Foundations of DL

Deep Learning

ALF

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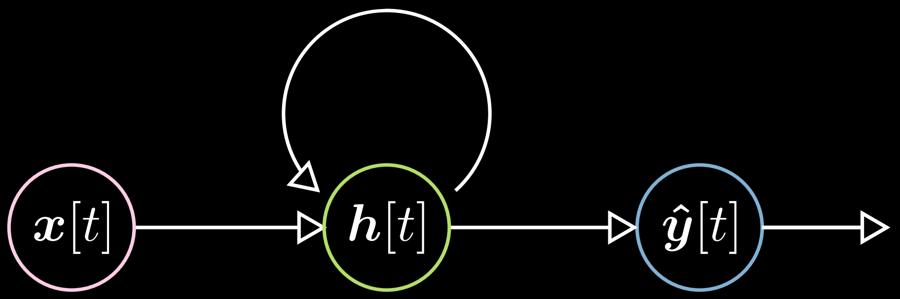
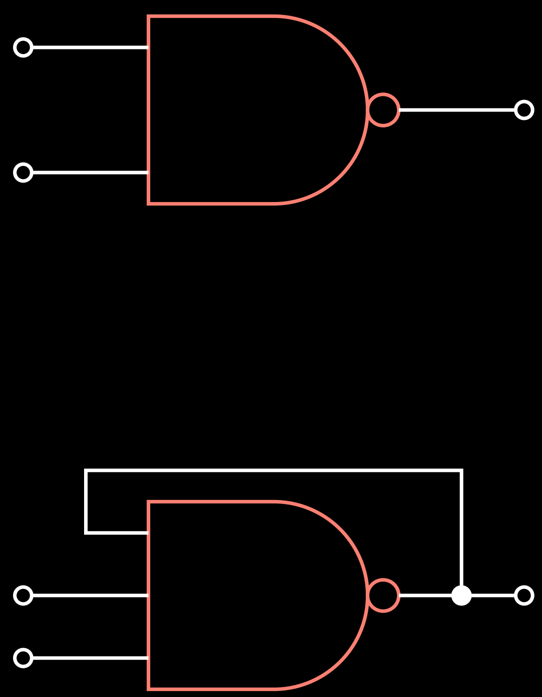
Recurrent Neural Nets

Handling sequential data

Vanilla and Recurrent NN

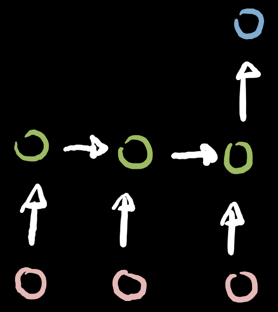


Combinatorial logic



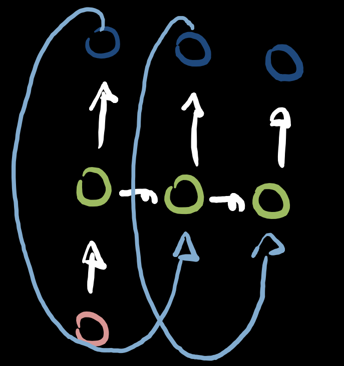
Sequential logic

Rationale



$\underline{x}[t] \longmapsto \hat{\underline{y}}[T]$

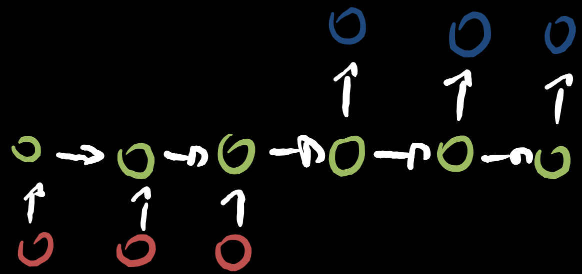
seq $\longmapsto$ vec

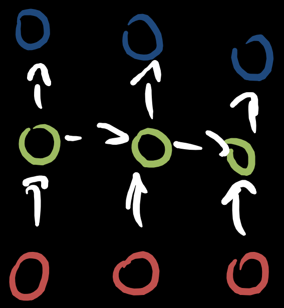


$\underline{x}[0] \longmapsto \hat{\underline{y}}[t]$

vec $\longmapsto$ seq

seq $\longmapsto$ seq





Vinyals *et al.* (2016) Show and Tell: Lessons learned from the 2015 MSCOCO Image Captioning Challenge

Learning to execute

- **Input:**

```
j=8584
for x in range(8):
    j+=920
b=(1500+j)
print((b+7567))
```

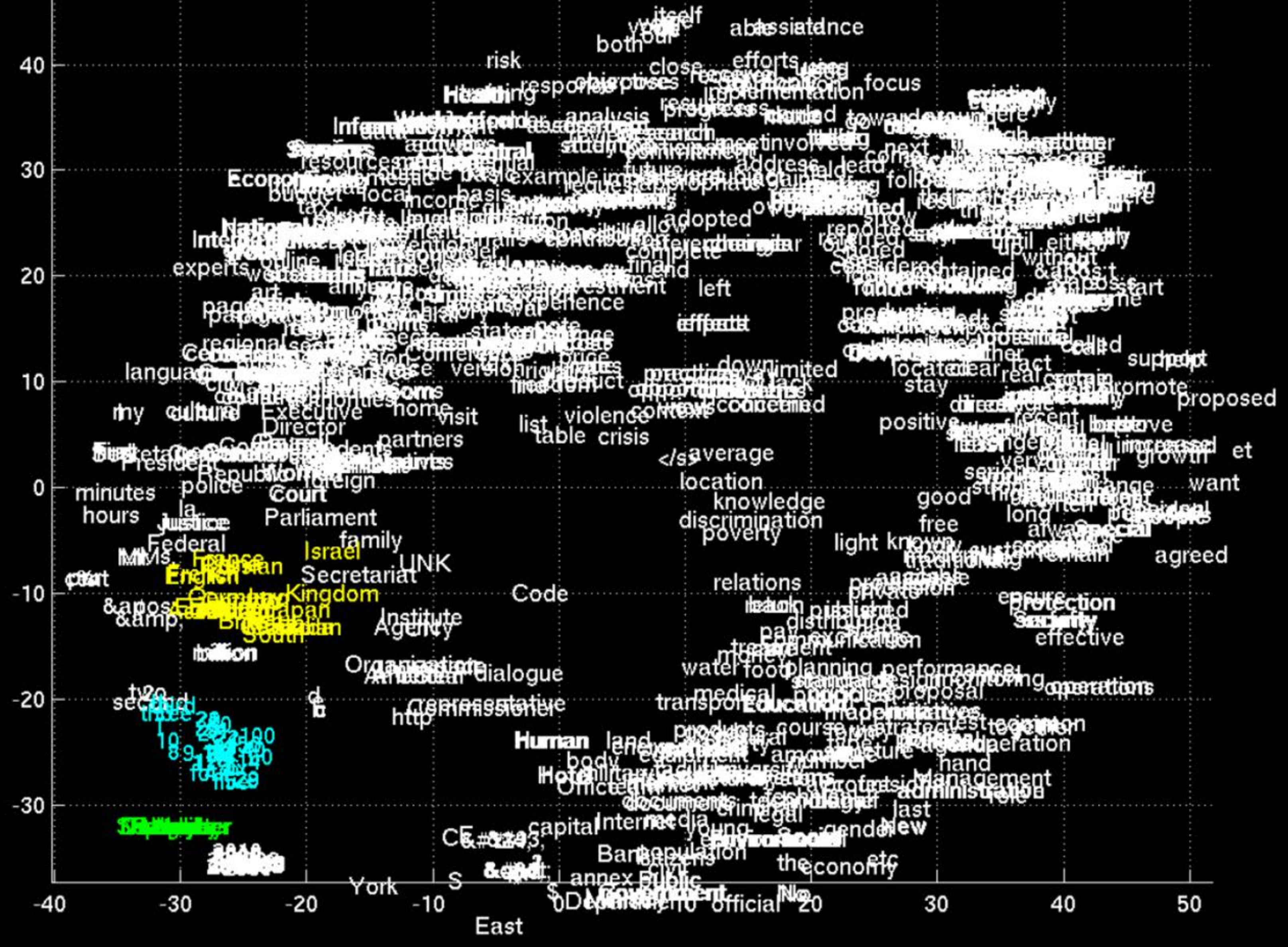
- **Target:** 25011.

