THE UNIVERSITY OF BRITISH COLUMBIA

Topics in AI (CPSC 532S):
Multimodal Learning with Vision, Language and Sound

Lecture 10: RNNs (Part 2)

Course **Logistics**

- **Assignment 3** due next week
- **Assignment 1 & 2** is being graded (solution will be out this week)

- Course **Projects**

Final **Project** – Reminder

- Group project (groups of 3 are encouraged, but fewer is OK)
- Groups are self-formed
- You need to come up with a **project proposal** and then work on the project as a group (each person in the group gets the same grade for the project)
- Project needs to be **research** oriented (not simply implementing an existing paper); you can use code of existing paper as a starting point though

Project proposal and class presentation

Presentation (~3-5 minutes irrespective of the group size)

1. Clear explanation of the **overall problem** you want to solve and relationship to the topics covered in class

2. What **model/algorithms** you planning to explore: this can be somewhat abstract (e.g., CNN+RNN)

3. The **dataset(s)** you will use and how will you **evaluate** performance

4. List of **papers** you plan to read as references

5. How will you **structure the project**, who will do what and a rough timeline

After proposal you will get the feedback from me

Project proposal and class presentation

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After proposal you will get the feedback from me

Proposal

— Same as above but in more detail, with well defined algorithms and timeline

— Will be in the form of the **PDF** document (initial paper draft)

Review: One Hot Encoding

Vocabulary

dog

cat

person

holding

tree

computer

using

*slide from V. Ordonex

Review: One Hot Encoding

Vocabulary

dog	1
cat	2
person	3
holding	4
tree	5
computer	6
using	7

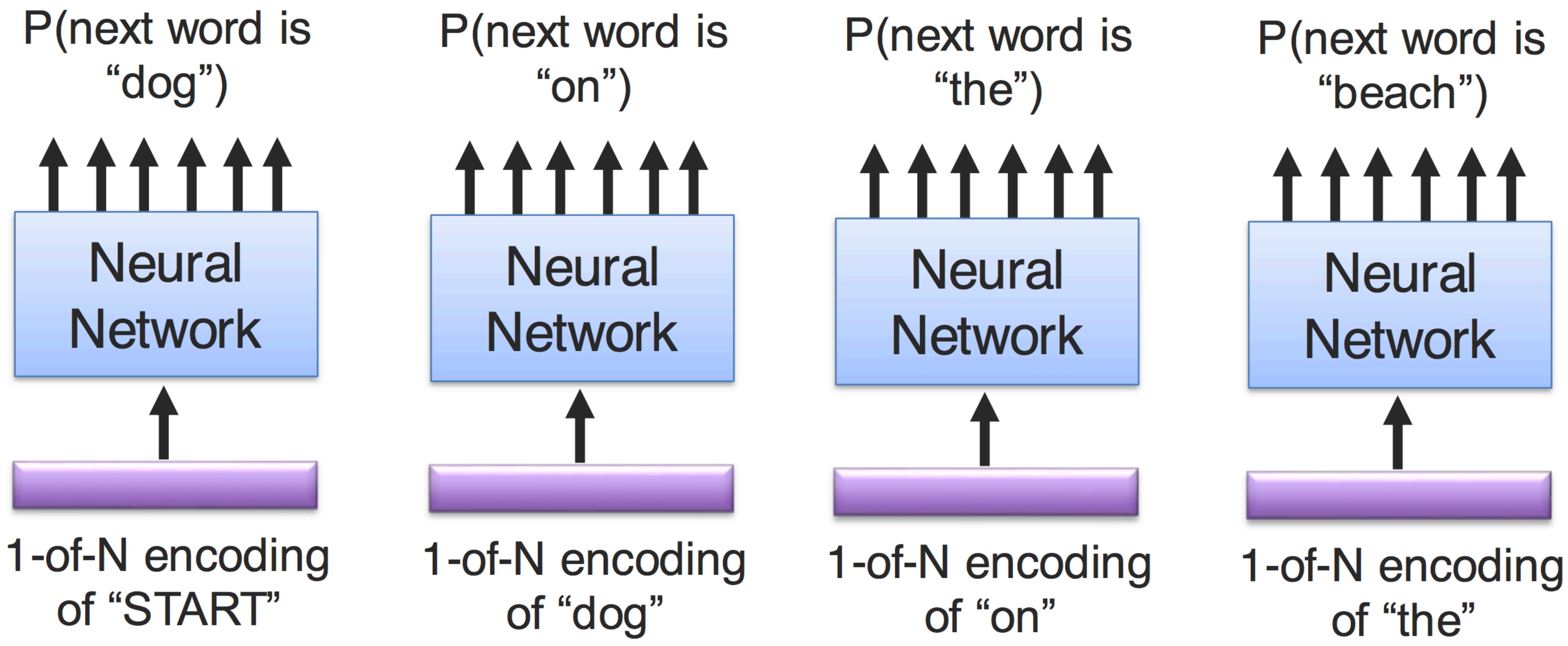
*slide from V. Ordonex

Review: One Hot Encoding

Vocabulary		**one-hot** encodings
dog	1	[1, 0, 0, 0, 0, 0, 0, 0, 0, 0]
cat	2	[0, 1, 0, 0, 0, 0, 0, 0, 0, 0]
person	3	[0, 0, 1, 0, 0, 0, 0, 0, 0, 0]
holding	4	[0, 0, 0, 1, 0, 0, 0, 0, 0, 0]
tree	5	[0, 0, 0, 0, 1, 0, 0, 0, 0, 0]
computer	6	[0, 0, 0, 0, 0, 1, 0, 0, 0, 0]
using	7	[0, 0, 0, 0, 0, 0, 1, 0, 0, 0]

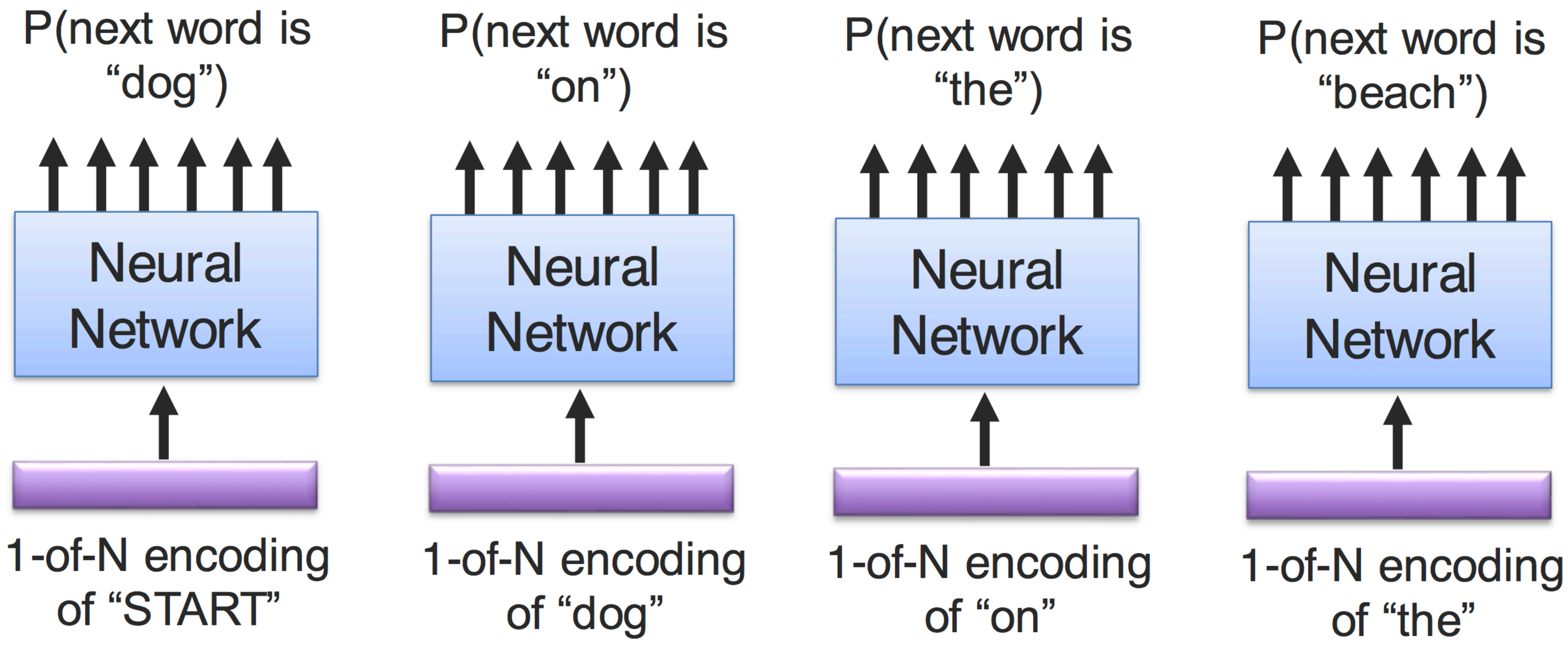
*slide from V. Ordonex

Review: Neural-based Language Mode



* Slides from Louis-Philippe Morency

Review: Neural-based Language Mode



Problem: Does not model sequential information (too local)

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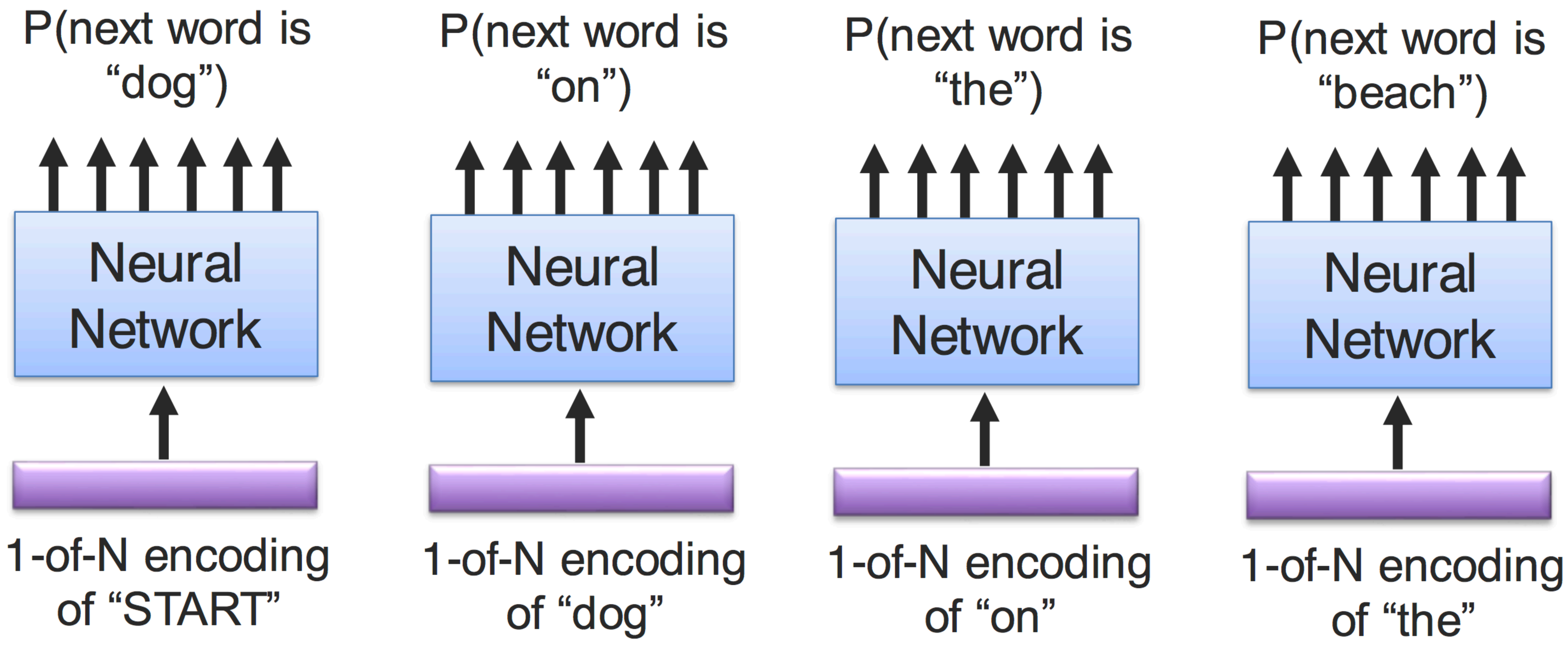
Review: Neural-based Language Mode

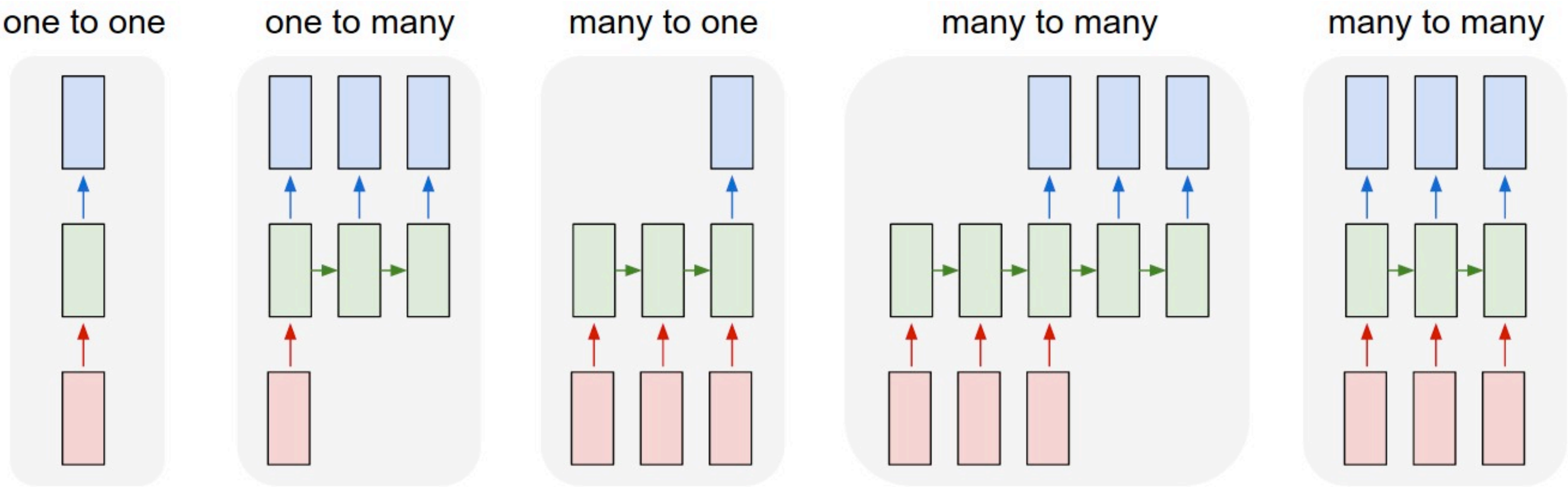


Problem: Does not model sequential information (too local)

We need sequence modeling!

* Slides from Louis-Philippe Morency

Review: Sequences Models



Input: No sequence
Output: No seq.
Example: "standard" classification / regression problems

Input: No sequence
Output: Sequence
Example: Im2Caption

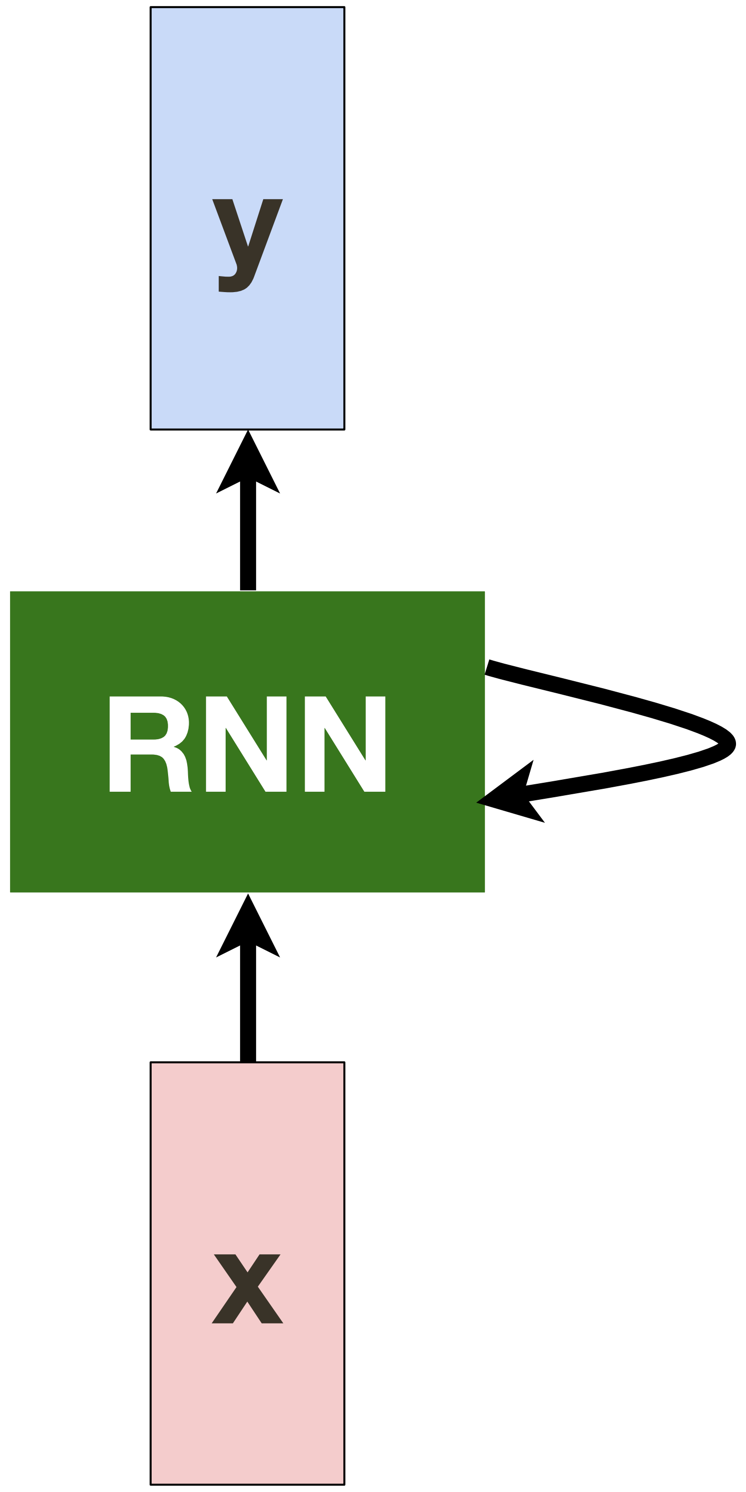
Input: Sequence
Output: No seq.
Example: sentence classification, multiple-choice question answering

Input: Sequence
Output: Sequence
Example: machine translation, video captioning, open-ended question answering, video question answering

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

(Vanilla) **Recurrent** Neural Network

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



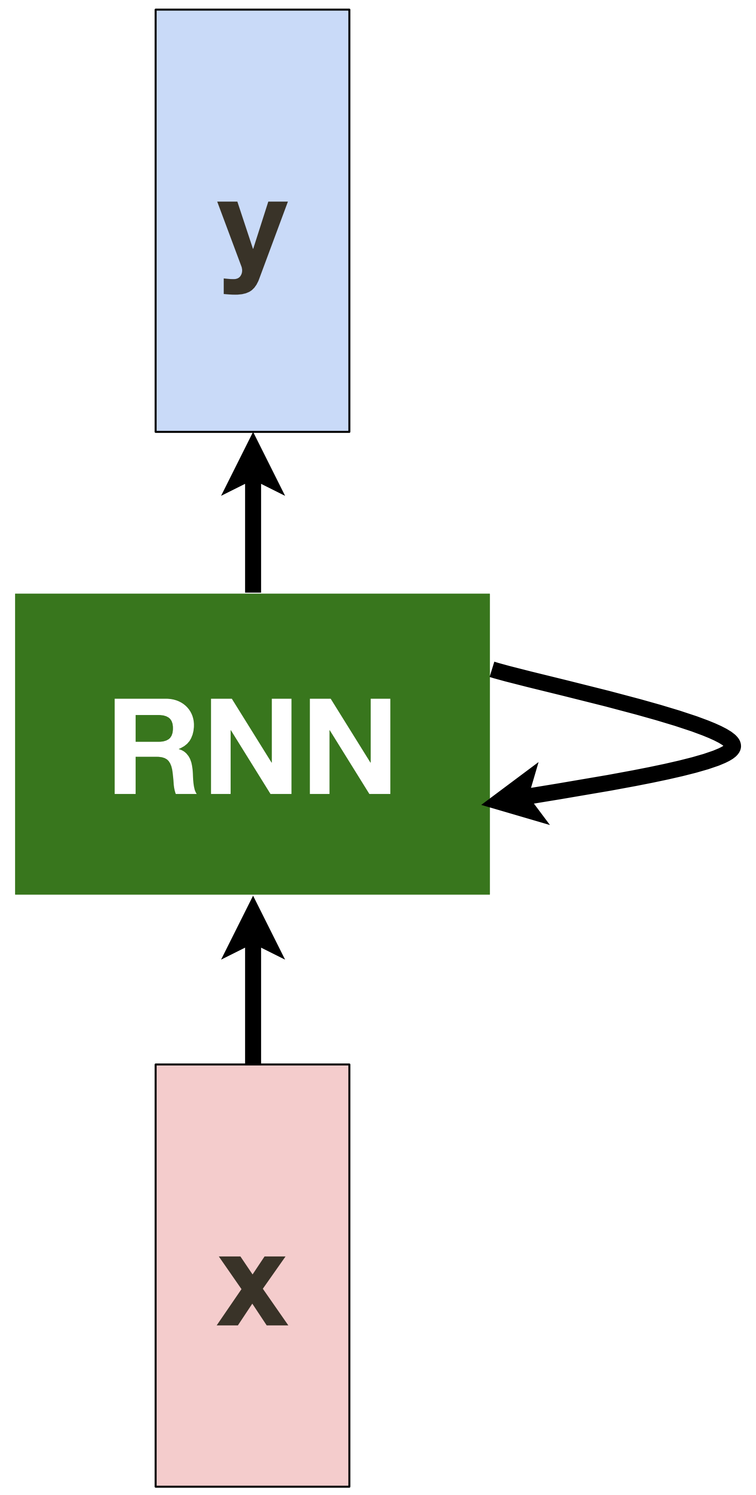
* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

(Vanilla) **Recurrent** Neural Network

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

$$\downarrow$$

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



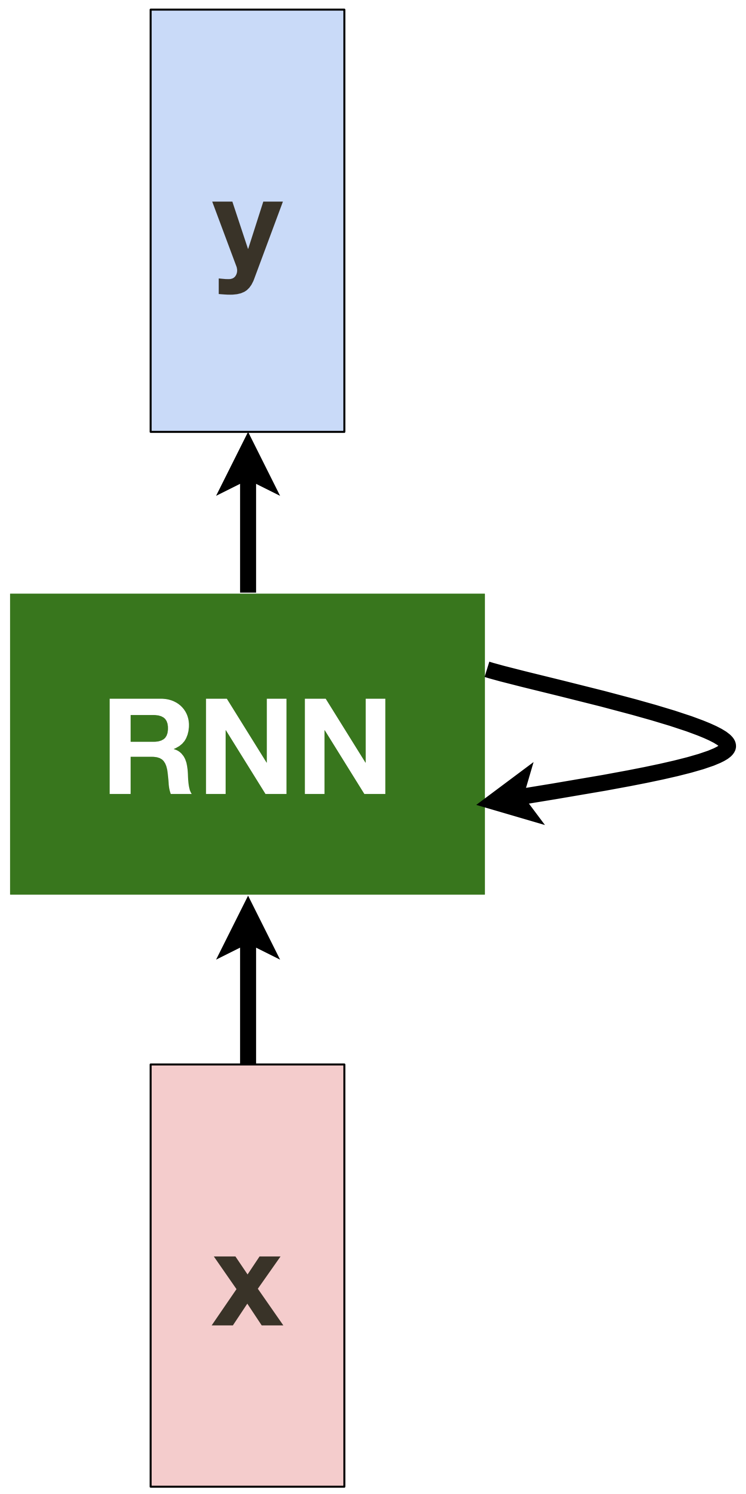
(Vanilla) **Recurrent** Neural Network

$$y_t = W_{hy}h_t + b_y$$

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

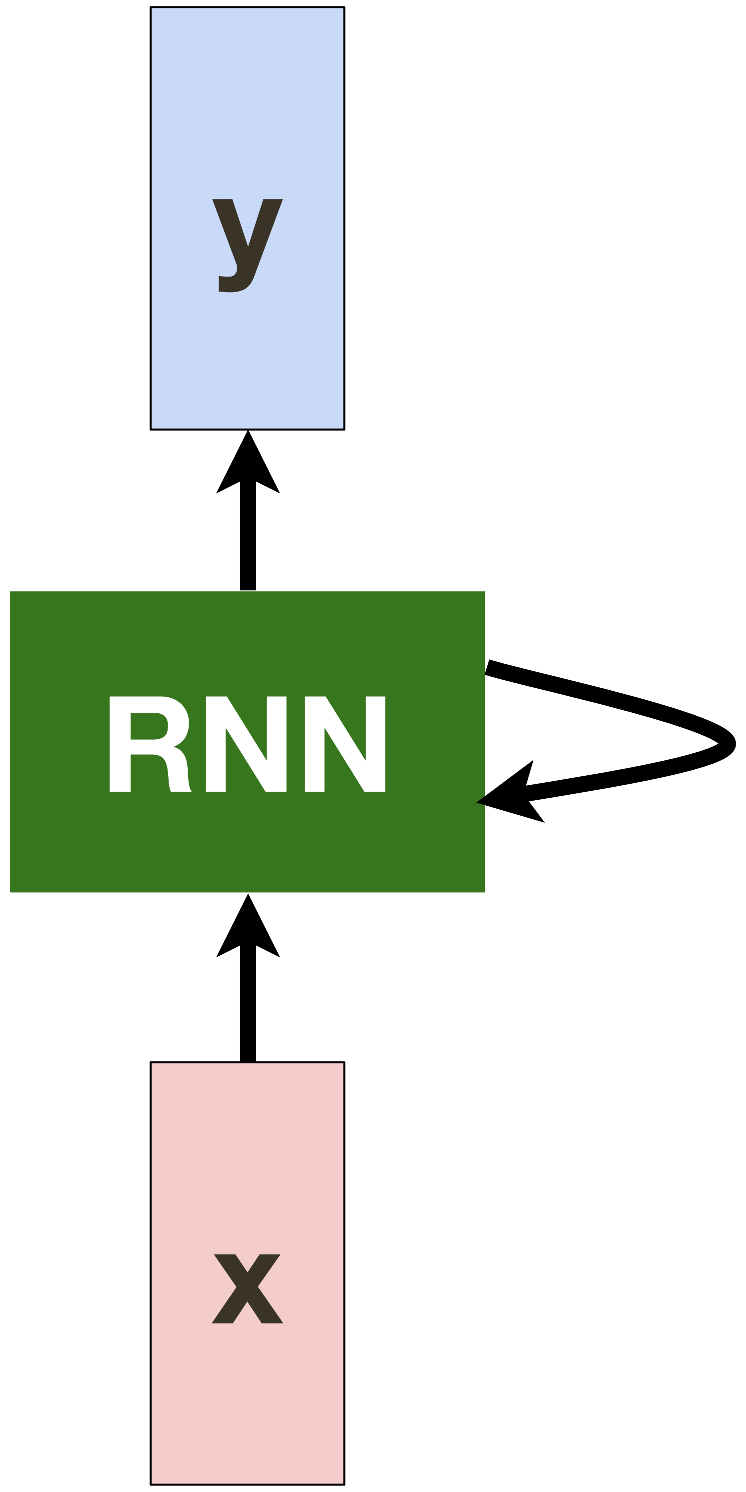
$$\downarrow$$

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



(Vanilla) **Recurrent** Neural Network

Intuition: RNN incorporates one element of sequence at a time
(e.g. letter, word, video frame, etc.)
building up a representation of the sequence “so far”



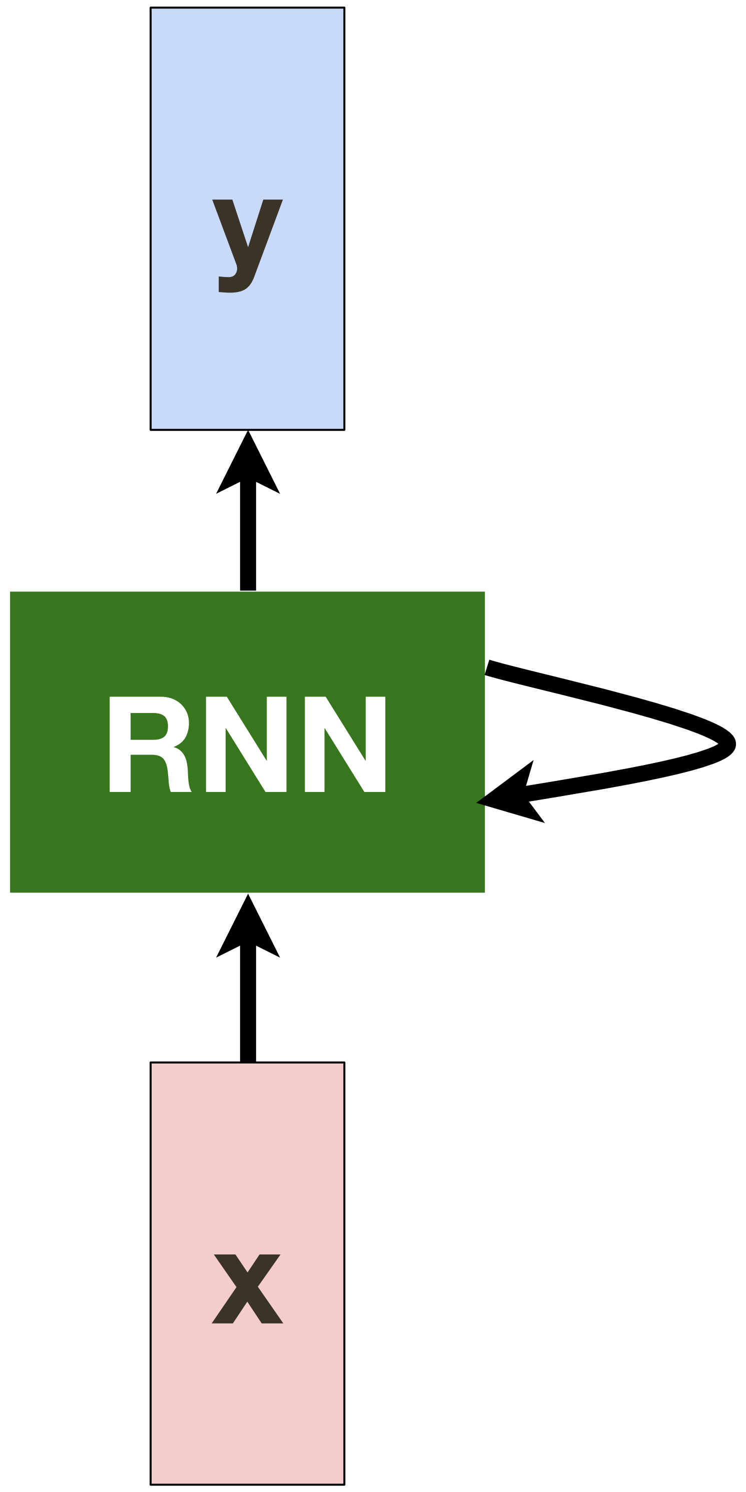
$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t + b_h)$$

(Vanilla) **Recurrent** Neural Network

Intuition: RNN incorporates one element of sequence at a time
(e.g. letter, word, video frame, etc.)
building up a representation of the sequence "so far"

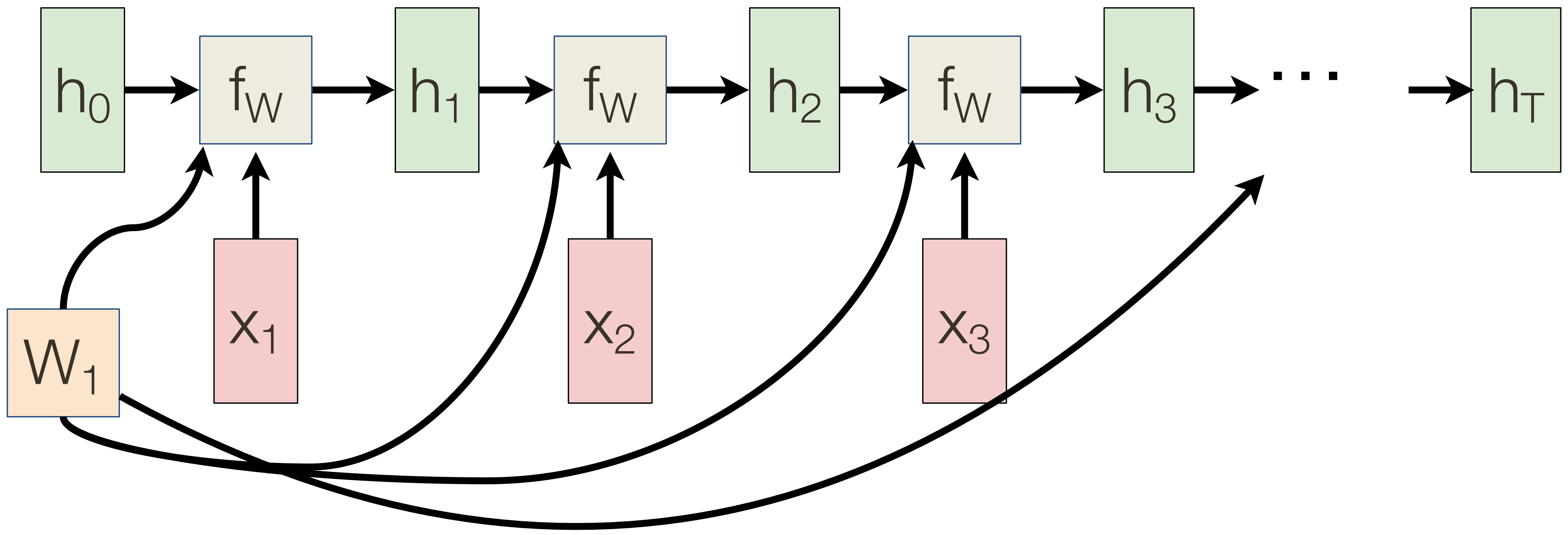
Alternative: RNN computes a representation of sequence element
(e.g. letter, word, video frame, etc.)
with context provided by all previous processed elements

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



Sequence to Sequence: Many to One + One to Many

Many to one: Encode input sequence in a single vector

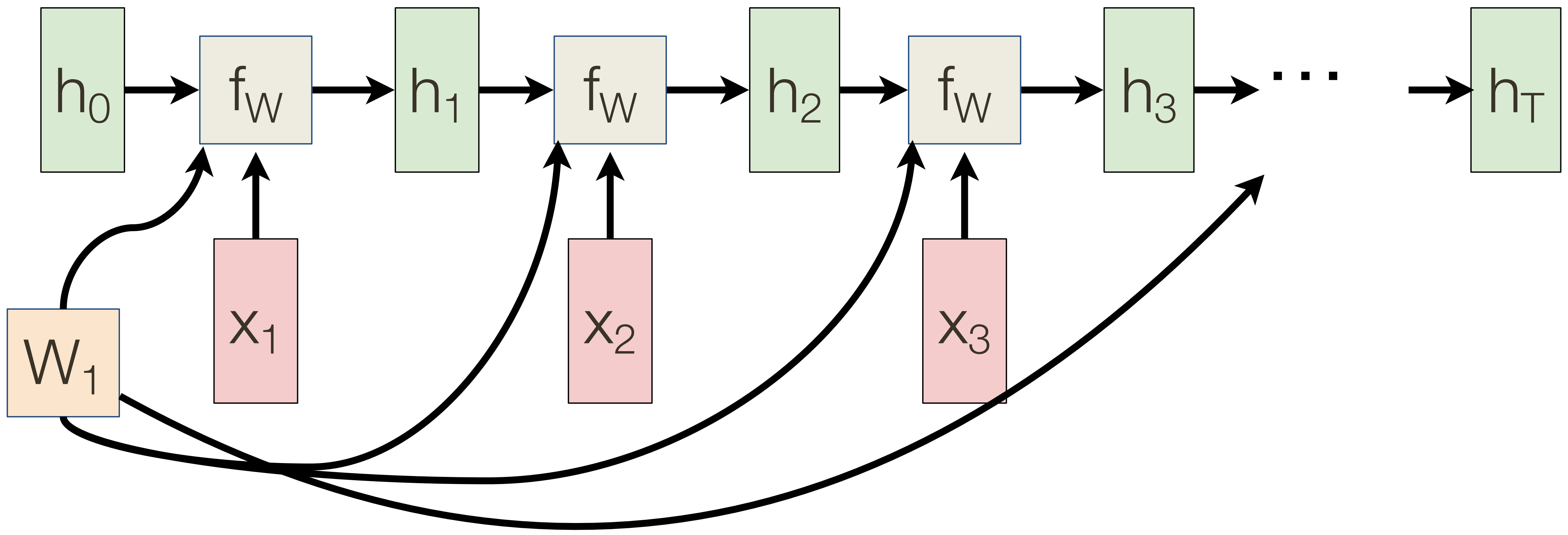


Sequence to Sequence: Many to One + One to Many

Many to one: Encode input sequence in a single vector

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

Basically a fully connected layer (with shared params)



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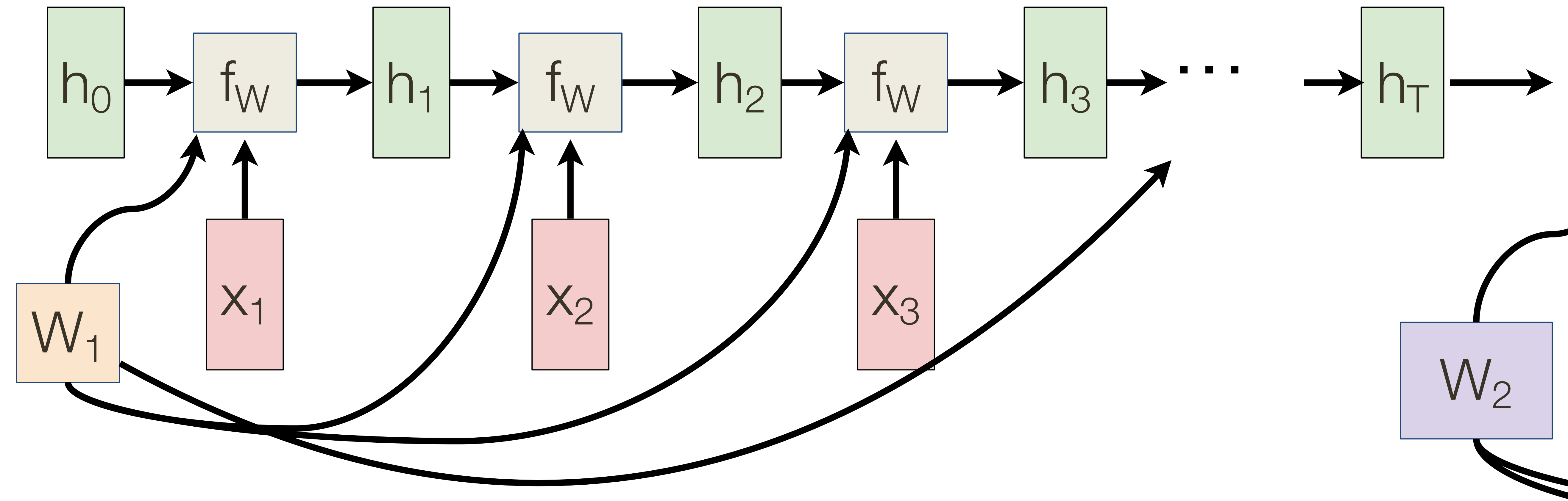
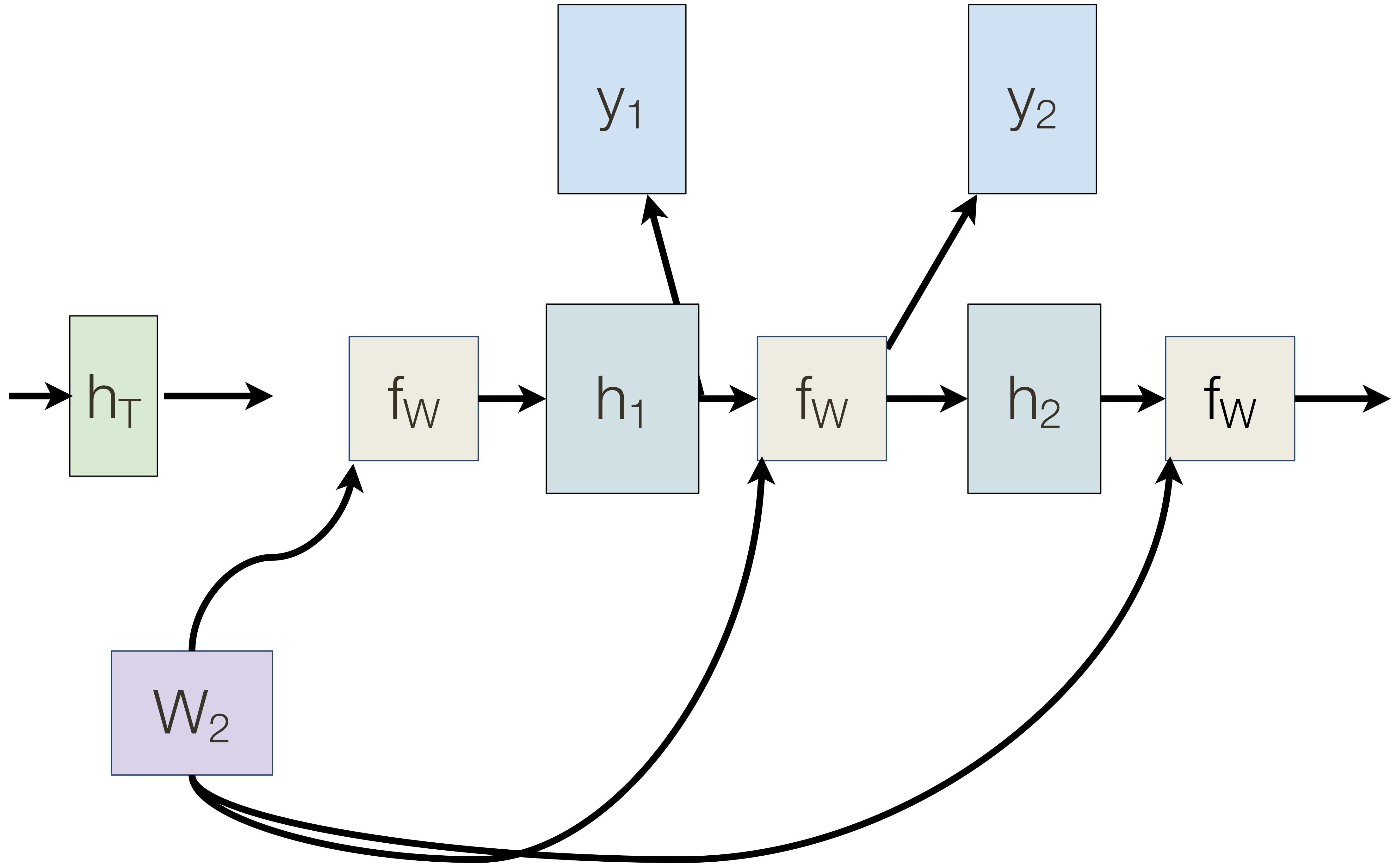


