NLP for Social Sciences

5. Neural Networks and Language Modelling

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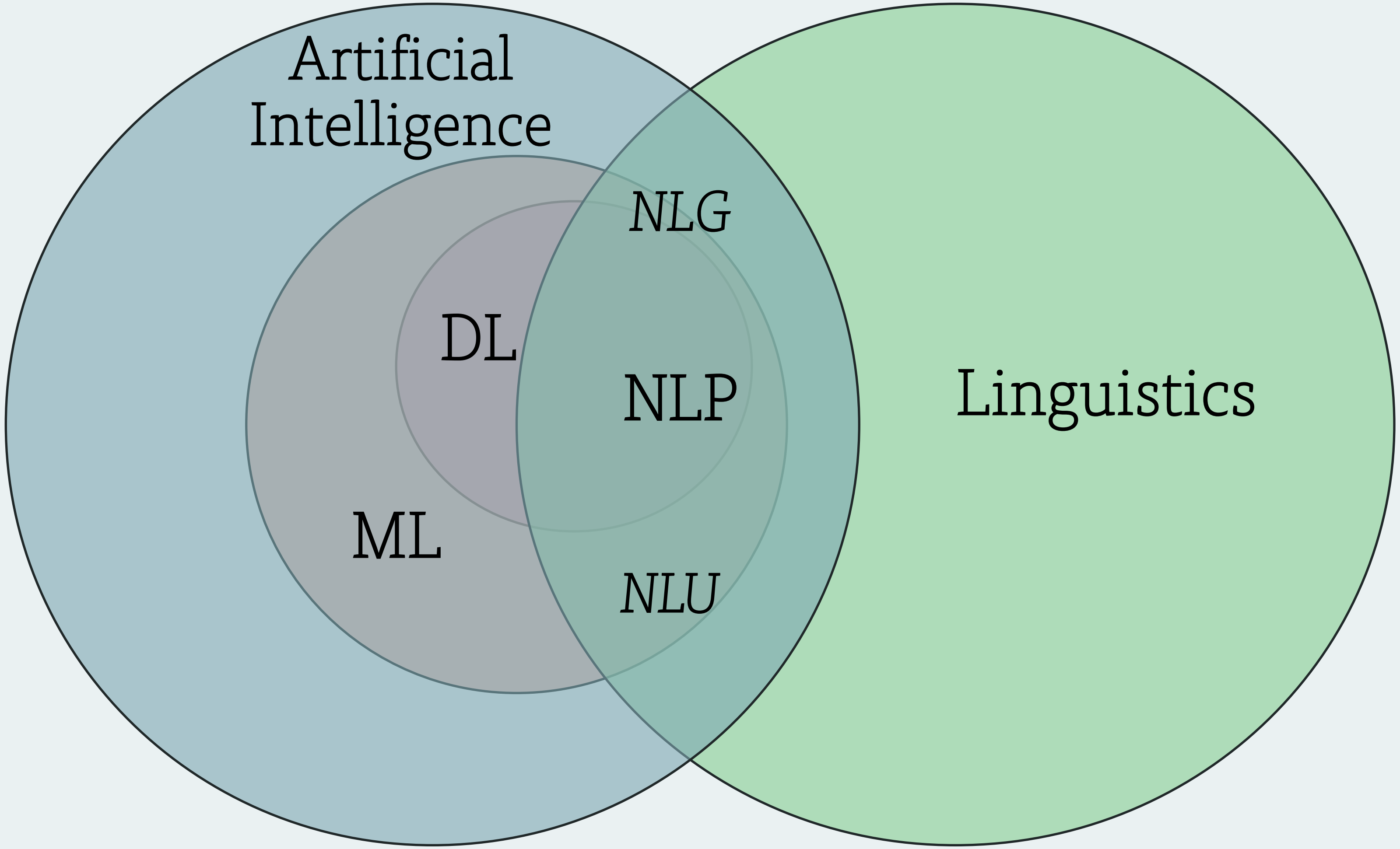
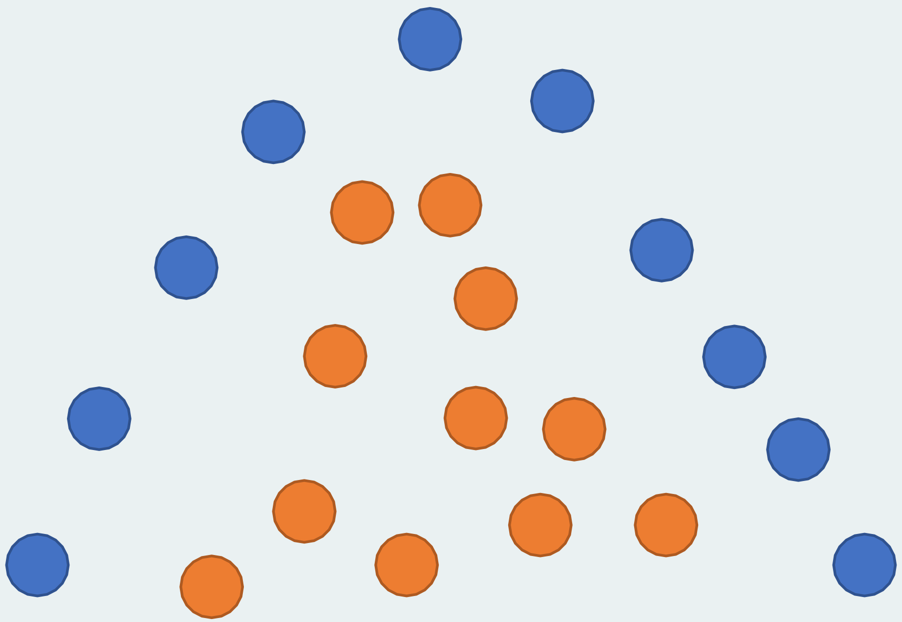
1. Neural Networks