- **Input:**

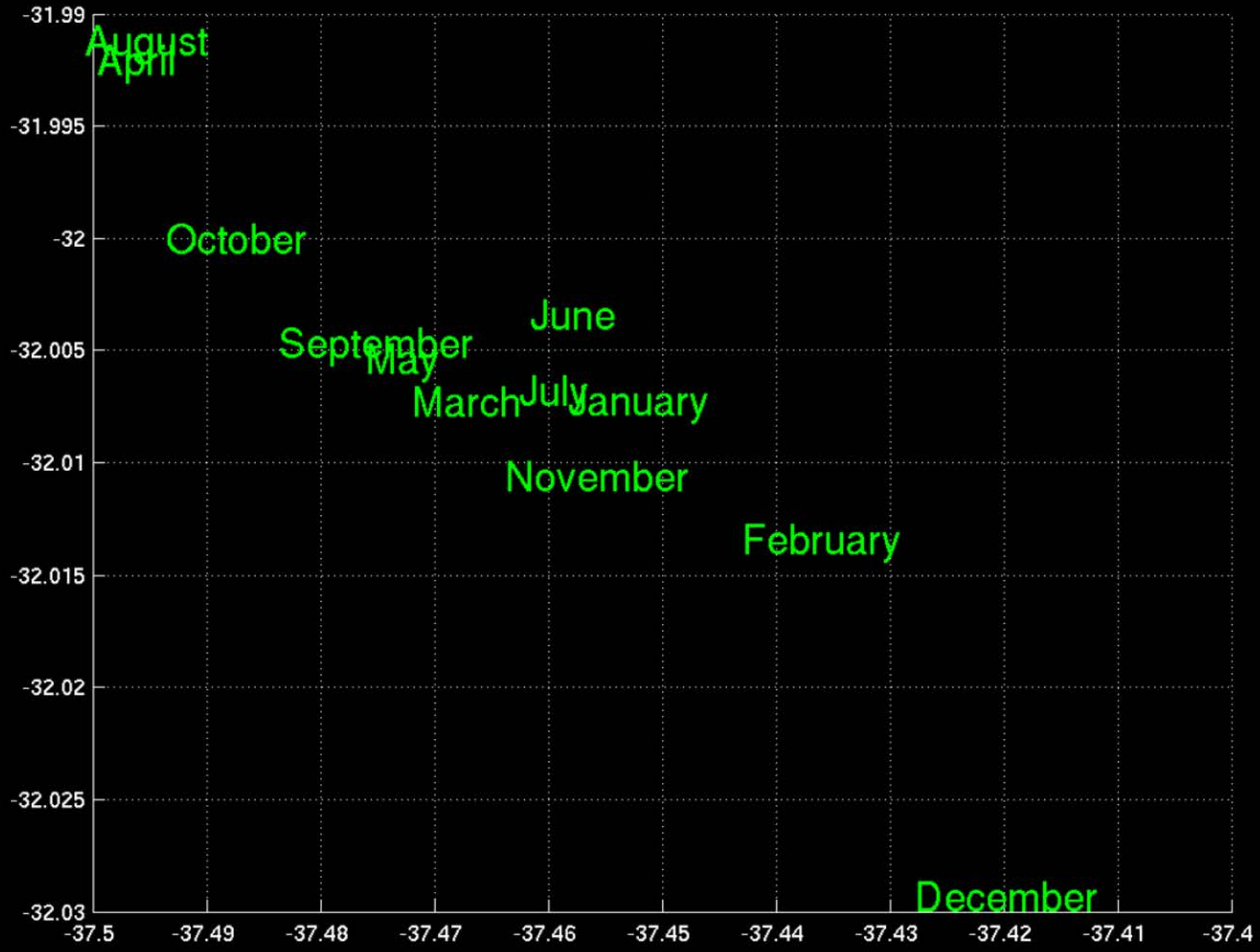
```
i=8827
c=(i-5347)
print((c+8704) if
2641<8500 else 5308)
```

- **Target:** 12184.

Zaremba & Sutskever (2015) Learning to Execute



Cho et al. (2014) Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation



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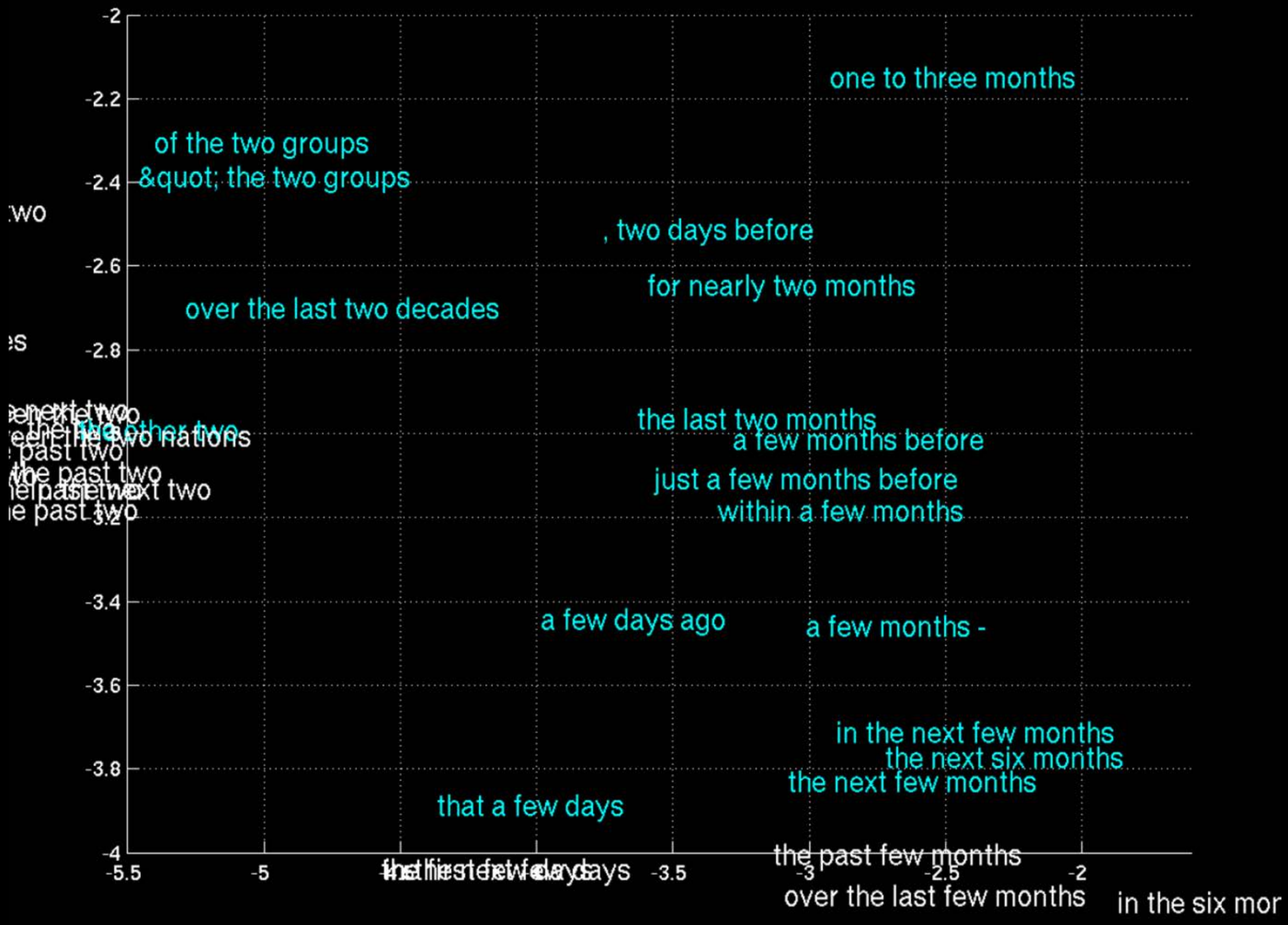

