Deep neural networks in a nutshell

Many inventions were inspired by the Nature









Incredibly poor analogy from biological point of view

It doesn't matter how you come up with the idea, but its utility is the only thing that matters.

NN Tasks and Utility

- Classification
- Classification with missing inputs
- Segmentation
- Regression (predict a numerical value given some input)
- Transcription (observe a relatively unstructured representation of some kind of data and transcribe it into discrete, textual form)
- Machine translation
- Structured output (e.g. sentence to its grammar tree)
- Anomaly detection
- Synthesis and sampling
- Imputation of missing values
- Denoising
- Density estimation or probability mass function estimation
- And many-many more.....



Classification is simple? Think once more.



Google uses NN for translation

DETECT LANGUAGE	RUSSIAN	ENGLISH	GERMAN	~	+	UKRAI	NIAN RUSSIAN ENGLISH 🗸		
Hello					×	Здрас	стуйте ⊘		
						Zdrastuyt	e		
•				5/5000	•	•		Ø	
						Translatic	ons of Hello!		
						Interjection	n	Frequ	end
						Алло!	Hello!, Hallo!, Halloa!, Hullo!, Hulloa!		-
						Ало!	Hello!		
						Вітаю!	Congratulations!, Hello!		
						Привіт!	Greetings!, Hello!, Hi!, Hallo!, Ave!, Chin-Chin!		1

Send feedback





self, olc.	dynamic	ground	road	sidewalk
parking	rail track	building	wall	fence
guard rail	bridge	tunnel	pole	polegroup
				1
traffic light	traffic sign	vegetation	terrain	sky
traffic light person	traffic sign rider	vegetation car	terrain truck	sky bus





Real noisy photos

Input



Output

















Caption	Generated Images
the flower shown has yellow anther red pistil and bright red petals	
this flower has petals that are yellow, white and purple and has dark lines	
the petals on this flower are white with a yellow center	
this flower has a lot of small round pink petals.	
this flower is orange in color, and has petals that are ruffled and rounded.	
the flower has yellow petals and the center of it is brown	



What is a neural network?

Single Neuron



Activation functions



Leaky ReLU
$$\max(0.1x, x)$$



 $\begin{array}{l} \textbf{Maxout} \\ \max(w_1^T x + b_1, w_2^T x + b_2) \end{array}$





input layer

hidden layer 1

hidden layer 2

output layer



Functionally, neural network is a gargantuan interpolator-approximator with millions internal parameters

Example: AlexNet, 62,378,344 parameters

Where do we get the points to approximate?

Three ways (maybe, you'll be the one to invent more)

- We define the desired output ourselves Supervised learning (classification, etc.)
- We cannot define the desired output, but we can tell how bad is the given output – Unsupervised learning (clustering, etc.)
- We allow NN to interact with the environment and assess the consequences – Reinforcement learning (play Atari game, etc.)

How do we know, neural network does its job good?

How do we know, it does what we want?

Cost Function also known as Loss Function



How to formalize that two rectangles match?

What is supposed to be "good"?













Now you have ground-truth



Which detect is better?

Where do we get internal parameters?

We train neural network

How do we train neural network?

Methodological point of view

- Supervised learning (classification, etc.)
- Unsupervised learning (clustering, etc.)
- Reinforcement learning (play Atari game, etc.)

Implementation point of view

Loss function, the formalization of how good NN performs, should be minimized (we could define "gain" function and maximize it)

What minimization methods do we know? What is the suitable one?

Parameters... Parameters everywhere...



Curse of dimensions

Function of millions of arguments...

How do we minimize it?

What properties can we rely on? (global or local)

We can rely on local properties only due to curse of dimensions

So neural network is just a function

 $f_{\alpha_1,\alpha_2,\ldots,\alpha_n}(x_1,x_2,\ldots,x_m)$
We can rely on local properties only due to curse of dimensions

So neural network is just a function

 $f_{\alpha_1,\alpha_2,\ldots,\alpha_n}(x_1,x_2,\ldots,x_m)$

It is philosophical question what to consider parameters and what should be arguments

 $f(\alpha_1, \alpha_2, \ldots, \alpha_n; x_1, x_2, \ldots, x_m)$









Δx and Δy not equal in general!



