GAN

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Identity Key	nava3000

	Level	Completed
	Beginner	4
	Intermediate	3
	Advanced	2
	Expert	0

Goal	
5722	15

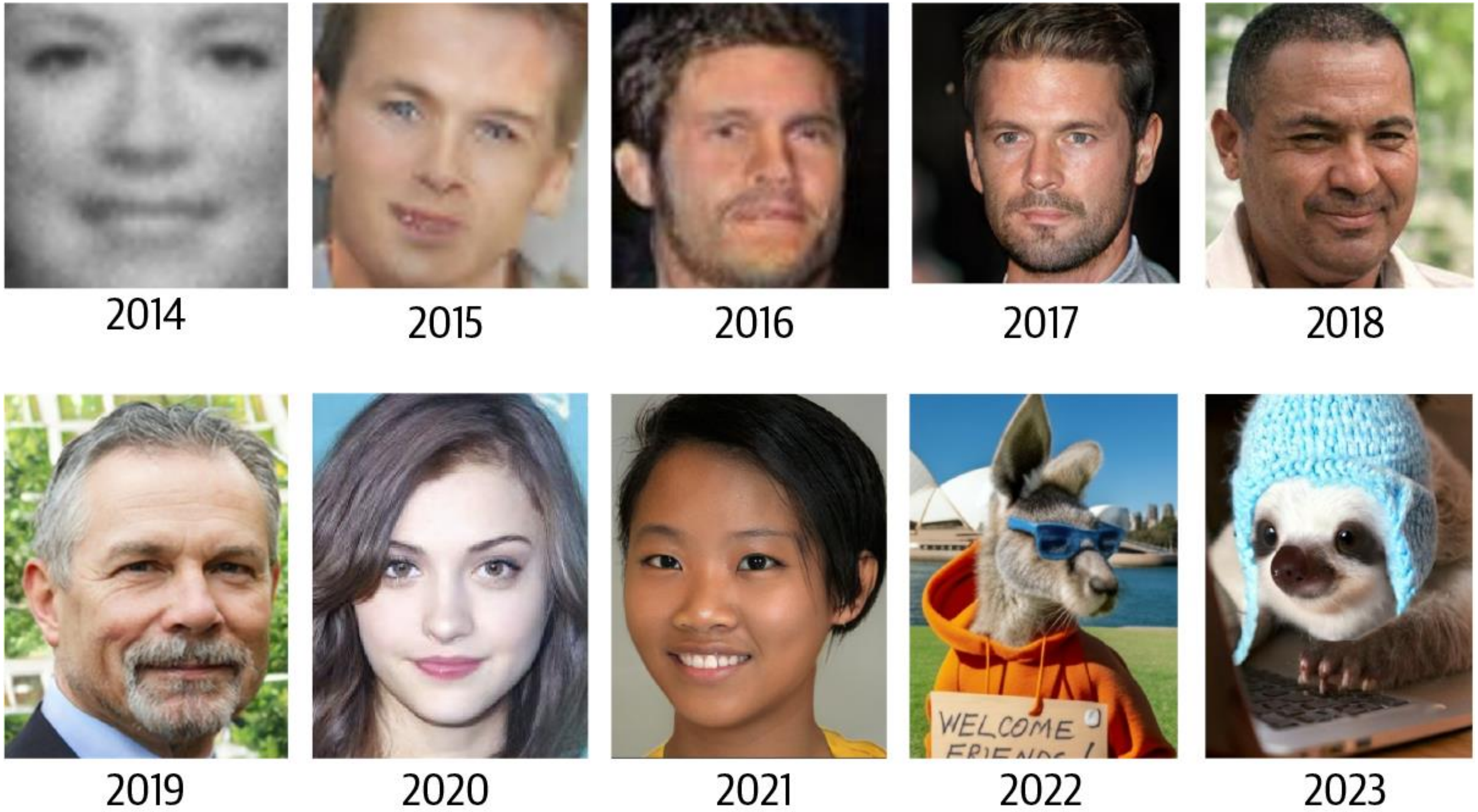
Total Completed
9

Generative Adversarial Network (GAN)

CSCI 5277: Computer Vision

Fall 2024

Dr. Tom Yeh



https://www.oreilly.com/library/view/generative-deep-learning/9781098134174/ch01.html

Generative Adversarial Nets

Ian J. Goodfellow,[*] Jean Pouget-Abadie,[†] Mehdi Mirza, Bing Xu, David Warde-Farley,
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Abstract

We propose a new framework for estimating generative models via an adversarial process, in which we simultaneously train two models: a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G. The training procedure for G is to maximize the probability of D making a mistake. This framework corresponds to a minimax two-player game. In the space of arbitrary functions G and D, a unique solution exists, with G recovering the training data distribution and D equal to $\frac{1}{2}$ everywhere. In the case where G and D are defined by multilayer perceptrons, the entire system can be trained with backpropagation. There is no need for any Markov chains or unrolled approximate inference networks during either training or generation of samples. Experiments demonstrate the potential of the framework through qualitative and quantitative evaluation of the generated samples.

1 Introduction

The promise of deep learning is to discover rich, hierarchical models [2] that represent probability distributions over the kinds of data encountered in artificial intelligence applications, such as natural images, audio waveforms containing speech, and symbols in natural language corpora. So far, the most striking successes in deep learning have involved discriminative models, usually those that map a high-dimensional, rich sensory input to a class label [14, 20]. These striking successes have primarily been based on the backpropagation and dropout algorithms, using piecewise linear units [17, 8, 9] which have a particularly well-behaved gradient . Deep *generative* models have had less of an impact, due to the difficulty of approximating many intractable probabilistic computations that arise in maximum likelihood estimation and related strategies, and due to difficulty of leveraging the benefits of piecewise linear units in the generative context. We propose a new generative model estimation procedure that sidesteps these difficulties. [1]

In the proposed *adversarial nets* framework, the generative model is pitted against an adversary: a discriminative model that learns to determine whether a sample is from the model distribution or the data distribution. The generative model can be thought of as analogous to a team of counterfeiters, trying to produce fake currency and use it without detection, while the discriminative model is analogous to the police, trying to detect the counterfeit currency. Competition in this game drives both teams to improve their methods until the counterfeits are indistiguishable from the genuine articles.

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[*] Ian Goodfellow is now a research scientist at Google, but did this work earlier as a UdeM student
[†] Jean Pouget-Abadie did this work while visiting Université de Montréal from Ecole Polytechnique.
[‡] Sherjil Ozair is visiting Université de Montréal from Indian Institute of Technology Delhi
[§] Yoshua Bengio is a CIFAR Senior Fellow.
[1] All code and hyperparameters available at `http://www.github.com/goodfeli/adversarial`

Share your AI-generated image of an ANN

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Activity: Share your AI-generated image of an ANN

Post a comment with your image, the prompt you provided, and the tool you

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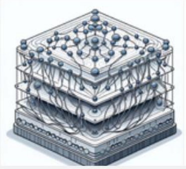
Tom Yeh (He/Him) Author 2m (edited)
Associate Professor of Computer Science at University of Colorado B...

Prompt:
Generate a graphic representation of an artificial neural network

Tool:
ChatGPT4



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Nathan Varghese
MS Aerospace Engineering at CU Boulder | Autonomous Systems

Prompt: Draw a graphic representation of a artificial neural network. I want you to show it as a complicated spaghetti-fied image.

Like | Reply

GAN Architecture

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Architecture Diagram

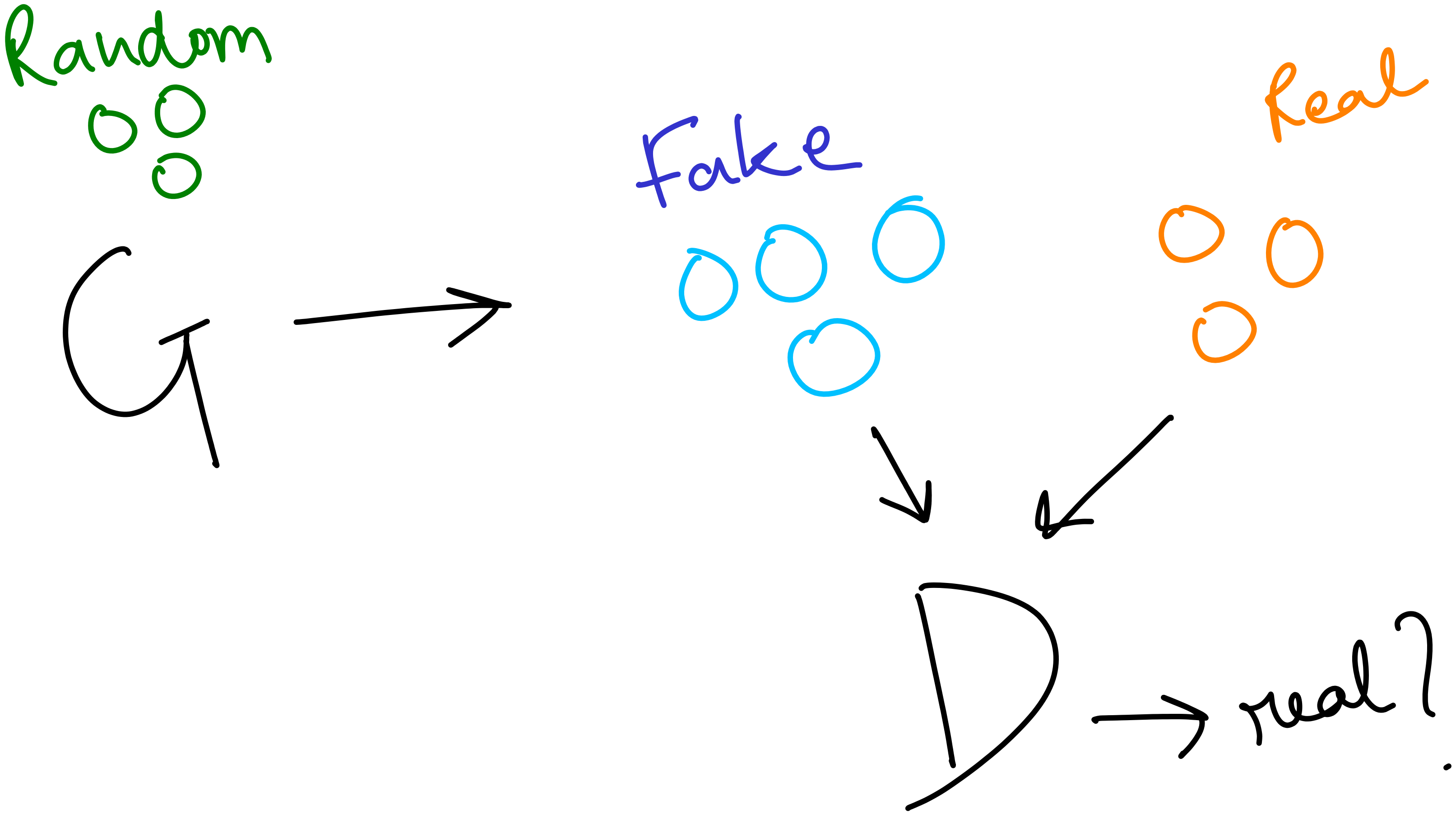
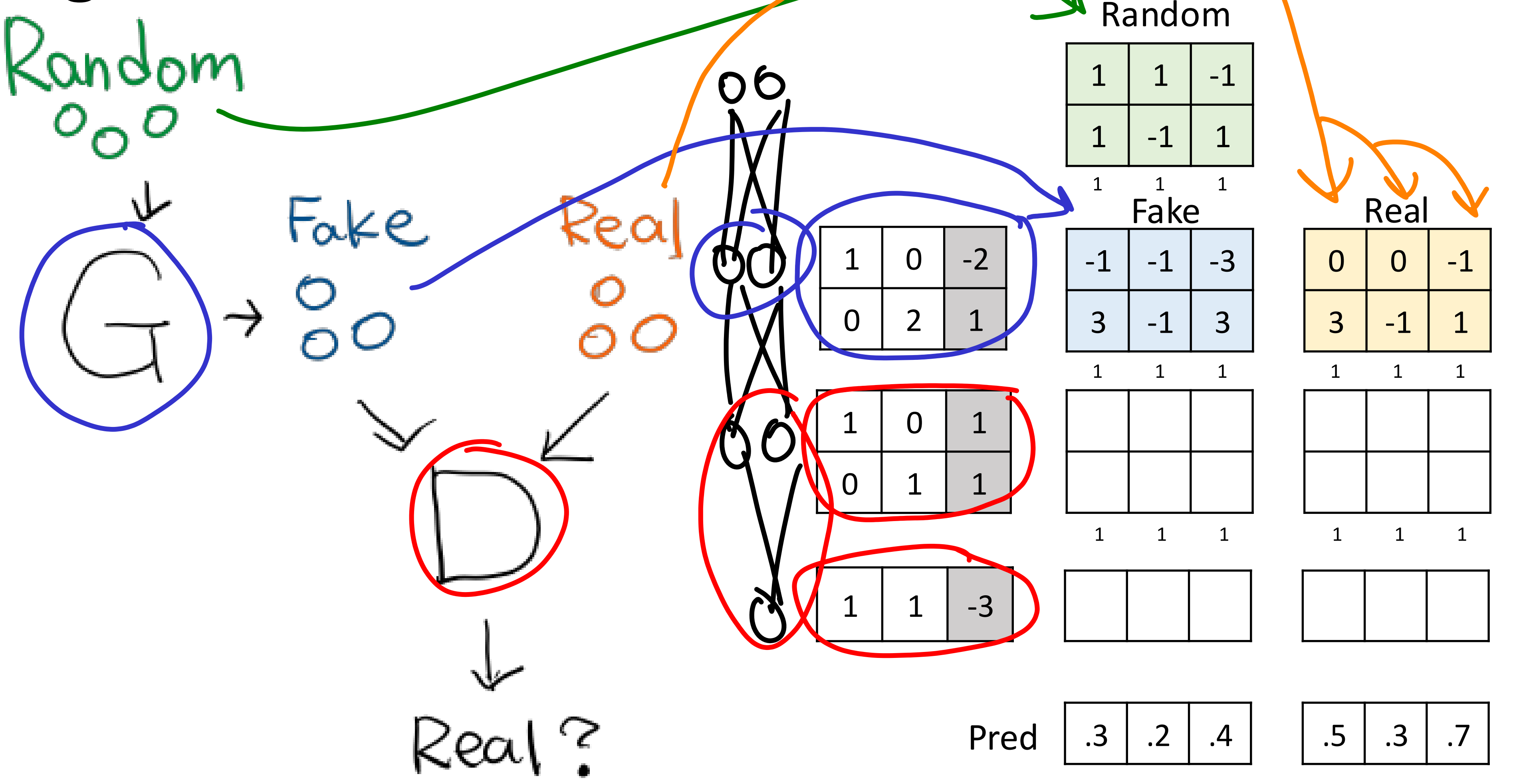