One to many: Produce output sequence from single input vector



Assignment 3: Part 1

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Example: Character-level Language Model (**Training**)

Assignment 3: <u>Decoder</u> of Part 1

(encoder is similar, but with no outputs, so easier)

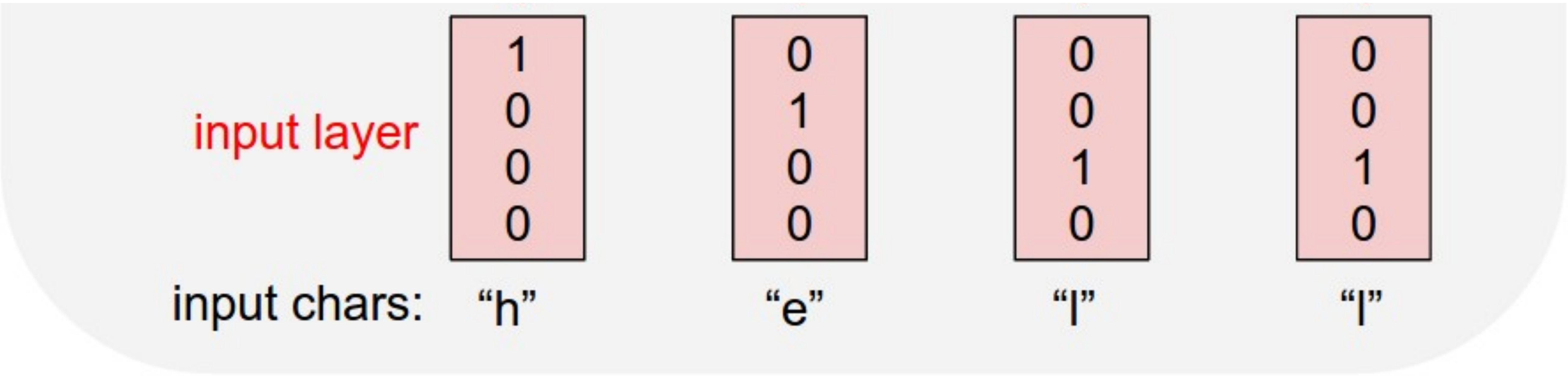
Example: Character-level Language Model (**Training**)

Vocabulary:

['h', 'e', 'l', 'o']

Example training sequence:

"hello"



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Example training sequence:
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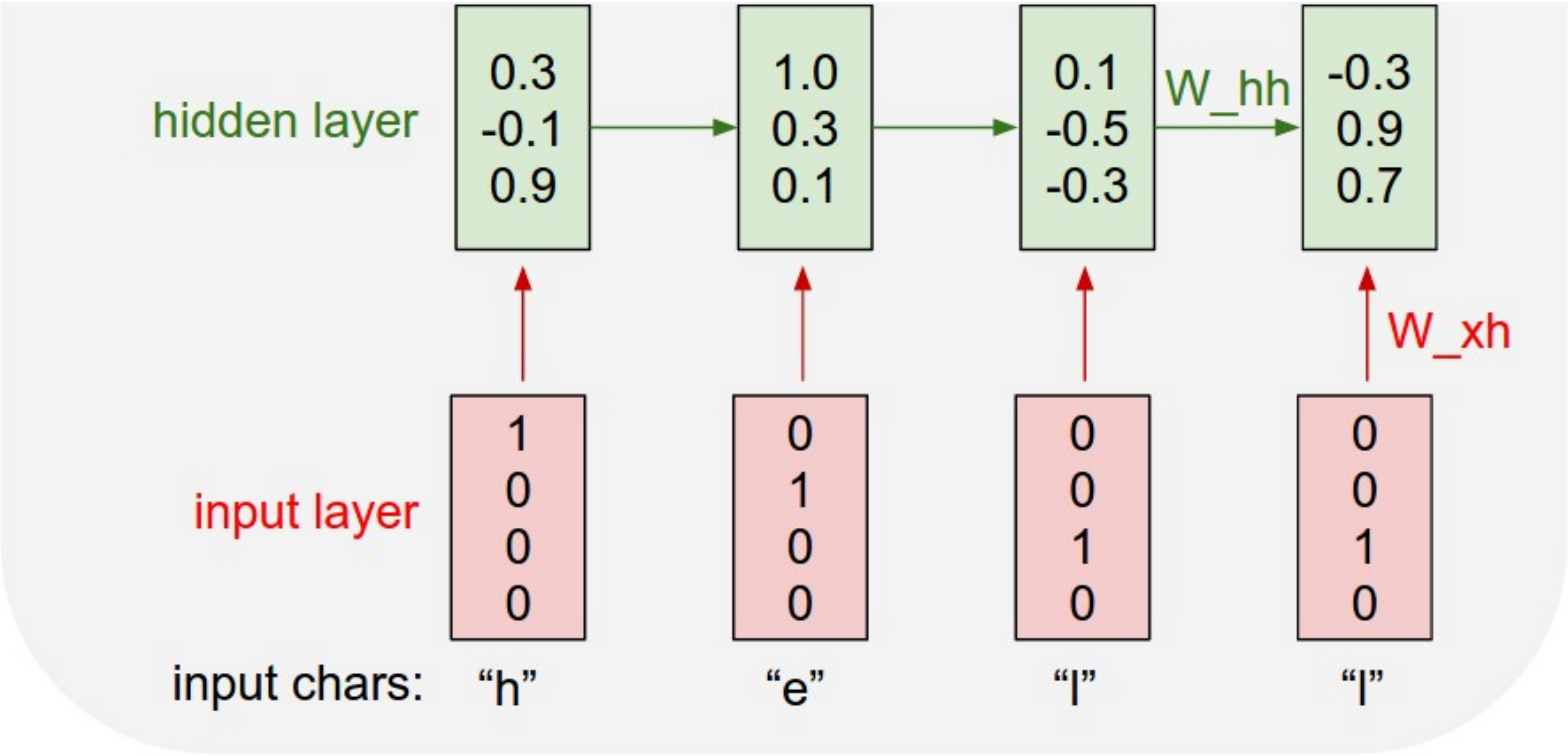

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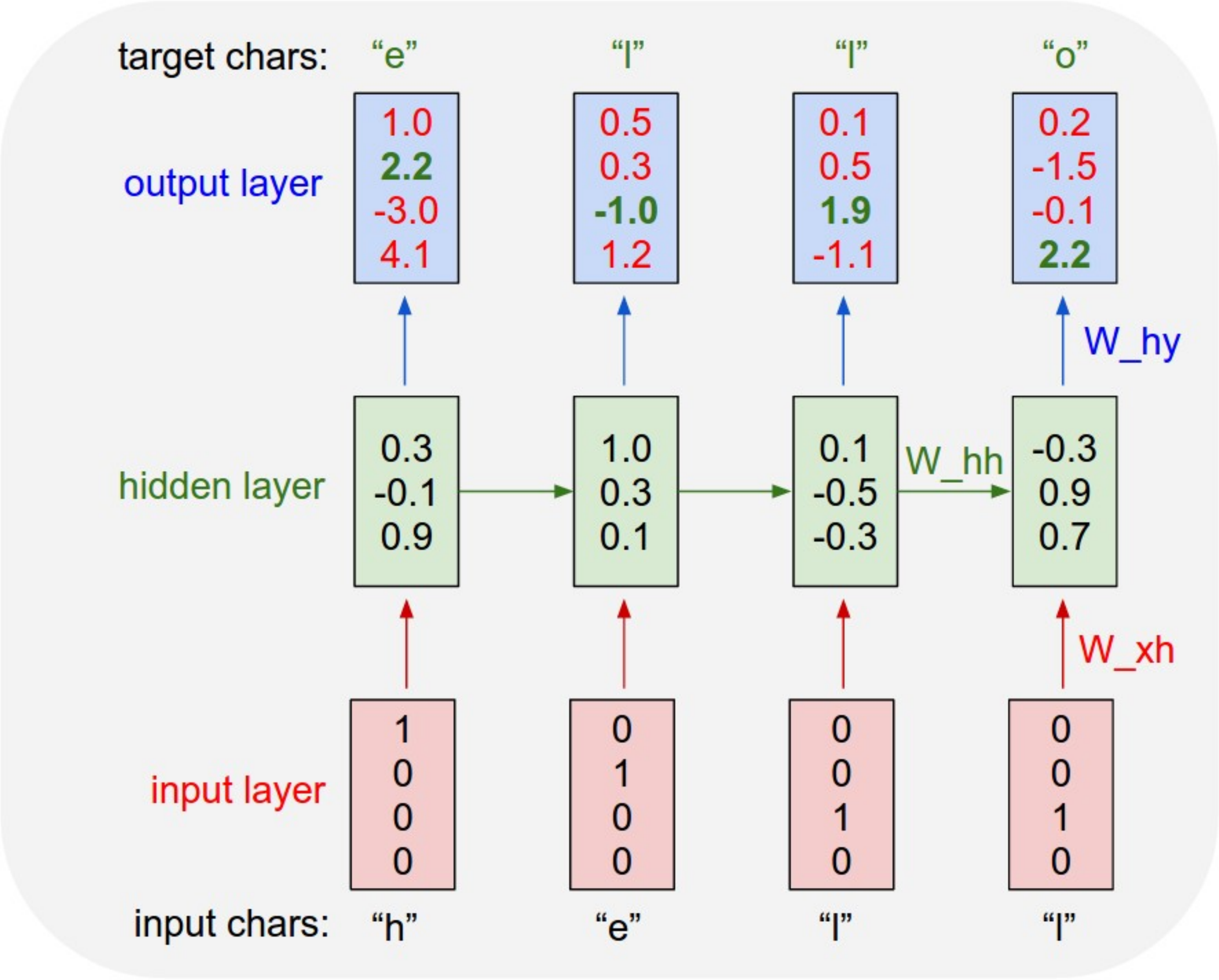

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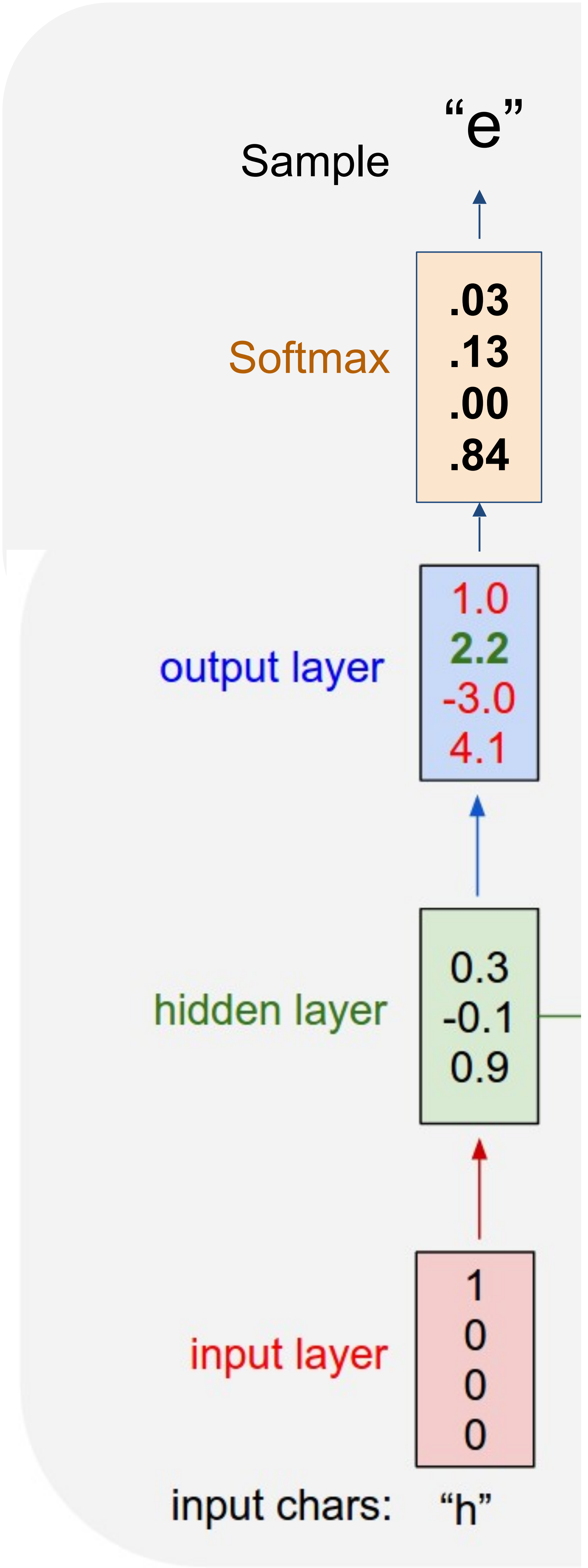
Example: Character-level Language Model (**Sampling**)

Vocabulary:

['h', 'e', 'l', 'o']

At test time sample one character at a time and feed back to the model



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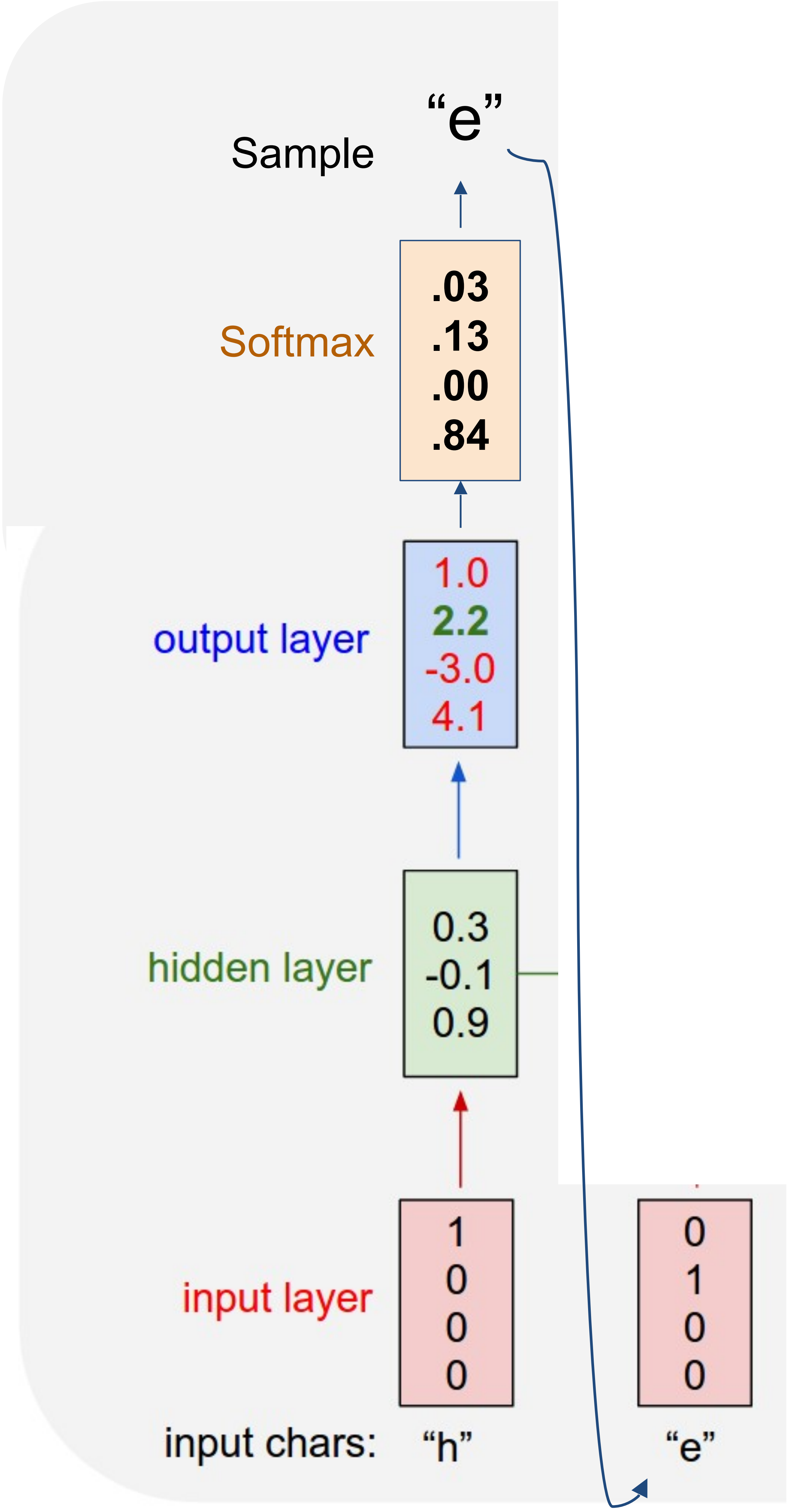

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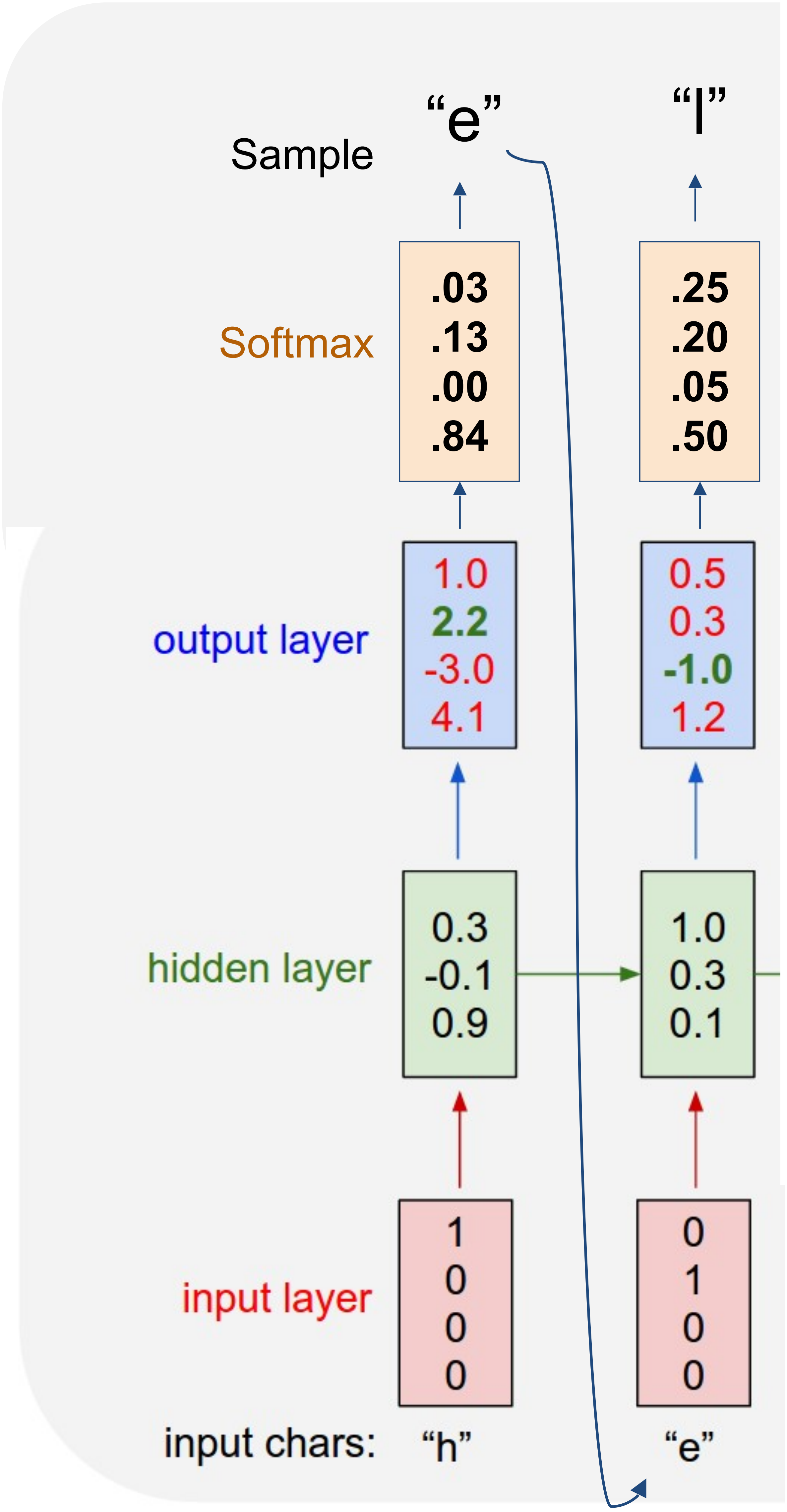

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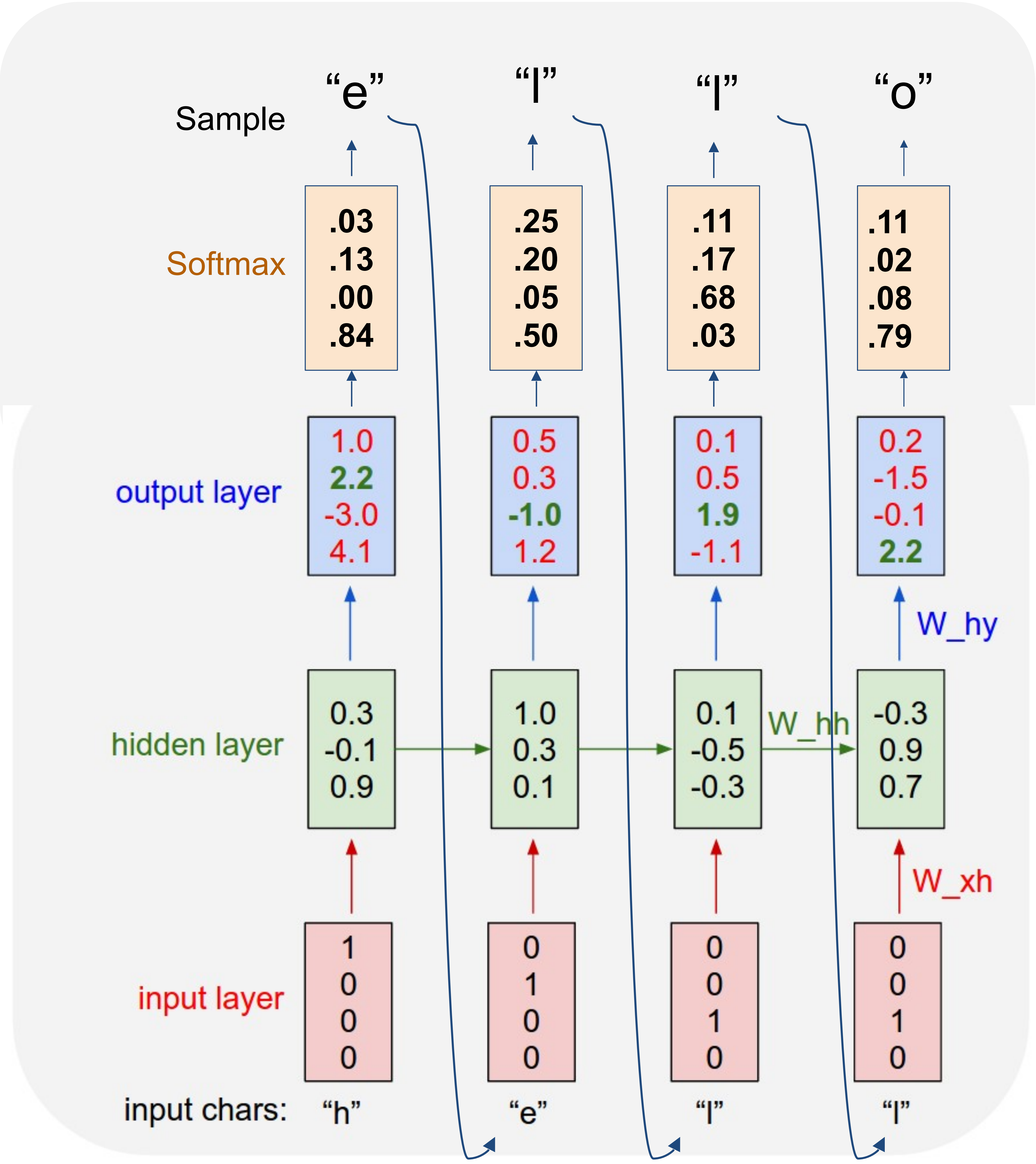

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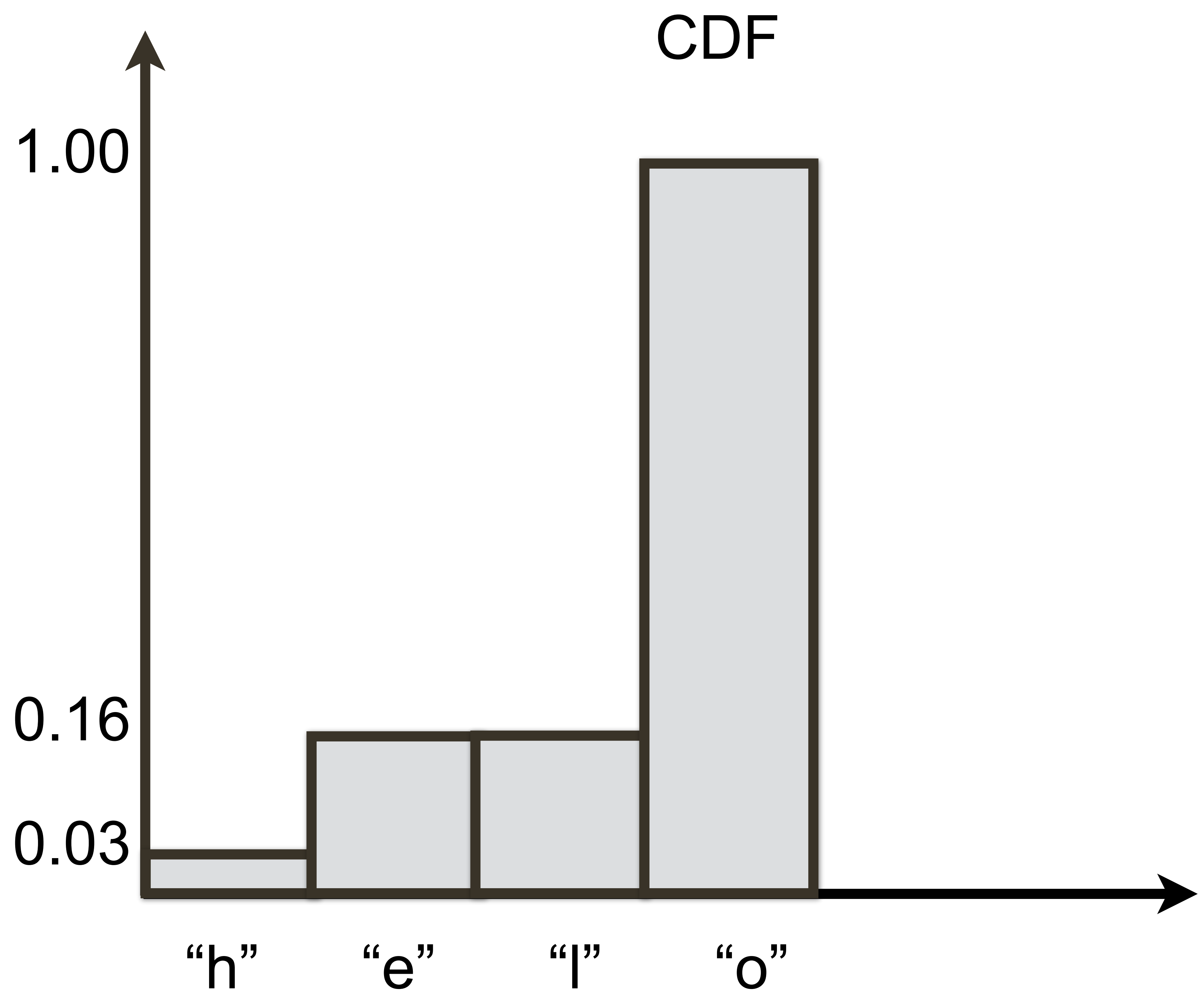
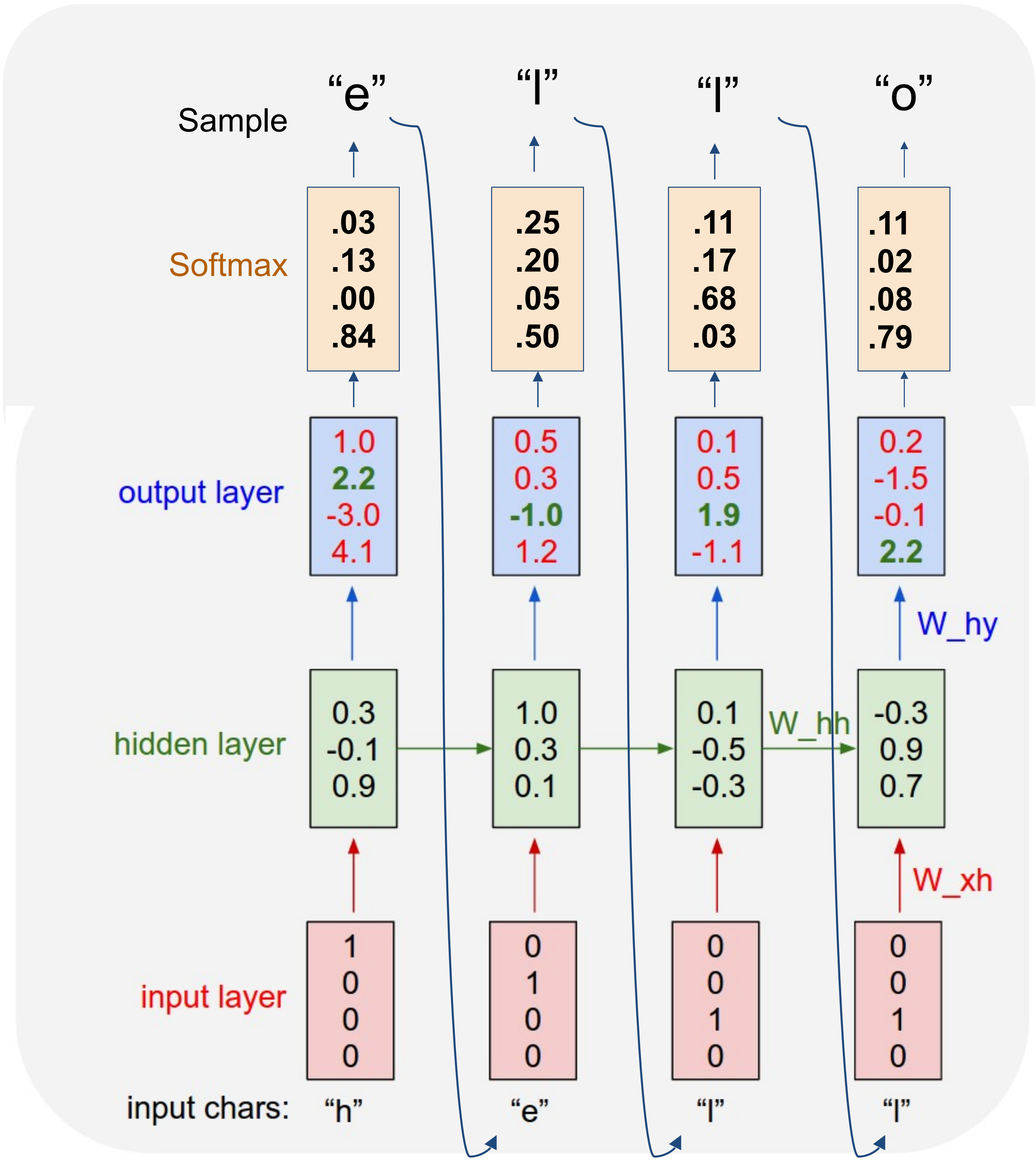
Example: Character-level Language Model (**Sampling**)

Inverse Transform Sampling



Draw rand() from Uniform, then look up the bin



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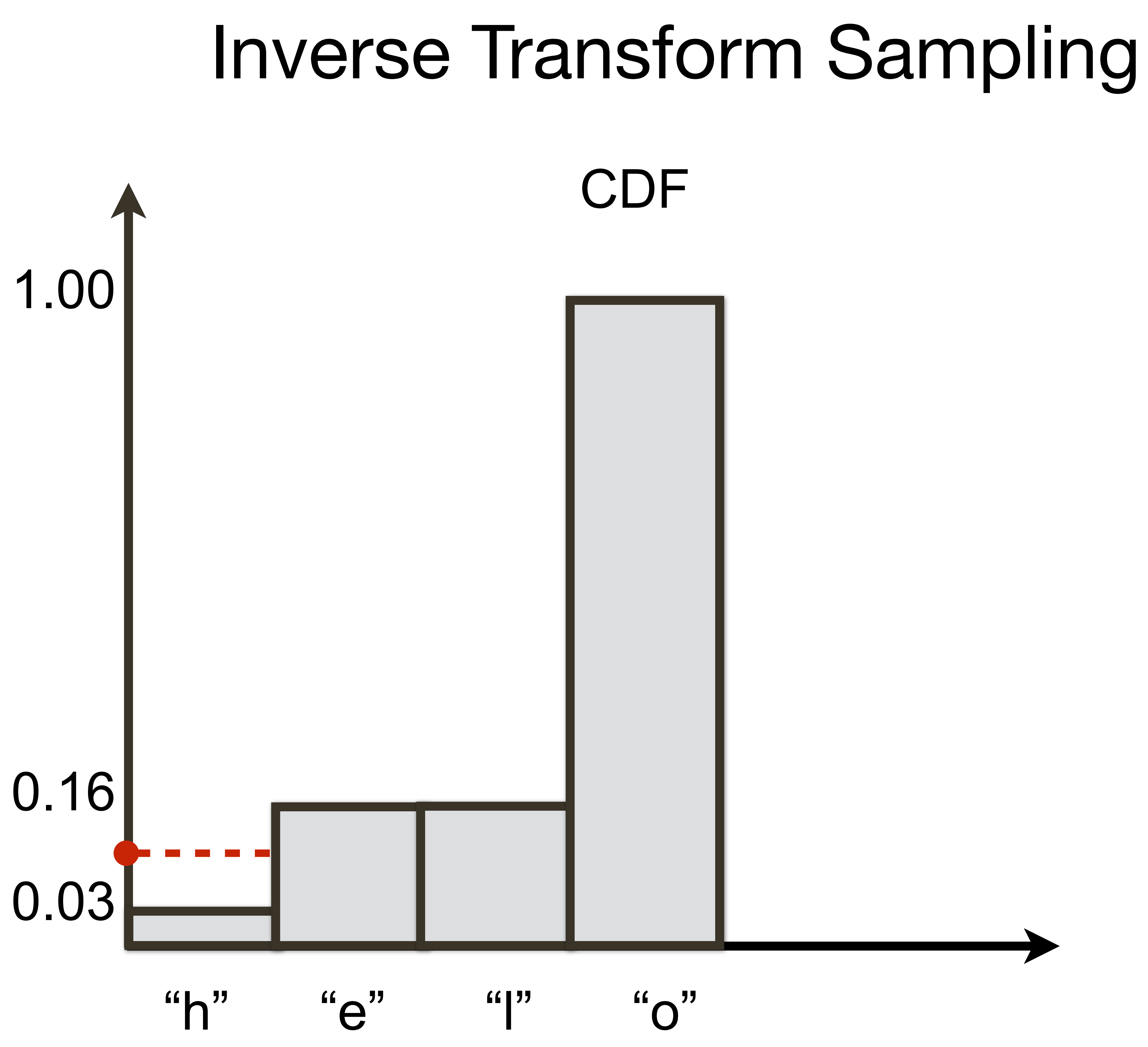
Example: Character-level Language Model (**Sampling**)



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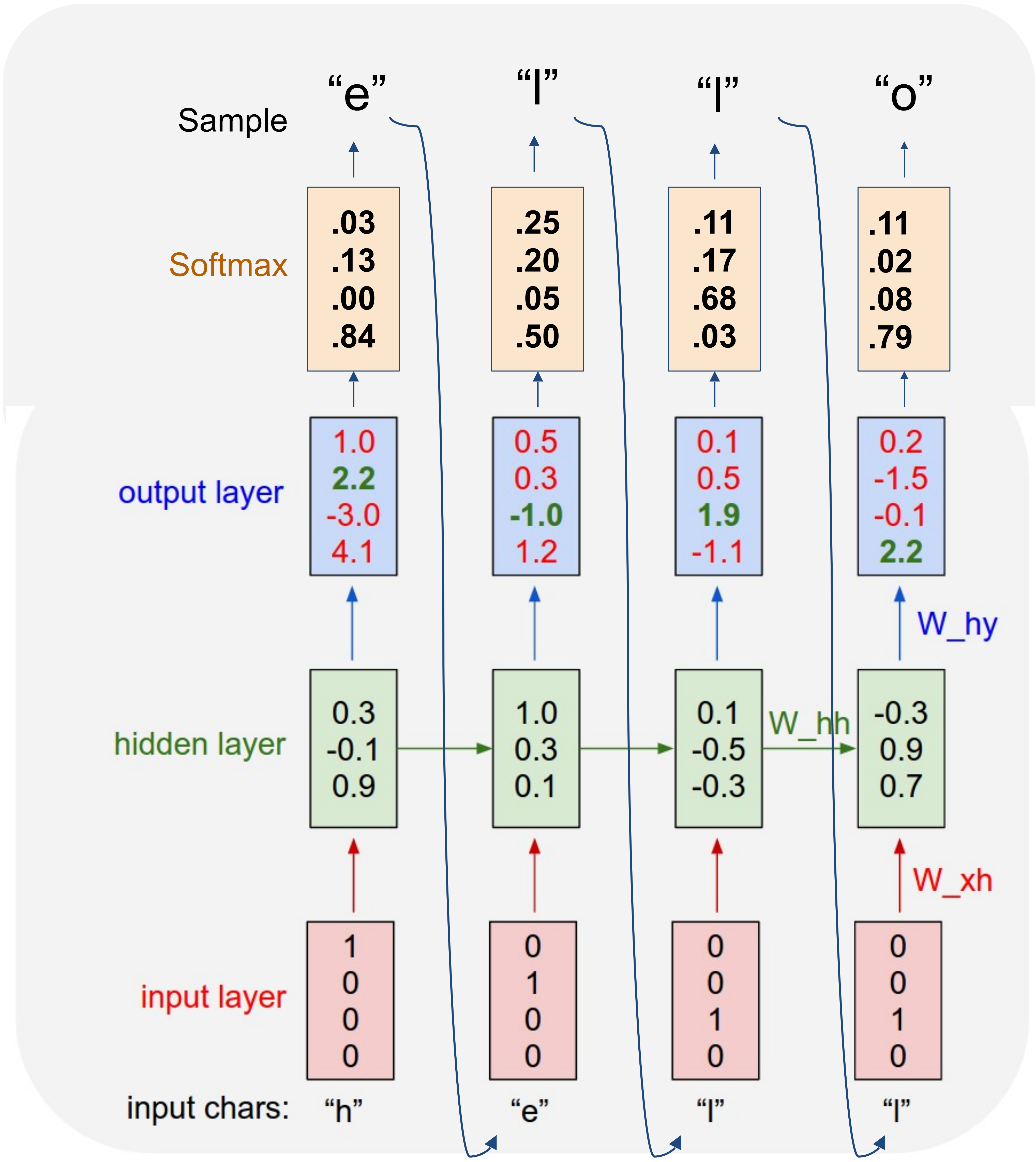

