Intro to Deep Learning

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Course Goals

Grading

Result = 0.4 * (mean(homeworks)) + 0.4 * project + 0.2 * exam

Homeworks

Result = 0.4 * (mean(homeworks)) + 0.4 * project + 0.2 * exam

- numpy n-layer NN
- PyTorch word2vec
- Classification
- GRU implementation
- Language modeling
- Attention
- Transfer learning

Homeworks

Result = 0.4 * (mean(homeworks)) + 0.4 * project + 0.2 * exam

- numpy n-layer NN
- PyTorch word2vec

HW1

- Classification
- GRU implementation

HW2

- Language modeling
- Attention
- Transfer learning

HW3

Project

Result = 0.4 * (mean(homeworks)) + 0.4 * project + 0.2 * exam

- Must include DL
- List of projects
- Your own
- Paper implementation
- Competition
- Max team size = 2 (3)
- Choose wisely

Project

Result = 0.4 * (mean(homeworks)) + 0.4 * project + 0.2 * exam

- Must include DL
- List of projects
- Your own
- Paper implementation
- Competition
- Max team size = 2 (3)
- Choose wisely

Exam

Result = 0.4 * (mean(homeworks)) + 0.4 * project + 0.2 * exam

- Test
- ~15 questions from course lectures

Syllabus

- Deep Learning
- Word embeddings
- Convolution NN
- Tricks in DL
- Engineering in DL
- Recurrent NN
- Sequence tagging

Syllabus

- Deep Learning
- Word embeddings
- Convolution NN
- Tricks in DL
- Engineering in DL
- Recurrent NN
- Sequence tagging
- Language models
- Ranking models
- Sequence2sequence
- Attention
- Transformer
- Transfer learning
- Dialogue systems

Framework

Simple **Hard**

Framework

Simple **Hard**

Framework

Simple **Hard**

Keras

TensorFlow

Framework

Simple **Hard**

Keras

TensorFlow

PyTorch

Framework

Simple **Hard**

Keras

TensorFlow

PyTorch

Deep Learning

Classic Machine Learning

Deep Learning

Classic Machine Learning

Deep Learning

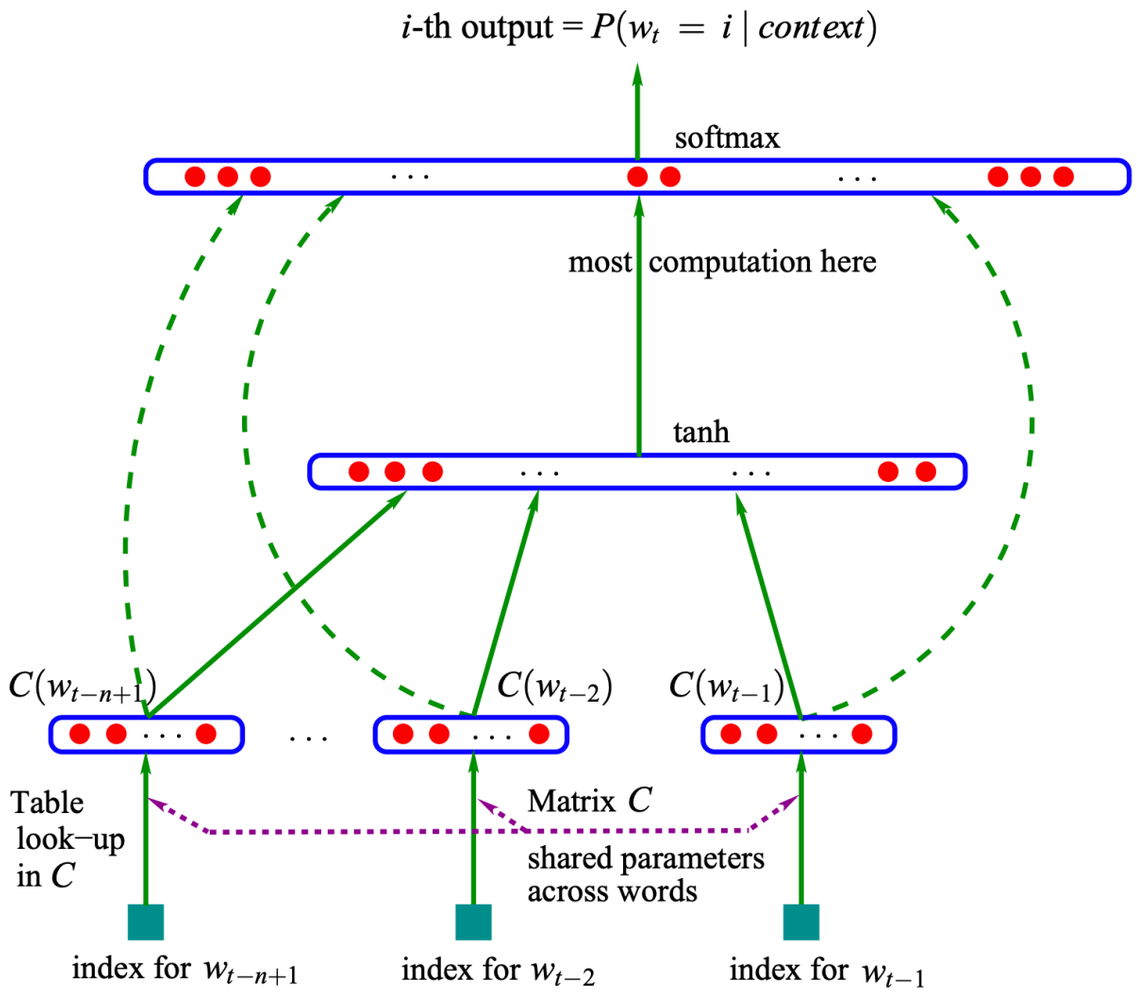
Classic Machine Learning

Deep Learning

Deep Learning

Neural Probabilistic Language Model

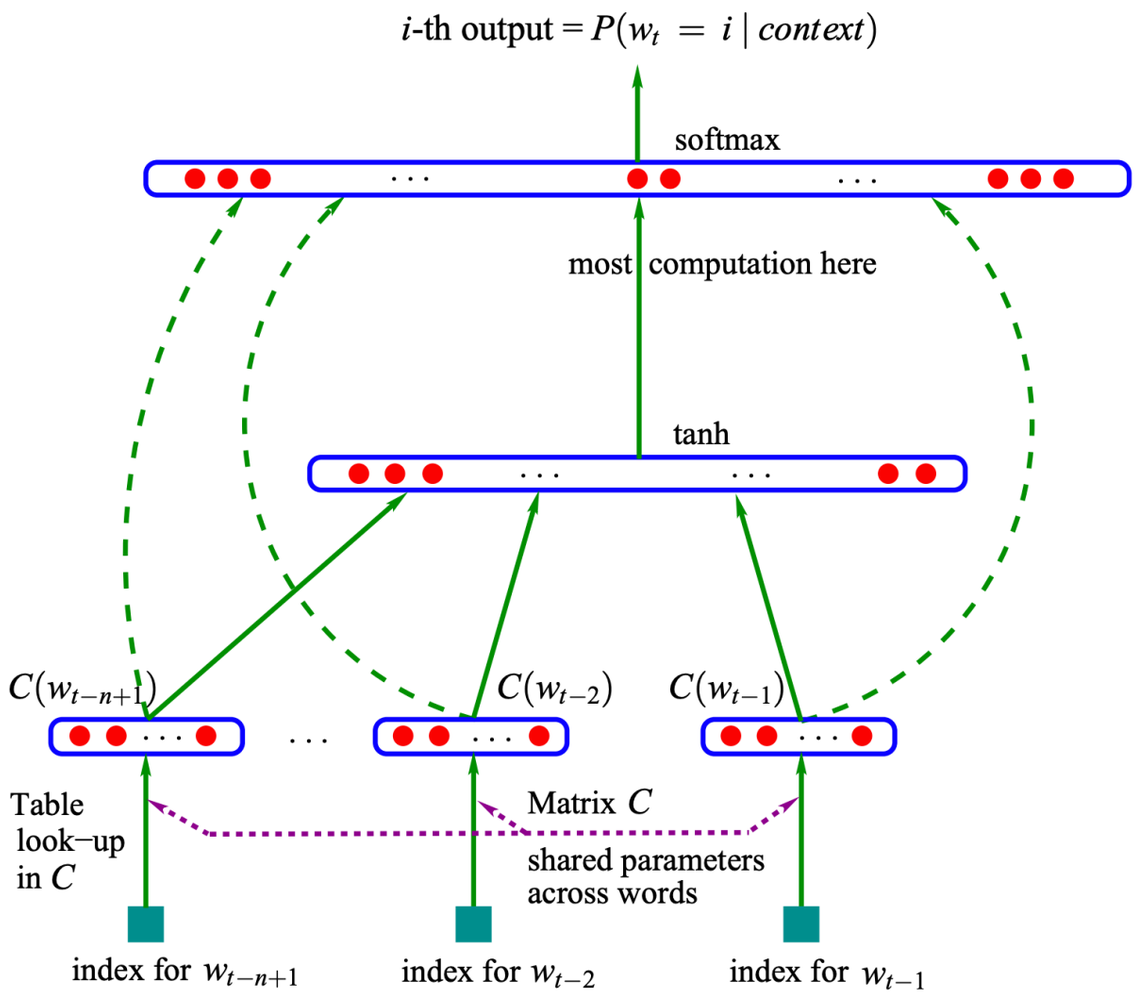
2003



Deep Learning

Neural Probabilistic Language Model

2003



BERT

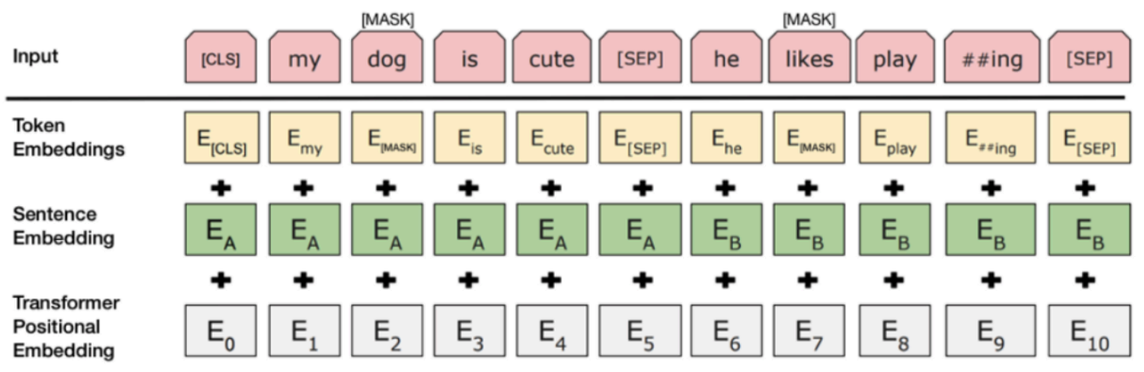
Q42018

24 Layers

Transformer Encoder

Transformer Encoder

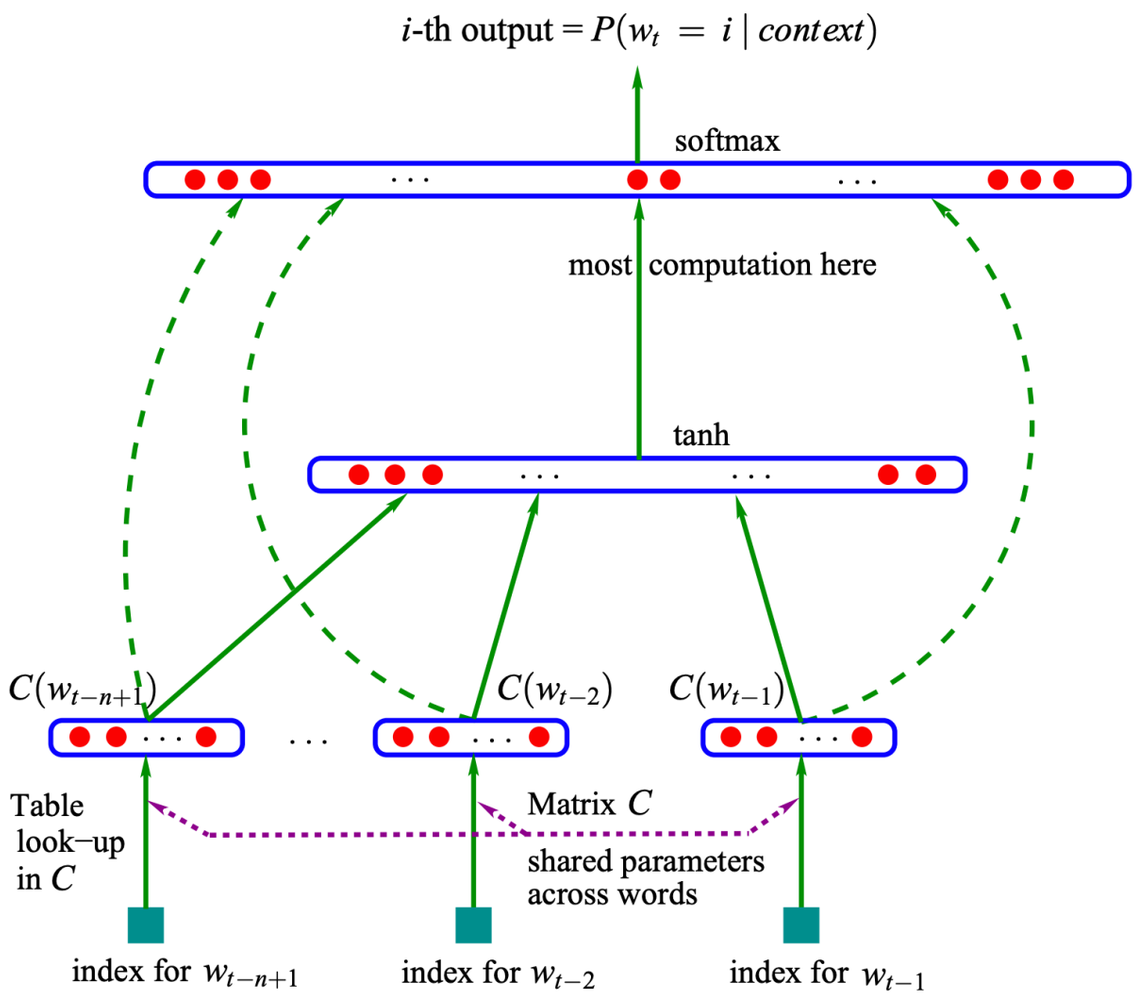
Transformer Encoder



Deep Learning

Neural Probabilistic Language Model

2003



BERT

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Transformer Encoder

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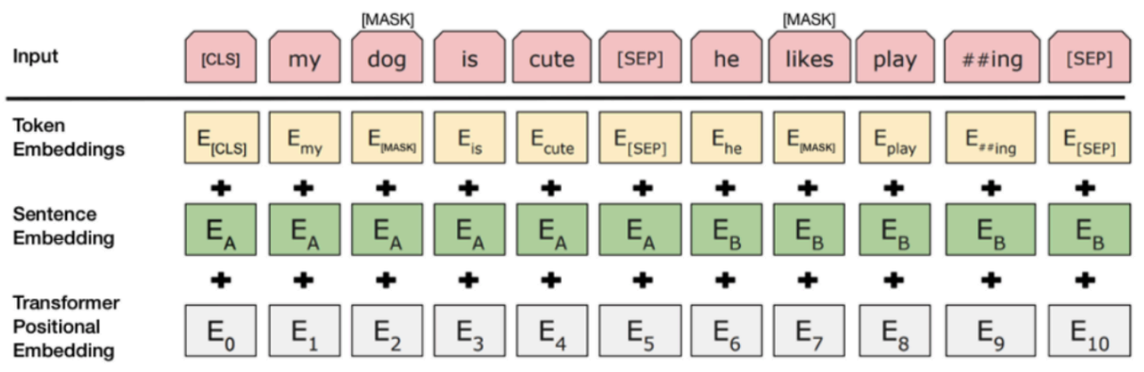
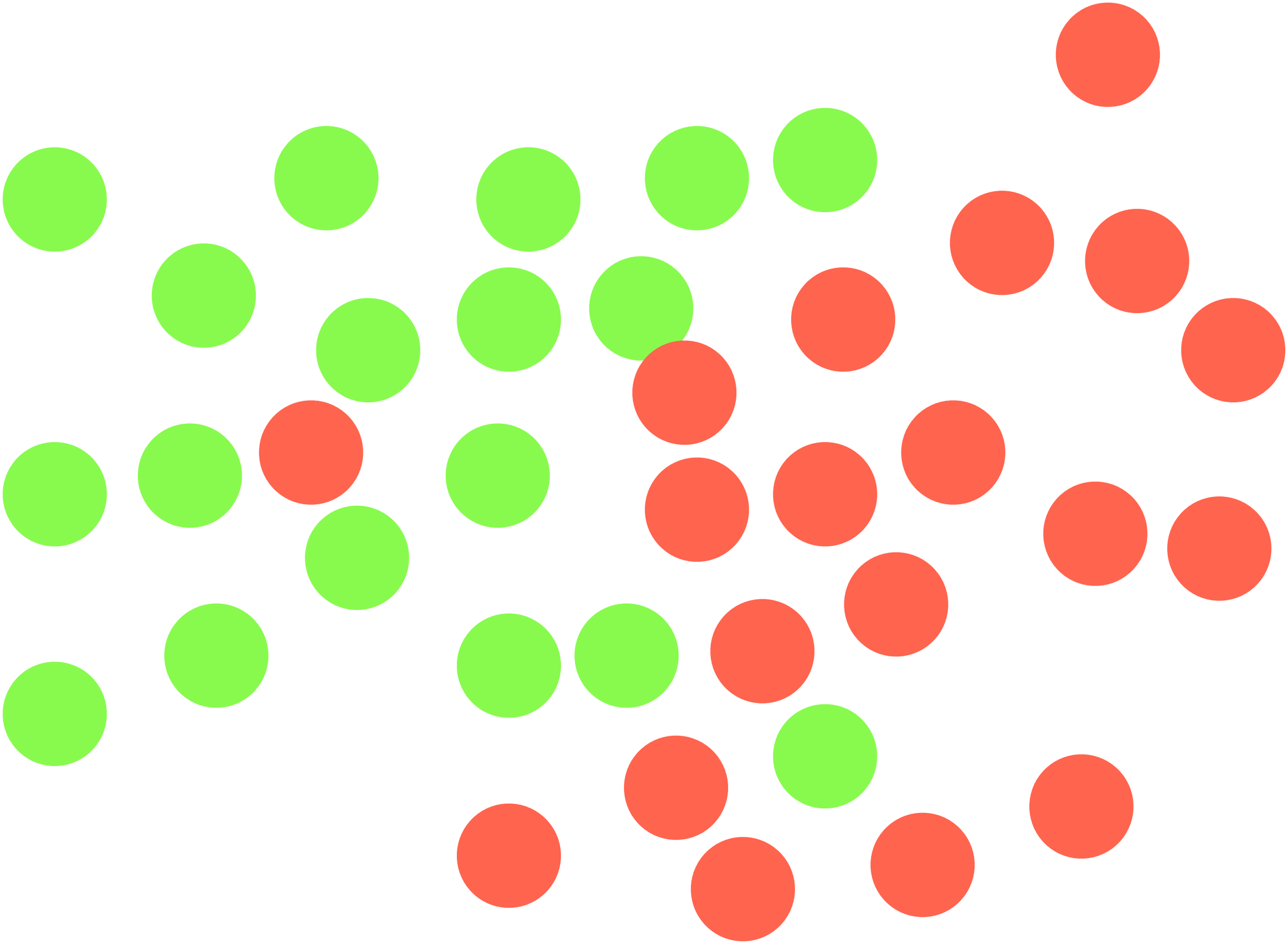
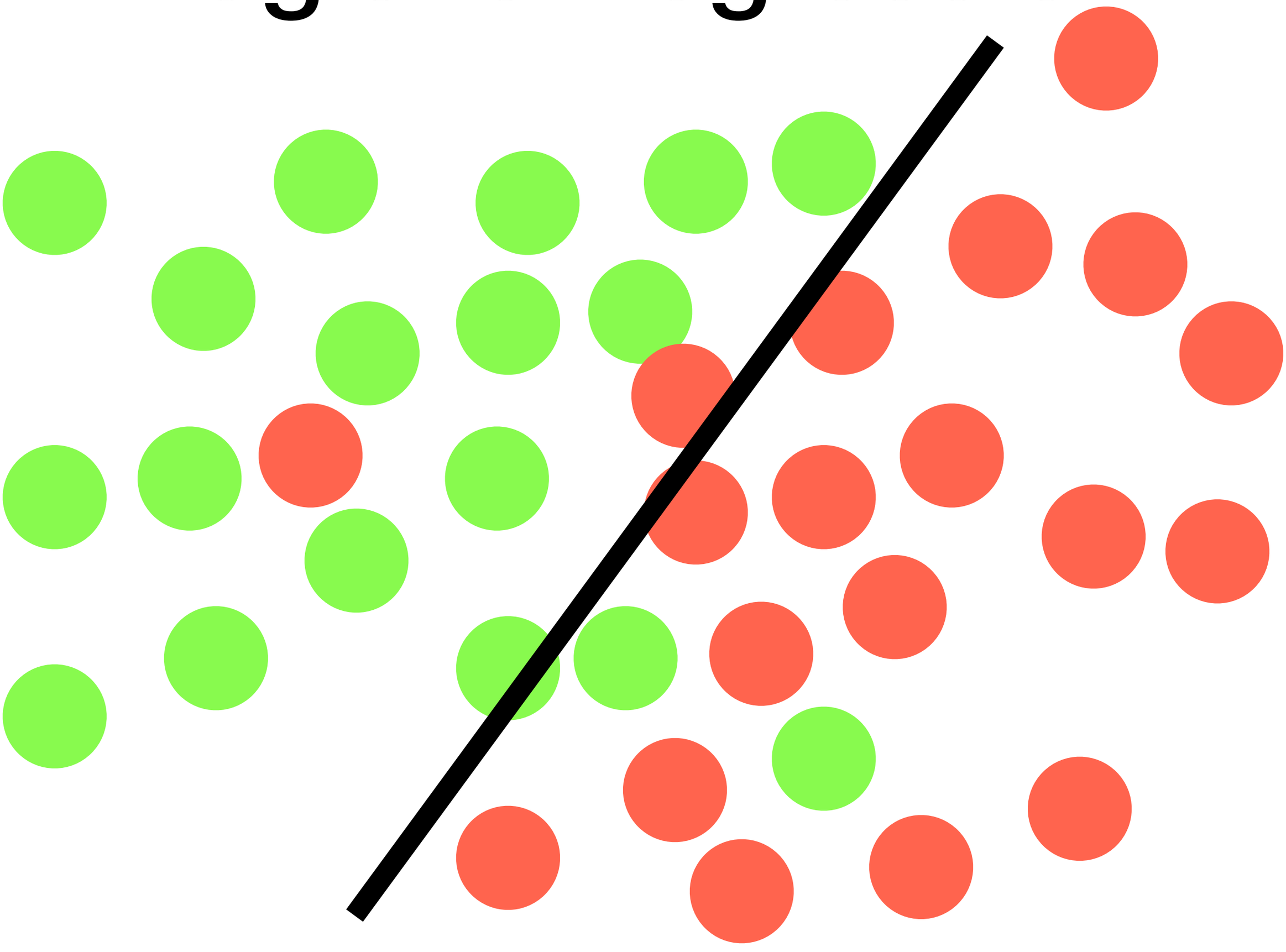


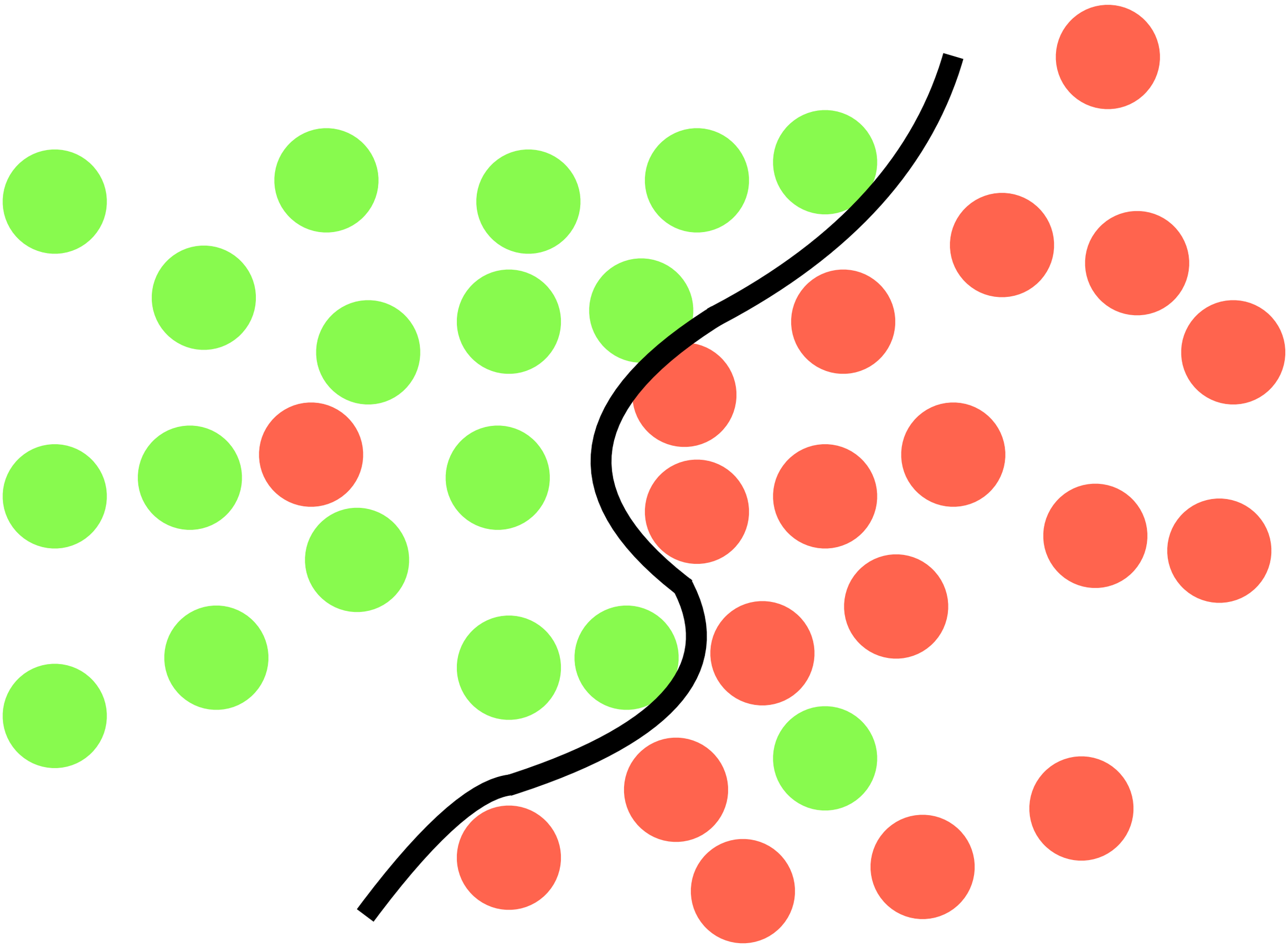
ML Recap



Logistic Regression



Neural Networks



Logistic Regression

Inference

(len(data), 3)

Logistic Regression

Inference

(len(data), 3)

```
array([[0.61417946, 0.14738907, 0.74942813],
       [0.54257148, 0.7955858 , 0.08140681],
       [0.31717539, 0.74551499, 0.11464107],
       [0.90179514, 0.17979926, 0.52133968],
       [0.63032386, 0.25433298, 0.17785144],
       [0.45850347, 0.92489706, 0.29492176],
       [0.38685861, 0.99961577, 0.89145302],
       [0.68854165, 0.87301941, 0.58840101],
       [0.39667669, 0.7582801 , 0.46032164],
       [0.4046151 , 0.53386007, 0.49388535]])
```

