# Building a Text Classification Model


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# Overview

Recurrent Neural Networks (RNNs) are another common NN architecture

Great for working with sequences

Classification using RNNs

PyTorch has built-in support for RNNs

# Recurrent Neural Networks (RNNs)

```
y = f(x)
```

# Machine Learning

**Machine learning algorithms seek to “learn” the function f that links the features and the labels**

$$y_t = f(x_t, y_{t-1})$$

# Learning the Past

**Relationships where past values of the effect variable drive current values are called auto-regressive**

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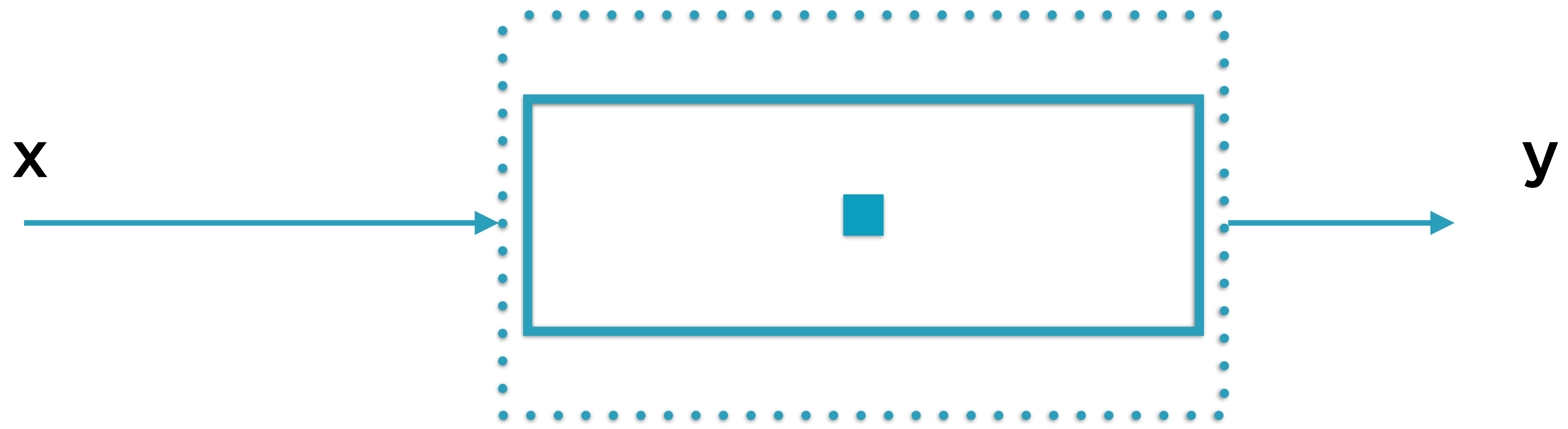
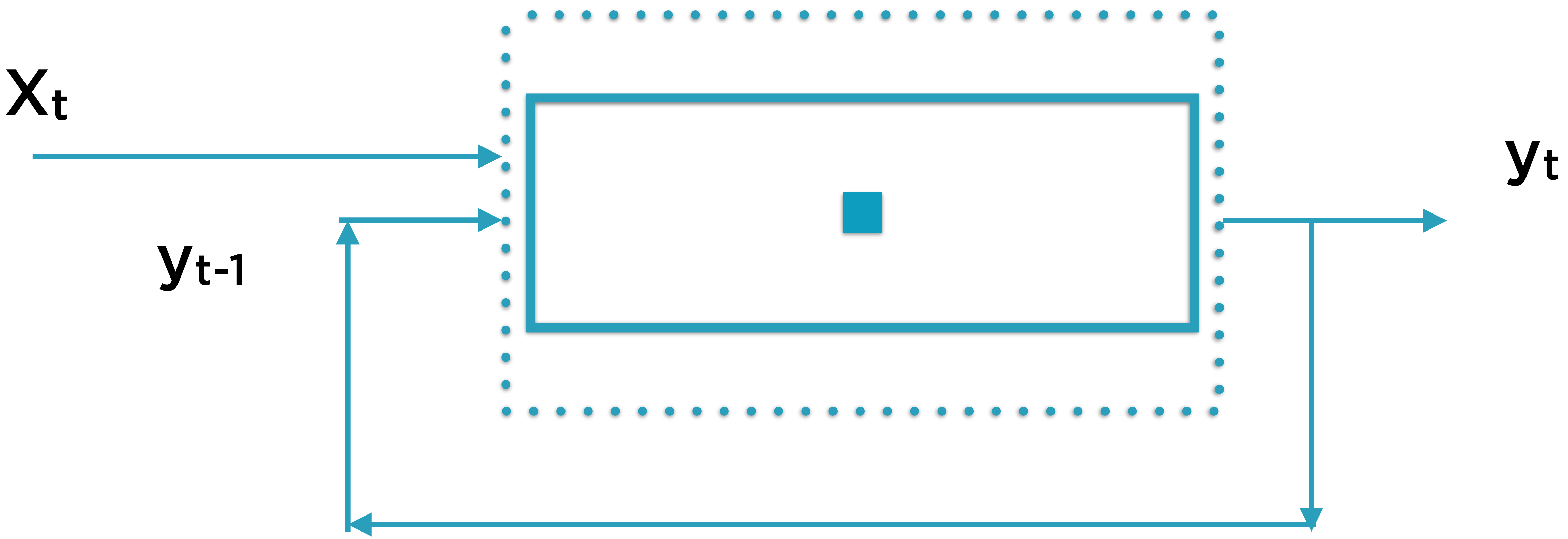
Feed-forward networks cannot learn from the **past**

