CS21si: AI for Social Good

Lecture 2: Basics of Neural Networks

Intro to Classification

- We want to generate a prediction from some input
- Output should give some probability of all our expected outputs
- Network should give highest probability to correct class most of the time

Last time we started **training a model** and ended on the idea of **loss**...

1. How do we calculate loss?

2. How do we use loss to get the right weights, bias?

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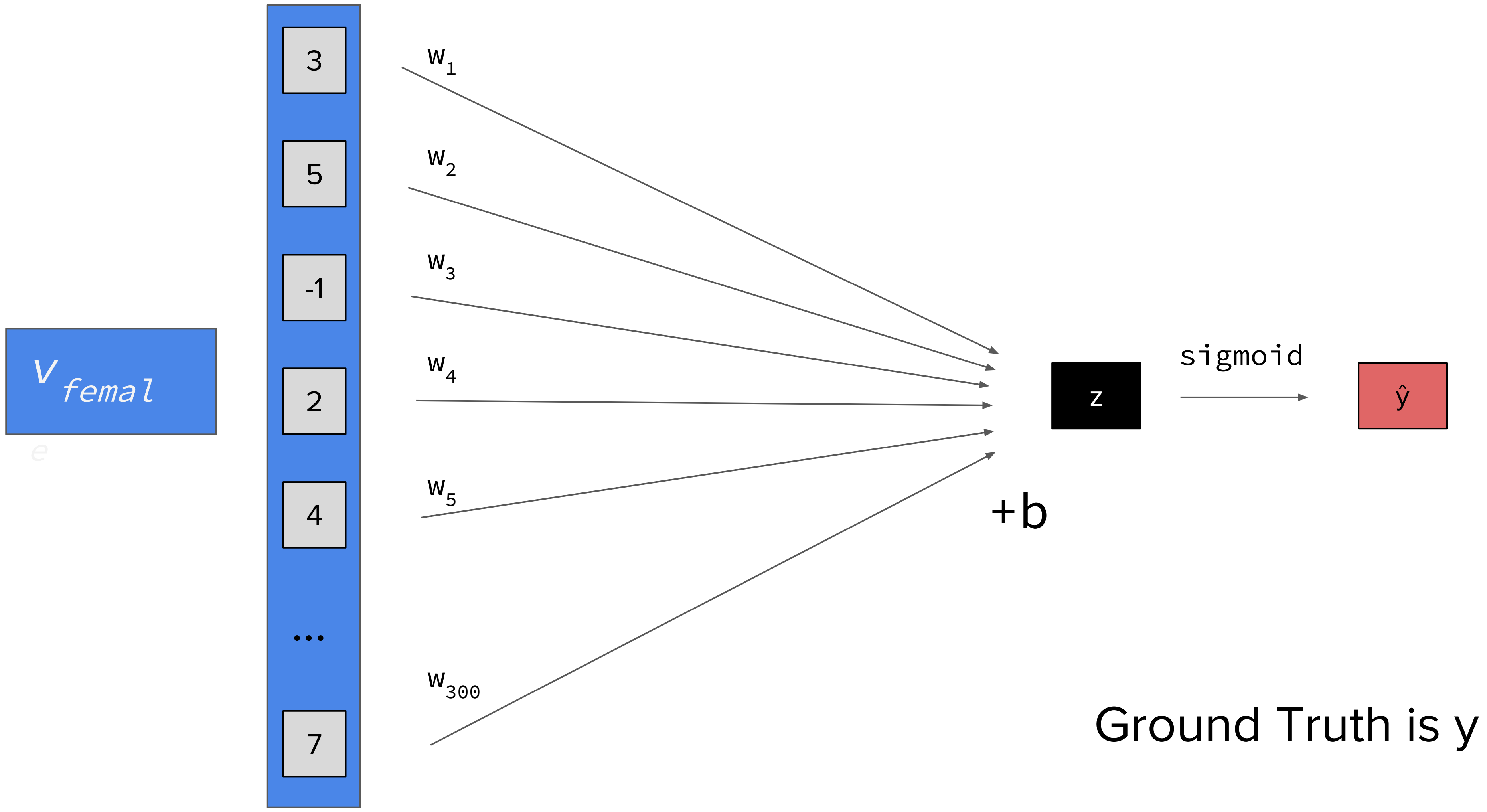
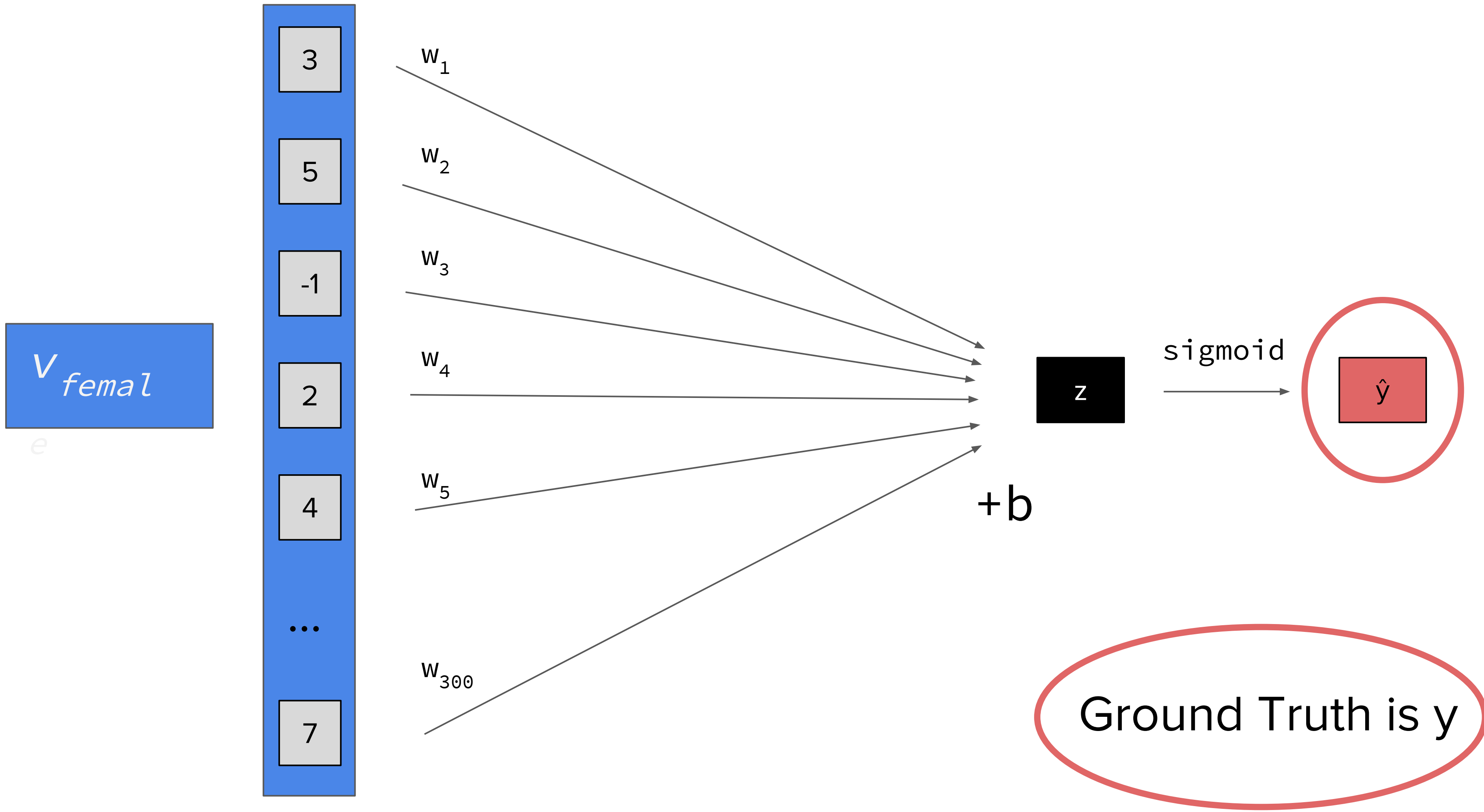


