Deep Sequence Modeling

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MIT 6.S191

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

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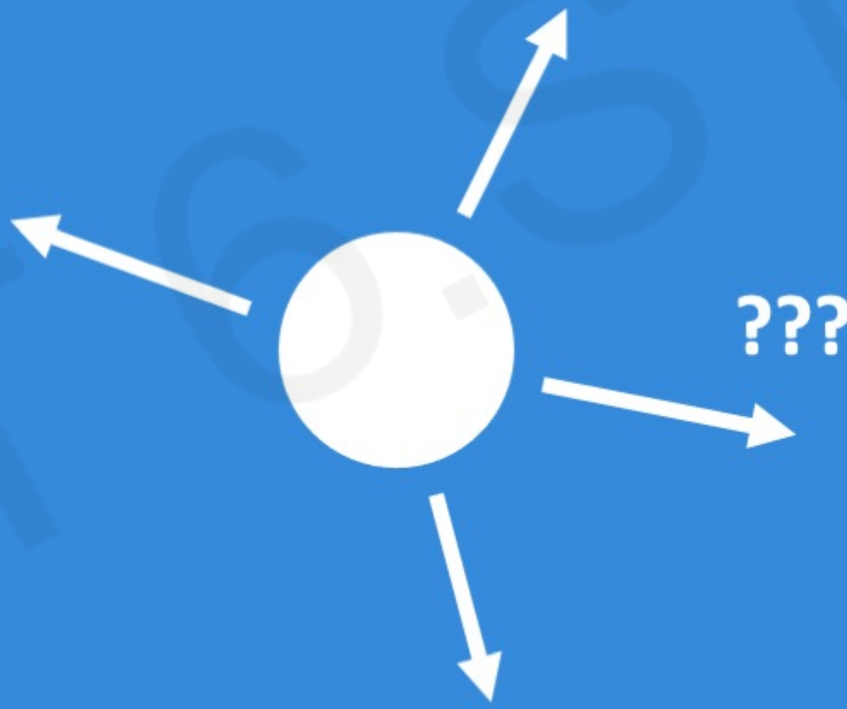

Given an image of a ball,
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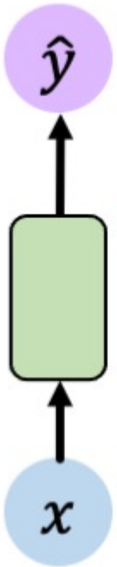
Sequences in the Wild

Audio

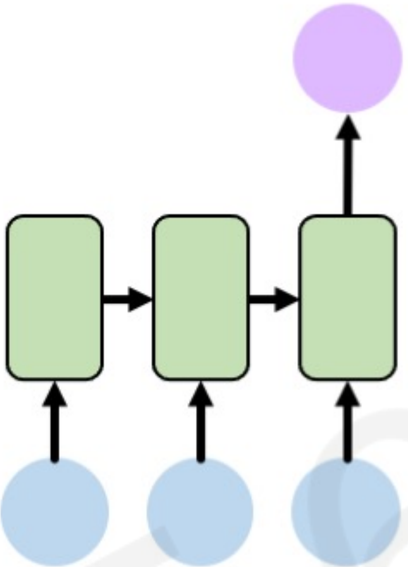
Sequences in the Wild

Sequence Modeling Applications

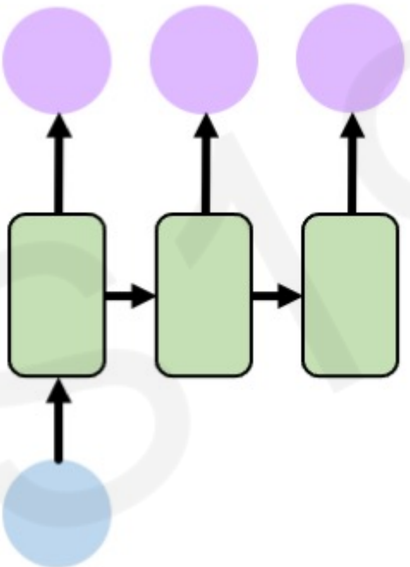


One to One
Binary Classification

"Will I pass this class?"
Student → Pass?

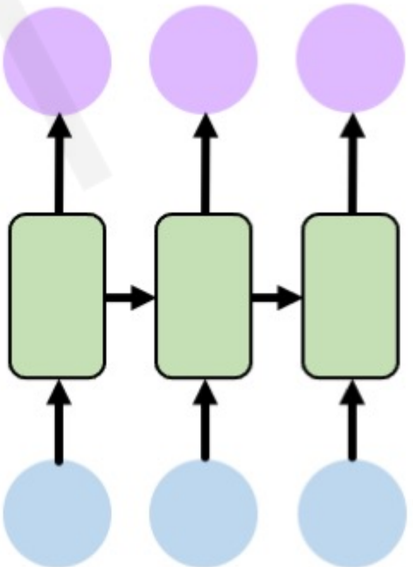


Many to One
Sentiment Classification



One to Many
Image Captioning

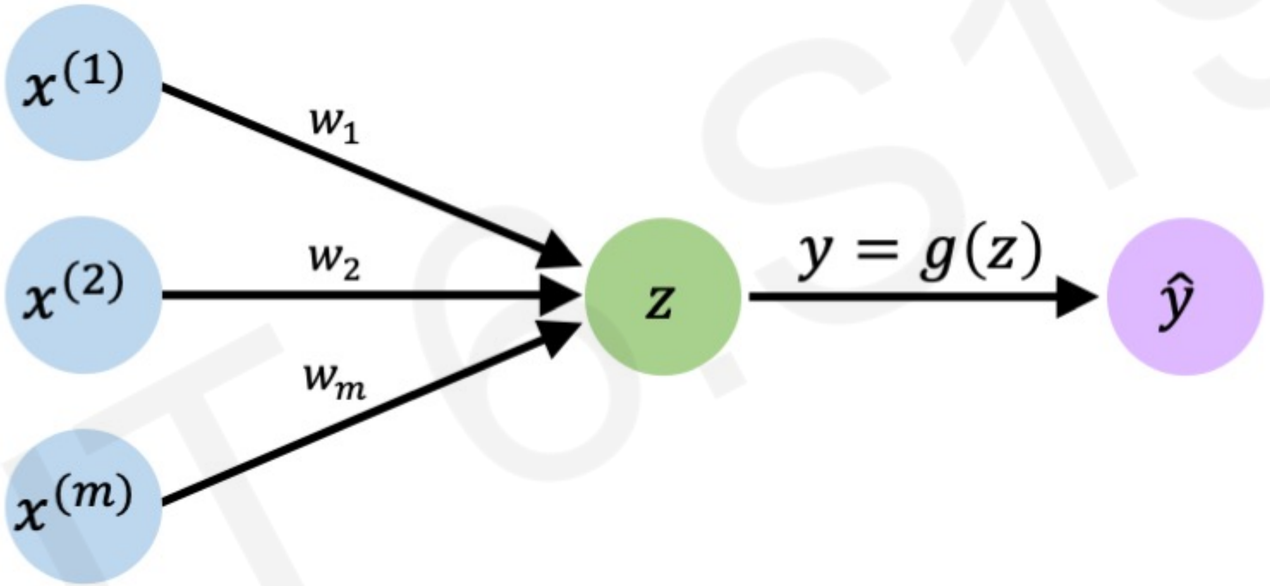
"A baseball player throws a ball."



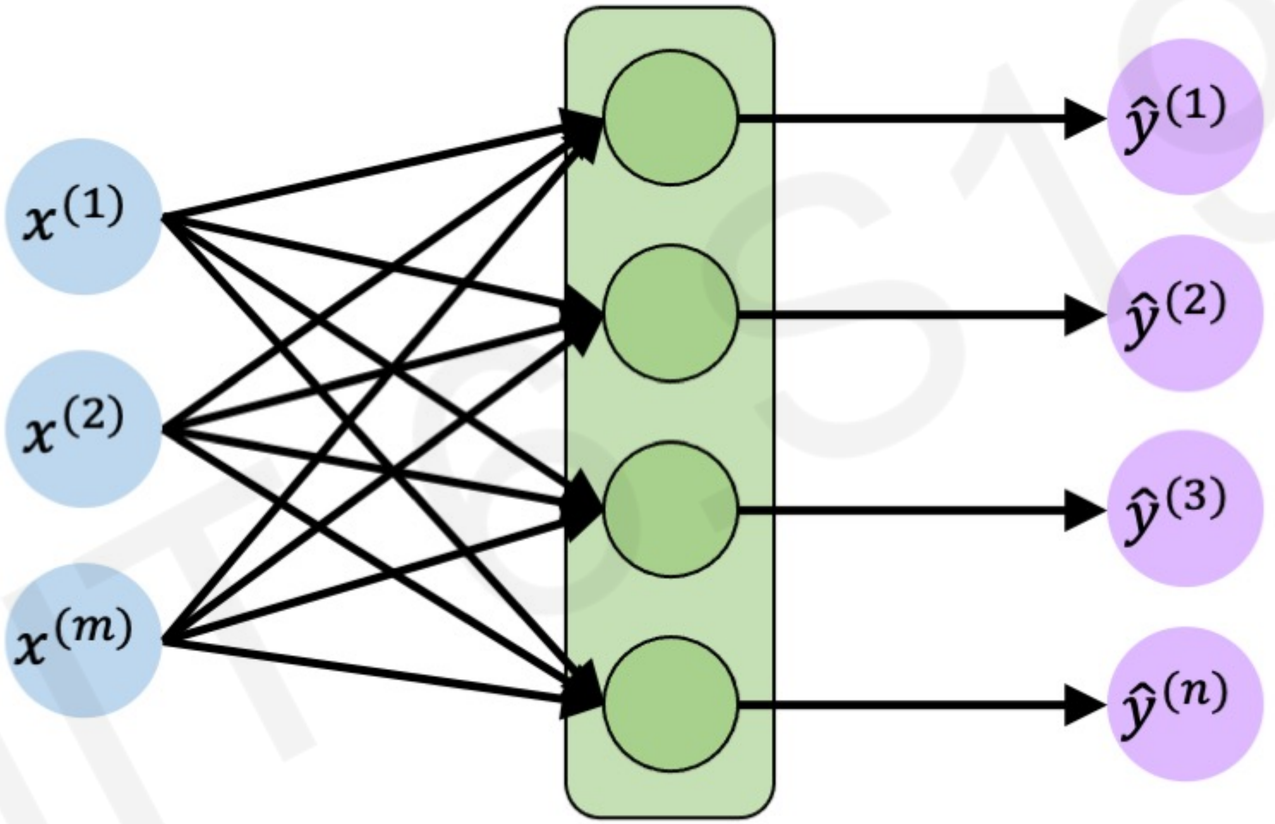
Many to Many
Machine Translation

Neurons with Recurrence

The Perceptron Revisited



Feed-Forward Networks Revisited



$\boldsymbol{x} \in \mathbb{R}^m$

$\hat{\boldsymbol{y}} \in \mathbb{R}^n$

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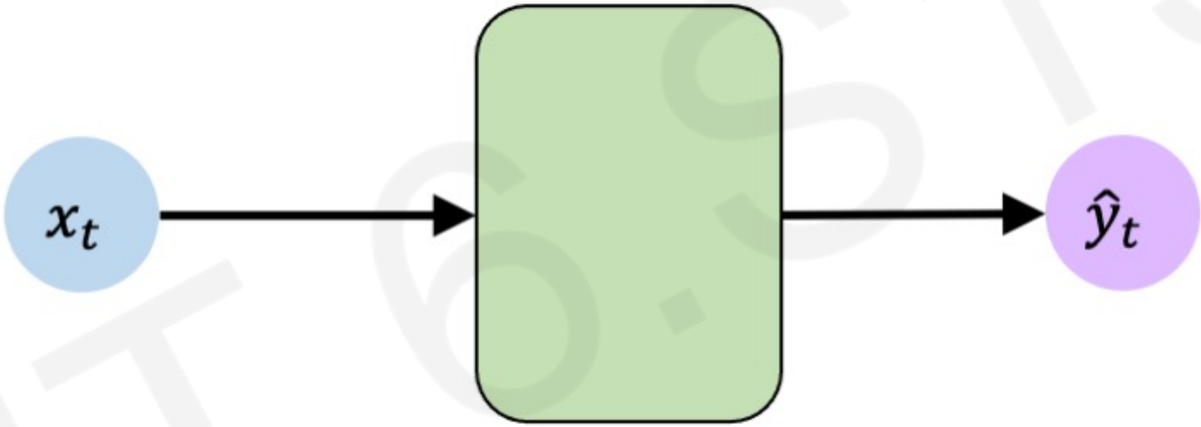
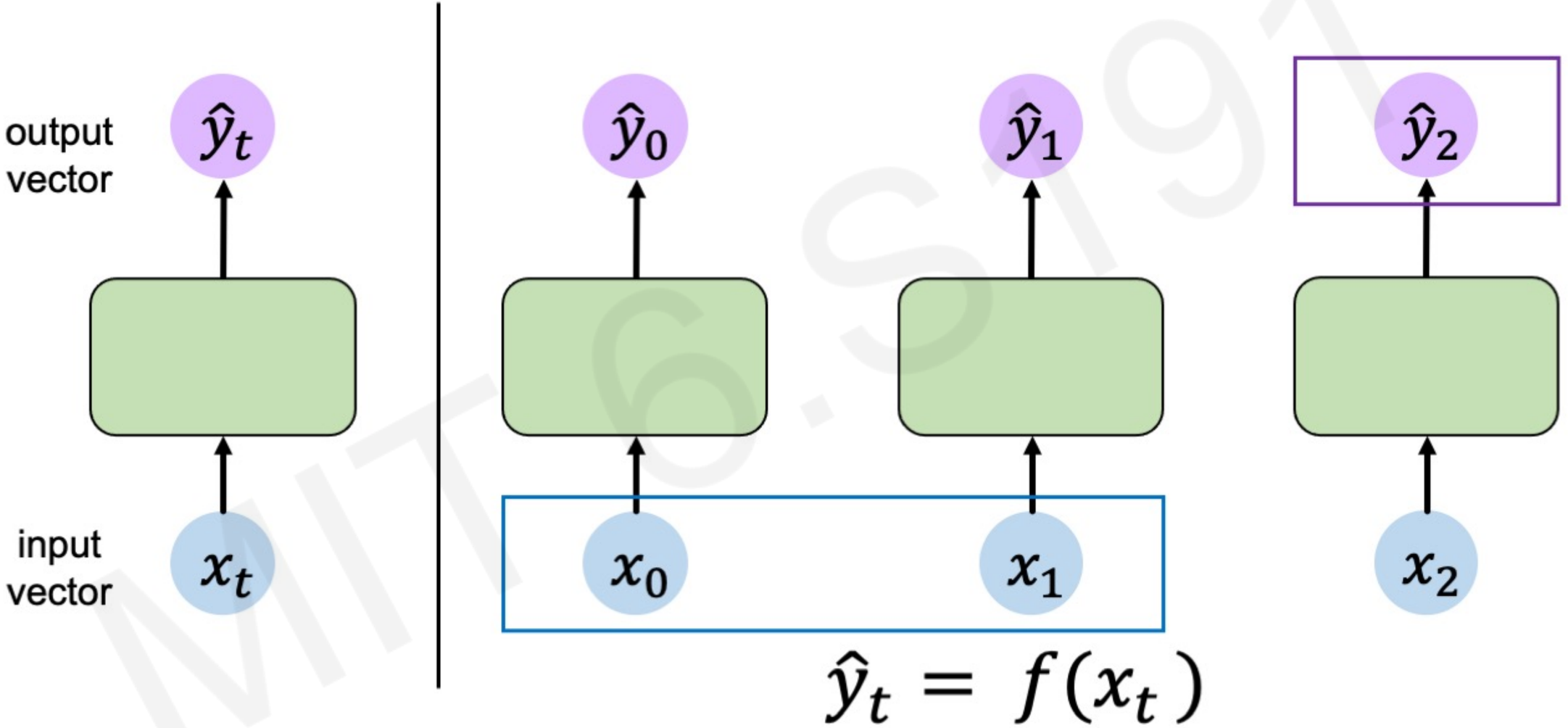


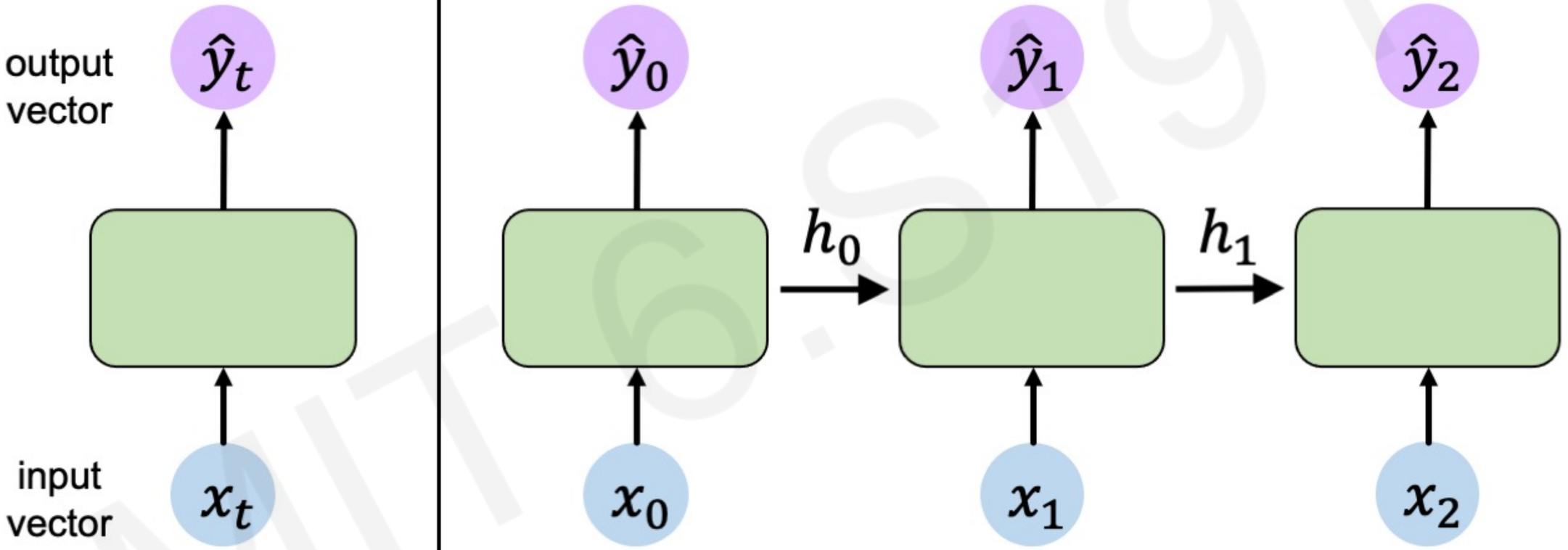
$$\boldsymbol{x_t} \in \mathbb{R}^m$$

$$\hat{\boldsymbol{y}}_t \in \mathbb{R}^n$$

Handling Individual Time Steps



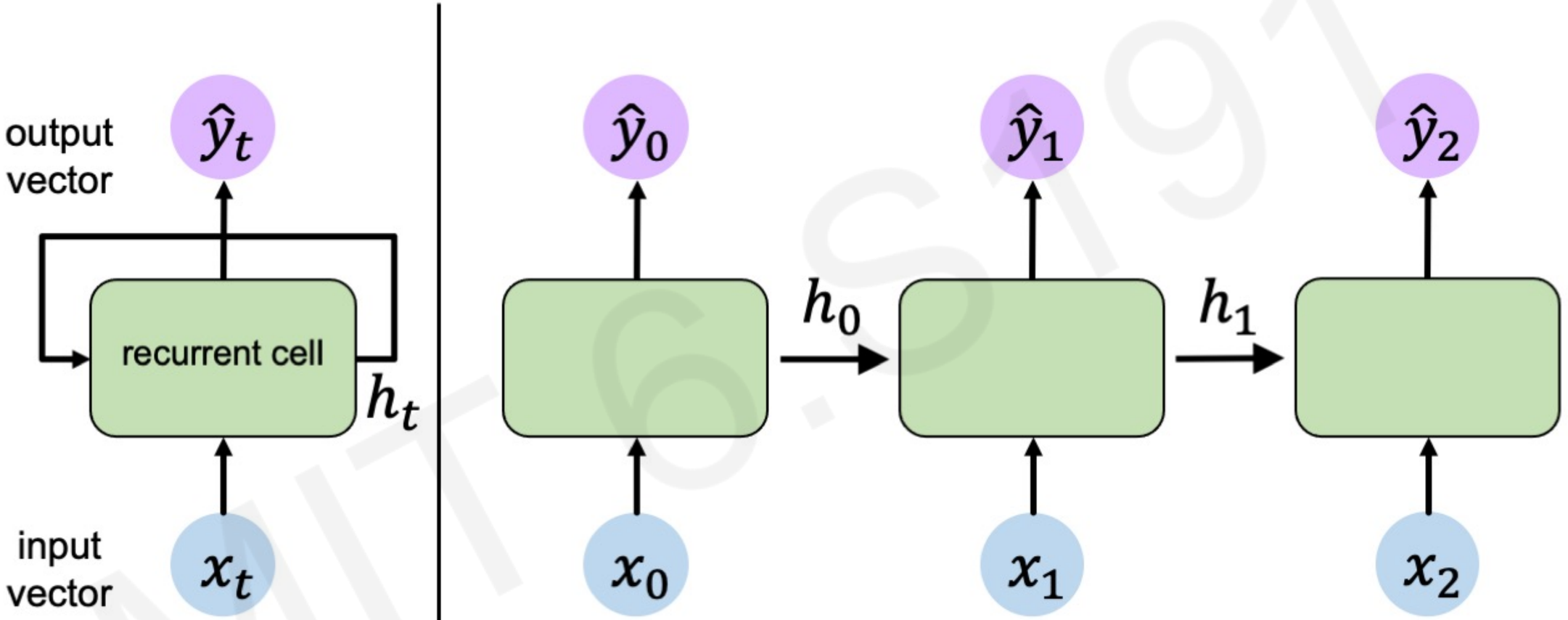
Neurons with Recurrence



$$\underline{\hat{y}_t} = f(\underline{x_t}, \underline{h_{t-1}})$$

output input past memory

Neurons with Recurrence



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Recurrent Neural Networks (RNNs)