Logistic Regression

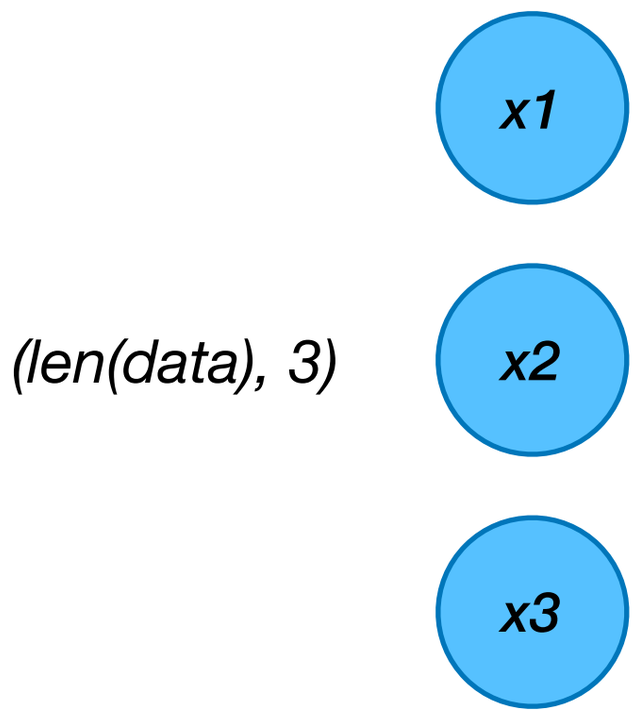
Inference

(len(data), 3)

	0	1	2
0	0.614179	0.147389	0.749428
1	0.542571	0.795586	0.081407
2	0.317175	0.745515	0.114641
3	0.901795	0.179799	0.521340
4	0.630324	0.254333	0.177851
5	0.458503	0.924897	0.294922
6	0.386859	0.999616	0.891453
7	0.688542	0.873019	0.588401
8	0.396677	0.758280	0.460322
9	0.404615	0.533860	0.493885

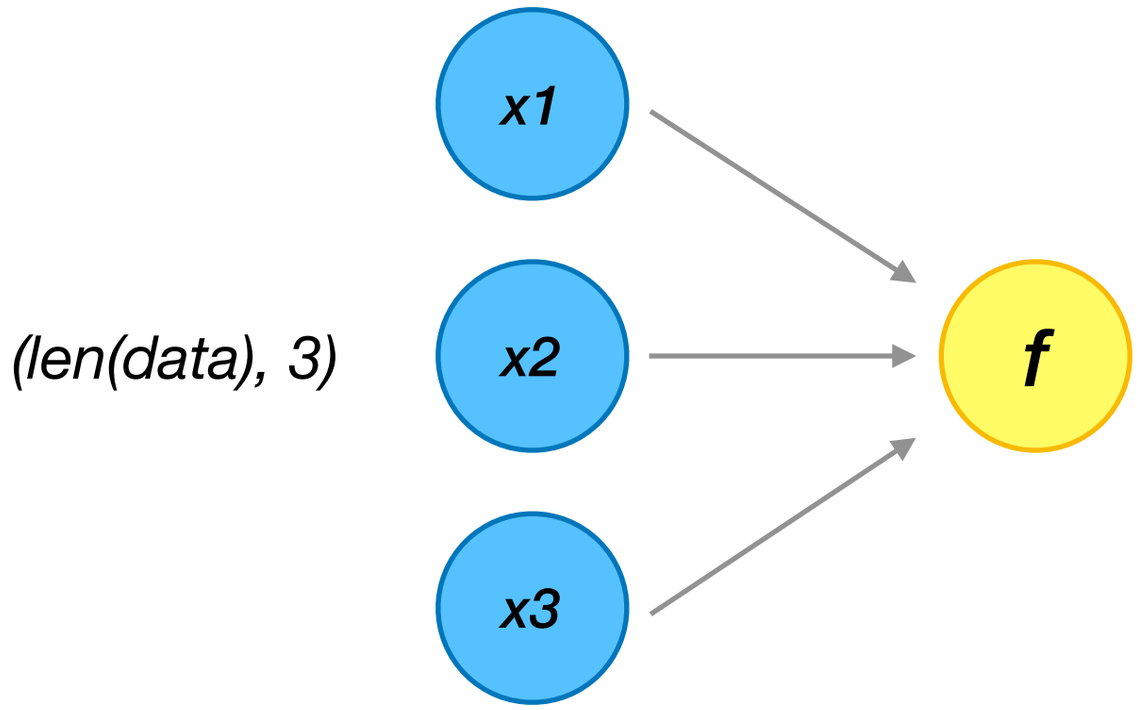
Logistic Regression

Inference



Logistic Regression

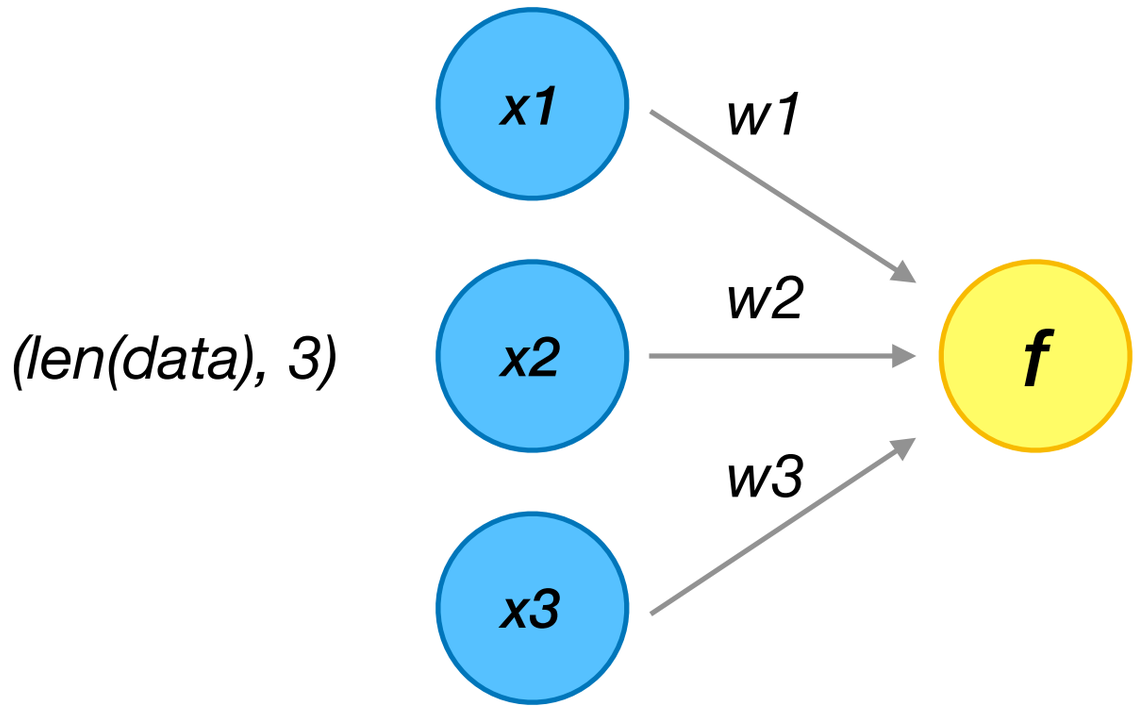
Inference



(len(data), 3)

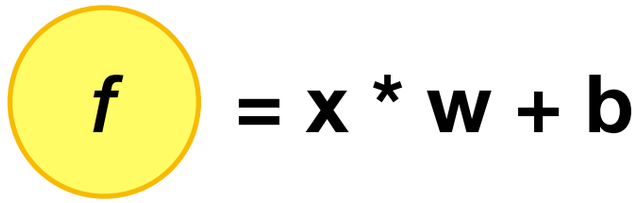
Logistic Regression

Inference



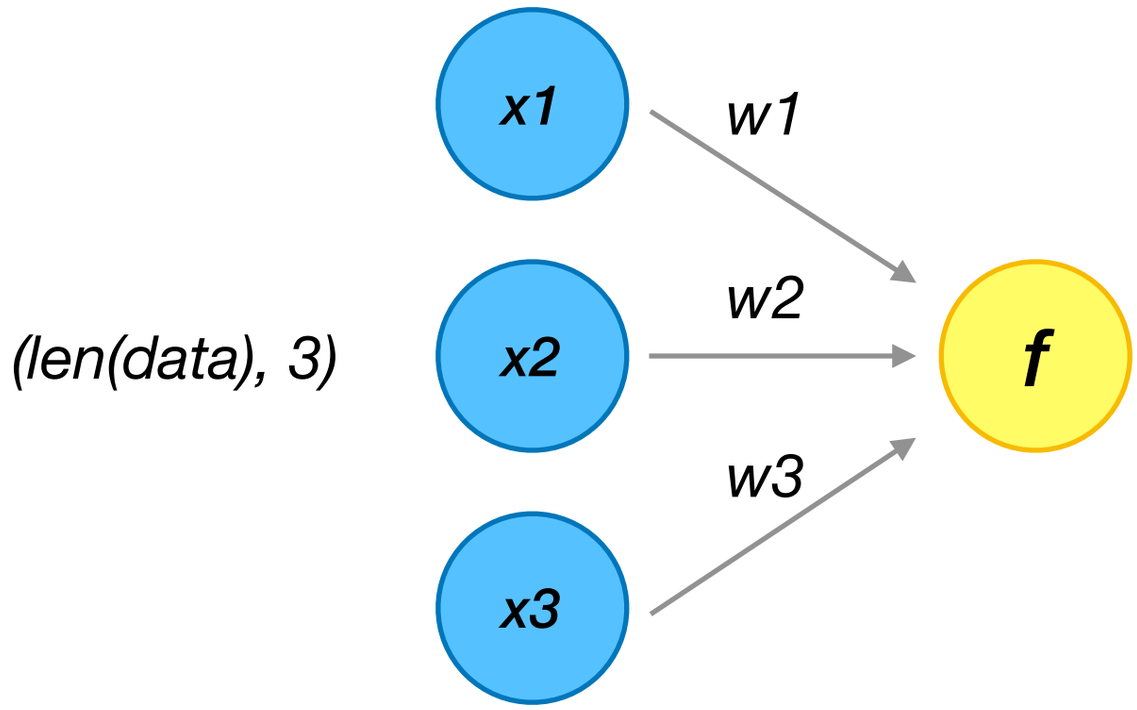
Logistic Regression

Inference



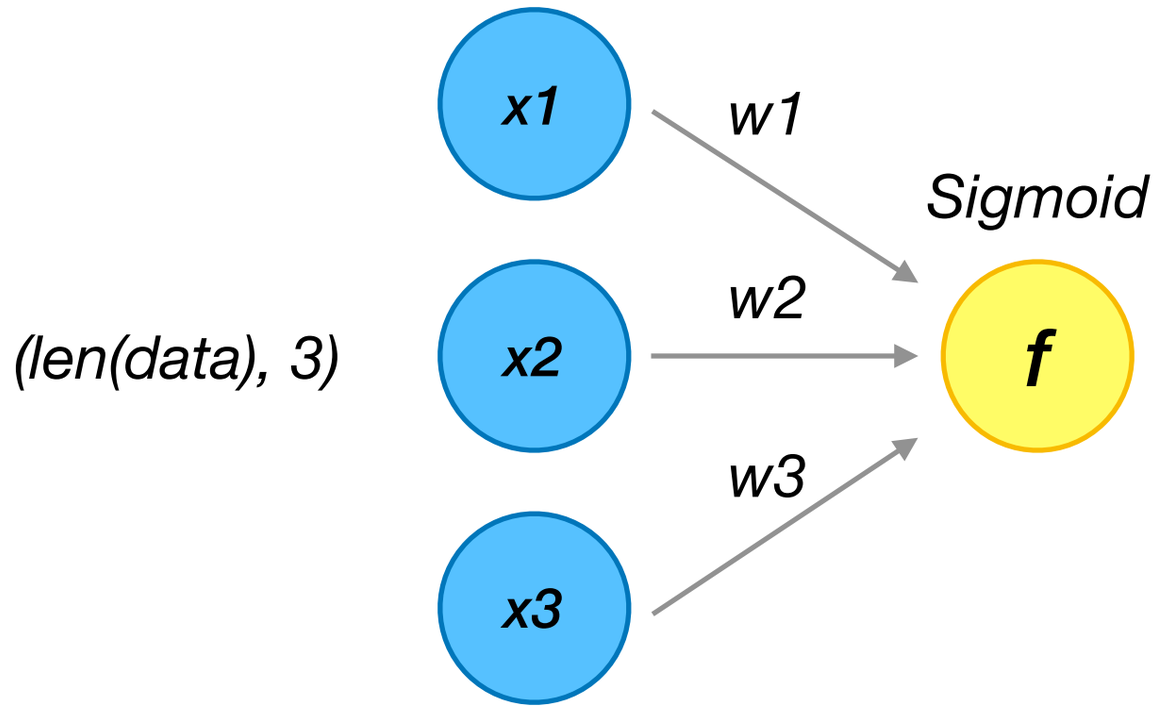
Logistic Regression

Inference



Logistic Regression

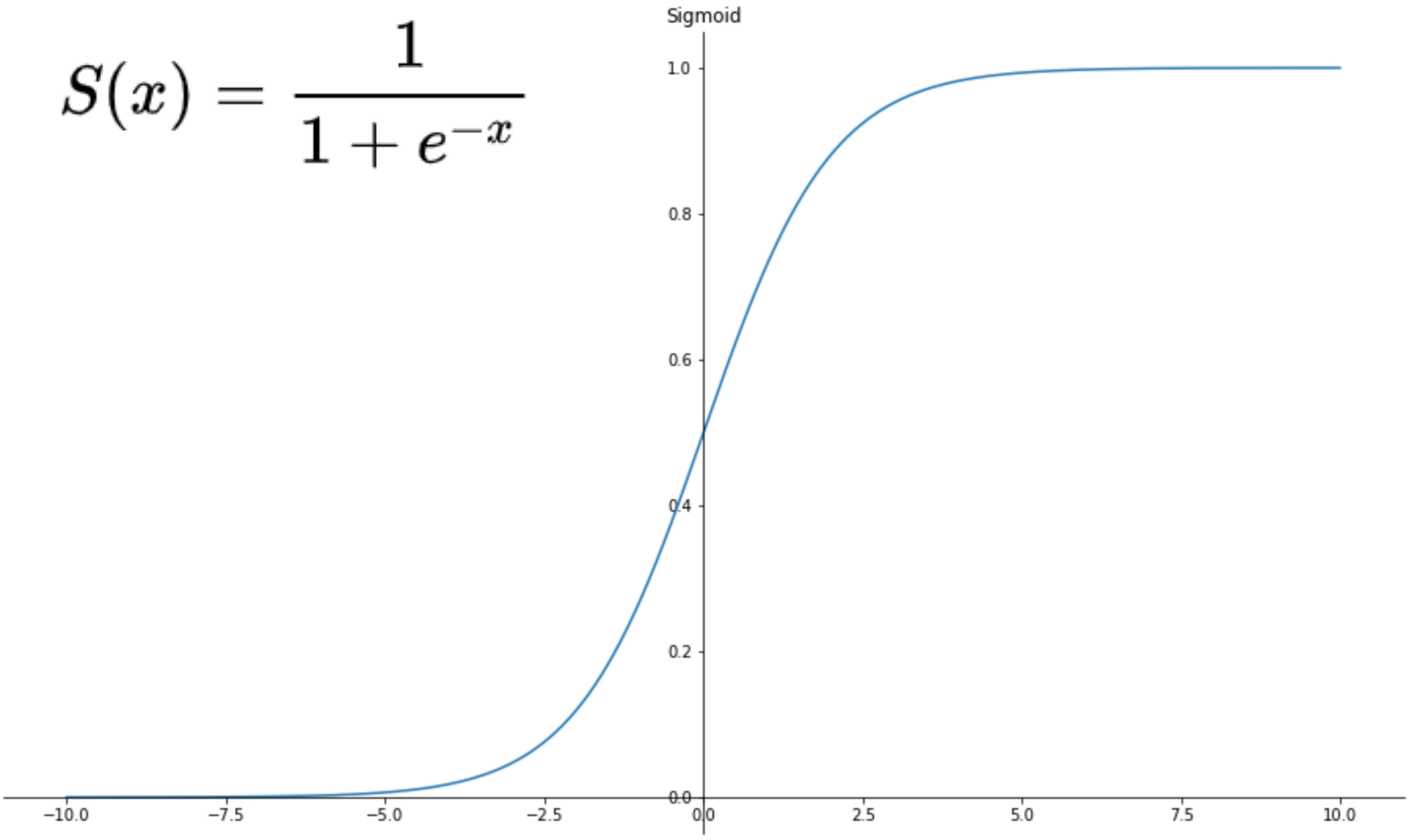
Inference



Logistic Regression

Sigmoid

$$S(x) = \frac{1}{1 + e^{-x}}$$



Logistic Regression

Inference

f = 1 / (1 + exp (- (x * w + b))

Logistic Regression

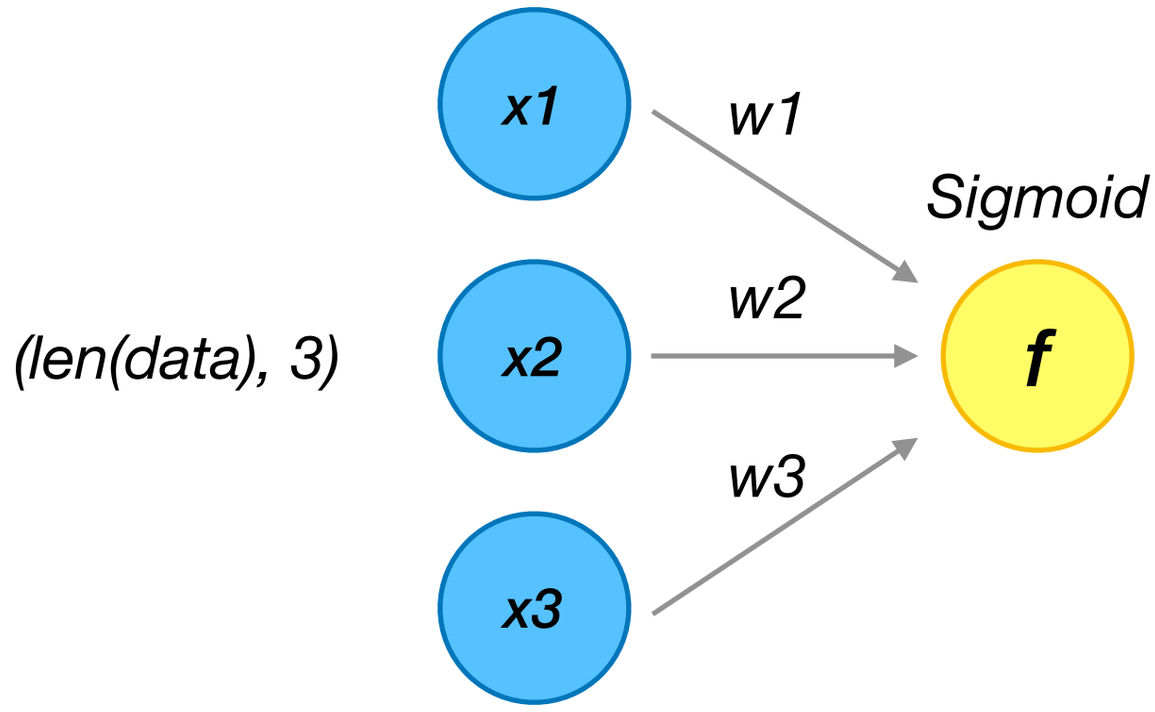
Inference

$$S(x) = \frac{1}{1 + e^{-x}}$$

f = 1 / (1 + exp (- (x * w + b))

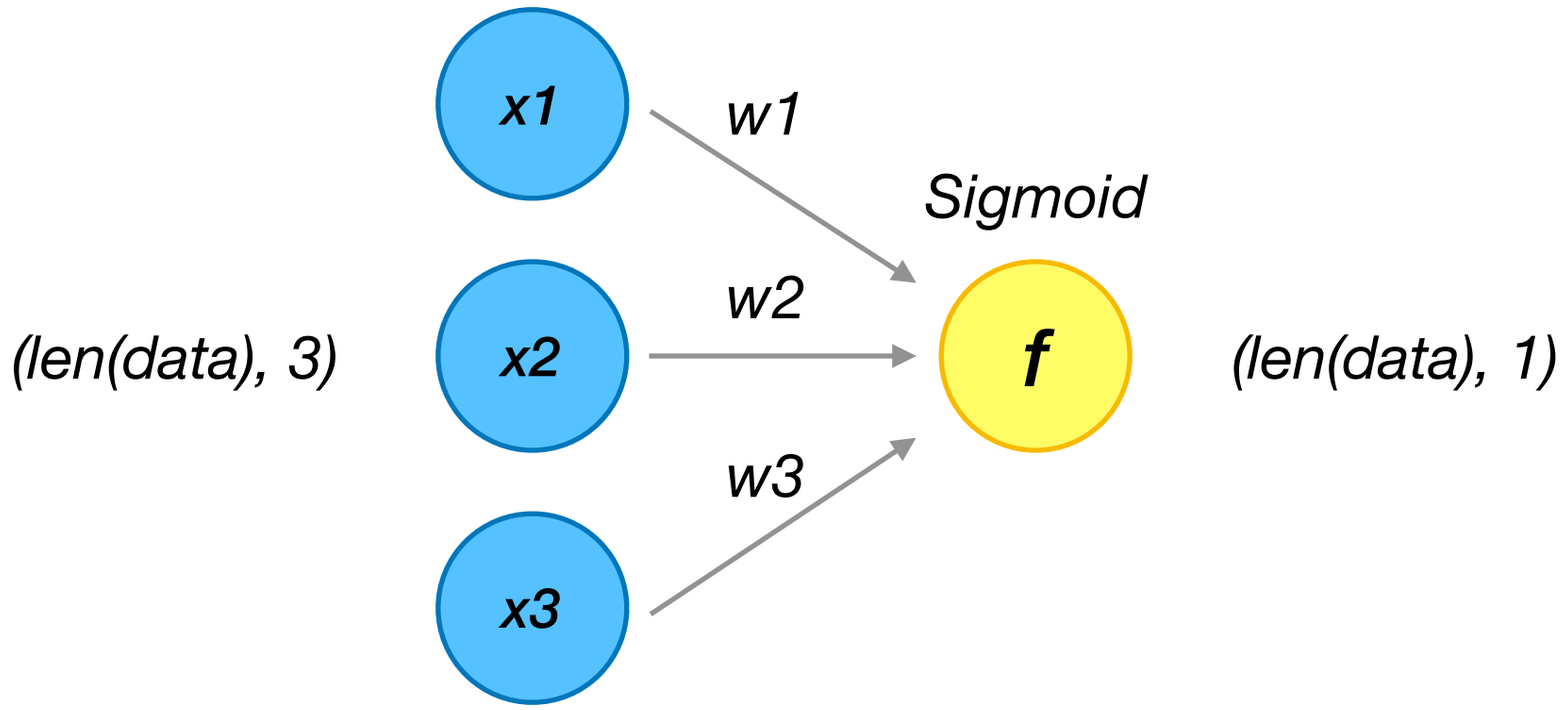
Logistic Regression

Inference



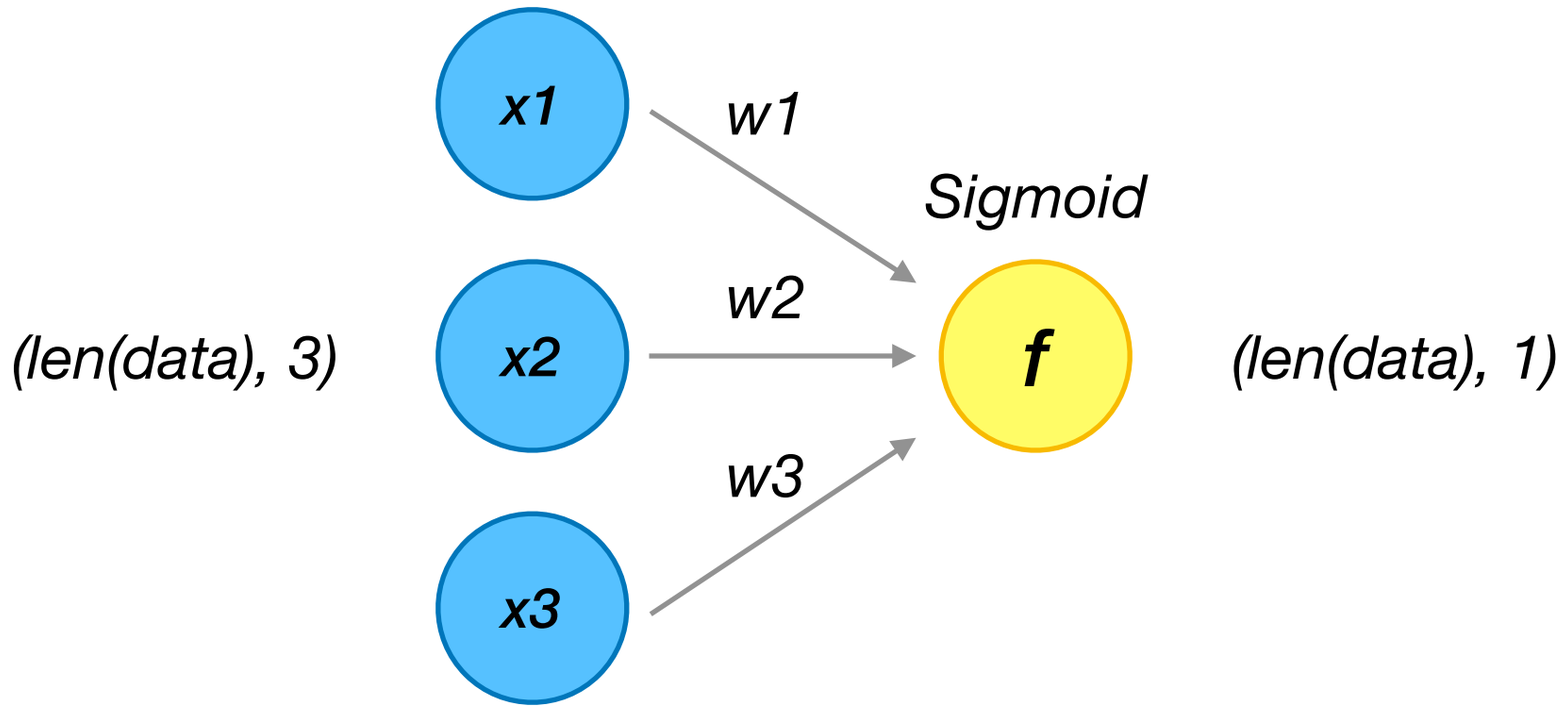
Logistic Regression

Inference



Logistic Regression

Inference



w.shape = ?

