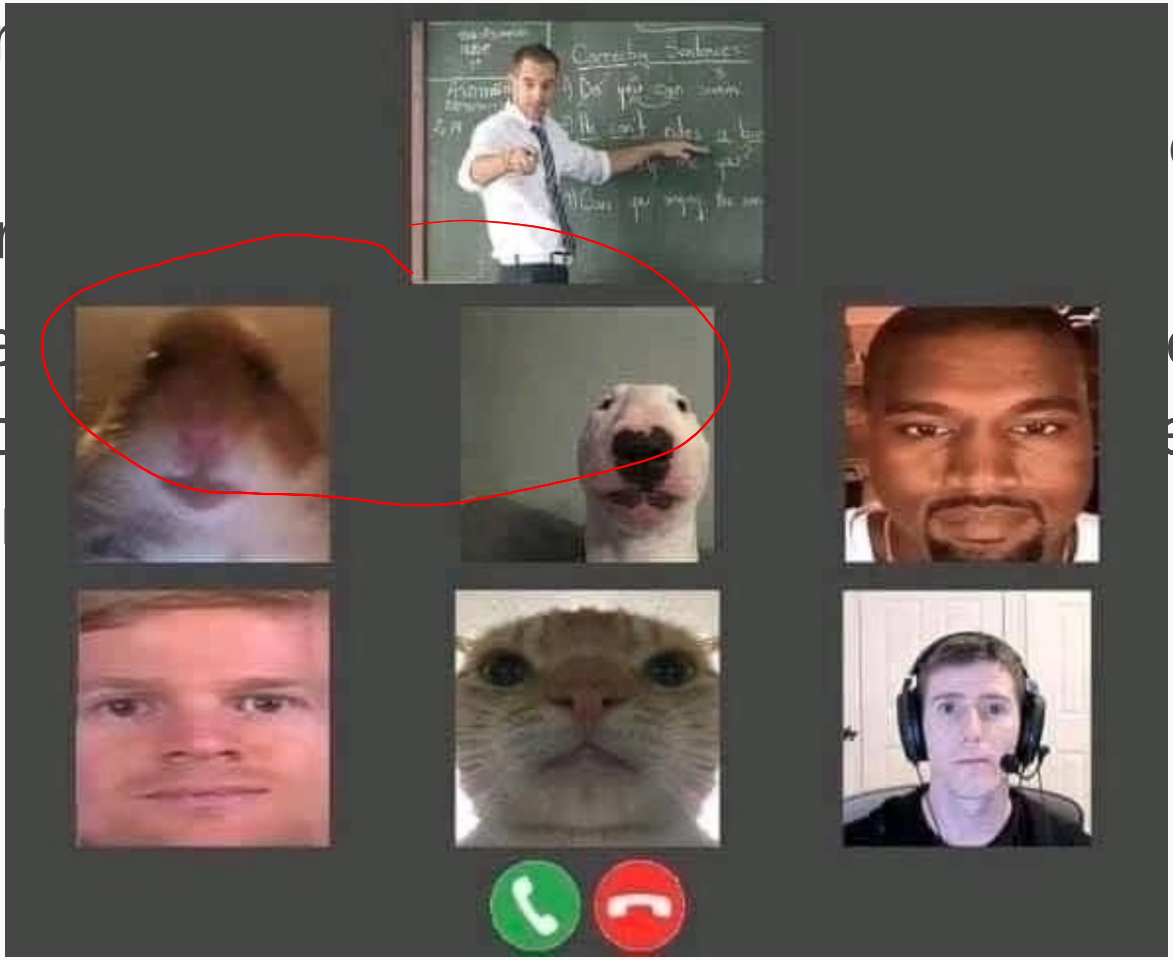
Lecture 14: Recurrent Neural Networks

CS109B Data Science 2

Pavlos Protopapas, Mark Glickman, and Chris Tanner

Online lectures guidelines

- We would prefer you have your video on, but it is OK if you have it off.
- We would pr
- All lectures, eamed and als available for
- We will have d during lecture you can also enter your own questions o ents.
- Quizzed will



Outline

Why Recurrent Neural Networks (RNNs)

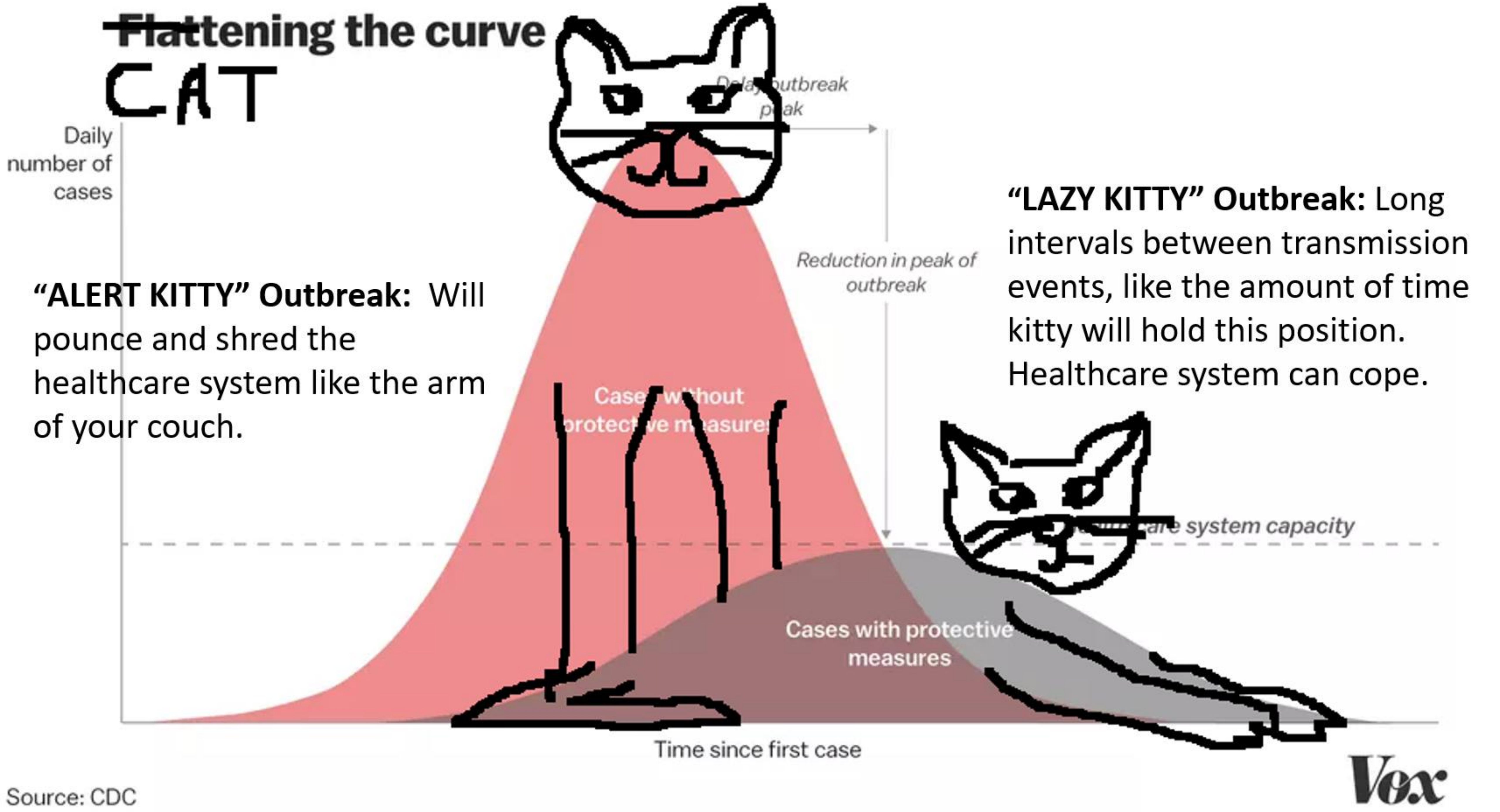
Main Concept of RNNs

More Details of RNNs

RNN training

Gated RNN

~~Flat~~tening the curve CAT

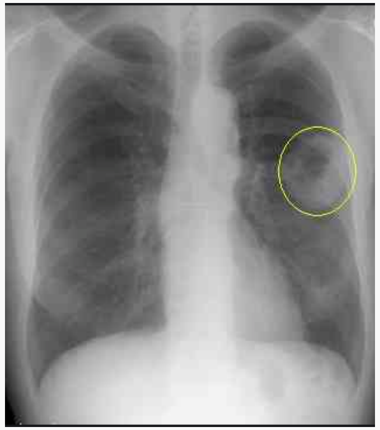


"ALERT KITTY" Outbreak: Will pounce and shred the healthcare system like the arm of your couch.

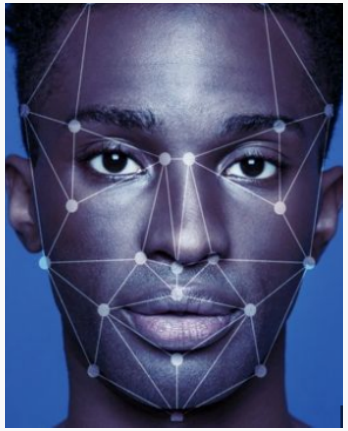
"LAZY KITTY" Outbreak: Long intervals between transmission events, like the amount of time kitty will hold this position. Healthcare system can cope.

Background

Many classification and regression tasks involve data that is assumed to be **independent and identically distributed (i.i.d.).** For example:



Detecting lung cancer



Face recognition

Risk of heart attack

Background

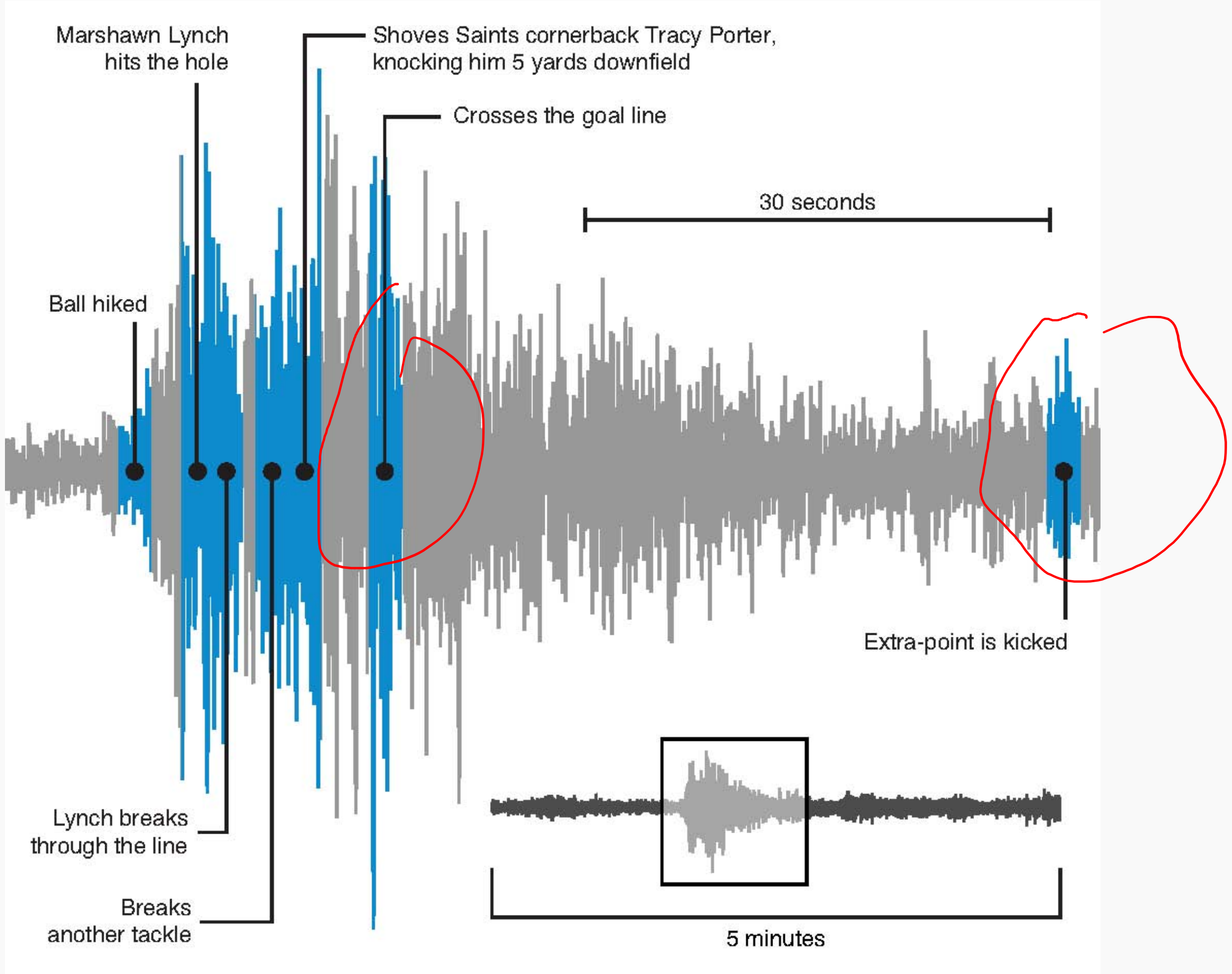
Much of our data is inherently **sequential**

scale	examples
WORLD	Natural disasters (e.g., earthquakes) Climate change
HUMANITY	Stock market Virus outbreaks
INDIVIDUAL PEOPLE	Speech recognition Machine Translation (e.g., English -> French) Cancer treatment

Background

Much of our data is inherently **sequential**

PREDICTING EARTHQUAKES



Background

Much of our data is inherently **sequential**

STOCK MARKET PREDICTIONS

Background

Much of our data is inherently **sequential**

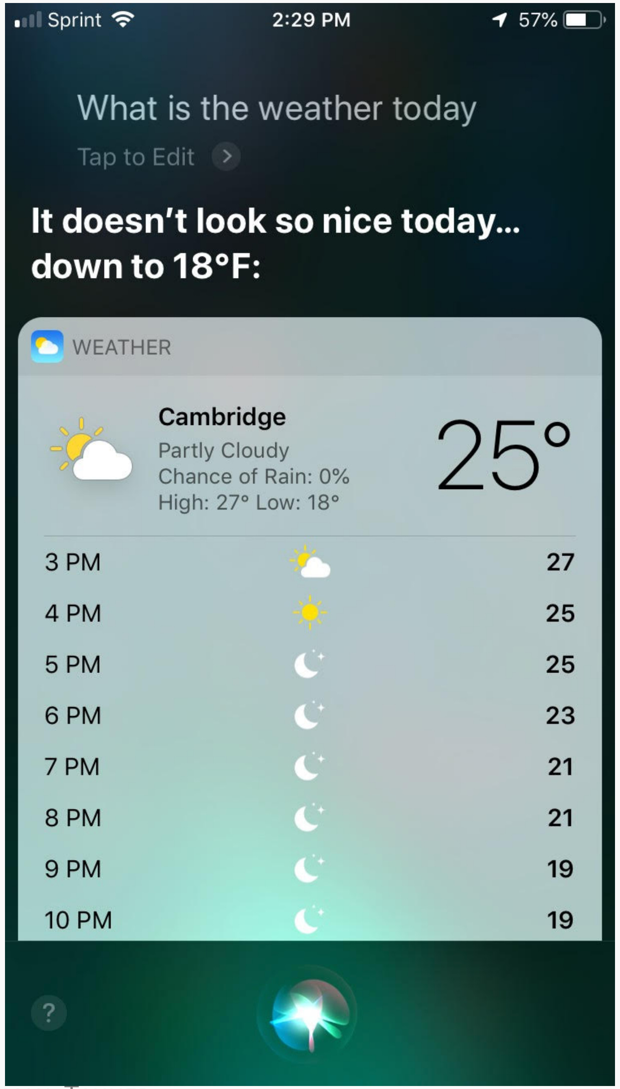
SPEECH RECOGNITION

"What is the weather today?"

