



Lecture 7: Feed-forward Neural Nets

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USC CSCI 544 Applied NLP
Sep 17, Fall 2024



Announcements + Logistics

Announcements + Logistics

- Thu: HW1 due / HW2 released
- Today: Quiz 2
- Next Thu: Project Proposal Due
- For queries, please contact all TAs / graders / myself through the mailing list:
 - Not just me
 - 2024f-csci544-staff@googlegroups.com

Lecture Outline

- Announcements
- Recap: Sparse and Dense Word Embeddings, word2vec
- GloVe
- Word Embeddings: Properties and Evaluation
- Quiz 2
- Feed-forward Neural Nets

Recap: Sparse Word Embeddings

Term-document matrix

Let us consider a collection of documents and count how frequently a word (**term**) appears in each. A document could be a play or a Wikipedia article. In general, documents can be anything; we often call each paragraph a document!

Each **document** is represented by a vector of words

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

Word-word co-occurrence matrix

Context
Window

is traditionally followed by **cherry** pie, a traditional dessert
often mixed, such as **strawberry** rhubarb pie. Apple pie
computer peripherals and personal **digital** assistants. These devices usually
a computer. This includes **information** available on the internet

Two words are similar in meaning if their context vectors are similar

Words, not
documents



	aardvark	...	computer	data	result	pie	sugar	...
cherry	0	...	2	8	9	442	25	...
strawberry	0	...	0	0	1	60	19	...
digital	0	...	1670	1683	85	5	4	...
information	0	...	3325	3982	378	5	13	...

Pointwise Mutual Information (PMI)

$$PMI(w_1, w_2) = \log \frac{P(w_1, w_2)}{P(w_1)P(w_2)}$$

- **PMI between two words:**

- Do words w_1 and w_2 co-occur more than if they were independent?
- PMI ranges from $-\infty$ to $+\infty$
 - Negative values are problematic: words are co-occurring less than we expect by chance
 - Only reliable under an enormous corpora
 - Imagine w_1 and w_2 whose probability of occurrence is each 10^{-6}
 - Hard to be sure $P(w_1, w_2)$ is significantly different than 10^{-12}
 - So we just replace negative PMI values by 0

- **Positive PMI**

$$PPMI(w_1, w_2) = \max \left(0, \log \frac{P(w_1, w_2)}{P(w_1)P(w_2)} \right)$$

Computing PPMI on a term-context matrix

Context c

	computer	data	result	pie	sugar	count(w)
Term w	2	8	9	442	25	486
cherry	0	0	1	60	19	80
strawberry	1670	1683	85	5	4	3447
digital	3325	3982	378	5	13	7703
information	4997	5673	473	512	61	11716
count(context)						

Frequency $f(w_i, c_j)$ or f_{ij} is the # times w_i occurs in context c_j

$$P_{ij} = \frac{f_{ij}}{\sum_{i=1}^W \sum_{j=1}^C f_{i,j}}$$

$$P_i = \sum_{j=1}^C P_{ij} \quad P_j = \sum_{i=1}^W P_{ij}$$

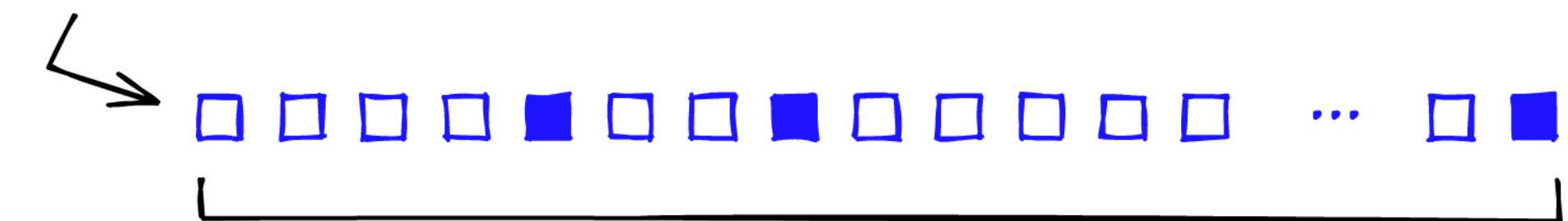
$$PPMI(w_i, c_j) = PPMI_{i,j} = \max \left(0, \log \frac{P_{ij}}{P_i P_j} \right)$$

The problem...

- PMI vectors are
 - long (length $|V| = 20,000$ to $50,000$)
 - sparse (most elements are zero)
- Alternative: learn vectors which are
 - short (length 50-1000)
 - dense (most elements are non-zero)
 - Therefore, easier to use (fewer parameters)

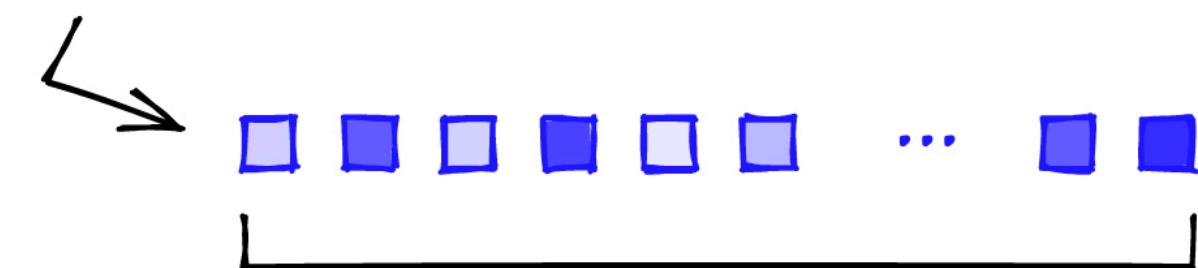
sparse

$[0, 0, 0, 1, 0, \dots, 0]$



dense

$[0.2, 0.7, 0.1, 0.8, 0.1, \dots, 0.9]$



Recap: Dense Word Embeddings (word2vec)

word2vec

- Short, dense vector or embedding
- Static embeddings
 - One embedding per word type
 - Does not change with context change
- Two algorithms for computing:
 - Skip-Gram with Negative Sampling or SGNS
 - CBOW or continuous bag of words
 - But we will study a slightly different version...
- Efficient training
- Easily available to download and plug in

Mikolov et al., ICLR 2013. Efficient estimation of word representations in vector space.

word2vec : Intuition

is traditionally followed by **cherry** pie, a traditional dessert
often mixed, such as **strawberry** rhubarb pie. Apple pie
computer peripherals and personal **digital** assistants. These devices usually
a computer. This includes **information** available on the internet

Instead of counting how often each word w occurs near another, e.g. “cherry”

- Train a classifier on a binary prediction task:
 - Is w likely to show up near “cherry”?
- We don't actually care about this task!!!
 - But we'll take the learned classifier weights as the word embeddings

What is x ? What is y ?

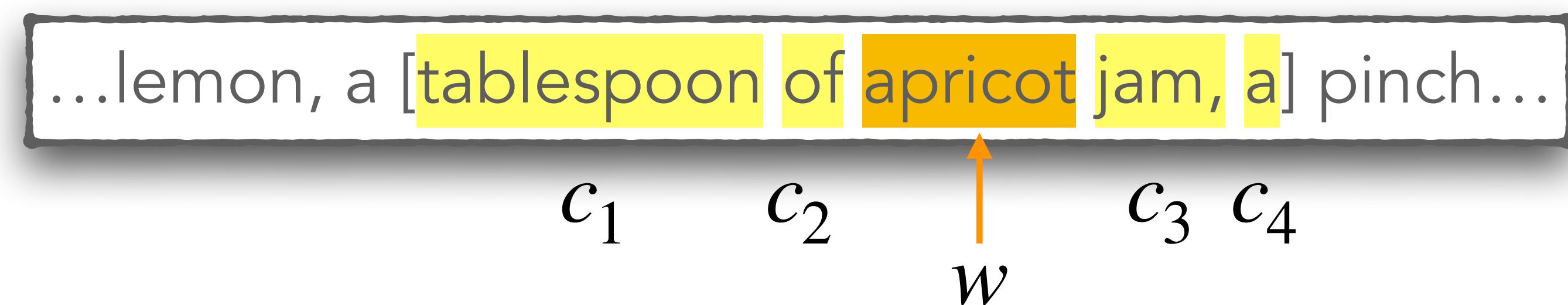
Word embedding itself is the learned parameter!

word2vec: Goal

Assume a +/- 2 word window, given training sentence:

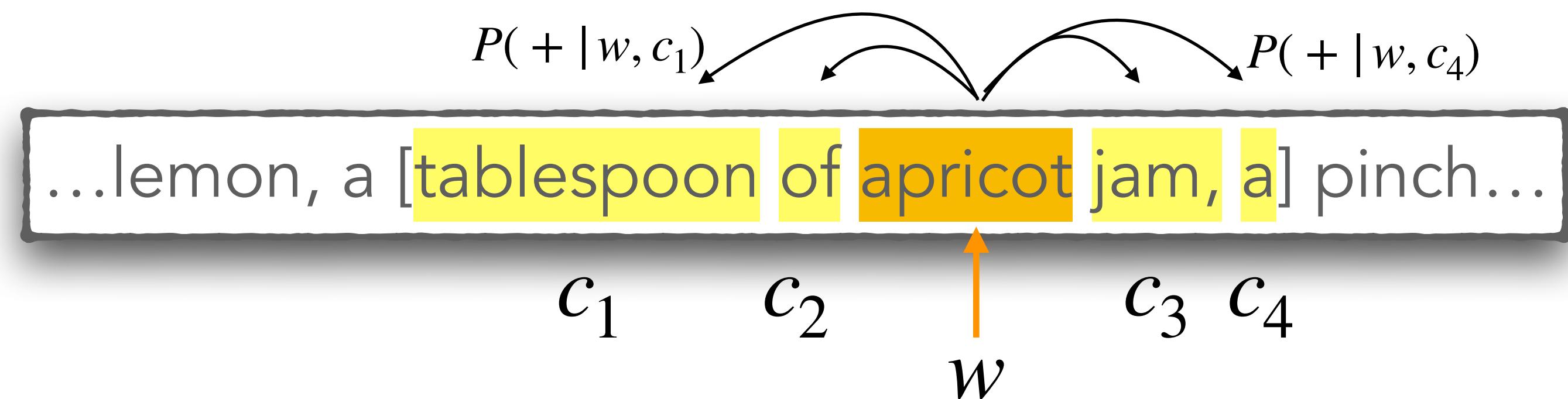
word2vec: Goal

Assume a +/- 2 word window, given training sentence:



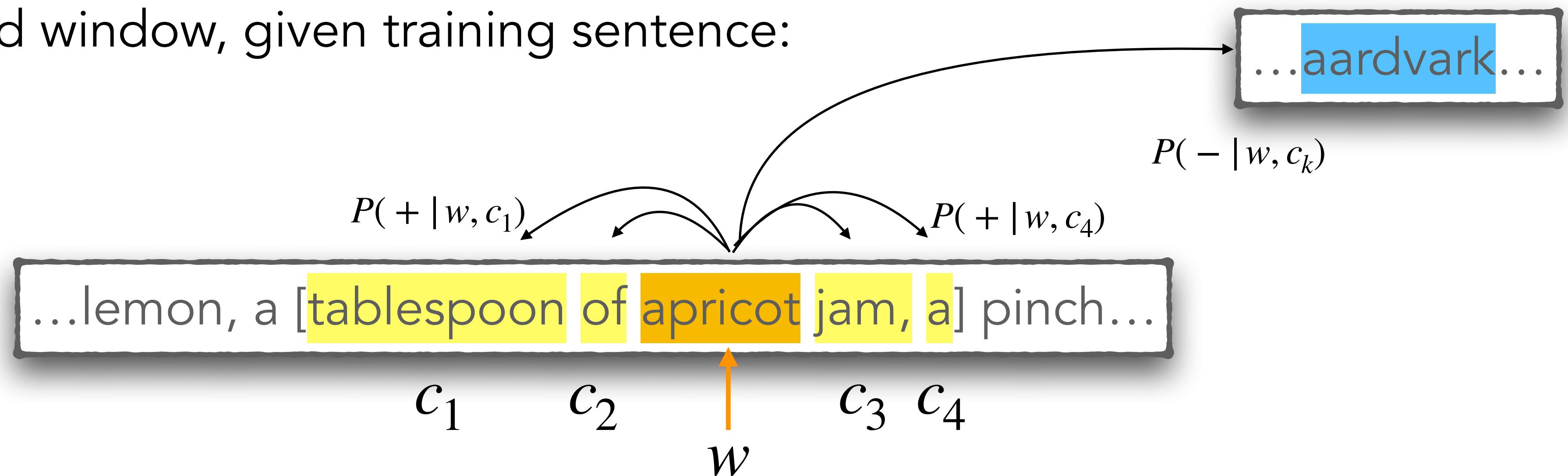
word2vec: Goal

Assume a +/- 2 word window, given training sentence:



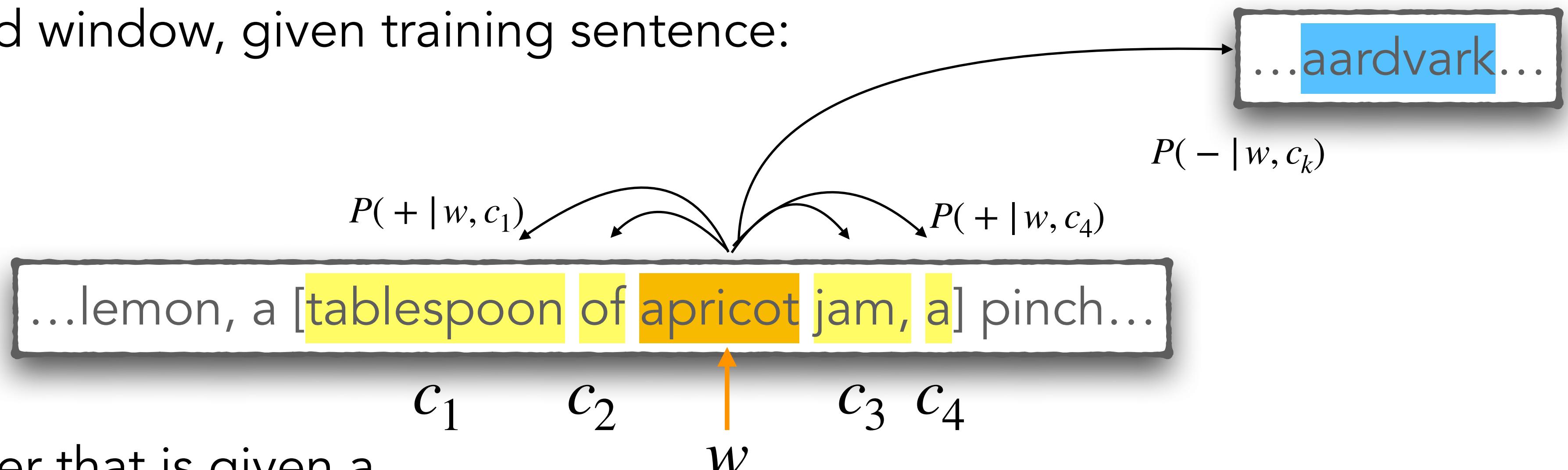
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word2vec: Goal

Assume a +/- 2 word window, given training sentence:



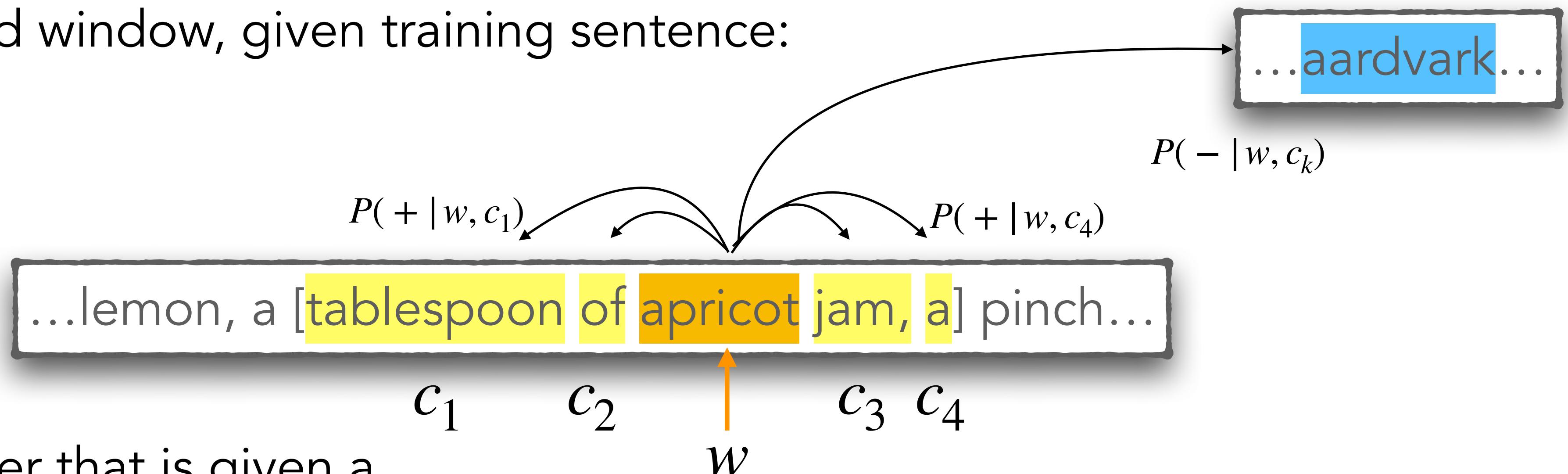
Goal: train a classifier that is given a candidate (word, context) pair, and corresponding label about co-occurrence :

- (apricot, jam), 1
- (apricot, tablespoon), 1
- (apricot, aardvark), 0

...

word2vec: Goal

Assume a +/- 2 word window, given training sentence:



Goal: train a classifier that is given a candidate (word, context) pair, and corresponding label about co-occurrence :

- (apricot, jam), 1
- (apricot, tablespoon), 1
- (apricot, aardvark), 0

And assigns each pair a probability:

$$\begin{aligned} P(+ | w, c) \\ P(- | w, c) = 1 - P(+ | w, c) \end{aligned}$$

...

Turning dot products into probabilities

Similarity:

$$\text{sim}(w, c) \approx \mathbf{w} \cdot \mathbf{c}$$

Turn into a probability using the sigmoid function:

Turning dot products into probabilities

Similarity:

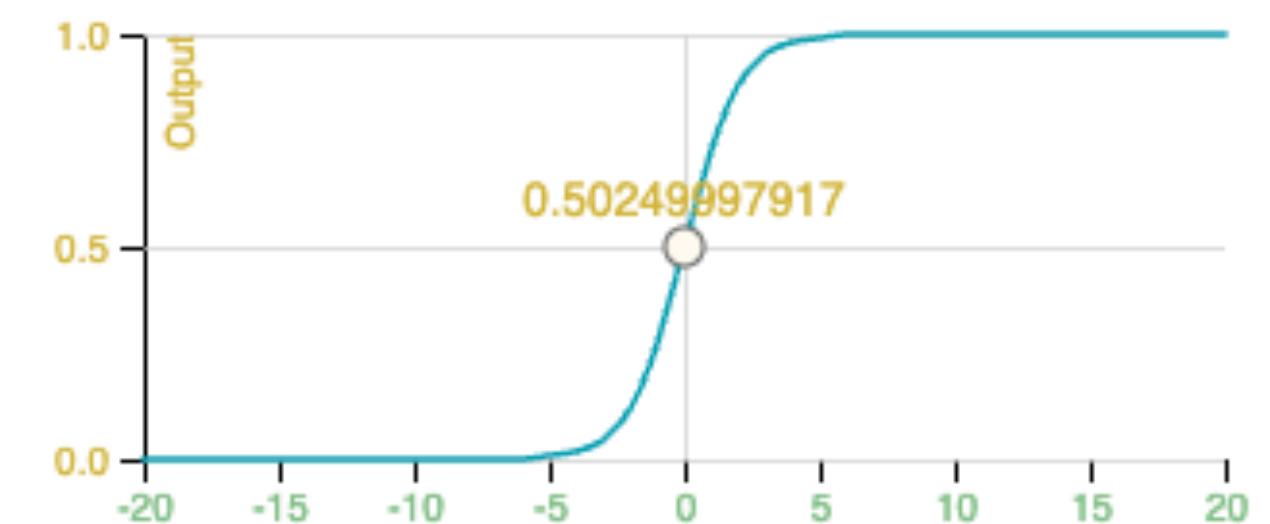
$$\text{sim}(w, c) \approx \mathbf{w} \cdot \mathbf{c}$$

Sigmoid



Turn into a probability using the sigmoid function:

$$f(0.01) = \frac{1}{1 + e^{-(0.01)}} = 0.50249997917$$



Turning dot products into probabilities

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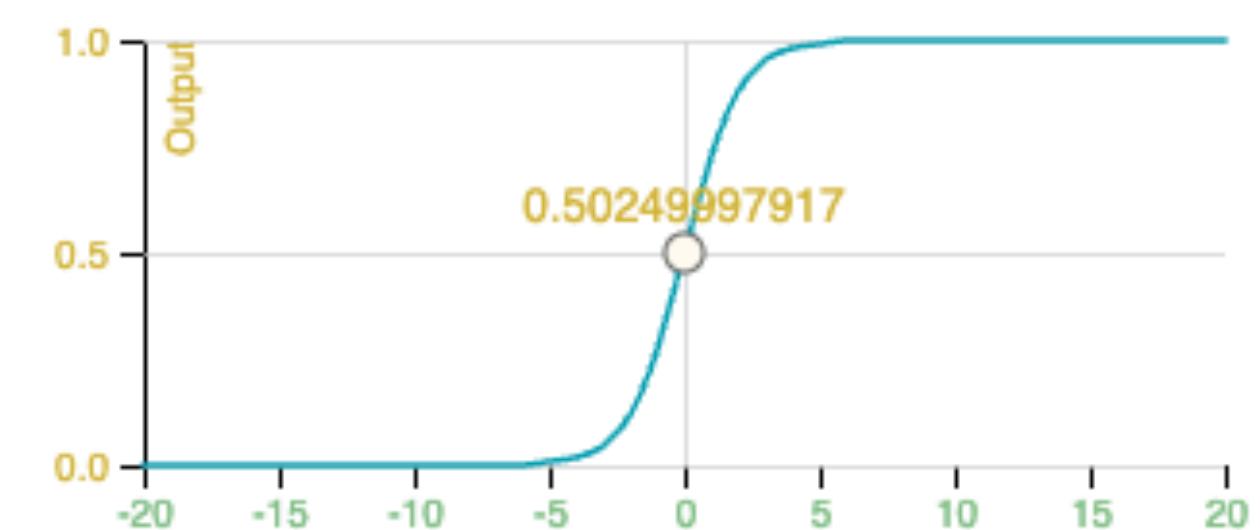
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Turn into a probability using the sigmoid function:

$$P(+) | w, c = \sigma(\mathbf{c} \cdot \mathbf{w}) = \frac{1}{1 + \exp(-\mathbf{c} \cdot \mathbf{w})}$$

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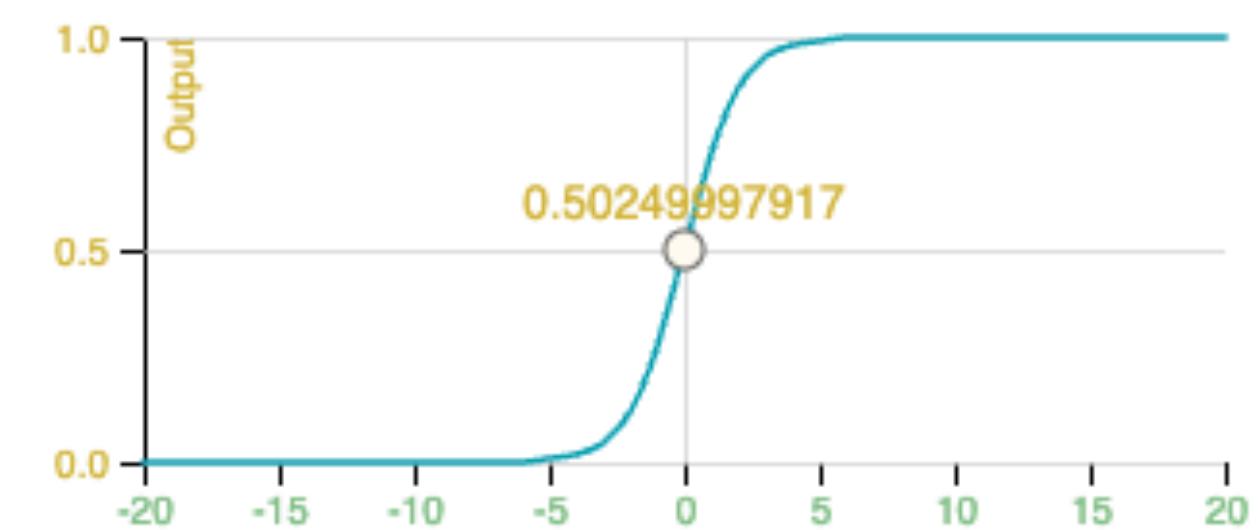


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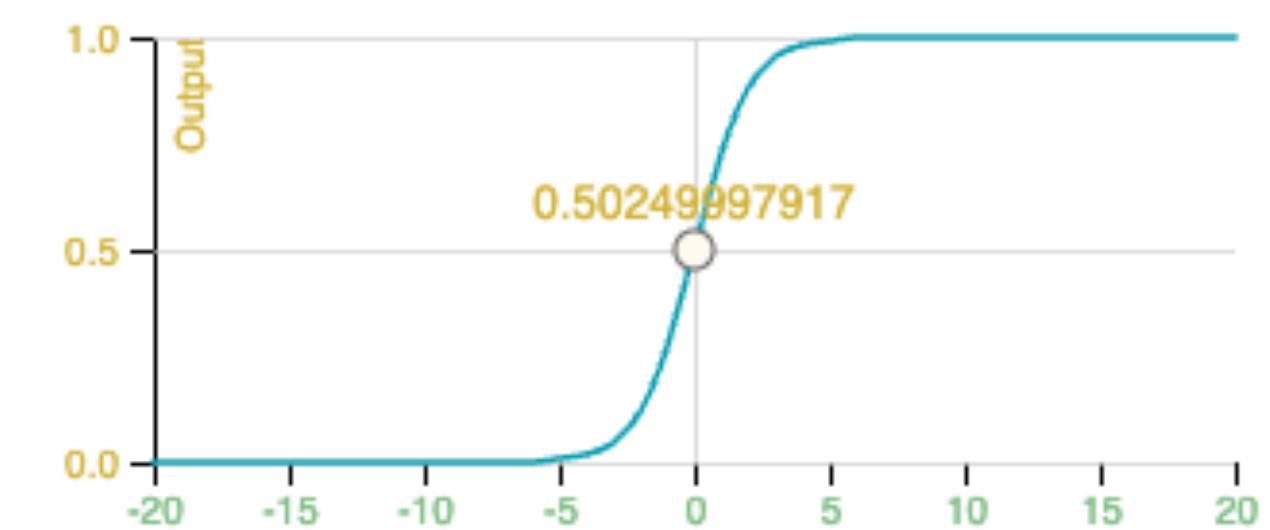


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Turning dot products into probabilities

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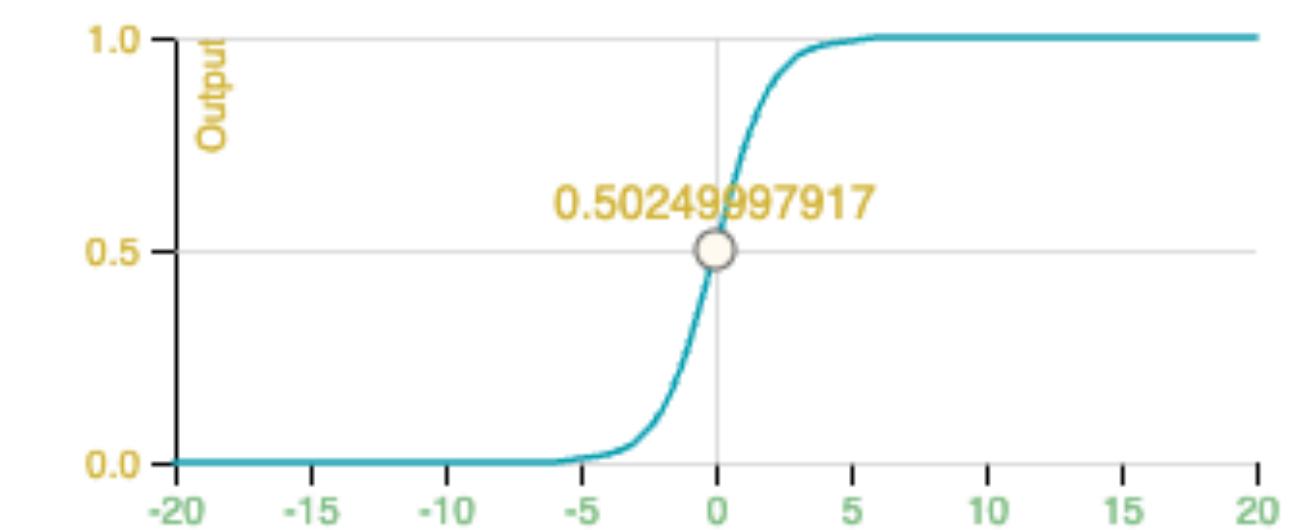


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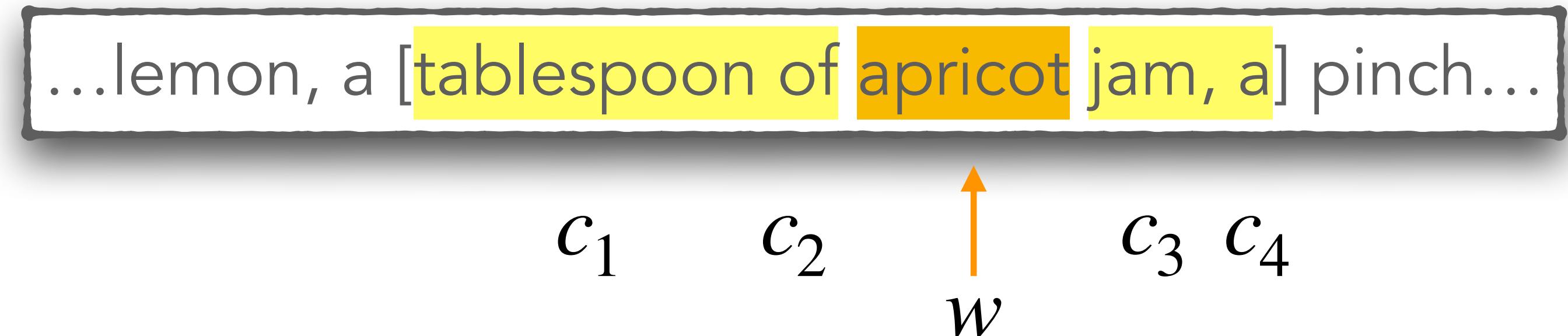
$$f(\text{ 0.01 }) = \frac{1}{1 + e^{-(\text{ 0.01 })}} = \text{ 0.50249997917 }$$



Logistic
Regression!

Accounting for a context window

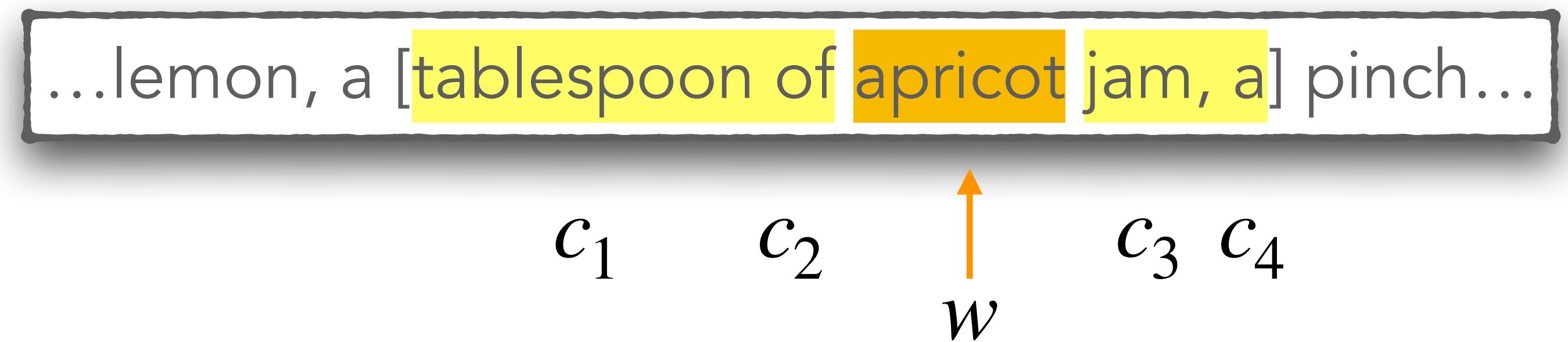
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Accounting for a context window

$$P(+ | w, c) = \sigma(\mathbf{c} \cdot \mathbf{w}) = \frac{1}{1 + \exp(-\mathbf{c} \cdot \mathbf{w})}$$

Single Context Word

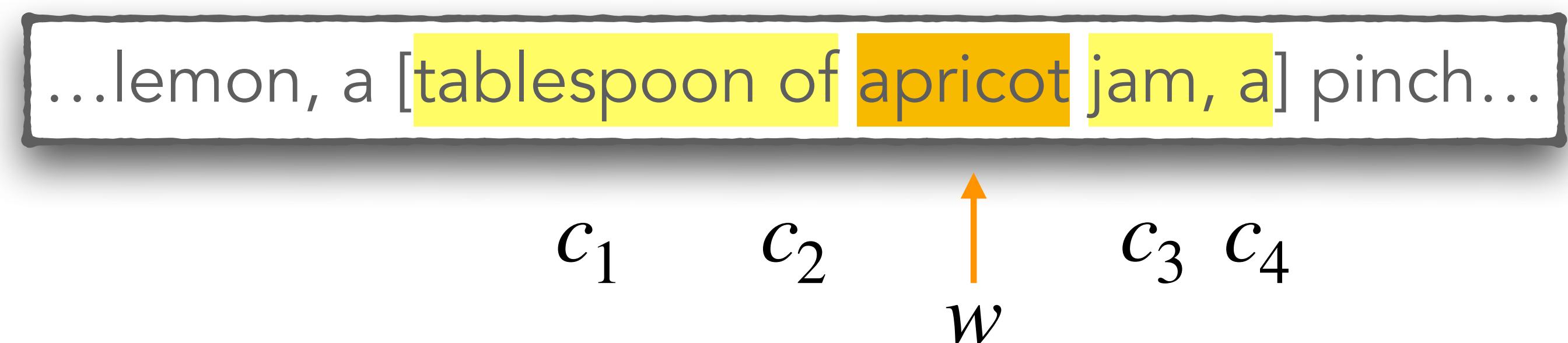


Accounting for a context window

$$P(+|w, c) = \sigma(\mathbf{c} \cdot \mathbf{w}) = \frac{1}{1 + \exp(-\mathbf{c} \cdot \mathbf{w})}$$

Single Context Word

But we have lots of context words



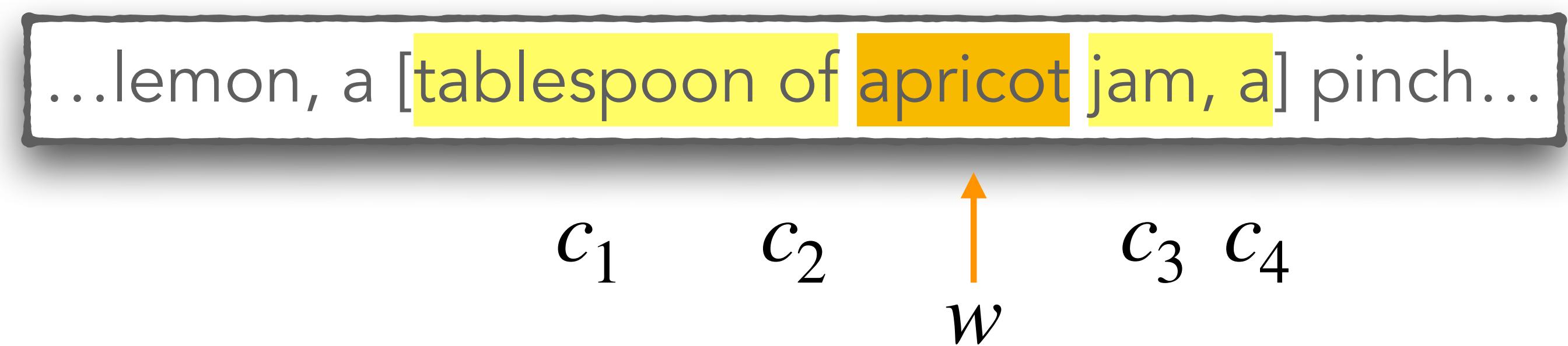
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- Depends on window size, L



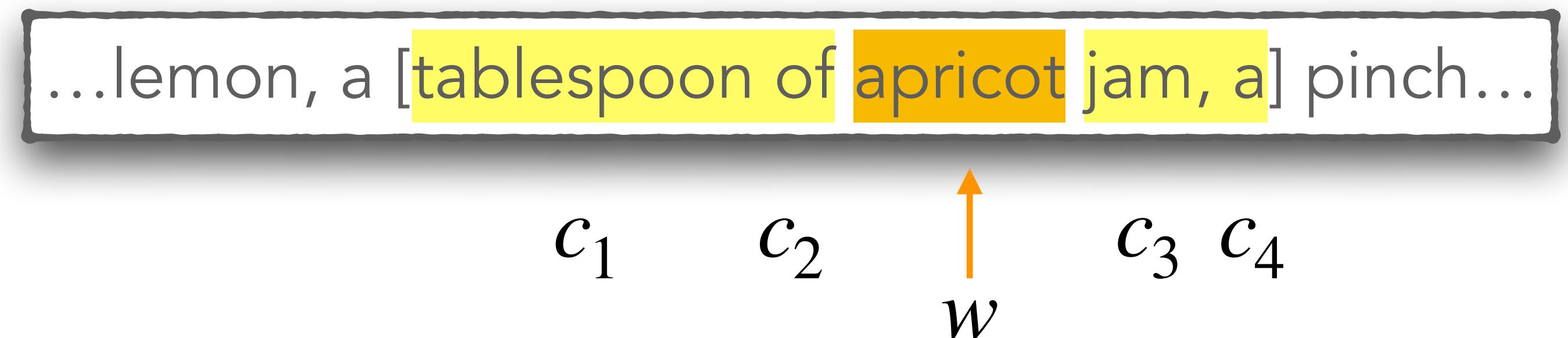
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Single Context Word

But we have lots of context words

- Depends on window size, L
- We'll assume independence and just multiply them



$$P(+ | w, c_{1:L}) = \prod_{i=1}^L \sigma(\mathbf{c}_i \cdot \mathbf{w})$$

$$\log P(+ | w, c_{1:L}) = \sum_{i=1}^L \log \sigma(\mathbf{c}_i \cdot \mathbf{w})$$

