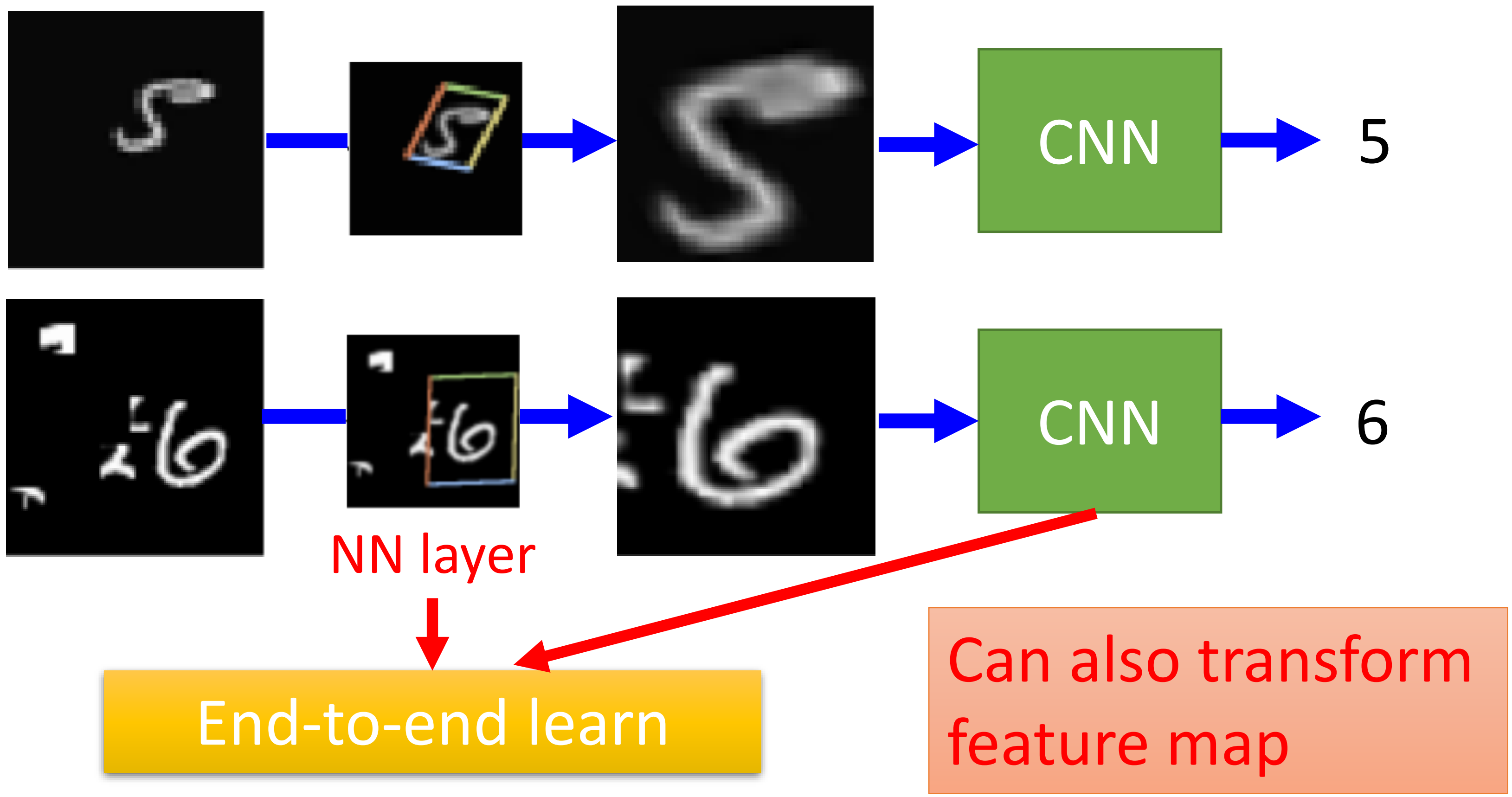
Spatial Transformer

Ref: Max Jaderberg, Karen Simonyan, Andrew Zisserman, Koray Kavukcuoglu, “Spatial Transformer Networks”, NIPS, 2015

Spatial Transformer Layer

- CNN is not invariant to scaling and rotation



Spatial Transformer Layer

- How to transform an image/feature map

Layer l-1

a_{11}^{l-1}	a_{12}^{l-1}	a_{13}^{l-1}
a_{21}^{l-1}	a_{22}^{l-1}	a_{23}^{l-1}
a_{31}^{l-1}	a_{32}^{l-1}	a_{33}^{l-1}

Spatial Transformer Layer

Translate

Layer l

a_{11}^{l}	a_{12}^{l}	a_{13}^{l}
a_{21}^{l}	a_{22}^{l}	a_{23}^{l}
a_{31}^{l}	a_{32}^{l}	a_{33}^{l}

General layer: $a_{nm}^{l} = \sum_{i=1}^{3} \sum_{j=1}^{3} w_{nm,ij}^{l} a_{ij}^{l-1}$

If we want translate as above: $a_{nm}^{l} = a_{(n-1)m}^{l-1}$

$w_{nm,ij}^{l} = 1 \quad if\ i = n-1, j = m \qquad w_{nm,ij}^{l} = 0 \quad otherwise$

Spatial Transformer Layer

- How to transform an image/feature map

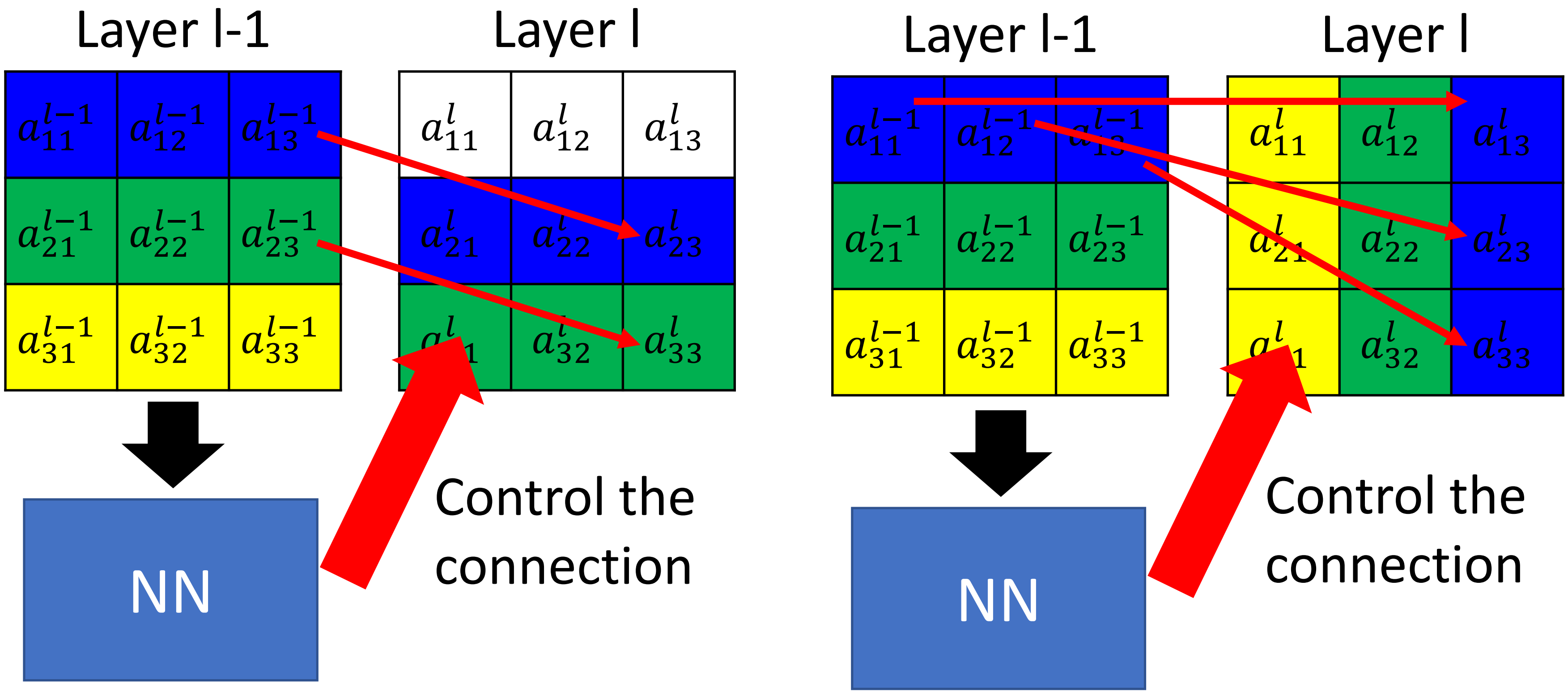
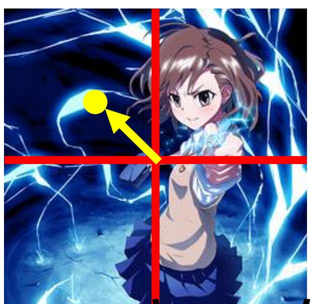


Image Transformation

<u>Expansion, Compression, Translation</u>

$$\begin{bmatrix} x \\ y \end{bmatrix}$$

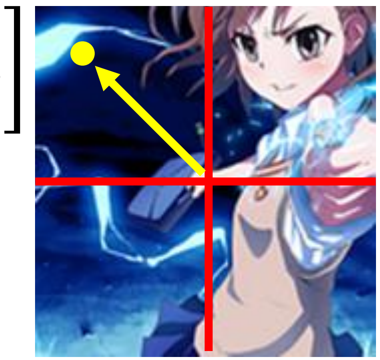


1

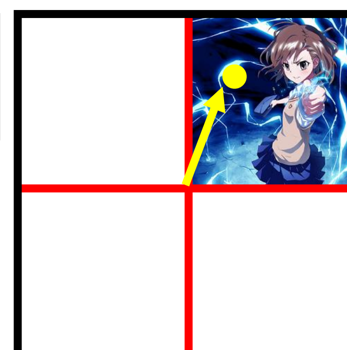
1

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix}$$



$$\begin{bmatrix} x' \\ y' \end{bmatrix}$$



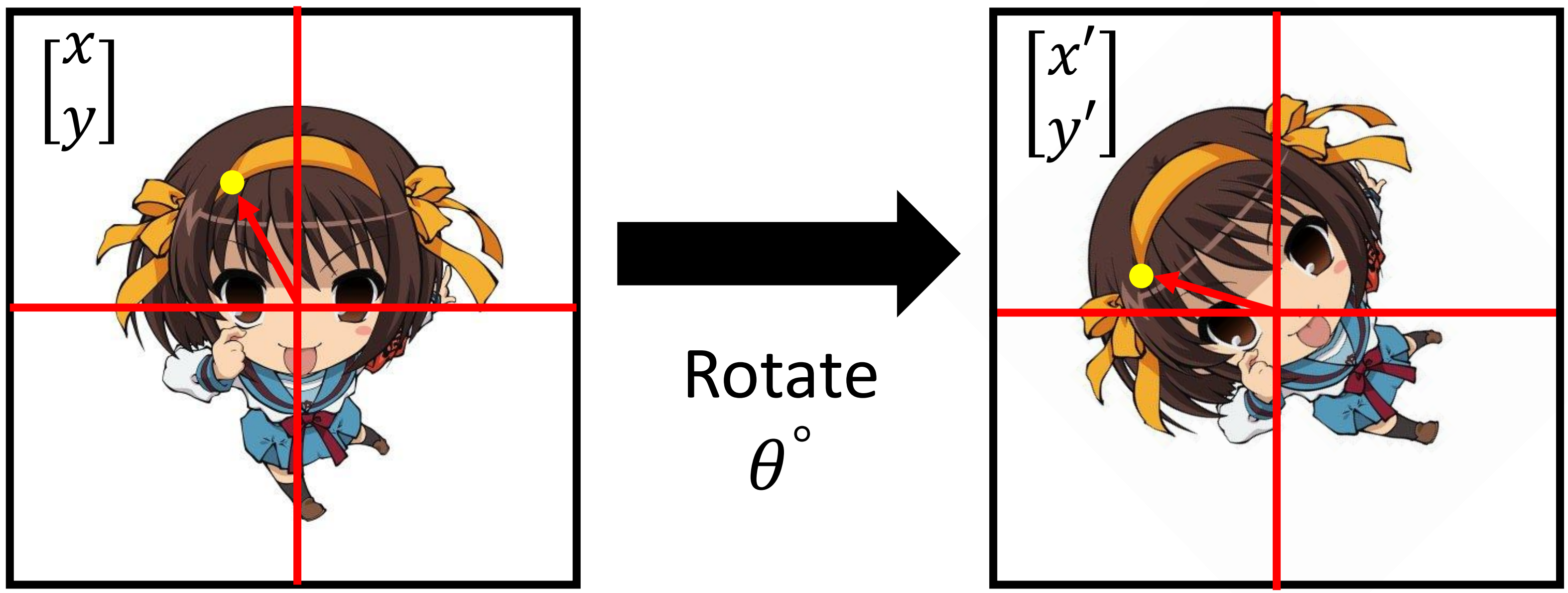
$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}$$