V female
3
5
-1
2
4
...
7
w1
w2
w3
w4
w5
w300
+b
z
sigmoid
ŷ
Ground Truth is y



V_{female}
3
5
-1
2
4
...
7
w_1
w_2
w_3
w_4
w_5
w_{300}
z
+b
sigmoid
ŷ
Ground Truth is y

$$Loss(y, \hat{y})$$

Ground truth

Predicted label

Idea: maximize this!

$$\hat{y}^{y} * (1 - \hat{y})^{1-y}$$

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

$$Loss = -y * \log \hat{y} - (1 - y) * \log (1 - \hat{y})$$

$$Cost = \sum_{i=1}^{m} Loss(y_i, \hat{y}_i)$$

Questions?

Jupyter Notebook Exercises: Part 1

You'll need:

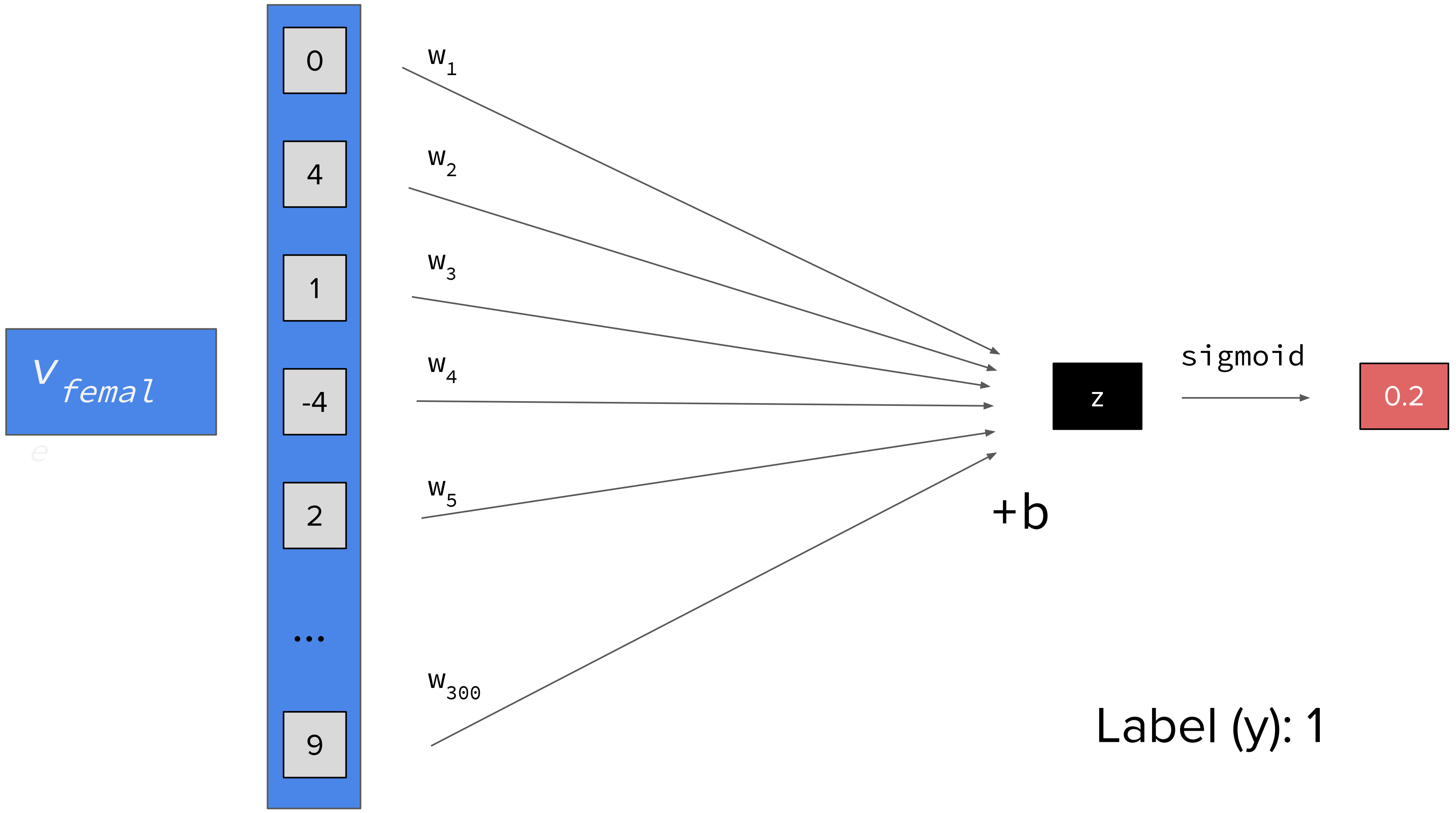
```
np.log(x)
```

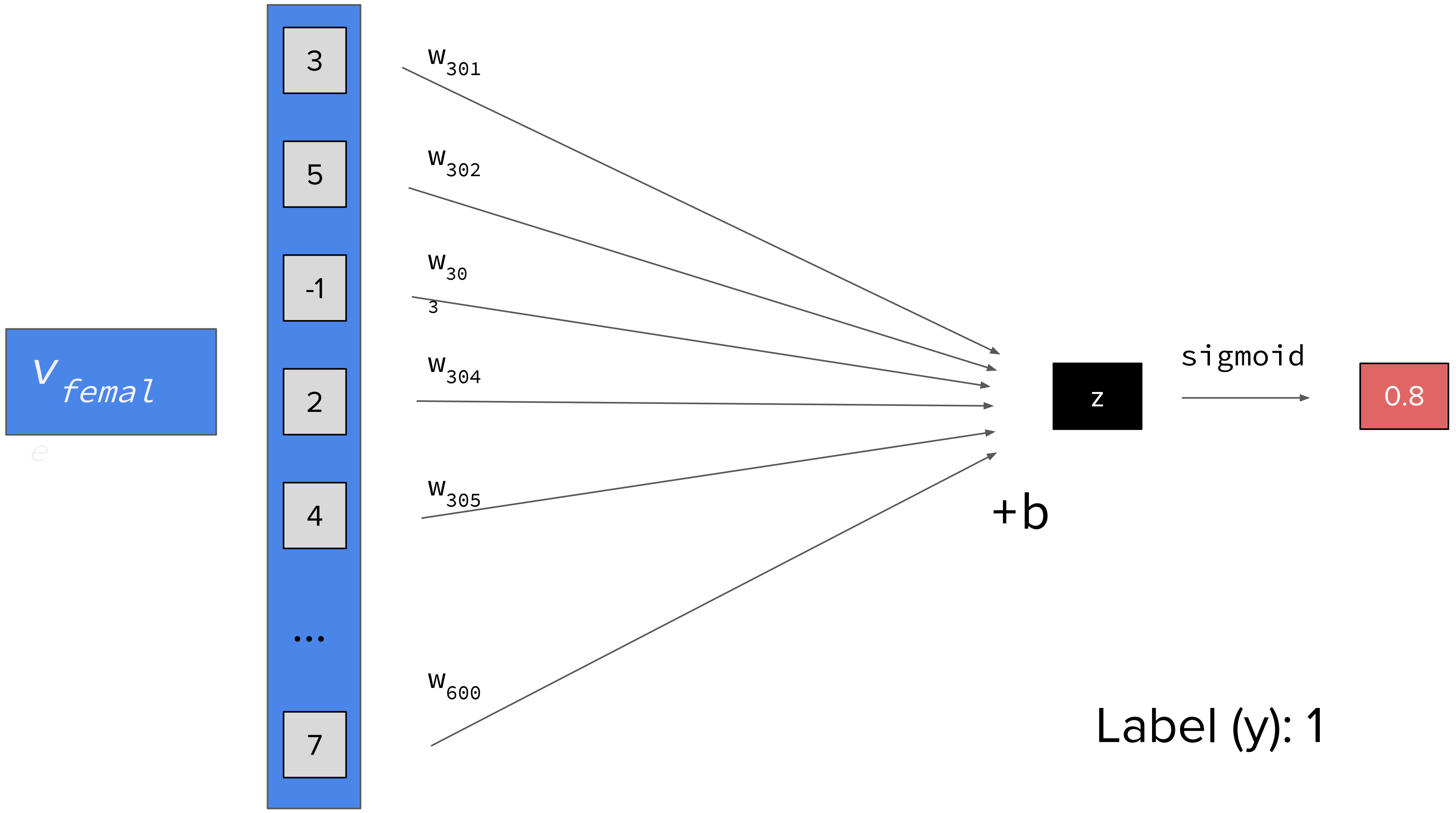
$$Loss = -y * \log \hat{y} - (1 - y) * \log (1 - \hat{y})$$