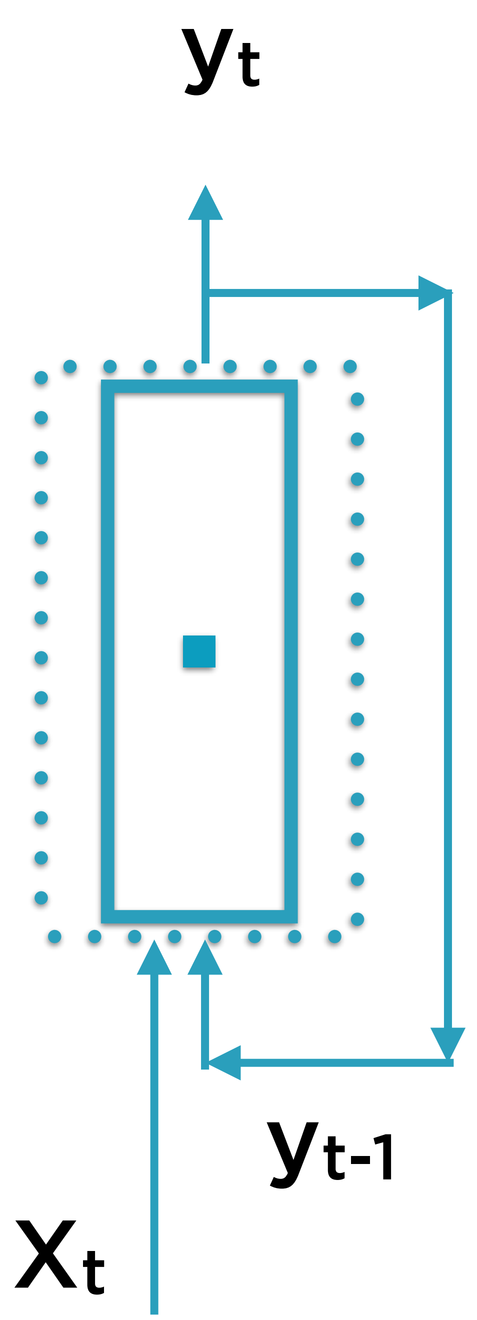
Recurrent neural networks can

# Simplest Feed-forward Neuron



# Simplest Recurrent Neuron





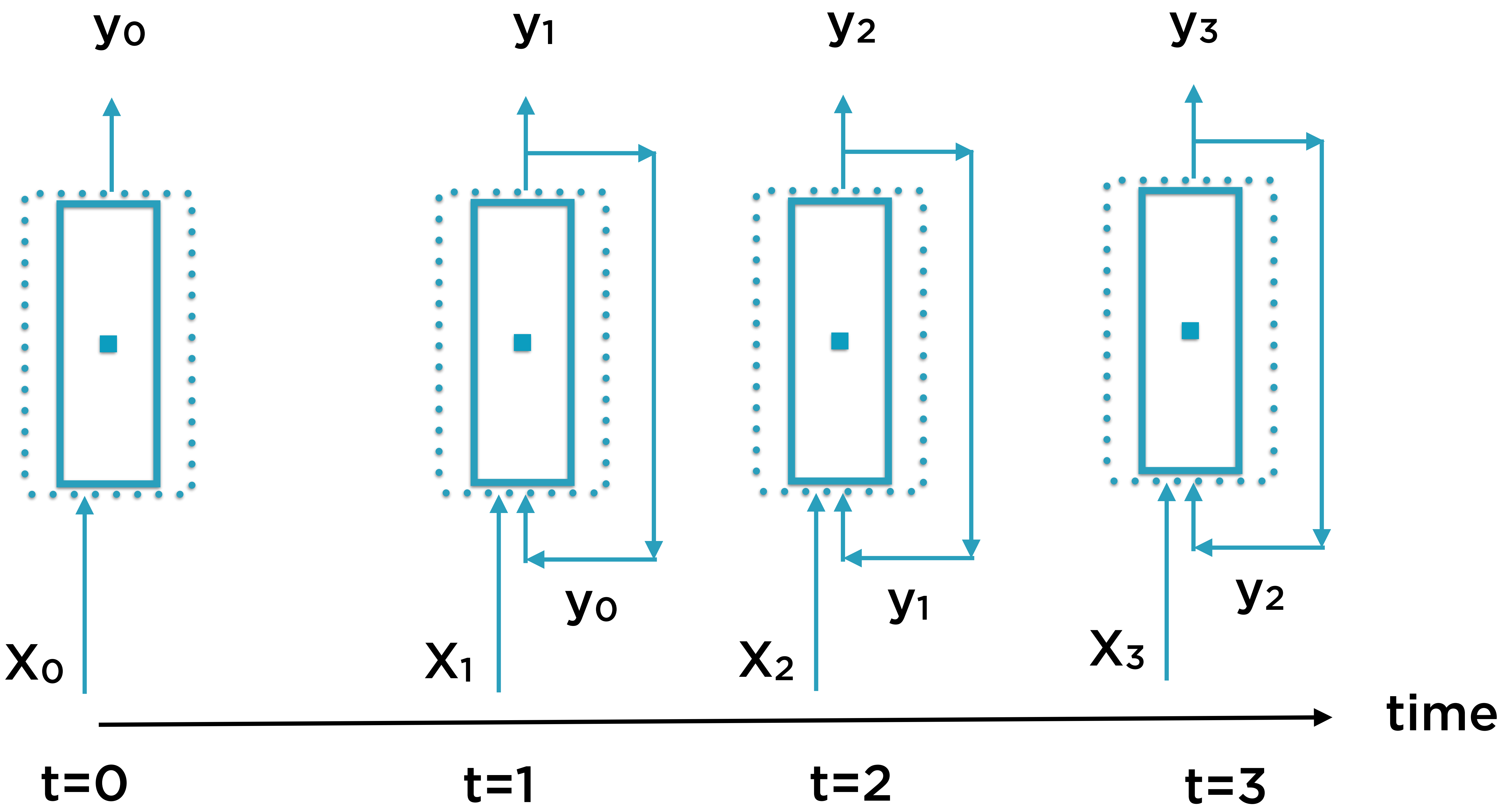

# Recurrent Neuron

$y_t$ = Output at time t

Depends upon

- $y_{t-1}$ = Output at time t - 1
- $x_t$ = New inputs available only at time t

# Unrolling Through Time



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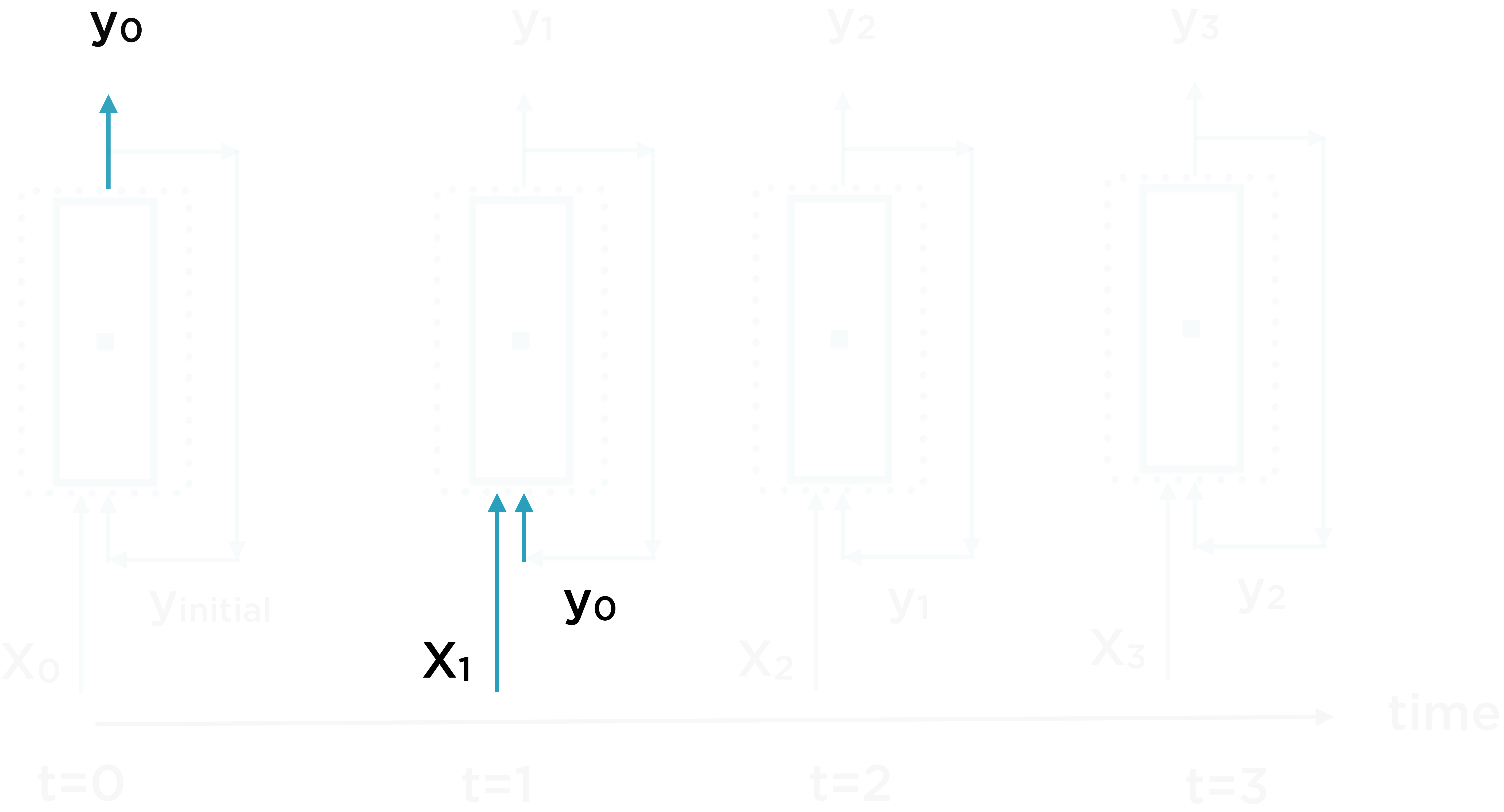

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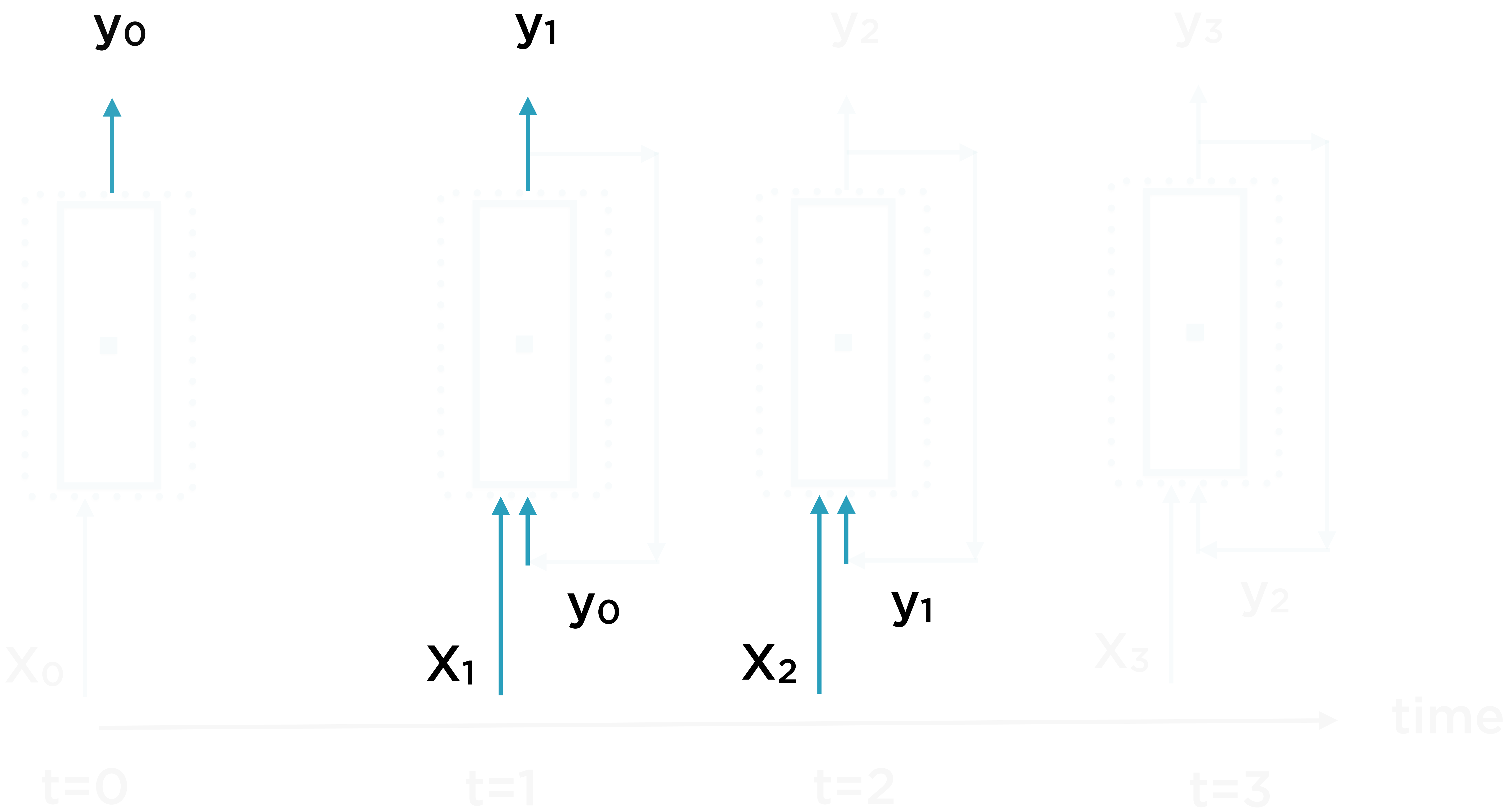

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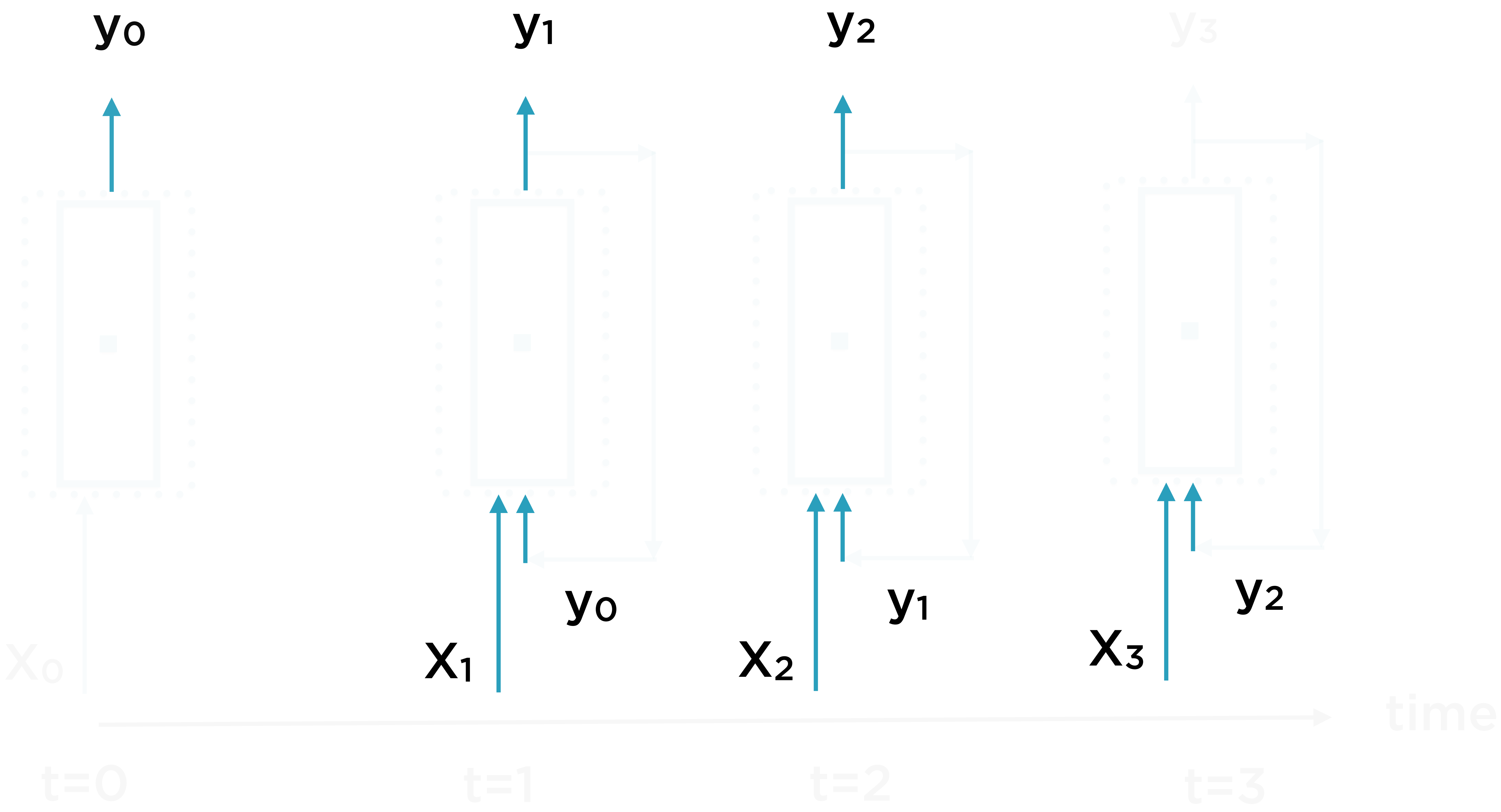

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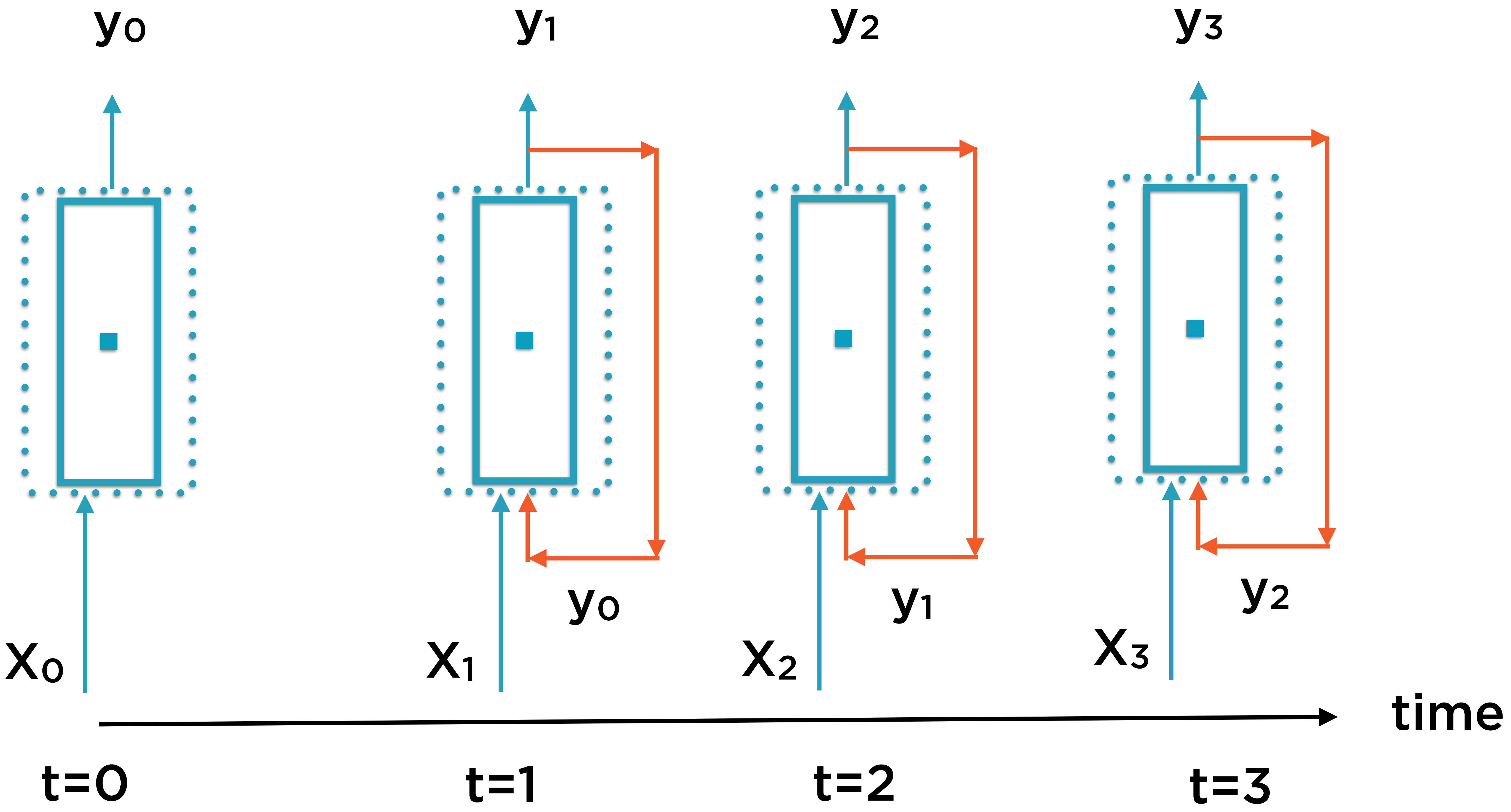