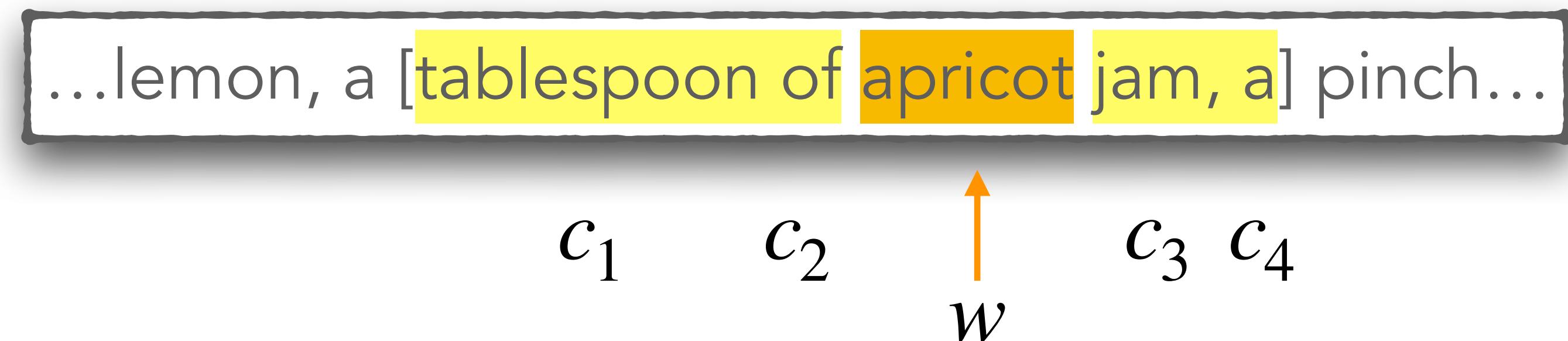
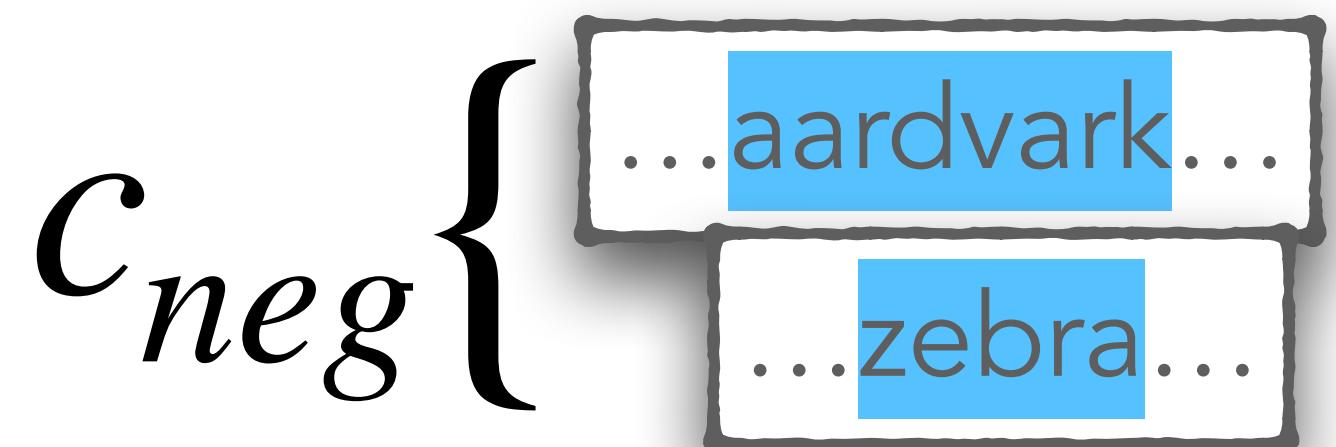
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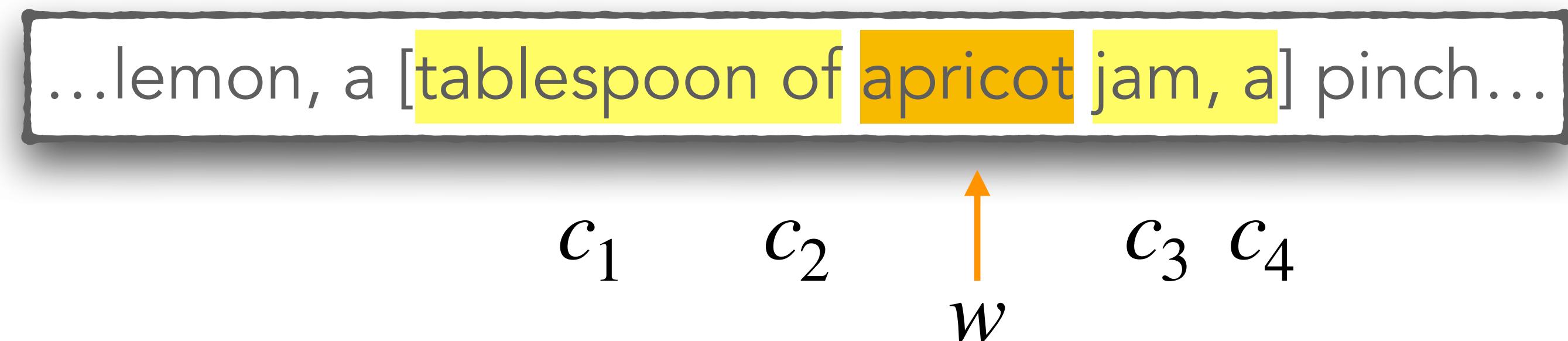
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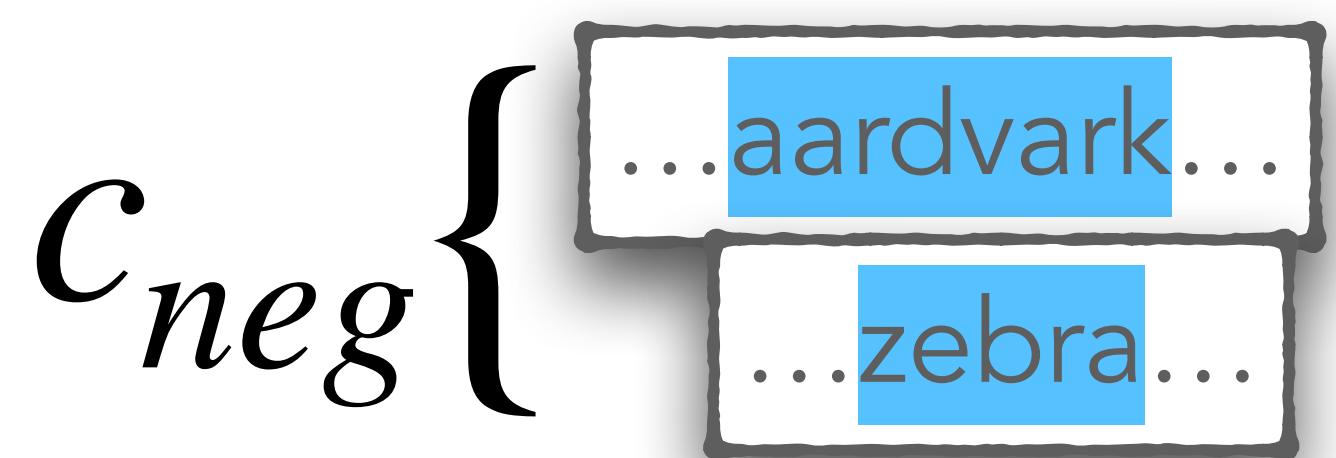
Single Context Word



But we have lots of context words

- Depends on window size, L
- We'll assume independence and just multiply them

Same with negative context words!



$$\log P(- | w, c_{neg}) = \sum_{c' \in c_{neg}} \log \sigma(-\mathbf{c}' \cdot \mathbf{w})$$

$$P(+ | w, c_{1:L}) = \prod_{i=1}^L \sigma(\mathbf{c}_i \cdot \mathbf{w})$$

$$\log P(+ | w, c_{1:L}) = \sum_{i=1}^L \log \sigma(\mathbf{c}_i \cdot \mathbf{w})$$

word2vec classifier: Summary

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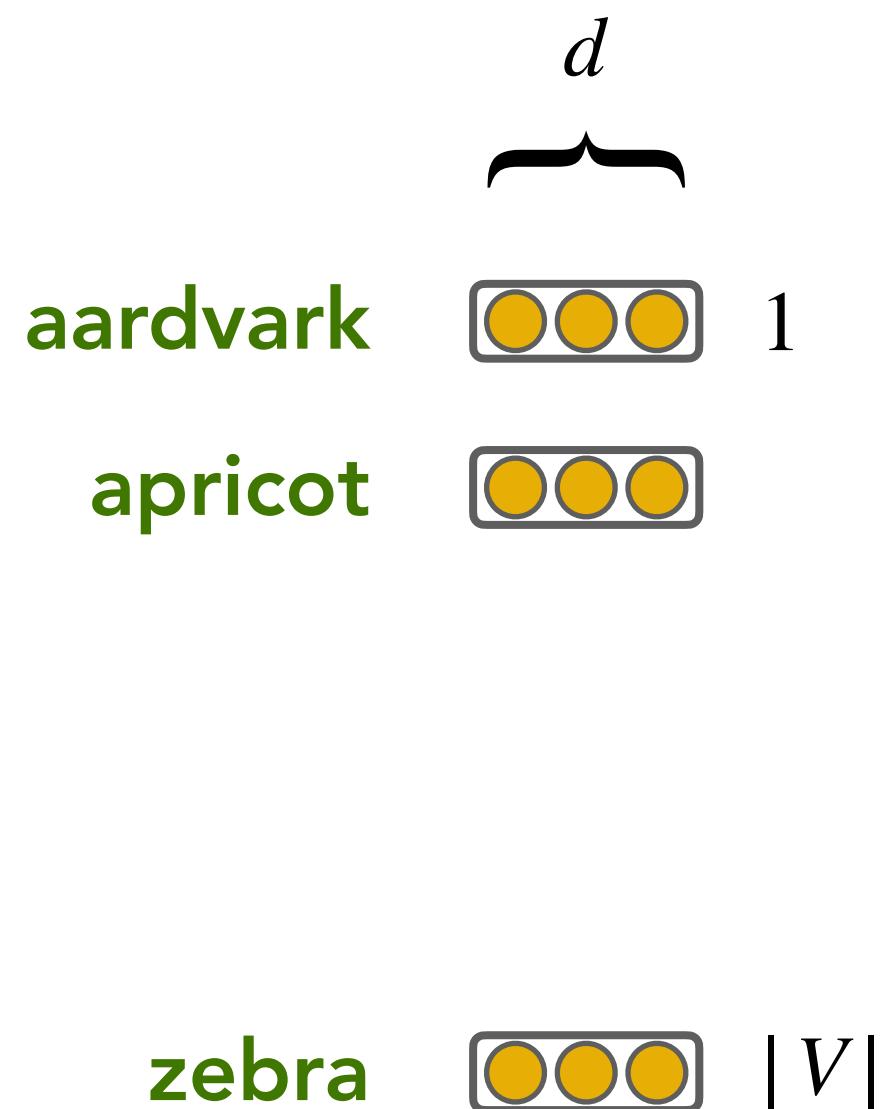
- A probabilistic classifier, given
 - a test target word w
 - its context window of L words $c_{1:L}$

word2vec classifier: Summary

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- Estimates probability that w occurs in this window based on similarity of w (embeddings) to $c_{1:L}$ (embeddings)

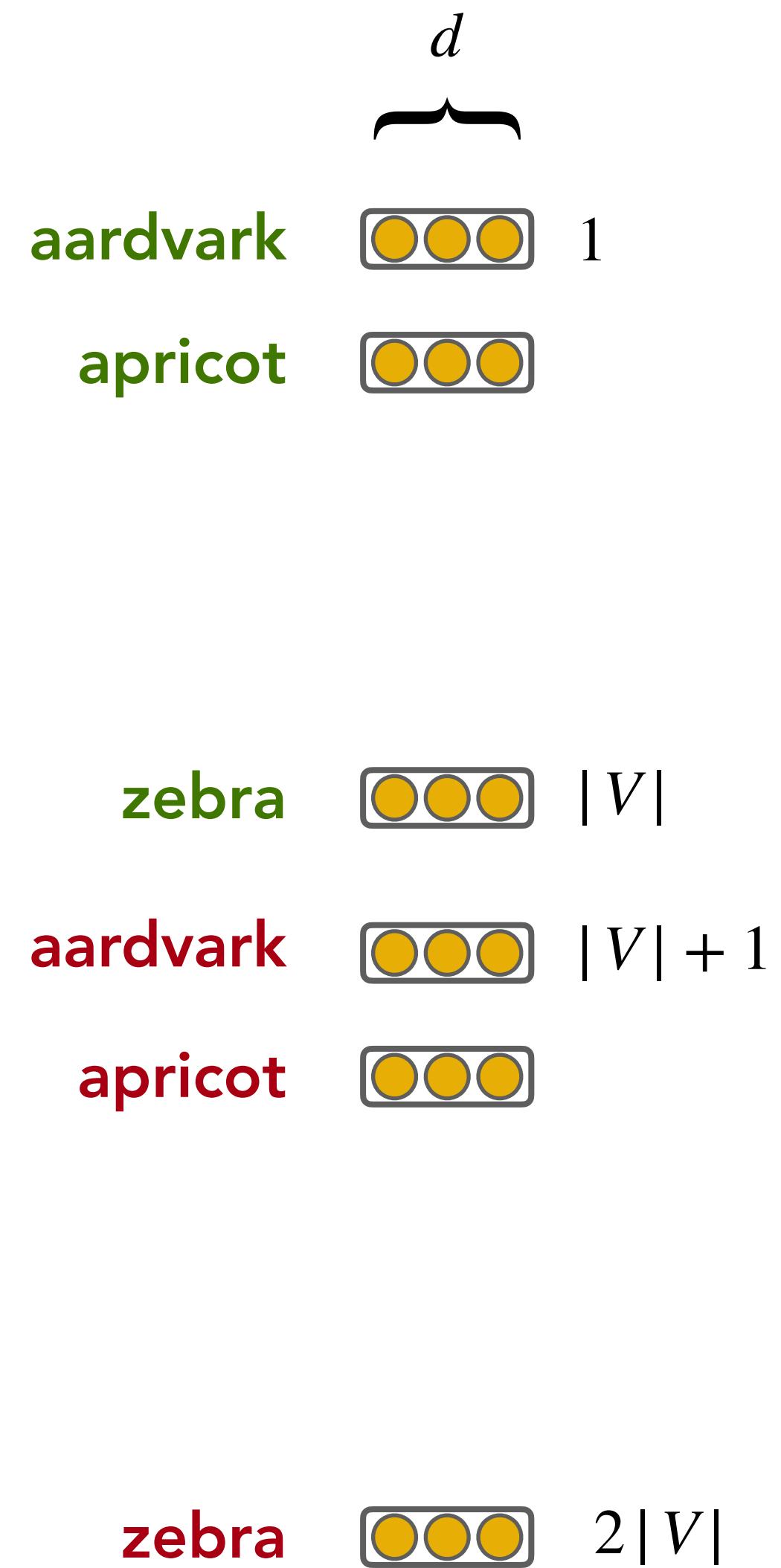
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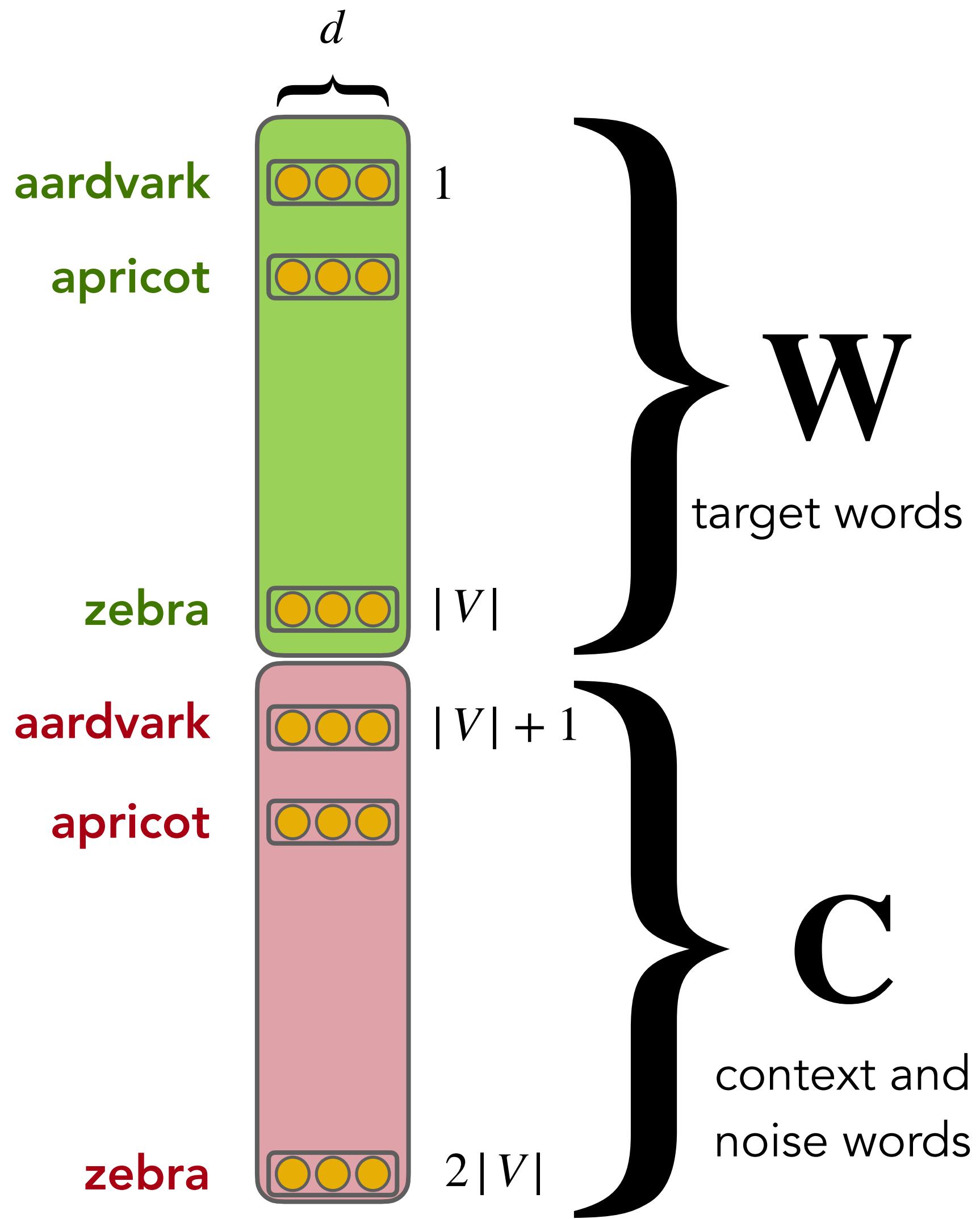
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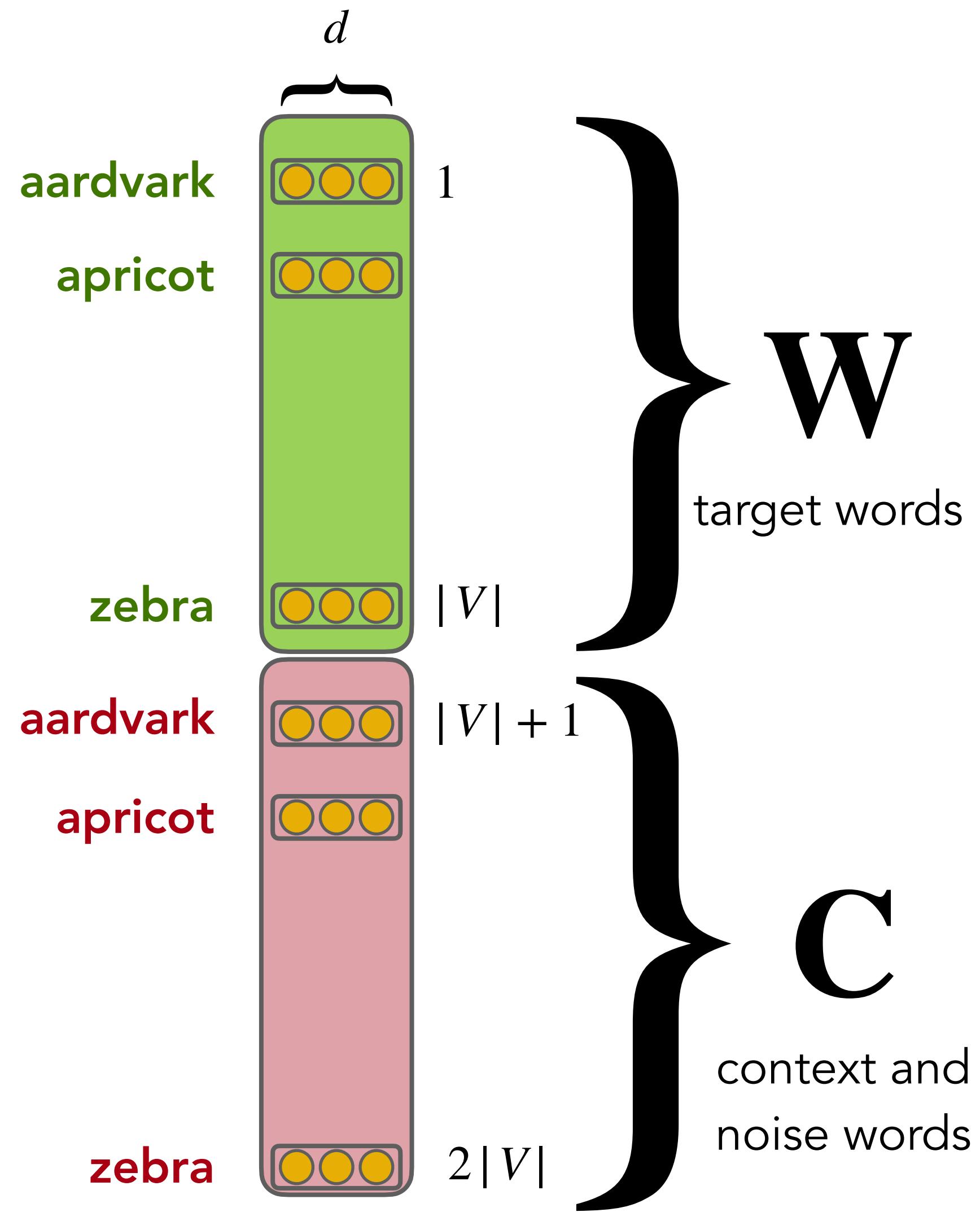
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- Estimates probability that w occurs in this window based on similarity of w (embeddings) to $c_{1:L}$ (embeddings)
- To compute this, we just need embeddings for all the words
 - Separate representations for targets and contexts
 - Same as the parameters we need to estimate!



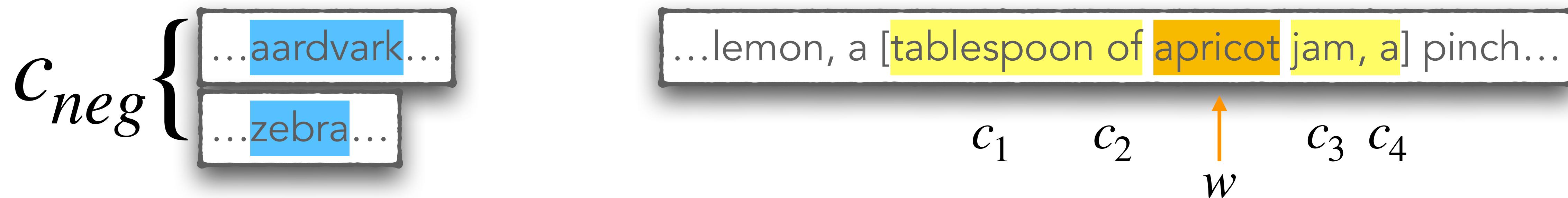
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Learning word2vec embeddings

Word2vec: Training Data

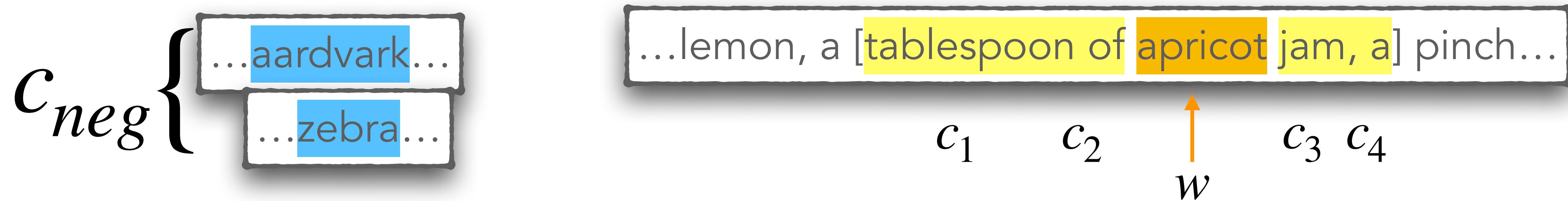
For each positive example we'll grab a set of negative examples, sampling by weighted unigram frequency



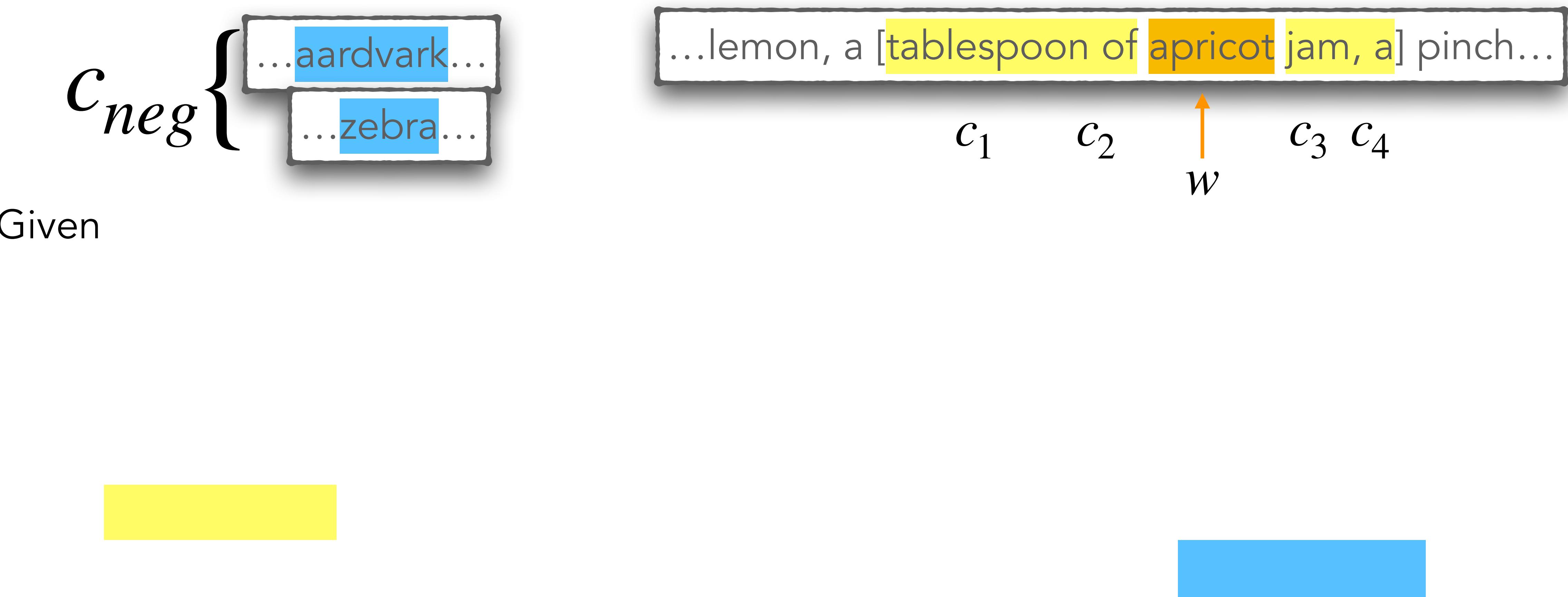
Negative examples	
w	c_{neg}
apricot	aardvark
apricot	zebra
apricot	where
apricot	adversarial

Positive examples	
w	c
apricot	tablespoon
apricot	of
apricot	jam
apricot	a

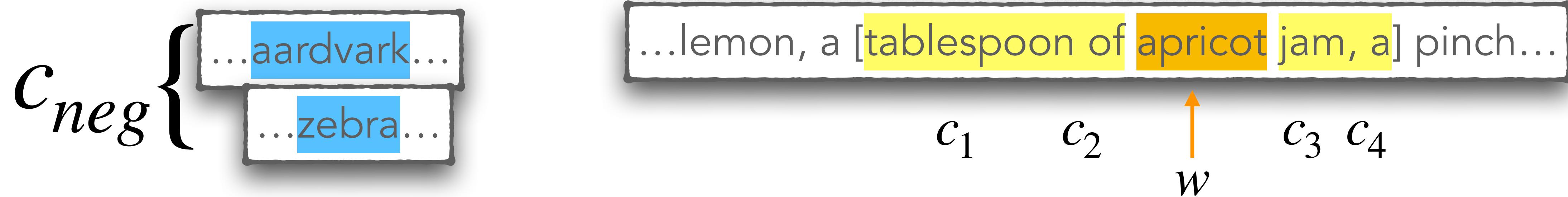
Word2vec: Learning Problem



Word2vec: Learning Problem



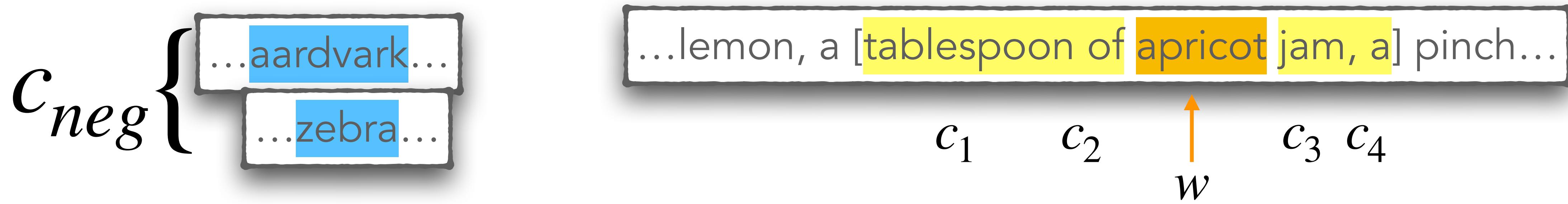
Word2vec: Learning Problem



Given

- the set of positive and negative training instances, and

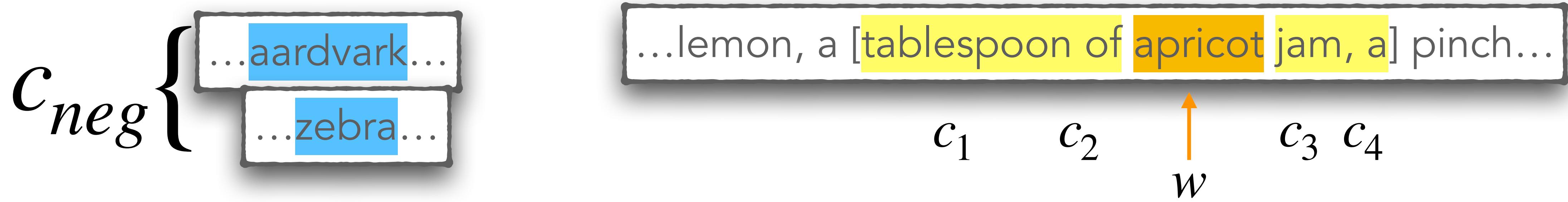
Word2vec: Learning Problem



Given

- the set of positive and negative training instances, and
- a set of randomly initialized embedding vectors of size $2|V|$,

Word2vec: Learning Problem



Given

- the set of positive and negative training instances, and
- a set of randomly initialized embedding vectors of size $2|V|$,

the goal of learning is to adjust those word vectors such that we:



Word2vec: Learning Problem



Given

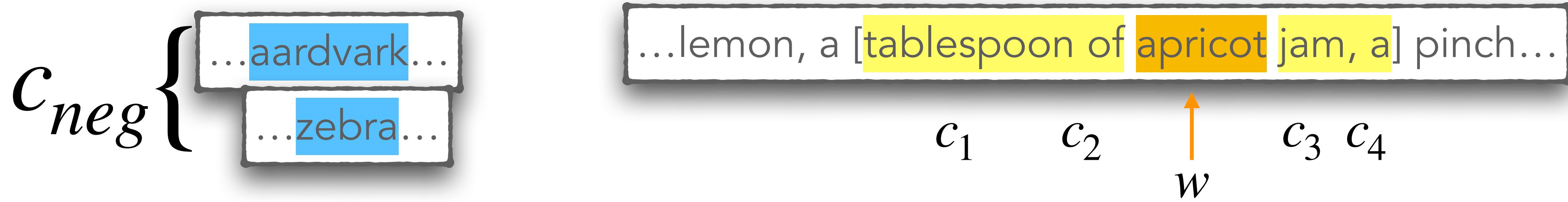
- the set of positive and negative training instances, and
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the goal of learning is to adjust those word vectors such that we:

- **Maximize** the similarity of the target word, context word pairs $(w, c_{1:L})$ drawn from the positive data



Word2vec: Learning Problem



Given

- the set of positive and negative training instances, and
- a set of randomly initialized embedding vectors of size $2|V|$,

the goal of learning is to adjust those word vectors such that we:

- **Maximize** the similarity of the target word, context word pairs $(w, c_{1:L})$ drawn from the positive data
- **Minimize** the similarity of the (w, c_{neg}) pairs drawn from the negative data

Loss function

Maximize the similarity of the target with the actual context words in a window of size L , and minimize the similarity of the target with the $K > L$ negative sampled non-neighbor words

Loss function

Maximize the similarity of the target with the actual context words in a window of size L , and minimize the similarity of the target with the $K > L$ negative sampled non-neighbor words

For every word,
context pair...

Loss function

Maximize the similarity of the target with the actual context words in a window of size L , and minimize the similarity of the target with the $K > L$ negative sampled non-neighbor words

For every word,
context pair... $L_{CE} = -\log[P(+) | \mathbf{w}, \mathbf{c}_{pos})P(- | \mathbf{w}, \mathbf{c}_{neg})]$

Loss function

Maximize the similarity of the target with the actual context words in a window of size L , and minimize the similarity of the target with the $K > L$ negative sampled non-neighbor words

For every word,
context pair...

$$L_{CE} = -\log[P(+) | \mathbf{w}, \mathbf{c}_{pos})P(- | \mathbf{w}, \mathbf{c}_{neg})]$$

Cross Entropy



Loss function

Maximize the similarity of the target with the actual context words in a window of size L , and minimize the similarity of the target with the $K > L$ negative sampled non-neighbor words

For every word,
context pair...

$$\begin{aligned} L_{CE} &= -\log[P(+ | \mathbf{w}, \mathbf{c}_{pos})P(- | \mathbf{w}, \mathbf{c}_{neg})] \\ &= -\left[\log P(+ | \mathbf{w}, \mathbf{c}_{pos}) + \sum_{j=1}^K \log P(- | \mathbf{w}, \mathbf{c}_{neg_j})\right] \end{aligned}$$

Cross Entropy

Loss function

Maximize the similarity of the target with the actual context words in a window of size L , and minimize the similarity of the target with the $K > L$ negative sampled non-neighbor words

For every word,
context pair...

$$\begin{aligned} L_{CE} &= -\log[P(+ | \mathbf{w}, \mathbf{c}_{pos})P(- | \mathbf{w}, \mathbf{c}_{neg})] \\ &= -\left[\log P(+ | \mathbf{w}, \mathbf{c}_{pos}) + \sum_{j=1}^K \log P(- | \mathbf{w}, \mathbf{c}_{neg_j})\right] \end{aligned}$$

Cross Entropy

$$= -\left[\log P(+ | \mathbf{w}, \mathbf{c}_{pos}) + \sum_{j=1}^K \log(1 - P(+ | \mathbf{w}, \mathbf{c}_{neg_j}))\right]$$

Loss function

Maximize the similarity of the target with the actual context words in a window of size L , and minimize the similarity of the target with the $K > L$ negative sampled non-neighbor words

For every word,
context pair...

$$\begin{aligned} L_{CE} &= -\log[P(+ | \mathbf{w}, \mathbf{c}_{pos})P(- | \mathbf{w}, \mathbf{c}_{neg})] \\ &= -\left[\log P(+ | \mathbf{w}, \mathbf{c}_{pos}) + \sum_{j=1}^K \log P(- | \mathbf{w}, \mathbf{c}_{neg_j})\right] \end{aligned}$$

Cross Entropy

$$\begin{aligned} &= -\left[\log P(+ | \mathbf{w}, \mathbf{c}_{pos}) + \sum_{j=1}^K \log(1 - P(+ | \mathbf{w}, \mathbf{c}_{neg_j}))\right] \\ &= -\left[\log \sigma(\mathbf{w} \cdot \mathbf{c}_{pos}) + \sum_{j=1}^K \log \sigma(-\mathbf{w} \cdot \mathbf{c}_{neg_j})\right] \end{aligned}$$

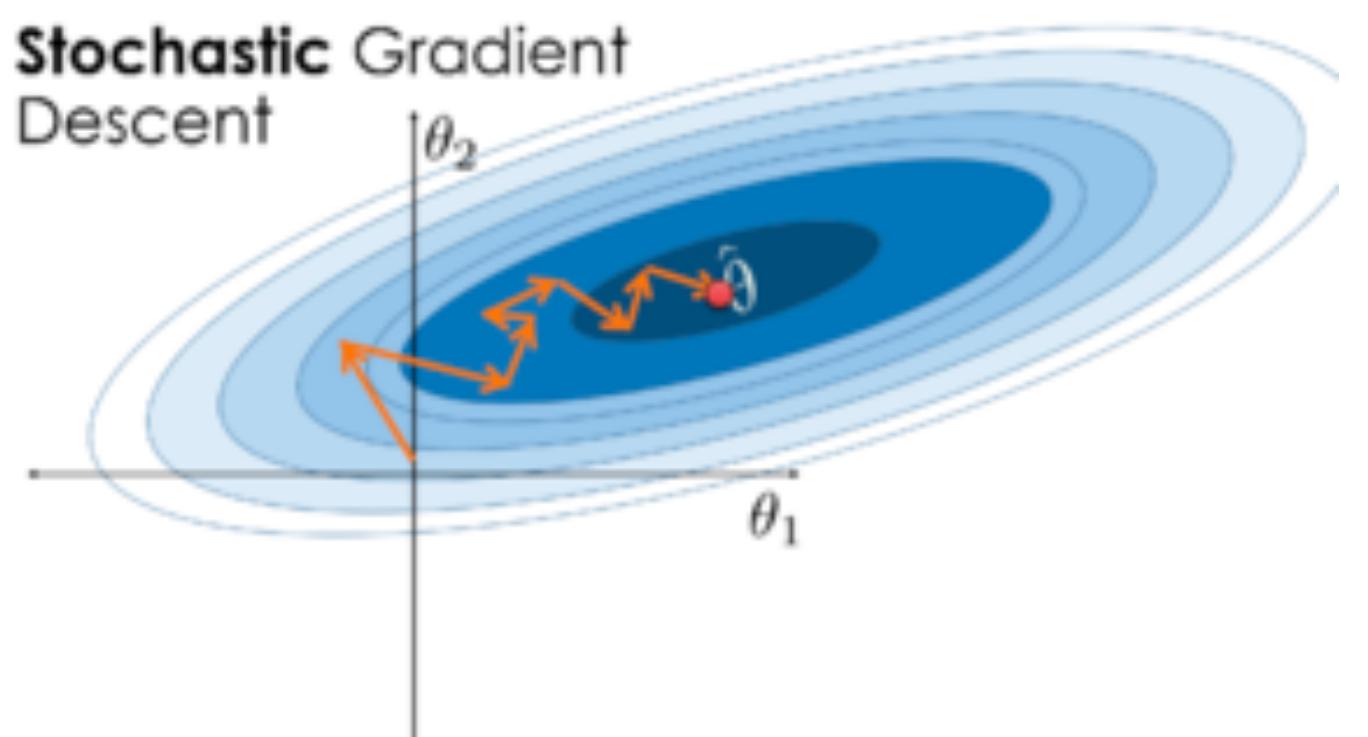
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Learning the classifier

- How to learn?

