Deep Learning

Episode 4

Recurrent Neural Networks

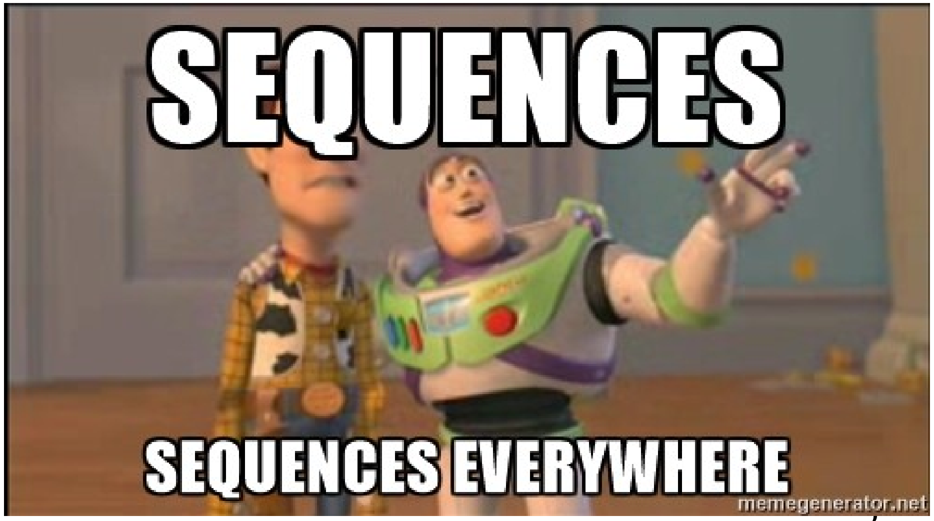
Yandex Data Factory

LAMBDA

British Hedgehog Preservation Society

Sequential data

- Time series
  - Financial data analysis
  - Demand prediction
  - Predict vehicle breakdown using sensor data
  - Medical sensors e.g. sugar level
- Sound
  - Speech recognition
  - Text to speech
  - Music generation
  - Music recommendation
  - …
- Text
  - Generating tweets, poetry
  - Sentiment analysis
  - See last lecture :)
- Spatio-temporal
  - Video
  - Precipitation maps
  - Ultrasonography



Could go on all day

Time series @finance

Data:

- Stock ~~indices~~ indexes
- Commodities
- Forex

Objectives:

- Portfolio management
- Volatility targeting
- Estimating true value
- ...

Time series @finance

Data:

- Stock ~~indices~~ indexes
- Commodities
- Forex

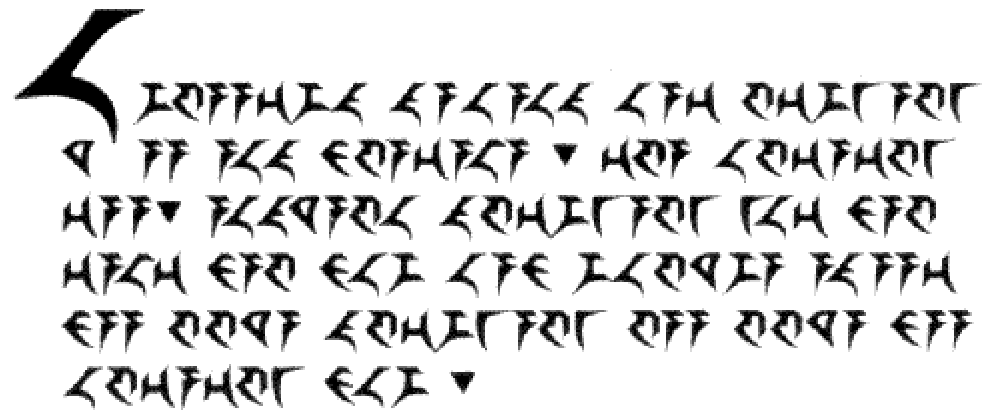
Objectives:

- ~~Portfolio management~~ ~ trading stuff
- ~~Volatility targeting~~ ~ evaluating risk
- Estimating true value
- ...

Natural language as time series

Data:

- Literature
- Conversation
- Tweets
- Book scans
- Speech

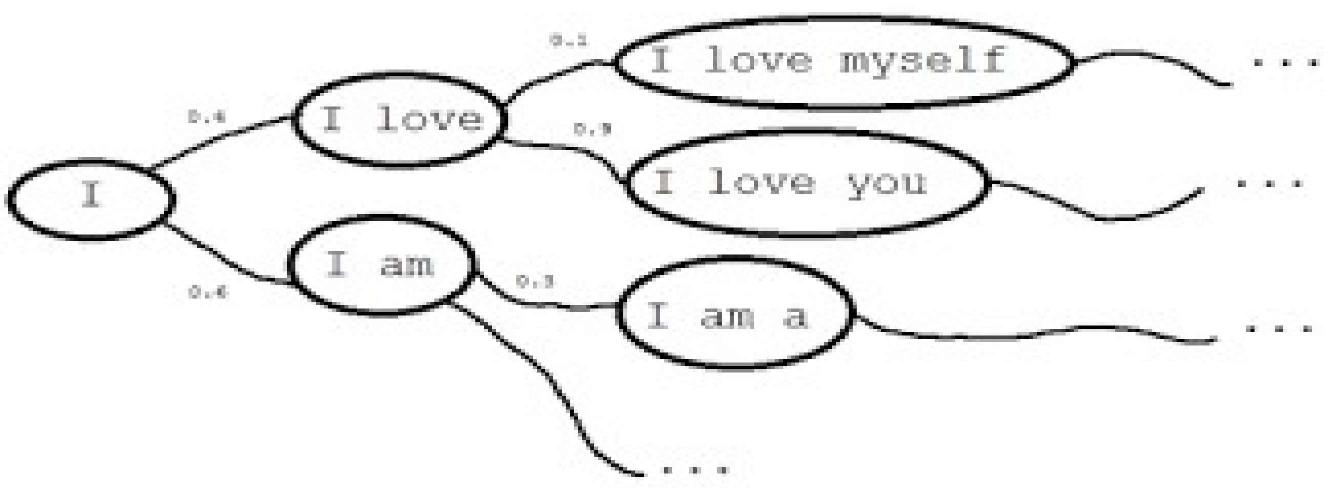


Language model

Objective:

- Learn P(text)

$$P(text) = P(w_{0,} w_{1,} \dots, w_n) = P(w_0) \cdot P(w_1 | w_0) \cdot P(w_2 | w_1 w_0) \cdot \dots \cdot P(w_n | \dots)$$



Language model

Why learning it?

- Detect languages as P(text|language)
- Sentiment analysis P(text|happy)
- Any text analysis you can imagine
- Generate texts!
  - Cool article http://bit.ly/1K610Ie
  - Generating clickbait: http://bit.ly/21cZM70

Language model

- Actual distribution

$$P(text) = P(w_{0,} w_{1,} \ldots, w_n) = P(w_0) \cdot P(w_1 | w_0) \cdot P(w_2 | w_1 w_0) \cdot \ldots \cdot P(w_n | \ldots)$$

- Bag of words assumption (independent words)

$$P(text) = P(w_{0,} w_{1,} \ldots, w_n) = P(w_0) \cdot P(w_1) \cdot P(w_2) \cdot \ldots \cdot P(w_n)$$

- **Anything better?**

Language model

- Actual distribution

$$P(text)=P(w_{0,}w_{1,}\dots,w_n)=P(w_0)\cdot P(w_1|w_0)\cdot P(w_2|w_1 w_0)\cdot\dots\cdot P(w_n|\dots)$$

- Bag of words assumption (independent words)

$$P(text)=P(w_{0,}w_{1,}\dots,w_n)=P(w_0)\cdot P(w_1)\cdot P(w_2)\cdot\dots\cdot P(w_n)$$

- Markov assumption

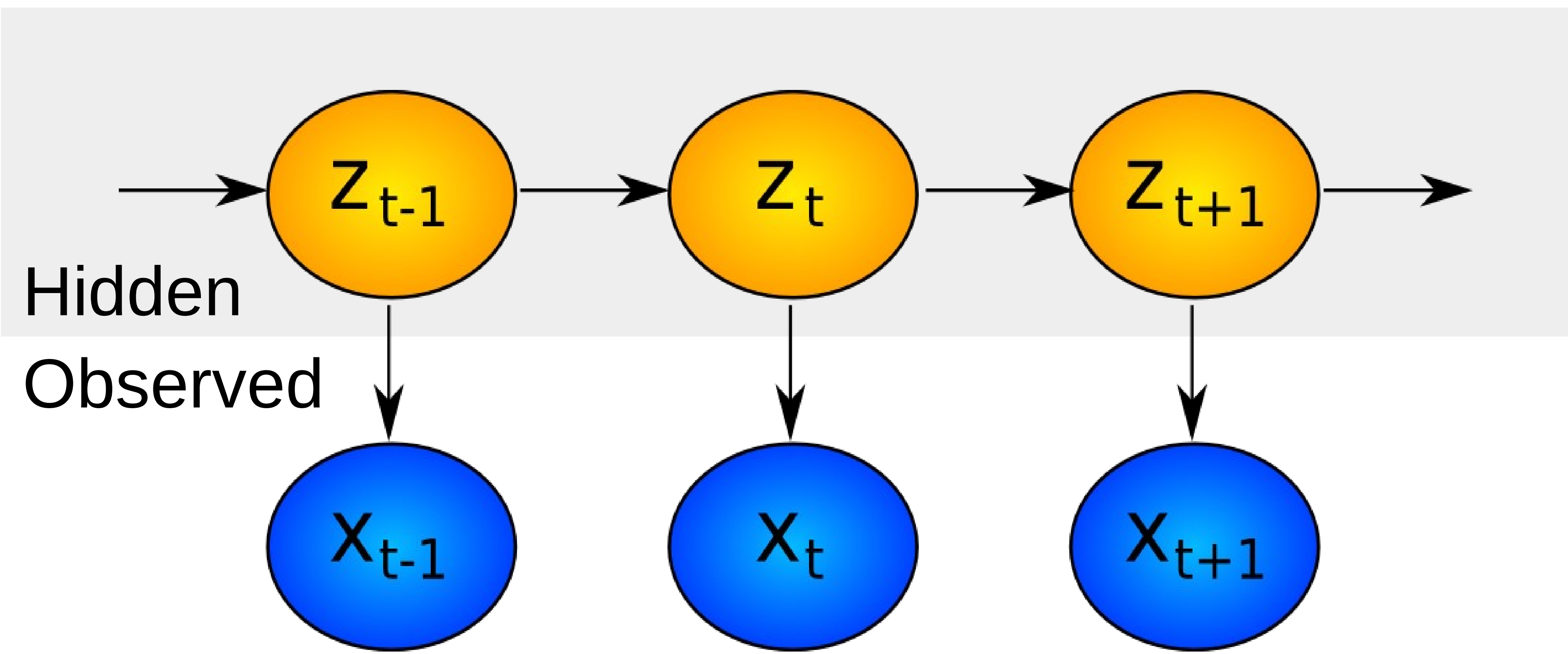
$$P(text)=P(w_{0,}w_{1,}\dots,w_n)=P(w_0)\cdot P(w_1|w\,0)\cdot P(w_2|w_1)\cdot\dots\cdot P(w_n|w_{n-1})$$

  - also 3-gram, 5-gram, 100-gram

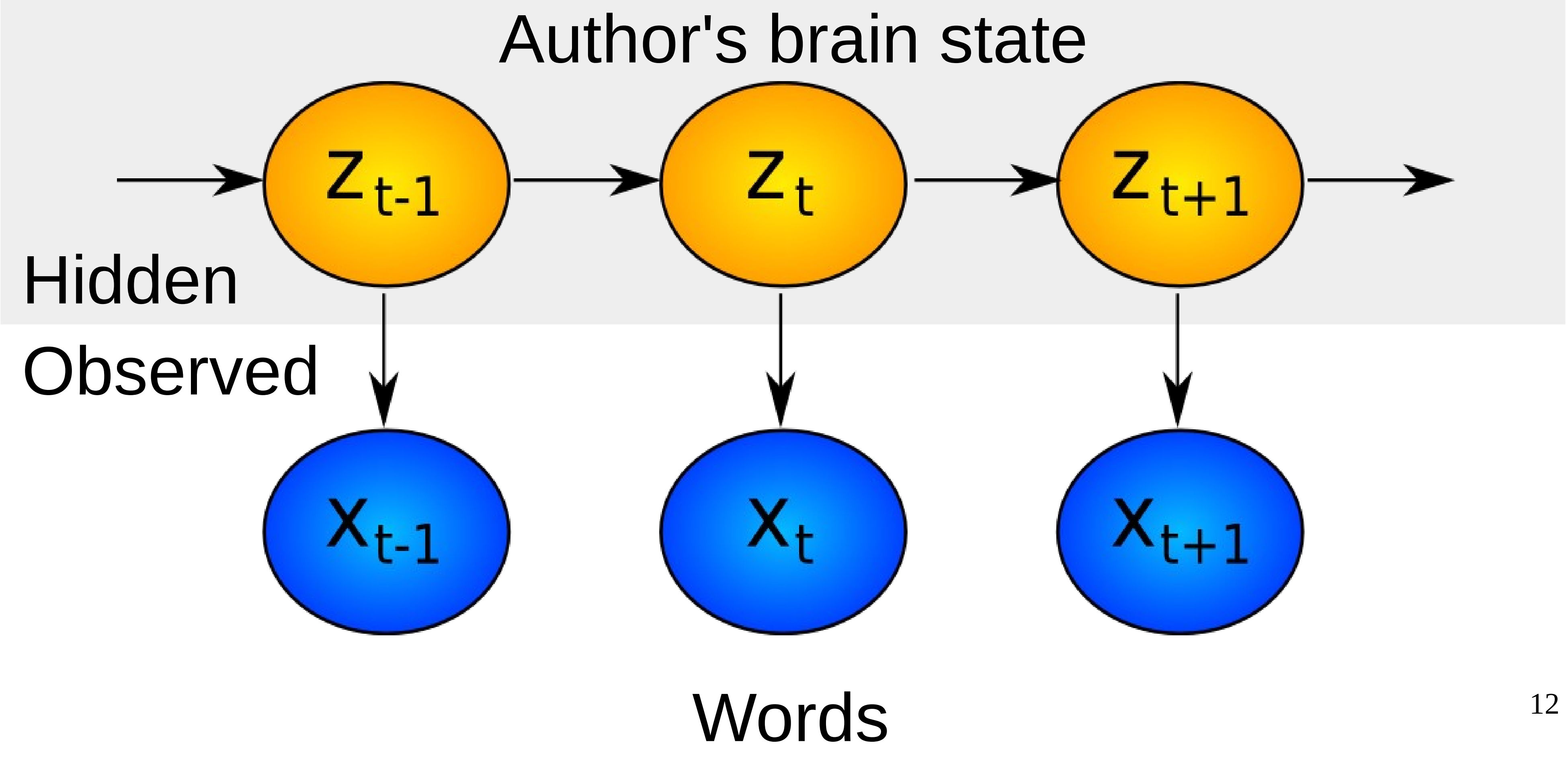
Can we learn* arbitrarily long dependencies?

