Introduction to **Deep Learning** for Question Answering

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Outline

Motivation

Neural Networks

Recurrent Neural Networks

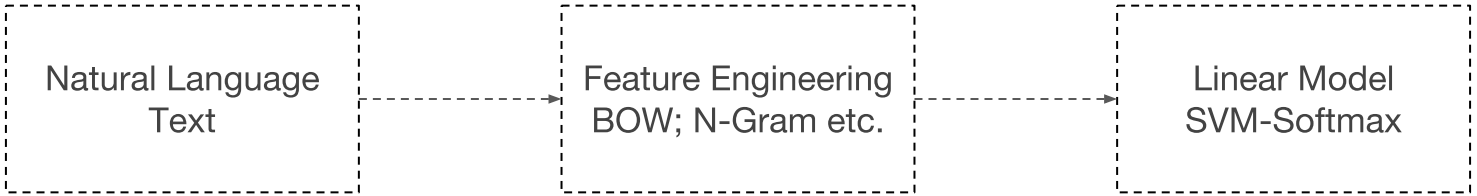
Trainings and Optimizations

Hands On

Future Directions

Motivation

Traditional ML based NLP Pipeline



Feature engineering for NLP is difficult.

Verbs in the sentence forms the relations.

Feature engineering for NLP is difficult.

✔ Name all the movies in which Robert Downey Jr **acted**?

× Name all the **parents** of Robert Downey Jr?

Feature engineering for NLP is difficult.

Verbs in the sentence forms the relations.

Words before the noun represents the relations.

Feature engineering for NLP is difficult.

✔ Name all the movies in which Robert Downey Jr **acted**?

✔ Name the **parents** of Robert Downey Jr?

× Name Robert Downey Jr's **parent**?

Feature engineering for NLP is difficult.

Verbs in the sentence forms the relations.

Words before the noun represents the relations.

Special keywords like “of”, “whose”, “not” etc.

NLP Ambiguity

Time flies like a arrow

V/S

Fruit flies like a banana

NLP Ambiguity

"I scream" vs. "ice cream" -

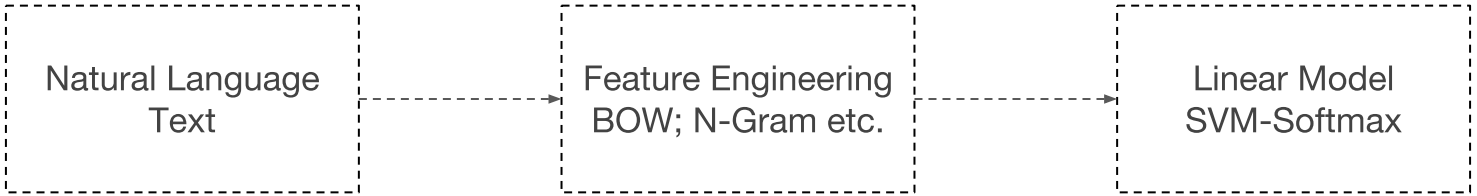
unionized = “union” + “ized” or “un” + “ionized”

Manual Feature engineering

Double counting.

Extending the rules to different domain is non-trivial

Traditional ML based NLP Pipeline



Issues

- × Cost Time
- × Domain Expertise
- × Manual Efforts


LET ME SPRINKLE SOME
DEEP LEARNING MAGIC
memegenerator.net

Deep learning based NLP Pipeline

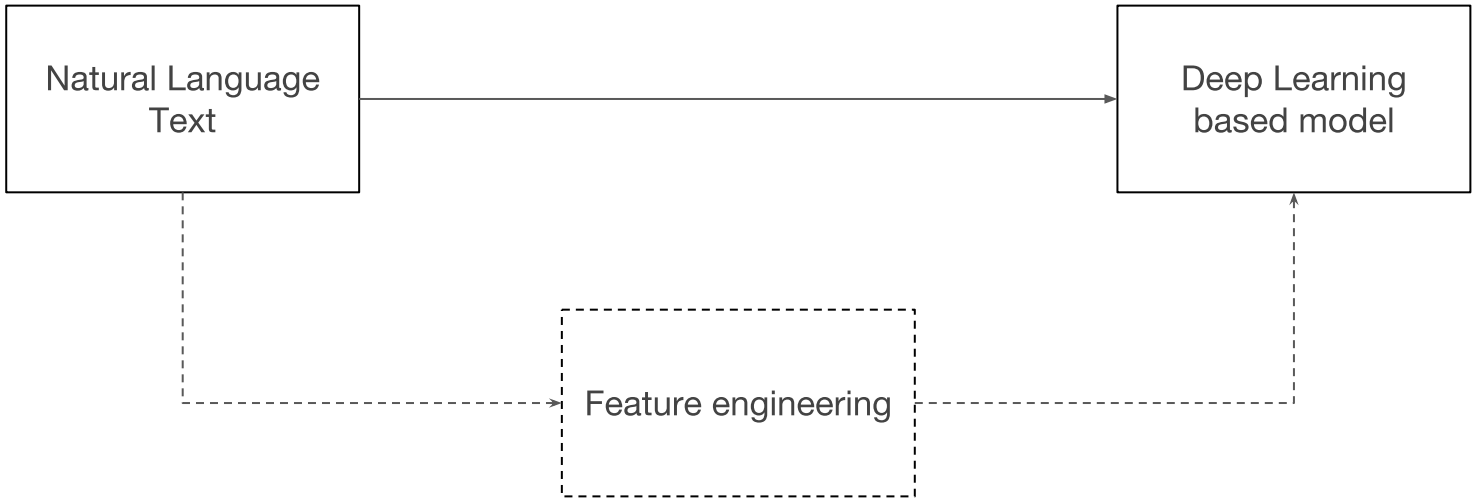
Ideally learns the features automatically a.k.a

Representation learning

More data beats clever algorithms, but better data beats more data

- Peter Norvig

Deep learning based NLP Pipeline



Empirical Validity

Sentiment Analysis

Image Captioning

Argument Mining

Structured Question Answering

Textual Entailment

Semantic Parsing

Word Embeddings

Language Modeling

Paraphrasing

Text based Question Answering

Named Entity Recognition

Machine Translation


THIS IS YOUR MACHINE LEARNING SYSTEM?
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.
WHAT IF THE ANSWERS ARE WRONG?
JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.
DATA
ANSWERS

Why now

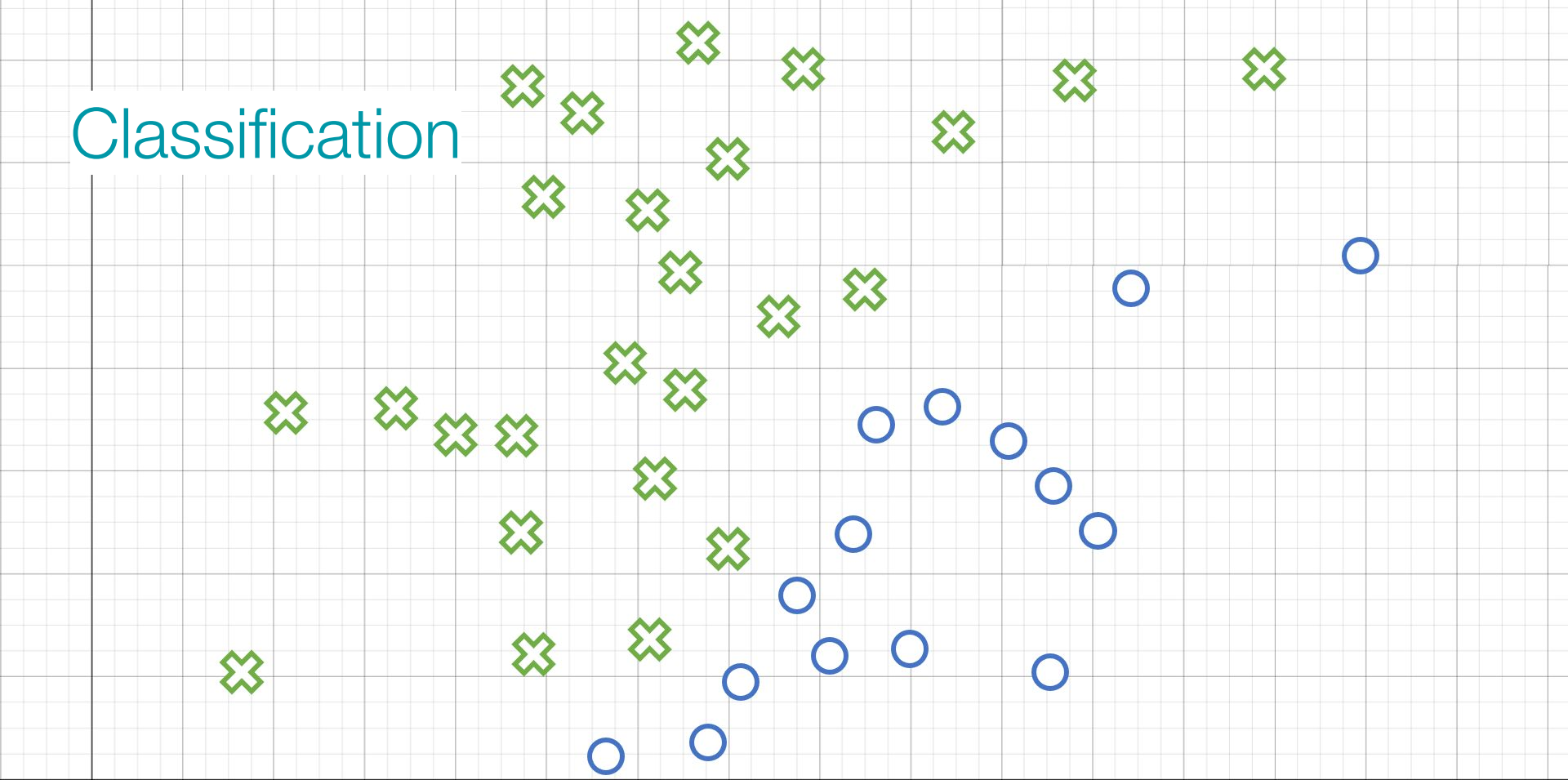
Faster, cheaper GPU’s

Simple to use libraries

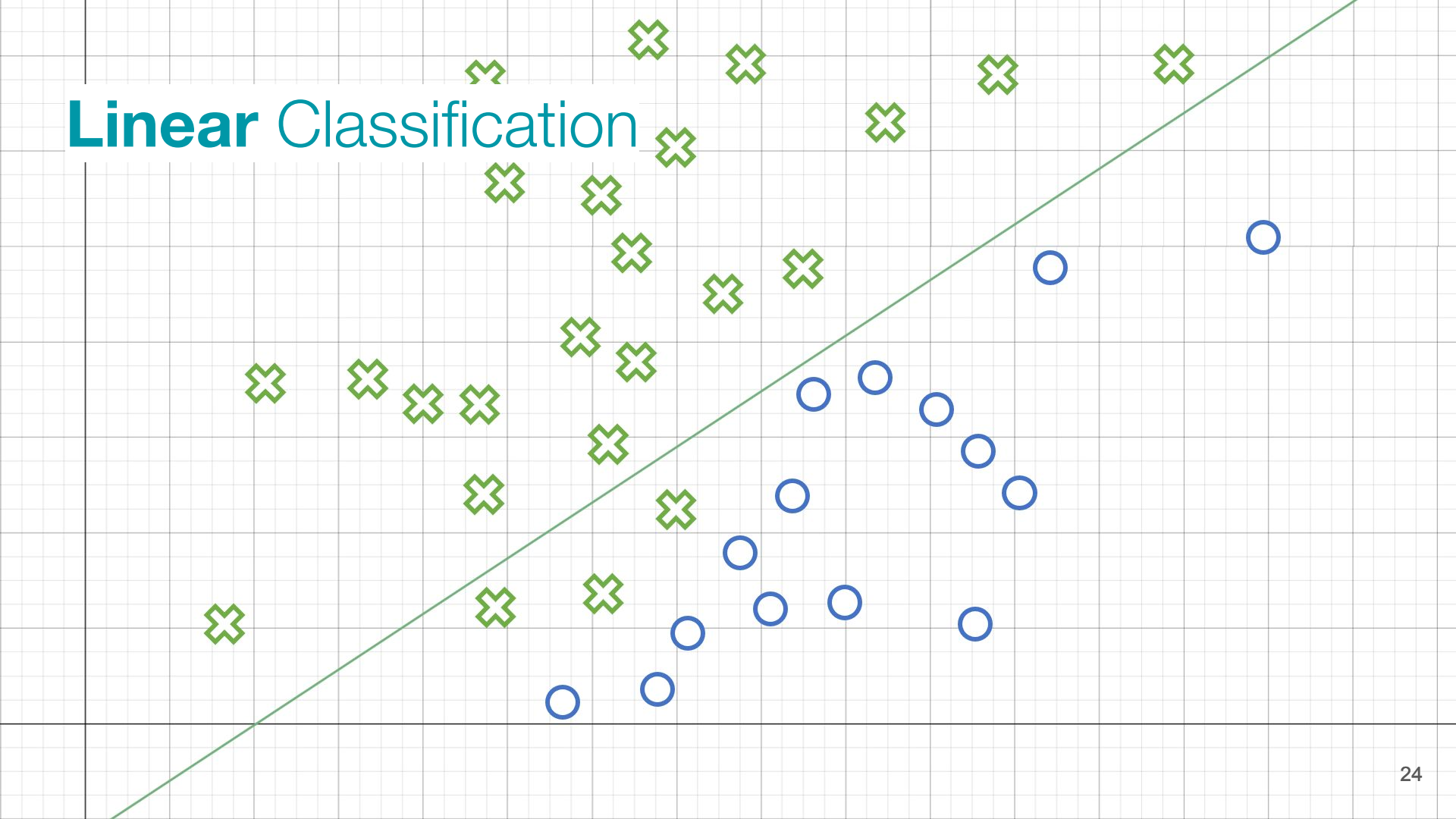
Large amount of data

Neural Networks

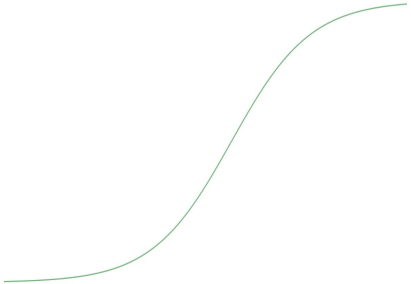
Classification



Linear Classification



Non Linear Classification



Non linearity

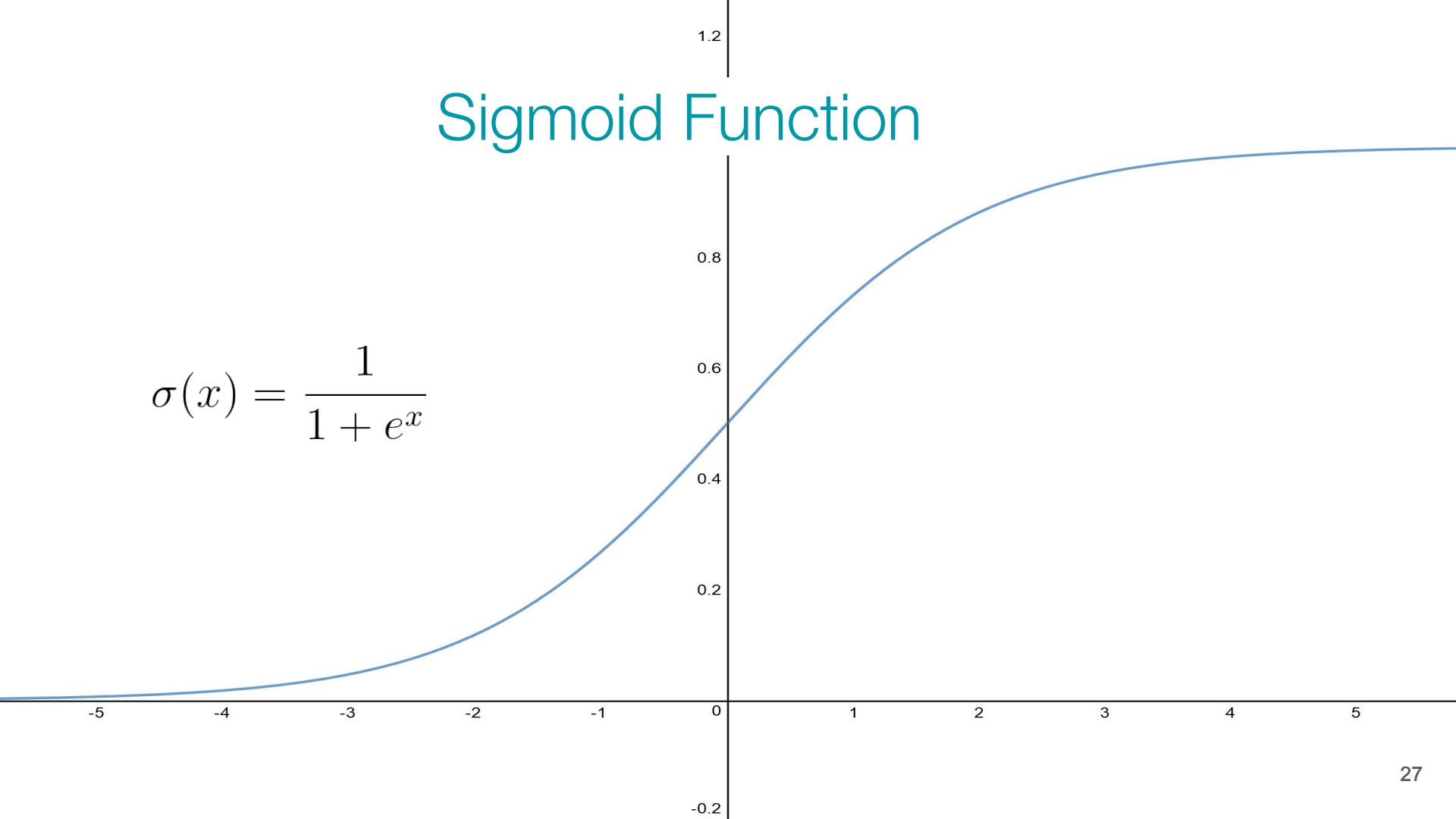
Can be stacked (composite functions) to increase expressivity.