Logistic Regression

Dot Product

Logistic Regression

Dot Product

$$A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{pmatrix}, B = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \end{pmatrix}$$

f = np.dot(x, w) + b

$$AB = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \end{pmatrix} = \begin{pmatrix} a_{11}b_{11} + a_{12}b_{21} & a_{11}b_{12} + a_{12}b_{22} & a_{11}b_{13} + a_{12}b_{23} \\ a_{21}b_{11} + a_{22}b_{21} & a_{21}b_{12} + a_{22}b_{22} & a_{21}b_{13} + a_{22}b_{23} \\ a_{31}b_{11} + a_{32}b_{21} & a_{31}b_{12} + a_{32}b_{22} & a_{31}b_{13} + a_{32}b_{23} \end{pmatrix}$$

Logistic Regression

Dot Product

$$c_{ij} = a_{i1}b_{1j} + a_{i2}b_{2j} + \ldots + a_{in}b_{nj} = \sum_{s=1}^{n} a_{sn}b_{sj}$$

$$A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{pmatrix}, B = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \end{pmatrix}$$

f **= np.dot(x, w) + b**

$$AB = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \end{pmatrix} = \begin{pmatrix} a_{11}b_{11} + a_{12}b_{21} & a_{11}b_{12} + a_{12}b_{22} & a_{11}b_{13} + a_{12}b_{23} \\ a_{21}b_{11} + a_{22}b_{21} & a_{21}b_{12} + a_{22}b_{22} & a_{21}b_{13} + a_{22}b_{23} \\ a_{31}b_{11} + a_{32}b_{21} & a_{31}b_{12} + a_{32}b_{22} & a_{31}b_{13} + a_{32}b_{23} \end{pmatrix}$$

Logistic Regression

Dot Product

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$$A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{pmatrix}, B = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \end{pmatrix}$$

f = np.dot(x, w) + b

$$AB = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \end{pmatrix} = \begin{pmatrix} a_{11}b_{11} + a_{12}b_{21} & a_{11}b_{12} + a_{12}b_{22} & a_{11}b_{13} + a_{12}b_{23} \\ a_{21}b_{11} + a_{22}b_{21} & a_{21}b_{12} + a_{22}b_{22} & a_{21}b_{13} + a_{22}b_{23} \\ a_{31}b_{11} + a_{32}b_{21} & a_{31}b_{12} + a_{32}b_{22} & a_{31}b_{13} + a_{32}b_{23} \end{pmatrix}$$

A.shape = (p, m)

B.shape = (n, k)

Logistic Regression

Dot Product

$$c_{ij} = a_{i1}b_{1j} + a_{i2}b_{2j} + \ldots + a_{in}b_{nj} = \sum_{s=1}^{n} a_{sn}b_{sj}$$

$$A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{pmatrix}, B = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \end{pmatrix}$$

f **= np.dot(x, w) + b**

$$AB = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \end{pmatrix} = \begin{pmatrix} a_{11}b_{11} + a_{12}b_{21} & a_{11}b_{12} + a_{12}b_{22} & a_{11}b_{13} + a_{12}b_{23} \\ a_{21}b_{11} + a_{22}b_{21} & a_{21}b_{12} + a_{22}b_{22} & a_{21}b_{13} + a_{22}b_{23} \\ a_{31}b_{11} + a_{32}b_{21} & a_{31}b_{12} + a_{32}b_{22} & a_{31}b_{13} + a_{32}b_{23} \end{pmatrix}$$

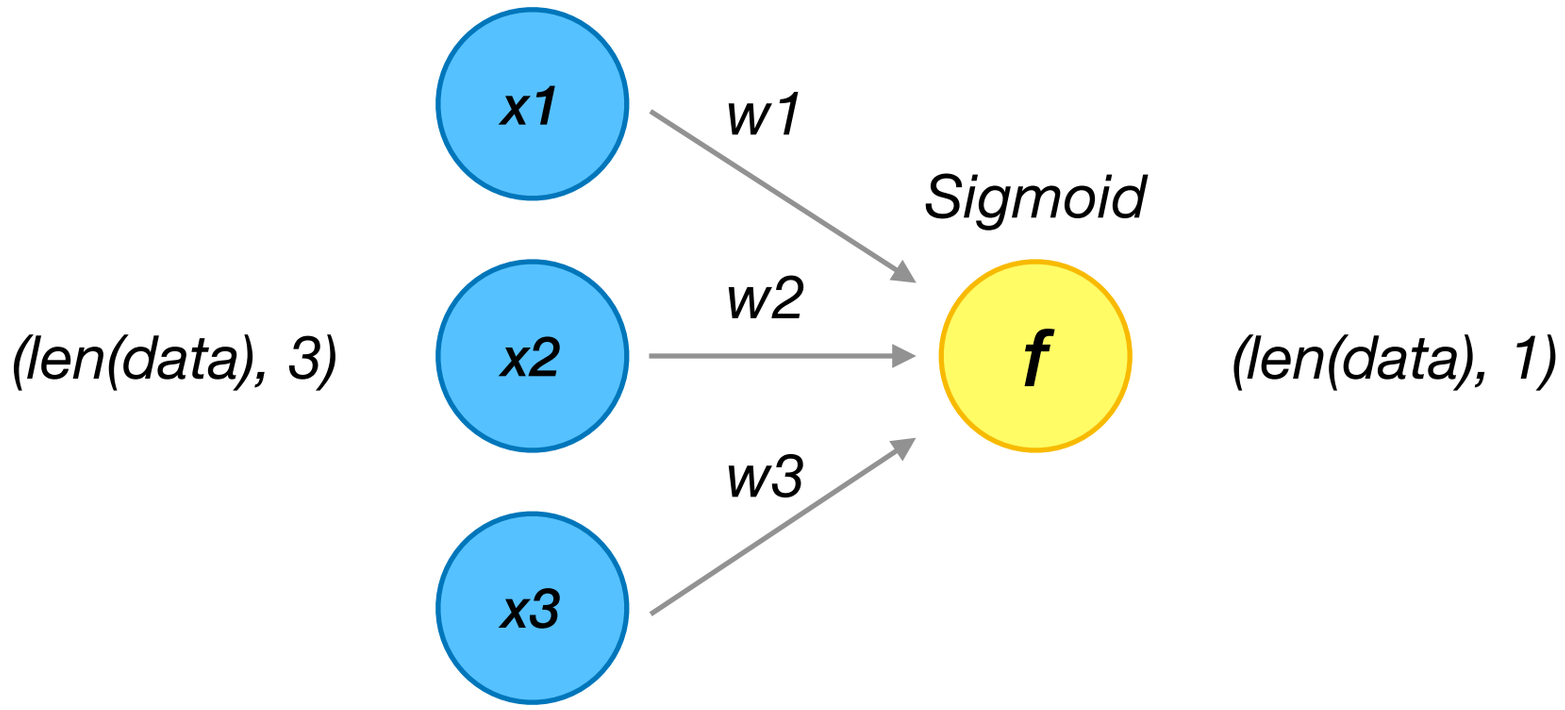
A.shape = (p, m)

B.shape = (n, k)

np.dot(A, B).shape = (p, k) if m == n

Logistic Regression

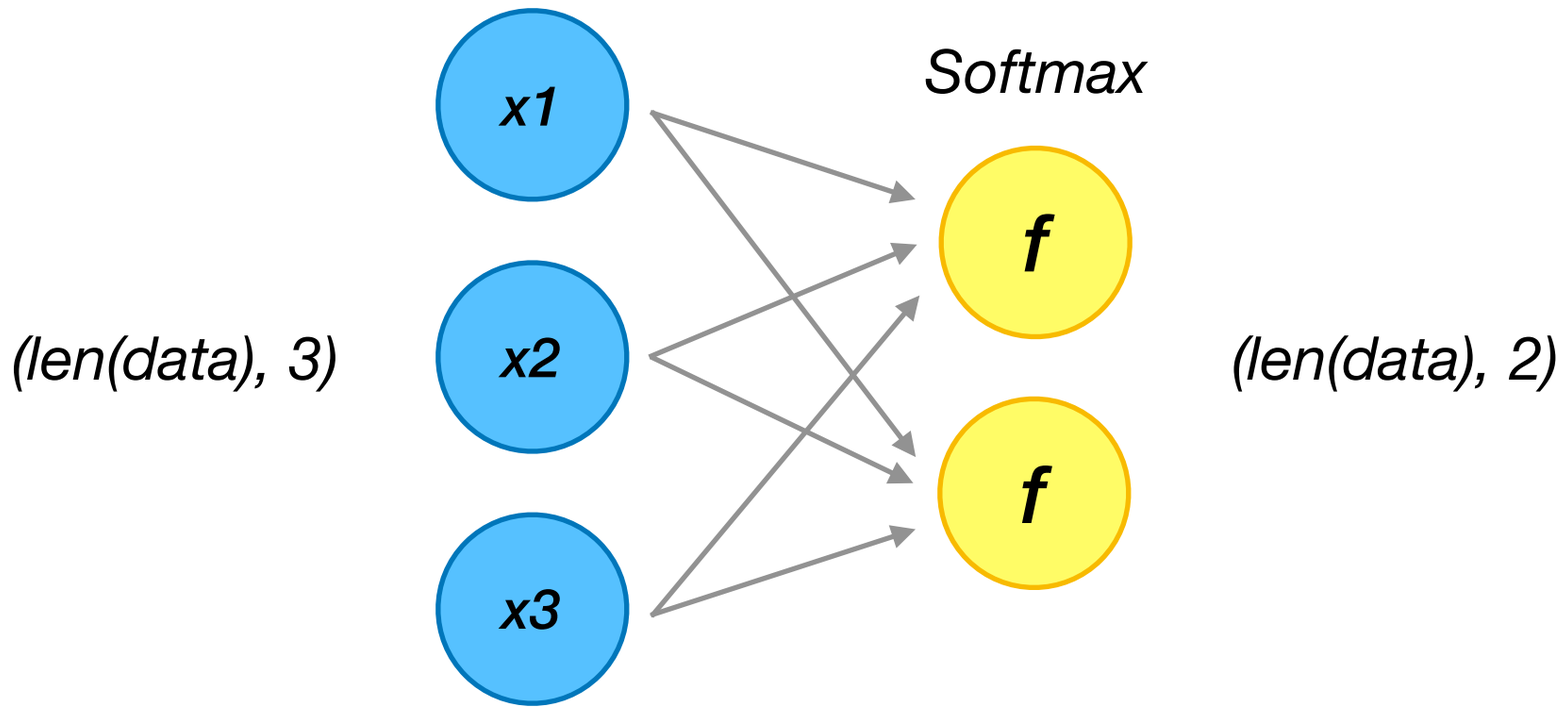
Inference



w.shape = (3, 1)

Logistic Regression

Inference



Logistic Regression

Softmax

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{k=1}^{K} e^{z_k}}$$

Logistic Regression

Softmax

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{k=1}^{K} e^{z_k}}$$

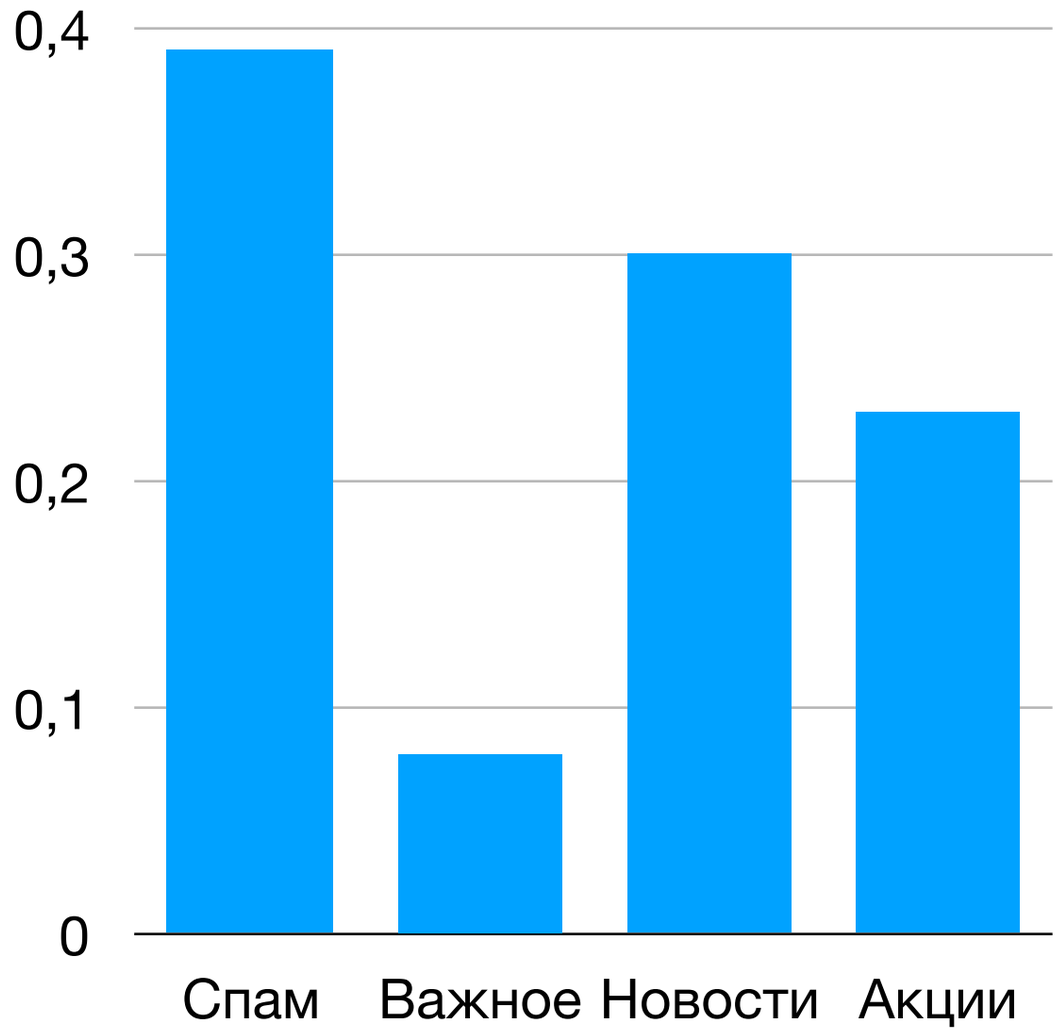
```
exp_scores = np.exp(pred)
```

```
softmax = exp_scores / exp_scores.sum()
```

Logistic Regression

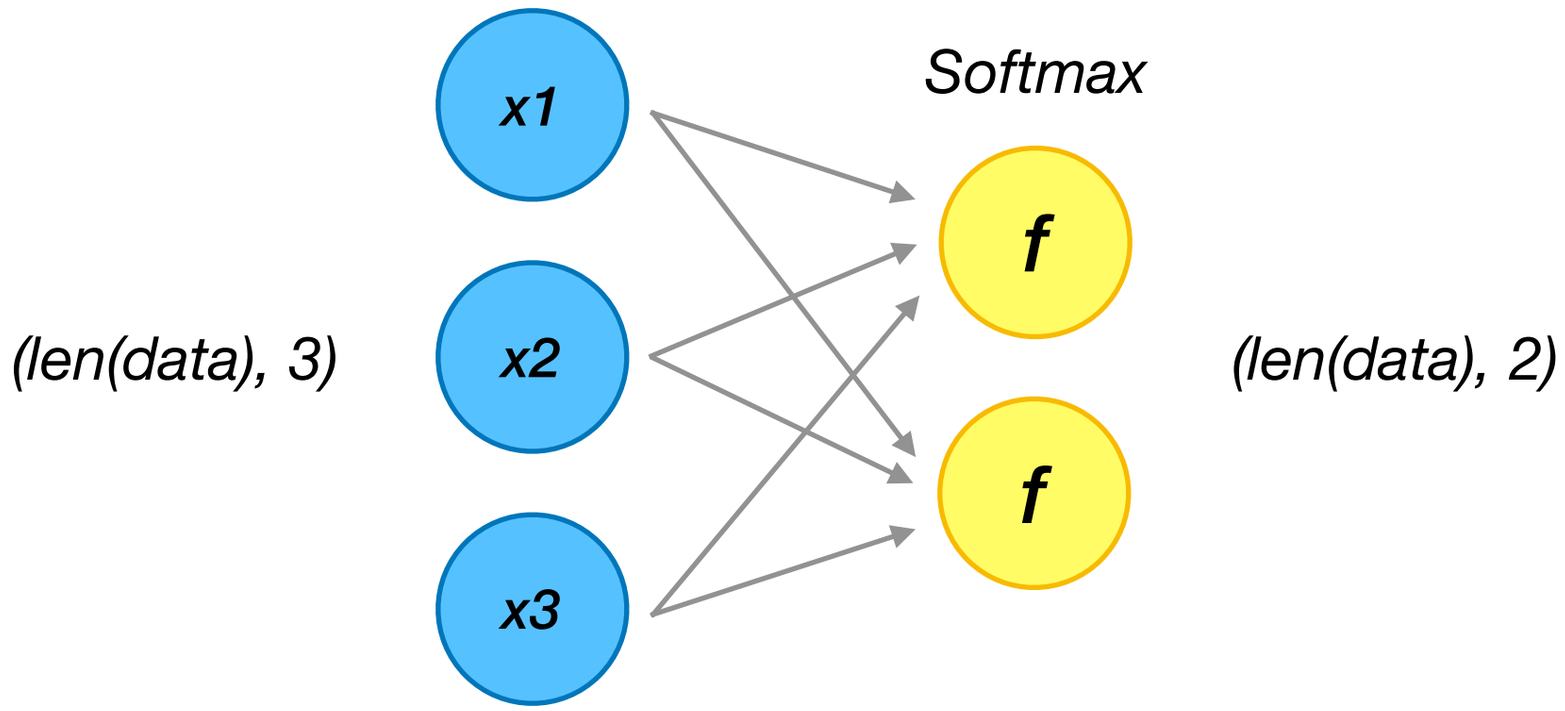
Softmax

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{k=1}^{K} e^{z_k}}$$



Logistic Regression

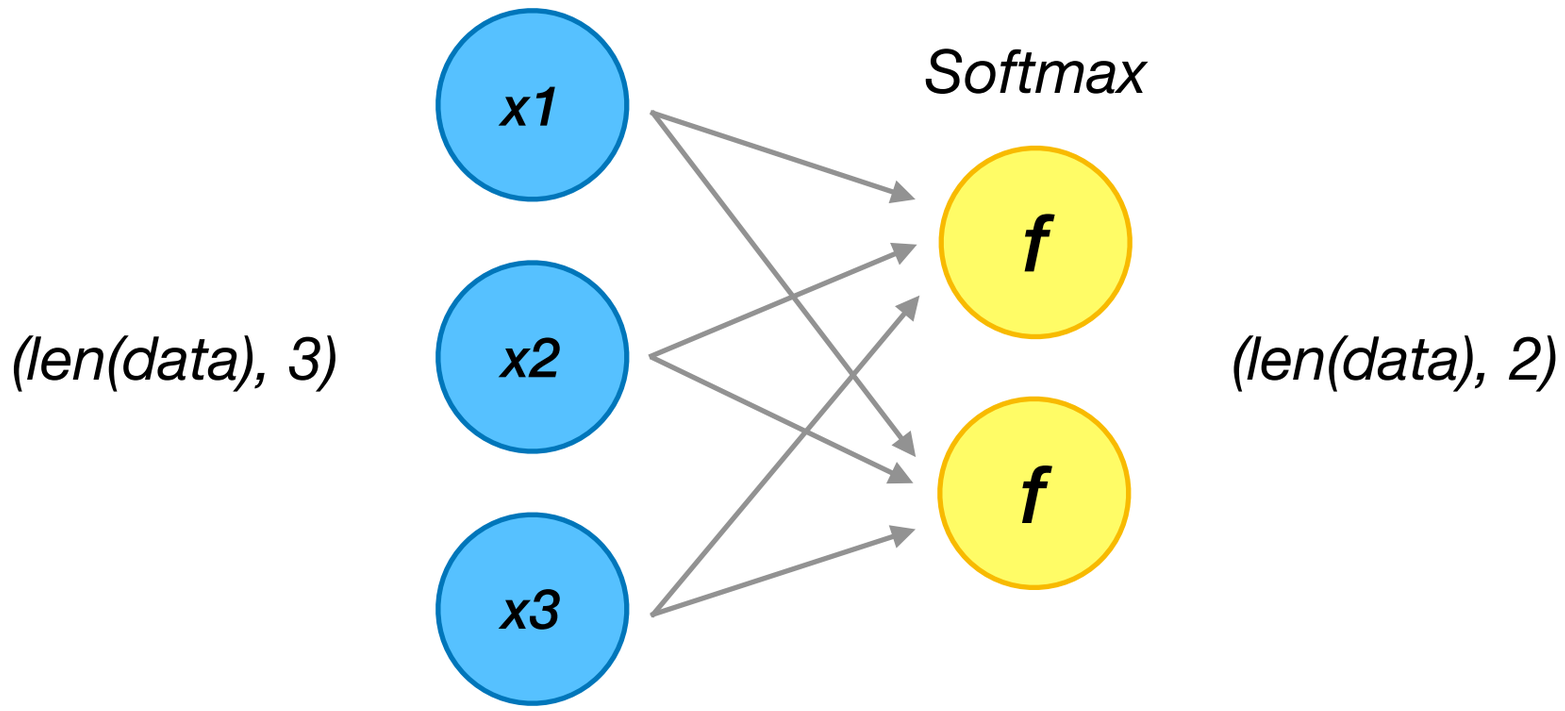
Inference



w.shape = ?

Logistic Regression

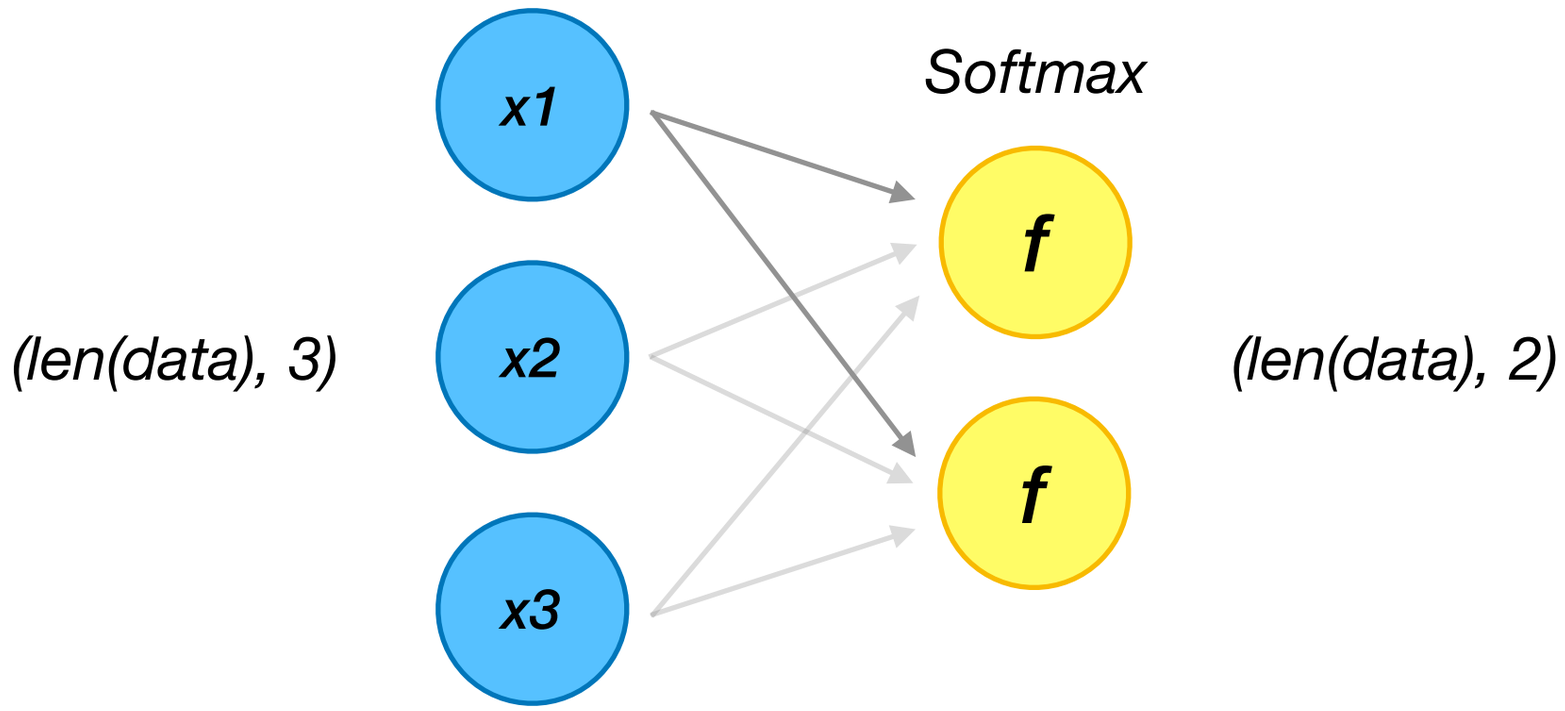
Inference



w.shape = (3, 2)

Logistic Regression

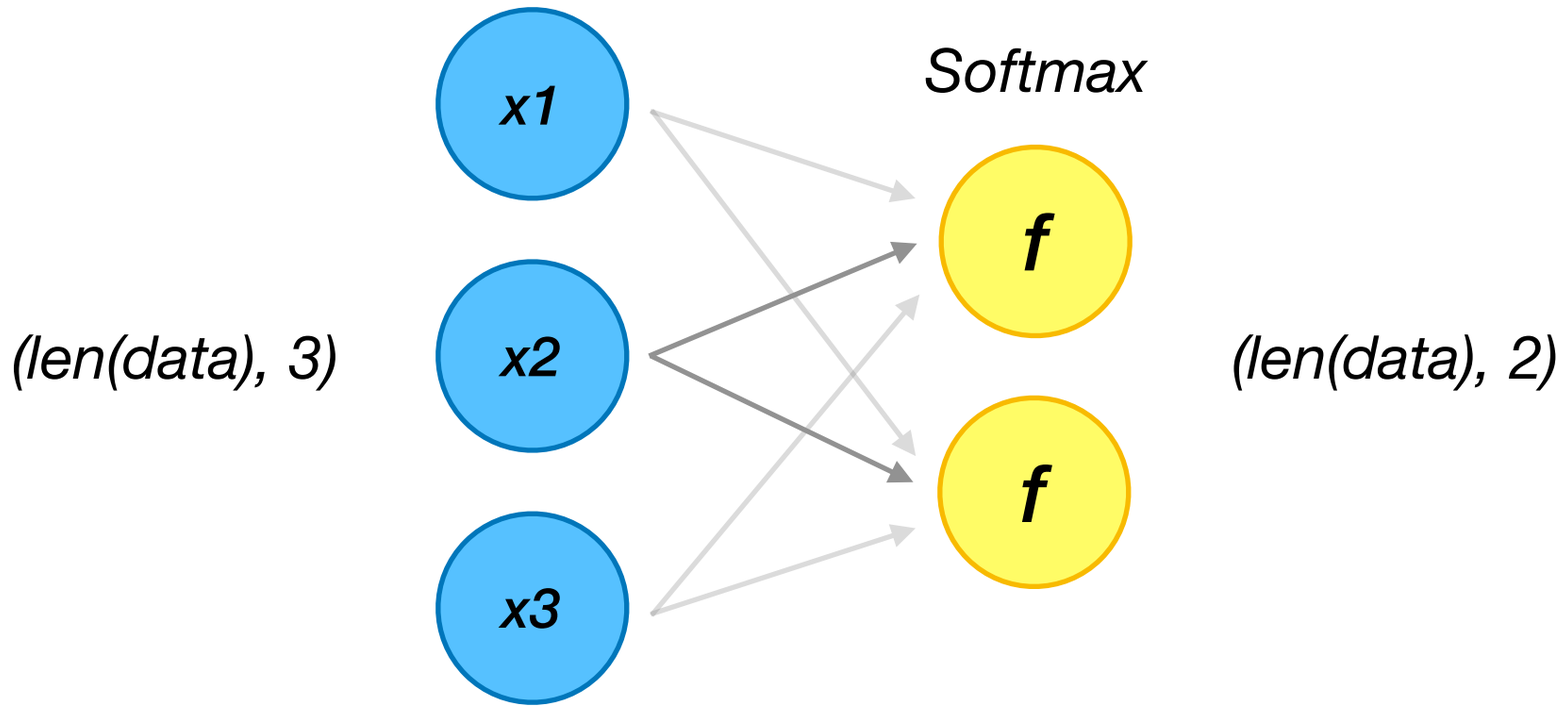
Inference



w.shape = (3, 2)

