Slides, Support, Code and Setup instructions:
bit.ly/hub-setup

Introductions

Keras/LSTM Text Classification Agenda

9:00 - 9:45	Keras/CNN Review	examples/keras-sign
9:45 - 10:30	Simple RNNs and Time Series	examples/lstm/time-series
10:30 - 11:00	Break	
10:30 - 11:00	LSTMs, GRUs applied to Text Generation	examples/lstm/text-gen
11:00 - 12:30	Text Classification with Word Embeddings, Hybrid CNN/LSTMs	examples/lstm/imdb-classifier

Code: github.com/lukas/ml-class

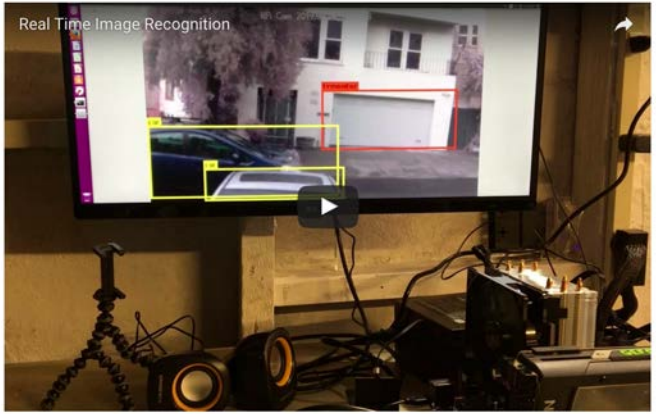

Keras
TensorFlow
CudNN
CUDA
GPU

Build your own box

Build a super fast deep learning machine for under $1,000

The adventures in deep learning and cheap hardware continue!

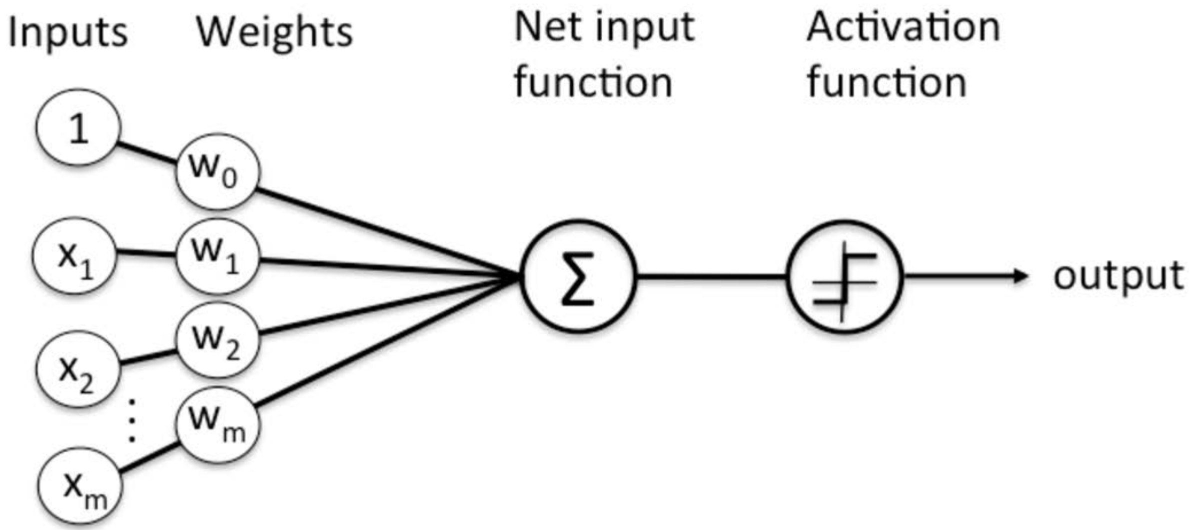
By Lukas Biewald. February 1, 2017



https://www.oreilly.com/learning/build-a-super-fast-deep-learning-machine-for-under-1000

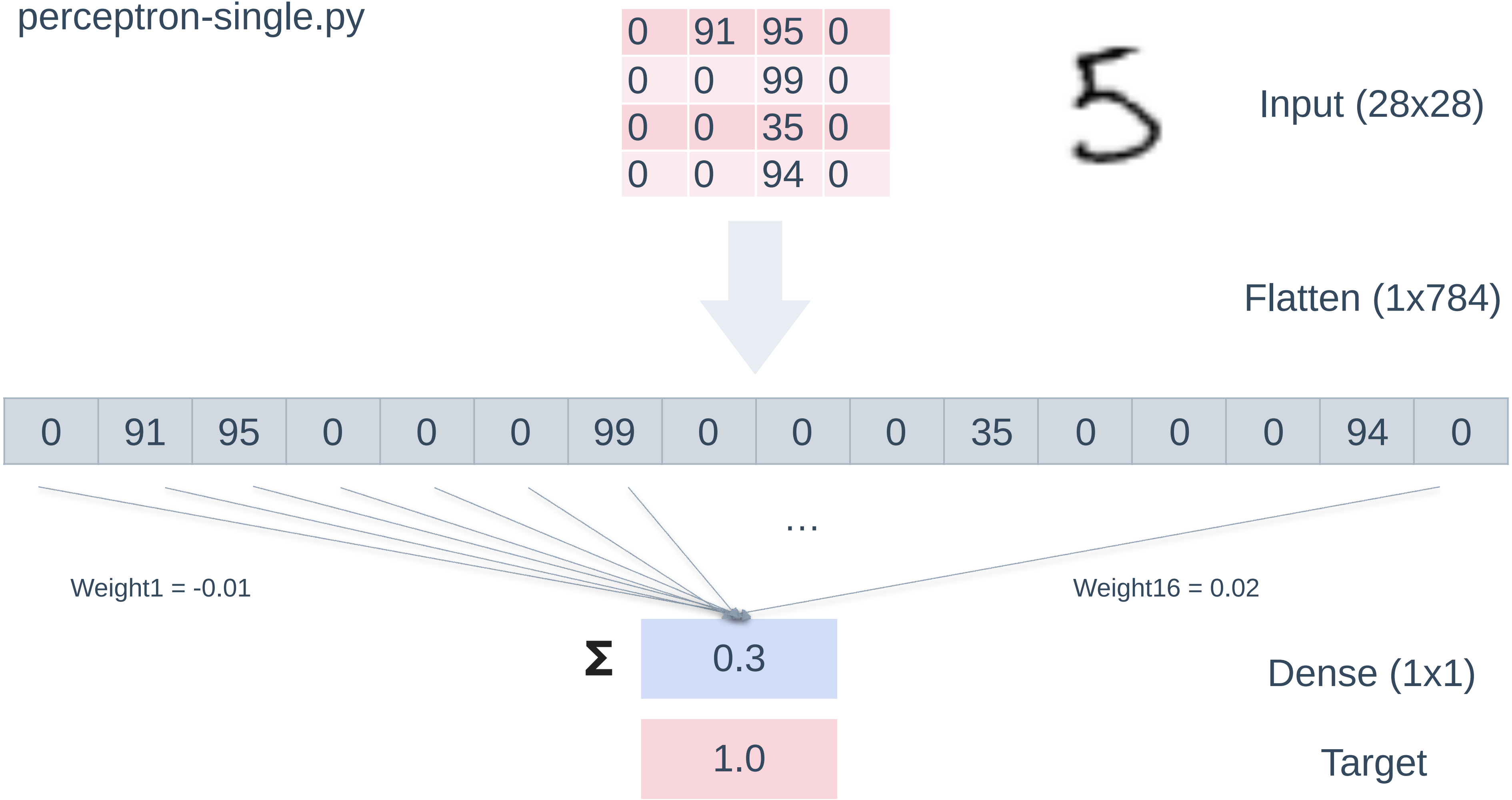
Keras Review (ml-class/examples/keras-sign)

Perceptron

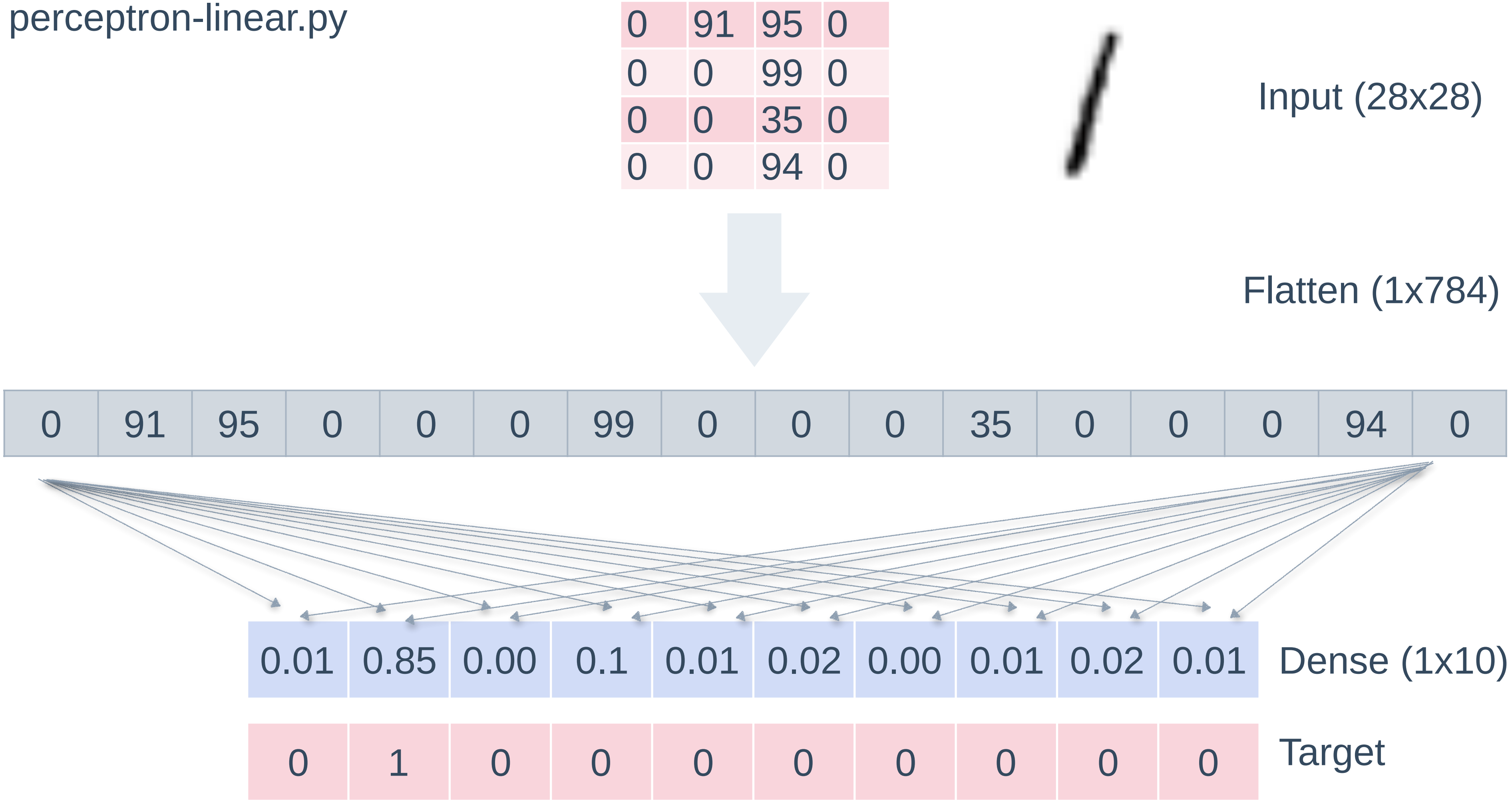


Schematic of Rosenblatt's perceptron.

perceptron-single.py



perceptron-linear.py

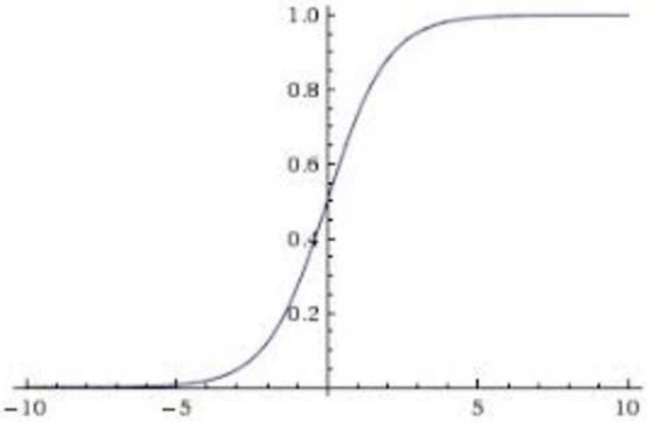


One hot encoding

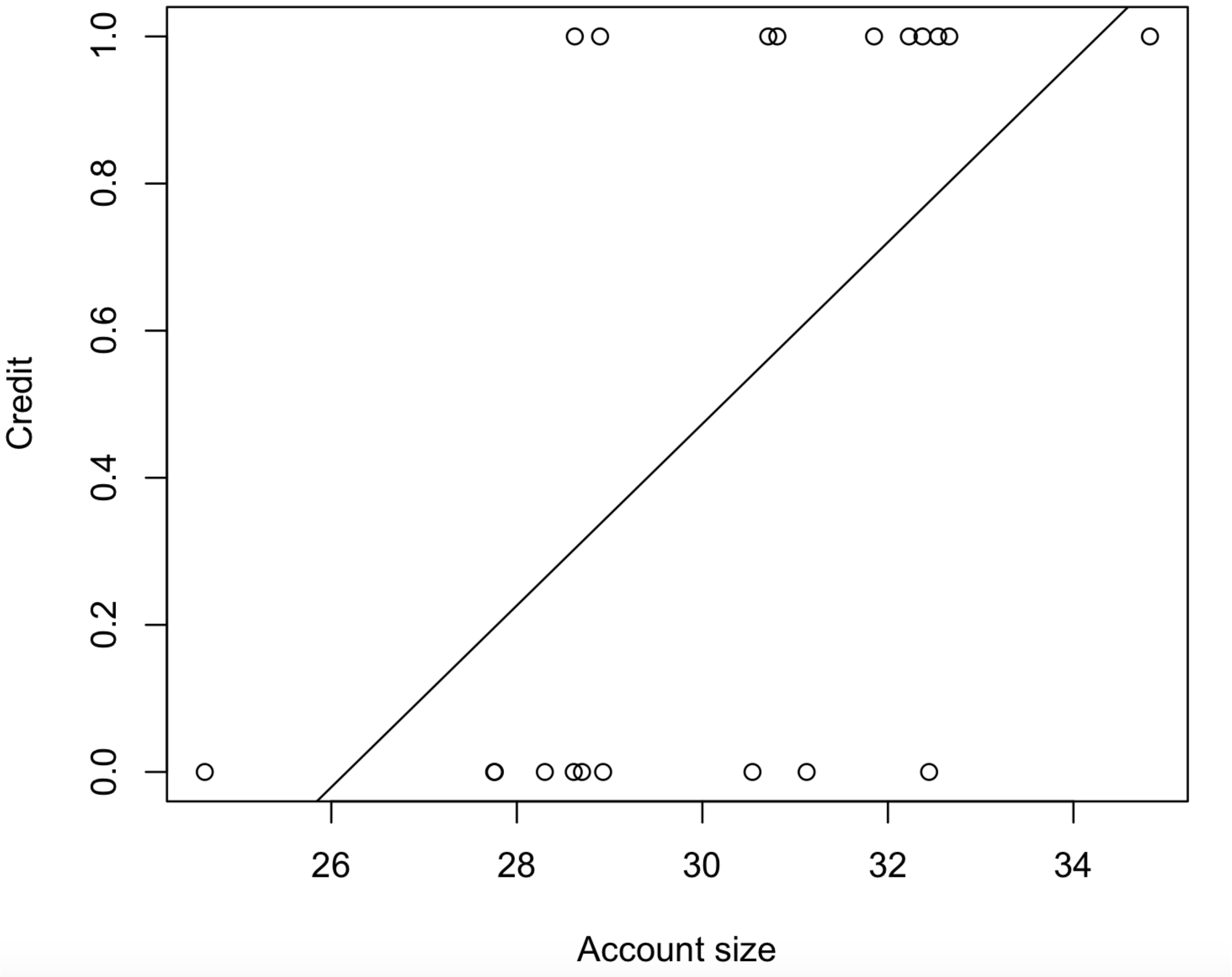
Label
0
4
4
3
0
9

0	1	2	3	4	5	6	7	8	9
1	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1

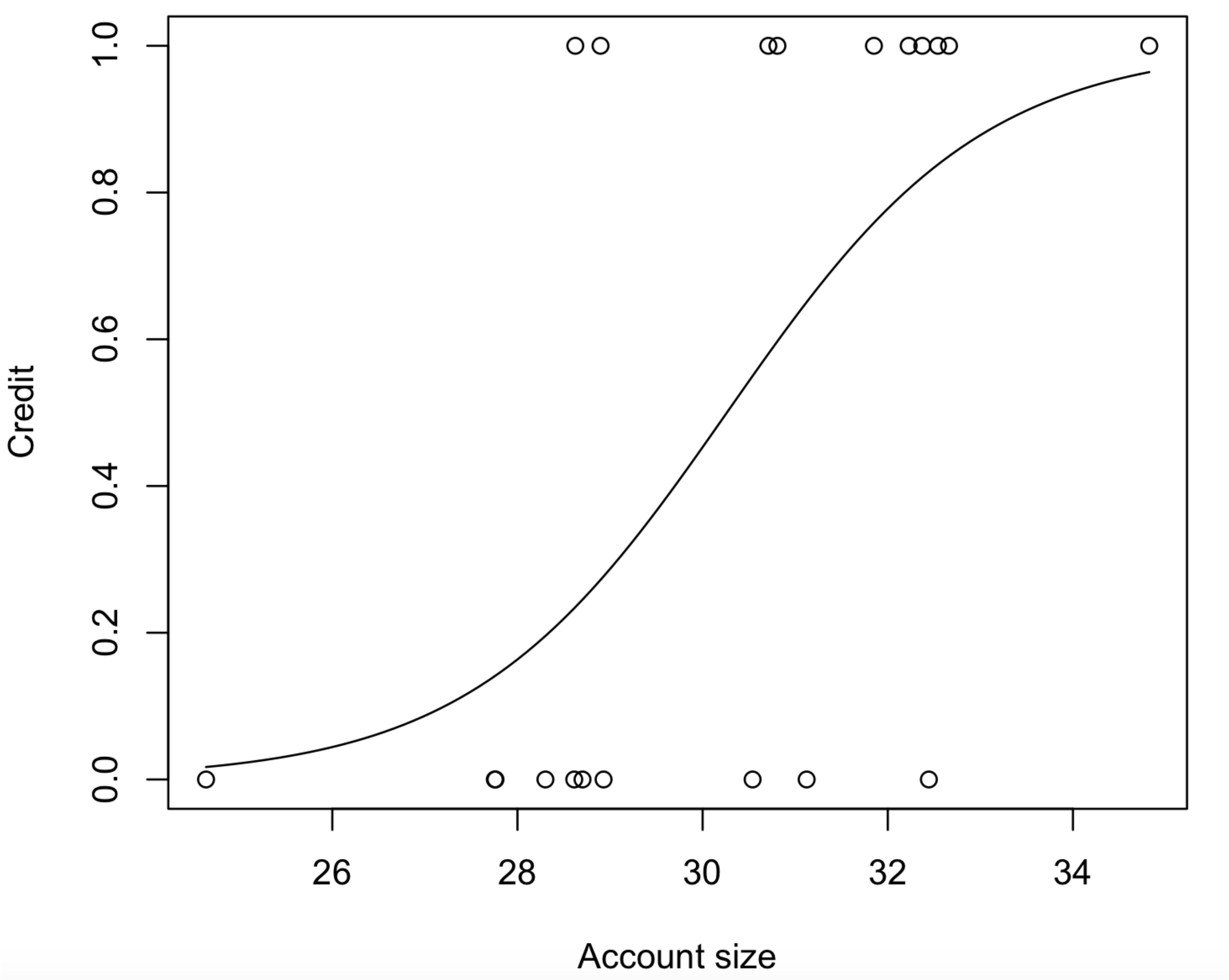
Activation Functions: Sigmoid



(special case of softmax and logistic)