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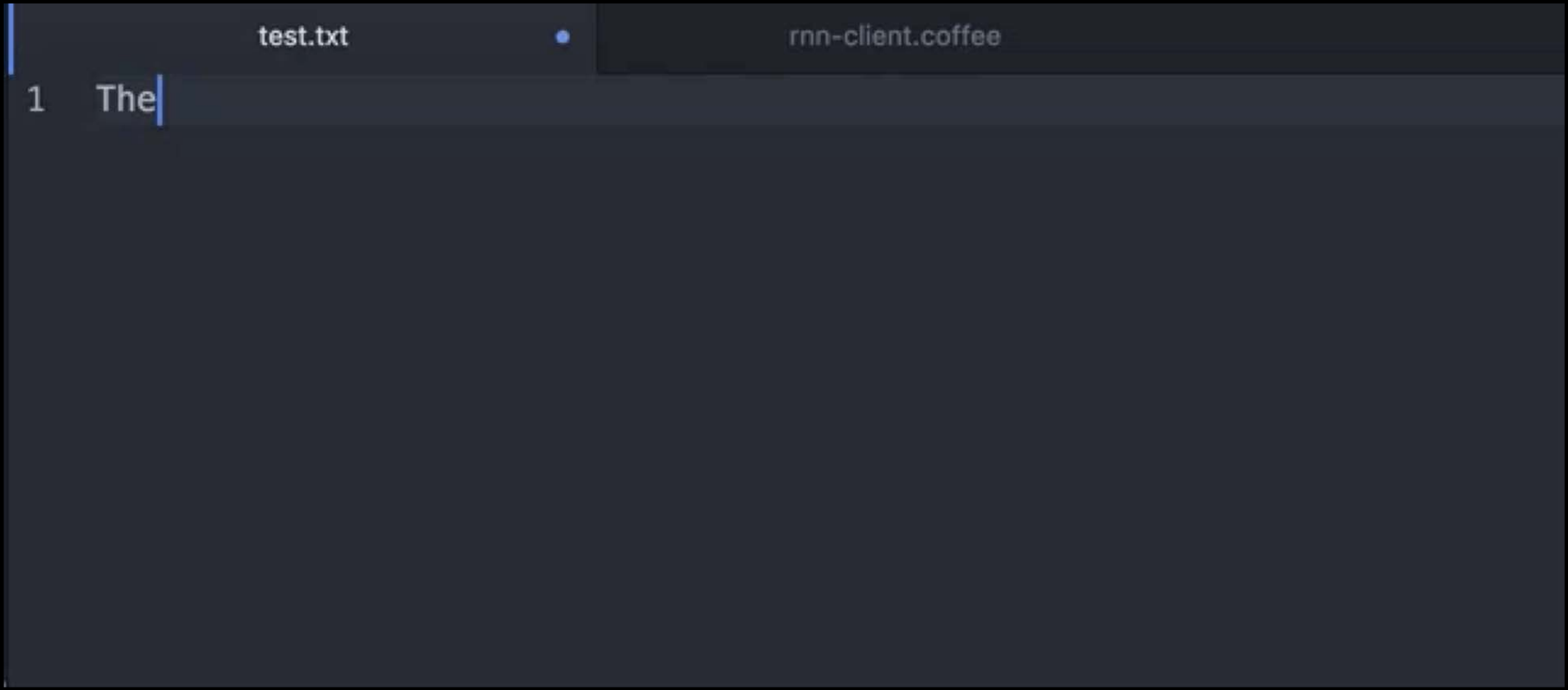
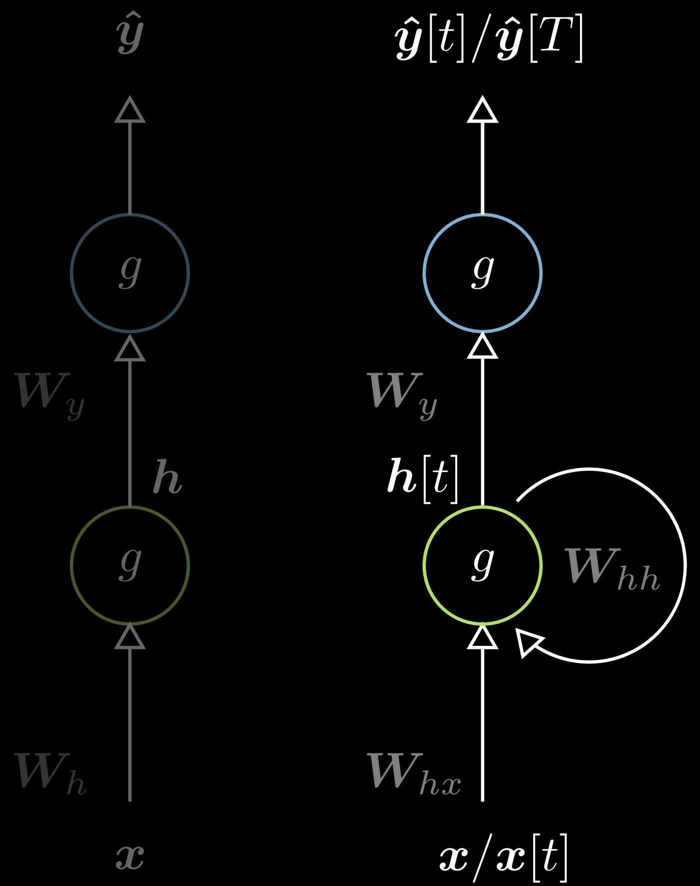


Sloan (2016) rnn-writer – github.com/robinsloan/rnn-writer

RNN training

Back propagation through time (BPTT)

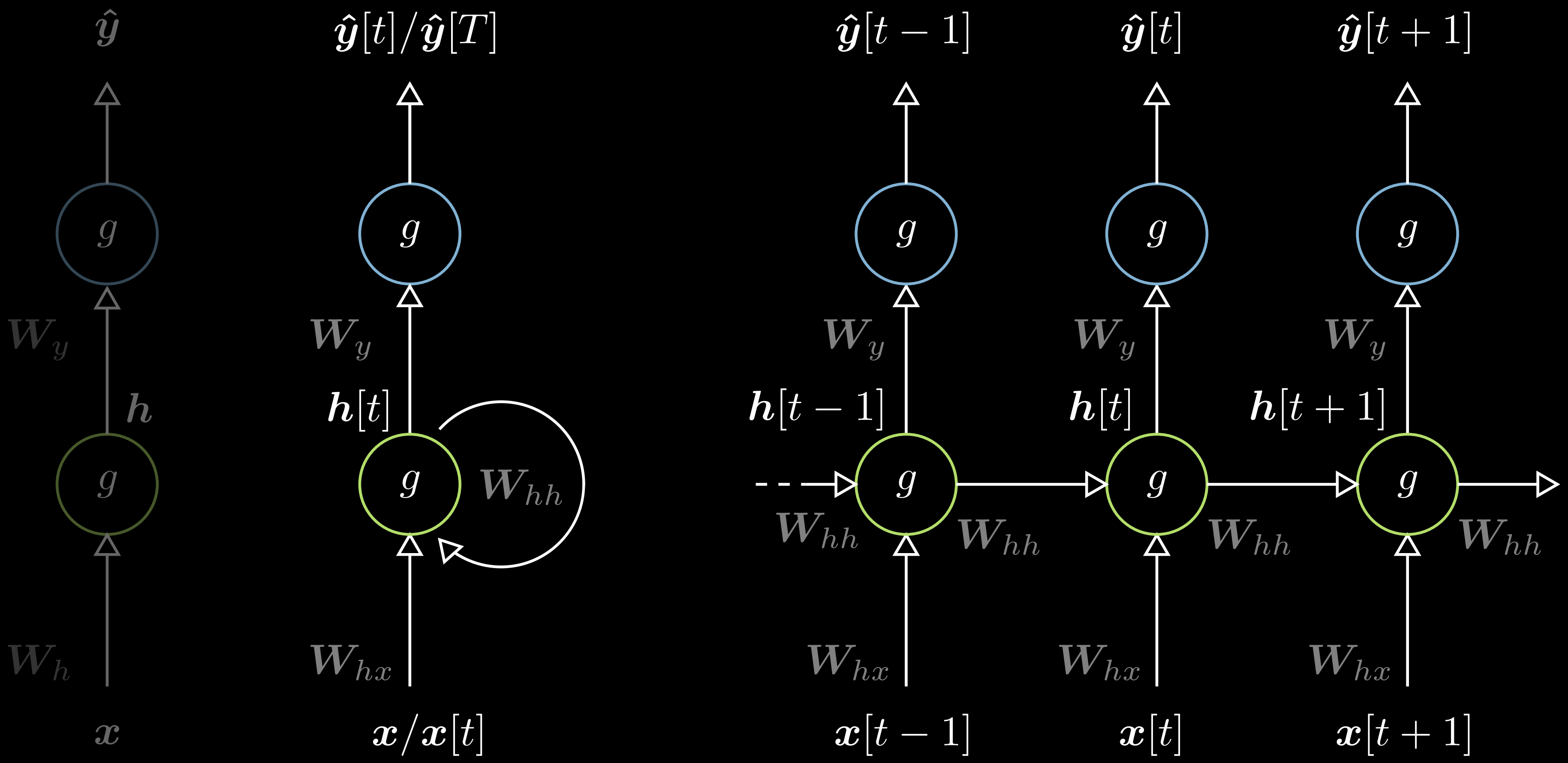


$$\boldsymbol{x} \in \mathbb{R}^q,\ \boldsymbol{h} \in \mathbb{R}^r,\ \boldsymbol{y} \in \mathbb{R}^s$$

