

Overview

- Sequences
- Amped up RNNs (LSTMs + GRUs)
- Encoder - Decoder (Seq2Seq)

Deep Learning and Sequences

- Sequences
 - Variable length
 - Relationships between elements of sequence
- Examples
 - Text
 - Time Series
- Models
 - Continuous Bag of Words (CBOW)
 - 1D CNN
 - Recurrent Neural Network (RNN)

Deep Learning and Sequences

- Sequences
 - Variable length
 - Relationships between elements of sequence
- Examples
 - Text
 - Time Series
- Models
 - Continuous Bag of Words (CBOW)
 - 1D CNN
 - Recurrent Neural Network (RNN)
 - Attention (Next!)

Deep Learning and Sequences

- Models
 - Continuous Bag of Words (CBOW)
 - 1D CNN
 - Recurrent Neural Network (RNN)
- Average feature vectors together to get fixed length input
- Lose a lot information about the sequence

Deep Learning and Sequences

- Models
 - Continuous Bag of Words (CBOW)
 - 1D CNN
 - Recurrent Neural Network (RNN)
- Doesn't care about sequence length
- Uses filters to construct features from local interactions
- Difficult to capture long range dependencies

Deep Learning and Sequences

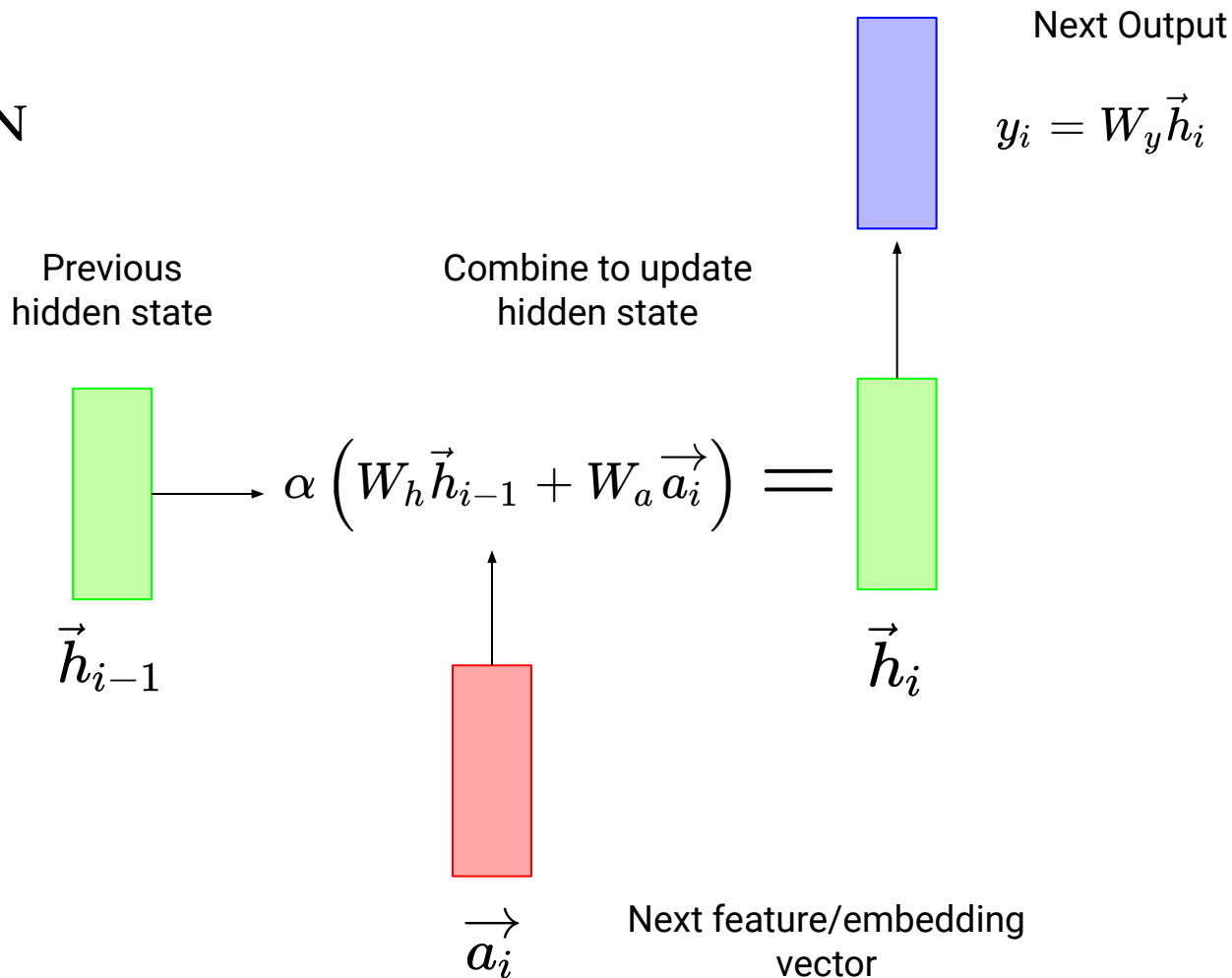
- Models
 - Continuous Bag of Words (CBOW)
 - 1D CNN
 - Recurrent Neural Network (RNN)
- Updates a hidden state as the sequence is fed into the RNN
- Vanishing/Exploding gradient problem
- Doesn't have great long-term memory
- Slow (can't parallelize updates to a hidden state)

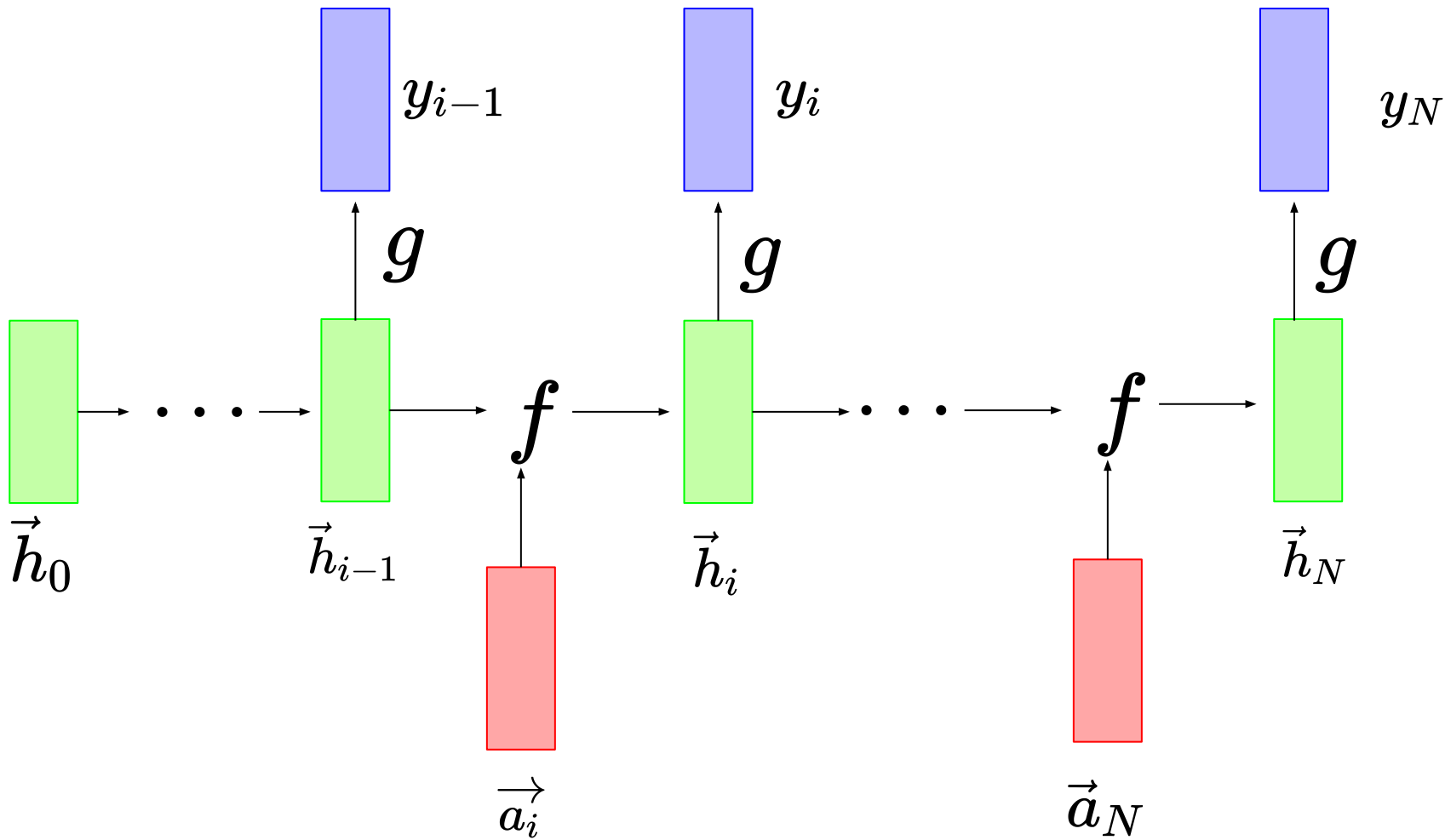
Deep Learning and Sequences

- Models
 - Continuous Bag of Words (CBOW)
 - 1D CNN
 - Recurrent Neural Network (RNN)
 - LSTMs, GRUs, and more!
- Fancier updates to a hidden state as the sequence is fed into the NN
- Helps with Vanishing/Exploding gradient problem
- Helps with long-term memory
- Still Slow (can't parallelize updates to a hidden state)

RNNs

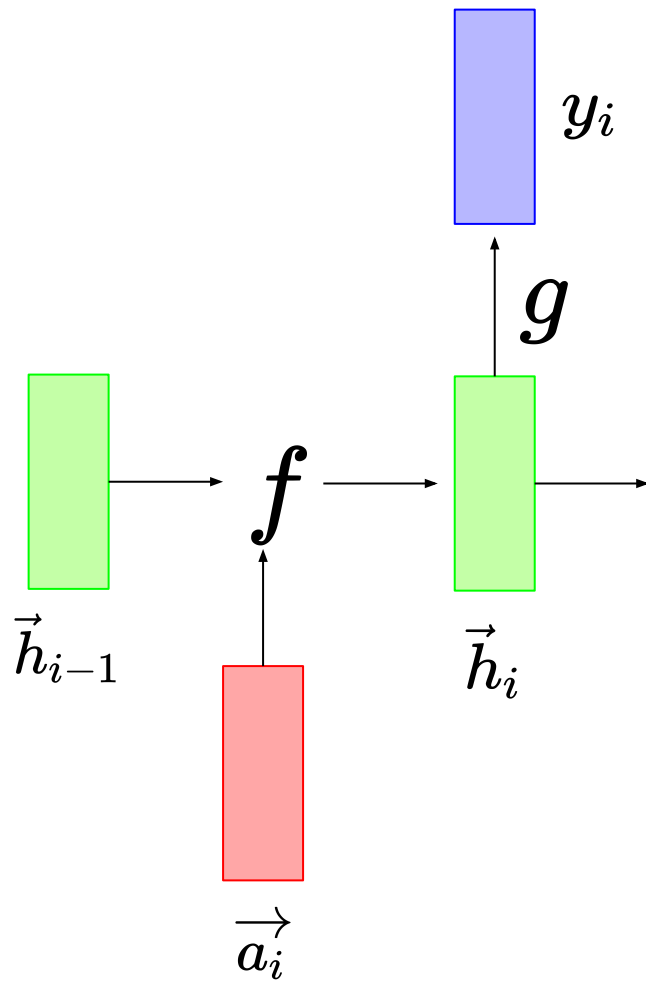
- Vanilla RNN



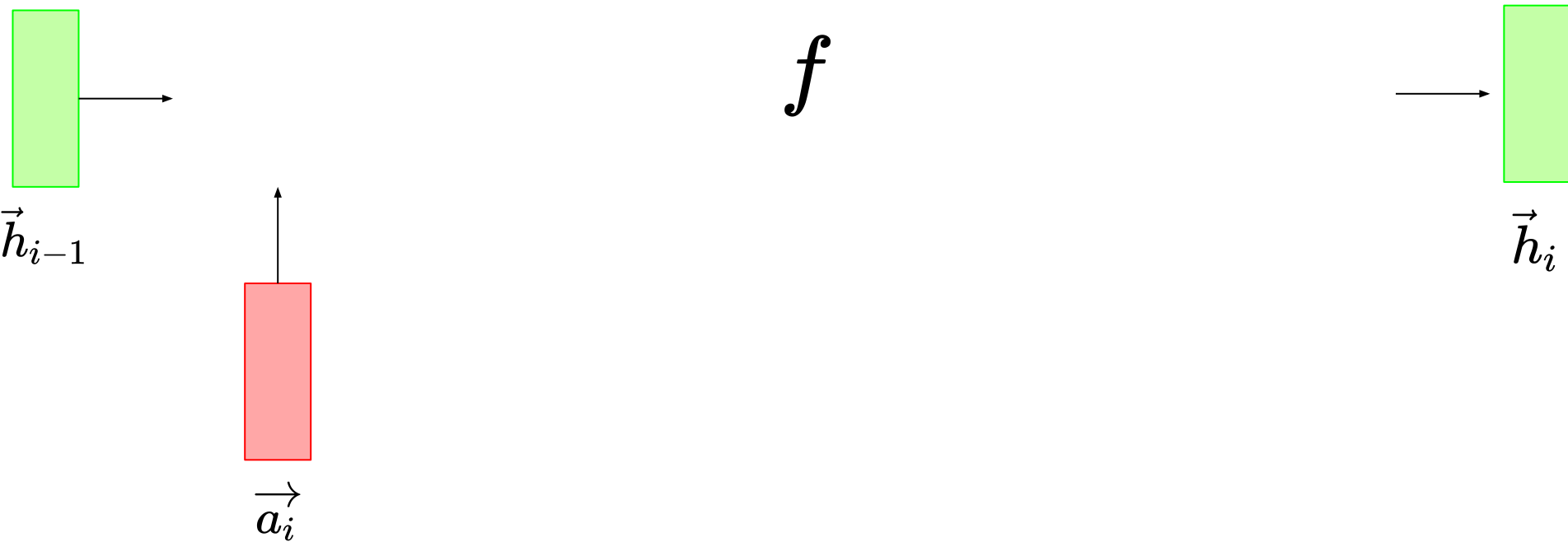


The GRU

- Gated Recurrent Unit
- Idea: Change the function f to address common RNN problems



