Recurrent Neural Networks

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Most slides have been adopted from Fei Fei Li and colleagues lectures, cs231n, Stanford and some slides from Bhiksha Raj, 11-785, CMU

Sequences in the wild

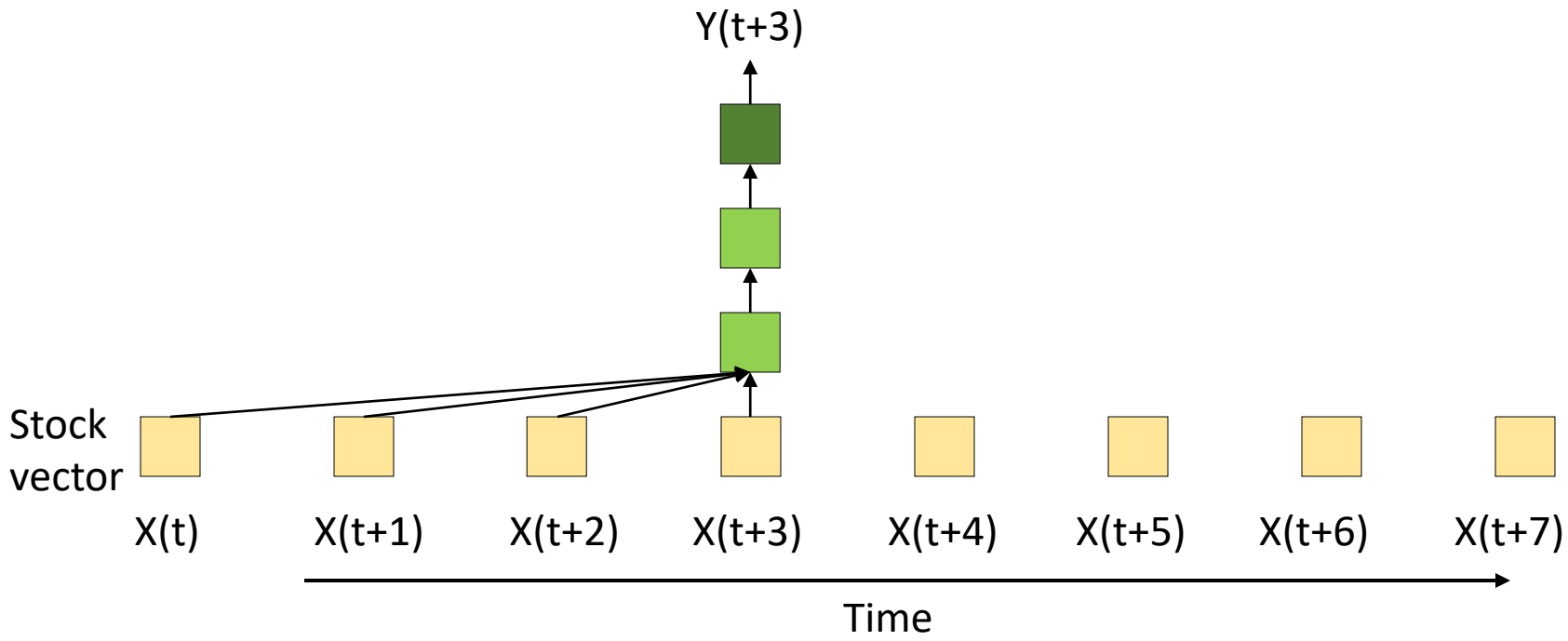
Source: Ava Amini & Alex Amini, Deep learning course, MIT

Modelling Series

- In many situations one must consider a *series* of inputs to produce an output
  - Outputs too may be a series

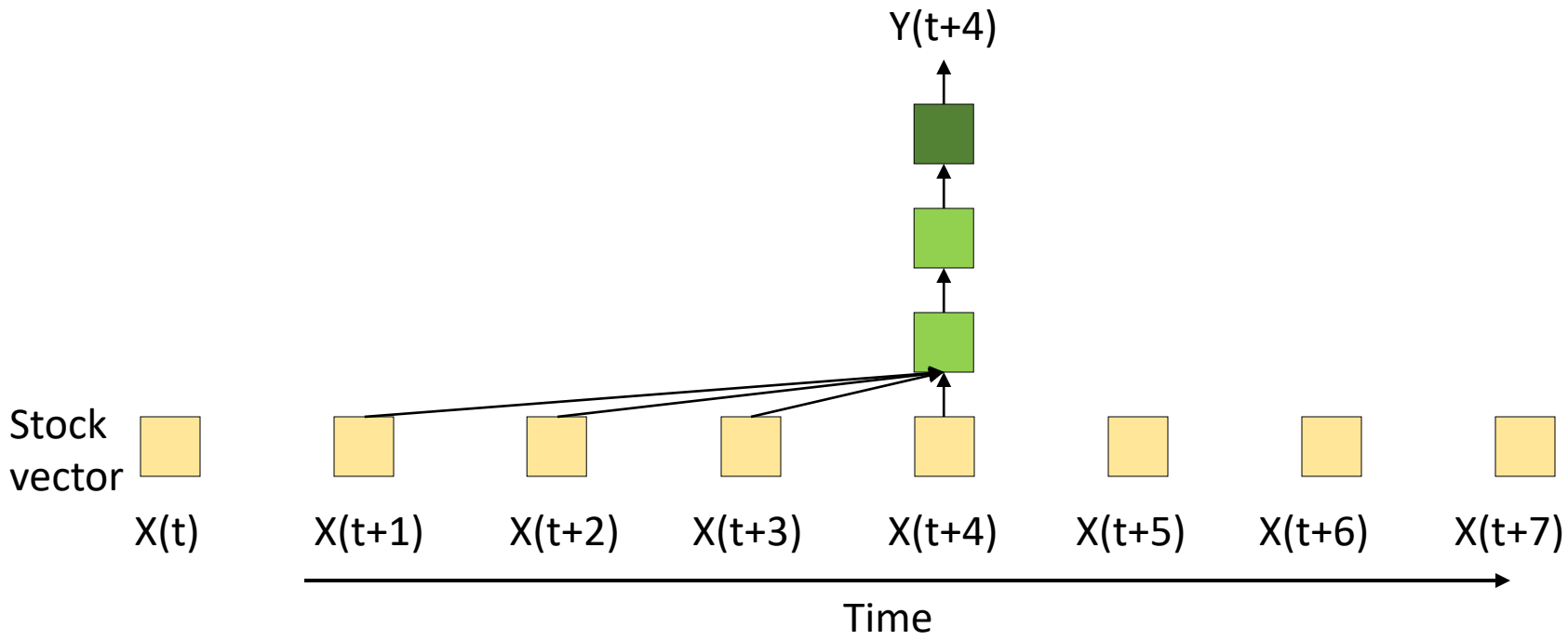
- Examples: ..

The stock predictor



- The sliding predictor
  - Look at the last few days
  - This is just a convolutional neural net applied to series data
    - Also called a *Time-Delay Neural Network (TDNN)*

The stock predictor



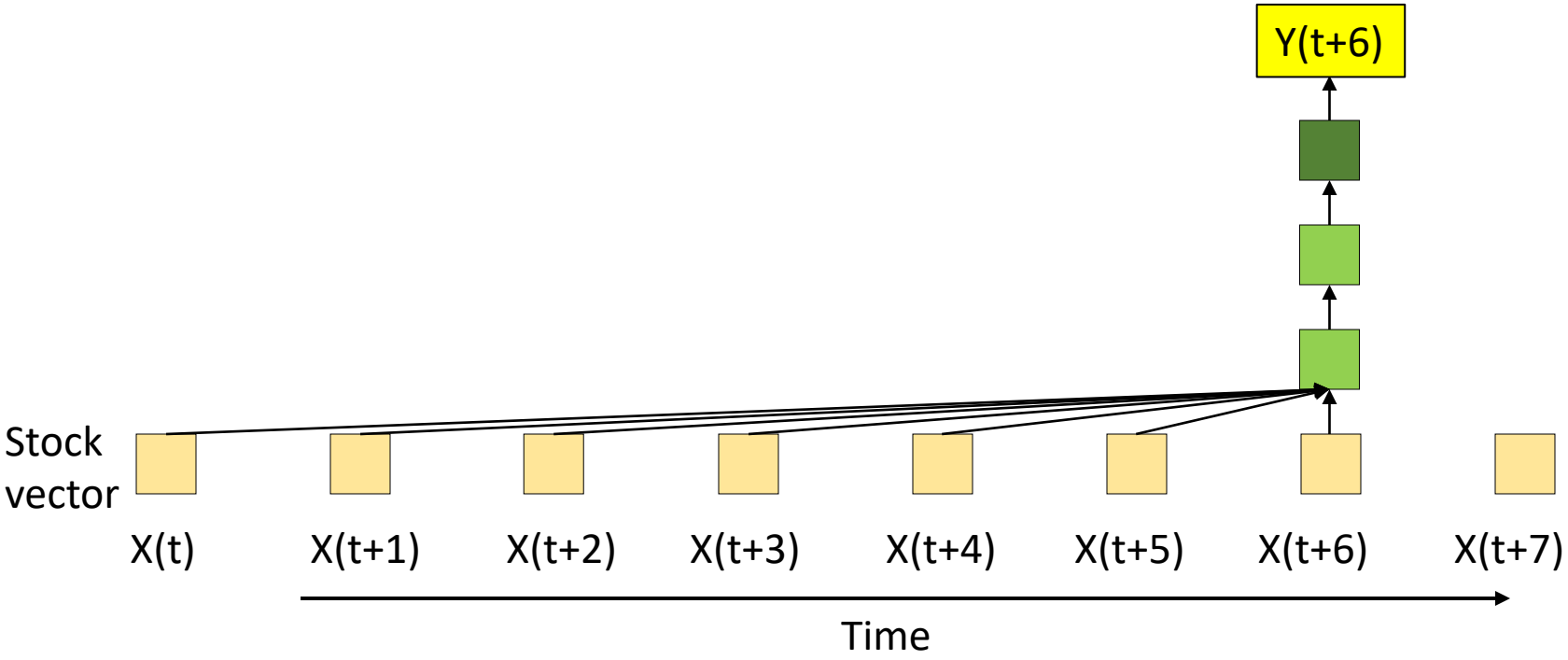
- The sliding predictor
  - Look at the last few days
  - This is just a convolutional neural net applied to series data
    - Also called a *Time-Delay Neural Network (TDNN)*

Finite-response model

- This is a *finite response* system
  - Something that happens *today* only affects the output of the system for N days into the future
    - N is the *width* of the system

$$Y_t = f(X_t, X_{t-1}, \ldots, X_{t-N})$$

Finite-response

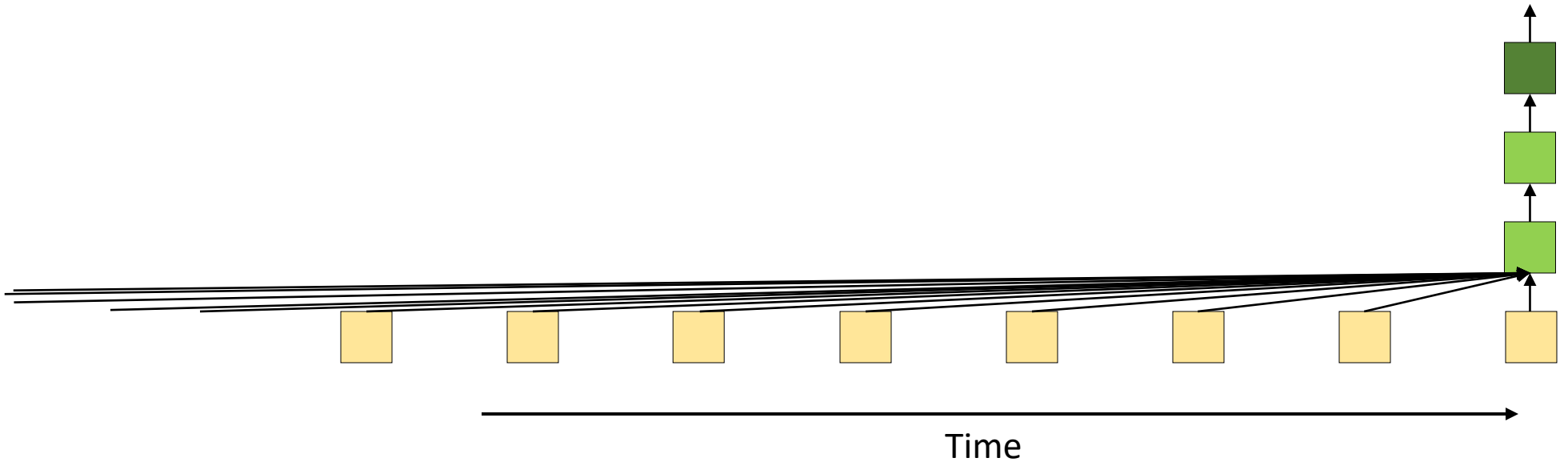


- Problem: Increasing the "history" makes the network more complex
  - No worries, we have the CPU and memory
    - Or do we?

Systems often have long-term dependencies

- Longer-term trends
  - Weekly trends in the market
  - Monthly trends in the market
  - Annual trends
  - Though longer historic tends to affect us less than more recent events..