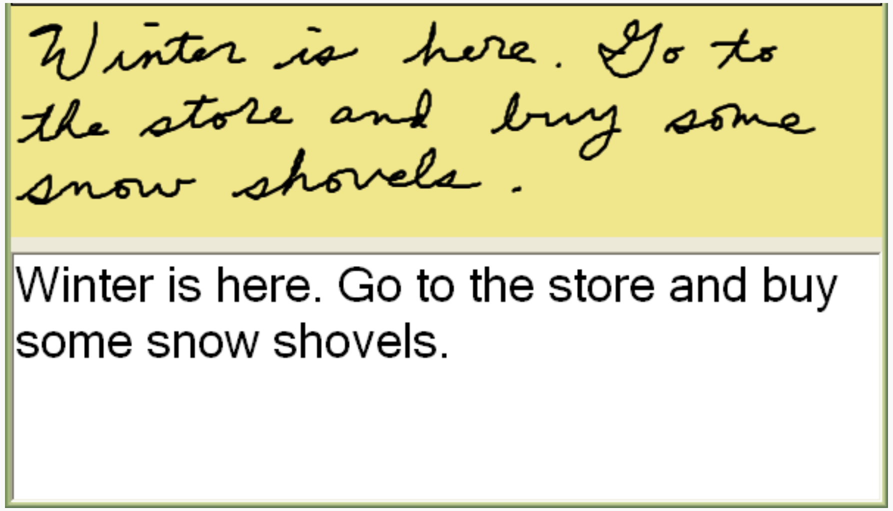
"What is the weather two day?"

"What is the whether too day?"

"What is, the Wrether to Dae?"



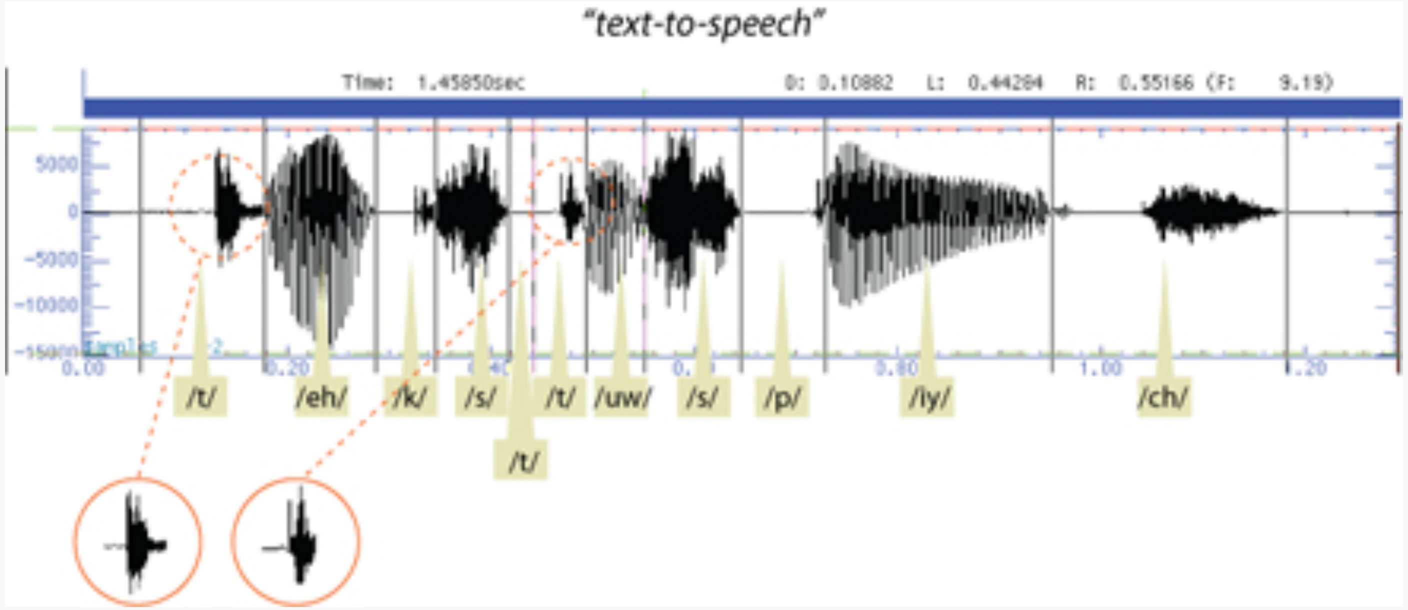
Sequence Modeling: Handwritten Text



- Input : Image
- Output: Text

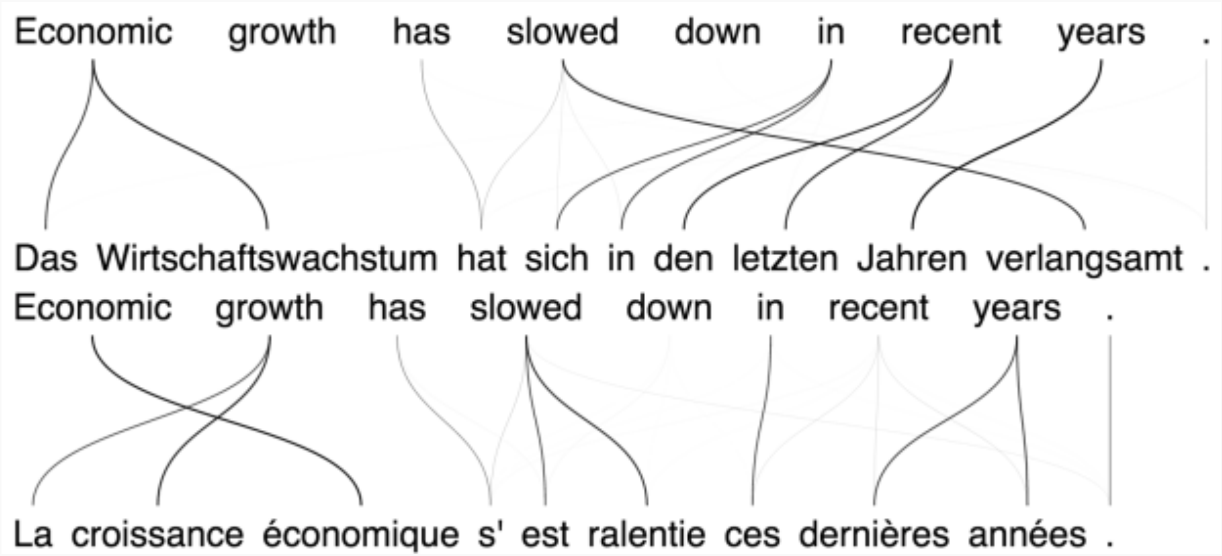
https://towardsdatascience.com/build-a-handwritten-text-recognition-system-using-tensorflow-2326a3487cd5

Sequence Modeling: Text-to-Speech



- Input : Text
- Output: Audio

Sequence Modeling: Machine Translation



- Input : Text
- Output: Translated Text

Outline

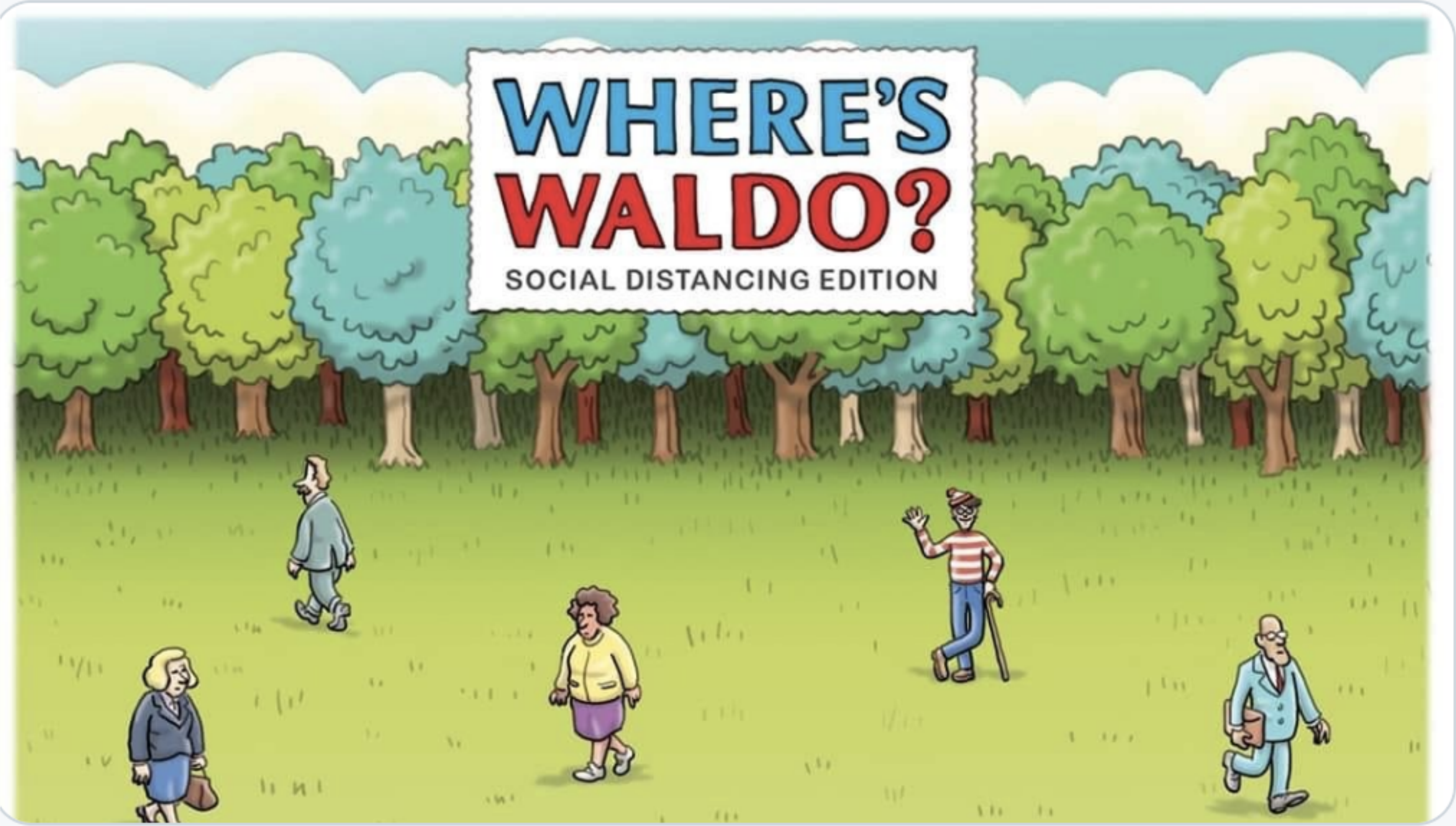
Why RNNs

Main Concept of RNNs (part 1)

More Details of RNNs

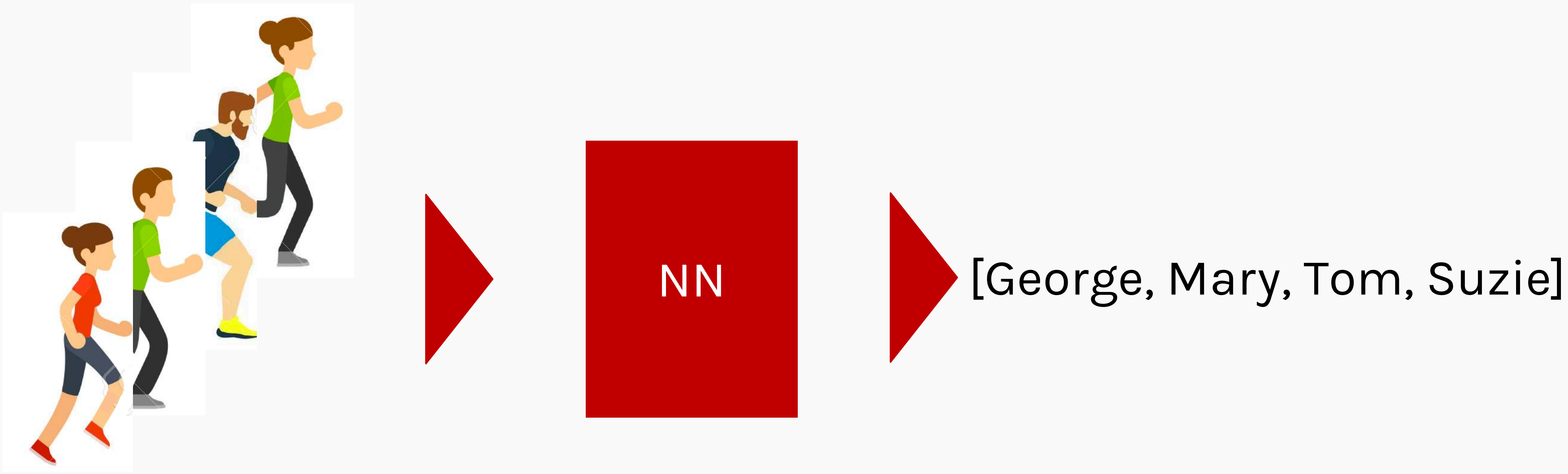
RNN training

Gated RNN


WHERE'S
WALDO?
SOCIAL DISTANCING EDITION

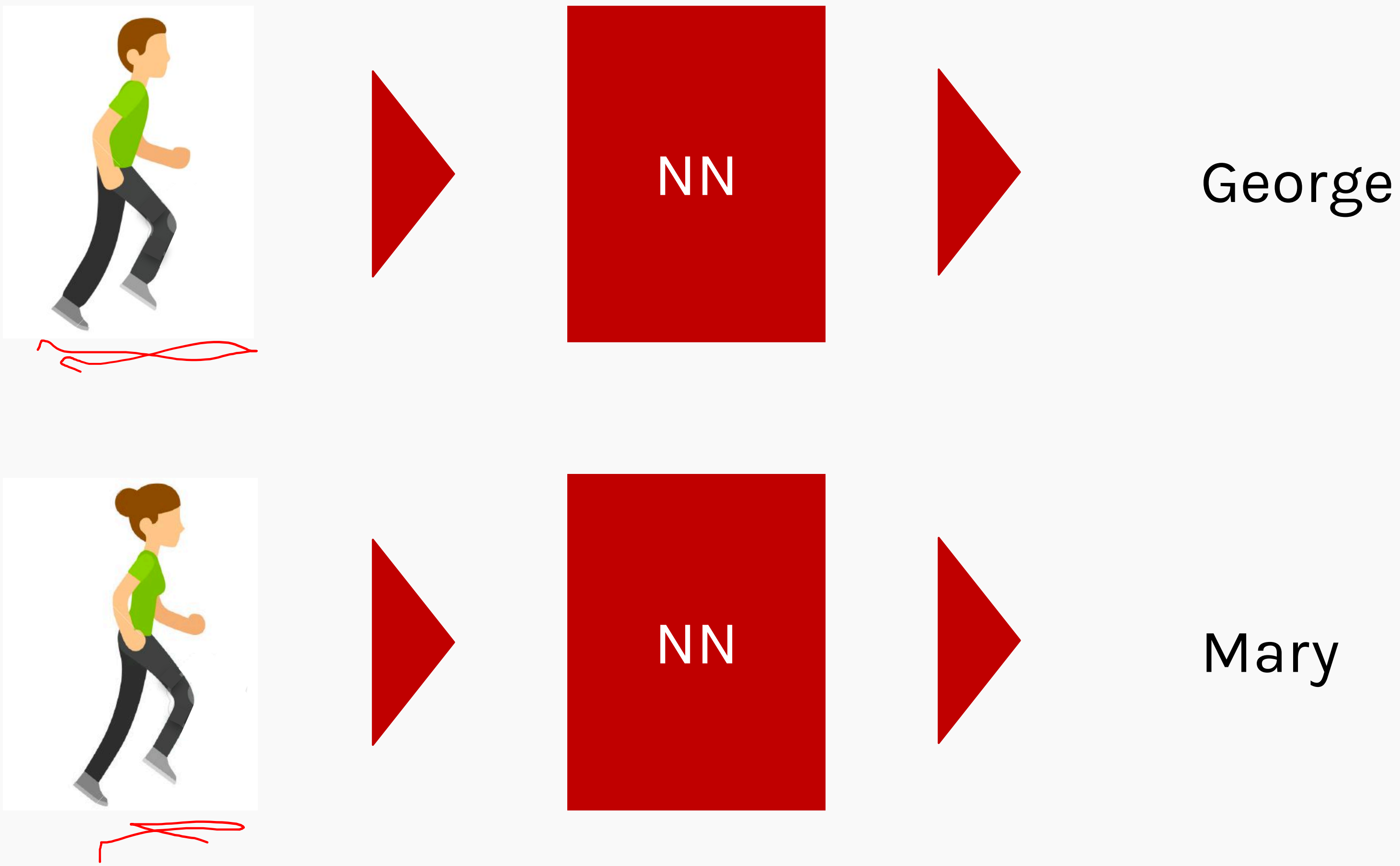
What can my NN do?

Training: Present to the NN examples and learn from them.



What can my NN do?