Logistic Regression

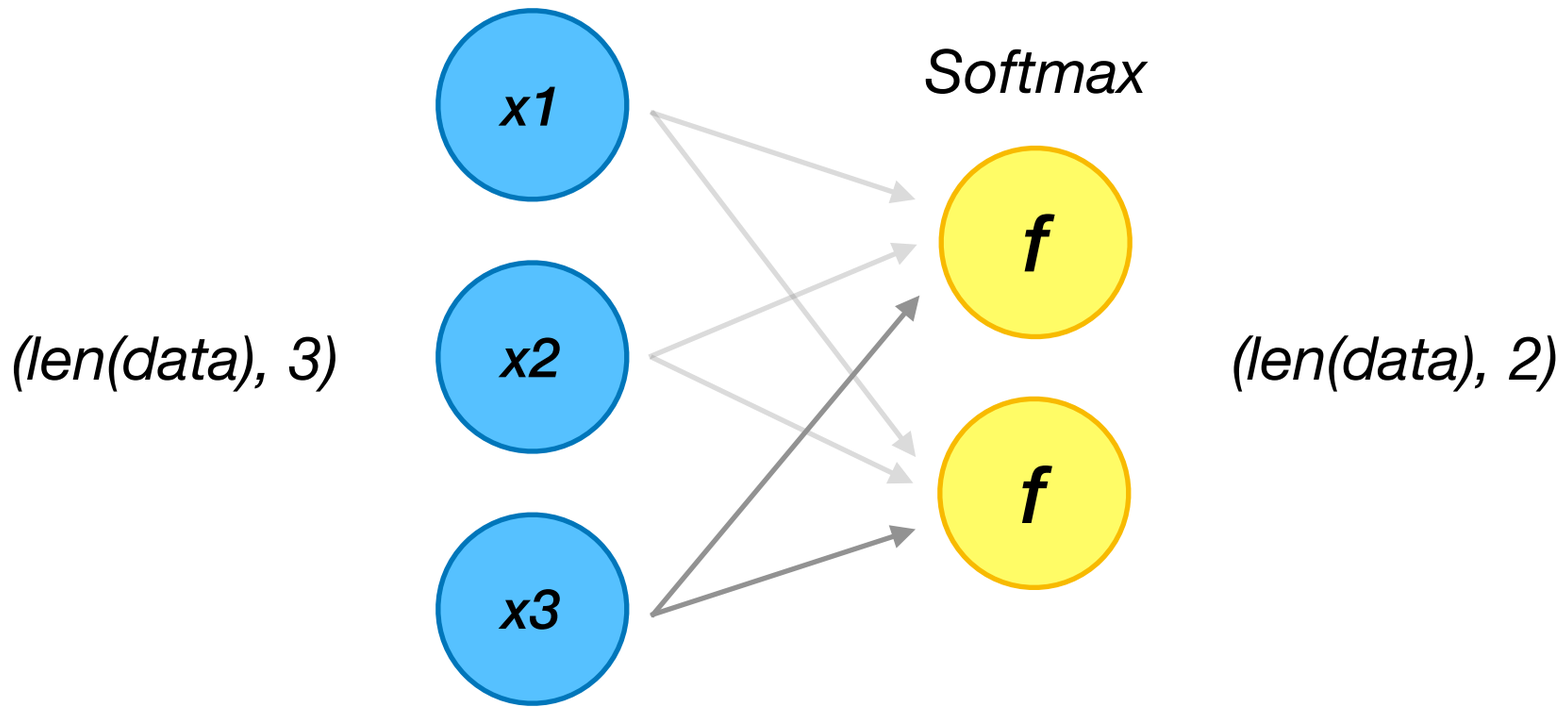
Inference



w.shape = (3, 2)

Logistic Regression

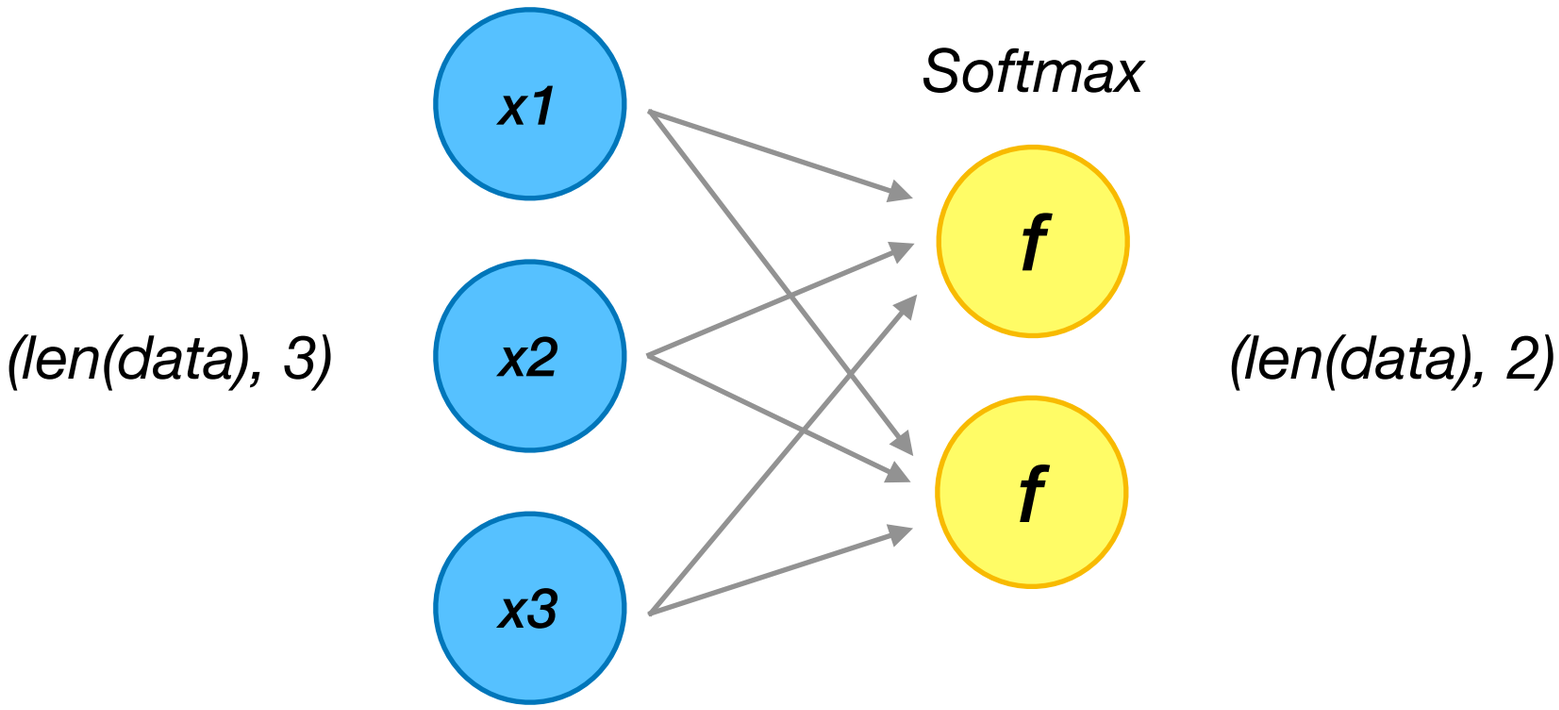
Inference



w.shape = (3, 2)

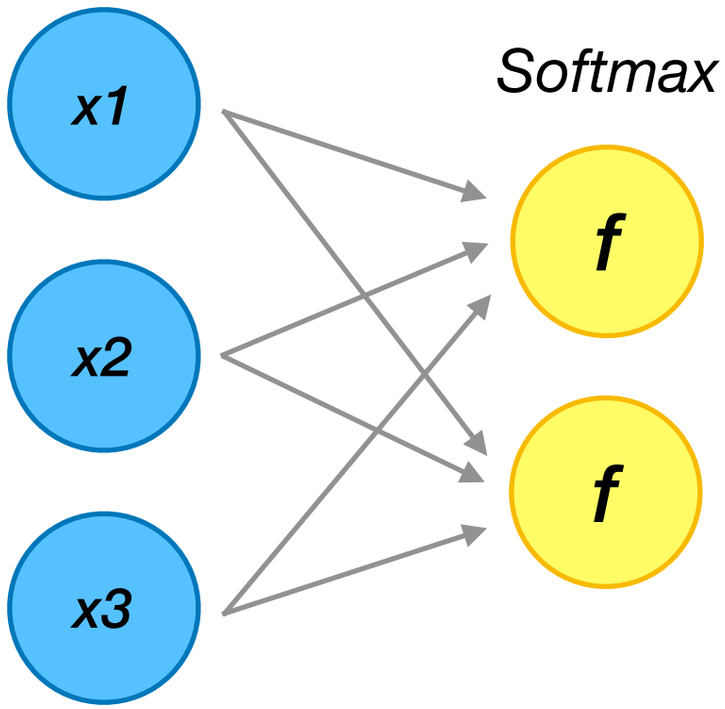
Logistic Regression

Train



Logistic Regression

Train



Softmax

(len(data), 3)

(len(data), 2)

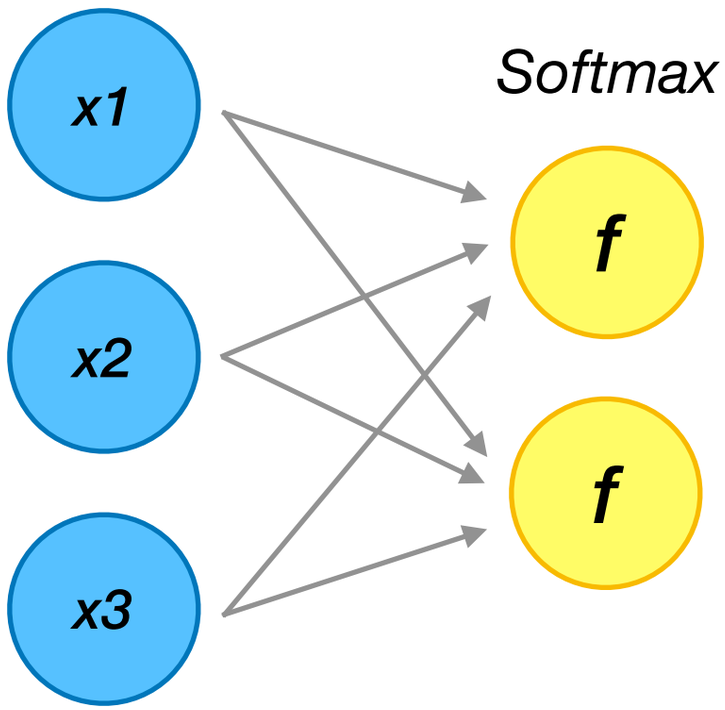
w.shape = (3, 2)

How we can update weights?

Logistic Regression

Train

(len(data), 3)



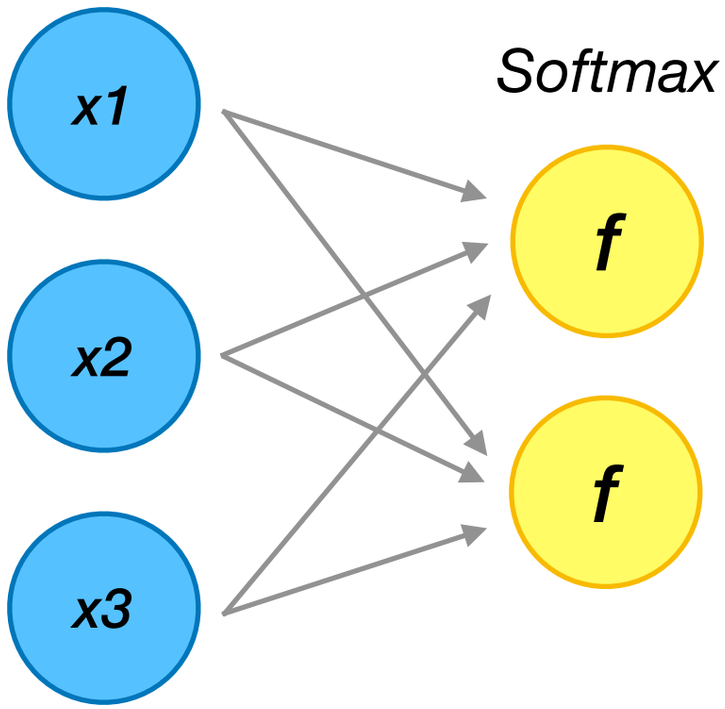
(len(data), 2)

Negative Log-Likelihood

w.shape = (3, 2)

Logistic Regression

Train



Softmax

(len(data), 3)

(len(data), 2)

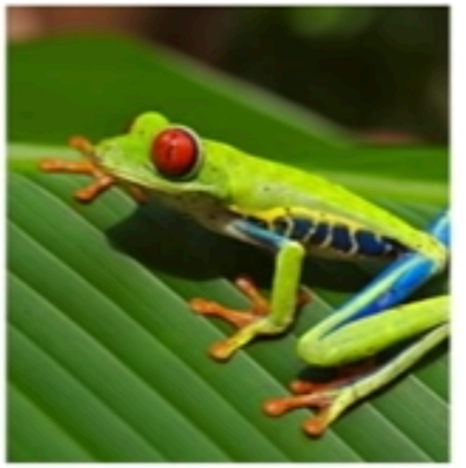
Negative Log-Likelihood

w.shape = (3, 2)

$$H_p(q) = -\sum_{c=1}^{C} q(y_c) \cdot log(p(y_c))$$

Logistic Regression

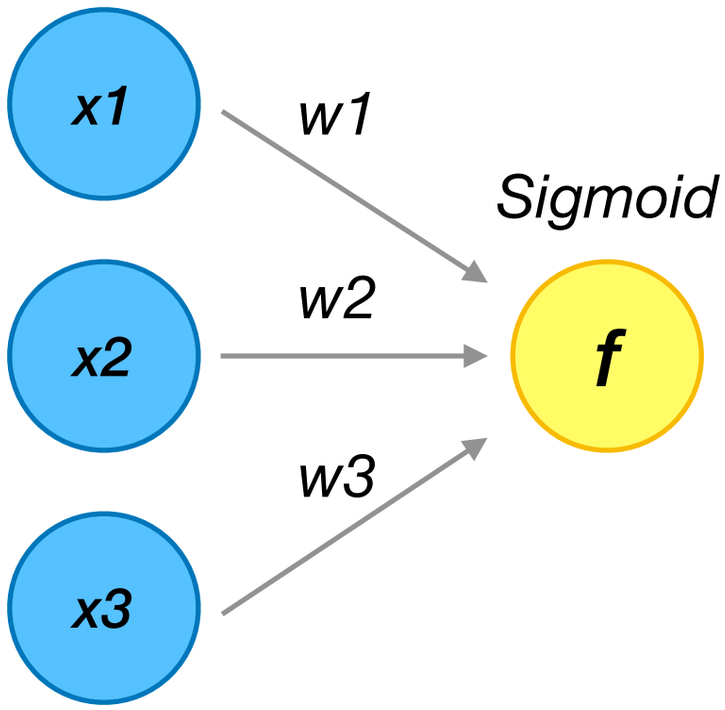
Negative Log-Likelihood



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**

Logistic Regression

Train



(len(data), 3)

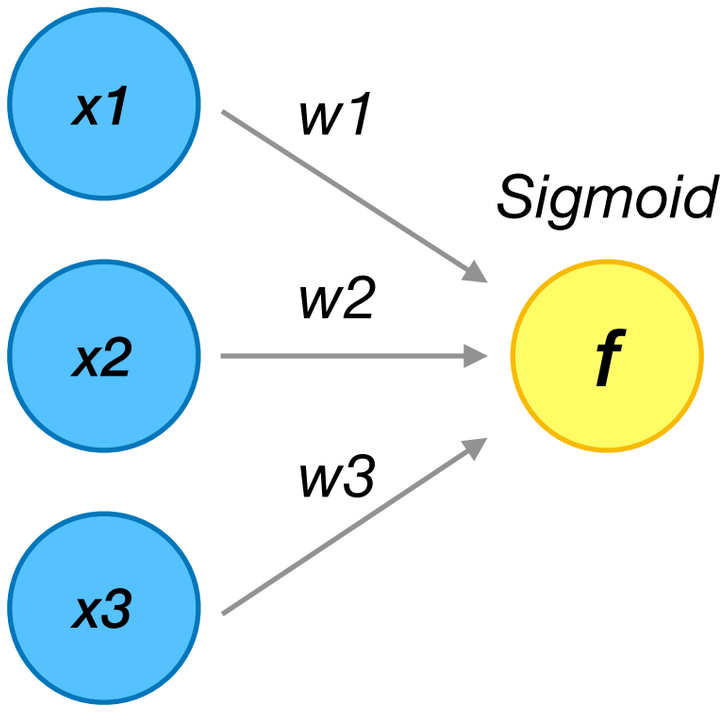
(len(data), 1)

Binary Cross Entropy

w.shape = (3, 1)

Logistic Regression

Train



(len(data), 3)

(len(data), 1)

Binary Cross Entropy

w.shape = (3, 1)

$$L(y, \hat{y}) = -\ (y * log(\hat{y}_i) + (1 - y) * log(1 - \hat{y}_i))$$

Gradient Descent

Gradient Descent

Gradient Descent

Numerical derivative

Random Search

Save weight if current loss better than best loss

Gradient Descent

Numerical derivative

~~**Random Search**~~

Save weight if current loss better than best loss

Gradient Descent

Numerical derivative

$$\frac{\partial L}{\partial w} \approx \frac{L(w+\epsilon) - L(w-\epsilon)}{2\epsilon}$$

Gradient Descent

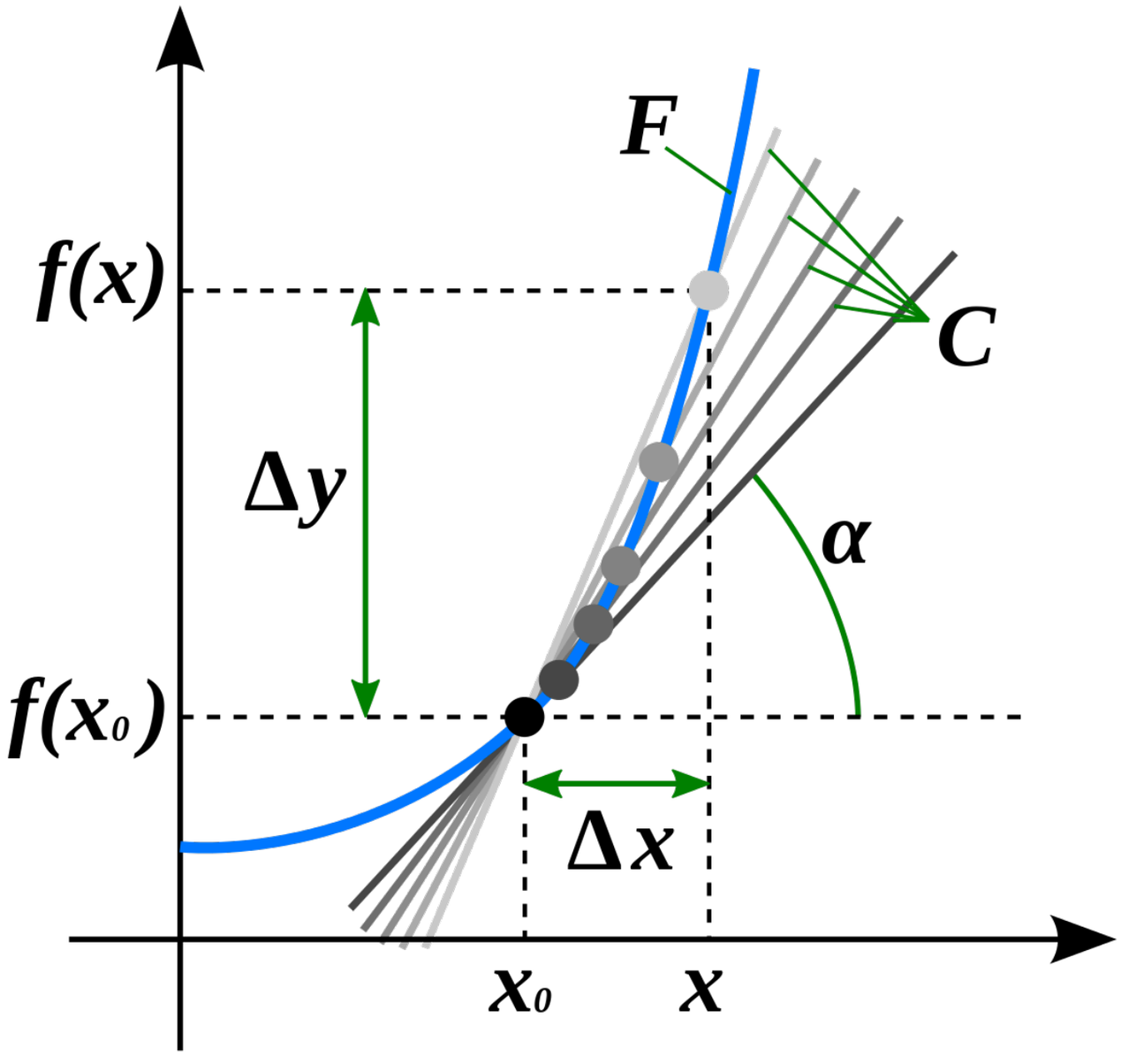
Numerical derivative

$$\frac{\partial L}{\partial w} \approx \frac{L(w+\epsilon) - L(w-\epsilon)}{2\epsilon}$$

But good for gradient checking

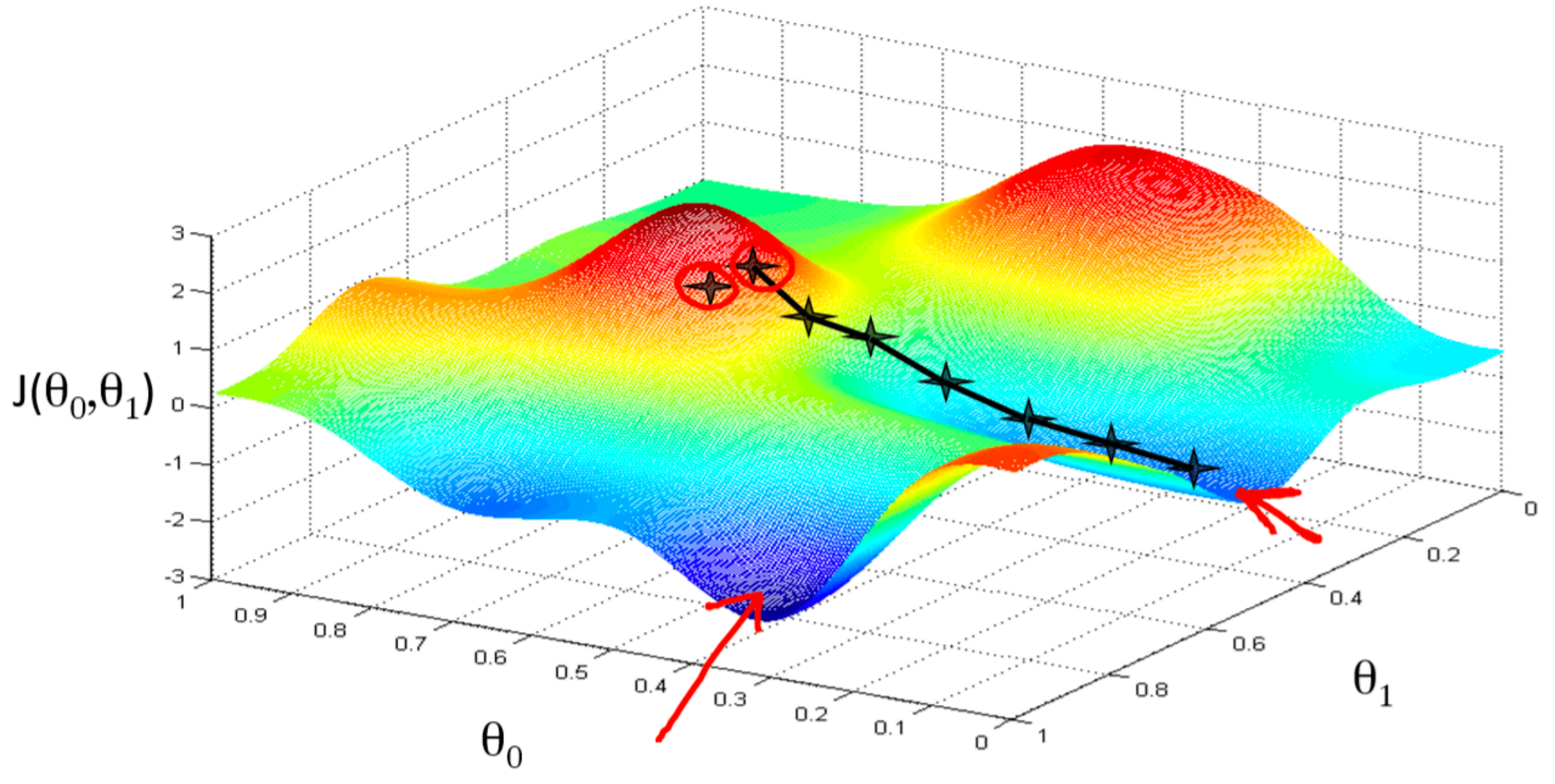
Gradient Descent

Derivative



Gradient Descent

Local minima



Gradient Descent

```
W = W - learning_rate * dLdW
b = b - learning_rate * dLdb
```