Diagram → ANN

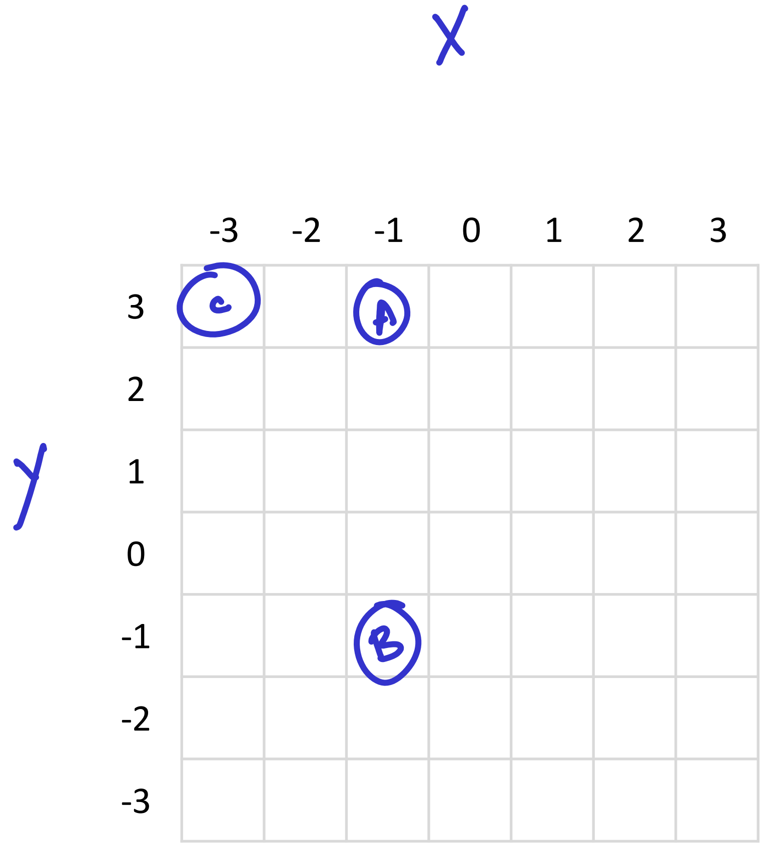

Random
G
Fake
Real
D
Real ?
Random
1 1 -1
1 -1 1
1 1 1
Fake
-1 -1 -3
3 -1 3
1 1 1
Real
0 0 -1
3 -1 1
1 1 1
1 0 -2
0 2 1
1 0 1
0 1 1
1 1 -3
1 1 1
1 1 1
Pred
.3 .2 .4
.5 .3 .7