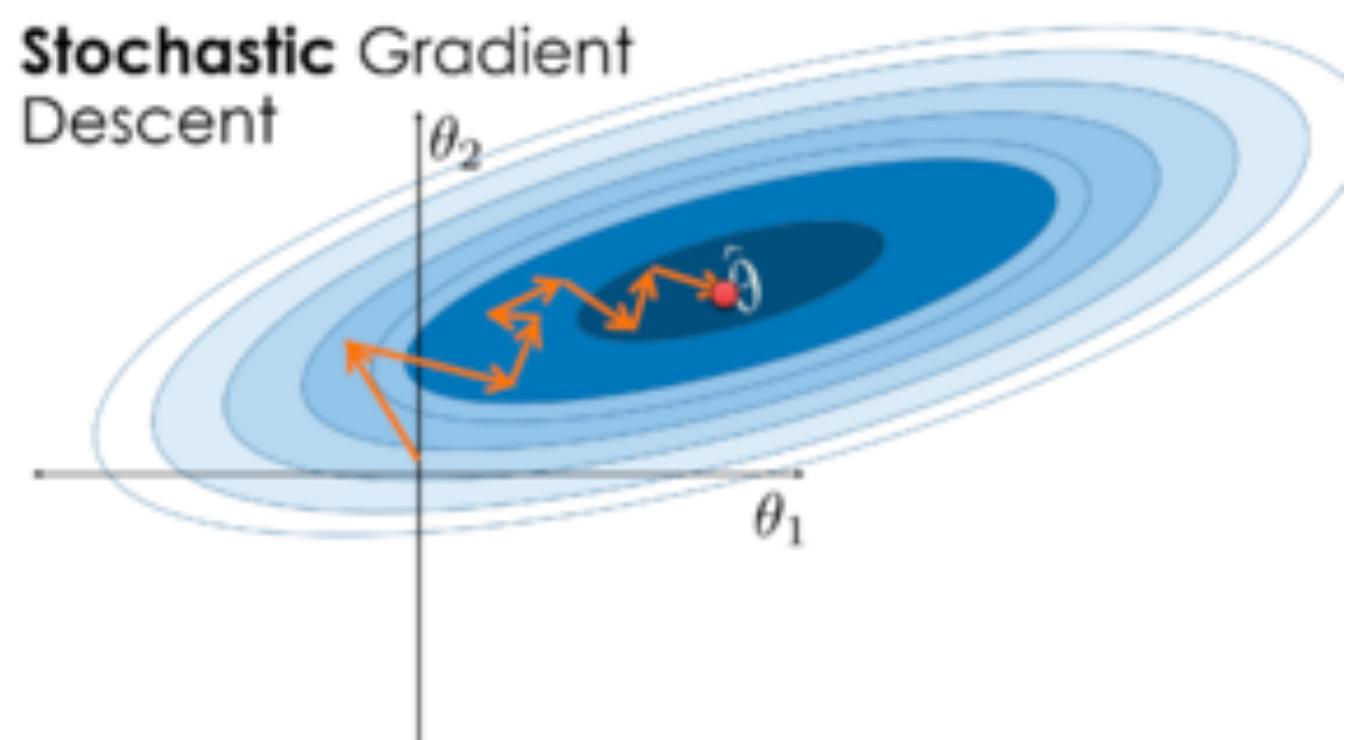
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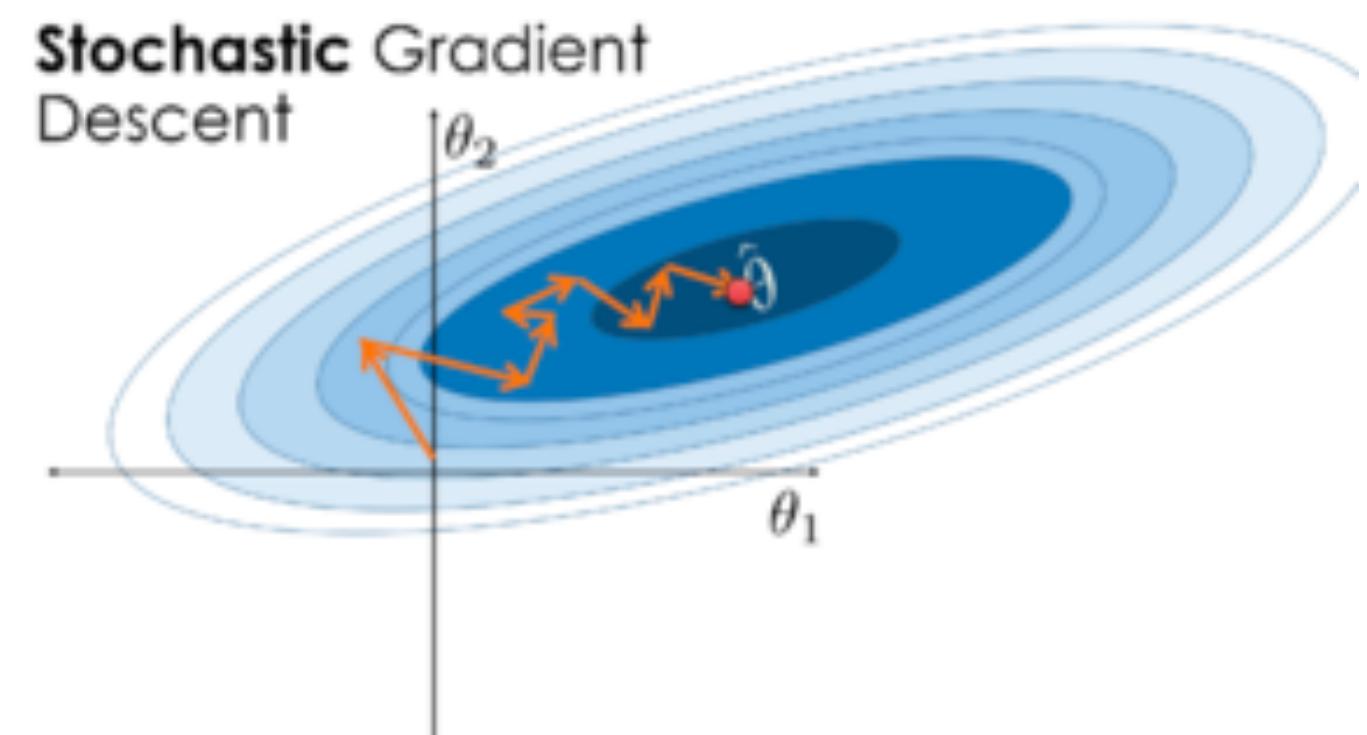
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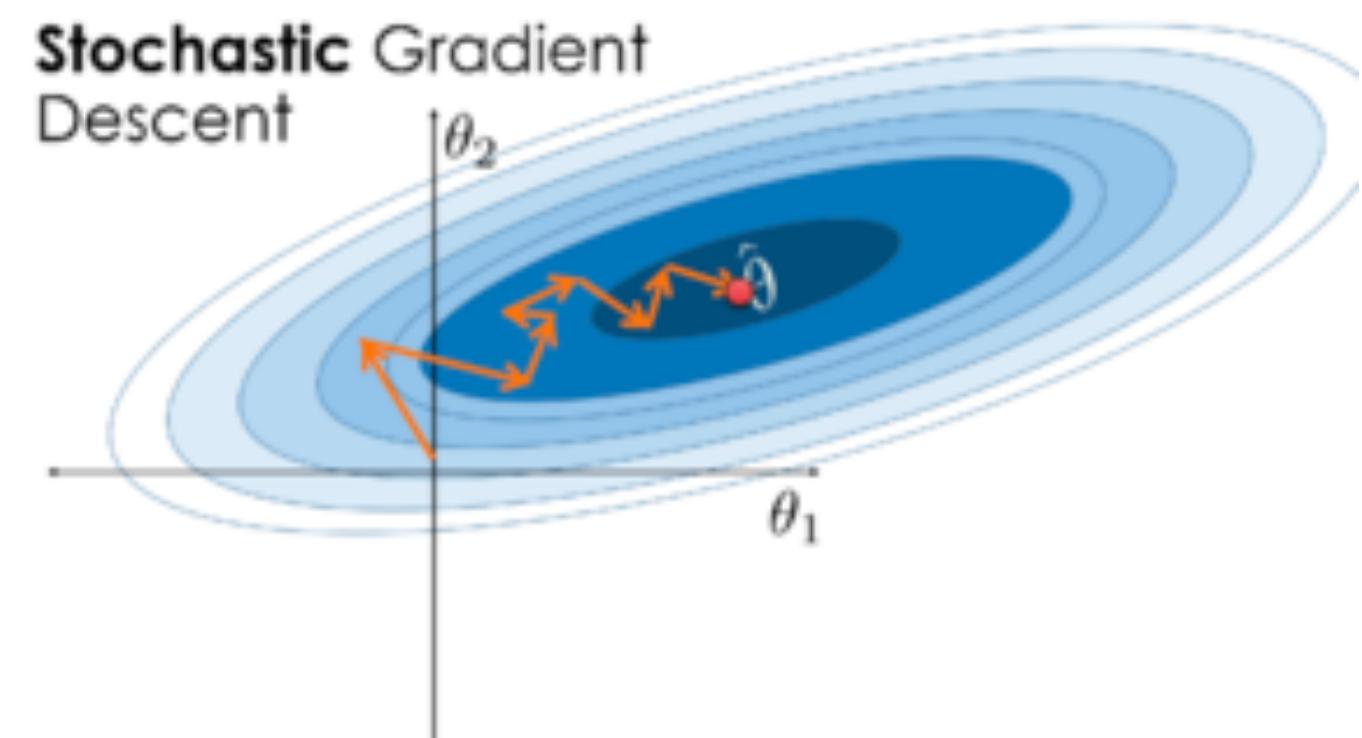
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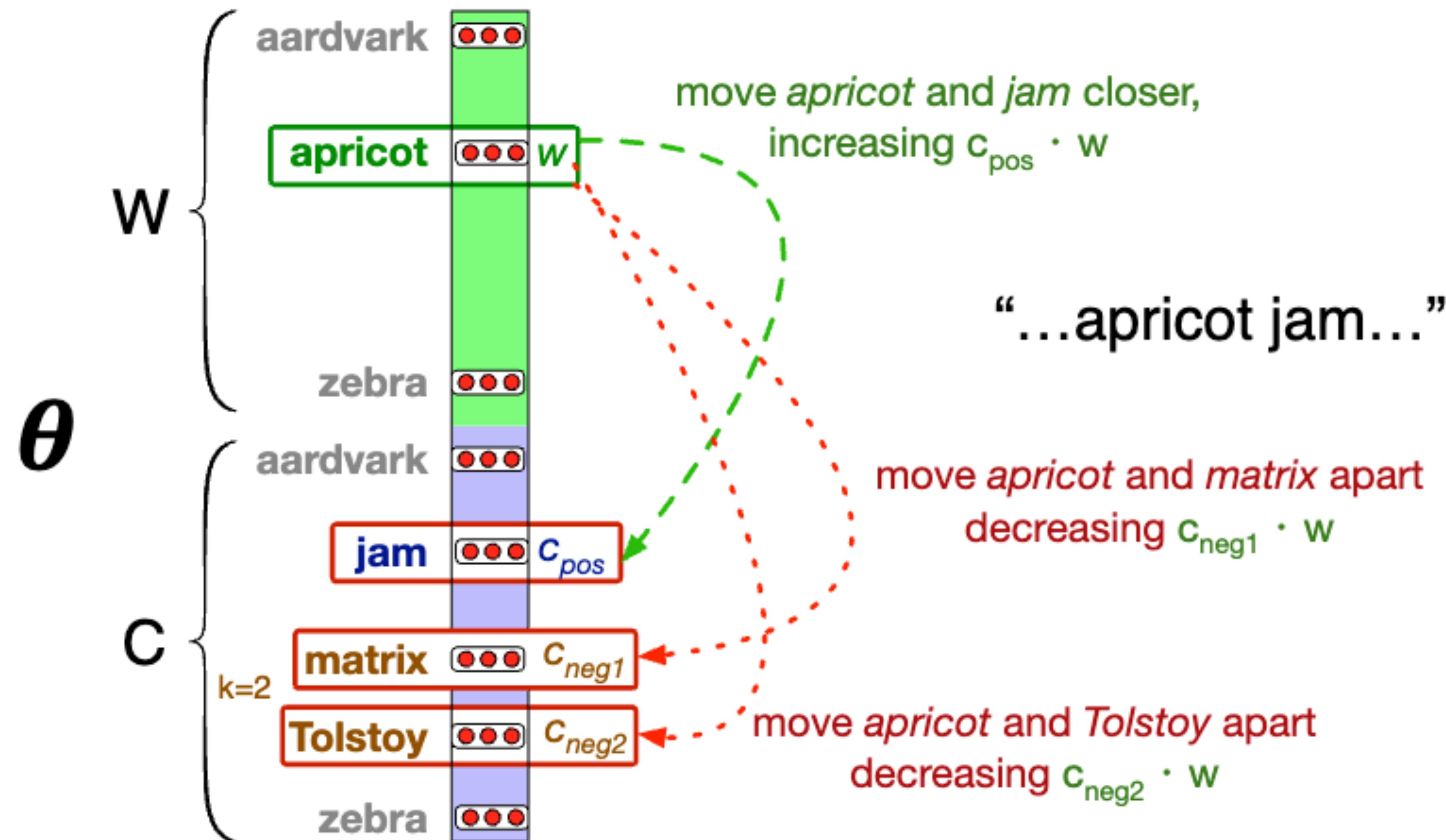


Learning the classifier

- How to learn?
 - Stochastic gradient descent!
 - Iterative process
 - Start with randomly initialized weights
 - Update the parameters by computing gradients of the loss w.r.t. parameters
 - Stop when the parameters (or, the loss) do not change much...
- We'll adjust the word weights to
 - make the positive pairs more likely
 - and the negative pairs less likely,
 - over the entire training set.



Intuition of one step of gradient descent



SGD: Derivates

$$L_{CE} = - \left[\log \sigma(\mathbf{w} \cdot \mathbf{c}_{pos}) + \sum_{j=1}^K \log \sigma(-\mathbf{w} \cdot \mathbf{c}_{neg_j}) \right]$$

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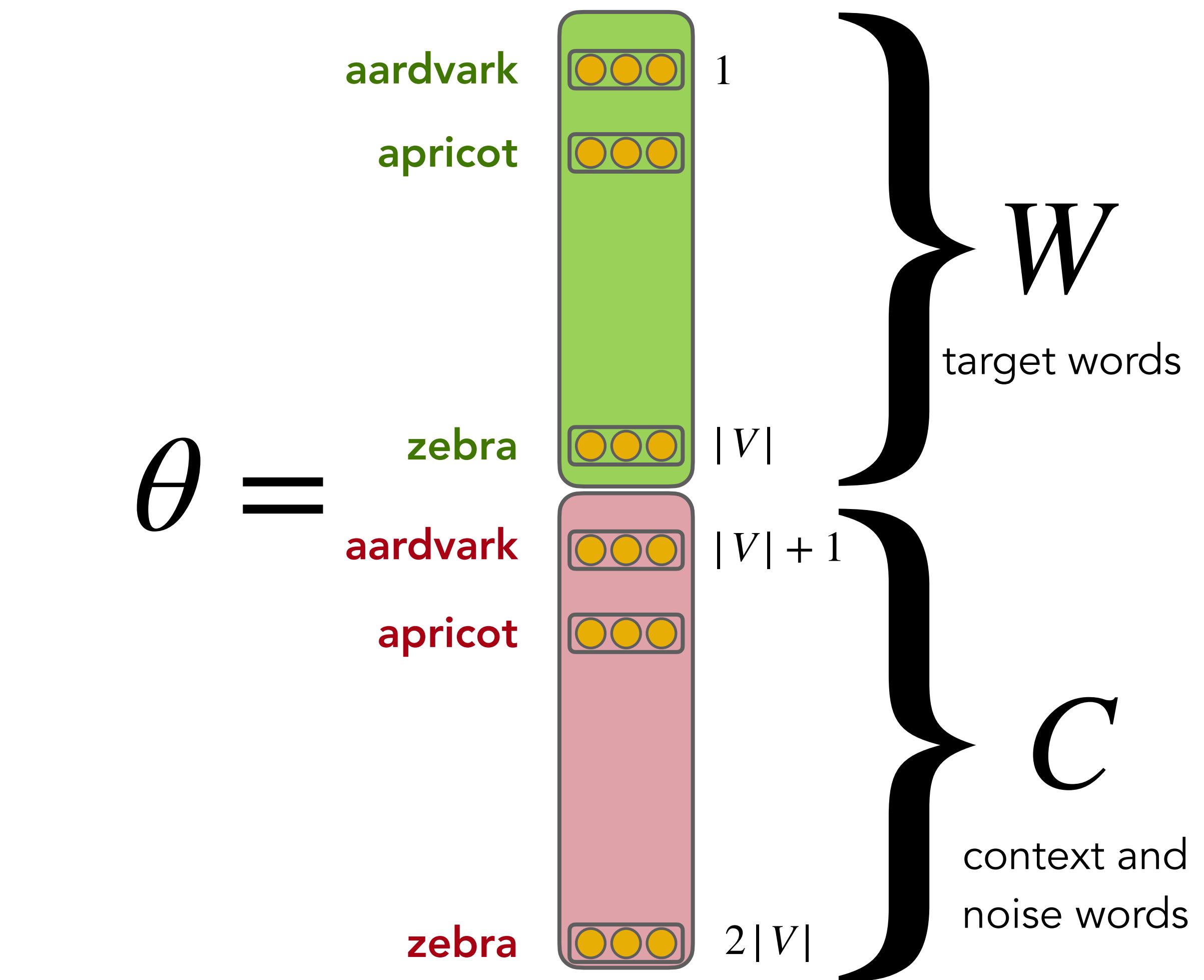
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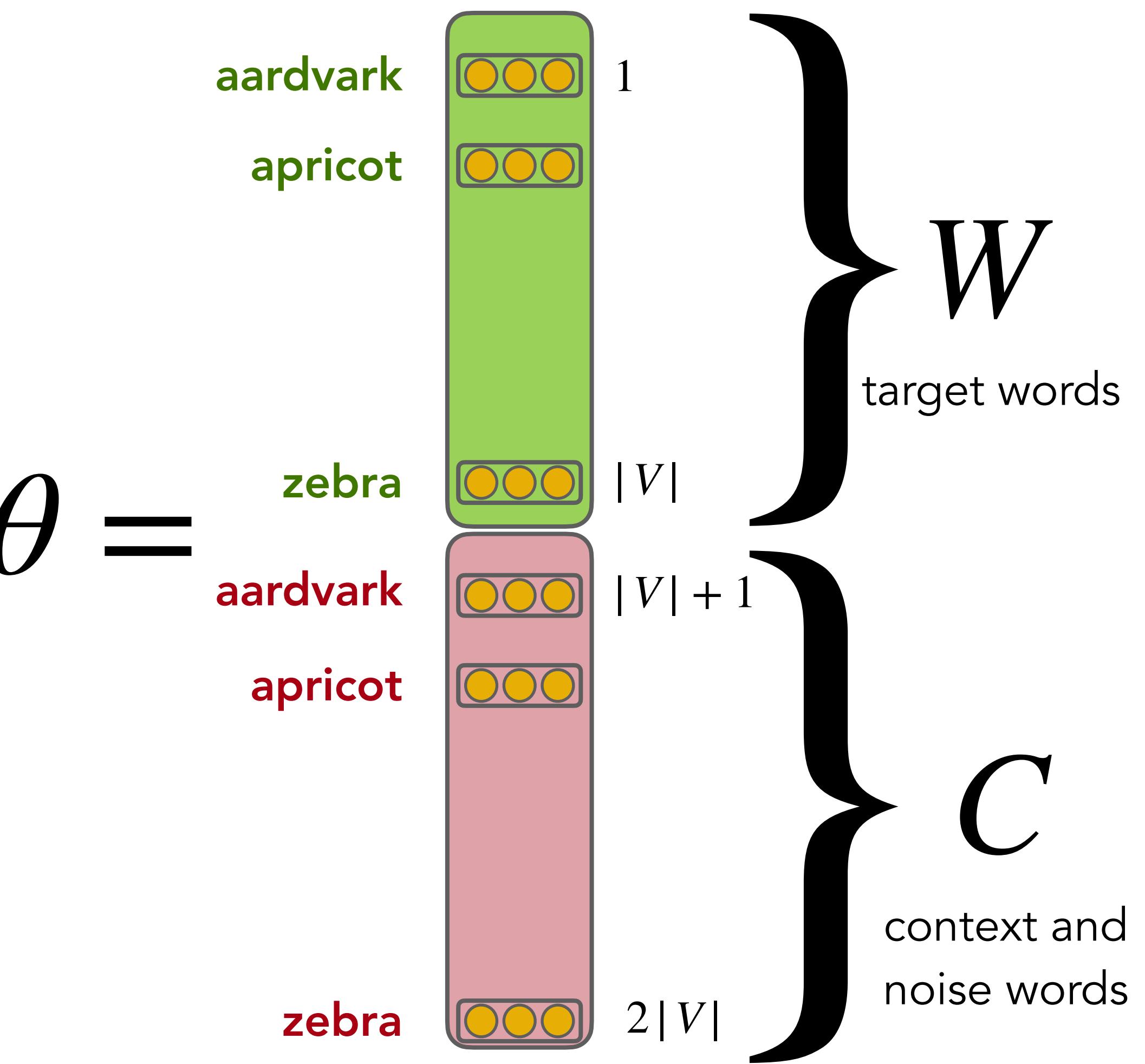
Update the parameters by
subtracting respective η -weighted
gradients

word2vec: Learned Embeddings



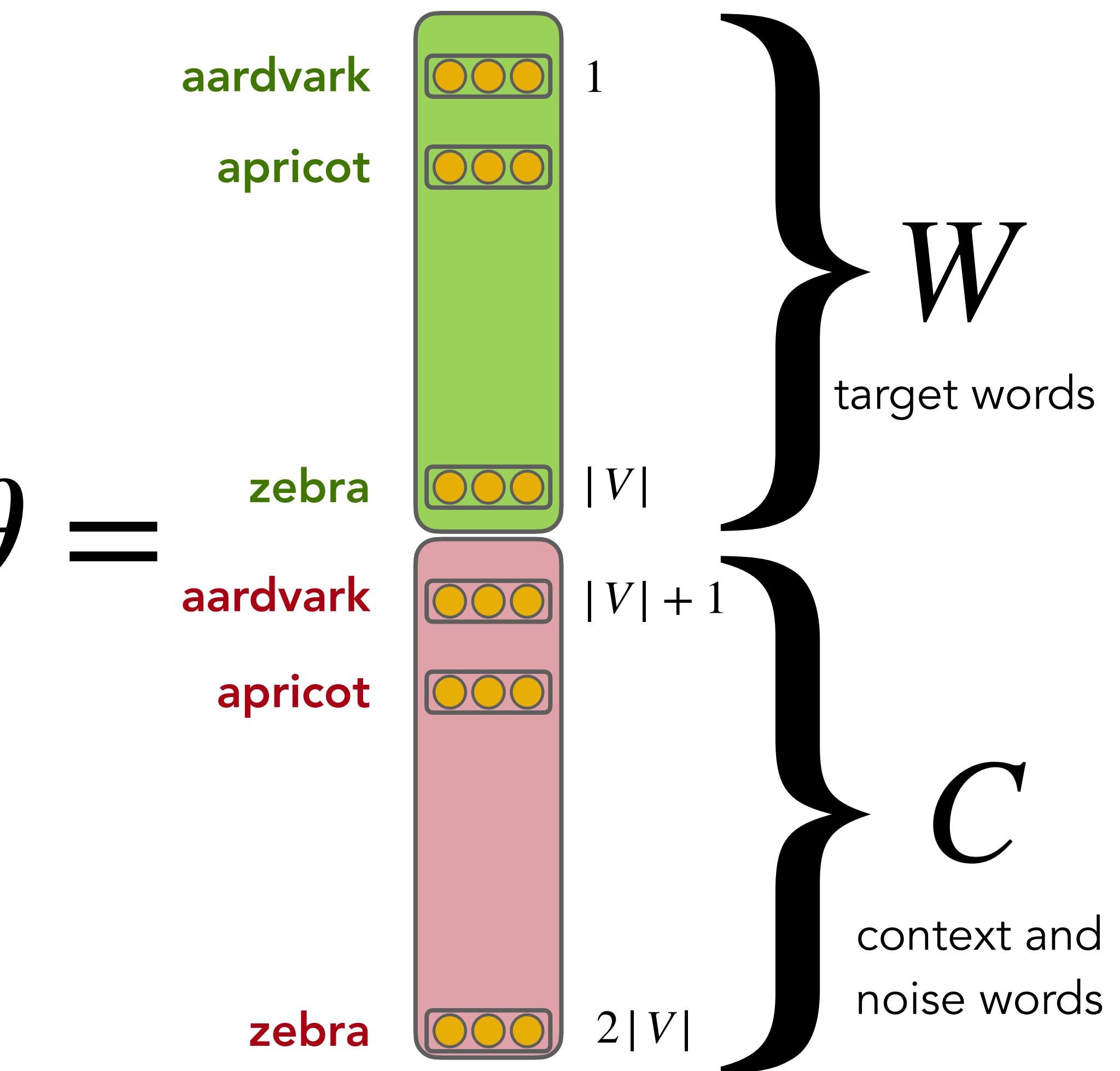
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- word2vec learns two sets of embeddings:
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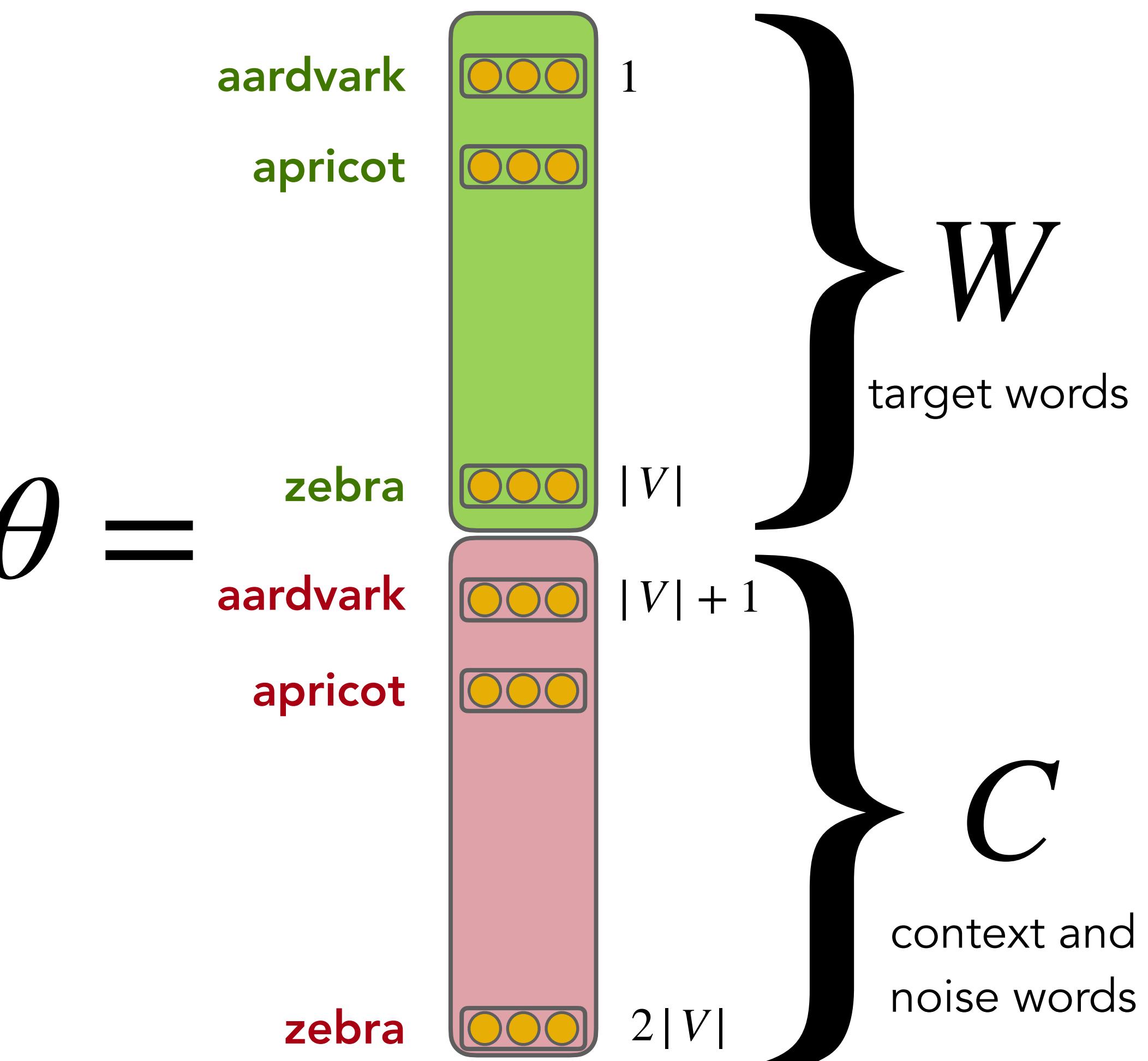
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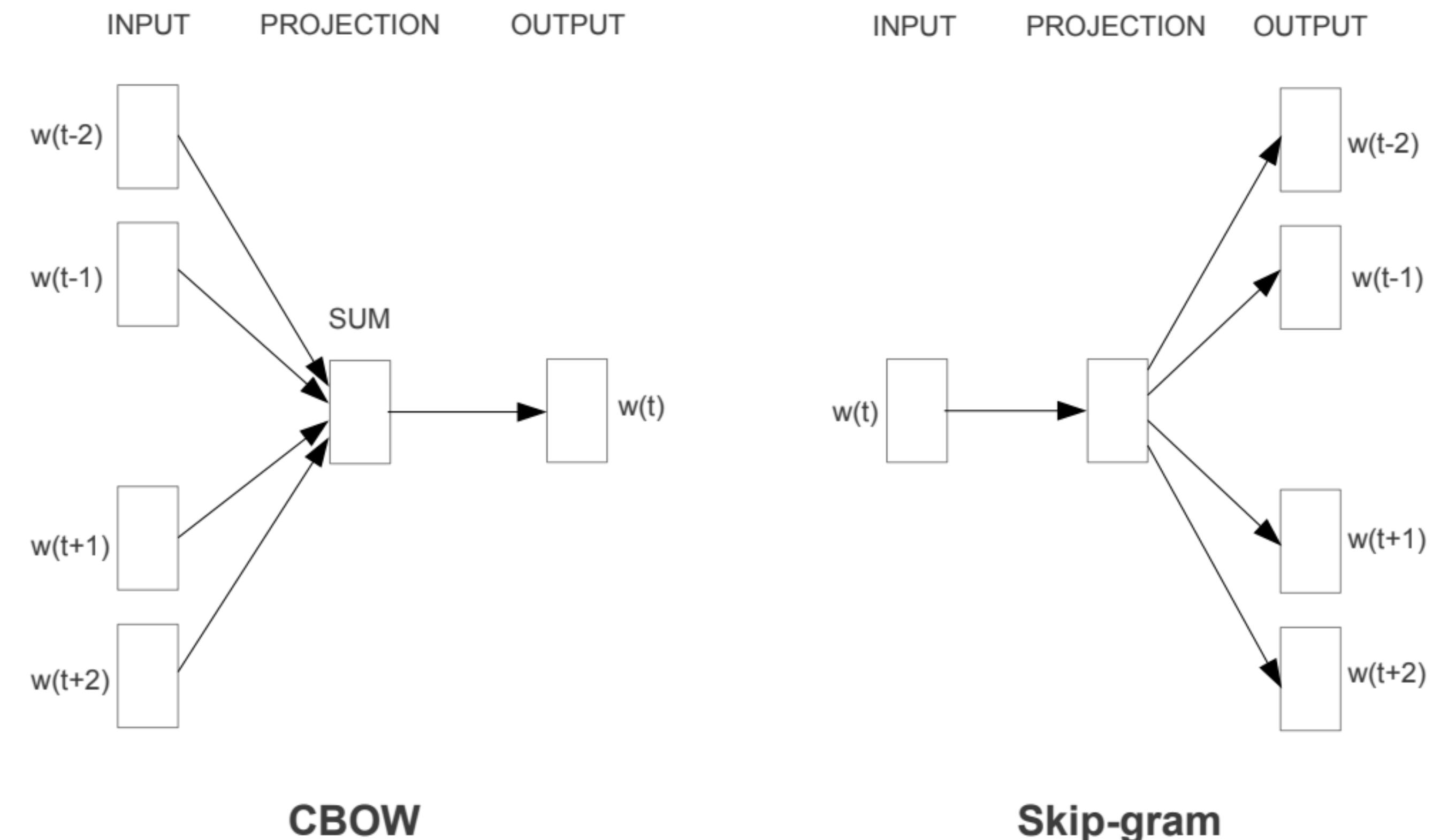
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What do the different dimensions in dense embeddings like word2vec represent?

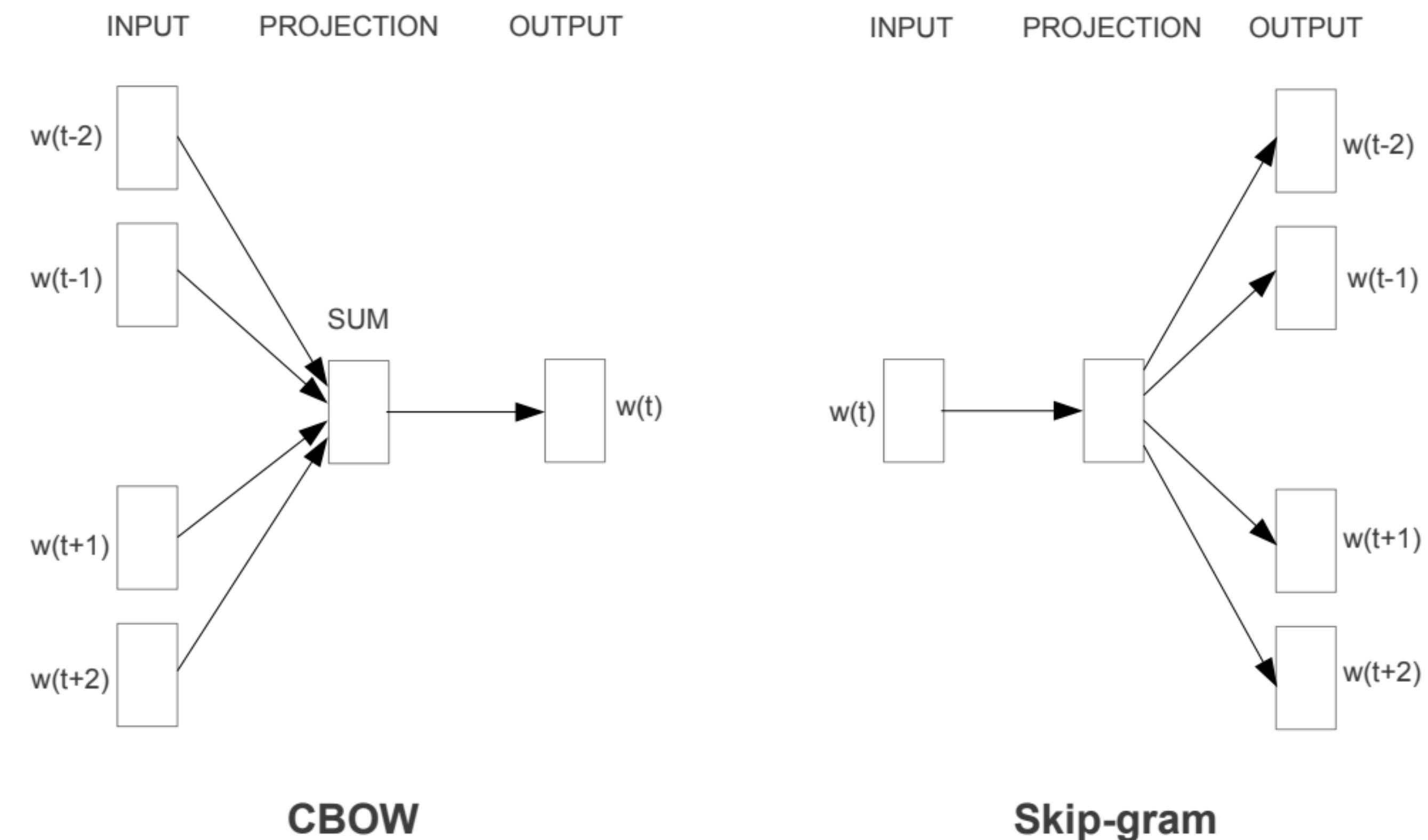
CBOW and Skipgram



Mikolov et al., 2013. Exploiting Similarities among Languages for Machine Translation.

