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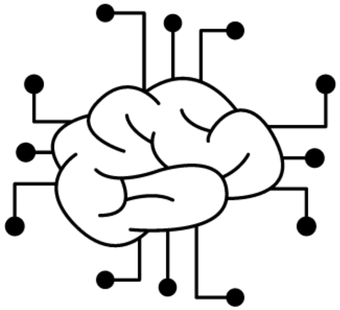
Neural Networks for Sentiment Analysis

Outline

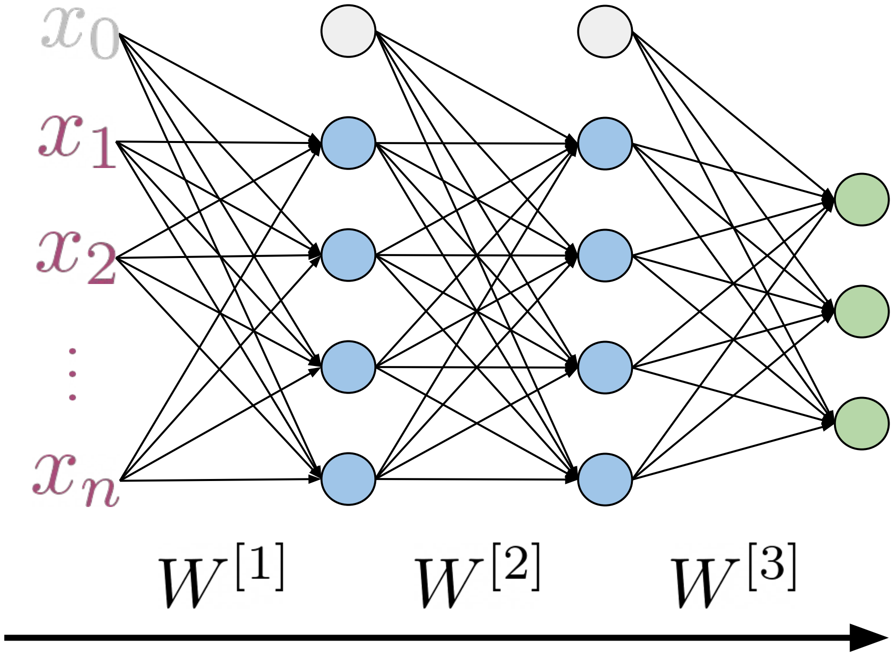
- Neural networks and forward propagation
- Structure for sentiment analysis



Neural Networks

$W^{[1]}$ $W^{[2]}$ $W^{[3]}$

Forward propagation



$a^{[i]}$ Activations ith layer

$$a^{[0]} = X$$

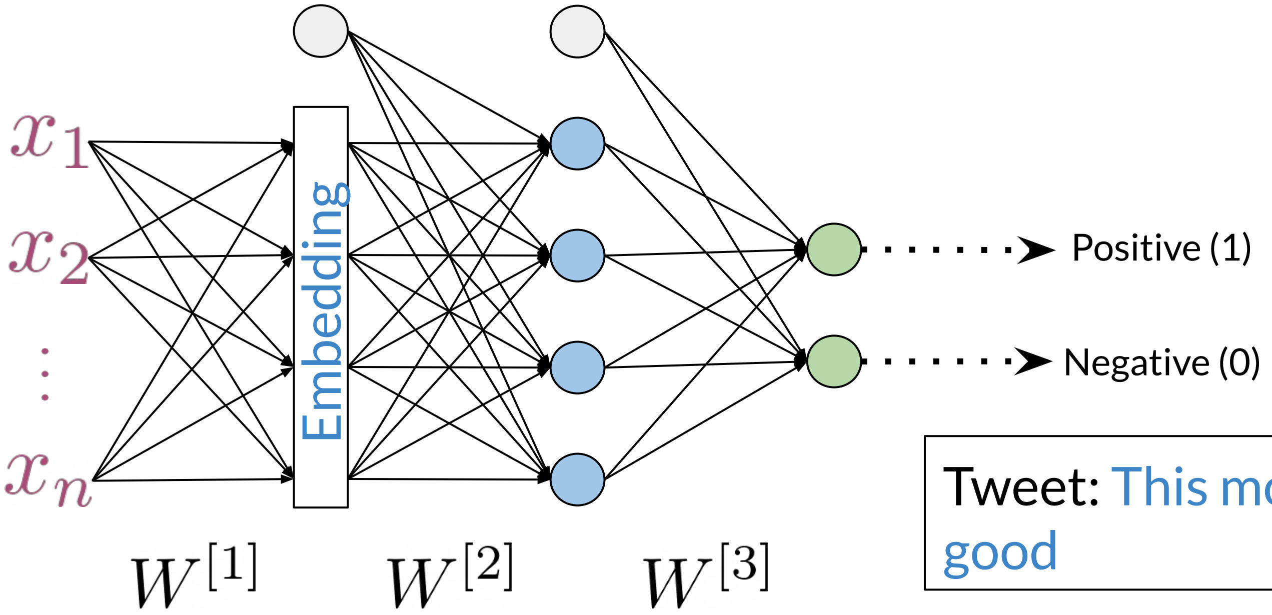
$$z^{[i]} = W^{[i]} a^{[i-1]}$$

$$a^{[i]} = g^{[i]}(z^{[i]})$$

Neural Networks for sentiment analysis

$W^{[1]}$ $W^{[2]}$ $W^{[3]}$

Neural Networks for sentiment analysis



Tweet: This movie was almost good

Initial Representation

Word	Number
a	1
able	2
about	3
...	...
hand	615
...	...
happy	621
...	...
zebra	1000

Tweet: This movie was almost good

↓

[700 680 720 20 55]

↓ Padding

[700 680 720 20 55 $\boxed{0\ 0\ 0\ 0\ 0\ 0\ 0}$]

To match size of longest tweet

Summary

- Structure for sentiment analysis
- Classify complex tweets
- Initial representation