Generator

Generator

A	B	C
1	1	-1
1	-1	1
1	1	1

1	0	-2	-1	-1	-3	x
0	2	1	3	-1	3	y



Discriminator

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Discriminator

A	B	C	D	E	F
-1	-1	-3	0	0	-1
3	-1	3	3	-1	1
1	1	1	1	1	1

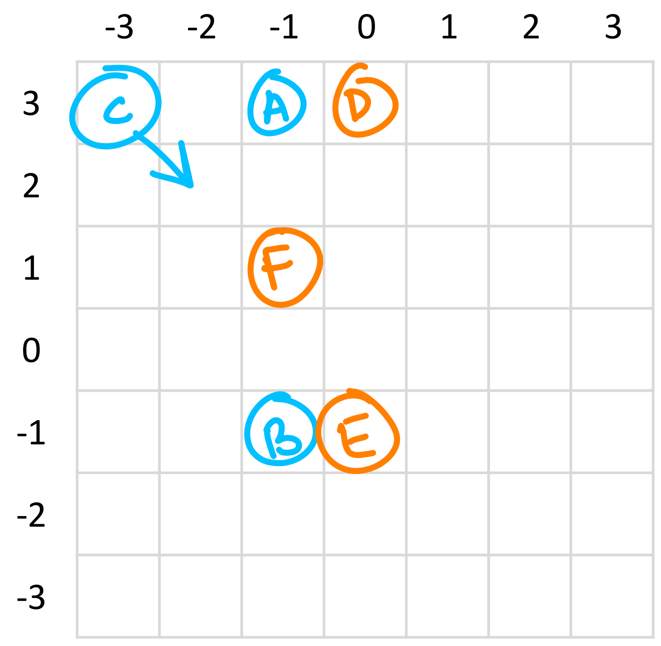
W_1

1	0	1
0	1	1

1	1	1	1	1	1

W_2

1	1	-3

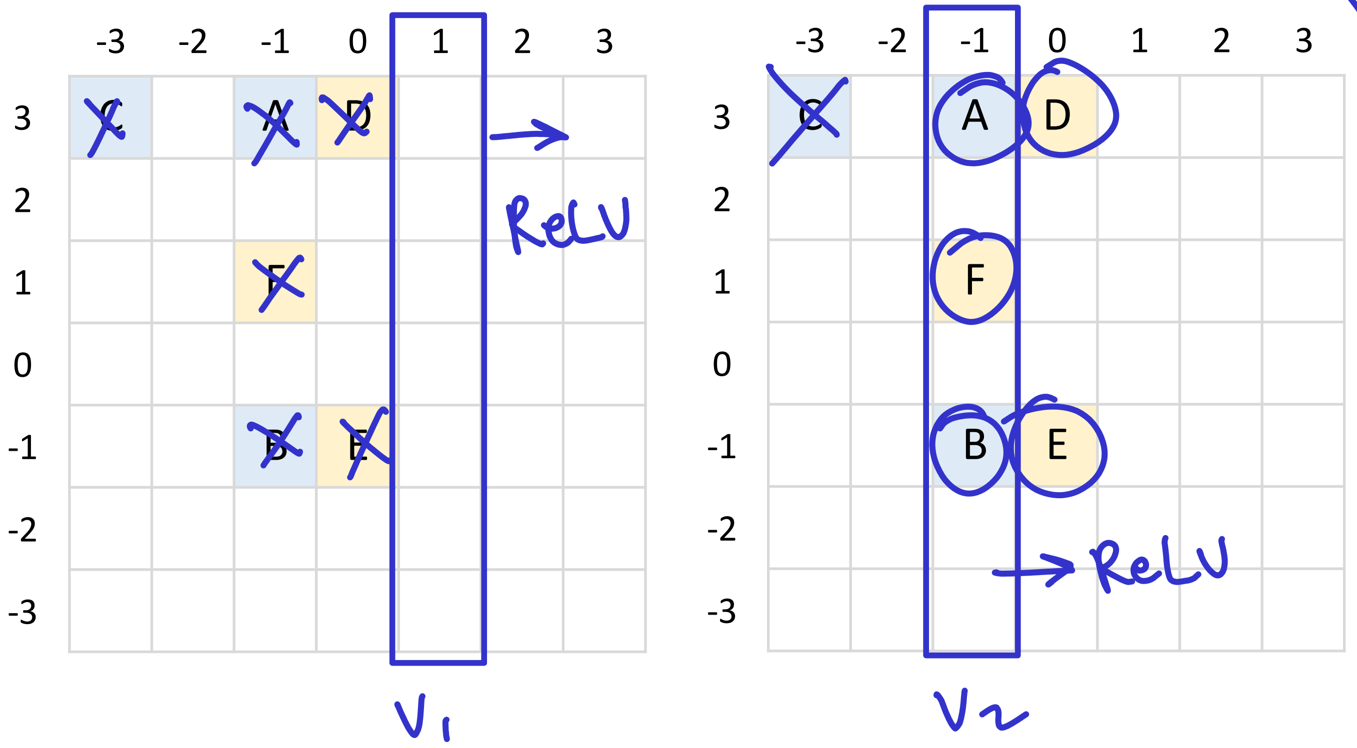


$x >= 1$

$x - 1 \geq 0$

$x >= \cancel{1} -1$

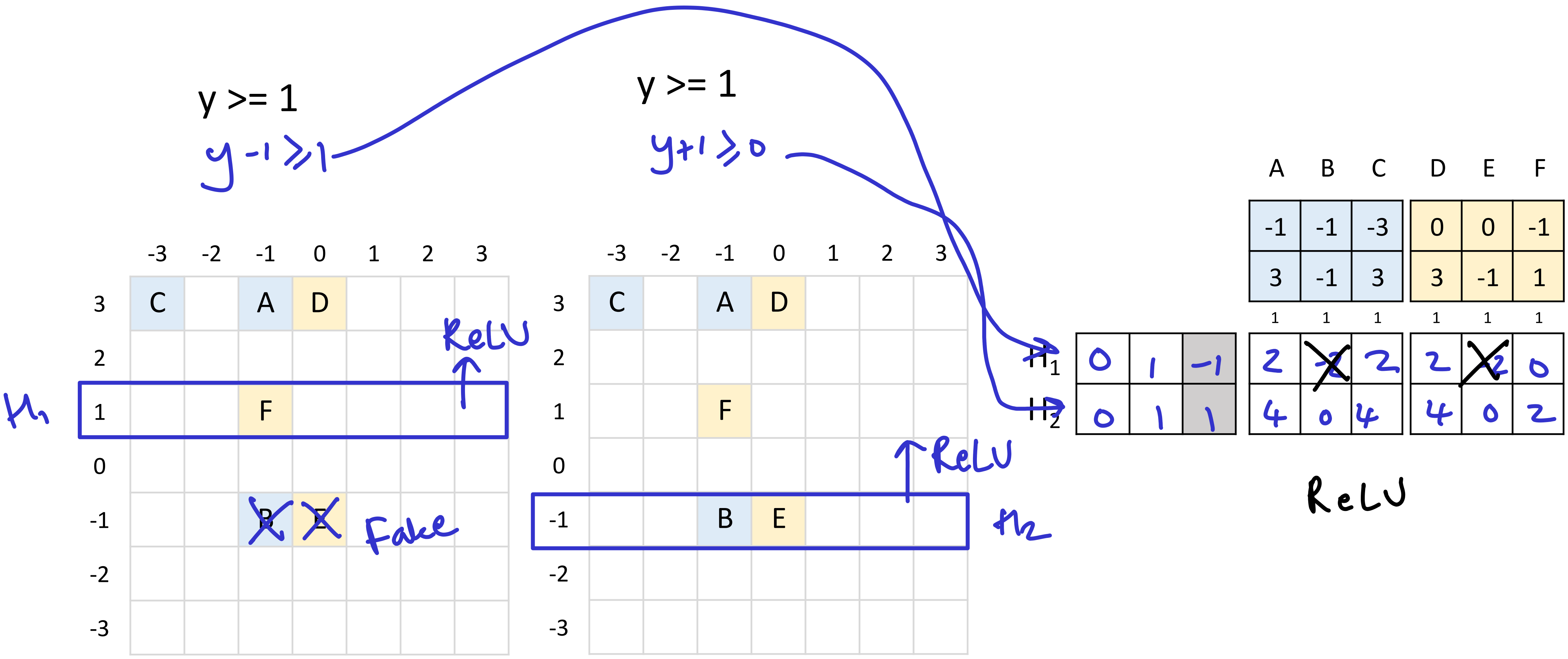
$x + 1 \geq 0$



	Fake			Real		
	A	B	C	D	E	F
	-1	-1	-3	0	0	-1
	3	-1	3	3	-1	1
	1	1	1	1	1	1

	x	y		A	B	C	D	E	F
V_1	1	0	-1	~~-2~~	~~-2~~	~~-4~~	~~-1~~	~~-1~~	~~-2~~
V_2	1	0	1	0	0	-2	1	1	0

ReLU


y >= 1
y-1 ≥ 1
y >= 1
y+1 ≥ 0
ReLU
Fake
ReLU
A B C D E F
H_1
H_2
ReLU

Activation Field (ReLU)

V: x = -1

$a_1 = \mathrm{ReLU}(x+1)$

V_2

	-3	-2	-1	0	1	2	3
3	0	0	0	1	2	3	4
2	0	0	0	1	2	3	4
1	0	0		1	2	3	4
0	0	0		1	2	3	4
-1	0	0		1	2	3	4
-2	0	0		1	2	3	4
-3	0	0		1	2	3	2

H: y = -1

$a_2 = \mathrm{ReLU}(y+1)$

H_2

	-3	-2	-1	0	1	2	3
3	4	4					
2	3	3					
1	2	2					
0	1	1					
-1	0	0					
-2	0	-1					
-3	0	-2					

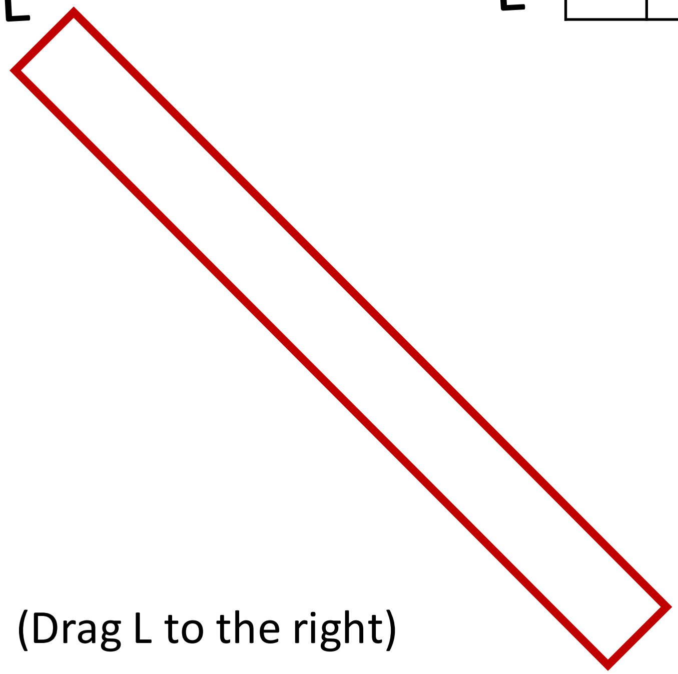
						ReLU	
				*			
				*			
				1			
V_2	1	0	1	$*f_1$			a_1
H_2	0	1	1	$*f_2$			a_2

Activation Field (b = 0)

L: x+y = 0 a: ReLU(x+y)

	-3	-2	-1	0	1 (a)	2	3 (b)	
3	0	1	2	3	4	5	6	
2	.	0	1	2	3	4	5	
1	.	.	0	1	2	3	4	
0	.	.	.	0	1	2	3	
-1	.	.	.	.	0	1	2	c
-2	.	.	.	.	.	0	1	
-3	0	0	.	.	.	.	0	

L



(Drag L to the right)

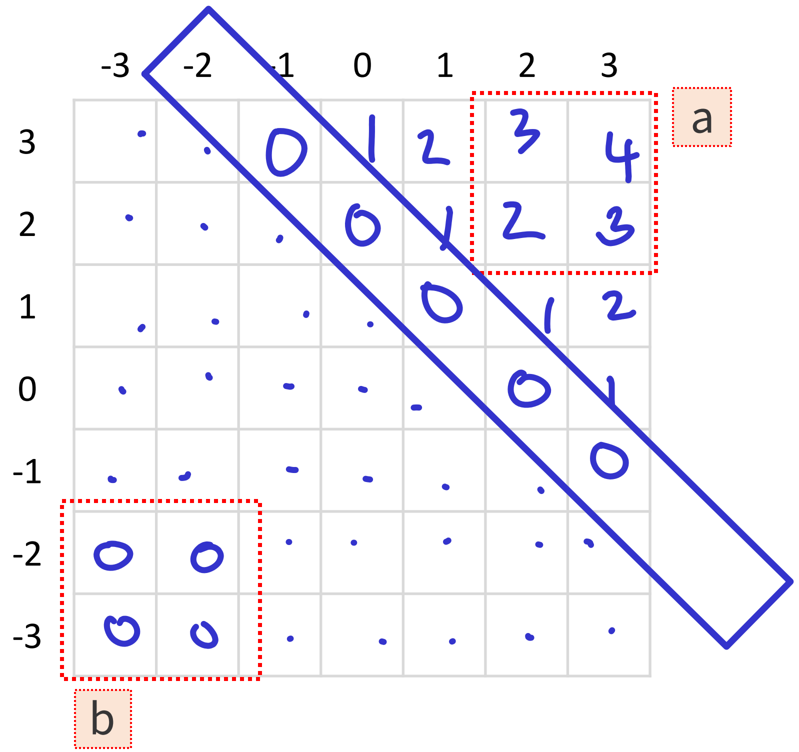
$$L \quad \begin{bmatrix} 1 & 1 & 0 \end{bmatrix} \begin{bmatrix} * \\ * \\ * \end{bmatrix} \overset{\text{ReLU}}{\approx} \boxed{?} \quad a$$

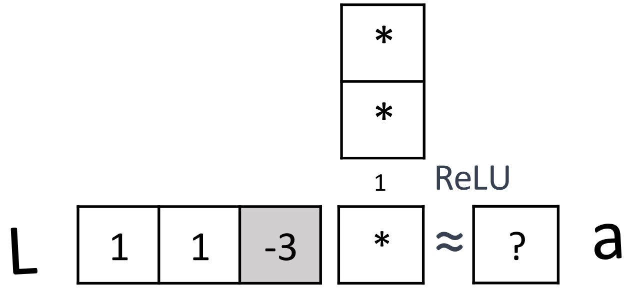
1

🔑 sum(a) = 7; sum(b) = 11; sum(c) = 3

Activation Field (b = -3)

L: $x+y = 3$ a: $\mathrm{ReLU}(x+y-3)$





$x+y-3=0$

$2+y-3=0$

$y=+1$

🔑 sum(a) = 8 ; sum(b) = 0

Weighted Sum Field

L: 2*x+y = 0

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

b

c

6+7 = 13

8+9 = 17

0

			*
			*
			1
2	1	0	?

L

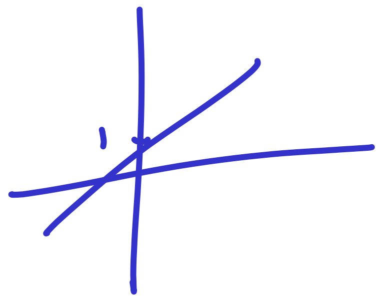
2x2 + 3 = 7

2(-1) + y = 0

-2 = -y

y = 2

2(-2)



2x+1

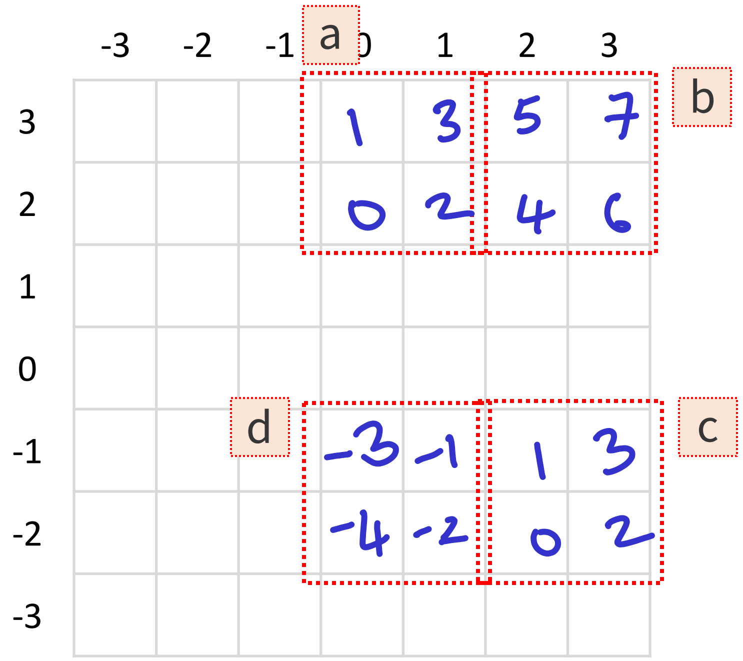
2x+1 = 0

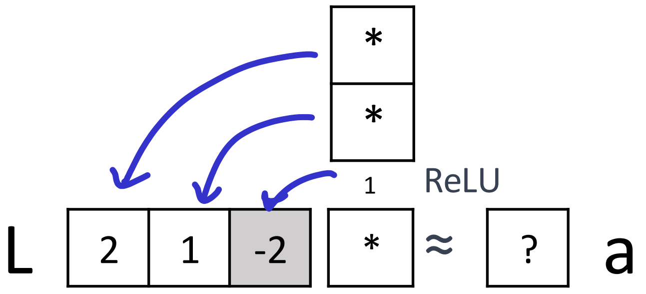
x = -1/2 ?