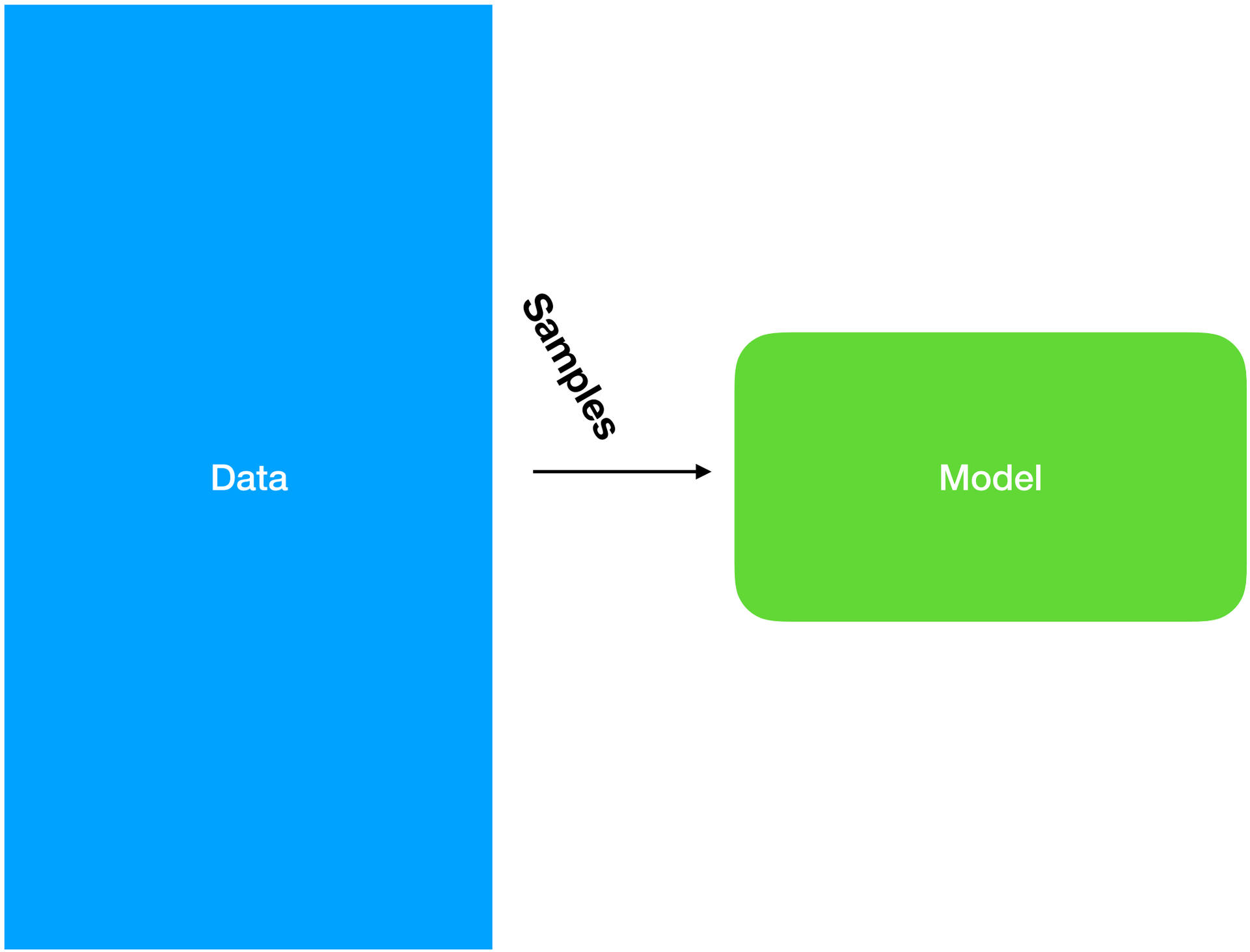
Gradient Descent

Features

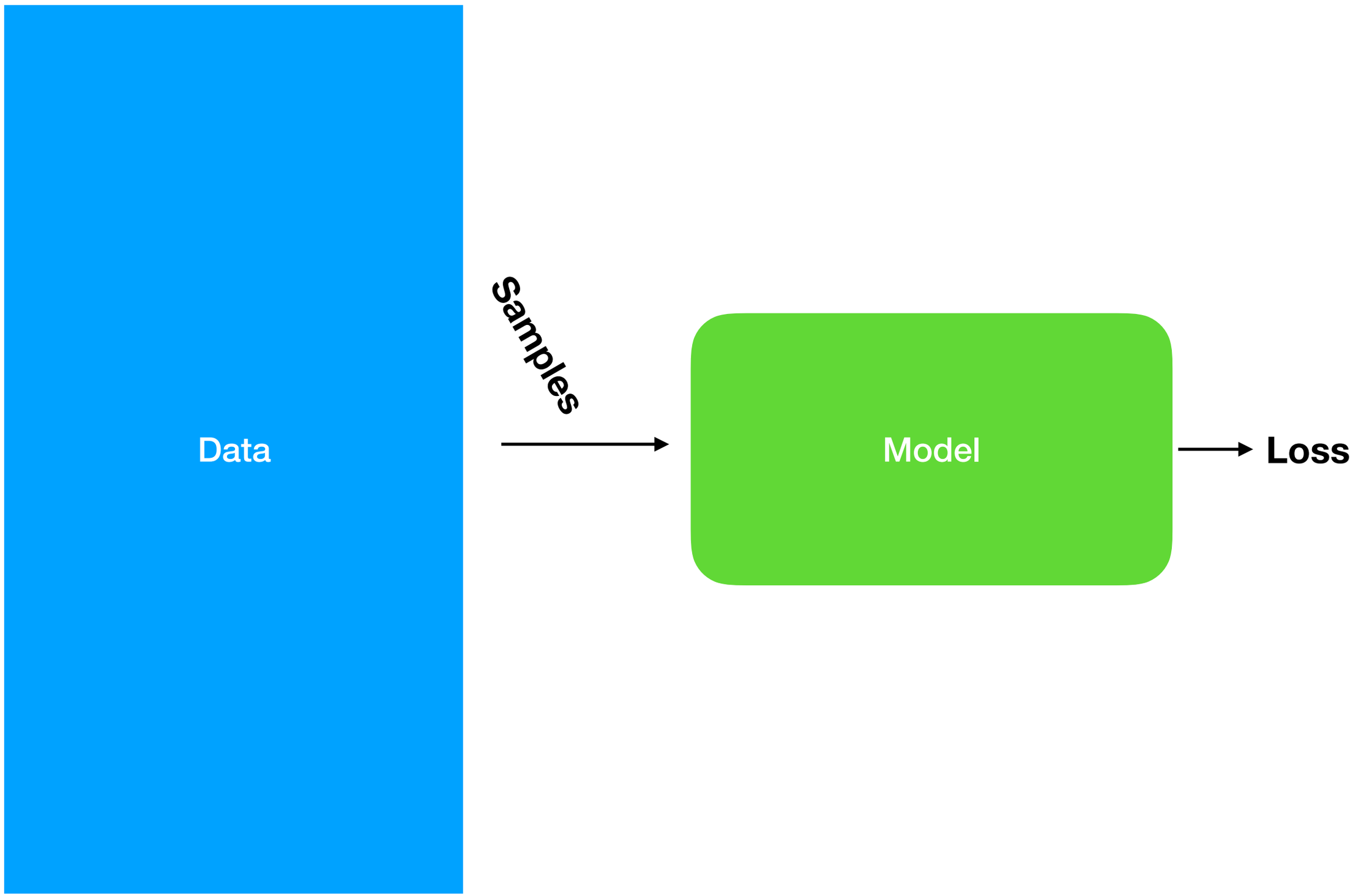
Data

Samples

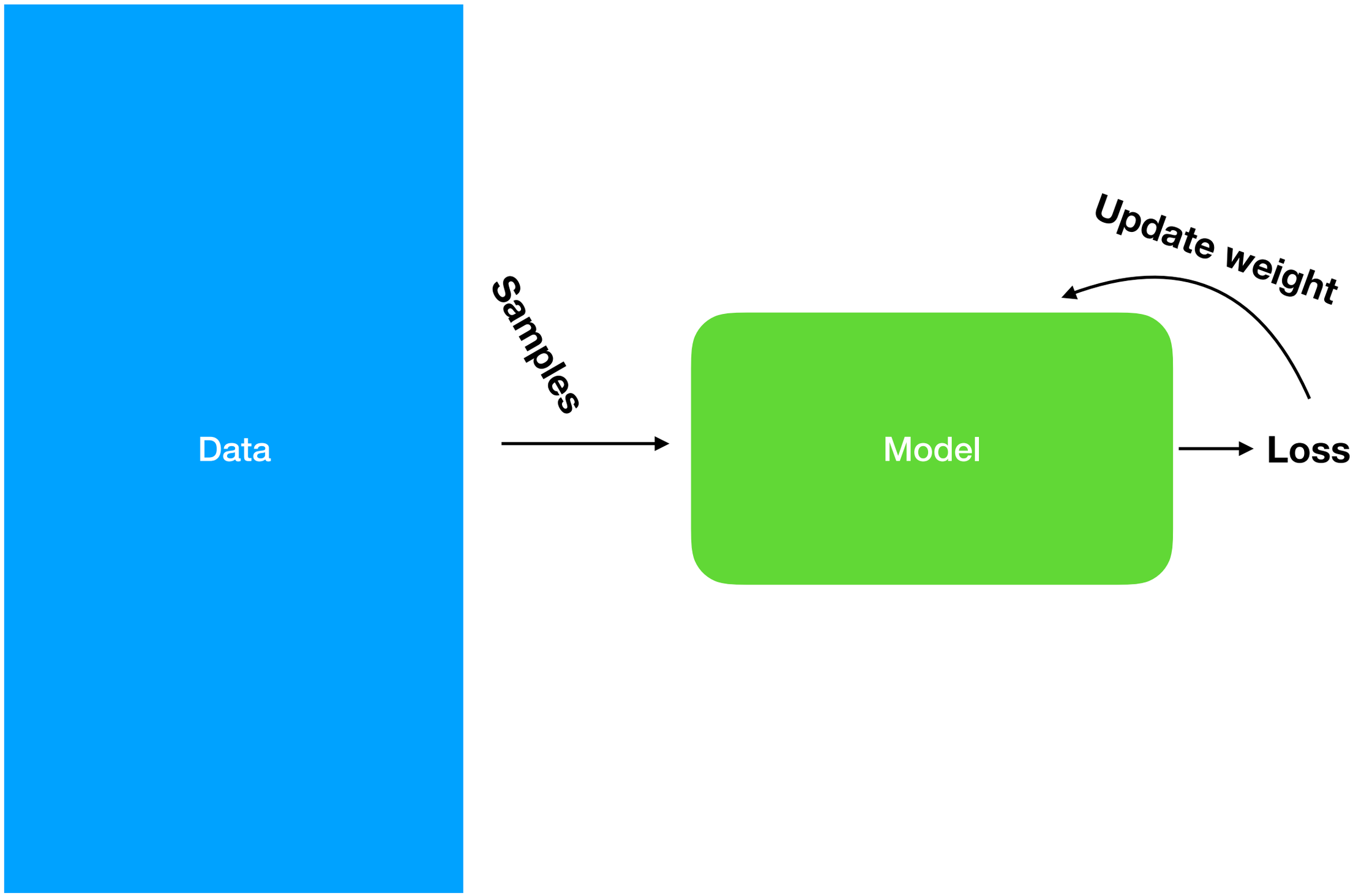
Gradient Descent



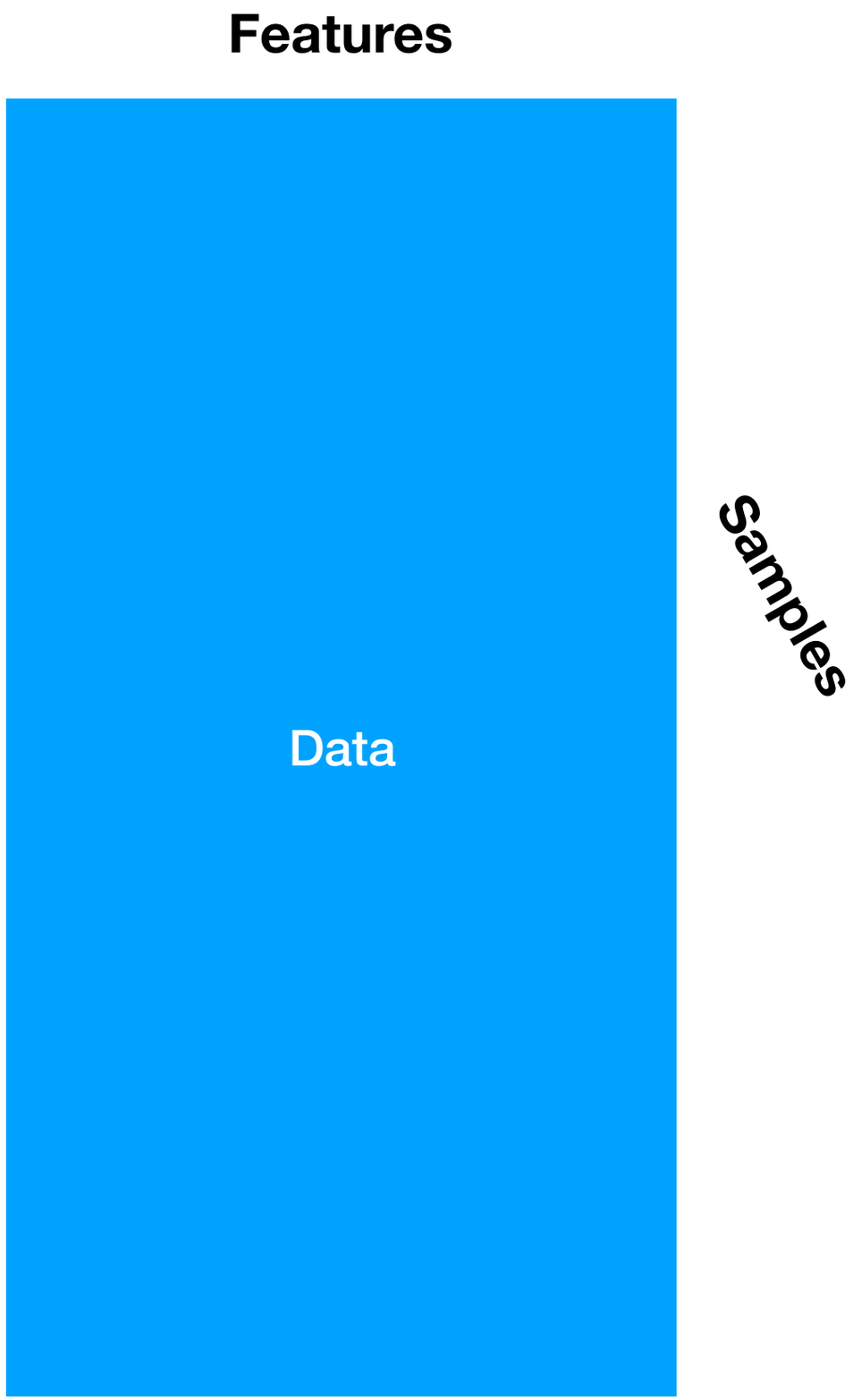
Gradient Descent



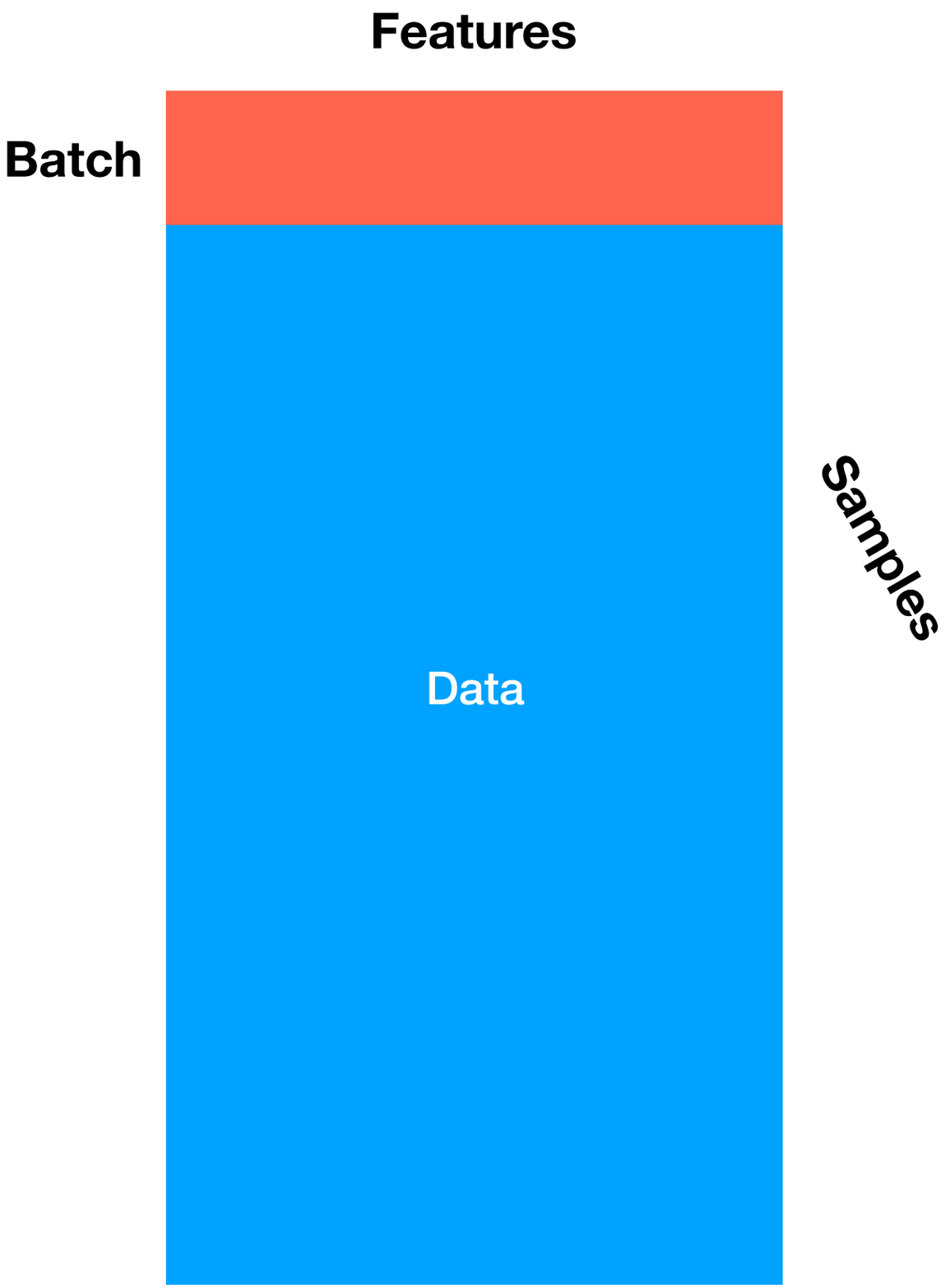
Gradient Descent



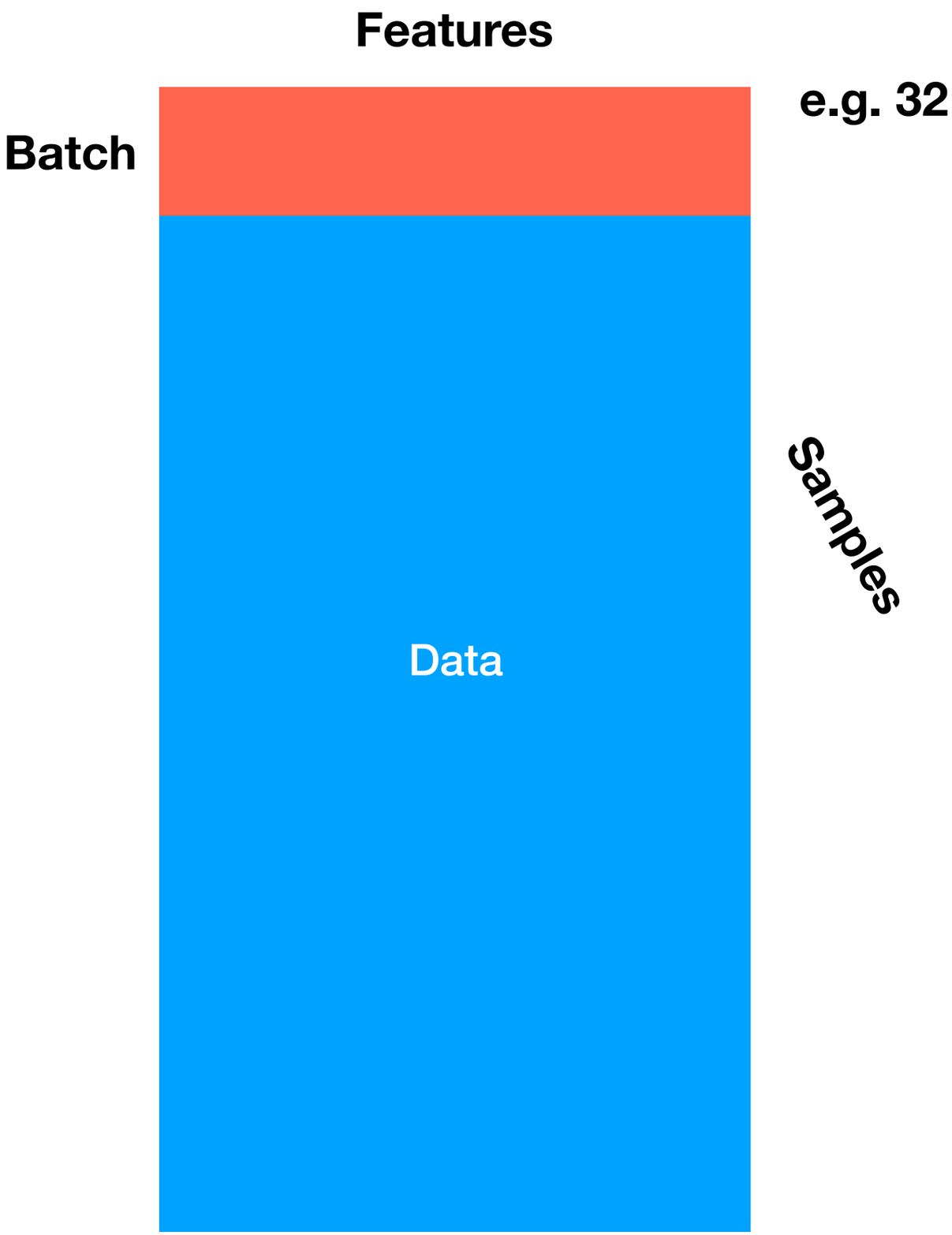
Stochastic Gradient Descent



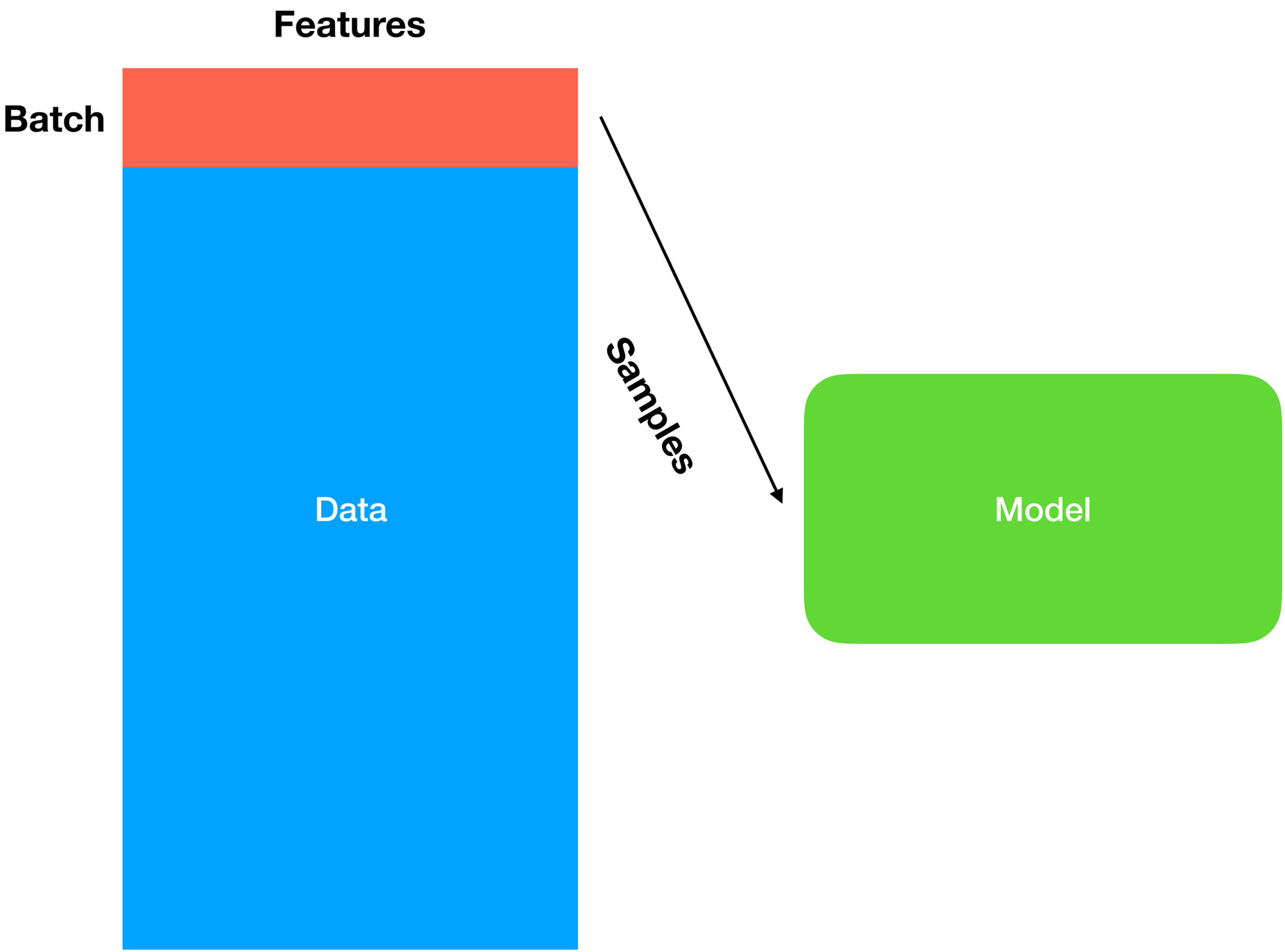
Stochastic Gradient Descent



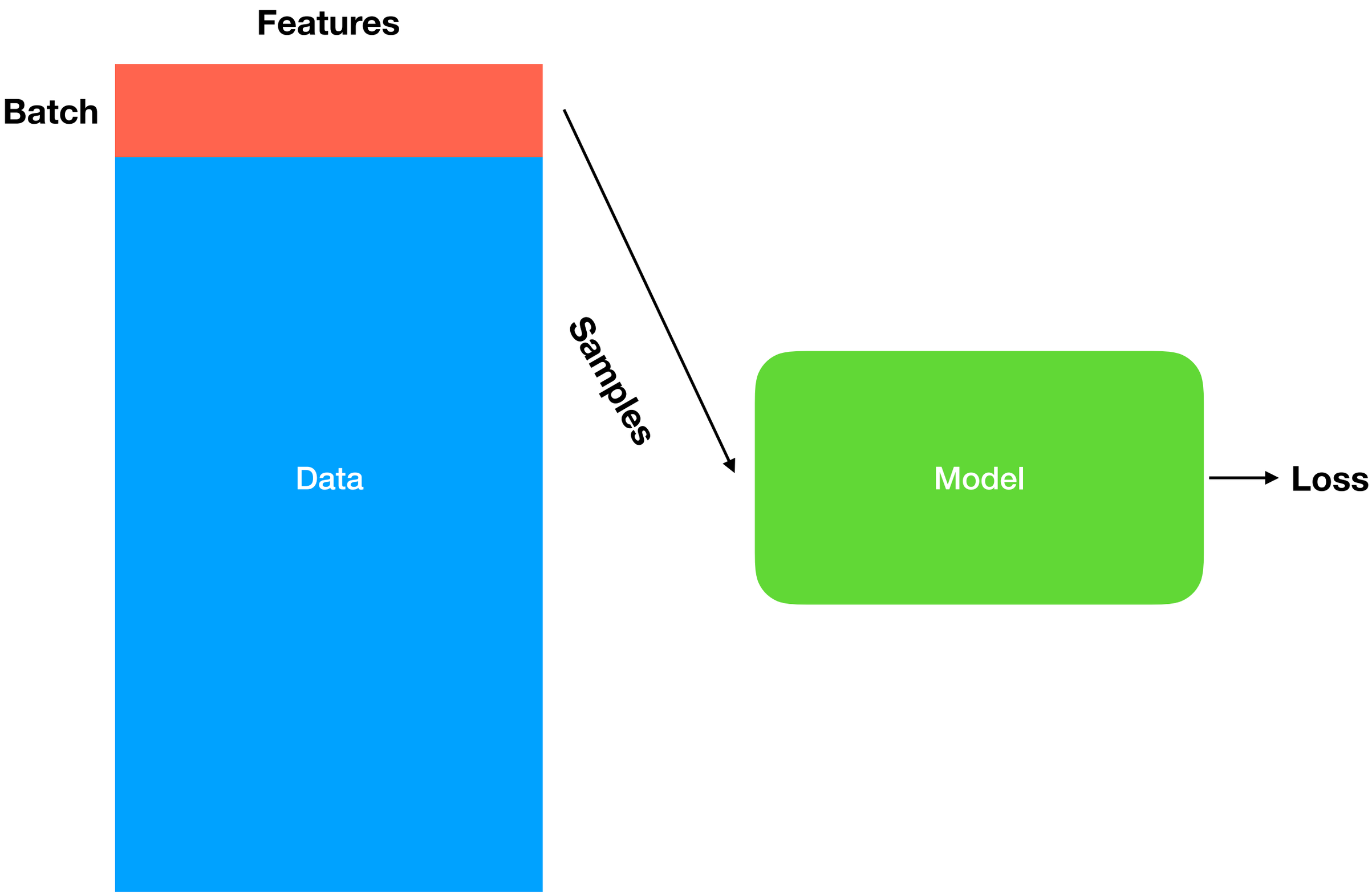
Stochastic Gradient Descent



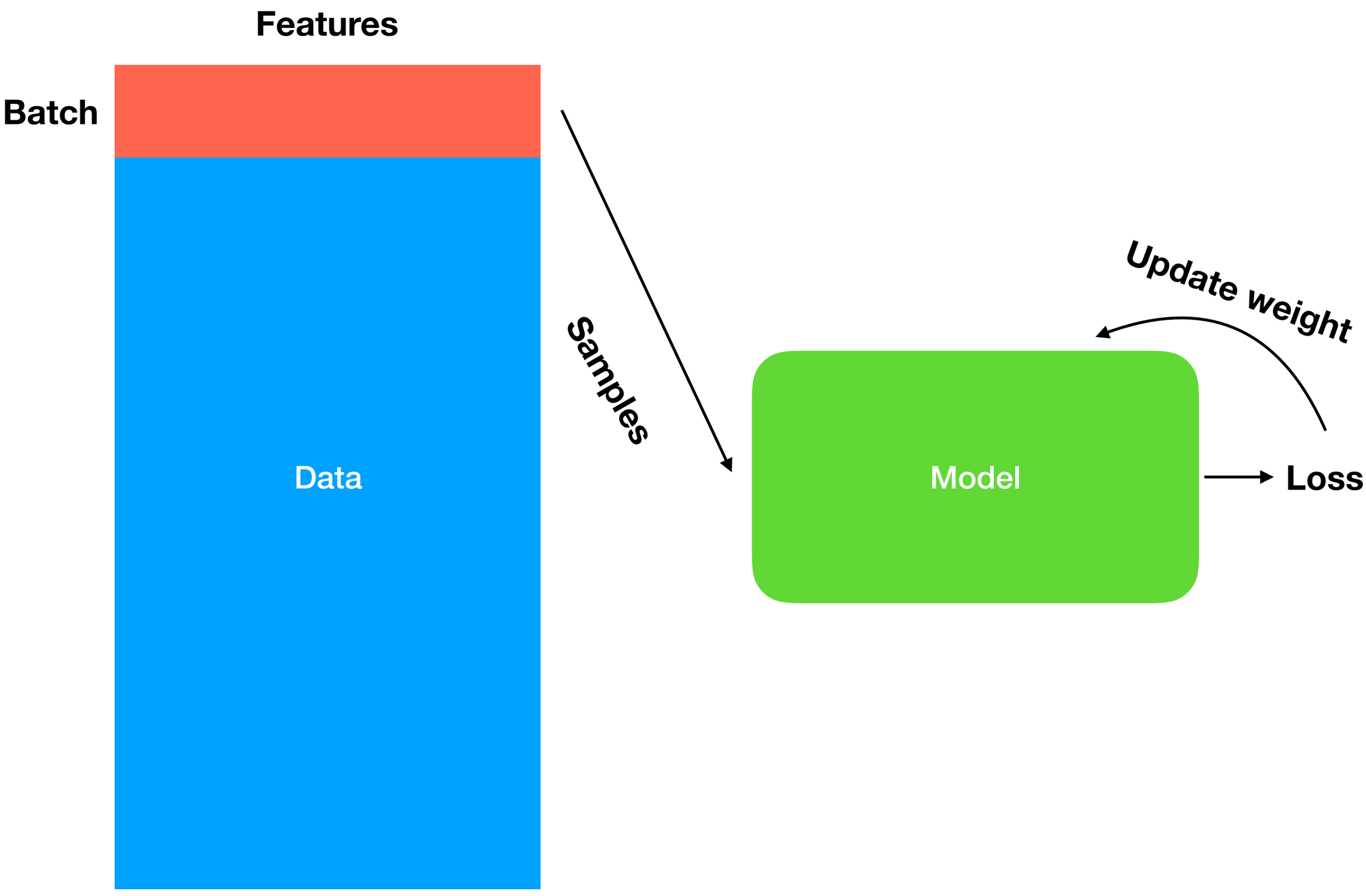
Stochastic Gradient Descent



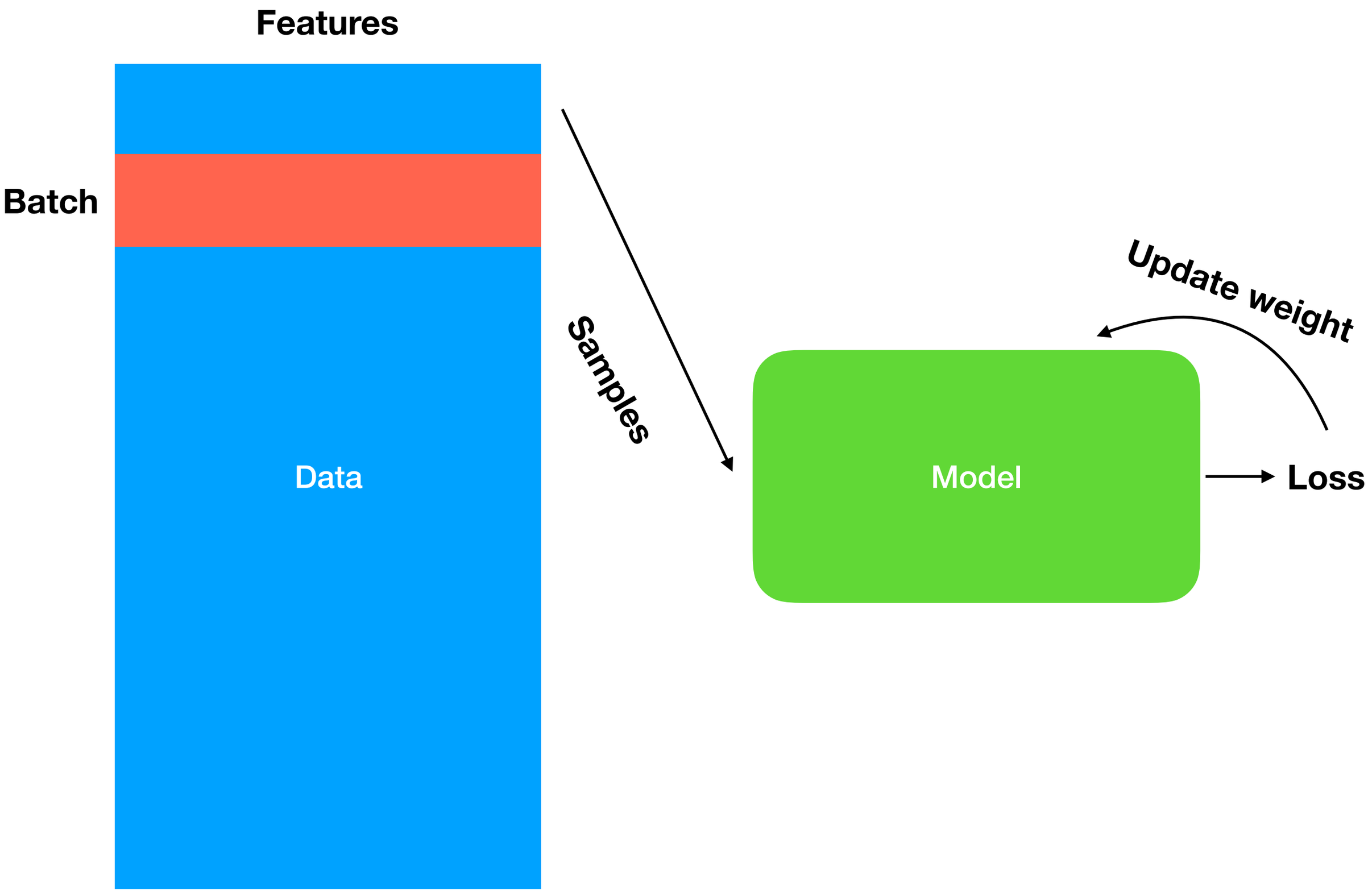
