Network Structure

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Three Steps for Deep Learning

Step 1. A neural network is a function composed of simple functions (neurons)

- ➢ Usually we design the network structure, and let machine find parameters from data

Step 2. Cost function evaluates how good a set of parameters is

- ➢ We design the cost function based on the task

Step 3. Find the best function set (e.g. gradient descent)

Outline

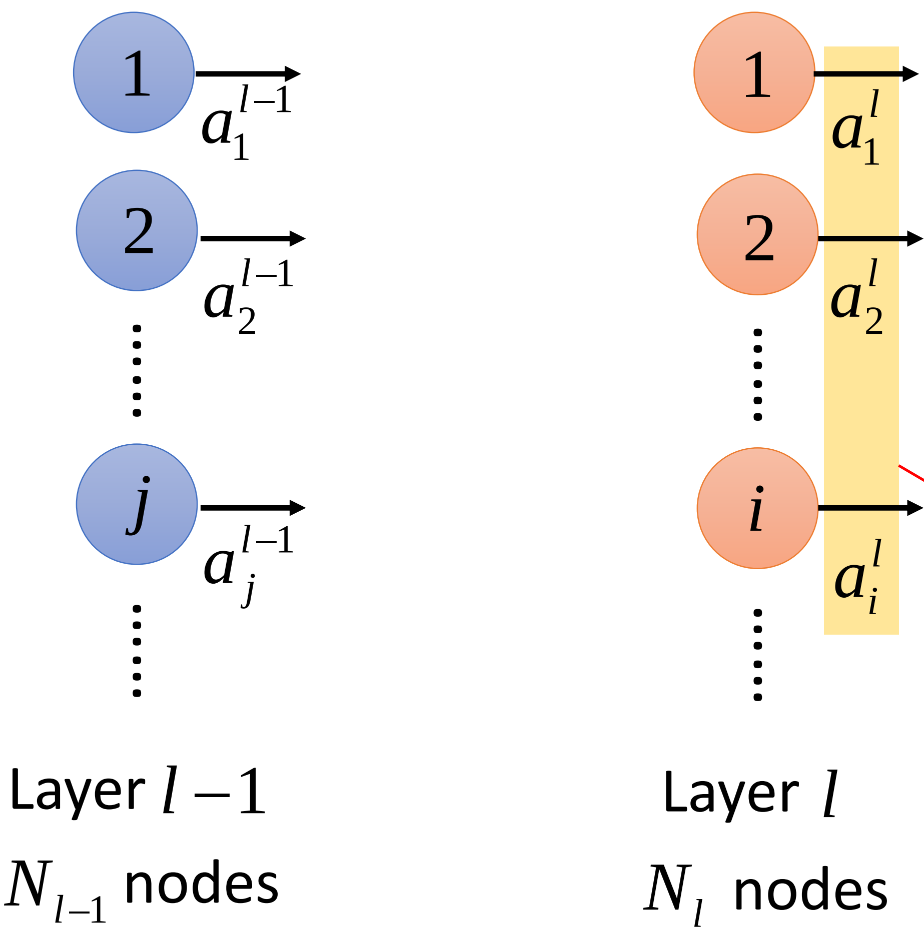
- Basic structure (3/03)
  - Fully Connected Layer
  - Recurrent Structure
  - Convolutional/Pooling Layer
- Special Structure (3/17)
  - Spatial Transformation Layer
  - Highway Network / Grid LSTM
  - Recursive Structure
  - Batch Normalization
  - Sequence-to-sequence / Attention (3/24)

Prerequisite

- Brief Introduction of Deep Learning
  - https://youtu.be/Dr-WRlEFefw?list=PLJV_el3uVTsPy9oCRY30oBPNLCo89yu49
- Convolutional Neural Network
  - https://youtu.be/FrKWiRv254g?list=PLJV_el3uVTsPy9oCRY30oBPNLCo89yu49
- Recurrent Neural Network (Part I)
  - https://youtu.be/xCGidAeyS4M?list=PLJV_el3uVTsPy9oCRY30oBPNLCo89yu49
- Recurrent Neural Network (Part II)
  - https://www.youtube.com/watch?v=rTqmWlnwz_0&list=PLJV_el3uVTsPy9oCRY30oBPNLCo89yu49&index=25

Basic Structure:
Fully Connected Layer

Fully Connected Layer



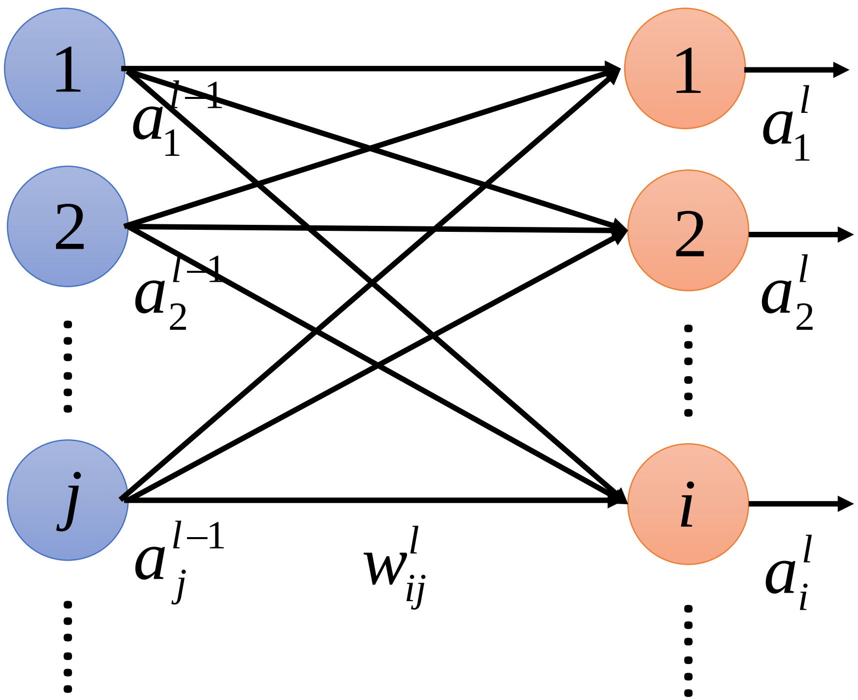
Output of a neuron:

a_i^l — l: Layer l; i: Neuron i

Output of one layer:

a^l : a vector

Fully Connected Layer



Layer $l-1$

N_{l-1} nodes

Layer l

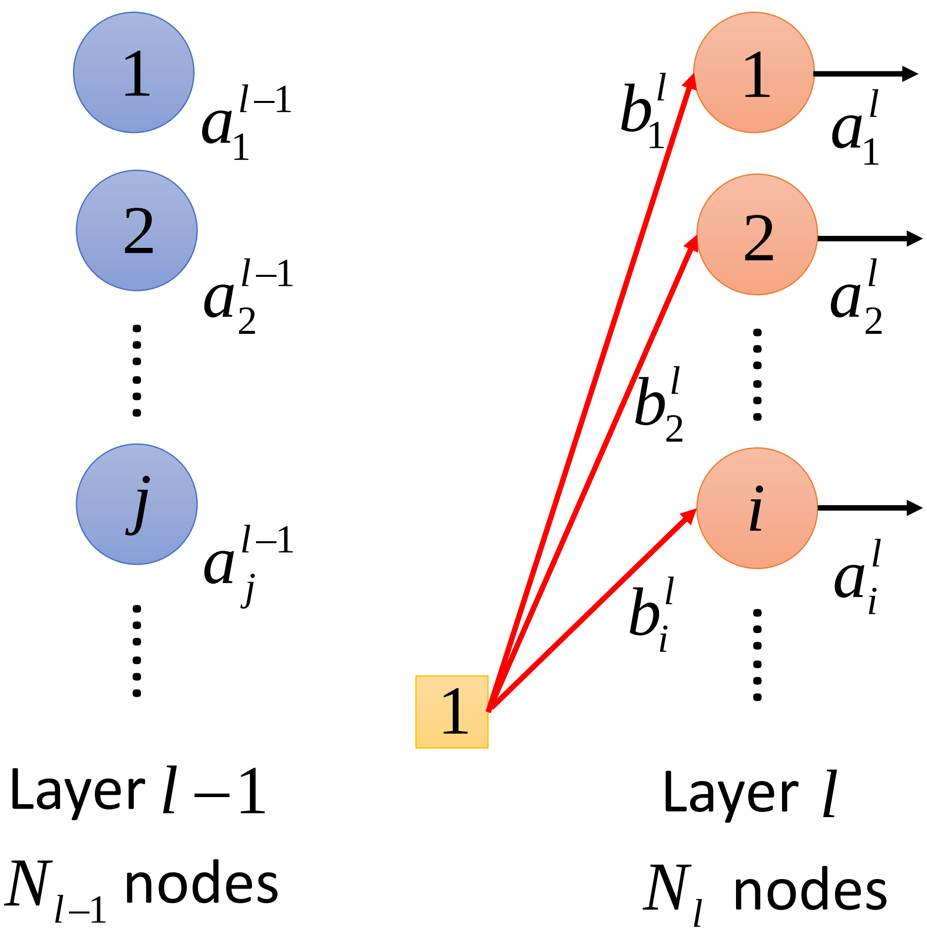
N_l nodes

w_{ij}^l → Layer $l-1$ to Layer l

↓ from neuron j (Layer $l-1$) to neuron i (Layer l)

$$W^l = \begin{array}{c} \overbrace{\hphantom{w_{11}^l \quad w_{12}^l \quad \cdots \quad}}^{N_{l-1}} \\ \left.\begin{bmatrix} w_{11}^l & w_{12}^l & \cdots & \\ w_{21}^l & w_{22}^l & & \\ \vdots & & \ddots & \\ & & & \end{bmatrix}\right\} N_l \end{array}$$

Fully Connected Layer

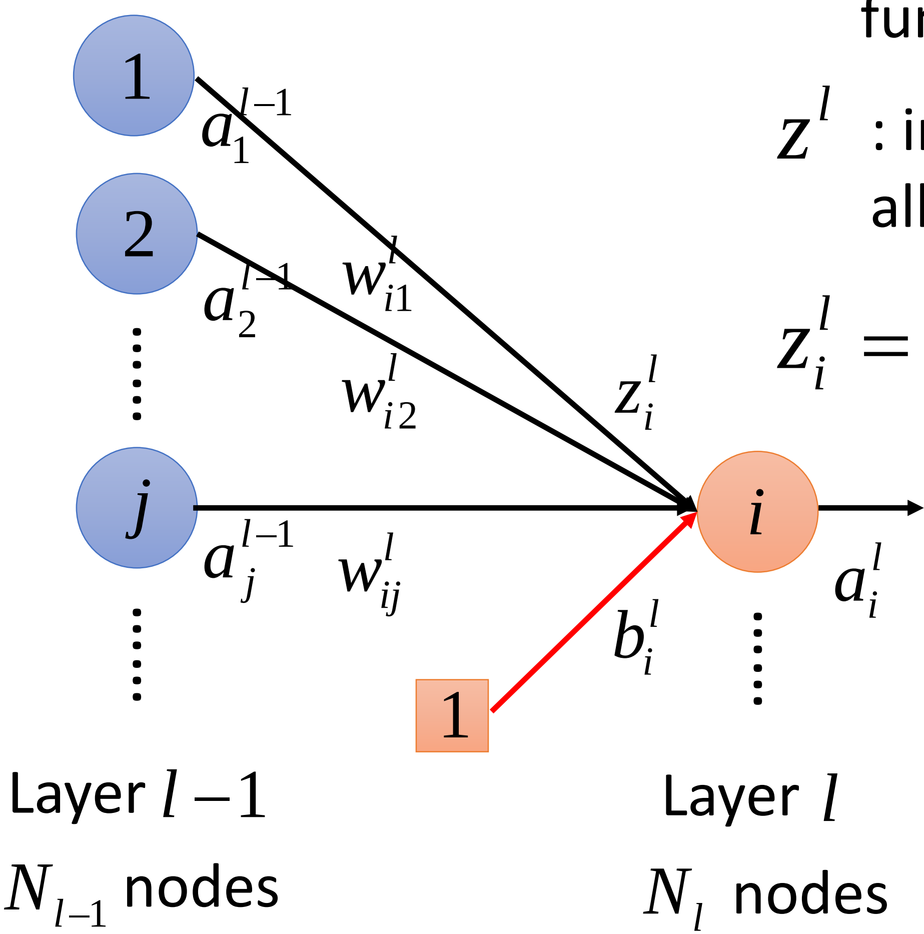


b_i^l : bias for neuron i at layer l

$$b^l = \begin{bmatrix} b_1^l \\ b_2^l \\ \vdots \\ b_i^l \\ \vdots \end{bmatrix}$$

bias for all neurons in layer l

Fully Connected Layer



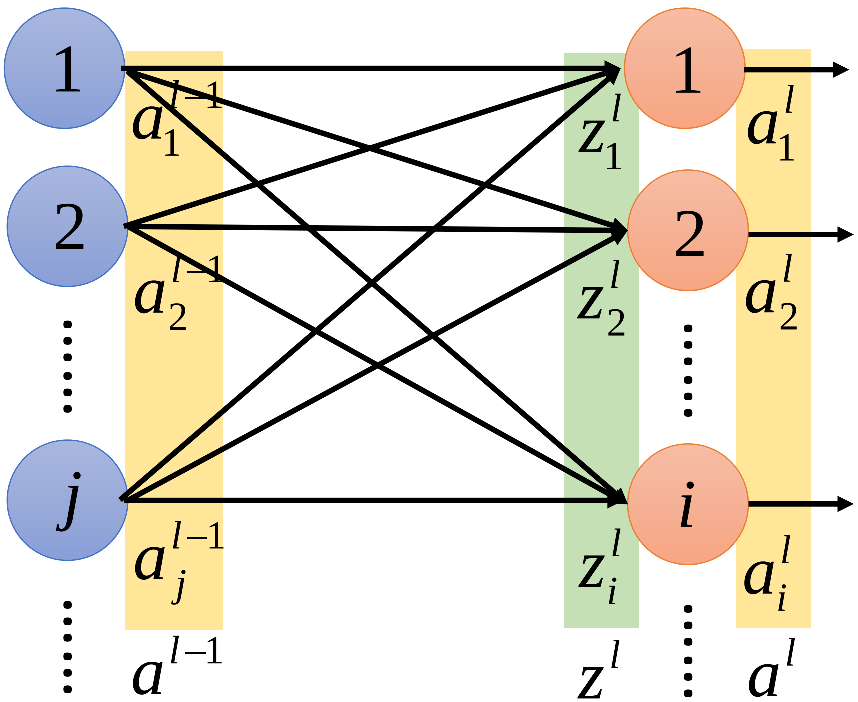
z_i^l : input of the activation function for neuron i at layer l

z^l : input of the activation function all the neurons in layer l

$$z_i^l = w_{i1}^l a_1^{l-1} + w_{i2}^l a_2^{l-1} \ldots + b_i^l$$

$$z_i^l = \sum_{j=1}^{N_{l-1}} w_{ij}^l a_j^{l-1} + b_i^l$$

Relations between Layer Outputs



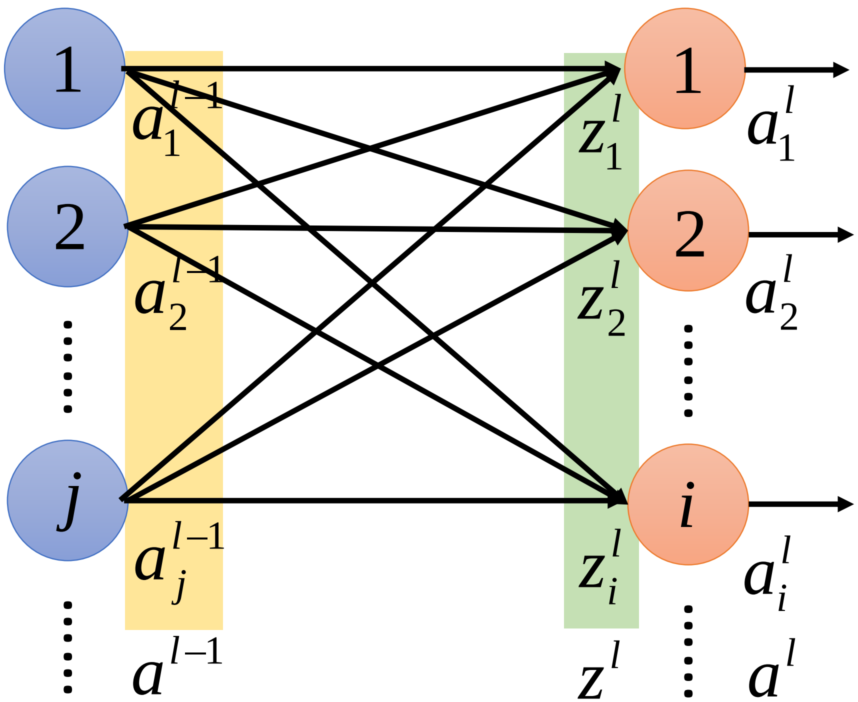
Layer $l-1$

N_{l-1} nodes

Layer l

N_l nodes

Relations between Layer Outputs



Layer $l-1$

N_{l-1} nodes

Layer l

N_l nodes

$$z_1^l = w_{11}^l a_1^{l-1} + w_{12}^l a_2^{l-1} + \cdots + b_1^l$$

$$z_2^l = w_{21}^l a_1^{l-1} + w_{22}^l a_2^{l-1} + \cdots + b_2^l$$

$$\vdots$$

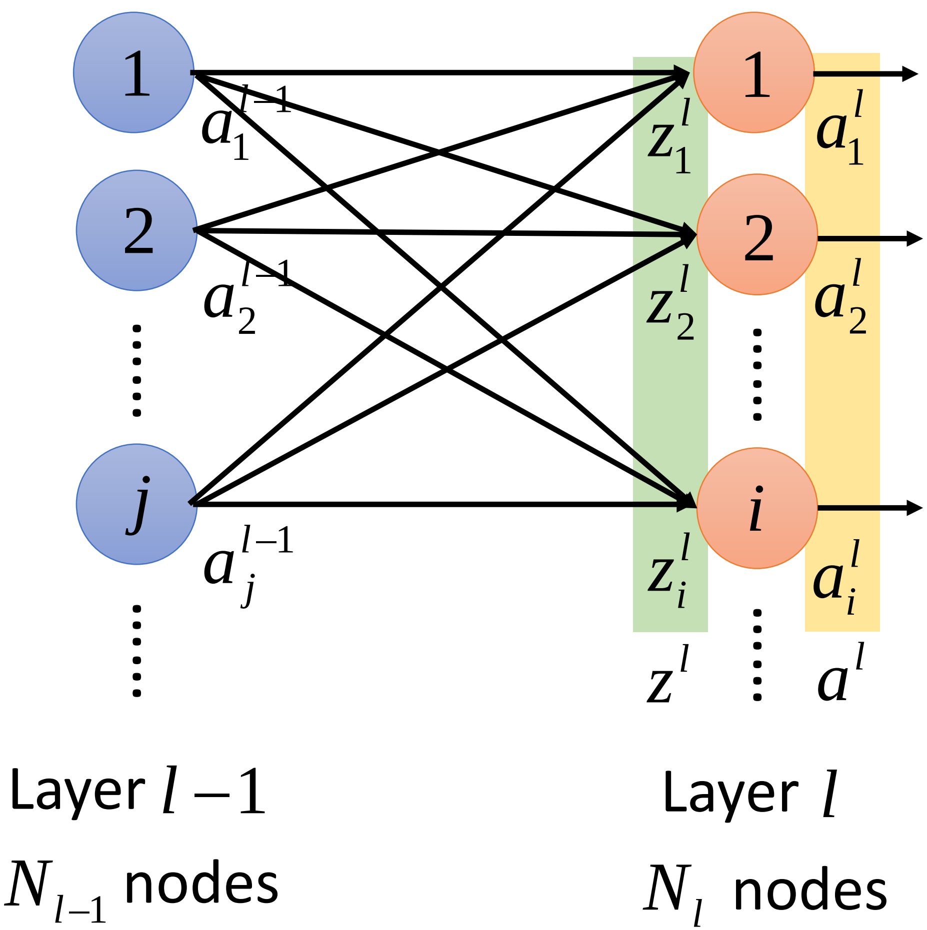
$$z_i^l = w_{i1}^l a_1^{l-1} + w_{i2}^l a_2^{l-1} + \cdots + b_i^l$$