We want *infinite* memory



- Required: *Infinite* response systems
  - What happens today can continue to affect the output forever
    - Possibly with weaker and weaker influence

$$Y_t = f(X_t, X_{t-1}, \ldots, X_{t-\infty})$$

An alternate model for infinite response: state-space model

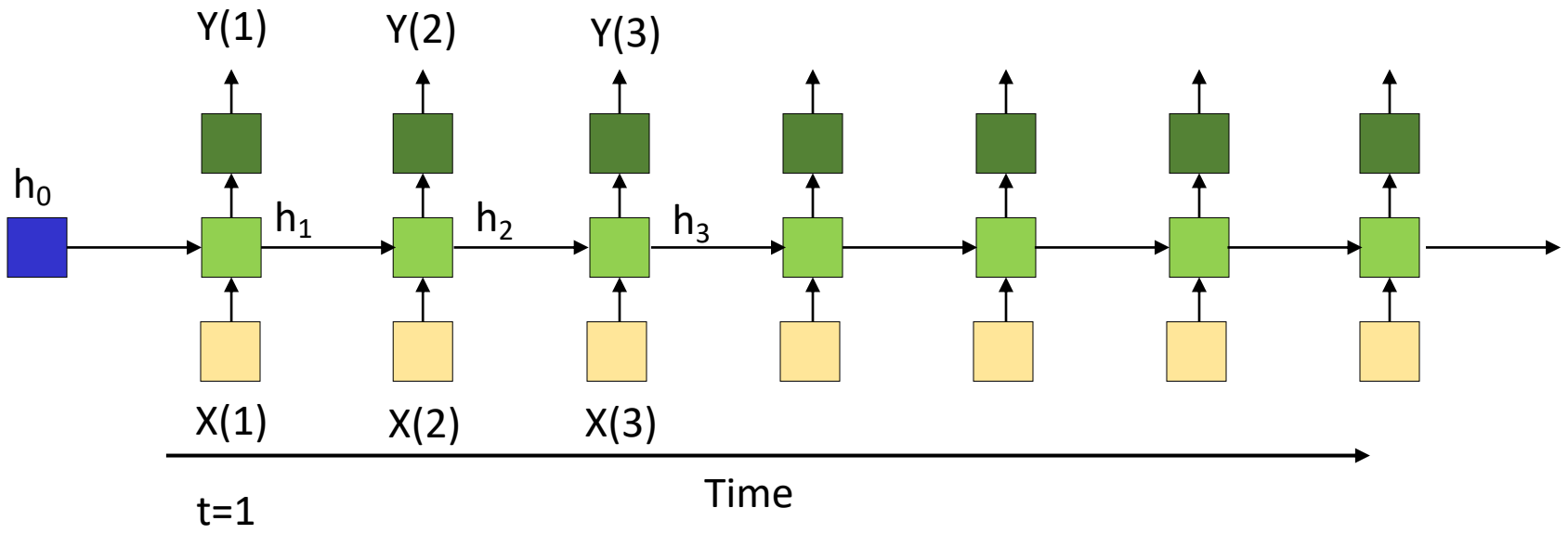
- State-space model:

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

$$y_t = g(h_t)$$

- h_t is the *state* of the network
  - Model directly embeds the memory in the state
- Need to define initial state h_0
- This is a *fully recurrent* neural network
  - Or simply a *recurrent neural network*
- *State* summarizes information about the entire past

The simple state-space model



- The state (green) at any time is determined by the input at that time, and the state at the previous time
- Also known as a recurrent neural net

Recurrent Neural Network

We can process a sequence of vectors **x** by applying a recurrence formula at every time step:

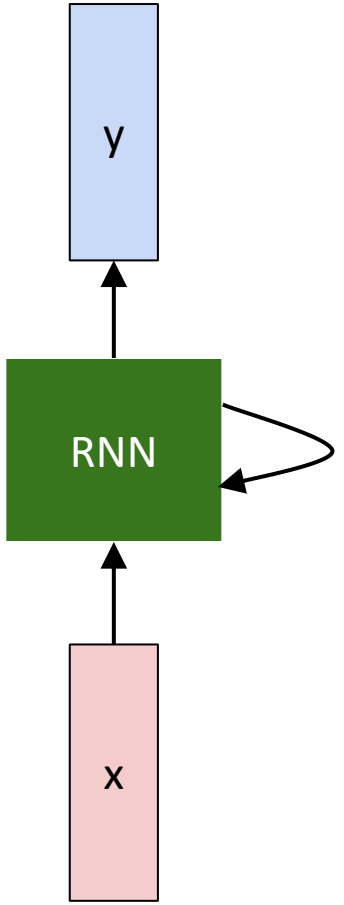
$$h_t = f_W(h_{t-1}, x_t)$$

new state

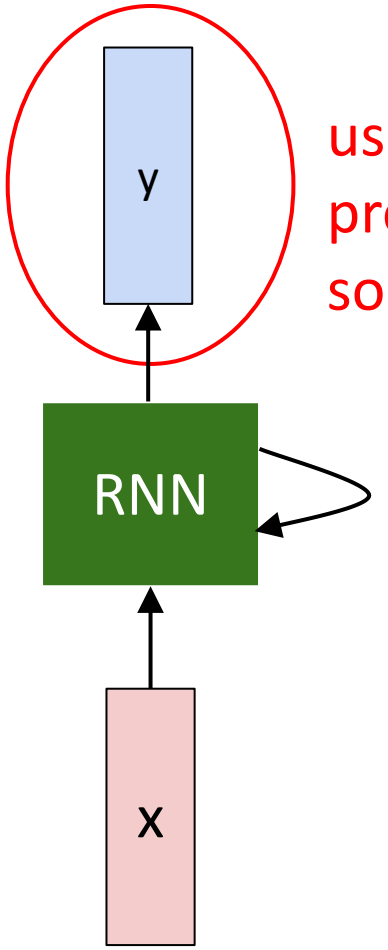
some function with parameters W

old state

input vector at some time step



Recurrent Neural Network

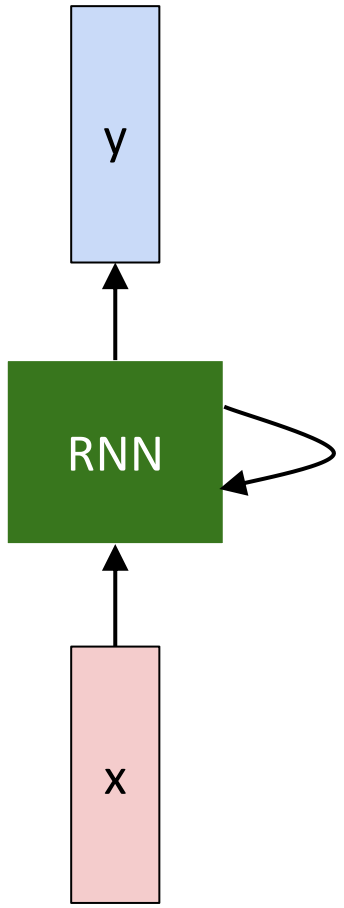


usually want to predict a vector at some time steps

Recurrent Neural Network

We can process a sequence of vectors **x** by applying a recurrence formula at every time step:

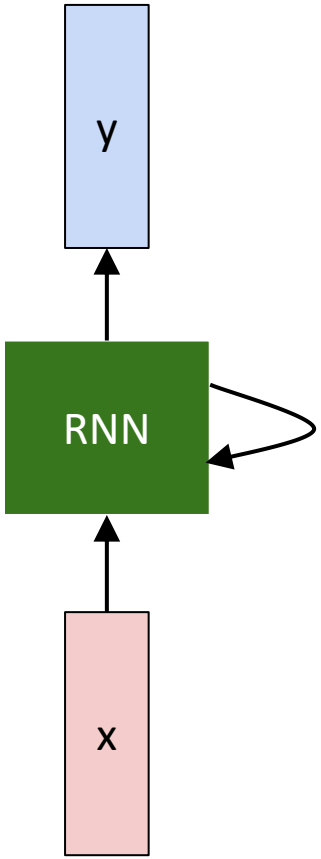
$$h_t = f_W(h_{t-1}, x_t)$$



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

(Vanilla) Recurrent Neural Network

The state consists of a single *"hidden"* vector **h**:

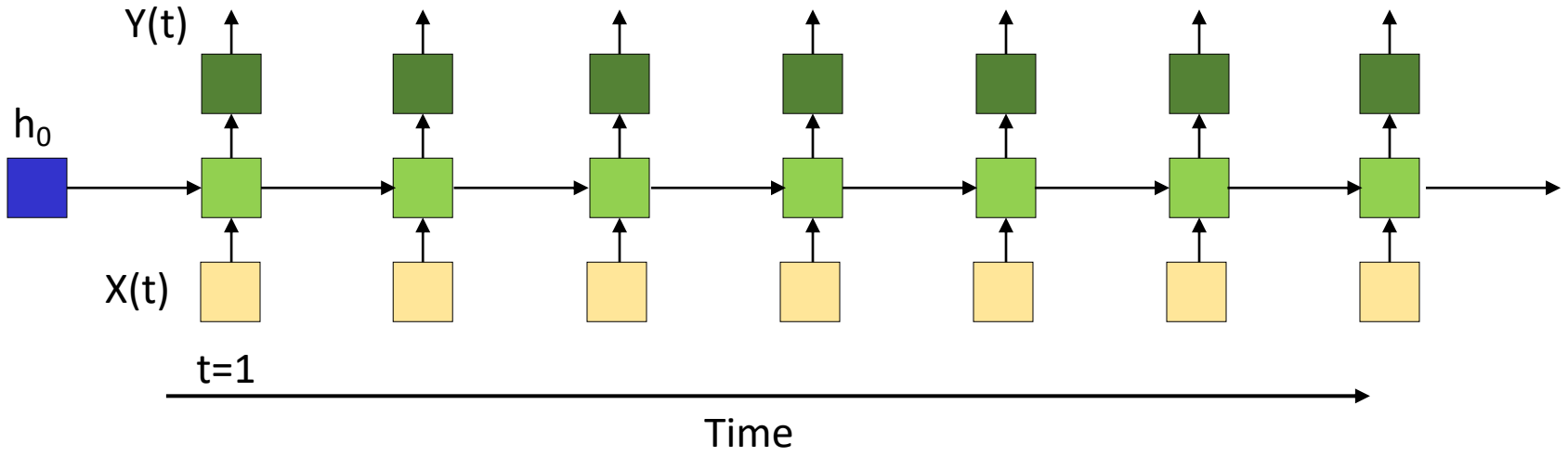


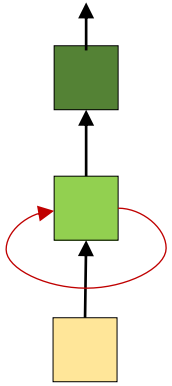
$$h_t = f_W(h_{t-1}, x_t)$$

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

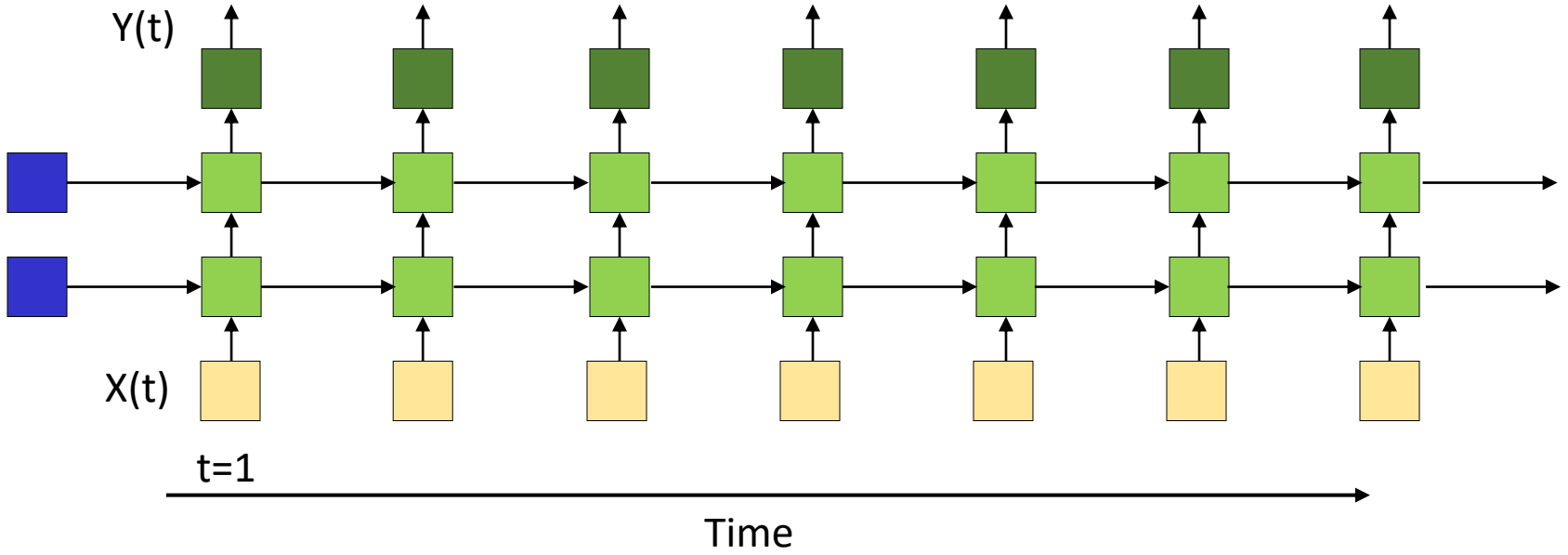
$$y_t = W_{hy}h_t$$

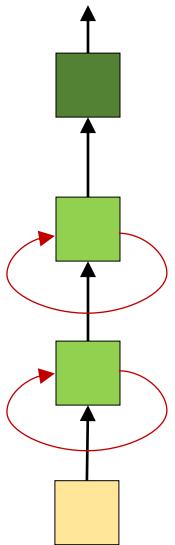
Single hidden layer RNN



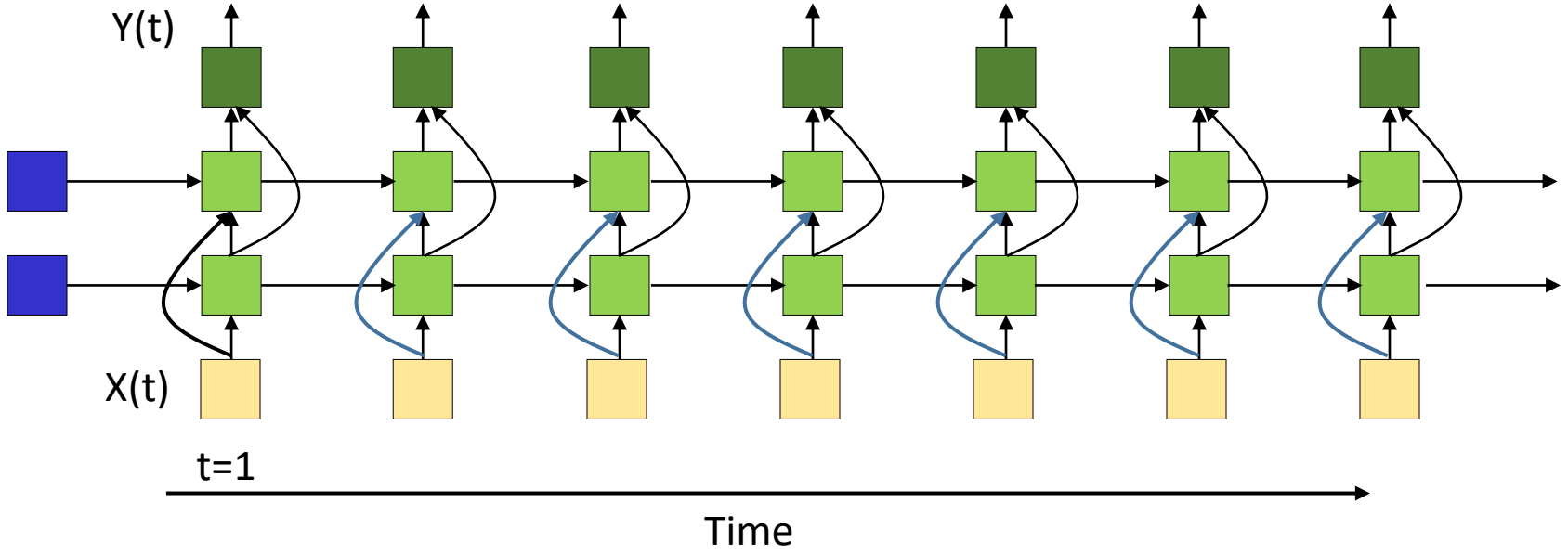


Multiple recurrent layer RNN

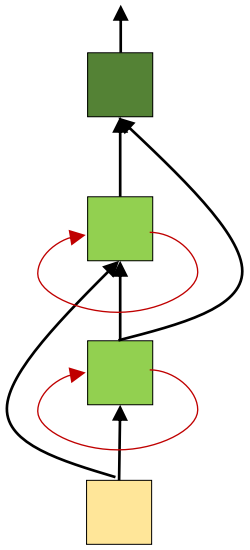




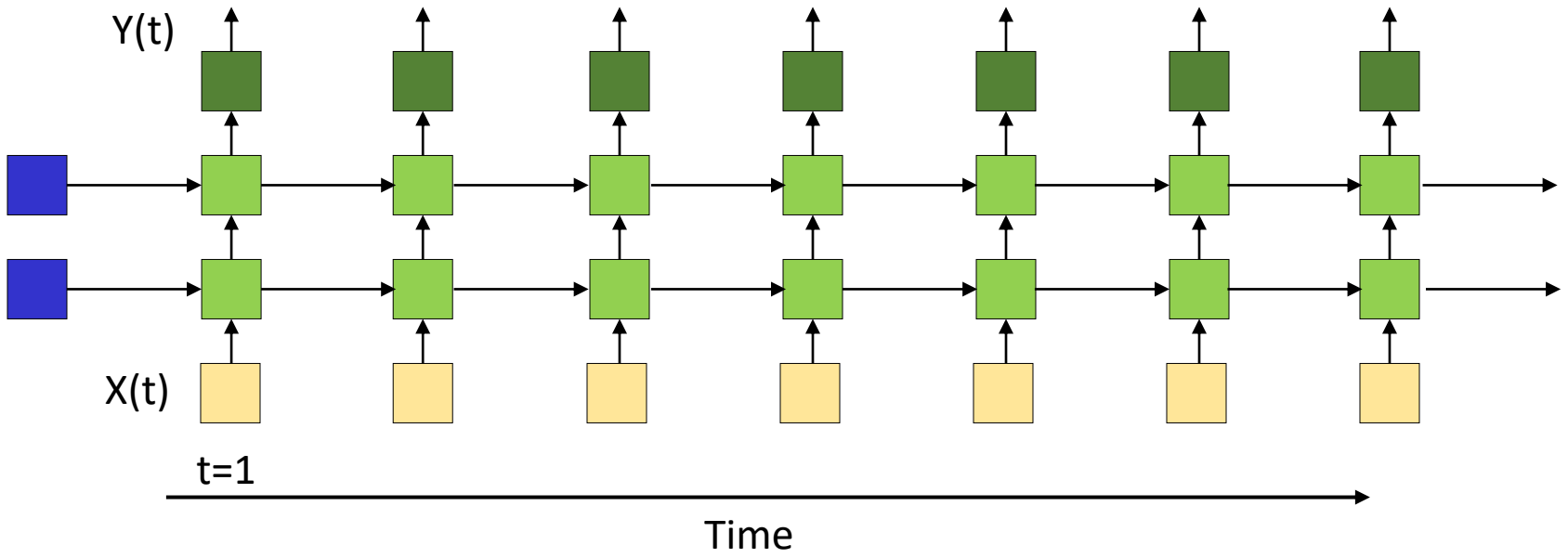
Multiple recurrent layer RNN



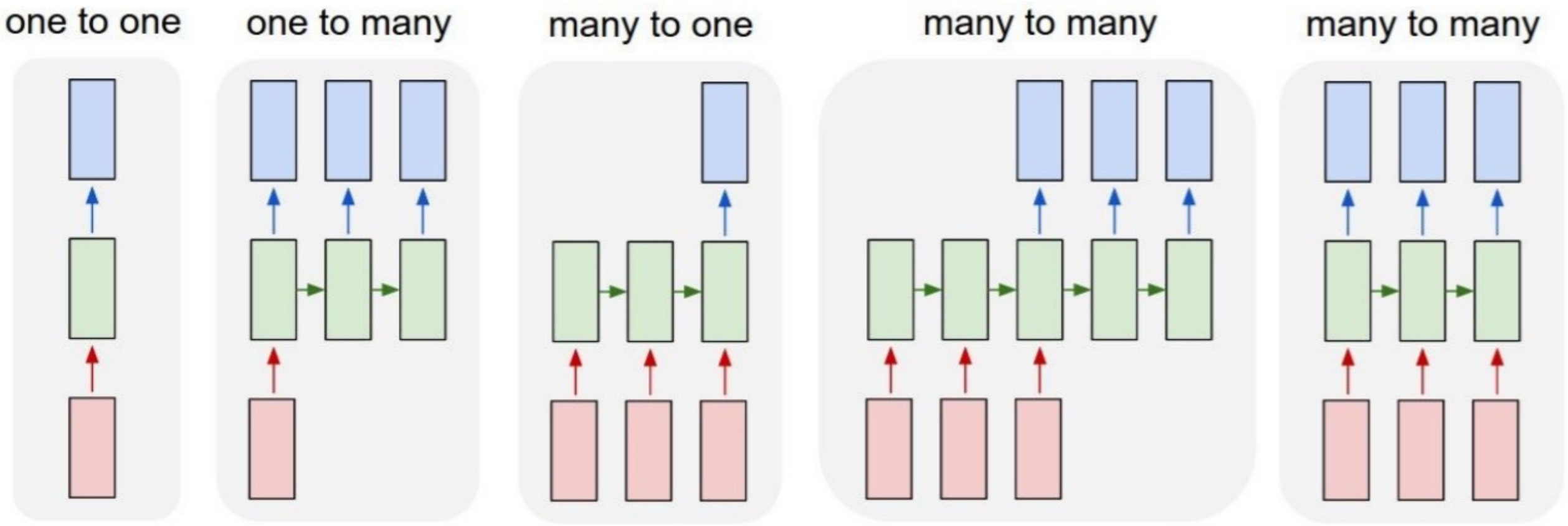
- We can also have skips..



The simplest structures are most popular



Recurrent Neural Networks: Process Sequences



"Vanilla" NN

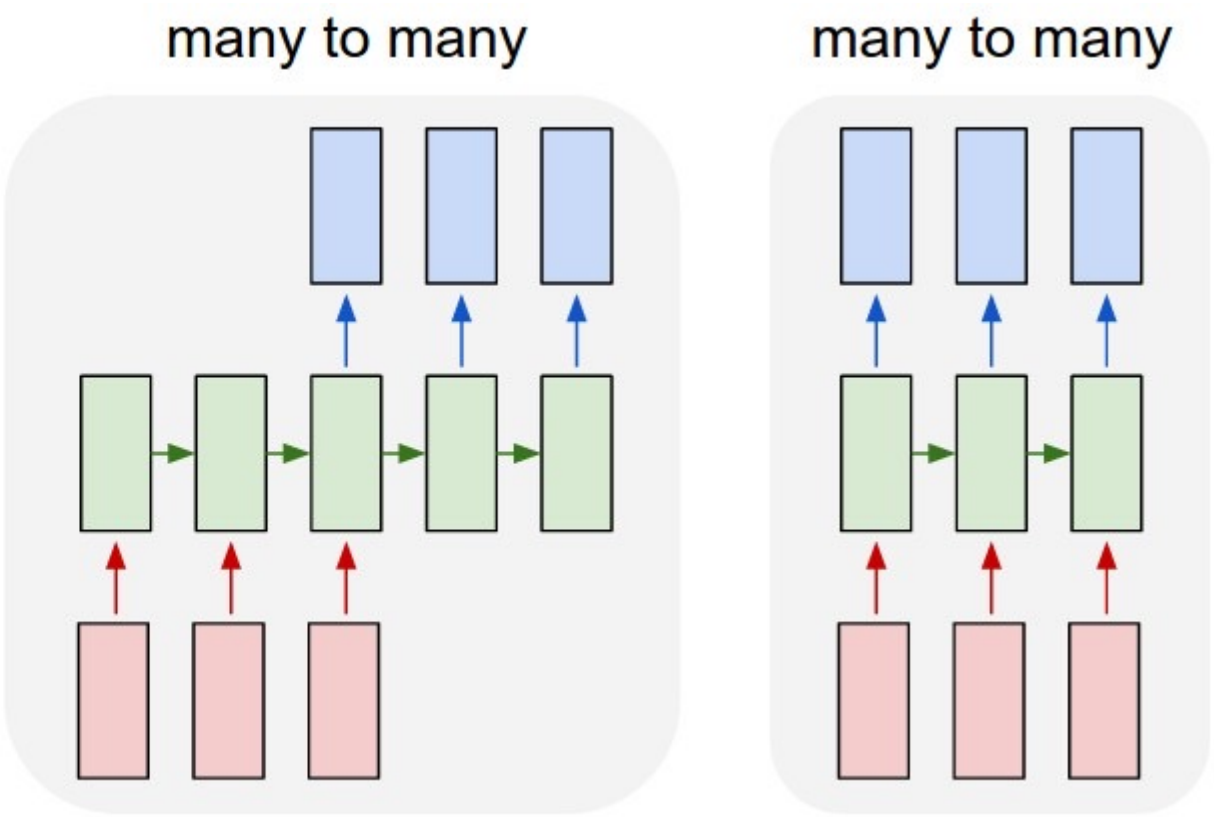
e.g. Image Captioning
image -> seq of words

e.g. Sentiment Classification
seq of words -> sentiment

e.g. Machine Translation
seq of words -> seq of words

e.g. Video classification on frame level

Variants

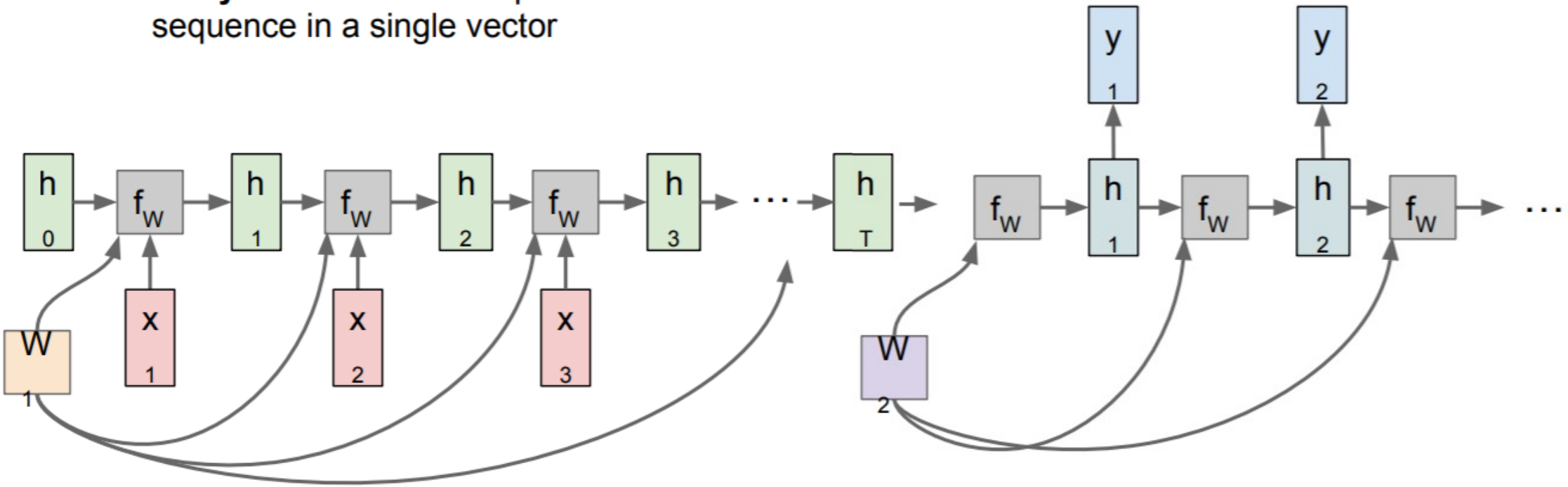


- 1: *Delayed* sequence to sequence
- 2: Sequence to sequence, e.g. stock problem, label prediction
- Etc…