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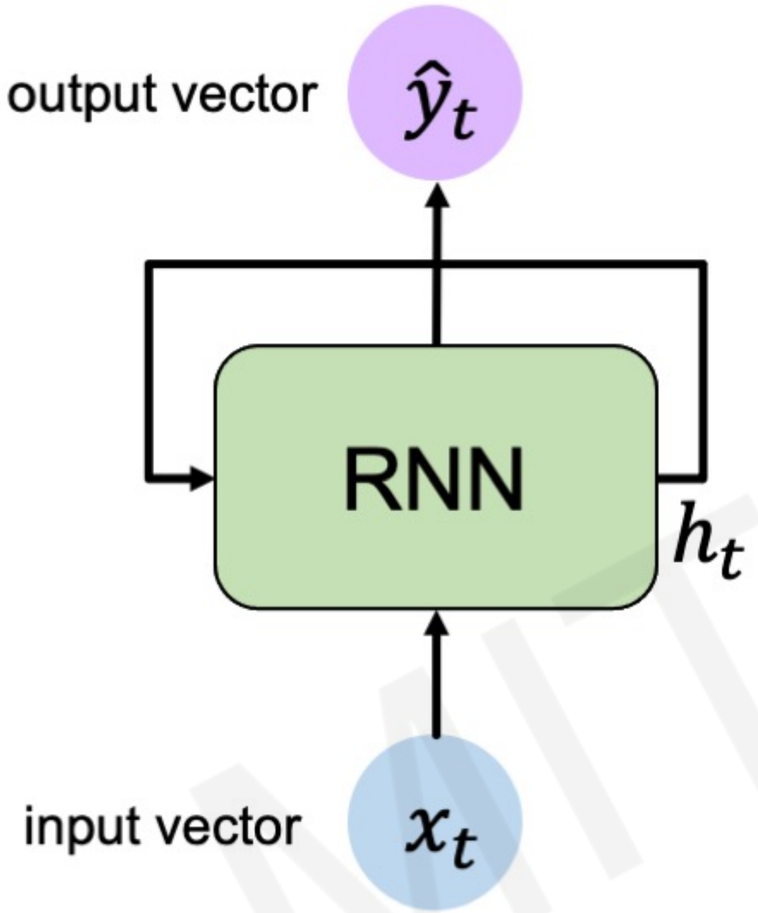


Apply a **recurrence relation** at every time step to process a sequence:

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

cell state

function with weights W

input

old state

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

RNNs have a **state**, h_t, that is updated **at each time step** as a sequence is processed

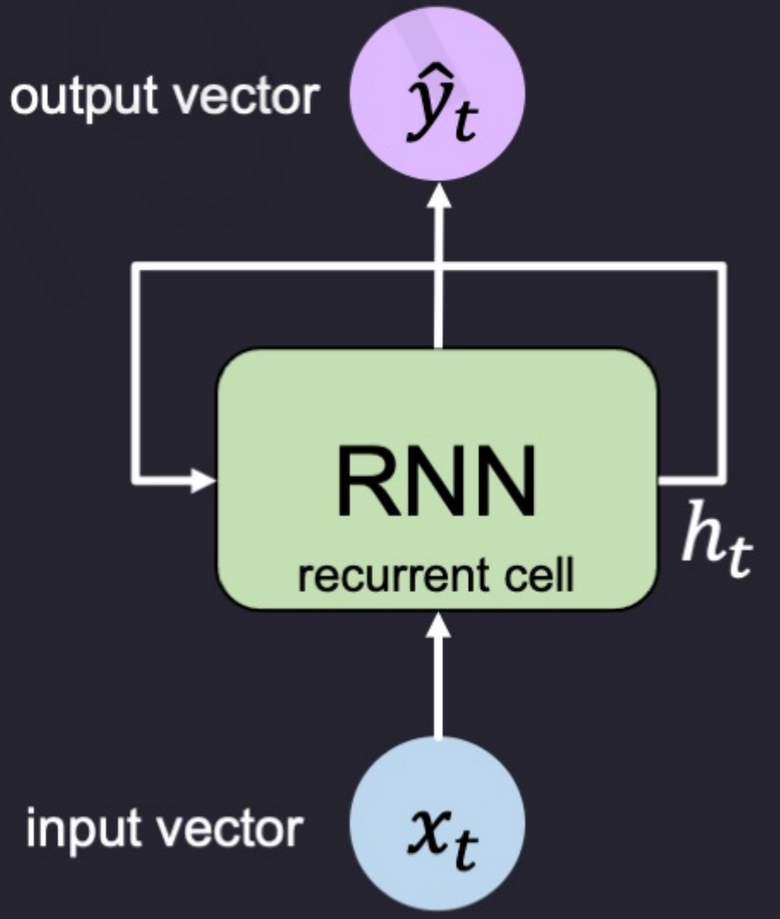
RNN Intuition

```
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!"
```



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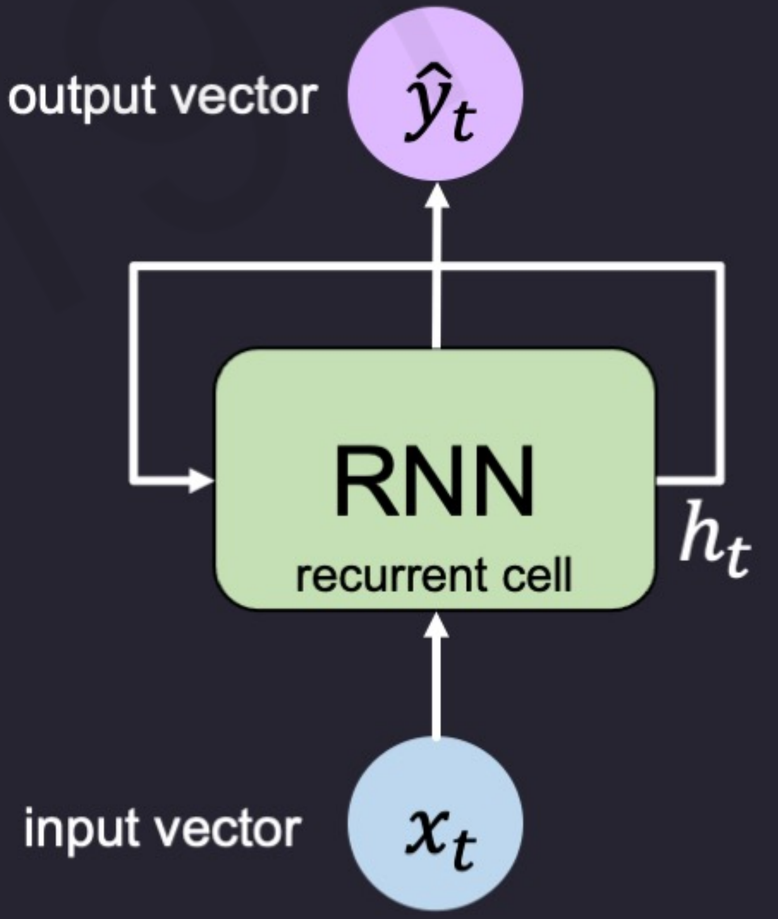

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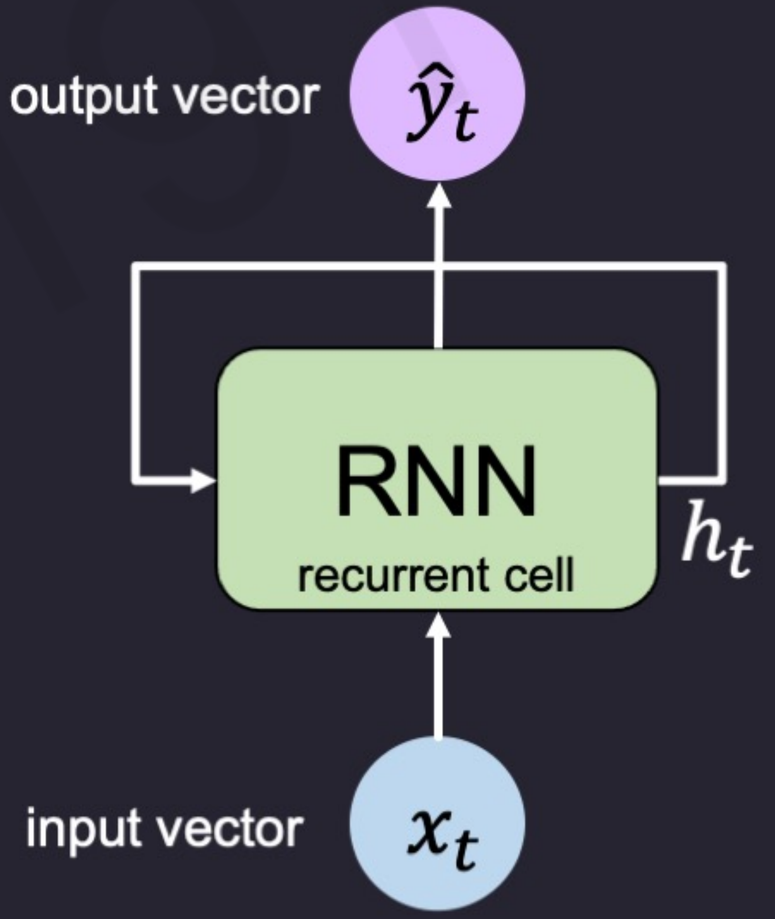
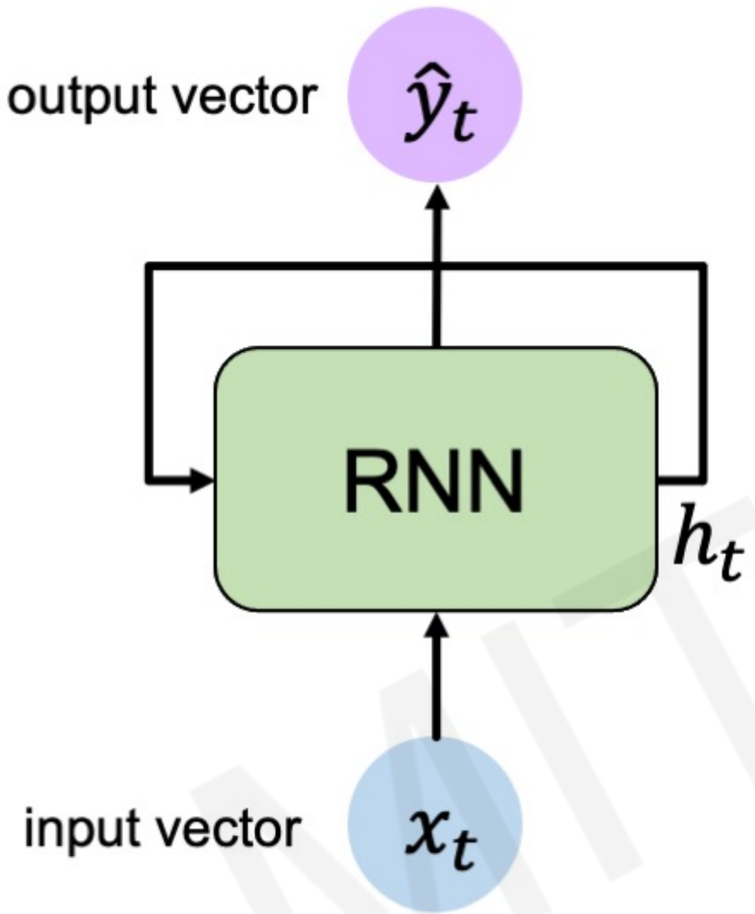


RNN State Update and Output



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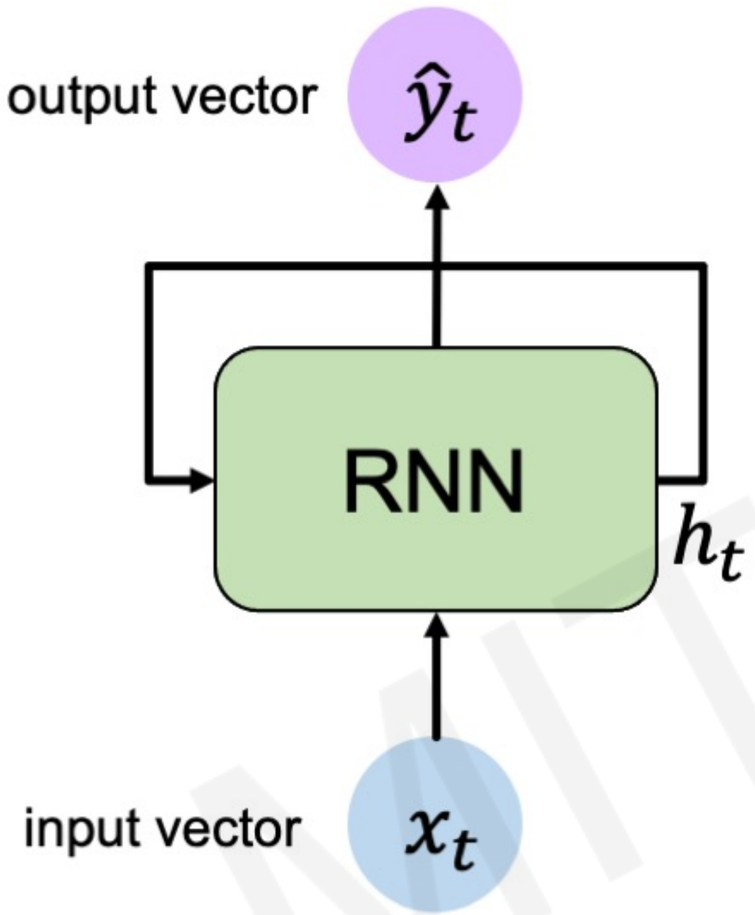
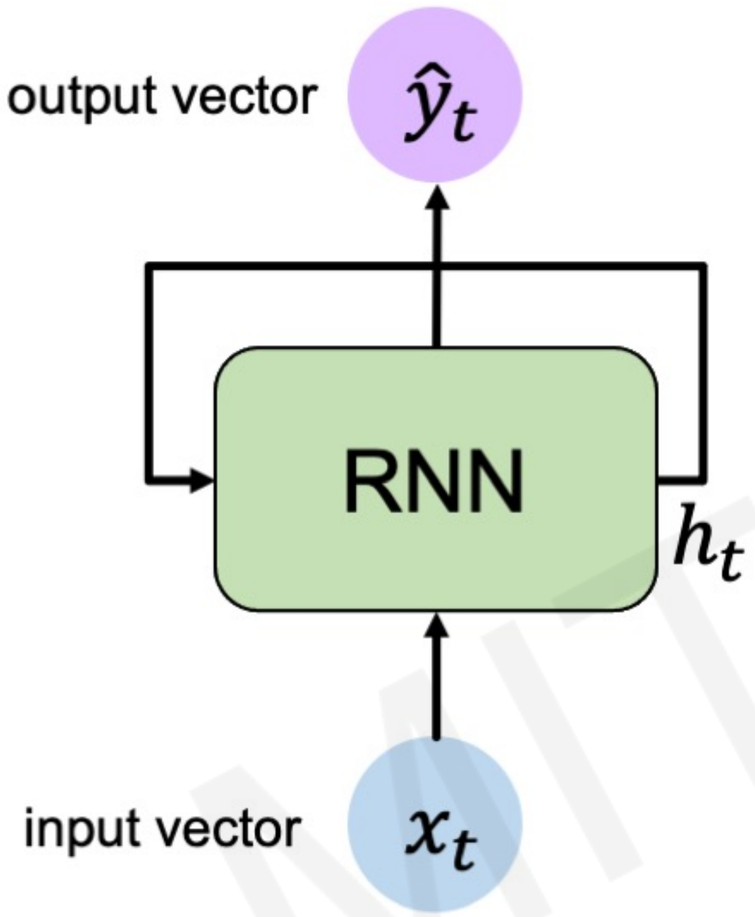