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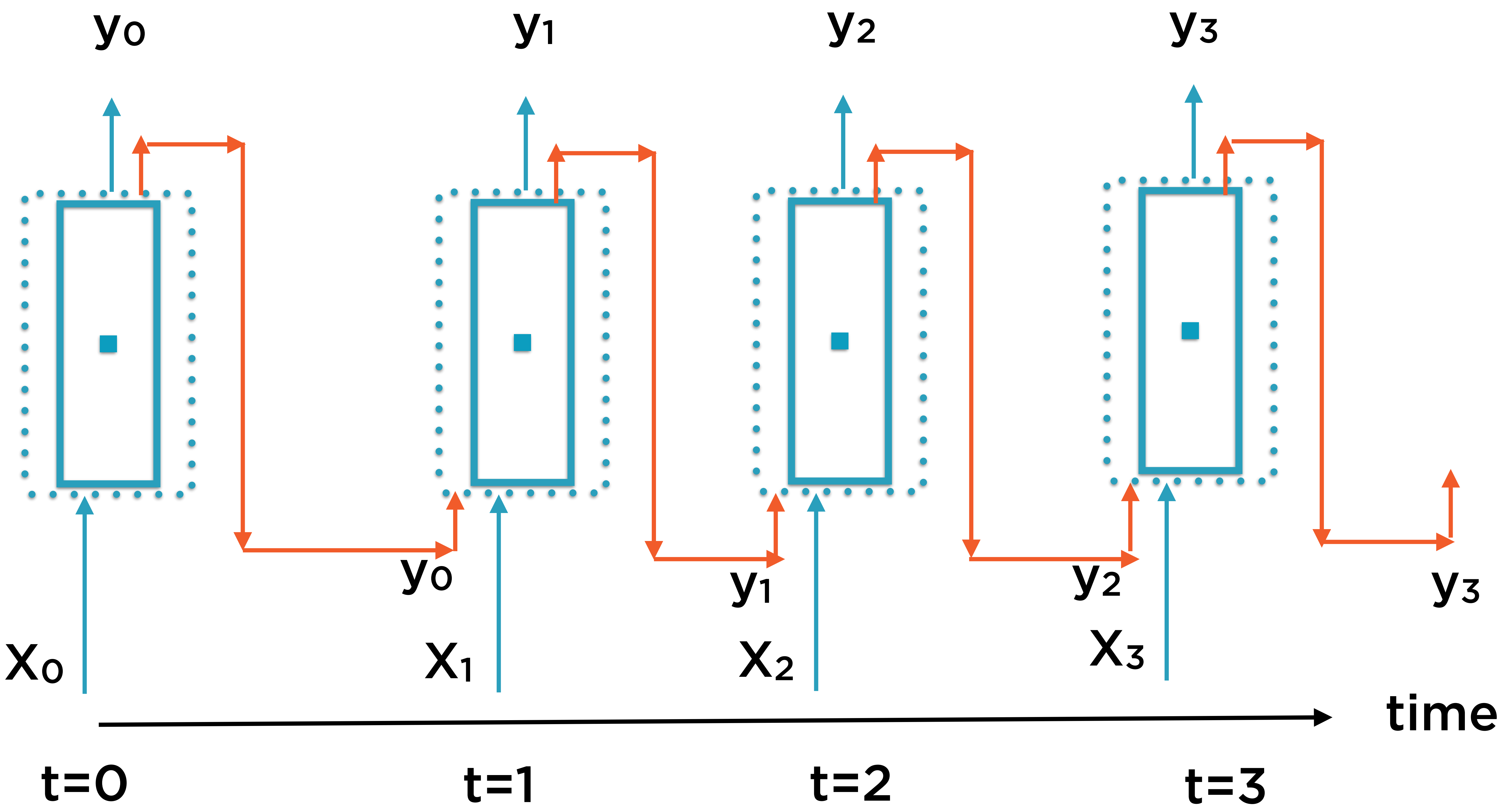
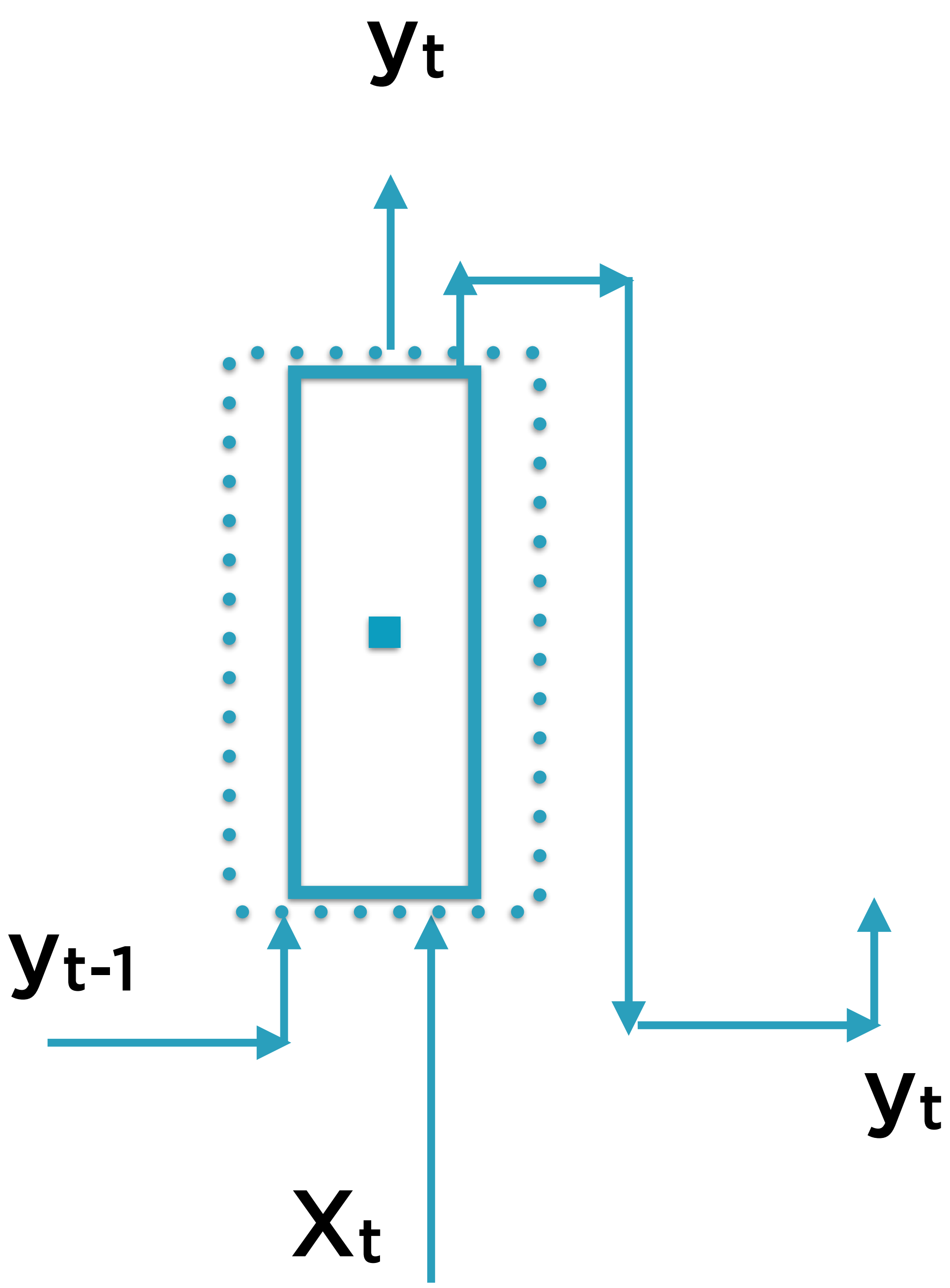





# Recurrent Neuron

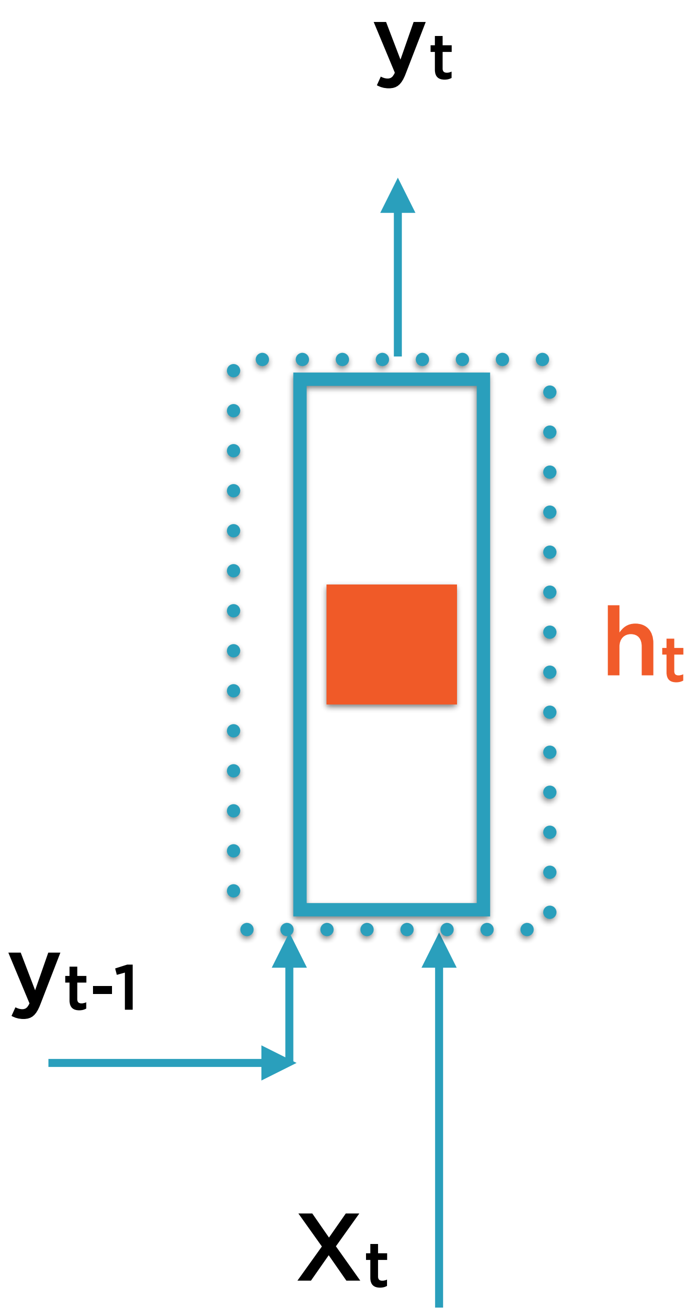
**Regular neuron: input is feature vector, output is scalar**