Natural Language Processing

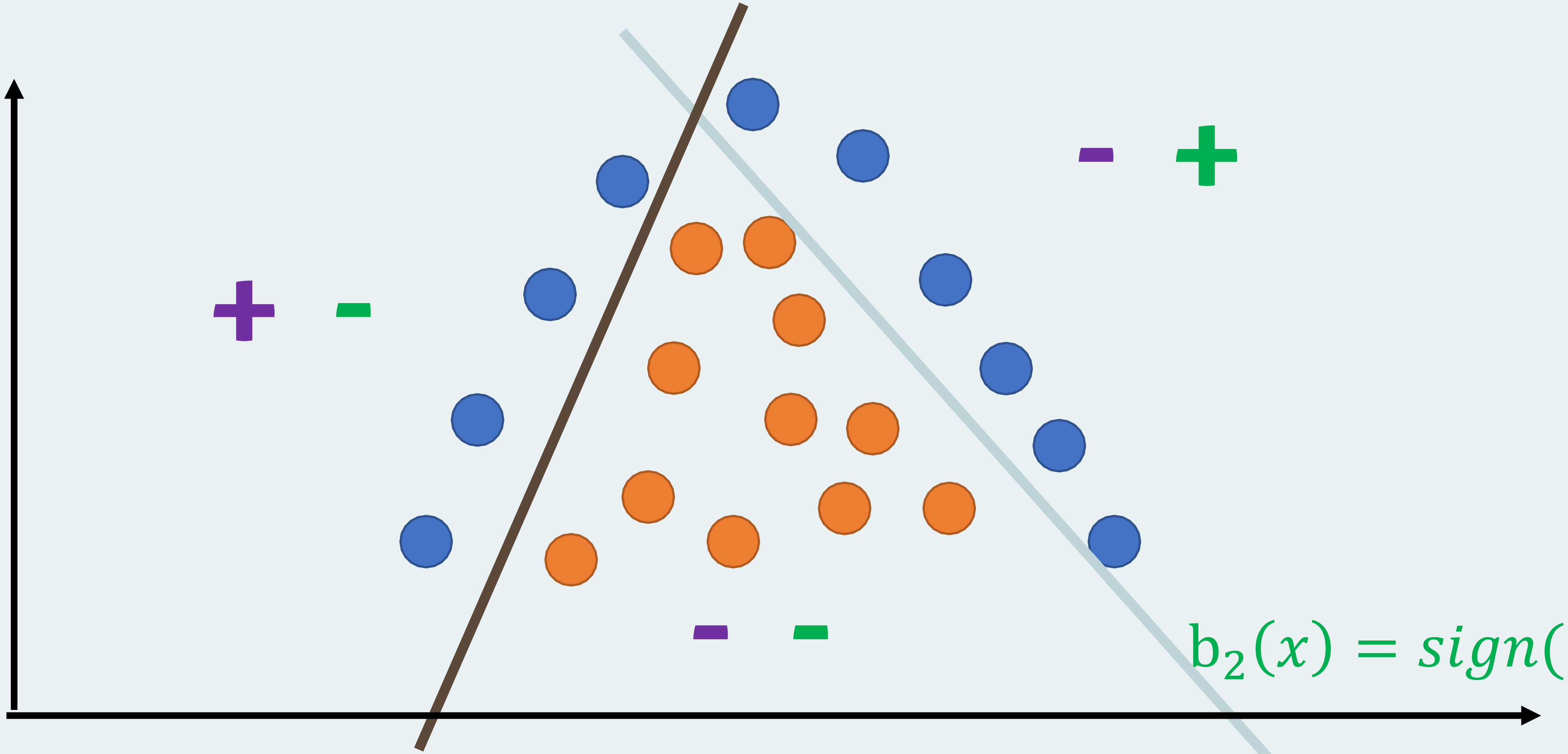


Neural Network Structure



Nonlinear patterns

Neural Network Structure

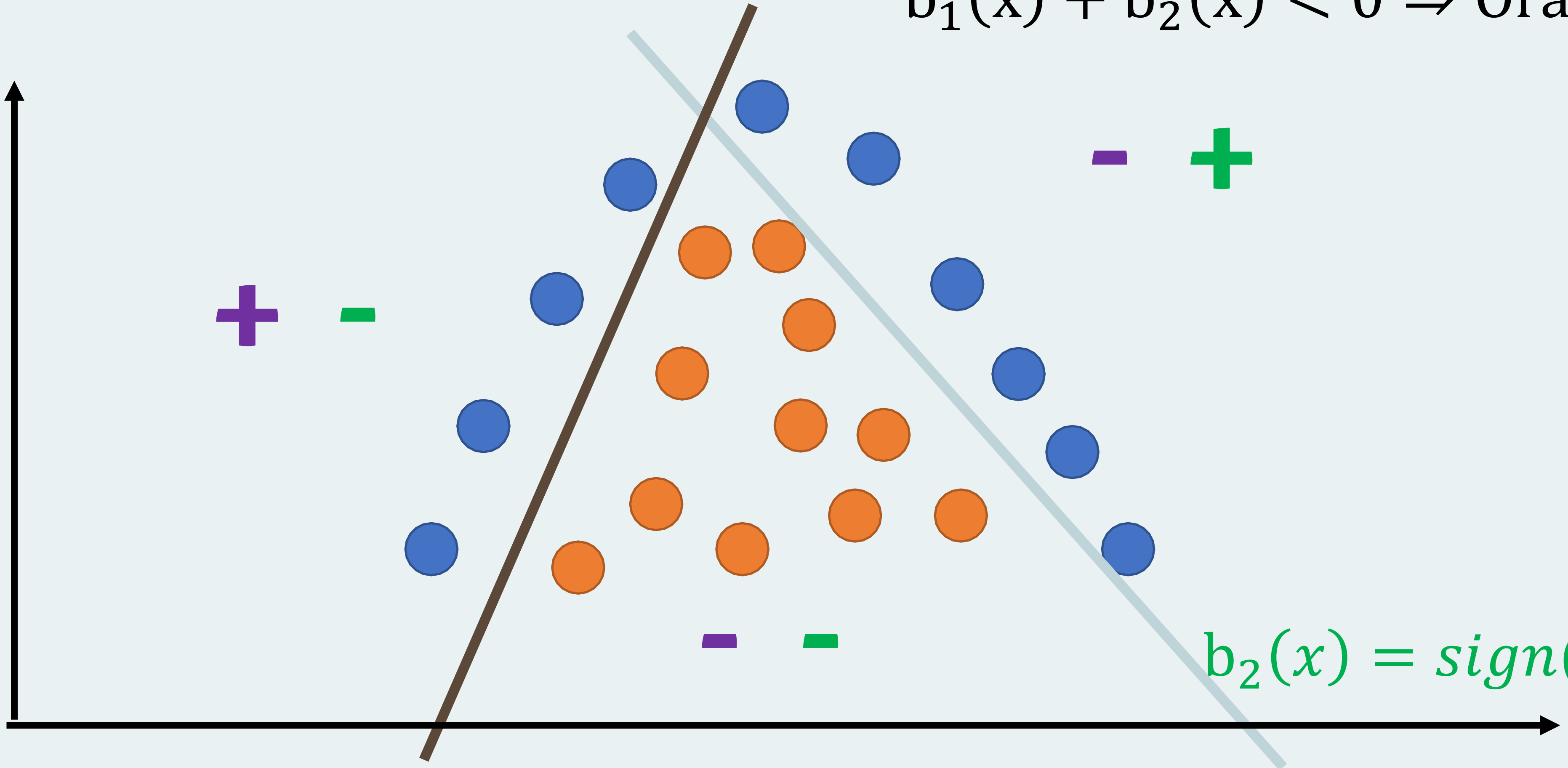


$b_2(x) = sign(2x_1 + x_2 -$

$b_1(x) = sign(-2x_1 + x_2 + 5)$

Neural Network Structure

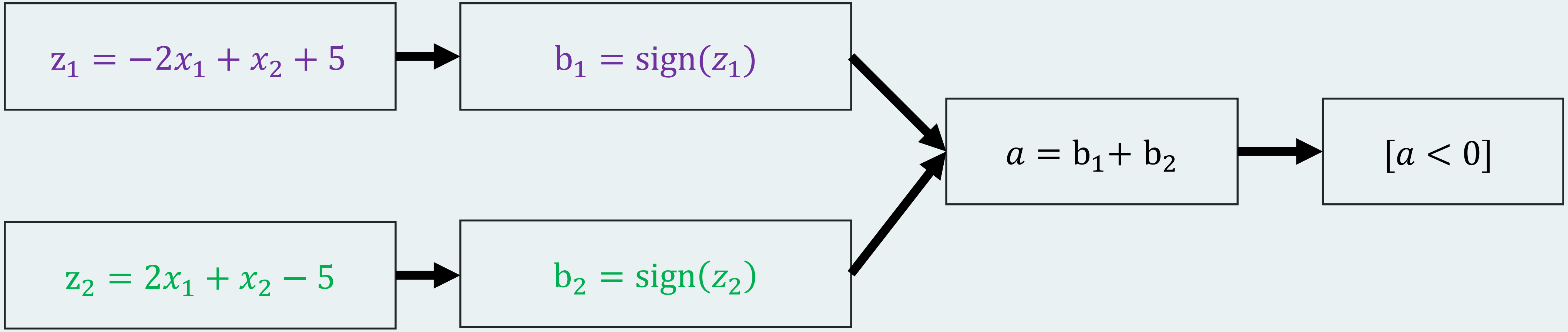
$$\mathrm{b}_1(\mathrm{x}) + \mathrm{b}_2(\mathrm{x}) < 0 \Rightarrow \text{Orange class}$$