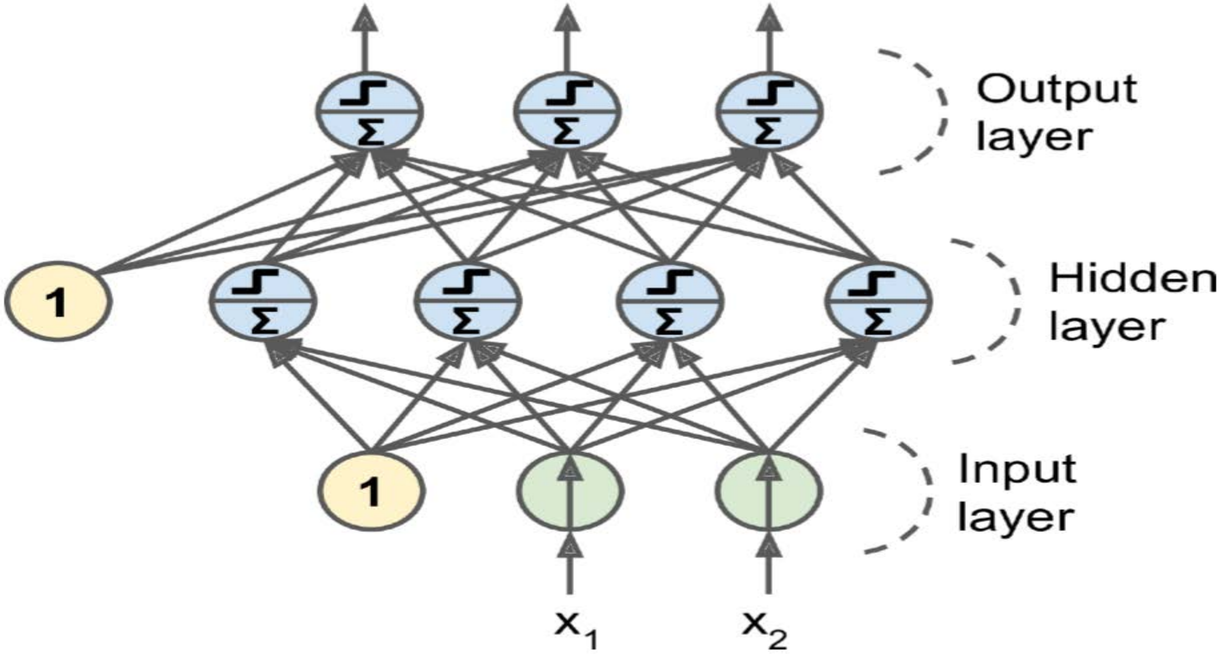


Credit
1.0
0.8
0.6
0.4
0.2
0.0
26
28
30
32
34
Account size

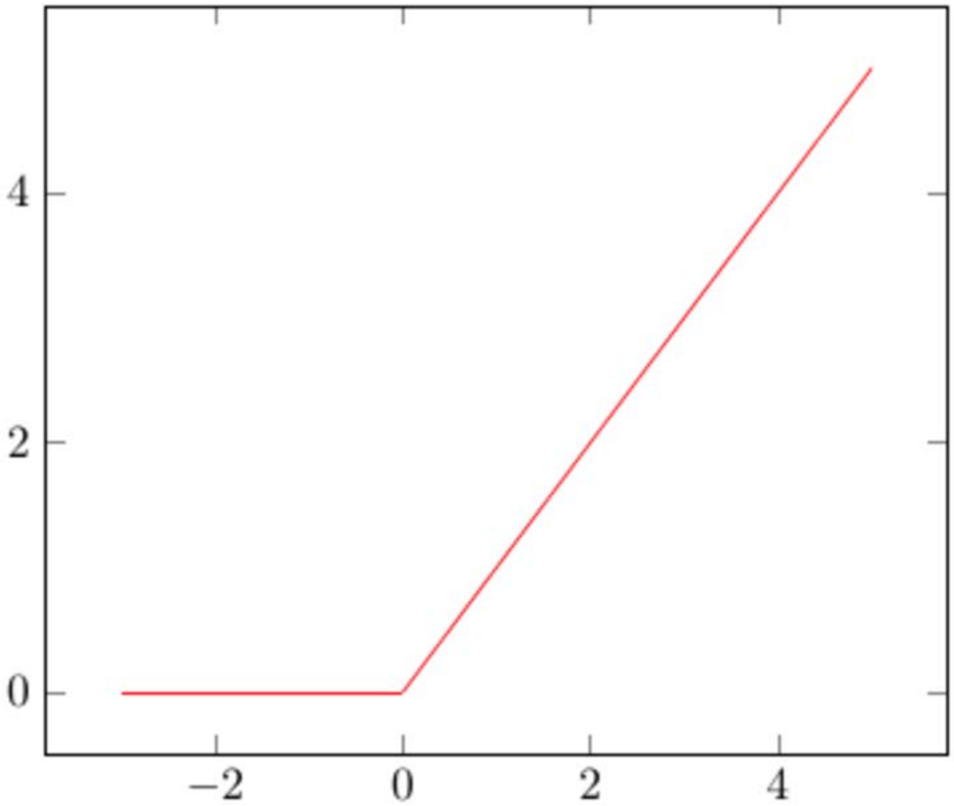


Credit
0.0
0.2
0.4
0.6
0.8
1.0
26
28
30
32
34
Account size

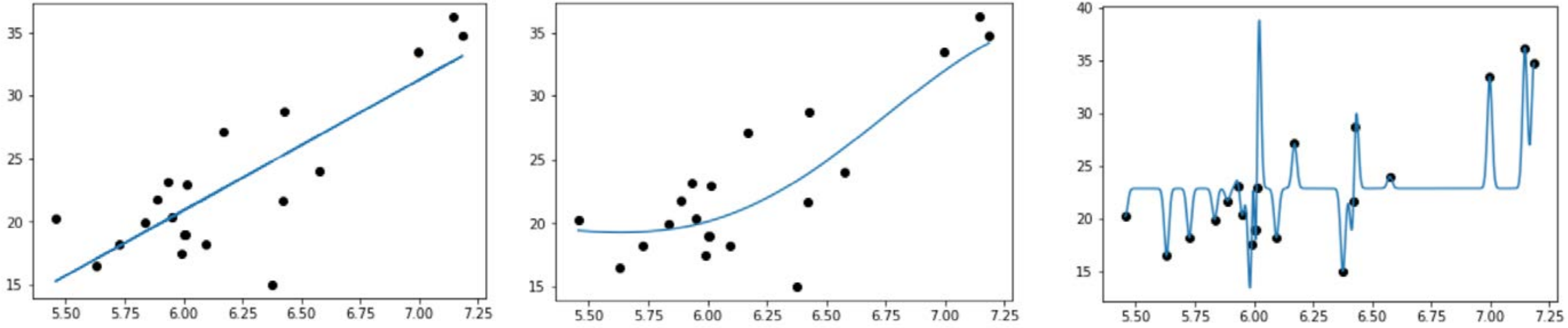
Two Layers of Perceptrons



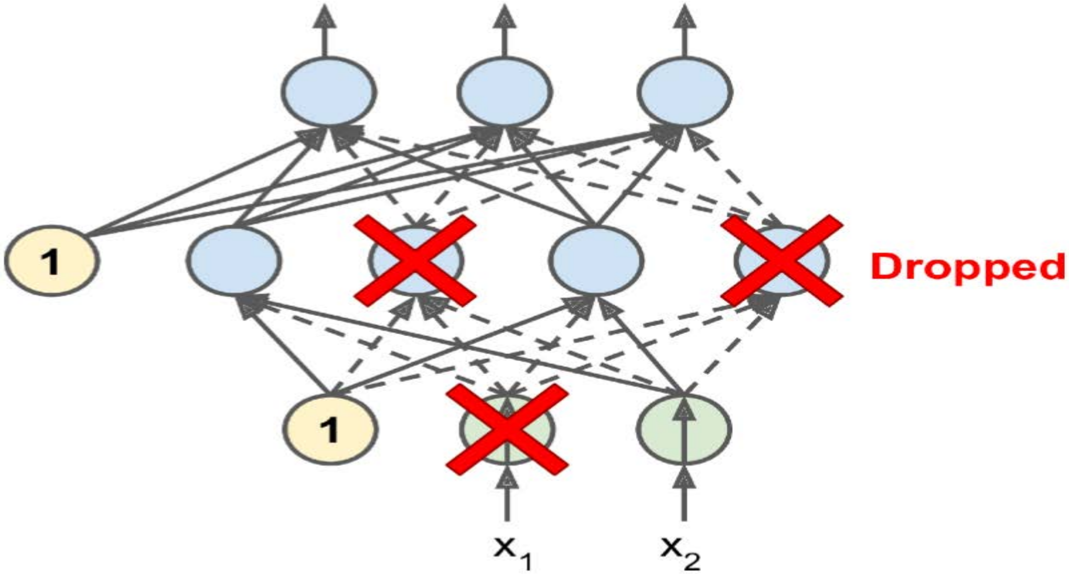
MLP Activation Function: ReLU

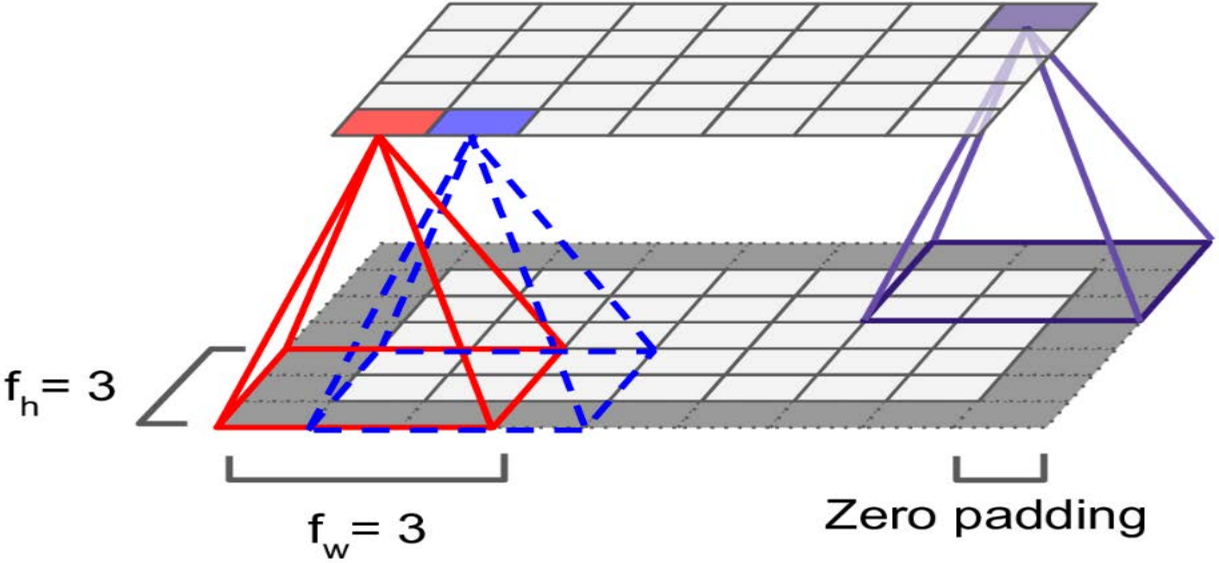


Overfitting

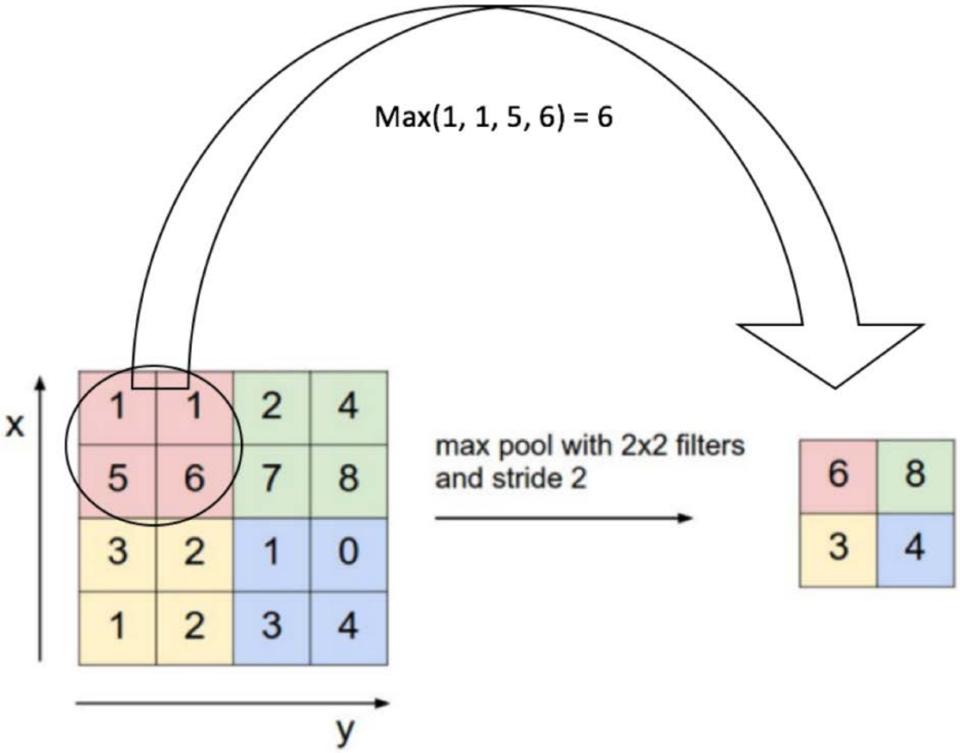


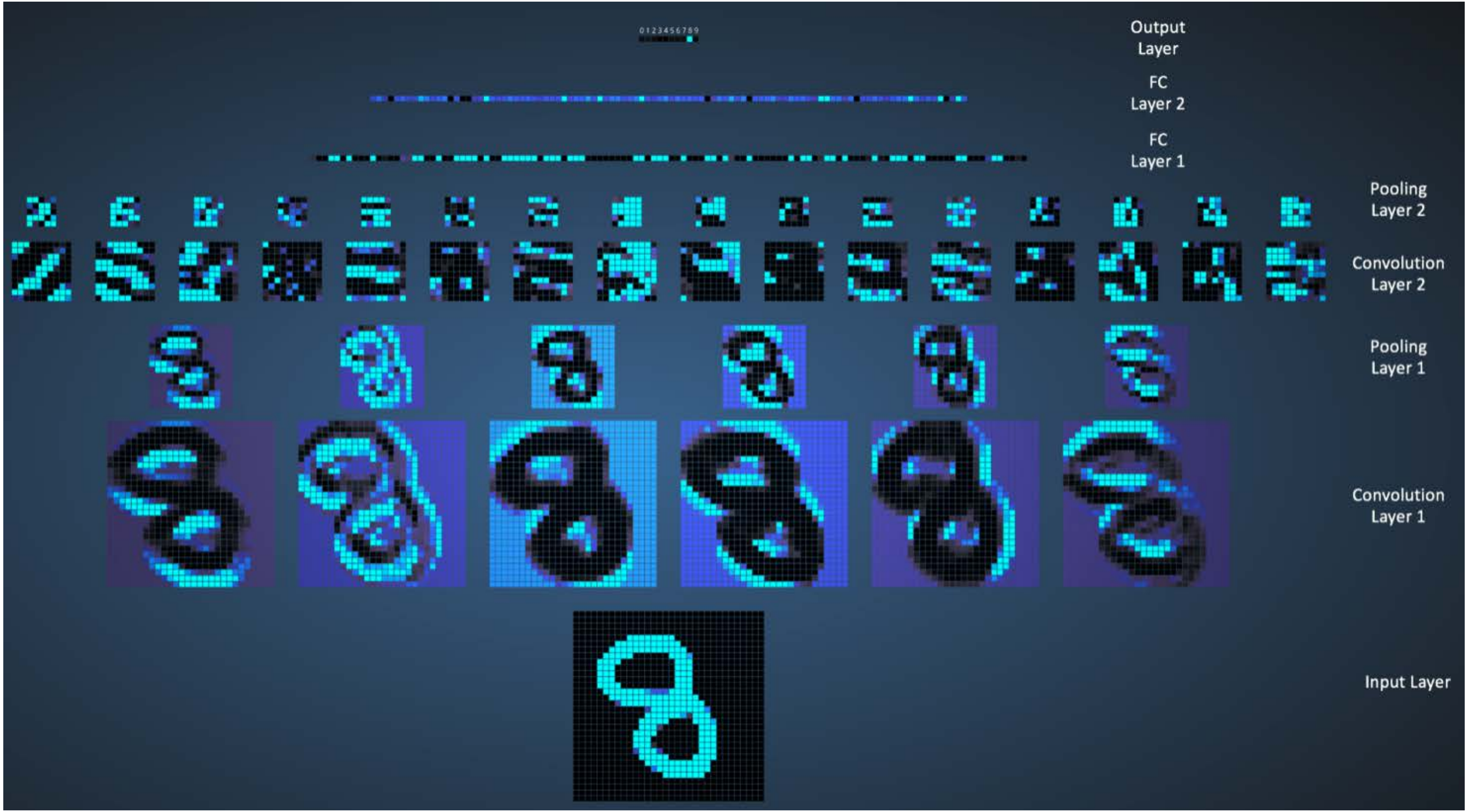
Dropout




$f_h = 3$
$f_w = 3$
Zero padding

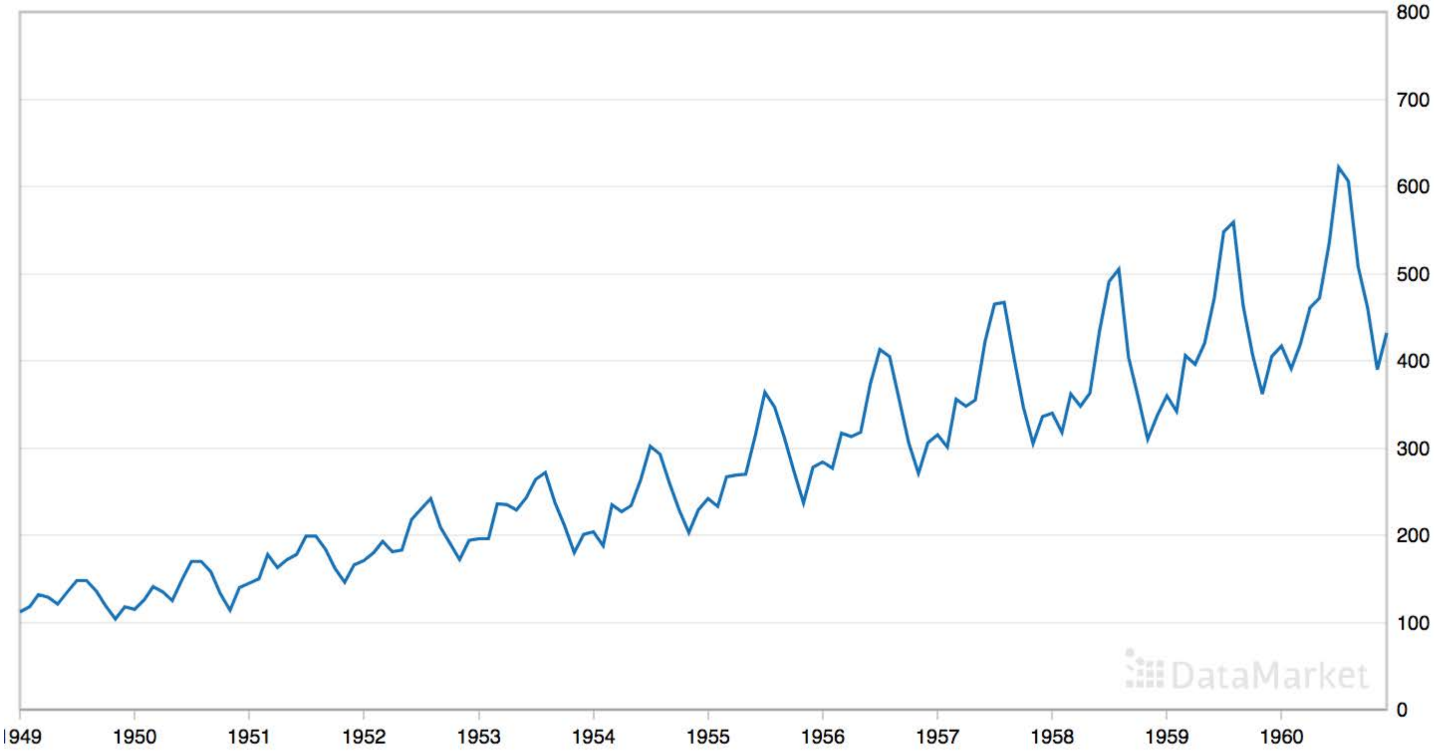
Pooling


Max(1, 1, 5, 6) = 6
x
y
1 1 2 4
5 6 7 8
3 2 1 0
1 2 3 4
max pool with 2x2 filters
and stride 2
6 8
3 4

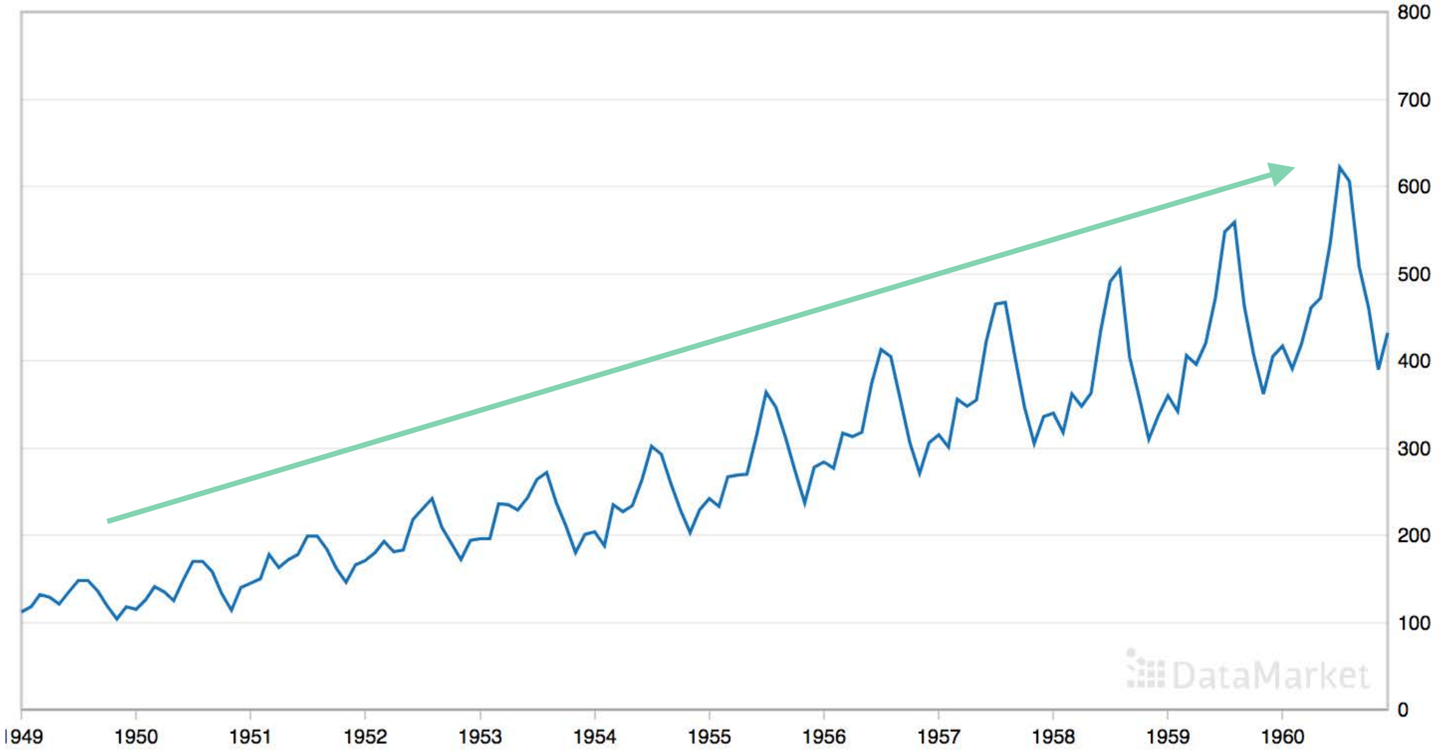

0123456789
Output Layer
FC Layer 2
FC Layer 1
Pooling Layer 2
Convolution Layer 2
Pooling Layer 1
Convolution Layer 1
Input Layer

Time Series and RNNs
(ml-class/examples/lstm/time-series)

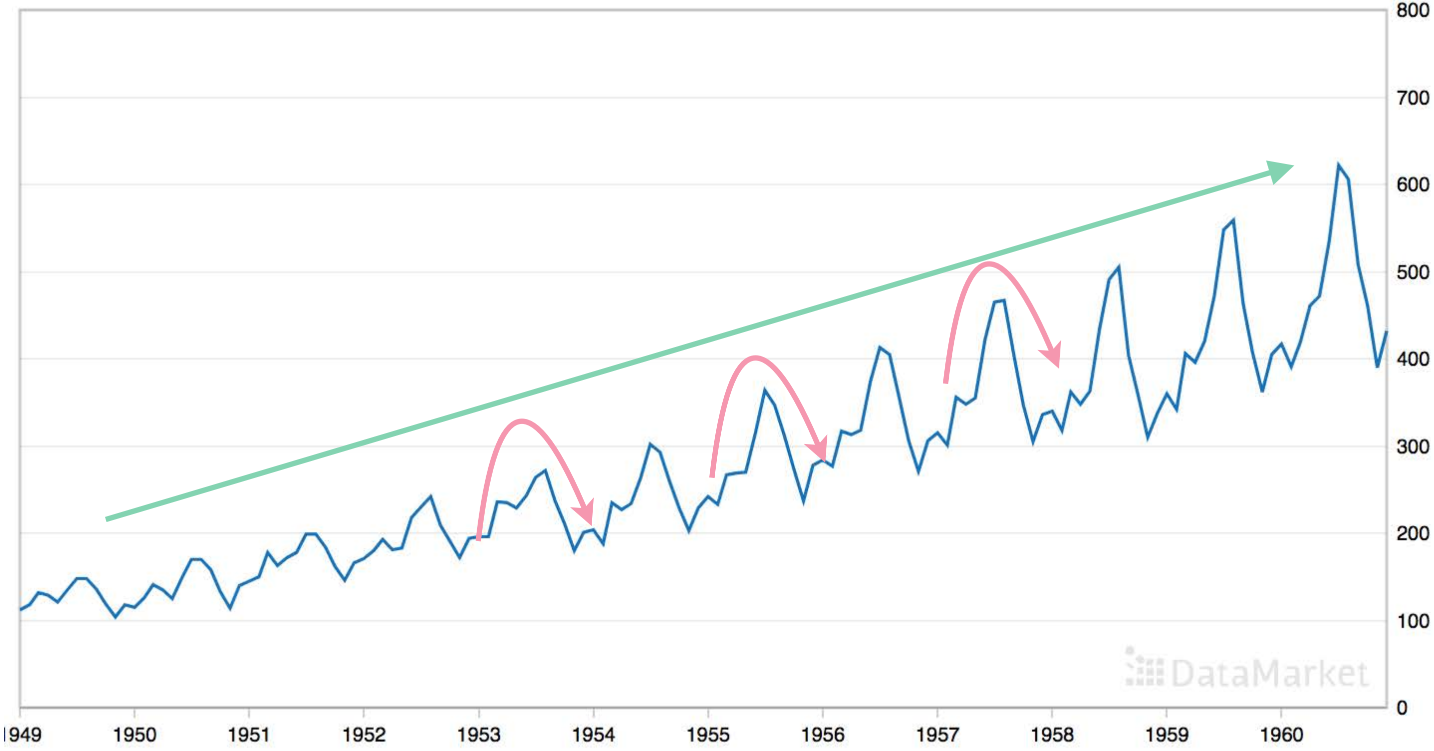
Timeseries (Airline Sales)



Timeseries (Airline Sales)



Timeseries (Airline Sales)



Framing Timeseries as an ML problem

Time	1	2	3	4	5	6	7	8	9	10	11	12	13
Airline Sales	1	3	4	7	11	18	29	31	42	55	62	74	78

Framing Timeseries as an ML problem

Time	1	2	3	4	5	6	7	8	9	10	11	12	13
Airline Sales	1	3	4	7	11	18	29	31	42	55	62	74	78

Train

Label

X1	X2	X3-9	X10	Label
1	3	…	55	62

Framing Timeseries as an ML problem

Time	1	2	3	4	5	6	7	8	9	10	11	12	13
Airline Sales	1	3	4	7	11	18	29	31	42	55	62	74	78

Train

Label

X1	X2	X3-9	X10	Label
1	3	…	55	62
3	4	…	62	74

Framing Timeseries as an ML problem

Time	1	2	3	4	5	6	7	8	9	10	11	12	13
Airline Sales	1	3	4	7	11	18	29	31	42	55	62	74	78

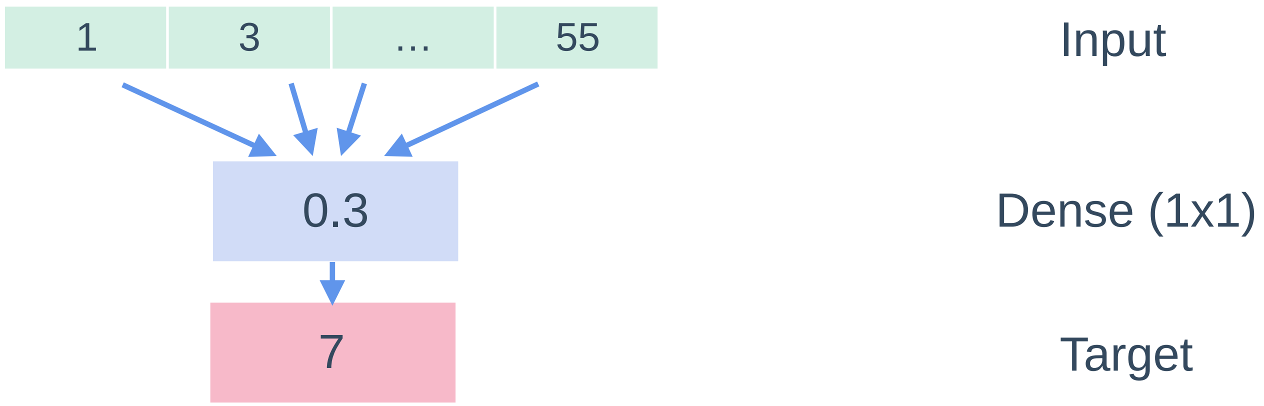
Train

Label

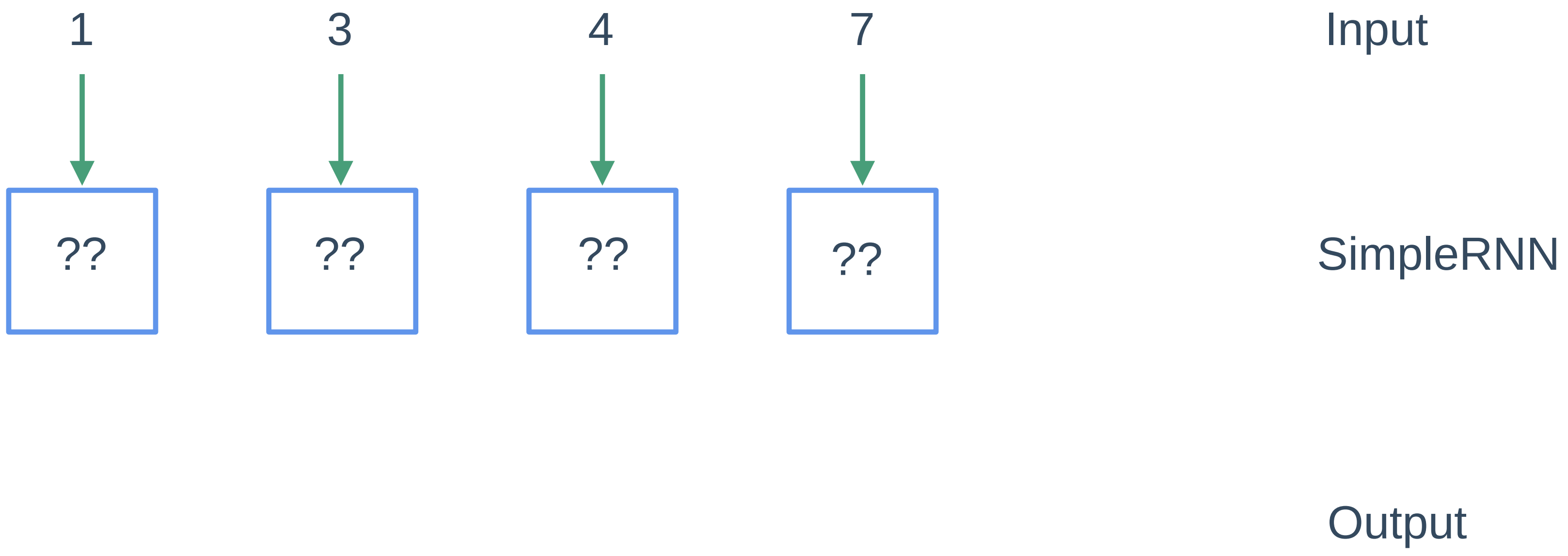
X1	X2	X3-9	X10	Label
1	3	…	55	62
3	4	…	62	74
4	7	…	74	78

Perceptron Classifier on Timeseries

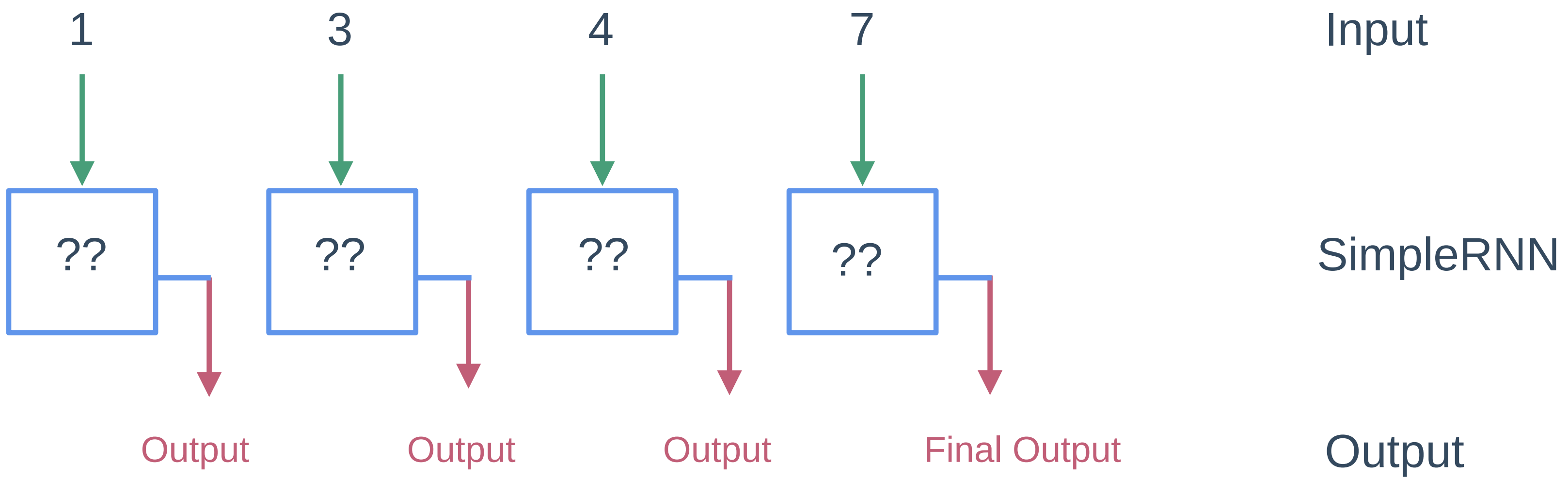
X1	X2	X3-9	X10	Label
1	3	…	55	62
3	4	…	62	74
4	7	…	74	78



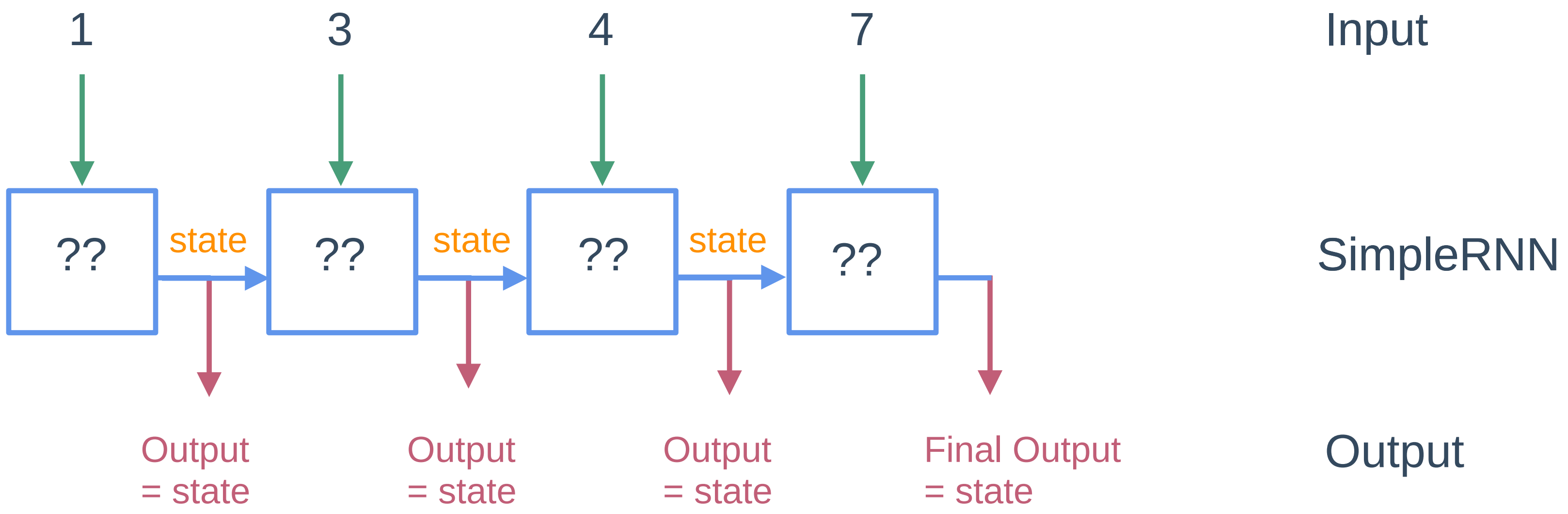
Recurrent Neural Network (RNN)