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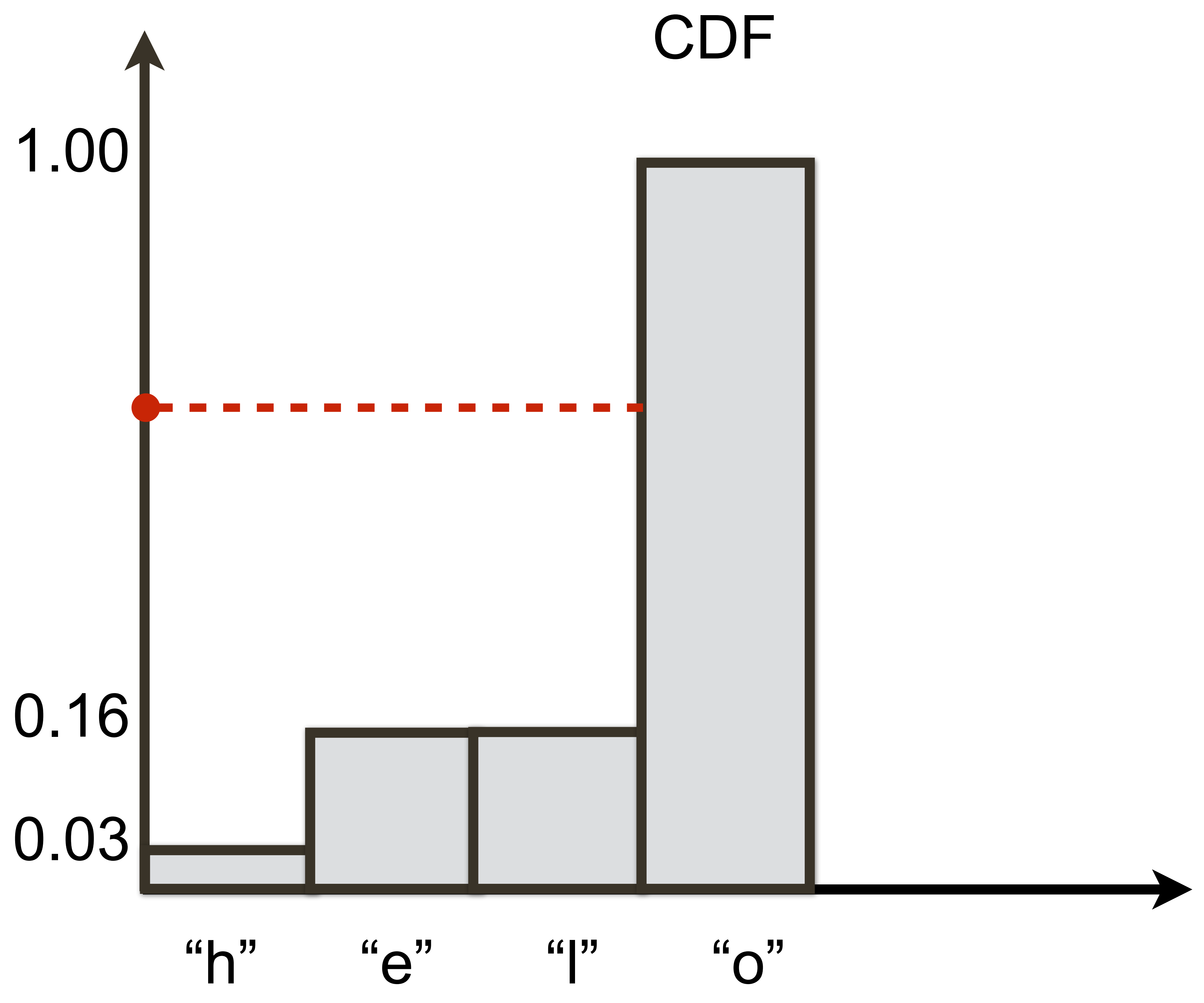

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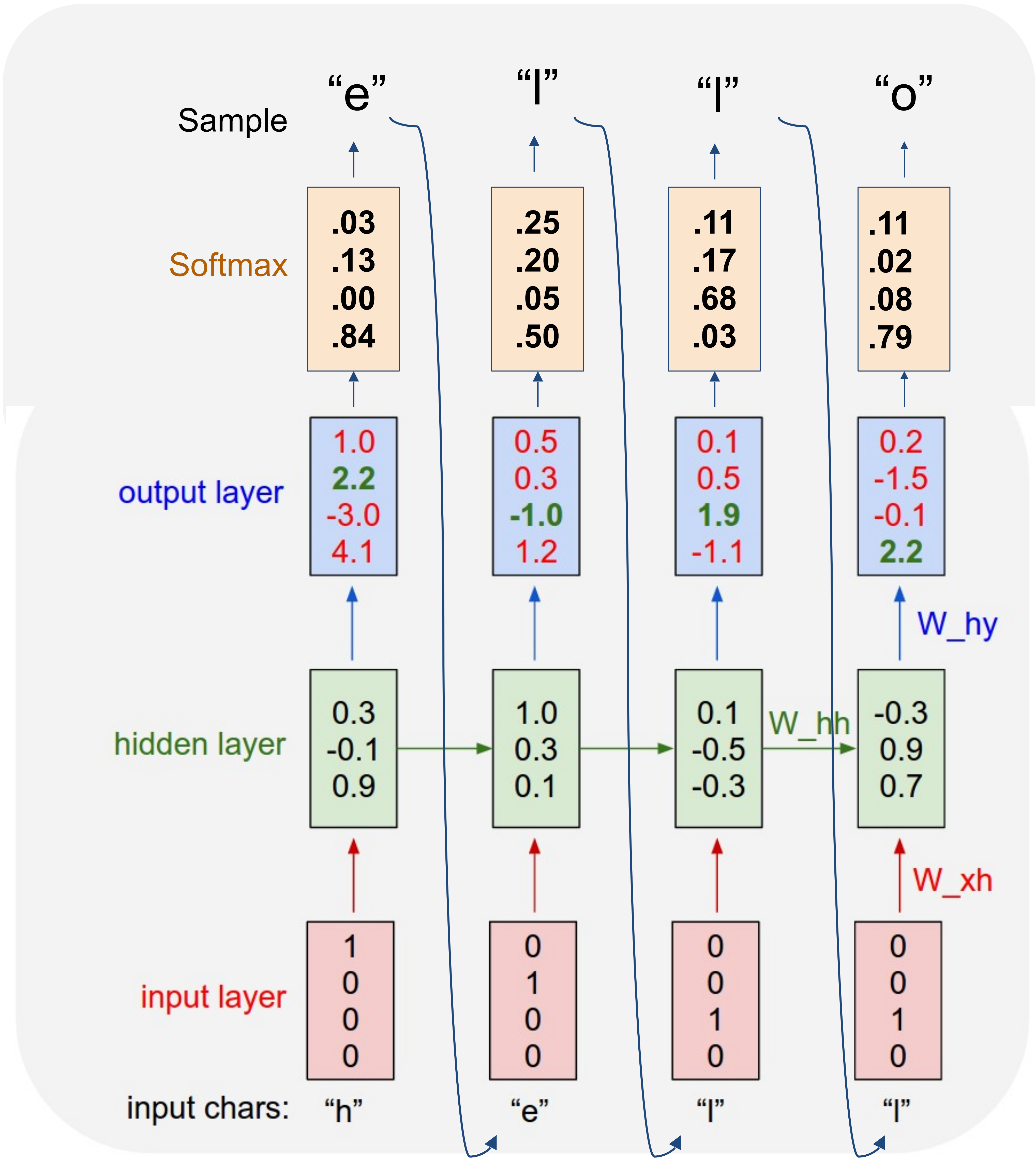

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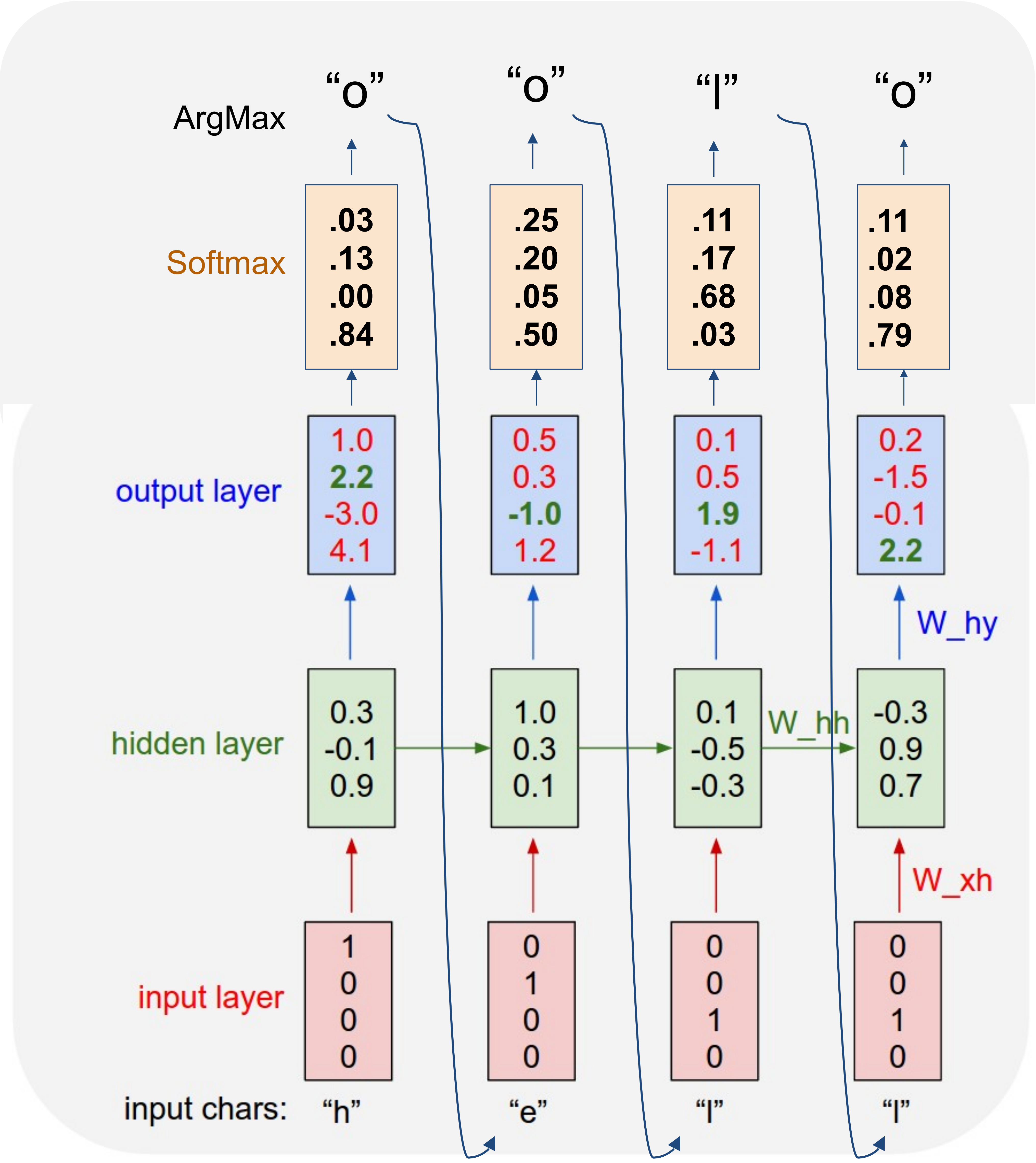
Sampling vs. **ArgMax** vs. **Beam Search**

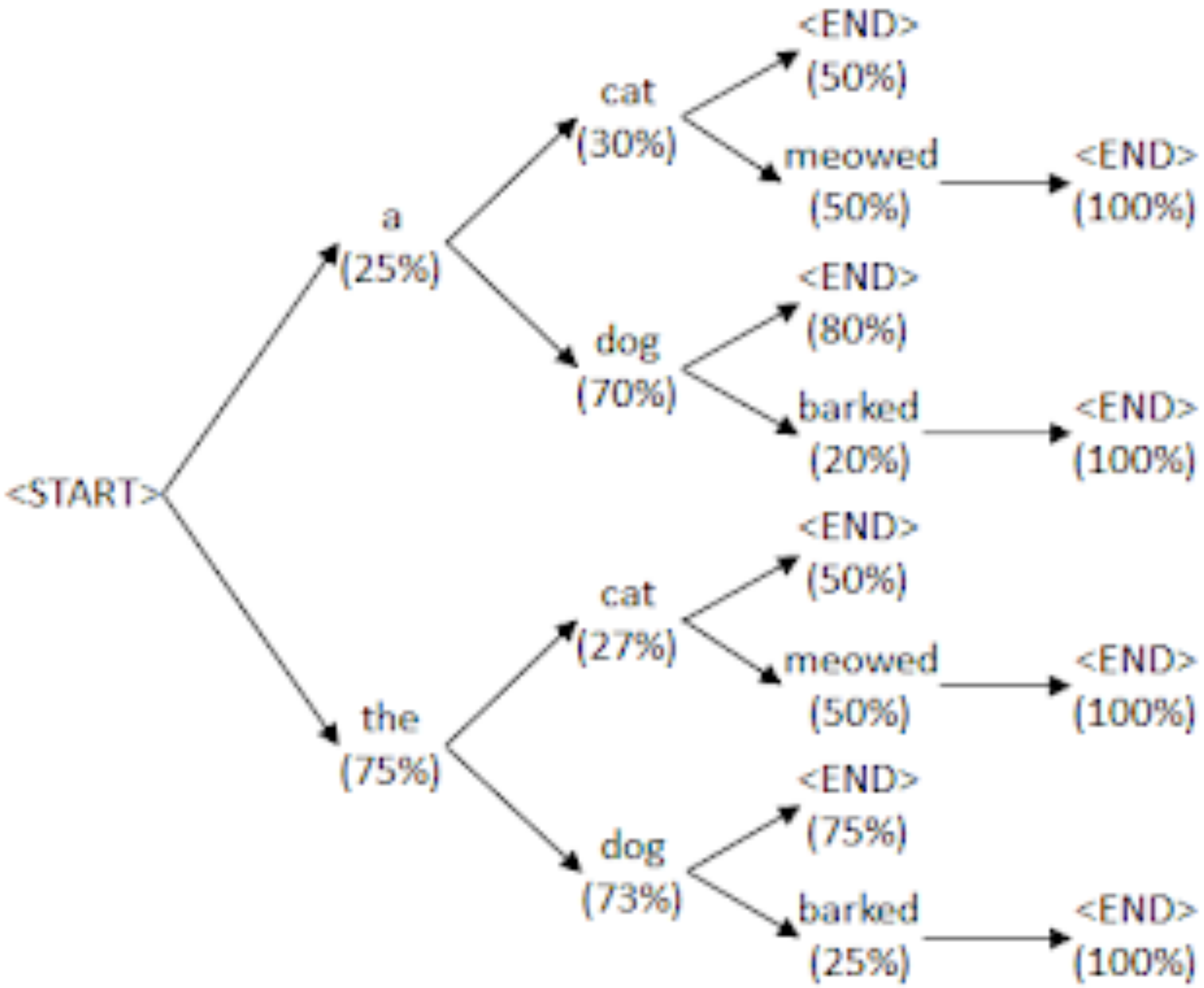
Sampling: allows to generate diverse outputs

ArgMax: could be more stable in practice

Beam Search: typically gets the best results



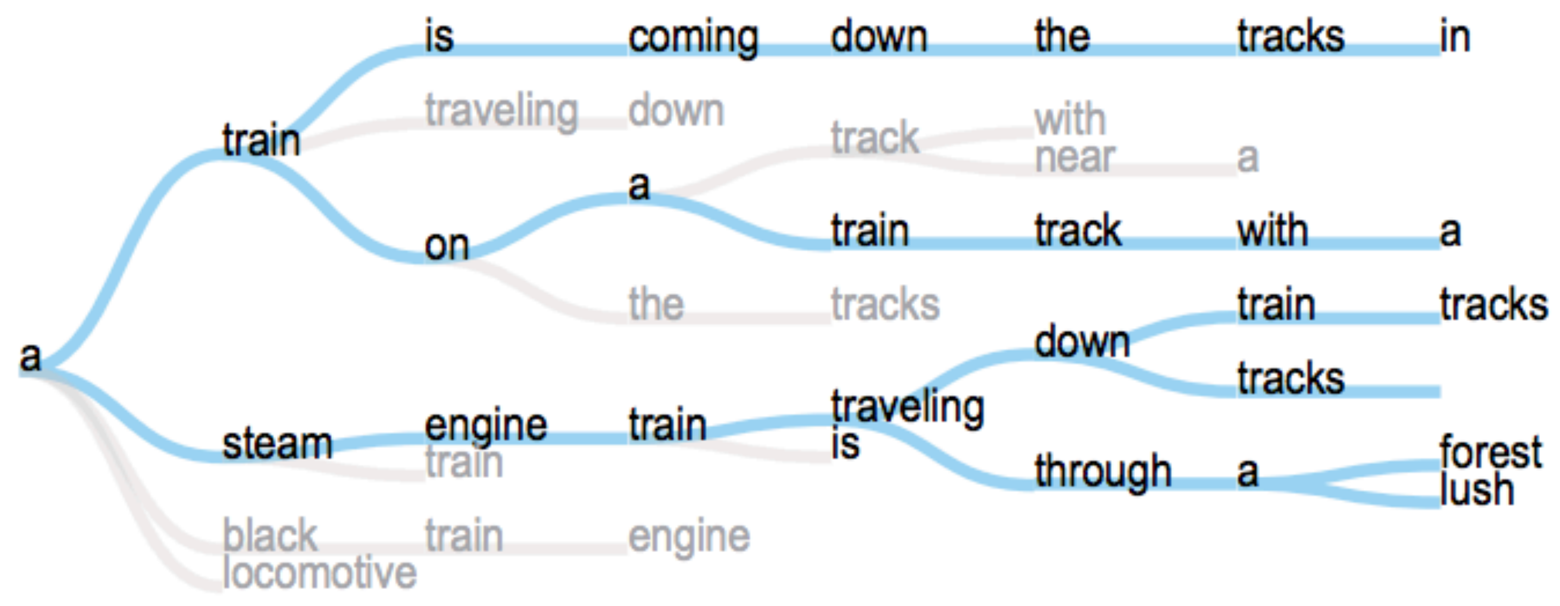
Beam Search



<START>
a
(25%)
the
(75%)
cat
(30%)
dog
(70%)
cat
(27%)
dog
(73%)
<END>
(50%)
meowed
(50%)
<END>
(80%)
barked
(20%)
<END>
(50%)
meowed
(50%)
<END>
(75%)
barked
(25%)
<END>
(100%)
<END>
(100%)
<END>
(100%)
<END>
(100%)

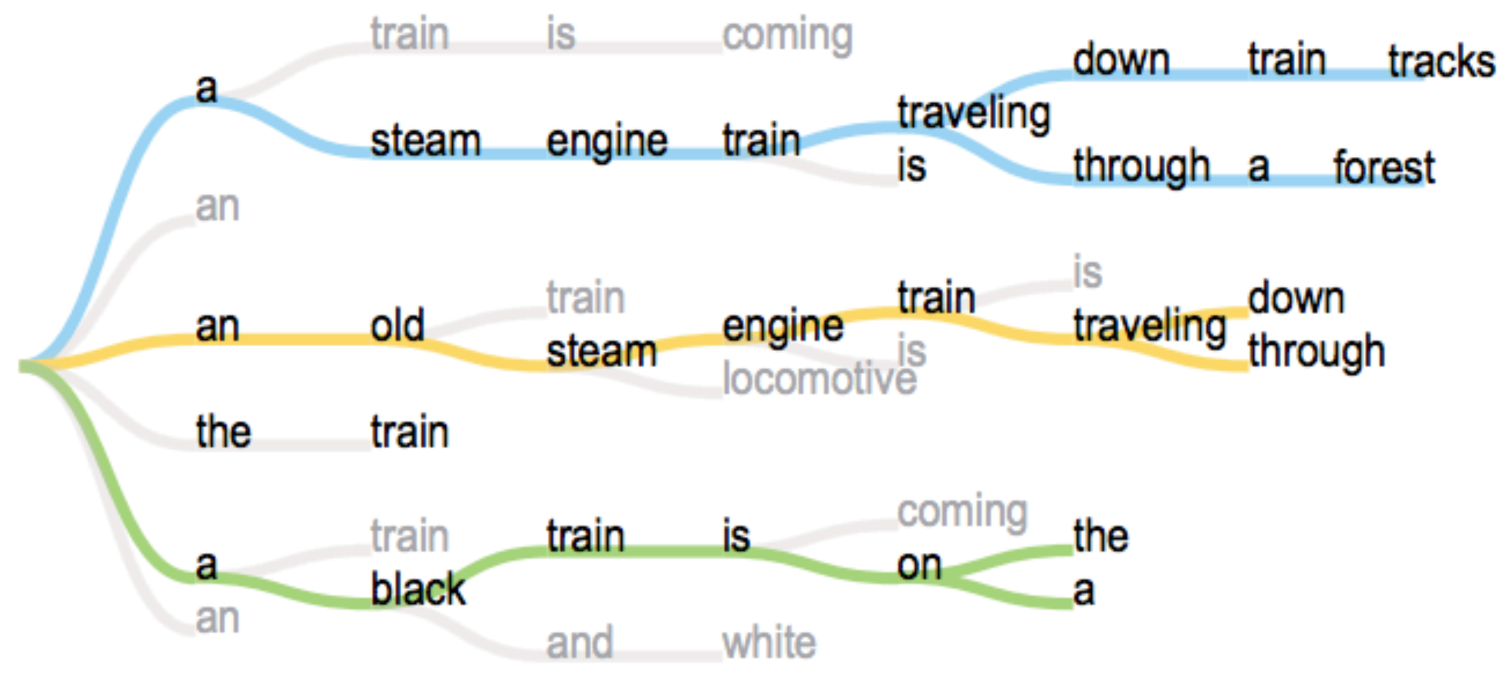
Beam Search

Beam Search



A steam engine train travelling down train tracks.
A steam engine train travelling down tracks.
A steam engine train travelling through a forest.
A steam engine train travelling through a lush green forest.
A steam engine train travelling through a lush green countryside
A train on a train track with a sky background.

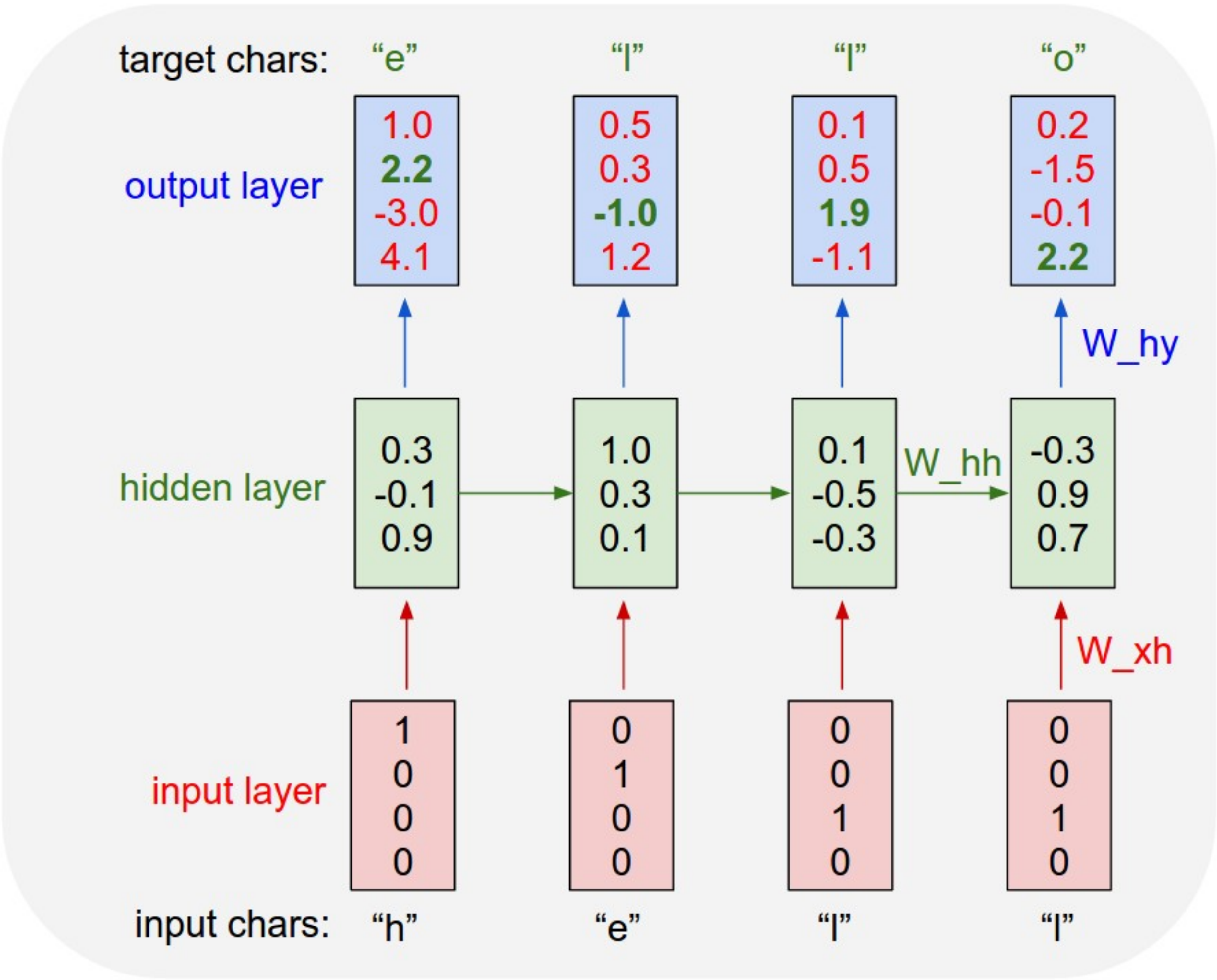
Diverse Beam Search



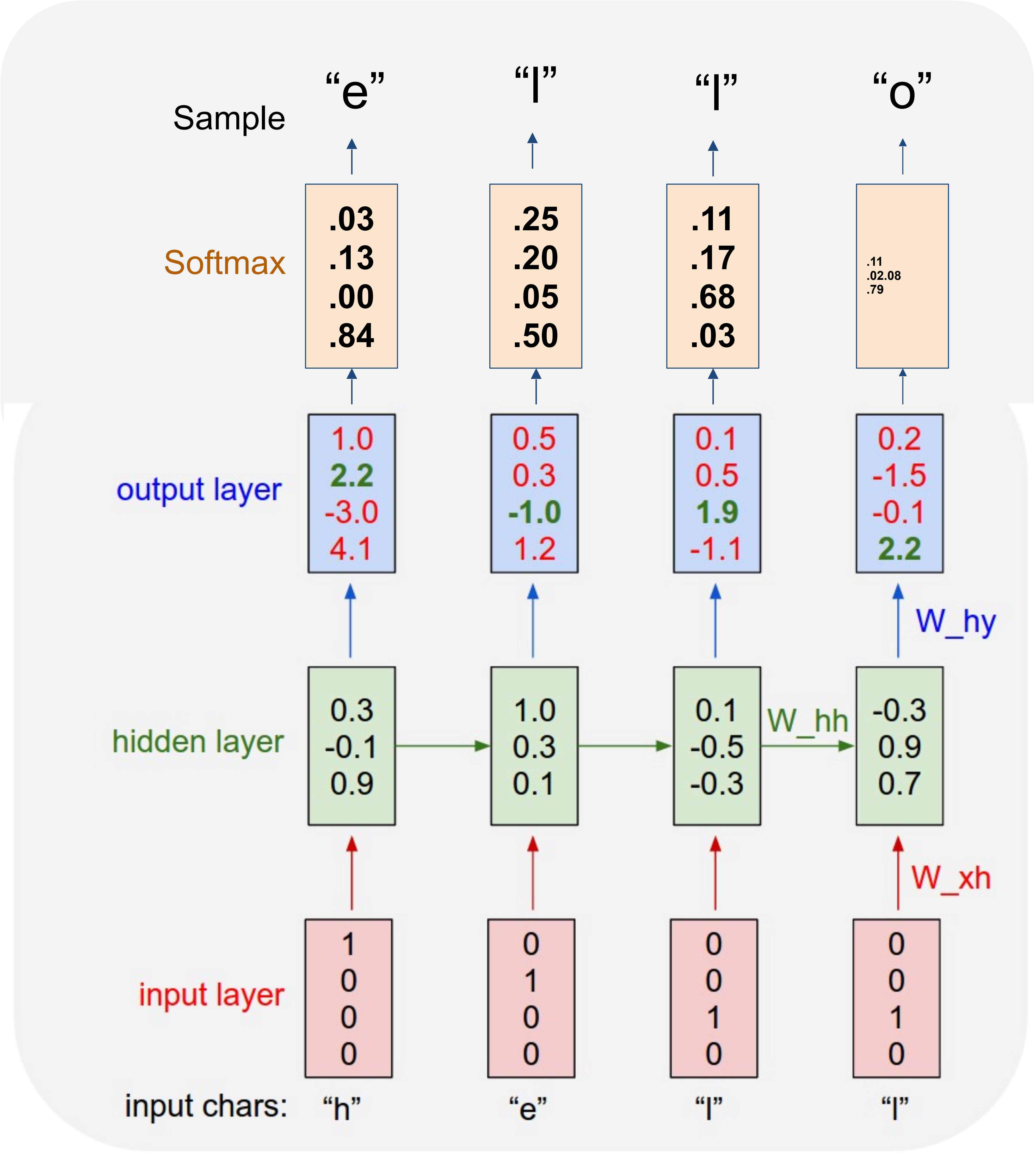
A steam engine travelling down train tracks.
A steam engine train travelling through a forest.
An old steam engine train travelling down train tracks.
An old steam engine train travelling through a forest.
A black train is on the tracks in a wooded area.
A black train is on the tracks in a rural area.

Teacher Forcing

Training Objective: Predict the next word
(cross entropy loss)



Testing: Sample the full sequence



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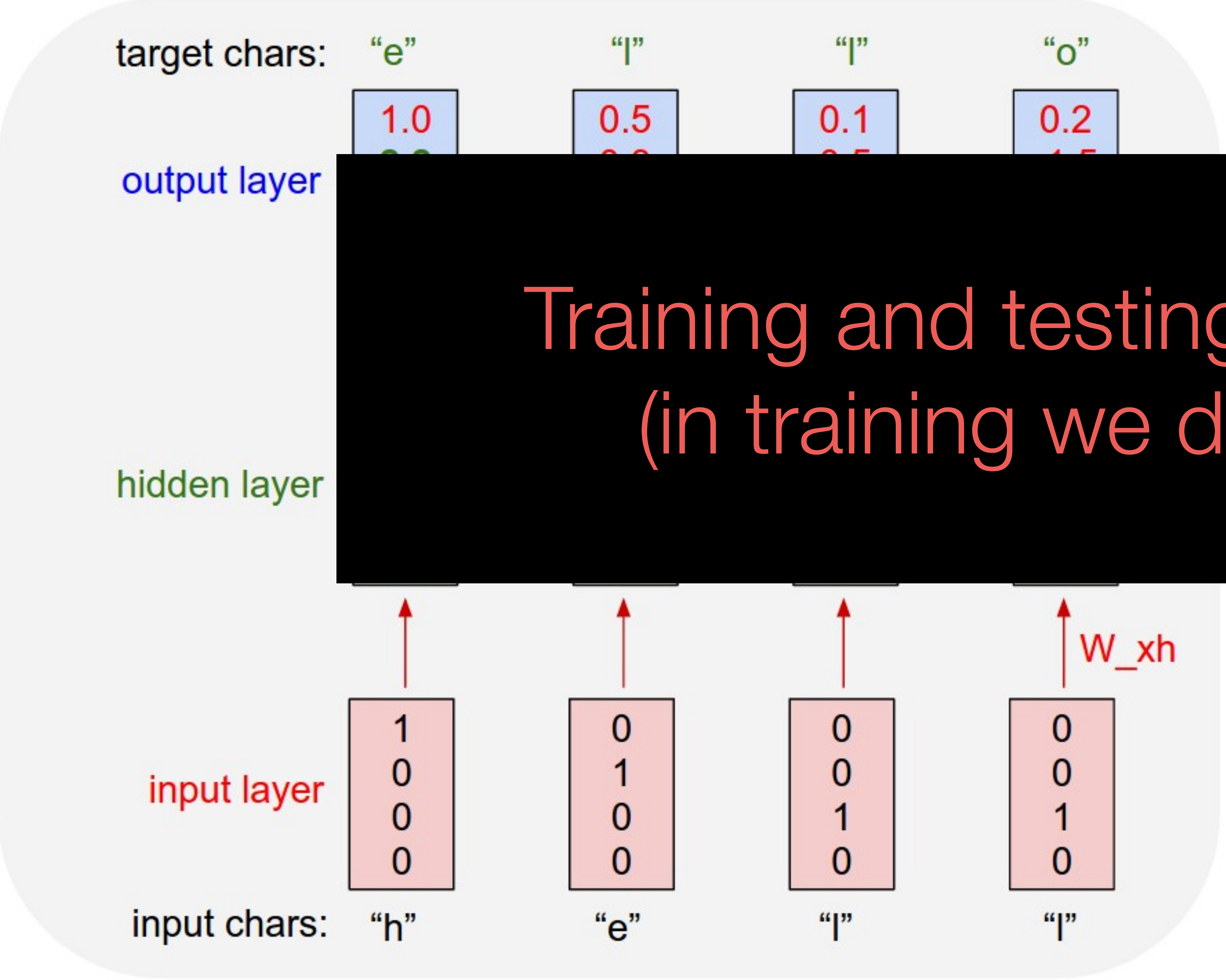
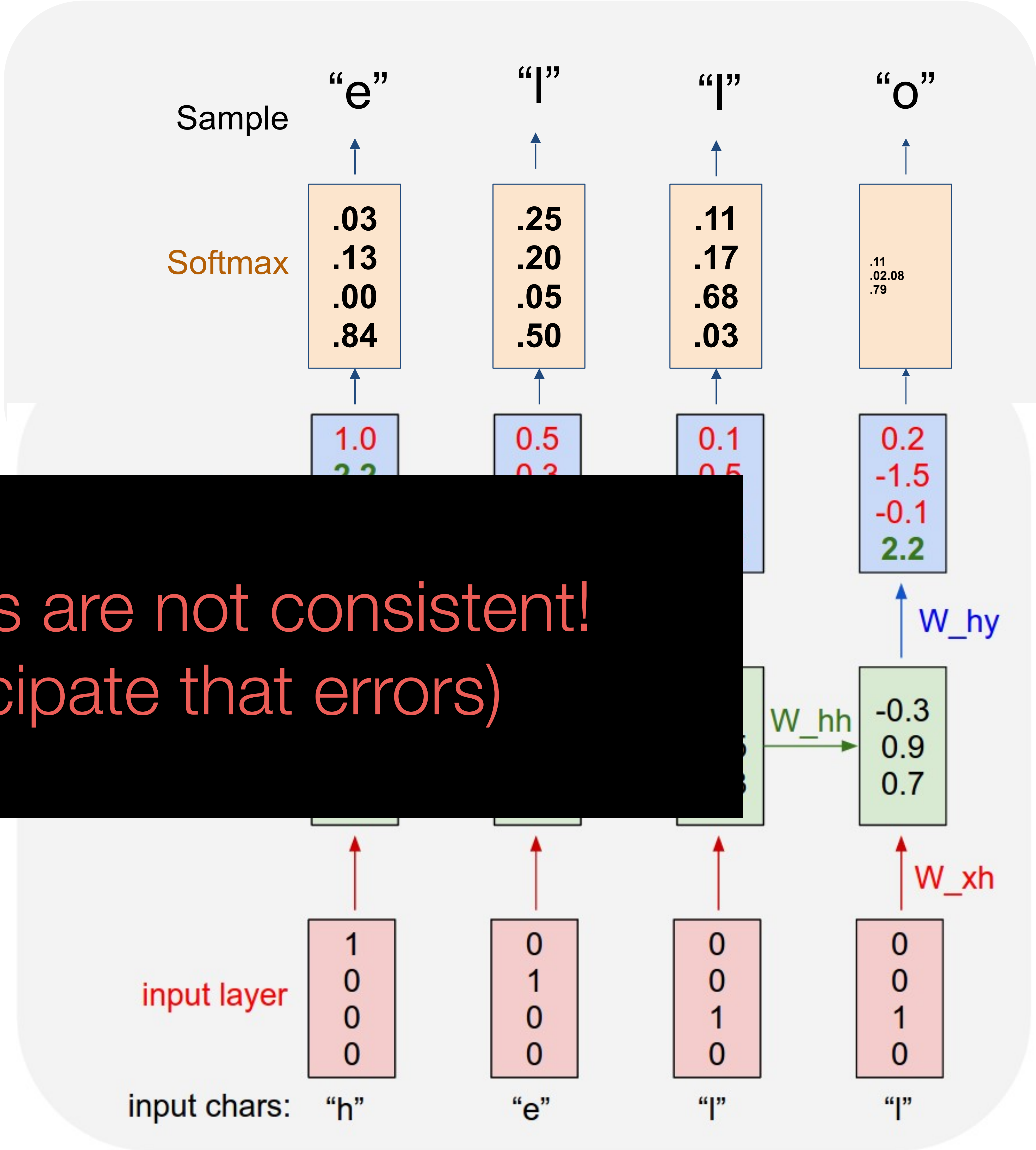
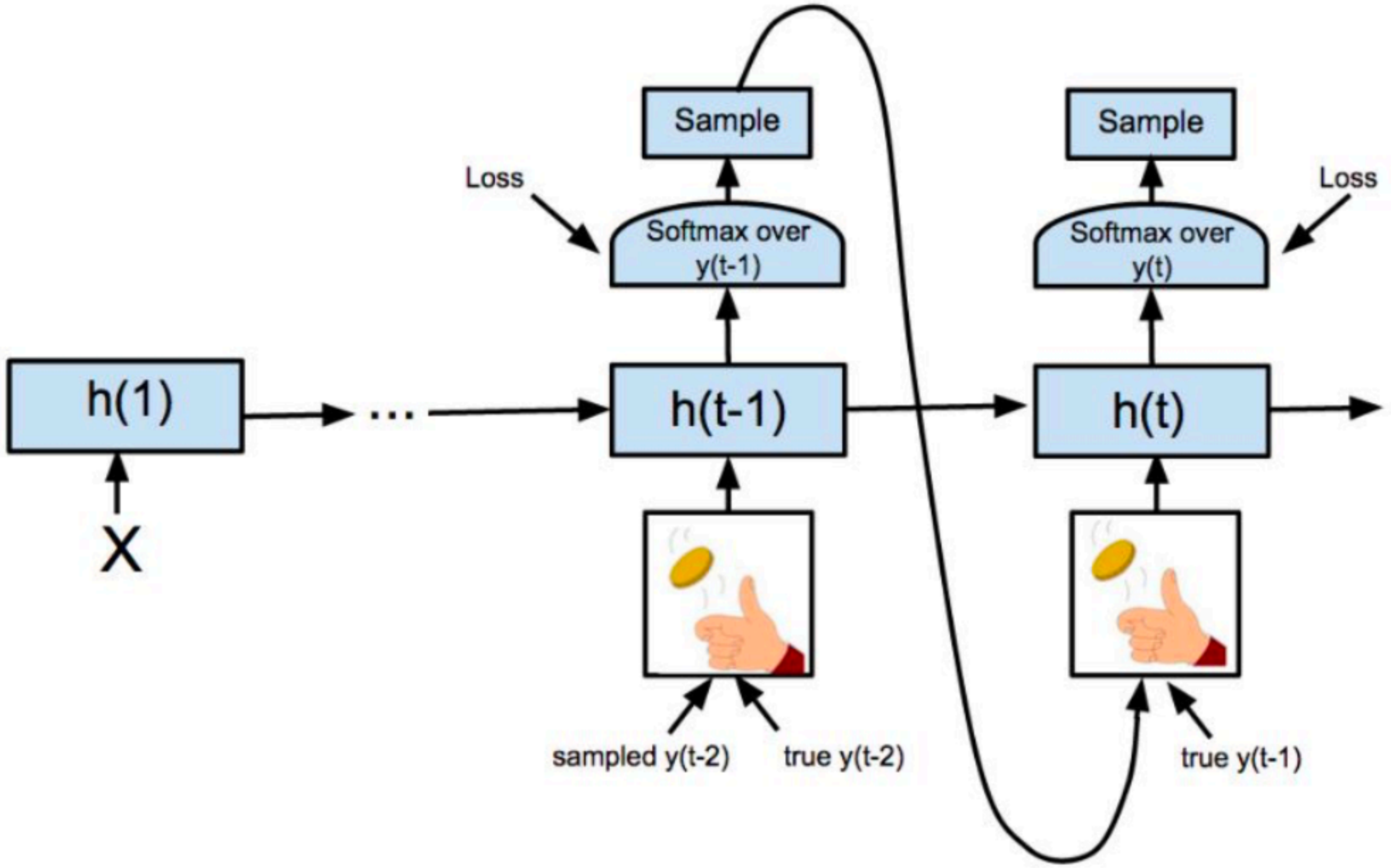




Training and testing objectives are not consistent!
(in training we did not anticipate that errors)

Teacher Forcing

Slowly move from *Teacher Forcing* to *Sampling*



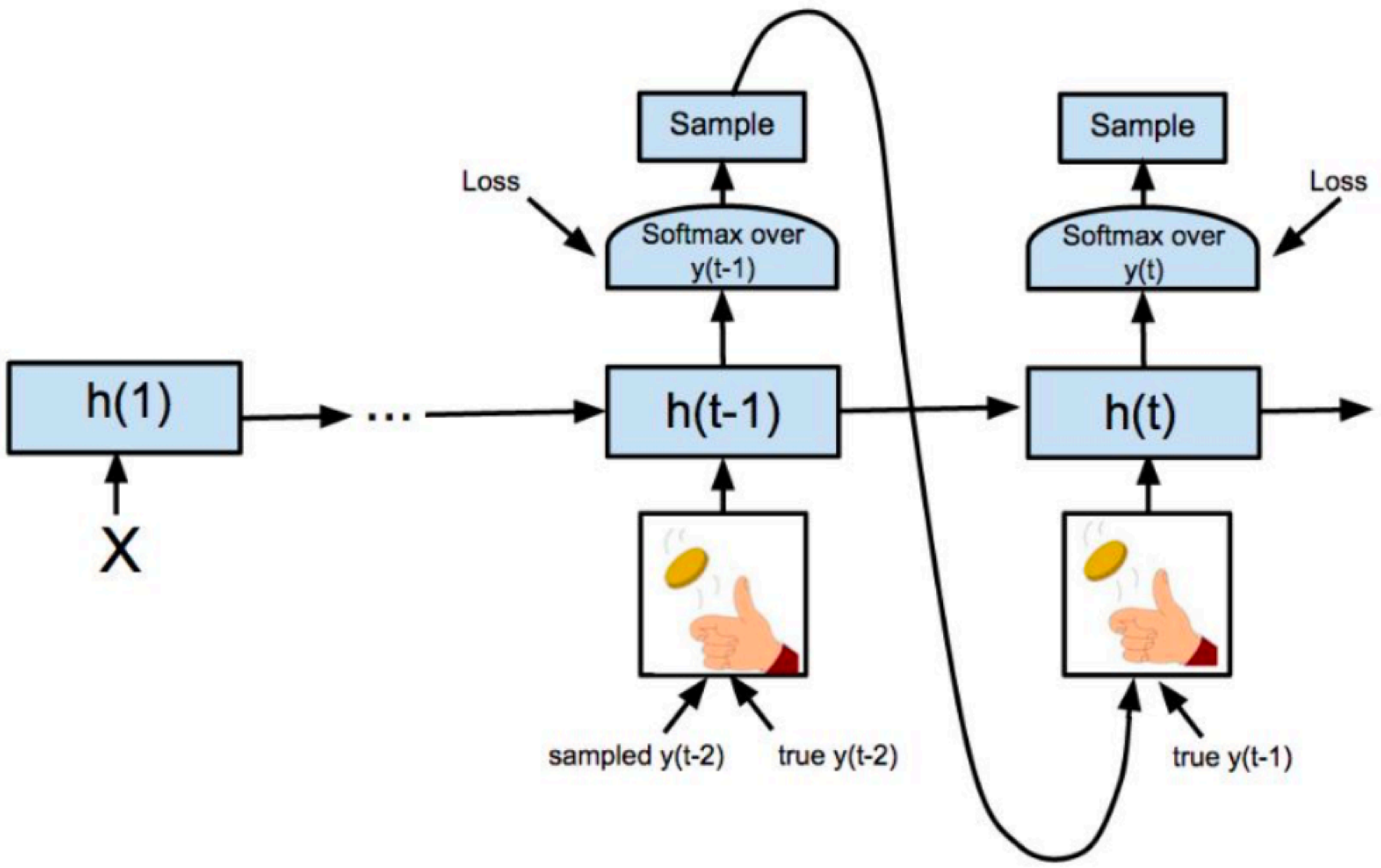
[Bengio et al., 2015]