Their gradients are smoother (derivatives of linear transformations are constant, regardless of the input.)

In any case, nonlinear functions are a generalization of linear functions.

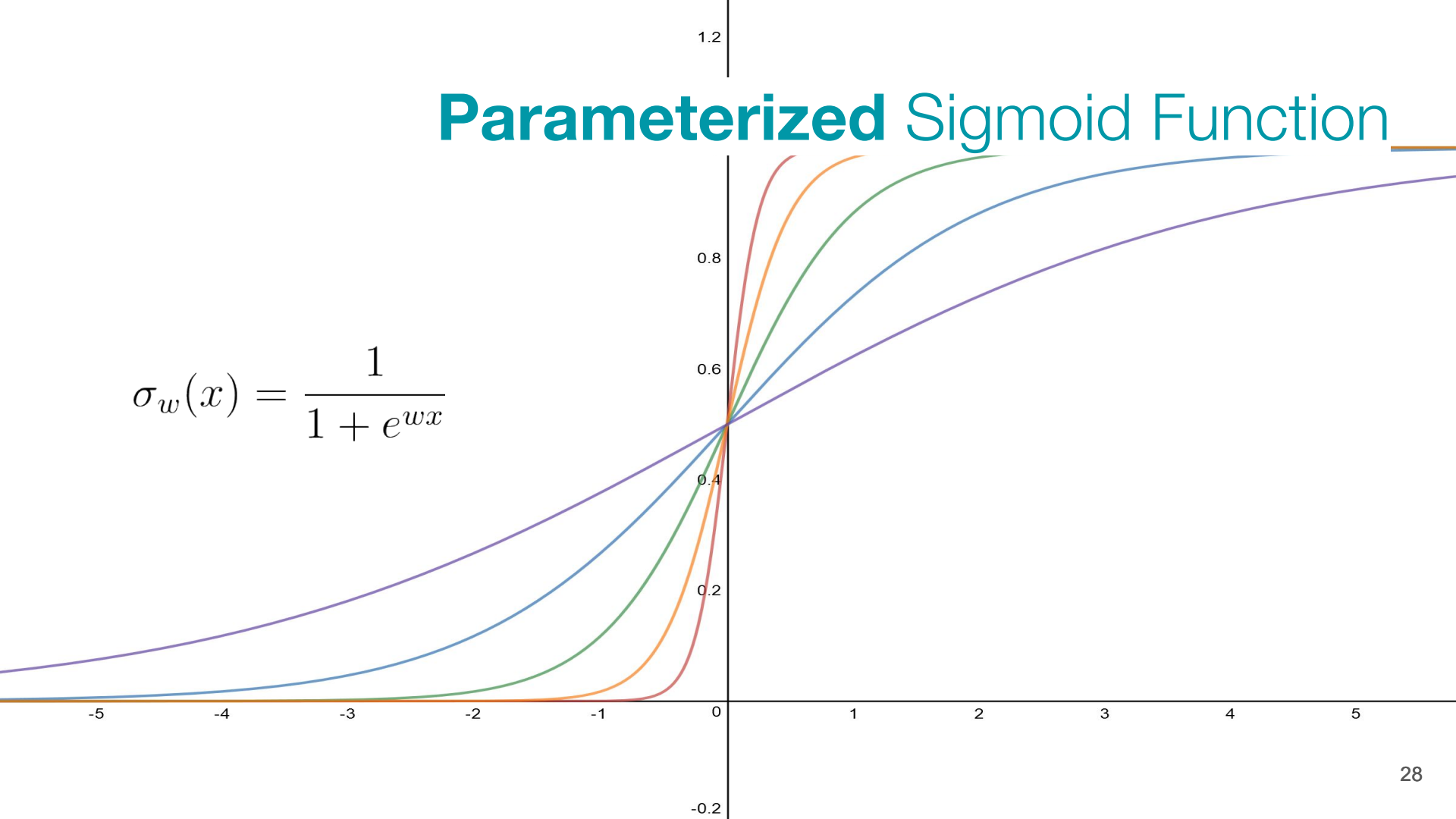
Sigmoid Function

$$\sigma(x) = \frac{1}{1 + e^{x}}$$



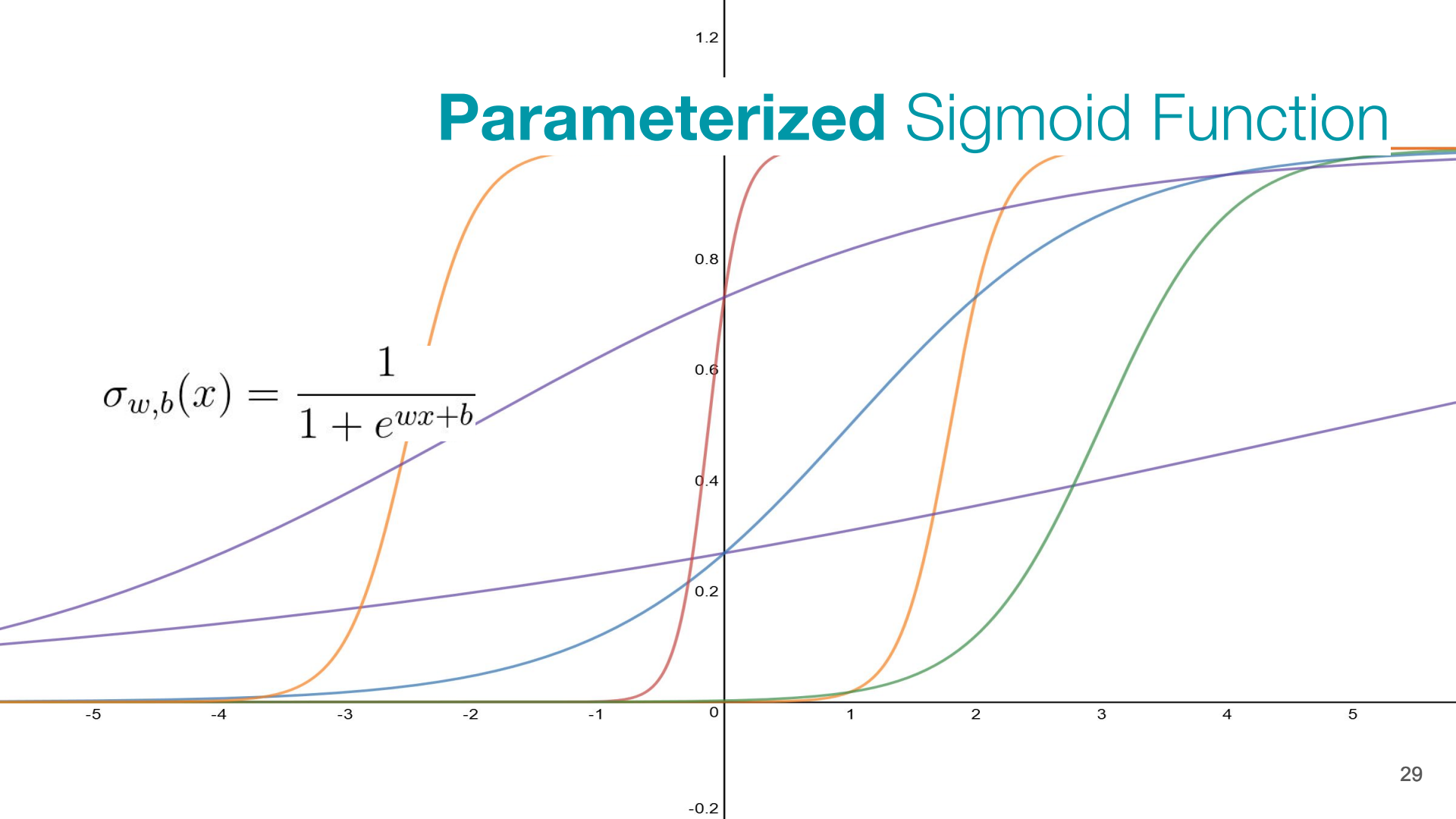
Parameterized Sigmoid Function

$$\sigma_w(x) = \frac{1}{1 + e^{wx}}$$

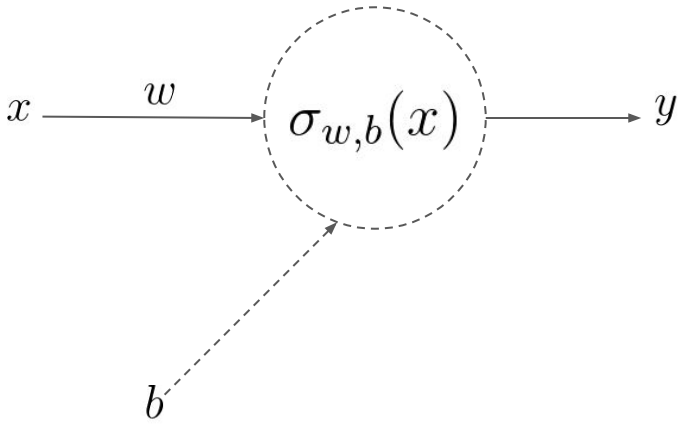


Parameterized Sigmoid Function

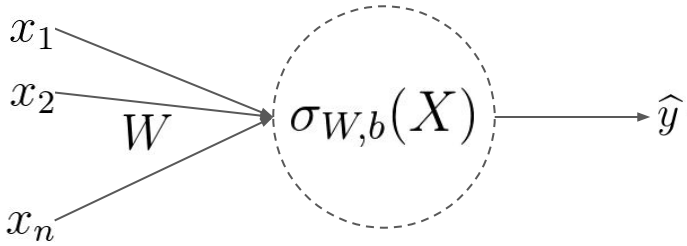
$$\sigma_{w,b}(x) = \frac{1}{1 + e^{wx+b}}$$



Neuron



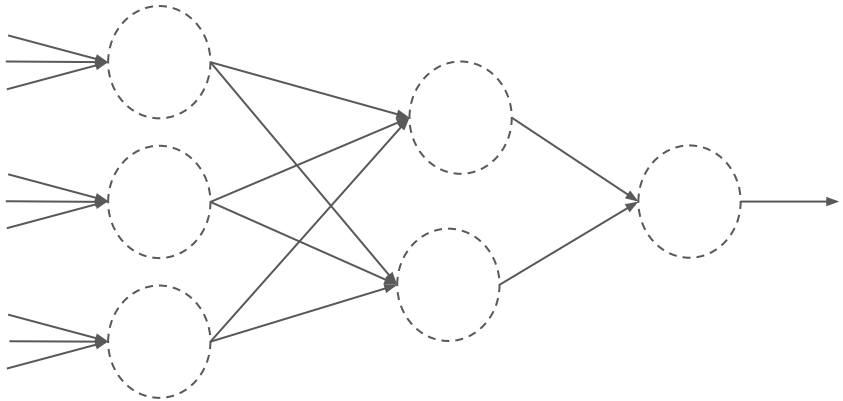
Vector Inputs to Neuron



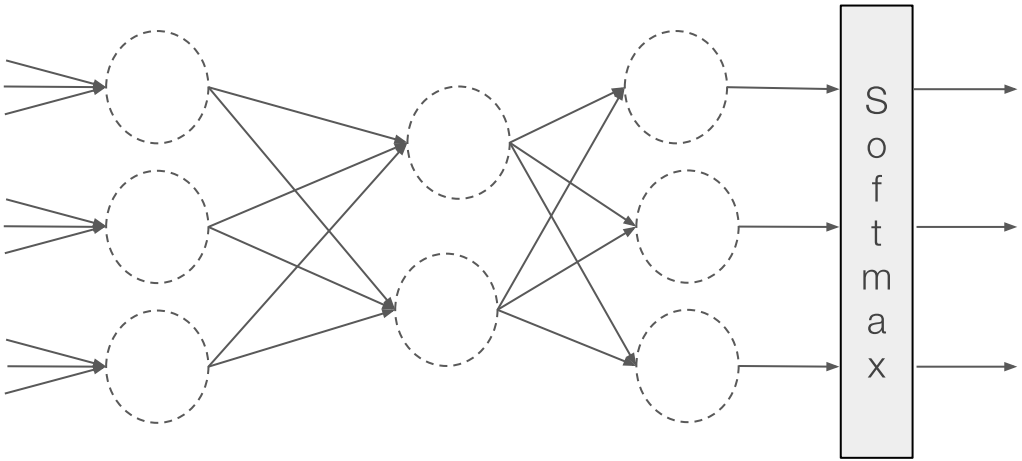
Stacking (Composite Functions)

$$\sigma_{W_2,b_2}(\sigma_{W_1,b_1}(X))$$

Feed Forward Network



Multi-class Classification



Activation Functions

Till now we have seen sigmoid function.