Red lines we assume to be parallel

$$\Delta f(\alpha_1, \alpha_2, \dots, \alpha_n; x_1, x_2, \dots, x_m) = \frac{\partial f}{\partial \alpha_1} \Delta \alpha_1 + \frac{\partial f}{\partial \alpha_2} \Delta \alpha_2 + \dots + \frac{\partial f}{\partial \alpha_n} \Delta \alpha_n$$

$$\Delta f(\alpha_1, \alpha_2, \dots, \alpha_n; x_1, x_2, \dots, x_m) = \frac{\partial f}{\partial \alpha_1} \Delta \alpha_1 + \frac{\partial f}{\partial \alpha_2} \Delta \alpha_2 + \dots + \frac{\partial f}{\partial \alpha_n} \Delta \alpha_n$$
Do a trick

$$(a_1, \alpha_2, \dots, \alpha_n; x_1, x_2, \dots, x_m) = \frac{\partial f}{\partial \alpha_1} \Delta \alpha_1 + \frac{\partial f}{\partial \alpha_2} \Delta \alpha_2 + \dots + \frac{\partial f}{\partial \alpha_n} \Delta \alpha_n$$

$$\Delta f(\alpha_1, \alpha_2, \dots, \alpha_n; x_1, x_2, \dots, x_m) = \left\{ \frac{\partial f}{\partial \alpha_1}; \frac{\partial f}{\partial \alpha_2}; \dots; \frac{\partial f}{\partial \alpha_n} \right\} \cdot \overline{\left\{ \Delta \alpha_1; \Delta \alpha_2; \dots; \Delta \alpha_n \right\}} = \vec{\nabla}_{\alpha} f \cdot \vec{\Delta}_{\alpha}$$

$$\Delta f(\alpha_1, \alpha_2, \dots, \alpha_n; x_1, x_2, \dots, x_m) = \frac{\partial f}{\partial \alpha_1} \Delta \alpha_1 + \frac{\partial f}{\partial \alpha_2} \Delta \alpha_2 + \dots + \frac{\partial f}{\partial \alpha_n} \Delta \alpha_n$$

DO a trick
$$\Delta f(\alpha_1, \alpha_2, \dots, \alpha_n; x_1, x_2, \dots, x_m) = \overline{\left\{\frac{\partial f}{\partial \alpha_1}; \frac{\partial f}{\partial \alpha_2}; \dots; \frac{\partial f}{\partial \alpha_n}\right\}} \cdot \overline{\left\{\Delta \alpha_1; \Delta \alpha_2; \dots; \Delta \alpha_n\right\}} = \vec{\nabla}_{\alpha} f \cdot \vec{\Delta}_{\alpha}$$

$$\Delta f(\alpha_1, \alpha_2, \dots, \alpha_n; x_1, x_2, \dots, x_m) = |\vec{\nabla}_{\alpha} f| \quad |\vec{\Delta}_{\alpha}| \cos(\varphi)$$

$$\Delta f(\alpha_{1}, \alpha_{2}, \dots, \alpha_{n}; x_{1}, x_{2}, \dots, x_{m}) = \frac{\partial f}{\partial \alpha_{1}} \Delta \alpha_{1} + \frac{\partial f}{\partial \alpha_{2}} \Delta \alpha_{2} + \dots + \frac{\partial f}{\partial \alpha_{n}} \Delta \alpha_{n}$$

$$Do \ a \ trick$$

$$\Delta f(\alpha_{1}, \alpha_{2}, \dots, \alpha_{n}; x_{1}, x_{2}, \dots, x_{m}) = \overline{\left\{\frac{\partial f}{\partial \alpha_{1}}; \frac{\partial f}{\partial \alpha_{2}}; \dots; \frac{\partial f}{\partial \alpha_{n}}\right\}} \cdot \overline{\left\{\Delta \alpha_{1}; \Delta \alpha_{2}; \dots; \Delta \alpha_{n}\right\}} = \vec{\nabla}_{\alpha} f \cdot \vec{\Delta}_{\alpha}$$

$$\Delta f(\alpha_{1}, \alpha_{2}, \dots, \alpha_{n}; x_{1}, x_{2}, \dots, x_{m}) = |\vec{\nabla}_{\alpha} f| \underbrace{|\vec{\Delta}_{\alpha}| \cos(\varphi)}_{\lambda}$$
How to make our function minimal?