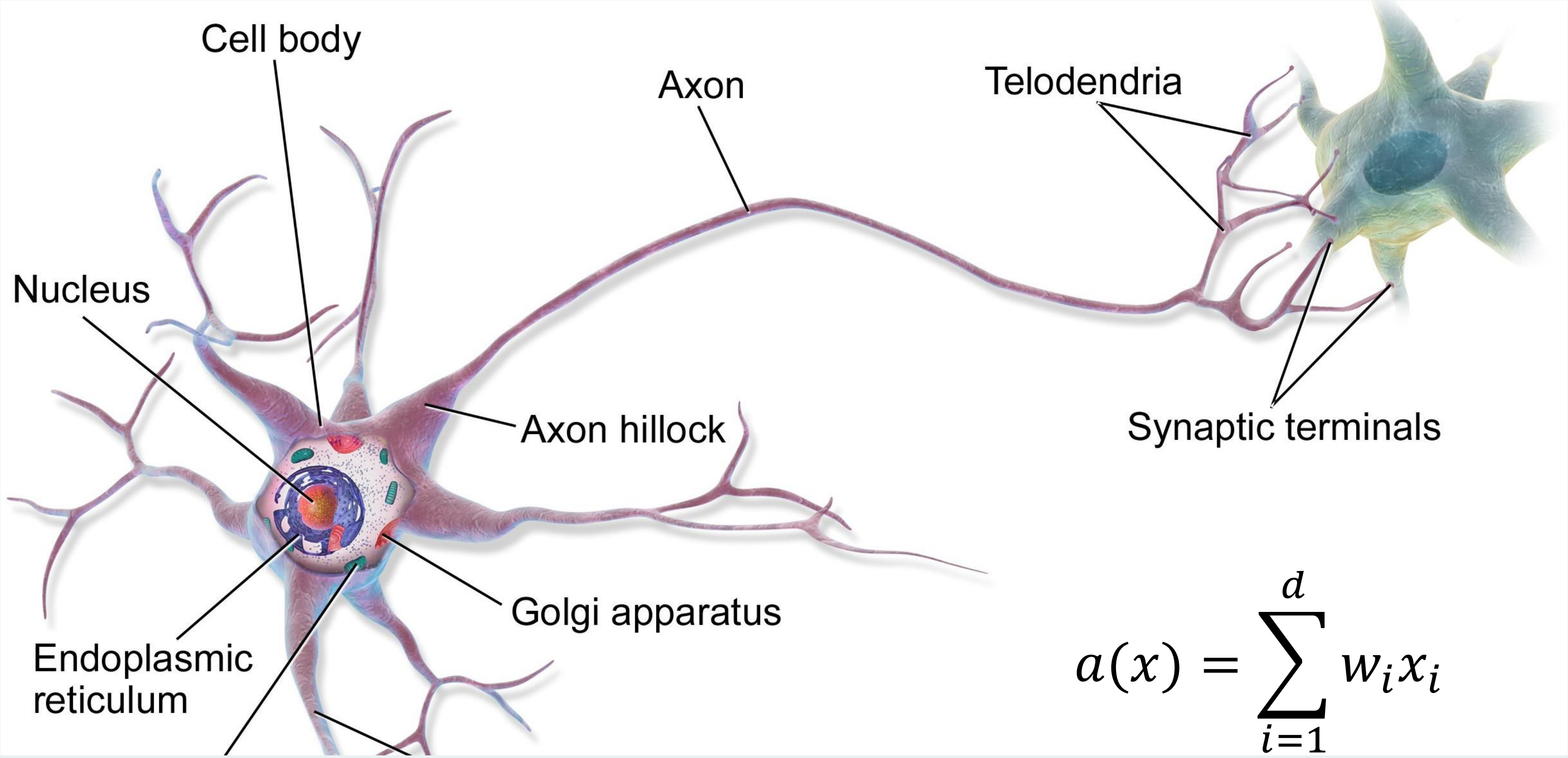
$$\mathrm{b}_2(x) = sign(2x_1 + x_2 -$$

$$\mathrm{b}_1(x) = sign(-2x_1 + x_2 + 5)$$

Neural Network Structure



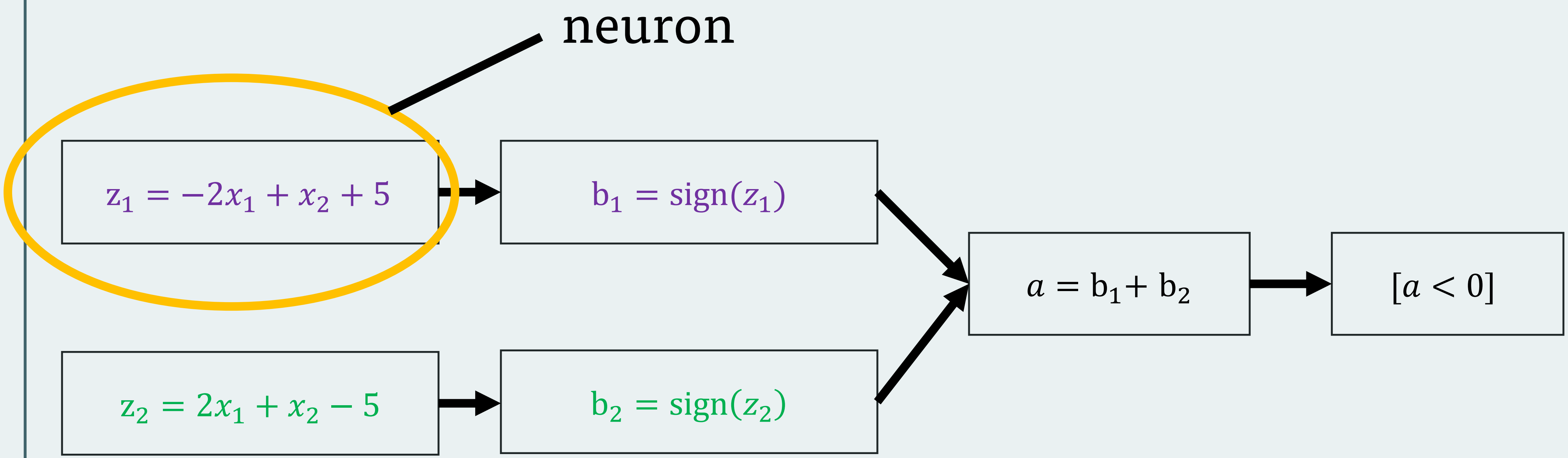
Neuron



$$a(x) = \sum_{i=1}^{d} w_i x_i$$

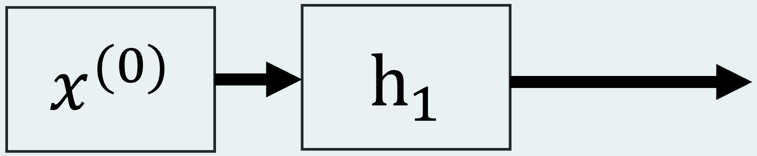
https://en.wikipedia.org/wiki/Neuron

Neural Network Structure

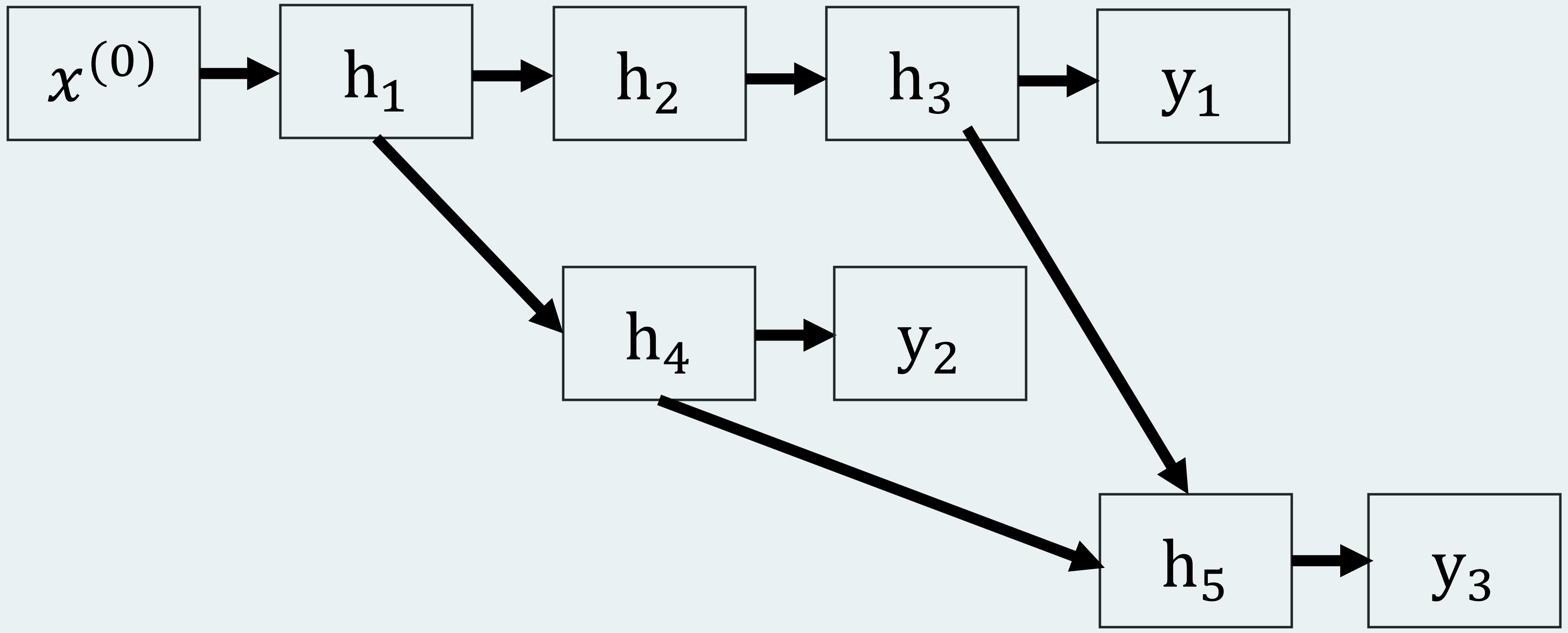


Computational graph (neural network)

- $x^{(0)}$ — input features (embedding)
- h_1 — hidden layer
- $x^{(1)}$ — output



Computational graph (neural network)



2. Fully connected layers

Fully connected layers

- The input consists of N values, and the output produces M values
- $x_1, \cdots x_N$ — input
- $y_1, \cdots y_M$— output

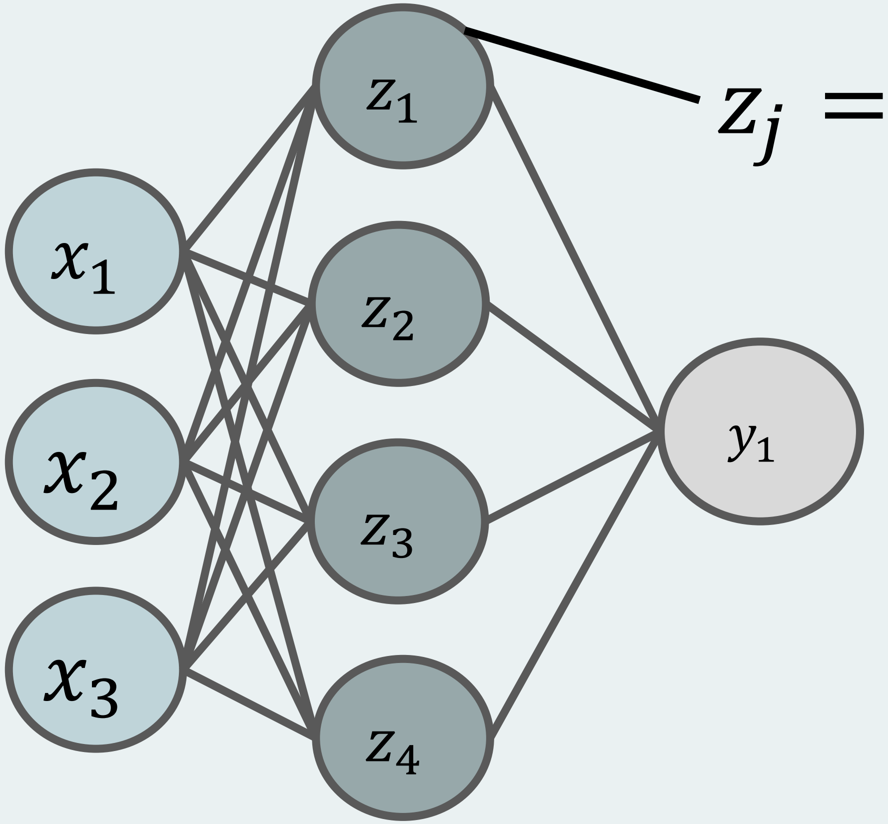
- Each output is the result of applying a linear model to the inputs.

$$z_j = \sum_{i=1}^{n} w_{ji} x_i + b_j$$

Fully connected layers

$$z_j = \sum_{i=1}^{n} w_{ji} x_i + b_j$$

1 Input layer



3 Output layer

2 Hidden layer

https://cs231n.github.io/convolutional-networks/

Fully connected layers

$$z_j = \sum_{i=1}^{n} w_{ji} x_i + b_j$$

- m linear models, each with $(n + 1)$ parameters
- in total, there are approximately mn parameters in a fully connected layer

torch.nn.Linear(20, 30)

keras.layers.Dense(64)