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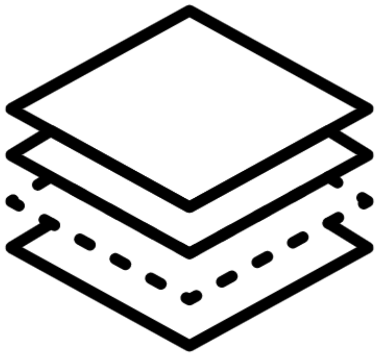
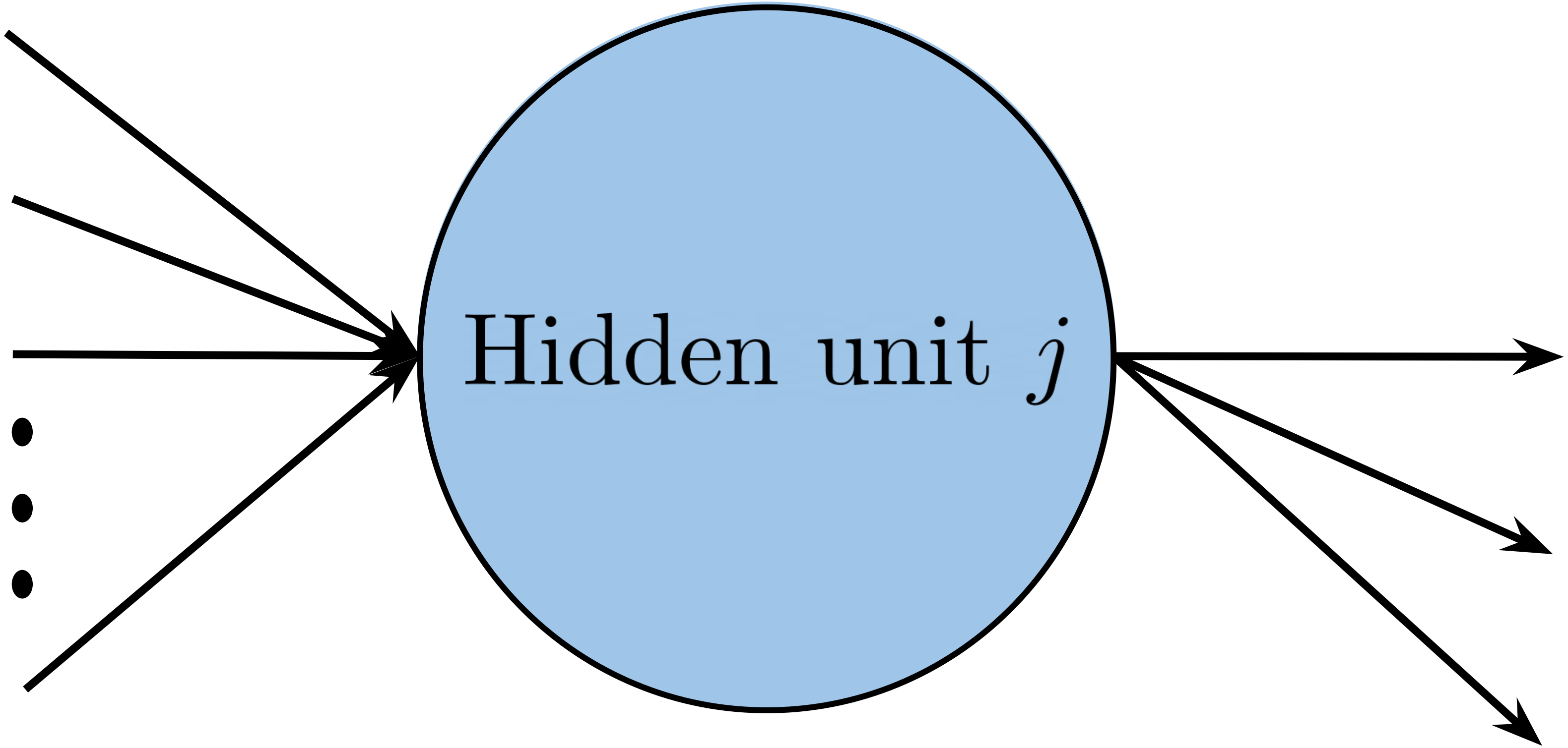
Dense and ReLU Layers

