Deep Neural Networks Are Our Friends

Wang Ling

Google DeepMind

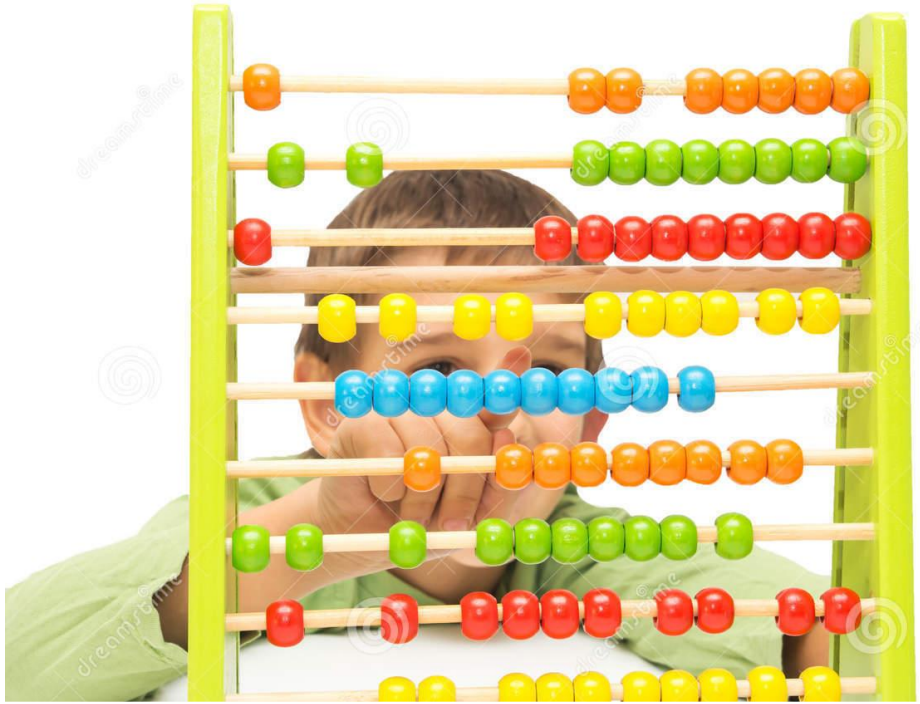
Outline

- Part I - Neural Networks are our friends
  - Numbers are our friends
  - Operators are our friends
  - Functions are our friends
  - Parameters are our friends
  - Cost Functions are our friends
  - Optimizers are our friends
  - Gradients are our friends
  - Computation Graphs are our friends

Outline

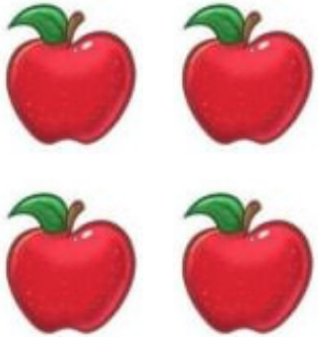
- Part I - Neural Networks are our friends
- Part 2 - Into Deep Learning
  - Nonlinear Neural Models
  - Multilayer Perceptrons
  - Using Discrete Variables
  - Example Applications

Numbers are our friends



Numbers are our friends

Abby Cadabby



How many apples does Abby have?

Numbers are our friends

Abby Cadabby

4 🍎

Numbers are our friends

- Types of Numbers:
  - Integers : 5 🍎🍎🍎🍎🍎
  - Rationals : 1/2 🍎
  - Reals : 1.4e10 🍎🍎🍎🍎🍎🍎🍎🍎🍎🍎🍎🍎🍎🍎🍎🍎🍎🍎 

Operators are our friends

4 🍎

Bert

Operators are our friends

4 🍎

1 🍎

Bert

If Abby has 4 apples, and gives Bert 1 apple, how many apples will Abby have?

Operators are our friends

3 🍎

1 🍎

Bert

Operators are our friends

- Arithmetic Operators
  - Addition : 23 + 12 = 35
  - Subtraction : 31 - 15 = 16
  - Multiplication : 4 x 5 = 20
  - Division : 20 / 5 = 4

Functions are our friends

4 🍎

1 🍎

Functions are our friends

4 🍎

1 🍎

? 🍌

5 🍌

If Bert always returns 3 bananas for each apple, how many bananas will Abby receive for 2 apples

Functions are our friends

$y = 3x$

- Input, x - Number of Apples given by Abby

Functions are our friends

$y = 3x$

- Input, x - Number of Apples given by Abby
- Output, y - Number of Bananas received by Abby

Functions are our friends

4 🍎

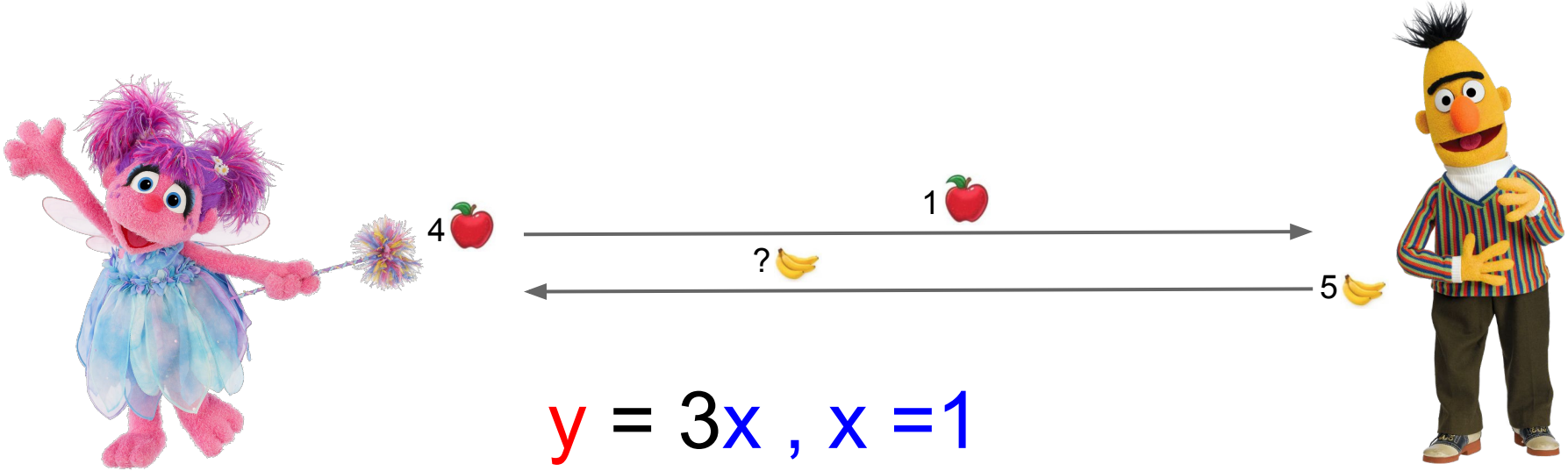
1 🍎

? 🍌

5 🍌

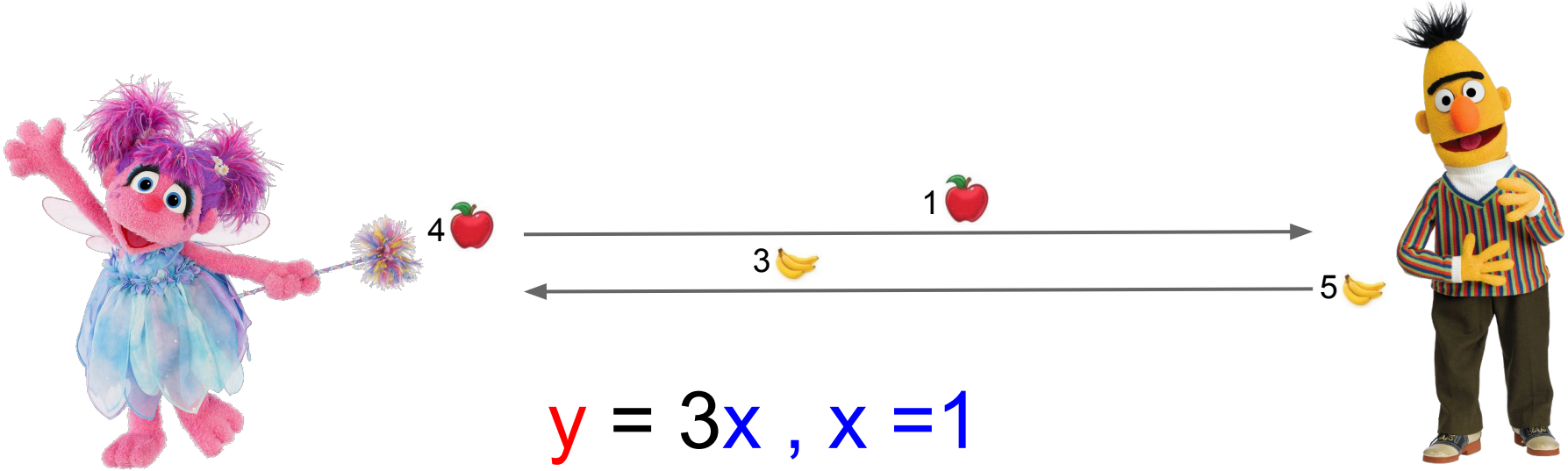
$y = 3x$

Functions are our friends



$y = 3x$, $x = 1$

Functions are our friends



$y = 3x$, $x = 1$

$y = 3$

Functions are our friends

$y = 3x$

Functions are our friends

$y = 3x$

Cookie Monster

Functions are our friends

$y = ??$

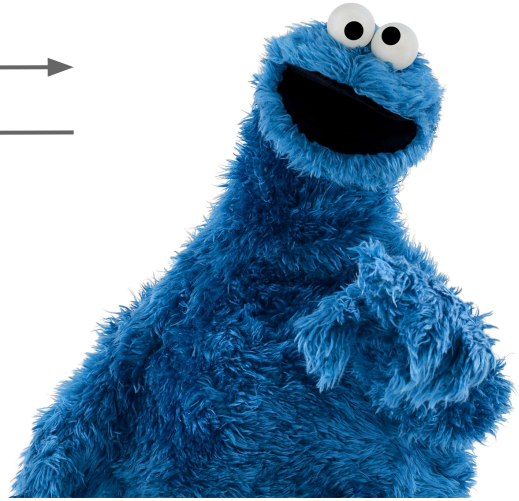
$y = 3x$

Functions are our friends

y = ??

1 🍎

0 🍌



Functions are our friends

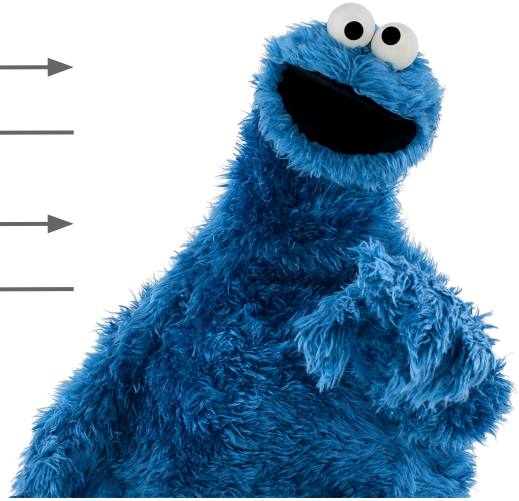
y = ??

1 🍎

0 🍌

5 🍎

16 🍌



Functions are our friends

y = ??

1 🍎

0 🍌

5 🍎

16 🍌

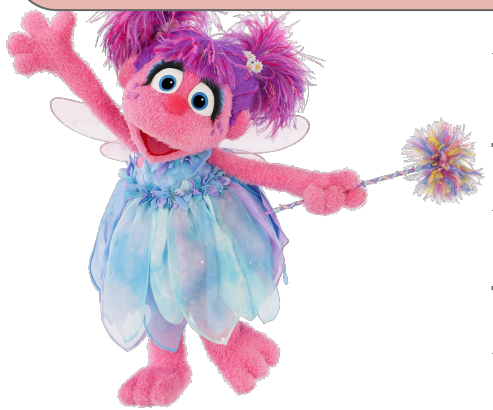
6 🍎

20 🍌

Functions are our friends

If Abby gives Cookie Monster 3 apples, how many bananas does she get?

y = ??



1 🍎

0 🍌

5 🍎

16 🍌

6 🍎

20 🍌

3 🍎

? 🍌

Parameters are our friends

$y = 3x + 1$

- Input
- Output

Parameters are our friends

$y = wx + b$

- Input
- Output
- Parameters

Input - Fixed, comes from data
Parameters - Need to be estimated

Parameters are our friends

$$y = wx + b$$

1 🍎

0 🍌

5 🍎

16 🍌

6 🍎

20 🍌

3 🍎

? 🍌

Parameters are our friends

$$y = wx + b$$

Parameters are our friends

$$y = wx + b$$

x	y
1	0
5	16
6	20

3 🍎

? 🍌

Parameters are our friends

Data

x	y
1	0
5	16
6	20

Model

$$y = wx + b$$

Parameters are our friends

Data

x	y
1	0
5	16
6	20

Model

$$y = wx + b$$

How to find the parameters w and b?

Parameters are our friends

Data

x	y
1	0
5	16
6	20

Model

$$y = wx + b$$

Model Candidate 1

$$y = 1x + 0$$

x	y	ŷ
1	0	1
5	16	5
6	20	6

Parameters are our friends

Data

x	y
1	0
5	16
6	20

Model

$$y = wx + b$$

Model Candidate 1

$$y = 1x + 0$$

x	y	ŷ
1	0	1
5	16	5
6	20	6

Model Candidate 2

$$y = 2x + 2$$

x	y	ŷ
1	0	4
5	16	12
6	20	14

Parameters are our friends

Data

x	y
1	0
5	16
6	20

Model

$$y = wx + b$$

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$$y = 1x + 0$$

x	y	ŷ
1	0	1
5	16	5
6	20	6

Model Candidate 2

$$y = 2x + 2$$

x	y	ŷ
1	0	4
5	16	12
6	20	14

Which one is better ?

Cost functions are our friends

Data

n	x	y
0	1	0
1	5	16
2	6	20

Model

$$y_n = wx_n + b$$

Model Candidate 1

$$y = 1x + 0$$

x	y	ŷ
1	0	1
5	16	5
6	20	6

Model Candidate 2

$$y = 2x + 2$$

x	y	ŷ
1	0	4
5	16	12
6	20	14

Cost functions are our friends

Data

n	x	y
0	1	0
1	5	16
2	6	20

Model

$$y_n = wx_n + b$$

Cost

$$C(w,b) = \sum_{n\in\{0,1,2\}} (y_n - \hat{y}_n)^2$$

Model Candidate 1

$$y = 1x + 0$$

x	y	ŷ
1	0	1
5	16	5
6	20	6

Model Candidate 2

$$y = 2x + 2$$

x	y	ŷ
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Cost functions are our friends

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n	x	y
0	1	0
1	5	16
2	6	20

Model

$$y_n = wx_n + b$$

Cost

$$C(w,b) = \sum_{n\in\{0,1,2\}} (y_n - \hat{y}_n)^2$$

Model Candidate 1

$$y = 1x + 0$$

n	x	y	$\hat{y}$	$(y-\hat{y})^2$
0	1	0	1	1
1	5	16	5	
2	6	20	6	

Model Candidate 2

$$y = 2x + 2$$

x	y	$\hat{y}$
1	0	4
5	16	12
6	20	14

Cost functions are our friends

Data

n	x	y
0	1	0
1	5	16
2	6	20

Model

$$y_n = wx_n + b$$

Cost

$$C(w,b) = \sum_{n \in \{0,1,2\}} (y_n - \hat{y}_n)^2$$

Model Candidate 1

$$y = 1x + 0$$

n	x	y	ŷ	$(y-\hat{y})^2$
0	1	0	1	1
1	5	16	5	121
2	6	20	6	

Model Candidate 2

$$y = 2x + 2$$

x	y	ŷ
1	0	4
5	16	12
6	20	14

Cost functions are our friends

Data

n	x	y
0	1	0
1	5	16
2	6	20

Model

$$y_n = wx_n + b$$

Model Candidate 1

$$y = 1x + 0$$

n	x	y	ŷ	$(y-\hat{y})^2$
0	1	0	1	1
1	5	16	5	121
2	6	20	6	196

Cost

$$C(w,b) = \sum_{n\in\{0,1,2\}} (y_n - \hat{y}_n)^2$$

Model Candidate 2

$$y = 2x + 2$$

x	y	ŷ
1	0	4
5	16	12
6	20	14

Cost functions are our friends

Data

n	x	y
0	1	0
1	5	16
2	6	20

Model

$$y_n = wx_n + b$$

Model Candidate 1

$$y = 1x + 0$$

n	x	y	ŷ	$(y-\hat{y})^2$
0	1	0	1	1
1	5	16	5	121
2	6	20	6	196
			C(1,0)	318

Cost

$$C(w,b) = \sum_{n\in\{0,1,2\}} (y_n-\hat{y}_n)^2$$

Model Candidate 2

$$y = 2x + 2$$

x	y	ŷ
1	0	4
5	16	12
6	20	14

Cost functions are our friends

Data

n	x	y
0	1	0
1	5	16
2	6	20

Model

$$y_n = wx_n + b$$

Cost

$$C(w,b) = \sum_{n\in\{0,1,2\}} (y_n - \hat{y}_n)^2$$

Model Candidate 1

$$y = 1x + 0$$

n	x	y	ŷ	$(y-\hat{y})^2$
0	1	0	1	1
1	5	16	5	121
2	6	20	6	196
			C(1,0)	318

Model Candidate 2

$$y = 2x + 2$$

n	x	y	ŷ	$(y-\hat{y})^2$
0	1	0	4	16
1	5	16	12	16
2	6	20	14	36
			C(2,2)	68

Cost functions are our friends

Data

n	x	y
0	1	0
1	5	16
2	6	20

Model

$$y_n = wx_n + b$$

Model Candidate 1

$$y = 1x + 0$$

$C(1,0)$ 318

Model Candidate 2

$$y = 2x + 2$$

Cost

$$C(w,b) = \sum_{n \in \{0,1,2\}} (y_n - \hat{y}_n)^2$$

$C(2,2)$ 68

Cost functions are our friends

Data

n	x	y
0	1	0
1	5	16
2	6	20

Model

$$y_n = wx_n + b$$

Cost

$$C(w,b) = \sum_{n \in \{0,1,2\}} (y_n - \hat{y}_n)^2$$

Cost functions are our friends

Data

n	x	y
0	1	0
1	5	16
2	6	20

Model

$$y_n = wx_n + b$$

How to find the parameters w and b?

Cost

$$C(w,b) = \sum_{n \in \{0,1,2\}} (y_n - \hat{y}_n)^2$$

Optimizers are our friends

Data

n	x	y
0	1	0
1	5	16
2	6	20

Model

$$y_n = wx_n + b$$

Cost

$$C(w,b) = \sum_{n\in\{0,1,2\}} (y_n - \hat{y}_n)^2$$

Optimizer

$$\arg\min_{w,b\in[-\infty,\infty]} C(w,b)$$

Optimizers are our friends

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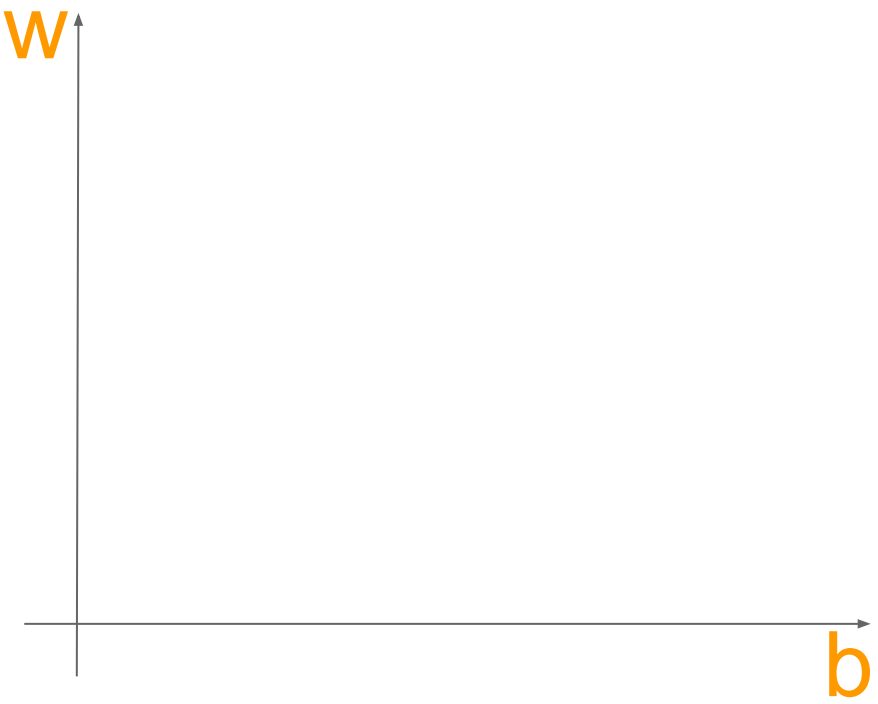
$$\arg\min_{w,b \in [-\infty,\infty]} C(w,b)$$

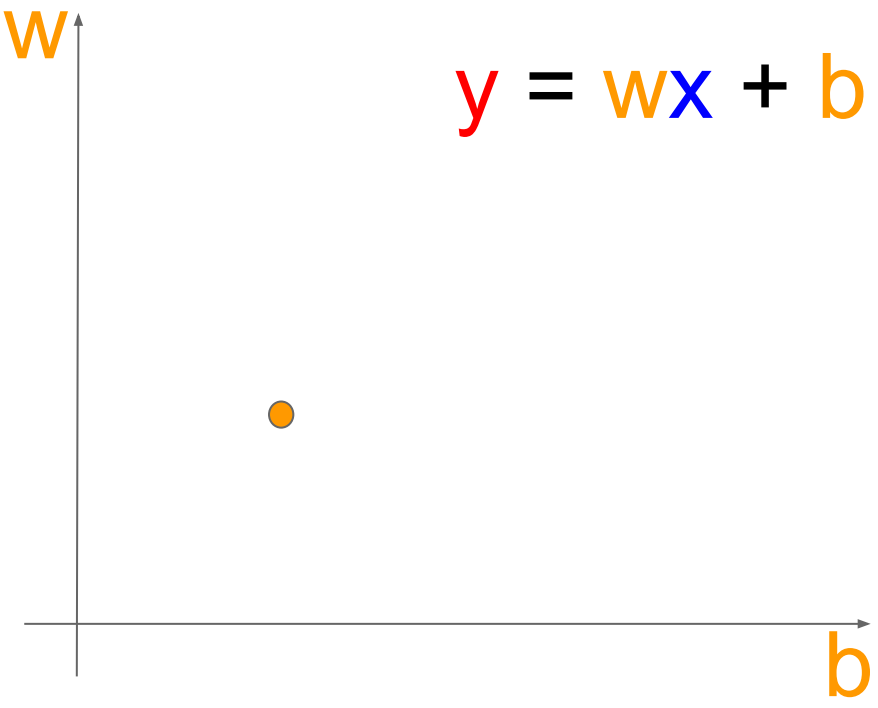


Optimizers are our friends

Optimizer

$$\arg\min_{w,b \in [-\infty,\infty]} C(w,b)$$

$w_0, b_0 = 2,2 : C(w_0,b_0) = 68$



$y = wx + b$

Optimizers are our friends

Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

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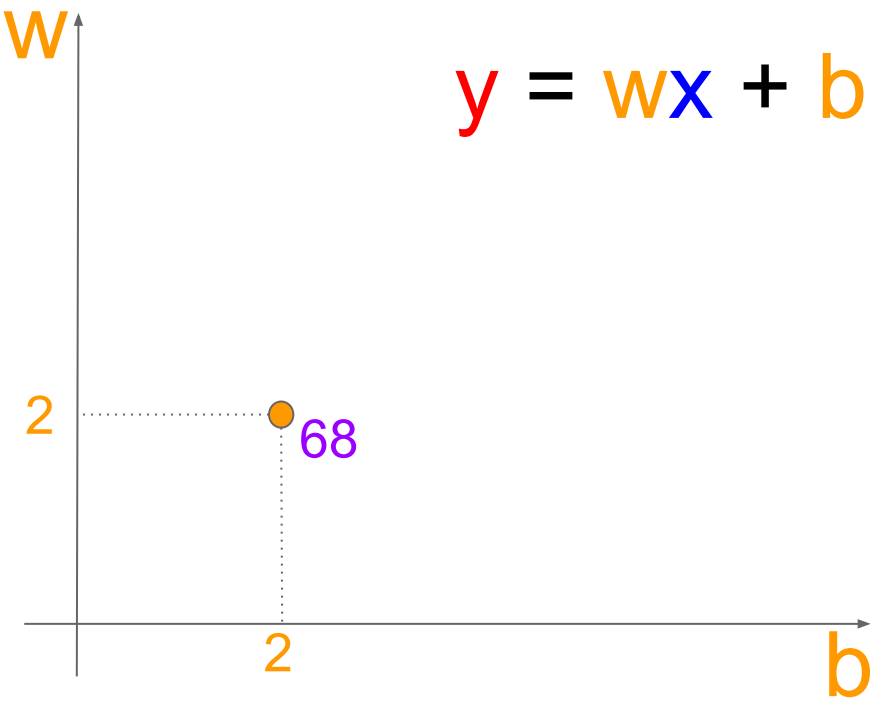

$$y = wx + b$$

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Optimizer

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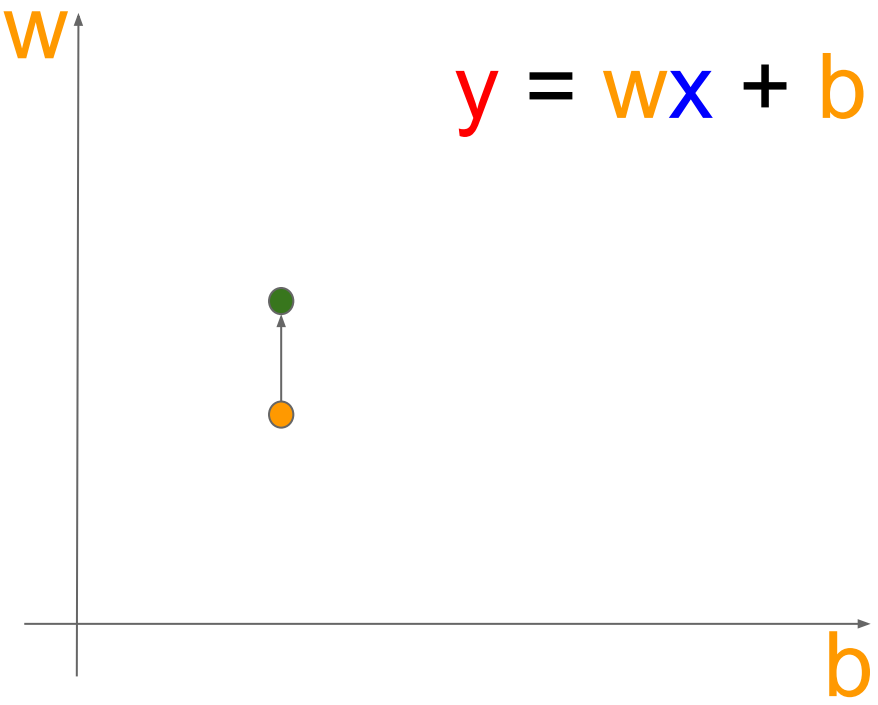
$w_0, b_0 = 2,2 : C(w_0,b_0) = 68$

$w_1, b_1 = 3,2 : C(w_1,b_1) = ?$



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Optimizers are our friends

Optimizer

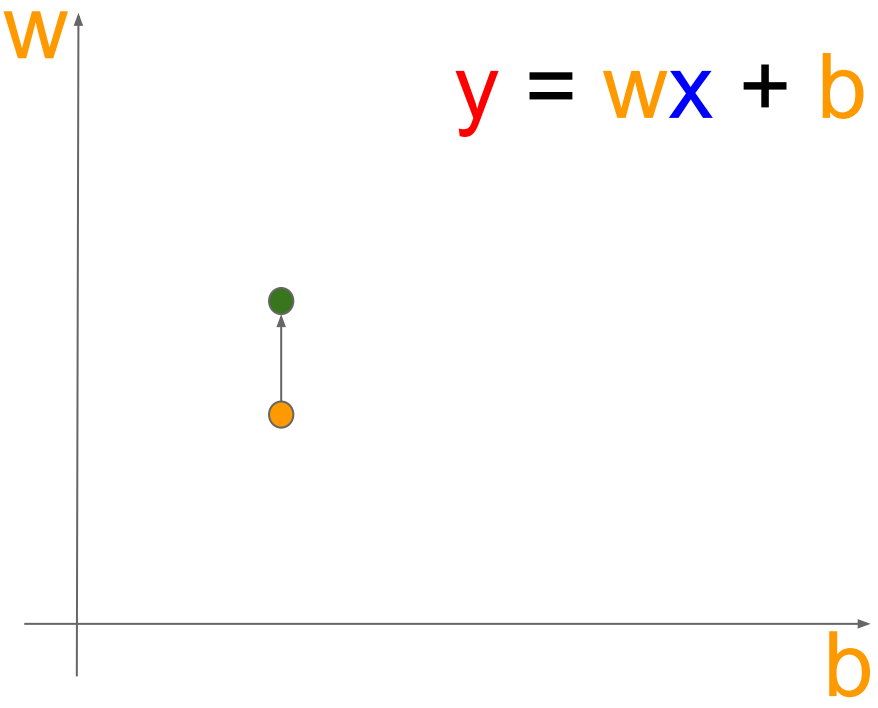
$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$w_0,b_0 = 2,2 : C(w_0,b_0) = 68$

$w_1,b_1 = 3,2 : C(w_1,b_1) = 26$

n	x	y	$\hat{y}$	$(y-\hat{y})^2$
0	1	0	5	25
1	5	16	17	1
2	6	20	20	0
			C(3,2)	26



$$y = wx + b$$

Optimizers are our friends

Optimizer

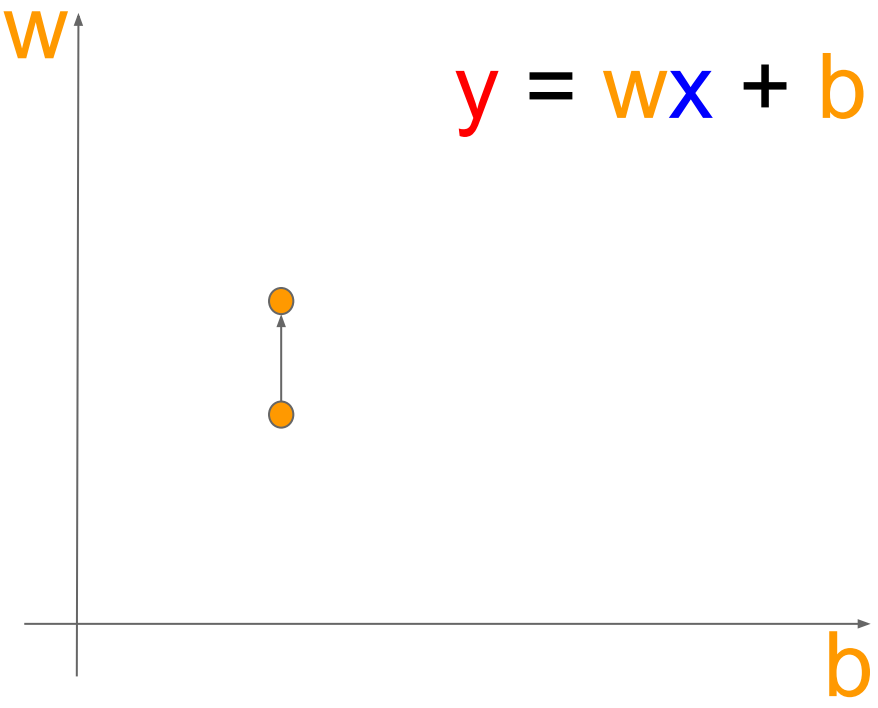
$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$w_0,b_0 = 2,2 : C(w_0,b_0) = 68$

$w_1,b_1 = 3,2 : C(w_1,b_1) = 26$

n	x	y	$\hat{y}$	$(y-\hat{y})^2$
0	1	0	5	25
1	5	16	17	1
2	6	20	20	0
			C(3,2)	26



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Optimizers are our friends

Optimizer

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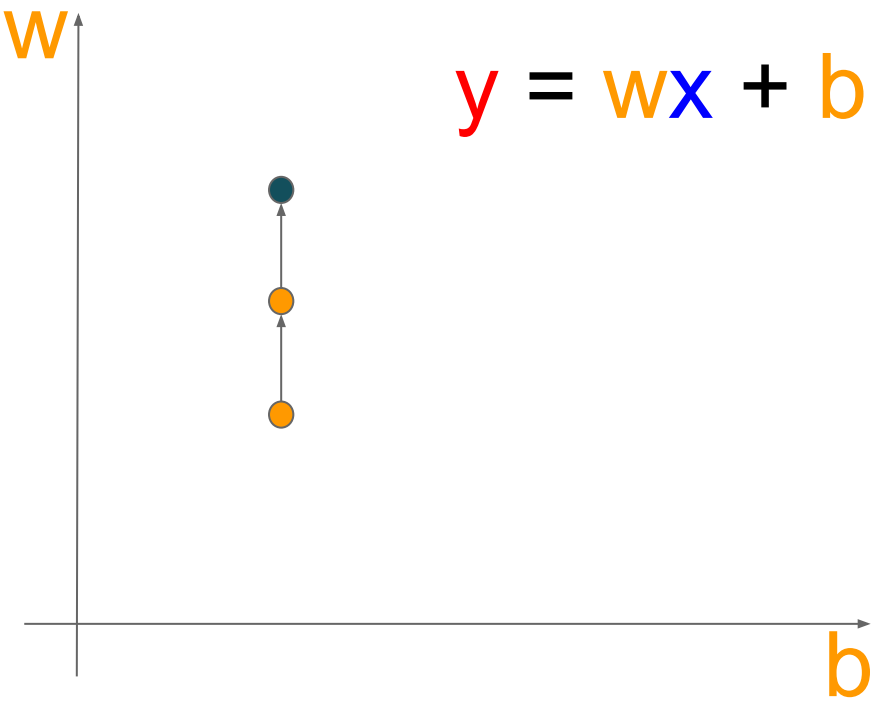
$w,b \in [-\infty,\infty]$

$w_1,b_1 = 3,2 : C(w_1,b_1) = 26$

$w_2,b_2 = 4,2 : C(w_2,b_2) = ??$



$y = wx + b$

Optimizers are our friends

Optimizer

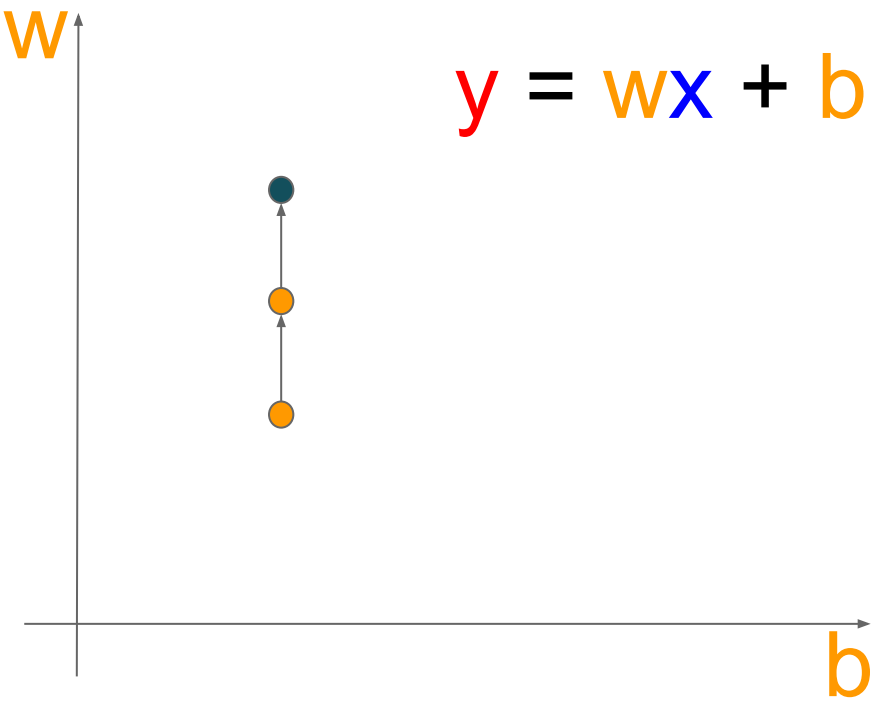
$$\arg\min_{w,b} C(w,b)$$

$w,b \in [-\infty,\infty]$

$w_1,b_1 = 3,2 : C(w_1,b_1) = 26$

$w_2,b_2 = 4,2 : C(w_2,b_2) = 136$

n	x	y	$\hat{y}$	$(y-\hat{y})^2$
0	1	0	6	36
1	5	16	22	64
2	6	20	26	36
			C(4,2)	136



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Optimizers are our friends

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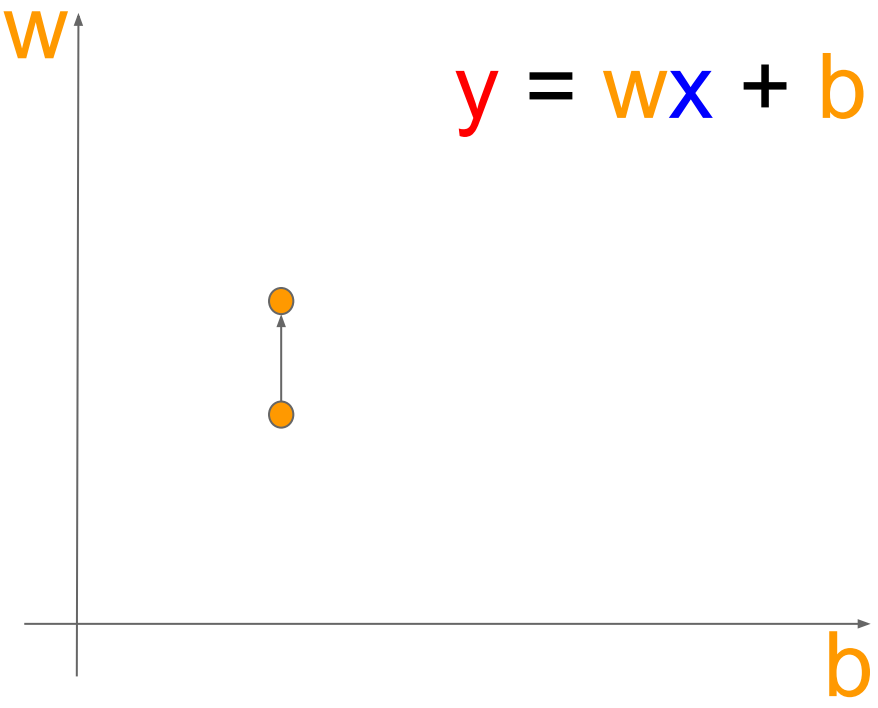

$$y = wx + b$$

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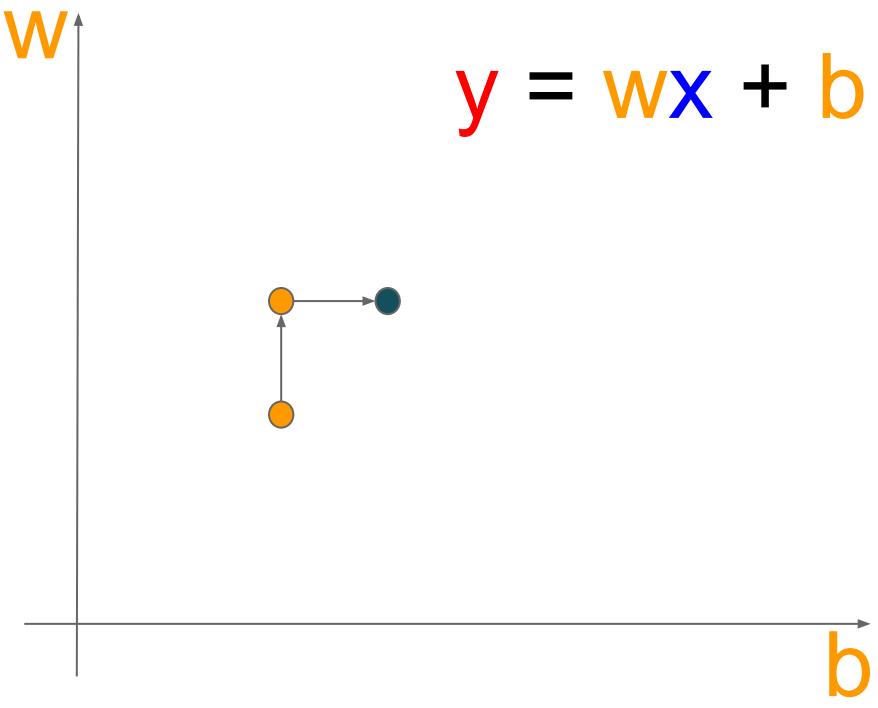
$w,b \in [-\infty,\infty]$

$w_1,b_1 = 3,2 : C(w_1,b_1) = 26$

$w_2,b_2 = 3,3 : C(w_2,b_2) = 41$

n	x	y	$\hat{y}$	$(y-\hat{y})^2$
0	1	0	6	36
1	5	16	18	4
2	6	20	21	1
			C(3,3)	41



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Optimizer

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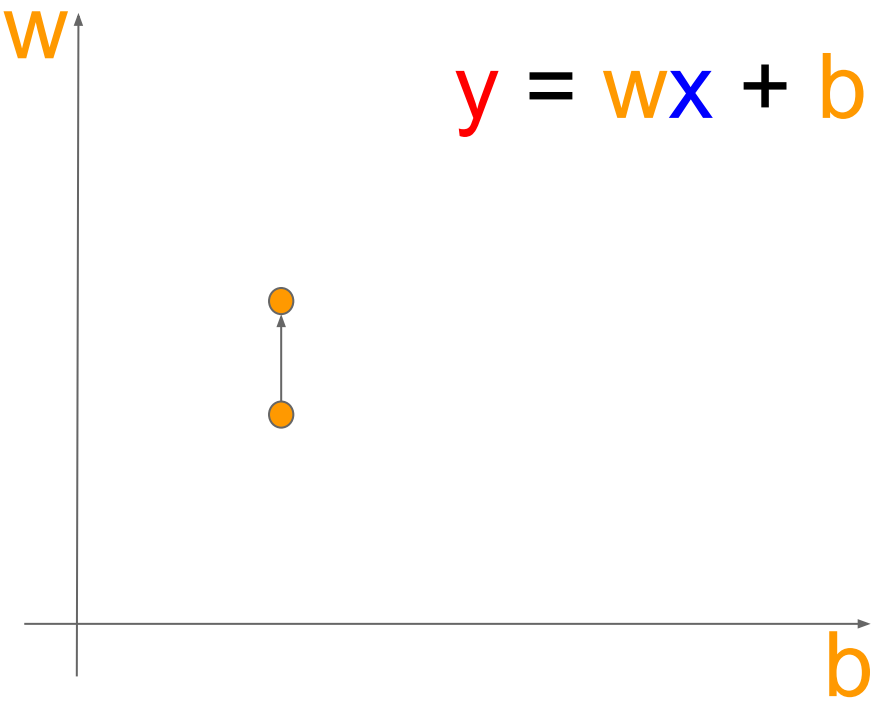

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$w,b \in [-\infty,\infty]$

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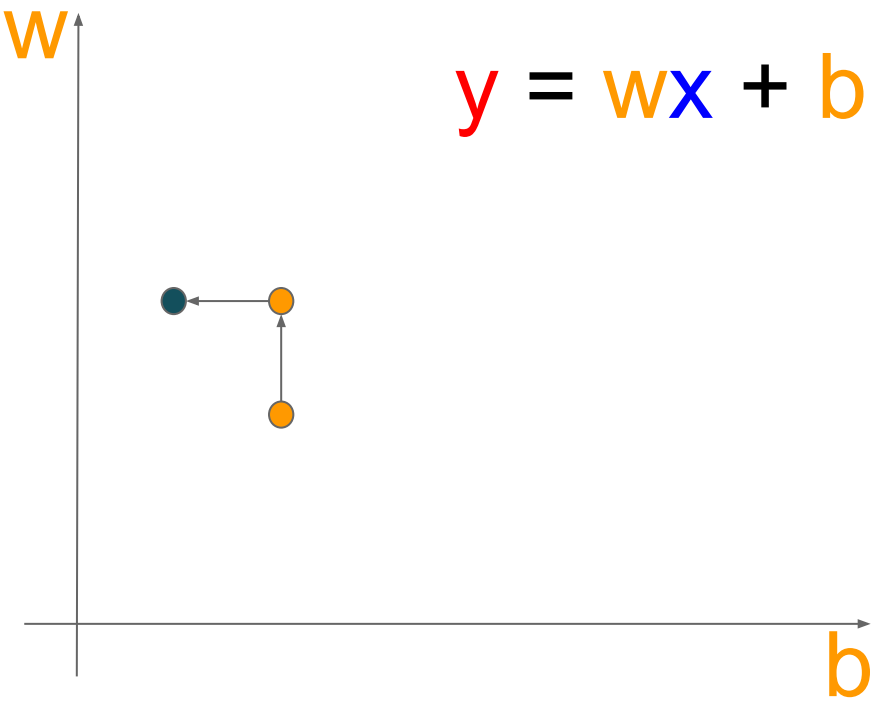
$w_2,b_2 = 3,1 : C(w_2,b_2) = 17$

n	x	y	$\hat{y}$	$(y-\hat{y})^2$
0	1	0	4	16
1	5	16	16	0
2	6	20	19	1
			C(3,1)	17



$$y = wx + b$$

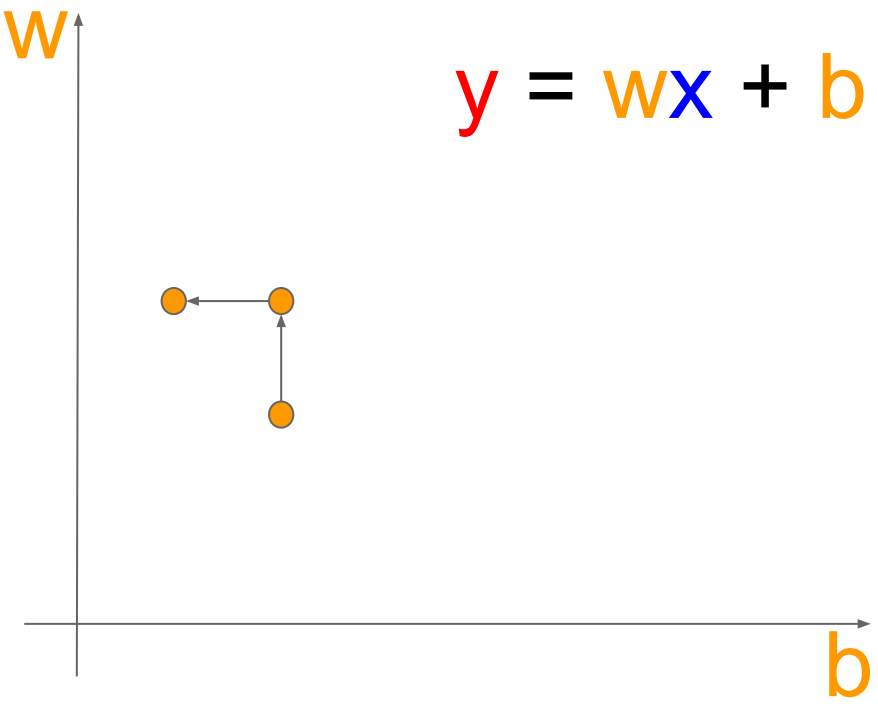
Optimizers are our friends

Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$$w_2,b_2 = 3,1 : C(w_2,b_2) = 17$$



$$y = wx + b$$

Optimizers are our friends

Optimizer

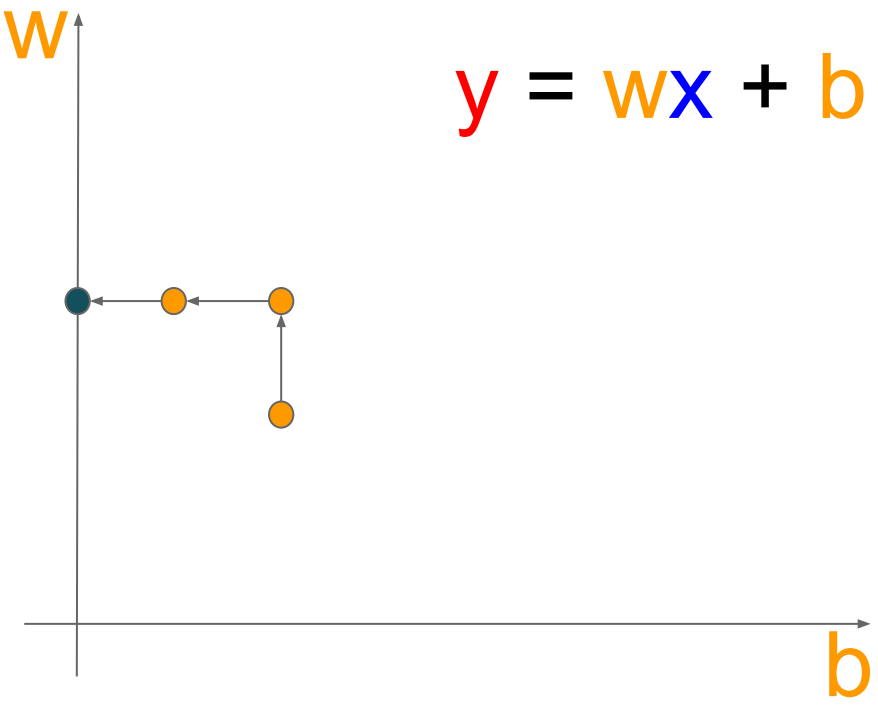
$$\arg\min_{w,b} C(w,b)$$

$w,b \in [-\infty,\infty]$

$w_2,b_2 = 3,1 : C(w_2,b_2) = 17$

$w_3,b_3 = 3,0 : C(w_3,b_3) = 13$

n	x	y	$\hat{y}$	$(y-\hat{y})^2$
0	1	0	3	9
1	5	16	15	1
2	6	20	18	4
			C(3,0)	13



$y = wx + b$

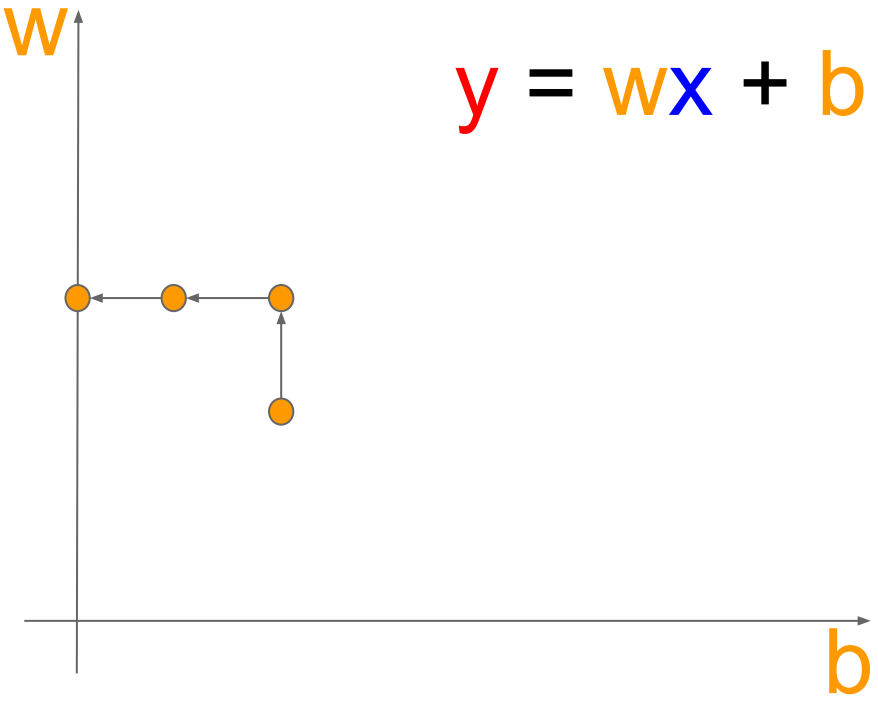
Optimizers are our friends

Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$$w_3,b_3 = 3,0 : C(w_3,b_3) = 13$$



$$y = wx + b$$

Optimizers are our friends

Optimizer

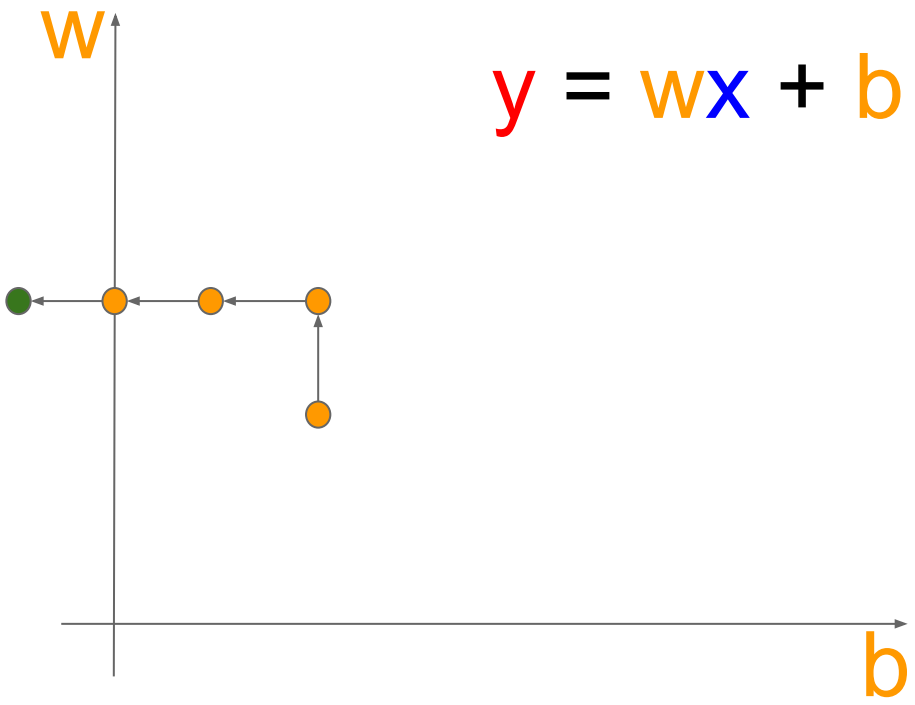
$$\arg\min_{w,b} C(w,b)$$

$w,b \in [-\infty,\infty]$

$w_3,b_3 = 3,0 : C(w_3,b_3) = 13$

$w_4,b_4 = 3,-1 : C(w_4,b_4) = 17$

n	x	y	$\hat{y}$	$(y-\hat{y})^2$
0	1	0	2	4
1	5	16	14	4
2	6	20	17	9
			$C(3,-1)$	17



$y = wx + b$

Optimizers are our friends

Optimizer

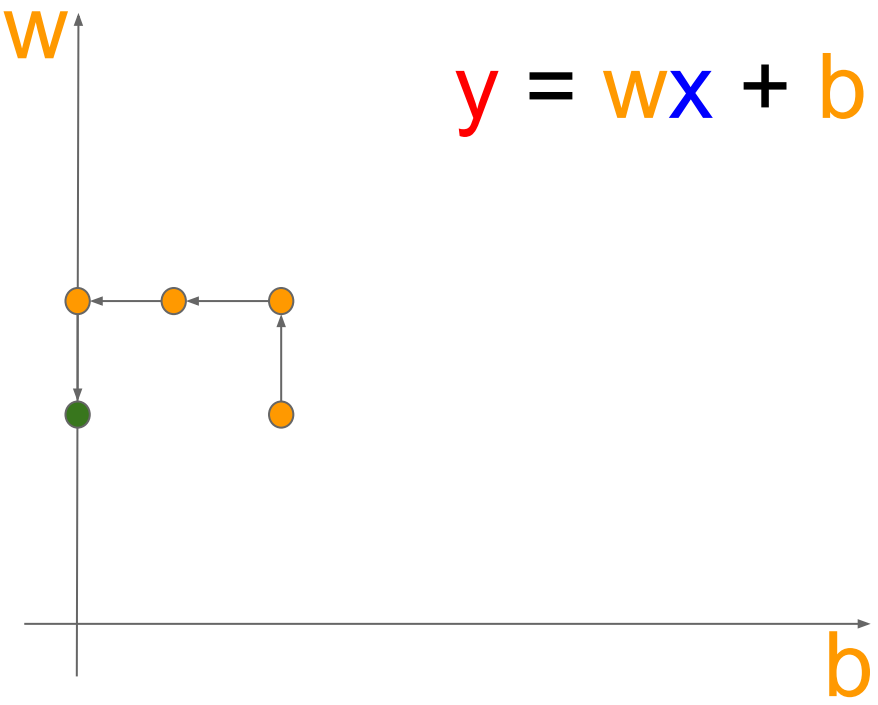
$$\arg\min_{w,b} C(w,b)$$

$w,b \in [-\infty,\infty]$

$w_3,b_3 = 3,0 : C(w_3,b_3) = 13$

$w_4,b_4 = 2,0 : C(w_4,b_4) = 104$

n	x	y	$\hat{y}$	$(y-\hat{y})^2$
0	1	0	2	4
1	5	16	10	36
2	6	20	12	64
			C(2,0)	104



$y = wx + b$

Optimizers are our friends

Optimizer

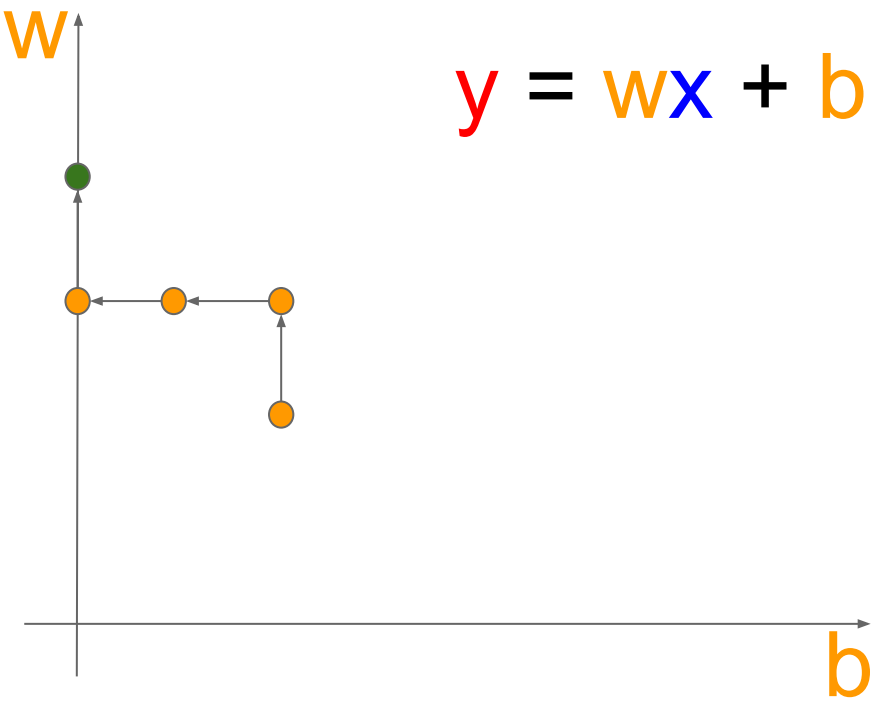
$$\arg\min C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$w_3,b_3 = 3,0 : C(w_3,b_3) = 13$