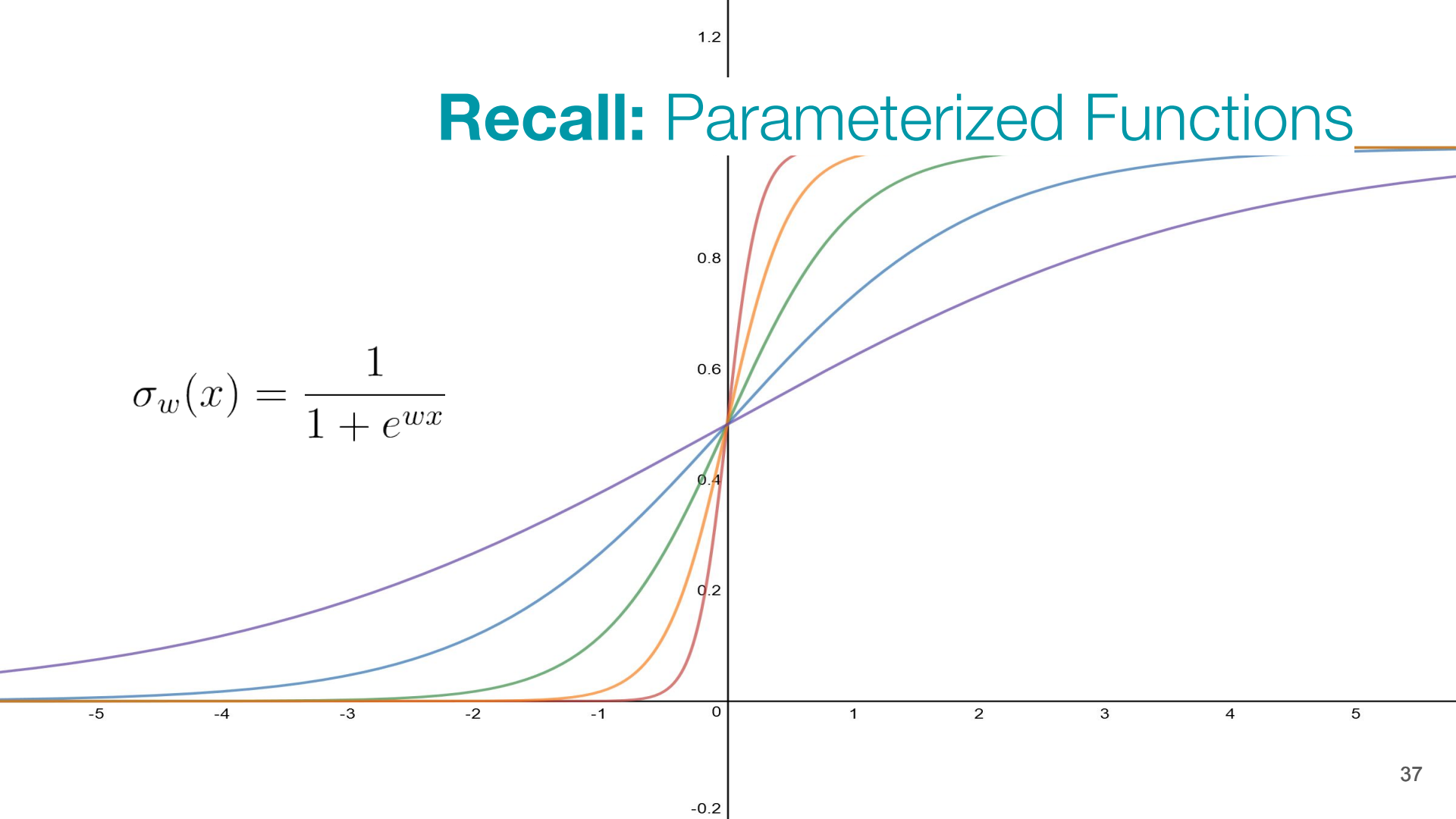
Can use several other functions such as

- Hyperbolic Tangent
- Rectifier

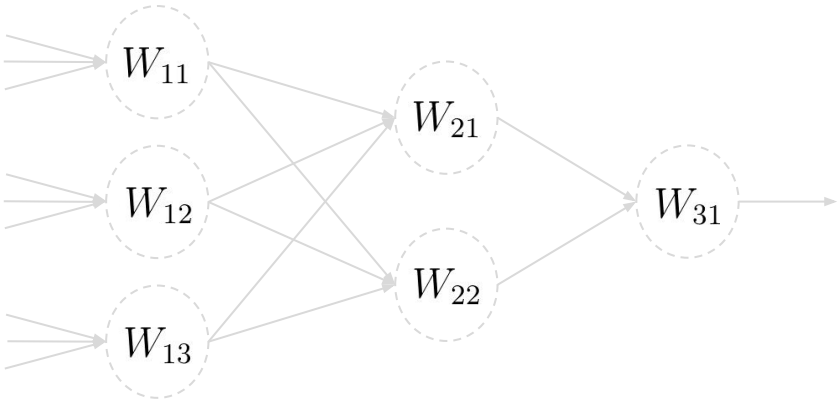
Training Neural Networks

Recall: Parameterized Functions

$$\sigma_w(x) = \frac{1}{1 + e^{wx}}$$



Parameters



* omitted biases for brevity's sake

Needles in a Haystack

Can we set them manually?

Weights (above):

No 🙈

Recommended?

~~Kill a kitten till it works~~

Needles in a Haystack

Can we set them manually?

- # Weights (above):
- No 🤷

Recommended?

- ~~Kill a kitten till it works~~
- Backpropagate

Do you even *backpropagate*?

Idea

Find the effect of every parameter on model's performance.

For that we first need a way to calculate model performance:

Loss Function (Error Function)

Loss Function

Difference between *model output* and *given label* for a data point.

$\hat{Y} = f_w(X)$ $\quad$ Y

$$E = L(\hat{Y}, Y)$$

Many ways to calculate loss. Eg. Mean Squared Error

$$L(\hat{Y}, Y) = \frac{1}{2n} \sum_{i=1}^{n} (\hat{y} - y)^2$$

Gradient Descent

Gradients of Error w.r.t. model parameters: change the parameter in that direction to *increase* the error.

Update $w_n = w_n - \eta \frac{dL}{dw_n}$

Summing it up

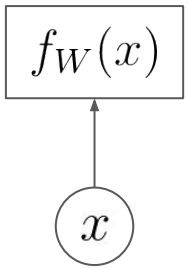
- input data: x

Summing it up

- input data: x
- input data label: y

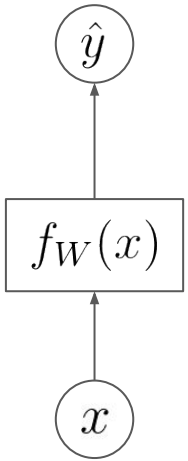
Summing it up

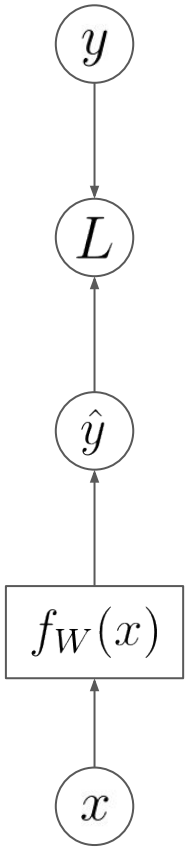
- input data: x
- input data label: y
- model: $f_W(x)$



Summing it up

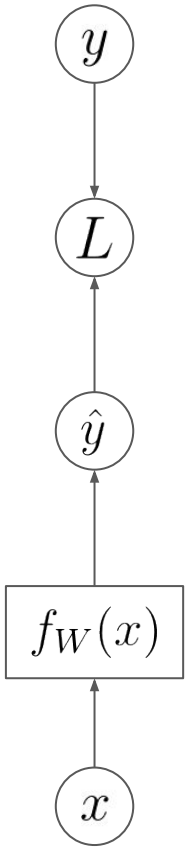
- input data: x
- input data label: y
- model: $f_W(x)$
- model output: $\hat{y} = f_W(x)$





Summing it up

- input data: x
- input data label: y
- model: $f_W(x)$
- model output: $\hat{y} = f_W(x)$
- loss: $L(\hat{y}, y)$



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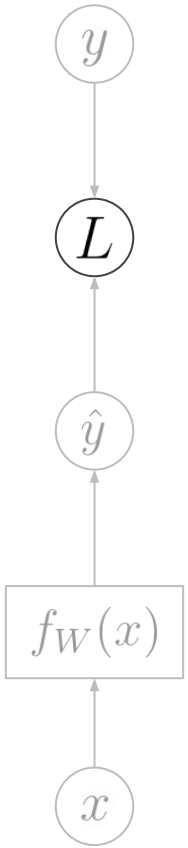
} Forward Propagation



Summing it up

- input data: x
- input data label: y
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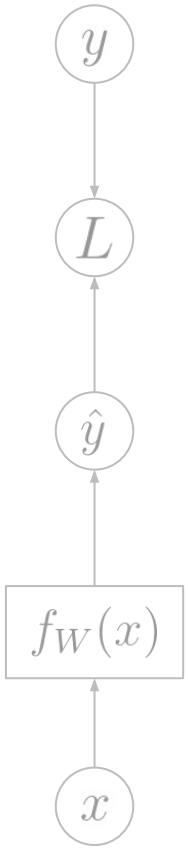
Forward Propagation

- gradients: $\dfrac{dL}{dW_{1:n}}$



Summing it up

- input data: x
- input data label: y
- model: $f_W(x)$
- model output: $\hat{y} = f_W(x)$
- loss: $L(\hat{y}, y)$

Forward Propagation

- gradients: $\dfrac{dL}{dW_{1:n}}$
- parameter update: $w_n = w_n - \eta \dfrac{dL}{dW_{1:n}}$

Backward Propagation

Training Neural Networks

Supervised Learning: Each example has an input vector, and a corresponding label.

We train the model to learn a mapping (function) from the input vector to the label.

Done by *optimizing parameters* using backpropagation.

Neural Networks for **NLP**

Representing Language

Words have inherent meanings.

Language is sequential in nature.

Words have inherent meanings

Neural Networks expect vectors as input.

How do we convert text to vector?

Desired Properties

✔ represent the semantic similarity of related words

✔ each word can be distinguished from others

One-hot Vectors

Word tokens are assigned a unique ID (represented by a one-hot vector)

```
name   = [ 1, 0, 0, 0, 0 ..., 0]
all    = [ 0, 0, 0, 1, 0 ..., 0]
movies = [ 0, 1, 0, 0, 0 ..., 0]
where  = [ 0, 0, 1, 0, 0 ..., 0]
```

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Desired Properties

✔ represent the semantic similarity of related words

✔ ~~each word can be distinguished from others~~

One-hot Vectors **Limitations**

Desired Properties

✔ represent the semantic similarity of related words

✔ ~~each word can be distinguished from others~~

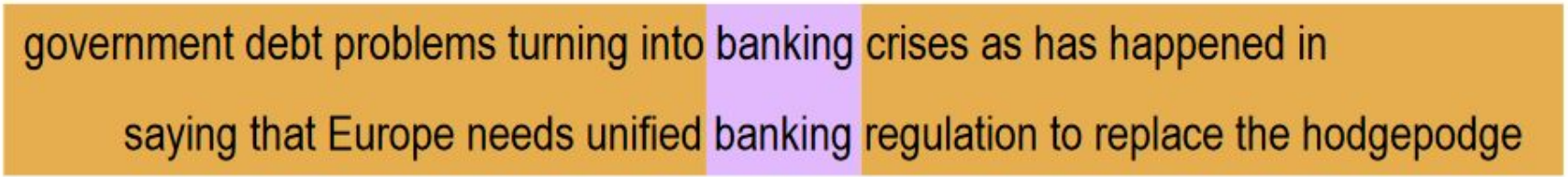
No useful information to the system regarding the relationships that may exist between the words.

One-hot vectors are sparse in nature.

Distributional Hypothesis

You shall know a word by the company it keeps

J. R. Firth,
1957: 11



↖ These words will represent *banking* ↗

Word Embeddings

Predictive model:

Given a word, what is the probable context.

or

Given a context, what is the probable word.

Desired Properties

✔ represent the semantic similarity of related words

✔ ~~each word can be distinguished from others~~

Word Embeddings

Desired Properties

✔ represent the semantic similarity of related words

✔ ~~each word can be distinguished from others~~

Predictive model:

Given a word, what is the probable context.

$$p(w_{t-2}, w_{t-1}, w_{t+1}, w_{t+2}|w_t)$$

or

Given a context, what is the probable word.

$$p(w_t|w_{t-2}, w_{t-1}, w_{t+1}, w_{t+2})$$

Word Embeddings

Dense Vector Space:

Force a fixed number of dimensions in the vector space.

Forces similar words to appear together (across some dimensions)

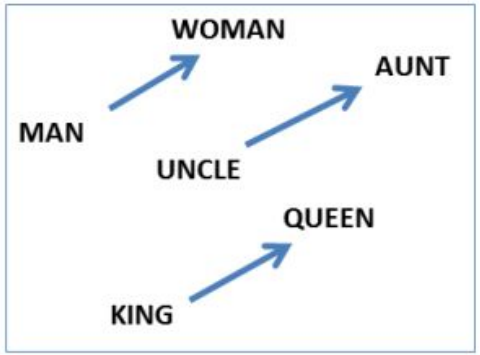
Desired Properties

✔ represent the semantic similarity of related words

✔ ~~each word can be distinguished from others~~

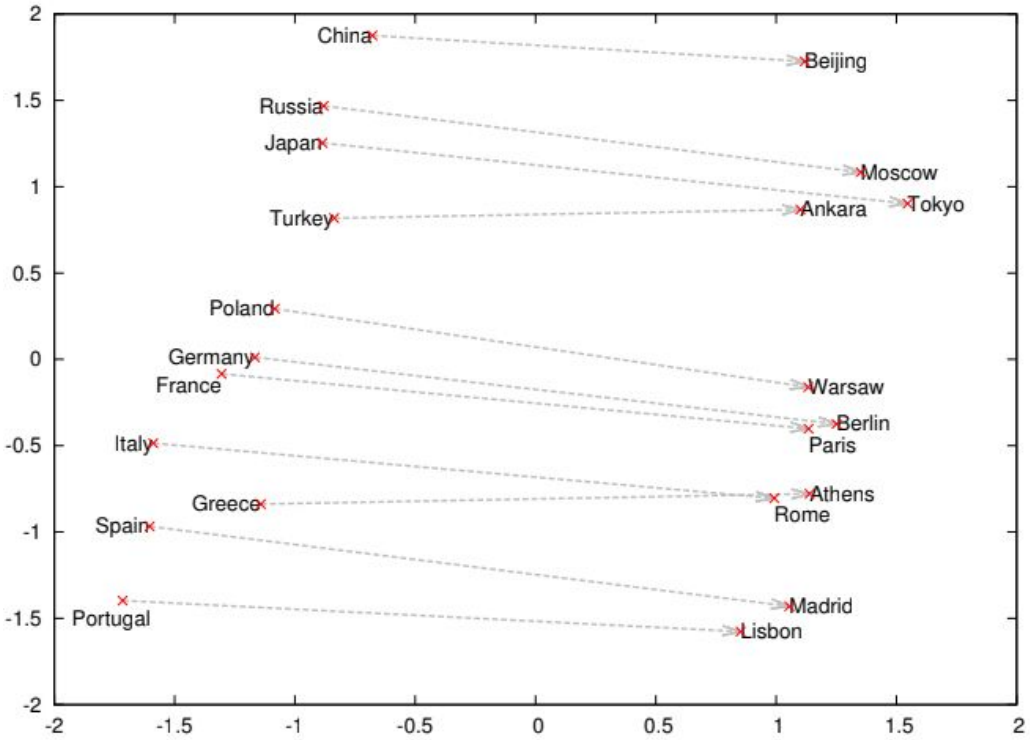
Word2Vec

"encodes semantic components as linear vector differences"