$$\Delta f(\alpha_{1}, \alpha_{2}, \dots, \alpha_{n}; x_{1}, x_{2}, \dots, x_{m}) = \frac{\partial f}{\partial \alpha_{1}} \Delta \alpha_{1} + \frac{\partial f}{\partial \alpha_{2}} \Delta \alpha_{2} + \dots + \frac{\partial f}{\partial \alpha_{n}} \Delta \alpha_{n}$$

$$DO \ a \ trick$$

$$\Delta f(\alpha_{1}, \alpha_{2}, \dots, \alpha_{n}; x_{1}, x_{2}, \dots, x_{m}) = \overline{\left\{\frac{\partial f}{\partial \alpha_{1}}; \frac{\partial f}{\partial \alpha_{2}}; \dots; \frac{\partial f}{\partial \alpha_{n}}\right\}} \cdot \overline{\left\{\Delta \alpha_{1}; \Delta \alpha_{2}; \dots; \Delta \alpha_{n}\right\}} = \overline{\nabla}_{\alpha} f \cdot \overline{\Delta}_{\alpha}$$

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How to make our function minimal?
$$\cos(\varphi) = -1; \qquad \lambda > 0$$

$$\Delta f(\alpha_1, \alpha_2, \dots, \alpha_n; x_1, x_2, \dots, x_m) = \frac{\partial f}{\partial \alpha_1} \Delta \alpha_1 + \frac{\partial f}{\partial \alpha_2} \Delta \alpha_2 + \dots + \frac{\partial f}{\partial \alpha_n} \Delta \alpha_n$$
$$Do \ a \ trick$$
$$\Delta f(\alpha_1, \alpha_2, \dots, \alpha_n; x_1, x_2, \dots, x_m) = \overline{\left\{\frac{\partial f}{\partial \alpha_1}; \frac{\partial f}{\partial \alpha_2}; \dots; \frac{\partial f}{\partial \alpha_n}\right\}} \cdot \overline{\left\{\Delta \alpha_1; \Delta \alpha_2; \dots; \Delta \alpha_n\right\}} = \vec{\nabla}_{\alpha} f \cdot \vec{\Delta}_{\alpha}$$
$$\Delta f(\alpha_1, \alpha_2, \dots, \alpha_n; x_1, x_2, \dots, x_m) = |\vec{\nabla}_{\alpha} f| \quad |\vec{\Delta}_{\alpha}| \cos(\varphi)$$

How to make our function \dot{m} inimal?

 $\cos(\varphi) = -1; \quad \lambda > 0$ Here comes the idea of gradient descent

$$\vec{x}^{(n+1)} = \vec{x}^{(n)} - \lambda \, \vec{\nabla}_{\alpha} f \, (\vec{x}^{(n)})$$

Gradient descent



Gradient descent



Modifications of gradient descent

- Momentum optimization
- Nesterov Momentum optimization
- AdaGrad
- RMSProp
- Adam optimization
- Learning rate scheduling

But I can't write NN as a single function (well... I can but it will take forever)

How do I find gradient?