Fully connected layers

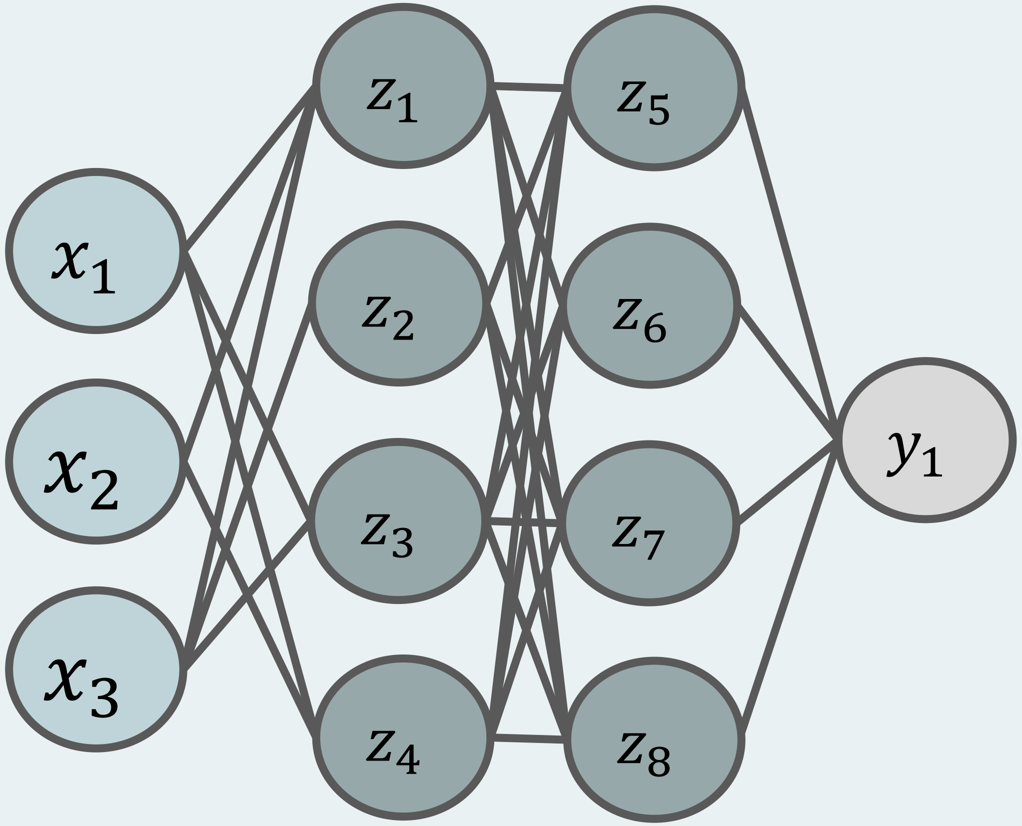
$$z_j = \sum_{i=1}^{n} w_{ji} x_i + b_j$$

- m linear models, each with $(n + 1)$ parameters
- in total, there are approximately mn parameters in a fully connected layer
- if we have 1,000,000 input features and 1000 outputs, it amounts to 1,000,000,000 parameters
- a substantial amount of data is needed for training

Important Questions in DL

How to build a useful model in deep learning?
Which layers to add?

Fully connected layers



- Can we have 2 fully-connected layers one after another?

Non-linearity

- Given 2 fully-connected layers

$$s_k = \sum_{j=1}^{m} v_{kj} z_j + c_k = \sum_{j=1}^{m} v_{kj} \sum_{j=1}^{m} w_{ji} x_i + \sum_{j=1}^{m} v_{kj} b_j + c_k =$$

$$= \sum_{j=1}^{m} (\sum_{j=1}^{m} \boldsymbol{v_{kj} w_{ji}} x_i + \boldsymbol{v_{kj} b_j} + \frac{\mathbf{1}}{\boldsymbol{m}} \boldsymbol{c_k})$$

$$\boxed{z_j = \sum_{i=1}^{n} \boldsymbol{w_{ji}} x_i + \boldsymbol{b_j}}$$

- **So, this is no better than a single fully connected layer**

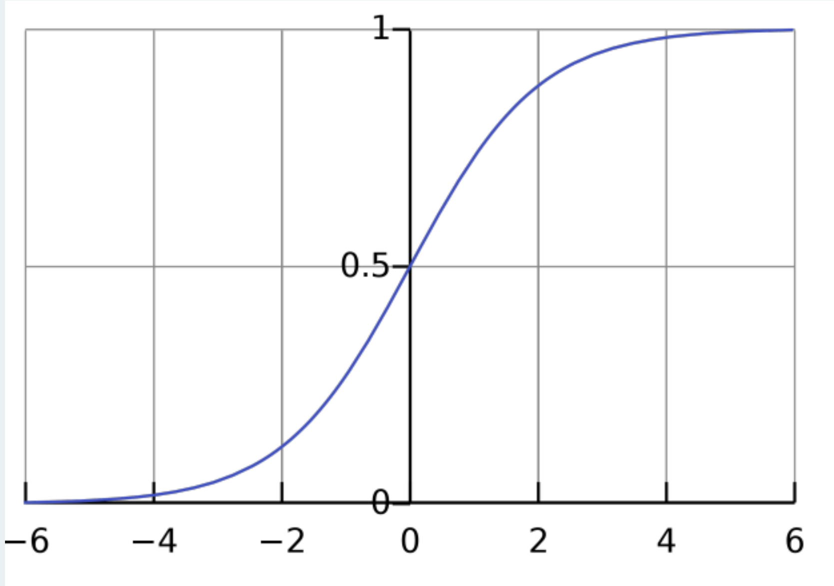
Activation functions

- It is necessary to add a non-linear activation function after the fully connected layer (`torch.nn.Sigmoid`)

$$z_j = f(\sum_{i=1}^{n} w_{ji}x_i + b_j)$$

1. $f(x) = \dfrac{1}{1 + \exp(-x)}$

Logistic / Sigmoid



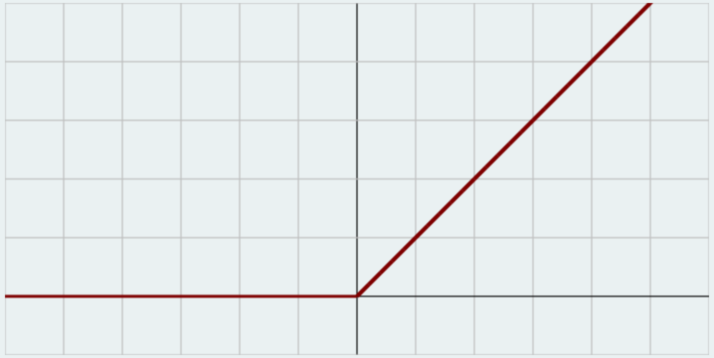
Activation functions

- It is necessary to add a non-linear activation function after the fully connected layer (`torch.nn.ReLU`)

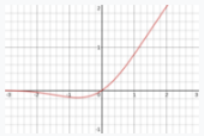
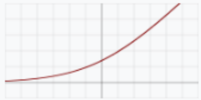
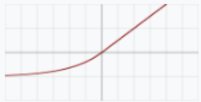
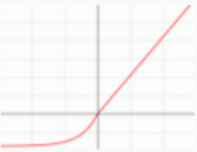
$$z_j = f(\sum_{i=1}^{n} w_{ji} x_i + b_j)$$

2. $f(x) = \max(0, x)$

(ReLU, REctified Linear Unit)



Activation Functions

Rectified linear unit (ReLU)[8]		$(x)^{+} \doteq \begin{cases} 0 & \text{if } x \leq 0 \\ x & \text{if } x > 0 \end{cases} = \max(0, x) = x\mathbf{1}_{x>0}$
Gaussian Error Linear Unit (GELU)[2]		$\frac{1}{2}x\left(1 + \text{erf}\left(\frac{x}{\sqrt{2}}\right)\right) = x\Phi(x)$
Softplus[9]		$\ln(1 + e^{x})$
Exponential linear unit (ELU)[10]		$\begin{cases} \alpha\left(e^{x} - 1\right) & \text{if } x \leq 0 \\ x & \text{if } x > 0 \end{cases}$ with parameter α
Scaled exponential linear unit (SELU)[11]		$\lambda \begin{cases} \alpha(e^{x} - 1) & \text{if } x < 0 \\ x & \text{if } x \geq 0 \end{cases}$ with parameters $\lambda = 1.0507$ and $\alpha = 1.67326$

https://en.wikipedia.org/wiki/Activation_function

A fully connected neural network

$$\boxed{x^{(0)}} \rightarrow \boxed{\mathrm{FC}_1} \rightarrow \boxed{f} \rightarrow \boxed{\mathrm{FC}_2} \rightarrow \boxed{f} \rightarrow \cdots$$

A fully connected neural network

$$\boxed{x^{(0)}} \rightarrow \boxed{\mathrm{FC}_1} \rightarrow \boxed{f} \rightarrow \boxed{\mathrm{FC}_2} \rightarrow \boxed{f} \rightarrow \cdots$$

- Features are fed into the network
- The dimension of the last layer = # target variables (# classes)