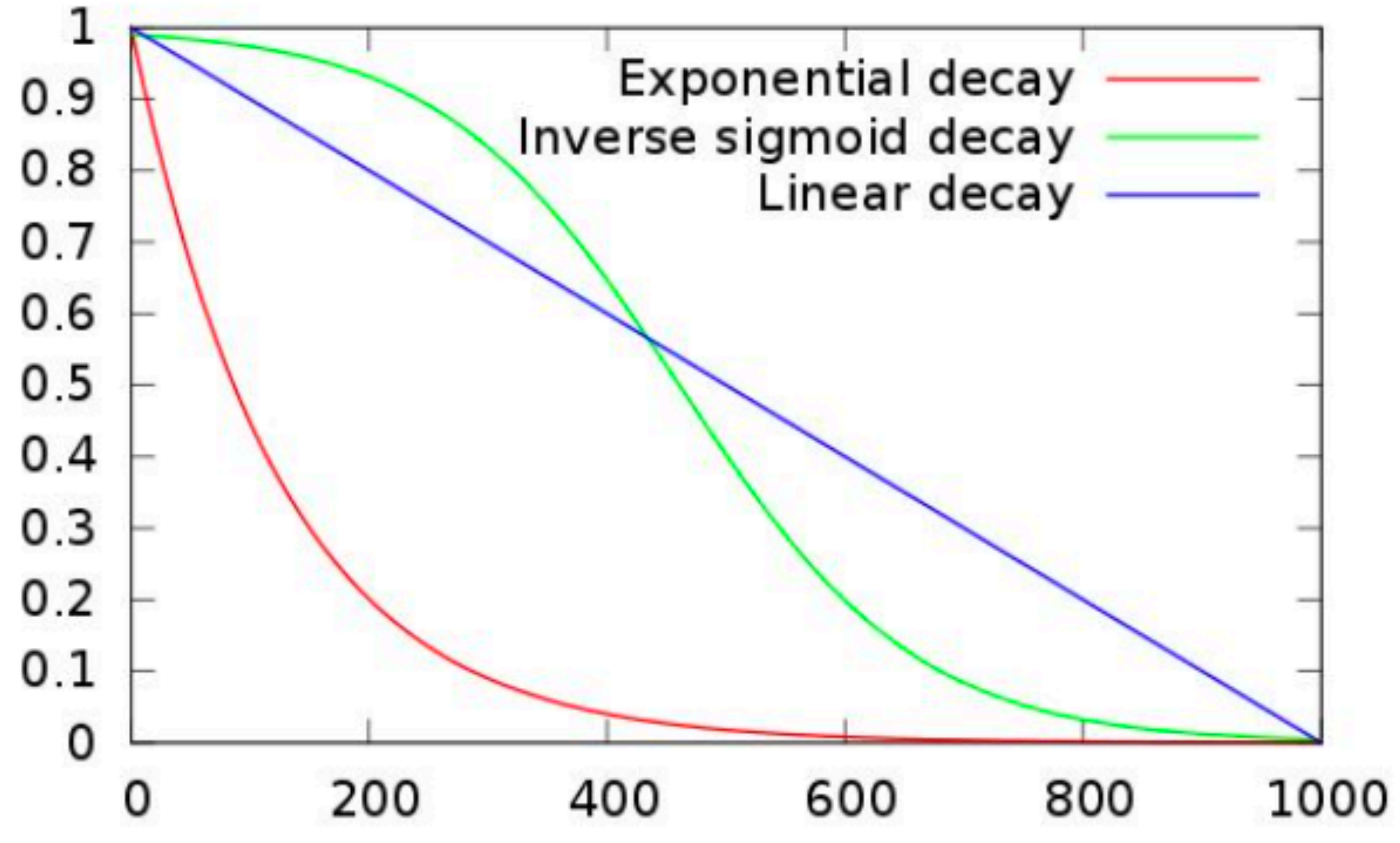
Note: for the Assignment 3 its OK to sample once per sequence (not per step as is illustrated here)

* slide from Marco Pedersoli and Thomas Lucas

Teacher Forcing

Slowly move from *Teacher Forcing* to *Sampling*





Probability of sampling from the ground truth

[Bengio et al., 2015]

Note: for the Assignment 3 its OK to sample once per sequence (not per step as is illustrated here)

* slide from Marco Pedersoli and Thomas Lucas

Teacher Forcing

Microsoft COCO developement set

Approach vs Metric	BLEU-4	METEOR	CIDER
Baseline	28.8	24.2	89.5
Baseline with Dropout	28.1	23.9	87.0
Always Sampling	11.2	15.7	49.7
Scheduled Sampling	**30.6**	**24.3**	**92.1**
Uniform Scheduled Sampling	29.2	24.2	90.9
Baseline ensemble of 10	30.7	25.1	95.7
Scheduled Sampling ensemble of 5	**32.3**	**25.4**	**98.7**

Baseline: Google NIC captioning model

Baseline **with Dropout**: Regularized RNN version

Always sampling: Use sampling from the beginning of training

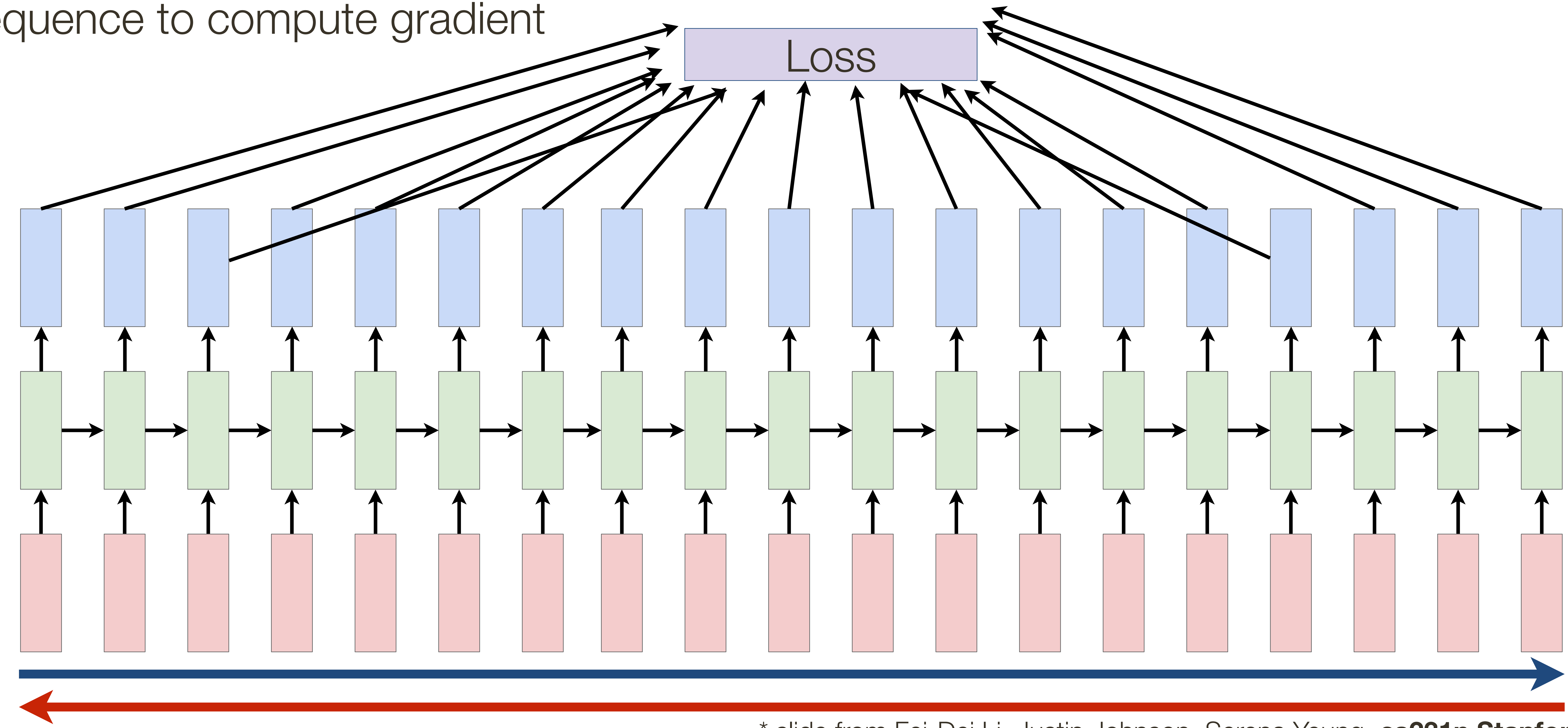
Scheduled sampling: Sampling with inverse Sigmoid decay

Uniformed scheduled sampling: Scheduled sampling but uniformly

* slide from Marco Pedersoli and Thomas Lucas

BackProp Through Time

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



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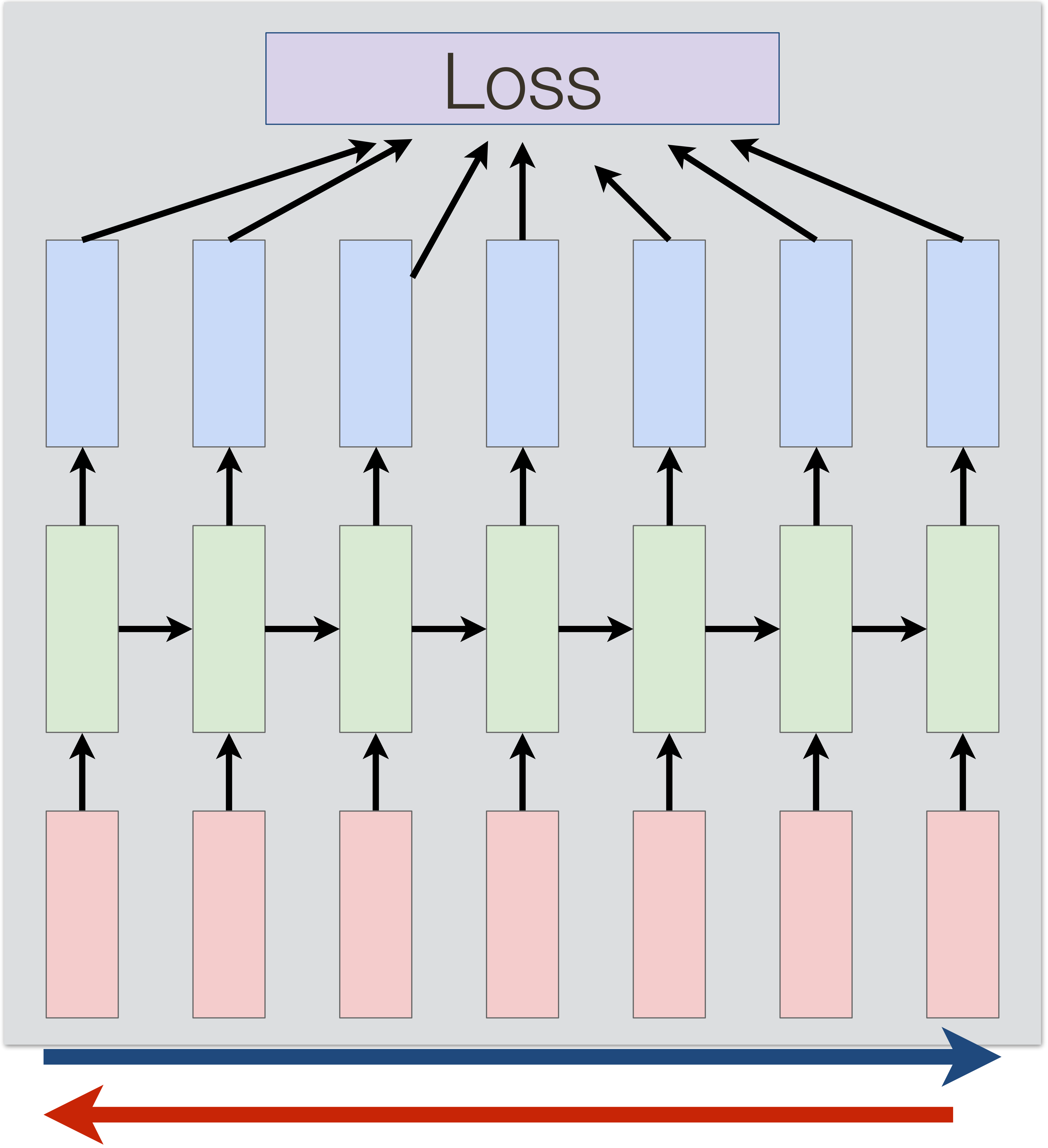
Truncated BackProp Through Time

Run backwards and forwards through (fixed length) **chunks of the sequence**, instead of the whole sequence



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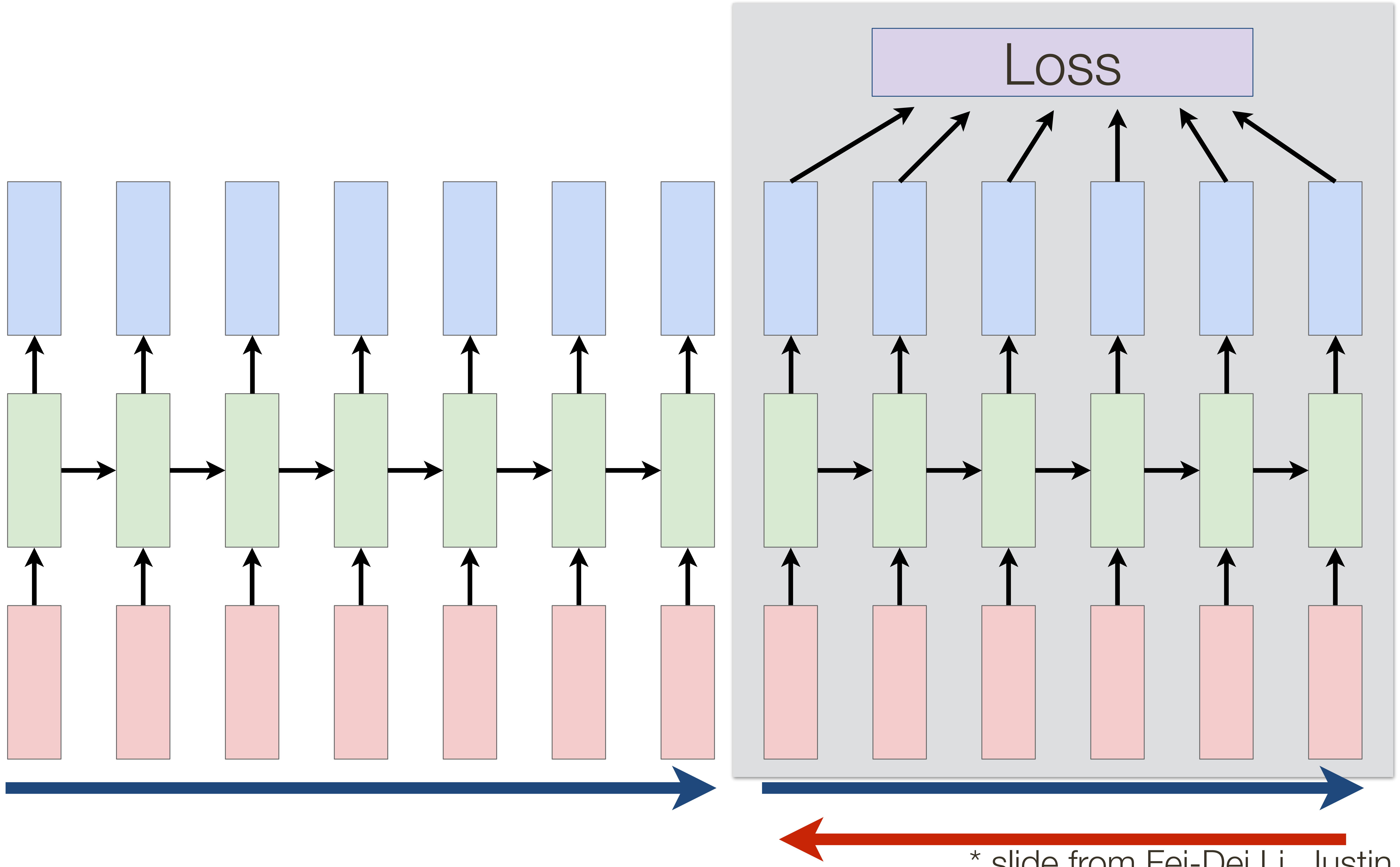

Carry hidden states forward, but only BackProp through some smaller number of steps

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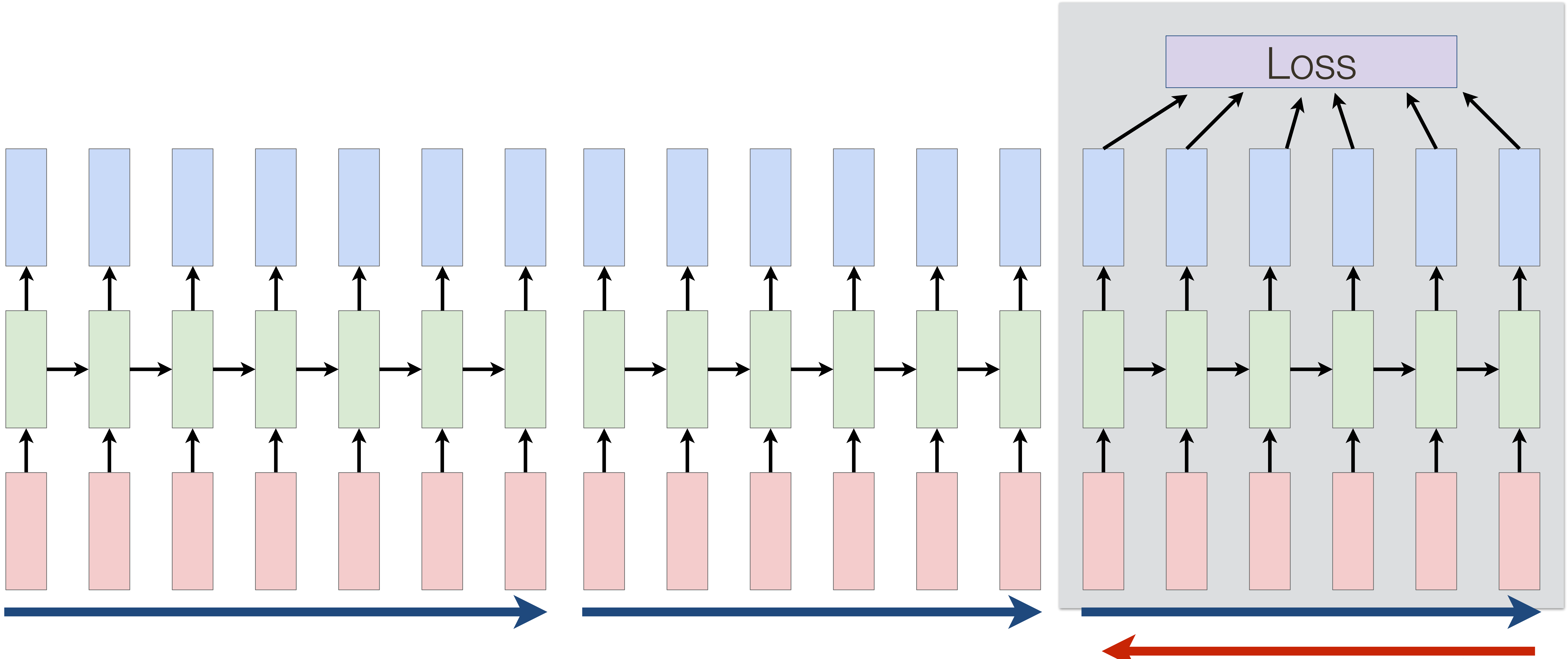

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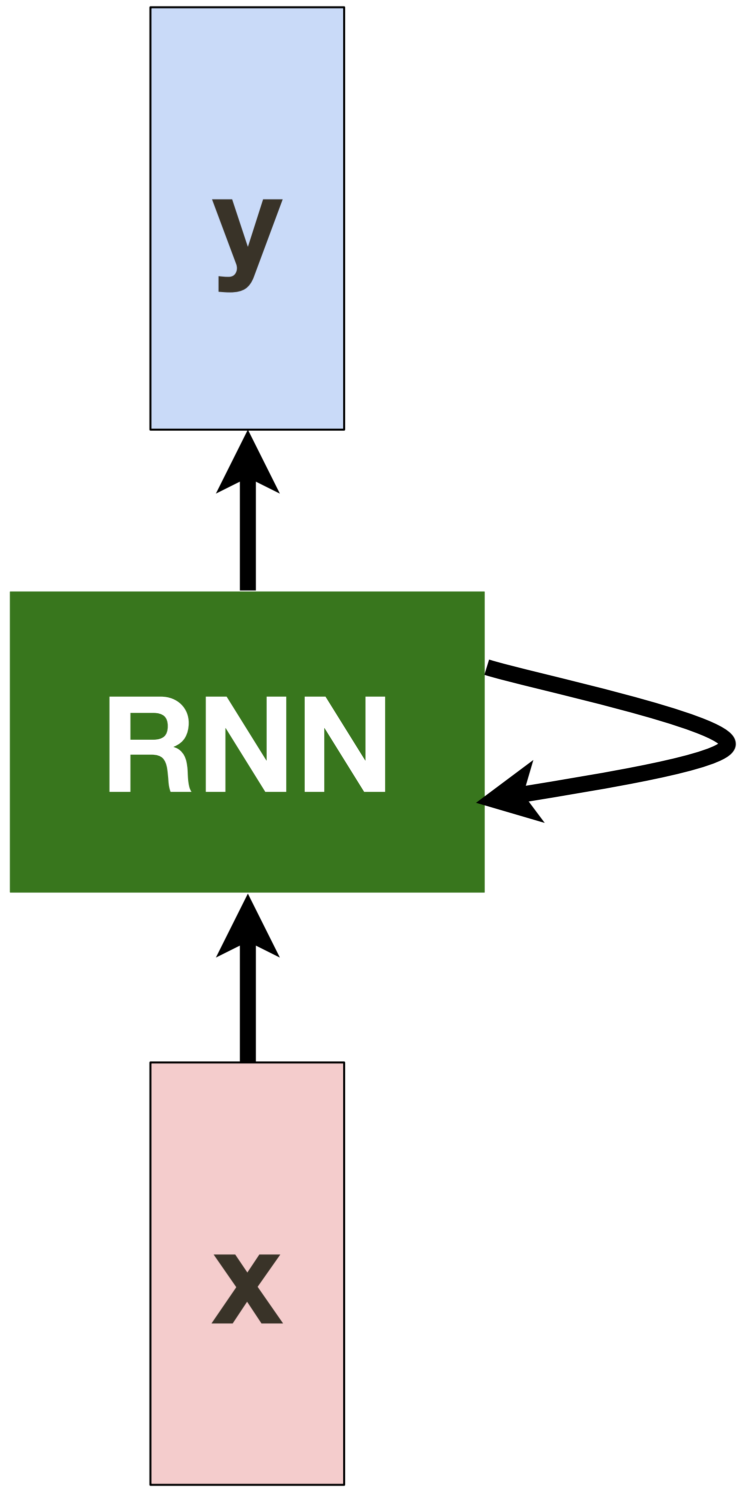
Learning to Write Like Shakespeare — Training **Decoder**

THE SONNETS

by William Shakespeare

From fairest creatures we desire increase,
That thereby beauty's rose might never die,
But as the riper should by time decease,
His tender heir might bear his memory:
But thou, contracted to thine own bright eyes,
Feed'st thy light's flame with self-substantial fuel,
Making a famine where abundance lies,
Thyself thy foe, to thy sweet self too cruel:
Thou that art now the world's fresh ornament,
And only herald to the gaudy spring,
Within thine own bud buriest thy content,
And tender churl mak'st waste in niggarding:
    Pity the world, or else this glutton be,
    To eat the world's due, by the grave and thee.

When forty winters shall besiege thy brow,
And dig deep trenches in thy beauty's field,
Thy youth's proud livery so gazed on now,
Will be a tatter'd weed of small worth held:
Then being asked, where all thy beauty lies,
Where all the treasure of thy lusty days;
To say, within thine own deep sunken eyes,
Were an all-eating shame, and thriftless praise.
How much more praise deserv'd thy beauty's use,
If thou couldst answer 'This fair child of mine
Shall sum my count, and make my old excuse,'
Proving his beauty by succession thine!
    This were to be new made when thou art old,
    And see thy blood warm when thou feel'st it cold.



* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Learning to Write Like Shakespeare … after training a bit

at first:

```
tyntd-iafhatawiaoihrdemot  lytdws  e ,tfti, astai f ogoh eoase rrranbyne 'nhthnee e
plia tklrgd t o idoe ns,smtt   h ne etie h,hregtrs nigtike,aoaenns lng
```

↓ train more

```
"Tmont thithey" fomesscerliund
Keushey. Thom here
sheulke, anmerenith ol sivh I lalterthend Bleipile shuwy fil on aseterlome
coaniogennc Phe lism thond hon at. MeiDimorotion in ther thize."
```

↓ train more

```
Aftair fall unsuch that the hall for Prince Velzonski's that me of
her hearly, and behs to so arwage fiving were to it beloge, pavu say falling misfort
how, and Gogition is so overelical and ofter.
```

↓ train more

```
"Why do what that day," replied Natasha, and wishing to himself the fact the
princess, Princess Mary was easier, fed in had oftened him.
Pierre aking his soul came to the packs and drove up his father-in-law women.
```

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Learning to Write Like Shakespeare … after training

```
PANDARUS:
Alas, I think he shall be come approached and the day
When little srain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:
They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:
Well, your wit is in the care of side and that.

Second Lord:
They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

Clown:
Come, sir, I will make did behold your worship.

VIOLA:
I'll drink it.
```

```
VIOLA:
Why, Salisbury must find his flesh and thought
That which I am not aps, not a man and in fire,
To show the reining of the raven and the wars
To grace my hand reproach within, and not a fair are hand,
That Caesar and my goodly father's world;
When I was heaven of presence and our fleets,
We spare with hours, but cut thy council I am great,
Murdered and by thy master's ready there
My power to give thee but so much as hell:
Some service in the noble bondman here,
Would show him to her wine.

KING LEAR:
O, if you were a feeble sight, the courtesy of your law,
Your sight and several breath, will wear the gods
With his heads, and my hands are wonder'd at the deeds,
So drop upon your lordship's head, and your opinion
Shall be against your honour.
```

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Learning Code

Trained on entire source code of Linux kernel

```
static void do_command(struct seq_file *m, void *v)
{
  int column = 32 << (cmd[2] & 0x80);
  if (state)
    cmd = (int)(int_state ^ (in_8(&ch->ch_flags) & Cmd) ? 2 : 1);
  else
    seq = 1;
  for (i = 0; i < 16; i++) {
    if (k & (1 << 1))
      pipe = (in_use & UMXTHREAD_UNCCA) +
        ((count & 0x00000000fffffff8) & 0x000000f) << 8;
    if (count == 0)
      sub(pid, ppc_md.kexec_handle, 0x20000000);
    pipe_set_bytes(i, 0);
  }
  /* Free our user pages pointer to place camera if all dash */
  subsystem_info = &of_changes[PAGE_SIZE];
  rek_controls(offset, idx, &soffset);
  /* Now we want to deliberately put it to device */
  control_check_polarity(&context, val, 0);
  for (i = 0; i < COUNTER; i++)
    seq_puts(s, "policy ");
}
```

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

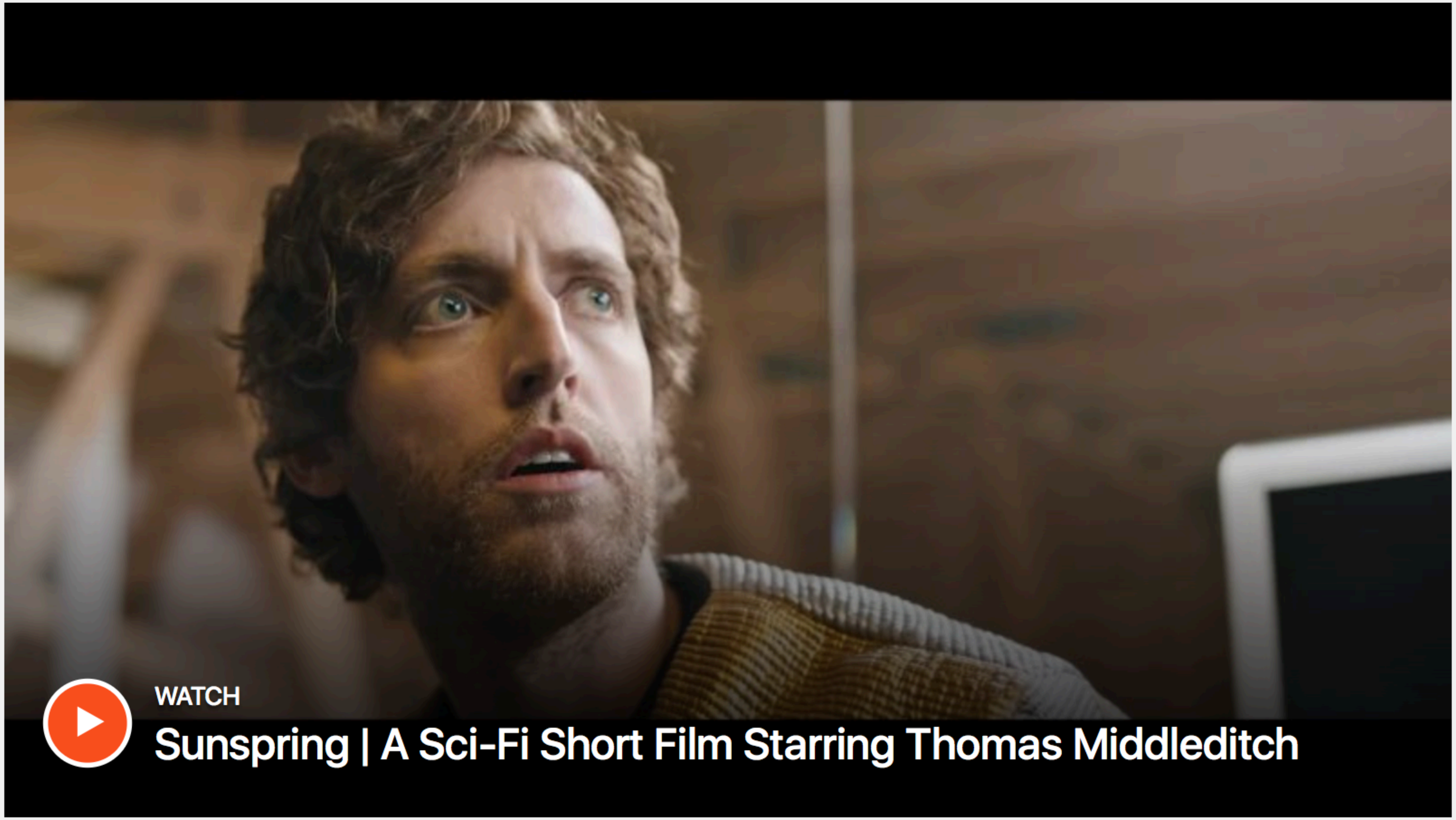
DopeLearning: Computational Approach to Rap Lyrics

Everybody got one	(2 Chainz - Extremely Blessed)
And all the pretty mommies want some	(Mos Def - Undeniable)
And what i told you all was	(Lil Wayne - Welcome Back)
But you need to stay such do not touch	(Common - Heidi Hoe)
They really do not want you to vote	(KRS One - The Mind)
what do you condone	(Cam'ron - Bubble Music)
Music make you lose control	(Missy Elliot - Lose Control)
What you need is right here ahh oh	(Wiz Khalifa - Right Here)
This is for you and me	(Missy Elliot - Hit Em Wit Da Hee)
I had to dedicate this song to you Mami	(Fat Joe - Bendicion Mami)
Now I see how you can be	(Lil Wayne - How To Hate)
I see u smiling i kno u hattig	(Wiz Khalifa - Damn Thing)
Best I Eva Had x4	(Nicki Minaj - Best I Ever Had)
That I had to pay for	(Ice Cube - X Bitches)
Do I have the right to take yours	(Common - Retrospect For Life)
Trying to stay warm	(Everlast - 2 Pieces Of Drama)

Rank	Artist	Rhyme density
1.	Inspectah Deck	1.187
2.	Rakim	1.180
3.	Redrama	1.168
30.	The Notorious B.I.G.	1.059
31.	Lil Wayne	1.056
32.	Nicki Minaj	1.056
33.	2Pac	1.054
39.	Eminem	1.047
40.	Nas	1.043
50.	Jay-Z	1.026
63.	Wu-Tang Clan	1.002
77.	Snoop Dogg	0.967
78.	Dr. Dre	0.966
94.	The Lonely Island	0.870

[Malmi et al., KDD 2016]

Sunspring: First movie generated by AI

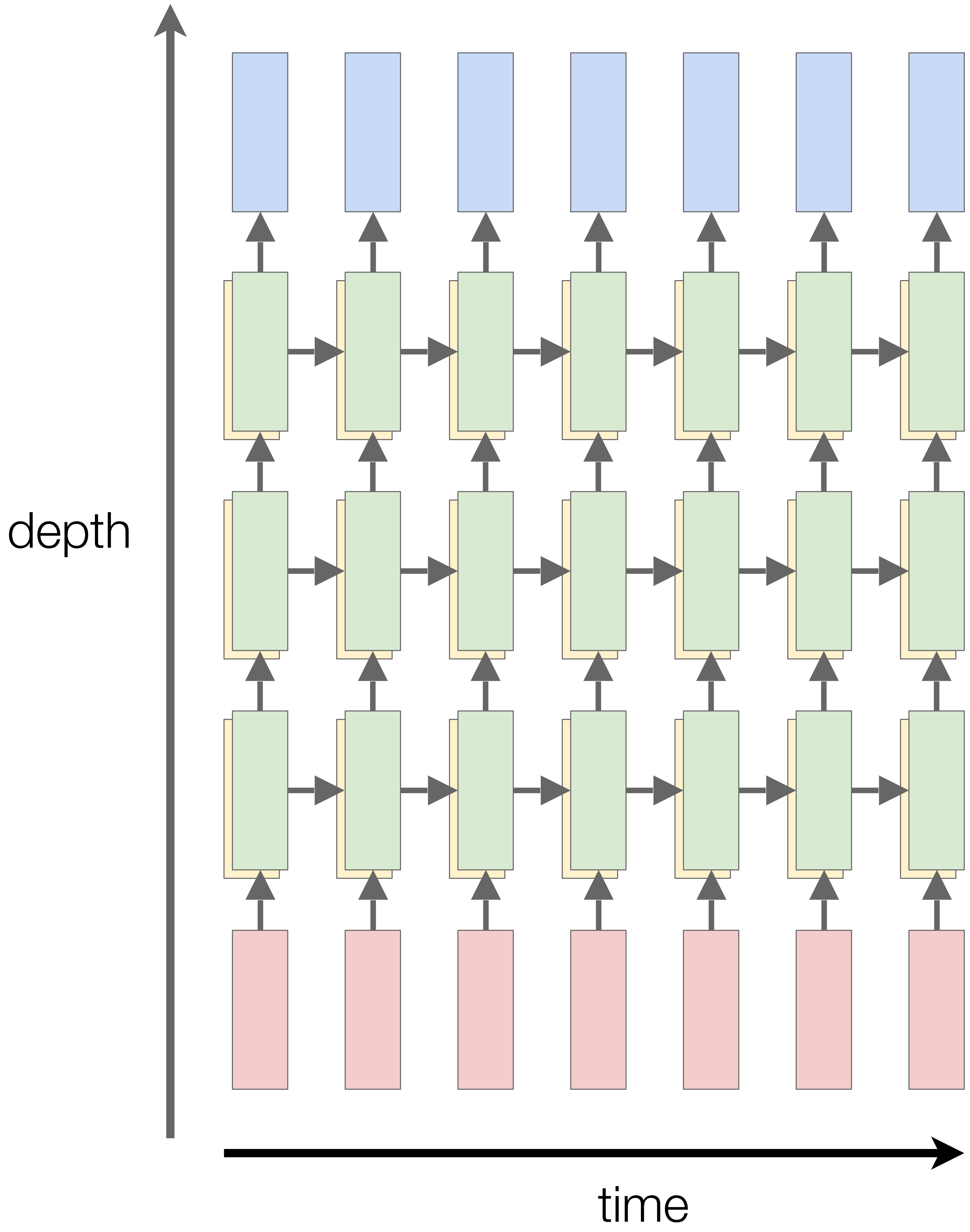


Sunspring, a short science fiction movie written entirely by AI, debuts exclusively on Ars today.