* without infinitely many parameters

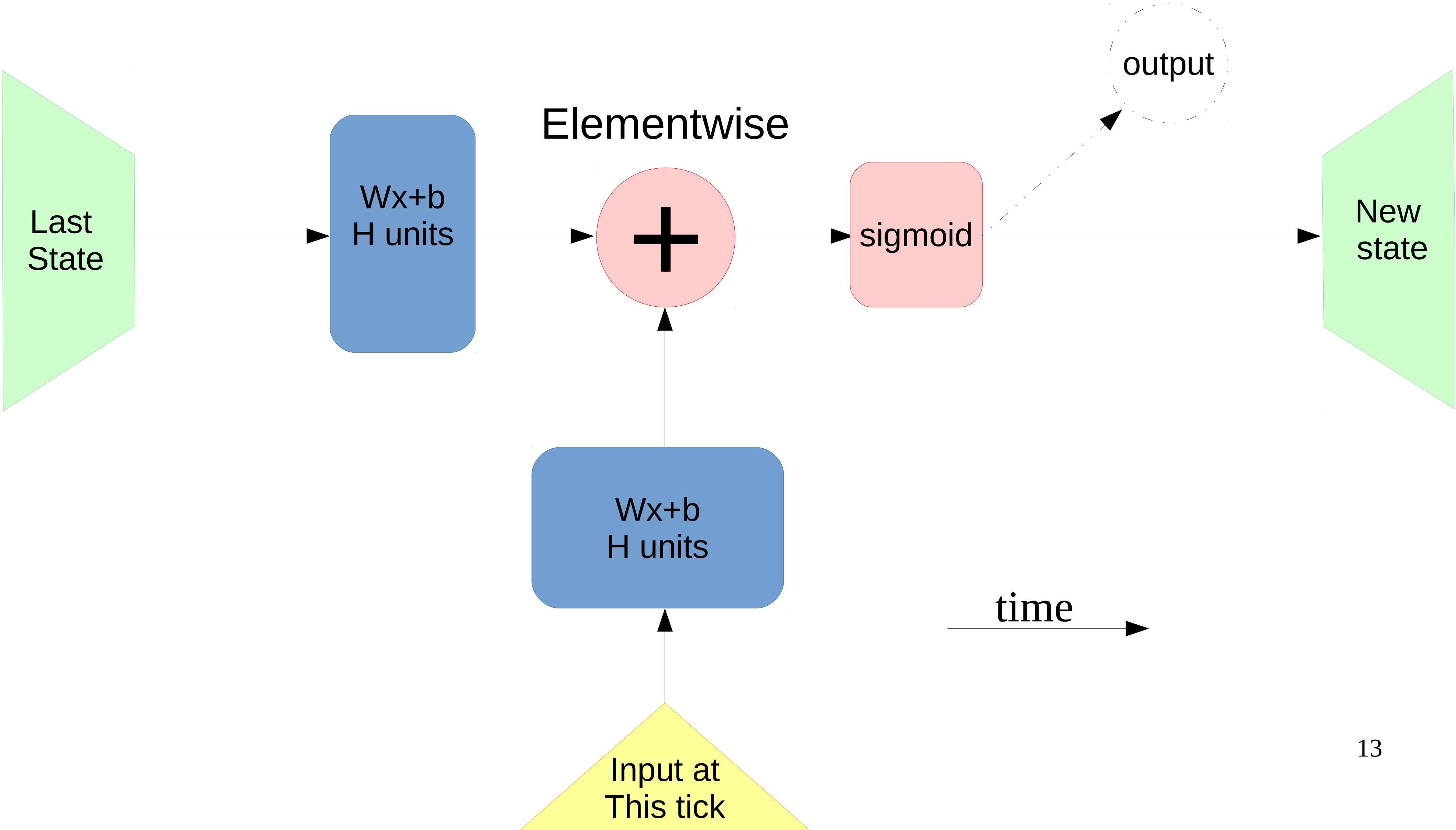
Hidden Markov Models: what is hidden



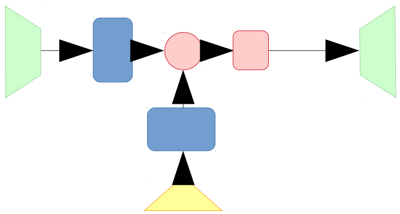
Hidden Markov Models: what is hidden



Recurrent neural network: one step

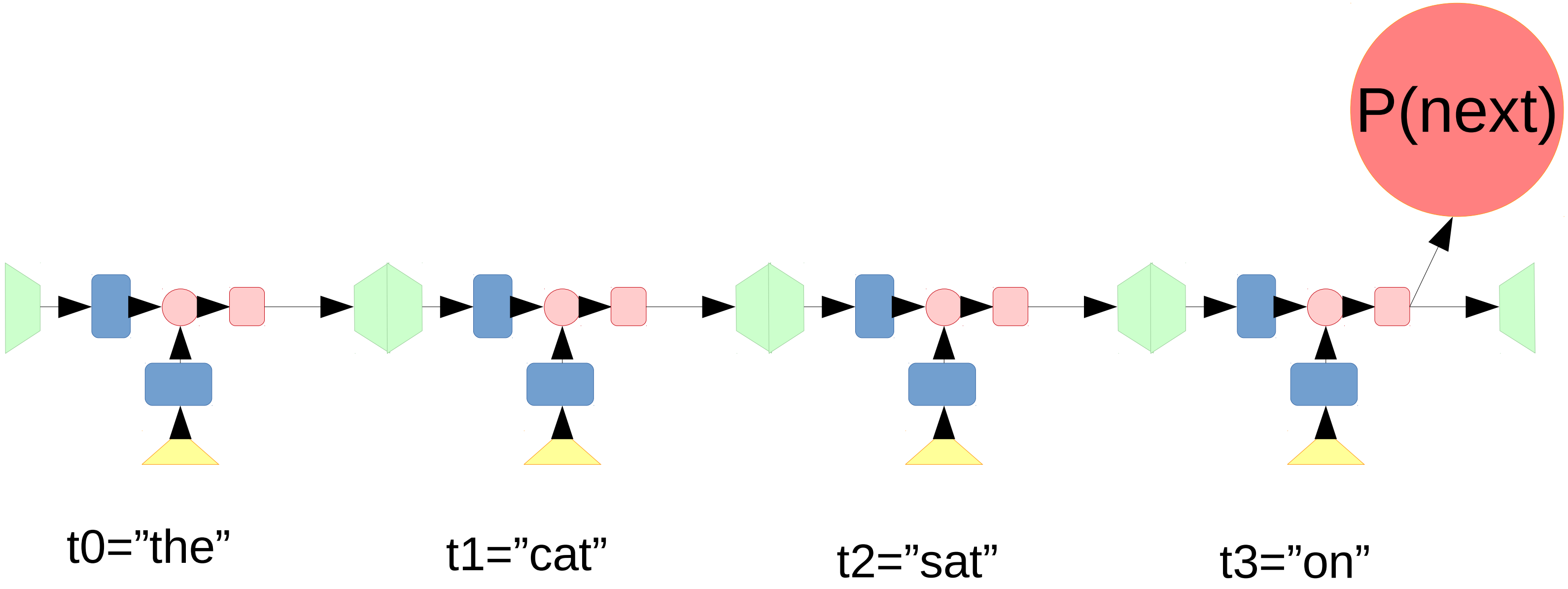


Recurrent neural network



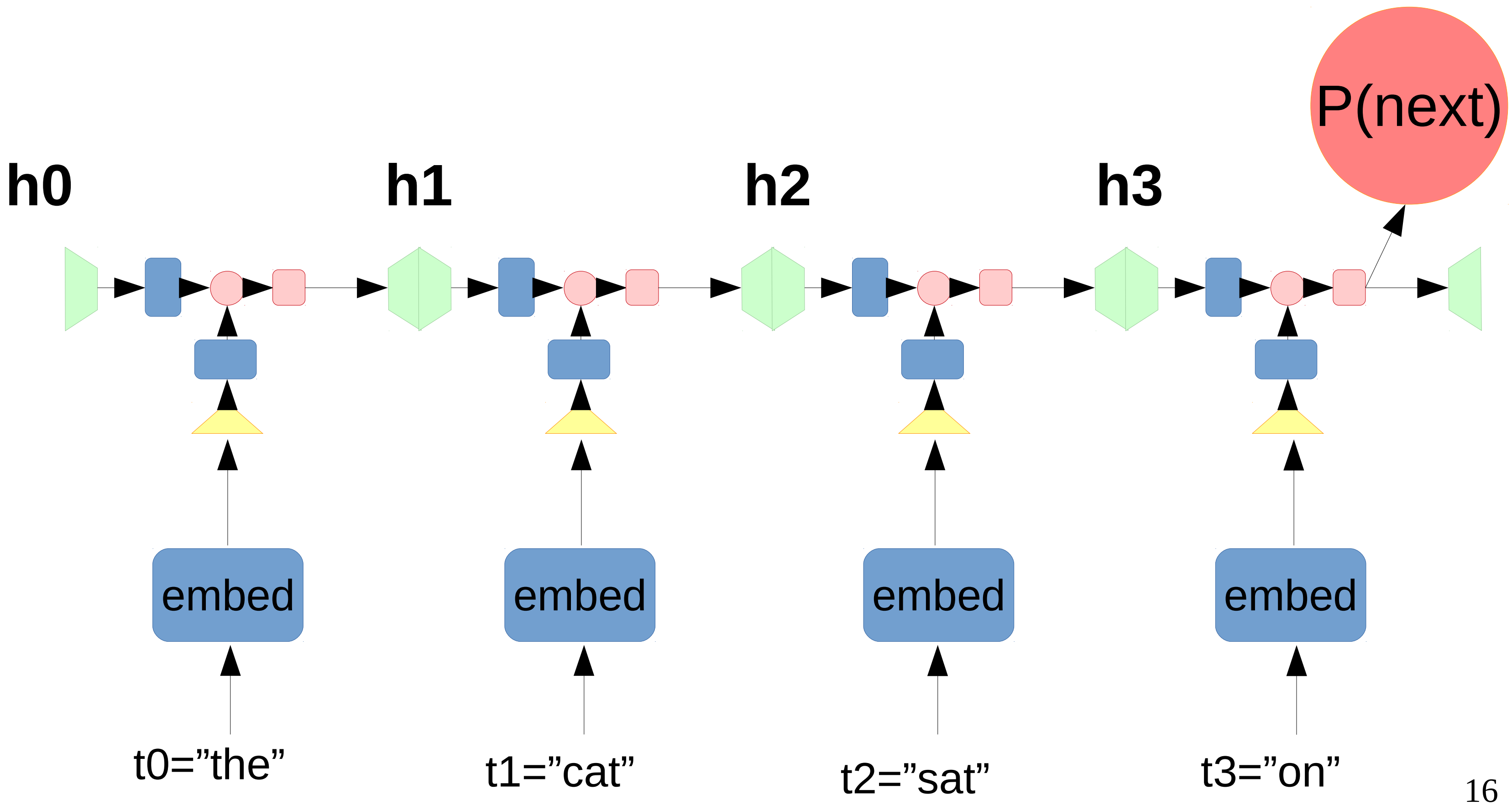
Zoom-out
of previous slide

Recurrent neural network



How can we represent words?

Recurrent neural network

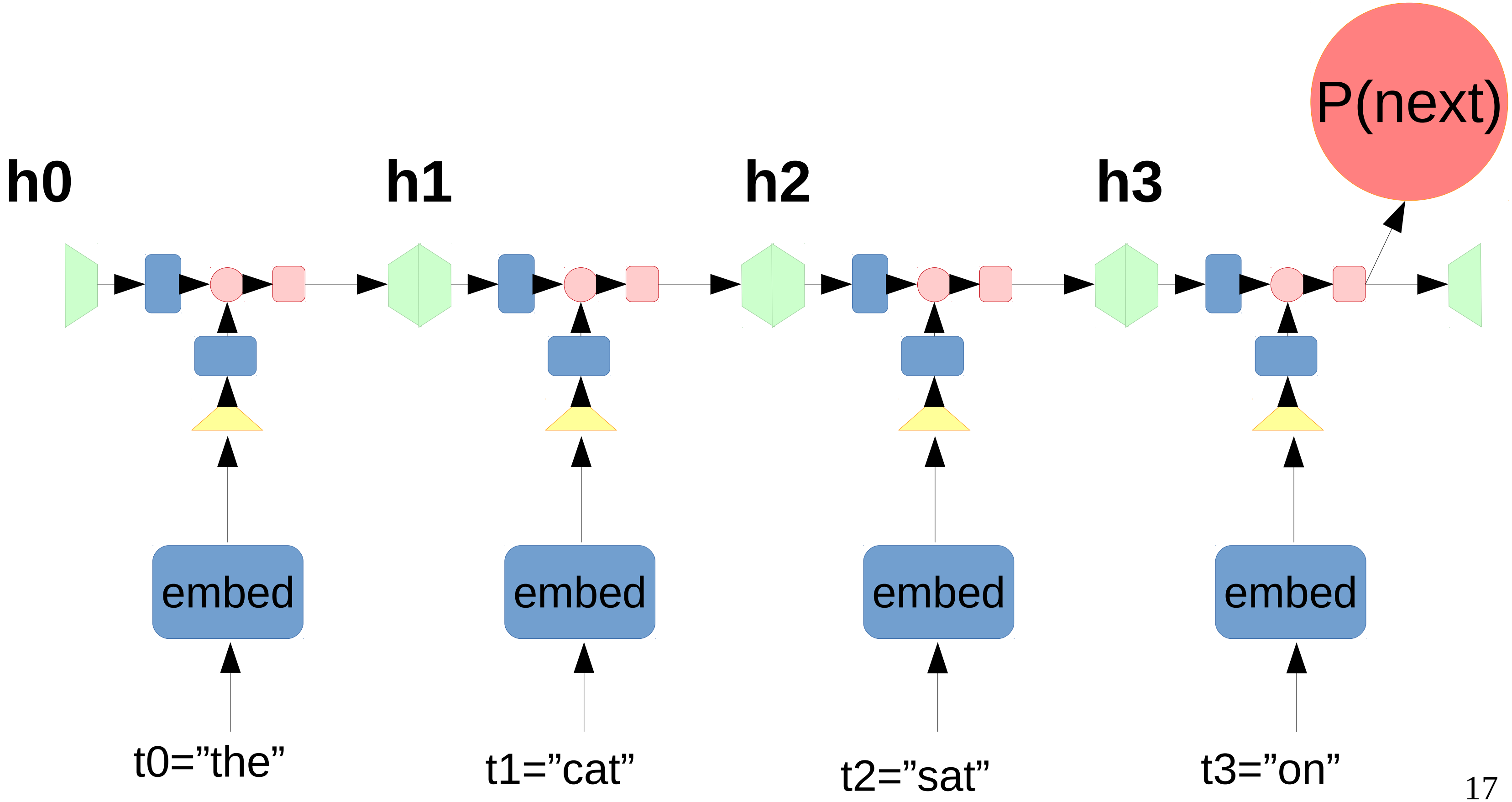


Recurrent neural network

$h_0 = \bar{0}$

$h_1 = \sigma(W_h \cdot h_0 + W_i \cdot t_0 + b)$

$h_2 = ?$



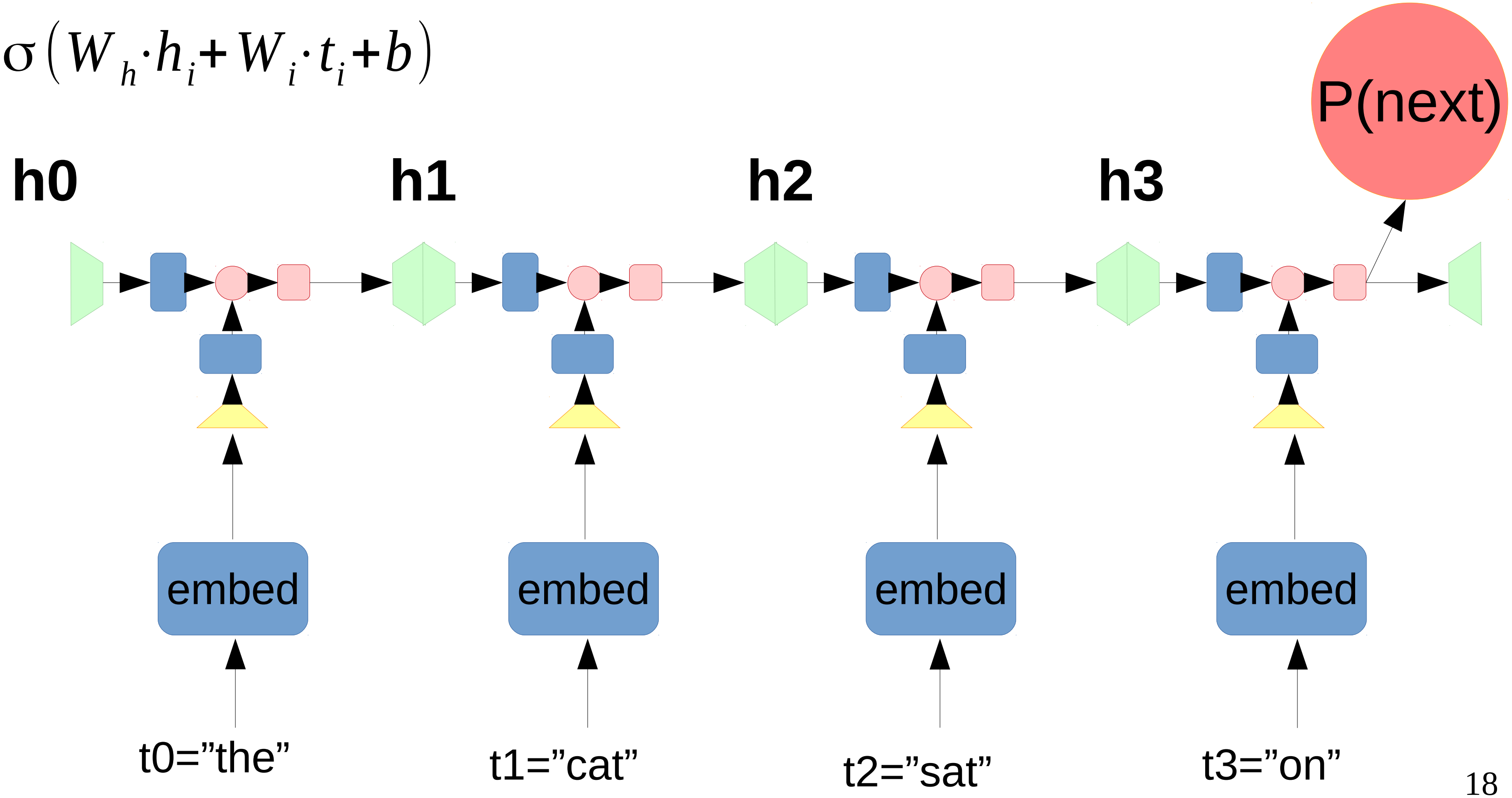
Recurrent neural network

$$h_0 = \bar{0}$$

$$h_1 = \sigma\left(W_h \cdot h_0 + W_i \cdot t_0 + b\right)$$

$$h_2 = \sigma\left(W_h \cdot h_1 + W_i \cdot t_1 + b\right) = \sigma\left(W_h \cdot \sigma\left(W_h \cdot h_0 + W_i \cdot t_0 + b\right) + W_i \cdot t_1 + b\right)$$

$$h_{i+1} = \sigma\left(W_h \cdot h_i + W_i \cdot t_i + b\right)$$



Recurrent neural network

$$h_0 = \bar{0}$$

$$h_1 = \sigma\left(W_h \cdot h_0 + W_i \cdot t_0 + b\right)$$

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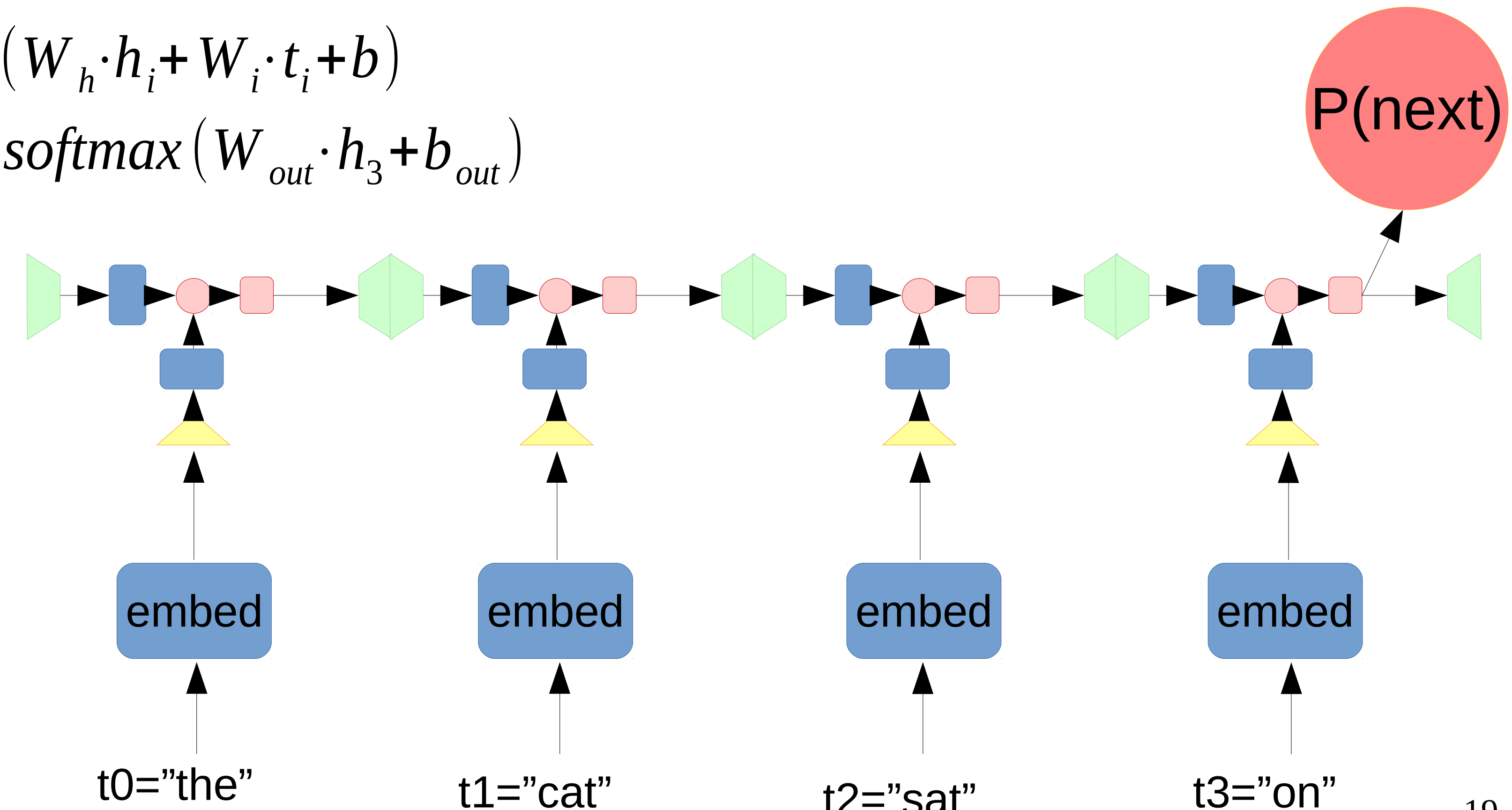
$$h_{i+1} = \sigma\left(W_h \cdot h_i + W_i \cdot t_i + b\right)$$