$$\vdots$$

$$\begin{bmatrix} z_1^l \\ z_2^l \\ \vdots \\ z_i^l \\ \vdots \end{bmatrix} = \begin{bmatrix} w_{11}^l & w_{12}^l & \cdots \\ w_{21}^l & w_{22}^l & \\ \vdots & & \ddots \end{bmatrix} \begin{bmatrix} a_1^{l-1} \\ a_2^{l-1} \\ \vdots \\ a_i^{l-1} \\ \vdots \end{bmatrix} + \begin{bmatrix} b_1^l \\ b_2^l \\ \vdots \\ b_i^l \\ \vdots \end{bmatrix}$$

$$z^l = W^l a^{l-1} + b^l$$

Relations between Layer Outputs

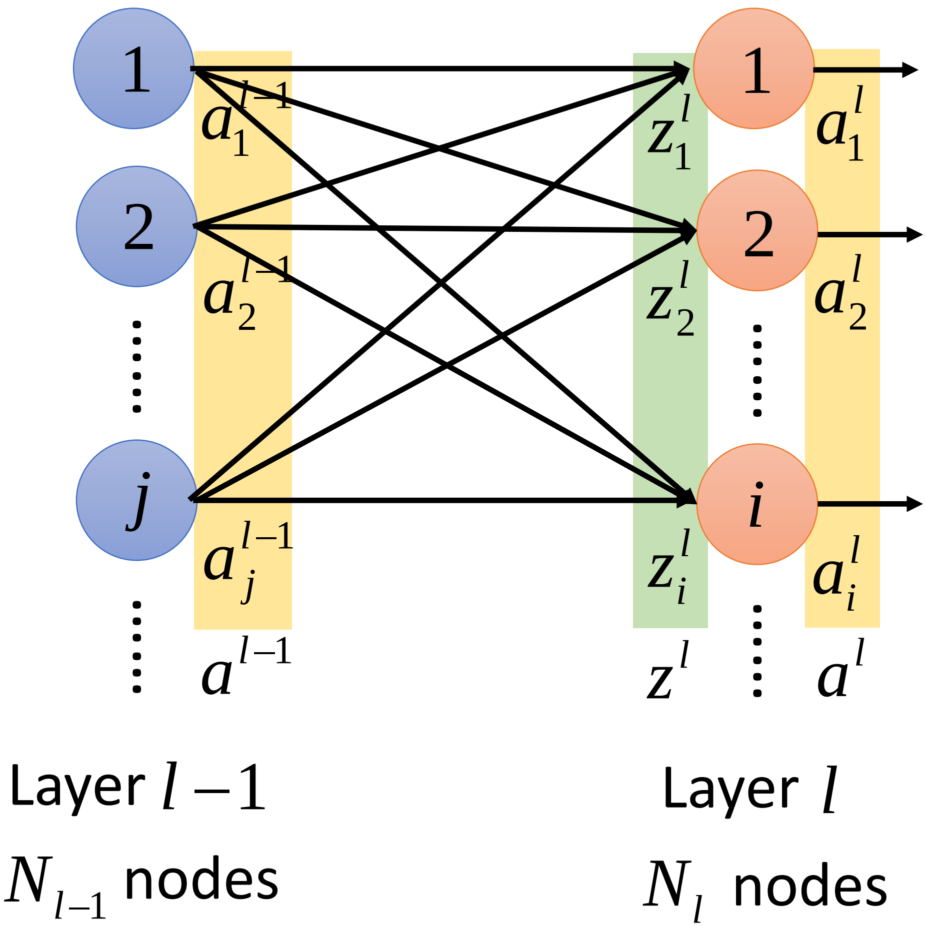


$$a_i^l = \sigma\left(z_i^l\right)$$

$$\begin{bmatrix} a_1^l \\ a_2^l \\ \vdots \\ a_i^l \\ \vdots \end{bmatrix} = \begin{bmatrix} \sigma\left(z_1^l\right) \\ \sigma\left(z_2^l\right) \\ \vdots \\ \sigma\left(z_i^l\right) \\ \vdots \end{bmatrix}$$

$$a^l = \sigma\left(z^l\right)$$

Relations between Layer Outputs



$$z^l = W^l a^{l-1} + b^l$$

$$a^l = \sigma\left(z^l\right)$$

$$a^l = \sigma\left(W^l a^{l-1} + b^l\right)$$

Basic Structure: Recurrent Structure

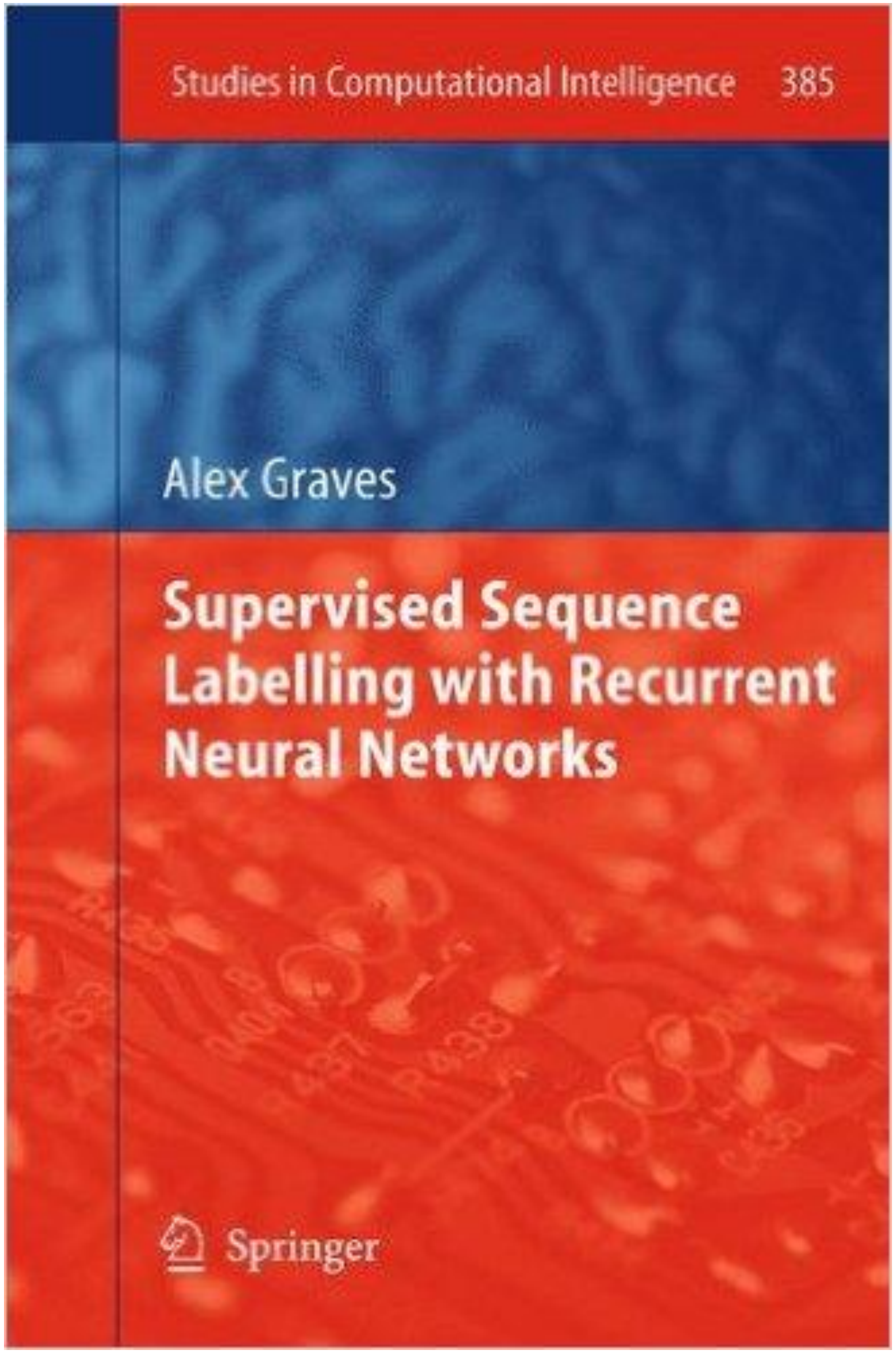
Simplify the network
by using the same function again and again

Reference

K. Greff, R. K. Srivastava, J. Koutník, B. R. Steunebrink, J. Schmidhuber, "LSTM: A Search Space Odyssey," in *IEEE Transactions on Neural Networks and Learning Systems*, 2016

Rafal Józefowicz, Wojciech Zaremba, Ilya Sutskever, “An Empirical Exploration of Recurrent Network Architectures,” in ICML, 2015

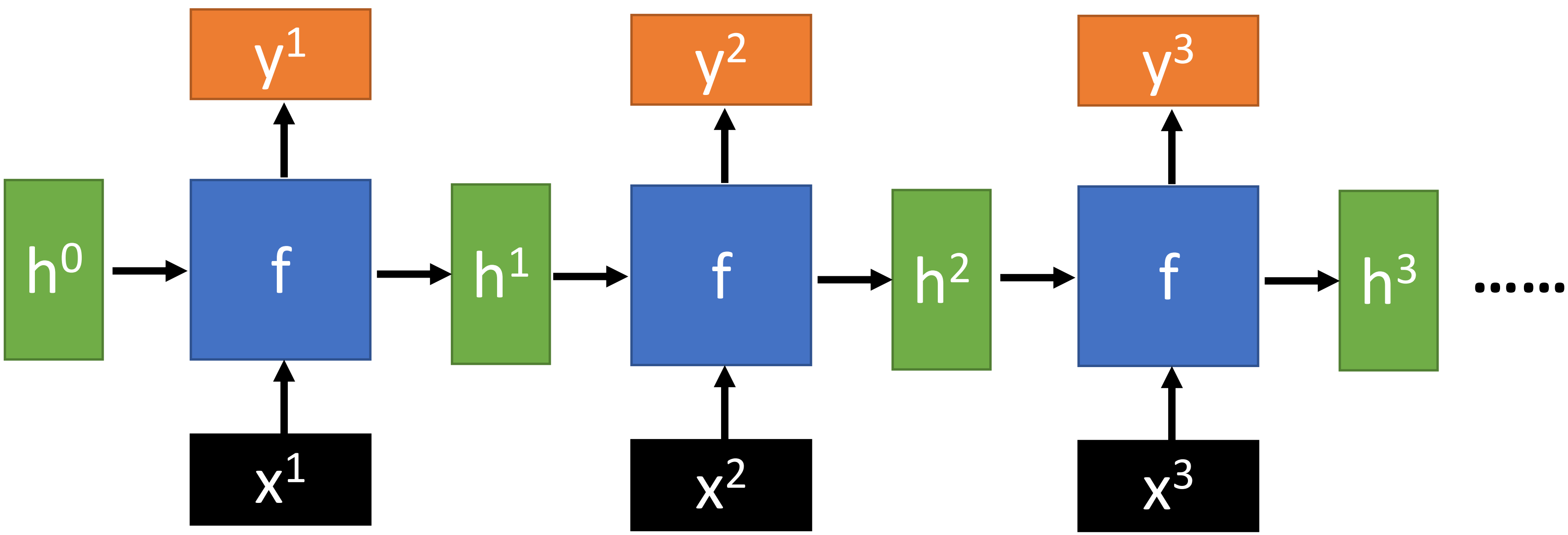
https://www.cs.toronto.edu/~graves/preprint.pdf



Recurrent Neural Network

- Given function f: $h', y = f(h, x)$

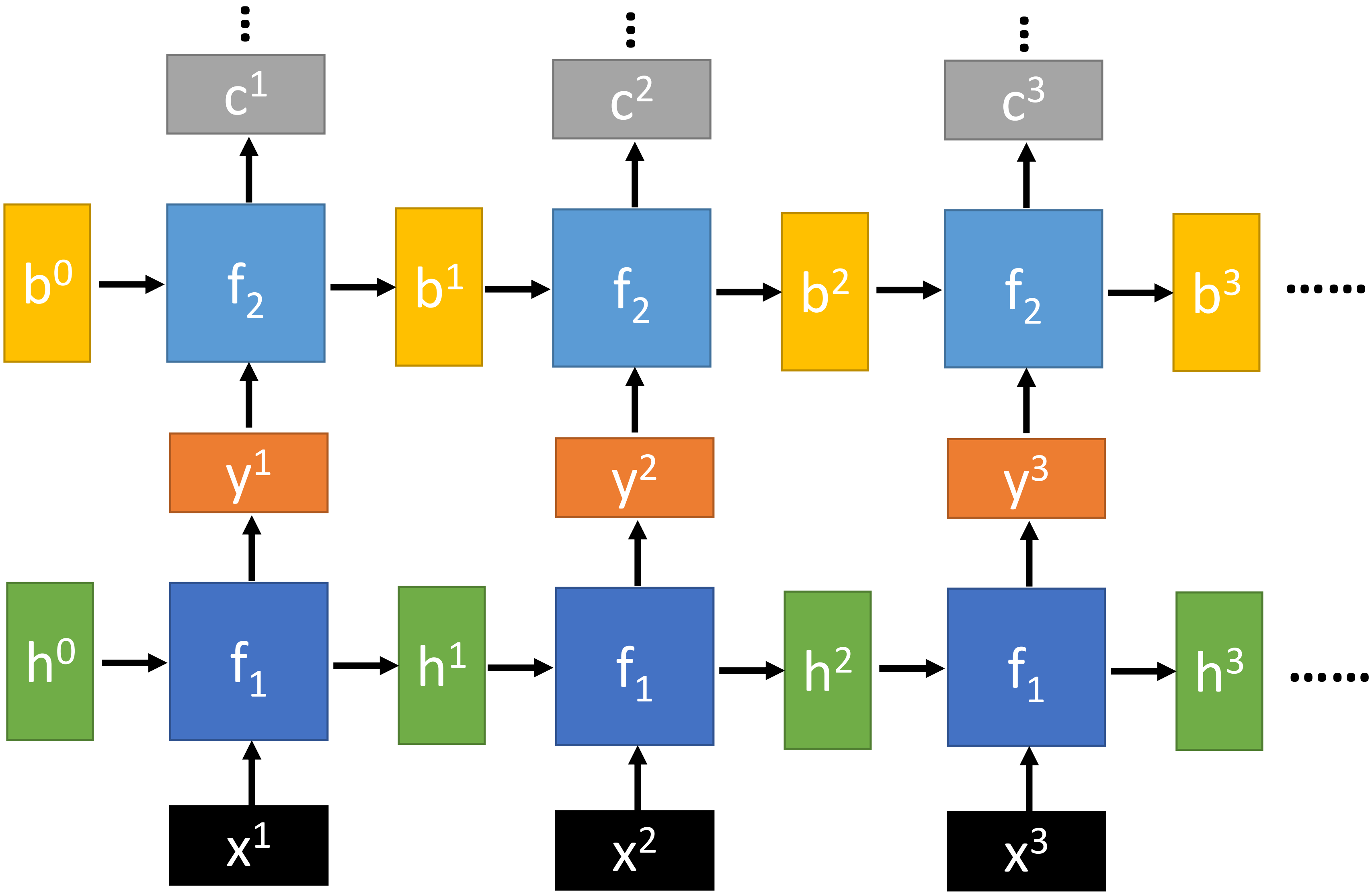
h and h’ are vectors with the same dimension



No matter how long the input/output sequence is, we only need one function f

Deep RNN

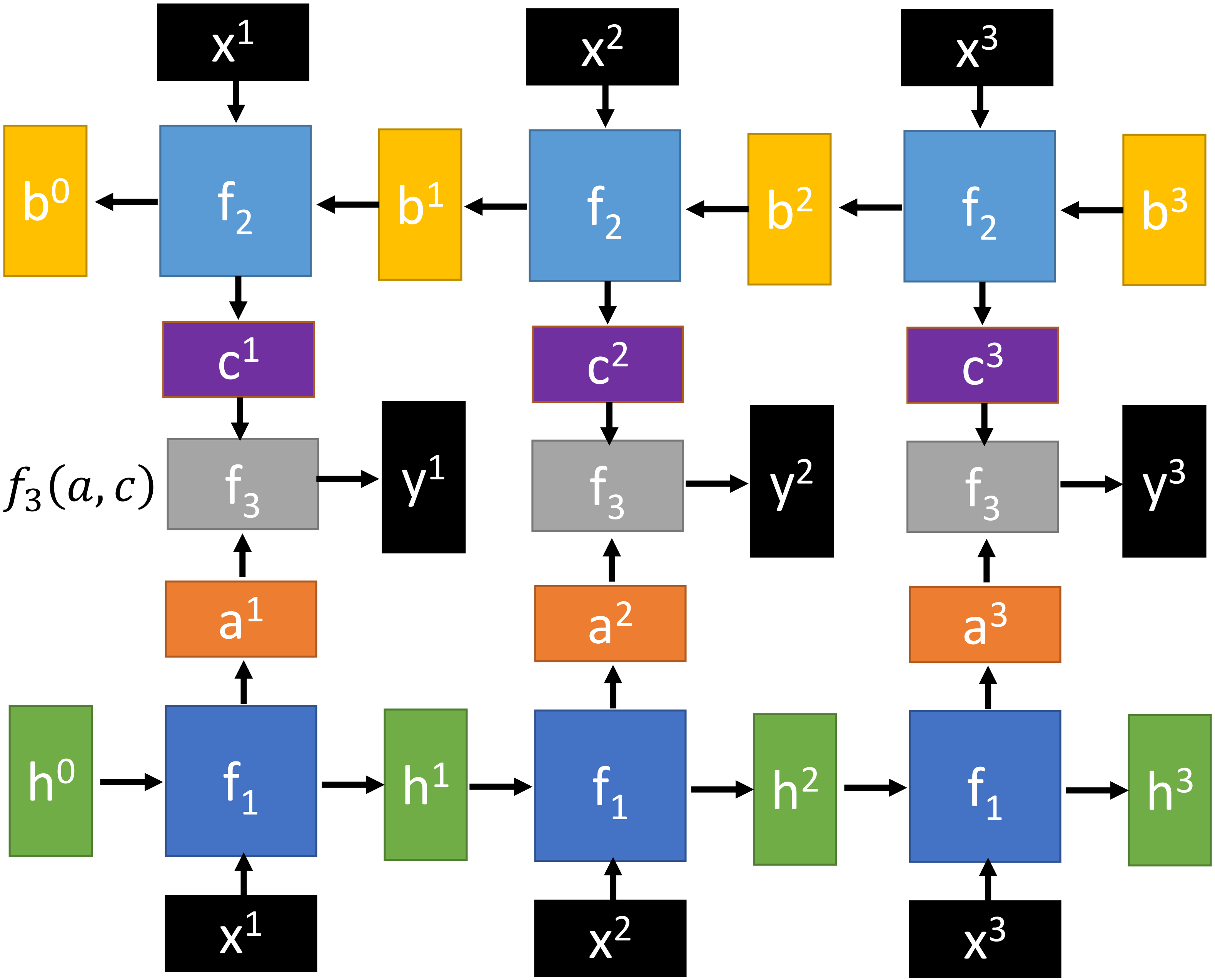
$h', y = f_1(h, x) \quad b', c = f_2(b, y) \quad \cdots$