1. How do we calculate loss?

2. How do we use loss to get the right weights, bias?

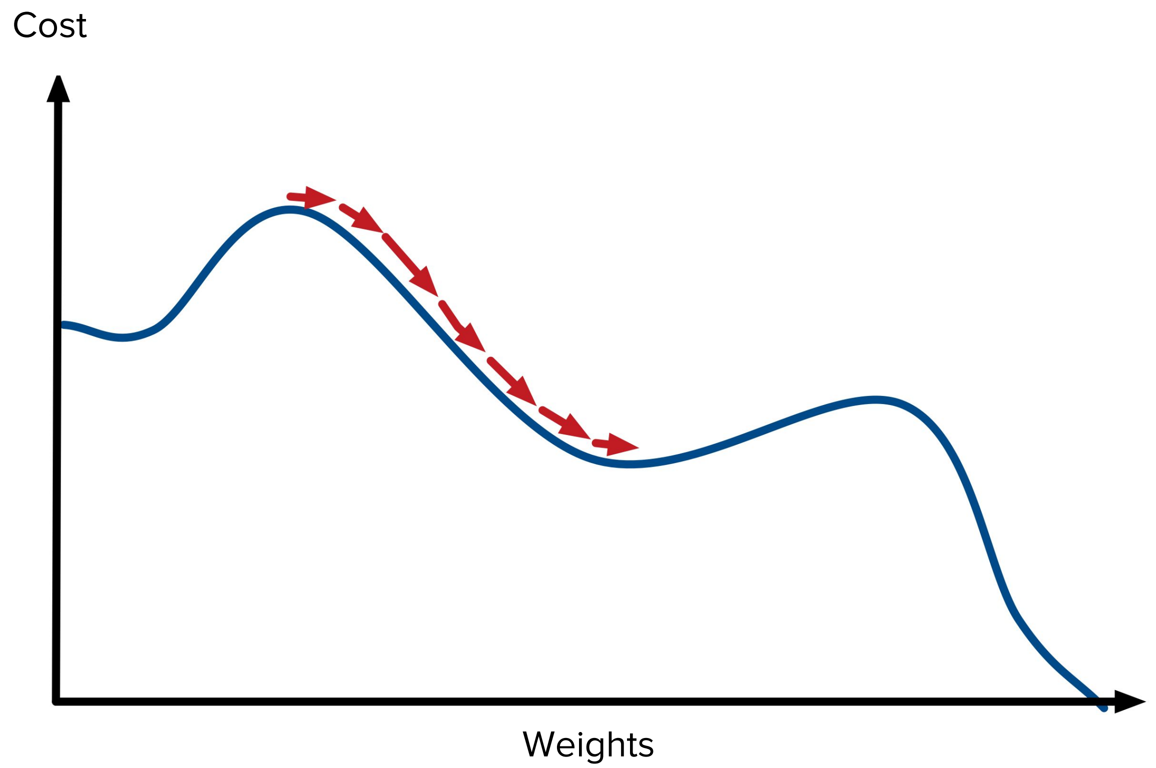
Can we randomly guess?