Input Vector

x_t

RNN State Update and Output



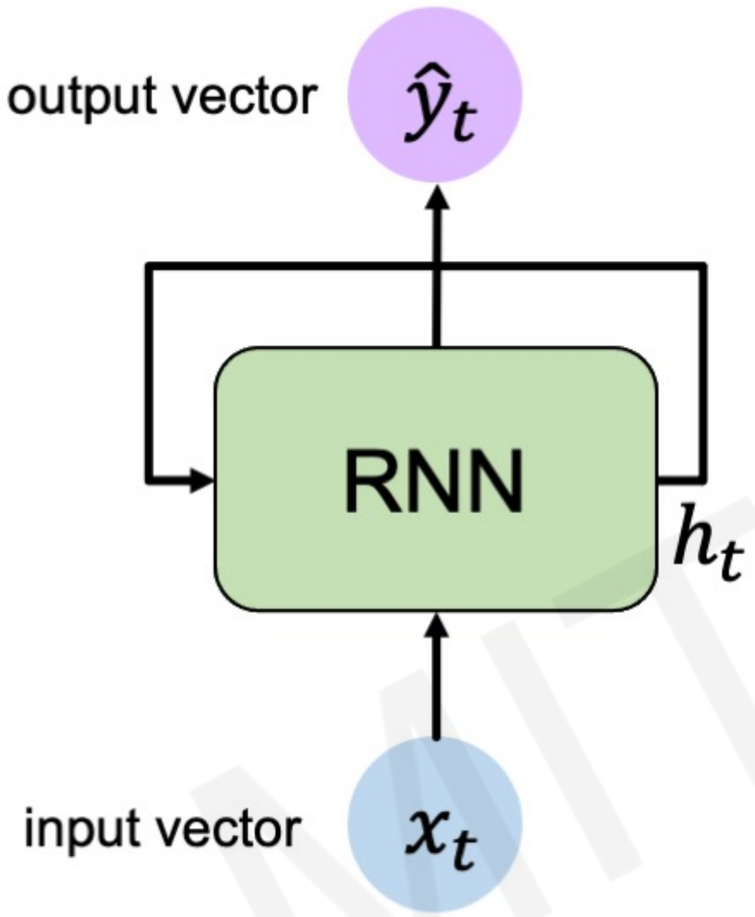
Update Hidden State

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

Input Vector

$$x_t$$

RNN State Update and Output



Output Vector

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

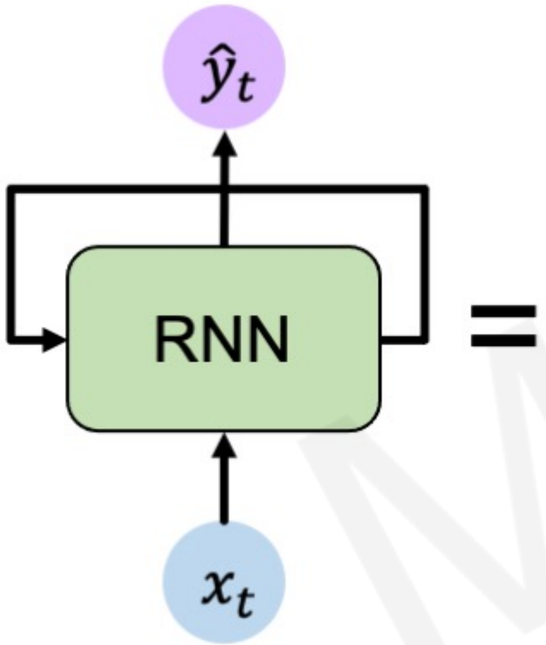
Update Hidden State

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

Input Vector

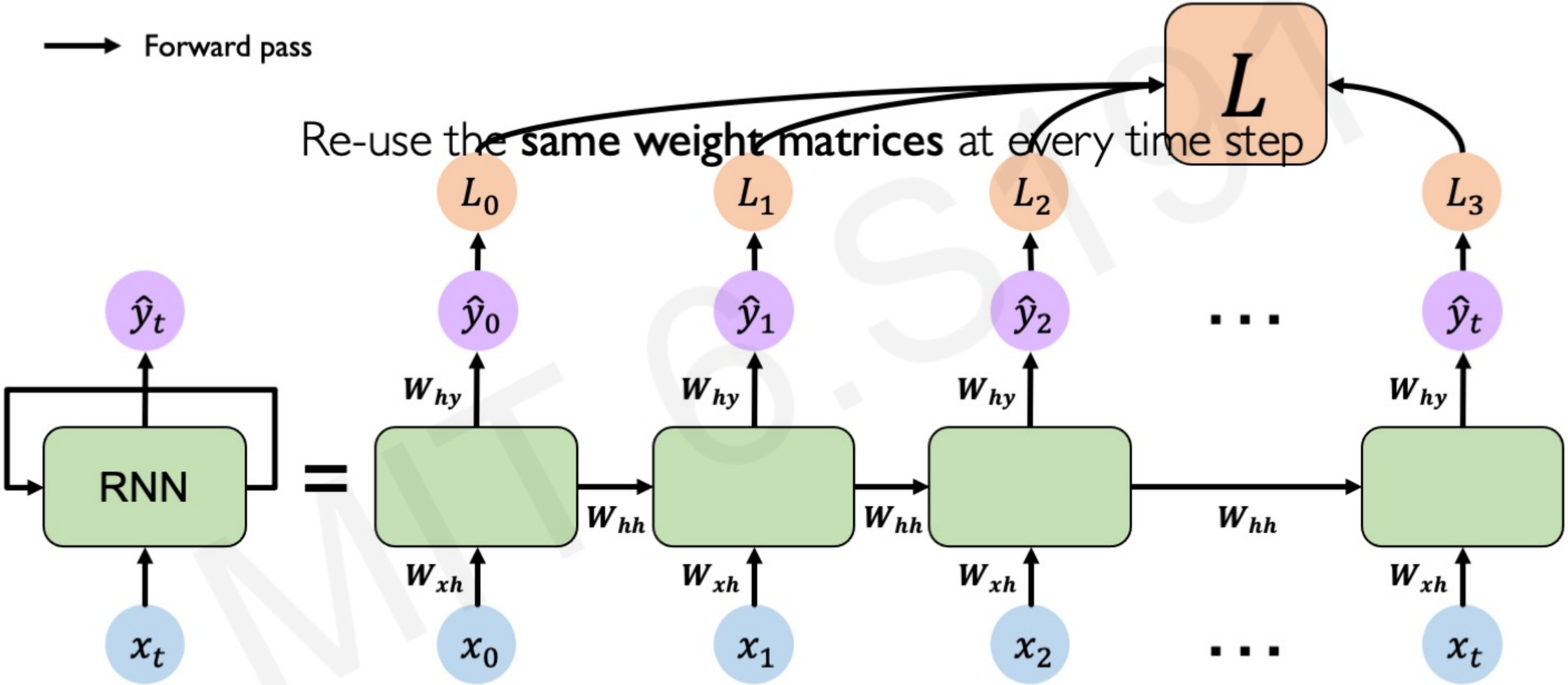
$$x_t$$

RNNs: Computational Graph Across Time



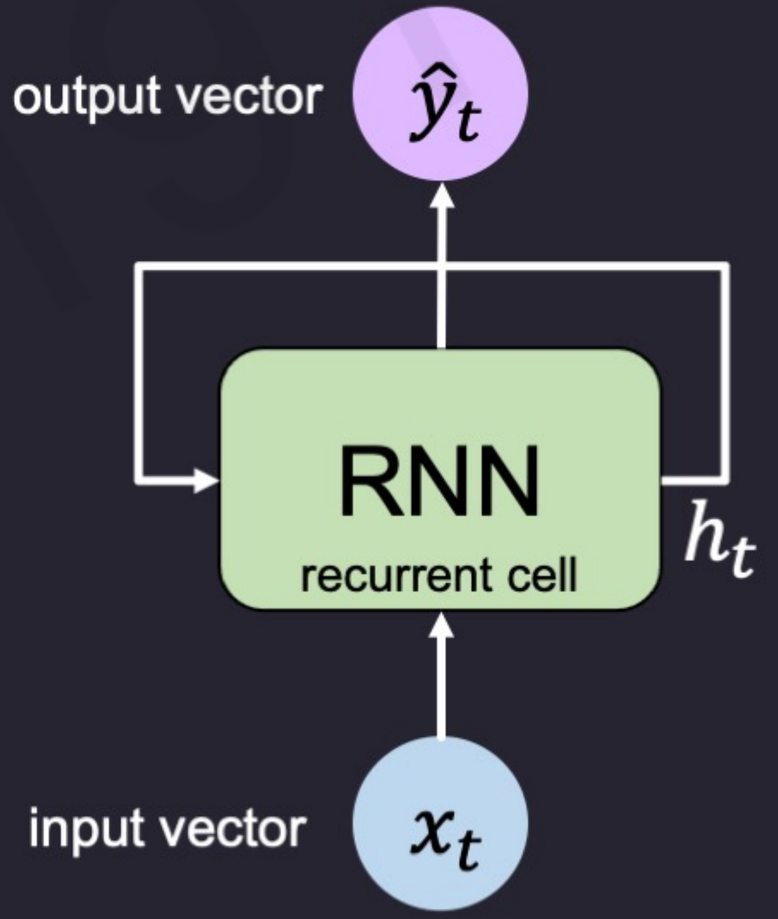
= Represent as computational graph unrolled across time

RNNs: Computational Graph Across Time



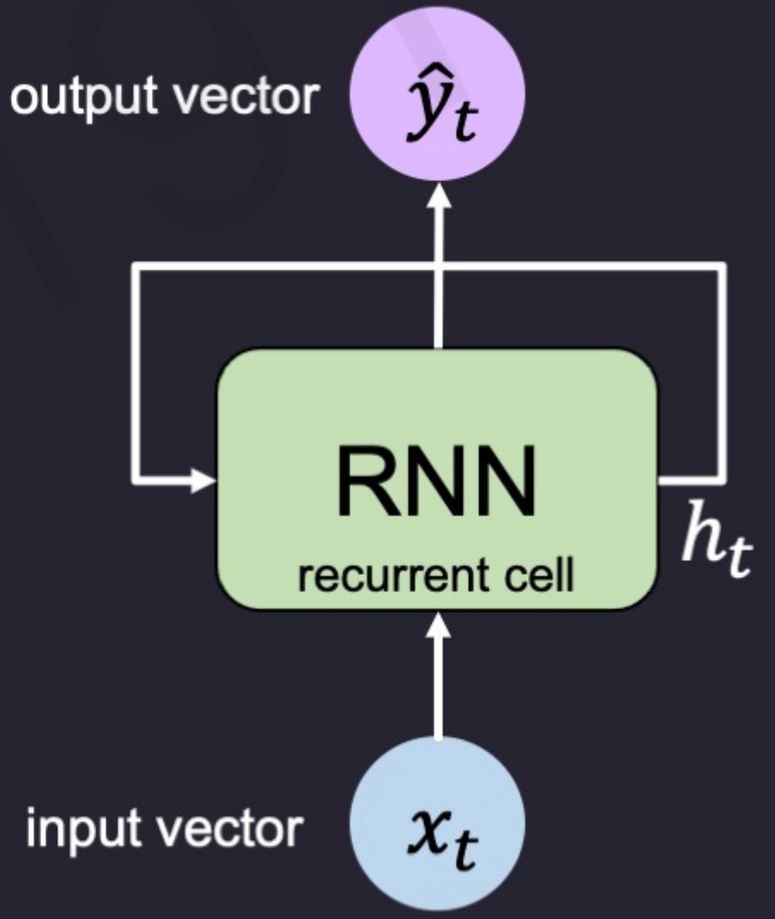
RNNs from Scratch

```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
```

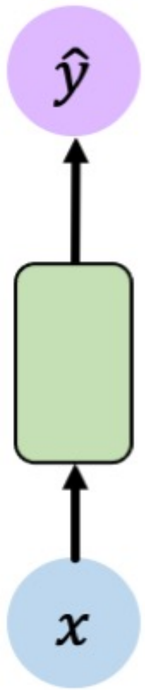


RNN Implementation in TensorFlow

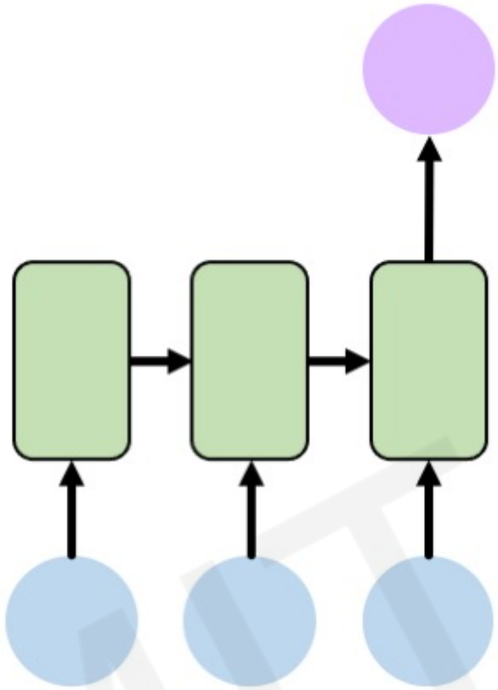
```
tf.keras.layers.SimpleRNN(rnn_units)
```



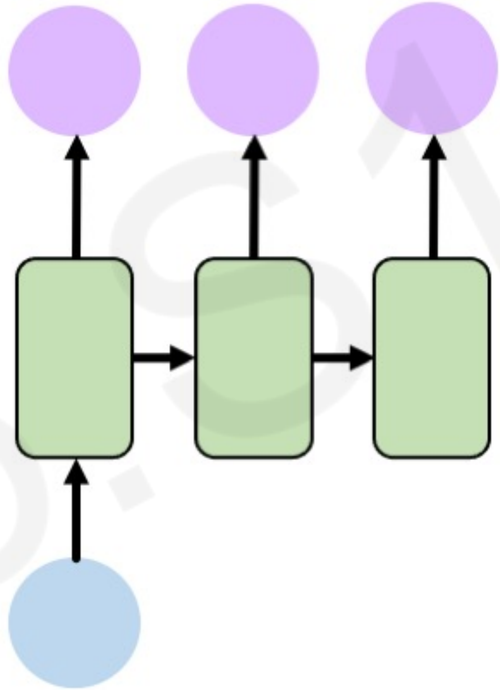
RNNs for Sequence Modeling



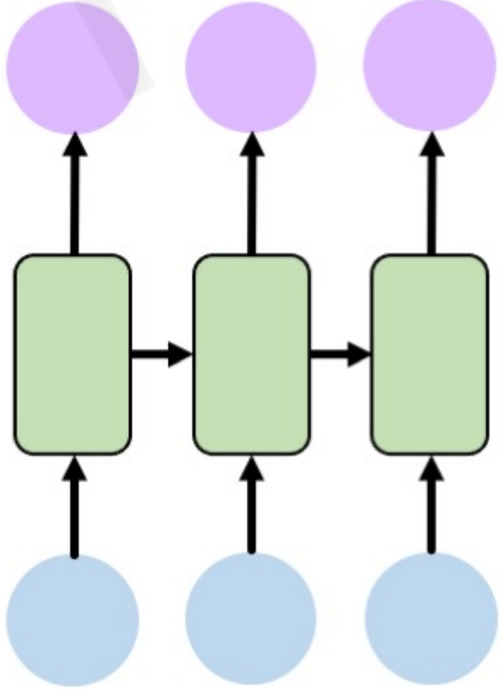
One to One
"Vanilla" NN
Binary classification



Many to One
Sentiment Classification



One to Many
Text Generation
Image Captioning



Many to Many
Translation & Forecasting
Music Generation

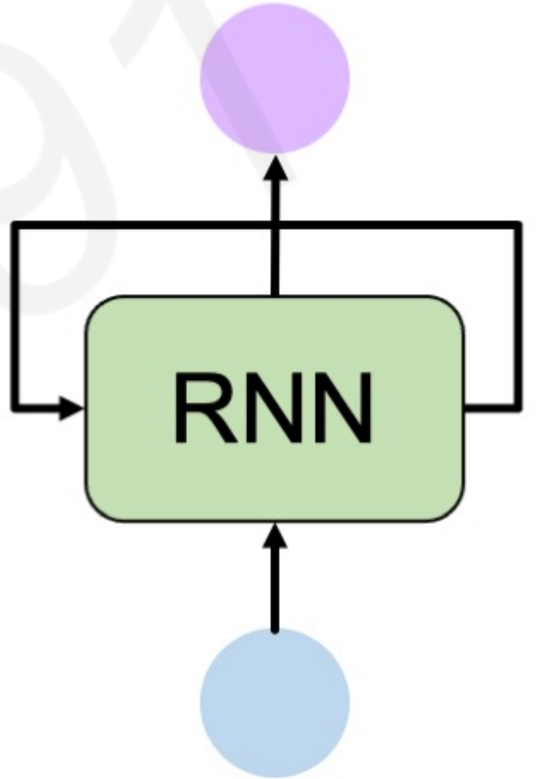
… and many other architectures and applications

6.S191 Lab!

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



Recurrent Neural Networks (RNNs) meet these sequence modeling design criteria

A Sequence Modeling Problem: Predict the Next Word

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

A Sequence Modeling Problem: Predict the Next Word

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

given these words

A Sequence Modeling Problem: Predict the Next Word

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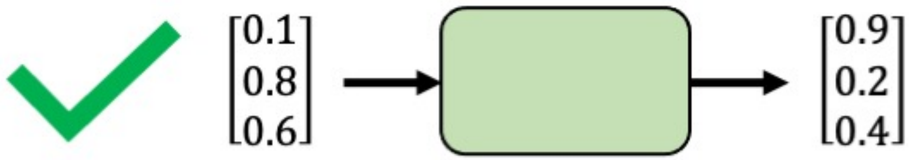
Representing Language to a Neural Network

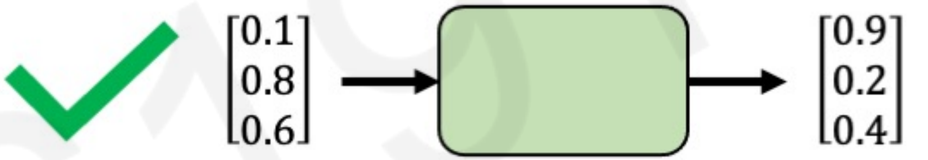
Neural networks cannot interpret words



Neural networks require numerical inputs

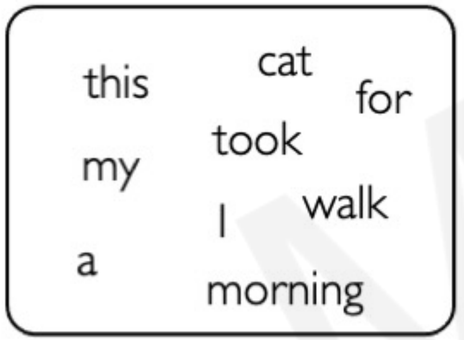
Encoding Language for a Neural Network

Neural networks cannot interpret words

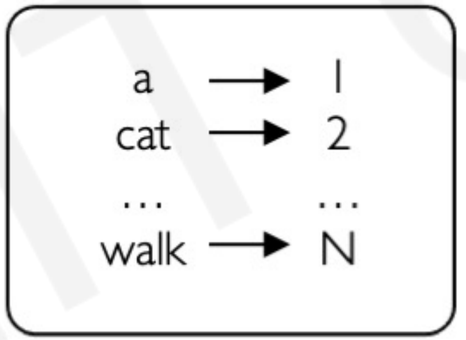


Neural networks require numerical inputs

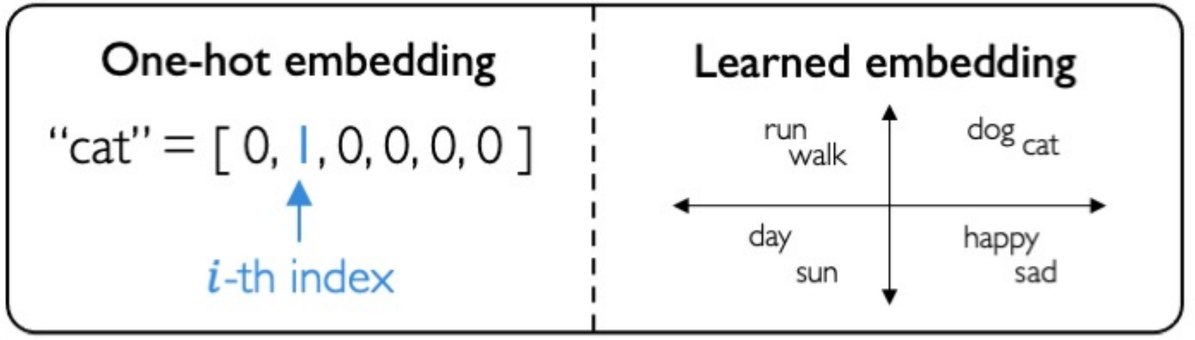
Embedding: transform indexes into a vector of fixed size.



1. Vocabulary:
Corpus of words



2. Indexing:
Word to index



3. Embedding:
Index to fixed-sized vector

Handle Variable Sequence Lengths

The food was great

vs.

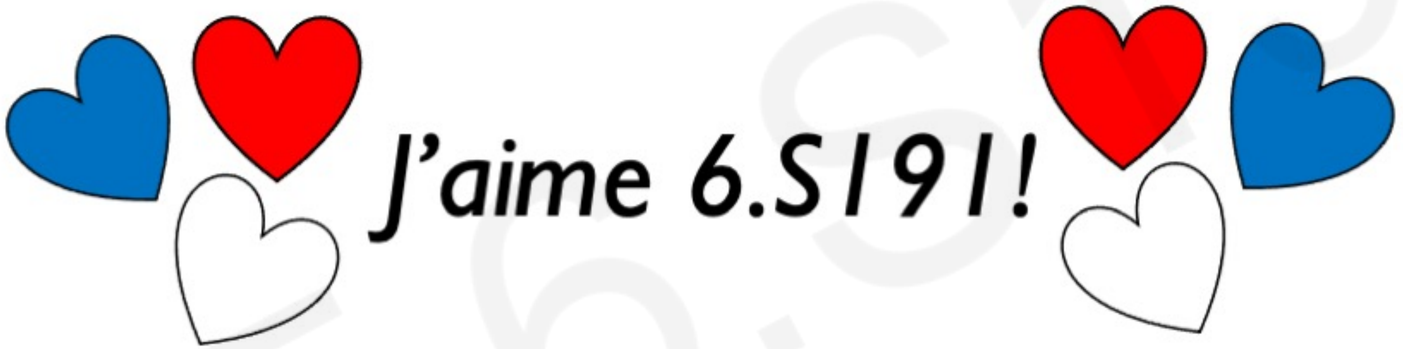
We visited a restaurant for lunch

vs.

We were hungry but cleaned the house before eating

Model Long-Term Dependencies

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



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

Capture Differences in Sequence Order

The food was good, not bad at all.

vs.

The food was bad, not good at all.