$$\boldsymbol{h} = g(\boldsymbol{W}_h \boldsymbol{x} + \boldsymbol{b}_h)$$
$$\hat{\boldsymbol{y}} = g(\boldsymbol{W}_y \boldsymbol{h} + \boldsymbol{b}_y)$$

$$\phi : \mathbb{R}^q \to \mathbb{R}^r \to \mathbb{R}^s, r \gg q, s$$

$$\boldsymbol{h}[t] = g\left(\boldsymbol{W}_h \begin{bmatrix} \boldsymbol{x}[t] \\ \boldsymbol{h}[t-1] \end{bmatrix} + \boldsymbol{b}_h\right)$$
$$\boldsymbol{h}[0] \doteq \boldsymbol{0}, \boldsymbol{W}_h \doteq \begin{bmatrix} \boldsymbol{W}_{hx} & \boldsymbol{W}_{hh} \end{bmatrix}$$
$$\hat{\boldsymbol{y}}[t] = g(\boldsymbol{W}_y \boldsymbol{h}[t] + \boldsymbol{b}_y)$$



$\hat{\boldsymbol{y}}$
$\boldsymbol{W}_y$
$\boldsymbol{h}$
g
g
$\boldsymbol{W}_h$
$\boldsymbol{x}$
$\hat{\boldsymbol{y}}[t]/\hat{\boldsymbol{y}}[T]$
$\boldsymbol{W}_y$
$\boldsymbol{h}[t]$
$\boldsymbol{W}_{hh}$
$\boldsymbol{W}_{hx}$
$\boldsymbol{x}/\boldsymbol{x}[t]$
$\hat{\boldsymbol{y}}[t-1]$
$\hat{\boldsymbol{y}}[t]$
$\hat{\boldsymbol{y}}[t+1]$
$\boldsymbol{W}_y$
$\boldsymbol{h}[t-1]$
$\boldsymbol{h}[t]$
$\boldsymbol{h}[t+1]$
$\boldsymbol{W}_{hh}$
$\boldsymbol{W}_{hx}$
$\boldsymbol{x}[t-1]$
$\boldsymbol{x}[t]$
$\boldsymbol{x}[t+1]$

Training example

Language modelling

Batch-ification

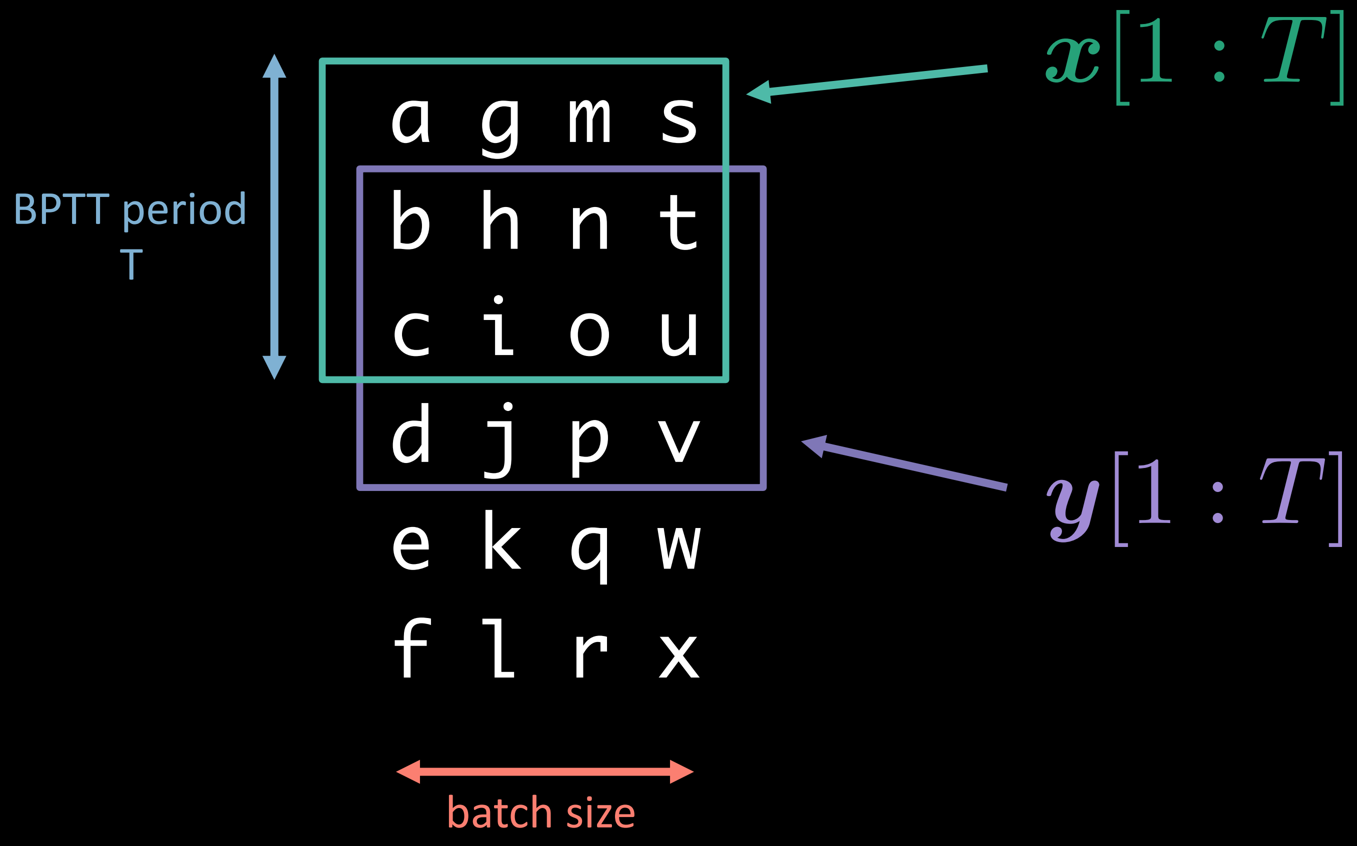
abcdefghijklmnopqrstuvwxyz

a	g	m	s
b	h	n	t
c	i	o	u
d	j	p	v
e	k	q	w
f	l	r	x

batch size

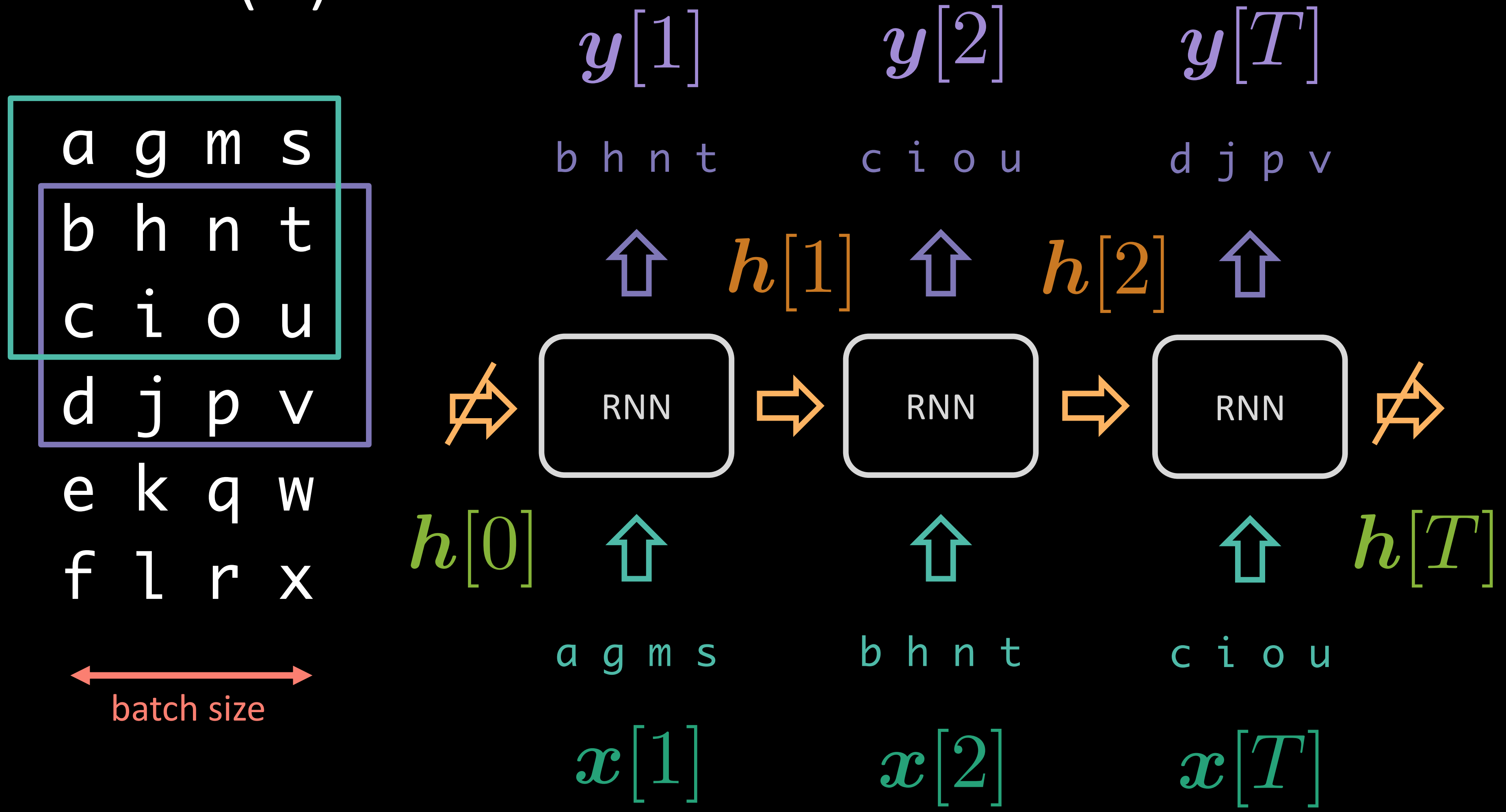
Check `word_language_model` @ `github.com/pytorch/examples/`