Meaningful syntactic and semantic regularities captured

Word2Vec



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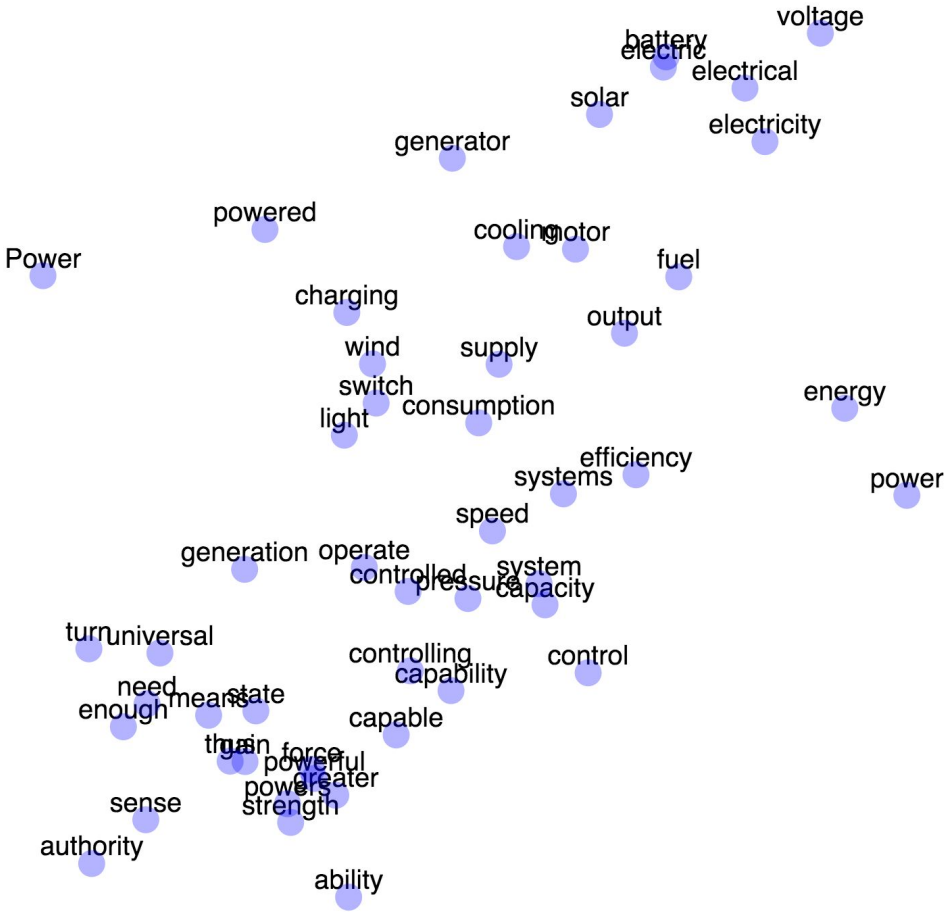

Meaningful syntactic and semantic regularities captured

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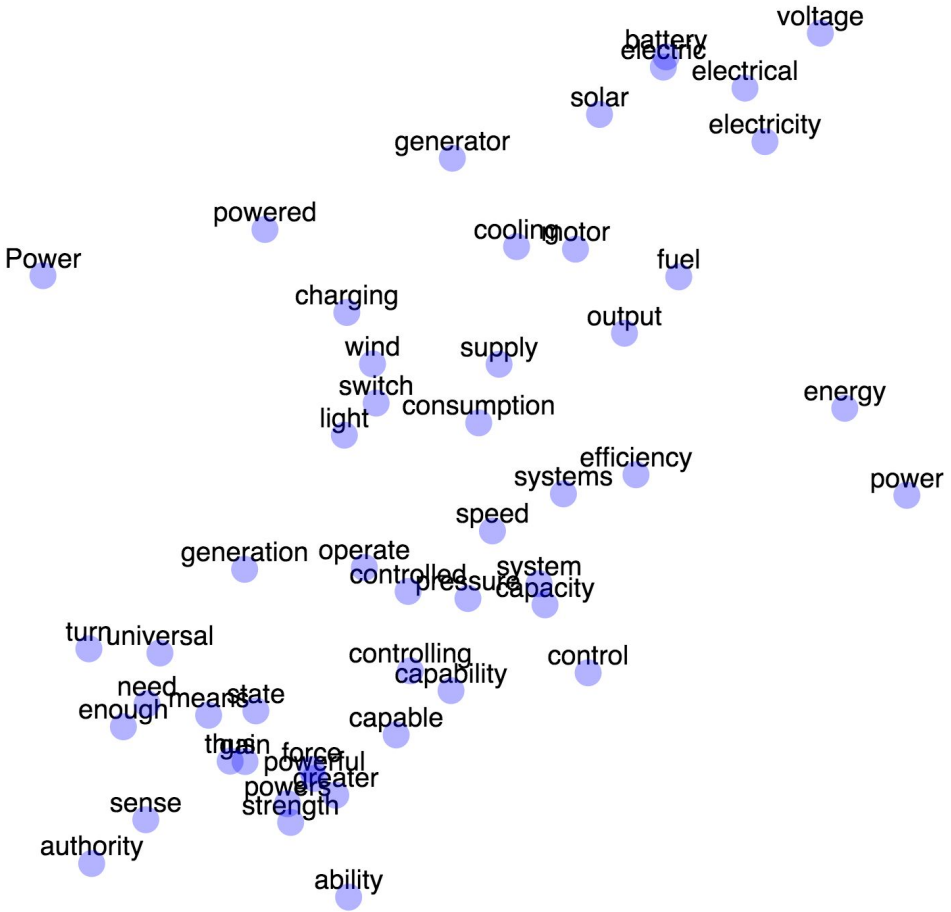


Word Embeddings

Widely used for most NLP tasks.

Numerous methods of training:

- word2vec
- GloVe
- fastText embeddings

Pre-trained, off the shelf solutions.

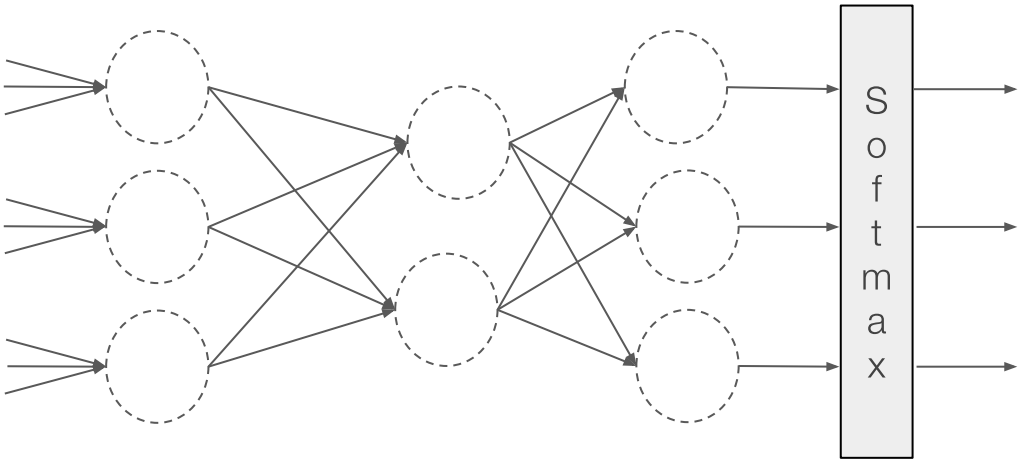
Word Embeddings are matrices

$$\begin{bmatrix} 0.21 & 0.42 & 0.16 & 0.86 & 0.67 \\ 0.86 & 0.90 & 0.20 & 0.38 & 0.19 \\ 0.49 & 0.24 & 0.87 & 0.95 & 0.88 \\ 0.80 & 0.64 & 0.19 & 0.32 & 0.38 \\ 0.71 & 0.54 & 0.66 & 0.61 & 0.40 \\ 0.39 & 0.17 & 0.19 & 0.54 & 0.41 \\ 0.17 & 0.30 & 0.32 & 0.96 & 0.76 \\ 0.05 & 0.32 & 0.80 & 0.92 & 0.81 \end{bmatrix}$$

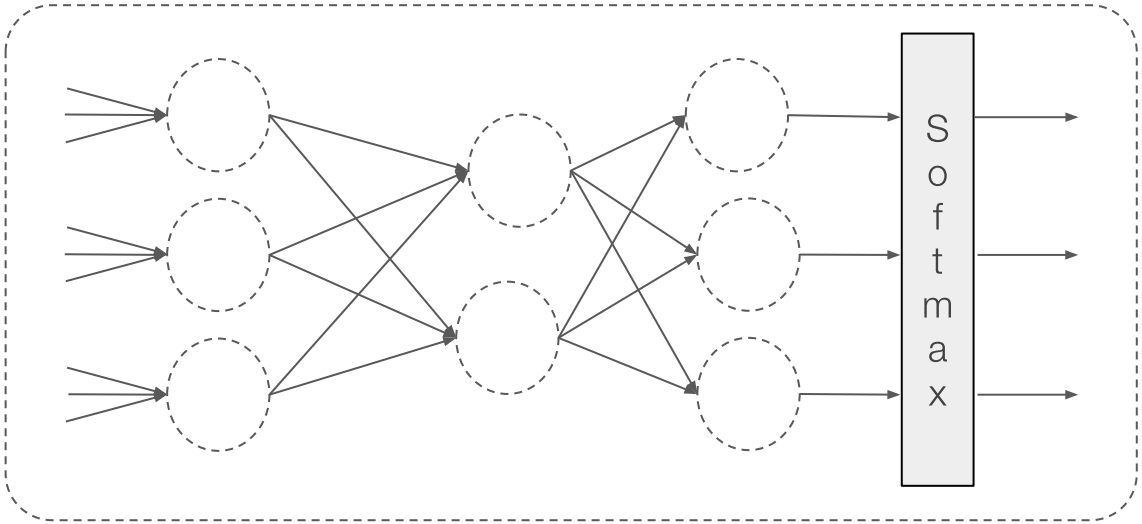
Word Embeddings are matrices

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} 0.21 & 0.42 & 0.16 & 0.86 & 0.67 \\ 0.86 & 0.90 & 0.20 & 0.38 & 0.19 \\ 0.49 & 0.24 & 0.87 & 0.95 & 0.88 \\ 0.80 & 0.64 & 0.19 & 0.32 & 0.38 \\ 0.71 & 0.54 & 0.66 & 0.61 & 0.40 \\ 0.39 & 0.17 & 0.19 & 0.54 & 0.41 \\ 0.17 & 0.30 & 0.32 & 0.96 & 0.76 \\ 0.05 & 0.32 & 0.80 & 0.92 & 0.81 \end{bmatrix} = \begin{bmatrix} 0.71 & 0.54 & 0.66 & 0.61 & 0.40 \end{bmatrix}$$

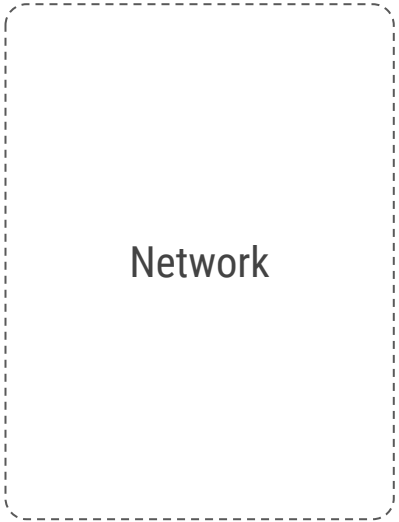
Using Word Embeddings in NN



Using Word Embeddings in NN

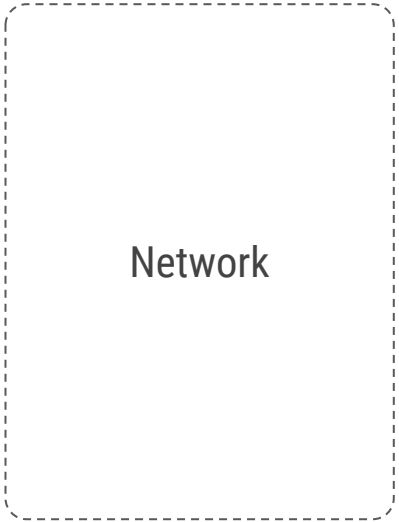


Using Word Embeddings in NN

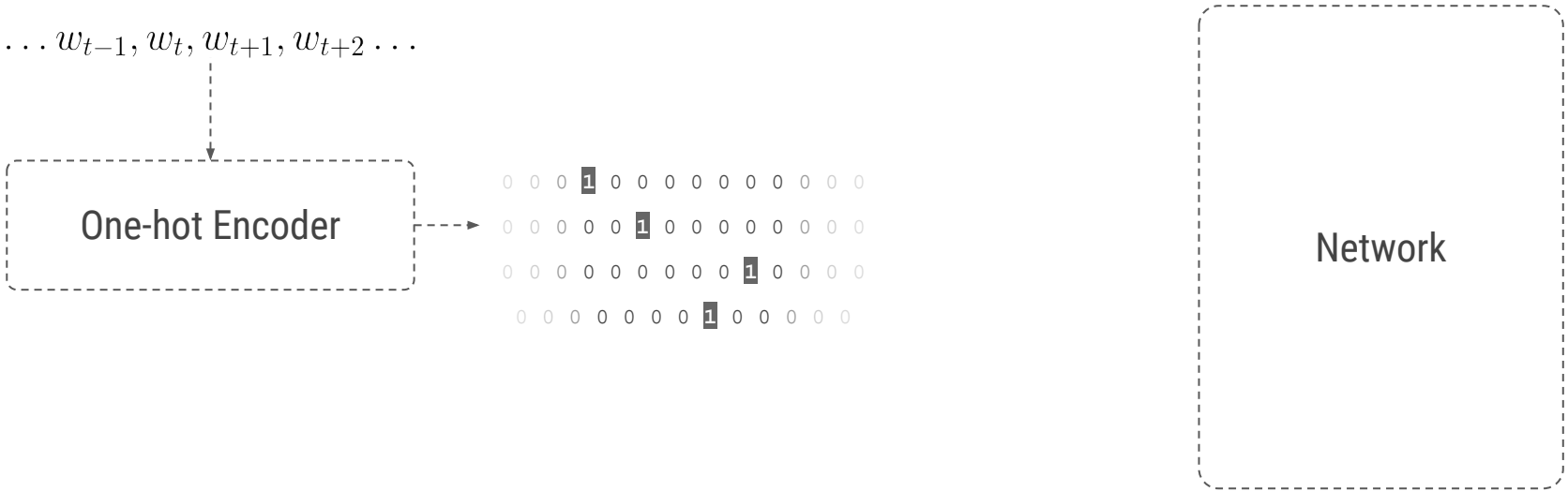


Using Word Embeddings in NN

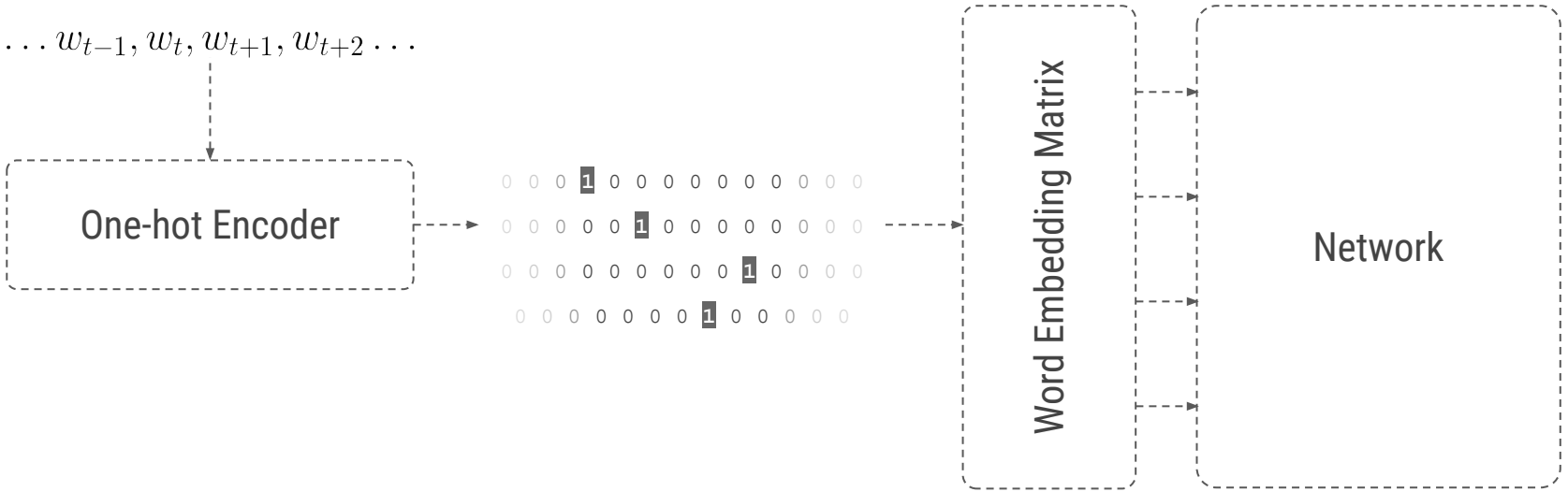
$\ldots w_{t-1}, w_t, w_{t+1}, w_{t+2} \ldots$