Sequence to Sequence: Many-to-one + one-to-many

Many to one: Encode input sequence in a single vector

One to many: Produce output sequence from single input vector



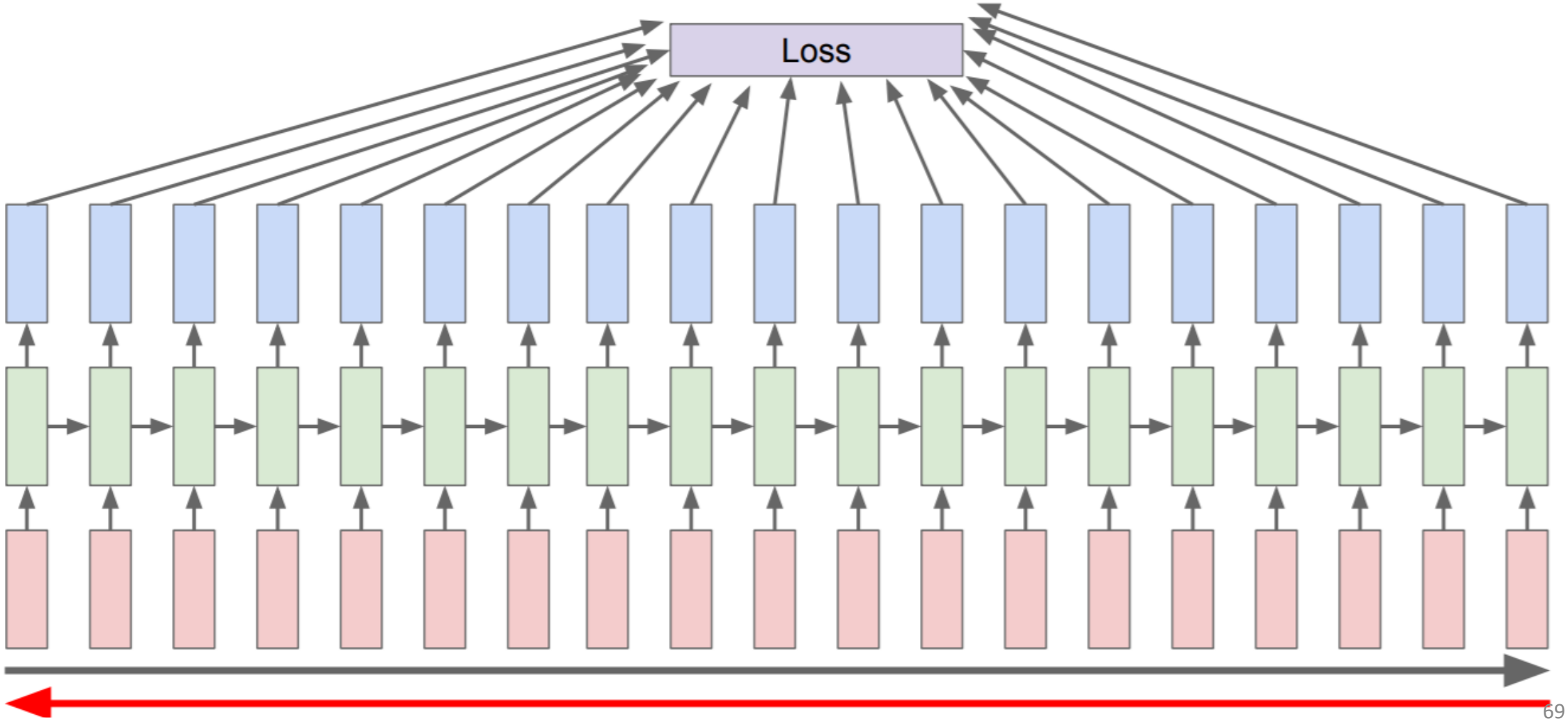
Story so far

- Time series analysis must consider past inputs along with current input
- Looking into the infinite past requires recursion

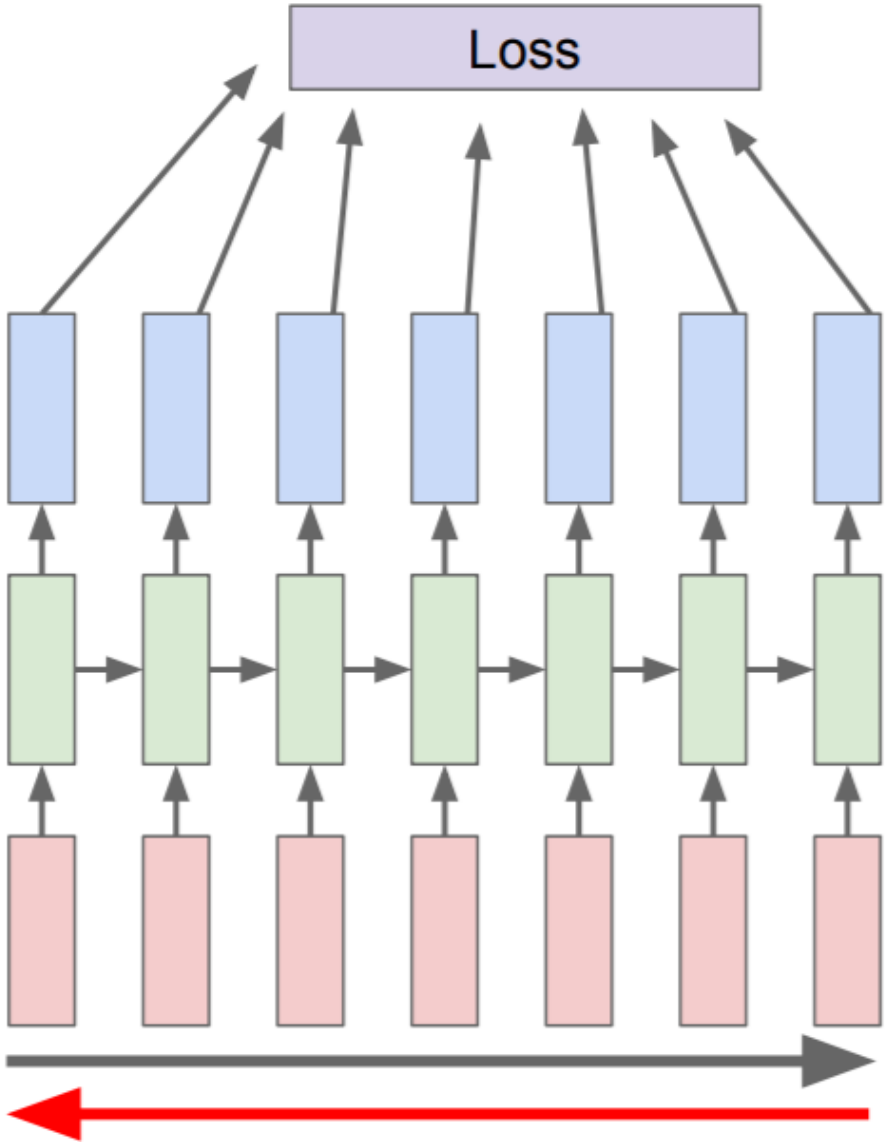
- State-space models retain information about the past through recurrent hidden states
  - These are "fully recurrent" networks
  - The initial values of the hidden states are generally learnable parameters as well

Backpropagation through time

Forward through entire sequence to compute loss, then backward through entire sequence to compute gradient

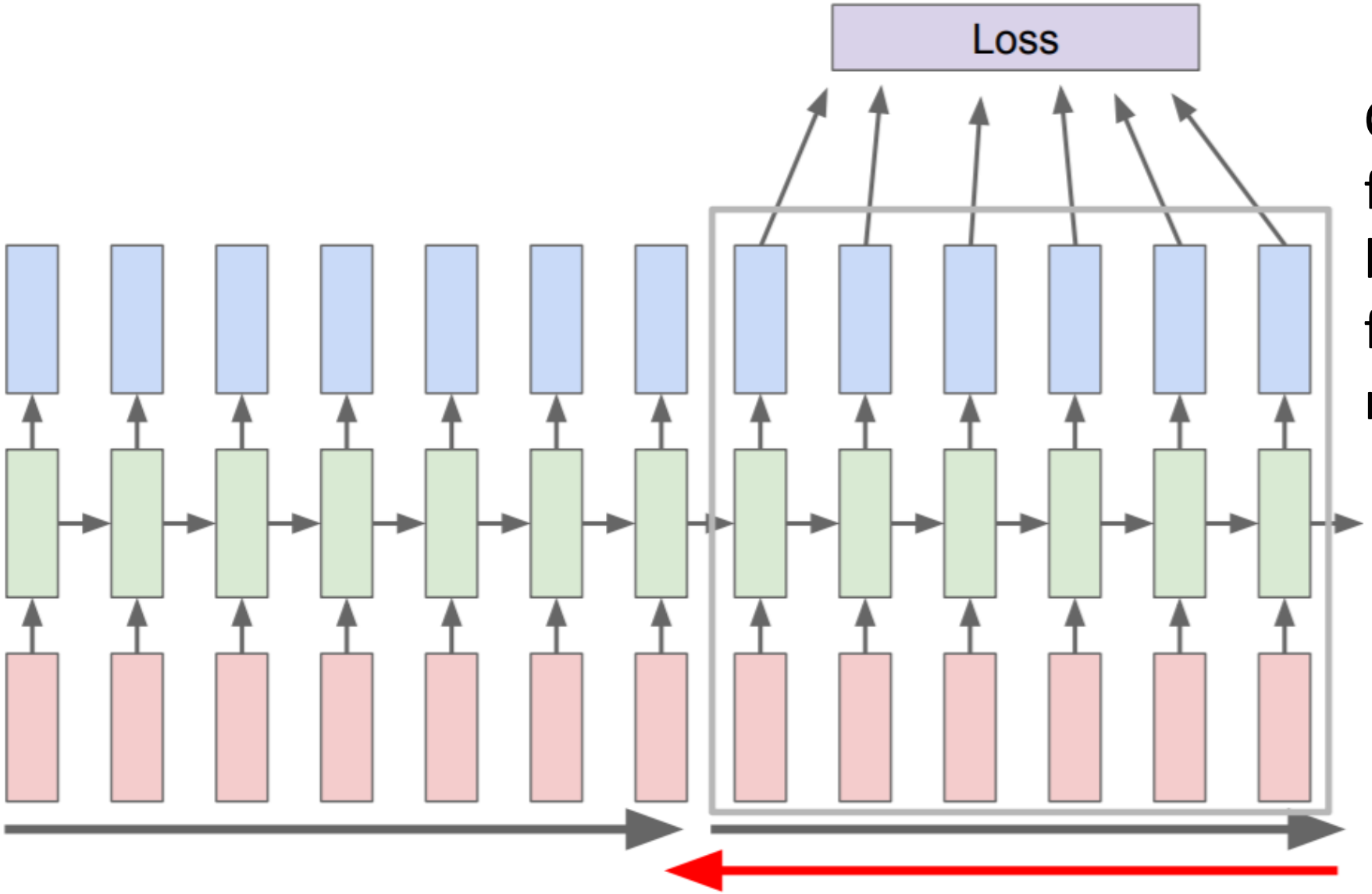


Truncated Backpropagation through time



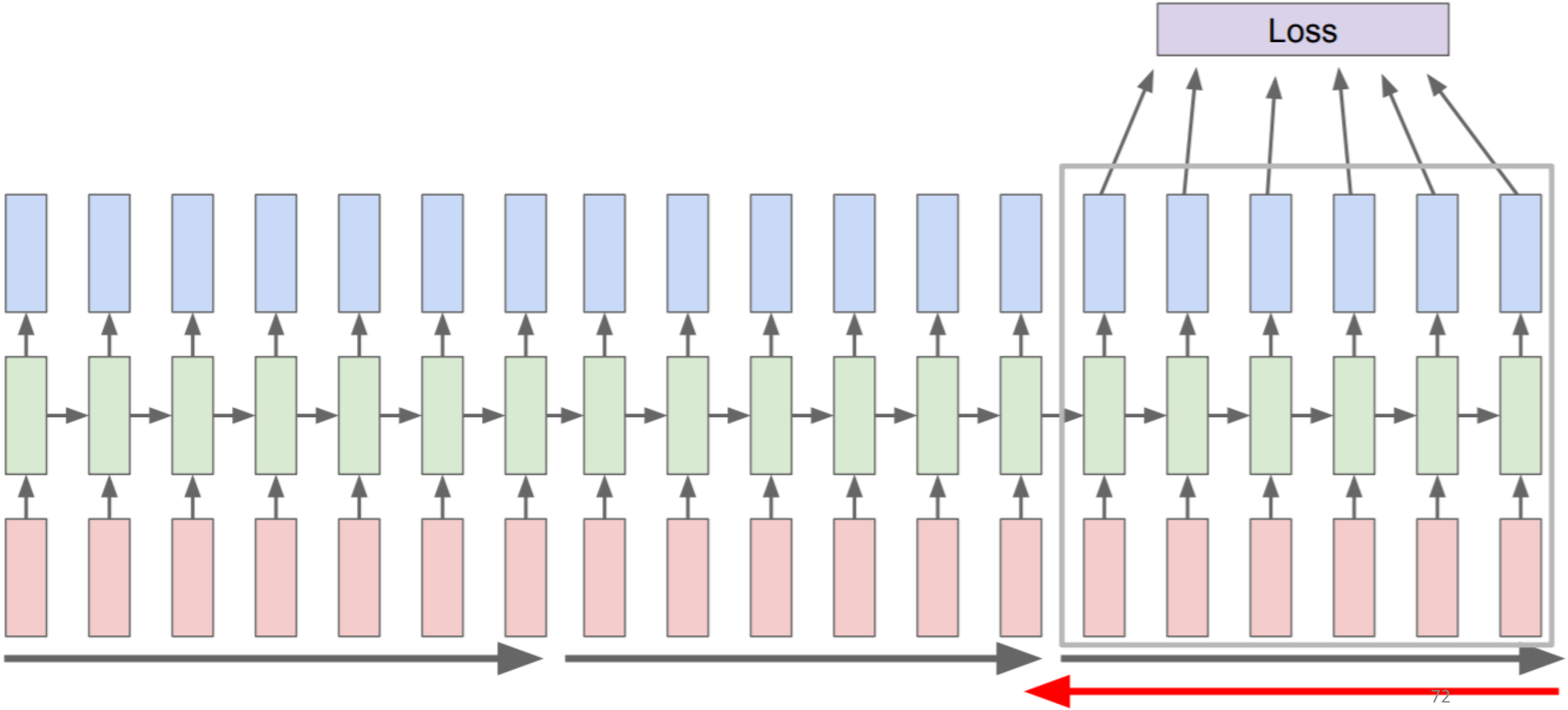
Run forward and backward through chunks of the sequence instead of whole sequence