Prediction: Given an example

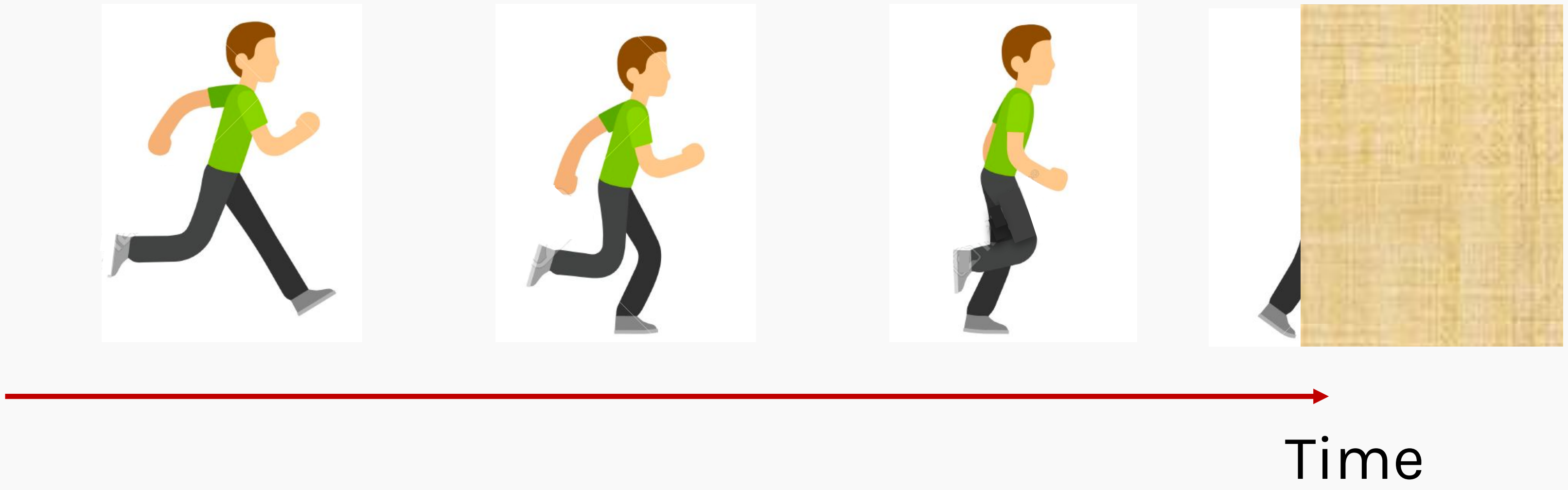


What my NN can NOT do?

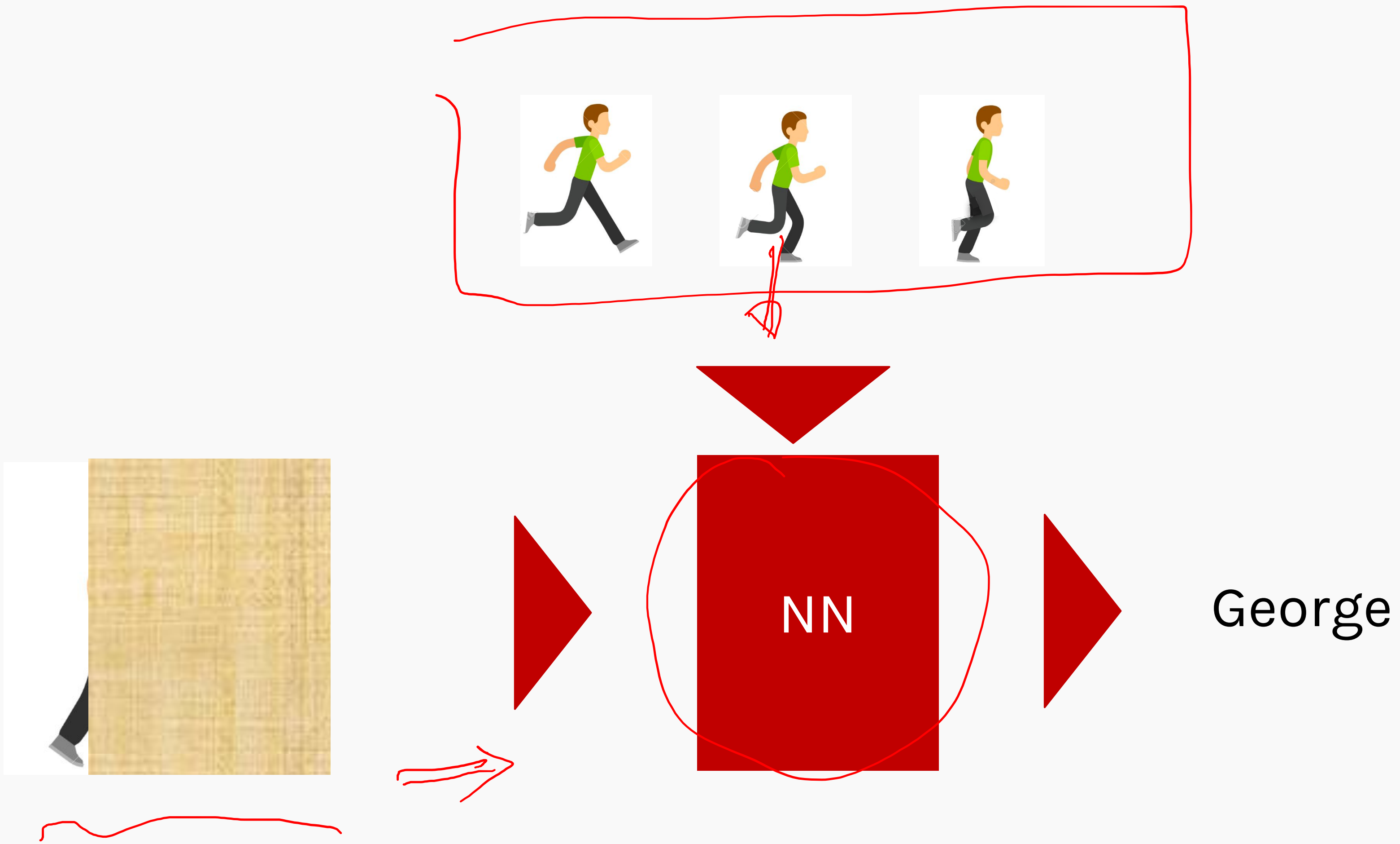
WHO IS IT?

?

Learn from previous examples



Recurrent Neural Network (RNN)



Recurrent Neural Network (RNN)

I have seen George moving in this way before.

NN

George

RNNs recognize the data's sequential characteristics and use patterns to predict the next likely scenario.

Recurrent Neural Network (RNN)

He told me I could have it

WHO IS HE?

I do not know. I need to know who said that and what he said before. Can you tell me more?

Our model requires context - or contextual information - to understand the subject (he) and the direct object (it) in the sentence.

RNN – Another Example with Text

- *Hellen: Nice sweater Joe.*
- *Joe: Thanks, Hellen. It used to belong to my brother and **he told me I could have it**.*

WHO IS HE?

I see what you mean now! The noun "he" stands for Joe's brother while "it" for the sweater.

After providing sequential information, the model recognize the subject (Joe's brother) and the object (sweater) in the sentence.


Introducing the new
Batch_size = 2048
shopping cart for all your paraniod needs...

Sequences

- We want a machine learning model to understand sequences, not isolated samples.
- Can MLP do this?
- Assume we have a sequence of temperature measurements and we want to take 3 sequential measurements and predict the next one

samples	features
1	35
2	32
3	45
4	48
5	41
6	39
7	36
…	…

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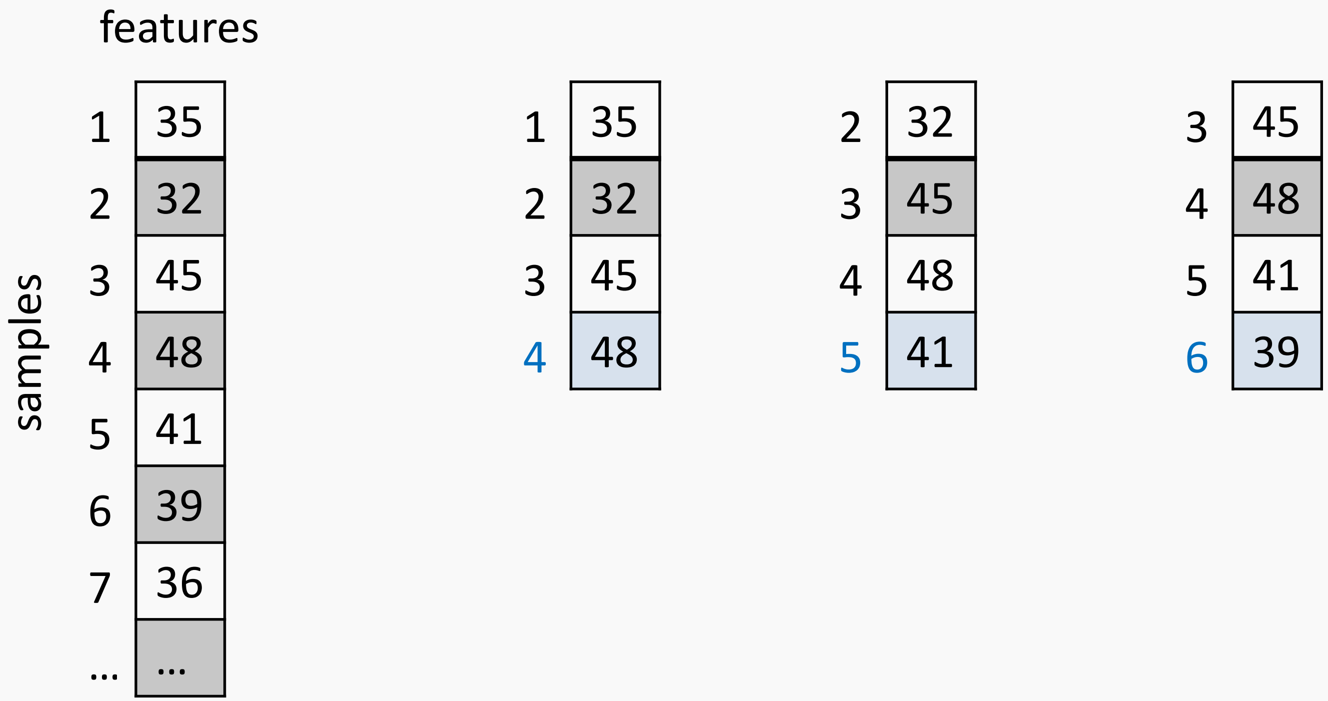

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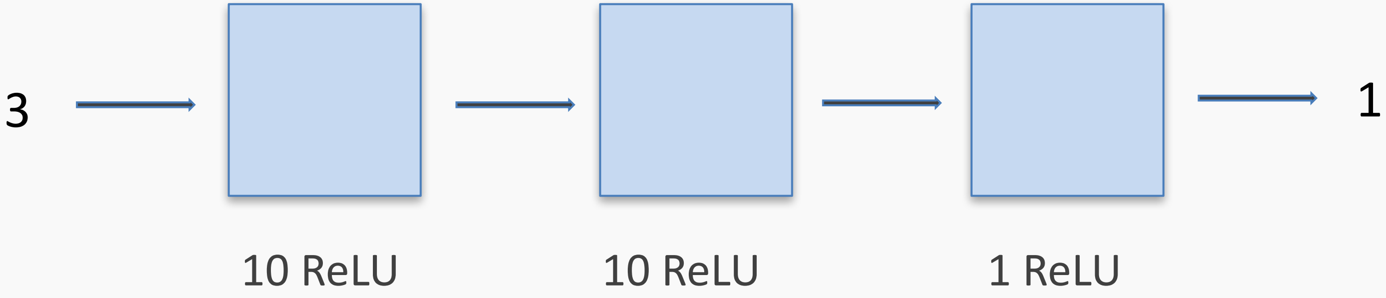
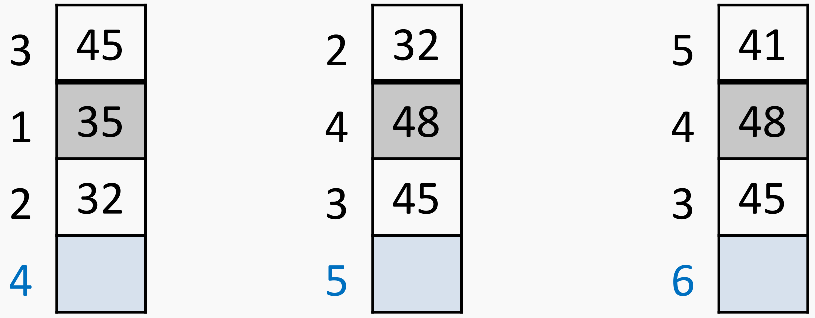
Windowed dataset

This is called **overlapping windowed** dataset, since we're windowing observations to create new.

We can easily do using a MLS:



But re-arranging the order of the inputs like:



will produce the same results

Why not CNNs or MLPs?

1. MLPs/CNNs require fixed input and output size

2. MLPs/CNNs can’t classify inputs in multiple places

Windowed dataset

What follows after: `` `I got in the car and' ? ``

`` `drove away' ``

What follows after: `` `In car the and I got' ? ``

Not obvious that it should be `` `drove away' ``

The order of words matters. This is true for most sequential data.

A fully connected network will not distinguish the order and therefore missing some information.


A couple of weeks of isolation with the
family. What can go wrong?

Outline

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Main Concept of RNNs

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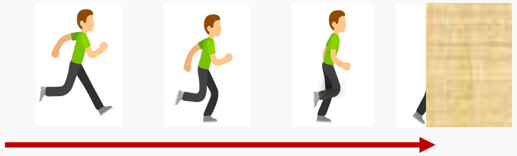
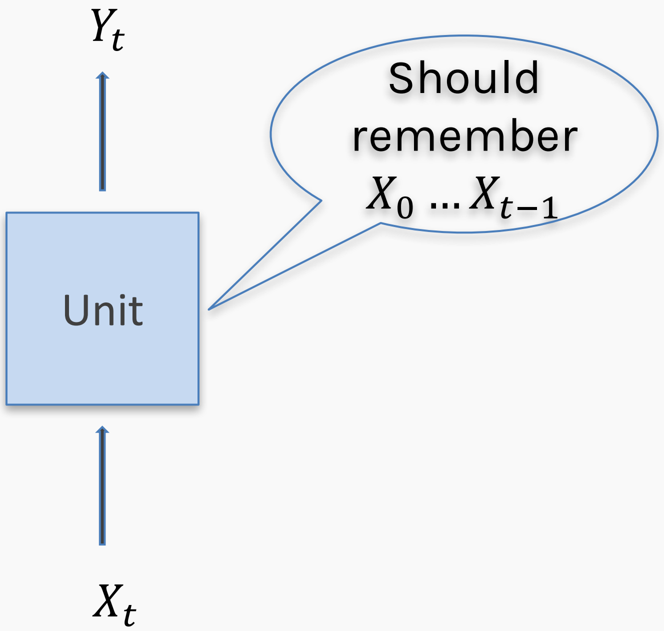
Gated RNN

Memory

Somehow the computational unit should remember what it has seen before.





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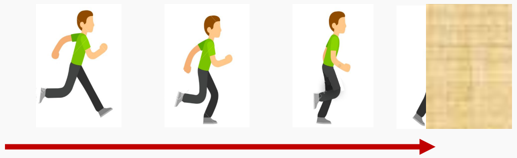
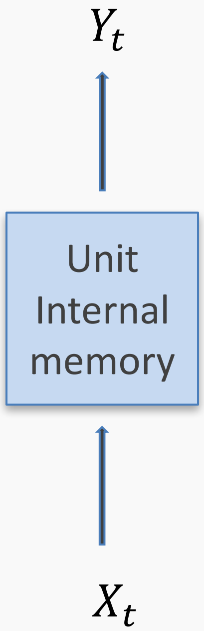
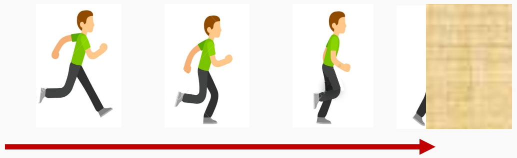


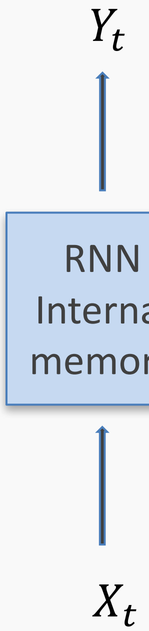


Memory

Somehow the computational unit should remember what it has seen before.