Sequence Modeling: Design Criteria

To model sequences, we need to:

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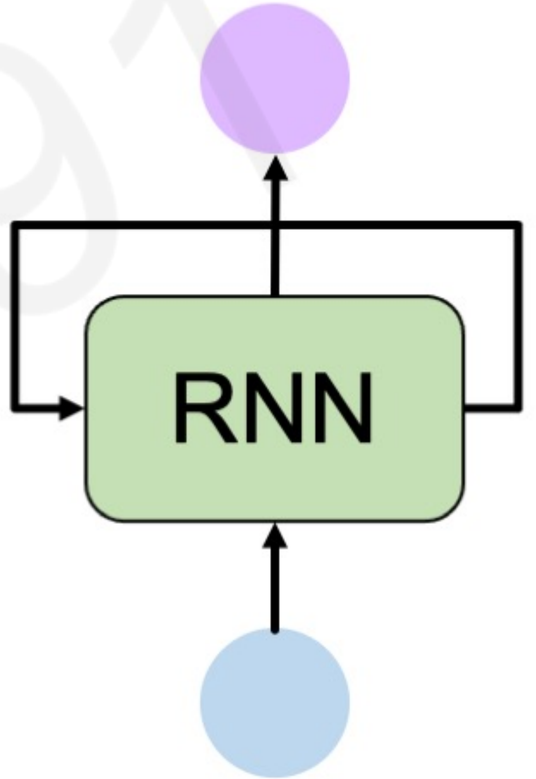
4. **Share parameters** across the sequence



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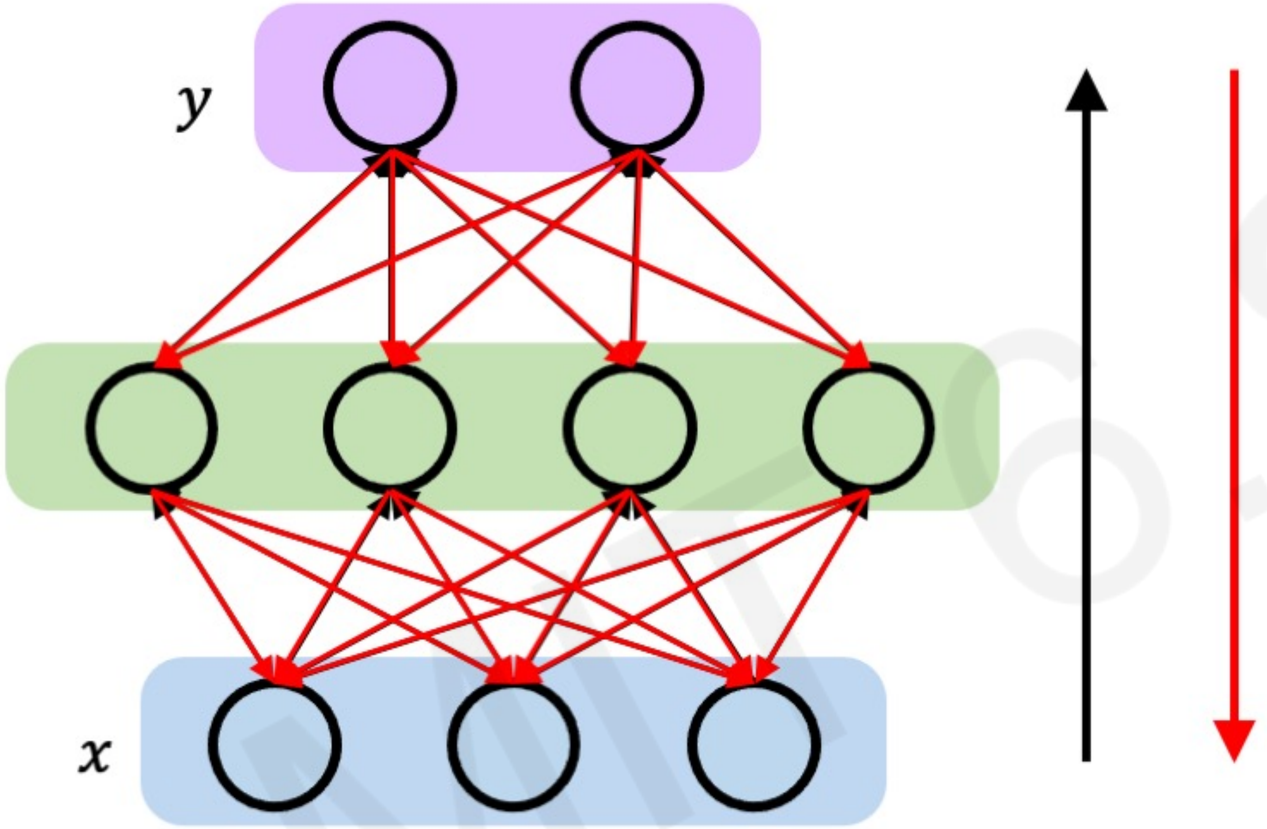
Backpropagation Through Time (BPTT)

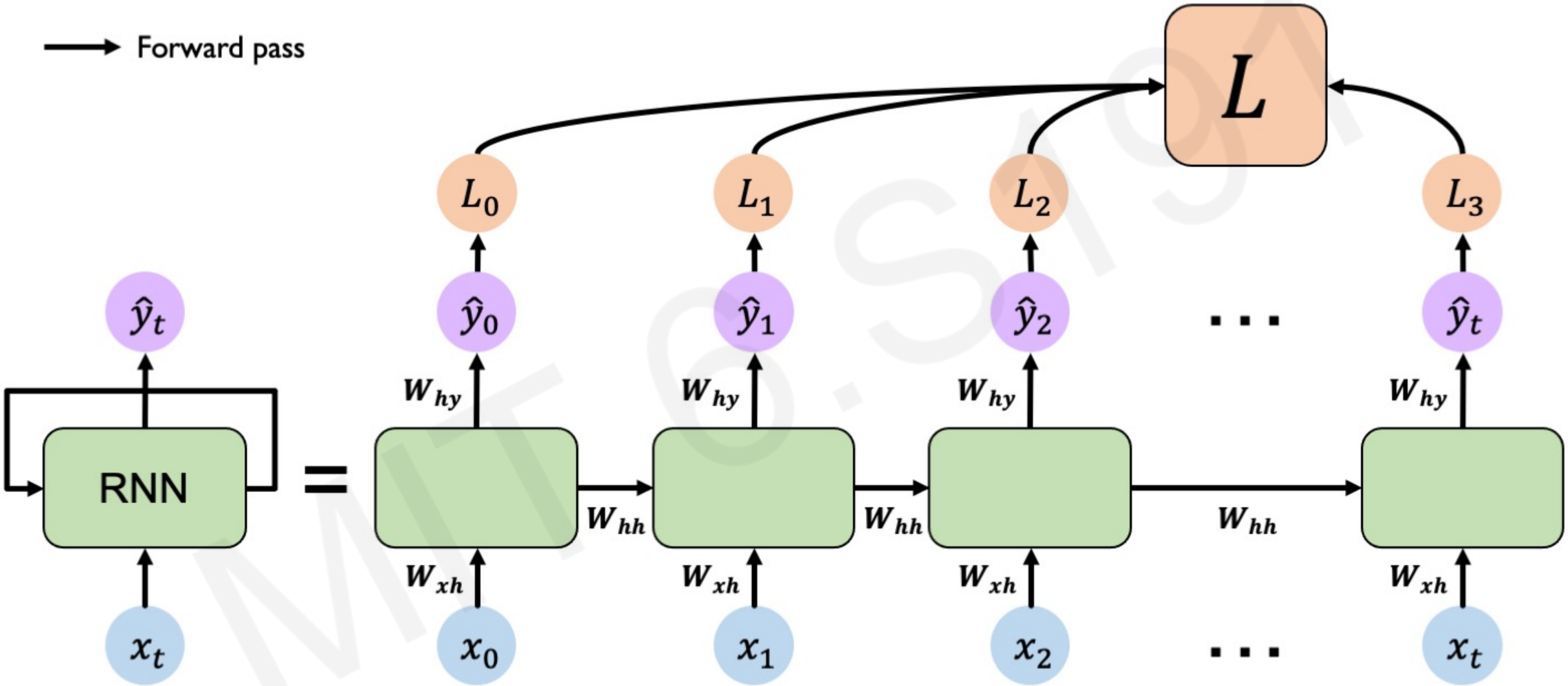
Recall: Backpropagation in Feed Forward Models



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



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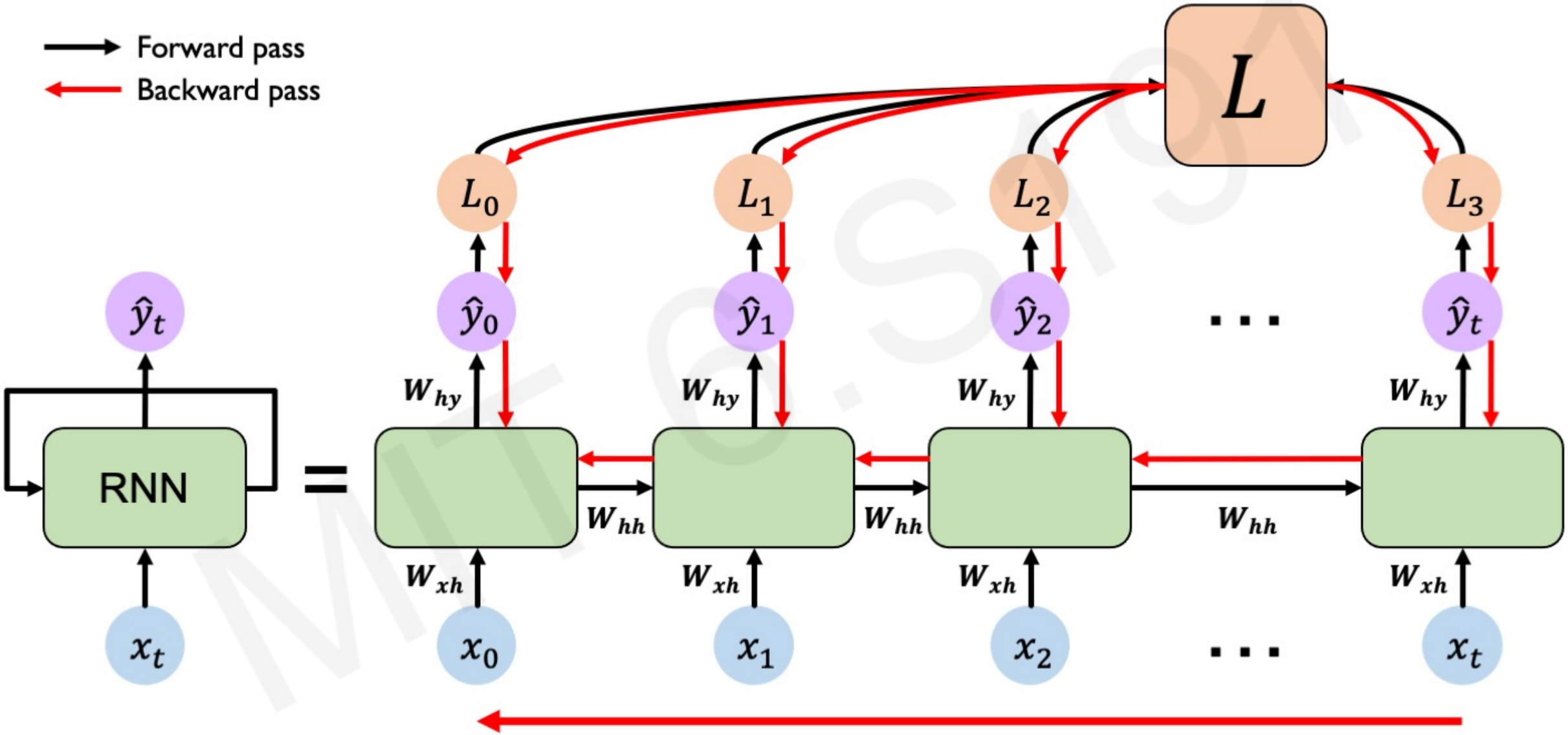
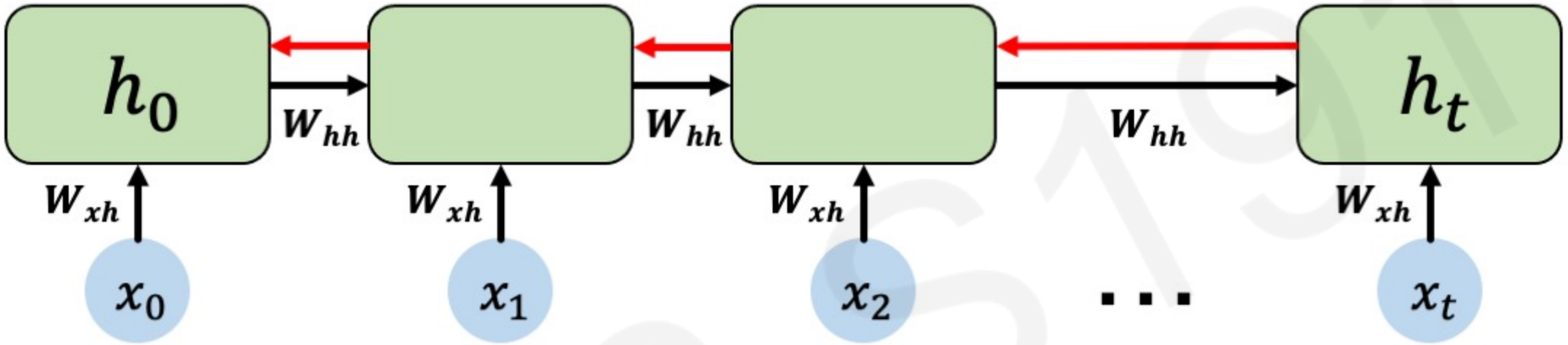


Standard RNN Gradient Flow



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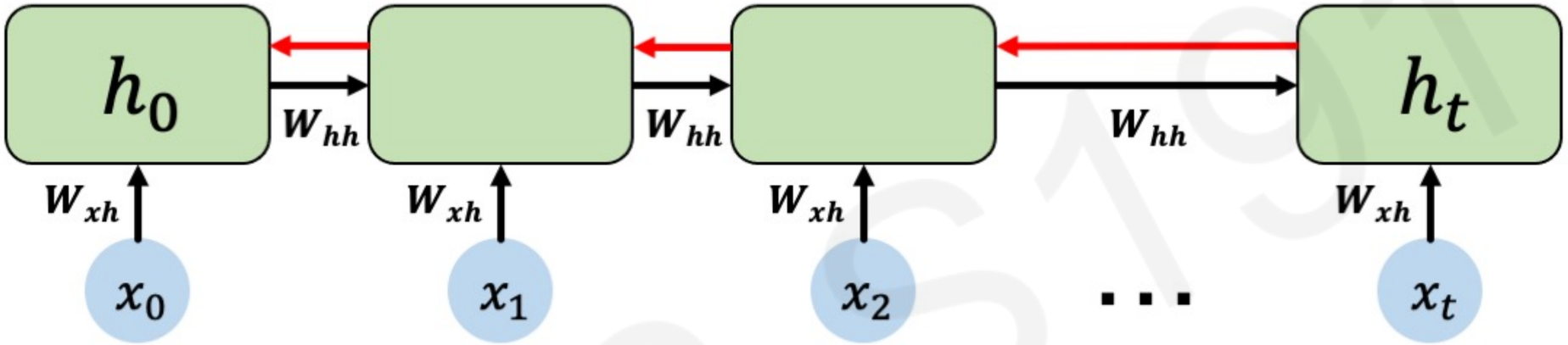
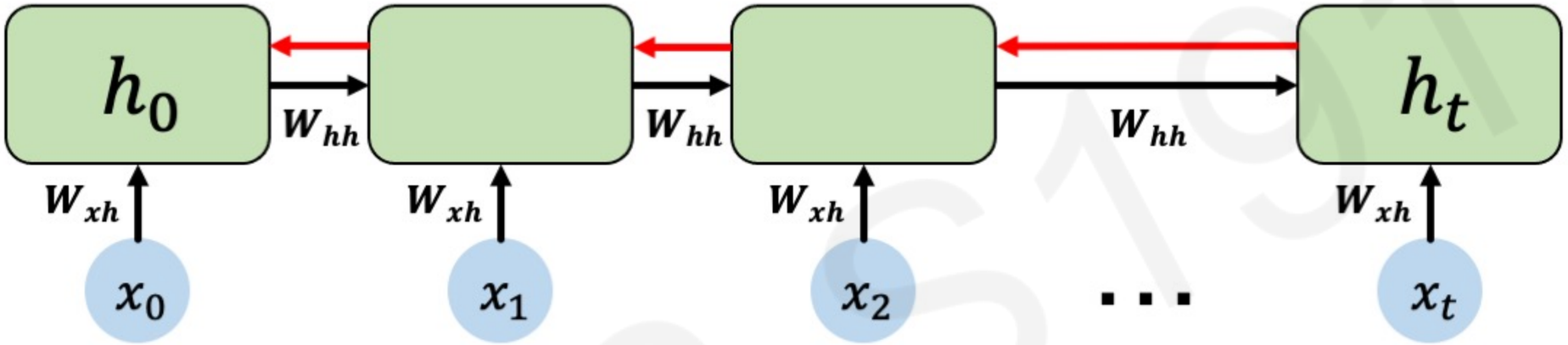


Computing the gradient wrt h_0 involves **many factors of W_{hh} + repeated gradient computation!**

Standard RNN Gradient Flow: Exploding Gradients

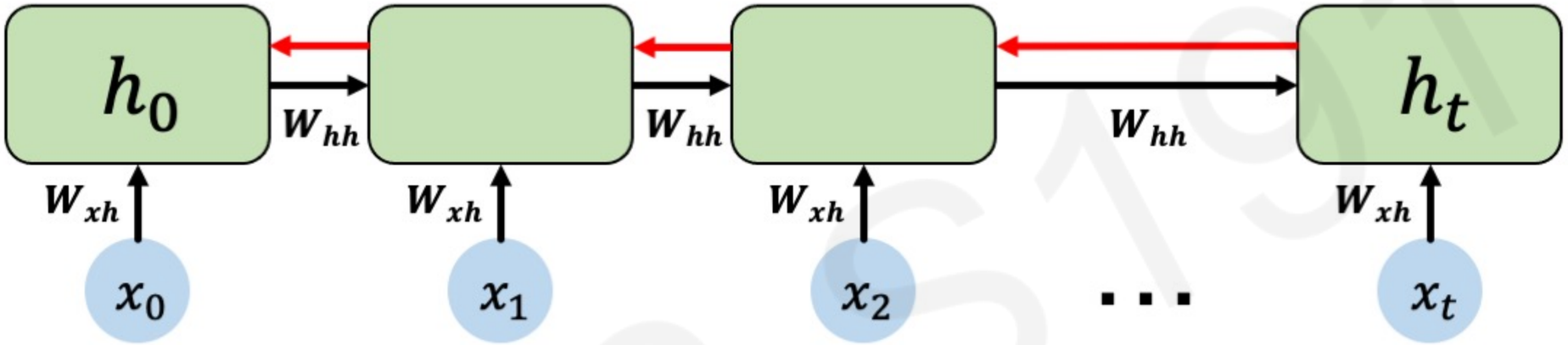


Computing the gradient wrt h_0 involves **many factors of W_{hh} + repeated gradient computation!**

Many values > 1:
exploding gradients

Gradient clipping to scale big 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

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

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

The Problem of Long-Term Dependencies

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Bias parameters to capture short-term dependencies

The Problem of Long-Term Dependencies

"The clouds are in the ___"

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Bias parameters to capture short-term dependencies

The Problem of Long-Term Dependencies

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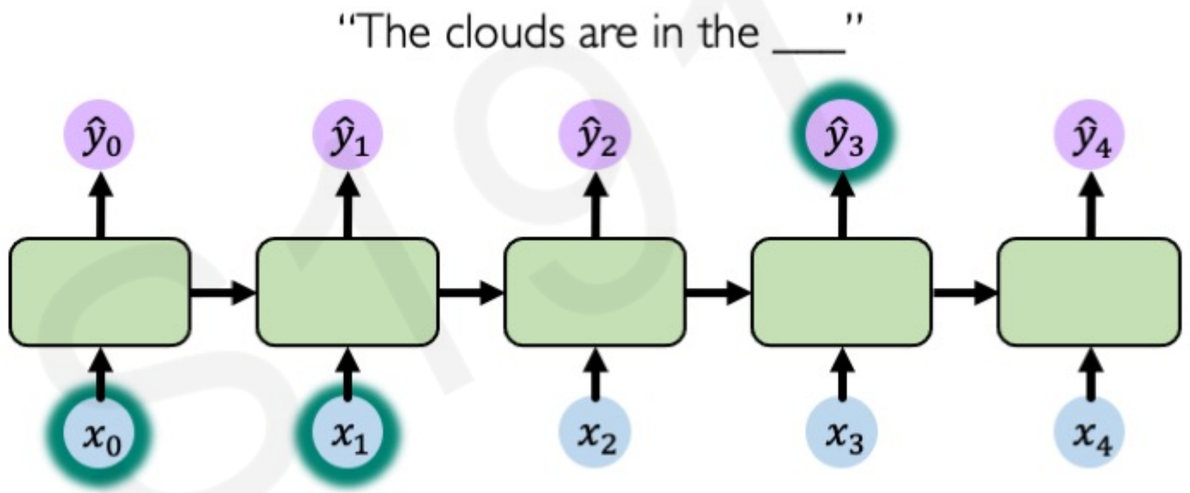
↓