Bidirectional RNN

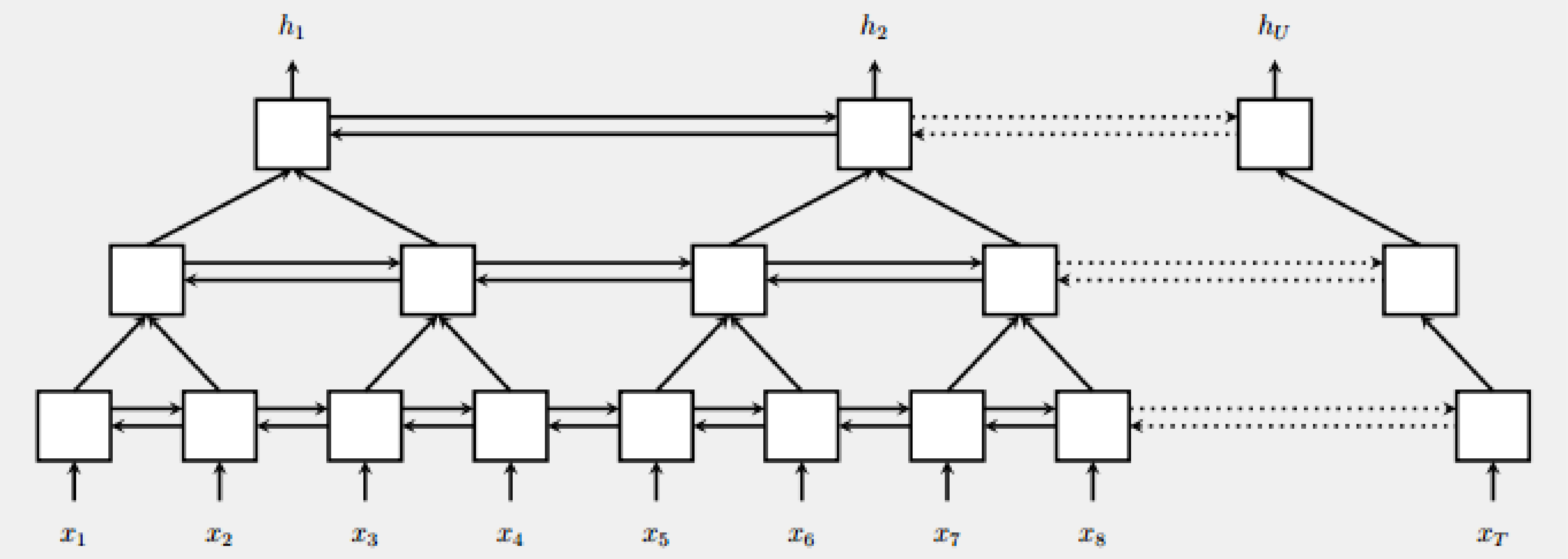
$$h', a = f_1(h, x) \qquad b', c = f_2(b, x)$$

$$y = f_3(a, c)$$



Pyramidal RNN

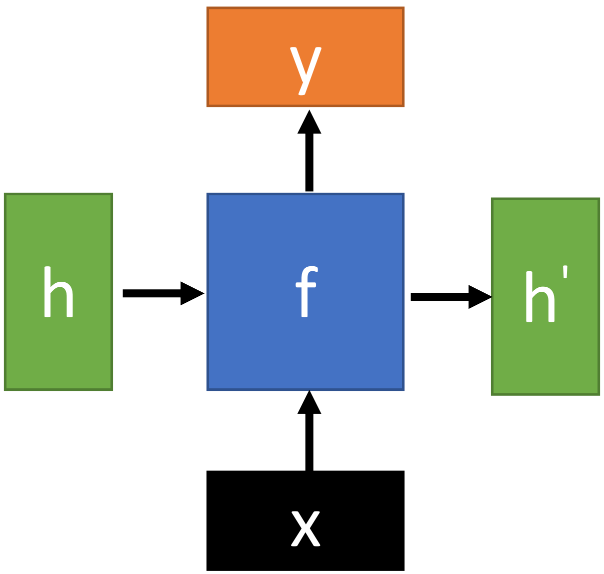
- Reducing the number of time steps



W. Chan, N. Jaitly, Q. Le and O. Vinyals, "Listen, attend and spell: A neural network for large vocabulary conversational speech recognition," ICASSP, 2016

Naïve RNN

- Given function f: $h', y = f(h, x)$



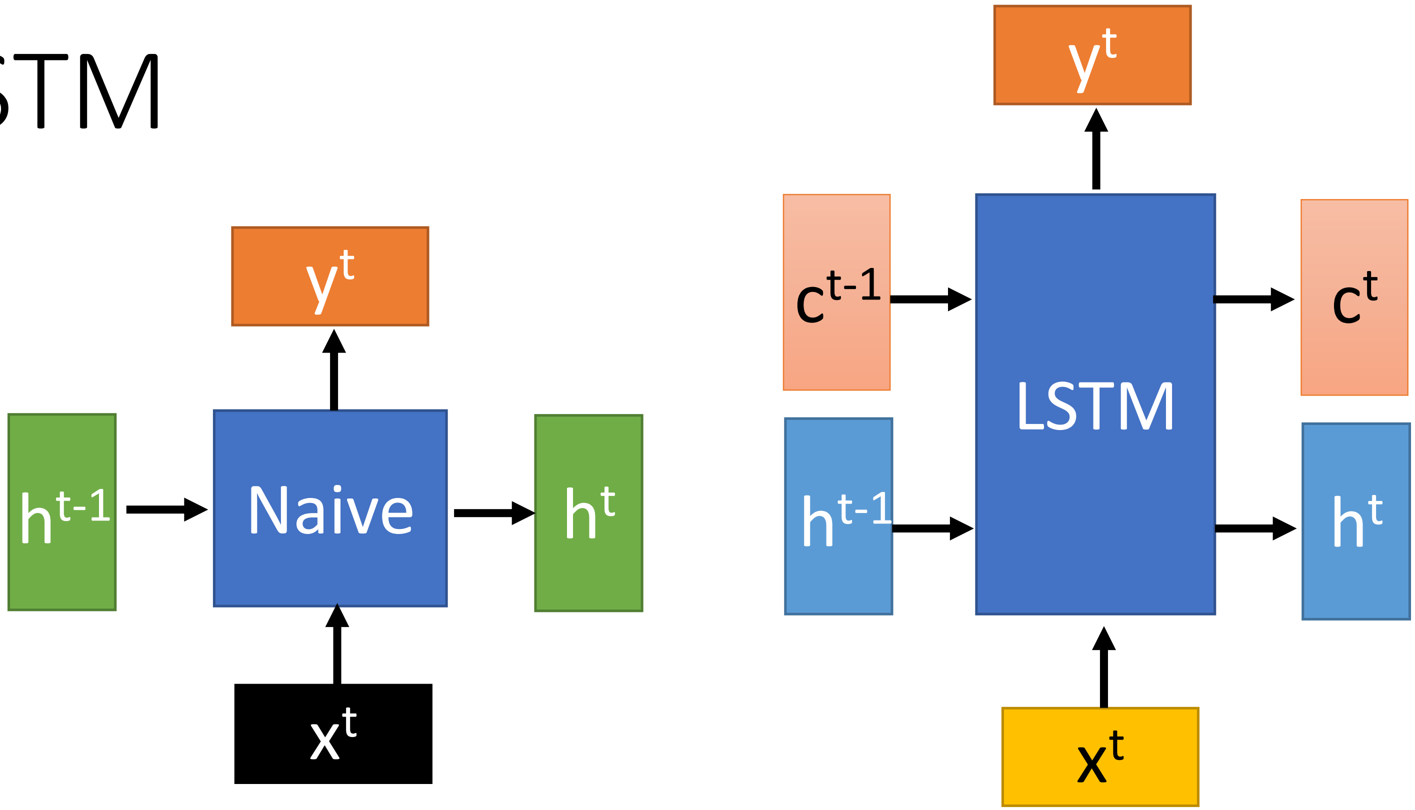
$$h' = \sigma(W^h h + W^i x)$$

$$y = \sigma(W^o h')$$

softmax

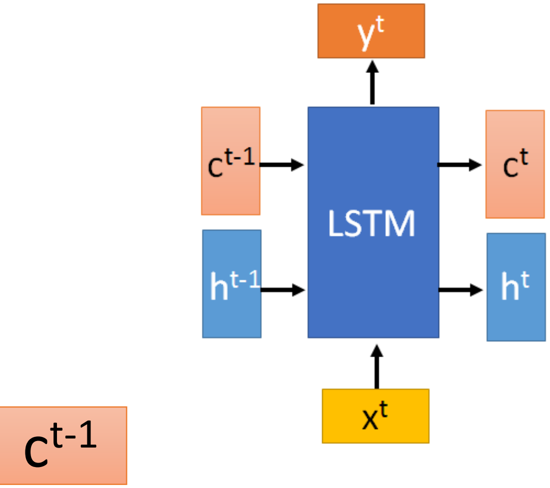
Ignore bias here

LSTM



c change slowly ➡ c^t is c^{t-1} added by something

h change faster ➡ h^t and h^{t-1} can be very different

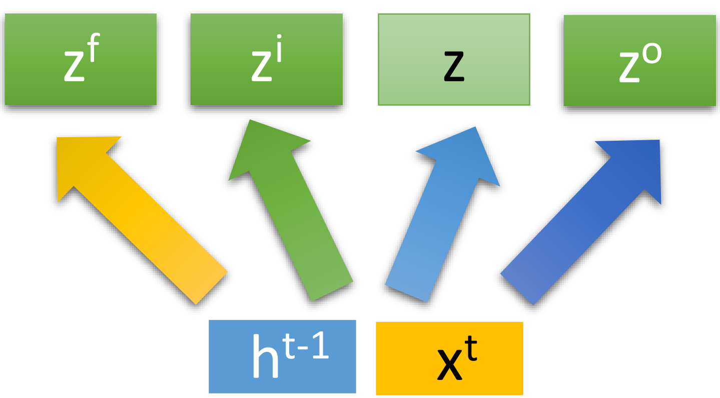


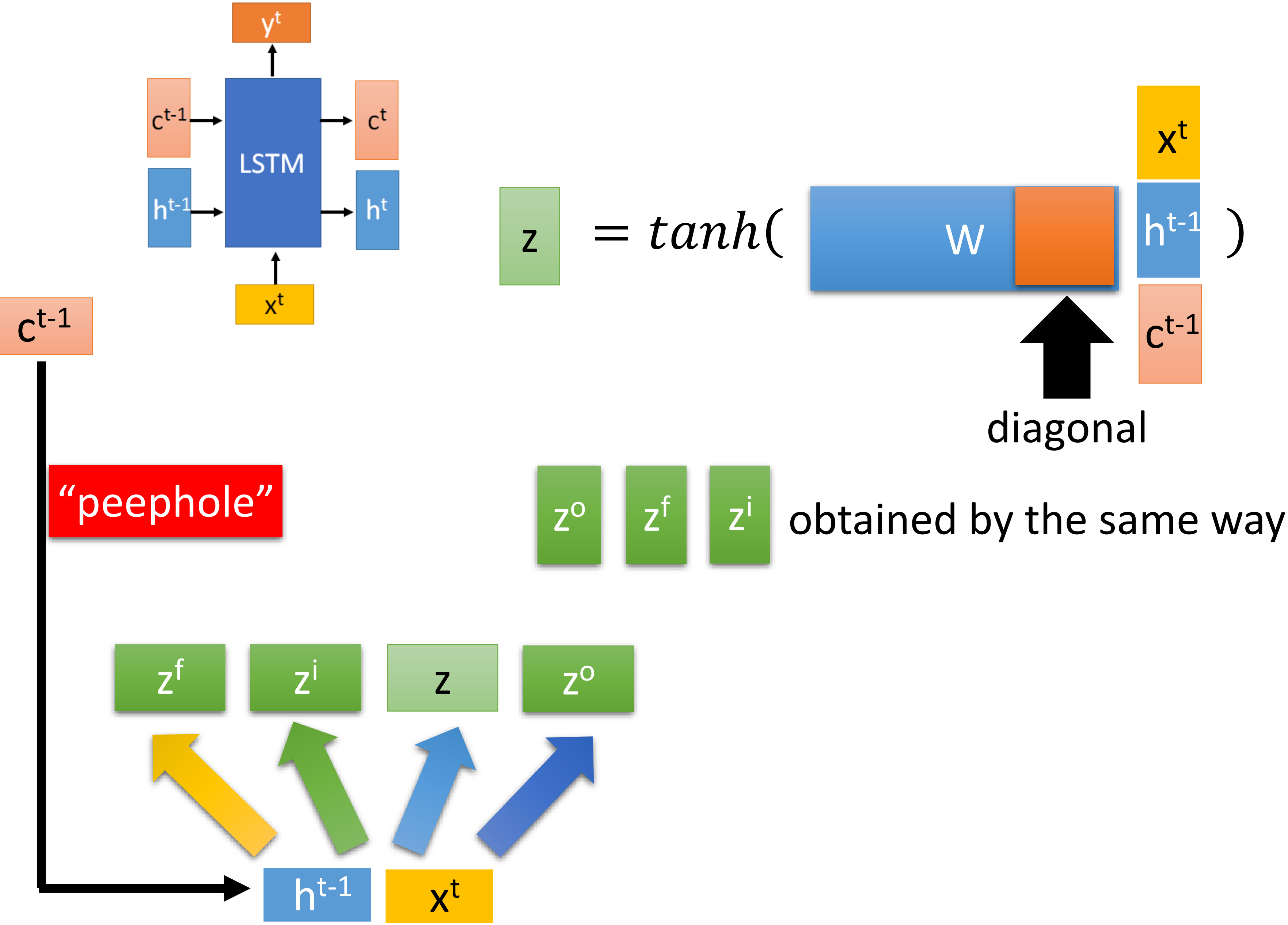
$$z = tanh\left(W \begin{bmatrix} x^t \\ h^{t-1} \end{bmatrix} \right)$$

$$z^i = \sigma\left(W^i \begin{bmatrix} x^t \\ h^{t-1} \end{bmatrix} \right)$$

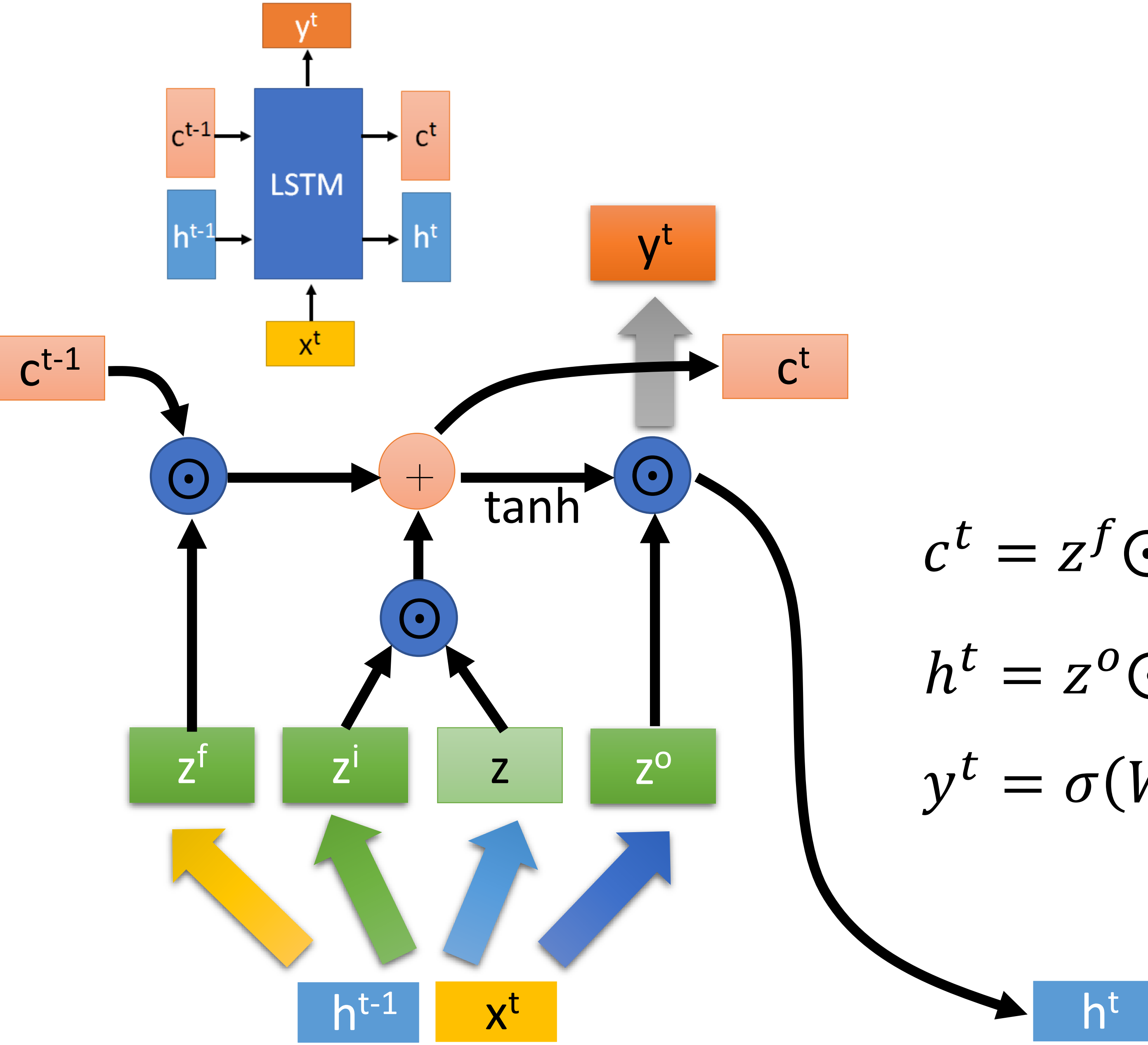
$$z^f = \sigma\left(W^f \begin{bmatrix} x^t \\ h^{t-1} \end{bmatrix} \right)$$

$$z^o = \sigma\left(W^o \begin{bmatrix} x^t \\ h^{t-1} \end{bmatrix} \right)$$





y^t
c^{t-1}
LSTM
c^t
h^{t-1}
h^t
x^t
$z = tanh($ W x^t h^{t-1} c^{t-1} $)$
diagonal
z^o z^f z^i obtained by the same way
c^{t-1}
"peephole"
z^f
z^i
z
z^o
h^{t-1}
x^t