$w_4,b_4 = 4,0 : C(w_4,b_4) = 104$

n	x	y	$\hat{y}$	$(y-\hat{y})^2$
0	1	0	4	16
1	5	16	20	16
2	6	20	24	16
			C(2,0)	54



$$y = wx + b$$

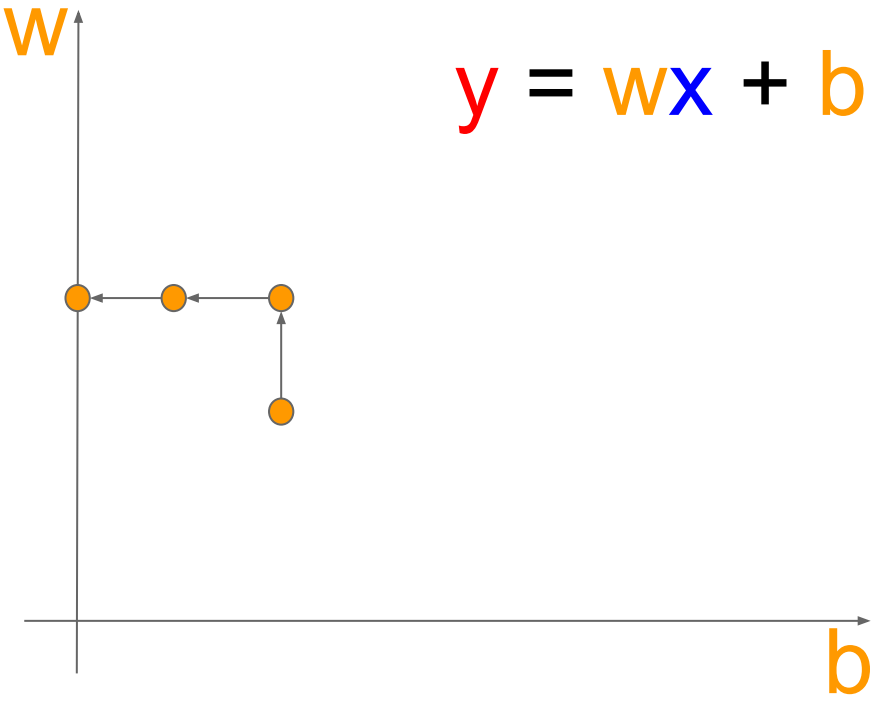
Optimizers are our friends

Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$$w_3,b_3 = 3,0 : C(w_3,b_3) = 13$$



$$y = wx + b$$

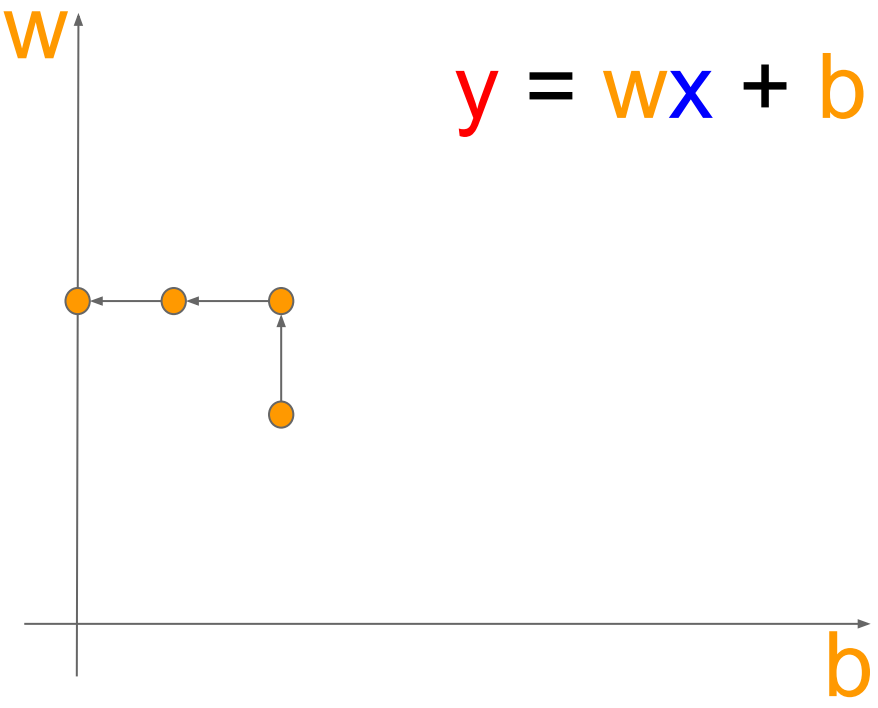
Optimizers are our friends

Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$$w_?,b_? = 4,-2 : C(w_?,b_?) = ??$$



$$y = wx + b$$

Optimizers are our friends

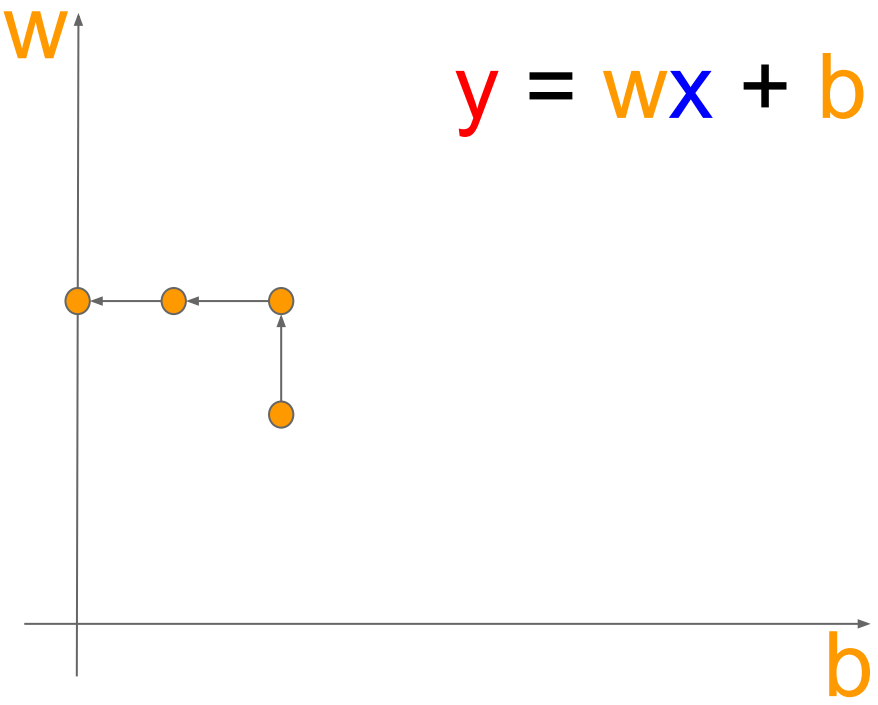
Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$$w_?,b_? = 4,-2 : C(w_?,b_?) = 12$$

n	x	y	$\hat{y}$	$(y-\hat{y})^2$
0	1	0	2	4
1	5	16	18	4
2	6	20	22	4
			C(4,-2)	12



$$y = wx + b$$

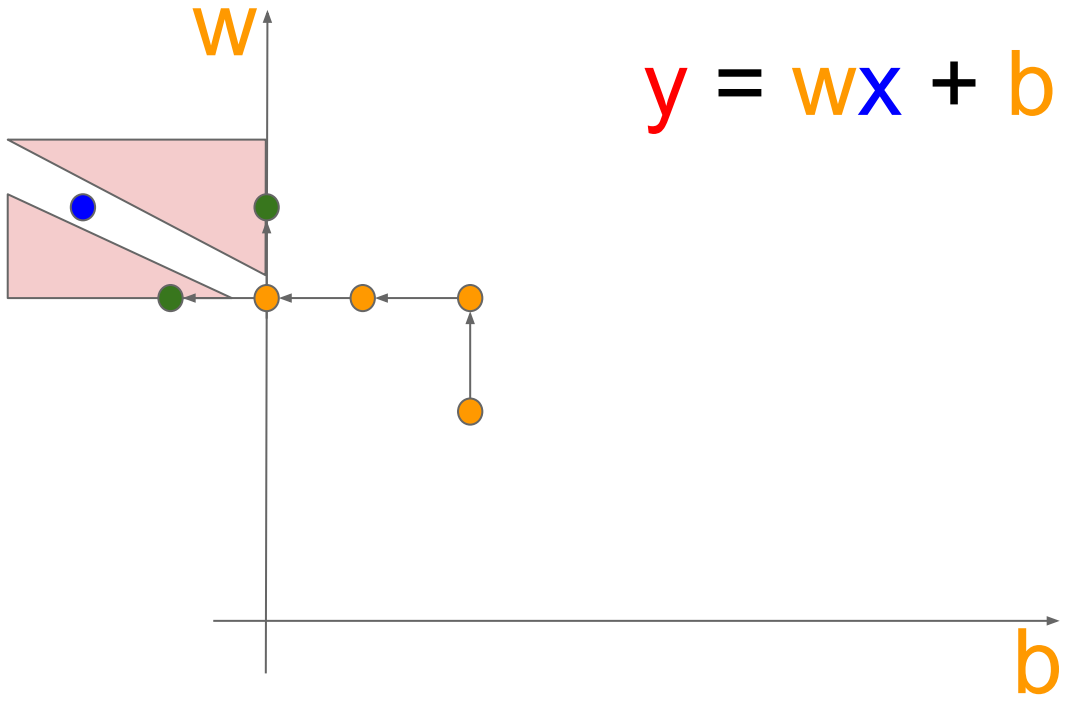
Optimizers are our friends

Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$$w_3,b_3 = 3,0 : C(w_3,b_3) = 13$$



$$y = wx + b$$

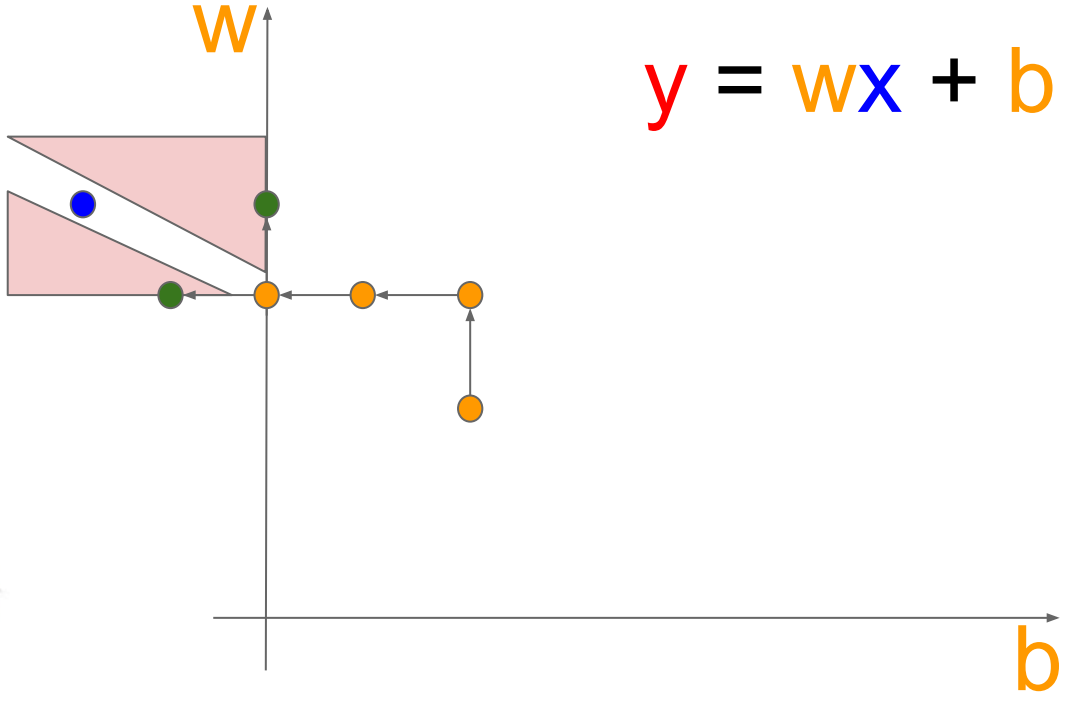
Optimizers are our friends

Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$$w_3,b_3 = 3,0 : C(w_3,b_3) = 13$$



$$y = wx + b$$

Search Problem

Optimizers are our friends

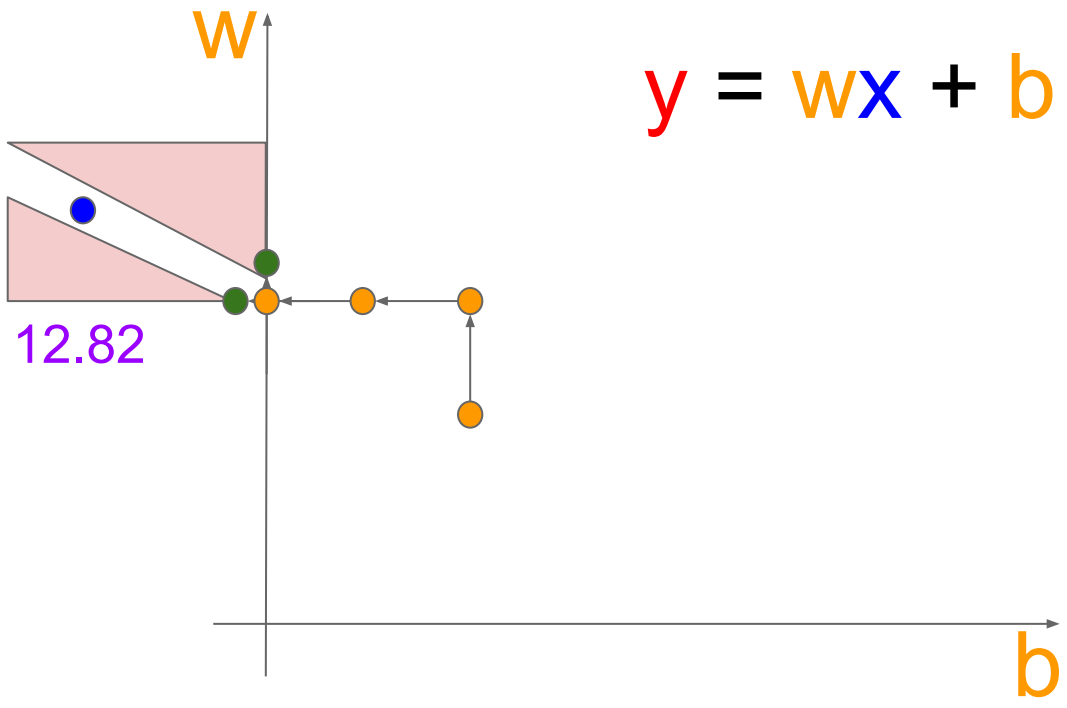
Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$w_3,b_3 = 3,0 : C(w_3,b_3) = 13$

$w_4,b_4 = 3.01,0 : C(w_4,b_4) = 12.82$



$$y = wx + b$$

n	x	y	$\hat{y}$	$(y-\hat{y})^2$
0	1	0	3.01	9.06
1	5	16	15.01	0.98
2	6	20	18.01	3.96
			C(3.01,0)	12.82

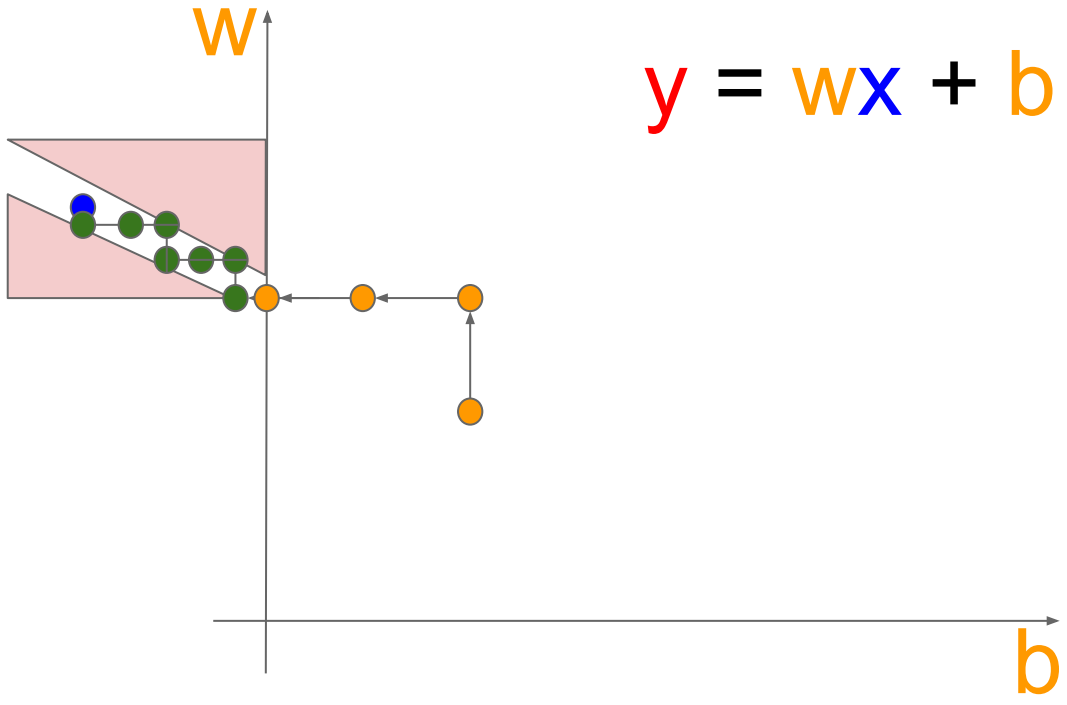
Optimizers are our friends

Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$$w^*,b^* = 4,-2 : C(w^*,b^*) = 12$$



$$y = wx + b$$

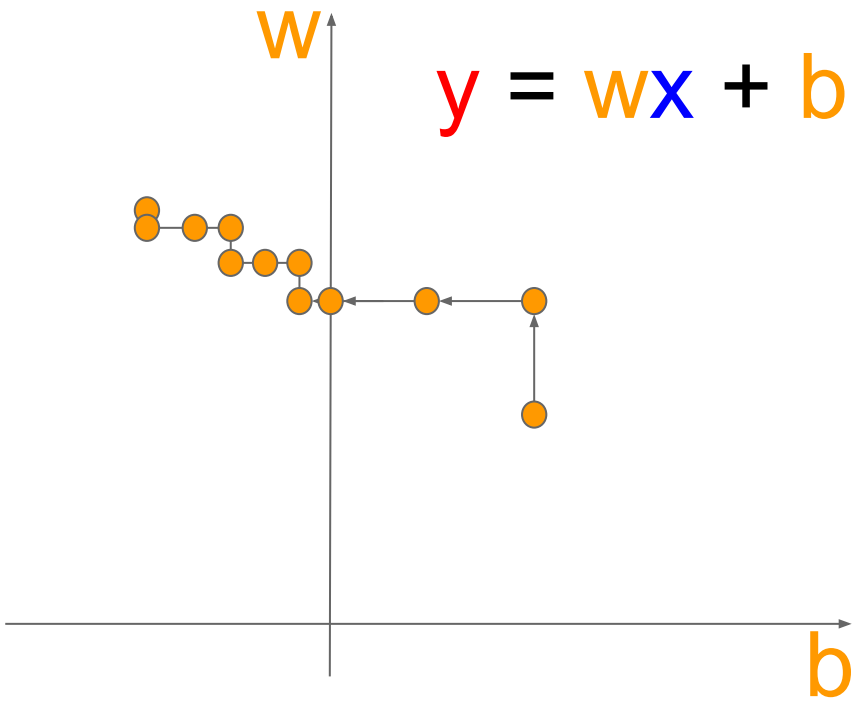
Optimizers are our friends

Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$$w^*,b^* = 4,-2 : C(w^*,b^*) = 12$$



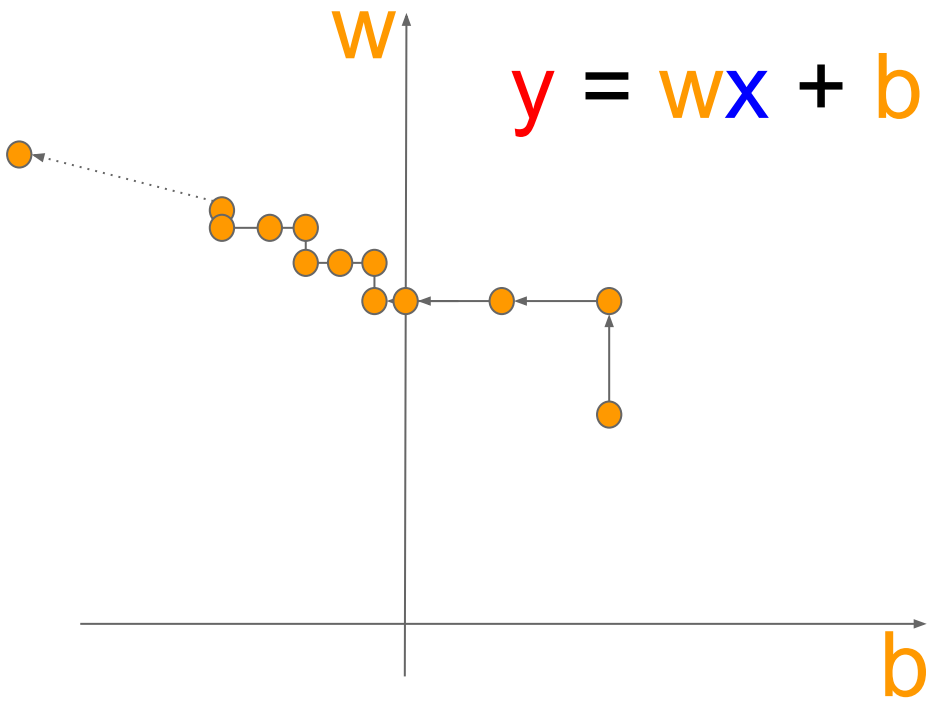
Optimizers are our friends

Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$$w^*,b^* = 4,-4 : C(w^*,b^*) = 0$$

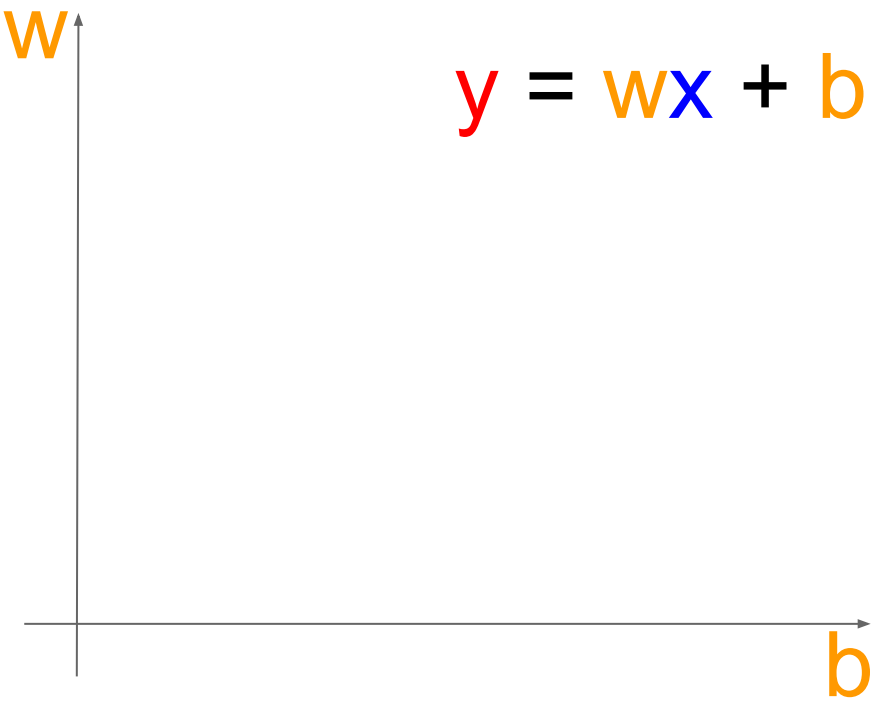


Gradients are our friends

Optimizer

$$\arg\min_{w,b \in [-\infty,\infty]} C(w,b)$$

Should be used sparingly



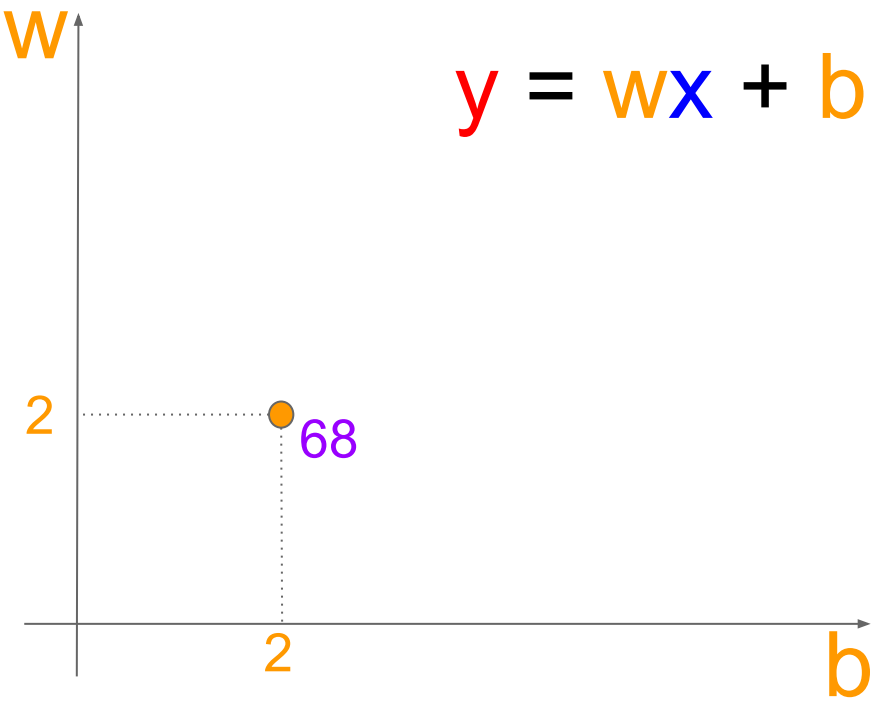
$$y = wx + b$$

Gradients are our friends

Optimizer

$$\arg\min_{w,b \in [-\infty,\infty]} C(w,b)$$

$w_0, b_0 = 2,2 : C(w_0,b_0) = 68$



$y = wx + b$

Gradients are our friends

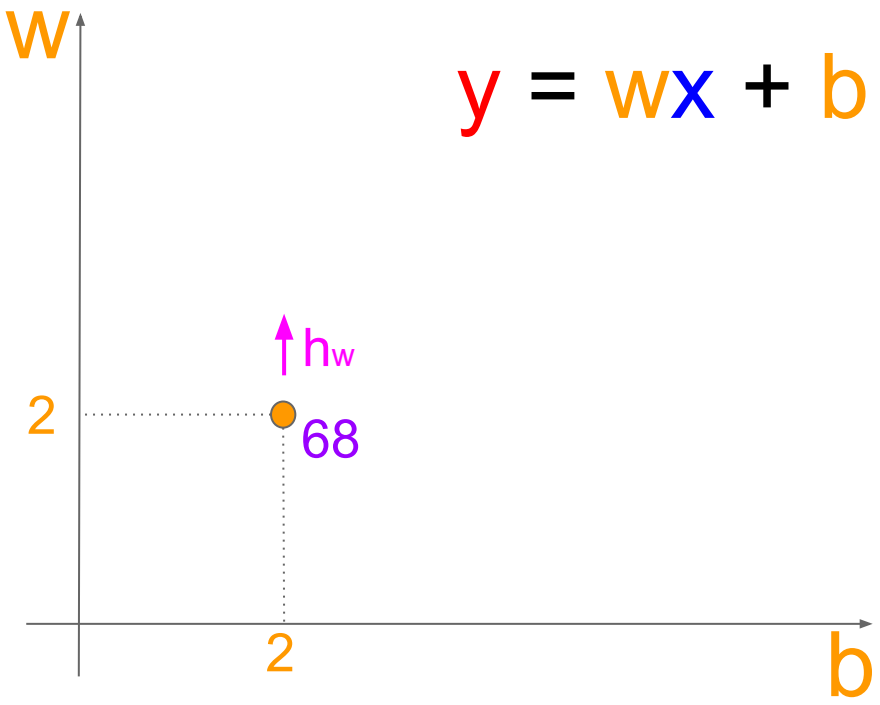
Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$w_0,b_0 = 2,2 : C(w_0,b_0) = 68$

$h_w = 1$



Gradients are our friends

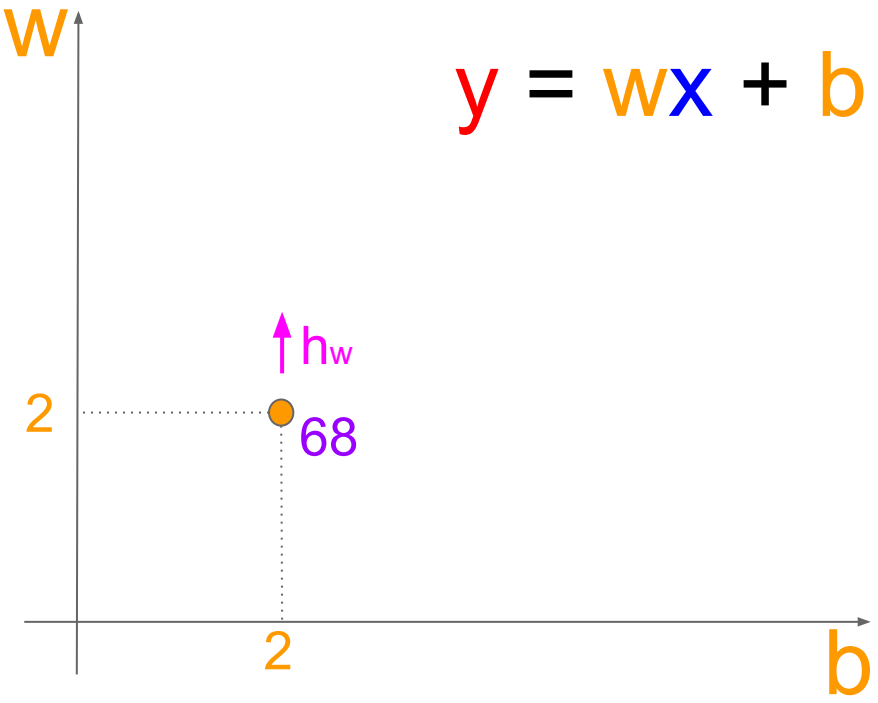
Optimizer

$$\arg\min_{w,b \in [-\infty,\infty]} C(w,b)$$

$w_0, b_0 = 2,2 : C(w_0,b_0) = 68$

$h_w = 1$

$C(w_0+h_w, b_0) = C(3,2) = 26$



$y = wx + b$

Gradients are our friends

Optimizer

$$\arg\min_{w,b \in [-\infty,\infty]} C(w,b)$$

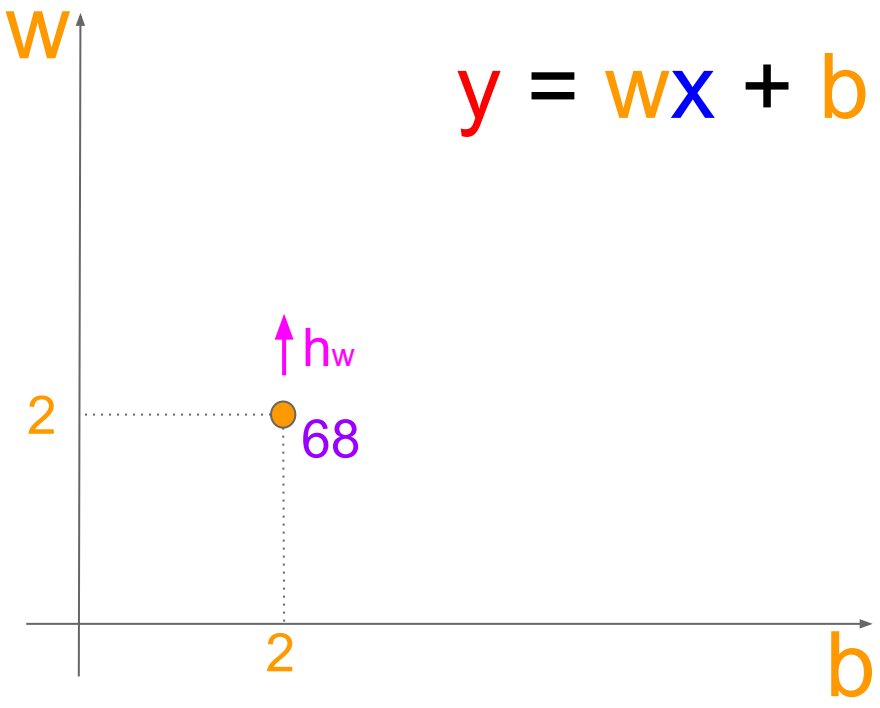
$w_0, b_0 = 2,2 : C(w_0,b_0) = 68$

$h_w = 1$

$C(w_0+h_w,b_0) = C(3,2) = 26$

$$r_w = \frac{(C(w_0+1,b_0)-C(w_0,b_0))}{1}$$

$$r_w = \frac{(C(3,2)-C(2,2))}{1} = -42$$



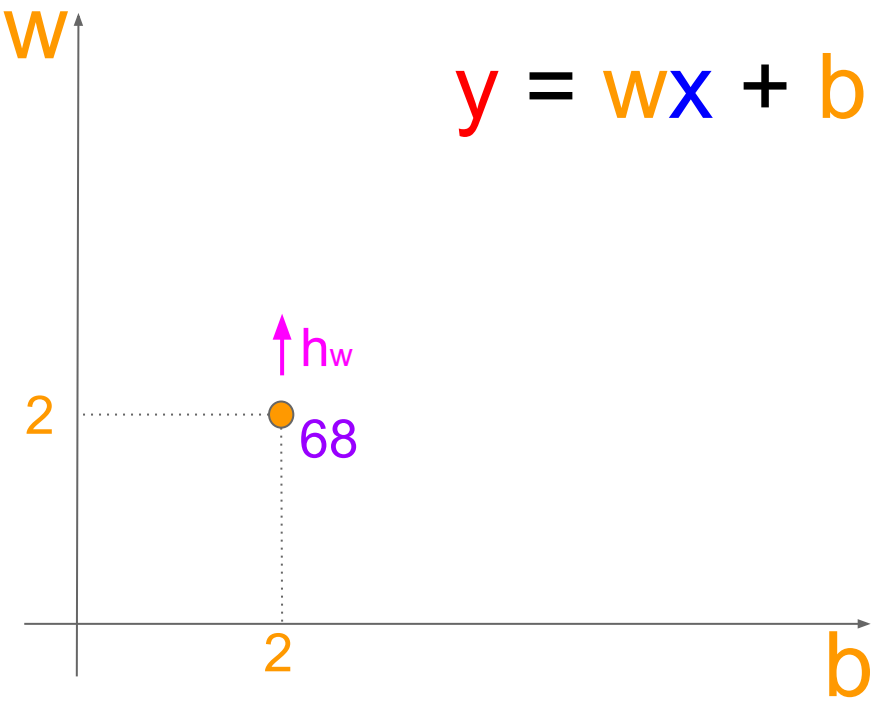
Gradients are our friends

Optimizer

$$\arg\min_{w,b \in [-\infty,\infty]} C(w,b)$$

$w_0, b_0 = 2,2 : C(w_0,b_0) = 68$

$h_w = 1$, r = -42
$h_w = 0.1$, r = -98
$h_w = 0.01$, r = -104
$h_w = 0.001$, r = -104



Gradients are our friends

Optimizer

$$\arg\min_{w,b \in [-\infty,\infty]} C(w,b)$$

$w_0, b_0 = 2,2 : C(w_0,b_0) = 68$

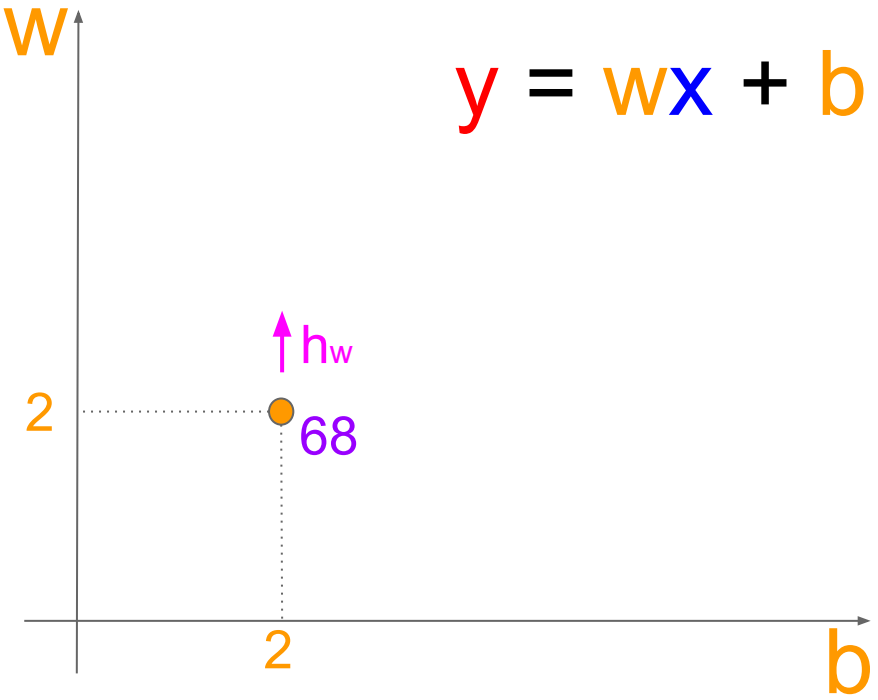
$h_w = 1$, r = -42

$h_w = 0.1$, r = -98

$h_w = 0.01$, r = -104

$h_w = 0.001$, r = -104

$h_w \to 0$, $r = \frac{\partial C}{\partial w}(w_0,b_0)$



$$D_{\mathbf{u}} f(\mathbf{a}) = \lim_{h \to 0} \frac{f(\mathbf{a}+h\mathbf{u}) - \mathbf{f}(\mathbf{a})}{h}$$

Gradients are our friends

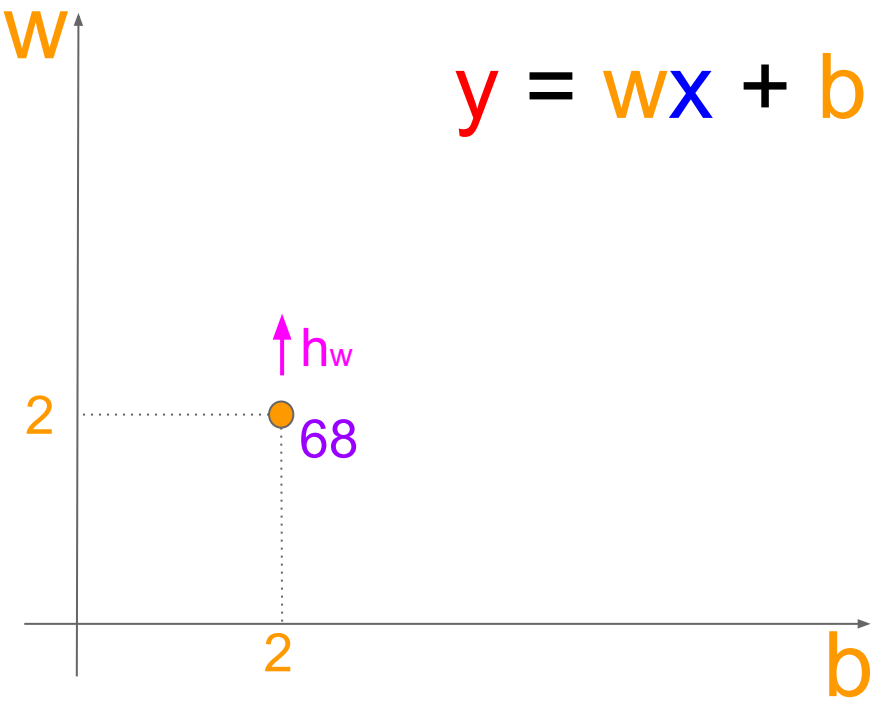
Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$$w_0,b_0 = 2,2 : C(w_0,b_0) = 68$$

$$\frac{\partial C}{\partial w} = \frac{\partial \sum_n (\hat{y}_n - y_n)^2}{\partial w}$$



Gradients are our friends

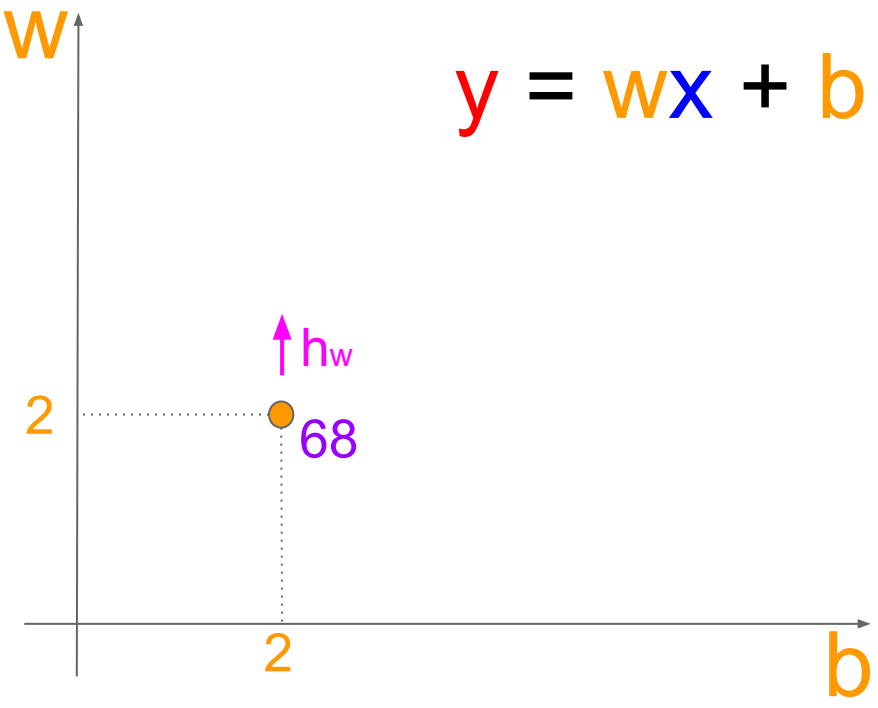
Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$$w_0,b_0 = 2,2 : C(w_0,b_0) = 68$$

$$\frac{\partial C}{\partial w} = \frac{\partial \sum_n (\hat{y}_n - y_n)^2}{\partial w} = \sum_n -2(\hat{y}_n - y_n)x_n$$



Gradients are our friends

Optimizer

$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$$w_0,b_0 = 2,2 : C(w_0,b_0) = 68$$

$$\frac{\partial C}{\partial w} = \frac{\partial \sum_n (\hat{y}_n - y_n)^2}{\partial w} = \sum_n -2(\hat{y}_n - y_n)x_n$$

$$h_w \rightarrow 0,\ r_w = \frac{\partial C}{\partial w}(w_0,b_0) = -104$$

n	x	y	ŷ	(ŷ-y)	-2(ŷ-y)x
0	1	0	4	4	8
1	5	16	12	-4	-40
2	6	20	14	-6	-72

Gradients are our friends

Optimizer

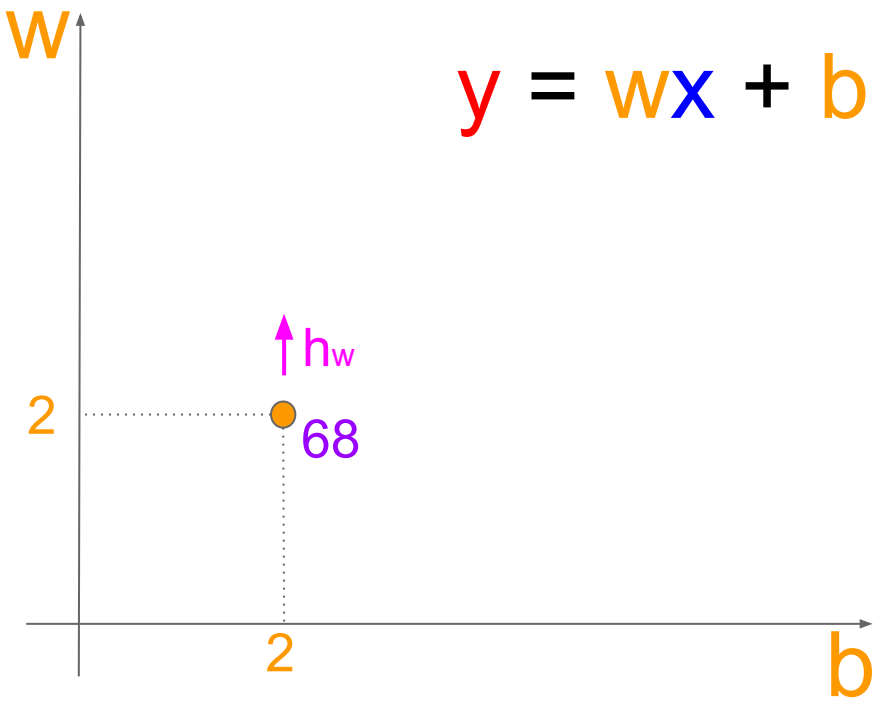
$$\arg\min_{w,b} C(w,b)$$

$$w,b \in [-\infty,\infty]$$

$$w_0,b_0 = 2,2 : C(w_0,b_0) = 68$$

$$\frac{\partial C}{\partial w} = \frac{\partial \sum_n (\hat{y}_n - y_n)^2}{\partial w} = \sum_n -2(\hat{y}_n - y_n)x_n$$

$$\frac{\partial C}{\partial b} = \frac{\partial \sum_n (\hat{y}_n - y_n)^2}{\partial b} = \sum_n -2(\hat{y}_n - y_n)$$



Gradients are our friends

Optimizer

$$\arg\min_{w,b \in [-\infty,\infty]} C(w,b)$$

$w_0, b_0 = 2,2 : C(w_0,b_0) = 68$

$h_w \to 0,\ r_w = \frac{\partial C}{\partial w}(w_0,b_0) = -104$

$h_b \to 0,\ r_b = \frac{\partial C}{\partial w}(w_0,b_0) = -12$

n	x	y	ŷ	(ŷ-y)	-2(ŷ-y)
0	1	0	4	4	8
1	5	16	12	-4	-8
2	6	20	14	-6	-12

Gradients are our friends

Optimizer

$$\arg\min_{w,b \in [-\infty,\infty]} C(w,b)$$

$w_0, b_0 = 2,2 : C(w_0,b_0) = 68$

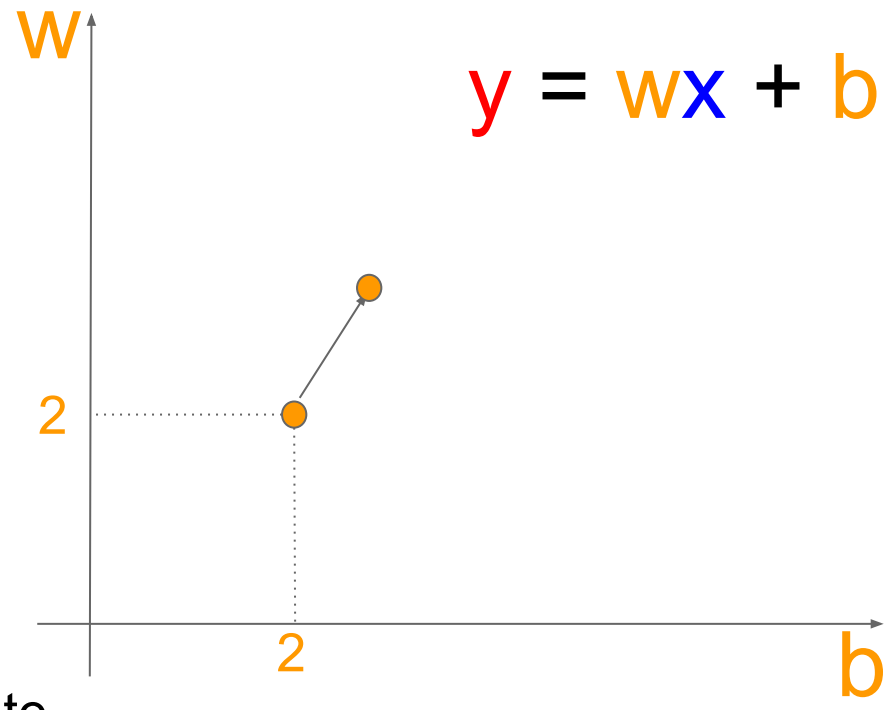
$h_w \to 0,\ r_w = \frac{\partial C}{\partial w}(w_0,b_0) = -104$

$h_b \to 0,\ r_b = \frac{\partial C}{\partial w}(w_0,b_0) = -12$

$w_1 = w_0 - r_w \alpha$

$b_1 = b_0 - r_b \alpha$

$\alpha \to$ Learning Rate

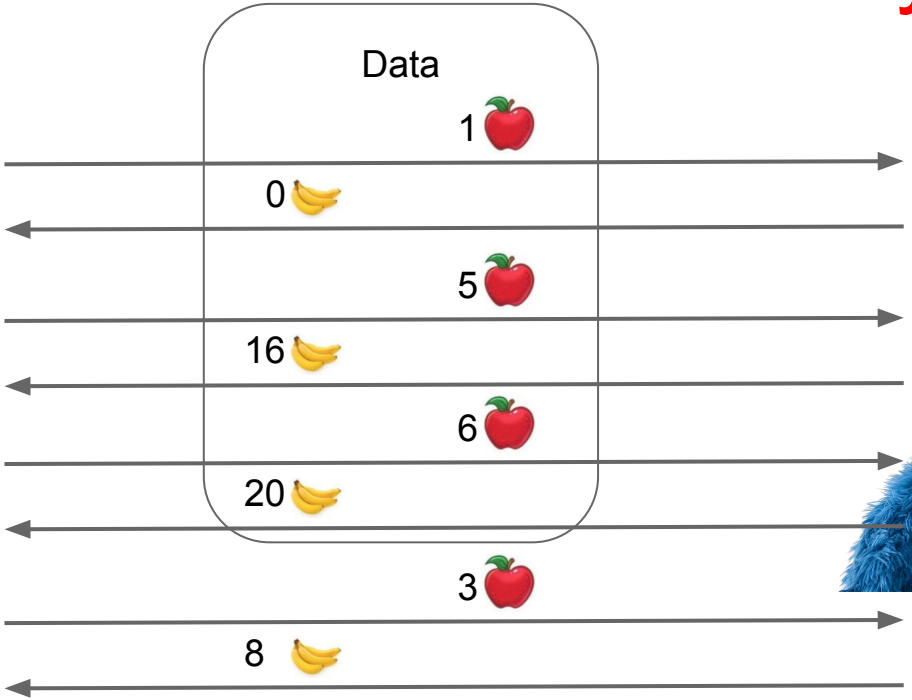


Gradients are our friends

$y = 4x-4$

Gradients are our friends

$y = 4x-4$

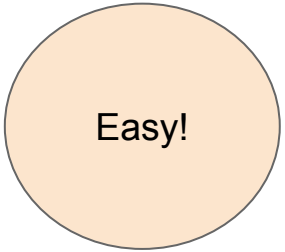


Computation Graphs are our friends

$$C(w,b) = \sum_{n \in \{0,1,2\}} (y_n - \hat{y}_n)^2 \qquad y = wx + b$$

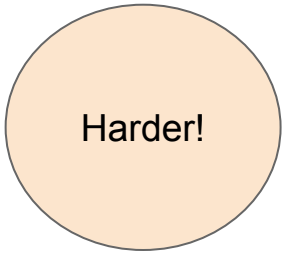
$$\frac{\partial C}{\partial w} = \frac{\partial \sum_n (\hat{y}_n - y_n)^2}{\partial w} = \sum_n -2(\hat{y}_n - y_n)x_n$$

$$\frac{\partial C}{\partial b} = \frac{\partial \sum_n (\hat{y}_n - y_n)^2}{\partial b} = \sum_n -2(\hat{y}_n - y_n)$$



Computation Graphs are our friends

$$y = wx + b + \tanh(yx + b)^2$$



Computation Graphs are our friends

$$y = wx + b + \tanh(yx + b)^2$$

Computation Graphs can compute gradients for you!