https://home.gamer.com.tw/creationDetail.php?sn=792585

Image Transformation

- ***Rotation***

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$



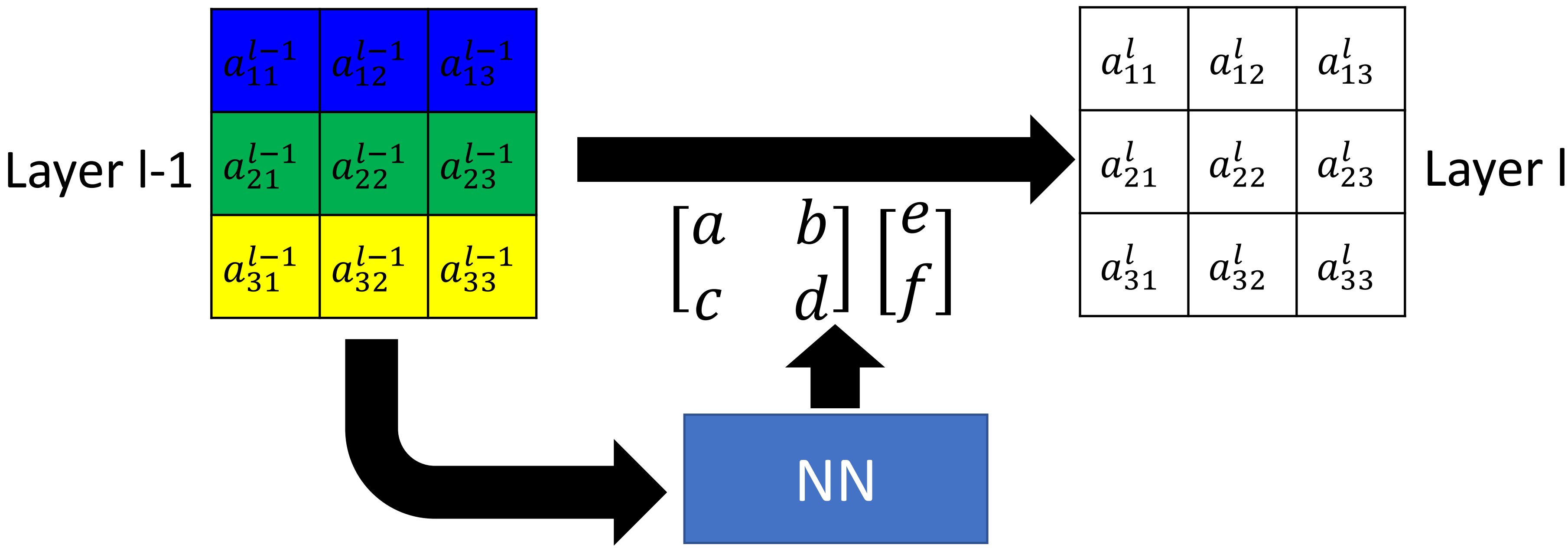
Spatial Transformer Layer

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} e \\ f \end{bmatrix}$$

6 parameters to describe the affine transformation

Index of layer l-1

Index of layer l



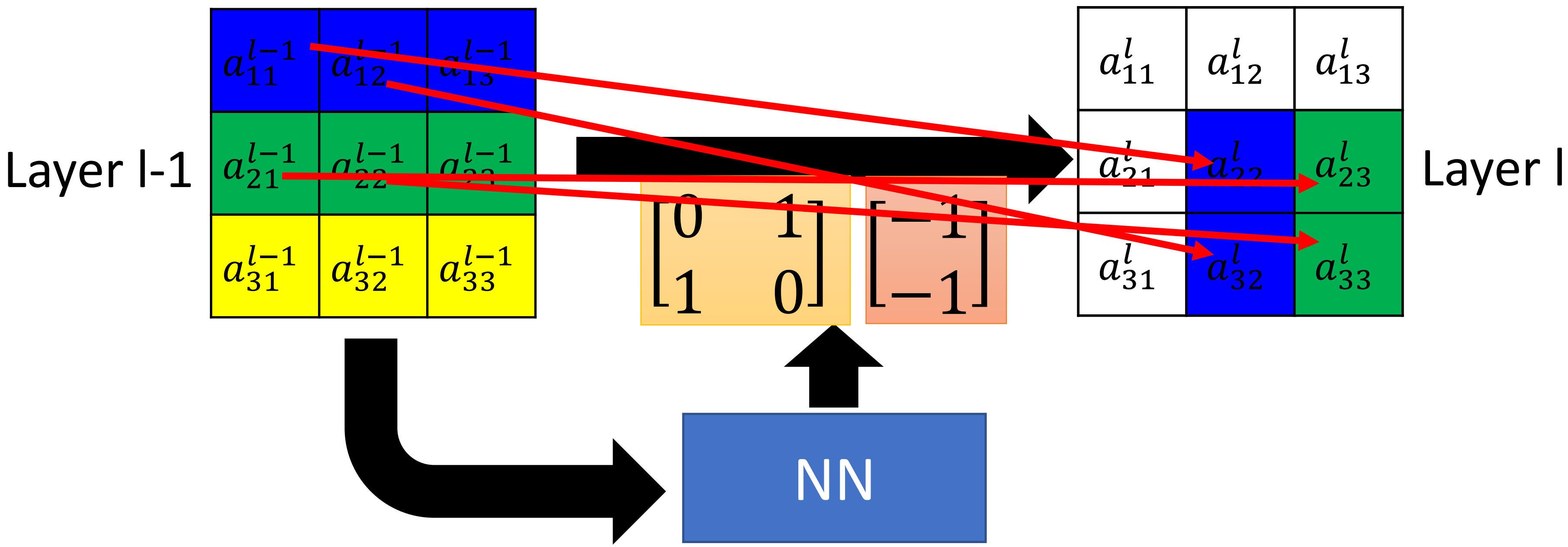
Spatial Transformer Layer

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} -1 \\ -1 \end{bmatrix}$$

6 parameters to describe the affine transformation

Index of layer l-1

Index of layer l



Spatial Transformer Layer

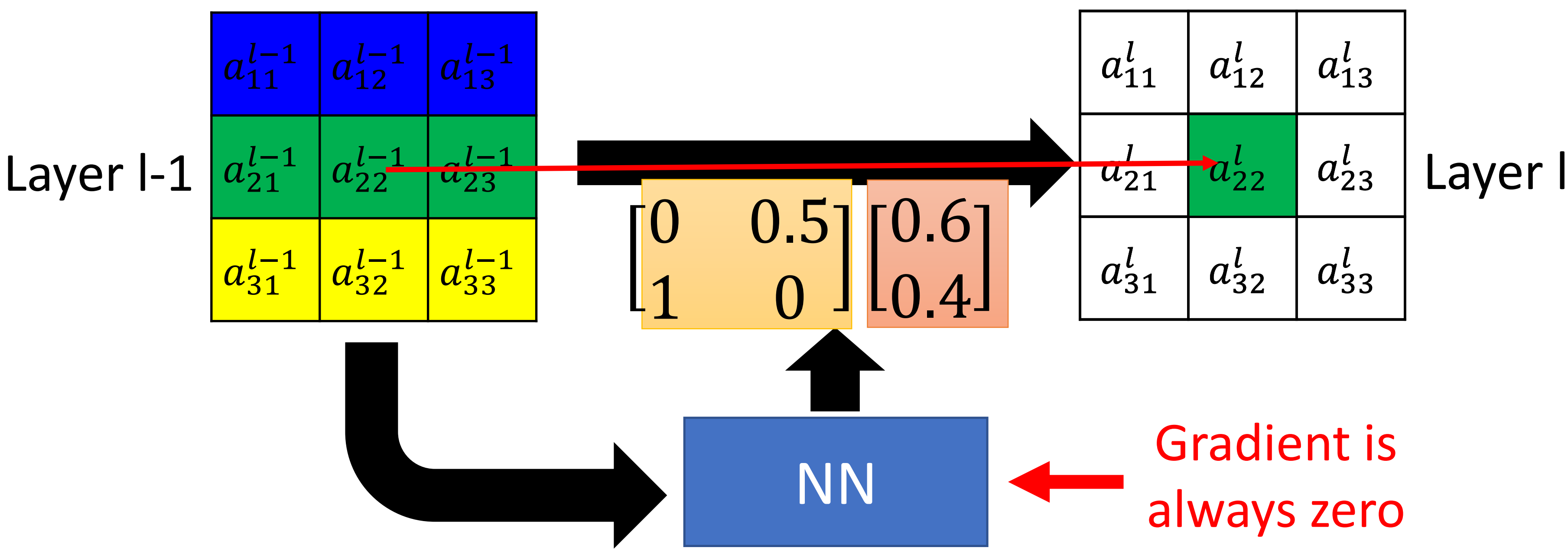
$$\begin{bmatrix}1.6\\2.4\end{bmatrix}=\begin{bmatrix}0 & 0.5\\1 & 0\end{bmatrix}\begin{bmatrix}2\\2\end{bmatrix}+\begin{bmatrix}0.6\\0.4\end{bmatrix}$$

Index of layer l-1

Index of layer l

6 parameters to describe the affine transformation

What is the problem?



Interpolation

Now we can use gradient descent

$$\begin{bmatrix}1.6\\2.4\end{bmatrix} = \begin{bmatrix}0 & 0.5\\1 & 0\end{bmatrix}\begin{bmatrix}2\\2\end{bmatrix} + \begin{bmatrix}0.6\\0.4\end{bmatrix}$$

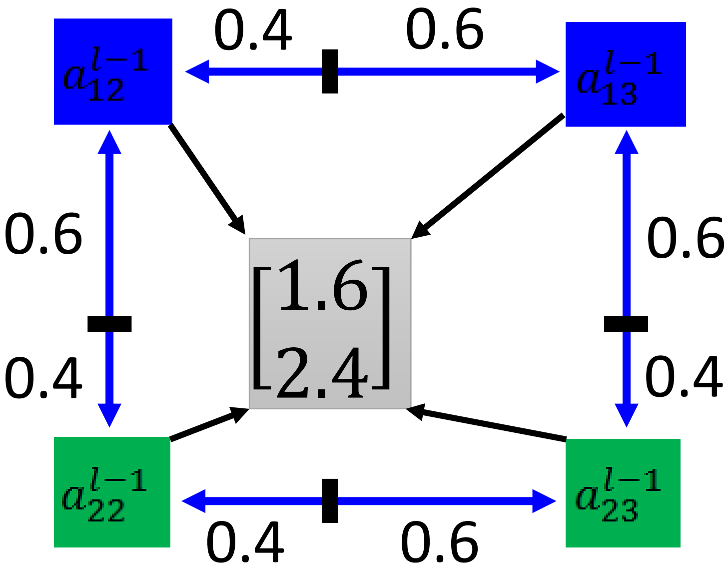
Index of layer l-1

Index of layer l

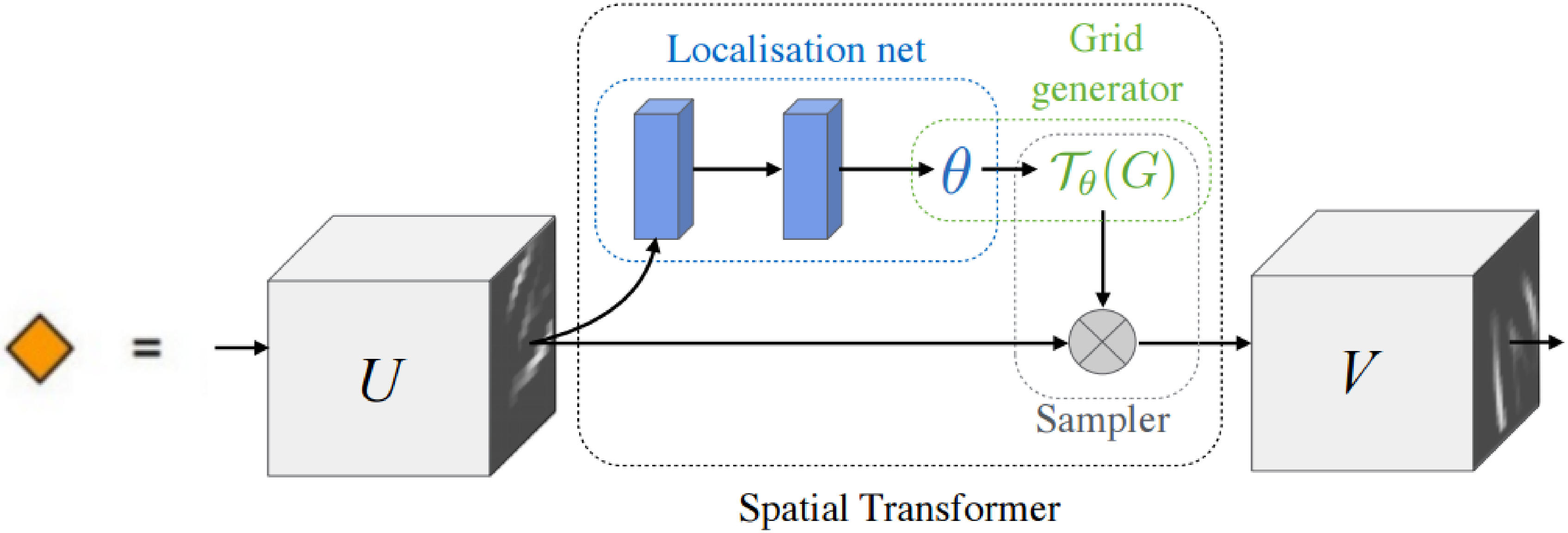
6 parameters to describe the affine transformation

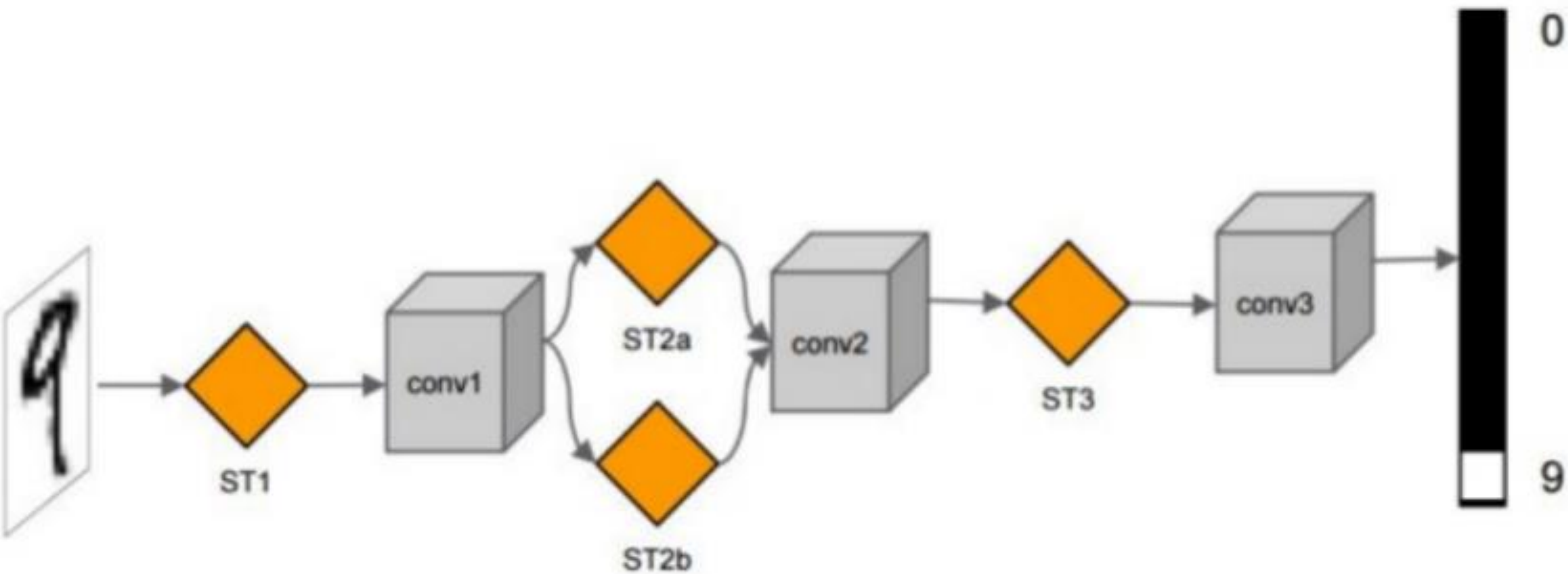
a_{11}^{l}	a_{12}^{l}	a_{13}^{l}
a_{21}^{l}	a_{22}^{l}	a_{23}^{l}
a_{31}^{l}	a_{32}^{l}	a_{33}^{l}

Layer l



$$\begin{aligned} a_{22}^{l} = & (1-0.4)\times(1-0.4)\times a_{22}^{l-1} \\ & +(1-0.6)\times(1-0.4)\times a_{12}^{l-1} \\ & +(1-0.6)\times(1-0.6)\times a_{13}^{l-1} \\ & +(1-0.4)\times(1-0.6)\times a_{23}^{l-1} \end{aligned}$$


Localisation net
Grid generator
θ
$\mathcal{T}_\theta(G)$
U
V
Sampler
Spatial Transformer

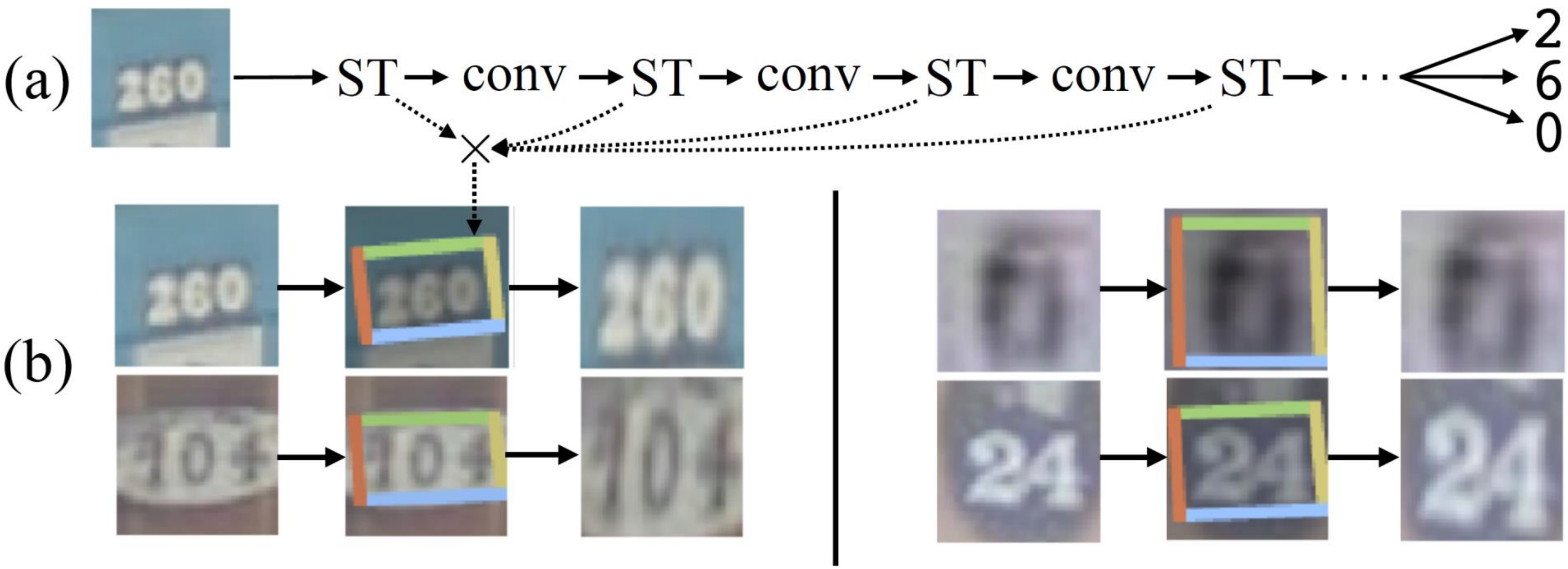

ST1
conv1
ST2a
ST2b
conv2
ST3
conv3
0
9

Street View House Number

Model		Size 64px	Size 128px
Maxout CNN [10]		4.0	-
CNN (ours)		4.0	5.6
DRAM* [1]		3.9	4.5
ST-CNN	Single	3.7	**3.9**
	Multi	**3.6**	**3.9**