CBOW and Skipgram

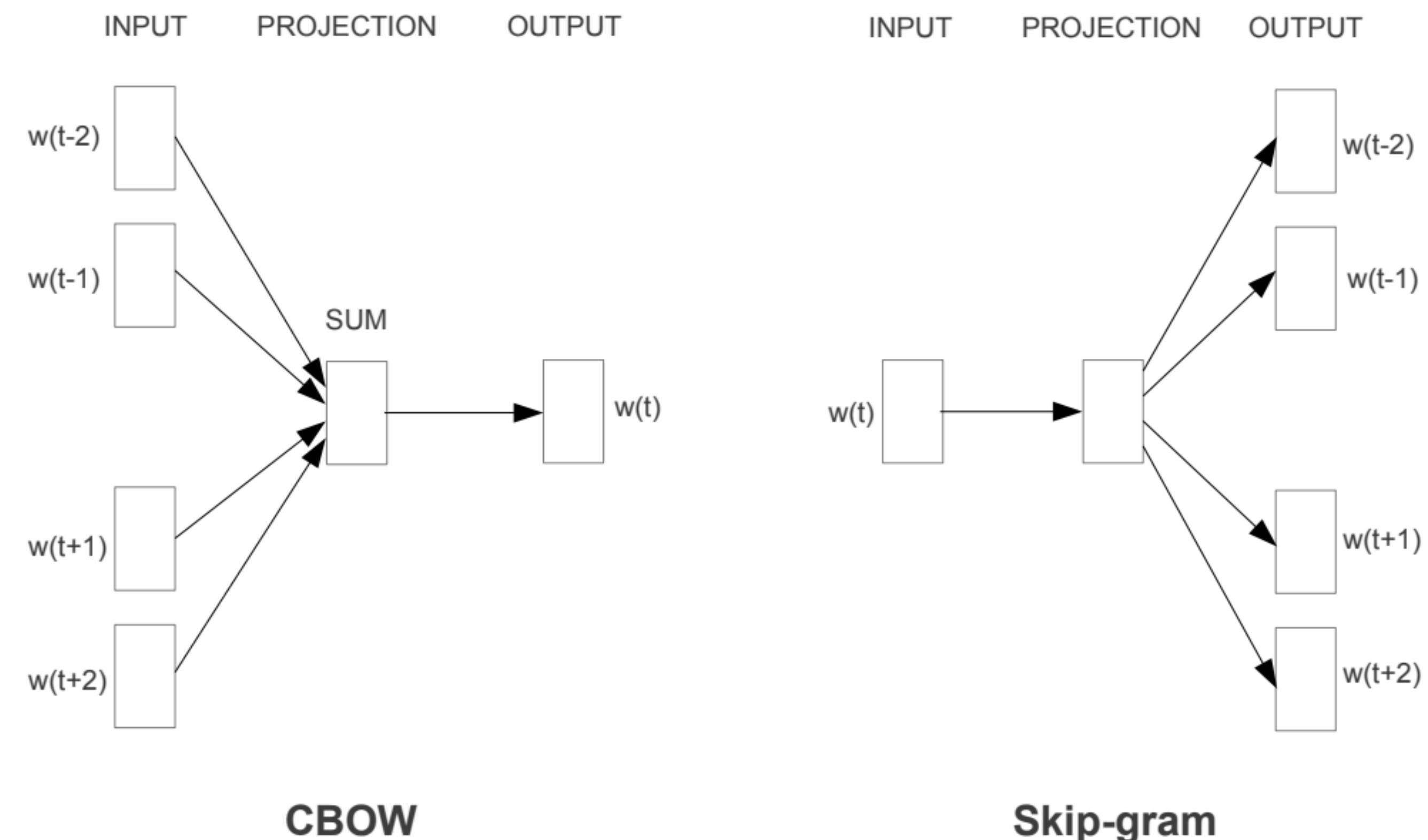
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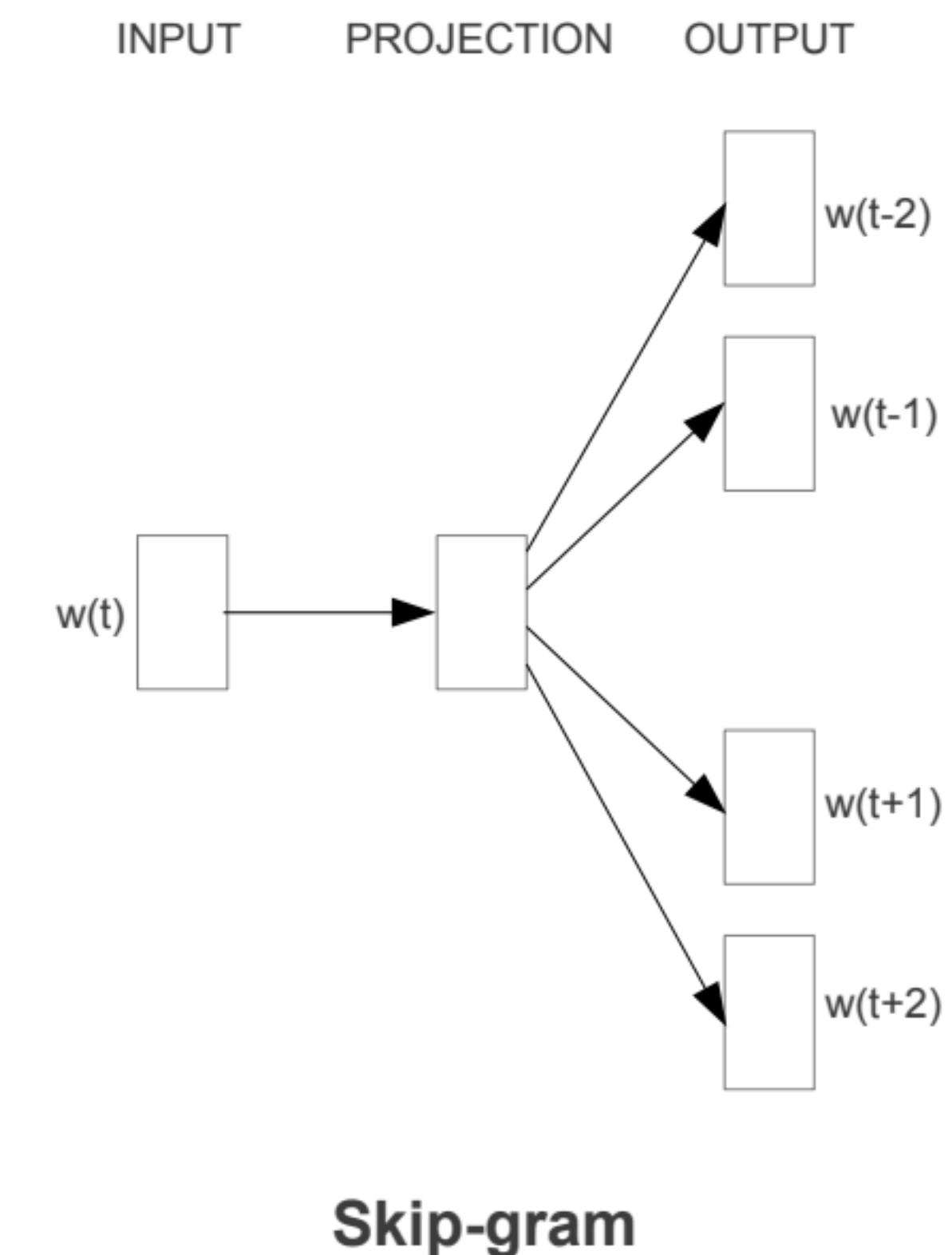
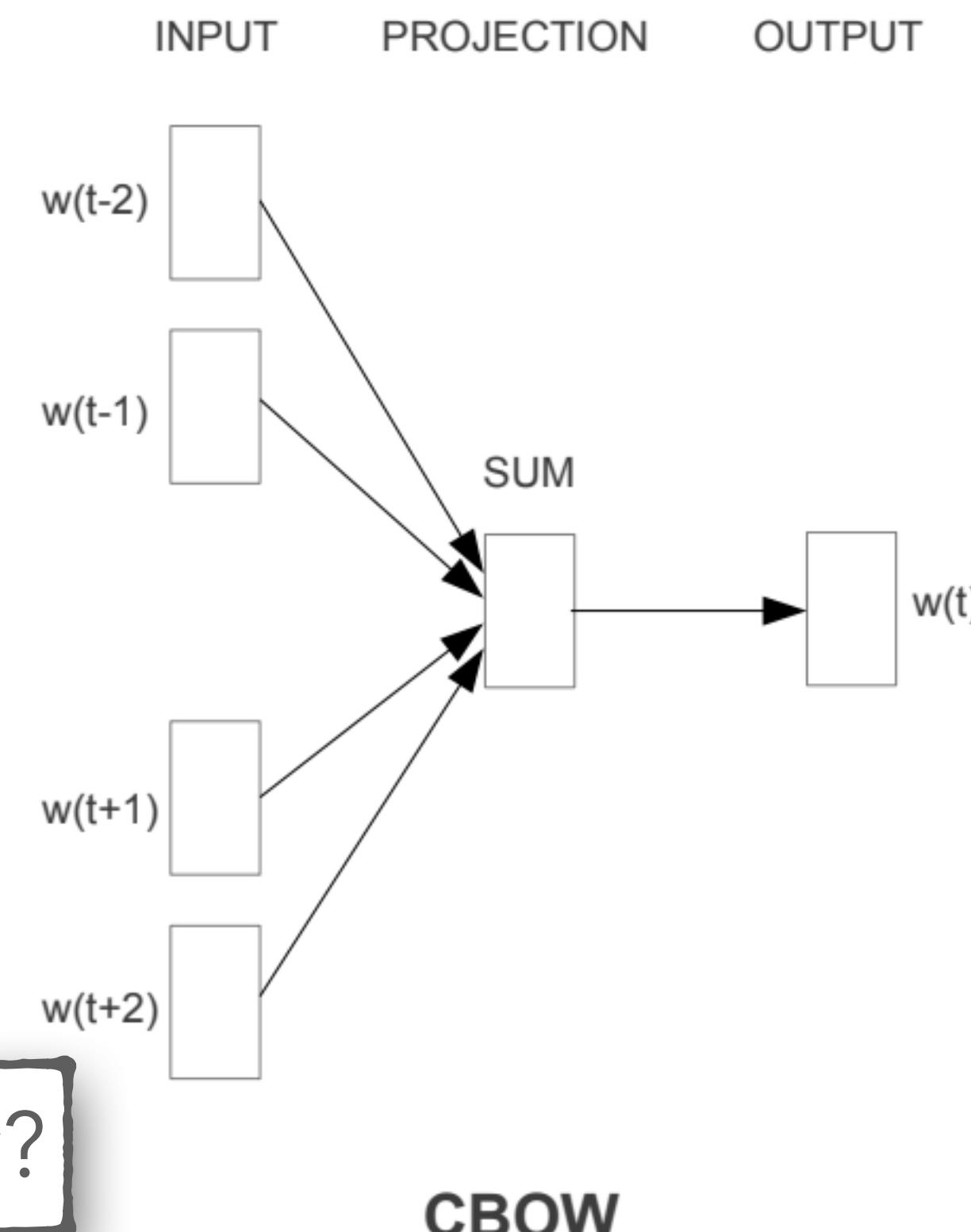
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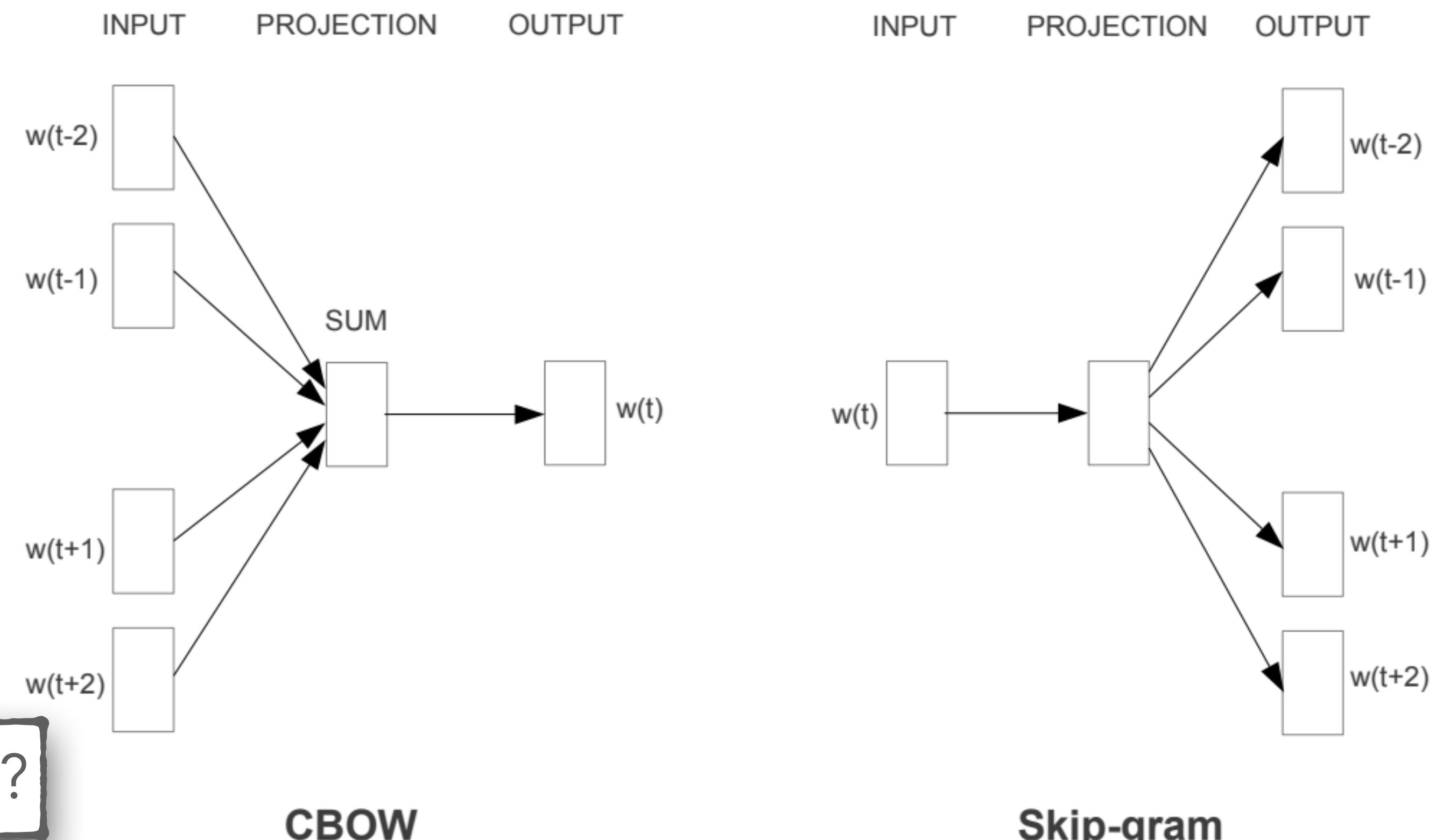
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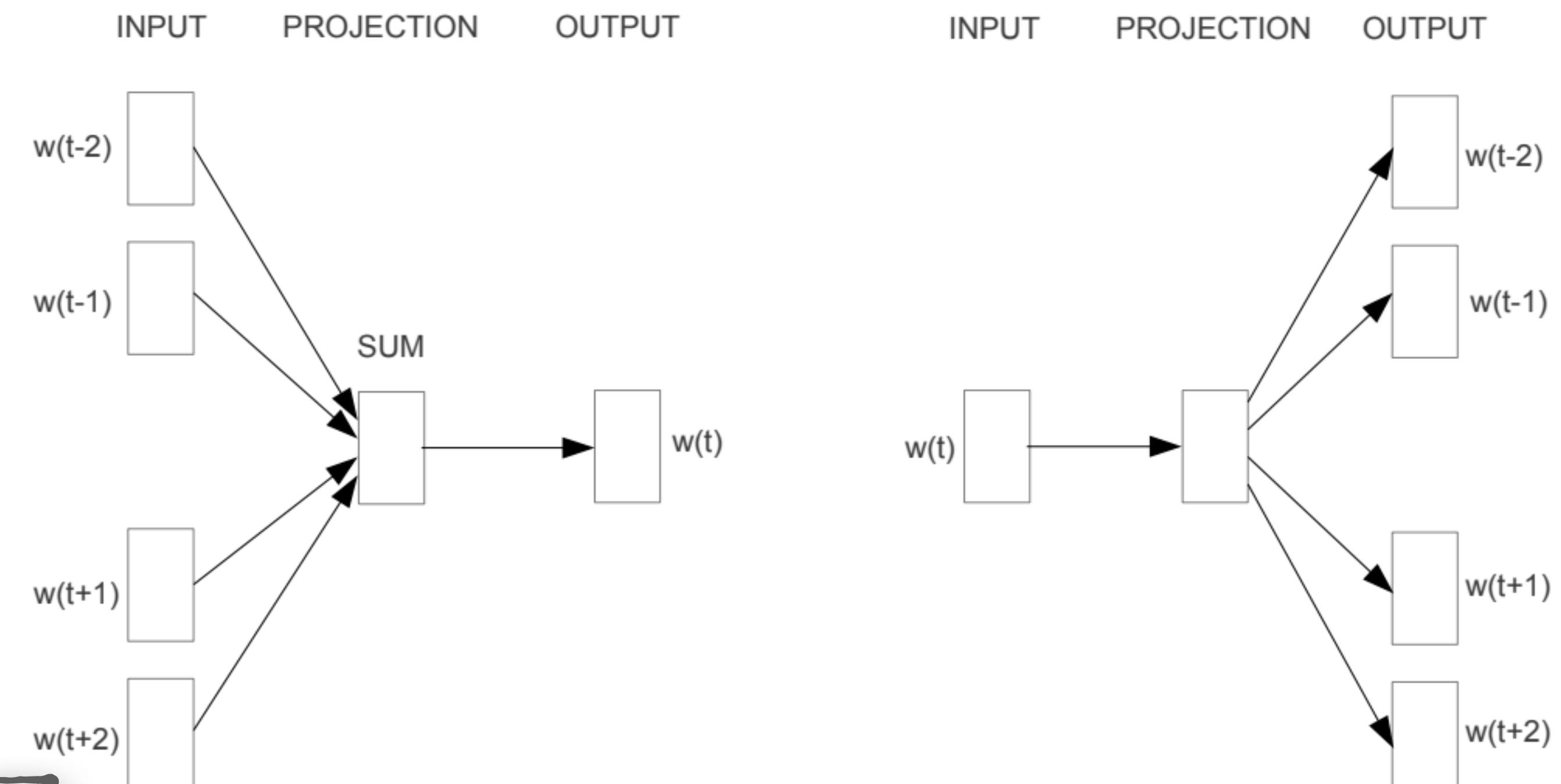
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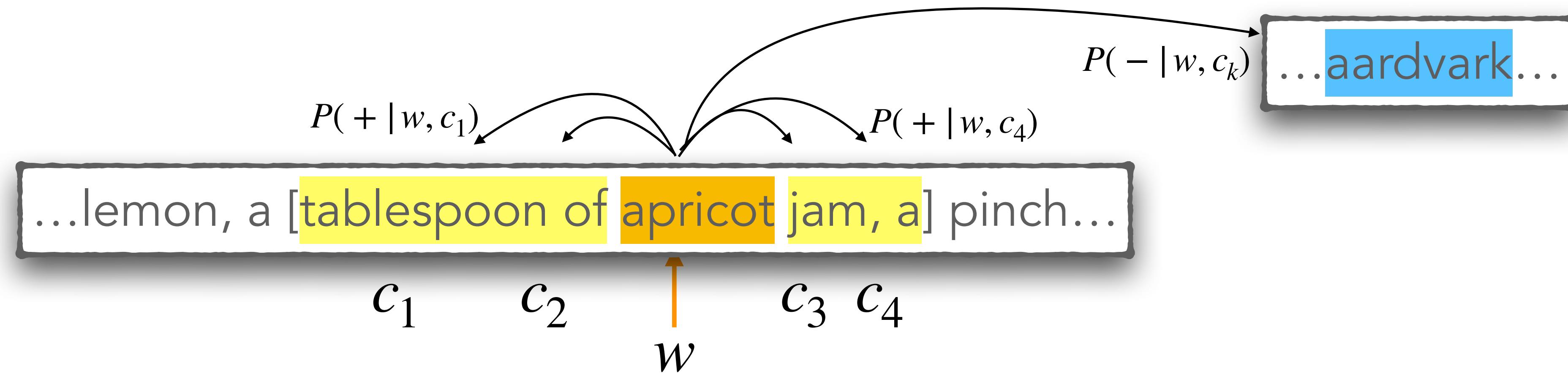
- Skip-gram generally works better

Why?



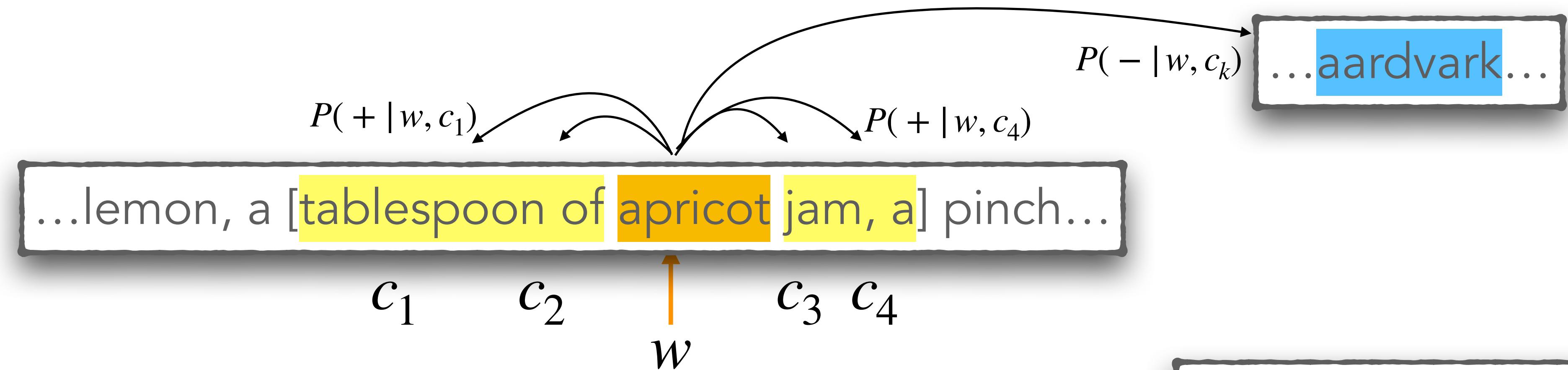
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word2vec: Summary



- Start with $2|V|$ random d -dimensional vectors as initial embeddings
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Can we learn only one embedding per token?

Lecture Outline

- Announcements
- Recap: Sparse and Dense Word Embeddings, word2vec
- GloVe
- Word Embeddings: Properties and Evaluation
- Quiz 2
- Feed-forward Neural Nets

GloVe

GloVe: Global Vectors

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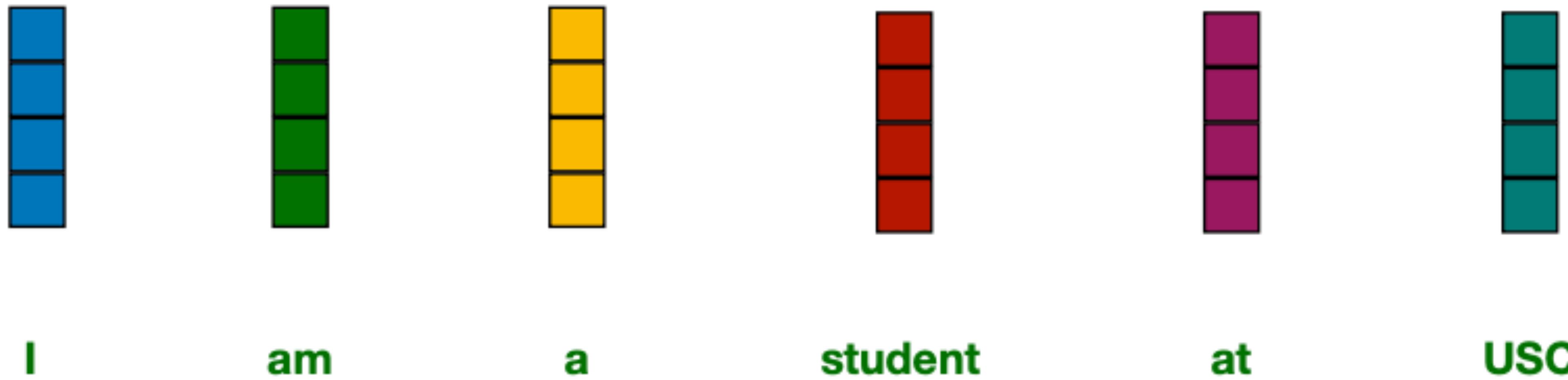
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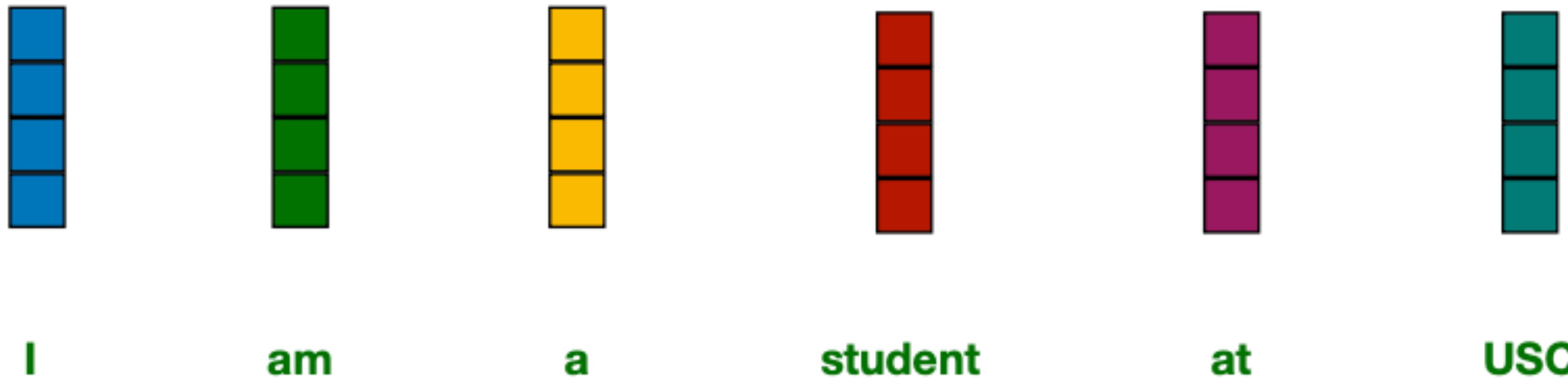
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- Fast training, scalable to huge corpora

Applying Word Embeddings to Classification Tasks



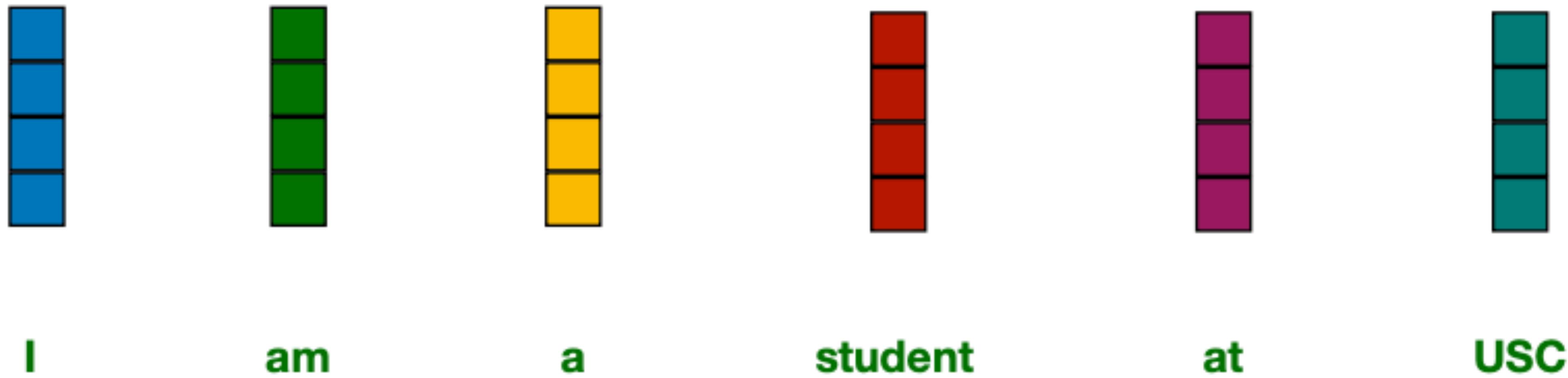
Applying Word Embeddings to Classification Tasks

- We need **a single feature vector** to feed into ML classifiers



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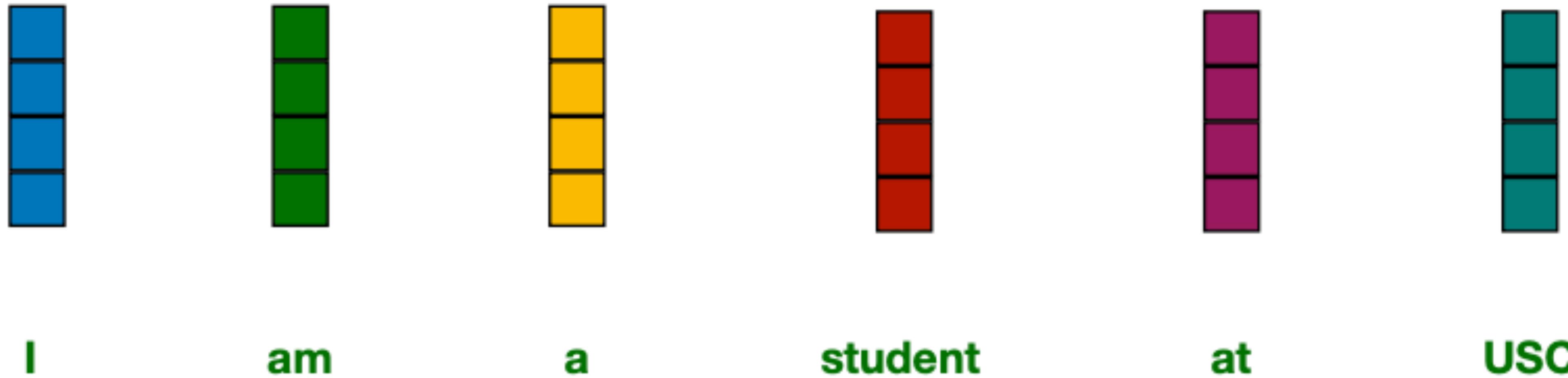
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Pooling may happen via
dimension-specific
averaging or max operations

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Properties and Evaluation of Word Embeddings

Effects of Context Window Size

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 - Hogwarts nearest neighbors are other fictional schools
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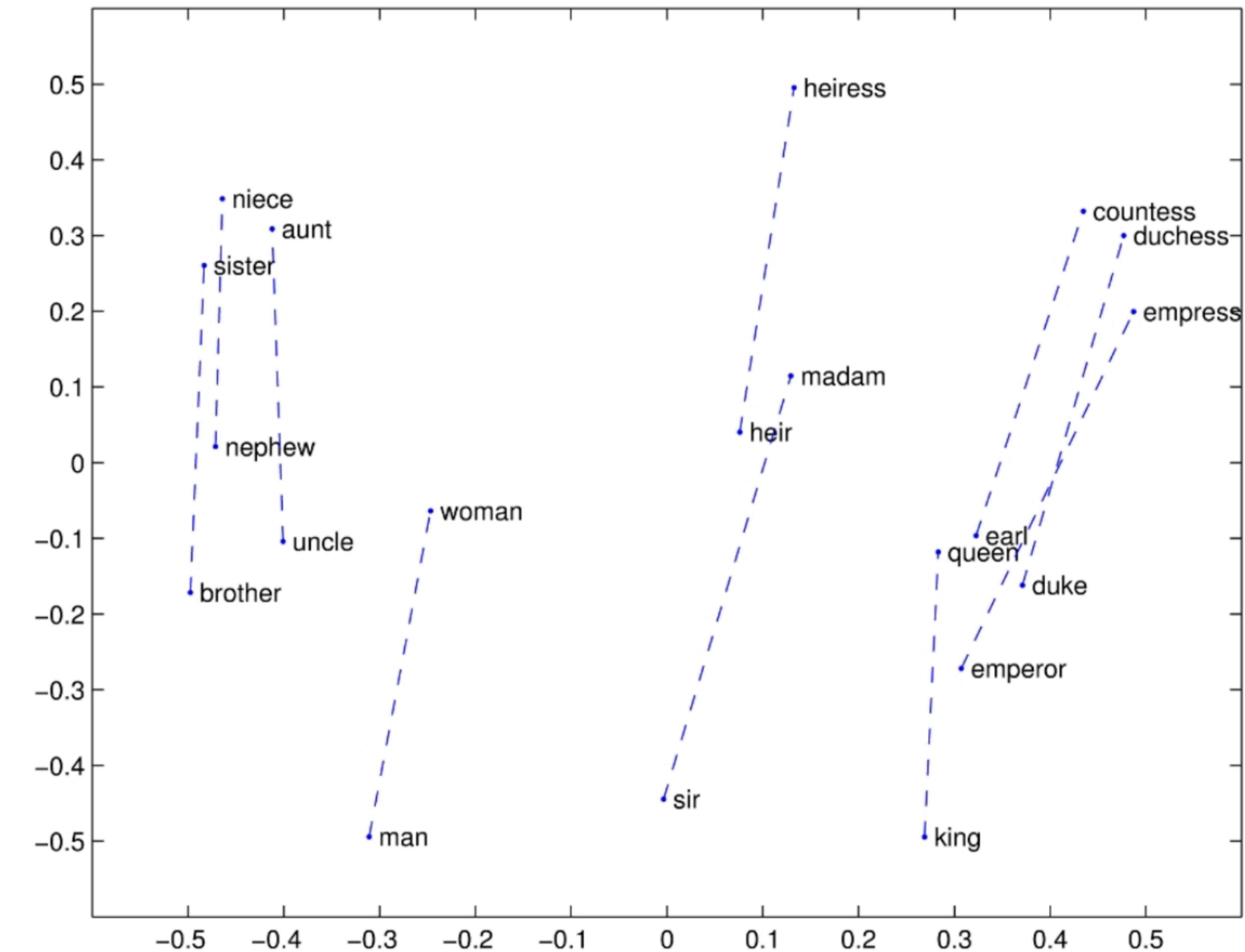
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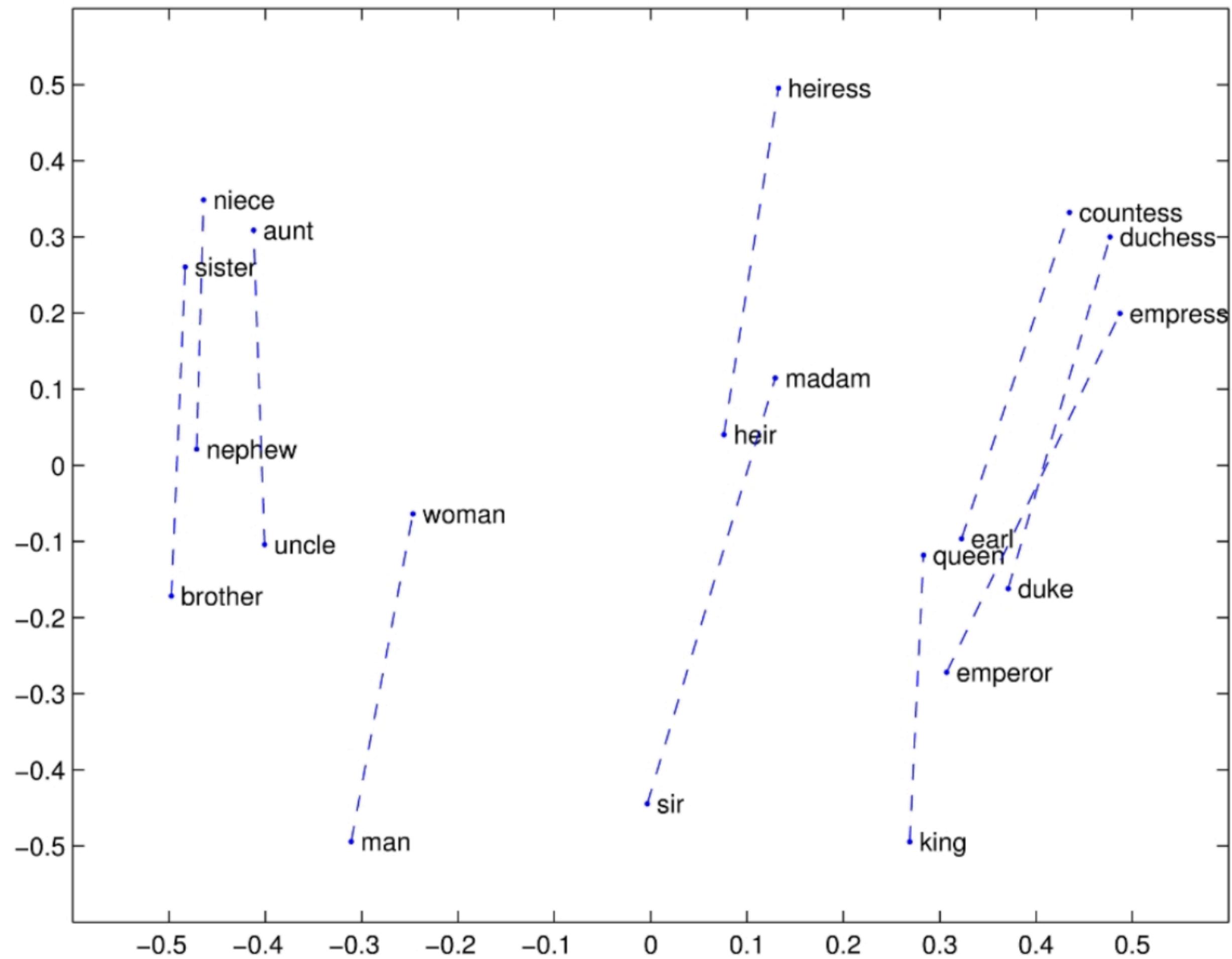
Why?

Evaluation: via Analogy Relations



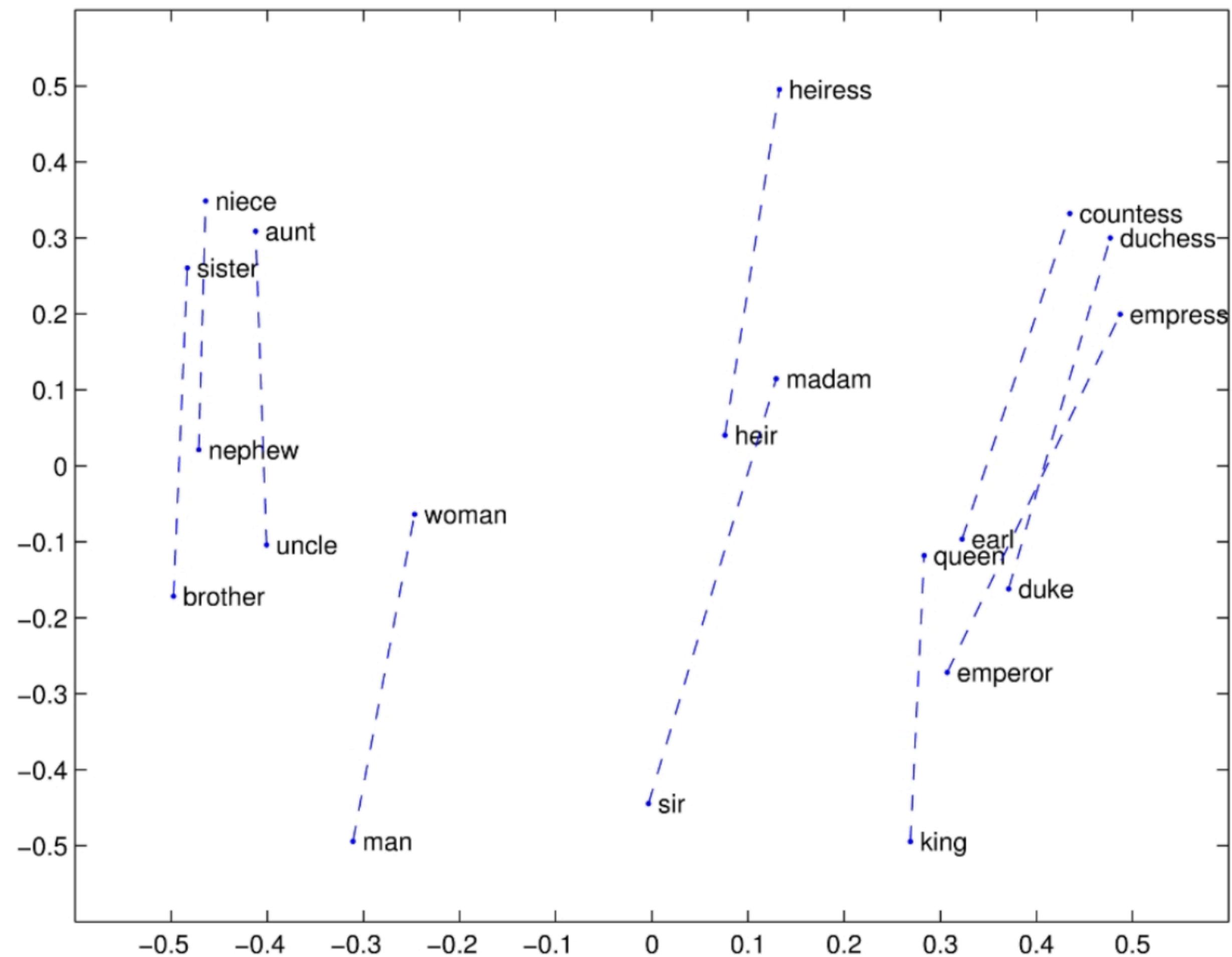
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- Better Evaluation: Performance on Downstream Tasks (Extrinsic Evaluation)



Embeddings reflect cultural bias!