Bias parameters to capture short-term dependencies



The Problem of Long-Term Dependencies

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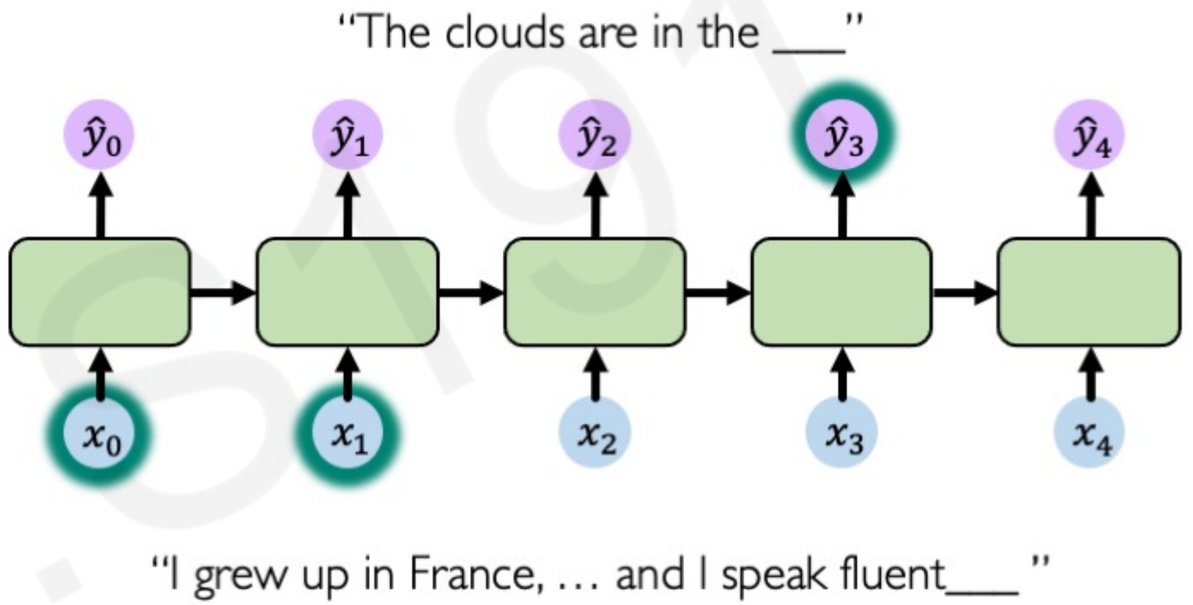
↓

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

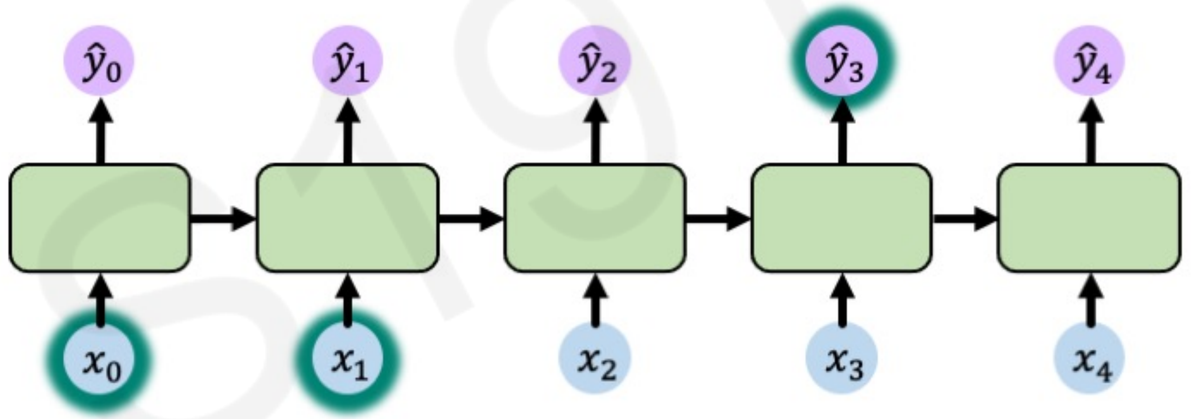
↓

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

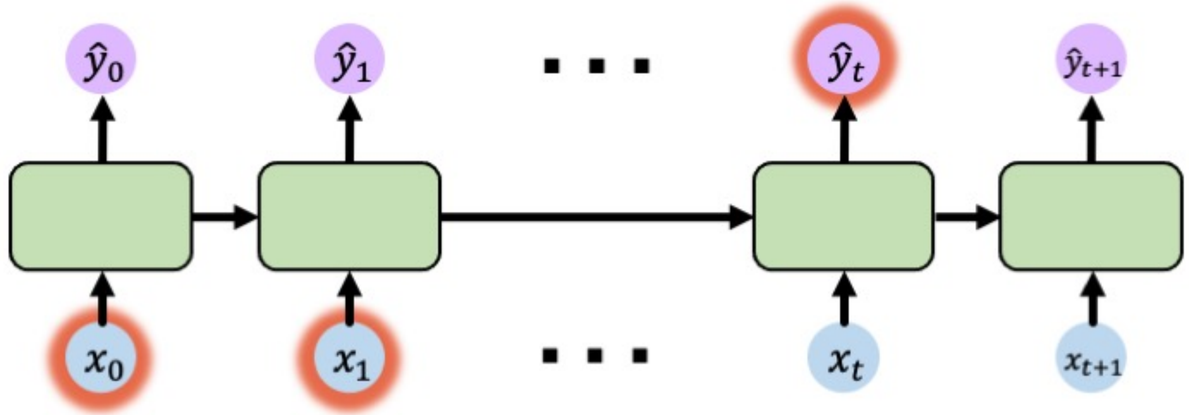
↓

Bias parameters to capture short-term dependencies

"The clouds are in the ___"

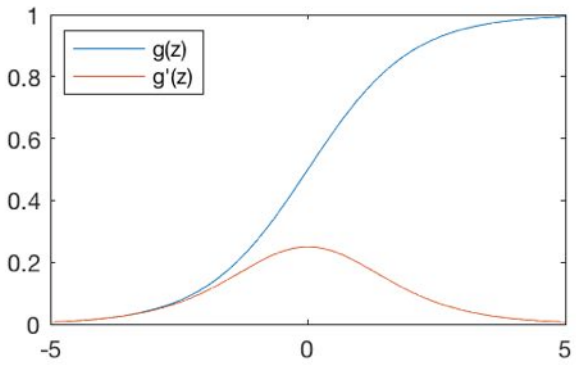


"I grew up in France, … and I speak fluent___ "



Common Activation Functions

Sigmoid Function

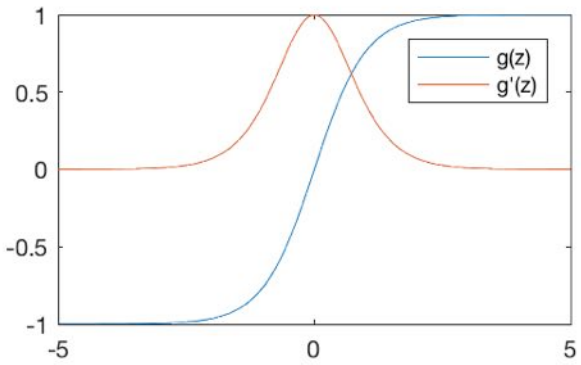


$$g(z) = \frac{1}{1 + e^{-z}}$$

$$g'(z) = g(z)(1 - g(z))$$

`tf.nn.sigmoid(z)`

Hyperbolic Tangent

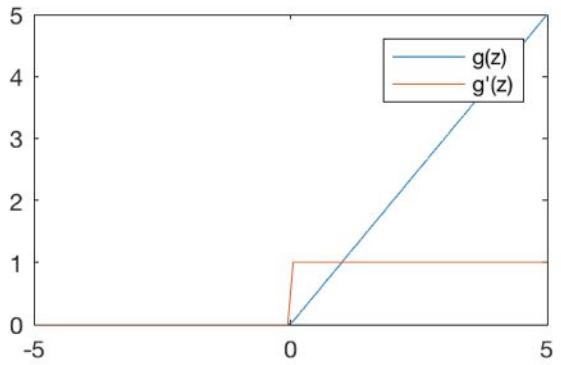


$$g(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$$

$$g'(z) = 1 - g(z)^2$$

`tf.nn.tanh(z)`

Rectified Linear Unit (ReLU)



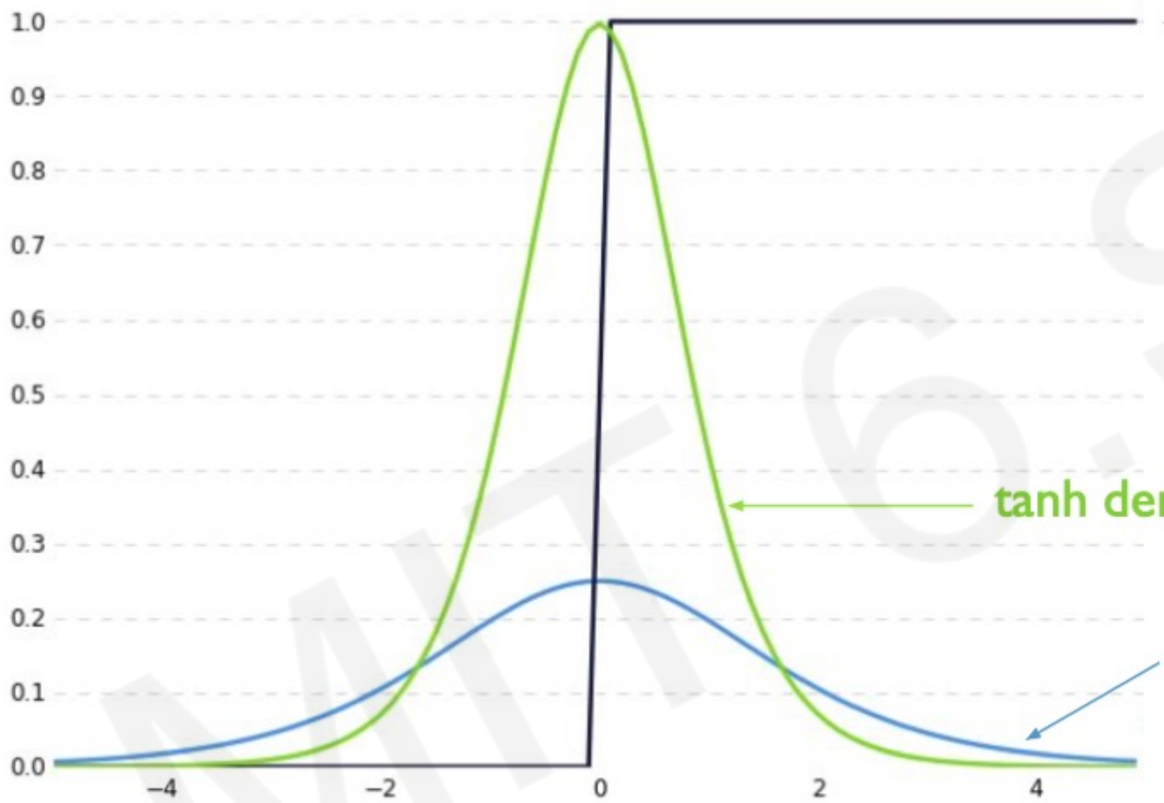
$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$

`tf.nn.relu(z)`

NOTE: All activation functions are **non-linear**

Trick #1: Activation Functions



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

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.

Solution #3: Gated Cells

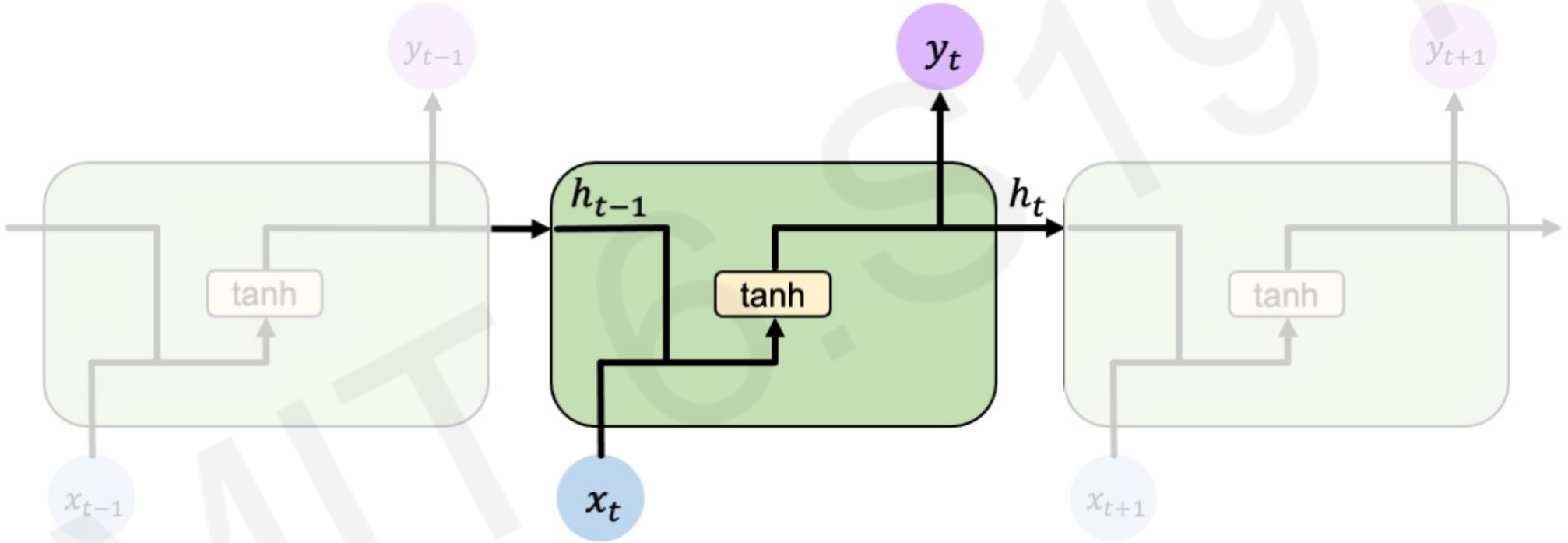
Idea: use a more **complex recurrent unit with gates** to control what information is passed through

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

Long Short Term Memory (LSTM) Networks

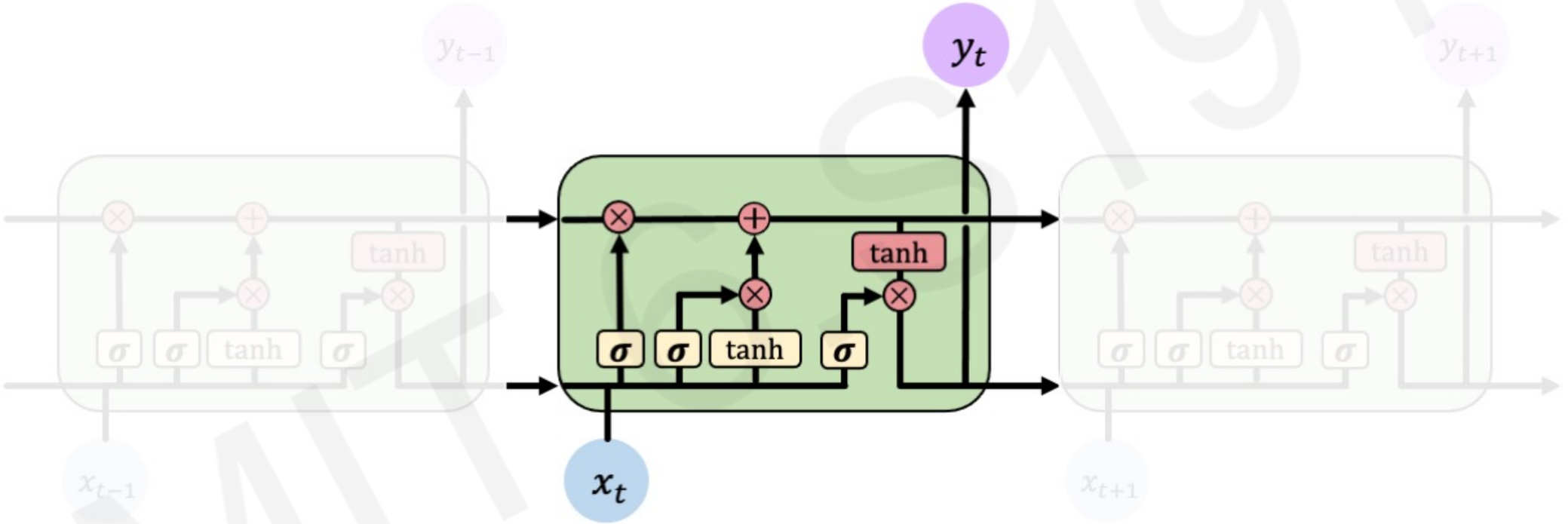
Standard RNN

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



Long Short Term Memory (LSTMs)

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

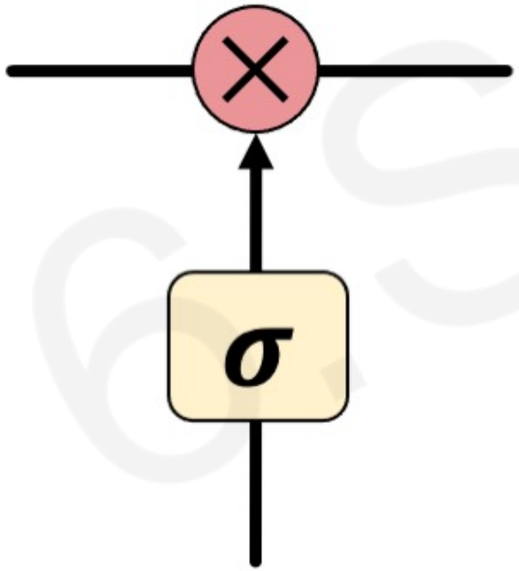


LSTM cells are able to track information throughout many timesteps

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

Long Short Term Memory (LSTMs)

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

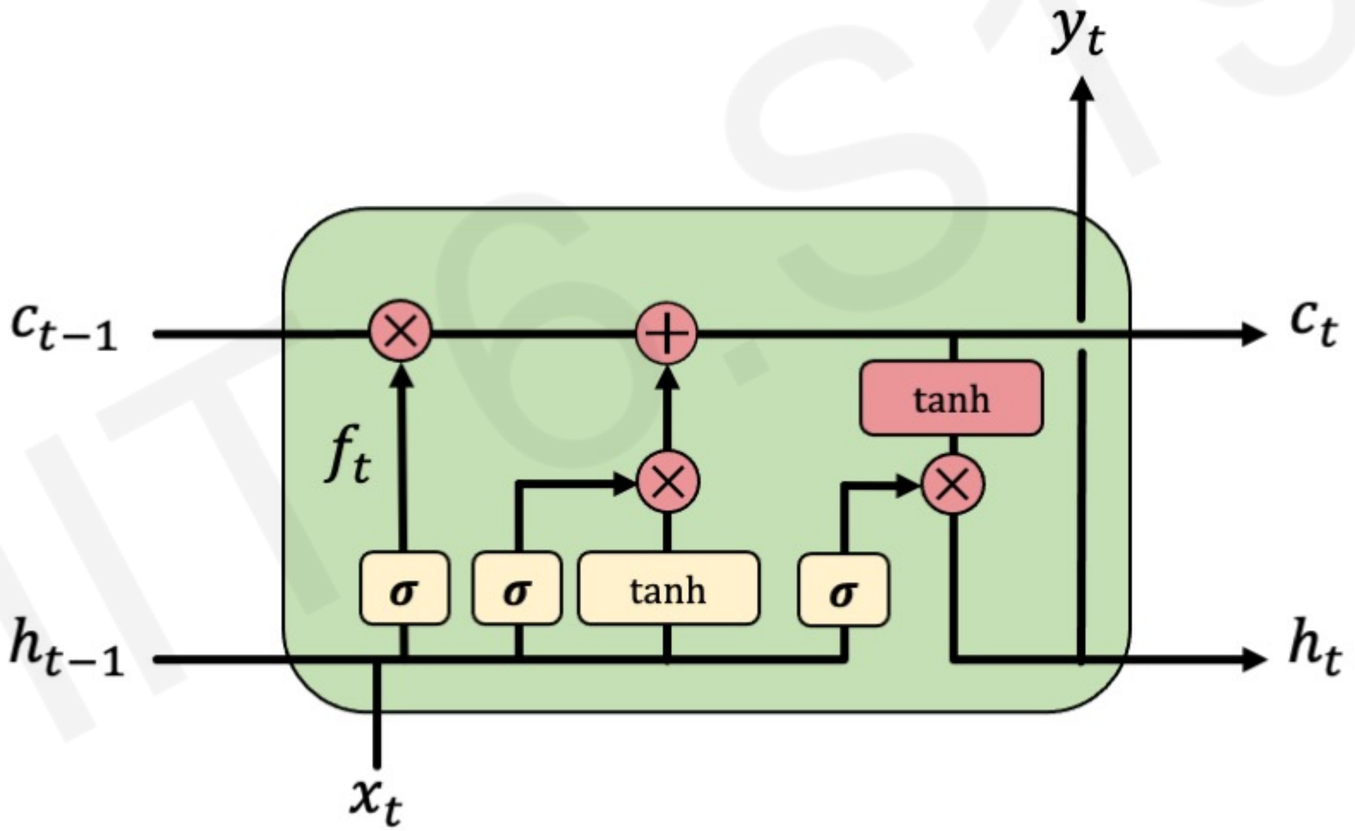


Gates optionally let information through, for example via a sigmoid neural net layer and pointwise multiplication

Long Short Term Memory (LSTMs)

How do LSTMs work?