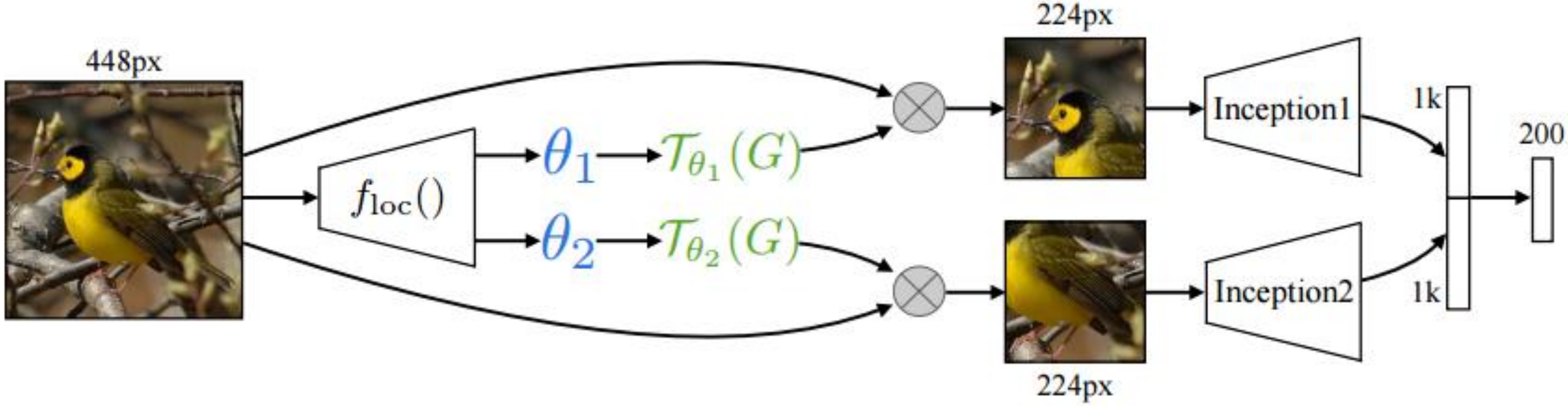
Single: one transformation layer

Multi: many transformation layer

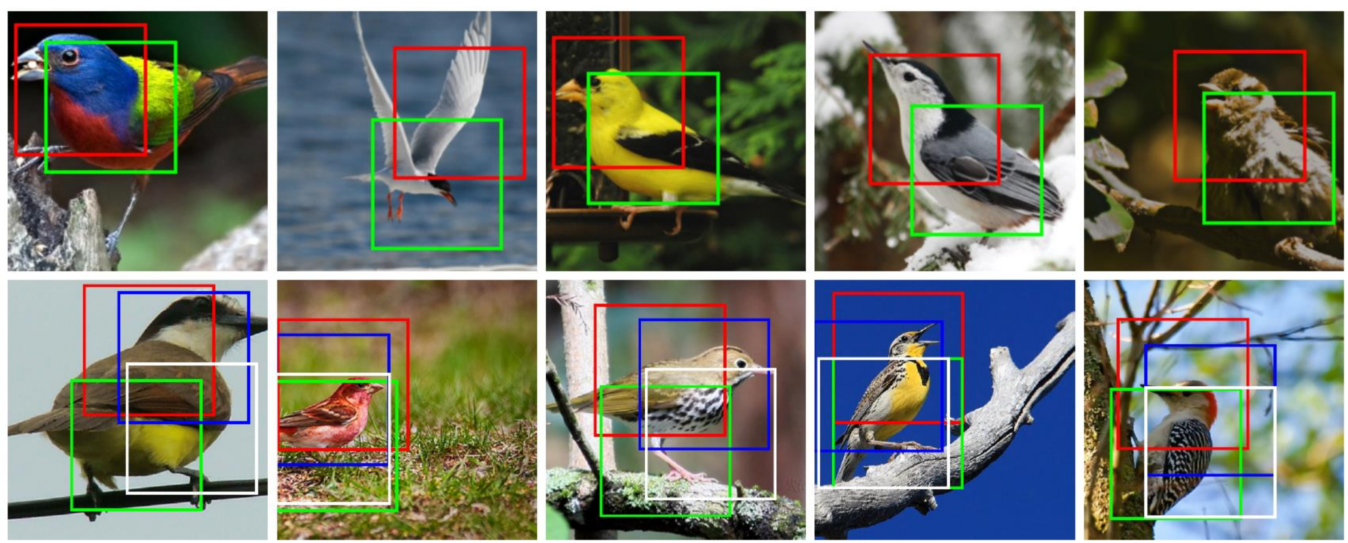


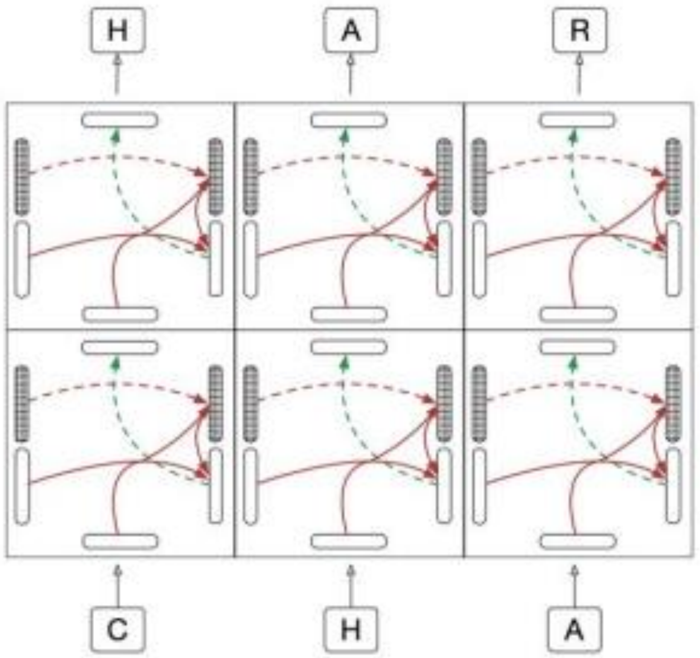
Brid Recognition

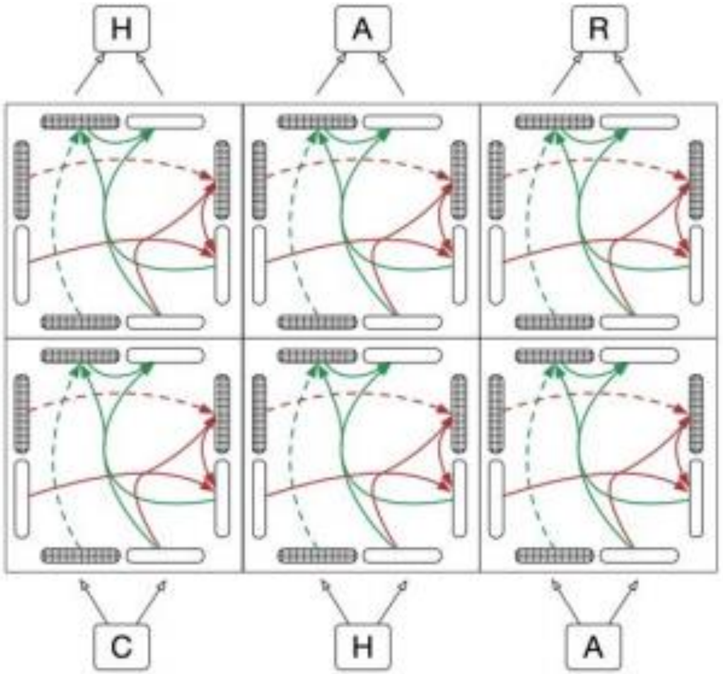
$$\begin{bmatrix} a & 0 \\ 0 & d \end{bmatrix} \begin{bmatrix} e \\ f \end{bmatrix}$$



Model		
Cimpoi '15 [4]		66.7
Zhang '14 [30]		74.9
Branson '14 [2]		75.7
Lin '15 [20]		80.9
Simon '15 [24]		81.0
CNN (ours)	224px	82.3
2×ST-CNN	224px	83.1
2×ST-CNN	448px	83.9
4×ST-CNN	448px	**84.1**