V_{female}
0
4
1
-4
2
...
9
w_1
w_2
w_3
w_4
w_5
w_{300}
+b
z
sigmoid
0.2
Label (y): 1



V_{female}
3
5
-1
2
4
...
7
w_{301}
w_{302}
w_{303}
w_{304}
w_{305}
w_{600}
z
+b
sigmoid
0.8
Label (y): 1

Gradient Descent



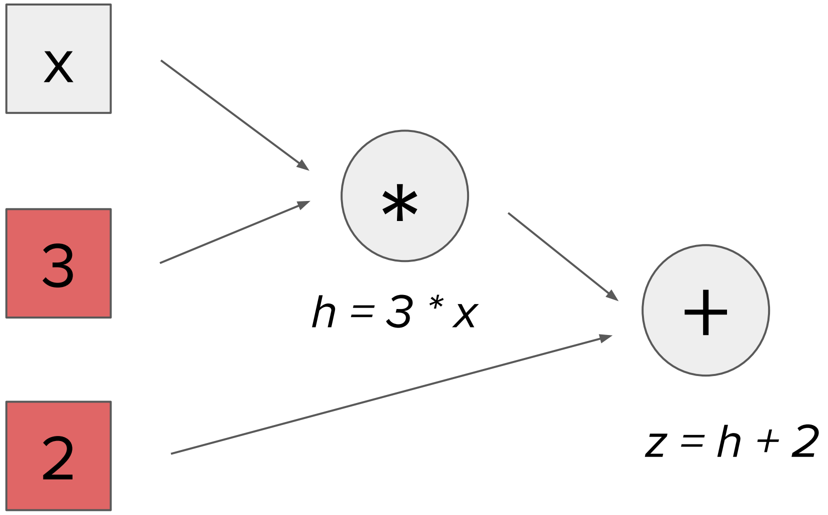
How do we calculate the gradients?

Backpropagation

- Each computation is represented as a node in a computational graph
- Gradients are computed at each node of the graph
- Chain rule is applied recursively to get total gradients on each weight