Truncated Backpropagation through time

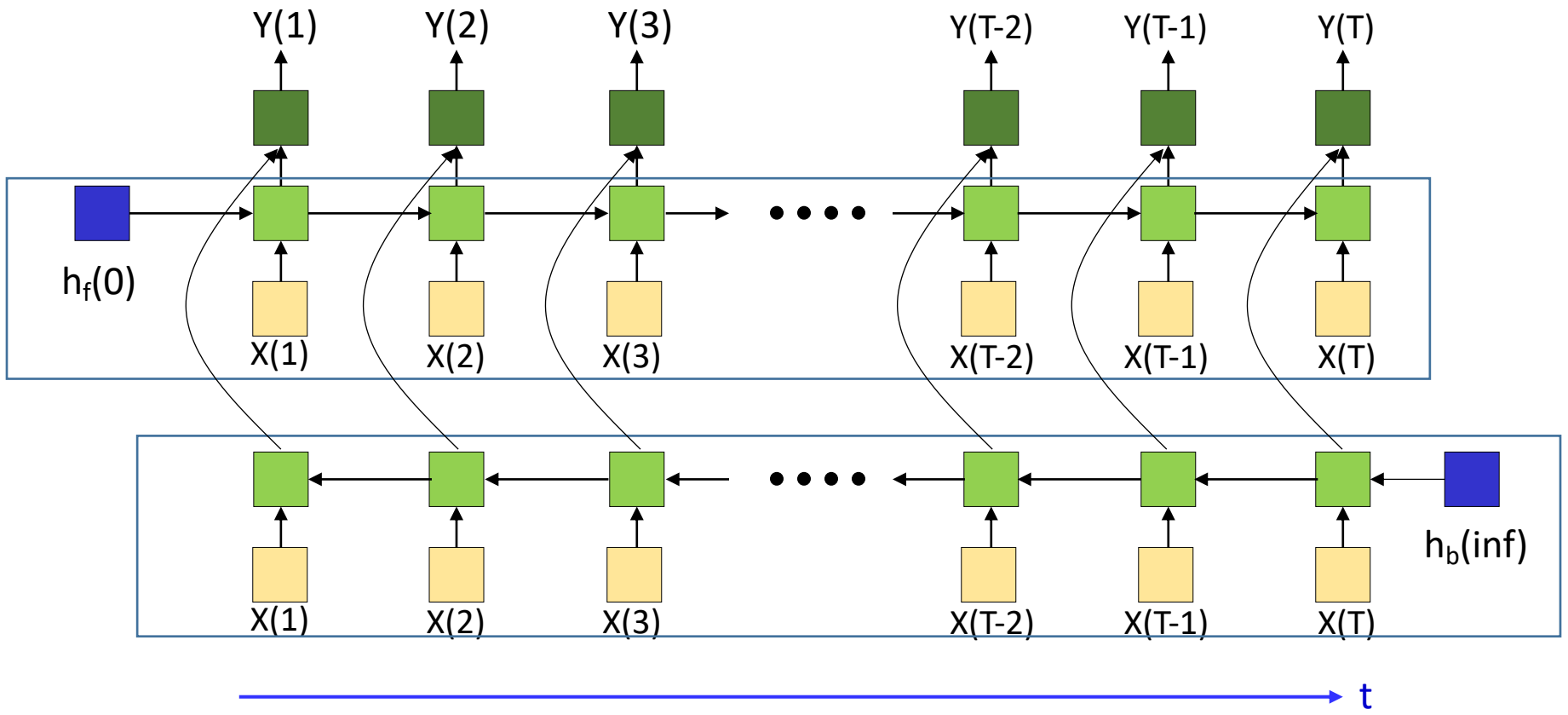


Carry hidden states forward in time forever, but only backpropagate for some smaller number of steps

Truncated Backpropagation through time

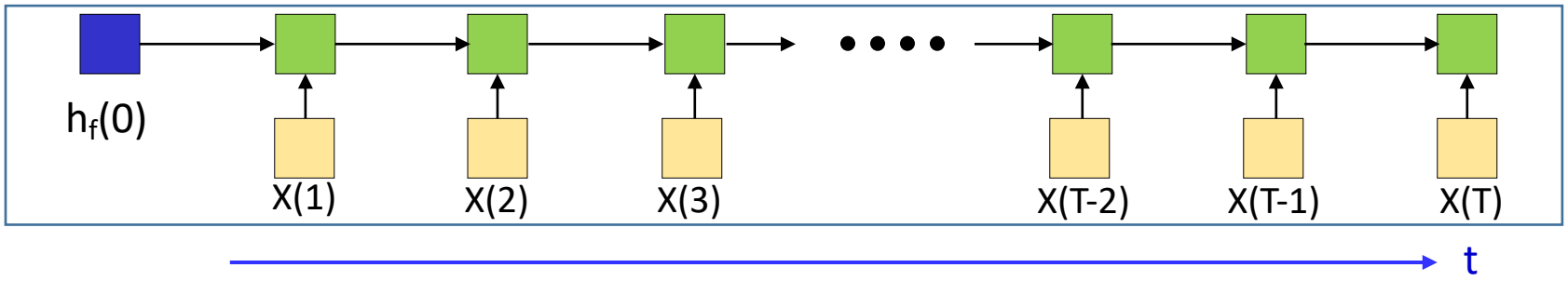


Bidirectional RNN



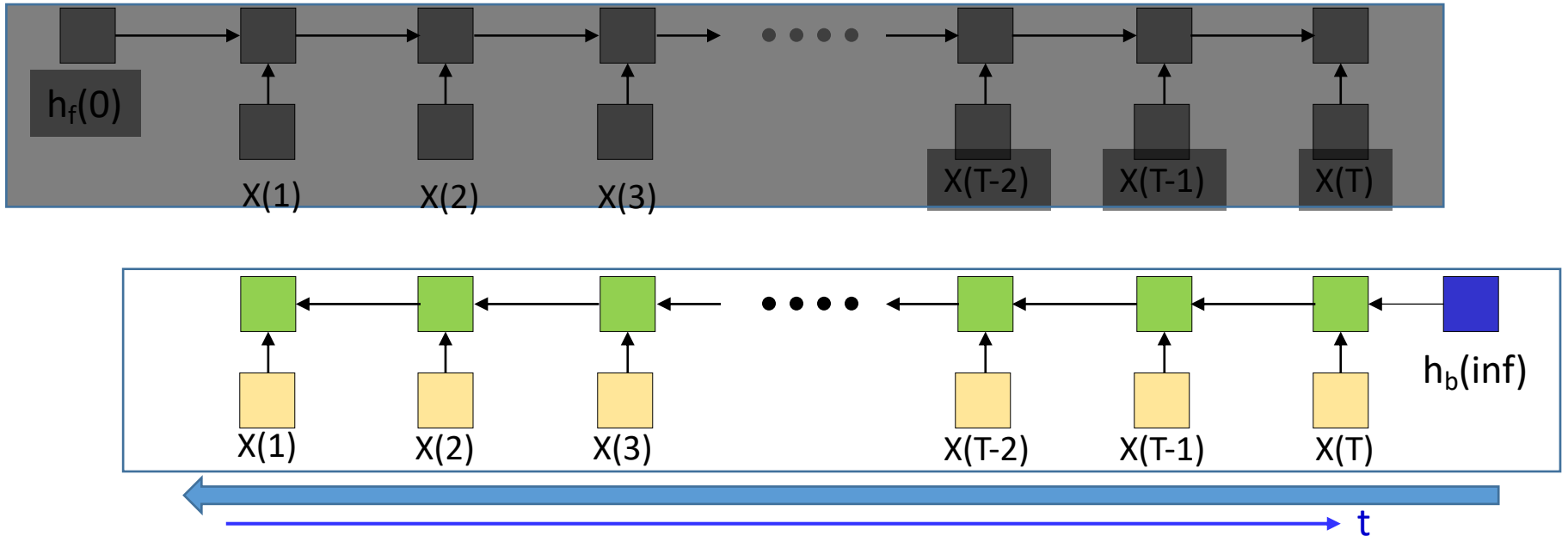
- A forward net process the data from t=1 to t=T
- A backward net processes it backward from t=T down to t=1

Bidirectional RNN: Processing an input string



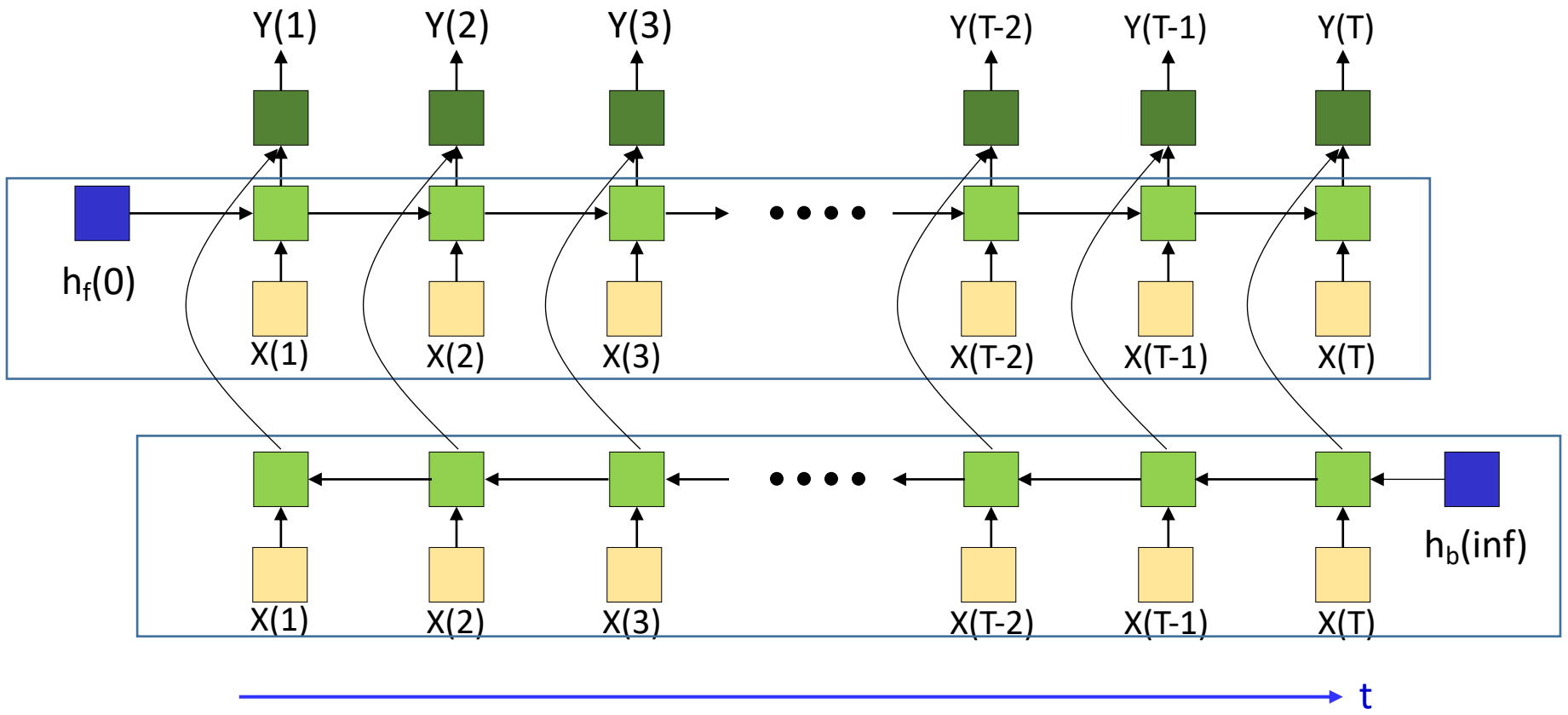
- The forward net process the data from t=1 to t=T
  - Only computing the hidden states, initially

Bidirectional RNN: Processing an input string



- The backward nets processes the input data in *reverse time,* end to beginning
  - Initially only the hidden state values are computed
    - Clearly, this is not an online process and requires the *entire* input data
  - Note: *This is not the backward pass of backprop.*

