Recurrent Neural Networks (RNNs) Improvements

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Motivation

Why Do We Need to Improve RNNs?

- Vanilla RNNs **fail at capturing long-term dependencies**
- Gradients either **vanish or explode** over long sequences
- This **limits learning** over time-based tasks like translation, conversation modeling, or video understanding

Solution: Modify RNN architecture to retain important past information without instability.

Learning Outcomes

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

- Explain why RNNs suffer from vanishing and exploding gradients
- Understand how LSTMs and GRUs solve these problems
- Compare LSTMs and GRUs in terms of performance and complexity
- Identify practical scenarios where each is preferred
- Recognize limitations and future directions in sequence modeling

Vanishing and Exploding Gradients

Backpropagation Through Time (BPTT) spreads gradients across many time steps.

Vanishing Gradients:

$$\left\| \frac{\partial L}{\partial h_t} \right\| \to 0$$

- Early layers barely learn
- Forget long-term dependencies

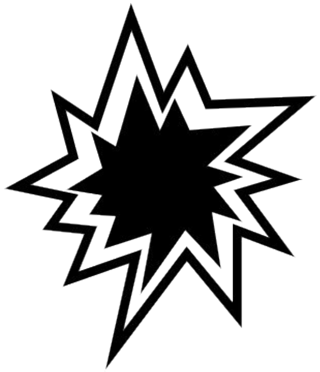
Exploding Gradients:

$$\left\| \frac{\partial L}{\partial h_t} \right\| \to \infty$$

- Unstable updates, diverging weights

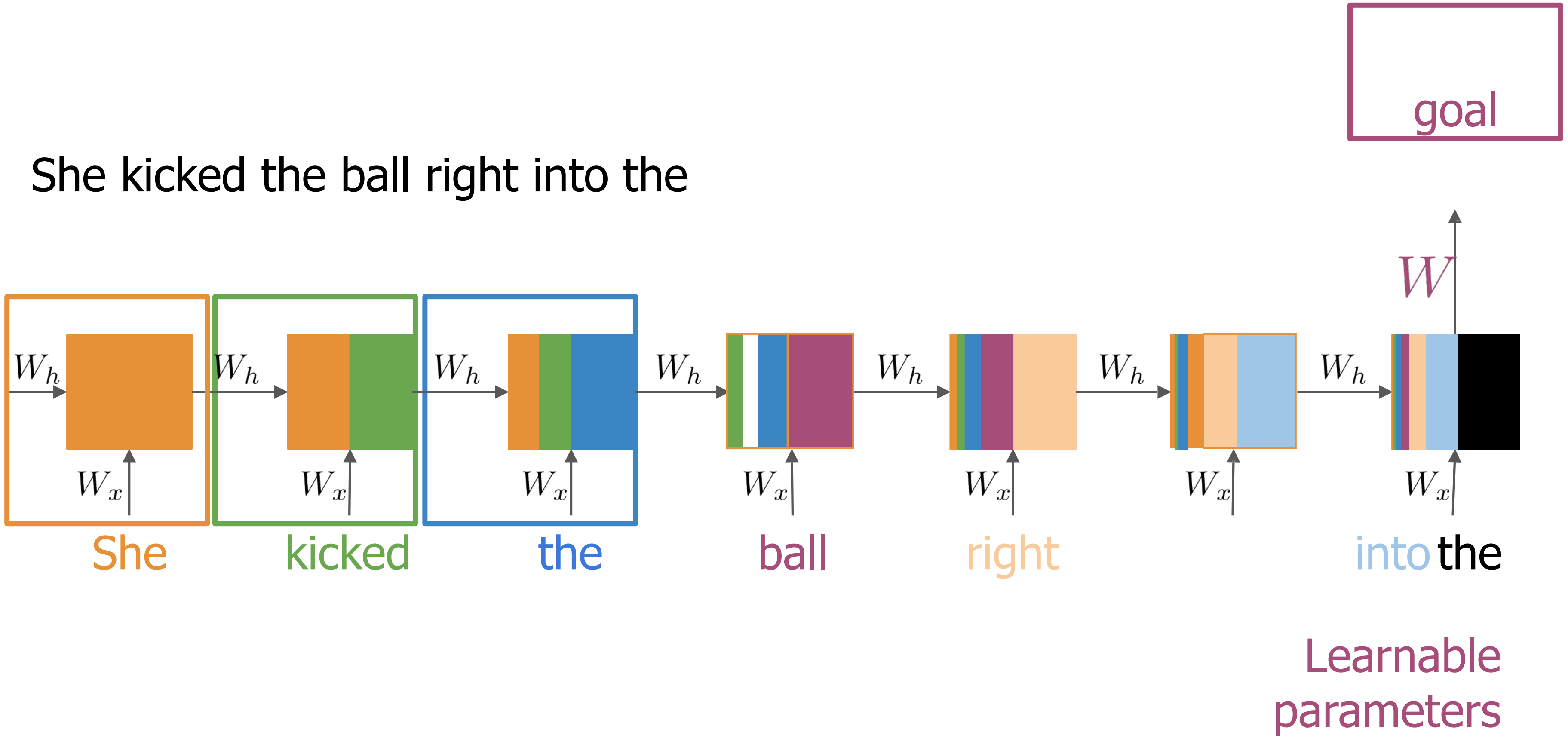
RNNs and Vanishing Gradients

- Backprop through time
- RNNs and vanishing/exploding gradients
- Solutions

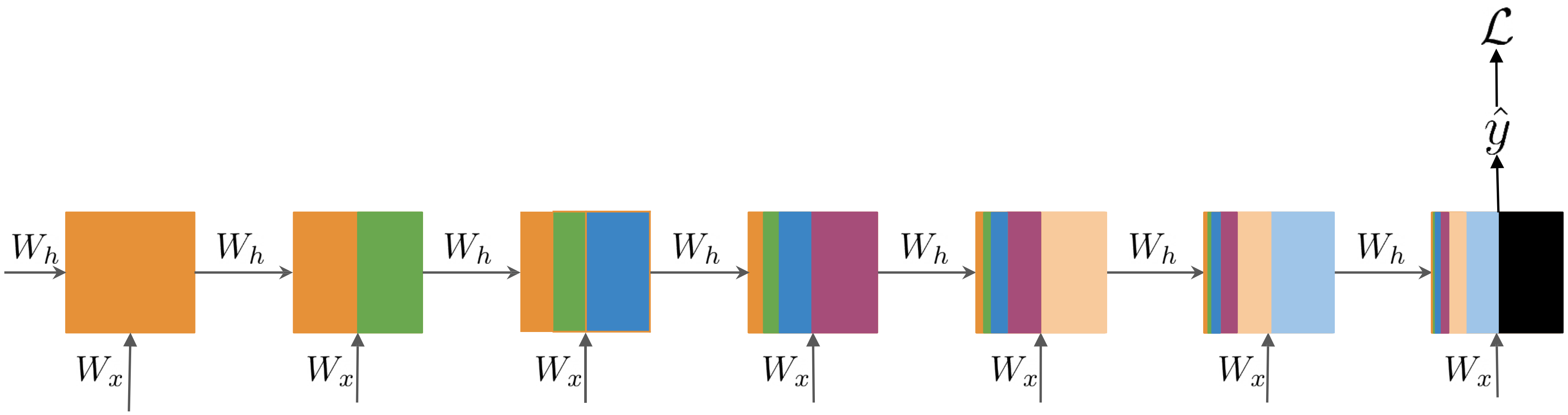


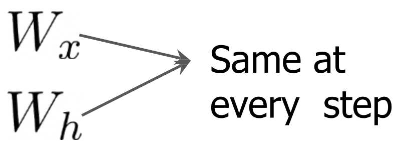
RNN Basic Structure

She kicked the ball right into the



Backpropagation through time





$$\frac{\partial L}{\partial W_h} \propto \sum_{1 \le k \le t} \left(\prod_{t \ge i > k} \frac{\partial h_i}{\partial h_{i-1}} \right) \frac{\partial h_k}{\partial W_h}$$

Gradient is proportional to a sum of partial derivative products

Backpropagation through time

$$\frac{\partial L}{\partial W_h} \propto \sum_{1 \le k \le t} \boxed{\left(\boxed{\prod_{t \ge i > k} \frac{\partial h_i}{\partial h_{i-1}}} \right) \frac{\partial h_k}{\partial W_h}}$$

Contribution of hidden state ***k***

Length of the product proportional to how far ***k*** is from ***t***

$$\boxed{\frac{\partial h_t}{\partial h_{t-1}} \frac{\partial h_{t-1}}{\partial h_{t-2}} \frac{\partial h_{t-2}}{\partial h_{t-3}} \frac{\partial h_{t-3}}{\partial h_{t-4}} \frac{\partial h_{t-4}}{\partial h_{t-5}} \frac{\partial h_{t-5}}{\partial h_{t-6}} \frac{\partial h_{t-6}}{\partial h_{t-7}} \frac{\partial h_{t-7}}{\partial h_{t-8}} \frac{\partial h_{t-8}}{\partial h_{t-9}} \frac{\partial h_{t-9}}{\partial h_{t-10}} \frac{\partial h_{t-10}}{\partial W_h}}$$

Contribution of hidden state ***t-10***

Backpropagation through time

$$\frac{\partial L}{\partial W_h} \propto \sum_{1 \leq k \leq t} \boxed{\left(\boxed{\prod_{t \geq i > k} \frac{\partial h_i}{\partial h_{i-1}}} \right) \frac{\partial h_k}{\partial W_h}}$$

Contribution of hidden state ***k***

Length of the product proportional to how far ***k*** is from ***t***

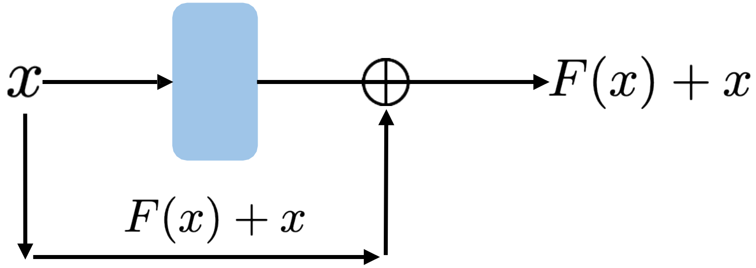
Partial derivatives <1	Contribution goes to 0	Vanishing Gradient
Partial derivatives >1	Contribution goes to infinity	**Exploding** Gradient

Solving for vanishing or exploding gradients

- Identity RNN with ReLU activation

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

- Gradient clipping
- Skip connections



RNNs: Advantages

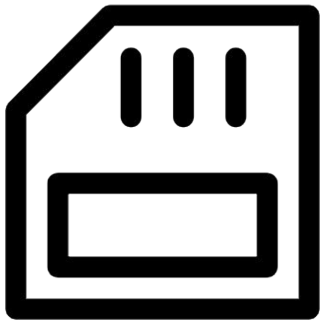
- Captures dependencies within a short range
- Takes up less RAM than other n-gram models

RNNs: Disadvantages

- Struggles to capture long term dependencies
- Prone to vanishing or exploding gradients

LSTMs

- Meet the Long short-term memory unit!
- LSTM architecture
- Applications



LSTM – Long Short-Term Memory

Introduced by Hochreiter & Schmidhuber (1997)

Core Idea: LSTM uses **gates** to control what to keep, forget, and output.