$$P\left(t_4\right) = softmax\left(W_{out} \cdot h_3 + b_{out}\right)$$

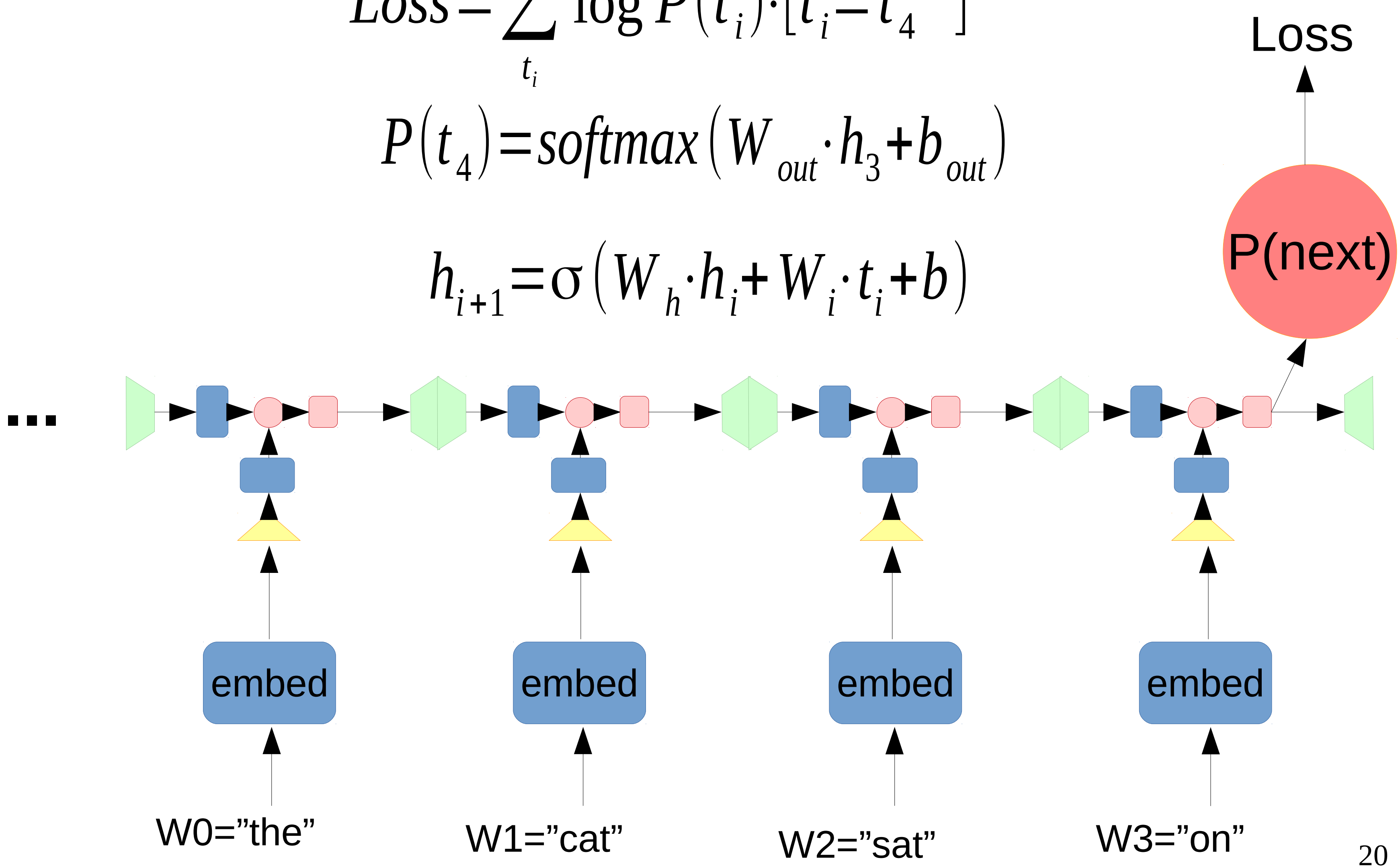


Recurrent neural network

$$Loss = \sum_{t_i} \log P(t_i) \cdot [t_i = t_4^{true}]$$

$$P(t_4) = softmax(W_{out} \cdot h_3 + b_{out})$$

$$h_{i+1} = \sigma(W_h \cdot h_i + W_i \cdot t_i + b)$$



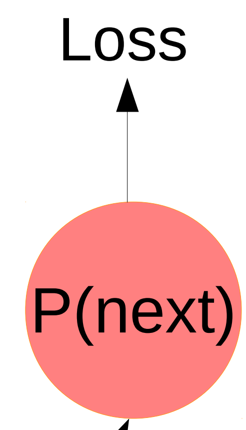
Recurrent neural network

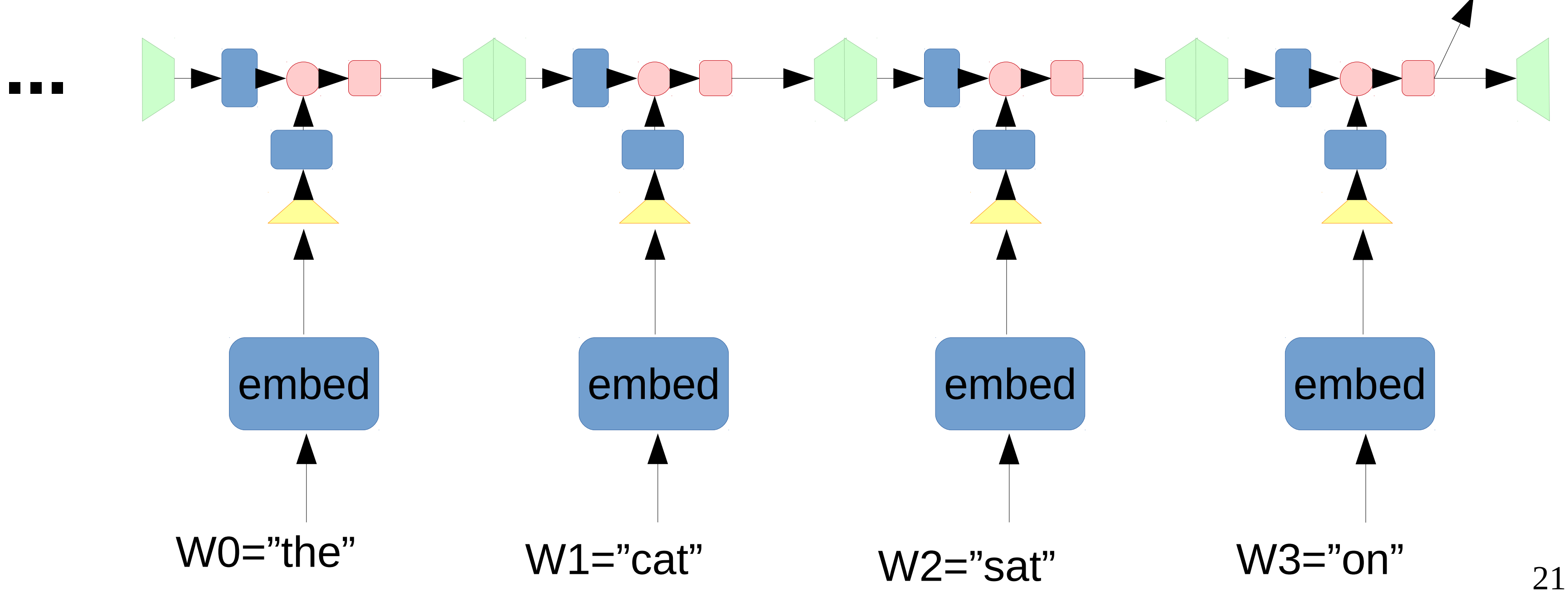
$$Loss = \sum_{t_i} \log P(t_i) \cdot [t_i = t_4^{true}]$$

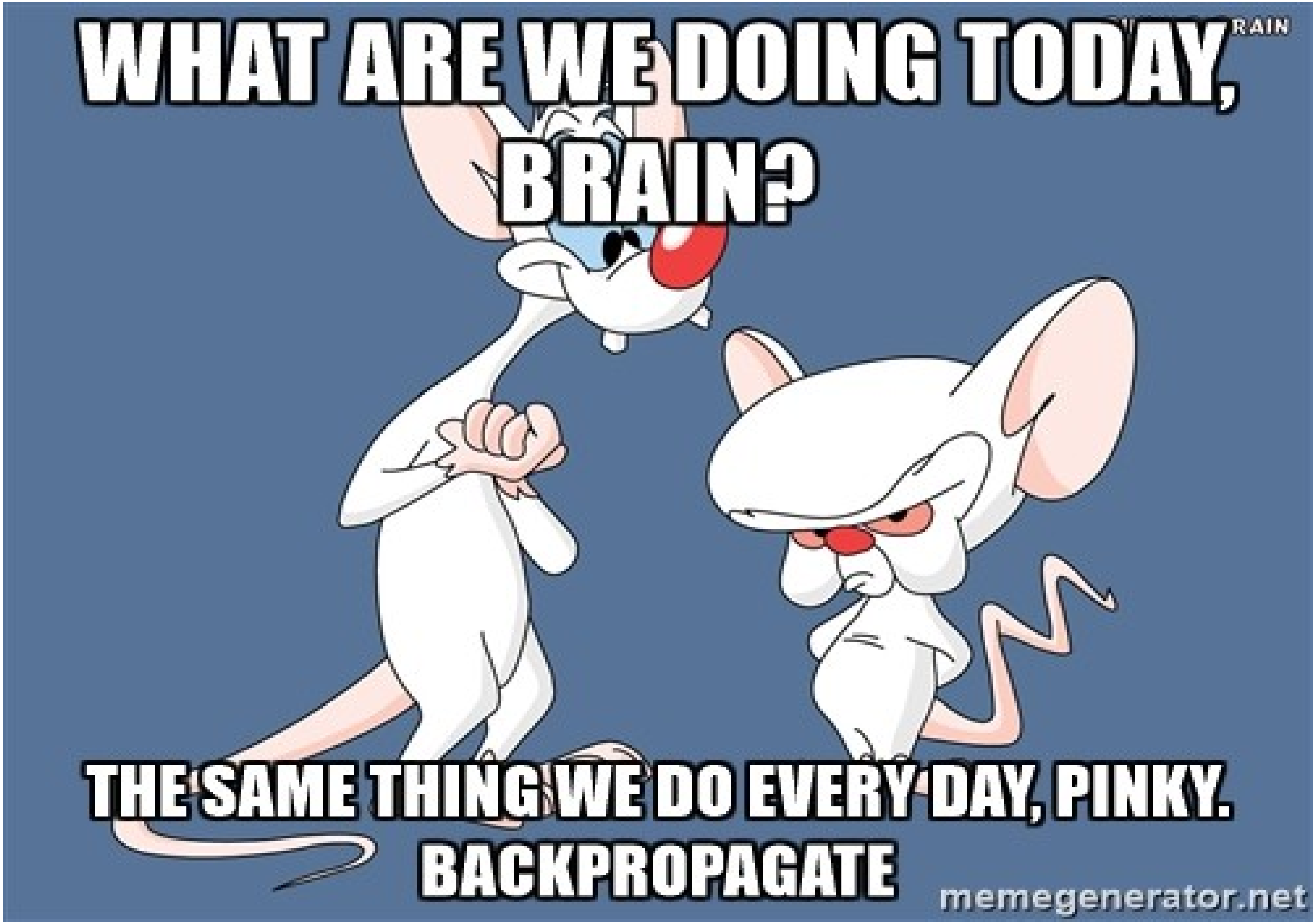
How do we train it?

