Recurrent Neural Networks (RNNs)

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NLP Applications

1. Classification (Sentiment Analysis)
2. seq-2-seq (Language translation)
3. Language Modelling (GPT4, Gemini 3.)

text Classification (Sentiment Analysis)

fixed size $\xleftarrow{\text{feature}}$

Reviews	Label
great product	1
great	1
this product is great	1
bad product	0
⋮	⋮

{this, great, product, is, bad}

tf-idf

[0, 1, 1, 0, 0]

[0, 1, 0, 0, 0]

[1, 1, 1, 1, 0]

[0, 0, 1, 0, 1]

Word Embedding

{a, apple . . . zebra}

$$\begin{array}{ccc} 1 & 2 & 80{,}000 \\ \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} & \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix} & \begin{bmatrix} 0 \\ \vdots \\ 1 \end{bmatrix} \end{array}$$

800 400

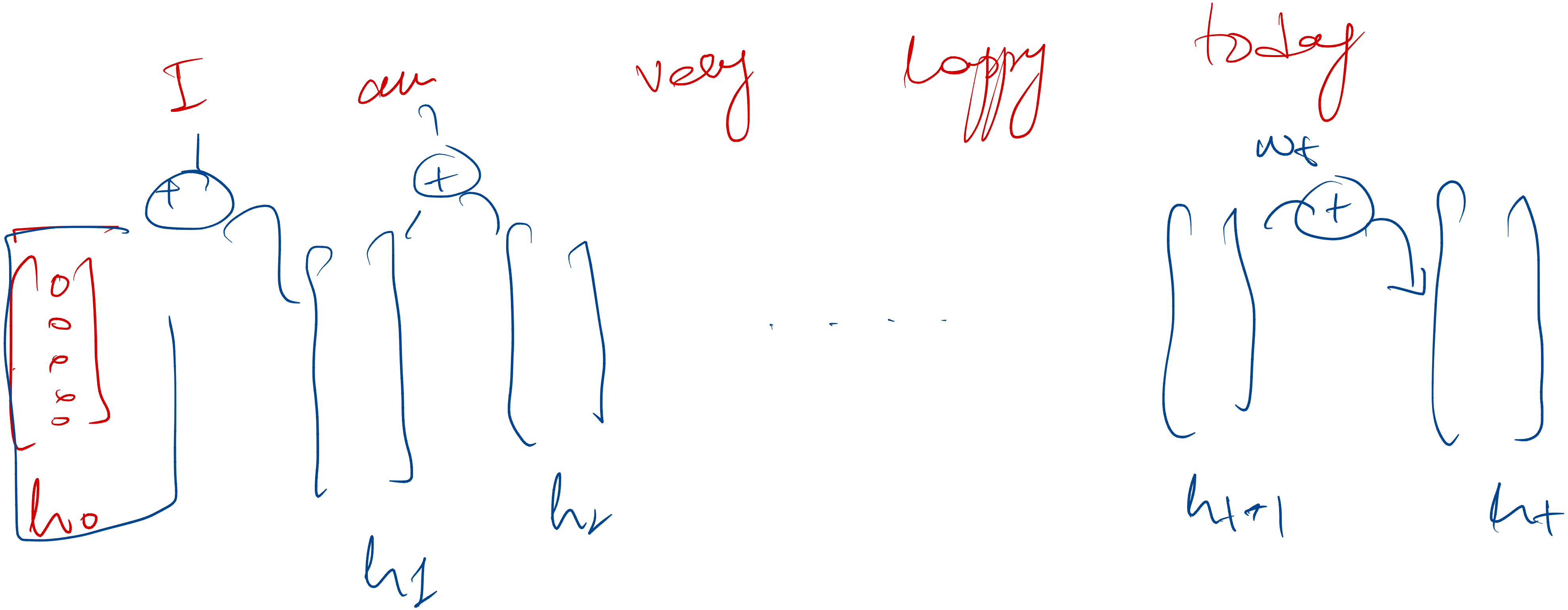
Seq-2-Seq (language translation)

انا احب الخبز	I like Khober
انا احب الذكاء الاصطناعي	I like AI
انا منزعج الاختبار	I am afraid about the exam