Key Components:

- **Forget Gate** f_t
- **Input Gate** i_t
- **Cell State** C_t
- **Output Gate** o_t

LSTM – Long Short-Term Memory

Equations:

$$
\begin{aligned}
f_t &= \sigma(W_f[x_t, h_{t-1}] + b_f) \\
i_t &= \sigma(W_i[x_t, h_{t-1}] + b_i) \\
\tilde{C}_t &= \tanh(W_C[x_t, h_{t-1}] + b_C) \\
C_t &= f_t * C_{t-1} + i_t * \tilde{C}_t \\
o_t &= \sigma(W_o[x_t, h_{t-1}] + b_o) \\
h_t &= o_t * \tanh(C_t)
\end{aligned}
$$

Helps retain long-term dependencies

LSTMs: a memorable solution

- Learns when to remember and when to forget
- Basic anatomy:
  - A cell state
  - A hidden state
  - Multiple gates
- Gates allow gradients to avoid vanishing and exploding

LSTMs: Based on previous understanding

Starting point with some irrelevant information

↓

Cell and Hidden States

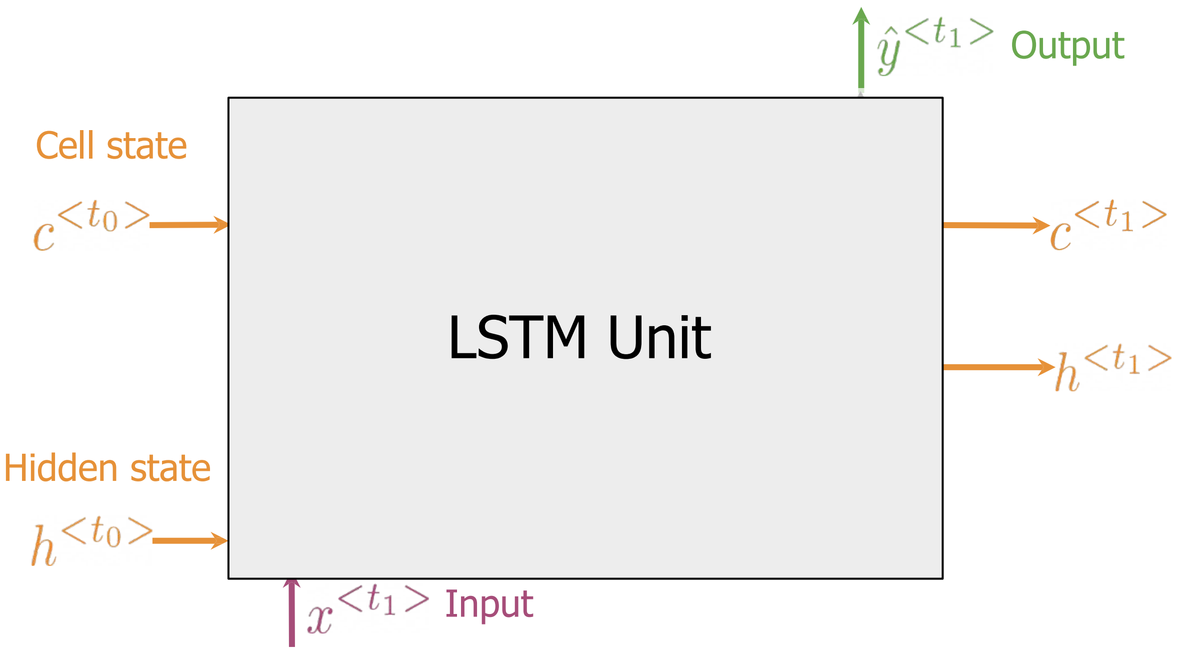
Discard anything irrelevant

Add important new information

Produce output

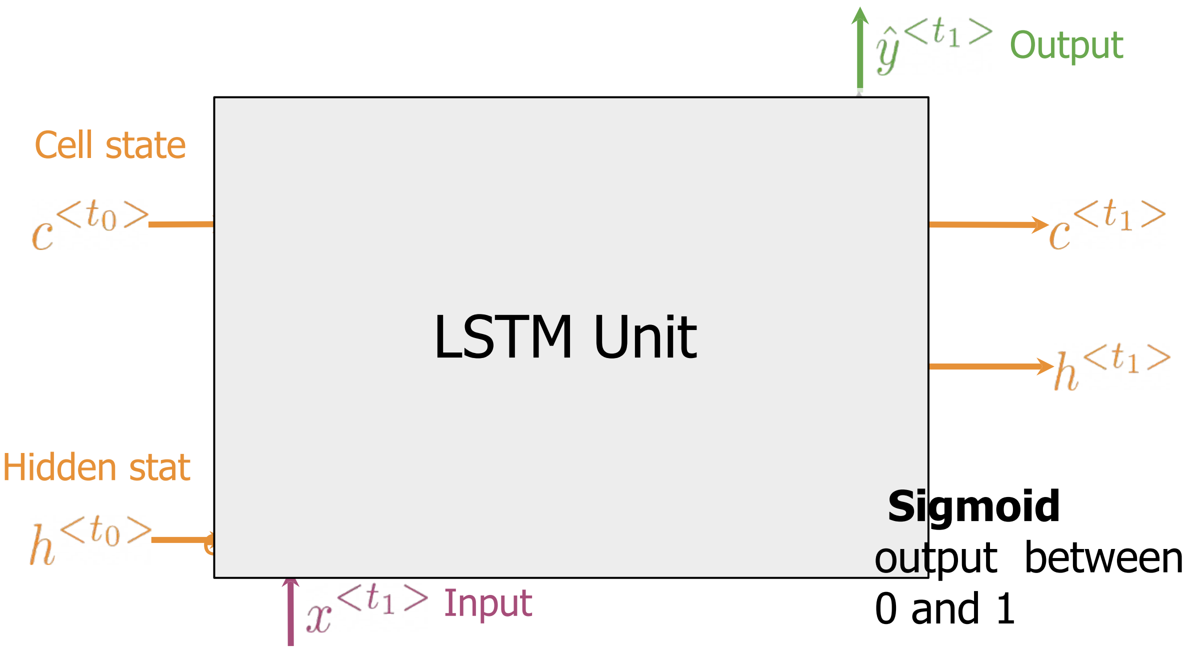
→ Gates

Gates in LSTM



1. **Forget Gate**: information that is no longer important
2. **Input Gate**: information to be stored
3. **Output Gate**: information to use at current step