`Y = activation(Wx + b)`

**Recurrent neuron: output is vector too**

**Input:** $[X_0, X_1, \ldots X_t]$

**Output:** $[Y_0, Y_1, \ldots Y_t]$



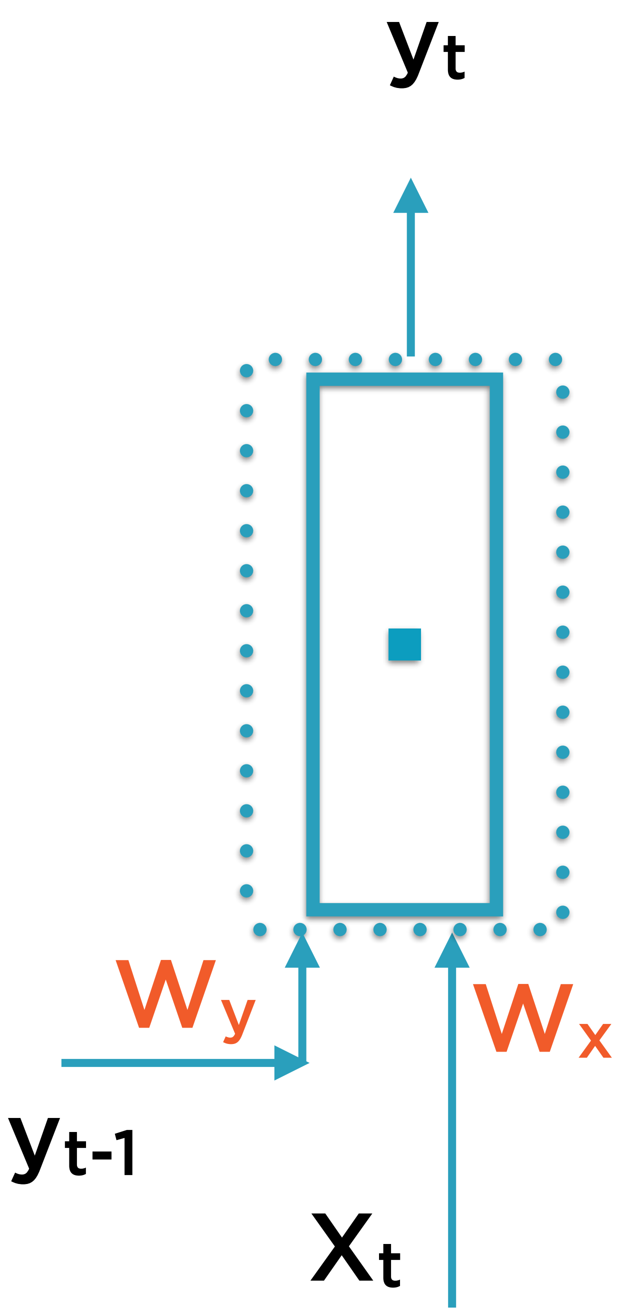

# Memory and State

Recurrent neurons remember the past

They possess ‘memory’

The stored state could be more complex than simply $y_{t-1}$

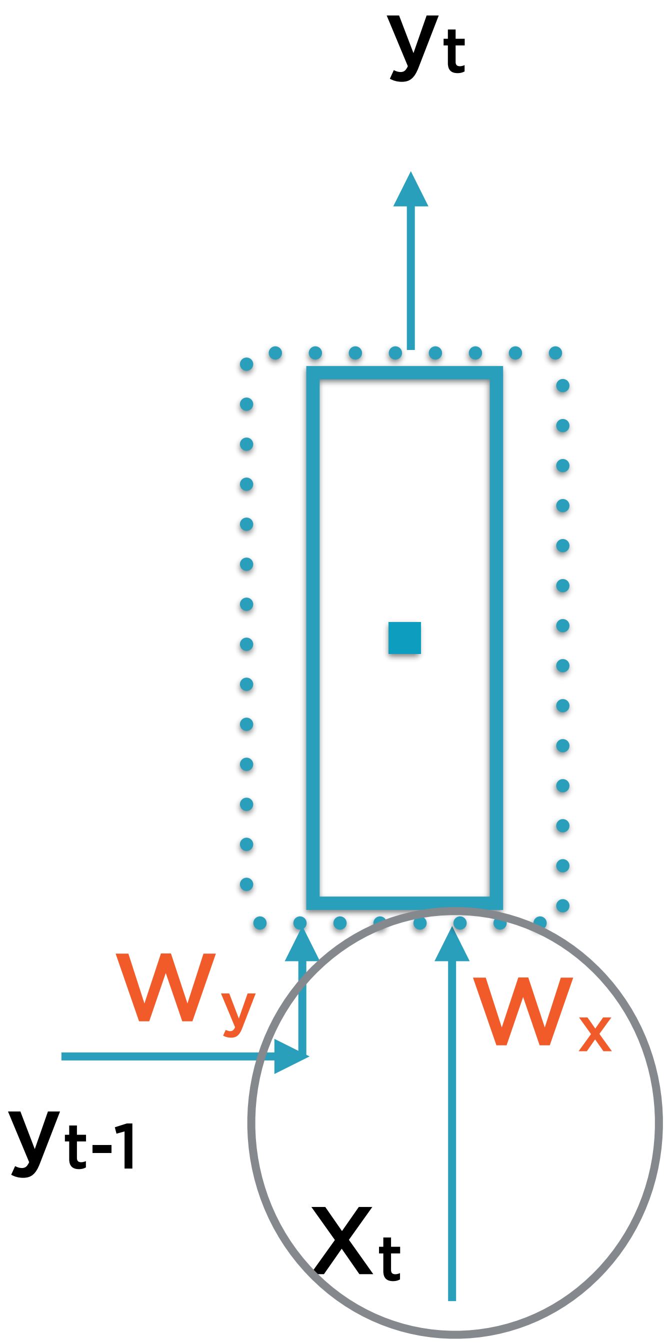
The internal state is represented by $h_t$




# Recurrent Neuron

Now, each neuron has two weight vectors

$W_x$, $W_y$

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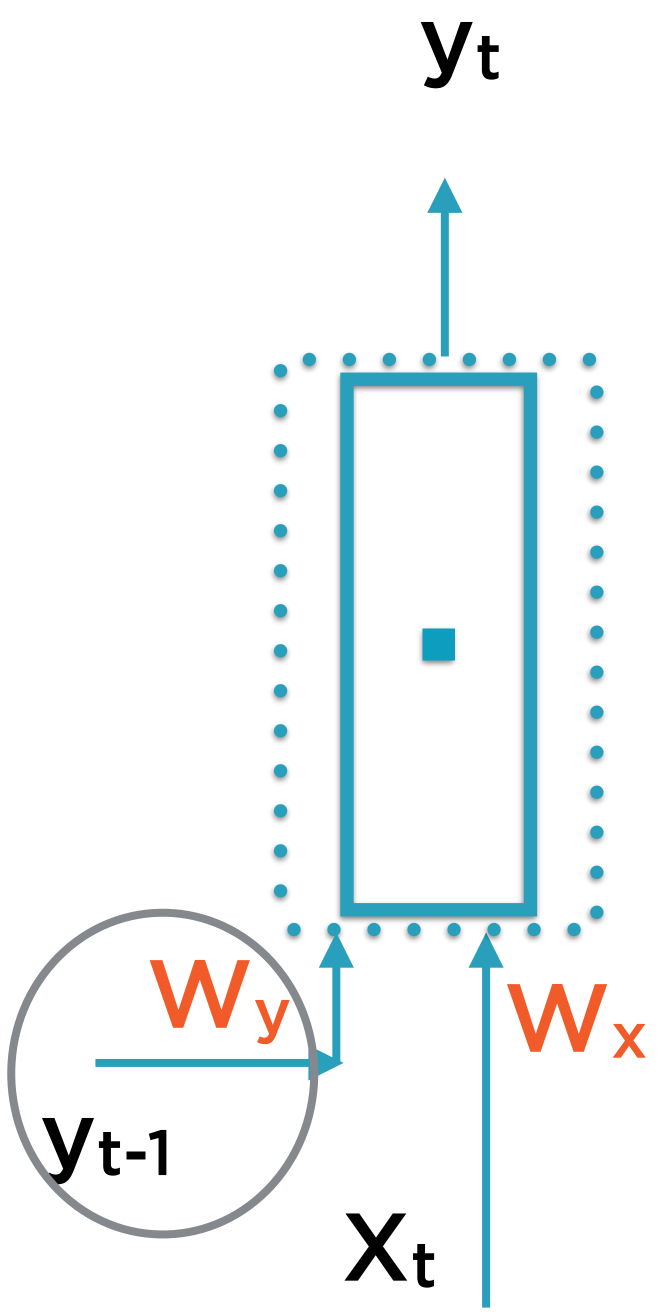


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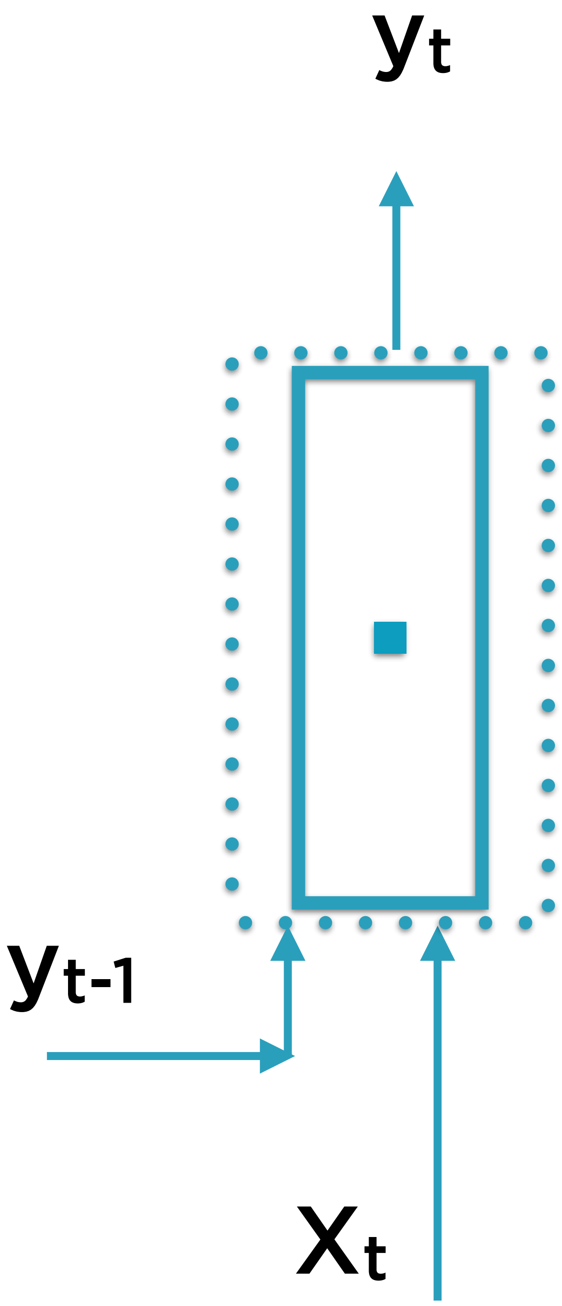



# Recurrent Neuron

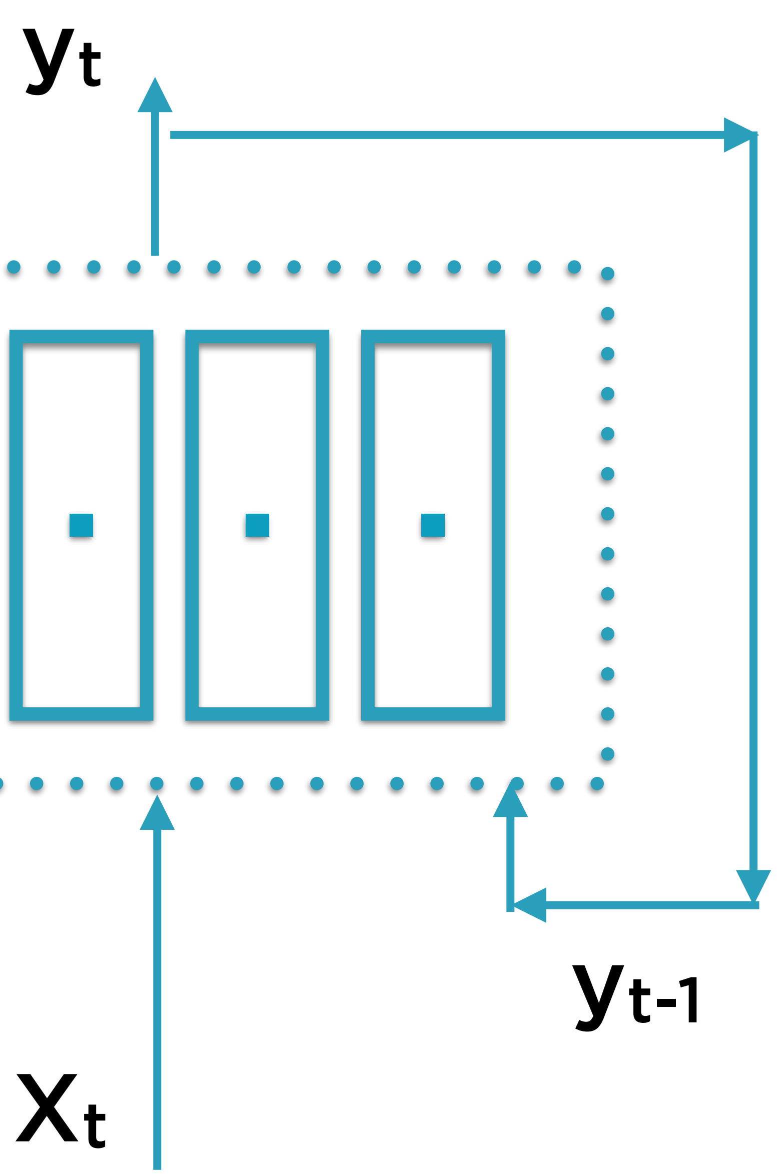
Output of neuron as a whole is given as

$$y_t = \Phi(X_t W_x + y_{t-1} W_y + b)$$

($\Phi$ is the activation function)