Stochastic Gradient Descent



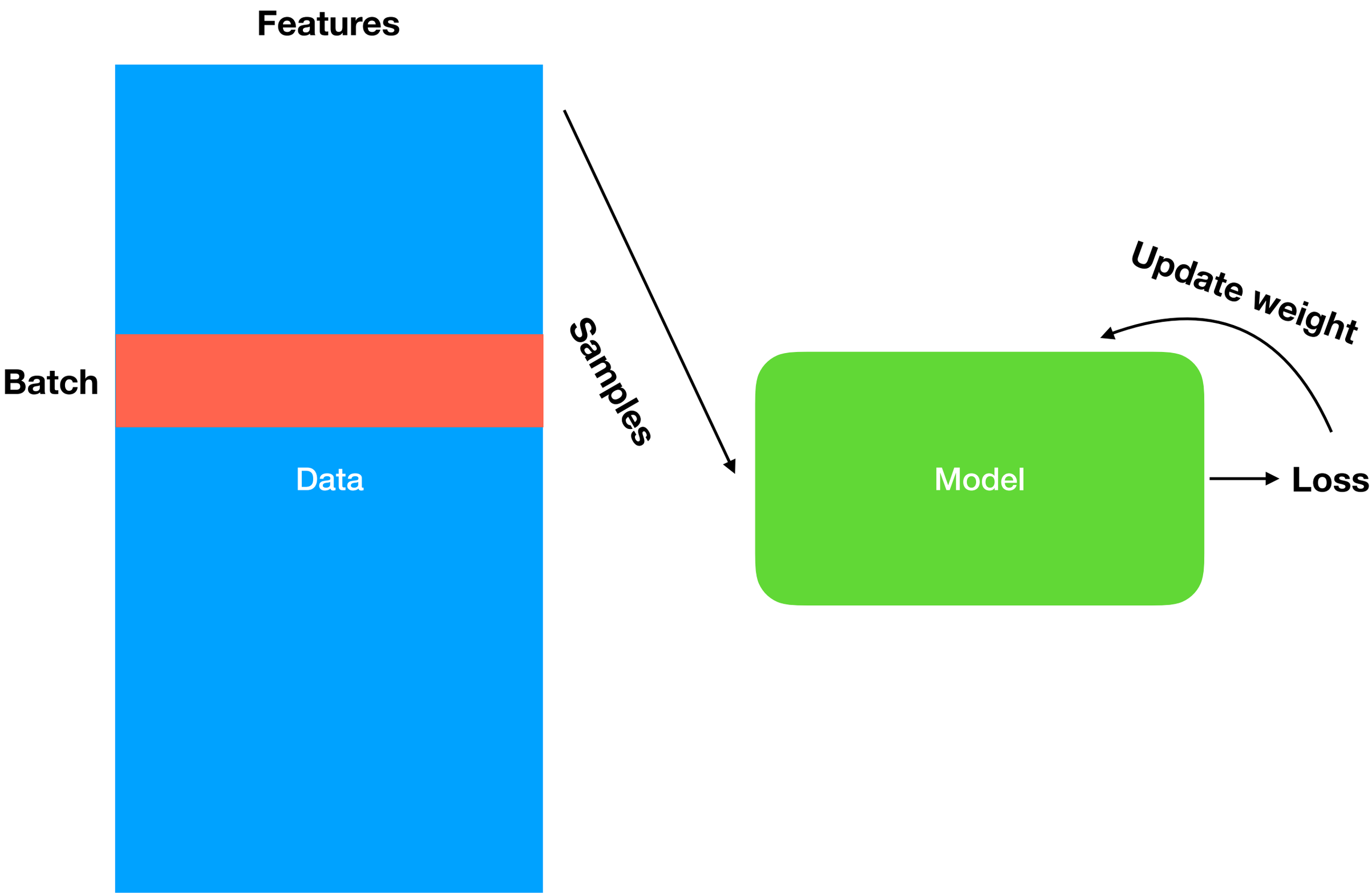
Stochastic Gradient Descent



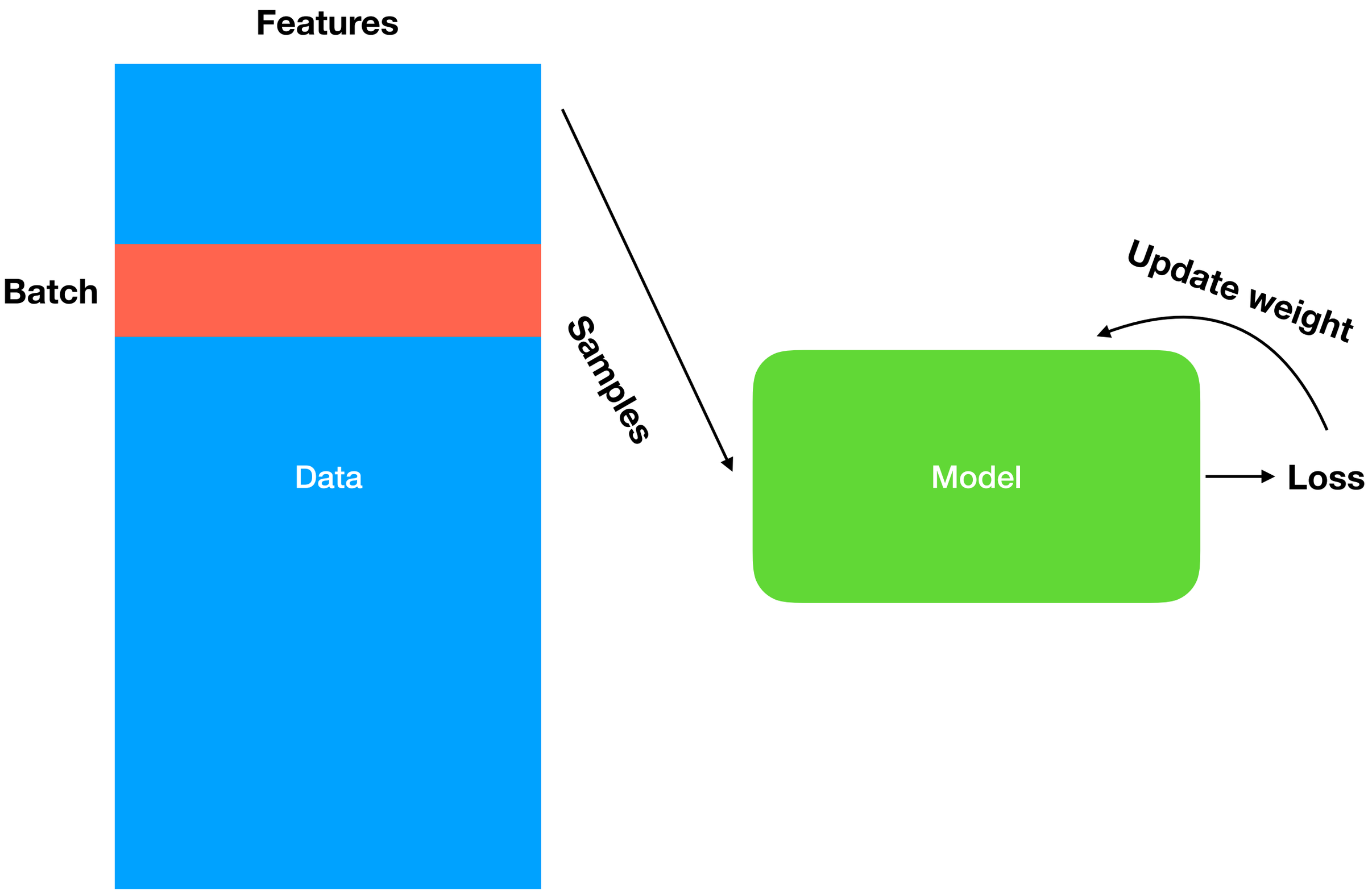
Stochastic Gradient Descent



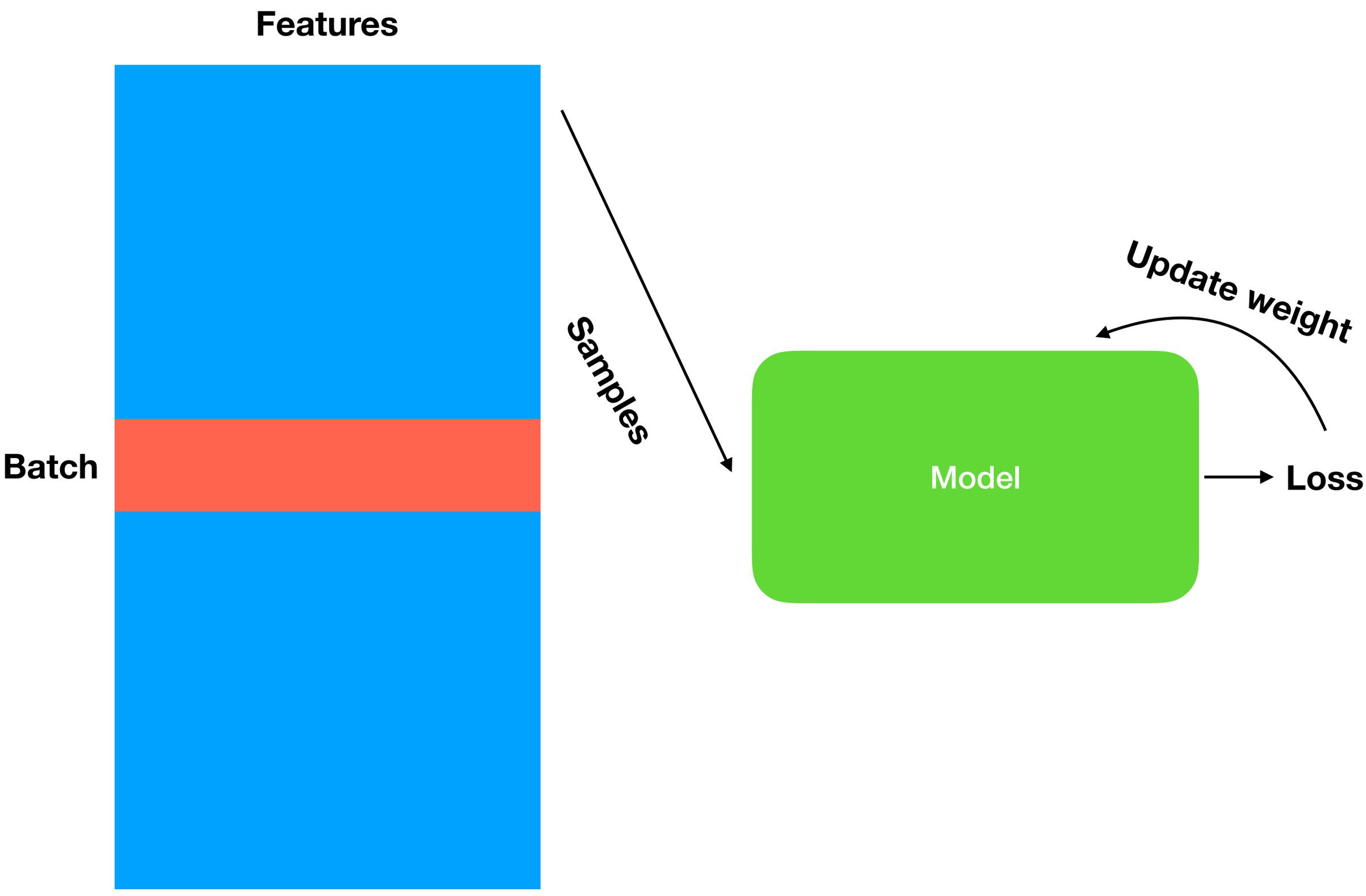
Stochastic Gradient Descent



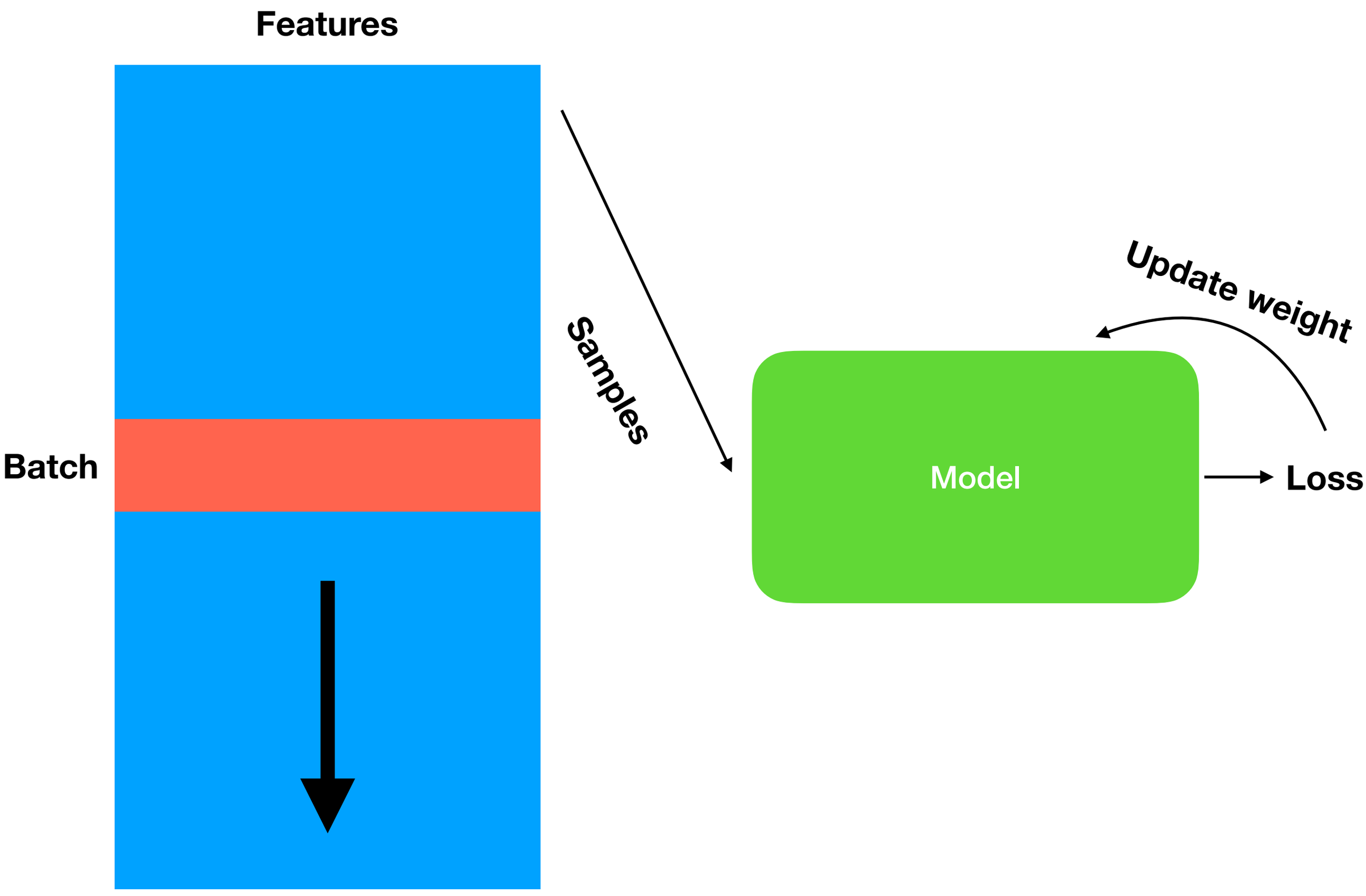
Stochastic Gradient Descent



Stochastic Gradient Descent

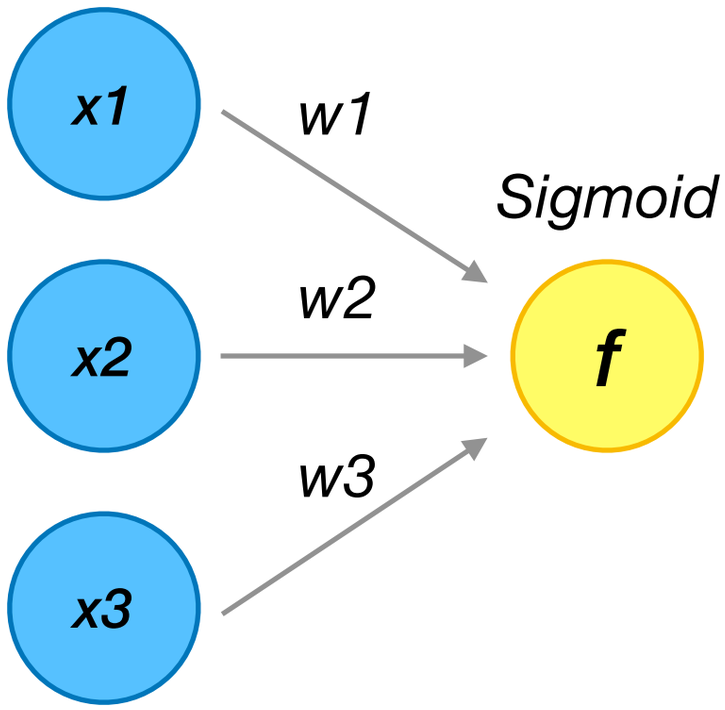


Stochastic Gradient Descent



Logistic Regression

Train



(len(data), 3)

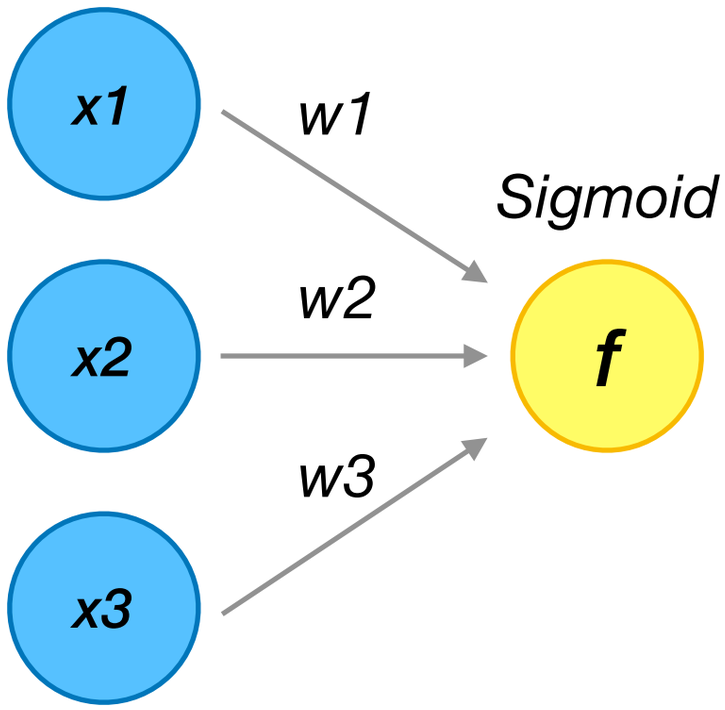
(len(data), 1)

Binary Cross Entropy

w.shape = (3, 1)

Logistic Regression

Train



(len(data), 3)

(len(data), 1)