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Allocational Harms

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Embeddings as a tool to study cultural bias!

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Quiz 2

(Password: embedding)

Time: 15 mins

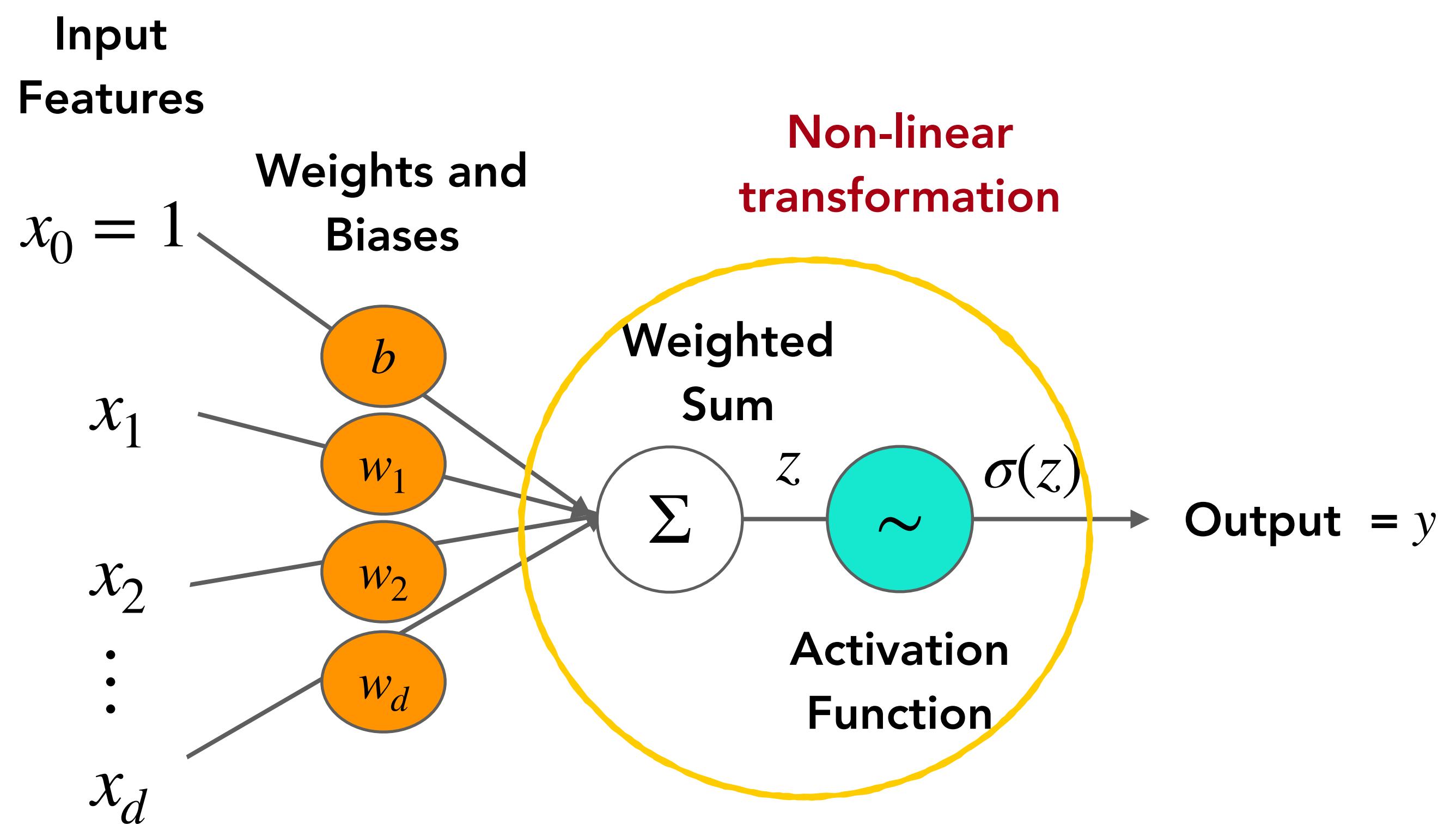
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Feed-Forward Neural Networks

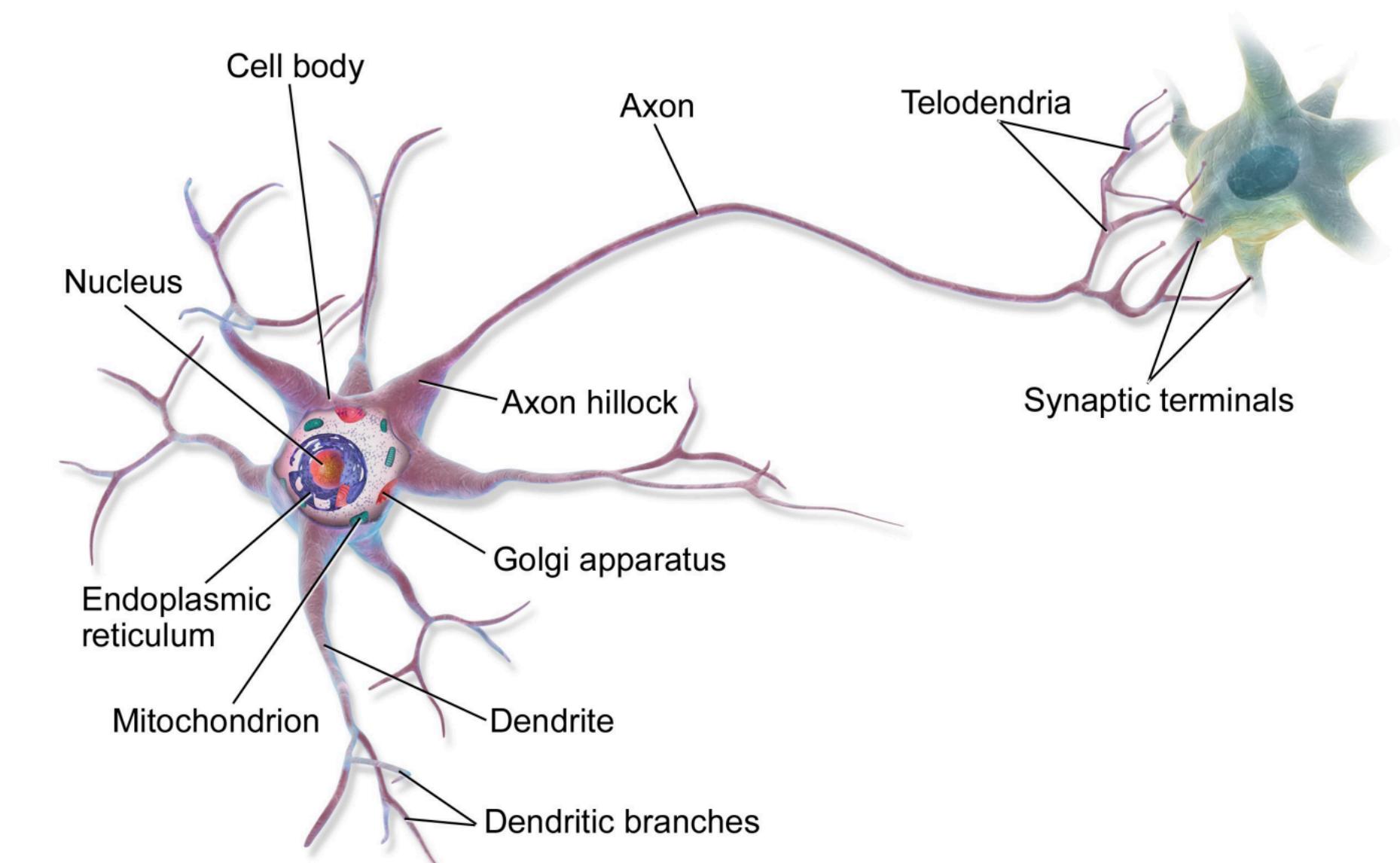
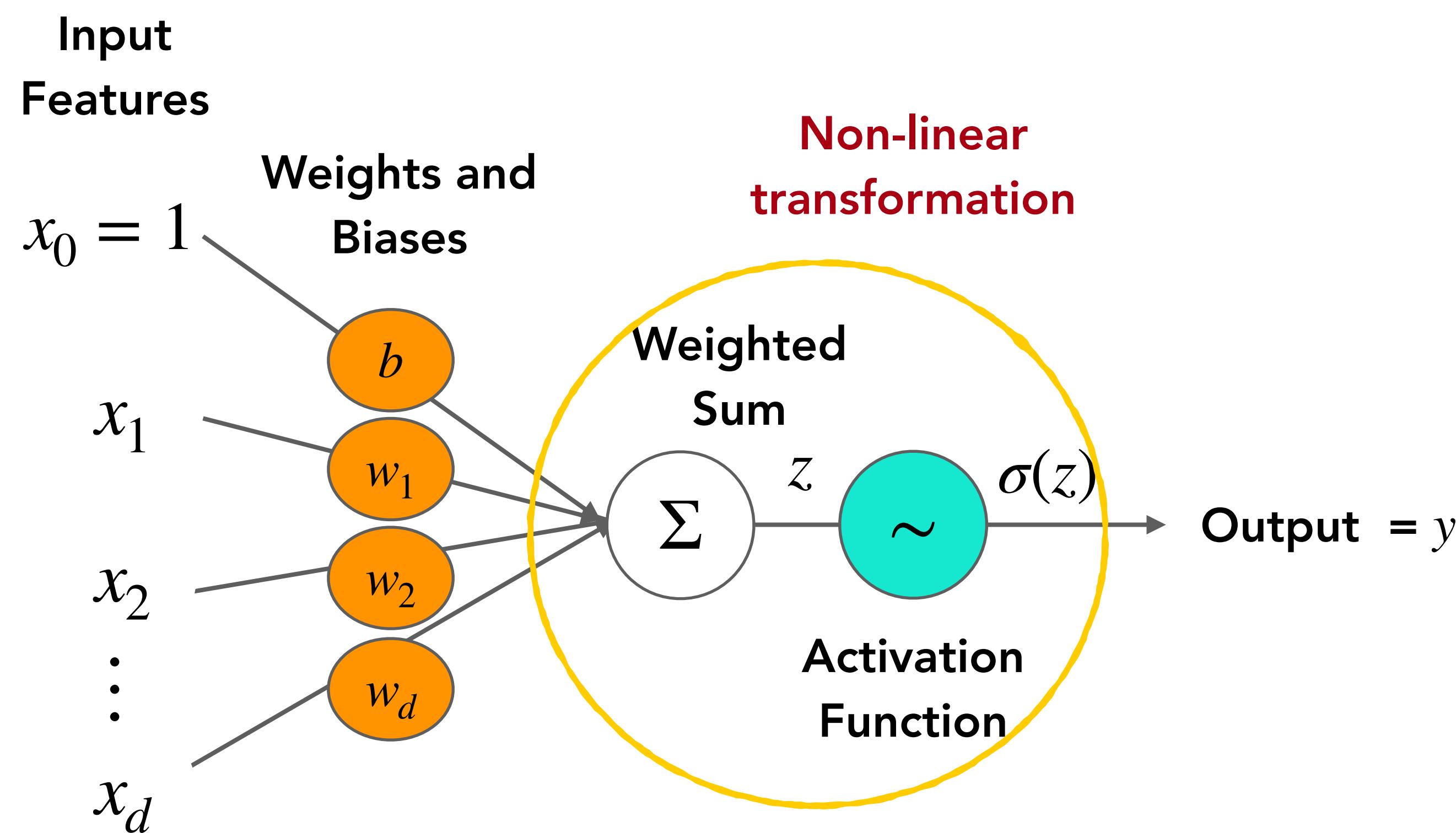
Neural Network Unit

Logistic Regression is a very simple neural network



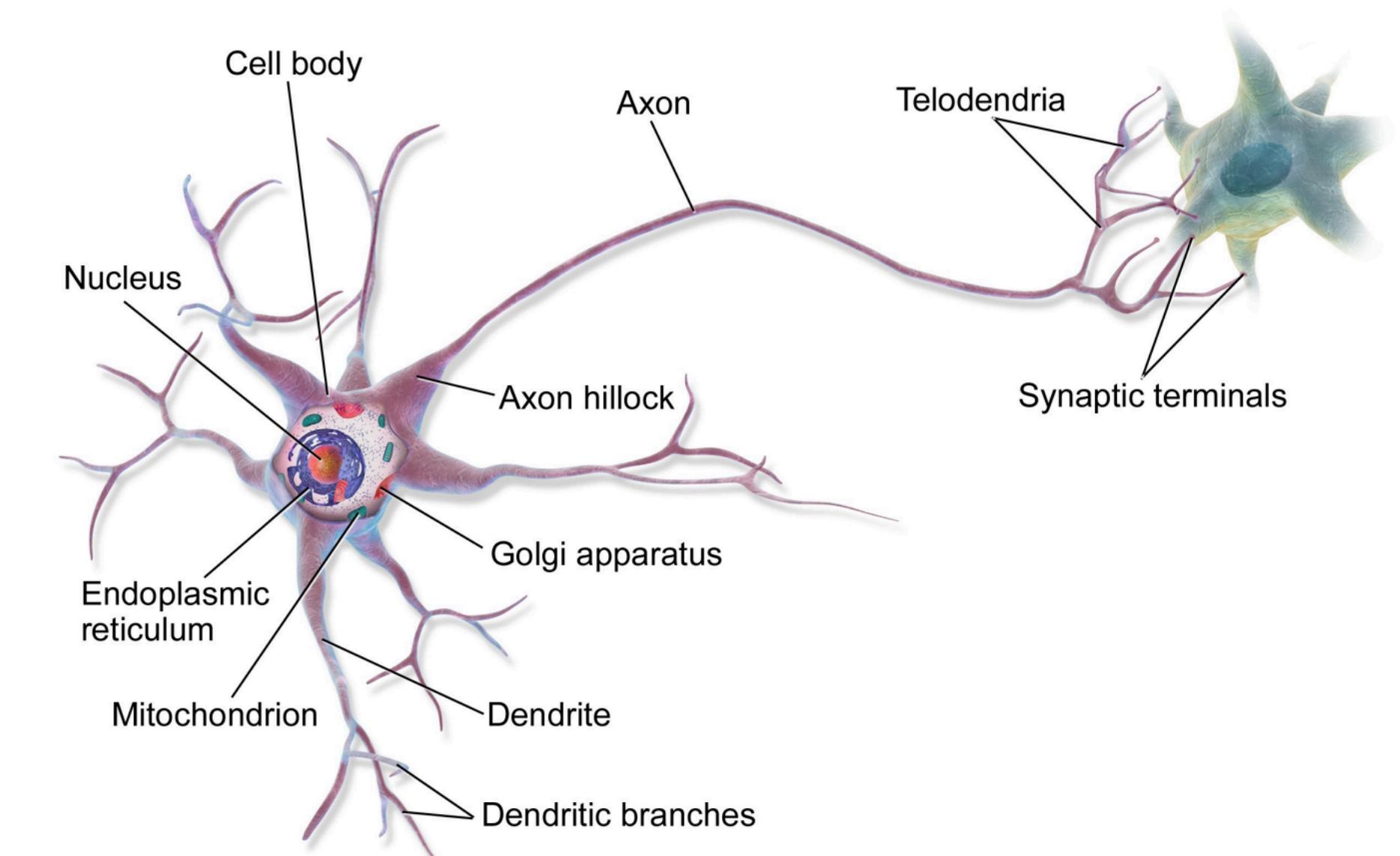
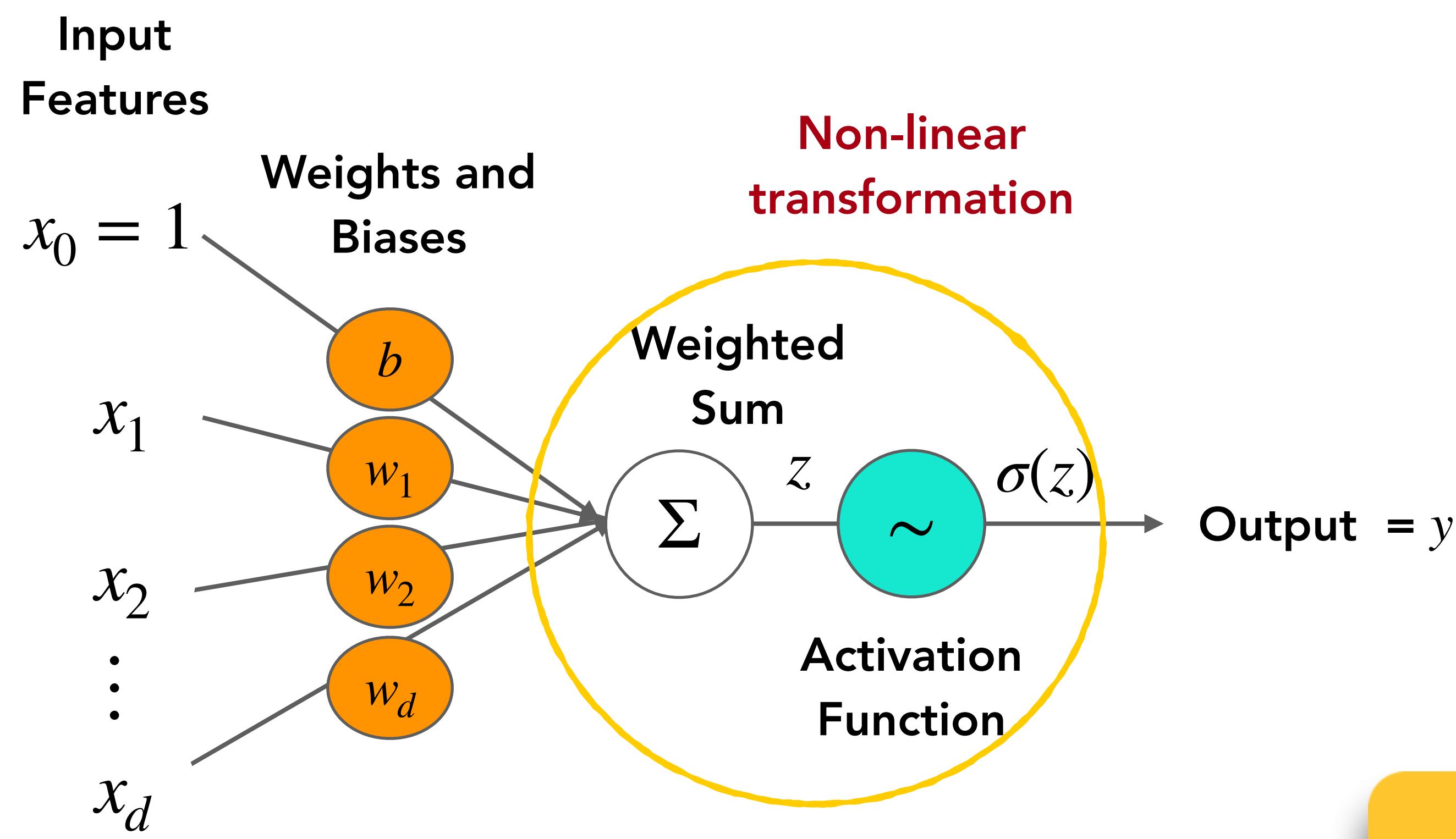
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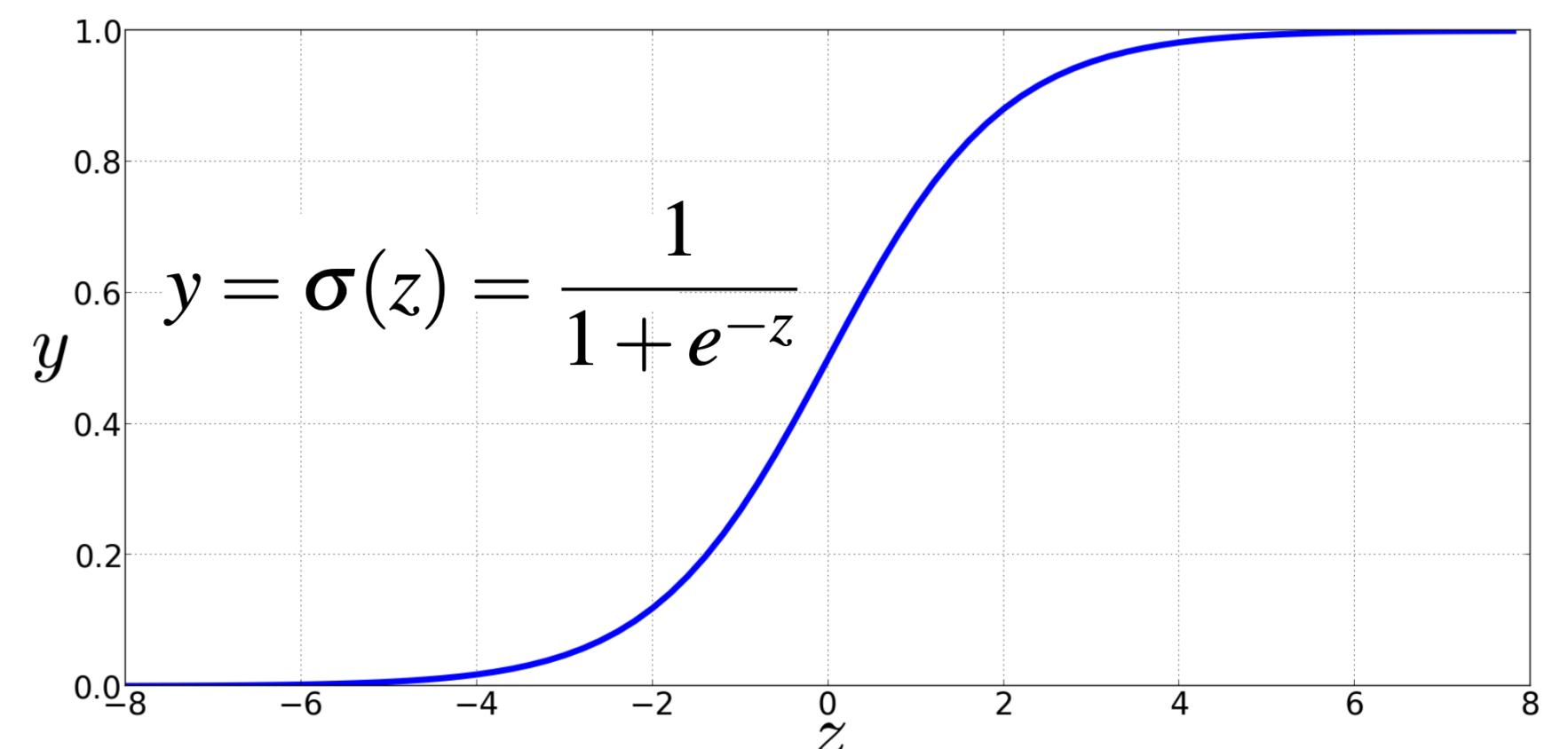
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Resembles a neuron in the brain!

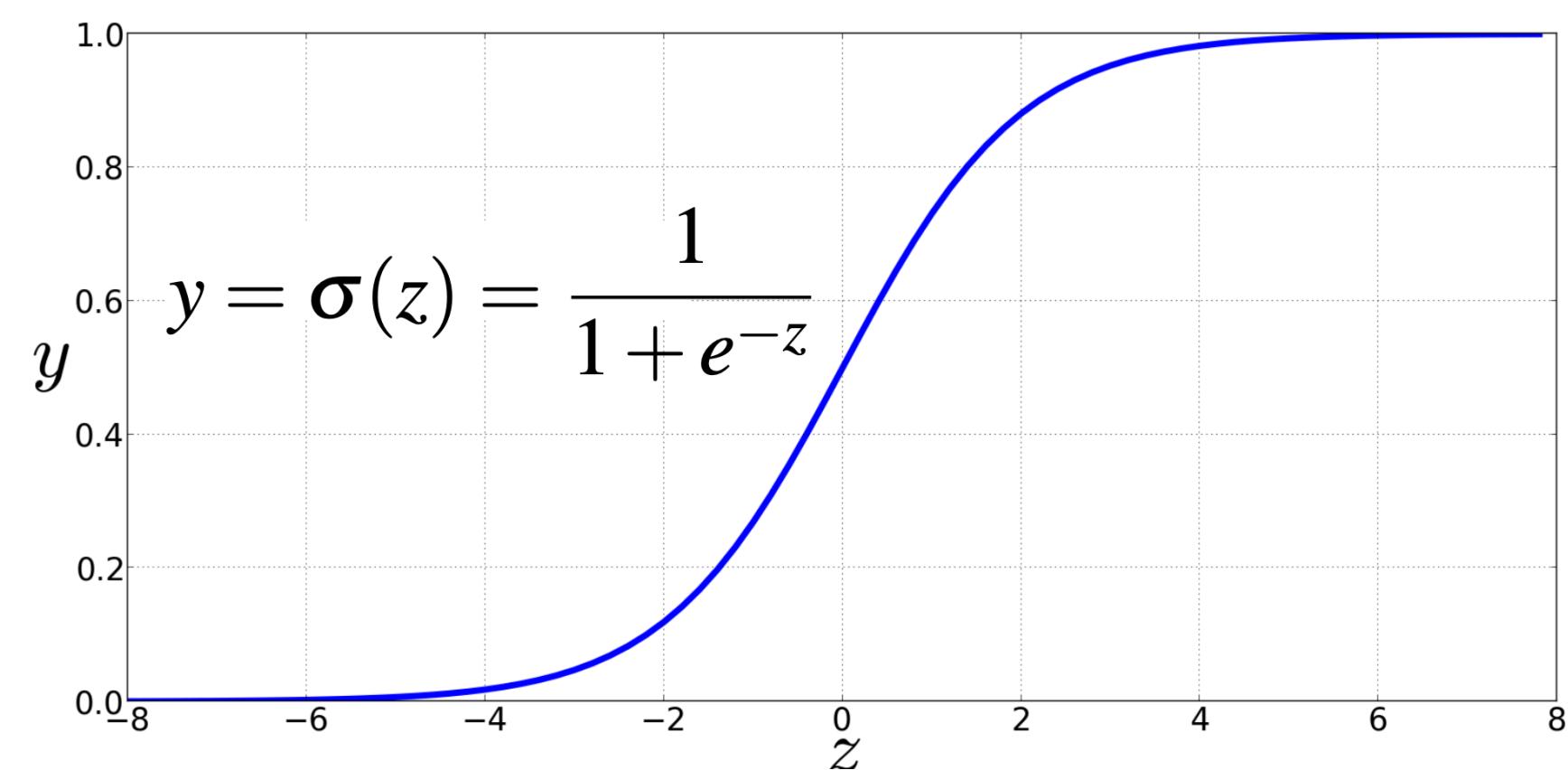
Non-Linear Activation Functions



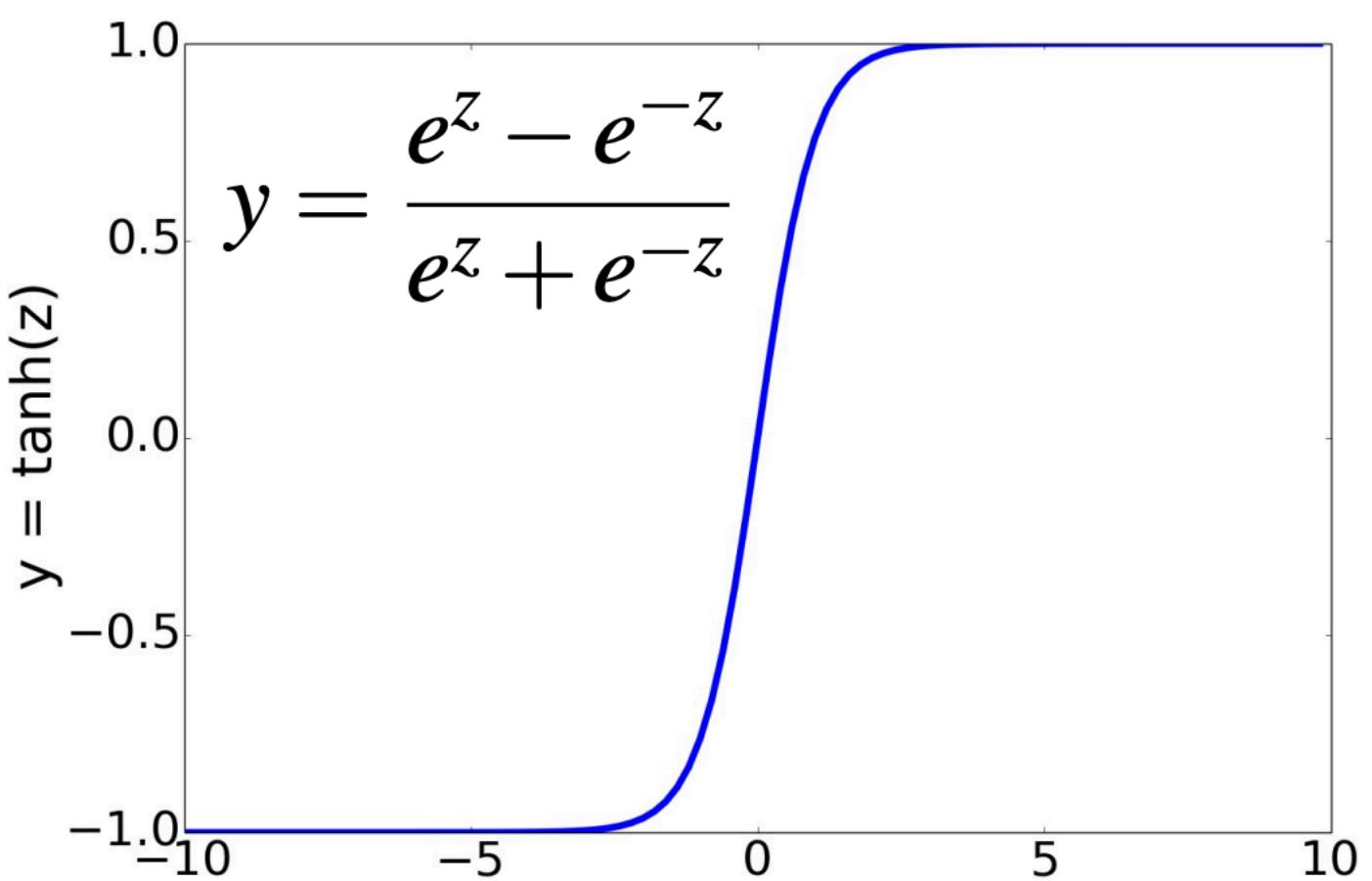
sigmoid

The key ingredient of a neural network is the non-linear activation function

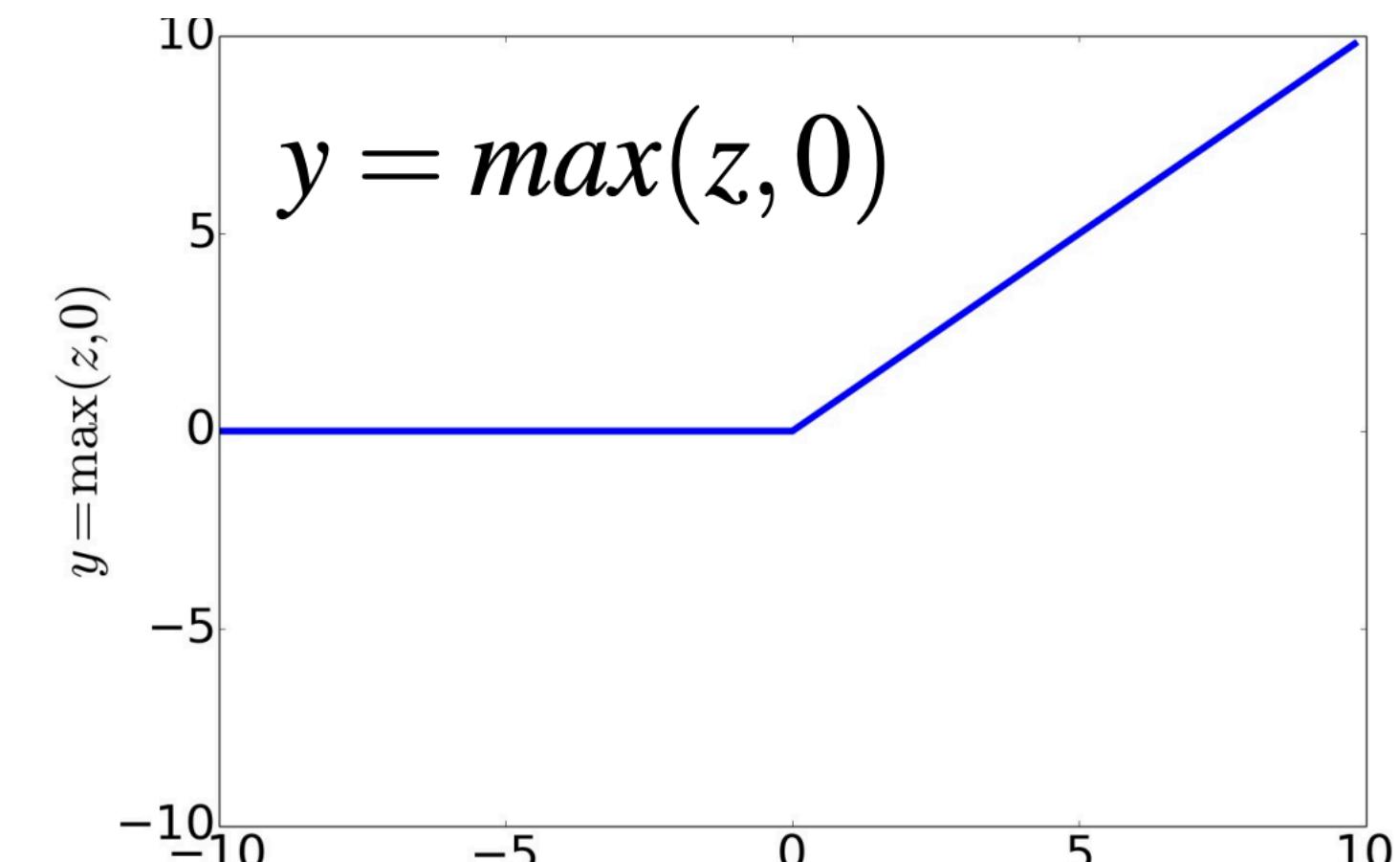
Non-Linear Activation Functions



sigmoid



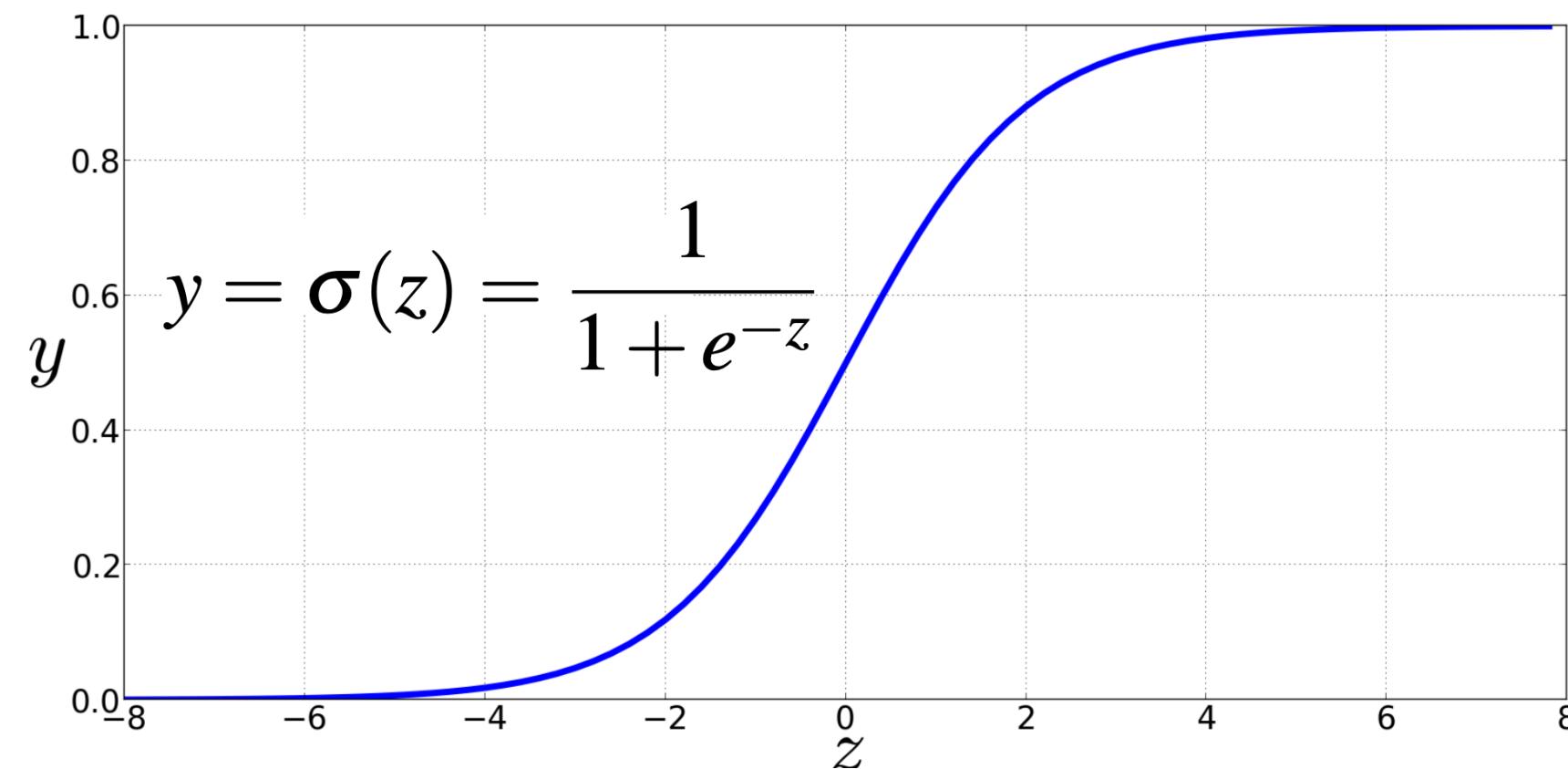
tanh



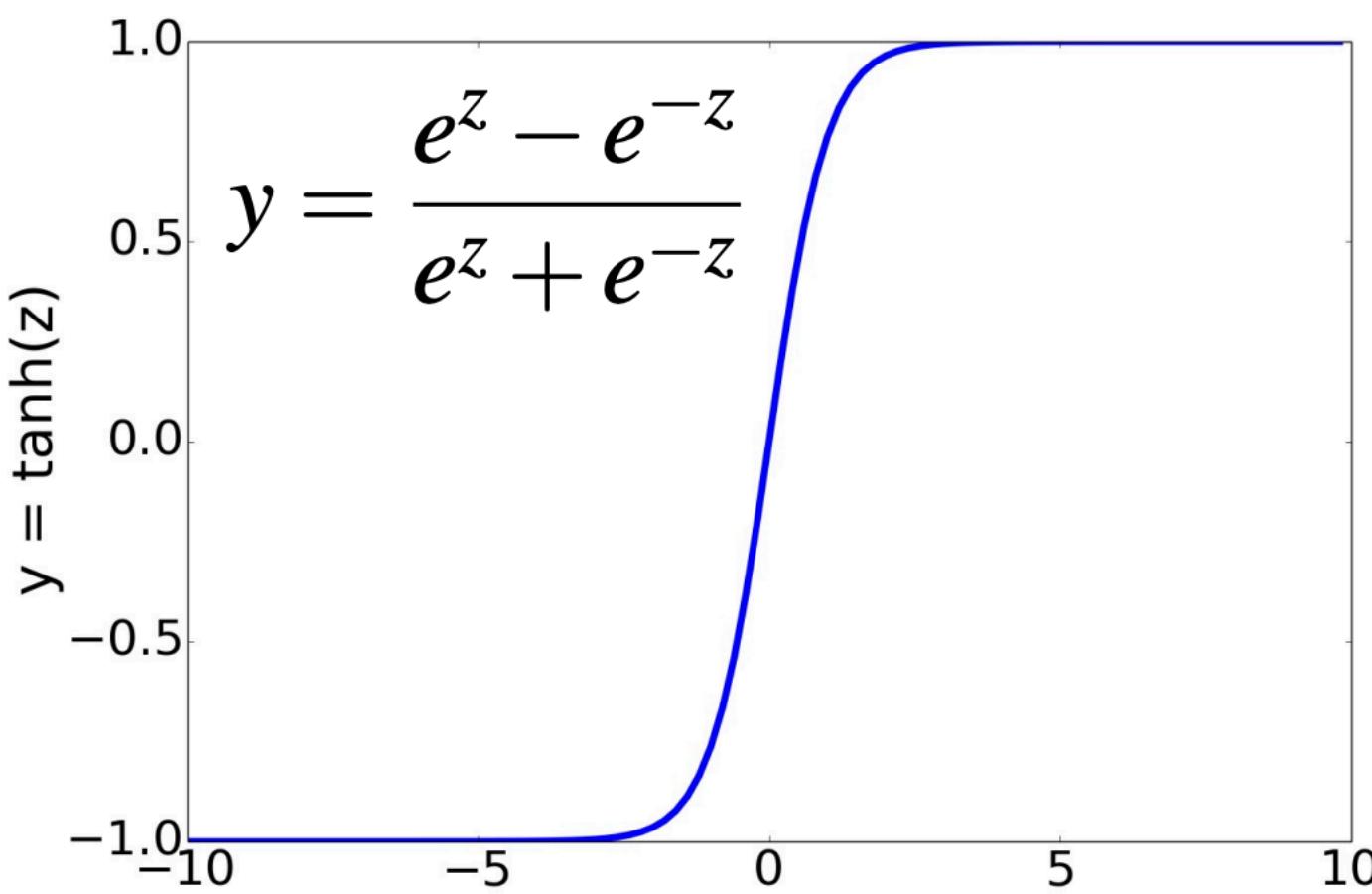
relu (Rectified Linear Unit)