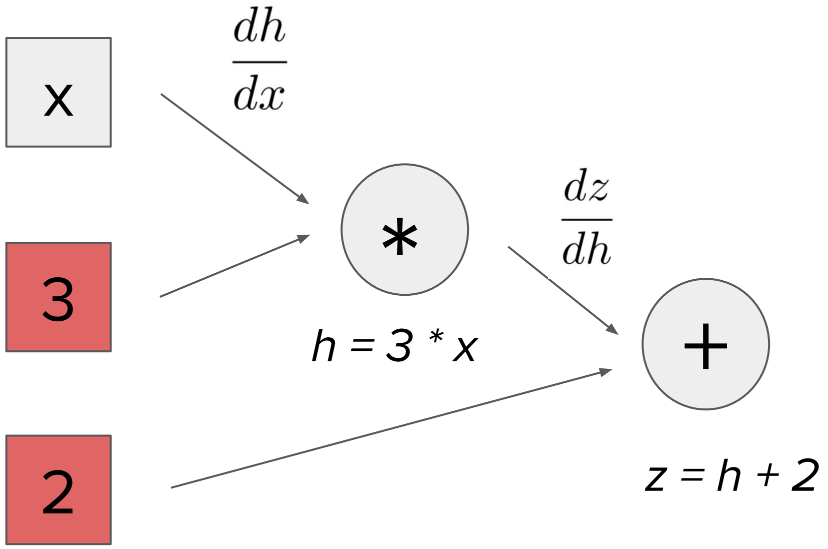
Backpropagation

3x + 2



Backpropagation

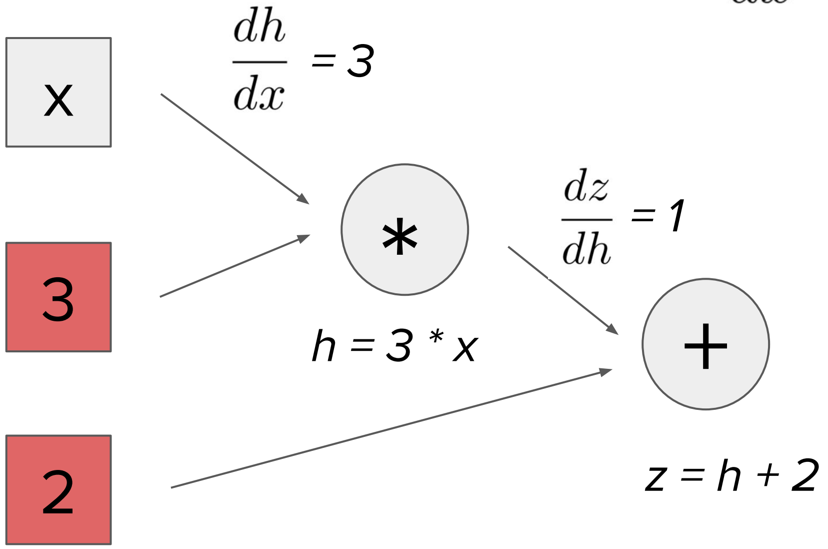
3x + 2



Backpropagation

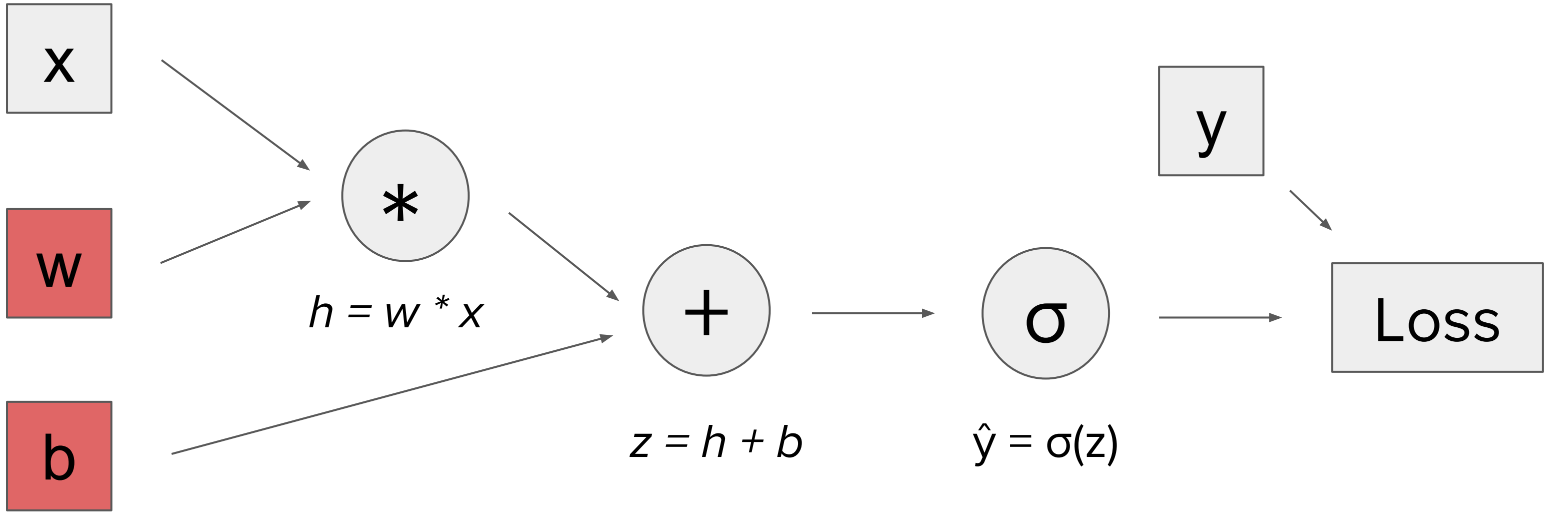
3x + 2

$$\frac{dz}{dx} = \frac{dz}{dh}\frac{dh}{dx} = 3$$

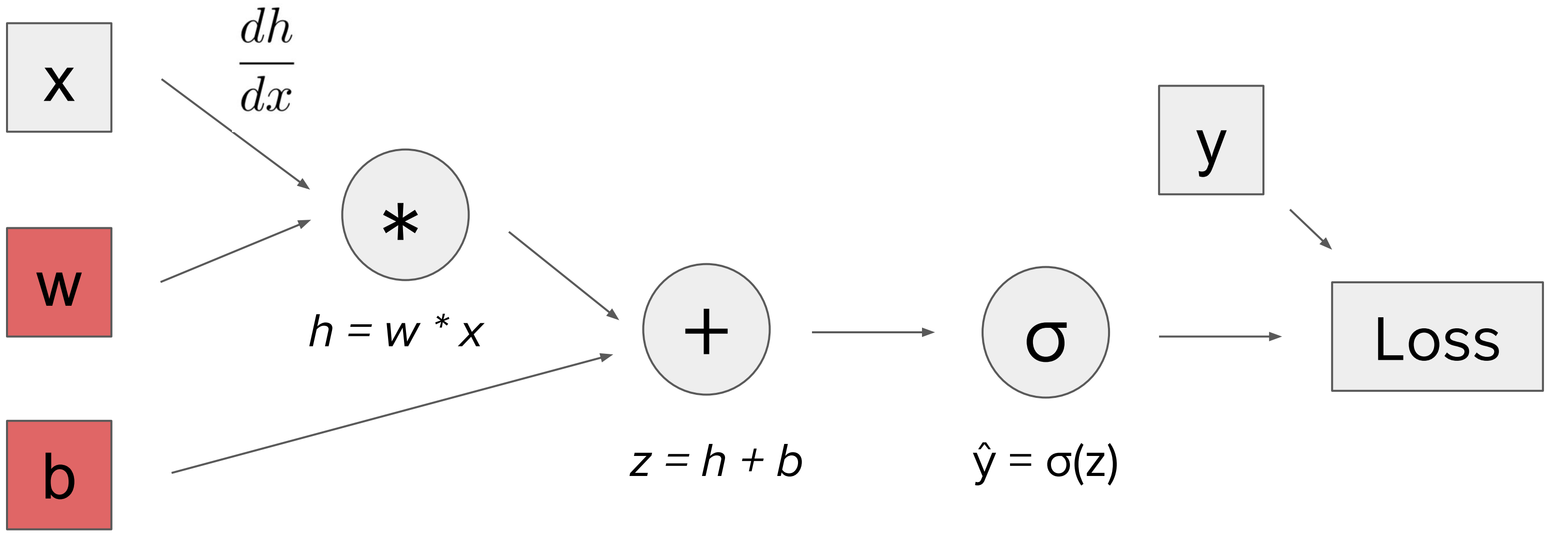


Questions?