sum(a) = -10; sum(b) = 3; sum(c) = 30;

Activation Field (b = -2)

L: 2*x+y = 2 a: ReLU(2*x+y – 2)





$2x+y-2=0$

$2(0)+y-2=0$

$y=2$

$0\times2+3-2=1$

$2+3-2=3$

$4+3-2=5$

$6+3-2=7$

$0\times2+2-2=0$

$2+2-2=2$

$0-1-2=-3$

$0-2-2=-4$

$2-1-2=-1$

$2-2-2=-2$

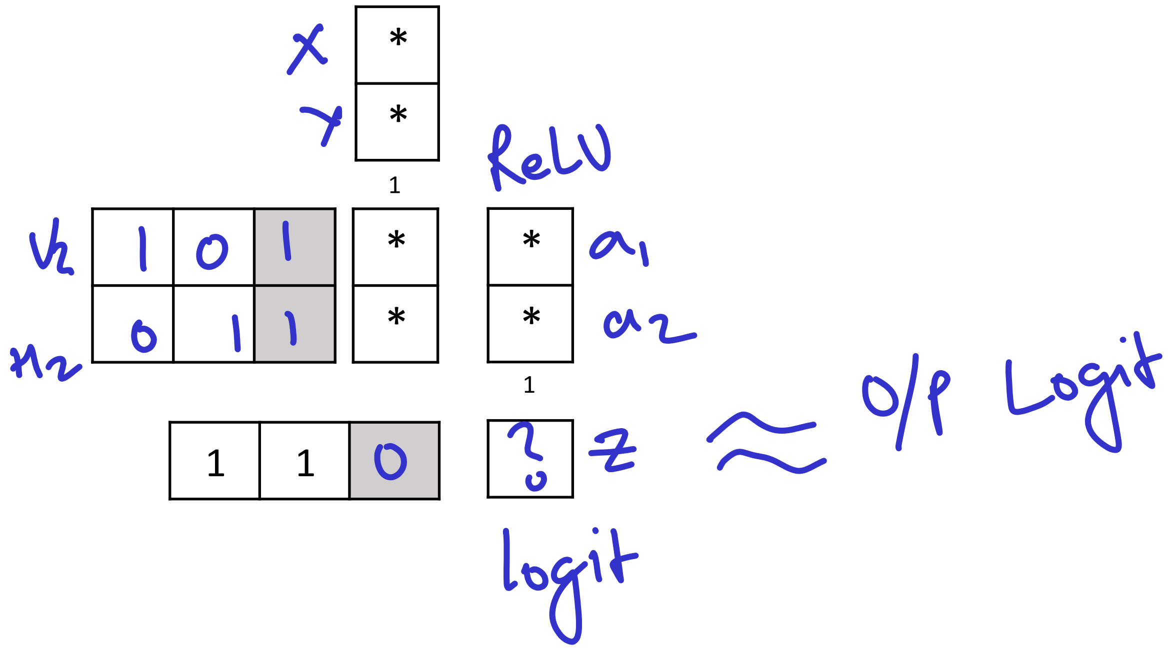
sum(a) = 6; sum(b) = 22; sum(c) = 6;

Logit Field (b = 0)

V_2:

H_2:

	-3	-2	-1 (V_2)	0	1	2	3
3	4	4	4	5	6	7	8
2	3	3	3	4	5	6	7
1	2	2	2	3	4	5	6
0	1	1	1	2	3	4	5
H_2 -1	0	0	0	1	2	3	4
-2	0	0	0	1	2	3	4
-3	0	0	0	1	2	3	4



Logit Field ($b = -3$)

V: $x = -1$

H: $y = -1$

a_1: ReLU($x+1$)

a_2: ReLU($y+1$)

$z = a_1+a_2$

	-3	-2	-1 (V_2)	0	1	2	3
3	4	4	4	5	6	7	5
2	0	0	0	4	5	3	7
1	-1	-1	-1	0	1	5	6
0	-2	-2	-2	-1	0	4	5
H_2 -1				-2	-1	0	4
-2				-2	-1	0	4
-3				-2	-1	0	4

$$\begin{array}{c} x \\ y \end{array}\begin{bmatrix} * \\ * \end{bmatrix}$$

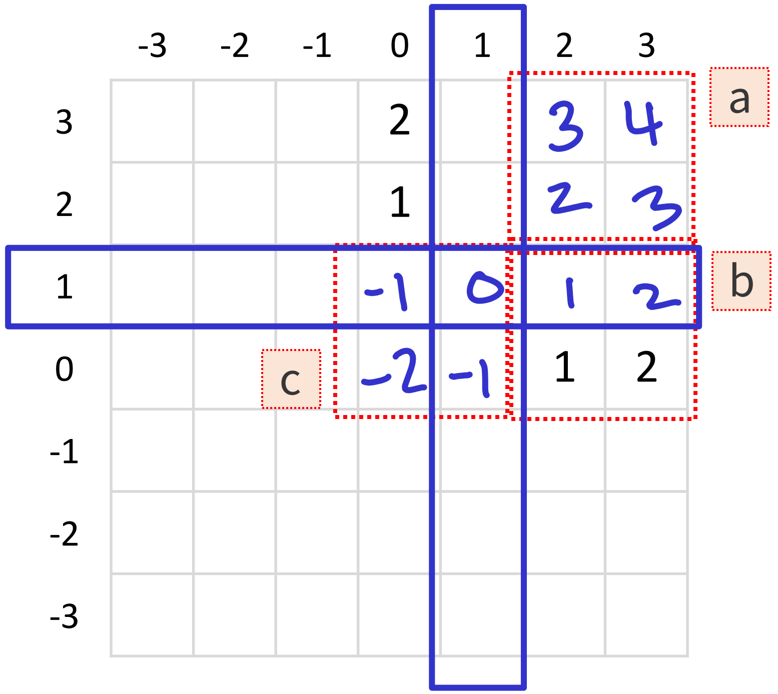
$$\begin{array}{c} V_2 \\ H_2 \end{array}\begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix}\begin{bmatrix} * \\ * \\ 1 \end{bmatrix} \overset{\text{ReLU}}{\approx} \begin{bmatrix} * \\ * \\ 1 \end{bmatrix}\begin{array}{c} a_1 \\ a_2 \\ \end{array}$$

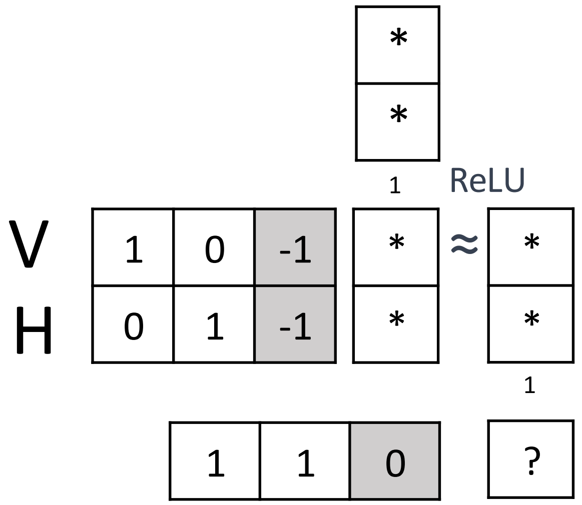
$$\begin{bmatrix} 1 & 1 & -3 \end{bmatrix} \quad \begin{bmatrix} ? \end{bmatrix} \; z$$

Logit Field (b = 0)

V: x = 1

H: y = 1





2-1 = 1
3-1 = 2 = 3

3-1 = 2 = 4
3-1 = 2

2-1 = 1
2-1 = 1 = 2

3-1 = 2
2-1 = 1 = 3

a

2-1=1
1-1=0 = 1

b

1-1=0
0-1=-1 = -1

-1

(Drag H, V to the right places)

sum(a) = 12; sum(b) = 6;

Logit Field

3-2 = 1
= 5

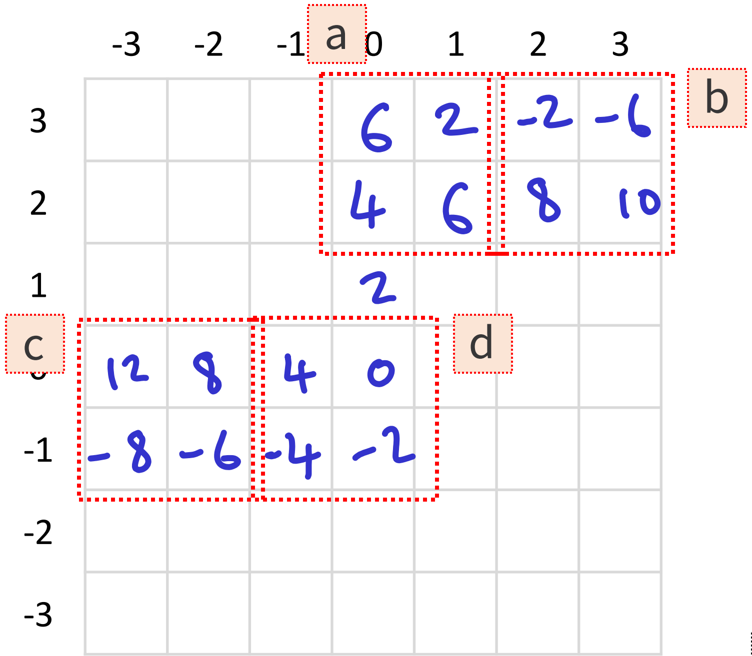
L_1: $x+y = 2$

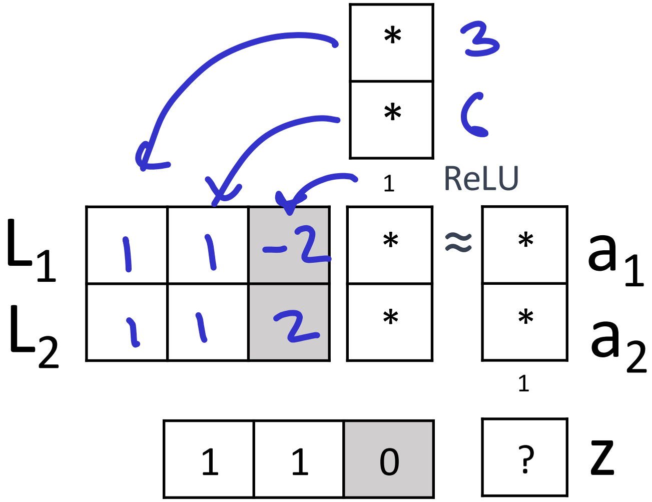
L_2: $x+y = -2$

a_1: ReLU($x+y-2$)

a_2: ReLU($-x-y-2$)