$$P(t_4) = softmax(W_{out} \cdot h_3 + b_{out})$$

$$h_{i+1} = \sigma(W_h \cdot h_i + W_i \cdot t_i + b)$$

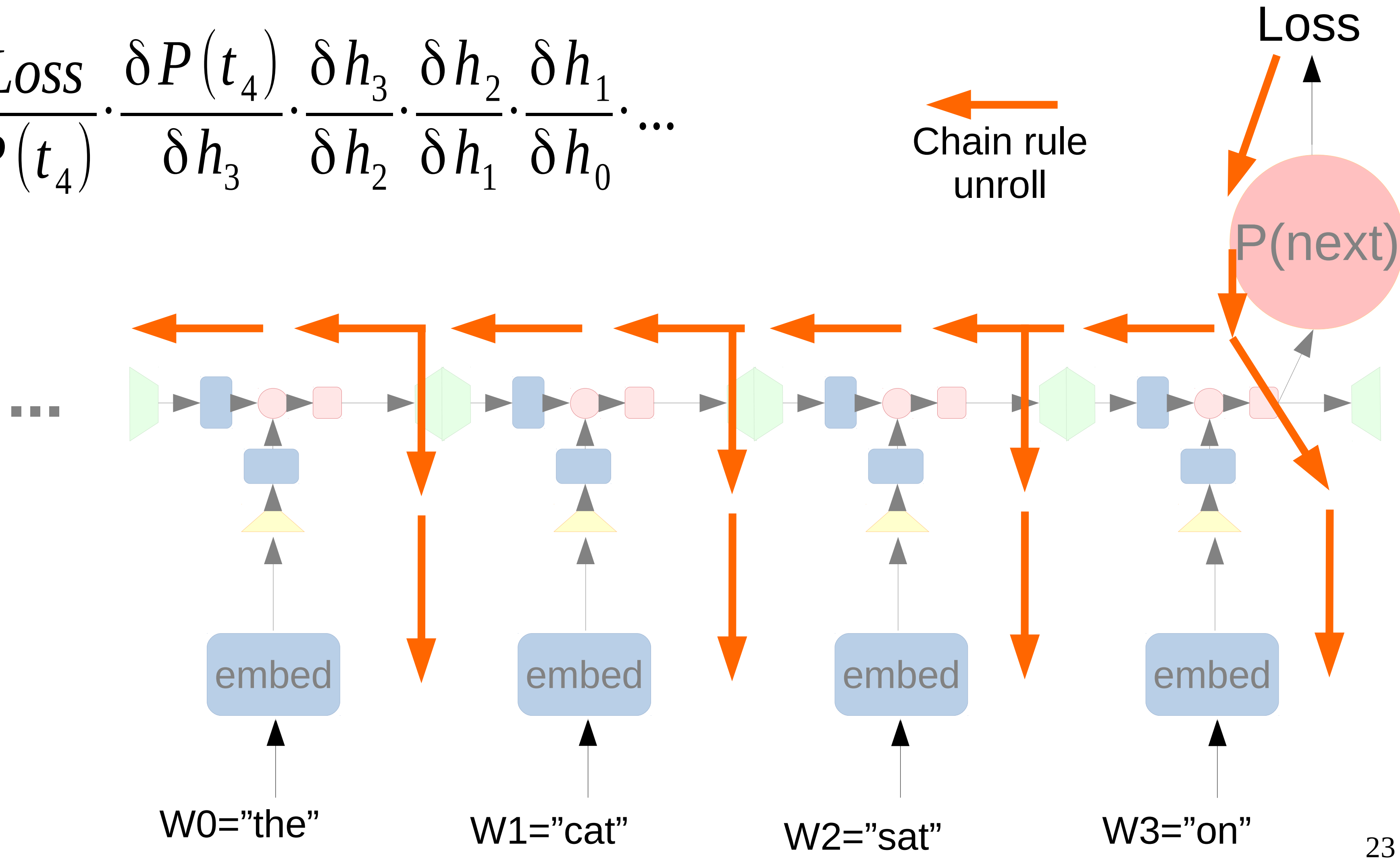





WHAT ARE WE DOING TODAY, BRAIN?
THE SAME THING WE DO EVERY DAY, PINKY. BACKPROPAGATE
memegenerator.net

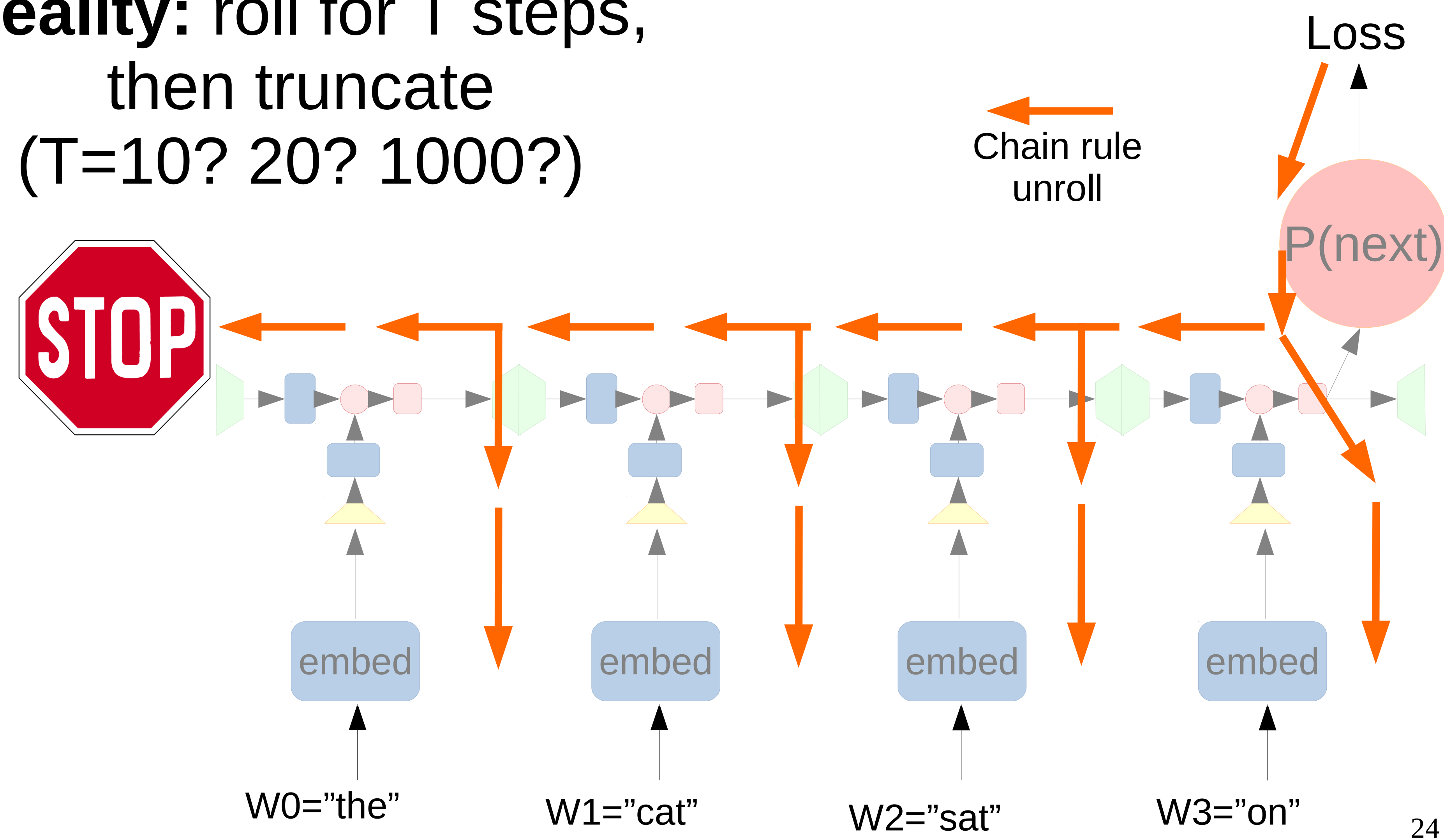
Backpropagation through time

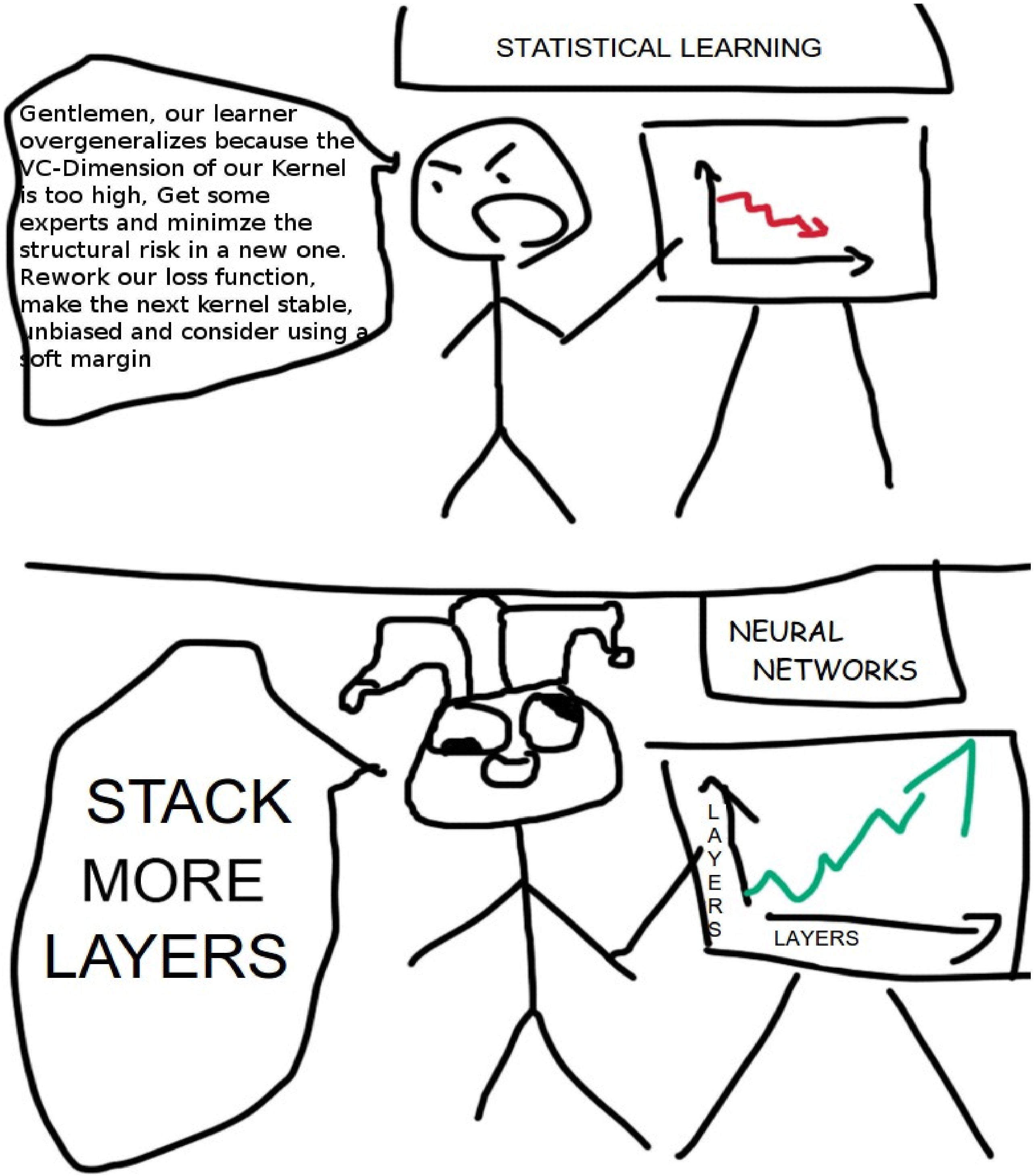
$$\frac{\delta Loss}{\delta P(t_4)} \cdot \frac{\delta P(t_4)}{\delta h_3} \cdot \frac{\delta h_3}{\delta h_2} \cdot \frac{\delta h_2}{\delta h_1} \cdot \frac{\delta h_1}{\delta h_0} \cdot \ldots$$



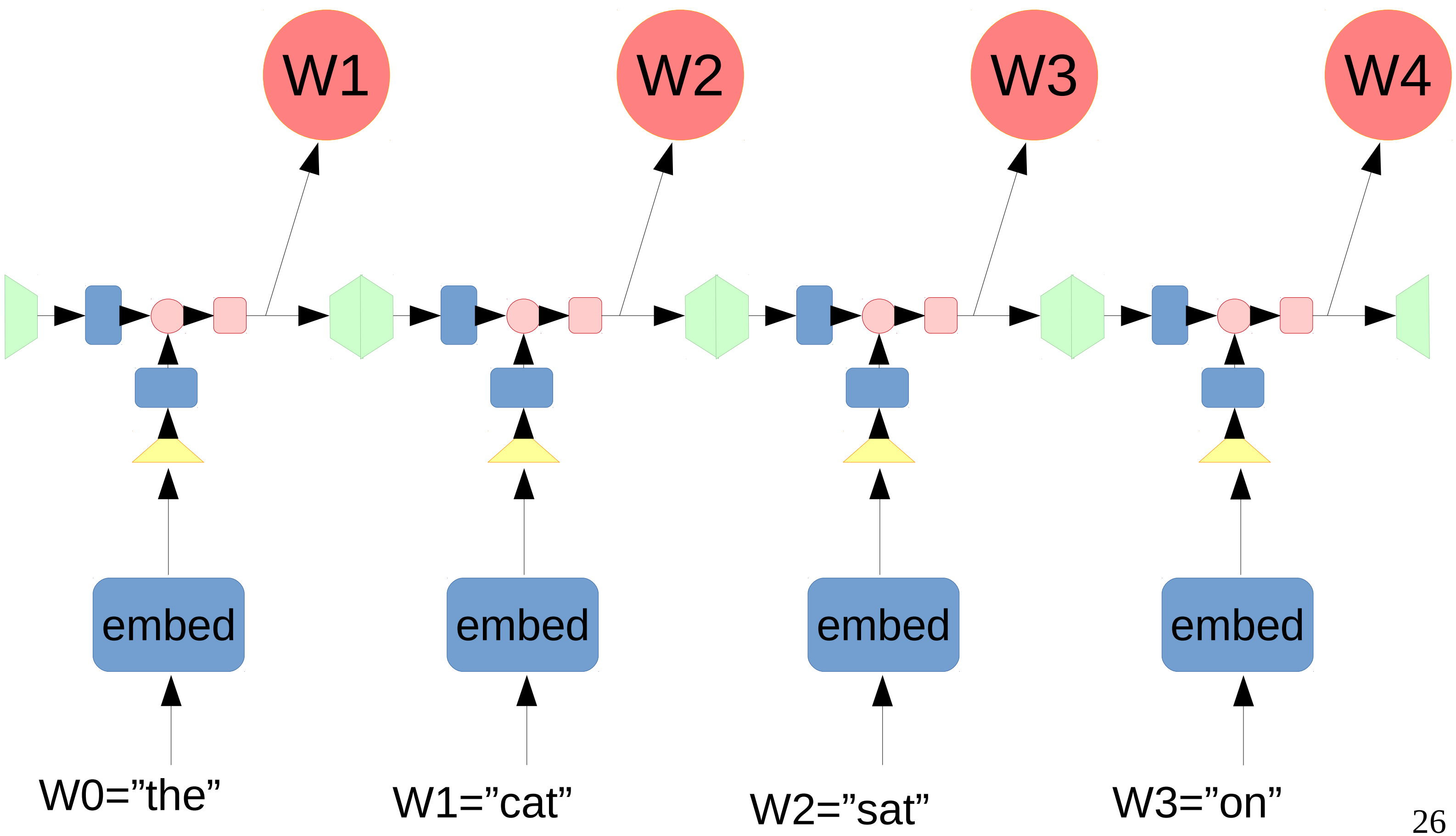
Truncated BPTT

Reality: roll for T steps,
then truncate
(T=10? 20? 1000?)



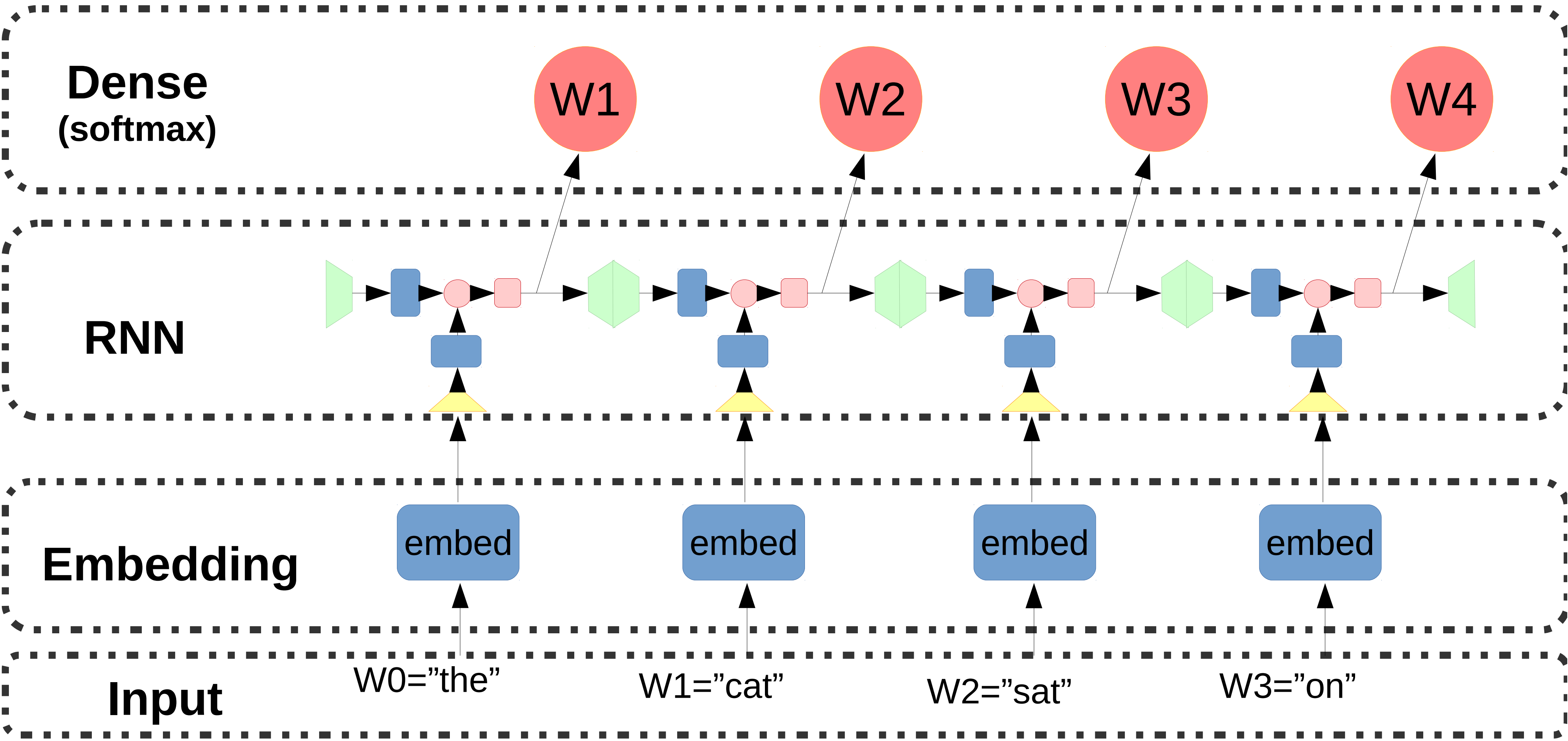

STATISTICAL LEARNING
Gentlemen, our learner overgeneralizes because the VC-Dimension of our Kernel is too high, Get some experts and minimze the structural risk in a new one. Rework our loss function, make the next kernel stable, unbiased and consider using a soft margin
NEURAL NETWORKS
STACK MORE LAYERS
LAYERS
LAYERS

What is layer, again?

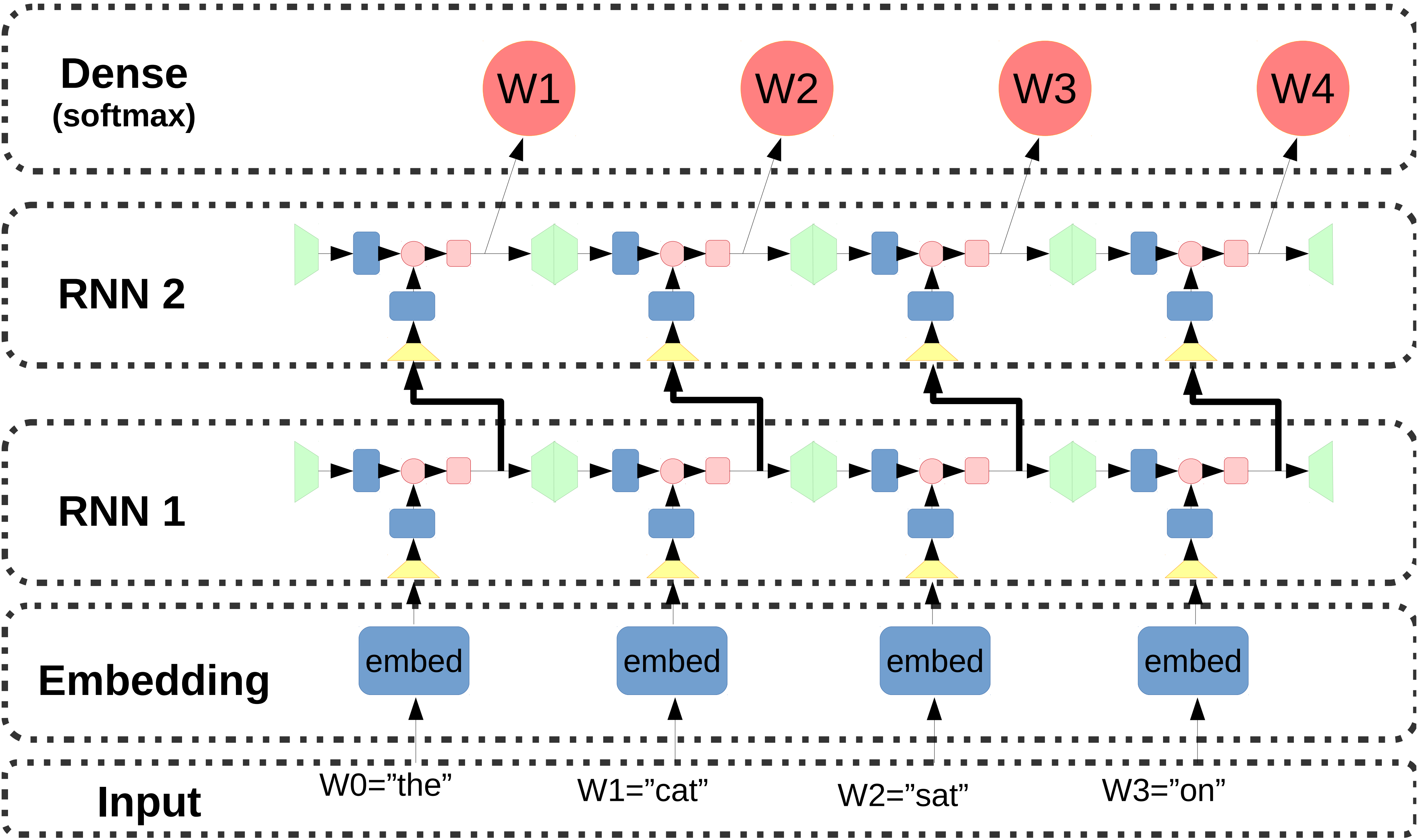


Layers

Where to stick more layers?