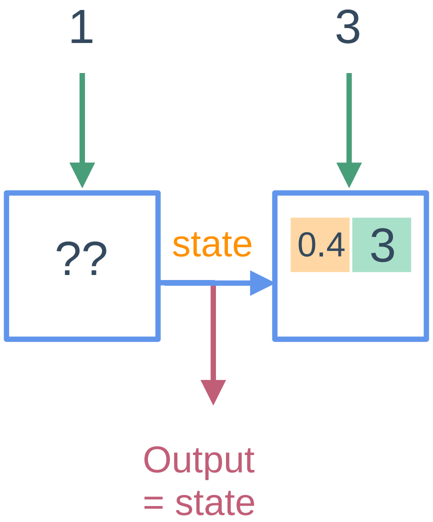
Recurrent Neural Network (RNN)



Recurrent Neural Network (RNN)



RNN



Input

SimpleRNN

Output

Inside the RNN

State	Input
0.4	3

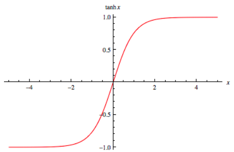
Input

0.2	0.4

Learned Weights

0.2*0.4 + 0.4*3 = 1.28

Weighted Sum

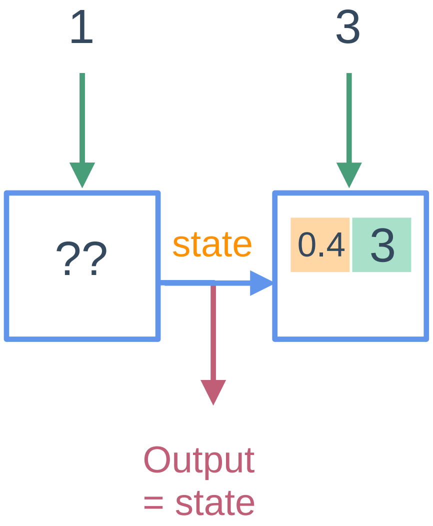


Activation Function

0.9

Output

RNN



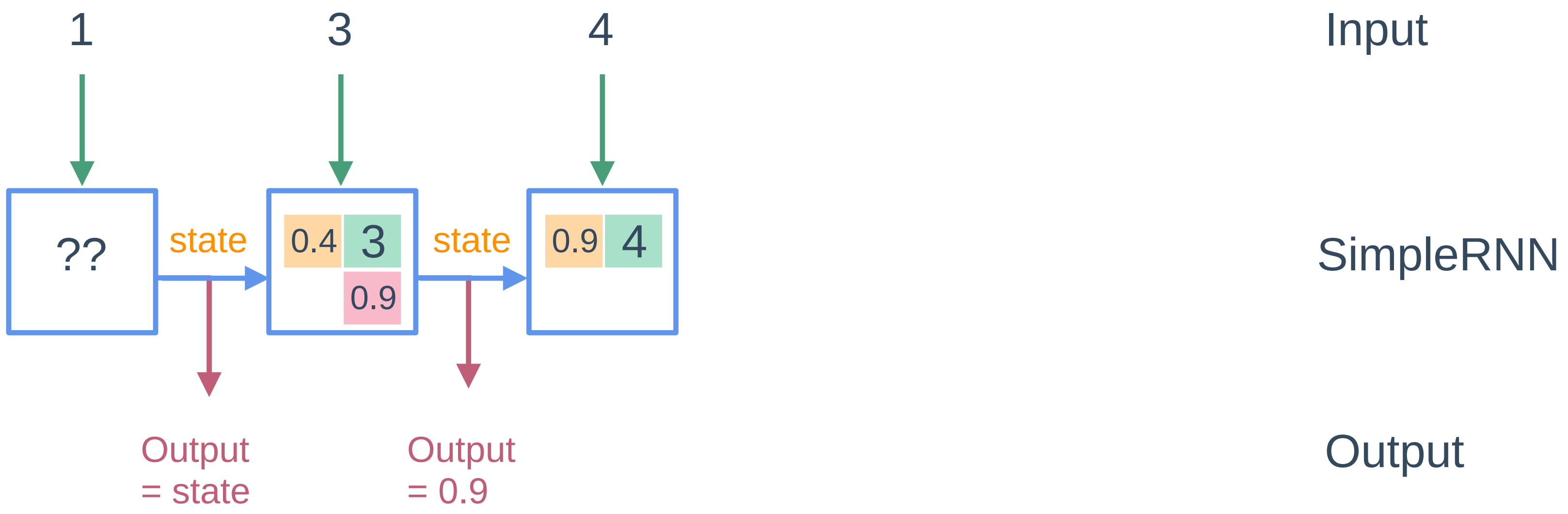
Input

SimpleRNN

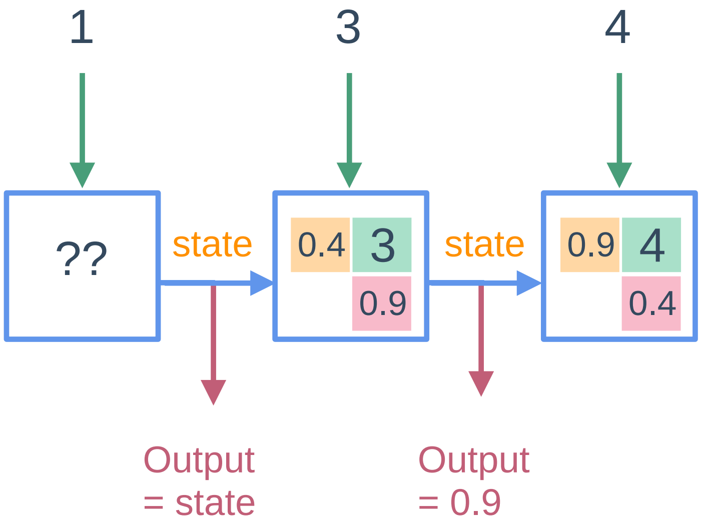
Output

Recurrent Neural Network (RNN)

Recurrent Neural Network (RNN)



Recurrent Neural Network (RNN)

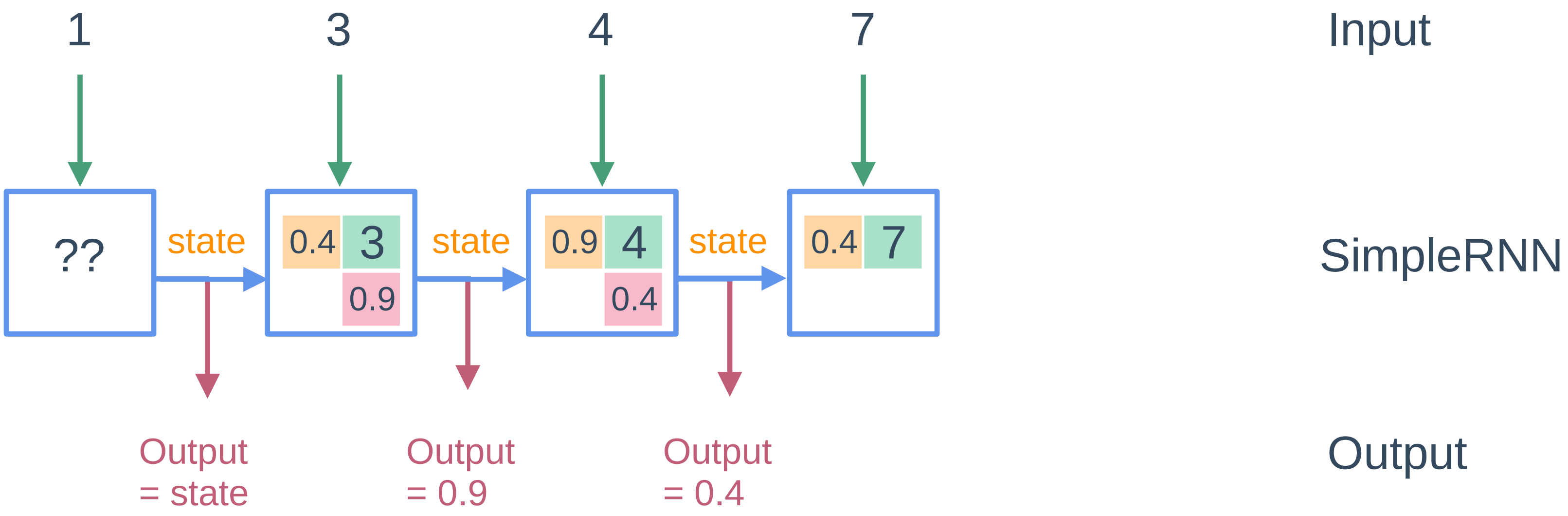


Input

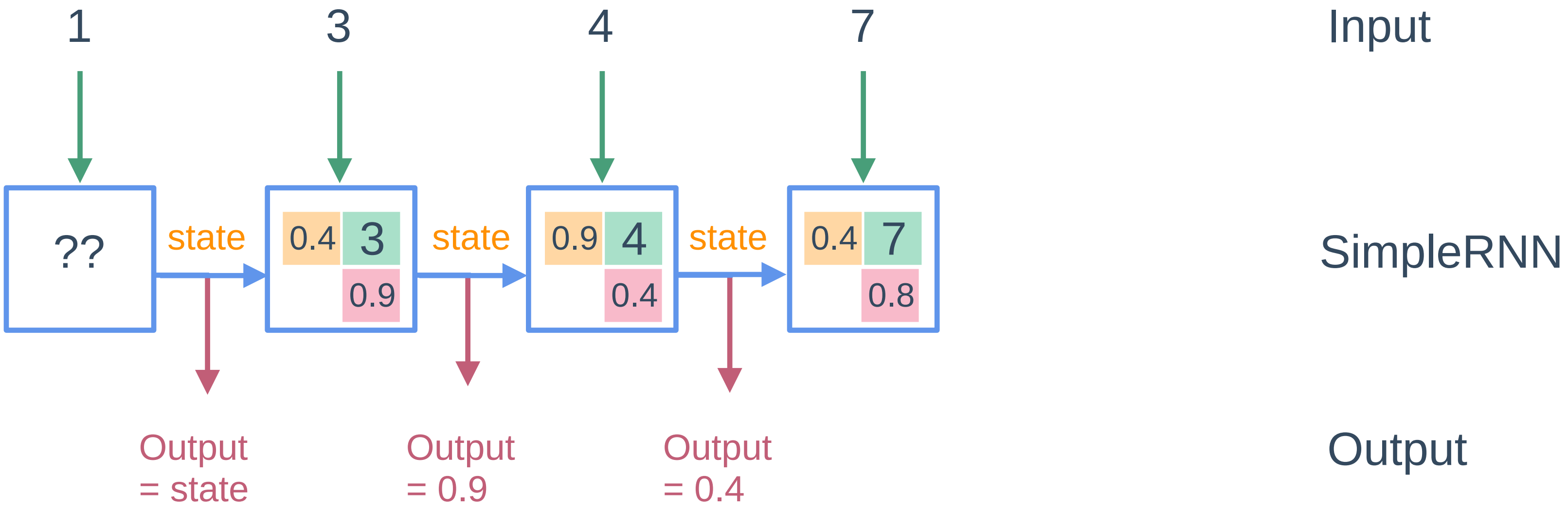
SimpleRNN

Output

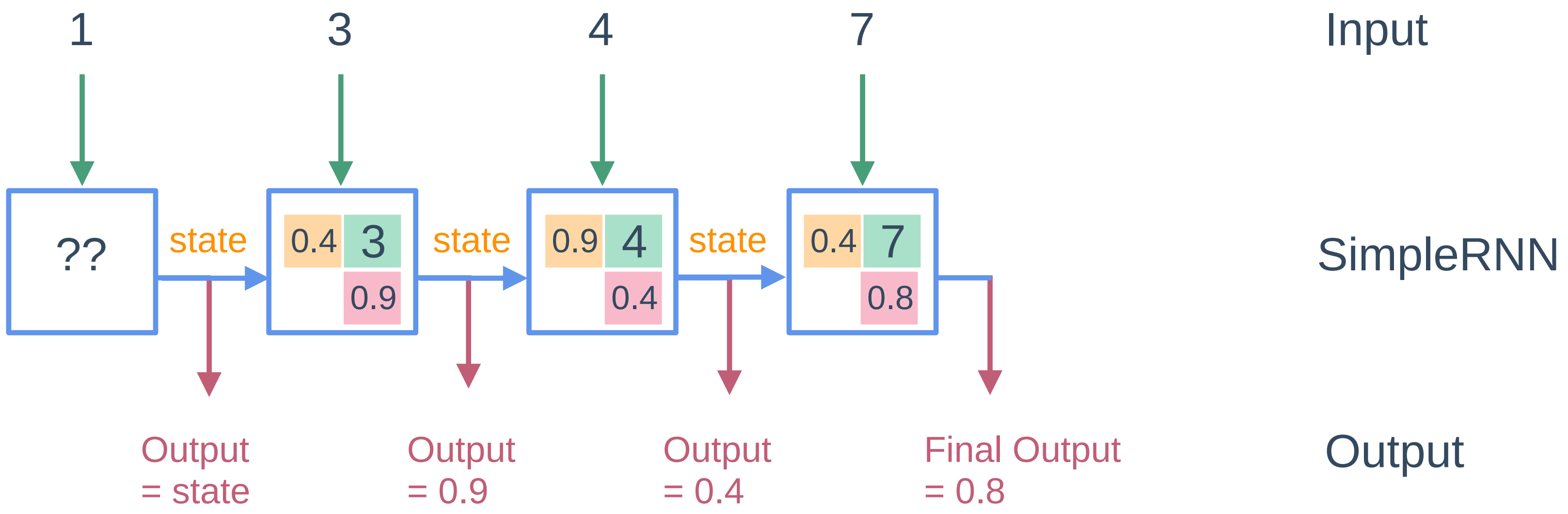
Recurrent Neural Network (RNN)



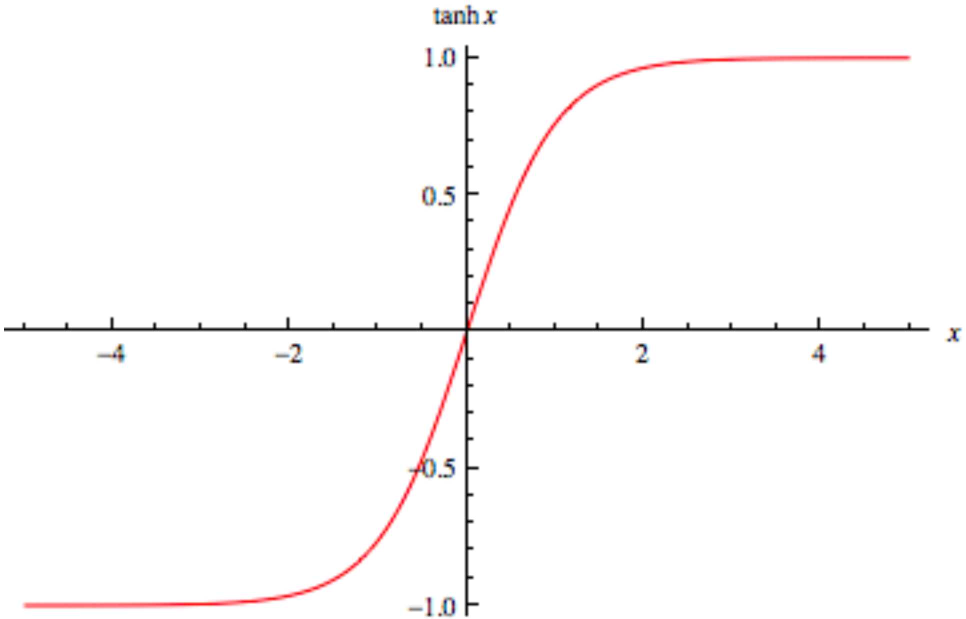
Recurrent Neural Network (RNN)



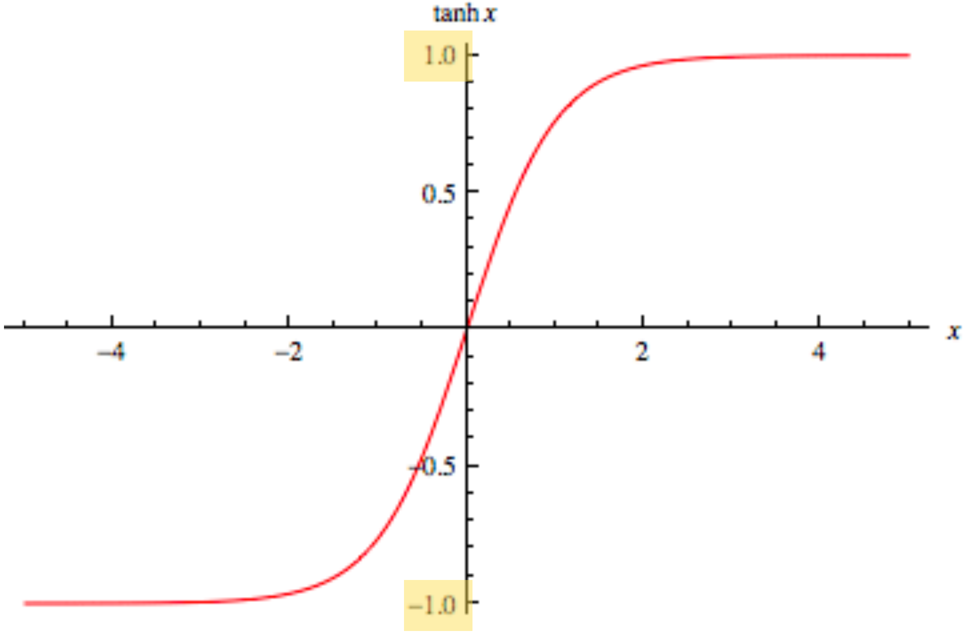
Recurrent Neural Network (RNN)



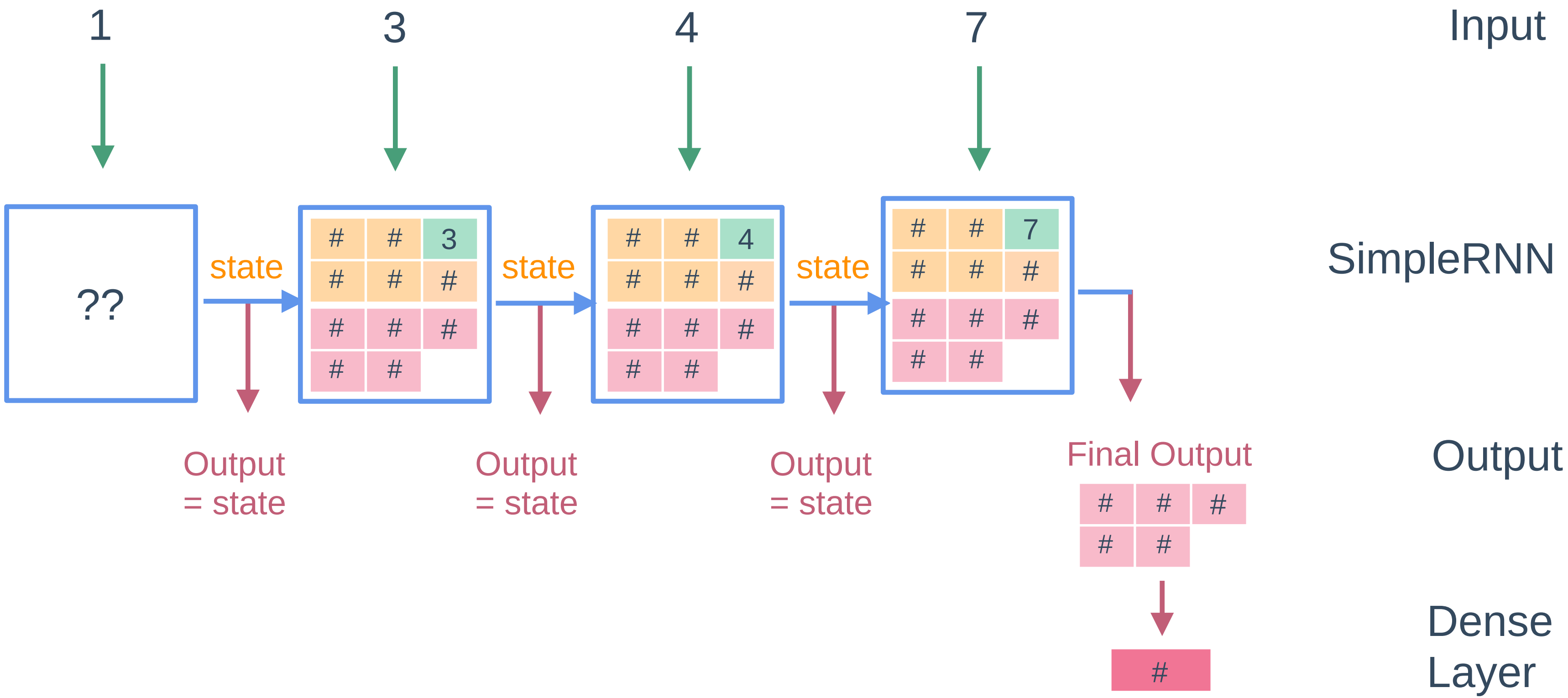
Hyperbolic Tangent Activation Function (tanh)



Hyperbolic Tangent Activation Function (tanh)



Multidimensional State RNN



LSTMs, GRUs & Text Generation

ml-class/examples/lstm/text-gen

Machine learning generated pranks

Put a pair of pants and shoes into your ice dispenser

Put marbles in the refrigerator

A meat and mash potato sundae makes for quite the hand soap dispenser

(Generated with an LSTM at aiweirdness.com)

One-hot encoding

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
L	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
K	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0

Text as time series (character-level)

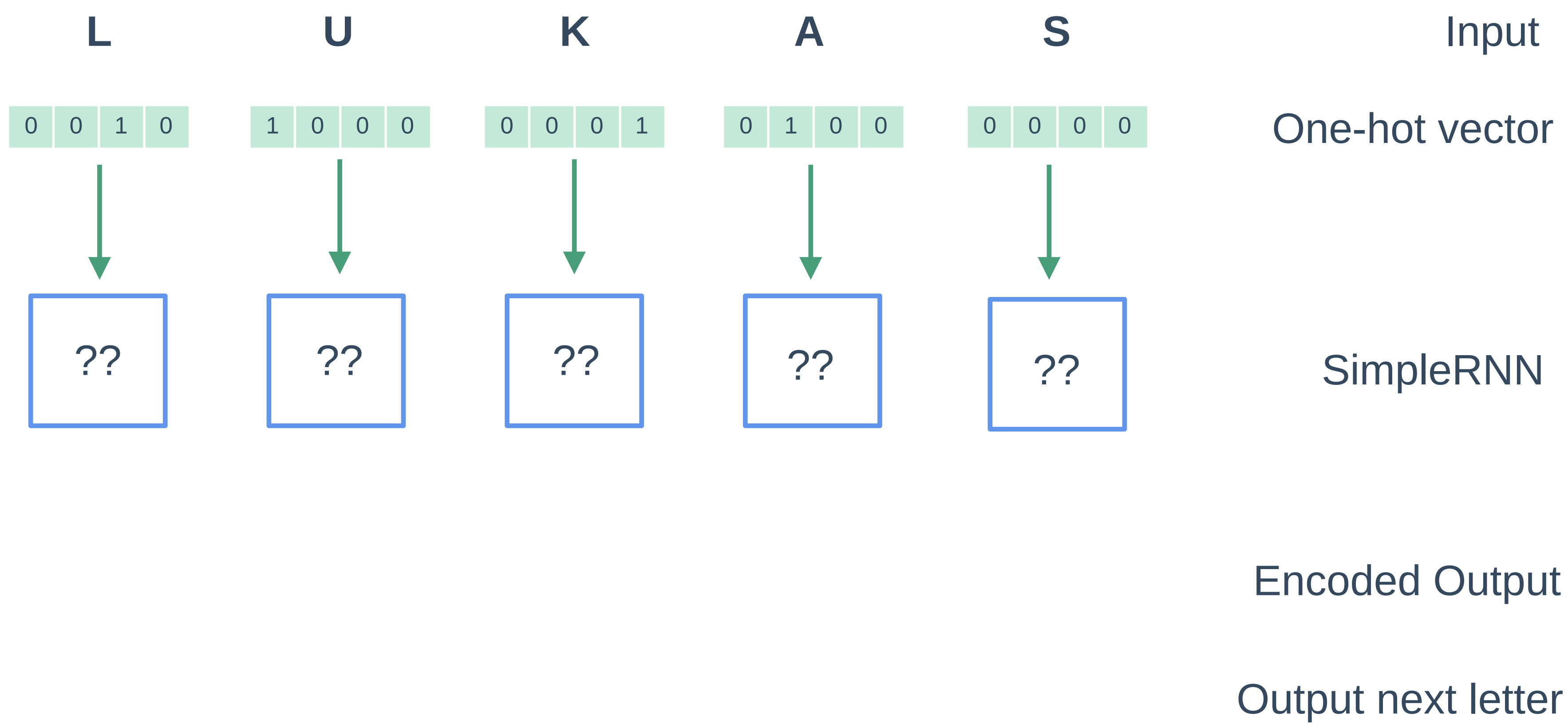
L	U	K	A	S	Input
0 0 1 0	1 0 0 0	0 0 0 1	0 1 0 0	0 0 0 0	One-hot vector