Computation Graphs are our friends

$$C(w,b) = \sum_{n \in \{0,1,2\}} (y_n - \hat{y}_n)^2 \qquad y = wx + b$$

$$\frac{\partial C}{\partial w} = \frac{\partial \sum_n (\hat{y}_n - y_n)^2}{\partial w} = \sum_n -2(\hat{y}_n - y_n)x_n$$

$$\frac{\partial C}{\partial b} = \frac{\partial \sum_n (\hat{y}_n - y_n)^2}{\partial b} = \sum_n -2(\hat{y}_n - y_n)$$

Computation Graphs are our friends

$$C(w,b) = \sum_{n \in \{0,1,2\}} (y_n - \hat{y}_n)^2 \qquad y = wx + b$$

$$\frac{\partial C}{\partial w} = \sum_n \frac{\partial (\hat{y}_n - y_n)^2}{\partial y_n} \frac{\partial y_n}{\partial w} = \sum_n -2(\hat{y}_n - y_n) x_n$$

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Computation Graphs are our friends

$$C(w,b) = \sum_{n \in \{0,1,2\}} (y_n - \hat{y}_n)^2$$

$$y = o + b$$

$$o = wx$$

$$\frac{\partial C}{\partial w} = \sum_n \frac{\partial (\hat{y}_n - y_n)^2}{\partial y_n} \frac{\partial y_n}{\partial w}$$

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$$c = d^2$$

$$d = y - \hat{y}$$

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Power 2

$$d = y - \hat{y}$$

Sub

$$y = o + b$$

Add

$$o = wx$$

Product

Sub

Computation Graphs are our friends

$$C(w,b) = \sum_{n \in \{0,1,2\}} c_n$$

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Power 2

$$d = y - \hat{y}$$

Sub

$$y = o + b$$

Add

$$o = wx$$

Product

Sub

forward(x,y) → z
backward(x,y,dz) → dx,dy

Computation Graphs are our friends

$$C(w,b) = \sum_{n \in \{0,1,2\}} c_n$$

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$$c = d^2$$

Power 2

$$d = y - \hat{y}$$

Sub

$$y = o + b$$

Add

$$o = wx$$

Product

Sub

forward(x,y) : return x - y
backward(x,y,dz) : return dz, -dz

Computation Graphs are our friends

$$C(w,b) = \sum_{n \in \{0,1,2\}} c_n$$

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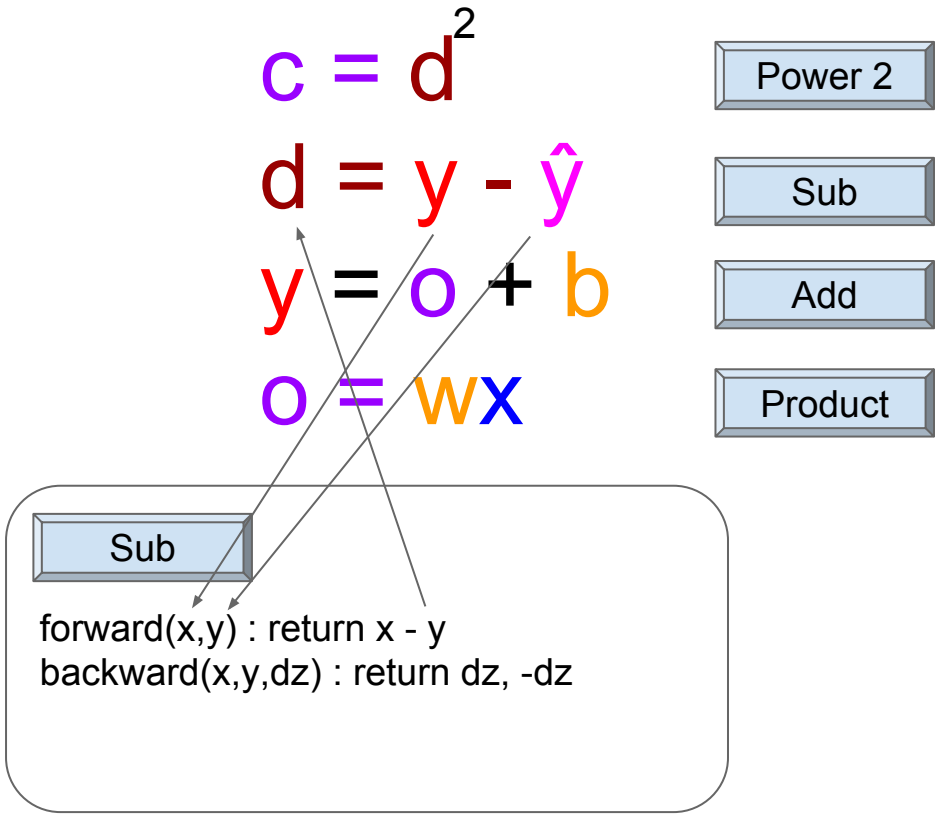

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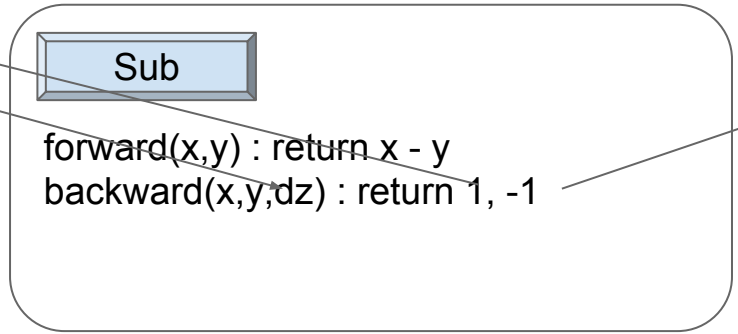

$$\frac{\partial d_n}{\partial \hat{y}_n}$$

Computation Graphs are our friends

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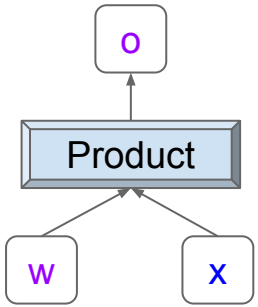

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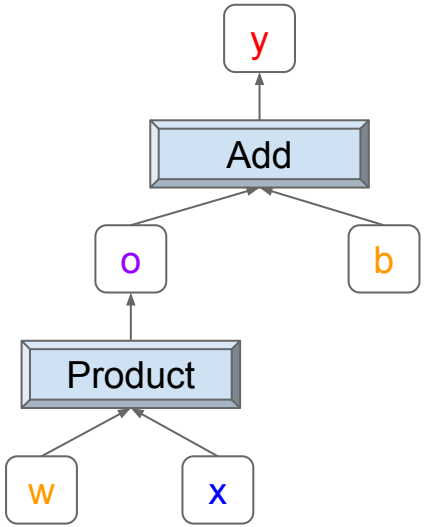

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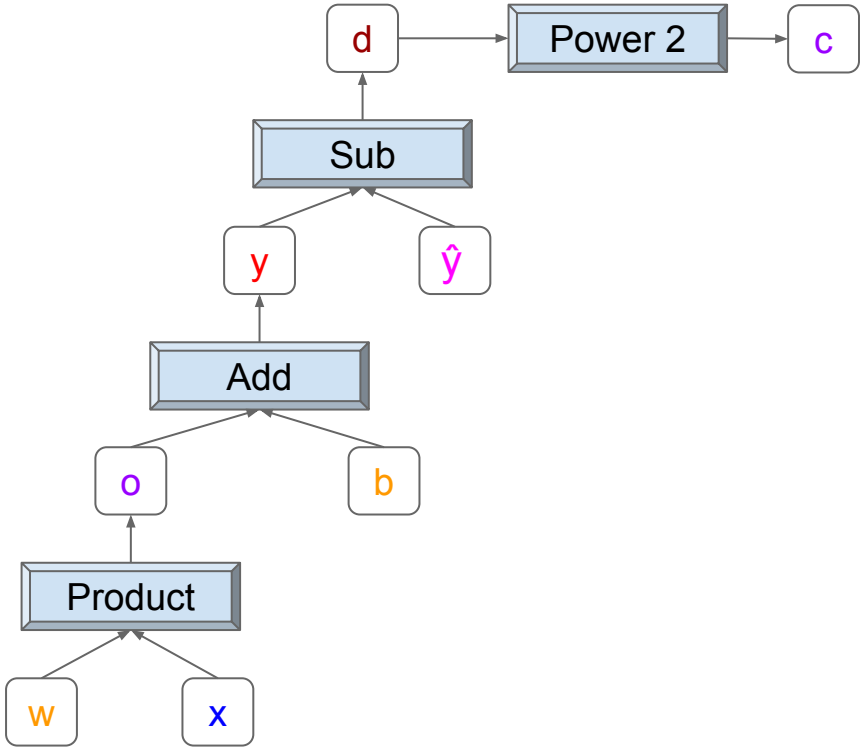

Computation Graphs are our friends

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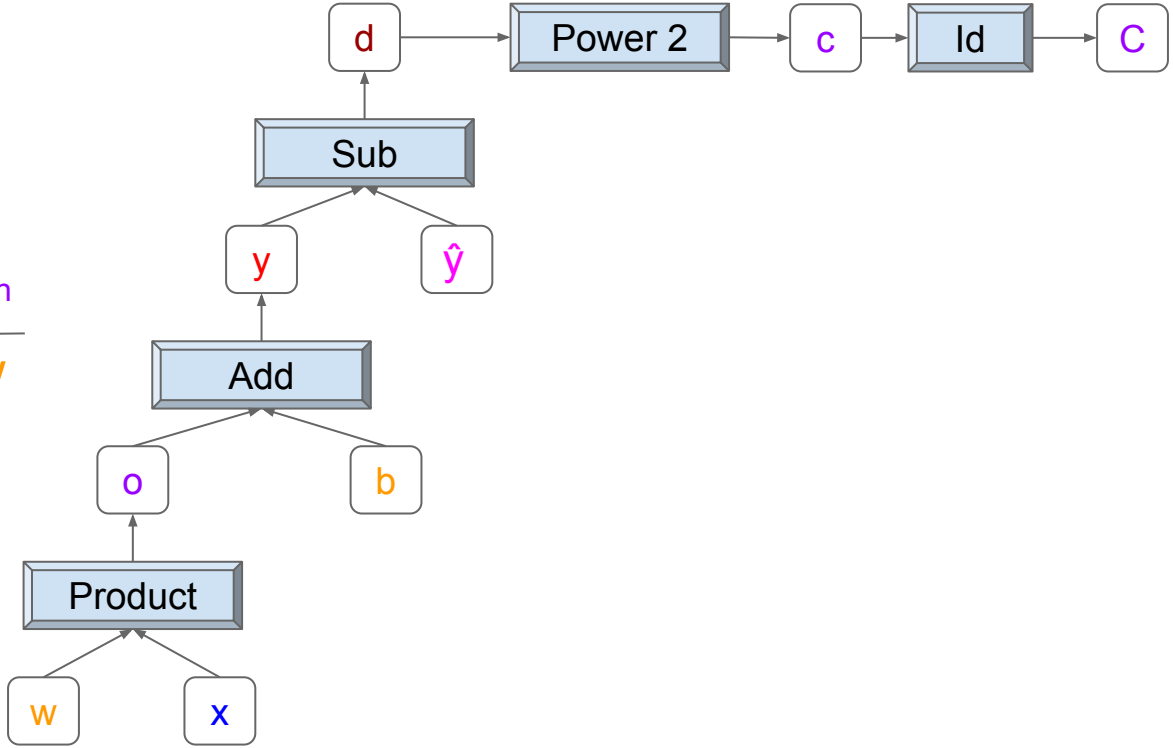

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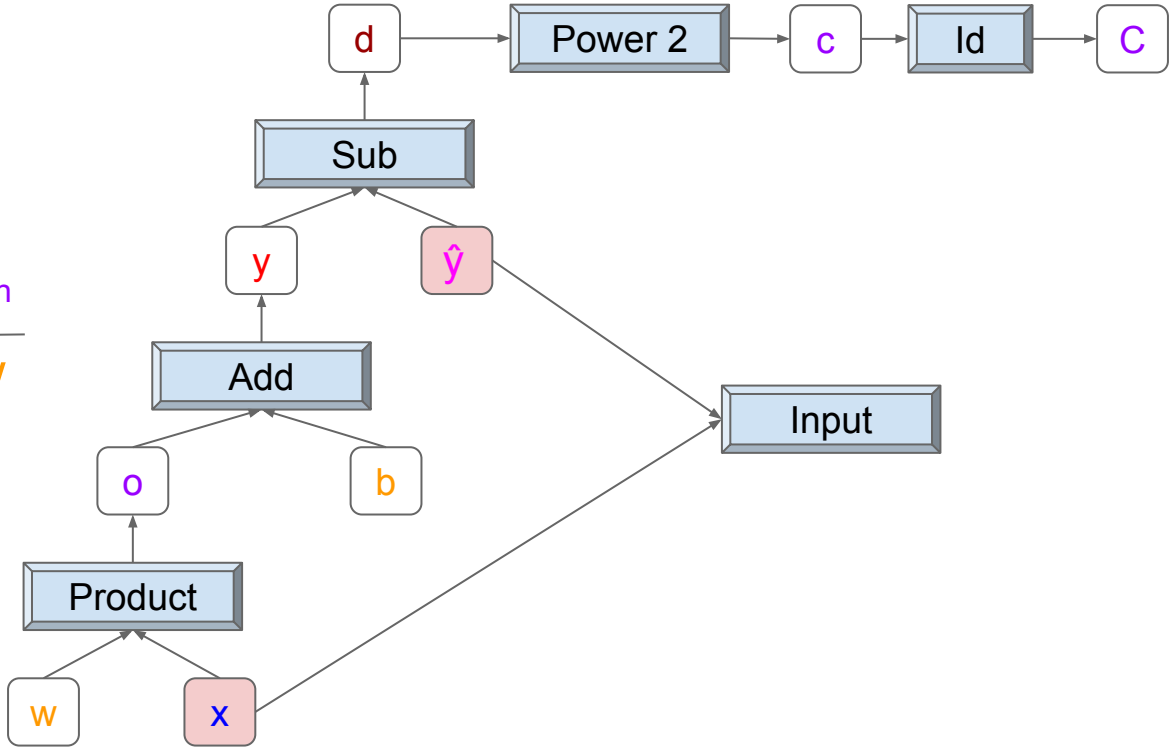

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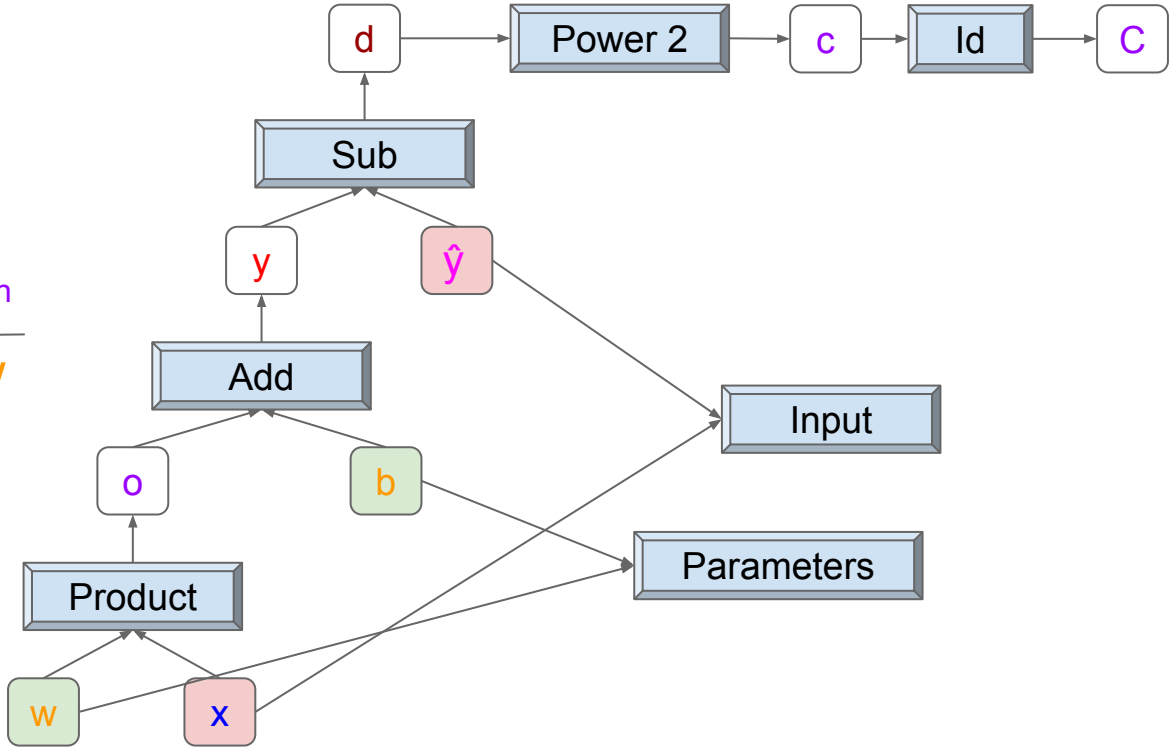
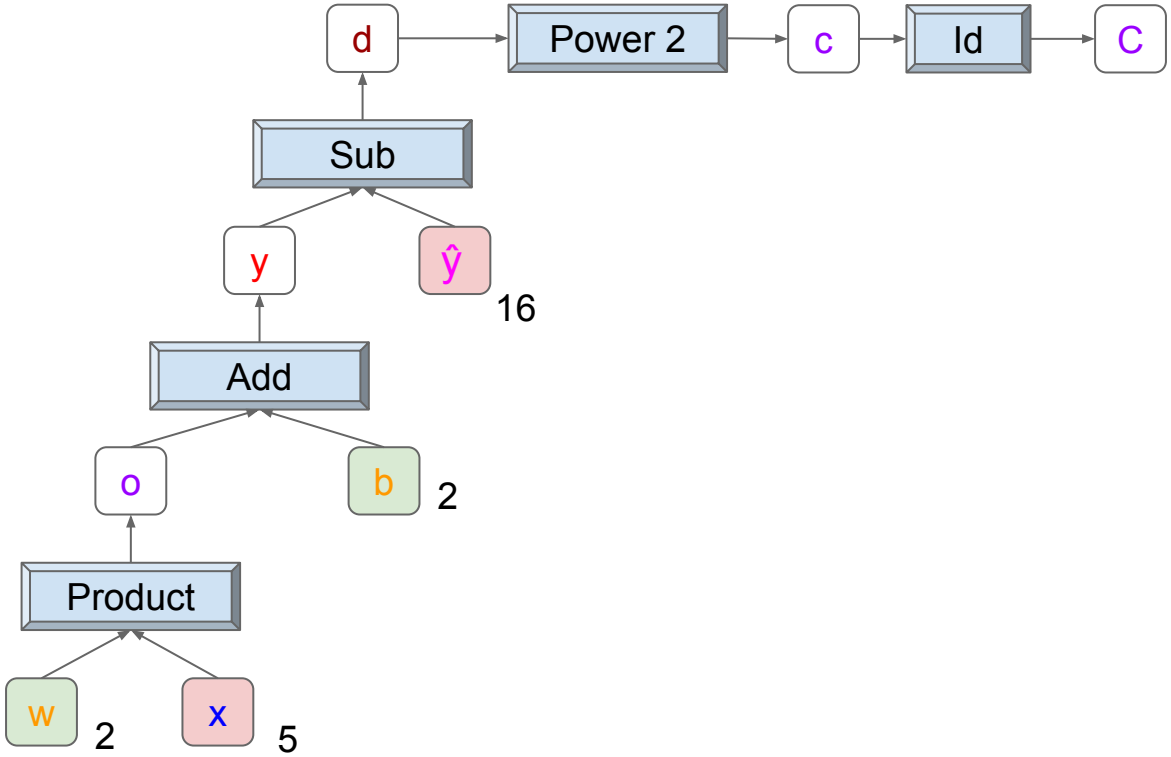


Computation Graphs are our friends

Forward:

1-Initialize inputs

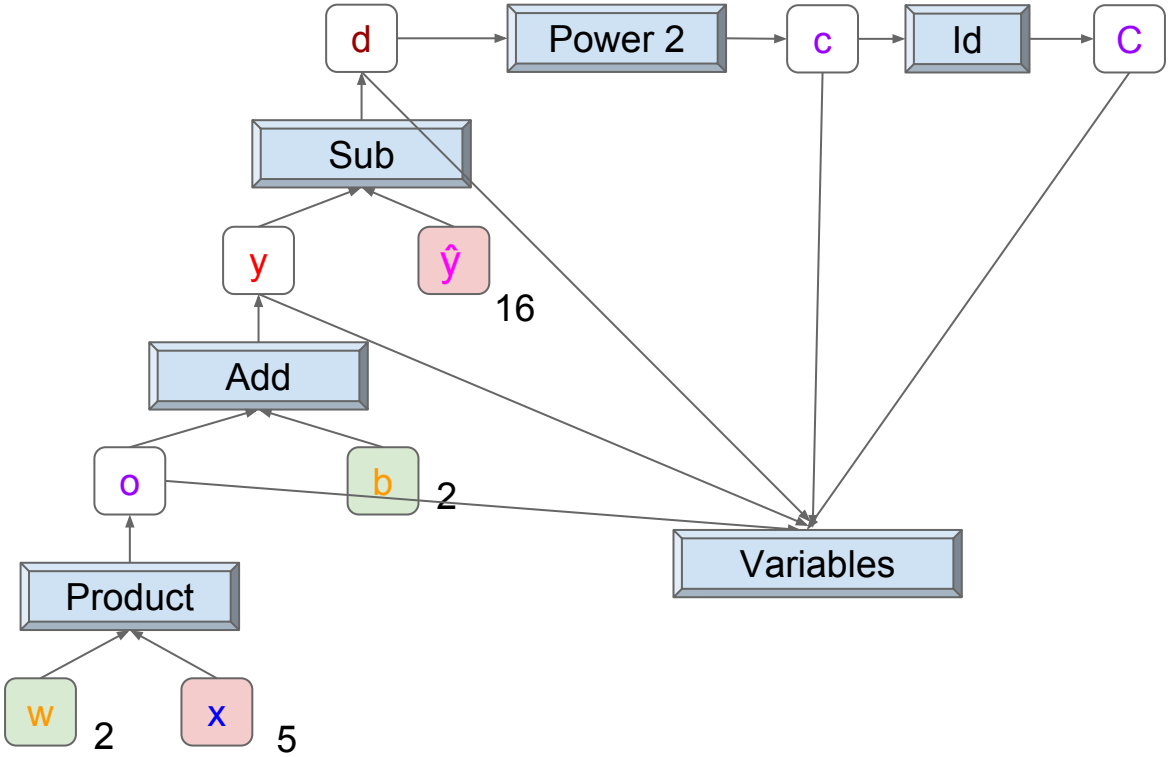


Computation Graphs are our friends

Forward:

1-Initialize inputs

2-Initialize variables



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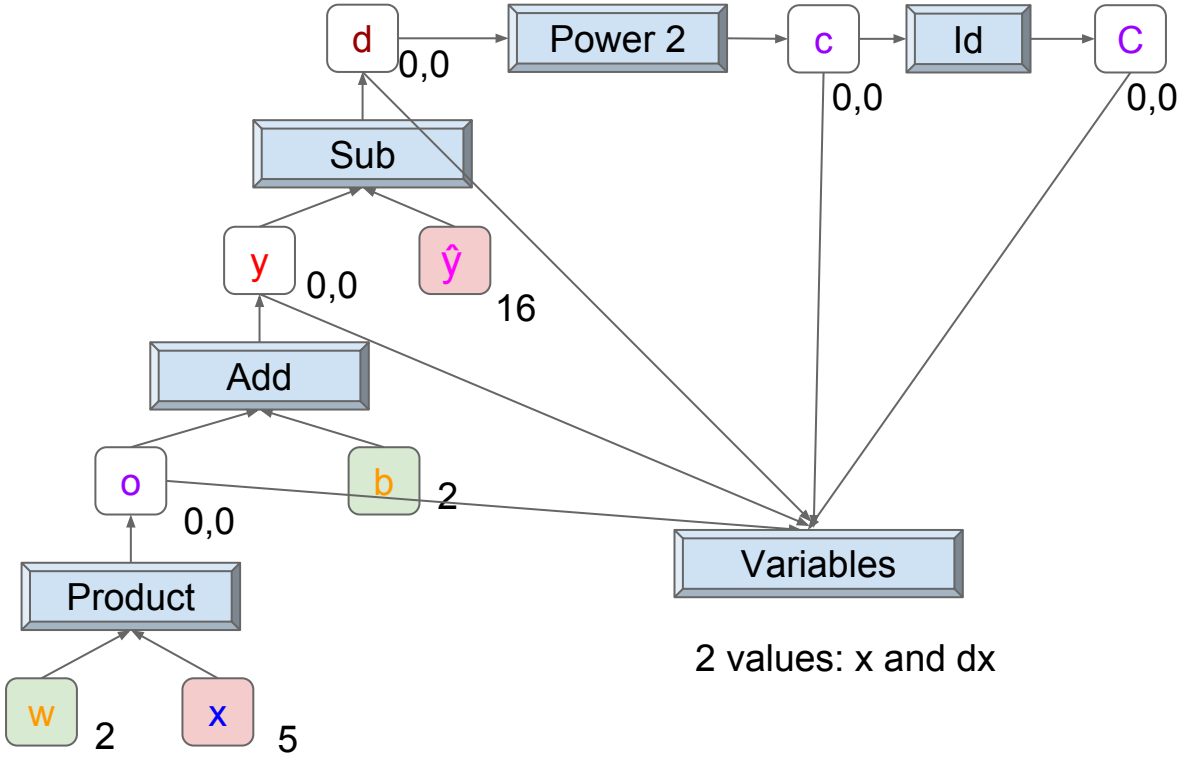

Computation Graphs are our friends

Forward:

1-Initialize inputs
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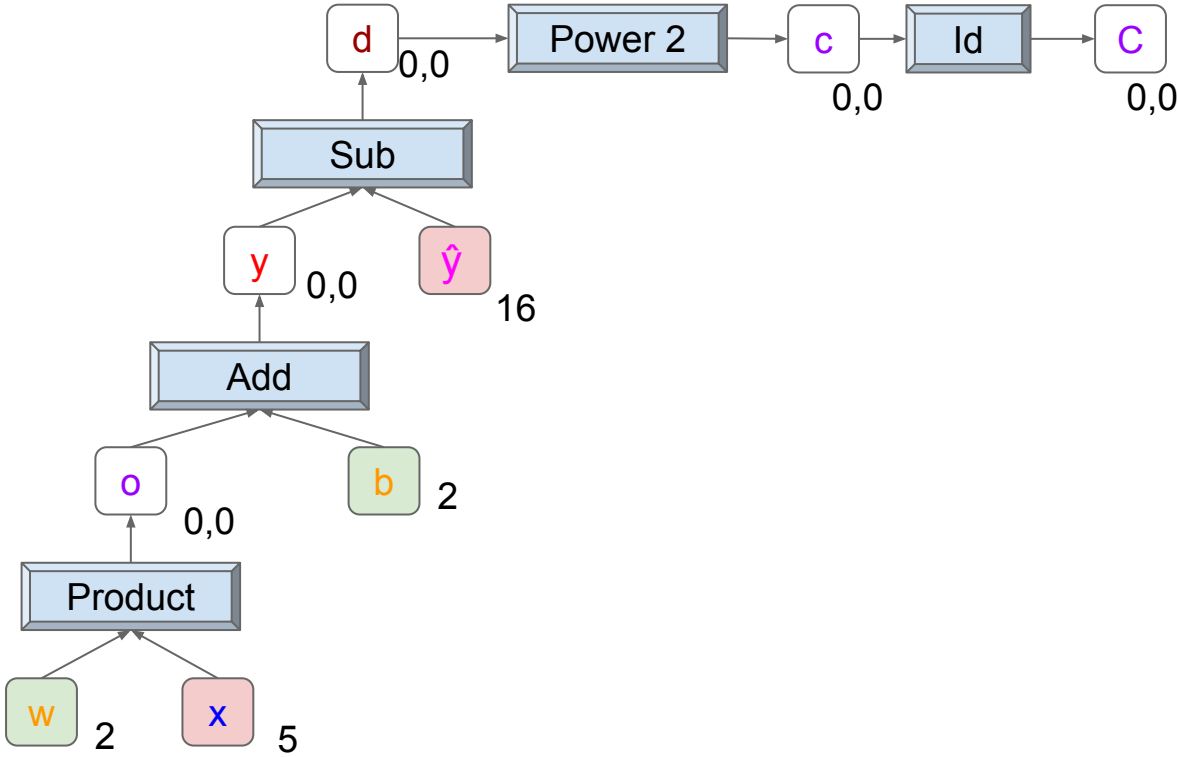

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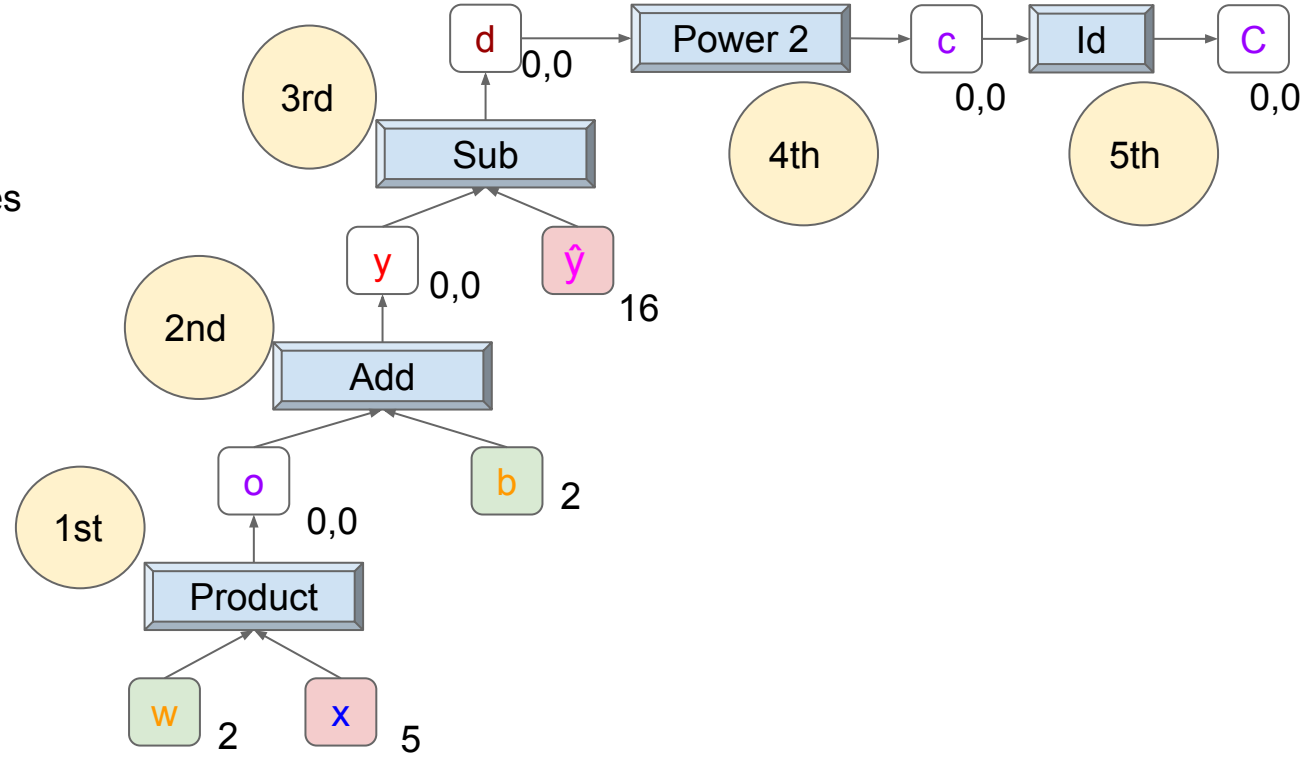

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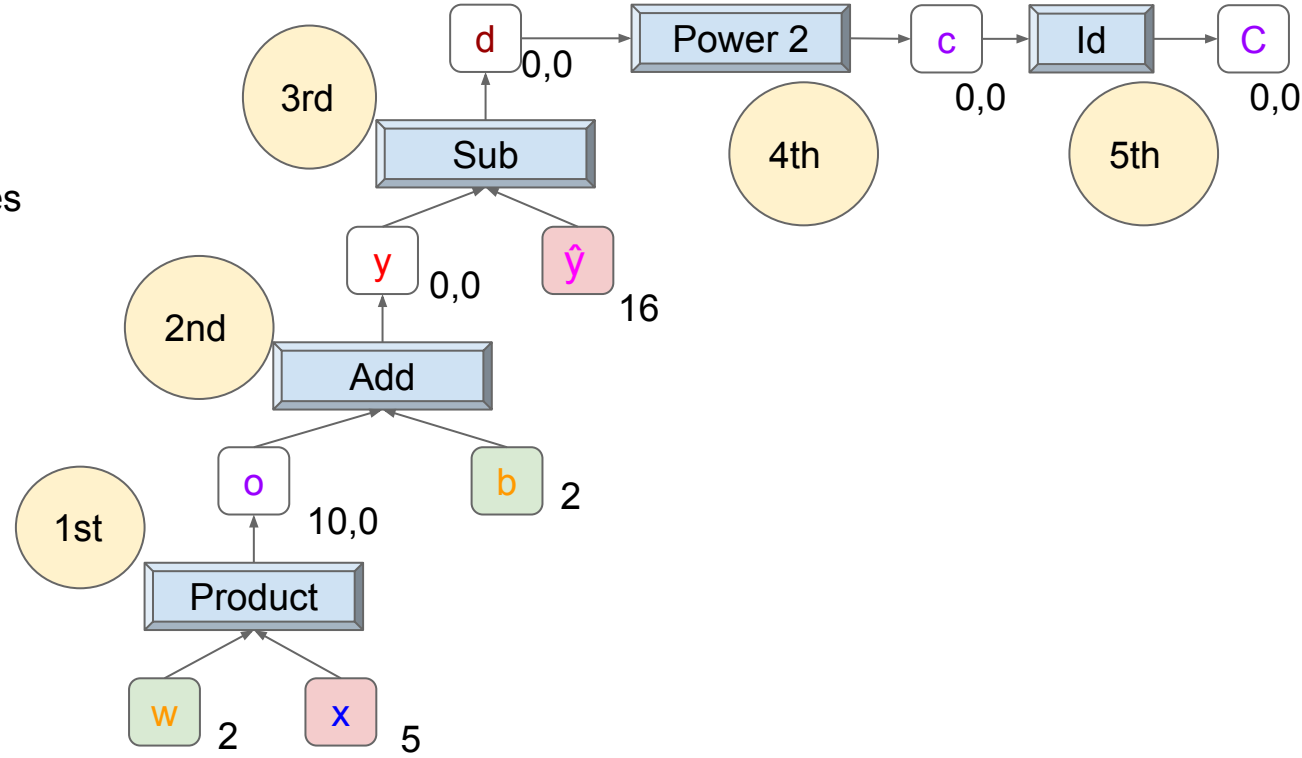

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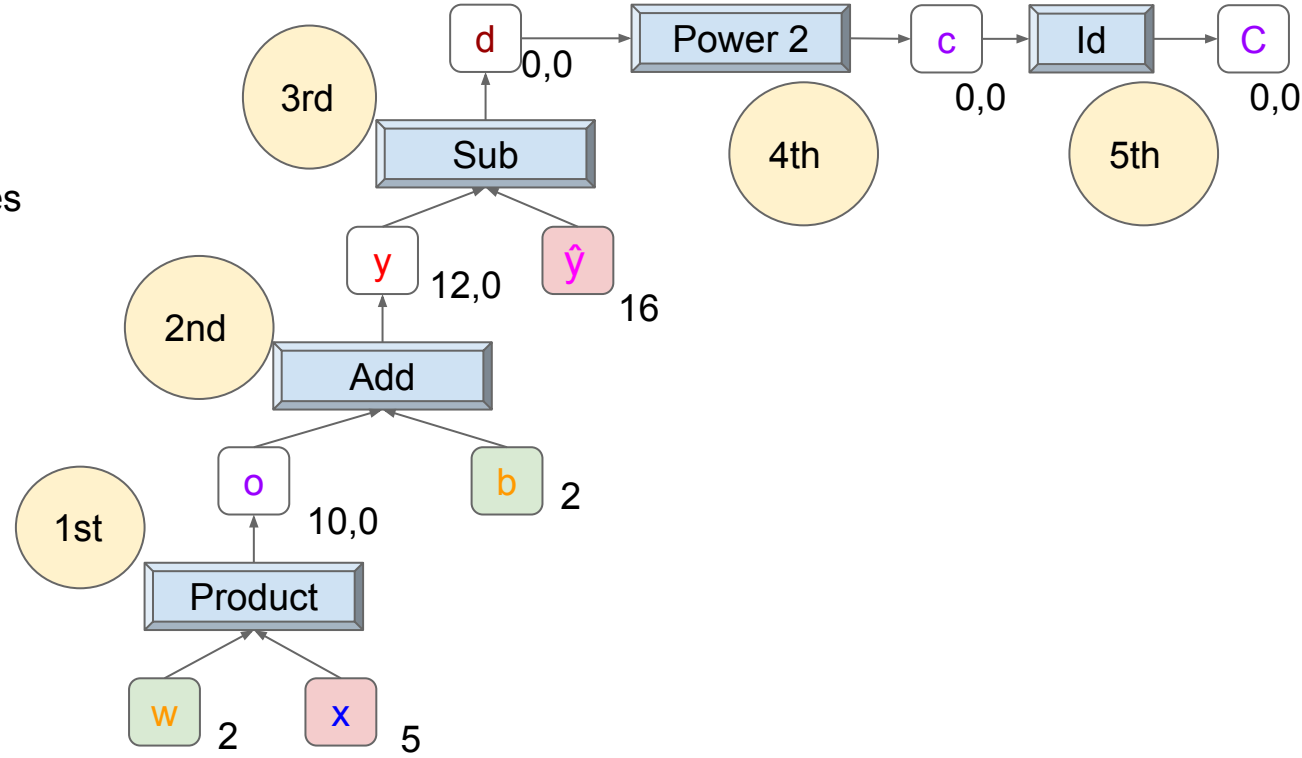

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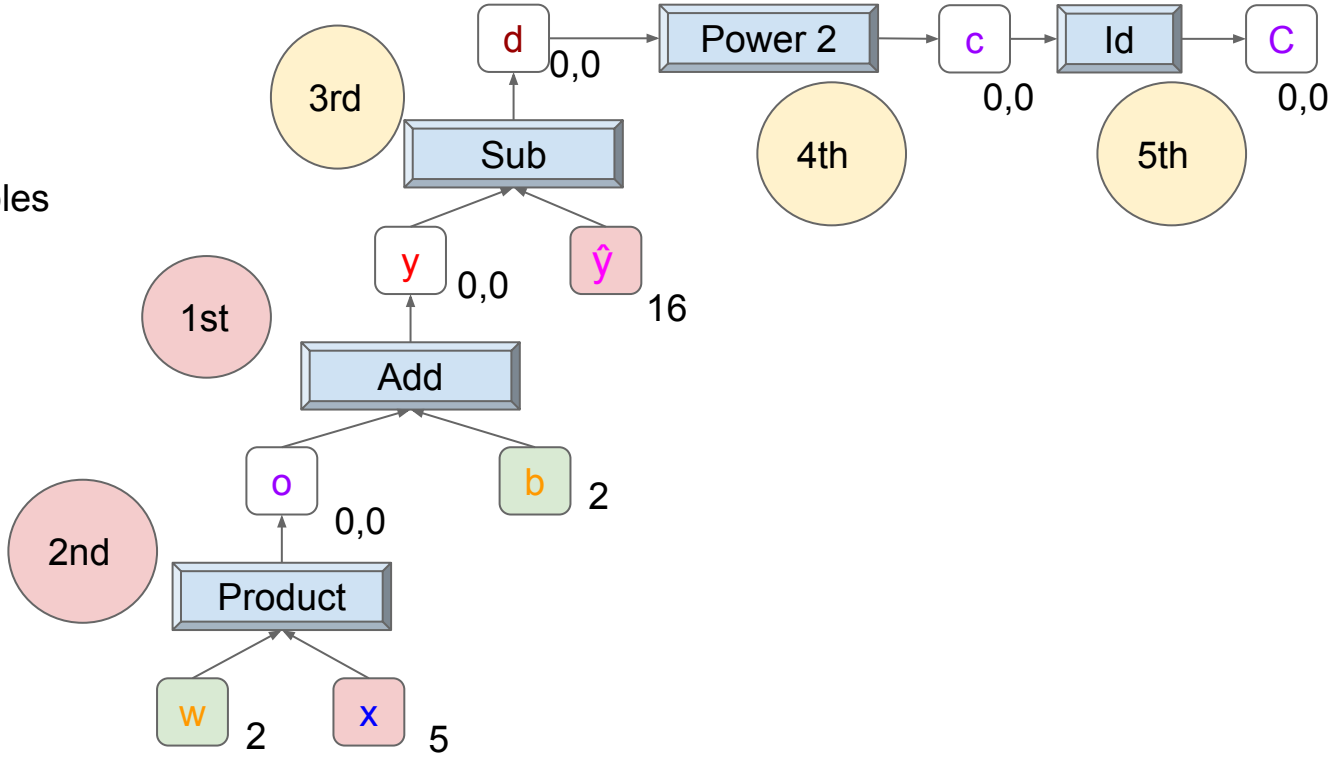

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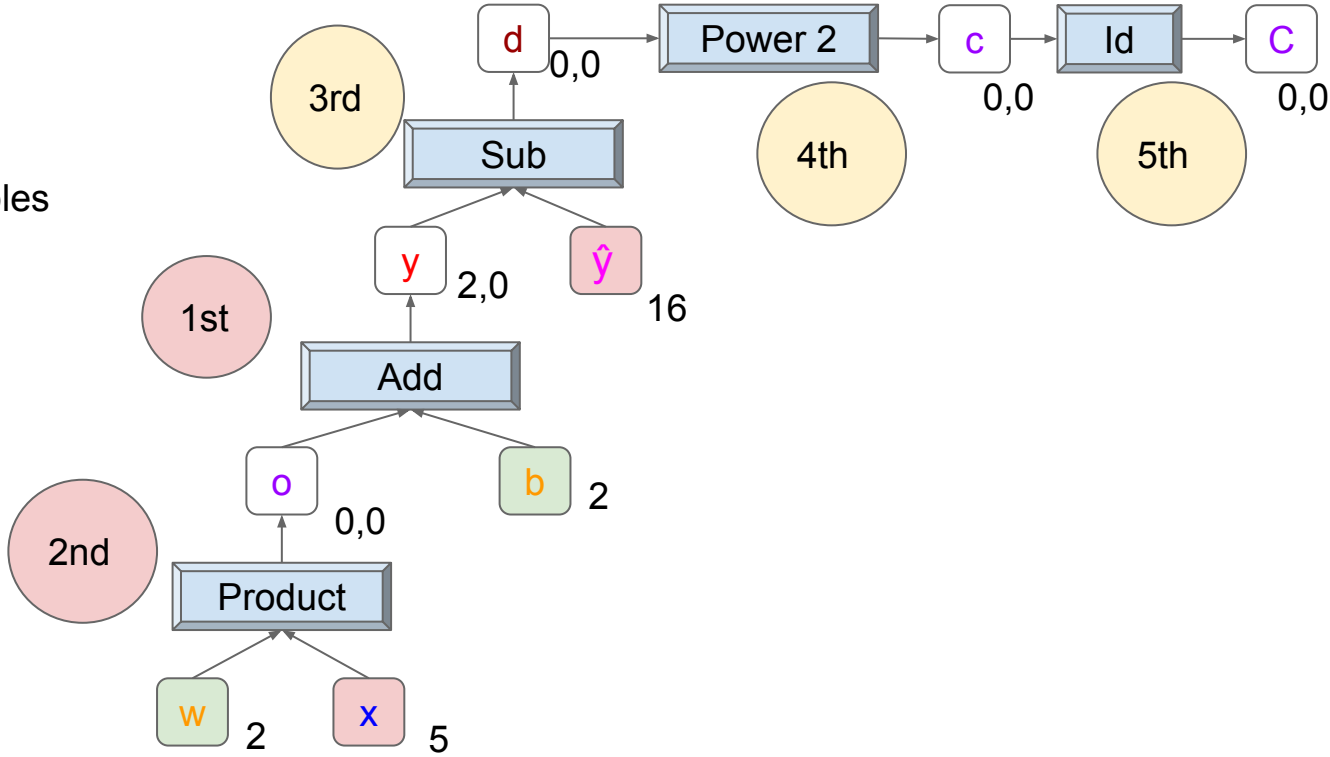

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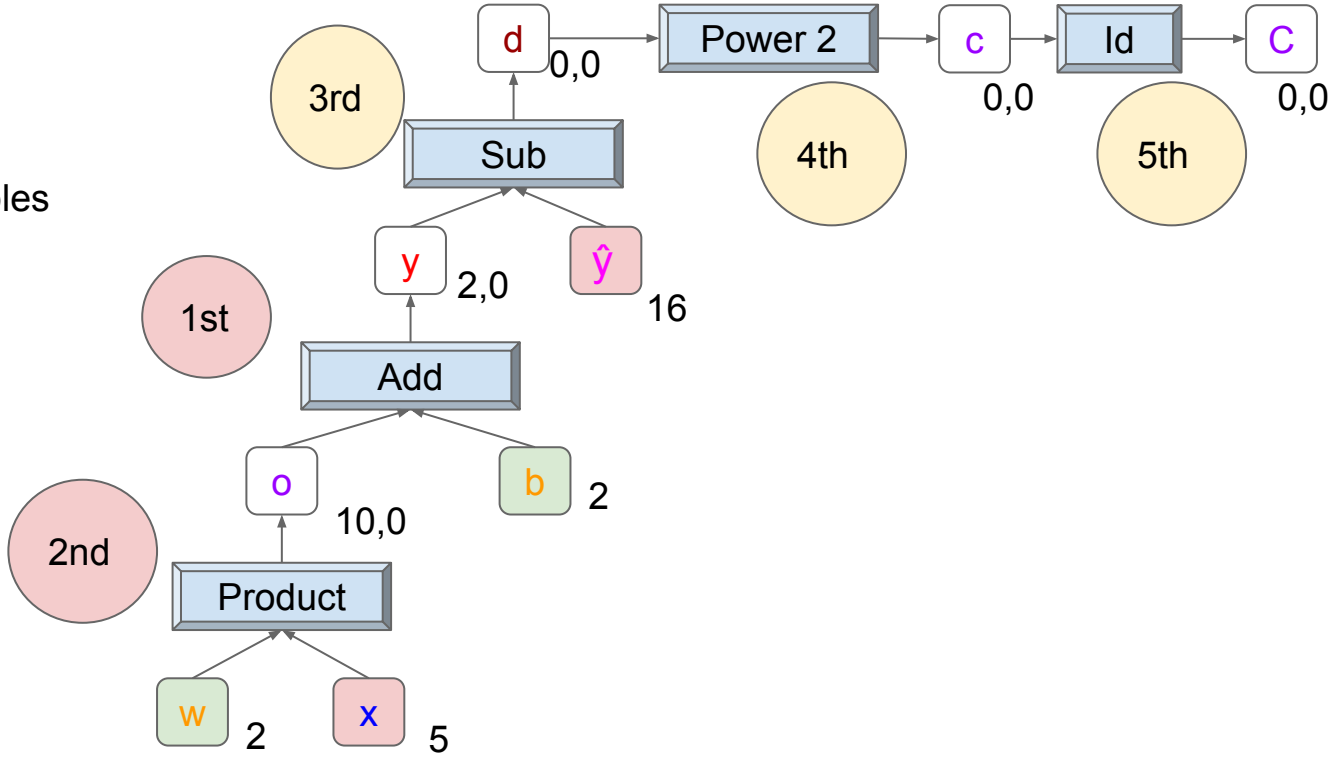

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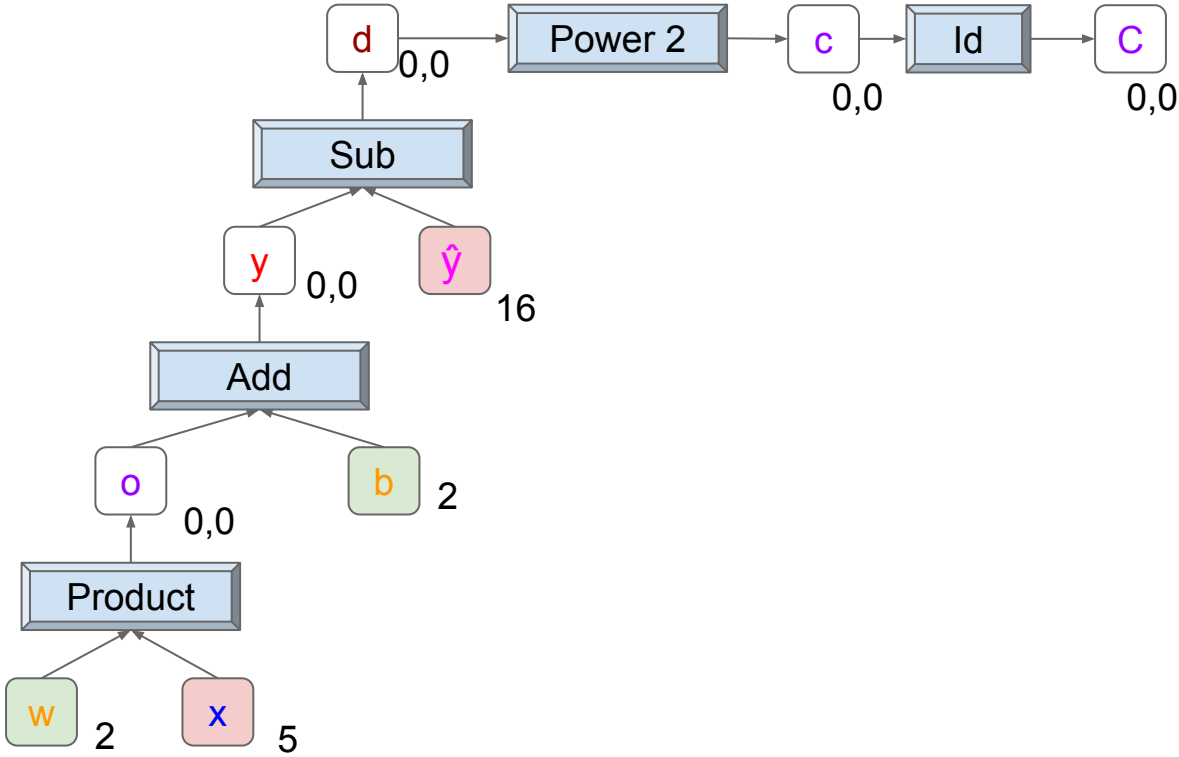

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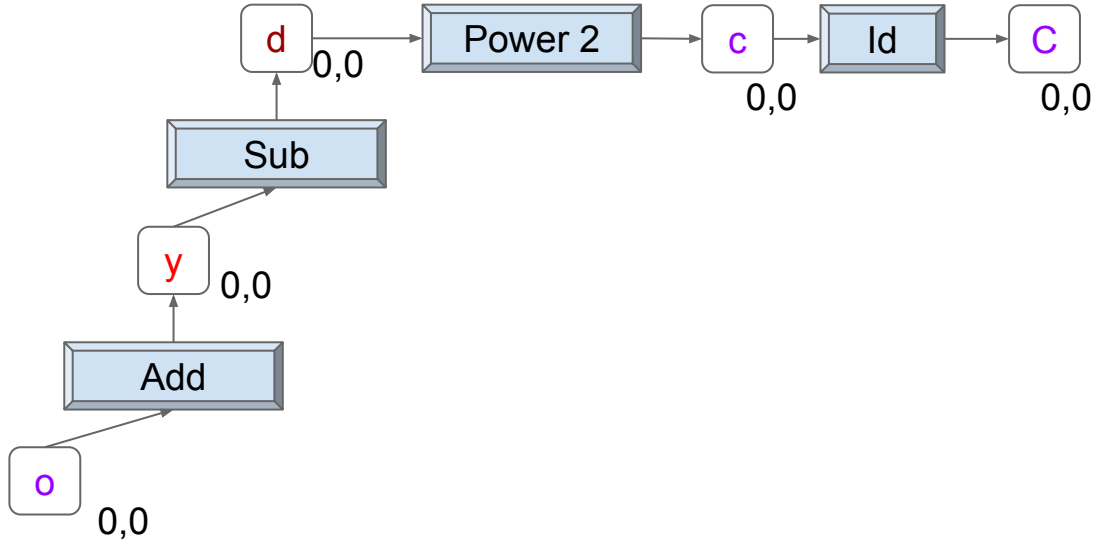

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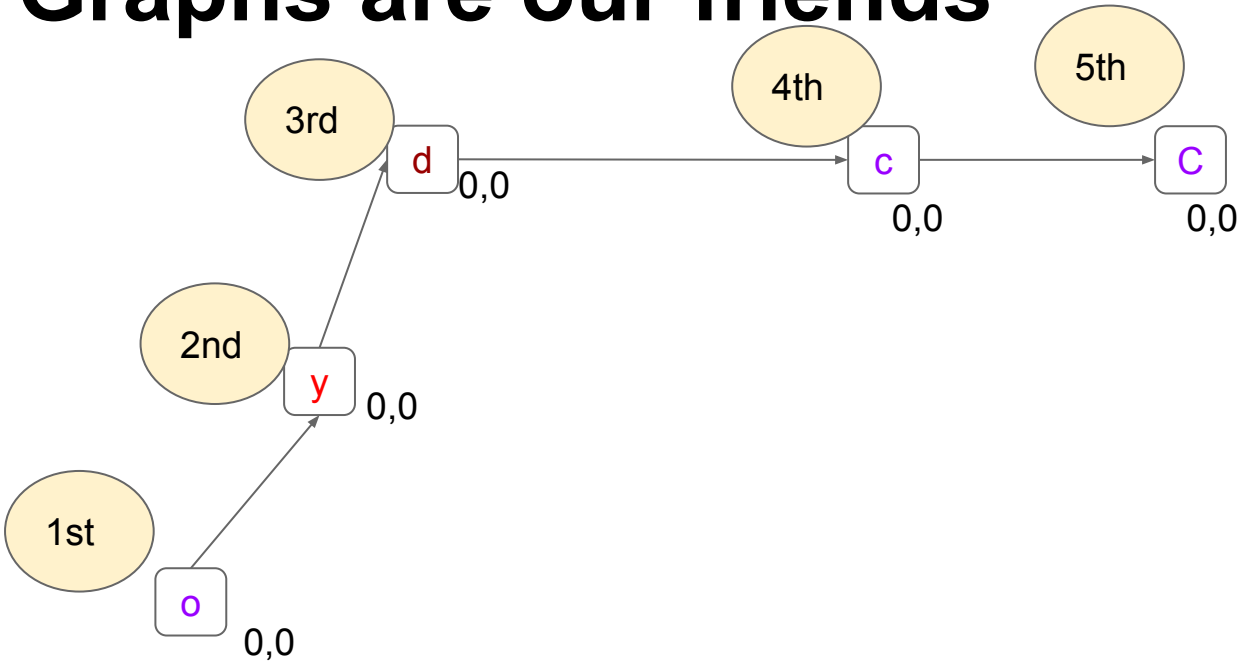

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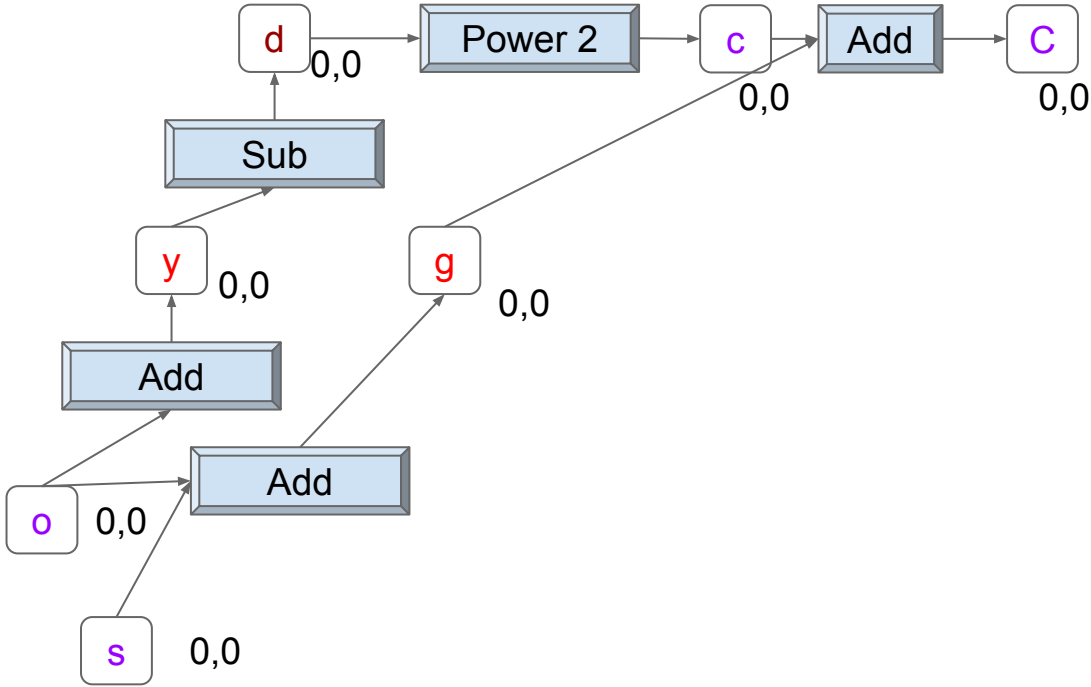

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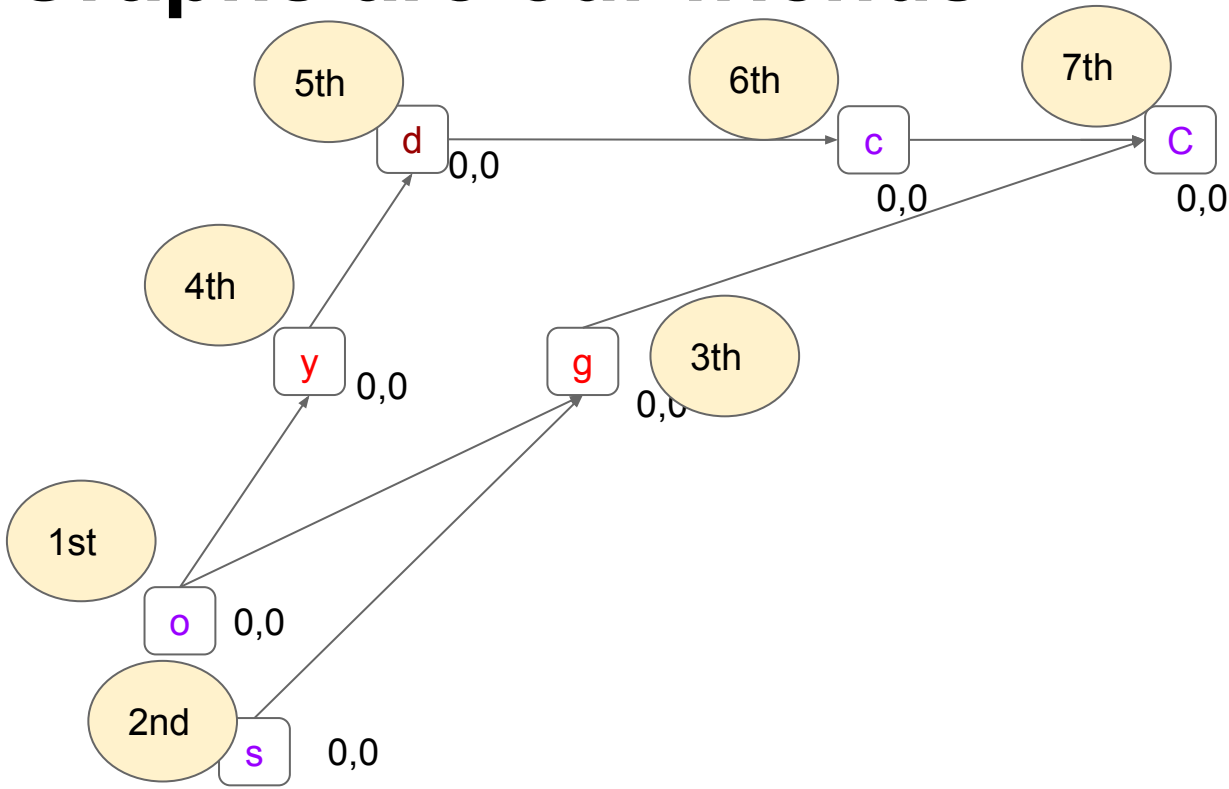
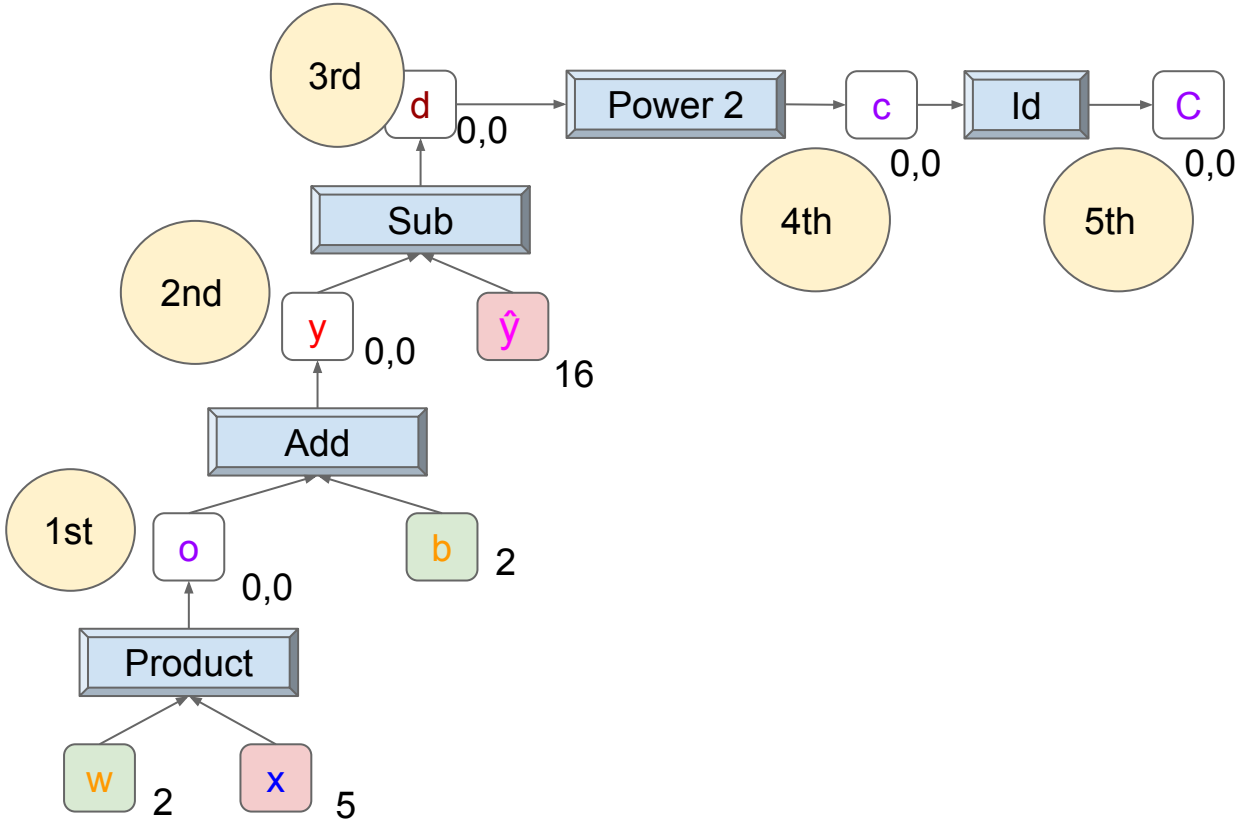


Computation Graphs are our friends

Forward:

1-Initialize inputs
2-Initialize variables
3-Topological Sort variables
4-For each variable in topological order, run the forward method of all operations that link to them



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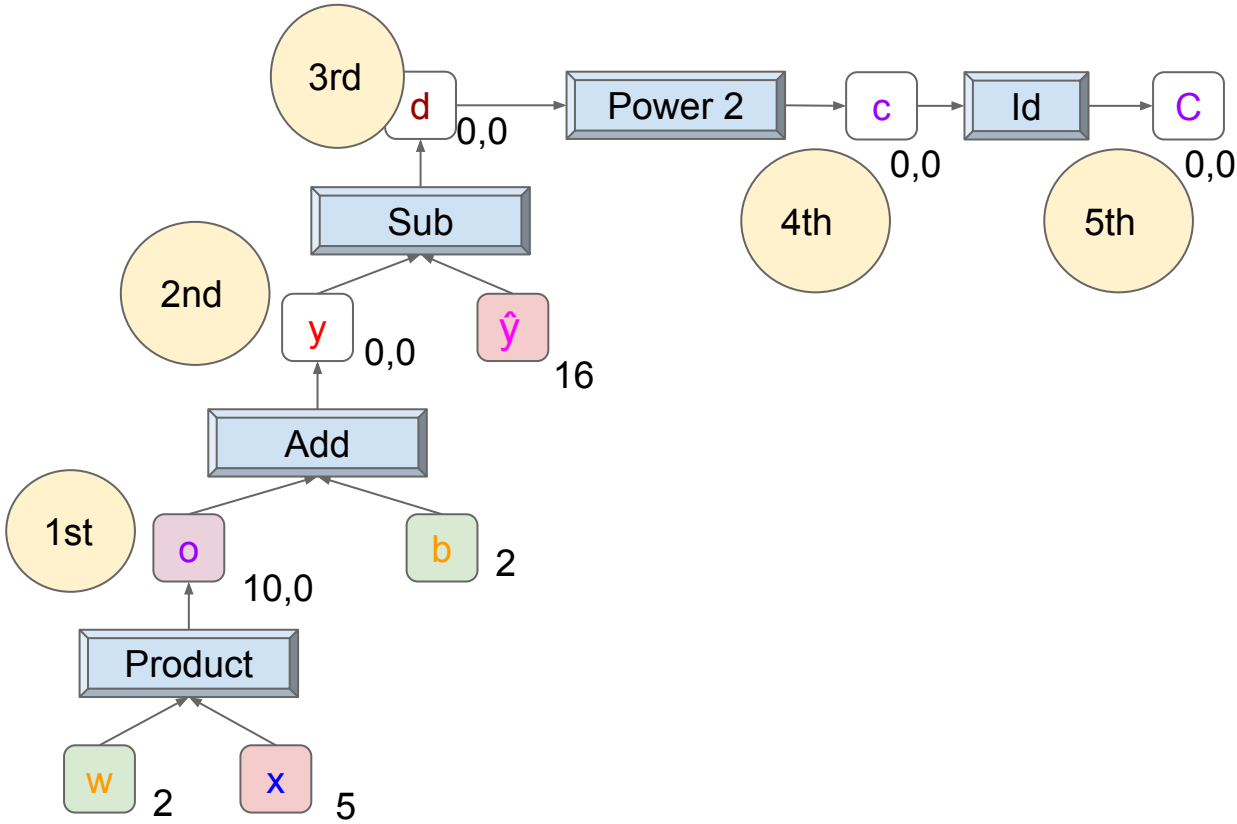