I like football

I am very happy

Recurrent Neural Networks



$$h_t = \underbrace{g(h_{t-1}, w_t)}$$

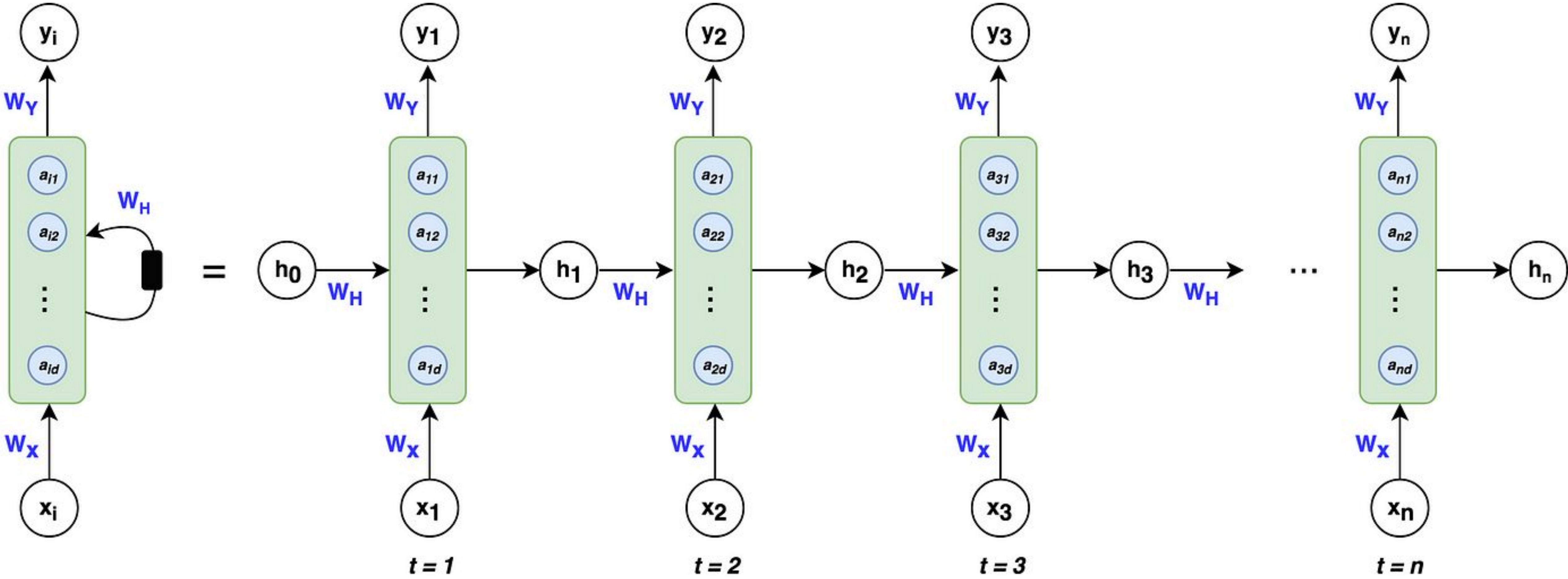
$$h_t = \sigma(W_1 \underline{h_{t-1}} + W_2 \underline{w_t})$$

$h_i \in \mathbb{R}^{100}$

$w \in \mathbb{R}^{200}$

$h_{t-1} \in \mathbb{R}^{100}$ $\quad$ $w_t \in \mathbb{R}^{200}$

$h_t \in \mathbb{R}^{100}$



y_i
W_Y
a_{i1}
a_{i2}
a_{id}
W_H
W_X
x_i
=
h_0
h_1
h_2
h_3
h_n
y_1
y_2
y_3
y_n
a_{11}
a_{12}
a_{1d}
a_{21}
a_{22}
a_{2d}
a_{31}
a_{32}
a_{3d}
a_{n1}
a_{n2}
a_{nd}
x_1
x_2
x_3
x_n
$t = 1$
$t = 2$
$t = 3$
$t = n$

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Motivation

Why Do We Need RNNs?

- Traditional feedforward networks don't handle **sequential data** effectively.
- Many applications (**language modeling, time-series prediction, speech recognition**) require memory of past inputs.
- RNNs enable **temporal dynamic behavior** by maintaining hidden states.

Examples Where Order Matters:

- Translating "I am happy" vs "Happy I am"
- Predicting next stock price based on past trends
- Understanding a sentence word-by-word

Key Idea

Add a feedback loop to remember previous computations — introducing memory into neural networks.

