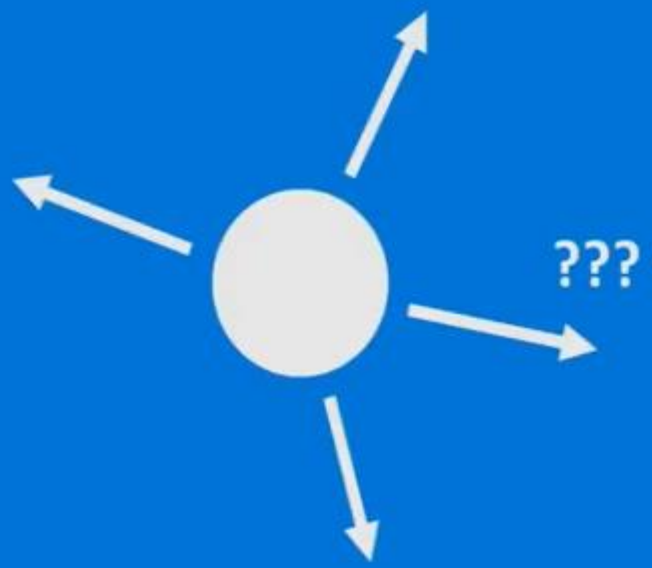
Deep Sequence Modeling

Ava Soleimany
MIT 6.S191

January 27, 2020

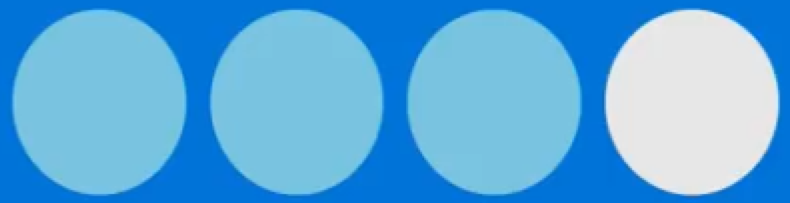
Given an image of a ball,
can you predict where it will go next?

Given an image of a ball,
can you predict where it will go next?



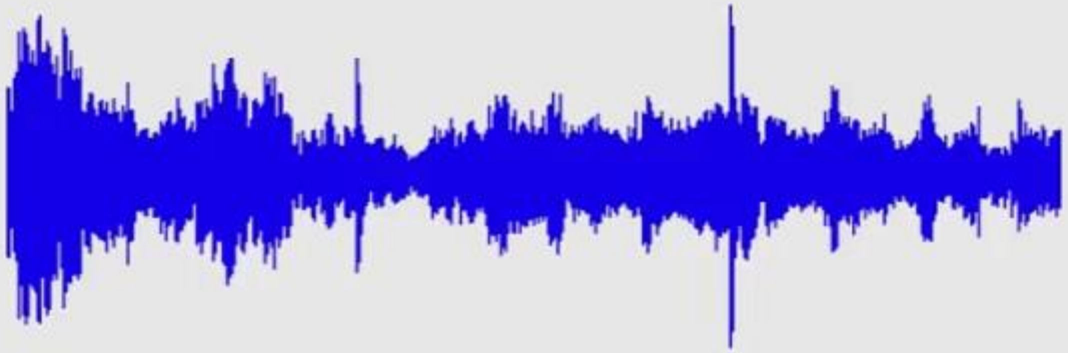
Deep Learning

Given an image of a ball,
can you predict where it will go next?



Given an image of a ball,
can you predict where it will go next?

Sequences in the Wild



Audio

Sequences in the Wild

Audio

Deep Learning

Sequences in the Wild

6.S191 Introduction to Deep Learning

Text

MIT Deep Learning

Sequences in the Wild

character: 6 . S 1 9 1

word: Introduction to Deep Learning

Text

Deep Learning

A Sequence Modeling Problem: Predict the Next Word

Deep
Learning

A Sequence Modeling Problem: Predict the Next Word

"This morning I took my cat for a walk."

Deep Learning

A Sequence Modeling Problem: Predict the Next Word

"This morning I took my cat for a walk."

given these words

Deep Learning

A Sequence Modeling Problem: Predict the Next Word

"This morning I took my cat for a walk."

given these words

predict the next word

Deep Learning

Idea #1: Use a Fixed Window

"This morning I took my cat for a walk."

given these two words

predict the next word

Deep Learning

Idea #1: Use a Fixed Window

"This morning I took my cat for a walk."

given these two words | predict the next word

One-hot feature encoding: tells us what each word is

$[\,1\;0\;0\;0\;0\;0\;1\;0\;0\;0\,]$

for a

prediction

Problem #1: Can't Model Long-Term Dependencies

"**France** is where I grew up, but I now live in Boston. I speak fluent ___."

J'aime 6.S191!

We need information from **the distant past** to accurately predict the correct word.

Idea #2: Use Entire Sequence as Set of Counts

"This morning I took my cat for a"

↓

"bag of words"

[0 1 0 0 1 0 0 ... 0 0 1 1 0 0 0 1]

↓

prediction

Problem #2: Counts Don't Preserve Order

The food was good, not bad at all.

vs.

The food was bad, not good at all.

Deep Learning

Idea #3: Use a Really Big Fixed Window

"This morning I took my cat for a walk."

given these words

predict the next word

[1 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 1 0 ...]

morning I took this cat

prediction

Problem #3: No Parameter Sharing

[1 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 1 0 ...]

this morning took the cat

Each of these inputs has a **separate parameter:**

Deep Learning

Problem #3: No Parameter Sharing

[1 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 1 0 ...]

this morning took the cat

Each of these inputs has a **separate parameter:**

[0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 1 ...]

this morning

Problem #3: No Parameter Sharing

[1 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 1 0 ...]

this morning took the cat

Each of these inputs has a **separate parameter:**

[0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 1 ...]

this morning

Things we learn about the sequence **won't transfer** if they appear **elsewhere** in the sequence.

Sequence Modeling: Design Criteria

To model sequences, we need to:

1. Handle **variable-length** sequences

Sequence Modeling: Design Criteria

To model sequences, we need to:

1. Handle **variable-length** sequences
2. Track **long-term** dependencies

Deep Learning

Sequence Modeling: Design Criteria

To model sequences, we need to:

1. Handle **variable-length** sequences
2. Track **long-term** dependencies
3. Maintain information about **order**

Deep Learning

Sequence Modeling: Design Criteria

To model sequences, we need to:

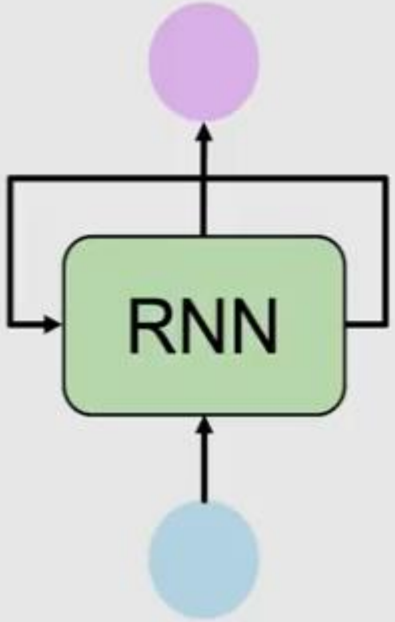
1. Handle **variable-length** sequences
2. Track **long-term** dependencies
3. Maintain information about **order**
4. **Share parameters** across the sequence

Deep Learning

Sequence Modeling: Design Criteria

To model sequences, we need to:

1. Handle **variable-length** sequences
2. Track **long-term** dependencies
3. Maintain information about **order**
4. **Share parameters** across the sequence



Today: **Recurrent Neural Networks (RNNs)** as an approach to sequence modeling problems

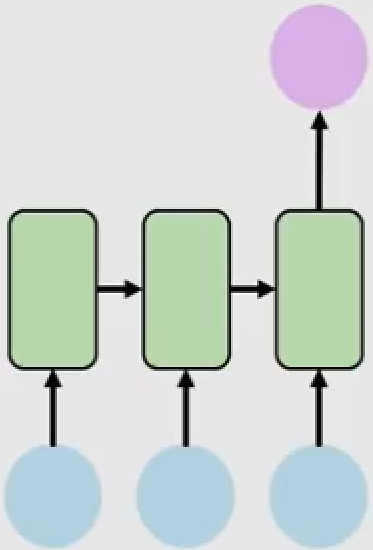
Recurrent Neural Networks (RNNs)

Standard Feed-Forward Neural Network

One to One
"Vanilla" neural network

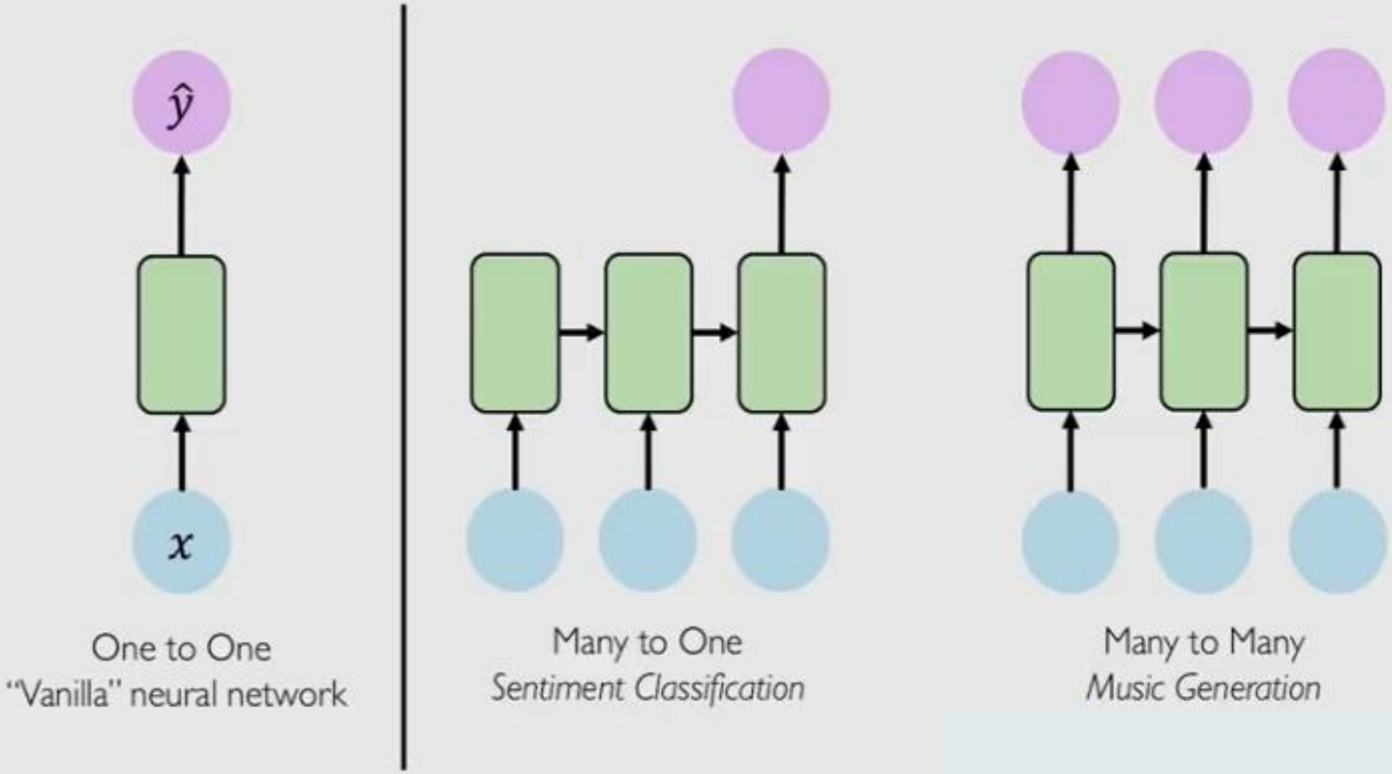
Recurrent Neural Networks for Sequence Modeling

One to One
"Vanilla" neural network



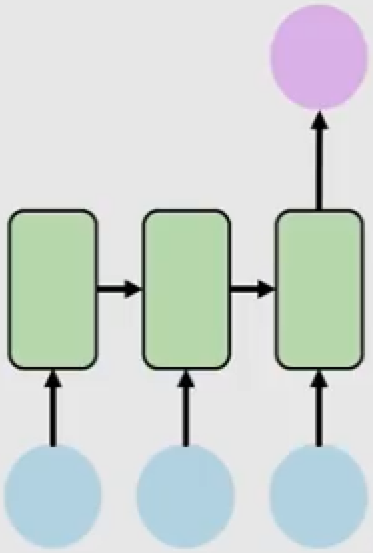
Many to One
Sentiment Classification

Recurrent Neural Networks for Sequence Modeling

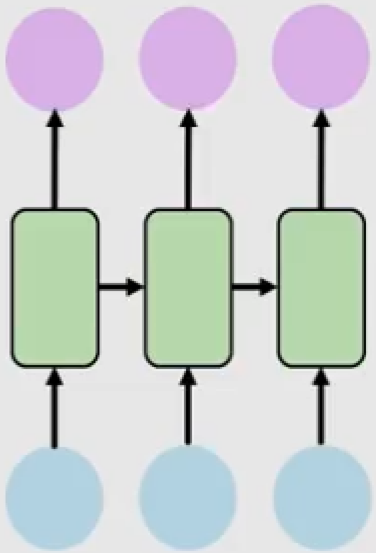


Recurrent Neural Networks for Sequence Modeling

One to One
"Vanilla" neural network



Many to One
Sentiment Classification

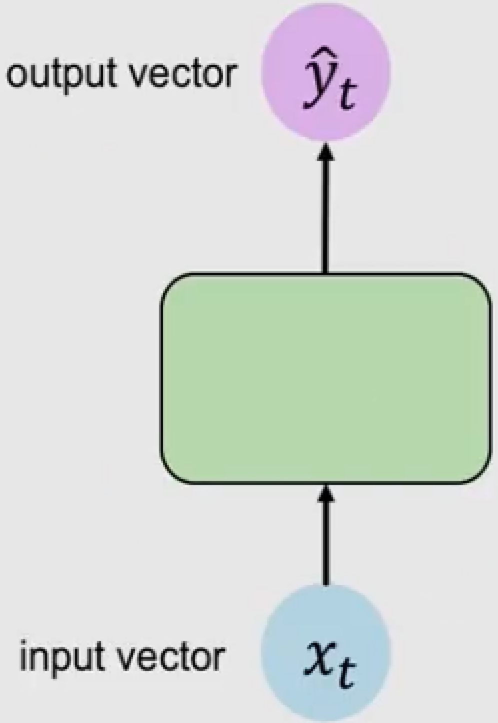


Many to Many
Music Generation

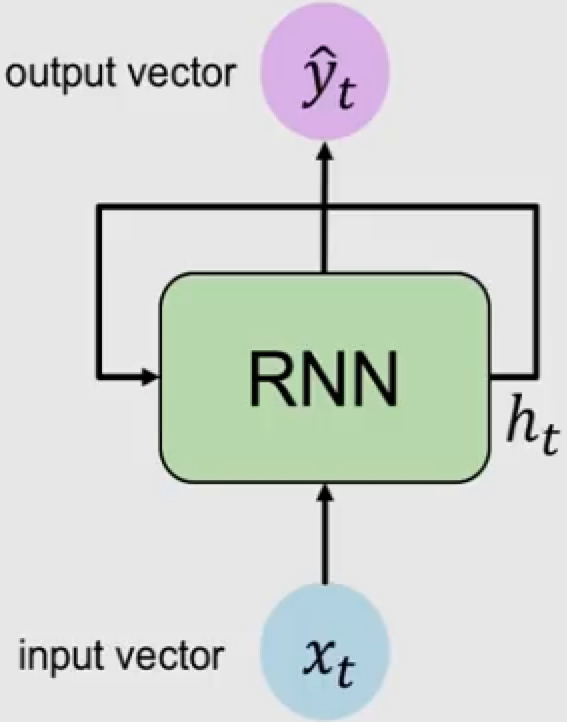
... and many other architectures and applications

MIT Deep Learning

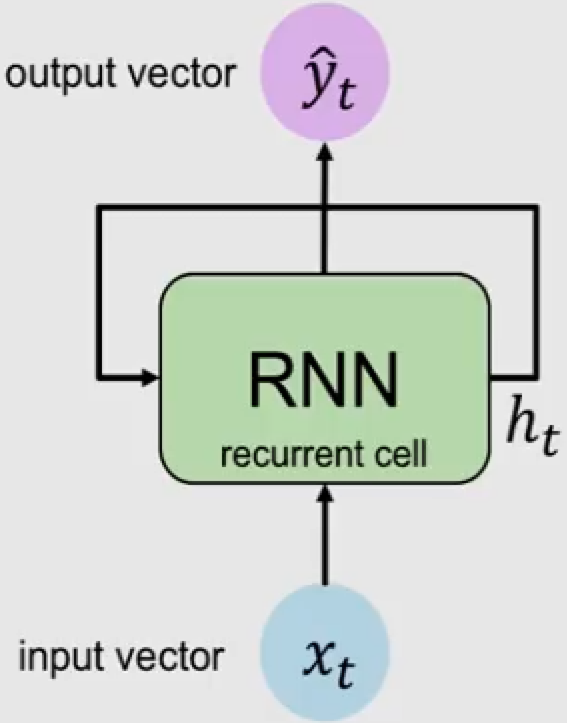
Standard "Vanilla" Neural Network



Recurrent Neural Network (RNN)

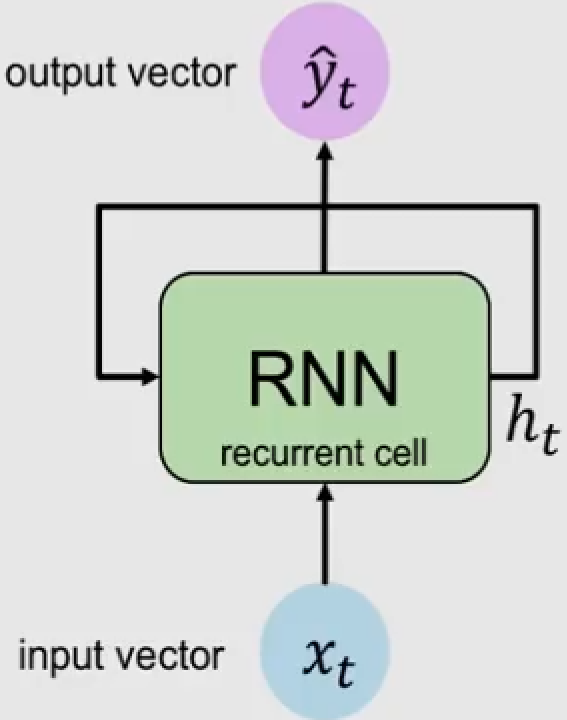


Recurrent Neural Network (RNN)



Apply a **recurrence relation** at every time step to process a sequence:

Recurrent Neural Network (RNN)

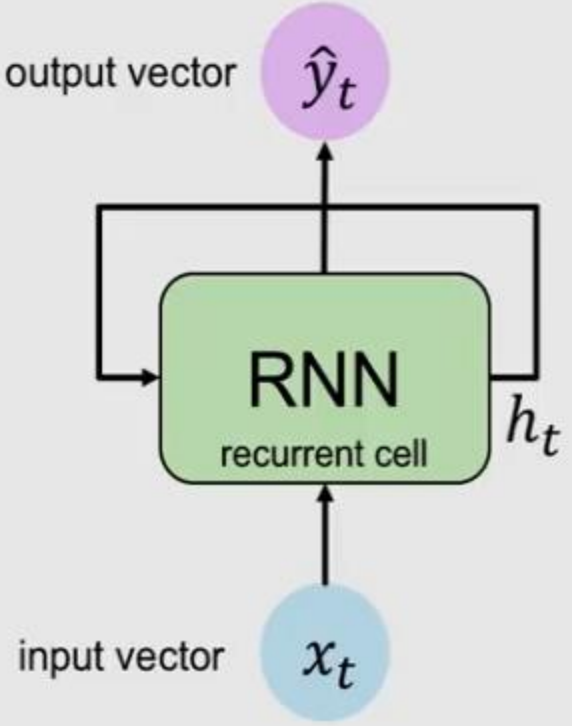


Apply a **recurrence relation** at every time step to process a sequence:

$$h_t = f_W(h_{t-1}, x_t)$$

MIT Deep Learning

Recurrent Neural Network (RNN)



