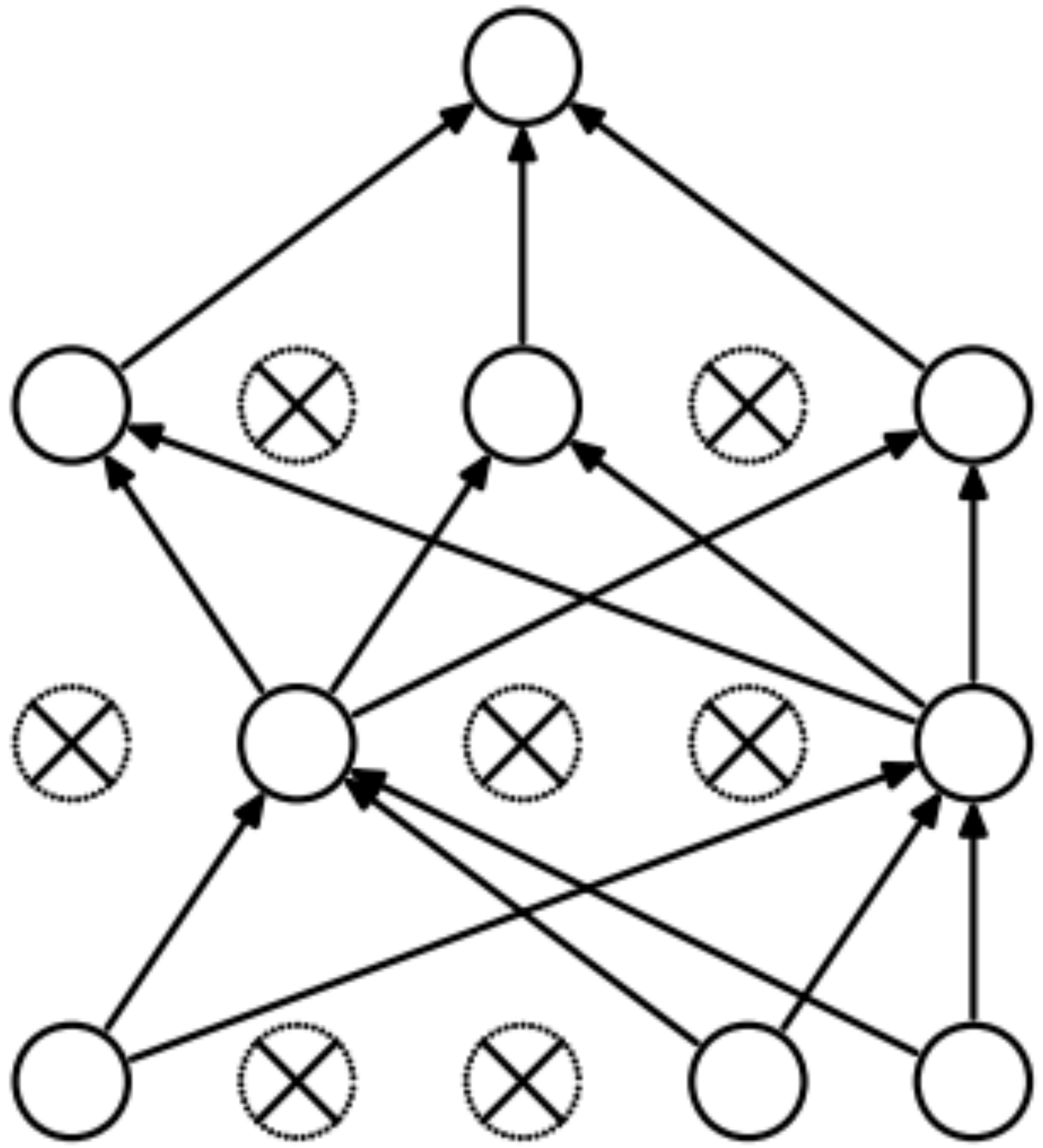

(b) After applying dropout.

- One line in Pytorch/Tensorflow

Srivastava et al. (2014)

Optimizer

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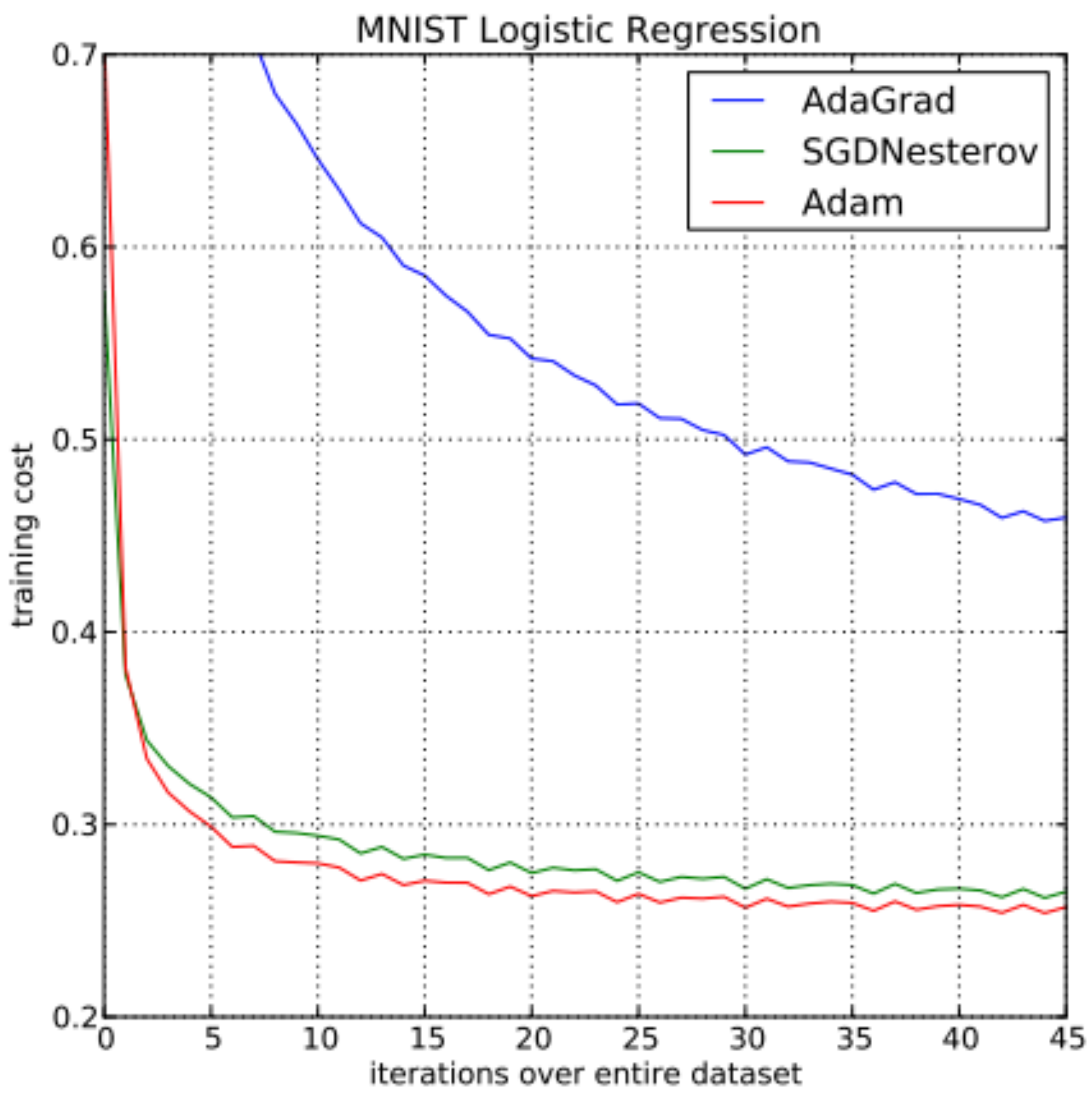

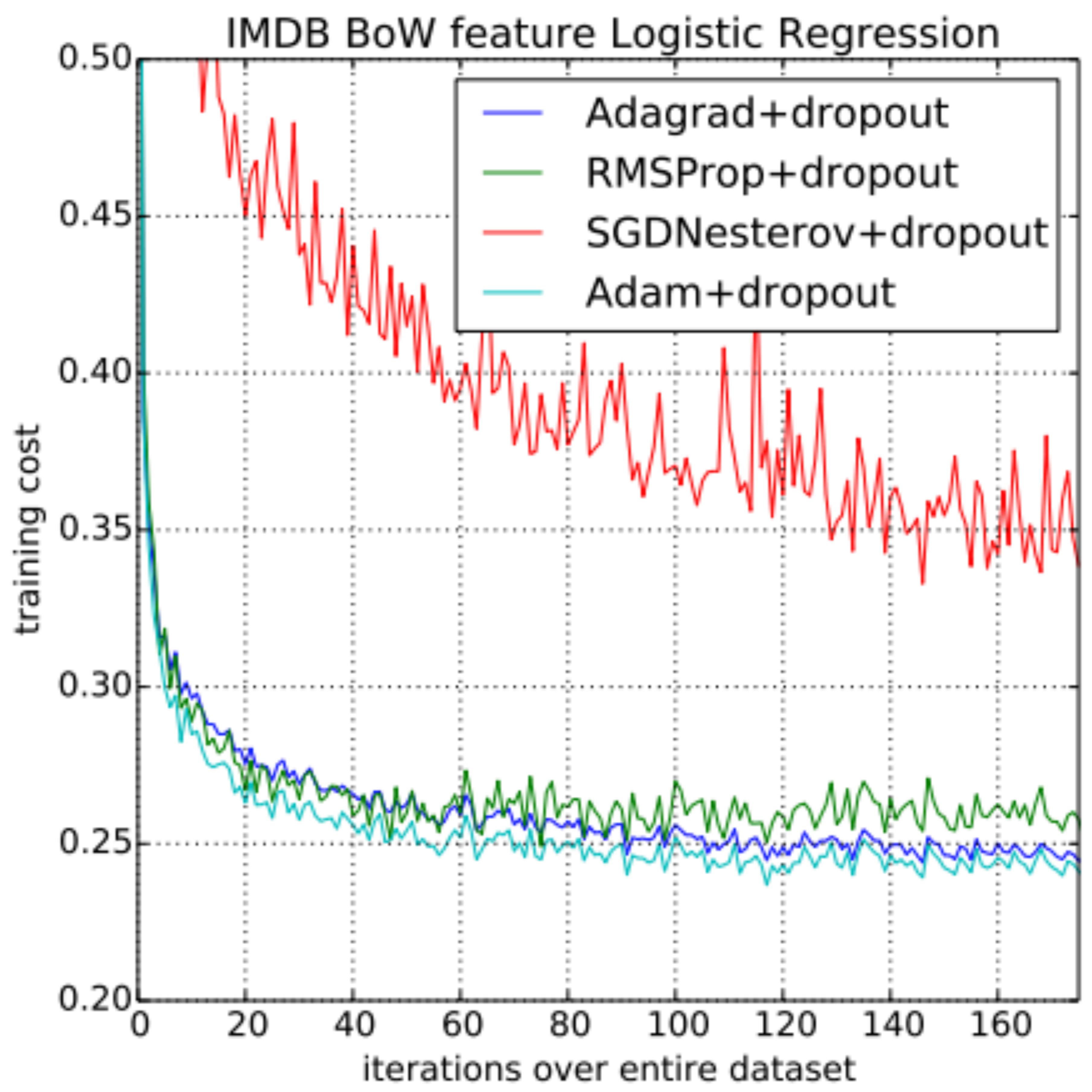

Optimizer

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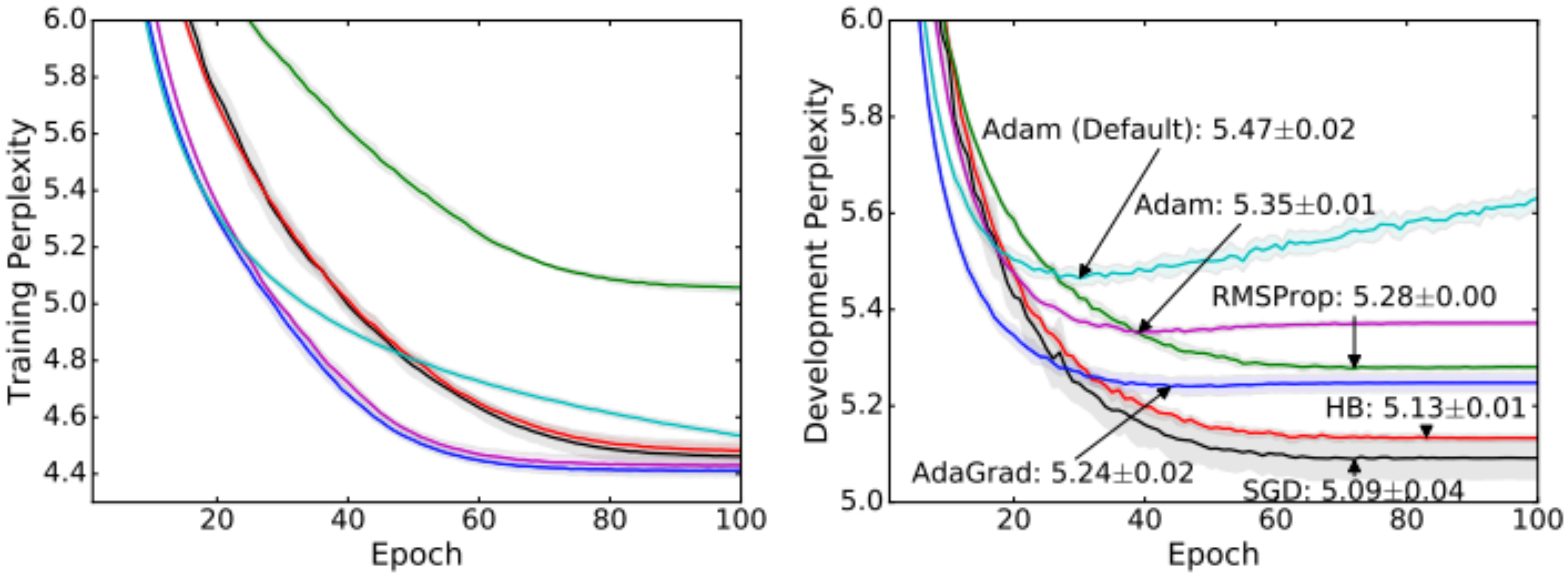

(e) Generative Parsing (Training Set) (f) Generative Parsing (Development Set)

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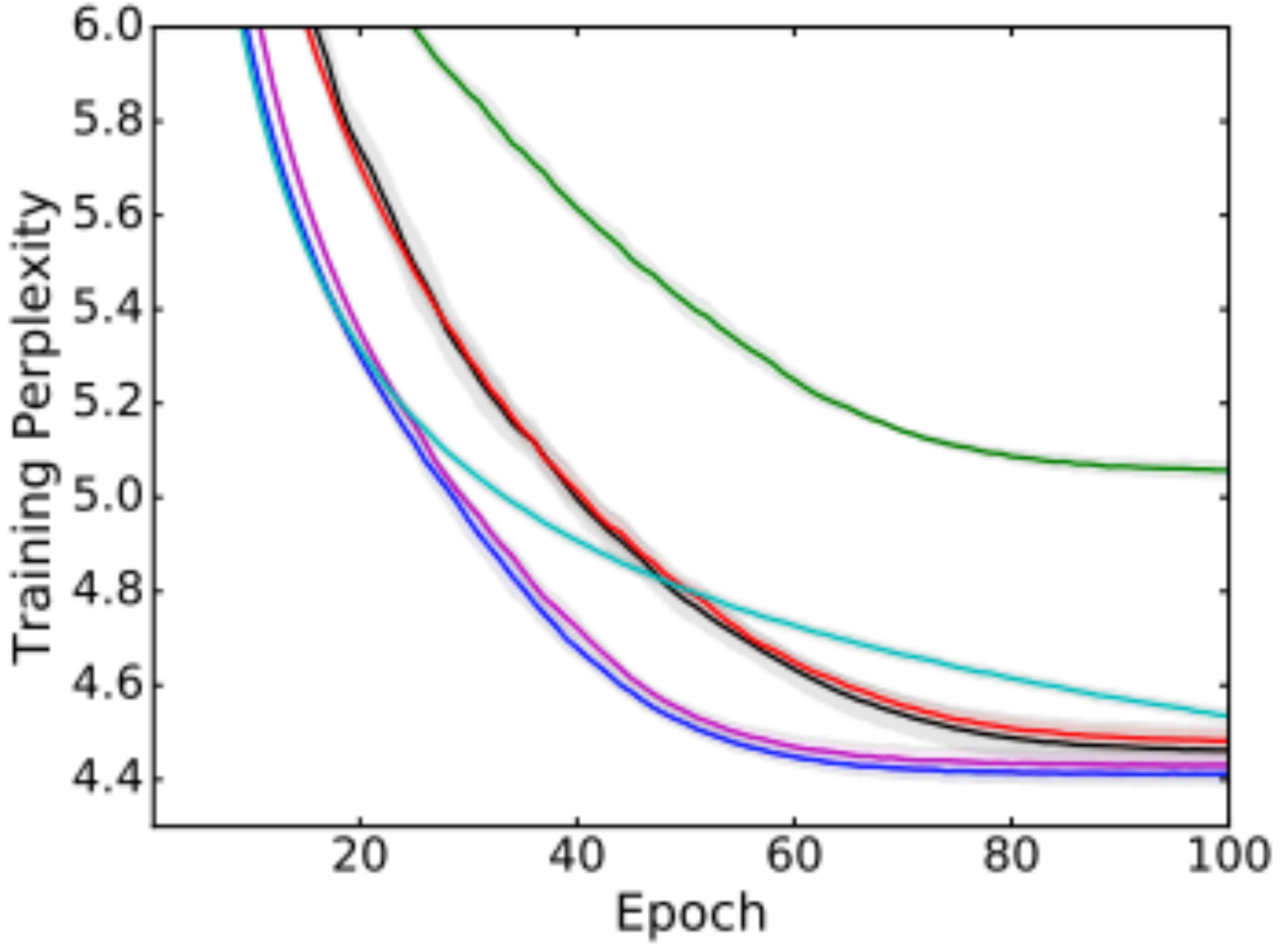
- Check dev set periodically, decrease learning rate if not making progress



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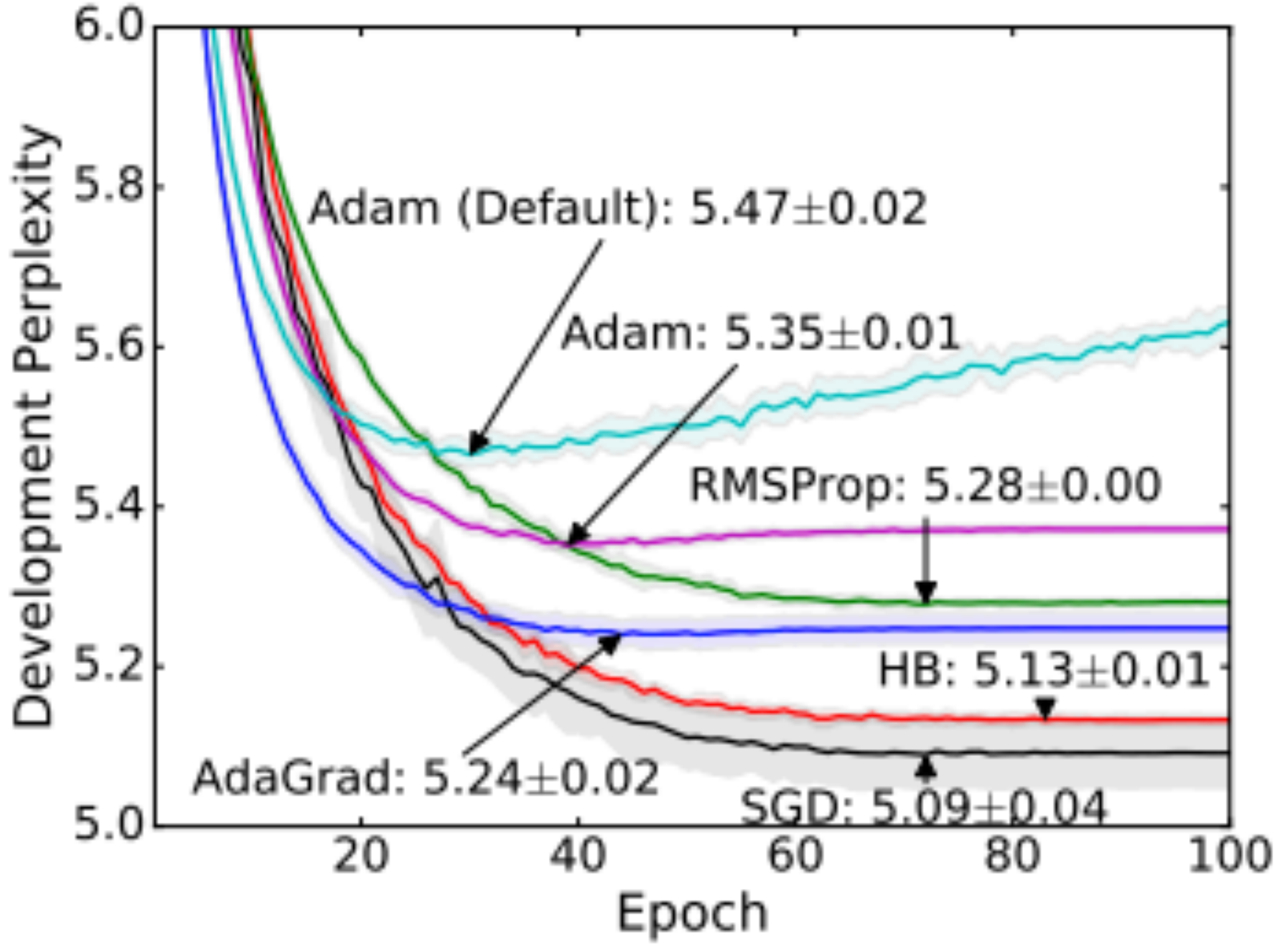

(f) Generative Parsing (Development Set)

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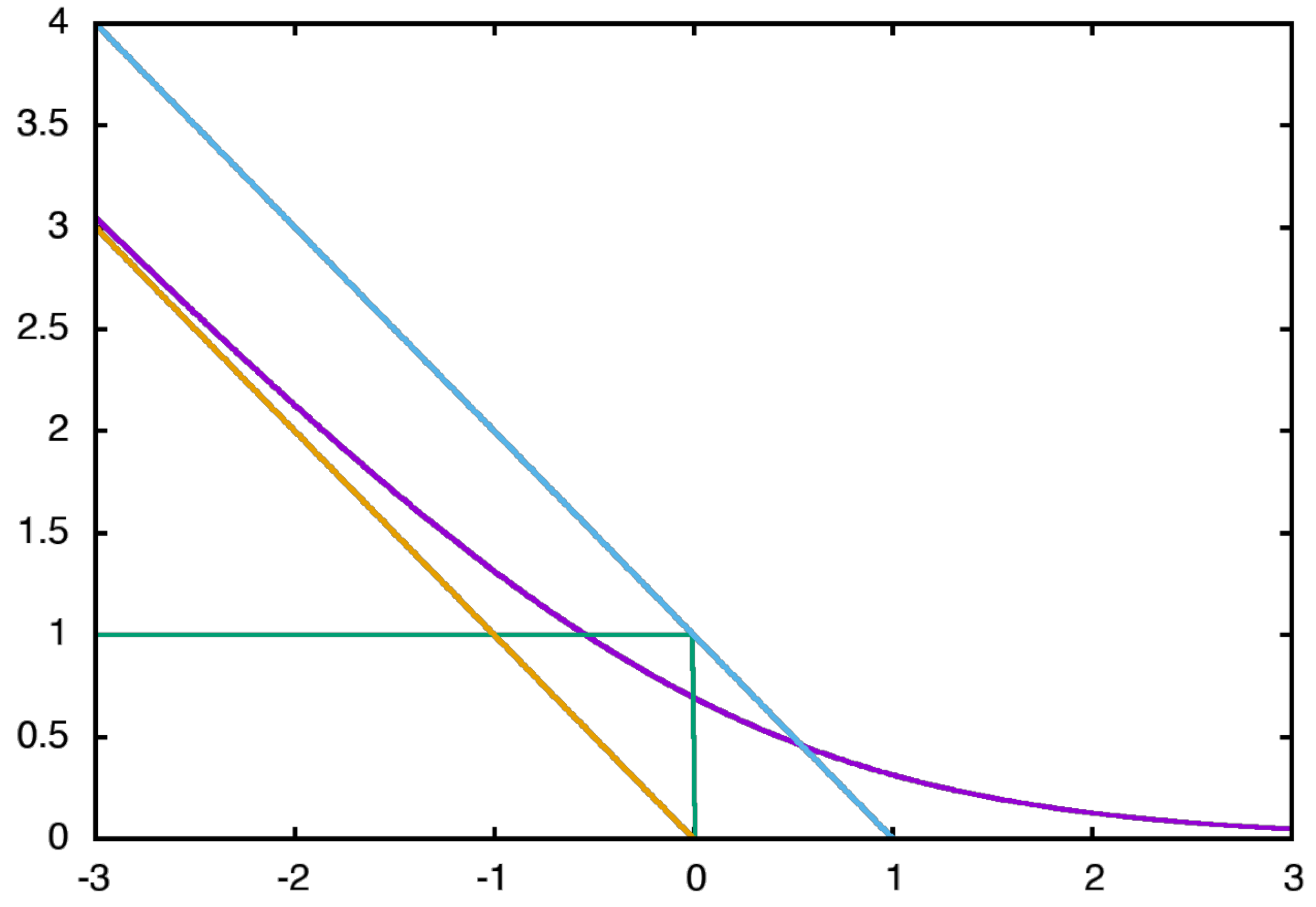

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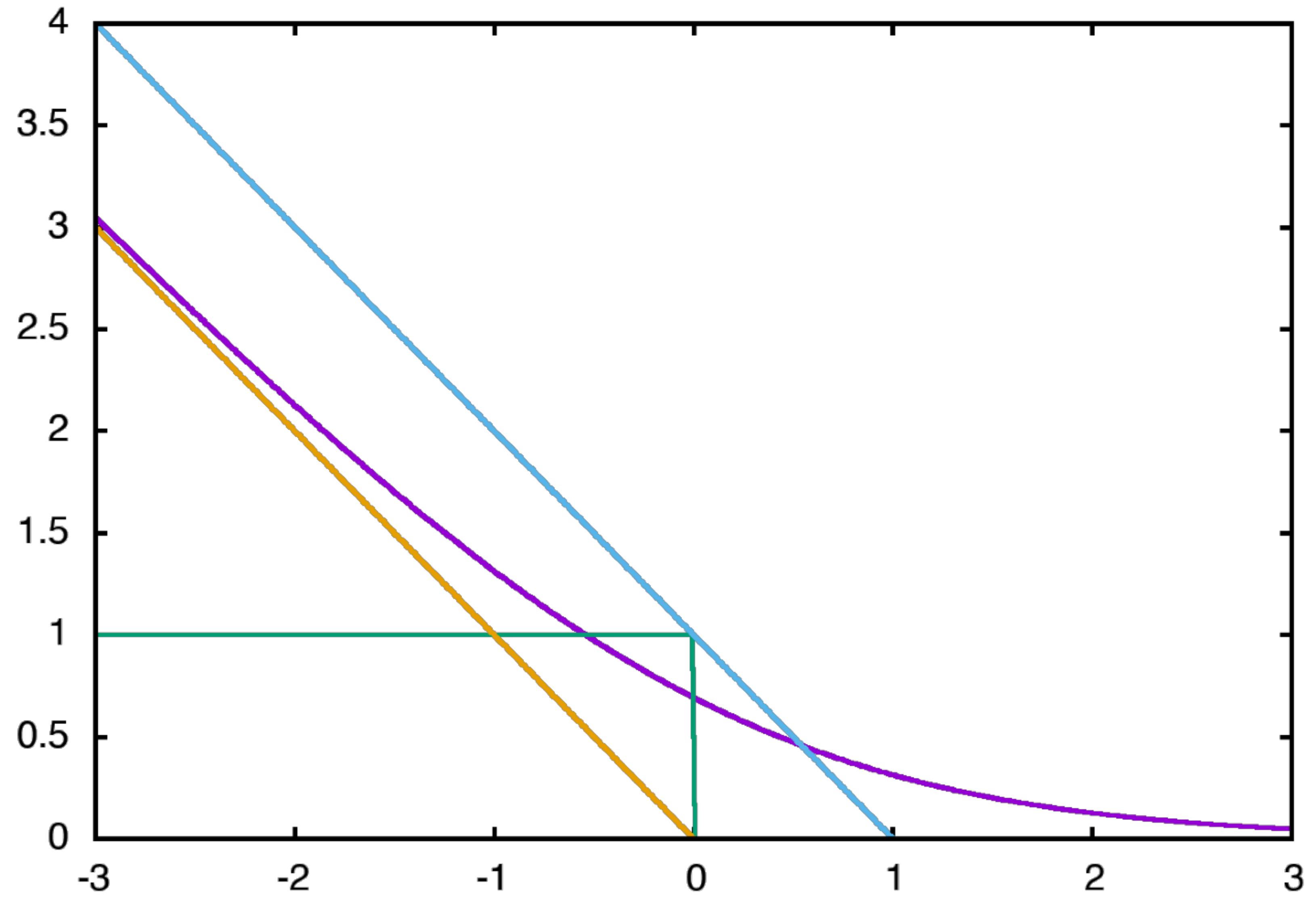

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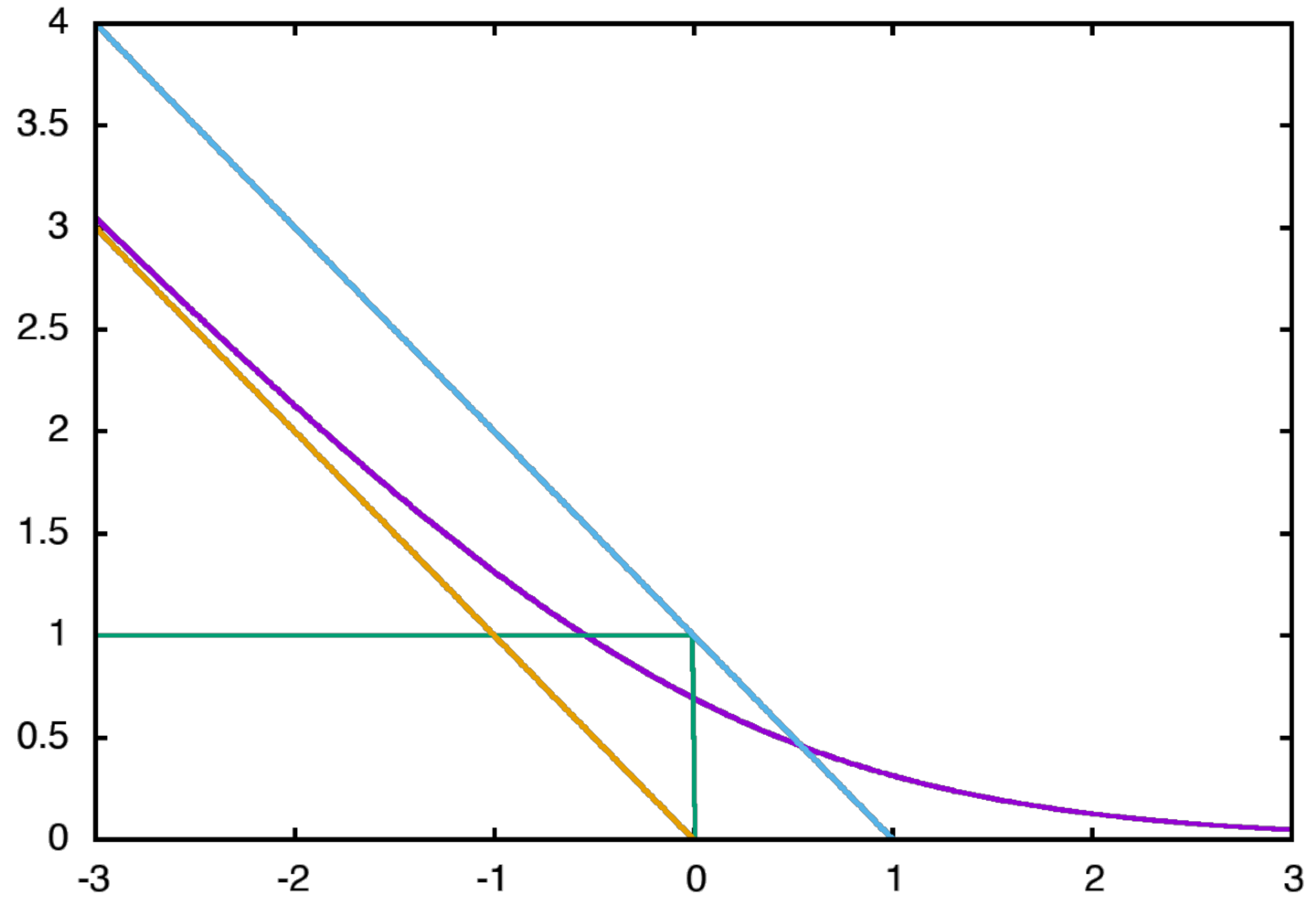

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- Training: lots of choices for optimization/hyperparameters

Word Representations

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slide credit: Dan Klein

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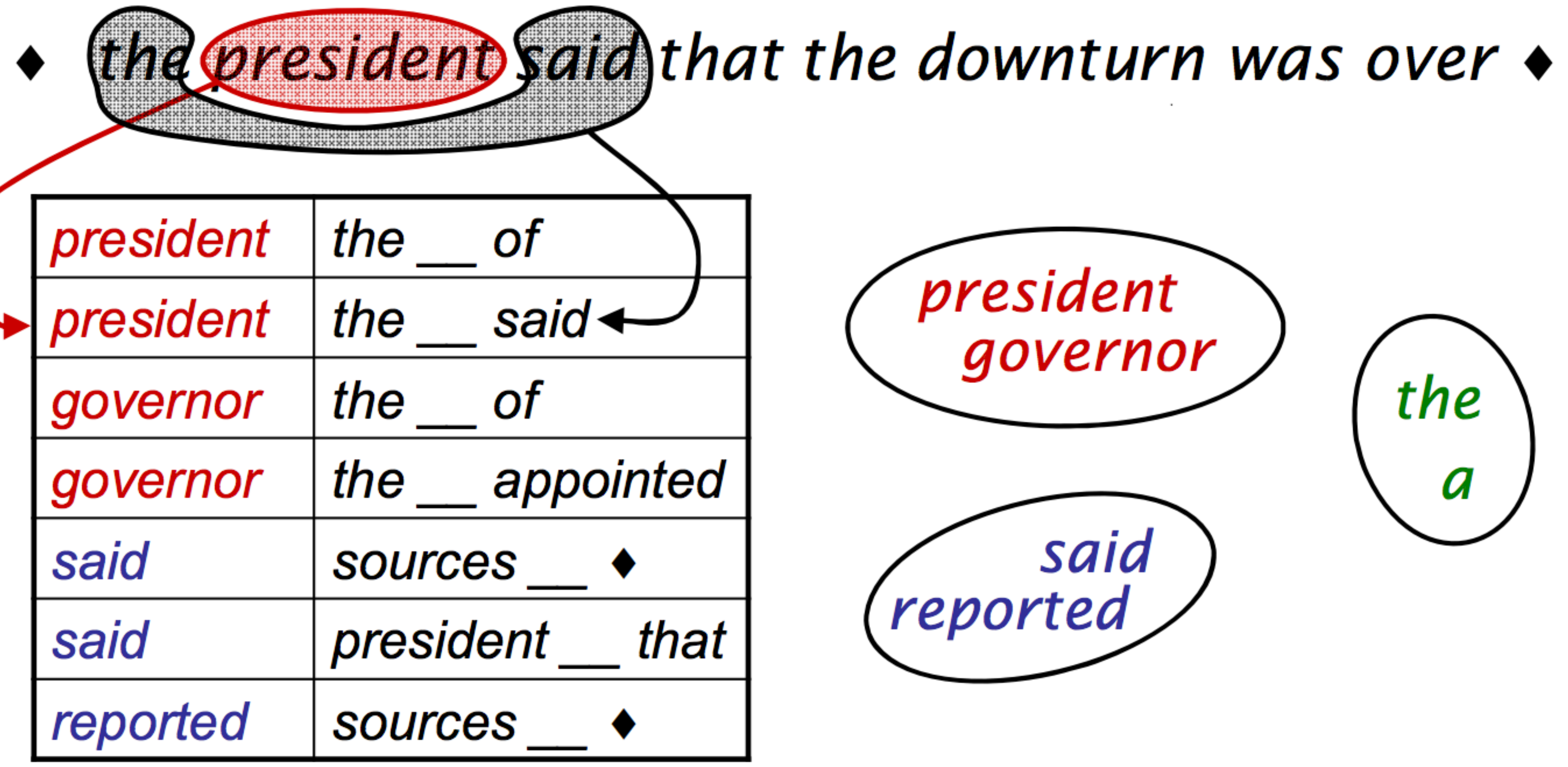
- Neural networks work very well at continuous data, but words are discrete
- Continuous model <-> expects continuous semantics from input
- “You shall know a word by the company it keeps” Firth (1957)



president	the __ of
president	the __ said
governor	the __ of
governor	the __ appointed
said	sources __ ♦
said	president __ that
reported	sources __ ♦