Binary Cross Entropy

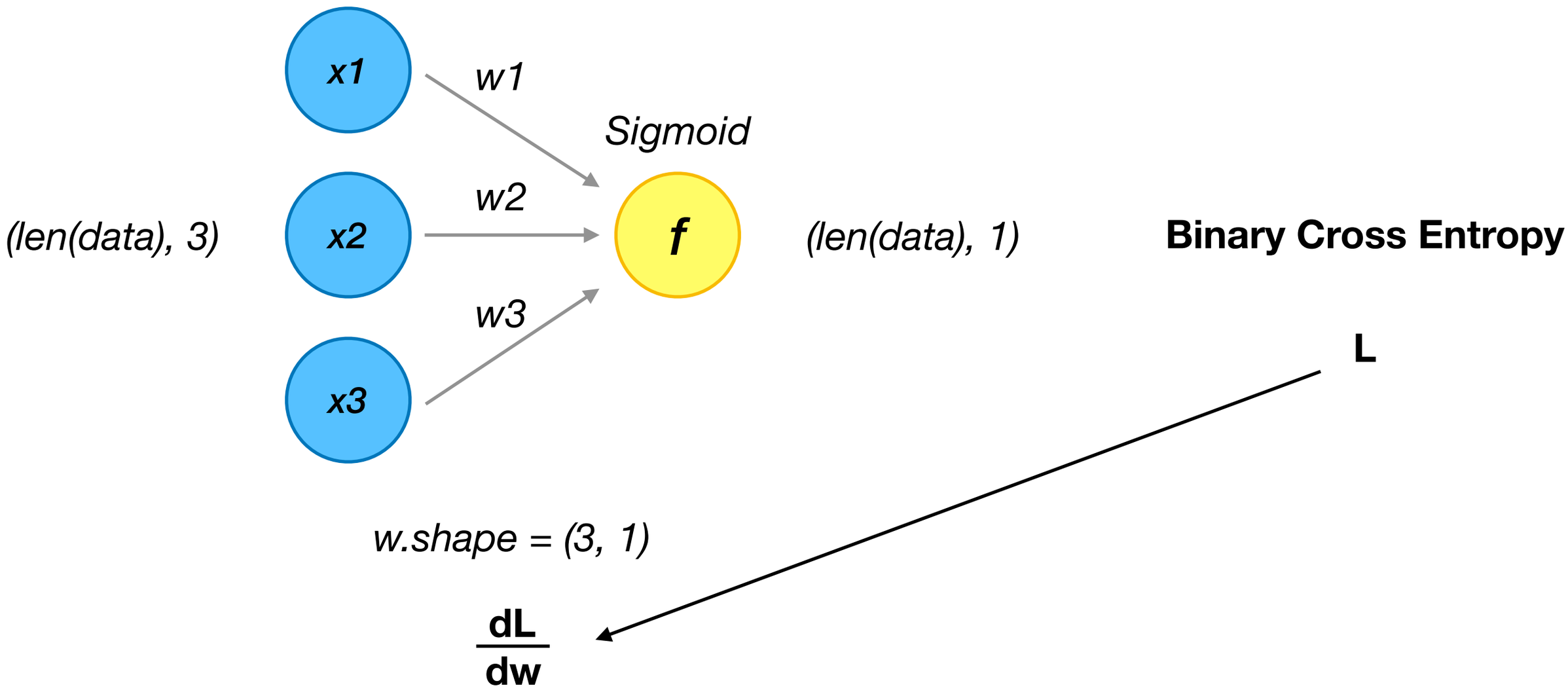
L

w.shape = (3, 1)

$$\frac{\mathbf{dL}}{\mathbf{dw}}$$

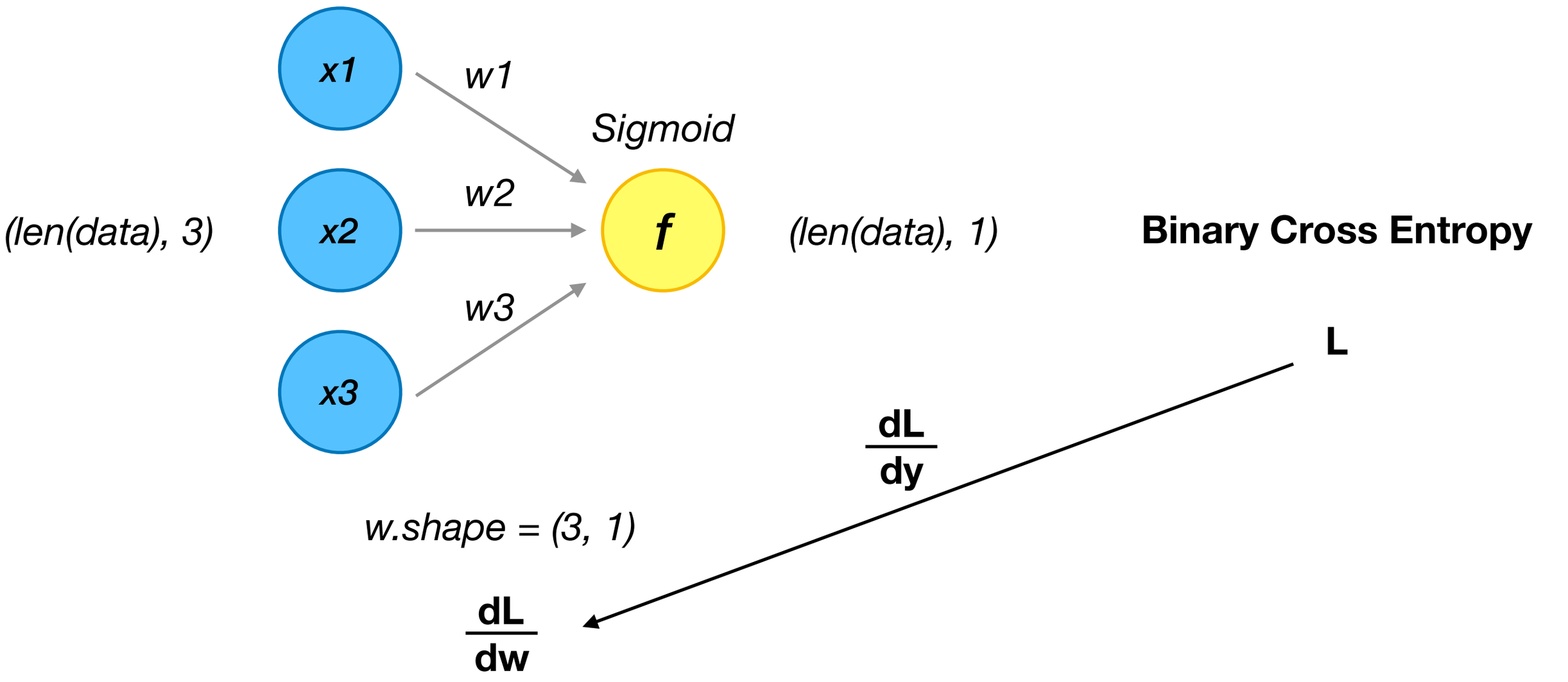
Logistic Regression

Train



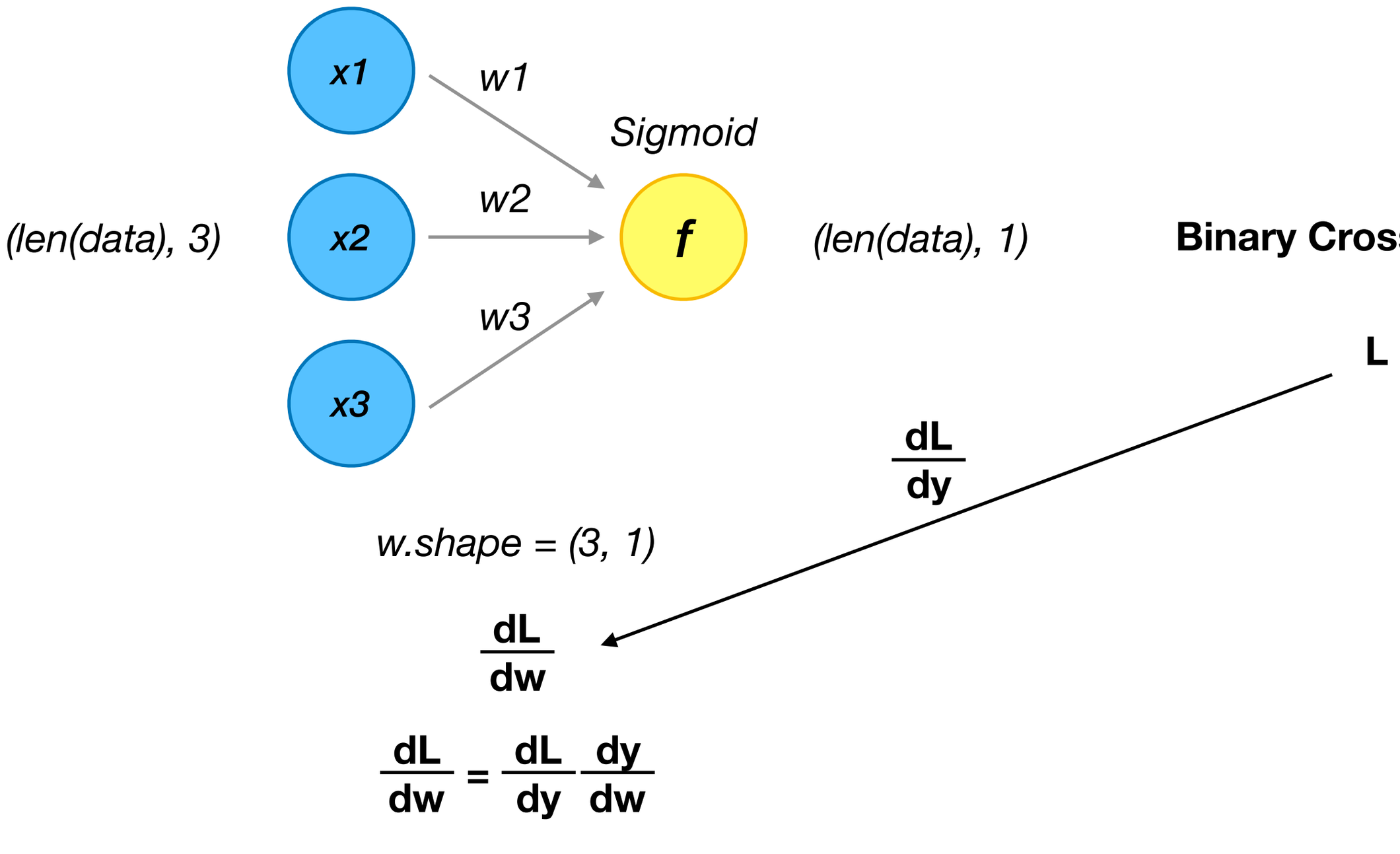
Logistic Regression

Train



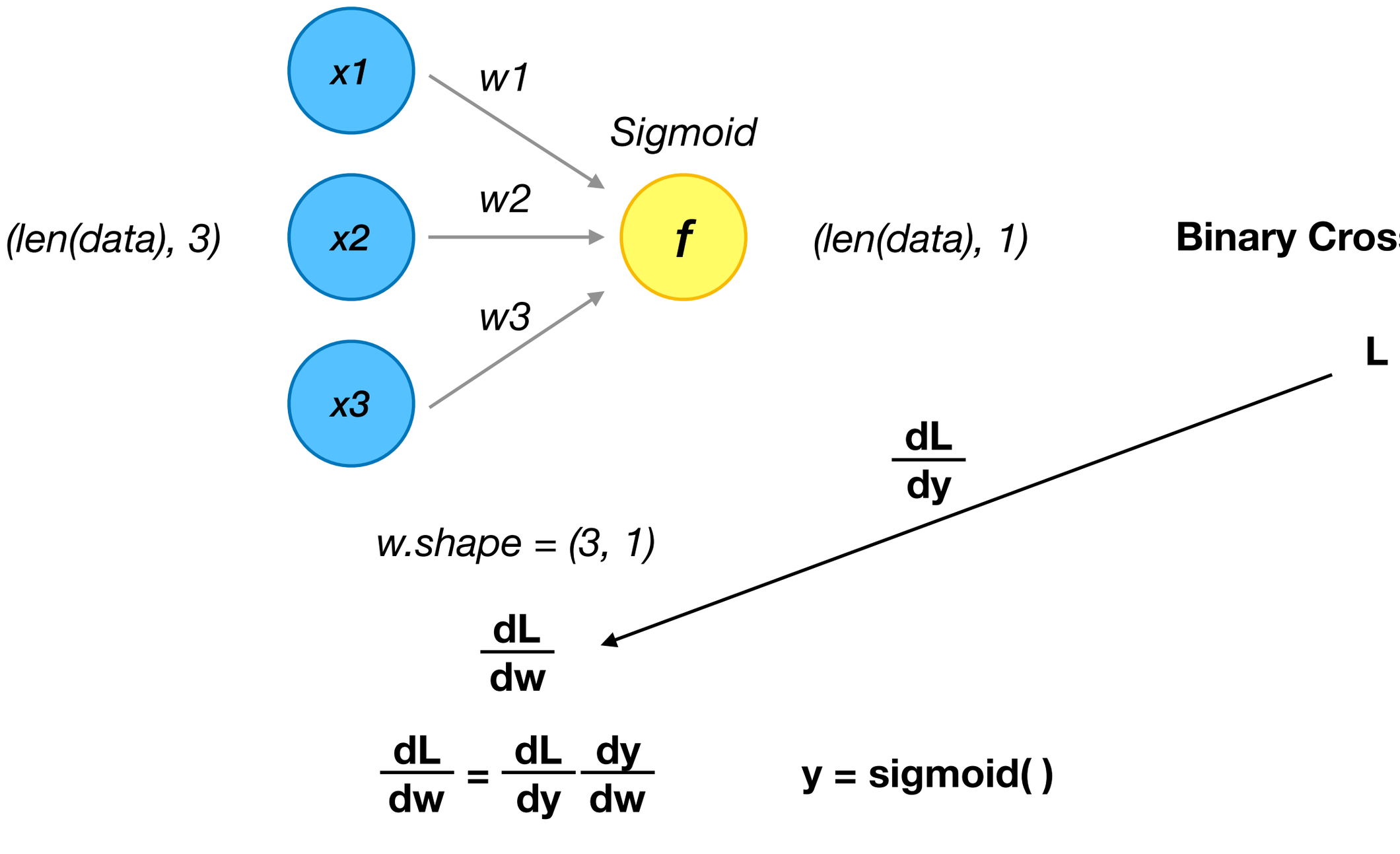
Logistic Regression

Train



Logistic Regression

Train



Regularization

BCELoss = - (y * log(pred) + (1 - y) * log(1 - pred))

Regularization

BCELoss = - (y * log(pred) + (1 - y) * log(1 - pred)) + reg * R(W)

reg - hyperparameter

Regularization

BCELoss = - (y * log(pred) + (1 - y) * log(1 - pred)) + reg * R(W)

reg - hyperparameter

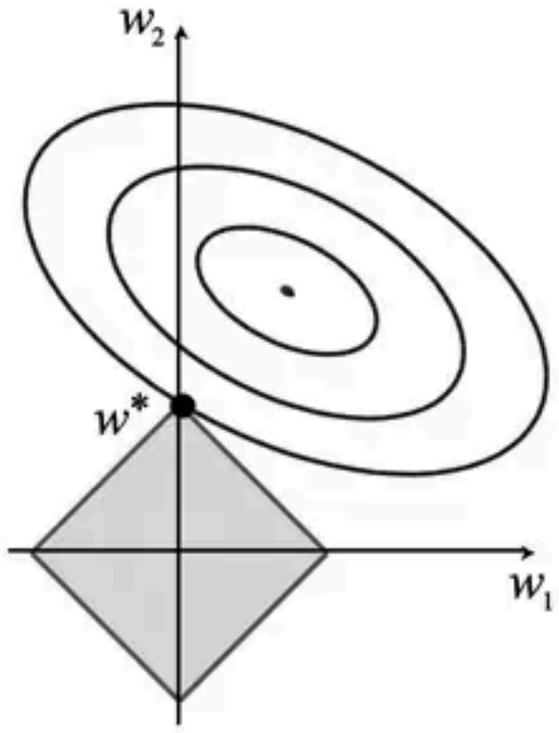
$$R(W) = \sum_k \sum_l W_{k,l}^2$$

$$R(W) = \sum_k \sum_l |W_{k,l}|$$

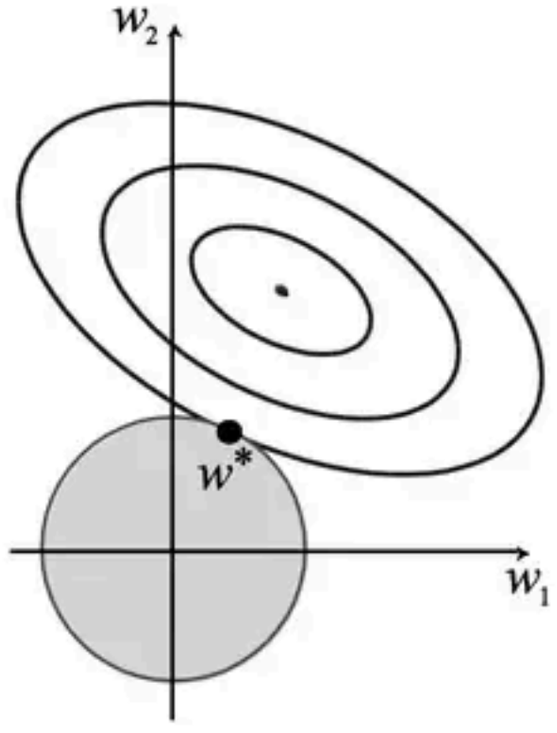
Regularization

L2 $R(W) = \sum_k \sum_l W_{k,l}^2$

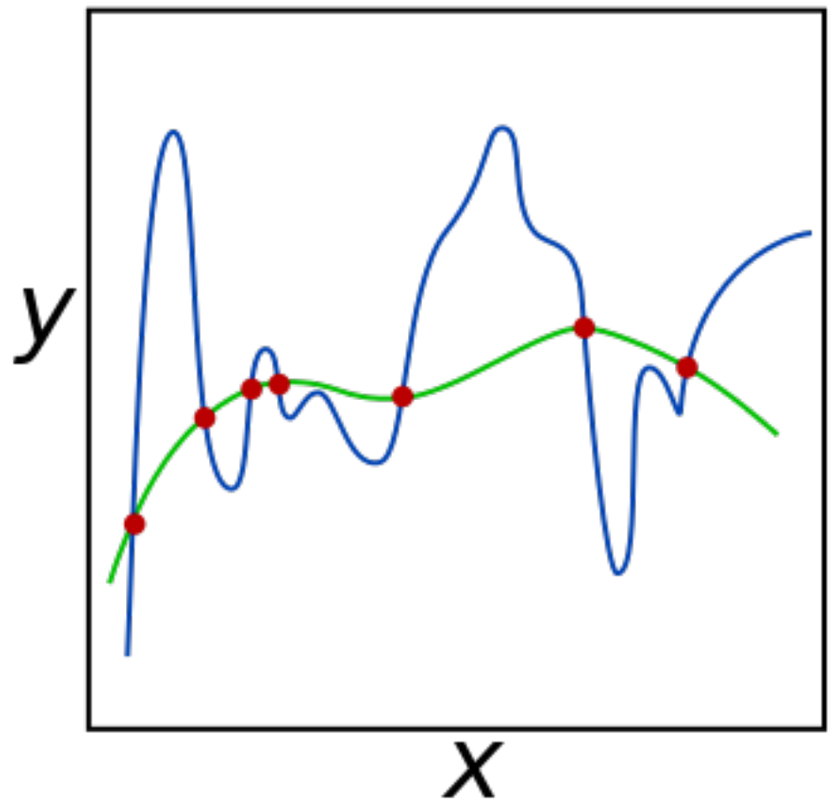
L1 $R(W) = \sum_k \sum_l |W_{k,l}|$



L1



L2

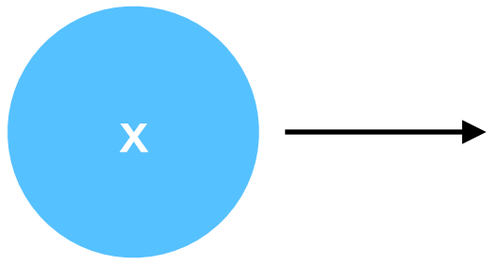


Neural Networks

Forward

Neural Networks

Forward



Neural Networks

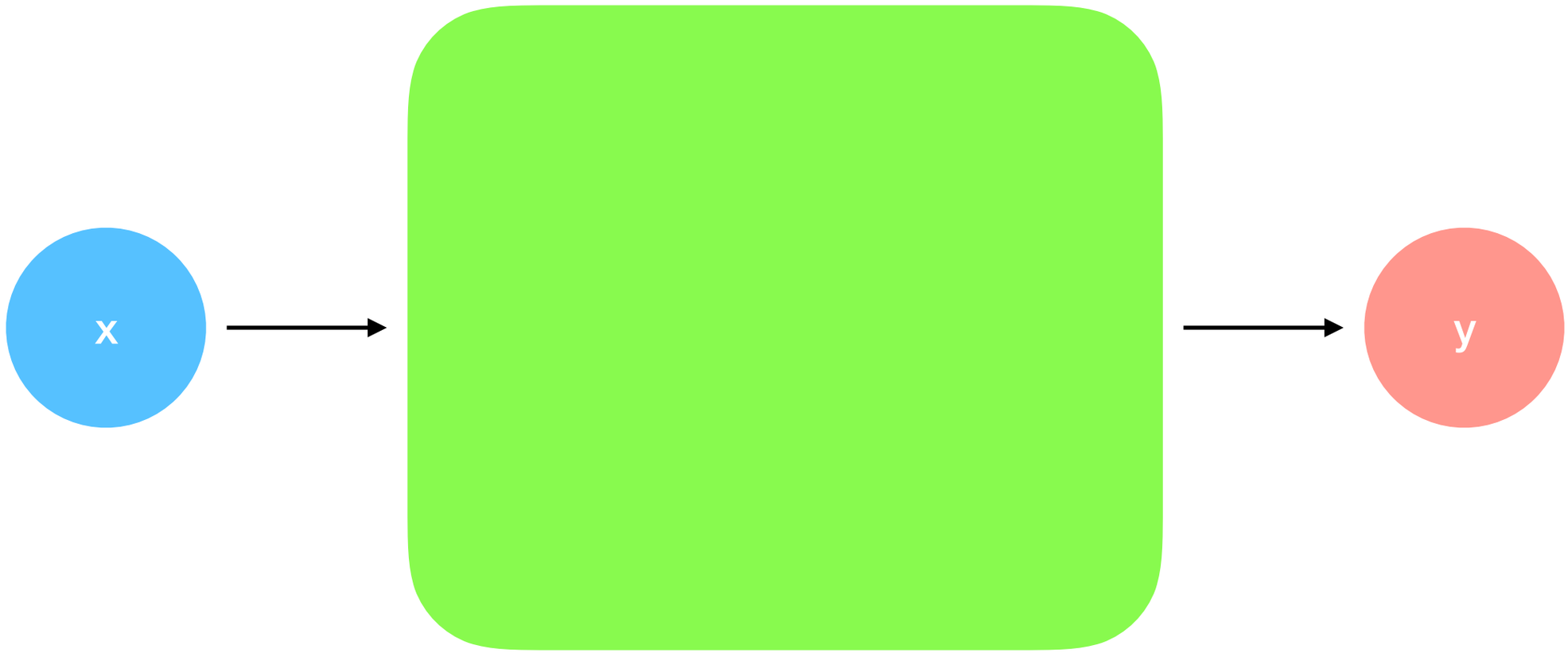
Forward

Neural Networks

Forward

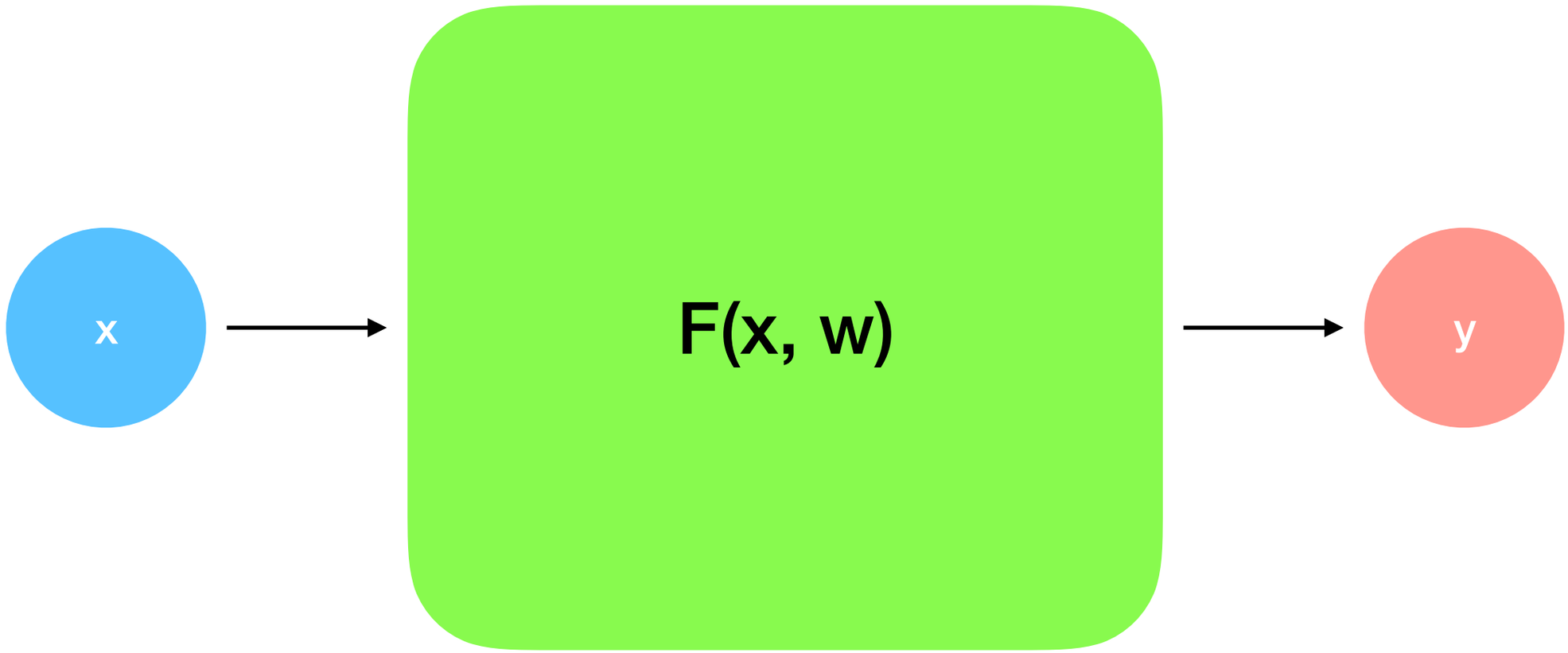
Neural Networks

Forward



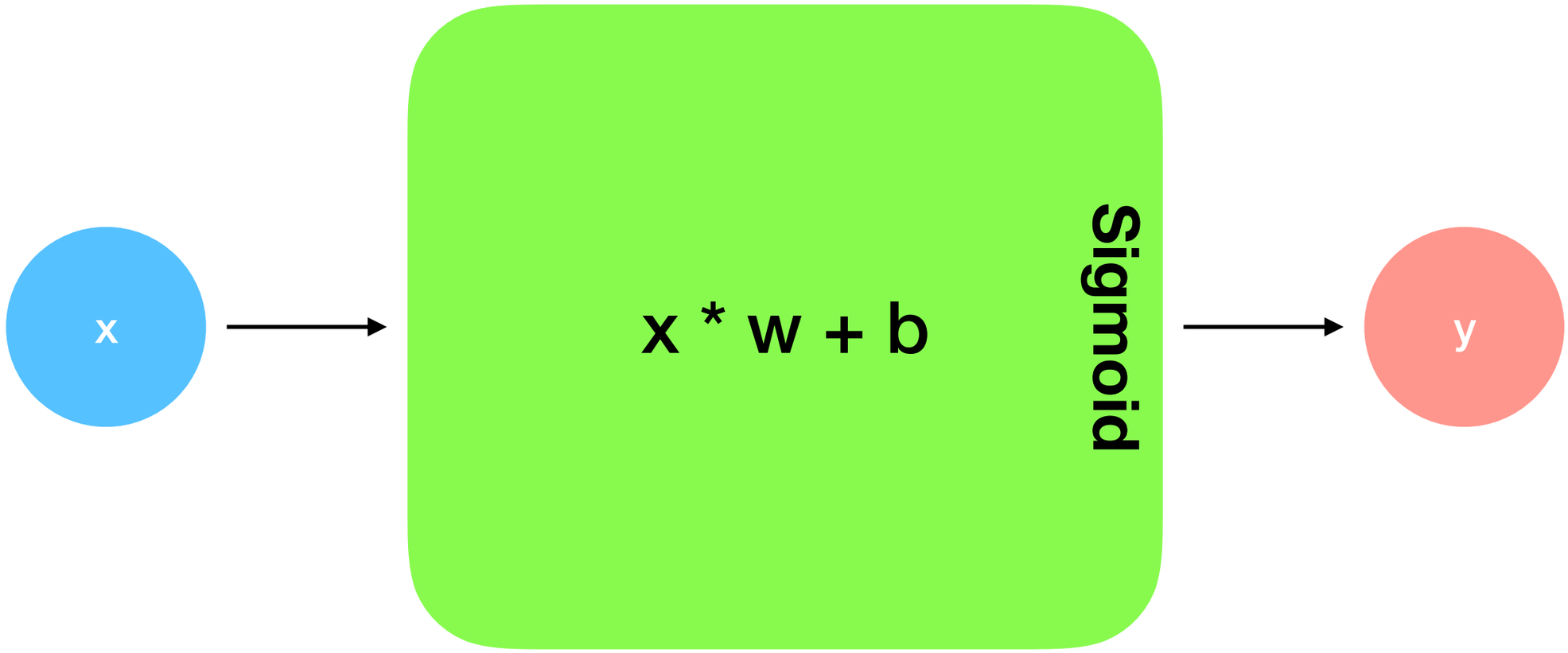
Neural Networks

Forward



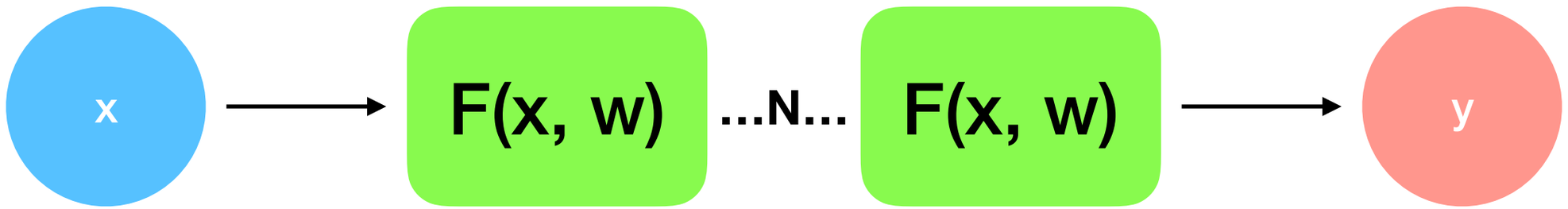
Neural Networks

Forward



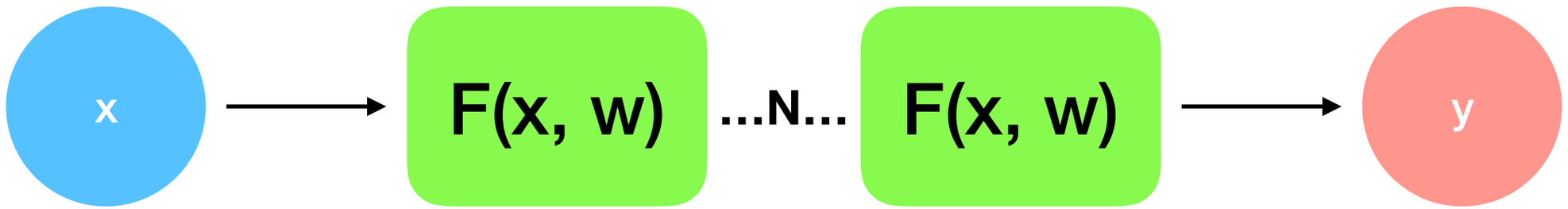
Neural Networks

Forward



Neural Networks

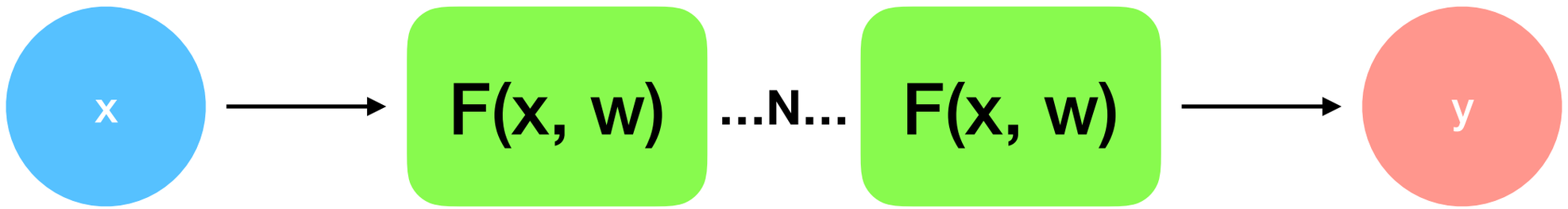
Forward



Fn(F3(F2(F1(x, w1), w2), w3), wn)