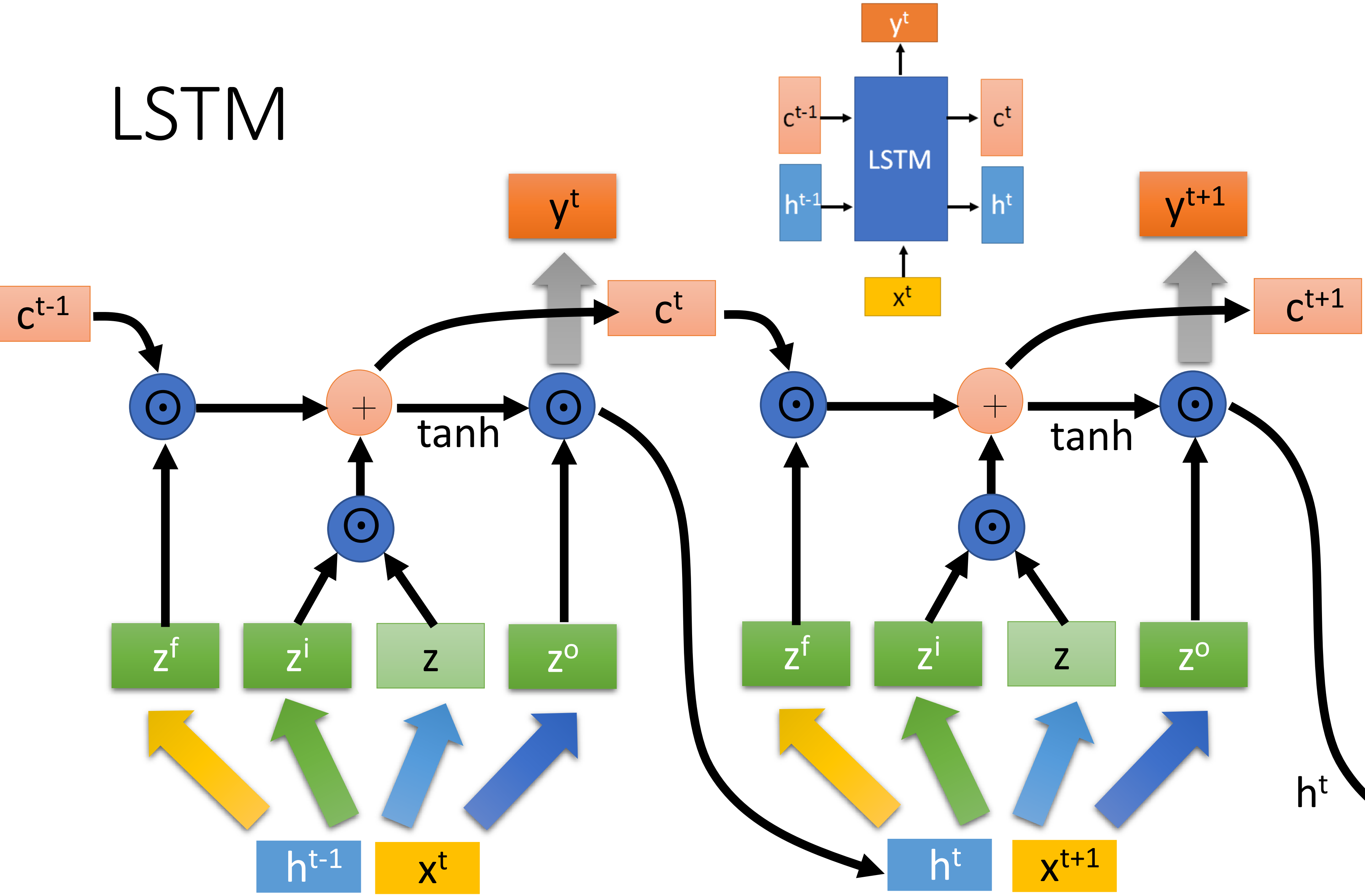


$$c^t = z^f \odot c^{t-1} + z^i \odot z$$

$$h^t = z^o \odot tanh(c^t)$$

$$y^t = \sigma(W' h^t)$$

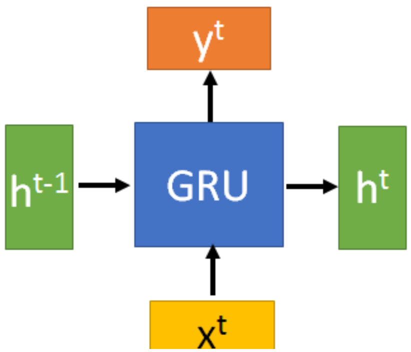
LSTM

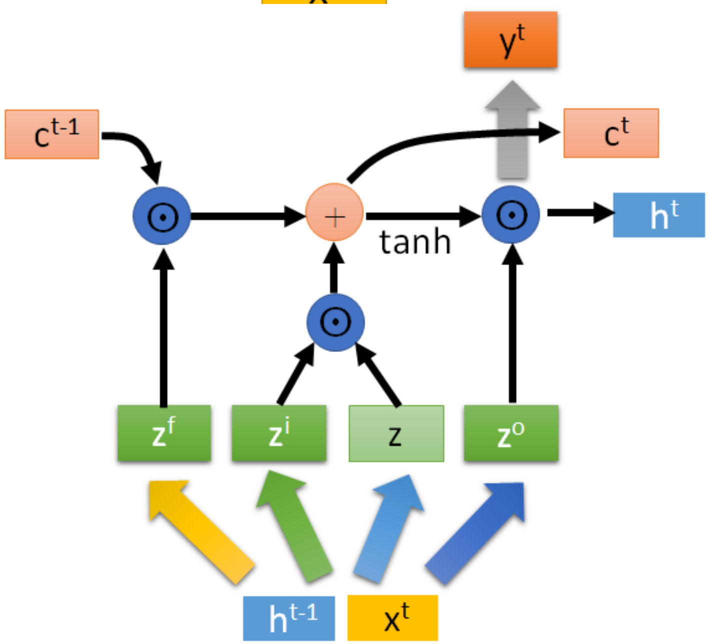


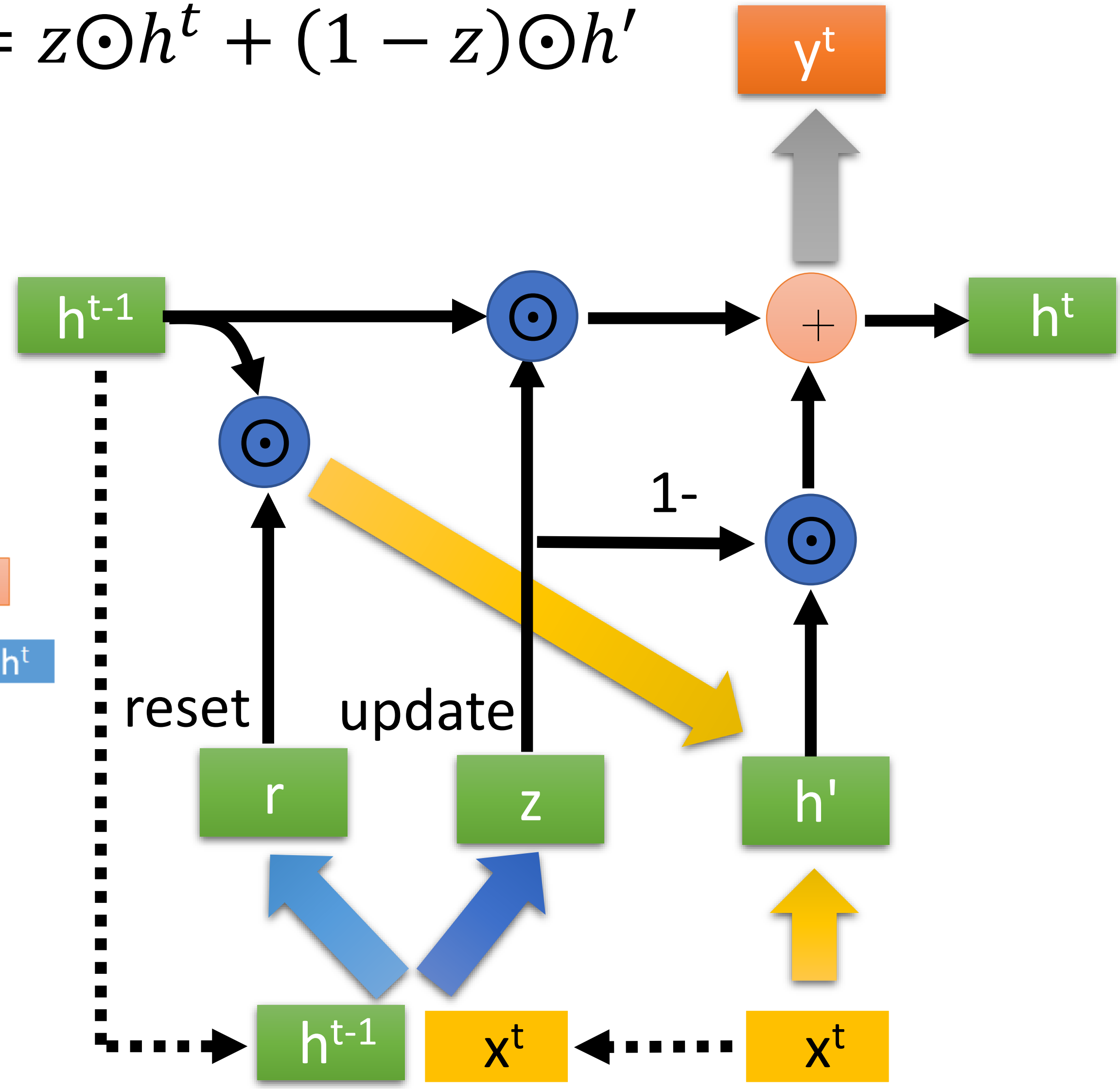
yt
ct-1
LSTM
ct
ht-1
ht
xt
yt
ct-1
ct
tanh
zf
zi
z
zo
ht-1
xt
yt+1
ct+1
tanh
zf
zi
z
zo
ht
xt+1
ht

GRU

$$h^t = z \odot h^t + (1 - z) \odot h'$$

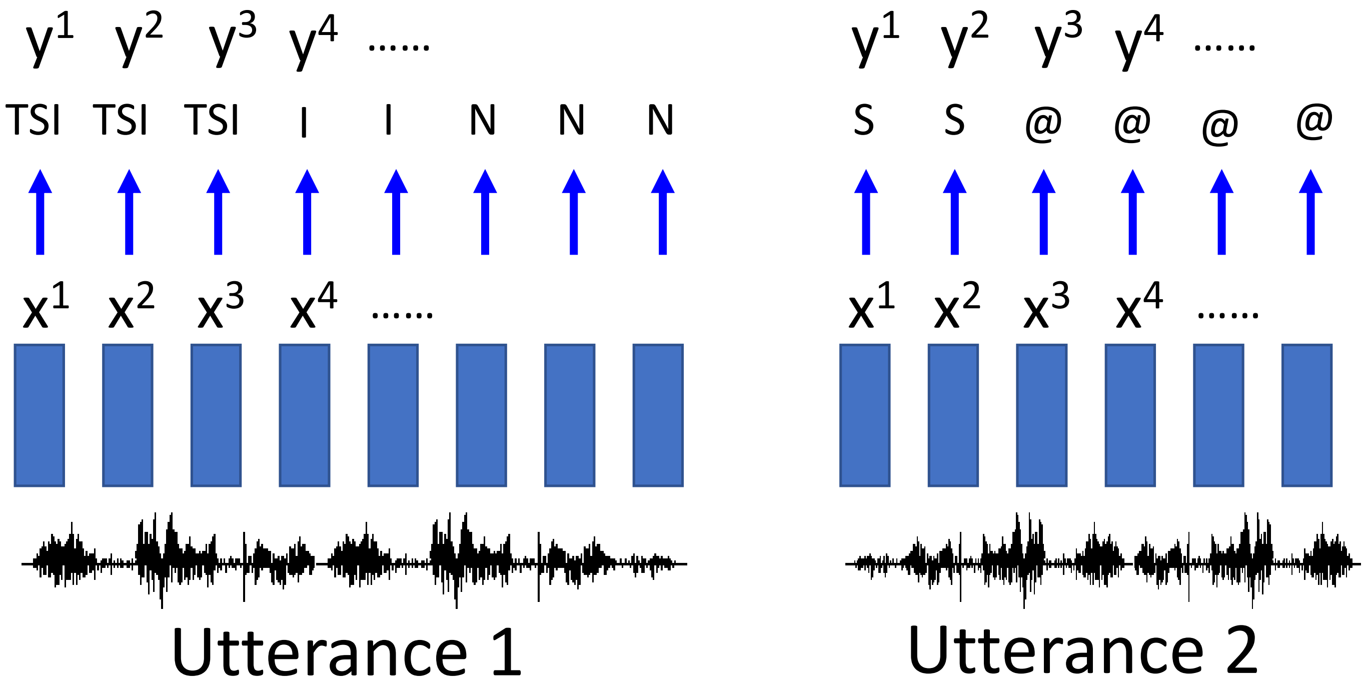






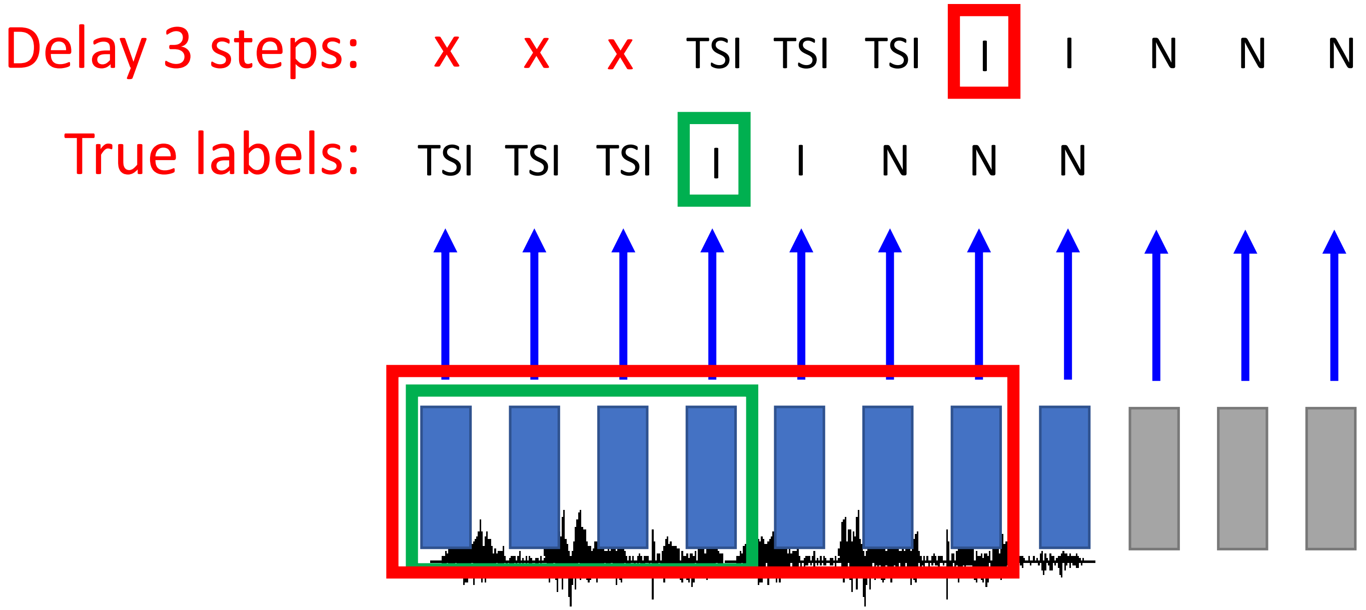
Example Task

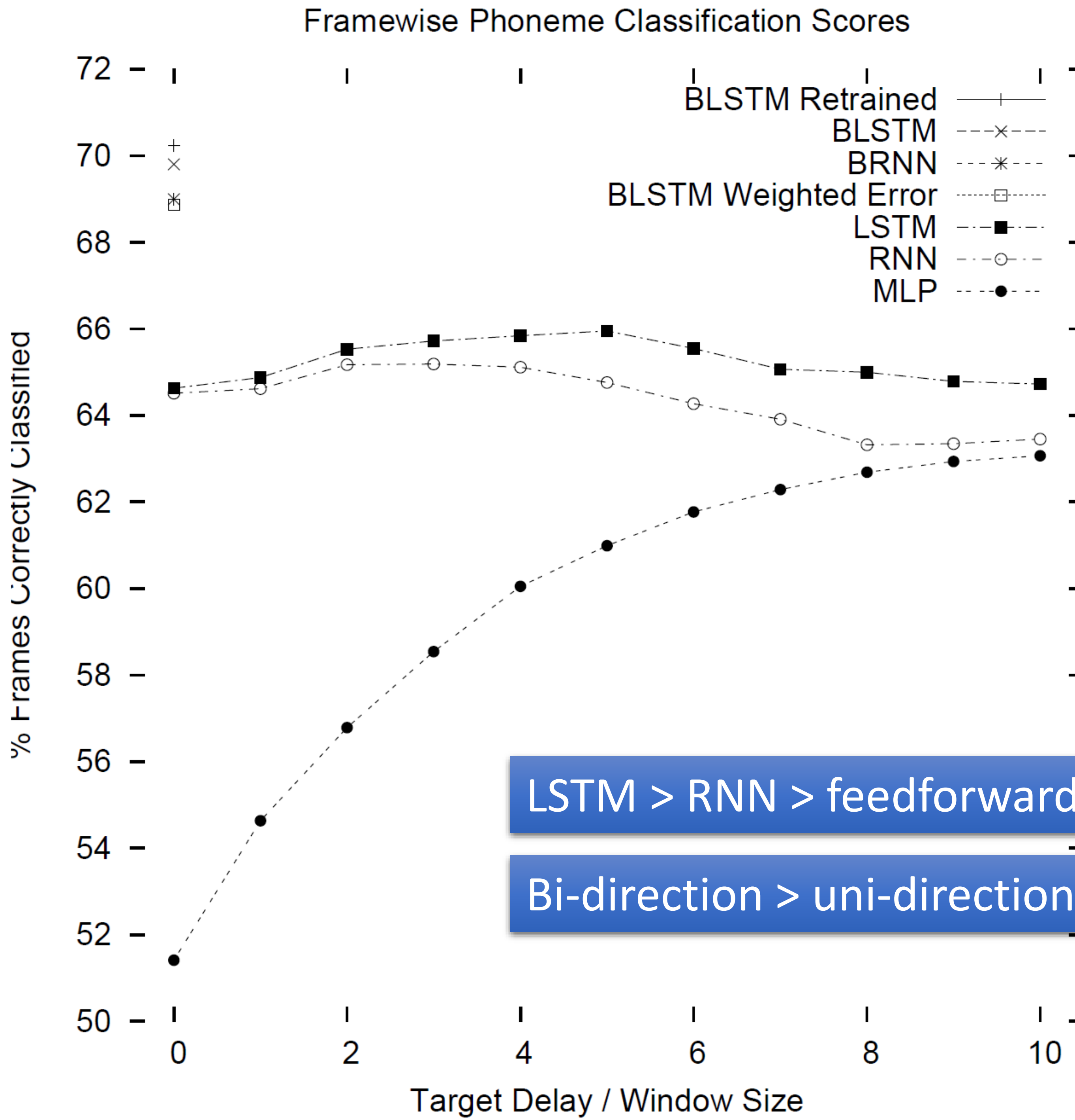
- (Simplified) Speech Recognition: Frame classification on TIMIT