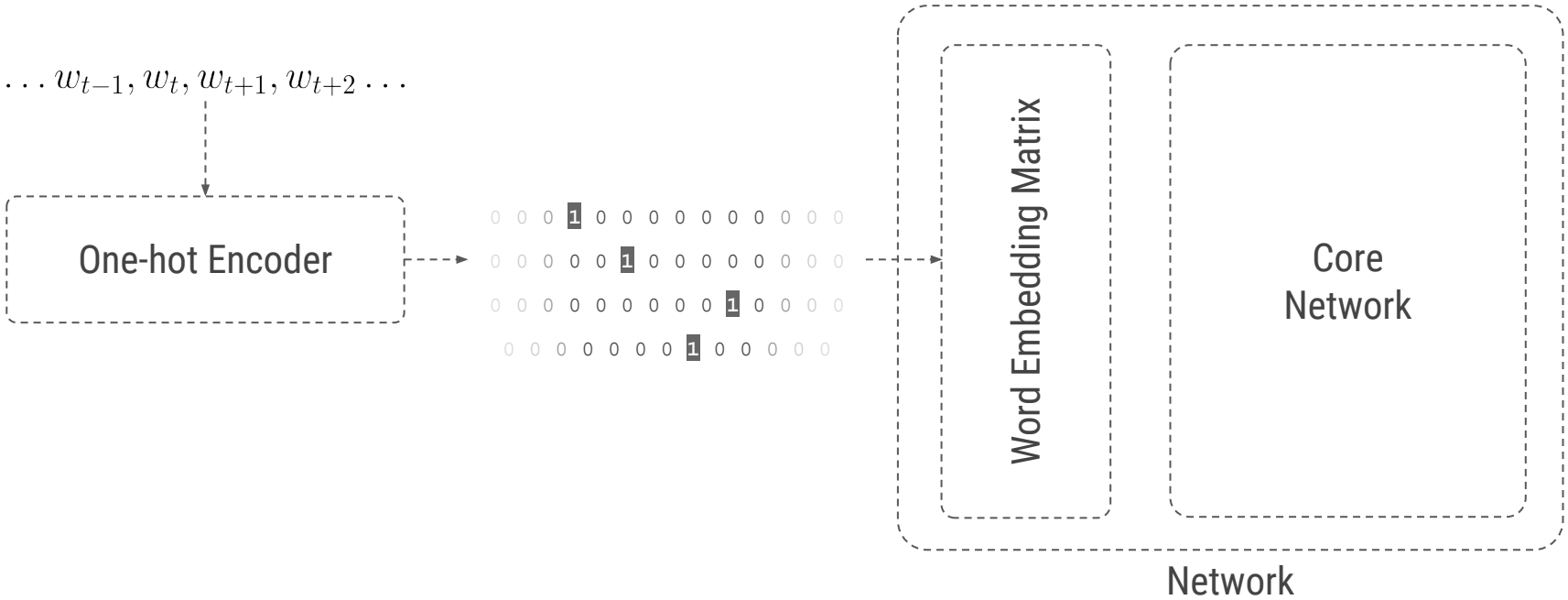
Using Word Embeddings in NN



Using Word Embeddings in NN



Trainable Embeddings



Representing Language

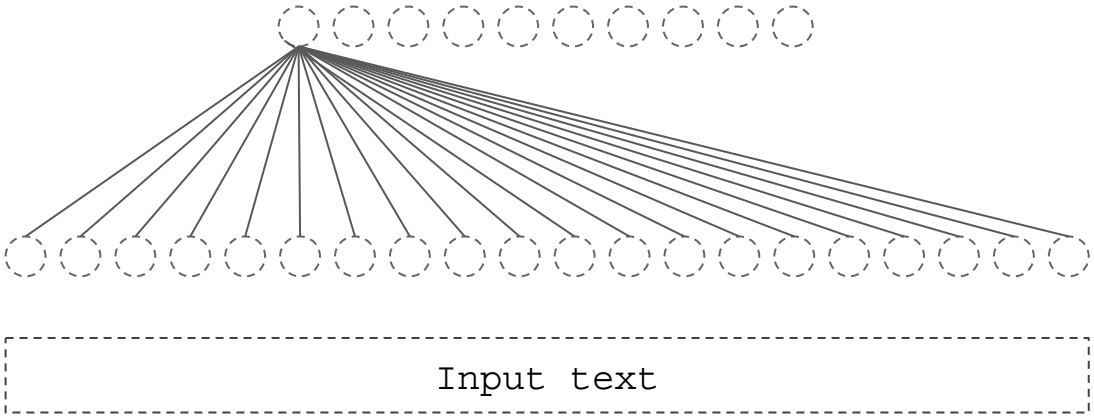
Words have inherent meanings.

Language is sequential in nature.

Problems with Feedforward Nets

Number of parameters:

20 x 10



Problems with Feedforward Nets

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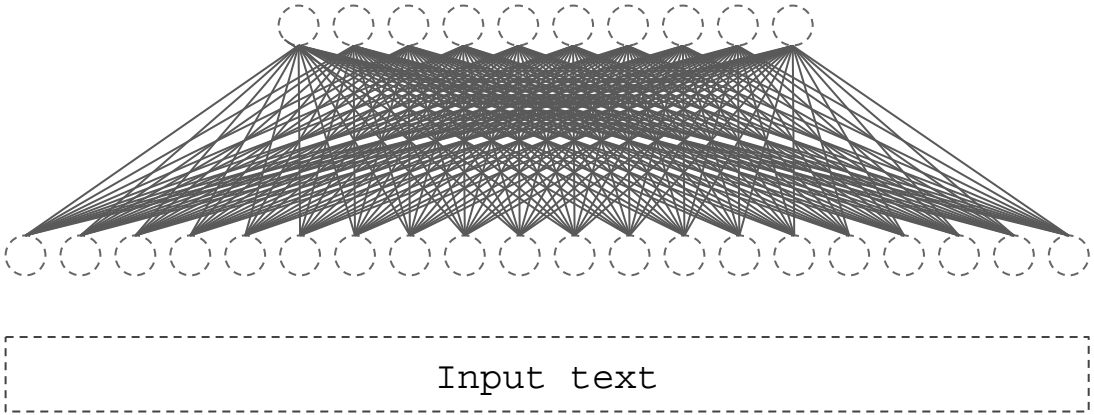
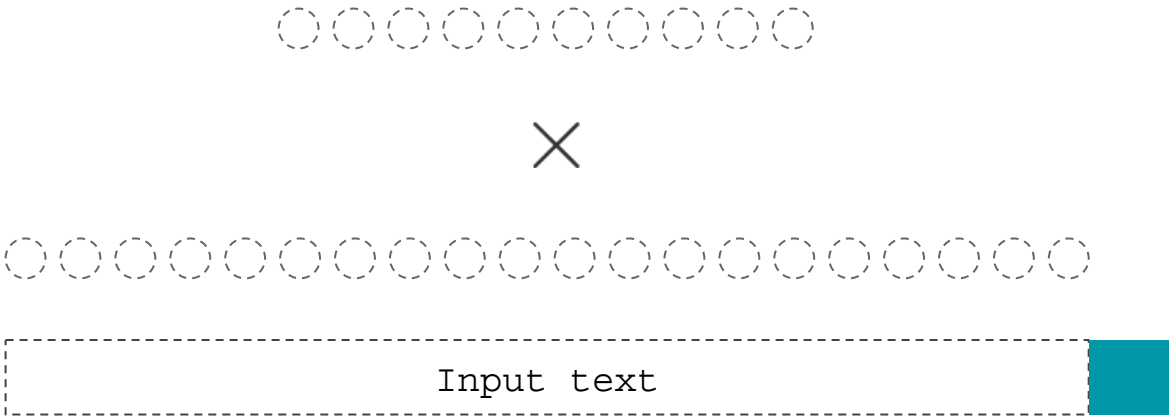


Problems with Feedforward Nets

Number of parameters:
20 x 10

Unseen length of text



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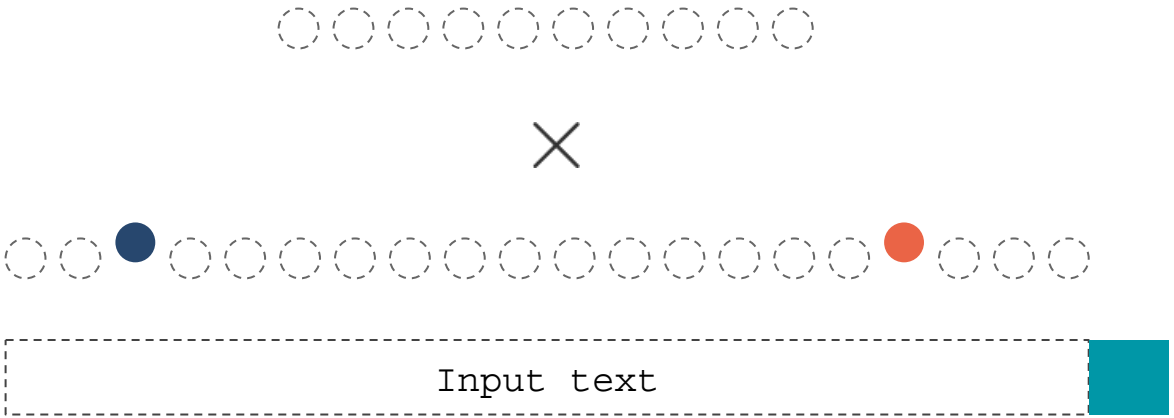
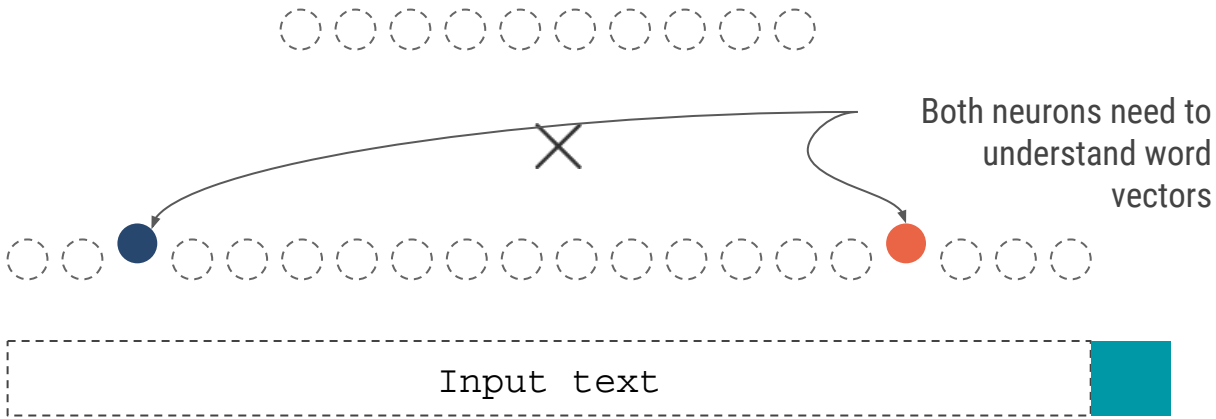


Problems with Feedforward Nets

Number of parameters:
20 x 10

Unseen length of text

Independent weights learning the same thing.



Problems with Feedforward Nets

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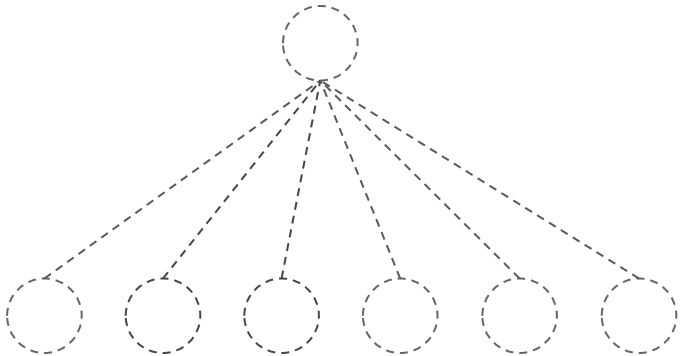

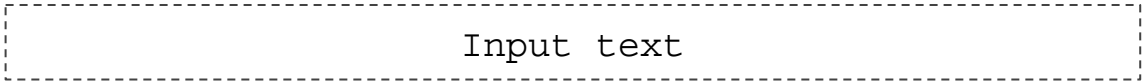

Problems with Feedforward Nets

Number of parameters:
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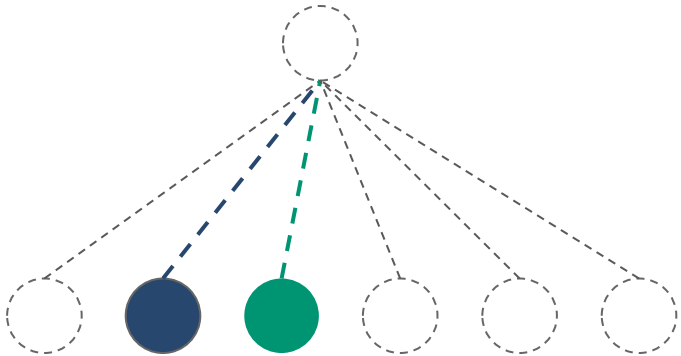
Independent weights learning the same thing.

Language is sequential.



A: United States is in North America

B: United States isn't in North America

Problems with Feedforward Nets

Number of parameters:
20 x 10

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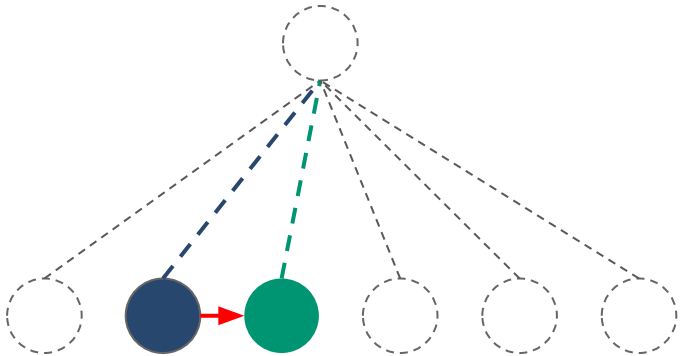
Independent weights learning the same thing.

Language is sequential.



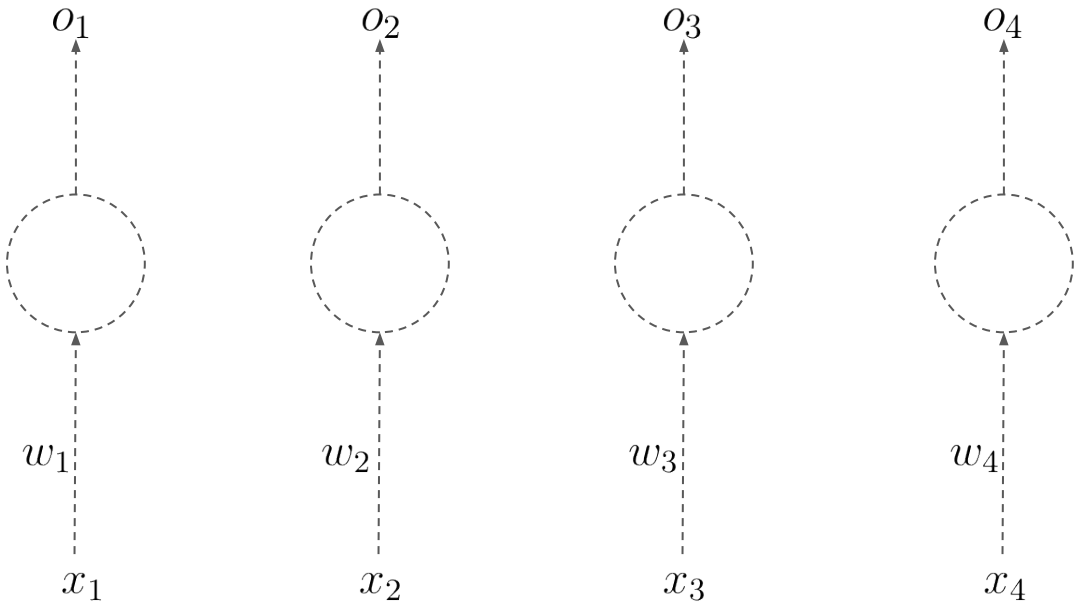
A: United States is in North America

B: United States isn't in North America

Cue **Sequential** Networks

Sequential Networks?