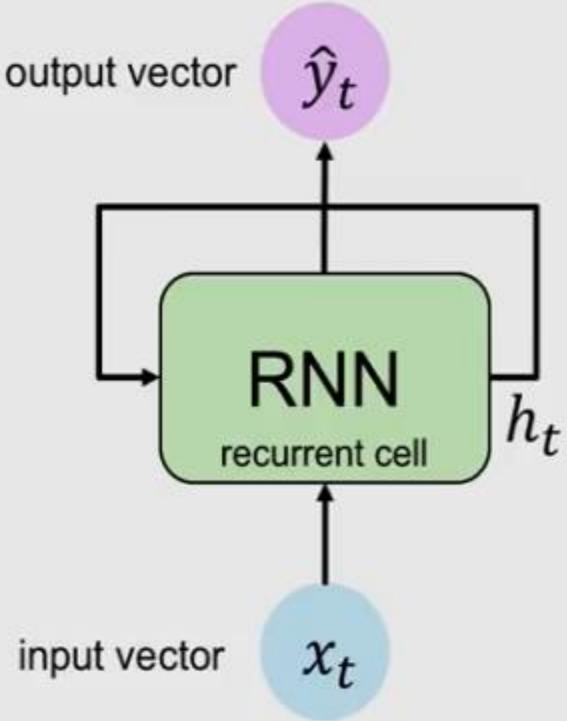
Apply a **recurrence relation** at every time step to process a sequence:

$$\boxed{h_t} = \boxed{f_W}(h_{t-1}, x_t)$$

cell state

function parameterized by W

Recurrent Neural Network (RNN)

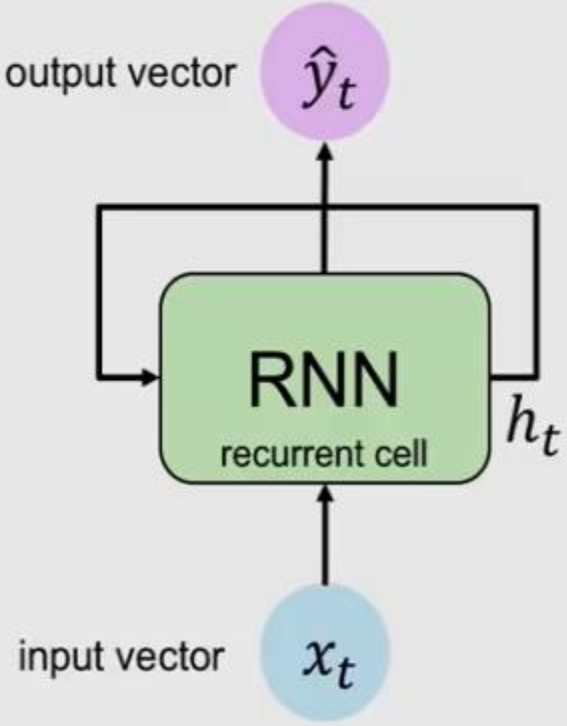


Apply a **recurrence relation** at every time step to process a sequence:

$$\underbrace{\boxed{h_t}}_{\text{cell state}} = \underbrace{\boxed{f_W}}_{\text{function parameterized by W}}(\underbrace{\boxed{h_{t-1}}}_{\text{old state}}, x_t)$$

Deep Learning

Recurrent Neural Network (RNN)



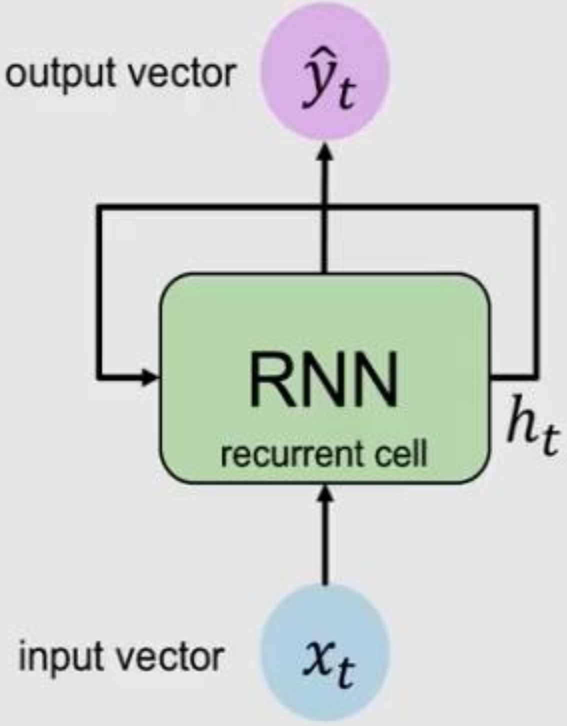
Apply a **recurrence relation** at every time step to process a sequence:

$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

cell state | function parameterized by W | old state | input vector at time step *t*

Deep Learning

Recurrent Neural Network (RNN)



Apply a **recurrence relation** at every time step to process a sequence:

$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

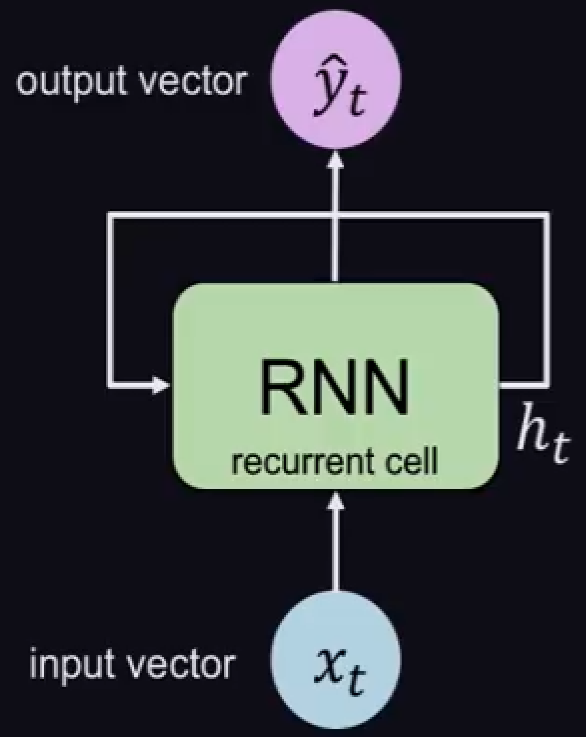
cell state — function parameterized by W — old state — input vector at time step *t*

Note: the same function and set of parameters are used at every time step

MIT Deep Learning

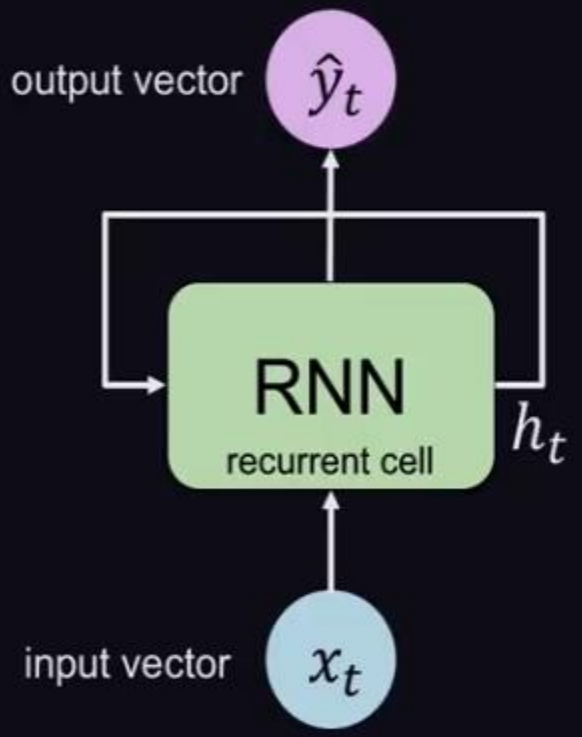
RNN Intuition

```
my_rnn = RNN()
hidden_state = [0, 0, 0, 0]

sentence = ["I", "love", "recurrent", "neural"]

for word in sentence:
    prediction, hidden_state = my_rnn(word, hidden_state)

next_word_prediction = prediction
# >>> "networks!"
```



RNN Intuition

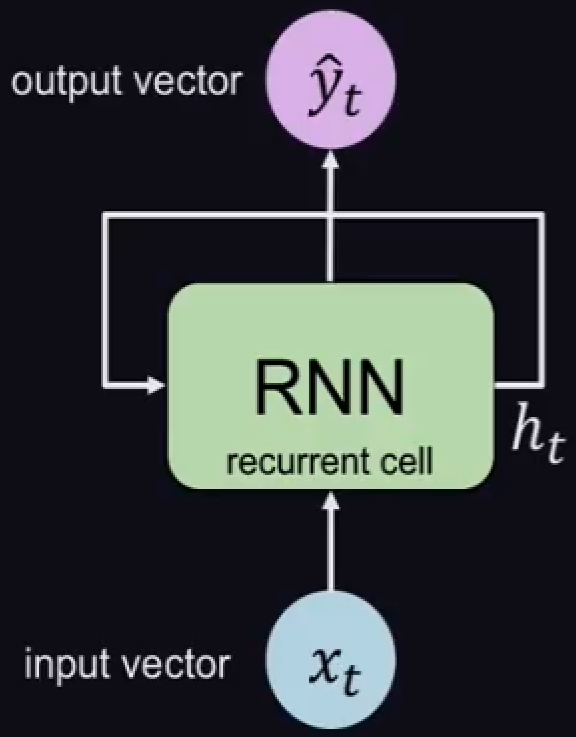
```
my_rnn = RNN()
hidden_state = [0, 0, 0, 0]

sentence = ["I", "love", "recurrent", "neural"]

for word in sentence:
    prediction, hidden_state = my_rnn(word, hidden_state)

next_word_prediction = prediction
# >>> "networks!"
```



Deep Learning

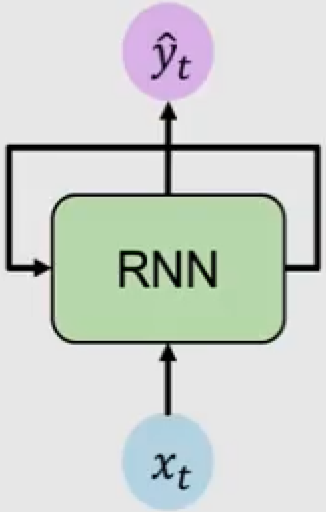
RNN Intuition

```
my_rnn = RNN()
hidden_state = [0, 0, 0, 0]

sentence = ["I", "love", "recurrent", "neural"]

for word in sentence:
    prediction, hidden_state = my_rnn(word, hidden_state)

next_word_prediction = prediction
# >>> "networks!"
```