Backpropagation

Backpropagation is based on the chain rule

 $\Delta f(\Delta u_1, \Delta u_2, \Delta u_3, \Delta u_4, \Delta u_5, \Delta u_6, \Delta v_1, \Delta v_2, \Delta v_3, \Delta v_4, \Delta w_1, \Delta w_2) =$



 $\Delta f(\Delta u_1, \Delta u_2, \Delta u_3, \Delta u_4, \Delta u_5, \Delta u_6, \Delta v_1, \Delta v_2, \Delta v_3, \Delta v_4, \Delta w_1, \Delta w_2) =$

I want change of the loss function dependent on all network's parameters



 $\Delta f(\Delta u_1, \Delta u_2, \Delta u_3, \Delta u_4, \Delta u_5, \Delta u_6, \Delta v_1, \Delta v_2, \Delta v_3, \Delta v_4, \Delta w_1, \Delta w_2) =$





$$\begin{split} \Delta f(\Delta u_1, \Delta u_2, \Delta u_3, \Delta u_4, \Delta u_5, \Delta u_6, \Delta v_1, \Delta v_2, \Delta v_3, \Delta v_4, \Delta w_1, \Delta w_2) &= \\ \frac{\partial f}{\partial w_1} \Delta w_1 + \frac{\partial f}{\partial w_2} \Delta w_2 + \\ &+ \frac{\partial f}{\partial x} \Delta x + \frac{\partial f}{\partial y} \Delta y \end{split}$$









$$\begin{split} \Delta f(\Delta u_1, \Delta u_2, \Delta u_3, \Delta u_4, \Delta u_5, \Delta u_6, \Delta v_1, \Delta v_2, \Delta v_3, \Delta v_4, \Delta w_1, \Delta w_2) &= \\ \frac{\partial f}{\partial w_1} \Delta w_1 + \frac{\partial f}{\partial w_2} \Delta w_2 + \\ &+ \frac{\partial f}{\partial x} \Delta x + \frac{\partial f}{\partial y} \Delta y \end{split}$$





$$\begin{split} &\Delta f(\Delta u_1, \Delta u_2, \Delta u_3, \Delta u_4, \Delta u_5, \Delta u_6, \Delta v_1, \Delta v_2, \Delta v_3, \Delta v_4, \Delta w_1, \Delta w_2) = \\ &\frac{\partial f}{\partial w_1} \Delta w_1 + \frac{\partial f}{\partial w_2} \Delta w_2 + \frac{\partial f}{\partial x} \frac{\partial x}{\partial v_1} \Delta v_1 + \frac{\partial f}{\partial x} \frac{\partial x}{\partial v_2} \Delta v_2 + \frac{\partial f}{\partial y} \frac{\partial y}{\partial v_3} \Delta v_3 + \frac{\partial f}{\partial y} \frac{\partial y}{\partial v_4} \Delta v_4 + \\ &+ \frac{\partial f}{\partial x} \frac{\partial x}{\partial a} \Delta a + \frac{\partial f}{\partial x} \frac{\partial x}{\partial b} \Delta b + \frac{\partial f}{\partial y} \frac{\partial y}{\partial b} \Delta b + \frac{\partial f}{\partial y} \frac{\partial y}{\partial c} \Delta c \end{split}$$



$$\begin{aligned} \Delta f(\Delta u_1, \Delta u_2, \Delta u_3, \Delta u_4, \Delta u_5, \Delta u_6, \Delta v_1, \Delta v_2, \Delta v_3, \Delta v_4, \Delta w_1, \Delta w_2) &= \\ \frac{\partial f}{\partial w_1} \Delta w_1 + \frac{\partial f}{\partial w_2} \Delta w_2 + \frac{\partial f}{\partial x} \frac{\partial x}{\partial v_1} \Delta v_1 + \frac{\partial f}{\partial x} \frac{\partial x}{\partial v_2} \Delta v_2 + \frac{\partial f}{\partial y} \frac{\partial y}{\partial v_3} \Delta v_3 + \frac{\partial f}{\partial y} \frac{\partial y}{\partial v_4} \Delta v_4 + \\ + \frac{\partial f}{\partial x} \frac{\partial x}{\partial a} \Delta a + \frac{\partial f}{\partial x} \frac{\partial x}{\partial b} \Delta b + \frac{\partial f}{\partial y} \frac{\partial y}{\partial b} \Delta b + \frac{\partial f}{\partial y} \frac{\partial y}{\partial c} \Delta c \end{aligned}$$