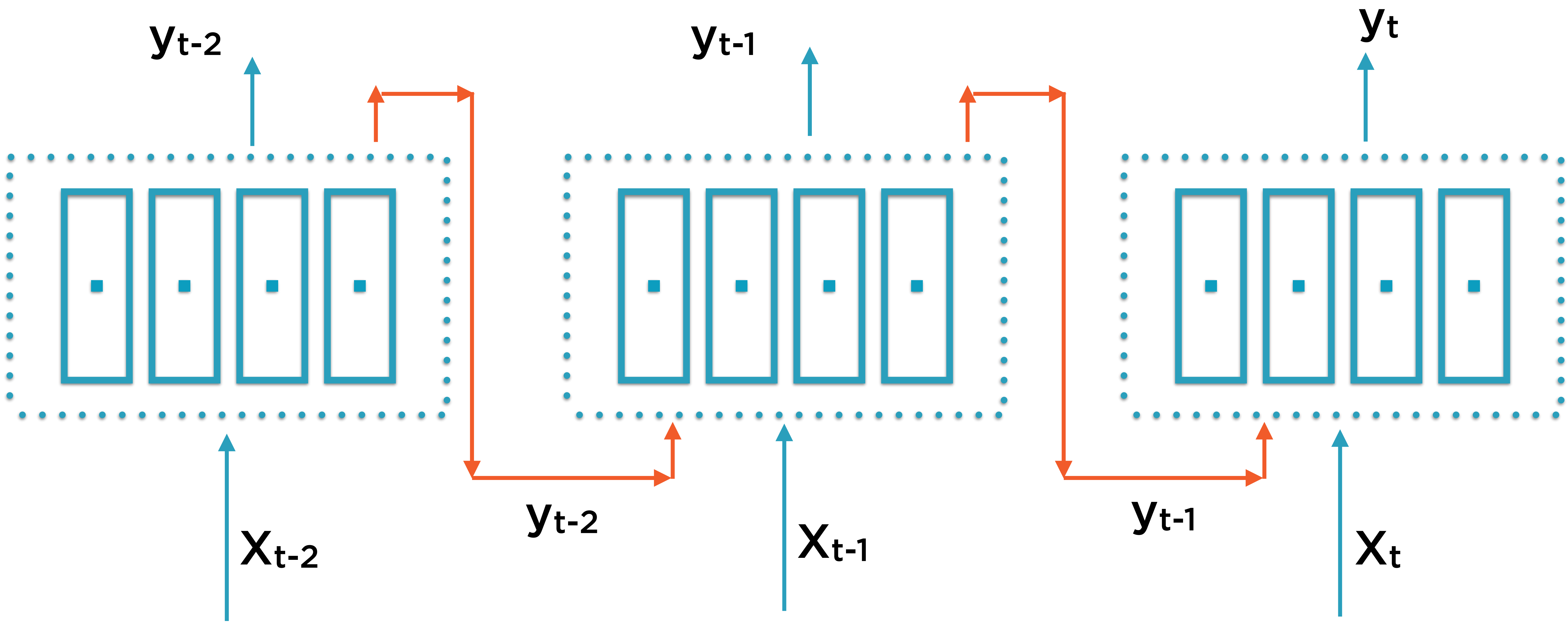
# Training a Recurrent Neural Network

# Layer of Recurrent Neurons




**A layer of neurons forms an RNN cell - basic cell, LSTM cell, GRU cell (more on these later)**

# Layer of Recurrent Neurons

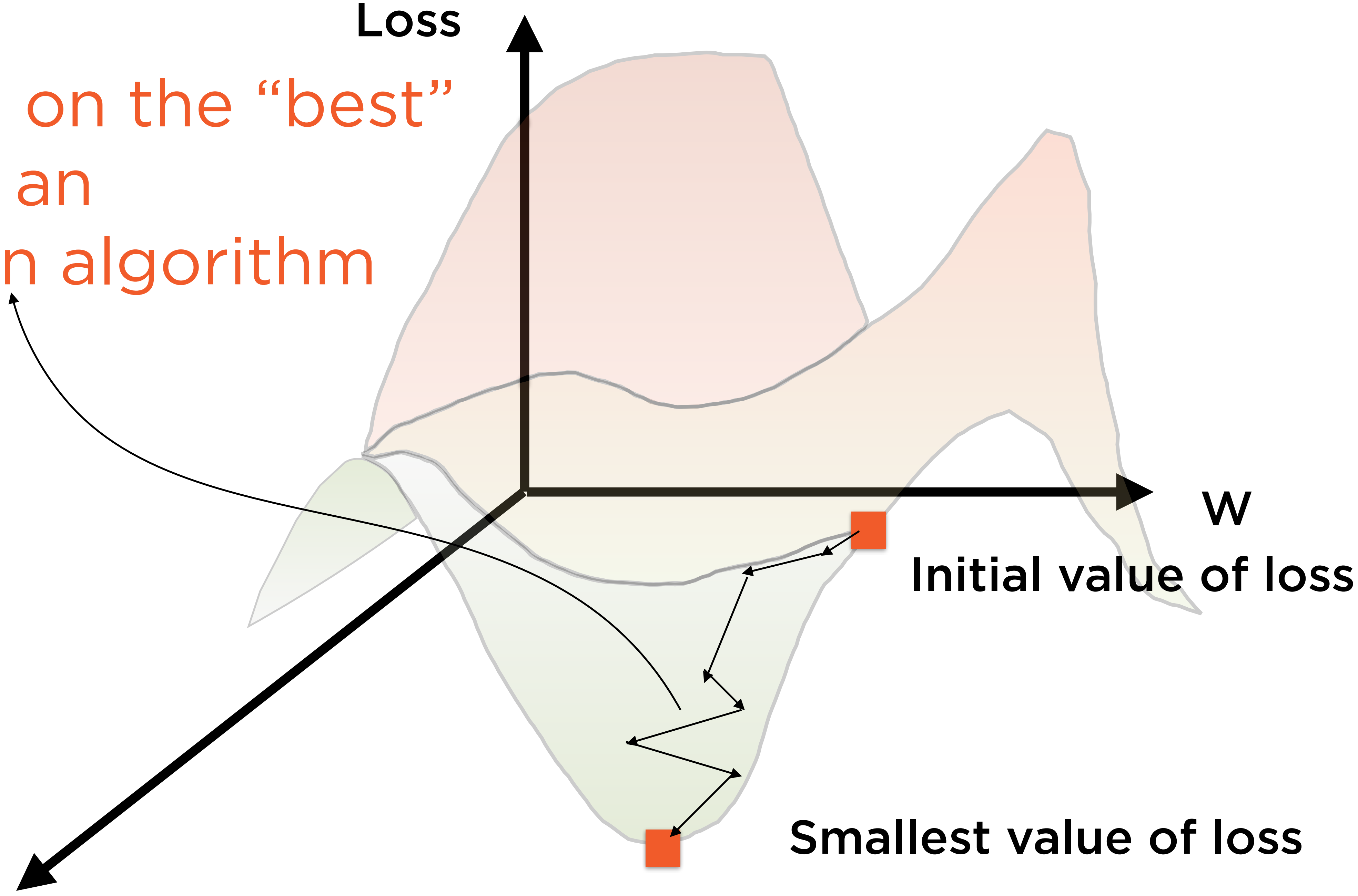



**The cells unrolled through time form the layers of the neural network**

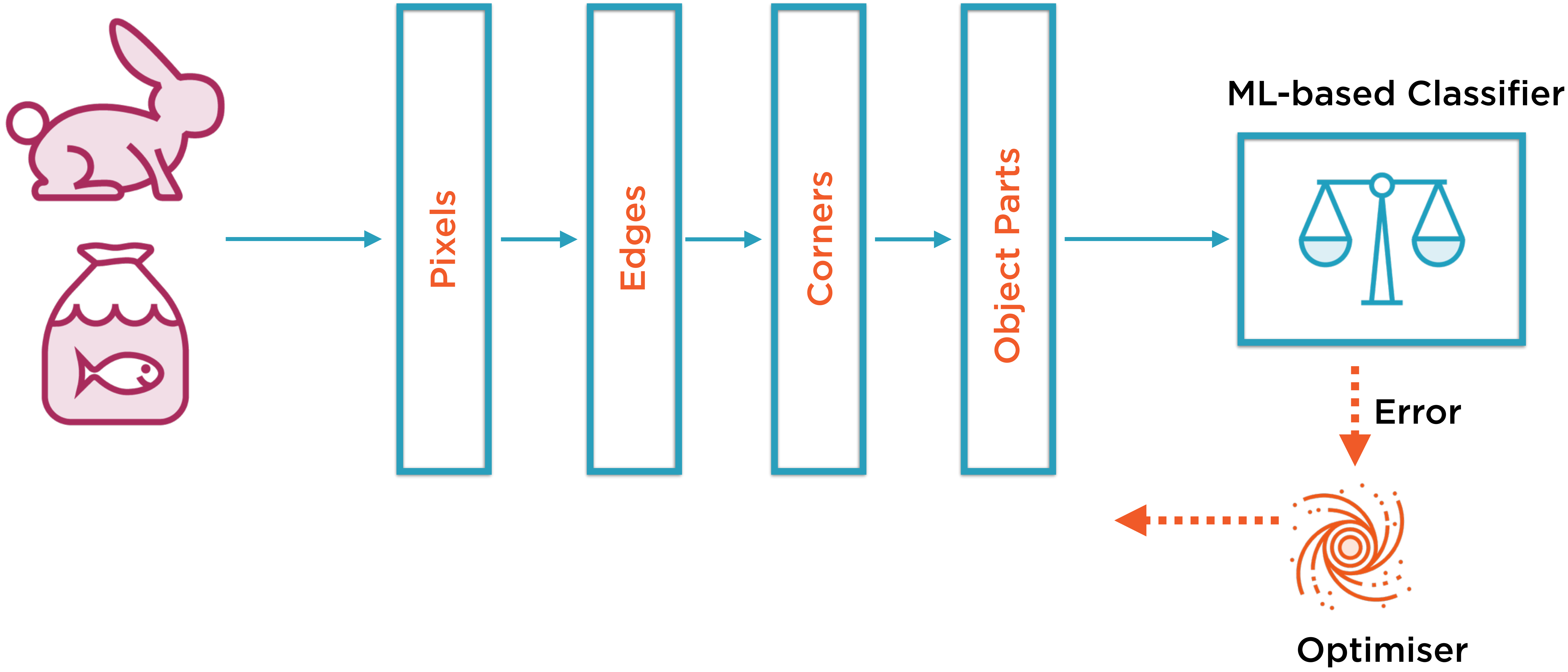
The actual training of a neural network happens via Gradient Descent Optimization

# Gradient Descent

Converging on the “best” value using an optimization algorithm



# Back Propagation Through Time



$$y_t = f(x_t, y_{t-1}, y_{t-2} \ldots, y_{t-1000})$$

# Learning the Distant Past

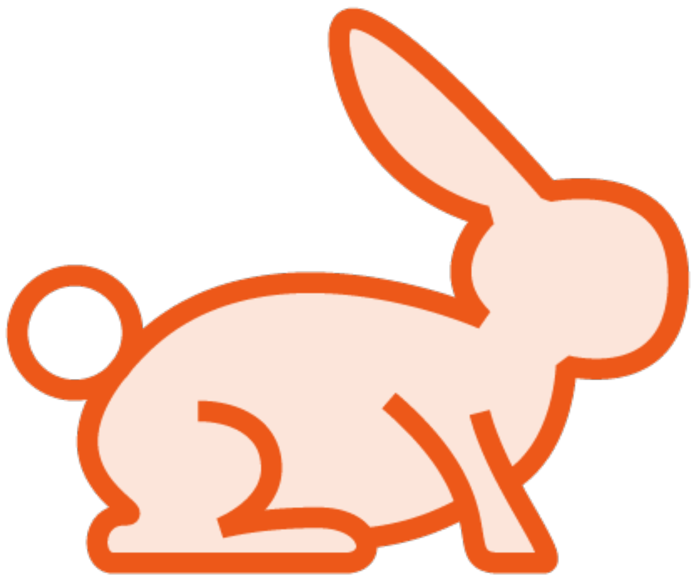
**The unrolled RNN will be very, very deep - many layers to train, the gradient has to be propagated a long way**