Get batch (I)



Check `word_language_model` @ `github.com/pytorch/examples/`

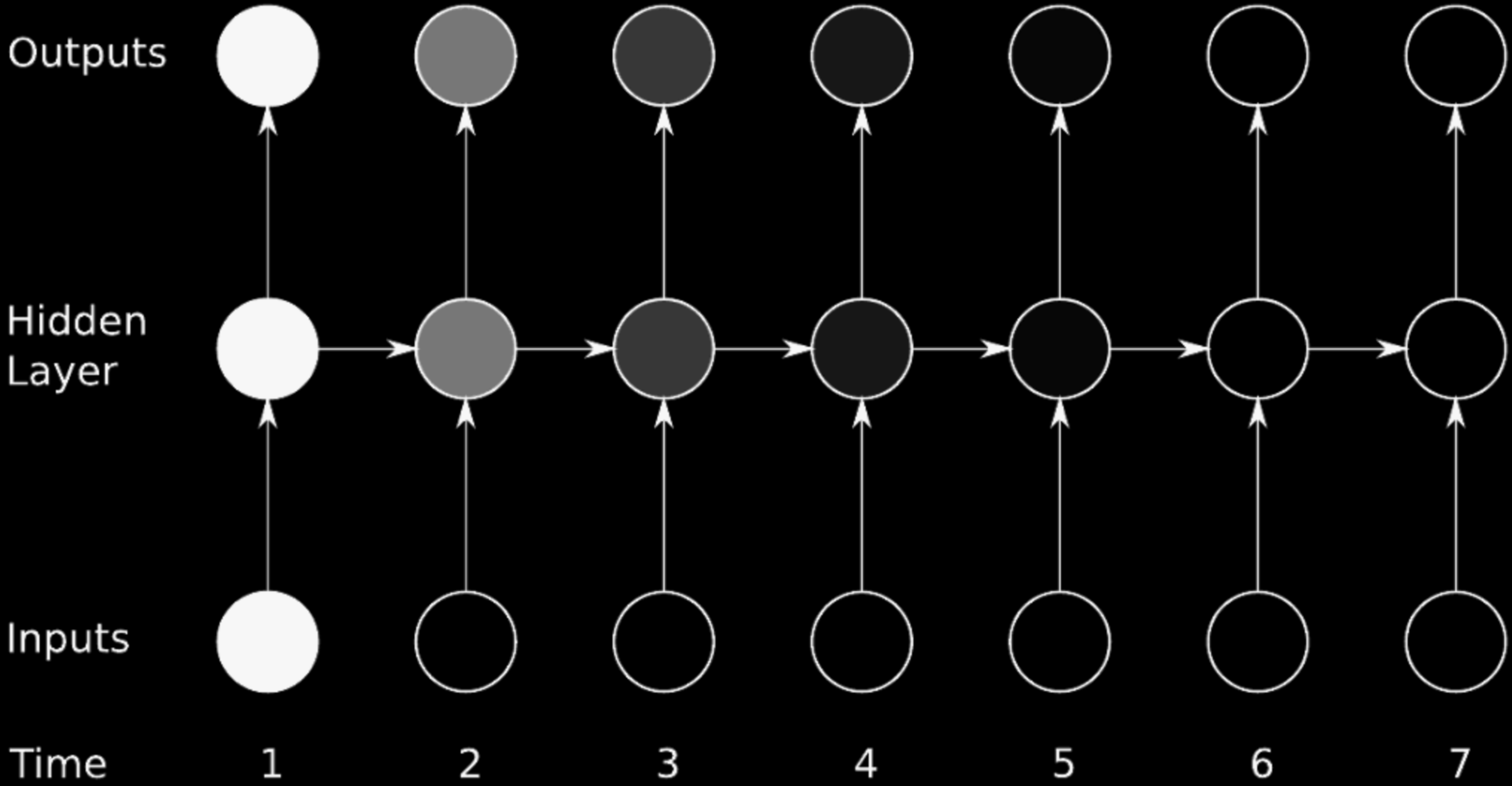
Get batch (II)



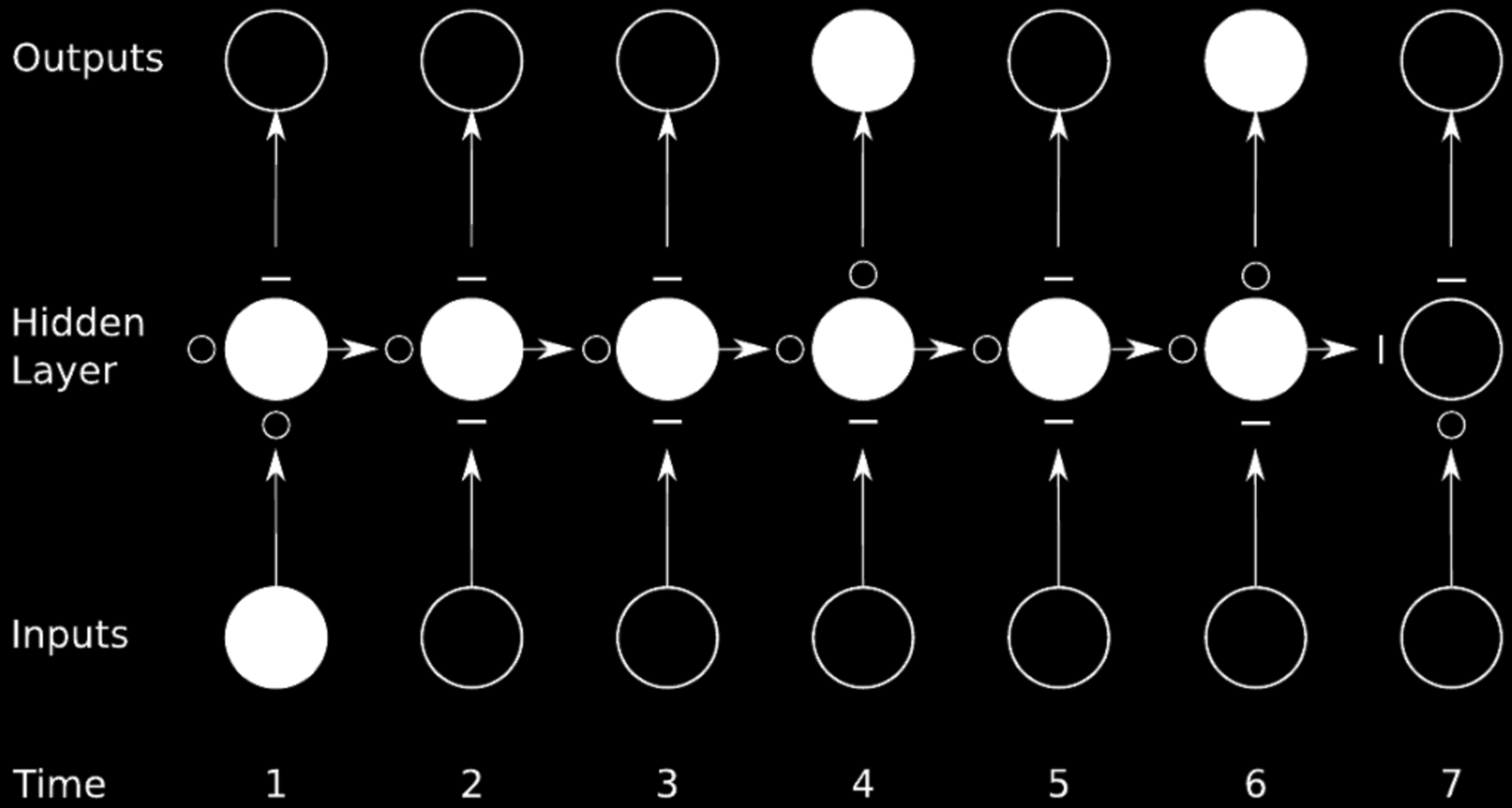
Check word_language_model @ github.com/pytorch/examples/