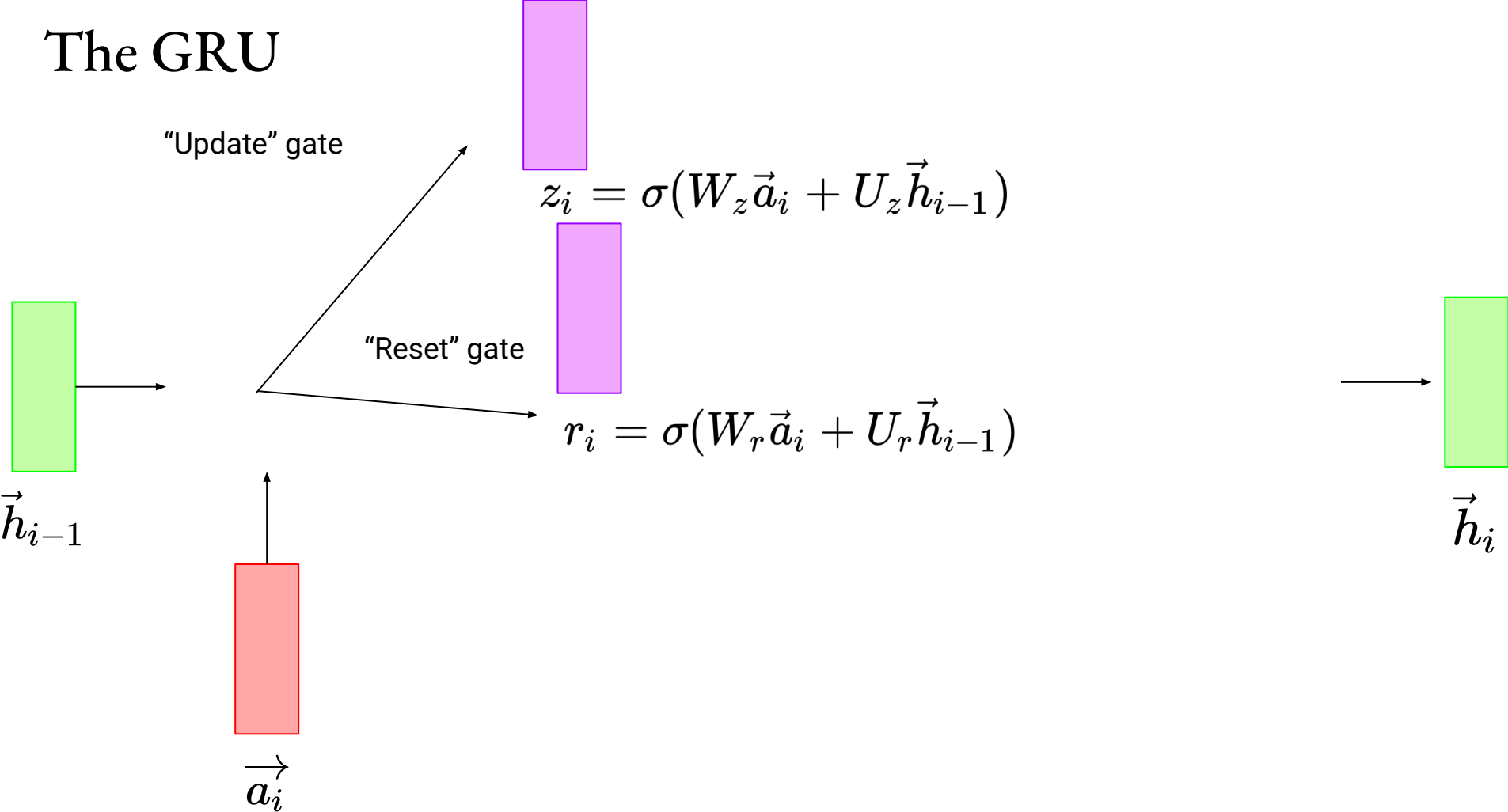
The GRU



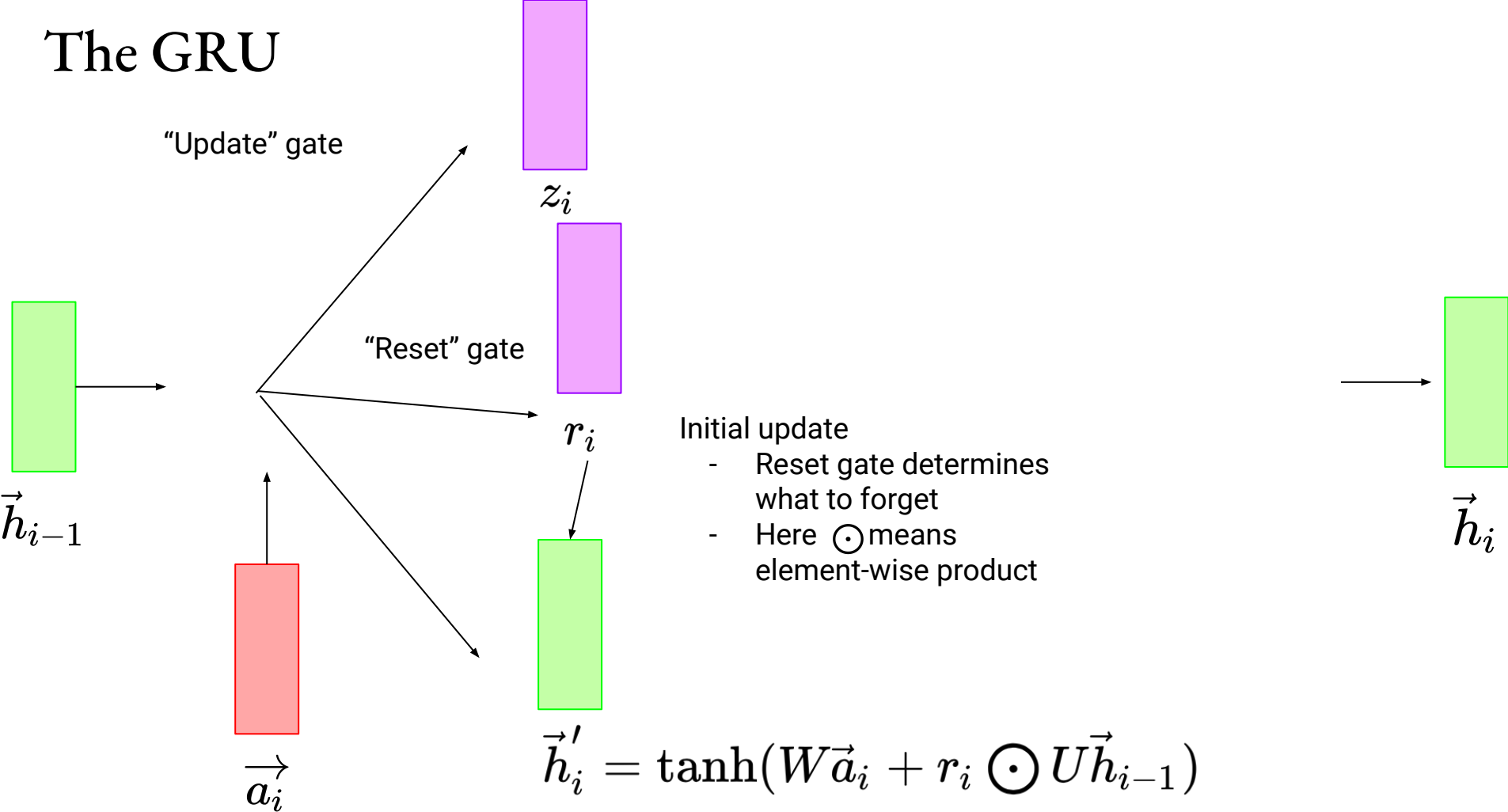
The GRU



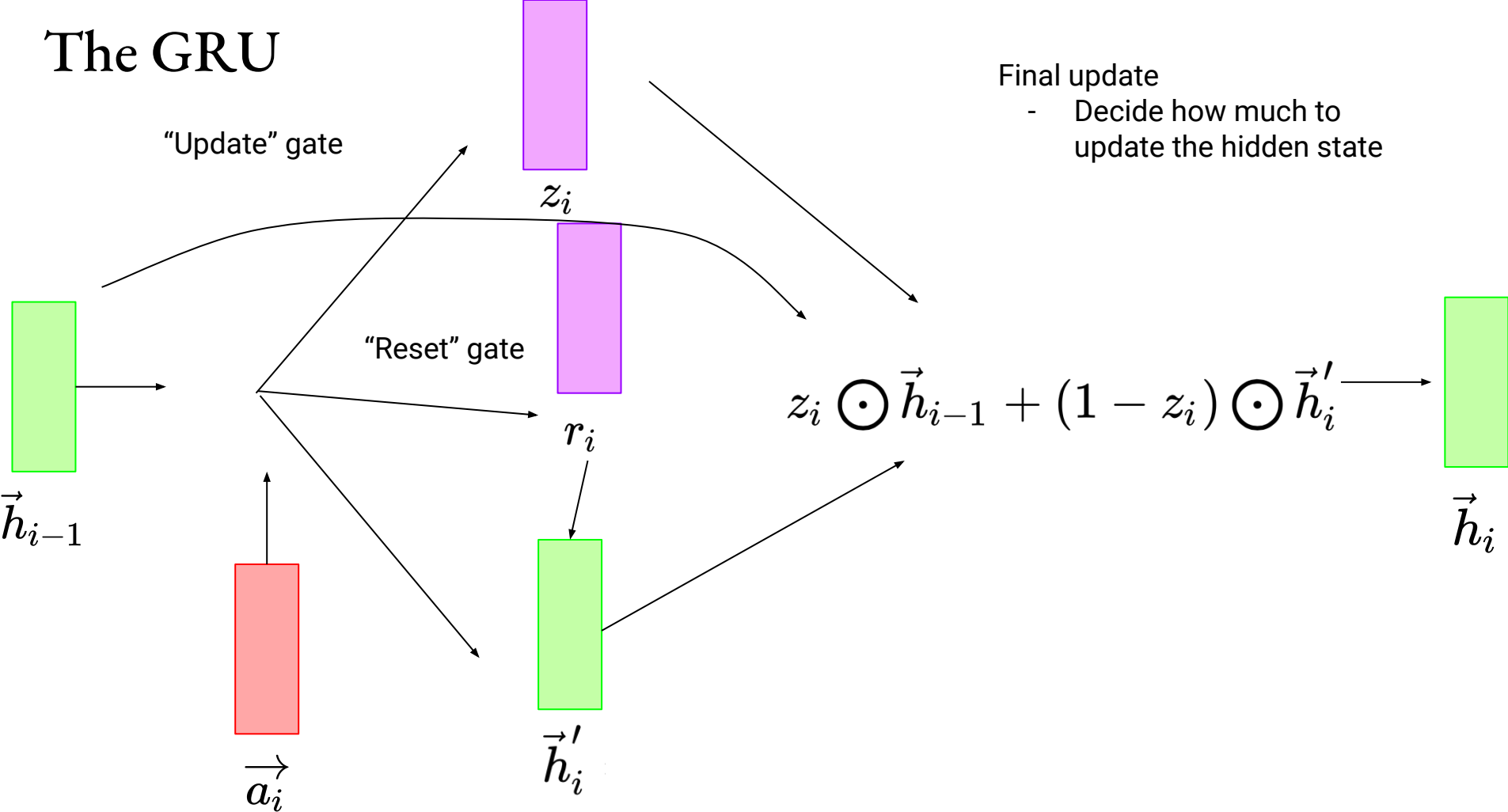
The GRU



The GRU

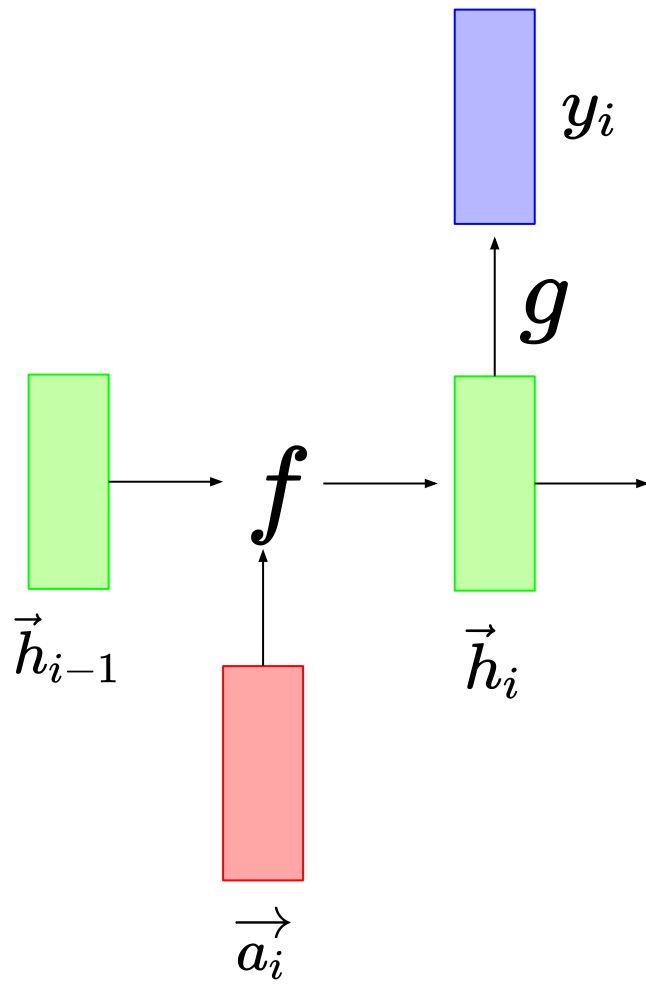


The GRU



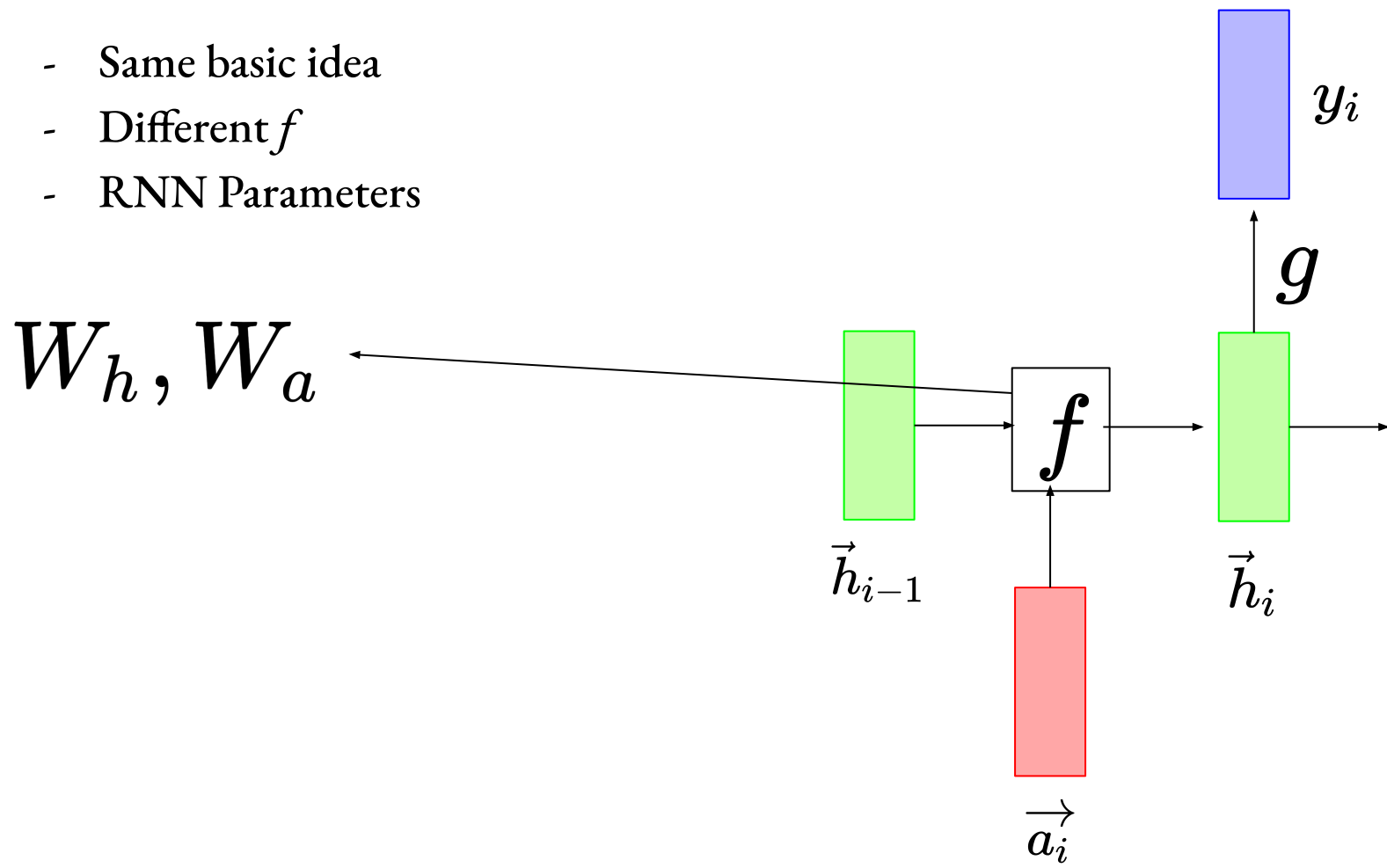
Recurrent Unit

- Same basic idea
- Different f



Recurrent Unit

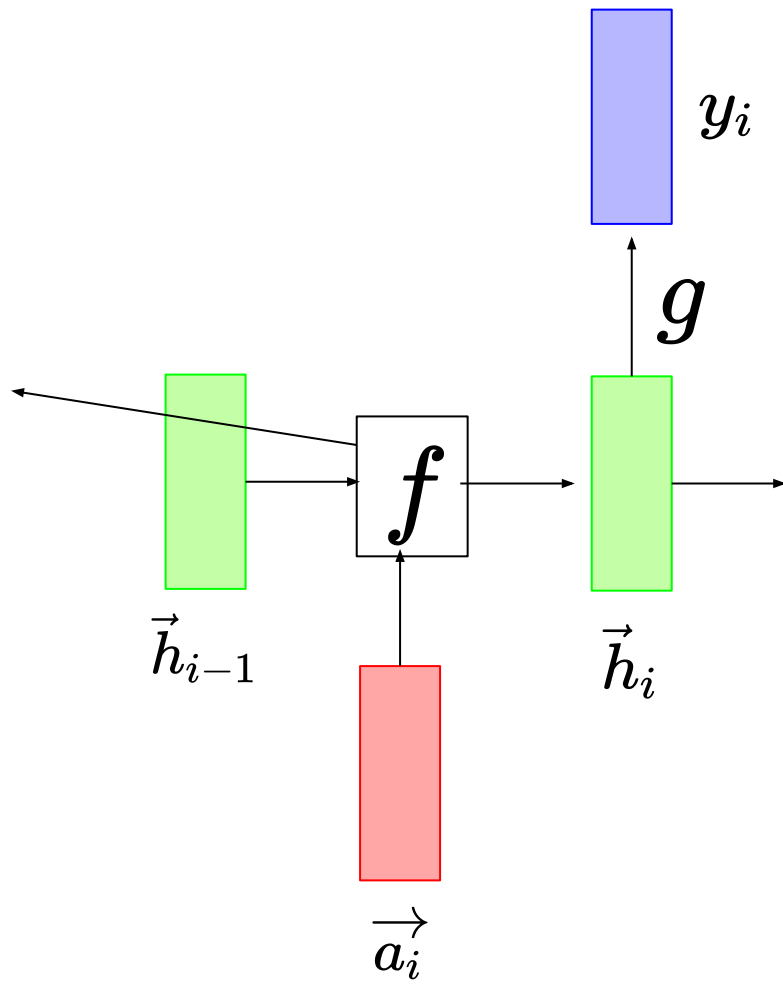
- Same basic idea
- Different f
- RNN Parameters