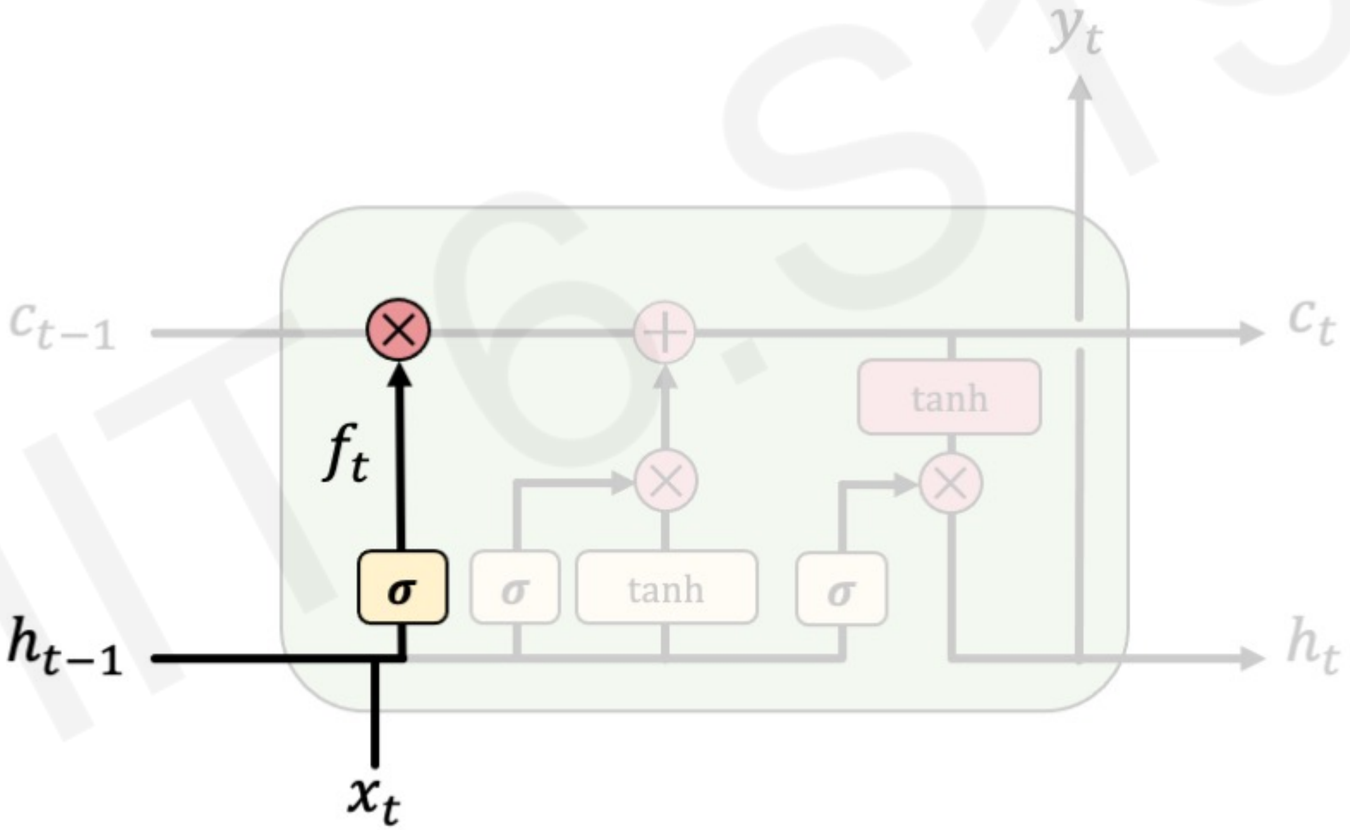
1) Forget 2) Store 3) Update 4) Output



Long Short Term Memory (LSTMs)

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

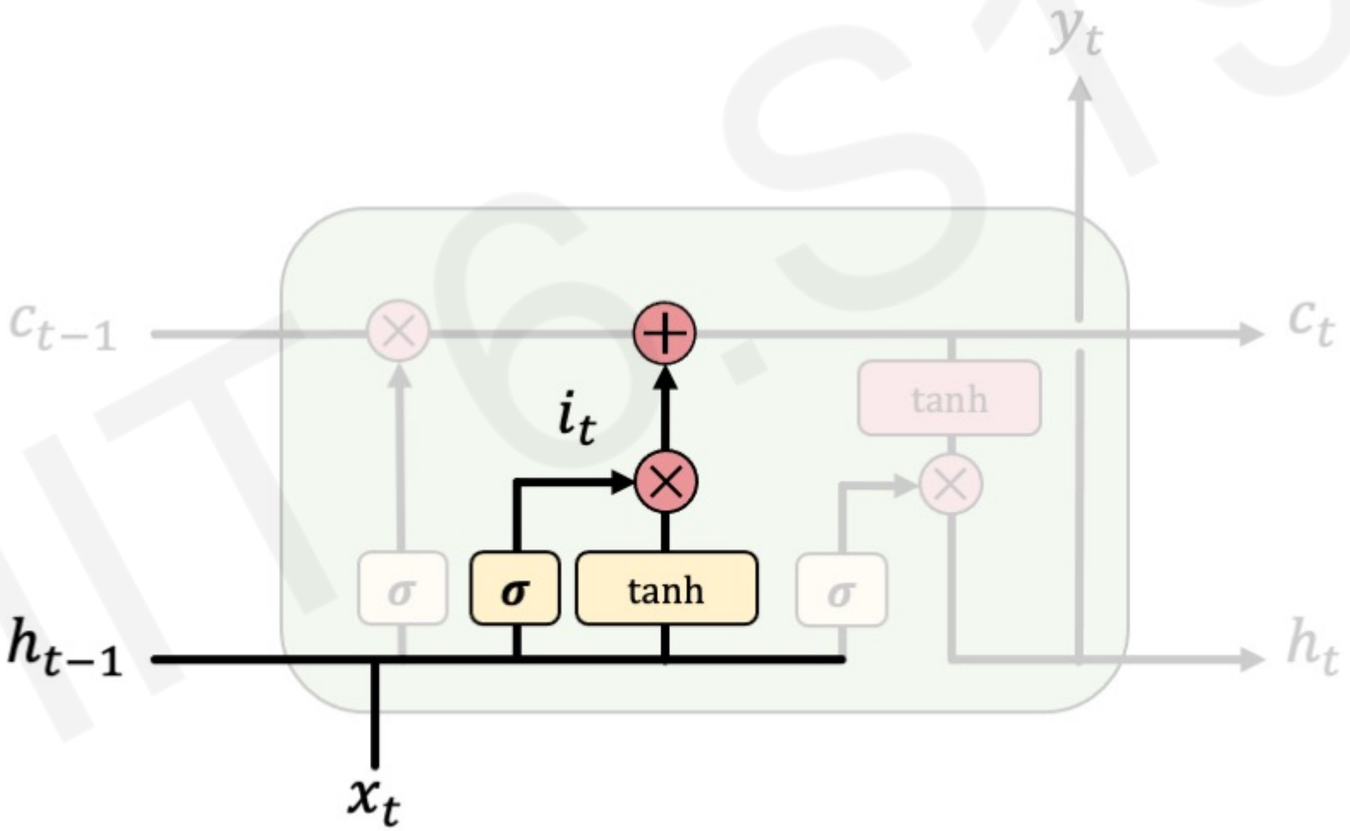
LSTMs **forget irrelevant** parts of the previous state



Long Short Term Memory (LSTMs)

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

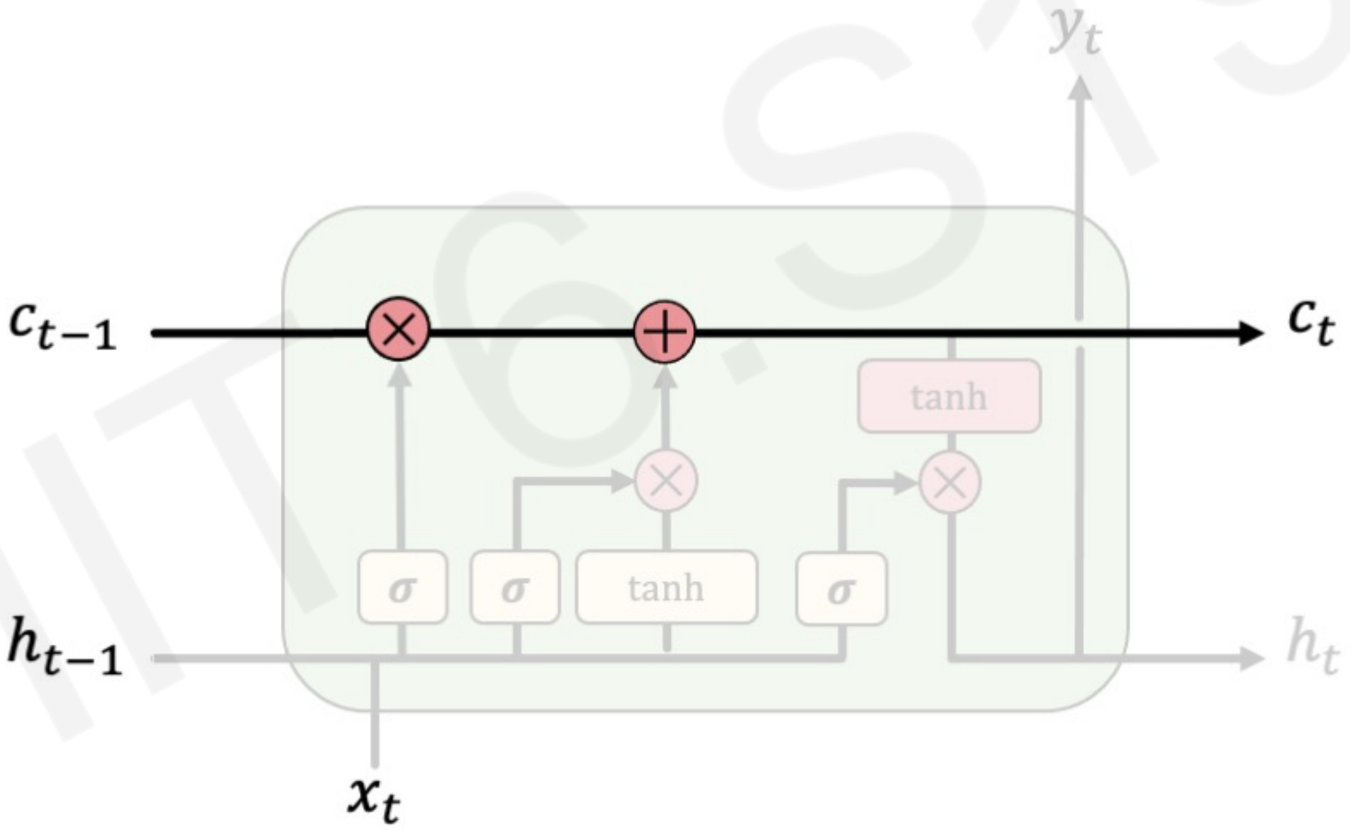
LSTMs **store relevant** new information into the cell state



Long Short Term Memory (LSTMs)

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

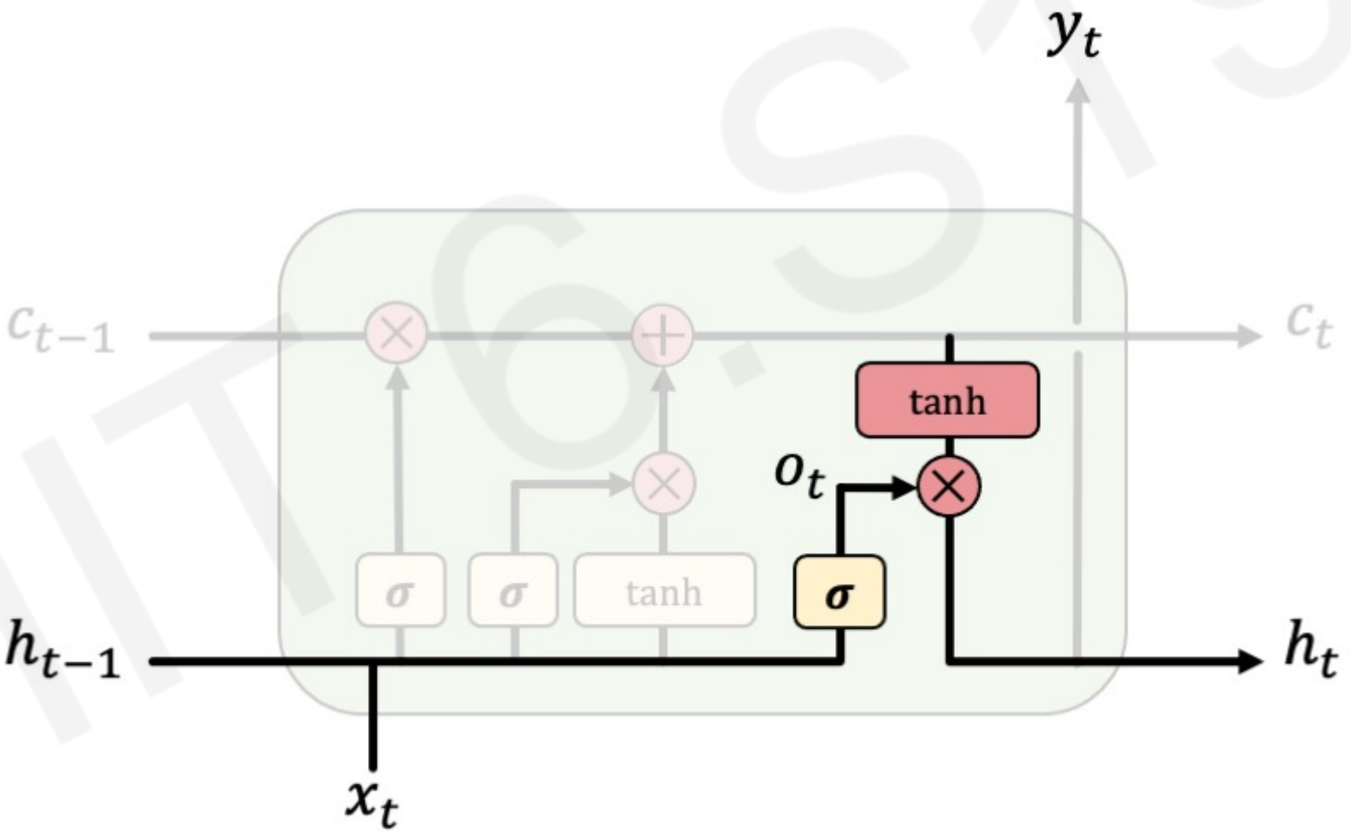
LSTMs **selectively update** cell state values



Long Short Term Memory (LSTMs)

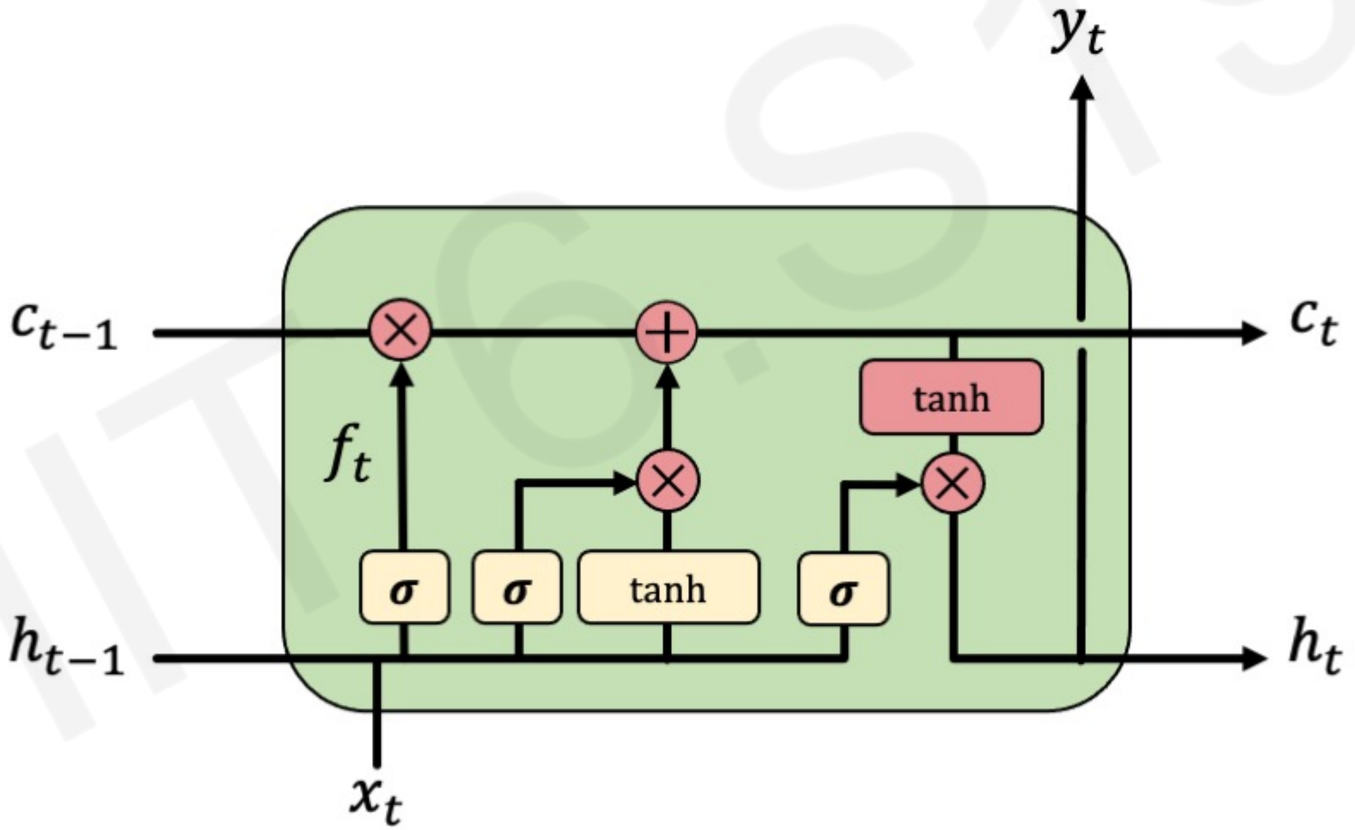
1) Forget 2) Store 3) Update **4) Output**