Multilayer RNNs

$$h_t^l = \tanh W^l \begin{pmatrix} h_t^{l-1} \\ h_{t-1}^l \end{pmatrix}$$

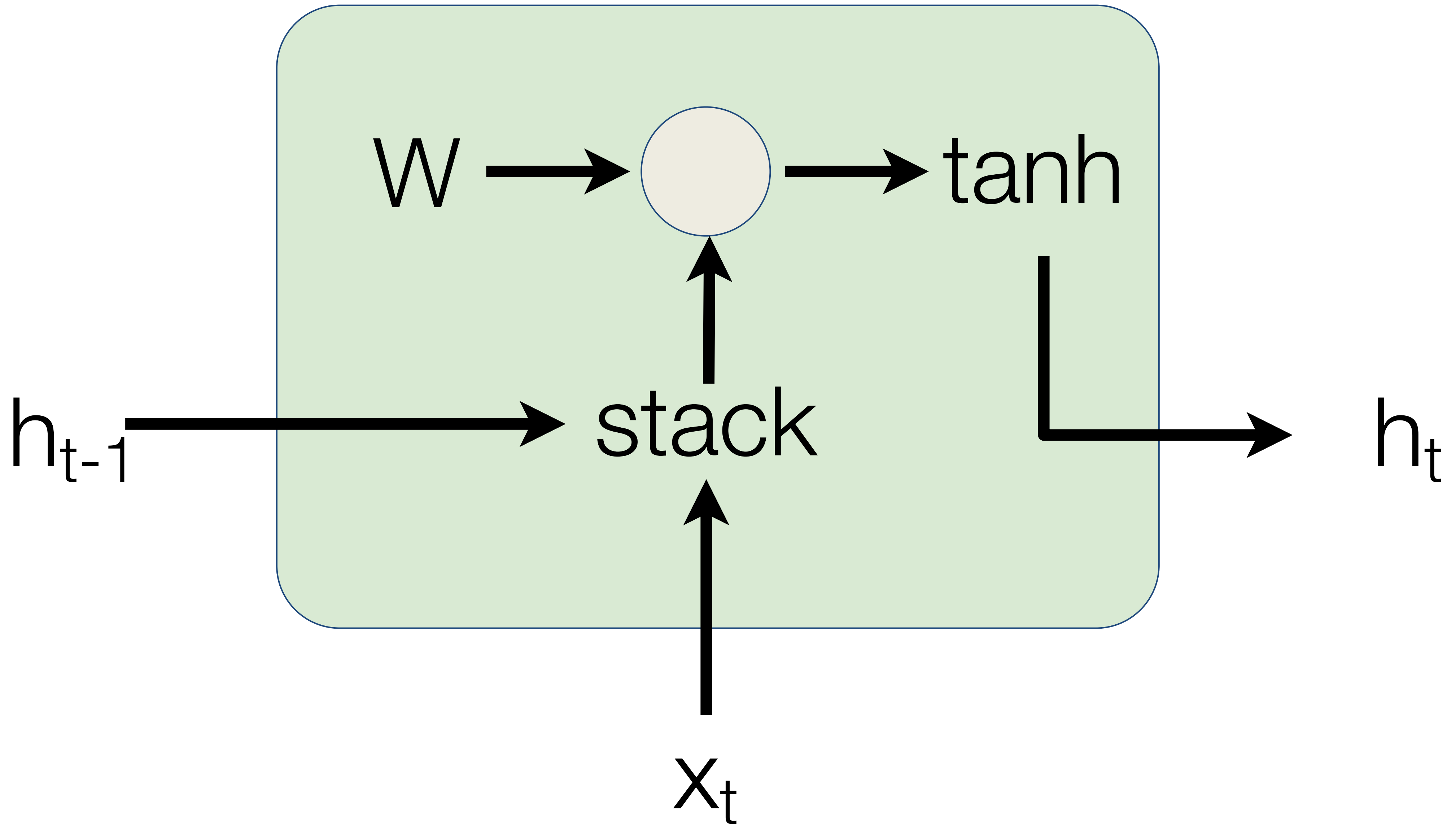
$h \in \mathbb{R}^n$ $\quad W^l \ [n \times 2n]$



* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Vanilla RNN **Gradient Flow**

[Bengio et al., 1994]
[Pascanu et al., ICML 2013]

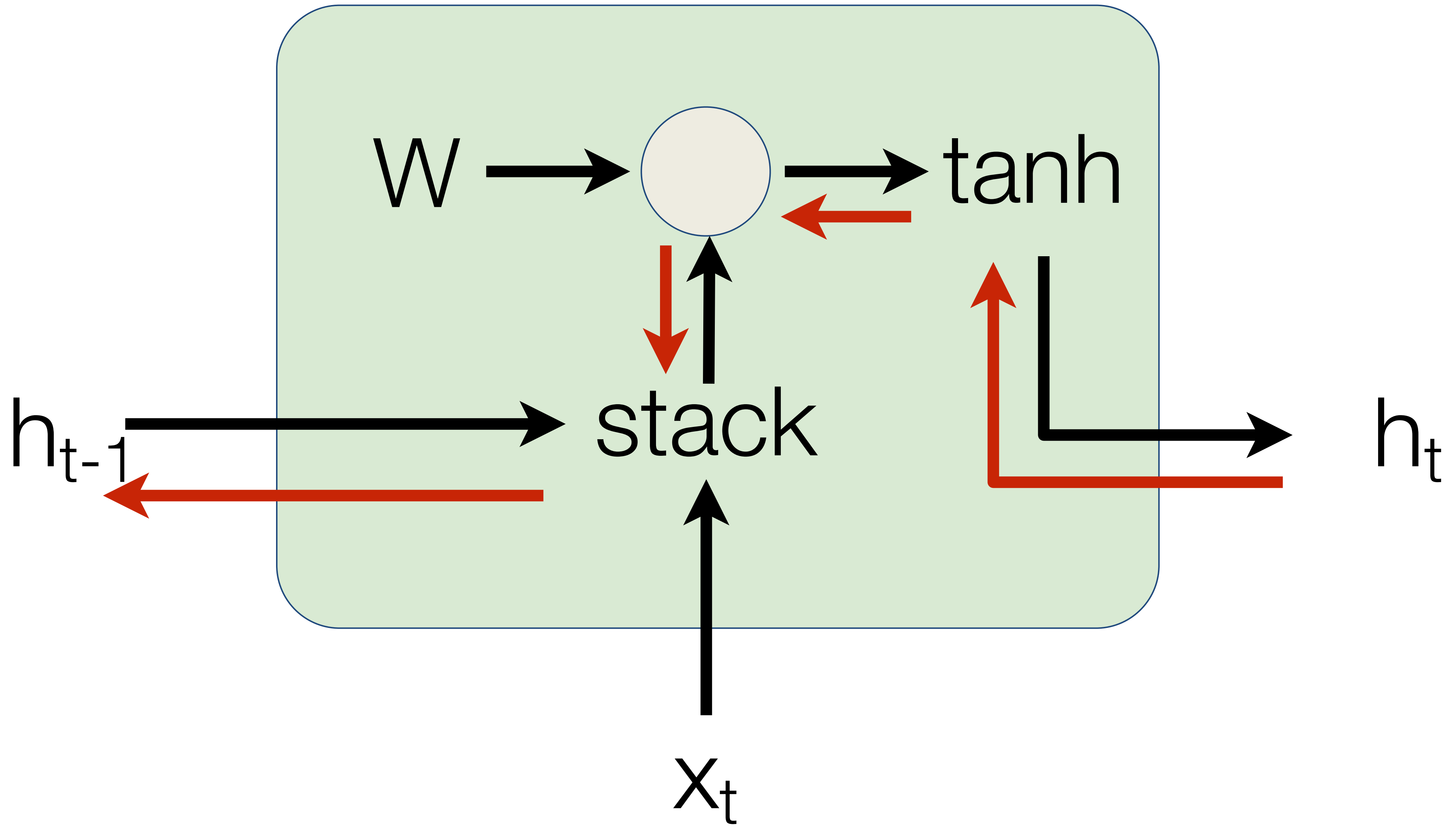


$$
\begin{aligned}
h_t &= \tanh(W_{hh}h_{t-1} + W_{xh}x_t) \\
&= \tanh\left(\begin{pmatrix} W_{hh} & W_{hx} \end{pmatrix} \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right) \\
&= \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)
\end{aligned}
$$

Vanilla RNN **Gradient Flow**

[Bengio et al., 1994]
[Pascanu et al., ICML 2013]

Backpropagation from h_t to h_{t-1} multiplies by W (actually W_{hh}^T)



$$
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h_t &= \tanh(W_{hh}h_{t-1} + W_{xh}x_t) \\
&= \tanh\left(\begin{pmatrix} W_{hh} & W_{hx} \end{pmatrix} \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right) \\
&= \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right)
\end{aligned}
$$

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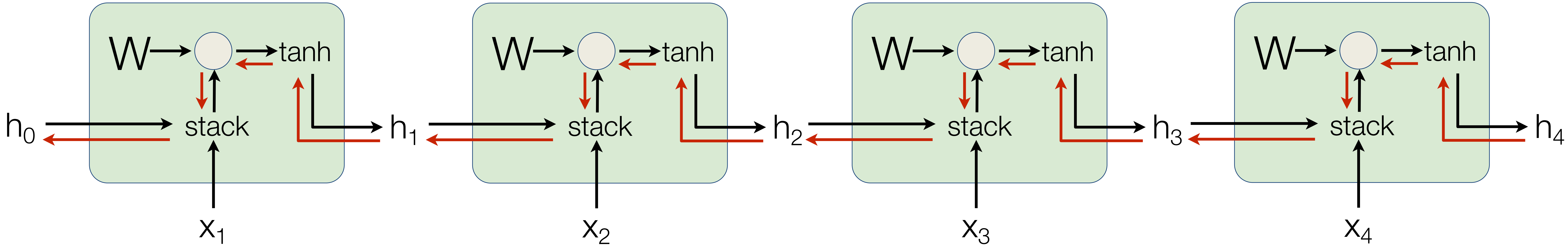

Computing gradient of h_0 involves many factors of W (and repeated tanh)

Vanilla RNN **Gradient Flow**

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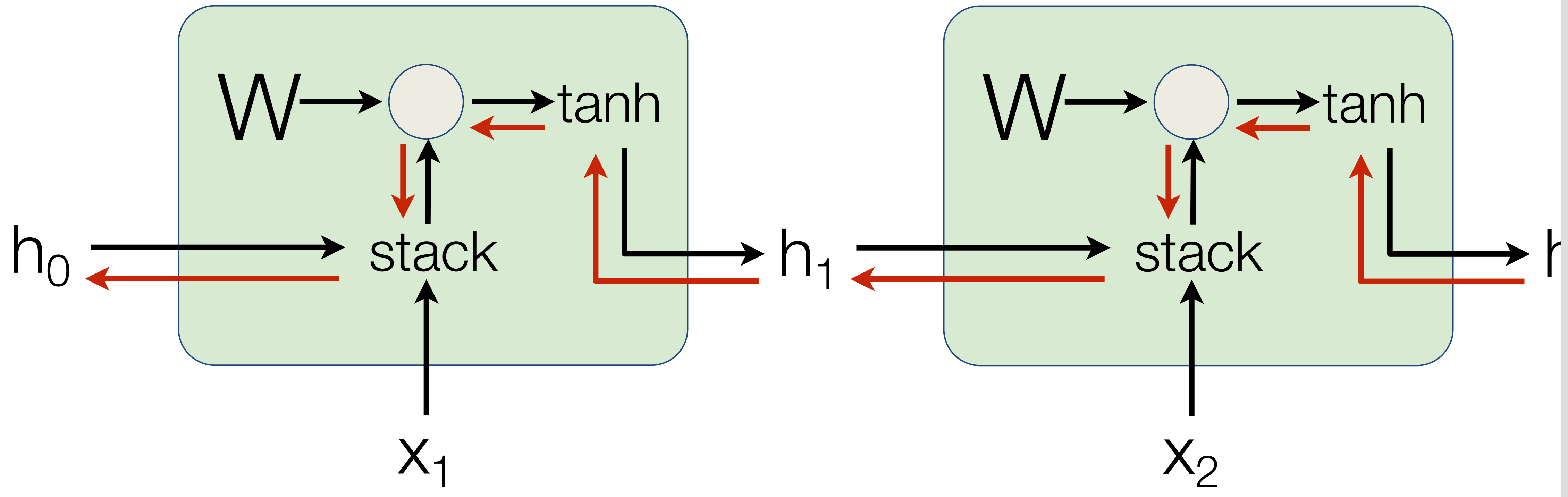

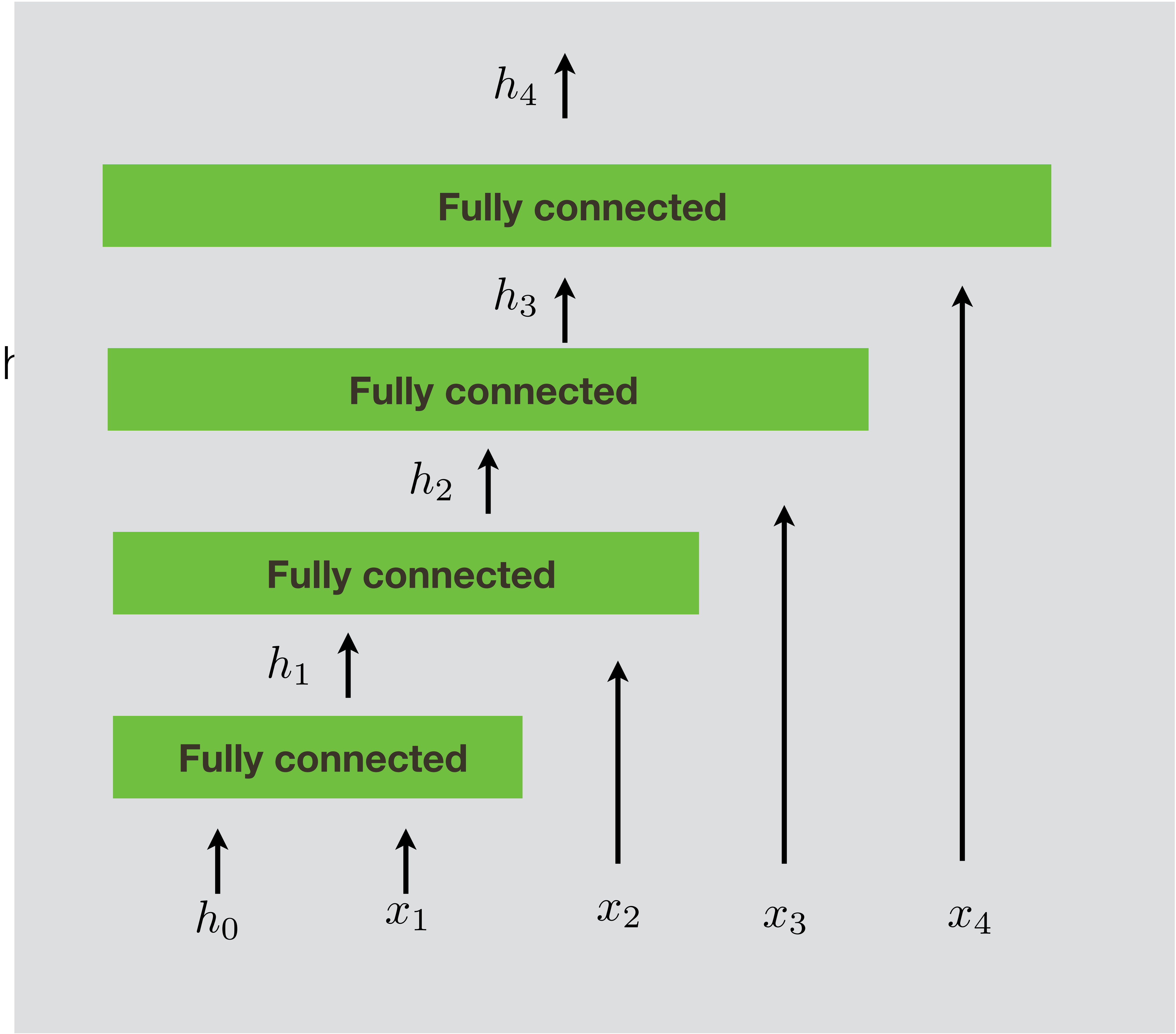

Computing gradient of h_0 involves many factors of W
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Vanilla RNN **Gradient Flow**

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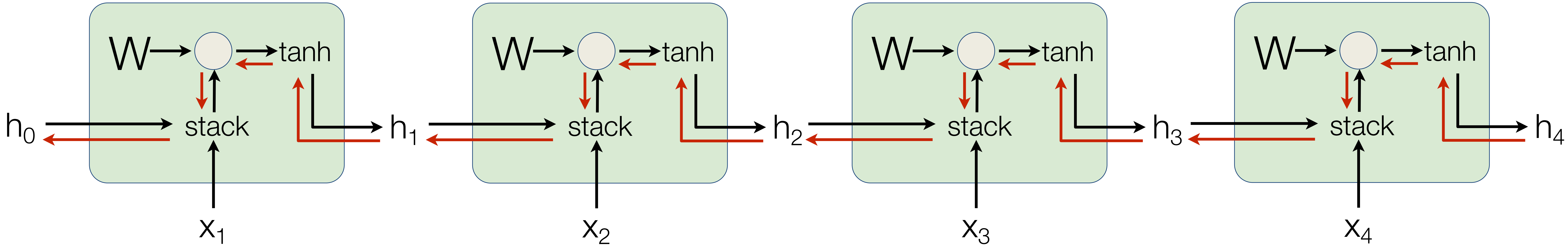


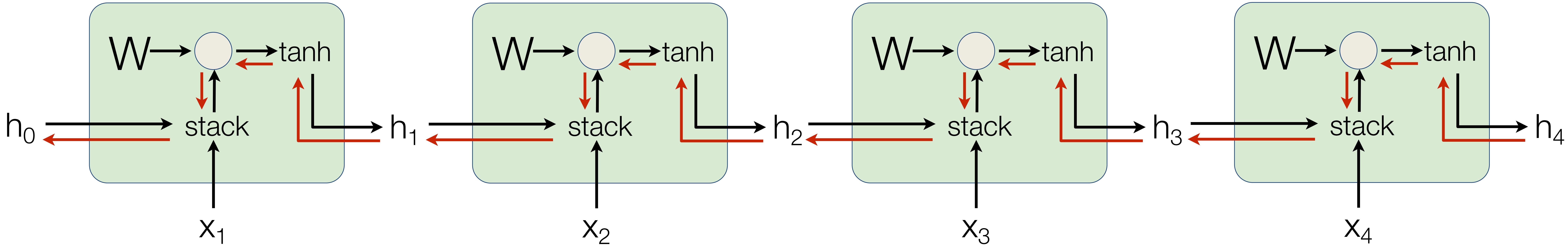
Computing gradient of h_0 involves many factors of W (and repeated tanh)

Largest singular value > 1:
Exploding gradients

Largest singular value < 1:
Vanishing gradients

Vanilla RNN **Gradient Flow**

[Bengio et al., 1994]
[Pascanu et al., ICML 2013]



Computing gradient of h_0 involves many factors of W (and repeated tanh)

Largest singular value > 1:
Exploding gradients

Largest singular value < 1:
Vanishing gradients

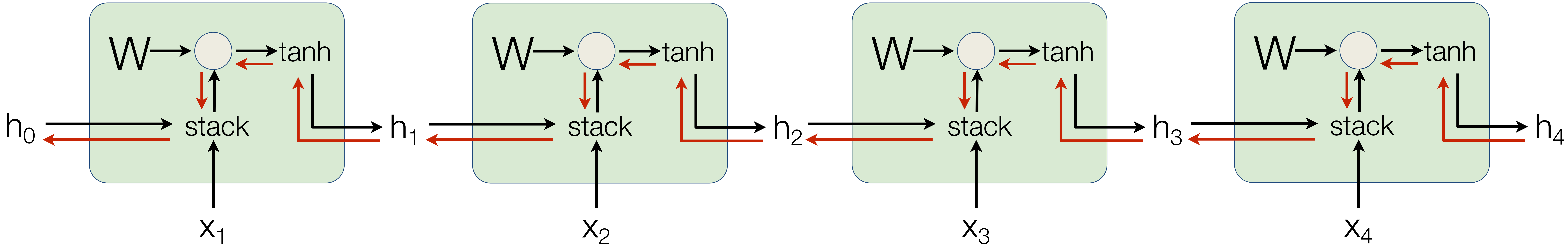
Gradient clipping: Scale gradient if its norm is too big

```
grad_norm = np.sum(grad * grad)
if grad_norm > threshold:
  grad *= (threshold / grad_norm)
```

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Vanilla RNN **Gradient Flow**

[Bengio et al., 1994]
[Pascanu et al., ICML 2013]



Computing gradient of h_0 involves many factors of W (and repeated tanh)

Largest singular value > 1:
Exploding gradients

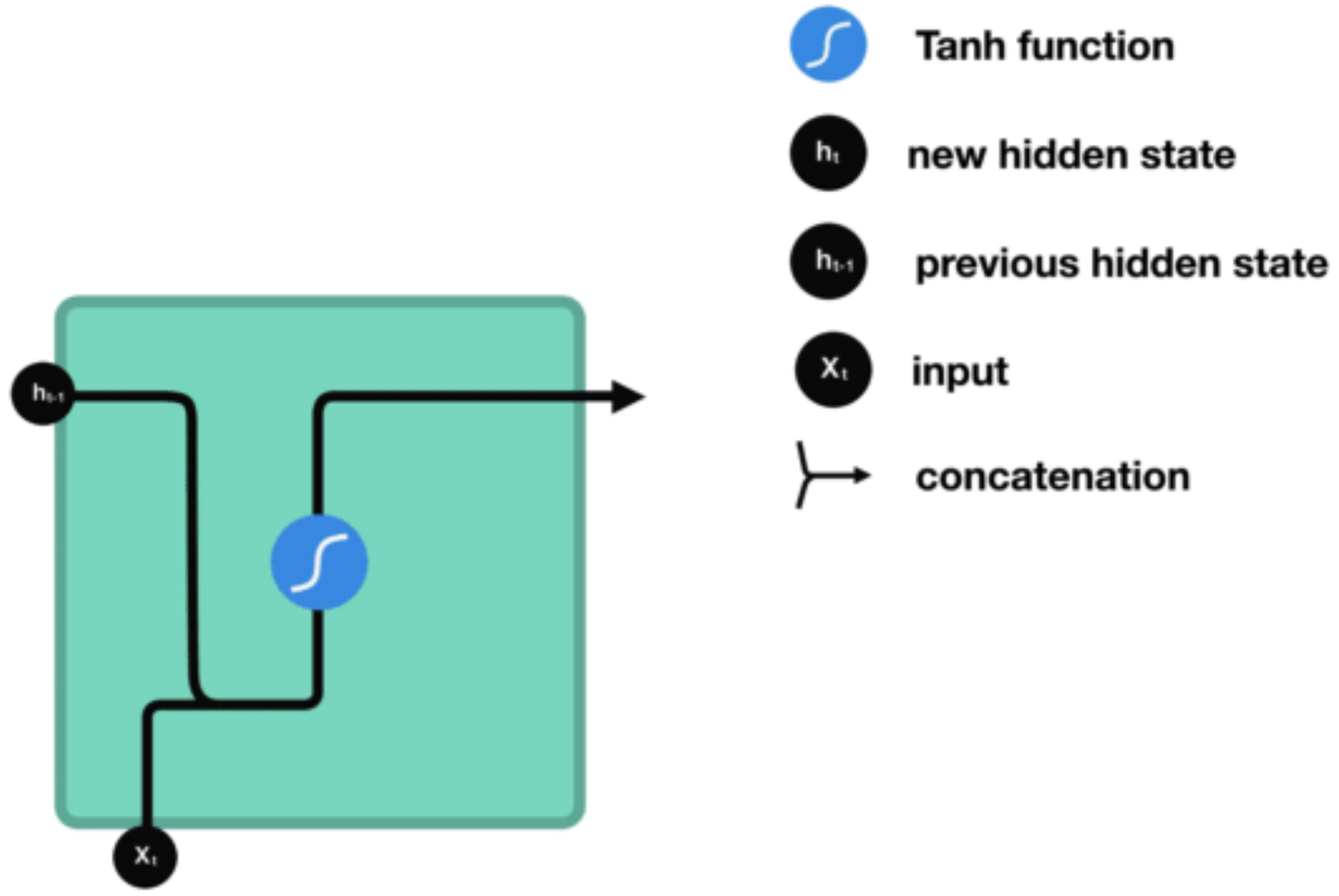
Largest singular value < 1:
Vanishing gradients

Change RNN architecture

Long-Short Term Memory (**LSTM**)

Vanilla RNN

$$h_t = \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$



fully connected layer of size |h| x (|x| + |h|) with tanh activation function

LSTM

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

four fully connected layers of size |h| x (|x| + |h|) with sigmoid and tanh activation function

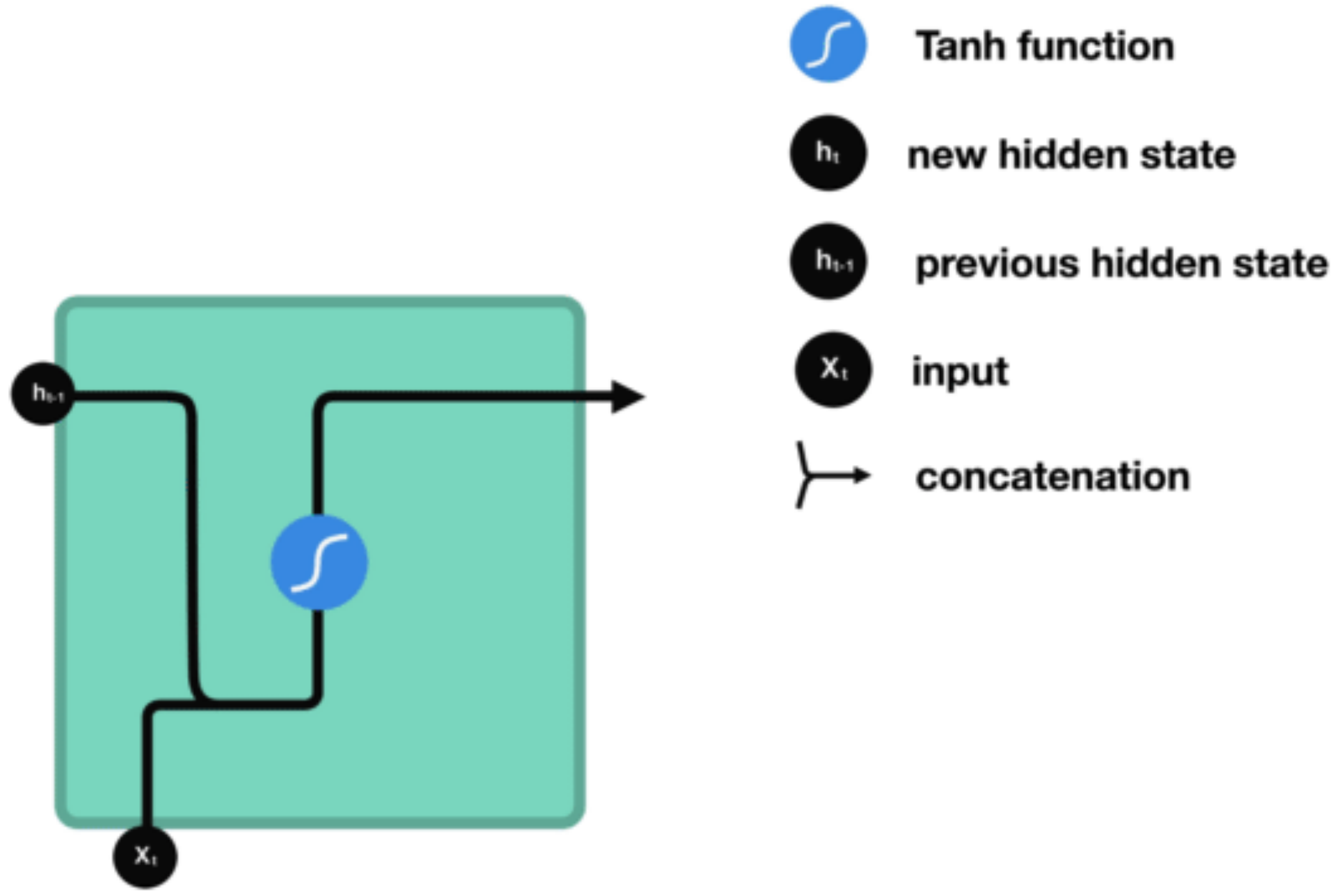
[Hochreiter and Schmidhuber, NC **1977**]

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Long-Short Term Memory (**LSTM**)

Vanilla RNN

$$h_t = \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$



fully connected layer of size |h| x (|x| + |h|) with tanh activation function

LSTM

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

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* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Long-Short Term Memory (**LSTM**)

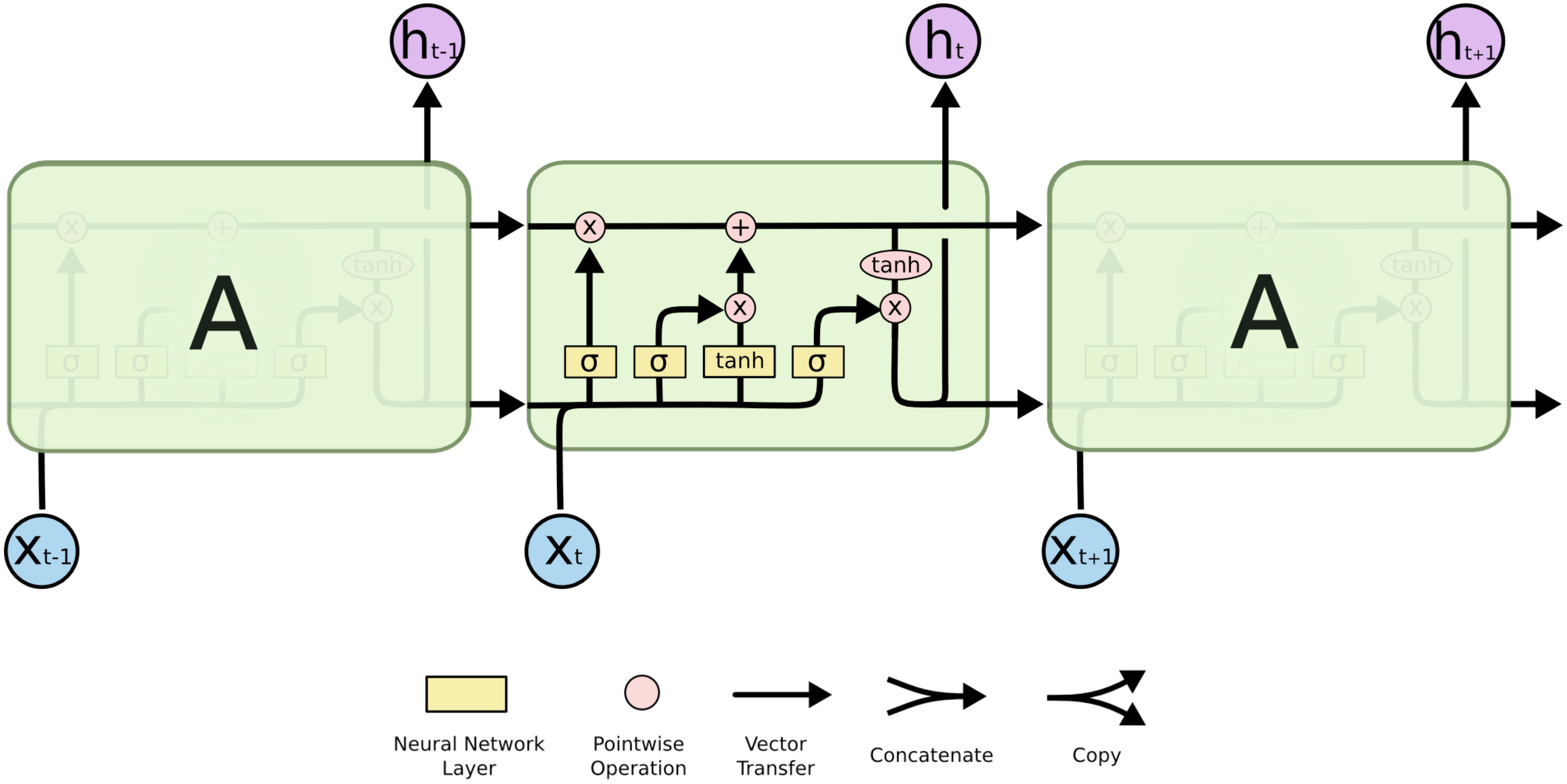


Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

Long-Short Term Memory (**LSTM**)

Cell state / **memory**

0.1
-0.6
0.1
0.55
-0.67
0.4
0.01
0.7
…
0.9

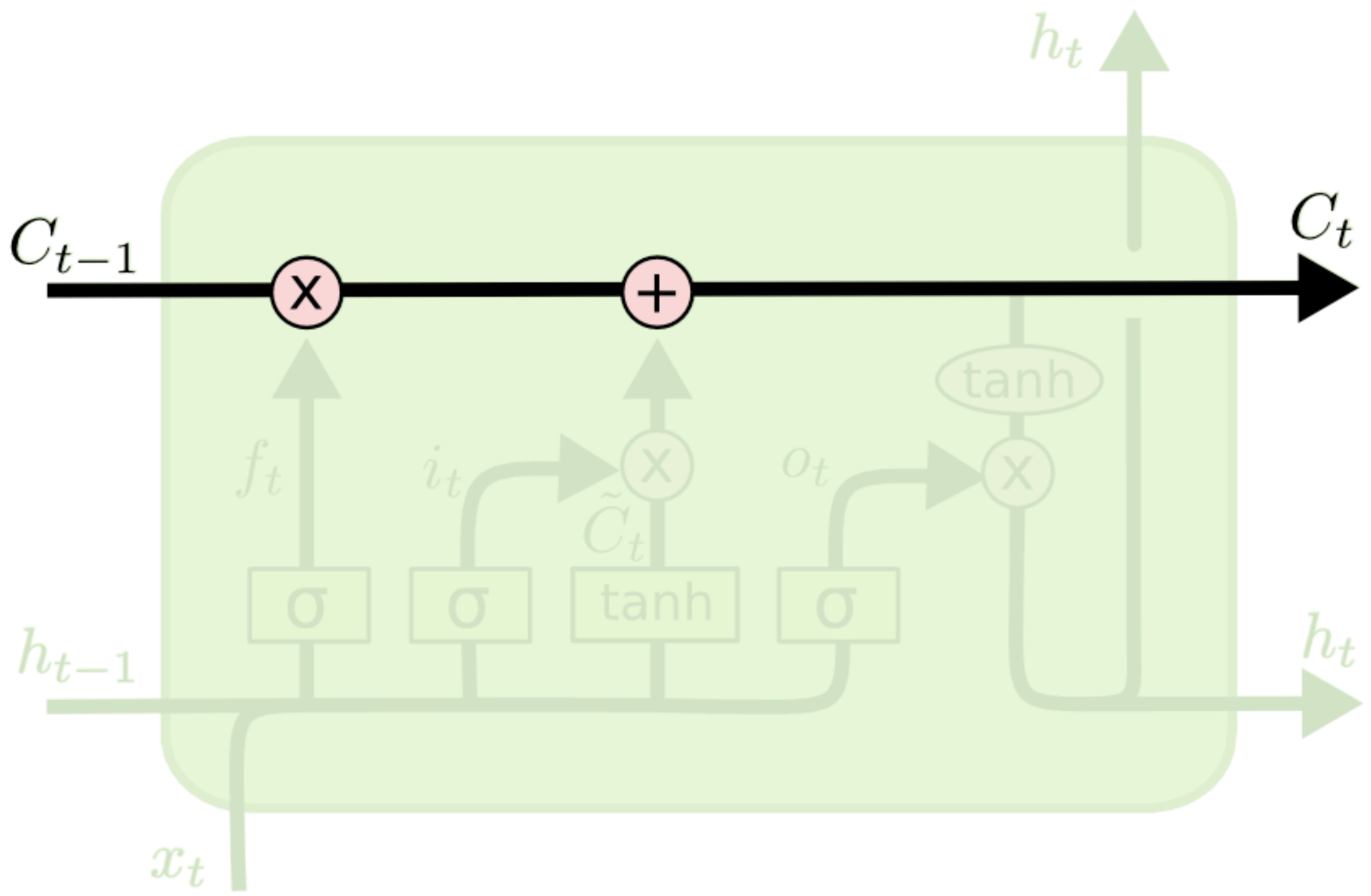


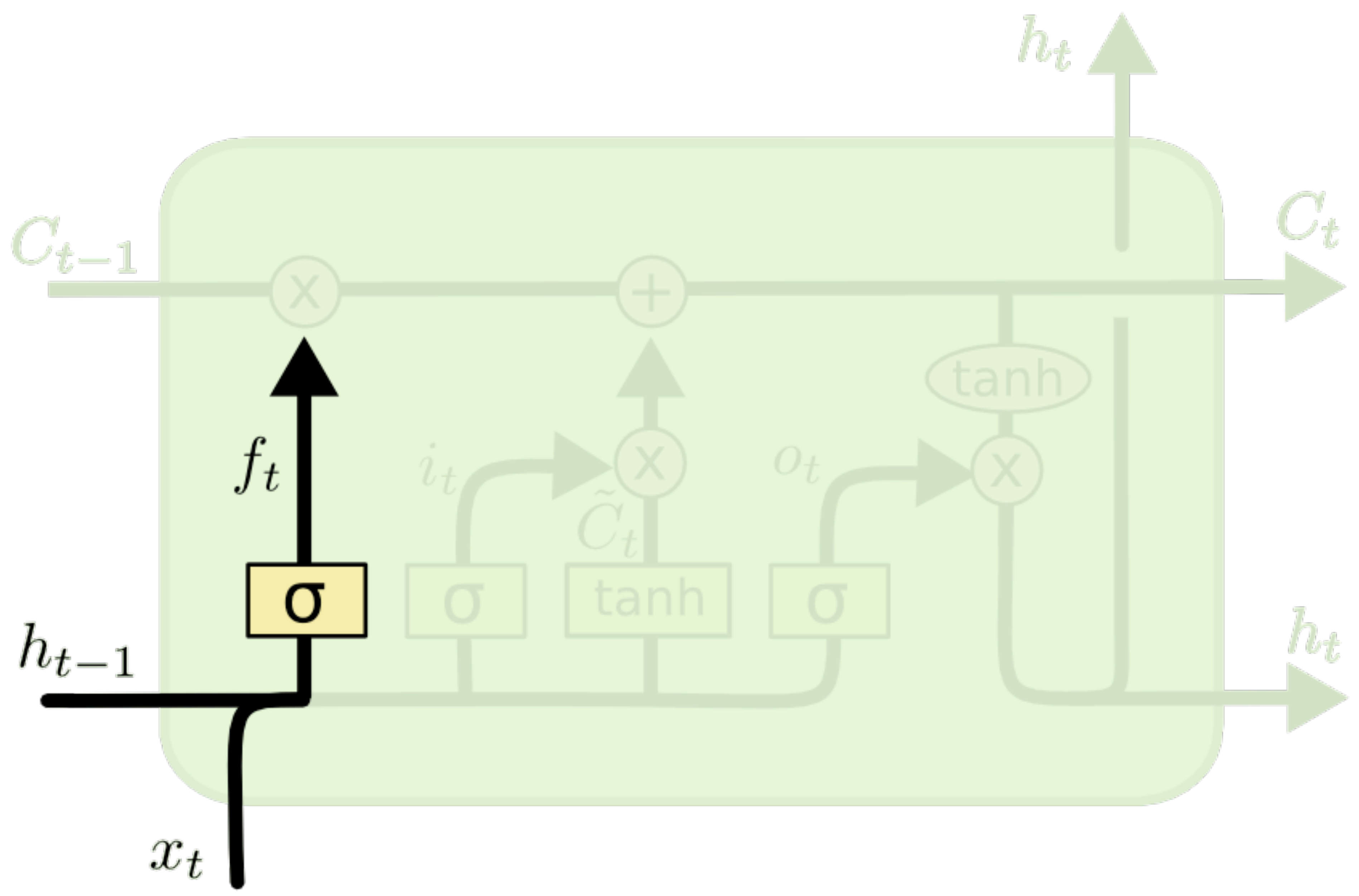
Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

LSTM Intuition: Forget Gate

Should we continue to **remember** this “bit” of information or not?

0.1
-0.6
0.1
0.55
-0.67
0.4
0.01
0.7
…
0.9



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

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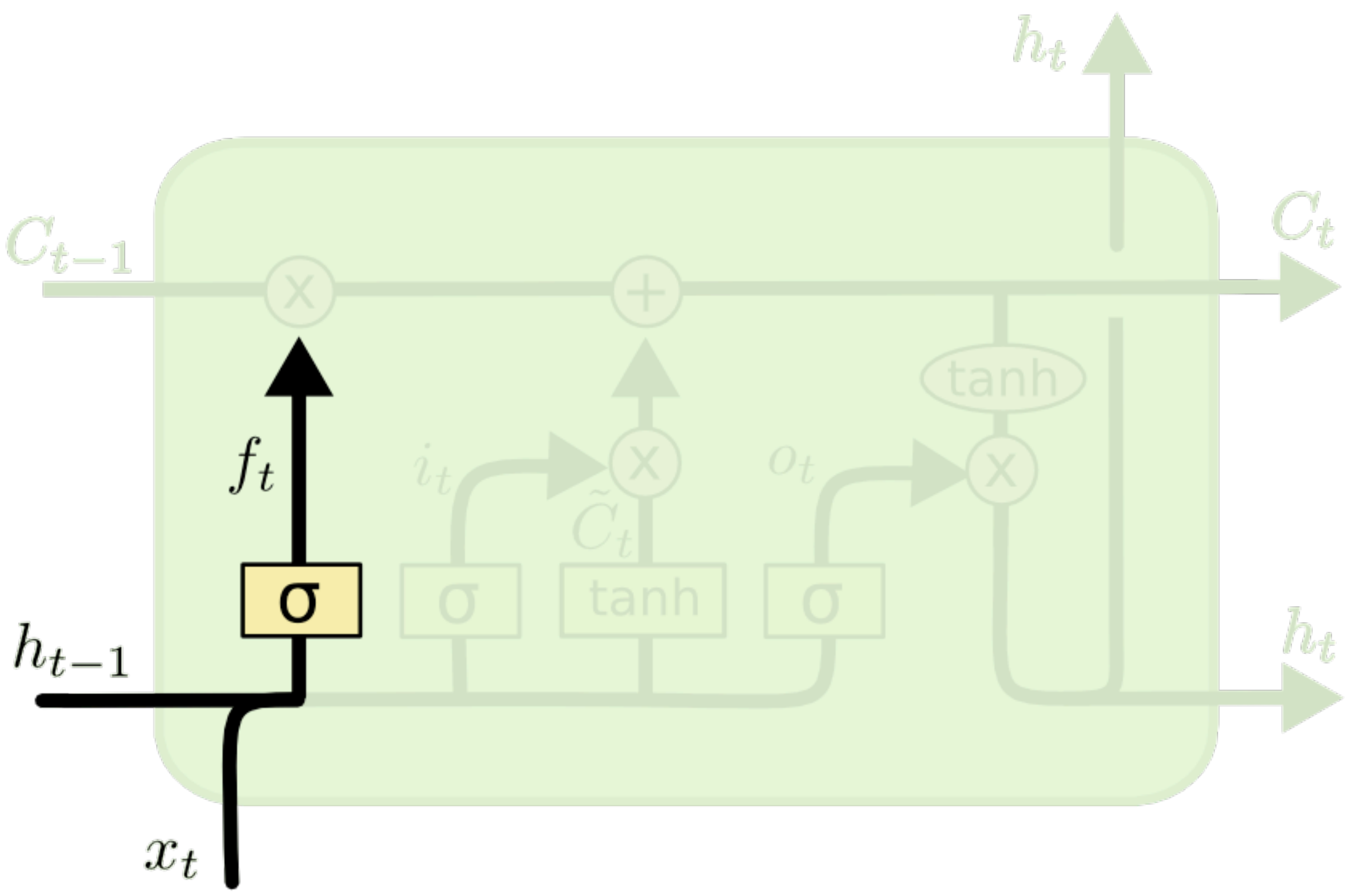
…
0.9



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

Intuition: memory and forget gate output multiply, output of forget gate can be though of as binary (0 or 1)

Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

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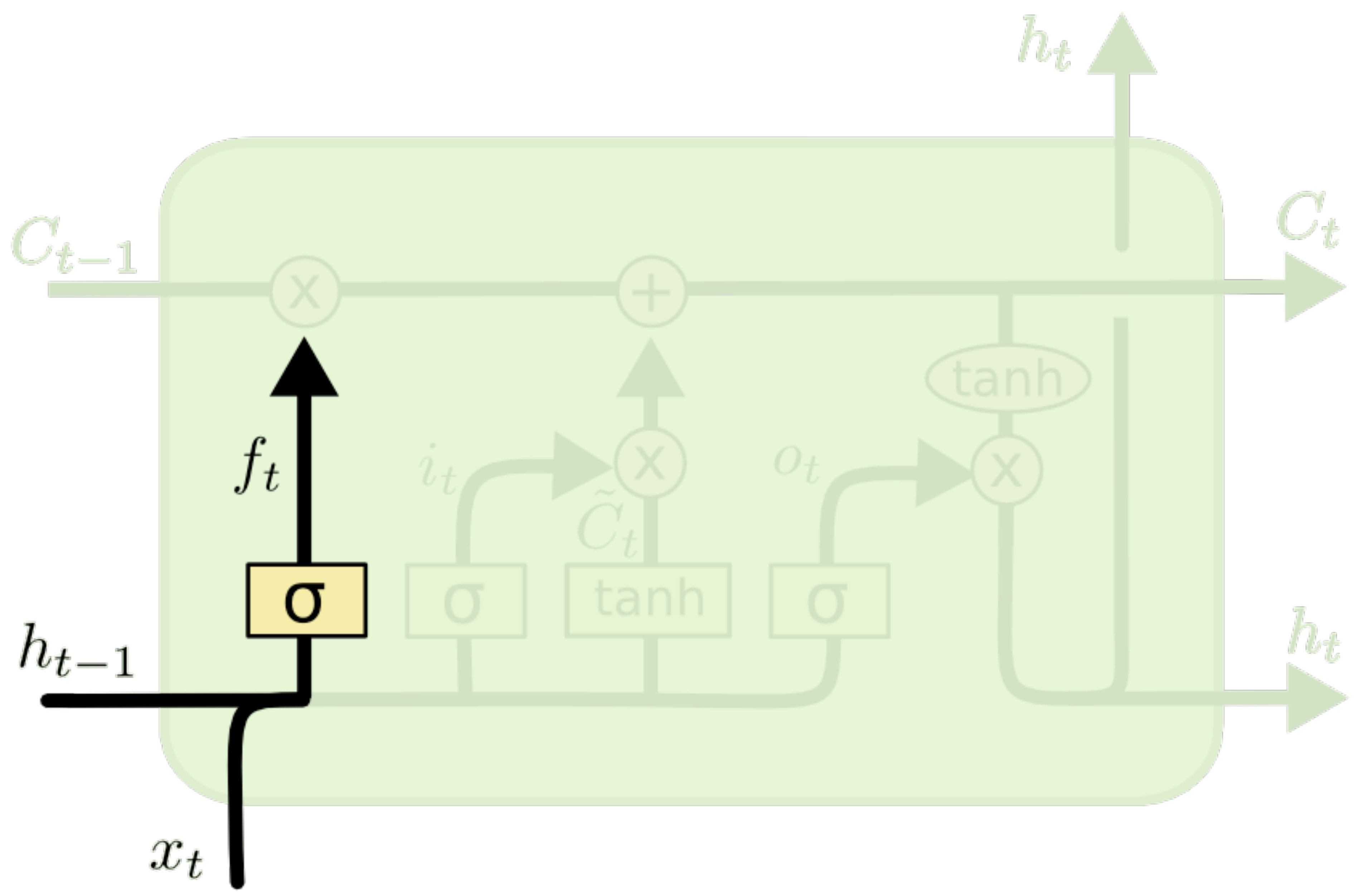
0.4
0.01
0.7
...
0.9



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

0
0
0
0
1
1
1
1
...
1

Intuition: memory and forget gate output multiply, output of forget gate can be though of as binary (0 or 1)

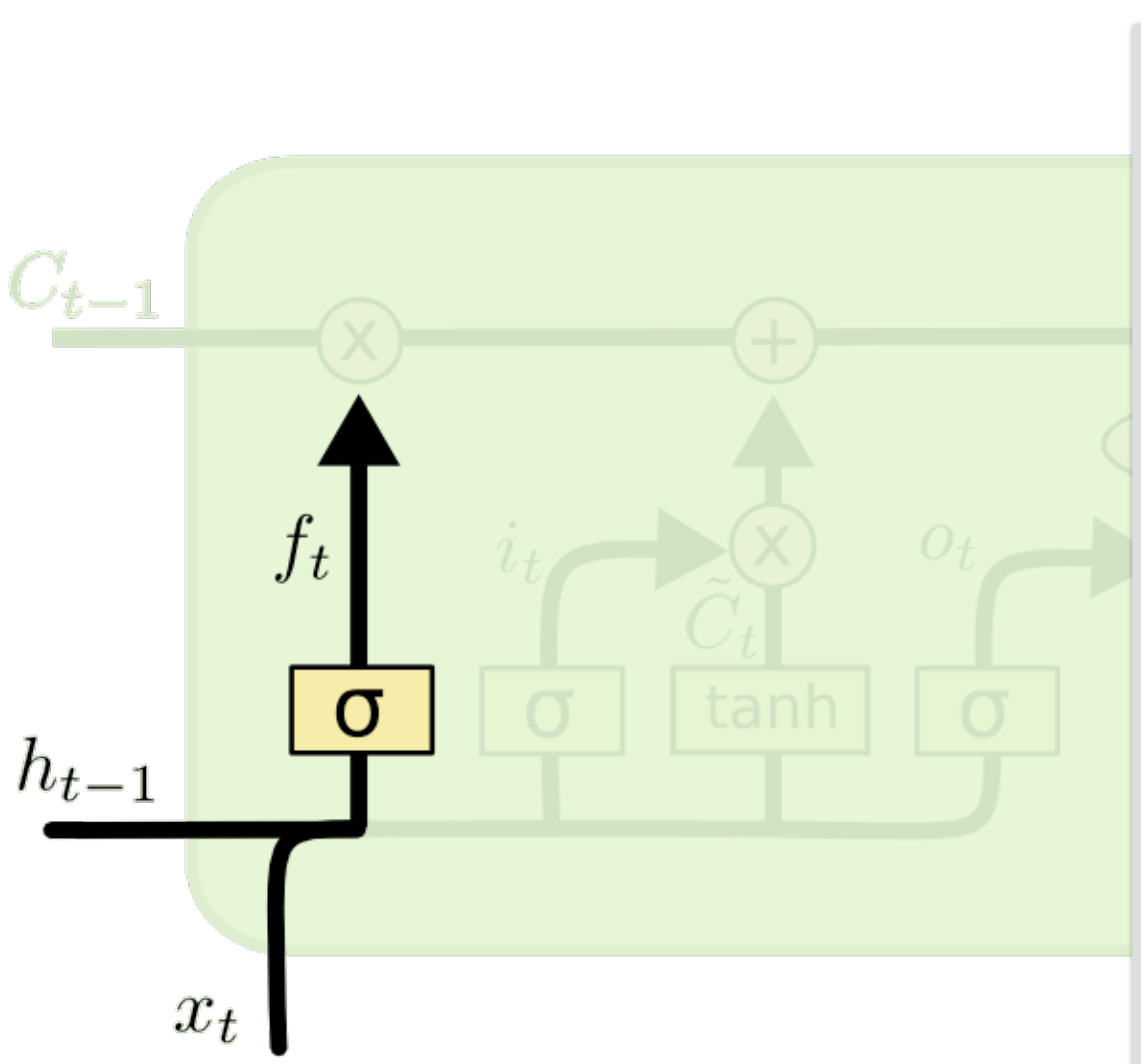
anything x 1 = anything (remember)
anything x 0 = 0 (forget)

Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

LSTM Intuition: Forget Gate

Should we continue to **remember** this “bit” of information or not?