[Finch and Chater 92, Shuetze 93, many others]

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Discrete Word Representations

Brown et al. (1992)

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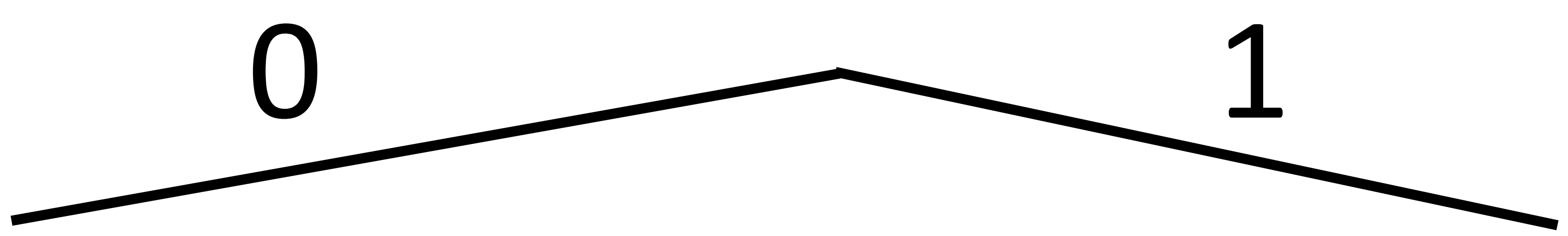

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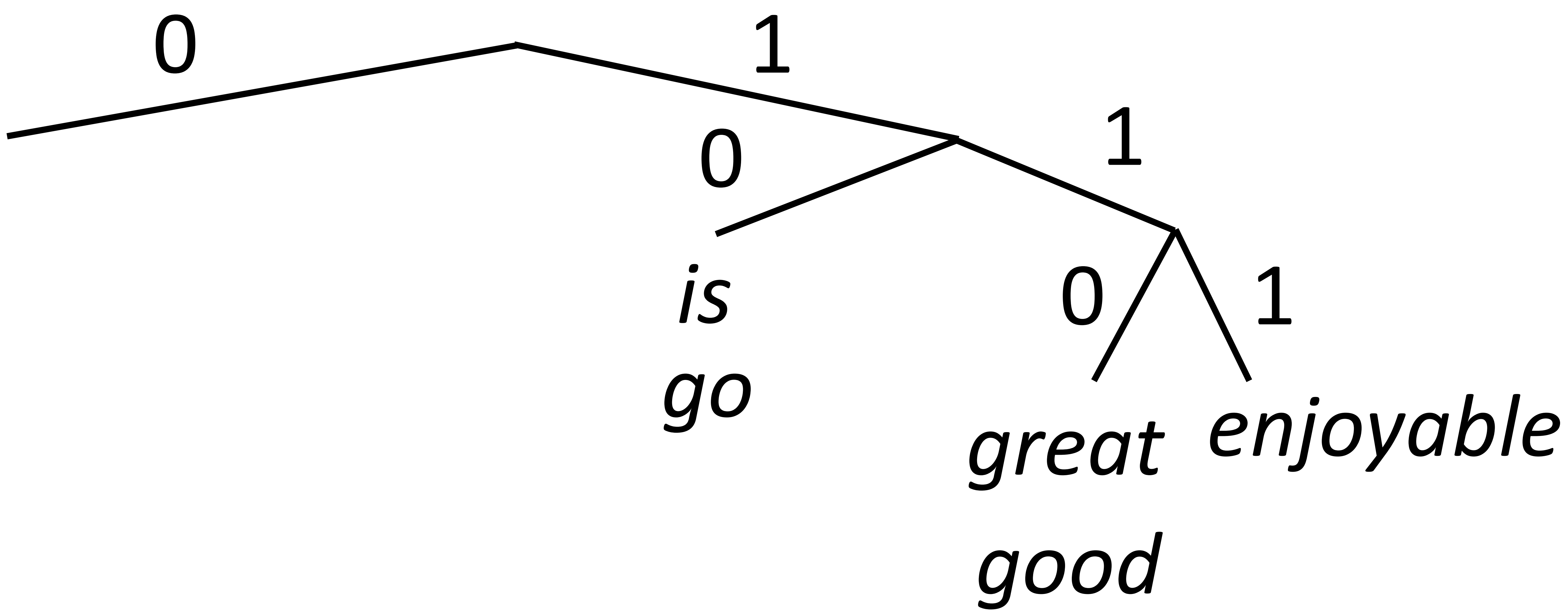

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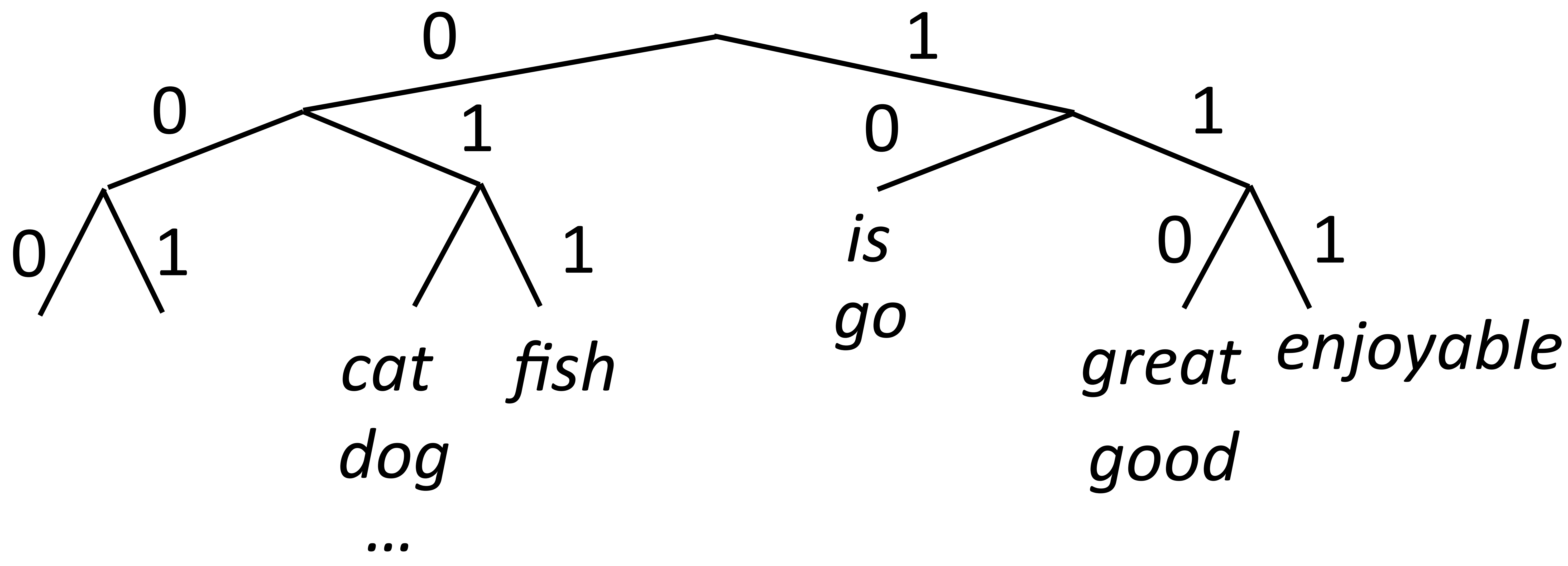

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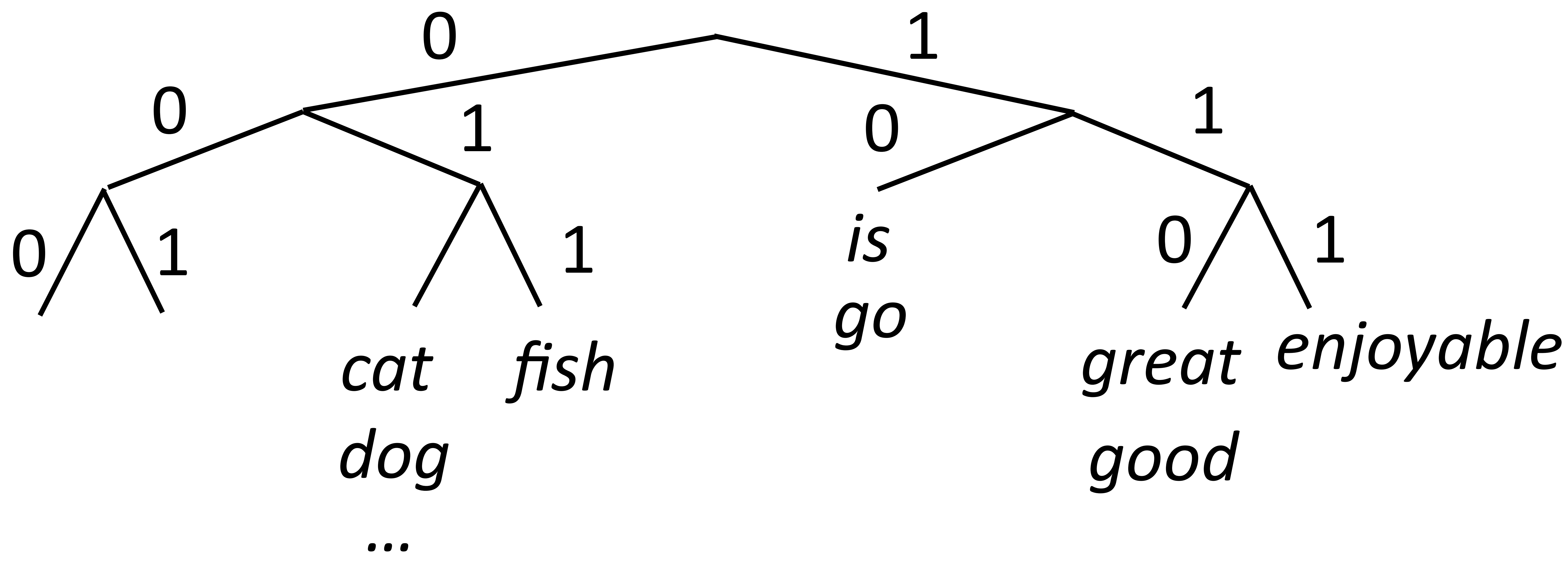

- Maximize $P(w_i|w_{i-1}) = P(c_i|c_{i-1})P(w_i|c_i)$

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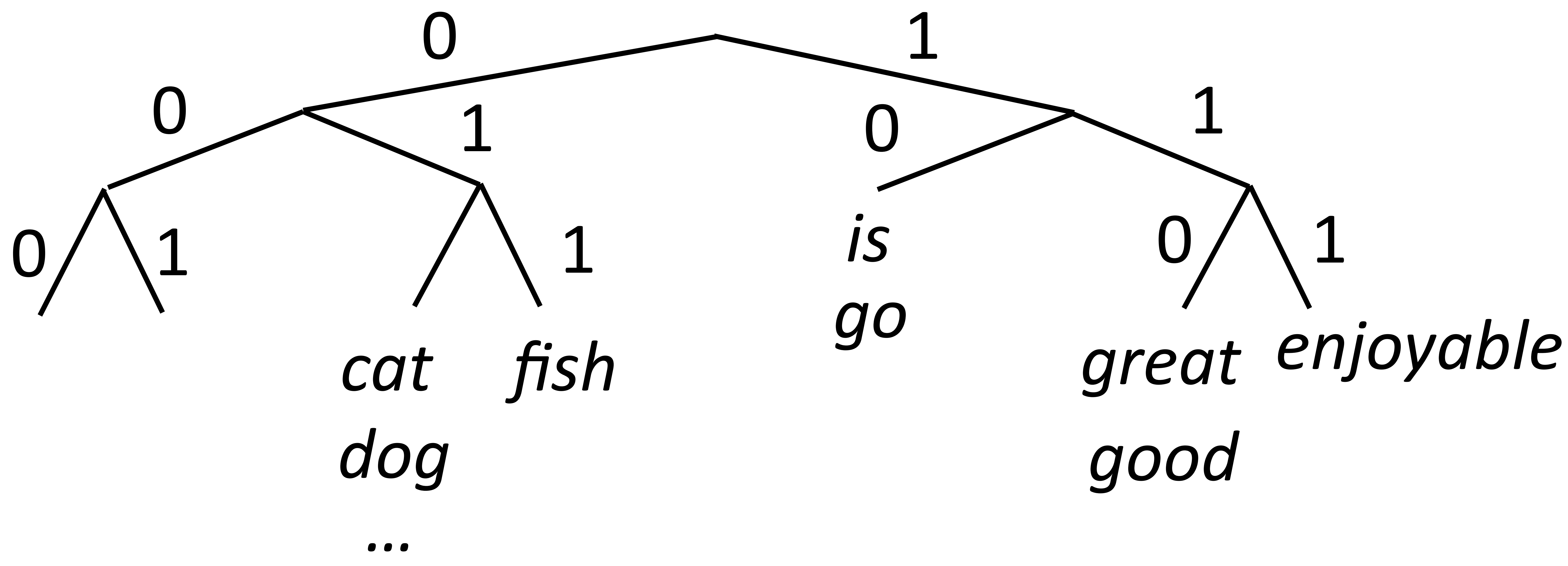

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- Useful features for tasks like NER, not suitable for NNs

Brown et al. (1992)

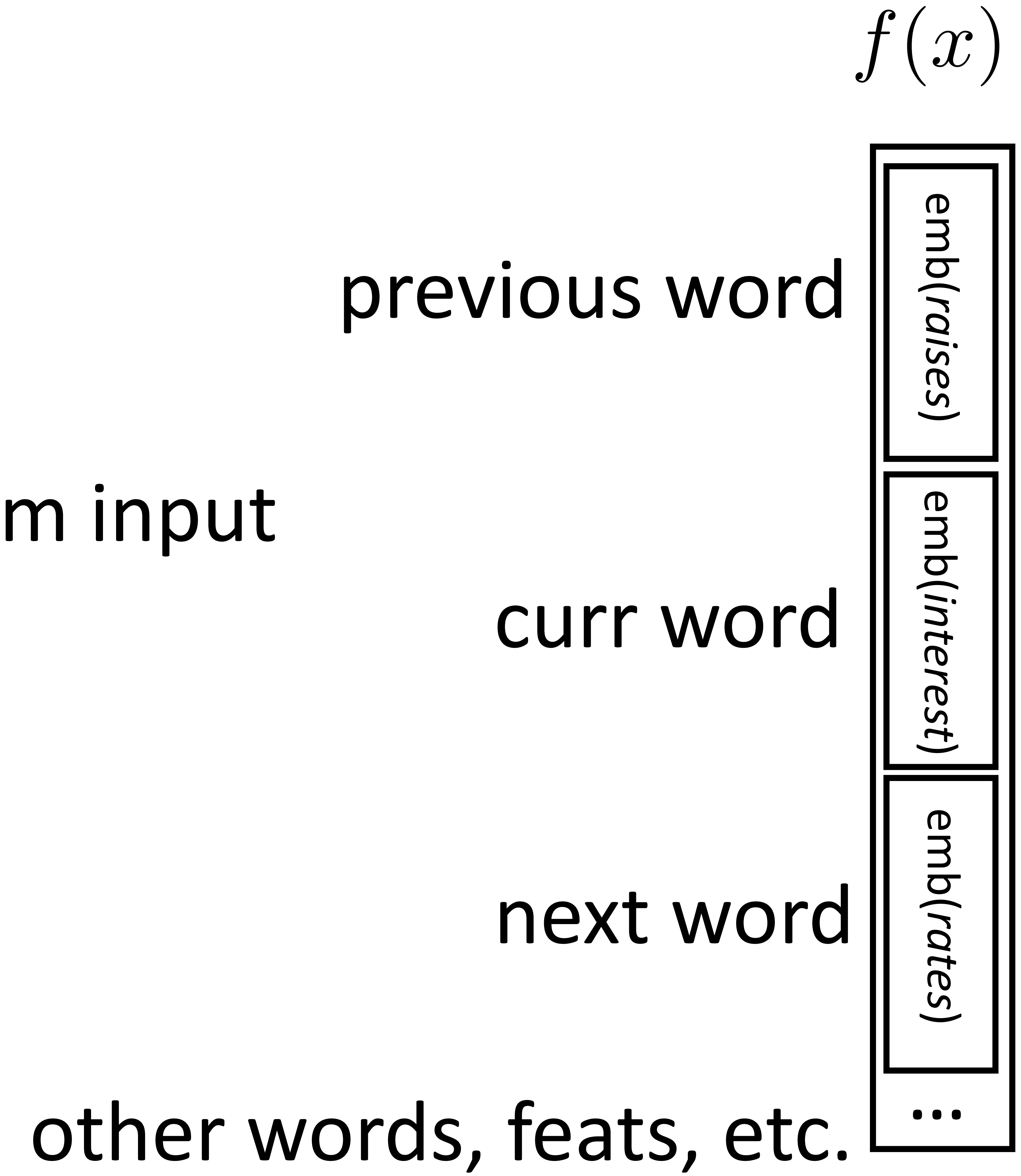
Word Embeddings

- 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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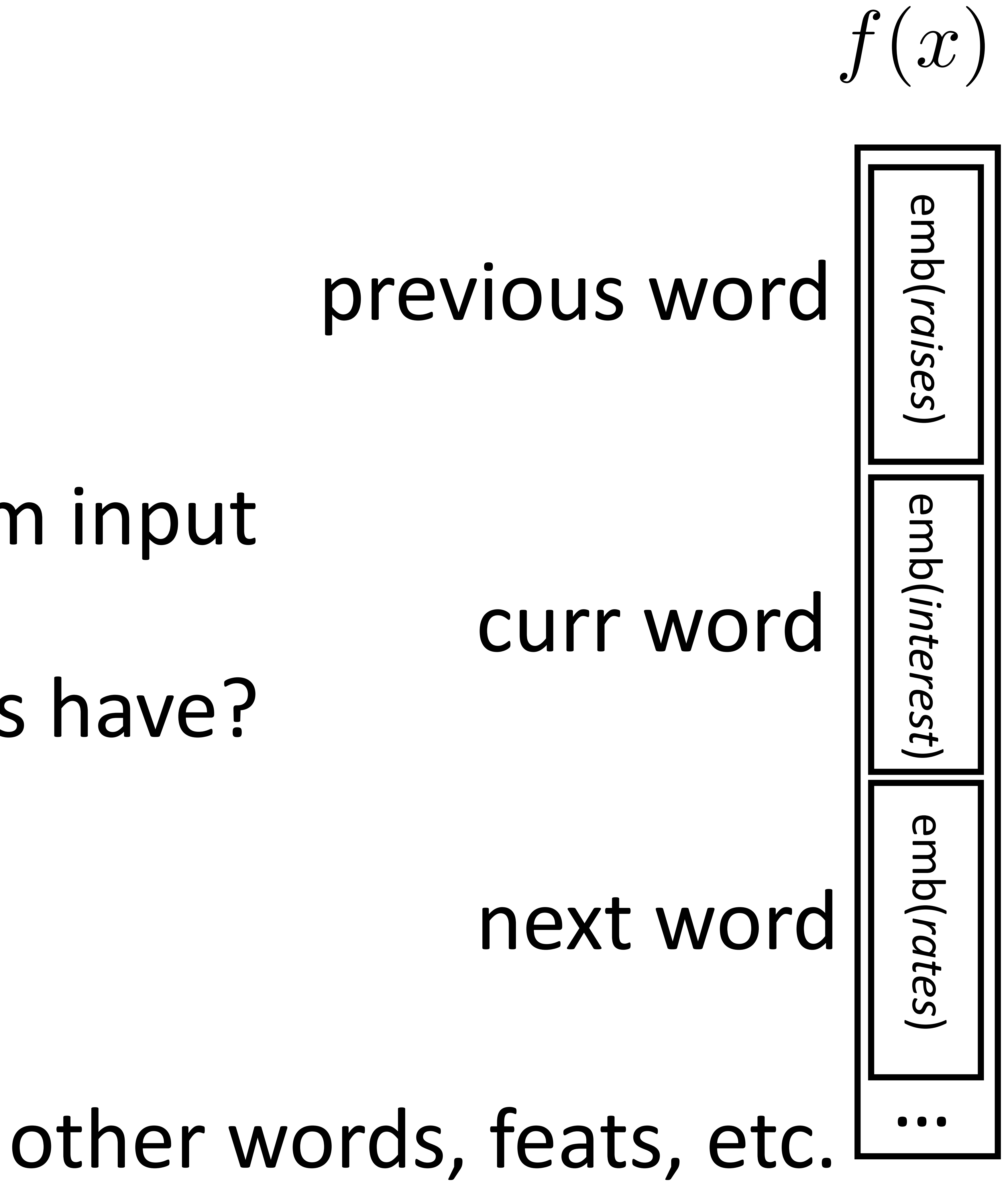
- What properties should these vectors have?



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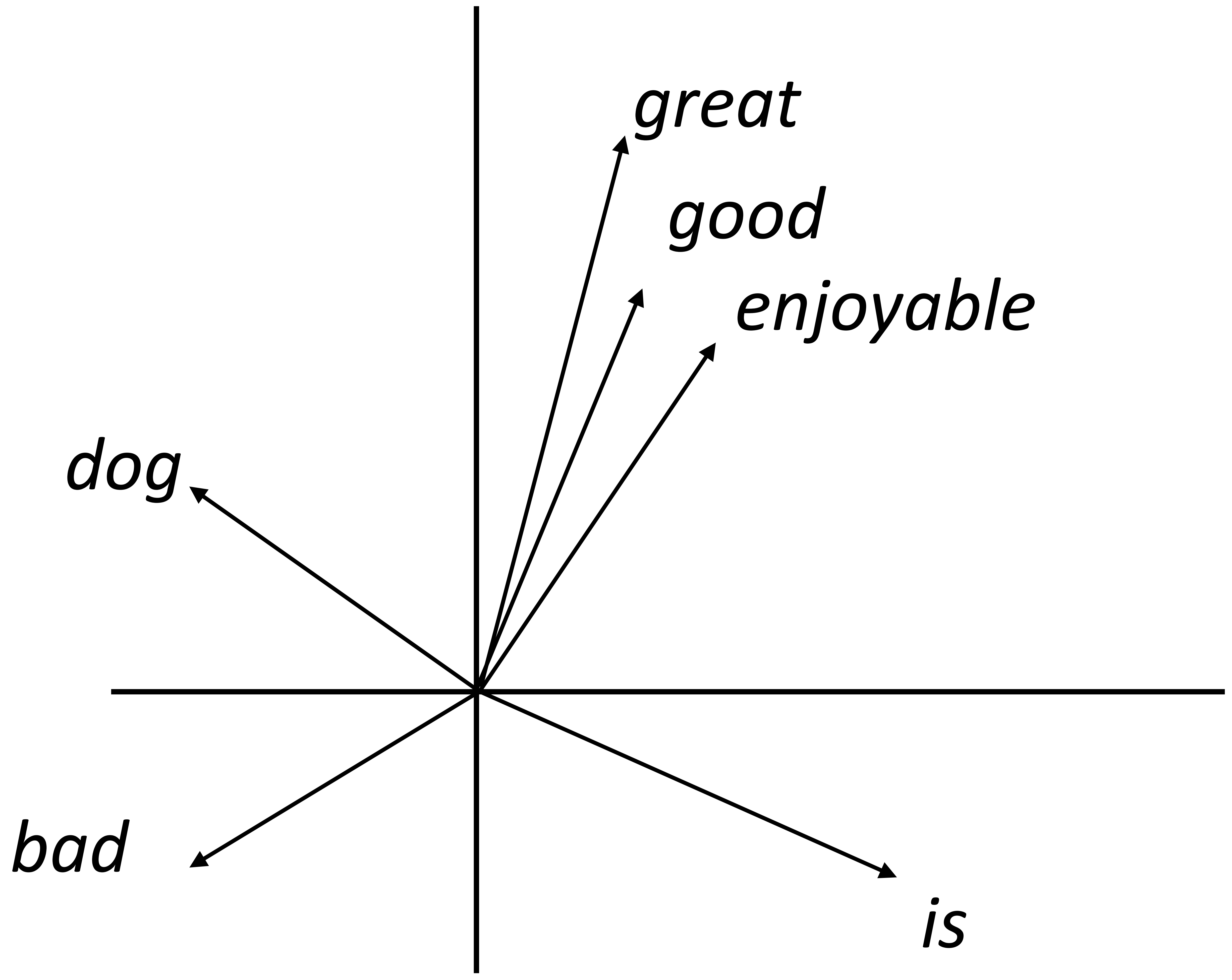
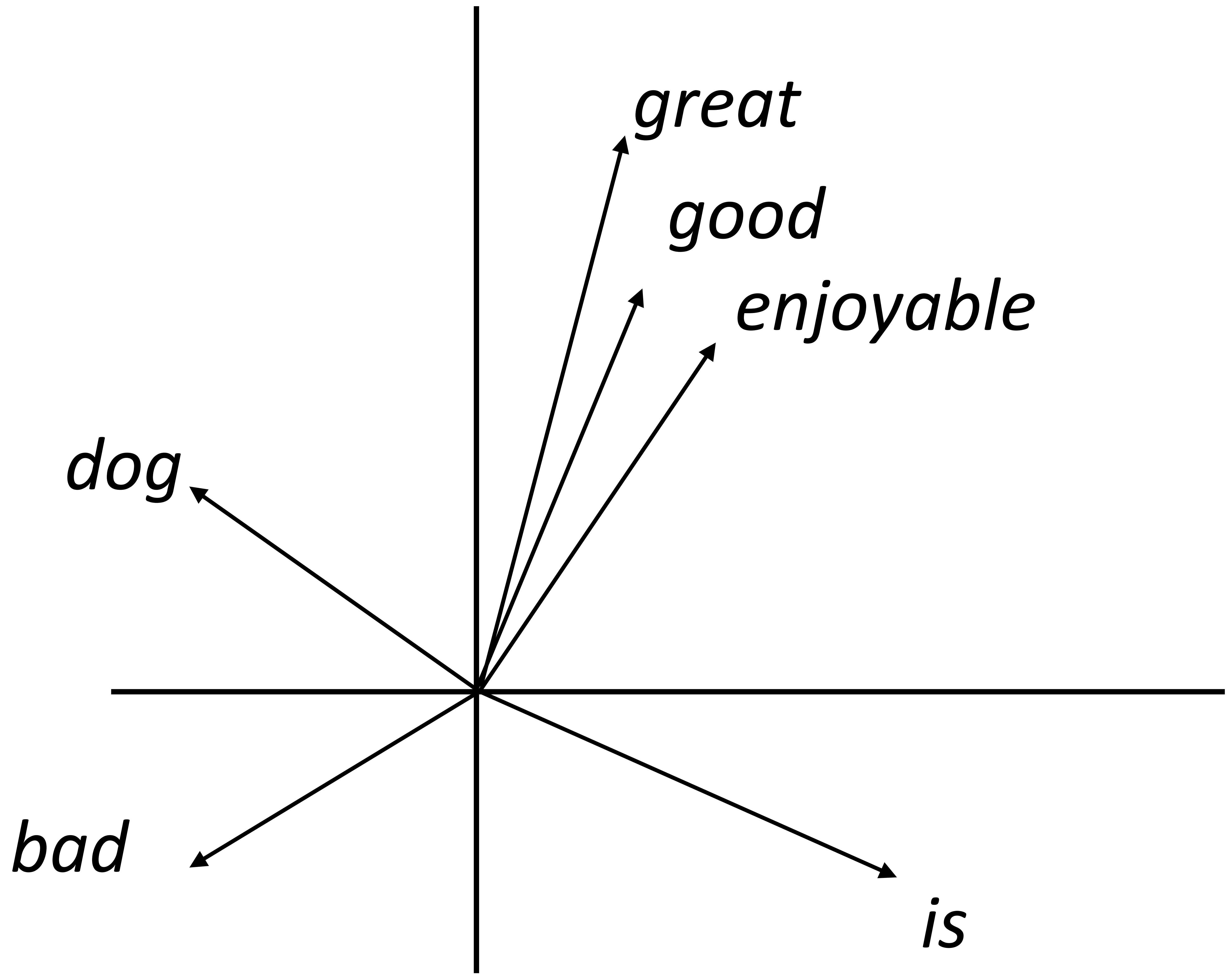


Word Embeddings

- Want a vector space where similar words have similar embeddings



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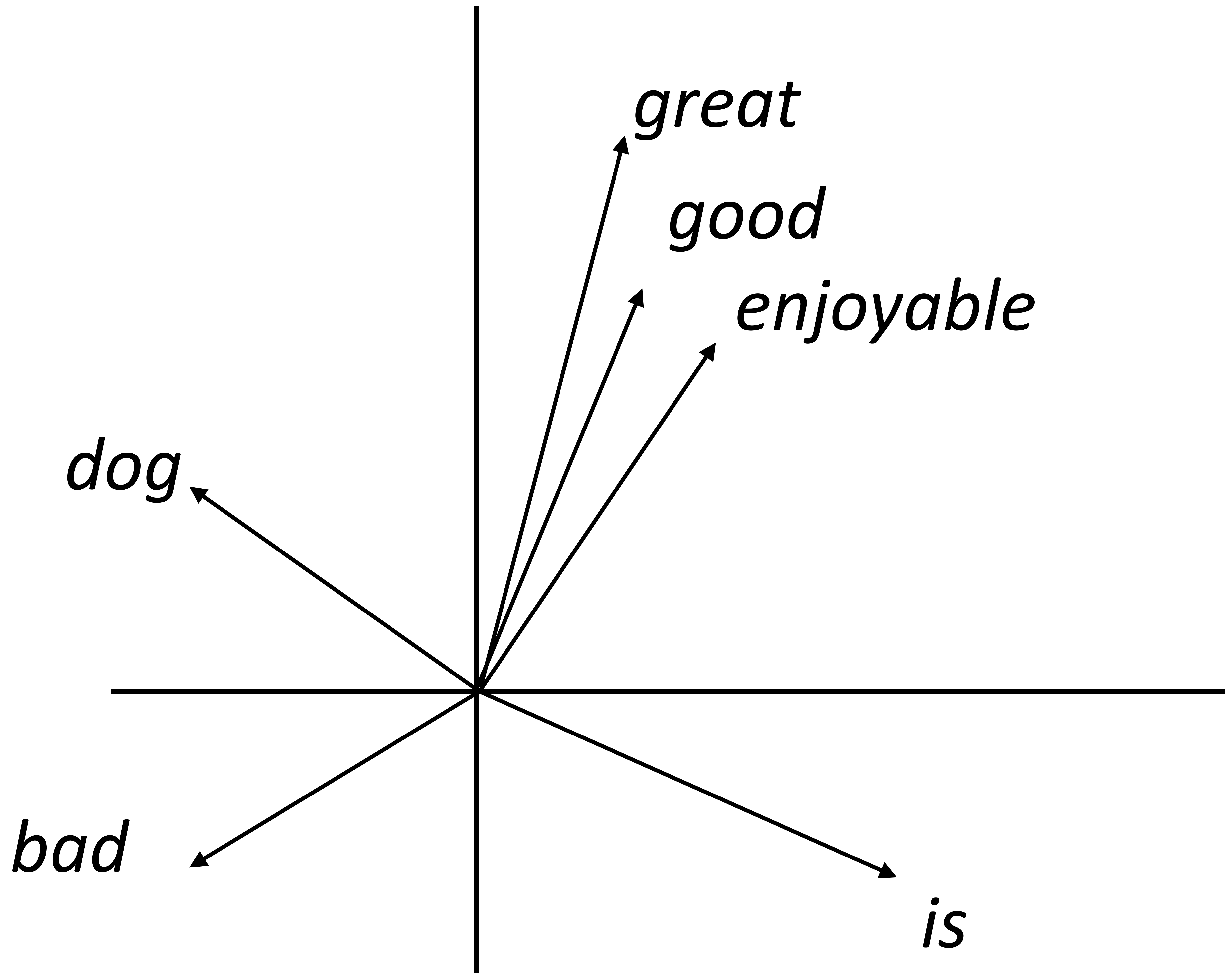

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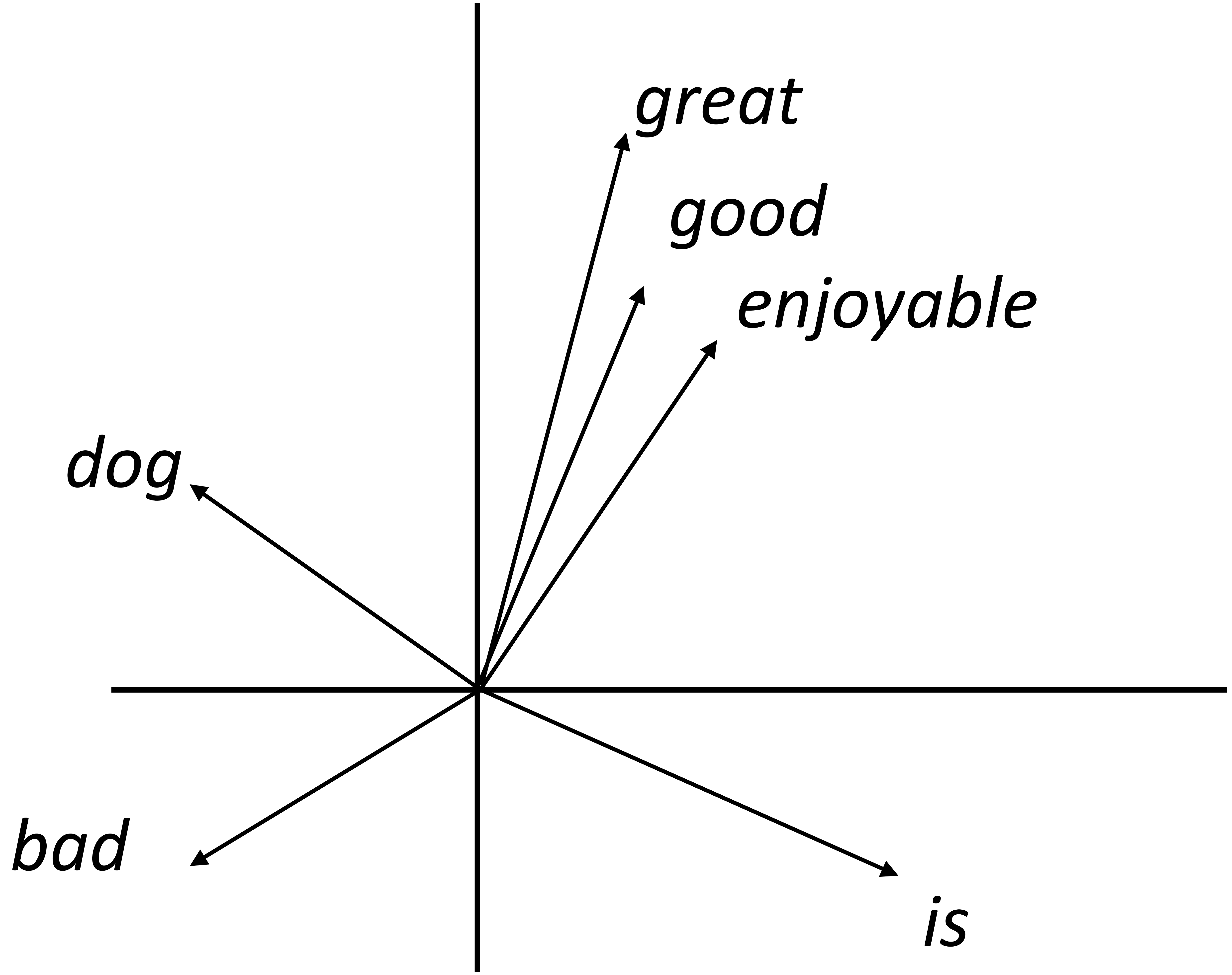

- Goal: come up with a way to produce these embeddings

word2vec/GloVe

Continuous Bag-of-Words

- Predict word from context

*the dog **bit** the man*

Mikolov et al. (2013)