Bidirectional RNN: Processing an input string



- The computed states of both networks are used to compute the final output at each time

Story so far

- RNNs for sequence modeling
  - Handle inputs with variable lengths
  - In theory, can track long term history
  - Share parameters across the sequence
  - Consider the order of inputs

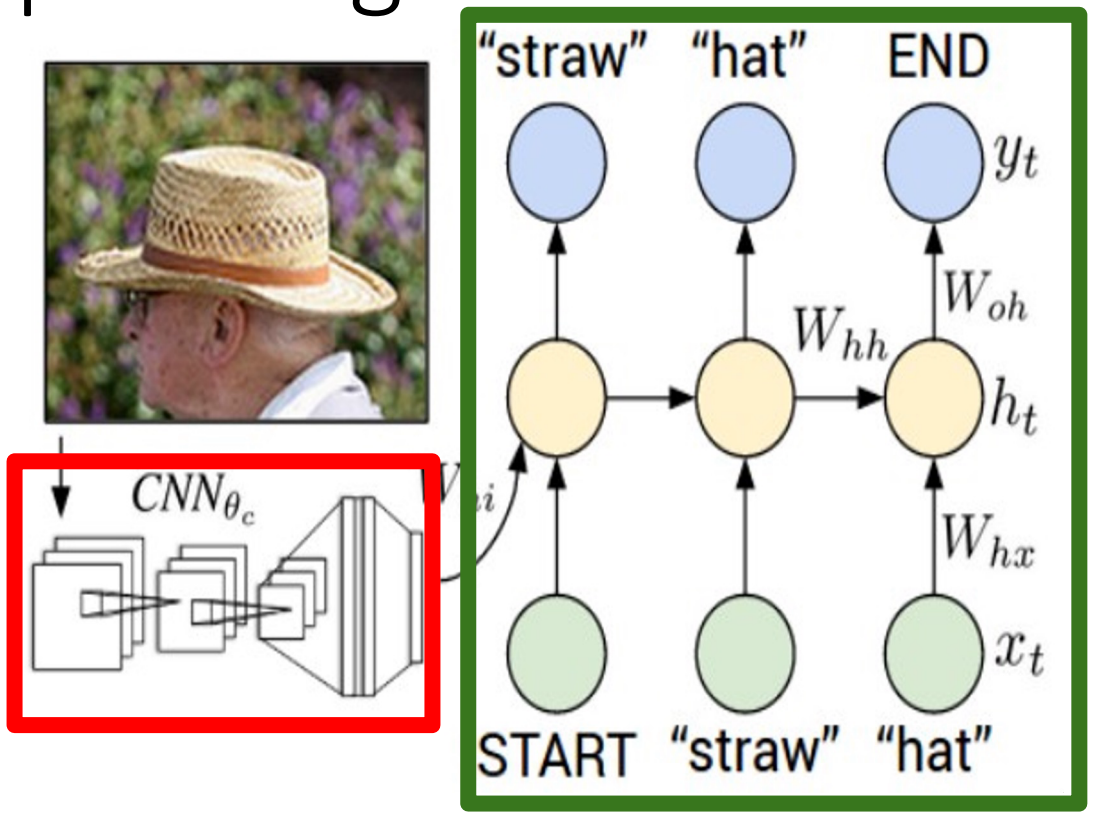
RNNs..

- Excellent models for time-series analysis tasks
  - Time-series prediction
  - Time-series classification
  - Sequence prediction..

RNN tradeoffs

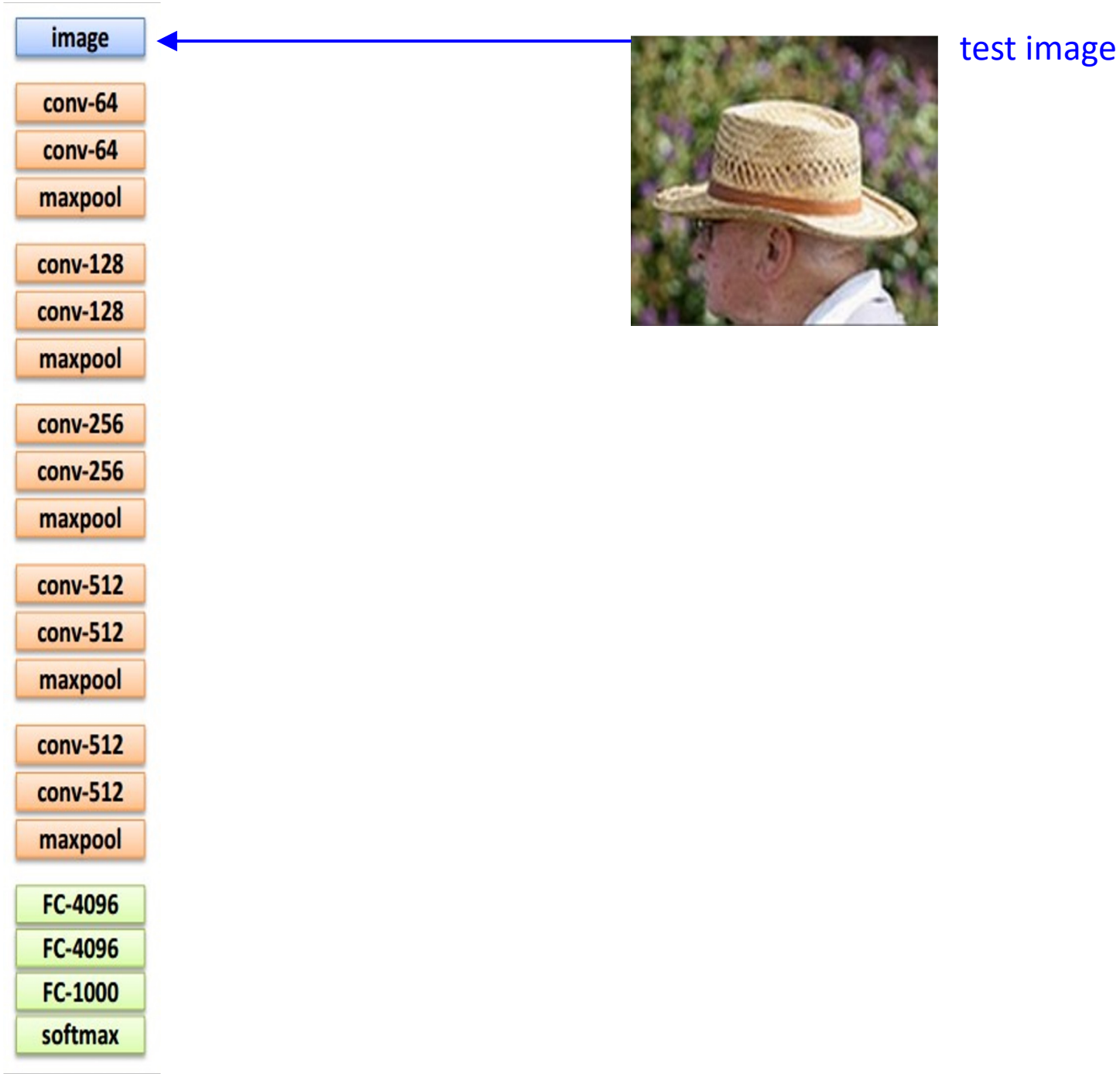
- RNN Advantages:
  - Can process any length input
  - Computation for step t can (in theory) use information from many steps back
  - Model size doesn't increase for longer input
  - Same weights applied on every timestep, so there is symmetry in how inputs are processed.
- RNN Disadvantages:
  - Recurrent computation is slow
  - In practice, difficult to access information from many steps back

Image Captioning



Deep Visual-Semantic Alignments for Generating Image Descriptions, Karpathy and Fei-Fei, CVPR 2016.

test image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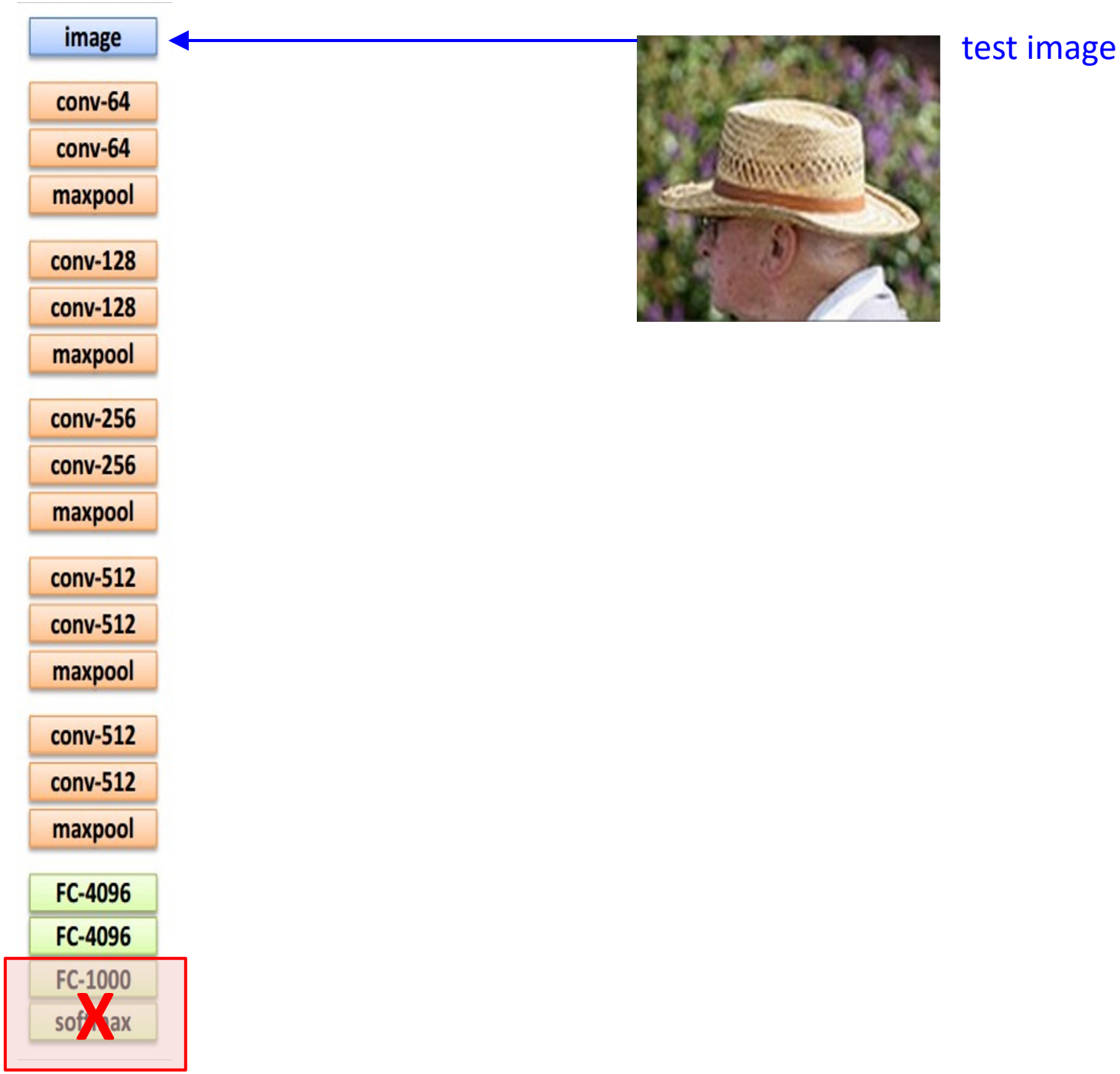
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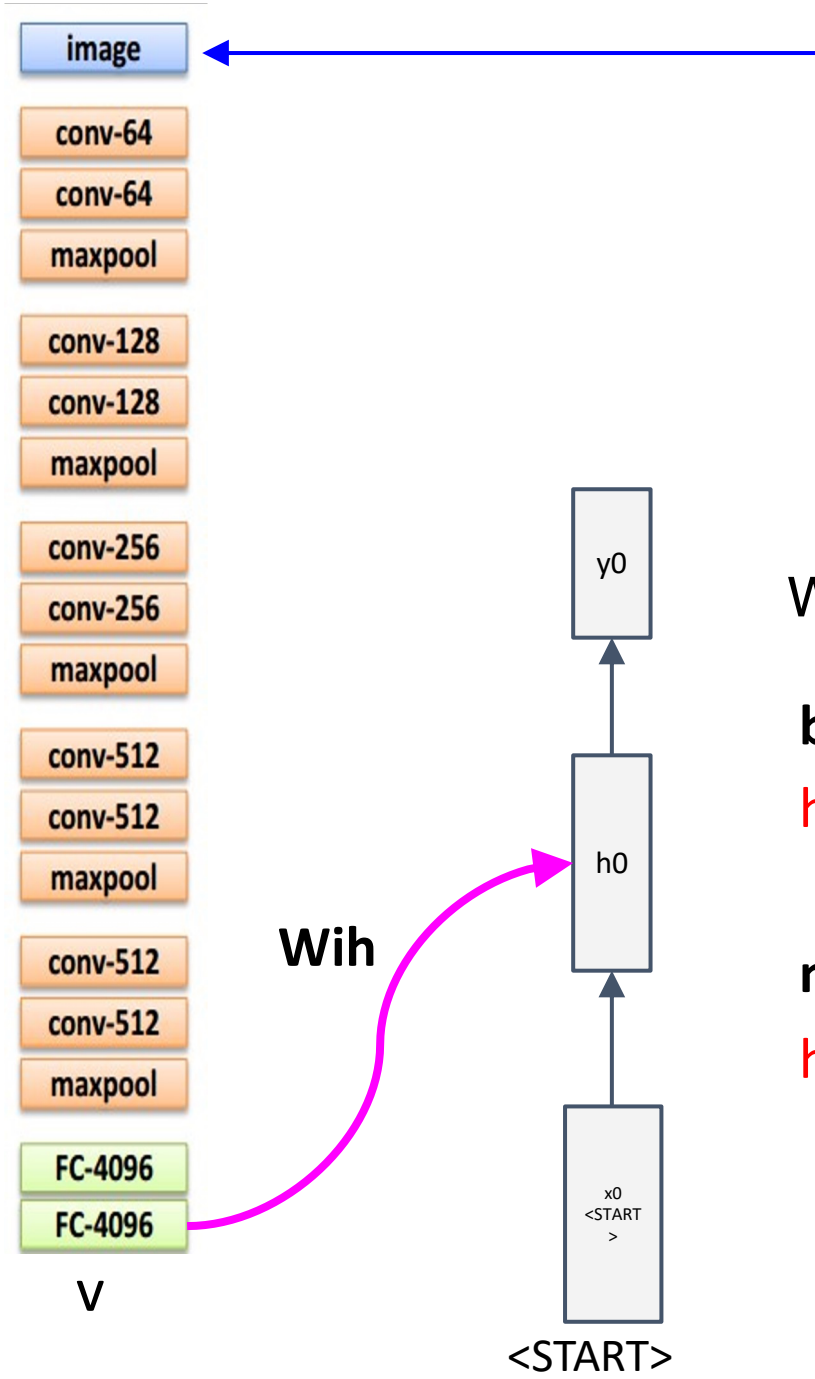