Recurrent Unit

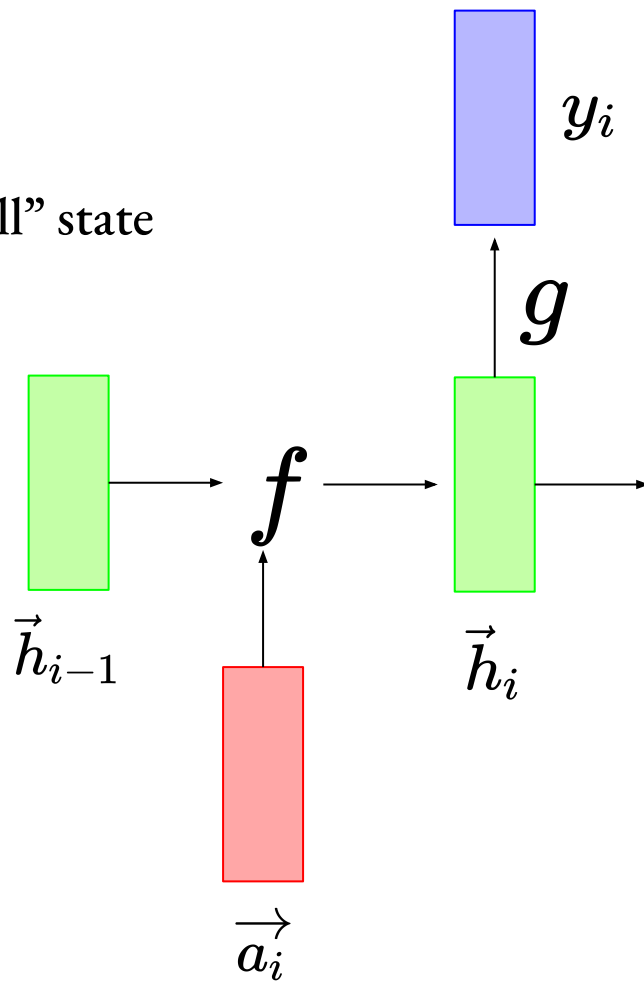
- Same basic idea
- Different f
- GRU Parameters

W, U, W_z, U_z, W_a, U_a



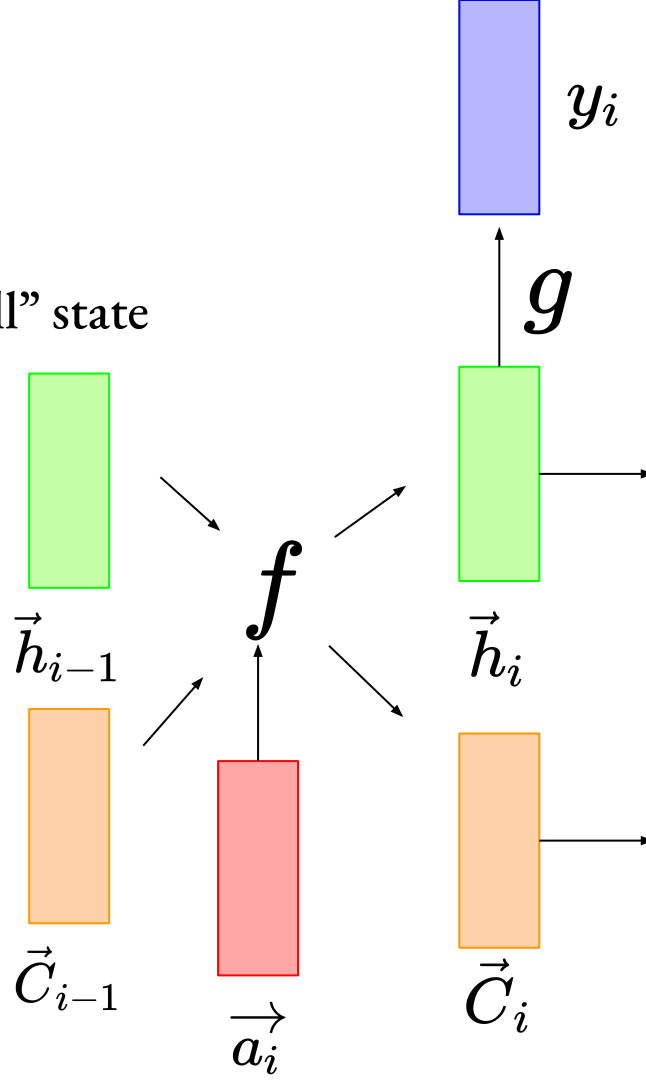
The LSTM

- Long Short-Term Memory
- Idea: Change the function f to address common RNN problems and add a “cell” state

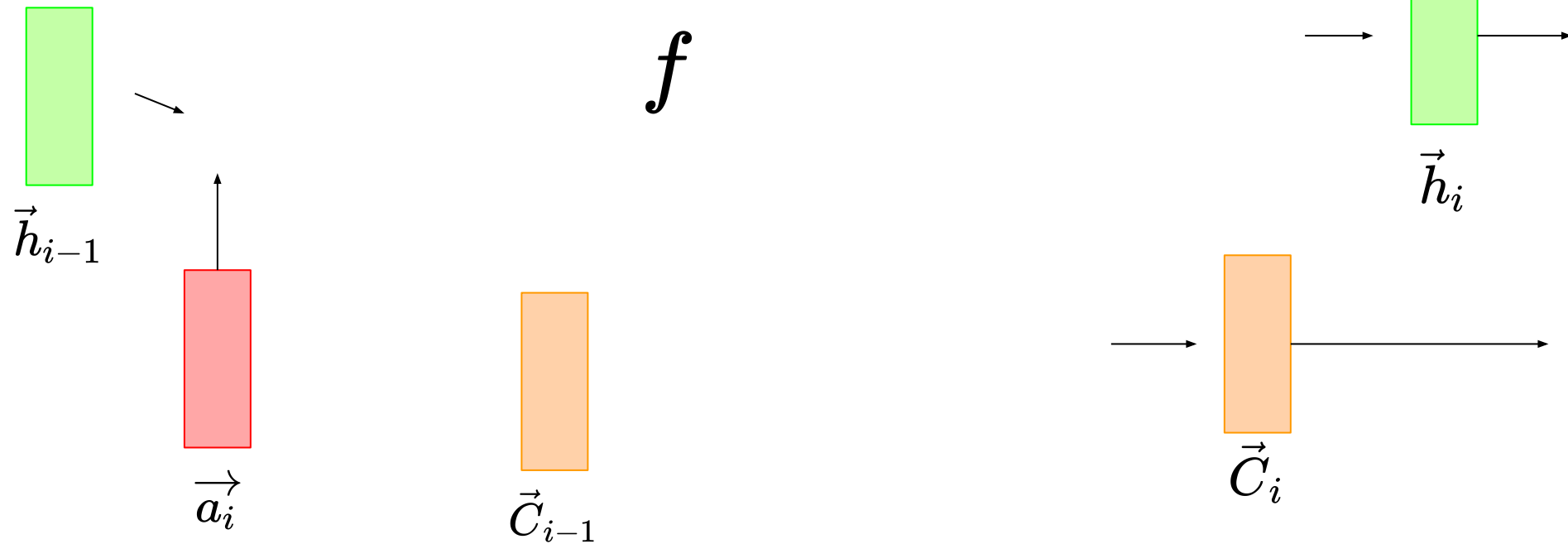


The LSTM

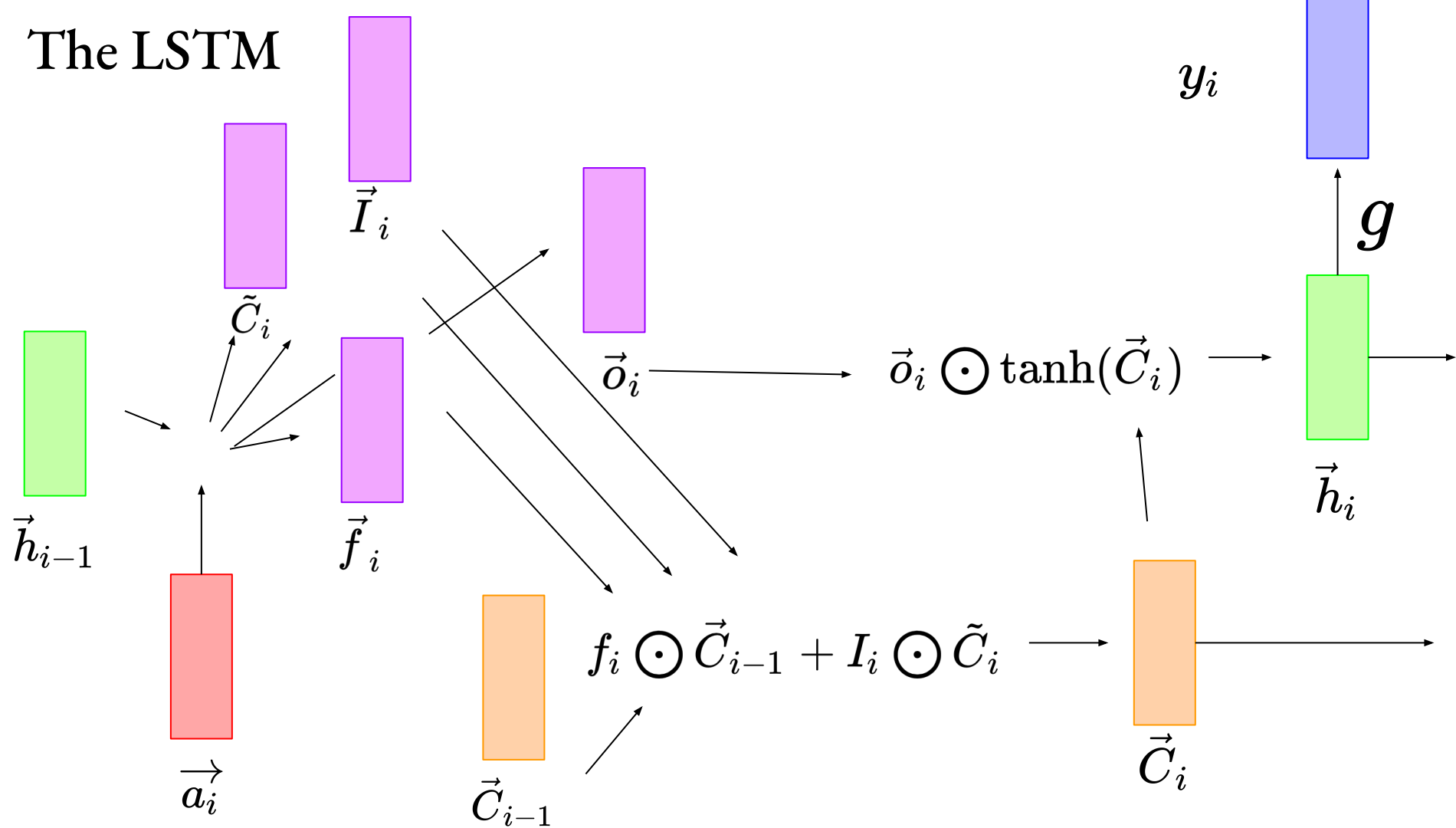
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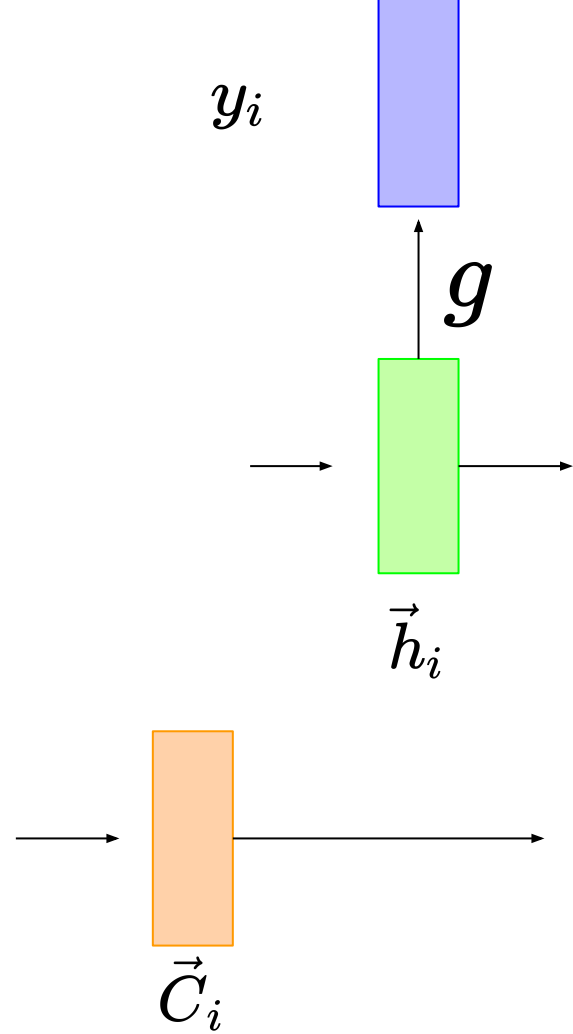
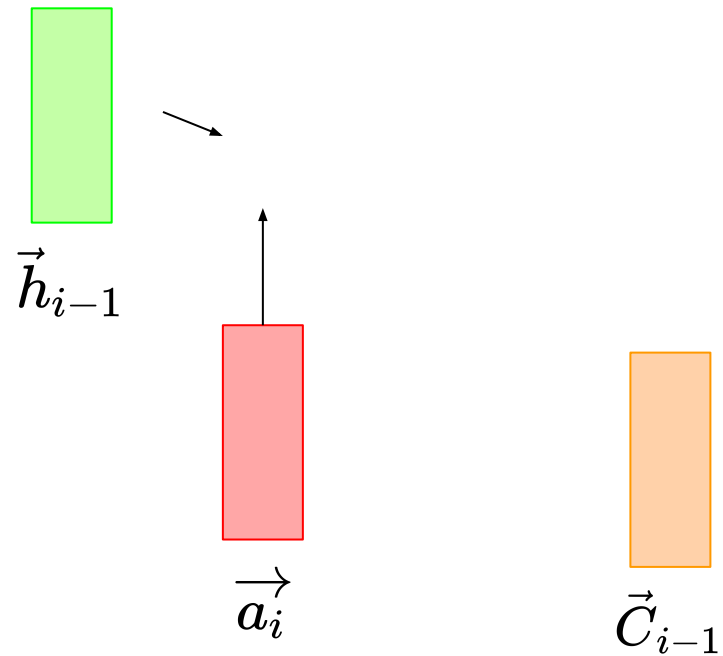
The LSTM