SimpleRNN

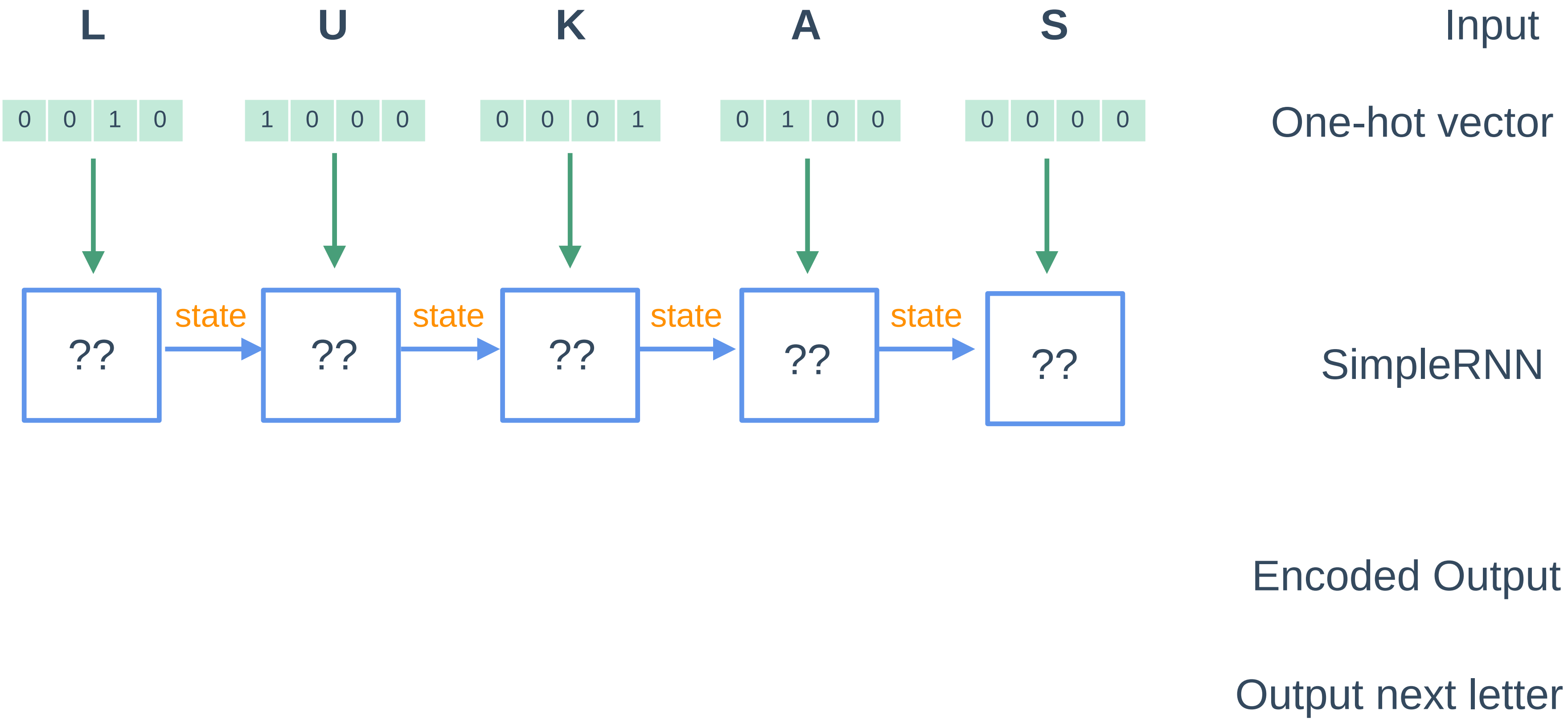
Encoded Output

Output next letter

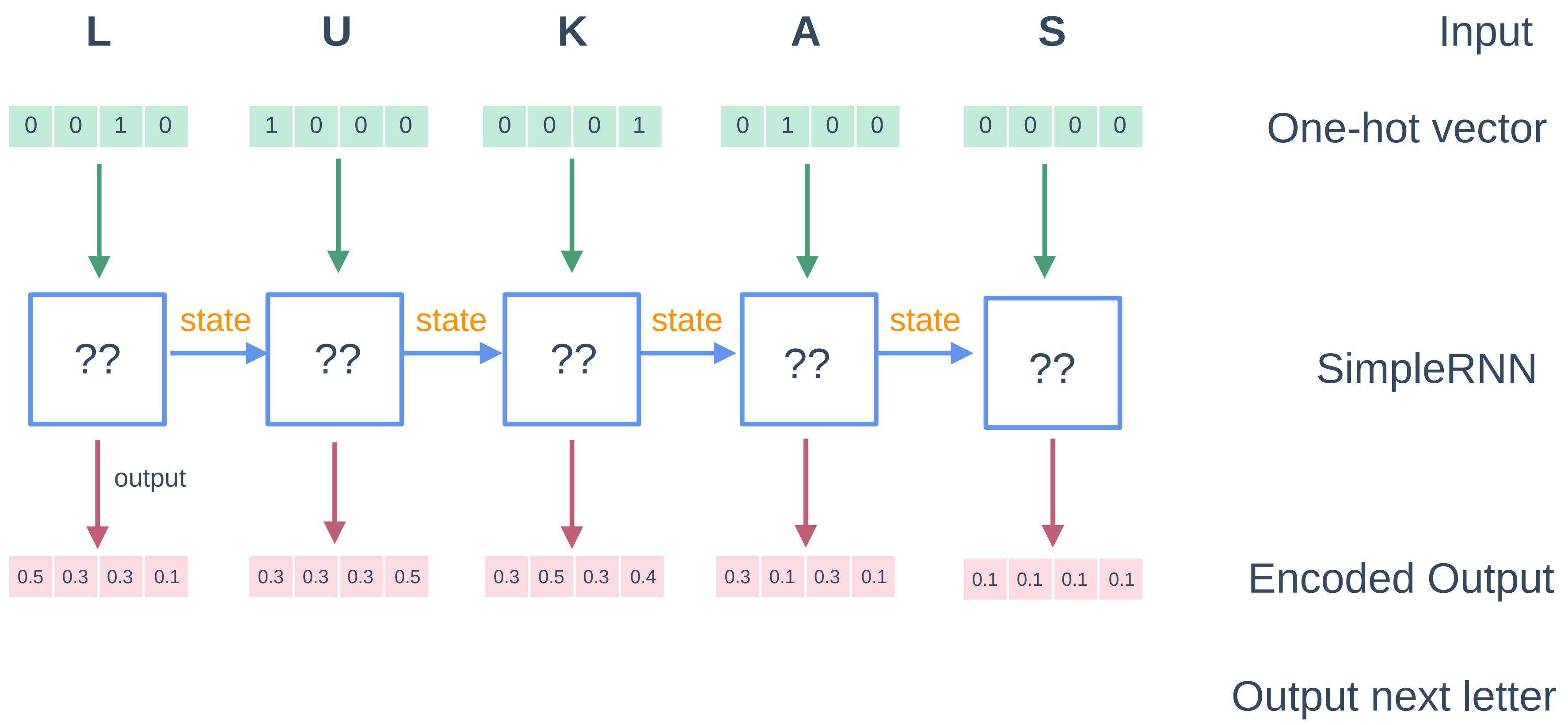
Text as time series (character-level)



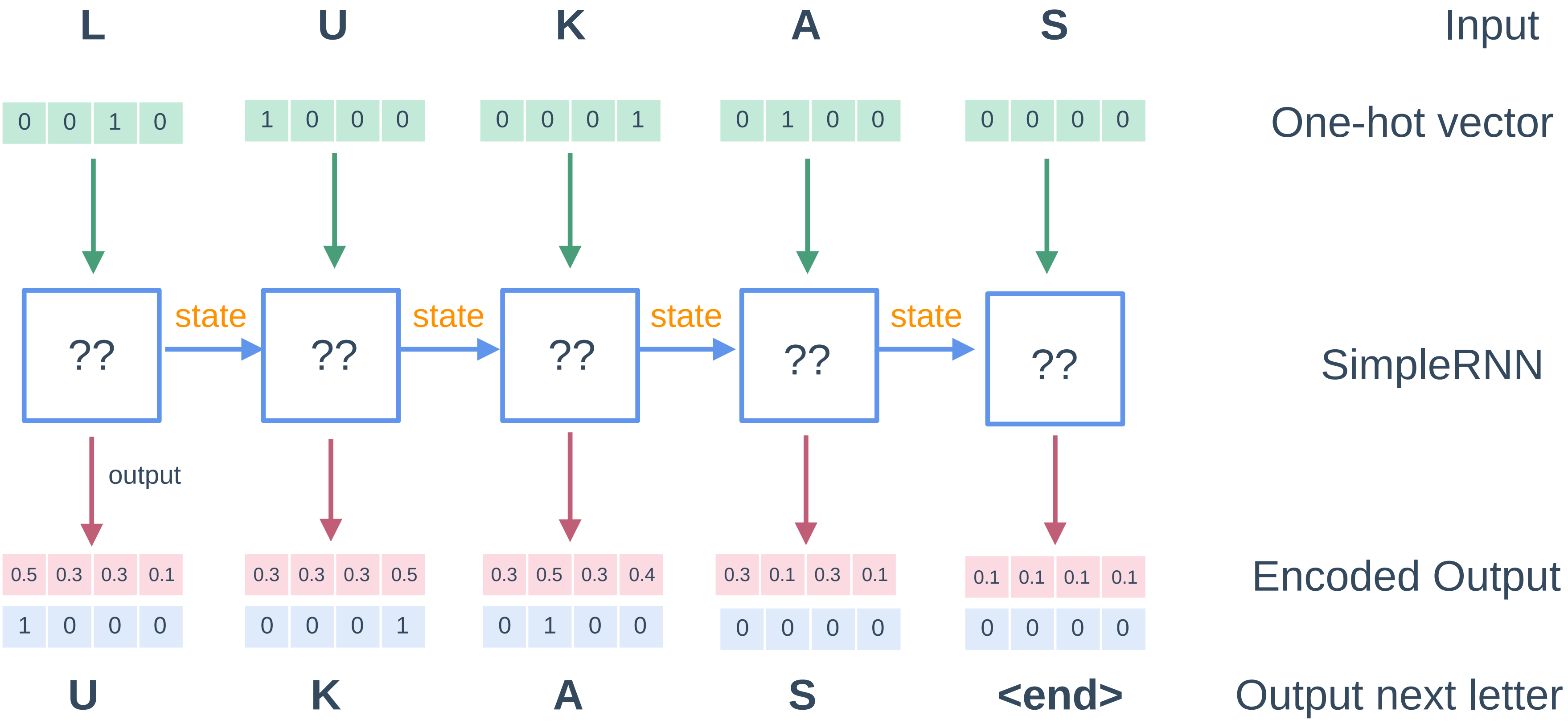
Text as time series (character-level)



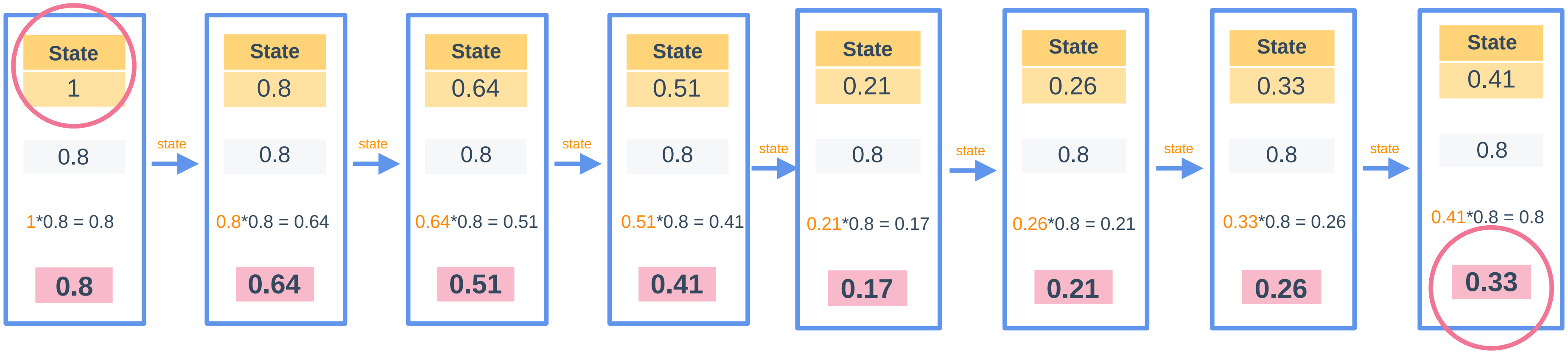
Text as time series (character-level)



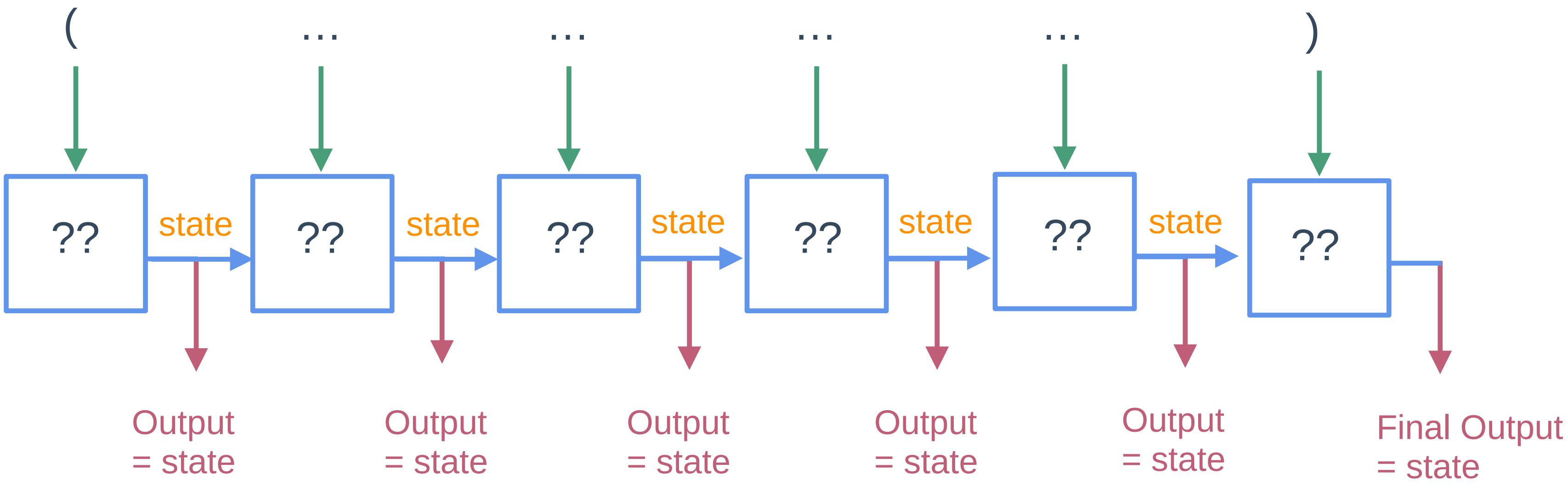
Text as time series (character-level)



The problem with simple RNNs



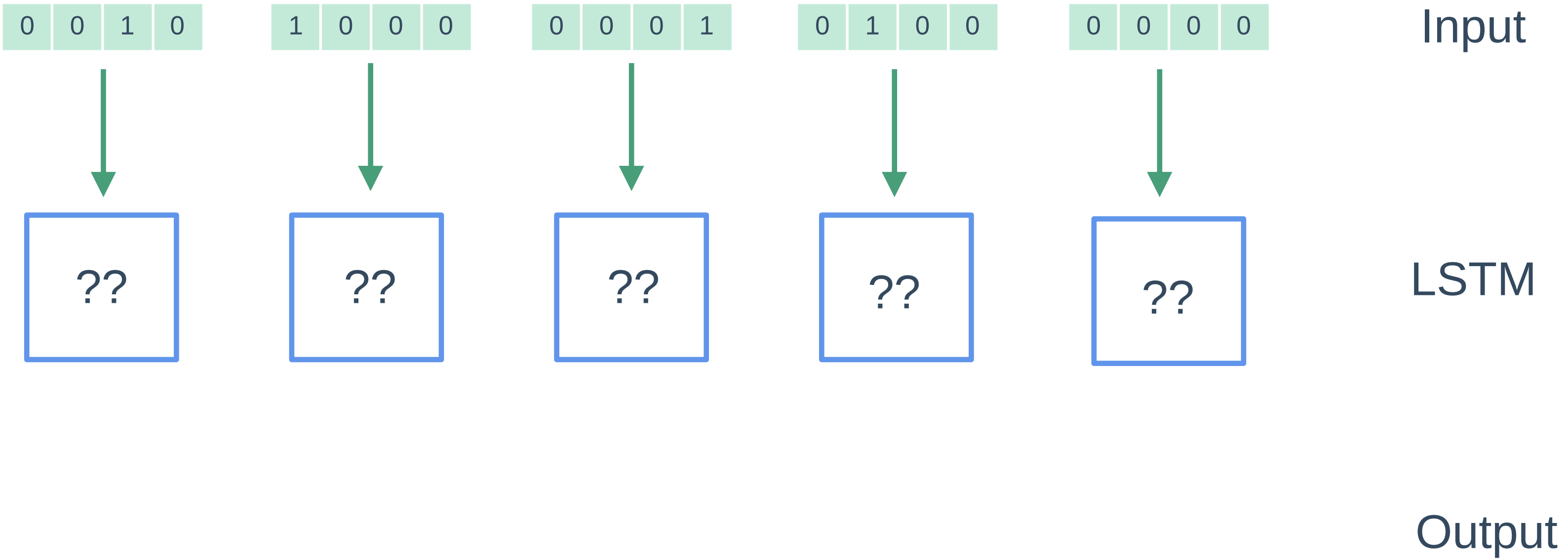
The problem with simple RNNs



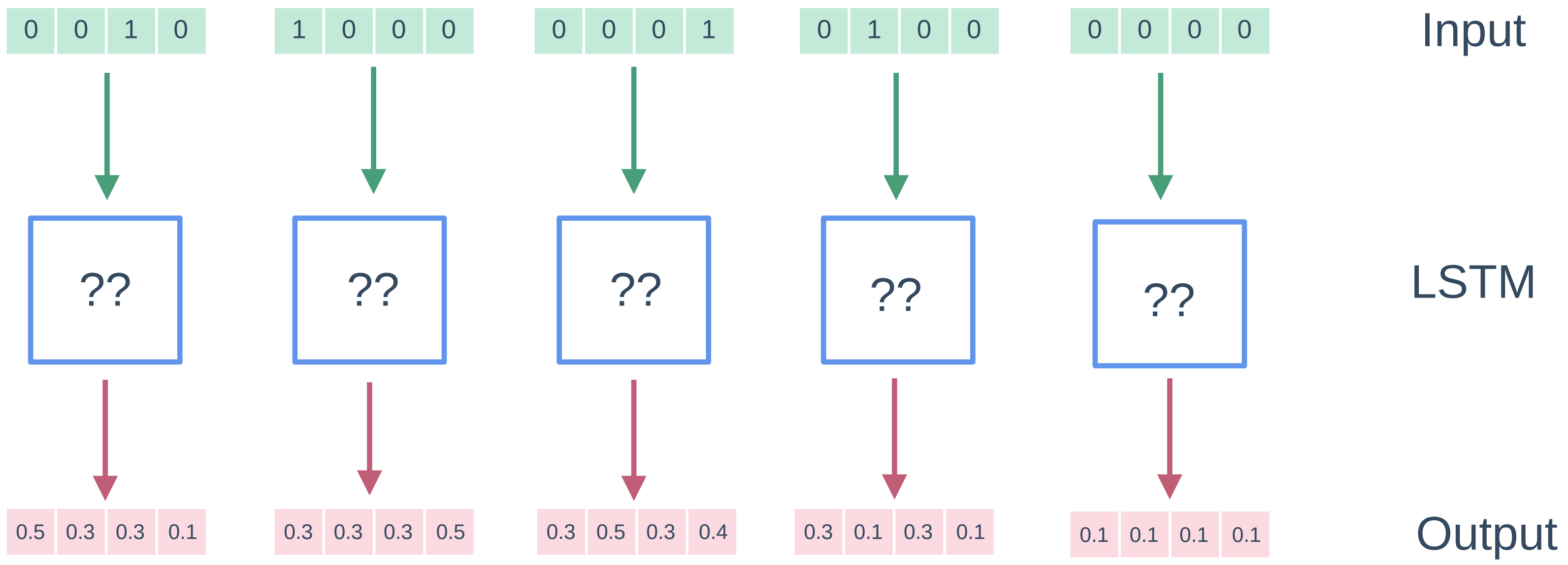
Long Short Term Memory (LSTM) 1997

$$
\begin{aligned}
f_t &= \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \\
i_t &= \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \\
o_t &= \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \\
c_t &= f_t \circ c_{t-1} + i_t \circ \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \\
h_t &= o_t \circ \sigma_h(c_t)
\end{aligned}
$$

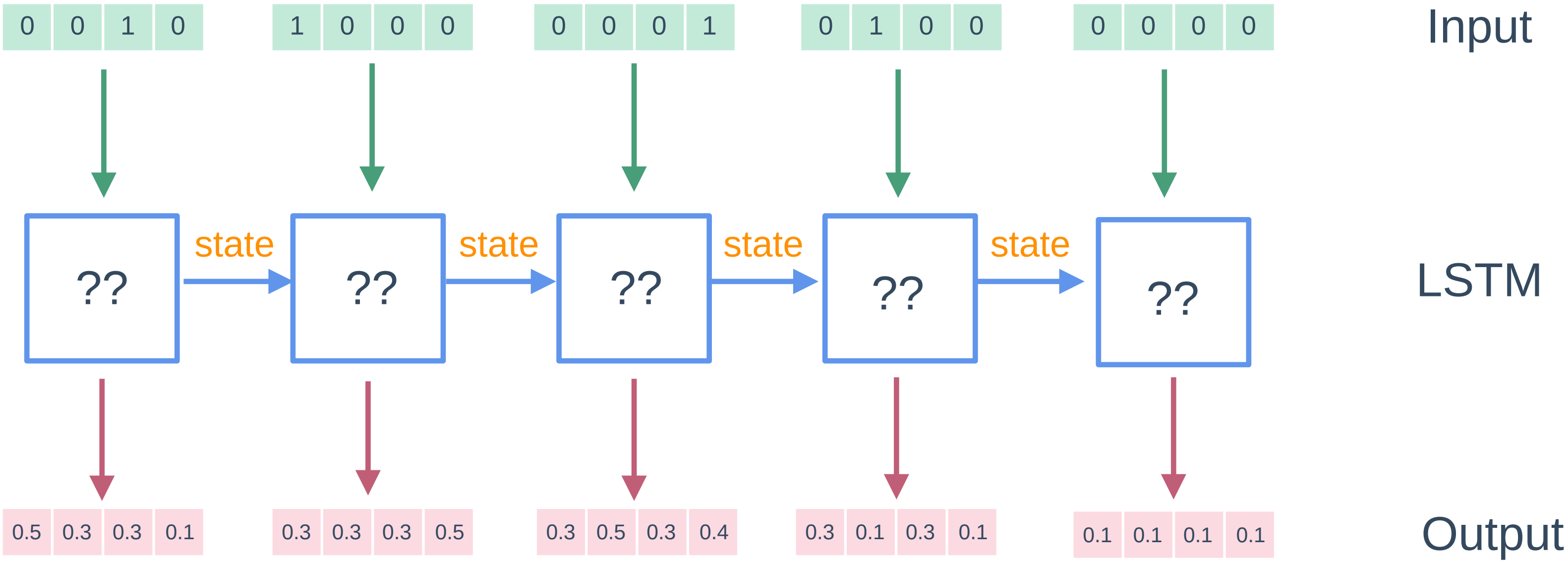
LSTM



LSTM

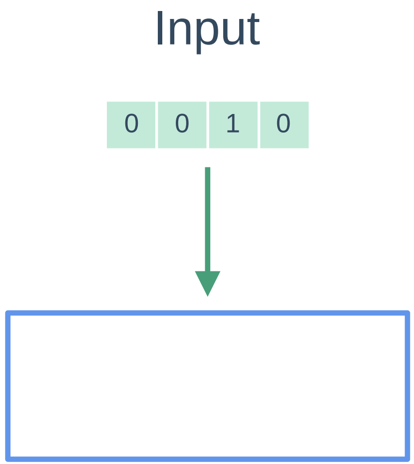

0 0 1 0
1 0 0 0
0 0 0 1
0 1 0 0
0 0 0 0
Input
??
??
??
??
??
LSTM
0.5 0.3 0.3 0.1
0.3 0.3 0.3 0.5
0.3 0.5 0.3 0.4
0.3 0.1 0.3 0.1
0.1 0.1 0.1 0.1
Output