test image

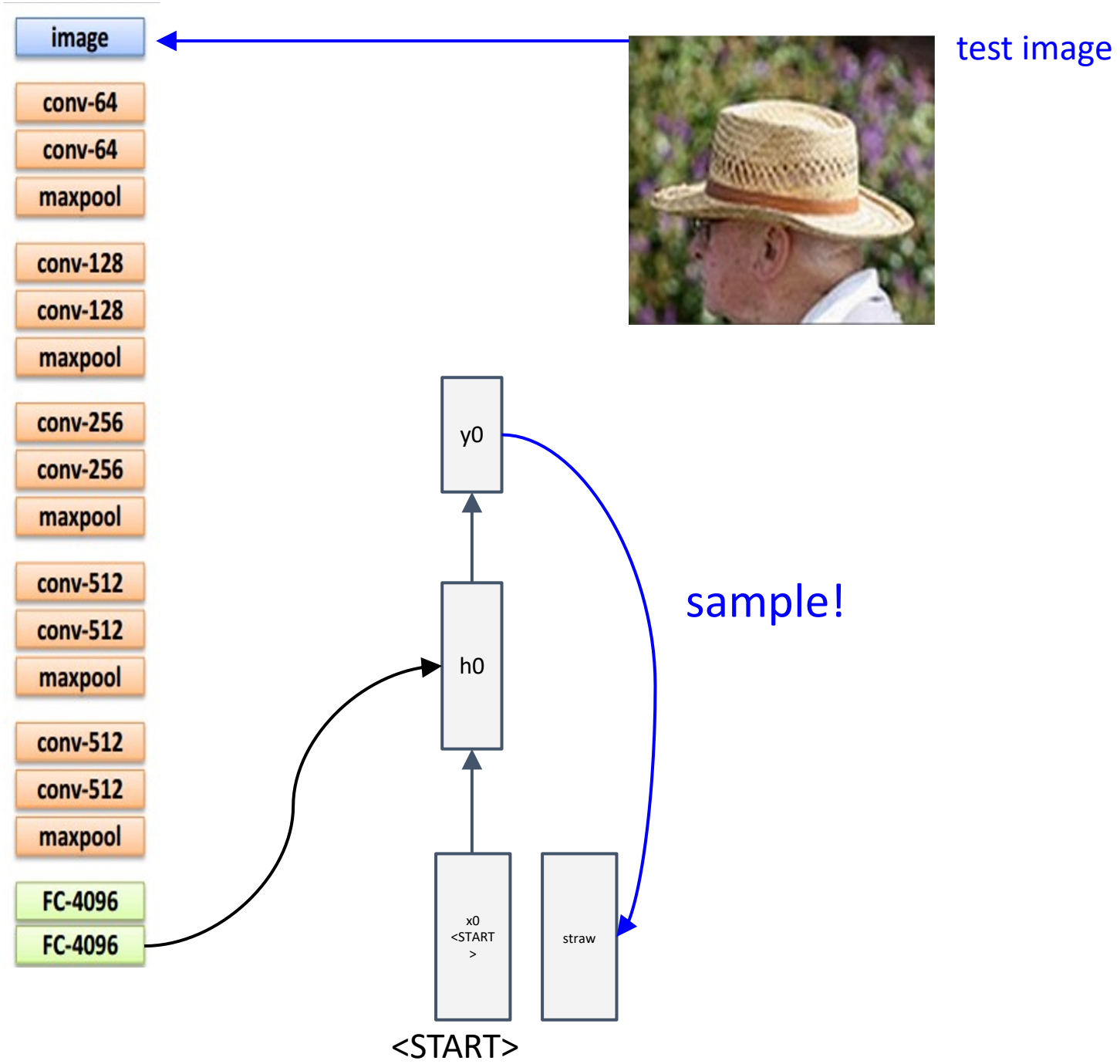
Why didn't we use "v" as the h_0?

before:

h = tanh(Wxh * x + Whh * h)

now:

h = tanh(Wxh * x + Whh * h + **Wih * v**)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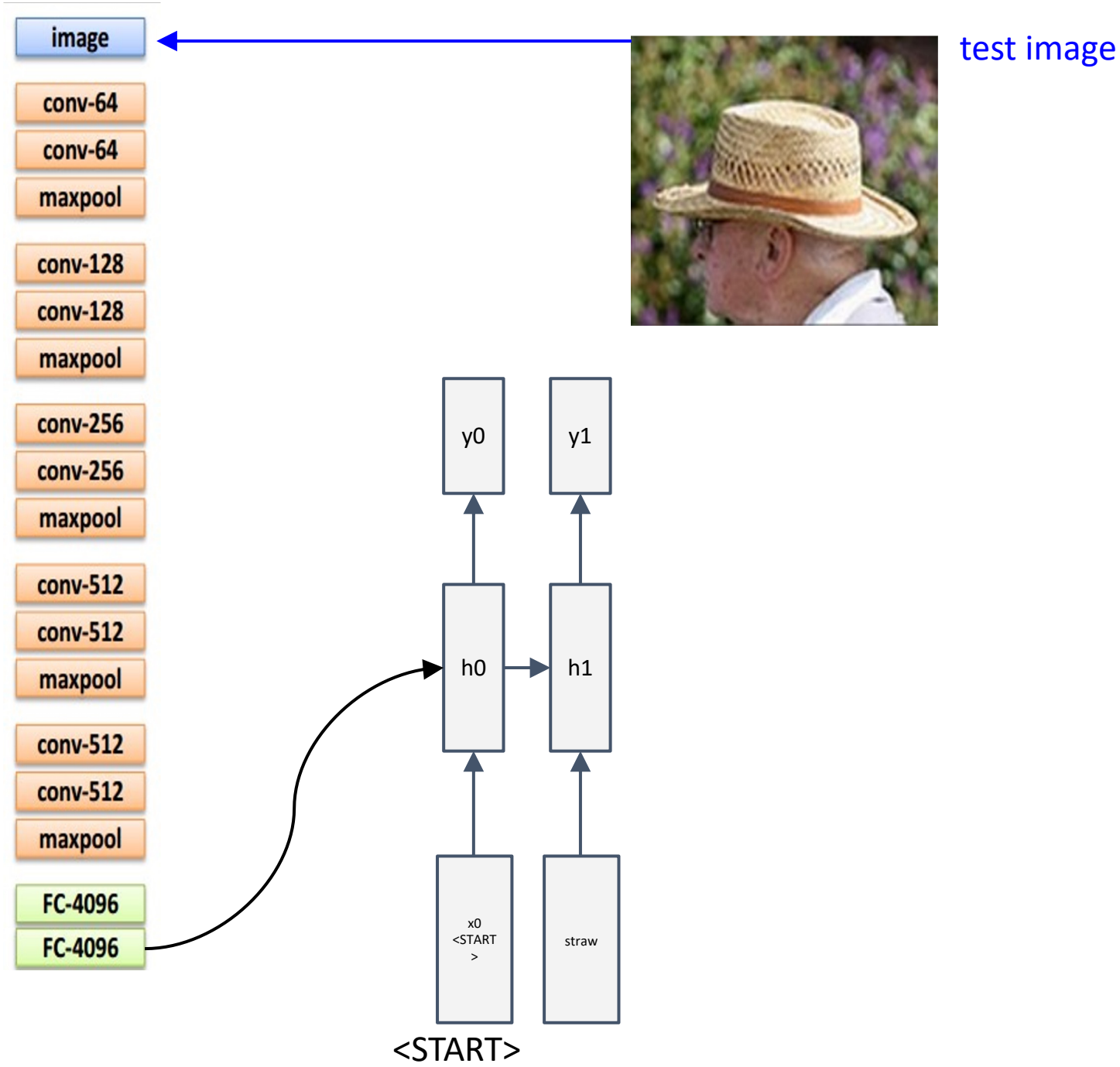
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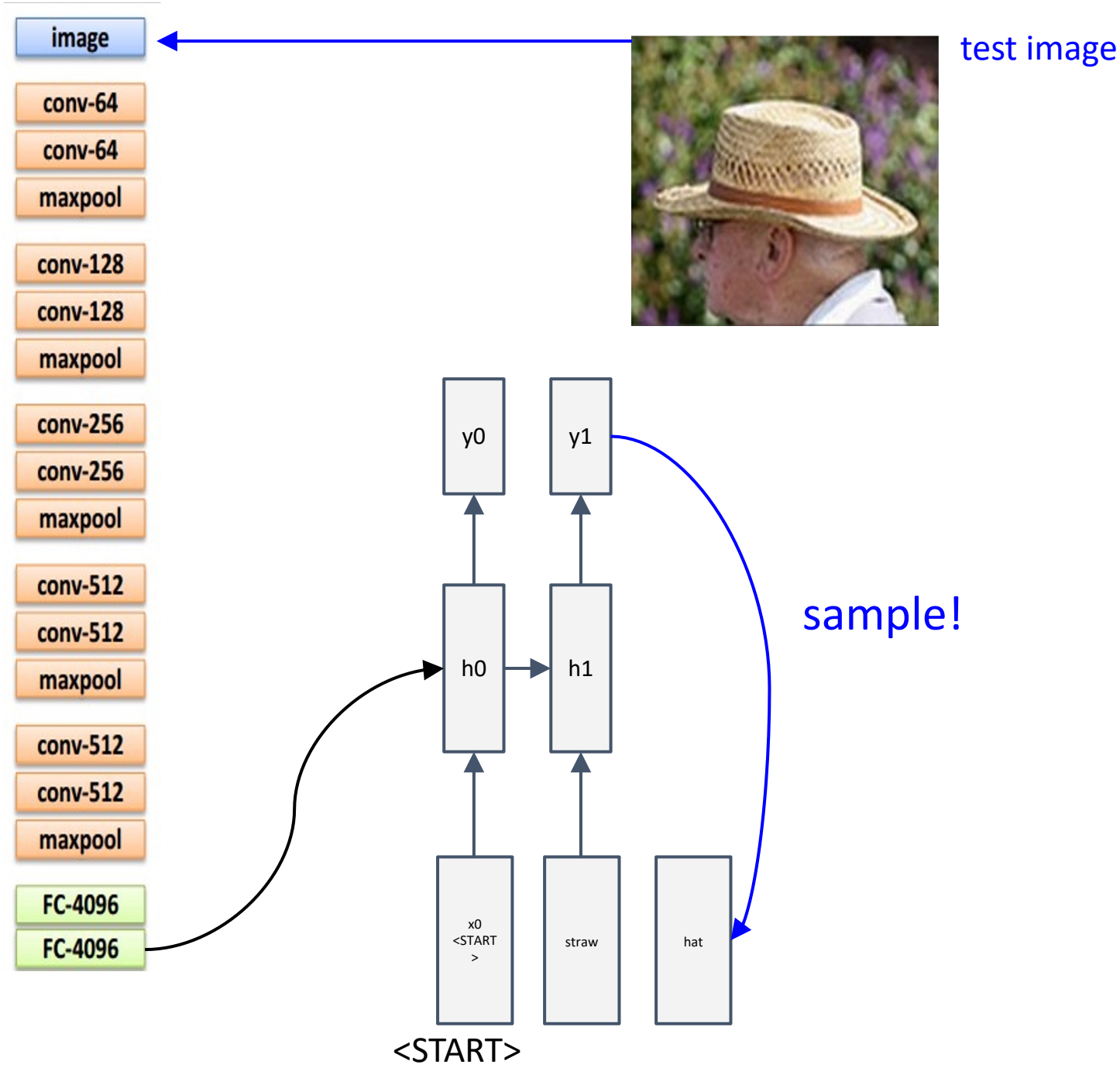
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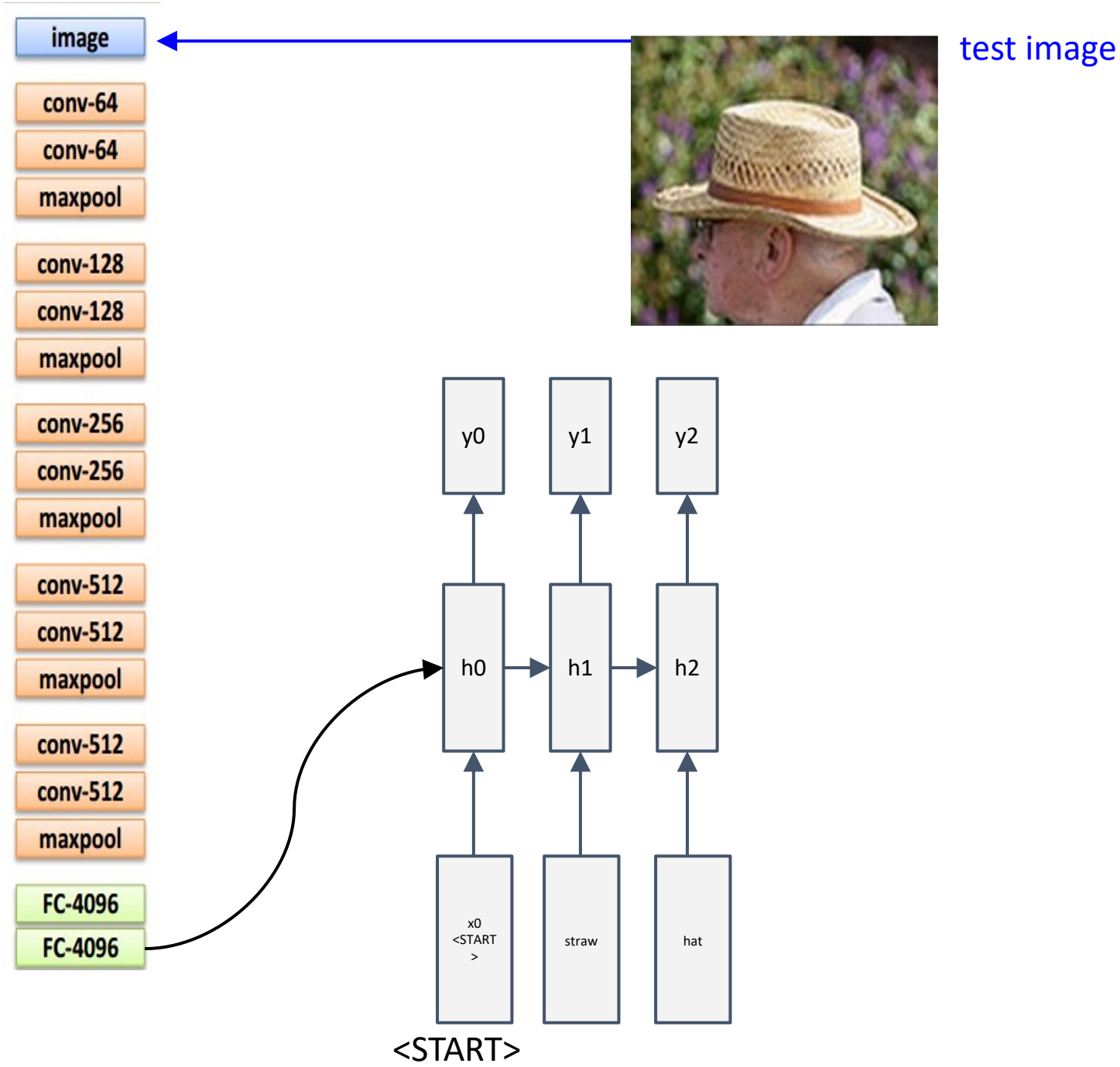
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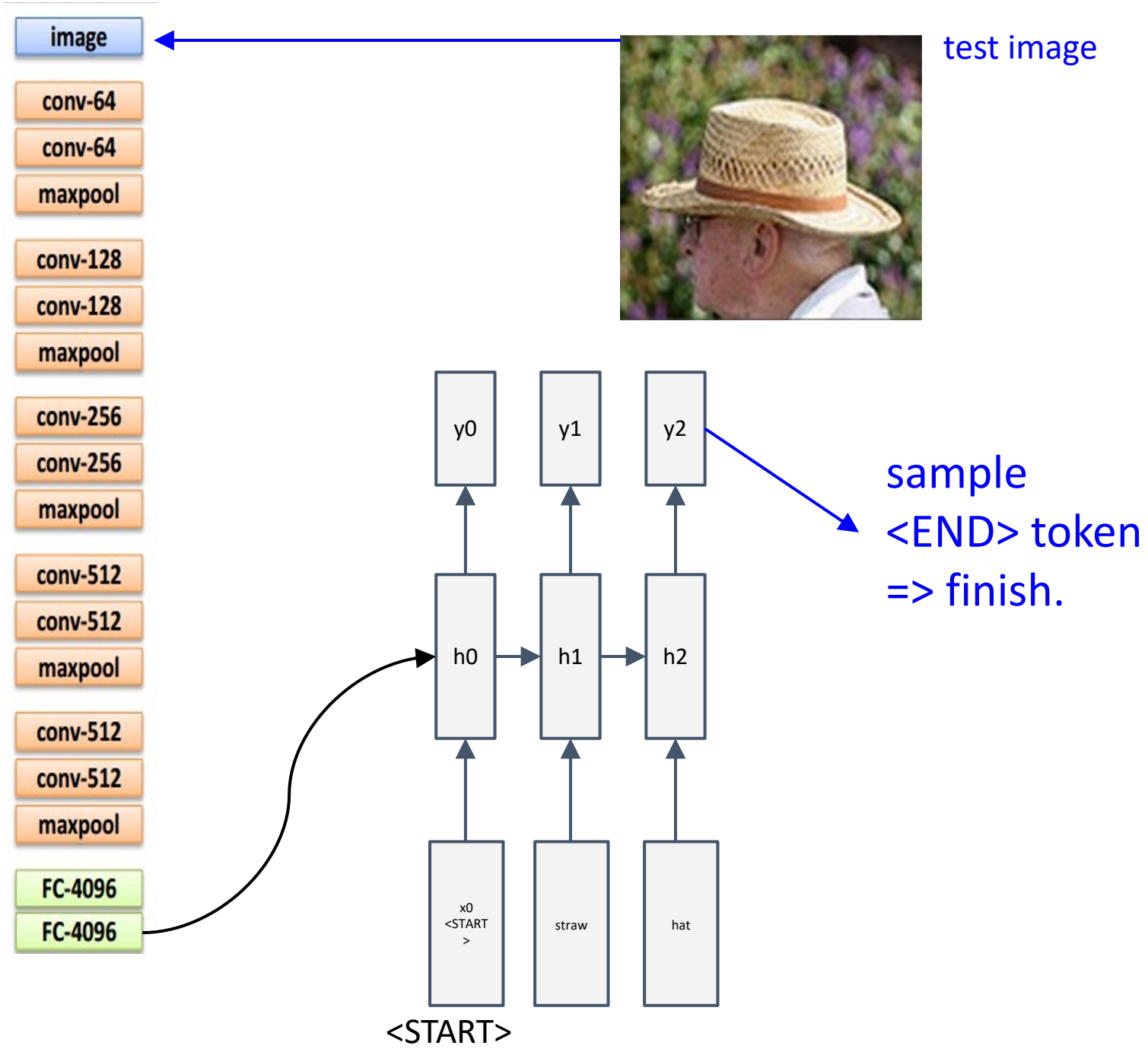
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Image Sentence Datasets