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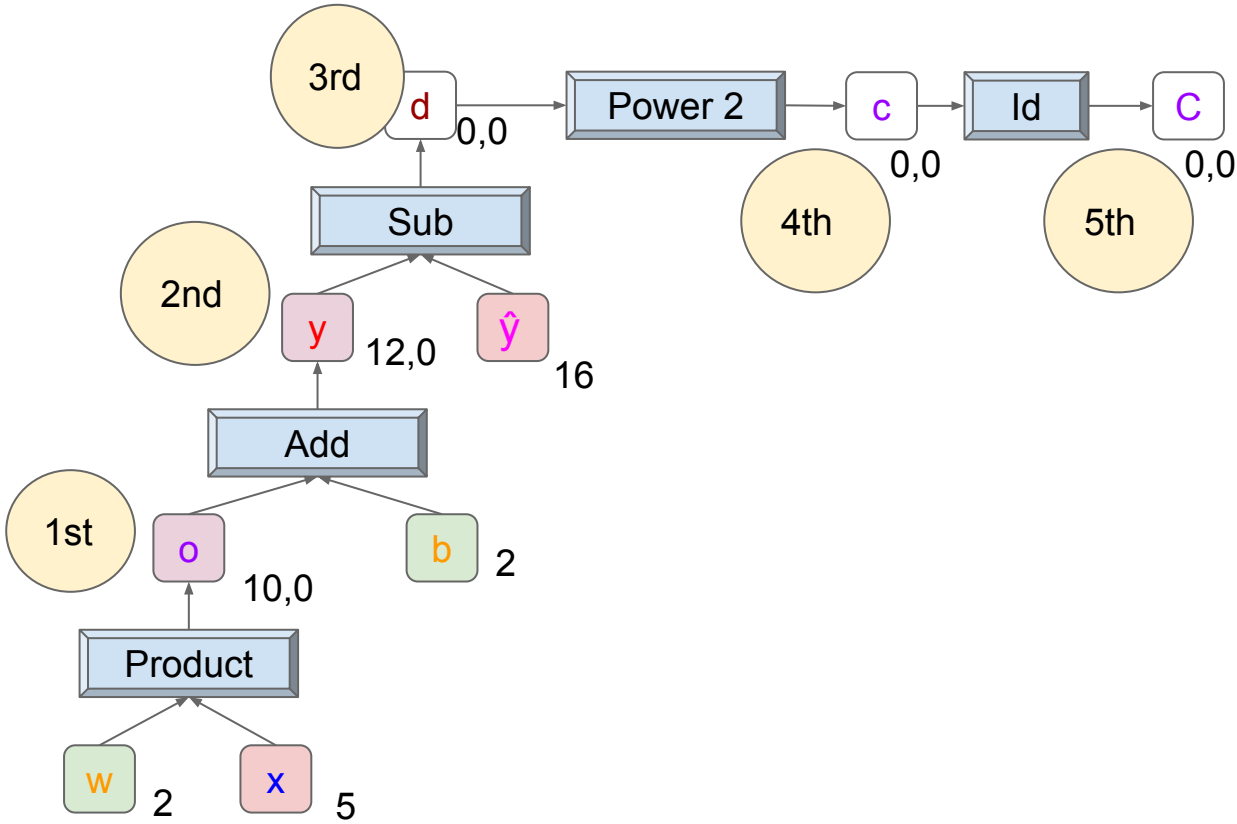
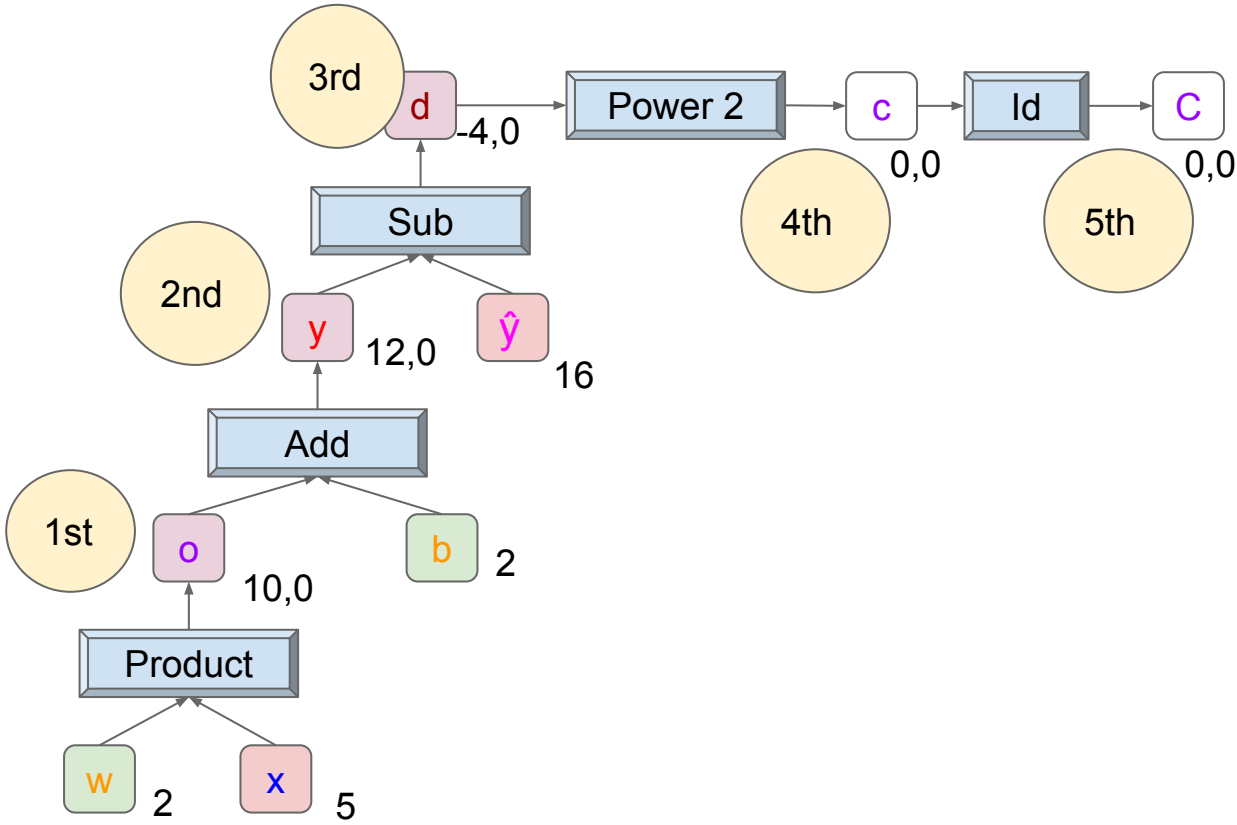


Computation Graphs are our friends

Forward:

1-Initialize inputs
2-Initialize variables
3-Topological Sort variables
4-For each variable in topological order, run the forward method of all operations that link to them



Computation Graphs are our friends

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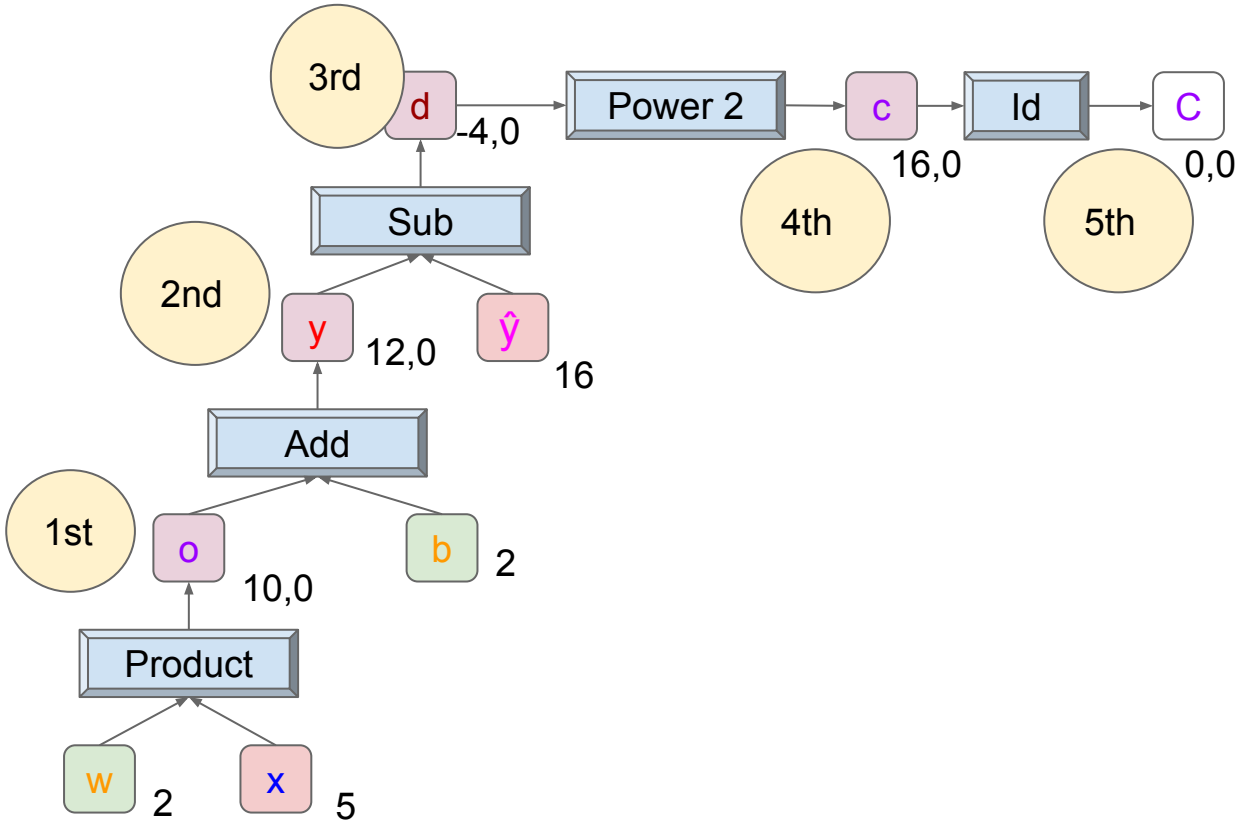

Computation Graphs are our friends

Forward:

1-Initialize inputs
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3-Topological Sort variables
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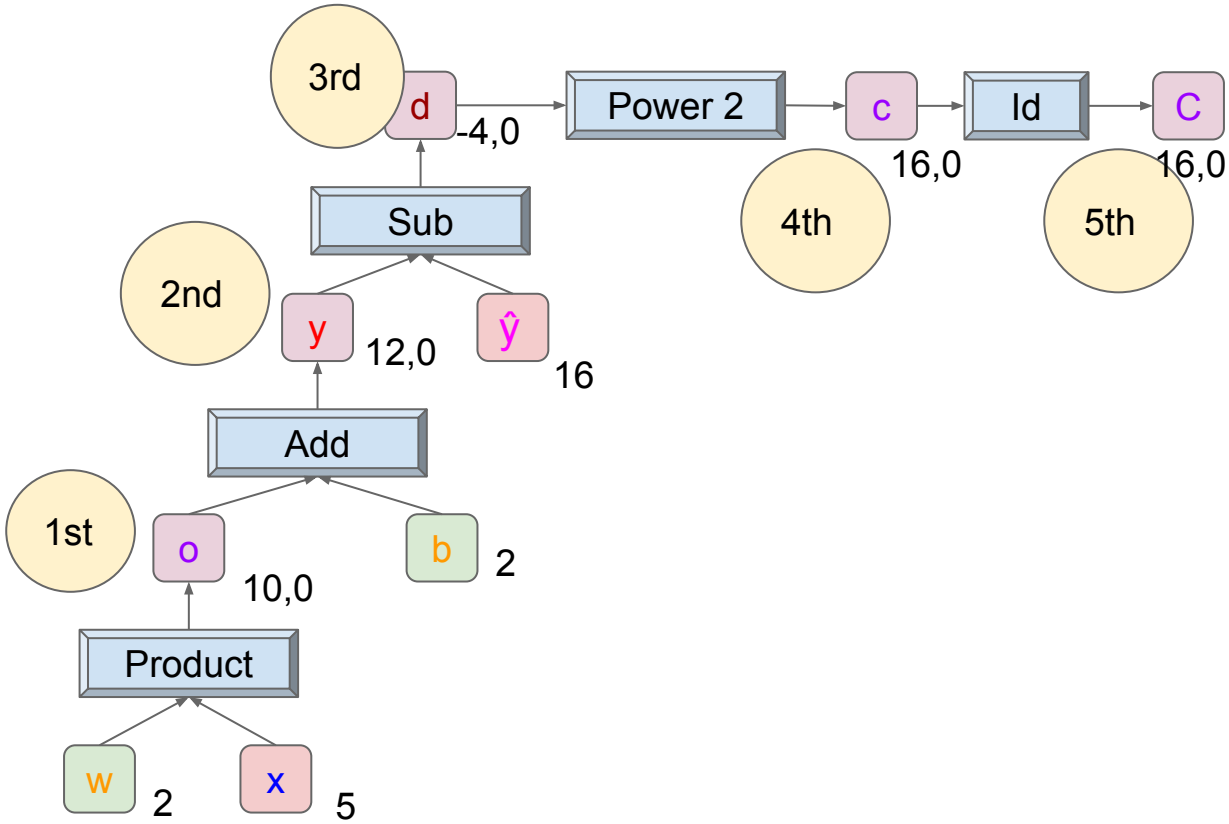


Computation Graphs are our friends

Forward:

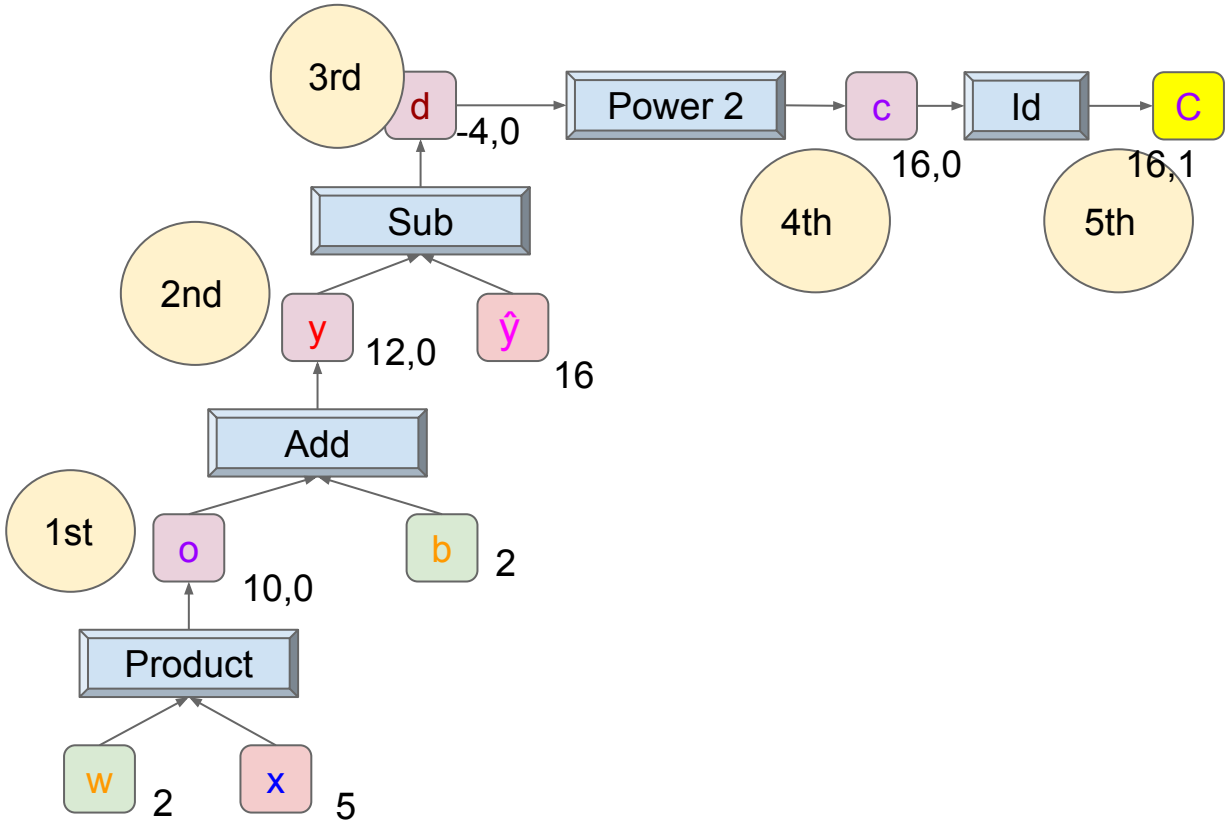
1-Initialize inputs

2-Initialize variables

3-Topological Sort variables

4-For each variable in topological order, run the forward method of all operations that link to them

5-Set gradients to final variables



Computation Graphs are our friends

Forward:

1-Initialize inputs

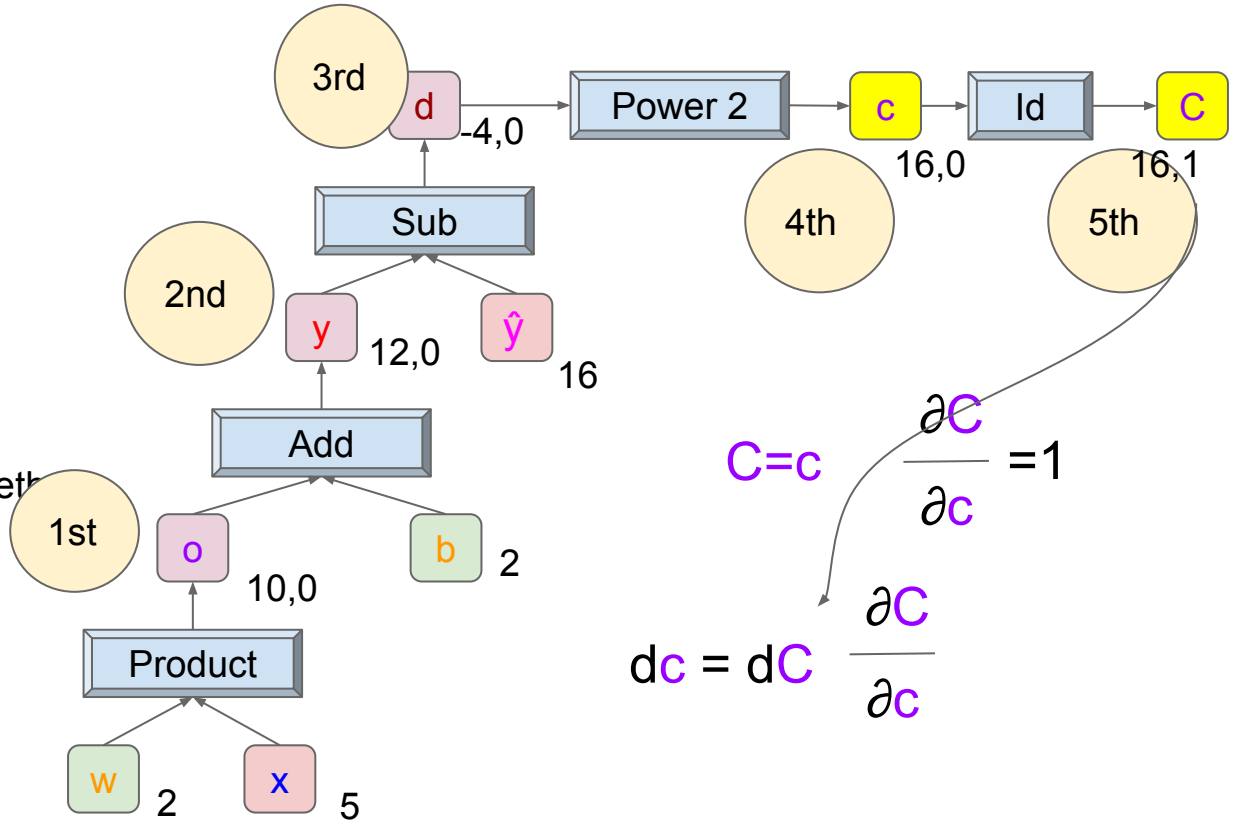
2-Initialize variables

3-Topological Sort variables

4-For each variable in topological order, run the forward method of all operations that link to them (Forward)

5-Set gradients to final variables

6-run the operations backward meth in reverse order (Backward)



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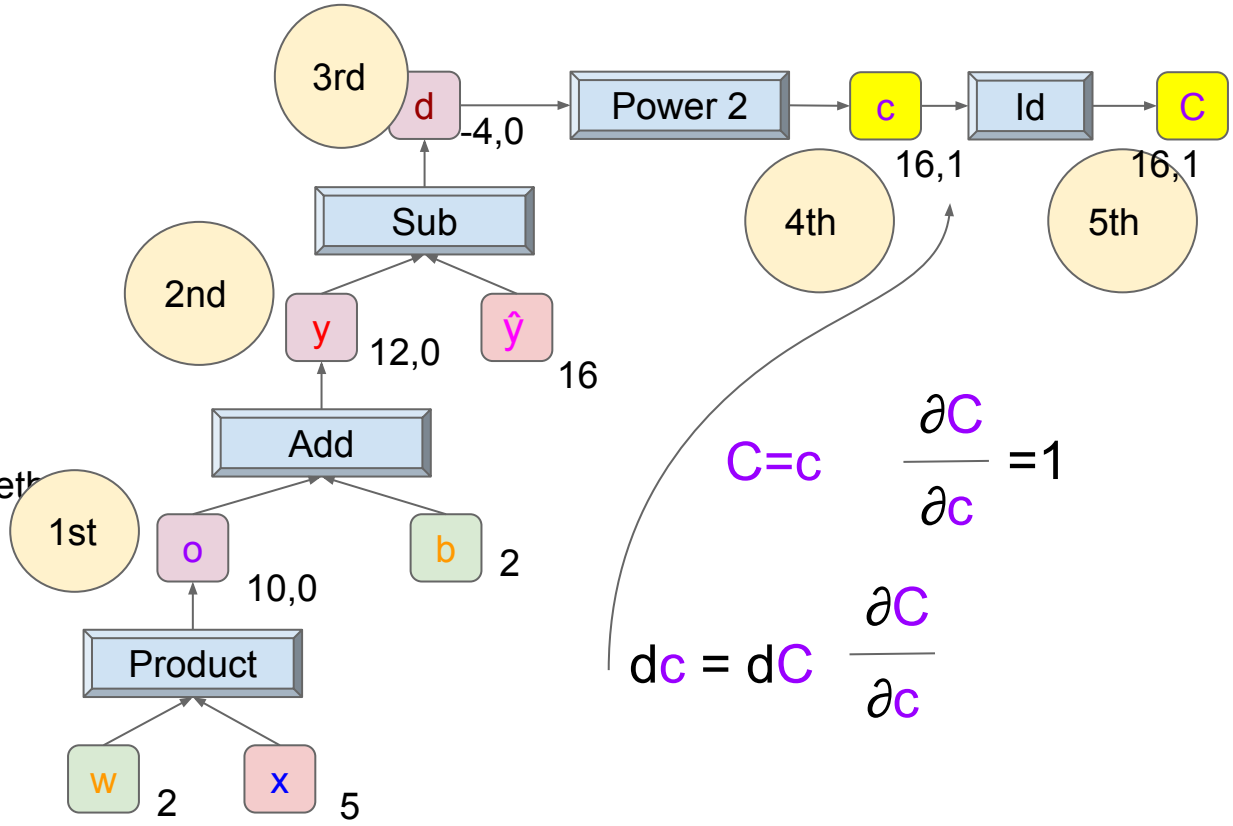

Computation Graphs are our friends

Forward:

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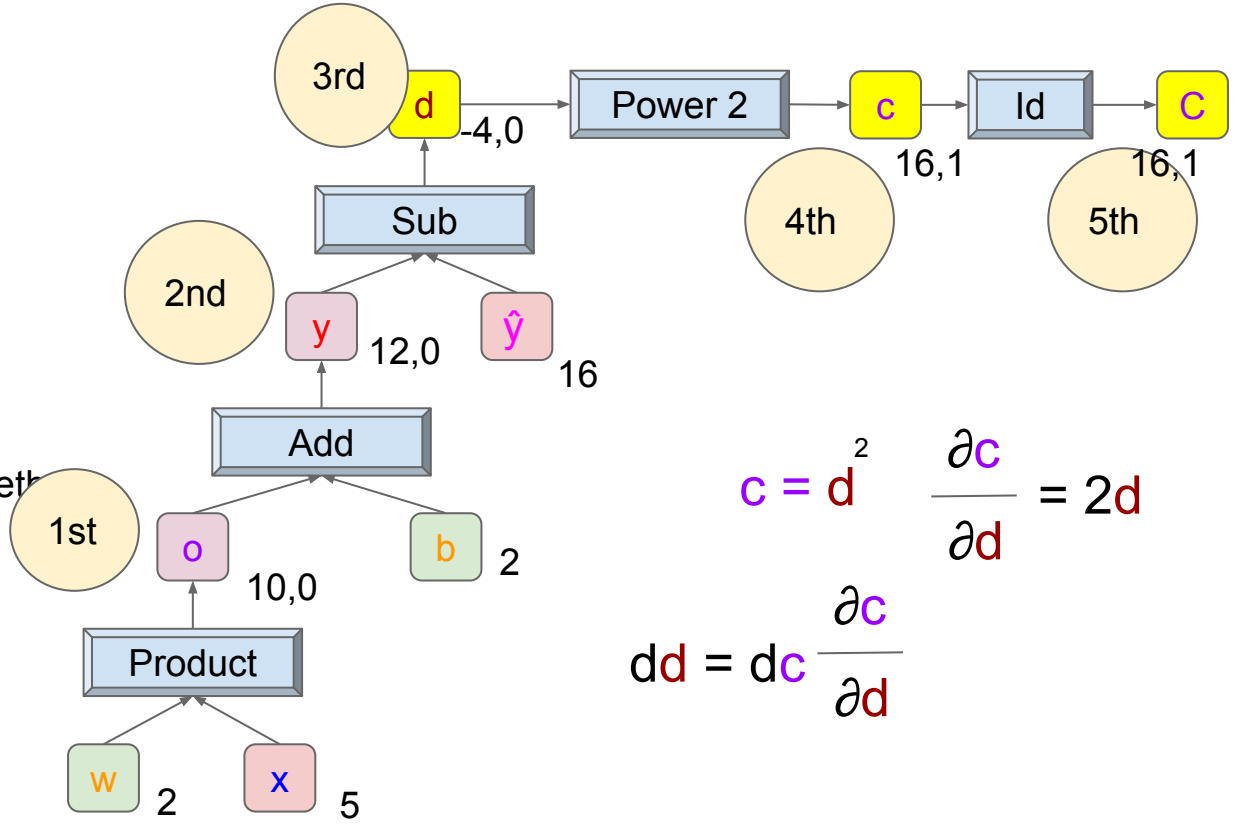


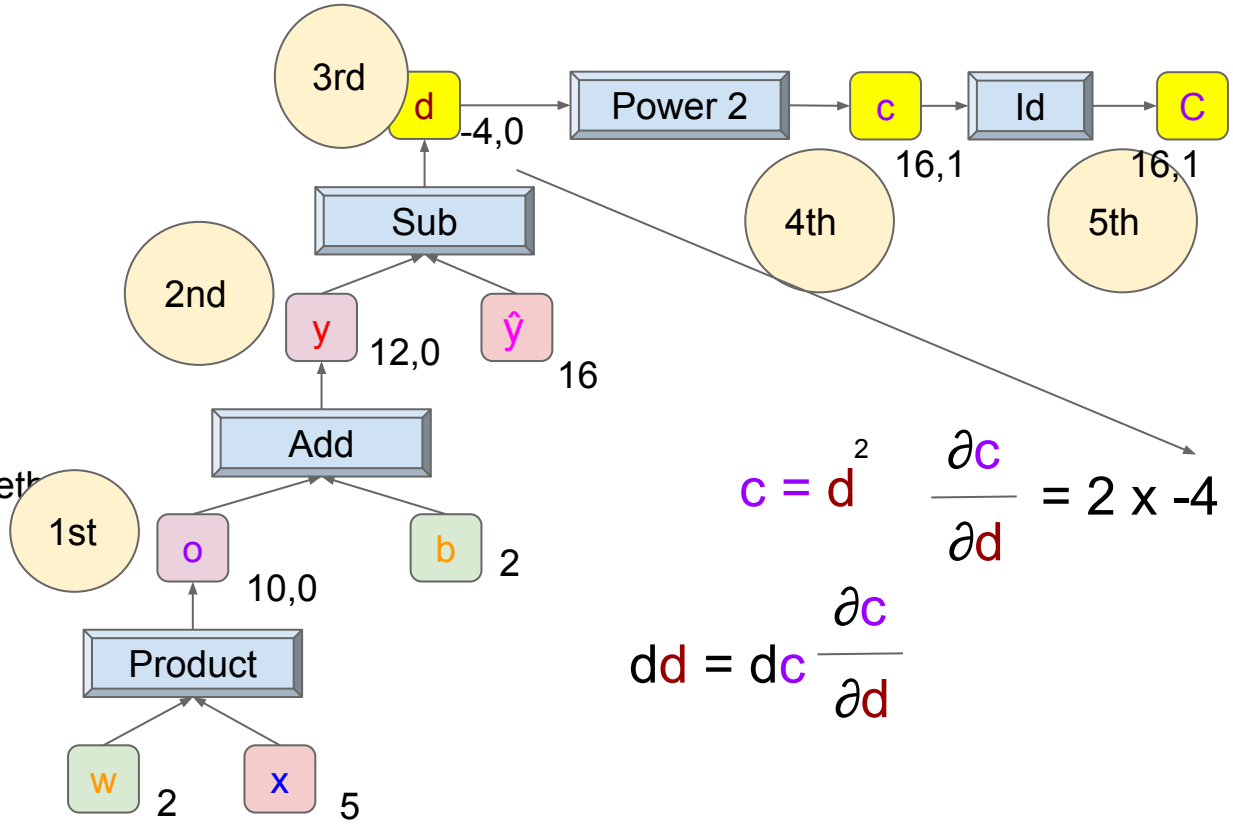
$$c = d^2 \qquad \frac{\partial c}{\partial d} = 2d$$

$$dd = dc \frac{\partial c}{\partial d}$$

Computation Graphs are our friends

Forward:

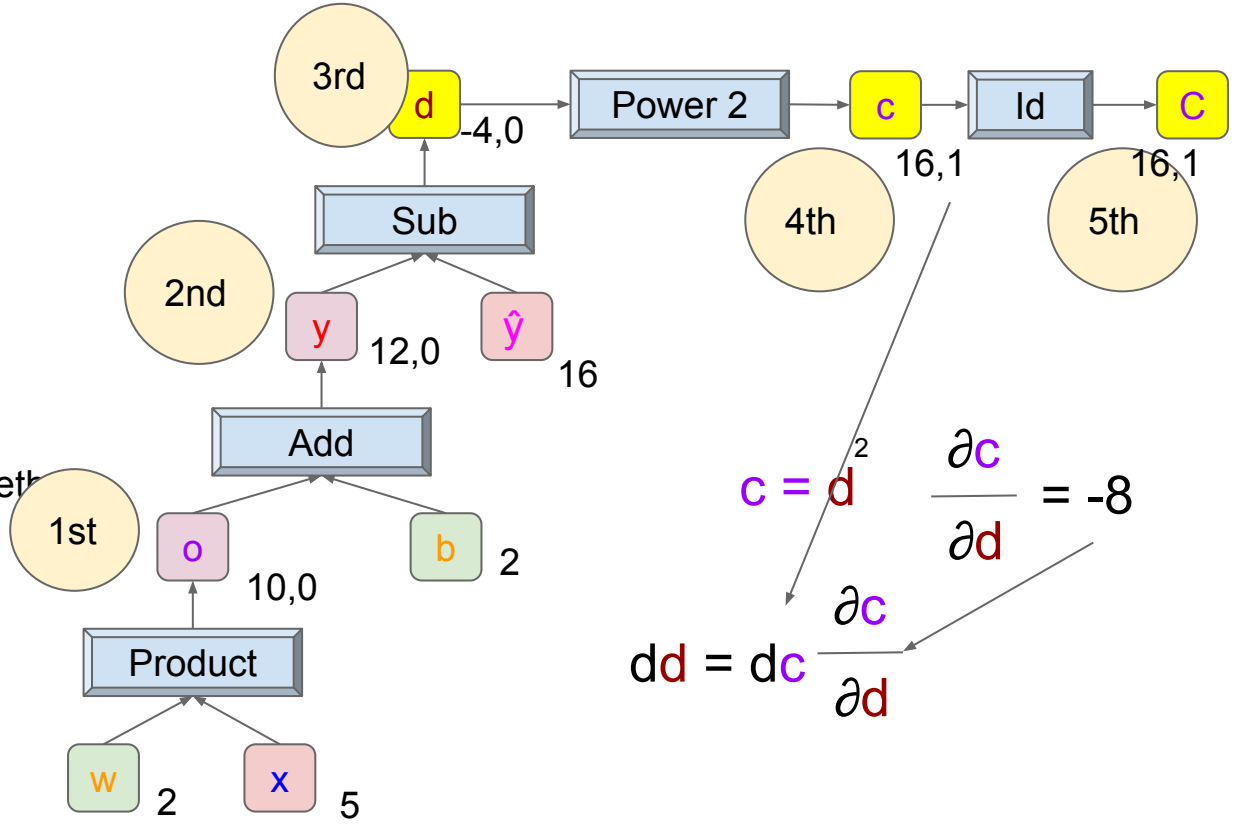
1-Initialize inputs
2-Initialize variables
3-Topological Sort variables
4-For each variable in topological order, run the forward method of all operations that link to them (Forward)
5-Set gradients to final variables
6-run the operations backward meth in reverse order (Backward)



Computation Graphs are our friends

Forward:

1-Initialize inputs
2-Initialize variables
3-Topological Sort variables
4-For each variable in topological order, run the forward method of all operations that link to them (Forward)
5-Set gradients to final variables
6-run the operations backward meth in reverse order (Backward)



Computation Graphs are our friends

Forward:

1-Initialize inputs

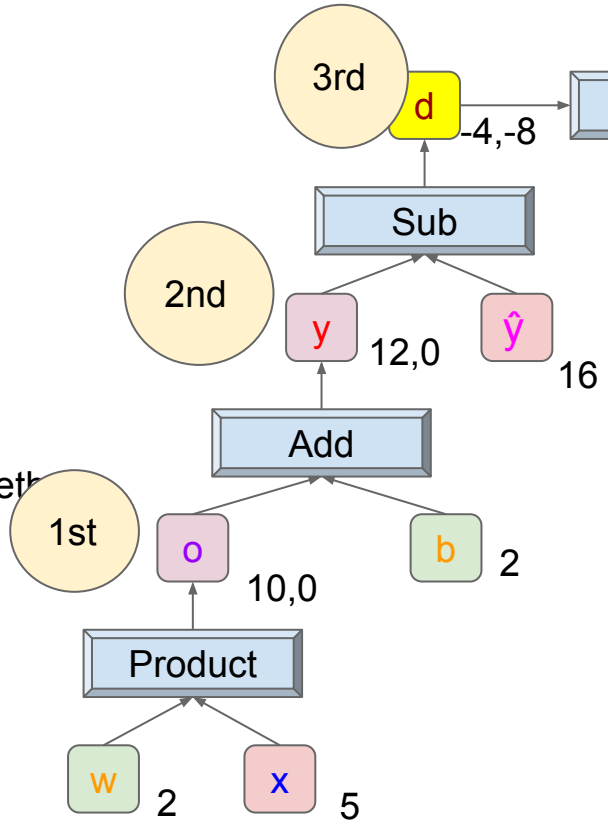
2-Initialize variables

3-Topological Sort variables

4-For each variable in topological order, run the forward method of all operations that link to them (Forward)

5-Set gradients to final variables

6-run the operations backward meth in reverse order (Backward)



$$c = d^2 \qquad \frac{\partial c}{\partial d} = -8$$

$$dd = dc \frac{\partial c}{\partial d}$$

Computation Graphs are our friends

Forward:

1-Initialize inputs

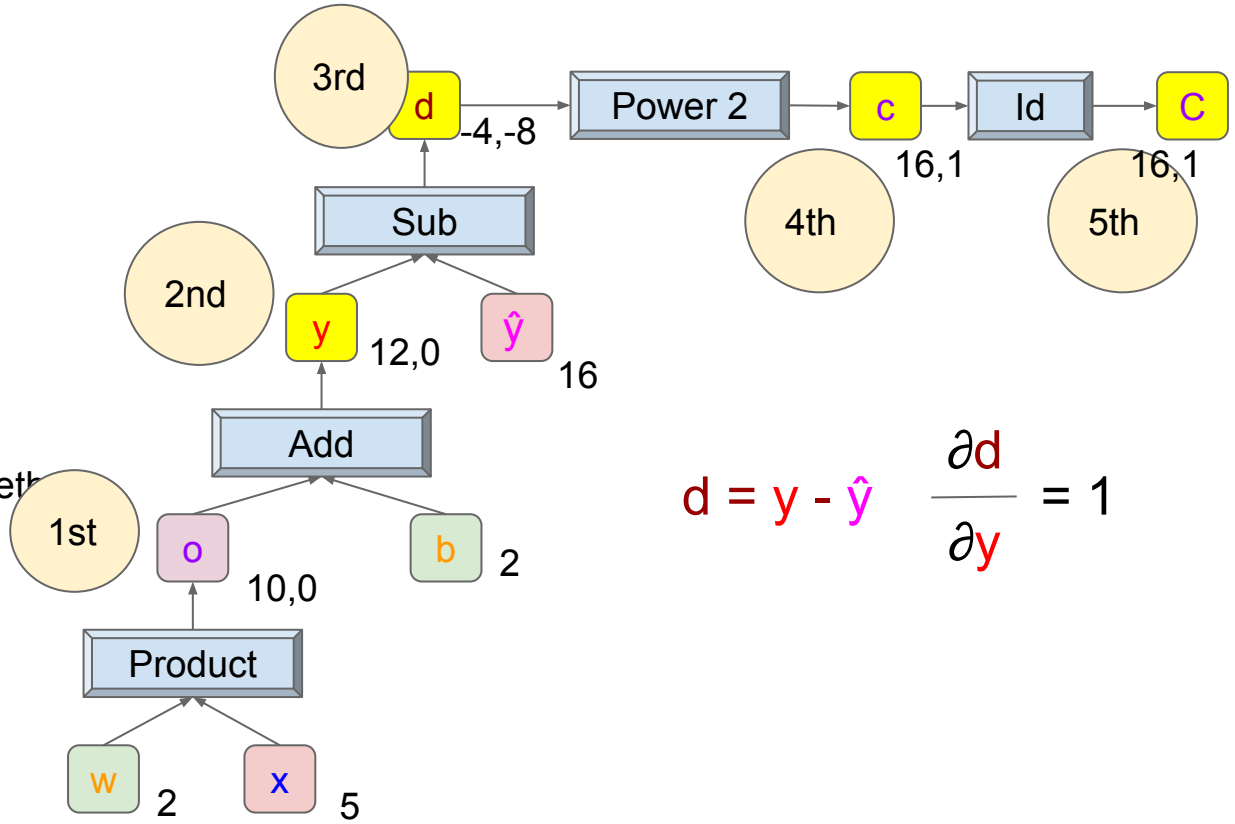
2-Initialize variables

3-Topological Sort variables

4-For each variable in topological order, run the forward method of all operations that link to them (Forward)

5-Set gradients to final variables

6-run the operations backward meth in reverse order (Backward)



$d = y - \hat{y}$ $\frac{\partial d}{\partial y} = 1$

Computation Graphs are our friends

Forward:

1-Initialize inputs

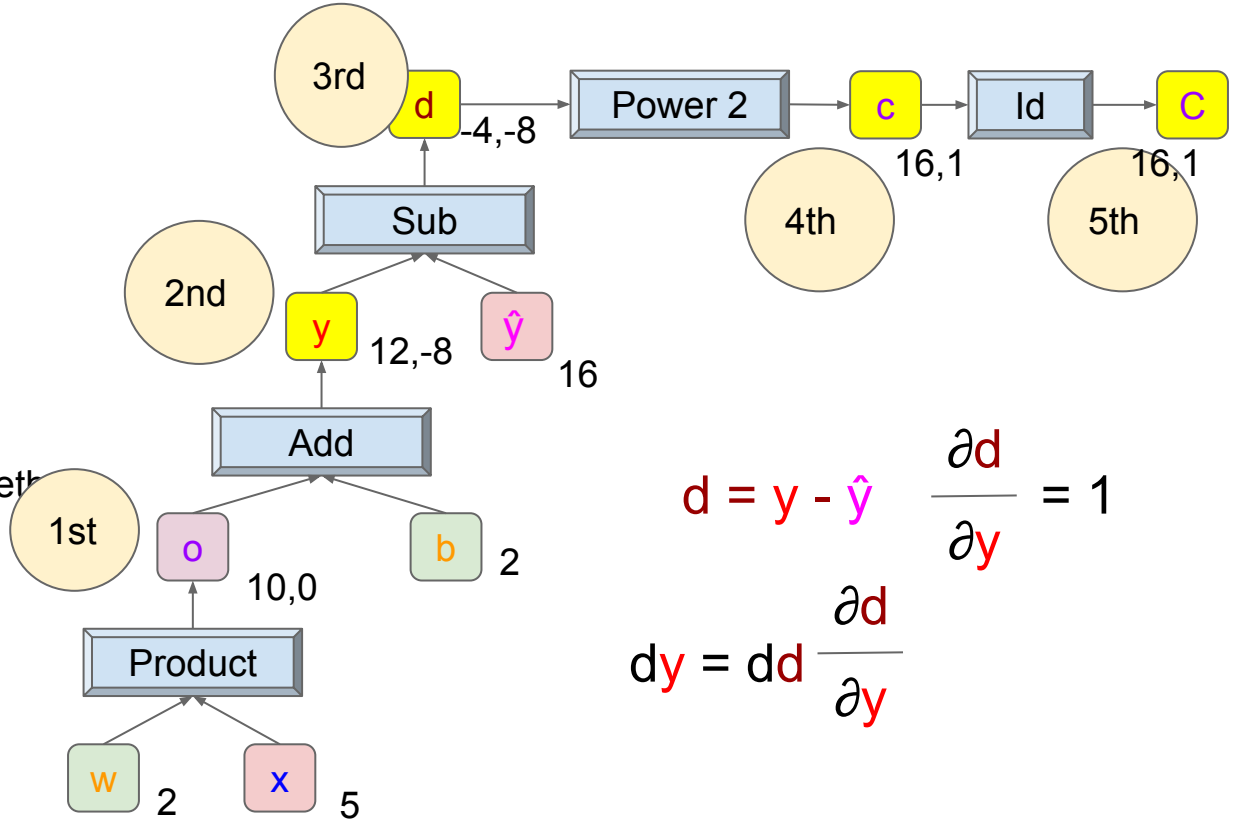
2-Initialize variables

3-Topological Sort variables

4-For each variable in topological order, run the forward method of all operations that link to them (Forward)

5-Set gradients to final variables

6-run the operations backward meth in reverse order (Backward)



$$d = y - \hat{y} \qquad \frac{\partial d}{\partial y} = 1$$

$$dy = dd \frac{\partial d}{\partial y}$$

Computation Graphs are our friends

Forward:

1-Initialize inputs

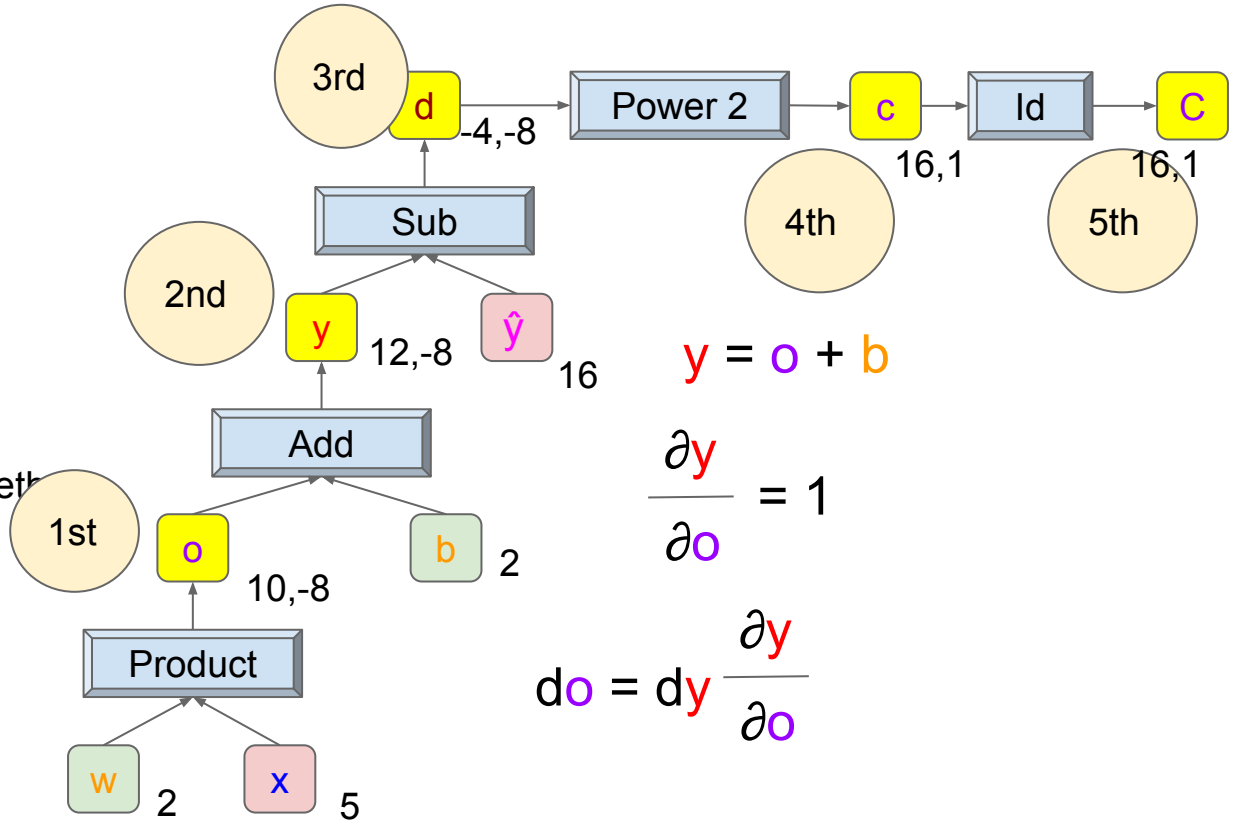
2-Initialize variables

3-Topological Sort variables

4-For each variable in topological order, run the forward method of all operations that link to them (Forward)

5-Set gradients to final variables

6-run the operations backward meth in reverse order (Backward)



$$y = o + b$$

$$\frac{\partial y}{\partial o} = 1$$

$$do = dy \frac{\partial y}{\partial o}$$

Computation Graphs are our friends

Forward:

1-Initialize inputs

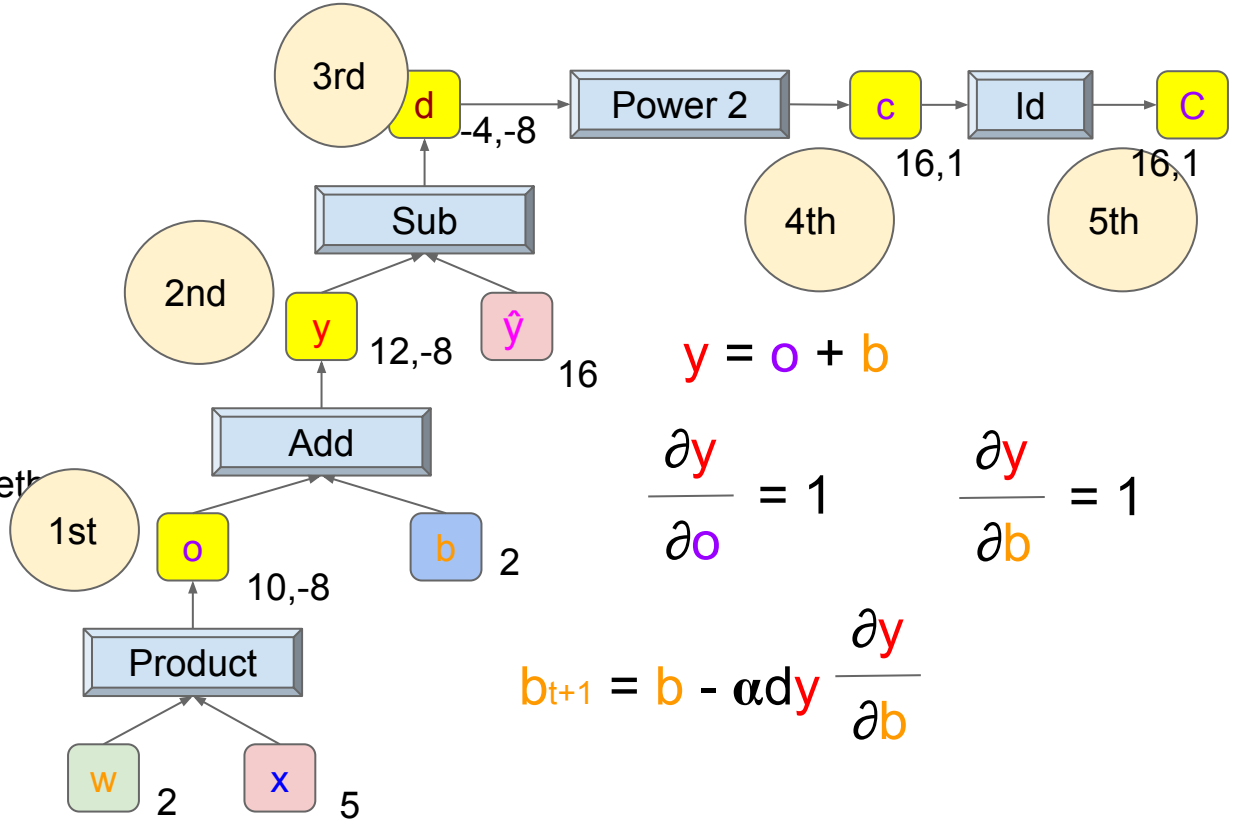
2-Initialize variables

3-Topological Sort variables

4-For each variable in topological order, run the forward method of all operations that link to them (Forward)

5-Set gradients to final variables

6-run the operations backward meth in reverse order (Backward)



$$y = o + b$$

$$\frac{\partial y}{\partial o} = 1 \qquad \frac{\partial y}{\partial b} = 1$$

$$b_{t+1} = b - \alpha dy \frac{\partial y}{\partial b}$$

Computation Graphs are our friends

Forward:

1-Initialize inputs

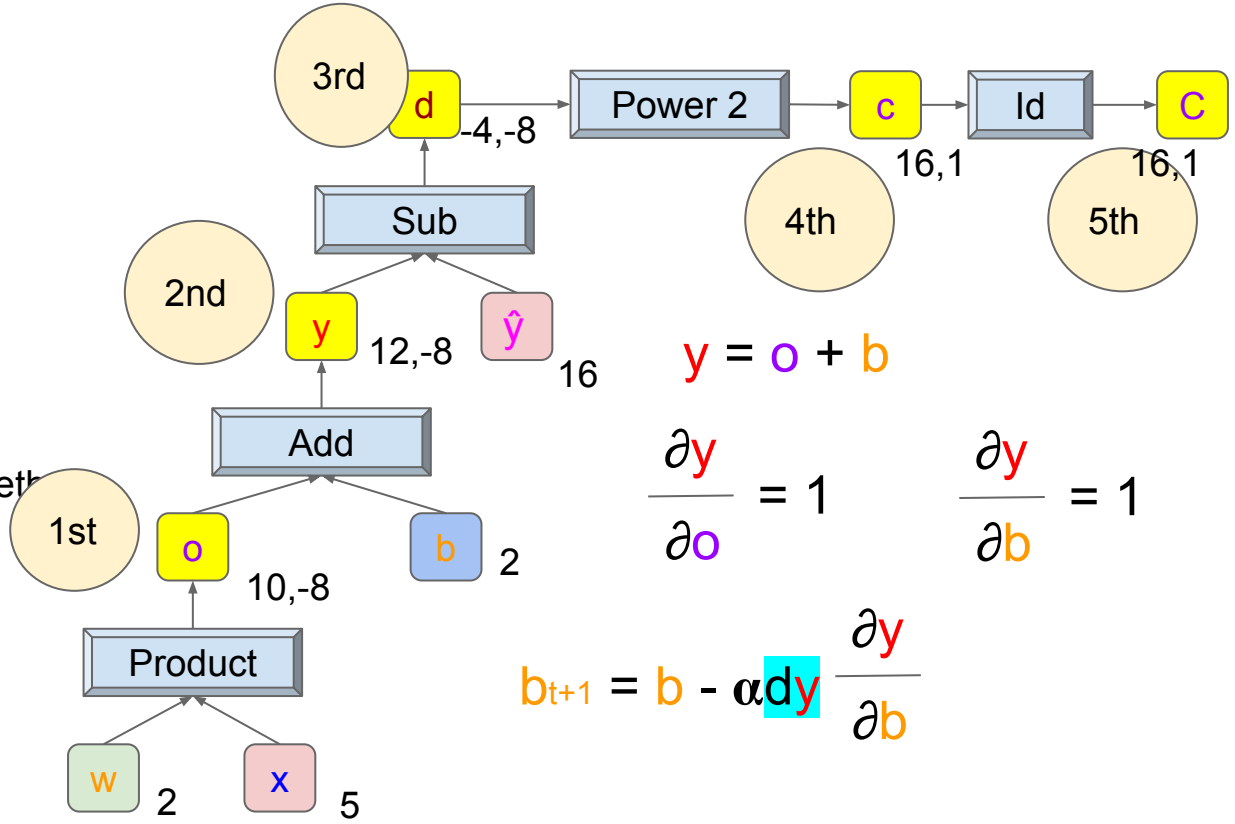
2-Initialize variables

3-Topological Sort variables

4-For each variable in topological order, run the forward method of all operations that link to them (Forward)

5-Set gradients to final variables

6-run the operations backward meth in reverse order (Backward)



$$y = o + b$$

$$\frac{\partial y}{\partial o} = 1 \qquad \frac{\partial y}{\partial b} = 1$$

$$b_{t+1} = b - \alpha dy \frac{\partial y}{\partial b}$$

Computation Graphs are our friends

Forward:

1-Initialize inputs

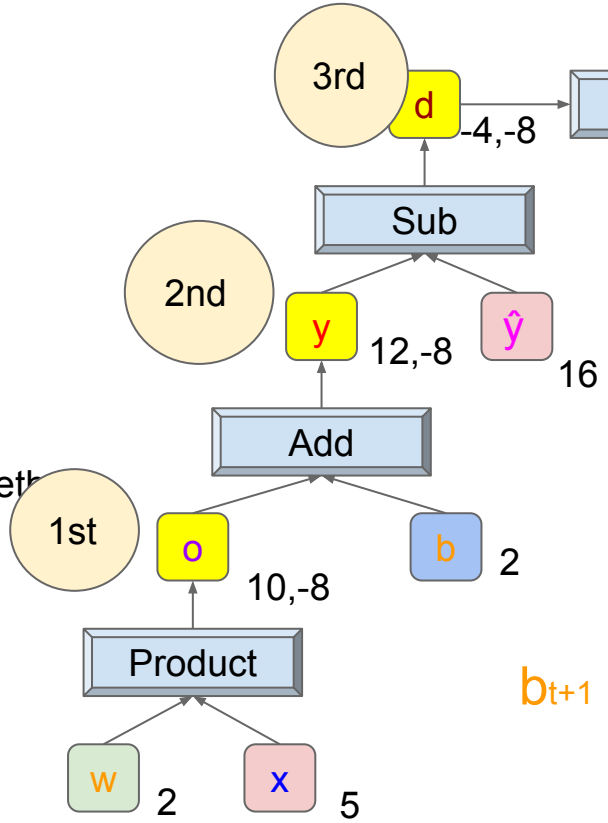
2-Initialize variables

3-Topological Sort variables

4-For each variable in topological order, run the forward method of all operations that link to them (Forward)

5-Set gradients to final variables

6-run the operations backward meth in reverse order (Backward)



$$y = o + b$$

$$\frac{\partial y}{\partial o} = 1 \qquad \frac{\partial y}{\partial b} = 1$$

$$b_{t+1} = b - \alpha \frac{\partial C}{\partial c} \frac{\partial c}{\partial d} \frac{\partial d}{\partial y} \frac{\partial y}{\partial b}$$

Computation Graphs are our friends

Forward:

1-Initialize inputs

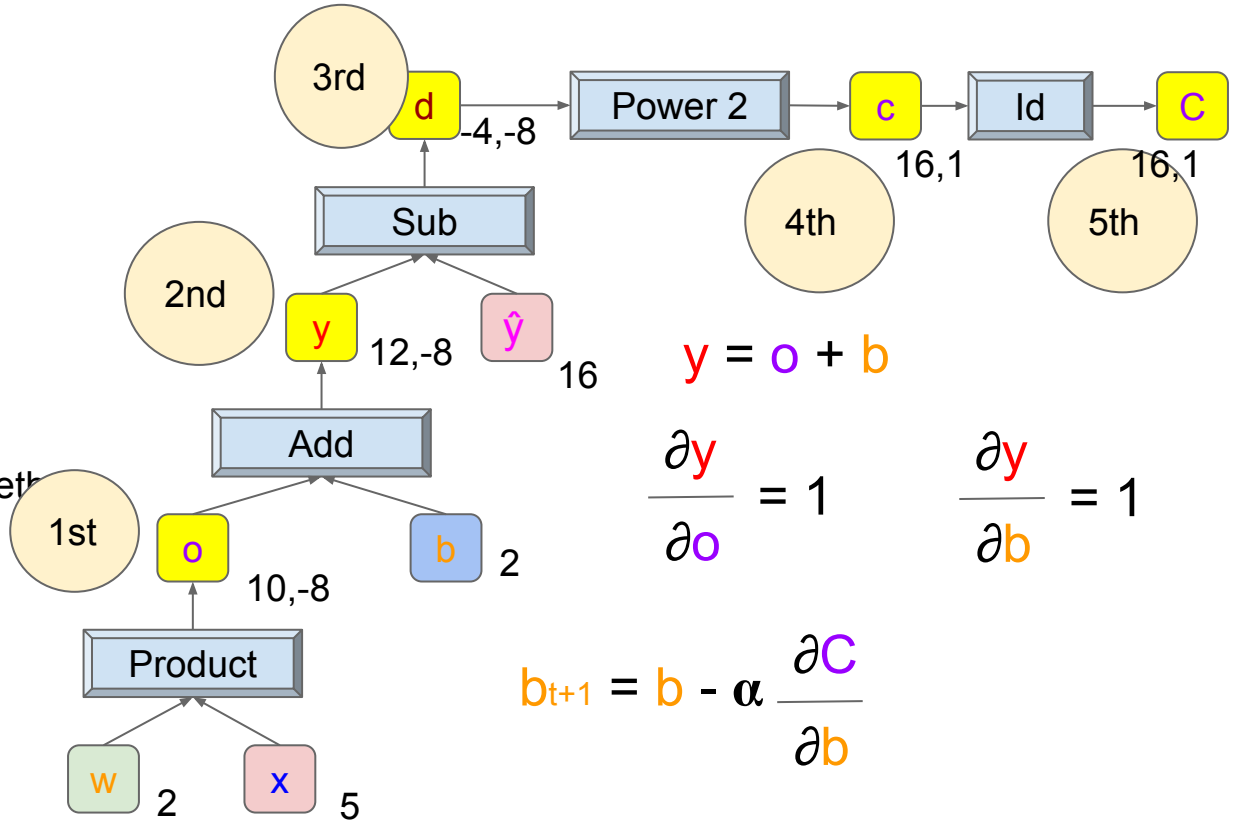
2-Initialize variables

3-Topological Sort variables

4-For each variable in topological order, run the forward method of all operations that link to them (Forward)