Two-layer network with **scalar** output

$y = \sigma(z)$ y is a scalar

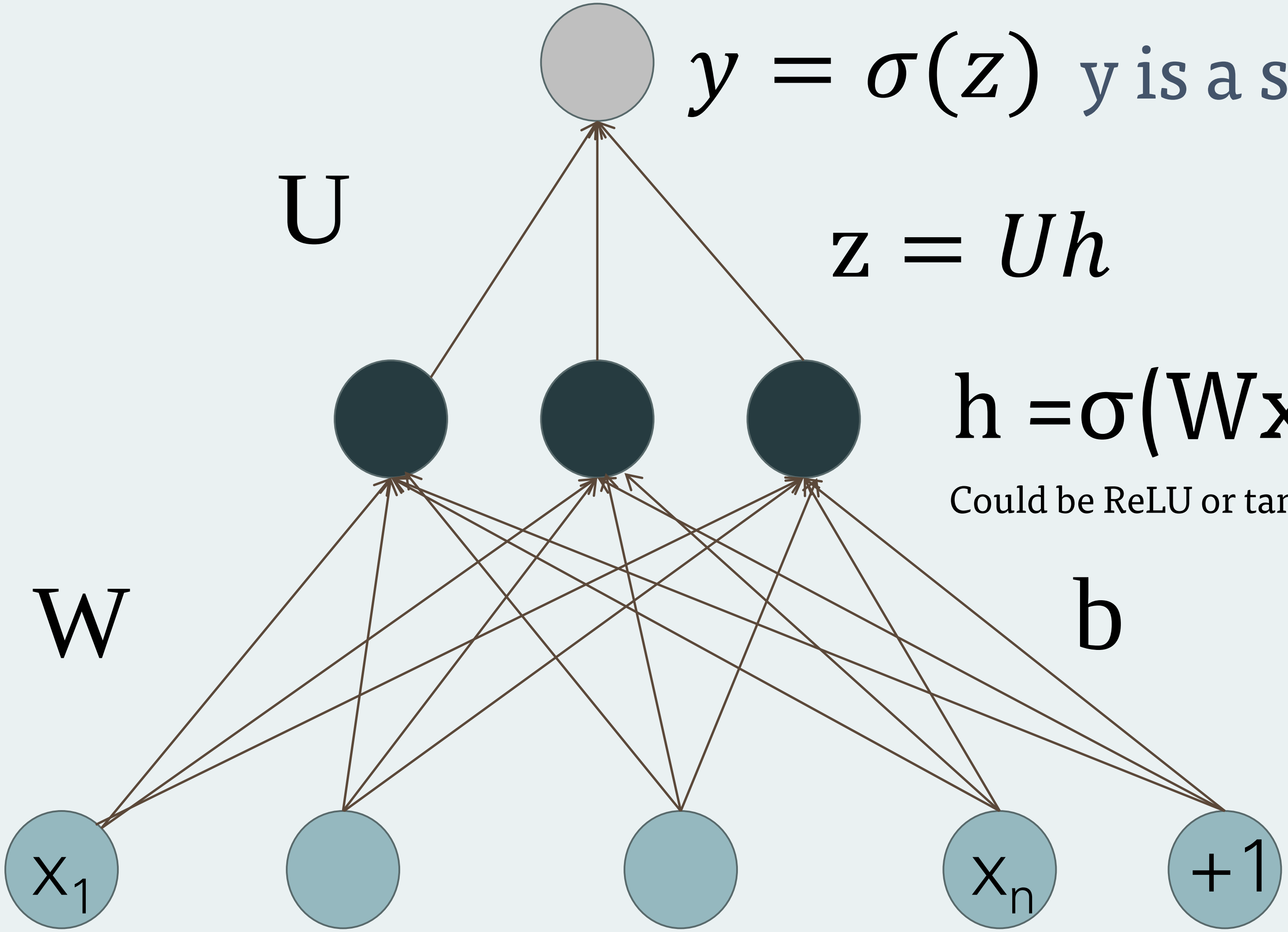
Output layer
(σ node)

$z = Uh$

$h = \sigma(Wx+b)$

Could be ReLU or tanh

Hidden units
(σ node)



Input layer
(vector)

Two-layer network with **softmax** output

$y = \text{softmax}(z)$
$z = Uh$

y is a vector

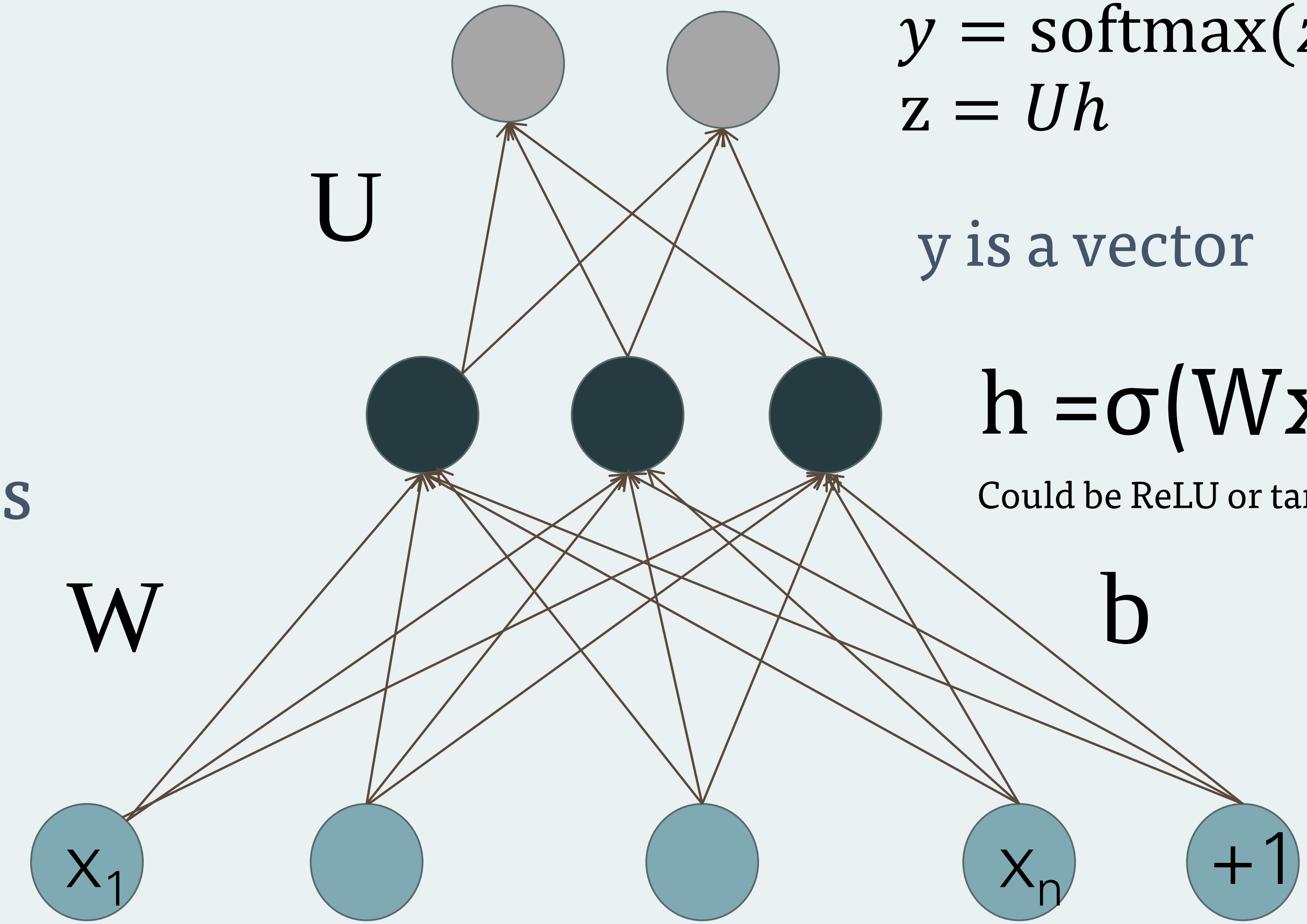
$h = \sigma(Wx+b)$

Could be ReLU or tanh

Output layer
(σ node)

Hidden units
(σ node)

Input layer
(vector)



The Cybenko universal approximation theorem

Summary:

- Let $g(x)$ be a continuous function. Then, it is possible to construct a two-layer neural network that approximates $g(x)$ with any predefined precision.
- In other words, two-layer neural networks are VERY powerful

3. Training neural networks

Warm-up

Which of this is the formula for a step in gradient descent?

1. $\mathrm{w}^{\mathrm{t}} = \mathrm{w}^{\mathrm{t}-1} + \eta\nabla Q(\mathrm{w}^{\mathrm{t}})$
2. $\mathrm{w}^{\mathrm{t}} = \mathrm{w}^{\mathrm{t}-1} - \eta\nabla Q(\mathrm{w}^{\mathrm{t}-1})$
3. $\mathrm{w}^{\mathrm{t}} = \mathrm{w}^{\mathrm{t}-1} - \eta\nabla Q(\mathrm{w}^{\mathrm{t}})$
4. $\mathrm{w}^{\mathrm{t}} = \mathrm{w}^{\mathrm{t}-1} + \eta\nabla Q(\mathrm{w}^{0})$

Convergence

- Stopping rule 1

$$\|w^t - w^{t-1}\| < \varepsilon$$

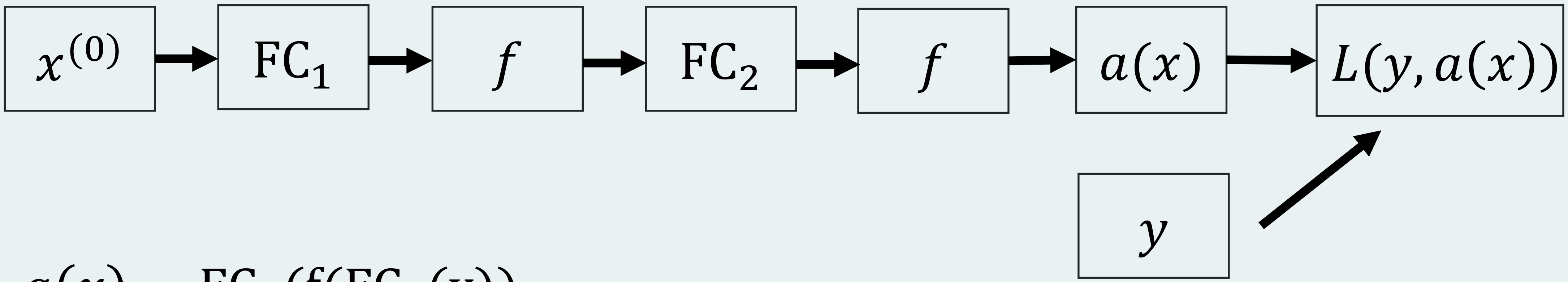
- Stopping rule 2

$$\|\nabla Q(w^t)\| < \varepsilon$$

- In DL: stop when the error on the test set stops decreasing

Training neural networks

- All layers are usually possible to differentiate, so it's possible to compute derivatives with respect to all parameters