Recurrent neural networks may be unrolled **very far back in time**

They're prone to the **vanishing** and **exploding** gradients issue

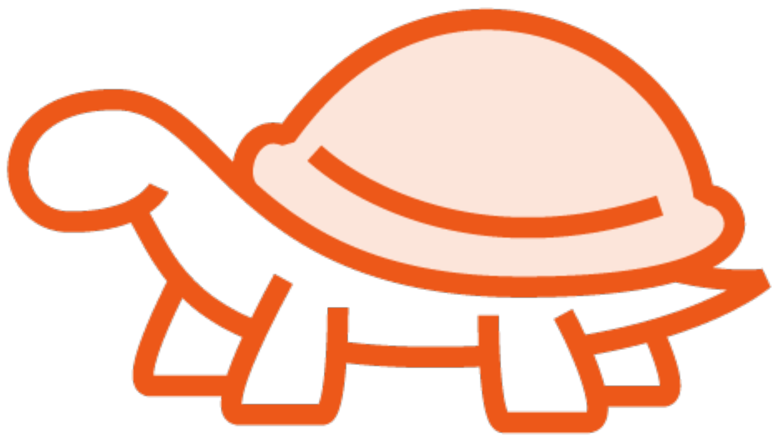
Deep neural networks are prone to overfitting

# Overfitting



**Low Training Error**

Model does very well in training...



**High Test Error**

...but poorly with real data

# Preventing Overfitting

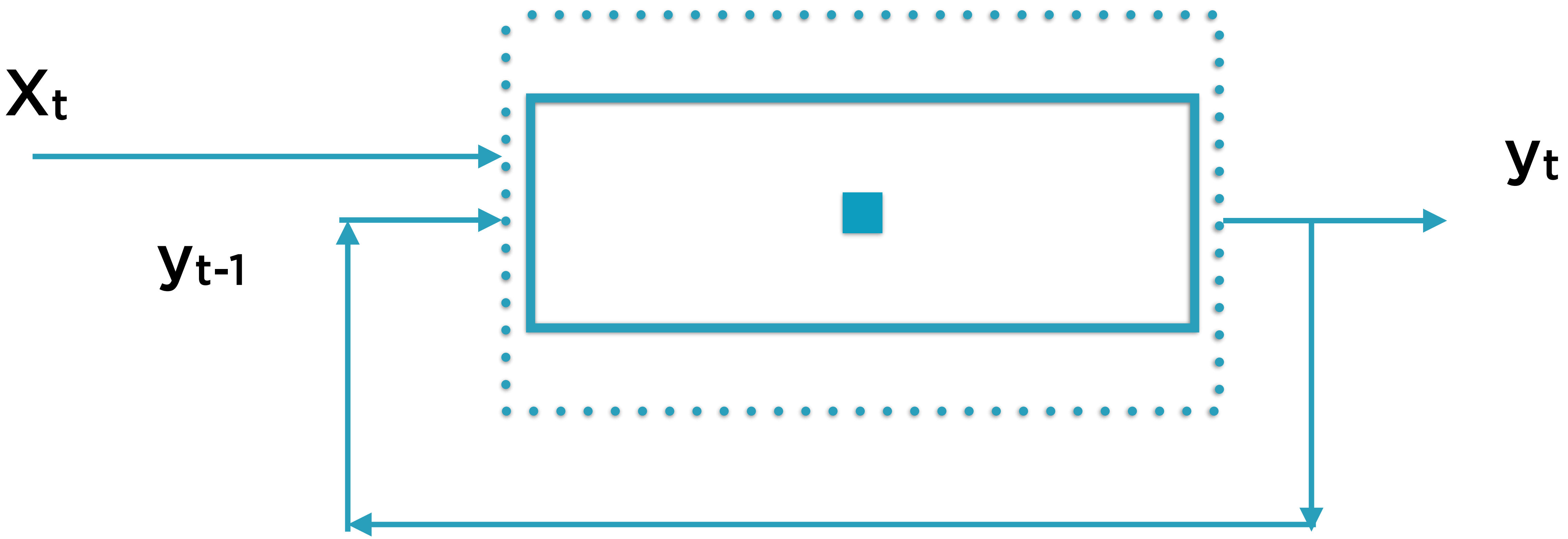

**Regularization - Penalize complex models**

**Cross-validation - Distinct training and validation phases**


**Dropout - Intentionally turn off some neurons during training**

# Long Memory RNN Cells

# Simplest Recurrent Neuron



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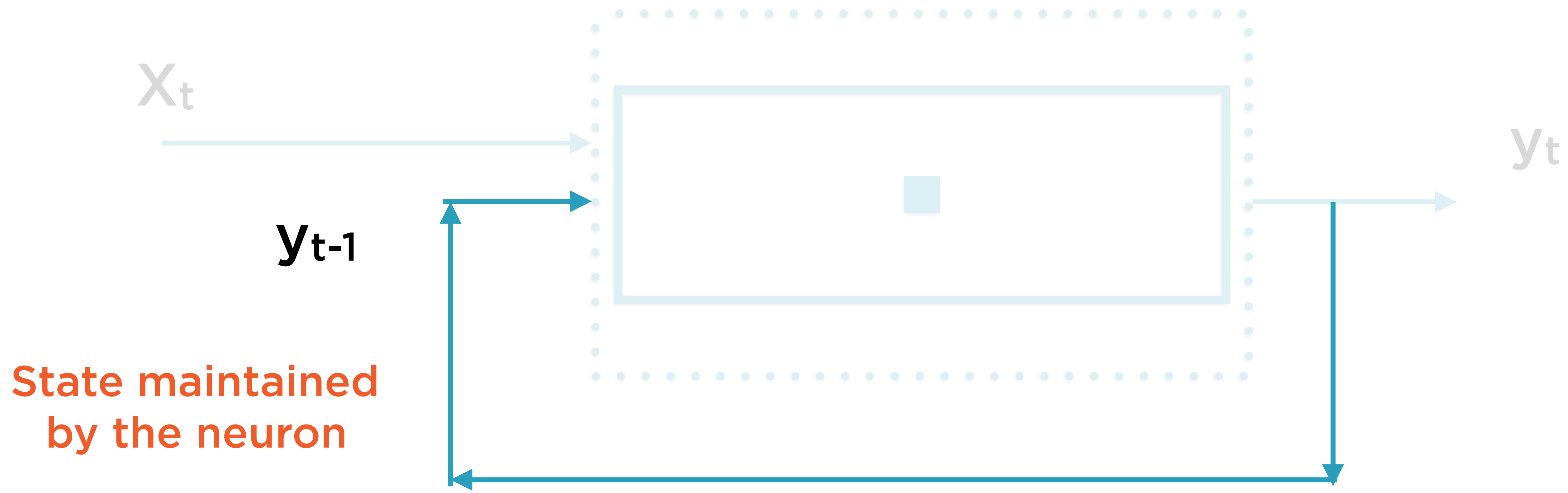
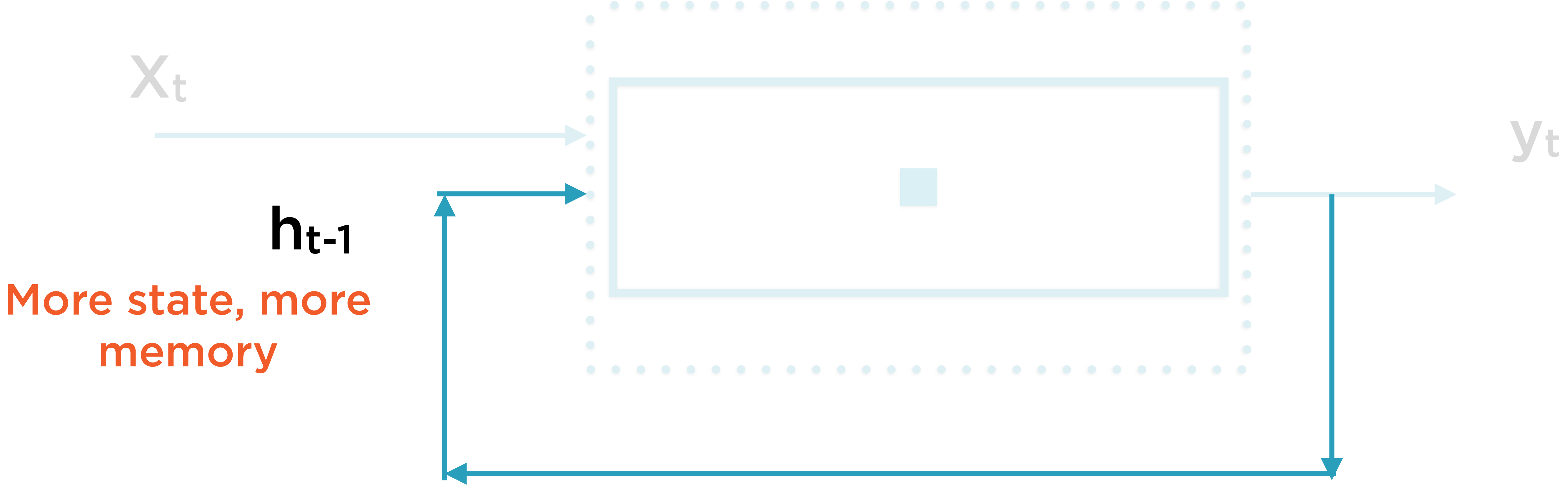
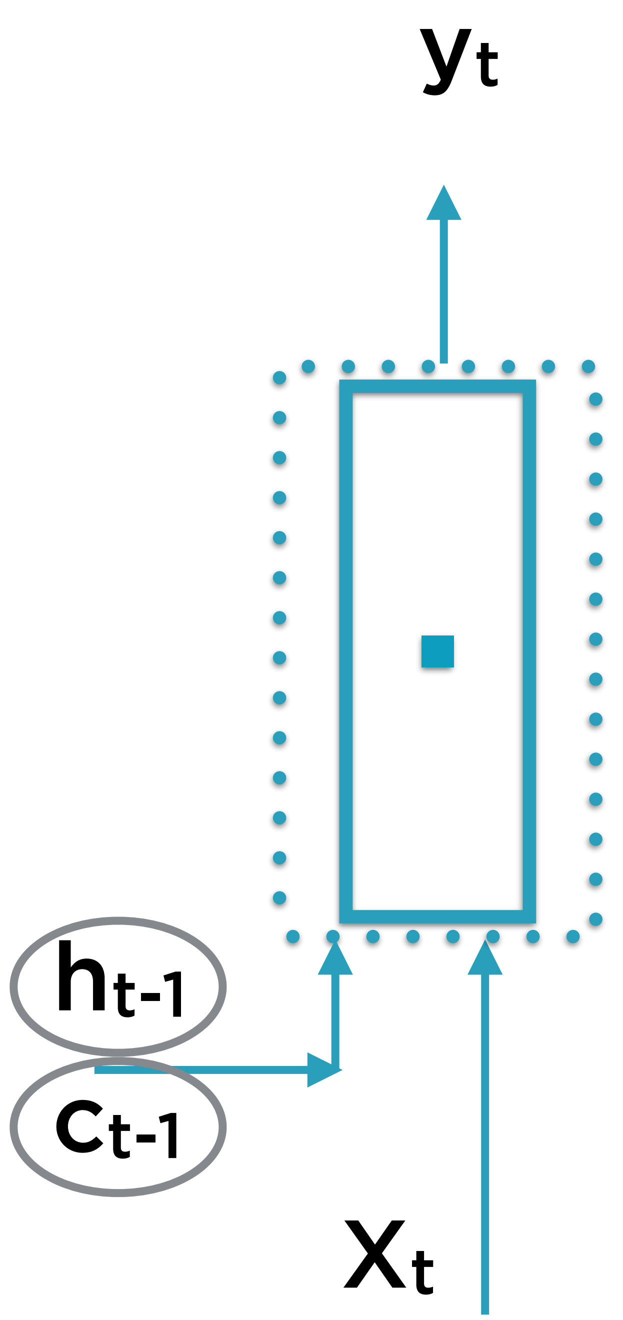