We'll call the information the unit's **state**.





Memory

In neural networks, once training is over, the weights do not change. This means that the network is done learning and done changing.

Then, we feed in values, and it simply applies the operations that make up the network, using the values it has learned.

But the RNN units can remember new information after training has completed.

That is, they're able to keep changing after training is over.

Memory

Question: How can we do this? How can build a unit that remembers the past?

The memory or **state** can be written to a file but in RNNs, we keep it inside the recurrent unit.

In an array or in a vector!

Work with an example:

Anna Sofia said her shoes are too ugly. Her here means Anna Sofia.

Nikolas put his keys on the table. His here means Nikolas

Memory

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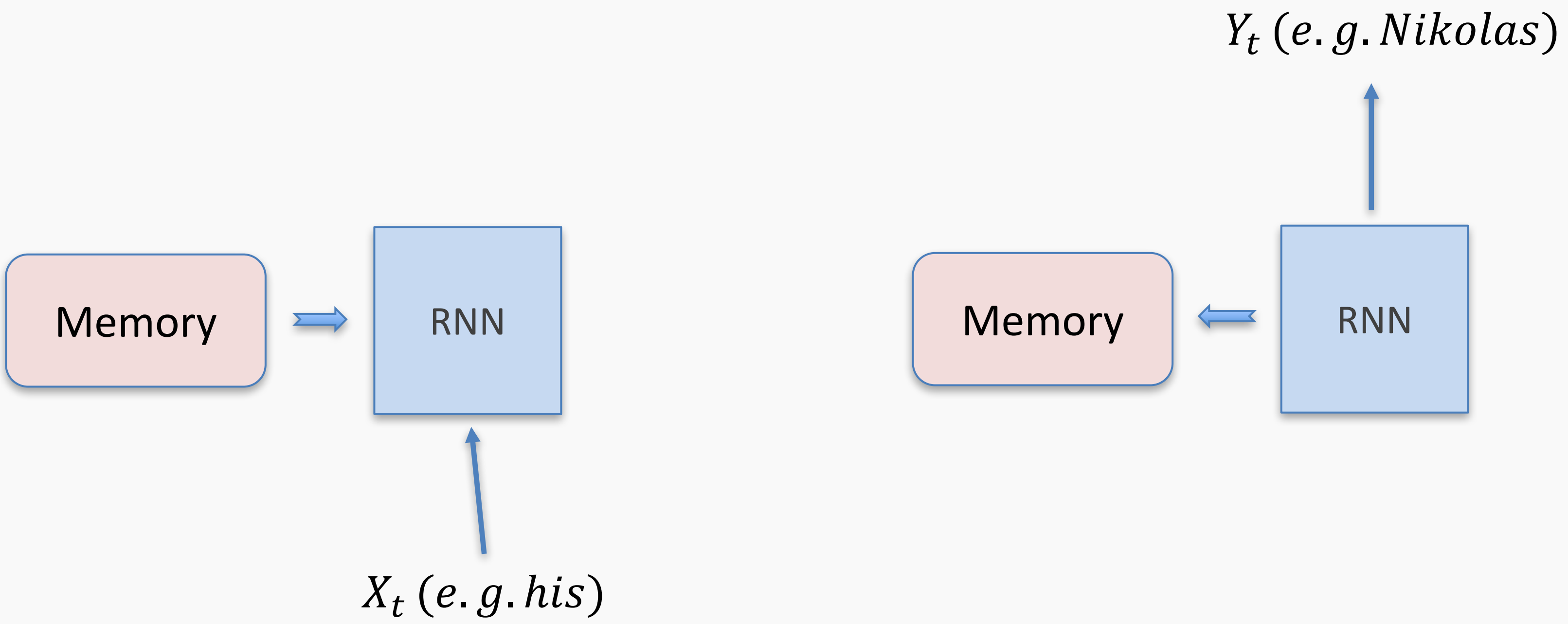
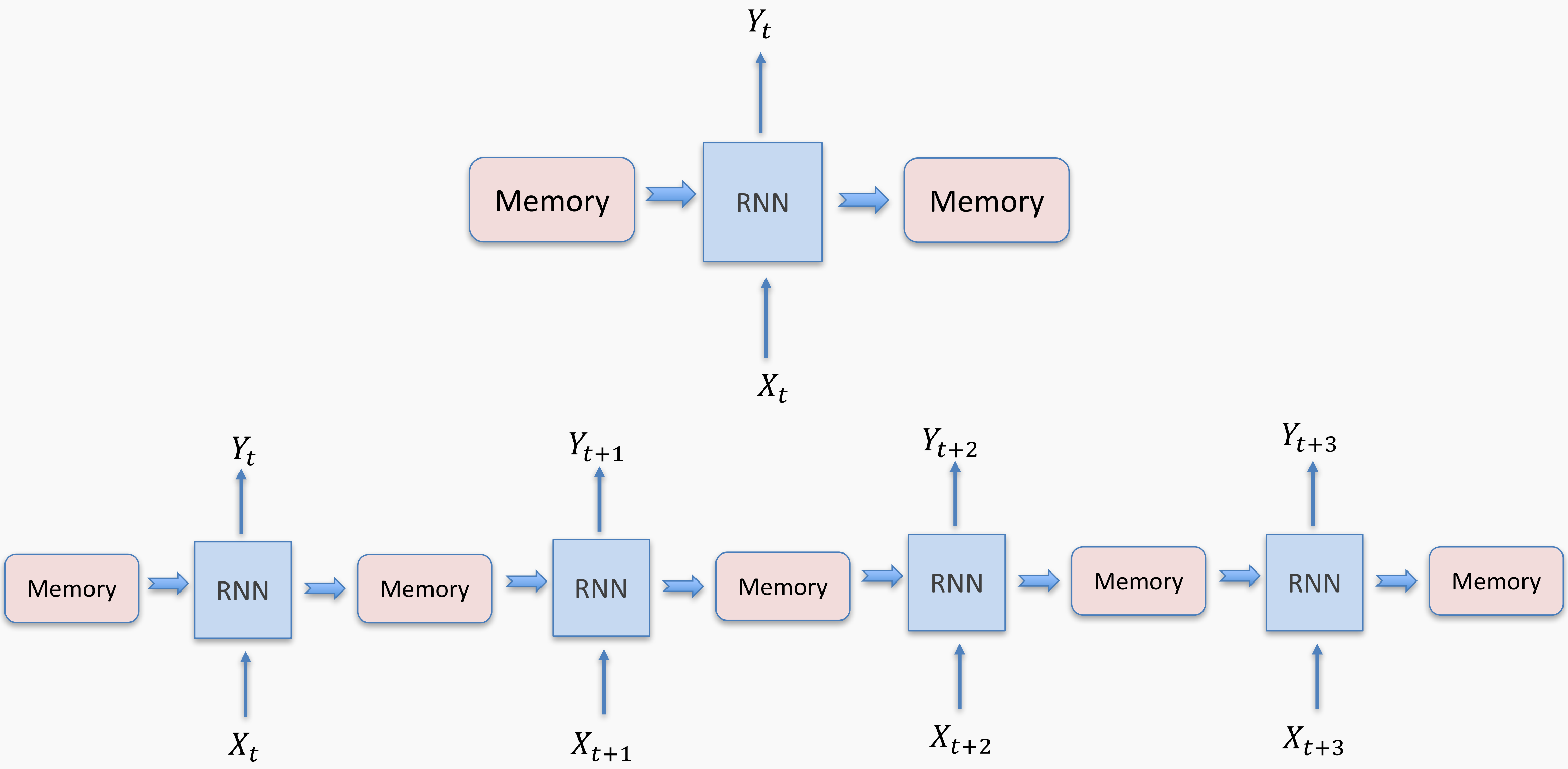
In an array or in a vector!



Building an RNN



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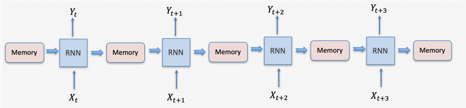
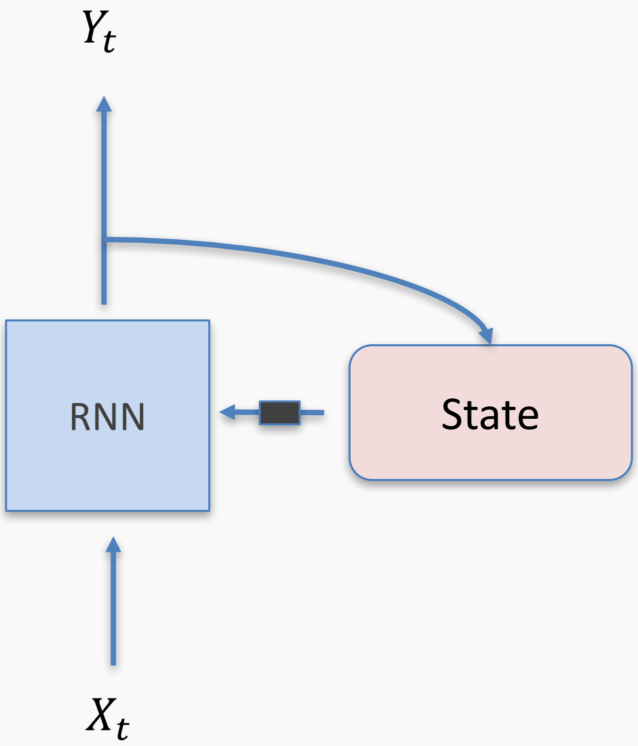
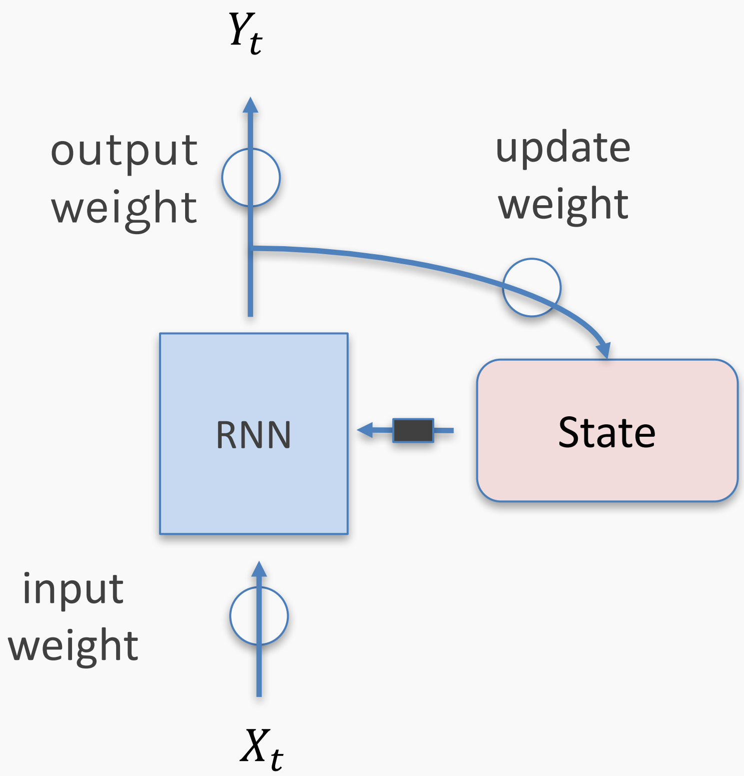
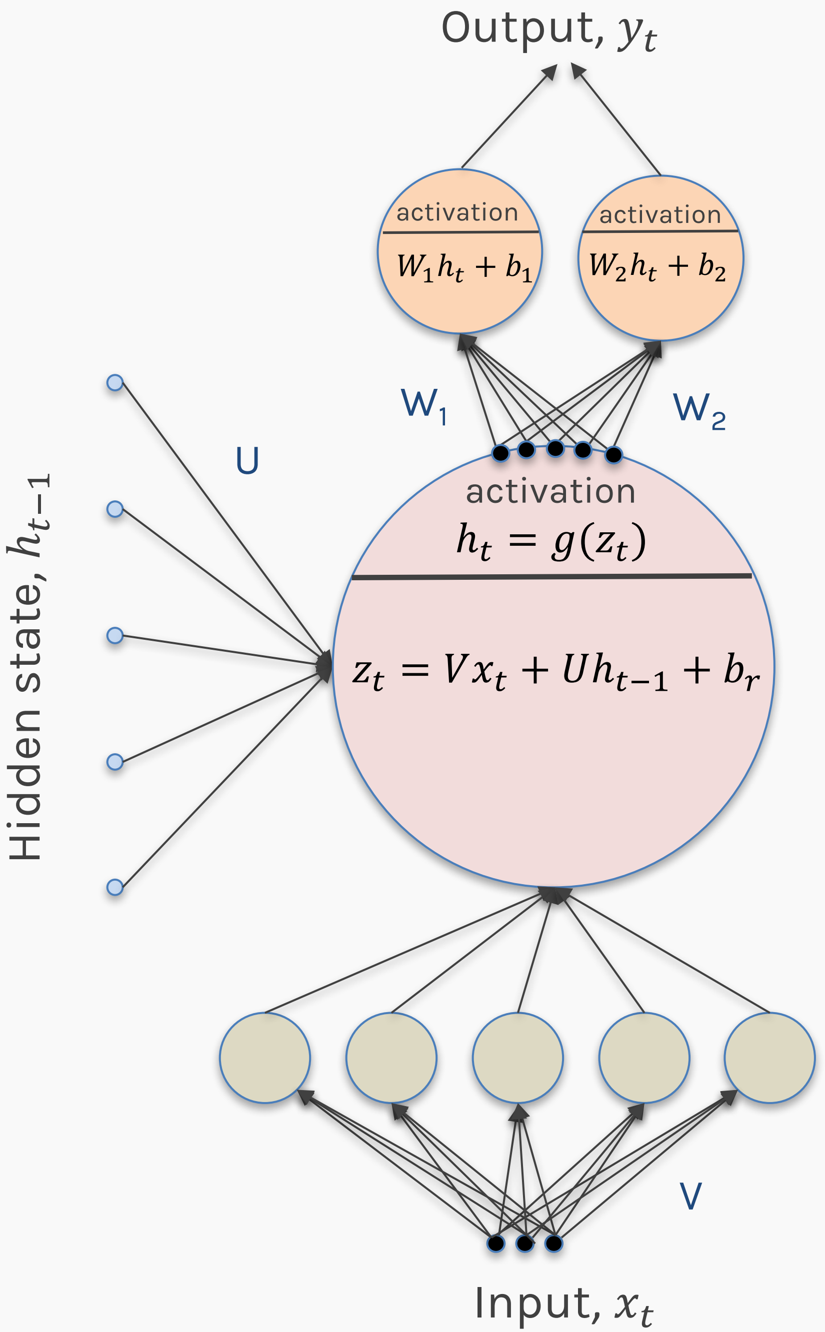
Structure of an RNN cell