Gates in LSTM

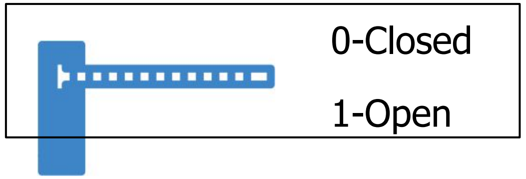


Sigmoid
output between
0 and 1

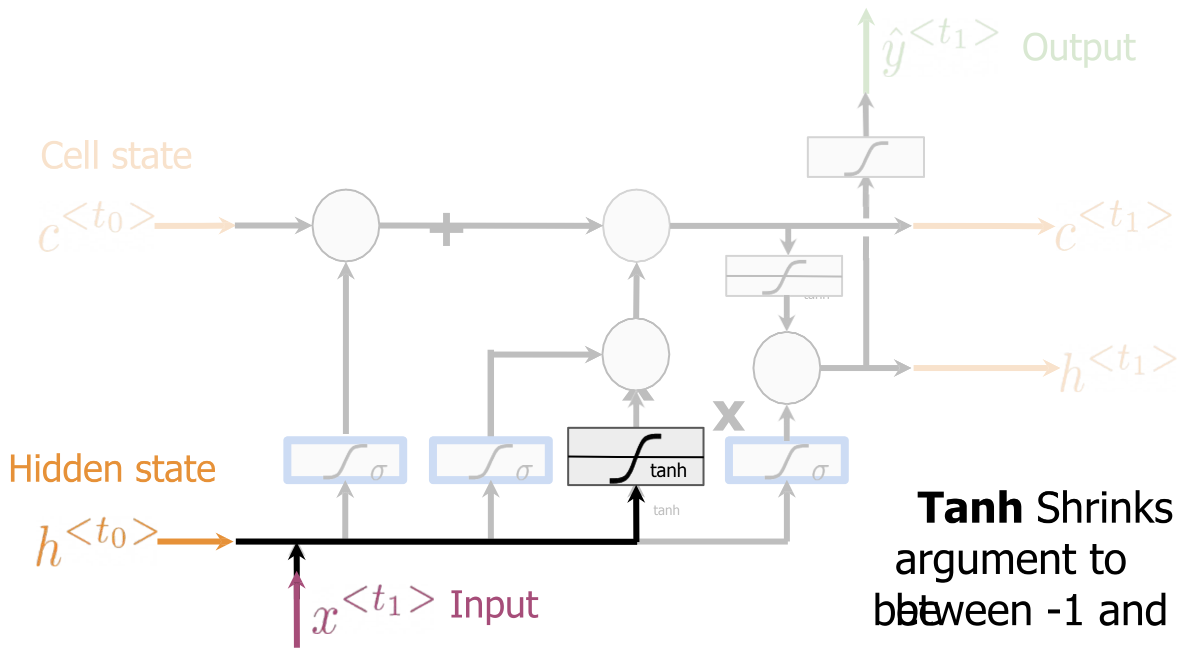
1. Forget Gate:
information that is no longer important