Learning Outcomes

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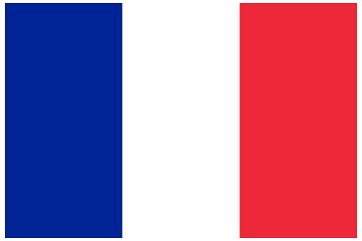
By the end of this session, you should be able to:

- Understand the structure and working of Recurrent Neural Networks (RNNs)
- Recognize various RNN architectures (One-to-Many, Many-to-One, Many-to-Many)
- Explain the concept of shared parameters in RNNs
- Evaluate RNN limitations and how advanced models improve them
- Explore potential future directions of sequential 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
$\boxed{\text{I saw the soccer game}}$	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

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

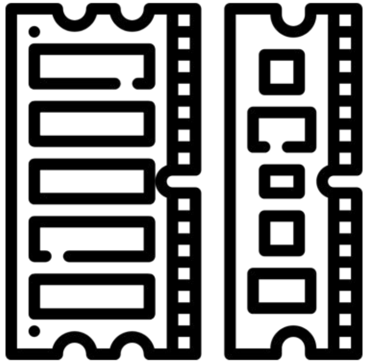
$$P(w_3|w_1, w_2) = \frac{\text{count}(w_1, w_2, w_3)}{\text{count}(w_1, w_2)} \qquad \text{Trigrams}$$

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

- Large N-grams 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



What is an RNN?

A neural network with loops — allowing information to persist.

Core Elements:

- **Hidden State** h_t: captures memory of previous inputs
- **Input** x_t, **Output** y_t
- Same weights used across time steps (parameter sharing)

Mathematical Formulation:

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t + b_h)$$
$$y_t = W_{hy}h_t + b_y$$

This recurrence allows information to propagate through time.