Continuous Bag-of-Words

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d-dimensional word embeddings

dog

the

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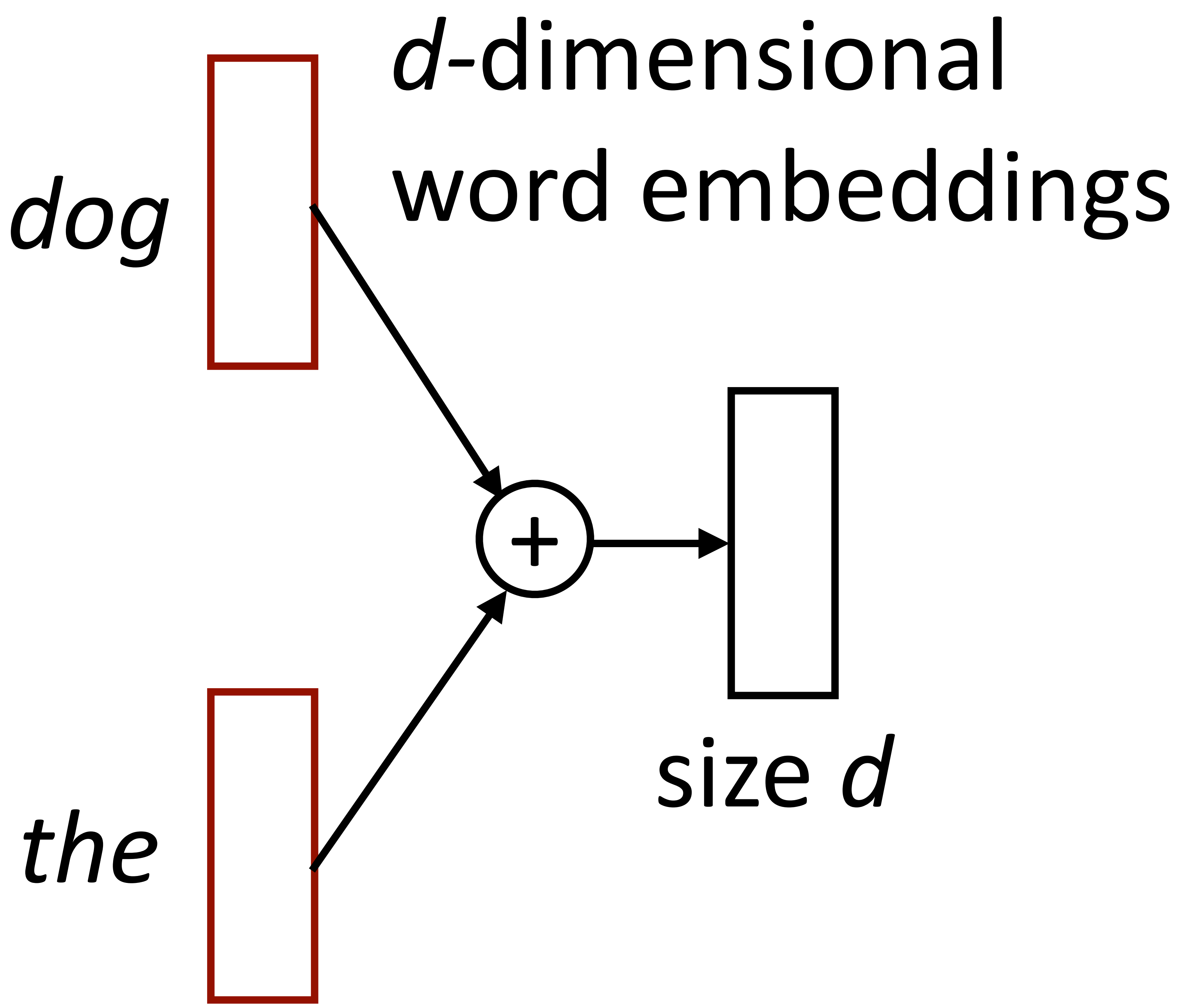

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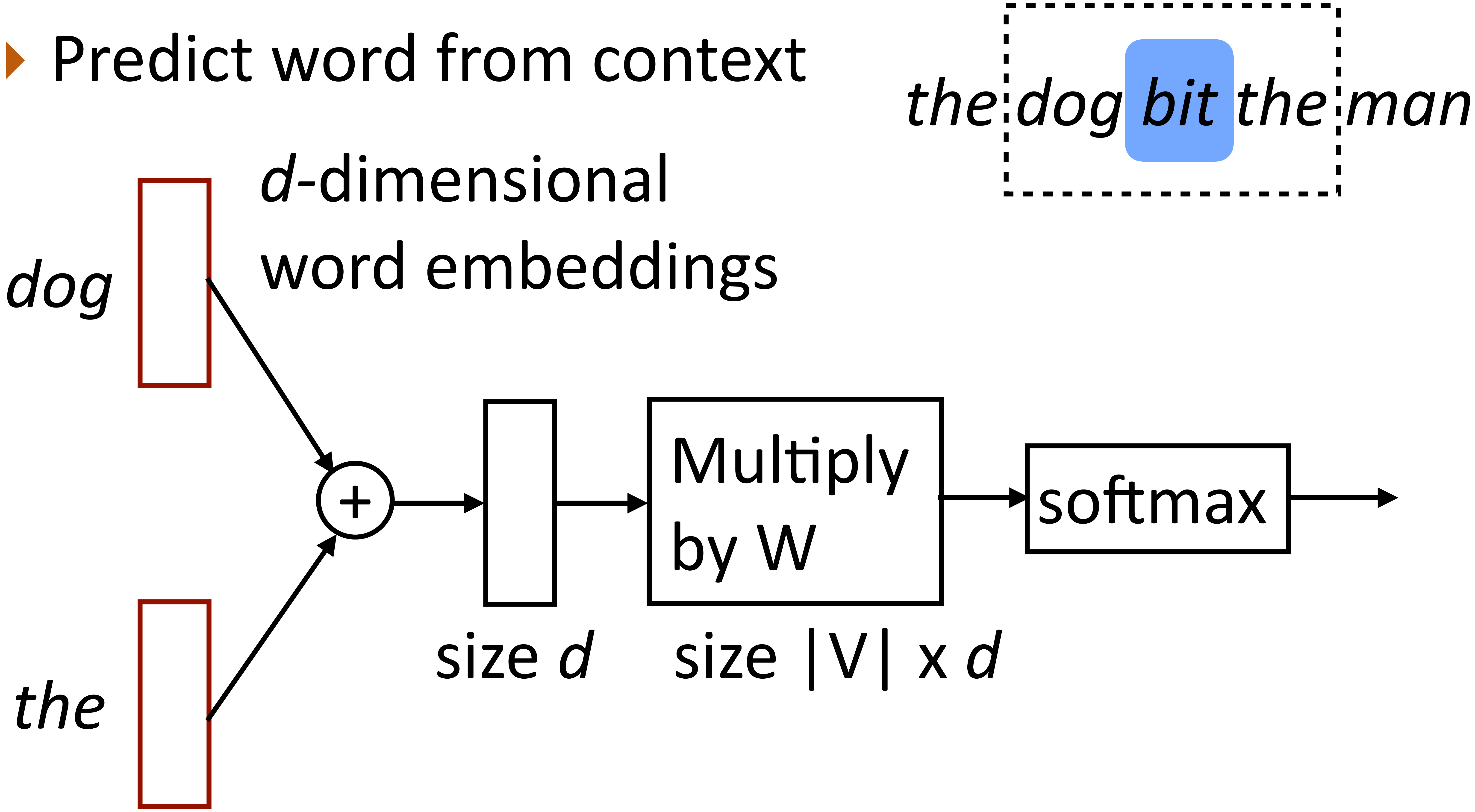

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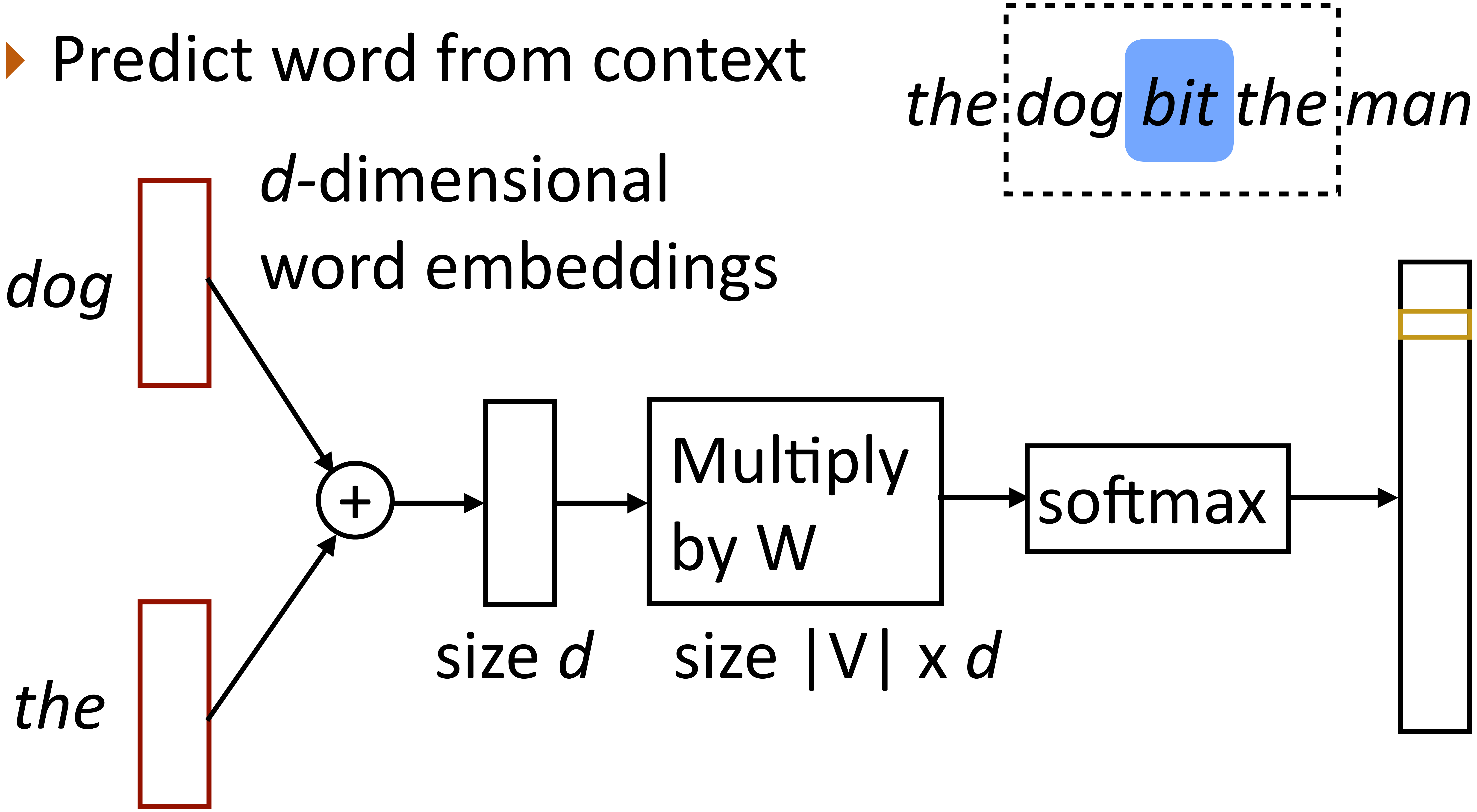

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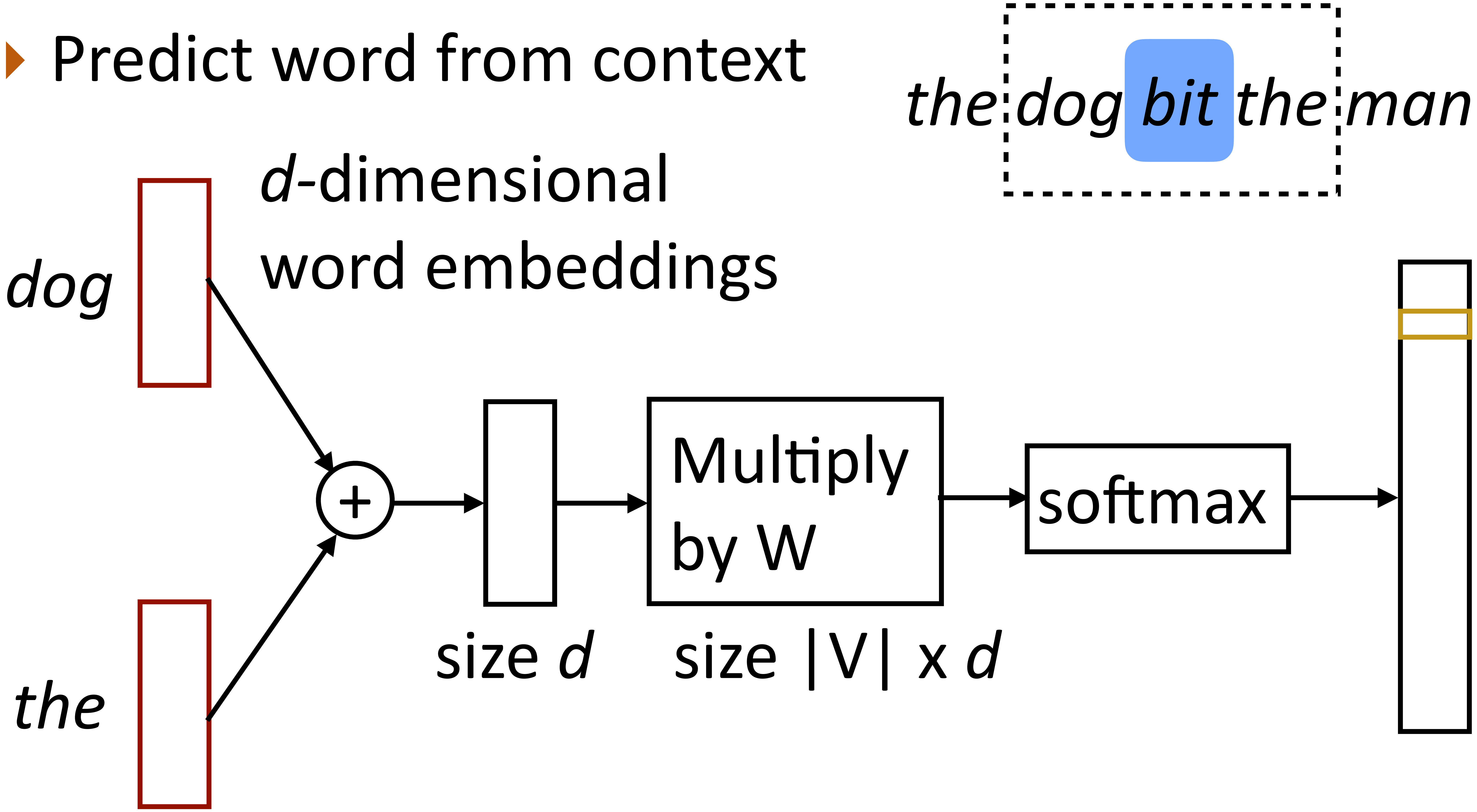
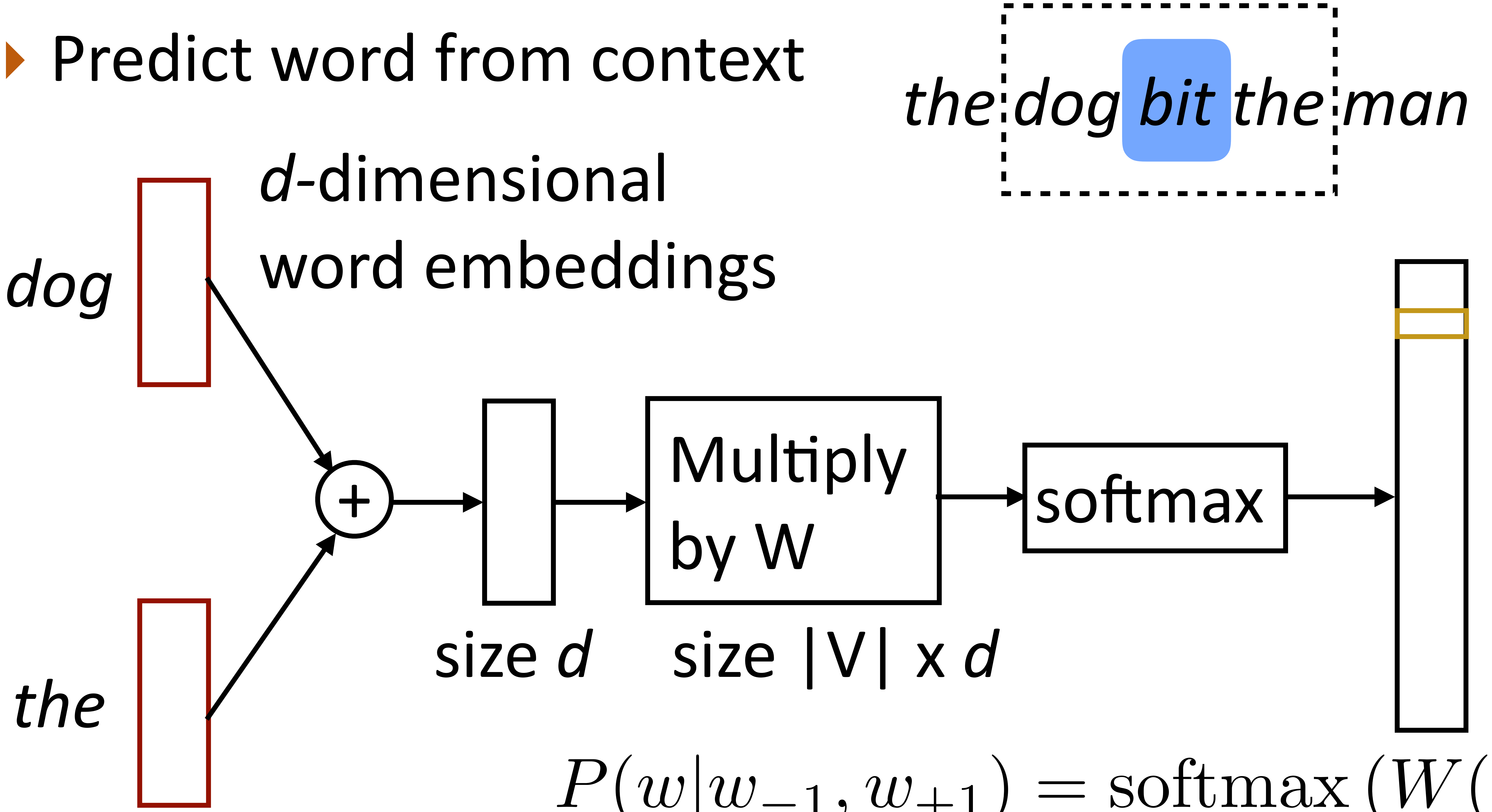


gold label = *bit*, no manual labeling required!

Mikolov et al. (2013)

Continuous Bag-of-Words

- Predict word from context



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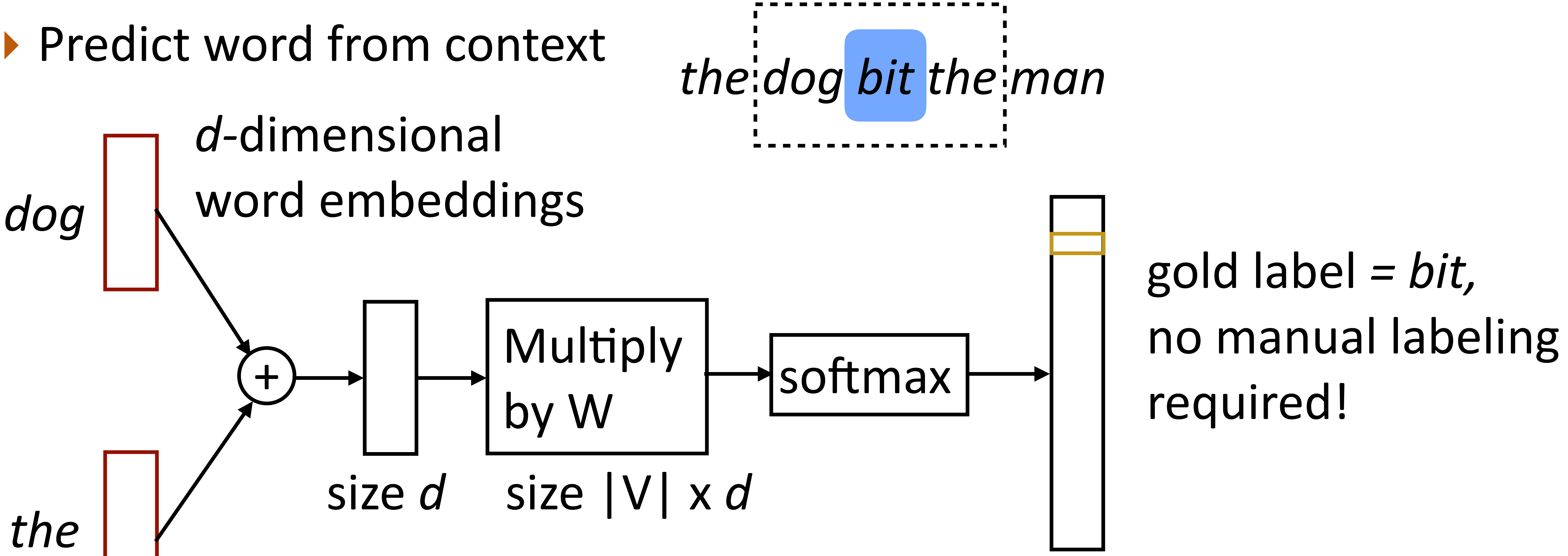

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- Parameters: *d* x |V| (one *d*-length vector per voc word),
  |V| x *d* output parameters (W)

Mikolov et al. (2013)

Skip-Gram

- Predict one word of context from word

the dog bit the man

Mikolov et al. (2013)

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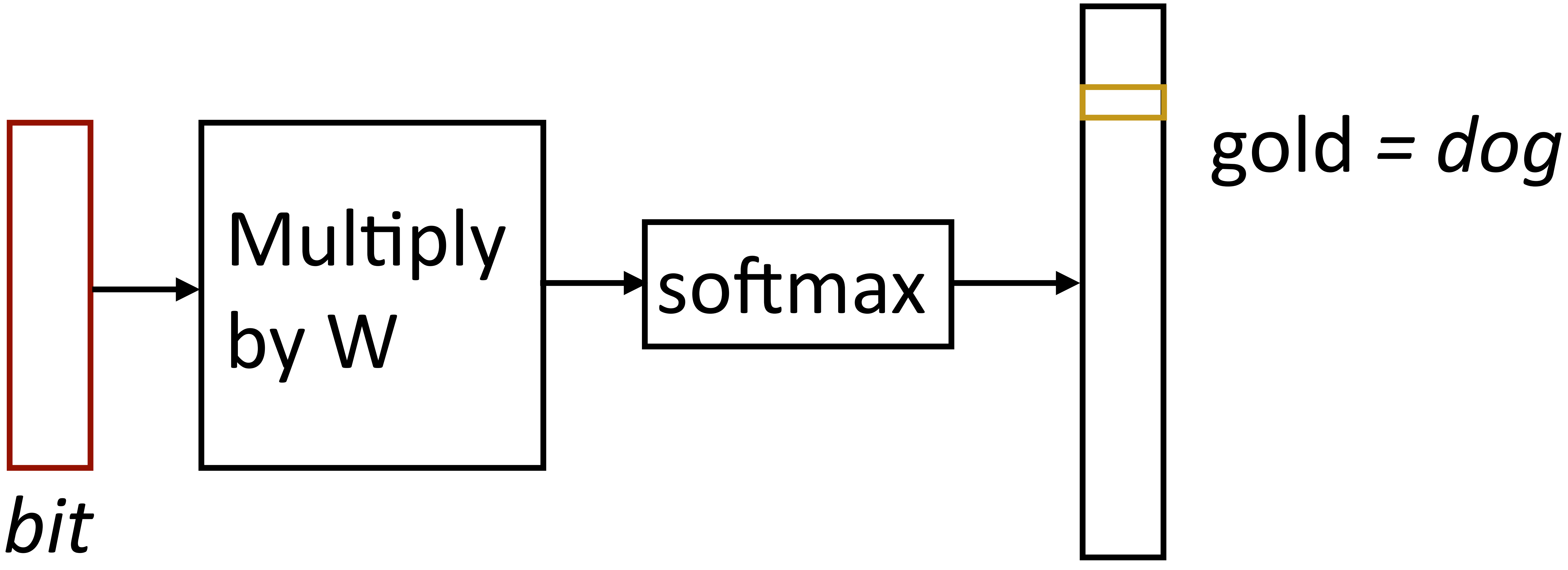

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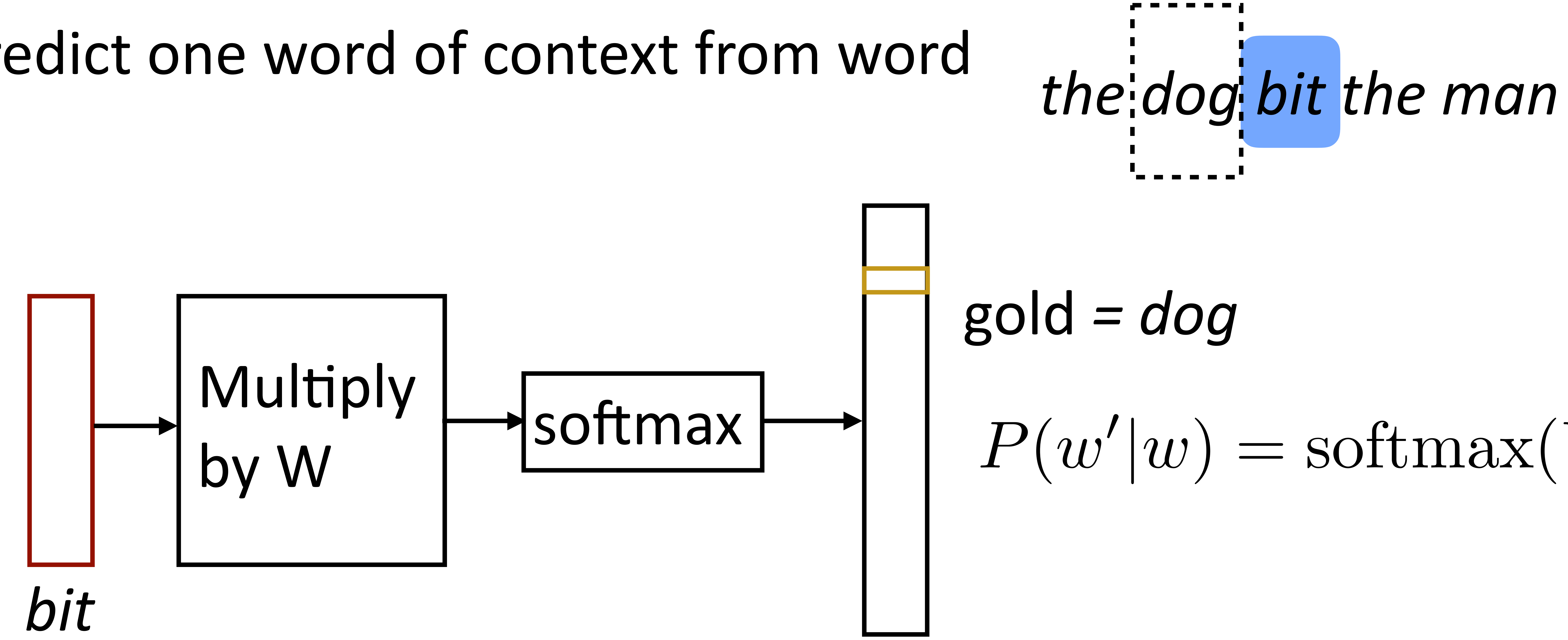

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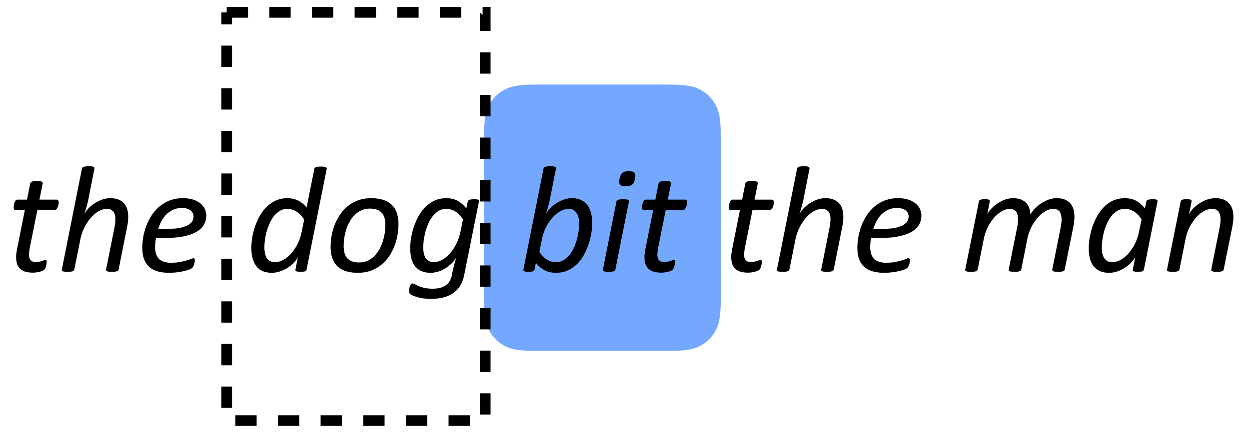

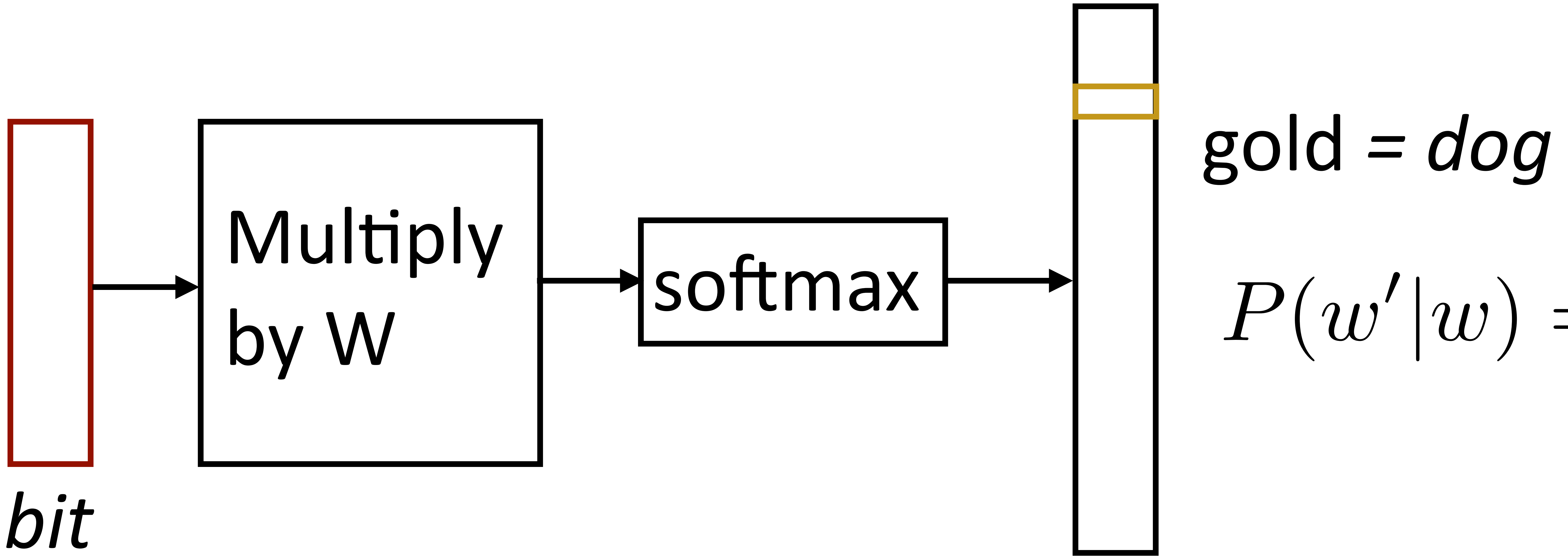

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- Another training example: *bit -> the*

Mikolov et al. (2013)

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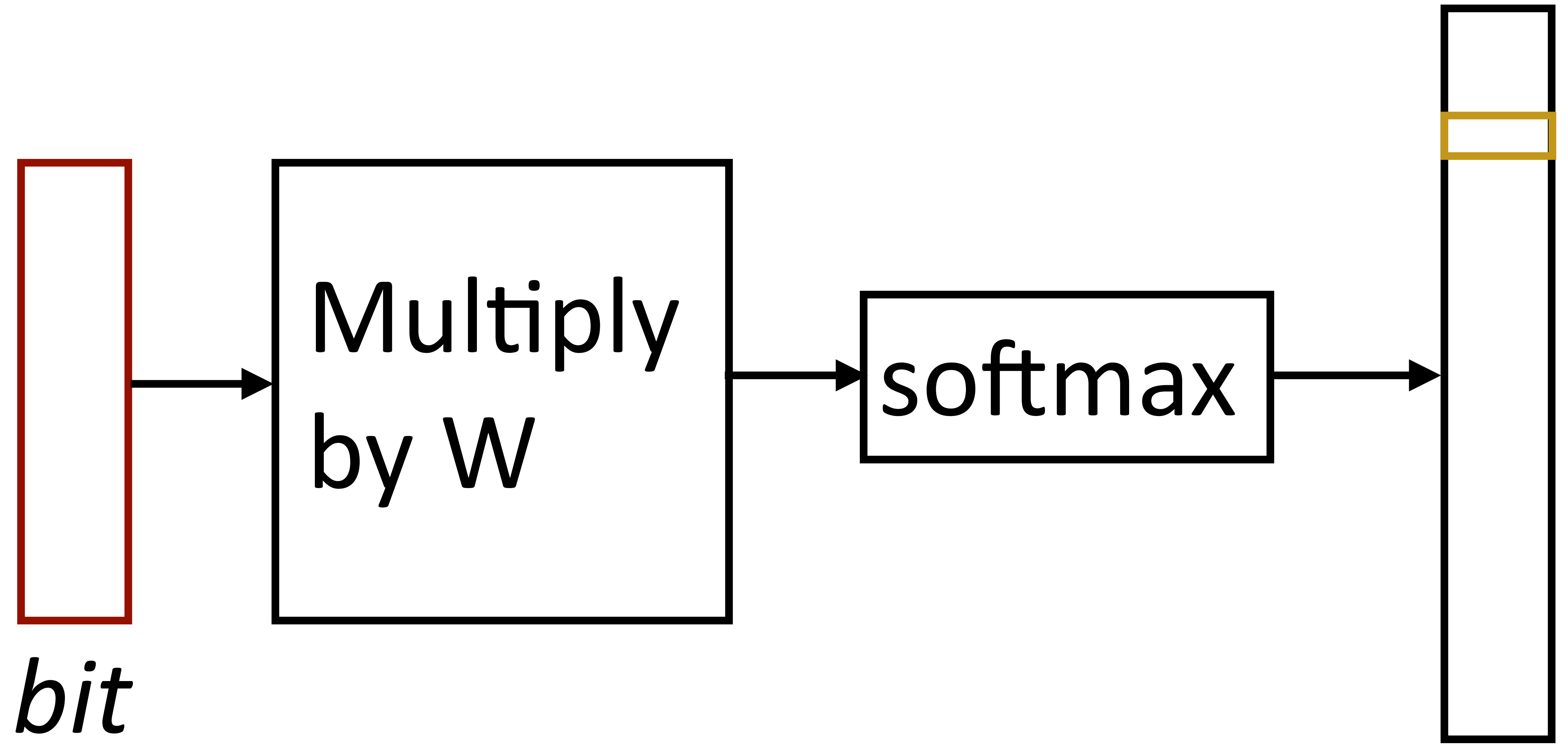

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- Another training example: *bit -> the*
- Parameters: d x |V| vectors, |V| x d output parameters (W) (also usable as vectors!)