The key ingredient of a neural network is the non-linear activation function

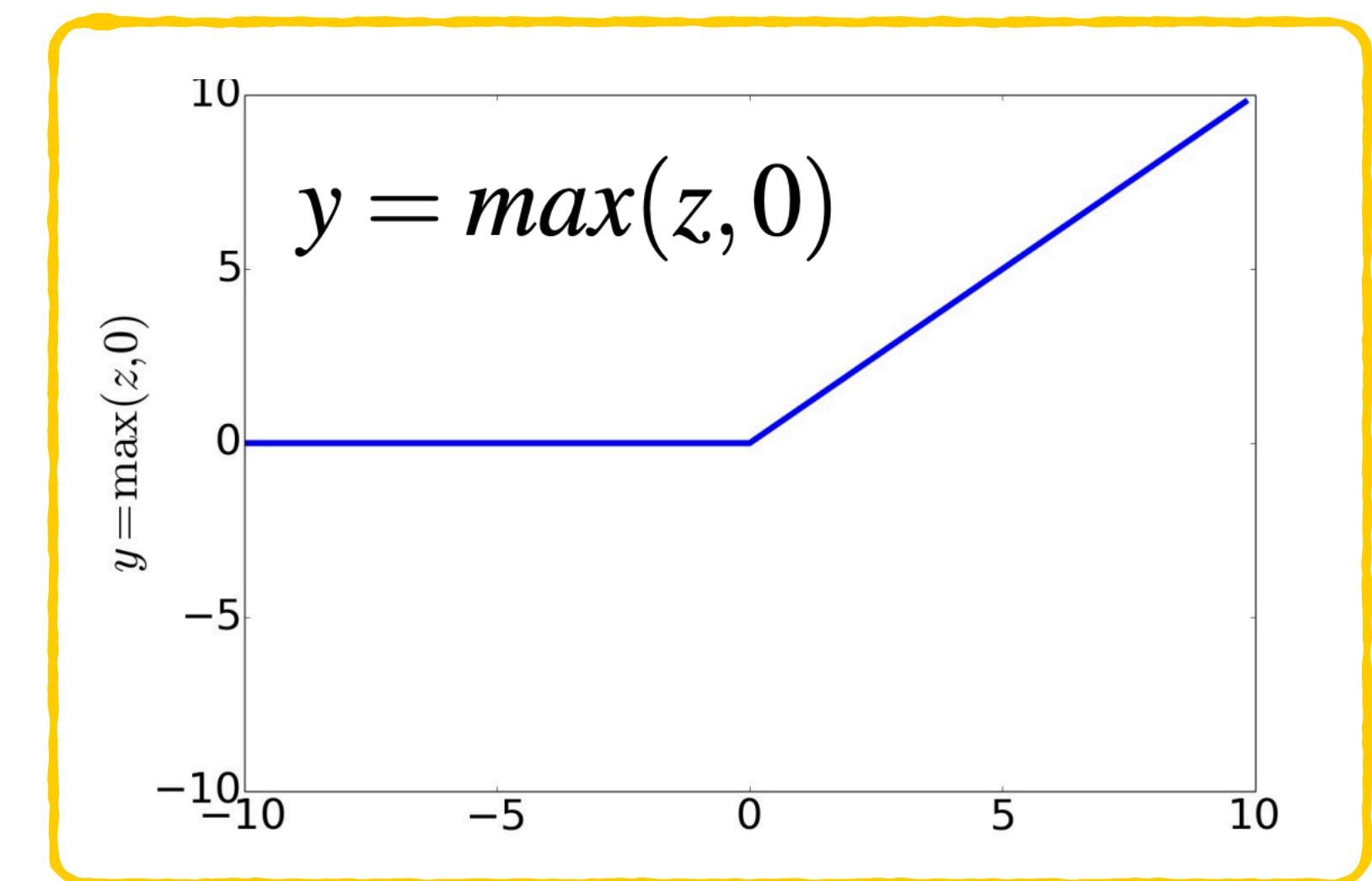
Non-Linear Activation Functions



sigmoid



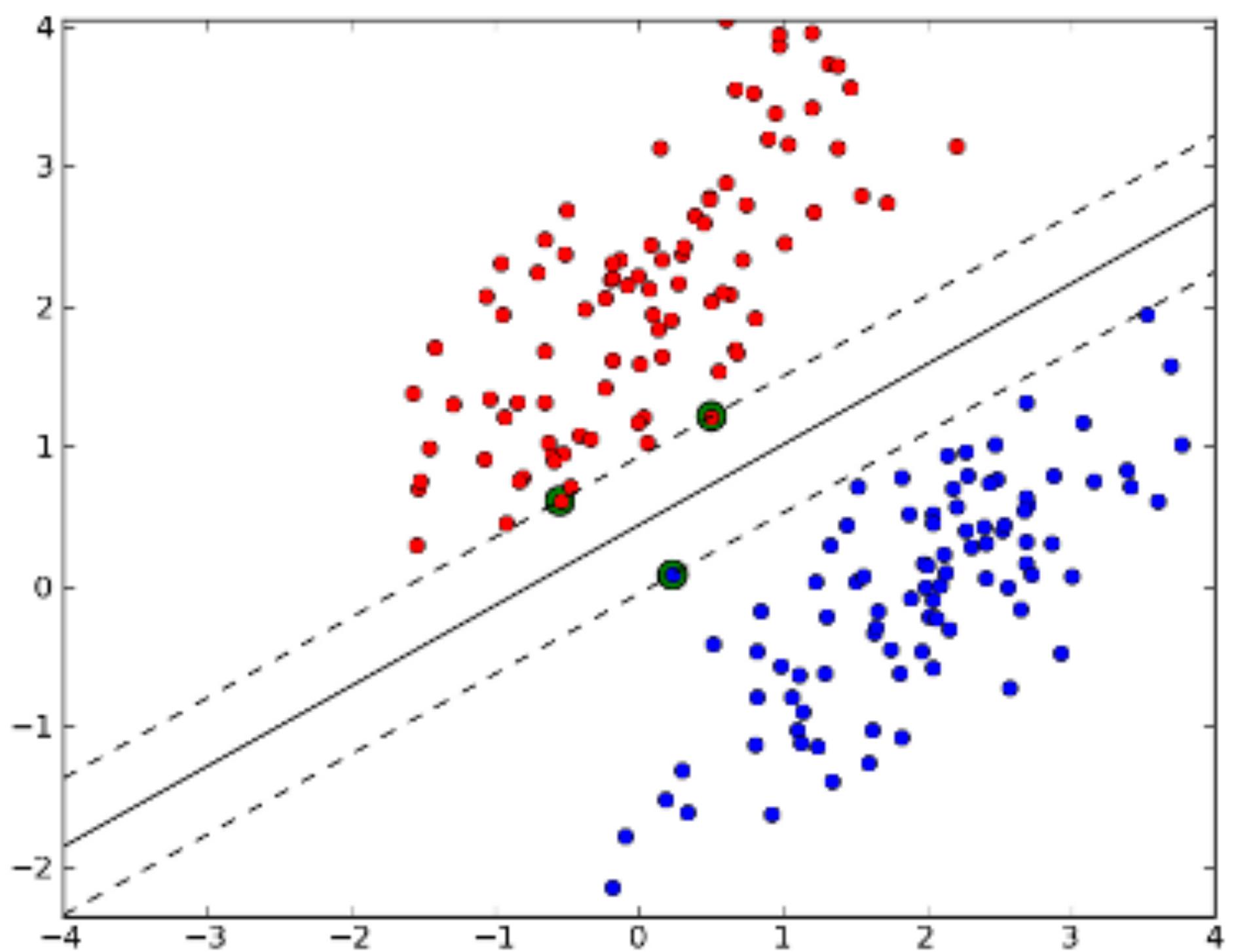
tanh



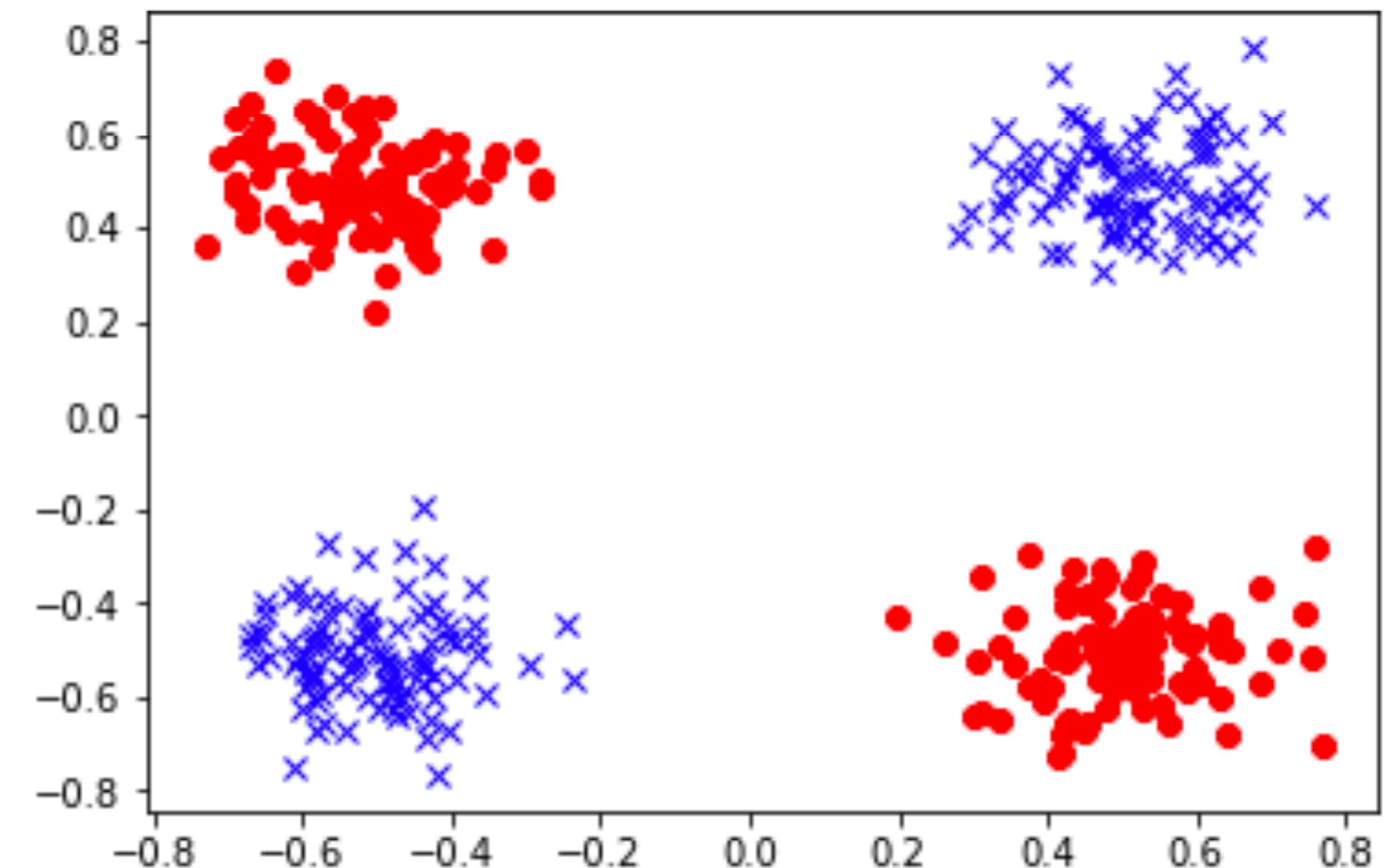
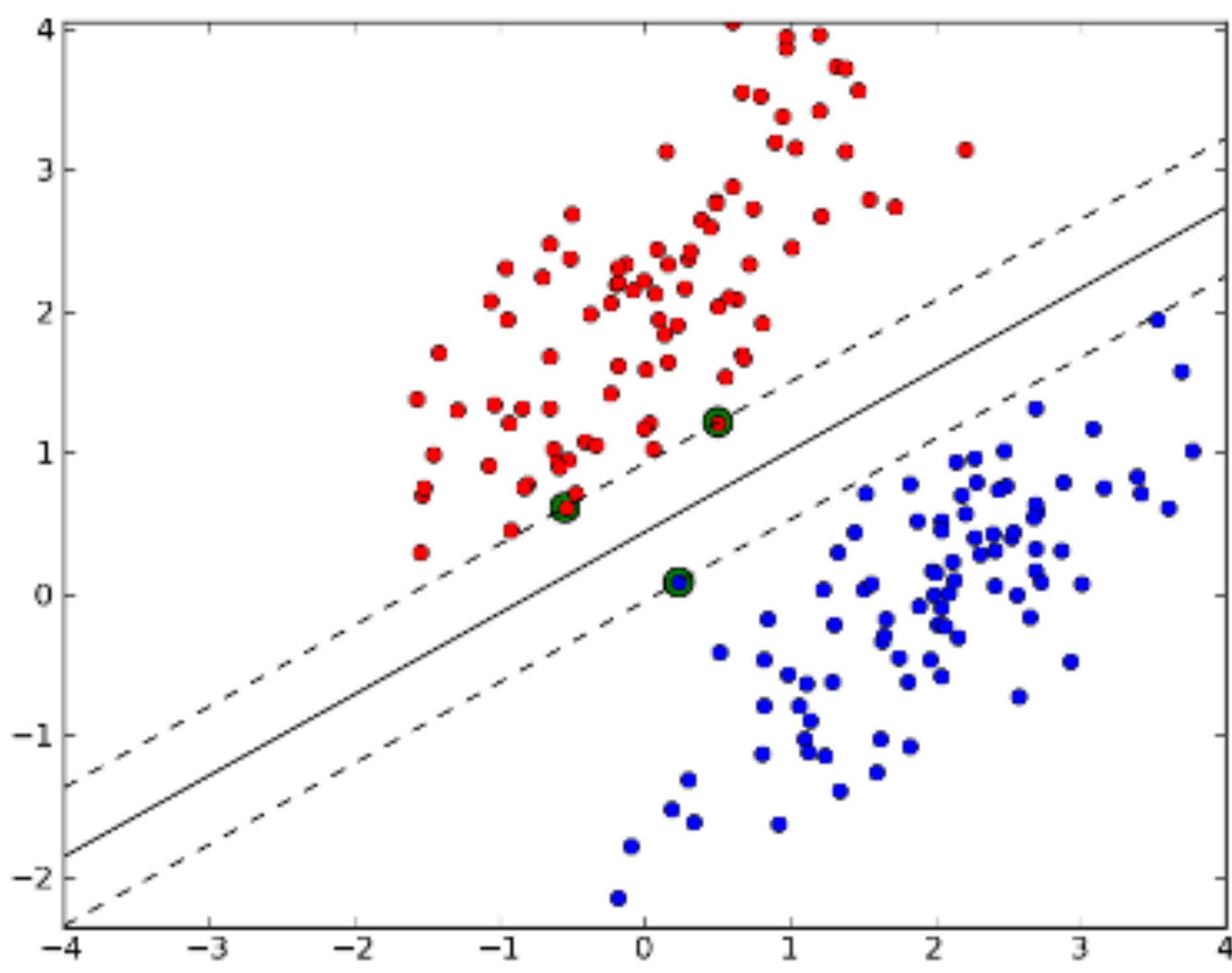
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The key ingredient of a neural network is the non-linear activation function

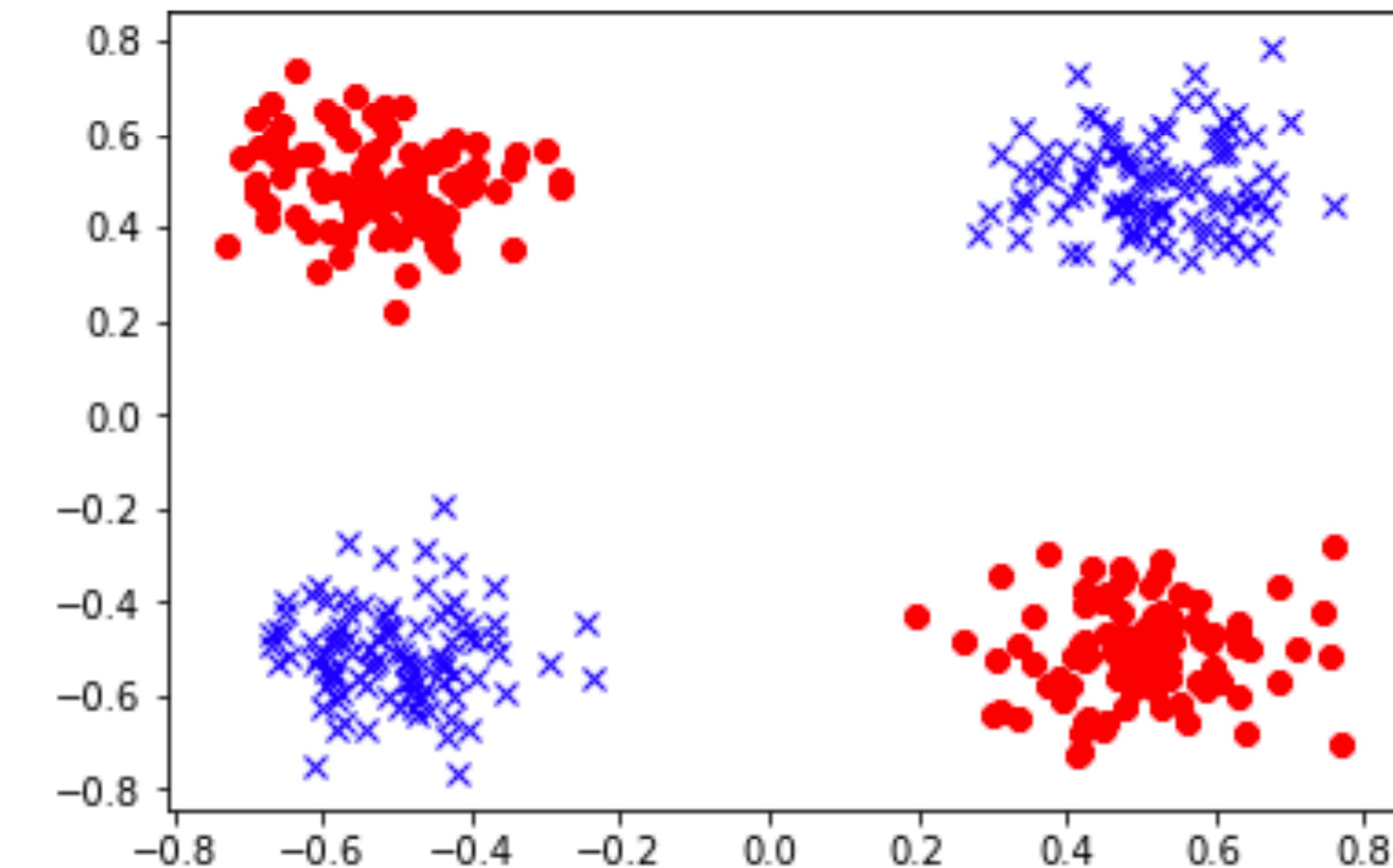
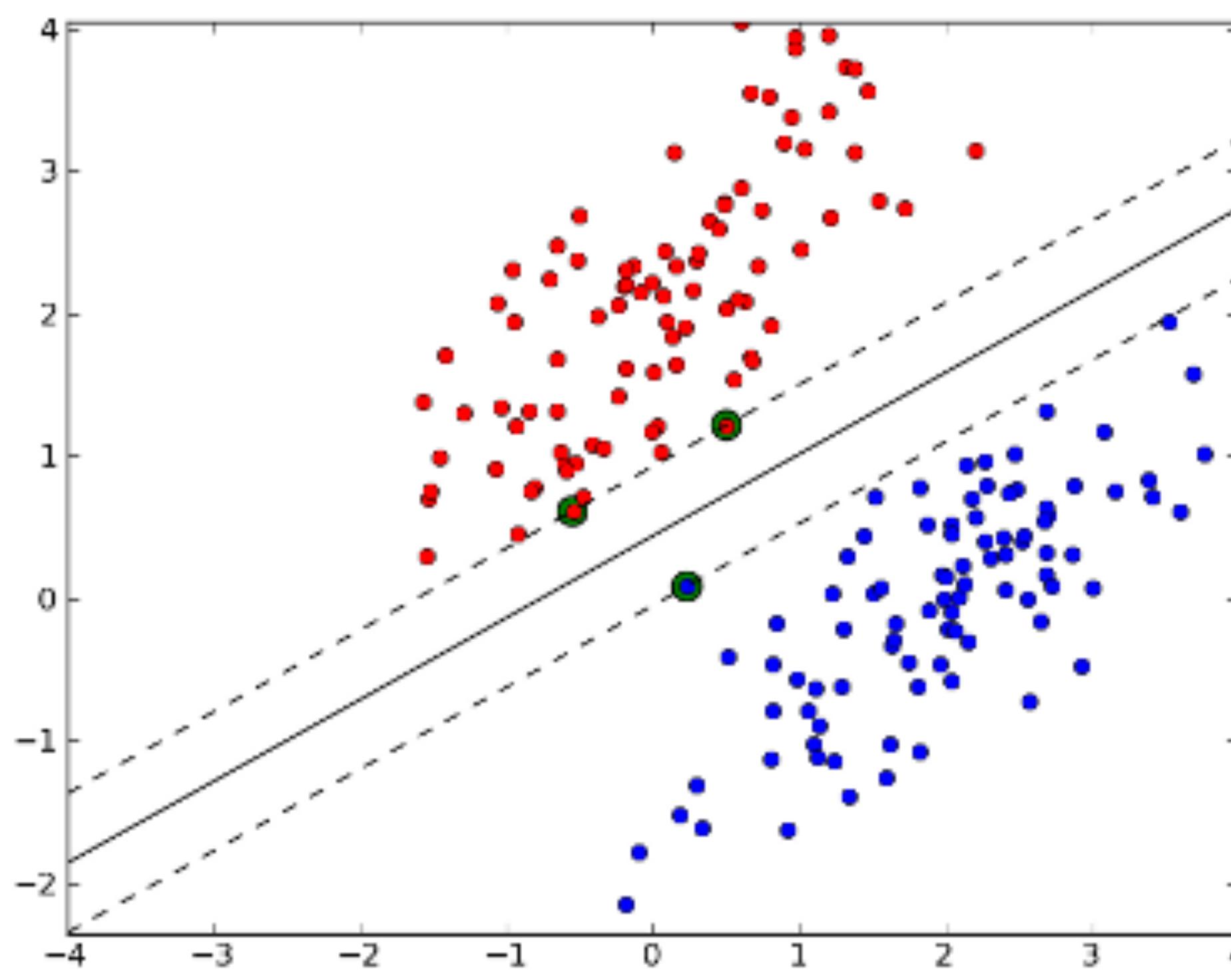
Linear vs. Non-linear Functions



Linear vs. Non-linear Functions



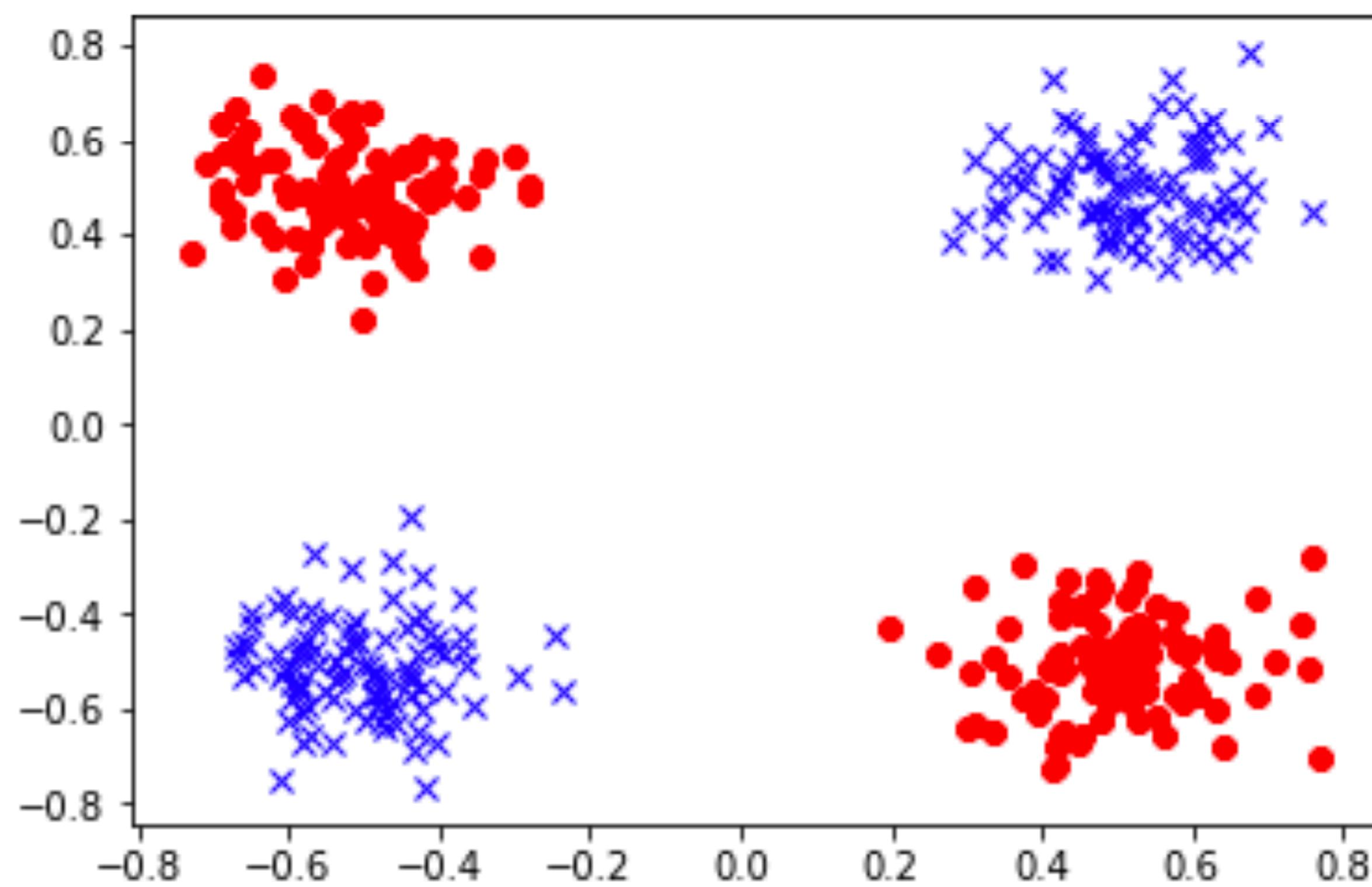
Linear vs. Non-linear Functions



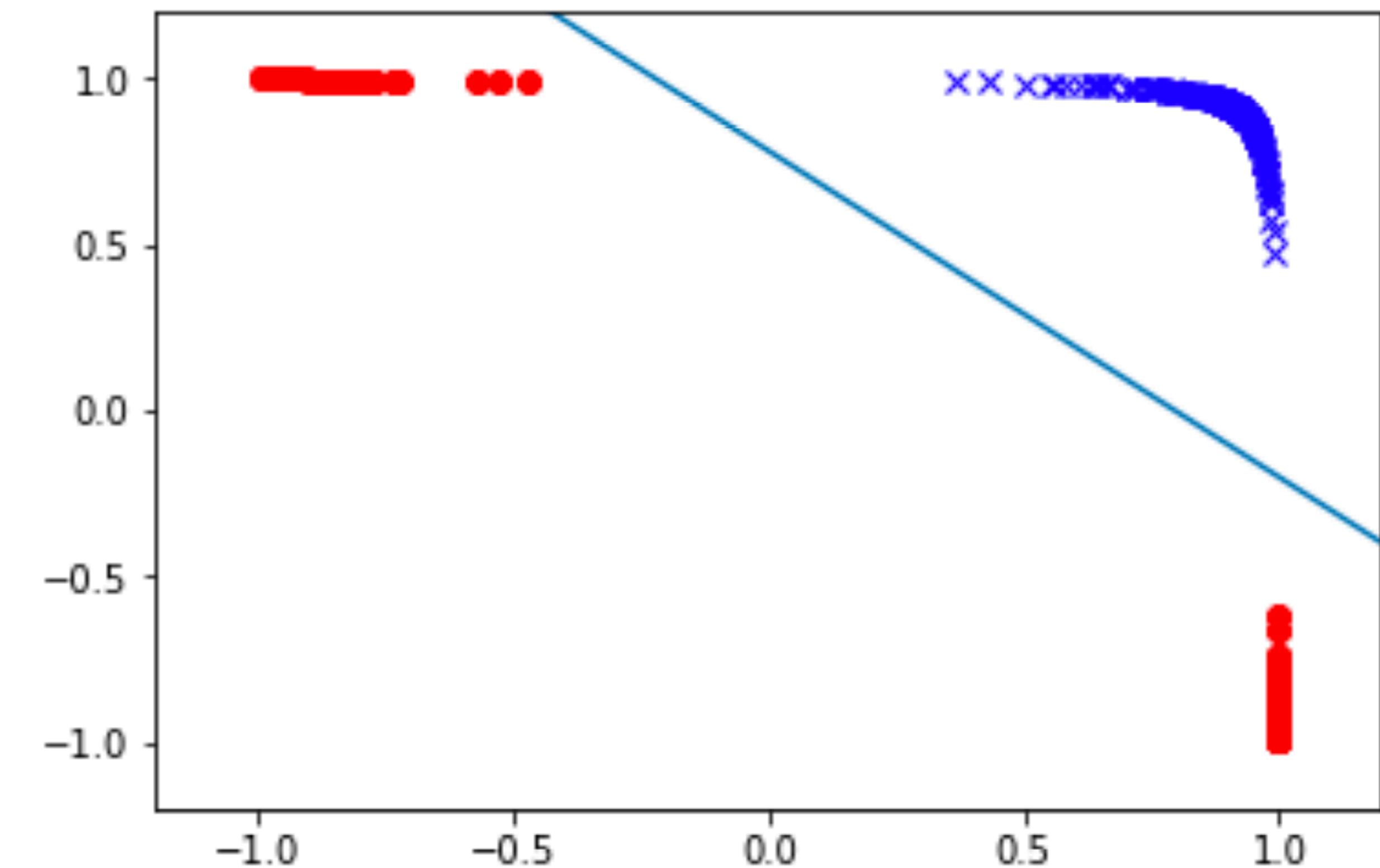
Linearly inseparable

Power of non-linearity

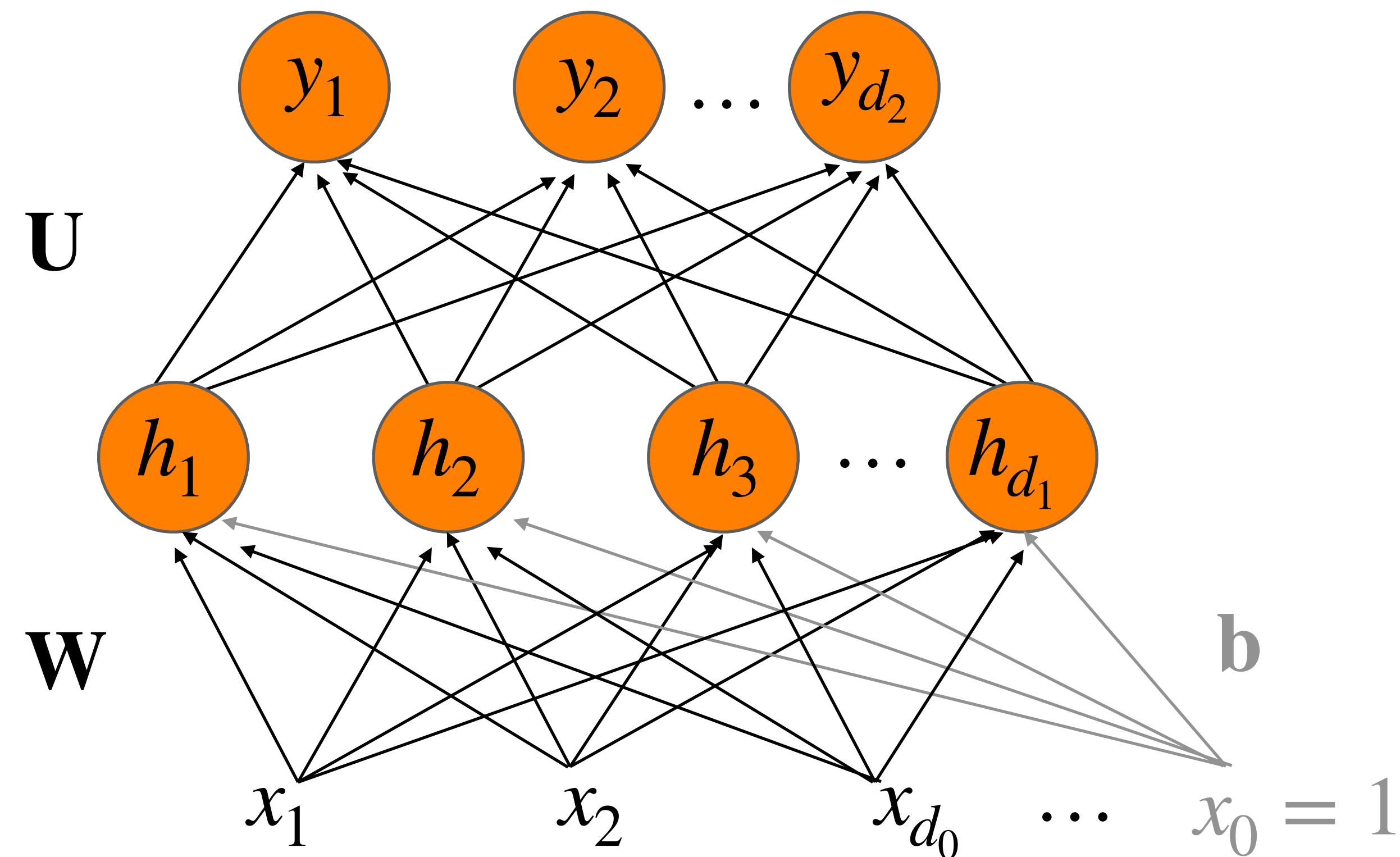
$$\tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$