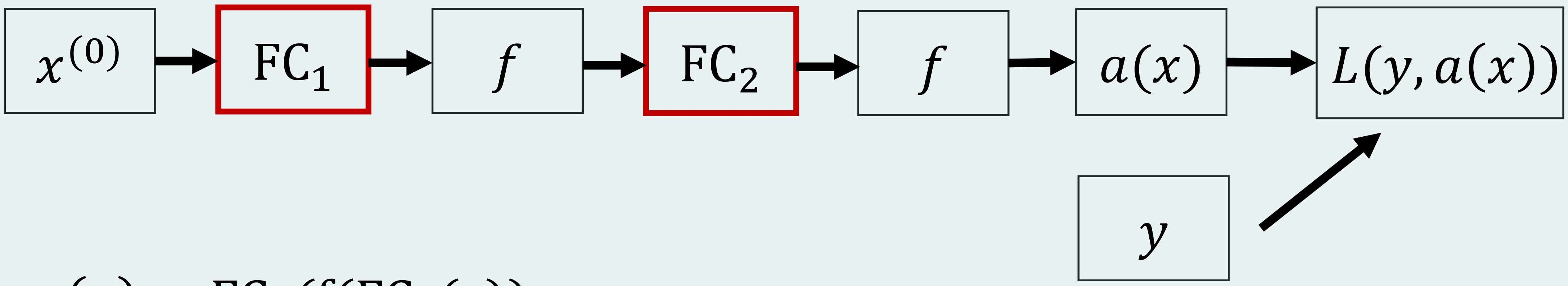


- $a(x) = \mathrm{FC}_2(\mathrm{f}(\mathrm{FC}_1(\mathrm{x}))$

- Where are the parameters in this neural network?

Training neural networks

- All layers are usually possible to differentiate, so it's possible to compute derivatives with respect to all parameters



- $a(x) = \mathrm{FC}_2(\mathrm{f}(\mathrm{FC}_1(\mathrm{x}))$
- Where are the parameters?

$$\frac{1}{\ell}\sum_{i=1}^{\ell} L(y_i, a(x_i)) \to \min_a$$

Computing derivatives

- For gradient descent, derivatives of the error with respect to the parameters are needed:

$$\frac{\partial}{\partial w_j}(a(x_i, w) - y_i)^2$$

$$\frac{\partial}{\partial w_j}(a(x_i, w) - y_i)^2 = 2(a(x_i, w) - y_i)\frac{\partial}{\partial w_j}a(x_i, w)$$

Computing derivatives

- For gradient descent, derivatives of the error with respect to the parameters are needed:

$$\frac{\partial}{\partial w_j}(a(x_i,w)-y_i)^2 = 2(a(x_i,w)-y_i)\frac{\partial}{\partial w_j}a(x_i,w)$$

- $a(x_i,w)=10, y_i=9.99$: $\quad 2*0.01*\frac{\partial}{\partial w_j}a(x_i,w)$
- $a(x_i,w)=10, y_i=1$: $\quad 2*9*\frac{\partial}{\partial w_j}a(x_i,w)$

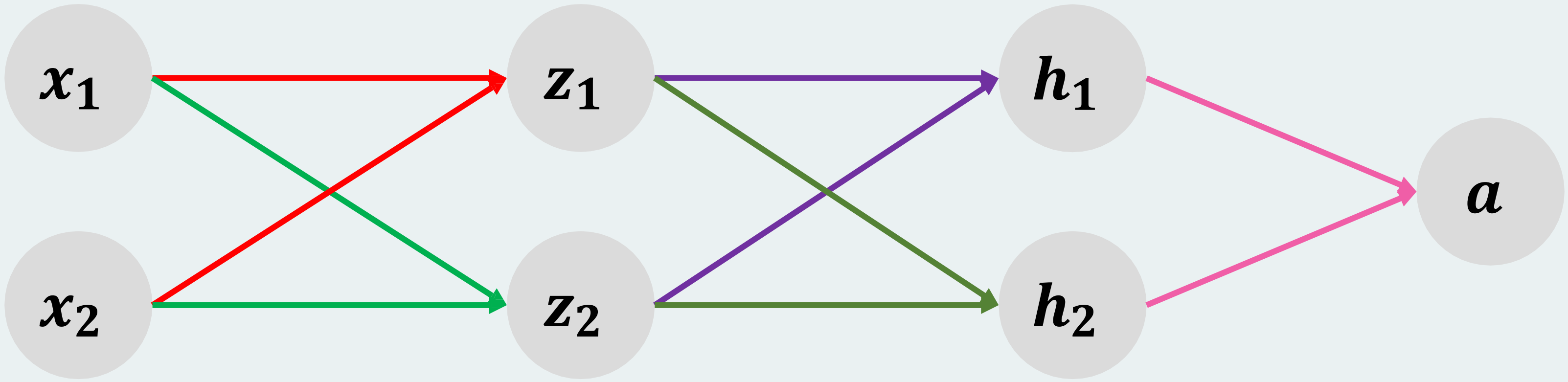
Computing derivatives

- For gradient descent, derivatives of the error with respect to the parameters are needed:

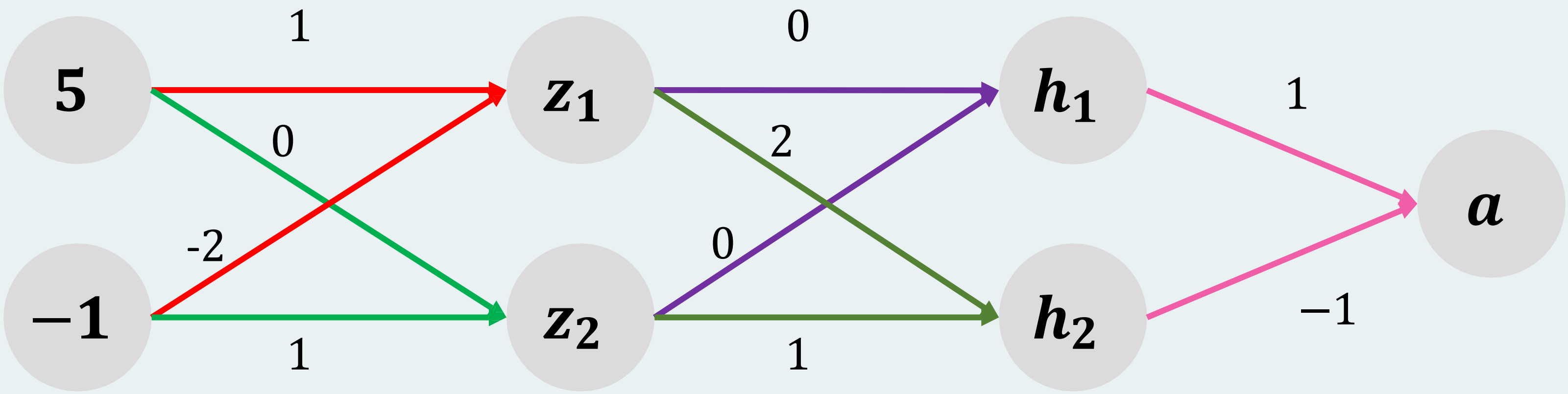
$$\frac{\partial}{\partial w_j}(a(x_i, w) - y_i)^2 = 2(a(x_i, w) - y_i)\frac{\partial}{\partial w_j}a(x_i, w)$$

$$\frac{\partial}{\partial w_j}L(y_i, a(x_i, w)) = \frac{\partial}{\partial z}L(y_i, z)\Big|_{z=a(x_i, w)}\frac{\partial}{\partial w_j}a(x_i, w)$$

How to compute derivatives?

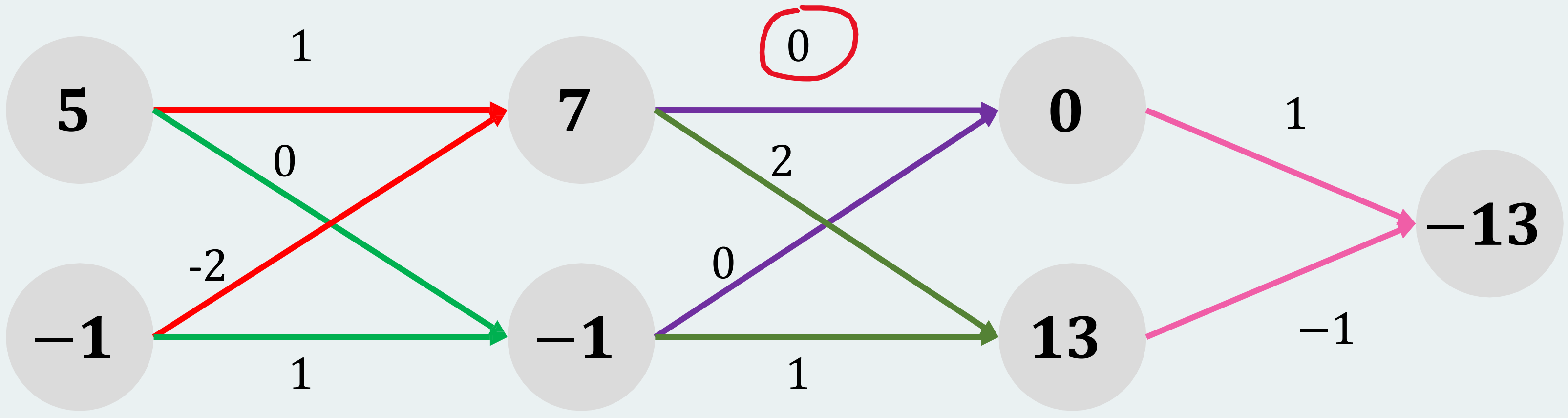


How to compute derivatives?