Advantages of RNNs

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

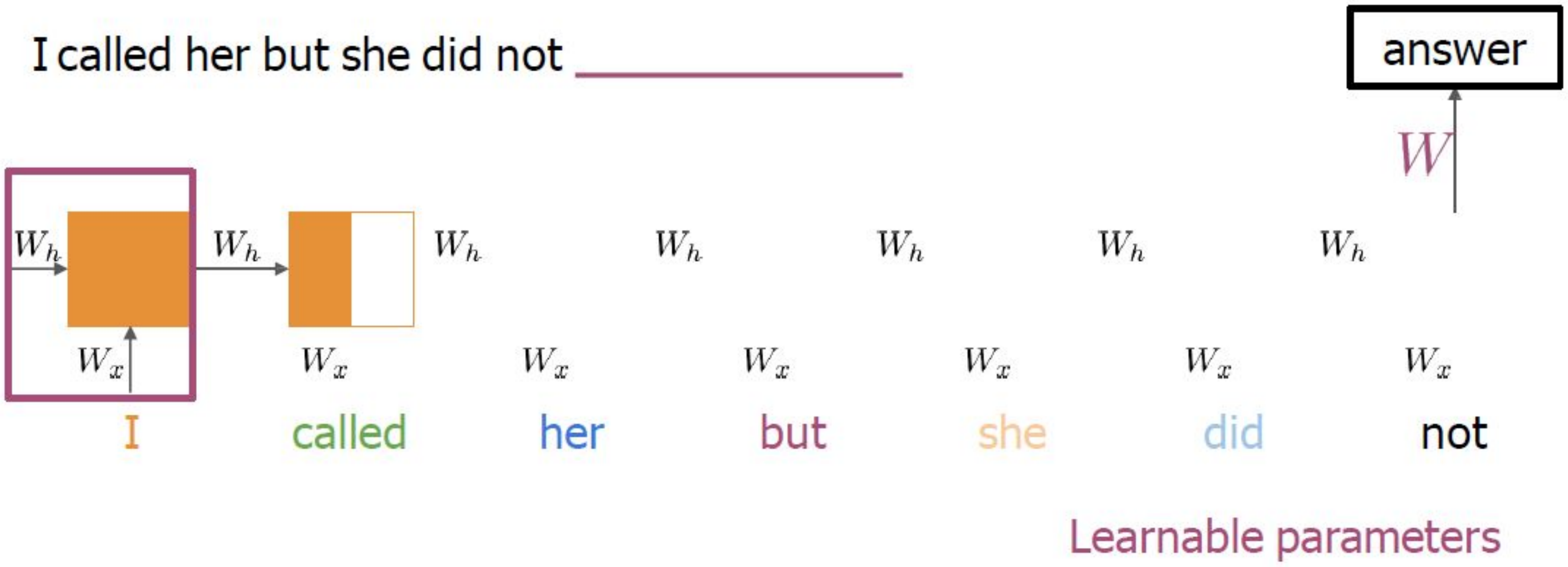
want

respond
choose
want
have
ask
attempt
answer
know

RNNs look at every previous word

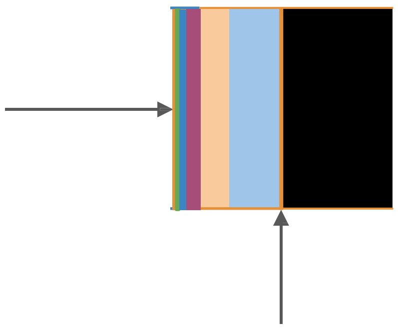
Similar probabilities with trigram

RNNs Basic Structure



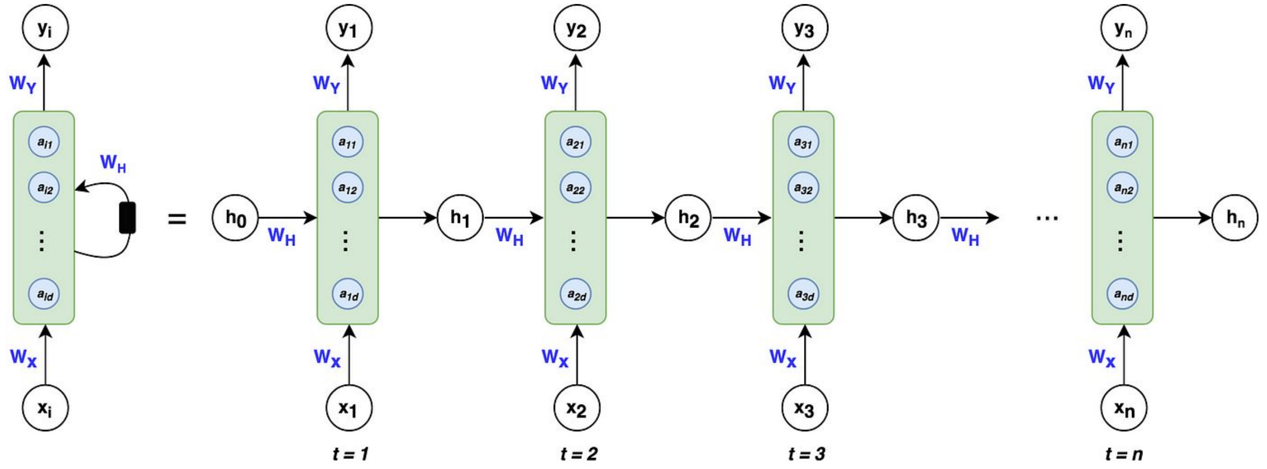
Summary

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



RNN Architecture: Unrolled View

Unrolled RNN:
An RNN is essentially a chain of repeating neural network modules, one for each time step.



Each time step shares the same parameters:

- Input x_t
- Hidden state h_t
- Output y_t

Key Idea

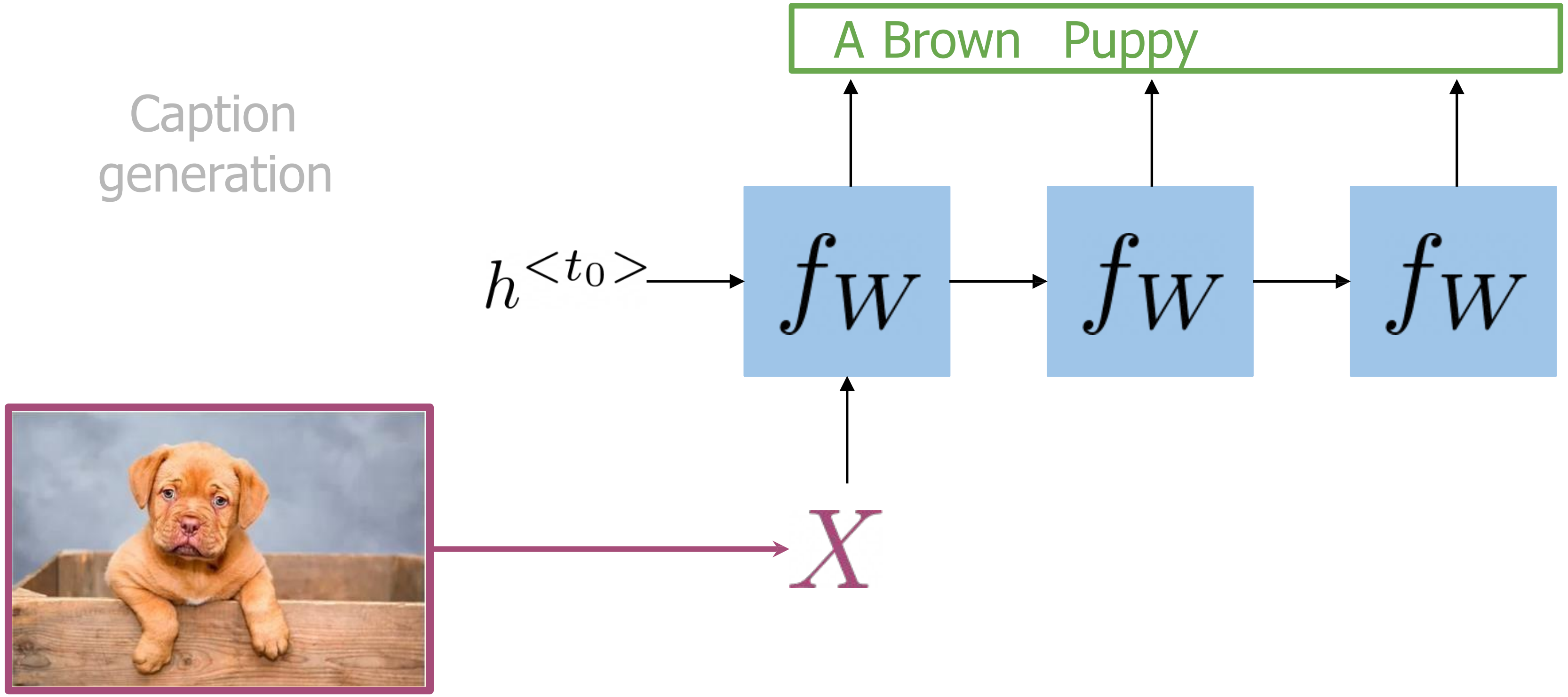
Temporal representation without increasing parameter count!