0.1		0		0
-0.6		0		0
0.1		0		0
0.55		0		0
-0.67		1		-0.67
0.4	X	1	=	0.4
0.01		1		0.01
0.7		1		0.7
…		…		…
0.9		1		0.9

selective read

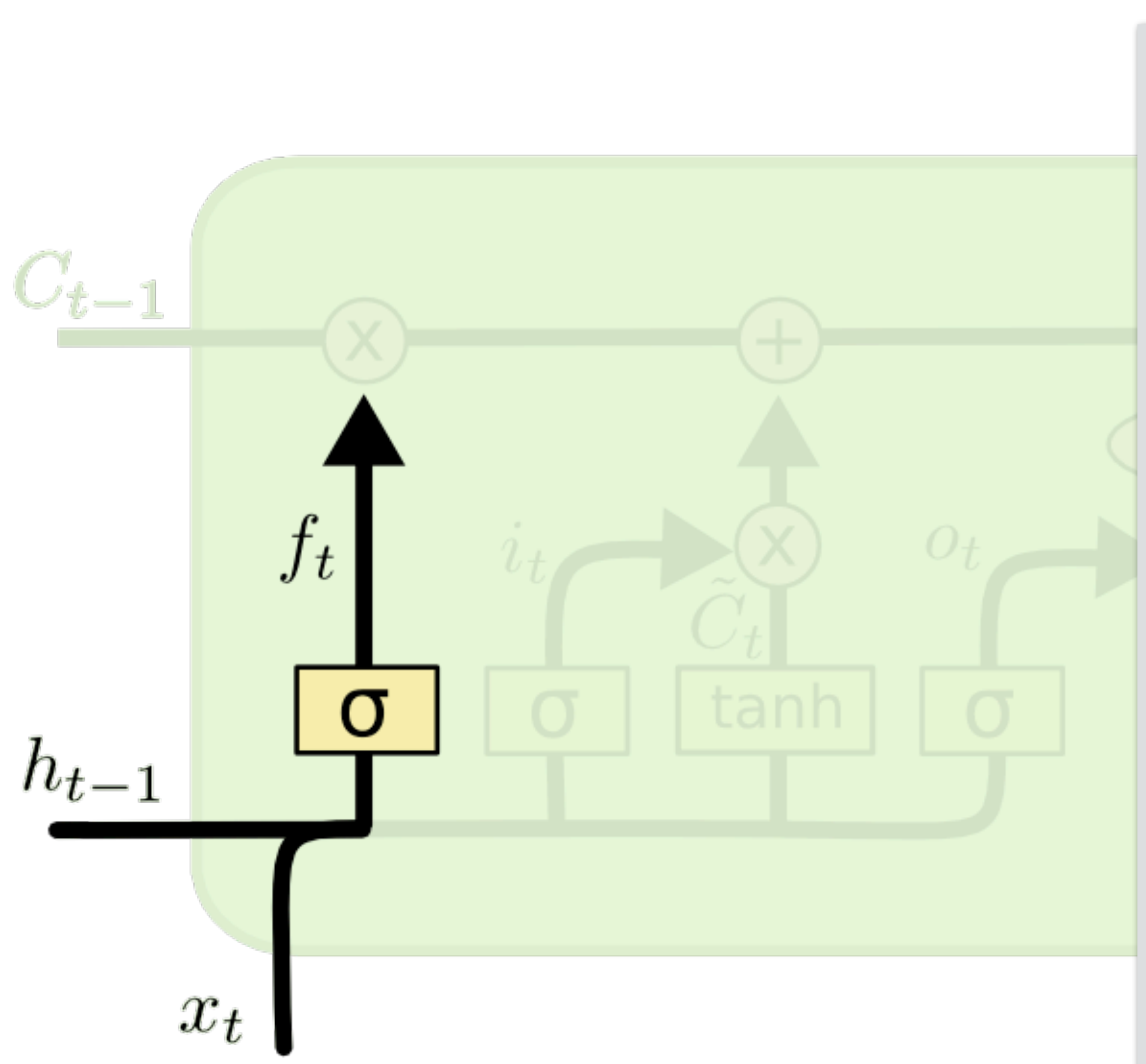
$h_{t-1}, x_t] \; + \; b_f)$

Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

LSTM Intuition: Forget Gate

Should we continue to **remember** this “bit” of information or not?



0.1		0.1		..
-0.6		0.6		..
0.1		0.5		..
0.55		0.3		..
-0.67	X	0.8	=	..
0.4		0.2		..
0.01		0.1		..
0.7		1		..
…		…		…
0.9		0.9		..

selective read

$h_{t-1}, x_t] + b_f)$

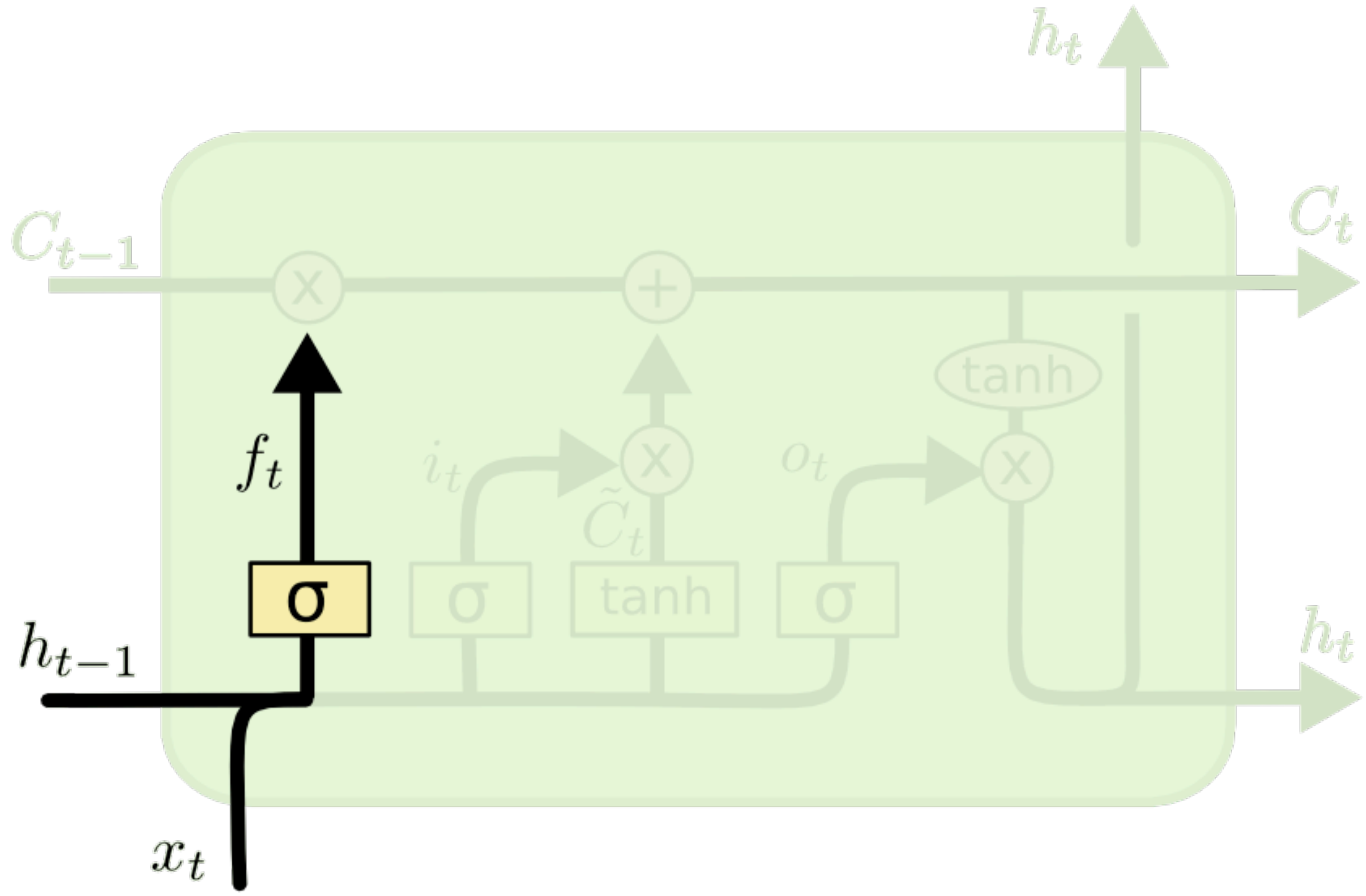
Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

LSTM Intuition: Forget Gate

Should we continue to **remember** this "bit" of information or not?

0.1
-0.6
0.1
0.55
-0.67
0.4
0.01
0.7
…
0.9



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

0.1
0.9
0.8
0.1
0
0.2
0
1
…
0.4

Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

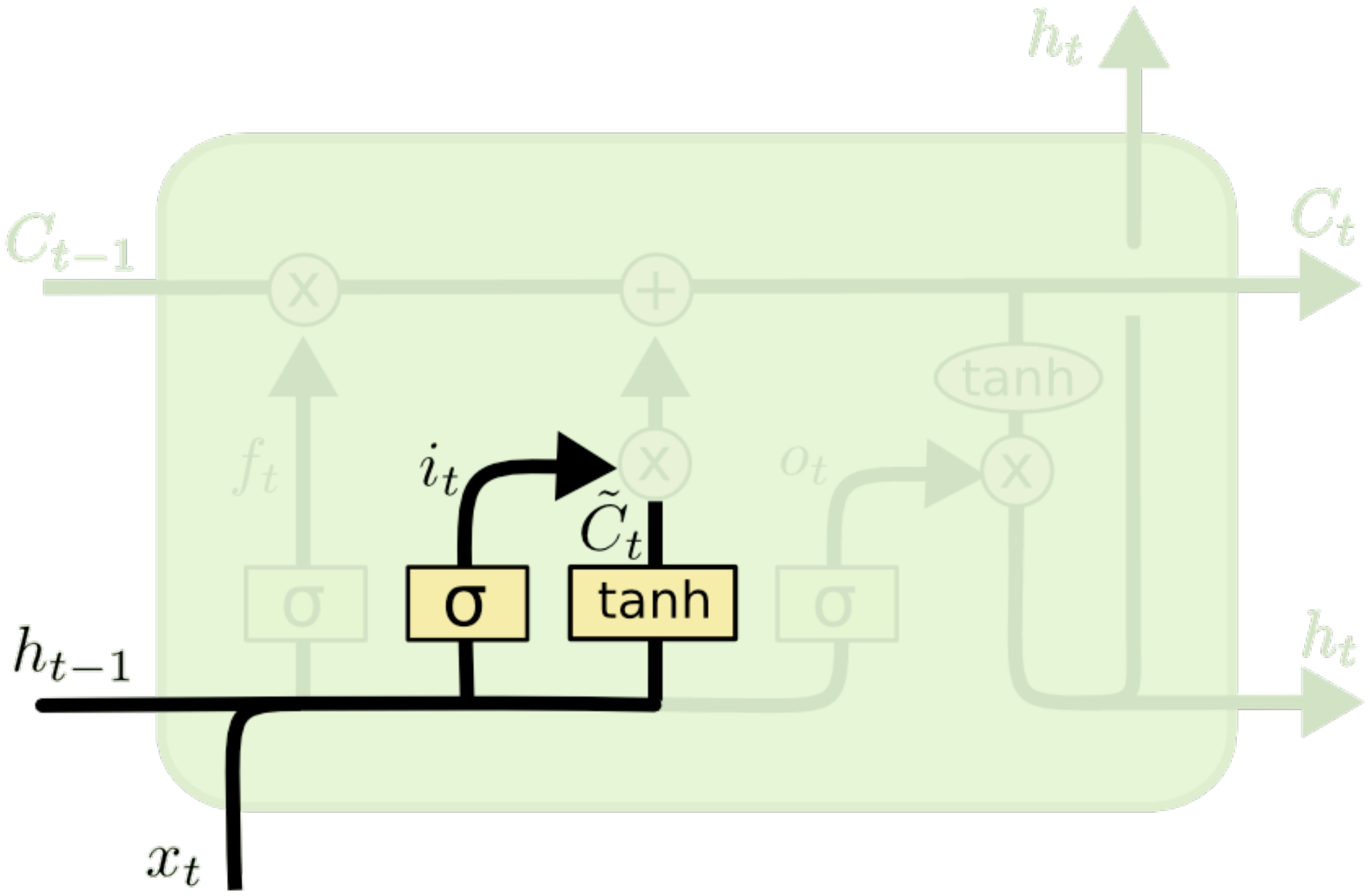
* slide from Dhruv Batra

LSTM Intuition: Input Gate

Should we **update** this "bit" of information or not?

If yes, then what should we **remember**?

0.1
-0.6
0.1
0.55
-0.67
0.4
0.01
0.7
…
0.9



1
1
1
1
0
0
0
0
…
0

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

0.3
0.5
0.62
-0.34
0.43
-0.78
0.1
-0.45
…
0.9

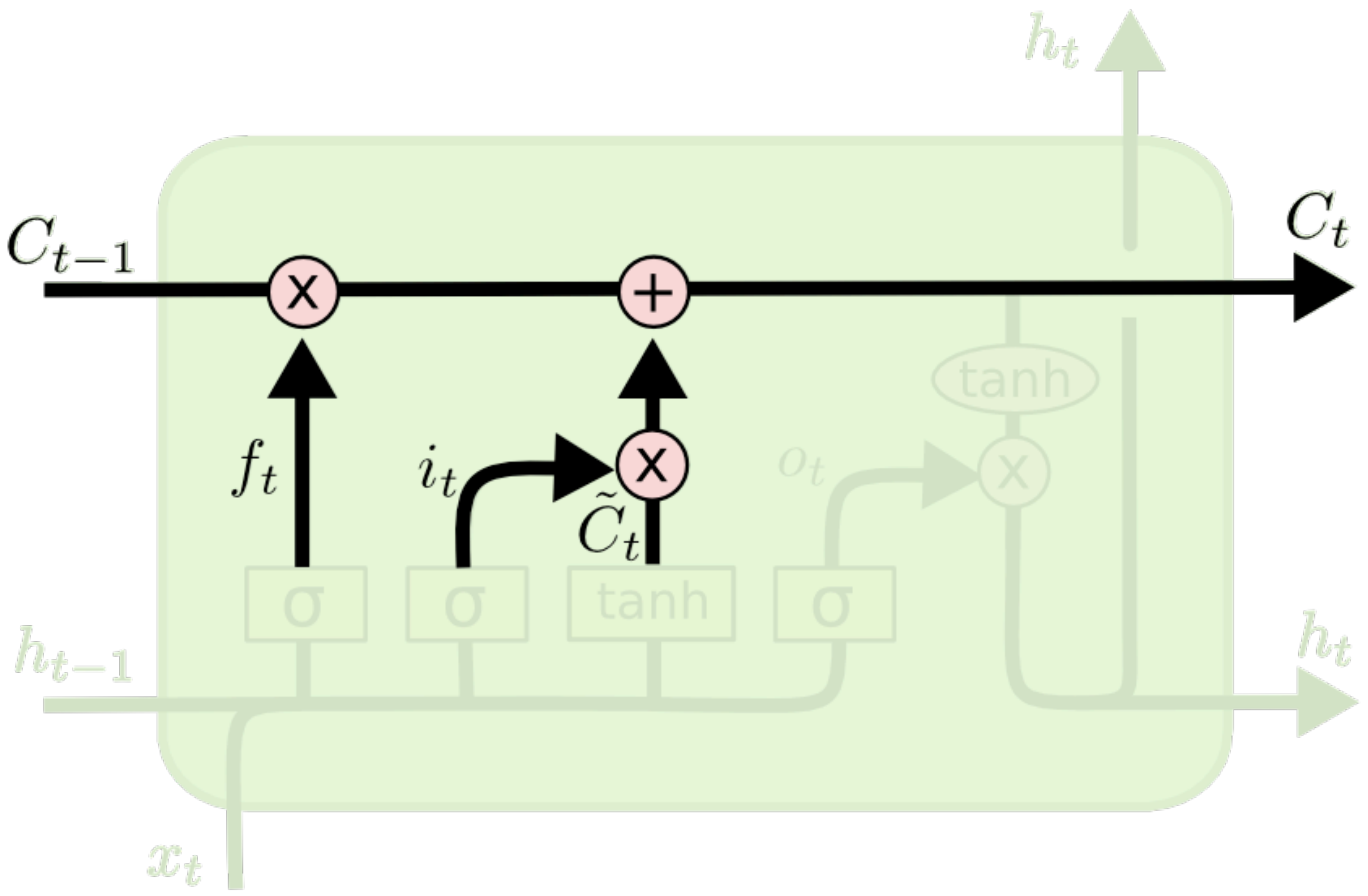
Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

LSTM Intuition: Memory Update

Forget what needs to be forgotten + memorize what needs to be remembered

0.1
-0.6
0.1
0.55
-0.67
0.4
0.01
0.7
…
0.9



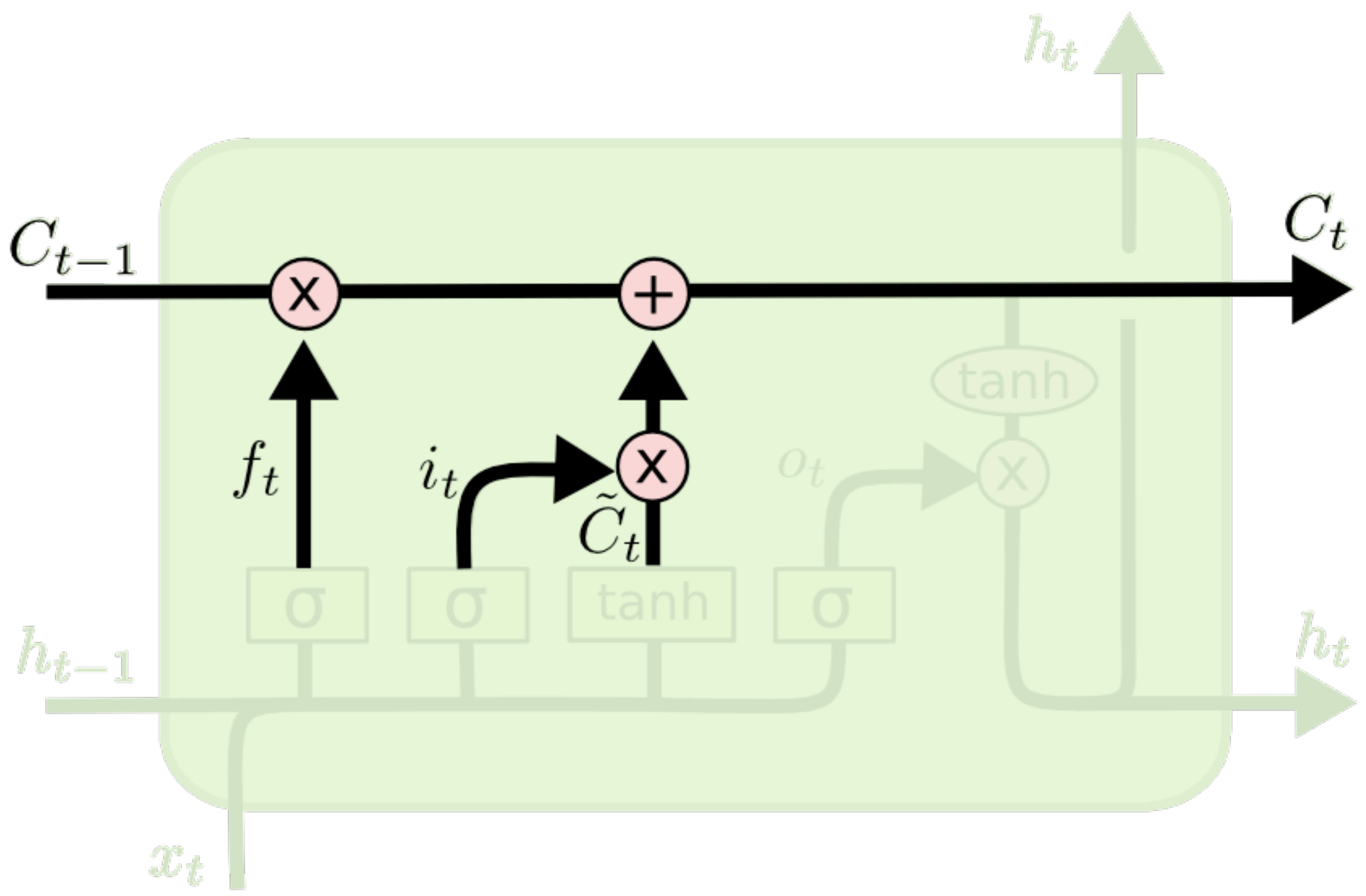
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

LSTM Intuition: Memory Update

Forget what needs to be forgotten + memorize what needs to be remembered

$$\begin{bmatrix}0.1\\-0.6\\0.1\\0.55\\-0.67\\0.4\\0.01\\0.7\\\dots\\0.9\end{bmatrix}$$



$$\begin{bmatrix}0.3\\0.5\\0.62\\-0.34\\-0.67\\0.4\\0.01\\0.7\\\dots\\0.9\end{bmatrix} = \begin{bmatrix}0.1\\-0.6\\0.1\\0.55\\-0.67\\0.4\\0.01\\0.7\\\dots\\0.9\end{bmatrix} \text{X} \begin{bmatrix}0\\0\\0\\0\\1\\1\\1\\1\\\dots\\1\end{bmatrix} + \begin{bmatrix}1\\1\\1\\1\\0\\0\\0\\0\\\dots\\0\end{bmatrix} \text{X} \begin{bmatrix}0.3\\0.5\\0.62\\-0.34\\0.43\\-0.78\\0.1\\-0.45\\\dots\\0.9\end{bmatrix}$$

selective write

Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

LSTM Intuition: Memory Update

Forget what needs to be forgotten + memorize what needs to be remembered

0.1
-0.6
0.1
0.55
-0.67
0.4
0.01
0.7
…
0.9

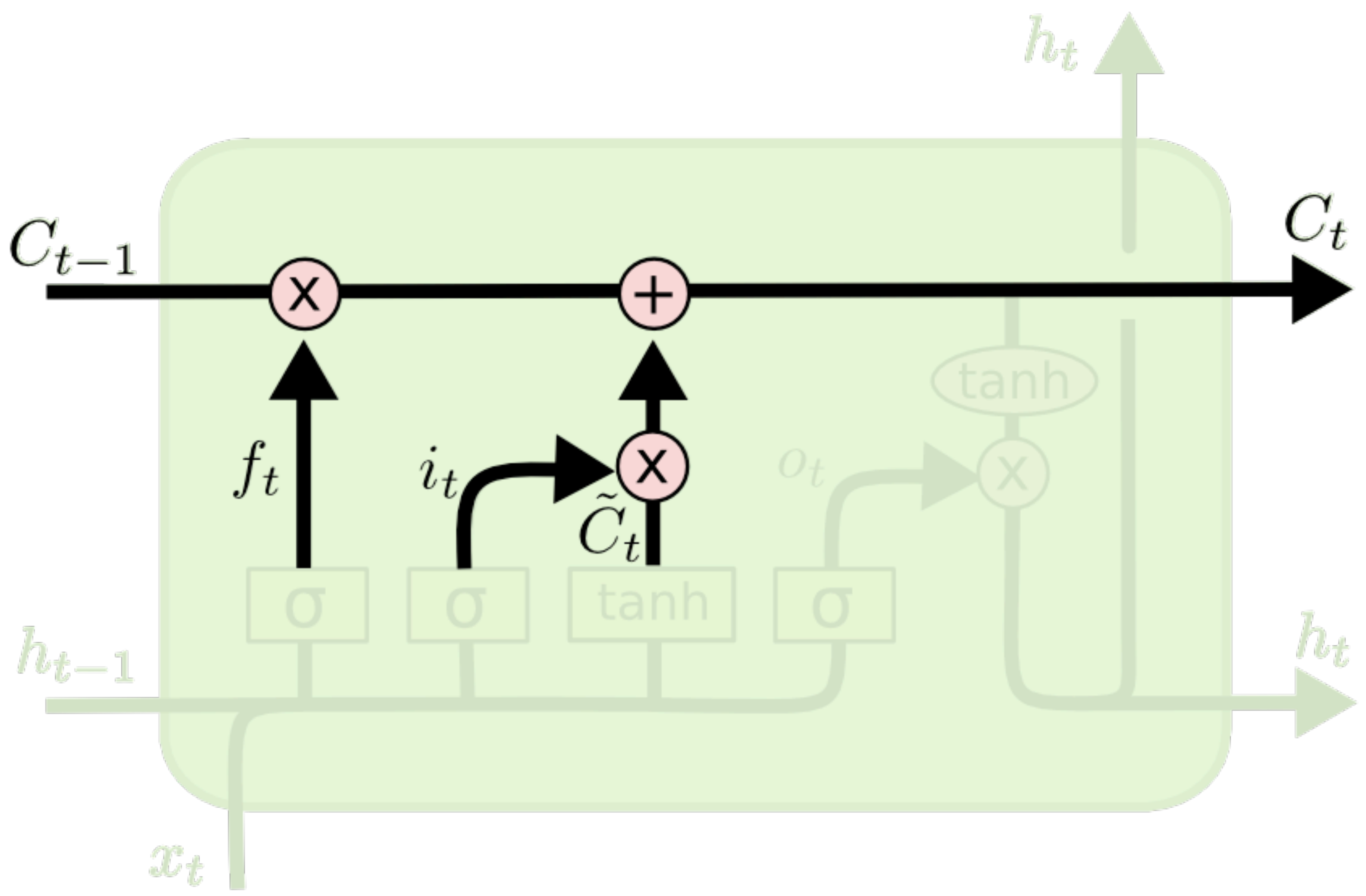
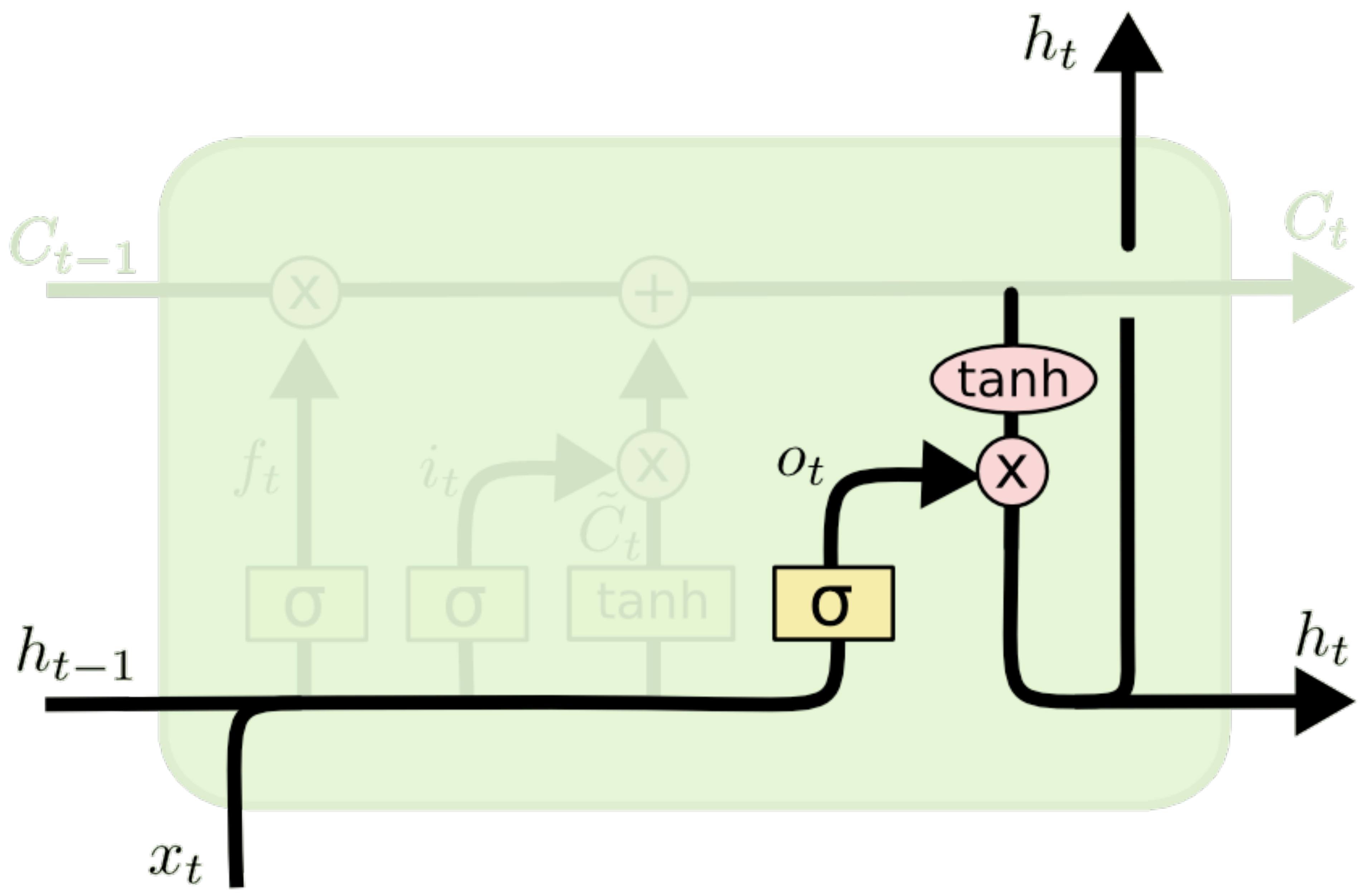


Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

LSTM Intuition: Output Gate

Should we output this bit of information (e.g., to "deeper" LSTM layers)?



$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

LSTM Intuition: Additive Updates

Backpropagation from c_t to c_{t-1} only elementwise multiplication by f, no matrix multiply by W

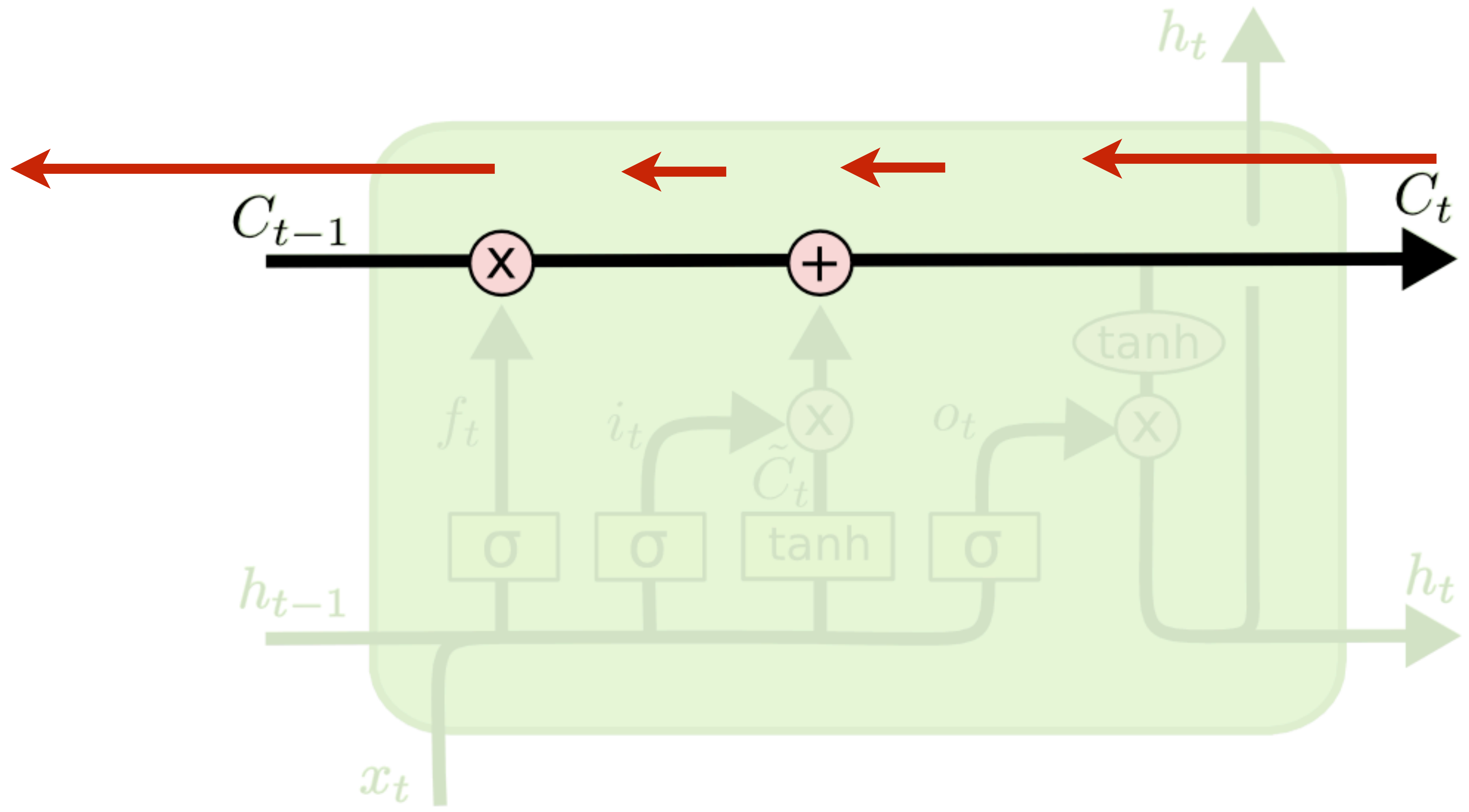
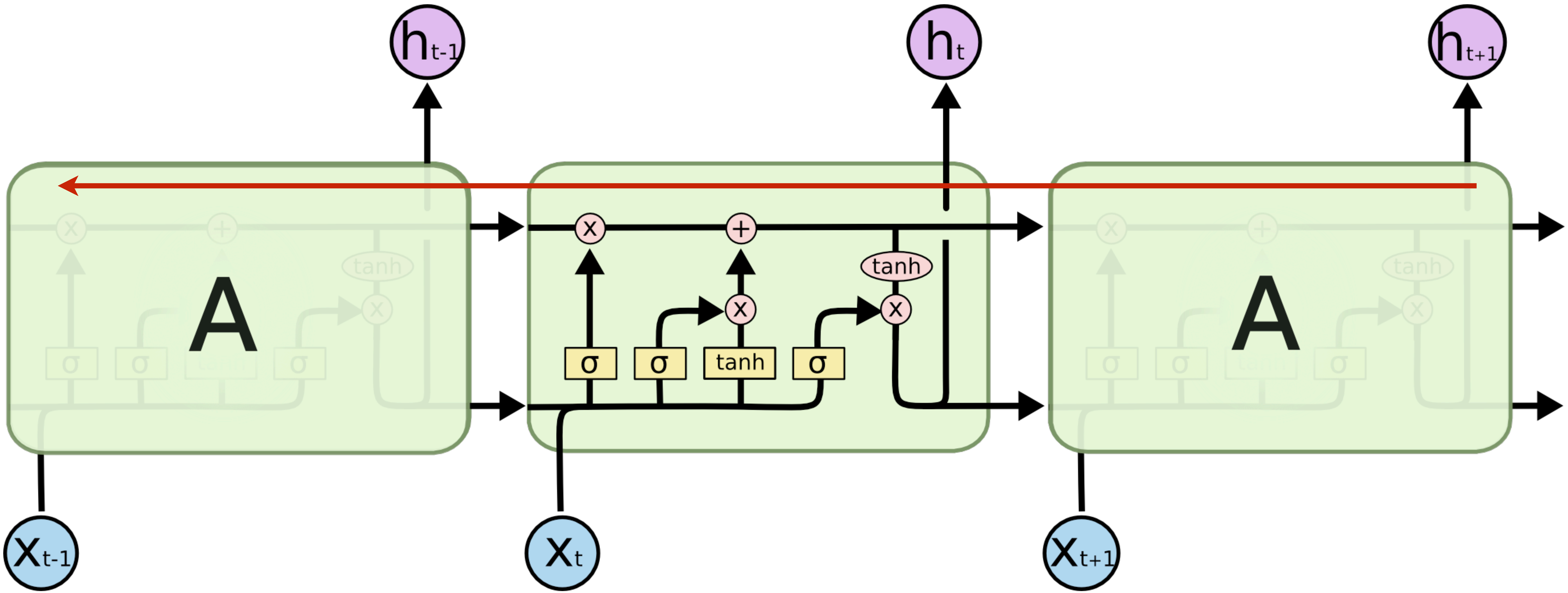


Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

LSTM Intuition: Additive Updates



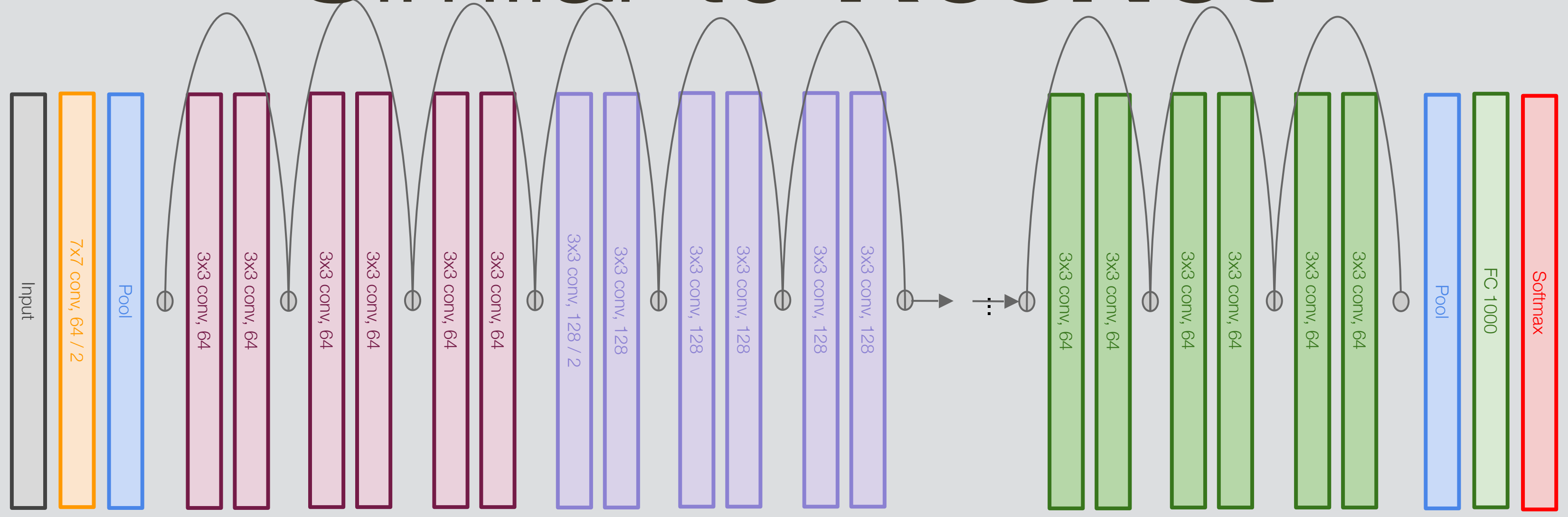
Uninterrupted gradient flow!