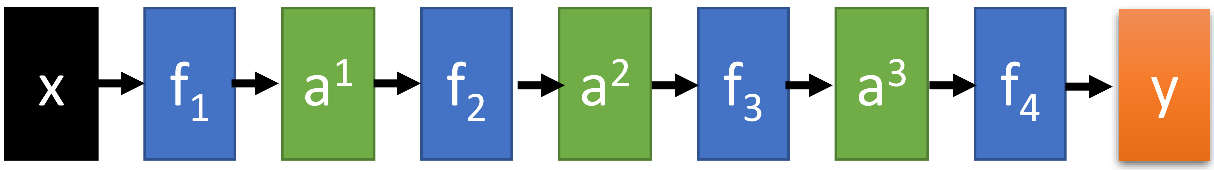




Highway Network & Grid LSTM

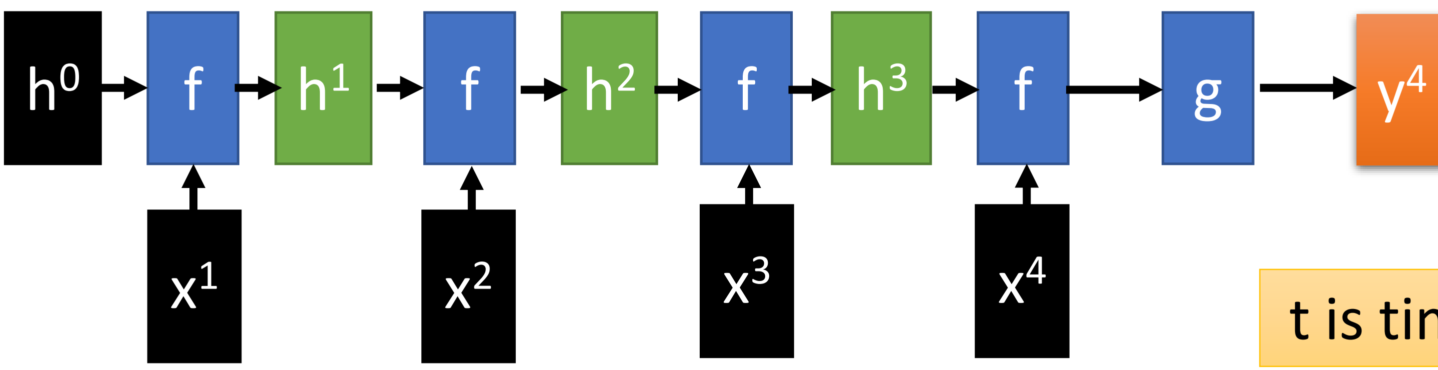
Feedforward v.s. Recurrent

1. Feedforward network does not have input at each step
2. Feedforward network has different parameters for each layer



$$a^t = f_l(a^{t-1}) = \sigma(W^t a^{t-1} + b^t)$$

t is layer



t is time step

$$a^t = f(a^{t-1}, x^t) = \sigma\left(W^h a^{t-1} + W^i x^t + b^i\right)$$

Applying gated structure in feedforward network

GRU → Highway Network

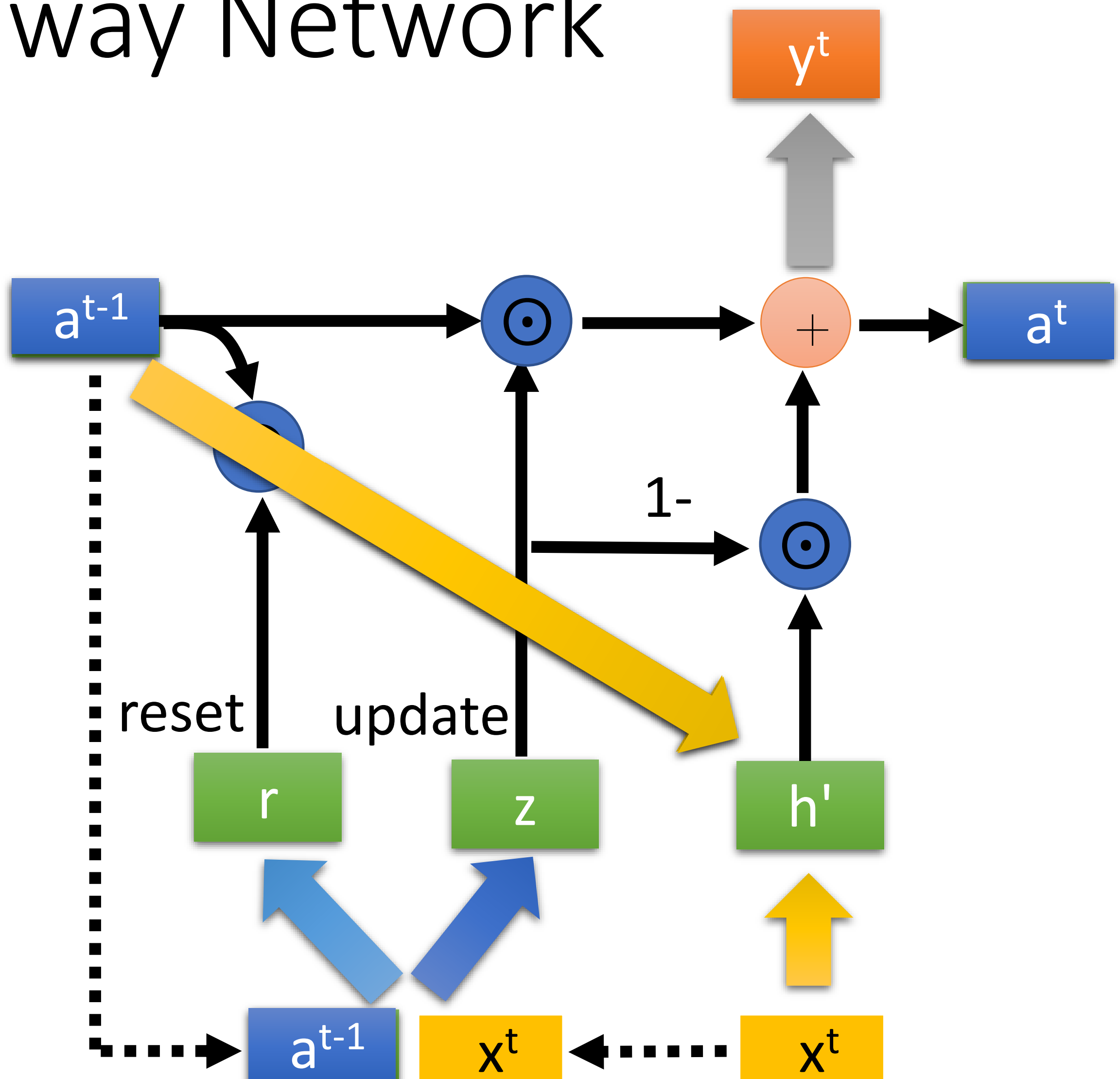
No input x^t at each step

No output y^t at each step

a^{t-1} is the output of the (t-1)-th layer

a^t is the output of the t-th layer

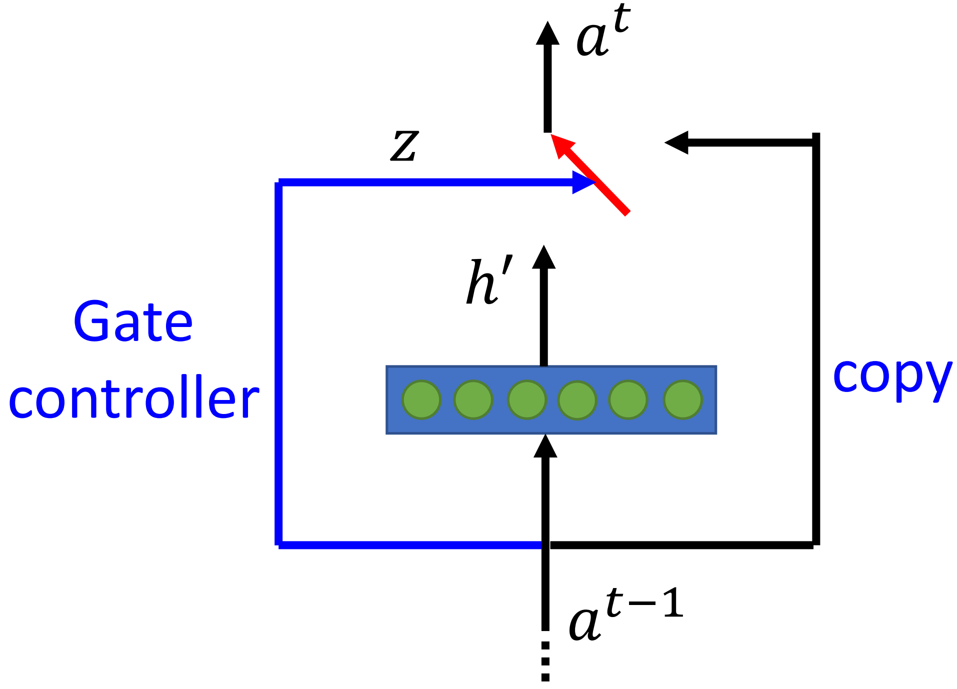
No reset gate



Highway Network

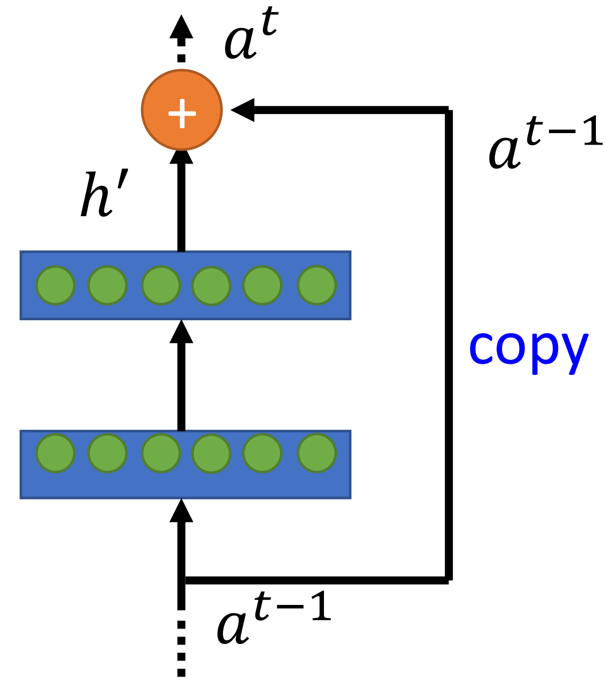
$$h' = \sigma(W a^{t-1})$$
$$z = \sigma(W' a^{t-1})$$
$$a^t = z \odot a^{t-1} + (1 - z) \odot h$$

- **Highway Network**

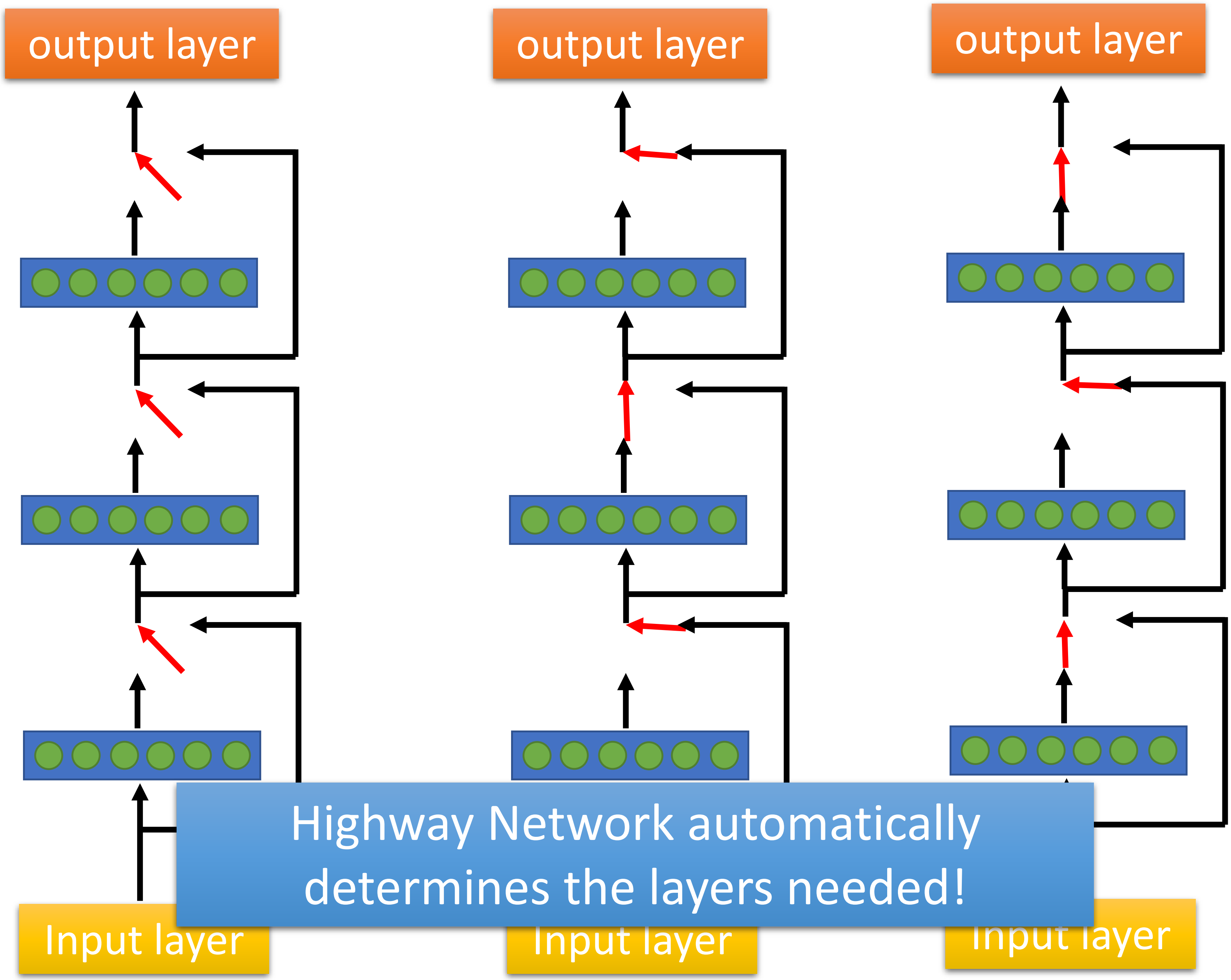


Training Very Deep Networks
https://arxiv.org/pdf/1507.06228v2.pdf

- **Residual Network**

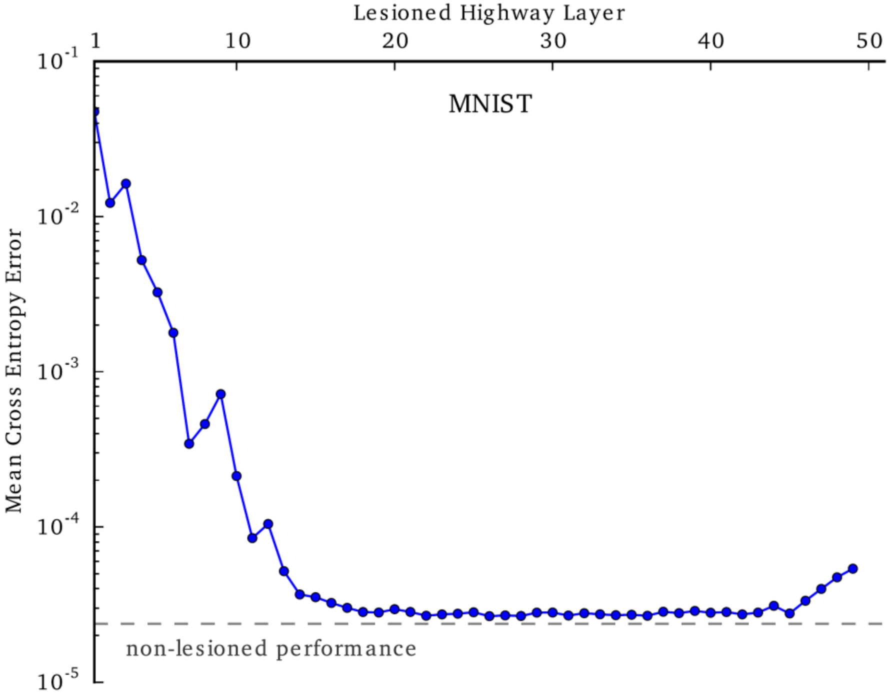


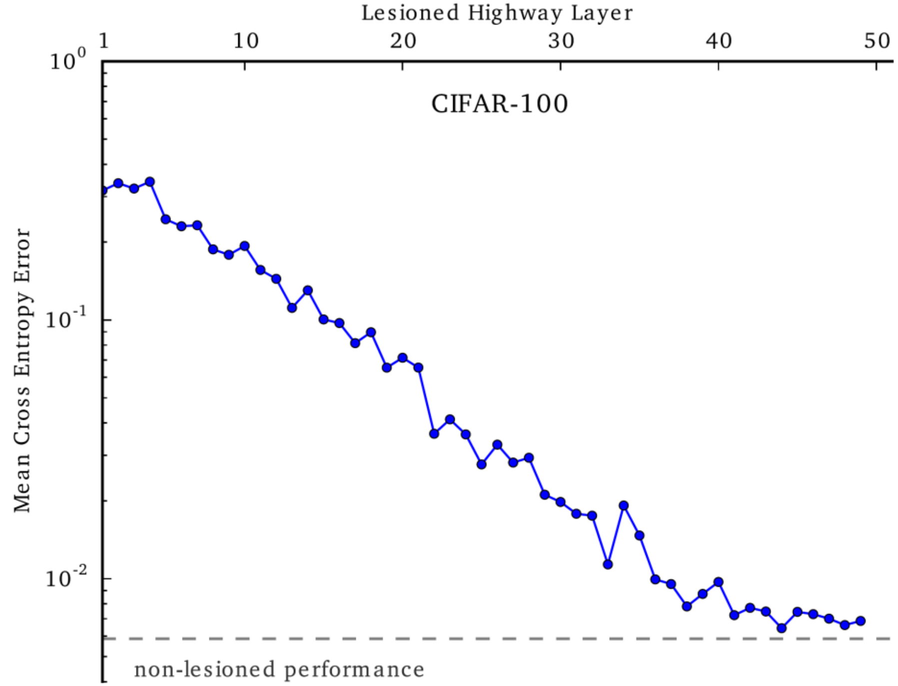
Deep Residual Learning for Image Recognition
http://arxiv.org/abs/1512.03385



Highway Network automatically determines the layers needed!