2. Input Gate:
information
to be stored

3. Output Gate:
information to use at current step



Candidate Cell State



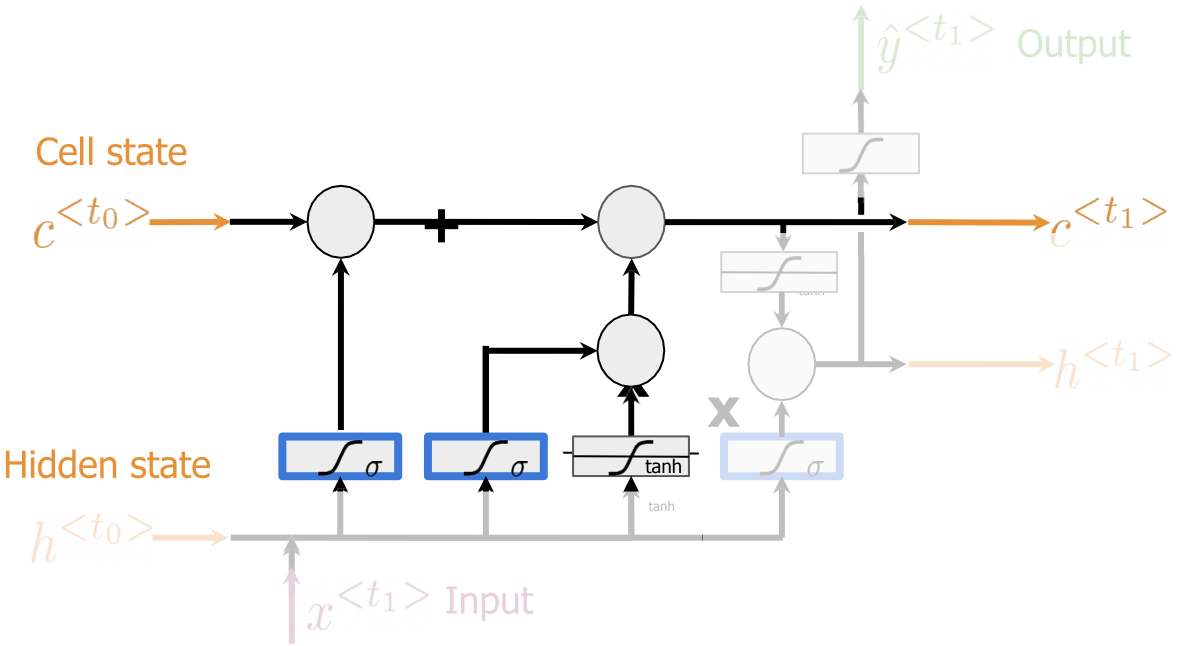
Candidate cell state

Information from the previous **hidden state** and current **input**

Tanh Shrinks argument to between -1 and 1

Other activations could be used

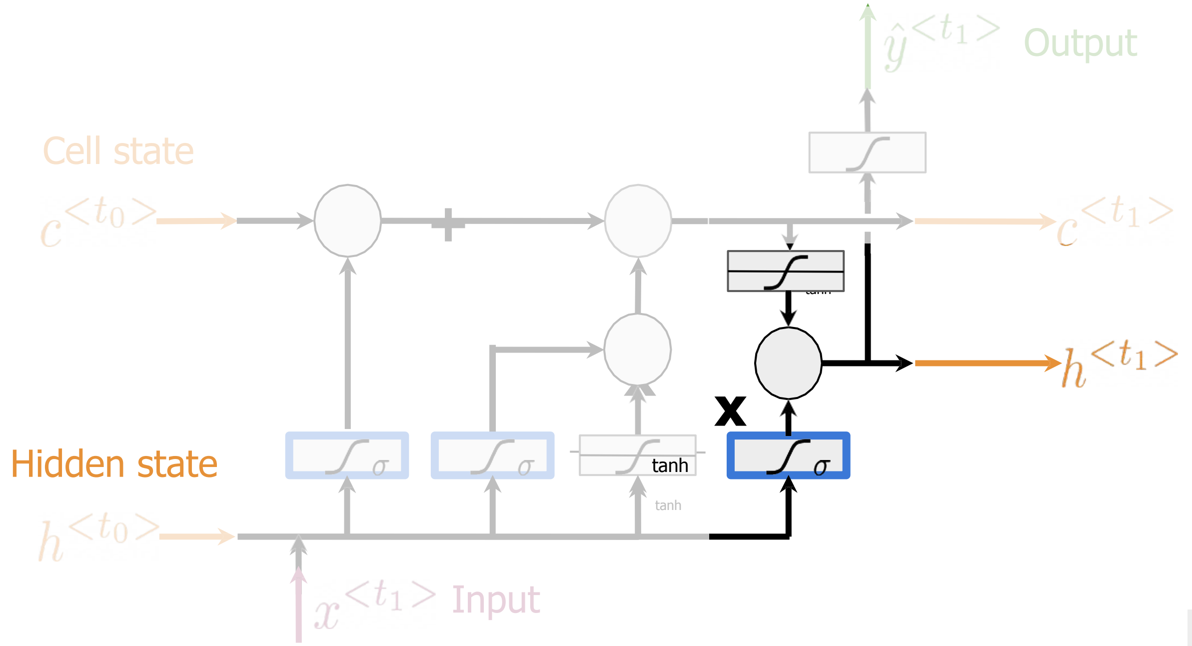
New Cell State



New Cell state

Add information from the **candidate cell state** using the **forget** and **input gates**

New Hidden State



New Hidden State

Select information from the **new cell state** using the **output gate**

The **Tanh** activation could be omitted

Applications of LSTMs

Next-character prediction

Chatbots

Music composition

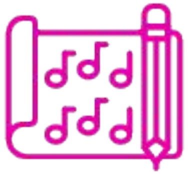


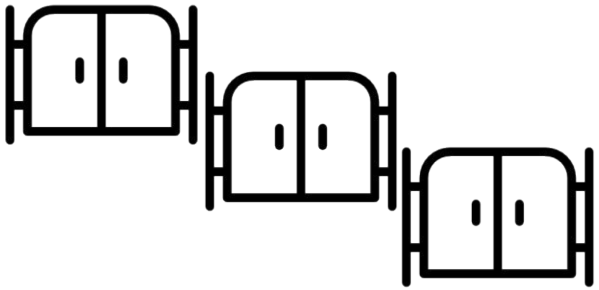
Image captioning

Speech recognition

Summary

- LSTMs offer a solution to vanishing gradients

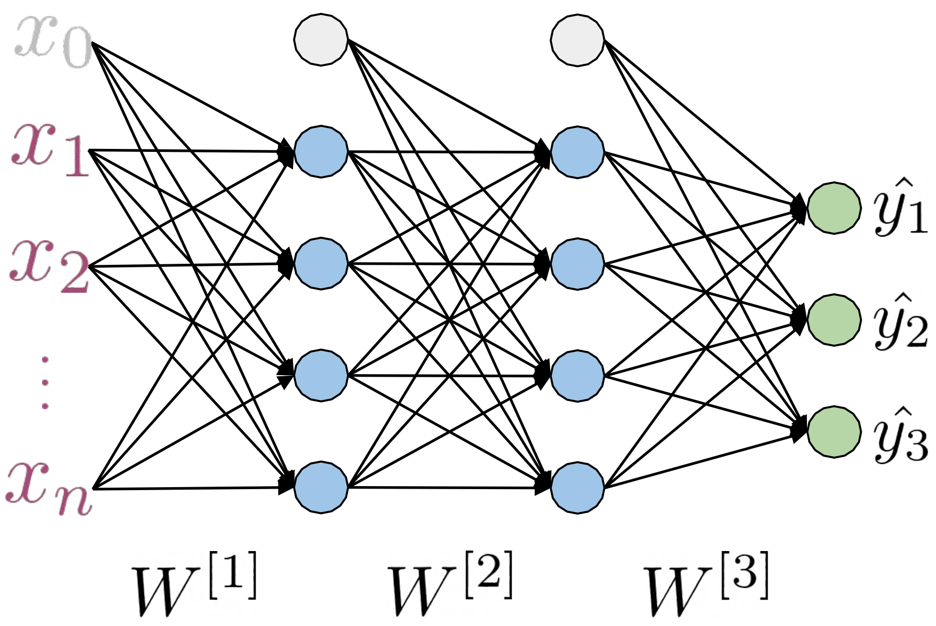
- Typical LSTMs have a cell and three gates:
  - Forget gate
  - Input gate
  - Output gate



Summary

- LSTMs use a series of gates to decide which information to keep:
  - Forget gate decides what to keep
  - Input gate decides what to add
  - Output gate decides what the next hidden state will be