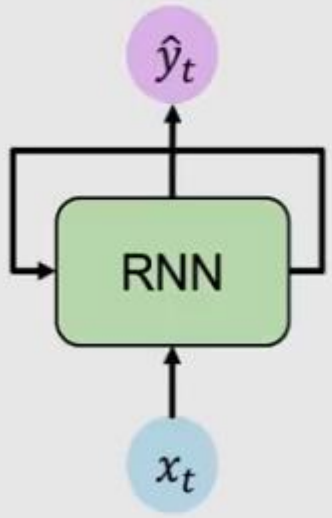


Deep Learning

RNNs: Computational Graph Across Time



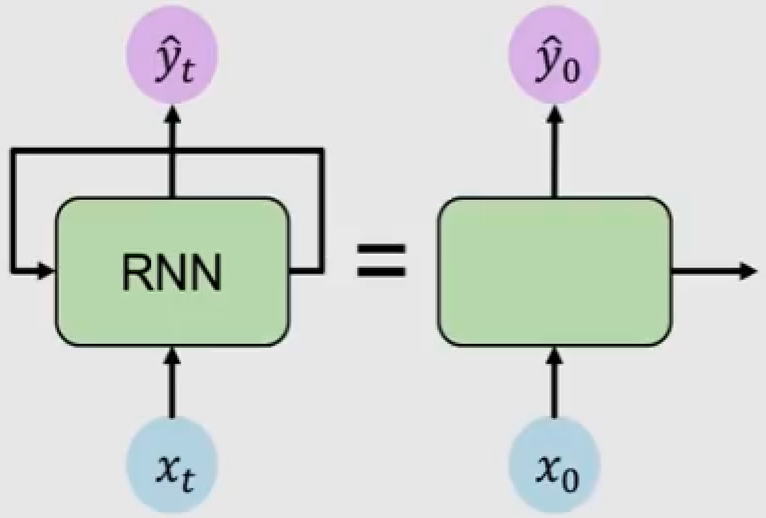
RNNs: Computational Graph Across Time



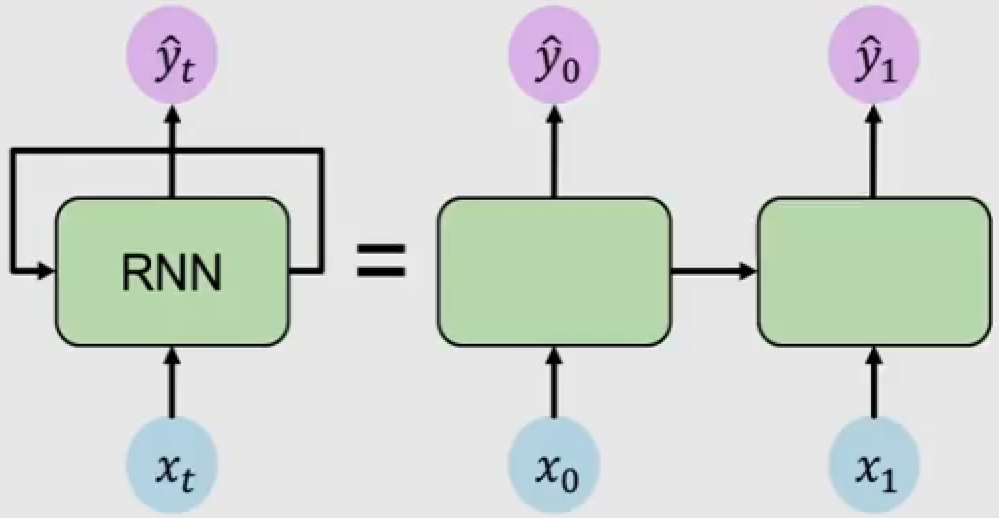
=

Represent as computational graph unrolled across time

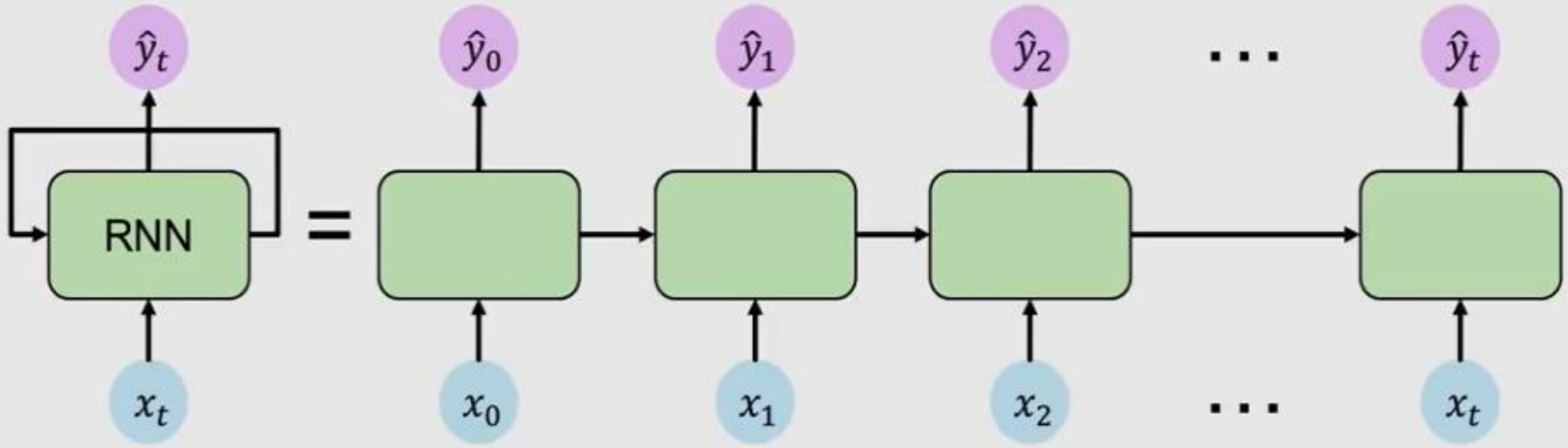
RNNs: Computational Graph Across Time



RNNs: Computational Graph Across Time

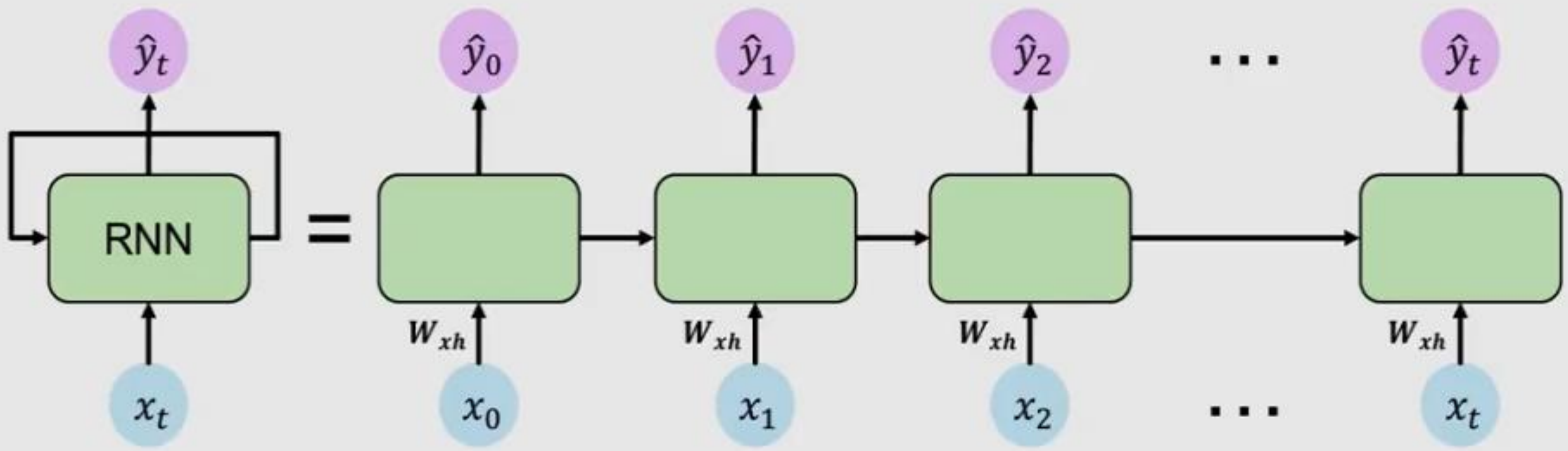


RNNs: Computational Graph Across Time



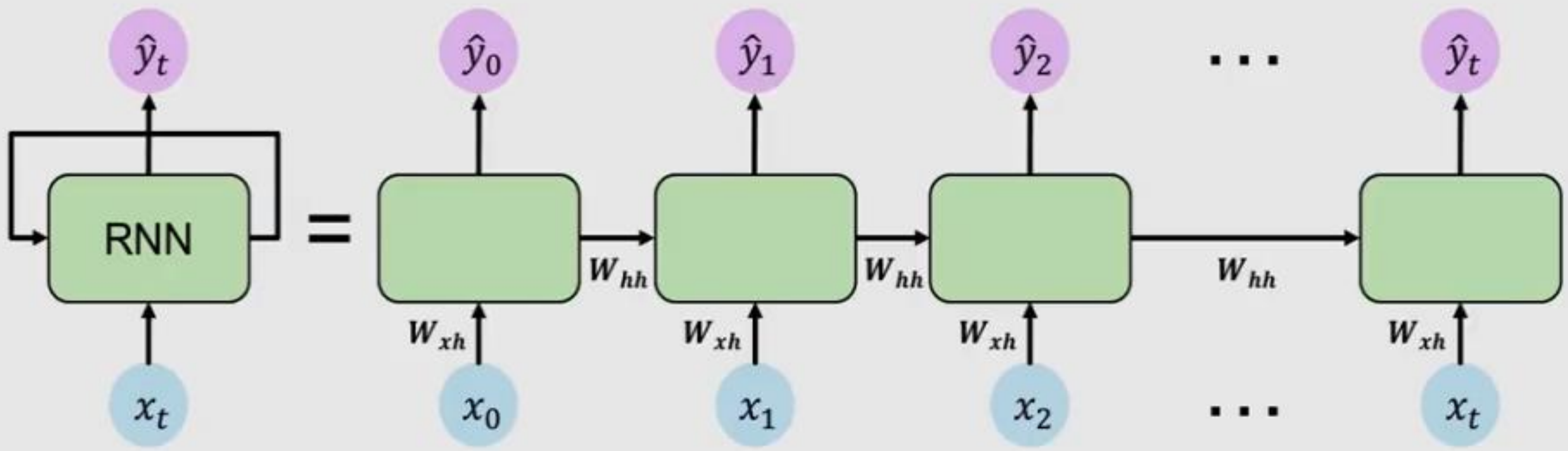
Deep Learning

RNNs: Computational Graph Across Time

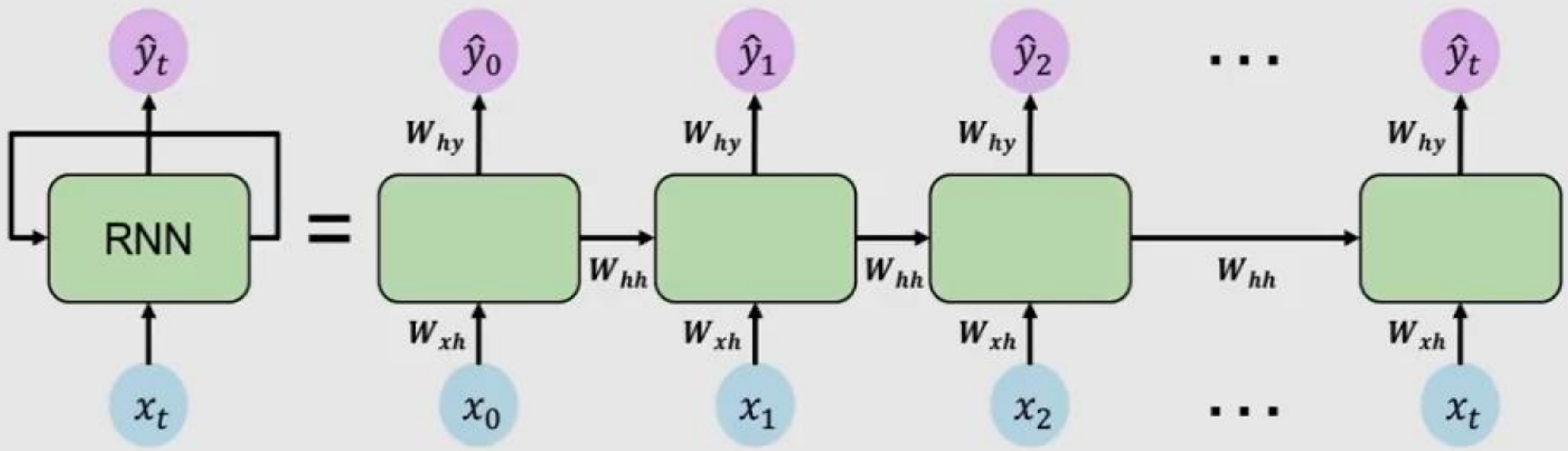


Deep Learning

RNNs: Computational Graph Across Time

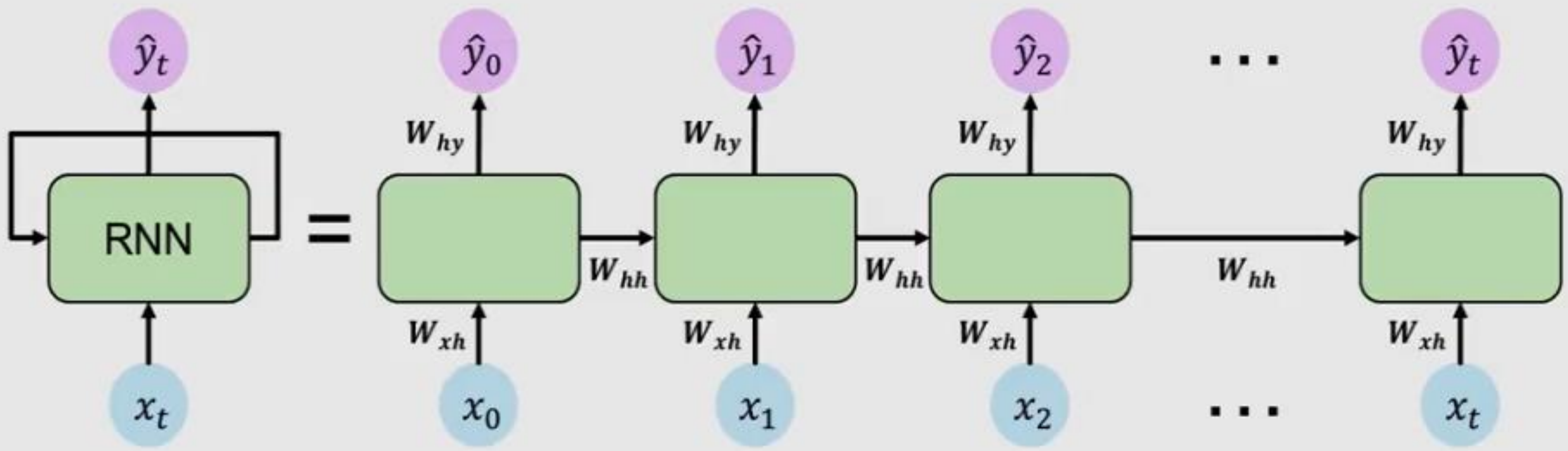


RNNs: Computational Graph Across Time



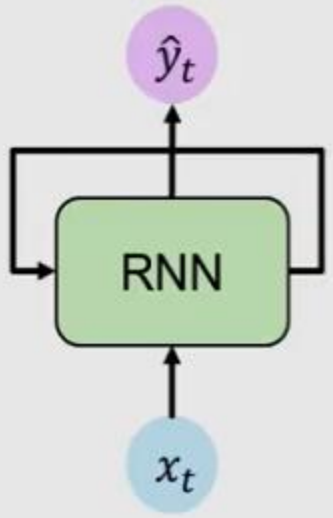
RNNs: Computational Graph Across Time

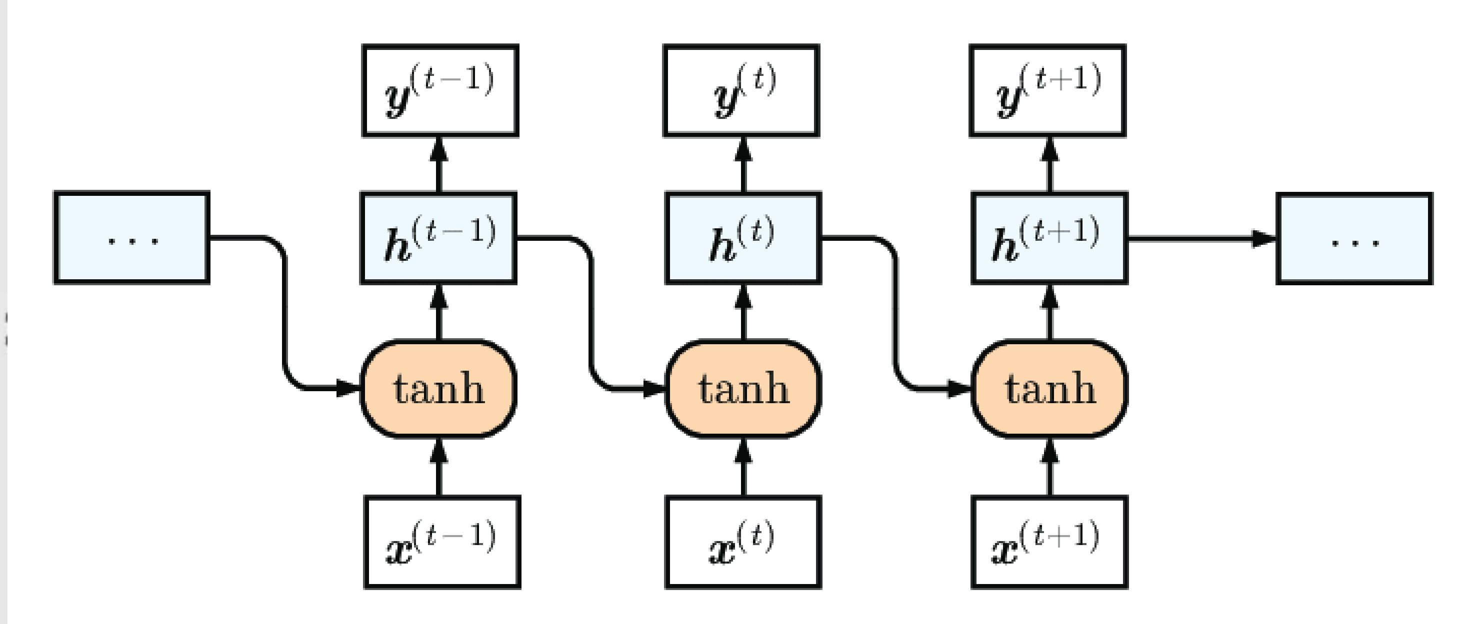
Re-use the **same weight matrices** at every time step



RNNs: Computational Graph Across Time

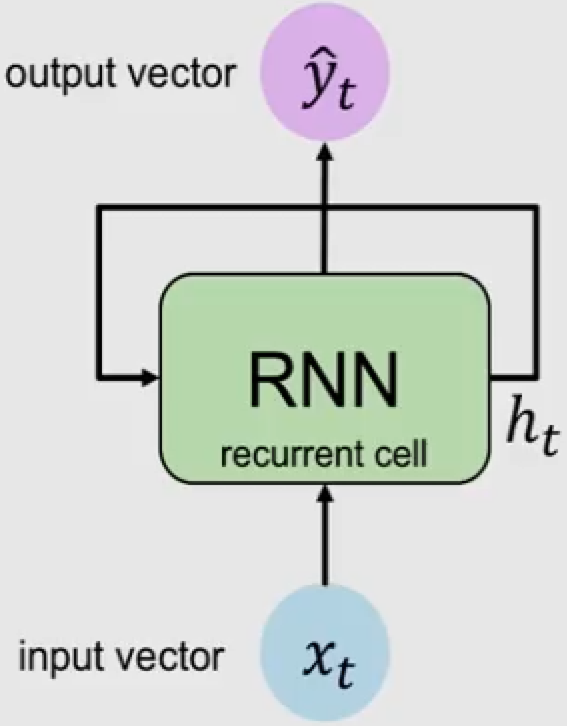
Re-use the **same weight matrices** at every time step

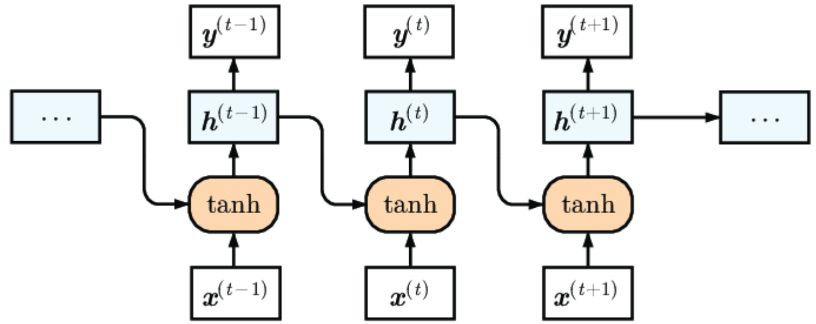




Deep Learning

RNN State Update and Output

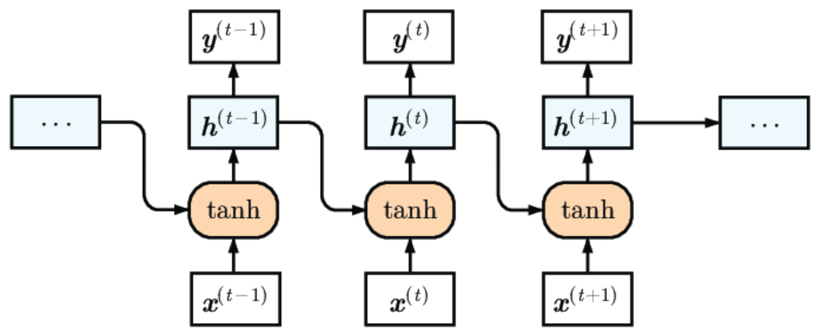




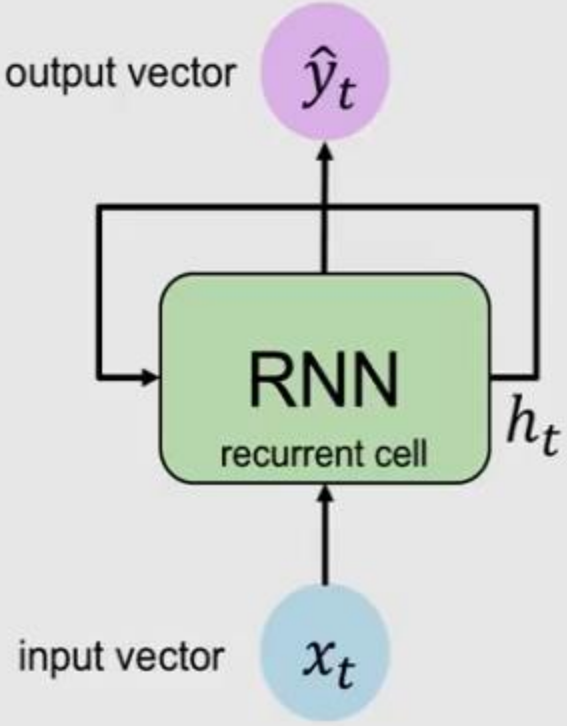
Input Vector

x_t

Deep Learning



RNN State Update and Output



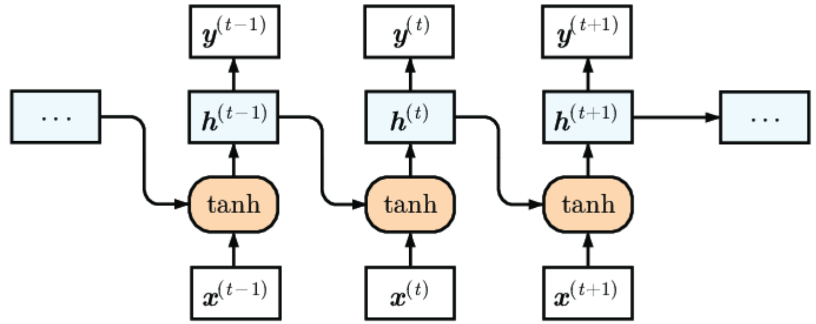
Update Hidden State

$$h_t = \tanh(\boldsymbol{W}_{hh}^{T} h_{t-1} + \boldsymbol{W}_{xh}^{T} x_t)$$

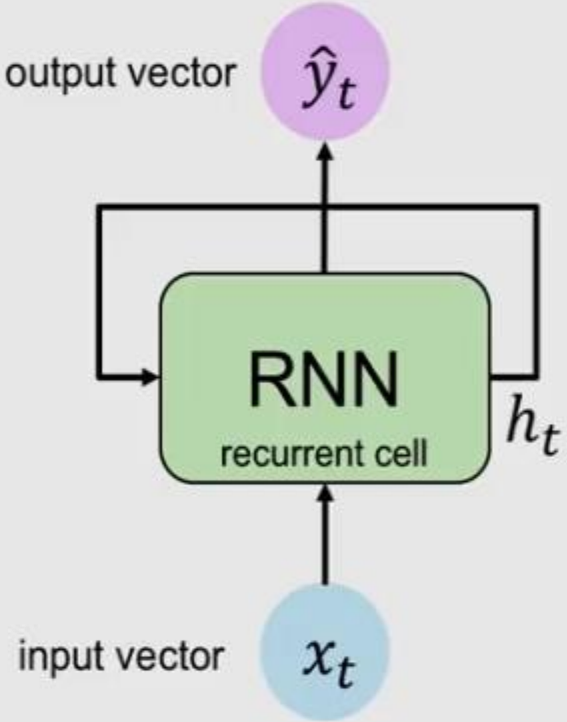
Input Vector

$$x_t$$

MIT Deep Learning



RNN State Update and Output



Output Vector

$$\hat{y}_t = \boldsymbol{W}_{hy}^{T} h_t$$

Update Hidden State

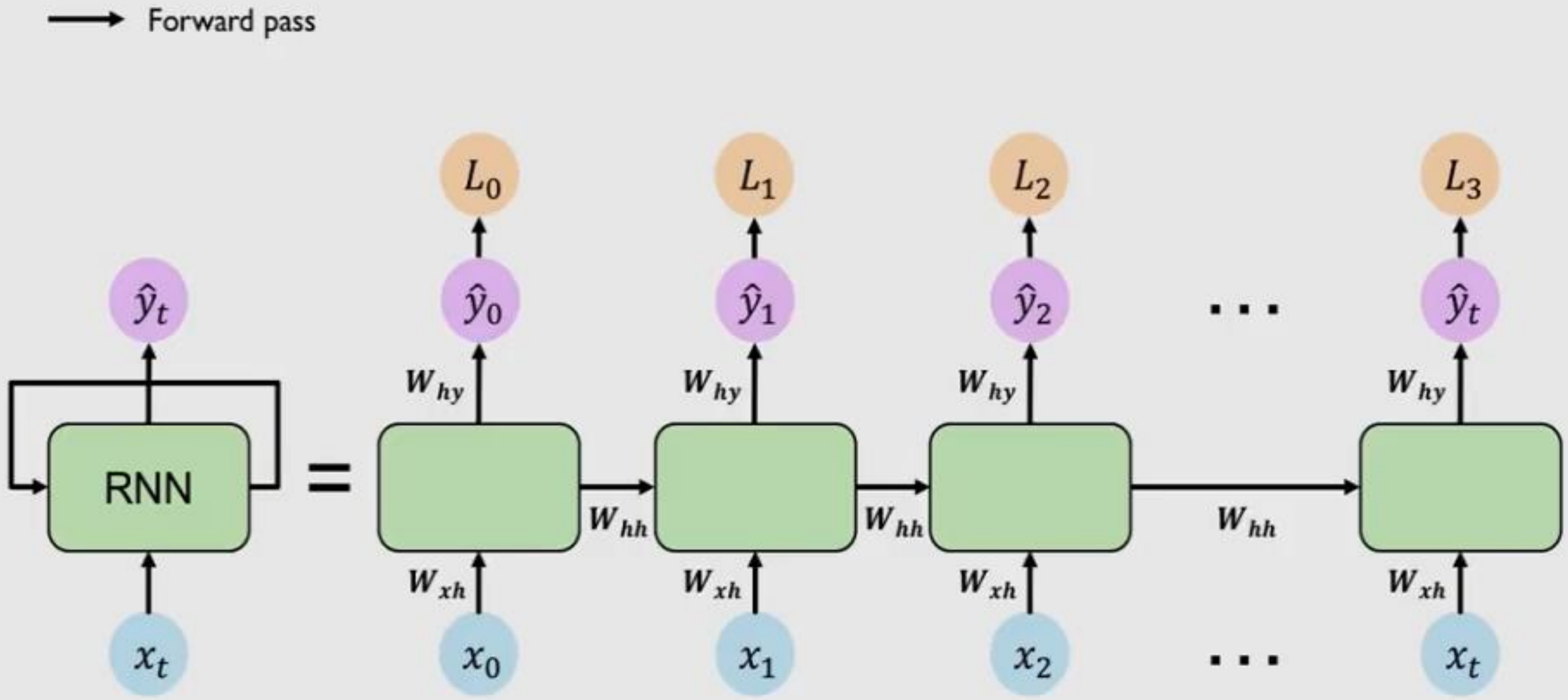
$$h_t = \tanh(\boldsymbol{W}_{hh}^{T} h_{t-1} + \boldsymbol{W}_{xh}^{T} x_t)$$