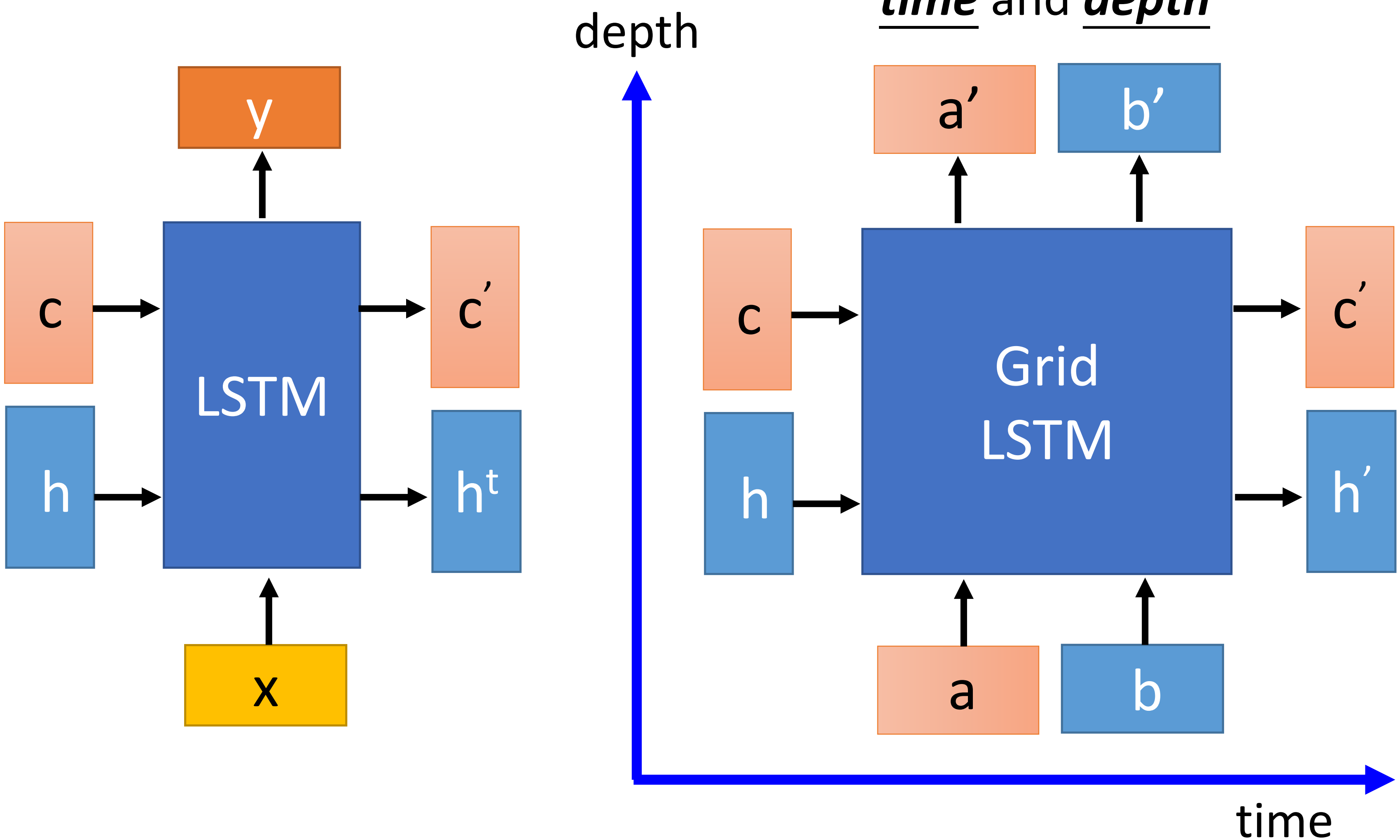
Highway Network

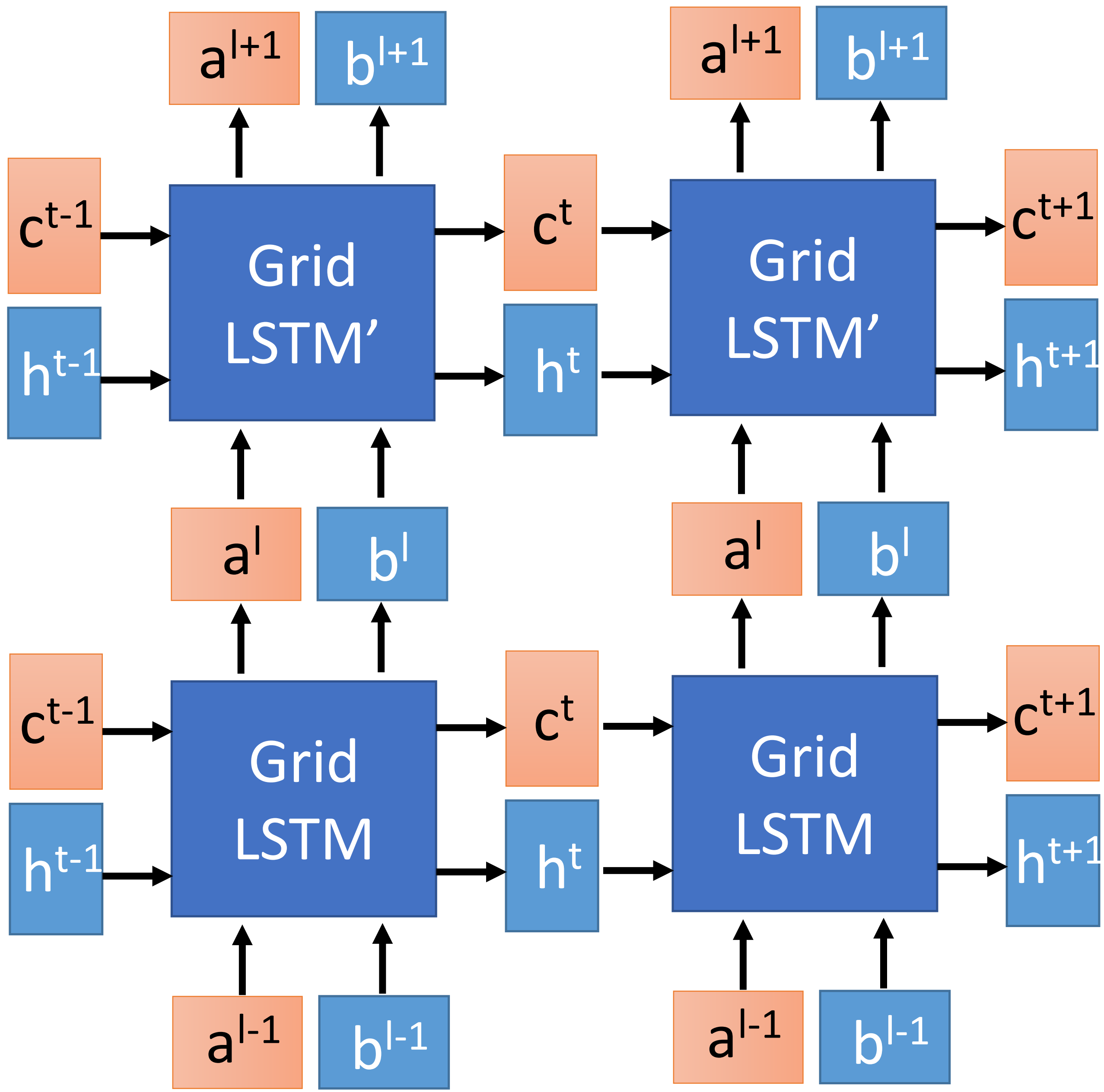




Grid LSTM

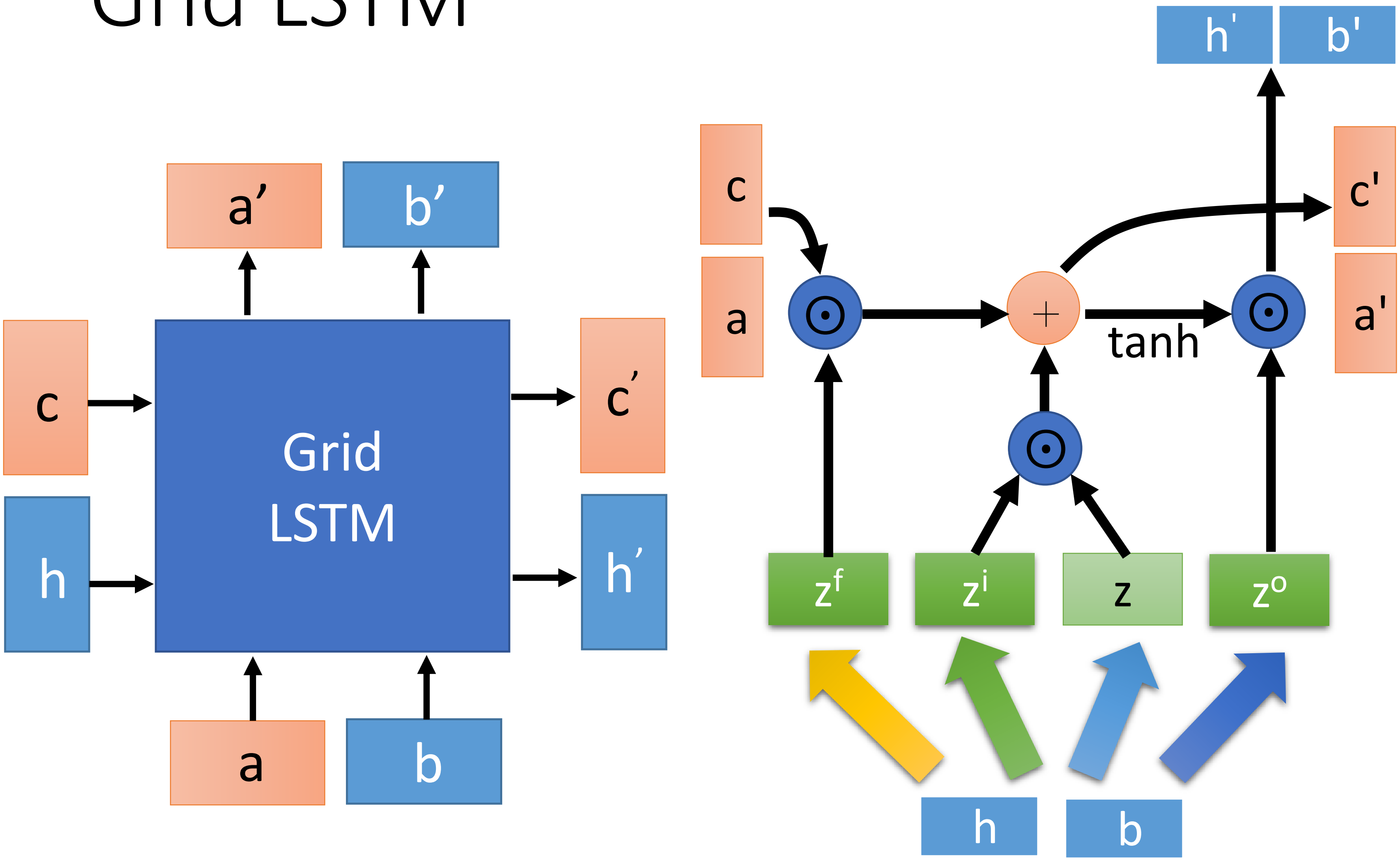
Memory for both ***time*** and ***depth***



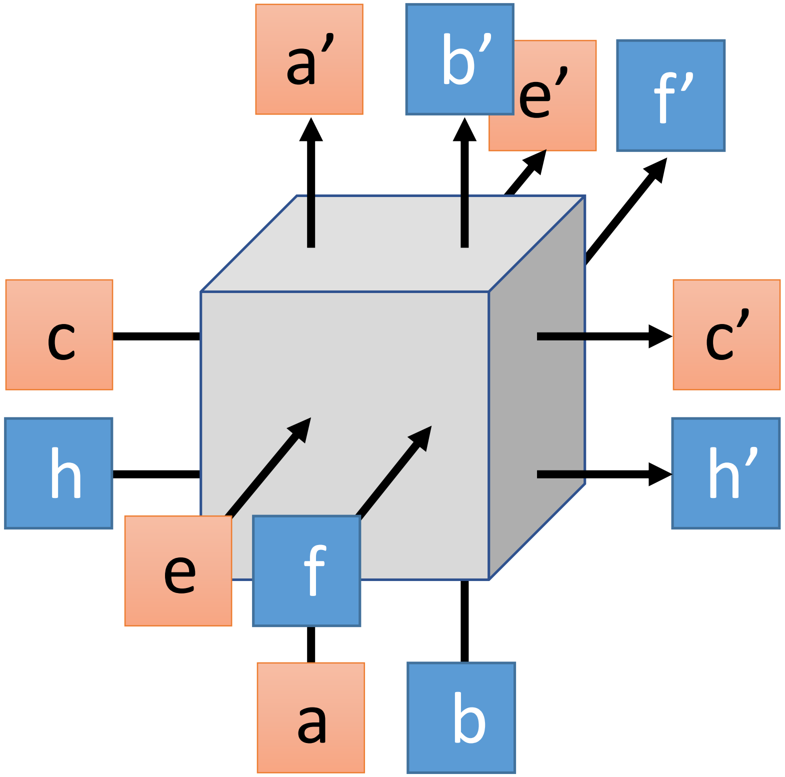


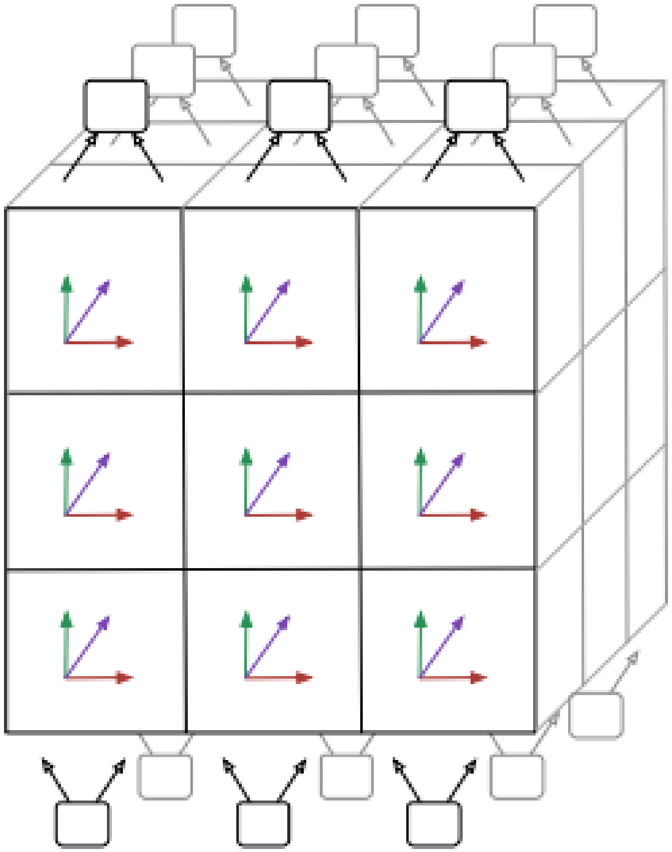
a^{l+1}
b^{l+1}
a^{l+1}
b^{l+1}
c^{t-1}
h^{t-1}
Grid LSTM'
c^t
h^t
Grid LSTM'
c^{t+1}
h^{t+1}
a^l
b^l
a^l
b^l
c^{t-1}
h^{t-1}
Grid LSTM
c^t
h^t
Grid LSTM
c^{t+1}
h^{t+1}
a^{l-1}
b^{l-1}
a^{l-1}
b^{l-1}