Cross Entropy Loss



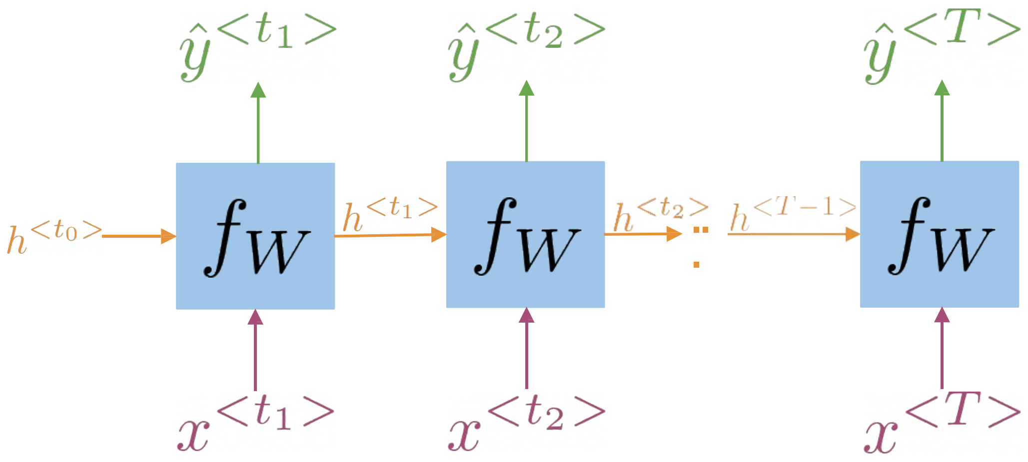
K - classes or possibilities

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 for RNNs



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

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

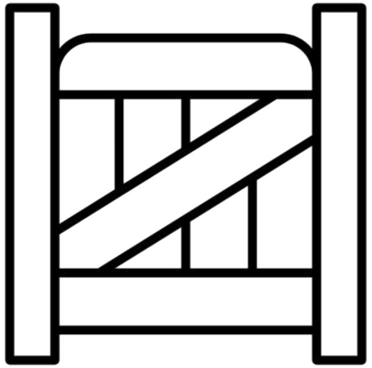
$$J = -\frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{K} y_j^{<t>} \log \hat{y}_j^{<t>}$$

Average with respect to time

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

Gated Recurrent Unit (GRU)

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



GRU – Gated Recurrent Unit

Introduced by Cho et al., 2014

Simpler than LSTM, with fewer gates

- No separate memory cell
- Combines forget and input into **update gate**

Key Components:

- **Update Gate** z_t
- **Reset Gate** r_t

GRU – Gated Recurrent Unit

Equations:

$$
\begin{aligned}
z_t &= \sigma(W_z[x_t, h_{t-1}]) \\
r_t &= \sigma(W_r[x_t, h_{t-1}]) \\
\tilde{h}_t &= \tanh(W_h[x_t, r_t * h_{t-1}]) \\
h_t &= (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t
\end{aligned}
$$

Comparable performance to LSTM
Faster training, fewer parameters

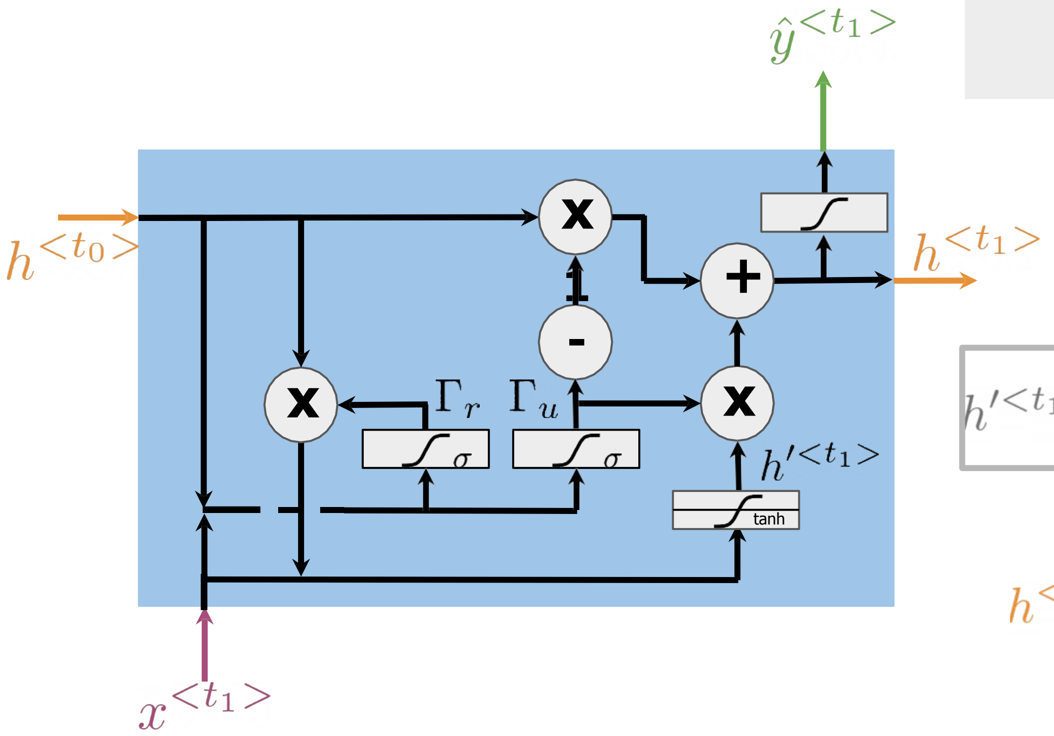
Gated Recurrent Units

“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

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

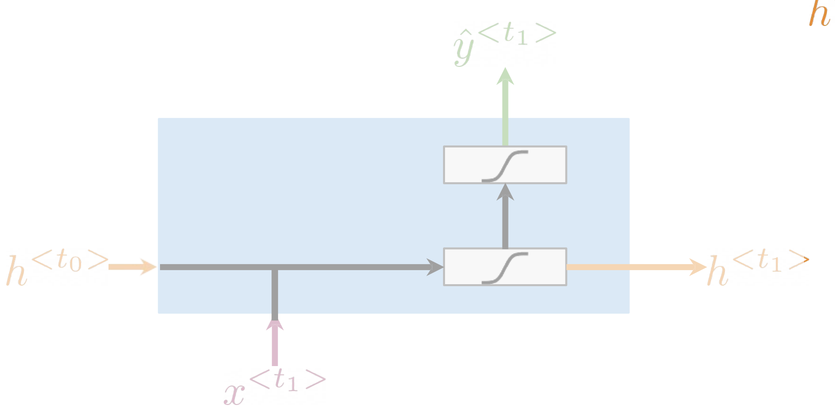
$$h'^{<t_1>} = \tanh\left(W_h[\Gamma_r * h^{<t_0>}, x^{<t_1>}] + b_h\right)$$