Vanishing & exploding gradients

Limitations of temporally deep nets



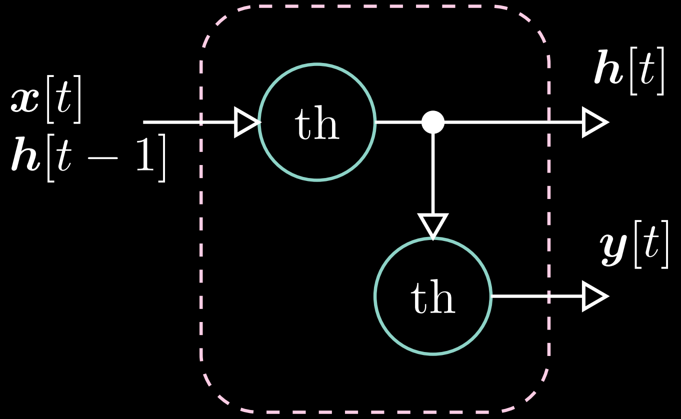
Graves (2012) Supervised sequence labelling



Graves (2012) Supervised sequence labelling

Long Short-Term Memory

Gated RNN



$$\boldsymbol{h}[t] = g\left(\boldsymbol{W}_h \begin{bmatrix} \boldsymbol{x}[t] \\ \boldsymbol{h}[t-1] \end{bmatrix} + \boldsymbol{b}_h\right)$$

$$\hat{\boldsymbol{y}}[t] = g(\boldsymbol{W}_y \boldsymbol{h}[t] + \boldsymbol{b}_y)$$

$$\boldsymbol{i}[t] = \sigma\left(\boldsymbol{W}_i \begin{bmatrix} \boldsymbol{x}[t] \\ \boldsymbol{h}[t-1] \end{bmatrix} + \boldsymbol{b}_i\right)$$

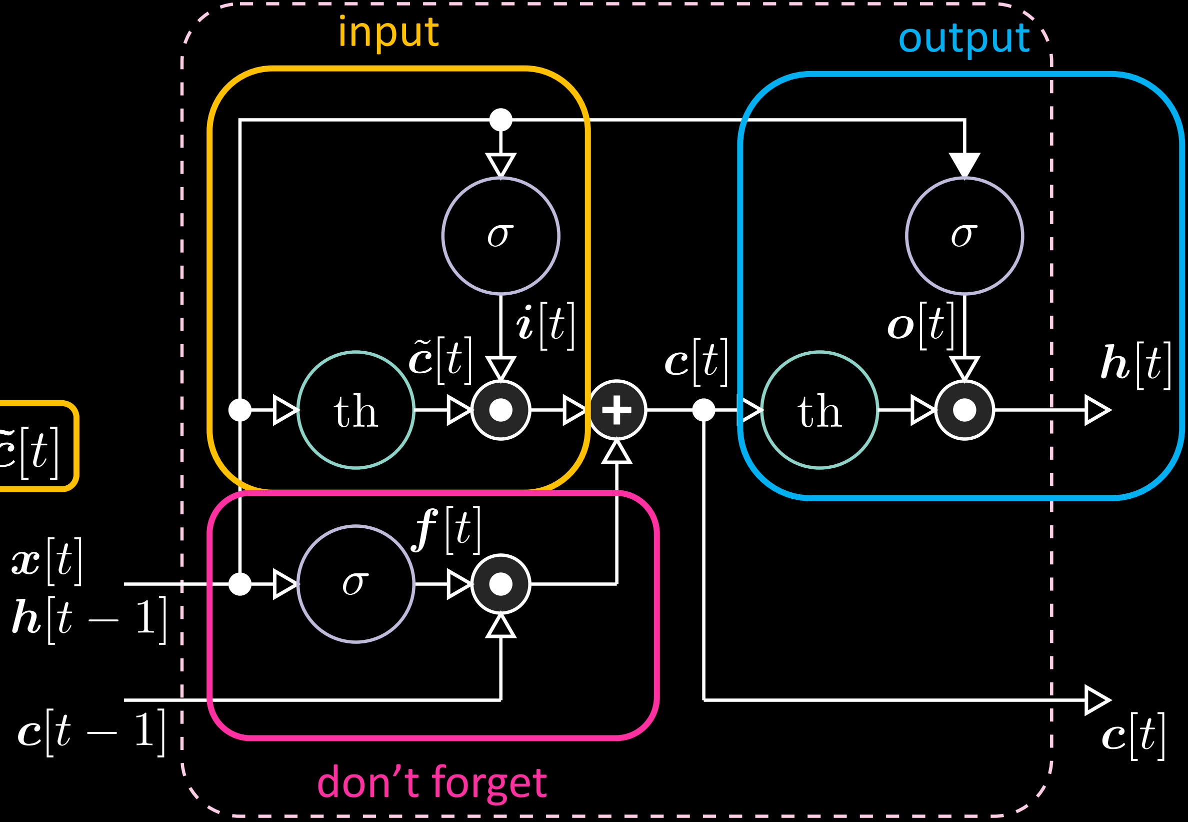
$$\boldsymbol{f}[t] = \sigma\left(\boldsymbol{W}_f \begin{bmatrix} \boldsymbol{x}[t] \\ \boldsymbol{h}[t-1] \end{bmatrix} + \boldsymbol{b}_f\right)$$

$$\boldsymbol{o}[t] = \sigma\left(\boldsymbol{W}_o \begin{bmatrix} \boldsymbol{x}[t] \\ \boldsymbol{h}[t-1] \end{bmatrix} + \boldsymbol{b}_o\right)$$

$$\tilde{\boldsymbol{c}}[t] = \tanh\left(\boldsymbol{W}_c \begin{bmatrix} \boldsymbol{x}[t] \\ \boldsymbol{h}[t-1] \end{bmatrix} + \boldsymbol{b}_c\right)$$

$$\boldsymbol{c}[t] = \boxed{\boldsymbol{f}[t] \odot \boldsymbol{c}[t-1]} + \boxed{\boldsymbol{i}[t] \odot \tilde{\boldsymbol{c}}[t]}$$

$$\boldsymbol{h}[t] = \boxed{\boldsymbol{o}[t] \odot \boxed{\tanh(\boldsymbol{c}[t])}}$$



Controlling the $\boxed{\text{output}}$ - OFF

Saturated sigmoid: green = 1, red = 0

$$\boldsymbol{i}[t] = \sigma\left(\boldsymbol{W}_i \begin{bmatrix}\boldsymbol{x}[t] \\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_i\right)$$