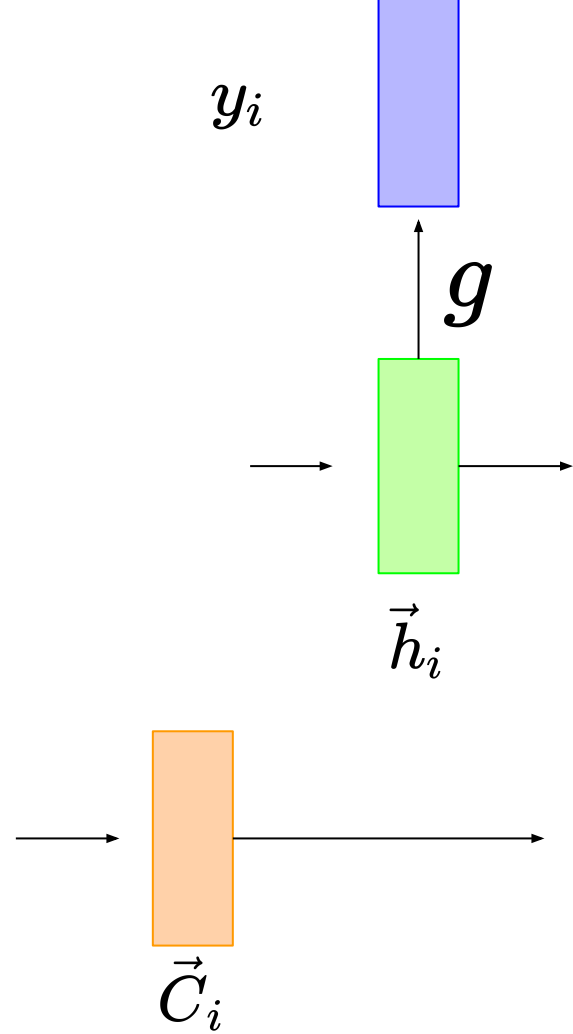
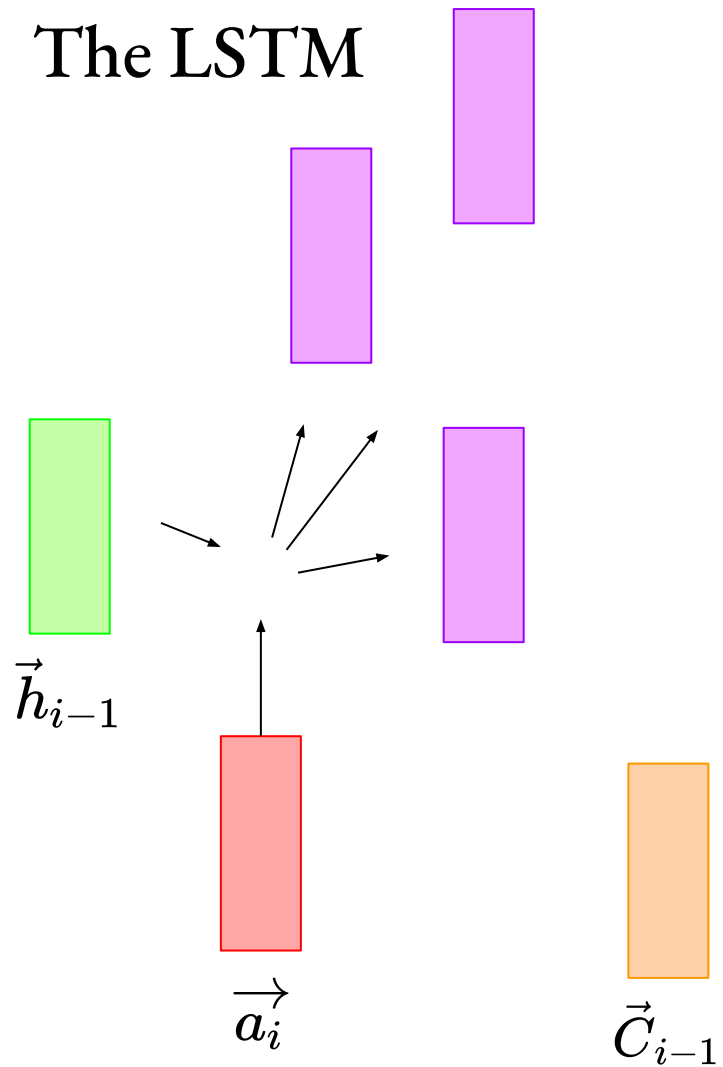
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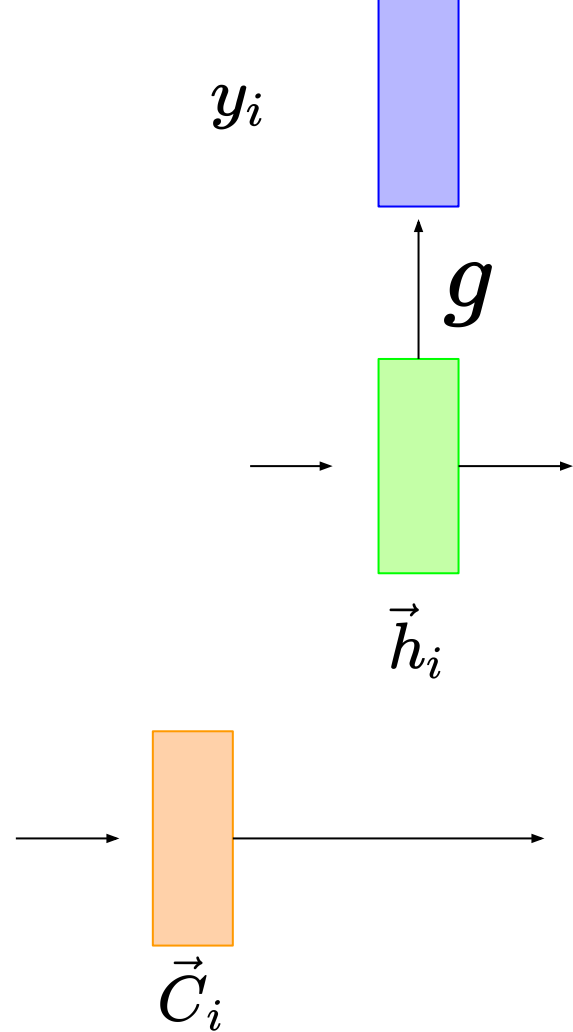
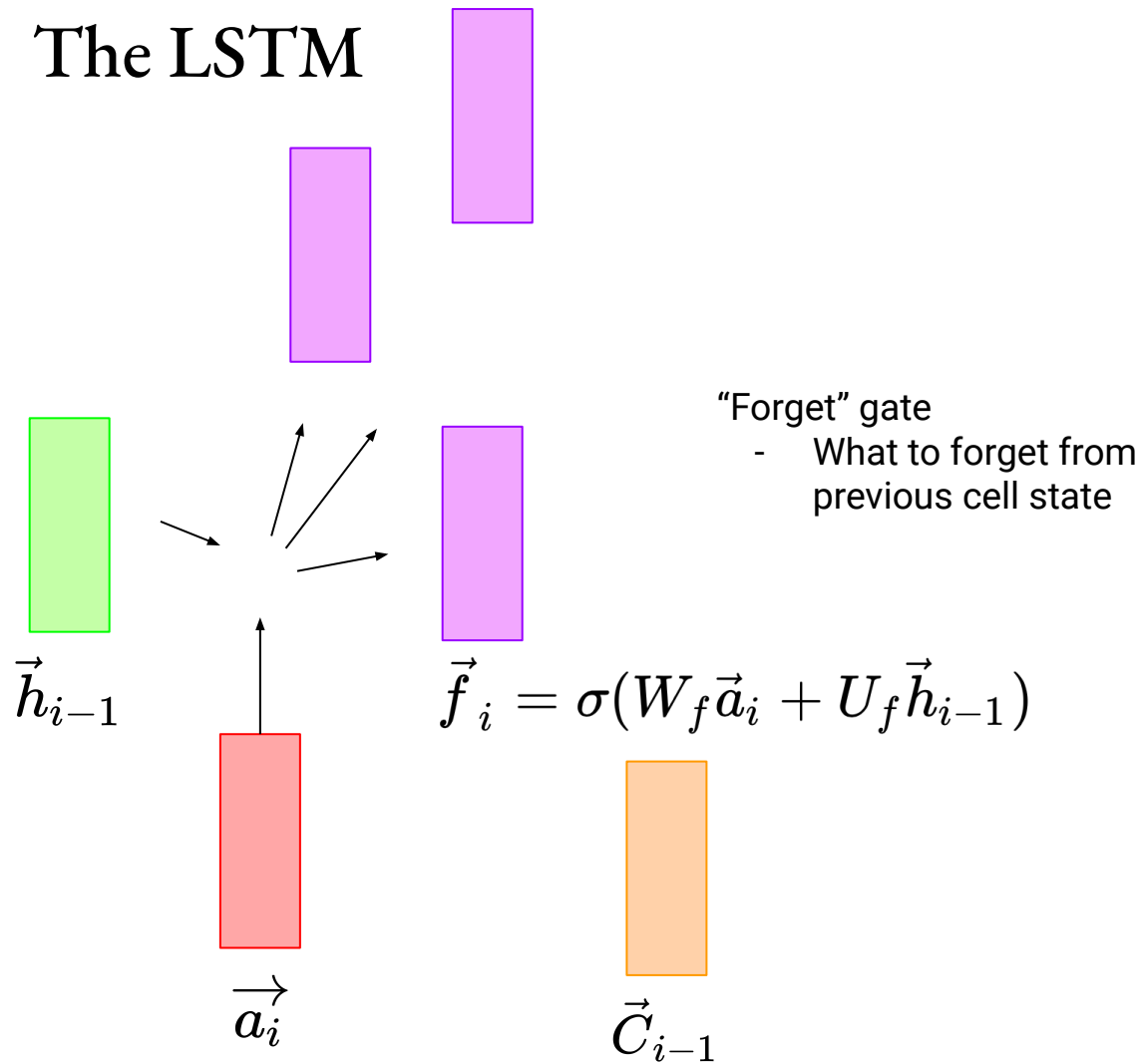
The LSTM



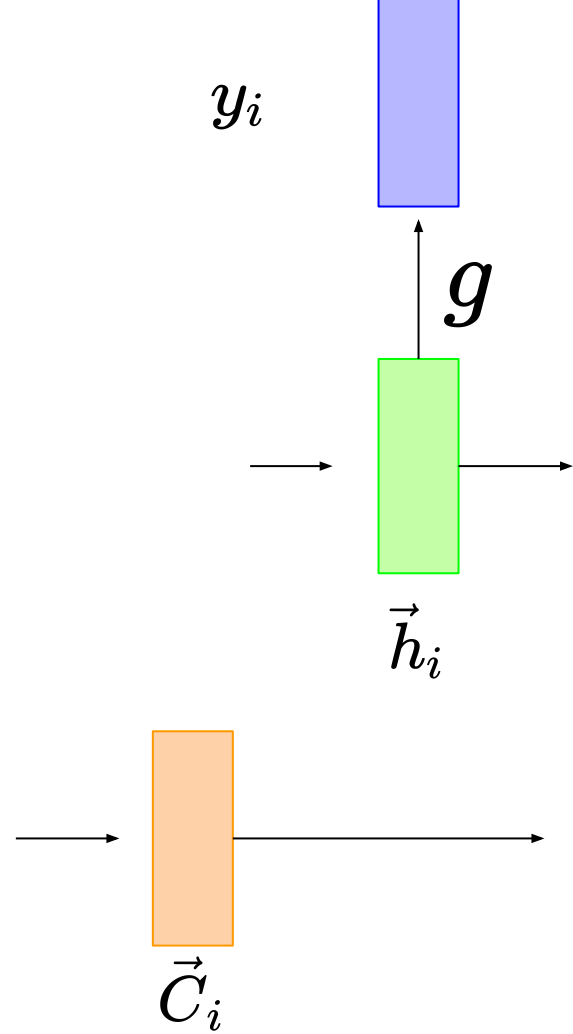
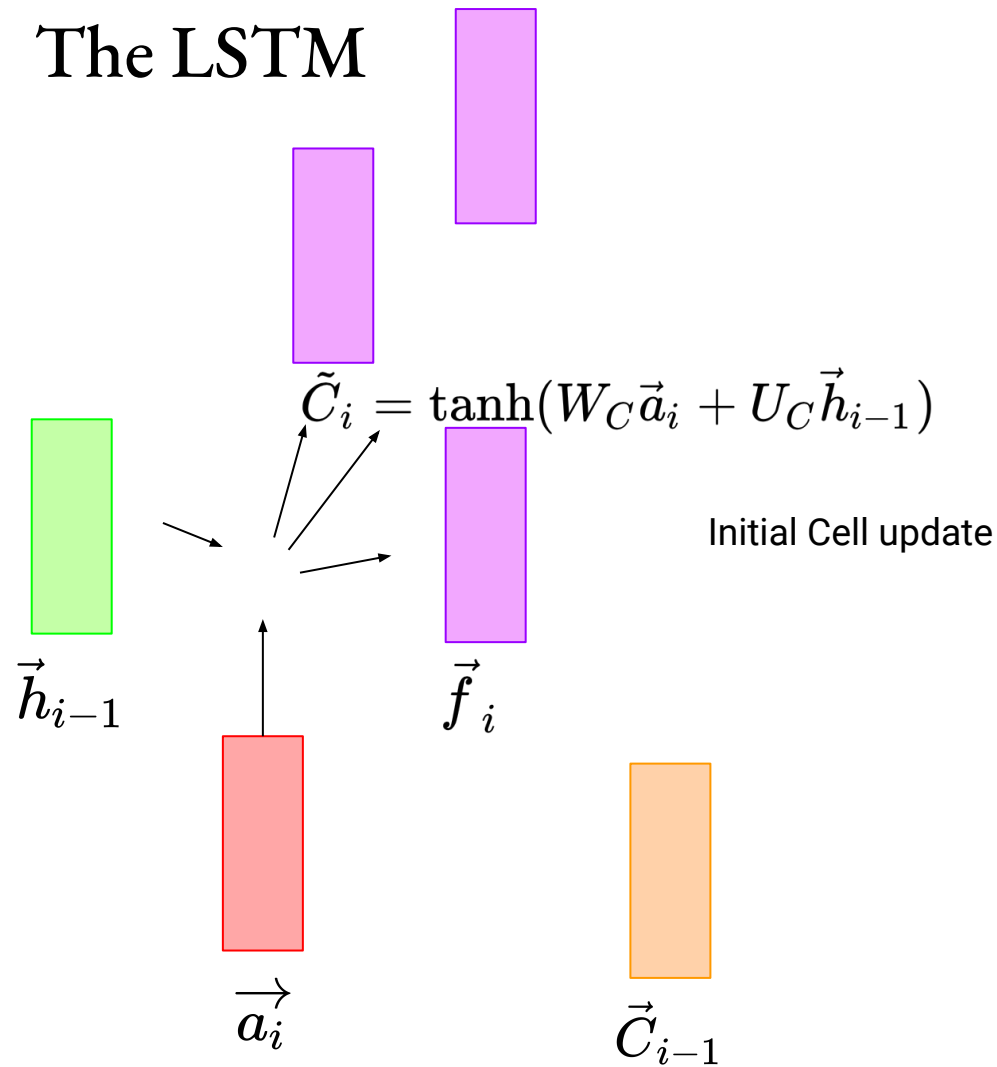
The LSTM



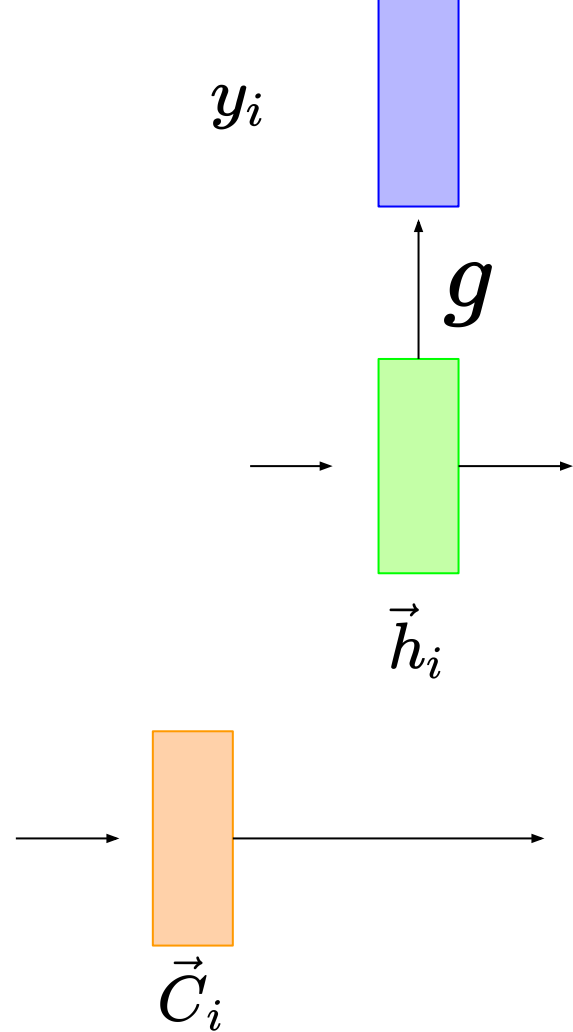
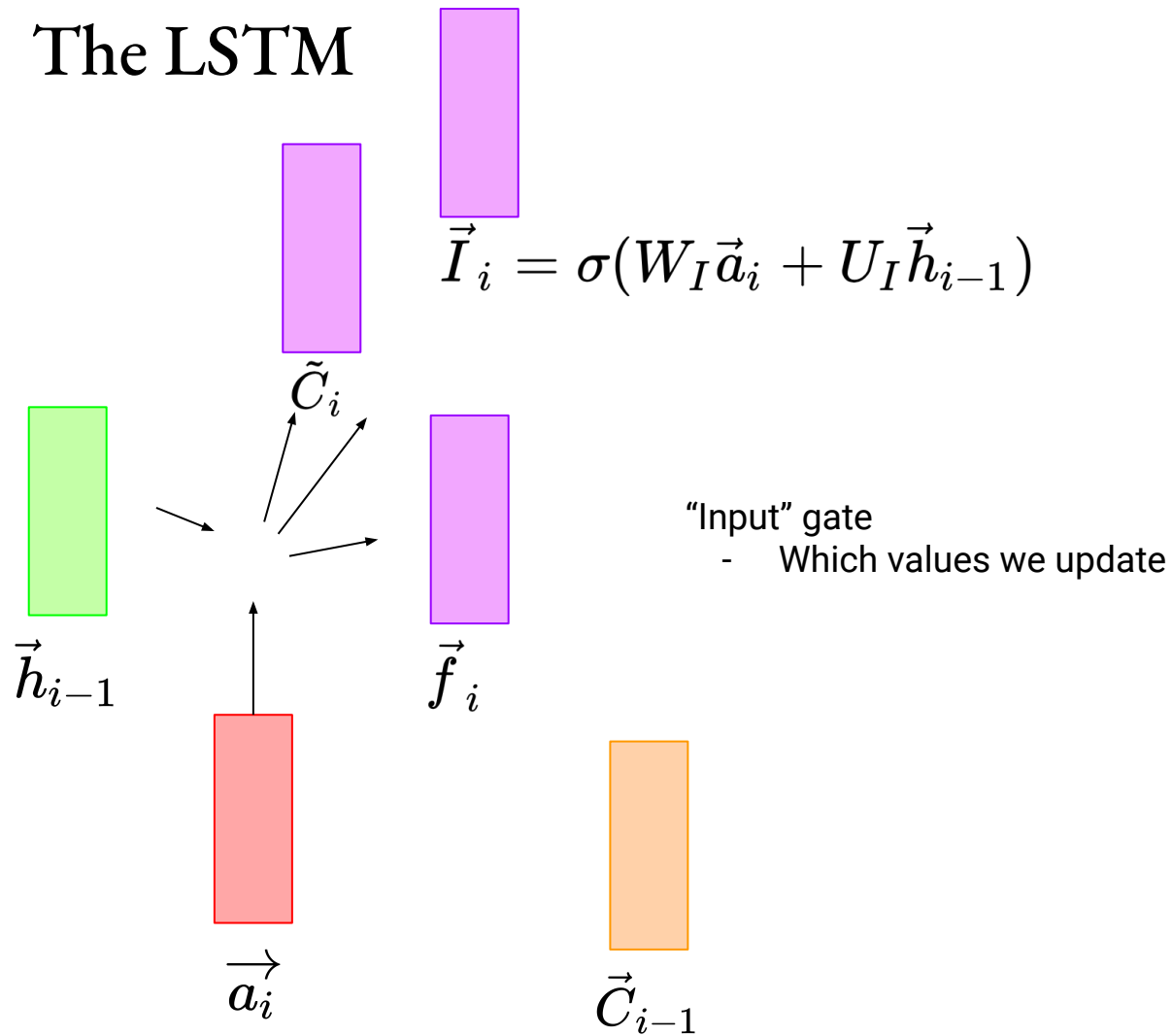
The LSTM