Mikolov et al. (2013)

Hierarchical Softmax

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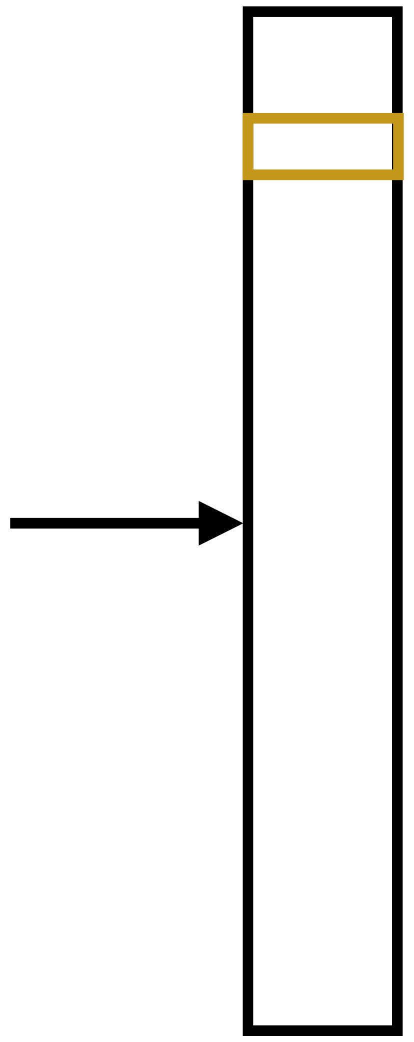

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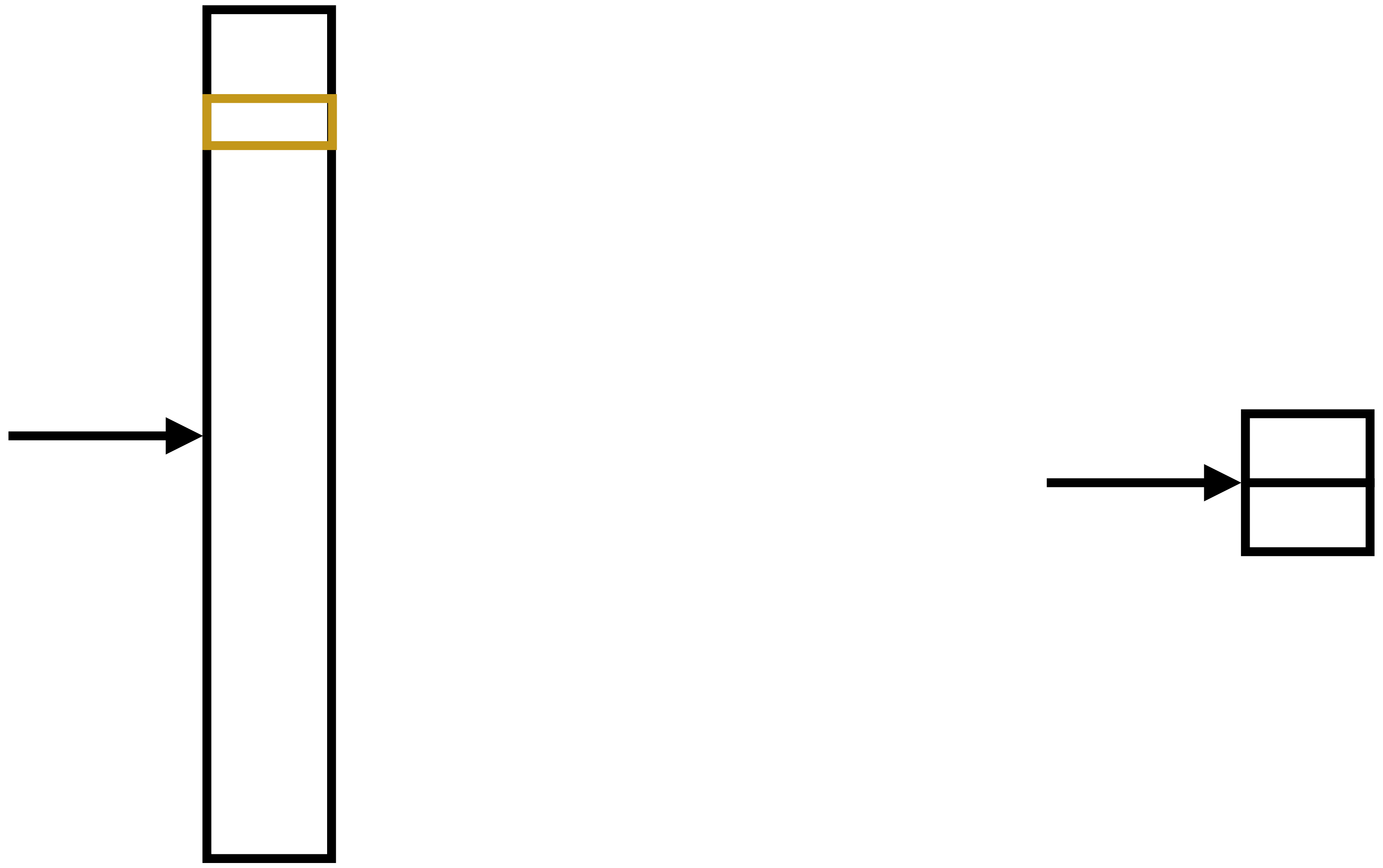

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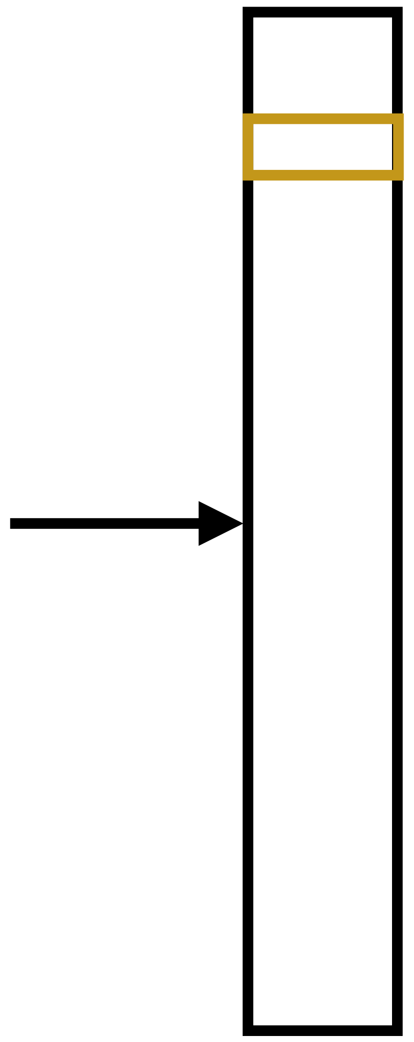

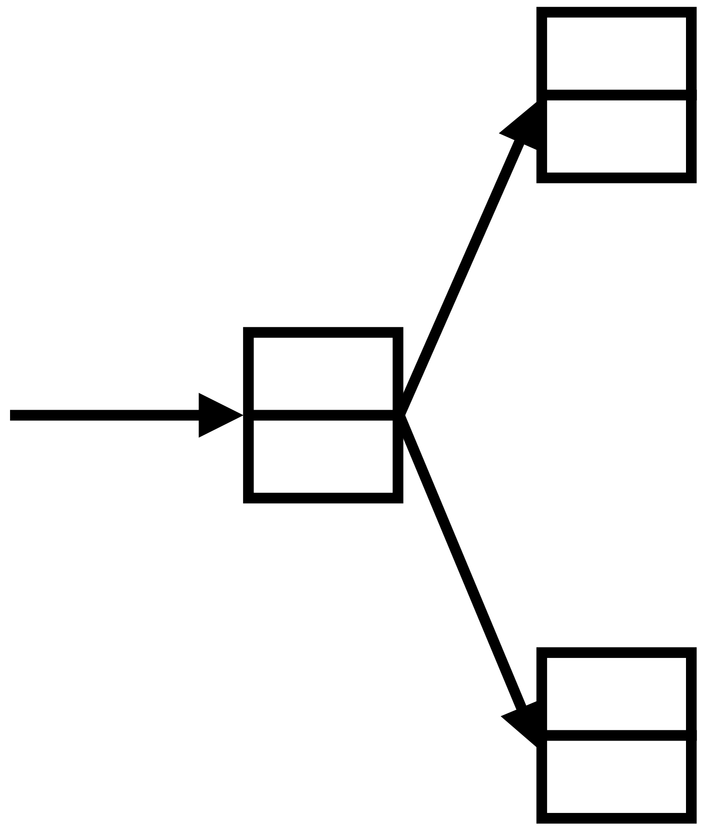

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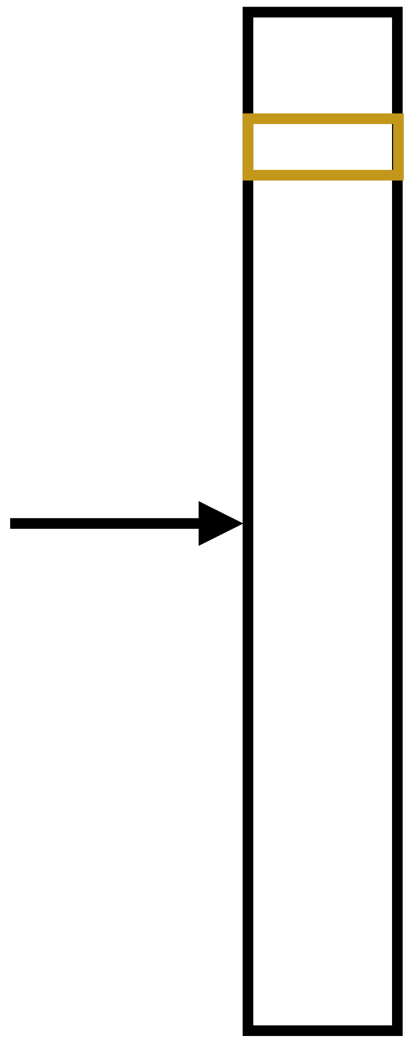

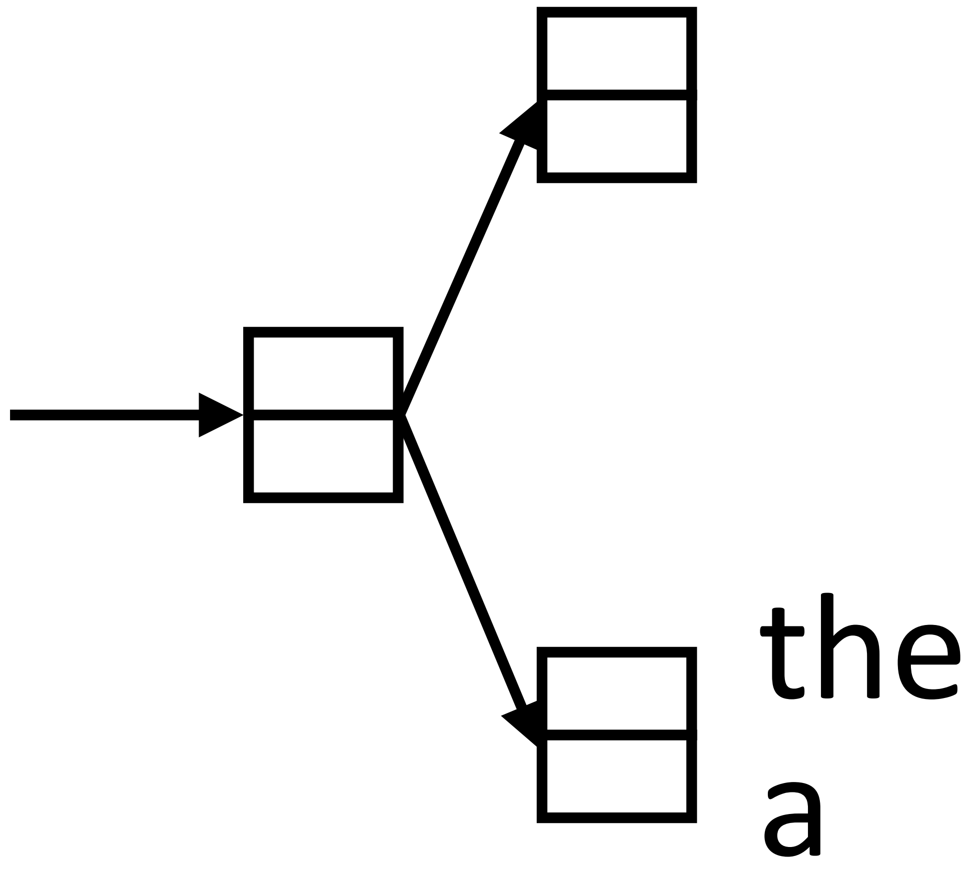

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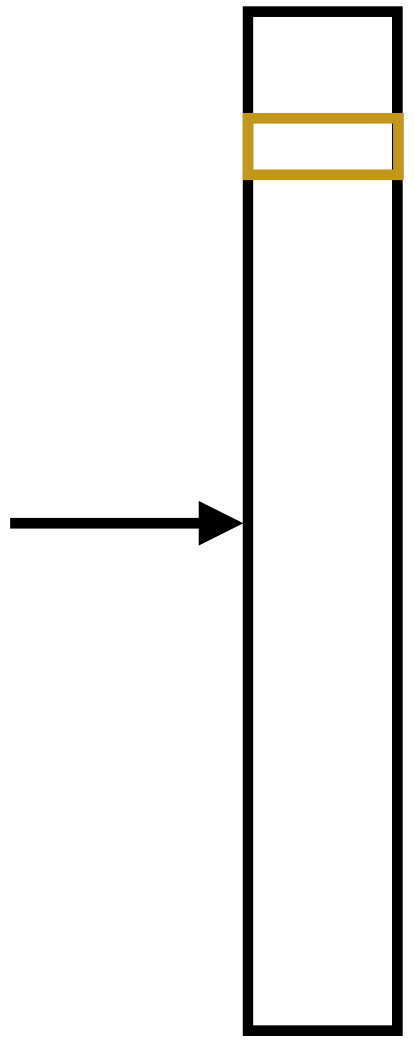

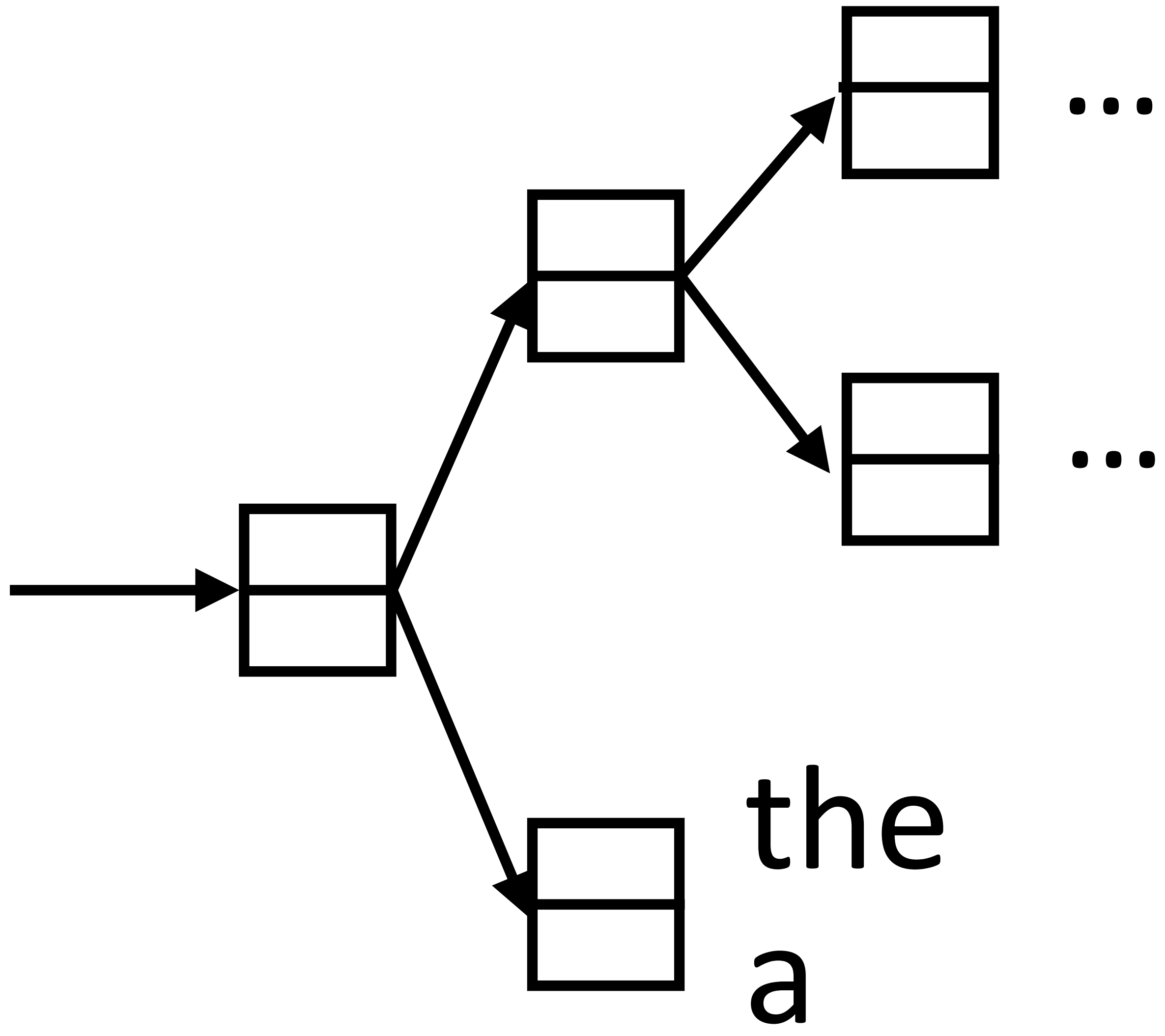

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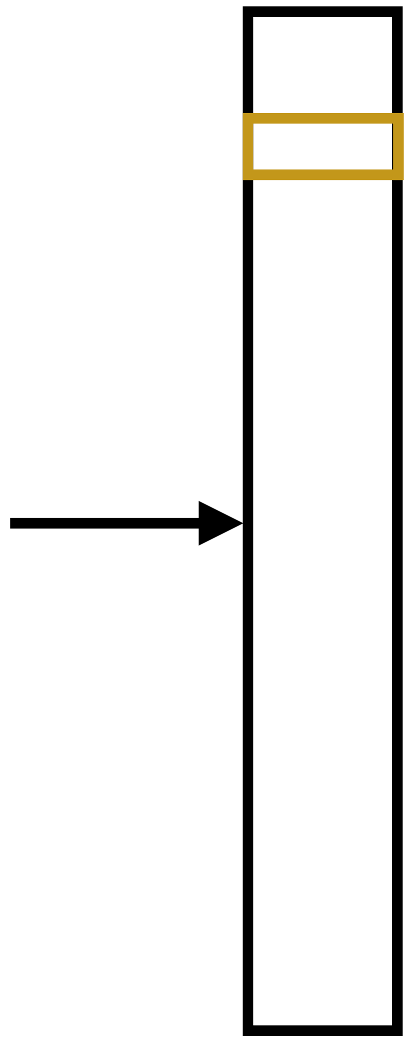

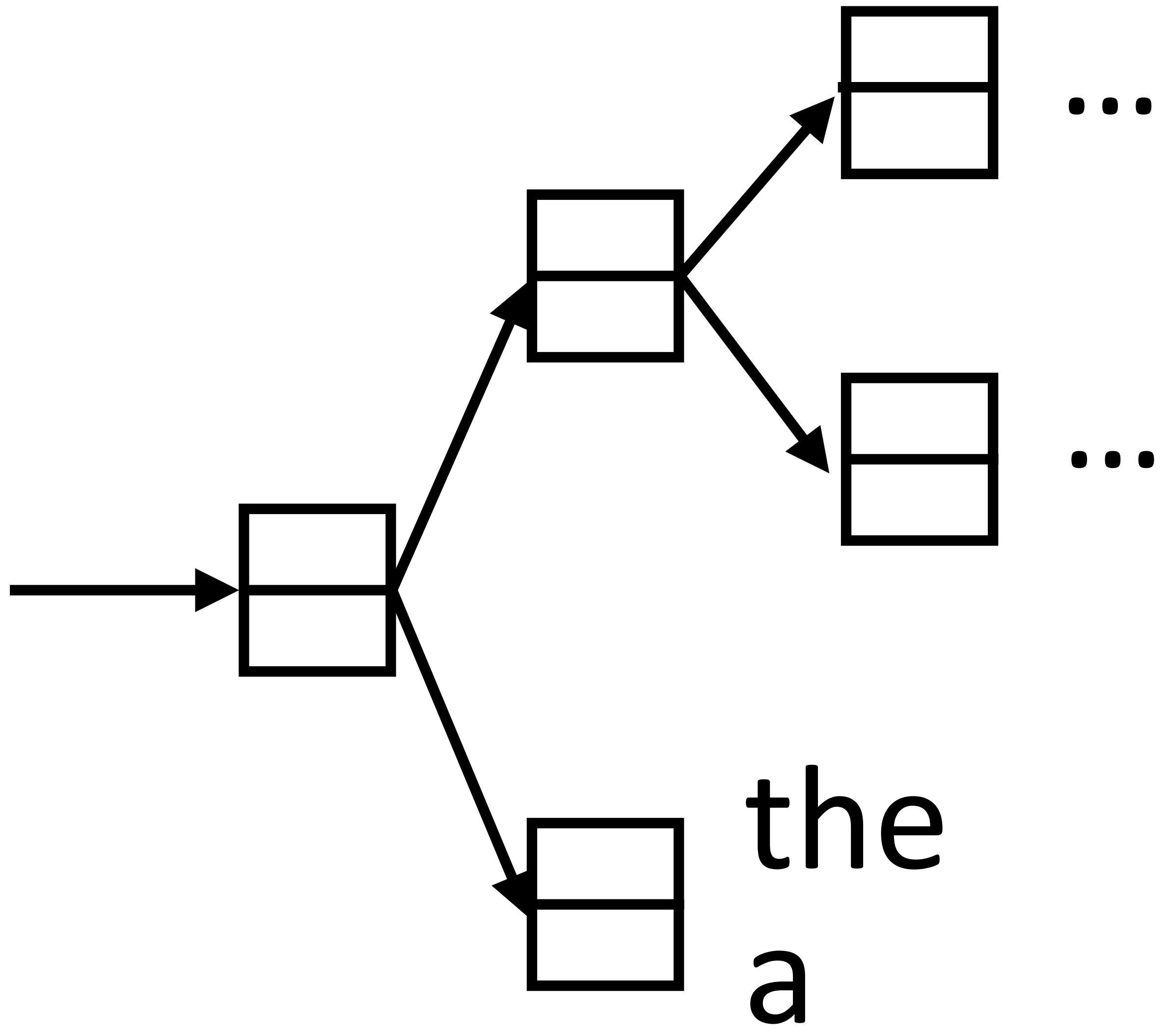

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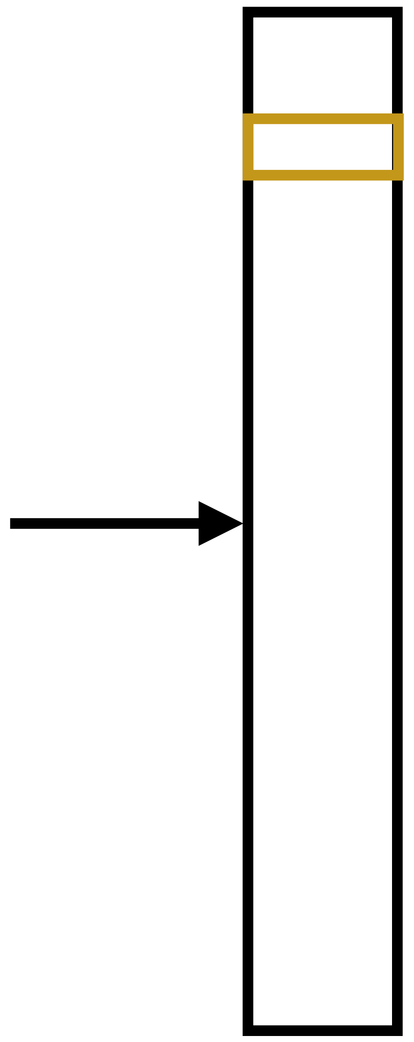

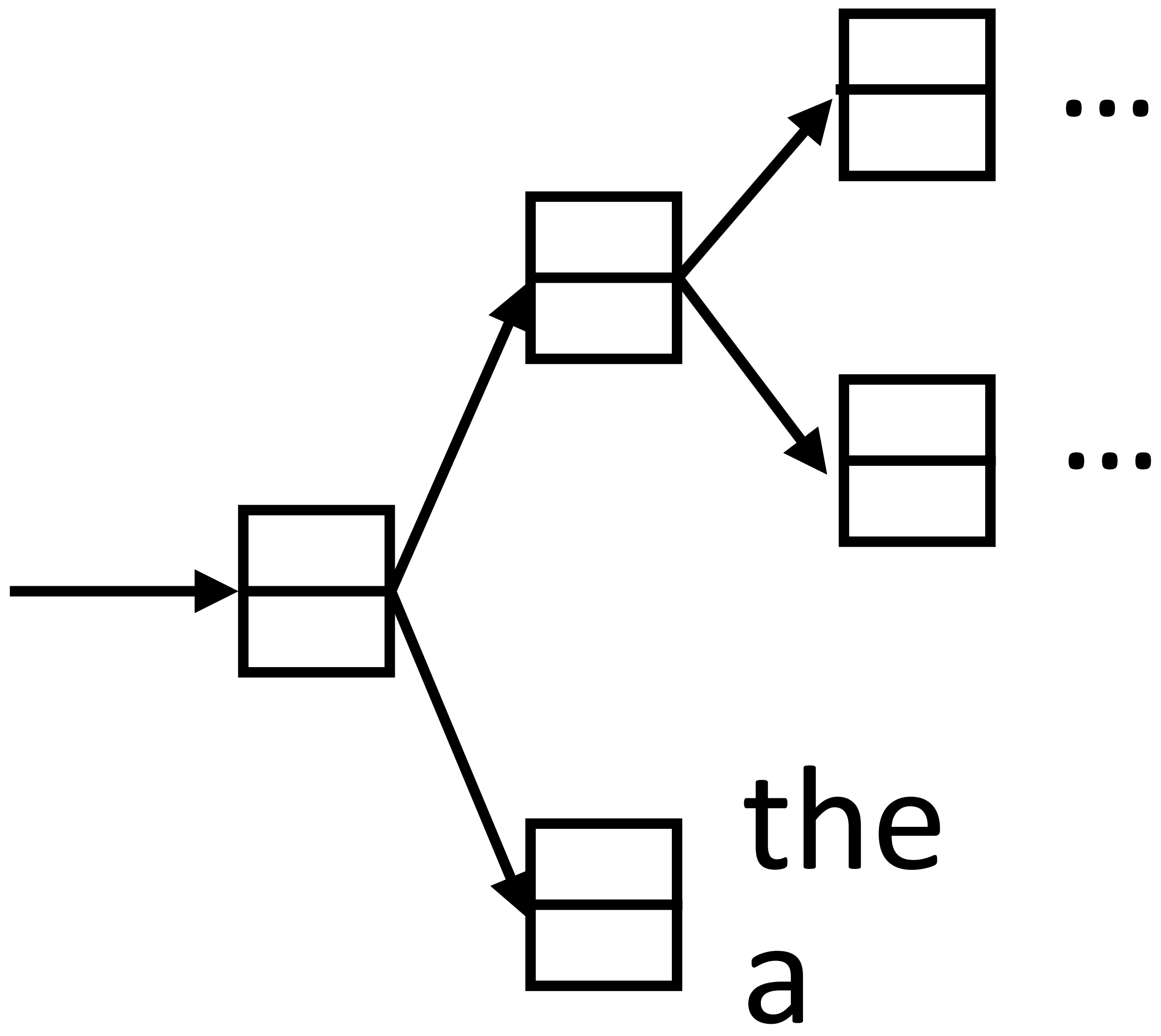

- Huffman encode vocabulary, use binary classifiers to decide which branch to take
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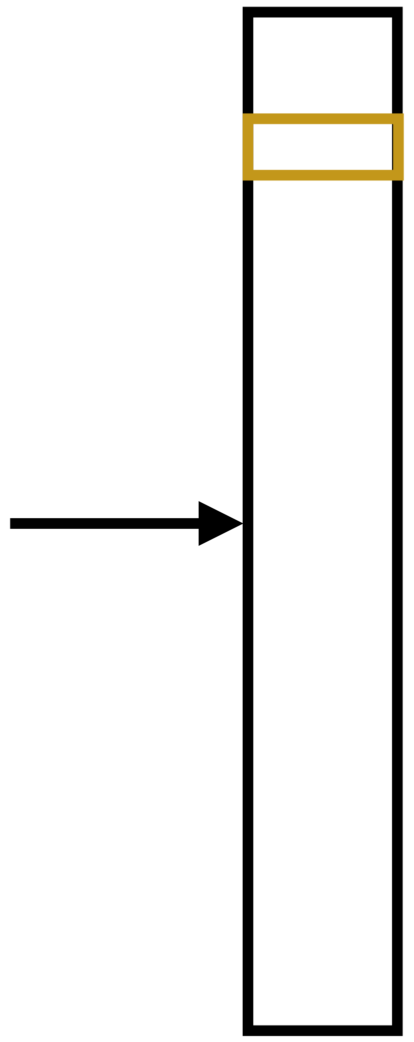

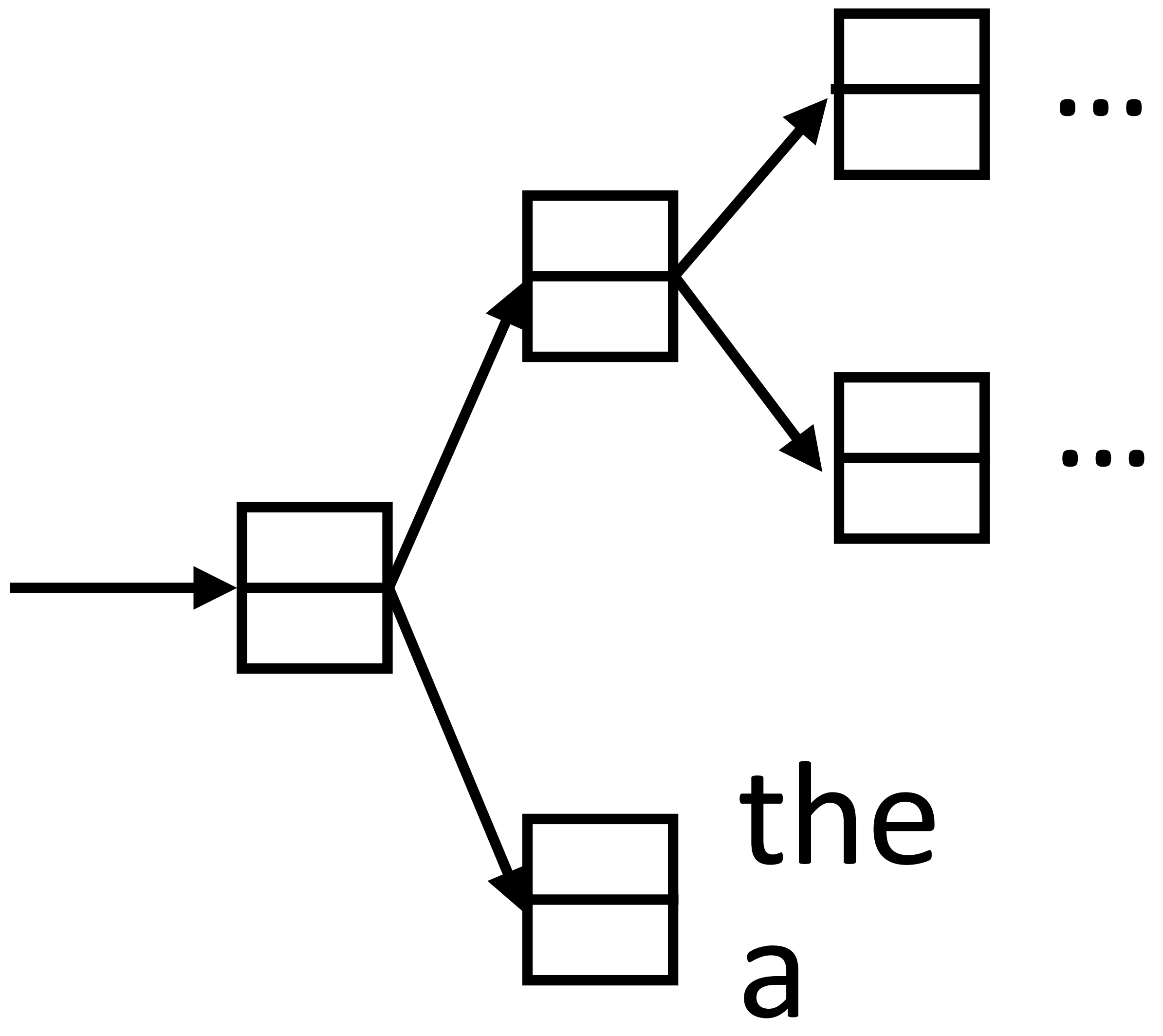

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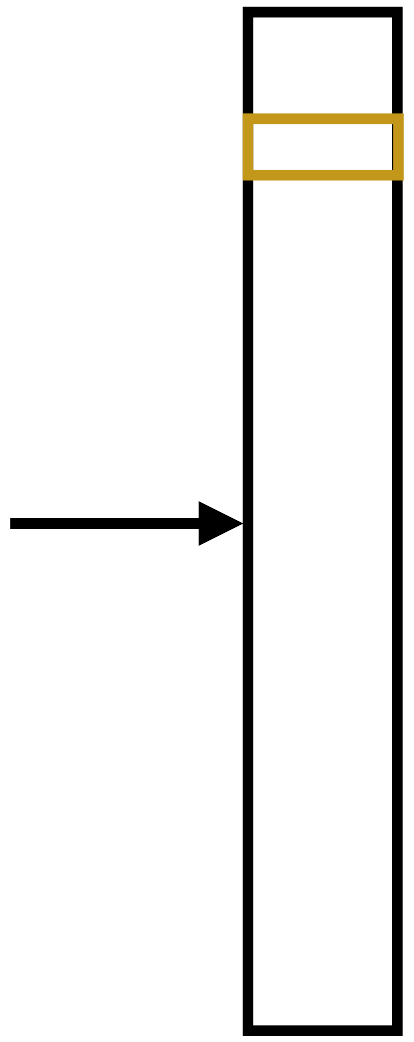

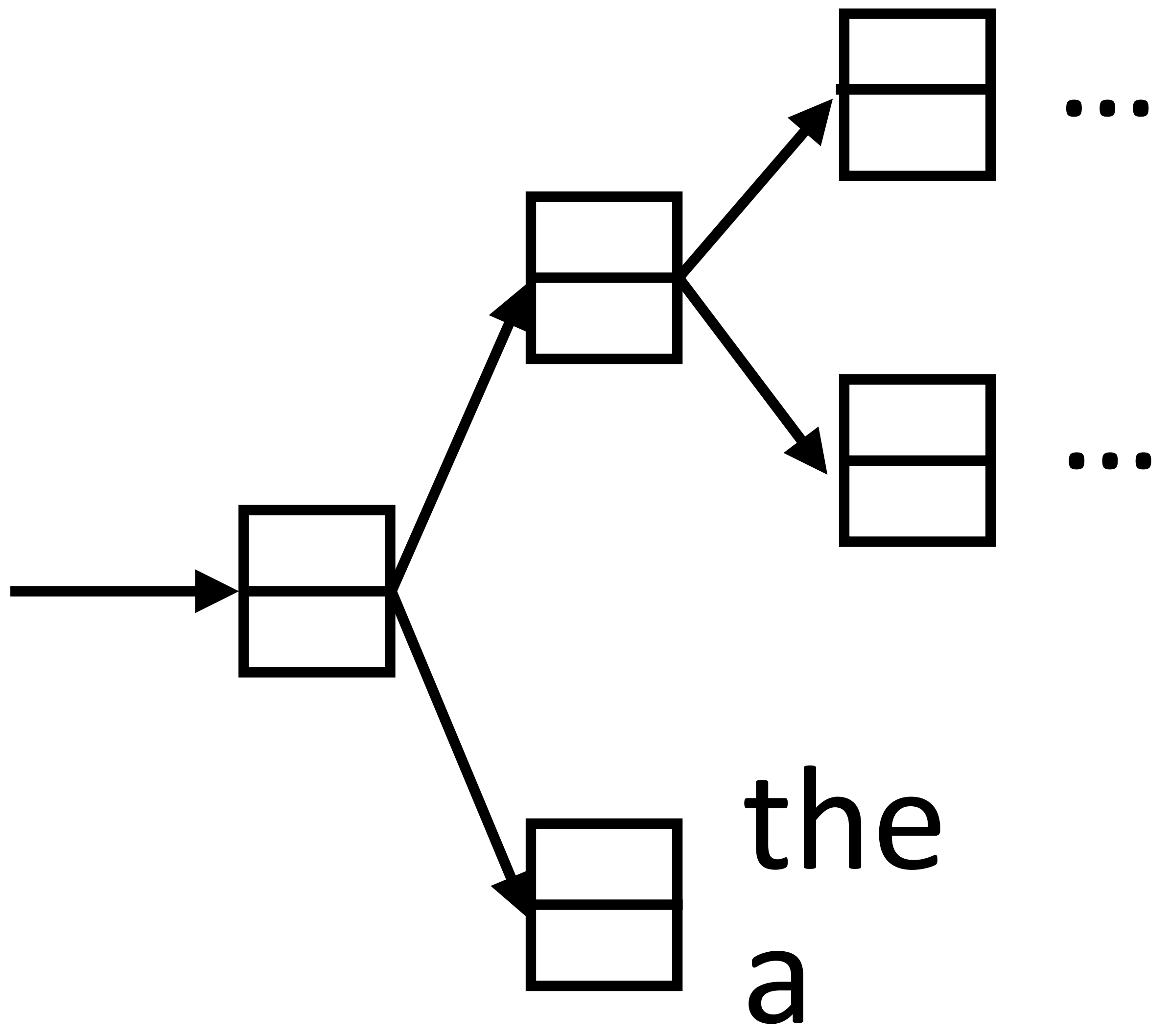

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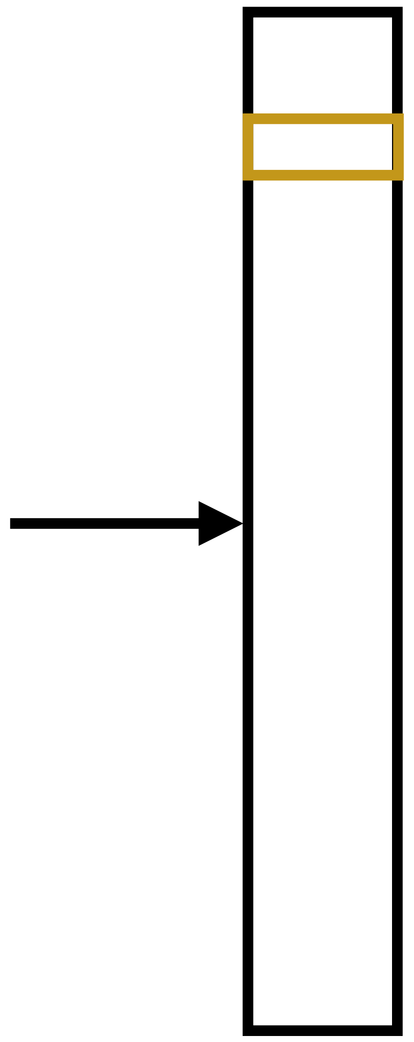