Grid LSTM



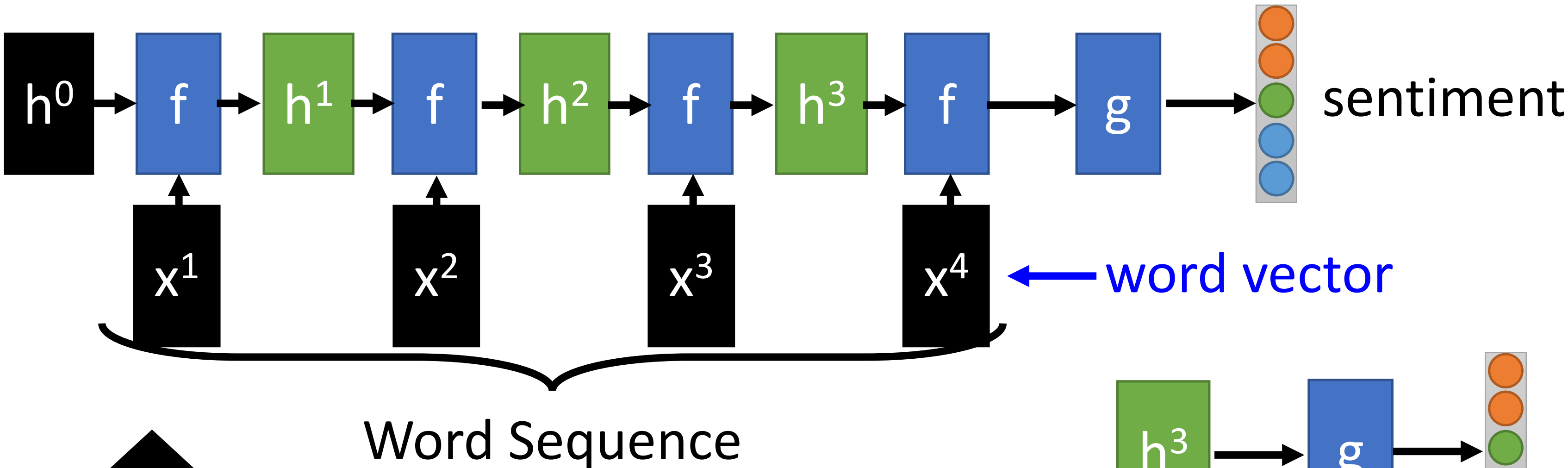
3D Grid LSTM





Recursive Structure

Application: Sentiment Analysis

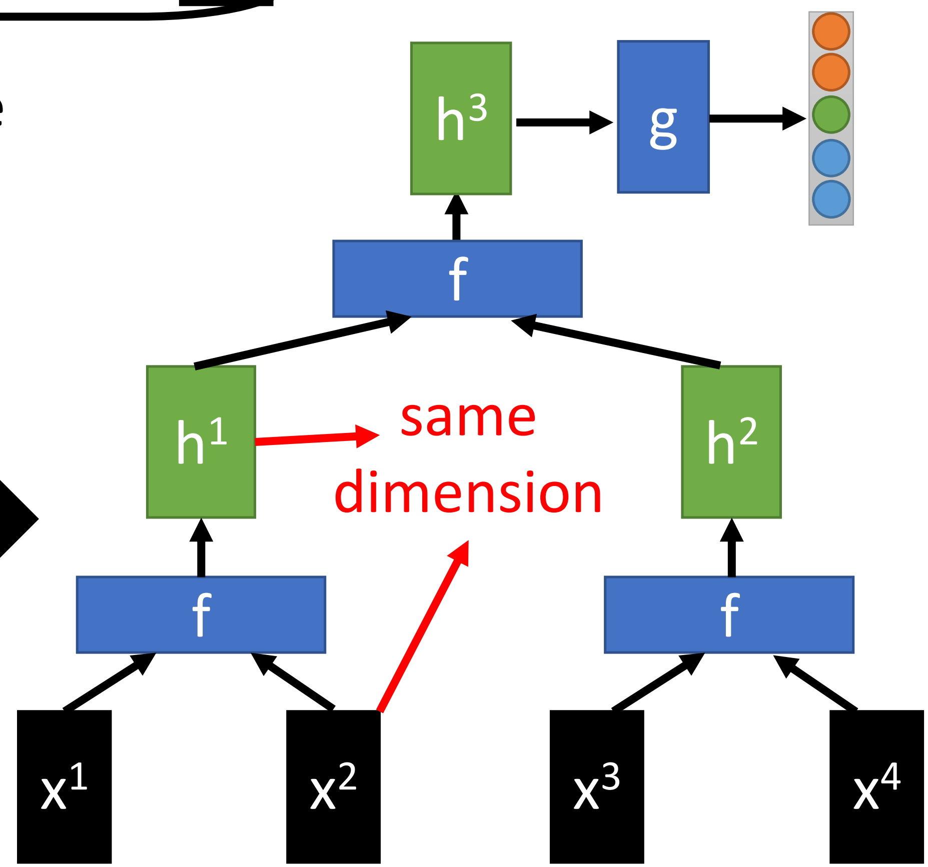


Recurrent Structure

Special case of recursive structure

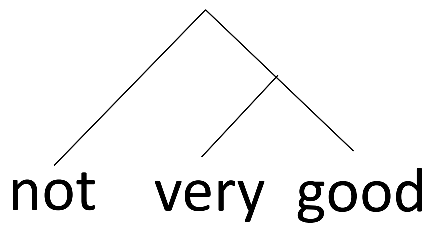
Recursive Structure

How to stack function f is already determined



Recursive Model

syntactic structure

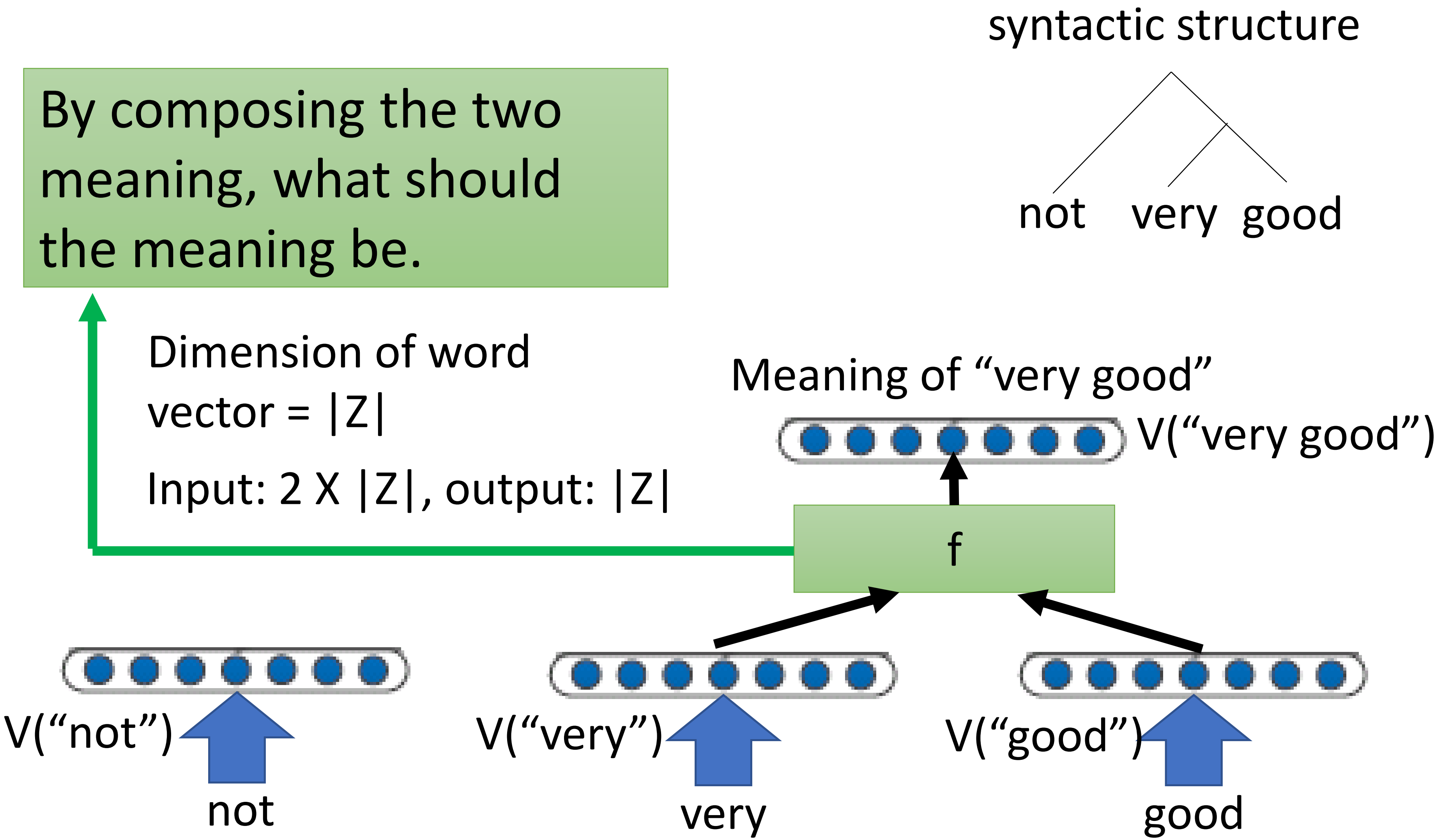


How to do it is out of the scope

word sequence:

not very good

Recursive Model



Recursive Model

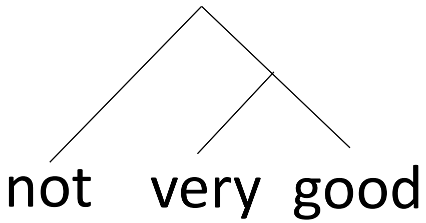
$V(w_A\, w_B) \neq V(w_A) + V(w_B)$

"not": neutral

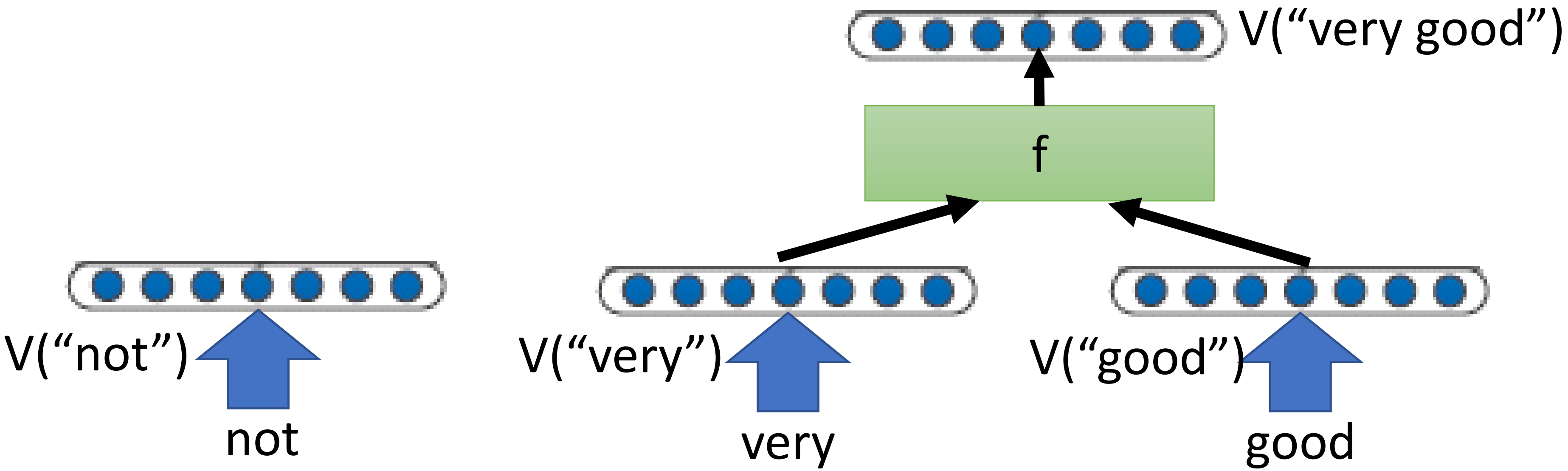
"good": positive

"not good": negative

syntactic structure



Meaning of "very good"