a man riding a bike on a dirt path through a forest.
bicyclist raises his fist as he rides on desert dirt trail.
this dirt bike rider is smiling and raising his fist in triumph.
a man riding a bicycle while pumping his fist in the air.
a mountain biker pumps his fist in celebration.

Microsoft COCO

[Tsung-Yi Lin et al. 2014]

mscoco.org

currently:

~120K images

~5 sentences each

Image Captioning: Example Results

Captions generated using neuraltalk2
All images are CC0 Public domain:
cat suitcase, cat tree, dog, bear,
surfers, tennis, giraffe, motorcycle

A cat sitting on a suitcase on the floor

A cat is sitting on a tree branch

A dog is running in the grass with a frisbee

A white teddy bear sitting in the grass

Two people walking on the beach with surfboards

A tennis player in action on the court

Two giraffes standing in a grassy field

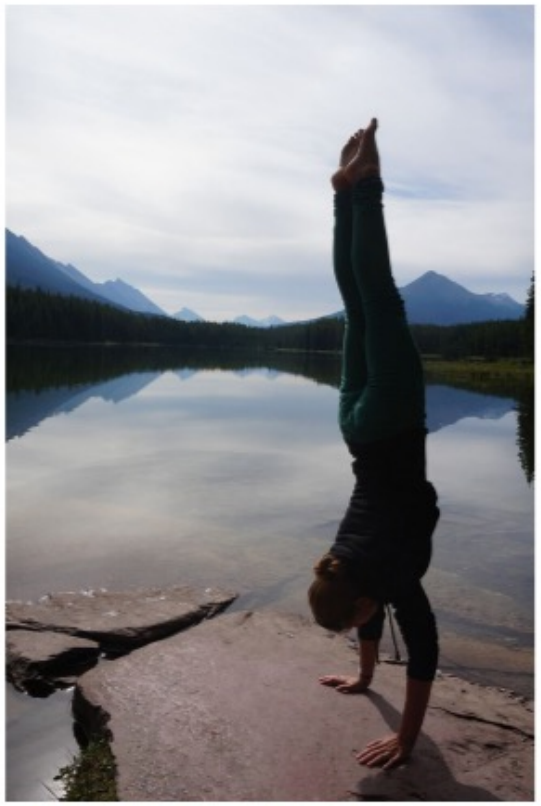
A man riding a dirt bike on a dirt track

Deep Visual-Semantic Alignments for Generating Image Descriptions, Karpathy and Fei-Fei, CVPR 2016.

Image Captioning: Failure Cases

Captions generated using neuraltalk2
All images are CC0 Public domain:
cat suitcase, cat tree, dog, bear,
surfers, tennis, giraffe, motorcycle

A woman is holding a cat in her hand



A woman standing on a beach holding a surfboard

A bird is perched on a tree branch

A person holding a computer mouse on a desk

A man in a baseball uniform throwing a ball

Visual Question Answering (VQA)

Q: What endangered animal is featured on the truck?

A: **A bald eagle.**
A: A sparrow.
A: A humming bird.
A: A raven.

Q: Where will the driver go if turning right?

A: **Onto 24 ¾ Rd.**
A: Onto 25 ¾ Rd.
A: Onto 23 ¾ Rd.
A: Onto Main Street.

Q: When was the picture taken?

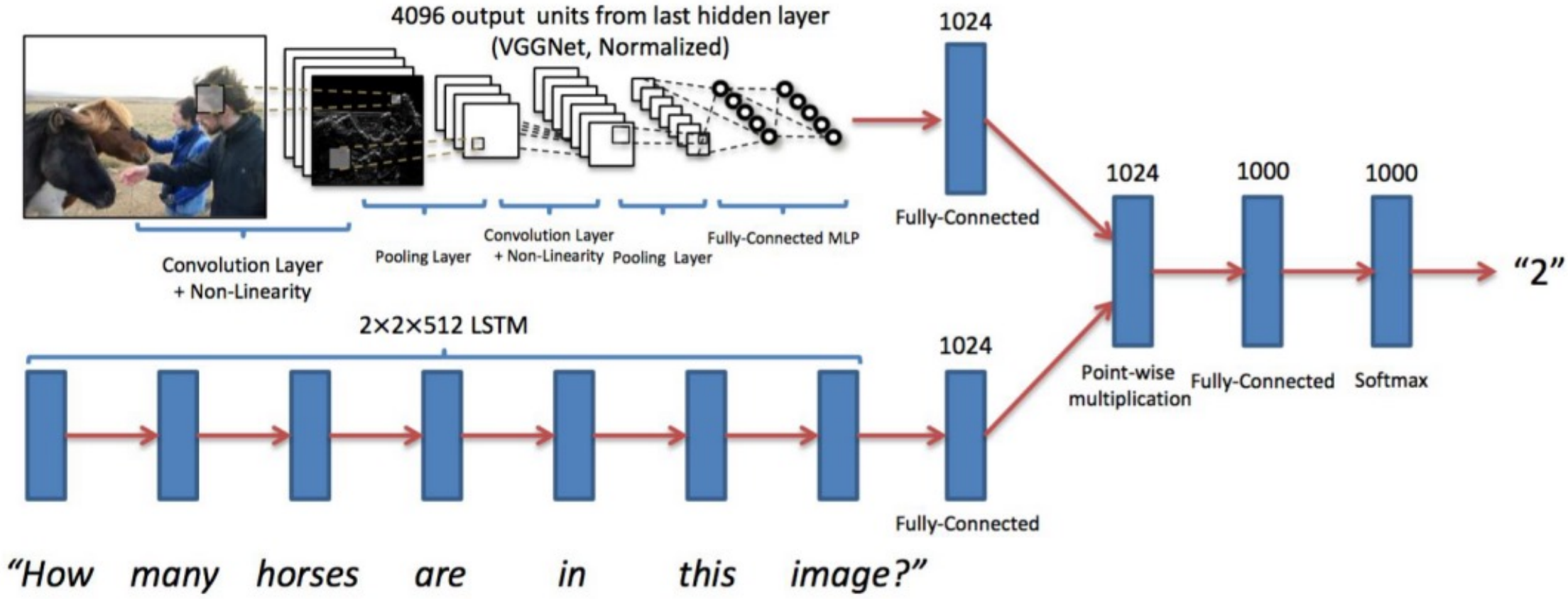
A: **During a wedding.**
A: During a bar mitzvah.
A: During a funeral.
A: During a Sunday church service

Q: Who is under the umbrella?

A: **Two women.**
A: A child.
A: An old man.
A: A husband and a wife.

Agrawal et al, "VQA: Visual Question Answering", ICCV 2015
Zhu et al, "Visual 7W: Grounded Question Answering in Images", CVPR 2016

Visual Question Answering (VQA)



Agrawal et al, "Visual 7W: Grounded Question Answering in Images", CVPR 2015
Figures from Agrawal et al, copyright IEEE 2015. Reproduced for educational purposes.

Sources:

- Sharif University of Technology, 40719 (DL Course), Spring 2025