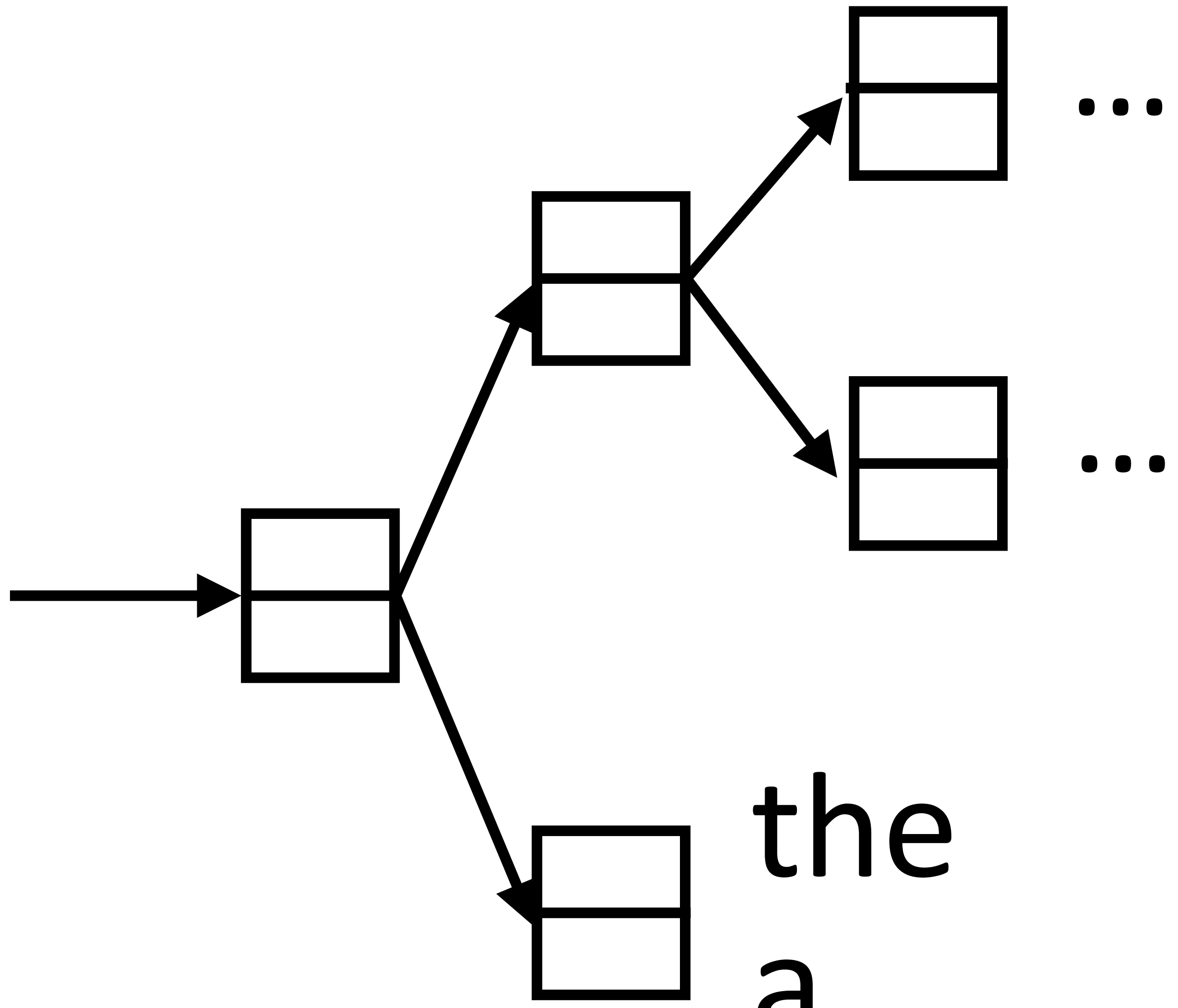

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Mikolov et al. (2013)

Skip-Gram with Negative Sampling

Mikolov et al. (2013)

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- Take (word, context) pairs and classify them as “real” or not. Create random negative examples by sampling from unigram distribution

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words in similar contexts select for similar *c* vectors

Mikolov et al. (2013)

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sampled

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Mikolov et al. (2013)

Connections with Matrix Factorization

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

Levy et al. (2014)

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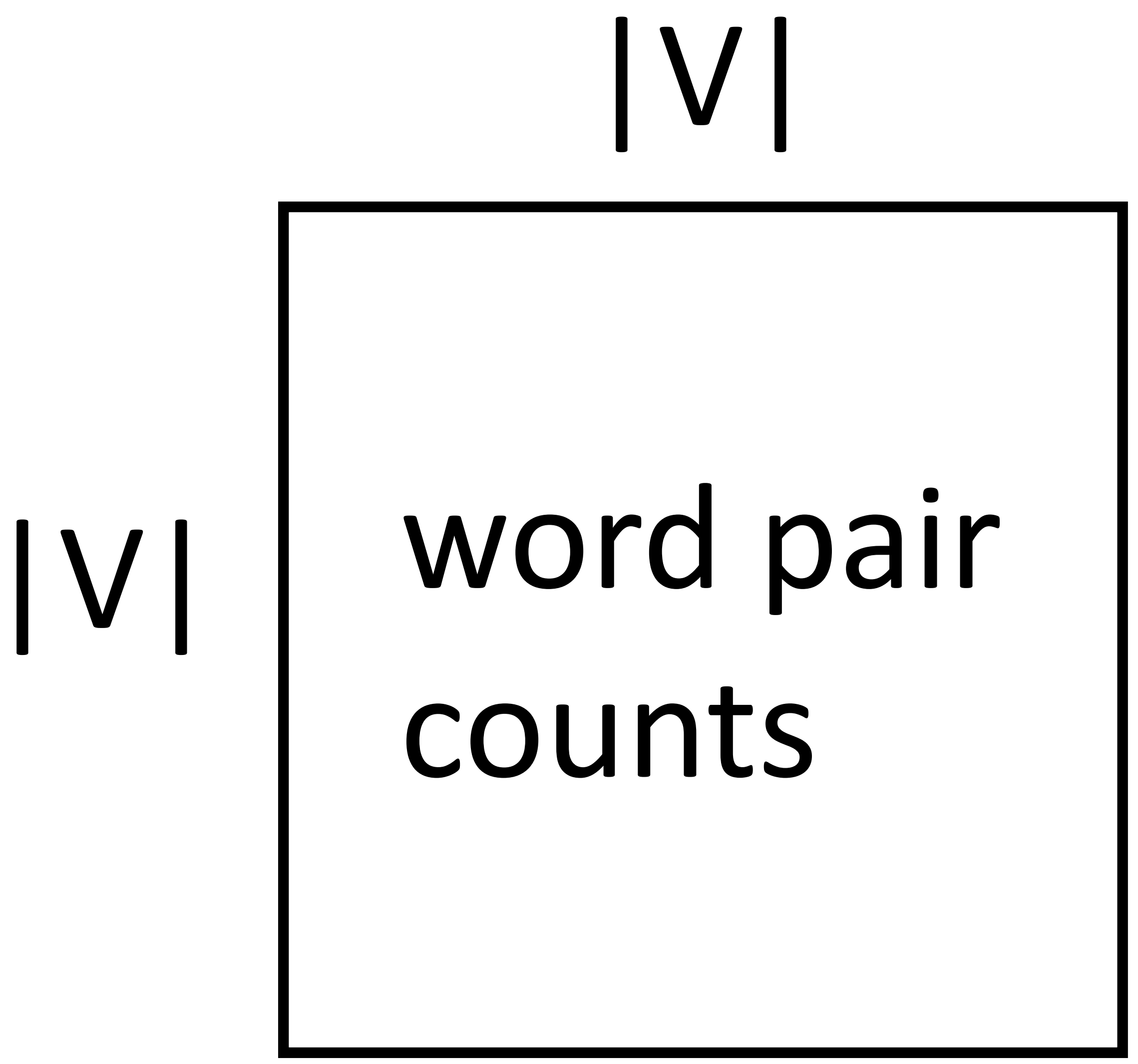

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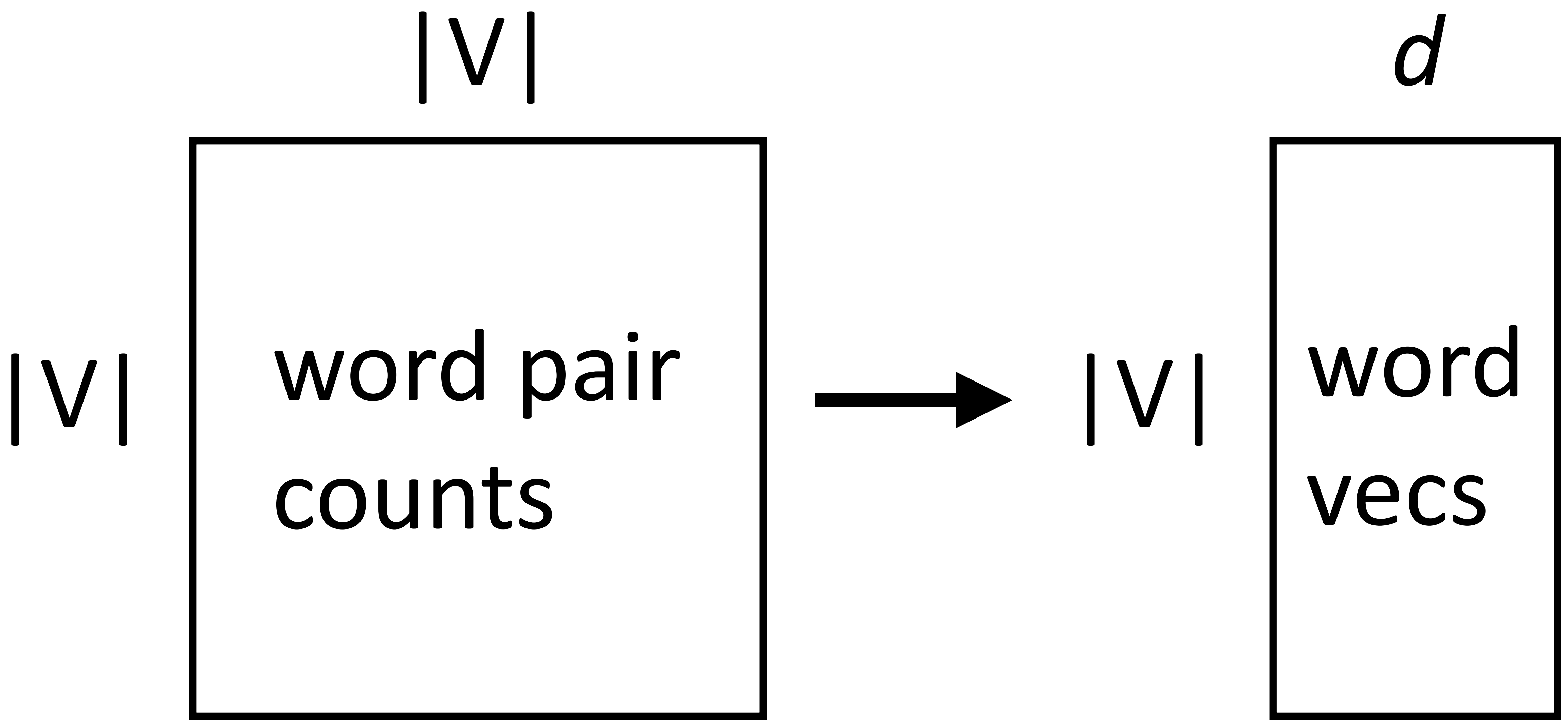

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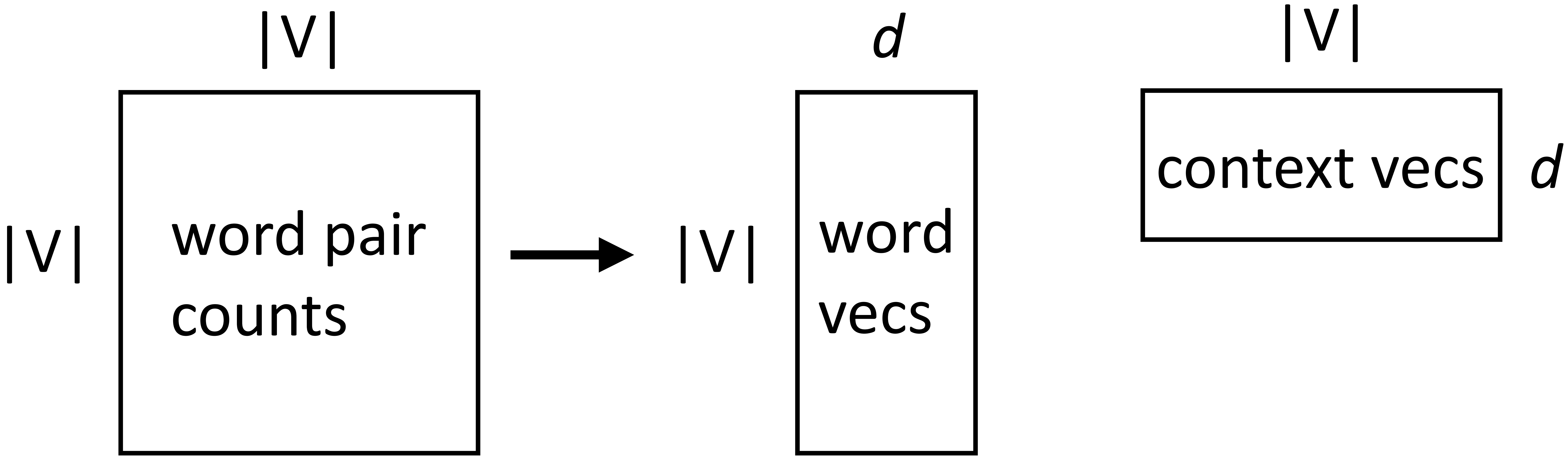

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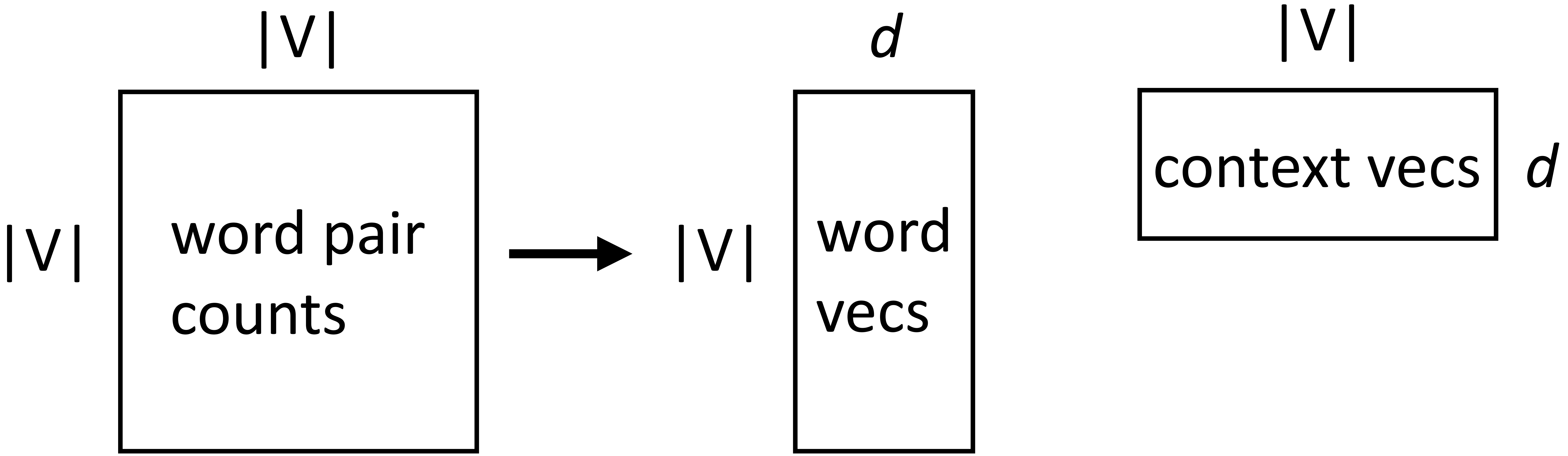
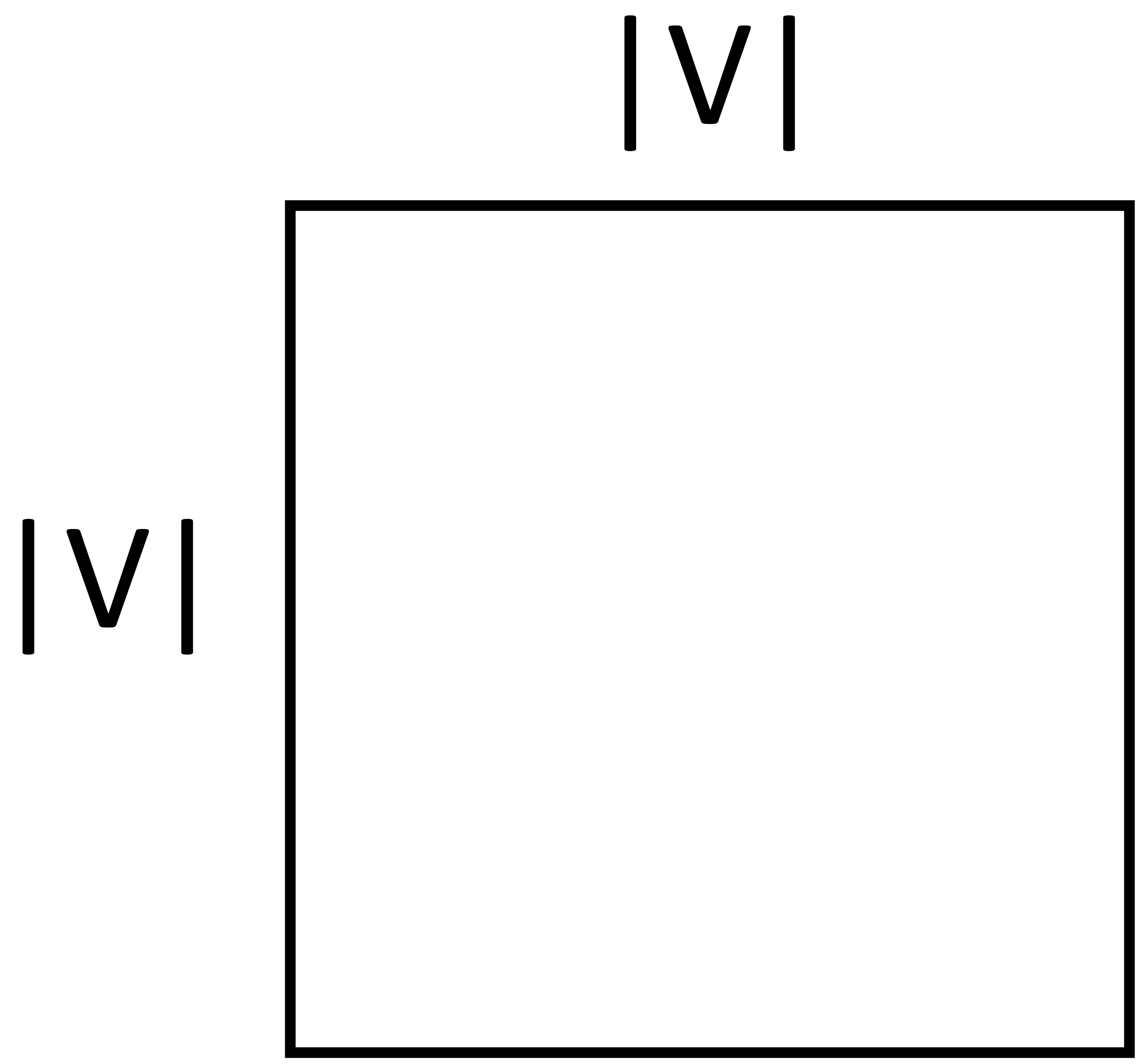


- Looks almost like a matrix factorization…can we interpret it this way?

Levy et al. (2014)

Skip-Gram as Matrix Factorization



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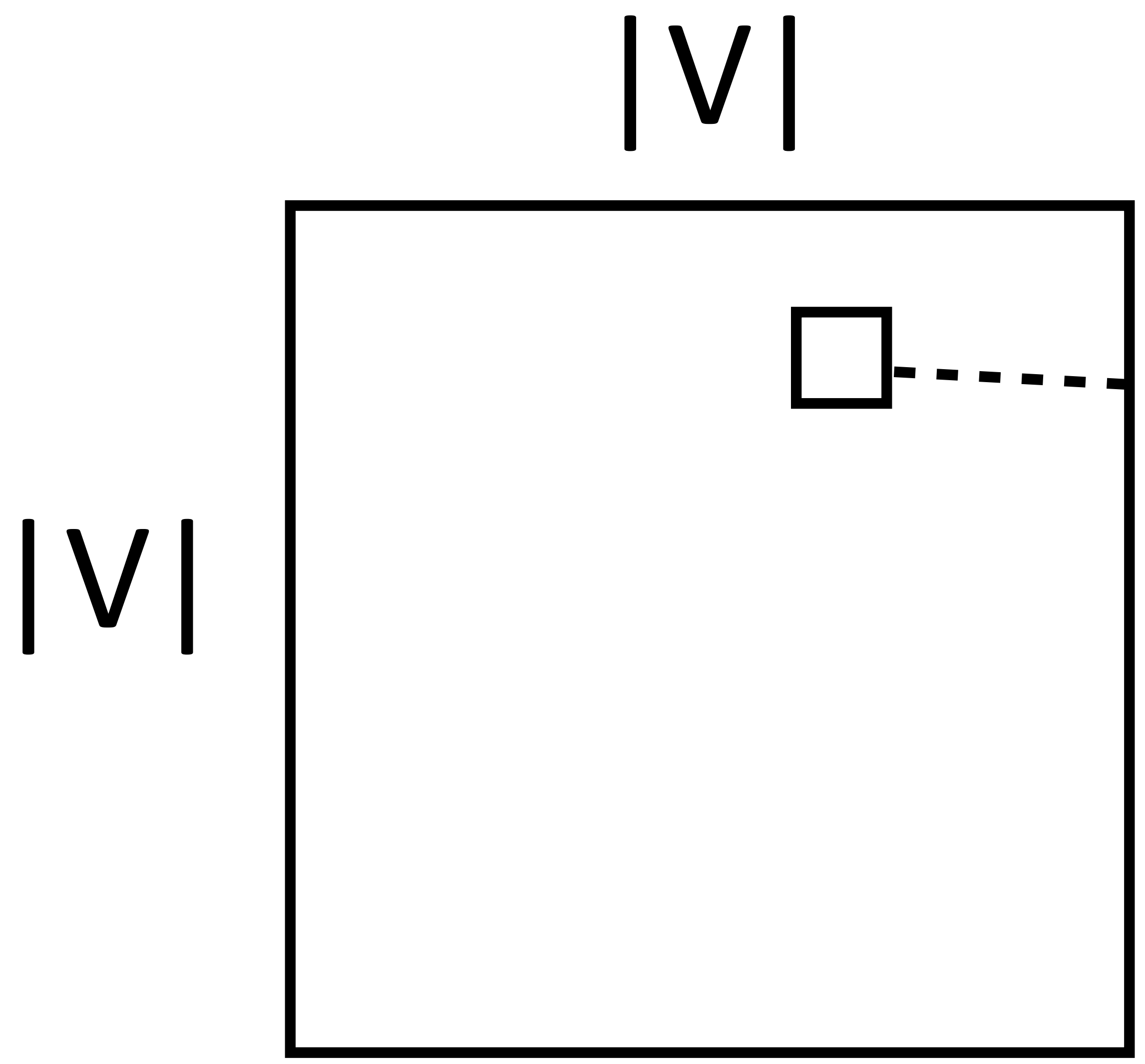

num negative samples

$$M_{ij} = \mathrm{PMI}(w_i, c_j) - \log k$$

Levy et al. (2014)

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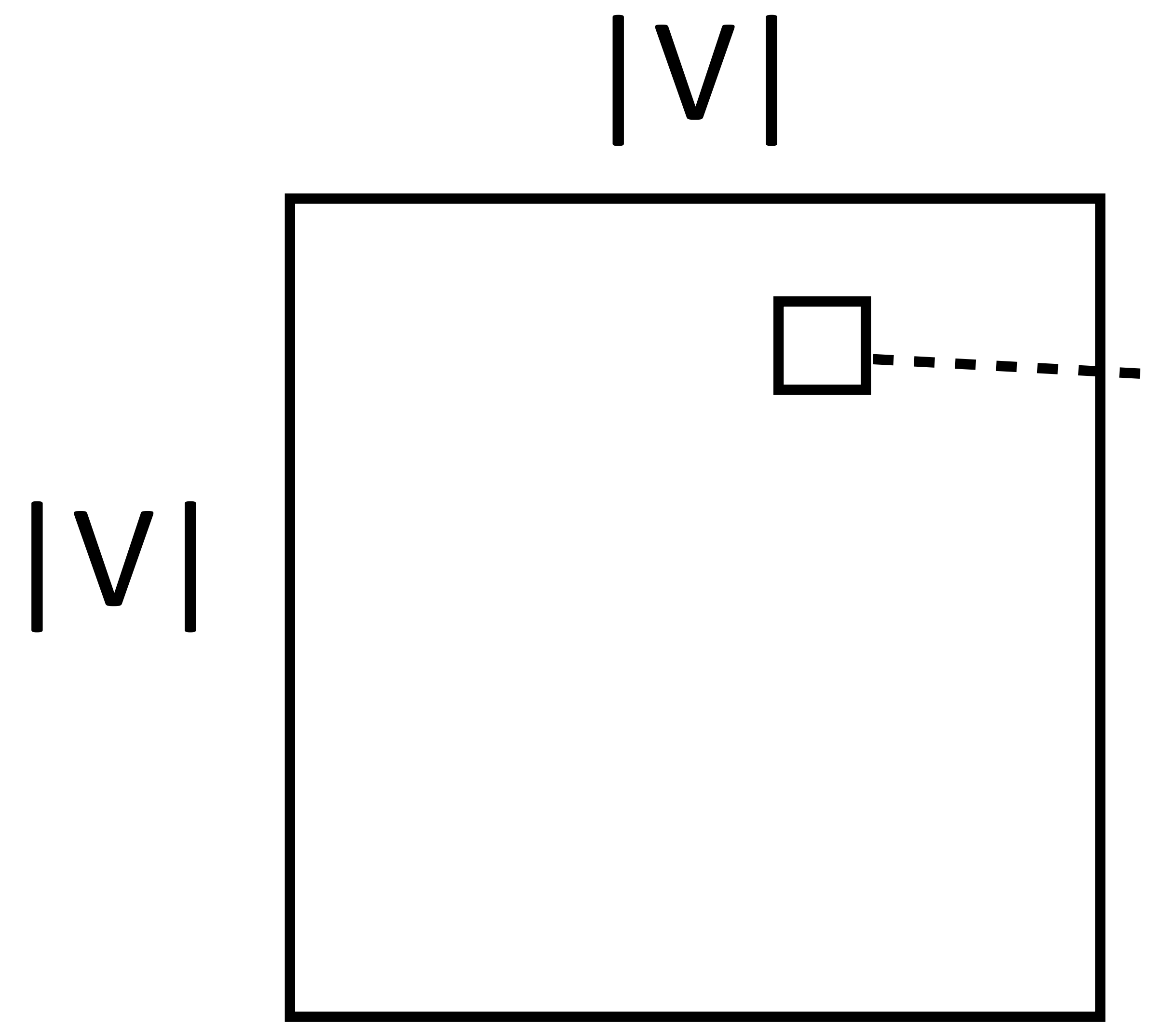

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$$\mathrm{PMI}(w_i, c_j) = \frac{P(w_i, c_j)}{P(w_i)P(c_j)} = \frac{\frac{\mathrm{count}(w_i, c_j)}{D}}{\frac{\mathrm{count}(w_i)}{D}\,\frac{count(c_j)}{D}}$$

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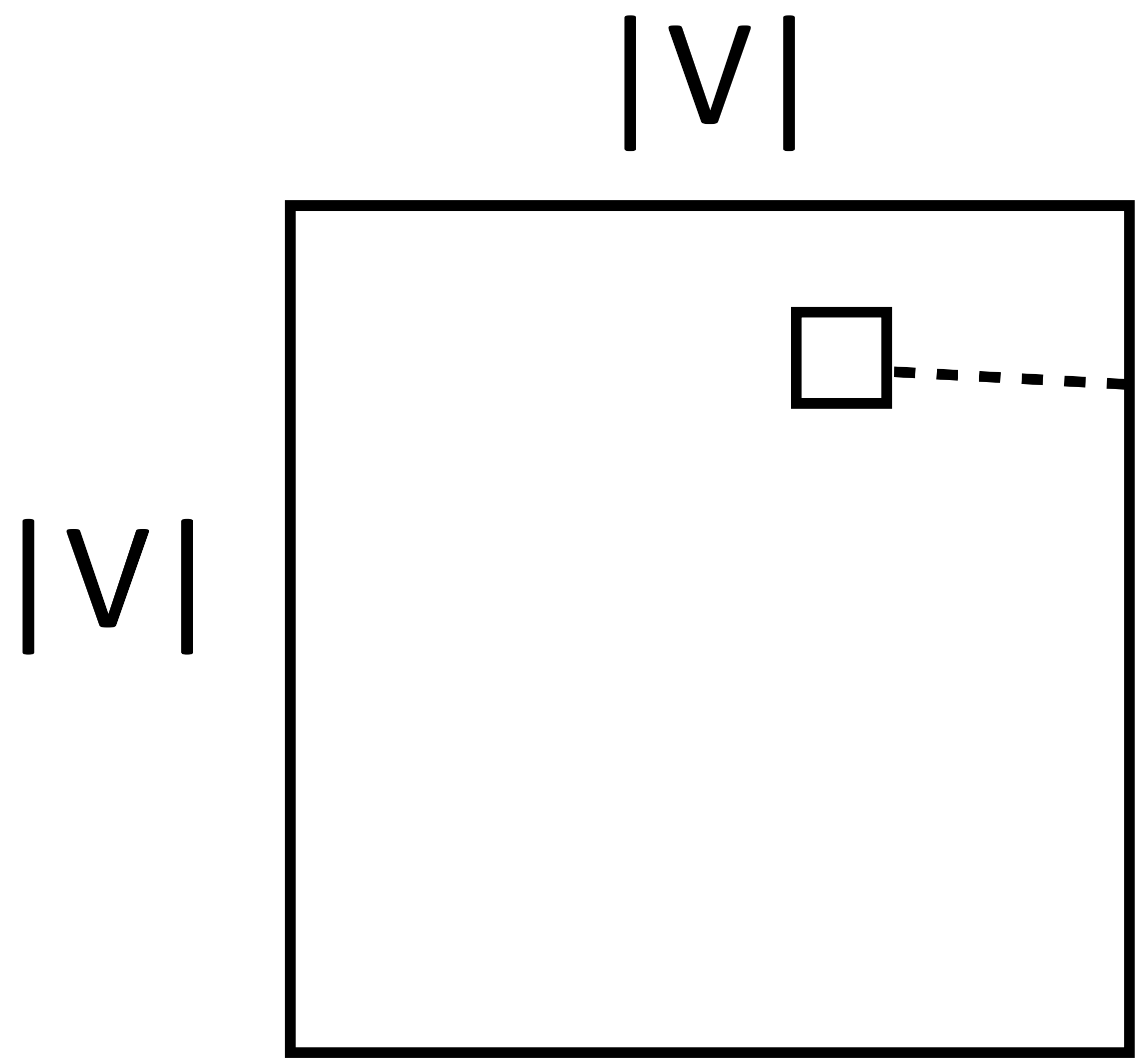

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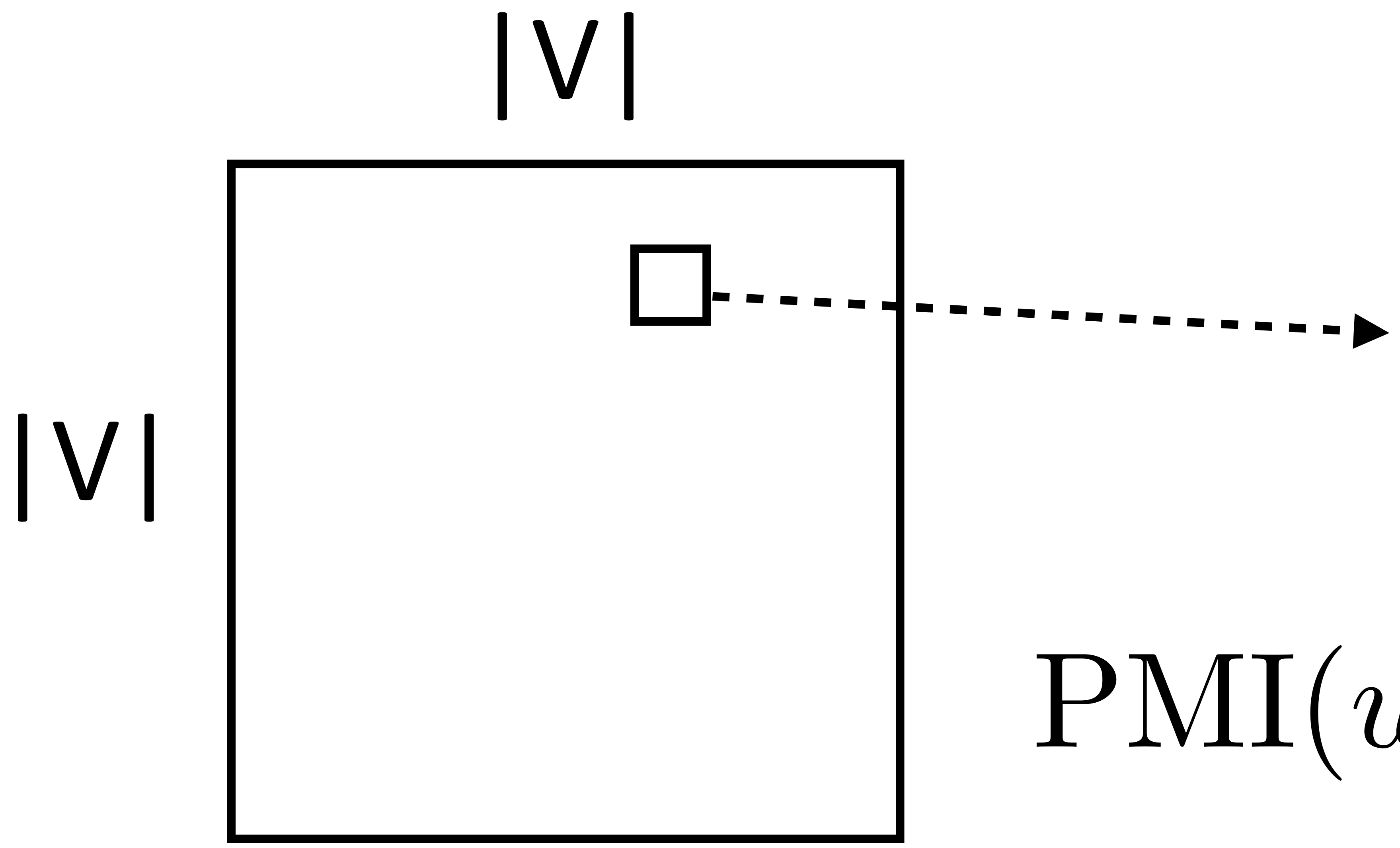
Skip-gram objective *exactly* corresponds to factoring this matrix:

Levy et al. (2014)

Skip-Gram as Matrix Factorization



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- *If* we sample negative examples from the uniform distribution over words

Levy et al. (2014)