Outline

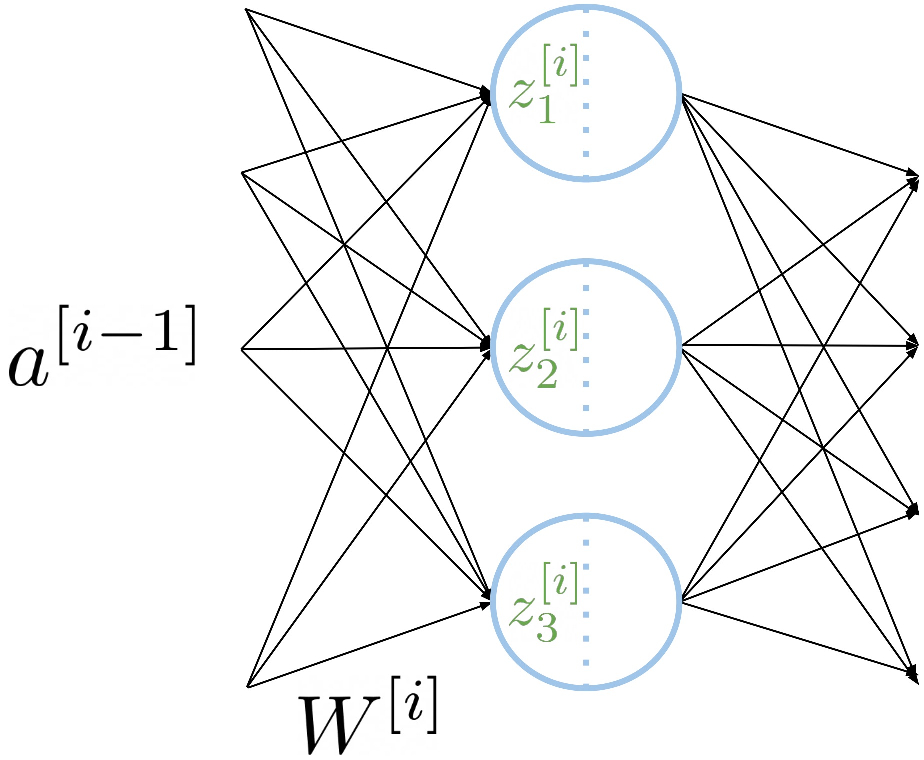
- Dense layer in detail
- ReLU function



Neural networks



Dense Layer



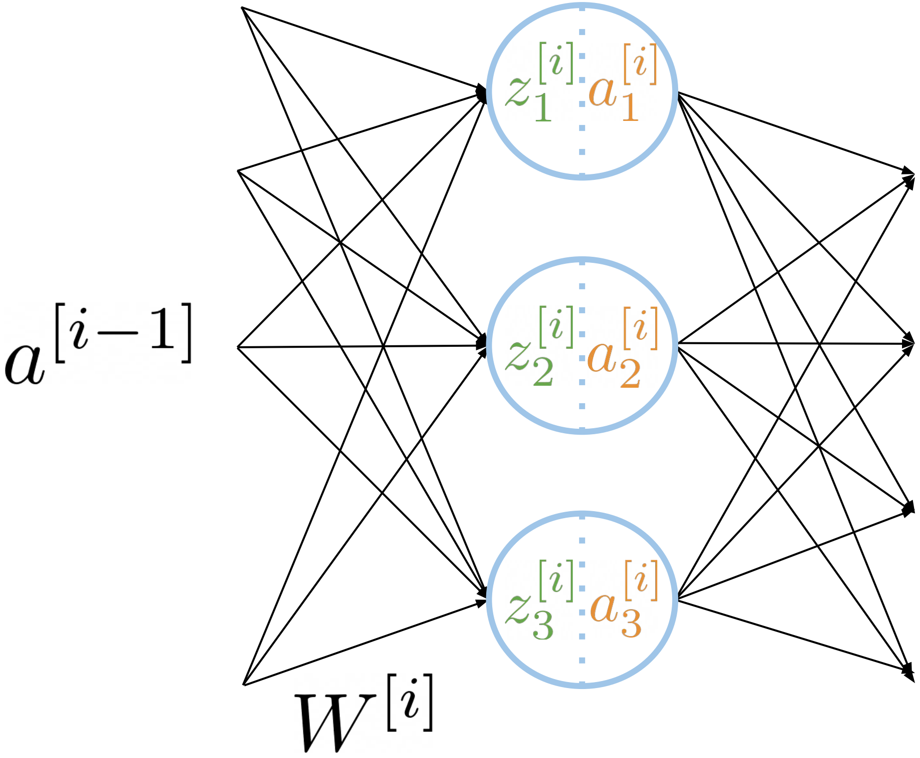
$$z_j^{[i]} = {w_j^{[i]}}^T a^{[i-1]}$$

Dense layer

$$z^{[i]} = \boxed{W^{[i]}} a^{[i-1]}$$

Trainable parameters

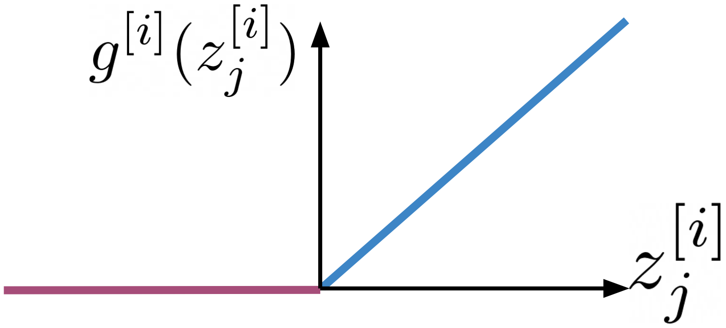
ReLU Layer



$$a_j^{[i]} = g^{[i]}(z_j^{[i]})$$

ReLU = Rectified linear unit

$$g(z^{[i]}) = \max(\underline{0}, \underline{z^{[i]}})$$



Summary

- Dense Layer $\longrightarrow$ $z^{[i]} = W^{[i]} a^{[i-1]}$
- ReLU Layer $\longrightarrow$ $g(z^{[i]}) = \max(0, z^{[i]})$

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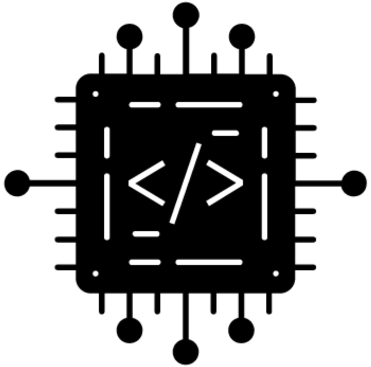
Other Layers

Outline

- Embedding layer
- Mean layer



Embedding Layer

Vocabulary	Index		
I	1	0.020	0.006
am	2	-0.003	0.010
happy	3	0.009	0.010
because	4	-0.011	-0.018
learning	5	-0.040	-0.047
NLP	6	-0.009	0.050
sad	7	-0.044	0.001
not	8	0.011	-0.022

Trainable weights

Vocabulary
x
Embedding

Mean Layer

Tweet: I am happy

Vocabulary	Index		
I	1	0.020	0.006
am	2	-0.003	0.010
happy	3	0.009	0.010

$$\begin{bmatrix} 0.020 & 0.006 \\ -0.003 & 0.010 \\ 0.009 & 0.010 \end{bmatrix}$$

$$\downarrow$$

Mean of the word embeddings

$$\begin{bmatrix} 0.009 \\ 0.009 \end{bmatrix}$$

No trainable parameters

Summary

- Embedding is trainable using an embedding layer
- Mean layer gives a vector representation

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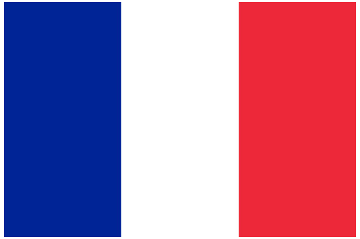
Traditional Language models

Traditional Language Models



J'ai vu le match de foot →

Sequence	$P(\text{Sequence})$
I saw the game of soccer	4.5 e-5
I saw the soccer game	6.0 e-5
I saw the soccer match	4.6 e-5
Saw I the game of soccer	2.6 e-9

N-grams

$$P(w_2|w_1) = \frac{\text{count}(w_1, w_2)}{\text{count}(w_1)} \longrightarrow \text{Bigrams}$$

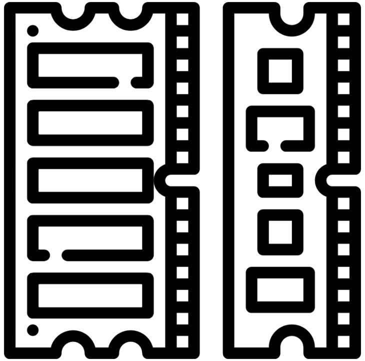
$$P(w_3|w_1, w_2) = \frac{\text{count}(w_1, w_2, w_3)}{\text{count}(w_1, w_2)} \longrightarrow \text{Trigrams}$$

$$\boxed{P(w_1, w_2, w_3) = P(w_1) \times P(w_2|w_1) \times P(w_3|w_2)}$$

- Large N-grams needed to capture dependencies between distant words
- Need a lot of space and RAM

Summary

- N-grams consume a lot of memory
- Different types of RNNs are the preferred alternative



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Recurrent Neural Networks

Advantages of RNNs

Nour was supposed to study with me. I called her but she did not have answer

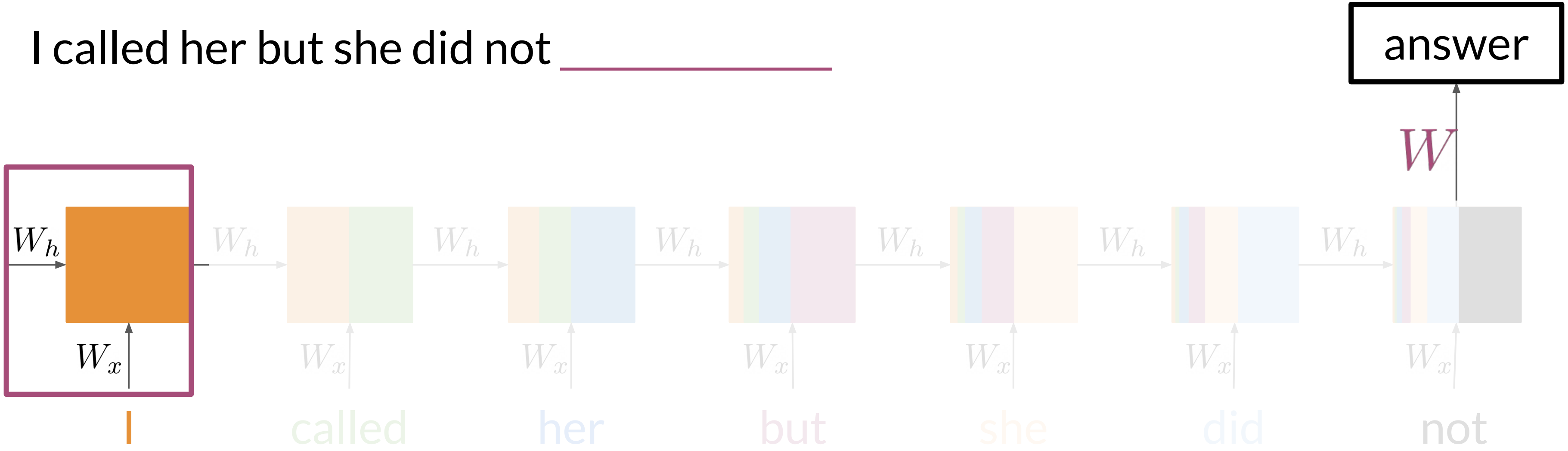
- want
- respond
- choose
- want
- have
- ask
- attempt
- answer
- know