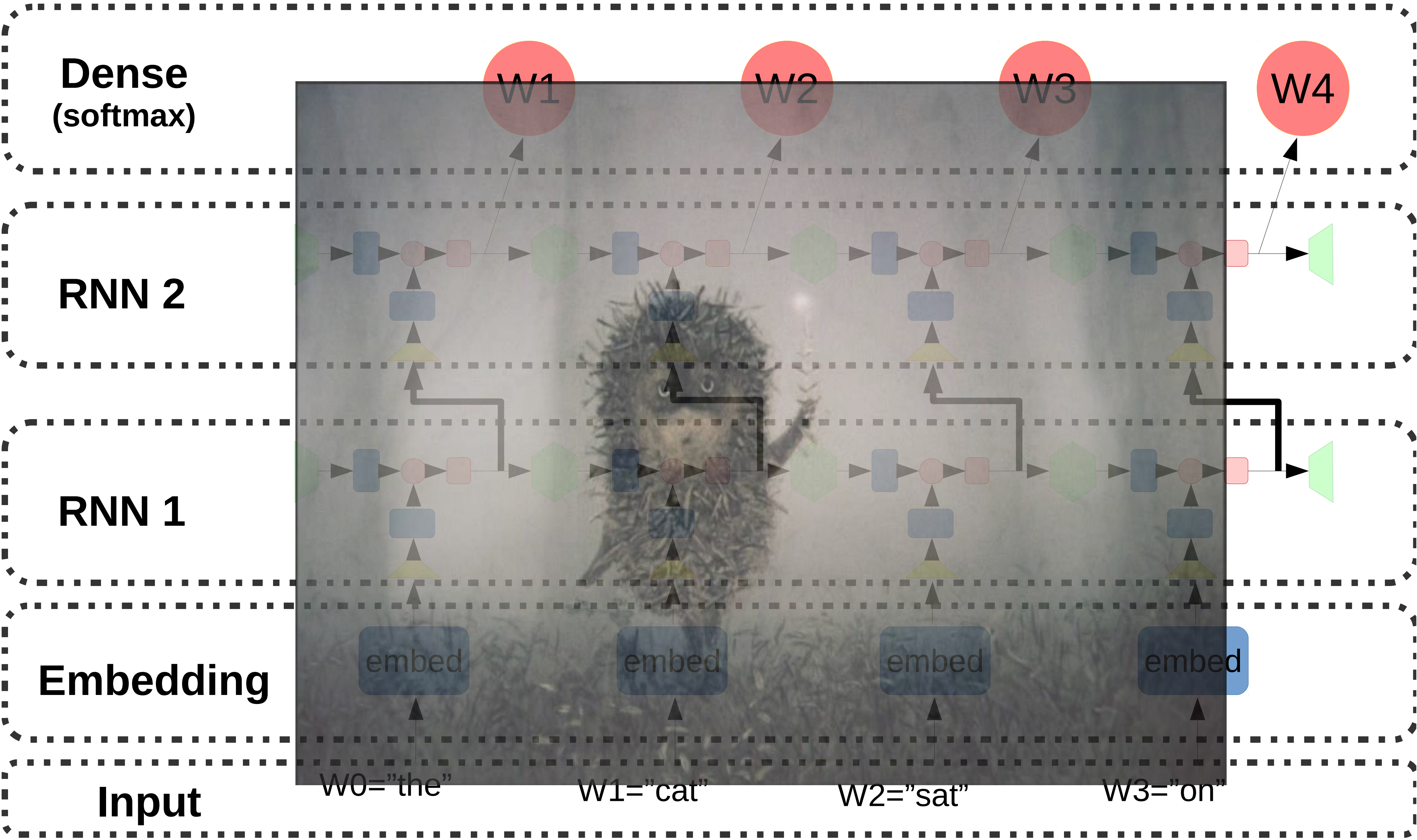


More layers

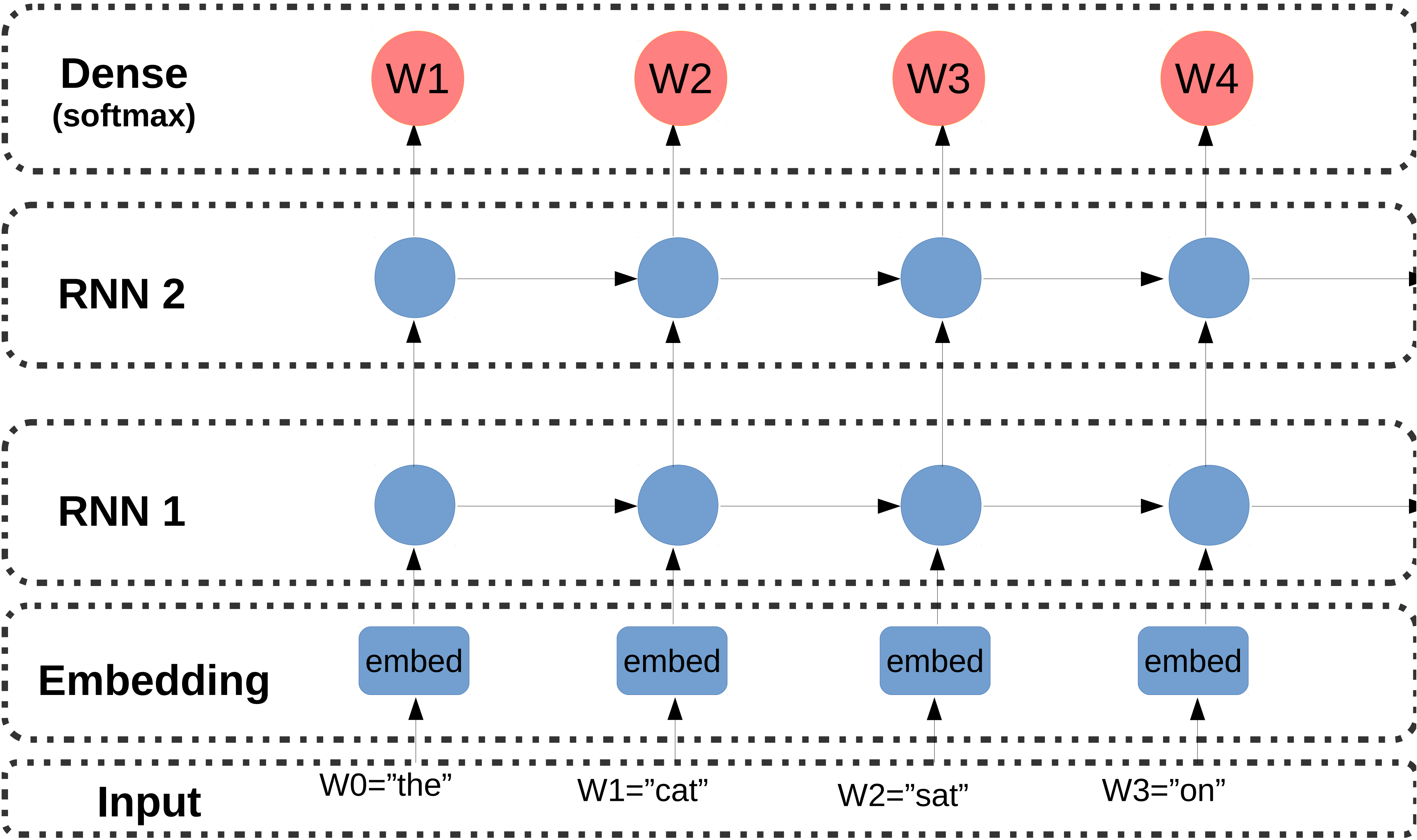


Dense
(softmax)
W1
W2
W3
W4
RNN 2
RNN 1
Embedding
embed
embed
embed
embed
Input
W0="the"
W1="cat"
W2="sat"
W3="on"

Too f**king complicated

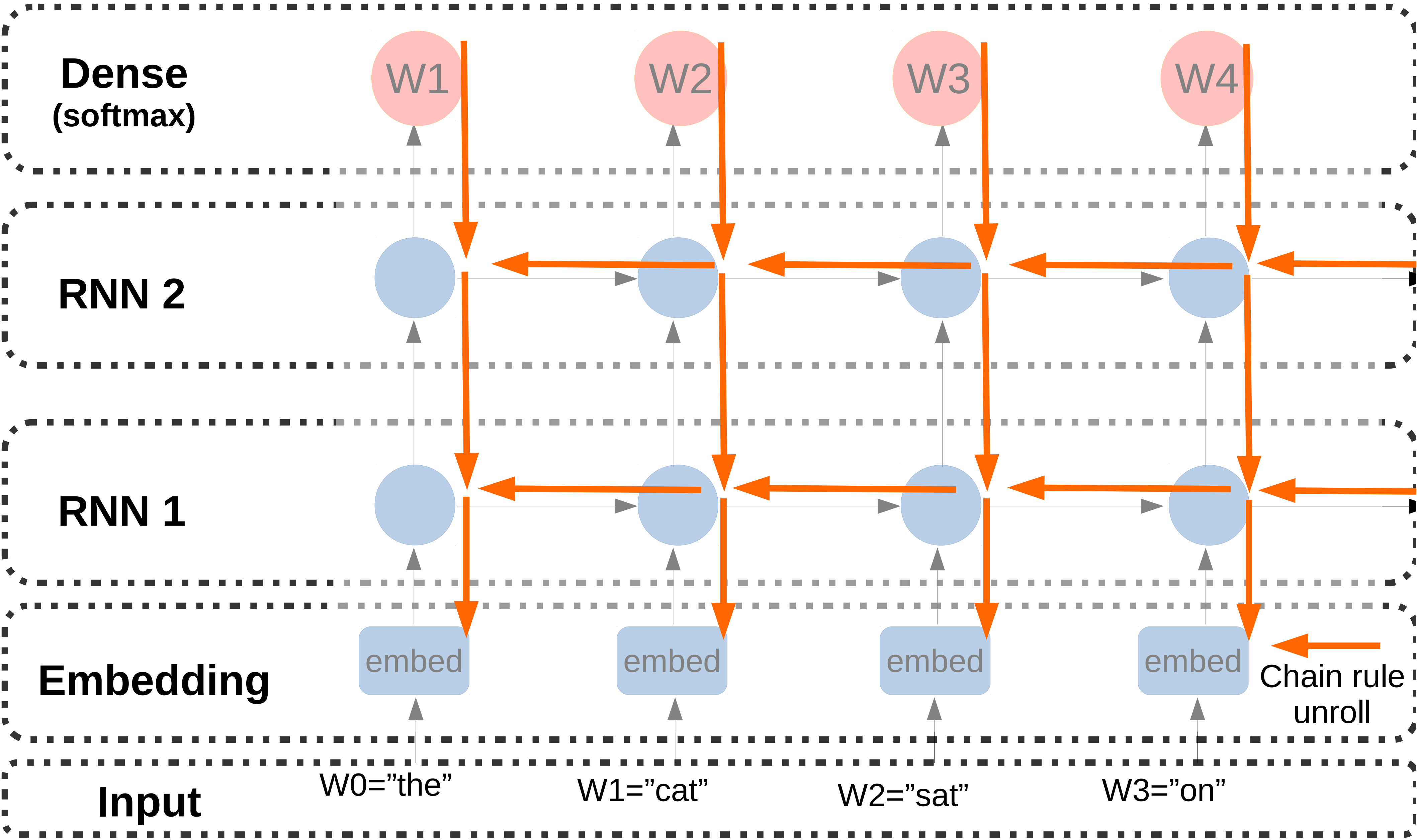


2-layer RNN



Dense
(softmax)
W1
W2
W3
W4
RNN 2
RNN 1
Embedding
embed
embed
embed
embed
Input
W0="the"
W1="cat"
W2="sat"
W3="on"

BPTT again

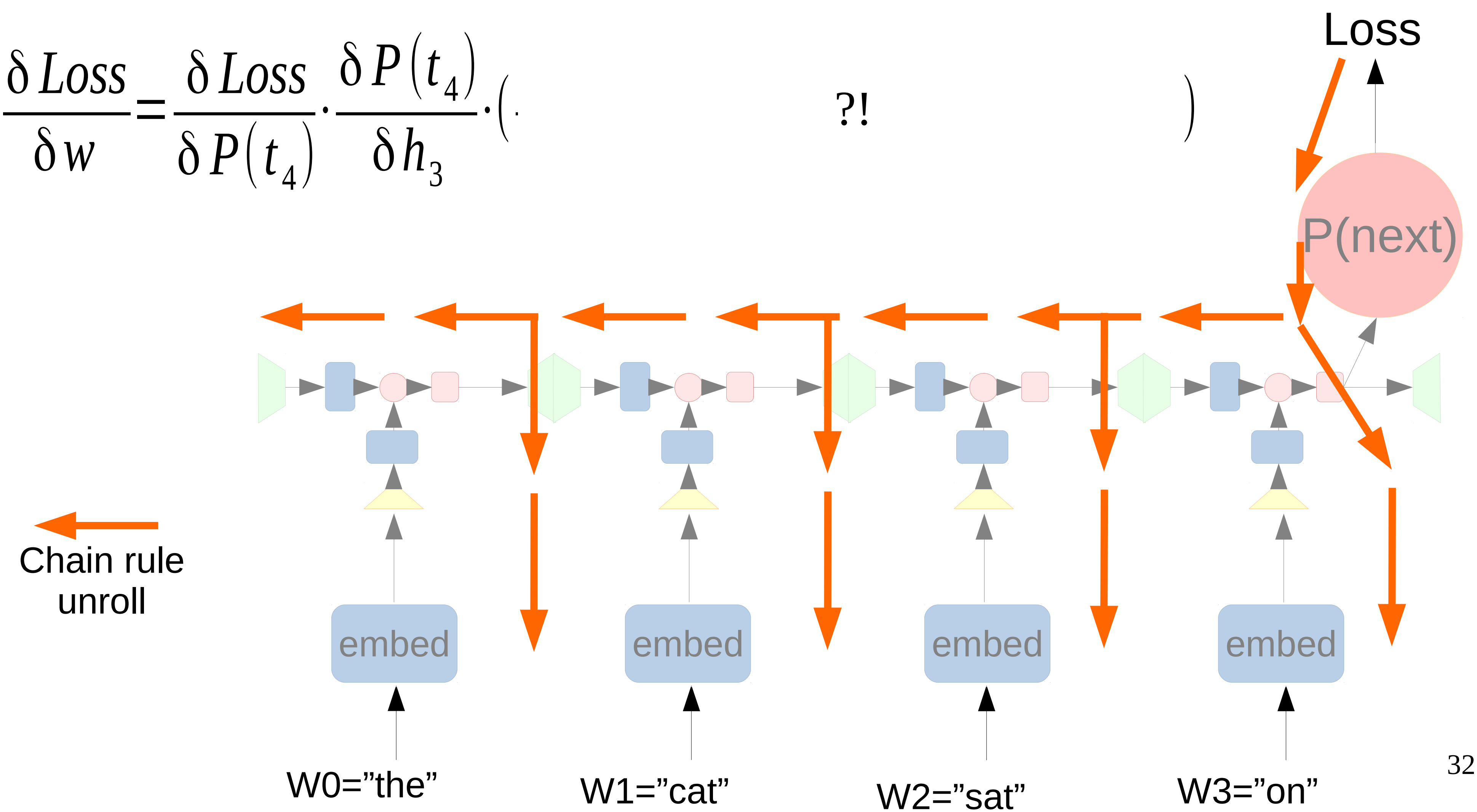


Dense
(softmax)
W1
W2
W3
W4
RNN 2
RNN 1
Embedding
embed
embed
embed
embed
Chain rule
unroll
Input
W0="the"
W1="cat"
W2="sat"
W3="on"

BPTT Again

$$h_{i+1} = \sigma\left(W_h \cdot h_i + W_i \cdot t_i + b\right)$$

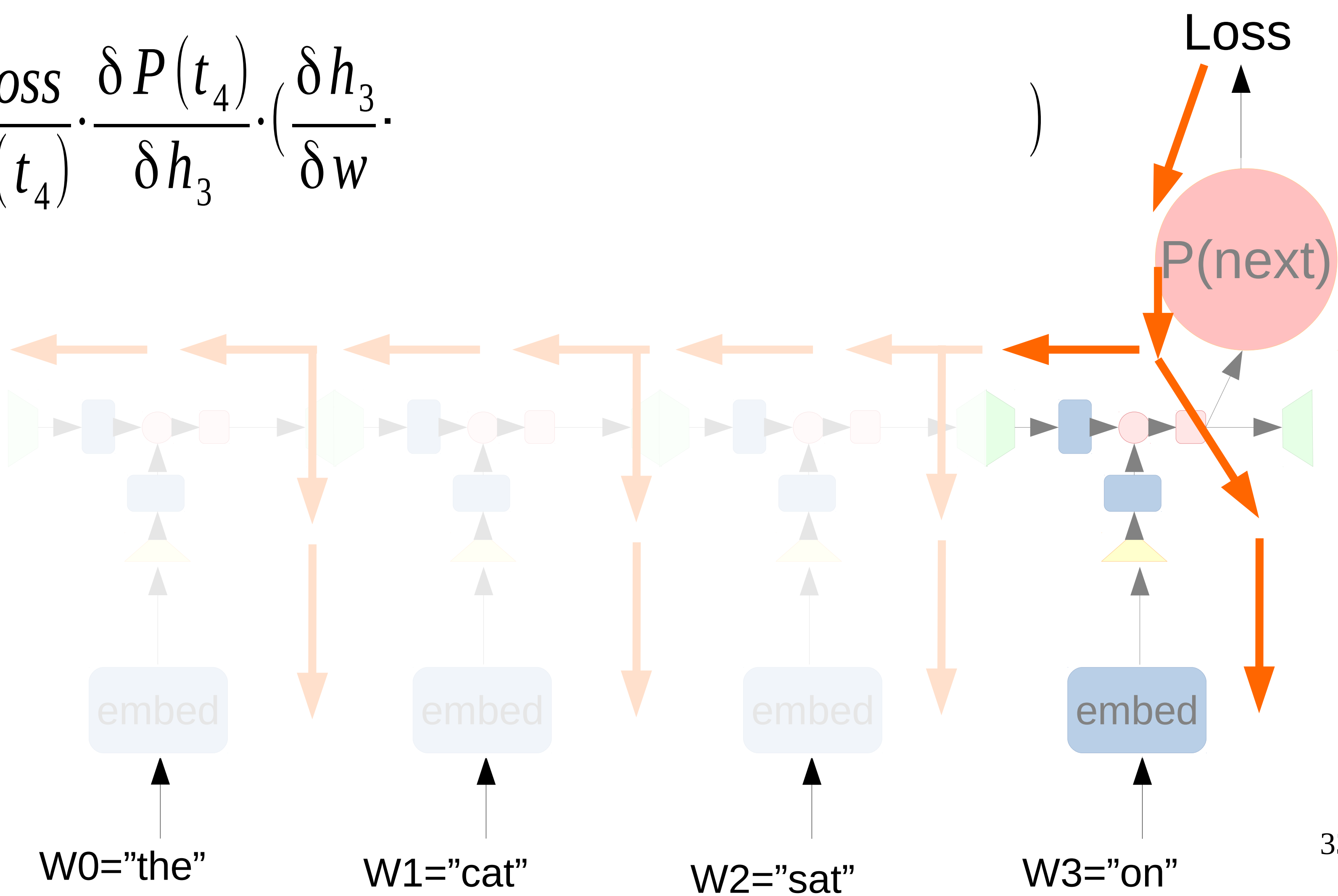
$$\frac{\delta\, Loss}{\delta w} = \frac{\delta\, Loss}{\delta P(t_4)} \cdot \frac{\delta P(t_4)}{\delta h_3} \cdot \left(\cdot \qquad ?! \qquad \right)$$



BPTT Again

$$h_{i+1} = \sigma\left(W_h \cdot h_i + W_i \cdot t_i + b\right)$$

$$\frac{\delta\, Loss}{\delta\, w} = \frac{\delta\, Loss}{\delta\, P(t_4)} \cdot \frac{\delta\, P(t_4)}{\delta\, h_3} \cdot \left(\frac{\delta\, h_3}{\delta\, w} \cdot \qquad\qquad\qquad\qquad \right)$$