Standard FF layer

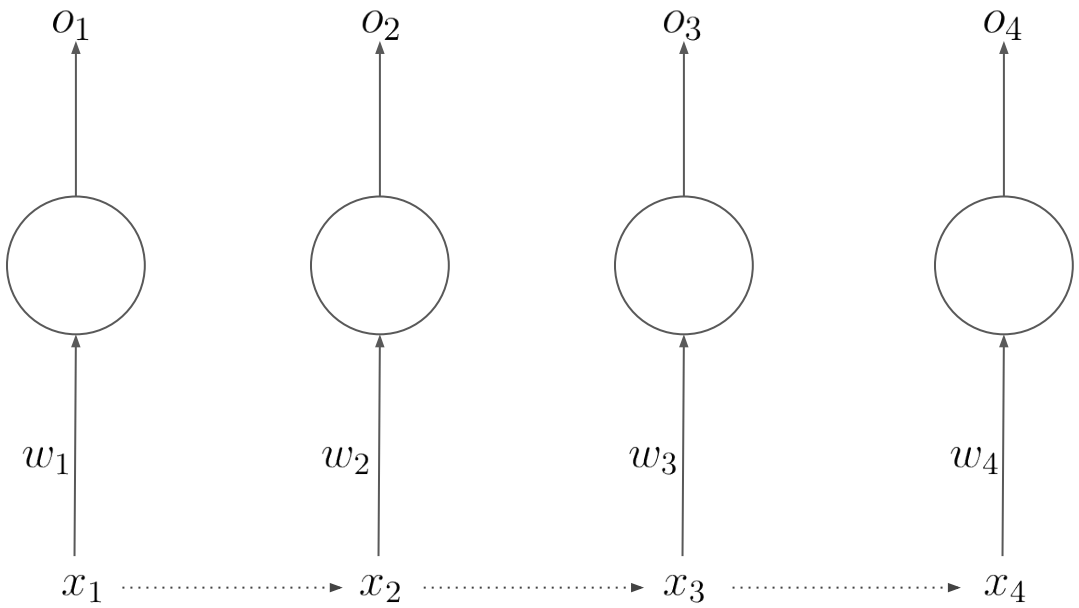


Sequential Networks?

Standard FF layer

But inputs might depend upon each other.

$$p(x_{t-1}, x_t) \neq p(x_{t-1}) \times p(x_t)$$



Sequential Networks

Standard FF layer

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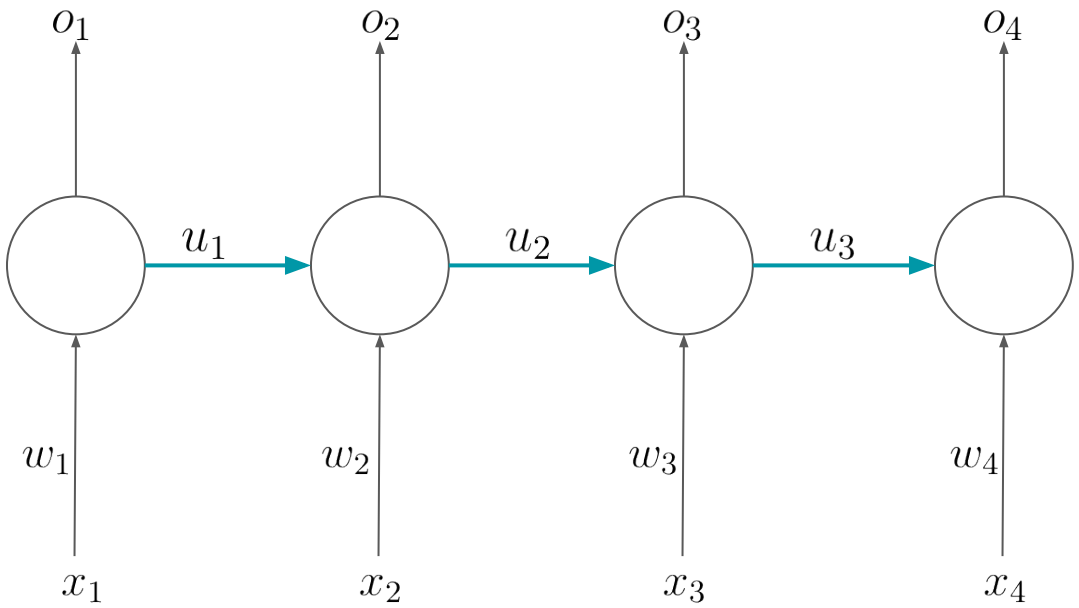
Neuron in **one layer** are now

- **Time dependent**
- Affect the next one



Sequential Networks

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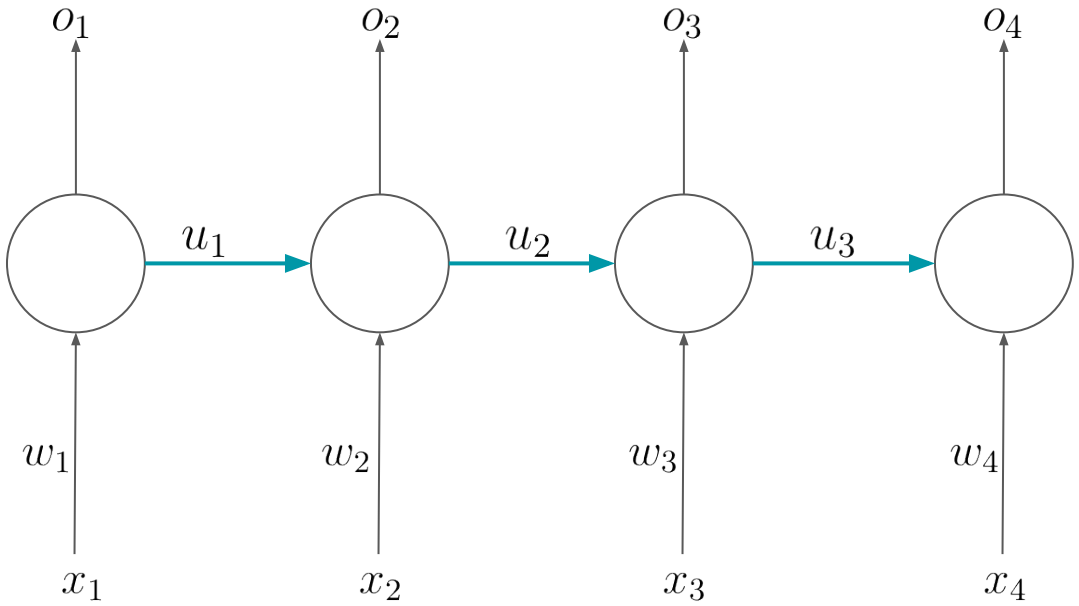


More parameters!
Every neuron must learn language individually, as well as take into account prev. input?

Sequential Networks

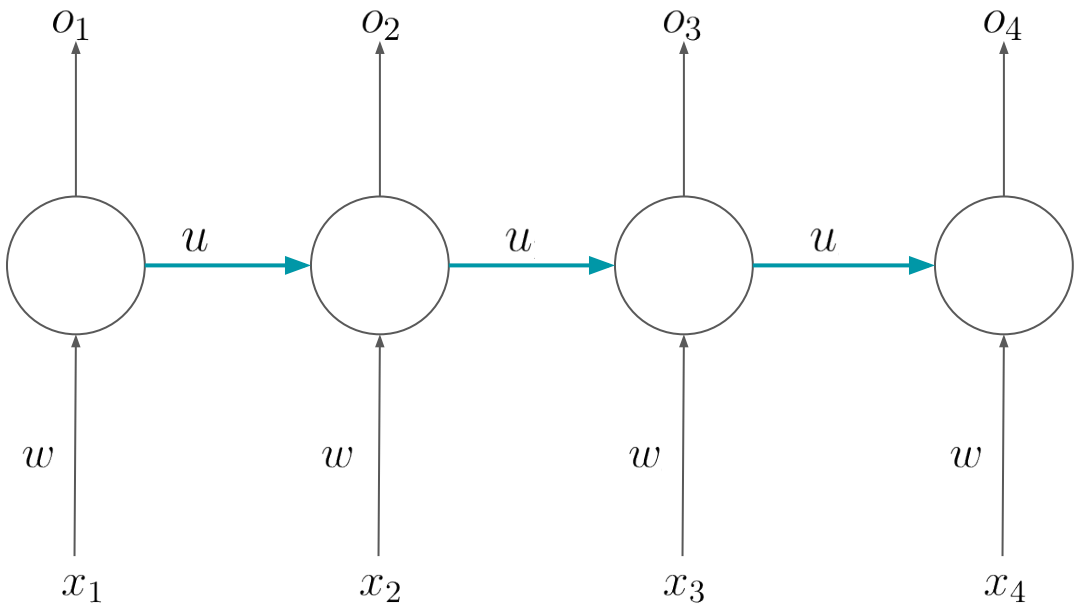
Standard FF layer

But inputs might depend upon each other.

$$p(x_{t-1}, x_t) \neq p(x_{t-1}) \times p(x_t)$$

Neuron in **one layer** are now

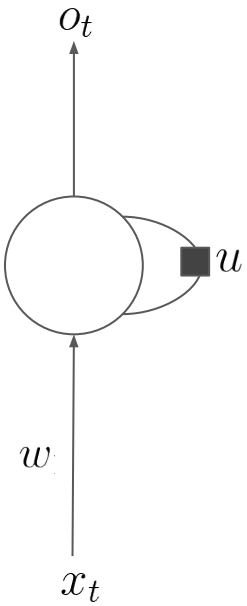
- Time dependent
- Affect the next one
- **Share Weights**