RNNs look at every previous word

Similar probabilities with trigram

RNNs Basic Structure

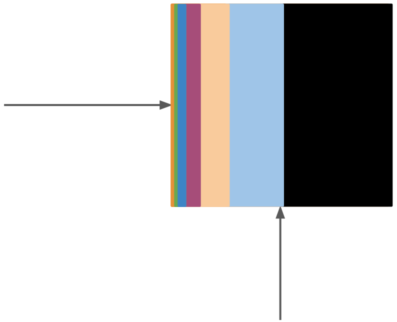
I called her but she did not ____________



Learnable parameters

Summary

- RNNs model relationships among distant words
- In RNNs a lot of computations share parameters



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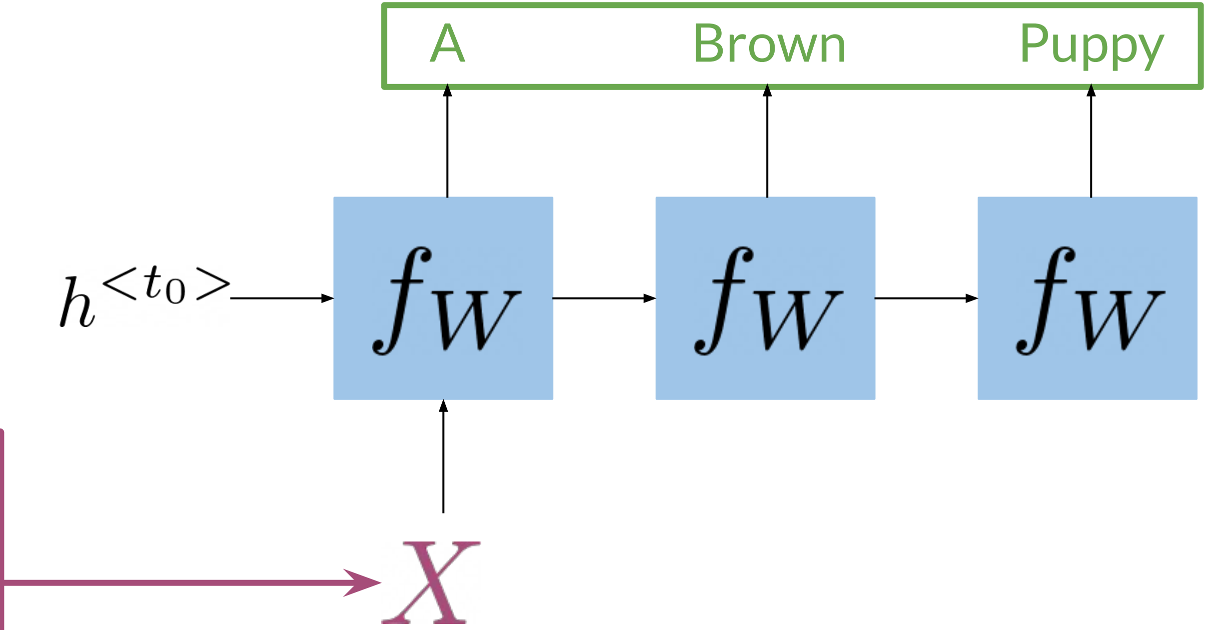
Applications of RNNs

One to One

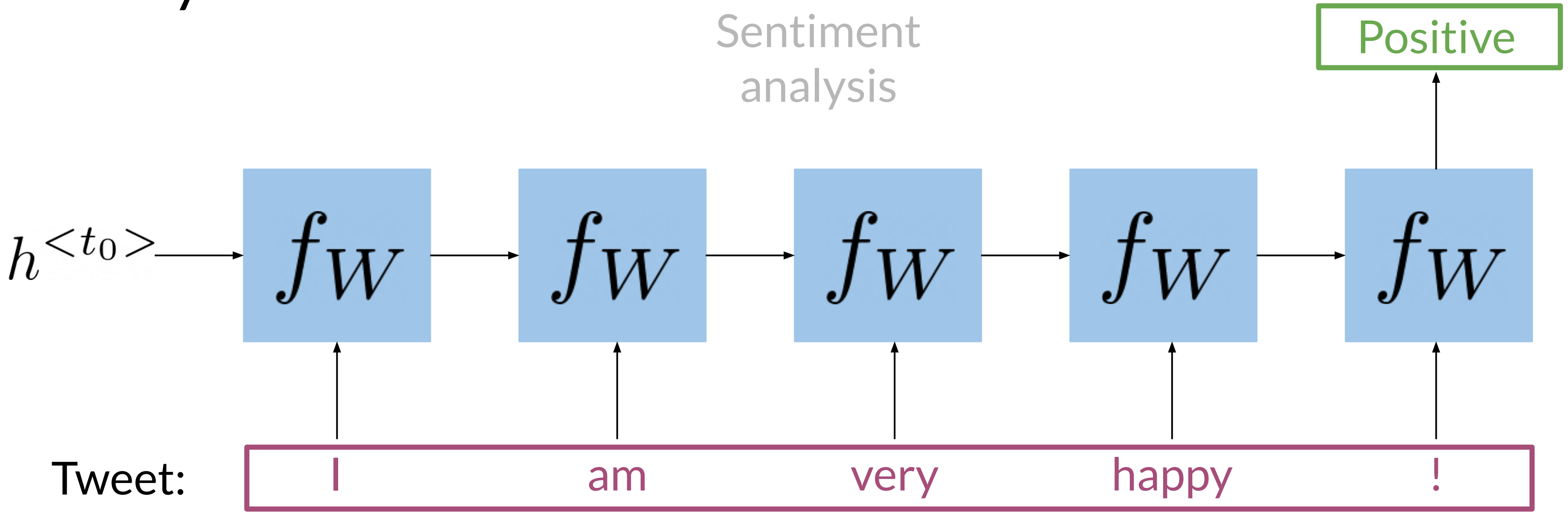

LaLiga
Santander
Real Valladolid
Real Zaragoza
Atletico Madrid
0 1
0 4
0 1
Real Madrid
Real Madrid
Real Madrid
$h^{<t_0>}$
f_W
X