LSTM

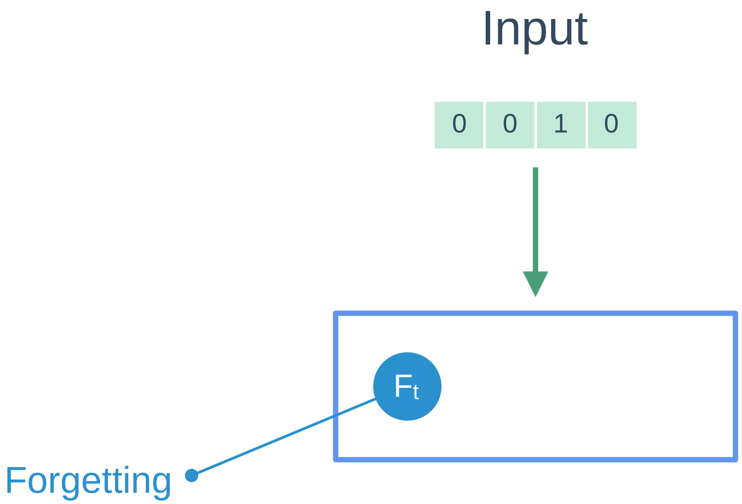


Output =/= state

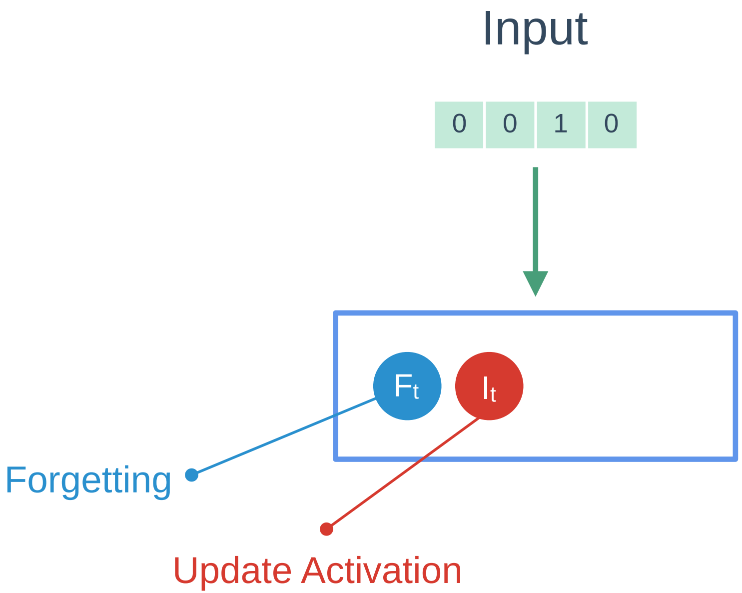
LSTM



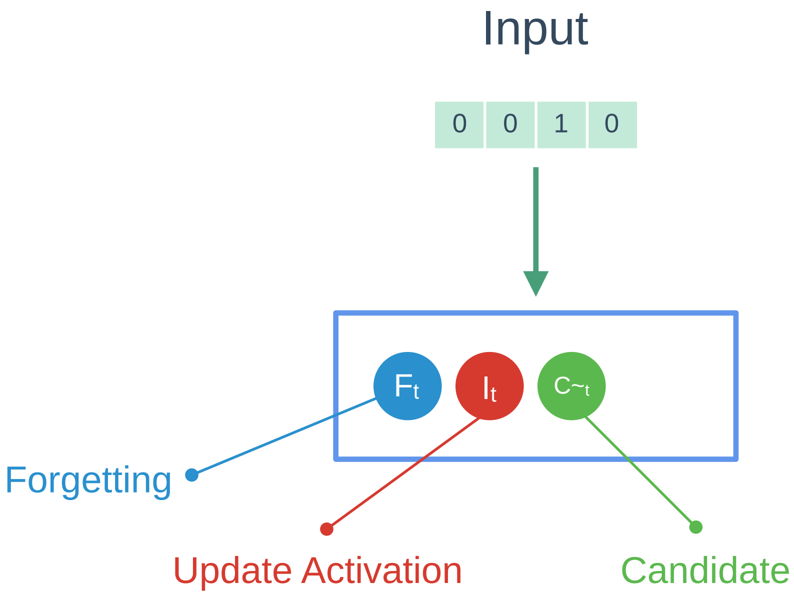
LSTM



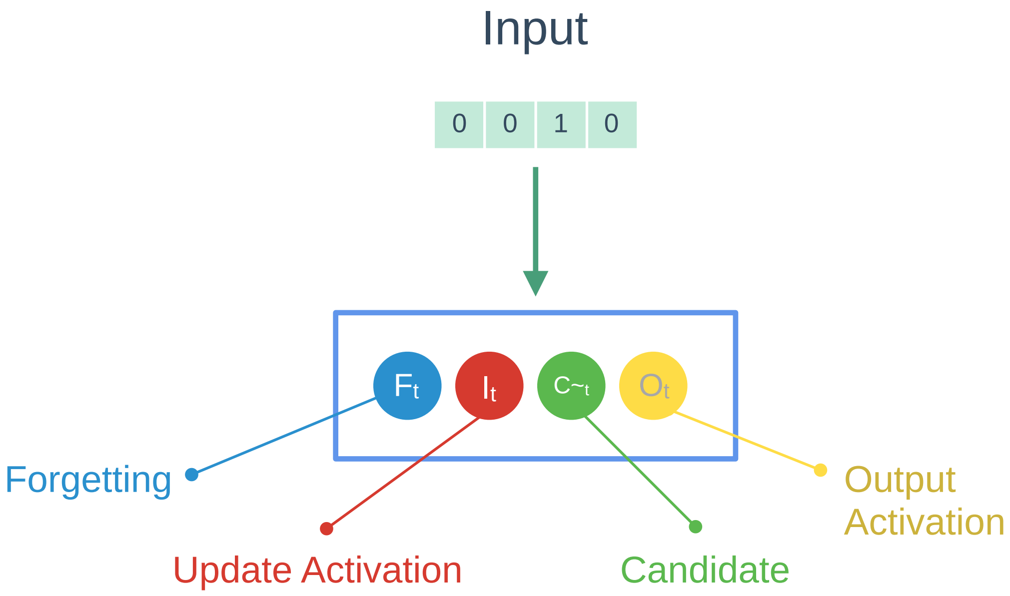
LSTM



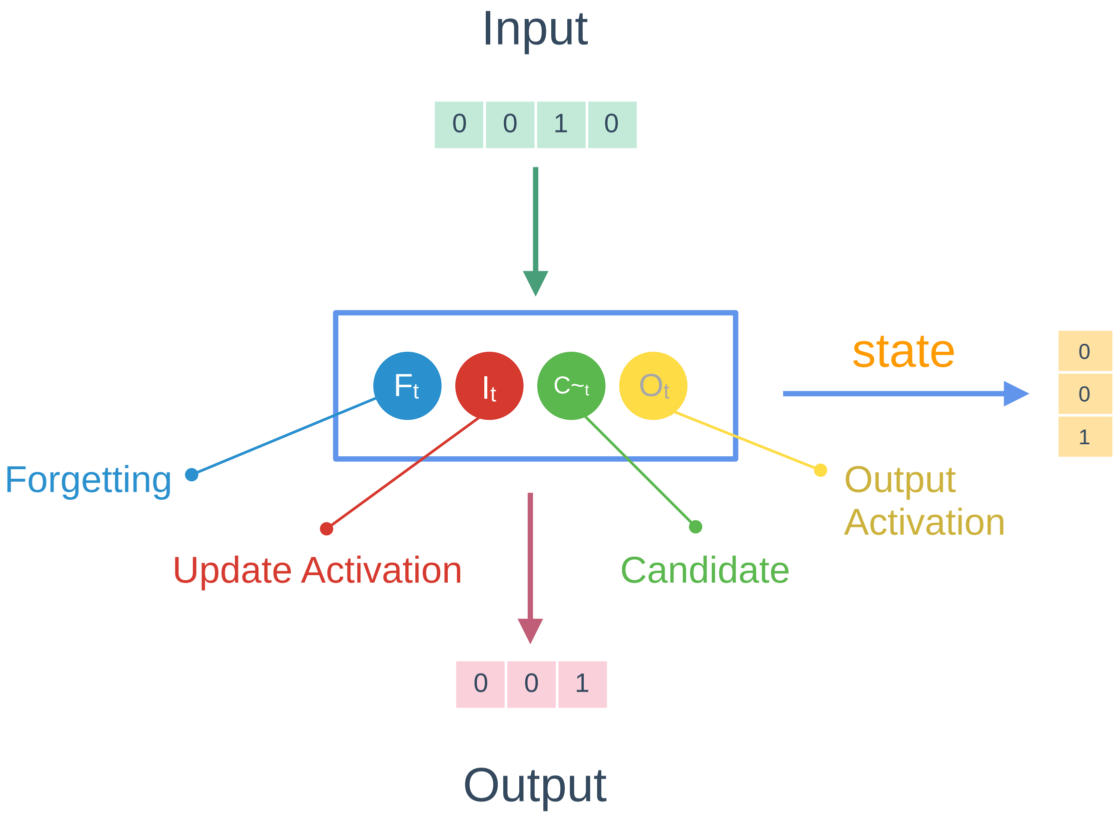
LSTM


Input
0 0 1 0
Ft
It
C~t
Forgetting
Update Activation
Candidate

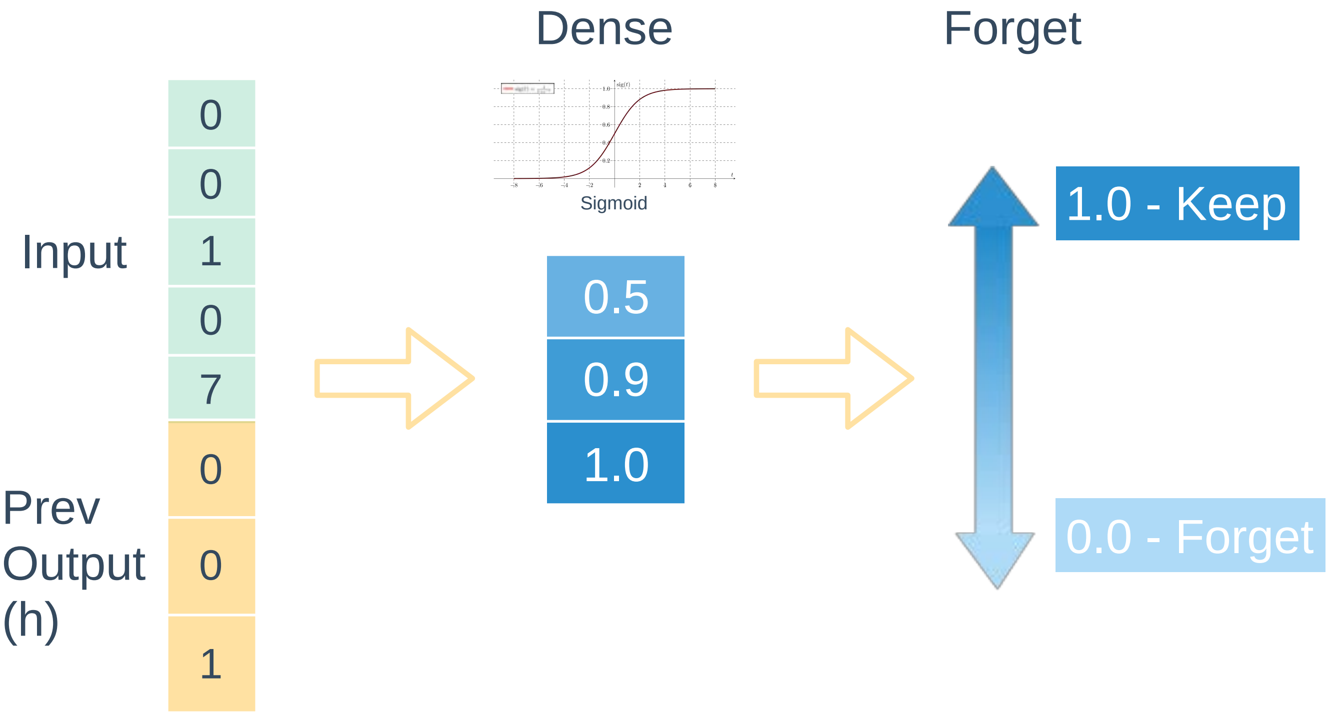
LSTM


Input
0
0
1
0
Ft
It
C~t
Ot
Forgetting
Update Activation
Candidate
Output
Activation

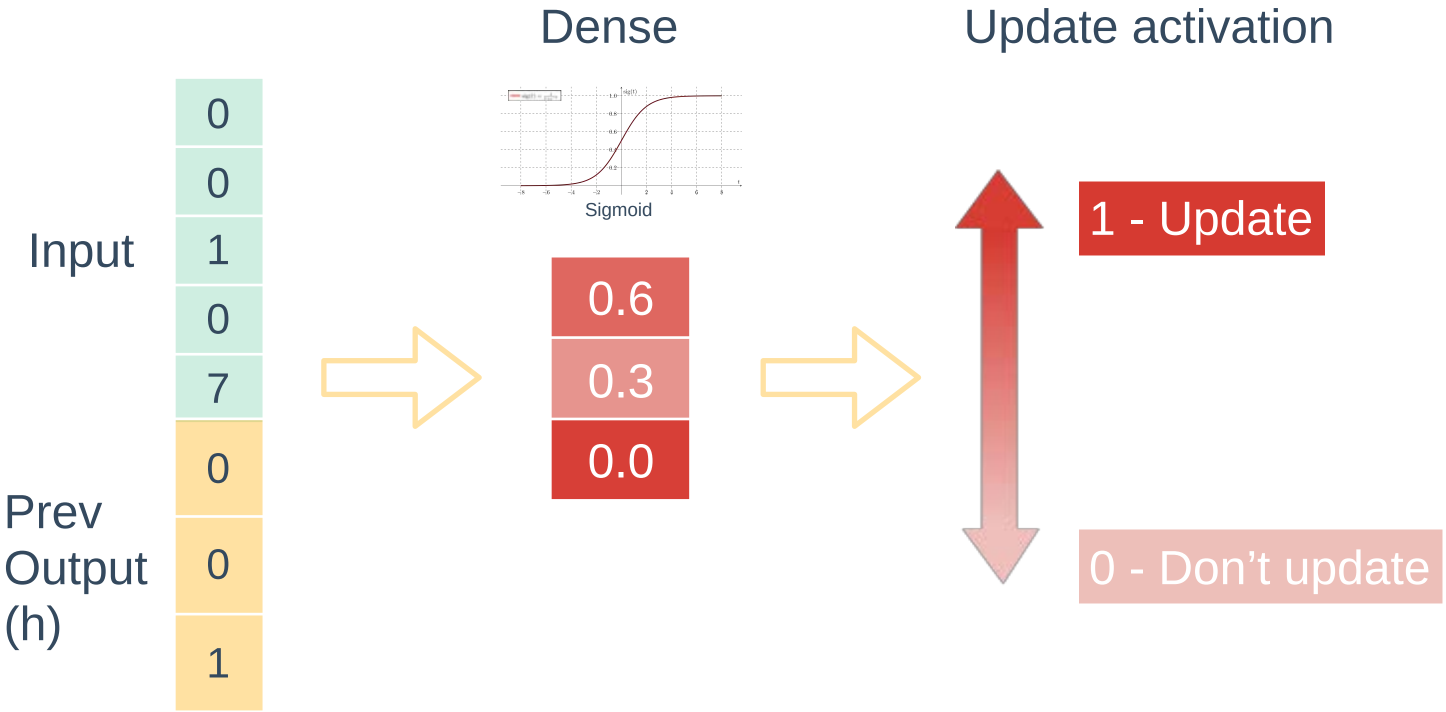
LSTM


Input
0 0 1 0
Ft
It
C~t
Ot
state
0
0
1
Forgetting
Update Activation
Candidate
Output Activation
0 0 1
Output

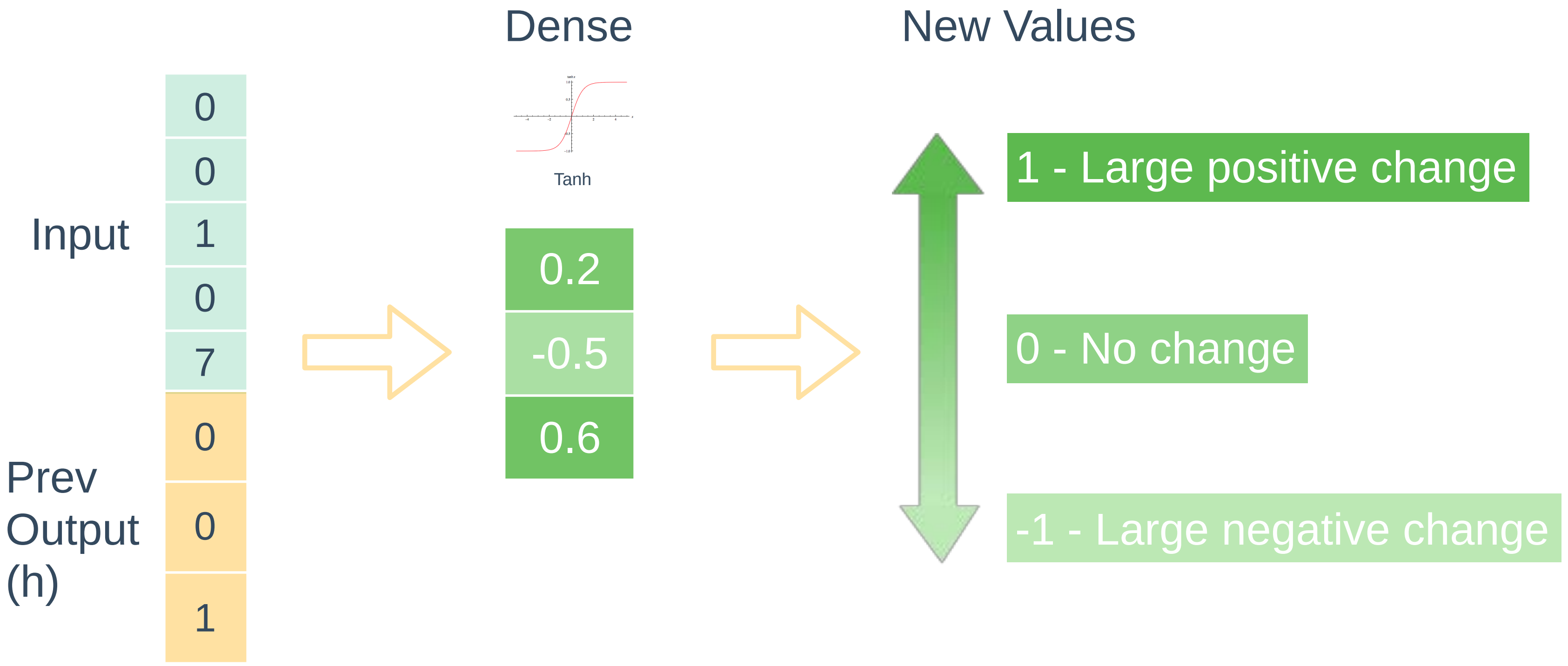
LSTM Forgetting (F_t)



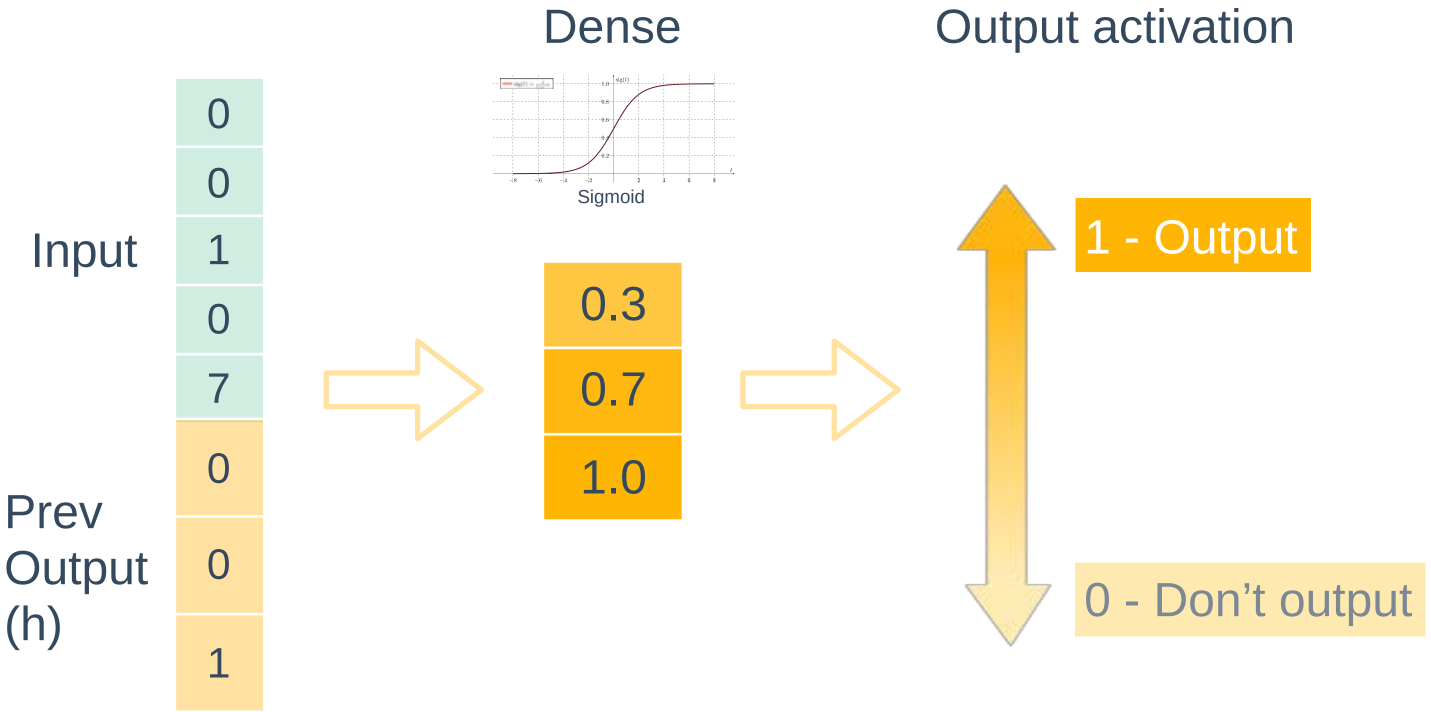
LSTM Update Activation (I_t)



LSTM Candidate ($\tilde{C}_t$)



LSTM Output Activation (O_t)



I_t $C\sim_t$ O_t

Putting it all together

Next State (C_t)		Prev State (C_{t-1})		Forget (F_t)
??		0		0.5
??	=	0	*	0.9
??		1		1.0

O_t

Putting it all together

Next State (C_t)		Prev State (C_{t-1})		Forget F_t		Update Activation I_t		Candidate $\tilde{C}_t$
??		0		0.5		0.6		0.2
??	=	0	*	0.9	+	0.3	*	-0.5
??		1		1.0		0.0		0.6

Putting it all together

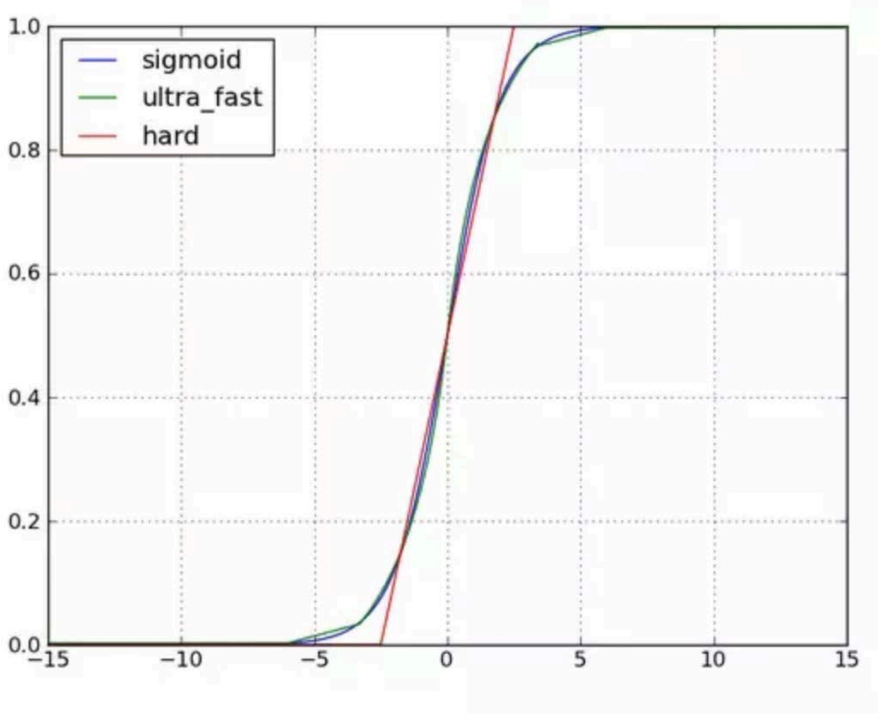
Next State (C_t) = Prev State (C_{t-1}) * Forget (F_t) + Update Activation (I_t) * Candidate ($C\sim_t$)

$$\begin{bmatrix} ?? \\ ?? \\ ?? \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} * \begin{bmatrix} 0.5 \\ 0.9 \\ 1.0 \end{bmatrix} + \begin{bmatrix} 0.6 \\ 0.3 \\ 0.9 \end{bmatrix} * \begin{bmatrix} 0.2 \\ -0.5 \\ 0.6 \end{bmatrix}$$

Output (H_t) = Output Activation (O_t) * tanh(Next State (C_t))

$$\begin{bmatrix} ? \\ ? \\ ? \end{bmatrix} = \begin{bmatrix} 0.3 \\ 0.7 \\ 1.0 \end{bmatrix} * \tanh\left(\begin{bmatrix} ?? \\ ?? \\ ?? \end{bmatrix} \right)$$

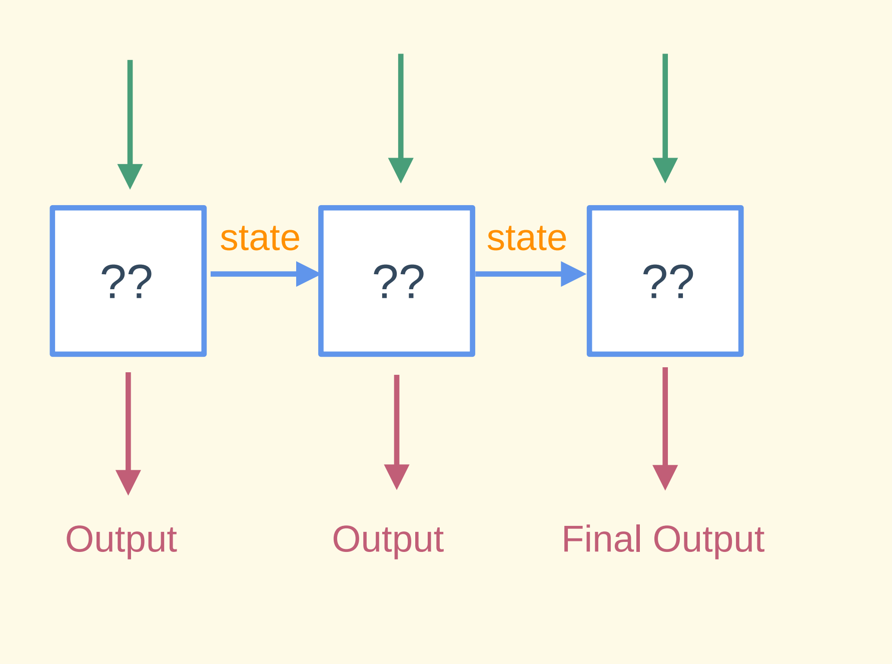
Hard Sigmoid



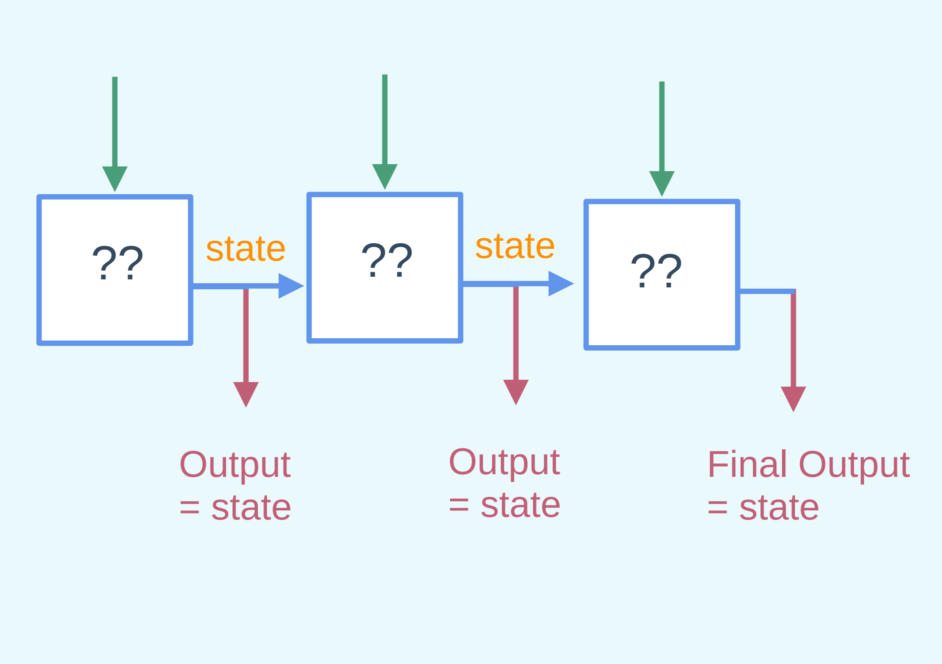
Gated Recurrent Unit (GRU) 2014

$$z_t = \sigma\big(x_t U^z + h_{t-1} W^z\big)$$
$$r_t = \sigma\big(x_t U^r + h_{t-1} W^r\big)$$
$$\tilde{h}_t = \tanh\big(x_t U^h + (r_t * h_{t-1}) W^h\big)$$
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

LSTMs vs GRUs (1)

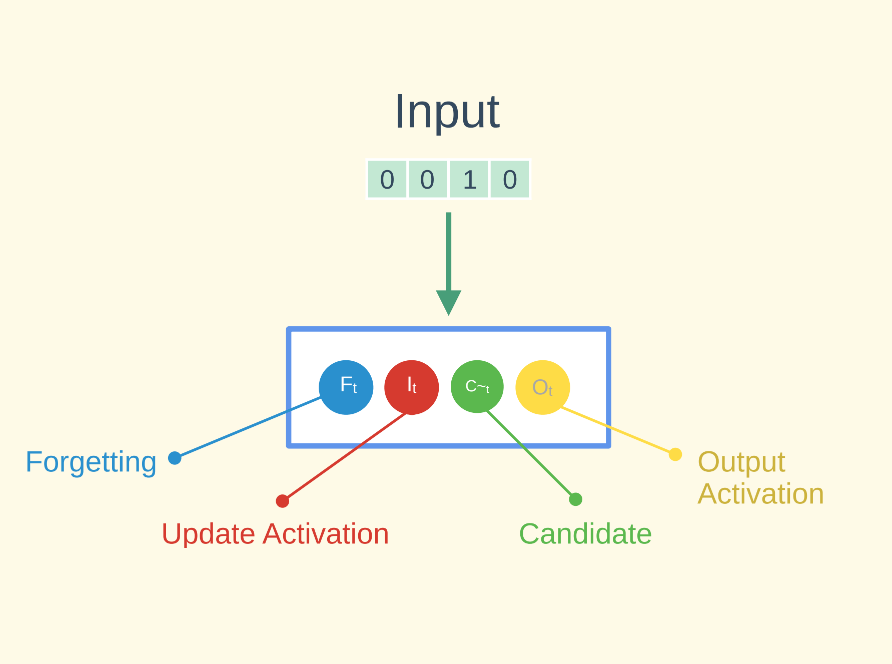


LSTM: State =/= Output

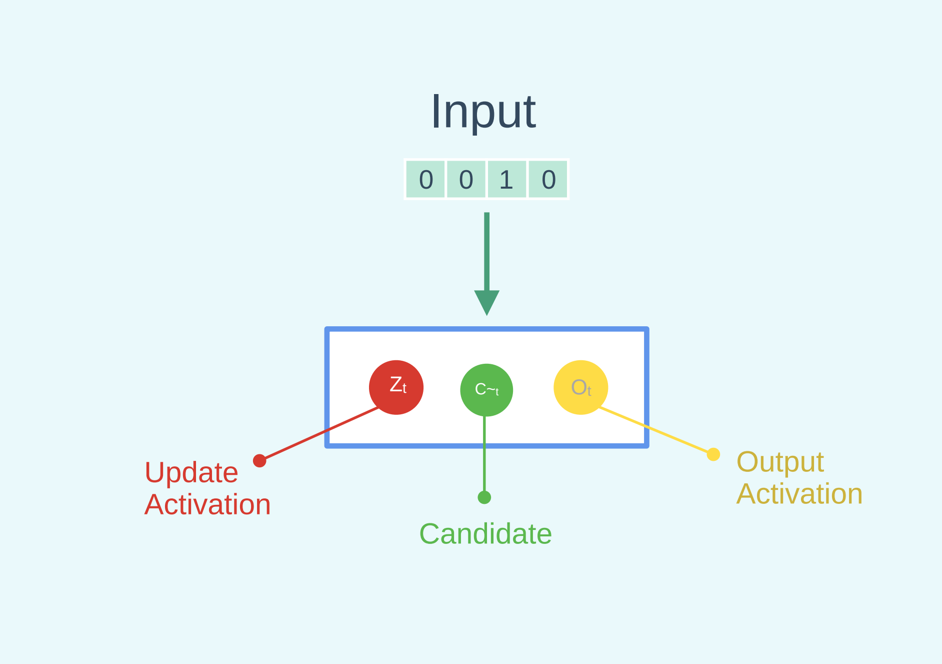


GRU: State == Output

LSTMs vs GRUs (2)



LSTM: 4 vectors



GRU: 3 vectors

Text Classification, Embeddings and 1D Convolutions

ml-class/examples/lstm/imdb-classifier

Character encoding

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
L	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
K	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0

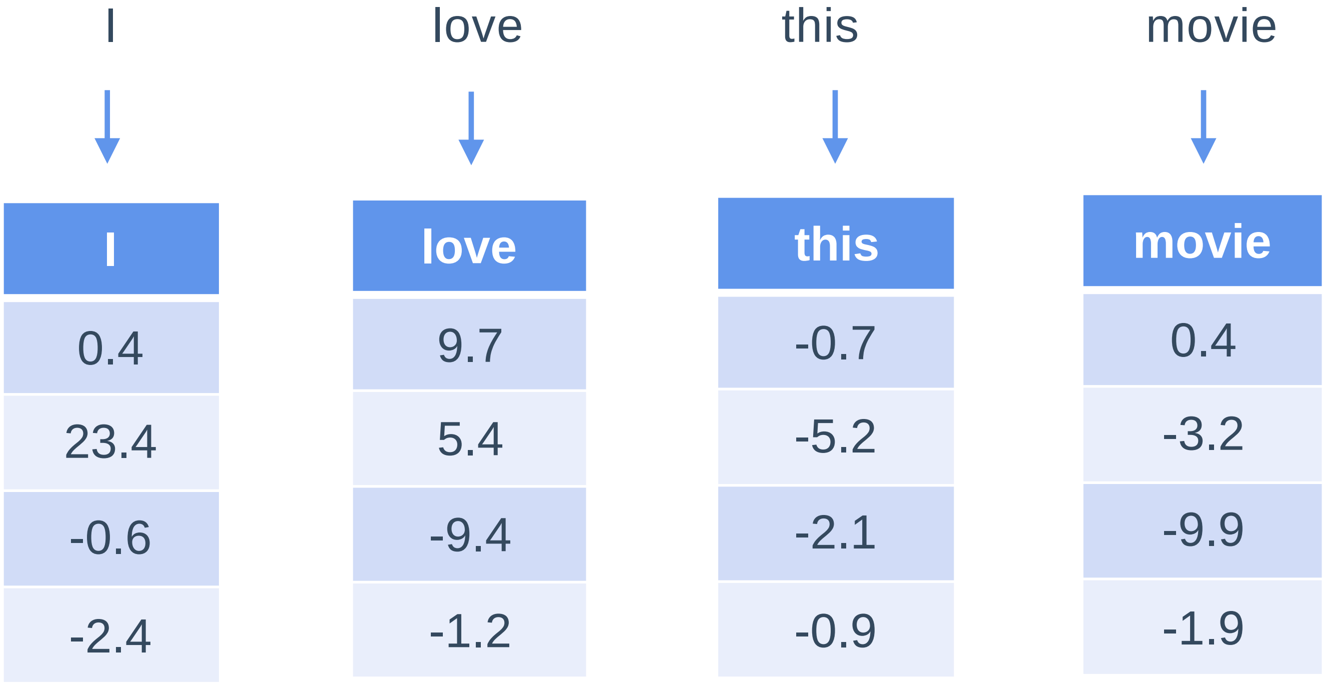
Bag of Words

Input Text

"Bag of Words"