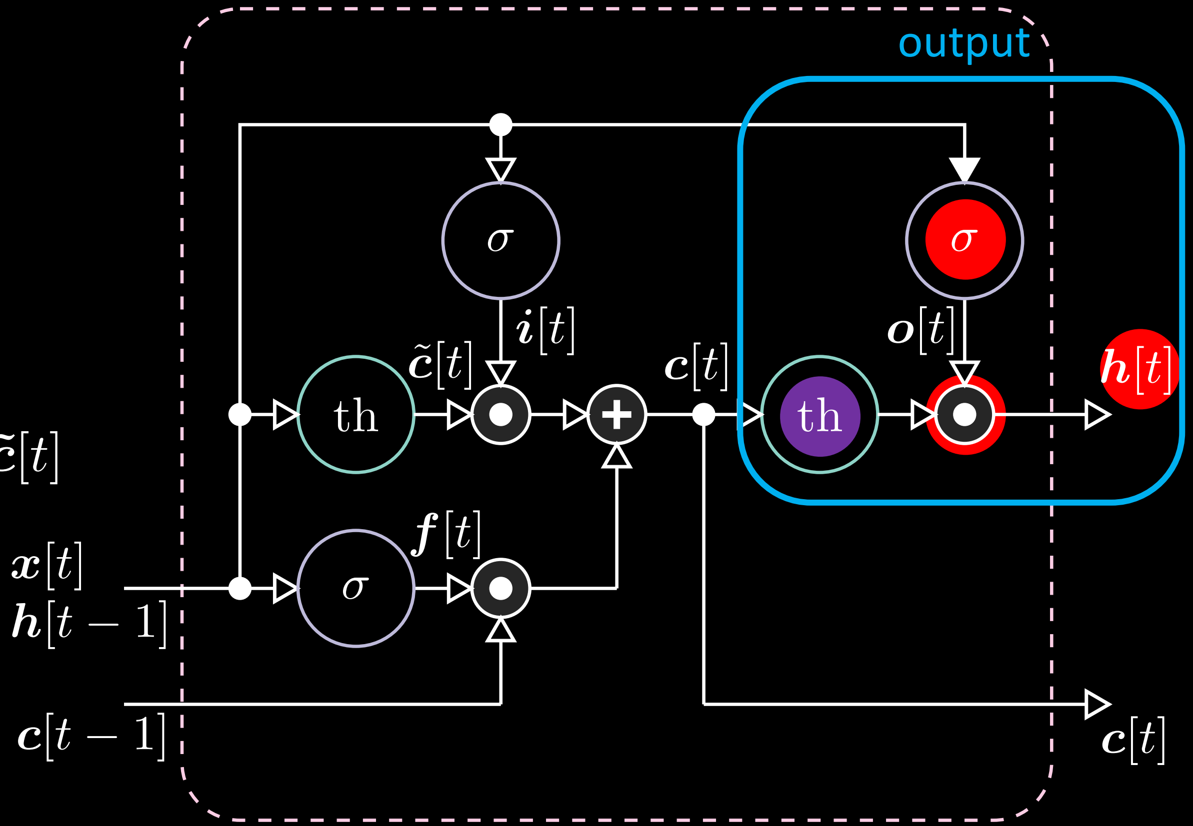
$$\boldsymbol{f}[t] = \sigma\left(\boldsymbol{W}_f \begin{bmatrix}\boldsymbol{x}[t] \\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_f\right)$$

$$\boxed{\boldsymbol{o}[t] = \sigma\left(\boldsymbol{W}_o \begin{bmatrix}\boldsymbol{x}[t] \\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_o\right)}$$

$$\tilde{\boldsymbol{c}}[t] = \tanh\left(\boldsymbol{W}_c \begin{bmatrix}\boldsymbol{x}[t] \\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_c\right)$$

$$\boldsymbol{c}[t] = \boldsymbol{f}[t] \odot \boldsymbol{c}[t-1] + \boldsymbol{i}[t] \odot \tilde{\boldsymbol{c}}[t]$$

$$\boldsymbol{h}[t] = \boxed{\boldsymbol{o}[t] \odot \tanh(\boldsymbol{c}[t])}$$



Controlling the $\boxed{\text{output}}$ - ON

Saturated sigmoid: green = 1, red = 0

$$\boldsymbol{i}[t] = \sigma\left(\boldsymbol{W}_i \begin{bmatrix}\boldsymbol{x}[t]\\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_i\right)$$

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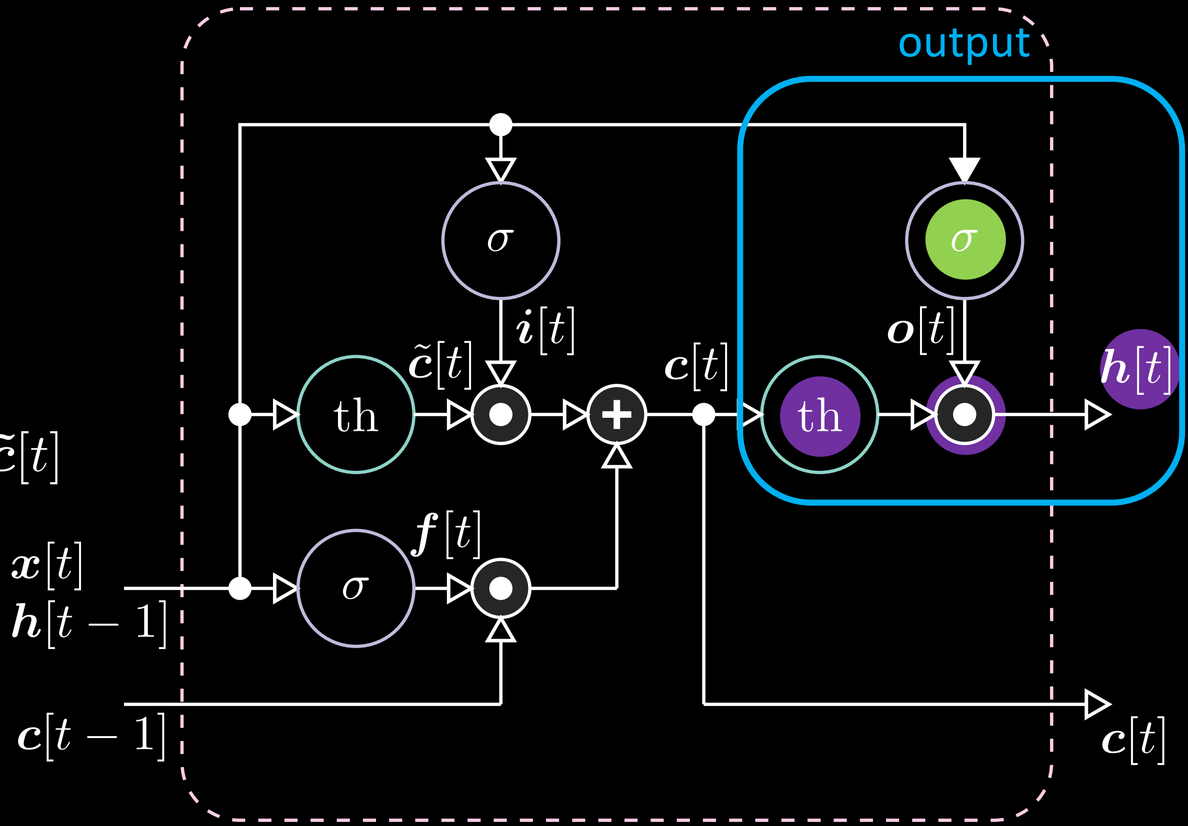
$$\boldsymbol{c}[t] = \boldsymbol{f}[t] \odot \boldsymbol{c}[t-1] + \boldsymbol{i}[t] \odot \tilde{\boldsymbol{c}}[t]$$

$$\boldsymbol{h}[t] = \boxed{\boldsymbol{o}[t] \odot \tanh(\boldsymbol{c}[t])}$$



Controlling the memory - reset

Saturated sigmoid = 1

= 0

$$\boxed{\boldsymbol{i}[t] = \sigma\left(\boldsymbol{W}_i \begin{bmatrix}\boldsymbol{x}[t]\\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_i\right)}$$