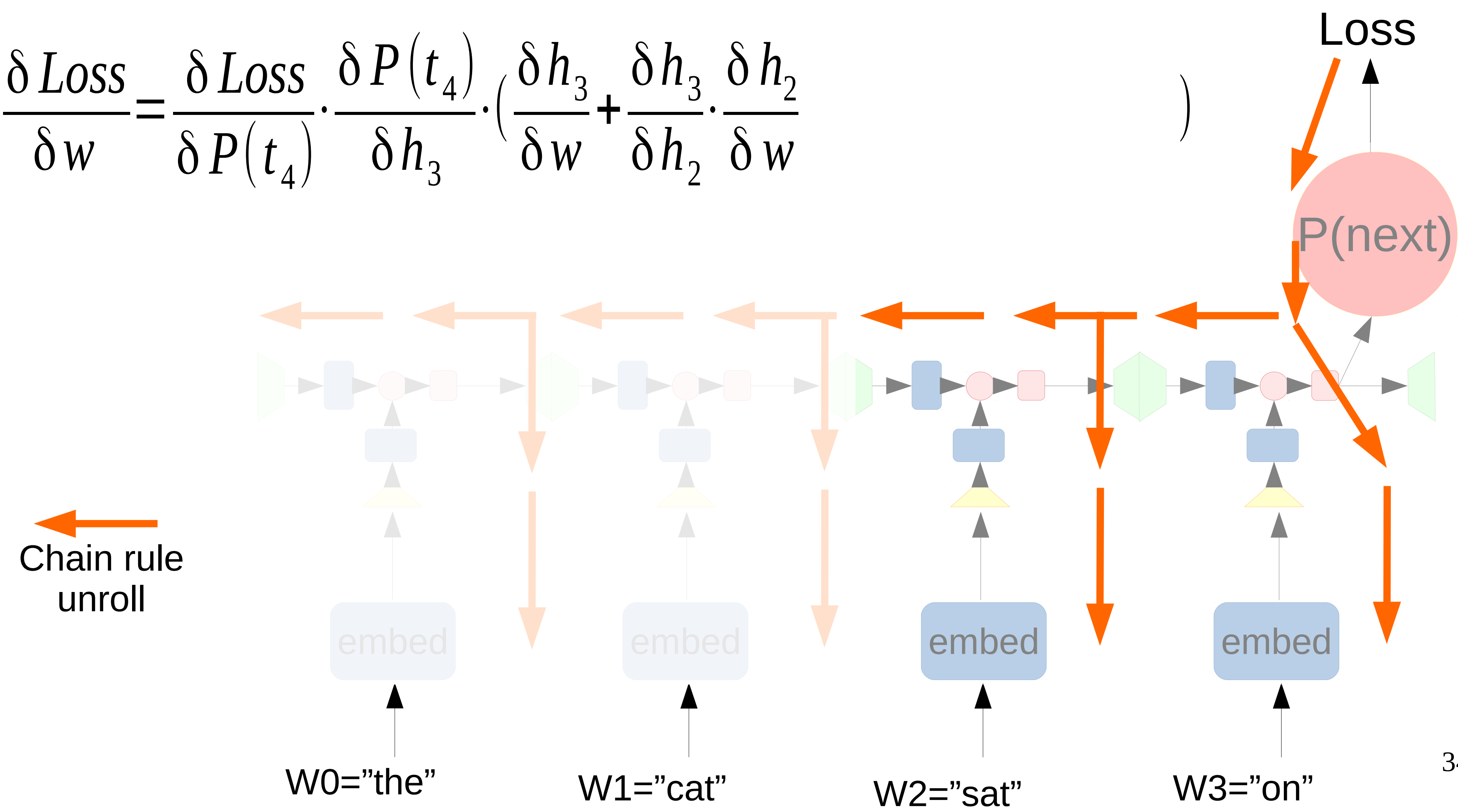


Chain rule
unroll

BPTT Again

$$h_{i+1} = \sigma\left(W_h \cdot h_i + W_i \cdot t_i + b\right)$$

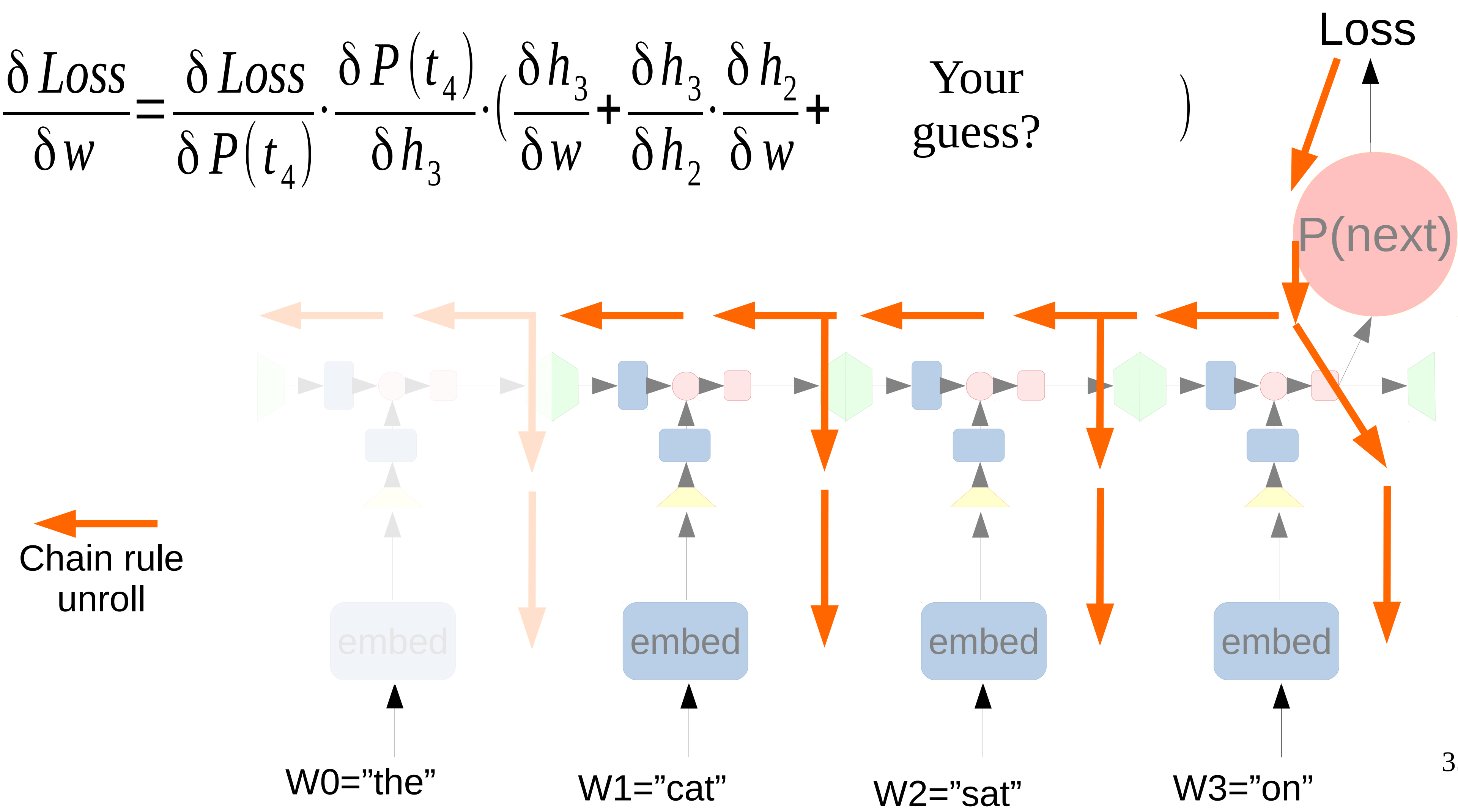
$$\frac{\delta Loss}{\delta w} = \frac{\delta Loss}{\delta P(t_4)} \cdot \frac{\delta P(t_4)}{\delta h_3} \cdot \left(\frac{\delta h_3}{\delta w} + \frac{\delta h_3}{\delta h_2} \cdot \frac{\delta h_2}{\delta w} \right)$$



BPTT Again

$$h_{i+1} = \sigma\left(W_h \cdot h_i + W_i \cdot t_i + b\right)$$

$$\frac{\delta Loss}{\delta w} = \frac{\delta Loss}{\delta P(t_4)} \cdot \frac{\delta P(t_4)}{\delta h_3} \cdot \left(\frac{\delta h_3}{\delta w} + \frac{\delta h_3}{\delta h_2} \cdot \frac{\delta h_2}{\delta w} + \quad \text{Your guess?} \quad \right)$$



BPTT Again

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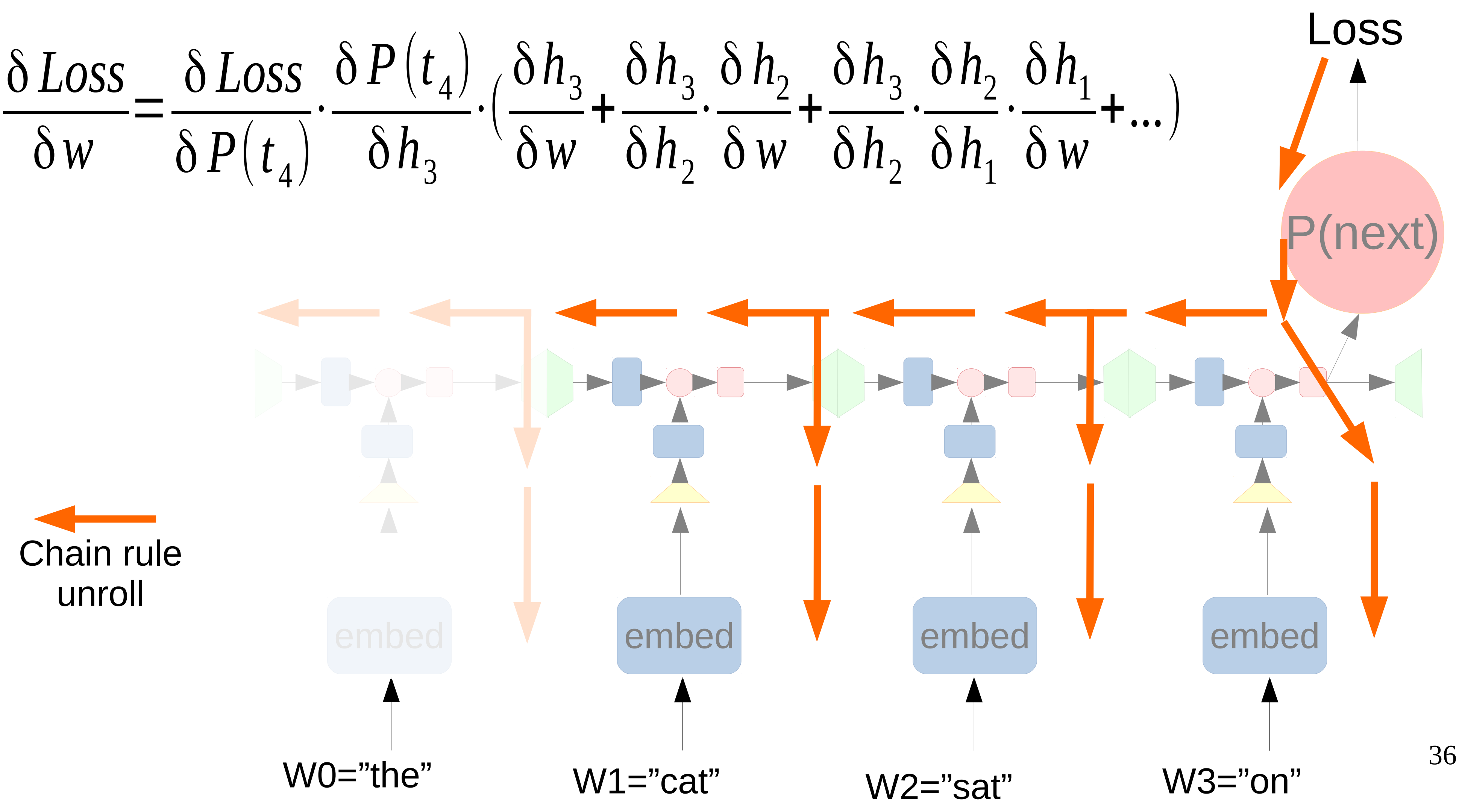


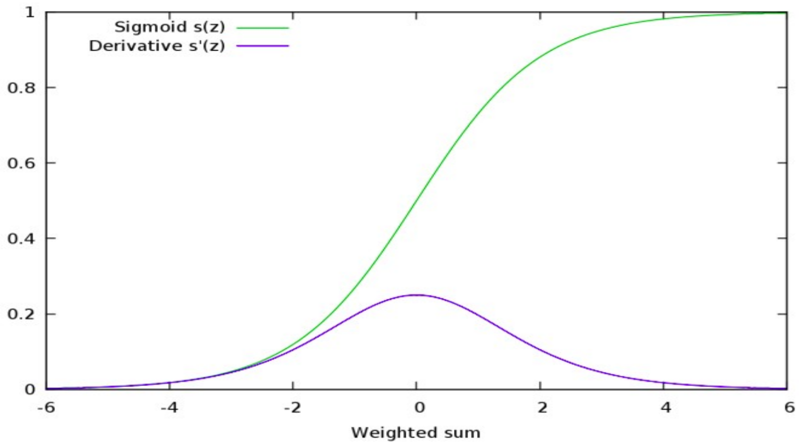
Gradient explosion and vanishing

$$h_{i+1} = \sigma\left(W_h \cdot h_i + W_i \cdot t_i + b\right)$$

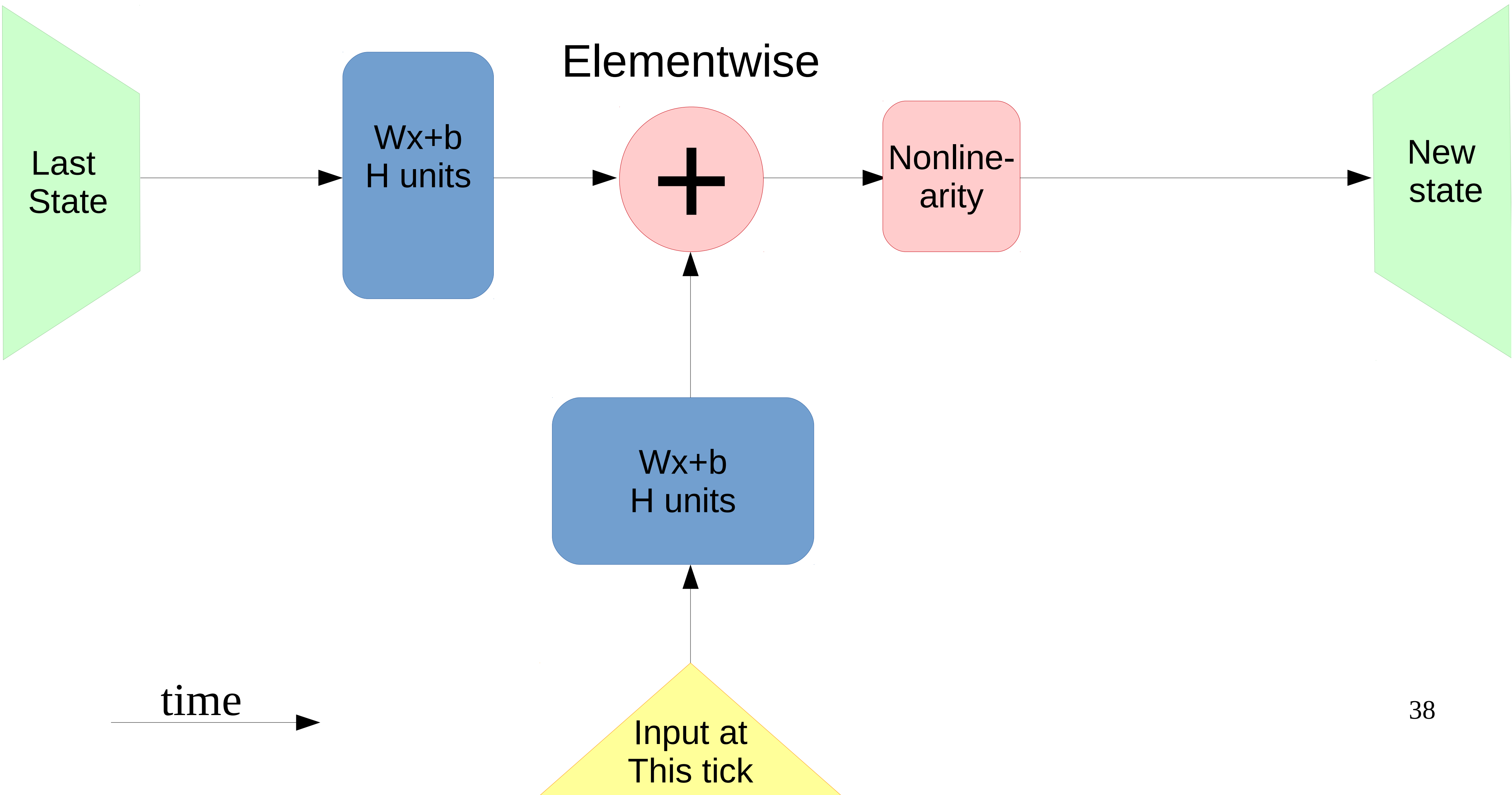
$$\frac{\delta Loss}{\delta w} = \frac{\delta Loss}{\delta P\left(t_4\right)} \cdot \frac{\delta P\left(t_4\right)}{\delta h_3} \cdot \left(\frac{\delta h_3}{\delta w} + \frac{\delta h_3}{\delta h_2} \cdot \frac{\delta h_2}{\delta w} + \frac{\delta h_3}{\delta h_2} \cdot \frac{\delta h_2}{\delta h_1} \cdot \frac{\delta h_1}{\delta w} + \dots\right)$$

- Many sigmoids near 0 or 1
  - Gradients → 0
  - Not training for long-term dependencies

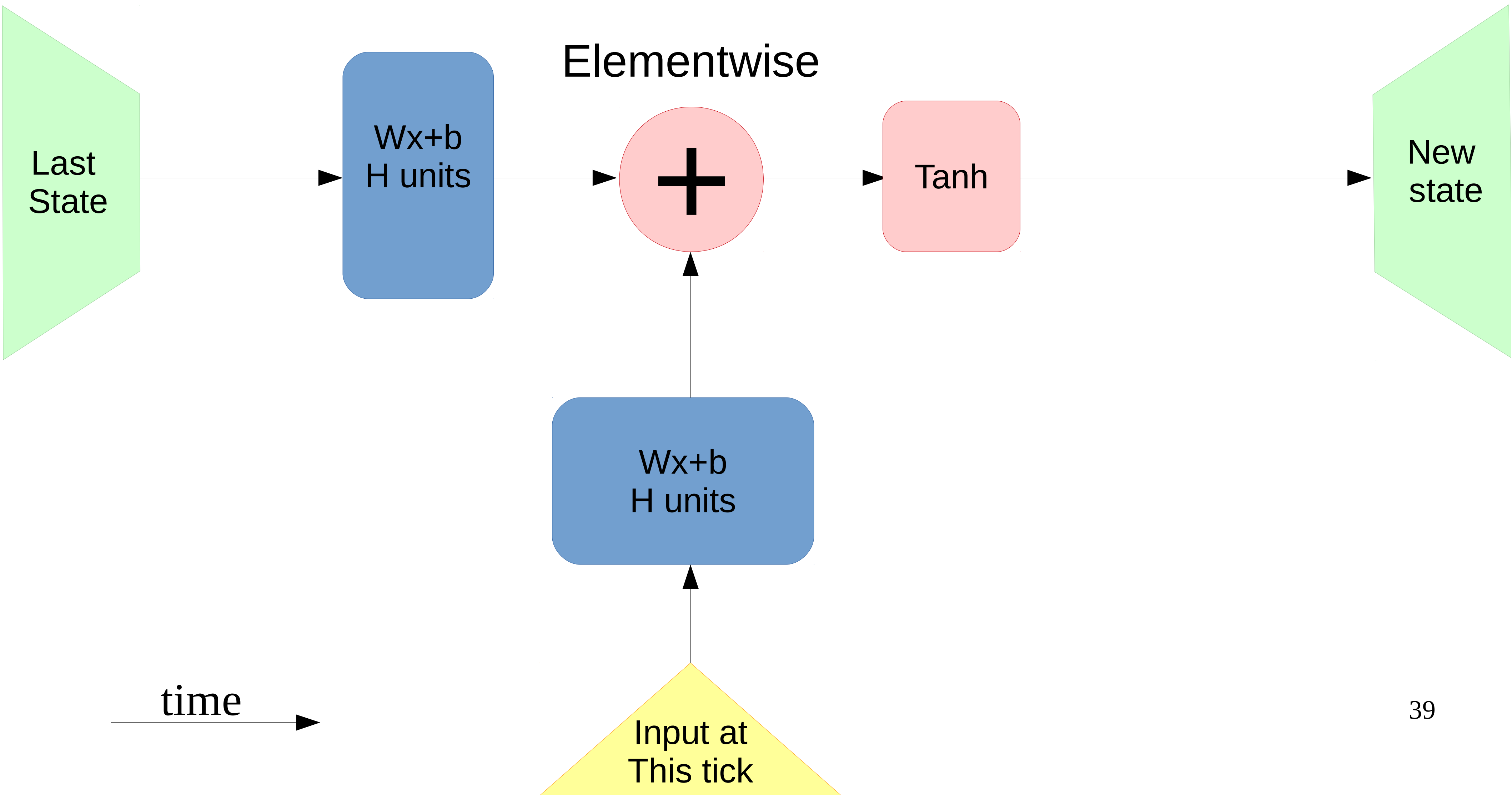
- Many nonzero values
  - Derivative stacks to >1
  - Gradients → inf
  - Weights → shit