Input Vector

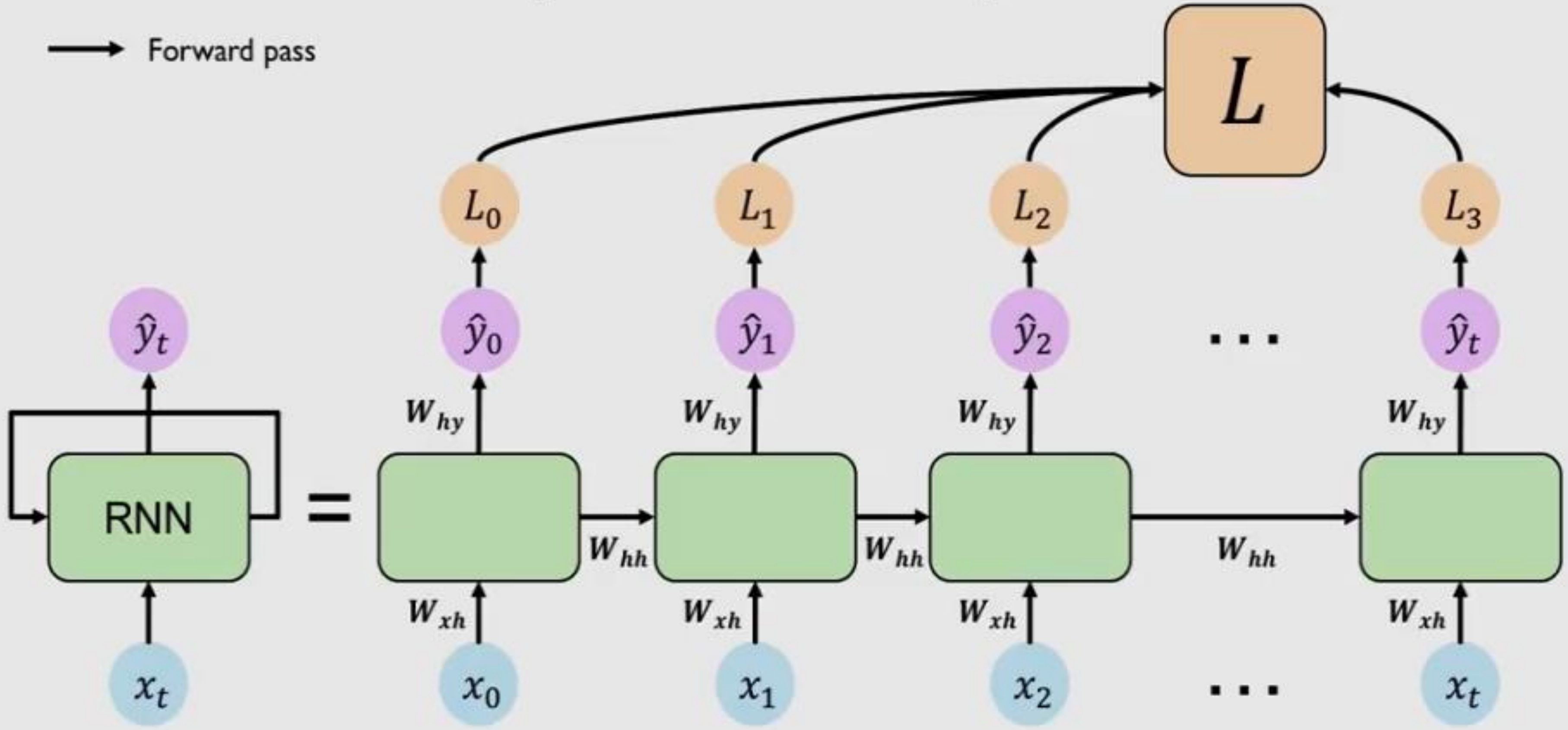
$$x_t$$

Deep Learning

RNNs: Computational Graph Across Time



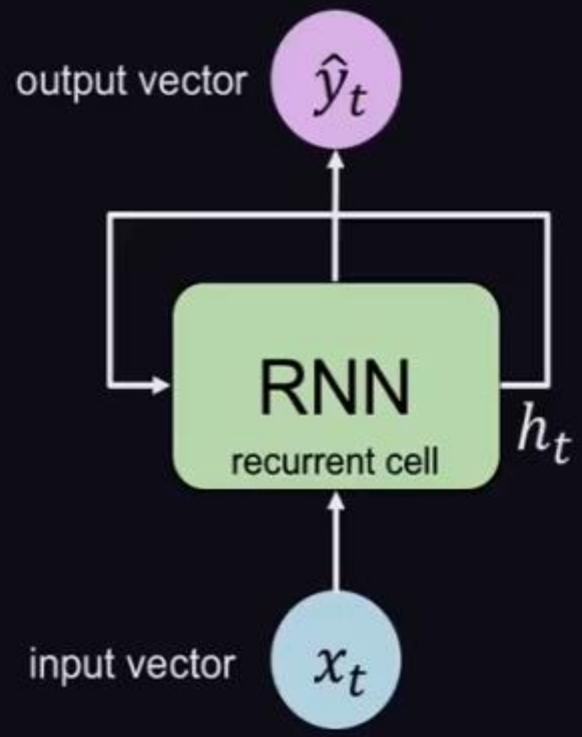
RNNs: Computational Graph Across Time



Deep Learning

RNNs from Scratch

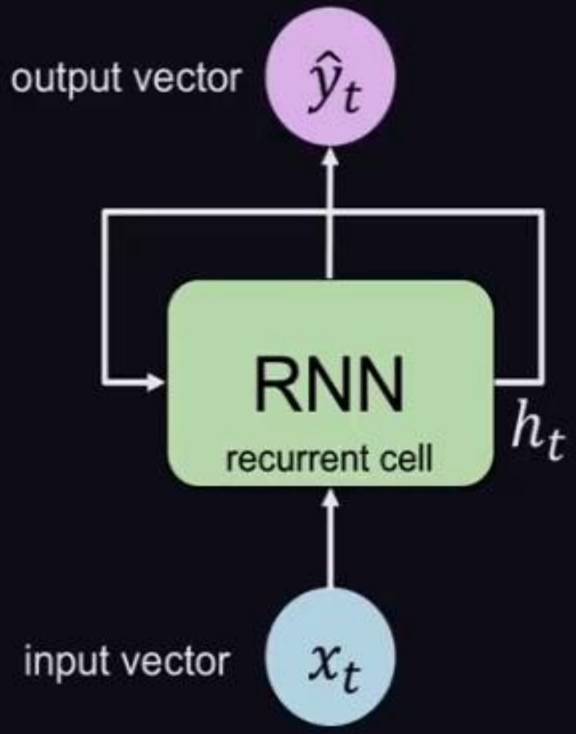
```python
class MyRNNCell(tf.keras.layers.Layer):
  def __init__(self, rnn_units, input_dim, output_dim):
    super(MyRNNCell, self).__init__()

    # Initialize weight matrices
    self.W_xh = self.add_weight([rnn_units, input_dim])
    self.W_hh = self.add_weight([rnn_units, rnn_units])
    self.W_hy = self.add_weight([output_dim, rnn_units])

    # Initialize hidden state to zeros
    self.h = tf.zeros([rnn_units, 1])
```



Deep Learning

RNNs from Scratch

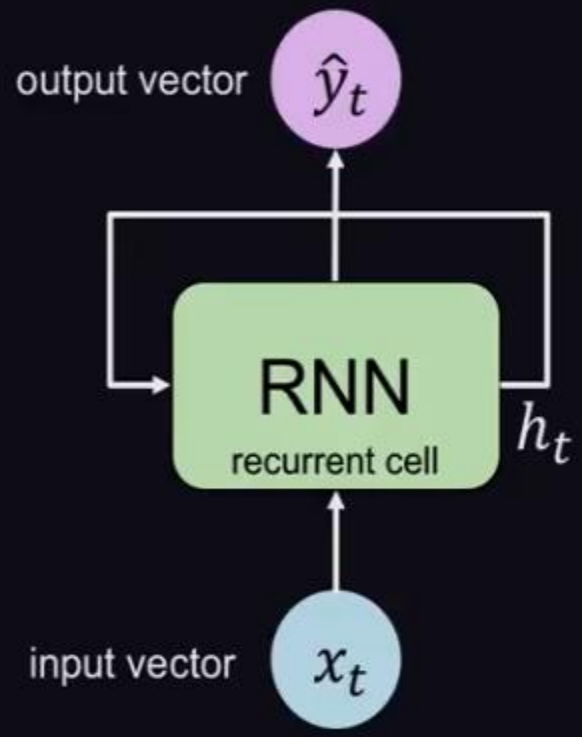
```
class MyRNNCell(tf.keras.layers.Layer):
  def __init__(self, rnn_units, input_dim, output_dim):
    super(MyRNNCell, self).__init__()

    # Initialize weight matrices
    self.W_xh = self.add_weight([rnn_units, input_dim])
    self.W_hh = self.add_weight([rnn_units, rnn_units])
    self.W_hy = self.add_weight([output_dim, rnn_units])

    # Initialize hidden state to zeros
    self.h = tf.zeros([rnn_units, 1])

  def call(self, x):
    # Update the hidden state
    self.h = tf.math.tanh( self.W_hh * self.h + self.W_xh * x )

    # Compute the output
    output = self.W_hy * self.h

    # Return the current output and hidden state
    return output, self.h
```



Deep Learning

RNNs from Scratch

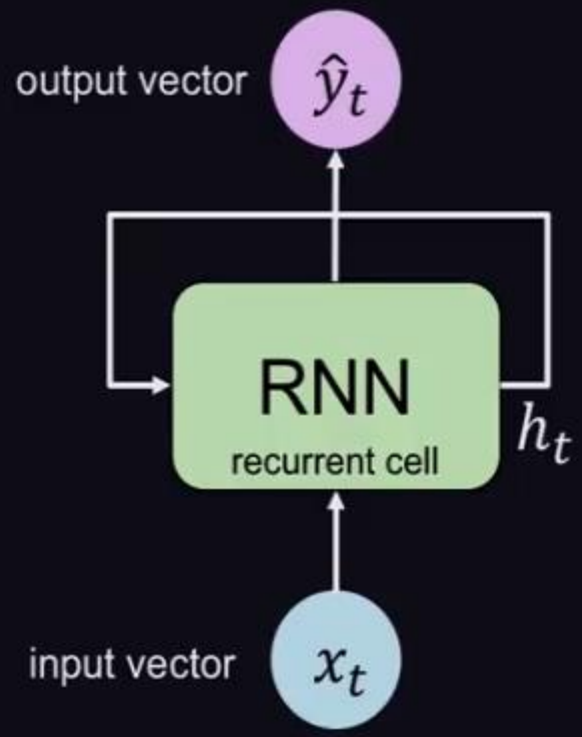
```python
class MyRNNCell(tf.keras.layers.Layer):
  def __init__(self, rnn_units, input_dim, output_dim):
    super(MyRNNCell, self).__init__()

    # Initialize weight matrices
    self.W_xh = self.add_weight([rnn_units, input_dim])
    self.W_hh = self.add_weight([rnn_units, rnn_units])
    self.W_hy = self.add_weight([output_dim, rnn_units])

    # Initialize hidden state to zeros
    self.h = tf.zeros([rnn_units, 1])

  def call(self, x):
    # Update the hidden state
    self.h = tf.math.tanh( self.W_hh * self.h + self.W_xh * x )

    # Compute the output
    output = self.W_hy * self.h

    # Return the current output and hidden state
    return output, self.h
```



Deep Learning

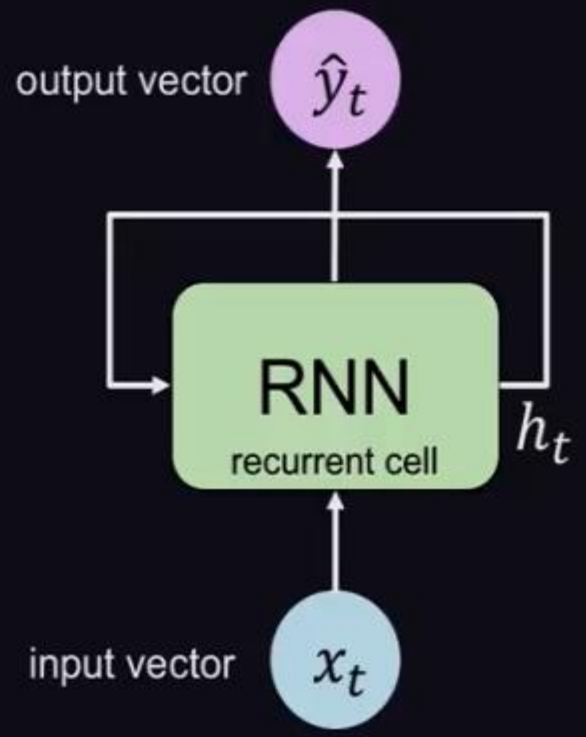
RNNs from Scratch

```python
class MyRNNCell(tf.keras.layers.Layer):
  def __init__(self, rnn_units, input_dim, output_dim):
    super(MyRNNCell, self).__init__()

    # Initialize weight matrices
    self.W_xh = self.add_weight([rnn_units, input_dim])
    self.W_hh = self.add_weight([rnn_units, rnn_units])
    self.W_hy = self.add_weight([output_dim, rnn_units])

    # Initialize hidden state to zeros
    self.h = tf.zeros([rnn_units, 1])

  def call(self, x):
    # Update the hidden state
    self.h = tf.math.tanh( self.W_hh * self.h + self.W_xh * x )

    # Compute the output
    output = self.W_hy * self.h

    # Return the current output and hidden state
    return output, self.h
```



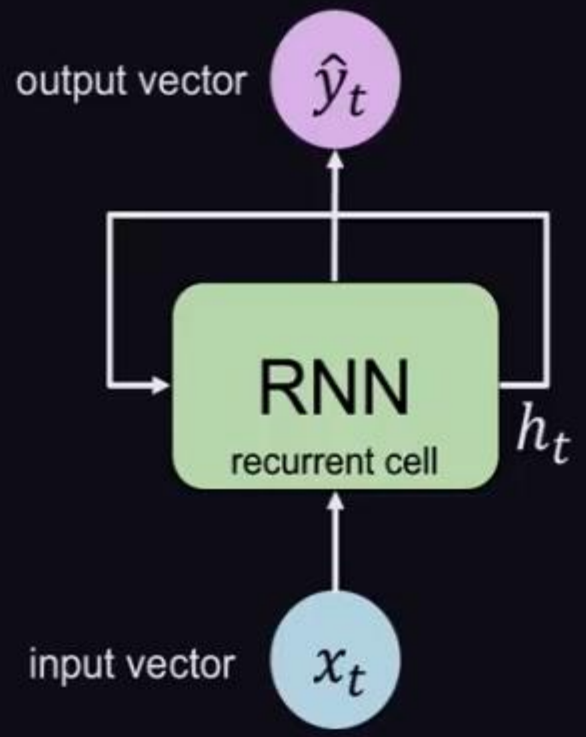
RNNs from Scratch

```python
class MyRNNCell(tf.keras.layers.Layer):
  def __init__(self, rnn_units, input_dim, output_dim):
    super(MyRNNCell, self).__init__()

    # Initialize weight matrices
    self.W_xh = self.add_weight([rnn_units, input_dim])
    self.W_hh = self.add_weight([rnn_units, rnn_units])
    self.W_hy = self.add_weight([output_dim, rnn_units])

    # Initialize hidden state to zeros
    self.h = tf.zeros([rnn_units, 1])

  def call(self, x):
    # Update the hidden state
    self.h = tf.math.tanh( self.W_hh * self.h + self.W_xh * x )

    # Compute the output
    output = self.W_hy * self.h

    # Return the current output and hidden state
    return output, self.h
```



RNN Implementation in TensorFlow

```
tf.keras.layers.SimpleRNN(rnn_units)
```



Deep Learning

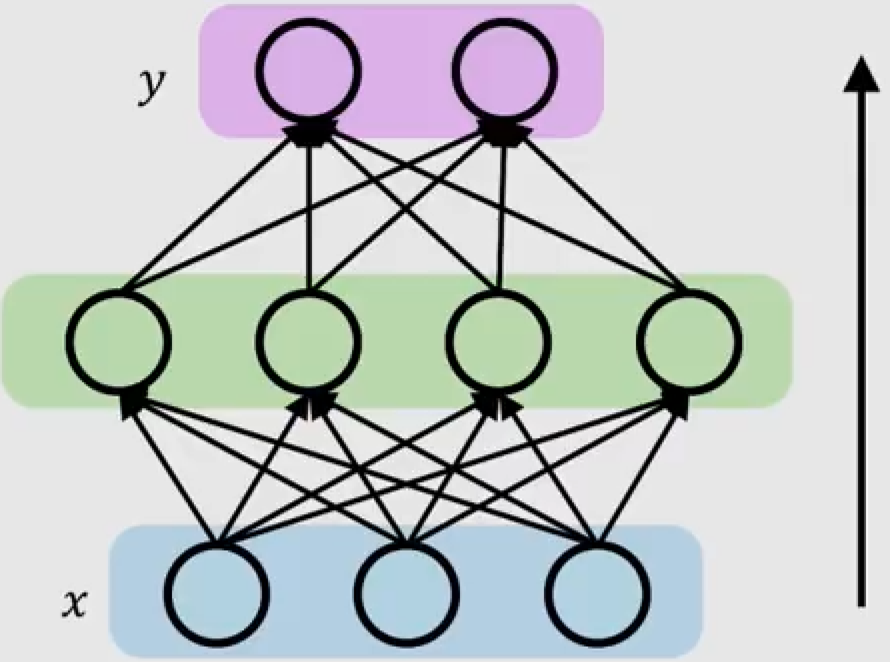
Backpropagation Through Time (BPTT)

MIT Deep Learning

Recall: Backpropagation in Feed Forward Models

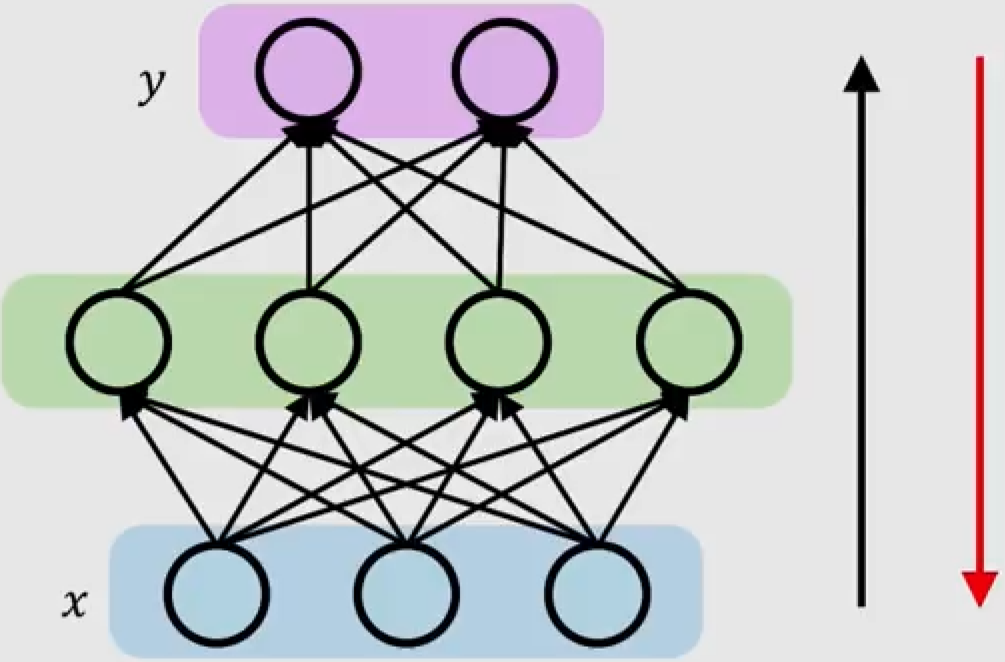
Deep Learning

Recall: Backpropagation in Feed Forward Models

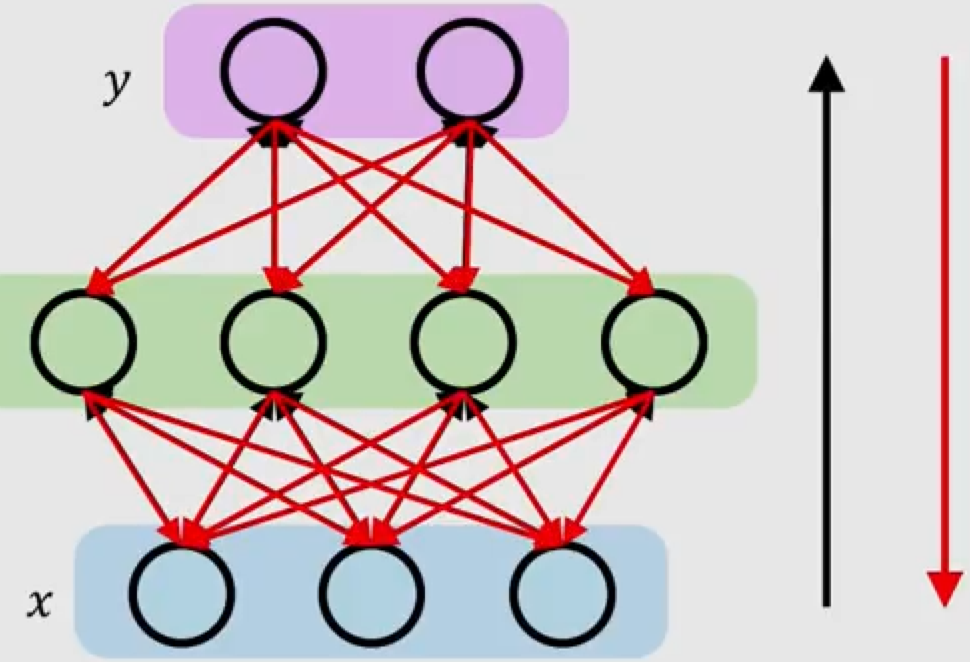


MIT Deep Learning

Recall: Backpropagation in Feed Forward Models

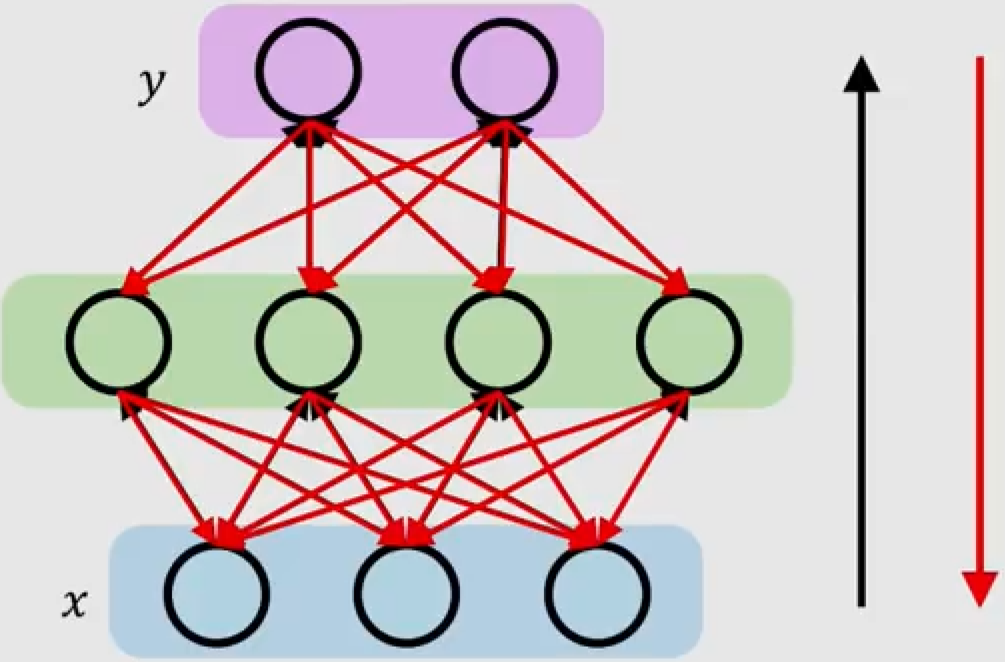


Recall: Backpropagation in Feed Forward Models



Backpropagation algorithm:

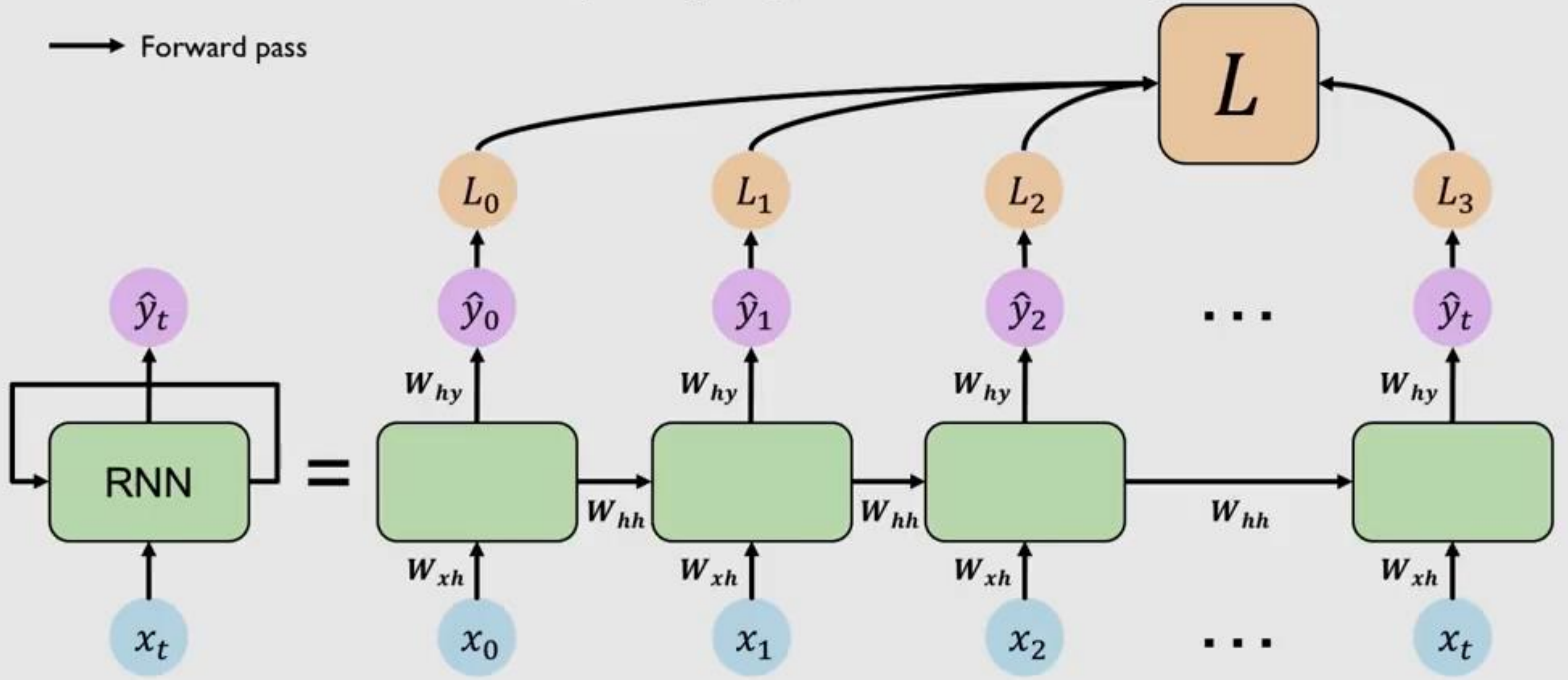
Recall: Backpropagation in Feed Forward Models



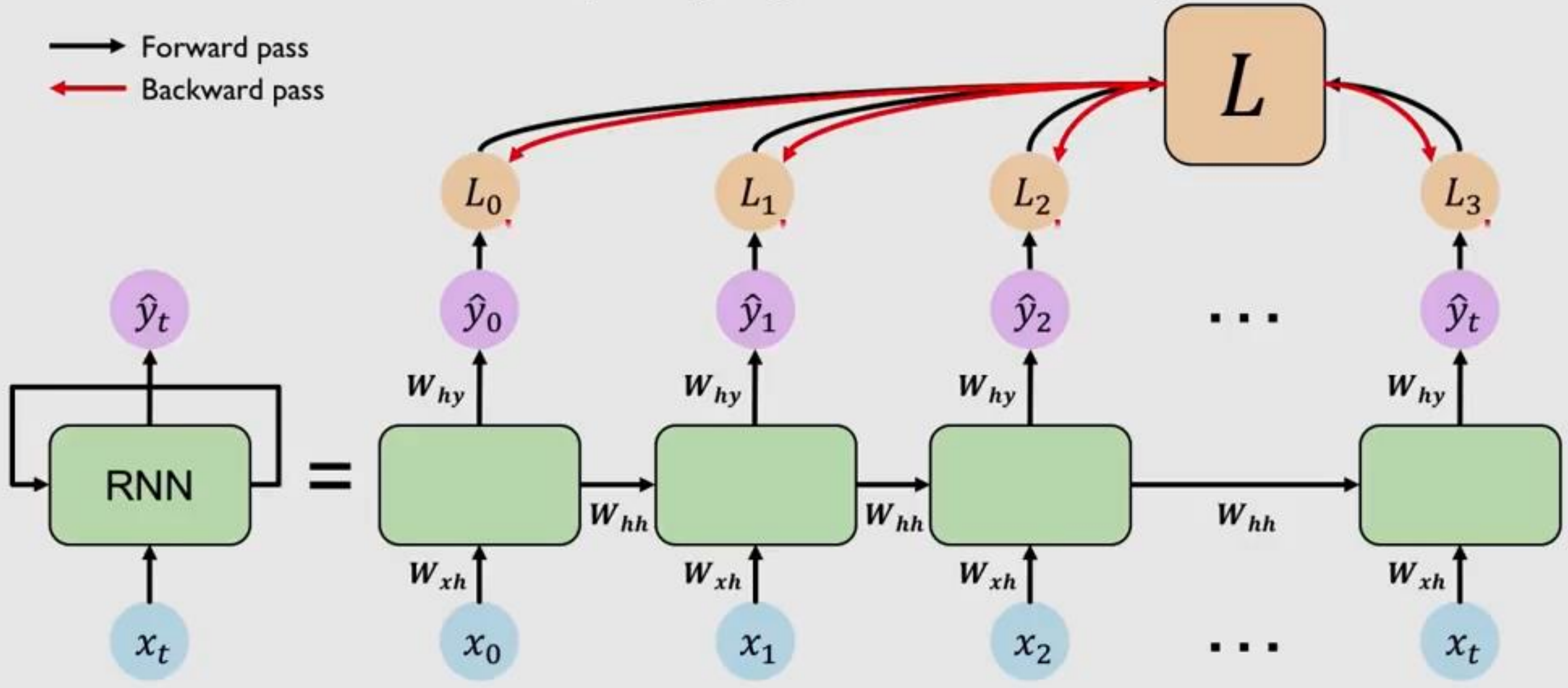
Backpropagation algorithm:

1. Take the derivative (gradient) of the loss with respect to each parameter
2. Shift parameters in order to minimize loss

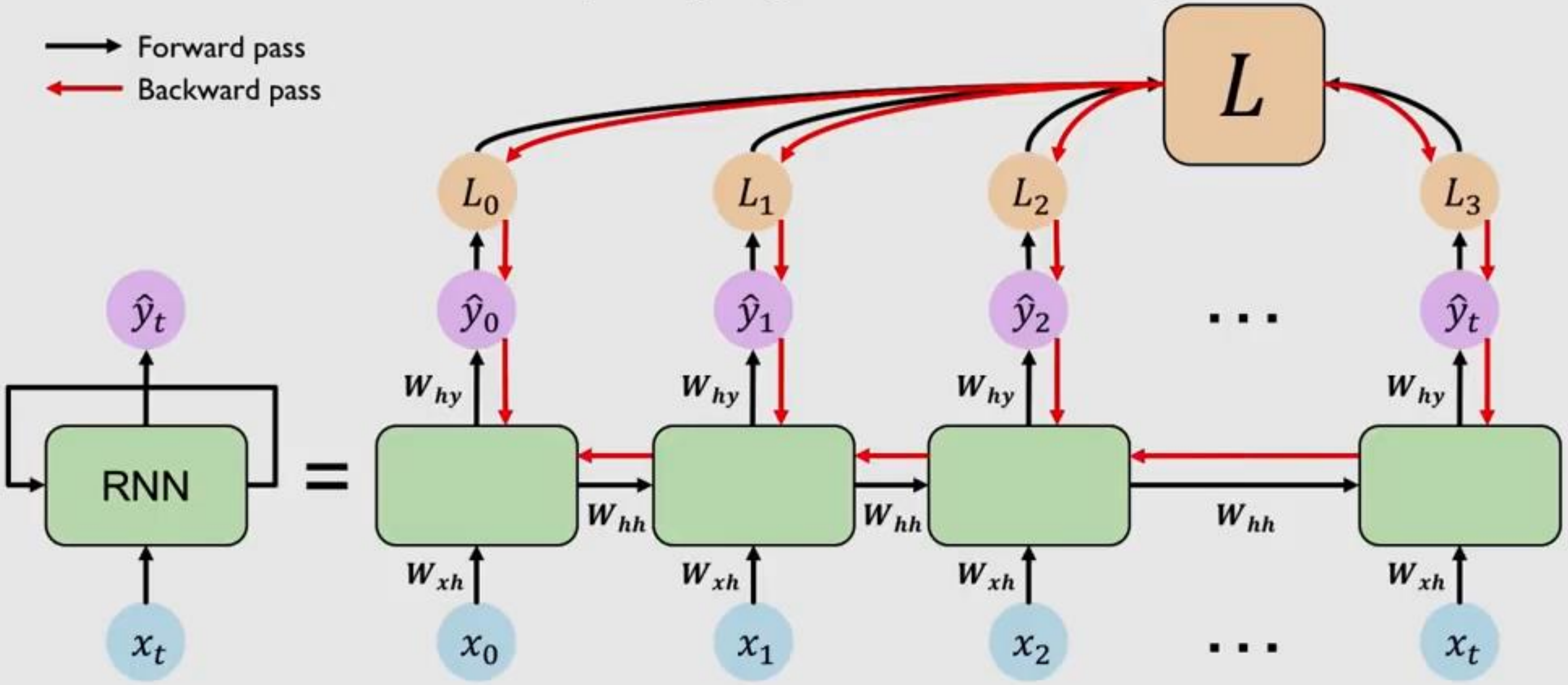
RNNs: Backpropagation Through Time



RNNs: Backpropagation Through Time

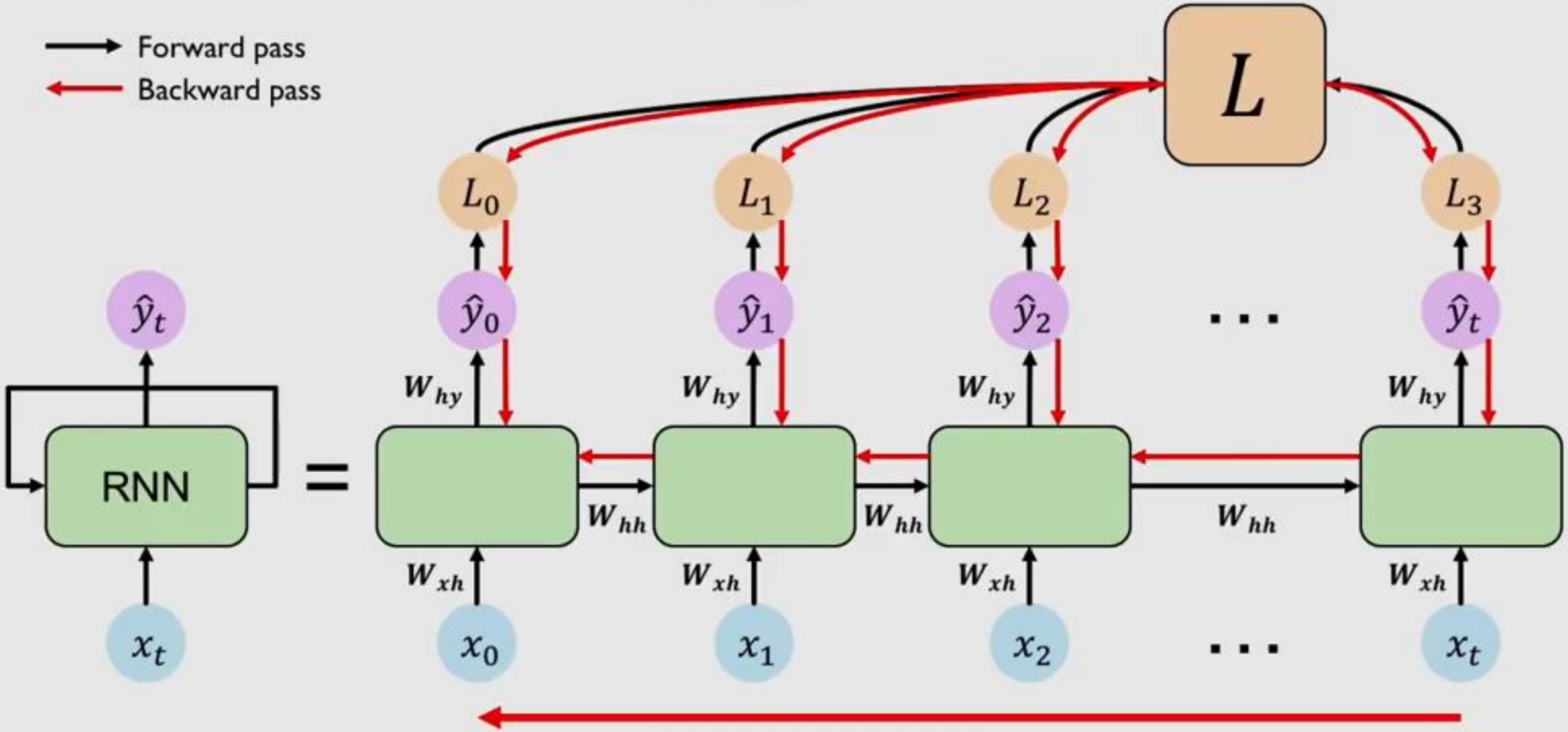


RNNs: Backpropagation Through Time

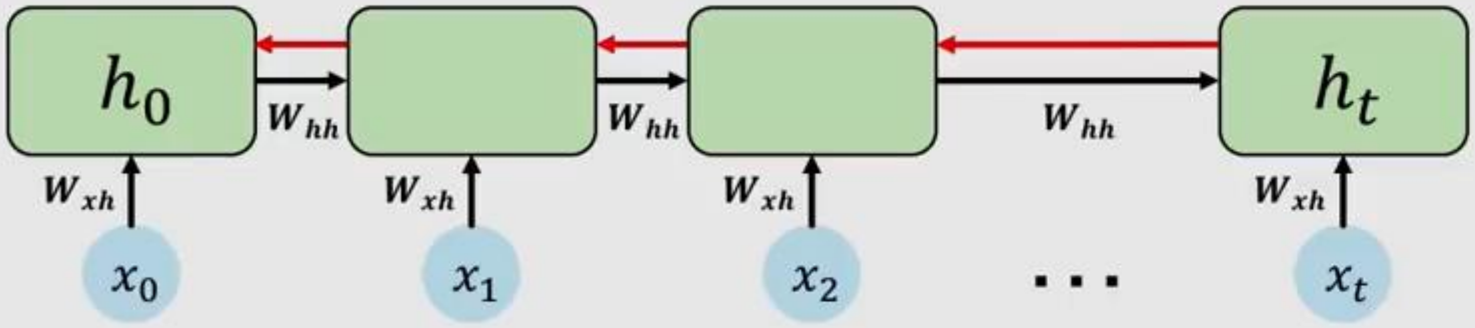


MIT Deep Learning

RNNs: Backpropagation Through Time

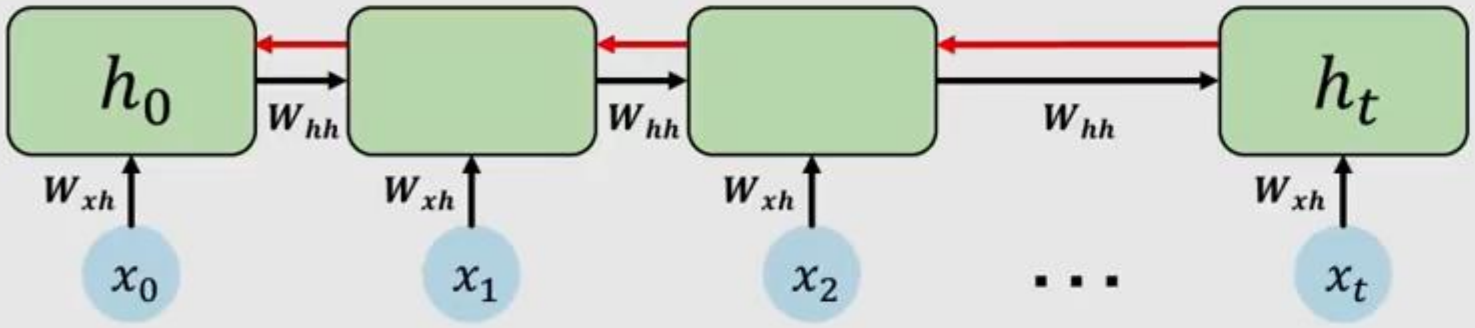


Standard RNN Gradient Flow



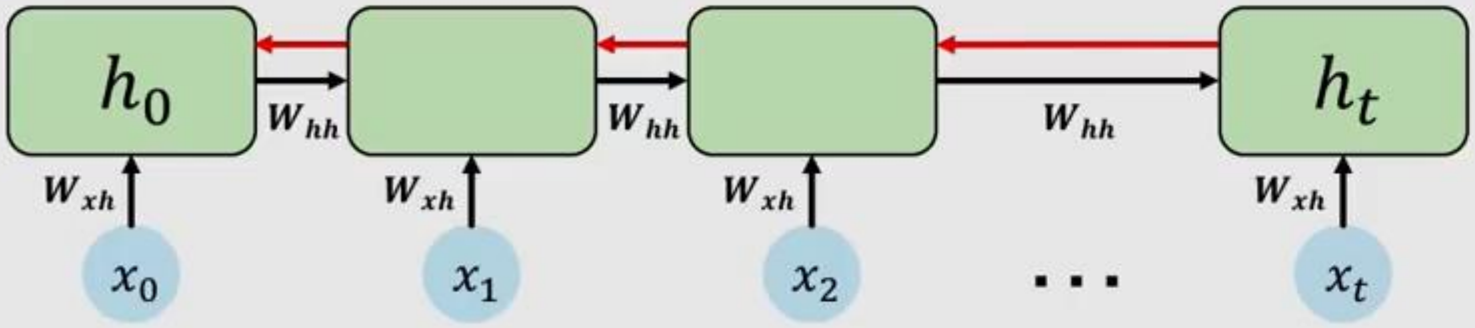
MIT Deep Learning

Standard RNN Gradient Flow



Computing the gradient wrt h_0 involves **many factors of W_{hh} + repeated gradient computation!**