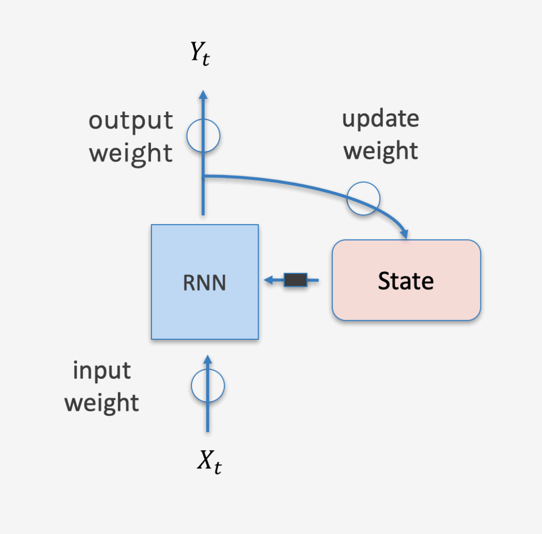






Anatomy of an RNN unit





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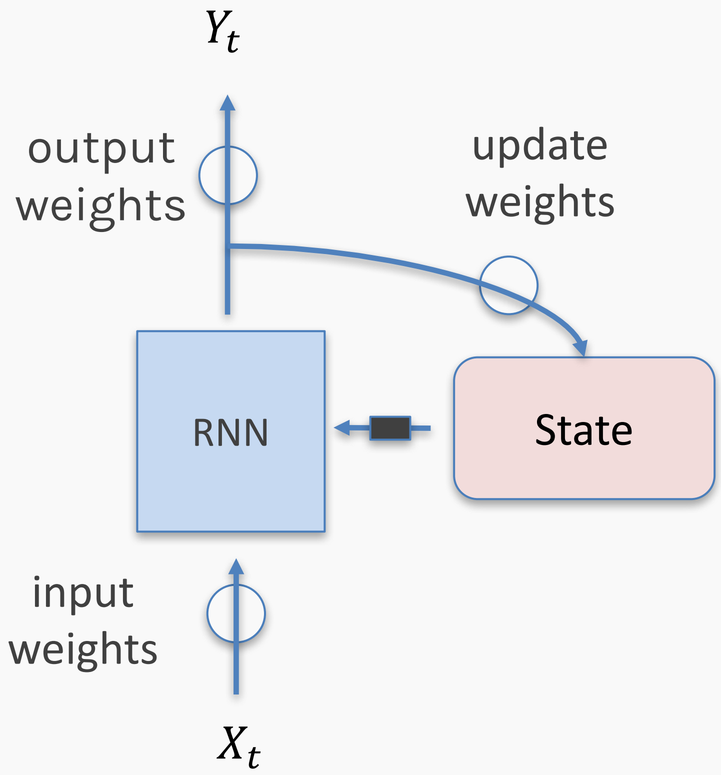
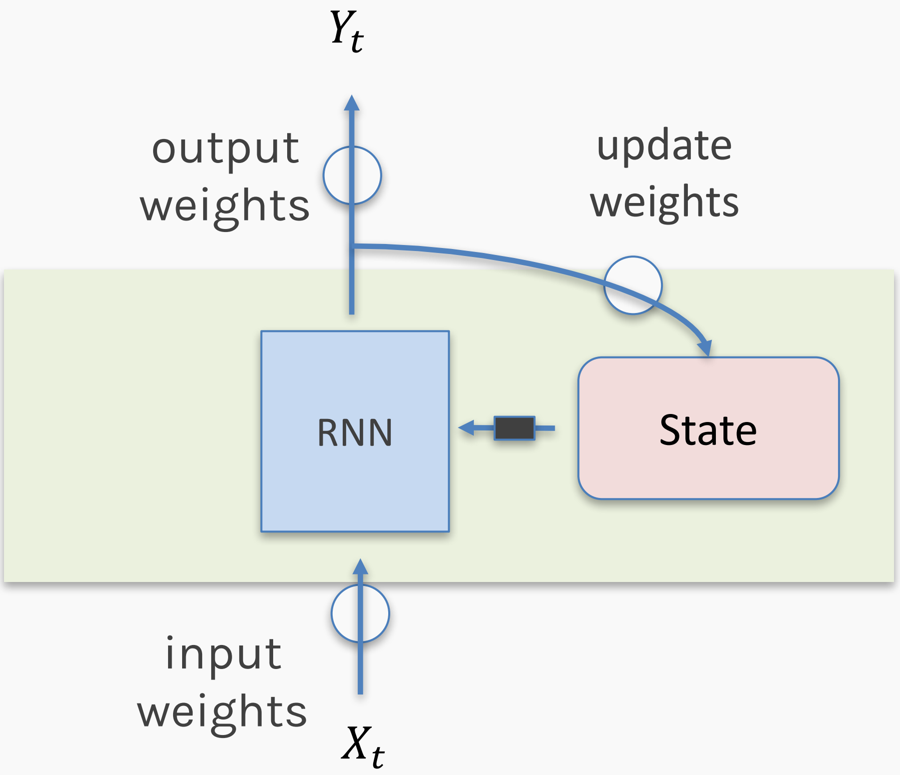
Backprop Through Time

- For each input, unfold network for the sequence length T
- Back-propagation: apply forward and backward pass on unfolded network
- Memory cost: $O(T)$

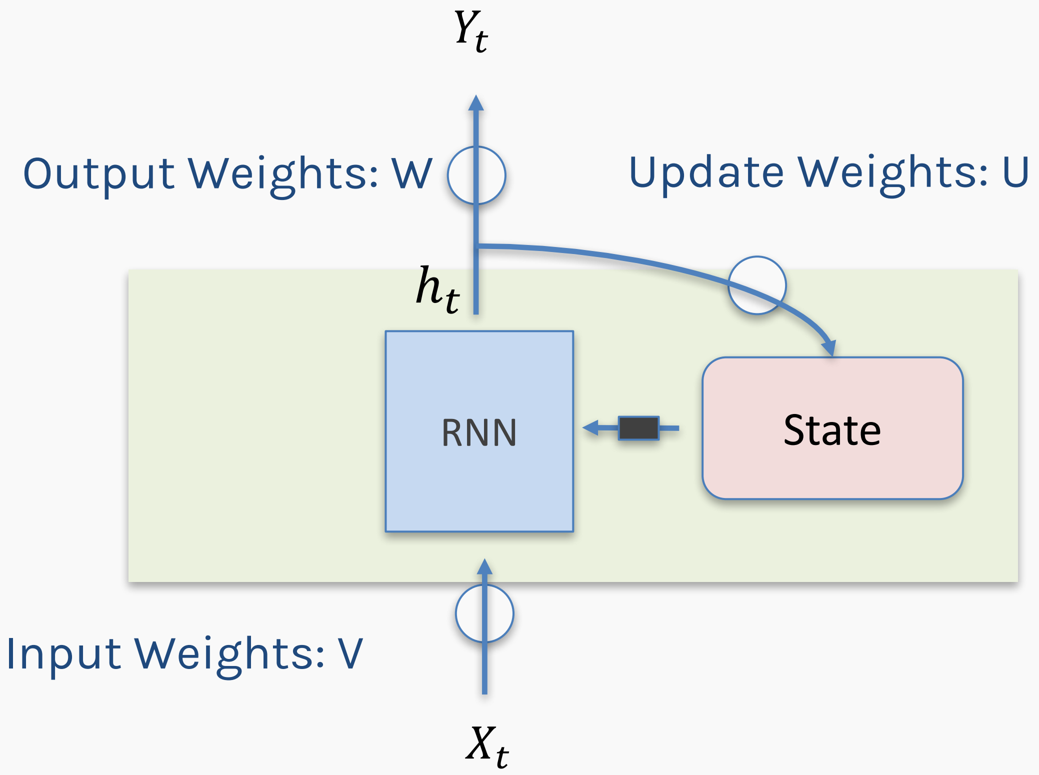
Backprop Through Time



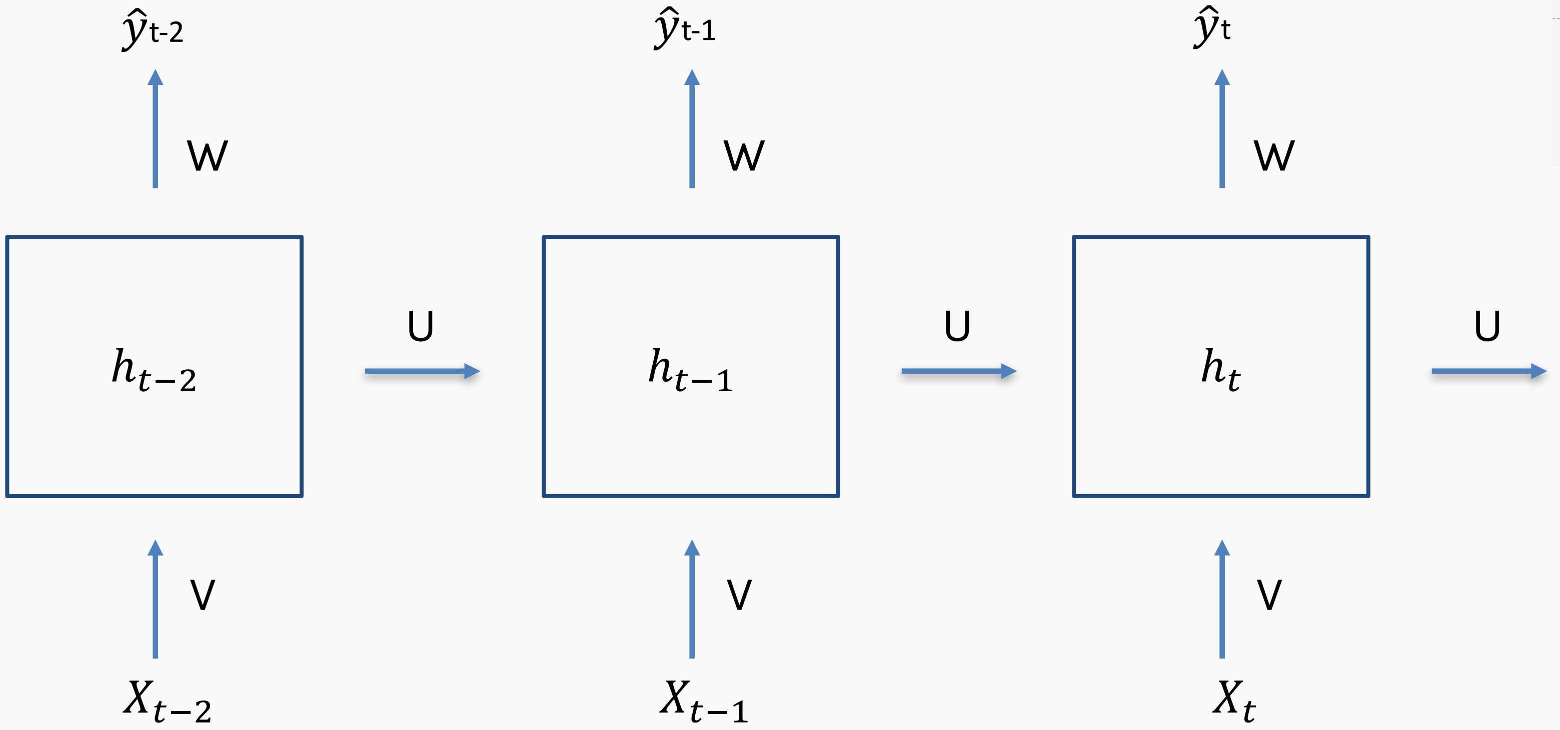
Backprop Through Time

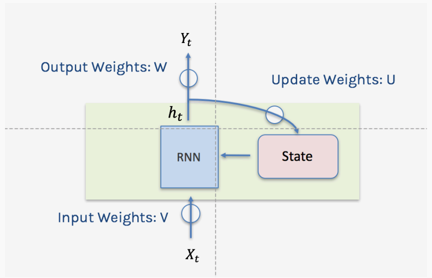


Backprop Through Time



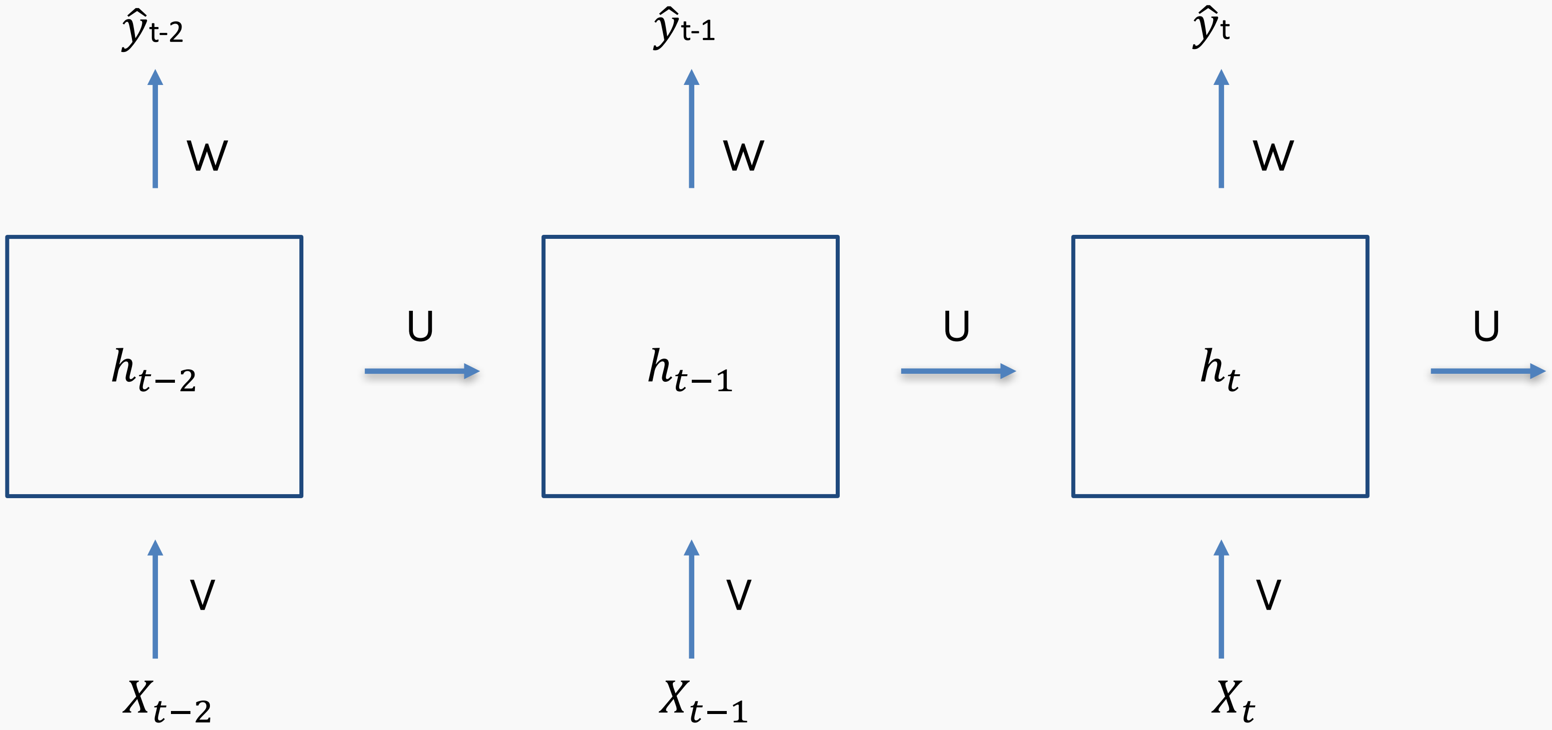
Backprop Through Time





You have two activation functions g_h which serves as the activation for the hidden state and g_y which is the activation of the output. In the example shown before g_y was the identity.