5-Set gradients to final variables

6-run the operations backward meth in reverse order (Backward)



$$y = o + b$$

$$\frac{\partial y}{\partial o} = 1 \qquad \frac{\partial y}{\partial b} = 1$$

$$b_{t+1} = b - \alpha \frac{\partial C}{\partial b}$$

Computation Graphs are our friends

Forward:

1-Initialize inputs

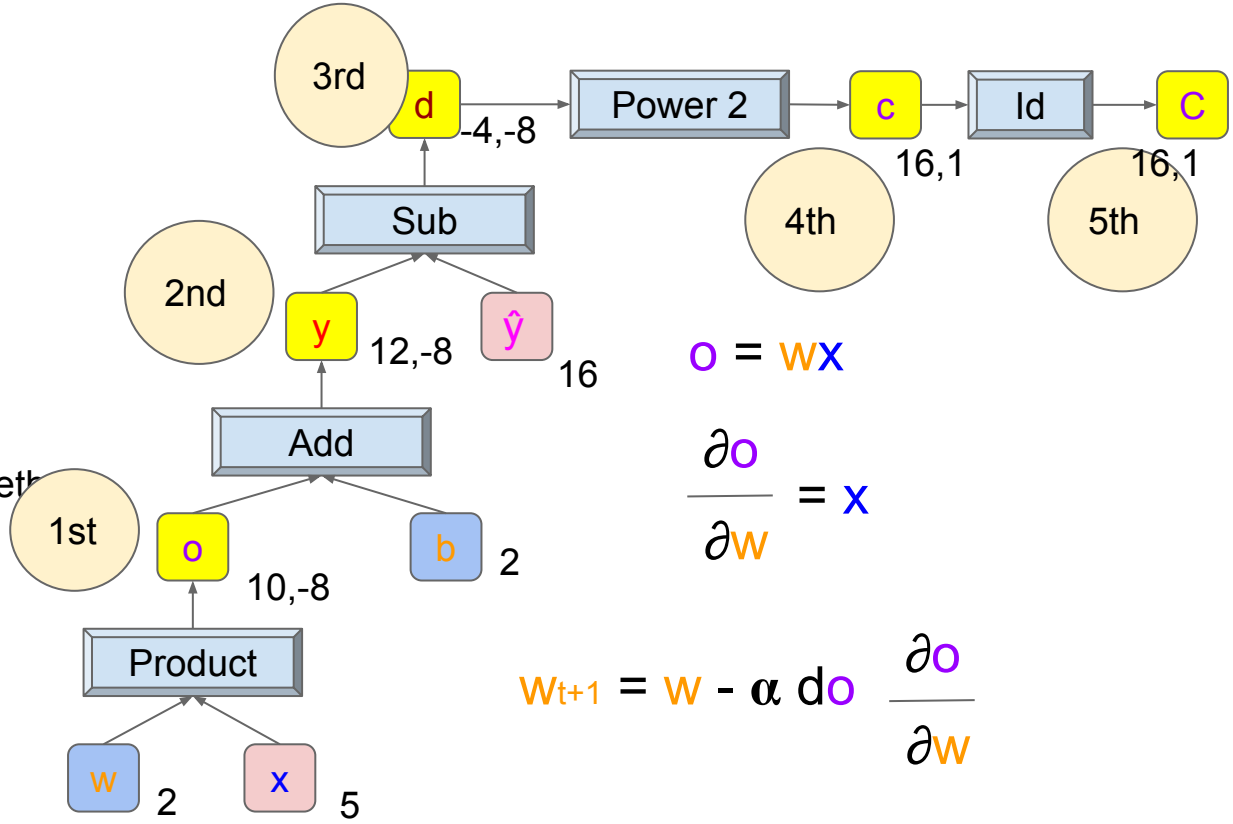
2-Initialize variables

3-Topological Sort variables

4-For each variable in topological order, run the forward method of all operations that link to them (Forward)

5-Set gradients to final variables

6-run the operations backward meth in reverse order (Backward)



$o = wx$

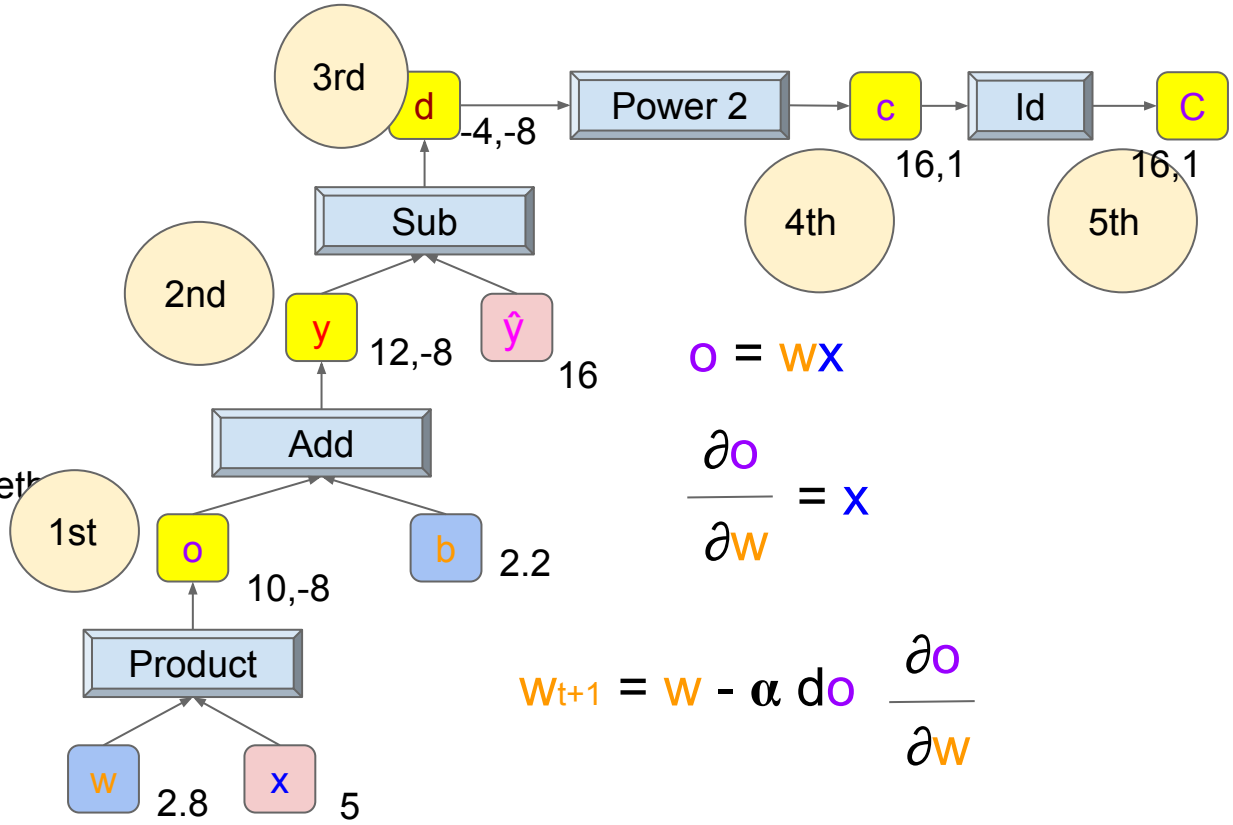
$$\frac{\partial o}{\partial w} = x$$

$$w_{t+1} = w - \alpha \, do \, \frac{\partial o}{\partial w}$$

Computation Graphs are our friends

Forward:

1-Initialize inputs
2-Initialize variables
3-Topological Sort variables
4-For each variable in topological order, run the forward method of all operations that link to them (Forward)
5-Set gradients to final variables
6-run the operations backward meth in reverse order (Backward)
7-update parameters



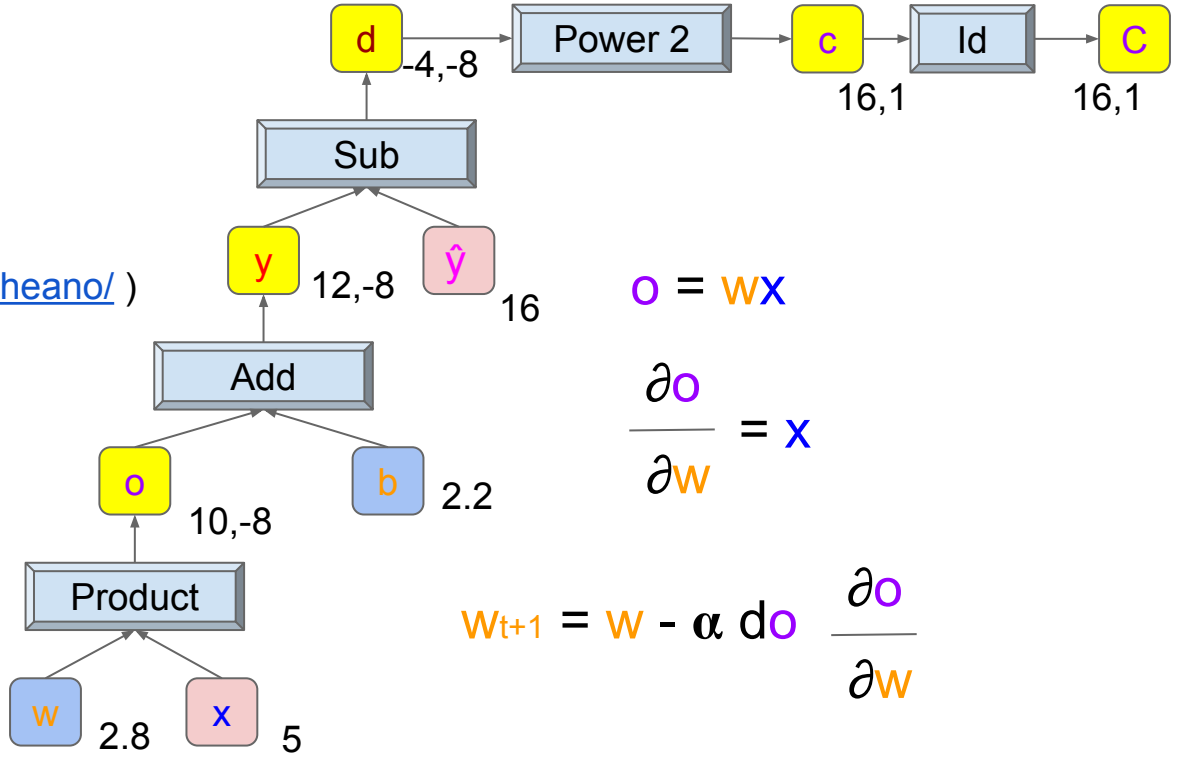
$$o = wx$$

$$\frac{\partial o}{\partial w} = x$$

$$w_{t+1} = w - \alpha \, do \, \frac{\partial o}{\partial w}$$

Computation Graphs are our friends

Existing Tools:
-Tensorflow (https://www.tensorflow.org)
-Torch (https://github.com/torch/nn)
-CNN (https://github.com/clab/cnn)
-JNN (https://github.com/wlin12/JNN)
-Theano (http://deeplearning.net/software/theano/)



$o = wx$

$$\frac{\partial o}{\partial w} = x$$

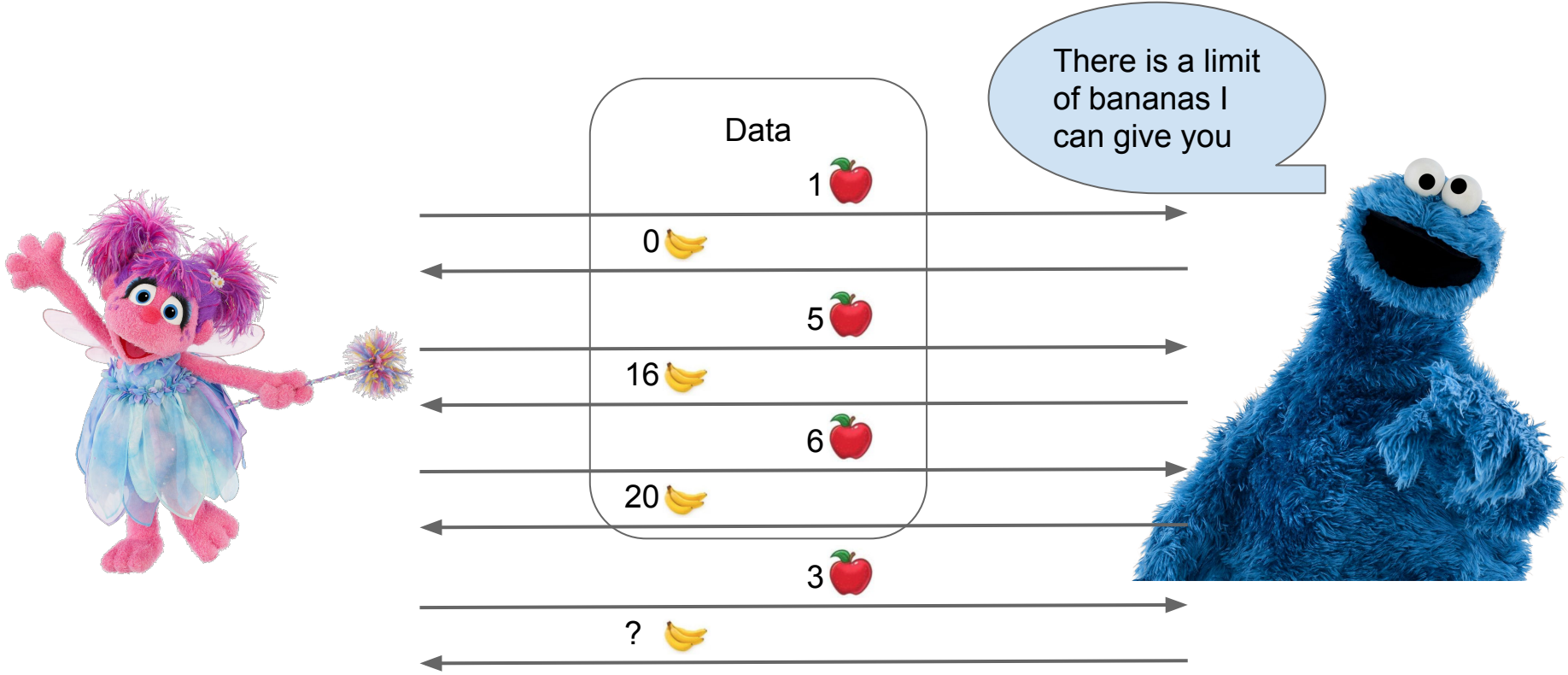
$$w_{t+1} = w - \alpha \, do \, \frac{\partial o}{\partial w}$$

Into Deep Learning

Nonlinear Neural Models

$y = 4x-4$

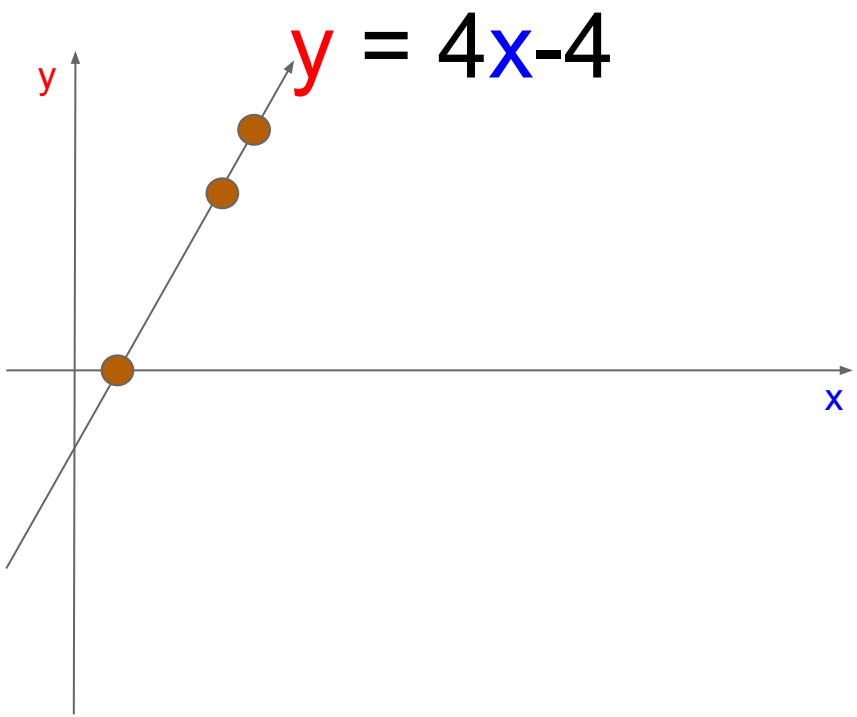
Nonlinear Neural Models



Nonlinear Neural Models

Data

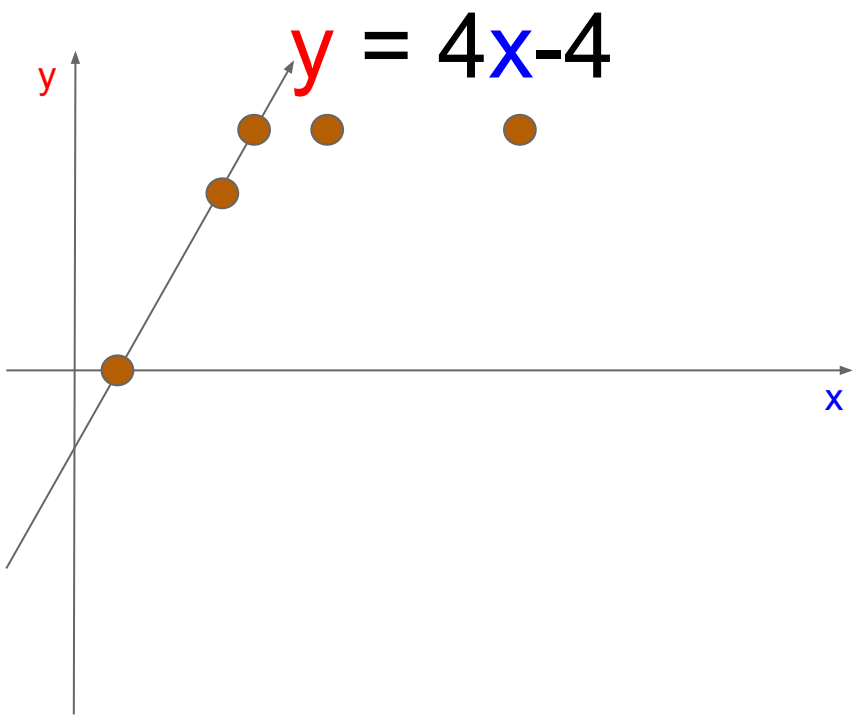
n	x	y
0	1	0
1	5	16
2	6	20



Nonlinear Neural Models

Data

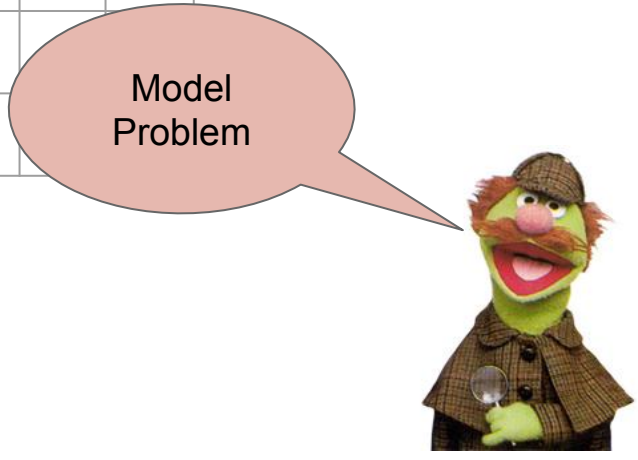
n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

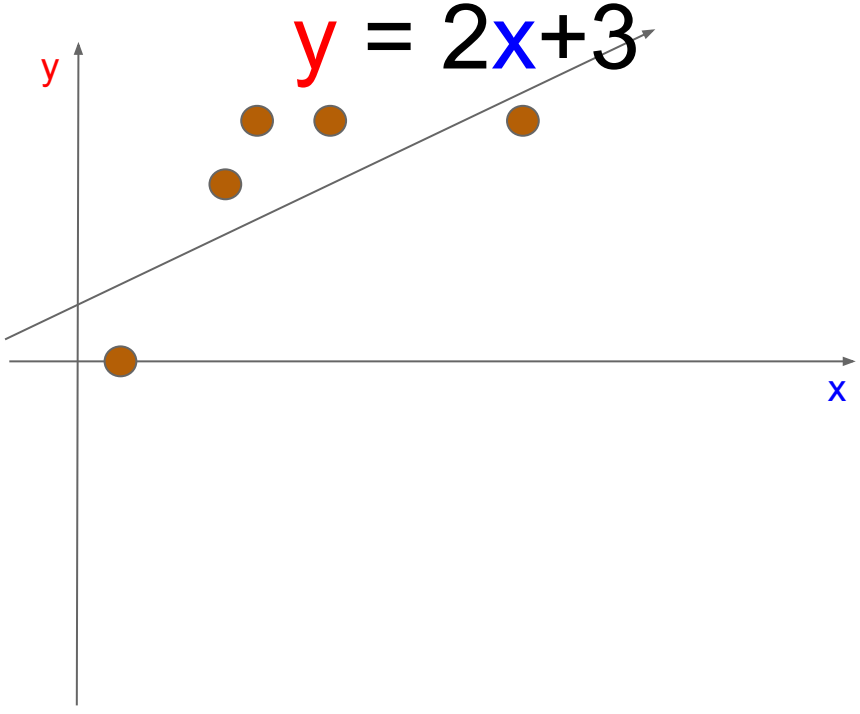


Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3		
4		

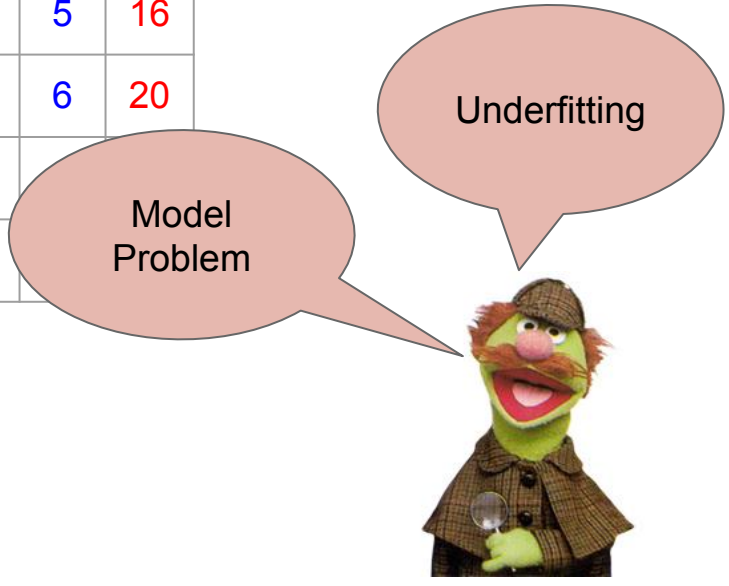


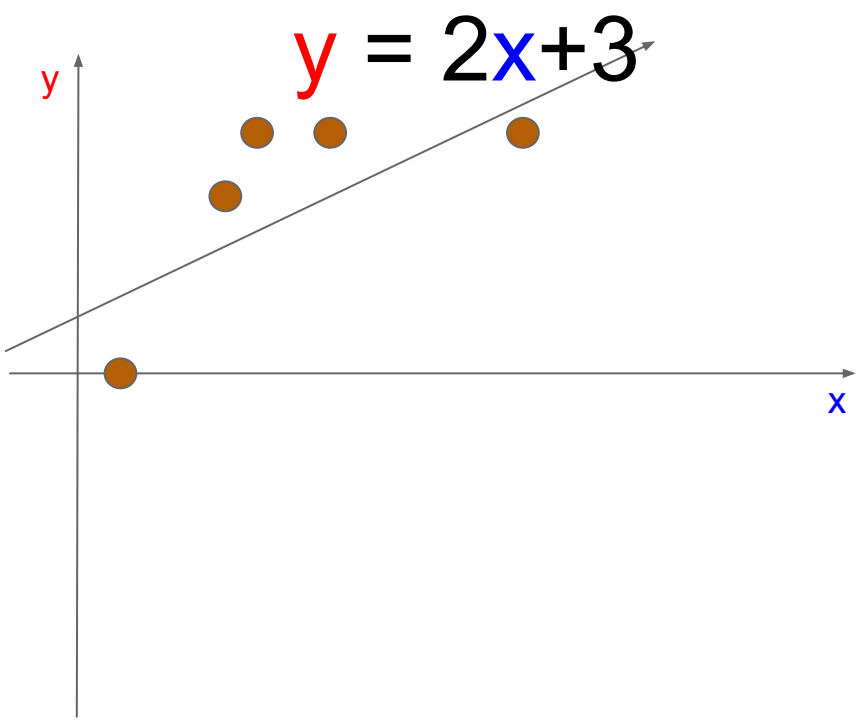


Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3		
4		



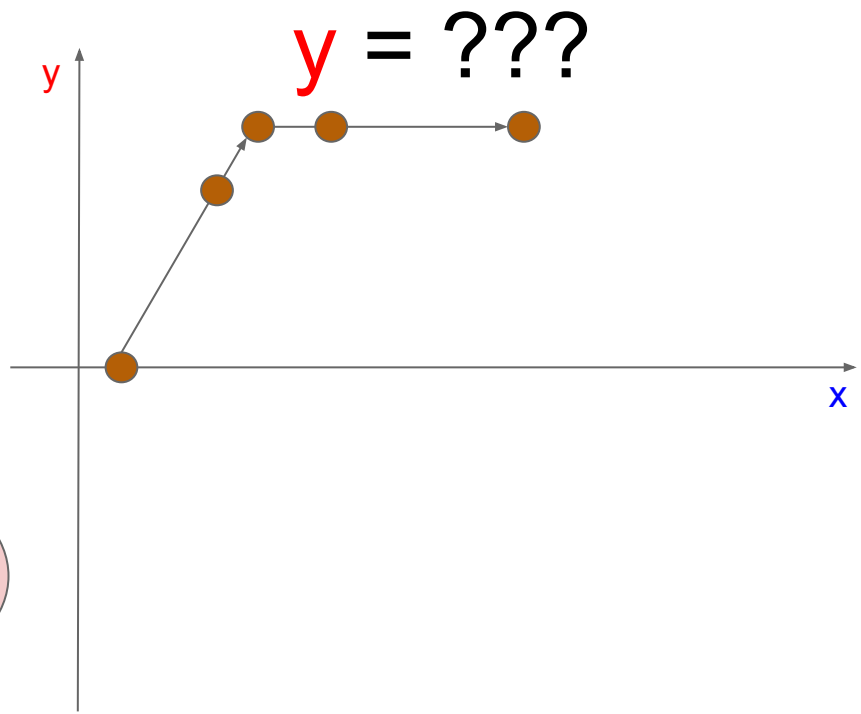


Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

Can we learn arbitrary functions?



Nonlinear Neural Models

$$y = (w_1 x + b_1)s_1 + (w_2 x + b_2)s_2$$

Use different linear functions depending on the value of x?

Nonlinear Neural Models

$$y = (w_1x + b_1)s_1 + (w_2x+b_2)s_2$$

s_1 - 1 if x < 6 and 0 otherwise

s_2 - 1 if x >= 6 and 0 otherwise

Nonlinear Neural Models

$$y = (w_1x + b_1)s_1 + (w_2x+b_2)s_2$$

s_1 - 1 if x < 6 and 0 otherwise

s_2 - 1 if x >= 6 and 0 otherwise

Data

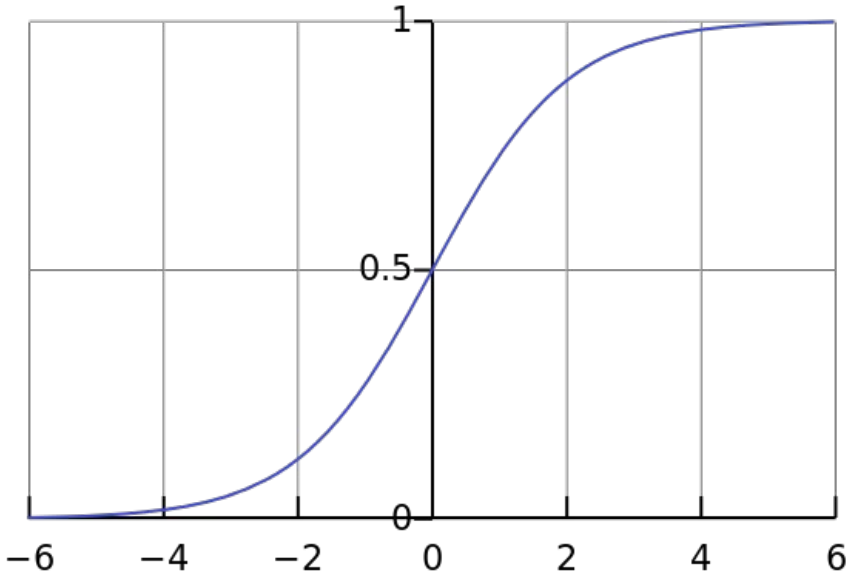
n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$$y = (4x - 4)s_1 + (0x+20)s_2$$

Nonlinear Neural Models

$$s = \sigma(wx + b)$$

$$\sigma(t) = \frac{1}{1 + e^{-t}}$$



Nonlinear Neural Models

$s = \sigma(1000x)$

$x = 0.1$ then $\sigma(1000x) = 1$

$x = -0.1$ then $\sigma(1000x) = 0$

Nonlinear Neural Models

$s = \sigma(1000x)$

$x = 0.1$ then $\sigma(1000x) = 1$

$x = -0.1$ then $\sigma(1000x) = 0$

Nonlinear Neural Models

$$s = \sigma(1000x - 6000)$$

$x = 6.1$ then $\sigma(1000x - 6000) = 1$

$x = 5.9$ then $\sigma(1000x - 6000) = 0$

Nonlinear Neural Models

$$y = (w_1 x + b_1)s_1 + (w_2 x + b_2)s_2$$

$$s1 = \sigma(w_3 x + b_3)$$

$$s2 = \sigma(w_4 x + b_4)$$

Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$$y = (4x - 4)s_1 + (0x+20)s_2$$

$$s1 = \sigma(-1000x + 6000)$$

$$s2 = \sigma(1000x - 6000)$$

Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$$y = (4x - 4)s_1 + (0x+20)s_2$$

$$s1 = \sigma(-1000x + 6000)$$

$$s2 = \sigma(1000x - 6000)$$

Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$$y = (16)s_1 + (0x+20)s_2$$

$$s1 = \sigma(-1000x + 6000)$$

$$s2 = \sigma(1000x - 6000)$$

Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$$y = (16)s_1 + (20)s_2$$

$$s1 = \sigma(-1000x + 6000)$$

$$s2 = \sigma(1000x - 6000)$$

Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$$y = (16)s_1 + (20)s_2$$

$$s1 = \sigma(1000)$$

$$s2 = \sigma(1000x - 6000)$$

Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$$y = (16)s_1 + (20)s_2$$

$$s1 = \boldsymbol{\sigma}(1000)$$

$$s2 = \boldsymbol{\sigma}(-1000)$$

Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$$y = (16)1 + (20)0$$

$$s1 = \sigma(1000)$$

$$s2 = \sigma(-1000)$$

Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$y = 16$

$s1 = \sigma(1000)$

$s2 = \sigma(-1000)$

Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$$y = (4x - 4)s_1 + (0x+20)s_2$$

$$s1 = \sigma(-1000x + 6000)$$

$$s2 = \sigma(1000x - 6000)$$

Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$$y = (32)s_1 + (0x+20)s_2$$

$$s1 = \sigma(-1000x + 6000)$$

$$s2 = \sigma(1000x - 6000)$$

Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$$y = (32)s_1 + (20)s_2$$

$$s1 = \sigma(-1000x + 6000)$$

$$s2 = \sigma(1000x - 6000)$$

Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$$y = (32)s_1 + (20)s_2$$

$$s1 = \sigma(-3000)$$

$$s2 = \sigma(1000x - 6000)$$

Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$$y = (32)s_1 + (20)s_2$$

$$s1 = \boldsymbol{\sigma}(-3000)$$

$$s2 = \boldsymbol{\sigma}(3000)$$

Nonlinear Neural Models

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$$y = (32)0 + (20)1$$

$$s1 = \sigma(-3000)$$

$$s2 = \sigma(3000)$$

Nonlinear Neural Models

Data

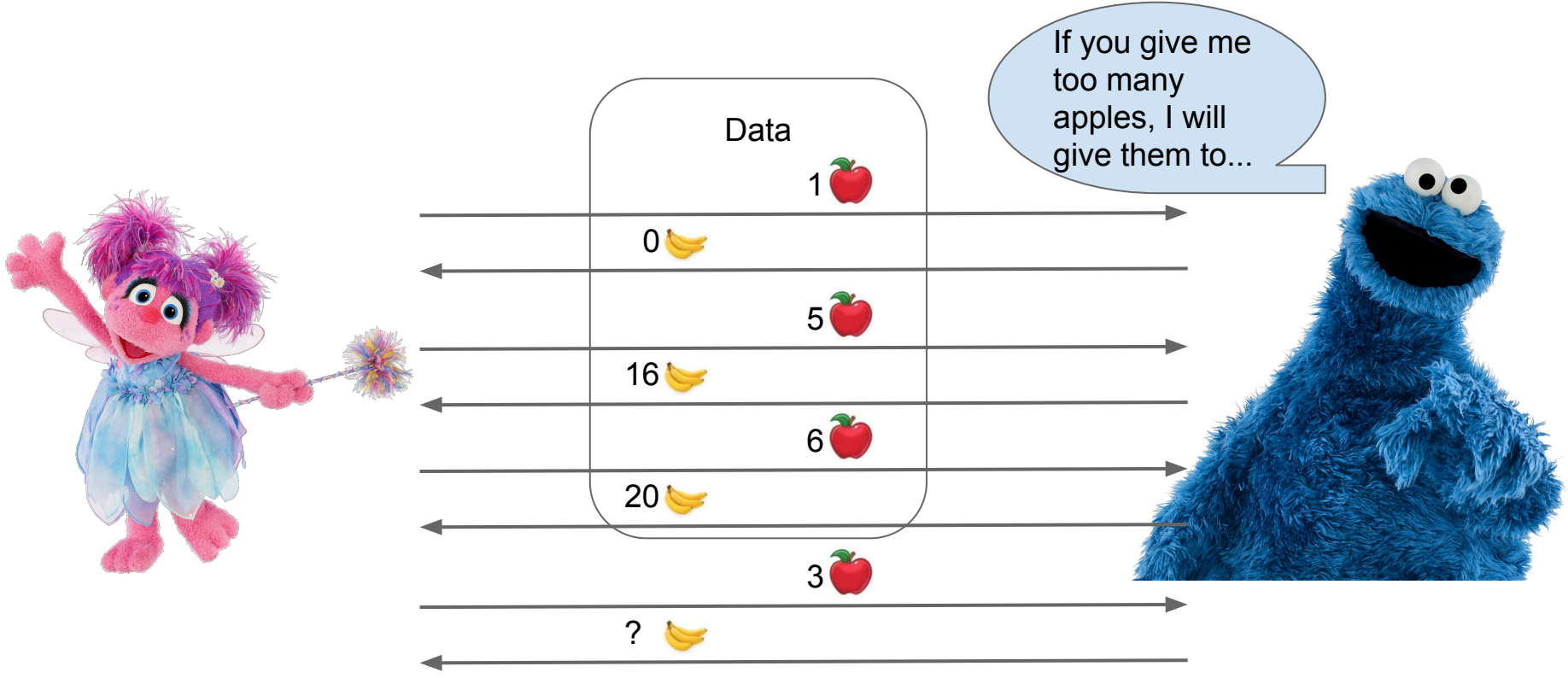
n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20

$y = 20$

$s1 = \sigma(-3000)$

$s2 = \sigma(3000)$

Nonlinear Neural Models



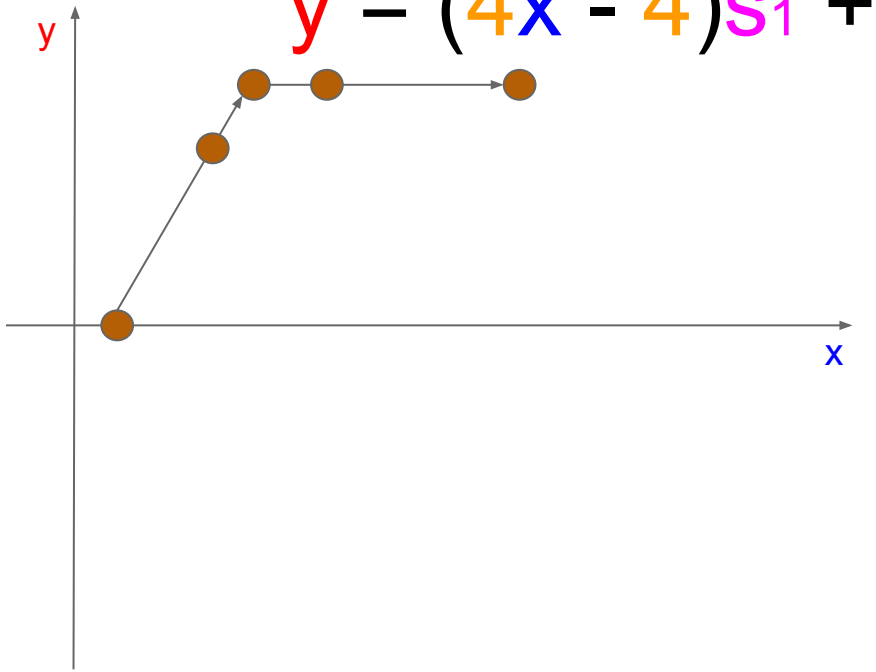
Nonlinear Neural Models

Count Von Count

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20



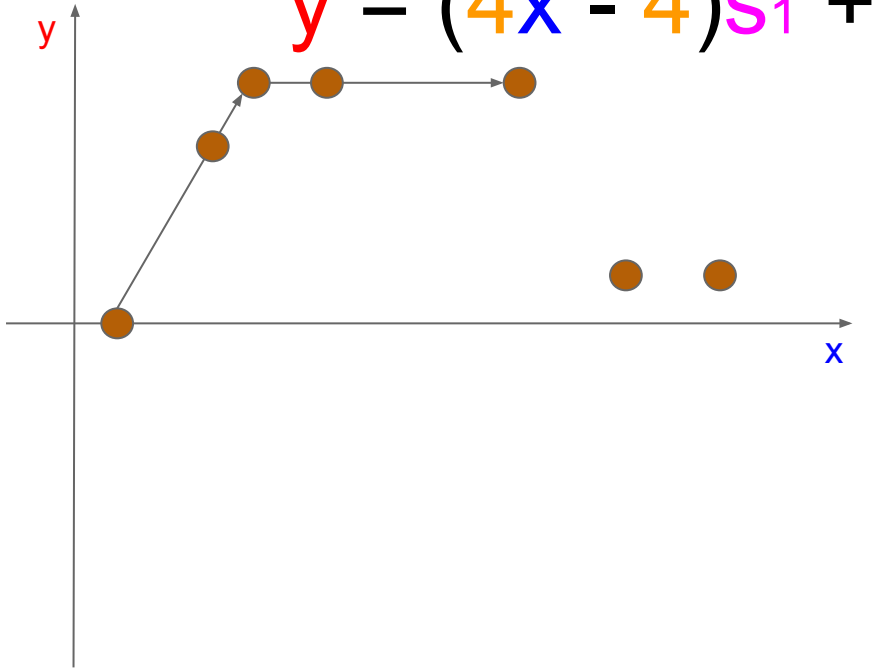
$$y = (4x - 4)s_1 + (0x+20)s_2$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (4x - 4)s_1 + (0x+20)s_2$$



Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (4x - 4)s_1 + (0x+20)s_2 + (0x+1)s_3$$

$$s_1 = \sigma(-1000x + 6000)$$

$$s_2 = ????$$

$$s_3 = \sigma(1000x - 15000)$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (4x - 4)s_1 + (0x+20)s_2 + (0x+1)s_3$$

$$s_1 = \sigma(-1000x + 6000)$$

$$s_2 = \text{not } s_1 \text{ and not } s_3$$

$$s_3 = \sigma(1000x - 15000)$$

Multilayer Perceptrons

$$y = (w_1x + b_1)s_1 + (w_2x+b_2)s_2 + (w_3x+b_3)s_3$$

$$s_1 = \sigma(w_4x + b_4)$$
$$s_2 = \sigma(w_5s_1 + w_6s_3 + b_5)$$
$$s_3 = \sigma(w_7x + b_6)$$

Multilayer Perceptrons

$$y = (w_1x + b_1)s_1 + (w_2x+b_2)s_2 + (w_3x+b_3)s_3$$

$$s_1 = \sigma(w_4x + b_4)$$

Layer 1 Perceptron

$$s_2 = \sigma(w_5s_1 + w_6s_3 + b_5)$$

$$s_3 = \sigma(w_7x + b_6)$$

Layer 1 Perceptron

Multilayer Perceptrons

$$y = (w_1x + b_1)s_1 + (w_2x+b_2)s_2 + (w_3x+b_3)s_3$$

$$s_1 = \sigma(w_4x + b_4)$$ Layer 1 Perceptron

$$s_2 = \sigma(w_5s_1 + w_6s_3 + b_5)$$ Layer 2 Perceptron

$$s_3 = \sigma(w_7x + b_6)$$ Layer 1 Perceptron

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (4x - 4)s_1 + (0x+20)s_2 + (0x+1)s_3$$

$$s_1 = \sigma(-1000x + 6000)$$

$$s_2 = \text{not } s_1 \text{ and not } s_3$$

$$s_3 = \sigma(1000x - 15000)$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (4x - 4)s_1 + (0x+20)s_2 + (0x+1)s_3$$

$$s_1 = \sigma(-1000x + 6000)$$

$$s_2 = \sigma(-1000s_1 - 1000s_3 + 500)$$

$$s_3 = \sigma(1000x - 15000)$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (4x - 4)s_1 + (0x+20)s_2 + (0x+1)s_3$$

$$s_1 = \sigma(-1000x + 6000)$$

$$s_2 = \sigma(-1000s_1 - 1000s_3 + 500)$$

$$s_3 = \sigma(1000x - 15000)$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (40)s_1 + (20)s_2 + (1)s_3$$

$$s_1 = \sigma(-1000x + 6000)$$

$$s_2 = \sigma(-1000s_1 - 1000s_3 + 500)$$

$$s_3 = \sigma(1000x - 15000)$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (40)s_1 + (20)s_2 + (1)s_3$$

$$s_1 = \sigma(-5000) = 0$$

$$s_2 = \sigma(-1000s_1 - 1000s_3 + 500)$$

$$s_3 = \sigma(-4000) = 0$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (40)s_1 + (20)s_2 + (1)s_3$$

$$s_1 = \sigma(-5000) = 0$$

$$s_2 = \sigma(-1000s_4 - 1000s_5 + 500)$$

$$s_3 = \sigma(-4000) = 0$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (40)s_1 + (20)s_2 + (1)s_3$$

$$s_1 = \sigma(-5000) = 0$$

$$s_2 = \sigma(500)$$

$$s_3 = \sigma(-4000) = 0$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (40)s_1 + (20)s_2 + (1)s_3$$

$$s_1 = \sigma(-5000) = 0$$

$$s_2 = \sigma(500) = 1$$

$$s_3 = \sigma(-4000) = 0$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (40)0 + (20)1 + (1)0$$

$$s_1 = \sigma(-5000) = 0$$

$$s_2 = \sigma(500) = 1$$

$$s_3 = \sigma(-4000) = 0$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$y = 20$

$s_1 = \sigma(-5000) = 0$

$s_2 = \sigma(500) = 1$

$s_3 = \sigma(-4000) = 0$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (4x - 4)s_1 + (0x+20)s_2 + (0x+1)s_3$$

$$s_1 = \sigma(-1000x + 6000)$$

$$s_2 = \sigma(-1000s_1 - 1000s_3 + 500)$$

$$s_3 = \sigma(1000x - 15000)$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (772)s_1 + (20)s_2 + (1)s_3$$

$$s_1 = \sigma(-1000x + 6000)$$

$$s_2 = \sigma(-1000s_4 - 1000s_5 + 500)$$

$$s_3 = \sigma(1000x - 15000)$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (772)s_1 + (20)s_2 + (1)s_3$$

$$s_1 = \sigma(-13000) = 0$$

$$s_2 = \sigma(-1000s_4 - 1000s_5 + 500)$$

$$s_3 = \sigma(4000) = 1$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (772)s_1 + (20)s_2 + (1)s_3$$

$$s_1 = \sigma(-13000) = 0$$

$$s_2 = \sigma(-1000 + 0 + 500)$$

$$s_3 = \sigma(4000) = 1$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (772)s_1 + (20)s_2 + (1)s_3$$

$$s_1 = \sigma(-13000) = 0$$

$$s_2 = \sigma(-500) = 0$$

$$s_3 = \sigma(4000) = 1$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (772)0 + (20)0 + (1)1$$

$$s_1 = \sigma(-13000) = 0$$

$$s_2 = \sigma(-500) = 0$$

$$s_3 = \sigma(4000) = 1$$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$y = 1$

$s_1 = \sigma(-13000) = 0$

$s_2 = \sigma(-500) = 0$

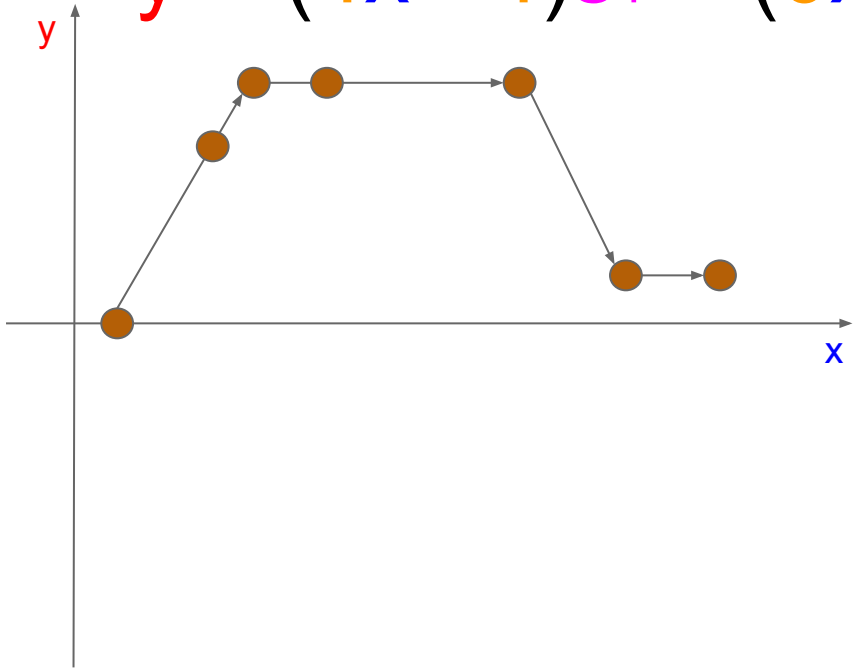
$s_3 = \sigma(4000) = 1$

Multilayer Perceptrons

Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1

$$y = (4x - 4)s_1 + (0x+20)s_2 + (0x+1)s_3$$



Multilayer Perceptrons

$$y = (w_1x + b_1)s_1 + (w_2x+b_2)s_2 + (w_3x+b_3)s_3$$

$$s_1 = \sigma(w_4x + b_4)$$ Layer 1 Perceptron

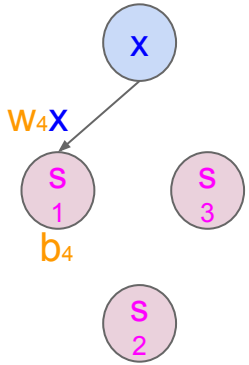
$$s_2 = \sigma(w_5s_1 + w_6s_3 + b_5)$$ Layer 2 Perceptron

$$s_3 = \sigma(w_7x + b_6)$$ Layer 1 Perceptron

Multilayer Perceptrons

$$y = (w_1x + b_1)s_1 + (w_2x+b_2)s_2 + (w_3x+b_3)s_3$$

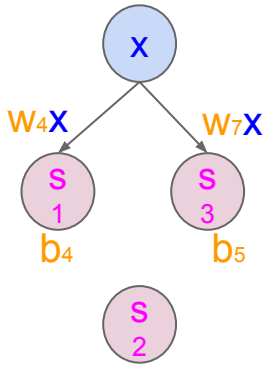
$$s_1 = \sigma(w_4x + b_4)$$
$$s_2 = \sigma(w_5s_1 + w_6s_3 + b_5)$$
$$s_3 = \sigma(w_7x + b_6)$$



Multilayer Perceptrons

$$y = (w_1x + b_1)s_1 + (w_2x+b_2)s_2 + (w_3x+b_3)s_3$$

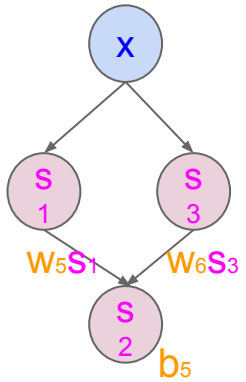
$$s_1 = \sigma(w_4x + b_4)$$
$$s_2 = \sigma(w_5s_1 + w_6s_3 + b_5)$$
$$s_3 = \sigma(w_7x + b_6)$$



Multilayer Perceptrons

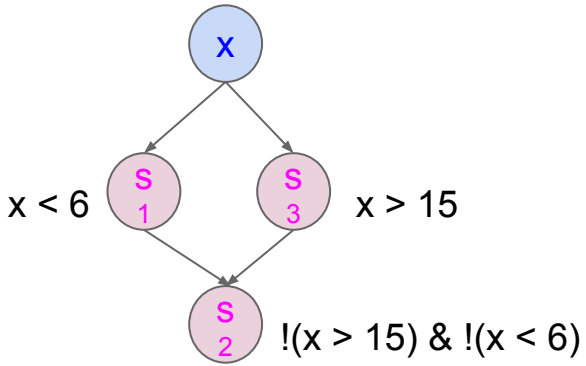
$$y = (w_1x + b_1)s_1 + (w_2x+b_2)s_2 + (w_3x+b_3)s_3$$

$$s_1 = \sigma(w_4x + b_4)$$
$$s_2 = \sigma(w_5s_1 + w_6s_3 + b_5)$$
$$s_3 = \sigma(w_7x + b_6)$$



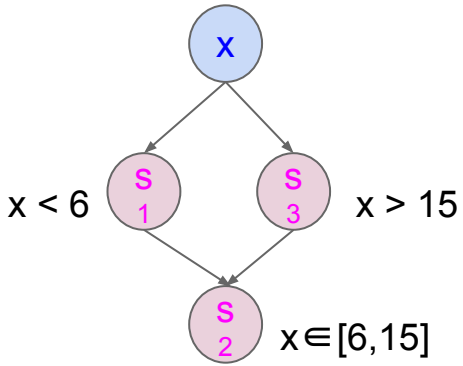
Multilayer Perceptrons

$$y = (w_1x + b_1)s_1 + (w_2x+b_2)s_2 + (w_3x+b_3)s_3$$

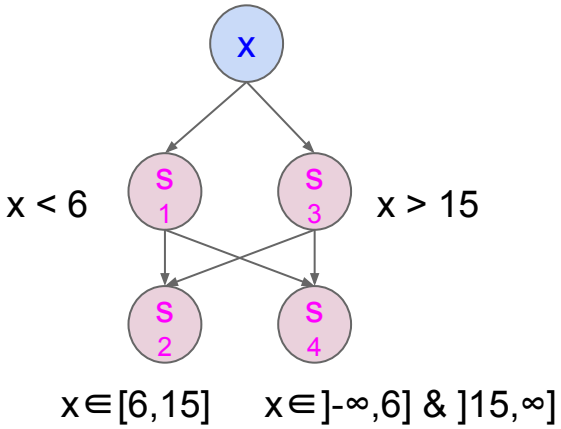


Multilayer Perceptrons

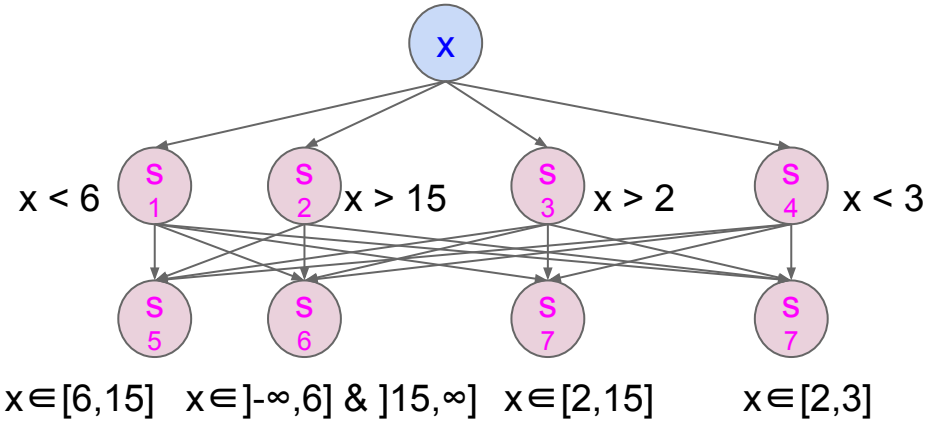
$$y = (w_1x + b_1)s_1 + (w_2x+b_2)s_2 + (w_3x+b_3)s_3$$