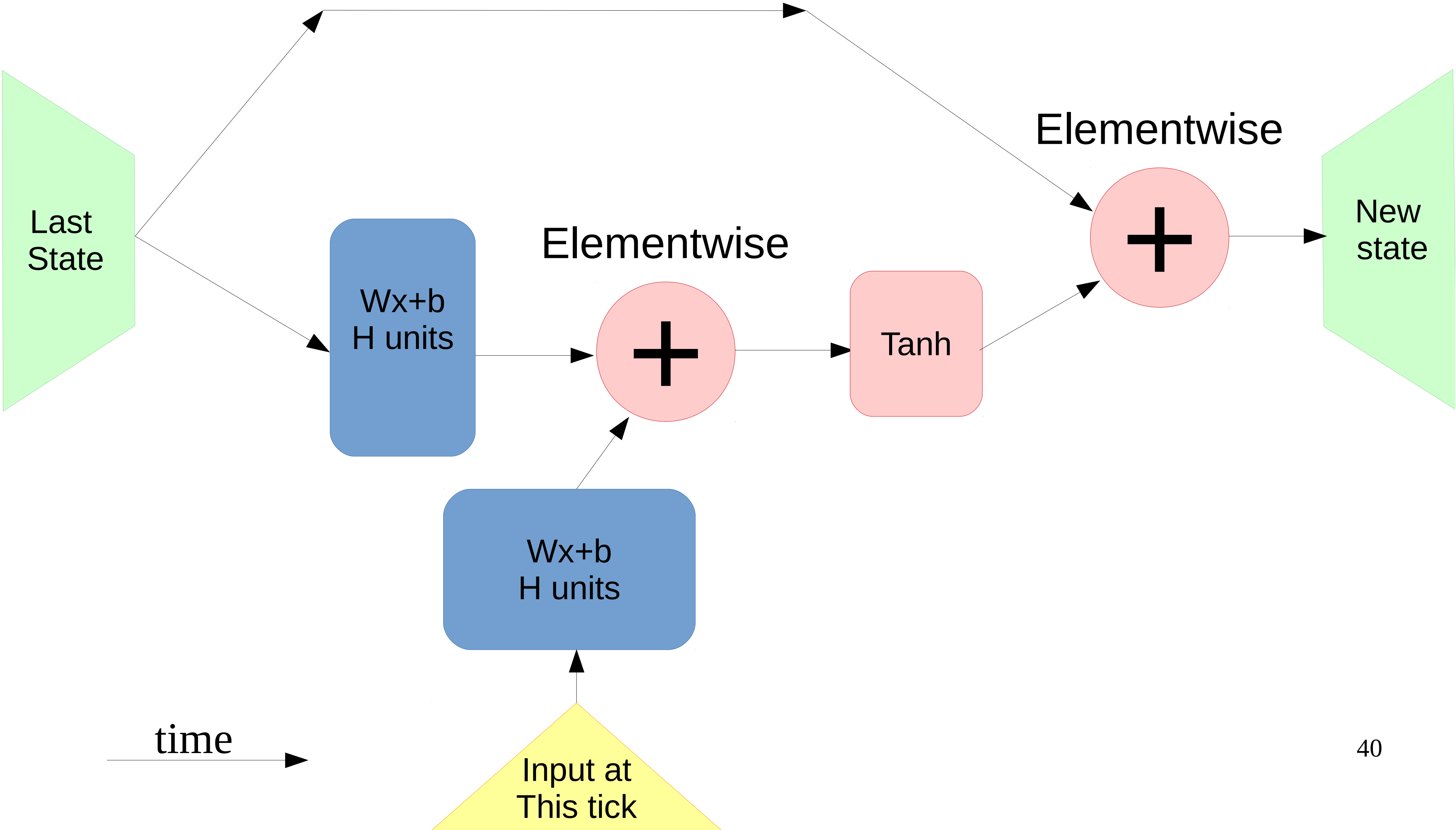
RNN step


Last
State
Wx+b
H units
Elementwise
+
Nonline-
arity
New
state
Wx+b
H units
Input at
This tick
time

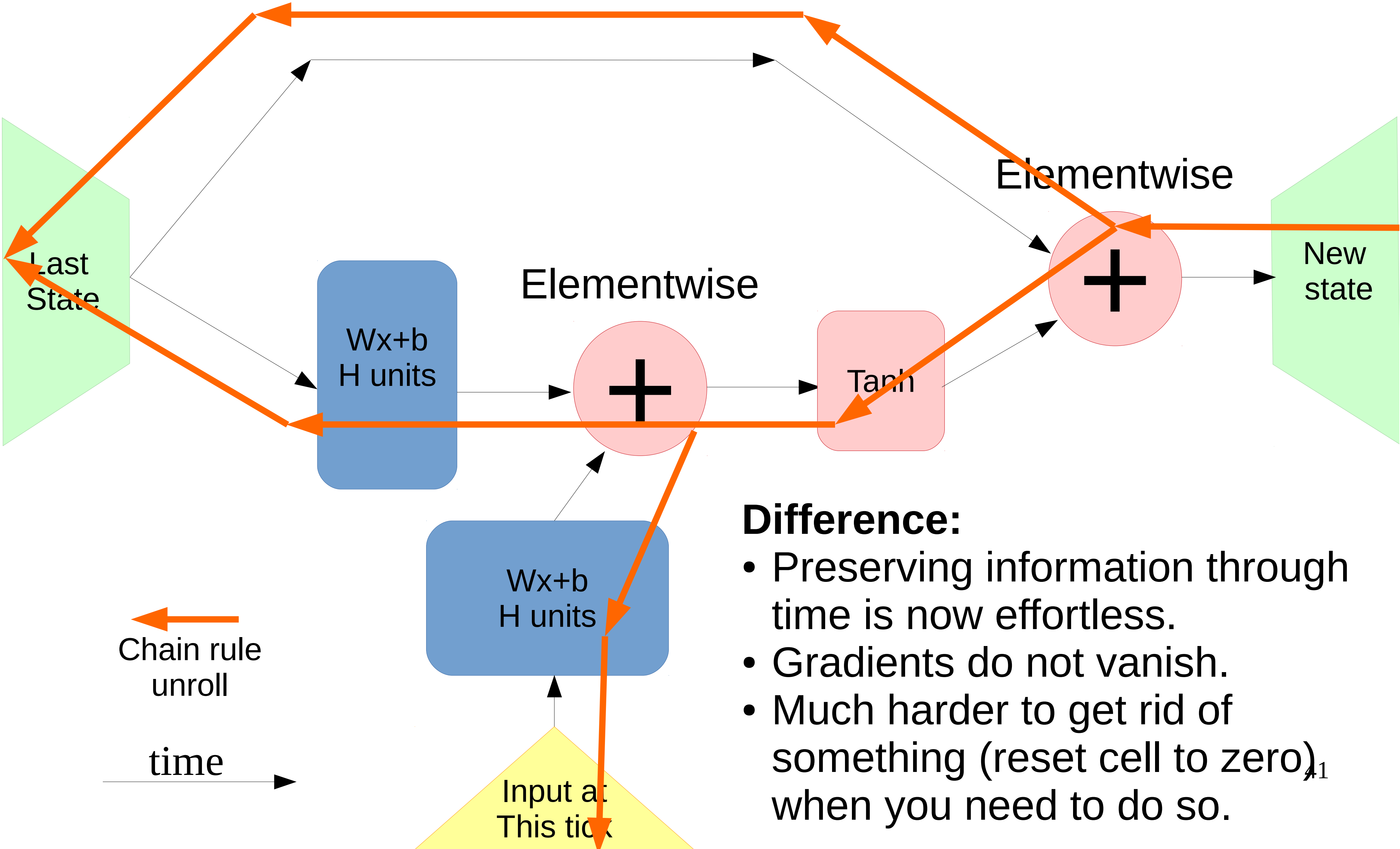
RNN step


Elementwise
Last
State
Wx+b
H units
+
Tanh
New
state
Wx+b
H units
Input at
This tick
time

Residual RNN step



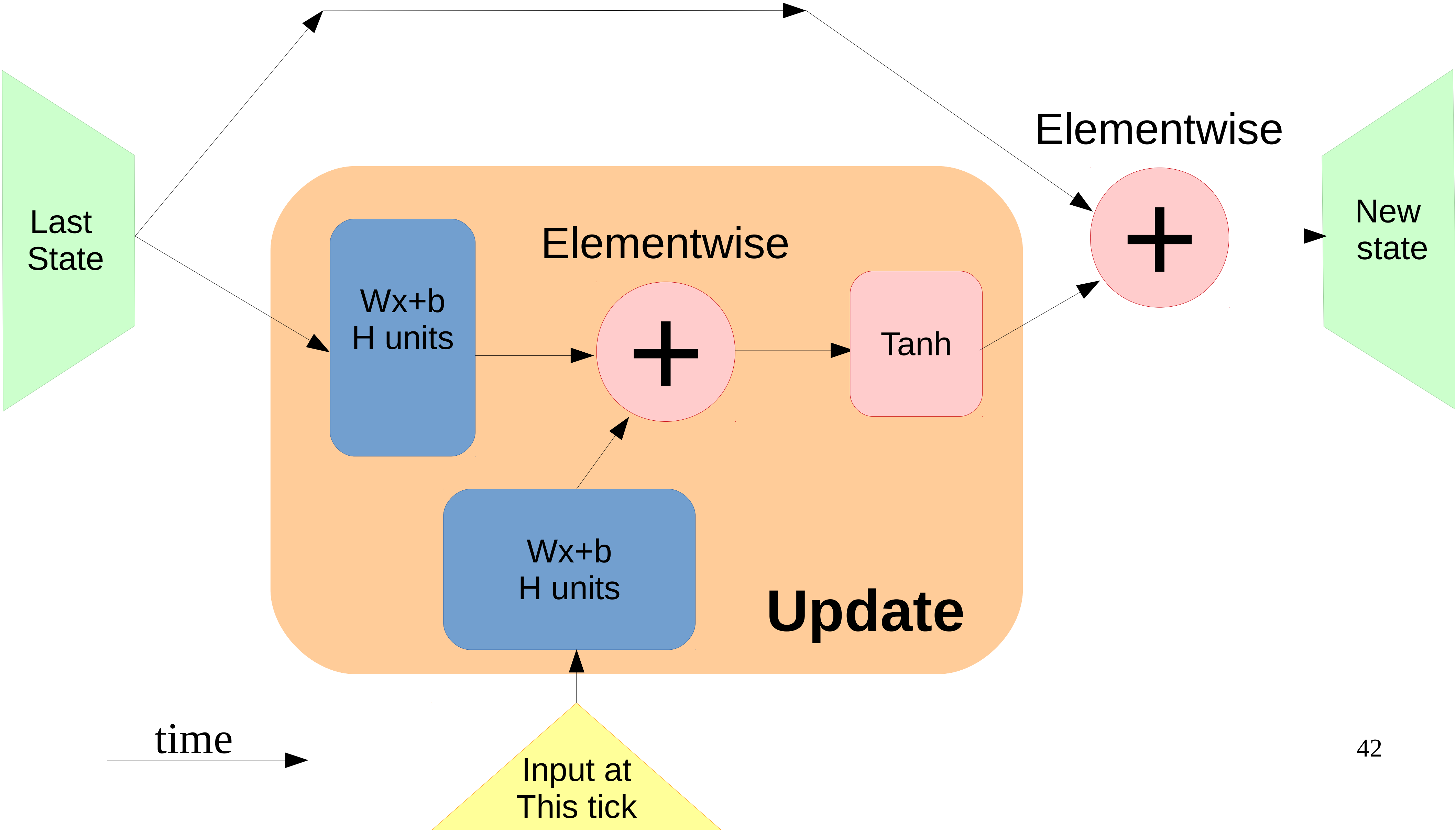
Residual RNN step



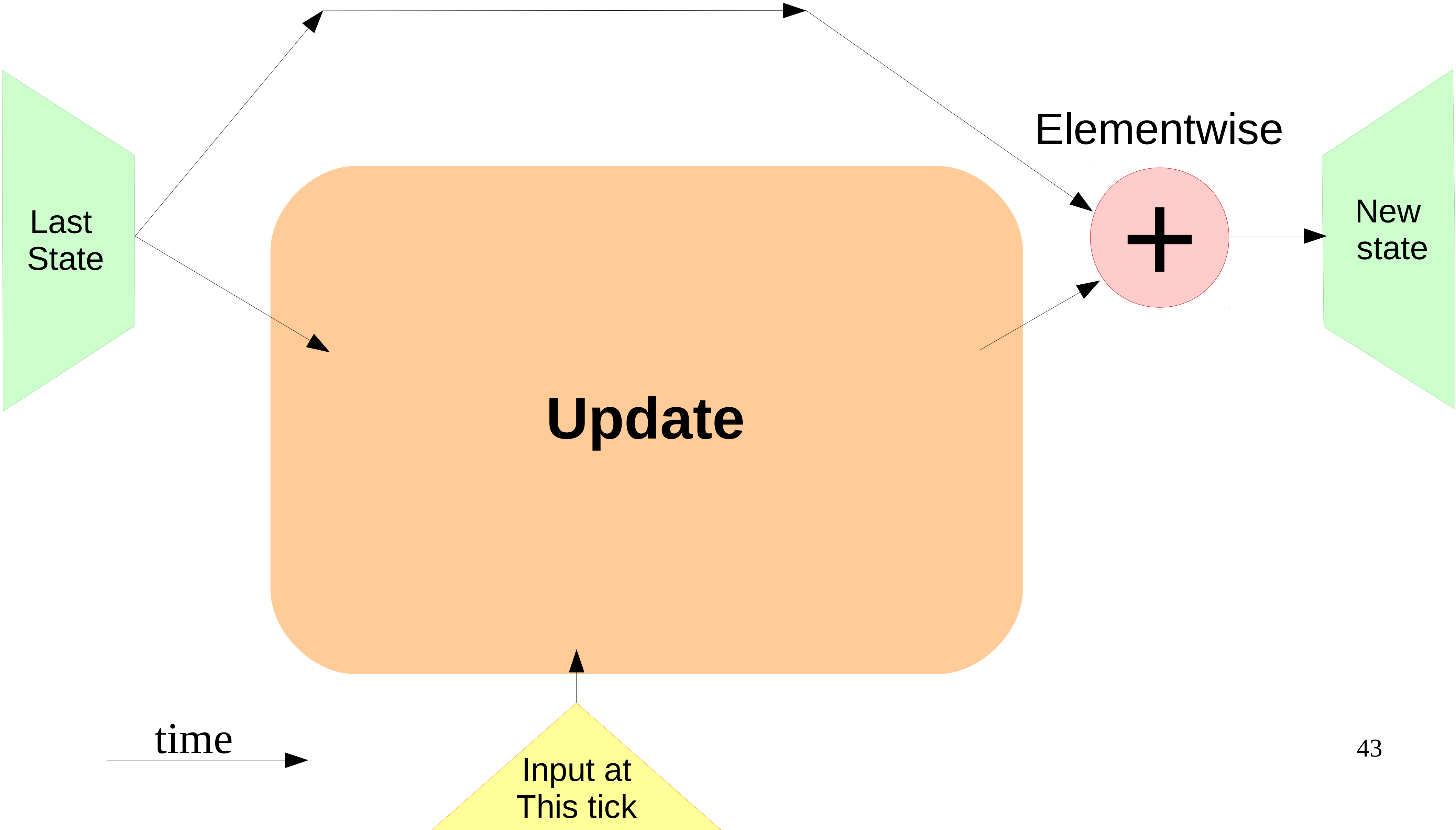
Difference:

- Preserving information through time is now effortless.
- Gradients do not vanish.
- Much harder to get rid of something (reset cell to zero) when you need to do so.