Backprop Through Time



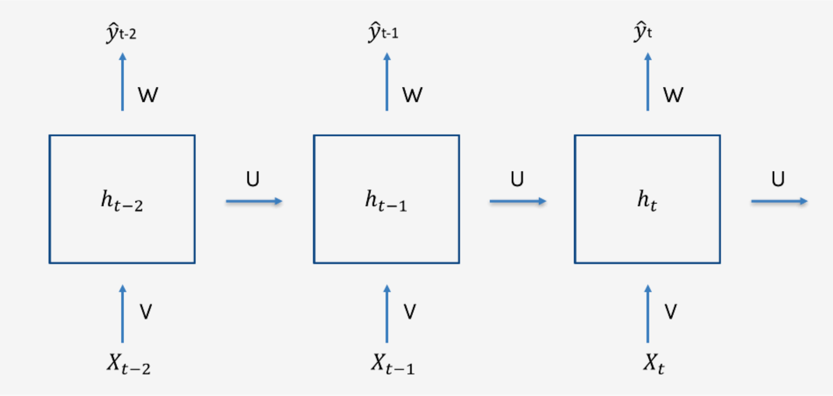
Backprop Through Time

$$\hat{y}_t = g_y(Wh_t + b)$$

$$L = \sum_t L_t \qquad\qquad L_t = L_t(\hat{y}_t)$$

$$\frac{dL}{dW} = \sum_t \frac{dL_t}{dW} = \sum_t \frac{\partial L_t}{\partial \hat{y}_t}\frac{\partial \hat{y}_t}{\partial W}$$

$$\frac{\partial \hat{y}_t}{\partial W} = g_y{}' h_t$$



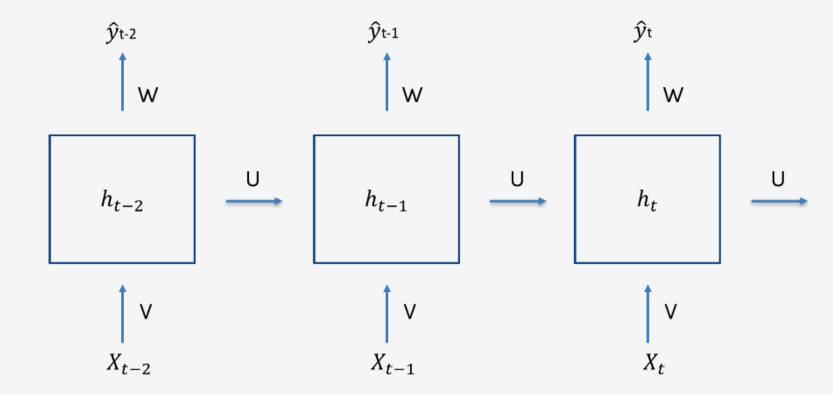
Backprop Through Time

$$\hat{y}_t = g_y(Wh_t + b)$$

$$h_t = g_h(Vx_t + Uh_{t-1} + b')$$

$$\hat{y}_t = g_y(Wg_h(Vx_t + Uh_{t-1} + b') + b)$$

$$L = \sum_t L_t \qquad L_t = L_t(\hat{y}_t)$$



$$\frac{dL}{dU} = \sum_t \frac{\partial L_t}{\partial \hat{y}_t}\frac{\partial \hat{y}_t}{\partial h_t}\frac{\partial h_t}{\partial U}$$

$$\frac{\partial h_j}{\partial h_{j-1}} = g'_h U$$

$$\frac{\partial h_t}{\partial U} = \sum_{k=1}^{t} \frac{\partial h_t}{\partial h_k}\frac{\partial h_k}{\partial U}$$

$$\frac{\partial h_t}{\partial h_k} = \frac{\partial h_t}{\partial h_{t-1}}\frac{\partial h_{t-1}}{\partial h_{t-2}} \cdots \frac{\partial h_{k+1}}{\partial h_k} = \prod_{j=k+1}^{t} \frac{\partial h_j}{\partial h_{j-1}}$$

$$\frac{\partial L_t}{\partial U} = \frac{\partial L_t}{\partial \hat{y}_t}\frac{\partial \hat{y}_t}{\partial h_t}\left(\frac{dh_t}{dU} + \frac{dh_t}{dh_{t-1}}\frac{dh_{t-1}}{dU} + \frac{dh_t}{dh_{t-1}}\frac{dh_{t-1}}{dh_{t-2}}\frac{dh_{t-2}}{dU} + \cdots\right)$$


TikTok
@kalesalad
“Quarantine day 6”

Gradient Clipping

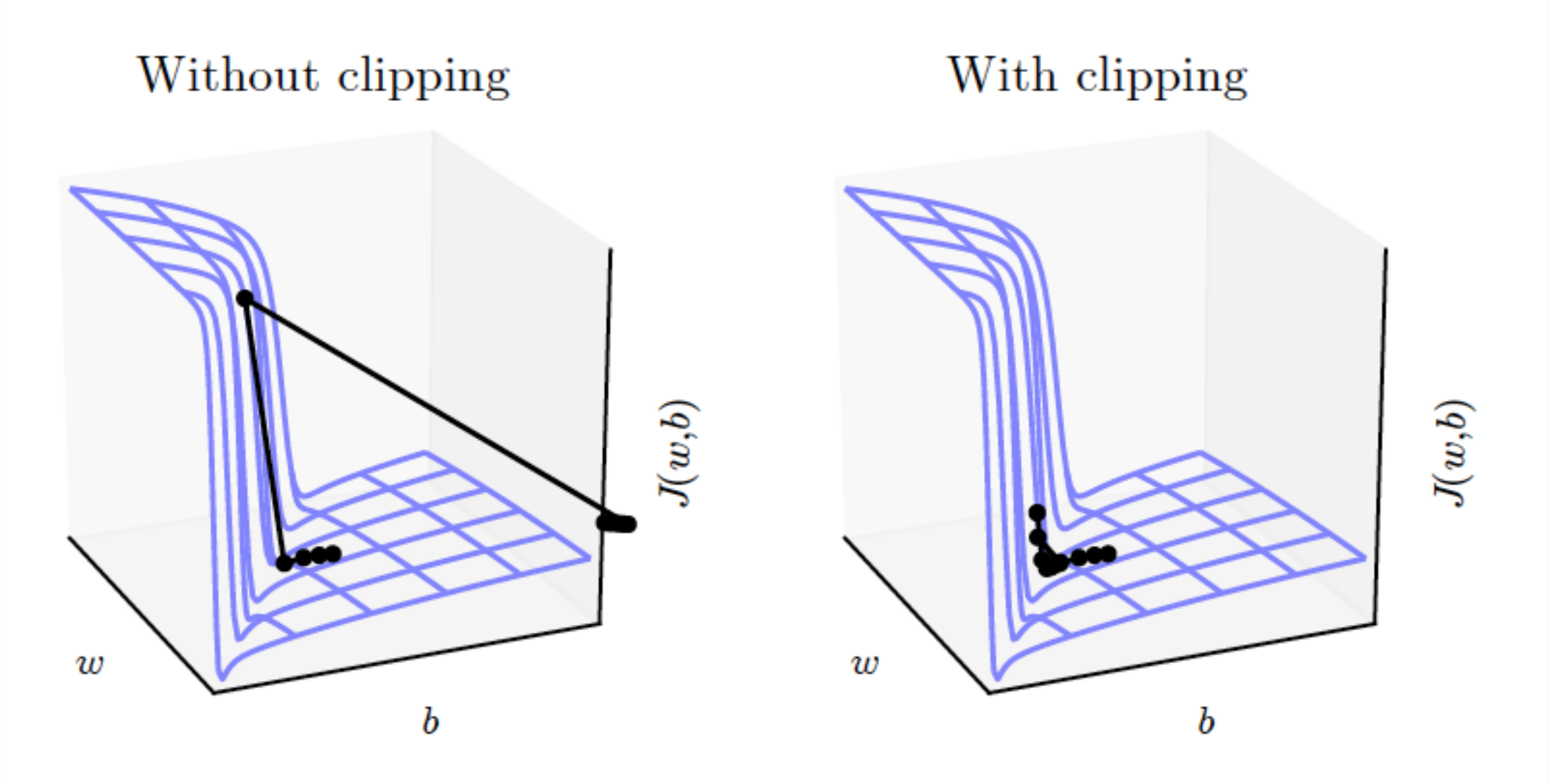
Prevents exploding gradients

Clip the norm of gradient before update.

For some derivative g, and some threshold u

$$\text{if } ||g|| > u$$

$$g \leftarrow \frac{gu}{||g||}$$



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Long-term Dependencies

Unfolded networks can be very deep

Long-term interactions are given exponentially smaller weights than small-term interactions

Gradients tend to either *vanish* or *explode*

Long Short-Term Memory

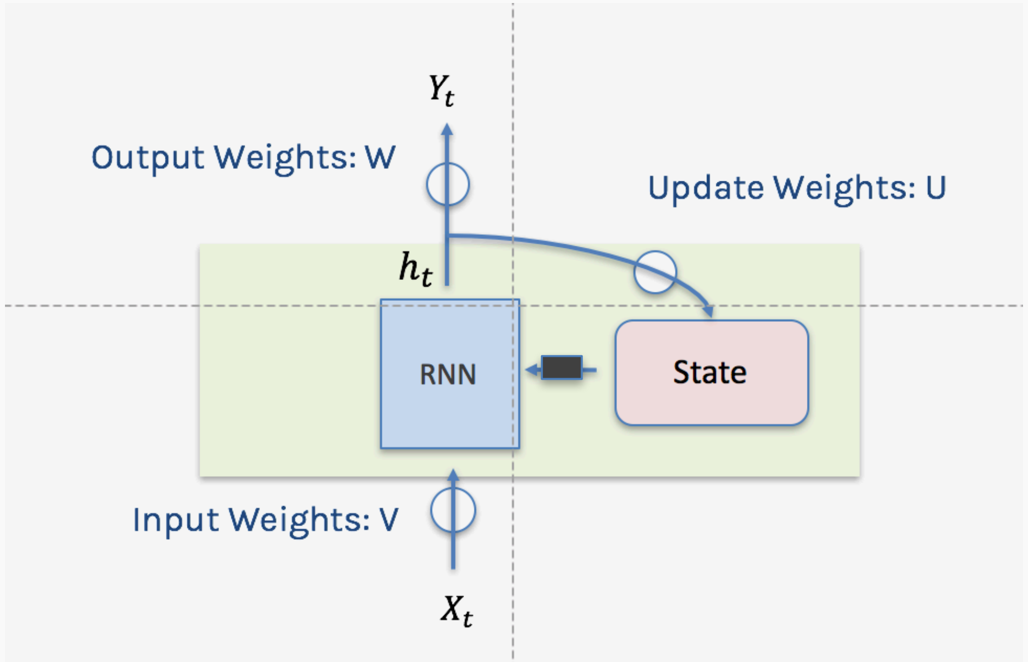
Handles long-term dependencies

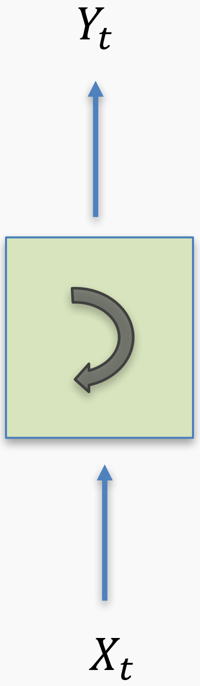
Leaky units where weight on self-loop α is context-dependent

Allow network to decide whether to accumulate or forget past info

Notation

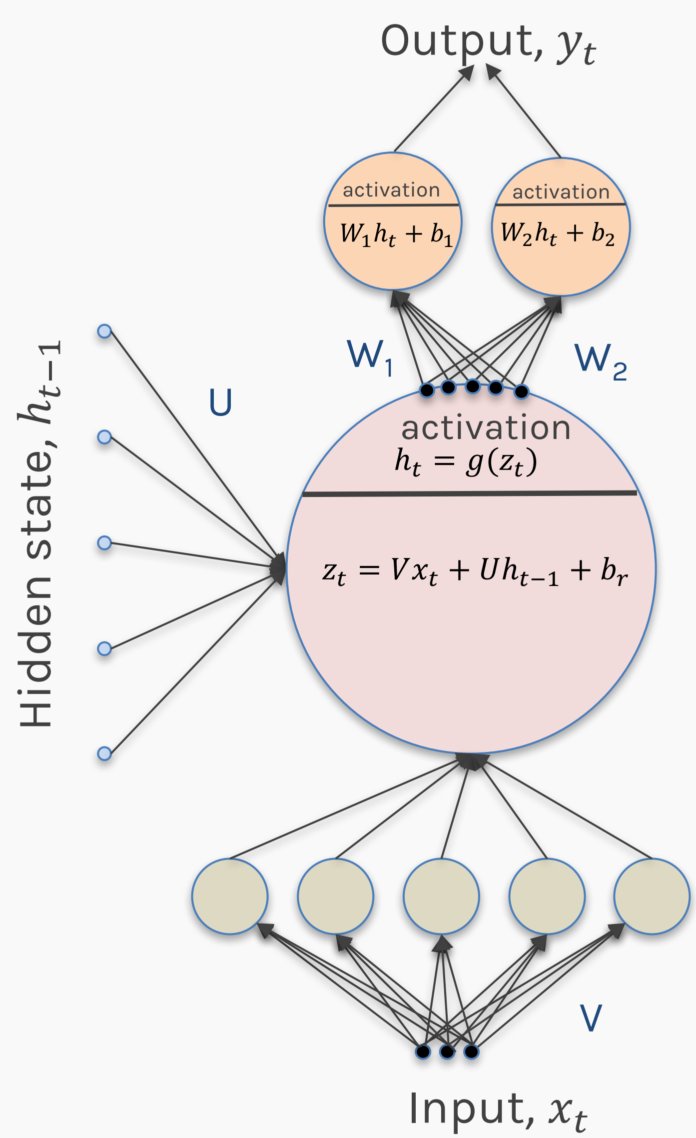
Using conventional and convenient notation

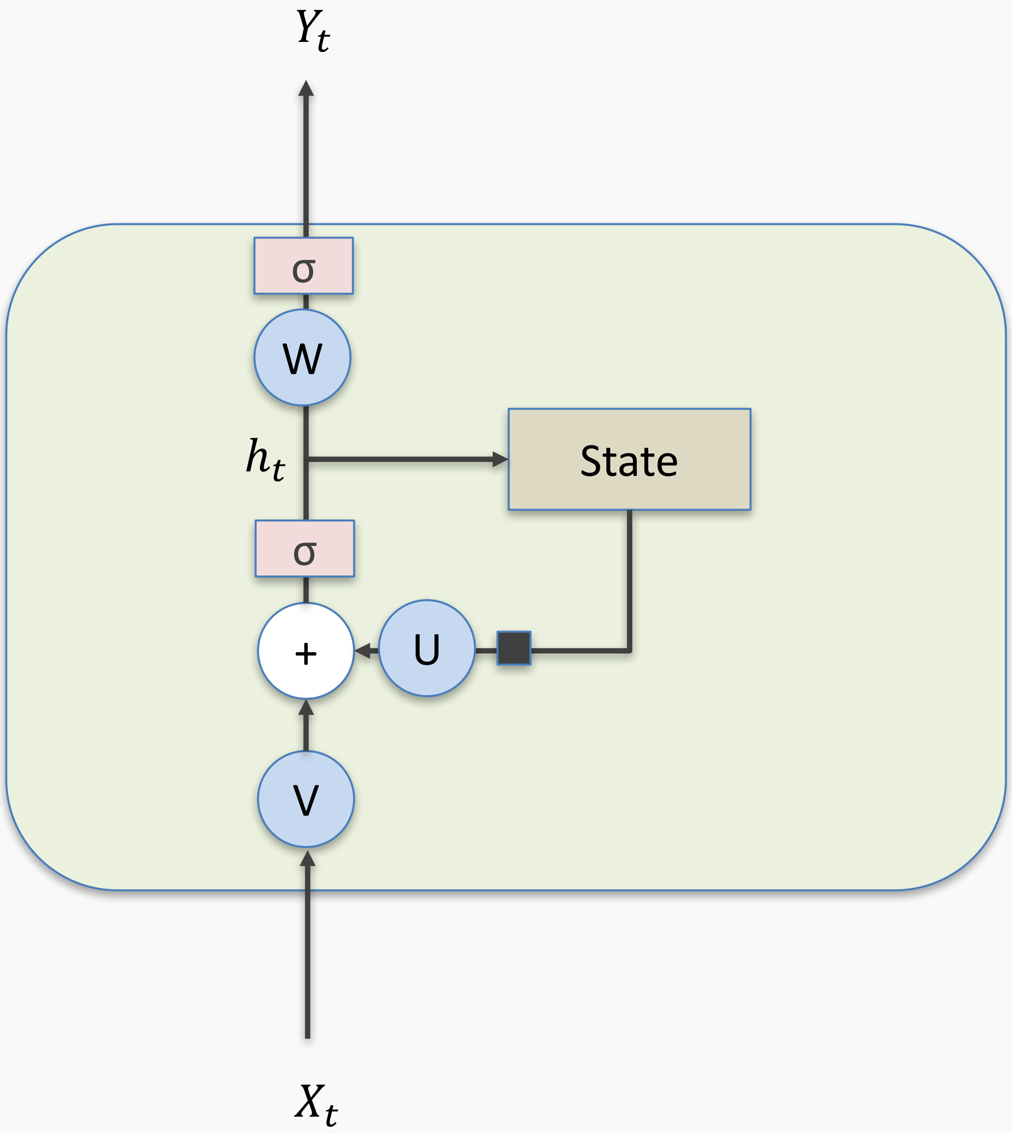




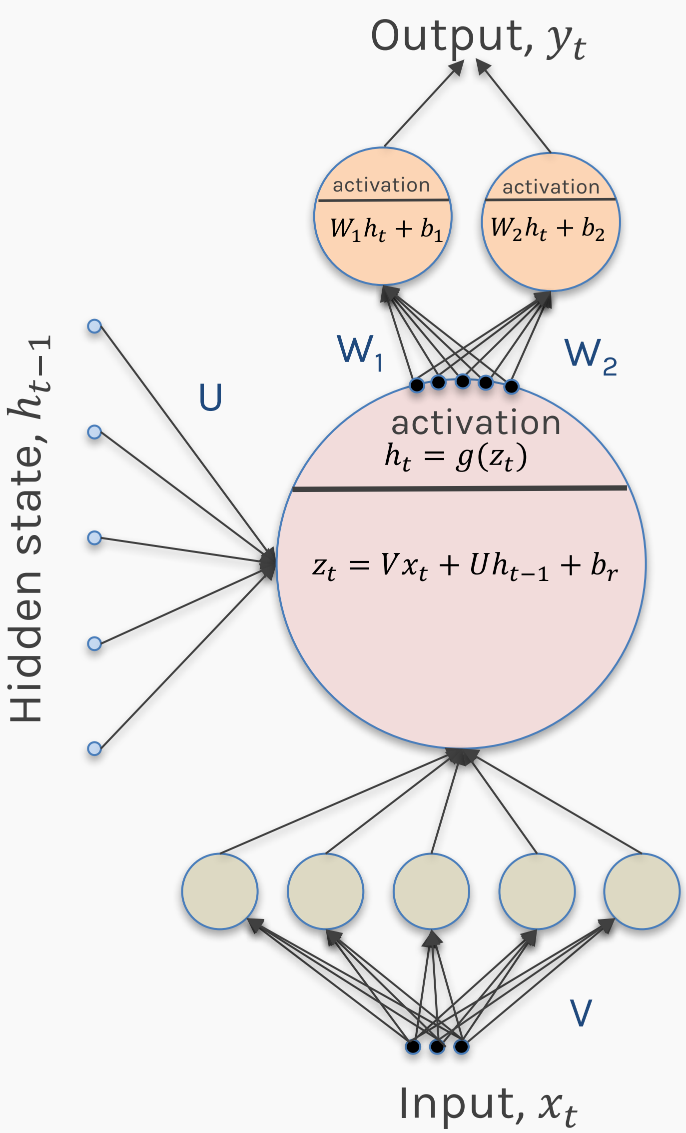

when your basic RNN isn't cabable of catching long-term dependencies
Things are about to get GRUesome