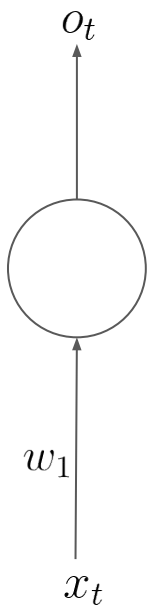
Unfolded Visualization

Neuron in **one layer** are now

- Time dependent
- Affect the next one
- Share weights

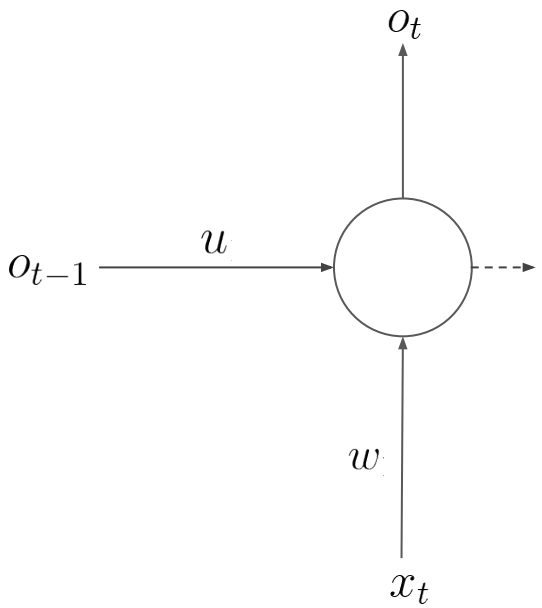


Non-Recurrent Neuron



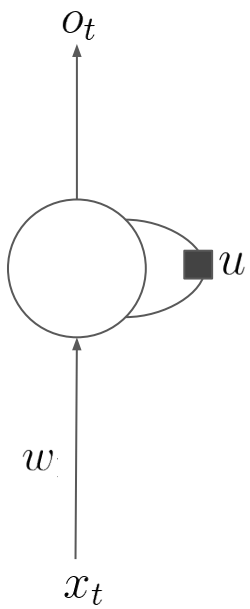
$$o_t = \sigma(w_t x_t + b_t)$$

Recurrent Neuron



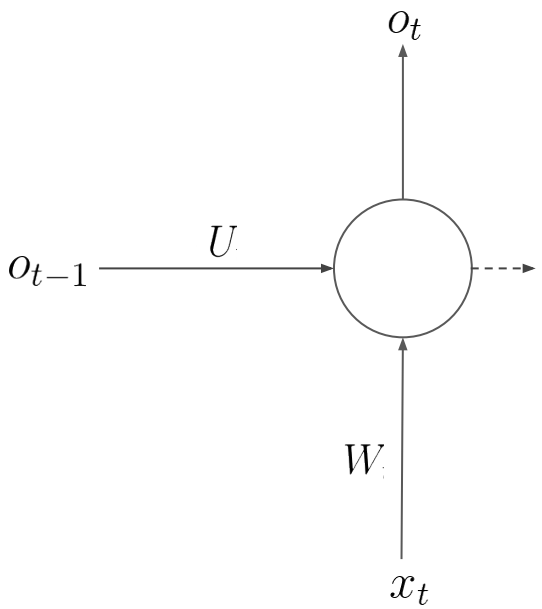
$$o_t = \sigma(wx_t + uo_{t-1} + b)$$

Recurrent Neuron



$$o_t = \sigma(wx_t + uo_{t-1} + b)$$

Recurrent Neuron



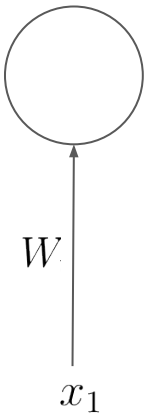
$$o_t = \sigma(wx_t + uo_{t-1} + b)$$

Unfolding Example

x_1

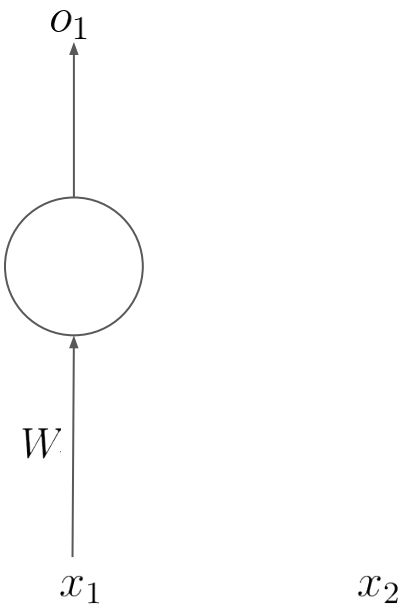
Unfolding Example

$$o_1 = \sigma(W x_1 + b)$$



Unfolding Example

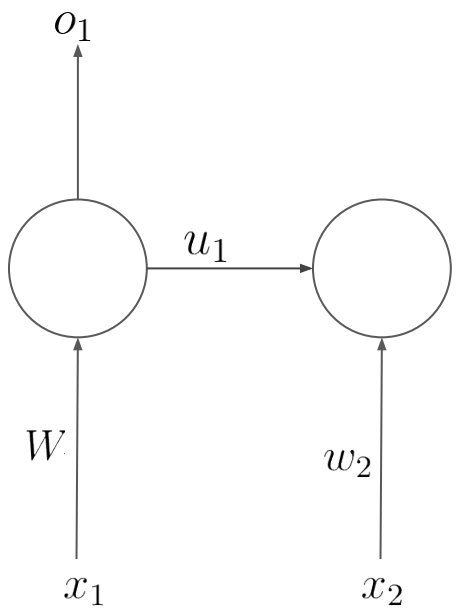
$o_1 = \sigma(W x_1 + b)$



Unfolding Example

$$o_1 = \sigma(Wx_1 + b)$$

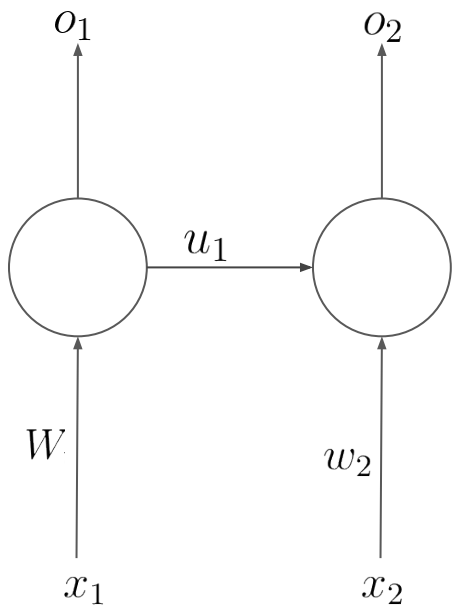
$$Wx_2 + Uo_1 + b$$



Unfolding Example

$$o_1 = \sigma(Wx_1 + b)$$

$$o_2 = \sigma(Wx_2 + Uo_1 + b)$$

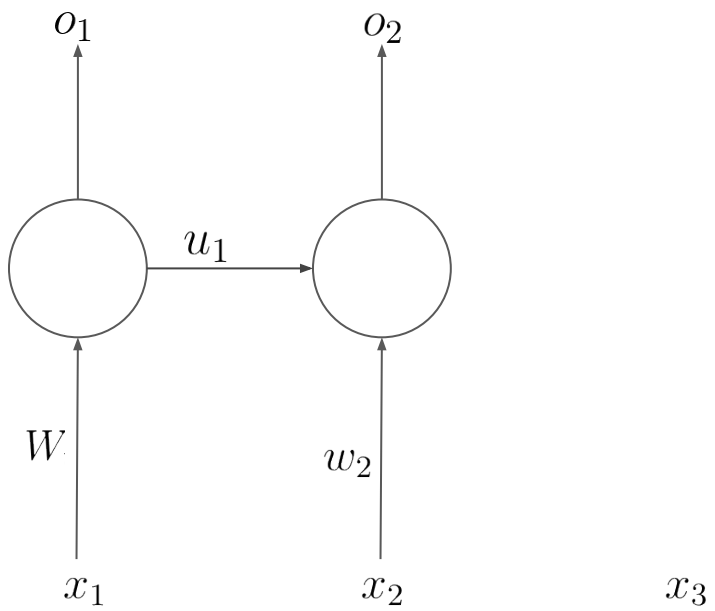


o_t is a lossy summary of input so far. Lossy due to fixed-size vector encoding information about varying sized input. Depending upon training, can learn to discard irrelevant parts.

Unfolding Example

$$o_1 = \sigma(Wx_1 + b)$$

$$o_2 = \sigma(Wx_2 + Uo_1 + b)$$

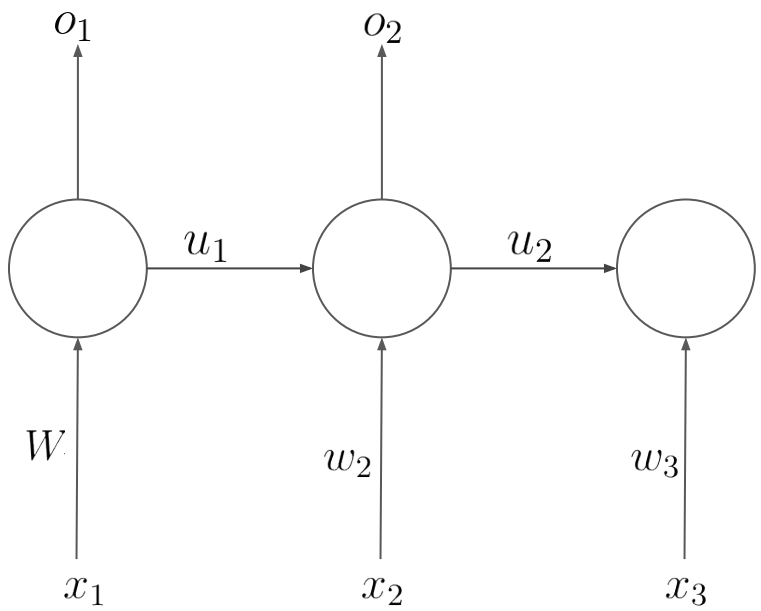


Unfolding Example

$$o_1 = \sigma(Wx_1 + b)$$

$$o_2 = \sigma(Wx_2 + Uo_1 + b)$$

$$Wx_3 + Uo_2 + b$$



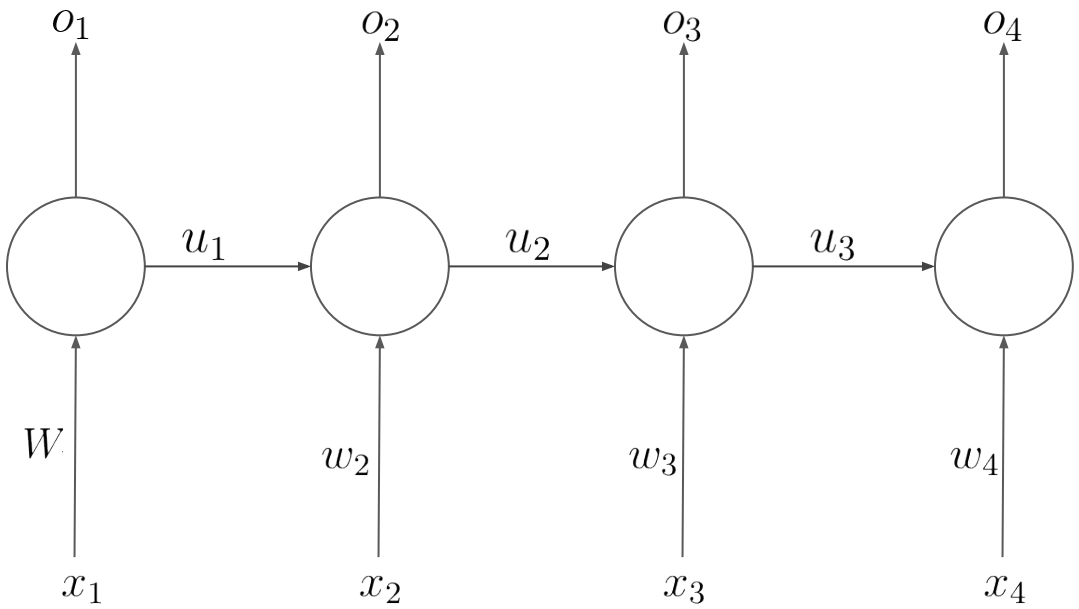
Unfolding Example

$$o_1 = \sigma(Wx_1 + b)$$

$$o_2 = \sigma(Wx_2 + Uo_1 + b)$$

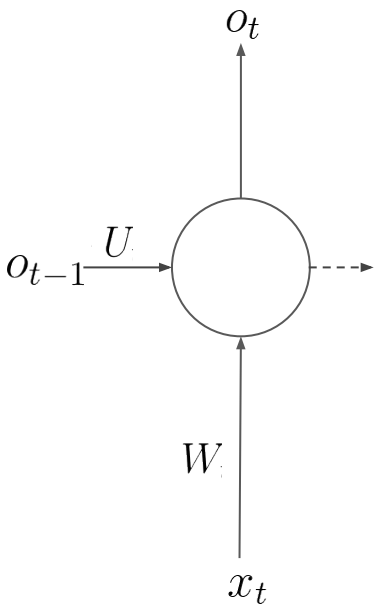
$$o_3 = \sigma(Wx_3 + Uo_2 + b)$$

$$o_4 = \sigma(Wx_4 + Uo_3 + b)$$



Advantages

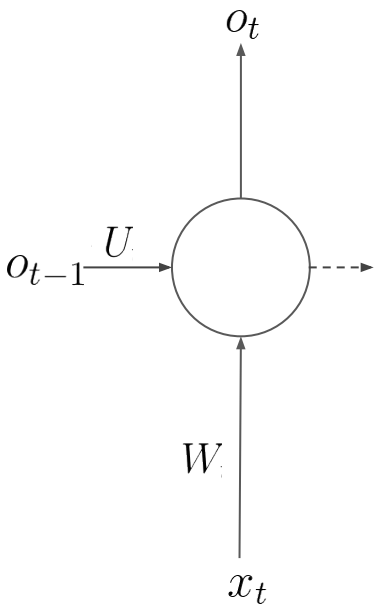
$$o_t = \sigma(wx_t + uo_{t-1} + b)$$



- Specialized for processing sequential input.

Advantages

$$o_t = \sigma(wx_t + uo_{t-1} + b)$$



- Specialized for processing sequential input.

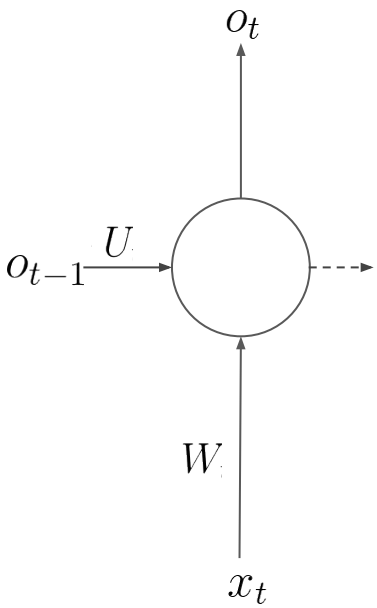
is `ready`

isn't `ready`

Can differentiate b/w two cases while processing "`ready`"

Advantages

$$o_t = \sigma(wx_t + uo_{t-1} + b)$$



- Specialized for processing sequential input.

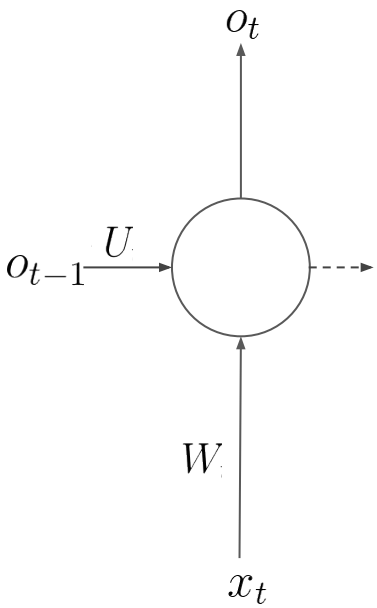
is	`ready`	Can differentiate b/w two cases
isn't	`ready`	while processing "`ready`"

Can't we use n-grams?

- effect limited to only d=$\frac{n}{2}$ words
- parameters would increase linearly with n
- RNN can (in theory) have effects across entire sequence.

Advantages

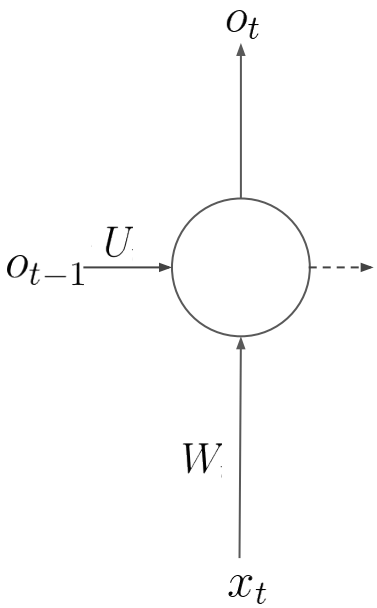
$$o_t = \sigma(wx_t + uo_{t-1} + b)$$



- Specialized for processing sequential input.
- Can generalize for sequences of unseen length

Advantages

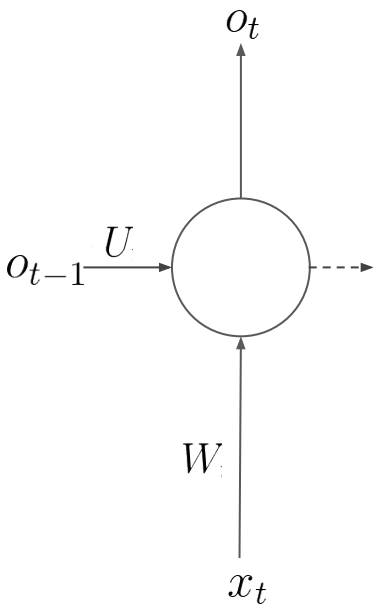
$$o_t = \sigma(wx_t + uo_{t-1} + b)$$



- Specialized for processing sequential input.
- Can generalize for sequences of unseen length
  - Shared parameters -> same update rule. Can unroll ad-infinitum.
  - Parameters learn to parse language. Can parse language ad-infinitum
  - Although in practice, effect of a word diminishes exponentially with time (has workarounds e.g. LSTM/GRU/Attention)

Advantages

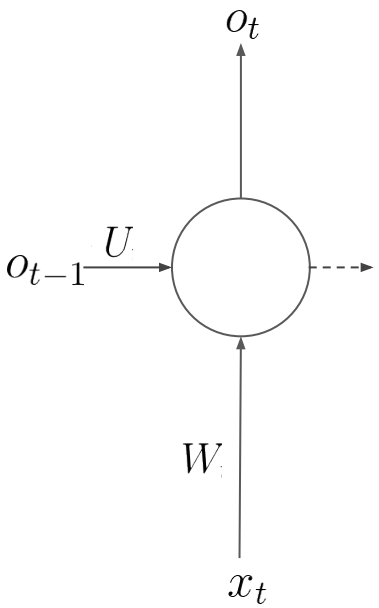
$$o_t = \sigma(wx_t + uo_{t-1} + b)$$



- Specialized for processing sequential input.
- Can generalize for sequences of unseen length
- Reduced parameters

Advantages

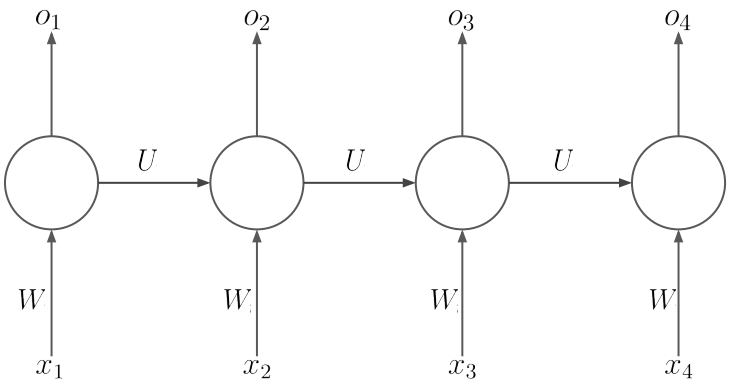
$$o_t = \sigma(wx_t + uo_{t-1} + b)$$



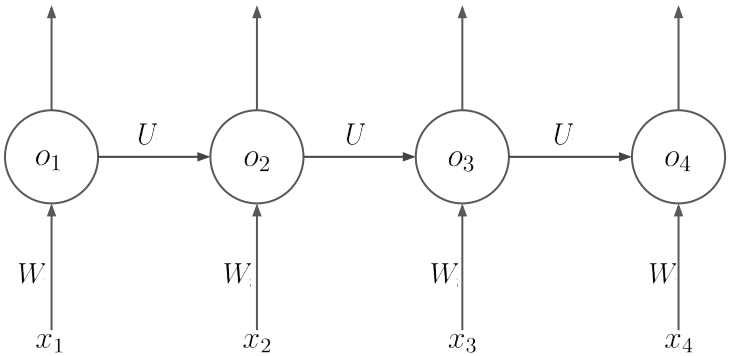
- Specialized for processing sequential input.
- Can generalize for sequences of unseen length
- Reduced parameters
  - Need lesser examples.
  - Less prone to overfit.