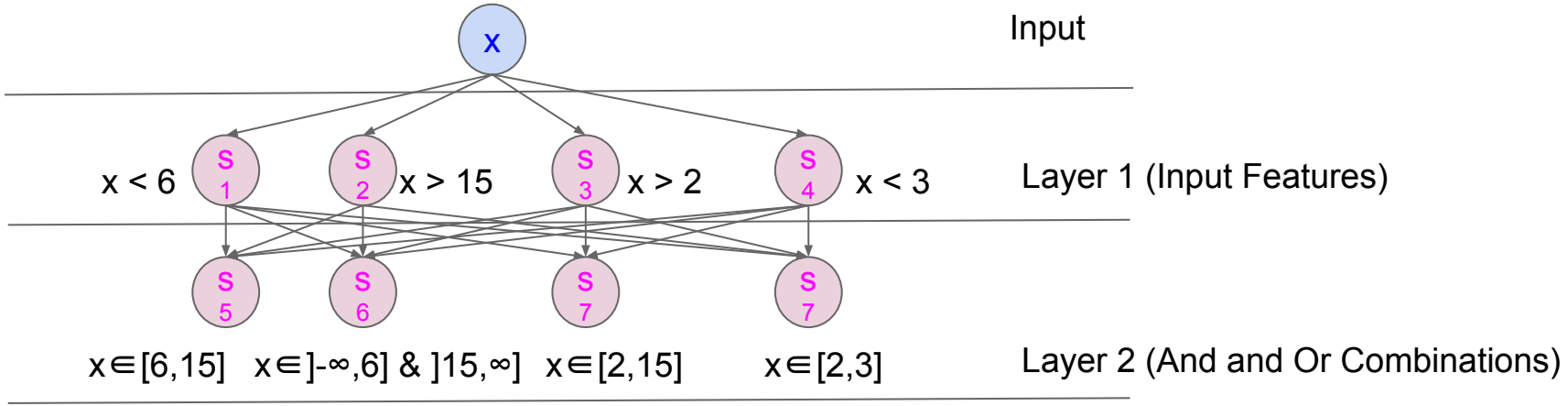
Multilayer Perceptrons



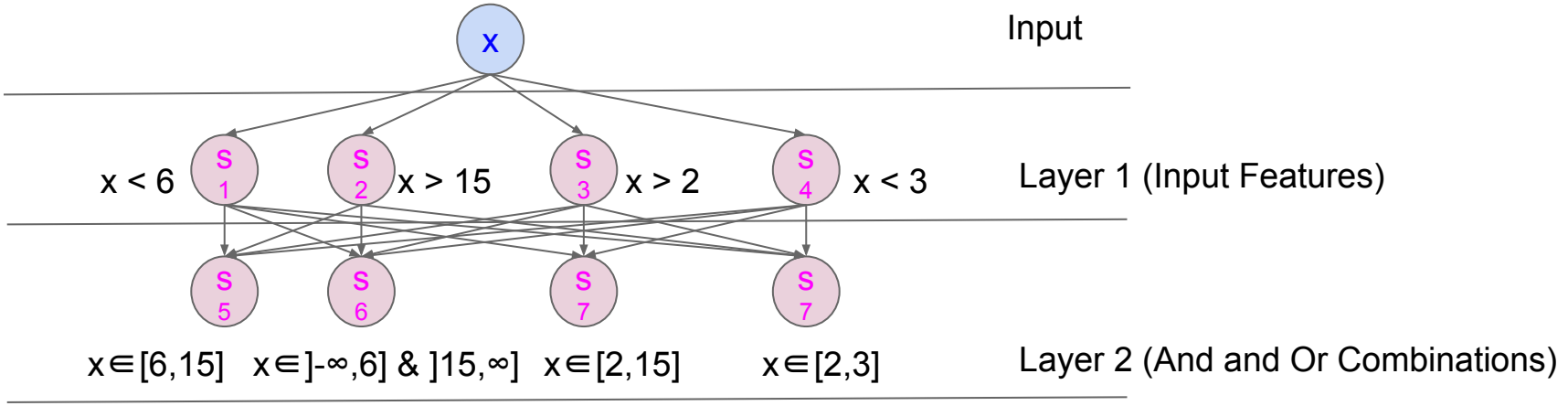
Multilayer Perceptrons



Multilayer Perceptrons



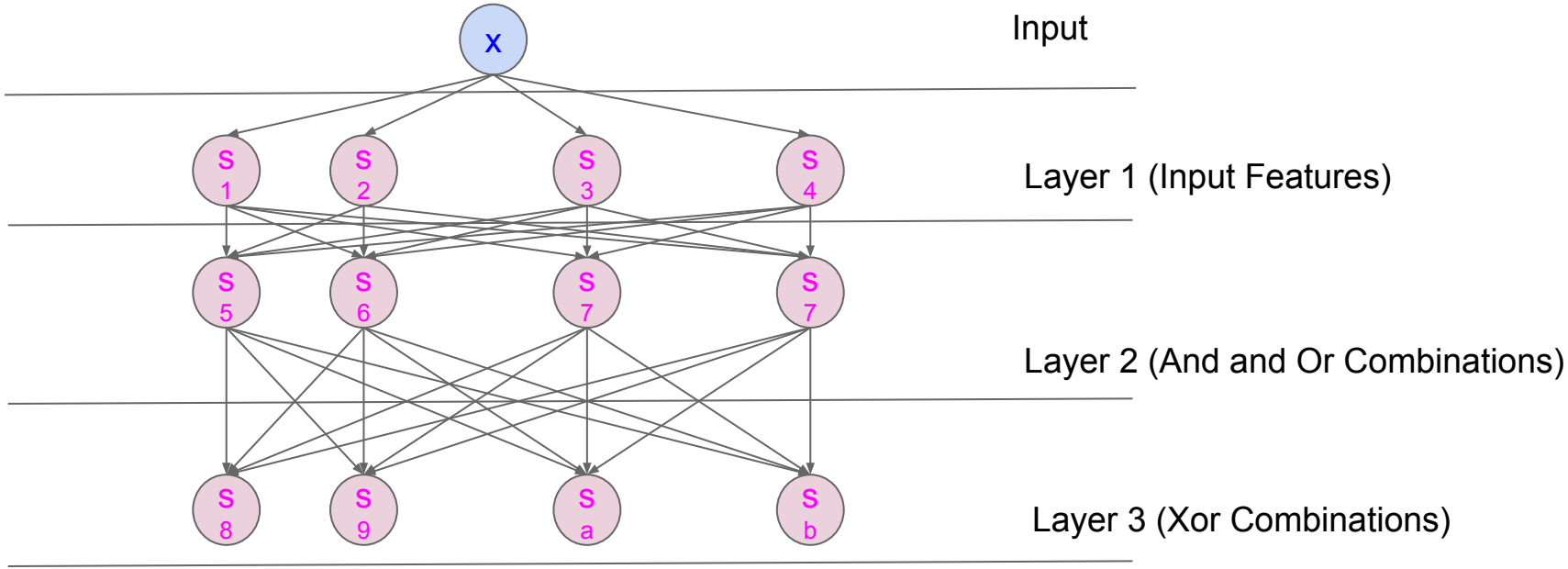
Multilayer Perceptrons



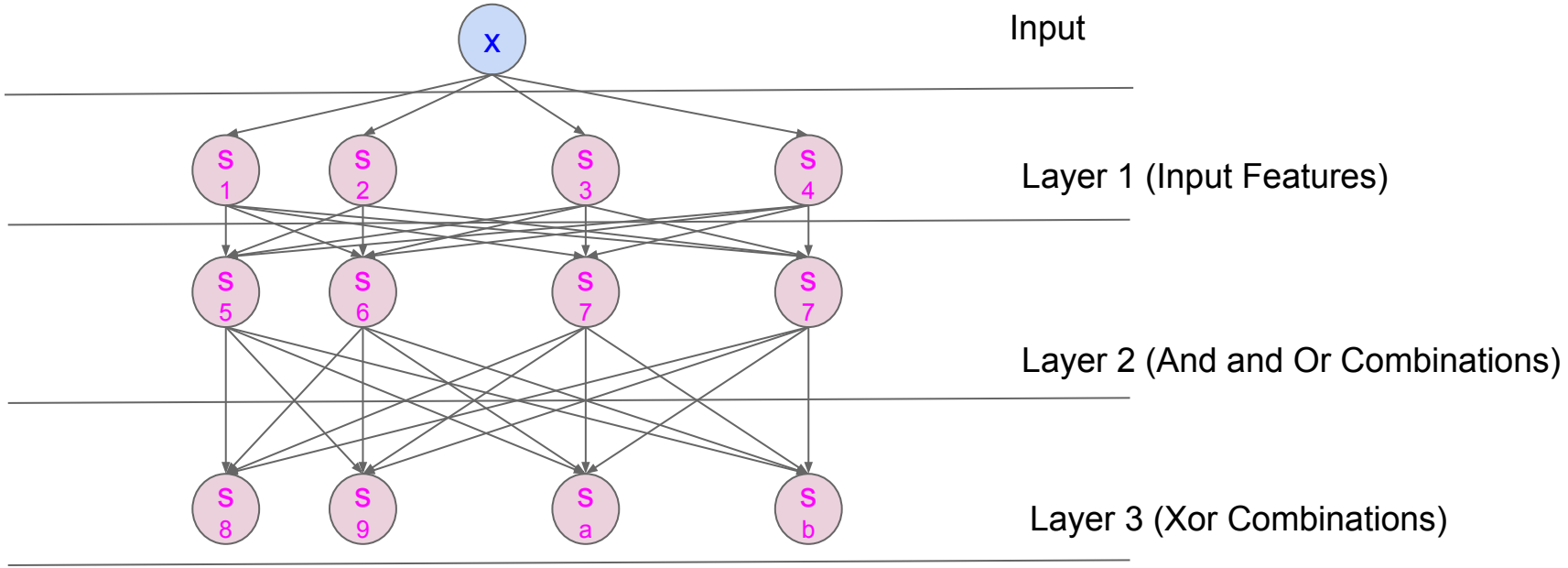
$$And(s_1,s_2) = \sigma(1000s_1 + 1000s_3 - 1500)$$

$$Or(s_1,s_2) = \sigma(1000s_1 + 1000s_3 - 500)$$

Multilayer Perceptrons

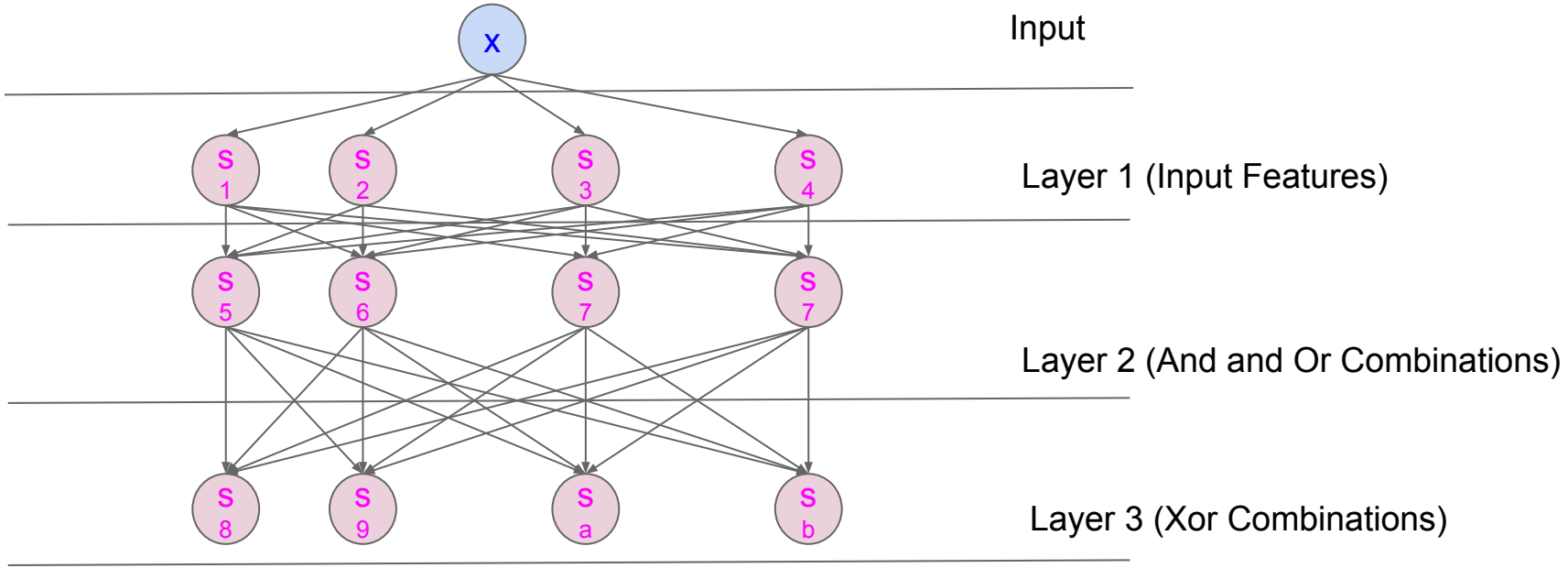


Multilayer Perceptrons



$Xor(s_1,s_2) = Or(And(s_1,!s_2), And(!s_1,s_2))$

Multilayer Perceptrons

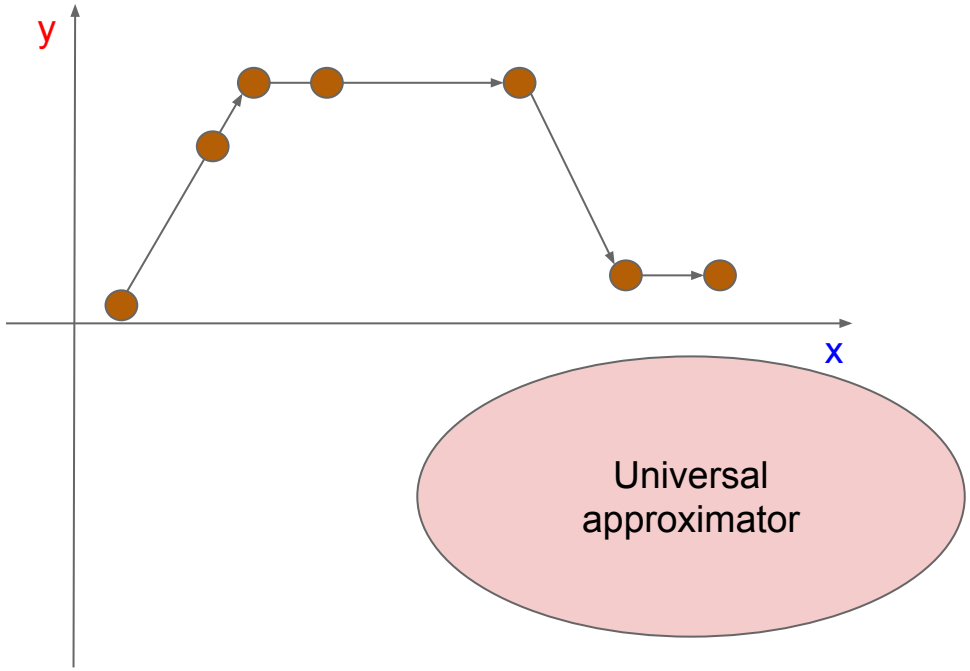


$Xor(s_1, s_2) = Or(s_5, s_6)$

Multilayer Perceptrons

Data

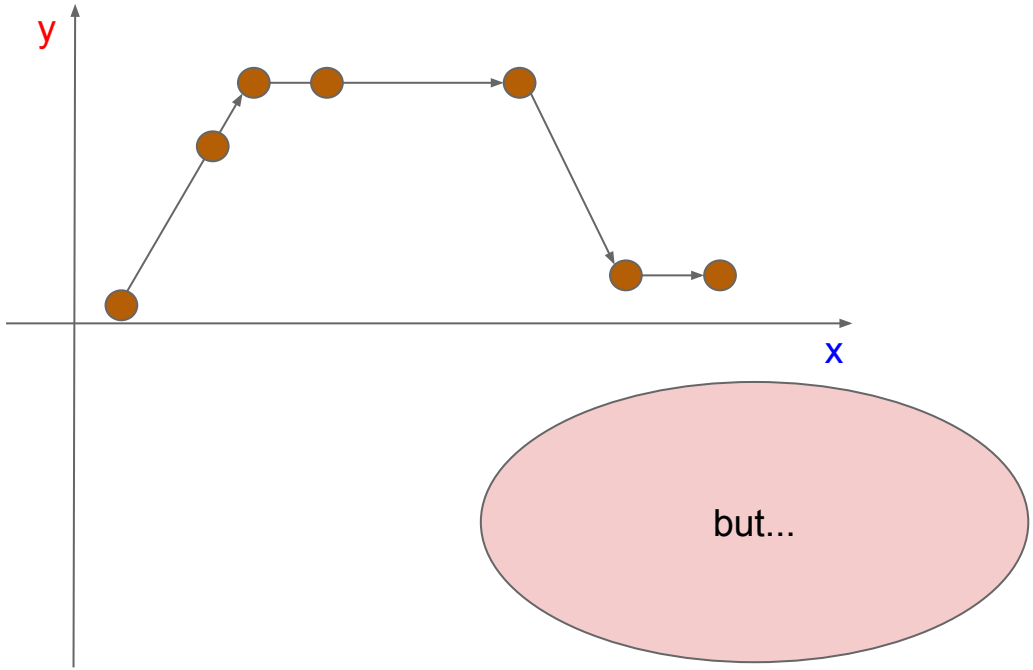
n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1



Multilayer Perceptrons

Data

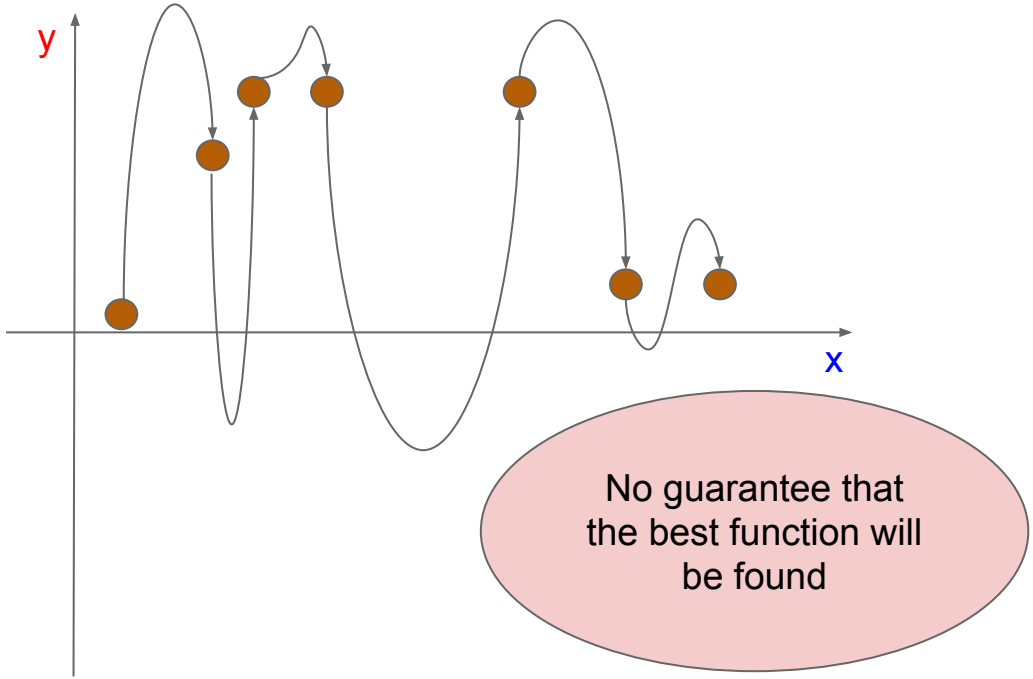
n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1