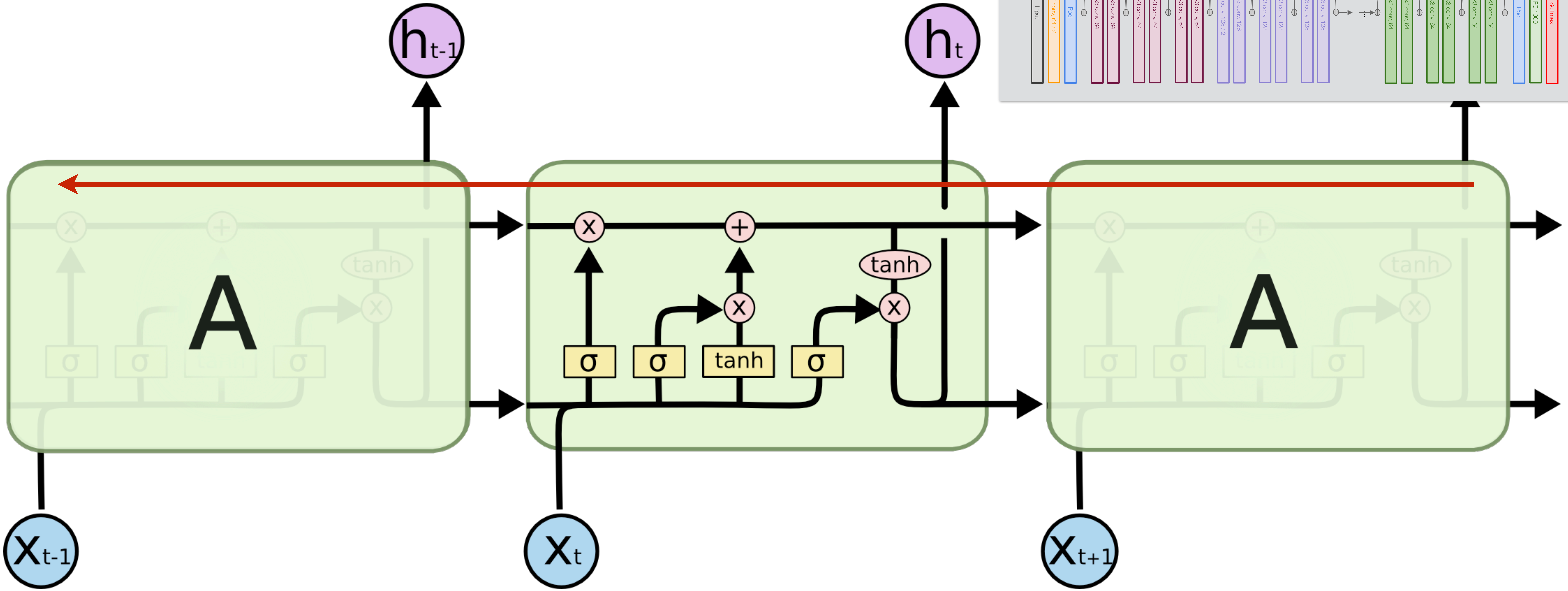
Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

LSTM Intuition: Additive Updates

Similar to **ResNet**





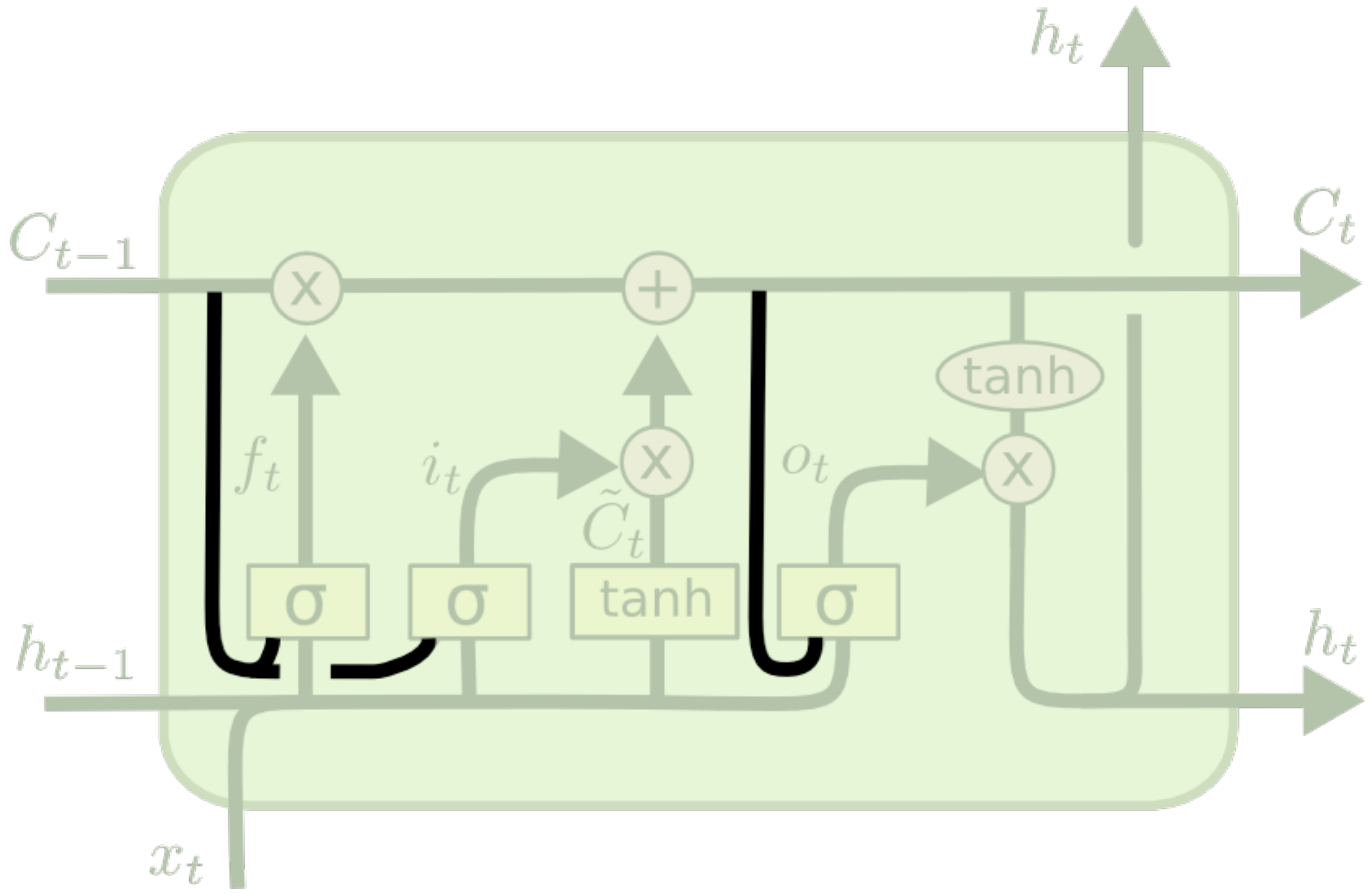
Uninterrupted gradient flow!

Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

LSTM Variants: with Peephole Connections

Lets gates see the cell state / memory



$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \ + \ b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \ + \ b_i\right)$$
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \ + \ b_o\right)$$

Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

LSTM Variants: with Peephole Connections

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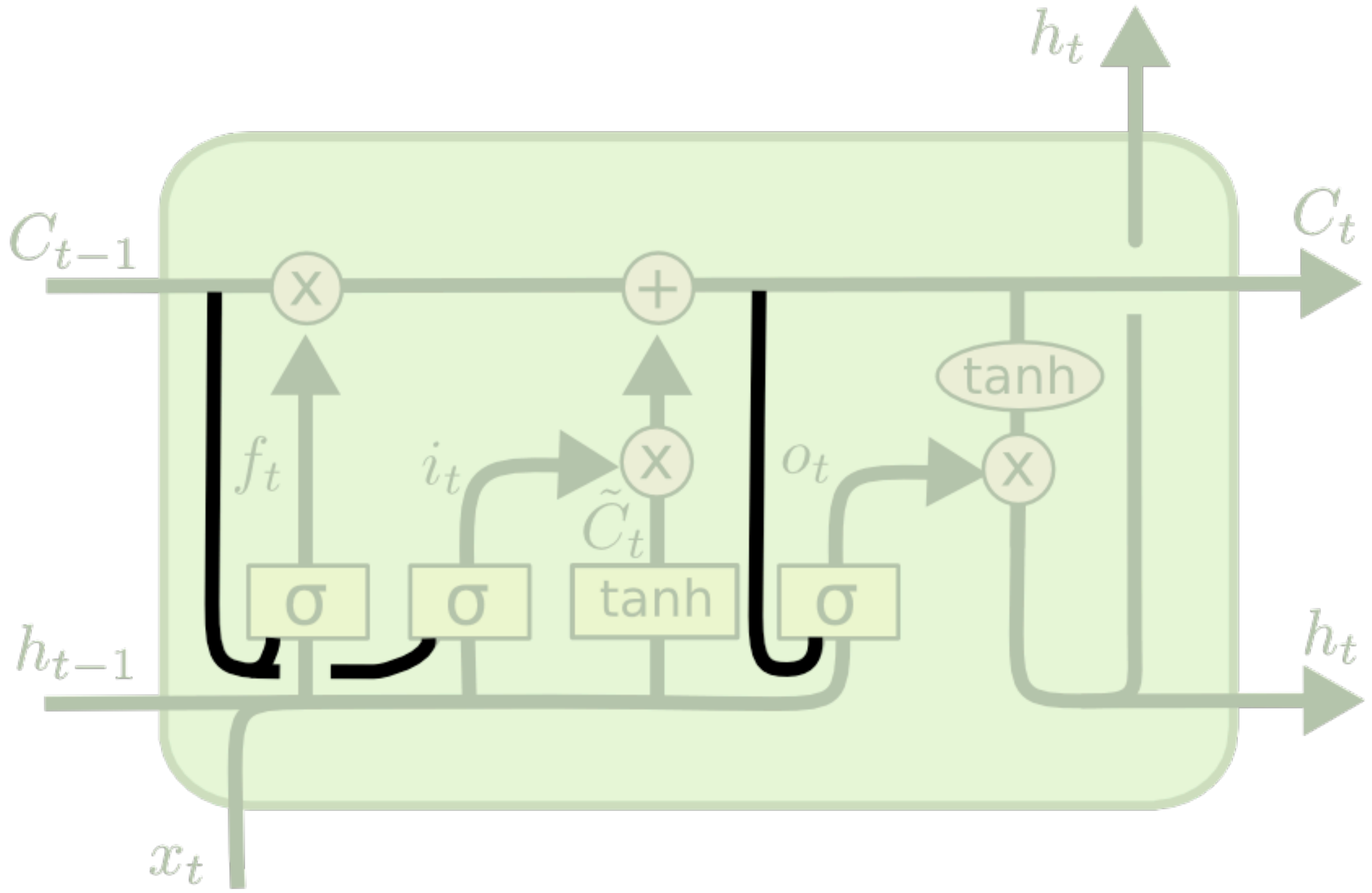

$$f_t = \sigma\left(W_f \cdot \left[\boldsymbol{C_{t-1}}, h_{t-1}, x_t\right] \ + \ b_f\right)$$
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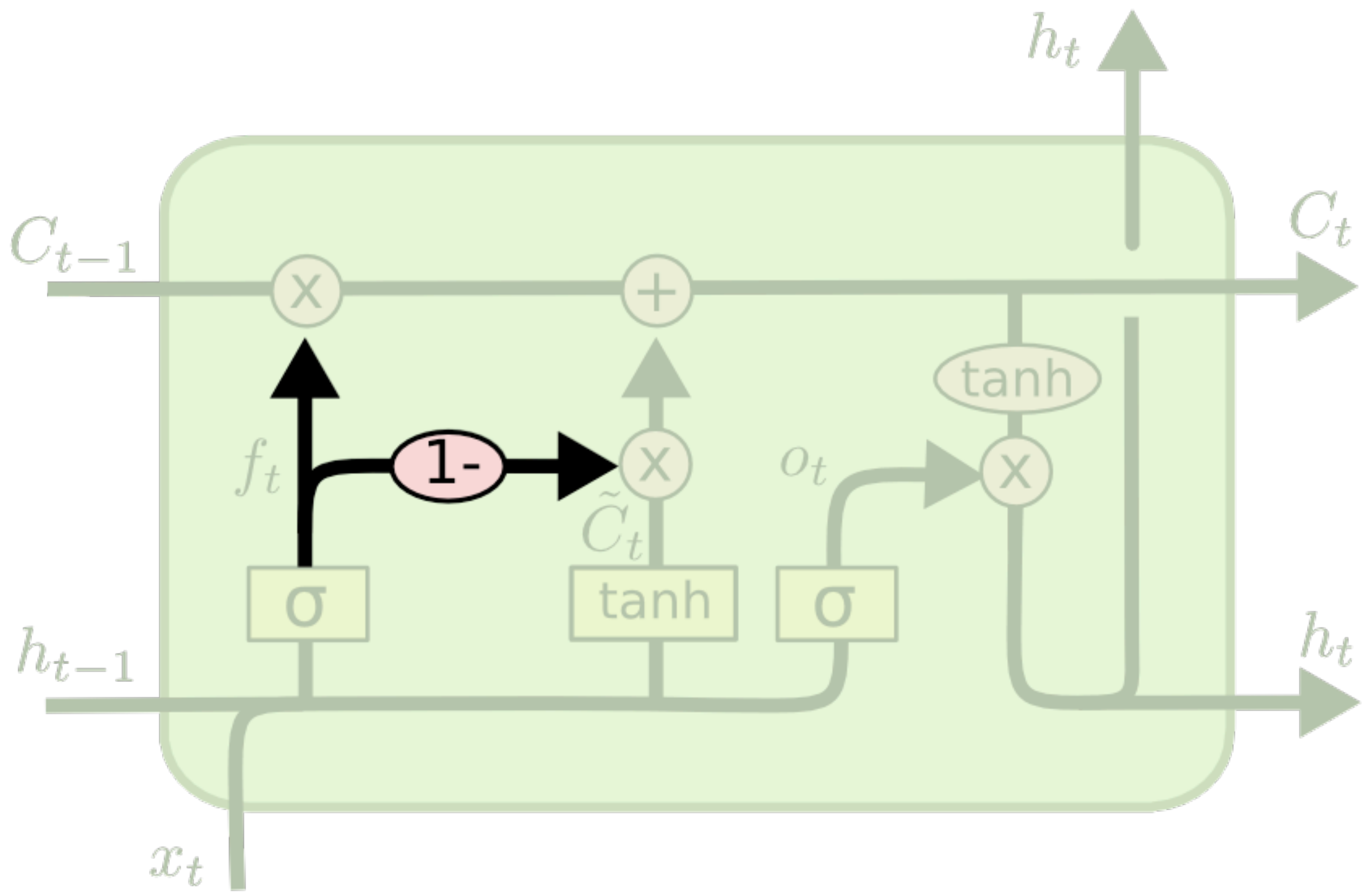
Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

LSTM Variants: with Coupled Gates

Only memorize new information when you're forgetting old



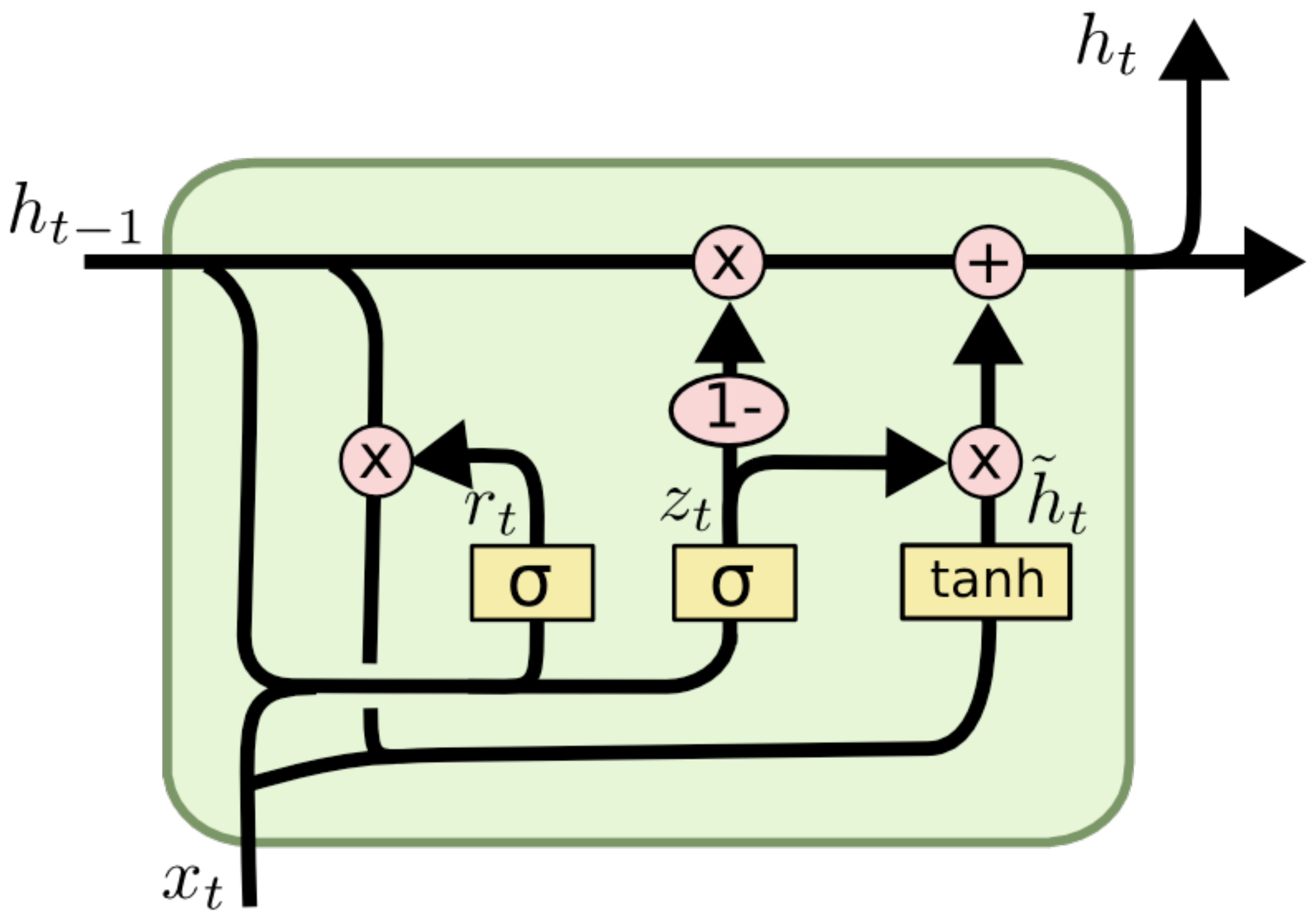
$$C_t = f_t * C_{t-1} + (1 - \boldsymbol{f_t}) * \tilde{C}_t$$

Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

Gated Recurrent Unit (**GRU**)

No explicit memory; memory = hidden output



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

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

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

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

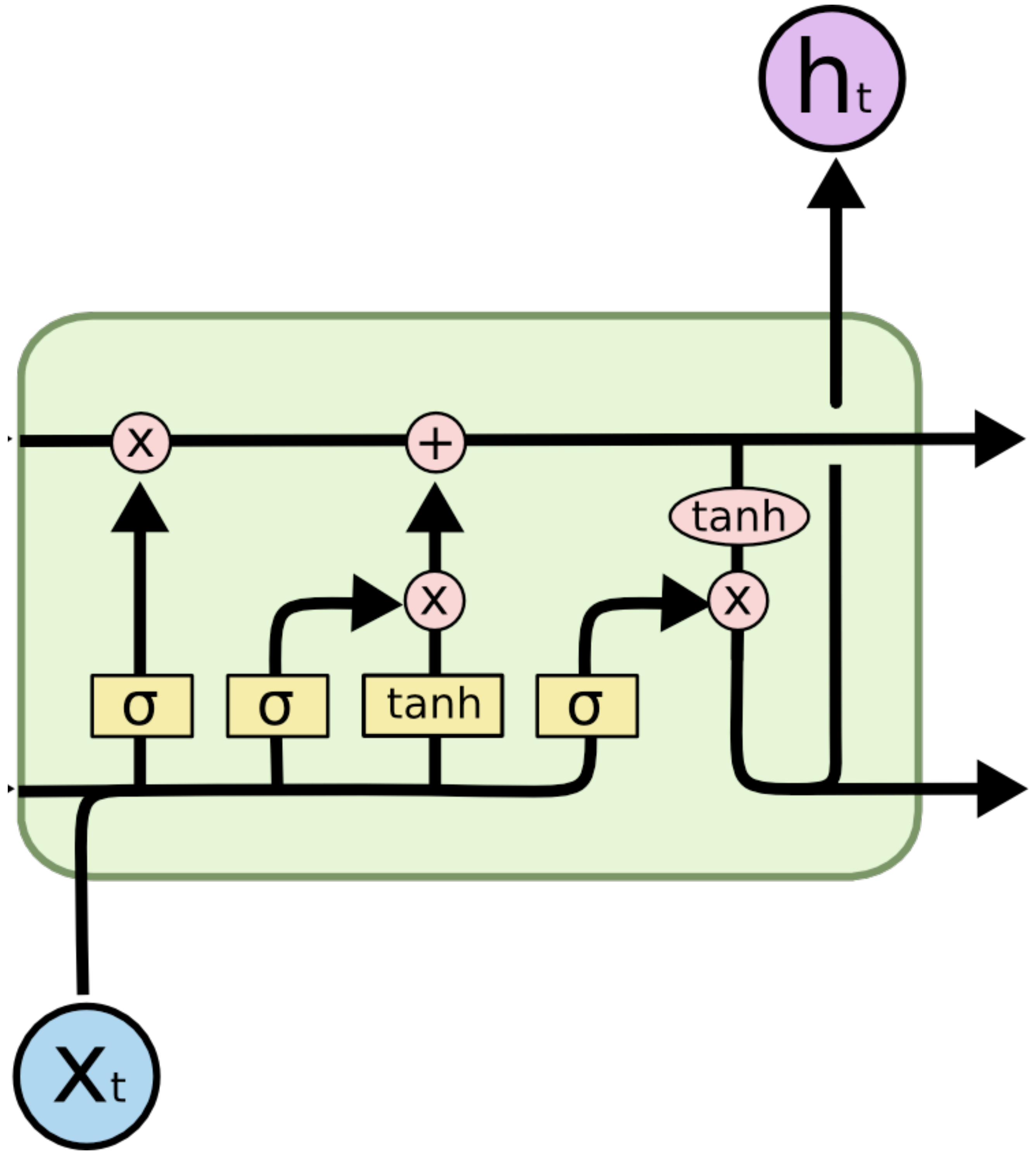
z = memorize new and forget old

Image Credit: Christopher Olah (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

* slide from Dhruv Batra

LSTM/RNN **Challenges**

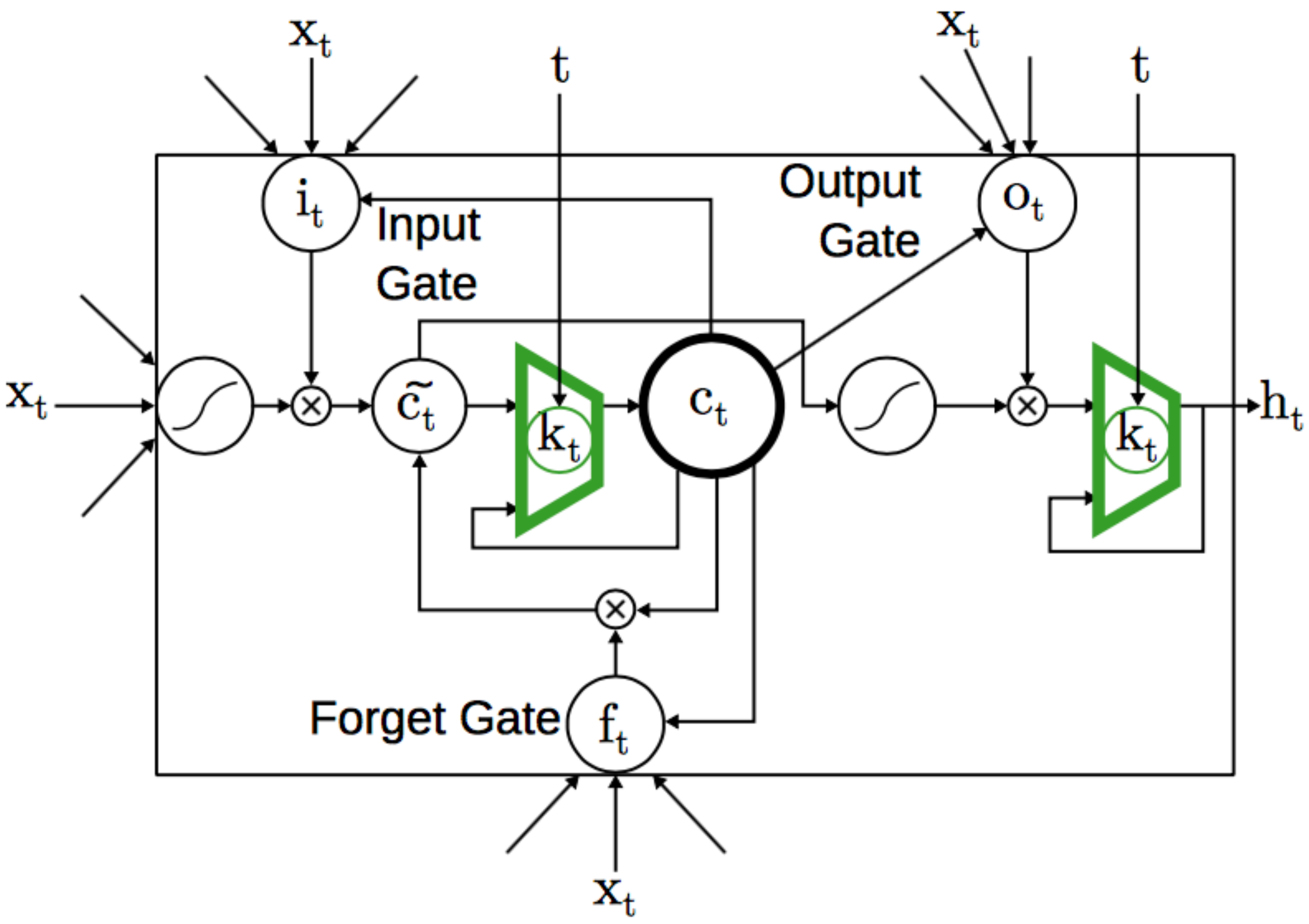
- LSTM can remember some history, but not too long
- LSTM assumes data is regularly sampled

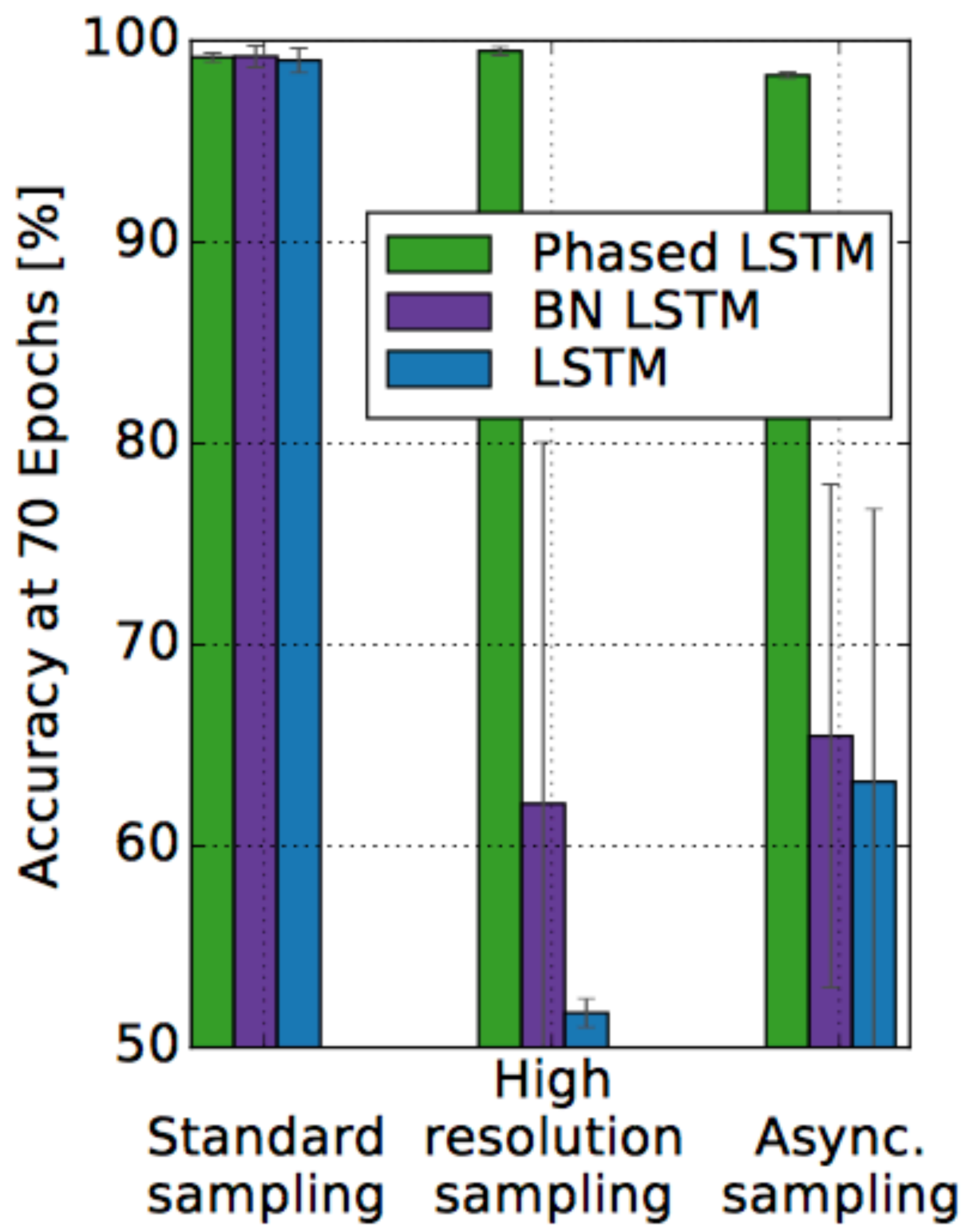


Phased LSTM

[Neil et al., 2016]

Gates are controlled by **phased** (periodic) **oscillations**



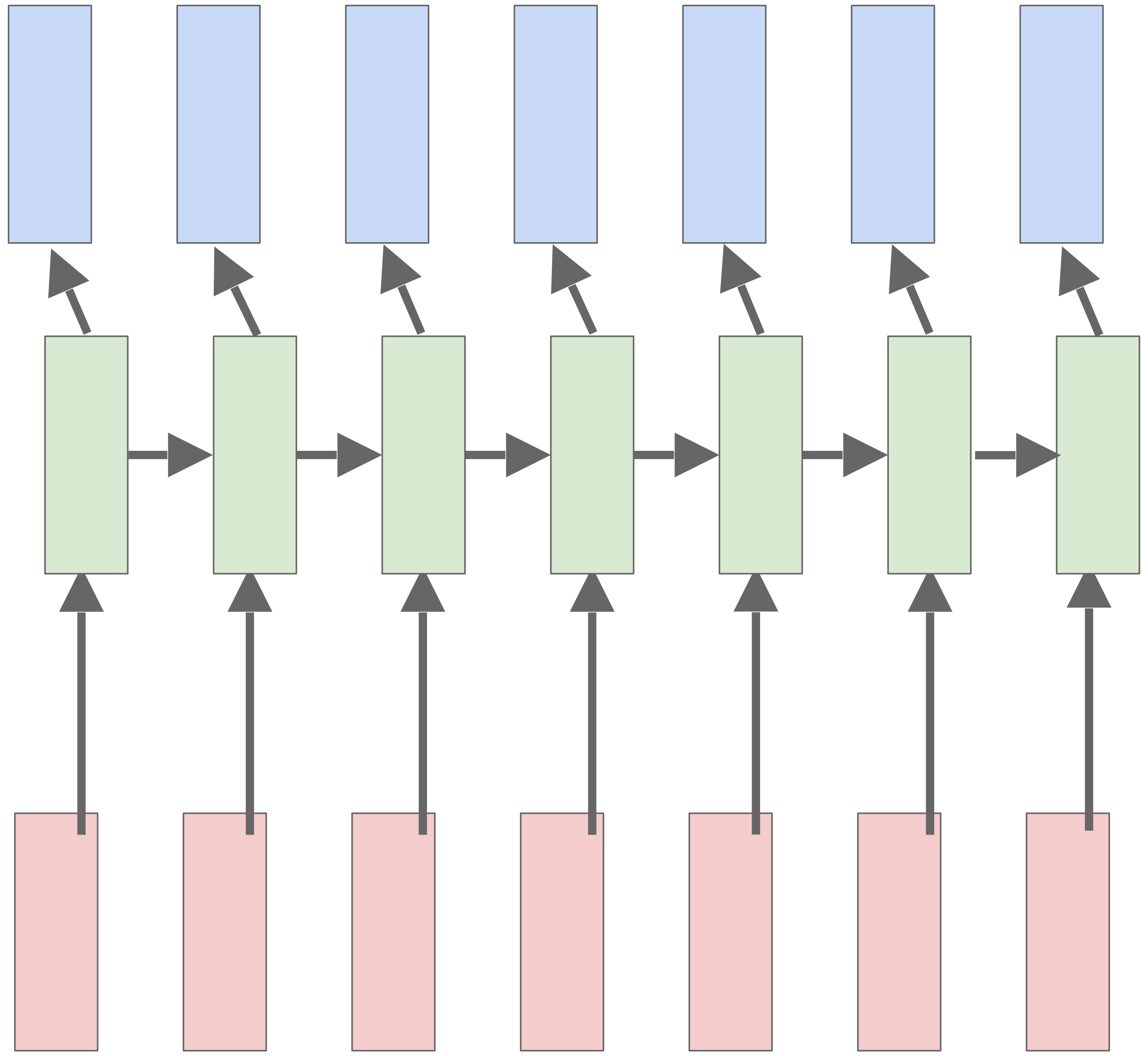


Bi-directional RNNs/LSTMs

$$y_t = W_{hy}h_t + b_y$$

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

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



Bi-directional RNNs/LSTMs

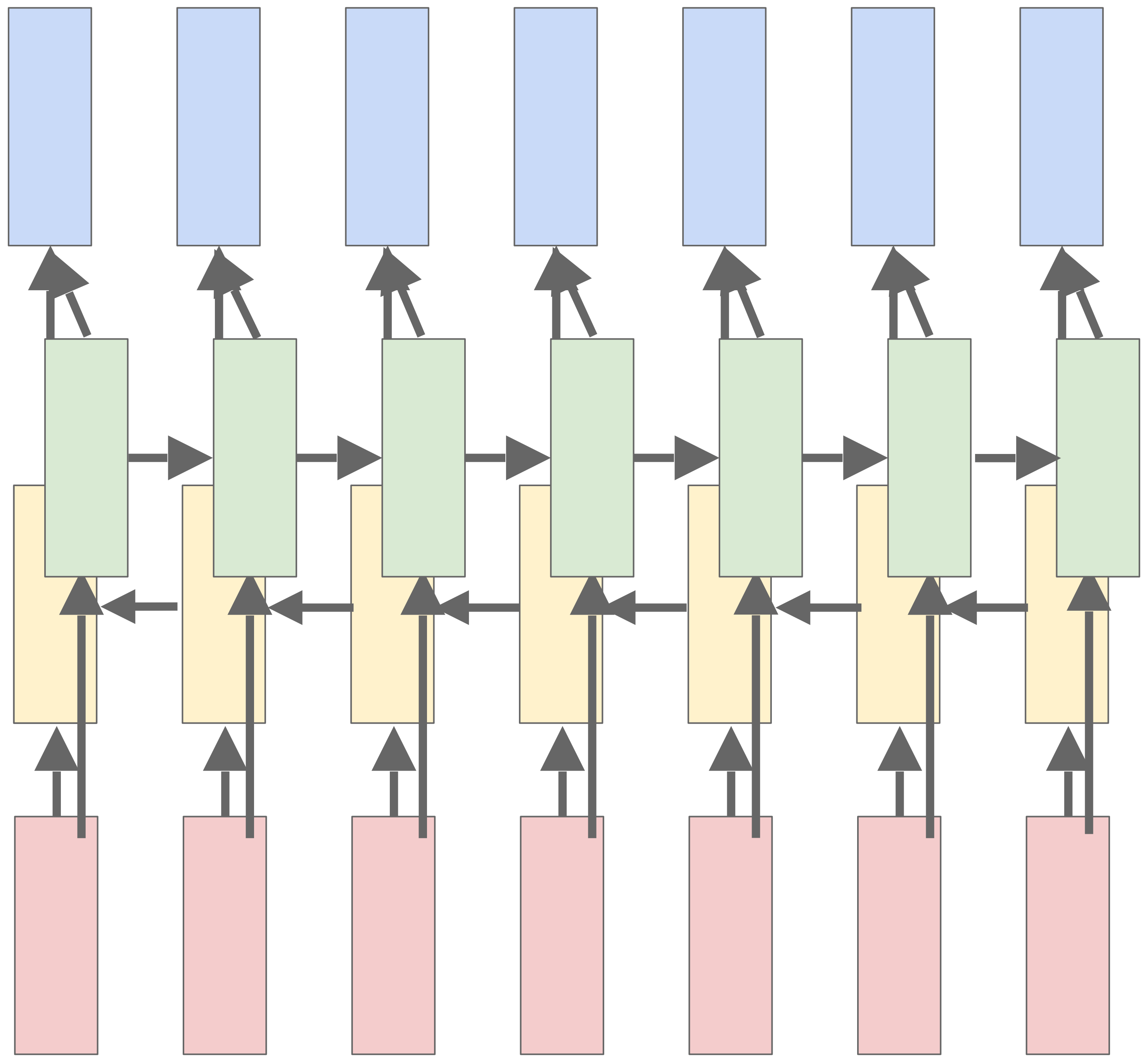
$$y_t = W_{hy}[\boxed{\overrightarrow{h}_t}, \boxed{\overleftarrow{h}_t}]^T + b_y$$

$$\overrightarrow{h}_t = f_{\overrightarrow{W}}(\overrightarrow{h}_{t-1}, x_t)$$

$$\overleftarrow{h}_t = f_{\overleftarrow{W}}(\overleftarrow{h}_{t+1}, x_t)$$

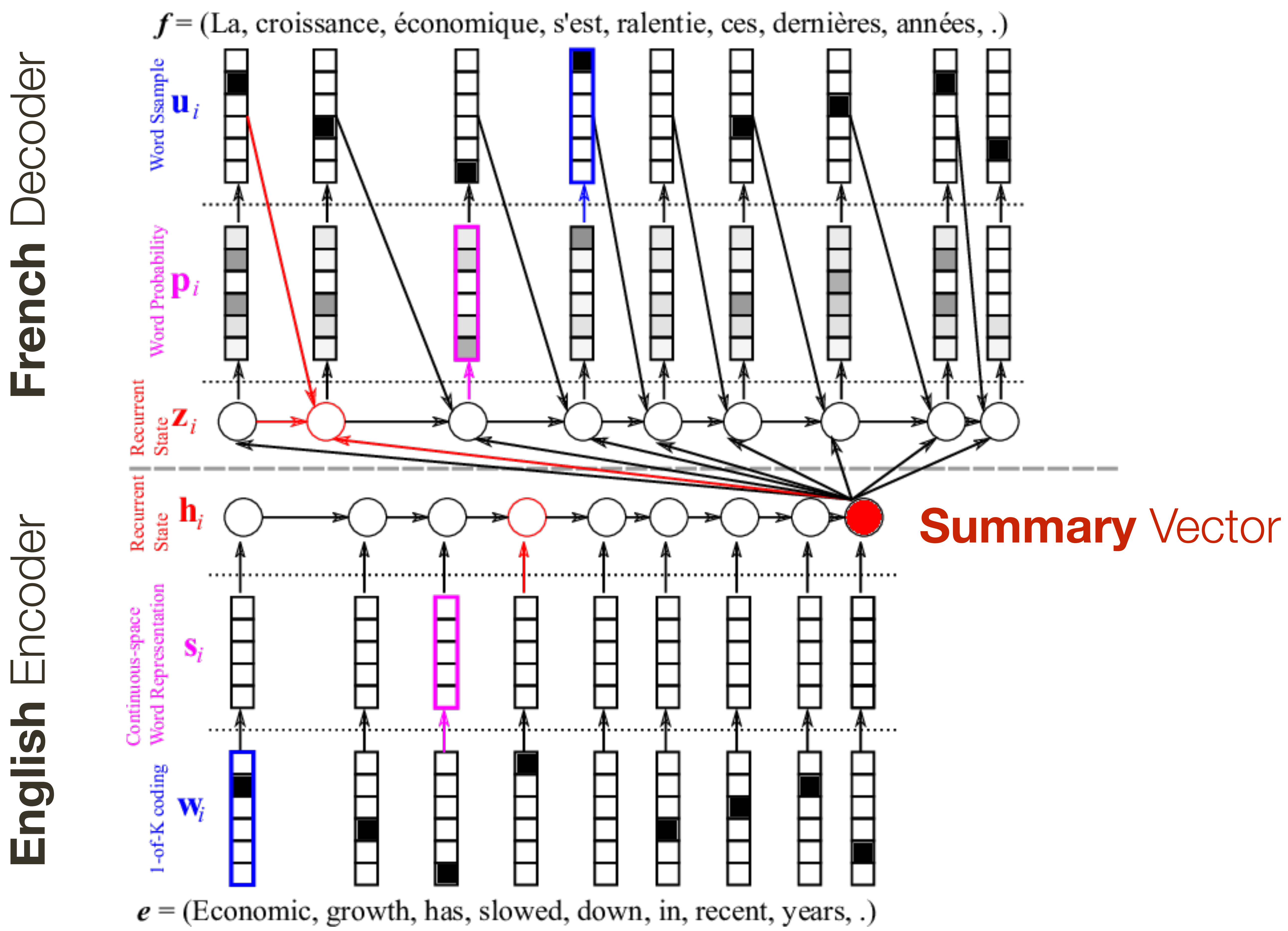
$$\overrightarrow{h}_t = \tanh(\overrightarrow{W}_{hh}\overrightarrow{h}_{t-1} + \overrightarrow{W}_{xh}x_t + \overrightarrow{b}_h)$$

$$\overleftarrow{h}_t = \tanh(\overleftarrow{W}_{hh}\overleftarrow{h}_{t+1} + \overleftarrow{W}_{xh}x_t + \overleftarrow{b}_h)$$



Attention Mechanisms and RNNs

Consider a **translation task**: This is one of the first neural translation models