Recurrent Networks in the Wild

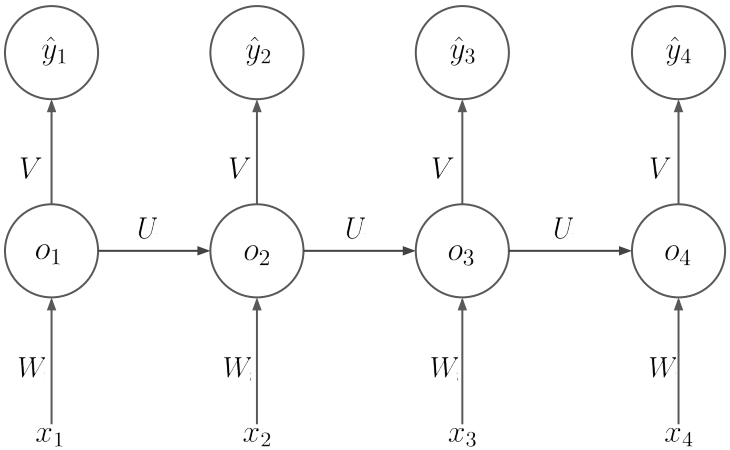
The complete Picture



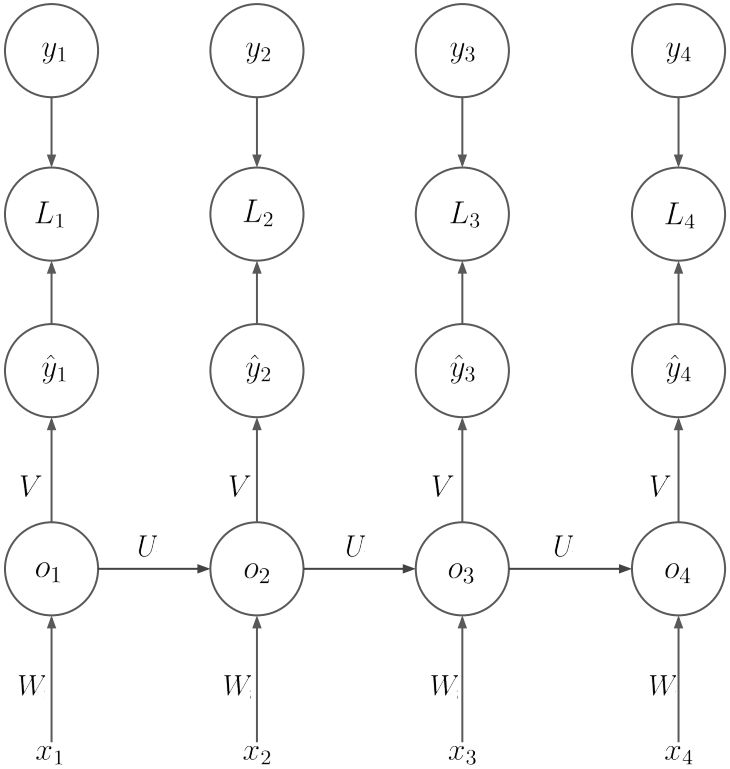
The complete Picture



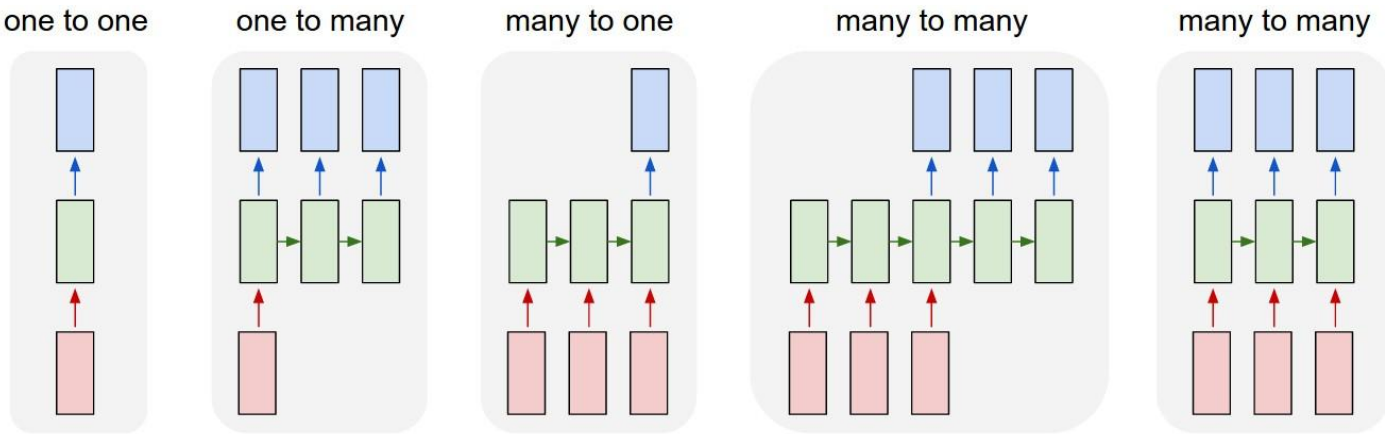
The complete Picture



The complete Picture



Alternatives



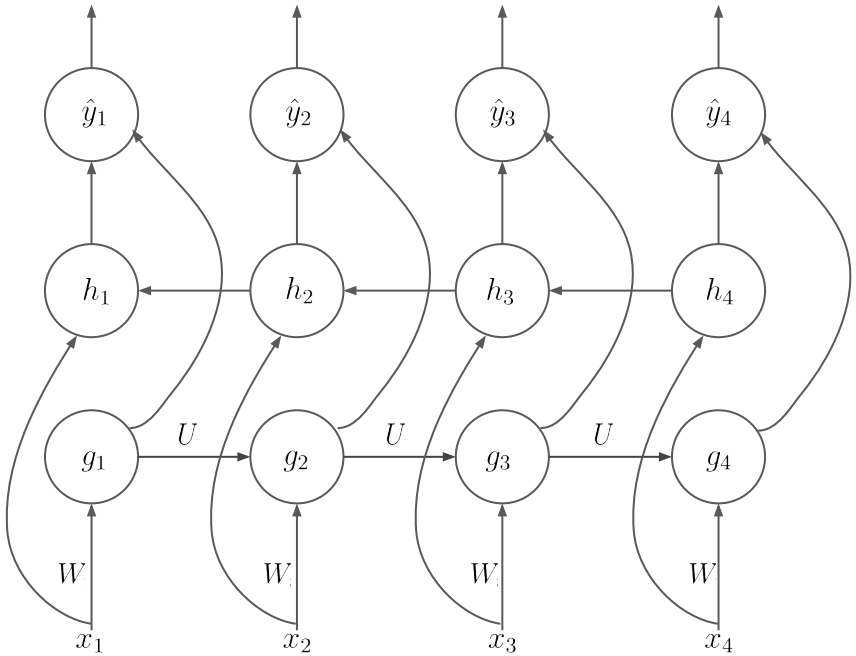
Limitations

Bidirectional RNN

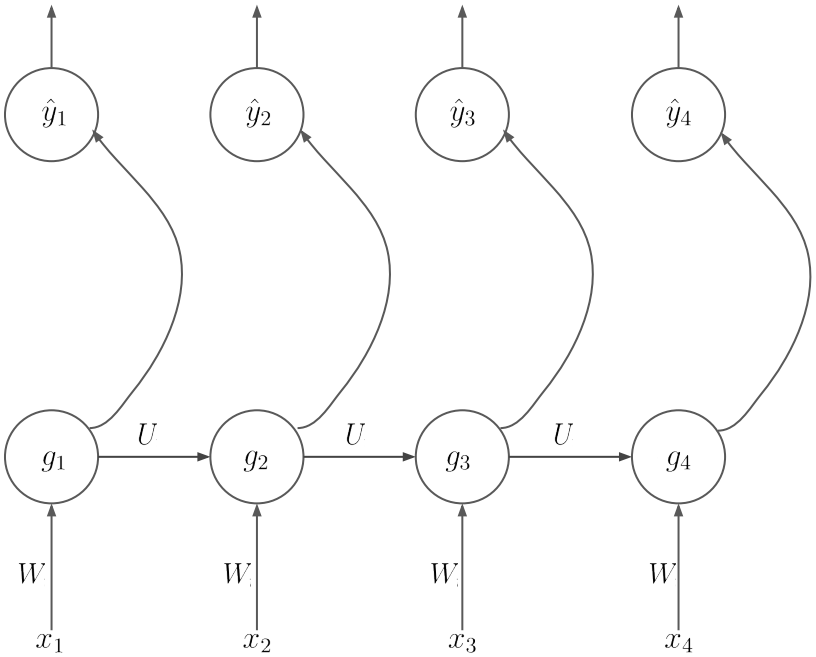
In some applications the information about *next word* might be useful for the current one.

Influence of start of sequence might diminish towards the end.

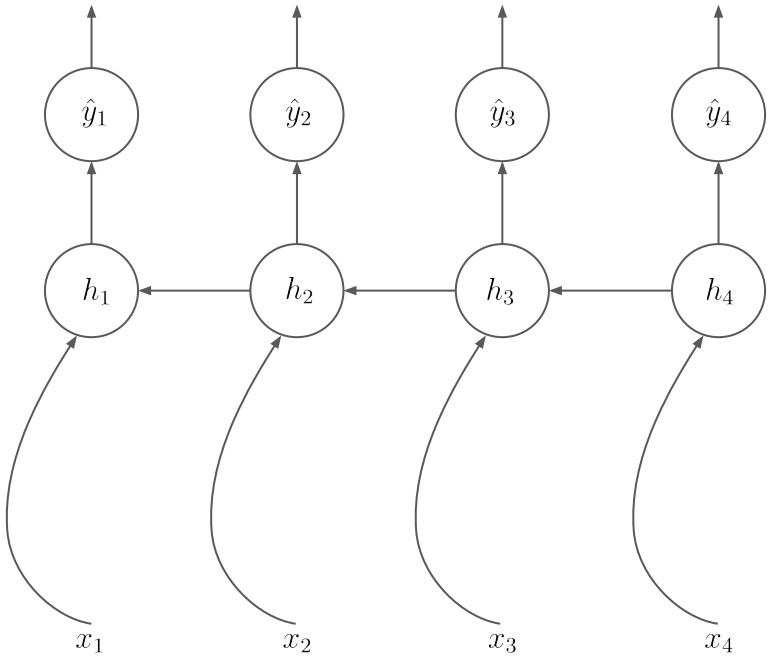
Bidirectional Network



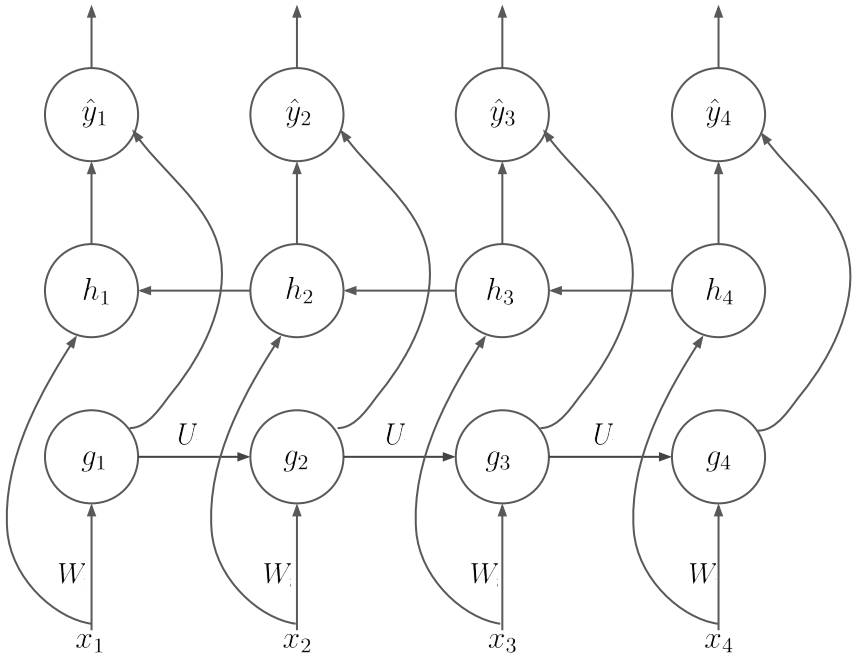
Bidirectional Network



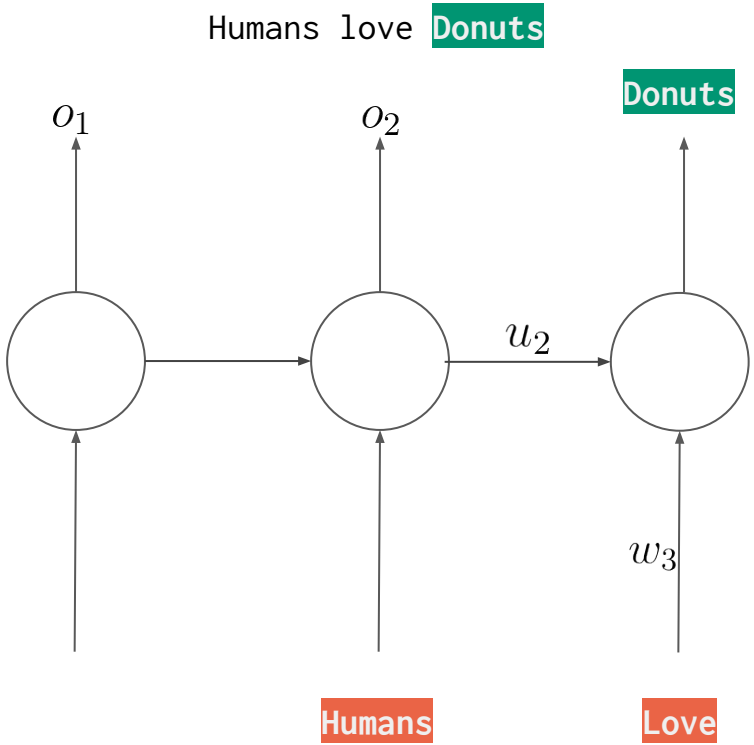
Bidirectional Network



Bidirectional Network



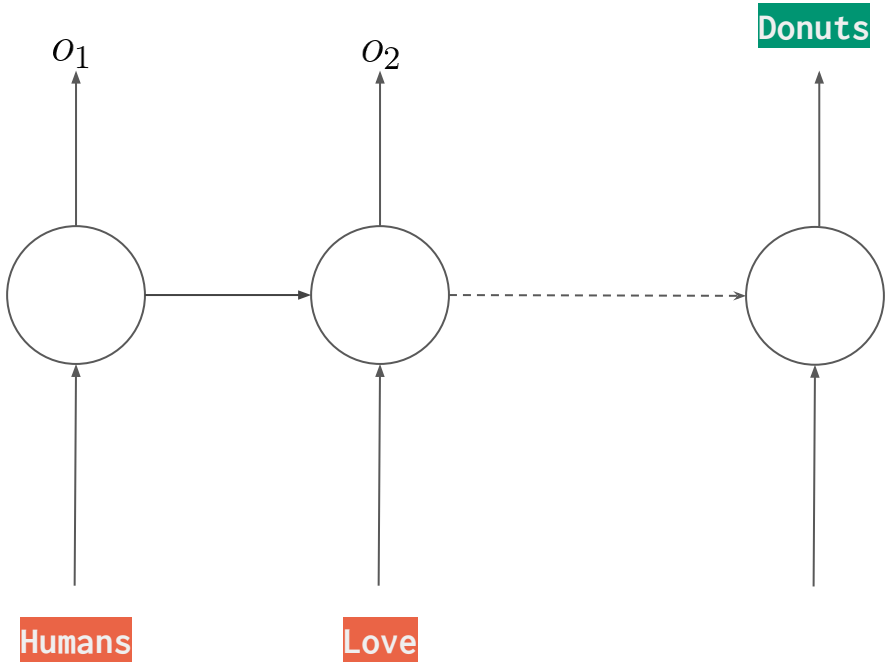
RNN Shortcoming



Consider a language model predicting next word.

Shortcoming

Humans love sweet things and Donuts are the best



Long range information is difficult to handle.

RNN shortcomings

- Lossy summary.
- Information is passed via gradients and if the gradients are small, information might be lost.

Long Short Term Memory Cell

- Cell has a memory to store information.
- Gates which decide whether to “forget” some of the memory, given new input.
- Learns when and what to “forget”, “input” and “output”