Hidden state candidate

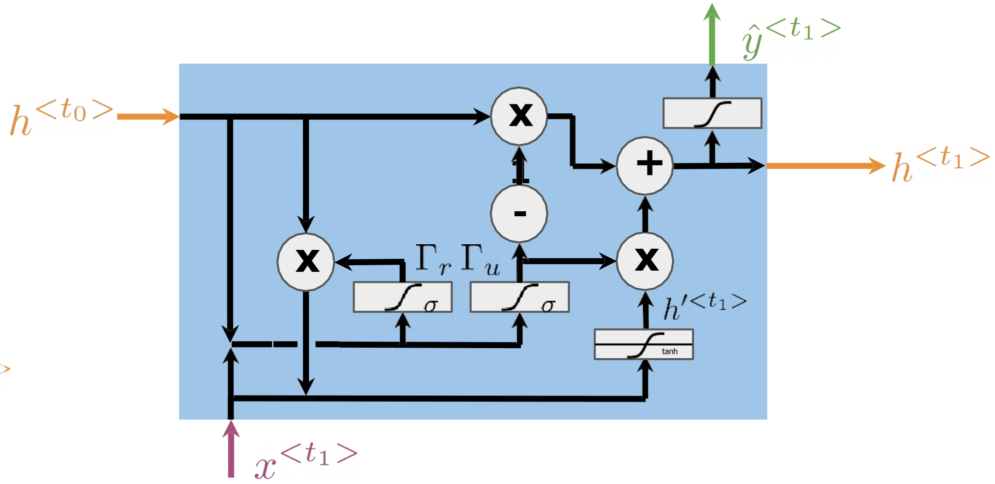
$$h^{<t_1>} = (1 - \Gamma_u) * h^{<t_0>} + \Gamma_u * h'^{<t_1>}$$

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

Vanilla RNN vs GRUs



$$h^{<t>} = g(W_h[h^{<t-1>}, x^{<t>}] + b_h)$$
$$\hat{y}^{<t>} = g(W_{yh}h^{<t>} + b_y)$$

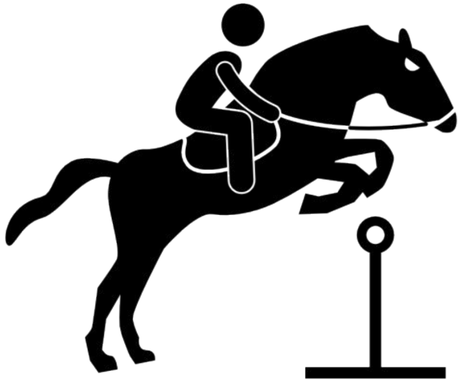


$$\Gamma_u = \sigma(W_u[h^{<t_0>}, x^{<t_1>}] + b_u)$$
$$\Gamma_r = \sigma(W_r[h^{<t_0>}, x^{<t_1>}] + b_r)$$
$$h'^{<t_1>} = \tanh\left(W_h[\Gamma_r * h^{<t_0>}, x^{<t_1>}] + b_h\right)$$
$$h^{<t_1>} = (1 - \Gamma_u) * h^{<t_0>} + \Gamma_u * h'^{<t_1>}$$
$$\hat{y}^{<t_1>} = g(W_y h^{<t_1>} + b_y)$$

Summary

- GRUs “decide” how to update the hidden state

- GRUs help preserve important information



LSTM vs GRU

Feature	LSTM	GRU
Gates	3 (i, f, o)	2 (z, r)
Memory Cell	Yes	No
Complexity	Higher	Lower
Training Speed	Slower	Faster
Performance	Great for long sequences	Similar or better on short tasks

Tip: Try GRU first for faster results; switch to LSTM if performance suffers.

Use Cases for GRU/LSTM

NLP Tasks

- Language Modeling
- Machine Translation
- Sentiment Analysis
- Chatbots

Audio & Time Series

- Music Generation
- Speech Recognition
- Anomaly Detection

Video & Sequential Vision

- Action Recognition
- Video Captioning

Limitations

Even with GRU/LSTM:

- Still sequential $\rightarrow$ Hard to parallelize
- Struggle with very long-range dependencies
- Architectural complexity
- Hard to interpret gate decisions
- Require lots of training data

Future Directions

- **Transformers:** Fully parallelized sequence modeling using attention
- **Efficient Attention:** Longformer, Linformer, etc. for long sequences
- **Neural Memory Networks:** Explicit memory read/write
- **Recurrent Attention Models**
- **Hybrid Architectures:** RNN + CNN + Attention

RNNs are still used in edge devices for efficient modeling

Summary

- RNNs struggle with long dependencies due to vanishing/exploding gradients
- GRU and LSTM improve memory retention using gating mechanisms
- GRU is simpler and faster; LSTM is more expressive
- Attention and transformers now dominate, but RNNs remain relevant in many domains

References

Foundational Papers:

- Hochreiter, S., & Schmidhuber, J. (1997). *Long Short-Term Memory*. Neural Computation.
- Cho, K., van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). *Learning Phrase Representations using RNN Encoder–Decoder with GRU*. EMNLP.
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- Bengio, Y., Simard, P., & Frasconi, P. (1994). *Learning long-term dependencies*. IEEE Transactions on Neural Networks.
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). *Attention Is All You Need*. NeurIPS.