Recursive Model

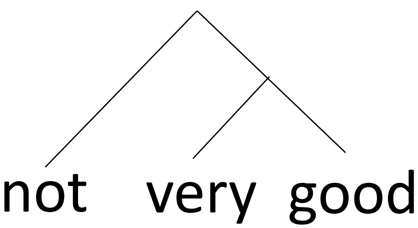
$V(w_A\, w_B) \neq V(w_A) + V(w_B)$

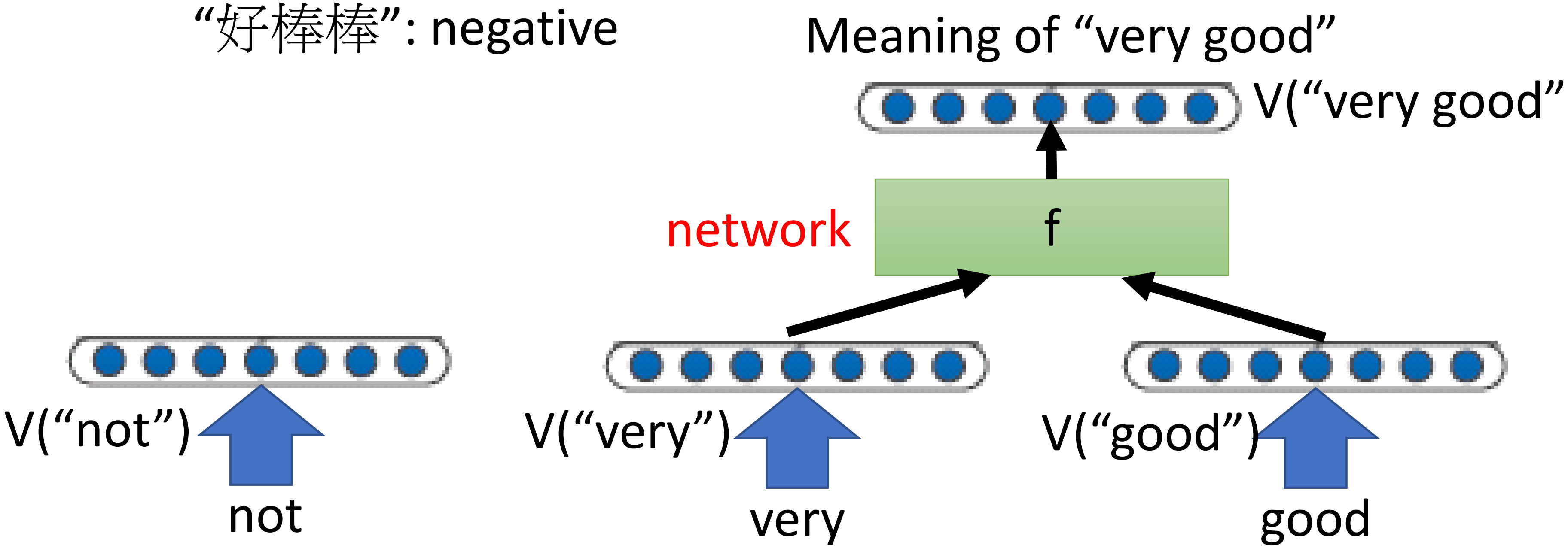
"棒": positive

"好棒": positive

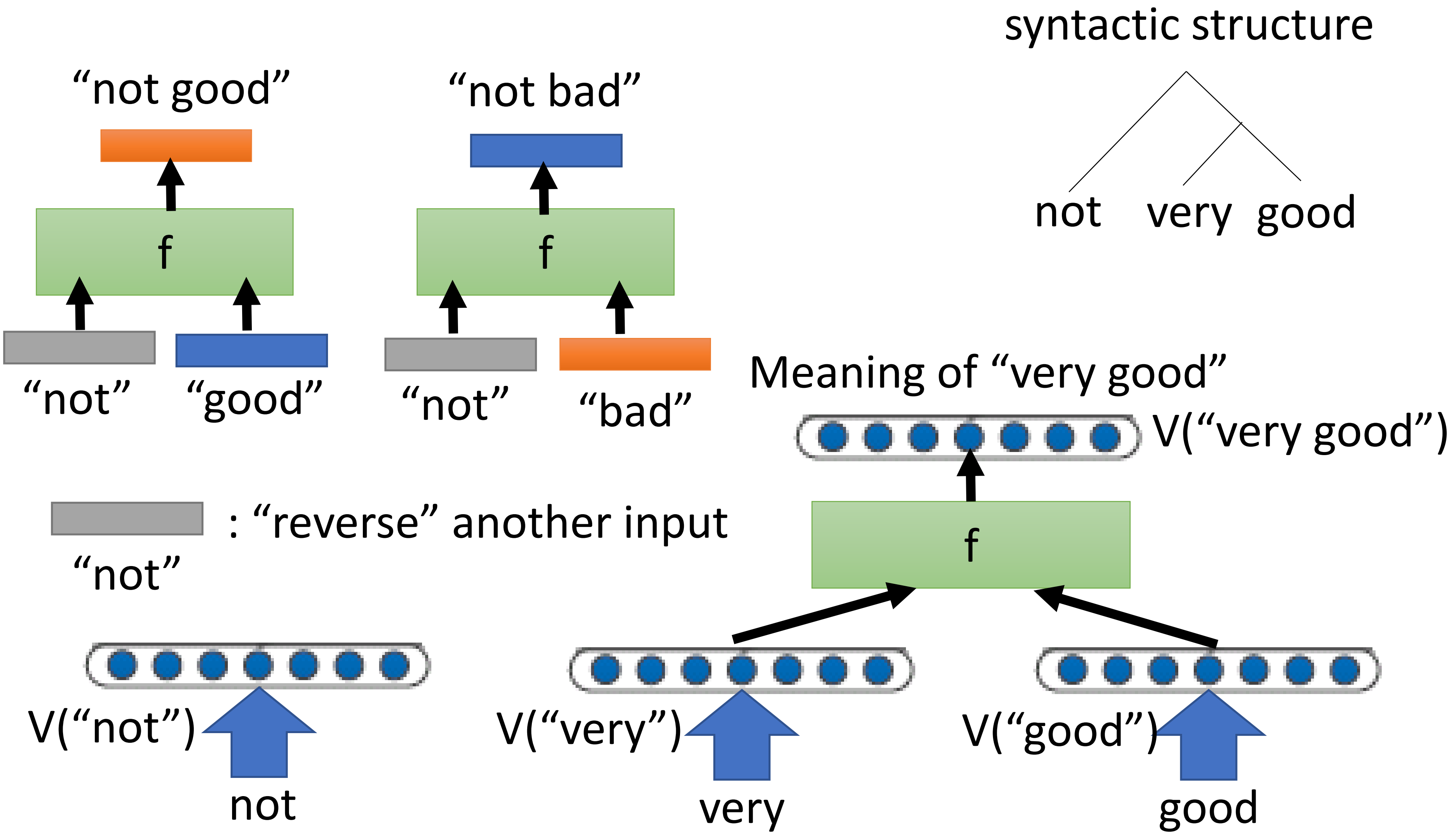
"好棒棒": negative

syntactic structure

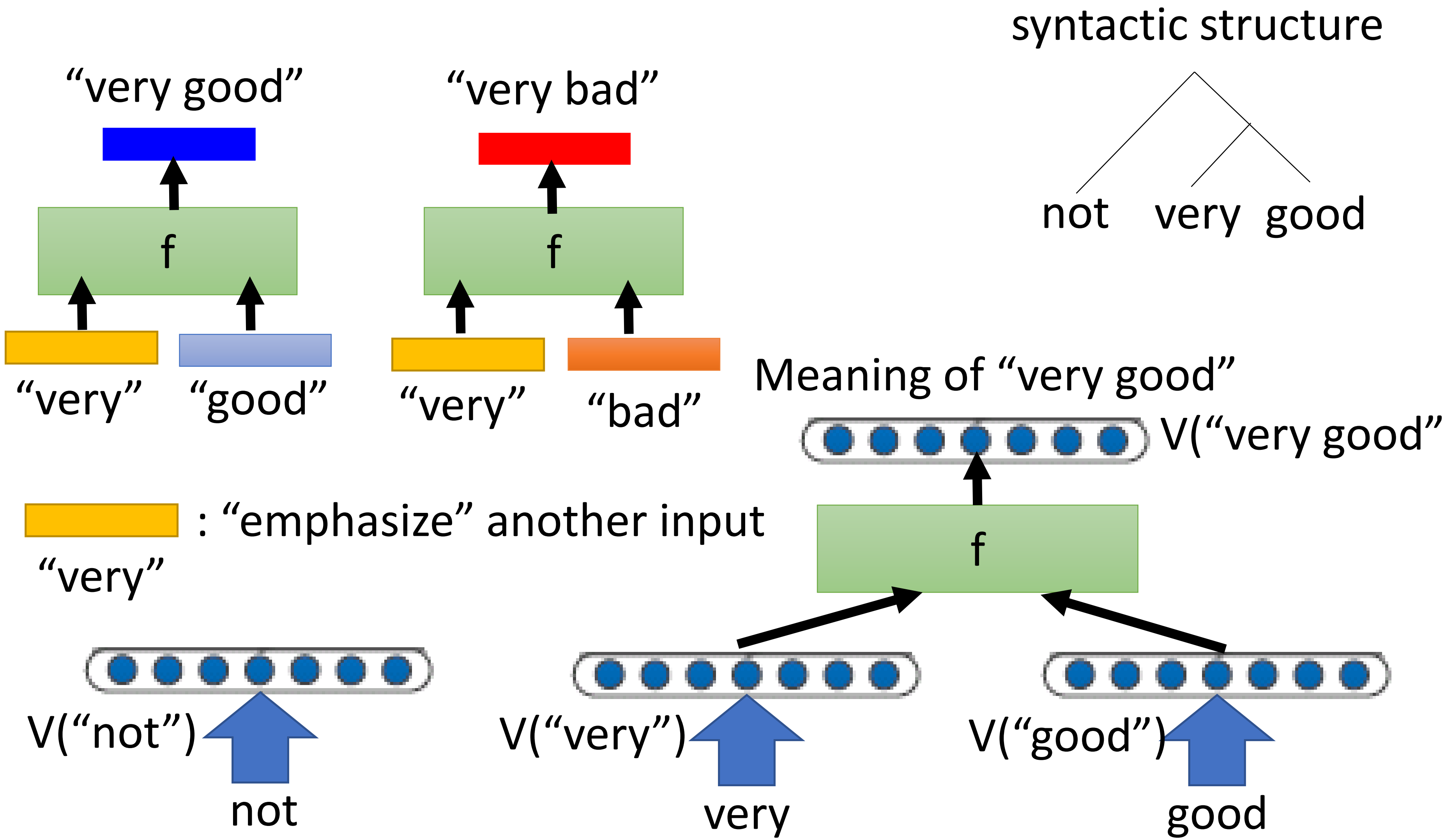


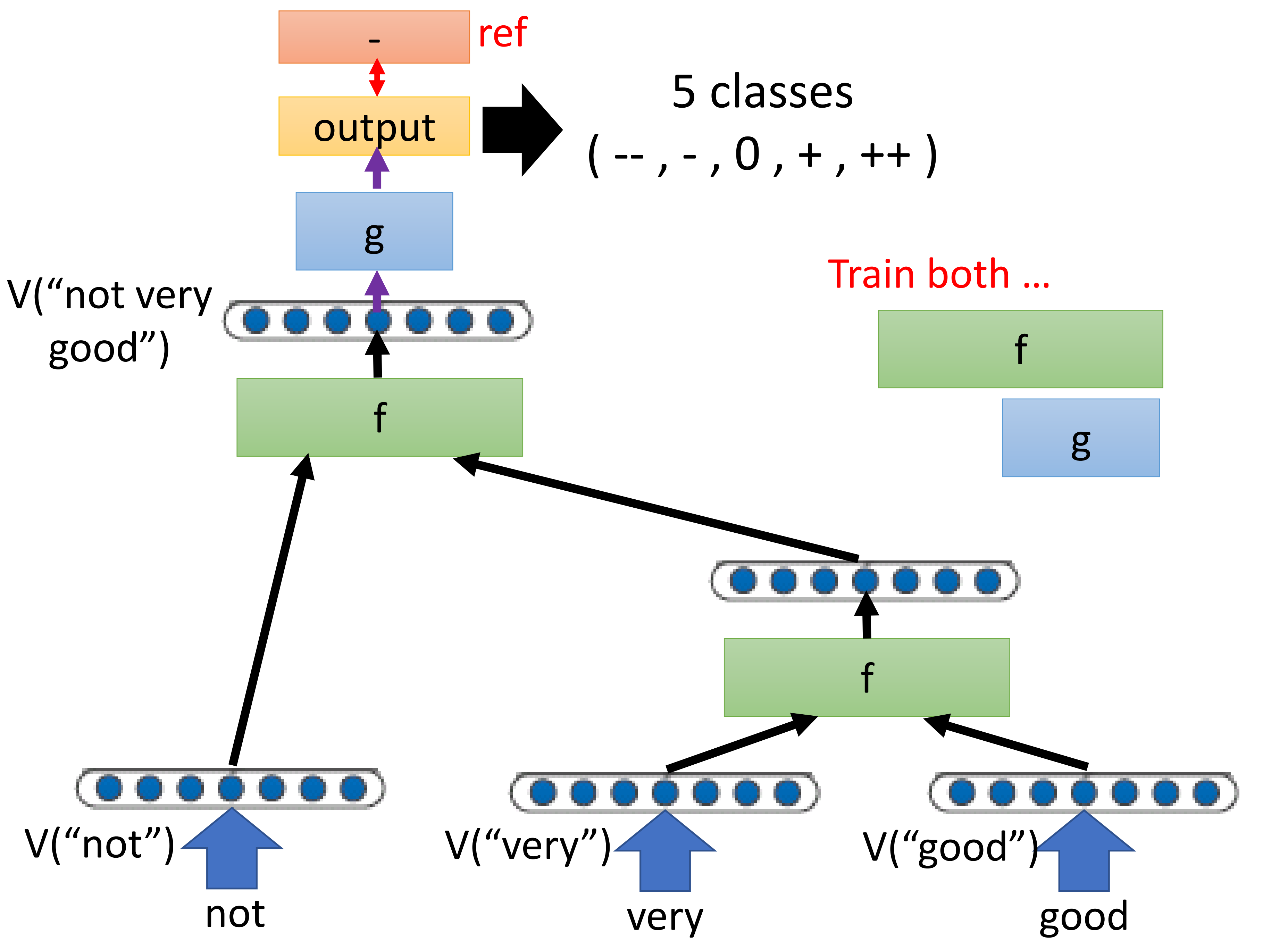


Recursive Model



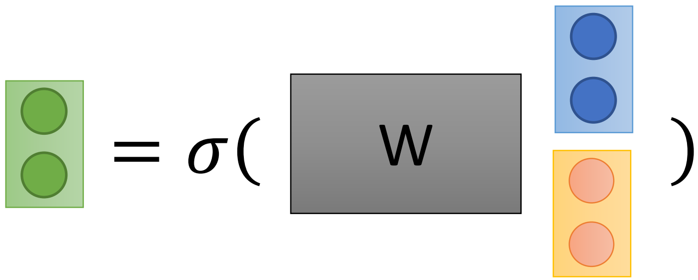
Recursive Model

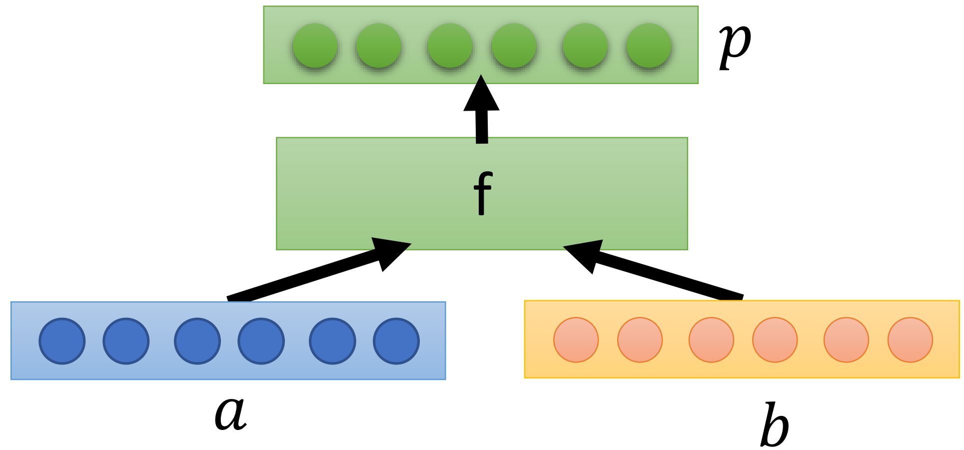




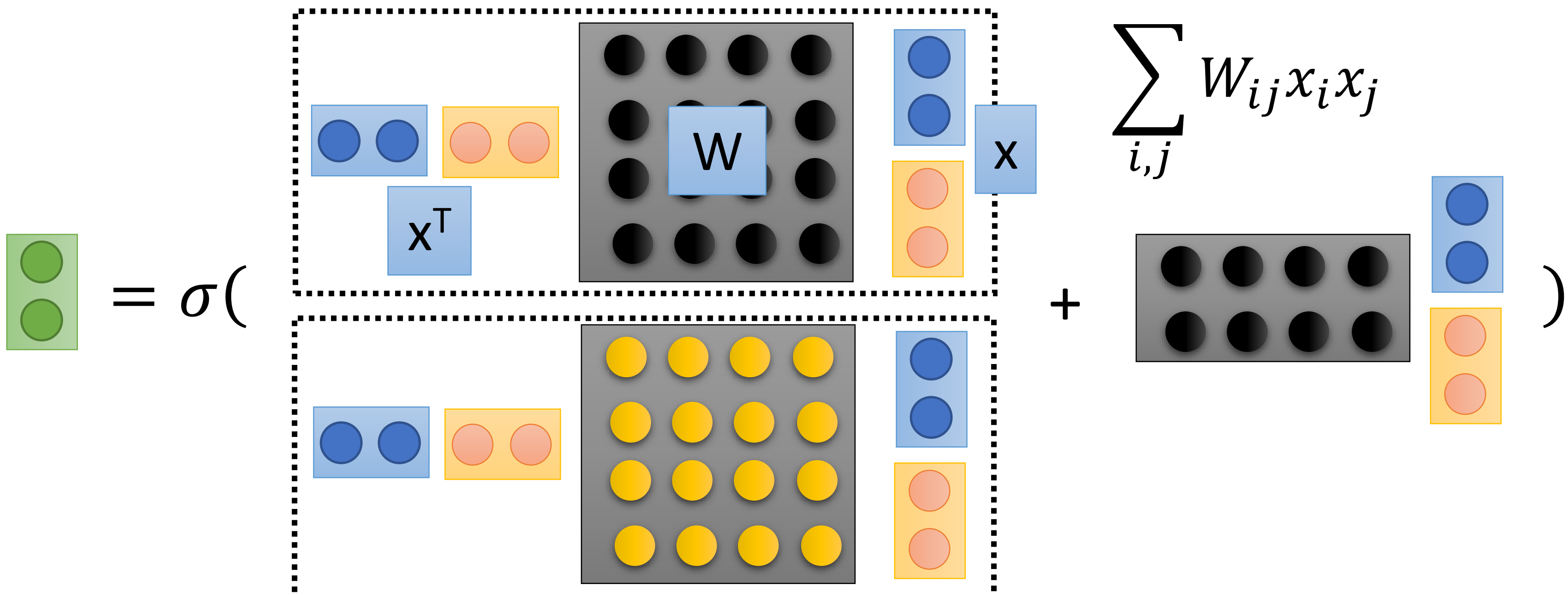
-
ref
output
5 classes
(-- , - , 0 , + , ++)
g
Train both …
V("not very good")
f
g
f
f
V("not")
not
V("very")
very
V("good")
good