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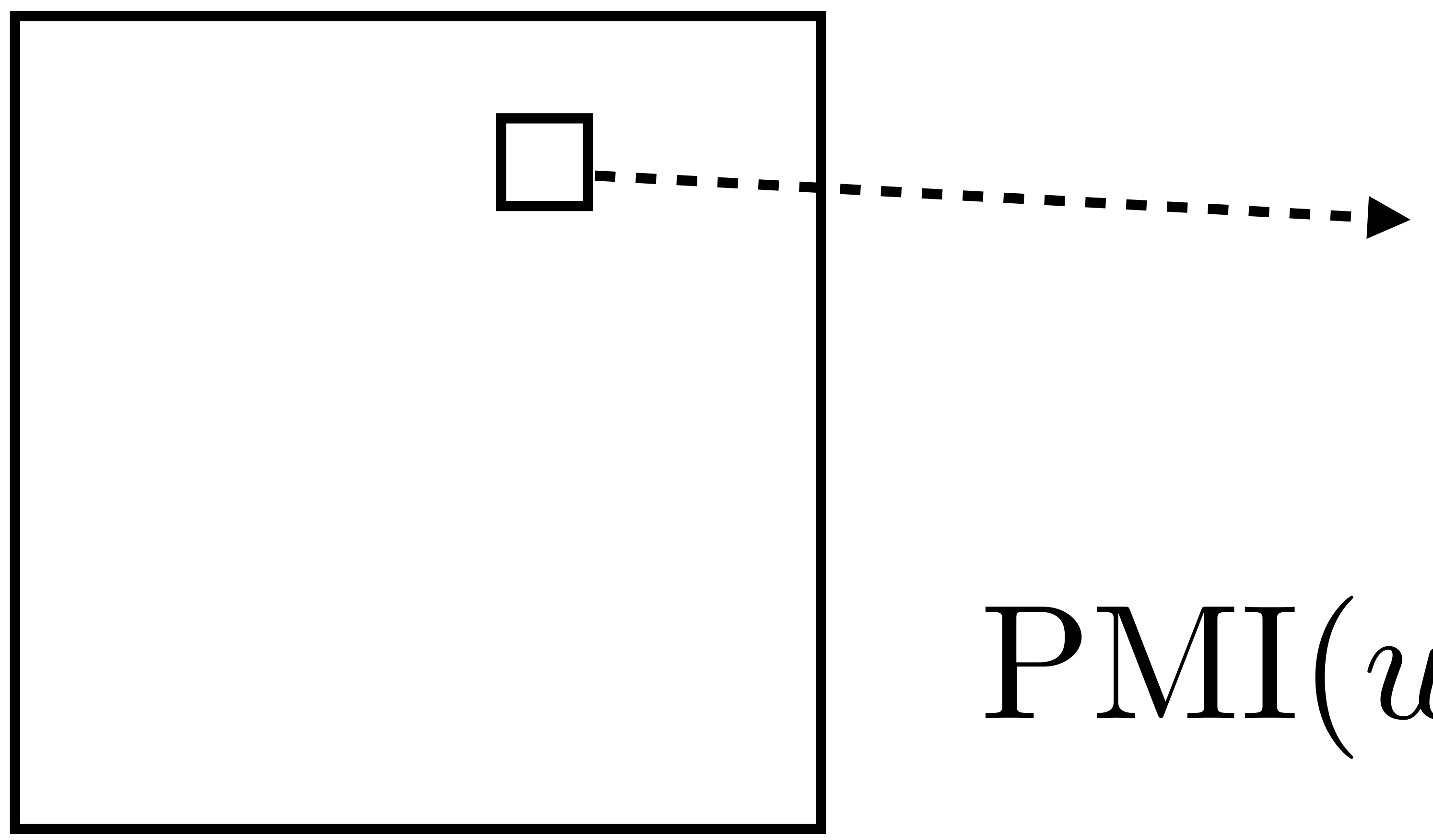

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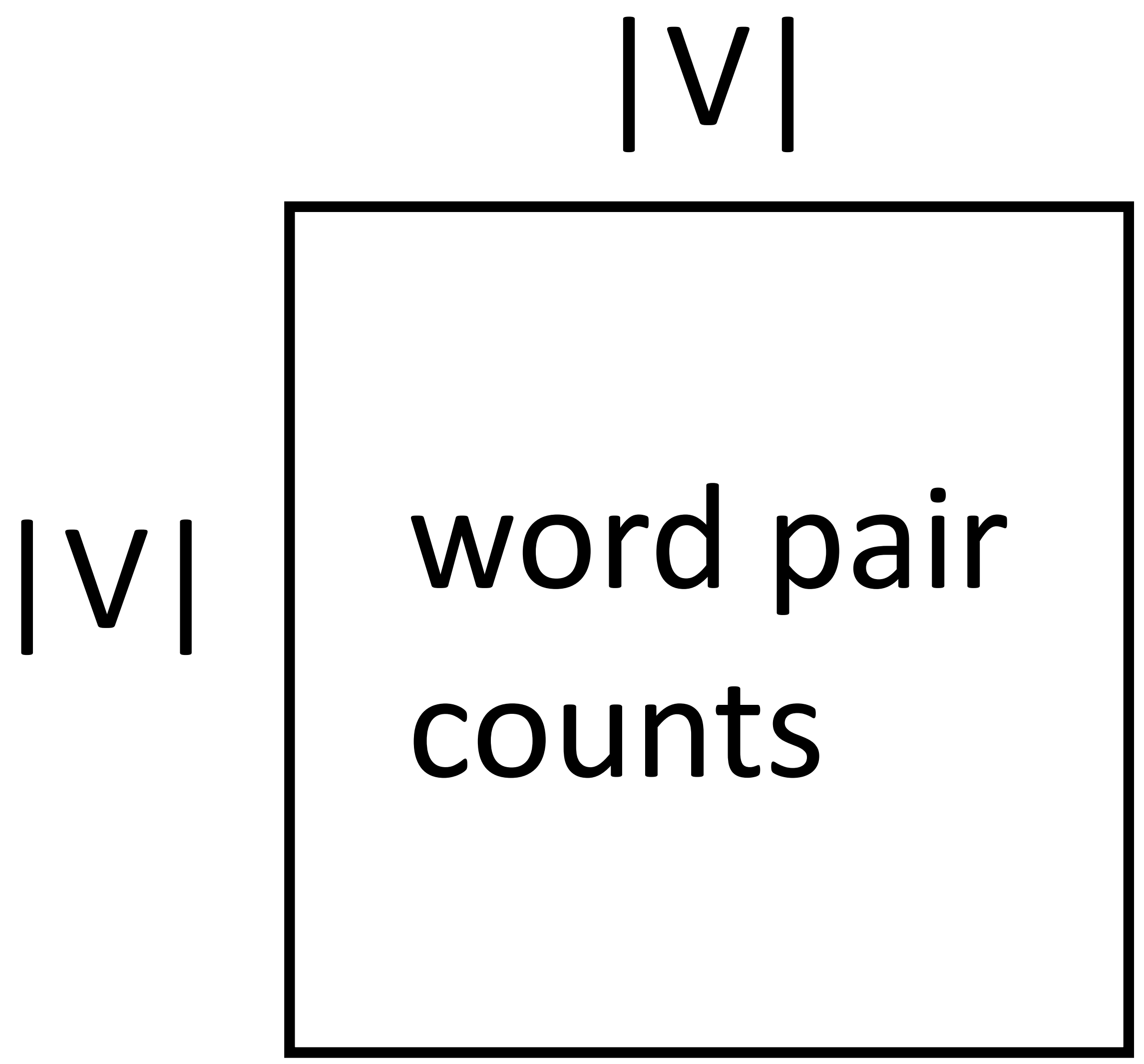
Skip-gram objective *exactly* corresponds to factoring this matrix:

- *If* we sample negative examples from the uniform distribution over words
- …and it's a *weighted* factorization problem (weighted by word freq)

Levy et al. (2014)

GloVe (**Glo**bal **Ve**ctors)

- Also operates on counts matrix, weighted regression on the log co-occurrence matrix



Pennington et al. (2014)

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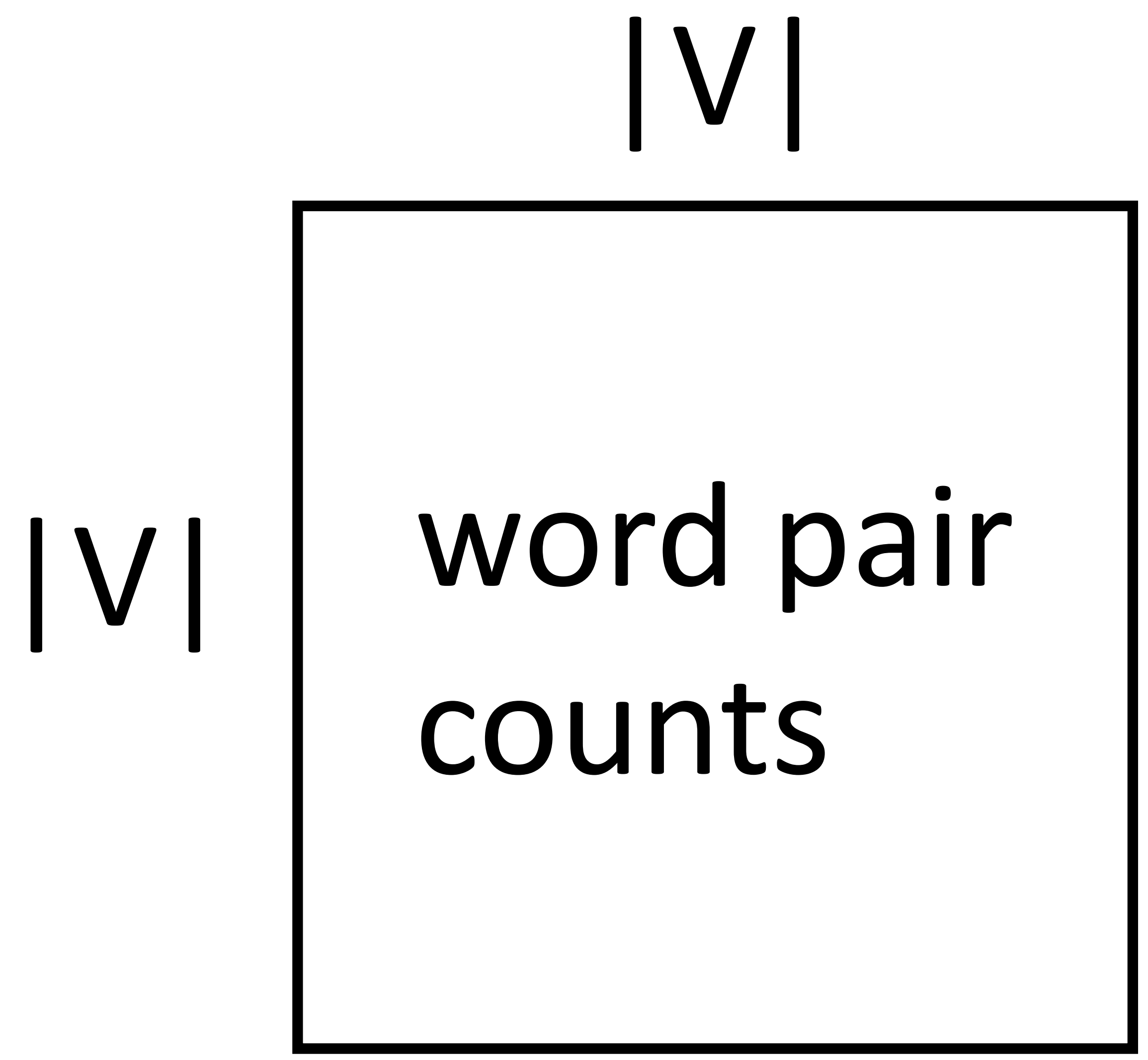

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- Loss $= \sum_{i,j} f(\mathrm{count}(w_i, c_j)) \left(w_i^\top c_j + a_i + b_j - \log \mathrm{count}(w_i, c_j))\right)^2$

Pennington et al. (2014)

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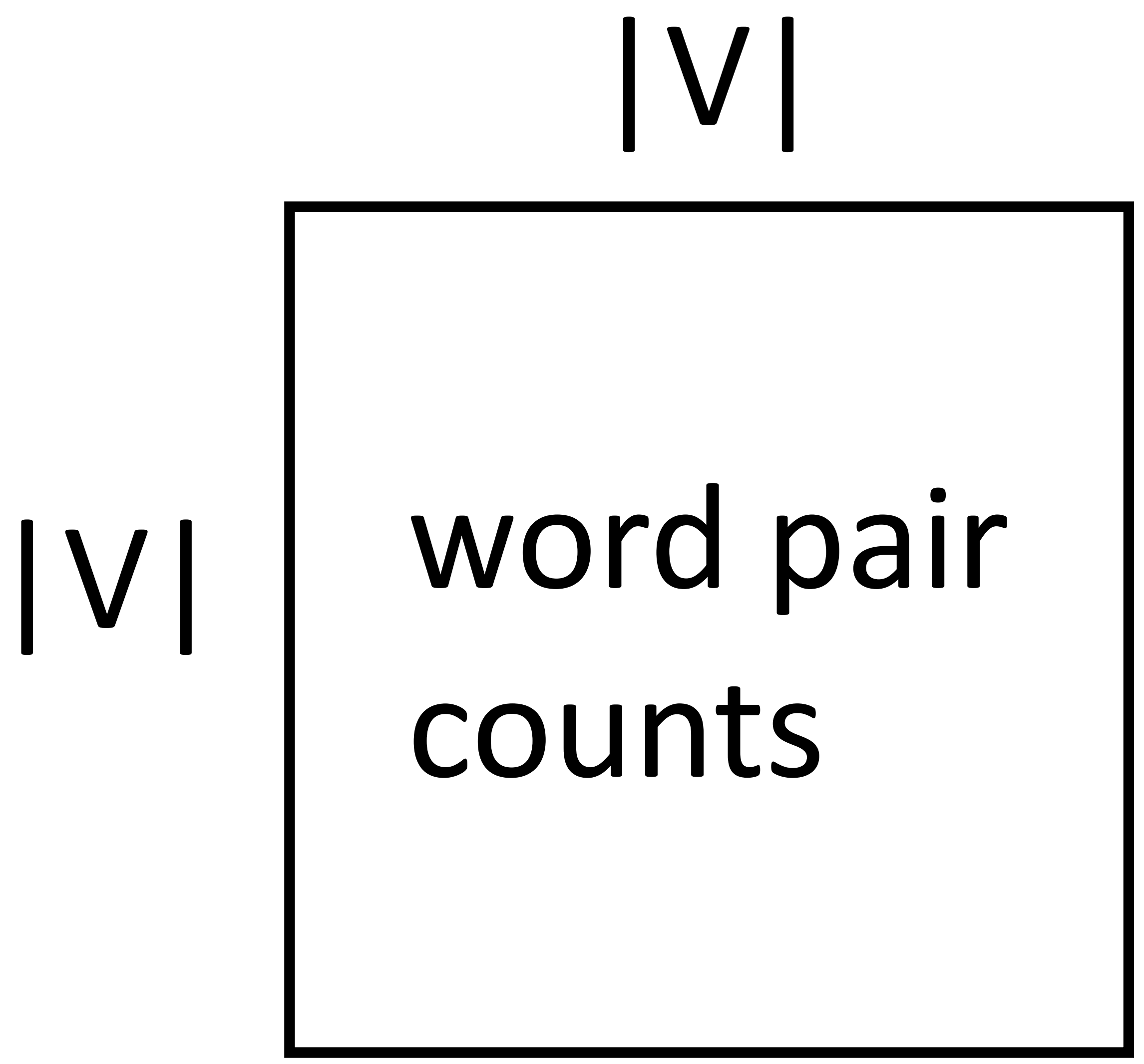

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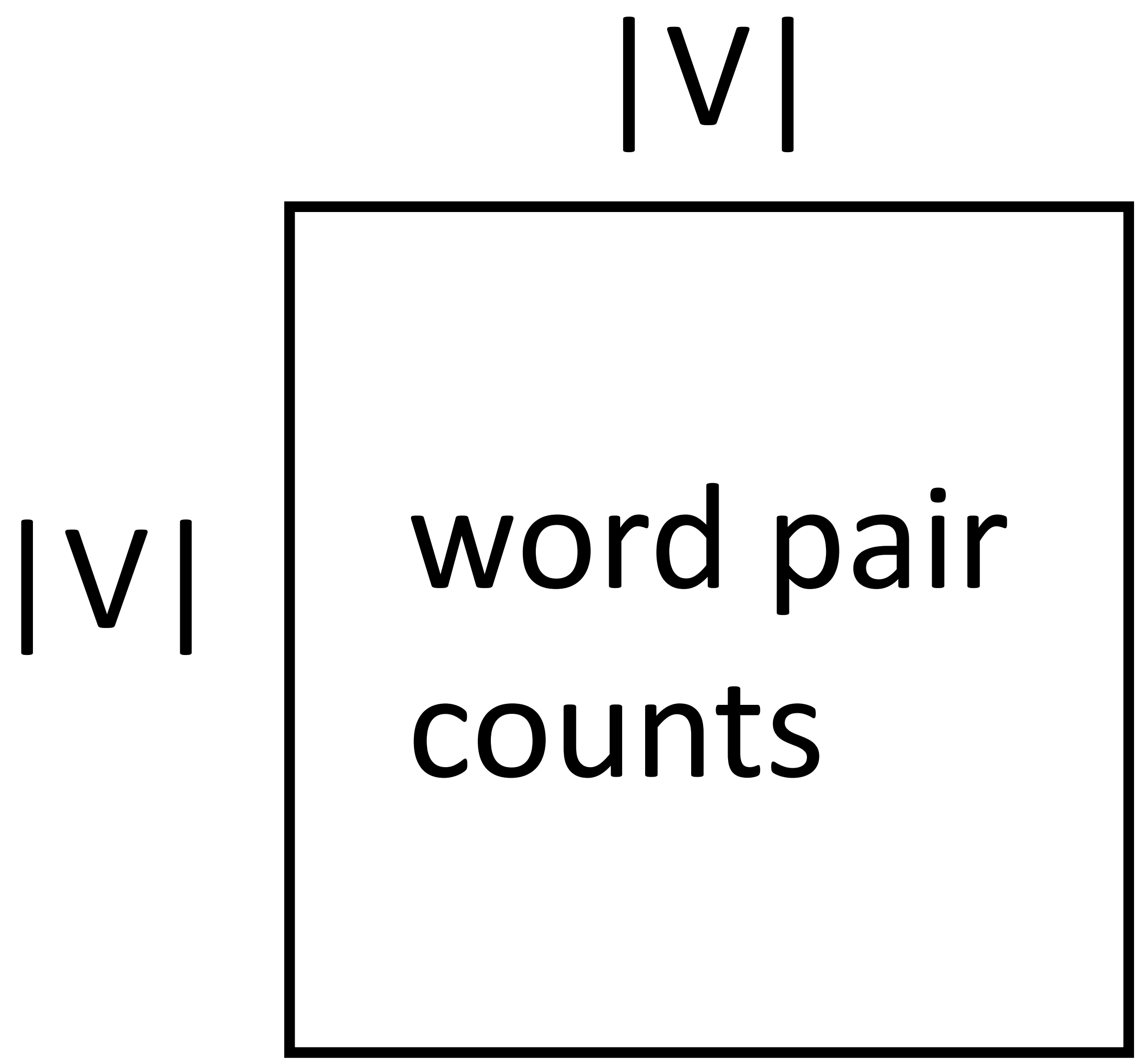

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- Constant in the dataset size (just need counts), quadratic in voc size
- By far the most common word vectors used today (5000+ citations)

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

Peters et al. (2018)

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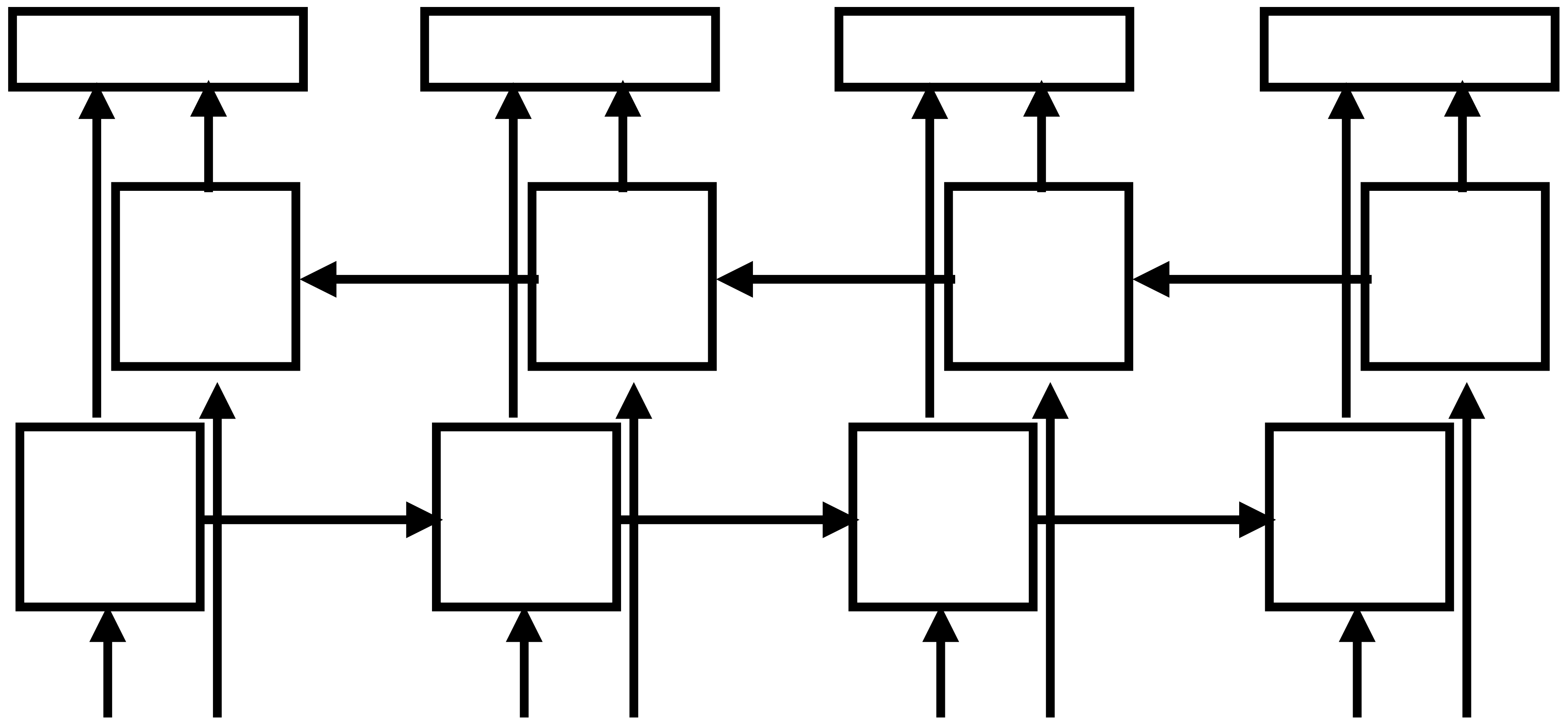

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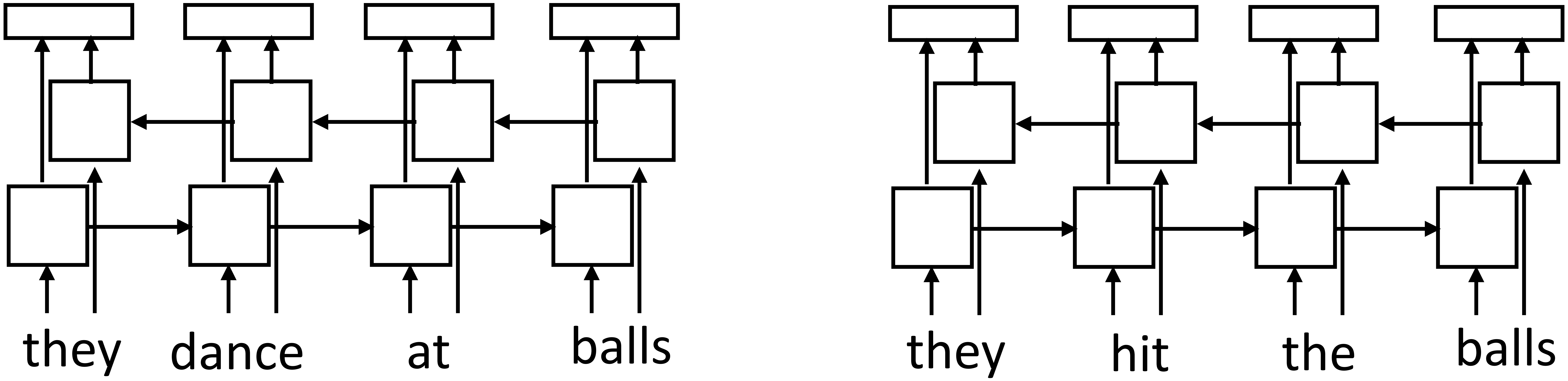

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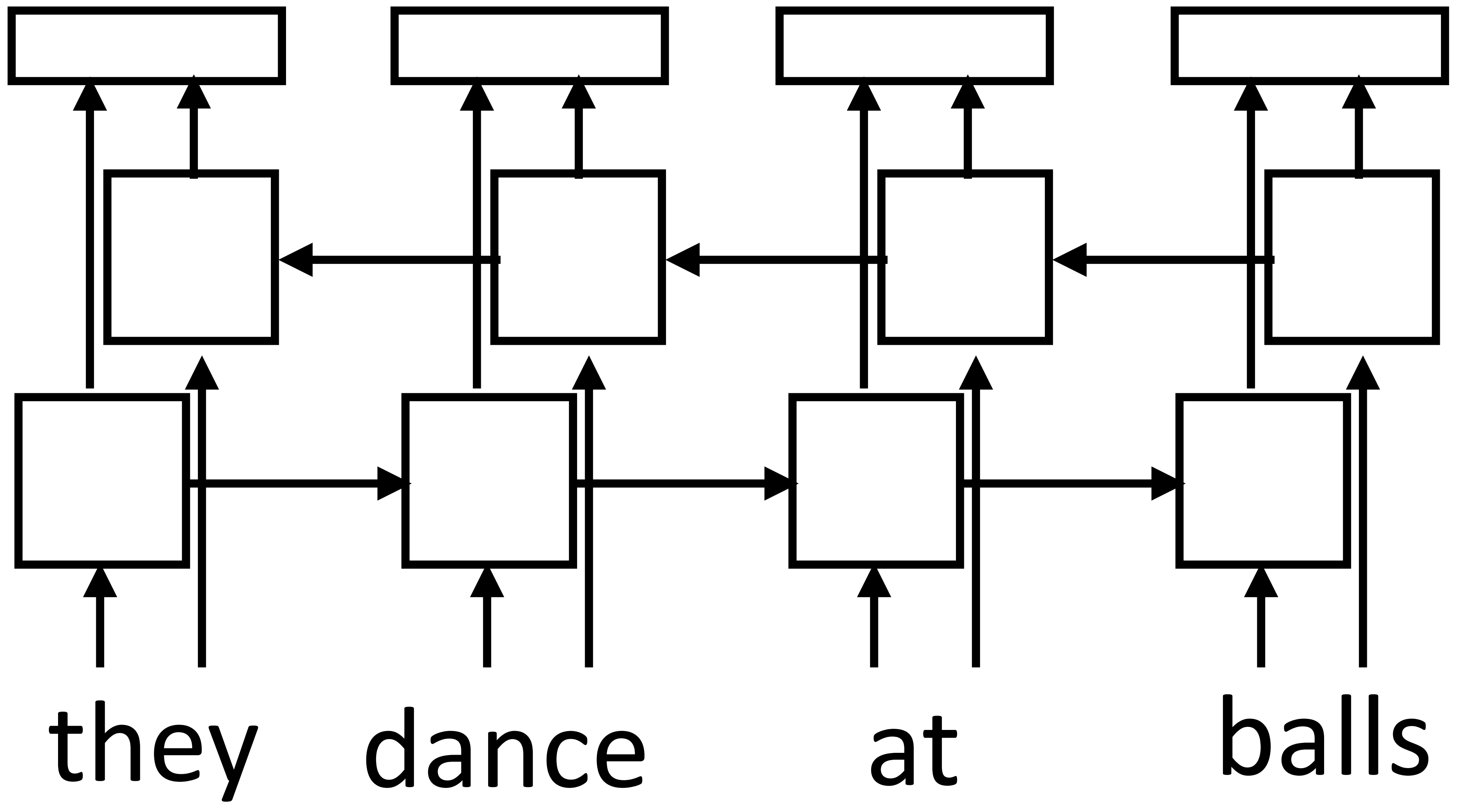

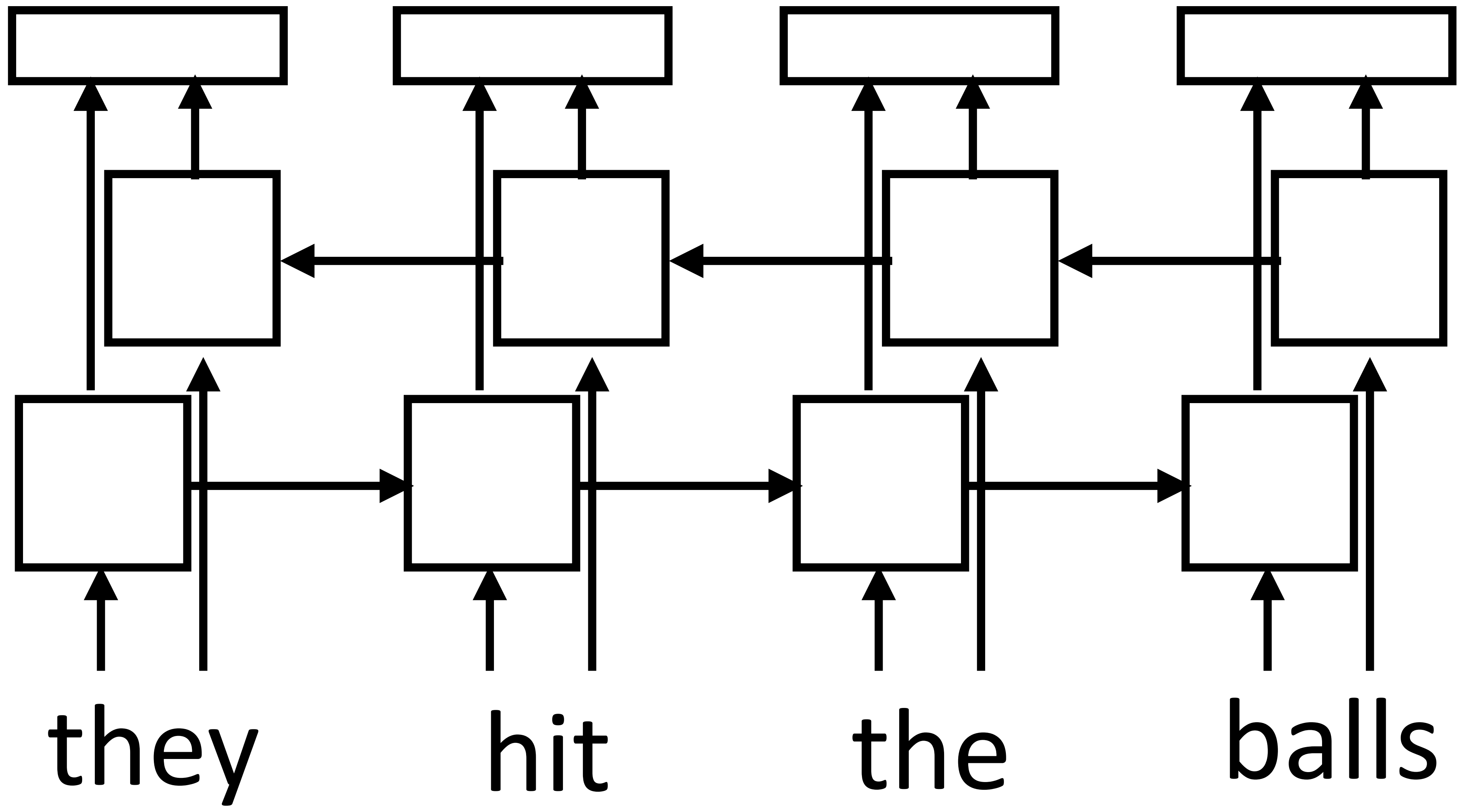

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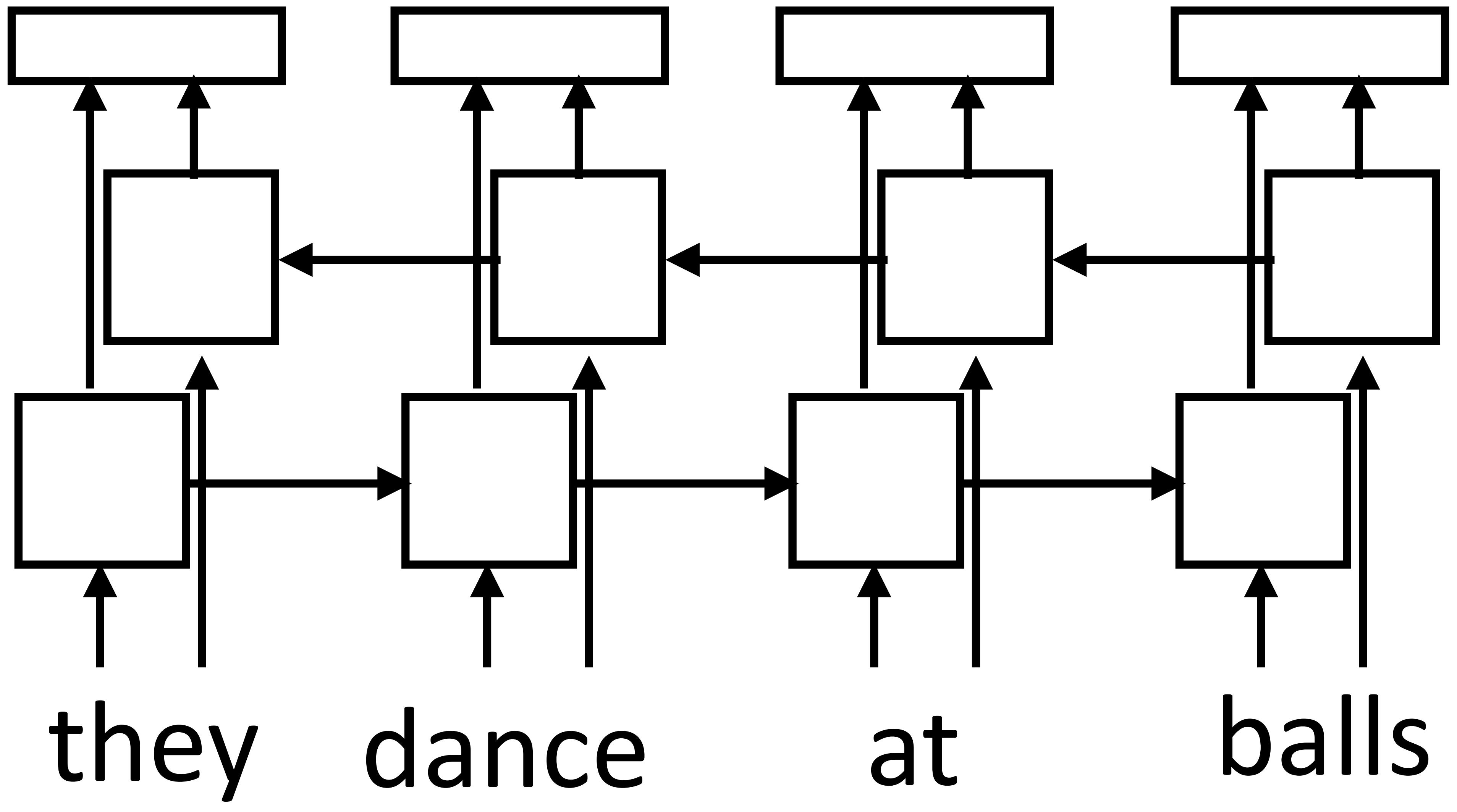

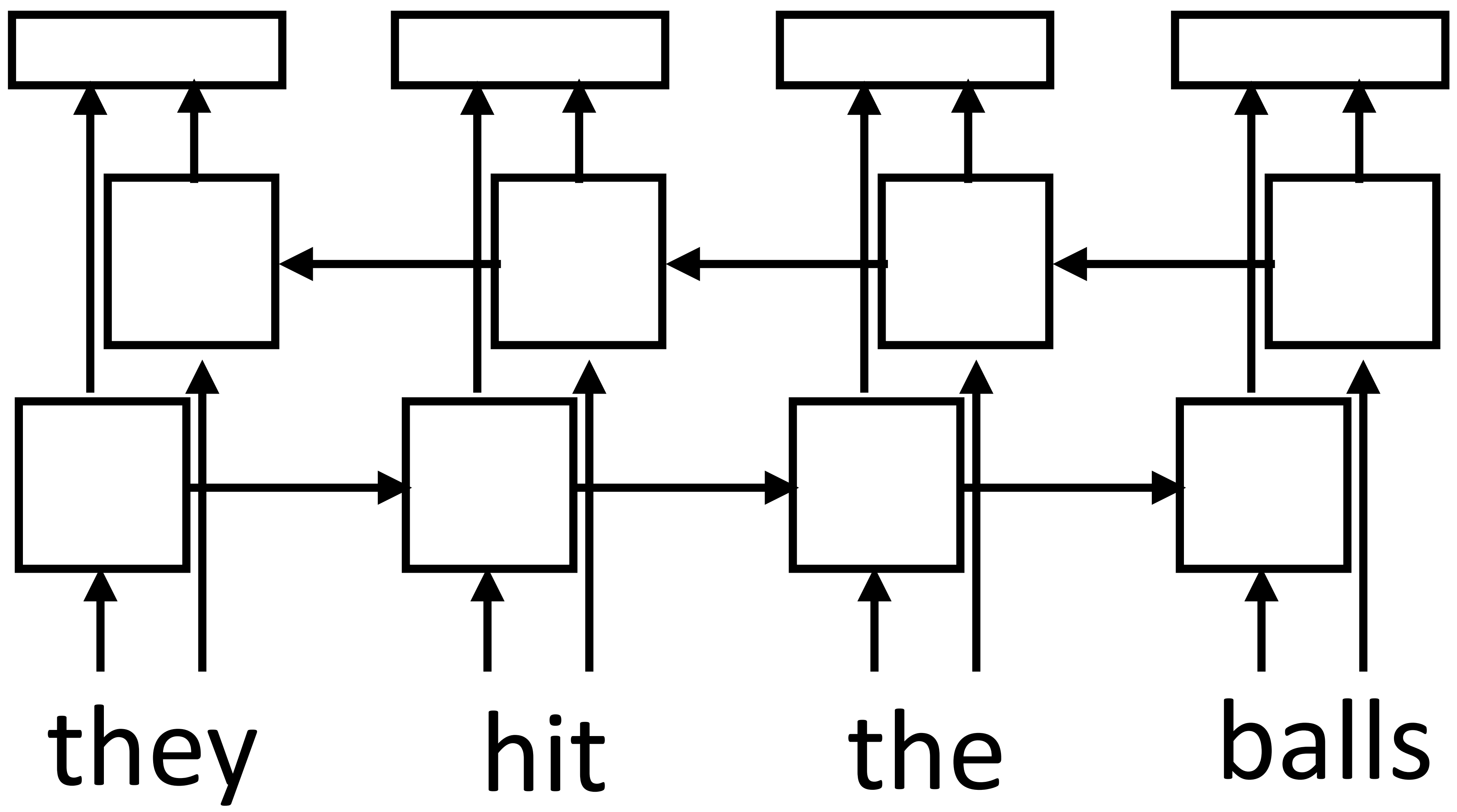

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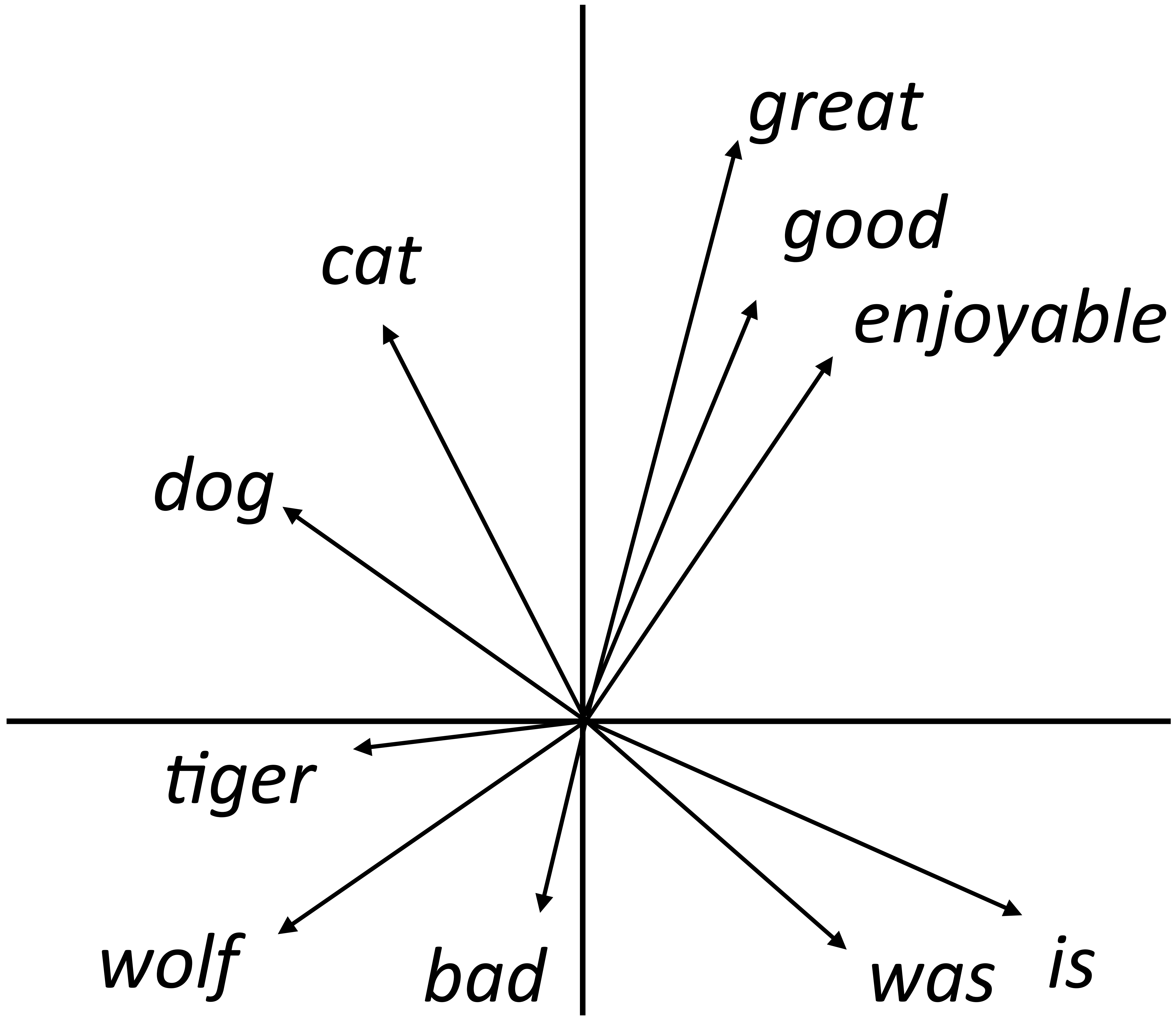
- *Context-sensitive* word embeddings: depend on rest of the sentence
- *Huge* improvements across nearly all NLP tasks over GloVe

Peters et al. (2018)

Evaluation

Evaluating Word Embeddings

- What properties of language should word embeddings capture?