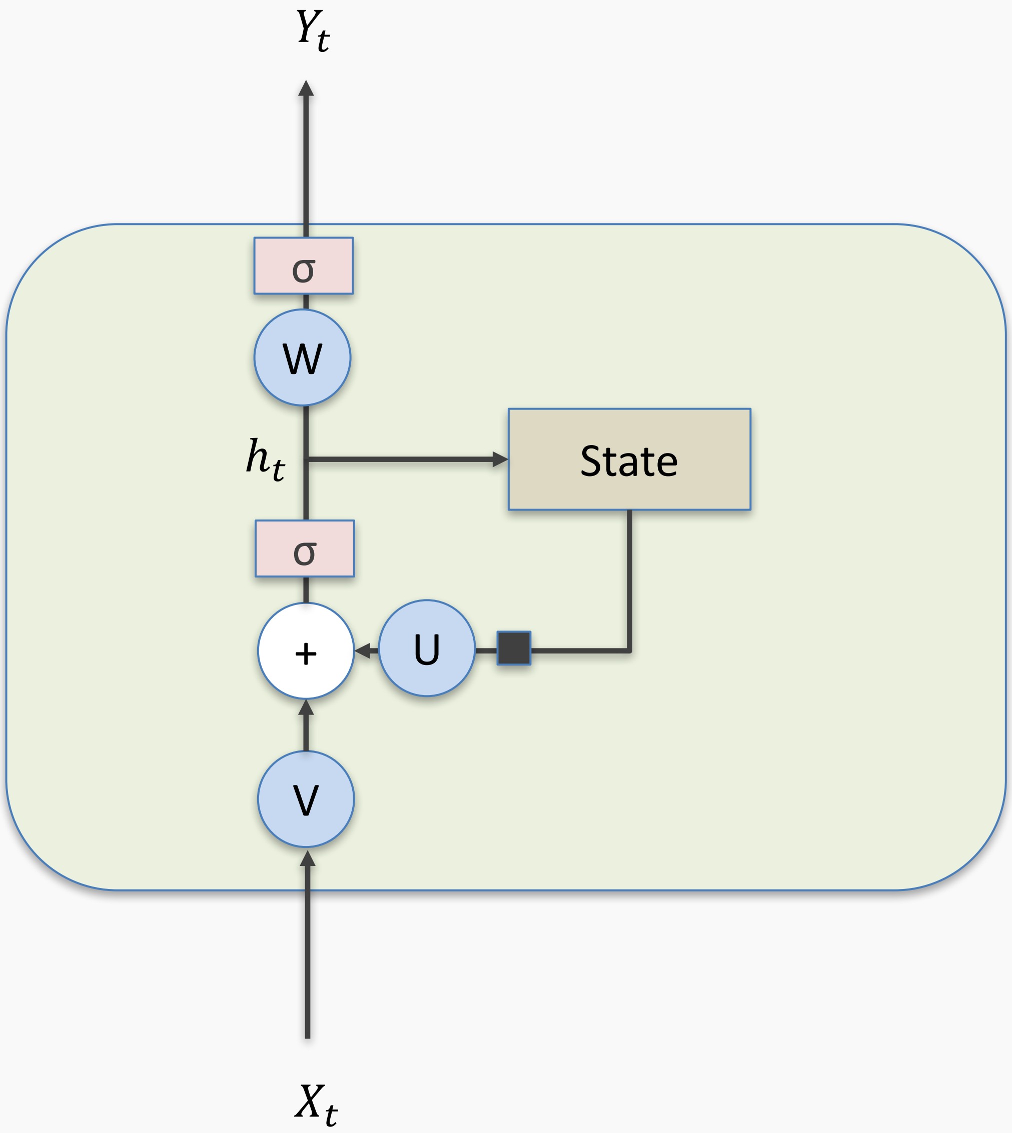
Simple RNN again



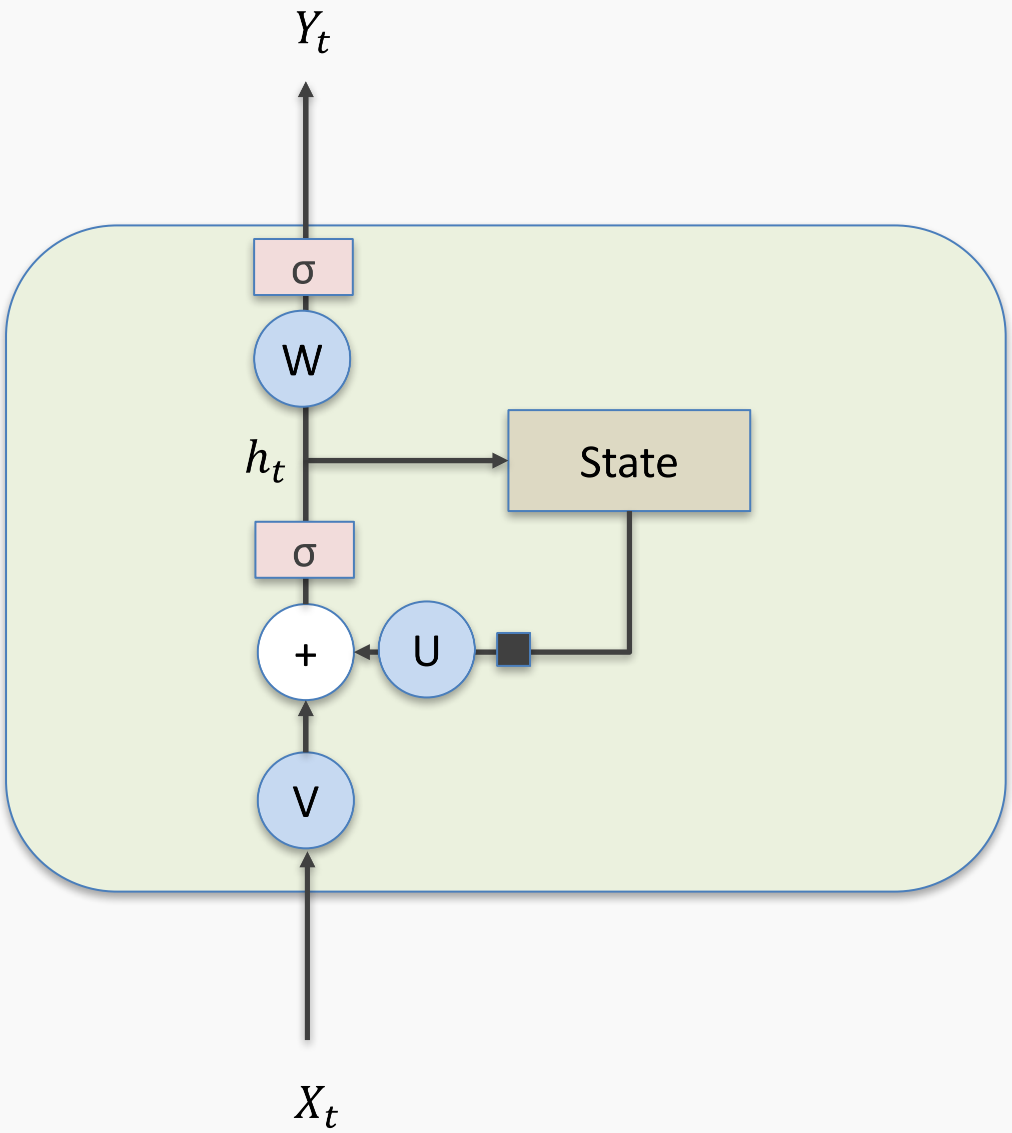


Simple RNN again

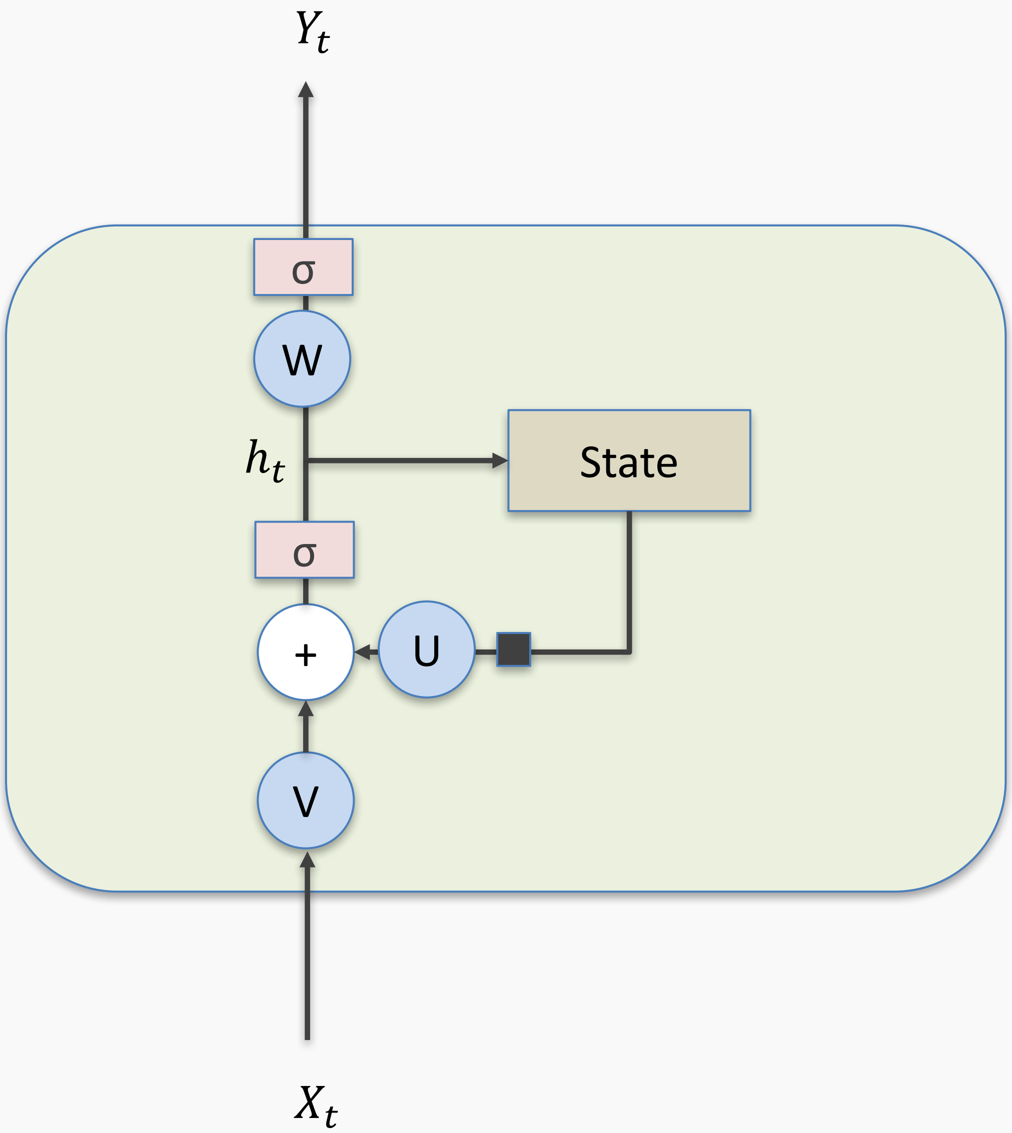




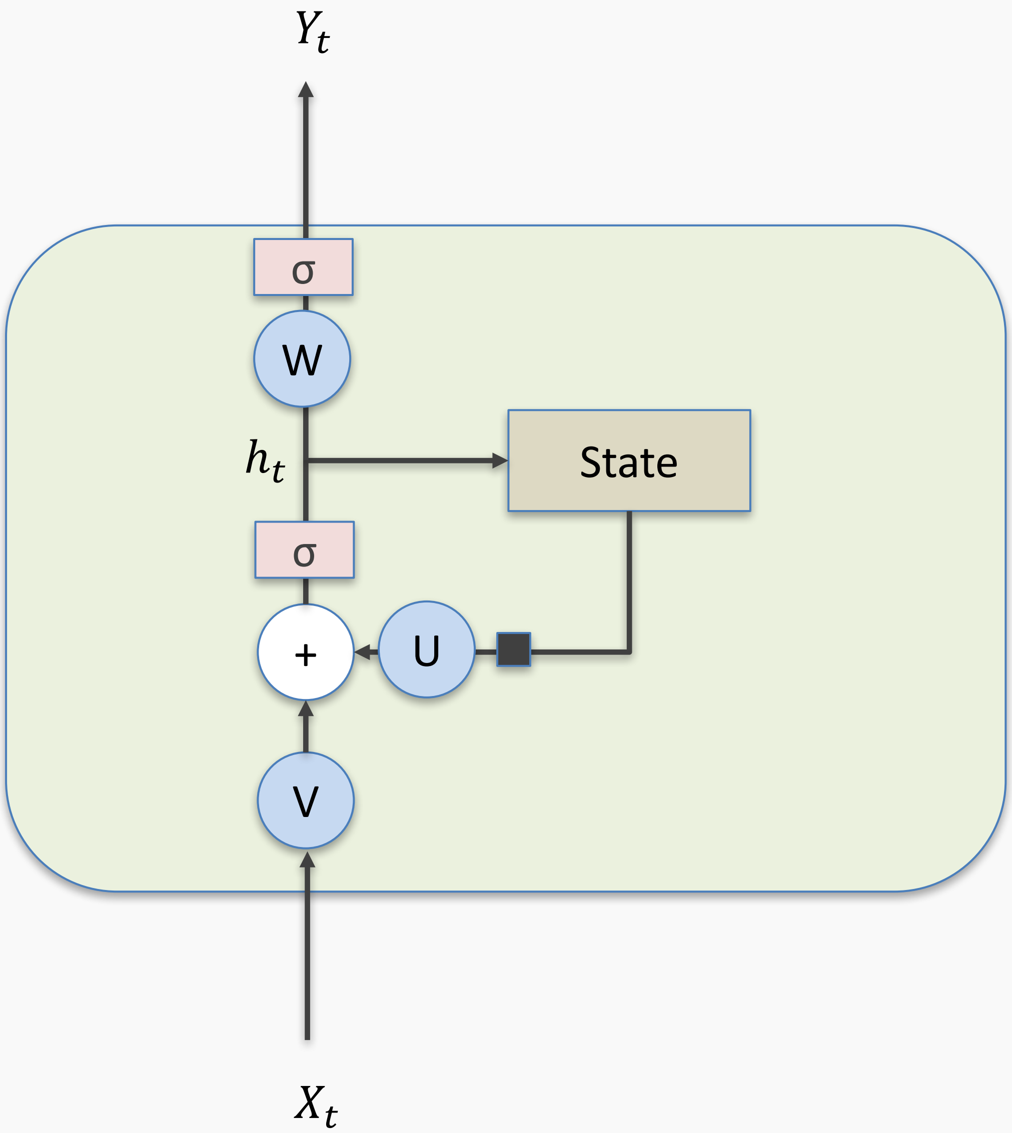
Simple RNN again: **Memories**

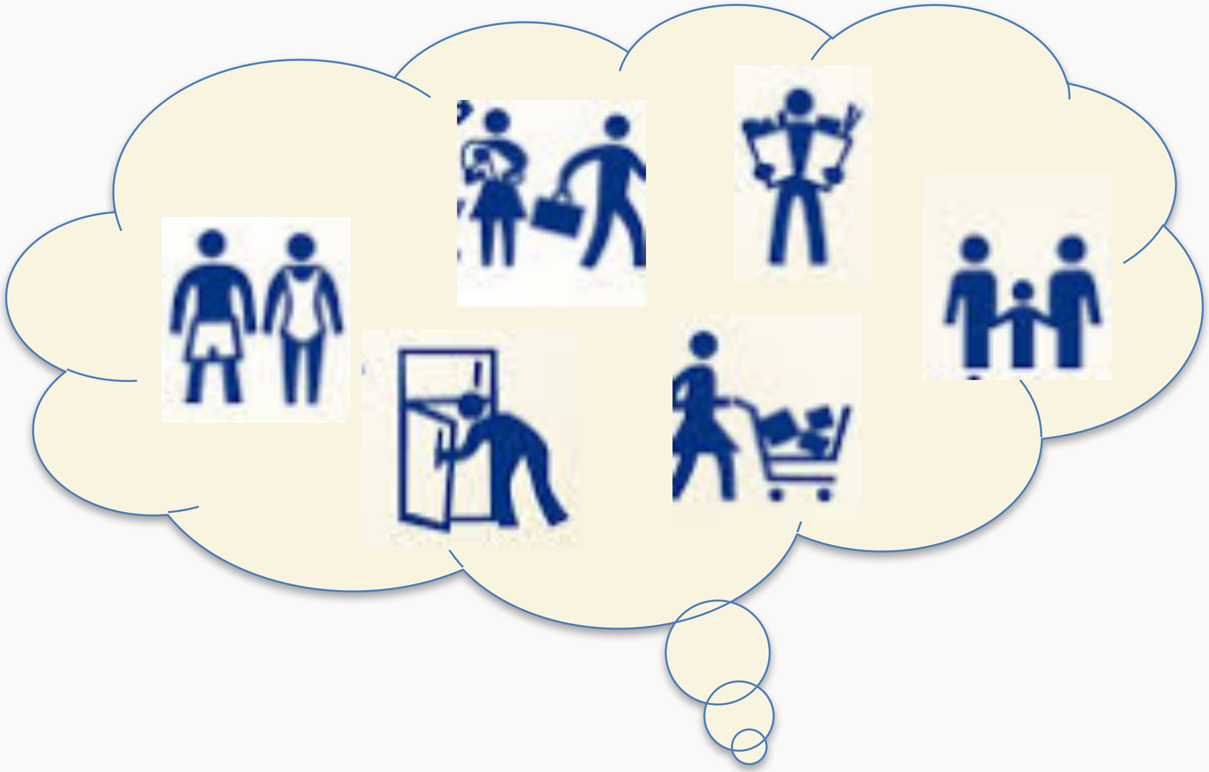


Simple RNN again: **Memories - Forgetting**