Target Delay

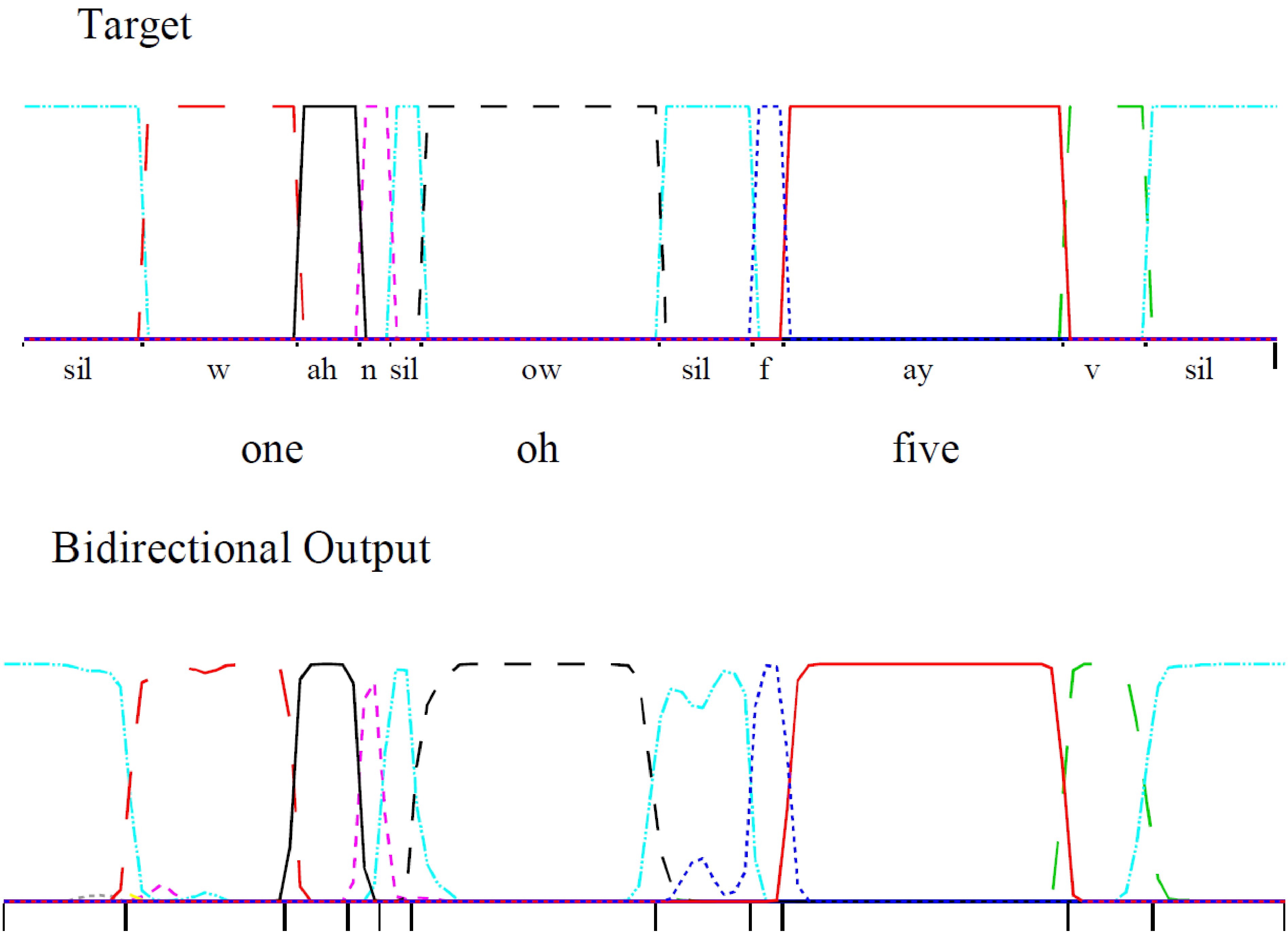
- Only for unidirectional RNN

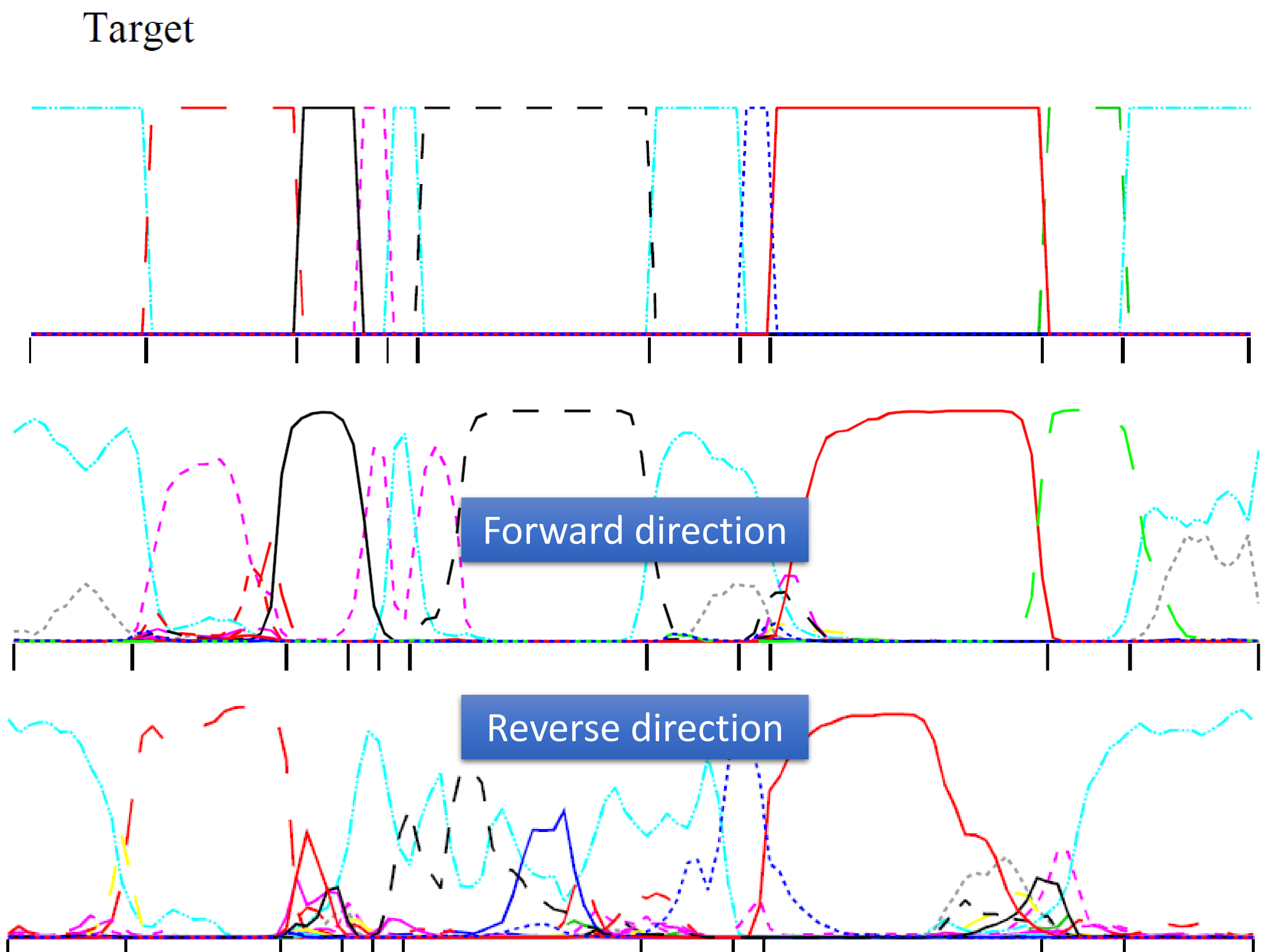




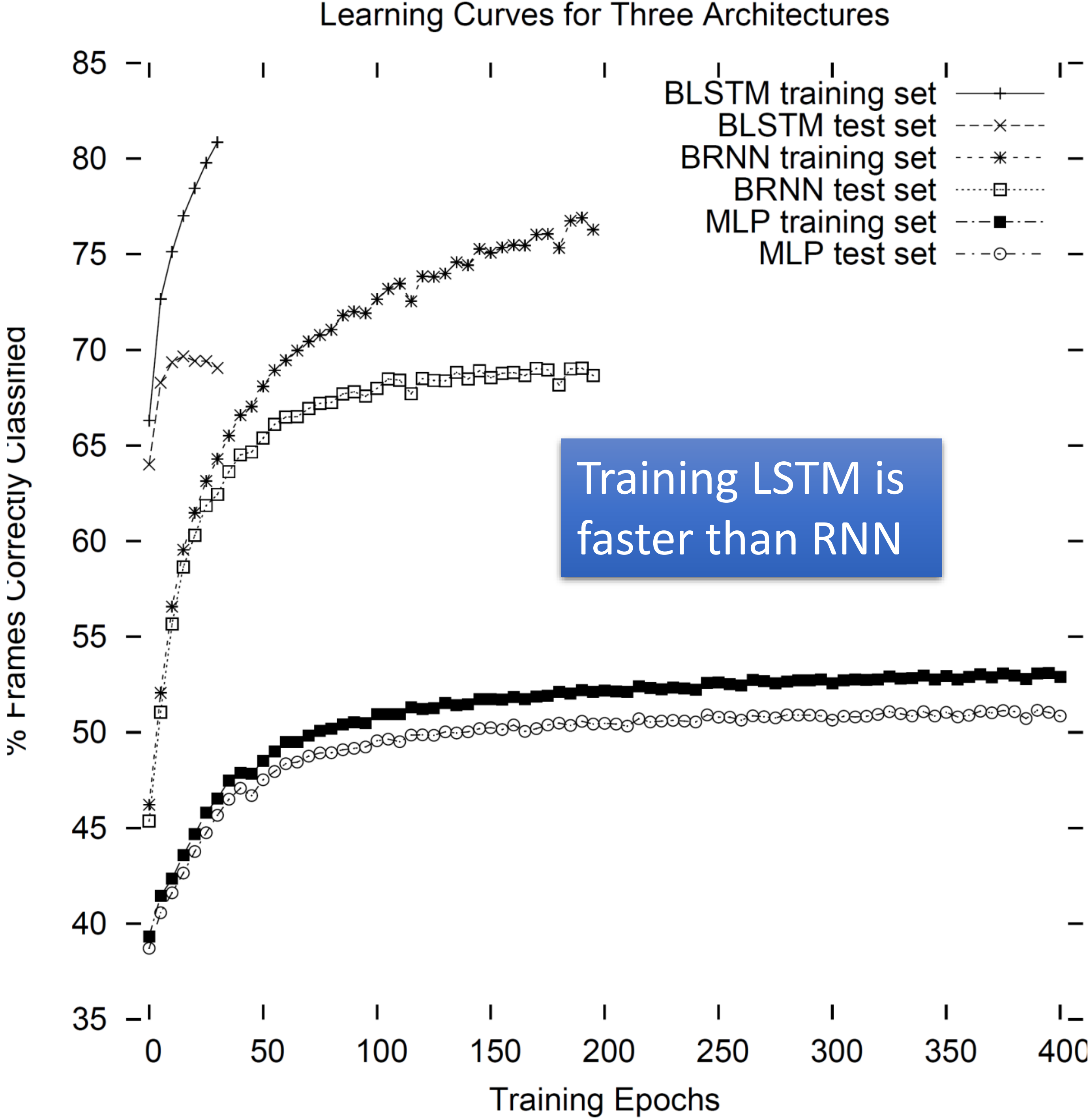
LSTM > RNN > feedforward

Bi-direction > uni-direction

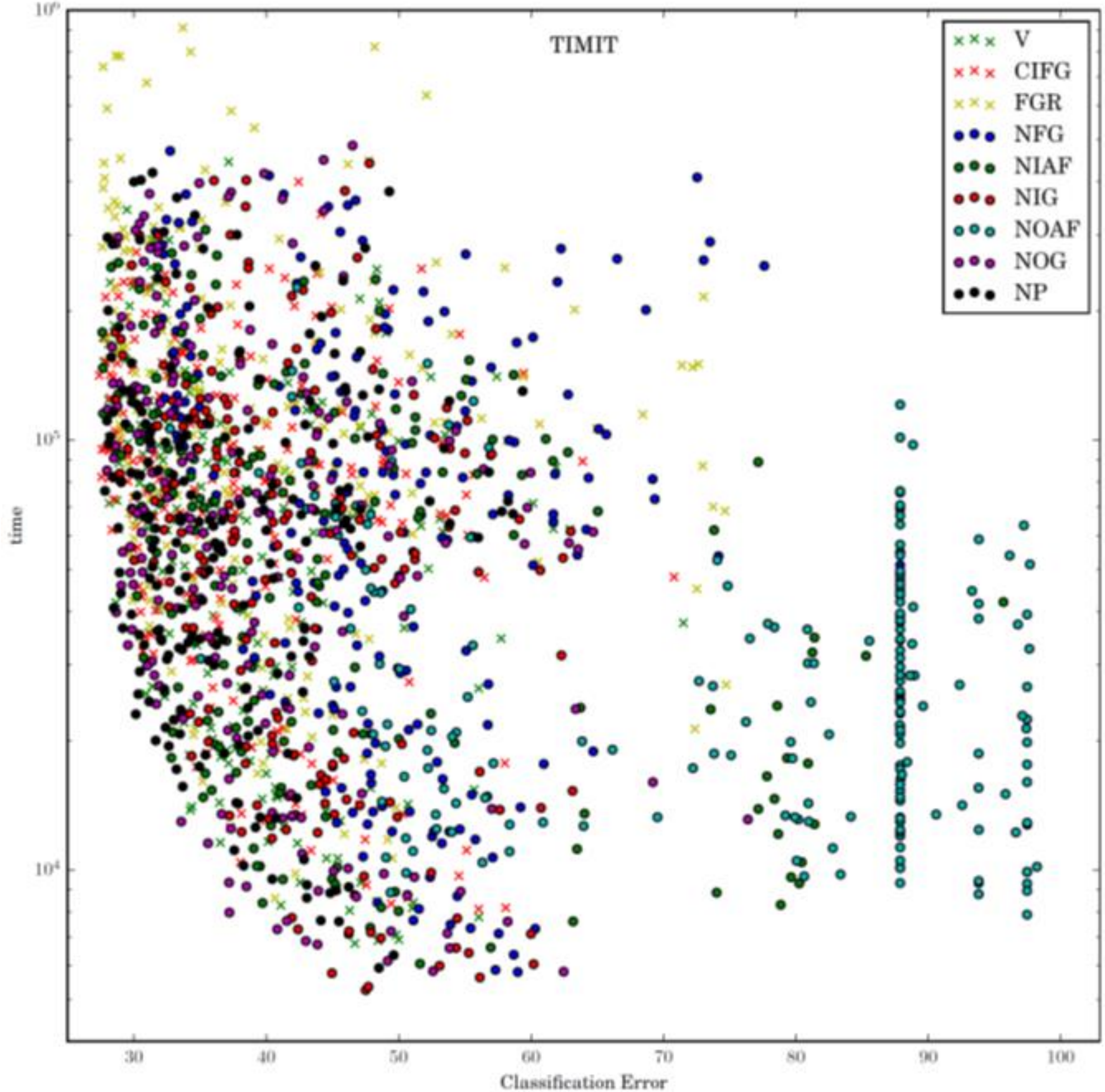

Target
sil
w
ah
n
sil
ow
sil
f
ay
v
sil
one
oh
five
Bidirectional Output



Target
Forward direction
Reverse direction



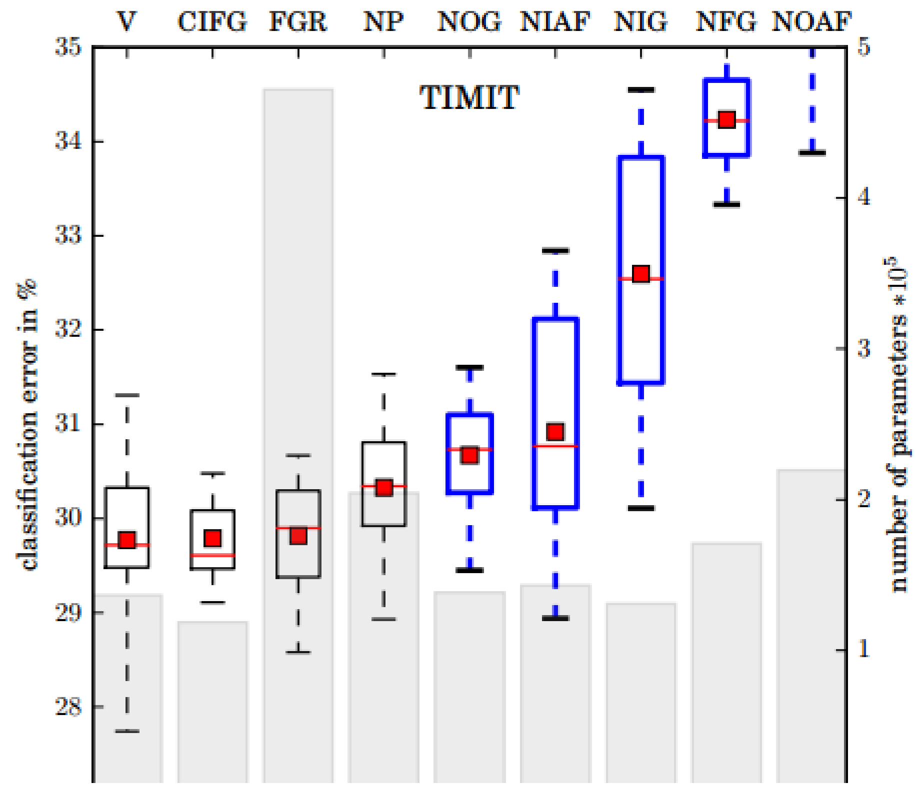
Learning Curves for Three Architectures
BLSTM training set
BLSTM test set
BRNN training set
BRNN test set
MLP training set
MLP test set
% Frames Correctly Classified
Training Epochs
85
80
75
70
65
60
55
50
45
40
35
0
50
100
150
200
250
300
350
400
Training LSTM is faster than RNN



TIMIT
V
CIFG
FGR
NFG
NIAF
NIG
NOAF
NOG
NP
time
Classification Error
30
40
50
60
70
80
90
100