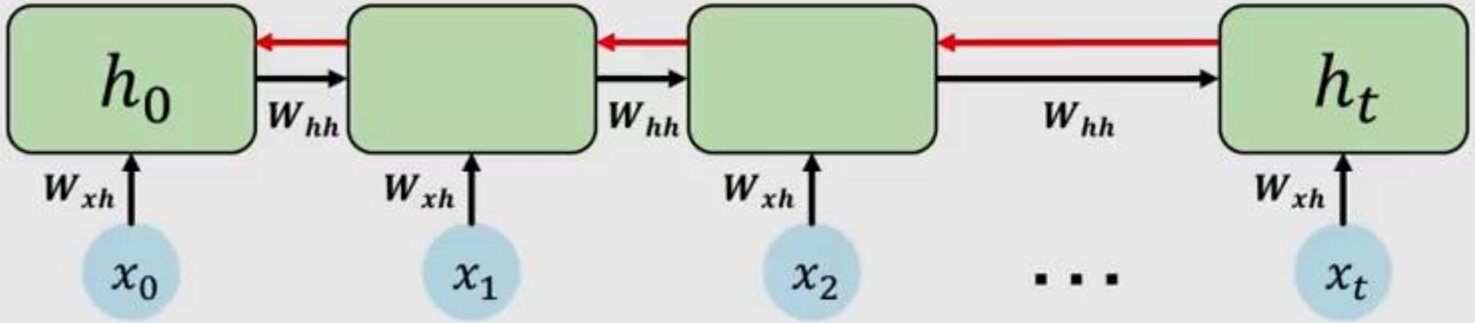
Standard RNN Gradient Flow: Exploding Gradients



Computing the gradient wrt h_0 involves **many factors of W_{hh} + repeated gradient computation!**

Many values > 1:
exploding gradients

Standard RNN Gradient Flow: Vanishing Gradients



Computing the gradient wrt h_0 involves **many factors of W_{hh} + repeated gradient computation!**

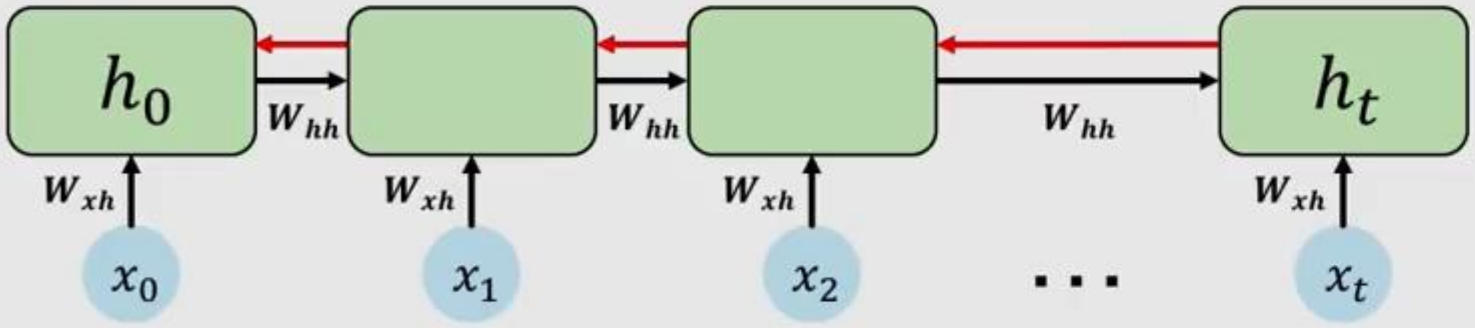
Many values > 1:
exploding gradients

Gradient clipping to scale big gradients

Many values < 1:
vanishing gradients

MIT Deep Learning

Standard RNN Gradient Flow: Vanishing Gradients



Computing the gradient wrt h_0 involves **many factors of W_{hh} + repeated gradient computation!**

Many values > 1:
exploding gradients

Gradient clipping to
scale big gradients

Many values < 1:
vanishing gradients

1. Activation function
2. Weight initialization
3. Network architecture

The Problem of Long-Term Dependencies

Why are vanishing gradients a problem?

The Problem of Long-Term Dependencies

Why are vanishing gradients a problem?

Multiply many **small numbers** together

The Problem of Long-Term Dependencies

Why are vanishing gradients a problem?

Multiply many **small numbers** together

↓

Errors due to further back time steps have smaller and smaller gradients

The Problem of Long-Term Dependencies

Why are vanishing gradients a problem?

Multiply many **small numbers** together

↓

Errors due to further back time steps have smaller and smaller gradients

↓

Bias parameters to capture short-term dependencies

Deep Learning

The Problem of Long-Term Dependencies

"The clouds are in the ___"

Why are vanishing gradients a problem?

Multiply many **small numbers** together

↓

Errors due to further back time steps have smaller and smaller gradients

↓

Bias parameters to capture short-term dependencies

The Problem of Long-Term Dependencies

Why are vanishing gradients a problem?

Multiply many **small numbers** together

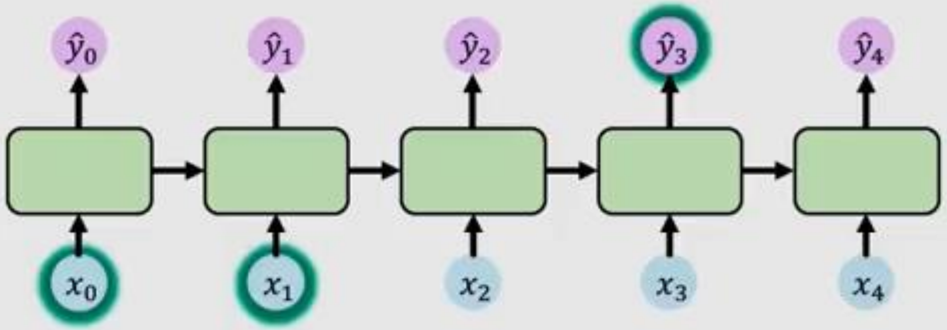
↓

Errors due to further back time steps have smaller and smaller gradients

↓

Bias parameters to capture short-term dependencies

"The clouds are in the ___"



MIT Deep Learning

The Problem of Long-Term Dependencies

Why are vanishing gradients a problem?

Multiply many **small numbers** together

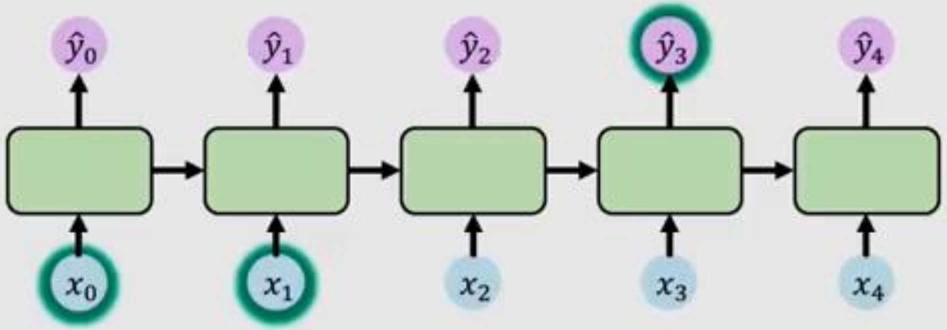
↓

Errors due to further back time steps have smaller and smaller gradients

↓

Bias parameters to capture short-term dependencies

"The clouds are in the ___"



"I grew up in France, … and I speak fluent___ "

Deep Learning

The Problem of Long-Term Dependencies

Why are vanishing gradients a problem?

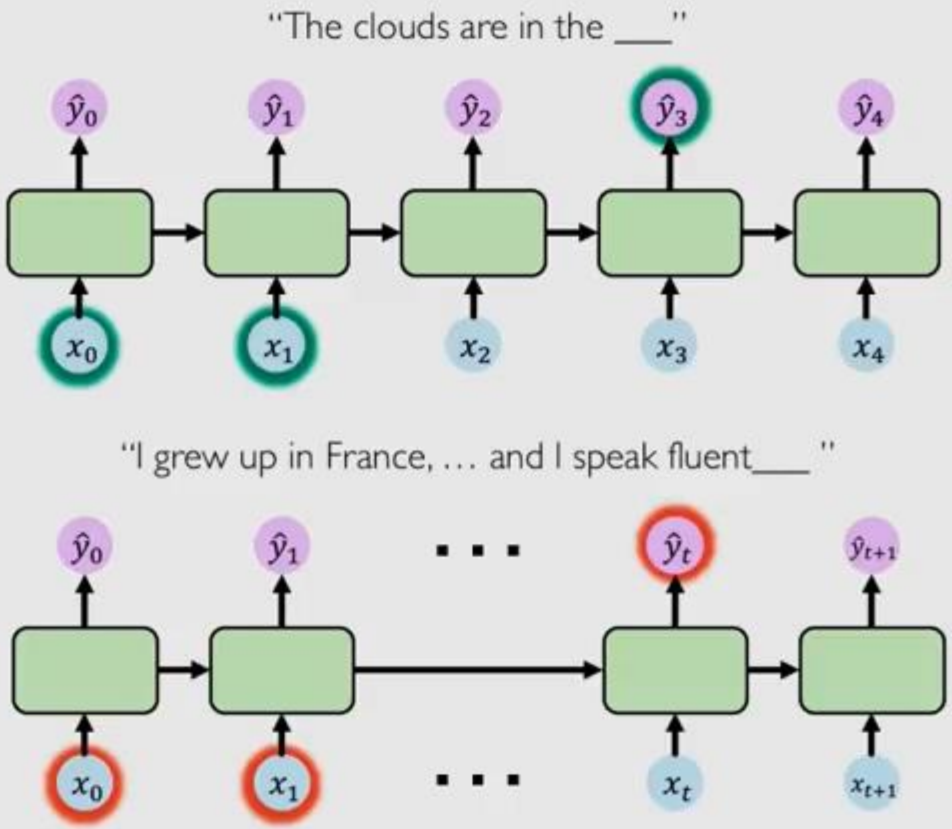
Multiply many **small numbers** together

↓

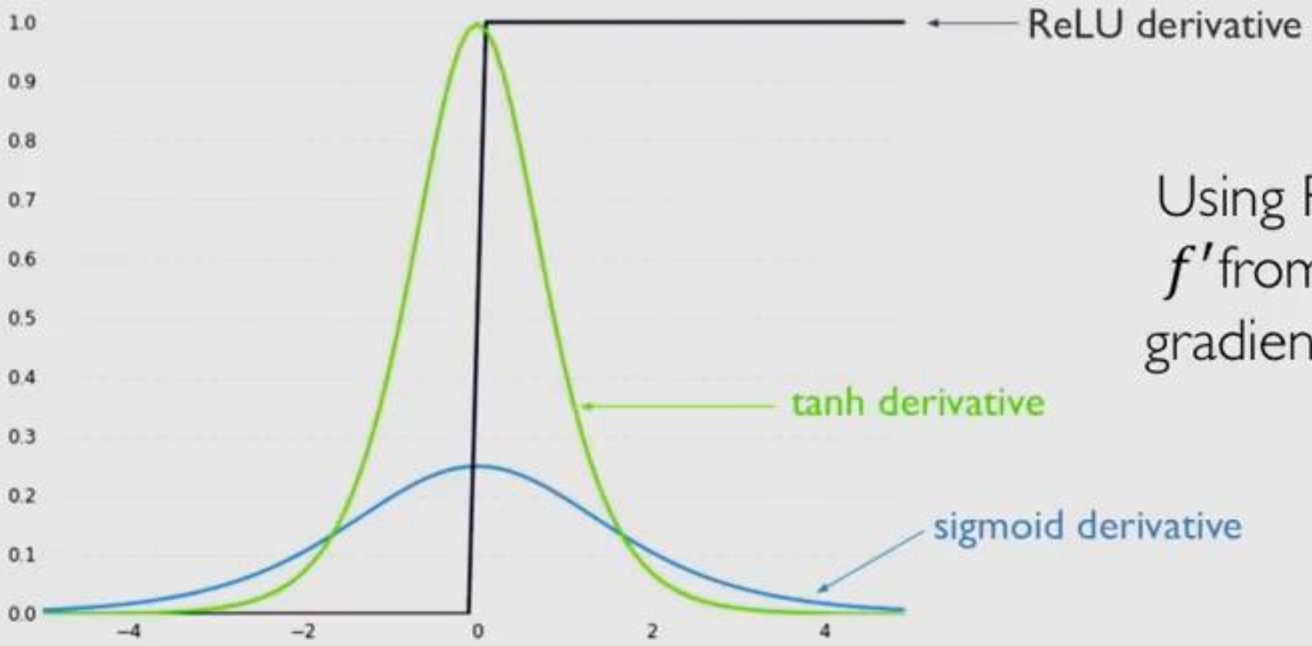
Errors due to further back time steps have smaller and smaller gradients

↓

Bias parameters to capture short-term dependencies



Trick #1: Activation Functions



Using ReLU prevents f' from shrinking the gradients when $x > 0$

Deep Learning

Trick #2: Parameter Initialization

Initialize **weights** to identity matrix

Initialize **biases** to zero

$$I_n = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix}$$

This helps prevent the weights from shrinking to zero.

Deep Learning

Solution #3: Gated Cells

Idea: use a more **complex recurrent unit with gates** to control what information is passed through

gated cell

LSTM, GRU, etc.

Solution #3: Gated Cells

Idea: use a more **complex recurrent unit with gates** to control what information is passed through

gated cell

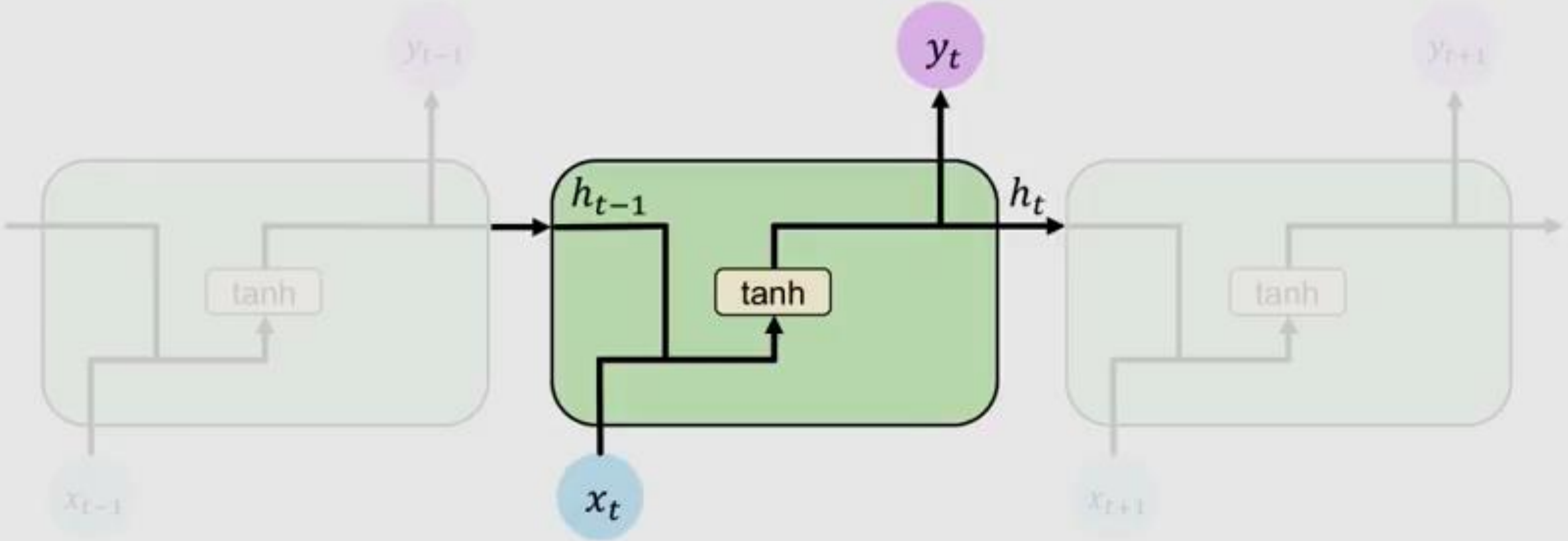
LSTM, GRU, etc.

Long Short Term Memory (LSTMs) networks rely on a gated cell to track information throughout many time steps.

Long Short Term Memory (LSTM) Networks

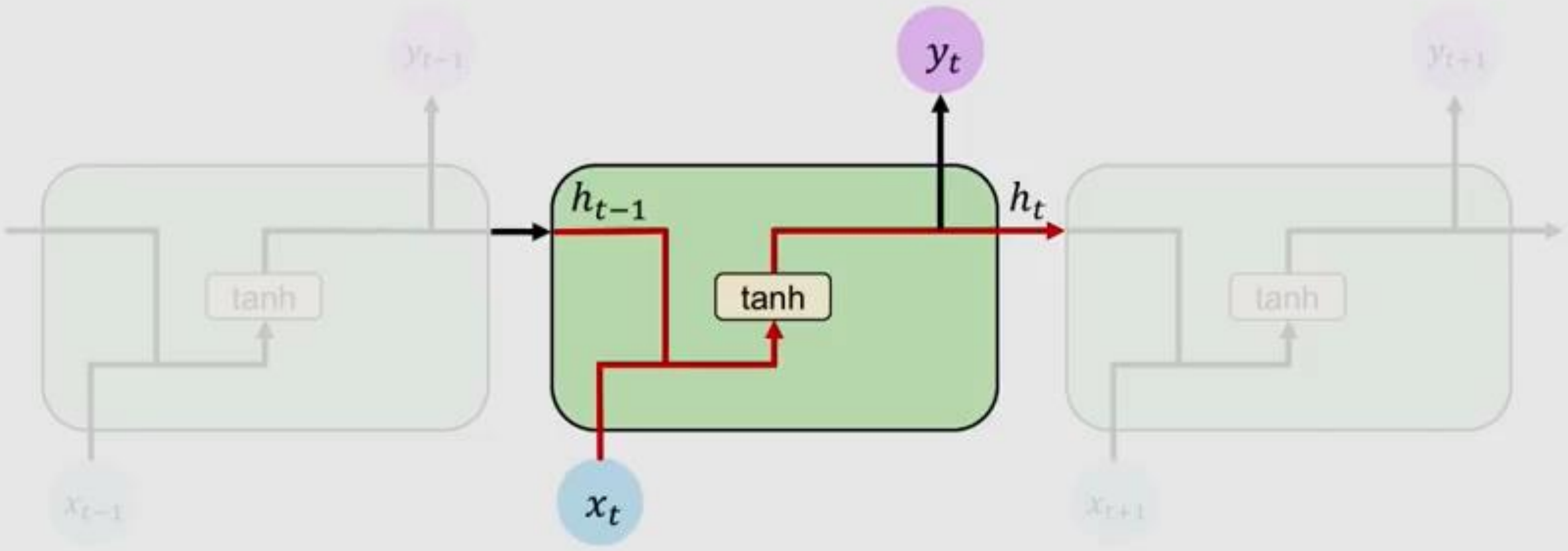
Standard RNN

In a standard RNN, repeating modules contain a **simple computation node**



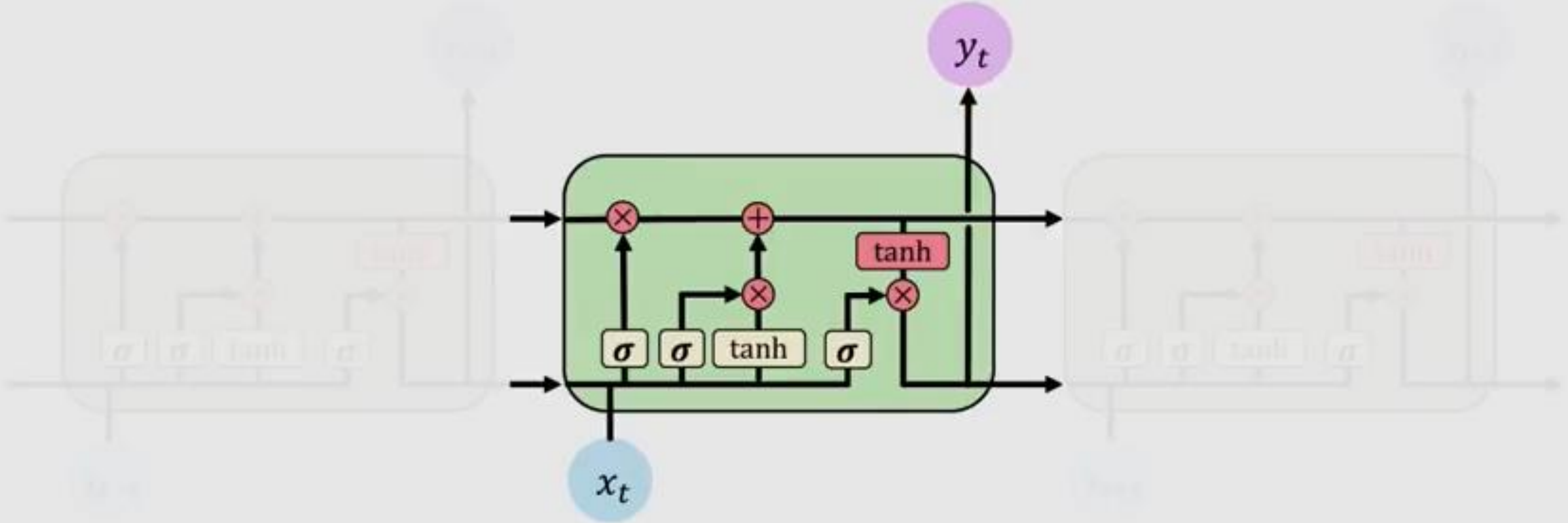
Standard RNN

In a standard RNN, repeating modules contain a **simple computation node**



Long Short Term Memory (LSTMs)