Recursive Neural Tensor Network



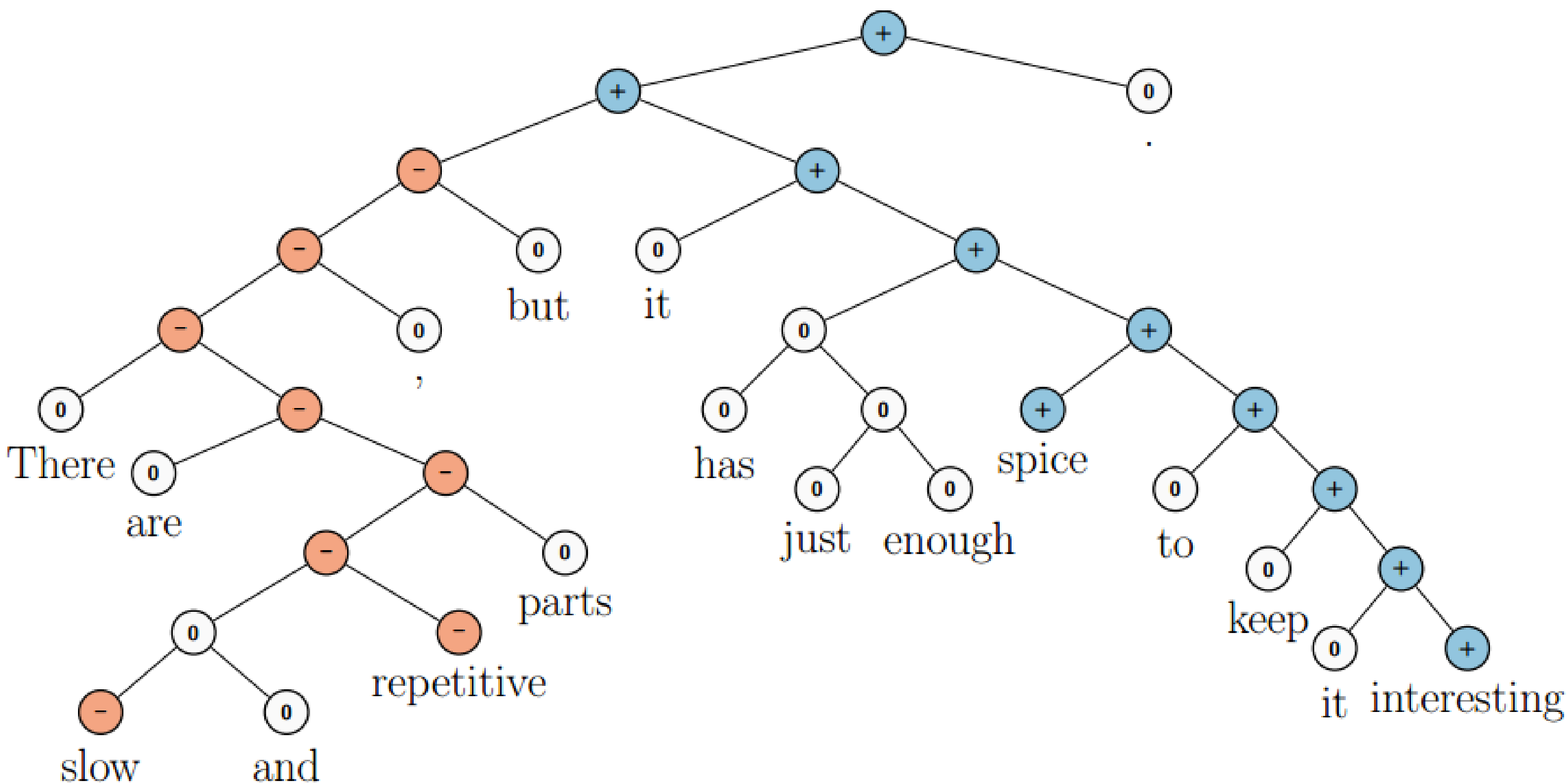


Little interaction between a and b



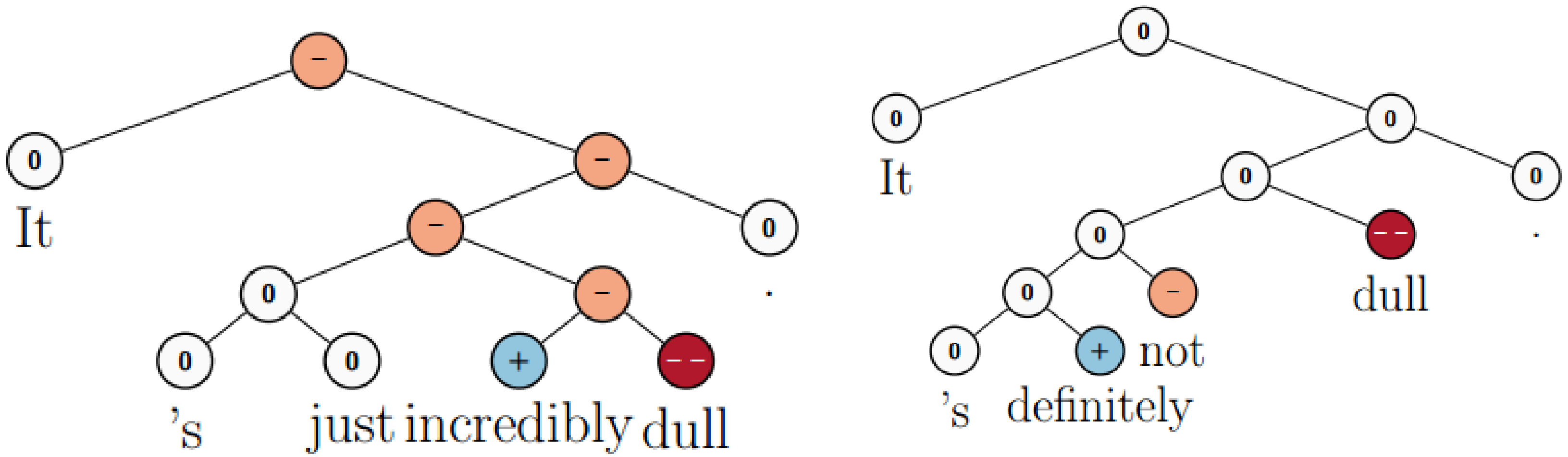
Experiments

5-class sentiment classification (-- , - , 0 , + , ++)



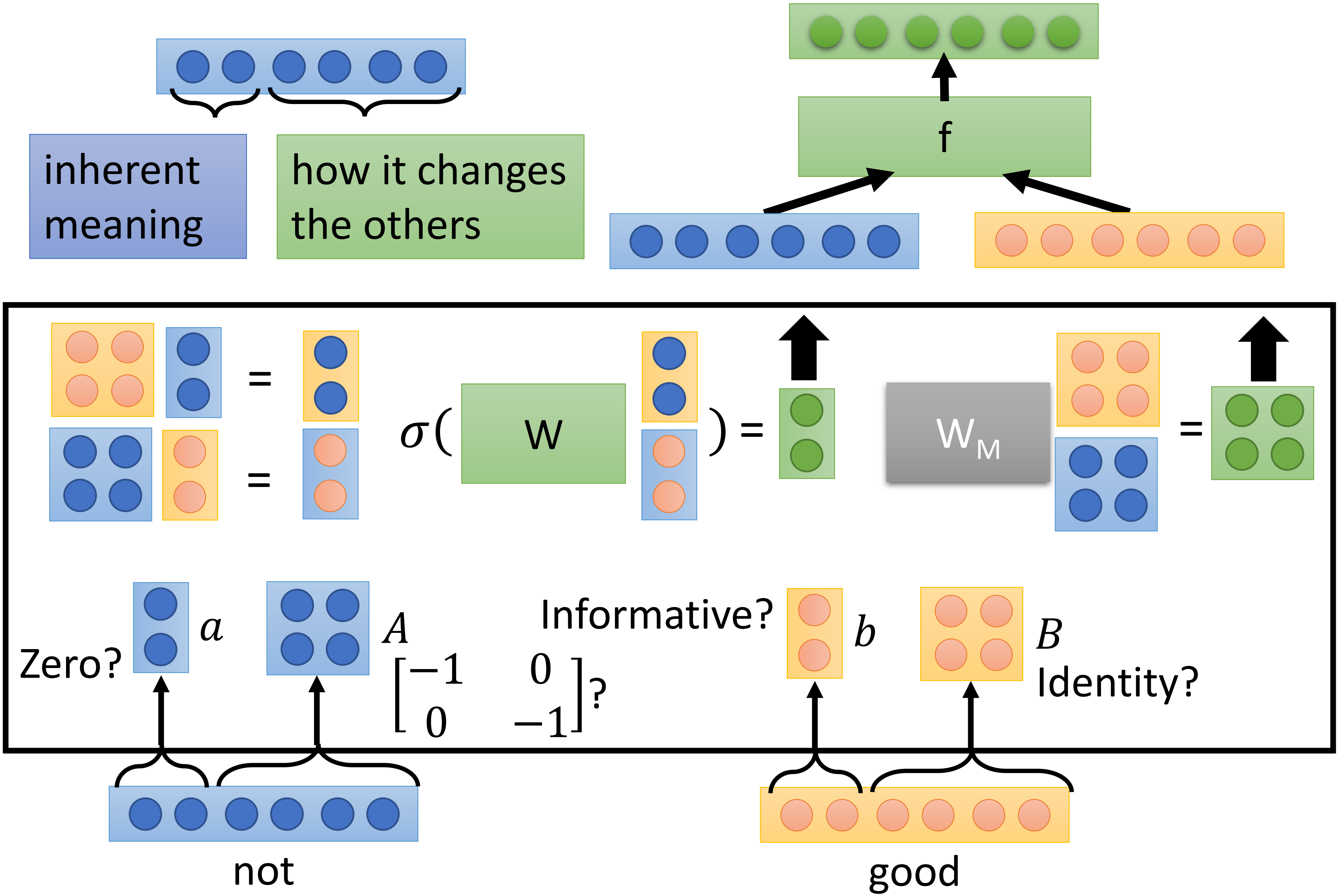
Demo: http://nlp.stanford.edu:8080/sentiment/rntnDemo.html

Experiments



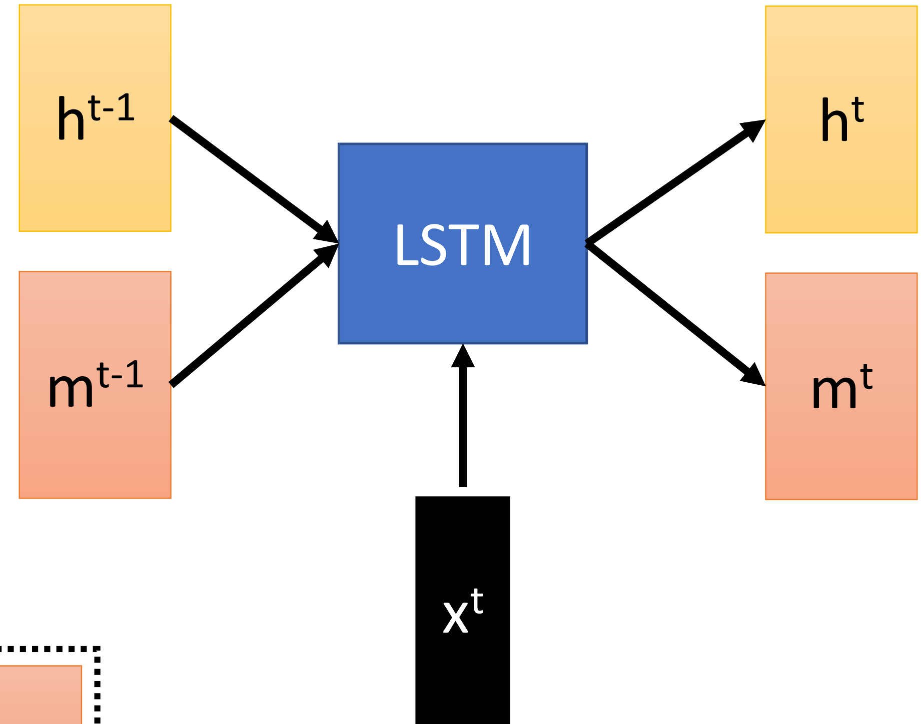
Socher, Richard, et al. "Recursive deep models for semantic compositionality over a sentiment treebank." *Proceedings of the conference on empirical methods in natural language processing (EMNLP)*. Vol. 1631. 2013.

Matrix-Vector Recursive Network

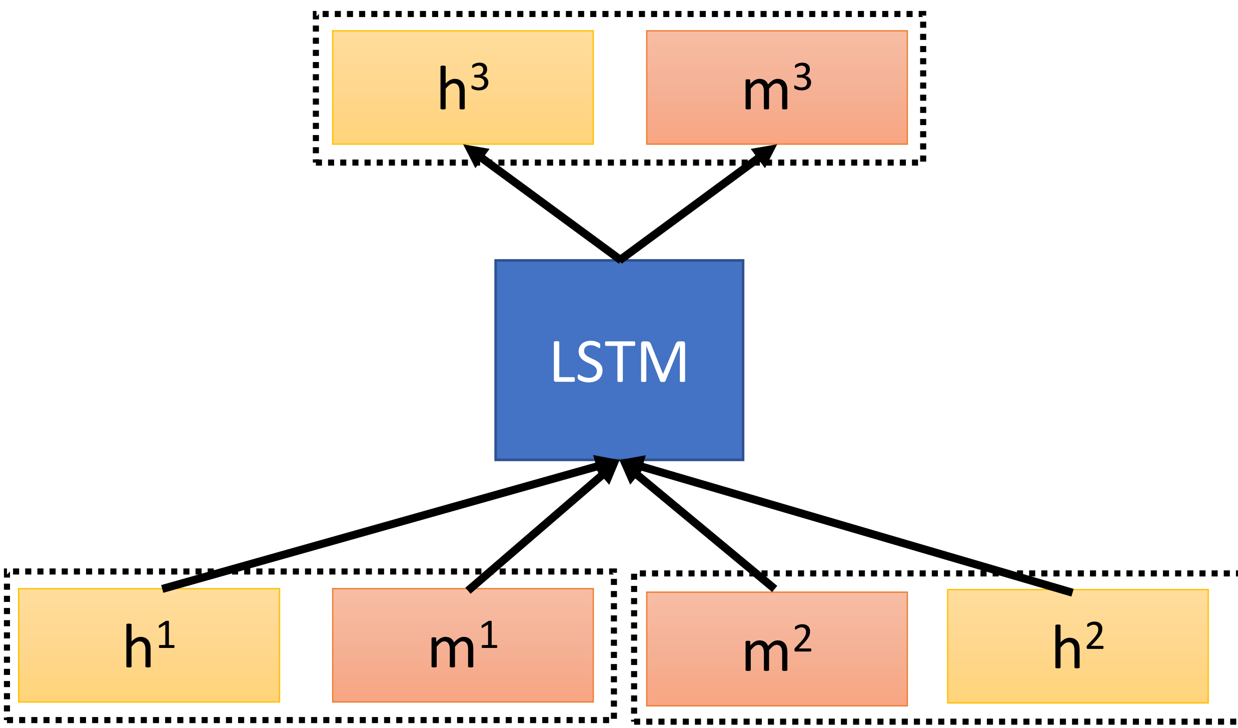


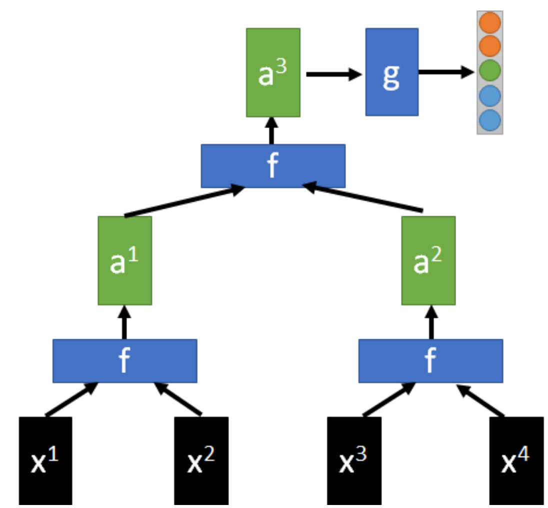
Tree LSTM

Typical LSTM



Tree LSTM

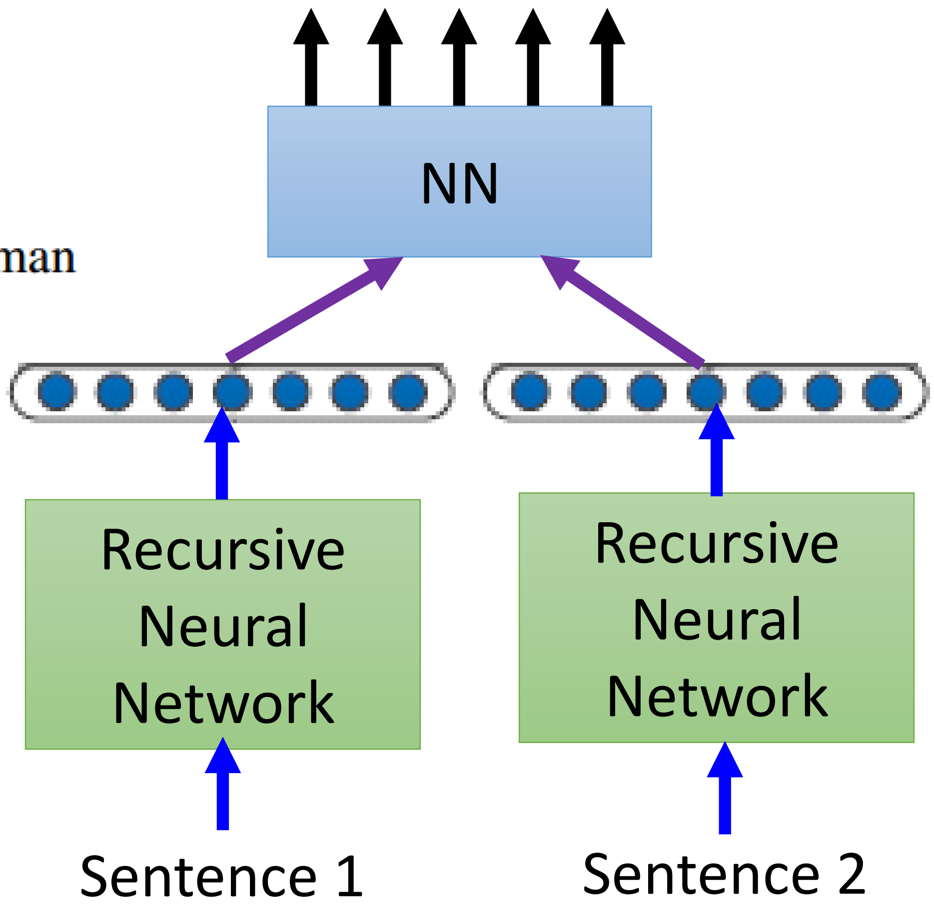




More Applications

- Sentence relatedness

	a woman is slicing potatoes
4.82	a woman is cutting potatoes
4.70	potatoes are being sliced by a woman
4.39	tofu is being sliced by a woman



Tai, Kai Sheng, Richard Socher, and Christopher D. Manning. "Improved semantic representations from tree-structured long short-term memory networks." *arXiv preprint arXiv:1503.00075* (2015).

Batch Normalization

Experimental Results