LSTM: A Search Space Odyssey

1. No Input Gate (NIG)
2. No Forget Gate (NFG)
3. No Output Gate (NOG)
4. No Input Activation Function (NIAF)
5. No Output Activation Function (NOAF)
6. No Peepholes (NP)
7. Coupled Input and Forget Gate (CIFG)
8. Full Gate Recurrence (FGR)



Standard LSTM works well

Simply LSTM: coupling input and forget gate, removing peephole

Forget gate is critical for performance

Output gate activation function is critical

An Empirical Exploration of Recurrent Network Architectures

Arch.	Arith.	XML	PTB
Tanh	0.29493	0.32050	0.08782
LSTM	0.89228	0.42470	0.08912
LSTM-f	0.29292	0.23356	0.08808
LSTM-i	0.75109	0.41371	0.08662
LSTM-o	0.86747	0.42117	0.08933
LSTM-b	0.90163	0.44434	0.08952
GRU	0.89565	0.45963	0.09069
MUT1	**0.92135**	**0.47483**	0.08968
MUT2	0.89735	**0.47324**	0.09036
MUT3	0.90728	0.46478	**0.09161**

LSTM-f/i/o: removing forget/input/output gates

LSTM-b: large bias

Importance: forget > input > output

Large bias for forget gate is helpful

An Empirical Exploration of Recurrent Network Architectures

MUT1:

$$\begin{aligned} z &= \mathrm{sigm}(W_{\mathrm{xz}} x_t + b_{\mathrm{z}}) \\ r &= \mathrm{sigm}(W_{\mathrm{xr}} x_t + W_{\mathrm{hr}} h_t + b_{\mathrm{r}}) \\ h_{t+1} &= \tanh(W_{\mathrm{hh}}(r \odot h_t) + \tanh(x_t) + b_{\mathrm{h}}) \odot z \\ &+ h_t \odot (1 - z) \end{aligned}$$

MUT2:

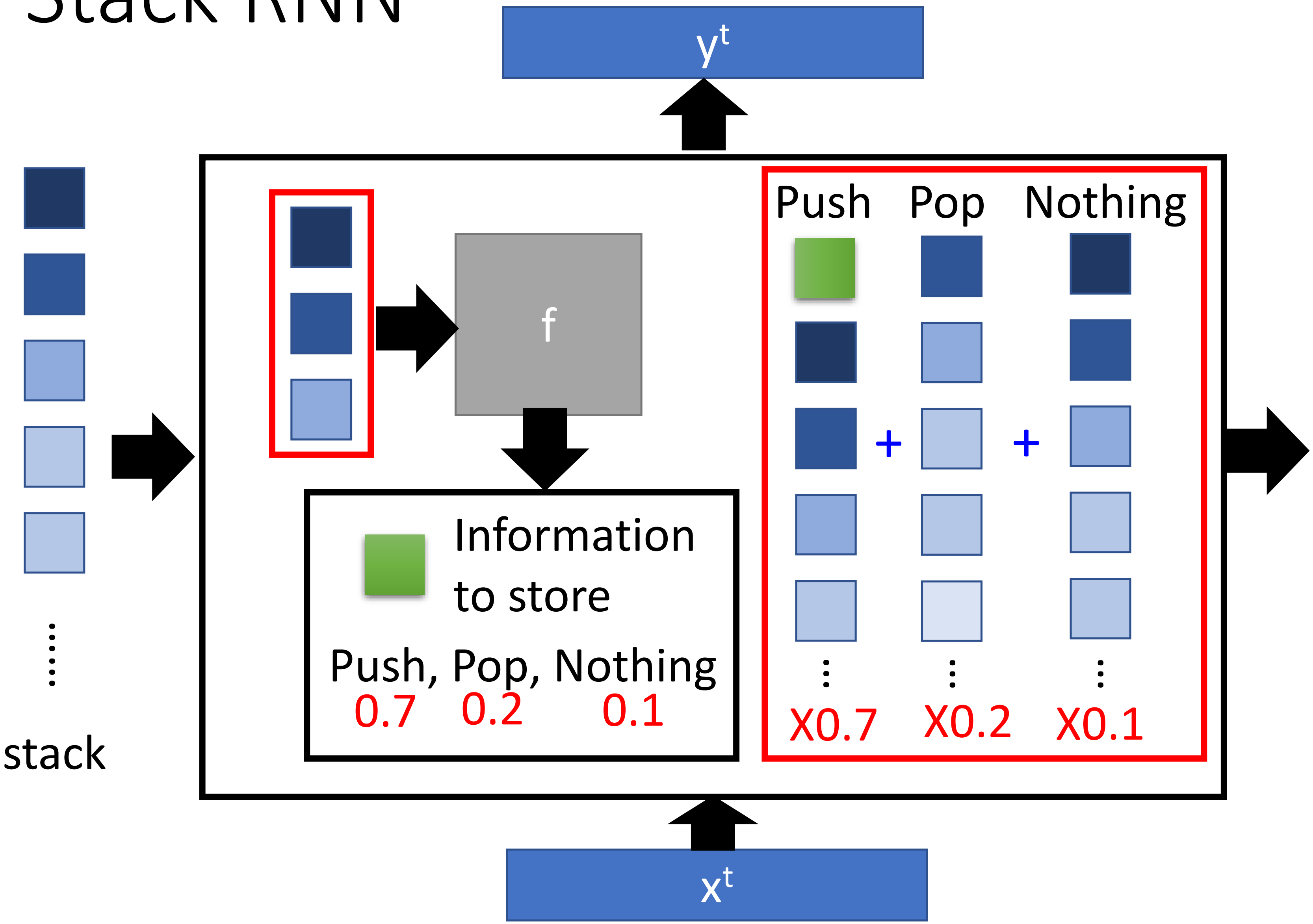
$$\begin{aligned} z &= \mathrm{sigm}(W_{\mathrm{xz}} x_t + W_{\mathrm{hz}} h_t + b_{\mathrm{z}}) \\ r &= \mathrm{sigm}(x_t + W_{\mathrm{hr}} h_t + b_{\mathrm{r}}) \\ h_{t+1} &= \tanh(W_{\mathrm{hh}}(r \odot h_t) + W_{xh} x_t + b_{\mathrm{h}}) \odot z \\ &+ h_t \odot (1 - z) \end{aligned}$$

MUT3:

$$\begin{aligned} z &= \mathrm{sigm}(W_{\mathrm{xz}} x_t + W_{\mathrm{hz}} \tanh(h_t) + b_{\mathrm{z}}) \\ r &= \mathrm{sigm}(W_{\mathrm{xr}} x_t + W_{\mathrm{hr}} h_t + b_{\mathrm{r}}) \\ h_{t+1} &= \tanh(W_{\mathrm{hh}}(r \odot h_t) + W_{xh} x_t + b_{\mathrm{h}}) \odot z \\ &+ h_t \odot (1 - z) \end{aligned}$$

Armand Joulin, Tomas Mikolov, Inferring Algorithmic Patterns with Stack-Augmented Recurrent Nets, arXiv Pre-Print, 2015

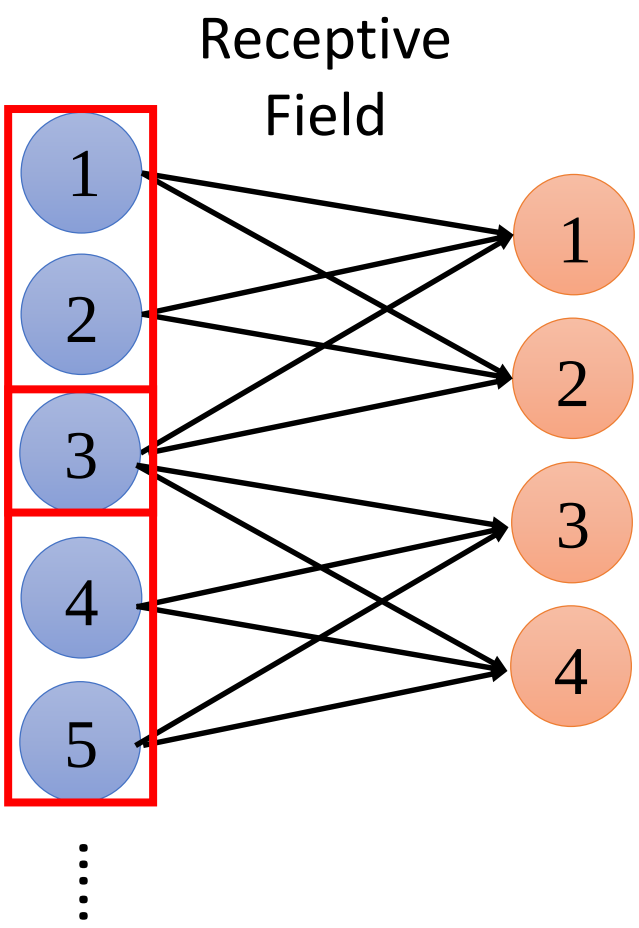
Stack RNN



Basic Structure: Convolutional / Pooing Layer

Simplify the neural network
(based on prior knowledge of the task)

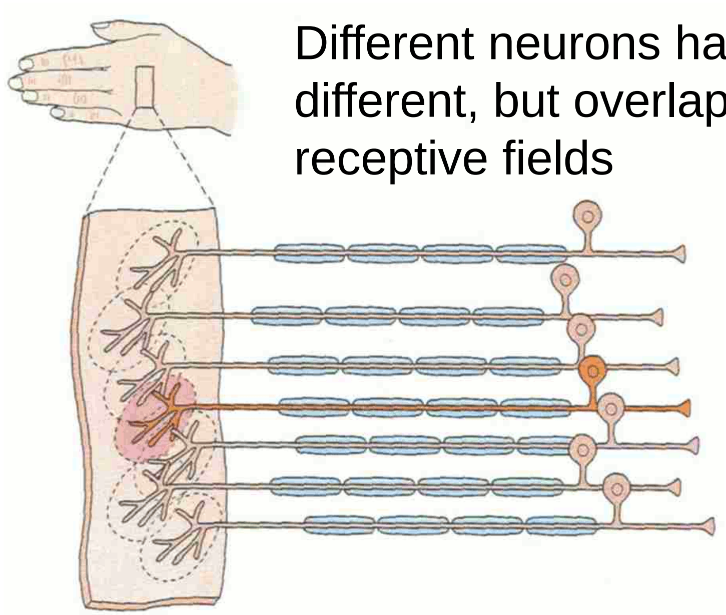
Convolutional Layer



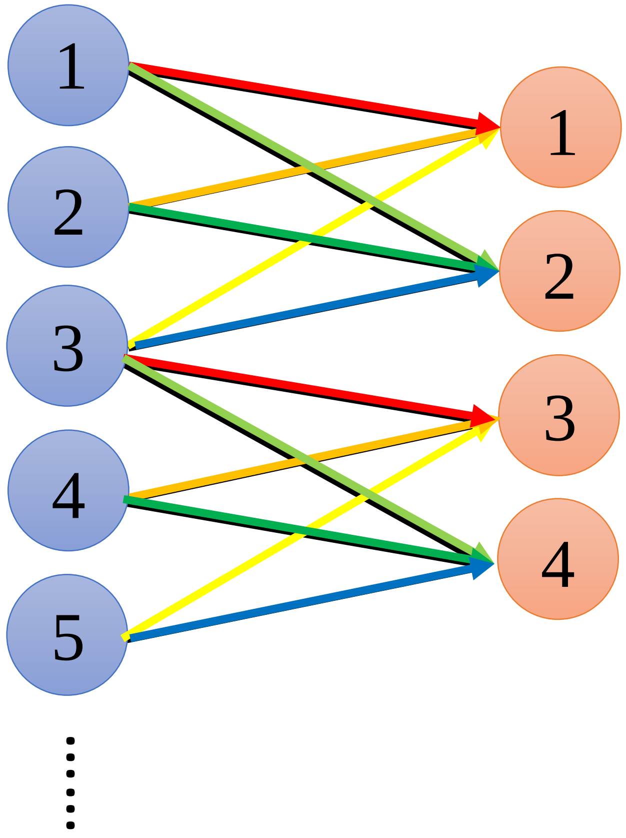
Sparse Connectivity

Each neural only connects to part of the output of the previous layer

Different neurons have different, but overlapping, receptive fields



Convolutional Layer



Sparse Connectivity

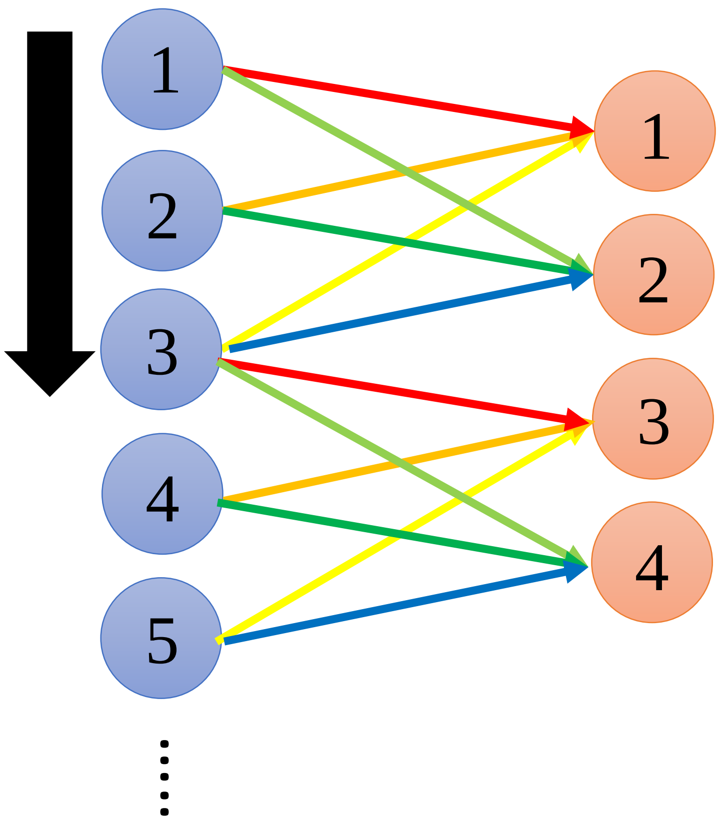
Each neural only connects to part of the output of the previous layer

Parameter Sharing

The neurons with different receptive fields can use the same set of parameters.

Less parameters then fully connected layer

Convolutional Layer



Considering neuron 1 and 3 as "filter 1" (kernel 1)

filter (kernel) size: size of the receptive field of a neuron

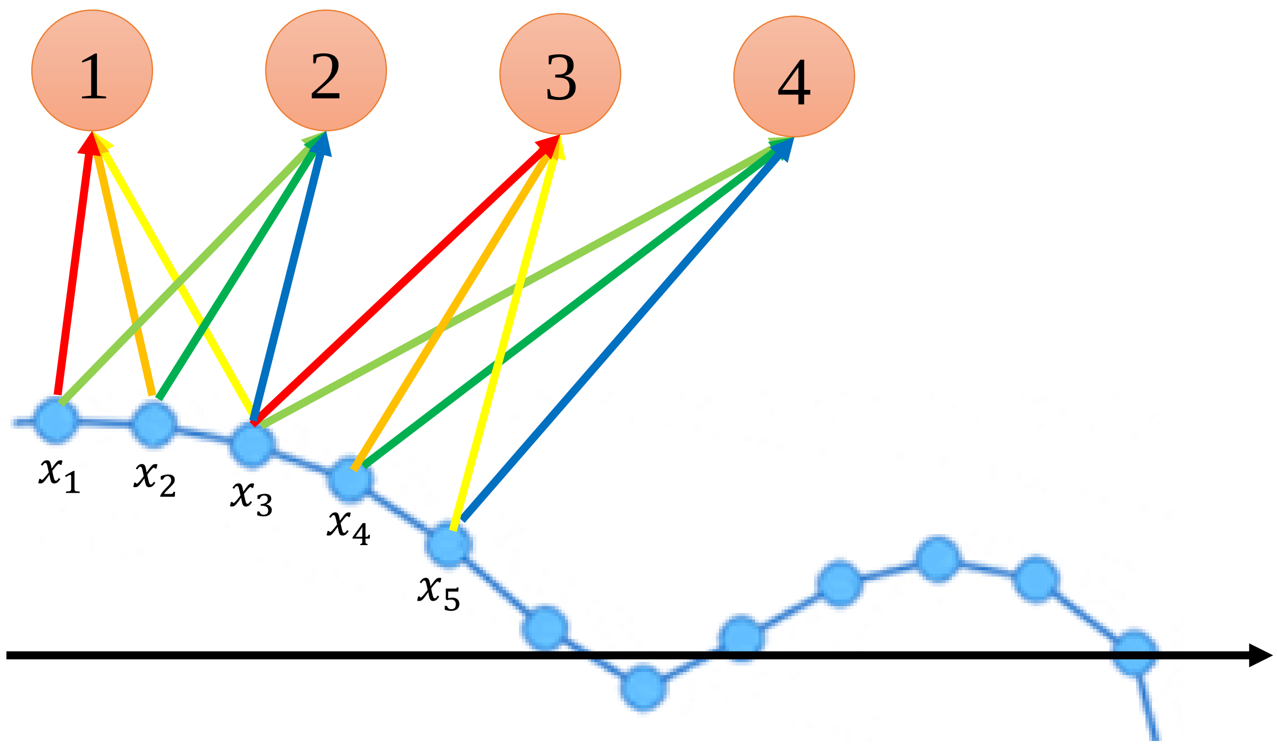
Stride = 2

Considering neuron 2 and 4 as "filter 2" (kernel 2)

Kernel size, no. of filter, stride are all designed by the developers.