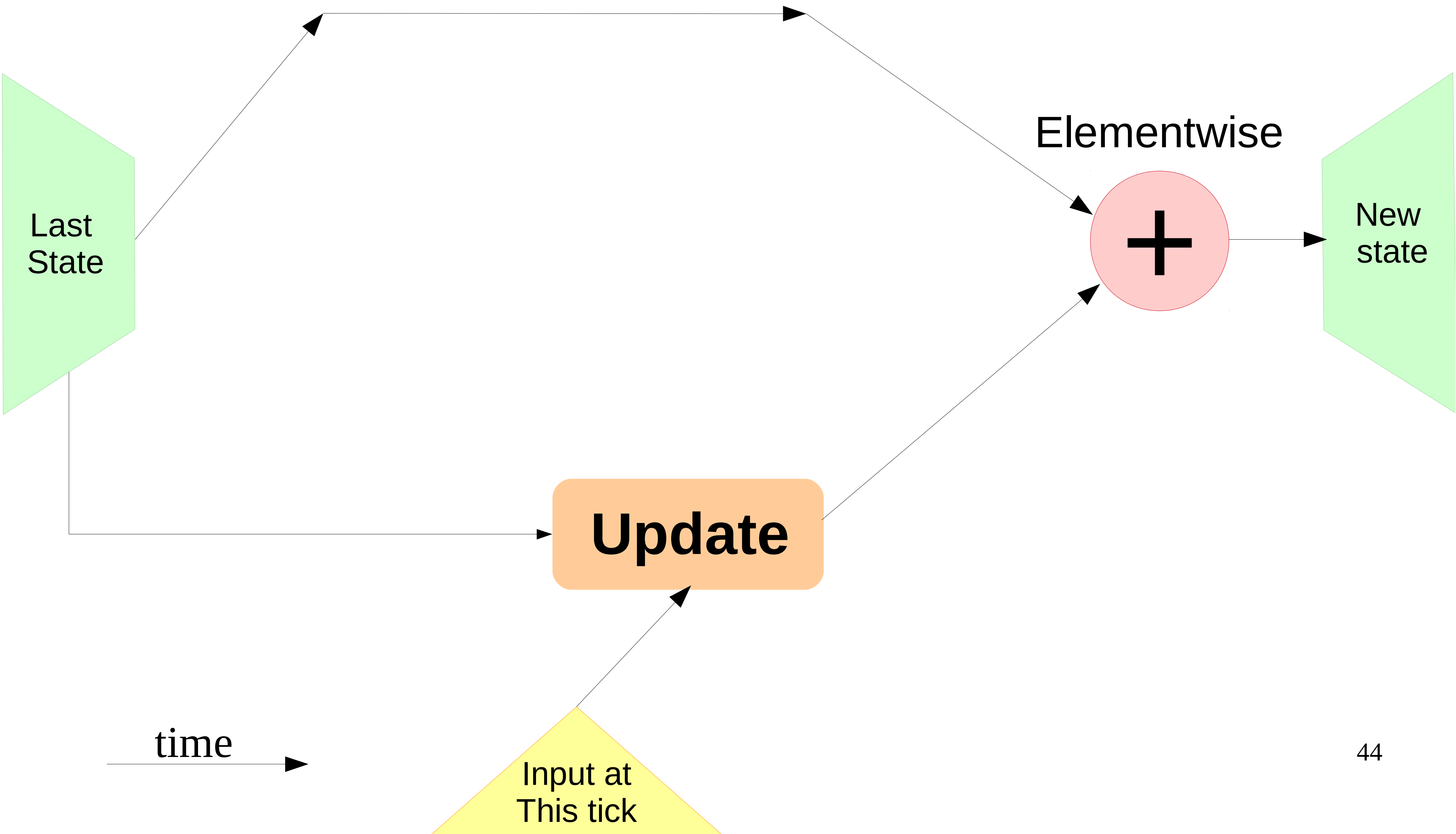
Residual RNN step



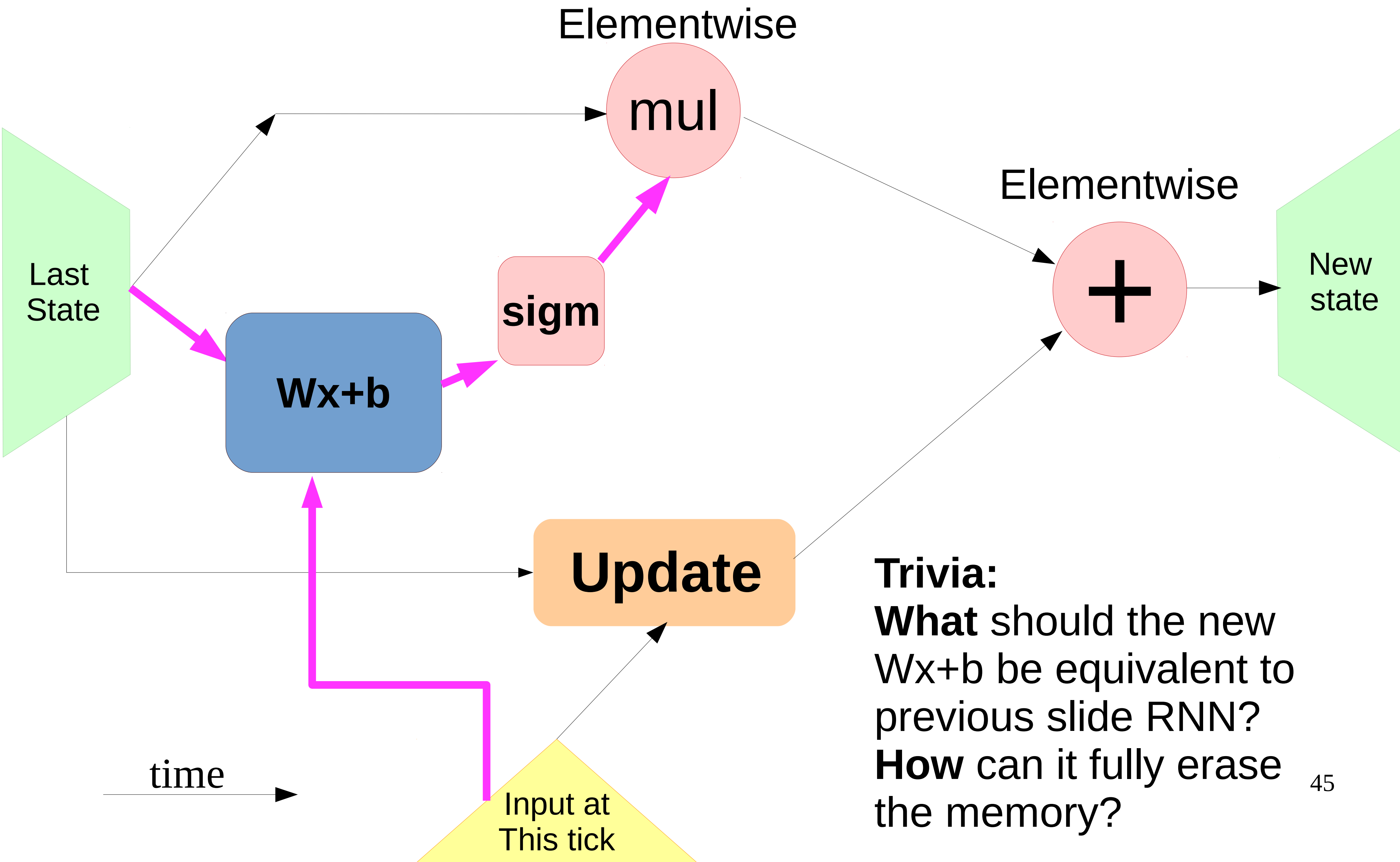
Residual RNN step



Residual RNN step

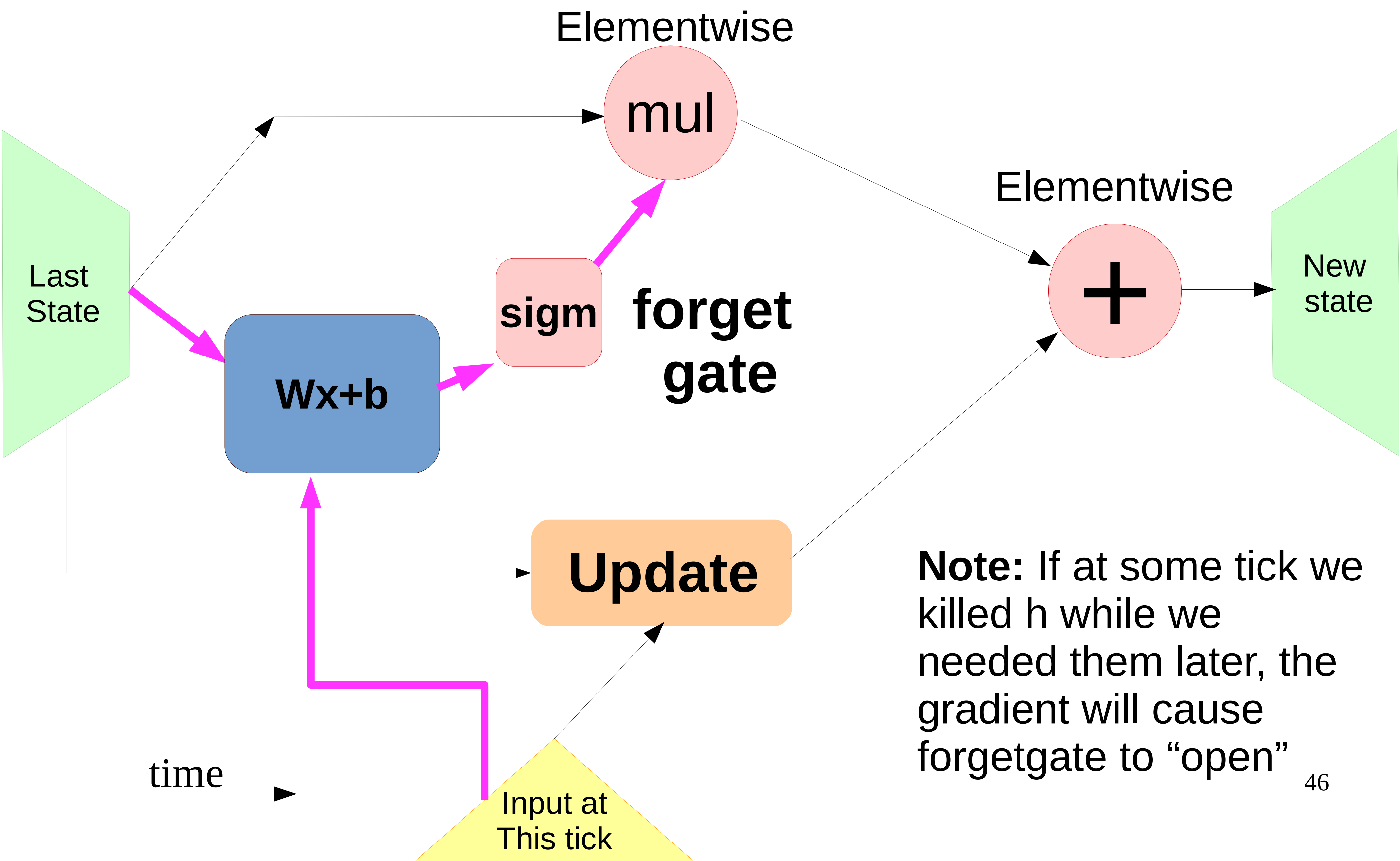


Residual RNN step



Trivia:
What should the new Wx+b be equivalent to previous slide RNN?
How can it fully erase the memory?

Residual RNN step



Note: If at some tick we killed h while we needed them later, the gradient will cause forgetgate to “open”

What we drew

$$update\left(x_i, h_{i-1}\right) = \tanh\left(W_h^{update} \cdot h_{i-1} + W_{inp}^{update} \cdot x_i + b^{update}\right)$$

What we drew

$$update(x_i, h_{i-1}) = \tanh\left(W_h^{update} \cdot h_{i-1} + W_{inp}^{update} \cdot x_i + b^{update}\right)$$

$$forget(x_i, h_{i-1}) = \sigma\left(W_h^{forget} \cdot h_{i-1} + W_{inp}^{forget} \cdot x_i + b^{forget}\right)$$

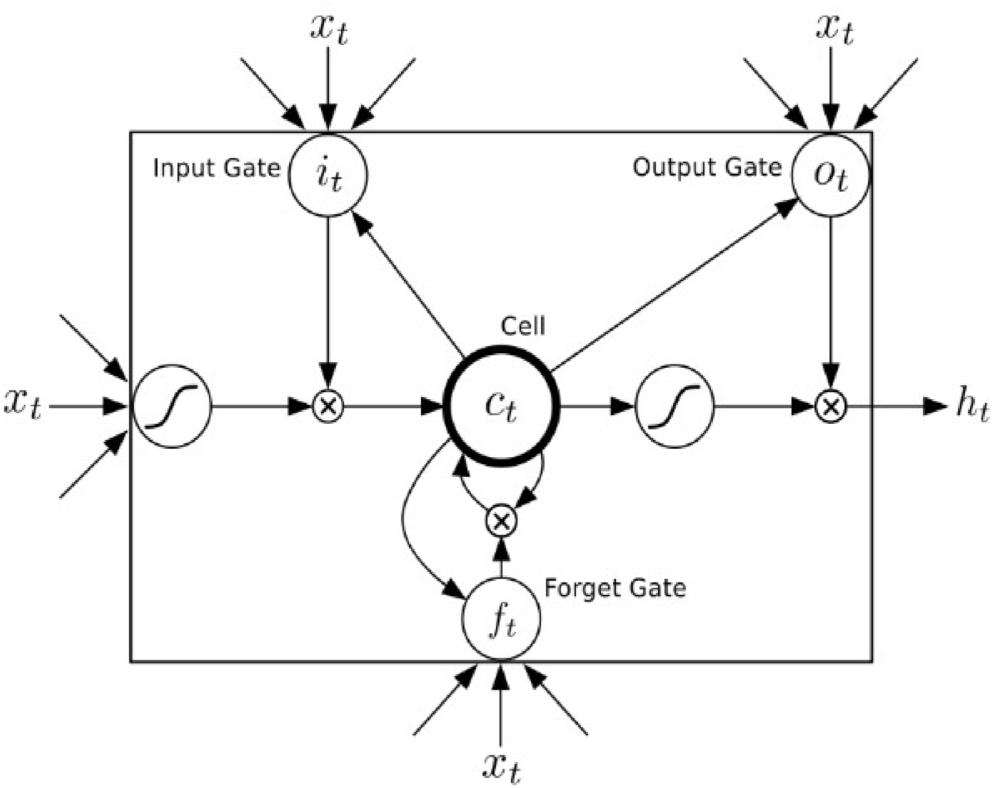
What we drew

$$update(x_i, h_{i-1}) = \tanh(W_h^{update} \cdot h_{i-1} + W_{inp}^{update} \cdot x_i + b^{update})$$

$$forget(x_i, h_{i-1}) = \sigma(W_h^{forget} \cdot h_{i-1} + W_{inp}^{forget} \cdot x_i + b^{forget})$$

$$h_i(x_i, h_{i-1}) = forget(x_i, h_{i-1}) \cdot h_{i-1} + update(x_i, h_{i-1})$$

LSTM



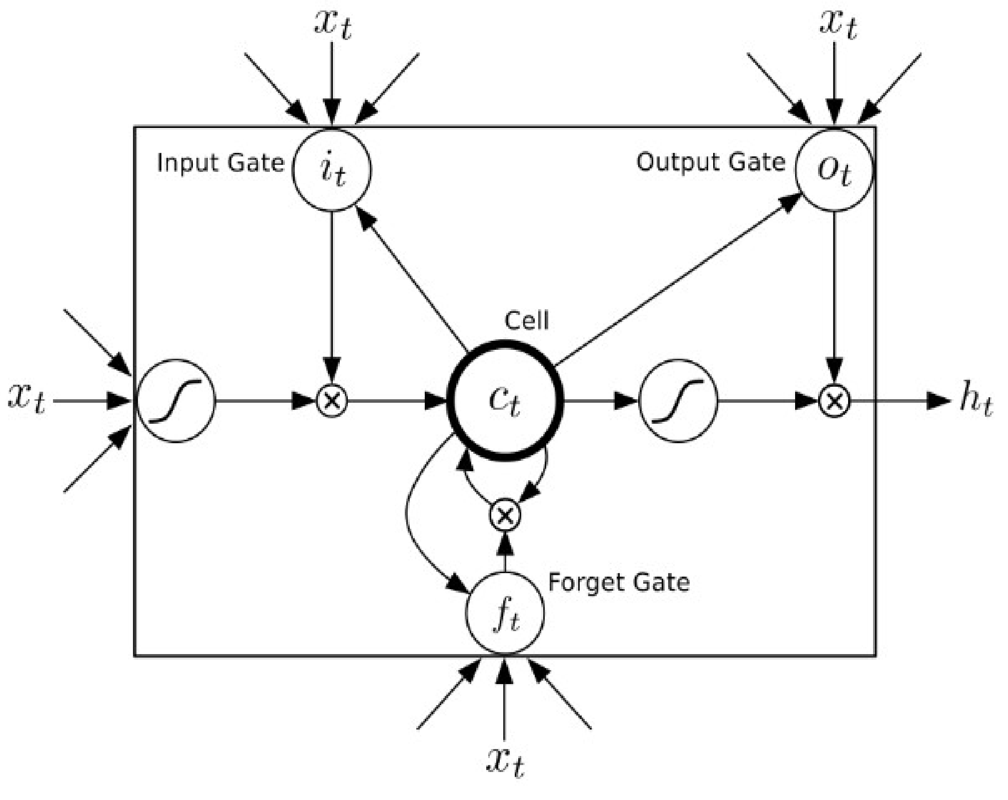
2 hidden states:

- Cell (“private” state)
- Output (“public” state)

4 blocks:

- Update
- Forget gate
- Input gate
- Output gate

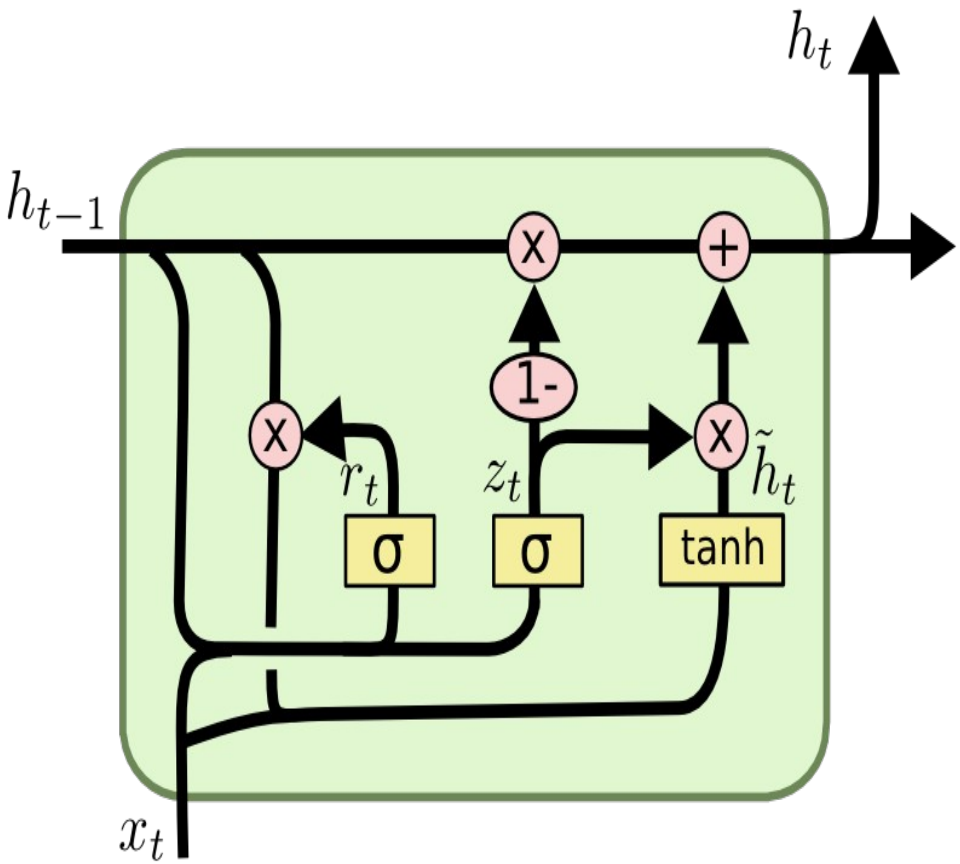
LSTM



$$i_t = Sigm(\theta_{xi} x_t + \theta_{hi} h_{t-1} + b_i)$$
$$f_t = Sigm(\theta_{xf} x_t + \theta_{hf} h_{t-1} + b_f)$$
$$o_t = Sigm(\theta_{xo} x_t + \theta_{ho} h_{t-1} + b_o)$$
$$g_t = Tanh(\theta_{xg} x_t + \theta_{hg} h_{t-1} + b_g)$$
$$c_t = f_t \otimes c_{t-1} + i_t \otimes g_t$$
$$h_t = o_t \otimes Tanh(c_t)$$

Life is to short to draw full sheme

GRU



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

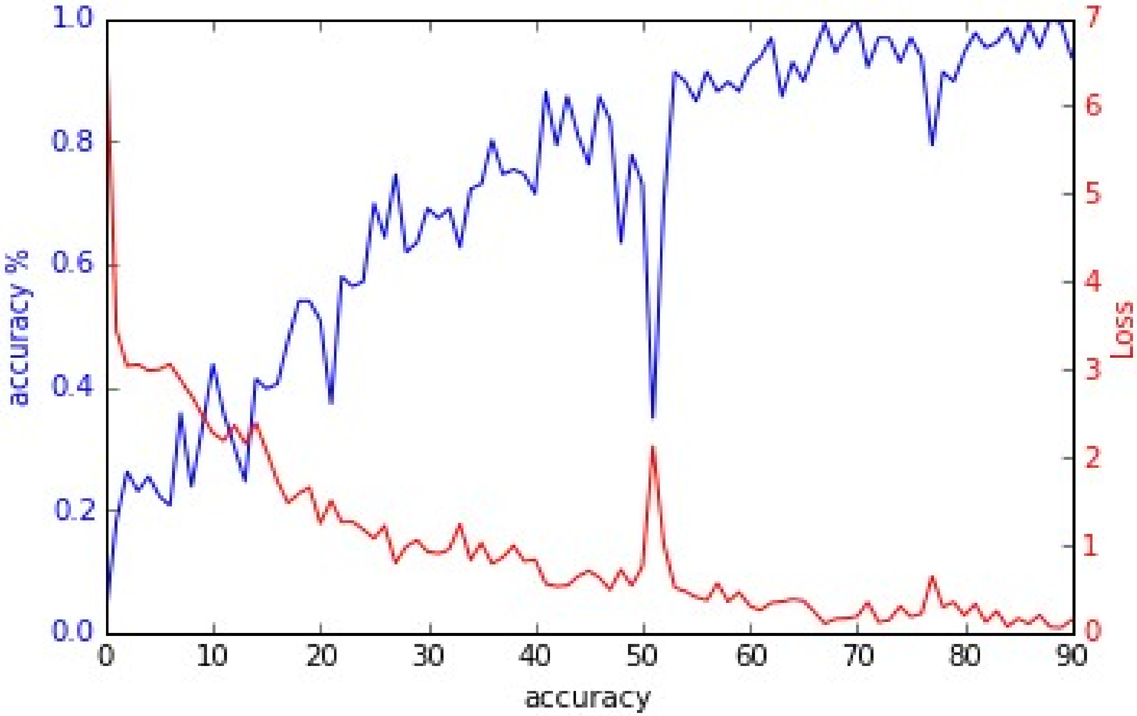
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Okay, the gradients no longer vanish

except they still do

But how do we deal with exploding grads?



Ideas?

Gradient clipping

At each time tick,

- check if grad abs value is more than … 5?
- If so, clip it
  - large positive is now 5,
  - large negative -5

- How large is too large?
  - Reduce clipping threshold until explosions disappear

Generating stuff

Easy:

- Names, small phrases
- Orthographically correct delirium

Medium:

- Grammatically coherent text
- Resembling particular author

Hard:

- C/C++ source code
- Music
- LaTex articles
- Your course projects

Nuff

Let's teach this network good manners!

Nuff

Let's teach this network good manners!