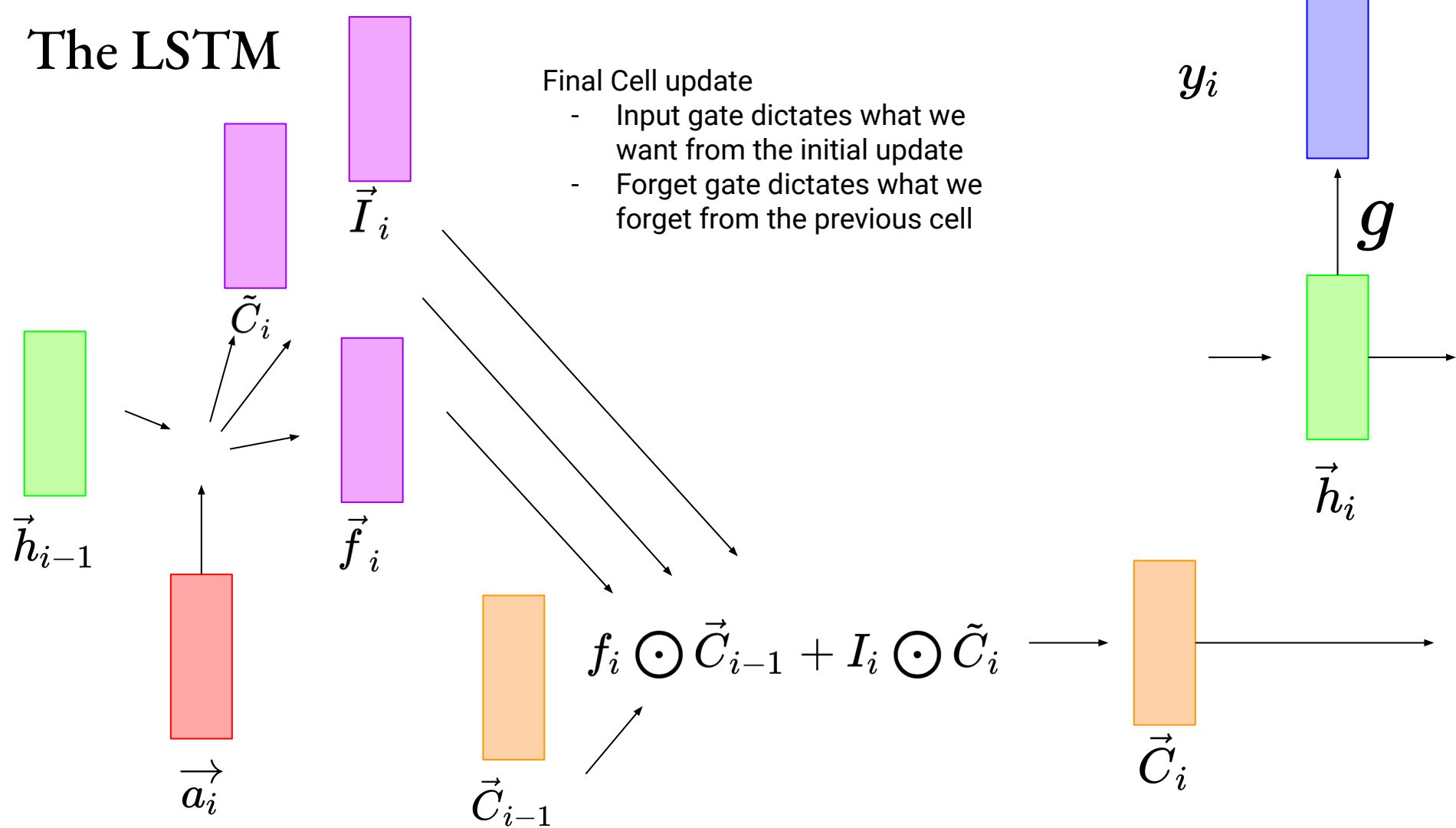
The LSTM



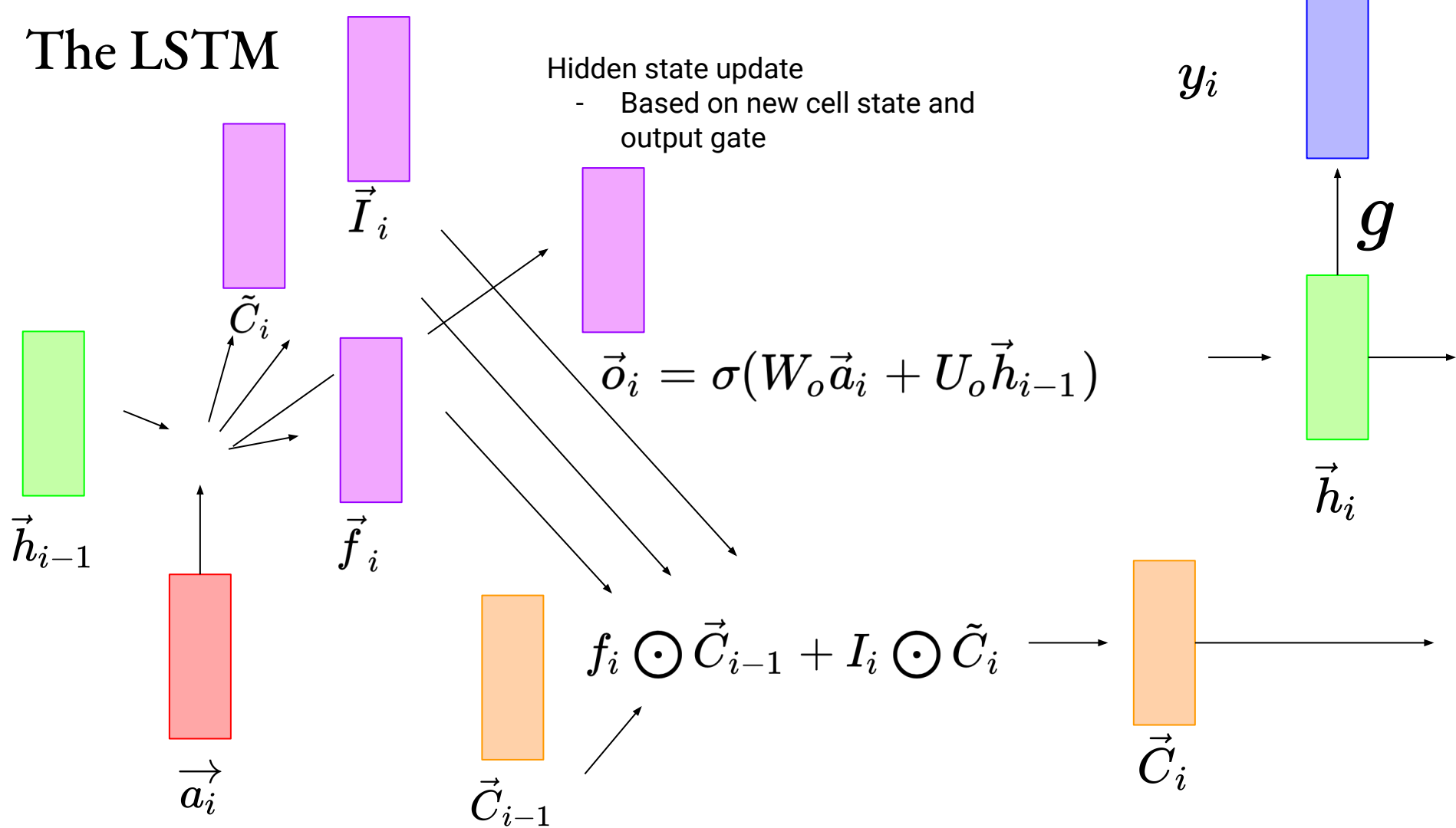
The LSTM



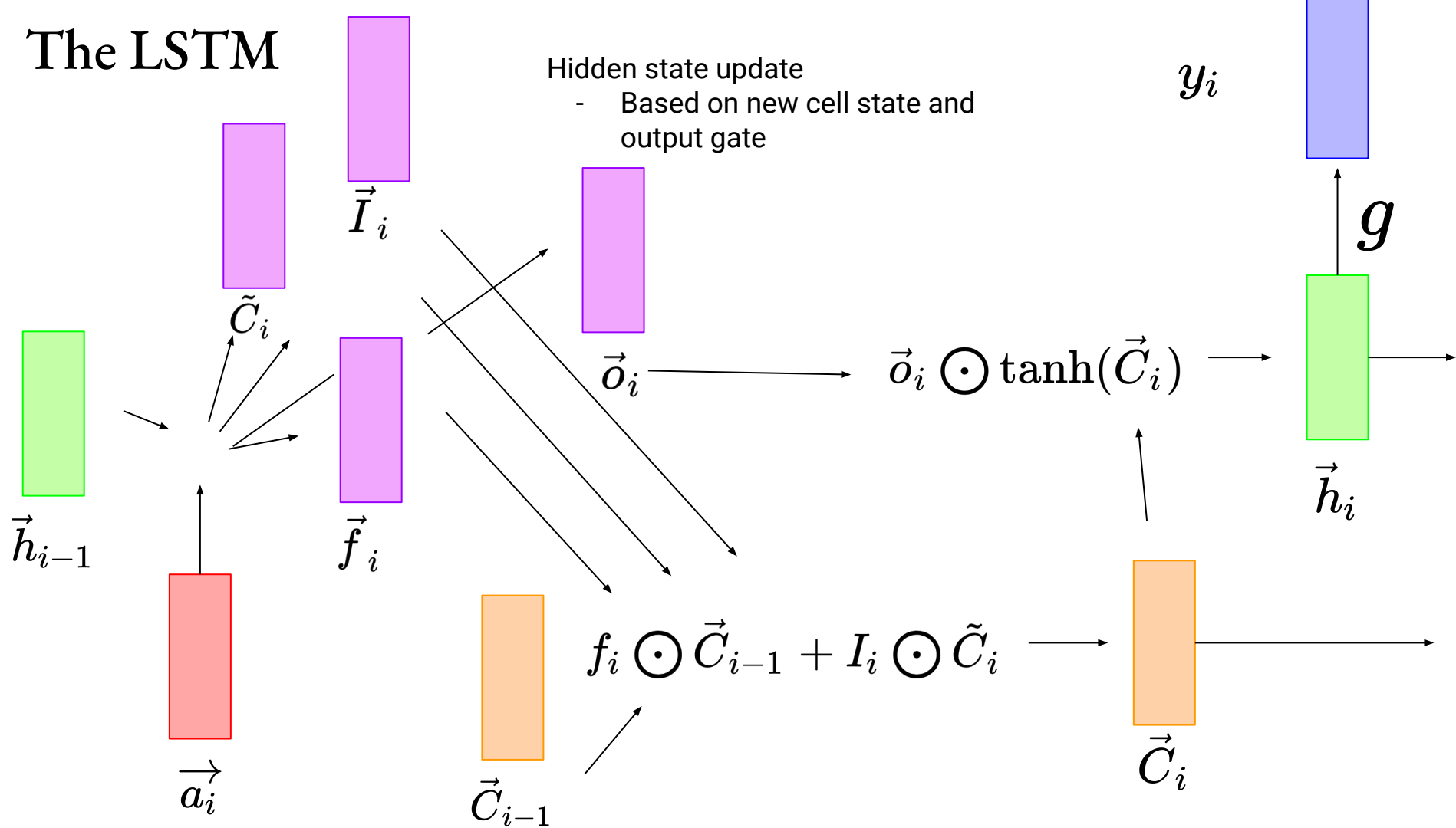
The LSTM

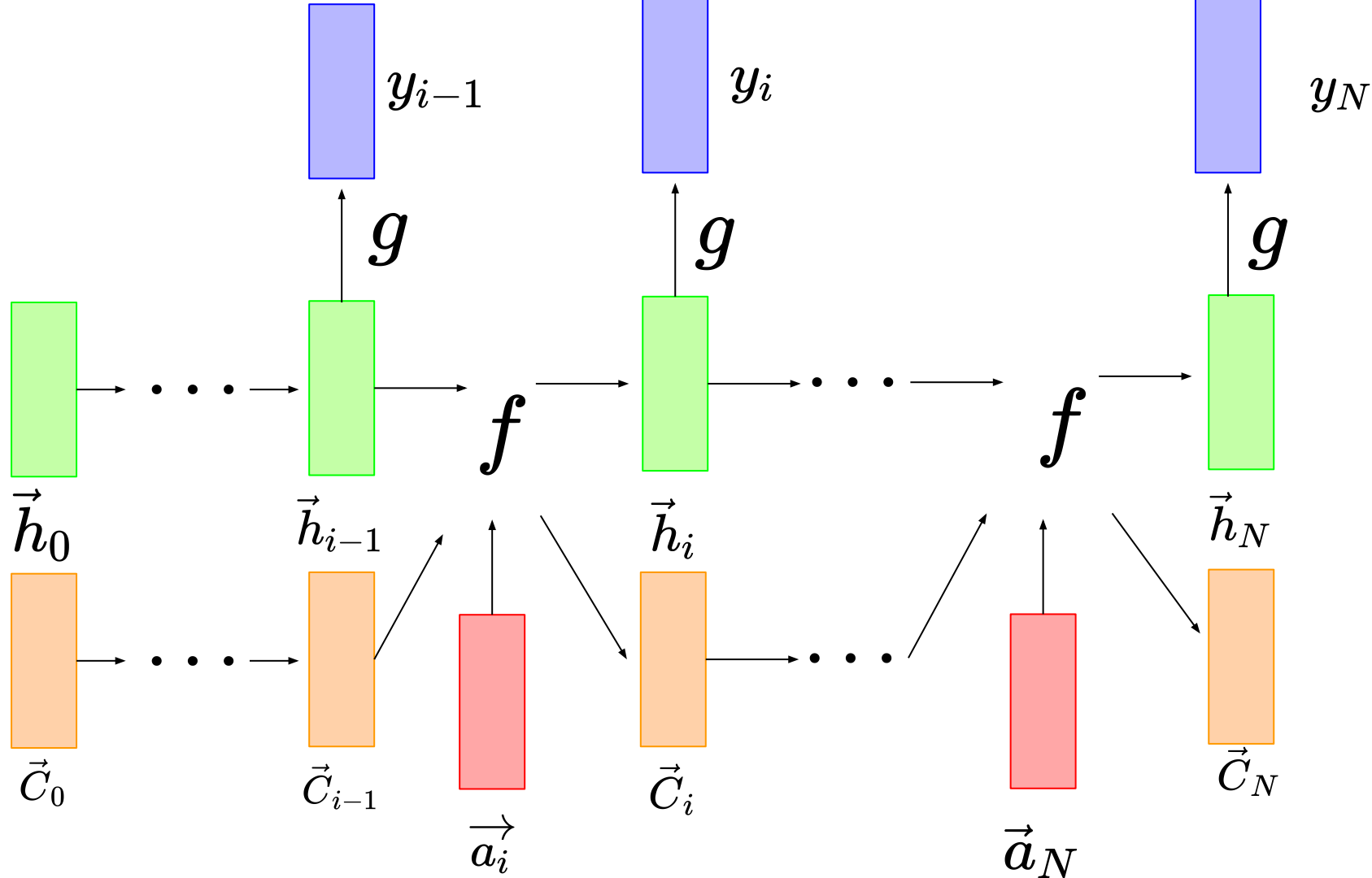


The LSTM



The LSTM

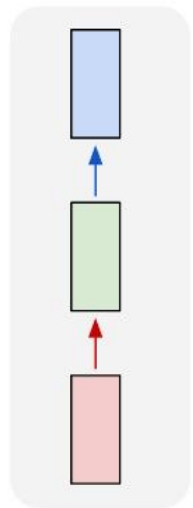




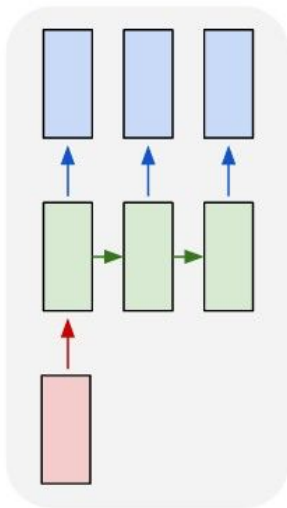
RNNs

- Different styles based on desired inputs/outputs

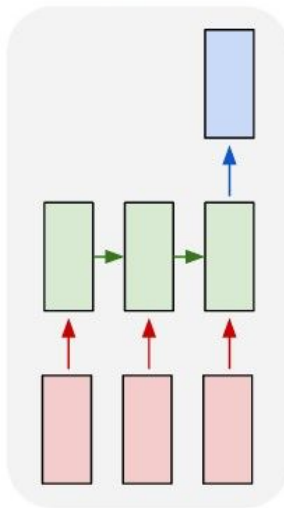
one to one



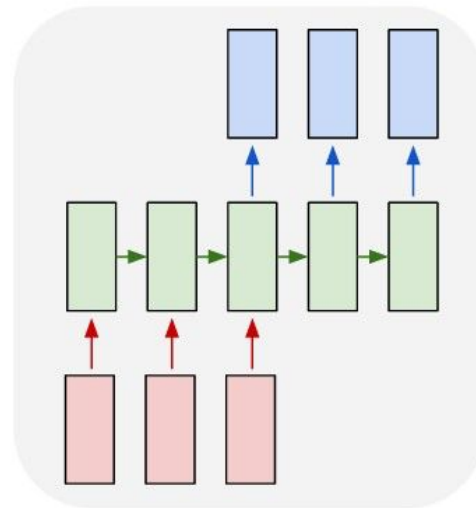
one to many



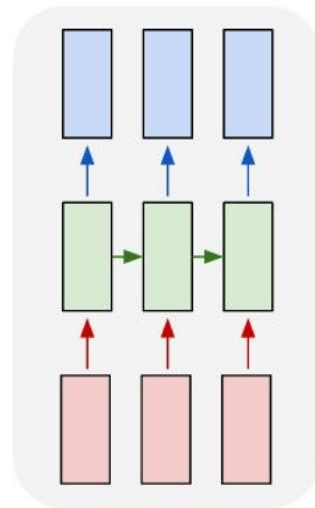
many to one



many to many



many to many



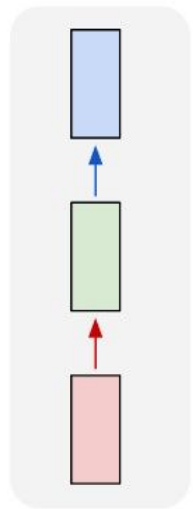
Questions?

- From last lecture?
- From the lab assignment?