Example –
1D Signal + Single Channel

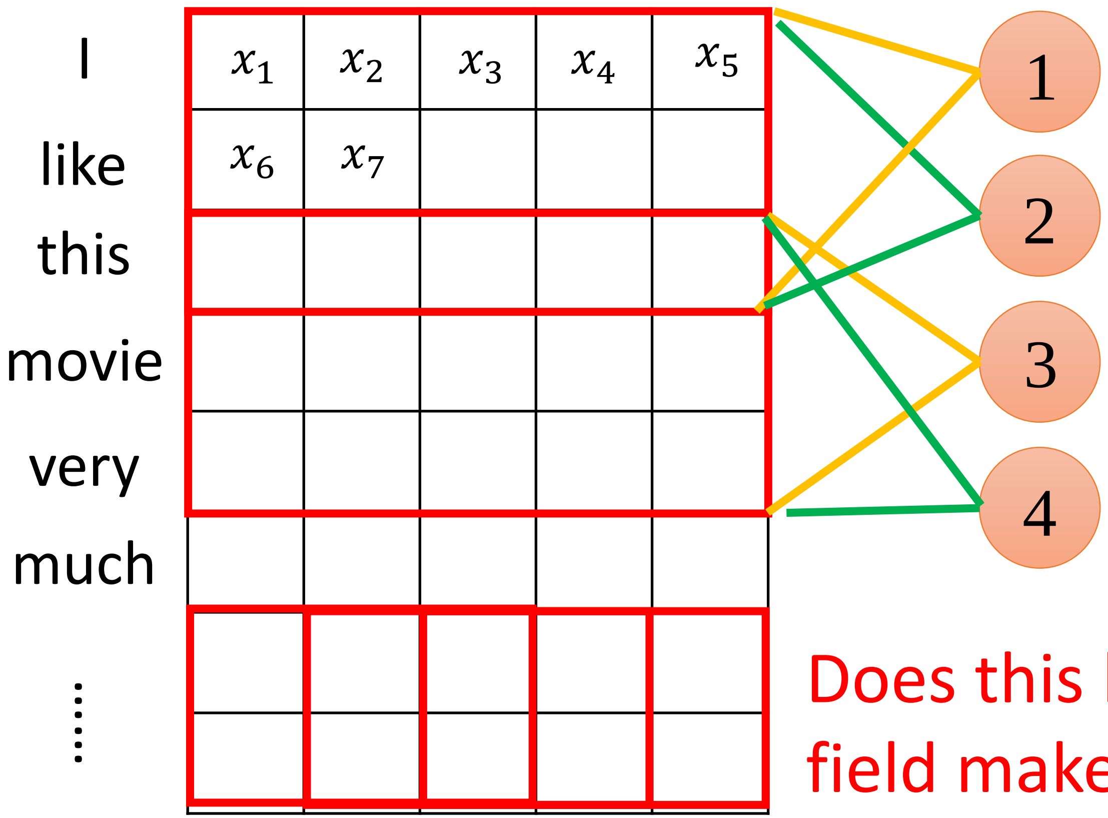
Classification, Predict the future …



Audio Signal,
Stock Value …

Example –
1D Signal + Multiple Channel

A document: each word is a vector



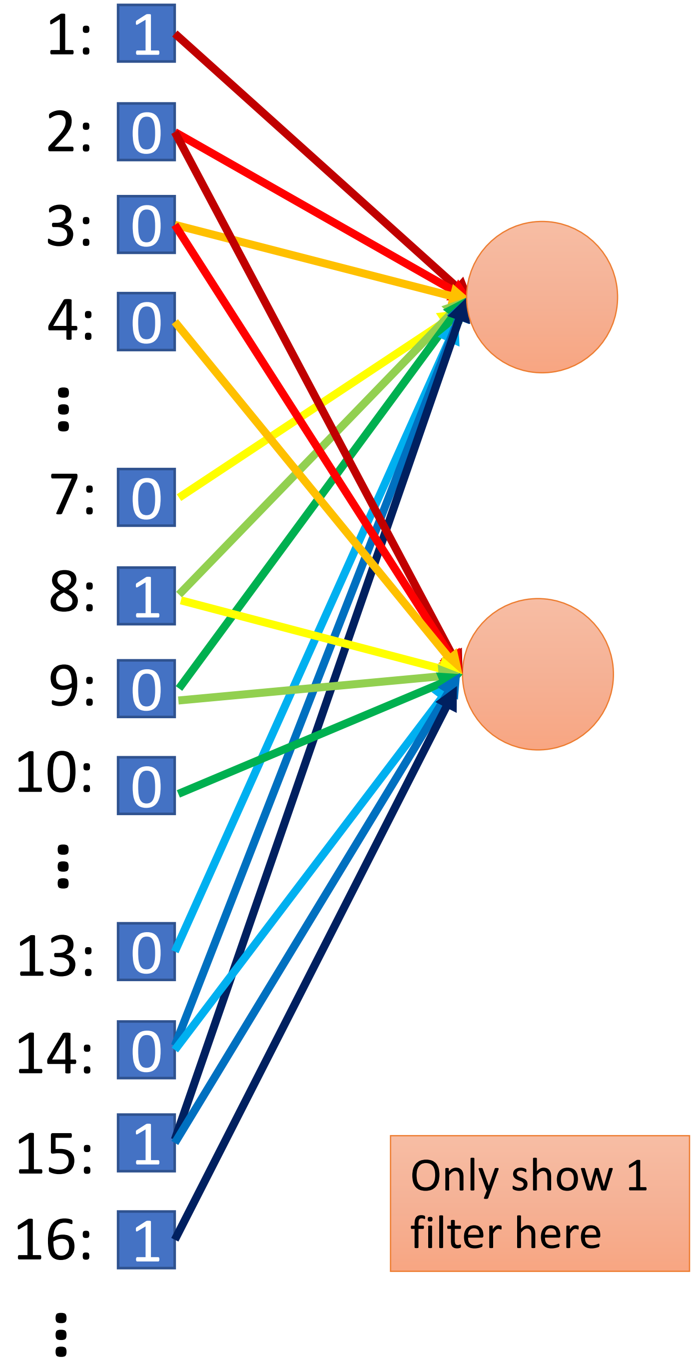
Does this kind of receptive field make sense?

Example –
2D Signal + Single Channel

Size of Receptive field
is 3x3, Stride is 1

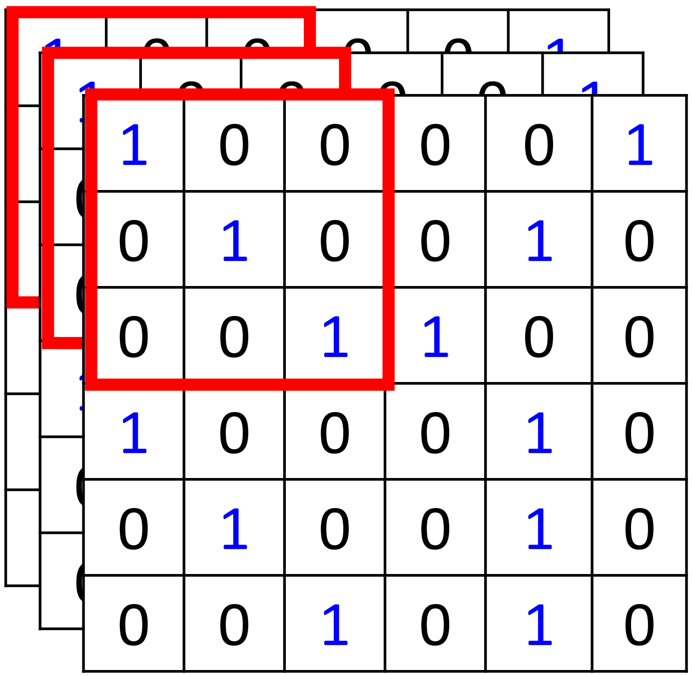
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 black & white
picture image

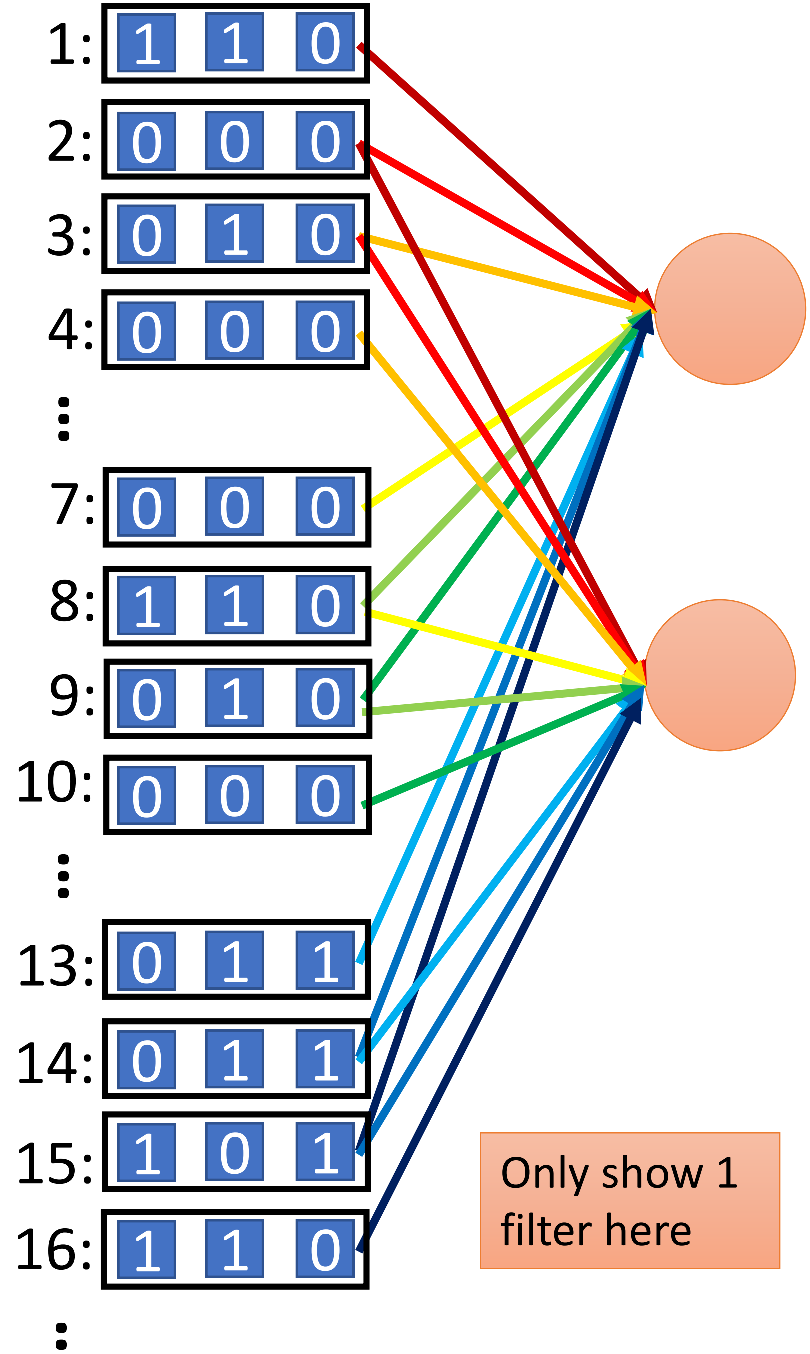


Example – 2D Signal + Multiple Channel

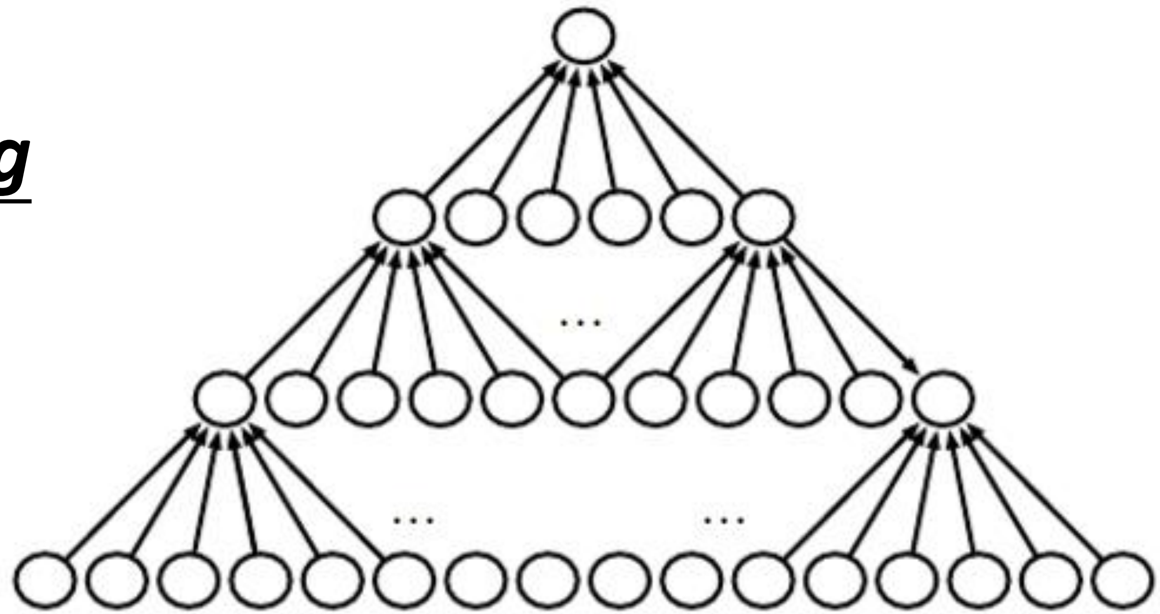
Size of Receptive field is 3x3x3, Stride is 1



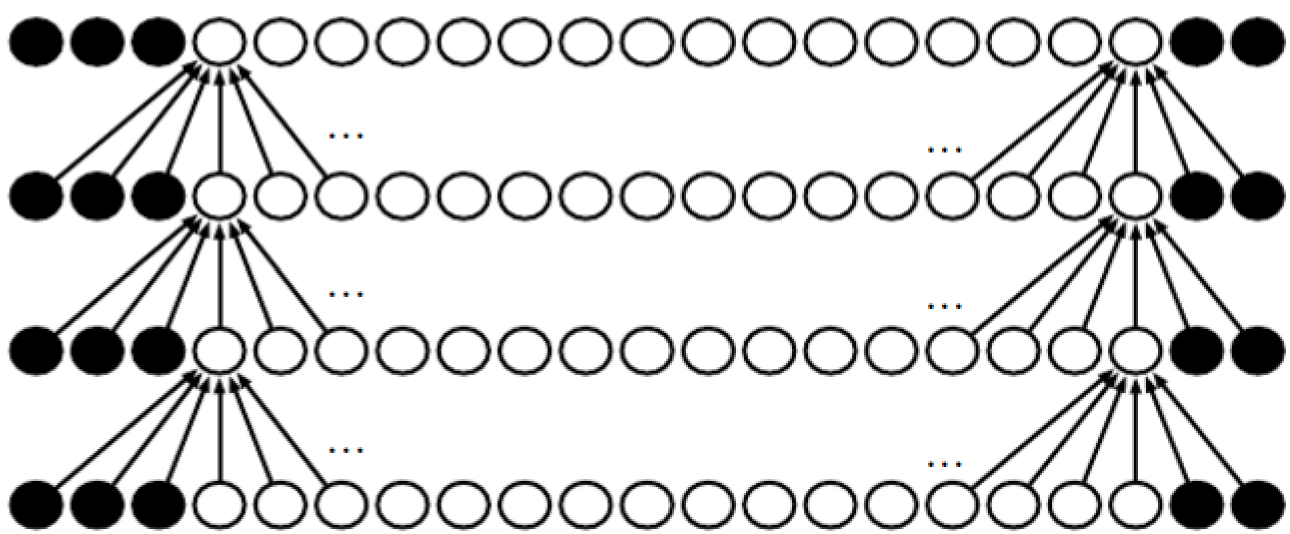
6 x 6 colorful image



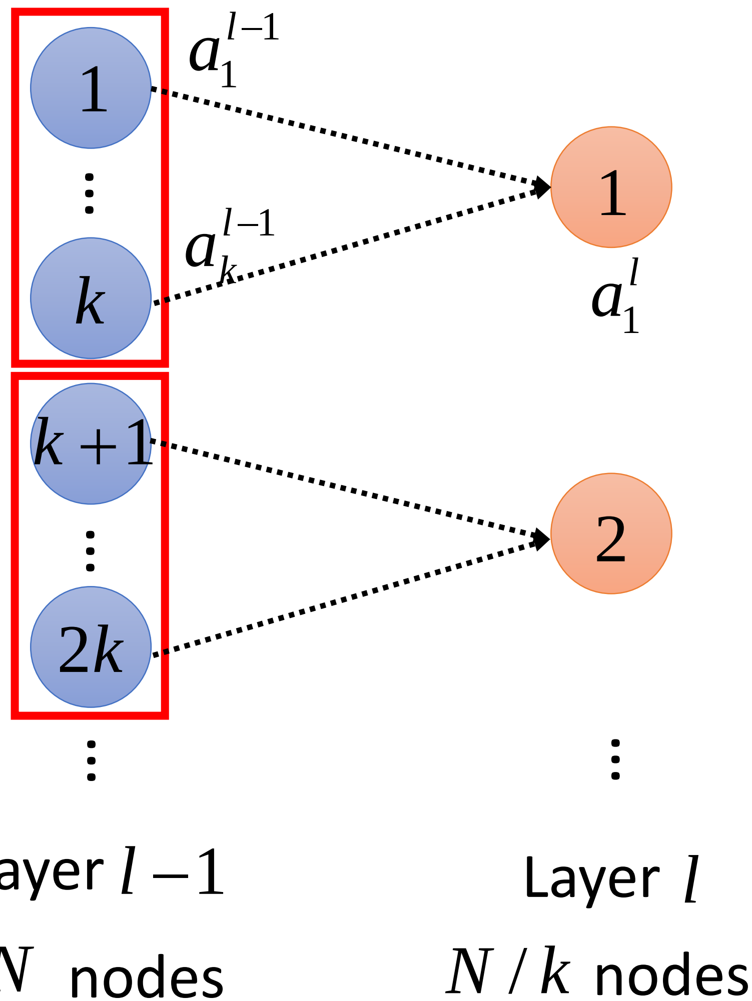
<u>*Without Zero Padding*</u>



<u>*Zero Padding*</u>



Pooling Layer



k outputs in layer $l-1$ are grouped together

Each output in layer l "summarizes" k inputs

Average Pooling:

$$a_1^l = \frac{1}{k}\sum_{j=1}^{k} a_j^{l-1}$$

Max Pooling:

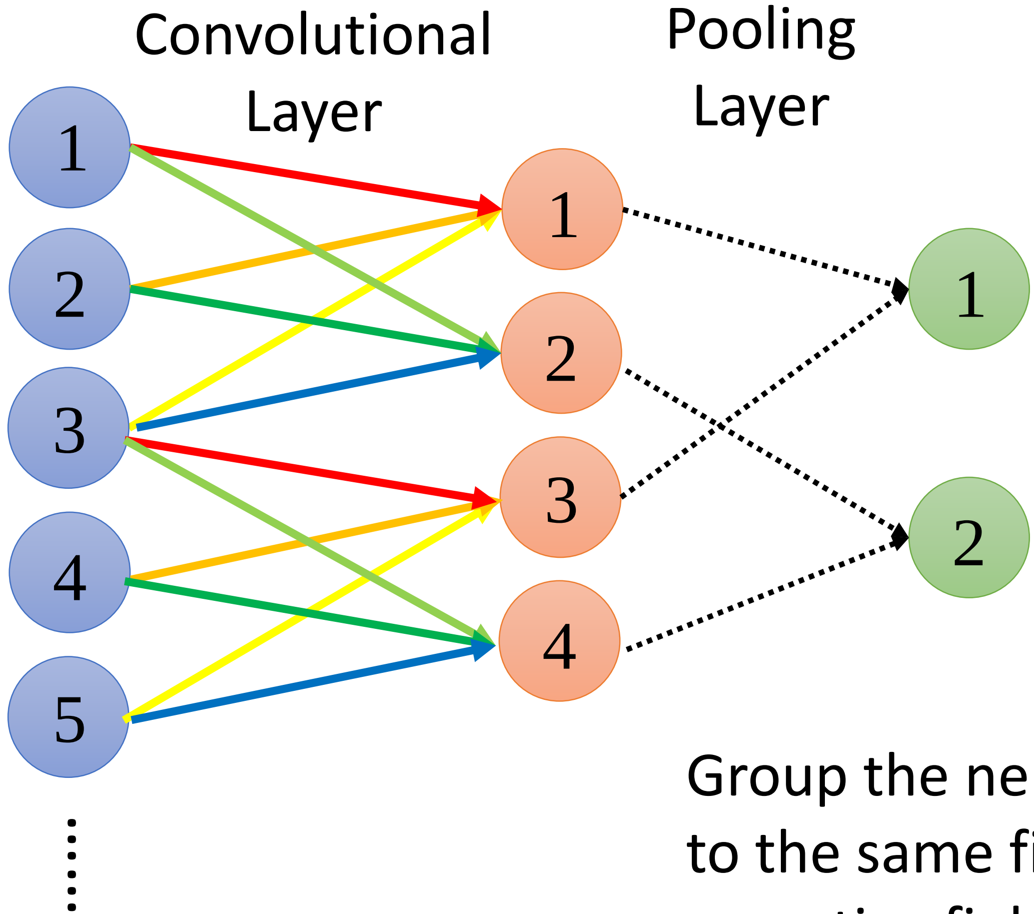
$$a_1^l = \max\left(a_1^{l-1}, a_2^{l-1}, \cdots, a_k^{l-1}\right)$$

L2 Pooling:

$$a_1^l = \frac{1}{k}\sqrt{\sum_{j=1}^{k}\left(a_j^{l-1}\right)^2}$$

Pooling Layer

Which outputs should be grouped together?