LSTM modules contain **computational blocks** that **control information flow**

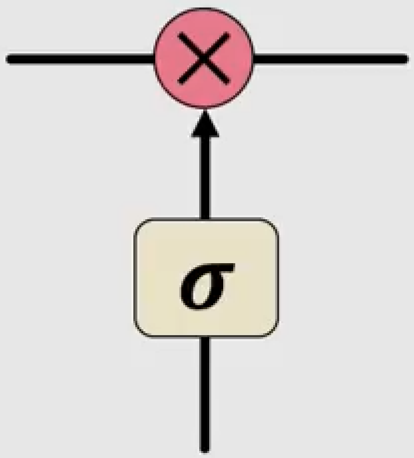


LSTM cells are able to track information throughout many timesteps

```
tf.keras.layers.LSTM(num_units)
```

Long Short Term Memory (LSTMs)

Information is **added** or **removed** through structures called **gates**

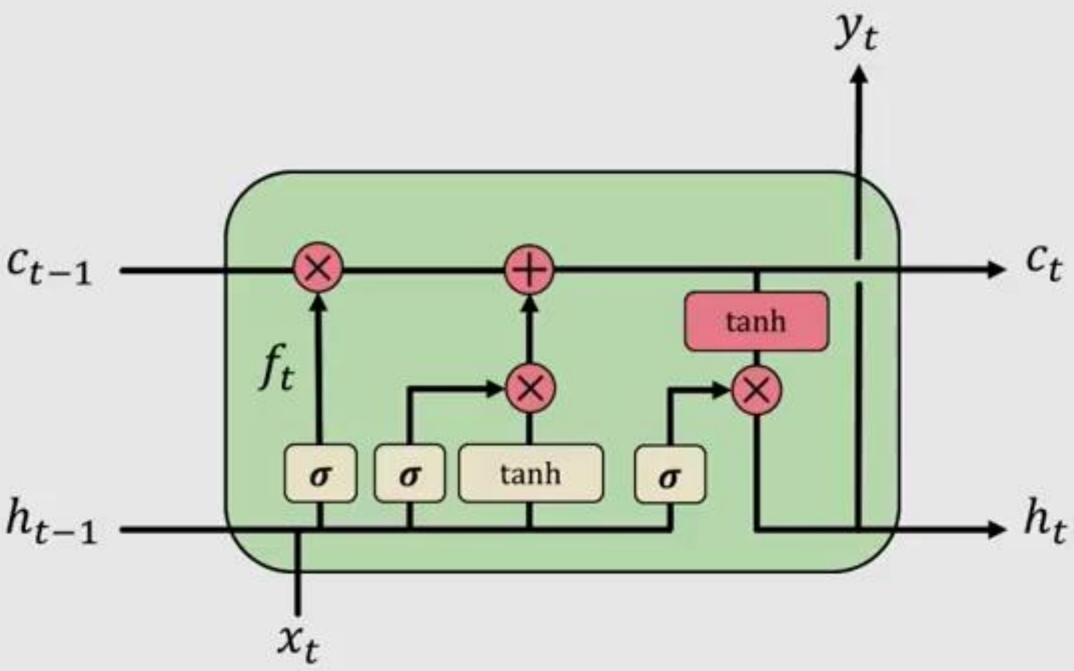


Gates optionally let information through, for example via a sigmoid neural net layer and pointwise multiplication

Long Short Term Memory (LSTMs)

How do LSTMs work?

1) Forget 2) Store 3) Update 4) Output

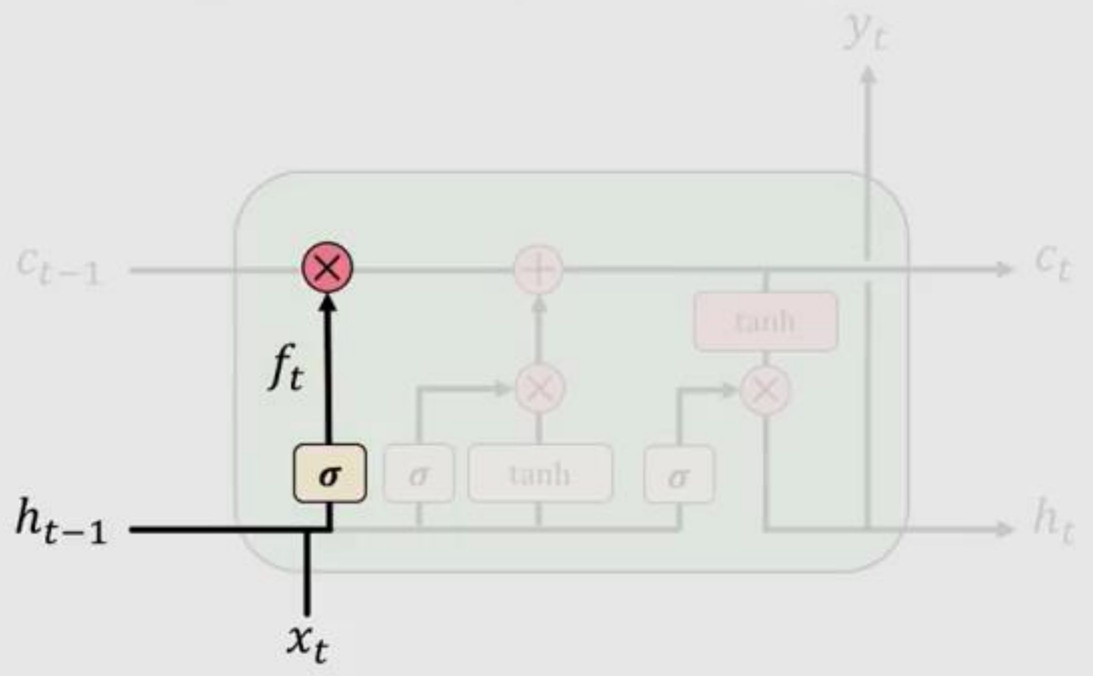


MIT Deep Learning

Long Short Term Memory (LSTMs)

1) Forget 2) Store 3) Update 4) Output

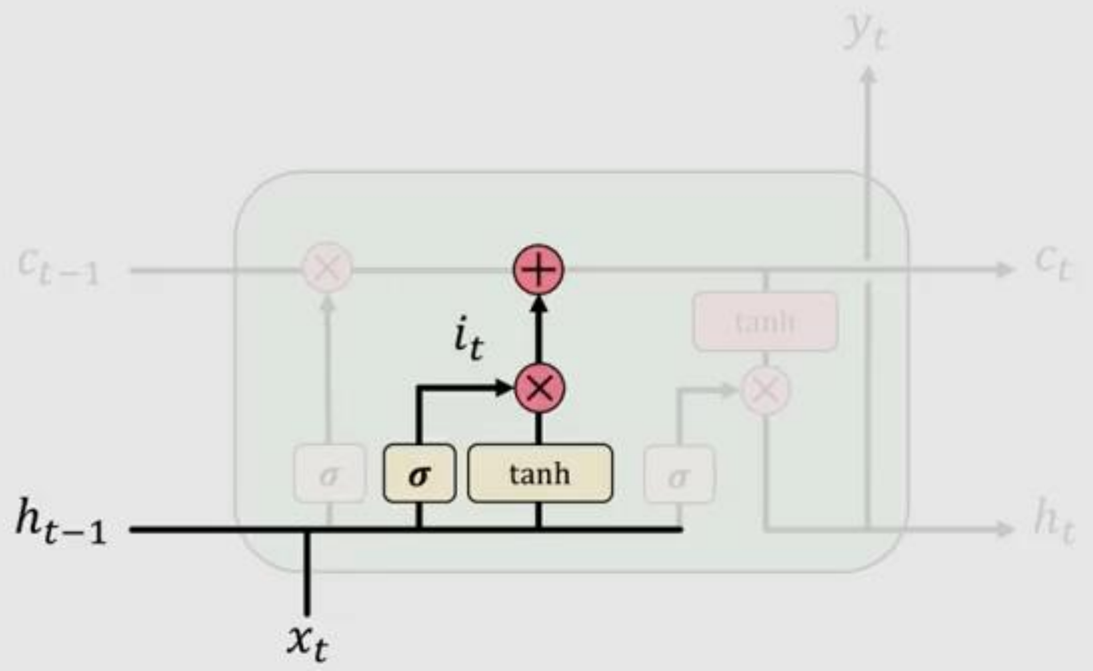
LSTMs **forget irrelevant** parts of the previous state



Long Short Term Memory (LSTMs)

1) Forget **2) Store** 3) Update 4) Output

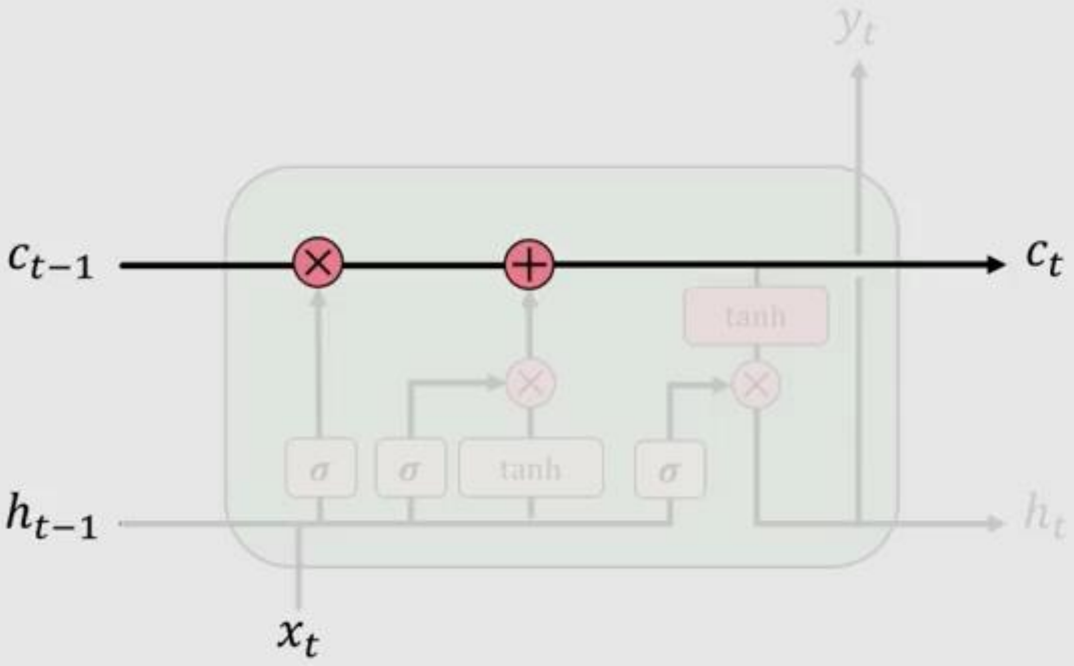
LSTMs **store relevant** new information into the cell state



Long Short Term Memory (LSTMs)

1) Forget 2) Store **3) Update** 4) Output

LSTMs **selectively update** cell state values

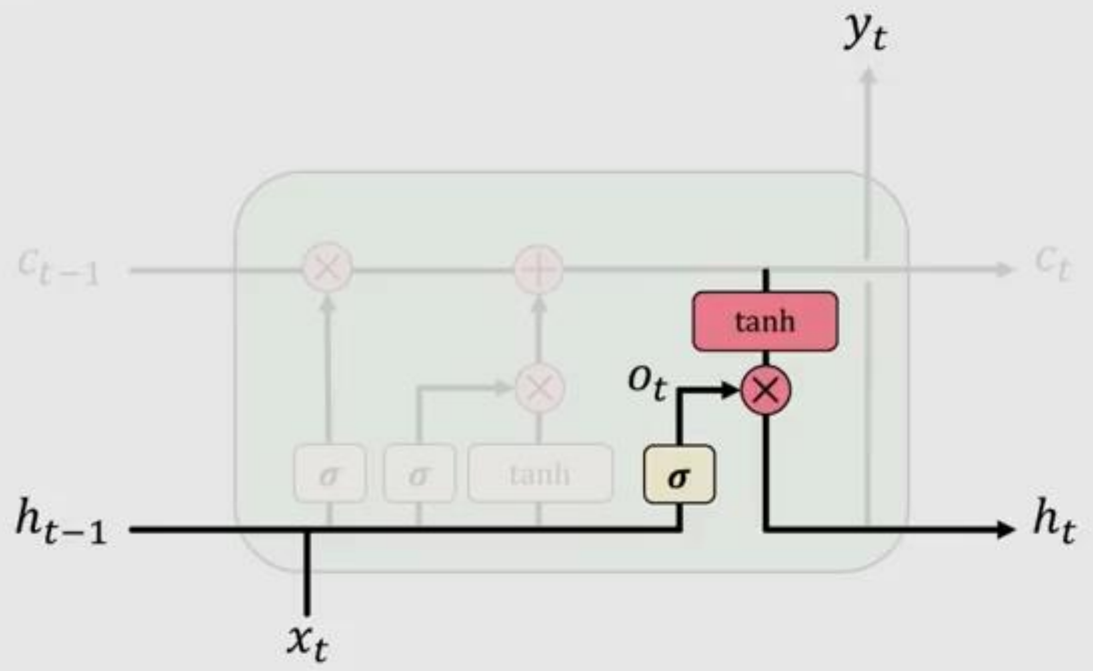


MIT Deep Learning

Long Short Term Memory (LSTMs)

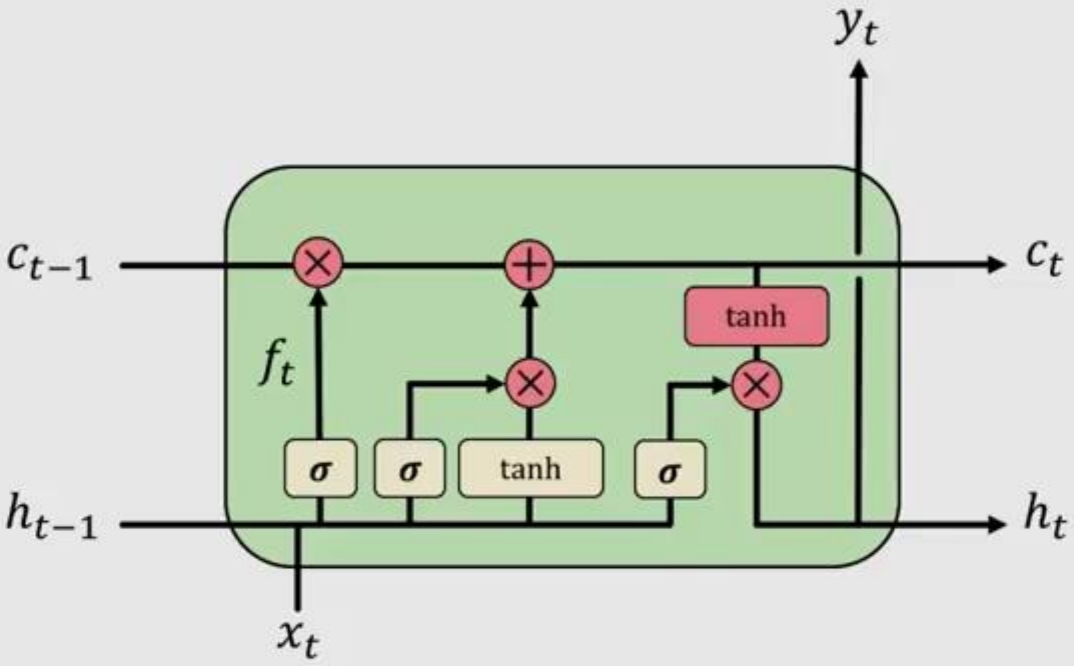
1) Forget 2) Store 3) Update **4) Output**

The **output gate** controls what information is sent to the next time step

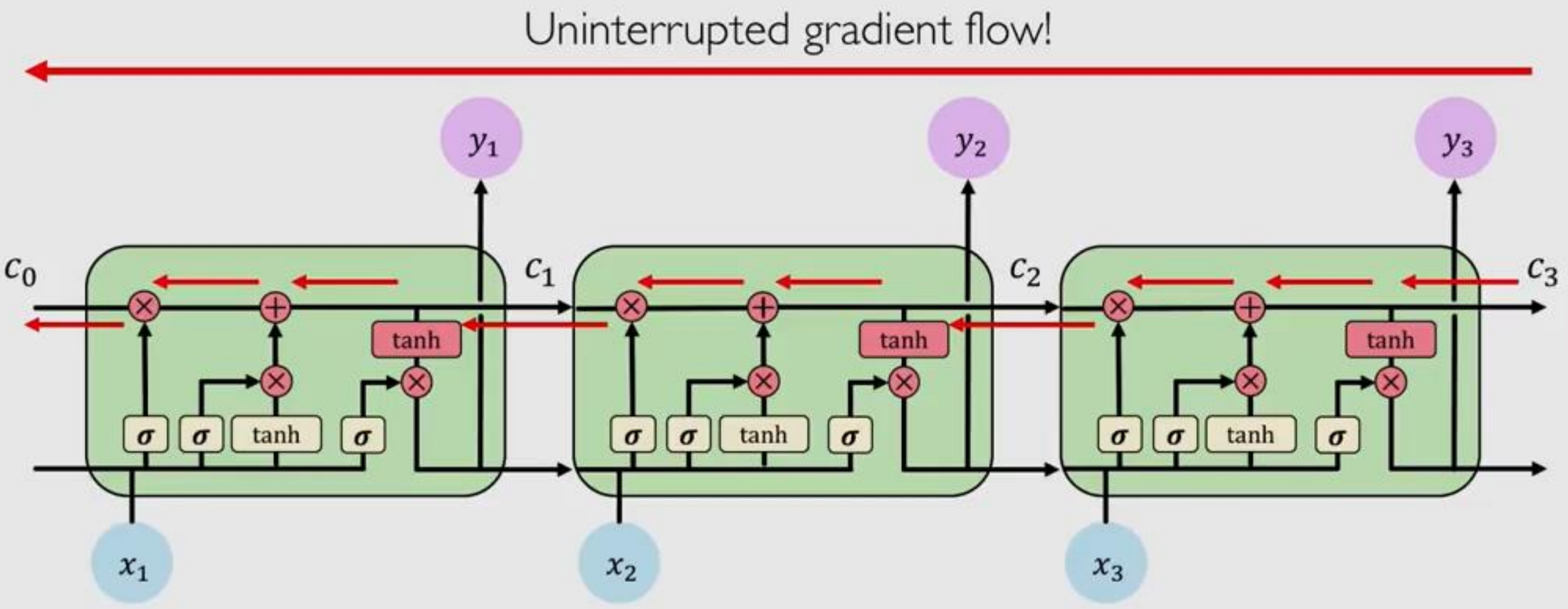


Long Short Term Memory (LSTMs)