# Long Memory Recurrent Neuron






# Long Memory RNNs

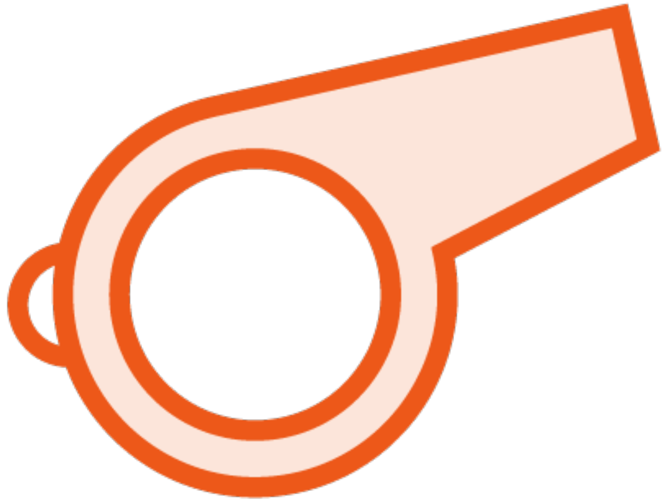
**Increase the amount of state in neuron**

**Effect is to increase memory of neuron**

**Could explicitly add:**

- long-term state (c)
- short-term state (h)

# Long Memory RNNs



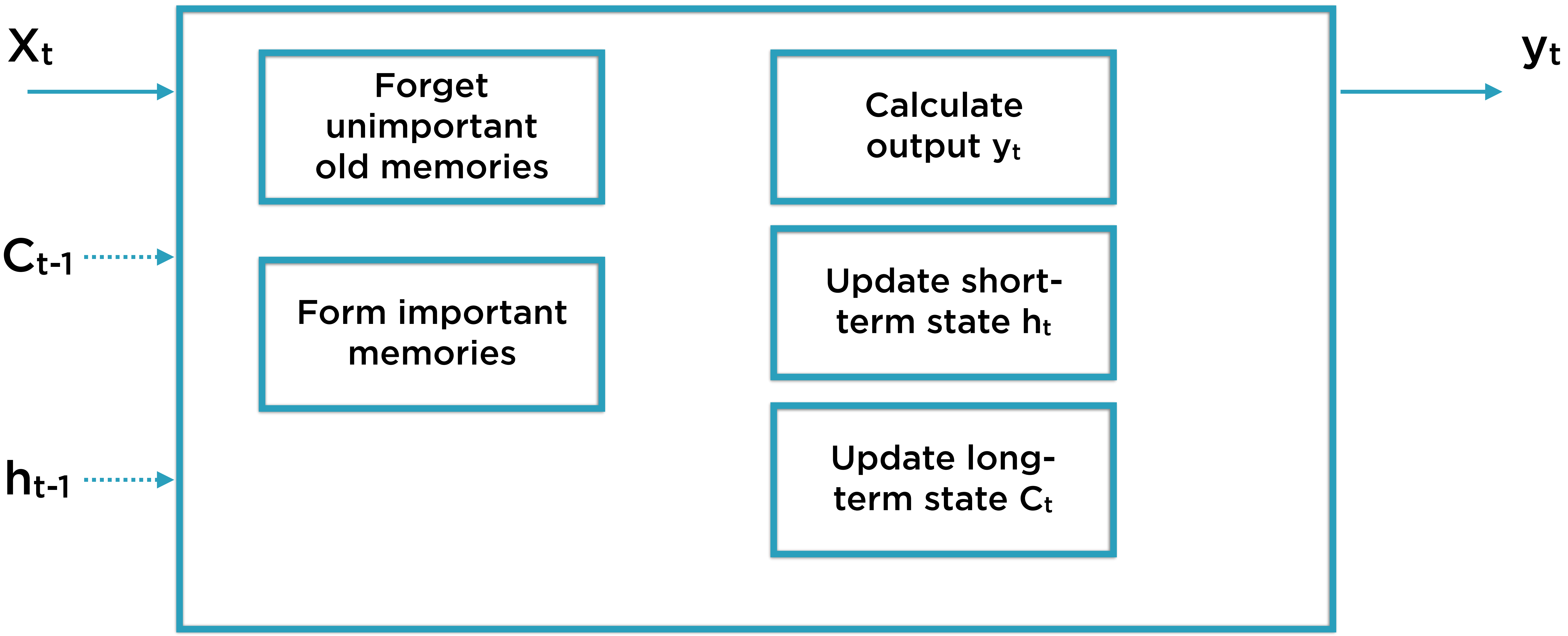
**Advantages in Training**

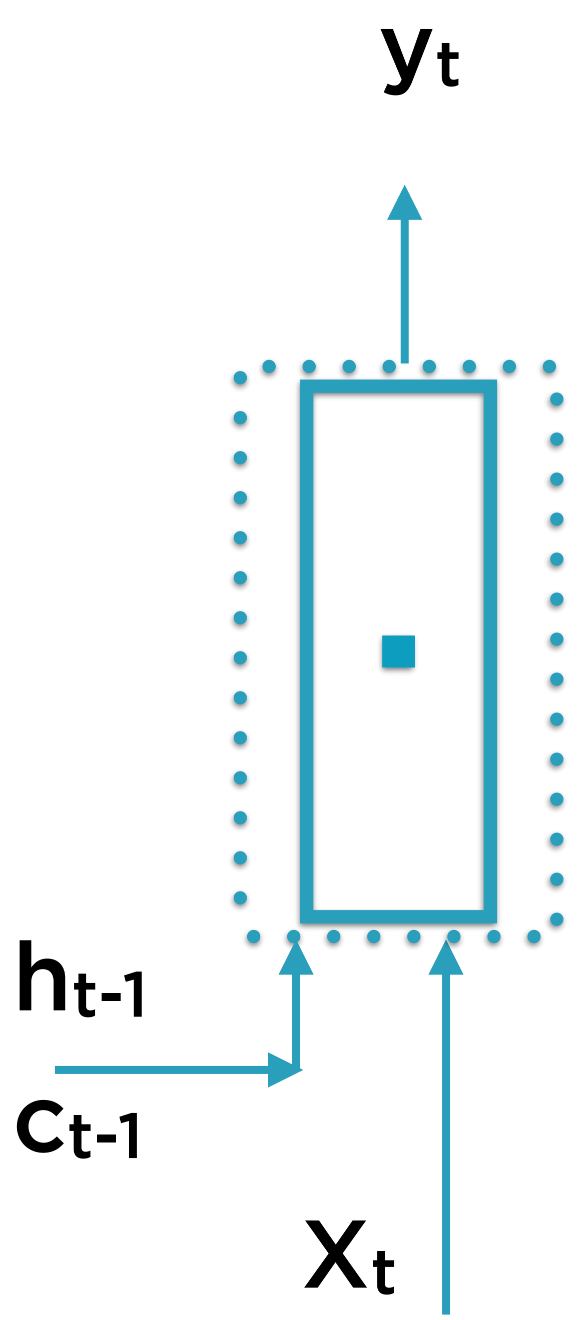
Faster training, nicer gradients

**Advantages in Prediction**

Works well with even very deep NNs

# Long/Short-Term Memory Cell (LSTM)






# LSTM Cells

Functionally like basic RNN cell

Performance far better

Amazing success at long-term patterns

Long text sequences, time series…

# Gender Prediction Based on Names

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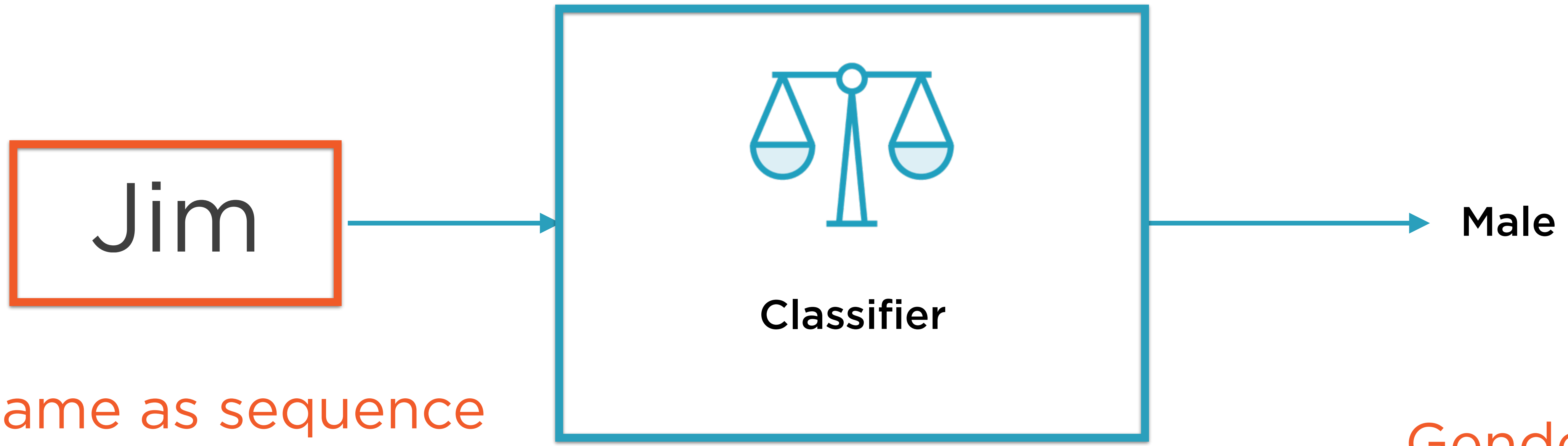


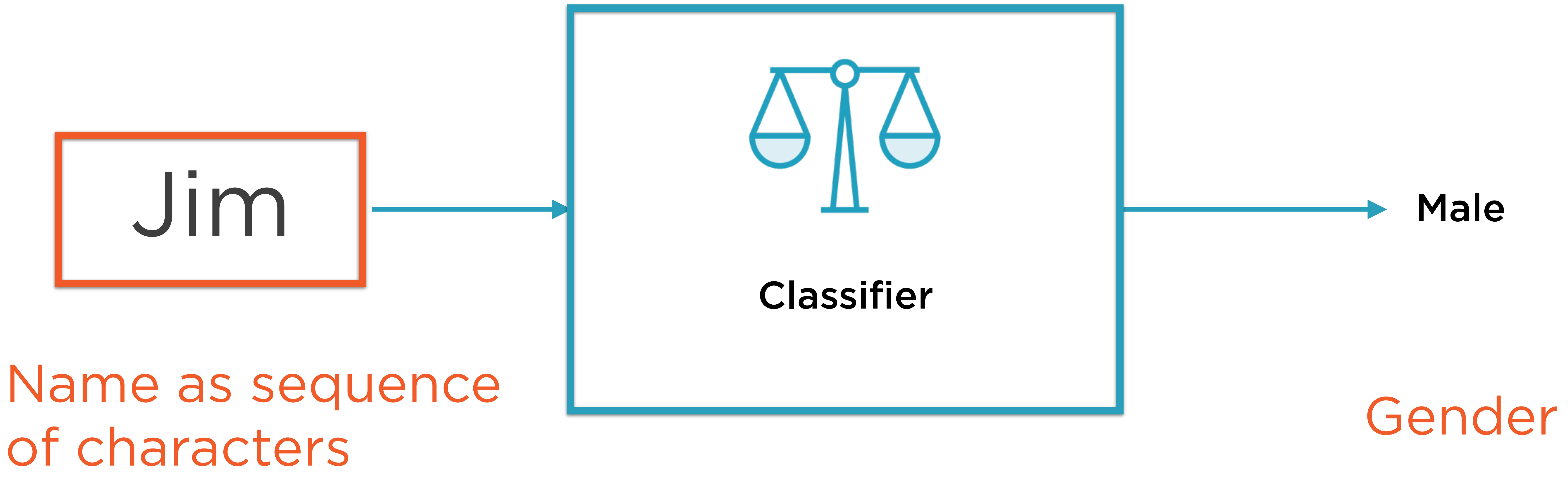

Name as sequence of characters

Gender

In PyTorch, because of dynamic computation graphs we do not need to pad names to be of the same length