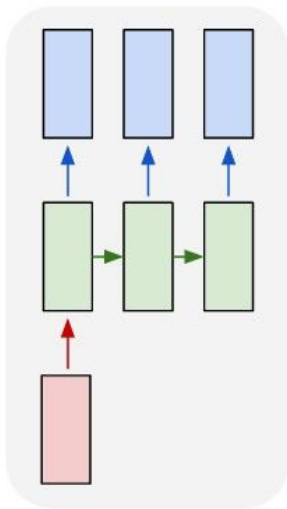
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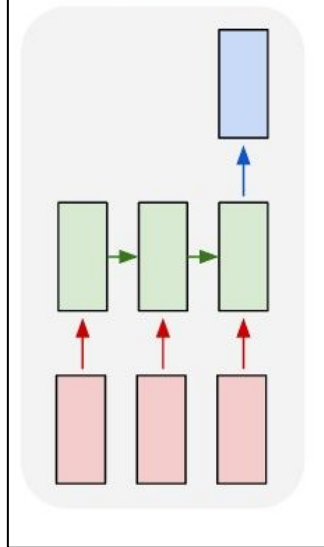
one to one



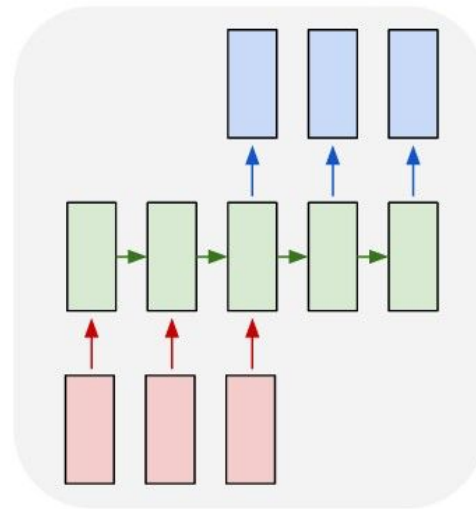
one to many



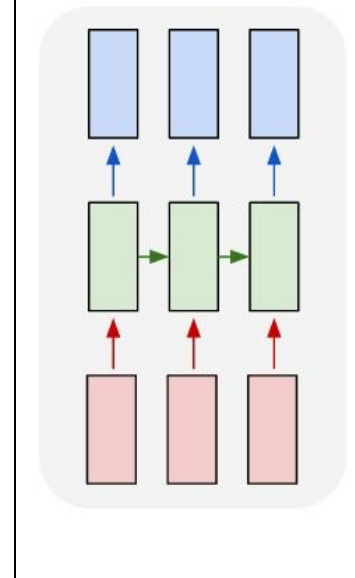
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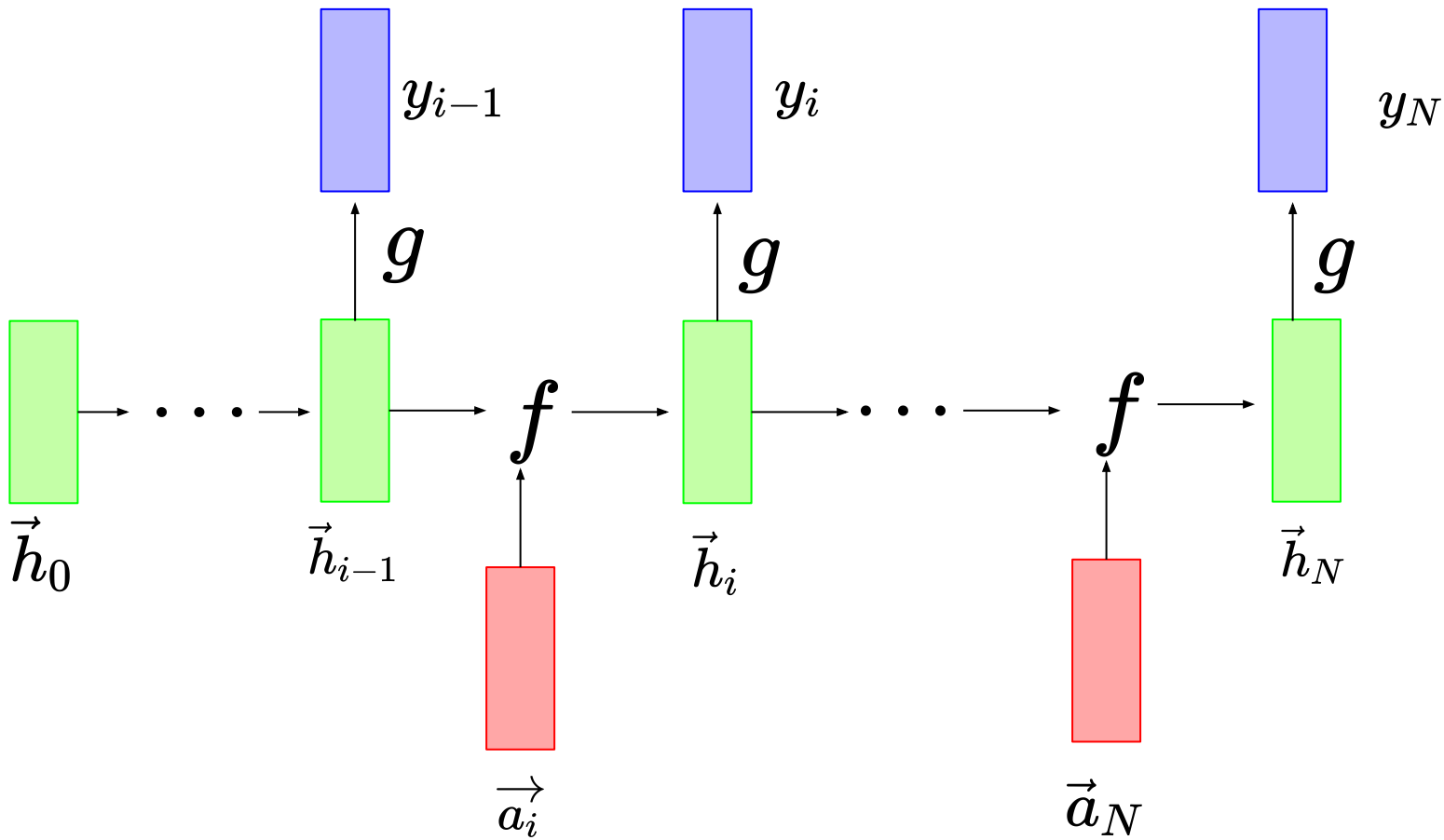
many to many



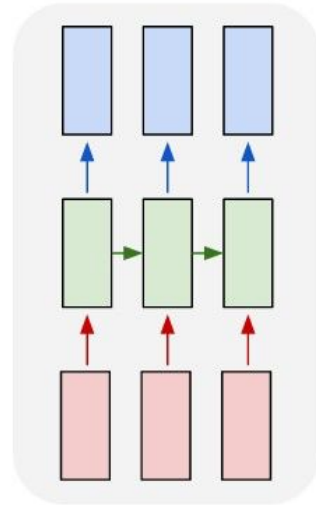
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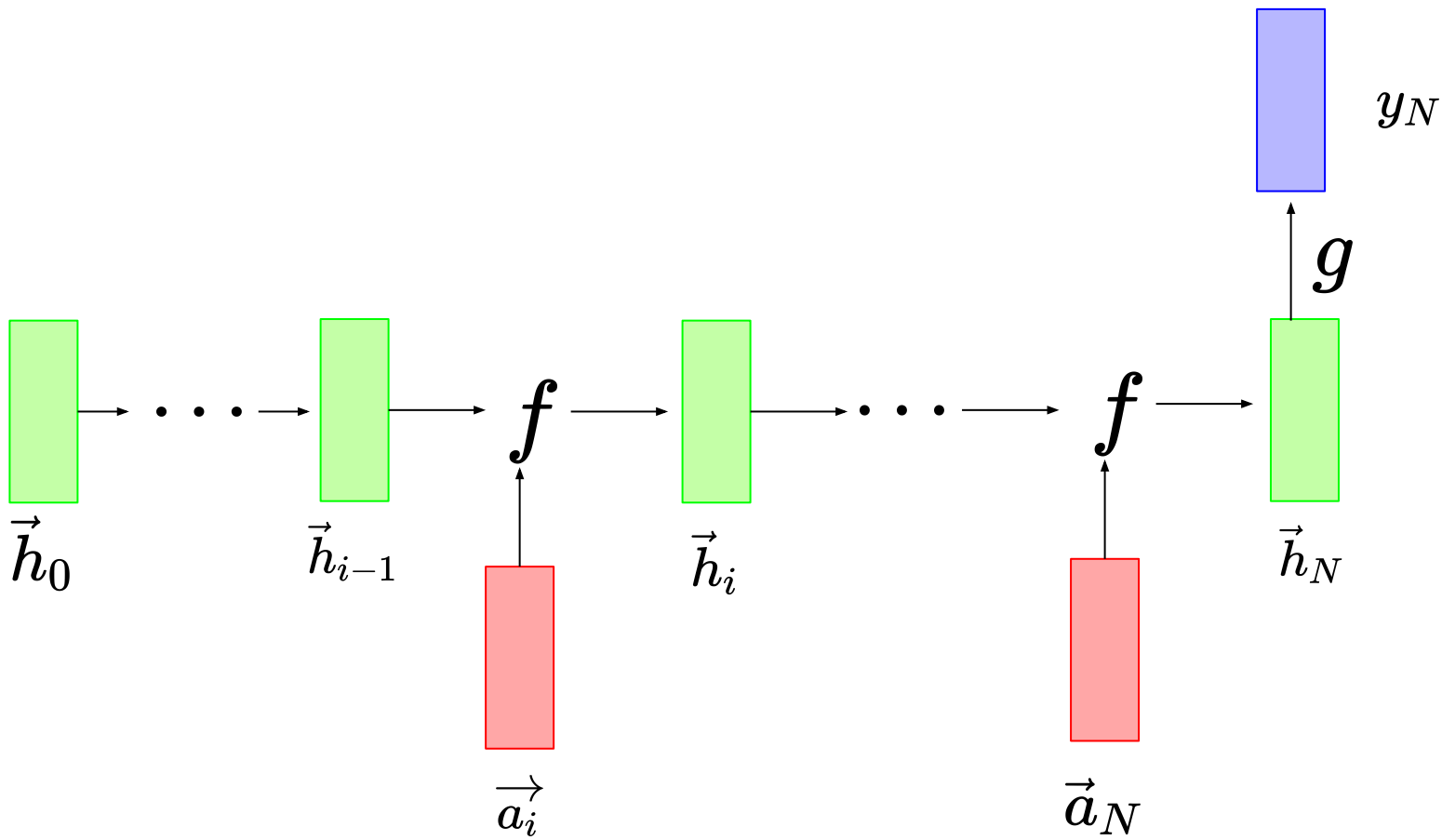
RNNs



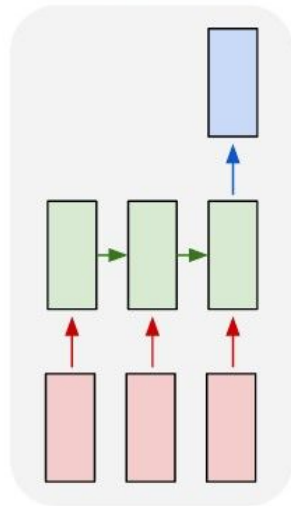
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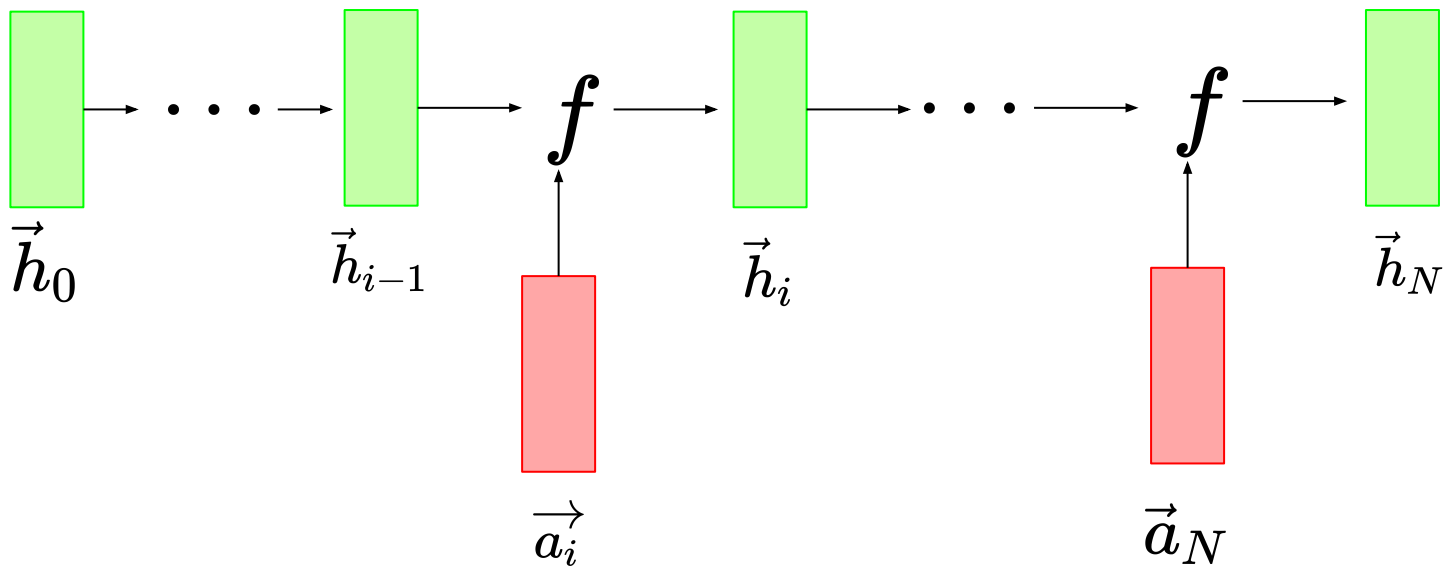
RNNs