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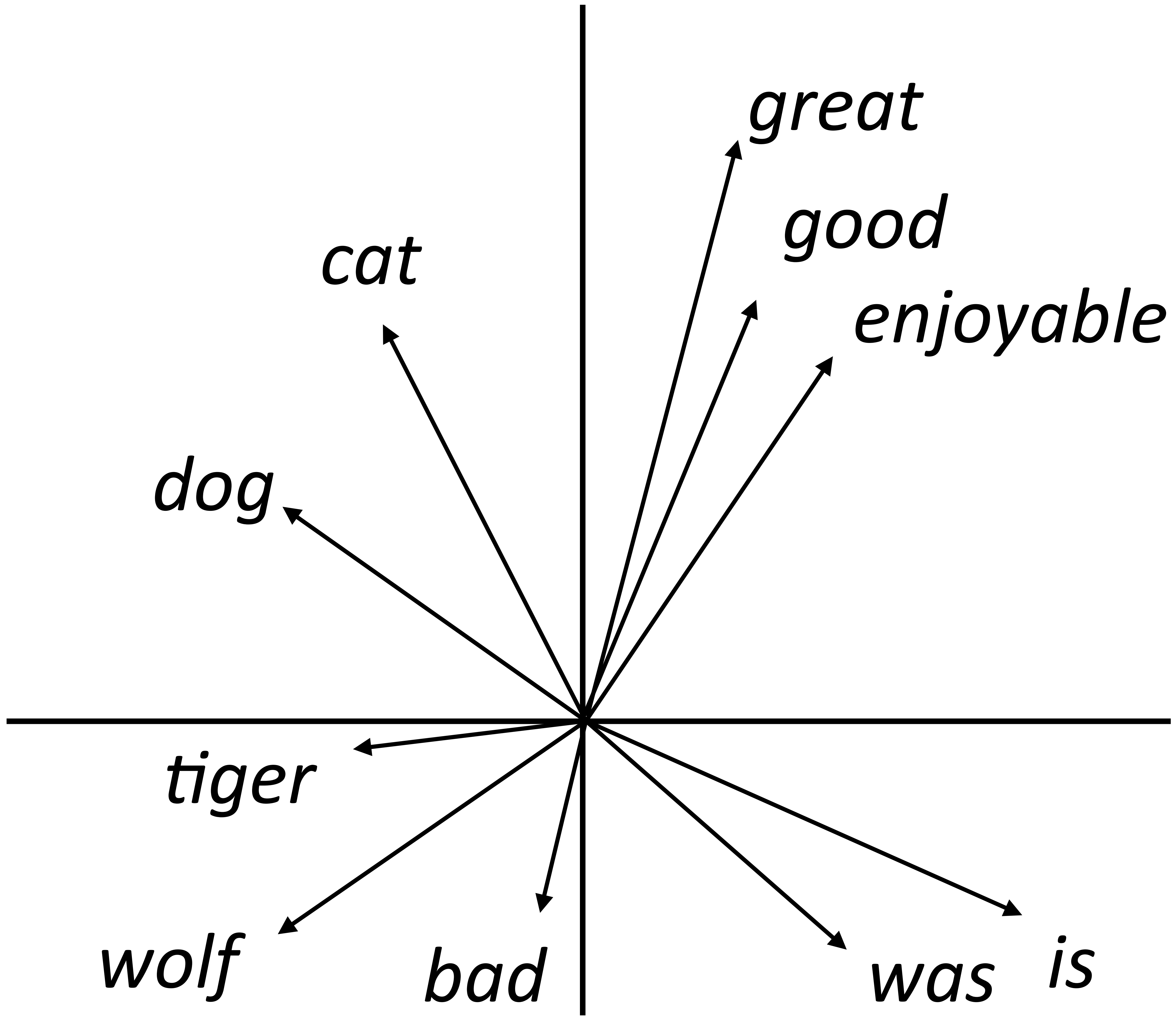

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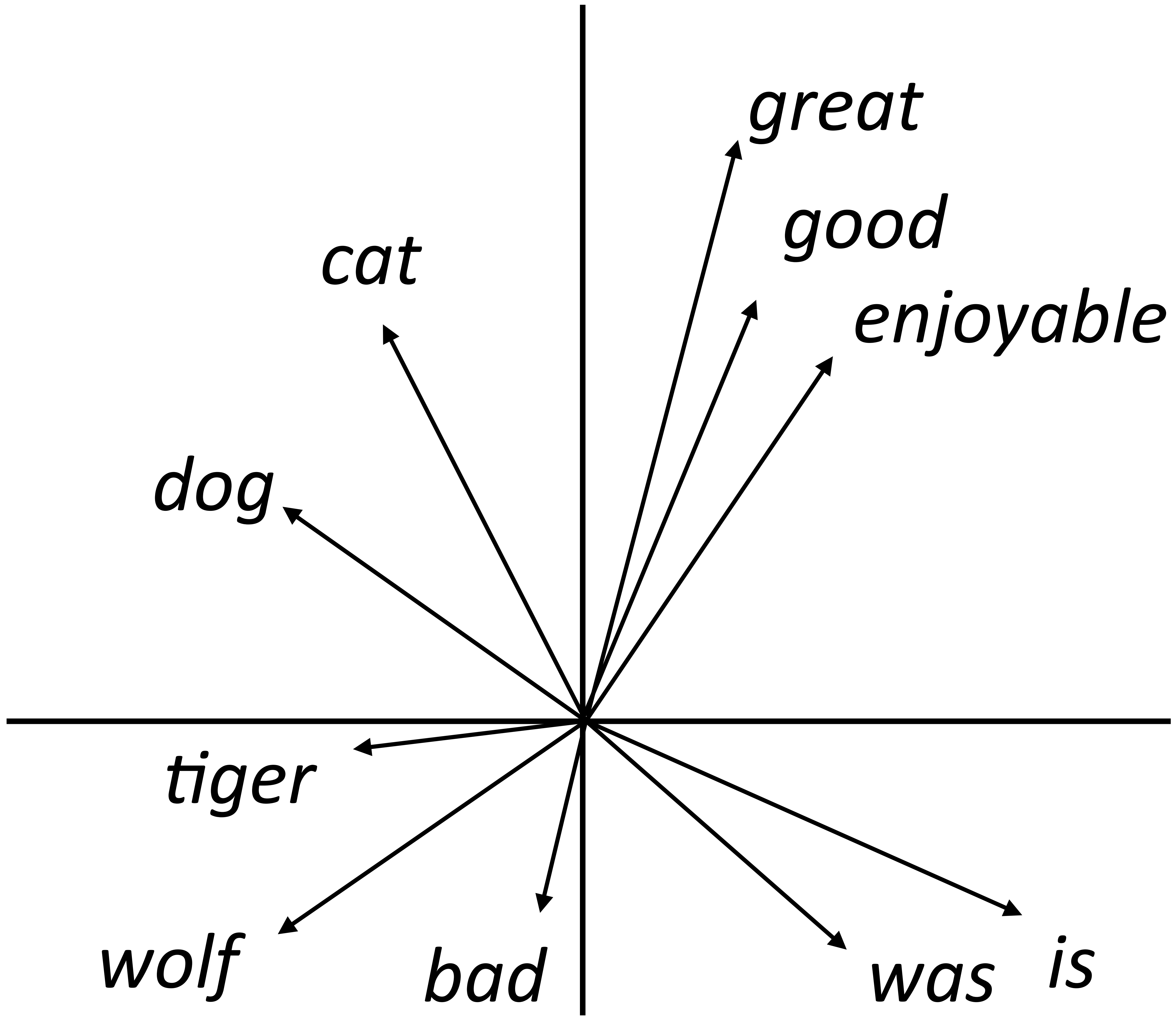

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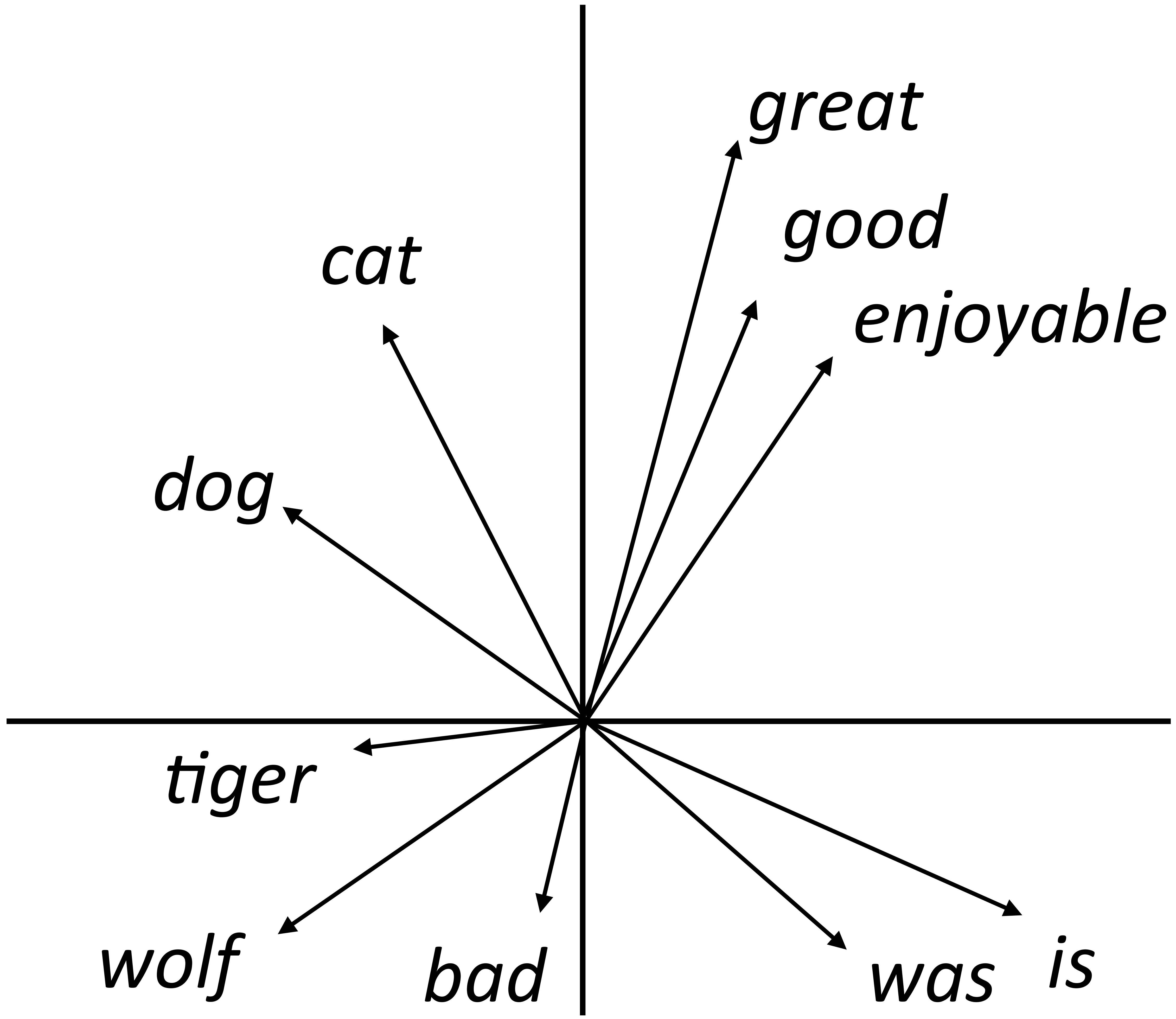

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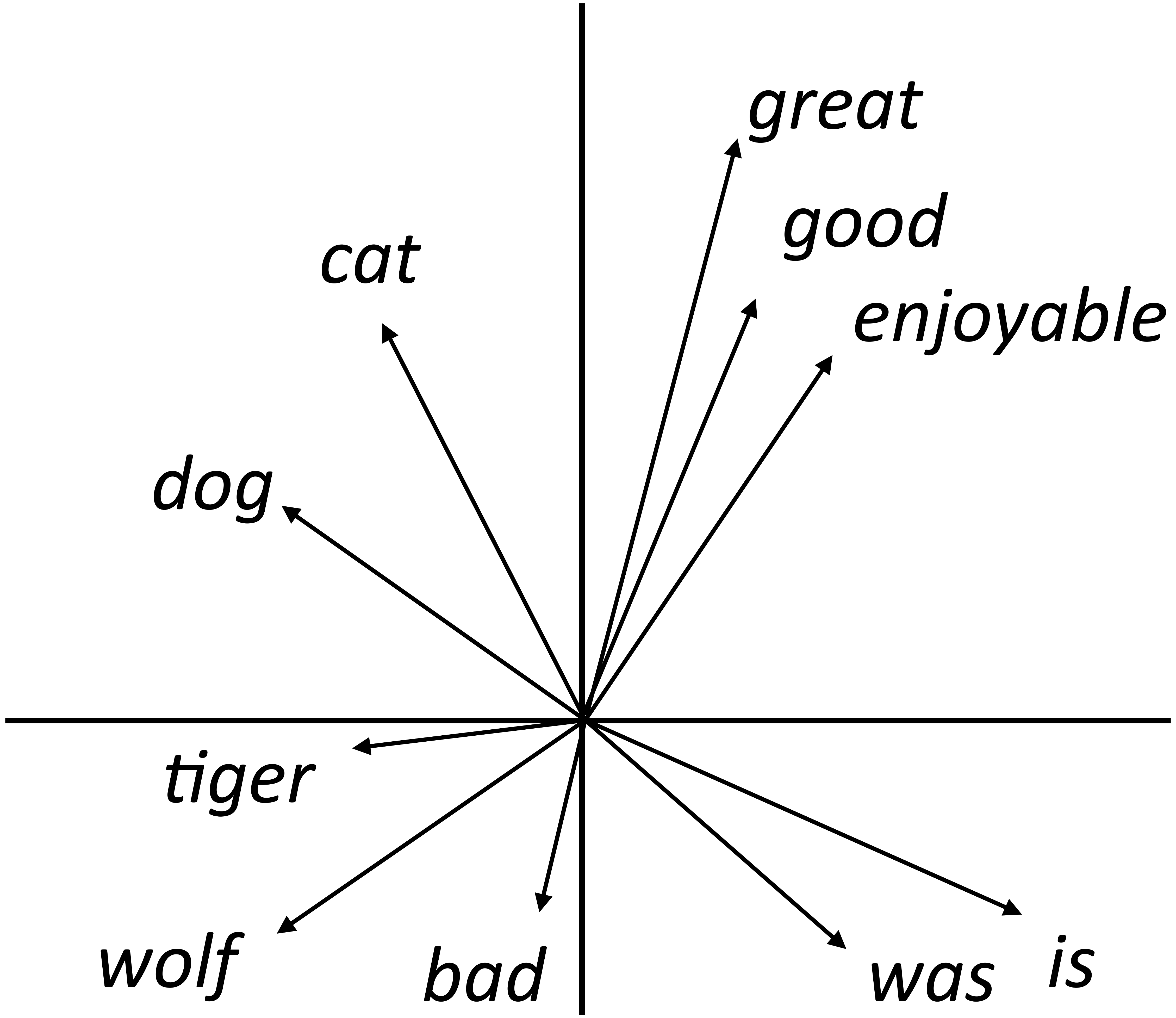

Similarity

Method	WordSim Similarity	WordSim Relatedness	Bruni et al. MEN	Radinsky et al. M. Turk	Luong et al. Rare Words	Hill et al. SimLex
PPMI	.755	**.697**	.745	.686	.462	.393
SVD	**.793**	.691	**.778**	.666	**.514**	.432
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- SVD = singular value decomposition on PMI matrix

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Levy et al. (2015)

Hypernymy Detection

- Hypernyms: detective *is a* person, dog *is a* animal

Chang et al. (2017)

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Word2Vec + C	52.1	**39.5**	20.7	**63.0**	25.3
GE + C	53.9	36.0	21.6	58.2	26.1
GE + KL	52.0	39.4	23.7	54.4	25.9
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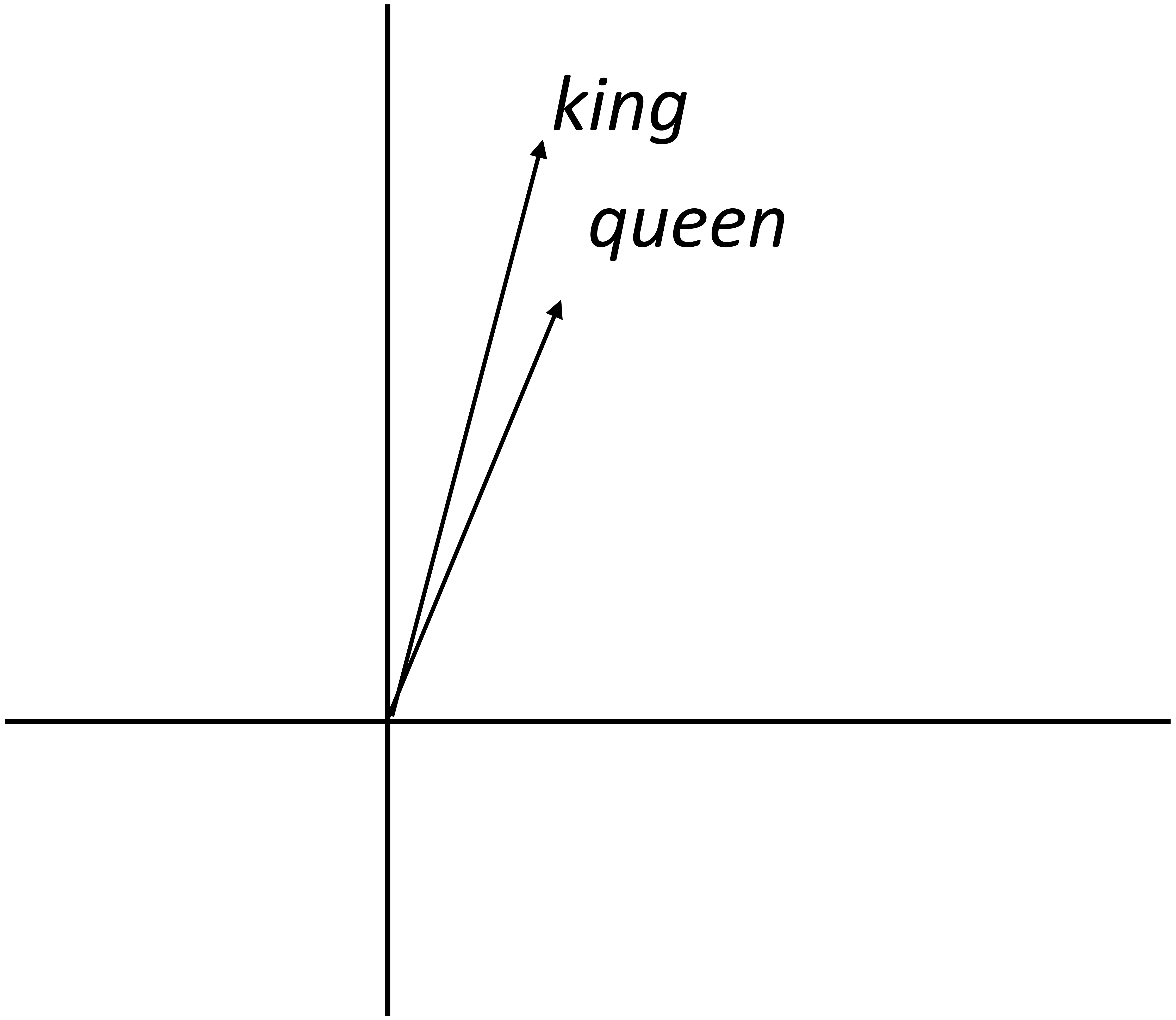
- word2vec (SGNS) works barely better than random guessing here

Chang et al. (2017)

Analogies



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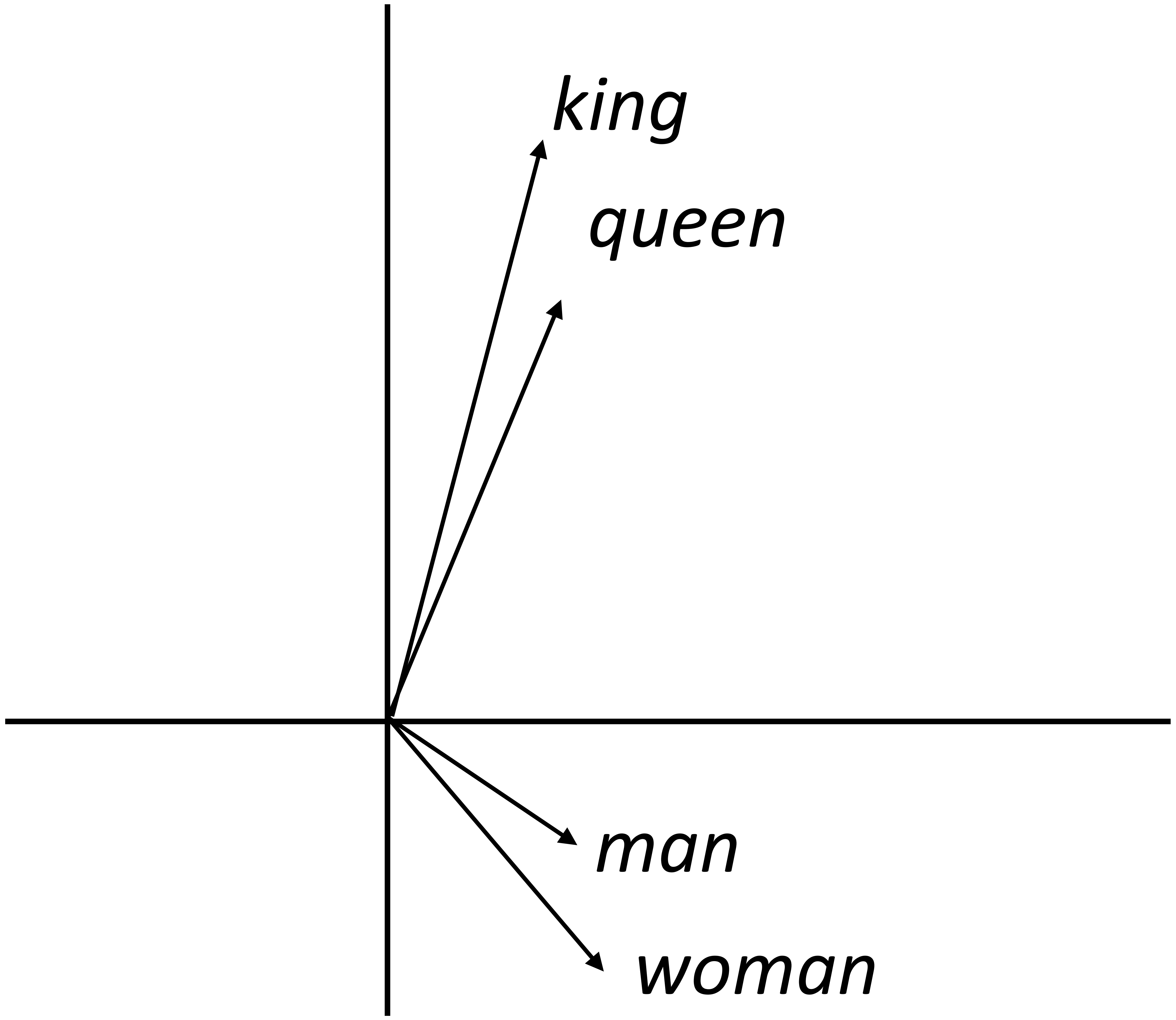
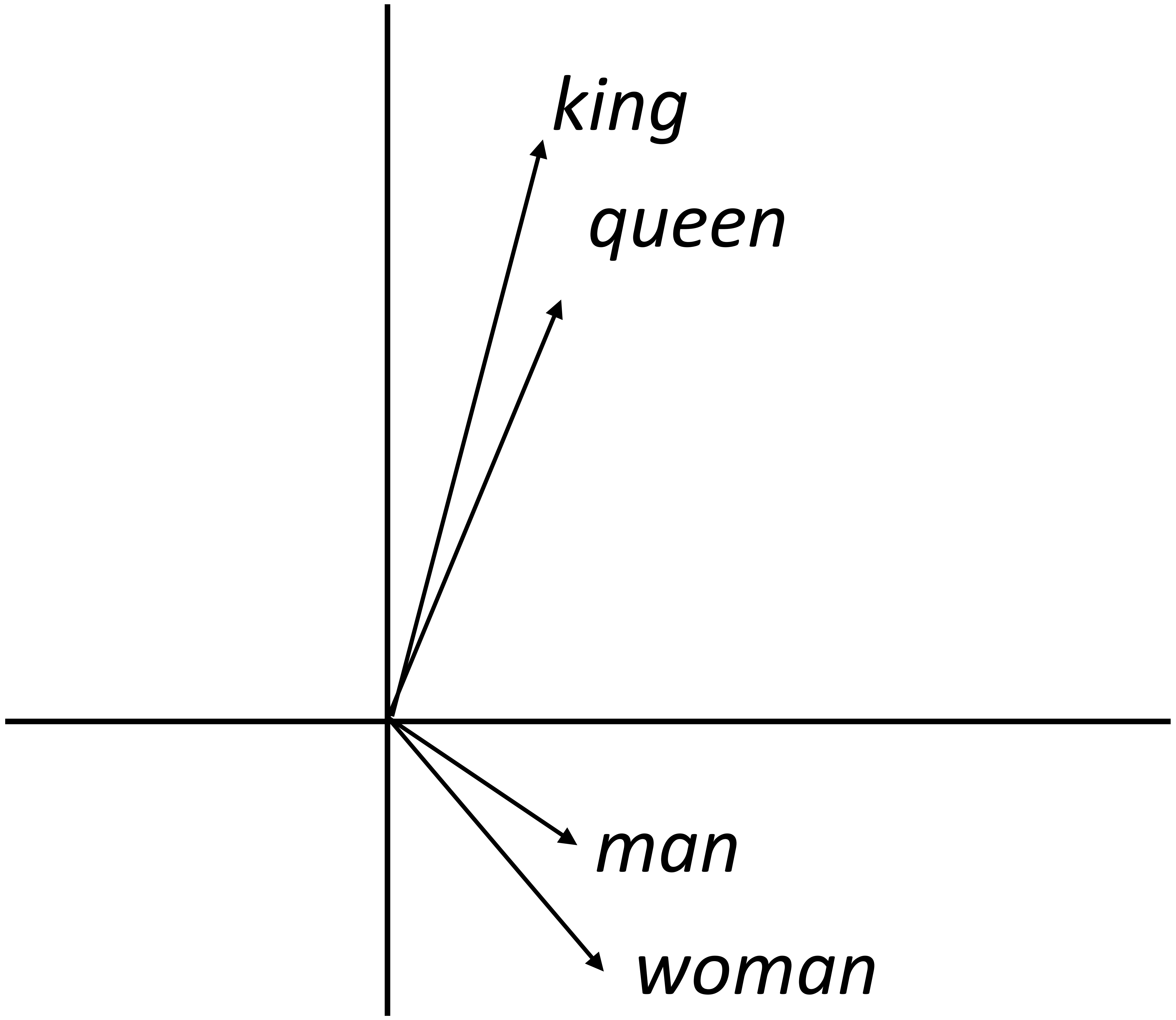


Analogies

(king - man) + woman = queen



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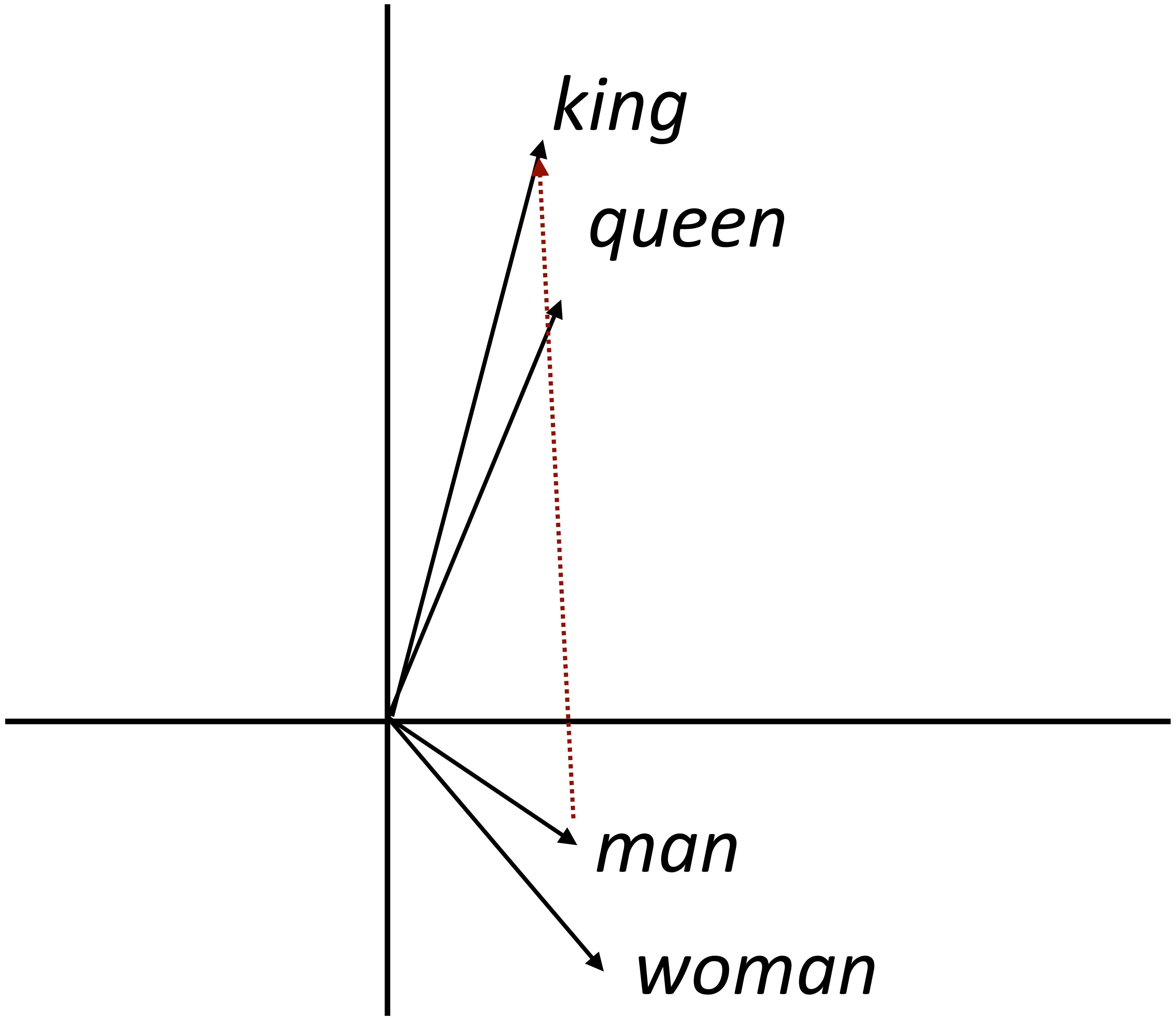