One to Many

Caption generation

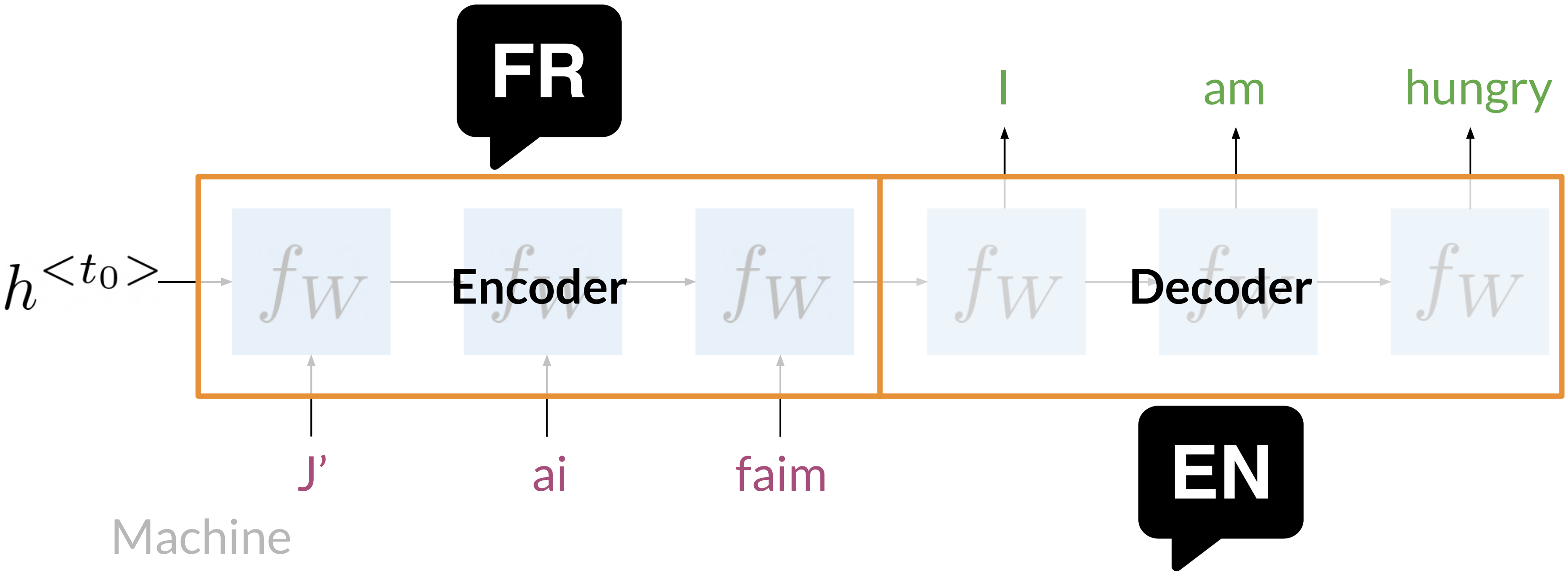


Many to One



Sentiment analysis
Positive
$h^{<t_0>}$
f_W
f_W
f_W
f_W
f_W
Tweet:
I
am
very
happy
!

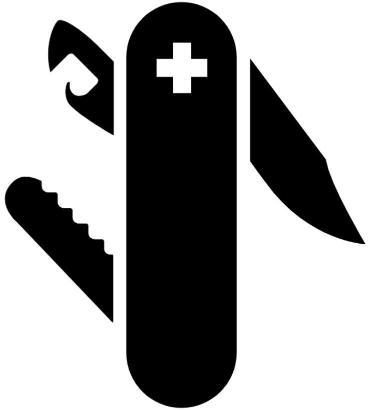
Many to Many



Machine Translation

Summary

- RNNs can be implemented for a variety of NLP tasks
- Applications include Machine translation and caption generation



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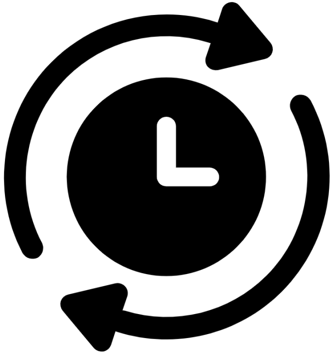
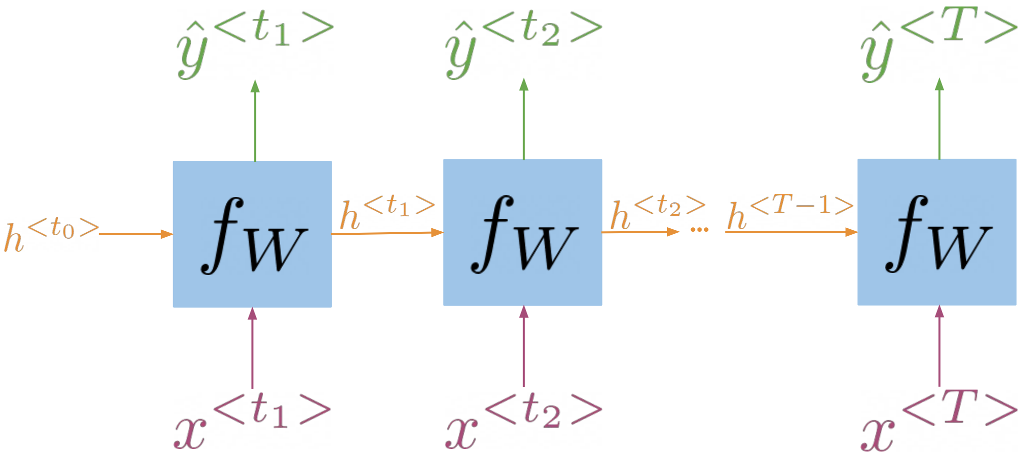
Math in Simple RNNs

Outline

- How RNNs propagate information (Through time!)
- How RNNs make predictions



A Vanilla RNN

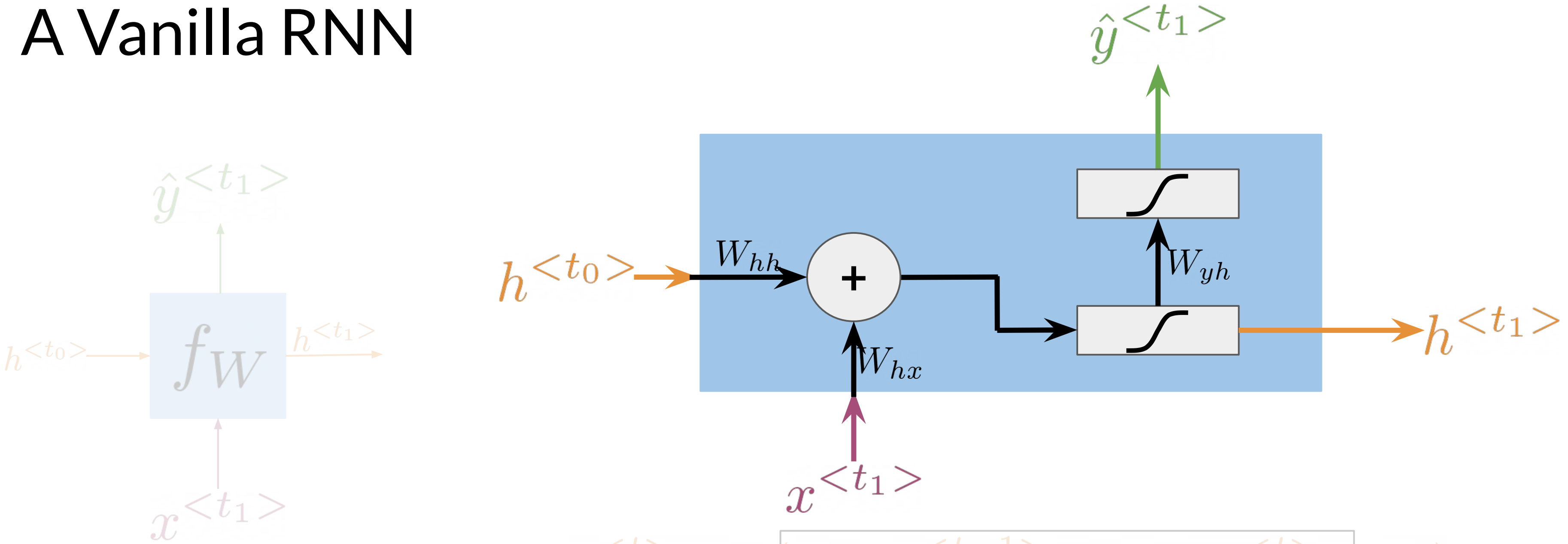


$$h^{<t>} = g(\boxed{W_h[h^{<t-1>}, x^{<t>}]}\boxed{+ b_h})$$

$$\hat{y}^{<t>} = g(W_{yh}h^{<t>} + b_y)$$

$$\boxed{h^{<t>} = g(W_{hh}h^{<t-1>} + W_{hx}x^{<t>} + b_h)}$$

A Vanilla RNN

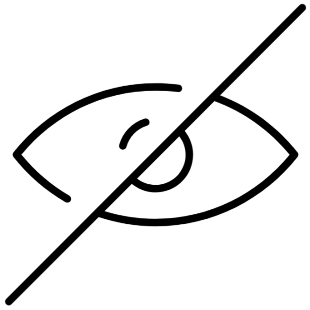


$$h^{<t>} = g(\boxed{W_{hh}h^{<t-1>} + W_{hx}x^{<t>}} + b_h)$$

$$\hat{y}^{<t>} = g(W_{yh}h^{<t>} + b_y)$$

Summary

- Hidden states propagate information through time
- Basic recurrent units have two inputs at each time: $h^{<t-1>}, \; x^{<t>}$