1) Forget 2) Store 3) Update 4) Output



LSTM Gradient Flow



LSTMs: Key Concepts

LSTMs: Key Concepts

1. Maintain a **separate cell state** from what is outputted

Deep Learning

LSTMs: Key Concepts

1. Maintain a **separate cell state** from what is outputted
2. Use **gates** to control the **flow of information**

Deep Learning

LSTMs: Key Concepts

1. Maintain a **separate cell state** from what is outputted
2. Use **gates** to control the **flow of information**
    - **Forget** gate gets rid of irrelevant information

LSTMs: Key Concepts

1. Maintain a **separate cell state** from what is outputted
2. Use **gates** to control the **flow of information**
   - **Forget** gate gets rid of irrelevant information
   - **Store** relevant information from current input

MIT Deep Learning

LSTMs: Key Concepts

1. Maintain a **separate cell state** from what is outputted
2. Use **gates** to control the **flow of information**
   - **Forget** gate gets rid of irrelevant information
   - **Store** relevant information from current input
   - Selectively **update** cell state

Deep Learning

LSTMs: Key Concepts

1. Maintain a **separate cell state** from what is outputted
2. Use **gates** to control the **flow of information**
    - **Forget** gate gets rid of irrelevant information
    - **Store** relevant information from current input
    - Selectively **update** cell state
    - **Output** gate returns a filtered version of the cell state

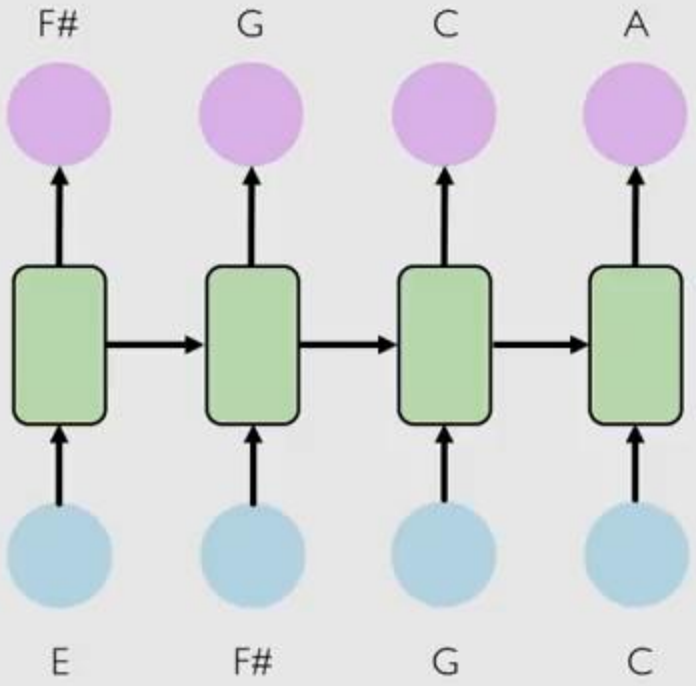
LSTMs: Key Concepts

1. Maintain a **separate cell state** from what is outputted
2. Use **gates** to control the **flow of information**
   - **Forget** gate gets rid of irrelevant information
   - **Store** relevant information from current input
   - Selectively **update** cell state
   - **Output** gate returns a filtered version of the cell state
3. Backpropagation through time with **uninterrupted gradient flow**

Deep Learning

RNN Applications

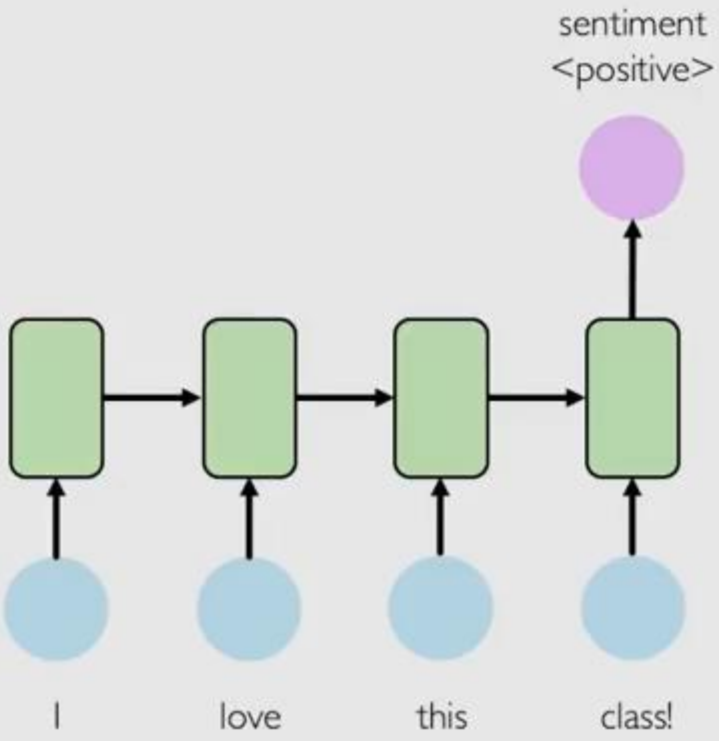
Example Task: Music Generation



Input: sheet music

Output: next character in sheet music

Example Task: Sentiment Classification

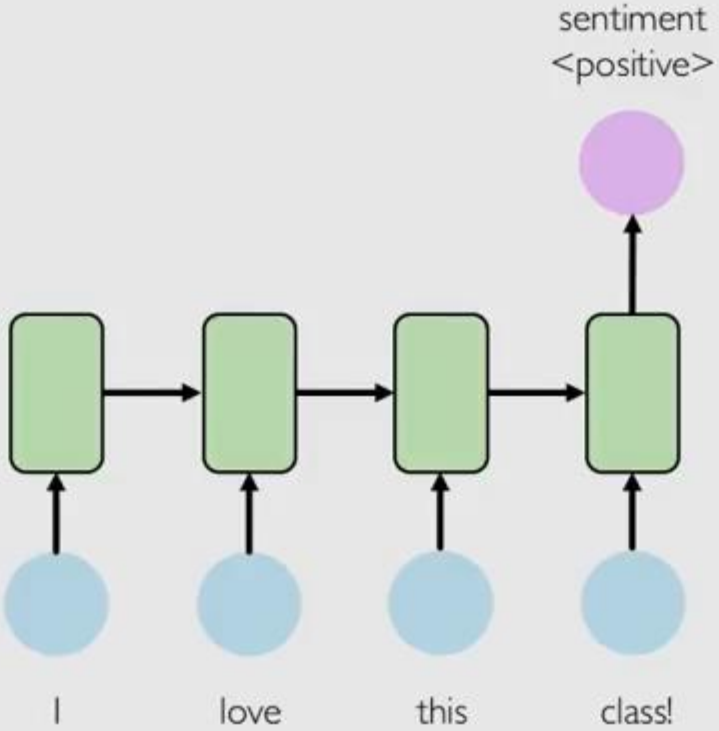


Input: sequence of words

Output: probability of having positive sentiment

```
loss = tf.nn.softmax_cross_entropy_with_logits(y, predicted)
```

Example Task: Sentiment Classification

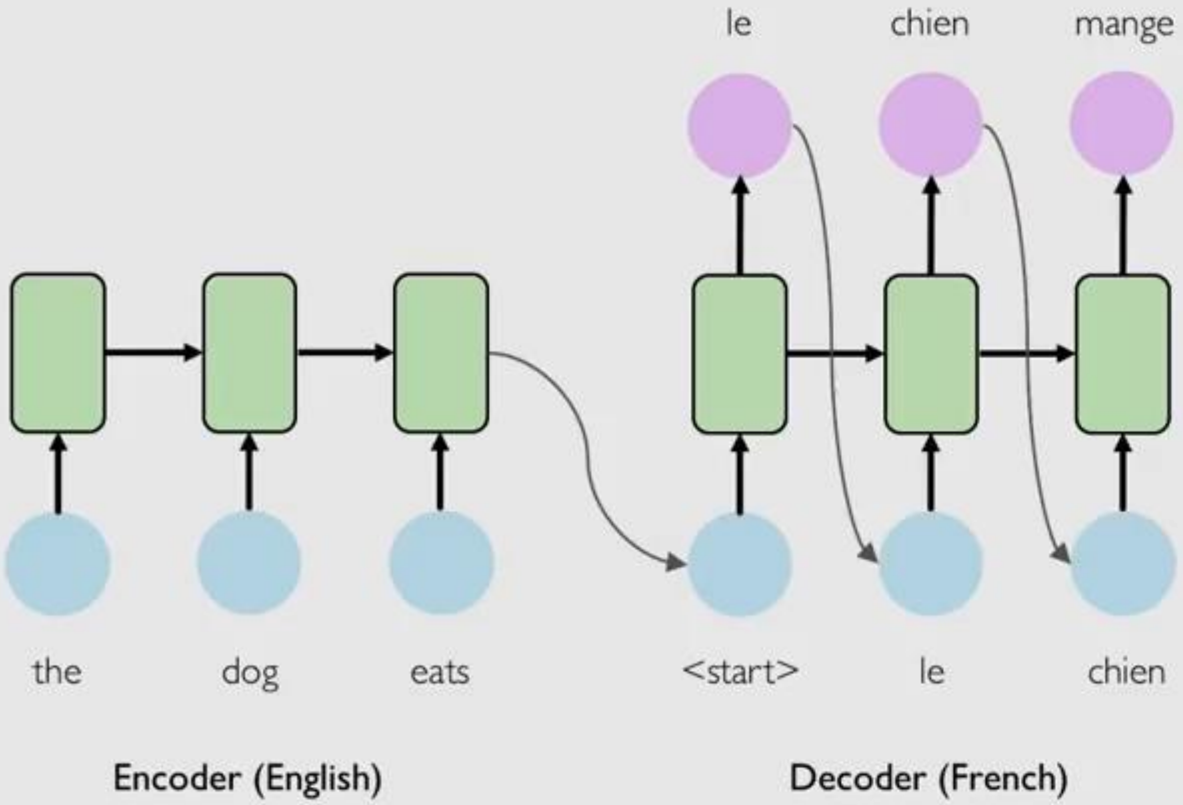


Tweet sentiment classification


Ivar Hagendoorn
@IvarHagendoorn
Follow
The @MIT Introduction to #DeepLearning is definitely one of the best courses of its kind currently available online introtodeeplearning.com
12:45 PM - 12 Feb 2018

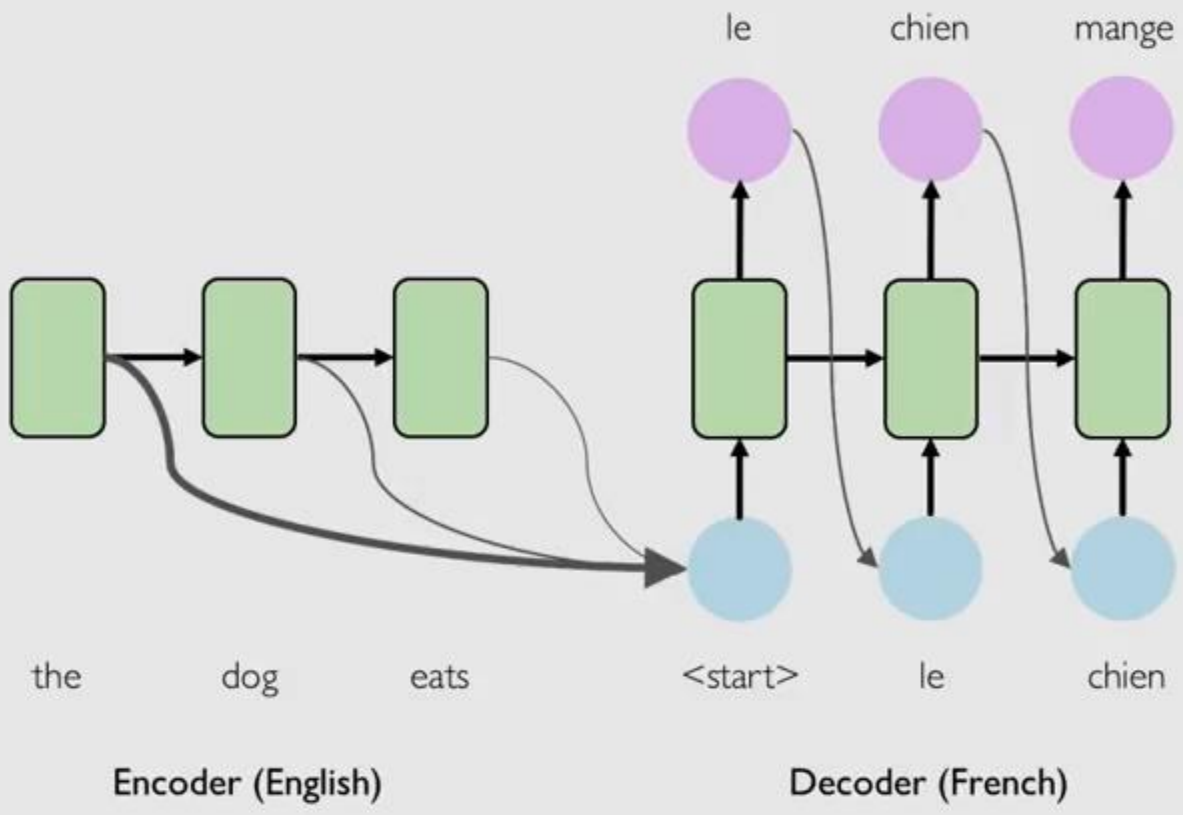
Deep Learning

Example Task: Machine Translation



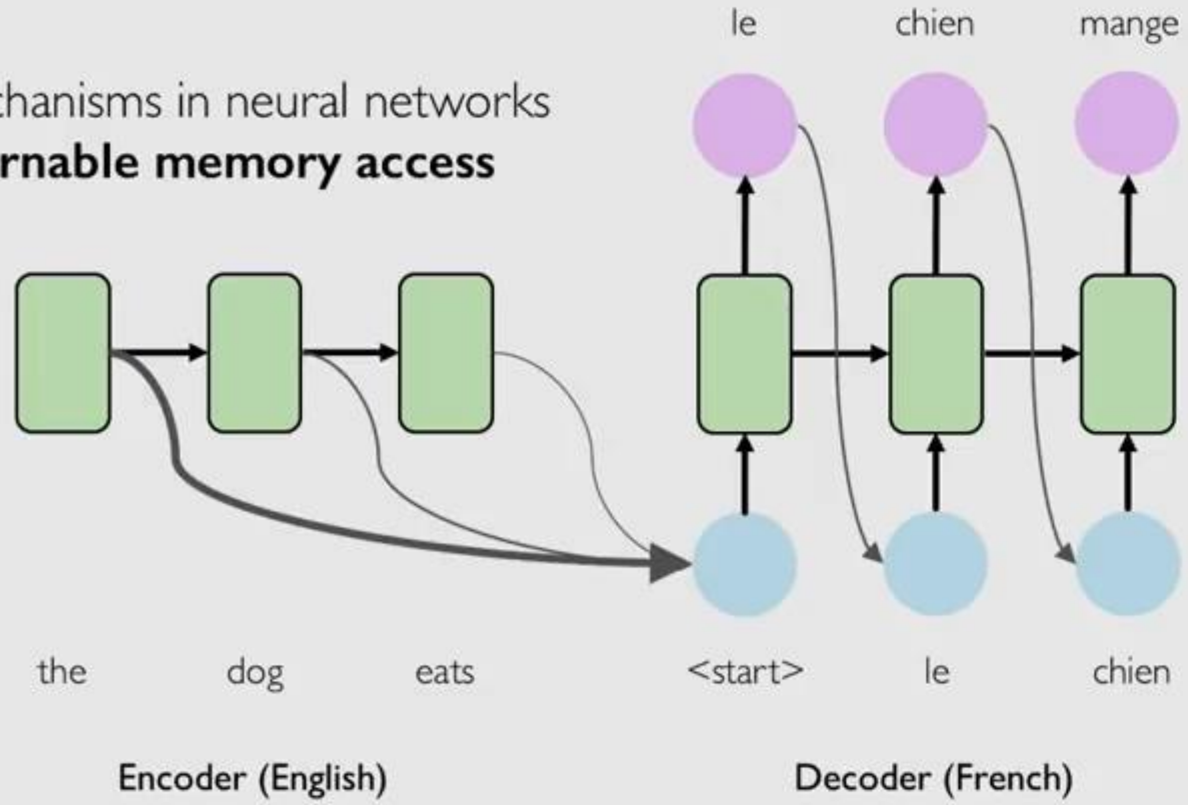
Deep Learning

Attention Mechanisms



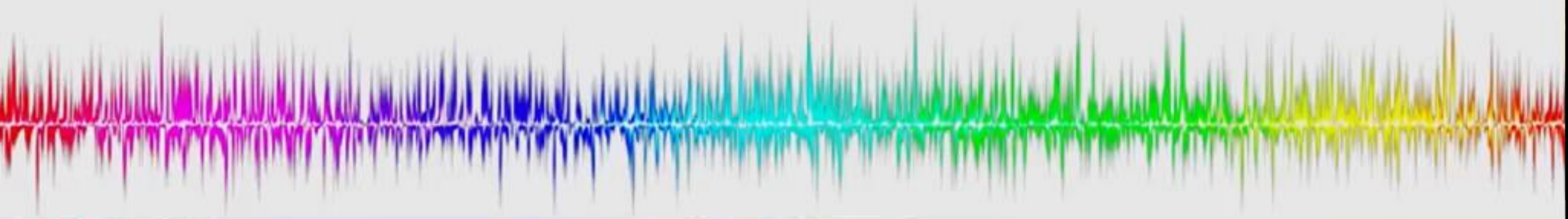
Attention Mechanisms

Attention mechanisms in neural networks provide **learnable memory access**



Deep Learning for Sequence Modeling: Summary

1. RNNs are well suited for **sequence modeling** tasks



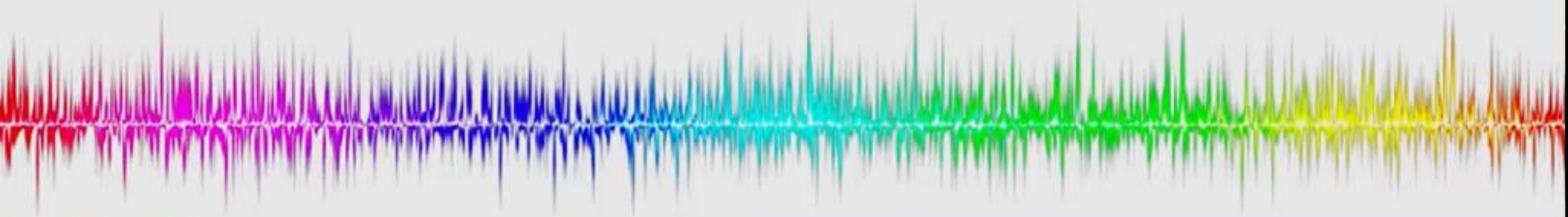
Deep Learning for Sequence Modeling: Summary

1. RNNs are well suited for **sequence modeling** tasks
2. Model sequences via a **recurrence relation**

Deep Learning

Deep Learning for Sequence Modeling: Summary

1. RNNs are well suited for **sequence modeling** tasks
2. Model sequences via a **recurrence relation**
3. Training RNNs with **backpropagation through time**



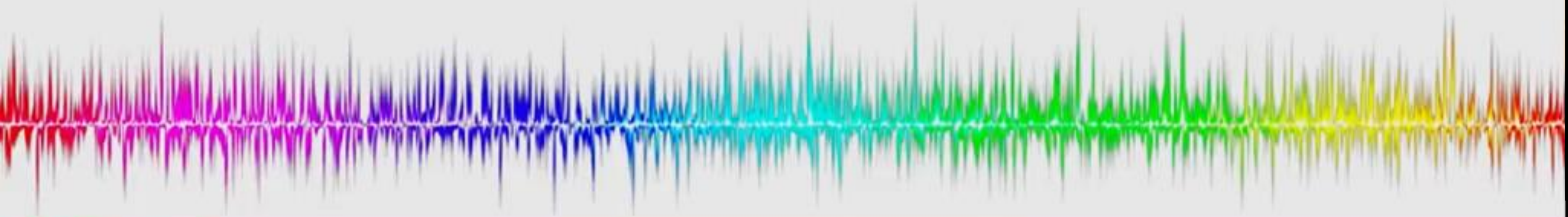
Deep Learning for Sequence Modeling: Summary

1. RNNs are well suited for **sequence modeling** tasks
2. Model sequences via a **recurrence relation**
3. Training RNNs with **backpropagation through time**
4. Gated cells like **LSTMs** let us model **long-term dependencies**

Deep Learning

Deep Learning for Sequence Modeling: Summary

1. RNNs are well suited for **sequence modeling** tasks
2. Model sequences via a **recurrence relation**
3. Training RNNs with **backpropagation through time**
4. Gated cells like **LSTMs** let us model **long-term dependencies**
5. Models for **music generation**, classification, machine translation, and more



THANK YOU!