Input Text		a	…	hate	I	iPhone	love	my	…	zoo
I love my iPhone	→	0	…	0	1	1	1	1	…	0
I hate my iPhone	→	0	…	1	1	1	0	1	…	0

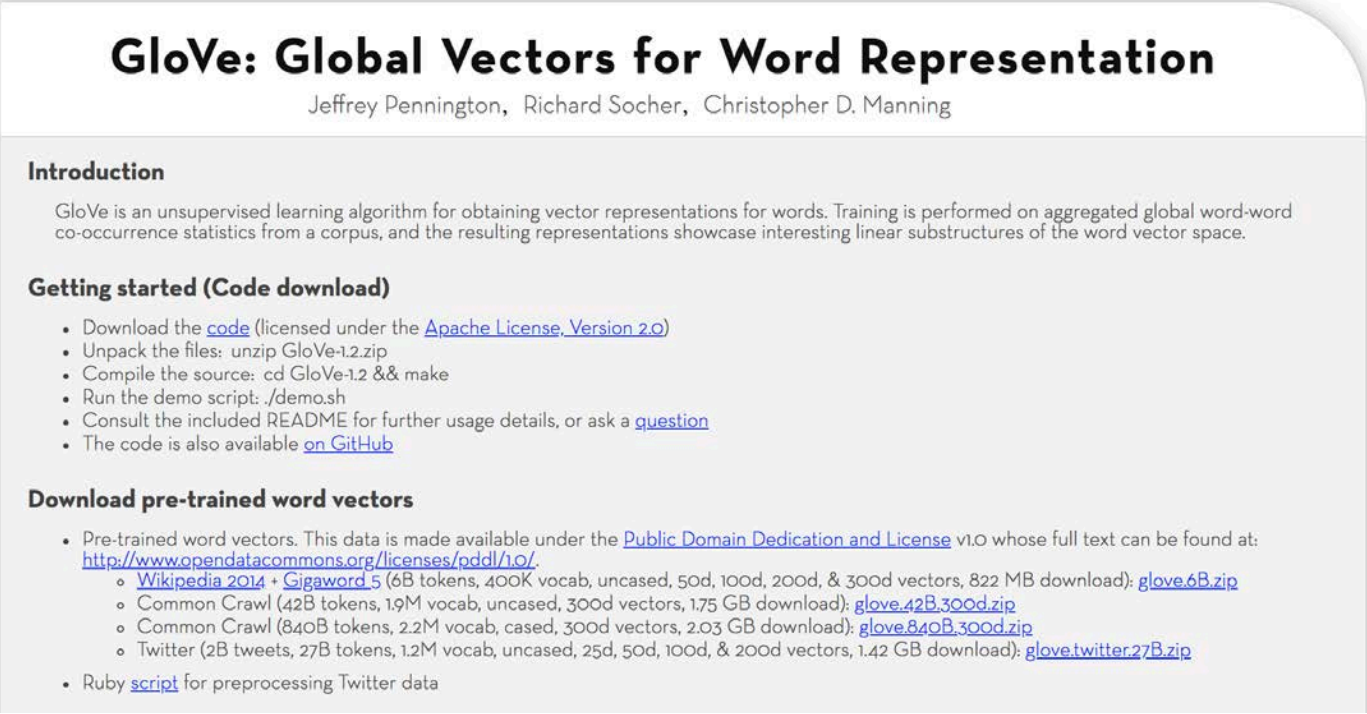
Word Embedding



Embeddings

	Val 1	Val 2	Val 3	Val 4
a	0.1	-0.3	1.7	2.4
aardvark	-2.3	4.1	-5.2	3.1
…	…	…	…	…
<unknown>	0.3	0.9	0.8	0.2

Pre-computing encoding



GloVe: Global Vectors for Word Representation

Jeffrey Pennington, Richard Socher, Christopher D. Manning

Introduction

GloVe is an unsupervised learning algorithm for obtaining vector representations for words. Training is performed on aggregated global word-word co-occurrence statistics from a corpus, and the resulting representations showcase interesting linear substructures of the word vector space.

Getting started (Code download)

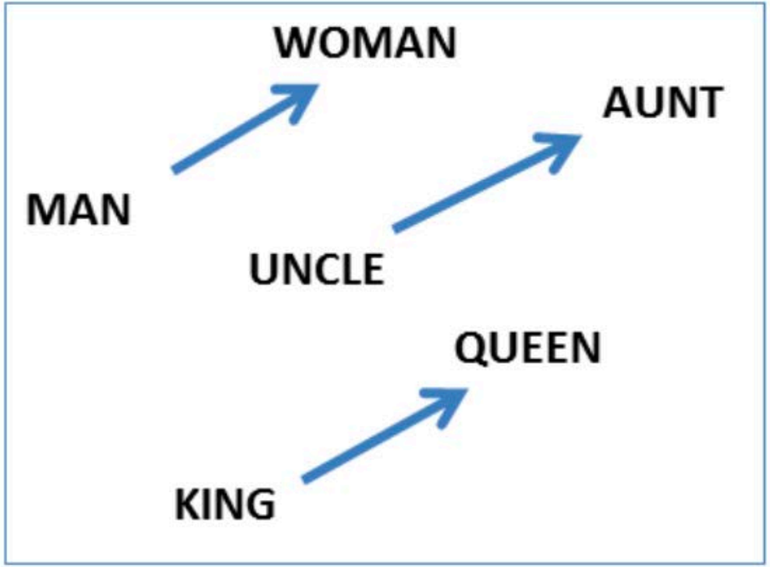
- Download the code (licensed under the Apache License, Version 2.0)
- Unpack the files: unzip GloVe-1.2.zip
- Compile the source: cd GloVe-1.2 && make
- Run the demo script: ./demo.sh
- Consult the included README for further usage details, or ask a question
- The code is also available on GitHub

Download pre-trained word vectors

- Pre-trained word vectors. This data is made available under the Public Domain Dedication and License v1.0 whose full text can be found at: http://www.opendatacommons.org/licenses/pddl/1.0/.
  - Wikipedia 2014 + Gigaword 5 (6B tokens, 400K vocab, uncased, 50d, 100d, 200d, & 300d vectors, 822 MB download): glove.6B.zip
  - Common Crawl (42B tokens, 1.9M vocab, uncased, 300d vectors, 1.75 GB download): glove.42B.300d.zip
  - Common Crawl (840B tokens, 2.2M vocab, cased, 300d vectors, 2.03 GB download): glove.840B.300d.zip
  - Twitter (2B tweets, 27B tokens, 1.2M vocab, uncased, 25d, 50d, 100d, & 200d vectors, 1.42 GB download): glove.twitter.27B.zip
- Ruby script for preprocessing Twitter data

keras-imdb/imdb-embedding.py

GloVe + word2vec



Word Analogy Task

man is to *woman* as *king* is to ___ ?

good is to *best* as *smart* is to ___ ?

china is to *beijing* as *russia* is to ___ ?

Turns out the word-context based vector model we just learnt is good for such analogy tasks,

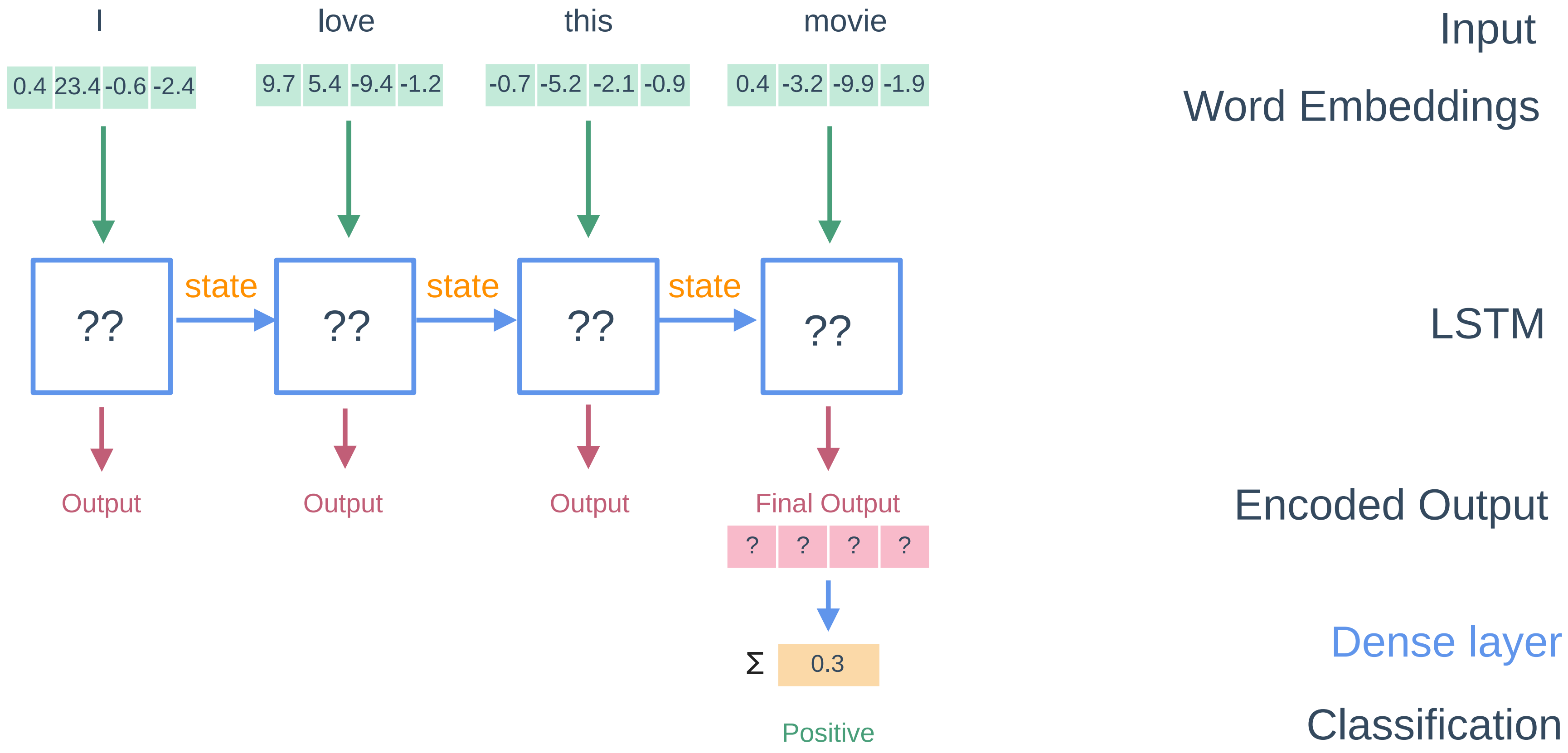
[king] – [man] + [woman] ≈ [queen]

Microsoft Levy, Goldberg, and Israel, Linguistic Regularities in Sparse and Explicit Word Representations, CoNLL 2014.

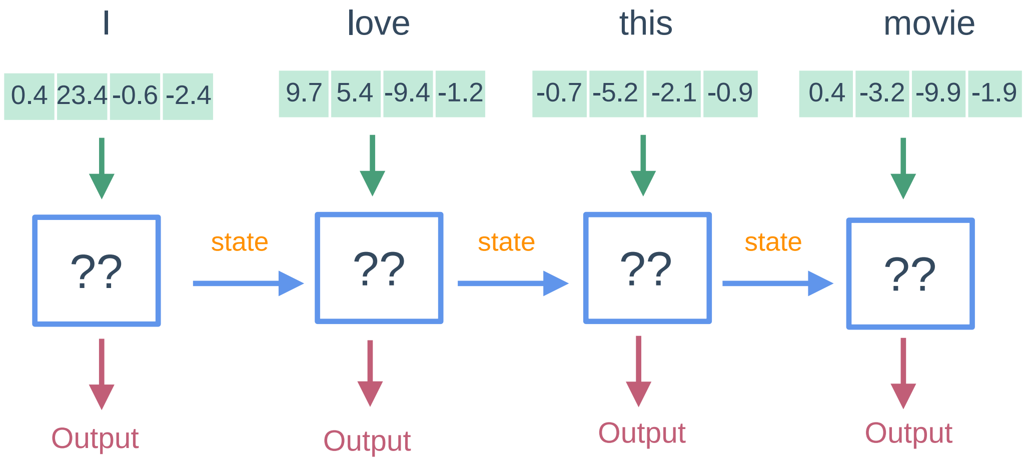
keras-imdb/imdb-embedding.py

Classification with LSTMs

Classification LSTM



Deep LSTM

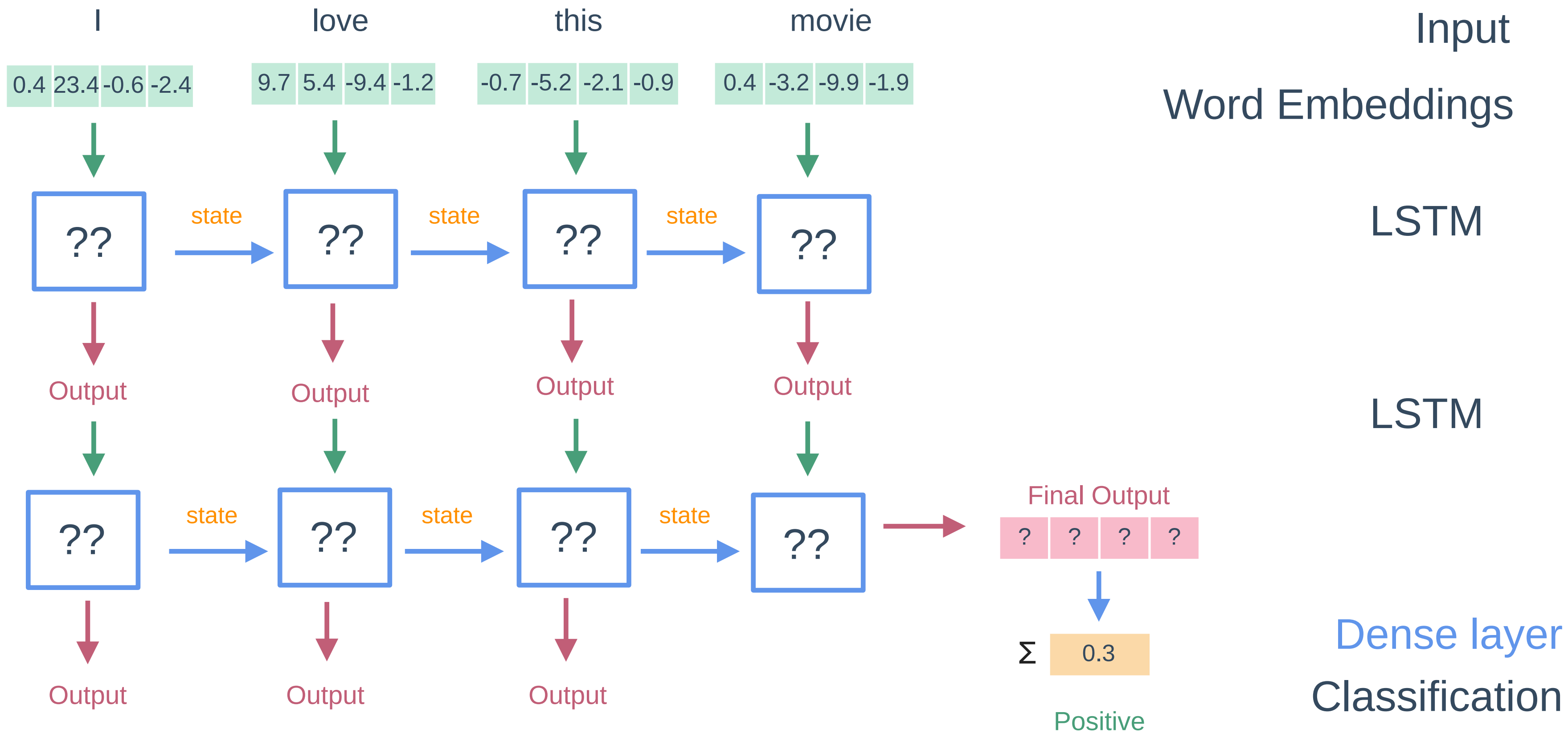


Input

Word Embeddings

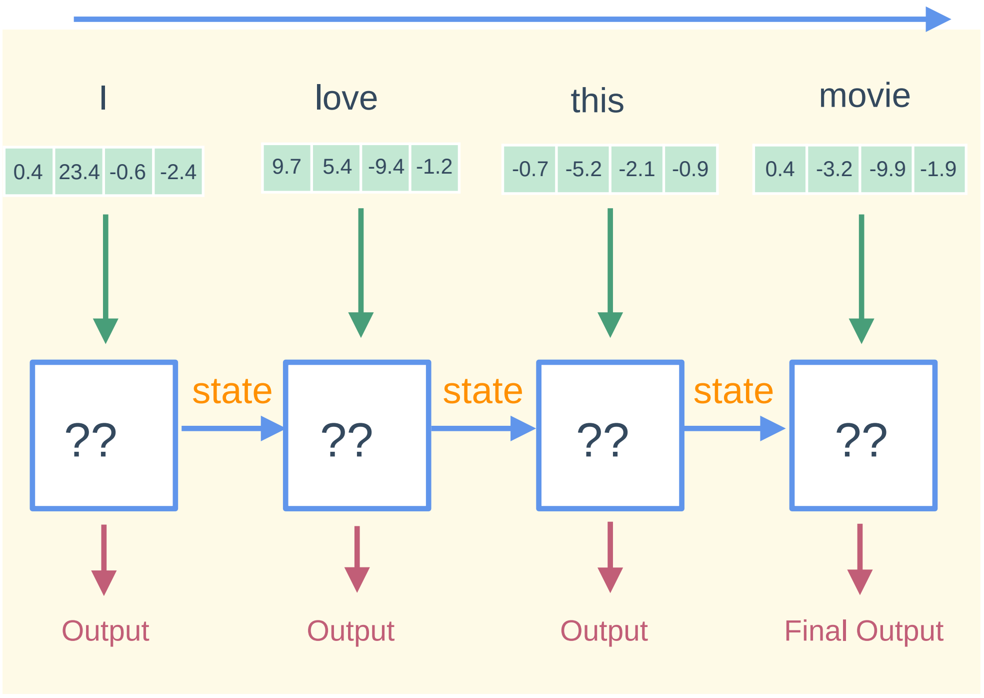
LSTM

Deep LSTM

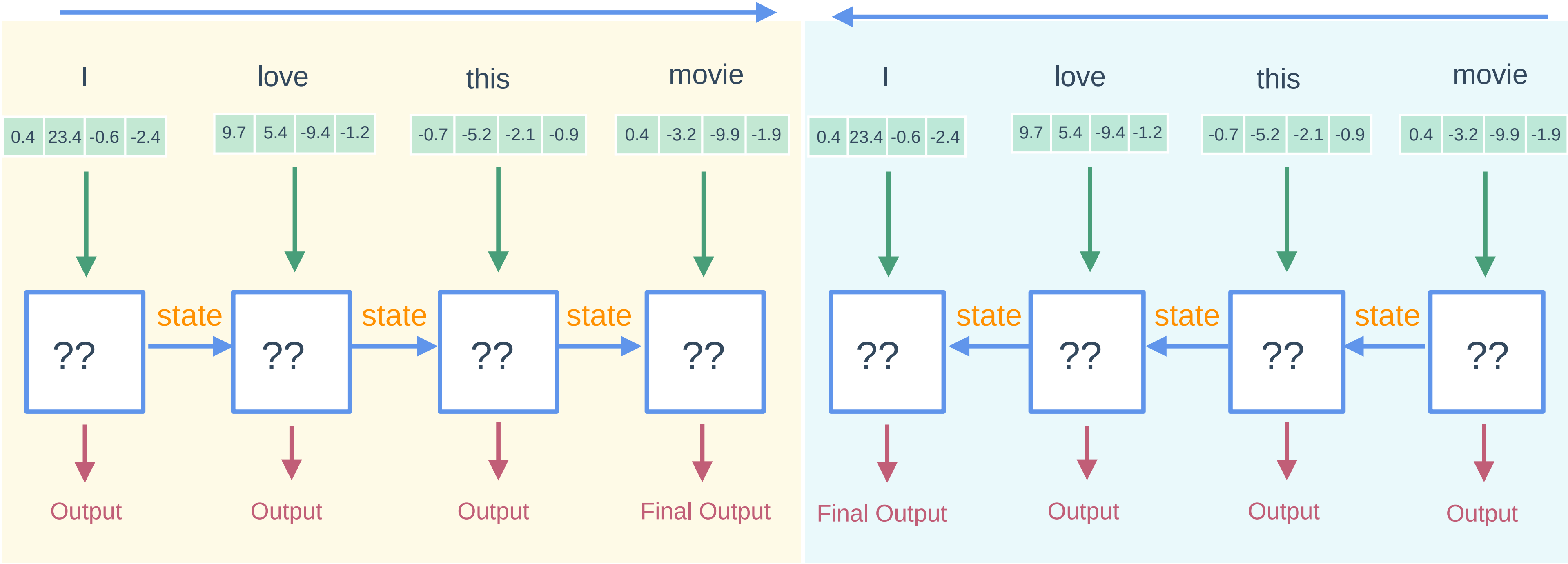


I
love
this
movie
Input
0.4 23.4 -0.6 -2.4
9.7 5.4 -9.4 -1.2
-0.7 -5.2 -2.1 -0.9
0.4 -3.2 -9.9 -1.9
Word Embeddings
?? state ?? state ?? state ??
LSTM
Output Output Output Output
LSTM
?? state ?? state ?? state ??
Output Output Output
Final Output
? ? ? ?
Σ 0.3
Positive
Dense layer
Classification

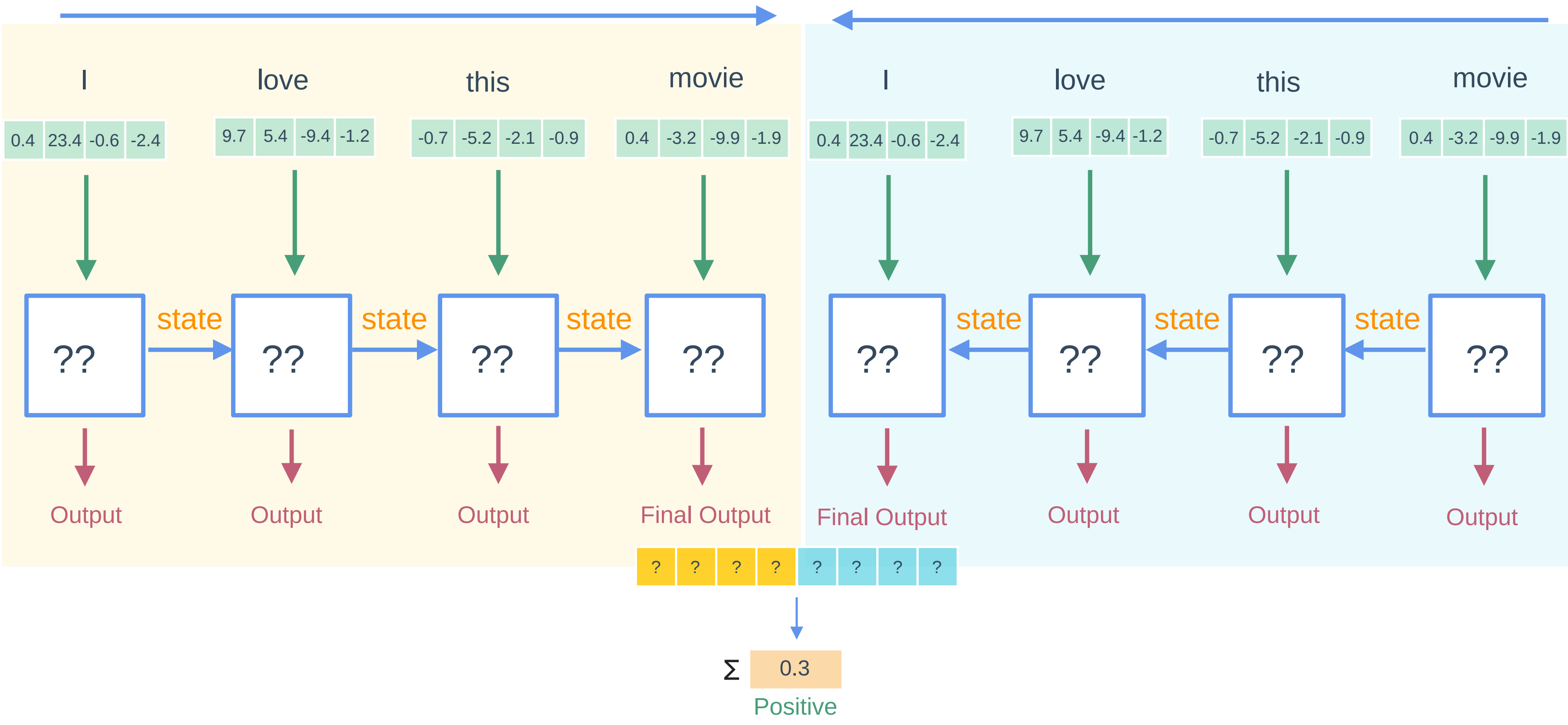
Bidirectional LSTM



Bidirectional LSTM

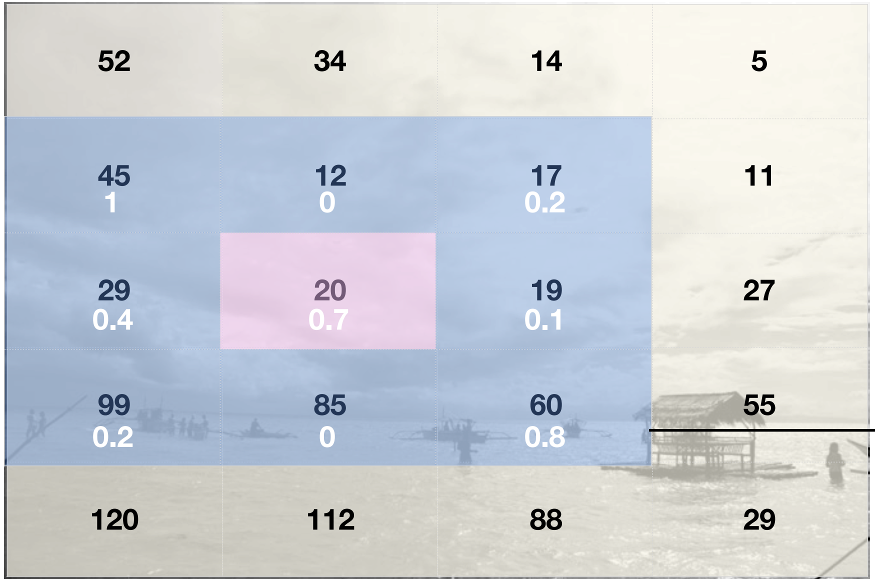


Bidirectional LSTM



Text Classification with CNNs

2D Convolution Review



Input * Kernel

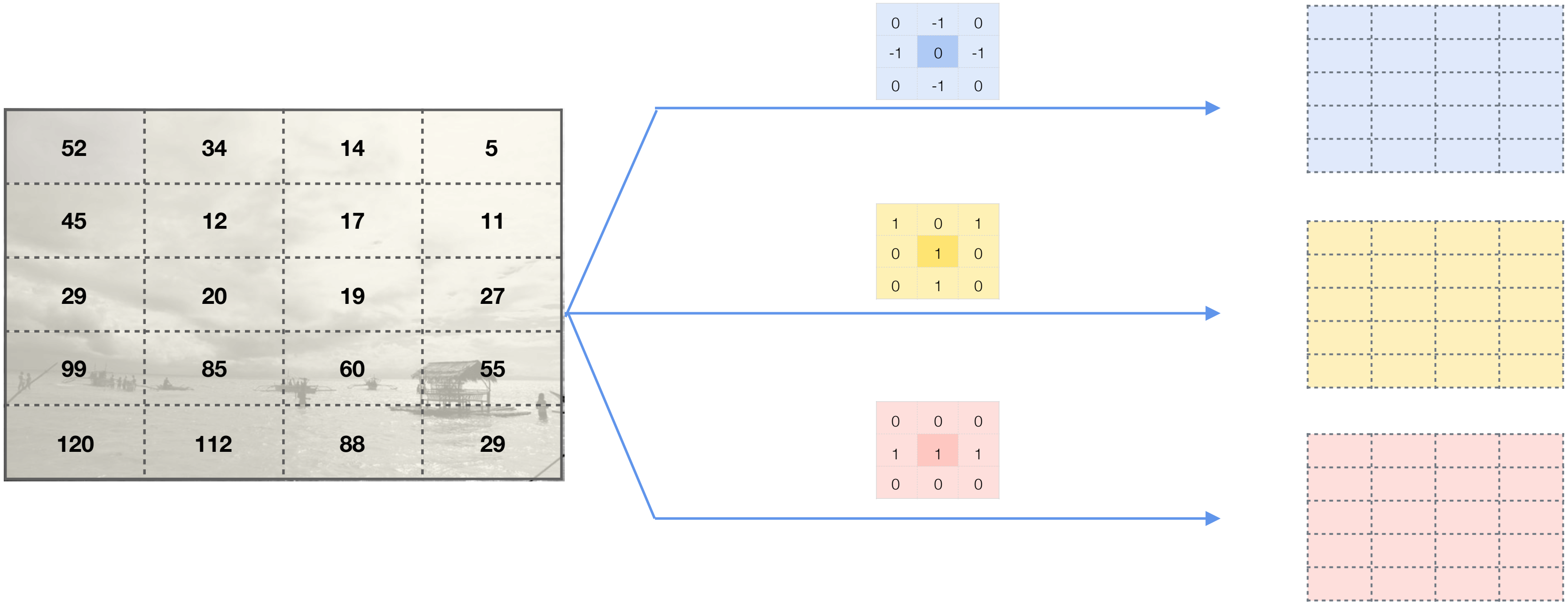
(45 x 1)
(12 x 0)
(17 x 0.2)
(29 x 0.4)
(20 x 0.7)
(19 x 0.1)
(99 x 0.2)
(85 x 0)
(60 x 0.8)
+