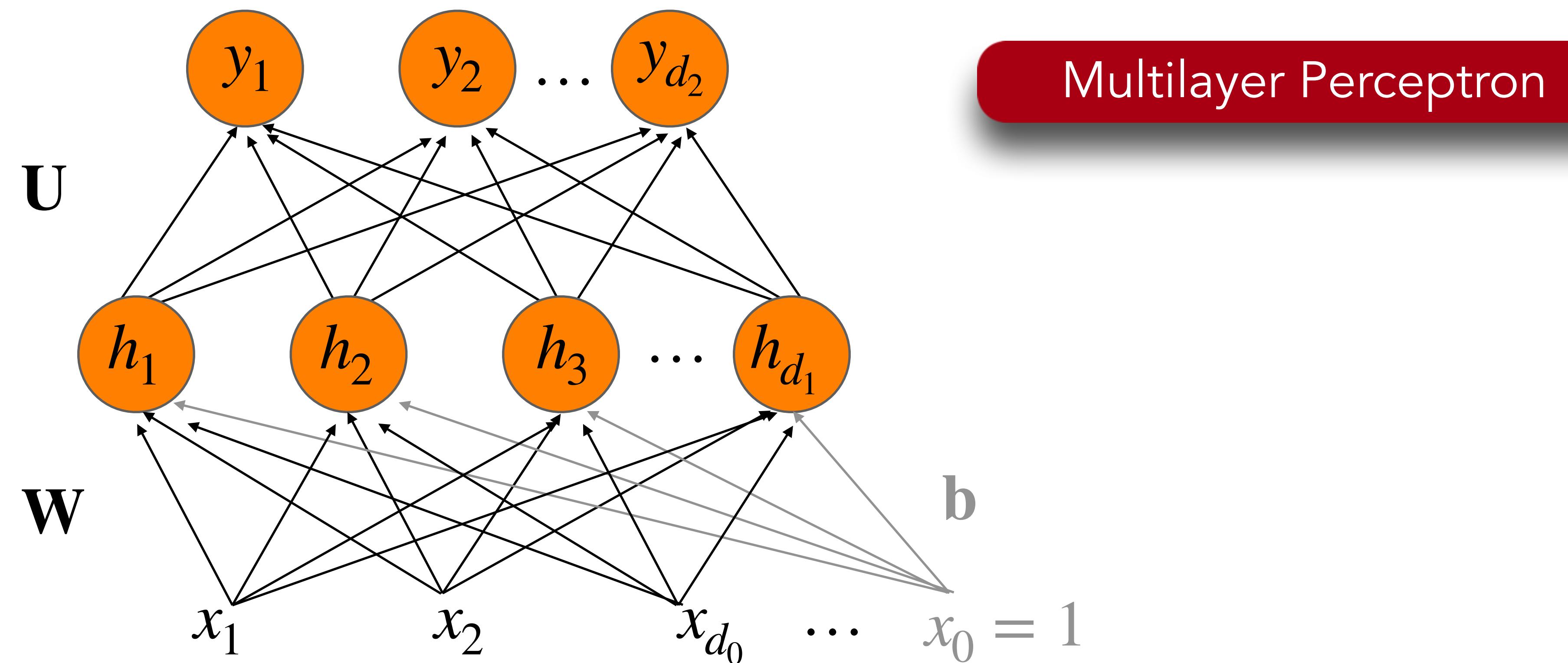
After a $\tanh(\cdot)$ transformation:



Feedforward Neural Nets

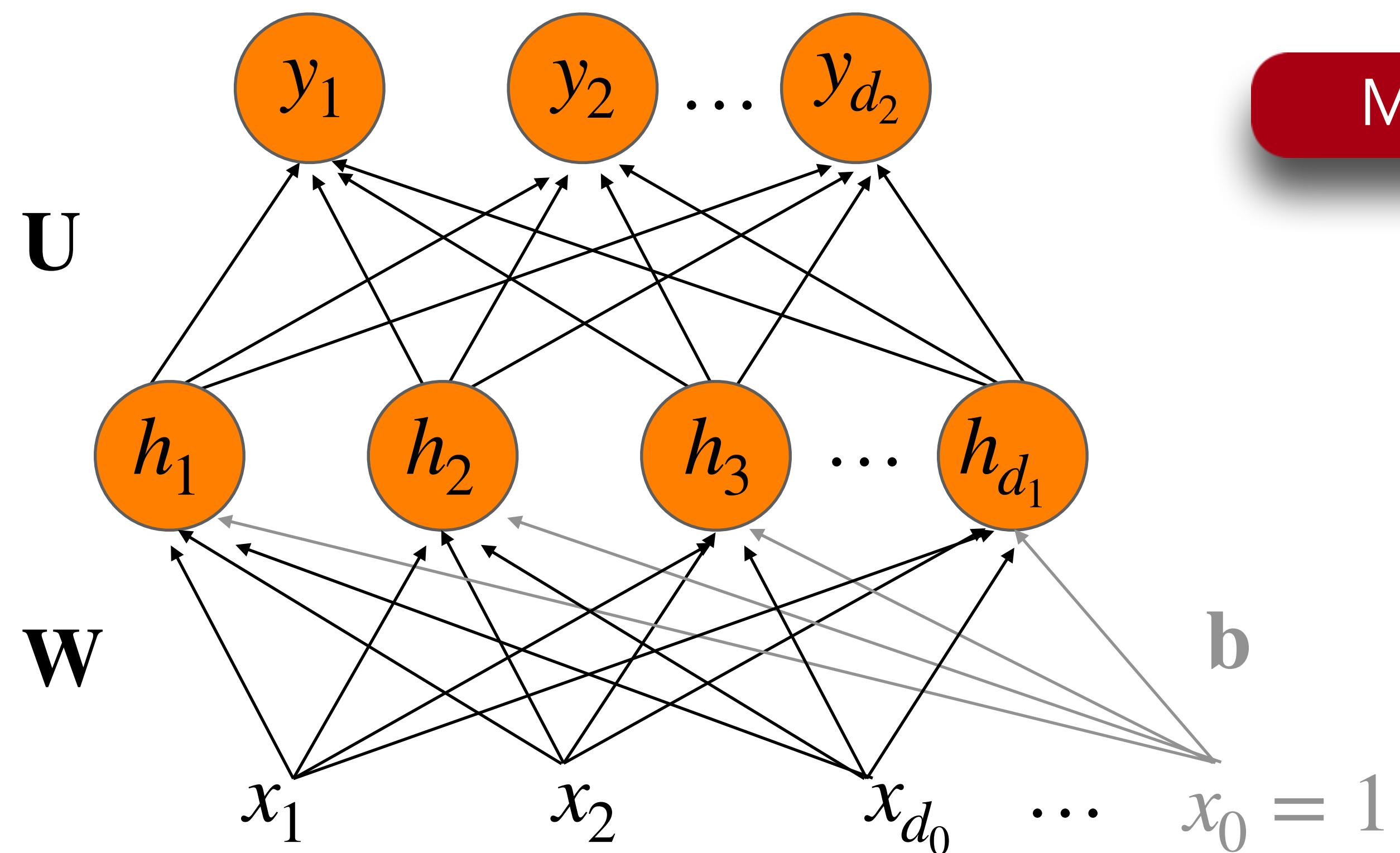


Feedforward Neural Nets



Feedforward Neural Nets

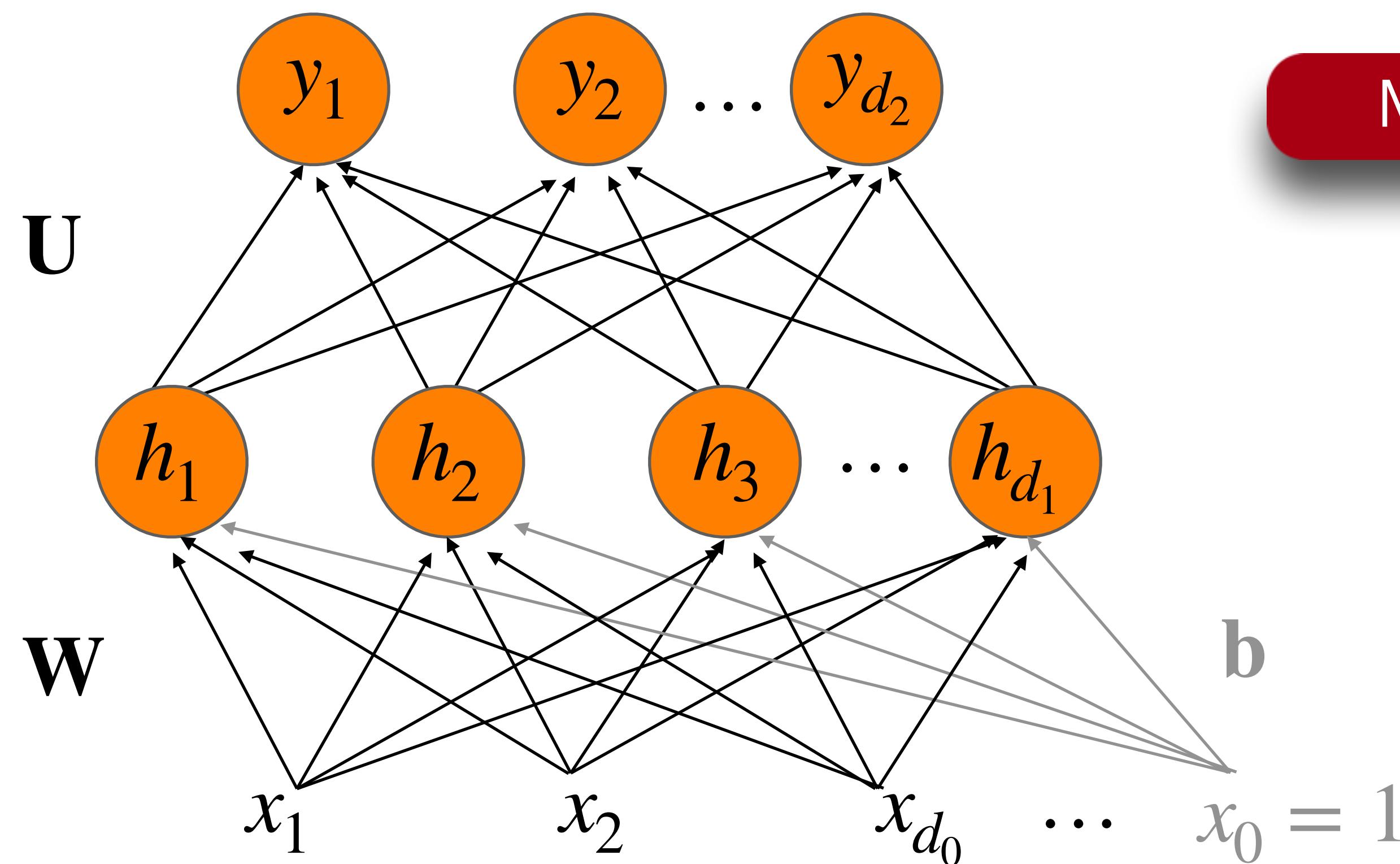
Technically, can learn any function!



Multilayer Perceptron

Feedforward Neural Nets

Technically, can learn any function!



Multilayer Perceptron

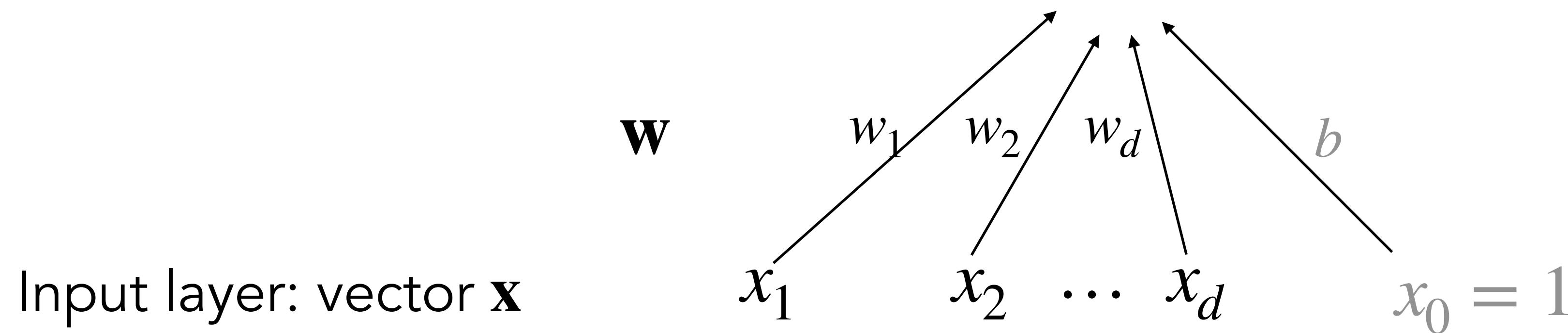
Let's break it down by revisiting our logistic regression model

Binary Logistic Regression

Binary Logistic Regression

Input layer: vector \mathbf{x} x_1 x_2 \cdots x_d $x_0 = 1$

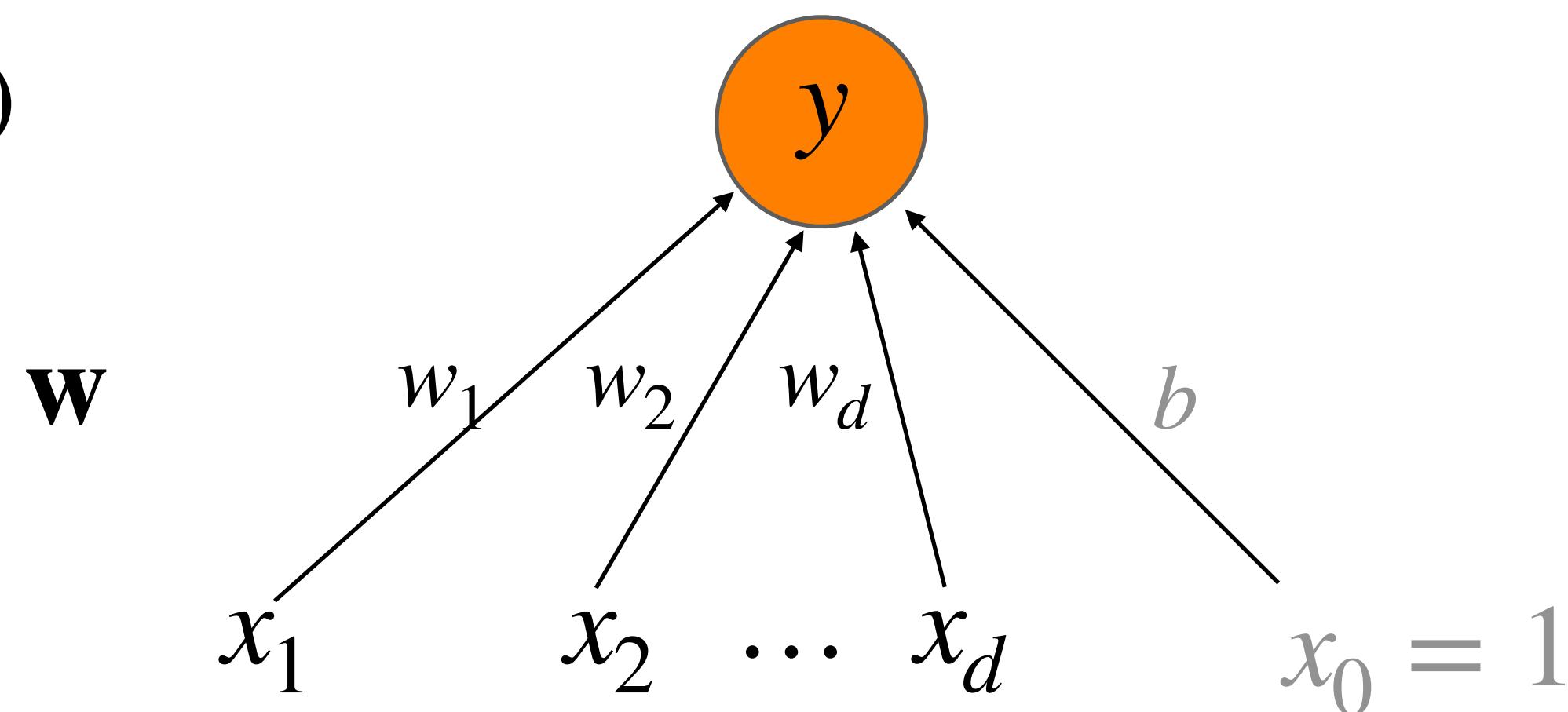
Binary Logistic Regression



Binary Logistic Regression

Output layer: $y = \sigma(\mathbf{w} \cdot \mathbf{x} + b)$

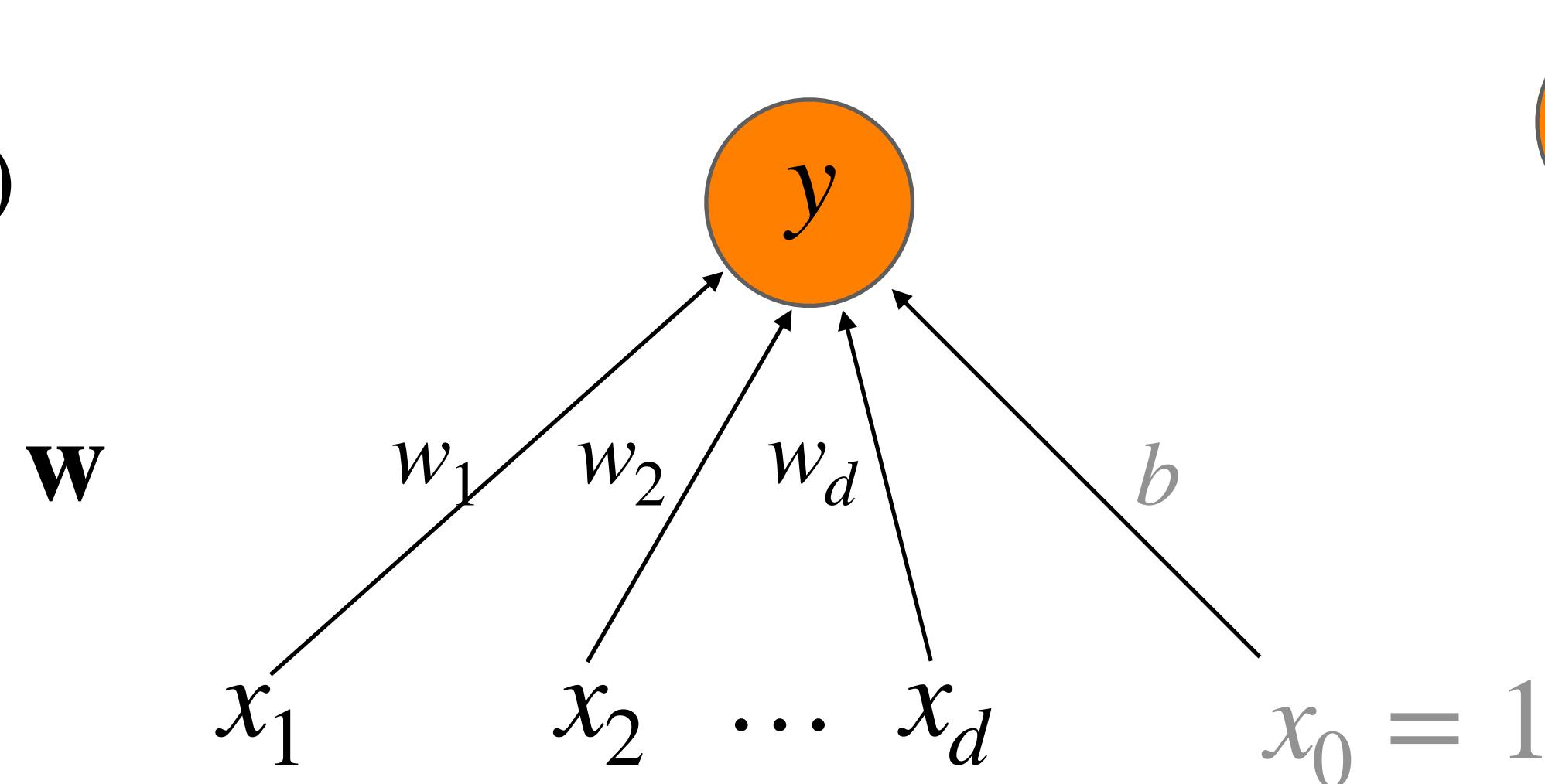
Input layer: vector \mathbf{x}



Binary Logistic Regression

Output layer: $y = \sigma(\mathbf{w} \cdot \mathbf{x} + b)$

Input layer: vector \mathbf{x}

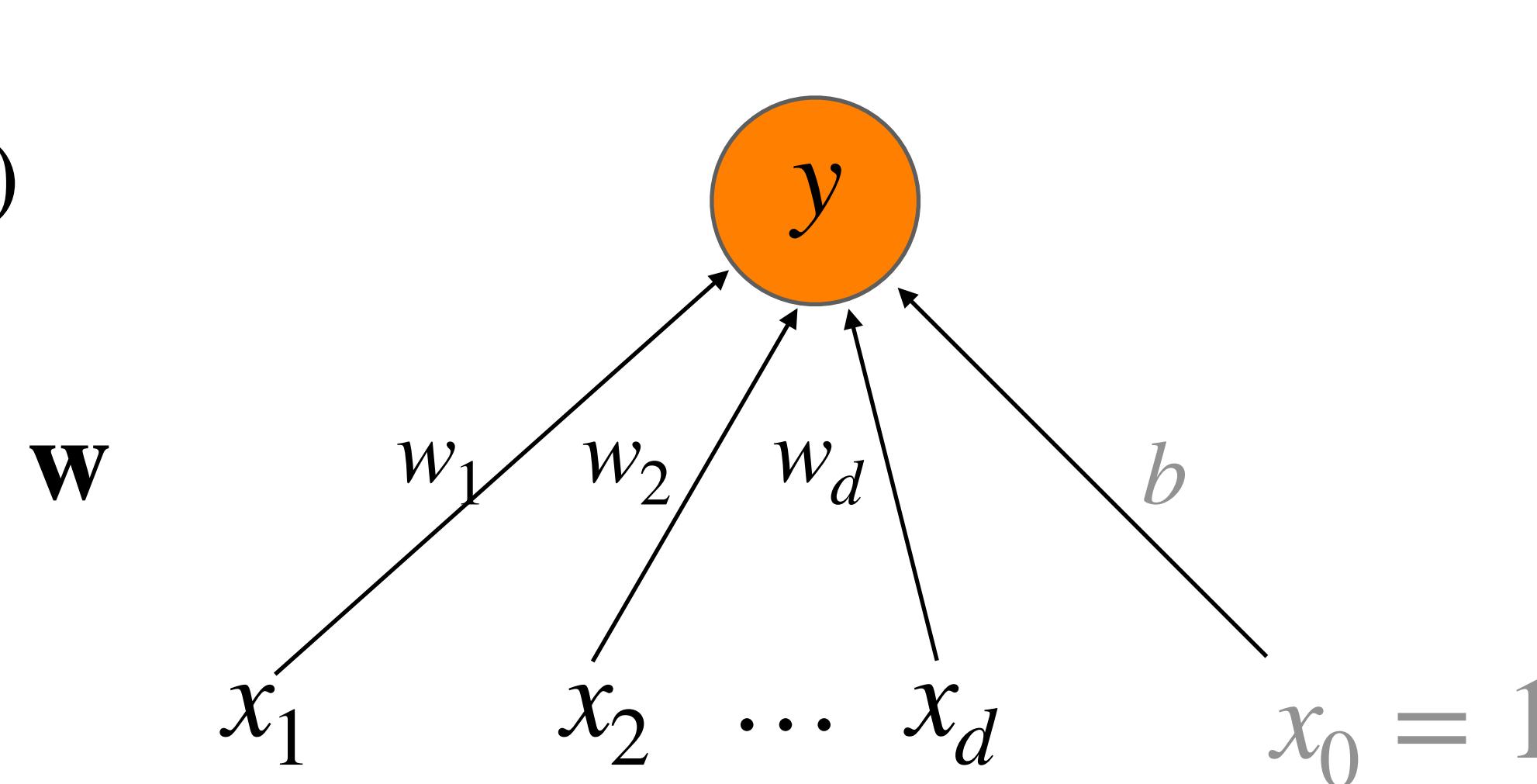


Weighted sum of all incoming, followed by a non-linear activation

Binary Logistic Regression

Output layer: $y = \sigma(\mathbf{w} \cdot \mathbf{x} + b)$

Input layer: vector \mathbf{x}



Weighted sum of all incoming, followed by a non-linear activation

1-layer Network

Don't count the input layer in counting layers!

Multinomial Logistic Regression

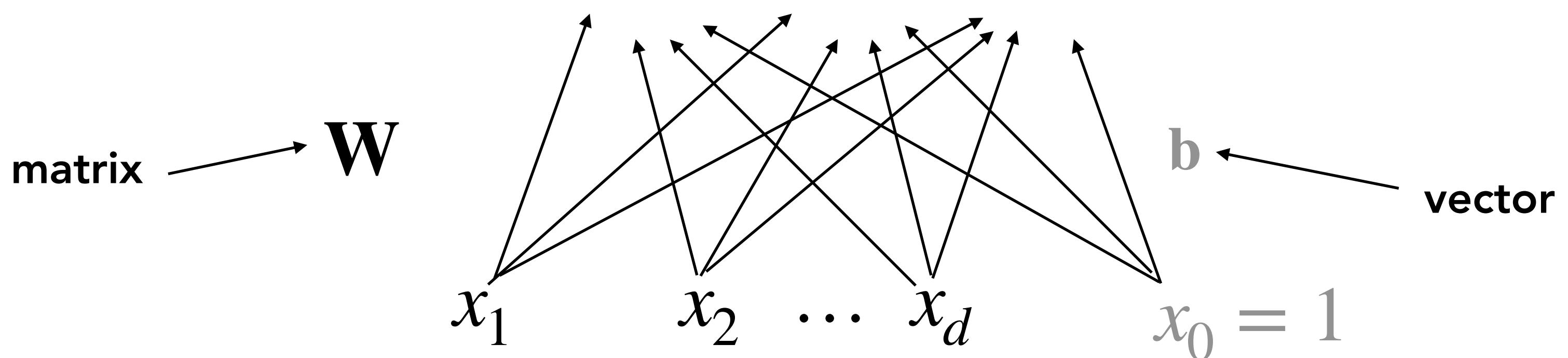
Multinomial Logistic Regression

Input layer: vector \mathbf{x}

$$x_1 \quad x_2 \quad \dots \quad x_d \quad x_0 = 1$$

Multinomial Logistic Regression

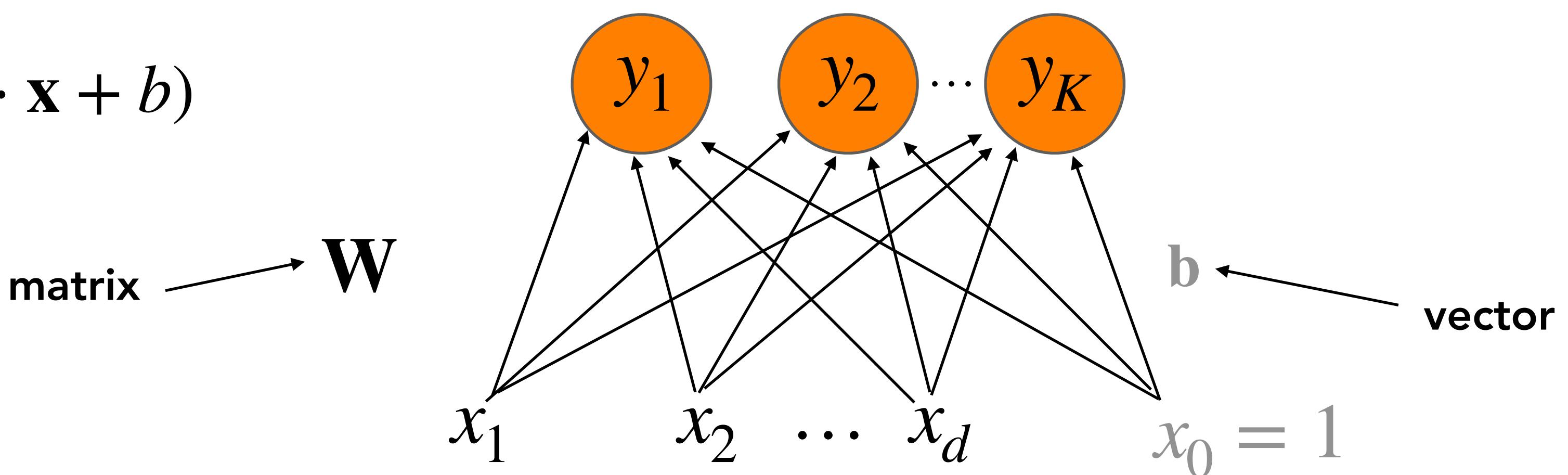
Input layer: vector \mathbf{x}



Multinomial Logistic Regression

Output layer: $\mathbf{y} = \text{softmax}(\mathbf{w} \cdot \mathbf{x} + \mathbf{b})$

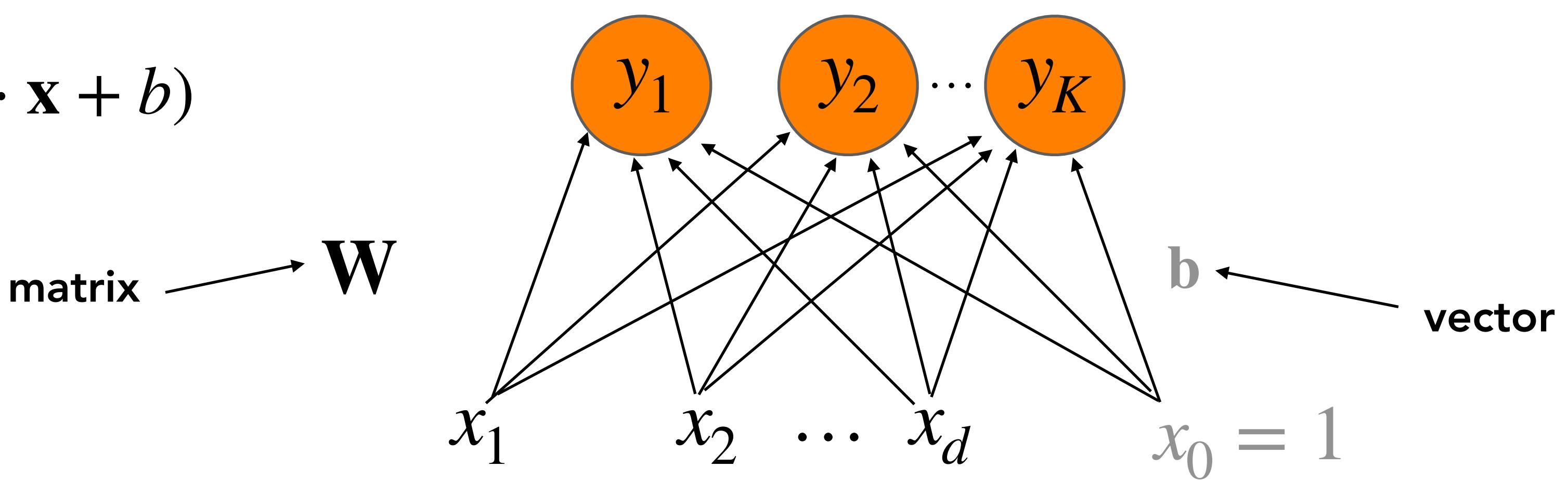
Input layer: vector \mathbf{x}



Multinomial Logistic Regression

Output layer: $\mathbf{y} = \text{softmax}(\mathbf{w} \cdot \mathbf{x} + \mathbf{b})$

Input layer: vector \mathbf{x}

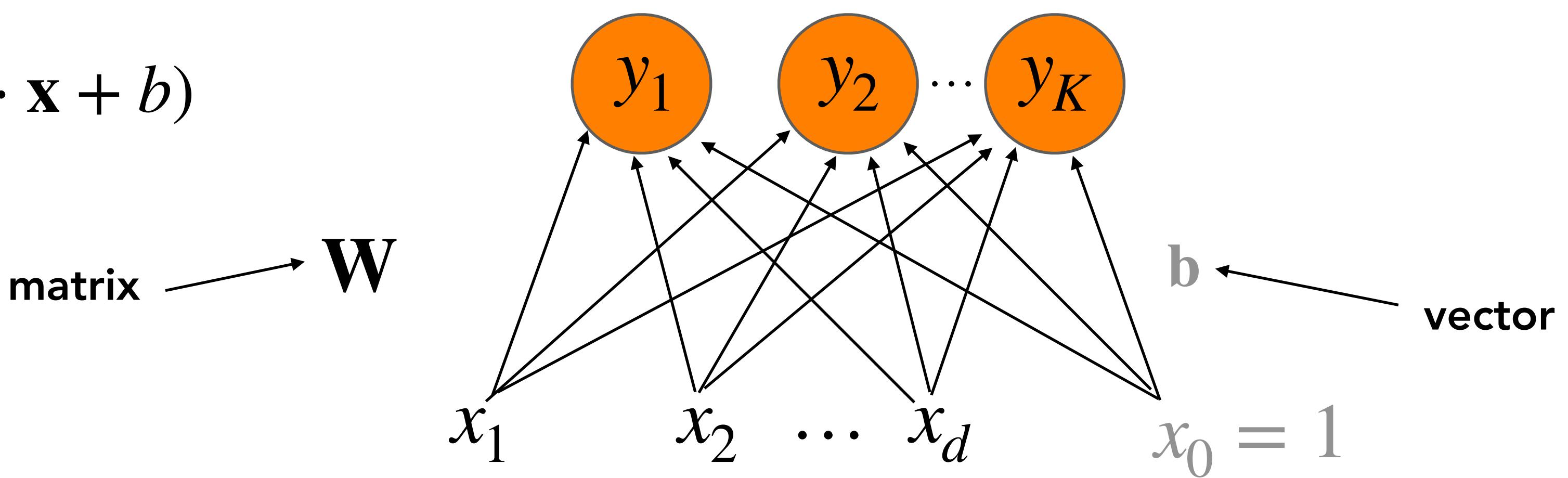


1-layer Network

Multinomial Logistic Regression

Output layer: $\mathbf{y} = \text{softmax}(\mathbf{w} \cdot \mathbf{x} + \mathbf{b})$