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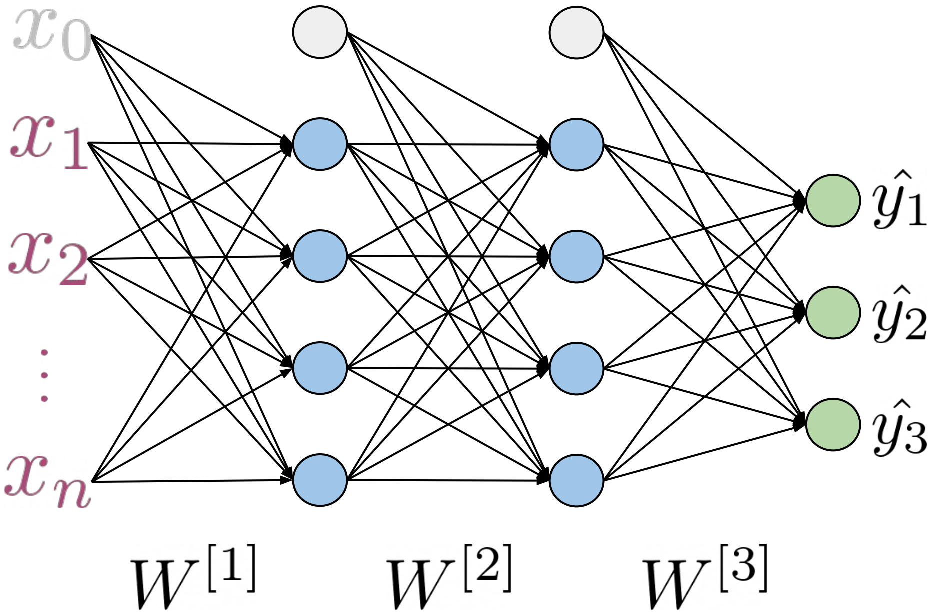
Cost Function for RNNs

Cross Entropy Loss



K - classes or possibilities

Either 0 or 1

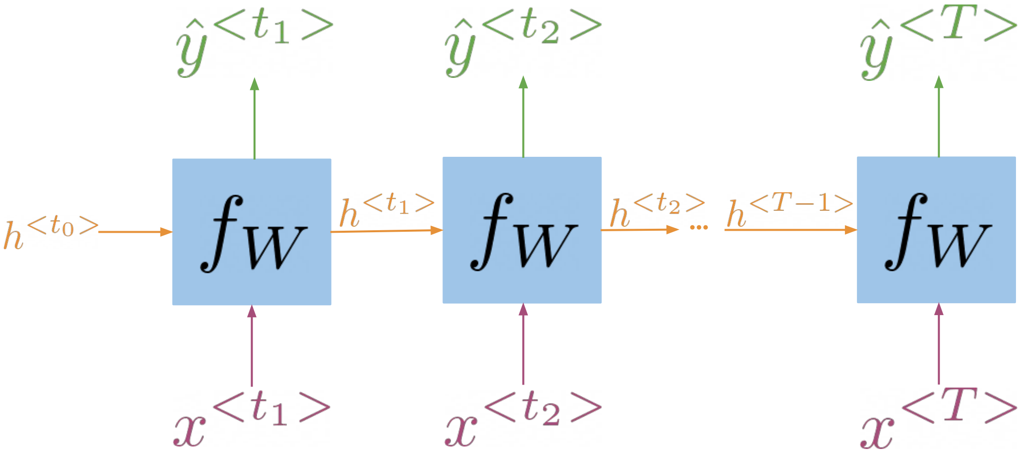
$$J = -\sum_{j=1}^{\boxed{K}} \boxed{y_j} \log \hat{y}_j$$

Looking at a single example (x, y)

Cross Entropy Loss

$$h^{<t>} = g(W_h[h^{<t-1>}, x^{<t>}] + b_h)$$

$$\hat{y}^{<t>} = g(W_{yh}h^{<t>} + b_y)$$



$$J = -\frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{K} y_j^{<t>} \log \hat{y}_j^{<t>}$$

Average with respect to time

Summary

For RNNs the loss function is just an average through time!

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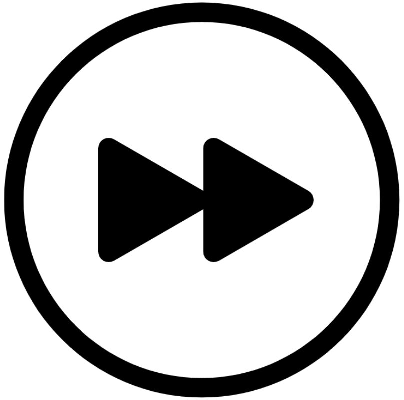
Implementation Note

Outline

- scan() function in tensorflow
- Computation of forward propagation using abstractions



tf.scan() function

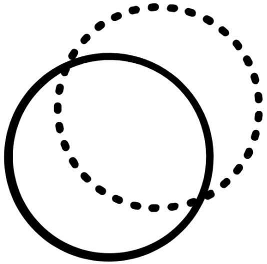

```
def scan(fn, elems, initializer=None, ...):

    cur_value = initializer
    ys = []

    for x in elems:
        y, cur_value = fn(x, cur_value)
        ys.append(y)

    return ys, cur_value
```

Frameworks like Tensorflow need this type of abstraction

Parallel computations and GPU usage

Summary

- Frameworks require abstractions
- tf.scan() mimics RNNs



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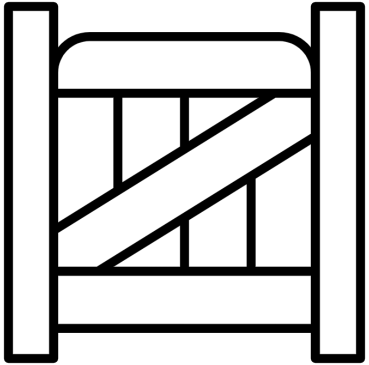
Gated Recurrent Units

Outline

- Gated recurrent unit (GRU) structure
- Comparison between GRUs and vanilla RNNs