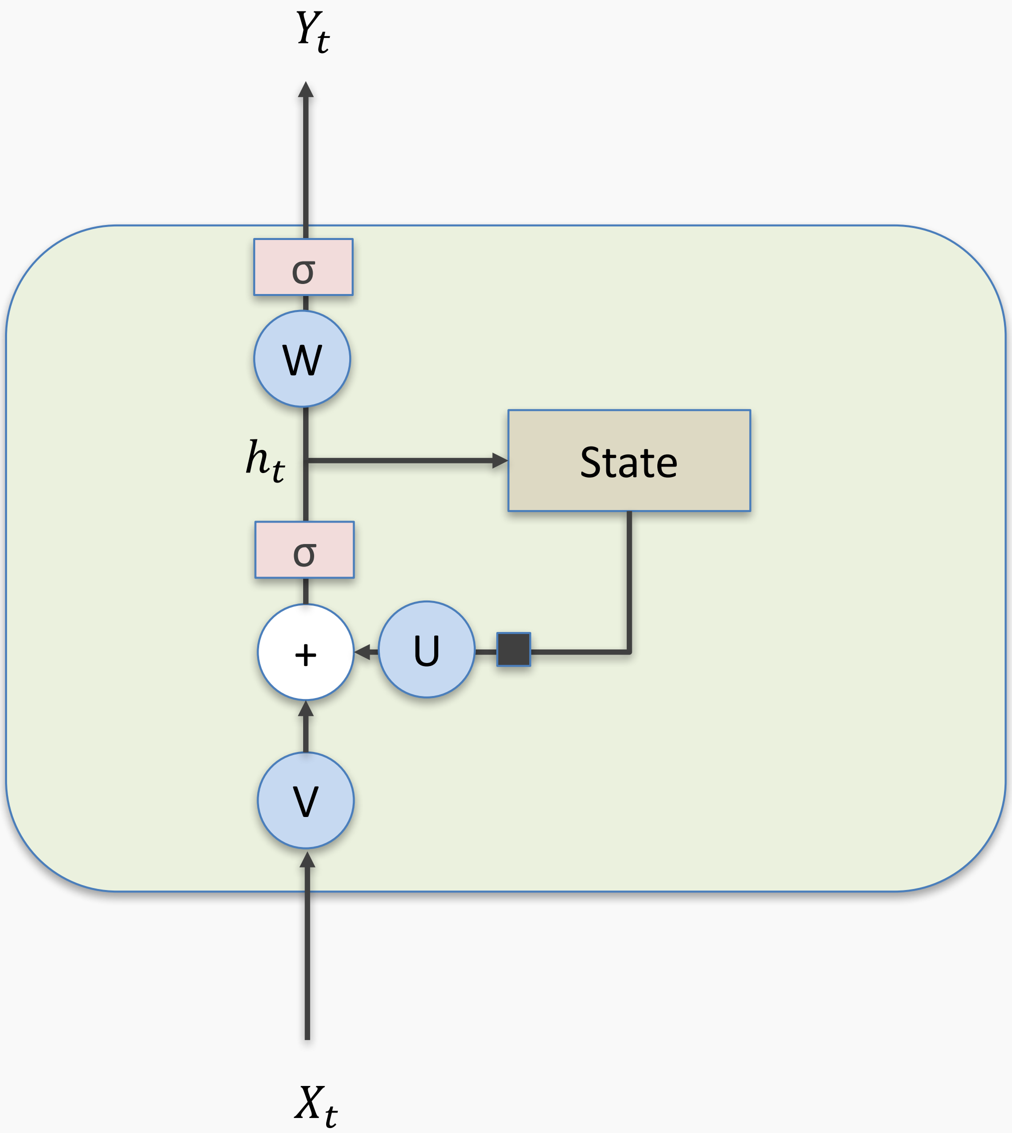


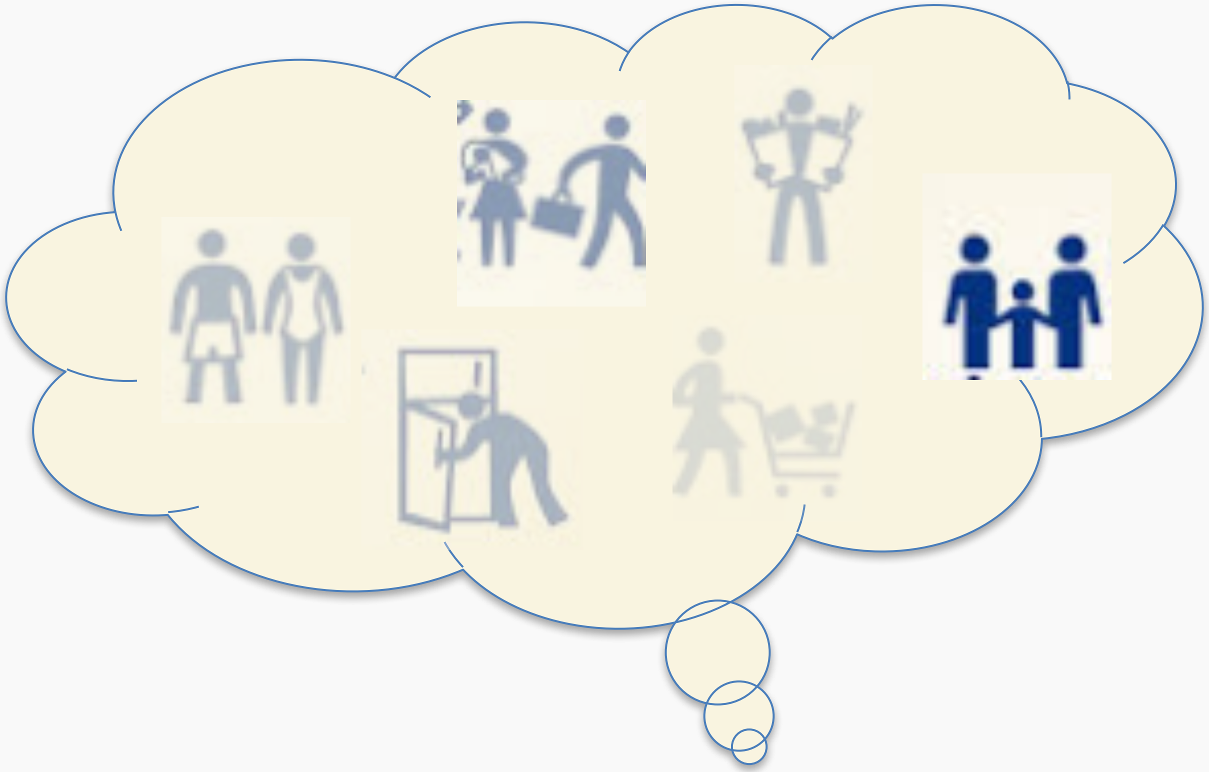
Simple RNN again: **New Events**



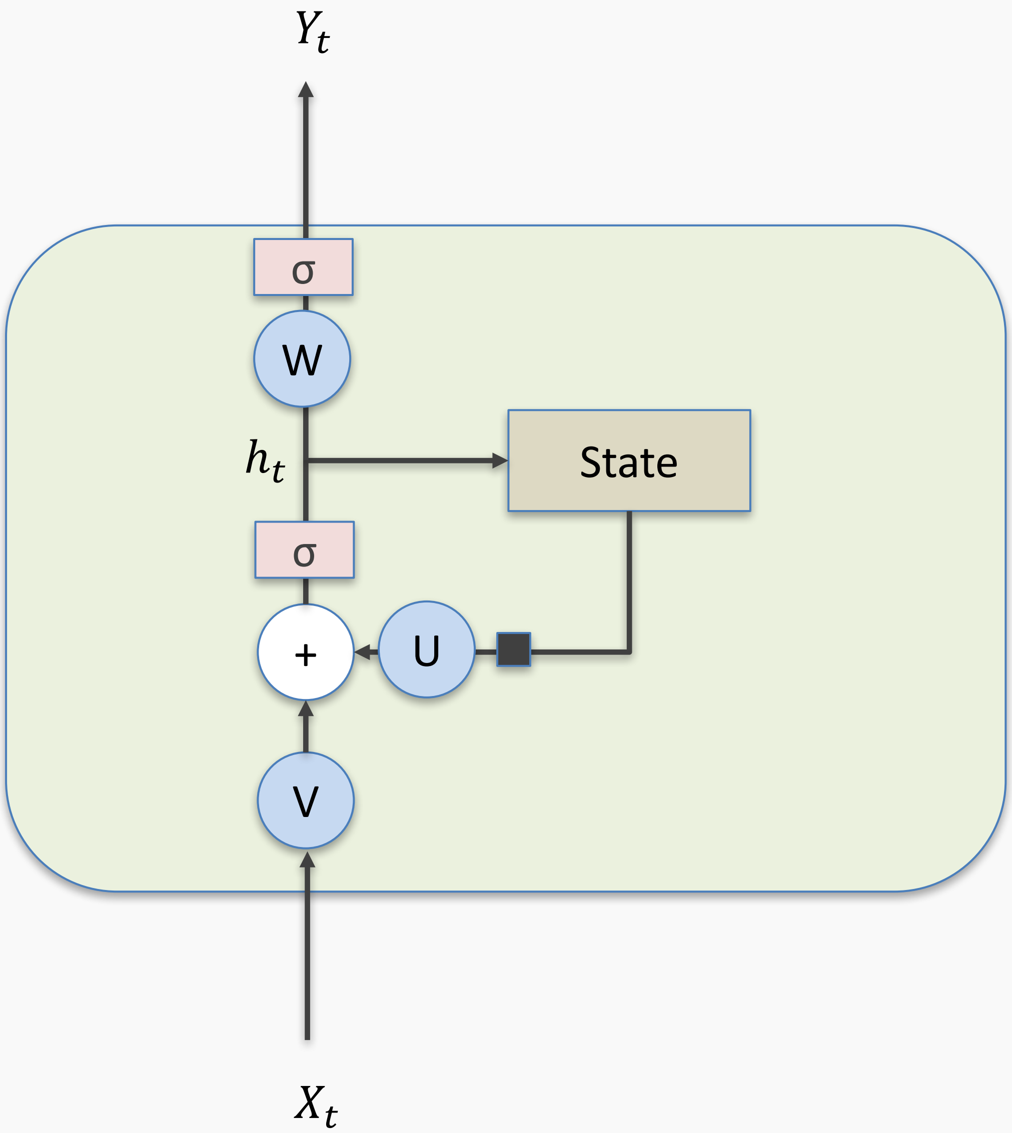


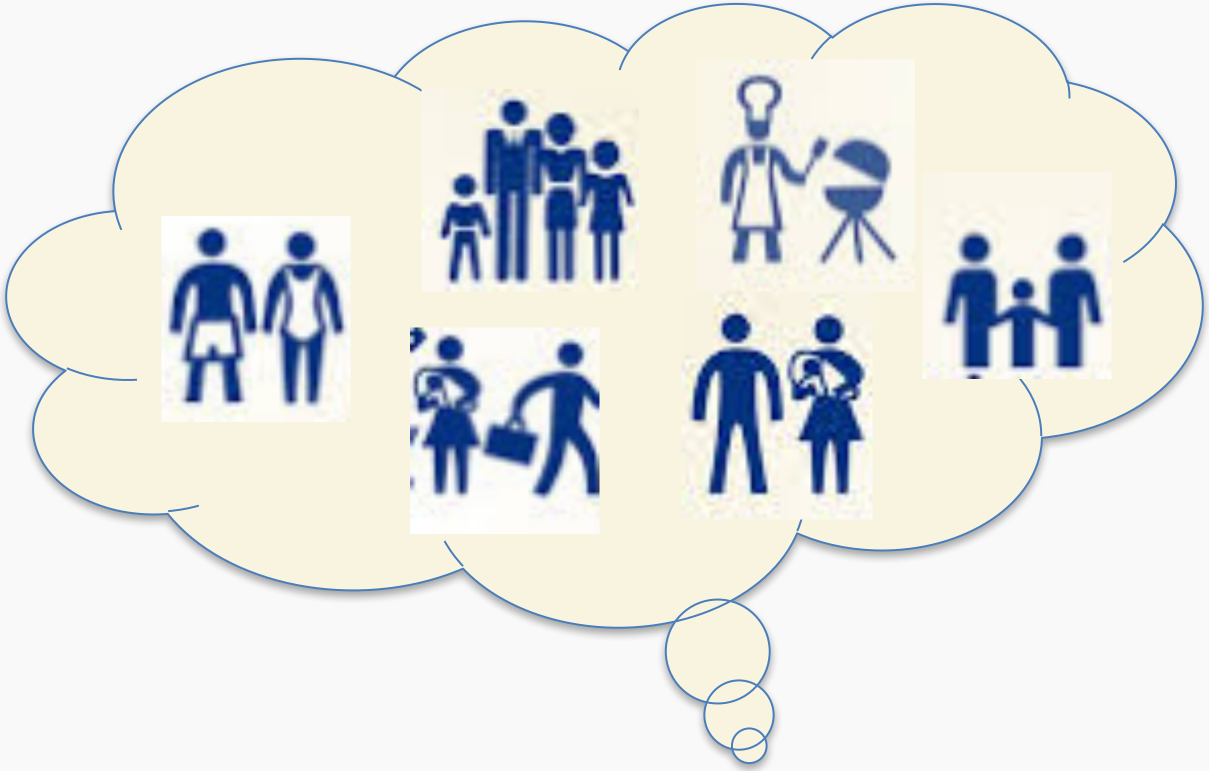
Simple RNN again: **New Events Weighted**





Simple RNN again: **Updated memories**





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