One to One

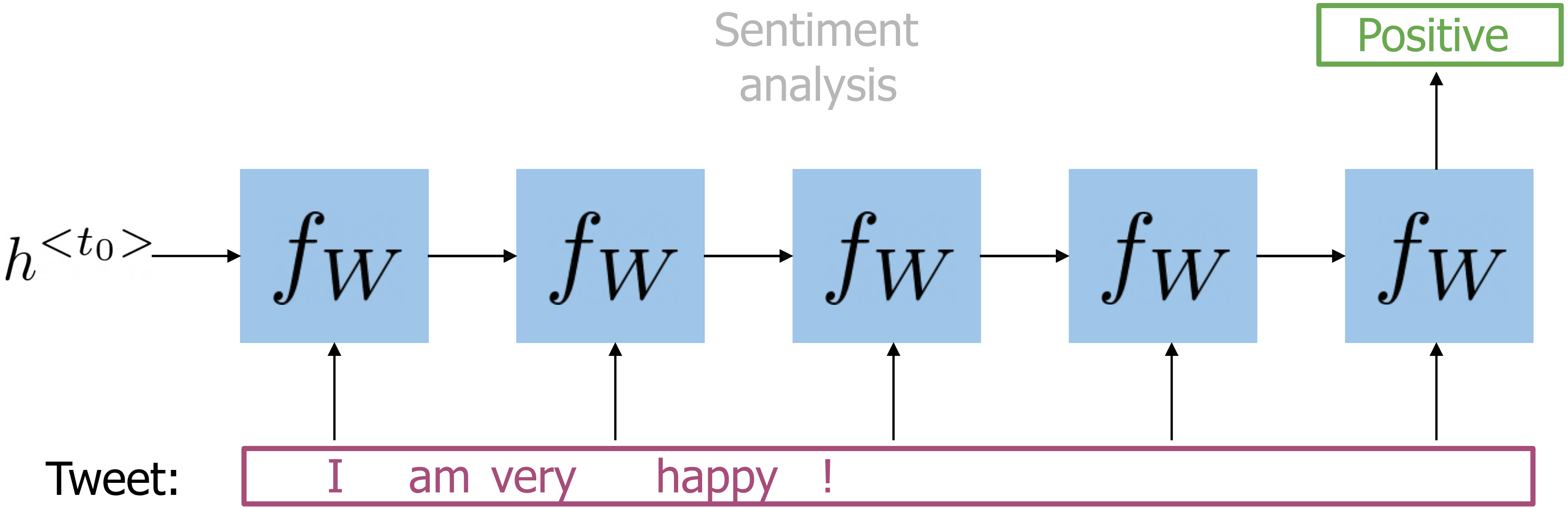

LaLiga
Santander
Real Valladolid
0 1
Real Madrid
Real Zaragoza
0 4
Real Madrid
Atletico Madrid
0 1
Real Madrid
$h^{<t_0>}$
f_W
X