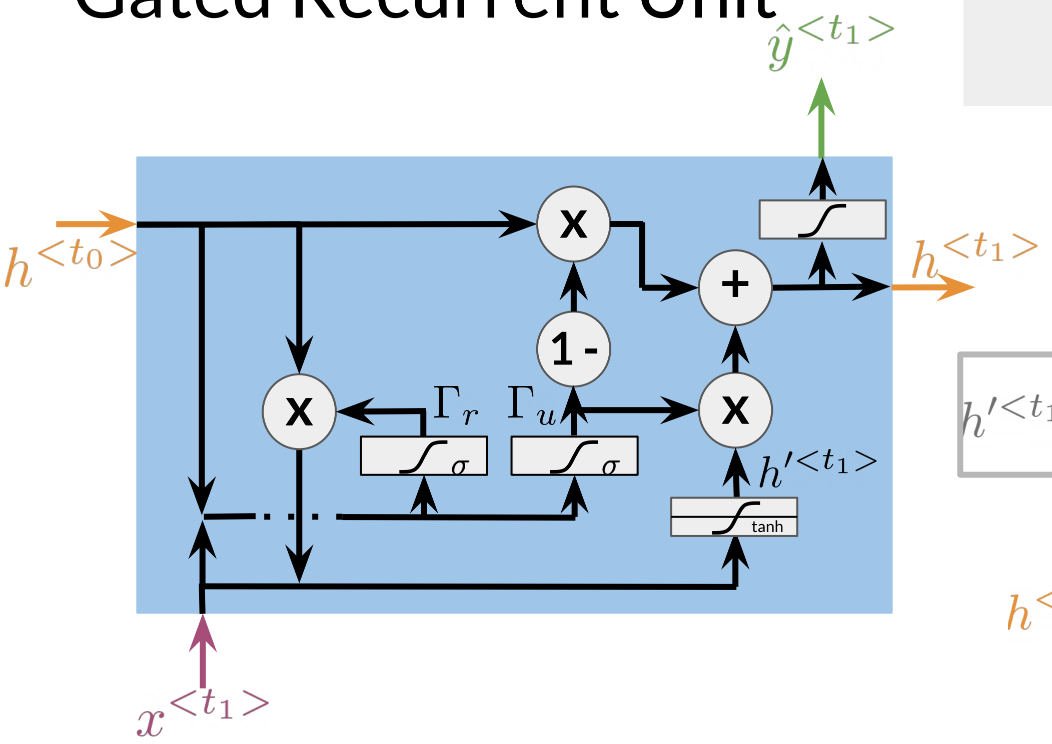
Gated Recurrent Units

"Ants are really interesting. ___They___ are everywhere."

Plural

Relevance and update gates to remember important prior information

Gated Recurrent Unit



Gates to keep/update relevant information in the hidden state

$$\Gamma_r = \sigma(W_r[h^{<t_0>}, x^{<t_1>}] + b_r)$$
$$\Gamma_u = \sigma(W_u[h^{<t_0>}, x^{<t_1>}] + b_u)$$

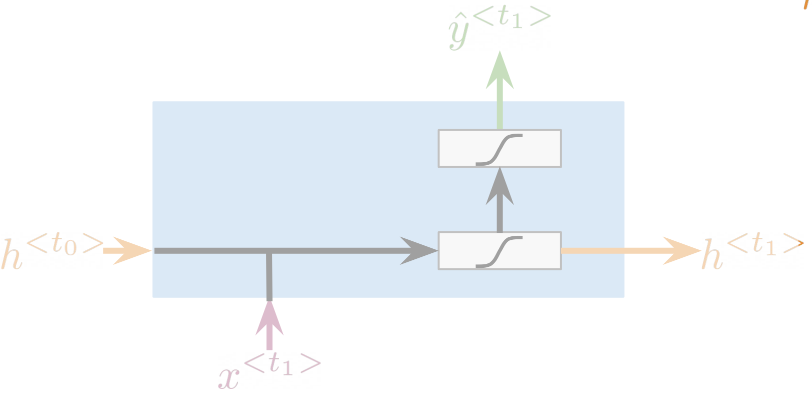
$$h'^{<t_1>} = \tanh\left(W_h[\Gamma_r * h^{<t_0>}, x^{<t_1>}] + b_h\right)$$

Hidden state candidate

$$h^{<t_1>} = (1 - \Gamma_u) * h^{<t_0>} + \Gamma_u * h'^{<t_1>}$$

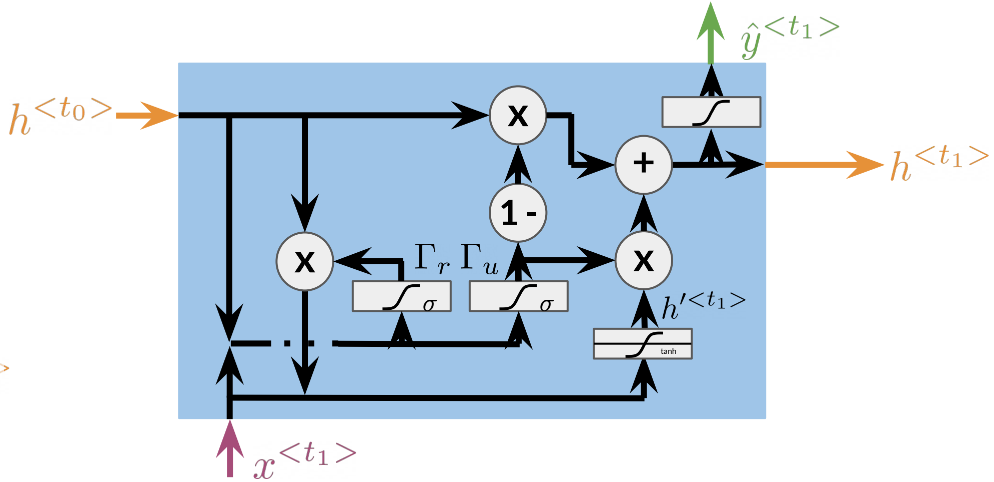
$$\hat{y}^{<t_1>} = g(W_y h^{<t_1>} + b_y)$$

Vanilla RNN vs GRUs



$$h^{<t>} = g(W_h[h^{<t-1>}, x^{<t>}] + b_h)$$

$$\hat{y}^{<t>} = g(W_{yh}h^{<t>} + b_y)$$



$$\Gamma_u = \sigma(W_u[h^{<t_0>}, x^{<t_1>}] + b_u)$$

$$\Gamma_r = \sigma(W_r[h^{<t_0>}, x^{<t_1>}] + b_r)$$

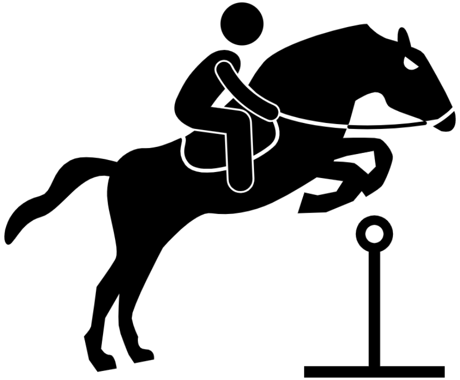
$$h'^{<t_1>} = \tanh\left(W_h[\Gamma_r * h^{<t_0>}, x^{<t_1>}] + b_h\right)$$

$$h^{<t_1>} = (1 - \Gamma_u) * h^{<t_0>} + \Gamma_u * h'^{<t_1>}$$

$$\hat{y}^{<t_1>} = g(W_y h^{<t_1>} + b_y)$$

Summary

- GRUs “decide” how to update the hidden state
- GRUs help preserve important information



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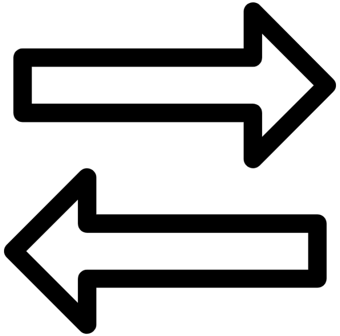
Deep and Bi-directional RNNs