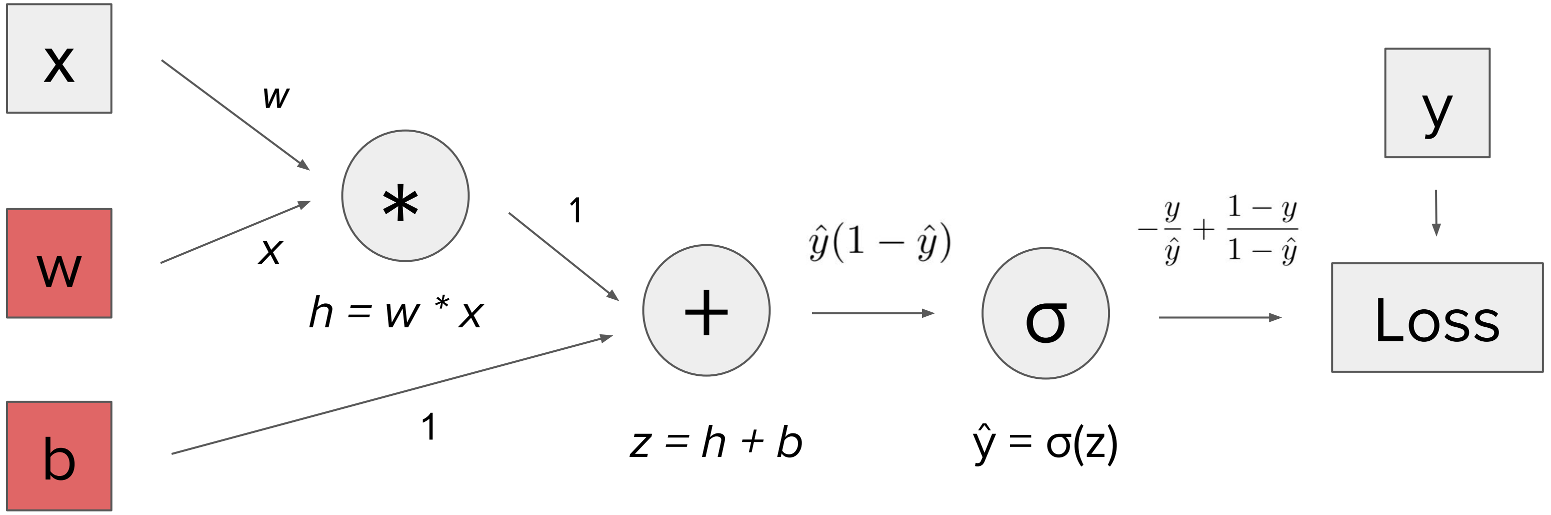
Backpropagation



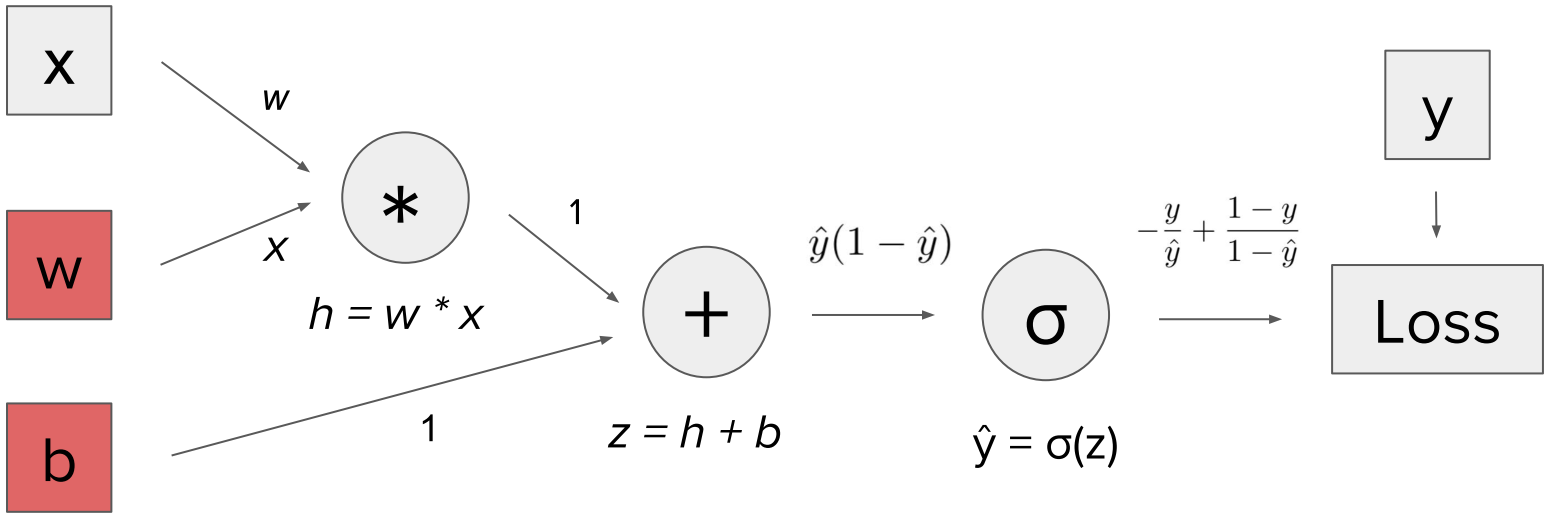
Backpropagation



Backpropagation



Backpropagation



$$\frac{\partial Loss}{\partial w} = (\hat{y} - y) * x \qquad \frac{\partial Loss}{\partial b} = \hat{y} - y$$

Jupyter Notebook Exercises: Part 2

You'll need:

$$\frac{\partial Loss}{\partial w} = (\hat{y} - y) * x \qquad \frac{\partial Loss}{\partial b} = \hat{y} - y$$

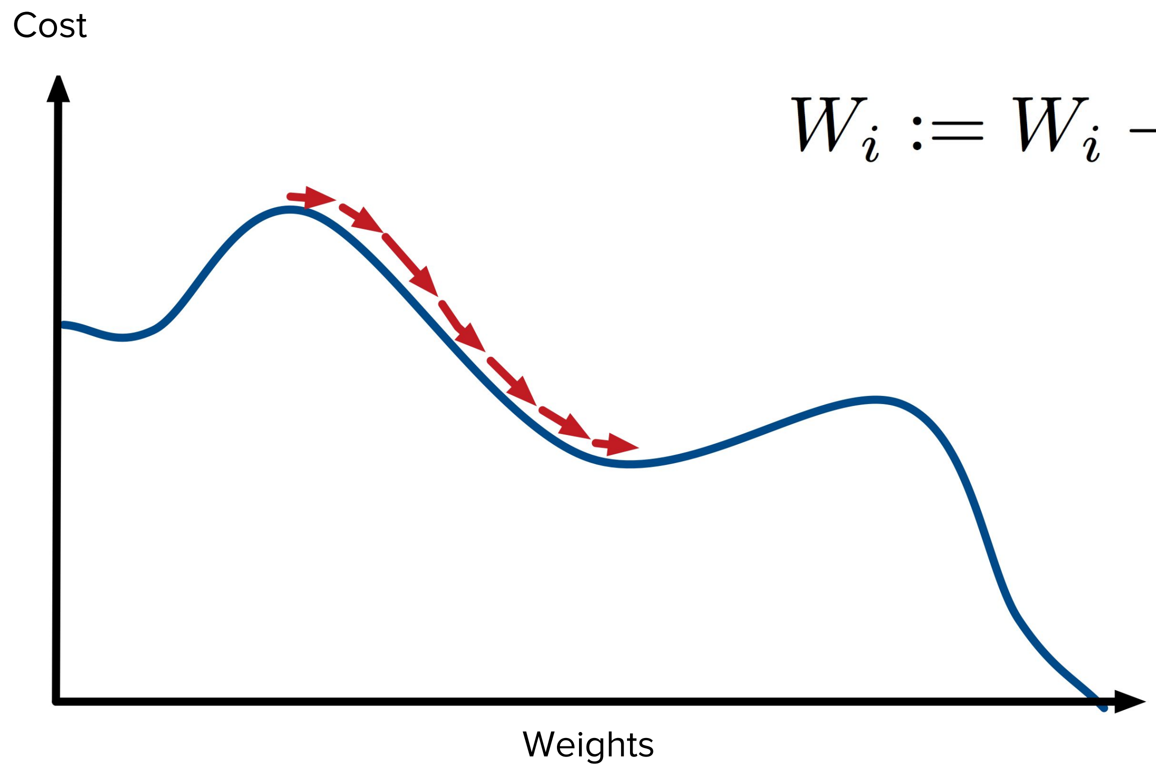
Training

Weight Update

- Once we find gradients, we must change each weight in the opposite direction
- We can use an update rule to accomplish this; the simplest is SGD:

$$W_i := W_i - \alpha \frac{\partial L}{\partial W_i}$$

Stochastic Gradient Descent



$$W_i := W_i - \alpha \frac{\partial L}{\partial W_i}$$

Jupyter Notebook Exercises: Part 3

You'll need:

```
np.random.randn(size)
```

Neural networks

- Logistic regression is a special case of a neural network
- By adding more “layers” of computation to a logistic regression model, you can turn it into a “deep” NN

What we’ve learned...

- You can train logistic regression using loss computation against ground truth to measure how badly you are doing
- How to minimize loss using SGD in a neural network
- By adding more “layers” of computation to logistic regression, you get a deep neural network