One to Many

Caption generation

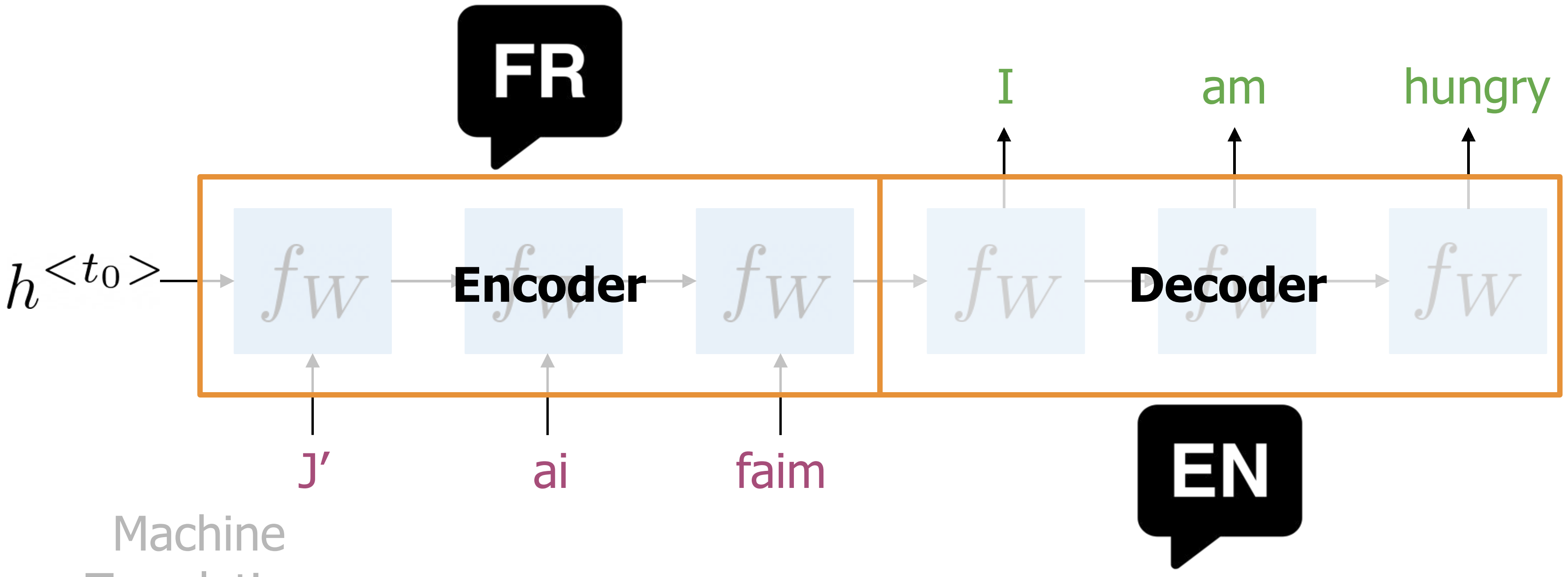


Many to One



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

Many to Many



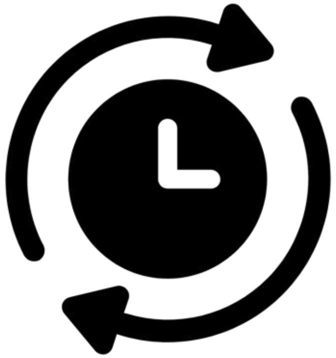
Machine Translation

Summary

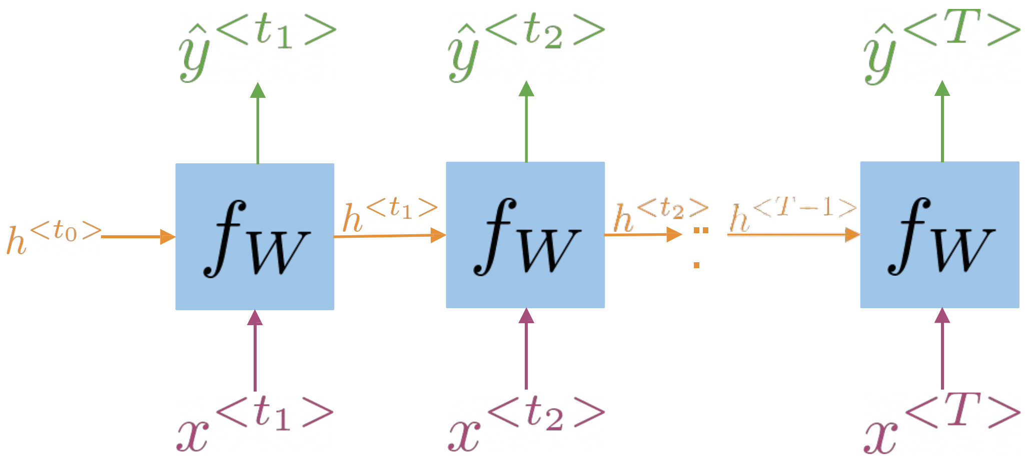
- RNNs can be implemented for a variety of NLP tasks
- Applications include Machine translation and caption generation

Math in Simple RNNs

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



A Vanilla RNN

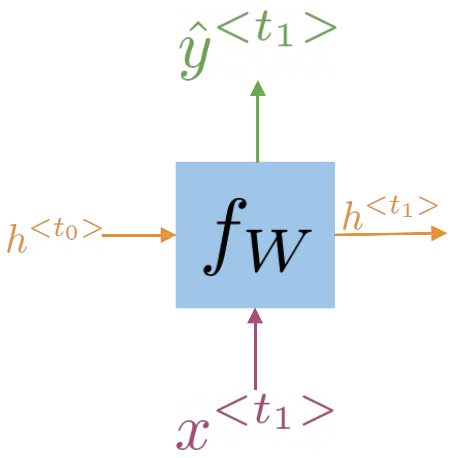


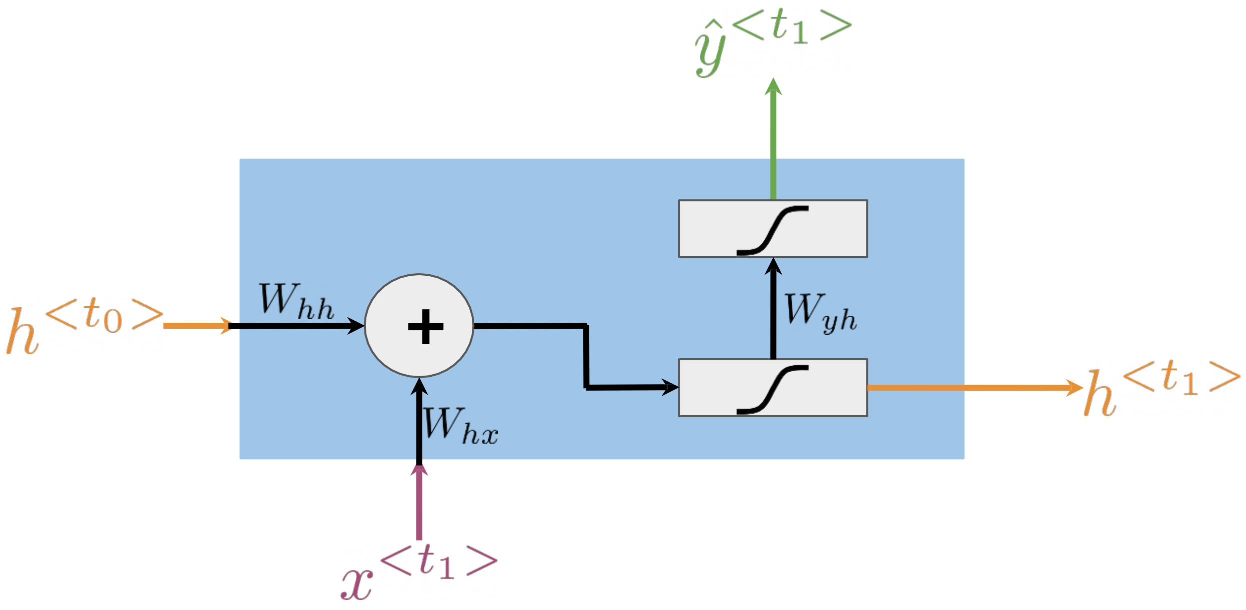
$$h^{<t>} = g(\boxed{W_h[h^{<t-1>}, x^{<t>}]} + \boxed{b_h})$$