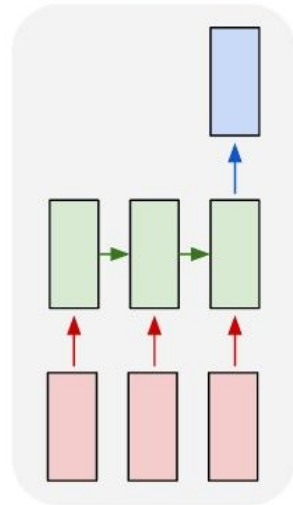
many to one



RNNs

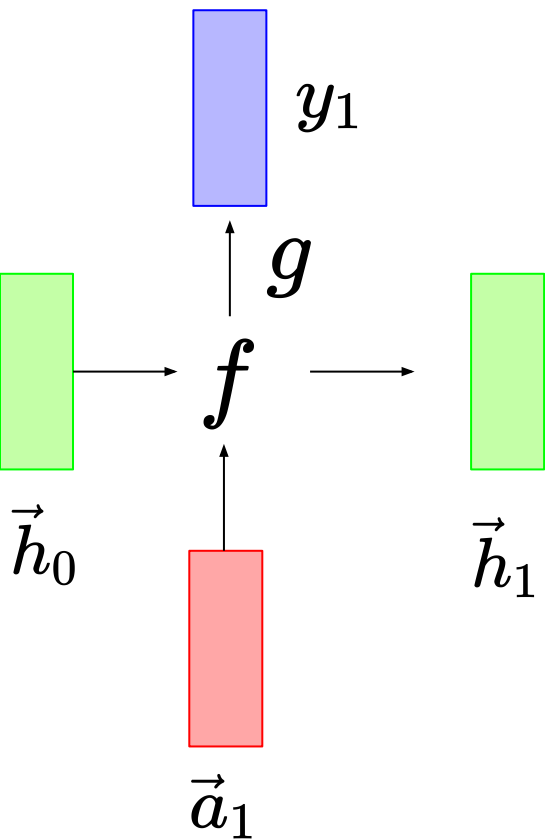


many to one

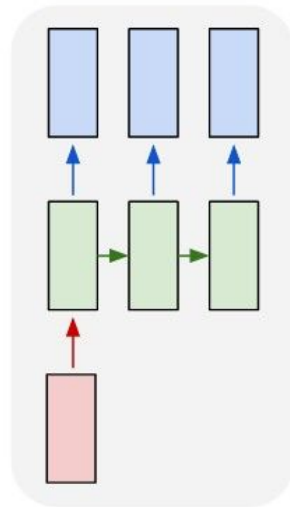


RNNs

- Generate a sequence from a single input

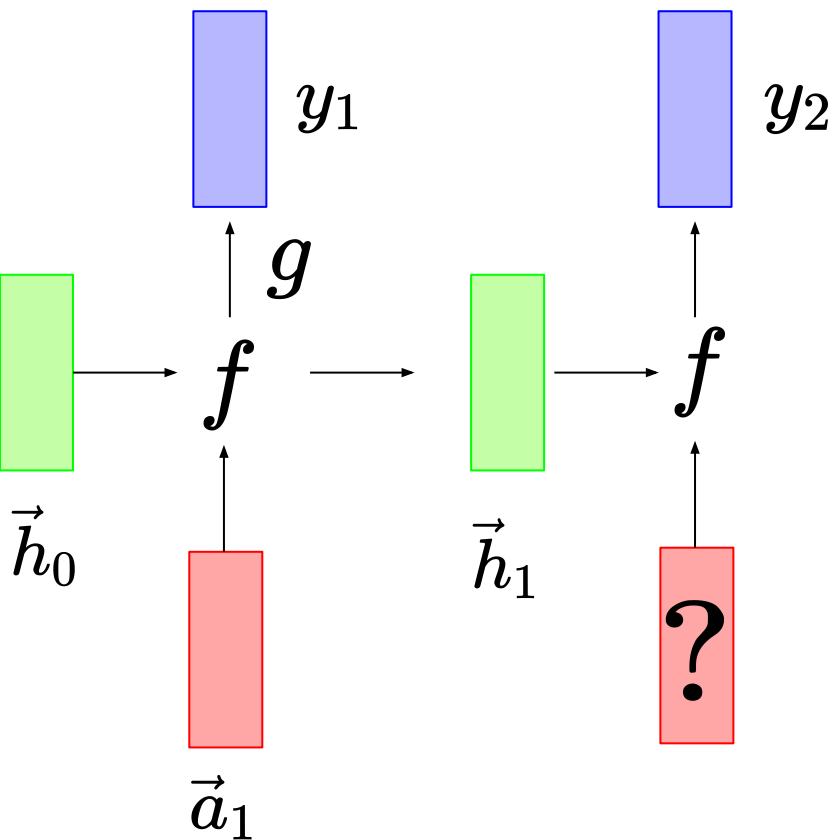


one to many

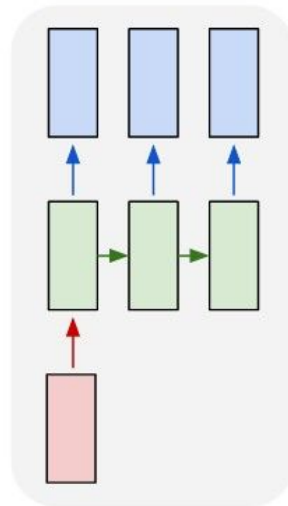


RNNs

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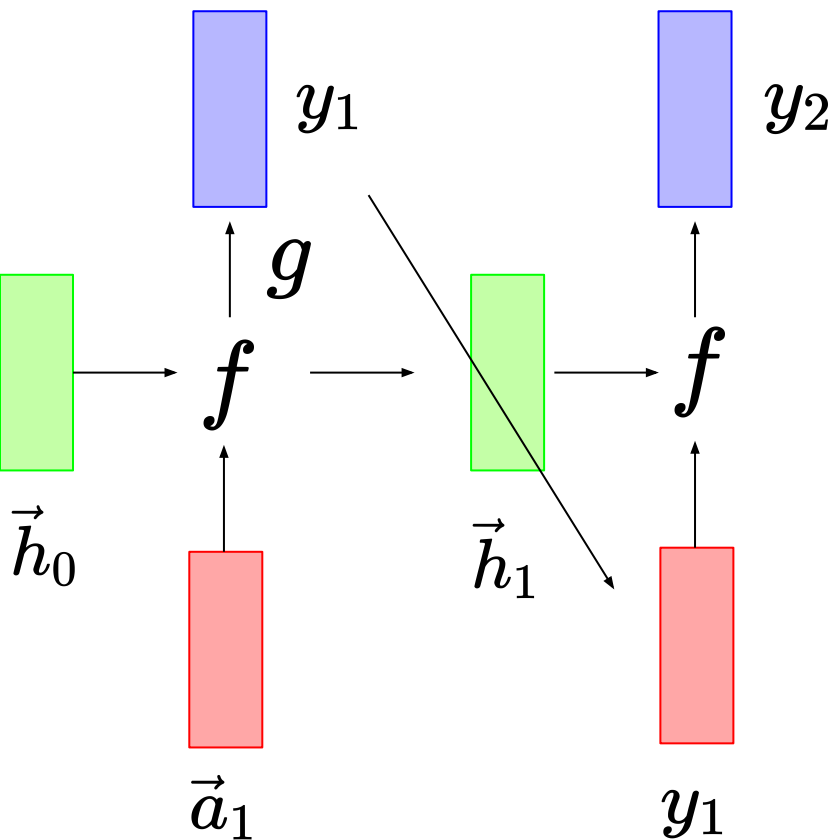


one to many

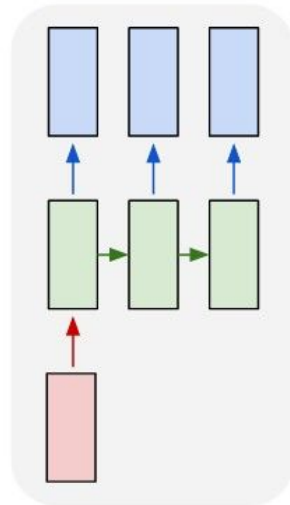


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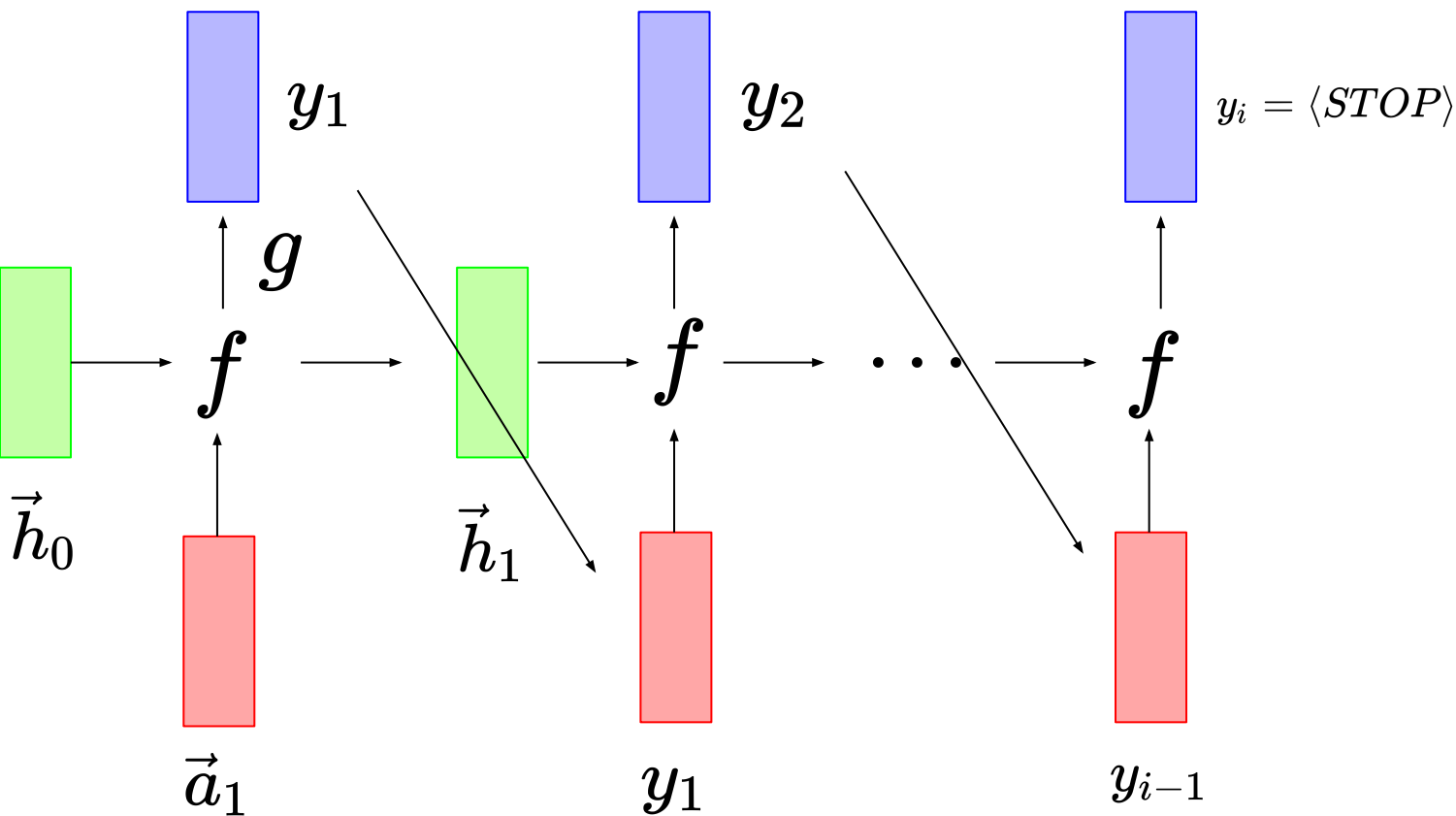


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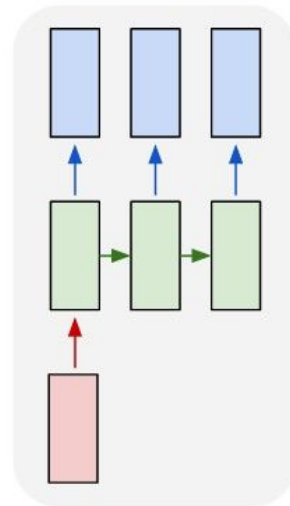


RNNs

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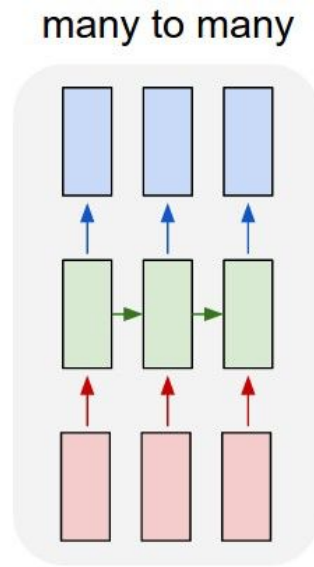


one to many



Problems with this set-up

- Late parts of input sequence don't inform early predictions

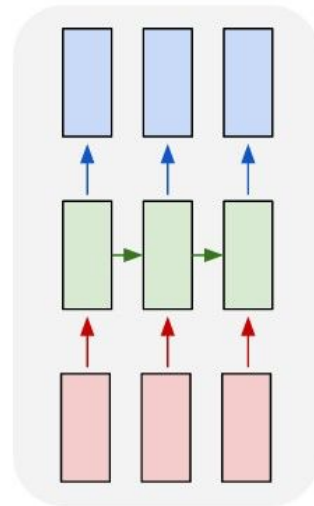


Problems with this set-up

- Late parts of input sequence don't inform early predictions
- Problem in translation

Ich muss auf den Markt gehen. → I must go to the Market

many to many

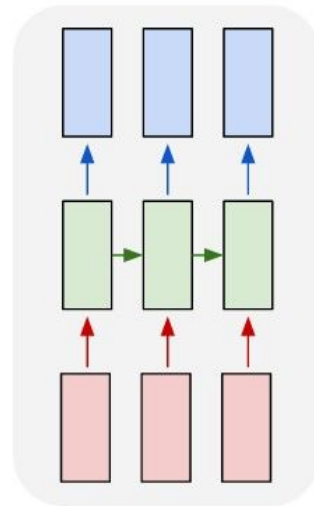


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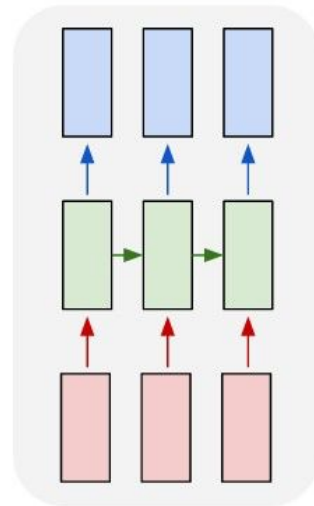


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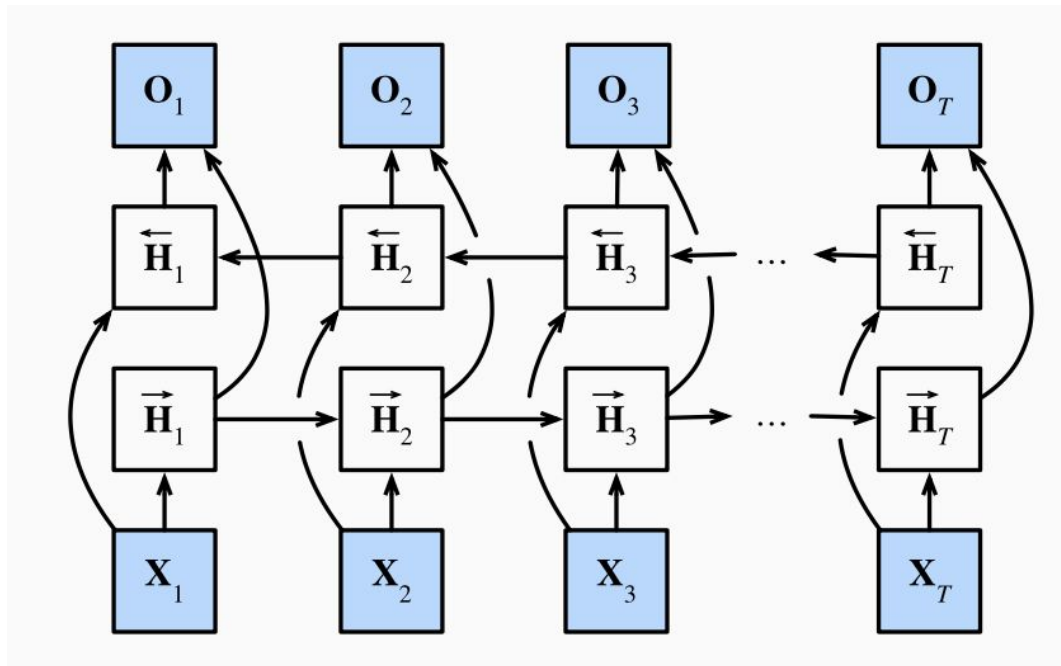
Ich muss auf den Markt gehen. → I must go to the Market
?