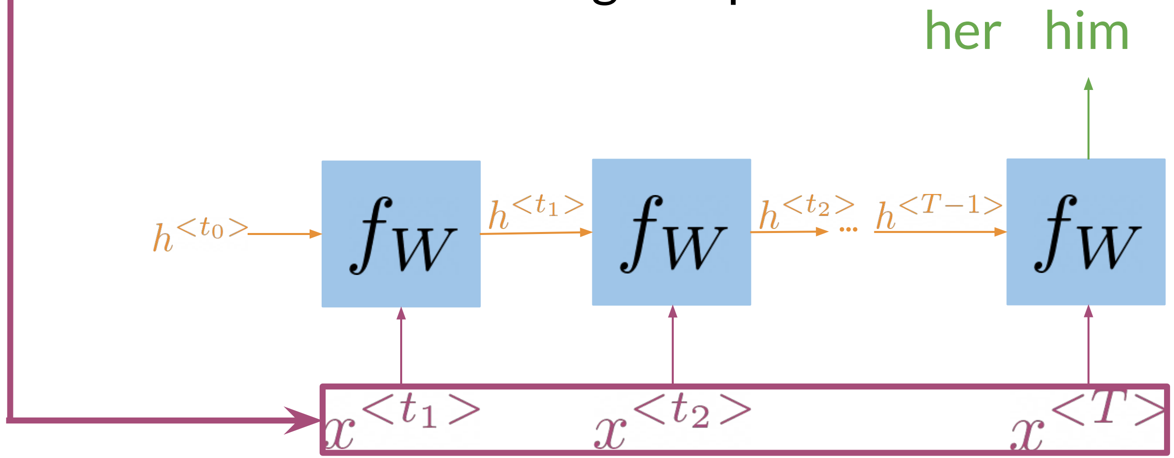
Outline

- How bidirectional RNNs propagate information
- Forward propagation in deep RNNs

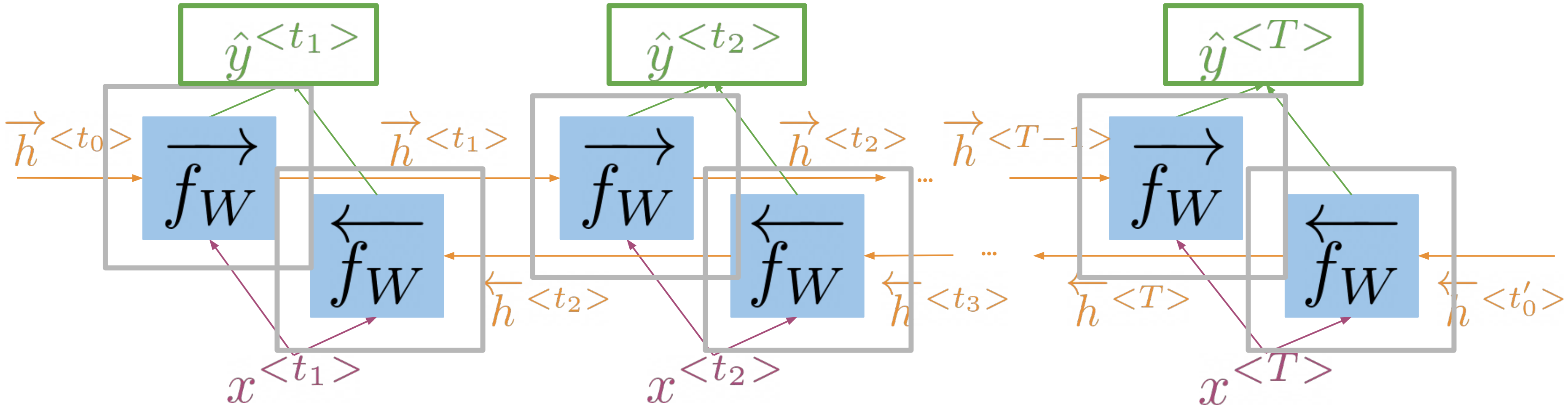


Bi-directional RNNs

I was trying really hard to get a hold of ___________. **Louise**, finally answered when I was about to give up.



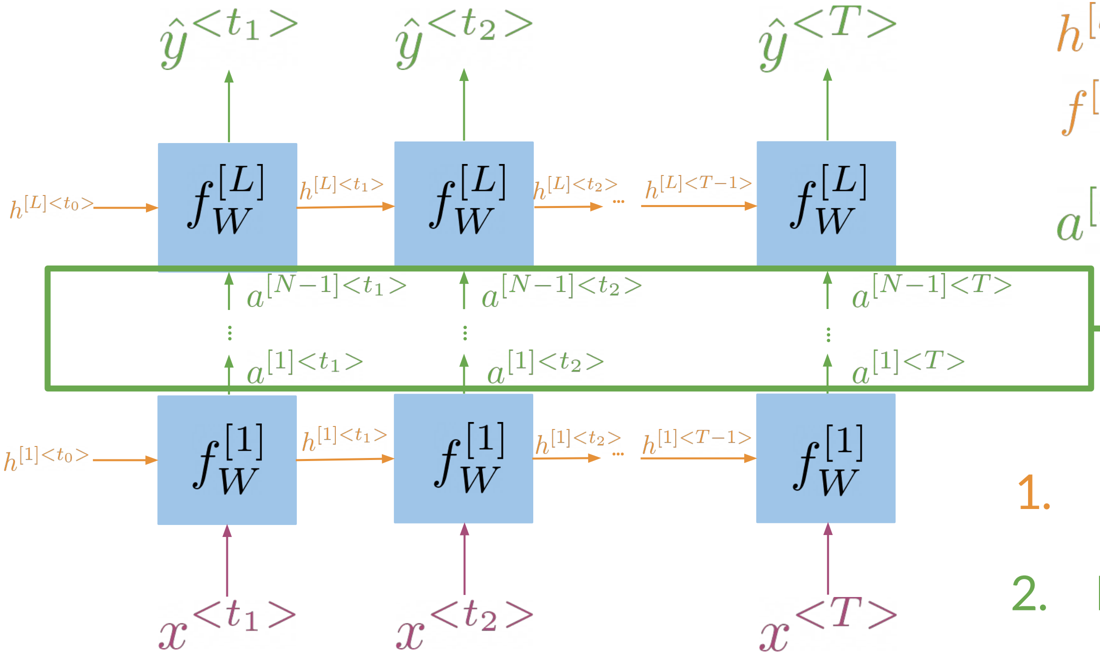
Bi-directional RNNs



Information flows from the past and from the future **independently**

$$\hat{y}^{<t>} = g(W_y[\overrightarrow{h}^{<t>}, \overleftarrow{h}^{<t>}] + b_y)$$

Deep RNNs



$$h^{[l]<t>} = f^{[l]}(W_h^{[l]}[h^{[l]<t-1>}, a^{[l-1]<t>}] + b_h^{[l]})$$

$$a^{[l]<t>} = f^{[l]}(W_a^{[l]} h^{[l]<t>} + b_a^{[l]})$$

Intermediate layers and activations

1. Get hidden states for current layer
2. Pass the activations to the next layer

Summary

- In bidirectional RNNs, the outputs take information from the past and the future
- Deep RNNs have more than one layer, which helps in complex tasks