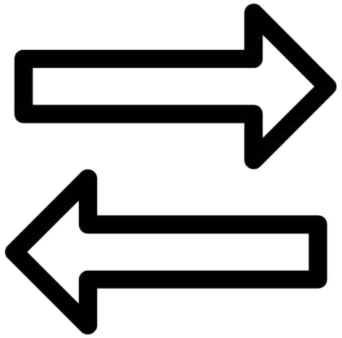
References

Resources:

- Karpathy's RNN Blog: https://karpathy.github.io/2015/05/21/rnn-effectiveness/
- CS231n Lecture Notes on RNNs and LSTM
- DeepLearning.ai NLP Specialization – Coursera
- MIT 6.S191 Deep Learning Lecture Slides

Deep and Bi- directional RNNs

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

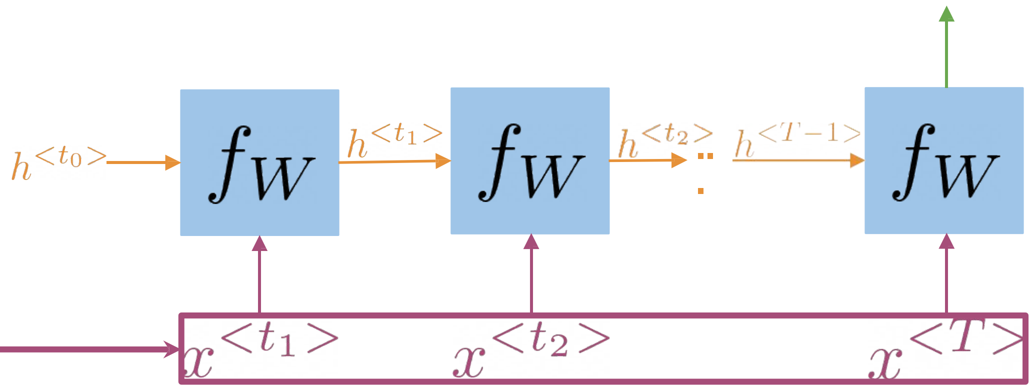


Bi-directional RNNs

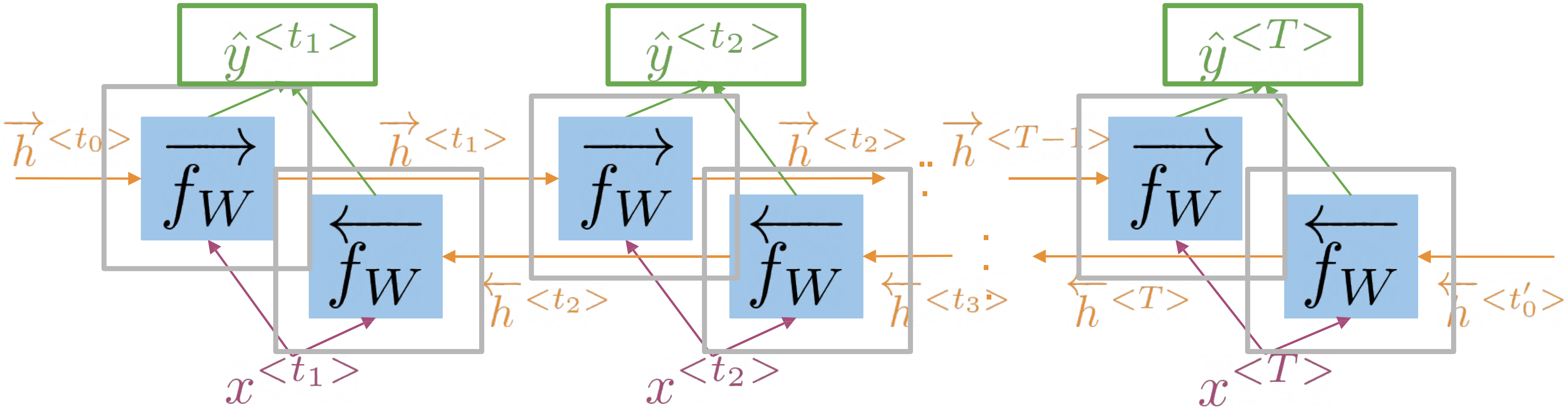
I was trying really hard to get a hold of
answered when I was about to give
up.

. **Louise,** finally

her him them



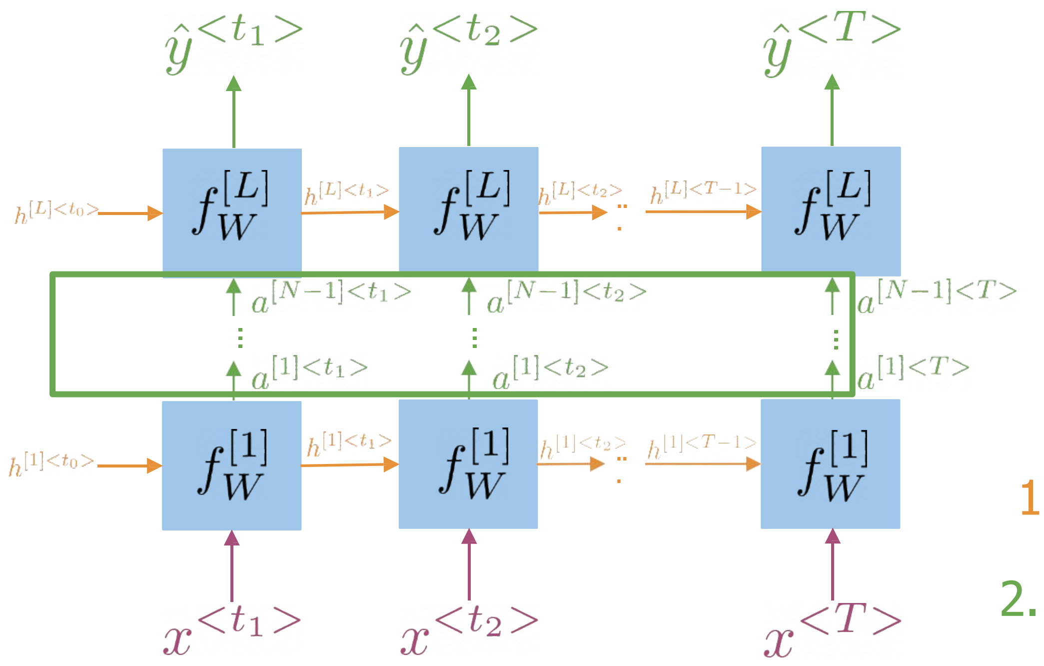
Bi-directional RNNs



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

References

These slides have been adapted from

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