z: a_1+a_2





sum(a) = 4; sum(b) = 12; sum(c) = 4

Logit Field

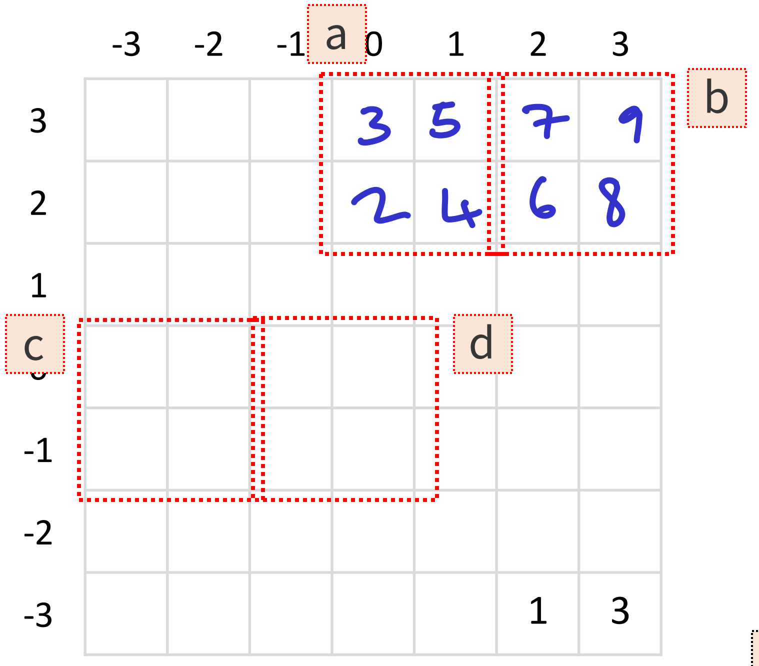
L: $x+y = -1$

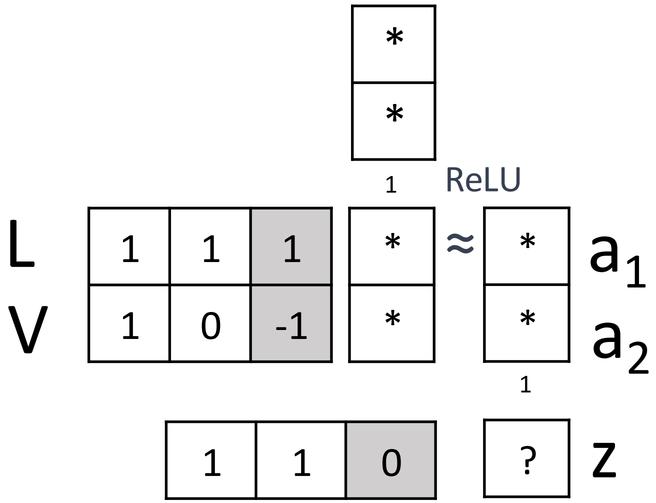
V: $x = 1$

a_1: ReLU$(x+y+1)$

a_2: ReLU$(x-1)$

z: a_1+a_2





$0+3+1=4$
$-1 = -1$

$1+3+1=5$
$1-1=0$

$0+2+1=3$
$=-1$

a

🔑 sum(a) = 16; sum(b) = 30;

Logit Field → Output Probability Field

V: $x = -1$

H: $y = -1$

a_1: ReLU(x+1)

a_2: ReLU(y+1)

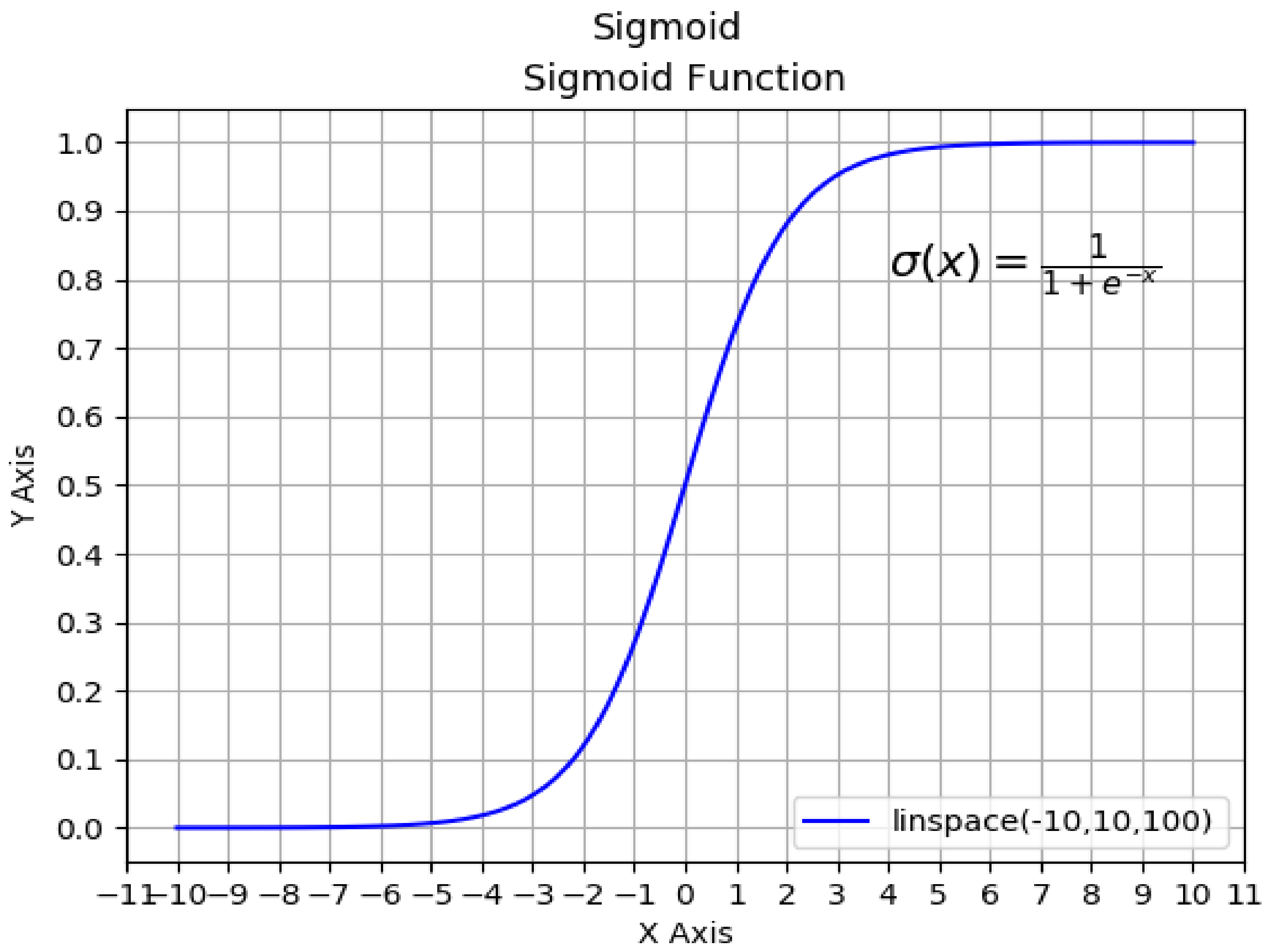
$z = a_1 + a_2 - 3$

		-3	-2	-1	0	1	2	3
	3	1	1	1	2	3	4	5
	2	0	0	0	1	2	3	4
	1	-1	-1	-1	0	1	2	3
	0	-2	-2	-2	-1	0	1	2
H	-1	-3	-3	-3	-2	-1	0	1
	-2	-3	-3	-3	-2	-1	0	1
	-3	-3	-3	-3	-2	-1	0	1
				V				

$$\begin{array}{c} V \\ H \end{array} \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} * \\ * \\ 1 \end{bmatrix} = \begin{bmatrix} * \\ * \end{bmatrix} \xrightarrow{\text{ReLU}} \approx \begin{bmatrix} * \\ * \\ 1 \end{bmatrix} \begin{array}{c} a_1 \\ a_2 \\ \end{array}$$

$$\begin{bmatrix} 1 & 1 & -3 \end{bmatrix} \quad \begin{bmatrix} \end{bmatrix} \; z$$

Approximate Sigmoid Function by Hand ✍️



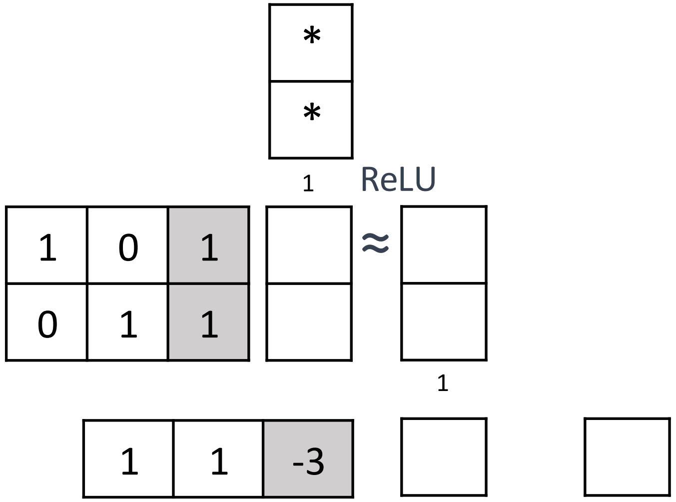
σ(<=-3) ≈
σ(-2) ≈
σ(-1) ≈
σ(0) ≈
σ(-1) ≈
σ(-2) ≈
σ(>=3) ≈

Image Credit: Alexander | Hackaday.io

Output Probability Field

	-3	-2	-1	0	1	2	3
3	1	1	1	2	3	4	5
2	0	0	0	1	2	3	4
1	-1	-1	-1	0	1	2	3
0	-2	-2	-2	-1	0	1	2
-1	-3	-3	-3	-2	-1	0	1
-2	-3	-3	-3	-2	-1	0	1
-3	-3	-3	-3	-2	-1	0	1

σ(<=-3) ≈ 0
σ(-2) ≈ 0.1
σ(-1) ≈ 0.3
σ(0) ≈ 0.5
σ(-1) ≈ 0.7
σ(-2) ≈ 0.9
σ(>=3) ≈ 1



GAN

Noise

1	1	-1
1	-1	1
1	1	1

G

1	0	-2
0	2	1

Fake A	Fake B	Fake C	Real D	Real E	Real F
-1	-1	-3	0	0	-1
3	-1	3	3	-1	1
1	1	1	1	1	1

D

1	0	1
0	1	1

[ReLU]

1	1	1	1	1	1

1	1	-3

o/p prob

0.7	0	0.7	0.9	0.1	0.3

C		A	D			
		F				
		B	E			

.7	.7	.7	.9	1	1	1
.5	.5	.5	.7	.9	1	1
.3	.3	.3	.5	.7	.9	1
.1	.1	.1	.3	.5	.7	.9
0	0	0	.1	.3	.5	.7
0	0	0	.1	.3	.5	.7
0	0	0	.1	.3	.5	.7

Binary Cross Entropy (BCE) Loss

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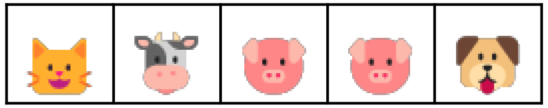
Categorical → Binary CE

	P_1	P_2	P_3	P_4	P_5
dog					
cat					
cow					
pig					

!dog

Σ



	Q_1	Q_2	Q_3	Q_4	Q_5
dog	0	0	.9	.1	1
cat	0	.9	.1	.9	0
cow	.1	.1	0	0	0
pig	.9	0	0	0	0

Σ

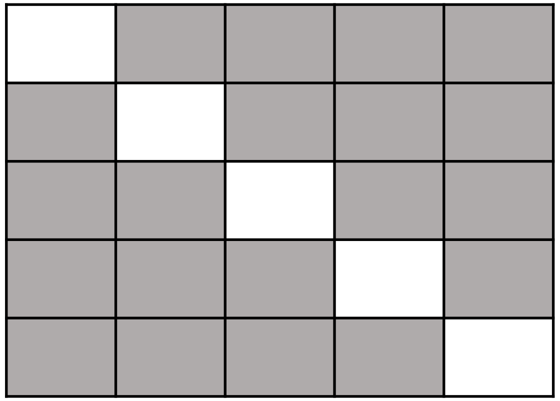
-log(0) ≈32
-log(-1) ≈ 3
-log(0.9) ≈ 0.2
-log(1) = 0

$-\log Q$

T

!dog

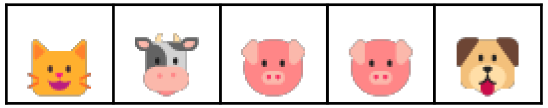
	dog	cat	cow	pig
P_1				
P_2				
P_3				
P_4				
P_5				