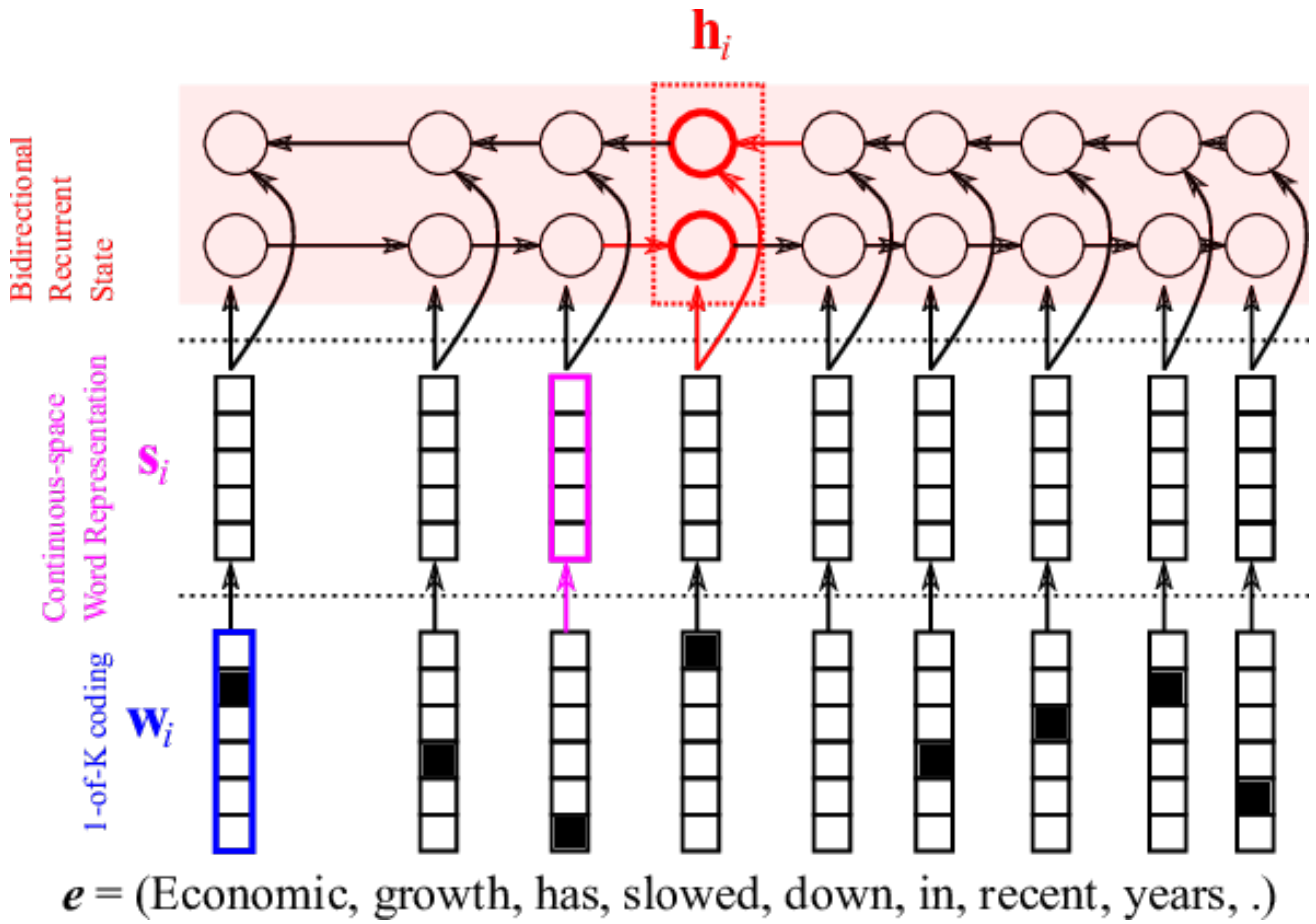


https://devblogs.nvidia.com/introduction-neural-machine-translation-gpus-part-3/

Attention Mechanisms and RNNs

Consider a **translation task** with a bi-directional encoder of the source language

English Encoder



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Attention Mechanisms and RNNs

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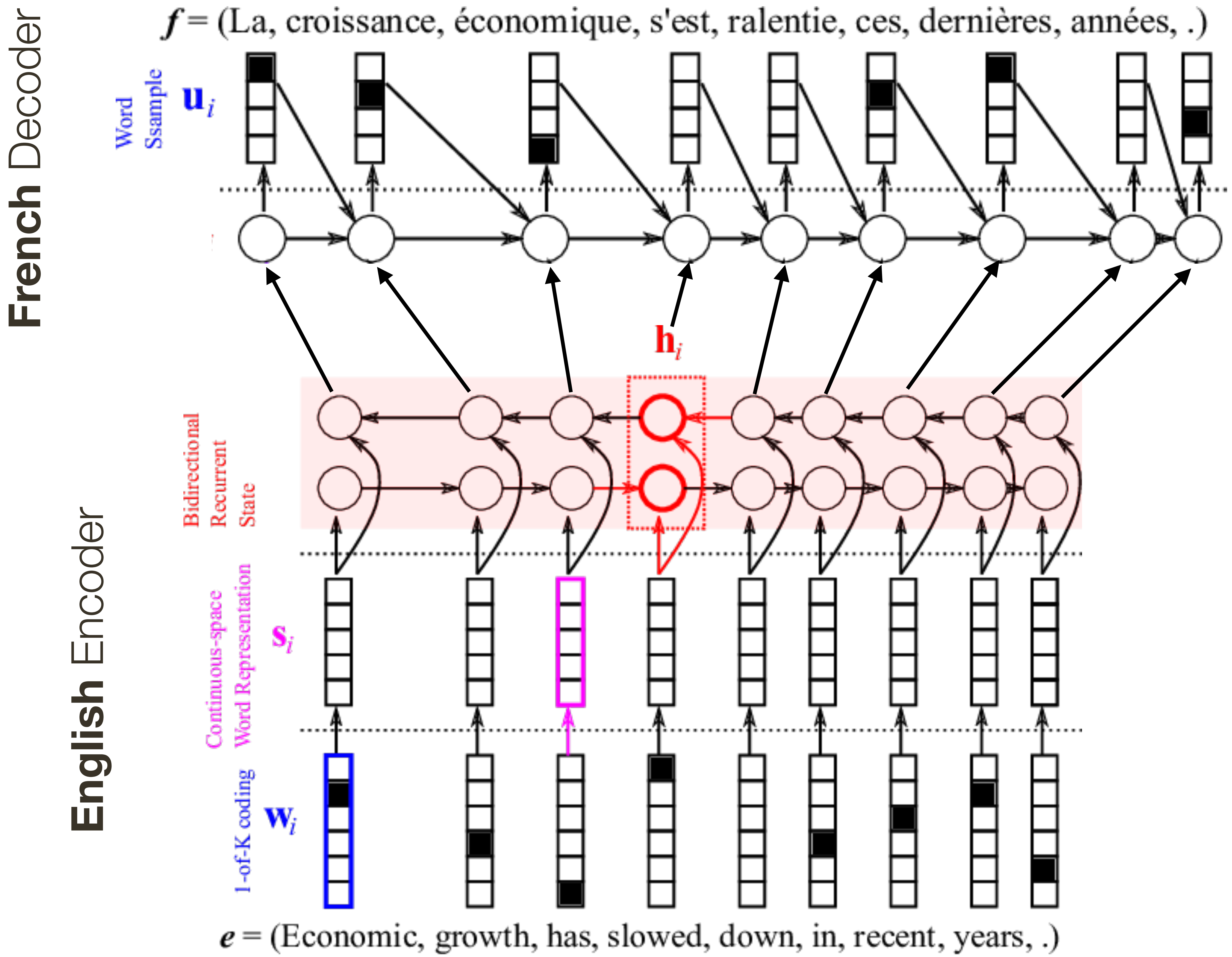

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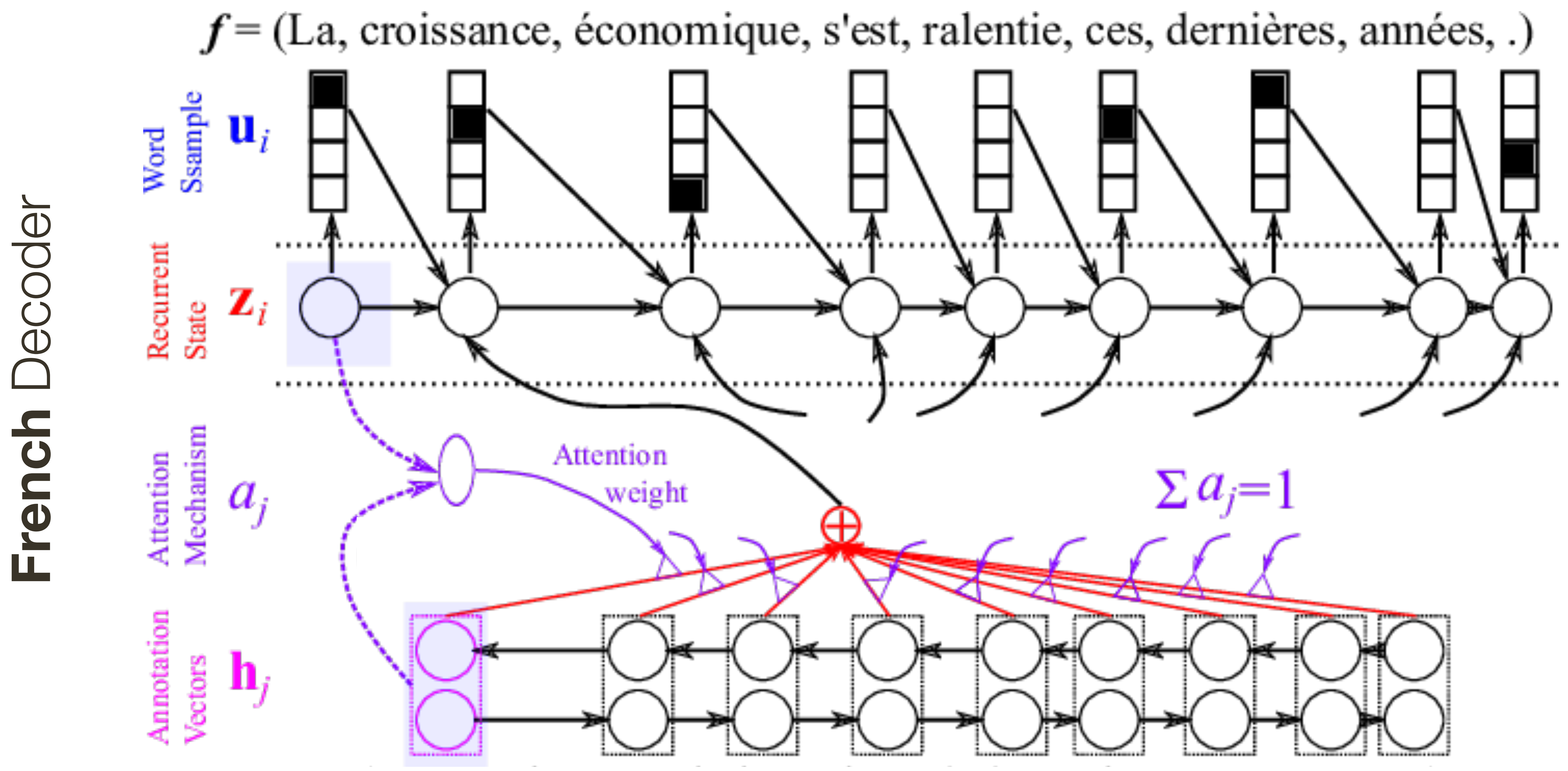

[Cho et al., 2015]

Build a **small neural network** (one layer) with softmax output that takes

(1) everything decoded so far and (encoded by previous decoder state Zi)

(2) encoding of the current word (encoded by the hidden state of encoder hj)

and predicts **relevance of every source word** towards next translation

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Attention Mechanisms and RNNs

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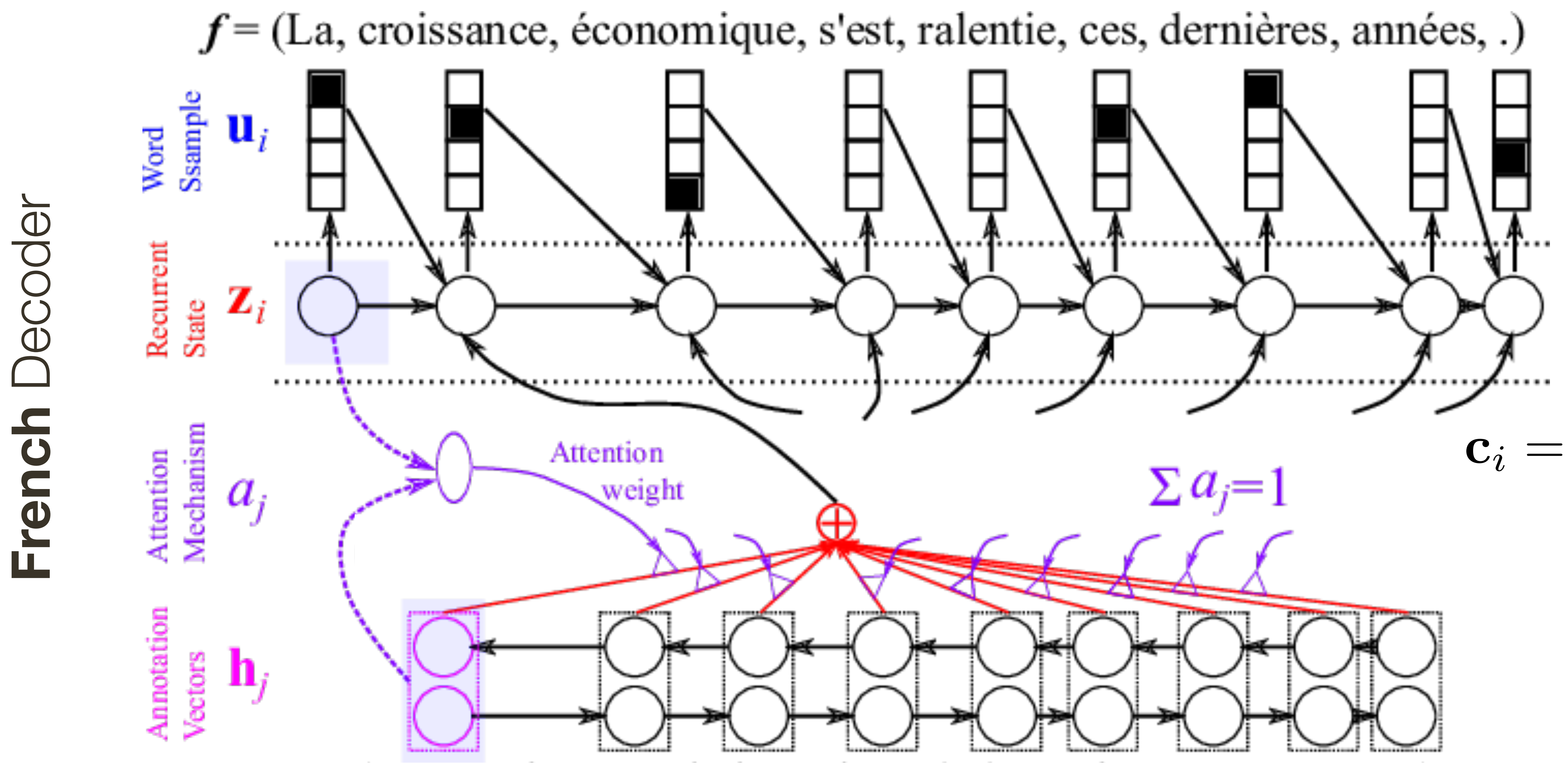

[Cho et al., 2015]

$$\mathbf{c}_i = \sum_{j=1}^{T} \alpha_j \mathbf{h}_j$$

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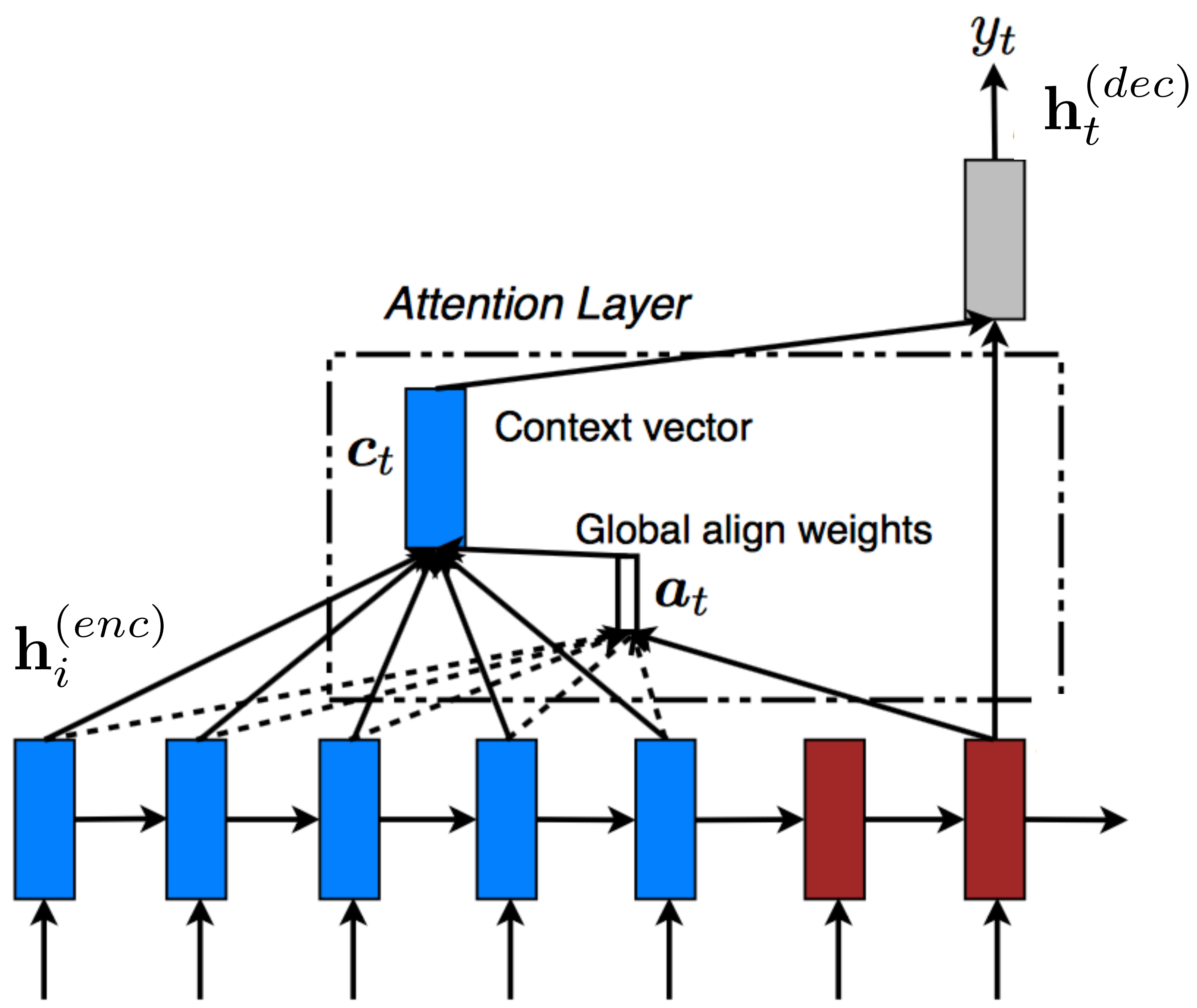
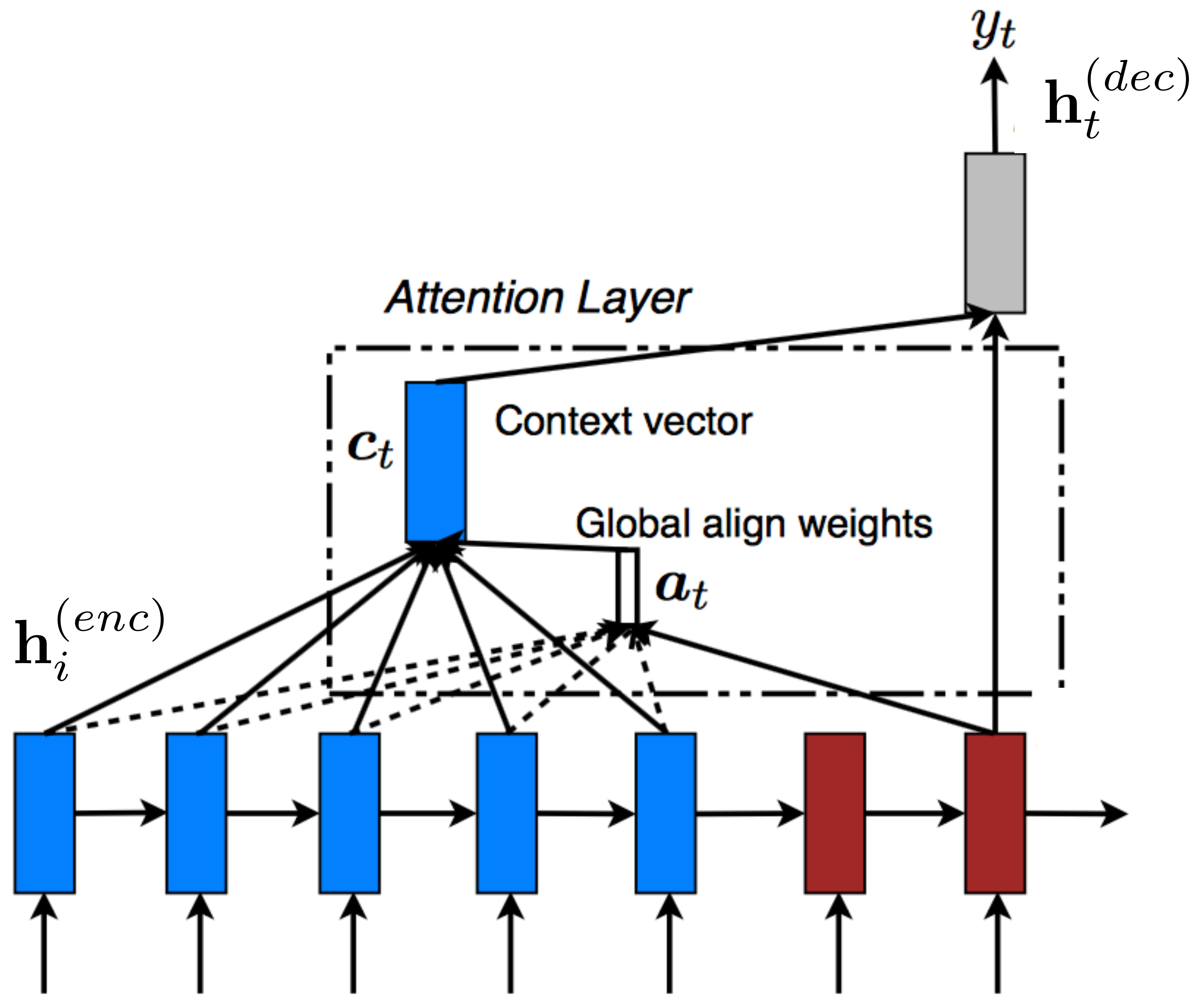
Soft **Attention** in details



Soft **Attention** in details

$$\beta_{i,t} = score(\mathbf{h}_i^{(enc)}, \mathbf{h}_t^{(dec)})$$

Relevance of encoding at token i for decoding token t



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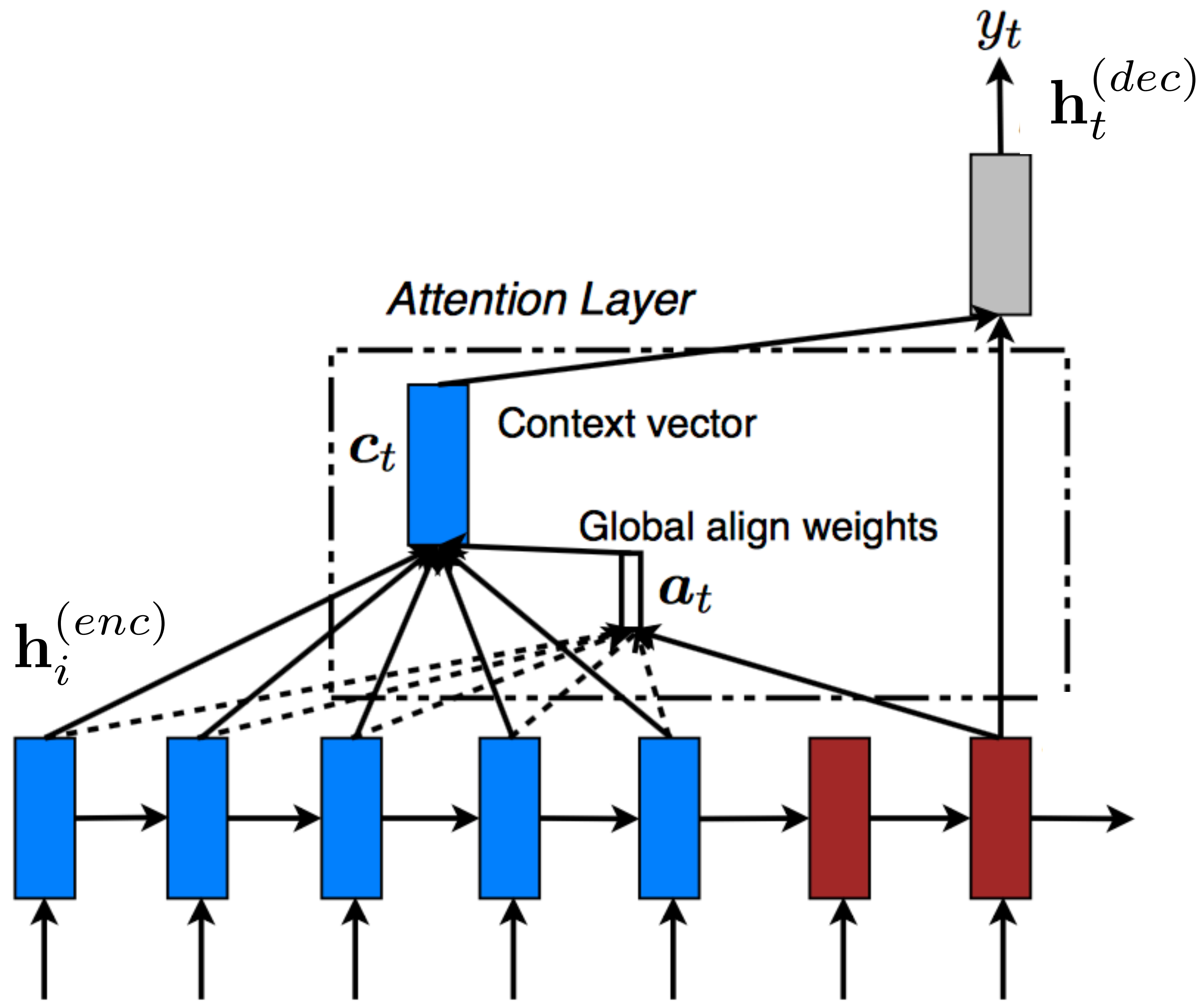

$$\alpha_{i,t} = \text{Softmax}(\beta_{i,t})$$

Normalize the weights to sum to 1

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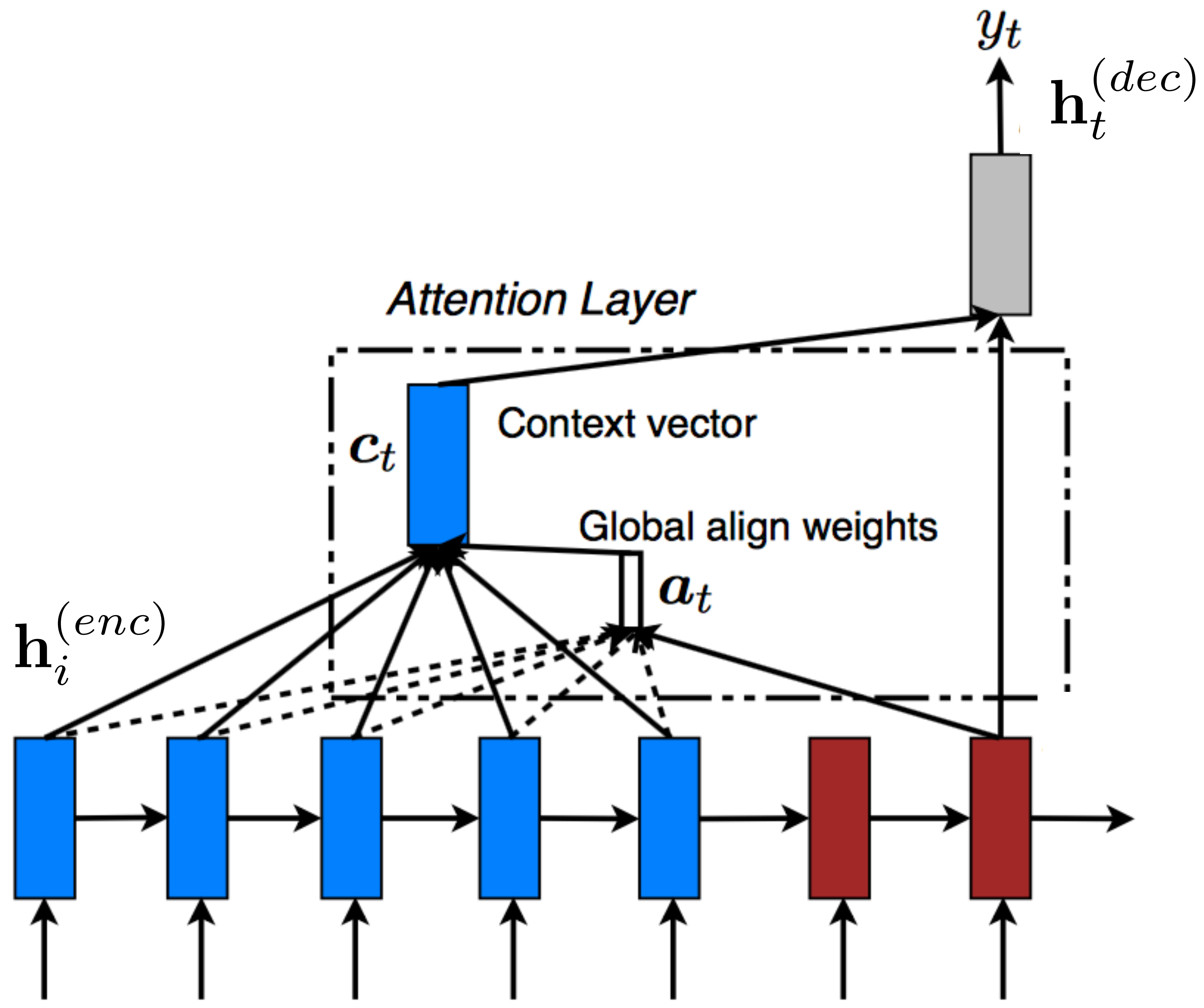


$$\alpha_{i,t} = \text{Softmax}(\beta_{i,t})$$

Normalize the weights to sum to 1

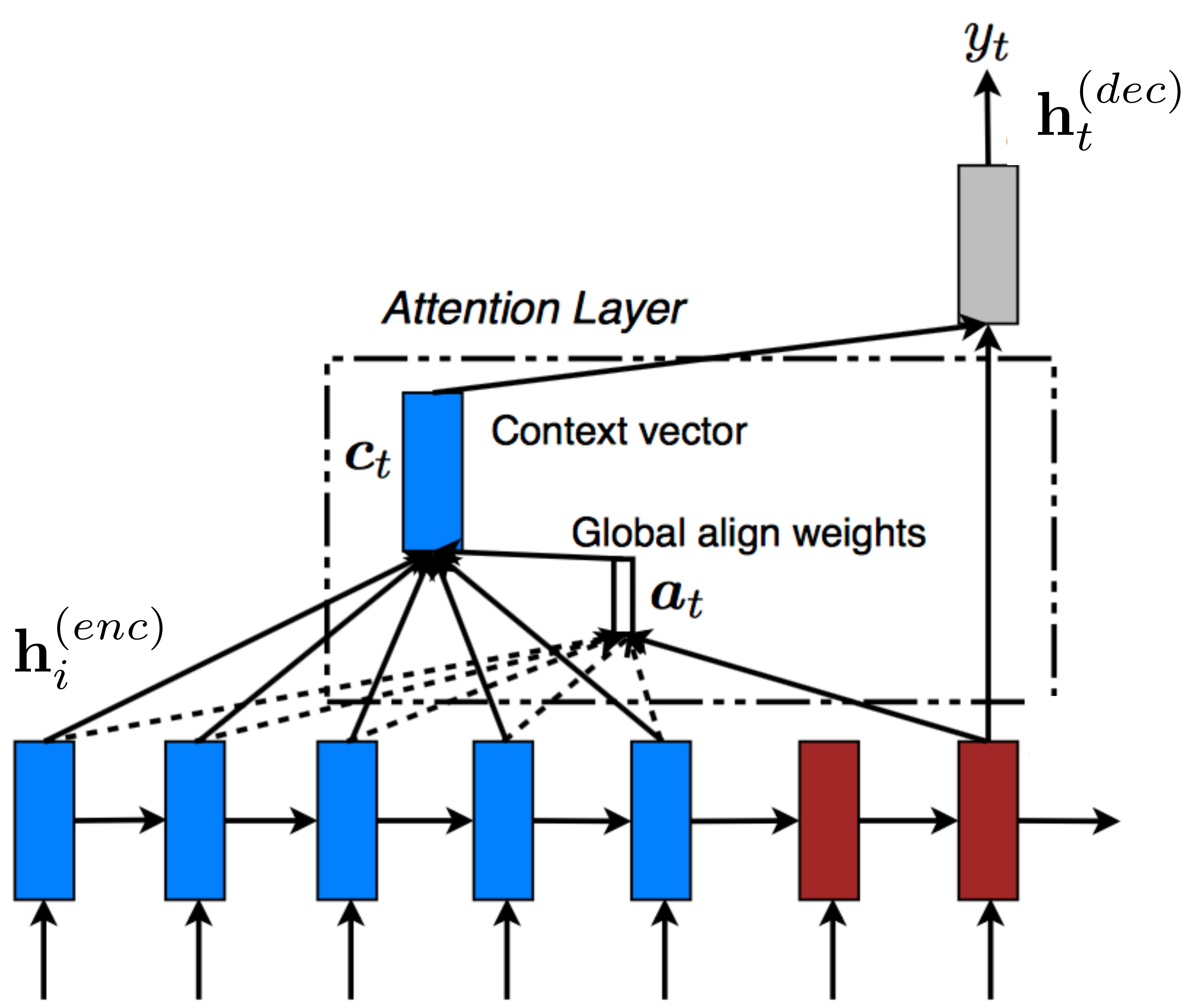
$$\mathbf{c}_t = \sum_i \alpha_{i,t} \mathbf{h}_i^{(enc)}$$

Form a context vector that would simply be added to the standard decoder input

Soft **Attention** in details

$$\beta_{i,t} = score(\mathbf{h}_i^{(enc)}, \cancel{\mathbf{h}_t^{(dec)}})$$

Relevance of encoding at
token i for decoding token t



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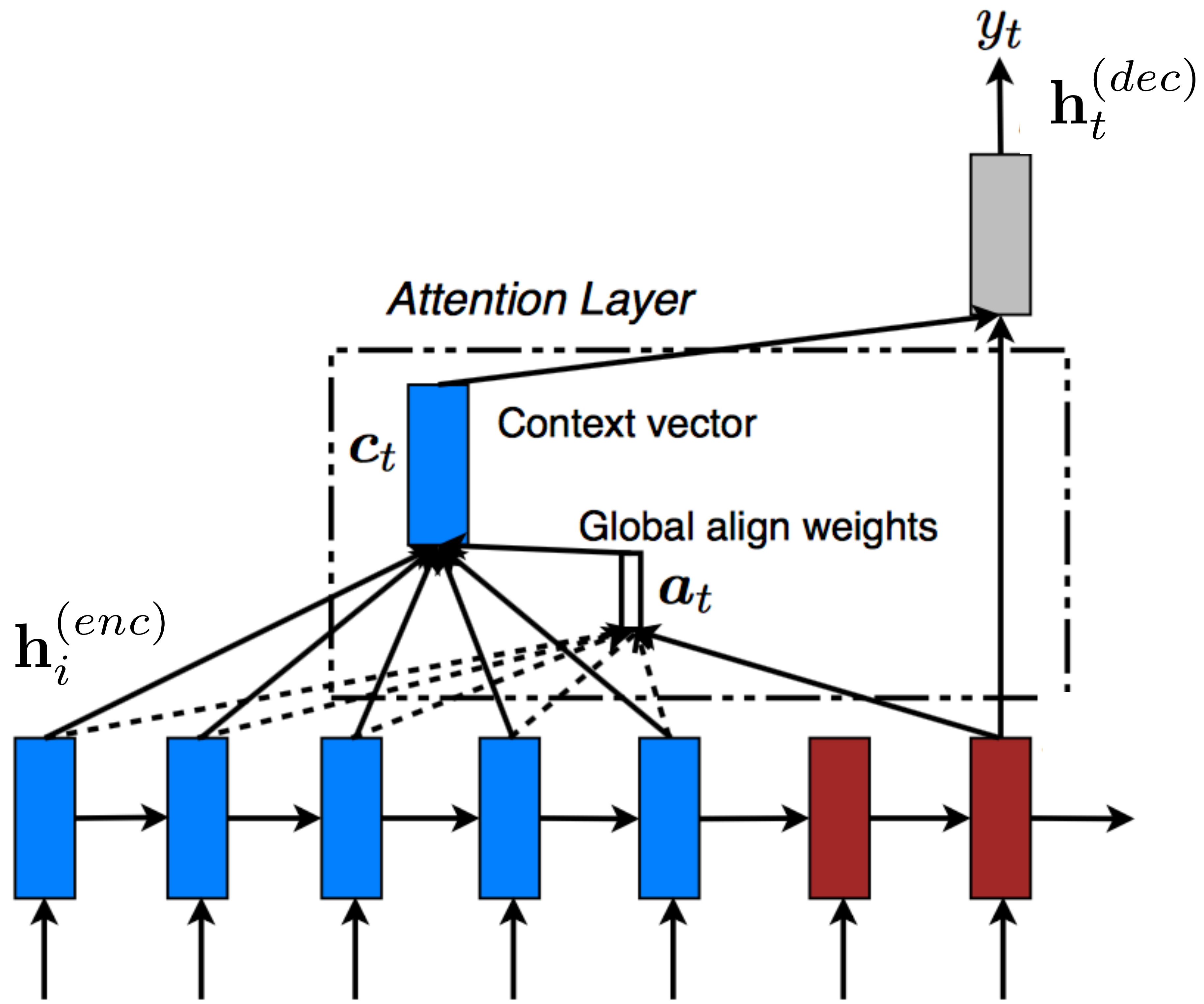
Relevance of encoding at token i for decoding token t

$$\beta_{i,t} = score(\mathbf{h}_i^{(enc)}, \mathbf{x}_t^{(dec)})$$

$$\beta_{i,t} = score(\mathbf{h}_i^{(enc)}, \mathbf{h}_{t-1}^{(dec)})$$

$$\beta_{i,t} = score(\mathbf{h}_i^{(enc)}, [\mathbf{x}_t^{(dec)}, \mathbf{h}_{t-1}^{(dec)}])$$



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$$\beta_{i,t} = score(\mathbf{h}_i^{(enc)}, \cancel{\mathbf{h}_t^{(dec)}})$$

Relevance of encoding at token i for decoding token t

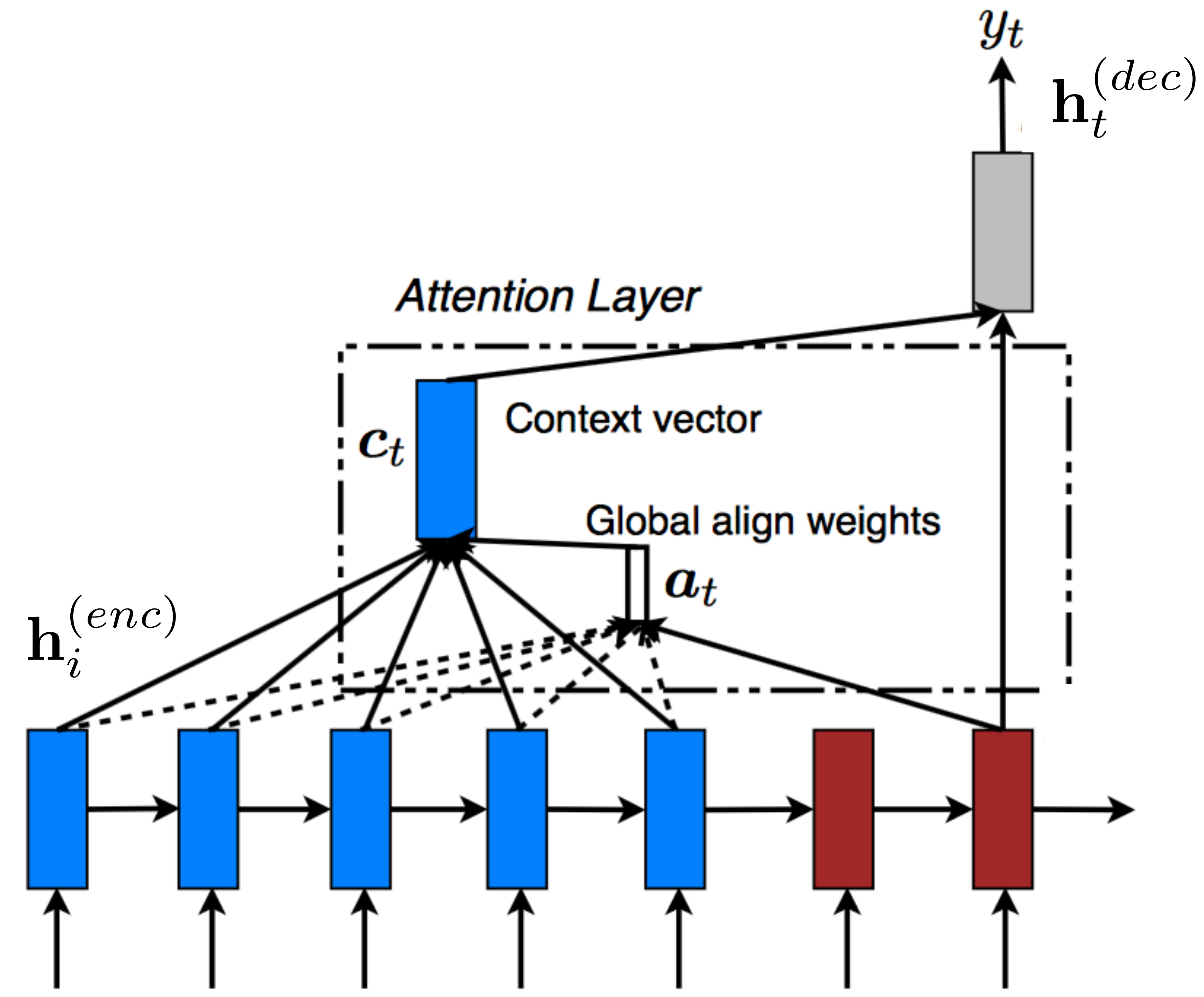
Query: $\mathbf{Q}_t$

$$\beta_{i,t} = score(\mathbf{h}_i^{(enc)}, \mathbf{x}_t^{(dec)})$$

$$\beta_{i,t} = score(\mathbf{h}_i^{(enc)}, \mathbf{h}_{t-1}^{(dec)})$$

$$\beta_{i,t} = score(\mathbf{h}_i^{(enc)}, [\mathbf{x}_t^{(dec)}, \mathbf{h}_{t-1}^{(dec)}])$$

Key: $\mathbf{K}_i$



$$\alpha_{i,t} = \text{Softmax}(\beta_{i,t})$$

Normalize the weights to sum to 1

$$\mathbf{c}_t = \sum_i \alpha_{i,t} \mathbf{h}_i^{(enc)}$$

Value: $\mathbf{V}_i$

Form a context vector that would simply be added to the standard decoder input