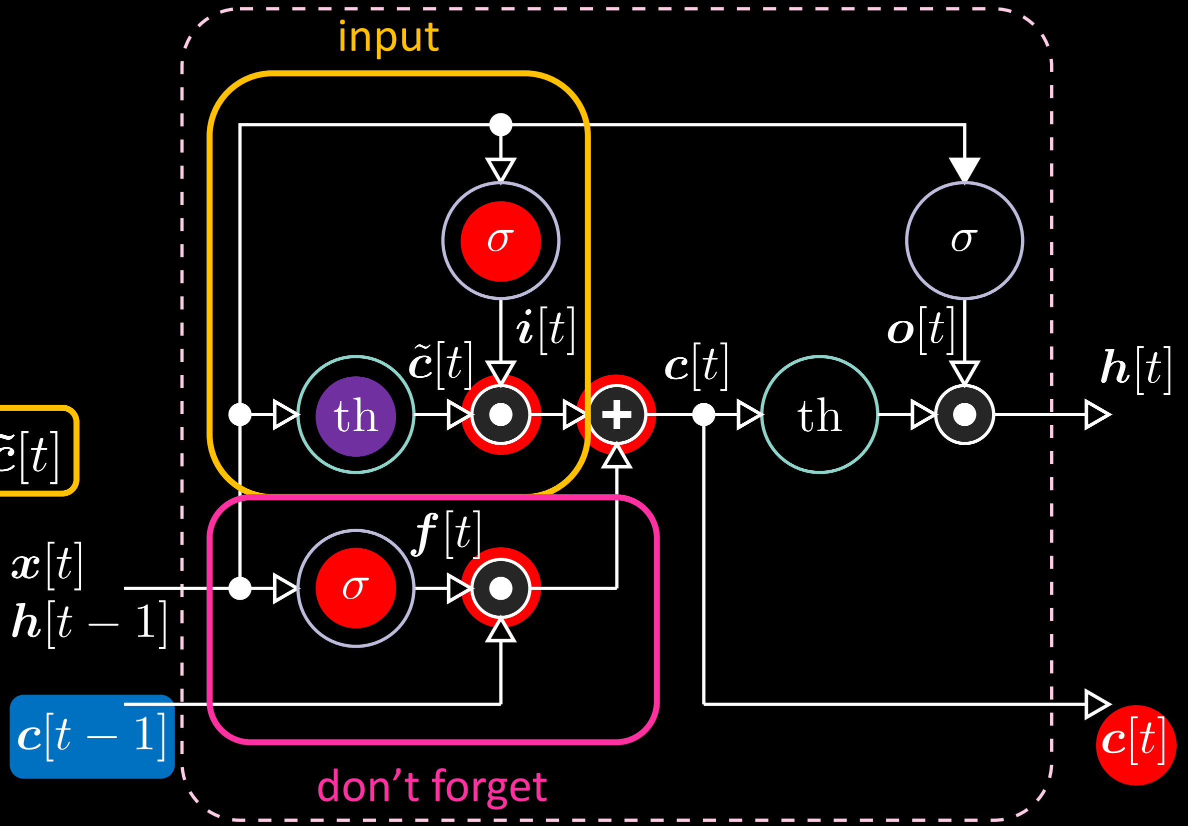
$$\boxed{\boldsymbol{f}[t] = \sigma\left(\boldsymbol{W}_f \begin{bmatrix}\boldsymbol{x}[t]\\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_f\right)}$$

$$\boldsymbol{o}[t] = \sigma\left(\boldsymbol{W}_o \begin{bmatrix}\boldsymbol{x}[t]\\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_o\right)$$

$$\tilde{\boldsymbol{c}}[t] = \tanh\left(\boldsymbol{W}_c \begin{bmatrix}\boldsymbol{x}[t]\\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_c\right)$$

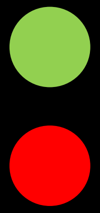
$$\boldsymbol{c}[t] = \boxed{\boldsymbol{f}[t] \odot \boldsymbol{c}[t-1]} + \boxed{\boldsymbol{i}[t] \odot \tilde{\boldsymbol{c}}[t]}$$

$$\boldsymbol{h}[t] = \boldsymbol{o}[t] \odot \tanh(\boldsymbol{c}[t])$$



Controlling the memory - keep

Saturated sigmoid



= 1

= 0

$$\boxed{\boldsymbol{i}[t] = \sigma\left(\boldsymbol{W}_i \begin{bmatrix}\boldsymbol{x}[t] \\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_i\right)}$$

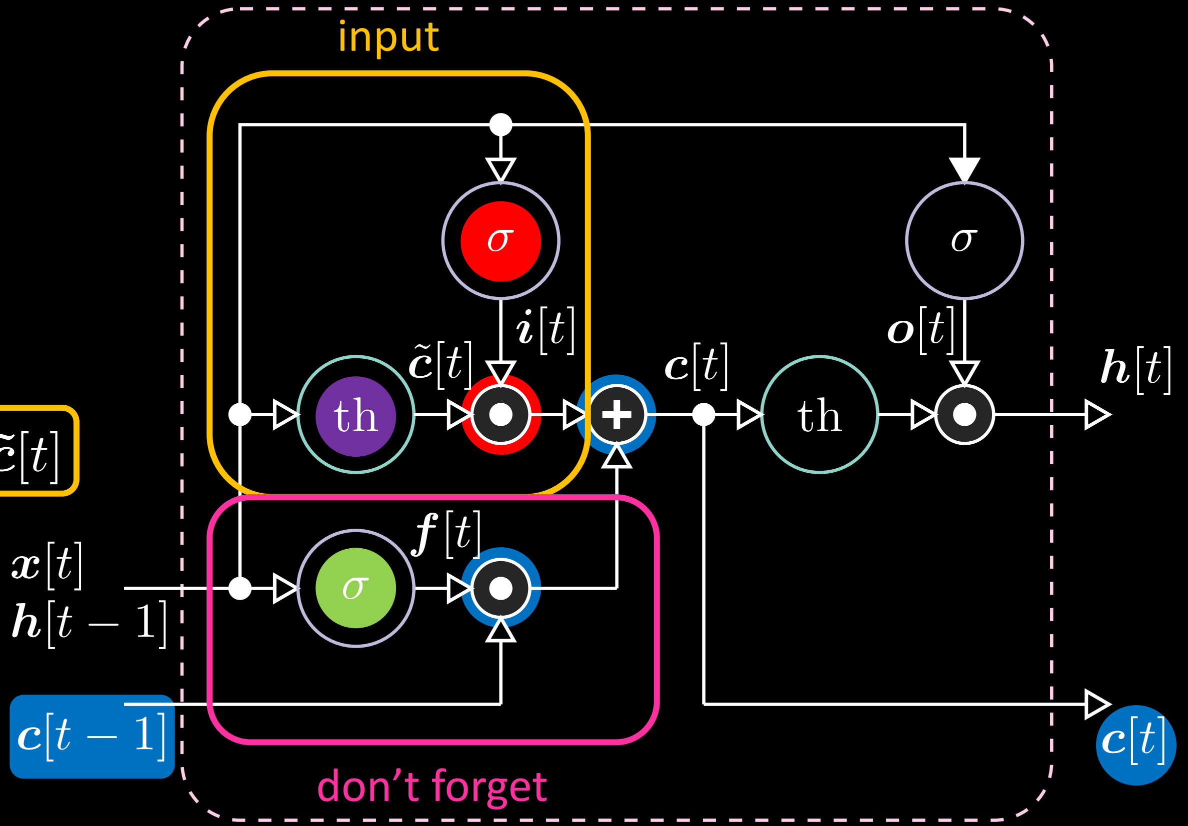
$$\boxed{\boldsymbol{f}[t] = \sigma\left(\boldsymbol{W}_f \begin{bmatrix}\boldsymbol{x}[t] \\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_f\right)}$$

$$\boldsymbol{o}[t] = \sigma\left(\boldsymbol{W}_o \begin{bmatrix}\boldsymbol{x}[t] \\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_o\right)$$

$$\tilde{\boldsymbol{c}}[t] = \tanh\left(\boldsymbol{W}_c \begin{bmatrix}\boldsymbol{x}[t] \\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_c\right)$$

$$\boldsymbol{c}[t] = \boxed{\boldsymbol{f}[t] \odot \boldsymbol{c}[t-1]} + \boxed{\boldsymbol{i}[t] \odot \tilde{\boldsymbol{c}}[t]}$$

$$\boldsymbol{h}[t] = \boldsymbol{o}[t] \odot \tanh(\boldsymbol{c}[t])$$



Controlling the memory - write

Saturated sigmoid = 1

= 0

$$\boxed{\boldsymbol{i}[t] = \sigma\left(\boldsymbol{W}_i \begin{bmatrix}\boldsymbol{x}[t] \\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_i\right)}$$

$$\boxed{\boldsymbol{f}[t] = \sigma\left(\boldsymbol{W}_f \begin{bmatrix}\boldsymbol{x}[t] \\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_f\right)}$$

$$\boldsymbol{o}[t] = \sigma\left(\boldsymbol{W}_o \begin{bmatrix}\boldsymbol{x}[t] \\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_o\right)$$

$$\tilde{\boldsymbol{c}}[t] = \tanh\left(\boldsymbol{W}_c \begin{bmatrix}\boldsymbol{x}[t] \\ \boldsymbol{h}[t-1]\end{bmatrix} + \boldsymbol{b}_c\right)$$

$$\boldsymbol{c}[t] = \boxed{\boldsymbol{f}[t] \odot \boldsymbol{c}[t-1]} + \boxed{\boldsymbol{i}[t] \odot \tilde{\boldsymbol{c}}[t]}$$

$$\boldsymbol{h}[t] = \boldsymbol{o}[t] \odot \tanh(\boldsymbol{c}[t])$$