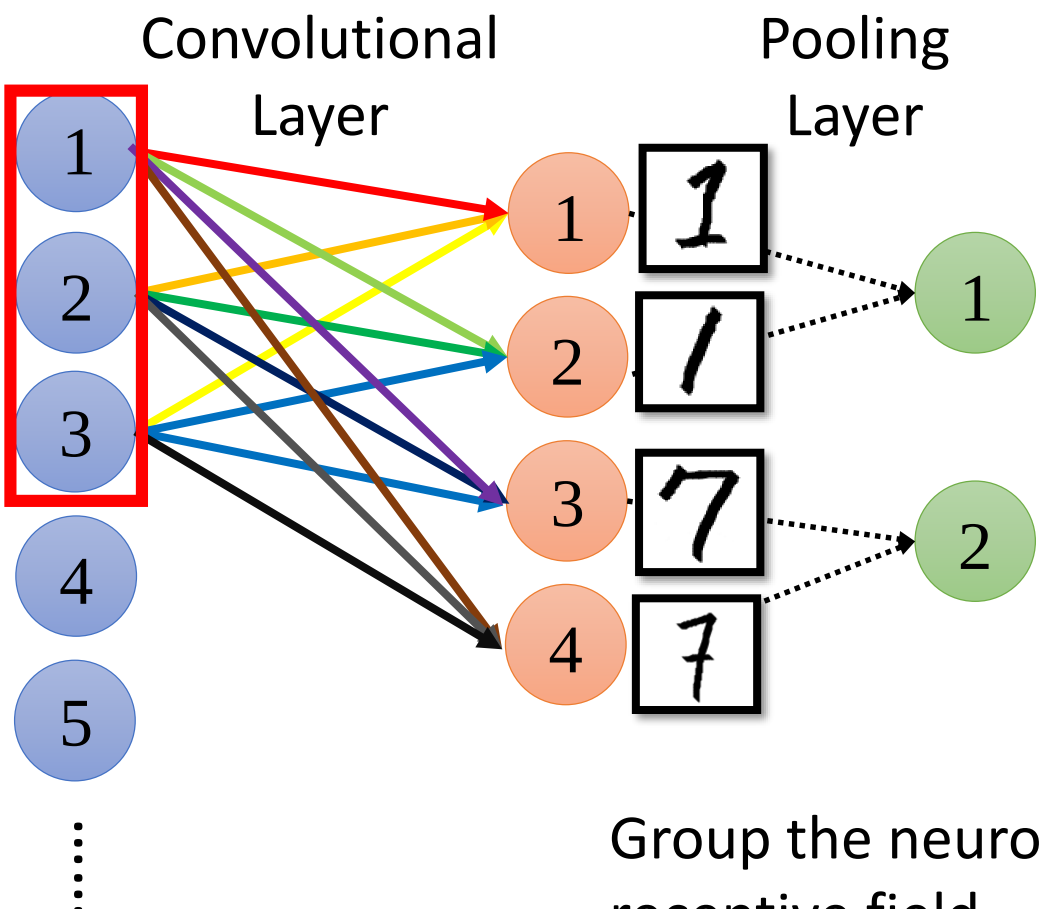


Subsampling

Group the neurons corresponding to the same filter with nearby receptive fields

Pooling Layer

Which outputs should be grouped together?



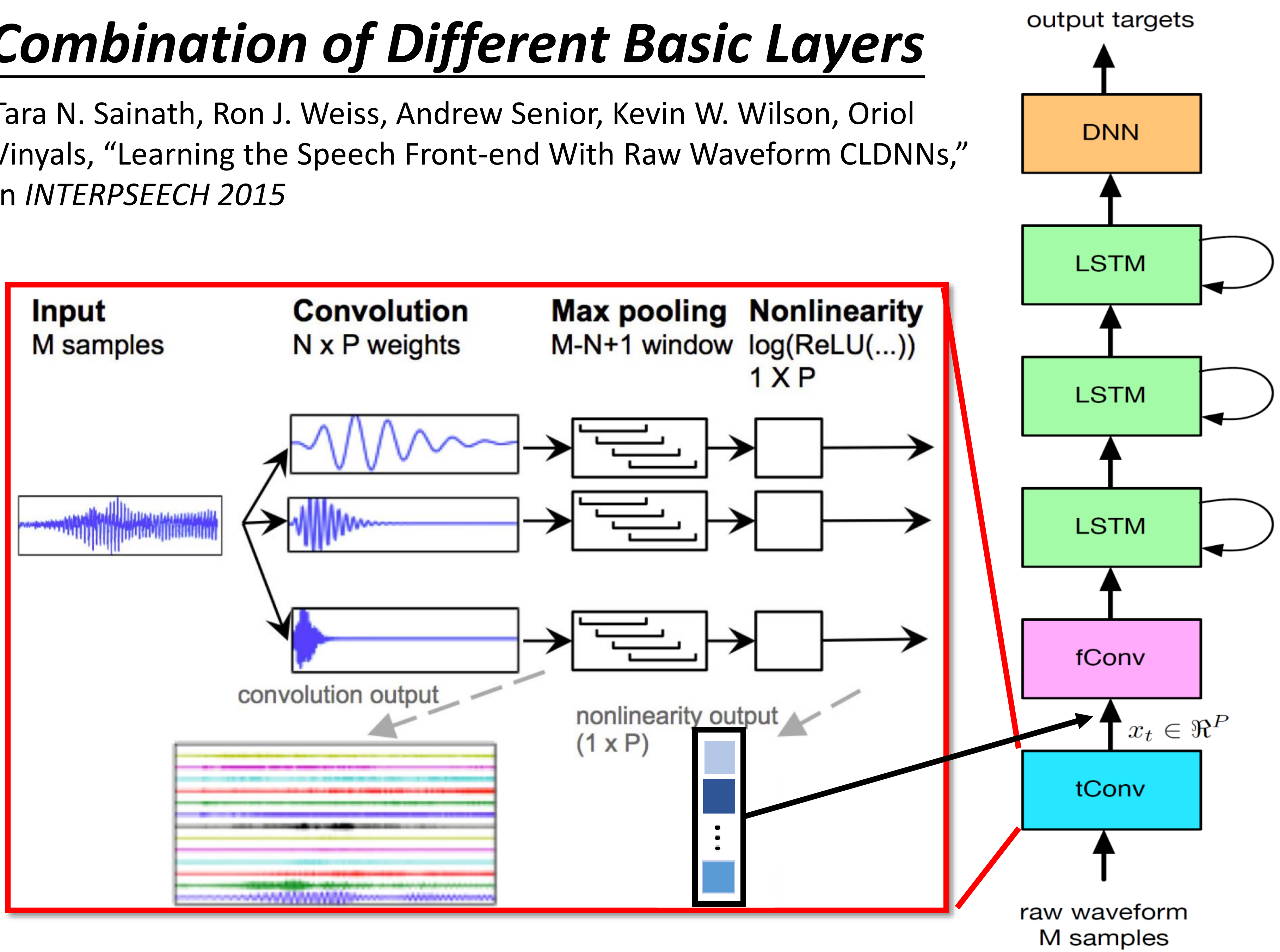
Maxout Network

How can you know whether the neurons detect the same pattern?

Group the neurons with the same receptive field

Combination of Different Basic Layers

Tara N. Sainath, Ron J. Weiss, Andrew Senior, Kevin W. Wilson, Oriol Vinyals, “Learning the Speech Front-end With Raw Waveform CLDNNs,” In *INTERPSEECH 2015*



Combination of Different Basic Layers

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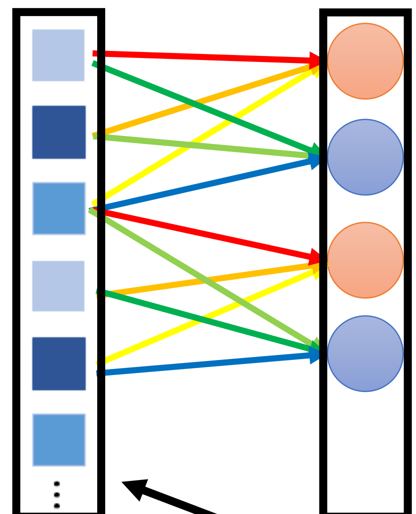

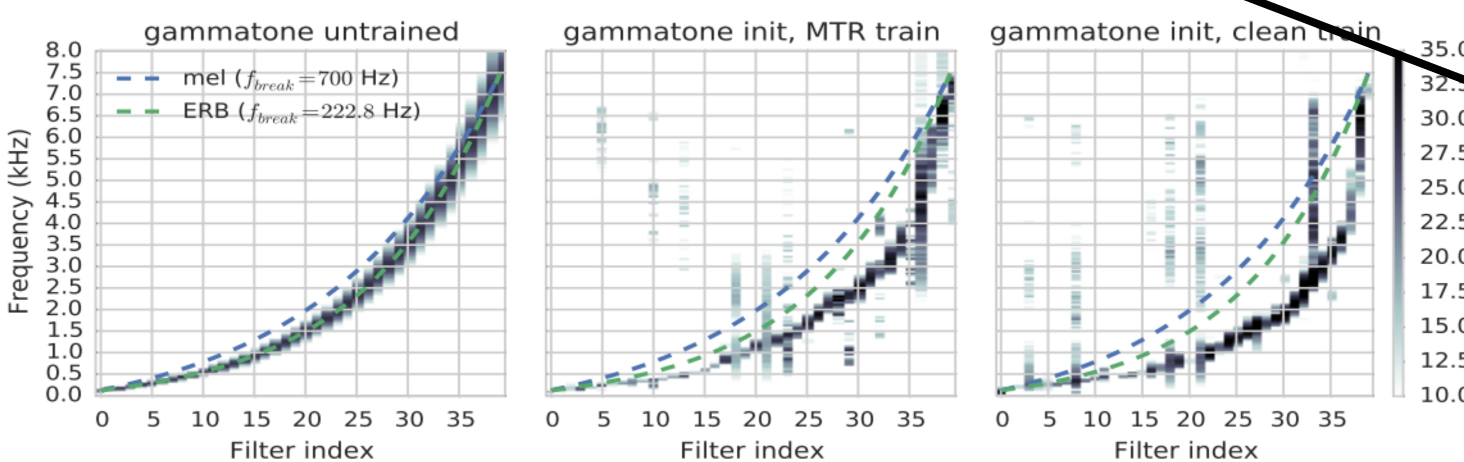

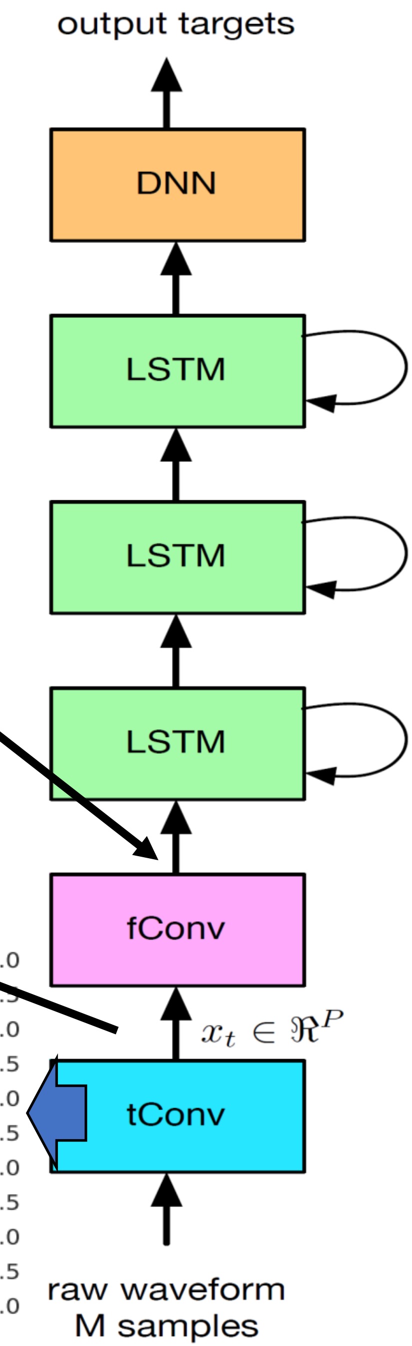

Combination of Different Basic Layers

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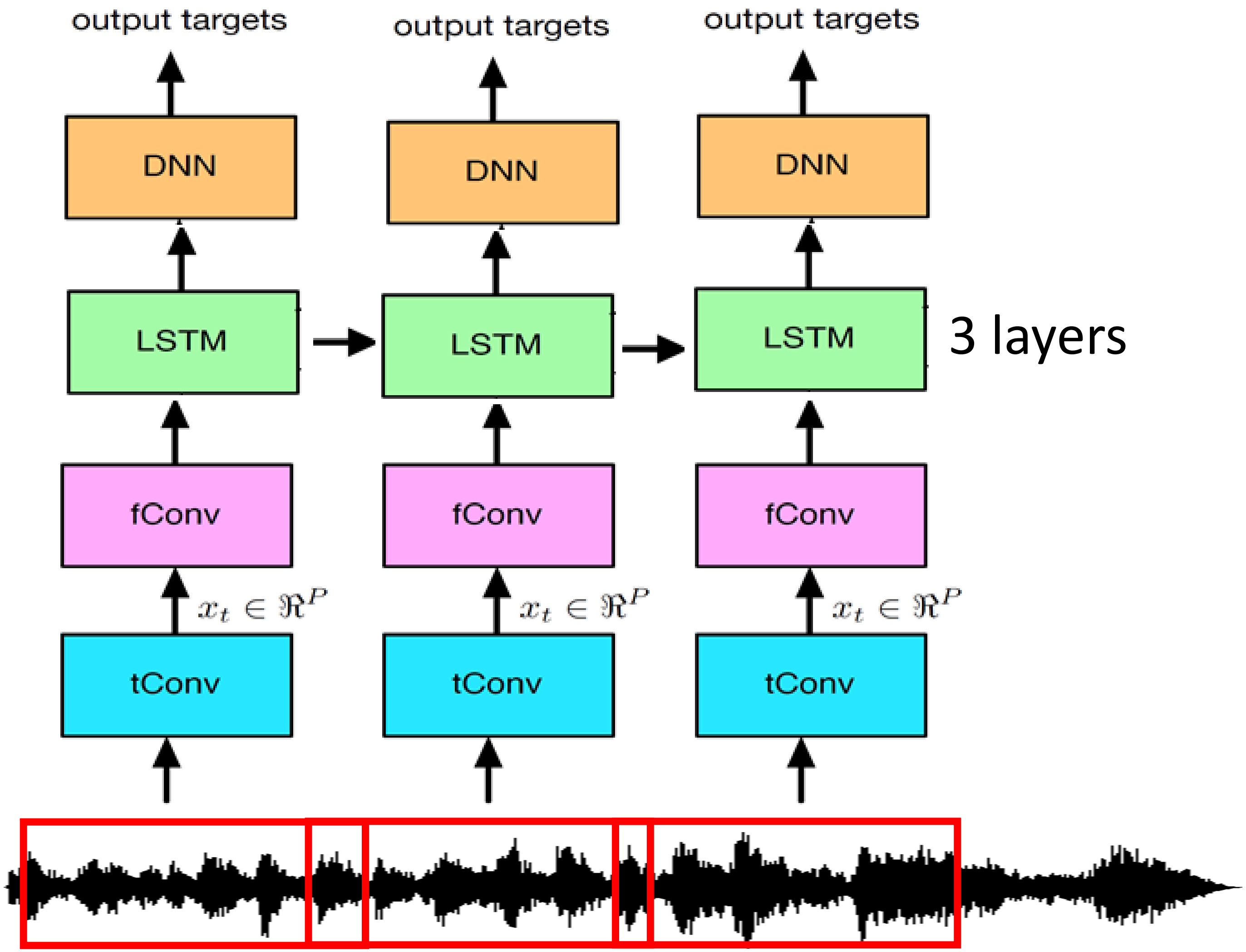

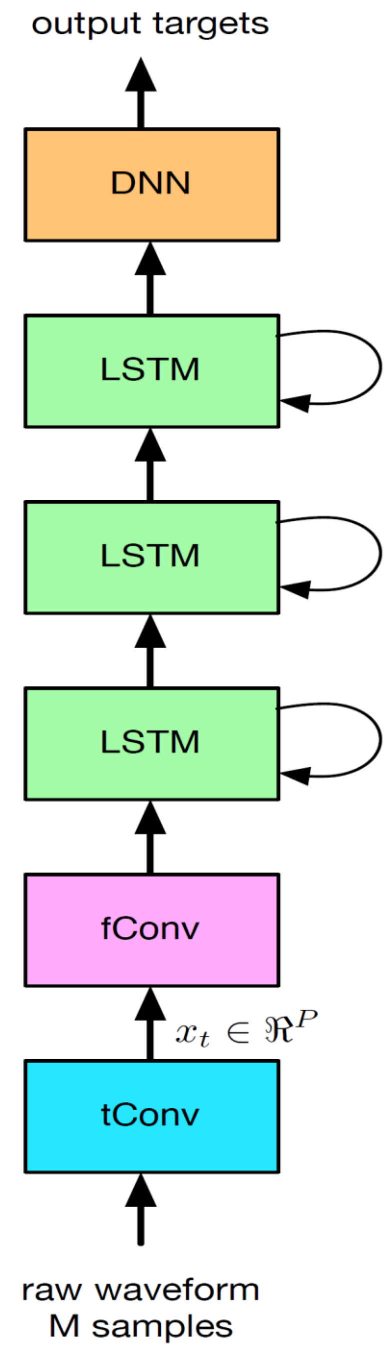

Next Time

- 3/10: TAs will teach TensorFlow
  - TensorFlow for regression
  - TensorFlow for word vector
    - word vector: https://www.youtube.com/watch?v=X7PH3NuYW0Q
  - TensorFlow for CNN
- If you want to learn Theano
  - http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/Theano%20DNN.ecm.mp4/index.html
  - http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/Theano%20RNN.ecm.mp4/index.html