Multilayer Perceptrons

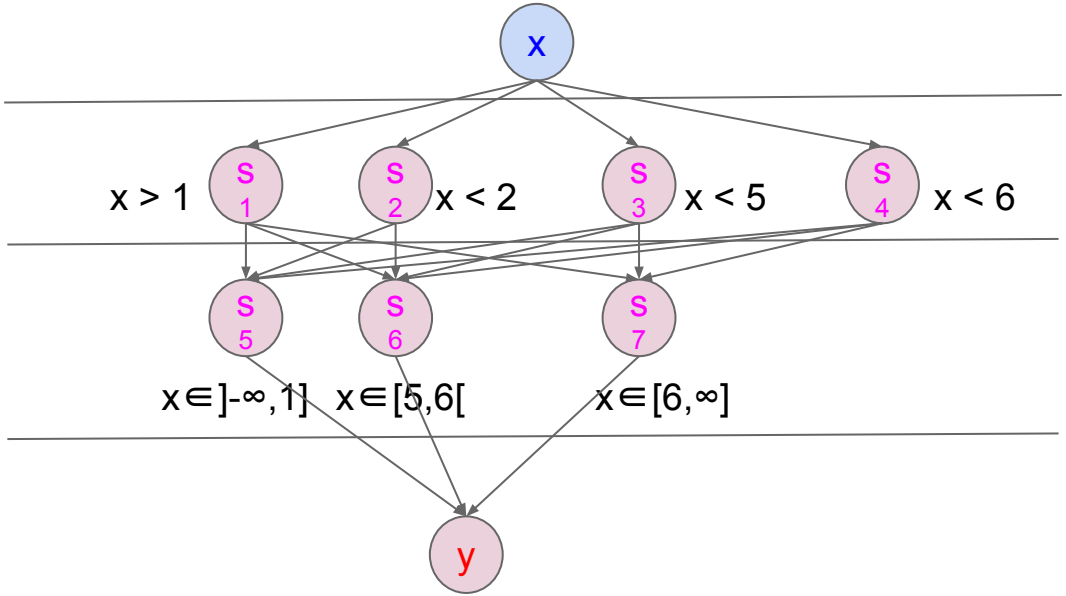
Data

n	x	y
0	1	0
1	5	16
2	6	20
3	9	20
4	11	20
5	15	1
6	19	1



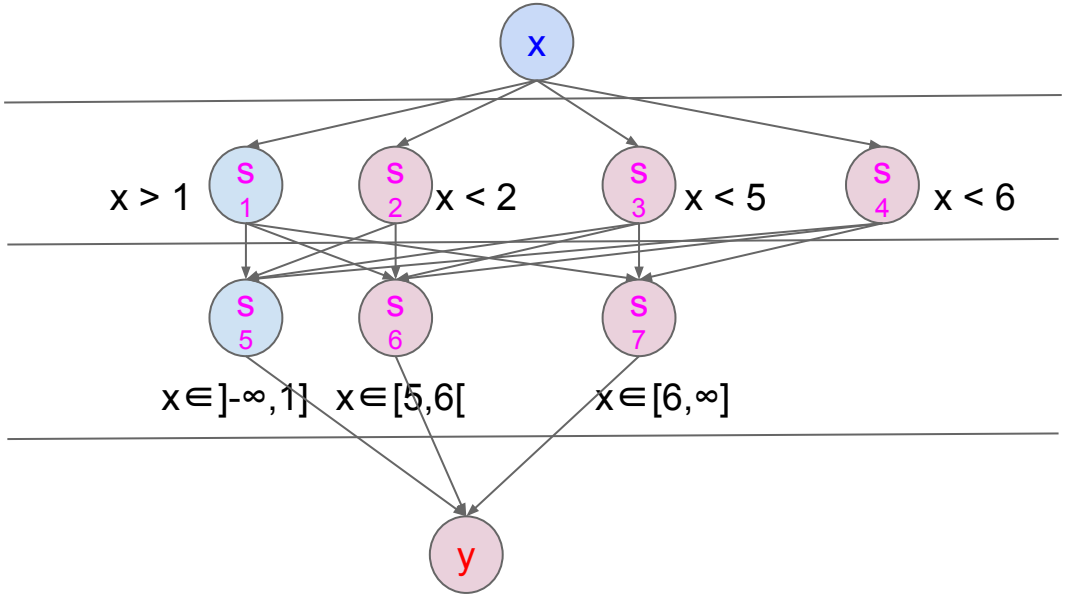
Multilayer Perceptrons

n	x	y
0	1	0
1	5	16
2	6	20



Multilayer Perceptrons

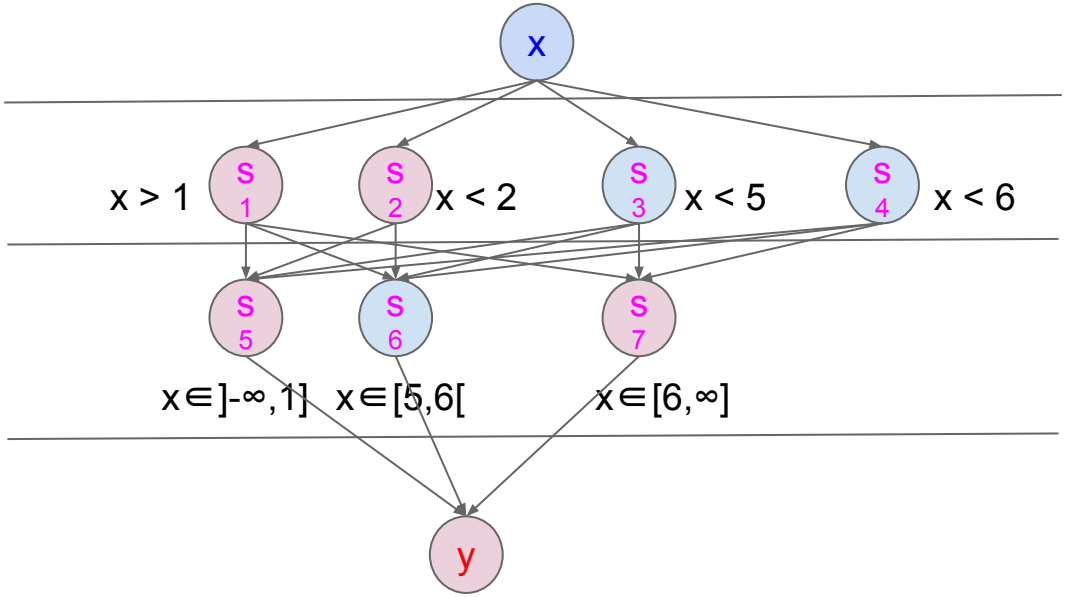
n	x	y
0	1	0
1	5	16
2	6	20



$$y = 0s_5 + 16s_6 + 20s_7$$

Multilayer Perceptrons

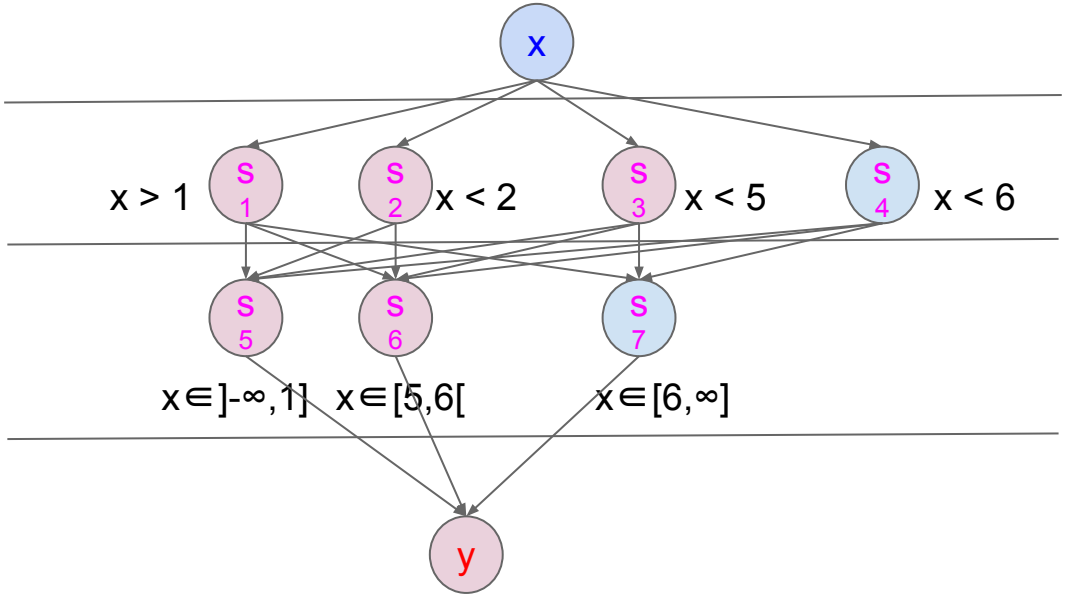
n	x	y
0	1	0
1	5	16
2	6	20



$$y = 0s_5 + 16s_6 + 20s_7$$

Multilayer Perceptrons

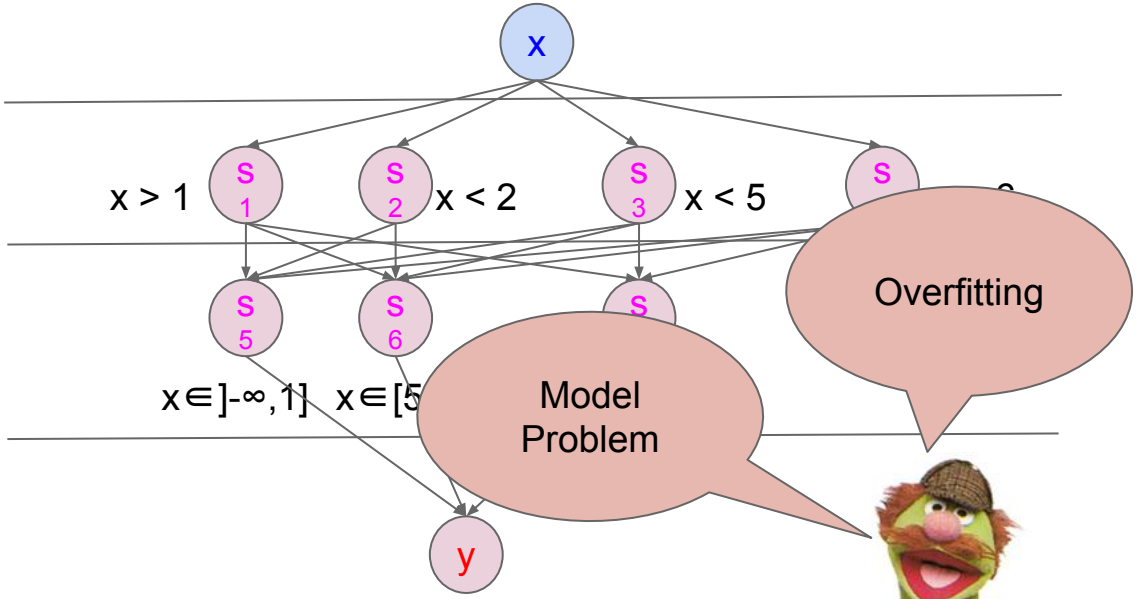
n	x	y
0	1	0
1	5	16
2	6	20



$$y = 0s_5 + 16s_6 + 20s_7$$

Multilayer Perceptrons

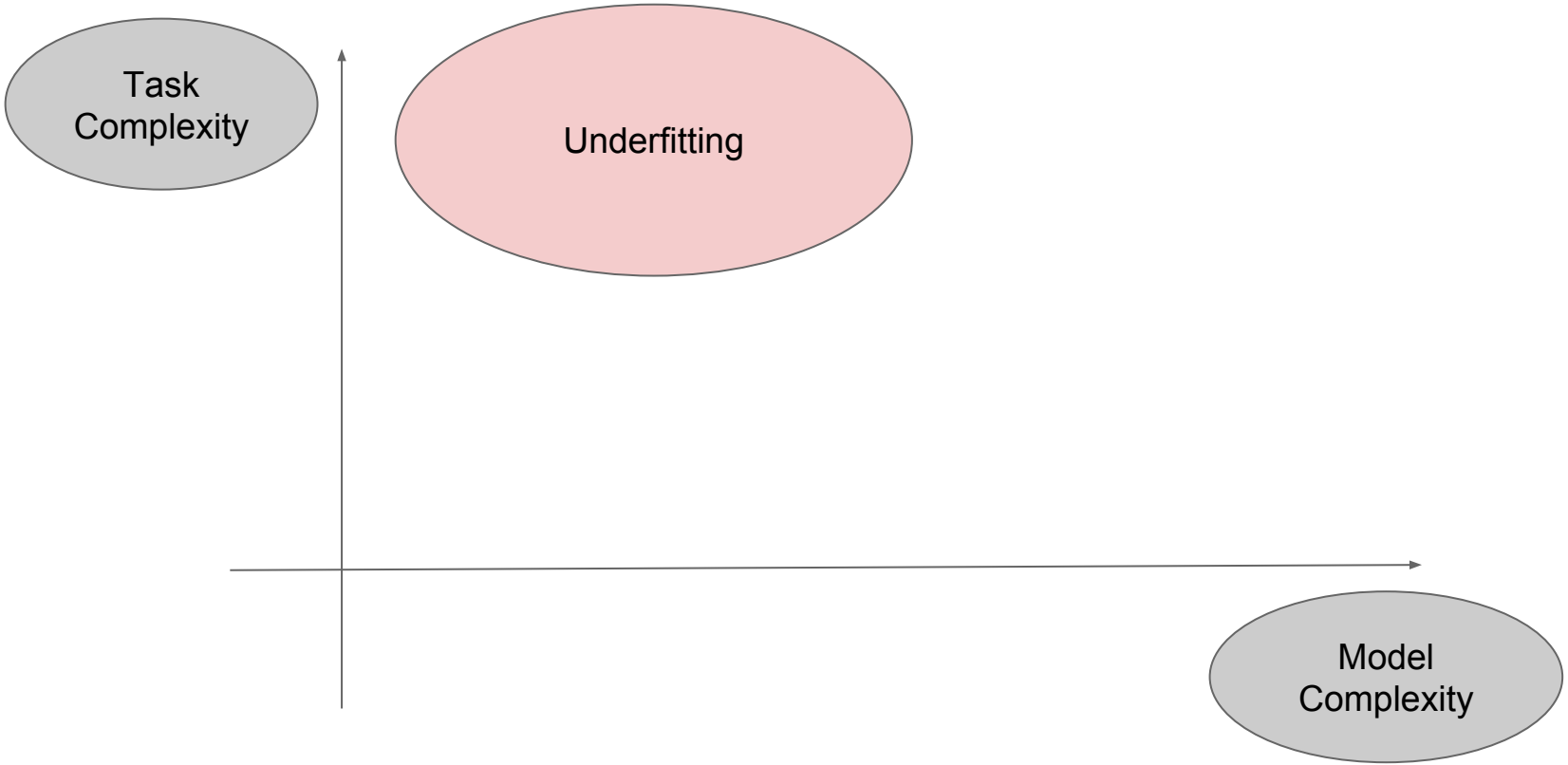
n	x	y
0	1	0
1	5	16
2	6	20



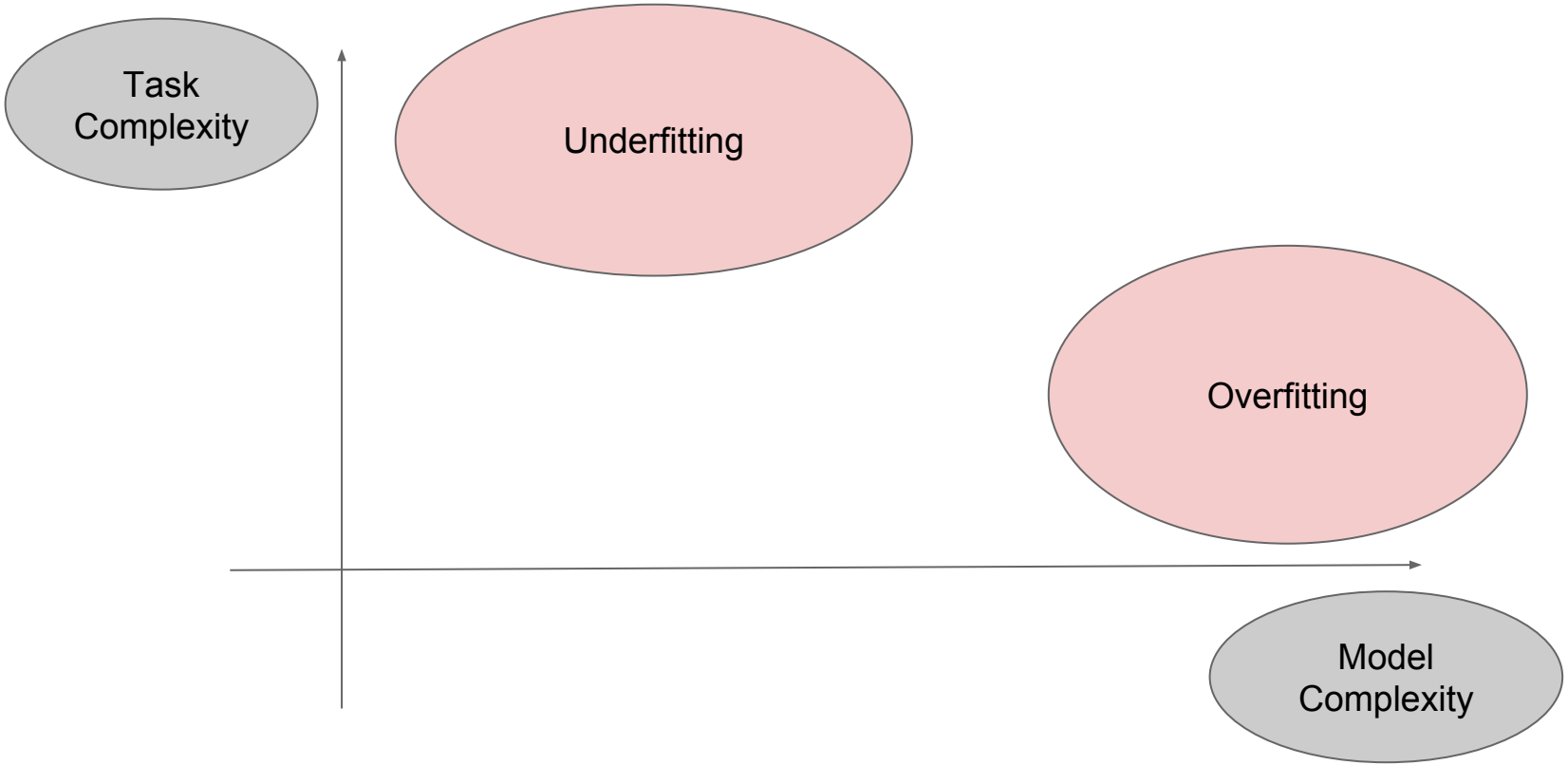
$$y = 0s_5 + 16s_6 + 20s_7$$

Multilayer Perceptrons

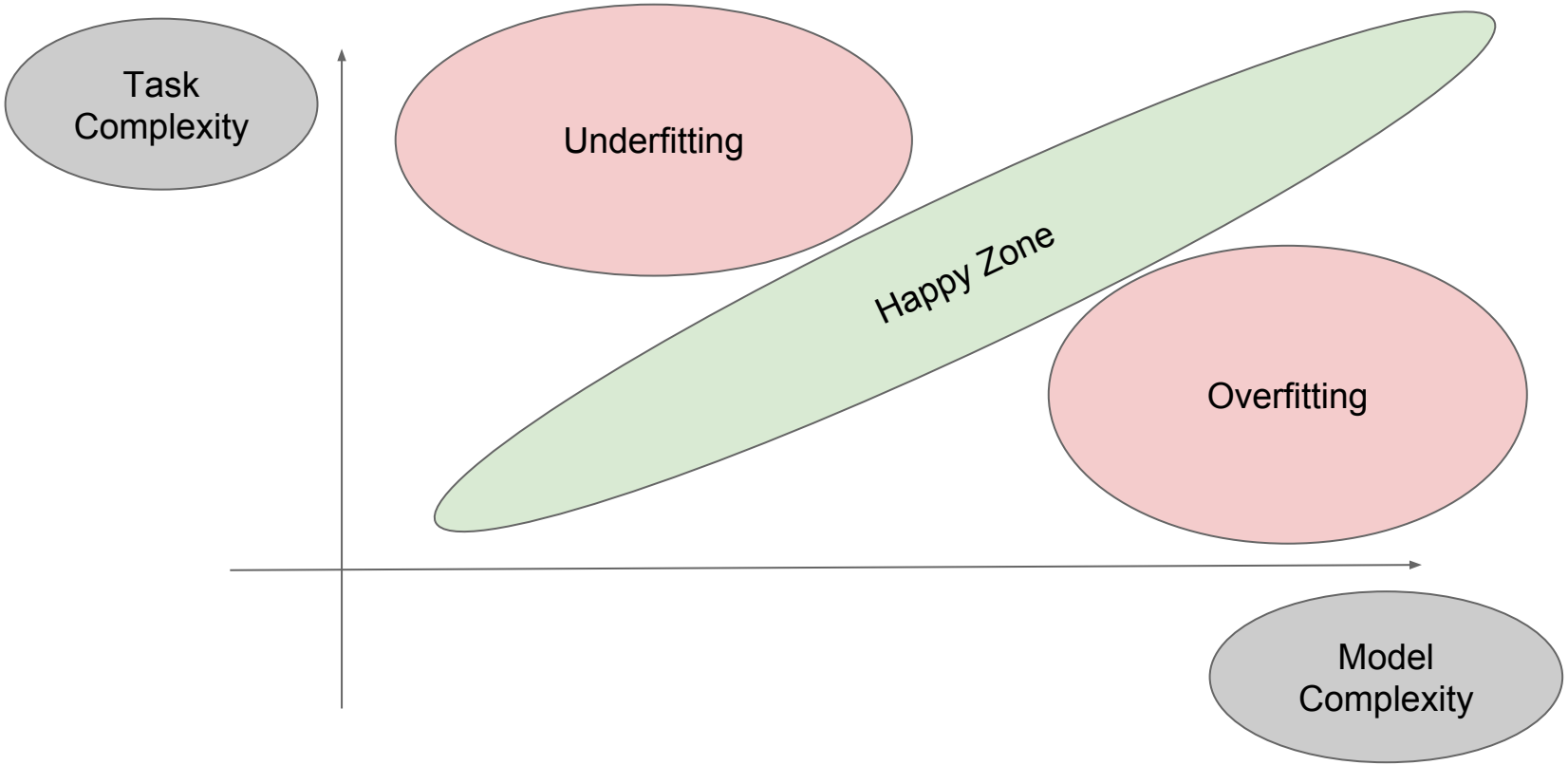
Multilayer Perceptrons



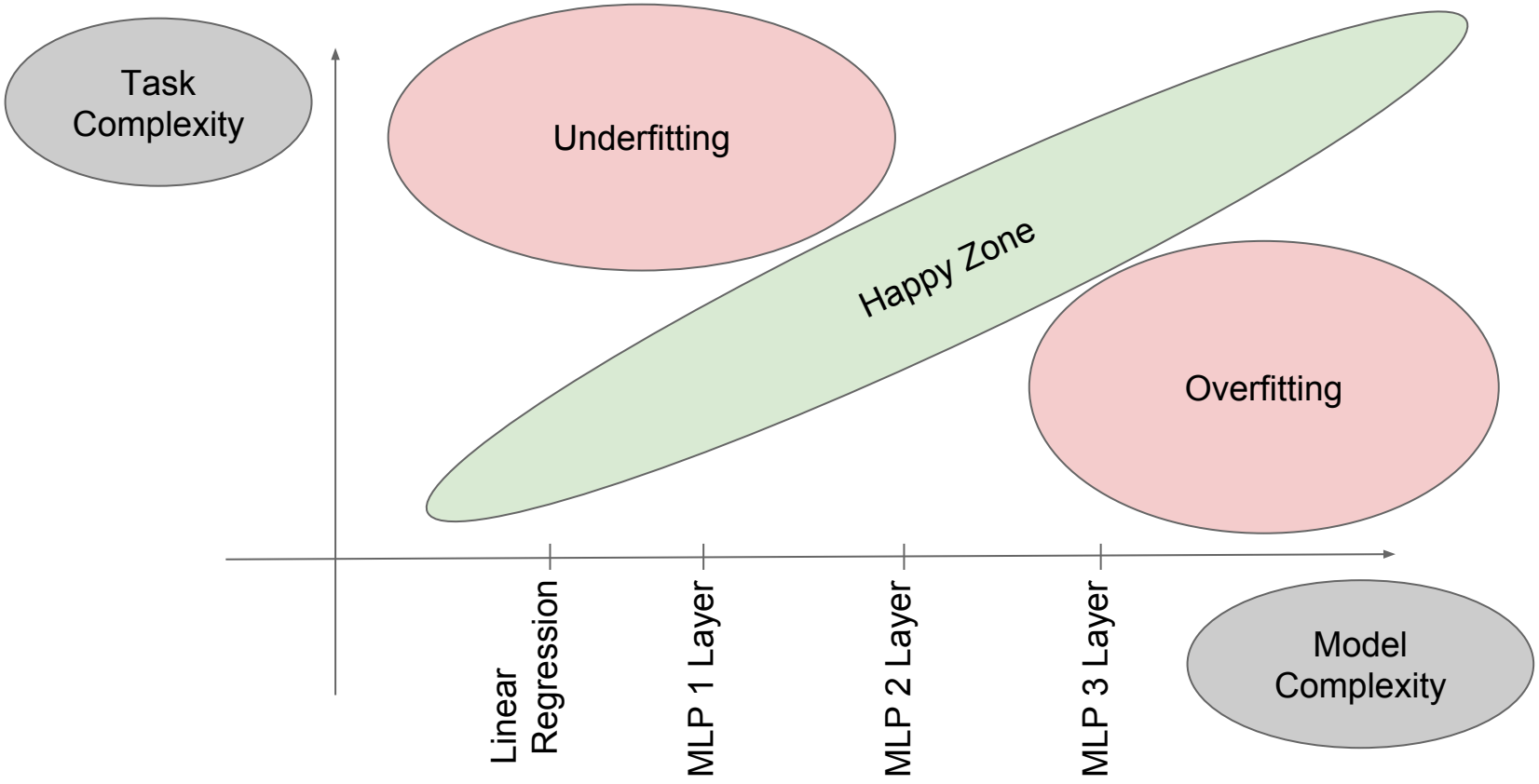
Multilayer Perceptrons



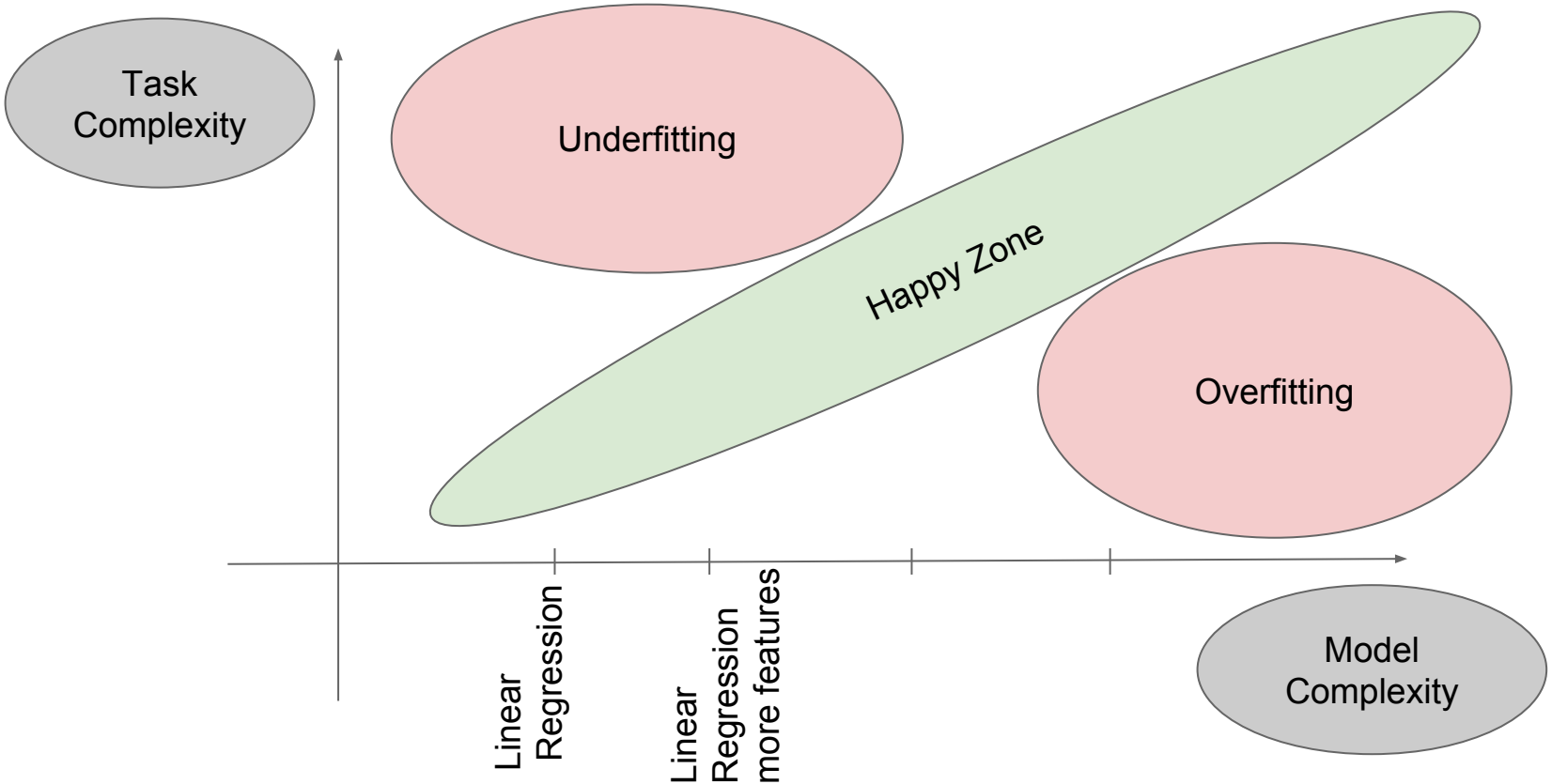
Multilayer Perceptrons



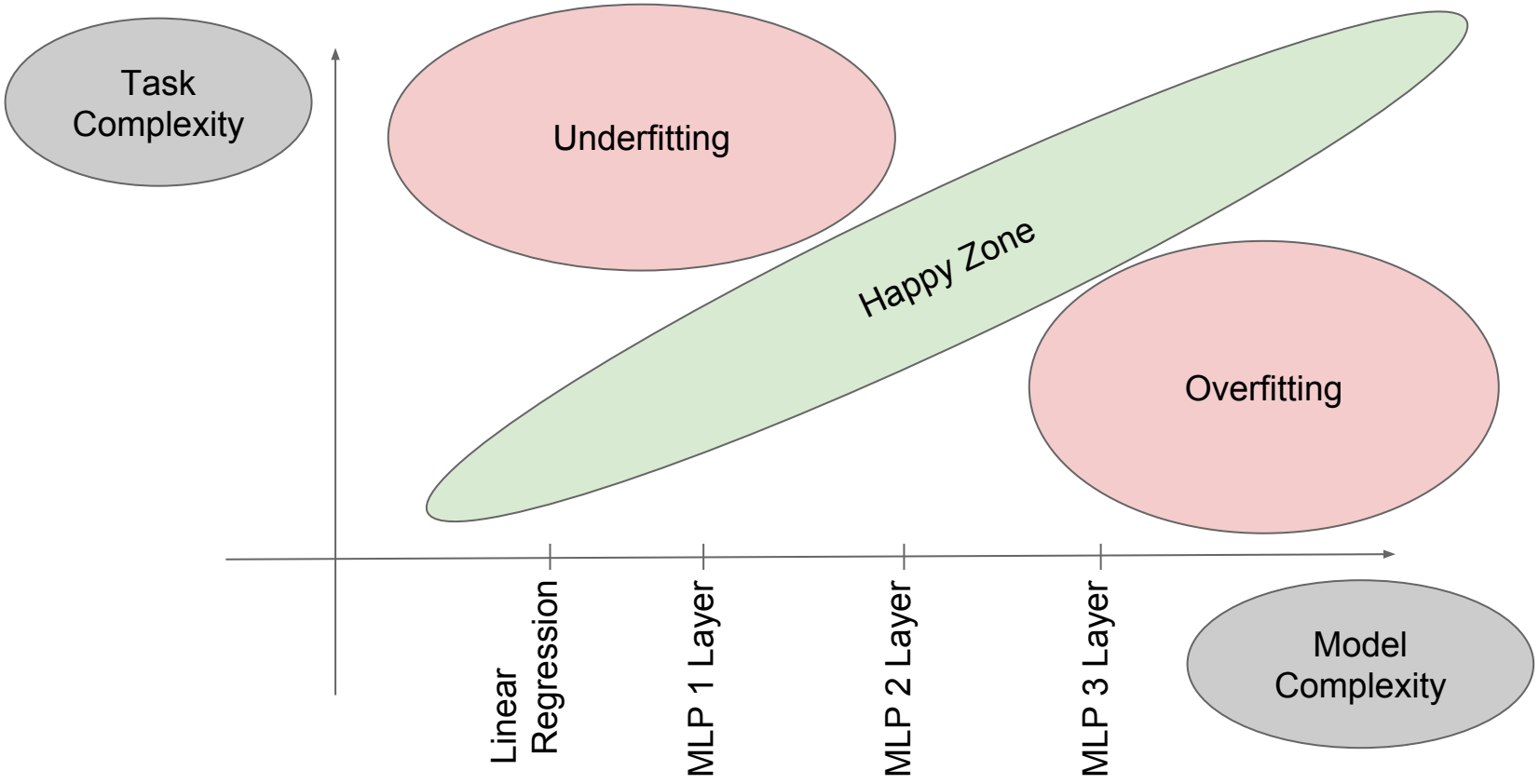
Multilayer Perceptrons



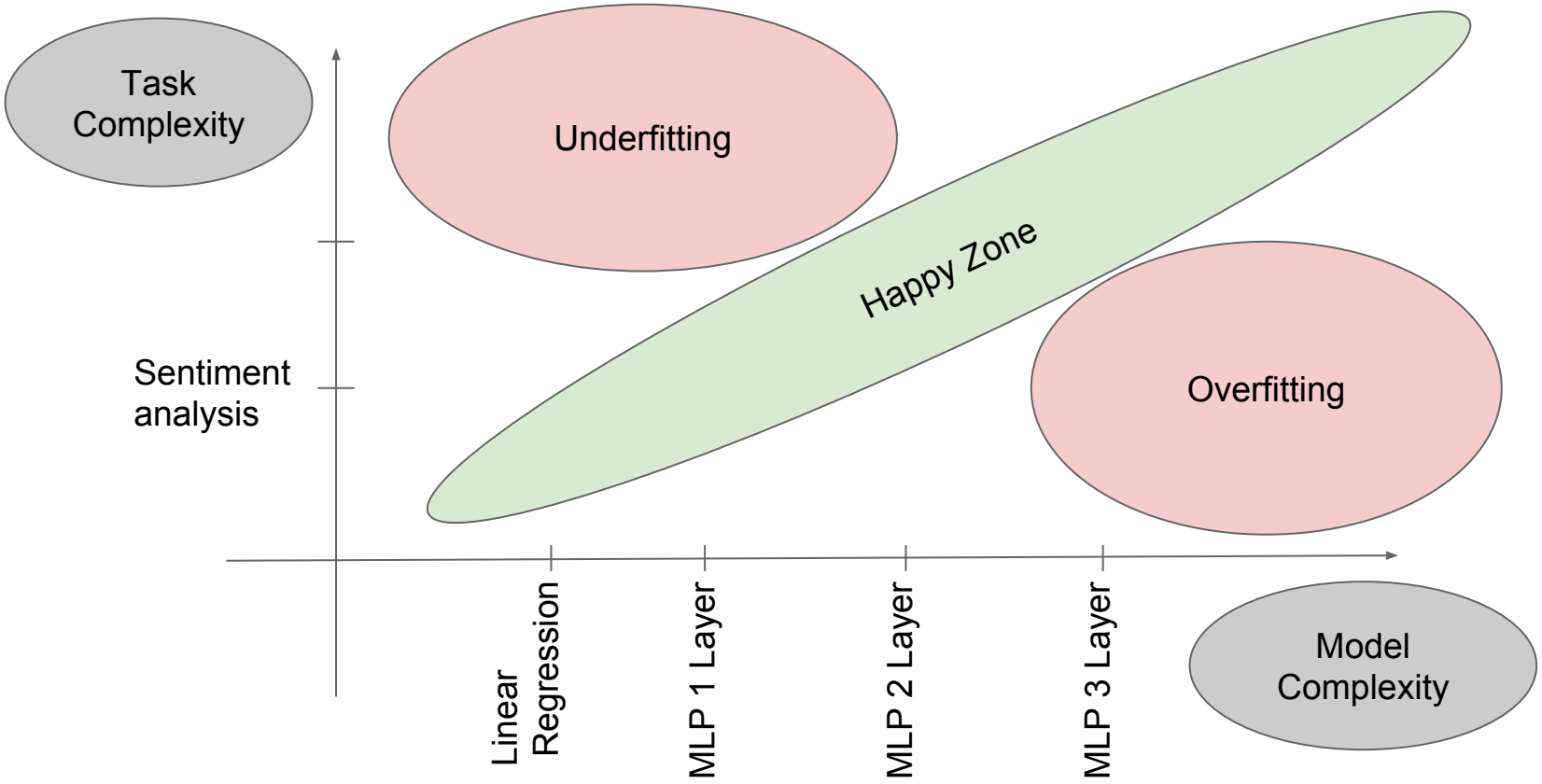
Multilayer Perceptrons



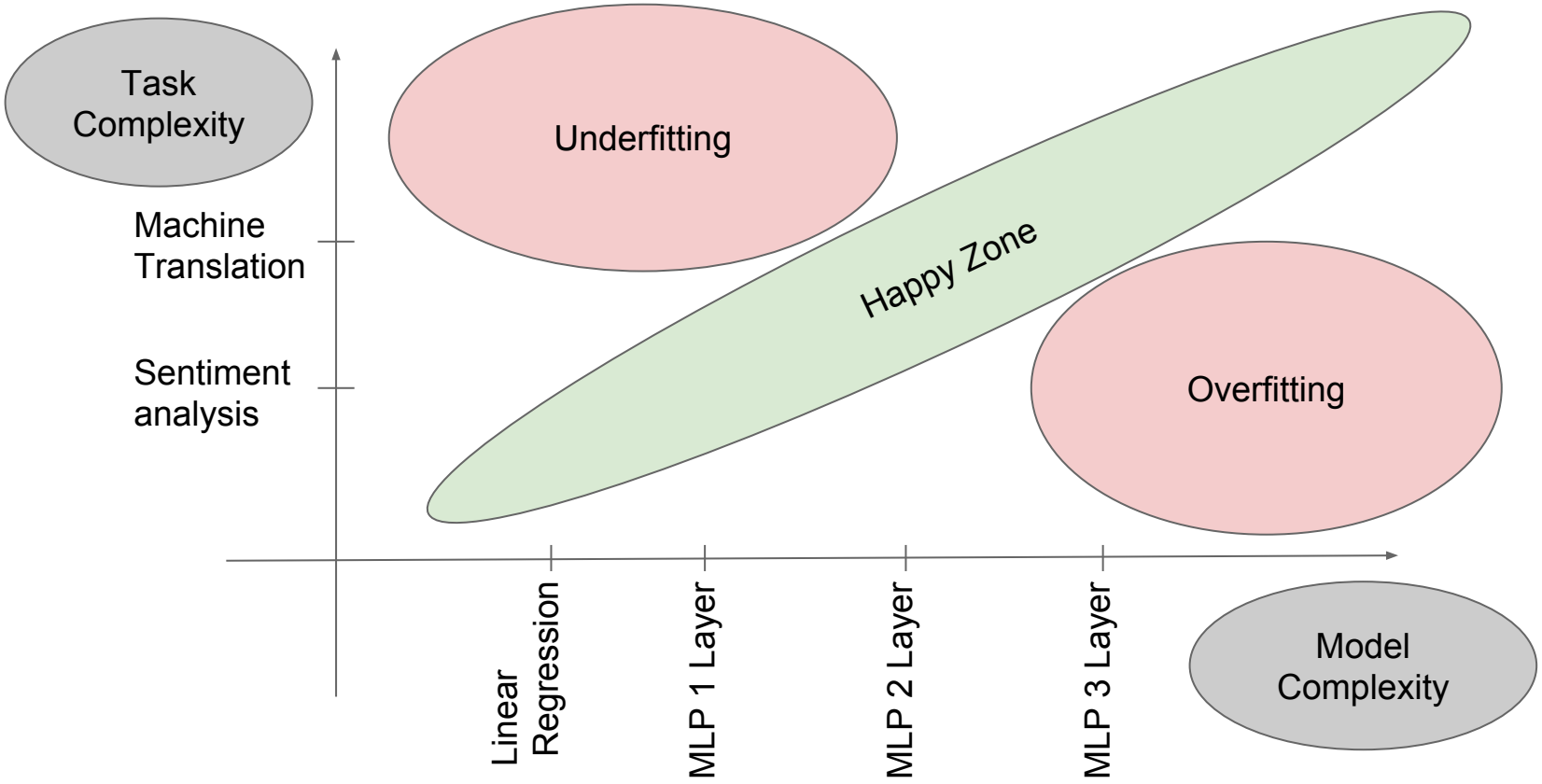
Multilayer Perceptrons



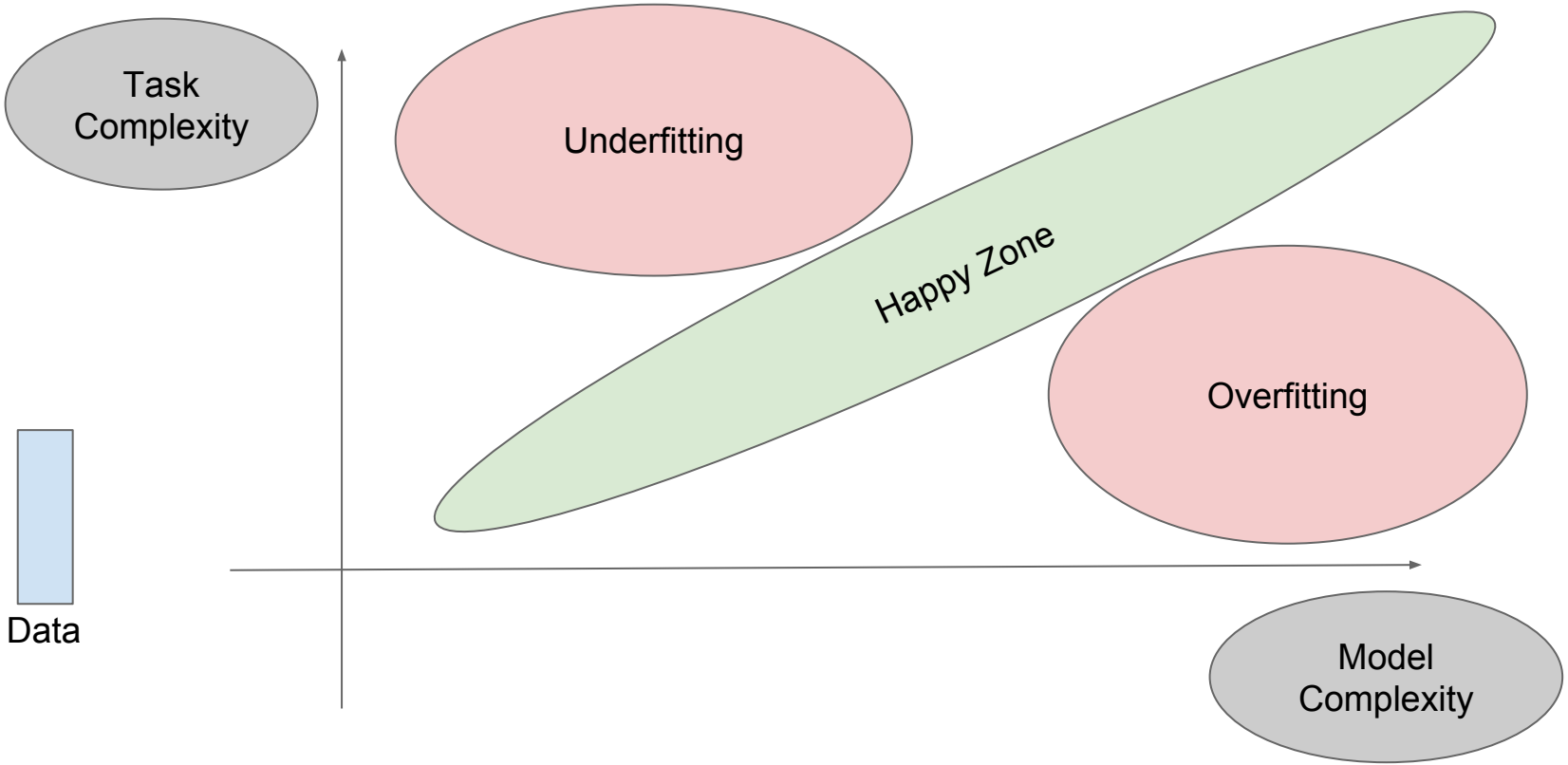
Multilayer Perceptrons



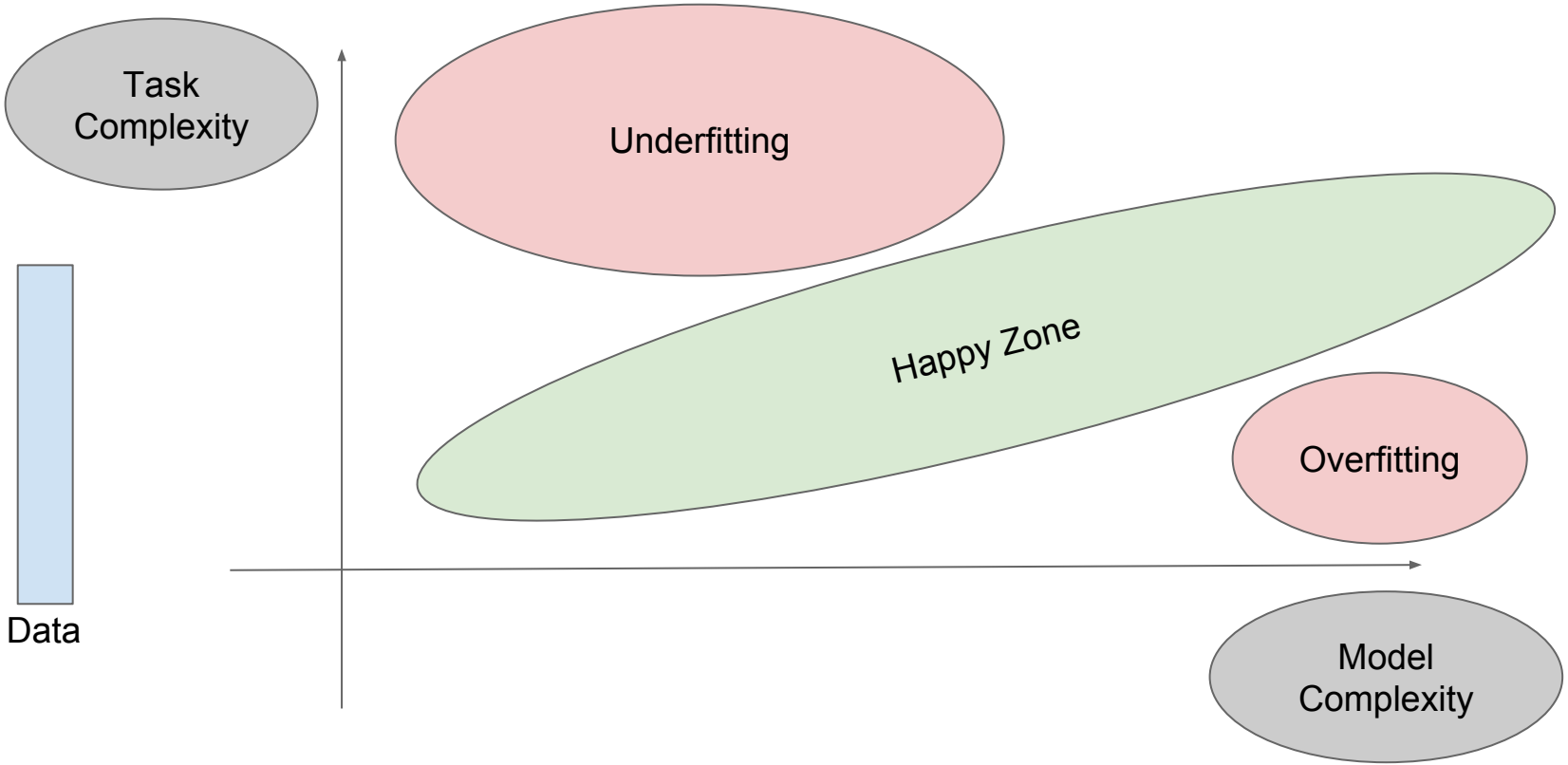
Multilayer Perceptrons



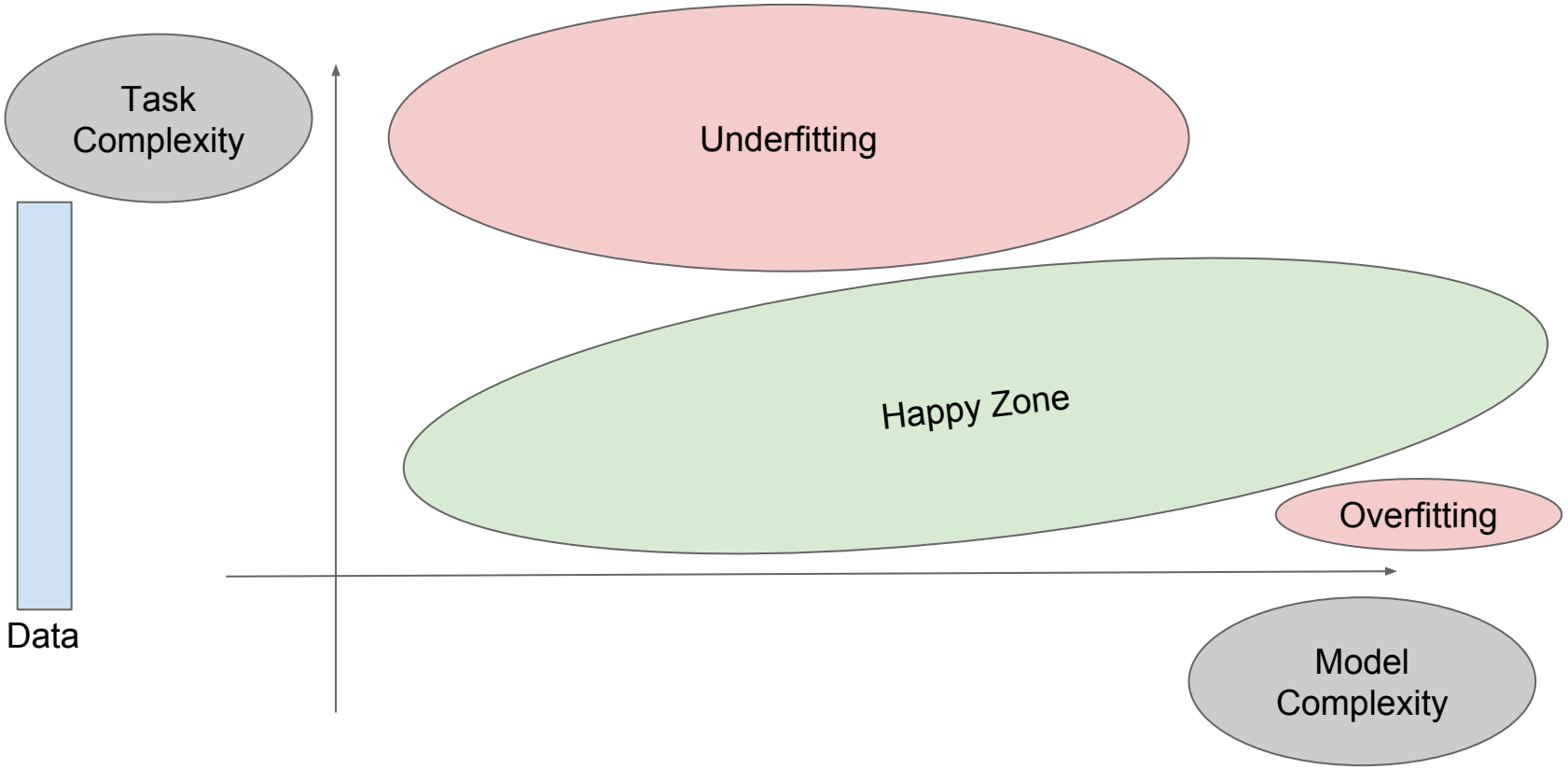
Multilayer Perceptrons



Multilayer Perceptrons

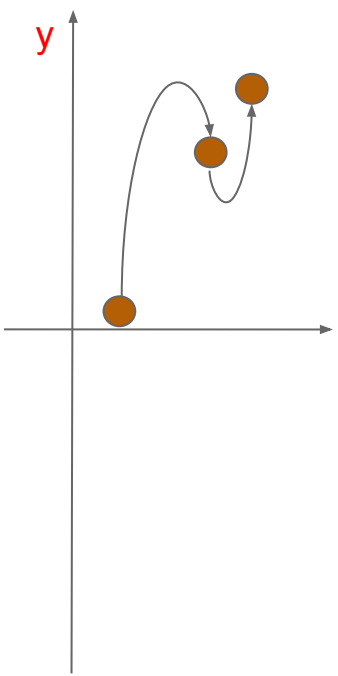


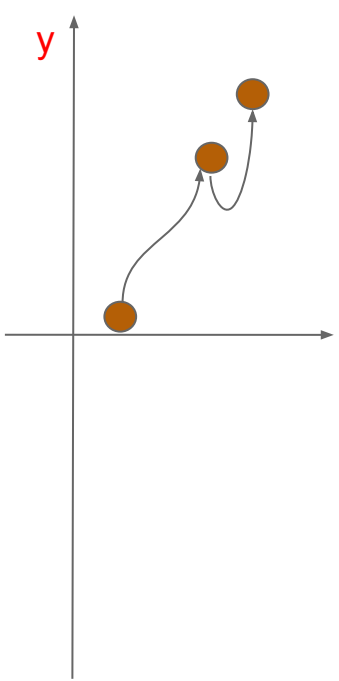
Multilayer Perceptrons

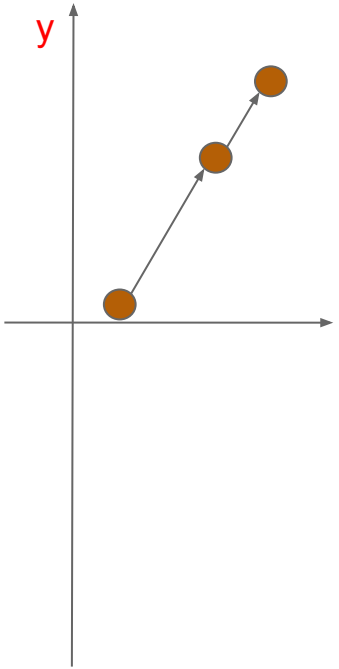


Multilayer Perceptrons

n	x	y
0	1	0
1	5	16
2	6	20

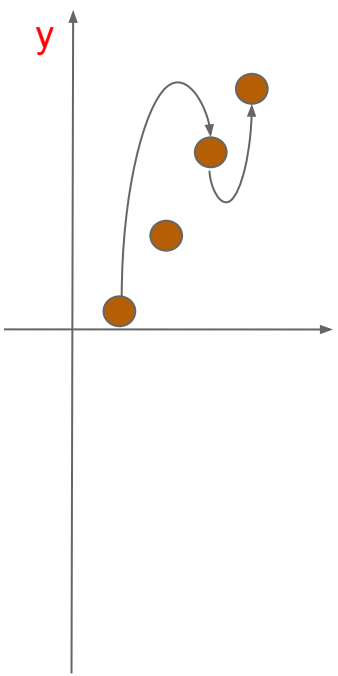


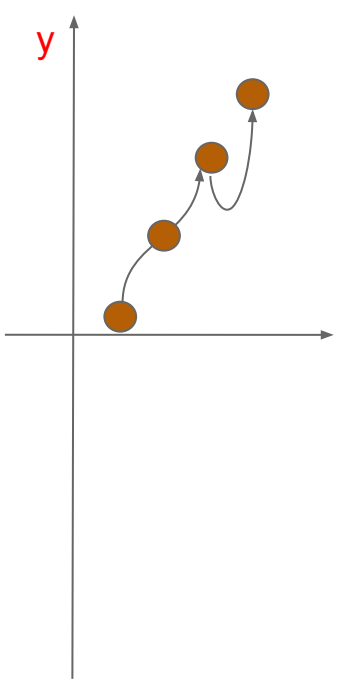


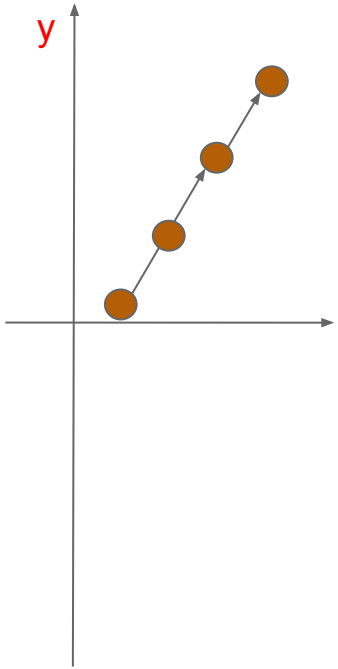


Multilayer Perceptrons

n	x	y
0	1	0
1	5	16
2	6	20
3	2	4

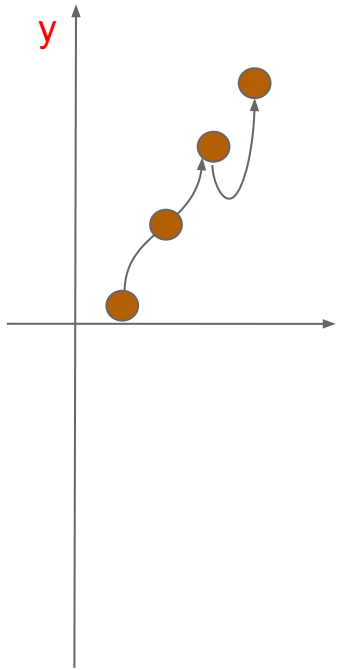


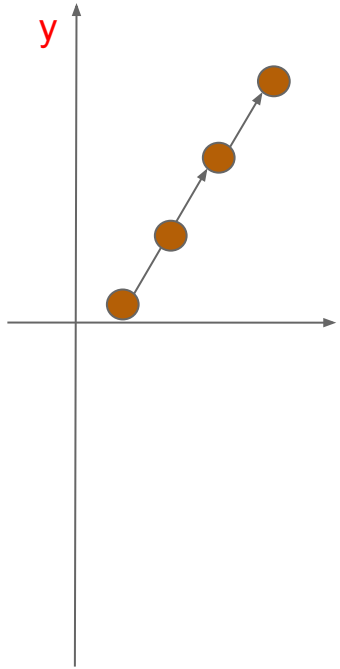




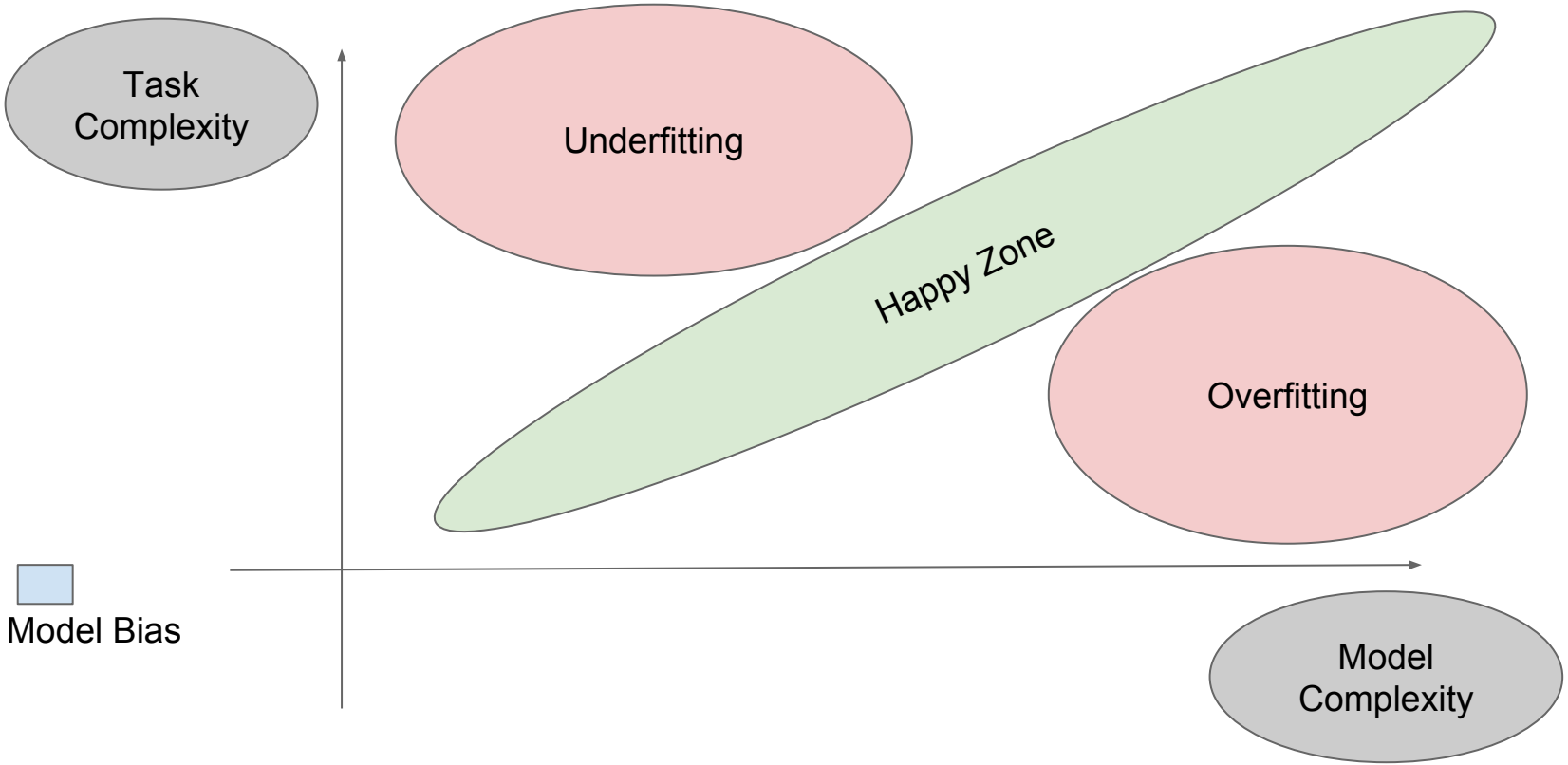
Multilayer Perceptrons

n	x	y
0	1	0
1	5	16
2	6	20
3	2	4

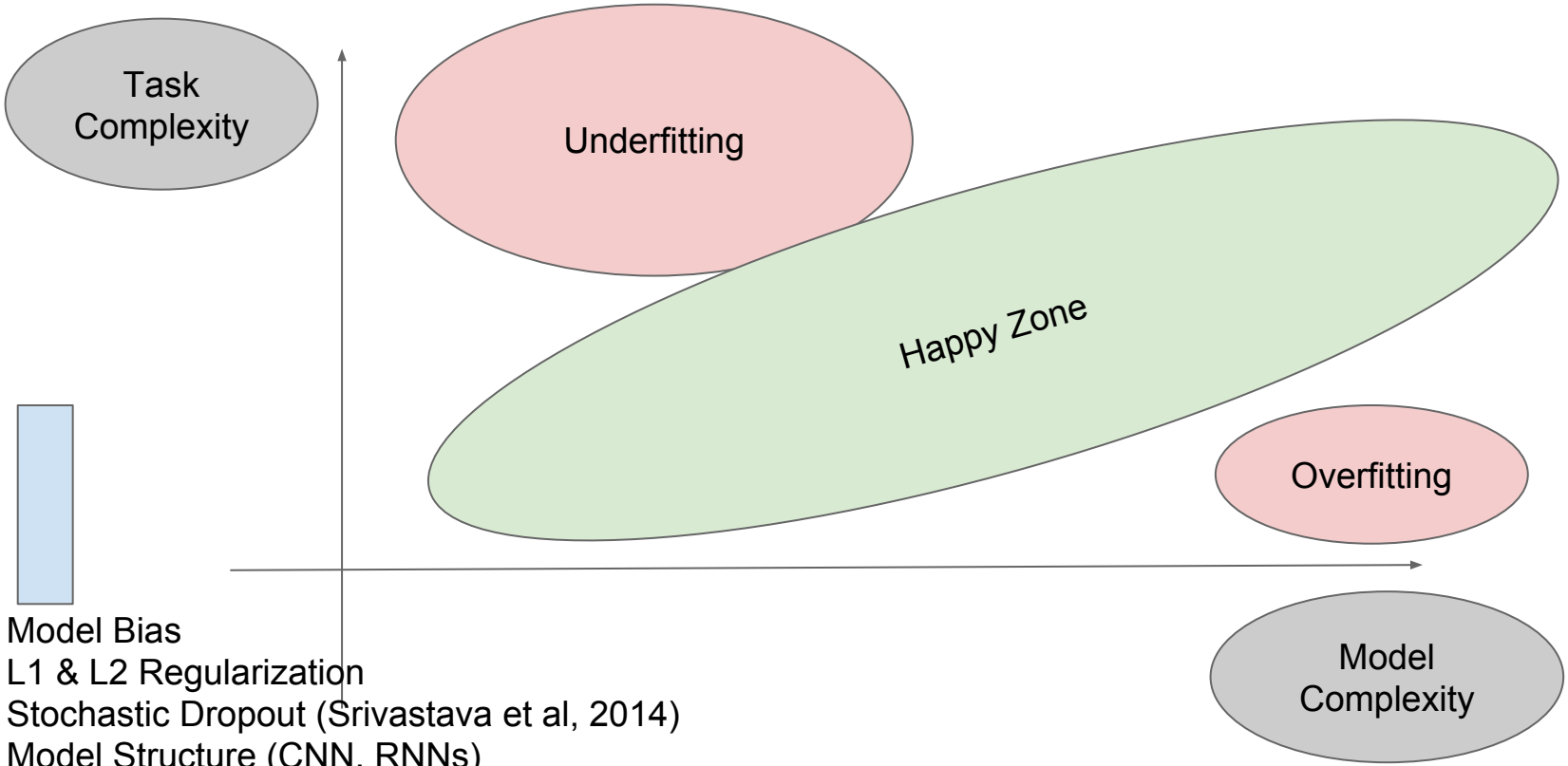




Multilayer Perceptrons



Multilayer Perceptrons



Model Bias
L1 & L2 Regularization
Stochastic Dropout (Srivastava et al, 2014)
Model Structure (CNN, RNNs)

Multilayer Perceptrons

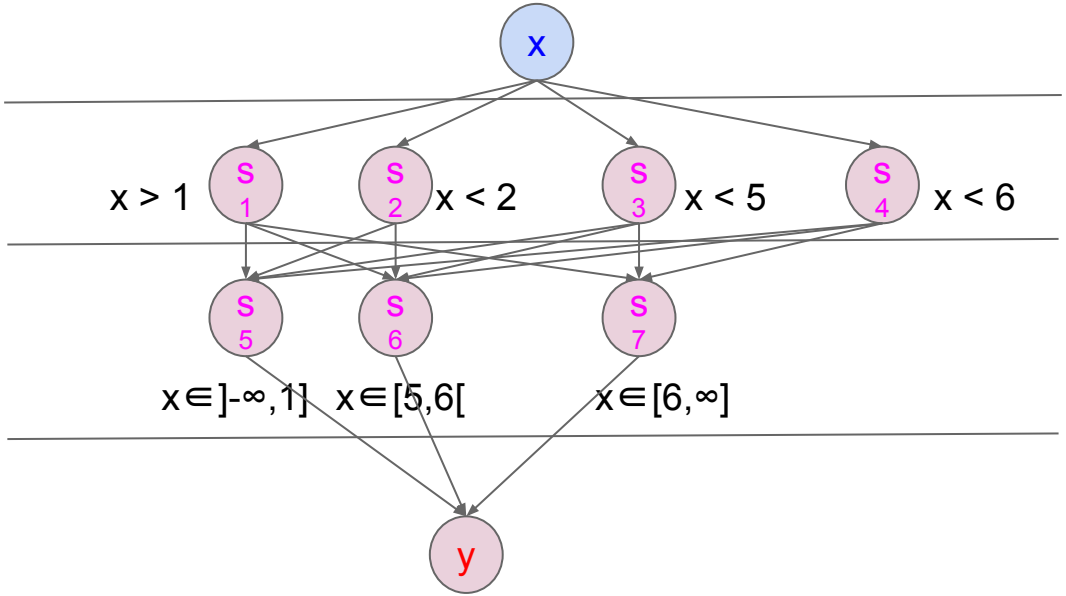
Regularization

$$C(w,b) = \sum_{n \in \{0,1,2\}} (y_n - \hat{y}_n)^2 + (w+b)ß$$

ß = Regularization constant

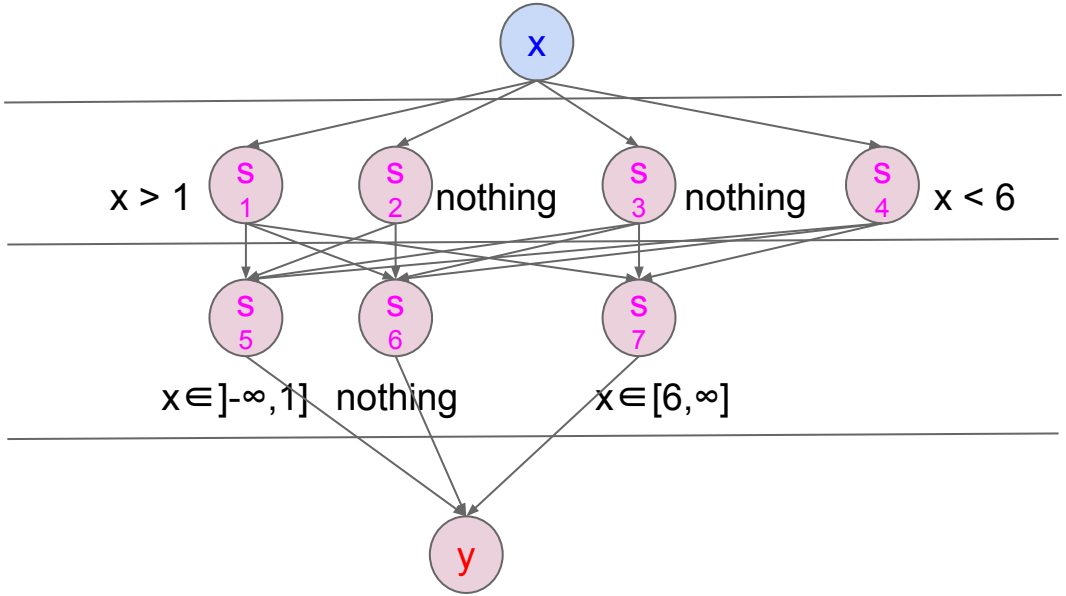
Multilayer Perceptrons

Regularization



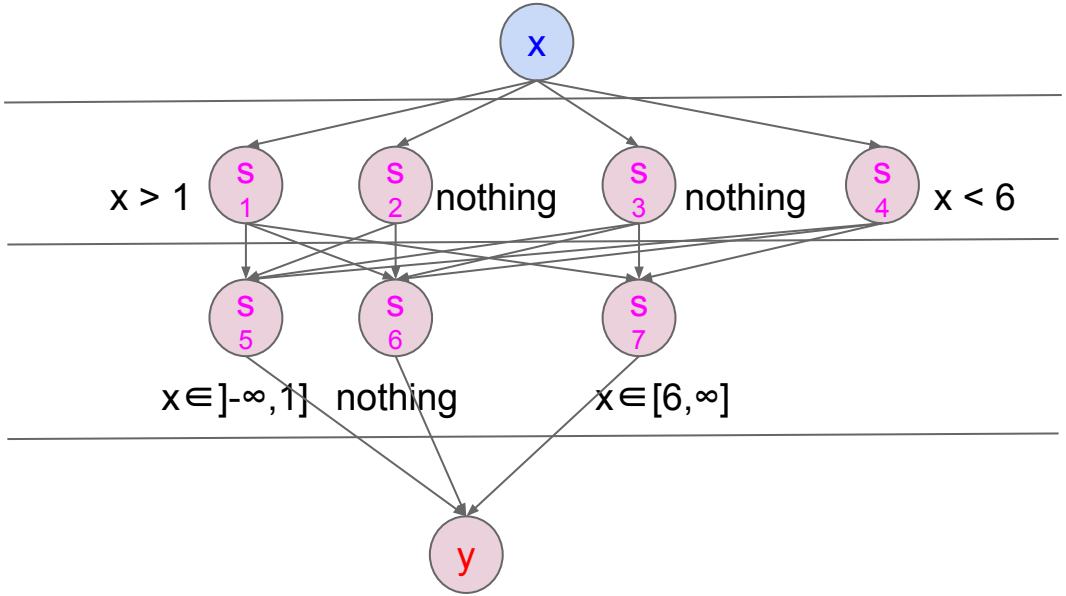
Multilayer Perceptrons

Regularization



Multilayer Perceptrons

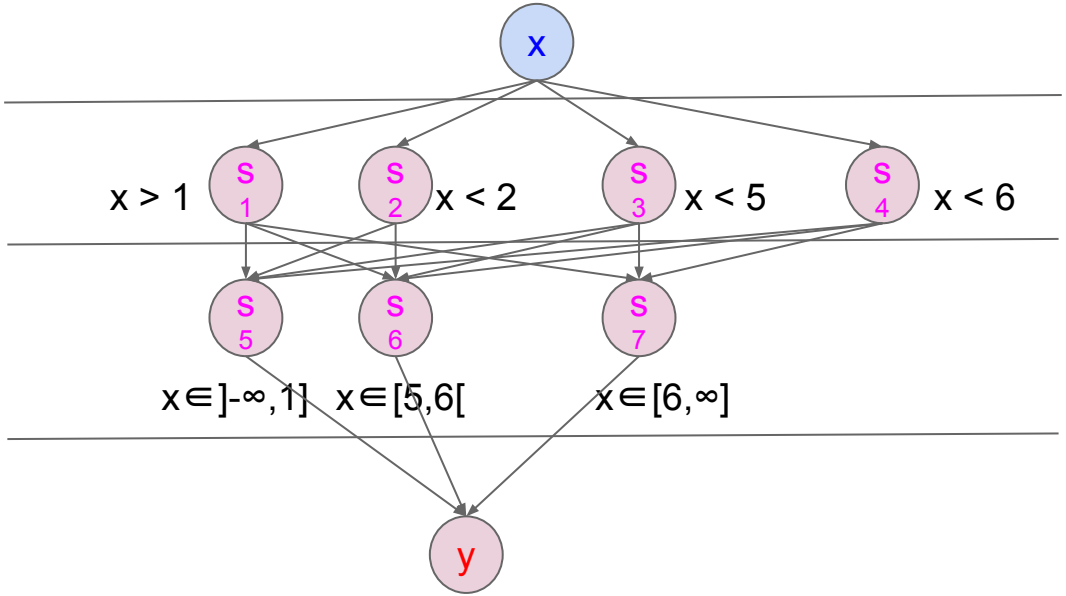
Regularization



Find solutions that require less effort

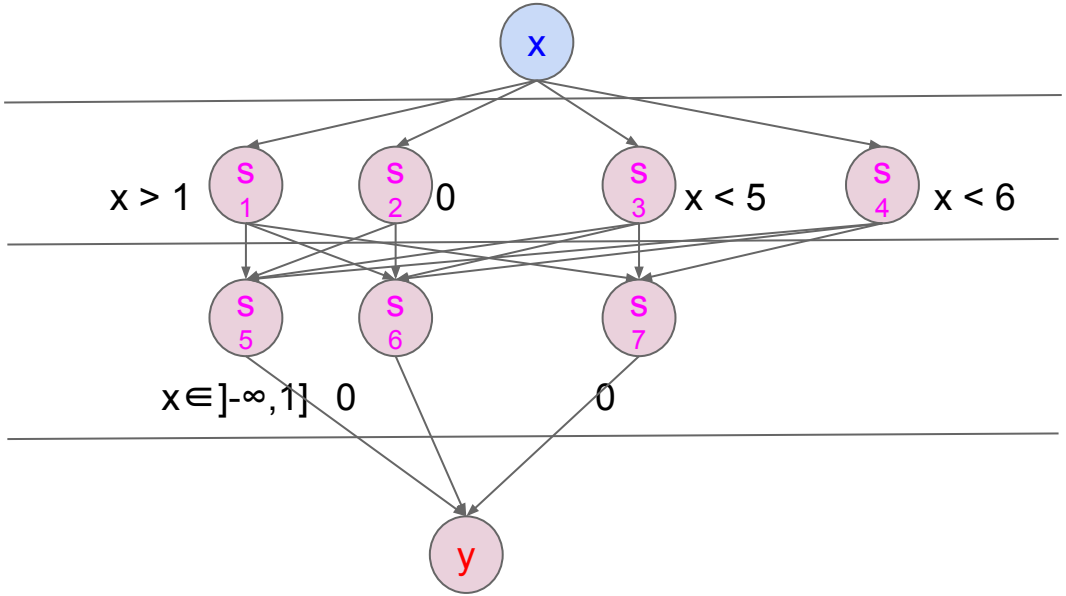
Multilayer Perceptrons

Stochastic Dropout (Srivastava et al, 2014)



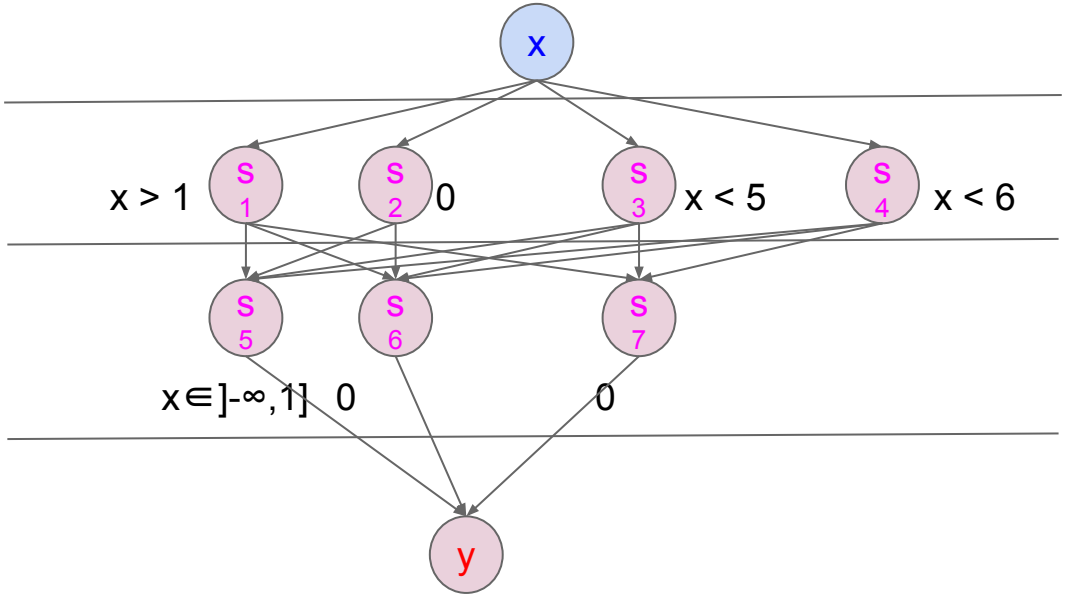
Multilayer Perceptrons

Stochastic Dropout (Srivastava et al, 2014)



Multilayer Perceptrons

Stochastic Dropout (Srivastava et al, 2014)



Find robust models

Multilayer Perceptrons

Model Structure

Weighted sum of linear functions VS MLP

$$y = (w_1x + b_1)s_1 + (w_2x+b_2)s_2 + (w_3x+b_3)s_3$$

Multilayer Perceptrons

Model Structure

Weighted sum of linear functions VS MLP

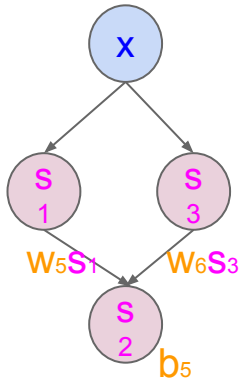
$$y = (w_1x + b_1)s_1 + (w_2x+b_2)s_2 + (w_3x+b_3)s_3$$

Convolutional Vs RNNs

Multilayer Perceptrons

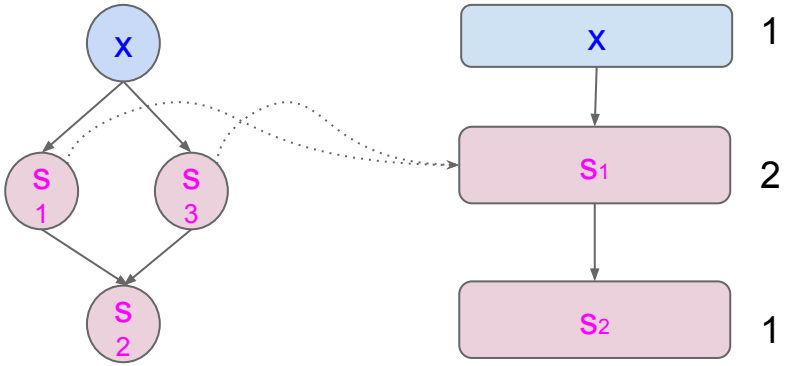
Representation

$$s_1 = \sigma(w_4 x + b_4)$$
$$s_2 = \sigma(w_5 s_1 + w_6 s_3 + b_5)$$
$$s_3 = \sigma(w_7 x + b_6)$$



Multilayer Perceptrons

Representation

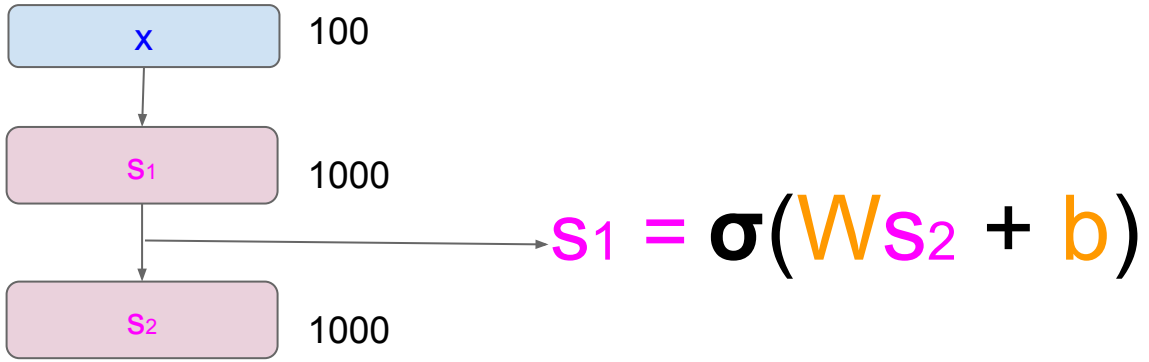


$$s_1 = \sigma(W_3 x + b_3)$$

$$s_2 = \sigma(W_4 s_1 + b_4)$$

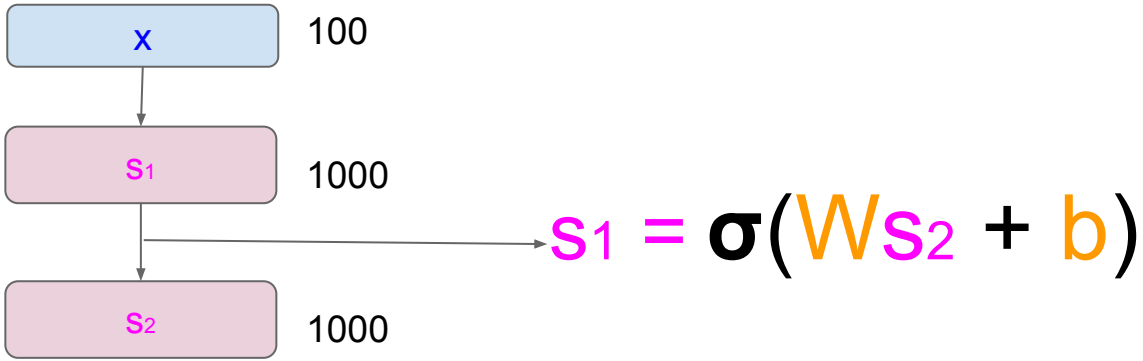
Multilayer Perceptrons

Representation



Multilayer Perceptrons

Representation

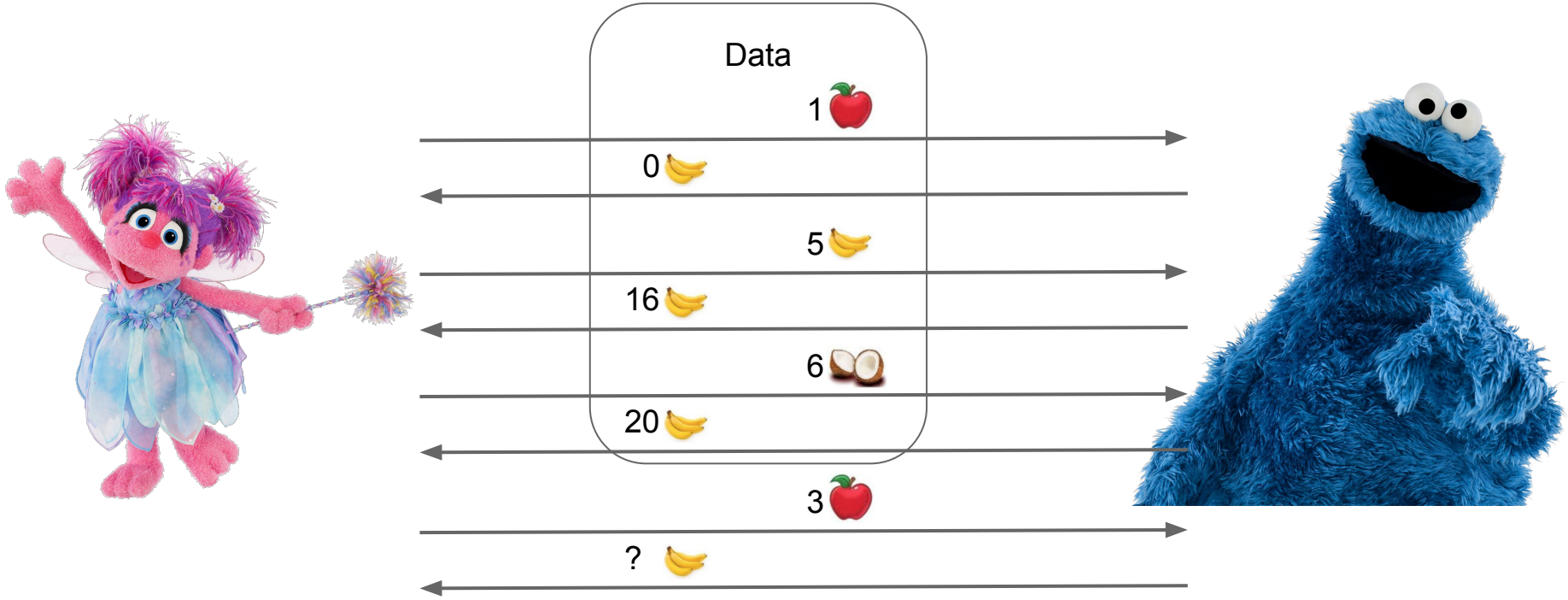


Tensoflow Code

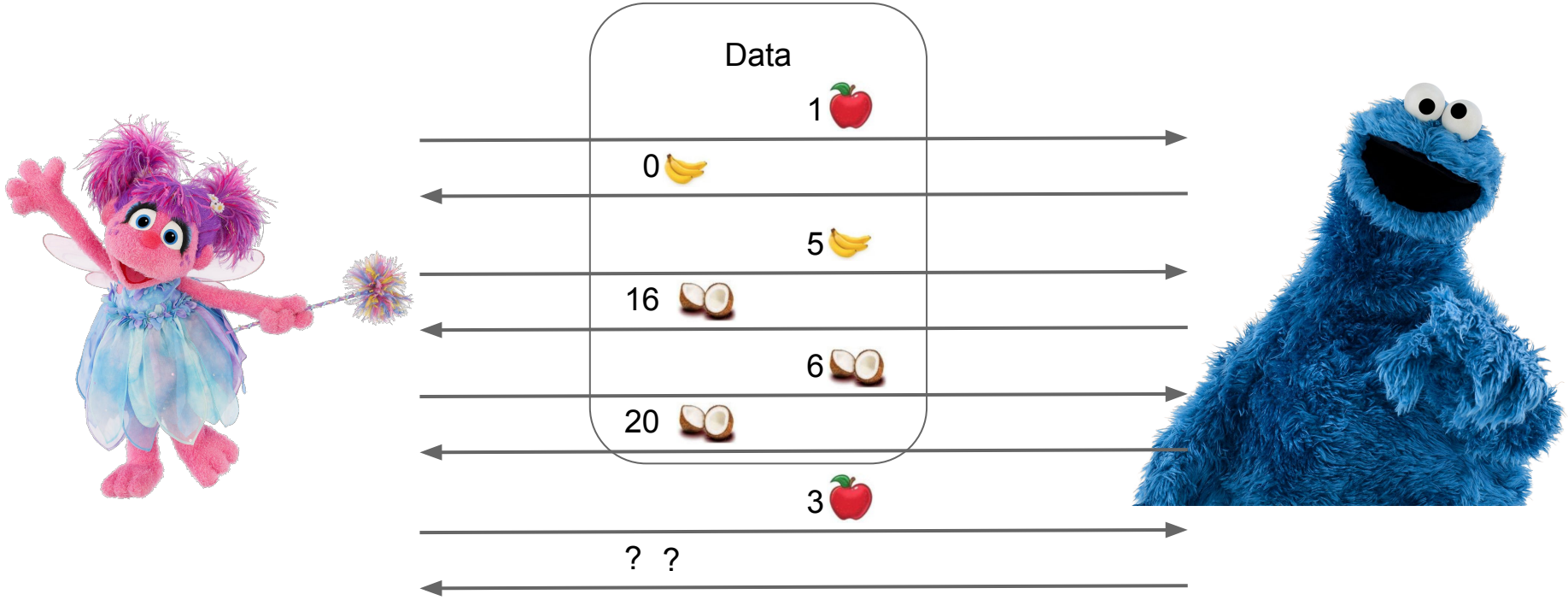
```
s1 = tf.matmul(x, W1) + b1
s1 = tf.nn.sigmoid(s1)
s2 = tf.matmul(s1, W2) + b2
s2 = tf.nn.sigmoid(s2)
```

Using Discrete Variables

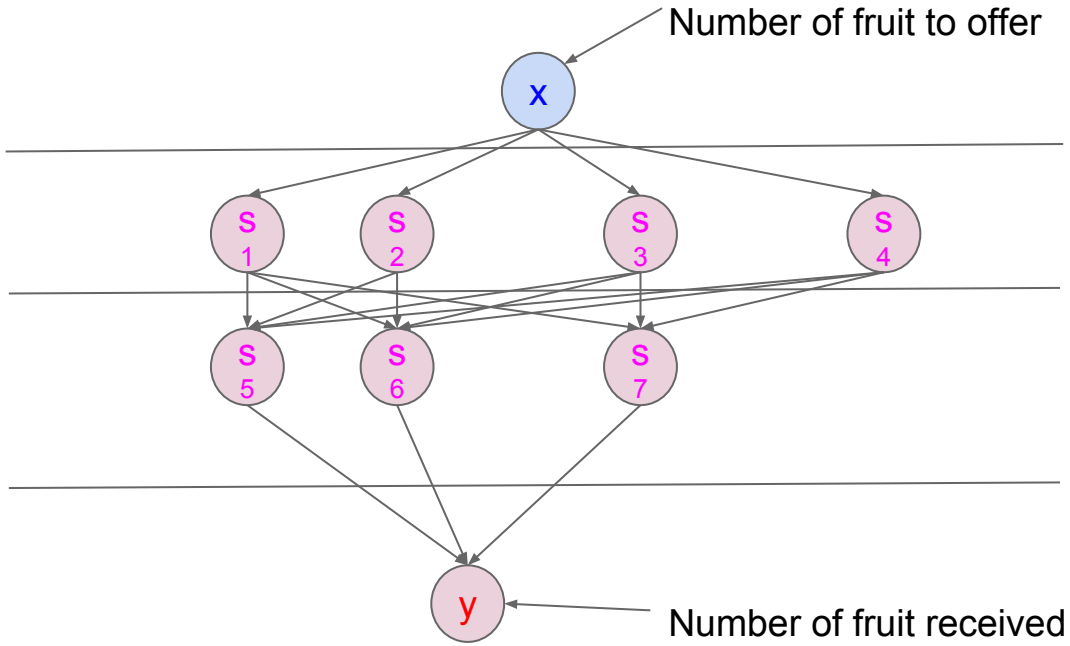
Using Discrete Variables



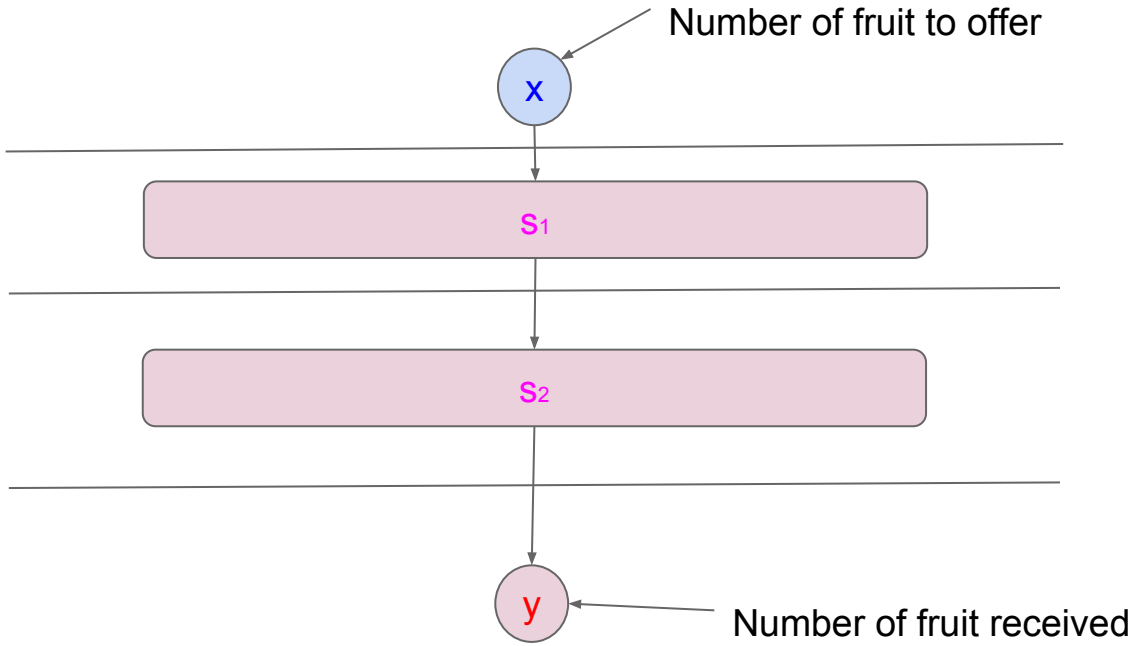
Using Discrete Variables



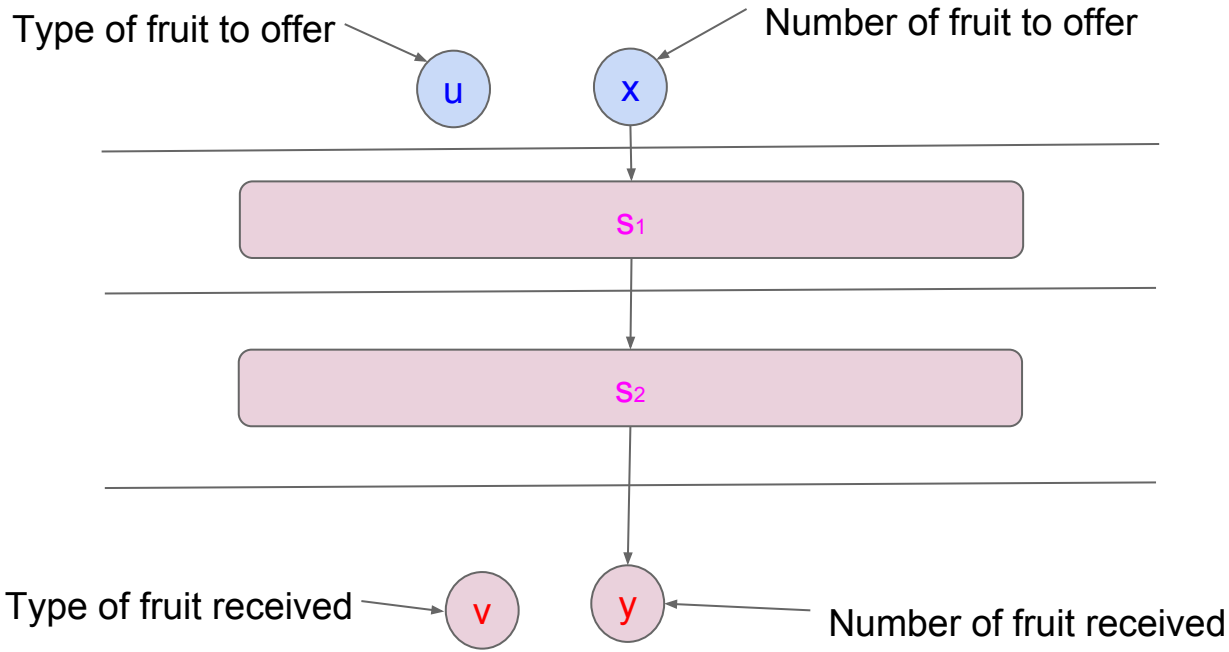
Using Discrete Variables



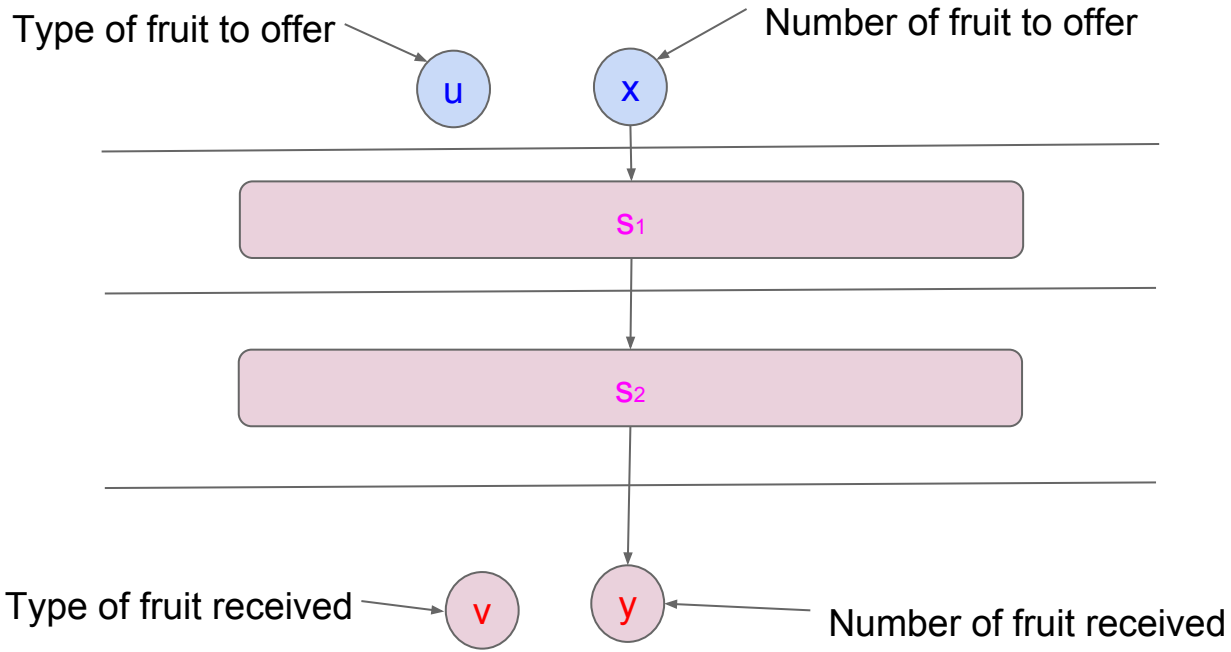
Using Discrete Variables



Using Discrete Variables



Using Discrete Variables



$u \in \{\text{Apple, Banana, Coconut}\}$

$v \in \{\text{Apple, Banana, Coconut}\}$

Using Discrete Variables

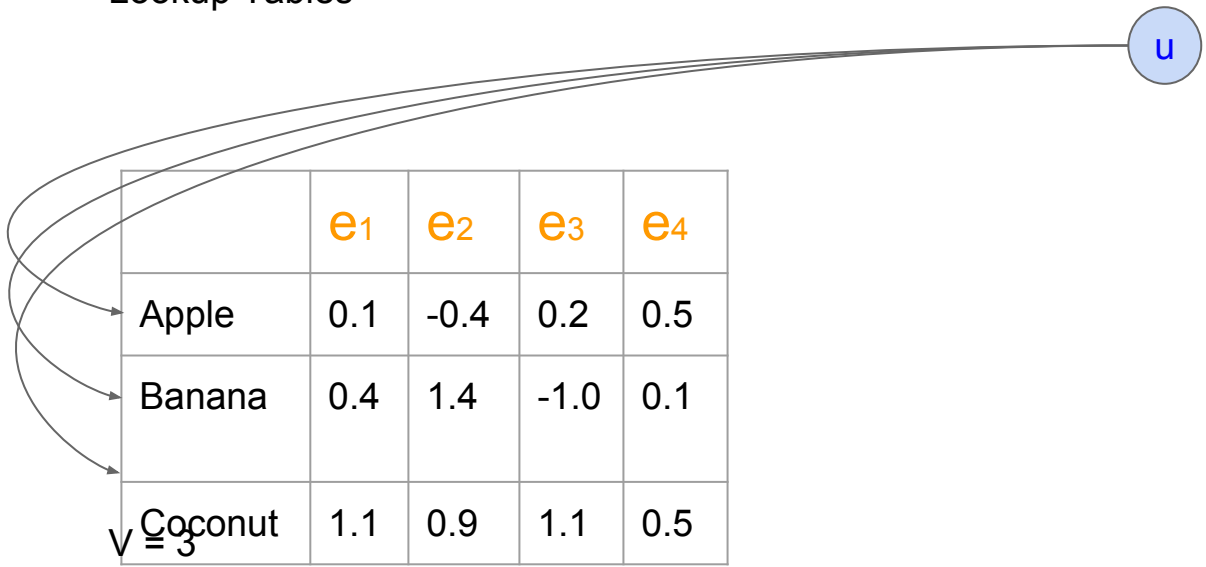
Lookup Tables

	e_1	e_2	e_3	e_4
Apple	0.1	-0.4	0.2	0.5
Banana	0.4	1.4	-1.0	0.1
Coconut	1.1	0.9	1.1	0.5