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$$\begin{array}{c} I_1 \\ & \Delta a = \frac{\partial f}{\partial x} \frac{\partial x}{\partial a} \frac{\partial a}{\partial u_1} \Delta u_1 + \frac{\partial f}{\partial x} \frac{\partial a}{\partial a} \frac{\partial a}{\partial u_2} \Delta u_2 + \\ & + \frac{\partial f}{\partial x} \frac{\partial x}{\partial a} \frac{\partial a}{\partial I_1} \Delta I_1 + \frac{\partial f}{\partial x} \frac{\partial x}{\partial a} \frac{\partial a}{\partial I_2} \Delta I_2 \end{array}$$

$$\begin{array}{c}
I_{5} \\
\hline I_{6} \\
\hline I_{5} \\
\hline I_{6} \\$$

$$\begin{split} &\Delta f(\Delta u_1, \Delta u_2, \Delta u_3, \Delta u_4, \Delta u_5, \Delta u_6, \Delta v_1, \Delta v_2, \Delta v_3, \Delta v_4, \Delta w_1, \Delta w_2) = \\ &\frac{\partial f}{\partial w_1} \Delta w_1 + \frac{\partial f}{\partial w_2} \Delta w_2 + \frac{\partial f}{\partial x} \frac{\partial x}{\partial v_1} \Delta v_1 + \frac{\partial f}{\partial x} \frac{\partial x}{\partial v_2} \Delta v_2 + \frac{\partial f}{\partial y} \frac{\partial y}{\partial v_3} \Delta v_3 + \frac{\partial f}{\partial y} \frac{\partial y}{\partial v_4} \Delta v_4 + \\ &+ \frac{\partial f}{\partial x} \frac{\partial x}{\partial a} \Delta a + + \left(\frac{\partial f}{\partial x} \frac{\partial x}{\partial b} + \frac{\partial f}{\partial y} \frac{\partial y}{\partial b}\right) \Delta b + \frac{\partial f}{\partial y} \frac{\partial y}{\partial c} \Delta c \end{split}$$





$$\begin{split} &\Delta f(\Delta u_1, \Delta u_2, \Delta u_3, \Delta u_4, \Delta u_5, \Delta u_6, \Delta v_1, \Delta v_2, \Delta v_3, \Delta v_4, \Delta w_1, \Delta w_2) = \\ &\frac{\partial f}{\partial w_1} \Delta w_1 + \frac{\partial f}{\partial w_2} \Delta w_2 + \frac{\partial f}{\partial x} \frac{\partial x}{\partial v_1} \Delta v_1 + \frac{\partial f}{\partial x} \frac{\partial x}{\partial v_2} \Delta v_2 + \frac{\partial f}{\partial y} \frac{\partial y}{\partial v_3} \Delta v_3 + \frac{\partial f}{\partial y} \frac{\partial y}{\partial v_4} \Delta v_4 + \\ &+ \frac{\partial f}{\partial x} \frac{\partial x}{\partial a} \Delta a + + \left(\frac{\partial f}{\partial x} \frac{\partial x}{\partial b} + \frac{\partial f}{\partial y} \frac{\partial y}{\partial b}\right) \Delta b + \frac{\partial f}{\partial y} \frac{\partial y}{\partial c} \Delta c \end{split}$$






Note: all derivatives are meant to be calculated at a certain point – they are numbers!