$\sum P \cdot -\log Q$

Binary CE Loss

-log(0) ≈32
-log(0.1) ≈ 3
-log(0.9) ≈ 0.2
-log(1) = 0



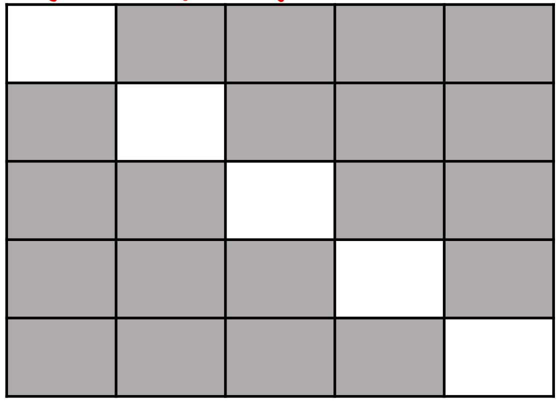
	Q_1	Q_2	Q_3	Q_4	Q_5	
dog	0	0	.9	.1	1	$\hat{y}$
!dog						$1-\hat{y}$

	P_1	P_2	P_3	P_4	P_5
dog	0	0	0	0	1
!dog	1	1	1	1	0

T

					$-\log(\hat{y})$
					$-\log(1-\hat{y})$

	dog	!dog
P_1	0	1
P_2	0	1
P_3	0	1
P_4	0	1
P_5	1	0
	y	$(1-y)$

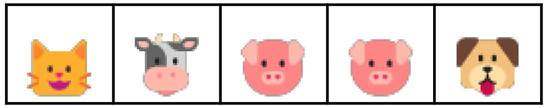


Binary Cross entropy loss

$$y \log(\hat{y}) + (1-y)\log(1-\hat{y})$$

Math: BCE Loss

	P_1	P_2	P_3	P_4	P_5
dog	0	0	0	0	1
!dog	1	1	1	1	0

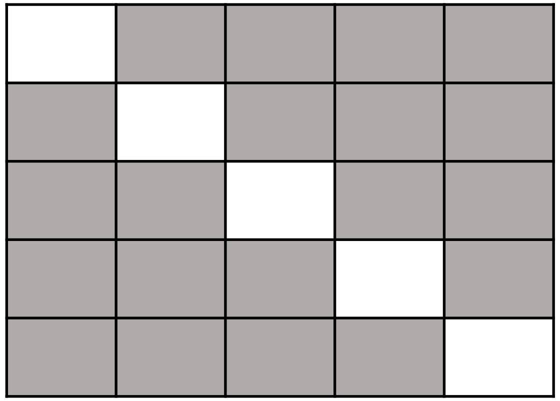


	Q_1	Q_2	Q_3	Q_4	Q_5
dog	0	0	.9	.1	1
!dog	1	1	0.1	0.9	0.9

T

				0
0	0	3	0.2	

	dog	!dog
P_1	0	
P_2	0	
P_3	0	
P_4	0	
P_5	1	



BCE Loss

-log(0) ≈32
-log(0.1) ≈ 3
-log(0.9) ≈ 0.2
-log(1) = 0

	P_1	P_2	P_3	P_4	P_5
pig	0	0	1	1	0
!pig	1	1	0	0	1

	Q_1	Q_2	Q_3	Q_4	Q_5
pig	0	1	.9	.1	0
!pig	1	0	0.1	0.9	1

·	·	0.2	3	·
0	32	·	·	0

T

	pig	!pig
P_1	0	1
P_2	0	1
P_3	1	0
P_4	1	0
P_5	0	1

a: 0				
	b: 32			
		c: 0.2		
			d: 3	
				e: 6

a+b+c+d+e =
35.2;

GAN’s Loss

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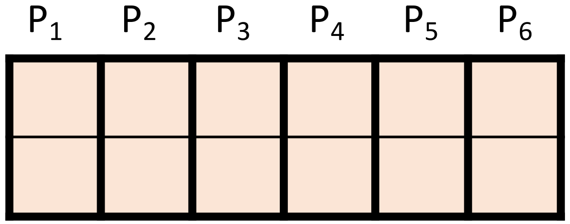
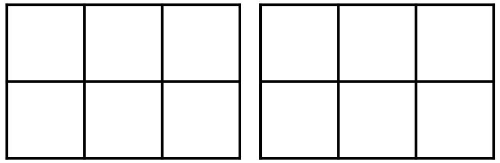
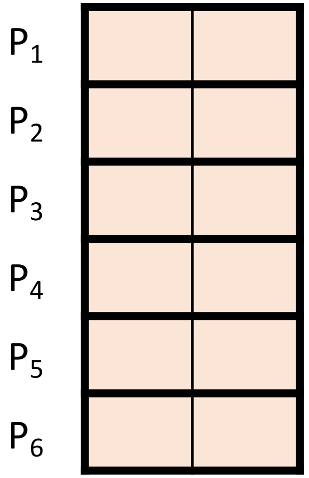
Discriminator Loss

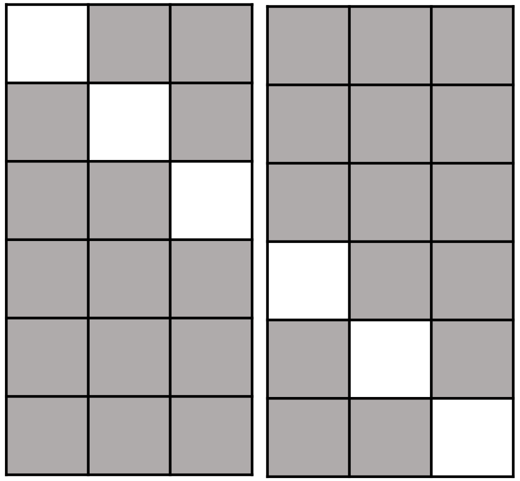
Fake			Real		
-1	-1	-3	0	0	-1
3	-1	3	3	-1	1



.7	0	.7	.9	.1	.3





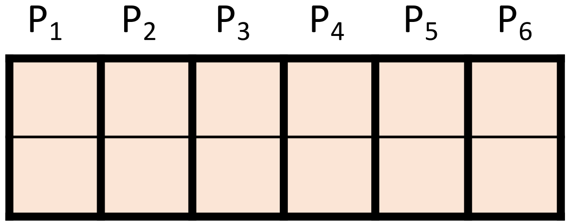


-log(0) ≈32
-log(0.1) ≈ 3
-log(0.3) ≈ 2
-log(0.5) ≈ 1
-log(0.7) ≈ 0.5
-log(0.9) ≈ 0.2
-log(1) = 0

Generator Loss

Fake		
-1	-1	-3
3	-1	3

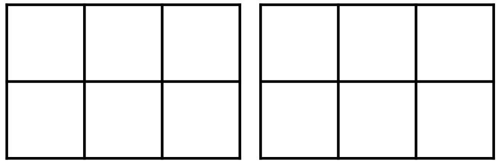
Real		
0	0	-1
3	-1	1

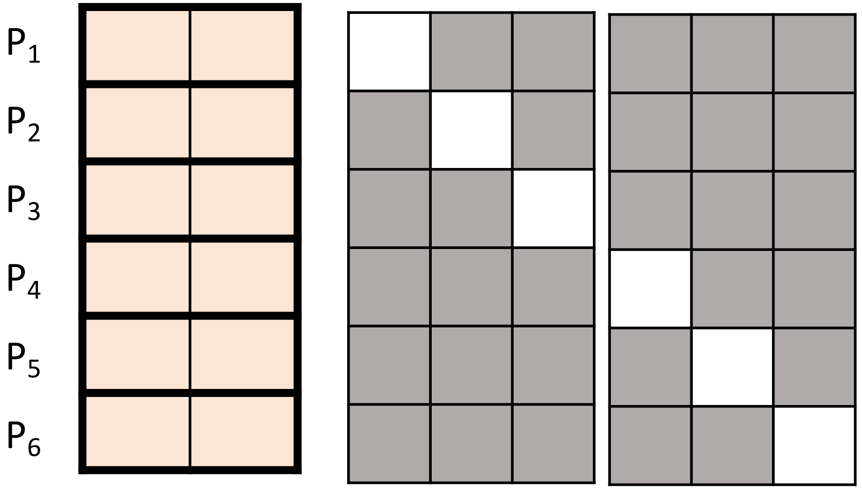


.7	0	.7

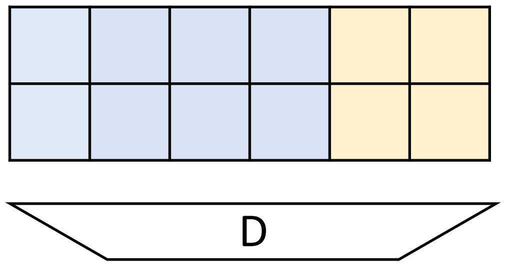
.9	.1	.3

-log(0) ≈32
-log(0.1) ≈ 3
-log(0.3) ≈ 2
-log(0.5) ≈ 1
-log(0.7) ≈ 0.5
-log(0.9) ≈ 0.2
-log(1) = 0





Discriminator Loss



Fake Real

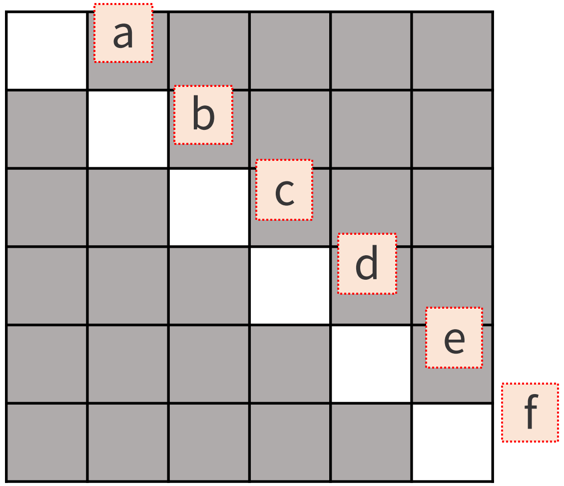
-log(0) ≈32
-log(0.1) ≈ 3
-log(0.3) ≈ 2
-log(0.5) ≈ 1
-log(0.7) ≈ 0.5
-log(0.9) ≈ 0.2
-log(1) = 0

	P_1	P_2	P_3	P_4	P_5	P_6
real	0	0	0	0	1	1
!real	1	1	1	1	0	0

.3	.7	.5	.3	.1	1	Y
						1-Y

						-log

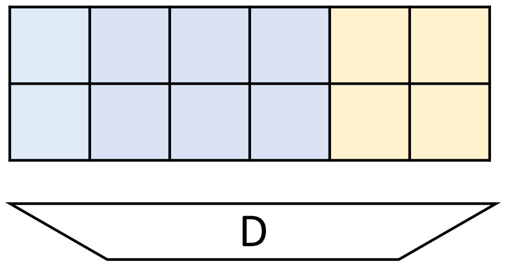
	real	!real
P_1	0	1
P_2	0	1
P_3	0	1
P_4	0	1
P_5	1	0
P_6	1	0



a+b+c+d+e+f = 7;

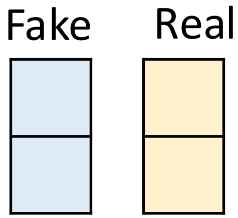
Generator Loss

	P_1	P_2	P_3	P_4	P_5	P_6
real	1	1	1	1	0	0
!real	0	0	0	0	0	0



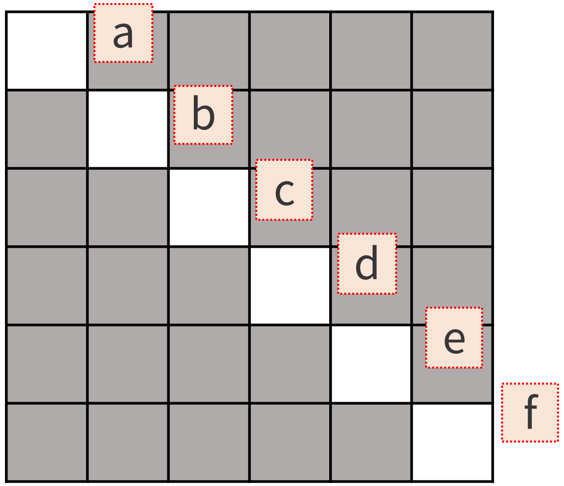
.3	.7	.5	.3	.1	1	Y
						1-Y

						-log



-log(0) ≈32
-log(0.1) ≈ 3
-log(0.3) ≈ 2
-log(0.5) ≈ 1
-log(0.7) ≈ 0.5
-log(0.9) ≈ 0.2
-log(1) = 0

	real	!real
P_1	1	0
P_2	1	0
P_3	1	0
P_4	1	0
P_5	0	0
P_6	0	0



a+b+c+d+e+f = 5.5;