many to many

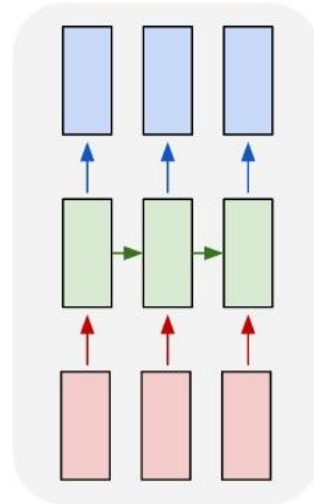


Problems with this set-up

- Late parts of input sequence don't inform early predictions
- Problem in translation
- Bidirectional RNN



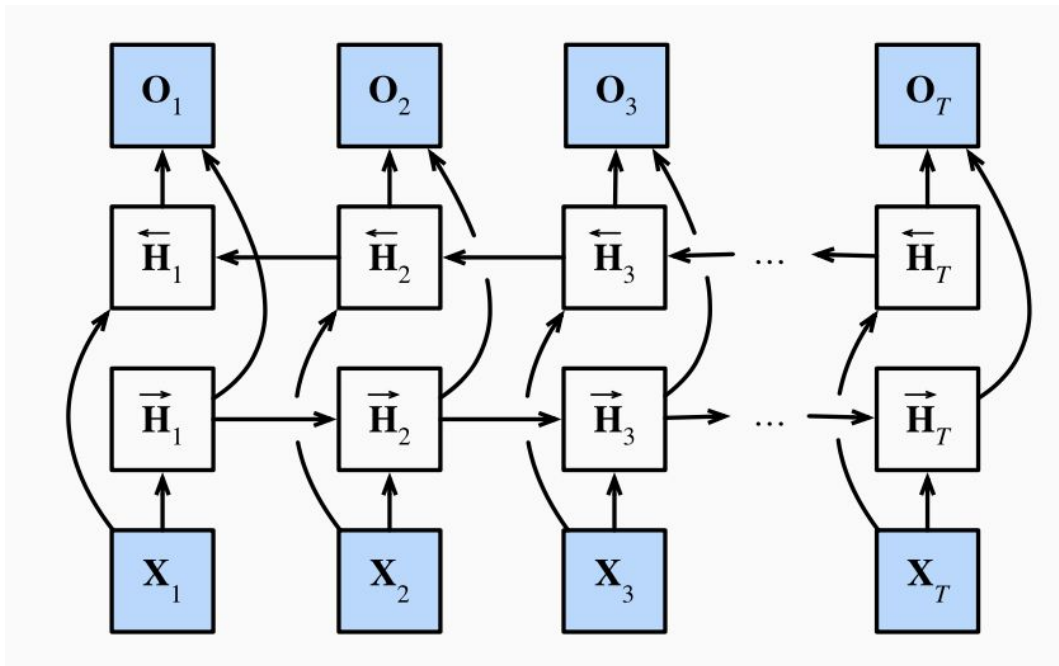
many to many



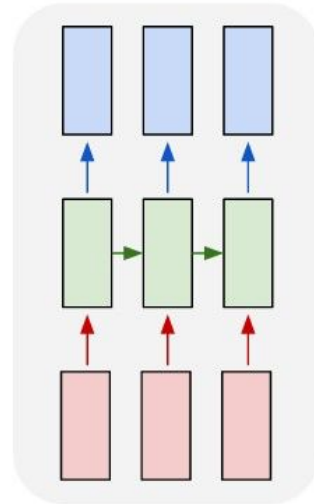
[Image source](#)

Problems with this set-up

- Late parts of input sequence don't inform early predictions
- Problem in translation
- Bidirectional RNN
 - SLOW



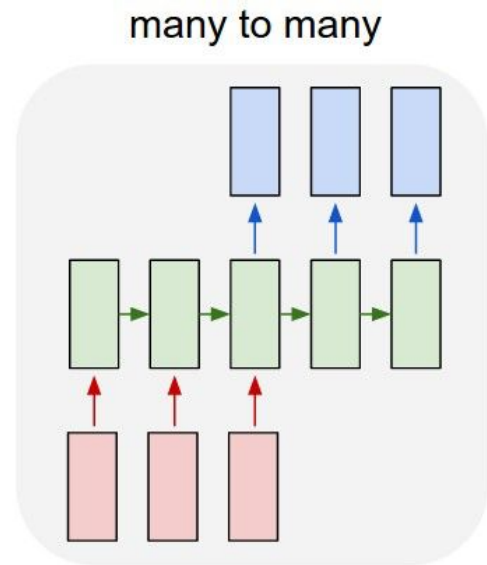
many to many



[Image source](#)

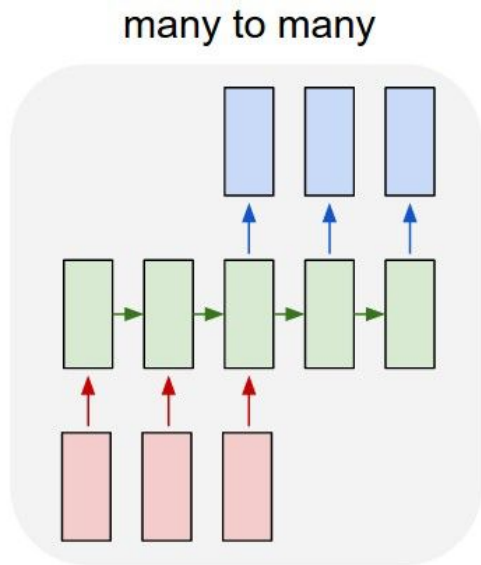
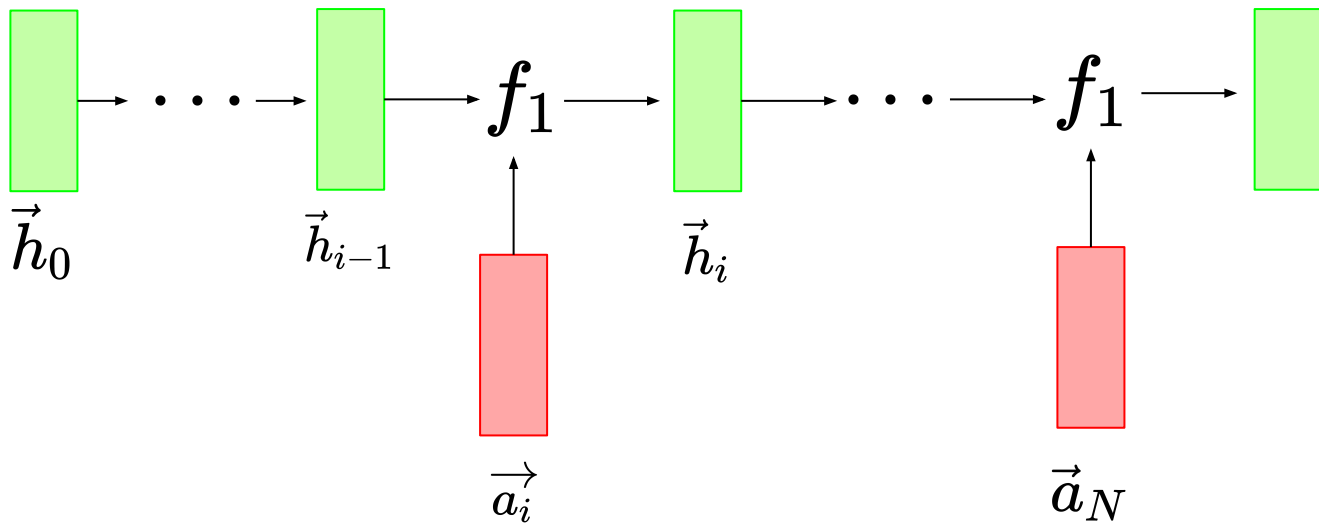
Seq2Seq Models

- Generate a sequence using encoder/decoder framework
- Idea: Different RNNs for encoding vs. decoding



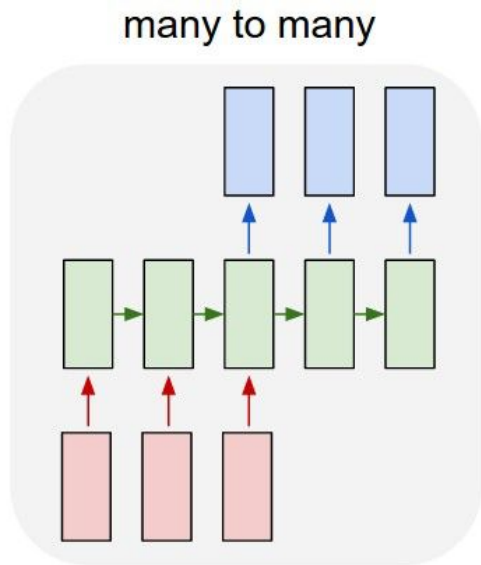
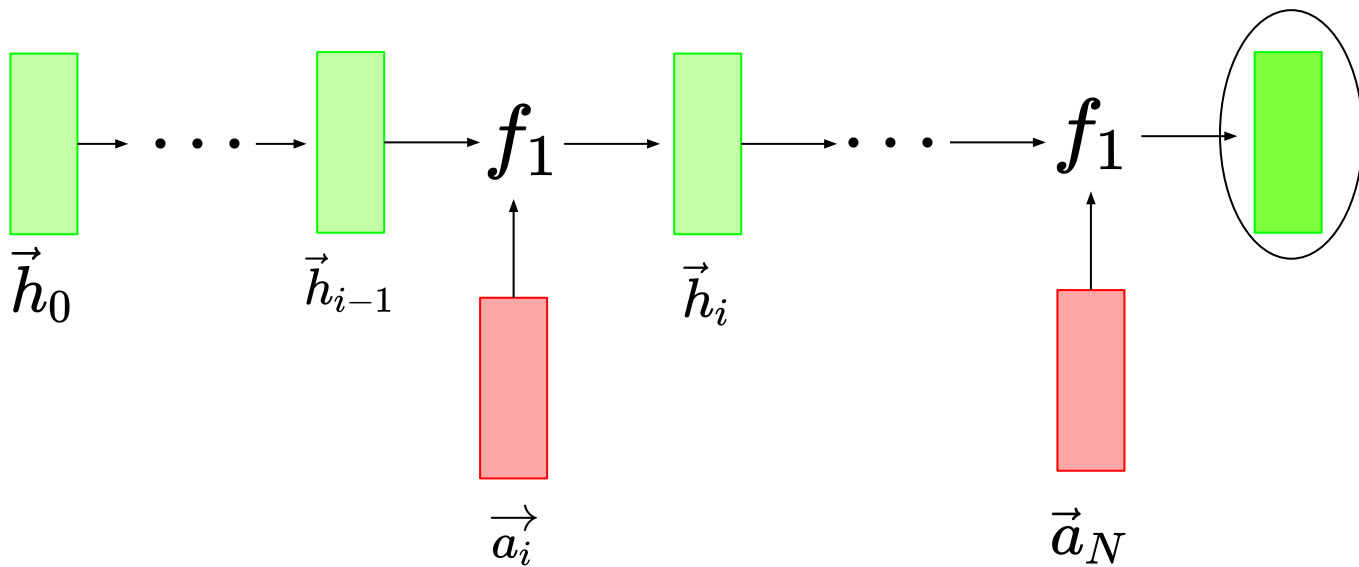
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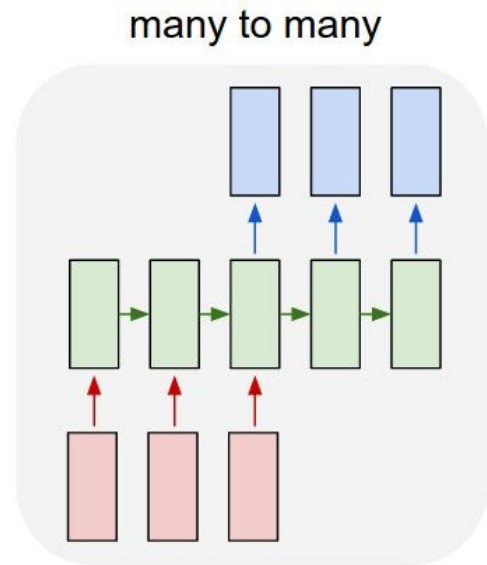
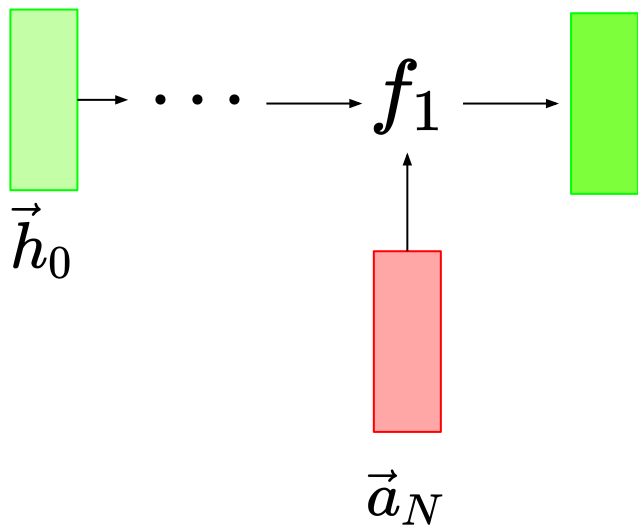
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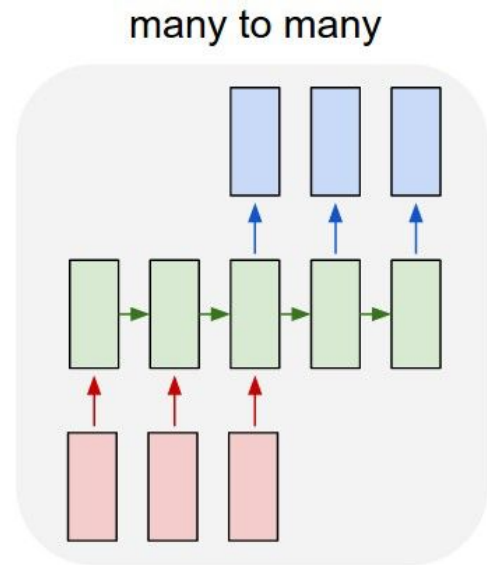
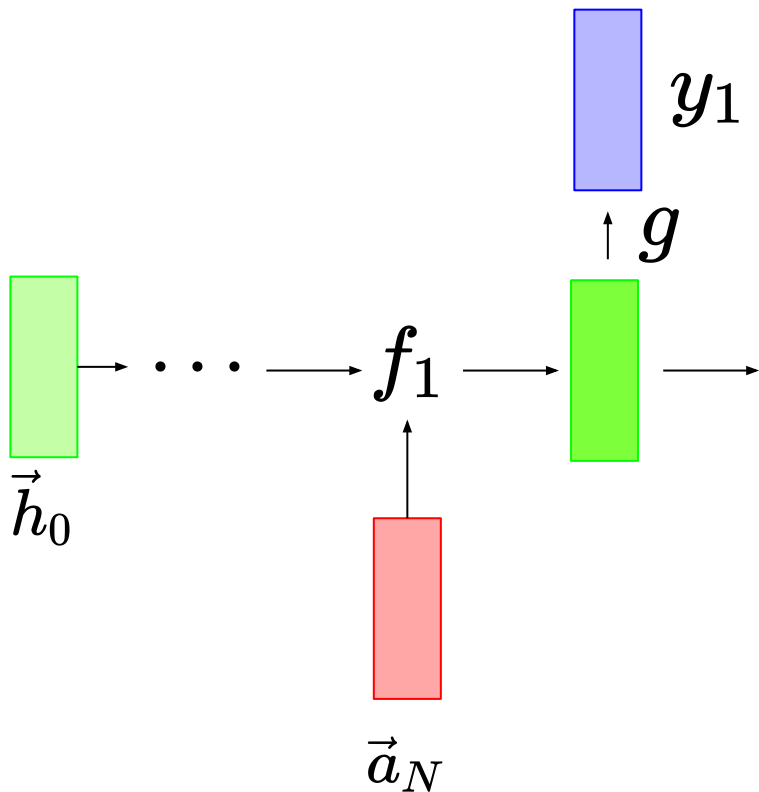
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