$V = 3$

Using Discrete Variables

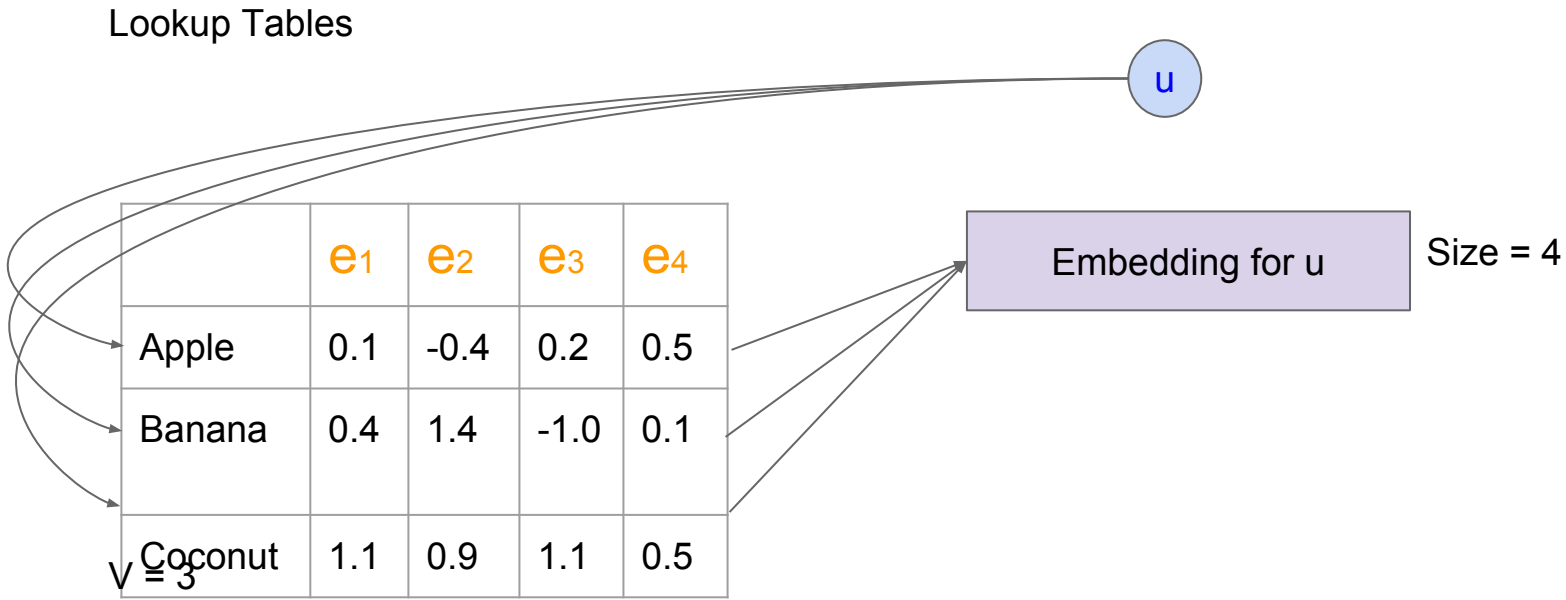
Lookup Tables



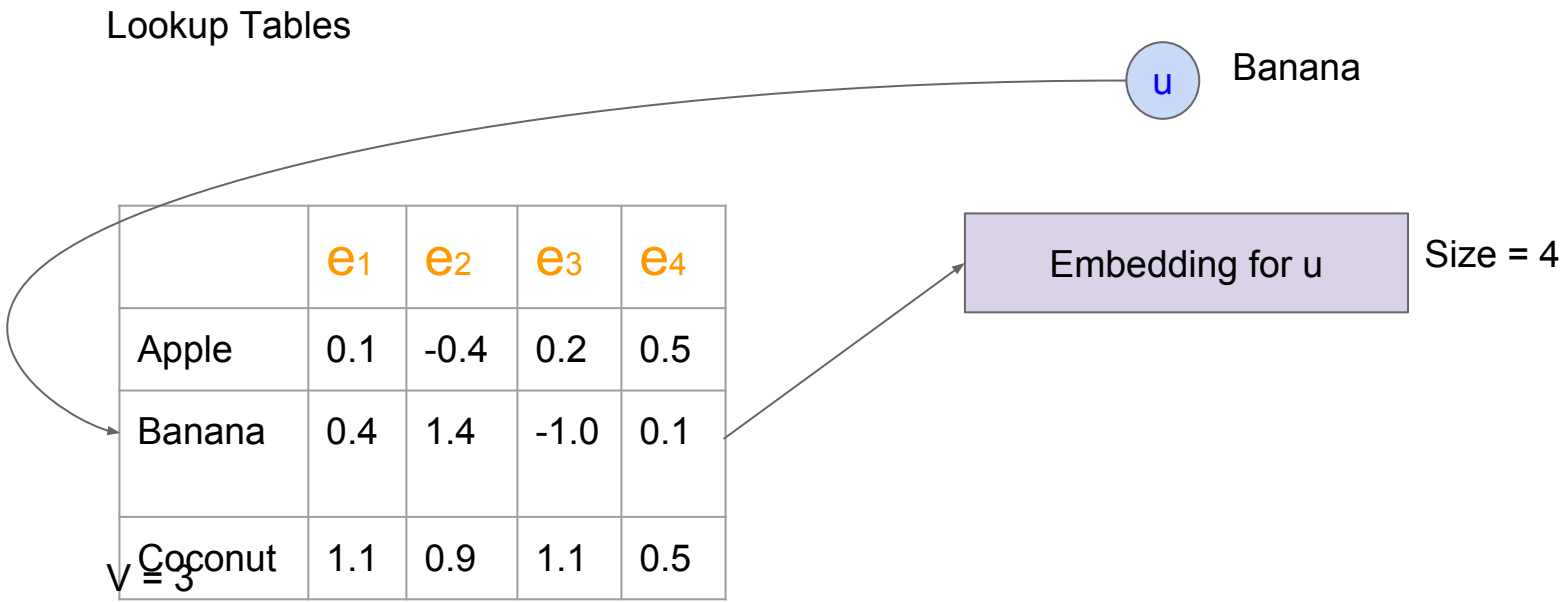
	e_1	e_2	e_3	e_4
Apple	0.1	-0.4	0.2	0.5
Banana	0.4	1.4	-1.0	0.1
Coconut	1.1	0.9	1.1	0.5

$V = 3$

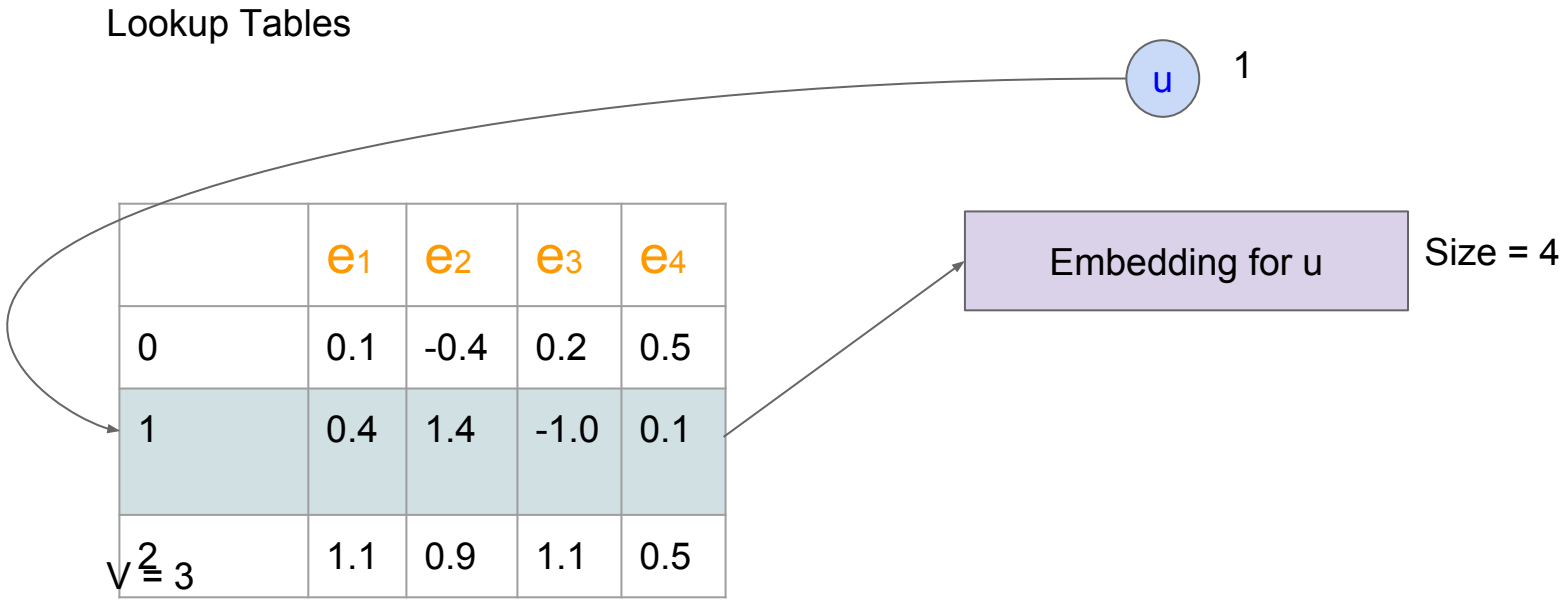
Using Discrete Variables



Using Discrete Variables

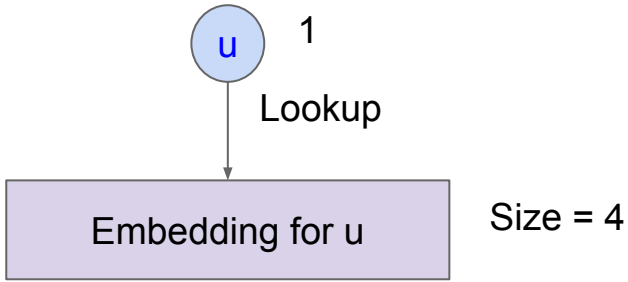


Using Discrete Variables

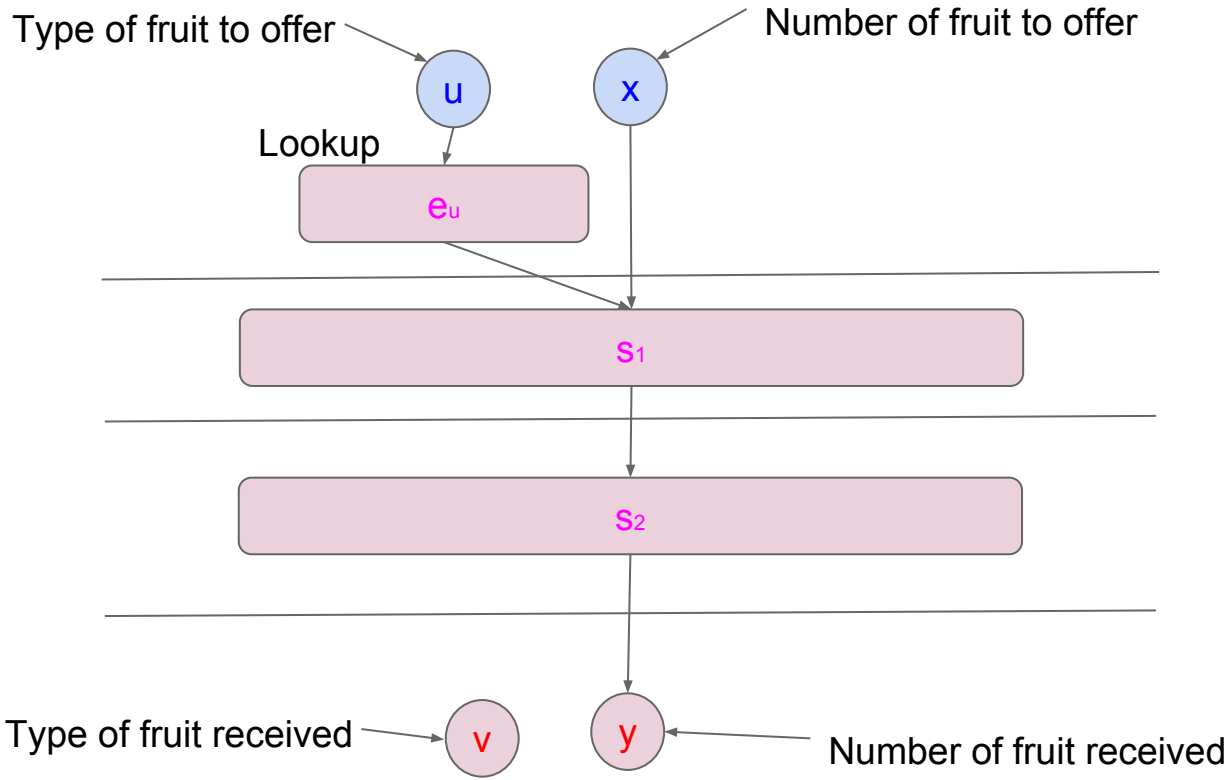


Using Discrete Variables

Lookup Tables



Using Discrete Variables



$u \in \{\text{Apple, Banana, Coconut}\}$

$v \in \{\text{Apple, Banana, Coconut}\}$

Using Discrete Variables

Softmax

V = 3

	Apple	Banana	Coconut
W_1	0.1	-0.4	0.2
W_2	0.4	1.4	-1.0
W_3	1.1	0.9	1.1
W_4	1.3	0.1	0.4

Using Discrete Variables

Softmax

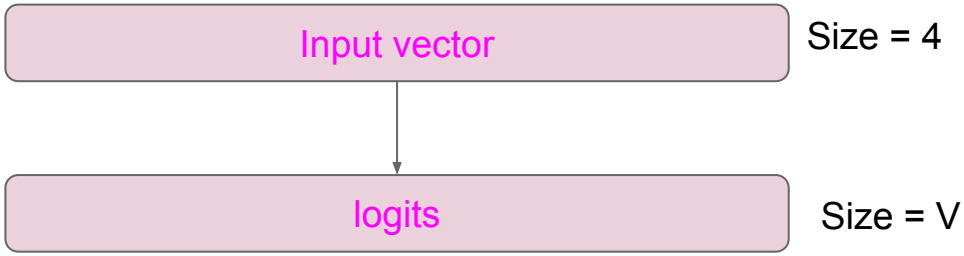
Size = 4

V = 3

	Apple	Banana	Coconut
W_1	0.1	-0.4	0.2
W_2	0.4	1.4	-1.0
W_3	1.1	0.9	1.1
W_4	1.3	0.1	0.4

Using Discrete Variables

Softmax

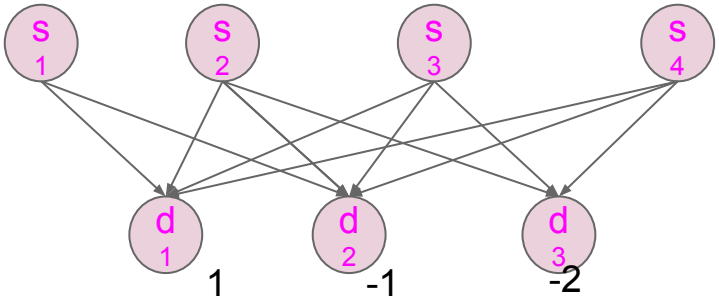


V = 3

	Apple	Banana	Coconut
W_1	0.1	-0.4	0.2
W_2	0.4	1.4	-1.0
W_3	1.1	0.9	1.1
W_4	1.3	0.1	0.4

Using Discrete Variables

Softmax



Input Vector

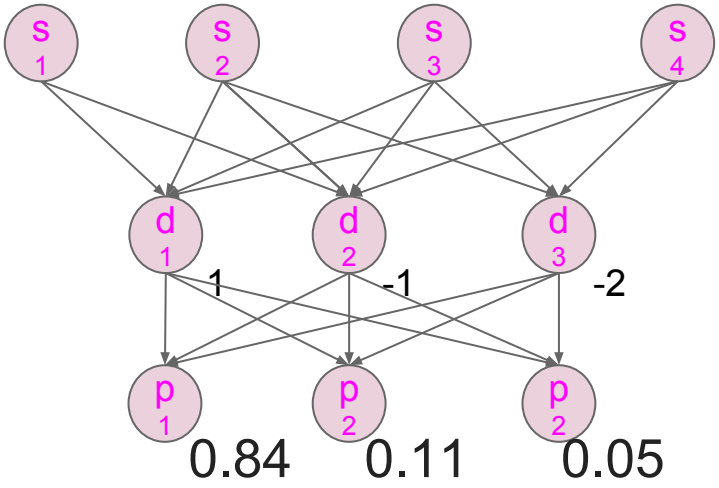
V = 3

Logits

	Apple	Banana	Coconut
W_1	0.1	-0.4	0.2
W_2	0.4	1.4	-1.0
W_3	1.1	0.9	1.1
W_4	1.3	0.1	0.4

Using Discrete Variables

Softmax



Input Vector

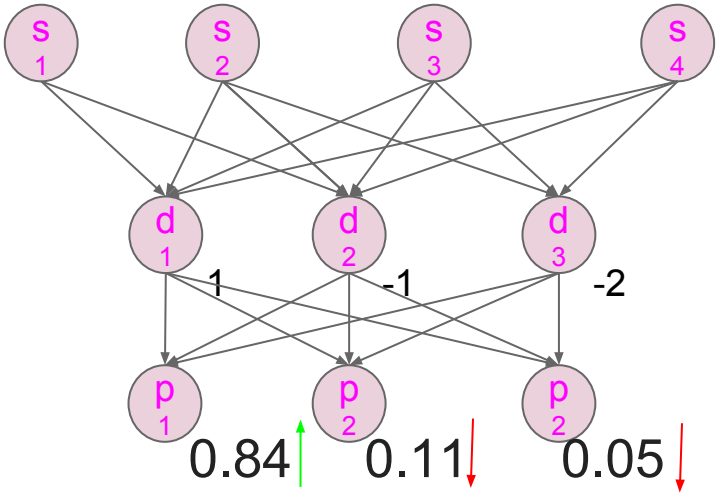
V = 3

Logits

	Apple	Banana	Coconut
w_1	0.1	-0.4	0.2
w_2	0.4	1.4	-1.0
w_3	1.1	0.9	1.1
w_4	1.3	0.1	0.4

Using Discrete Variables

Softmax



Input Vector

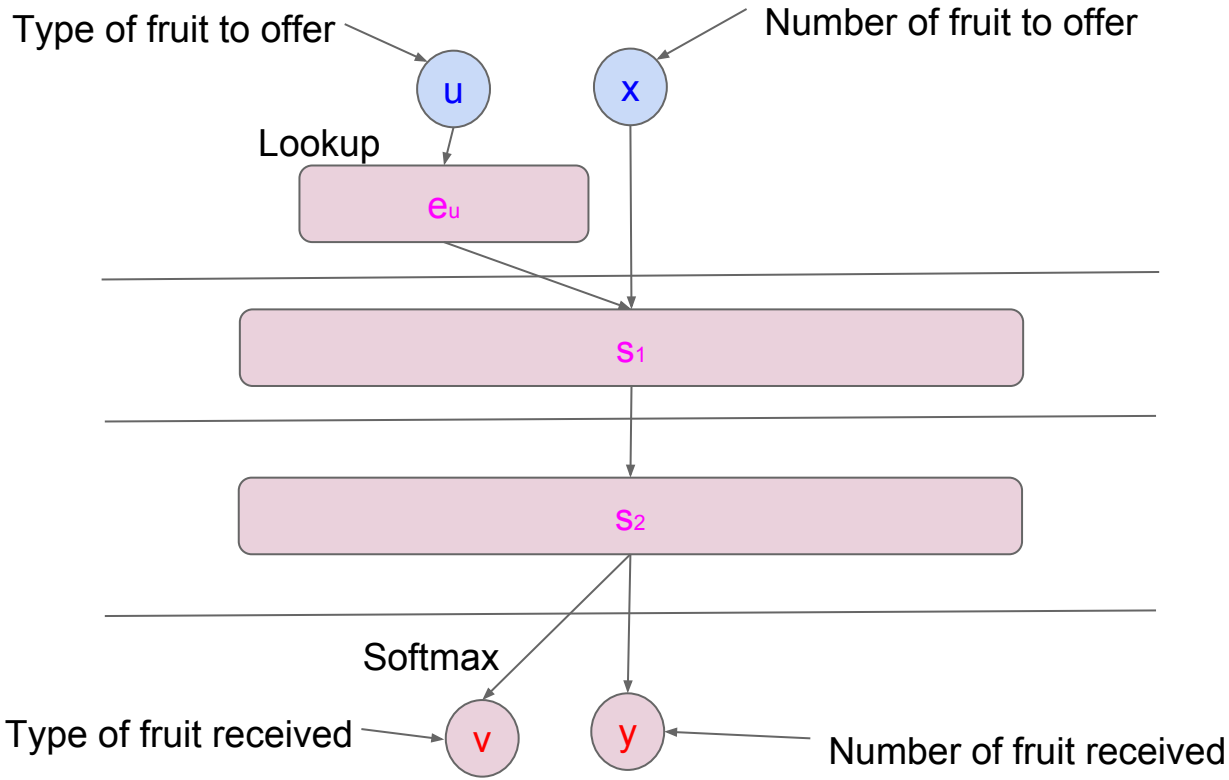
Logits

Apple

V = 3

	Apple	Banana	Coconut
w_1	0.1	-0.4	0.2
w_2	0.4	1.4	-1.0
w_3	1.1	0.9	1.1
w_4	1.3	0.1	0.4

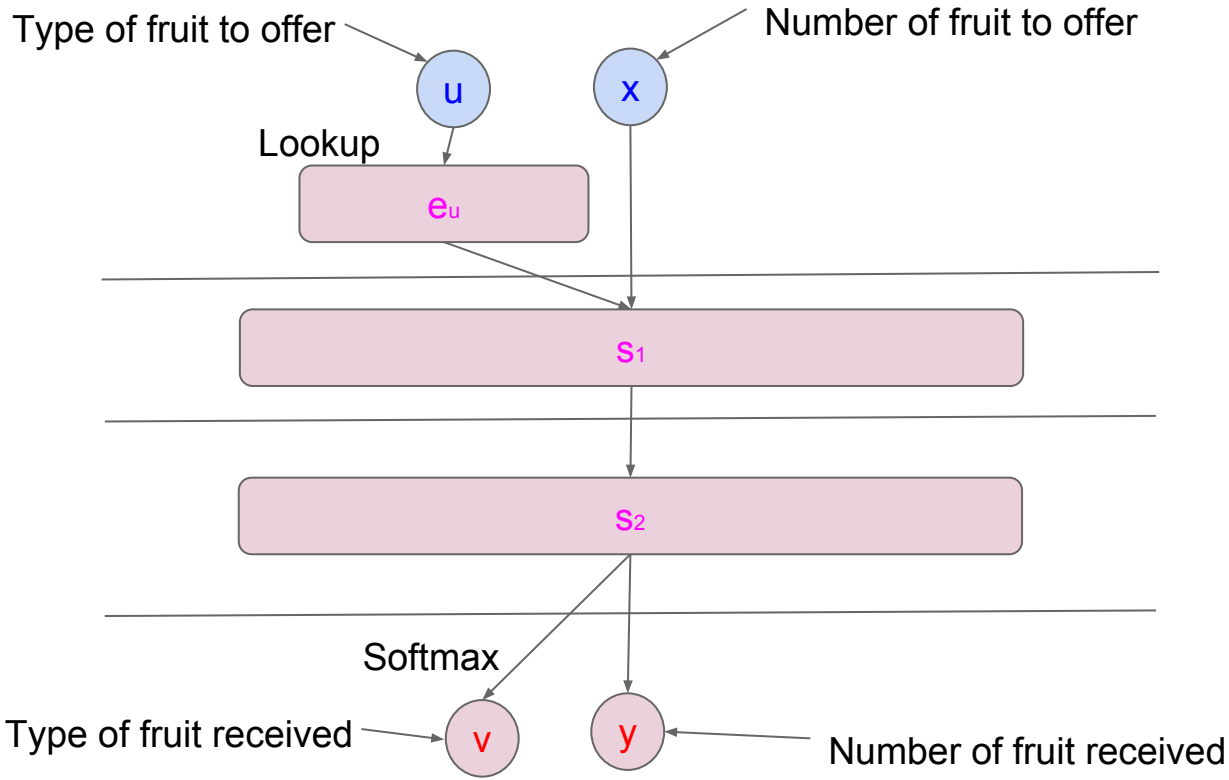
Using Discrete Variables



u∈{Apple, Banana, Coconut}

v∈{Apple, Banana, Coconut}

Using Discrete Variables

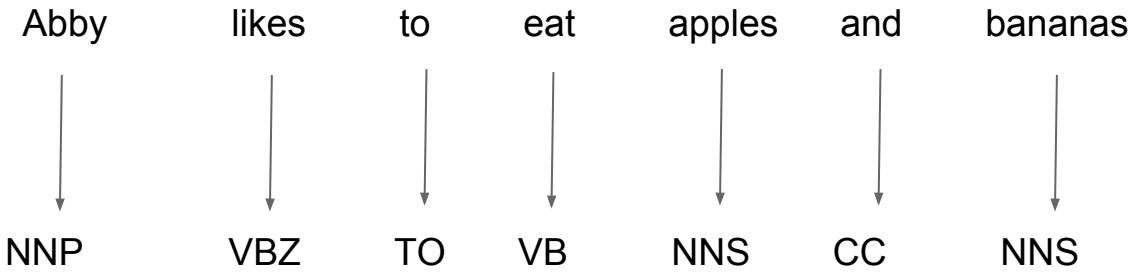


u∈{Apple, Banana, Coconut}

v∈{Apple, Banana, Coconut}

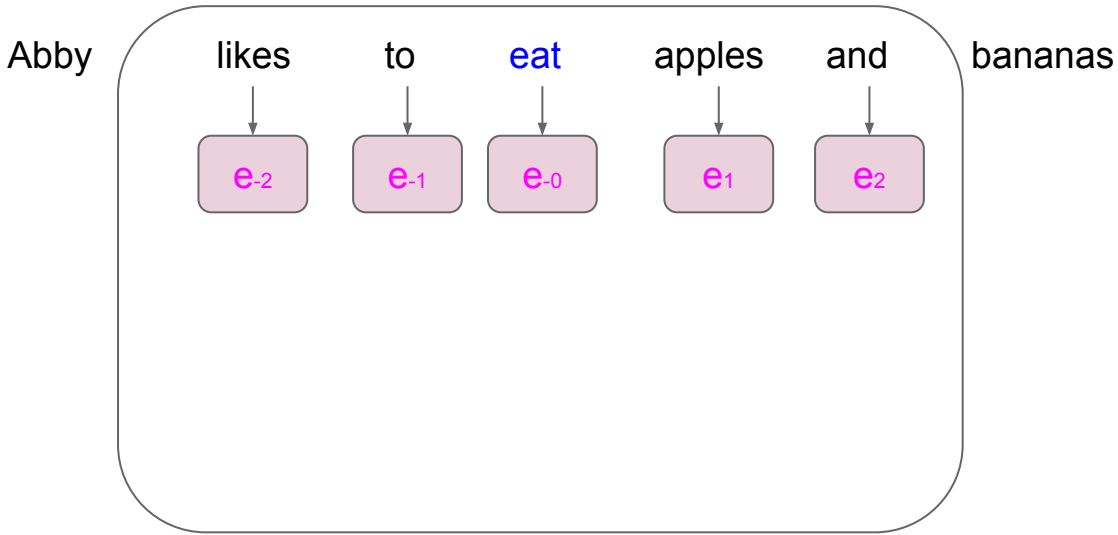
Example Applications

Window-based Tagging (Collobert et al, 2011)



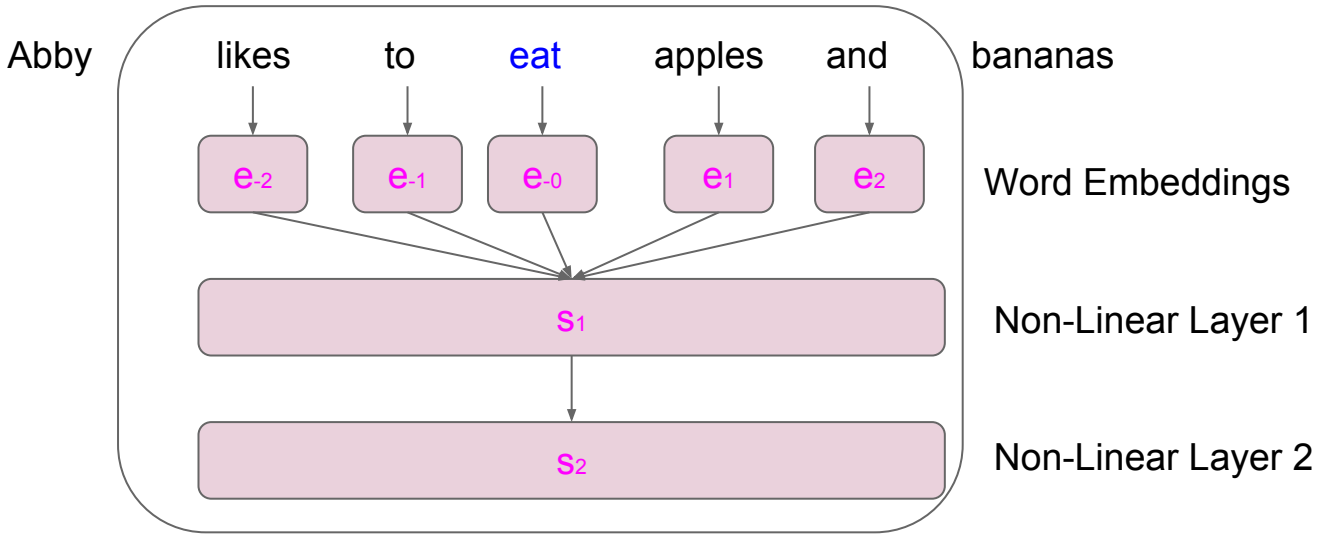
Example Applications

Window-based Tagging (Collobert et al, 2011)



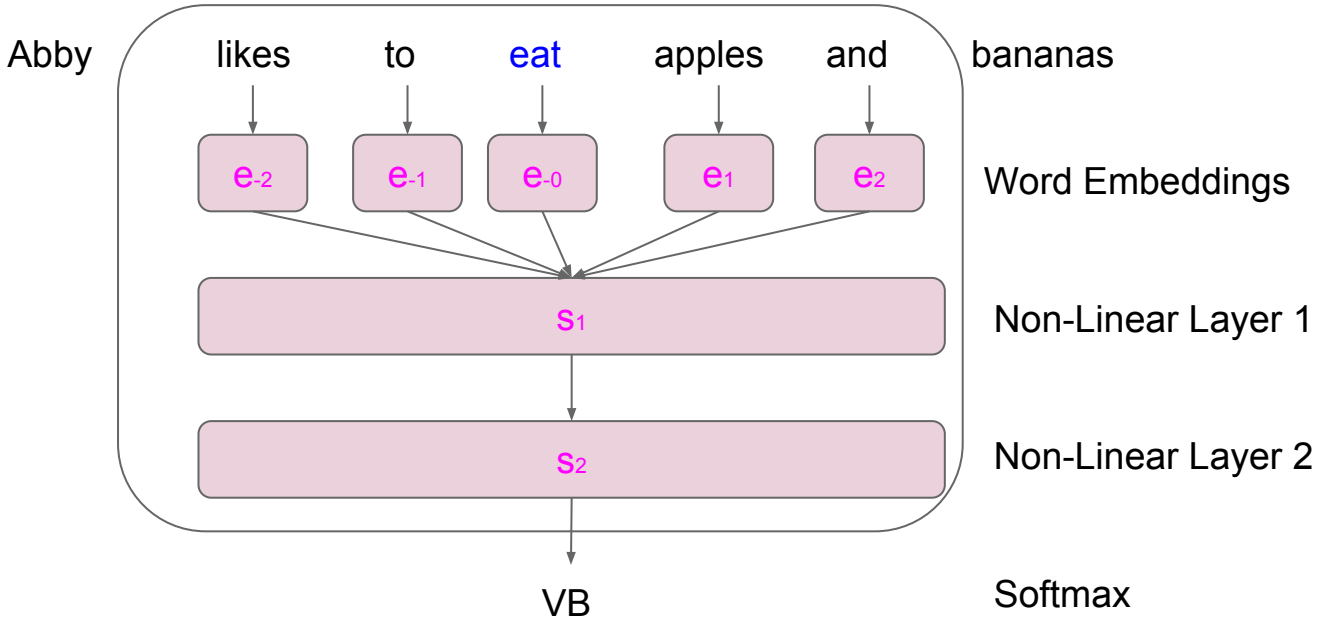
Example Applications

Window-based Tagging (Collobert et al, 2011)



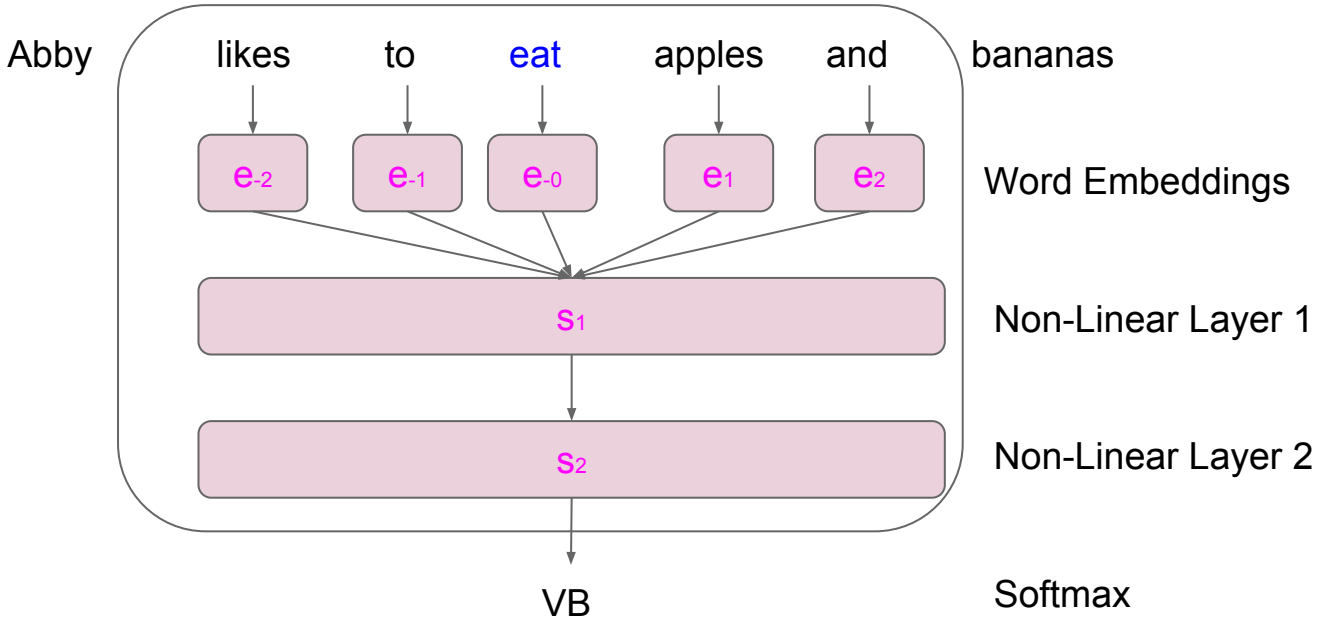
Example Applications

Window-based Tagging (Collobert et al, 2011)



Example Applications

Window-based Tagging (Collobert et al, 2011)



Example Applications

Window-based Tagging (Collobert et al, 2011)

Approach	POS (PWA)	CHUNK (F1)	NER (F1)	SRL
Benchmark Systems	97.24	94.29	89.31	77.92
NN+SLL+LM2	97.20	93.63	88.67	74.15
NN+SLL+LM2+Suffix2	97.29	–	–	–
NN+SLL+LM2+Gazetteer	–	–	89.59	–
NN+SLL+LM2+POS	–	94.32	88.67	–
NN+SLL+LM2+CHUNK	–	–	–	74.72

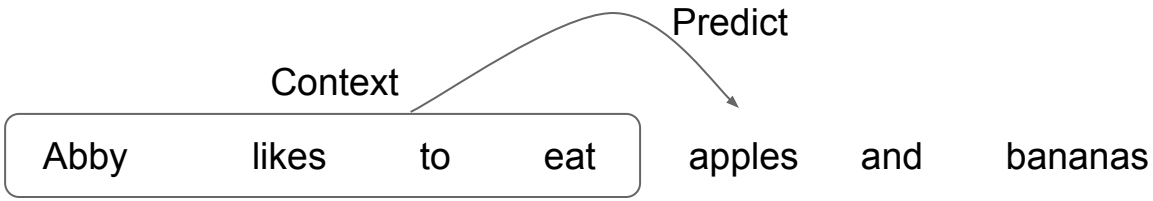
Example Applications

Translation Rescoring (Devlin et al, 2014)

Abby likes to eat apples and bananas

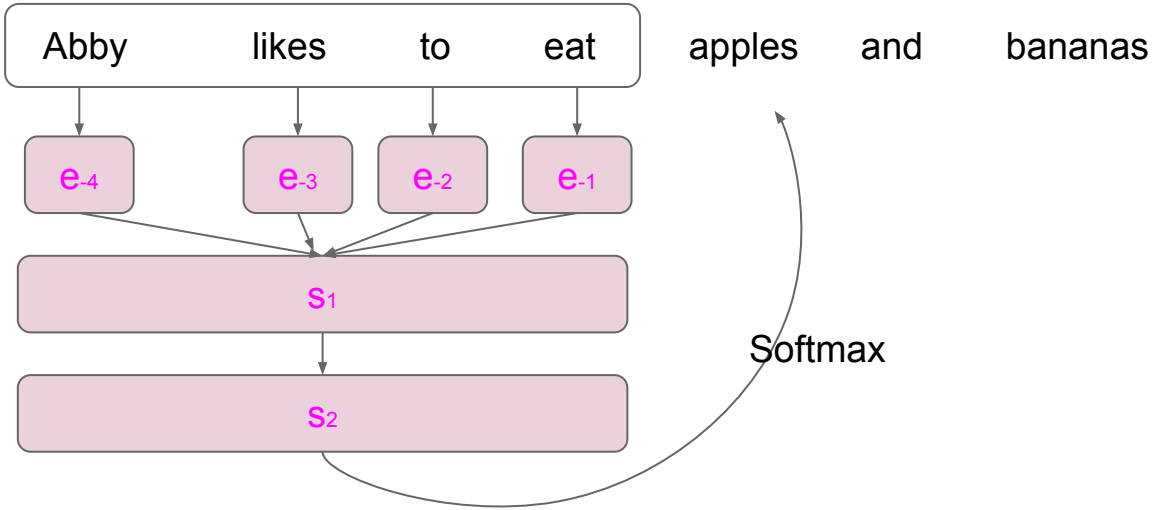
Example Applications

Translation Rescoring (Devlin et al, 2014)



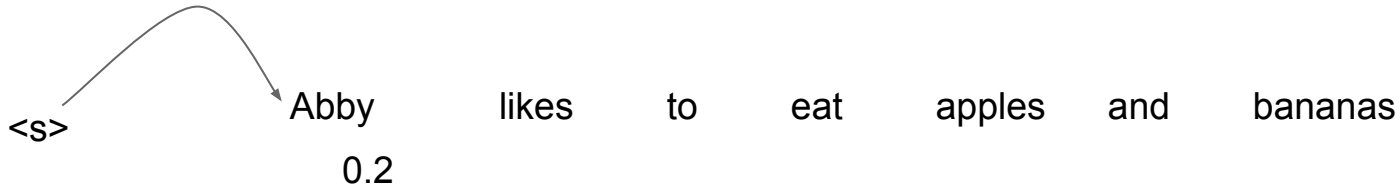
Example Applications

Translation Rescoring (Devlin et al, 2014)



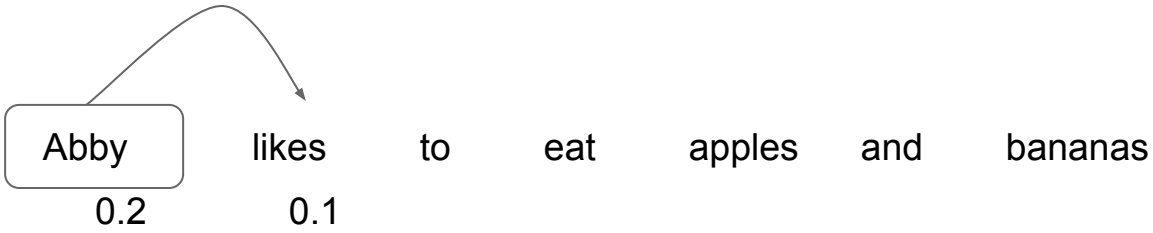
Example Applications

Translation Rescoring (Devlin et al, 2014)



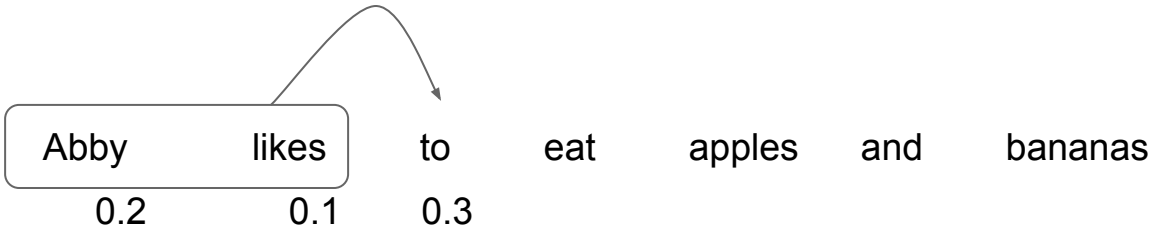
Example Applications

Translation Rescoring (Devlin et al, 2014)



Example Applications

Translation Rescoring (Devlin et al, 2014)



Example Applications

Translation Rescoring (Devlin et al, 2014)

Abby	likes	to	eat	apples	and	bananas	0.000378
0.2	0.1	0.3	0.5	0.7	0.4	0.2	

Example Applications

Translation Rescoring (Devlin et al, 2014)

John does to eat coconuts and bananas	0.00003
Abby likes to eat apples and bananas	0.000378
Abby dislikes to drink apples and bananas	0.00012

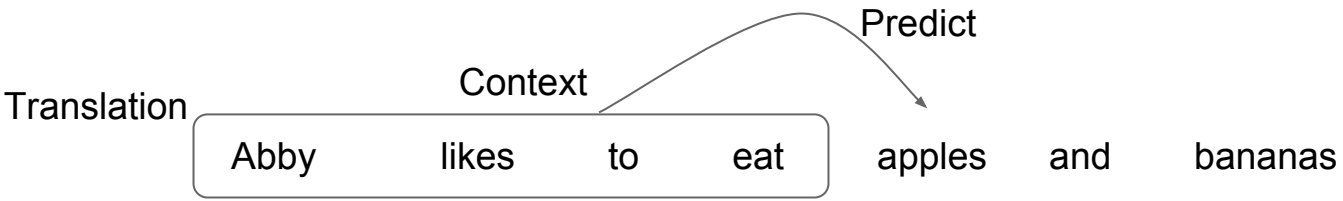
Example Applications

Translation Rescoring (Devlin et al, 2014)

John	does	to	eat	coconuts	and	bananas	0.00003
Abby	likes	to	eat	apples	and	bananas	0.000378
Abby	dislikes	to	drink	apples	and	bananas	0.00012

Example Applications

Translation Rescoring (Devlin et al, 2014)

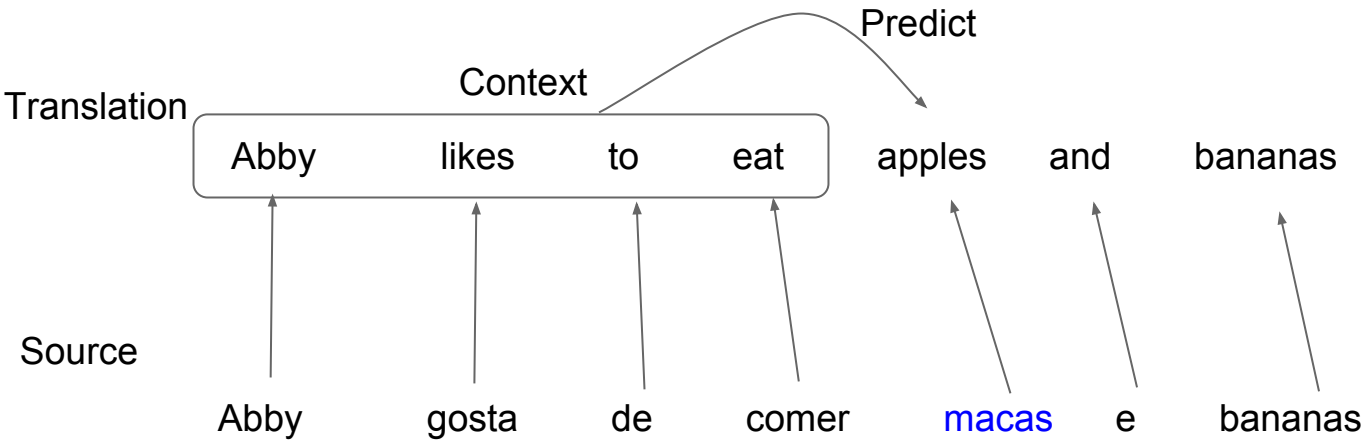


Source

Abby gosta de comer macas e bananas

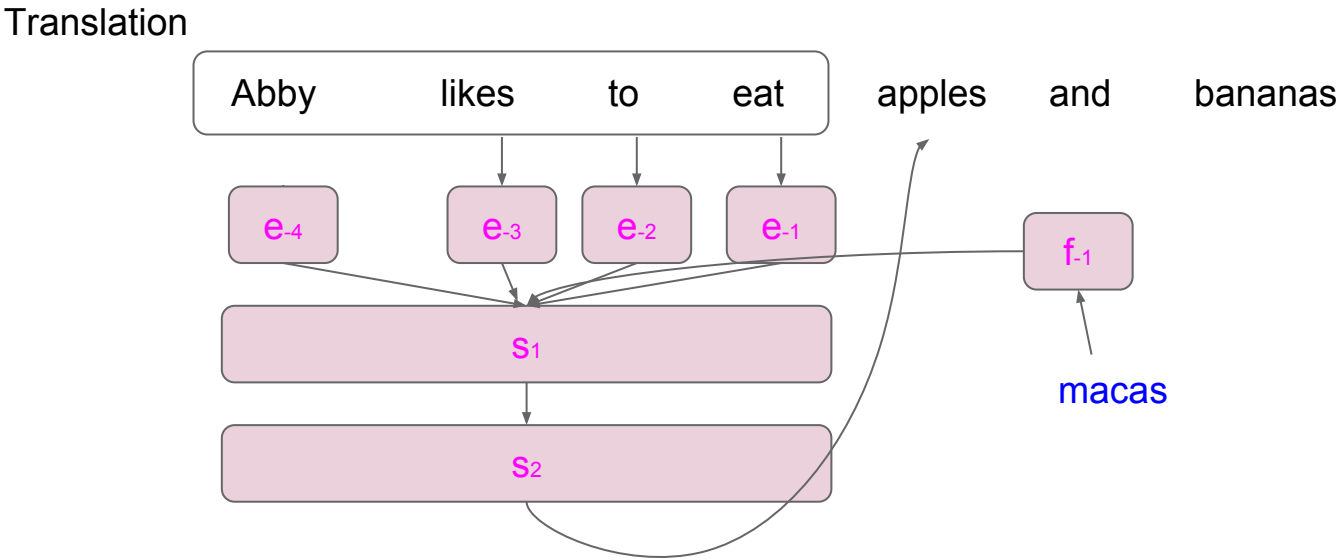
Example Applications

Translation Rescoring (Devlin et al, 2014)



Example Applications

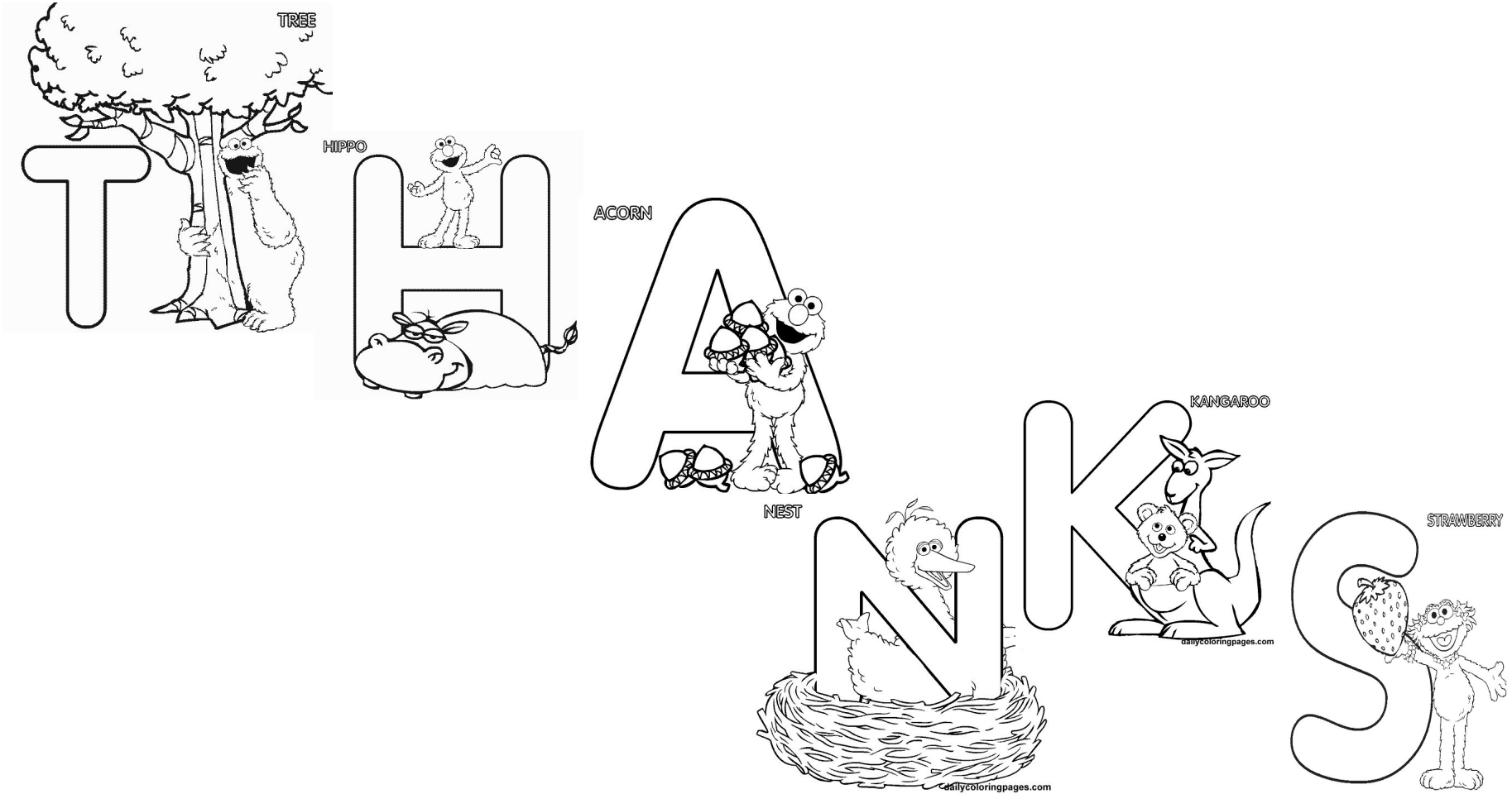
Translation Rescoring (Devlin et al, 2014)



Example Applications

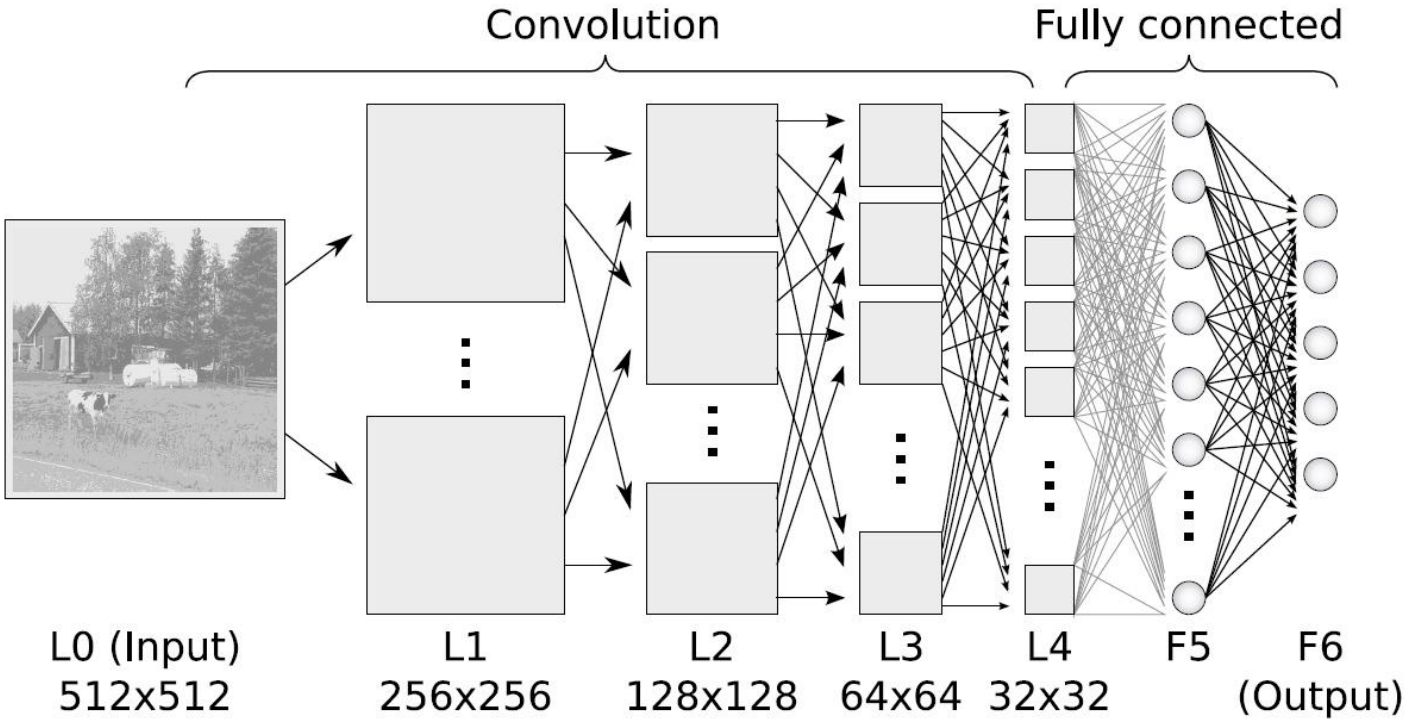
Translation Rescoring (Devlin et al, 2014)

Translation Score (BLEU)	Arabic - English	Chinese - English
Best Rescored System	52.8	34.7
1st OpenMT12	49.5	32.6
Hierarchical	43.4	30.1


TREE
HIPPO
ACORN
NEST
KANGAROO
STRAWBERRY
dailycoloringpages.com
dailycoloringpages.com

Deep Neural Networks are our friends?

Convolutional Neural Network



Deep Neural Networks are our friends?

Convolutional Neural Network

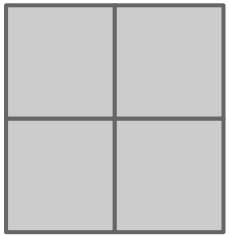
x1	x2	x3	x4
x5	x6	x7	x8
x9	x10	x11	x12
x13	x14	x15	x16

4x4 image

Deep Neural Networks are our friends?

Convolutional Neural Network

x1	x2	x3	x4
x5	x6	x7	x8
x9	x10	x11	x12
x13	x14	x15	x16



4x4 image

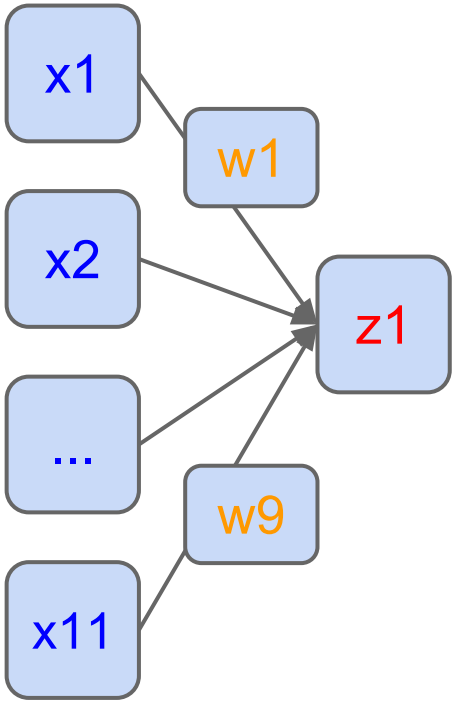
Deep Neural Networks are our friends?

Convolutional Neural Network

x1	x2	x3	x4
x5	x6	x7	x8
x9	x10	x11	x12
x13	x14	x15	x16

4x4 image

z1	



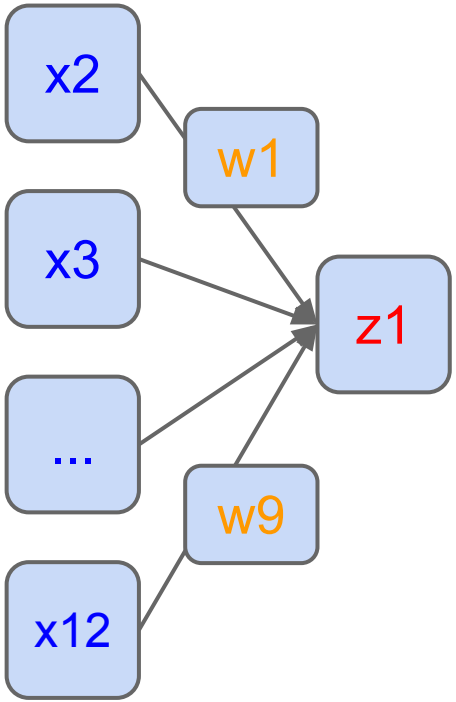
Deep Neural Networks are our friends?

Convolutional Neural Network

x1	x2	x3	x4
x5	x6	x7	x8
x9	x10	x11	x12
x13	x14	x15	x16

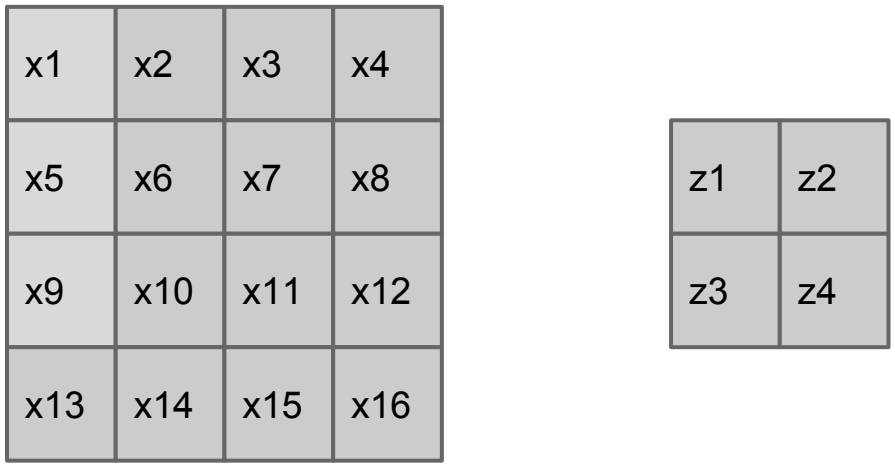
4x4 image

z1	z2



Deep Neural Networks are our friends?

Convolutional Neural Network



4x4 image

Deep Neural Networks are our friends?

Convolutional Neural Network

x1	x2	x3	x4
x5	x6	x7	x8
x9	x10	x11	x12
x13	x14	x15	x16

4x4 image

z1	z2
z3	z4