Discriminator Loss

Fake Real

	P1	P2	P3	P4	P5	P6
real						
!real						

D

.3	.1	.5	.9	.1	0	Y
						1-Y

-log

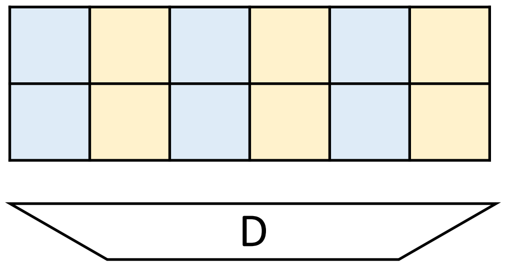
	real	!real
P_1		
P_2		
P_3		
P_4		
P_5		
P_6		

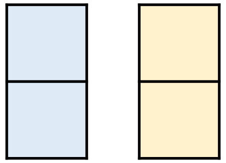
a b c d e f

- $-\log(0) \approx 32$
- $-\log(0.1) \approx 3$
- $-\log(0.3) \approx 2$
- $-\log(0.5) \approx 1$
- $-\log(0.7) \approx 0.5$
- $-\log(0.9) \approx 0.2$
- $-\log(1) = 0$

a+b+c+d+e+f =
36.9;

Generator Loss





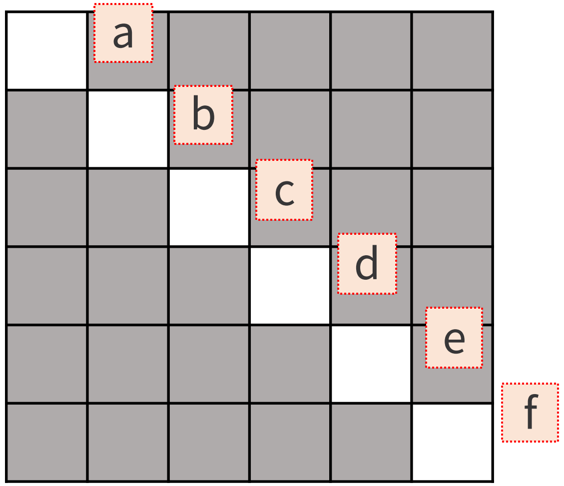
	P_1	P_2	P_3	P_4	P_5	P_6
real	1		1		1	
!real						

.3	.1	.5	.9	.1	0	Y
						1-Y

						-log

-log(0) ≈32
-log(0.1) ≈ 3
-log(0.3) ≈ 2
-log(0.5) ≈ 1
-log(0.7) ≈ 0.5
-log(0.9) ≈ 0.2
-log(1) = 0

	real	!real
P_1	1	
P_2		
P_3	1	
P_4		
P_5	1	
P_6		



a+b+c+d+e+f = 6;

BCE Loss Gradients

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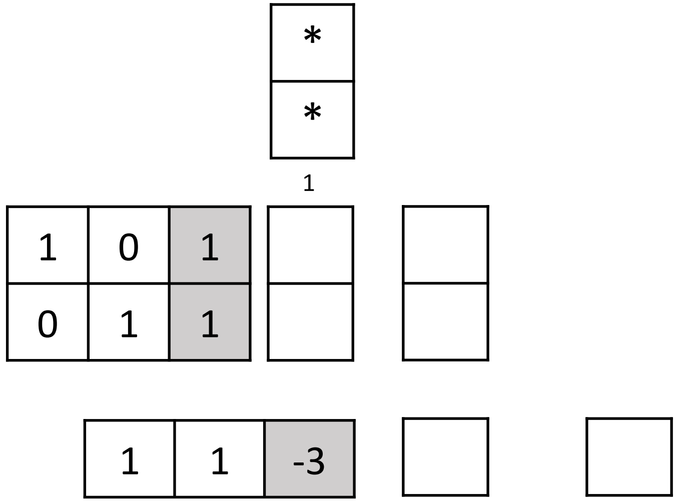
Update a parameter

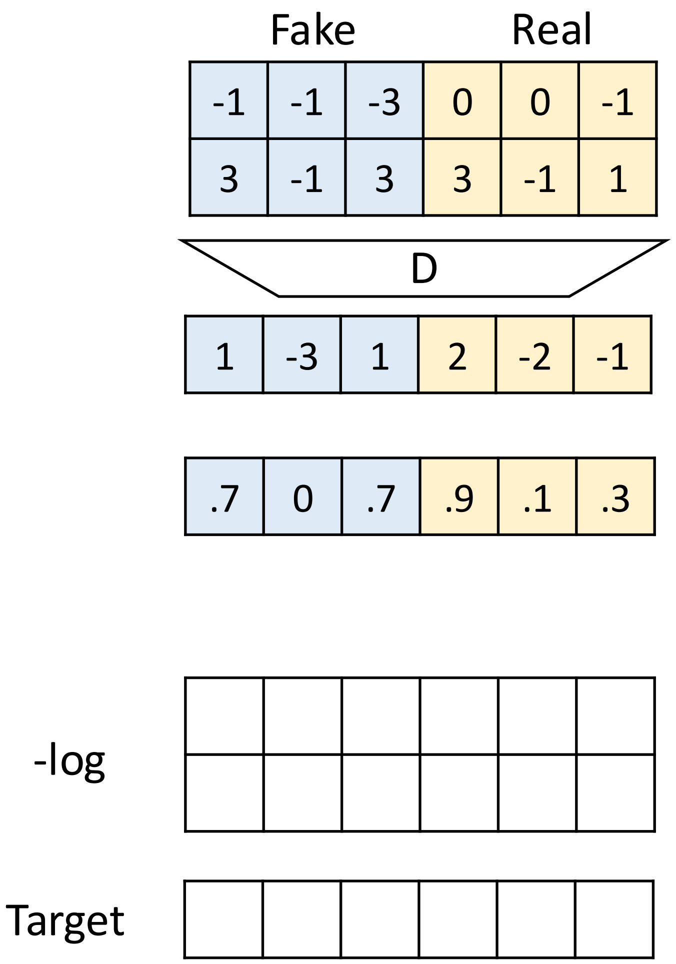


1	1	1	2	3	4	5
0	0	0	1	2	3	4
-1	-1	-1	0	1	2	3
-2	-2	-2	-1	0	1	2
-3	-3	-3	-2	-1	0	1
-3	-3	-3	-2	-1	0	1
-3	-3	-3	-2	-1	0	1

.7	.7	.7	.9	1	1	1
.5	.5	.5	.7	.9	1	1
.3	.3	.3	.5	.7	.9	1
.1	.1	.1	.3	.5	.7	.9
0	0	0	.1	.3	.5	.7
0	0	0	.1	.3	.5	.7
0	0	0	.1	.3	.5	.7

Fake			Real		
.7	0	.7	.9	.1	.3

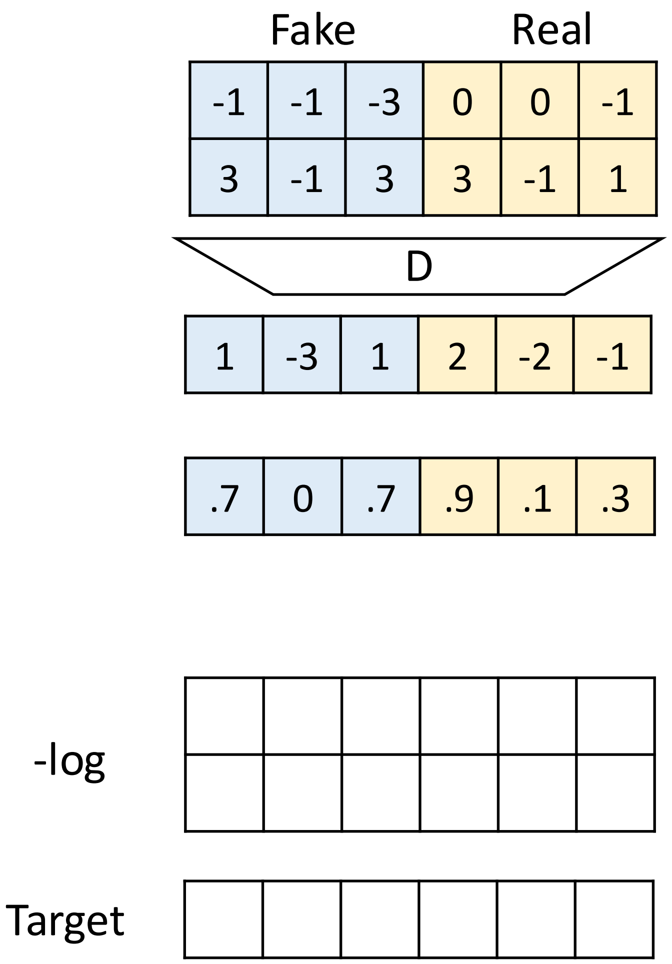
Discriminator Loss Gradients



$\sigma(<=-3) \approx 0$
$\sigma(-2) \approx 0.1$
$\sigma(-1) \approx 0.3$
$\sigma(0) \approx 0.5$
$\sigma(1) \approx 0.7$
$\sigma(2) \approx 0.9$
$\sigma(>=3) \approx 1$

$-\log(0) \approx 32$
$-\log(0.1) \approx 3$
$-\log(0.3) \approx 2$
$-\log(0.5) \approx 1$
$-\log(0.7) \approx 0.5$
$-\log(0.9) \approx 0.2$
$-\log(1) = 0$