$$\begin{split} \Delta f & \Delta u_1, \Delta u_2, \Delta u_3, \Delta u_4, \Delta u_5, \Delta u_6, \Delta v_1, \Delta v_2, \Delta v_3, \Delta v_4, \Delta w_1, \Delta w_2) = \\ & \frac{\partial f}{\partial w_1} \Delta w_1 + \frac{\partial f}{\partial w_2} \Delta w_2 + \frac{\partial f}{\partial x} \frac{\partial x}{\partial v_1} \Delta v_1 + \frac{\partial f}{\partial x} \frac{\partial x}{\partial v_2} \Delta v_2 + \frac{\partial f}{\partial y} \frac{\partial y}{\partial v_3} \Delta v_3 + \frac{\partial f}{\partial y} \frac{\partial y}{\partial v_4} \Delta v_4 + \\ & + \frac{\partial f}{\partial x} \frac{\partial x}{\partial a} \Delta a + + \left(\frac{\partial f}{\partial x} \frac{\partial x}{\partial b} + \frac{\partial f}{\partial y} \frac{\partial y}{\partial b} \right) \Delta b + \frac{\partial f}{\partial y} \frac{\partial y}{\partial c} \Delta c \end{split}$$



Now small variation of cost function is written in form it depends on internal parameters only

$$\begin{split} &\Delta f(\Delta u_1, \Delta u_2, \Delta u_3, \Delta u_4, \Delta u_5, \Delta u_6, \Delta v_1, \Delta v_2, \Delta v_3, \Delta v_4, \Delta w_1, \Delta w_2) = \\ &\frac{\partial f}{\partial w_1} \Delta w_1 + \frac{\partial f}{\partial w_2} \Delta w_2 + \frac{\partial f}{\partial x} \frac{\partial x}{\partial v_1} \Delta v_1 + \frac{\partial f}{\partial x} \frac{\partial x}{\partial v_2} \Delta v_2 + \frac{\partial f}{\partial y} \frac{\partial y}{\partial v_3} \Delta v_3 + \frac{\partial f}{\partial y} \frac{\partial y}{\partial v_4} \Delta v_4 + \frac{\partial f}{\partial x} \frac{\partial a}{\partial u_1} \Delta u_1 + \frac{\partial f}{\partial x} \frac{\partial a}{\partial u_2} \Delta u_2 + \\ &+ \left(\frac{\partial f}{\partial x} \frac{\partial x}{\partial b} + \frac{\partial f}{\partial y} \frac{\partial y}{\partial b} \right) \frac{\partial b}{\partial u_3} \Delta u_3 + \left(\frac{\partial f}{\partial x} \frac{\partial x}{\partial b} + \frac{\partial f}{\partial y} \frac{\partial y}{\partial b} \right) \frac{\partial b}{\partial u_4} \Delta u_4 + \frac{\partial f}{\partial y} \frac{\partial y}{\partial c} \frac{\partial c}{\partial u_5} \Delta u_5 + \frac{\partial f}{\partial y} \frac{\partial y}{\partial c} \frac{\partial c}{\partial u_6} \Delta u_6 \end{split}$$

Now we have all numbers needed to make the gradient descent step!

$$\Delta f(\Delta u_1, \Delta u_2, \Delta u_3, \Delta u_4, \Delta u_5, \Delta u_6, \Delta v_1, \Delta v_2, \Delta v_3, \Delta v_4, \Delta w_1, \Delta w_2) = \\ \frac{\partial f}{\partial w_1} \Delta w_1 + \frac{\partial f}{\partial w_2} \Delta w_2 + \frac{\partial f}{\partial v_1} \Delta v_1 + \frac{\partial f}{\partial v_2} \Delta v_2 + \frac{\partial f}{\partial v_3} \Delta v_3 + \frac{\partial f}{\partial v_4} \Delta v_4 + \frac{\partial f}{\partial u_1} \Delta u_1 + \frac{\partial f}{\partial u_2} \Delta u_2 + \frac{\partial f}{\partial u_3} \Delta u_3 + \frac{\partial f}{\partial u_4} \Delta u_4 + \frac{\partial f}{\partial u_5} \Delta u_5 + \frac{\partial f}{\partial u_6} \Delta u_6 + \frac{\partial f}{\partial u_6} + \frac{\partial f}{\partial u_6}$$

Example



Remove unnecessary derivatives





Initialize parameters











































Possible issues with deep networks

Single Neuron



Activation functions



Leaky ReLU
$$\max(0.1x, x)$$



 $\begin{array}{l} \textbf{Maxout} \\ \max(w_1^T x + b_1, w_2^T x + b_2) \end{array}$