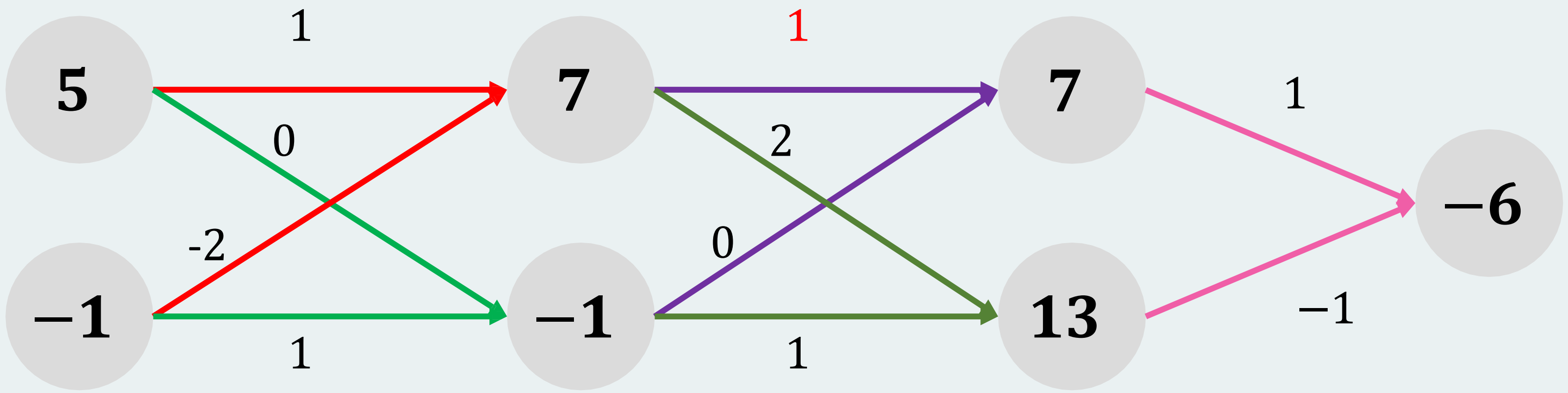


How to compute derivatives?

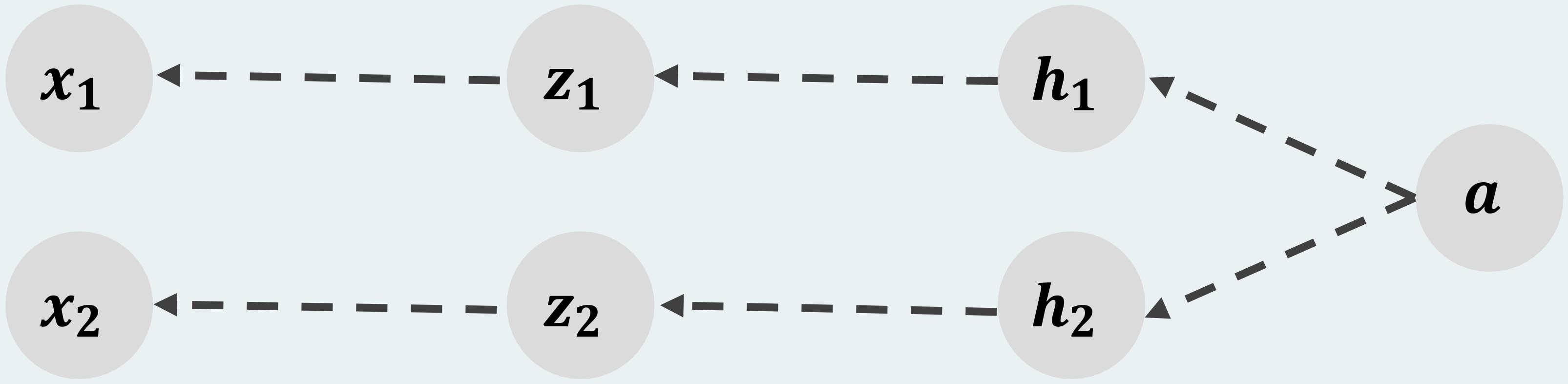
Will the output (-13) change if we change this weight from 0 to 1?



How to compute derivatives?



How to compute derivatives?



- We move in the opposite direction along the graph and calculate derivatives
- Backpropagation

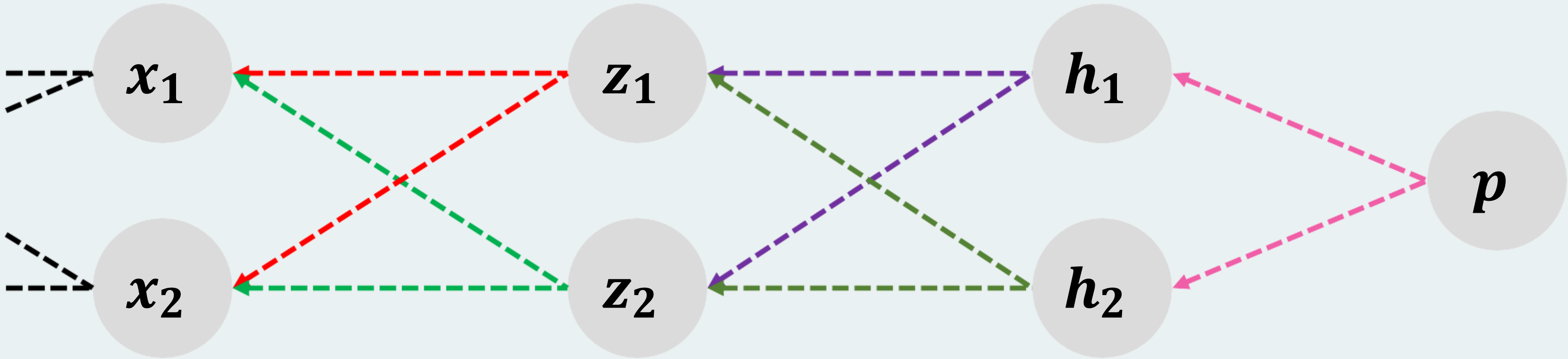
3: $\frac{\partial p}{\partial h_1}$ $\frac{\partial p}{\partial h_2}$

2: $\frac{\partial p}{\partial z_1} = \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_1} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_1}$ $\frac{\partial p}{\partial z_2} = \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_2} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_2}$

1:

$$\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_1}\frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_1}\frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_2}\frac{\partial z_2}{\partial x_1} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_2}\frac{\partial z_2}{\partial x_1}$$

$$\frac{\partial p}{\partial x_2} = \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_1}\frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_1}\frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_2}\frac{\partial z_2}{\partial x_2} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_2}\frac{\partial z_2}{\partial x_2}$$



Backpropagation

- Many formulas have the same derivatives
- In backpropagation, each partial derivative is computed only once—computing derivatives for layer N is reduced to multiplying the matrix of derivatives for layer N+1 by some vector

4. Neural Networks for NLP problems

Use cases for feedforward networks

Let's consider two sample tasks:

1. Text classification
2. Language modeling

State of the art systems use more powerful neural architectures, but simple models are still useful to consider!

Classification: Sentiment Analysis

- We could do exactly what we did with logistic regression
- Input layer are binary features as before
- Output layer is 0 or 1

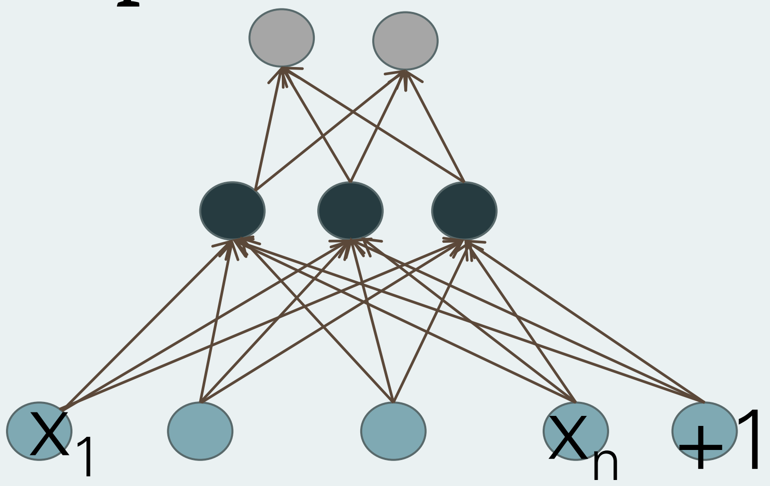
Sentiment Features

Var	Definition
x_1	count(positive lexicon) $\in$ doc)
x_2	count(negative lexicon) $\in$ doc)
x_3	$\begin{cases} 1 & \text{if ``no''} \in \text{doc} \\ 0 & \text{otherwise} \end{cases}$
x_4	count(1st and 2nd pronouns $\in$ doc)
x_5	$\begin{cases} 1 & \text{if ``!''} \in \text{doc} \\ 0 & \text{otherwise} \end{cases}$
x_6	log(word count of doc)

Feedforward nets for simple classification

Just adding a hidden layer to logistic regression :