143.7

131	122	97	17
114	104	78	88
	144		

Output

2D Convolution Review Multiple Outputs

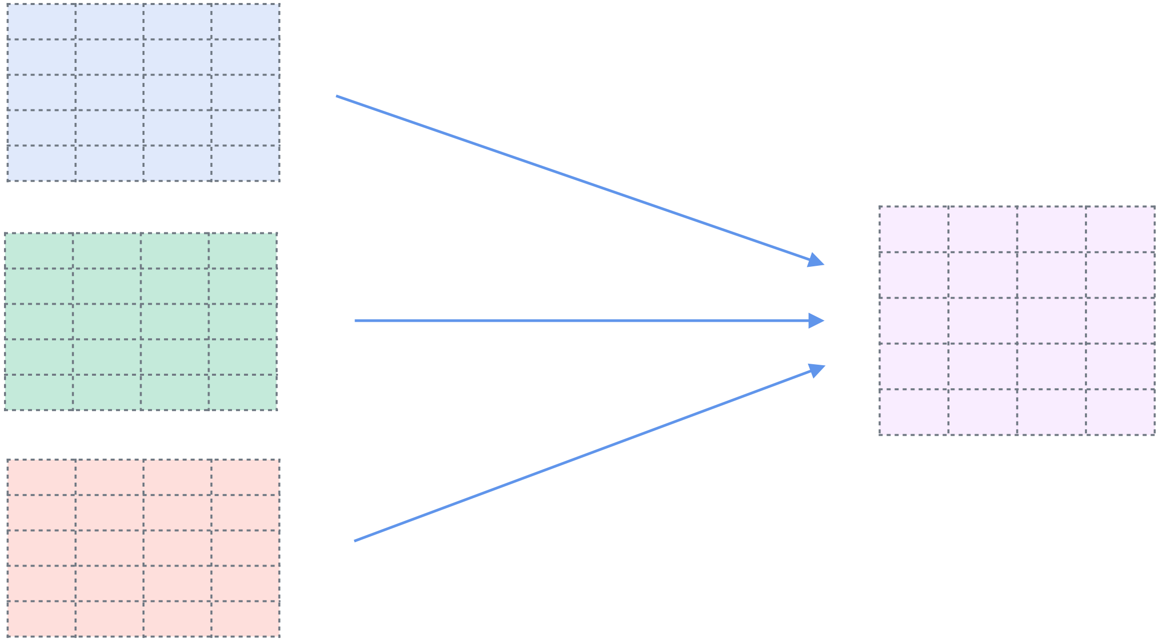


Original Image

3 Convolutions with different kernels

Multiple Outputs

2D Convolution Review Multiple Inputs



Multiple Convolutions

Sum all convolutions

1D Convolution

	I	love	this	movie
Channel 1	0.4 0.2	9.7 0.3	-0.7 0.2	0.4
Channel 2	23.4	5.4	-5.2	-3.2
Channel 3	-0.6	-9.4	-2.1	-9.9
Channel 4	-2.4	-1.2	-0.9	-1.9

$0.4*0.2 + 9.7*0.3 + (-0.7)*0.2$
$= 2.85$

Conv 1
2.85

1D Convolution

	I	love	this	movie
Channel 1	0.4	9.7	-0.7	0.4
Channel 2	23.4 0.2	5.4 0.3	-5.2 0.2	-3.2
Channel 3	-0.6	-9.4	-2.1	-9.9
Channel 4	-2.4	-1.2	-0.9	-1.9

23.4*0.2 + 5.4*0.3 + (-5.2)*0.2
= 5.26

Conv 1
2.85
5.26

1D Convolution

	I	love	this	movie
Channel 1	0.4	9.7	-0.7	0.4
Channel 2	23.4	5.4	-5.2	-3.2
Channel 3	-0.6 (0.2)	-9.4 (0.3)	-2.1 (0.2)	-9.9
Channel 4	-2.4	-1.2	-0.9	-1.9

$(-0.6)*0.2 + (-9.4)*0.3 + (-2.1)*0.2$
$= -3.36$

Conv 1
2.85
5.26
-3.36

1D Convolution

	I	love	this	movie
Channel 1	0.4	9.7	-0.7	0.4
Channel 2	23.4	5.4	-5.2	-3.2
Channel 3	-0.6	-9.4	-2.1	-9.9
Channel 4	-2.4 0.2	-1.2 0.3	-0.9 0.2	-1.9

(-2.4)*0.2 + (-1.2)*0.3 + (-0.9)*0.2
= -1.02

Conv 1
2.85
5.26
-3.36
-1.02

1D Convolution

	I	love	this	movie
Channel 1	0.4	9.7 0.3	-0.7 0.3	0.4 0.1
Channel 2	23.4	5.4	-5.2	-3.2
Channel 3	-0.6	-9.4	-2.1	-9.9
Channel 4	-2.4	-1.2	-0.9	-1.9

Conv 1	Conv 2
2.85	2.74
5.26	
-3.36	
-1.02	

9.7*0.3 + (-0.7)*0.3 + 0.4*0.1
= 2.74

1D Convolution

	I	love	this	movie
Channel 1	0.4	9.7	-0.7	0.4
Channel 2	23.4	5.4 0.3	-5.2 0.3	-3.2 0.1
Channel 3	-0.6	-9.4	-2.1	-9.9
Channel 4	-2.4	-1.2	-0.9	-1.9

Conv 1	Conv 2
2.85	2.74
5.26	-0.26
-3.36	
-1.02	

$$5.4*0.3 + (-5.2)*0.3 + (-3.2)*0.1$$
$$= -0.26$$

1D Convolution

	I	love	this	movie
Channel 1	0.4	9.7	-0.7	0.4
Channel 2	23.4	5.4	-5.2	-3.2
Channel 3	-0.6	-9.4 0.3	-2.1 0.3	-9.9 0.1
Channel 4	-2.4	-1.2	-0.9	-1.9

Conv 1
2.85
5.26
-3.36
-1.02

Conv 2
2.74
-0.26
-4.44

$$(-9.4)*0.3 + (-2.1)*0.3 + (-9.9)*0.1 = -4.44$$

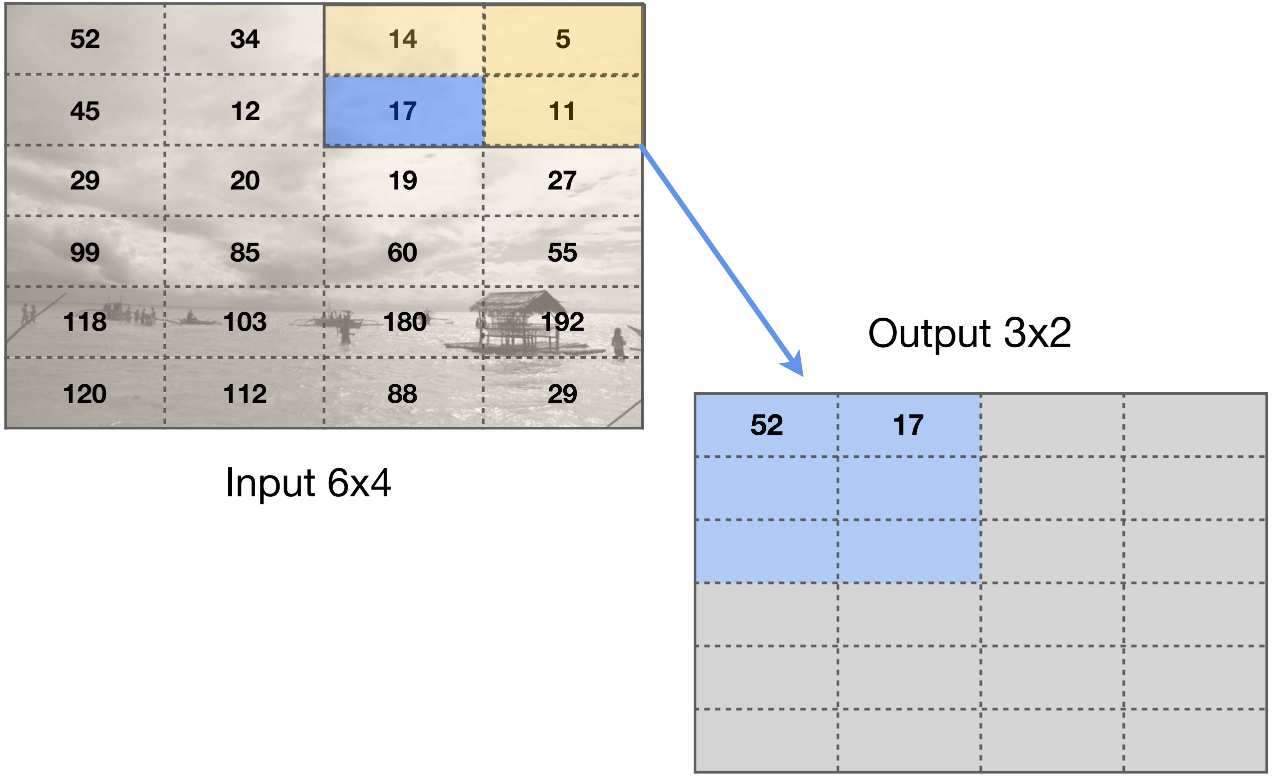
1D Convolution

	I	love	this	movie
Channel 1	0.4	9.7	-0.7	0.4
Channel 2	23.4	5.4	-5.2	-3.2
Channel 3	-0.6	-9.4	-2.1	-9.9
Channel 4	-2.4	-1.2 0.3	-0.9 0.3	-1.9 0.1

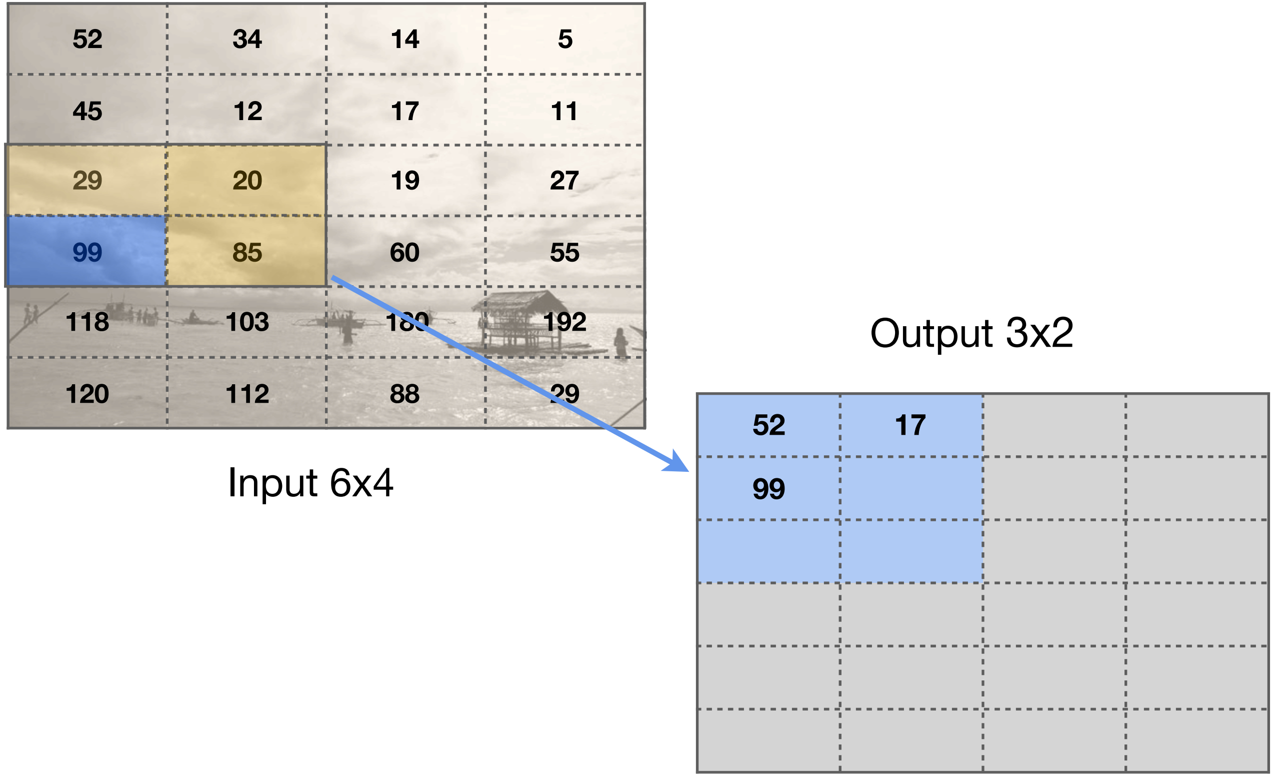
Conv 1	Conv 2
2.85	2.74
5.26	-0.26
-3.36	-4.44
-1.02	-0.82

(-1.2)*0.3 + (-0.9)*0.3 + (-1.9)*0.1
= -0.82

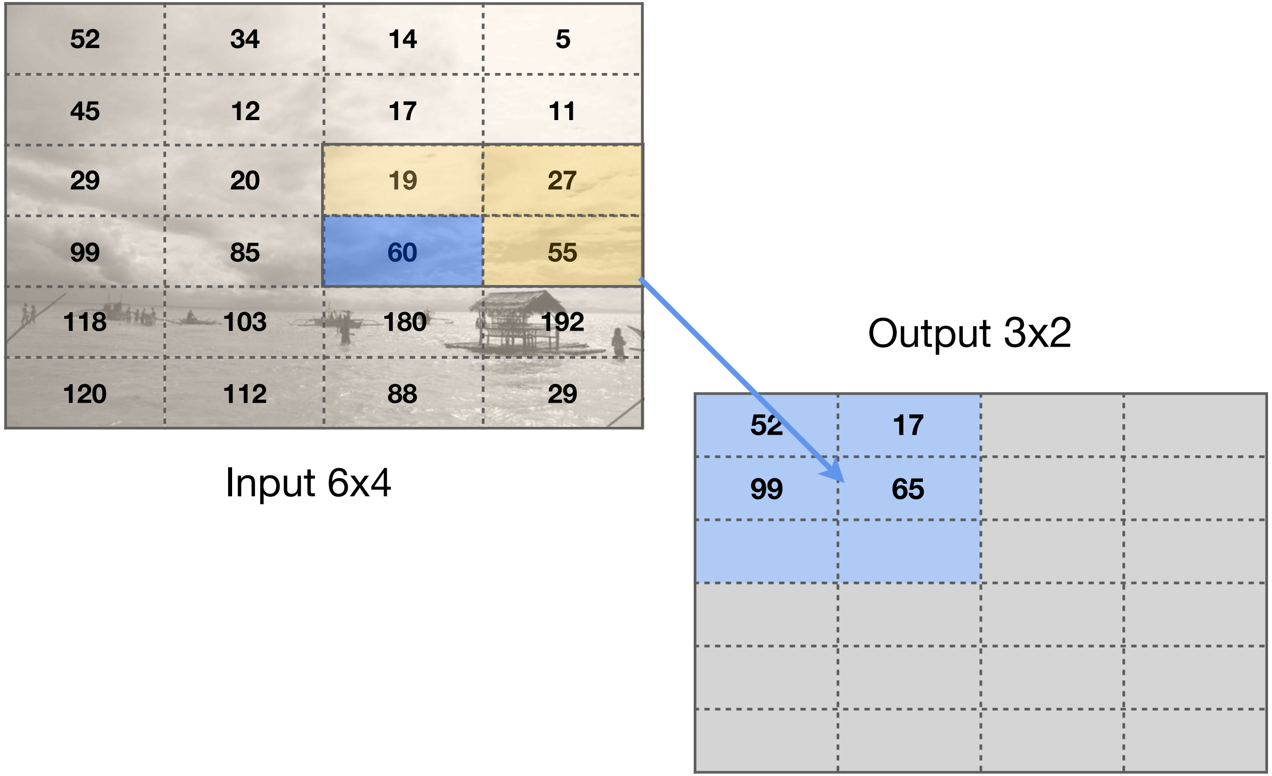
2D Max Pooling Review



2D Max Pooling Review



2D Max Pooling Review



1D Max Pooling

	I	love	this	movie
Channel 1	0.4	9.7	-0.7	0.4
Channel 2	23.4	5.4	-5.2	-3.2
Channel 3	-0.6	-9.4	-2.1	-9.9
Channel 4	-2.4	-1.2	-0.9	-1.9

Max Pooling 1	Max Pooling 2
9.7	

1D Max Pooling

	I	love	this	movie
Channel 1	0.4	9.7	-0.7	0.4
Channel 2	23.4	5.4	-5.2	-3.2
Channel 3	-0.6	-9.4	-2.1	-9.9
Channel 4	-2.4	-1.2	-0.9	-1.9

Max Pooling 1	Max Pooling 2
9.7	
23.4	

1D Max Pooling

	I	love	this	movie
Channel 1	0.4	9.7	-0.7	0.4
Channel 2	23.4	5.4	-5.2	-3.2
Channel 3	-0.6	-9.4	-2.1	-9.9
Channel 4	-2.4	-1.2	-0.9	-1.9

Max Pooling 1	Max Pooling 2
9.7	
23.4	
-0.6	

1D Max Pooling

	I	love	this	movie
Channel 1	0.4	9.7	-0.7	0.4
Channel 2	23.4	5.4	-5.2	-3.2
Channel 3	-0.6	-9.4	-2.1	-9.9
Channel 4	-2.4	-1.2	-0.9	-1.9

Max Pooling 1
9.7
23.4
-0.6
-1.2

Max Pooling 2

1D Max Pooling

	I	love	this	movie
Channel 1	0.4	9.7	-0.7	0.4
Channel 2	23.4	5.4	-5.2	-3.2
Channel 3	-0.6	-9.4	-2.1	-9.9
Channel 4	-2.4	-1.2	-0.9	-1.9

Max Pooling 1	Max Pooling 2
9.7	0.4
23.4	
-0.6	
-1.2	

1D Max Pooling

	I	love	this	movie
Channel 1	0.4	9.7	-0.7	0.4
Channel 2	23.4	5.4	-5.2	-3.2
Channel 3	-0.6	-9.4	-2.1	-9.9
Channel 4	-2.4	-1.2	-0.9	-1.9

Max Pooling 1
9.7
23.4
-0.6
-1.2

Max Pooling 2
0.4
-3.2

1D Max Pooling

	I	love	this	movie
Channel 1	0.4	9.7	-0.7	0.4
Channel 2	23.4	5.4	-5.2	-3.2
Channel 3	-0.6	-9.4	-2.1	-9.9
Channel 4	-2.4	-1.2	-0.9	-1.9

Max Pooling 1	Max Pooling 2
9.7	0.4
23.4	-3.2
-0.6	-2.1
-1.2	

1D Max Pooling

	I	love	this	movie
Channel 1	0.4	9.7	-0.7	0.4
Channel 2	23.4	5.4	-5.2	-3.2
Channel 3	-0.6	-9.4	-2.1	-9.9
Channel 4	-2.4	-1.2	-0.9	-1.9

Max Pooling 1	Max Pooling 2
9.7	0.4
23.4	-3.2
-0.6	-2.1
-1.2	-0.9

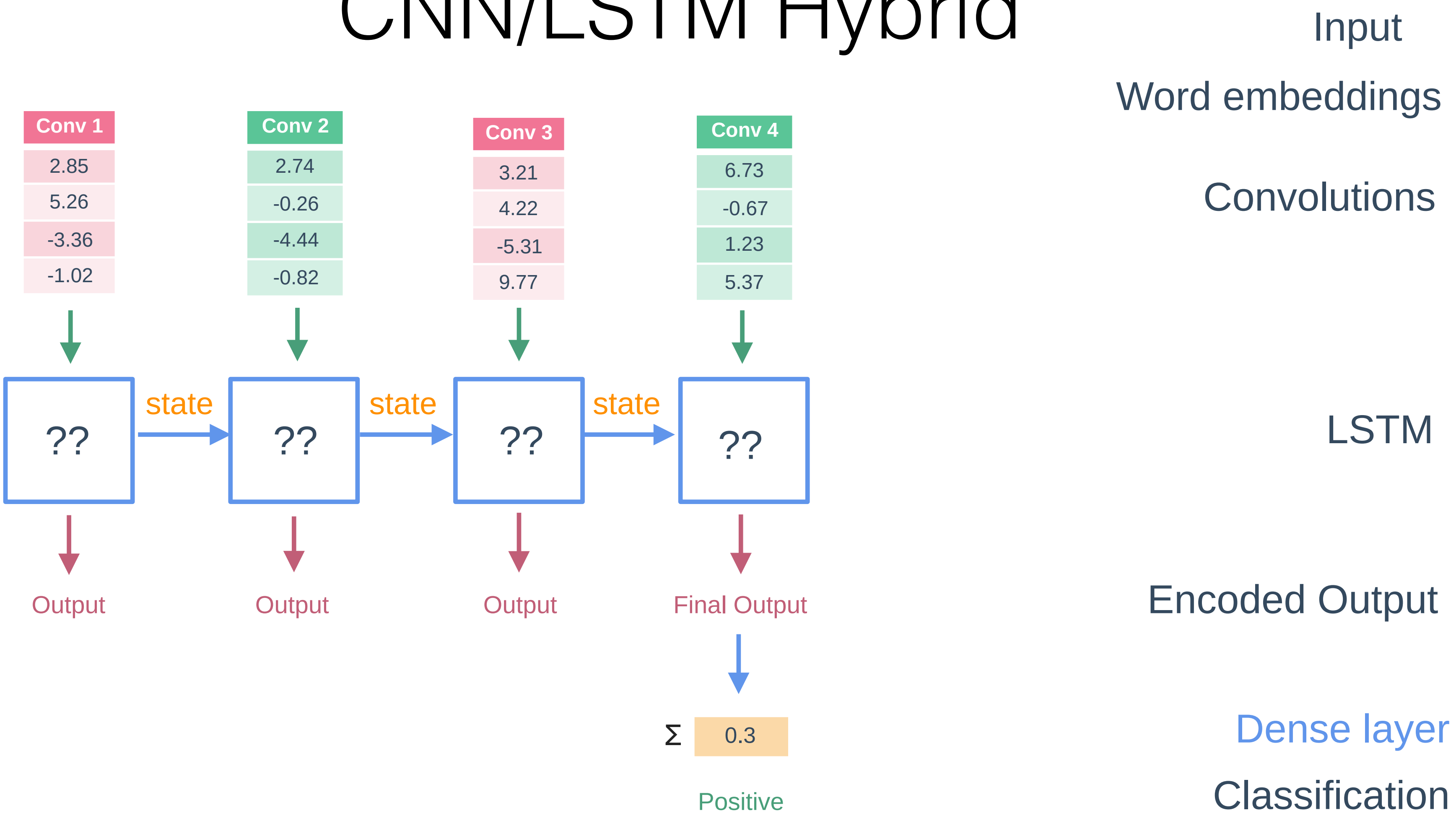
1D Convolution

	I	love	this	movie
Channel 1	0.4	9.7	-0.7	0.4
Channel 2	23.4	5.4	-5.2	-3.2
Channel 3	-0.6	-9.4	-2.1	-9.9
Channel 4	-2.4	-1.2	-0.9	-1.9
		0.3	0.3	0.1

Conv 1	Conv 2
2.85	2.74
5.26	-0.26
-3.36	-4.44
-1.02	-0.82

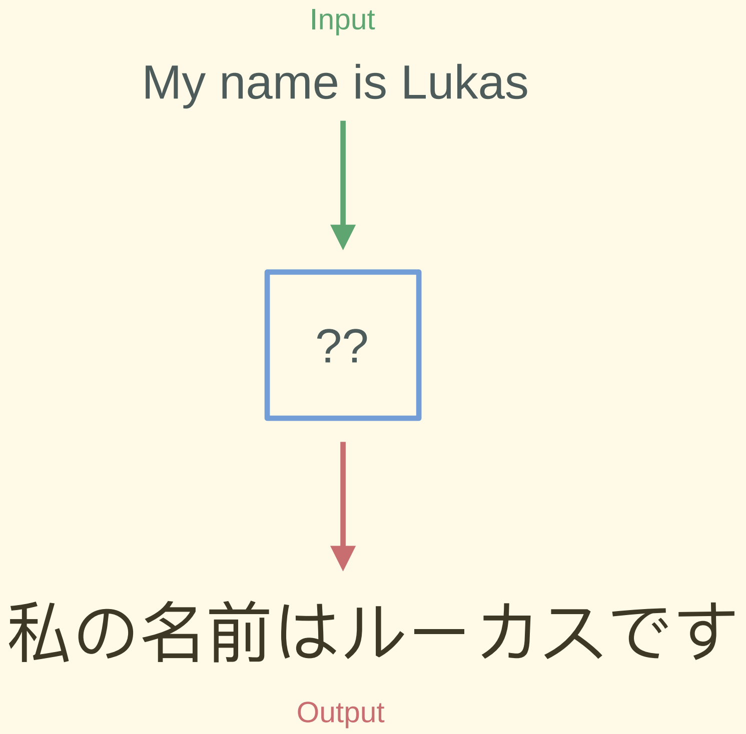
(-1.2)*0.3 + (-0.9)*0.3 + (-1.9)*0.1
= -0.82

CNN/LSTM Hybrid



Seq2Seq
ml-class/lstm/seq2seq

Seq2Seq in translation



seq2seq: the clown car of deep learning

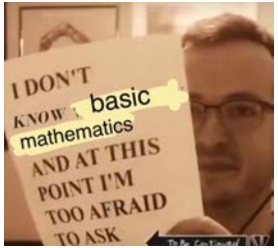
tl; dr: Translating arbitrary-length sequences back and forth is easier than you think