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

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

A Vanilla RNN





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

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

RNN Training Challenges

Backpropagation Through Time (BPTT):

- Training RNNs involves **unfolding** the network across time steps.
- Standard backpropagation is applied through this unrolled structure.

RNN Training Challenges

Problems:

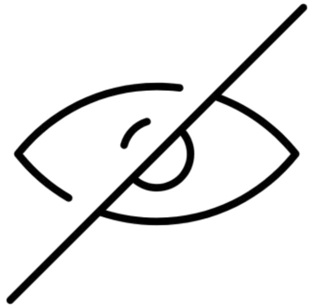
- **Vanishing Gradients:** Gradients shrink as they are propagated back, making it hard to learn long-term dependencies.
- **Exploding Gradients:** Gradients grow exponentially, leading to unstable updates.

Solutions Preview (covered in future modules):

- Use of LSTM and GRU architectures
- Gradient Clipping

Summary

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



Applications of RNNs

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Natural Language Processing

- Language modeling
- Named Entity Recognition
- Machine Translation

Time-Series Forecasting

- Stock prediction
- Weather forecasting

Audio Processing

- Speech recognition
- Music generation

Cognitive Modeling

- Simulating memory in brain-like systems

Limitations of RNNs

- Sequential computation — hard to parallelize
- Forget long-term dependencies
- Slow training due to sequential nature
- Struggle with varying-length sequences

Key Developments

- **LSTM and GRU:** Designed to address memory and gradient issues
- **Transformers:** Non-recurrent, highly parallelizable models

Future Directions: What's Beyond Vanilla RNNs?

- **LSTM (Long Short-Term Memory):** Overcomes vanishing gradients
- **GRU (Gated Recurrent Unit):** Simpler than LSTM, efficient gating
- **Attention Mechanisms:** Focus on relevant parts of the input sequence
- **Transformers & Self-Attention:** Replace recurrence with parallelizable attention
- **Neural ODEs:** Model continuously evolving hidden states

Hybrid Models:

- Combine RNNs, CNNs, and Attention for complex tasks (e.g., video, multimodal text)

Summary

- RNNs introduce memory into neural nets for sequence modeling
- Use shared weights across time steps
- Architectures like One-to-Many, Many-to-One fit various tasks
- RNNs face training and memory limitations
- Advances like LSTM, GRU, and Transformers push beyond RNNs

References

These slides have been adapted from

- Younes Mourri & Lukasz Kaiser, [Natural Language Processcing Specialization, DeepLearning.Ai]

References

Core Papers:

- Elman, J. L. (1990). Finding structure in time. *Cognitive Science*.
- Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*.
- Mikolov, T., Karafiát, M., Burget, L., Cernocký, J., & Khudanpur, S. (2010). Recurrent neural network based language model. *Interspeech*.
- Bengio, Y., Simard, P., & Frasconi, P. (1994). Learning long-term dependencies with gradient descent is difficult. *IEEE Transactions on Neural Networks*.
- Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to Sequence Learning with Neural Networks. *NeurIPS*.