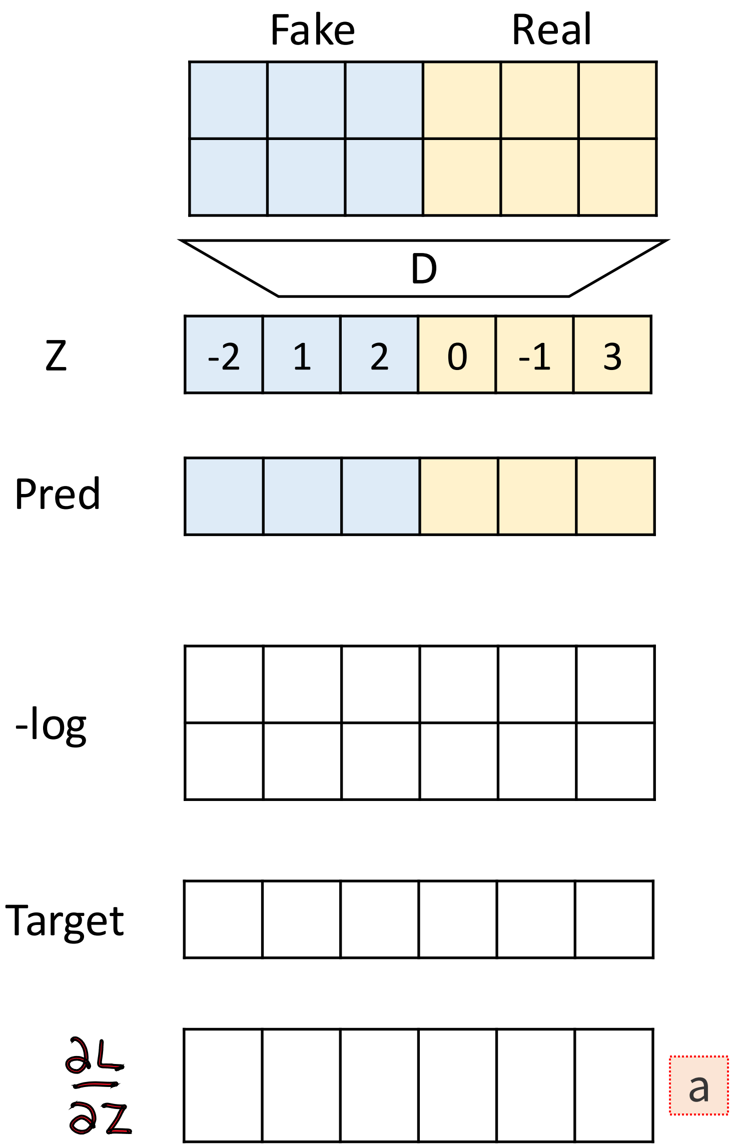
Generator Loss Gradients



σ(<=-3) ≈ 0
σ(-2) ≈ 0.1
σ(-1) ≈ 0.3
σ(0) ≈ 0.5
σ(1) ≈ 0.7
σ(2) ≈ 0.9
σ(>=3) ≈ 1

-log(0) ≈32
-log(0.1) ≈ 3
-log(0.3) ≈ 2
-log(0.5) ≈ 1
-log(0.7) ≈ 0.5
-log(0.9) ≈ 0.2
-log(1) = 0

Discriminator Loss Gradients



$\sigma(<=-3) \approx 0$
$\sigma(-2) \approx 0.1$
$\sigma(-1) \approx 0.3$
$\sigma(0) \approx 0.5$
$\sigma(1) \approx 0.7$
$\sigma(2) \approx 0.9$
$\sigma(>=3) \approx 1$

$-\log(0) \approx 32$
$-\log(0.1) \approx 3$
$-\log(0.3) \approx 2$
$-\log(0.5) \approx 1$
$-\log(0.7) \approx 0.5$
$-\log(0.9) \approx 0.2$
$-\log(1) = 0$

🔑 |sum(a)| = .5

Generator Loss Gradients

	Fake			Real		
Z	-2	1	2	0	-1	3
Pred						
-log						
Target						
$\frac{\partial L}{\partial z}$						

D

a

$\sigma(<=-3) \approx 0$
$\sigma(-2) \approx 0.1$
$\sigma(-1) \approx 0.3$
$\sigma(0) \approx 0.5$
$\sigma(1) \approx 0.7$
$\sigma(2) \approx 0.9$
$\sigma(>=3) \approx 1$

$-\log(0) \approx 32$
$-\log(0.1) \approx 3$
$-\log(0.3) \approx 2$
$-\log(0.5) \approx 1$
$-\log(0.7) \approx 0.5$
$-\log(0.9) \approx 0.2$
$-\log(1) = 0$

$|sum(a)| = 1.3$

Adversarial Training

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Train Discriminator

1	1	-1
1	-1	1

1 1 1

1	0	-2
0	2	1

Fake

-1	-1	-3
3	-1	3

1 1 1

Real

0	0	-1
3	-1	1

1 1 1

1	0	1
0	1	1

1 1 1

1 1 1

1	1	-3

Pred

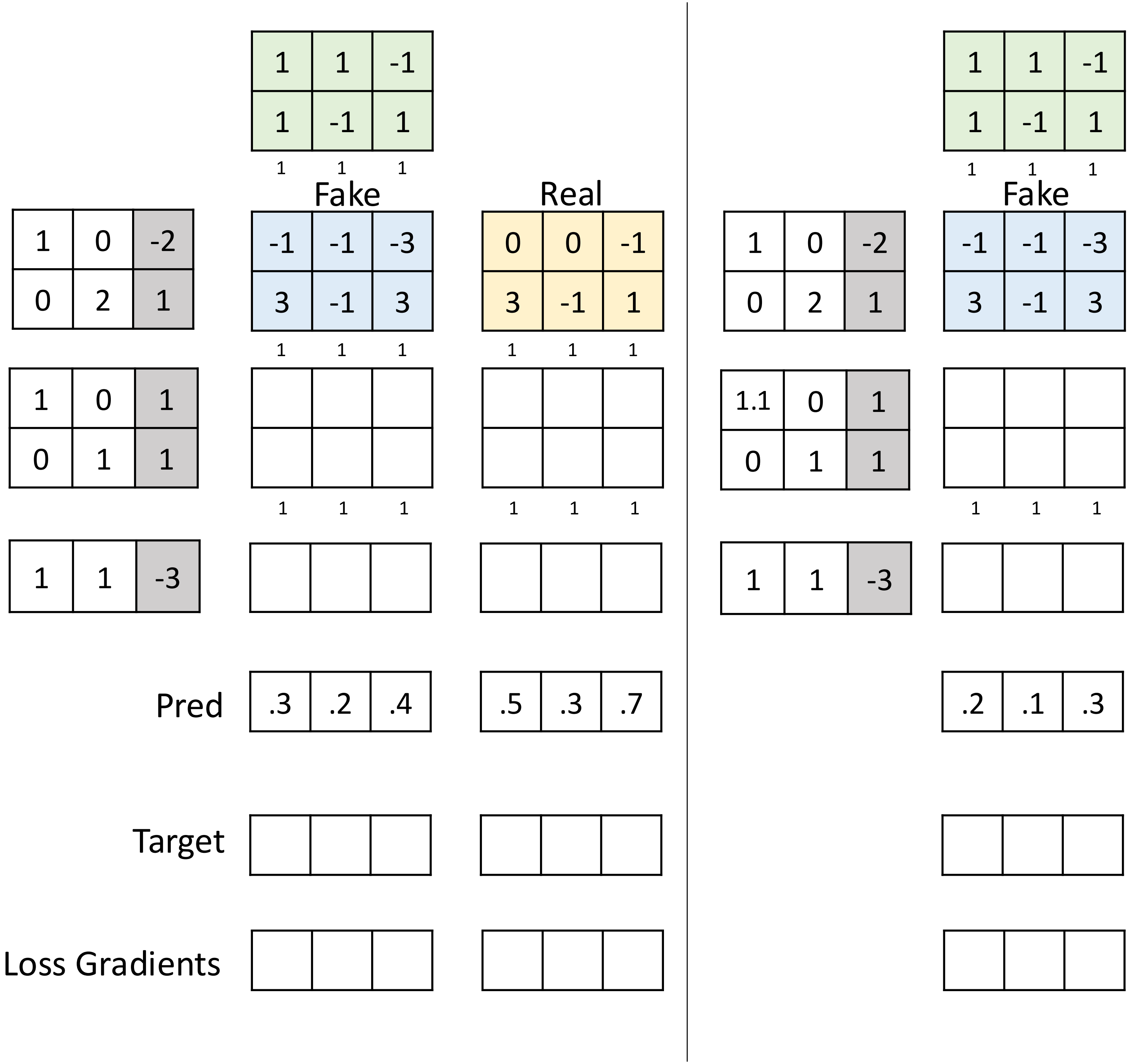
.3	.2	.4

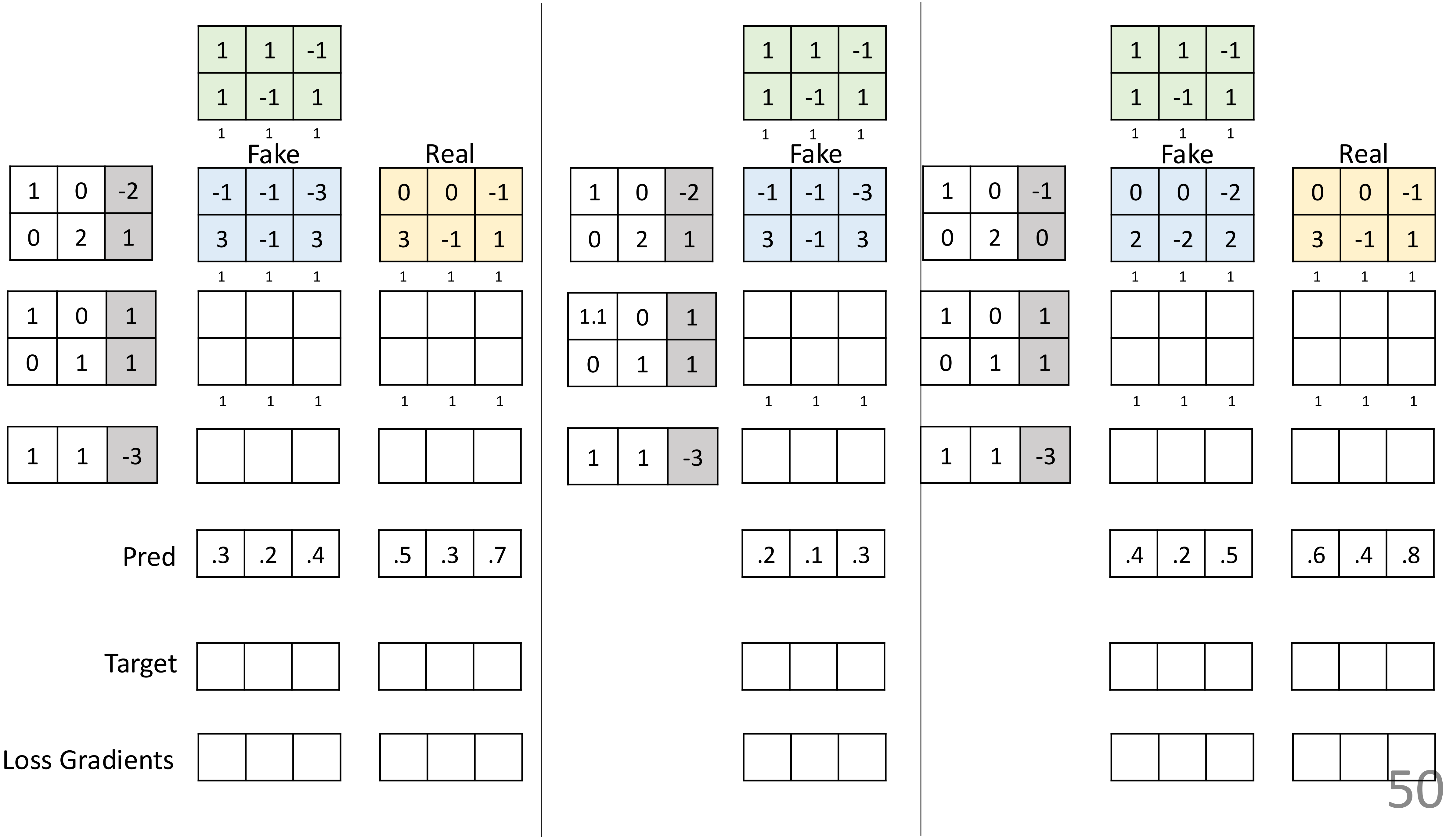
.5	.3	.7

Target

Loss Gradients

Train Generator




1 1 -1
1 -1 1
1 1 1
Fake
Real
1 0 -2
0 2 1
-1 -1 -3
3 -1 3
0 0 -1
3 -1 1
1 1 1
1 0 1
0 1 1
1 1 -3
Pred
.3 .2 .4
.5 .3 .7
Target
Loss Gradients
1 0 -2
0 2 1
-1 -1 -3
3 -1 3
1.1 0 1
0 1 1
1 1 -3
.2 .1 .3
1 0 -1
0 2 0
0 0 -2
2 -2 2
0 0 -1
3 -1 1
1 0 1
0 1 1
1 1 -3
.4 .2 .5
.6 .4 .8