This is a significant improvement over TensorFlow

# Gender Prediction Based on Names



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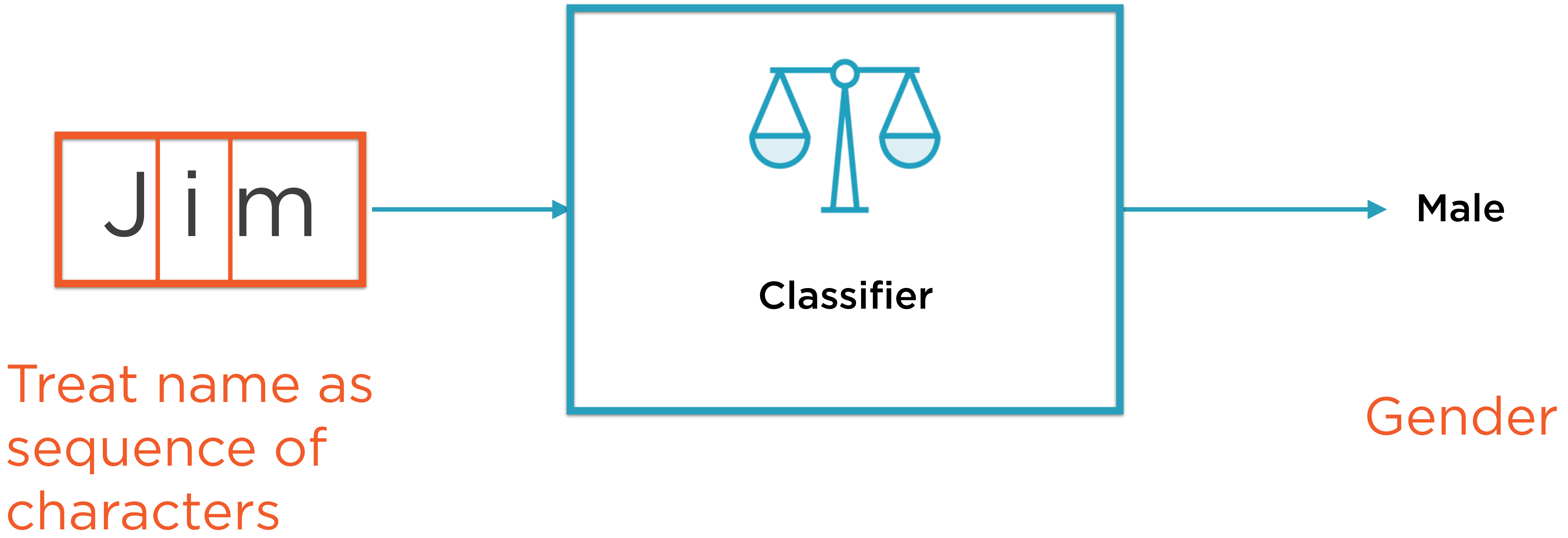

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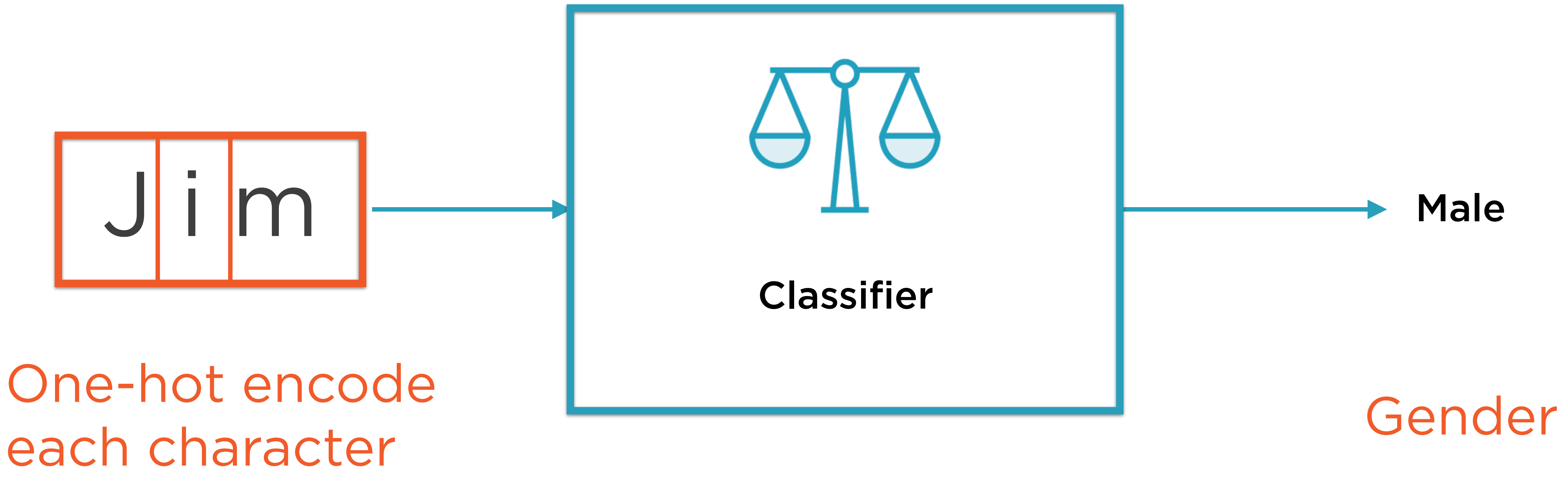

# One-hot Encoded Characters

| Letter | a | … | j | … | i | … | m | … |
|---|---|---|---|---|---|---|---|---|
| J | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| i | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| m | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |

26 elements

# One-hot Encoded Characters

| Letter | a | ... | j | ... | i | ... | m | ... |
|---|---|---|---|---|---|---|---|---|
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26 elements

# Gender Prediction Using RNNs

**Prepare Data**

Download and extract

File manipulation - simple

**Encode Names as Tensors**

No padding needed in PyTorch!

Sequence of one-hot encoded characters

**Create Neural Network**

Two linear layers

LogSoftMax output layer

**Train Model**

Backprop with loss.backward()

NLL loss to go with LogSoftMax

**Evaluate Model**

Confusion Matrix

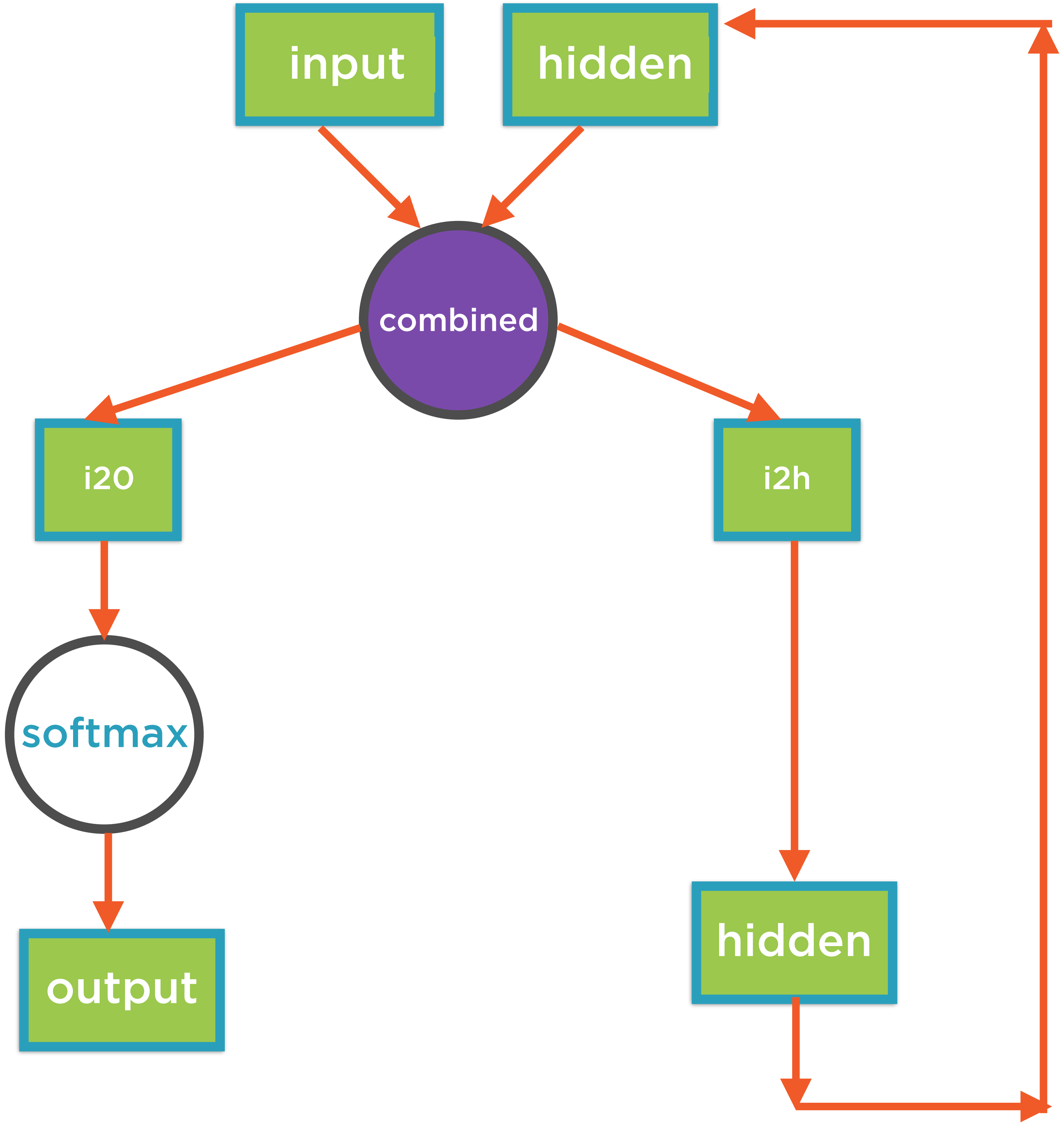
Similar to training, but no backprop

**Use in Prediction**

Ready to go!

Could add REST API server

```
class RNN(nn.Module):

# In constructor

  self.i2h = nn.Linear()

  self.i2o = nn.Linear()

  self.softmax = nn.LogSoftmax()

# Forward method

  def forward(self, input, hidden):

        combined = torch.cat((input, hidden), 1)

        hidden = self.i2h(combined)

        output = self.i2o(combined)

        output = self.softmax(output)

        return output, hidden
```



# Demo

**Gender prediction/classification from names using RNNs**

# Confusion Matrix in Evaluating Classifiers

# Confusion Matrix

Predicted Labels

Actual Label

| | Cancer | No Cancer |
|---|---|---|
| **Cancer** | **10 instances** | **4 instances** |
| **No Cancer** | **5 instances** | **1000 instances** |

# Confusion Matrix

Predicted Labels

Actual Label

| | Cancer | No Cancer |
|---|---|---|
| Cancer | **10** instances | **4** instances |
| No Cancer | **5** instances | **1000** instances |

# Confusion Matrix

Predicted Labels

Actual Label

| | Cancer | No Cancer |
|---|---|---|
| Cancer | 10 | 4 |
| No Cancer | 5 | 1000 |

# True Positive

Predicted Labels

Actual Label

| | Cancer | No Cancer |
|---|---|---|
| Cancer | 10 TP | 4 |
| No Cancer | 5 | 1000 |

Actual Label = Predicted Label

# False Positive

| Actual Label \ Predicted Labels | Cancer | No Cancer |
|---|---|---|
| Cancer | 10 | 4 |
| No Cancer | 5 FP | 1000 |

Actual Label ≠ Predicted Label

# True Negative

Predicted Labels

Actual Label

| | Cancer | No Cancer |
|---|---|---|
| Cancer | 10 | 4 |
| No Cancer | 5 | 1000 TN |

Actual Label = Predicted Label

# False Negative

Predicted Labels

Actual Label

| | Cancer | No Cancer |
|---|---|---|
| Cancer | 10 | 4 FN |
| No Cancer | 5 | 1000 |

Actual Label ≠ Predicted Label

# Accuracy

Predicted Labels

Actual Label

| | Cancer | No Cancer |
|---|---|---|
| Cancer | TP 10 | FN 4 |
| No Cancer | FP 5 | TN 1000 |

$$\text{Accuracy} = \frac{\text{TP + TN}}{\text{Num Instances}} = \frac{1010}{1019} = 99.12\%$$

# Precision

| Actual Label | Predicted Labels: Cancer | Predicted Labels: No Cancer |
|---|---|---|
| Cancer | 10 TP | 4 FN |
| No Cancer | 5 FP | 1000 TN |

Precision = Accuracy when classifier flags cancer

# Recall

| Actual Label \ Predicted Labels | Cancer | No Cancer |
|---|---|---|
| Cancer | TP 10 | FN 4 |
| No Cancer | FP 5 | TN 1000 |

Recall = Accuracy when cancer actually present

# Summary

Recurrent Neural Networks (RNNs) are another common NN architecture

Great for working with sequences

Classification using RNNs

PyTorch has built-in support for RNNs

# Related Courses

Building Classification Models with TensorFlow

Building Unsupervised Learning Models with TensorFlow

Deep Learning Using TensorFlow and Apache MXNet on AWS SageMaker

Building and Deploying Keras in a Multi-cloud Environment