Input layer: vector \mathbf{x}



1-layer Network

Fully connected single layer network

Two-layer Feedforward Network

Two-layer Feedforward Network

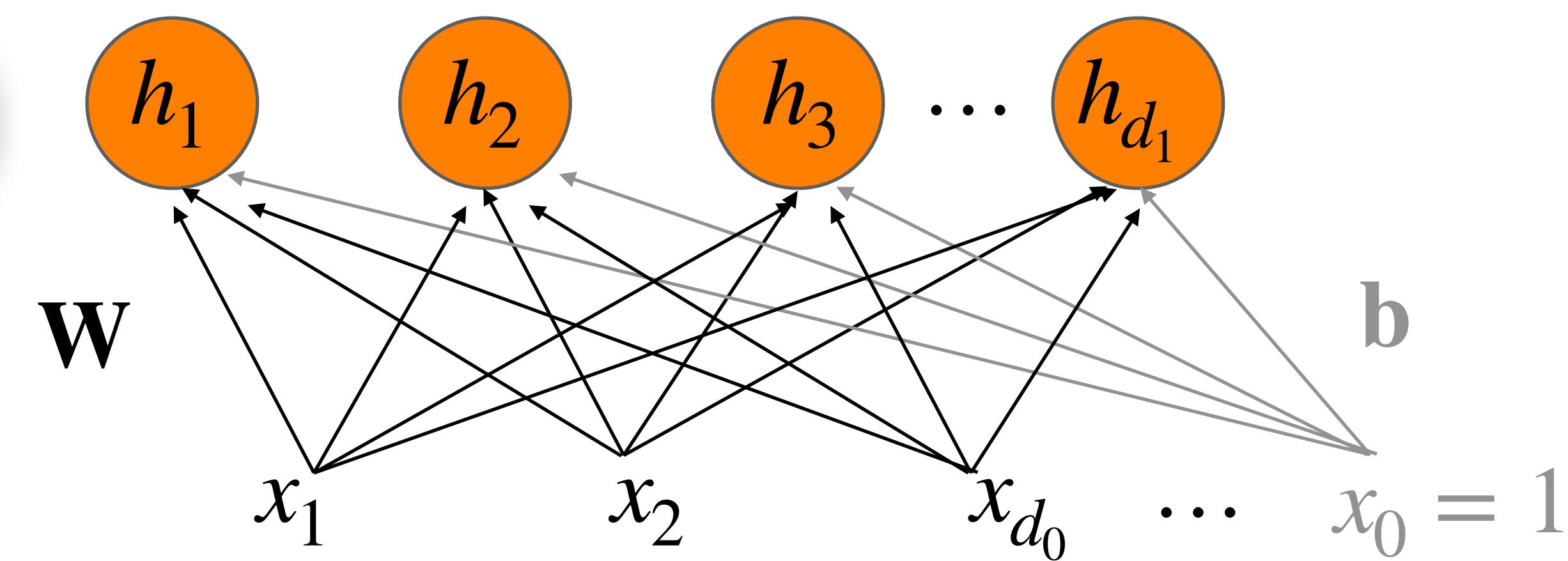
Input layer: vector \mathbf{x}

$$x_1 \quad x_2 \quad x_{d_0} \quad \dots \quad x_0 = 1$$

Two-layer Feedforward Network

Hidden layer: $\mathbf{h} = g(\mathbf{Wx} + \mathbf{b})$

Input layer: vector \mathbf{x}

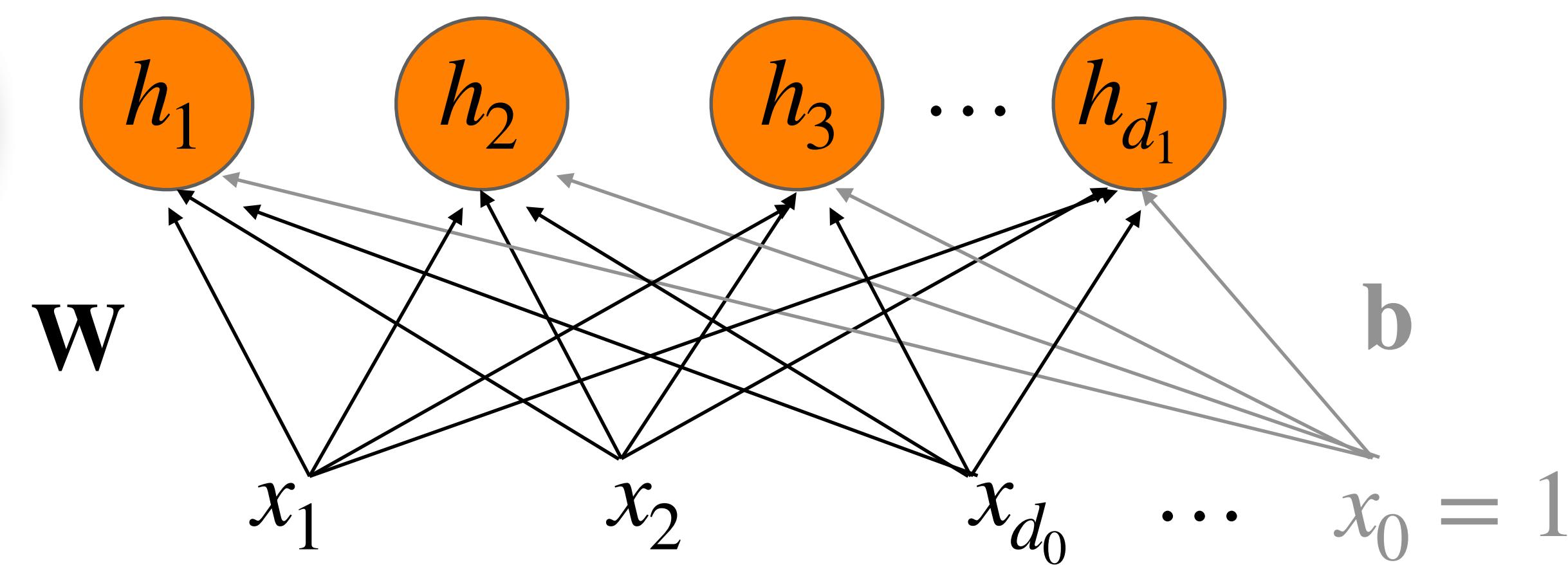


Two-layer Feedforward Network

Hidden layer: $\mathbf{h} = g(\mathbf{Wx} + \mathbf{b})$

Usually ReLU or tanh

Input layer: vector \mathbf{x}



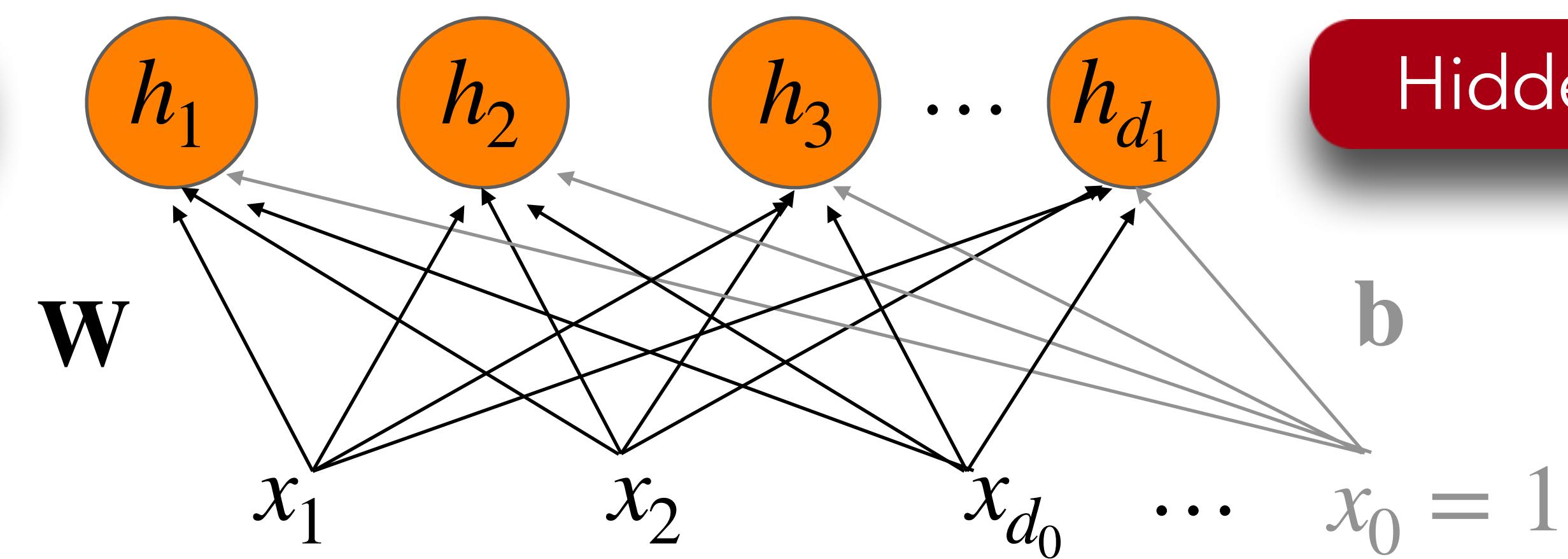
Two-layer Feedforward Network

Hidden layer: $\mathbf{h} = g(\mathbf{Wx} + \mathbf{b})$

Usually ReLU or tanh

Input layer: vector \mathbf{x}

Hidden Unit, h_i



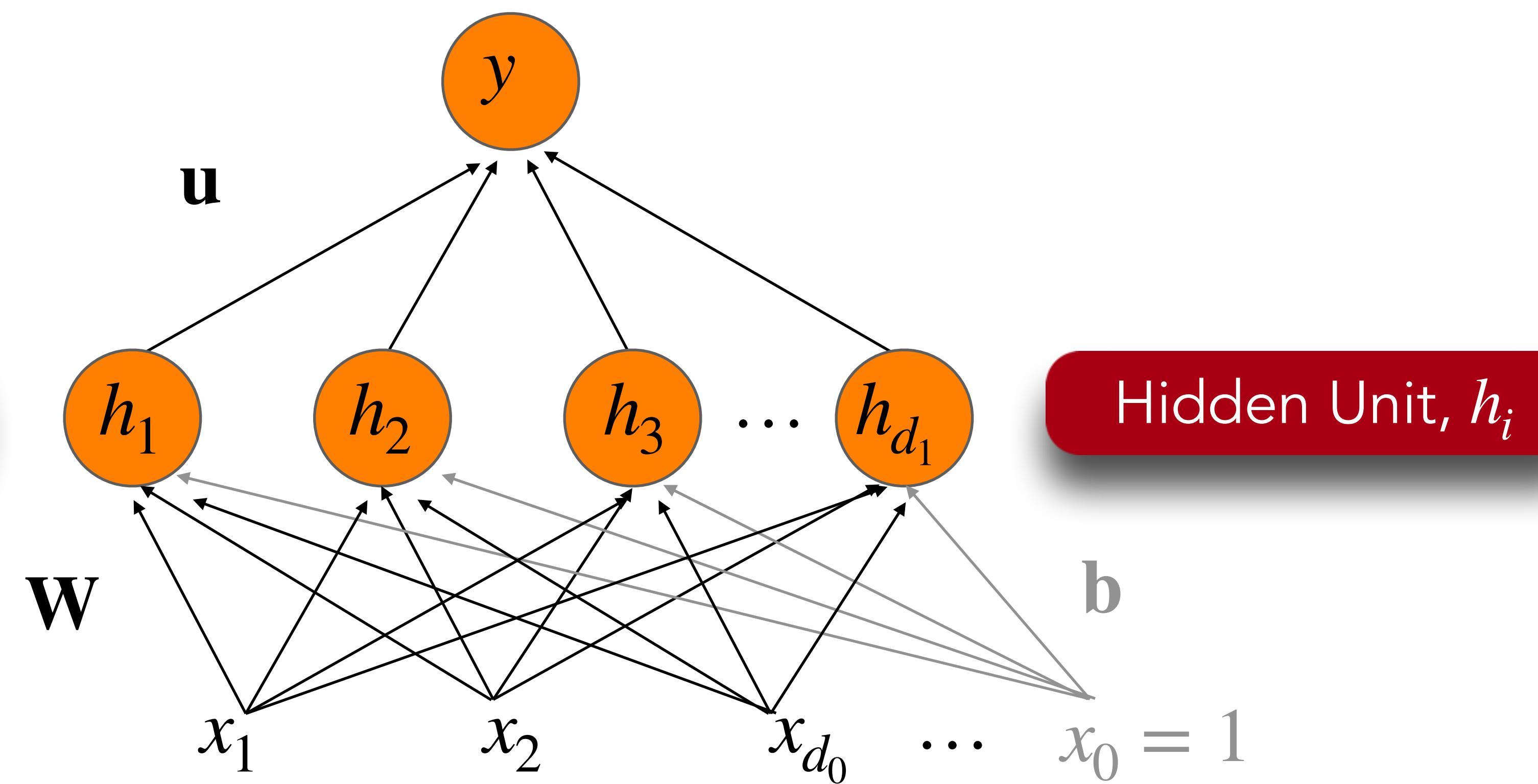
Two-layer Feedforward Network

Output layer: $y = \sigma(\mathbf{u}\mathbf{h})$

Hidden layer: $\mathbf{h} = g(\mathbf{W}\mathbf{x} + \mathbf{b})$

Usually ReLU or tanh

Input layer: vector \mathbf{x}



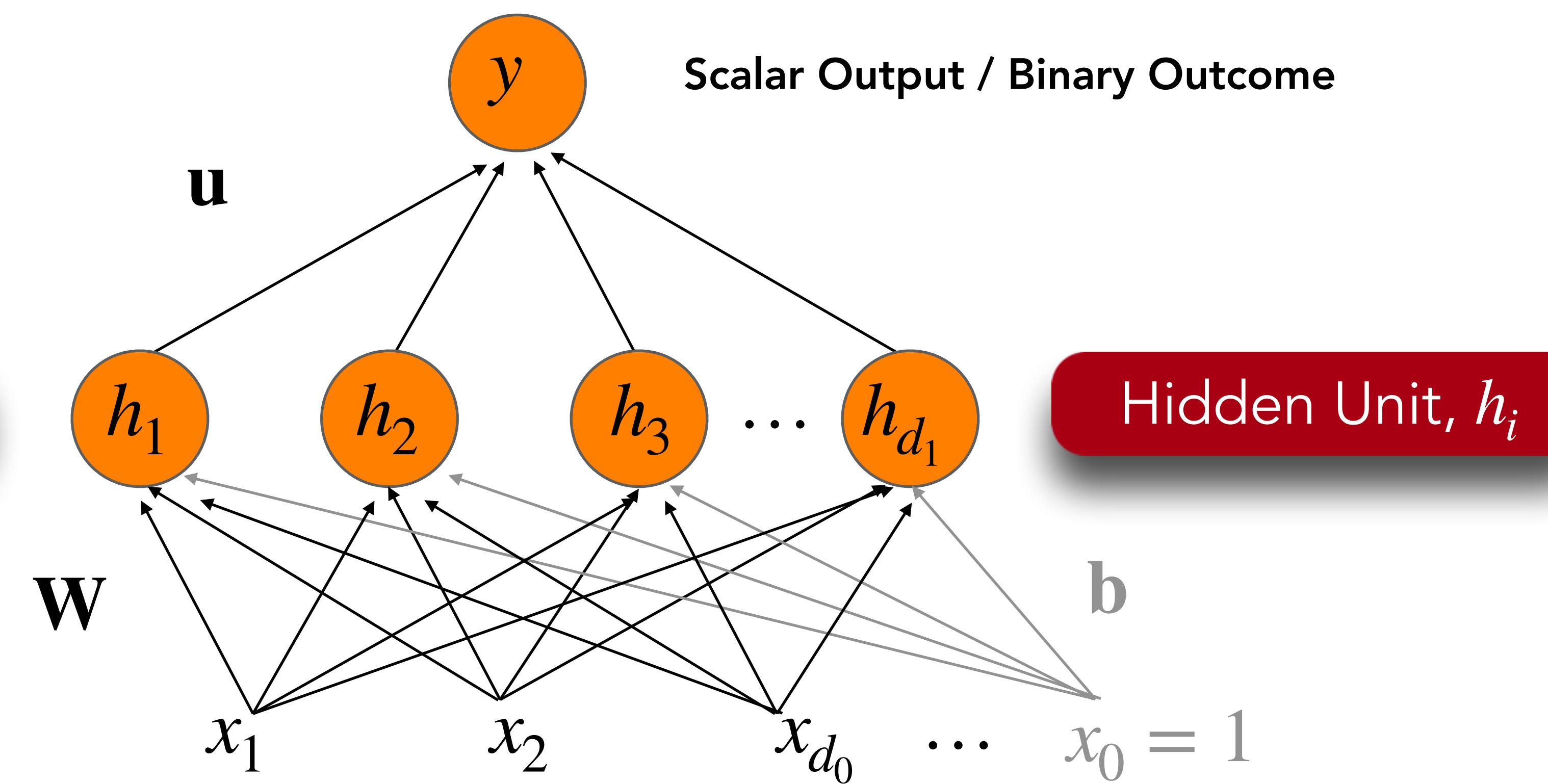
Two-layer Feedforward Network

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Input layer: vector \mathbf{x}



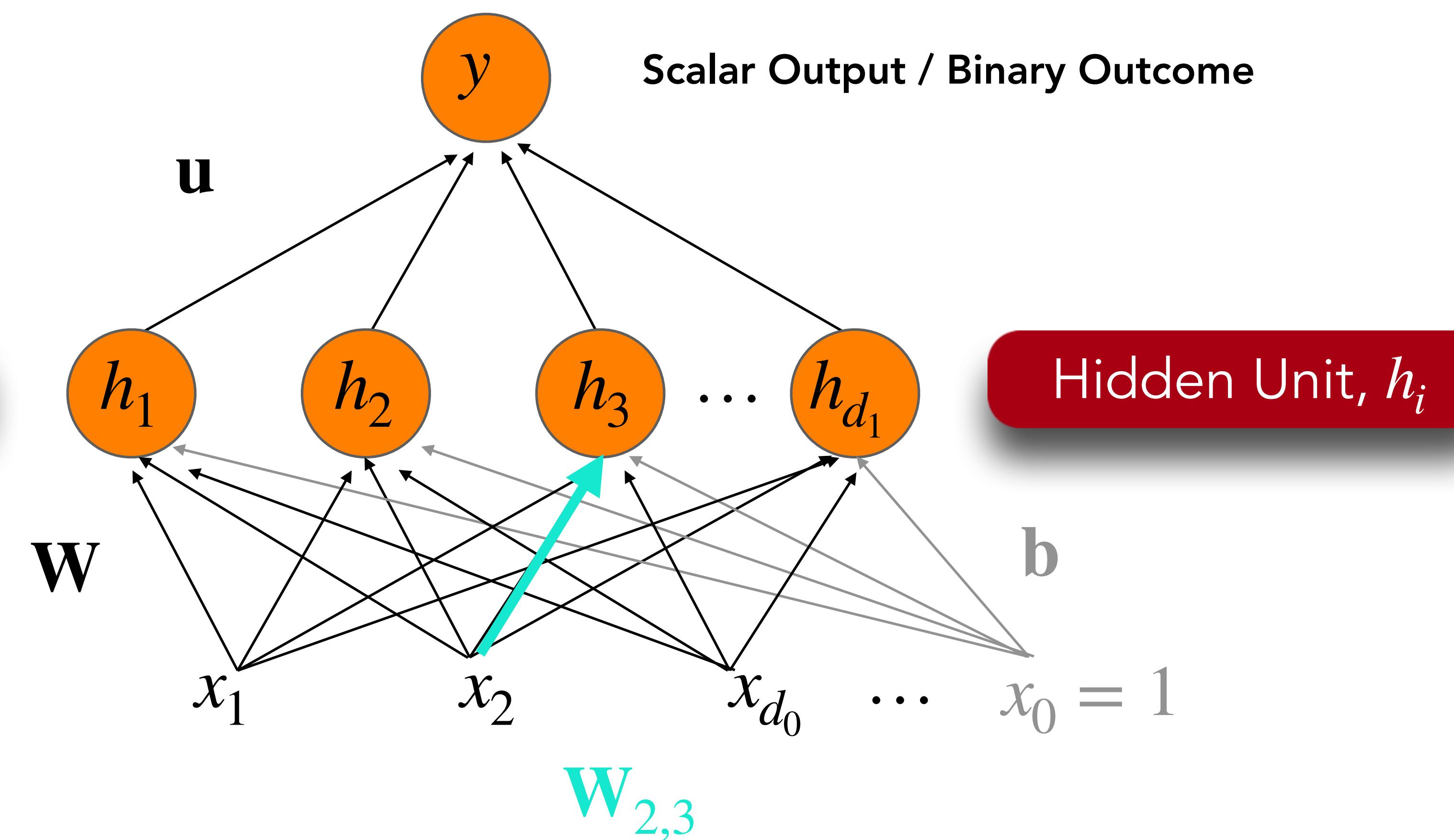
Two-layer Feedforward Network

Output layer: $y = \sigma(\mathbf{u}\mathbf{h})$

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Usually ReLU or tanh

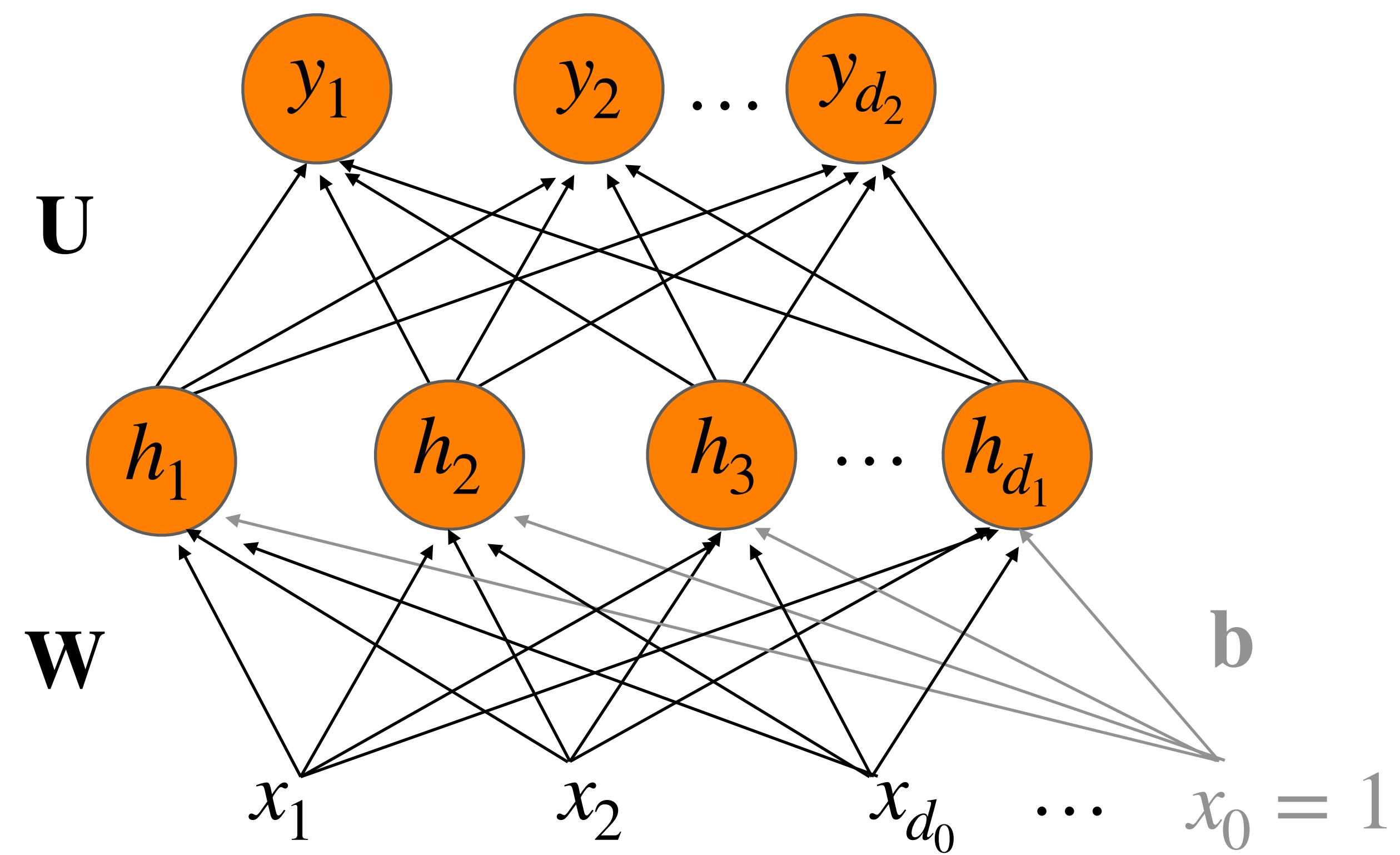
Input layer: vector \mathbf{x}



Two-layer Feedforward Network with Softmax Output

Output layer: $\mathbf{y} = \text{softmax}(\mathbf{U} \cdot \mathbf{h})$

Input layer: vector \mathbf{x}



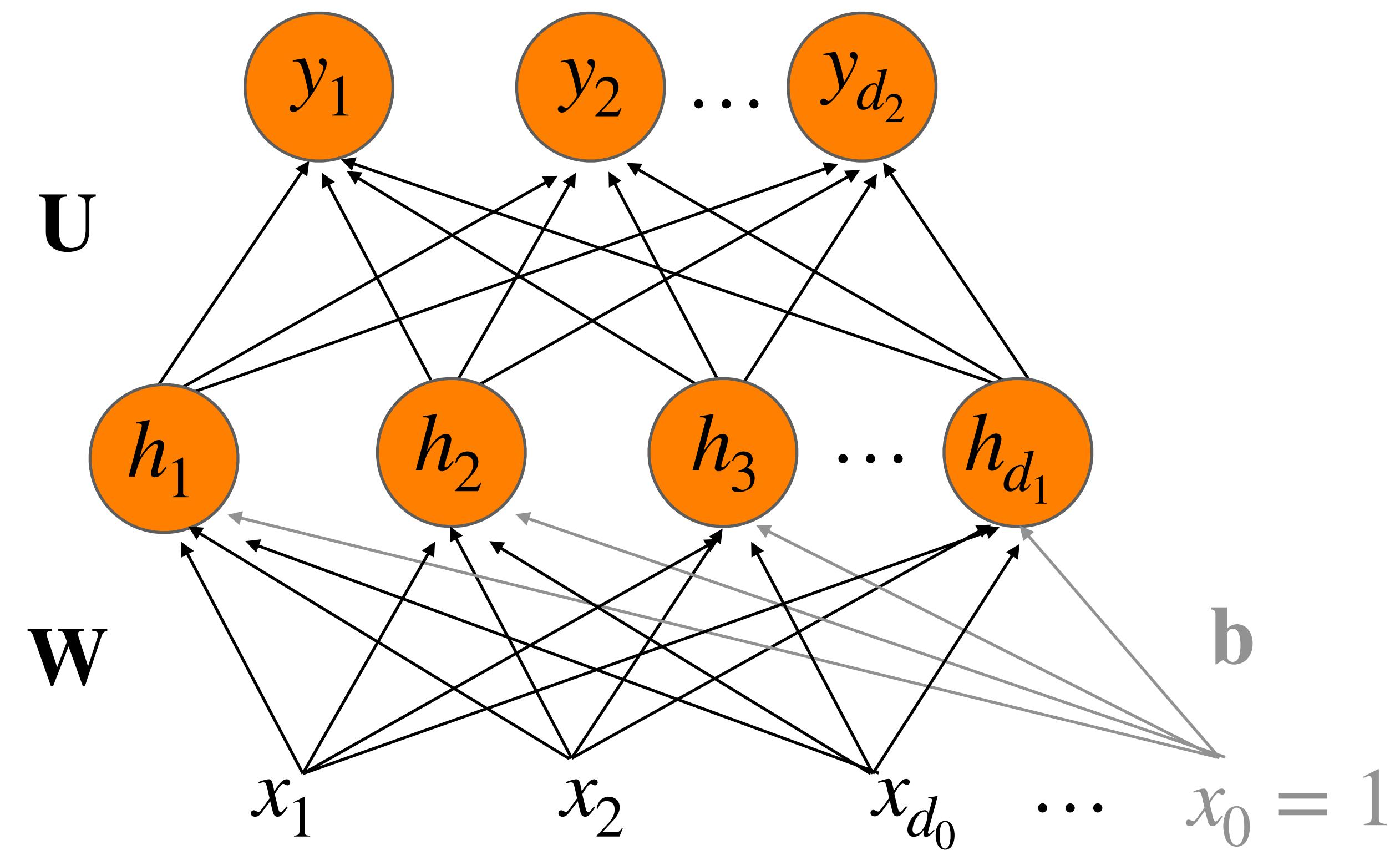
Two-layer Feedforward Network with Softmax Output

Output layer: $\mathbf{y} = \text{softmax}(\mathbf{U} \cdot \mathbf{h})$

Hidden layer: $\mathbf{h} = g(\mathbf{W}\mathbf{x} + \mathbf{b})$

Usually ReLU or tanh

Input layer: vector \mathbf{x}



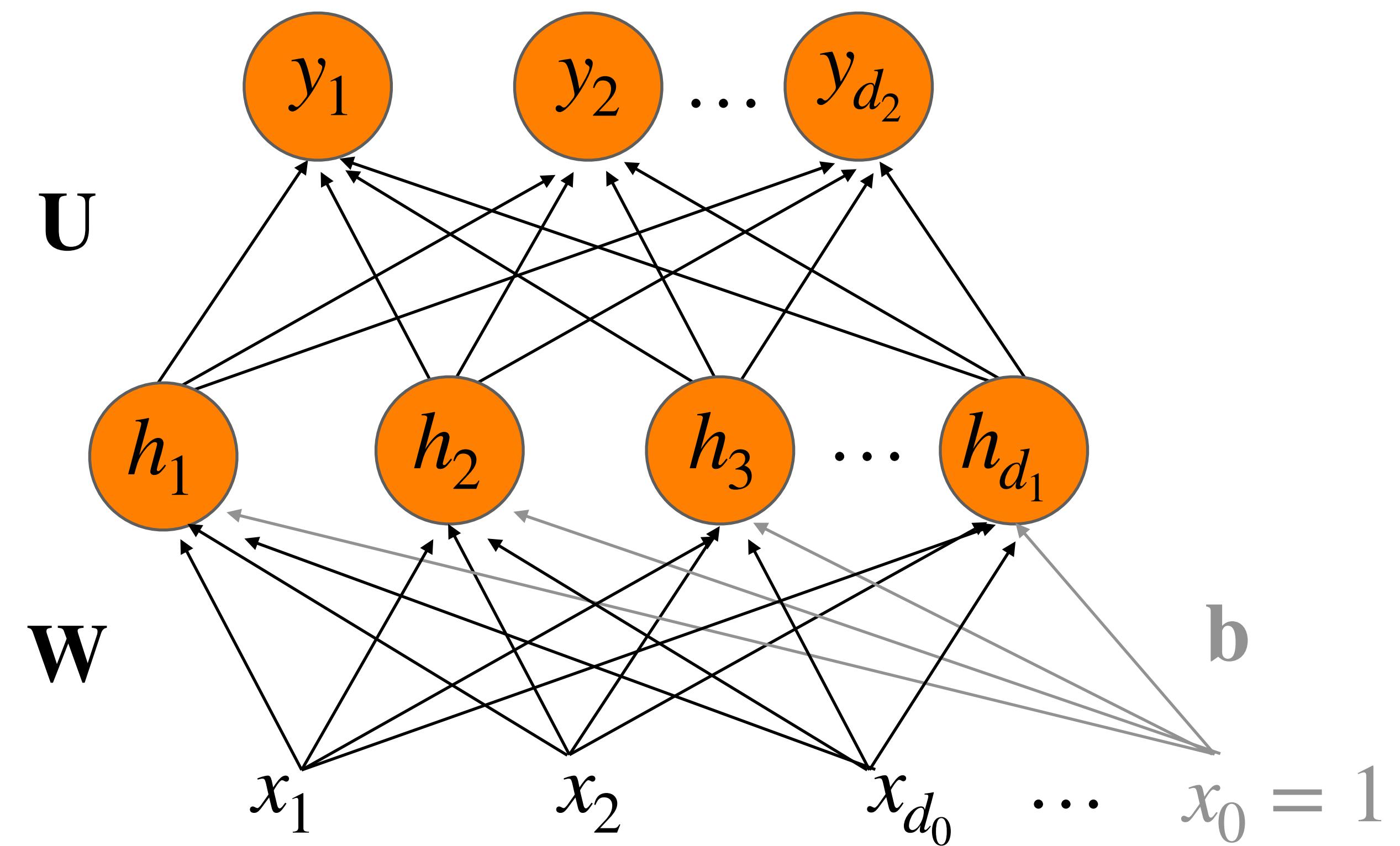
Two-layer Feedforward Network with Softmax Output

Output layer: $\mathbf{y} = \text{softmax}(\mathbf{U} \cdot \mathbf{h})$

Hidden layer: $\mathbf{h} = g(\mathbf{W}\mathbf{x} + \mathbf{b})$

Usually ReLU or tanh

Input layer: vector \mathbf{x}



What is \mathbf{y} ?

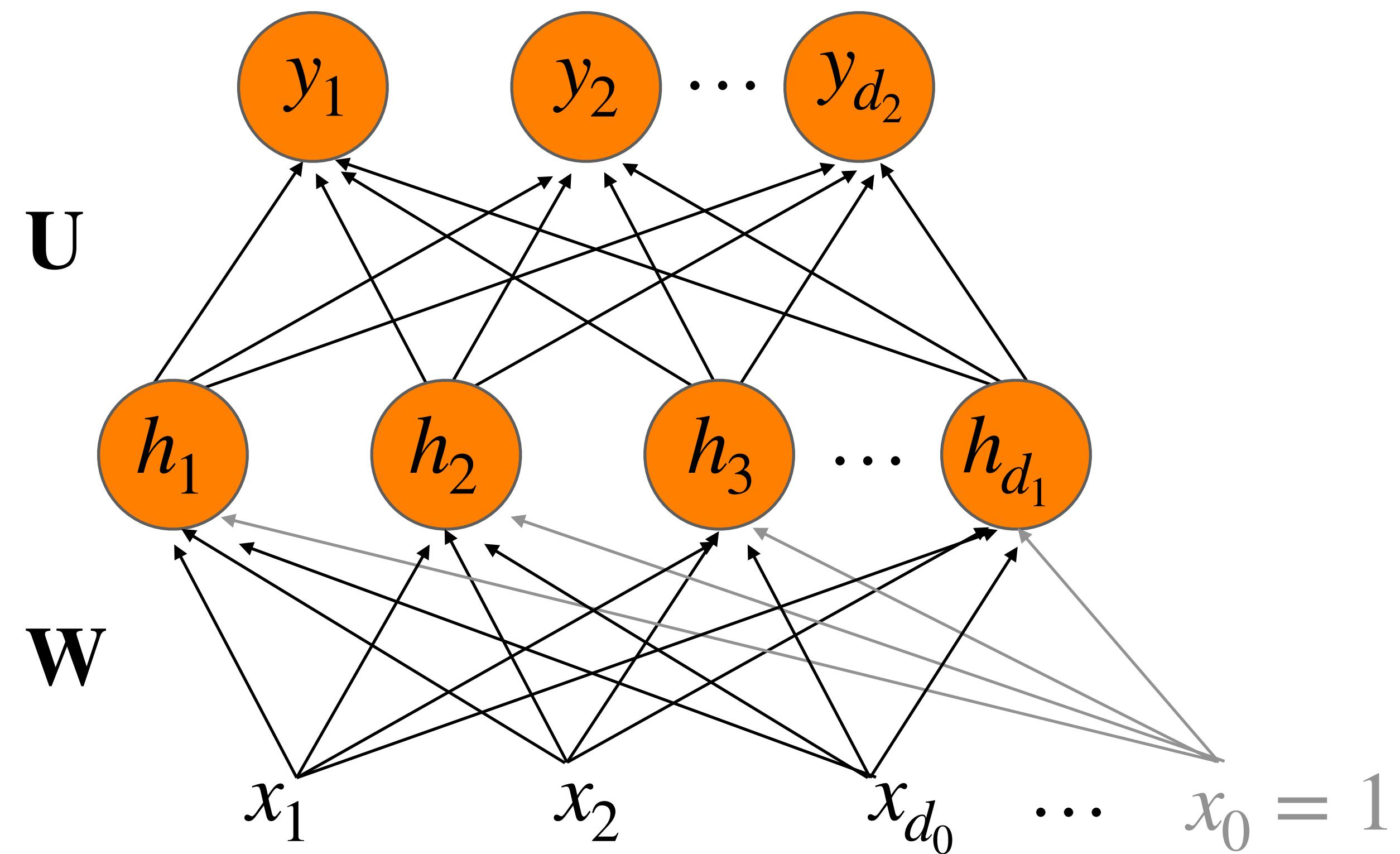
Two-layer FFNN: Notation

Output layer: $\mathbf{y} = \text{softmax}(\mathbf{U} \cdot \mathbf{h})$

Hidden layer: $\mathbf{h} = g(\mathbf{W}\mathbf{x}) = g\left(\sum_{i=0}^{d_0} \mathbf{W}_{ji} \mathbf{x}_i\right)$

Usually ReLU or tanh

Input layer: vector \mathbf{x}



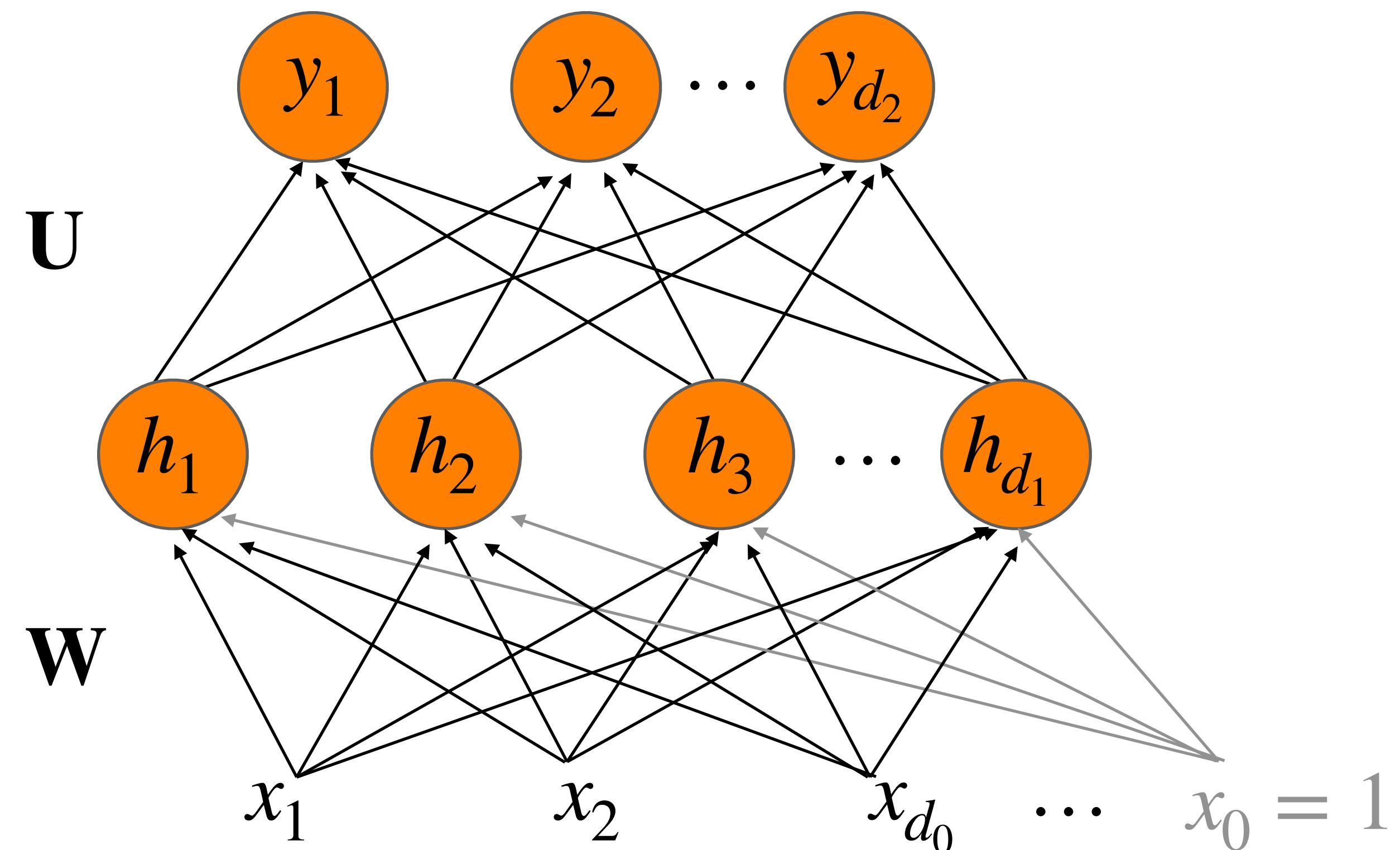
Two-layer FFNN: Notation

Output layer: $\mathbf{y} = \text{softmax}(\mathbf{U} \cdot \mathbf{h})$

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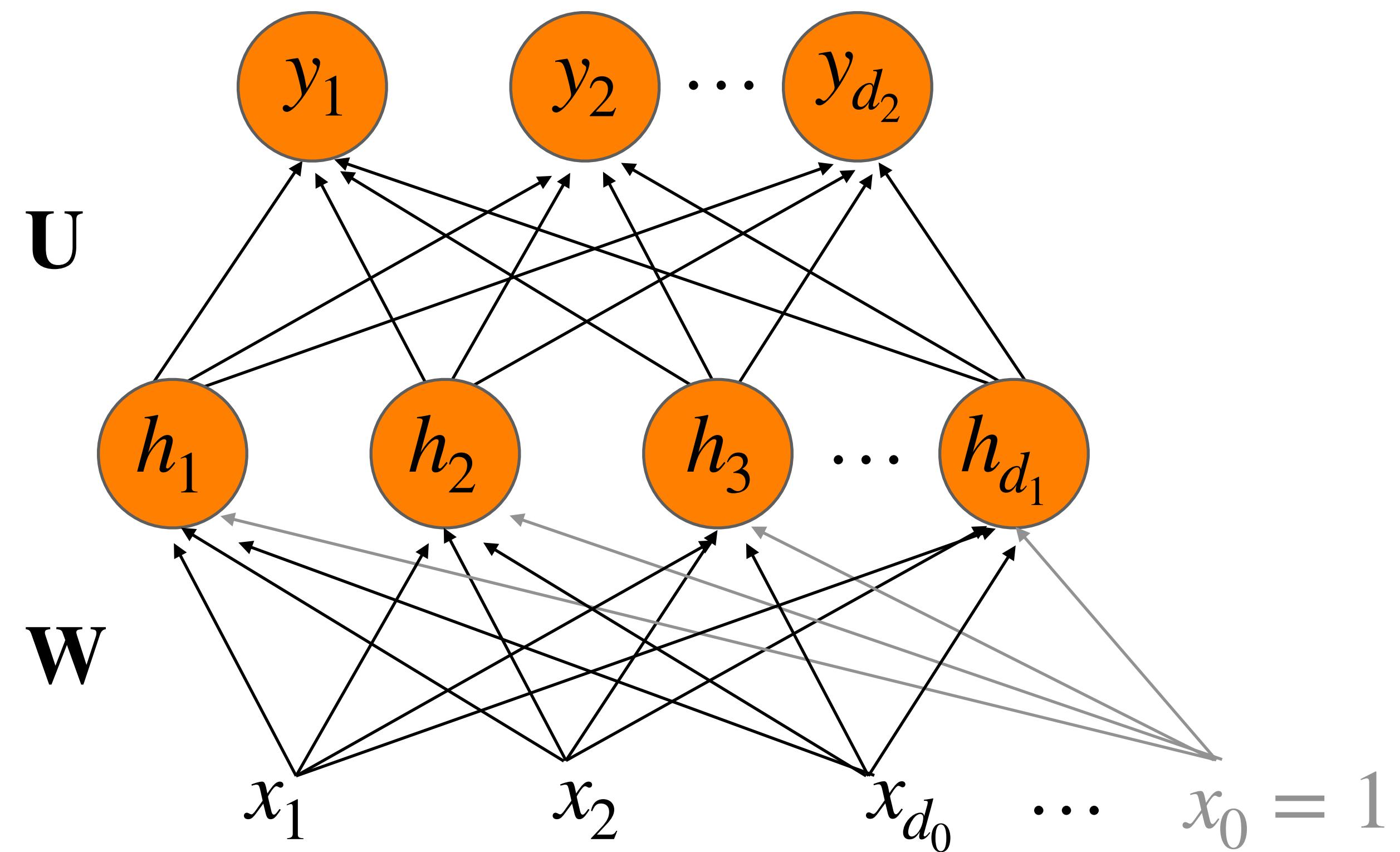
Usually ReLU or tanh

Input layer: vector \mathbf{x}



We usually drop the \mathbf{b} and add one dimension to the \mathbf{W} matrix

Concluding Thoughts



Concluding Thoughts

Next Class:

- More on Feedforward neural nets
- Backpropagation