Seq2Seq in this tutorial

Seq2Seq in this tutorial

Input

10 + 12

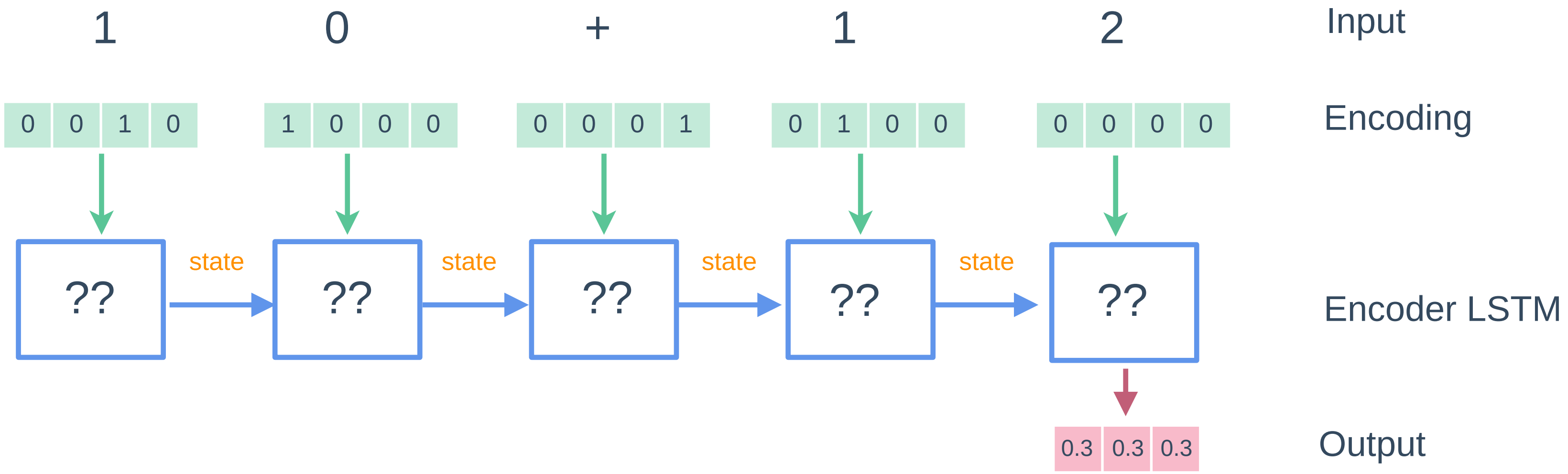


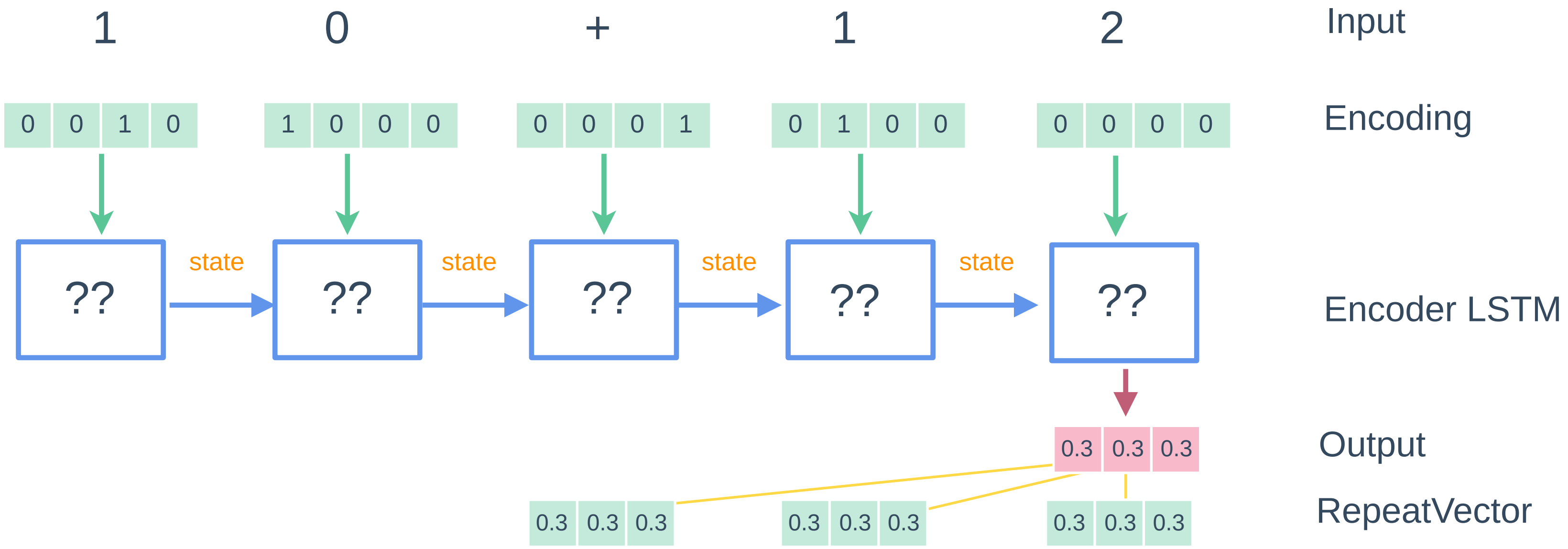
22

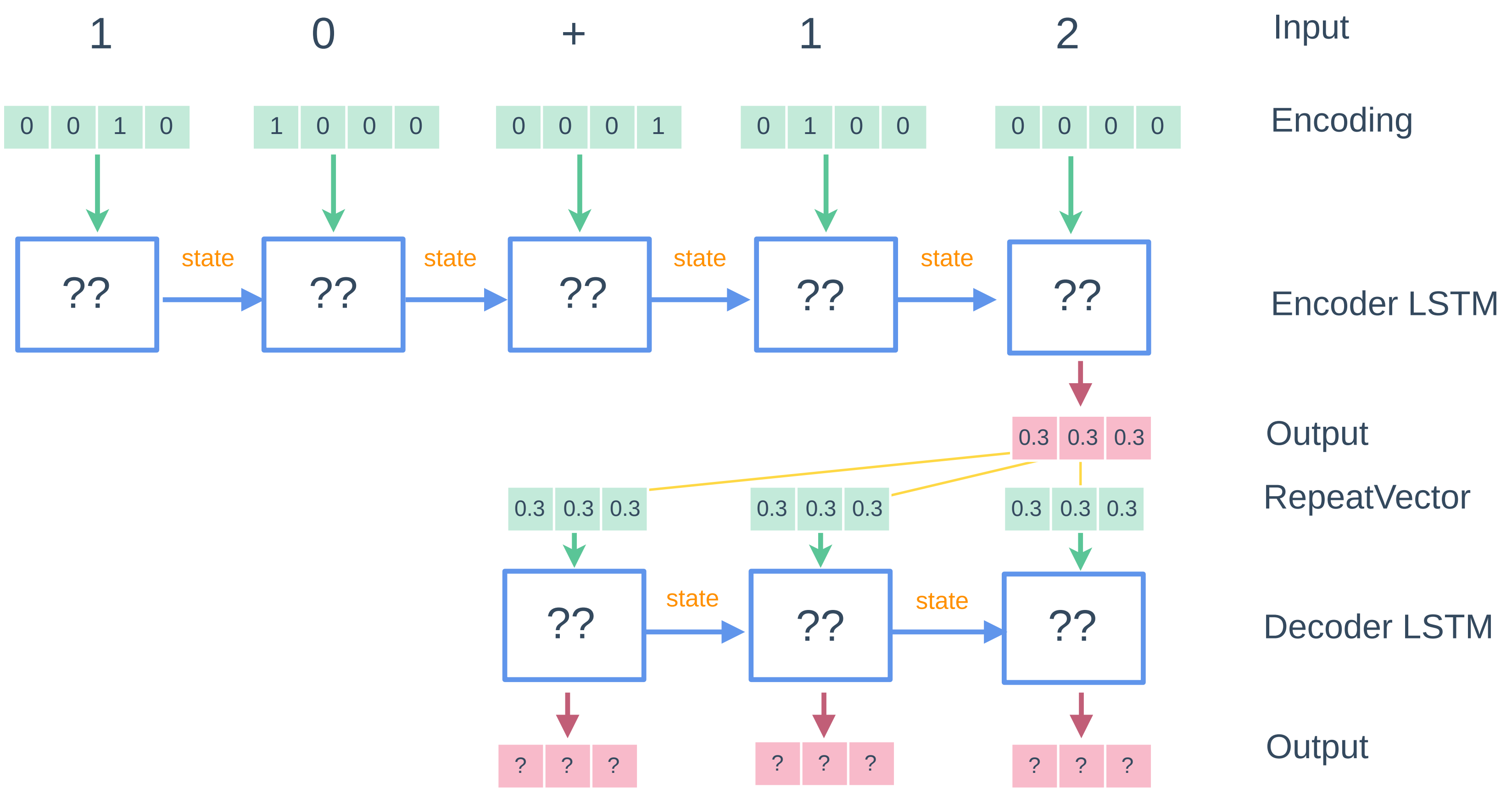
Output

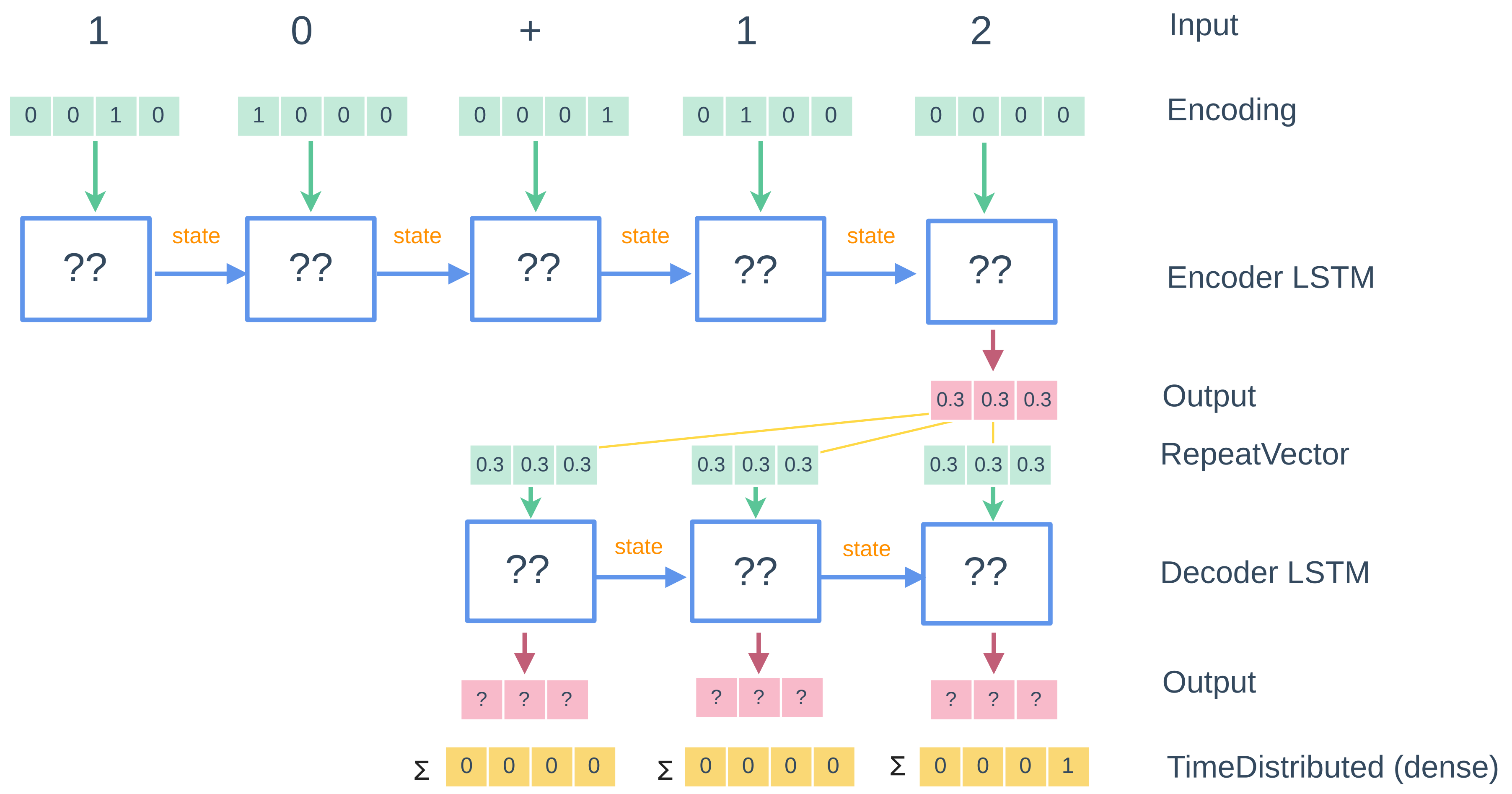
1 0 + 1 2 Input

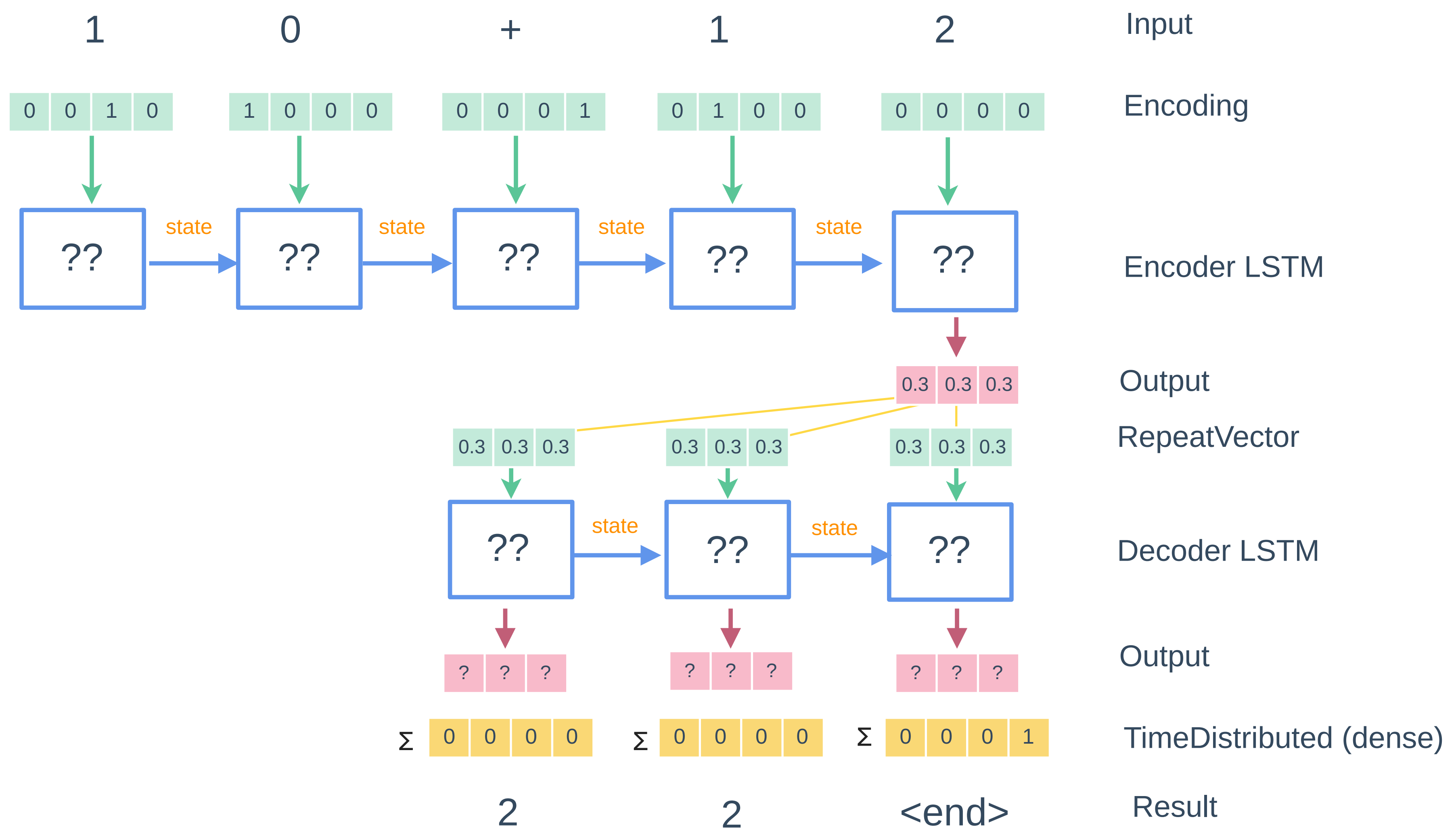
1	0	+	1	2	Input
0 0 1 0	1 0 0 0	0 0 0 1	0 1 0 0	0 0 0 0	Encoding


1
0
+
1
2
Input
0 0 1 0
1 0 0 0
0 0 0 1
0 1 0 0
0 0 0 0
Encoding
??
state
??
state
??
state
??
state
??
Encoder LSTM
0.3 0.3 0.3
Output


1
0
+
1
2
Input
0 0 1 0
1 0 0 0
0 0 0 1
0 1 0 0
0 0 0 0
Encoding
??
state
??
state
??
state
??
state
??
Encoder LSTM
0.3 0.3 0.3
Output
0.3 0.3 0.3
0.3 0.3 0.3
0.3 0.3 0.3
RepeatVector

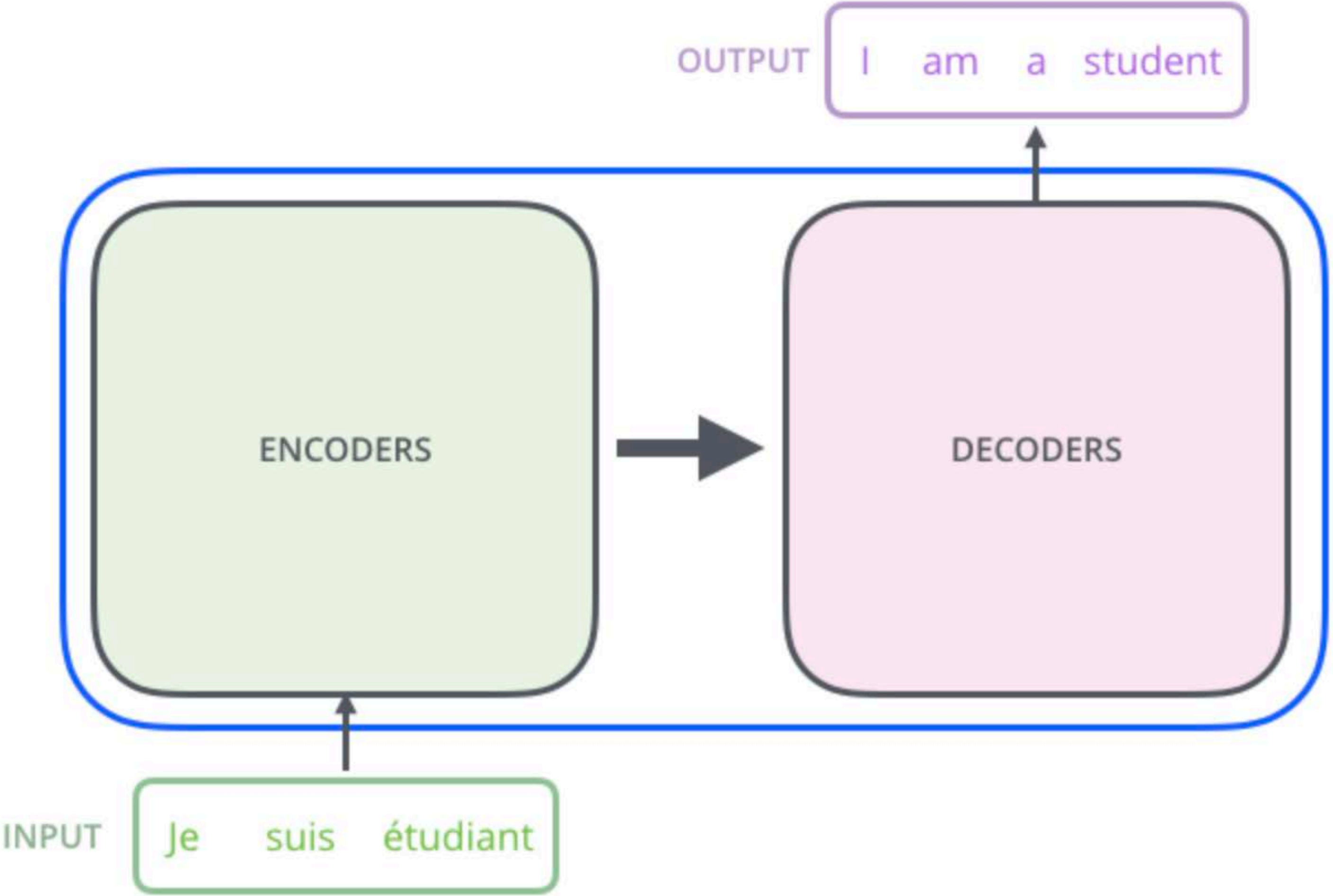

Input
1
0
+
1
2
Encoding
0 0 1 0
1 0 0 0
0 0 0 1
0 1 0 0
0 0 0 0
Encoder LSTM
??
state
Output
0.3 0.3 0.3
RepeatVector
0.3 0.3 0.3
Decoder LSTM
??
state
Output
? ? ?


1
0
+
1
2
Input
0 0 1 0
1 0 0 0
0 0 0 1
0 1 0 0
0 0 0 0
Encoding
??
state
??
state
??
state
??
state
??
Encoder LSTM
0.3 0.3 0.3
Output
0.3 0.3 0.3
0.3 0.3 0.3
0.3 0.3 0.3
RepeatVector
??
state
??
state
??
Decoder LSTM
? ? ?
? ? ?
? ? ?
Output
Σ 0 0 0 0
Σ 0 0 0 0
Σ 0 0 0 1
TimeDistributed (dense)

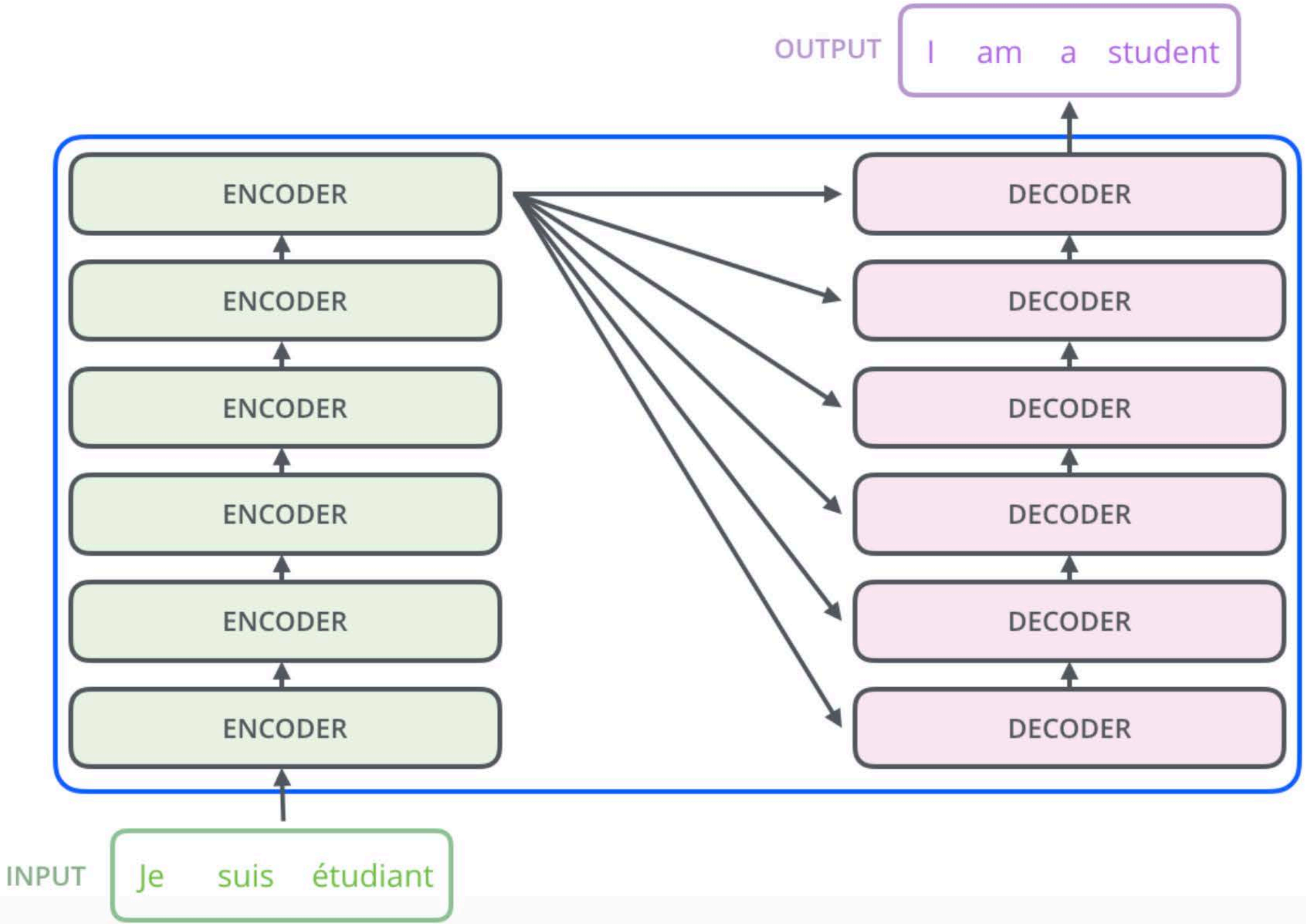


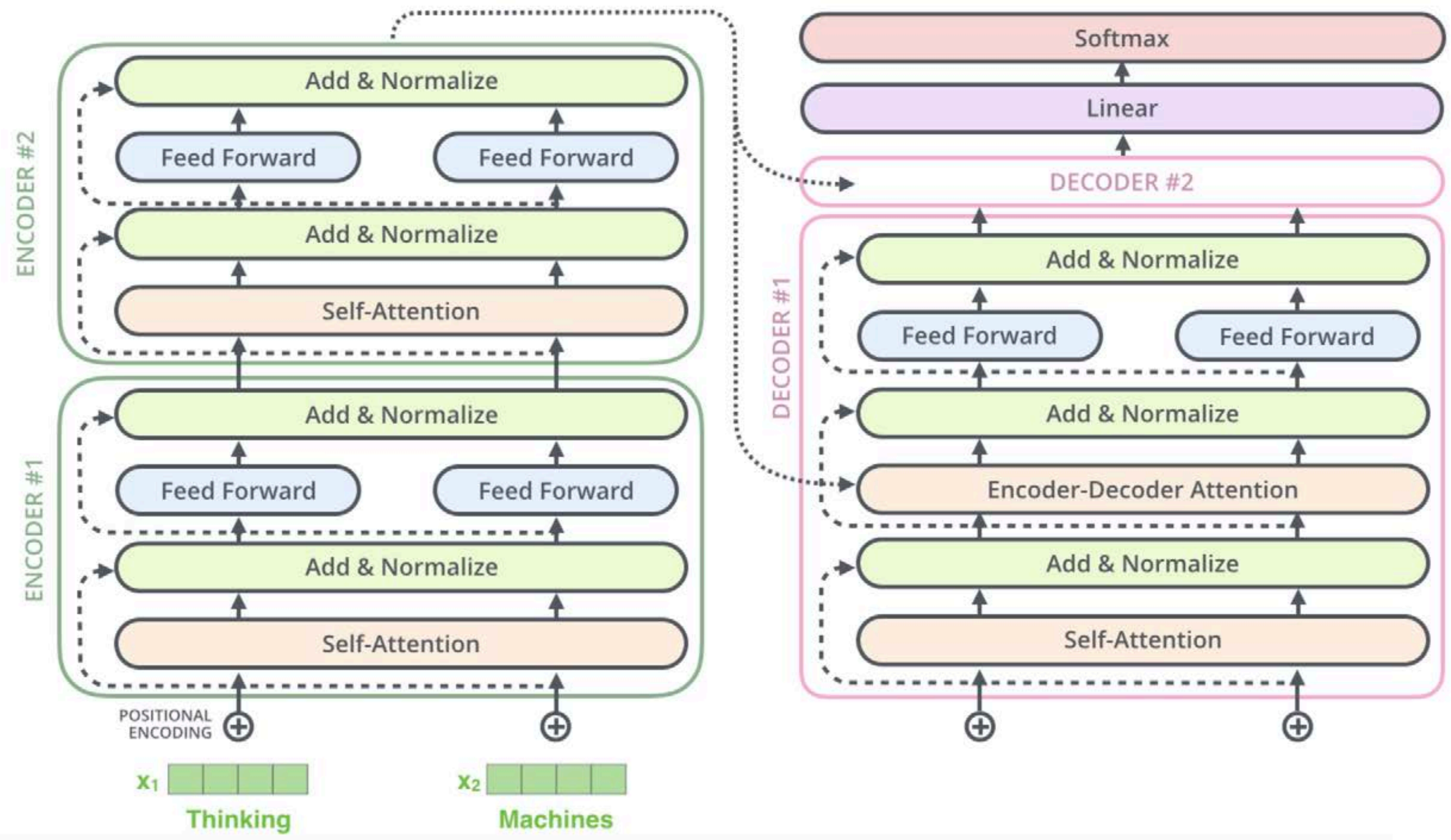
1
0
+
1
2
Input
0 0 1 0
1 0 0 0
0 0 0 1
0 1 0 0
0 0 0 0
Encoding
??
state
Encoder LSTM
0.3 0.3 0.3
Output
RepeatVector
Decoder LSTM
? ? ?
Output
Σ
0 0 0 0
0 0 0 1
TimeDistributed (dense)
2
2
<end>
Result

Transformers



http://jalammar.github.io/illustrated-transformer/


OUTPUT
I am a student
ENCODER
ENCODER
ENCODER
ENCODER
ENCODER
ENCODER
DECODER
DECODER
DECODER
DECODER
DECODER
DECODER
INPUT
Je suis étudiant


Softmax
Linear
DECODER #2
DECODER #1
Add & Normalize
Feed Forward
Feed Forward
Add & Normalize
Encoder-Decoder Attention
Add & Normalize
Self-Attention
ENCODER #2
Add & Normalize
Feed Forward
Feed Forward
Add & Normalize
Self-Attention
ENCODER #1
Add & Normalize
Feed Forward
Feed Forward
Add & Normalize
Self-Attention
POSITIONAL ENCODING
x1
x2
Thinking
Machines

Conclusion

More about LSTMs

- More online tutorials https://www.wandb.com/classes
- Colah's blog http://colah.github.io/posts/2015-08-Understanding-LSTMs/
- Andrej's blog http://karpathy.github.io/2015/05/21/rnn-effectiveness/
- Attention networks https://richliao.github.io/supervised/classification/2016/12/26/textclassifier-HATN/
- Stanford CS 224N

More Resources for Deep Learning/ML

- Books
  - Deep Learning Book (http://www.deeplearningbook.org/)
  - Artificial Intelligence: A Modern Approach
  - Hands-On Machine Learning with Scikit-Learn and TensorFlow
  - Deep Learning with Python
- Video Classes
  - wandb.com/classes
- Hands-on
  - wandb.com/benchmarks