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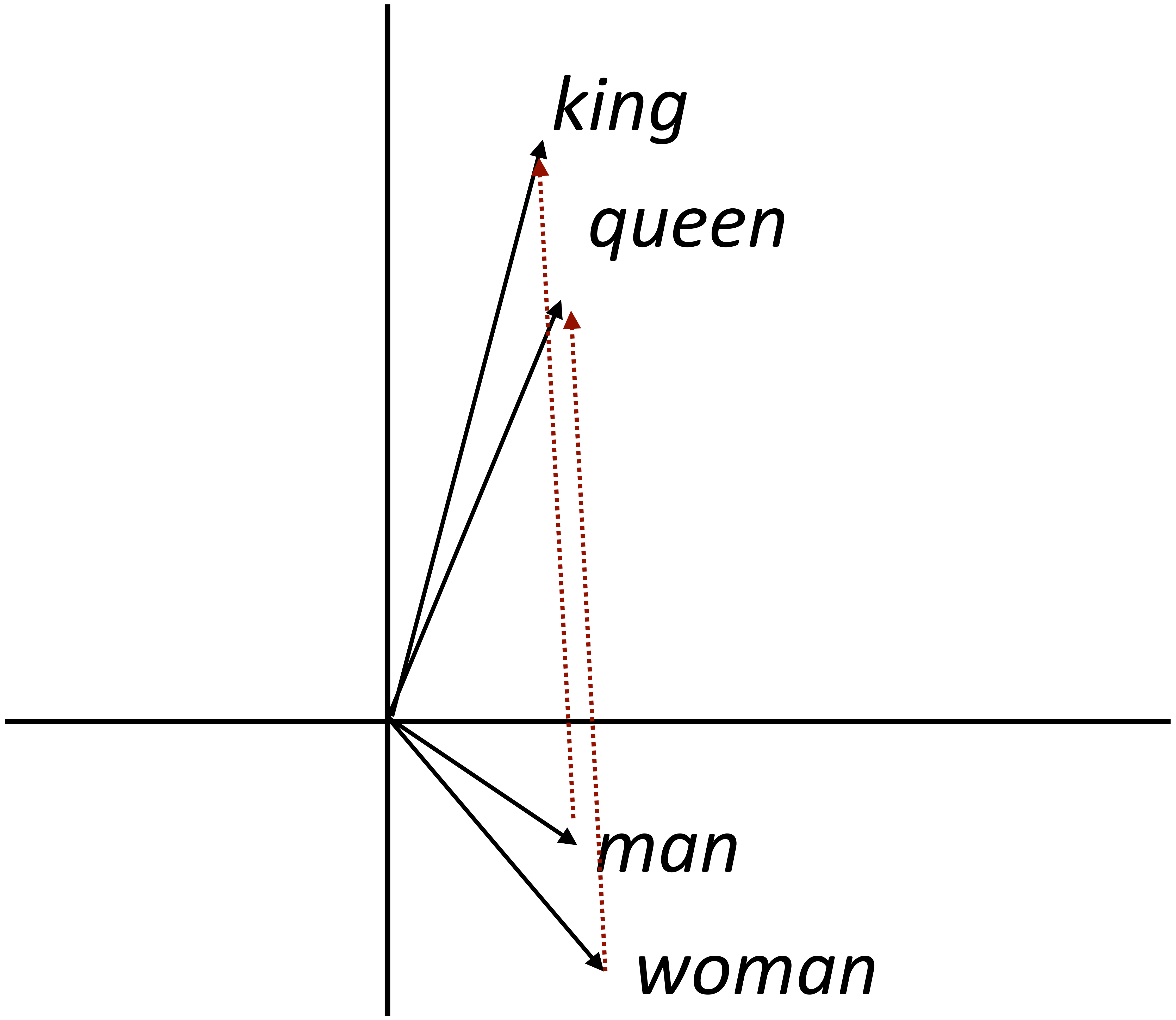

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(king - man) + woman = queen

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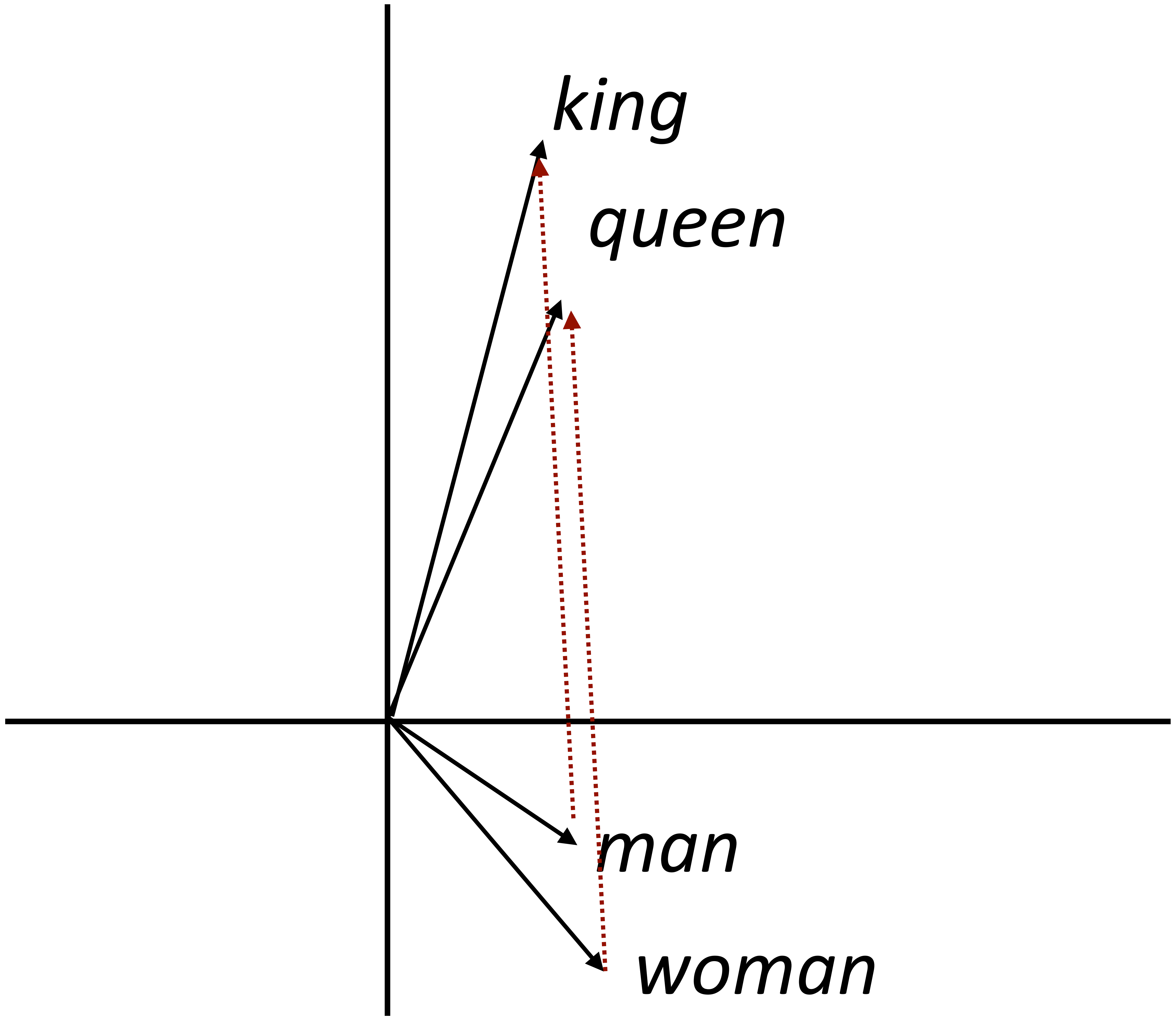

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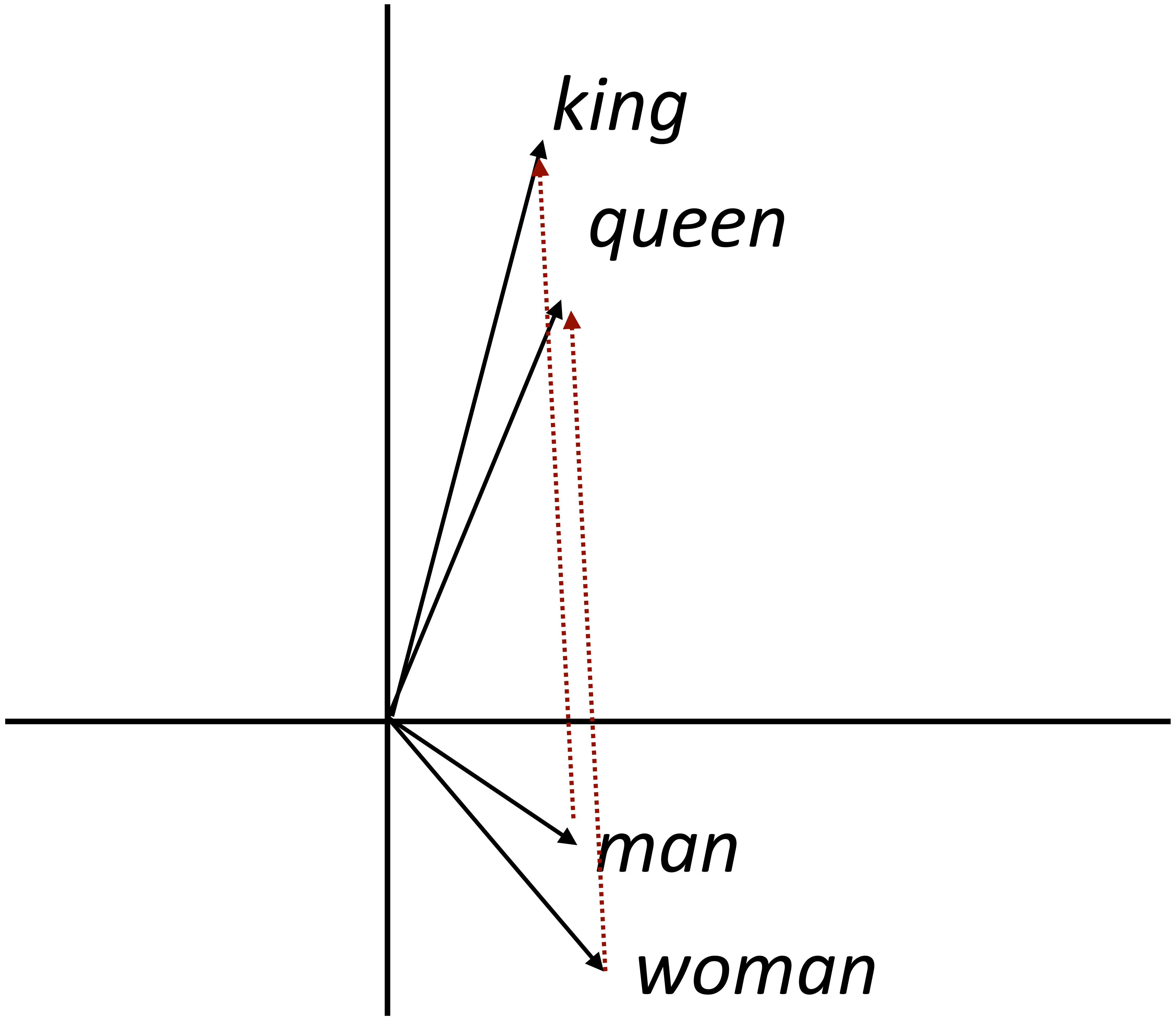

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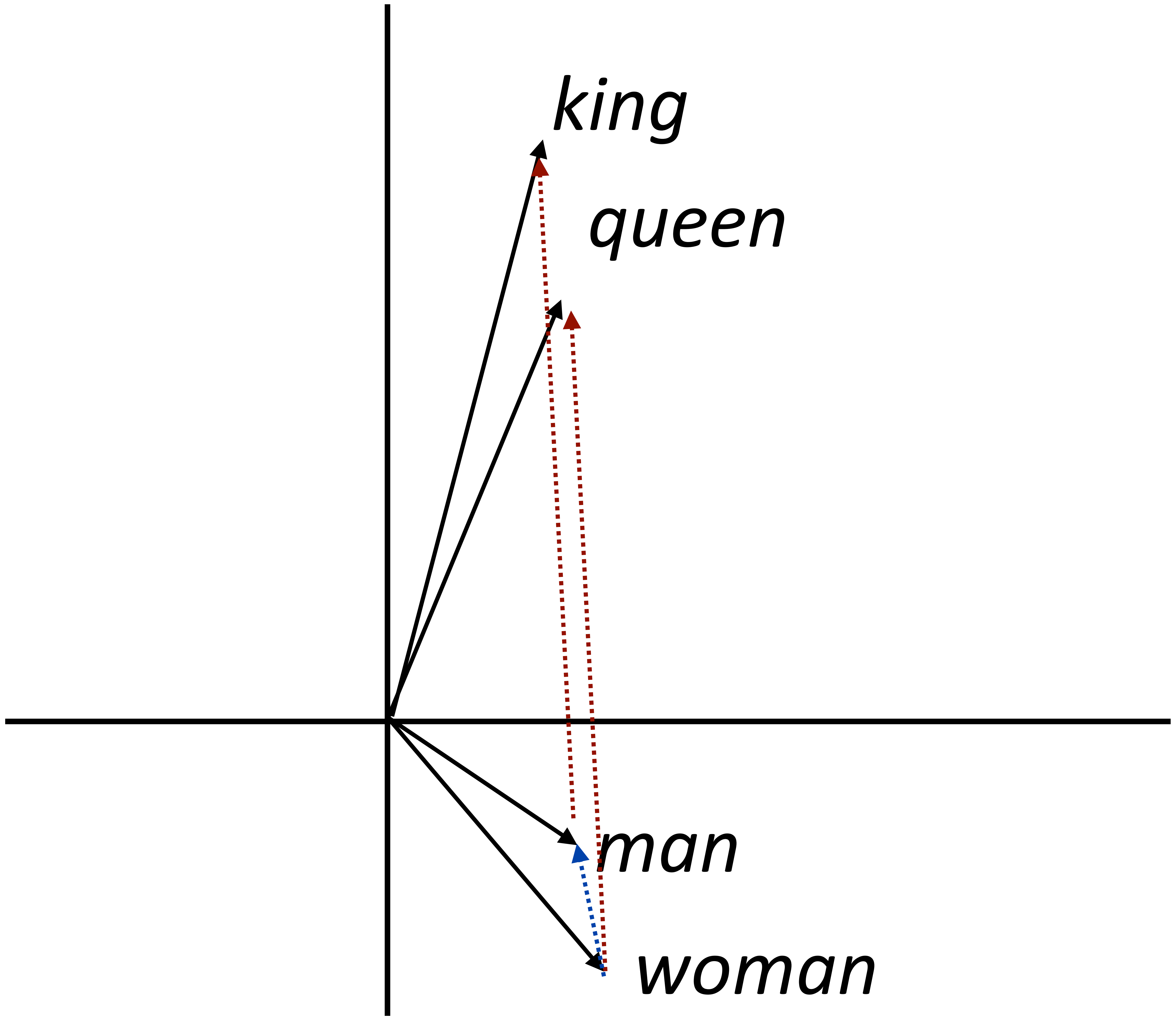

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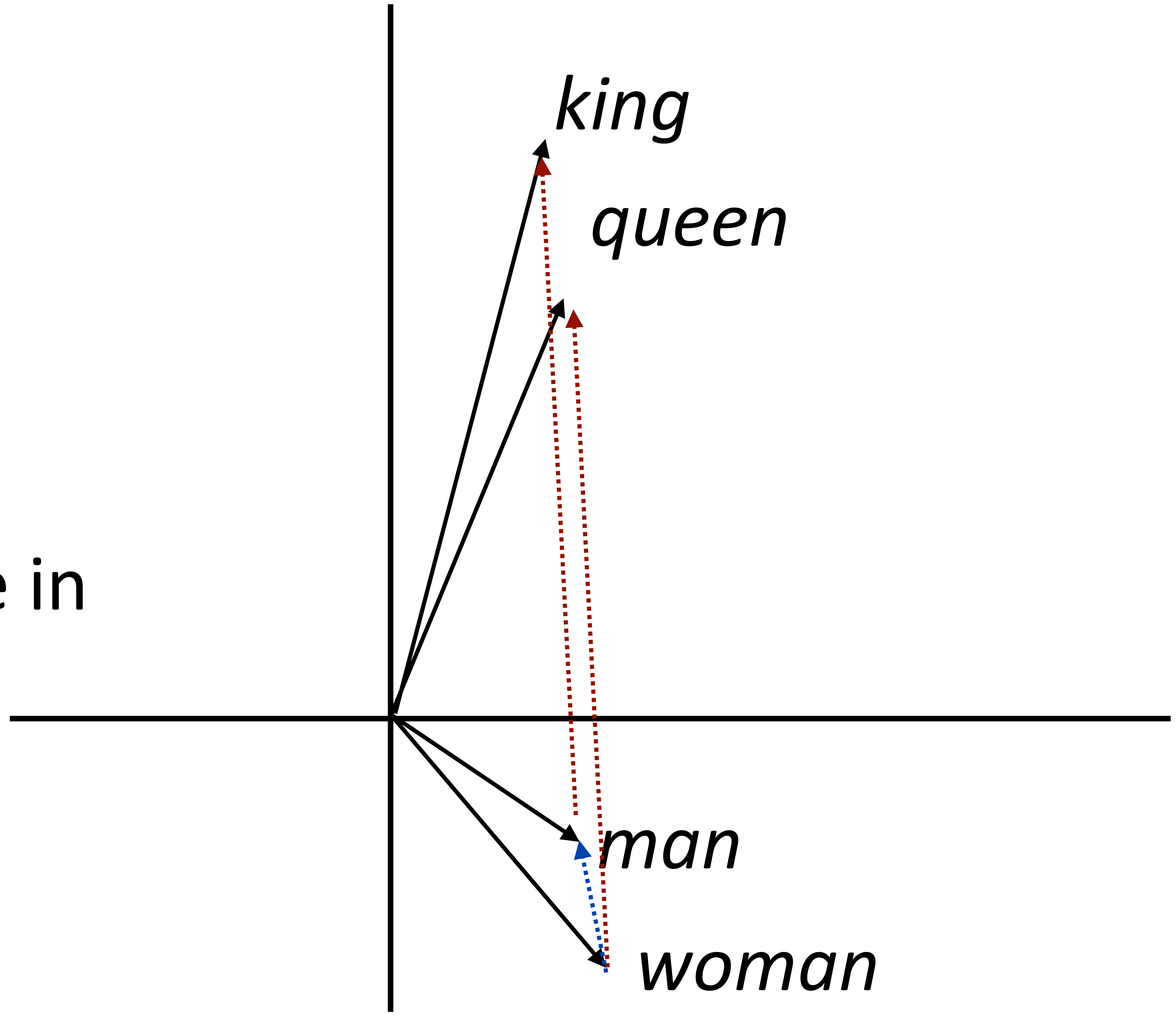

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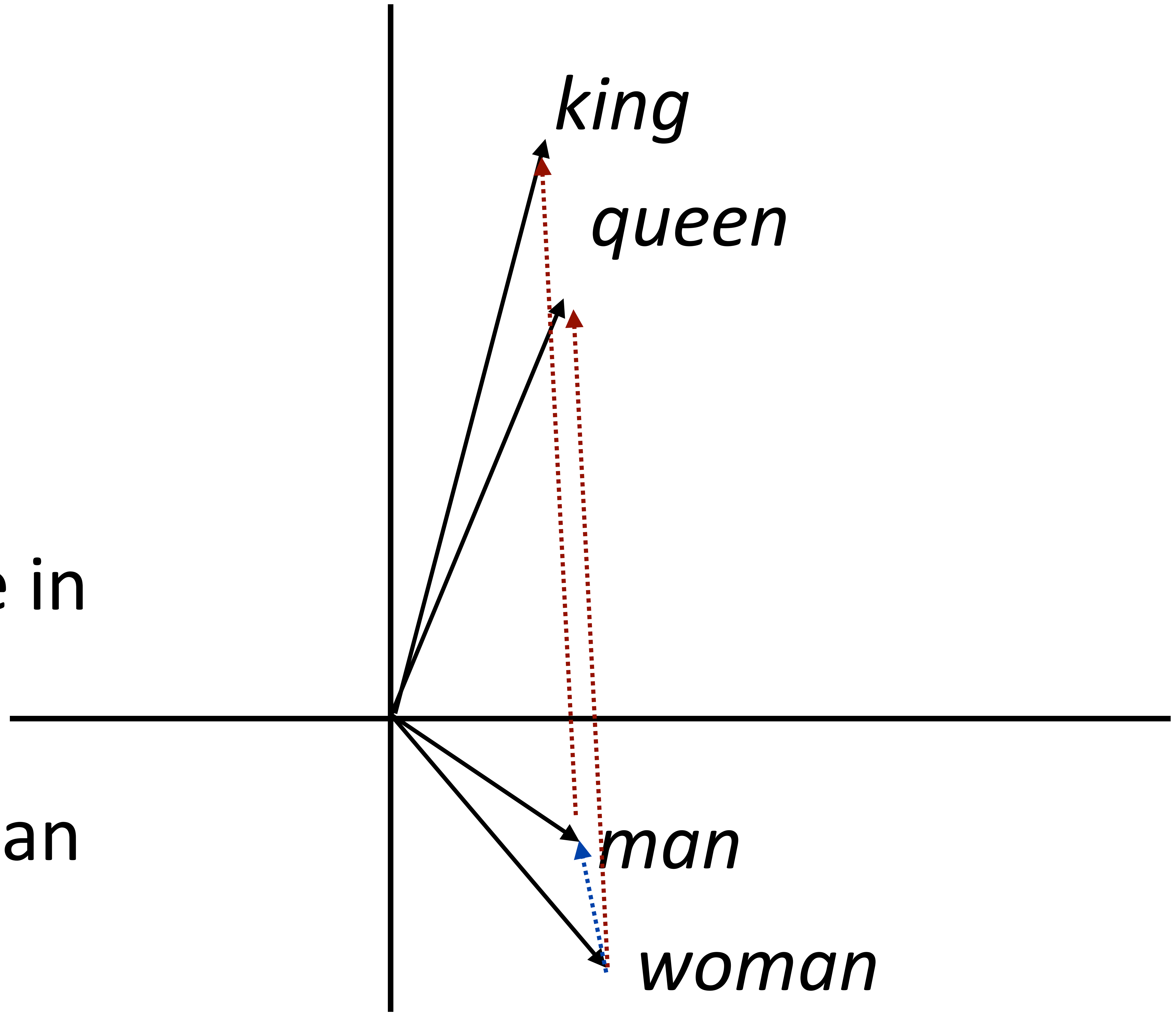
- Dominant change: more “he” with man and “she” with woman — similar to difference between king and queen



Analogies

Method	Google Add / Mul	MSR Add / Mul
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Levy et al. (2015)

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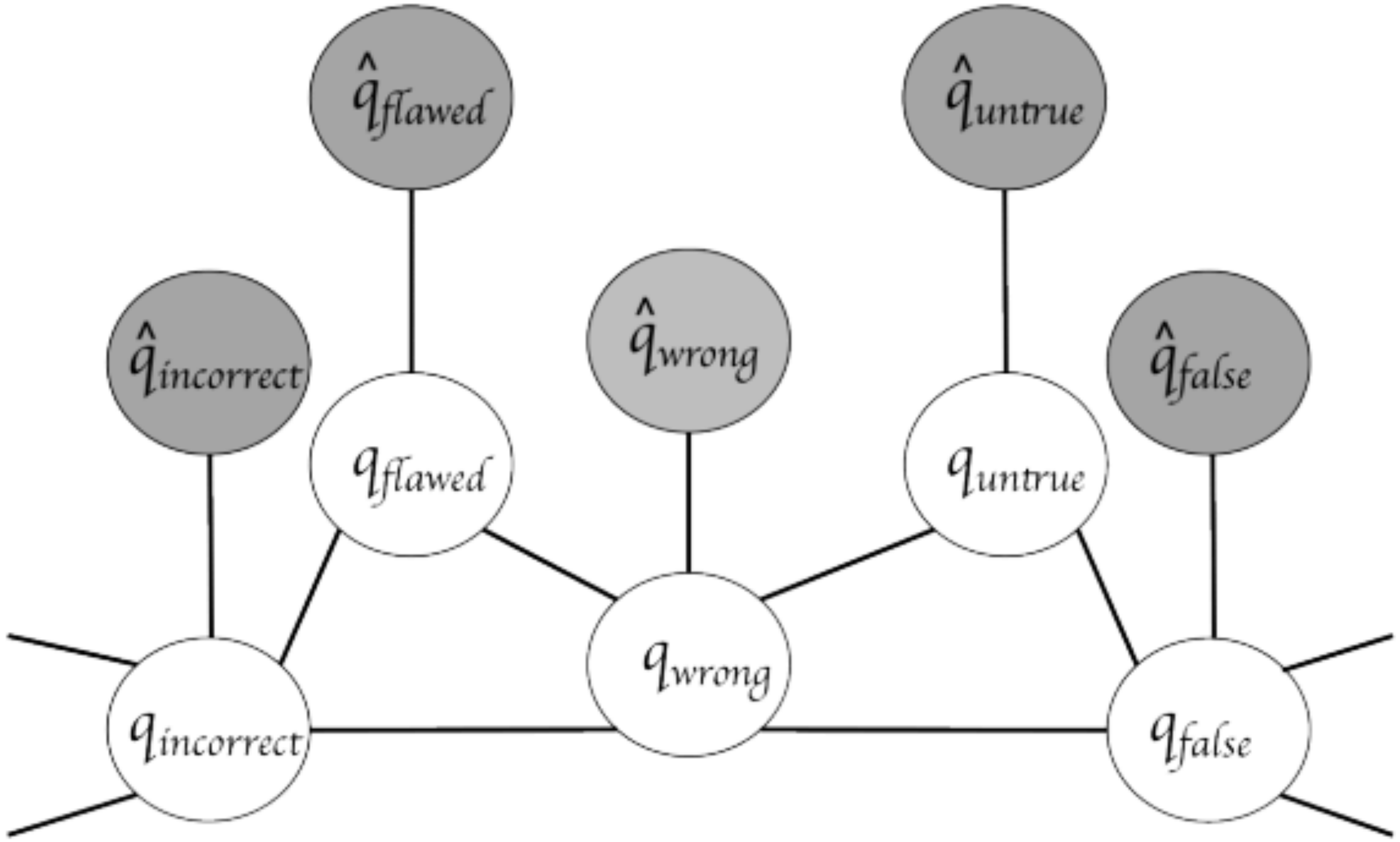
Maximizing for *b*: Add = $\cos(b, a_2 - a_1 + b_1)$ Mul = $\dfrac{\cos(b_2, a_2)\cos(b_2, b_1)}{\cos(b_2, a_1) + \epsilon}$

Levy et al. (2015)

Using Semantic Knowledge



Faruqui et al. (2015)

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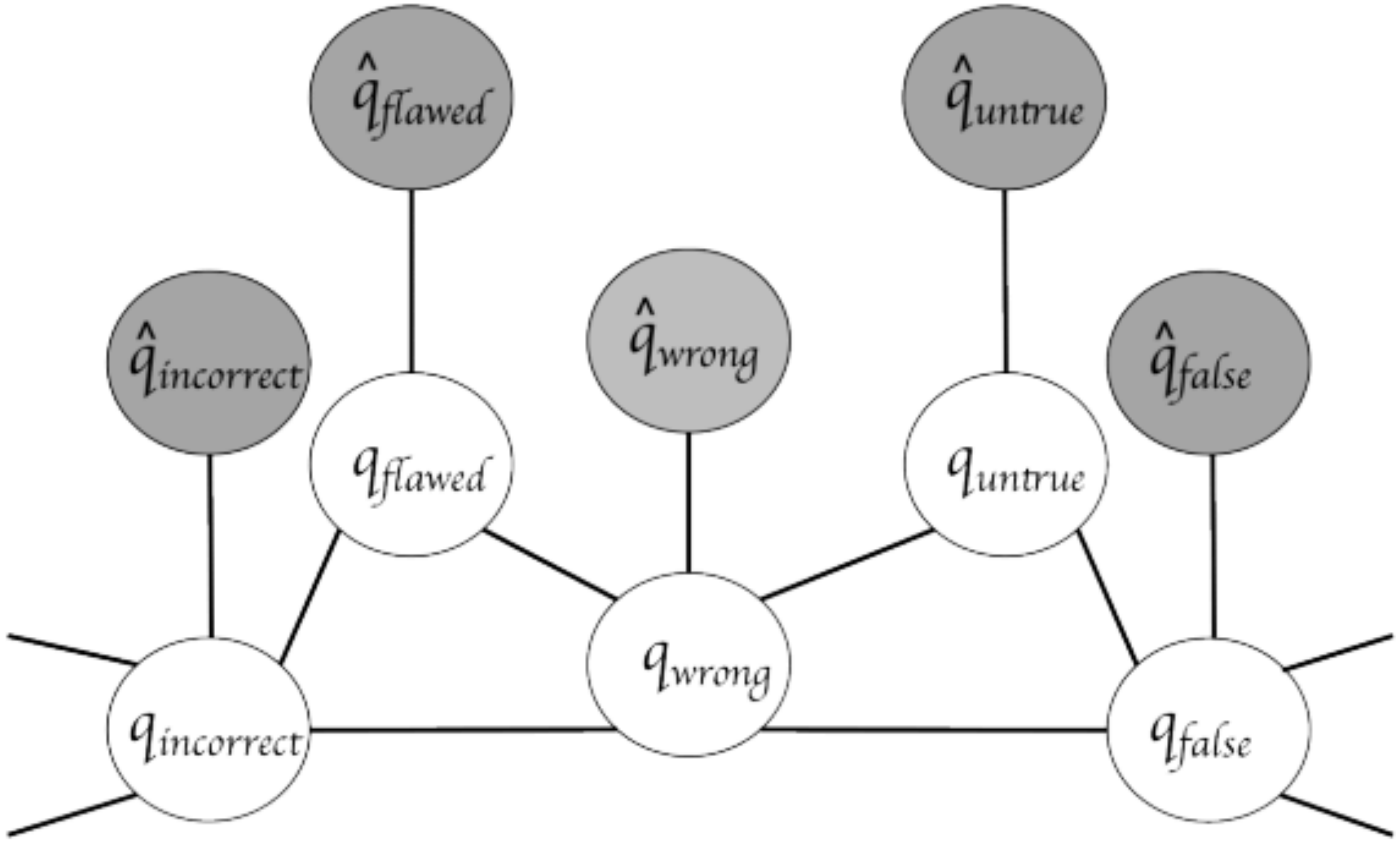

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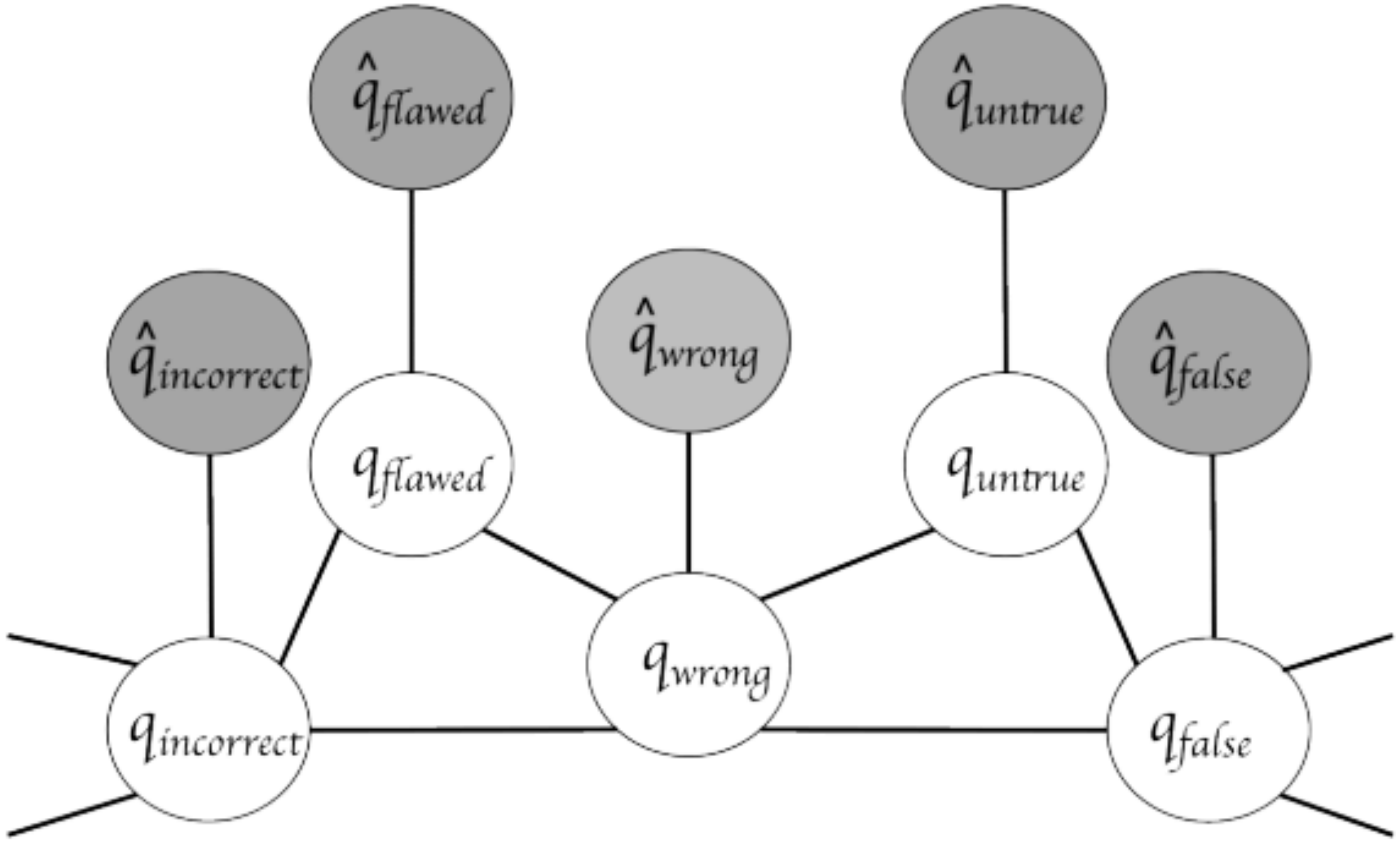

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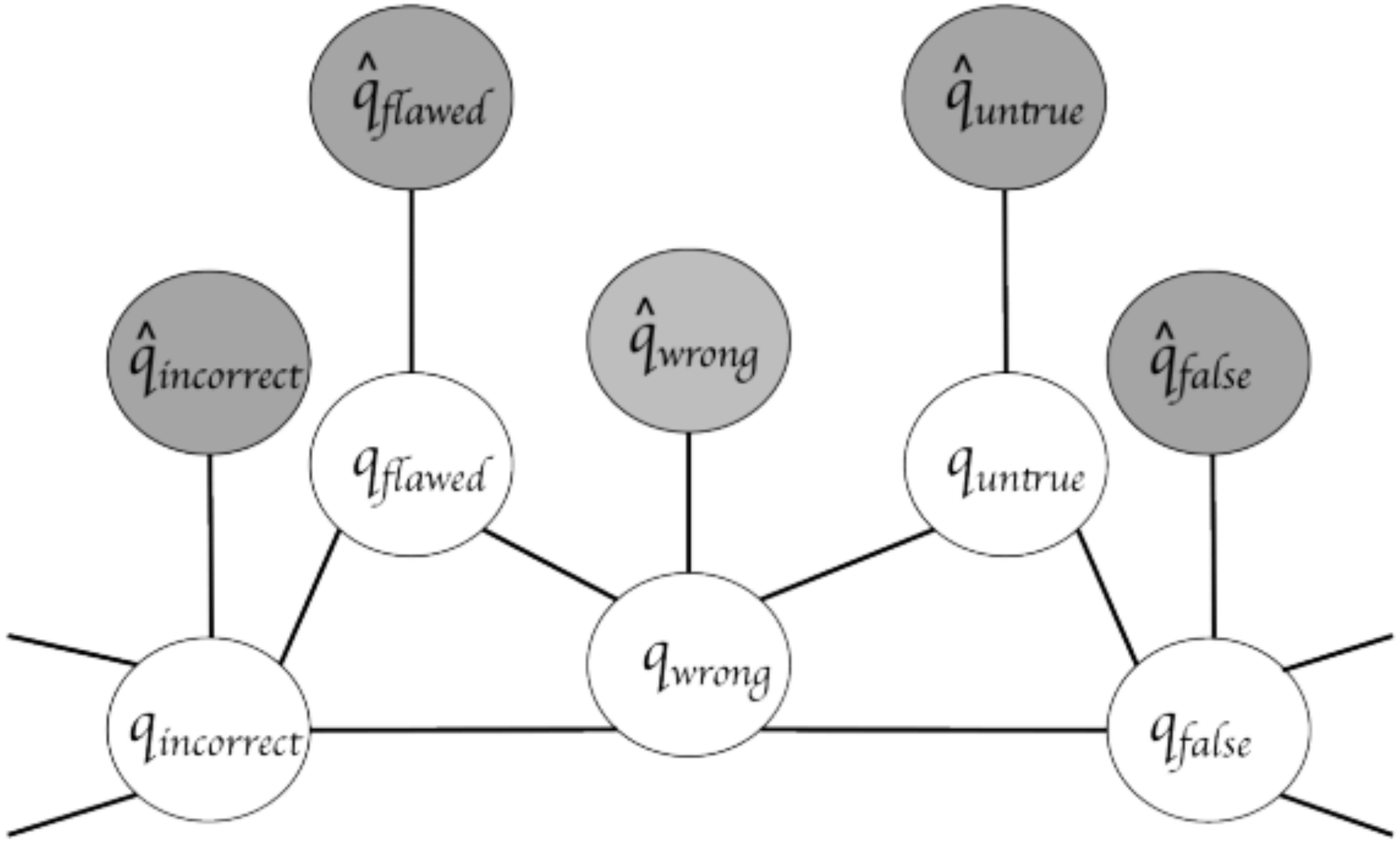

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- Structure derived from a resource like WordNet
- Doesn't help most problems

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- 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 as we move on to syntax and semantics

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- Next time: RNNs and CNNs