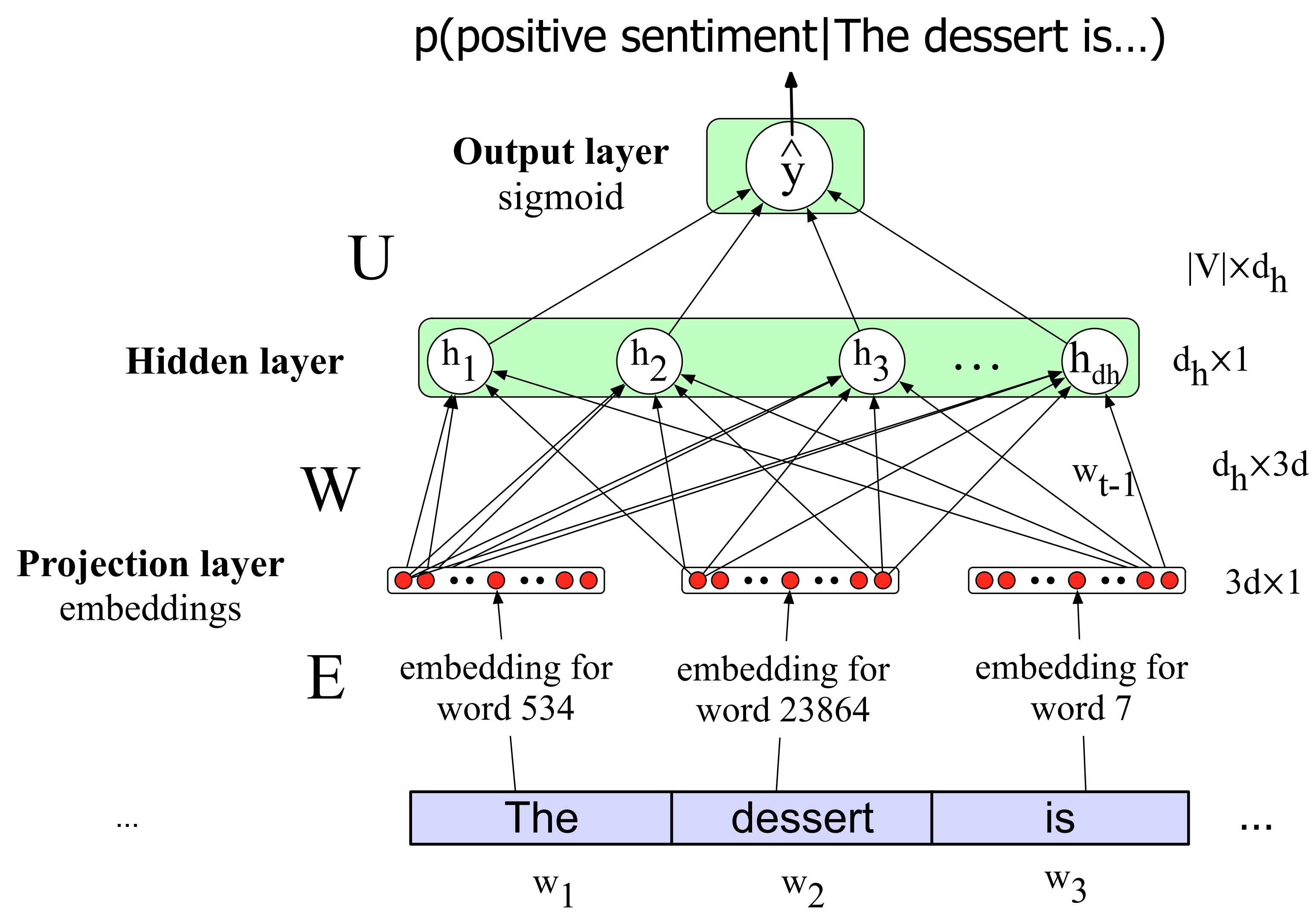
- allows the network to use non-linear interactions between features
- which may (or may not) improve performance
- Input: sentiment features
- Output: softmax layer



Even better: representation learning

- The real power of deep learning comes from the ability to **learn** features from the data
- Instead of using hand-built human-engineered features for classification
- Use learned representations like embeddings!
- Input: embeddings
- Output: softmax layer

Neural Net Classification with embeddings as input features!

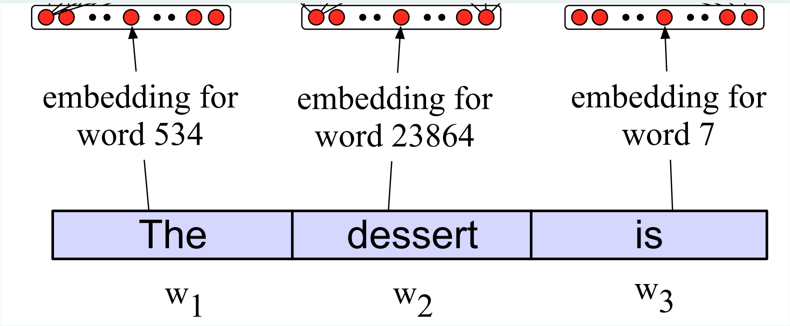


Issue: texts come in different sizes

This assumes a fixed size length (3)! Kind of unrealistic. Solutions:

Make the input the length of the longest review

- If shorter then **pad** with zero embeddings
- **Truncate** if you get longer reviews at test time



Reminder: Multiclass Outputs

- What if you have more than two output classes?
  - Add more output units (one for each class)
  - And use a "softmax layer"

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \quad 1 \leq i \leq D$$

Neural Language Models (LMs)

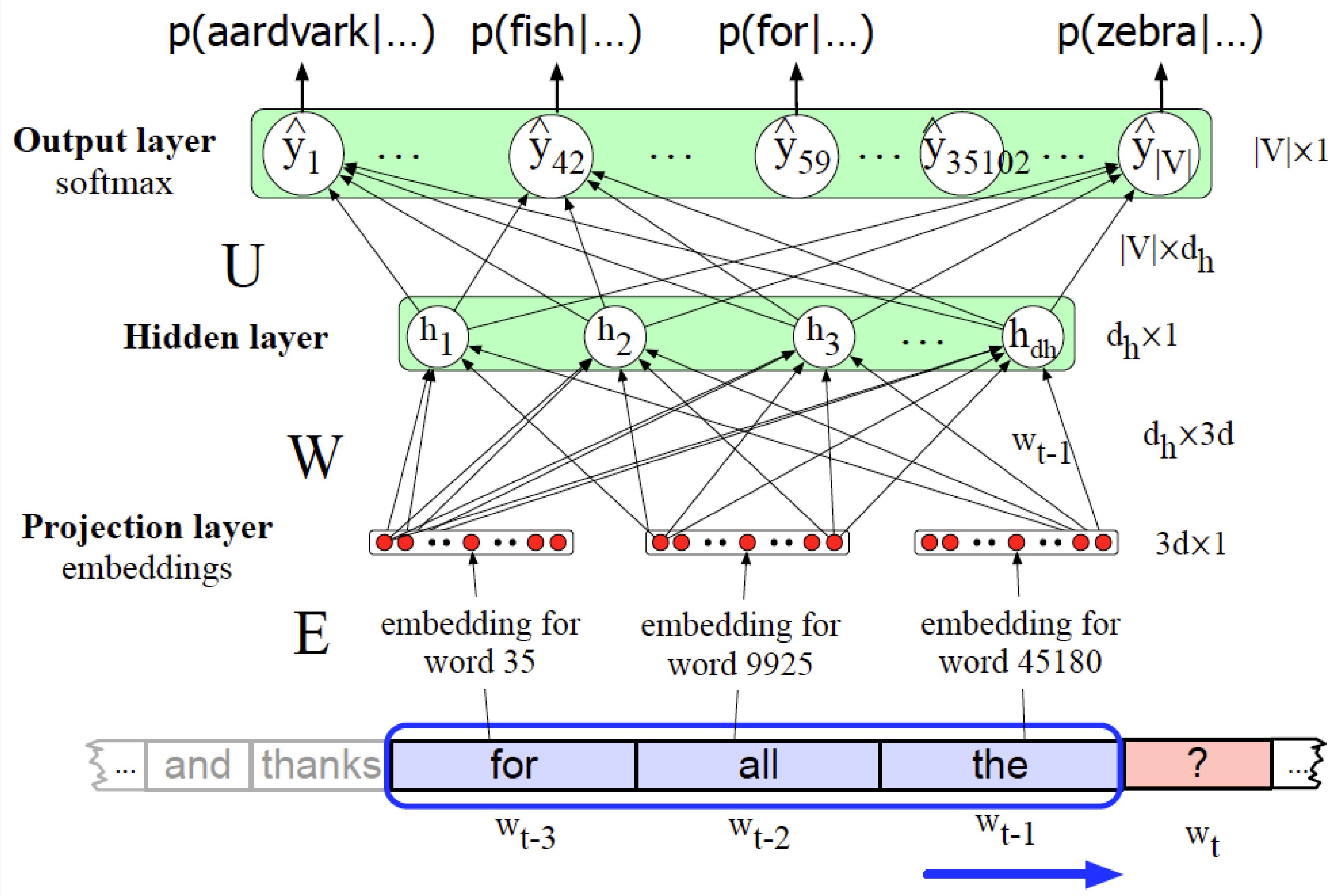
- **Language Modeling**: Calculating the probability of the next word in a sequence given some history.
- We've seen N-gram based LMs
- But neural network LMs far outperform n-gram language models
- State-of-the-art neural LMs are based on more powerful neural network technology like Transformers
- But **simple feedforward LMs** can do almost as well!

Simple feedforward Neural Language Models

- **Task**: predict next word w_t,given prior words w_{t-1}, w_{t-2}, w_{t-3}, …
- **Problem**: Now we're dealing with sequences of arbitrary length.
- **Solution**: Sliding windows (of fixed length)

$$P(w_t|w_1^{t-1}) \approx P(w_t|w_{t-N+1}^{t-1})$$

Neural Language Model



Why Neural LMs work better than N-gram LMs

Training data:

- We've seen: I have to make sure that the cat gets fed.
- Never seen: dog gets fed

Test data:

- I forgot to make sure that the dog gets ___
- N-gram LM can't predict "fed"!
- Neural LM can use similarity of "cat" and "dog" embeddings to generalize and predict "fed" after dog

Advantages of neural networks

- Parallelism
- Generalization Abilities: Often remarkable, particularly in pattern recognition for images and text (but not limited to these areas!).
- Ease of Implementation: Simple to set up for a wide range of problems.
- Value in low-information contexts and low-resource languages: Generally effective for problems where little prior information is available.

Limitations

- **Training**: Neural networks require significant resources for training.
  Hugging Face model size estimator:
  https://huggingface.co/docs/accelerate/usage_guides/model_size_estimator
- "**Black Box**" Nature: No explanation for predictions (Shapley values, LIME)
- **Network architecture selection**: Choosing the right architecture and hyperparameters is challenging
- **Complex Optimization Problem**: The search space is large, and finding the global optimum is difficult