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

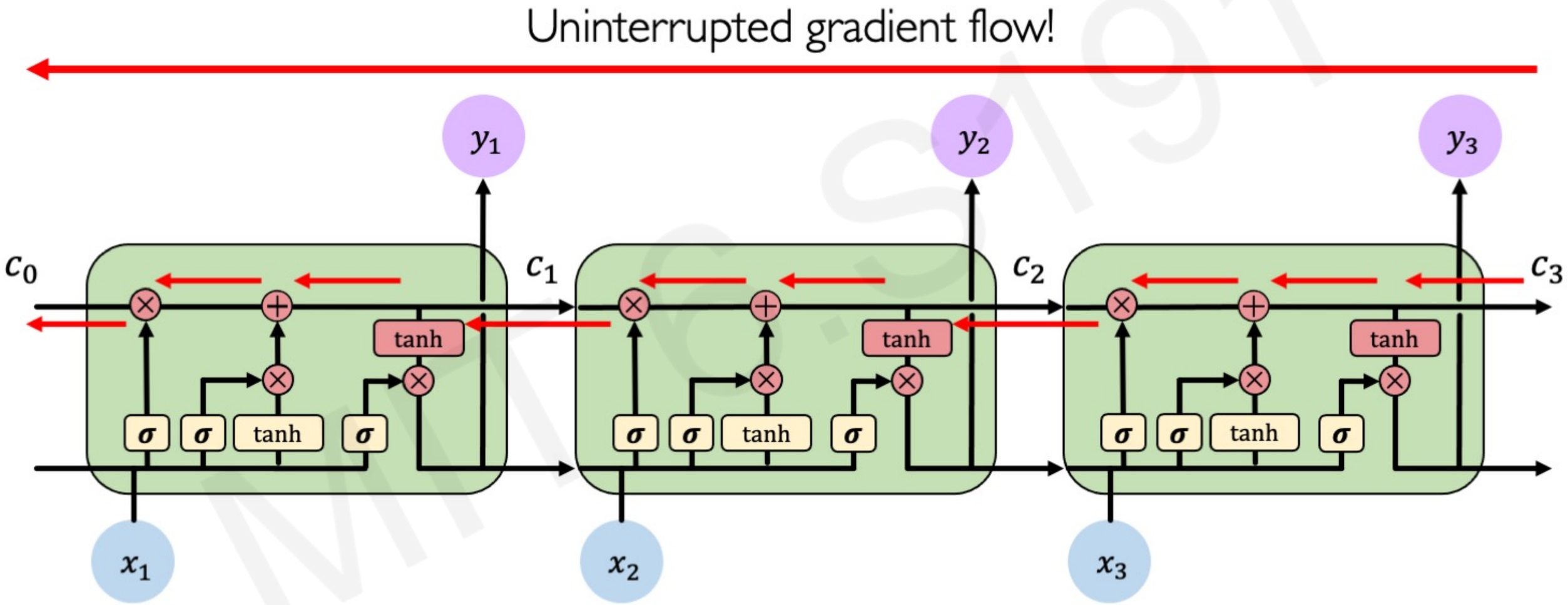


Long Short Term Memory (LSTMs)

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



LSTM Gradient Flow

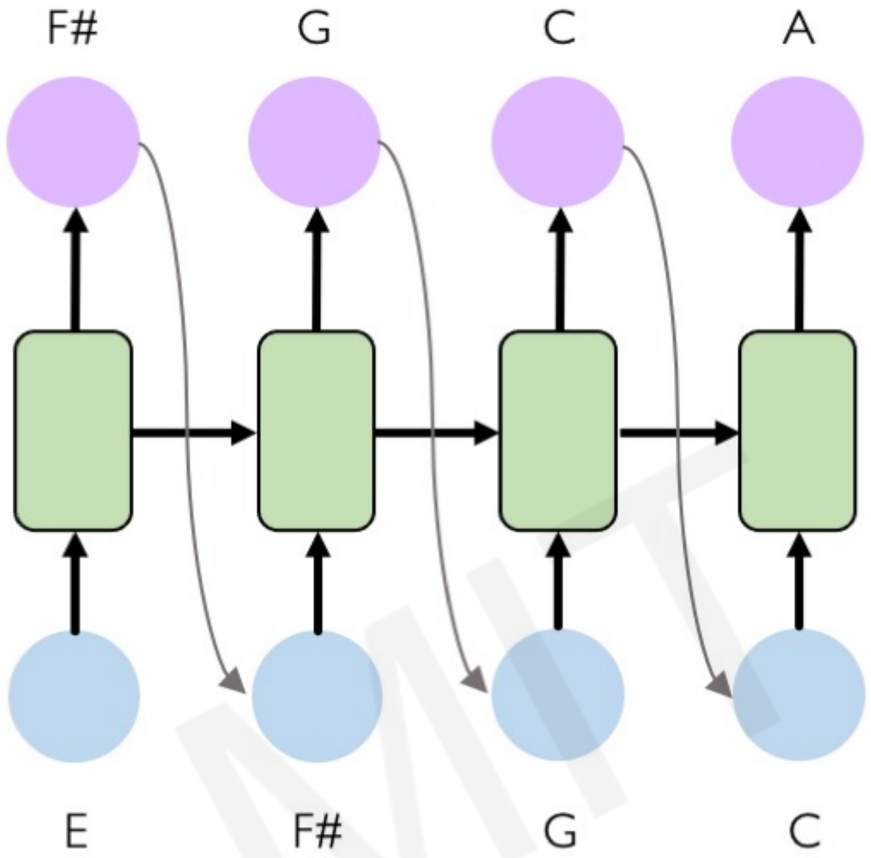


LSTMs: Key Concepts

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**

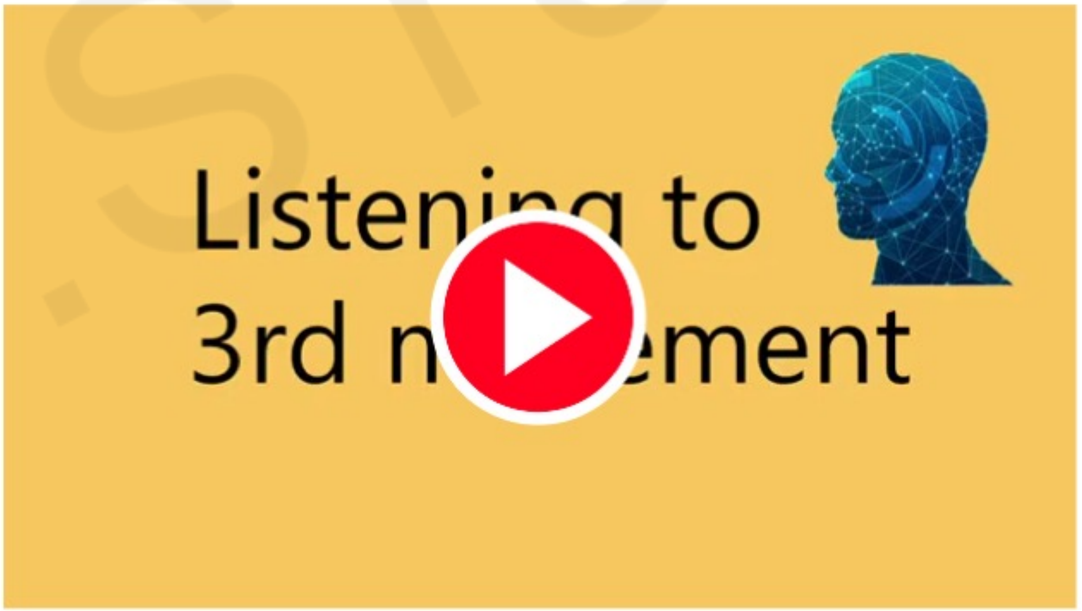
RNN Applications

Example Task: Music Generation



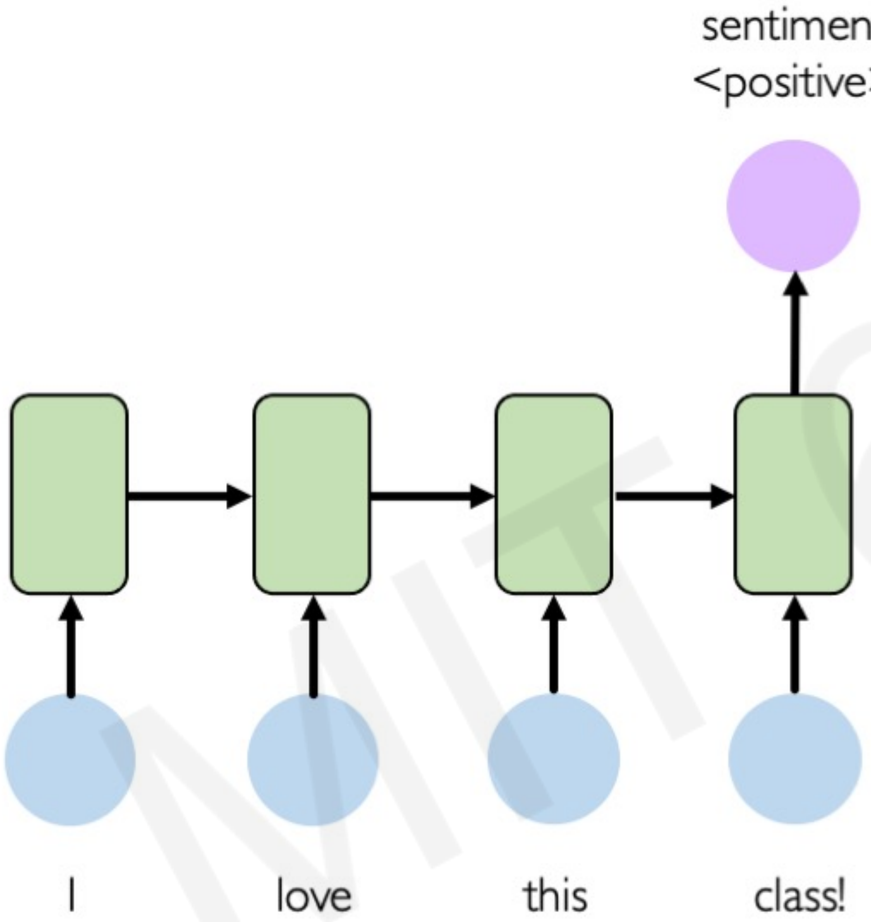
Input: sheet music

Output: next character in sheet music



6.S191 Lab!

Example Task: Sentiment Classification

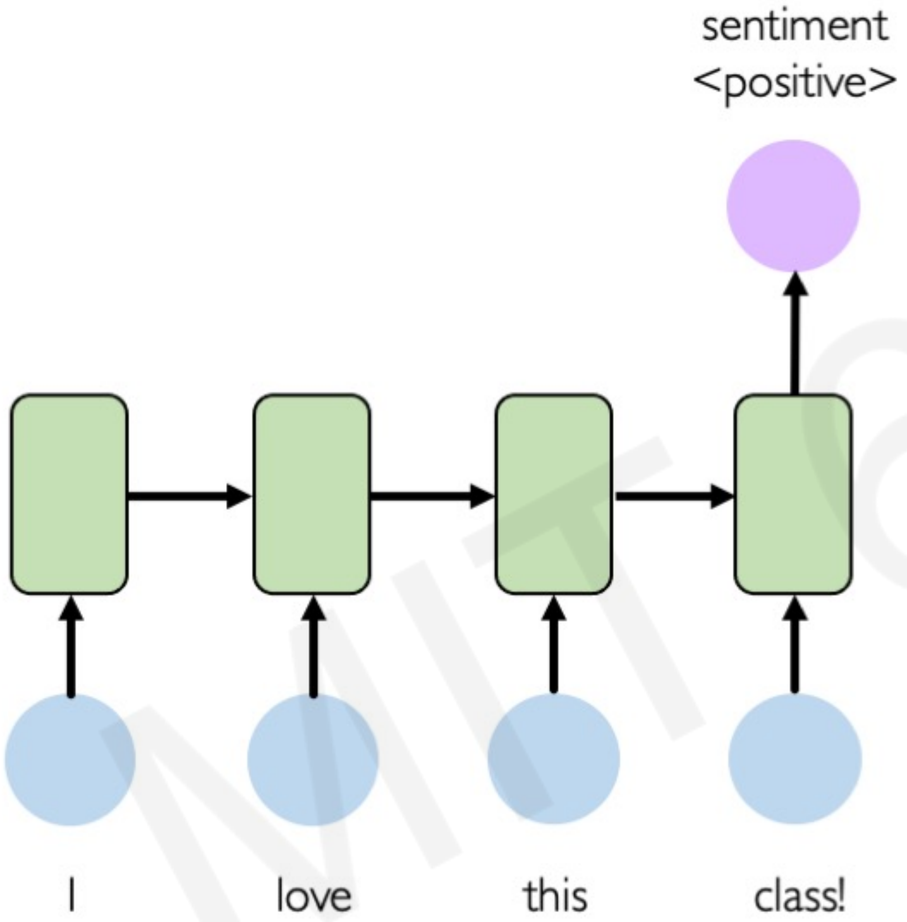


Input: sequence of words

Output: probability of having positive sentiment

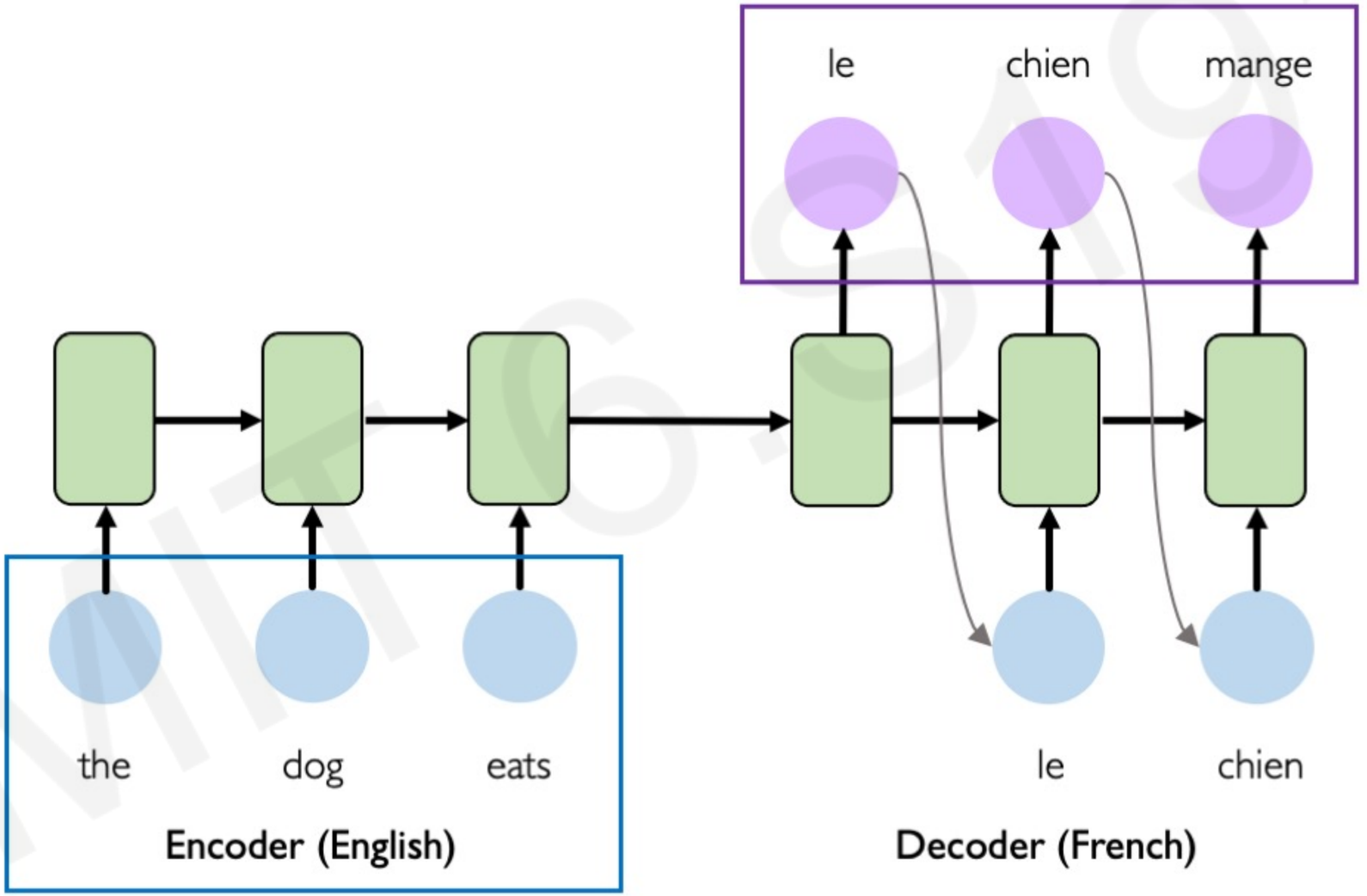
```
loss = tf.nn.softmax_cross_entropy_with_logits(y, predicted)
```