Vanishing/exploding gradients problems

- Xavier and He initialization
- Non-saturating activation functions
- Batch Normalization
- Gradient clipping





Fitting problems



Avoid overfitting

- Early Stopping
- L1 and L2 regularization
- Dropout
- Max-norm regularization
- Data augmentation





Convolution operation

Convolution



Two basic ideas:

- geometrical proximity has significant meaning
- translational invariance



w1[:,:	,0]
-1	0	1
-1	1	1
-1	-1	0
w1[:,:	,1]
-1	-1	1
-1	-1	-1
-1	1	1
w1[:,:	,2]
0	0	1
-1	0	-1
-1	0	0
Dias	hl	(1 v 1 v 1)

0[:	,÷,	0]
-2	-4	-1
0	-1	-1
-1	0	1
10		11
U.	<i>'</i> • <i>'</i>	τ1
3	-3	<u>-6</u>
3 -2	-3 -4	-6 -9
3 -2 5	-3 -4 -4	-6 -9 -7

Bias b1 (1x1x1) b1[:,:,0] 0

toggle movement



:,:	,0]		
0	1		
1	1		
-1	0		
:,:	,1]		
-1	1		
-1	-1		
1	1		
w1[:,:,2]			
0	1		
0	-1		
0	0		
	:,: 0 -1 -1 -1 -1 1 :,: 0 0 0 0		

0[:	,:,	0]
-2	-4	-1
0	-1	-1
-1	0	1
0[:	,:,	1]
o[: 3	,:, -3	1] -6
∘[: 3 -2	-3 -4	1] -6 -9

Bias b1 (1x1x1) b1[:,:,0] 0

toggle movement


w1[:,:	,0]
-1	0	1
-1	1	1
-1	-1	0
w1[:,:	,1]
-1	-1	1
-1	-1	-1
-1	1	1
w1[:,:	,2]
0	0	1
-1	0	-1
-1	0	0
-1	0	0

toggle movement

0[:,:,0]

-2 -4 -1

0 -1 -1

-1 0 1

0[:,:,1]

3 -3 -6

-2 -4 -9

5 -4 -7







w1[:,:	:,0]
-1	0	1
-1	1	1
-1	-1	0
w1[:,	,1]
-1	-1	1
-1	-1	-1
-1	1	1
w1[:,	,2]
0	0	1
-1	0	-1
-1	0	0

toggle movement

0[:,:,0]

-2 -4 -1

0 -1 -1

-1 0 1

o[:,:,1]

3 -3 -6

-2 -4 -9

5 -4 -7



w1[:,:	,0]	
-1	0	1	
-1	1	1	
-1	-1	0	
w1[:,:	,1]	
-1	-1	1	
-1	-1	-1	
-1	1	1	
w1[:,:	,2]	
0	0	1	
-1	0	-1	
-1	0	0	

toggle movement

0[:,:,0]

-2 -4 -1

0 -1 -1

-1 0 1

0[:,:,1]

3 -3 -6

-2 -4 -9

5 -4 -7



w1[:,:,0]			
-1	0	1	
-1	1	1	
-1	-1	0	
w1[:,:,1]			
-1	-1	1	
-1	-1	-1	
-1	1	1	
w1[:,:,2]			
0	0	1	
-1	0	-1	
-1	0	0	

toggle movement

0[:,:,0]

-2 -4 -1

-1 -1

0 1

-3 -6

0[:,:,1]

-2 -4 -9

5 -4 -7

0

-1

3



w1[:,:,0]				
-1	0	1		
-1	1	1		
-1	-1	0		
w1[:,:,1]				
-1	-1	1		
-1	-1	-1		
-1	1	1		
w1[:,:,2]				
0	0	1		
-1	0	-1		
-1	0	0		

toggle movement

0[:,:,0]

-2 -4 -1

0 -1 -1

0[:,:,1]

3 -3 -6

-2 -4 -9

5 -4 -7

1

-1 0



















Two famous deep NN architecture



ResNet