Example Task: Sentiment Classification



Tweet sentiment classification

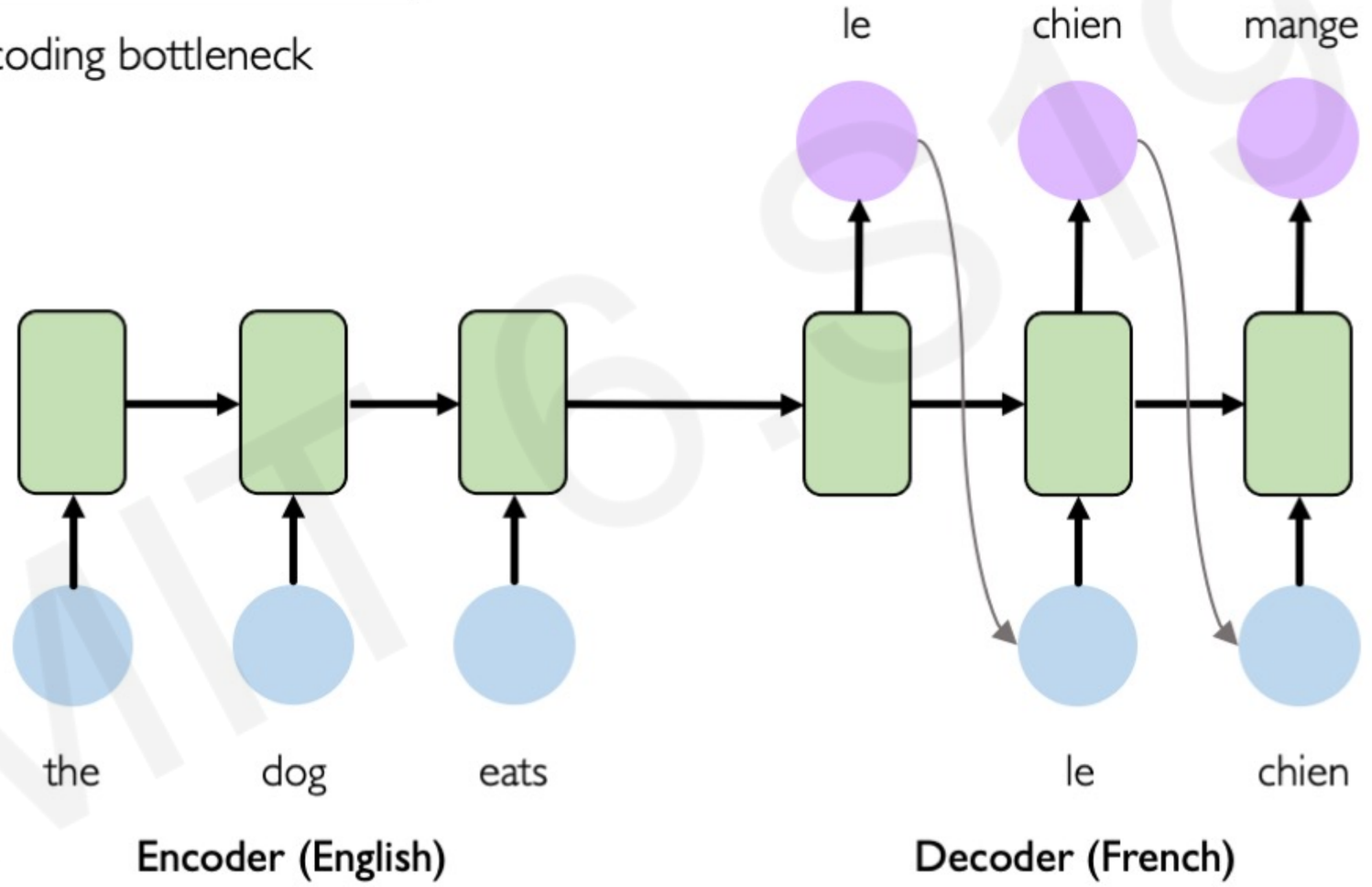
Example Task: Machine Translation



Example Task: Machine Translation

Potential Issues

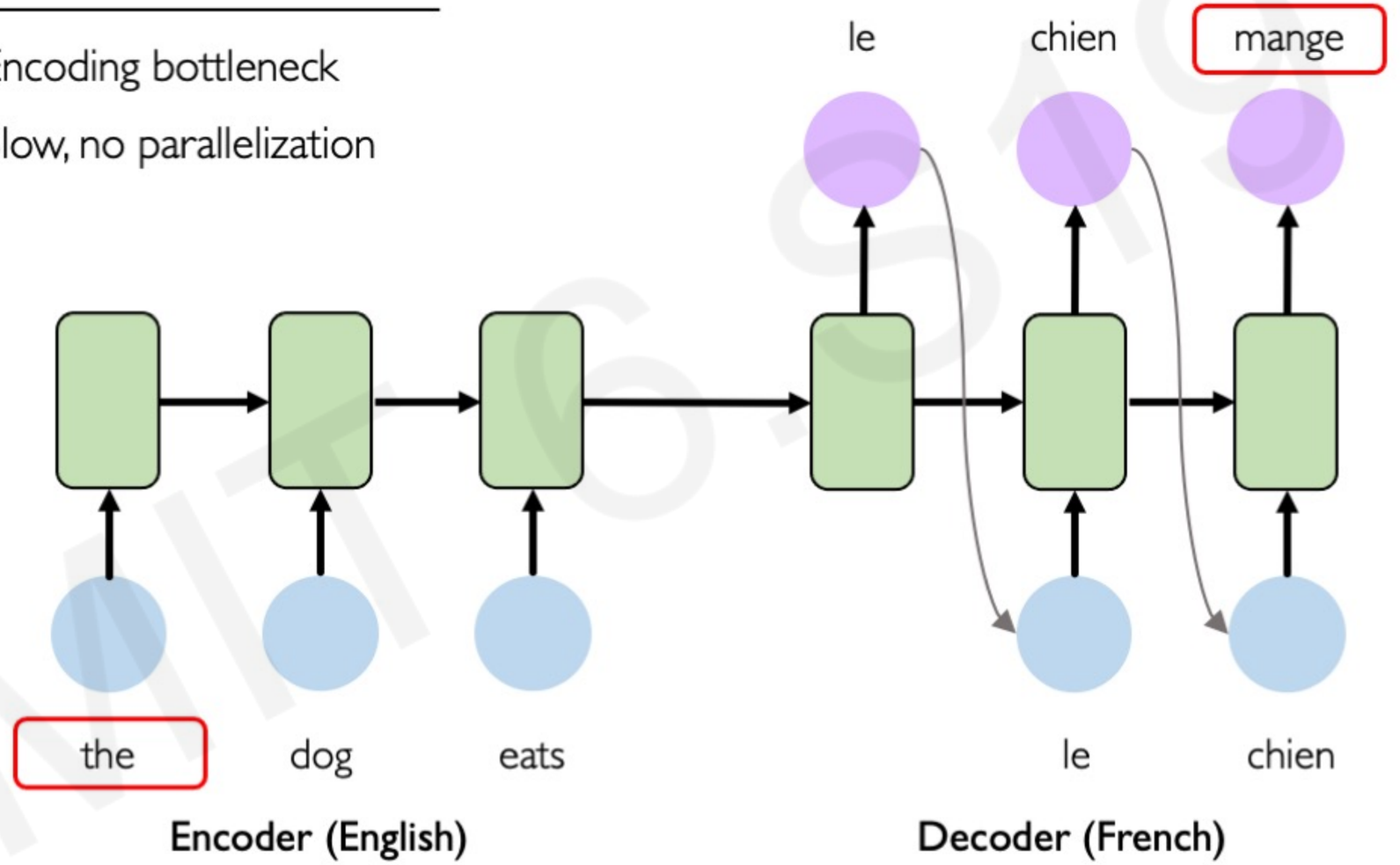
- Encoding bottleneck



Example Task: Machine Translation

Potential Issues

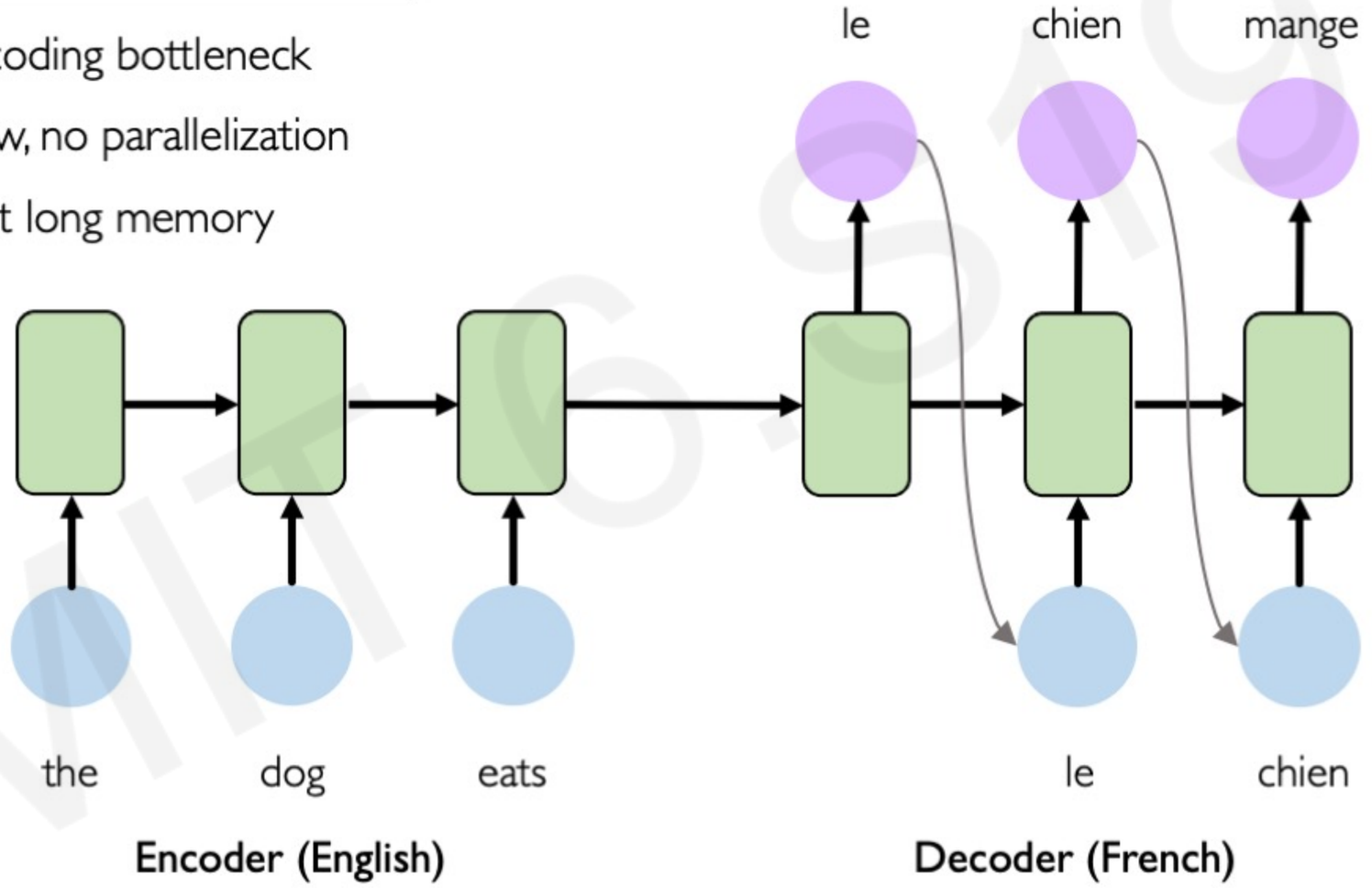
- Encoding bottleneck
- Slow, no parallelization



Example Task: Machine Translation

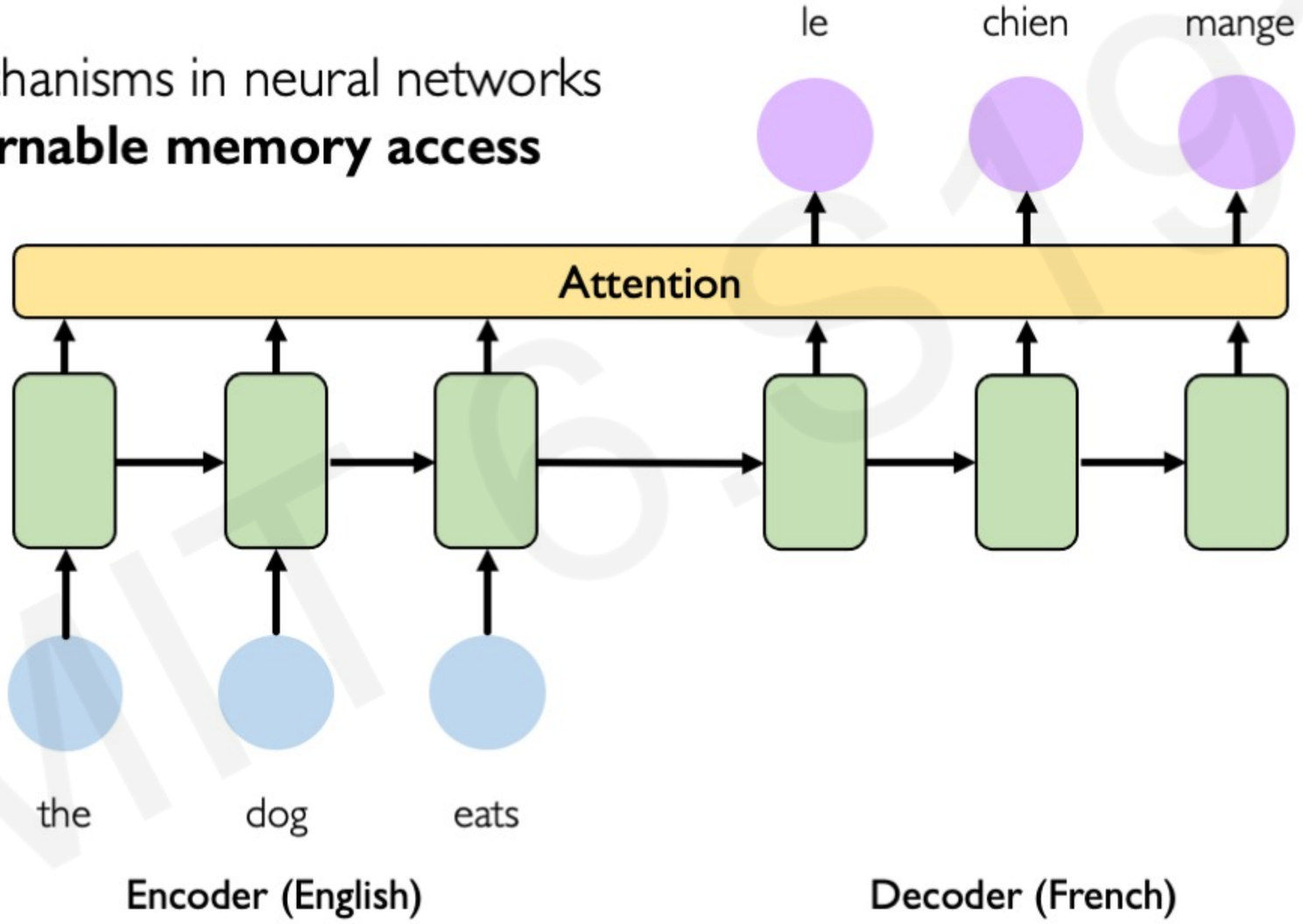
Potential Issues

- Encoding bottleneck
- Slow, no parallelization
- Not long memory

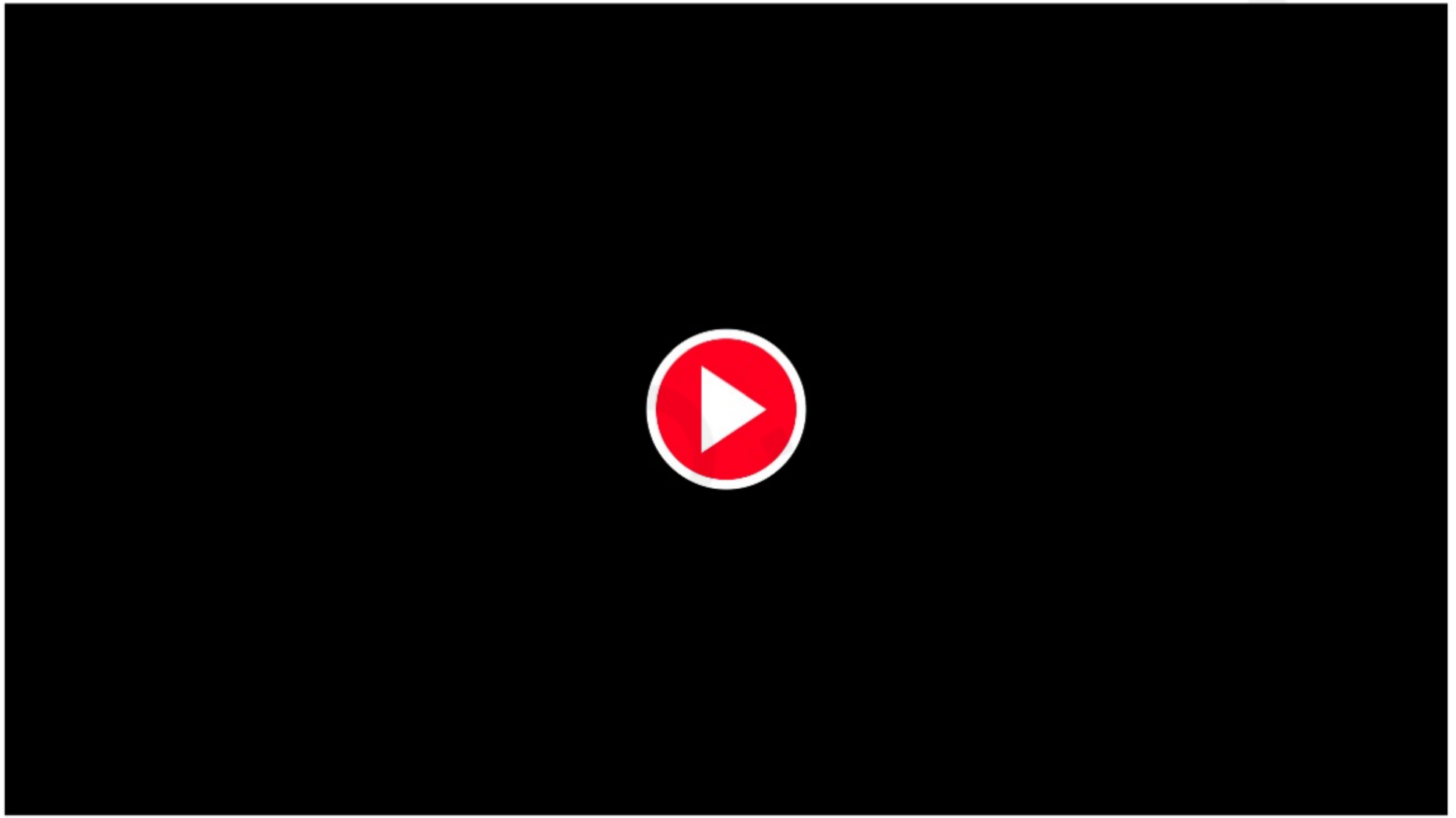


Example Task: Machine Translation

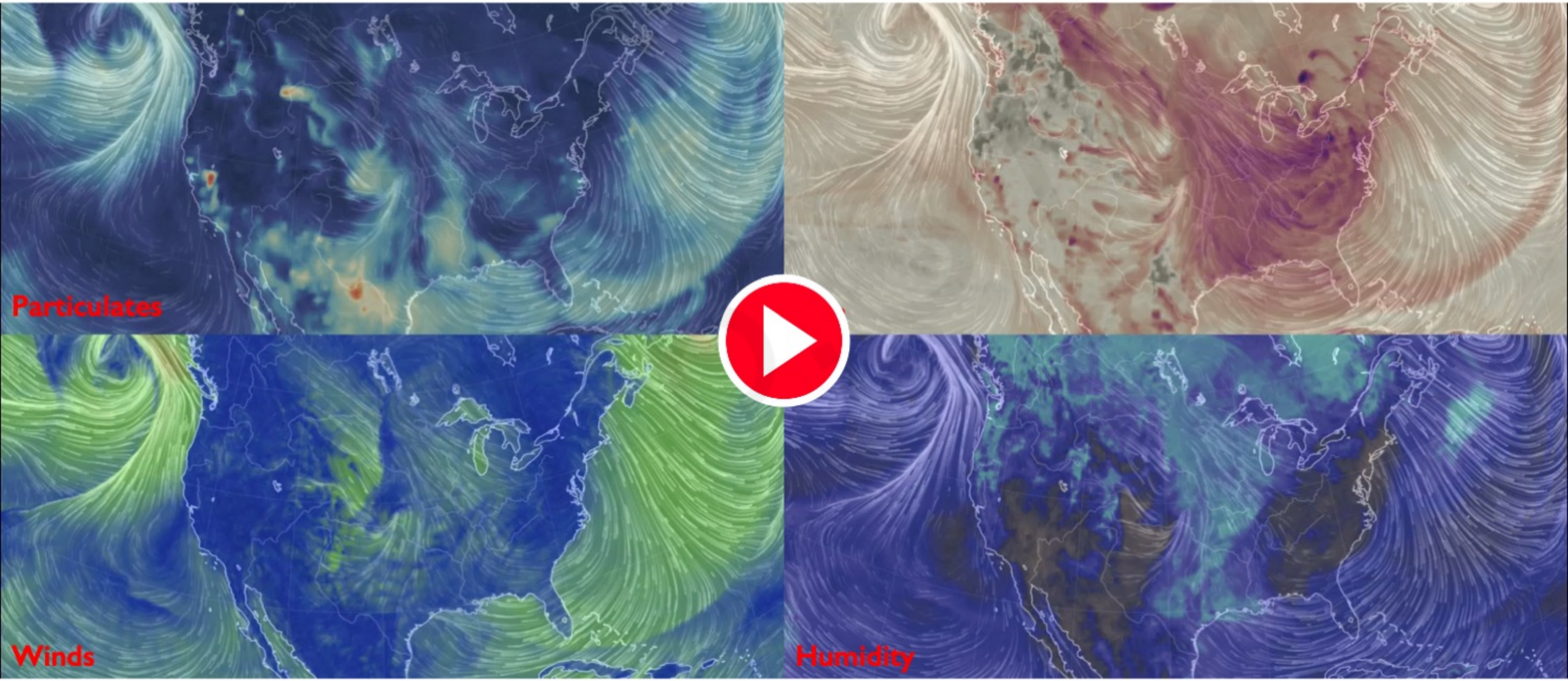
Attention mechanisms in neural networks provide **learnable memory access**



Application: Trajectory Prediction for Self-Driving Cars

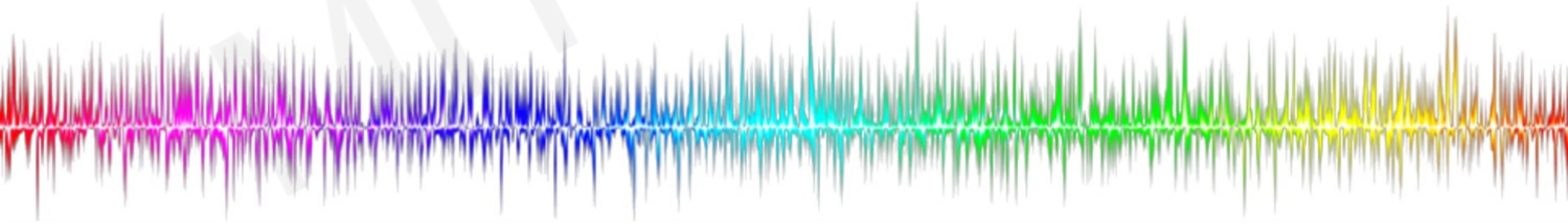


Application: Environmental Modeling



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



6.S191: Introduction to Deep Learning

Lab 1: Introduction to TensorFlow and Music Generation with RNNs

Link to download labs:
http://introtodeeplearning.com#schedule

1. Open the lab in Google Colab
2. Start executing code blocks and filling in the #TODOs
3. Need help? Come to the class Gather.Town!