Neural Networks

Forward

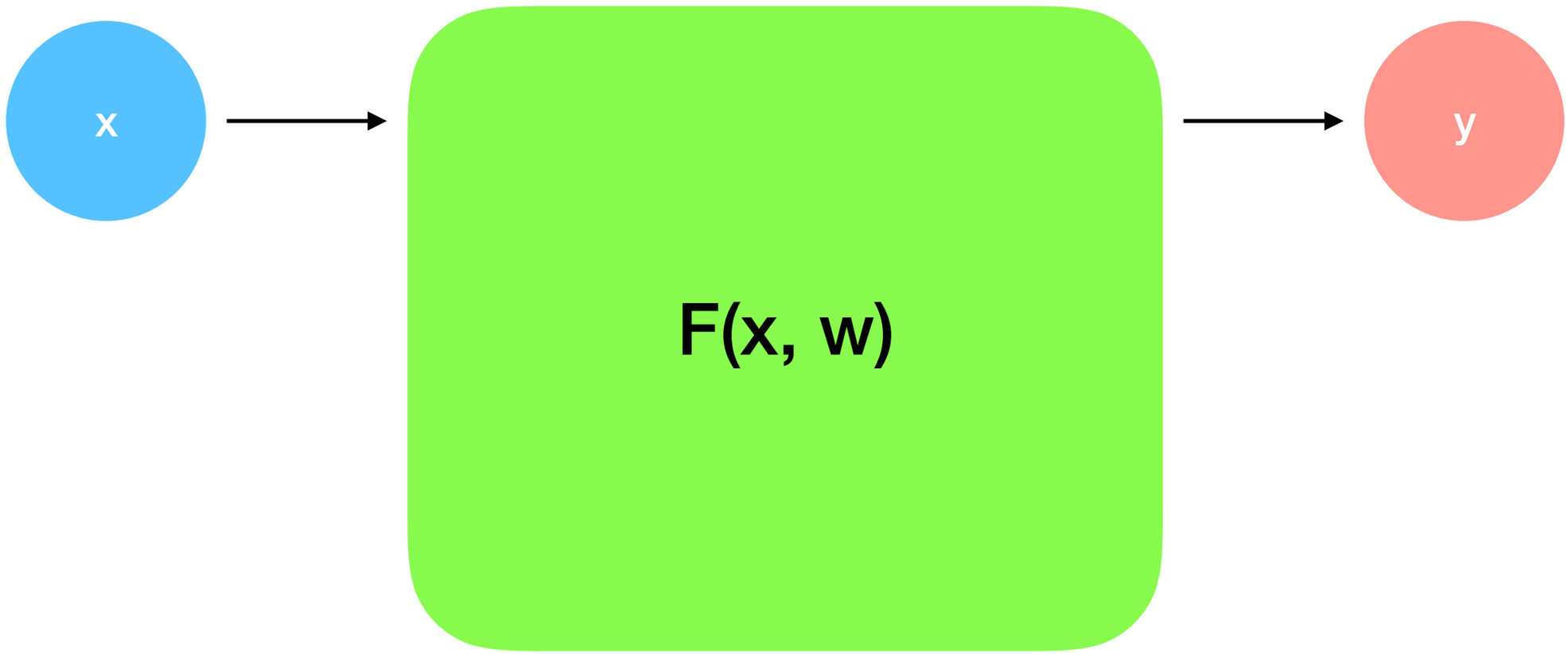


Fn(F3(F2(F1(x, w1), w2), w3), wn)

F(x, w) = non-linearity(x * w + b)

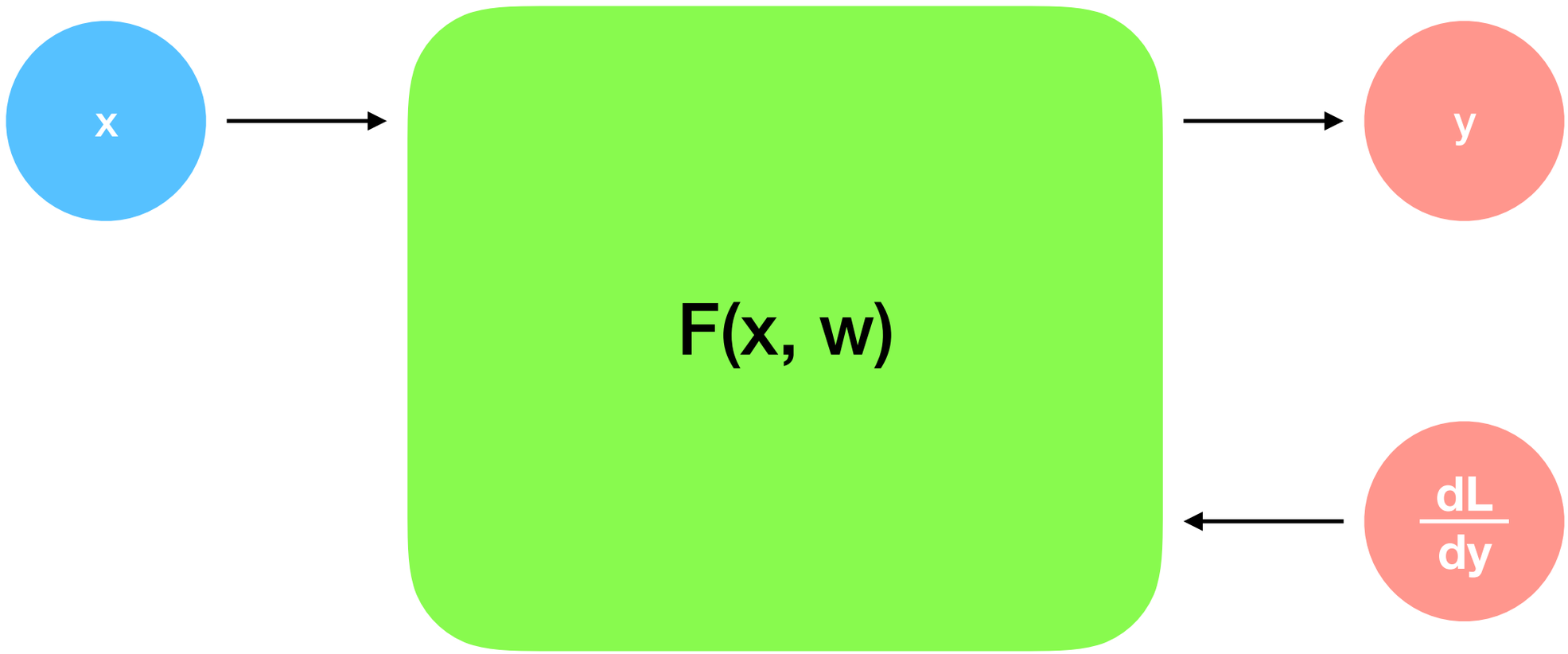
Neural Networks

Backward



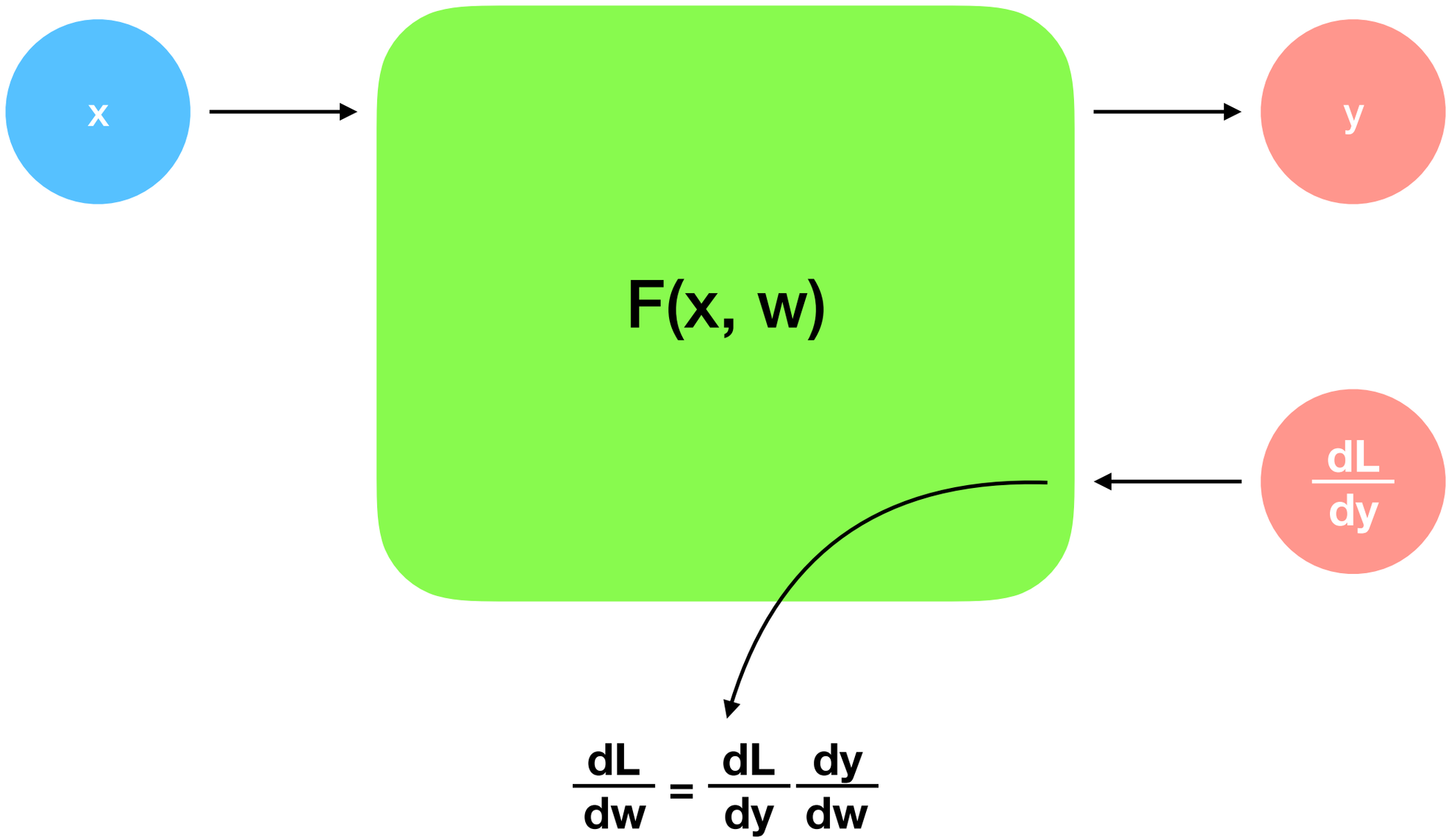
Neural Networks

Backward



Neural Networks

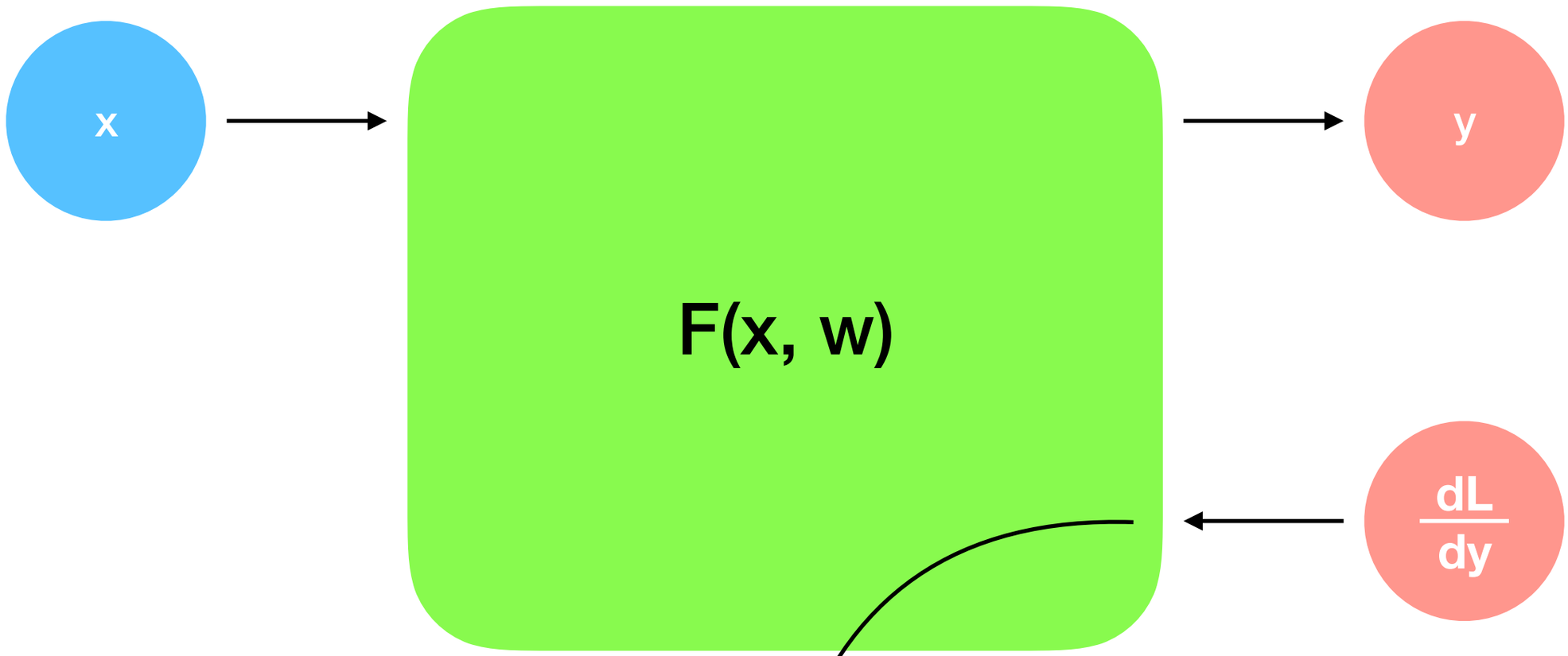
Backward



$$\frac{dL}{dw} = \frac{dL}{dy}\frac{dy}{dw}$$

Neural Networks

Backward

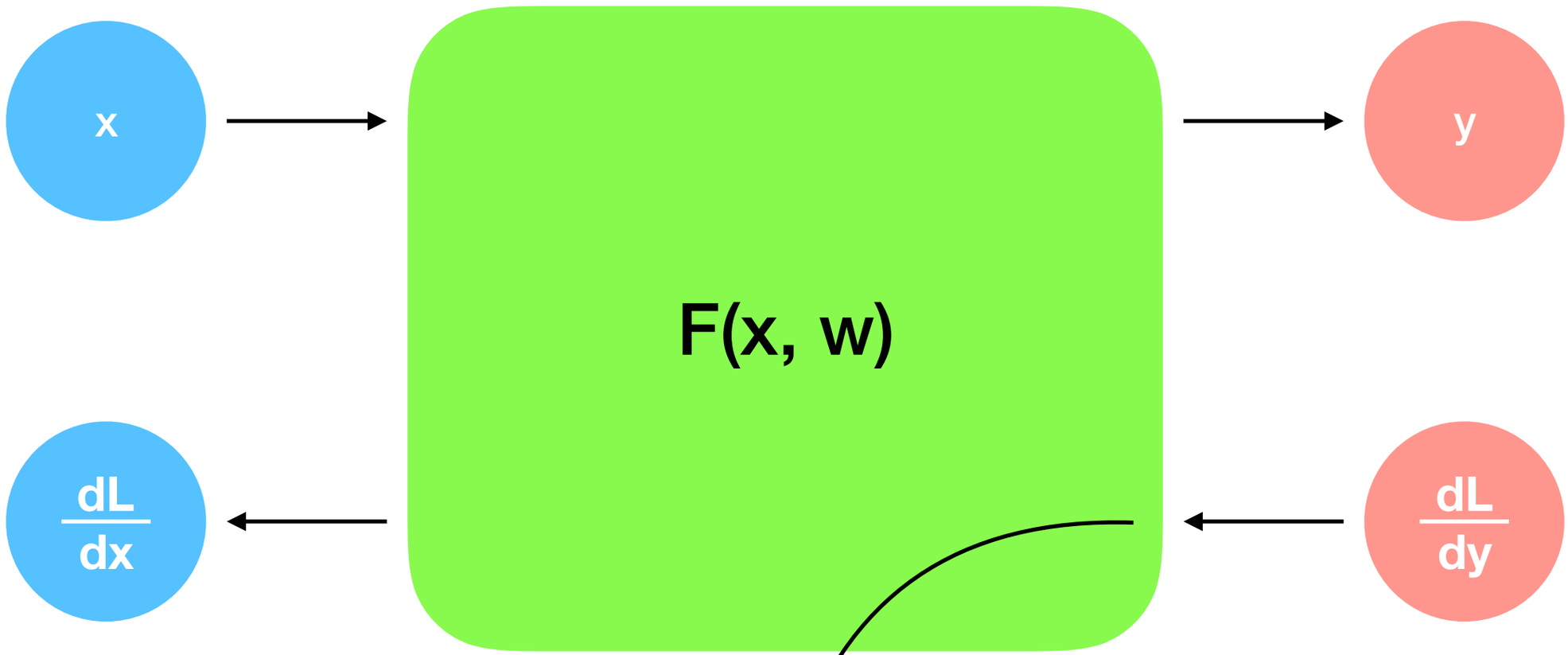


$$\frac{dL}{dw} = \frac{dL}{dy}\frac{dy}{dw}$$

$$w = w - learning\_rate * \frac{dL}{dw}$$

Neural Networks

Backward

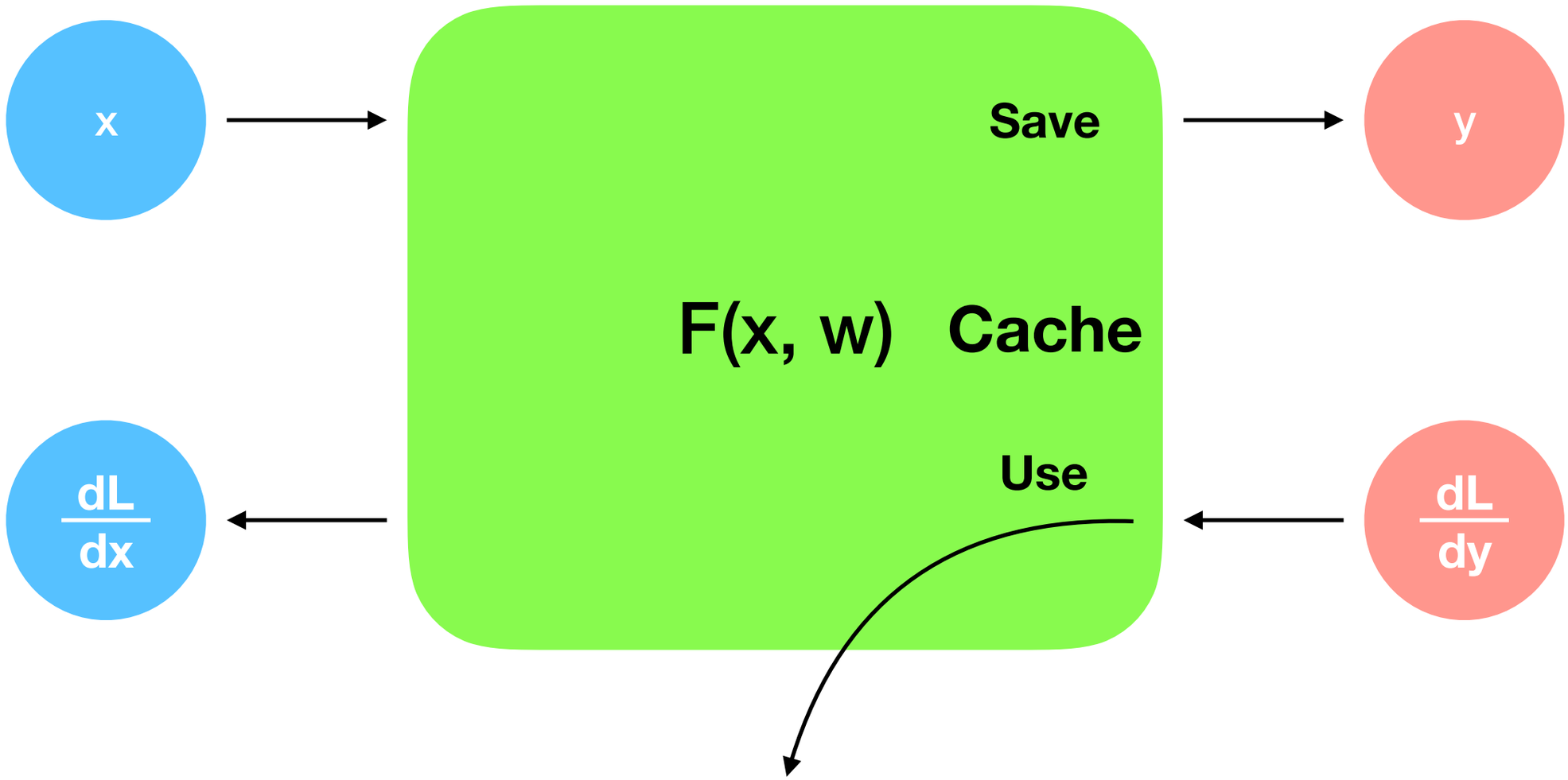


$$\frac{dL}{dw} = \frac{dL}{dy}\frac{dy}{dw}$$

$$w = w - learning\_rate * \frac{dL}{dw}$$

Neural Networks

Backward

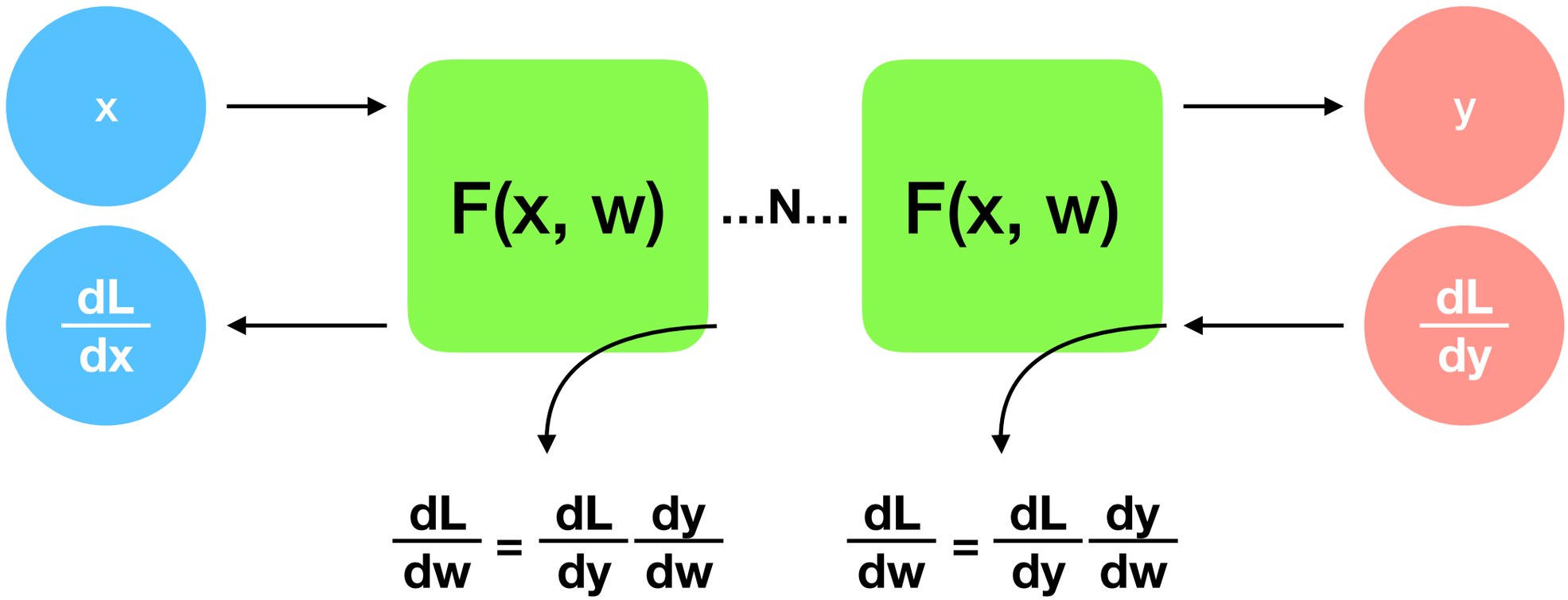


$$\frac{dL}{dw} = \frac{dL}{dy}\frac{dy}{dw}$$

$$w = w - learning\_rate * \frac{dL}{dw}$$

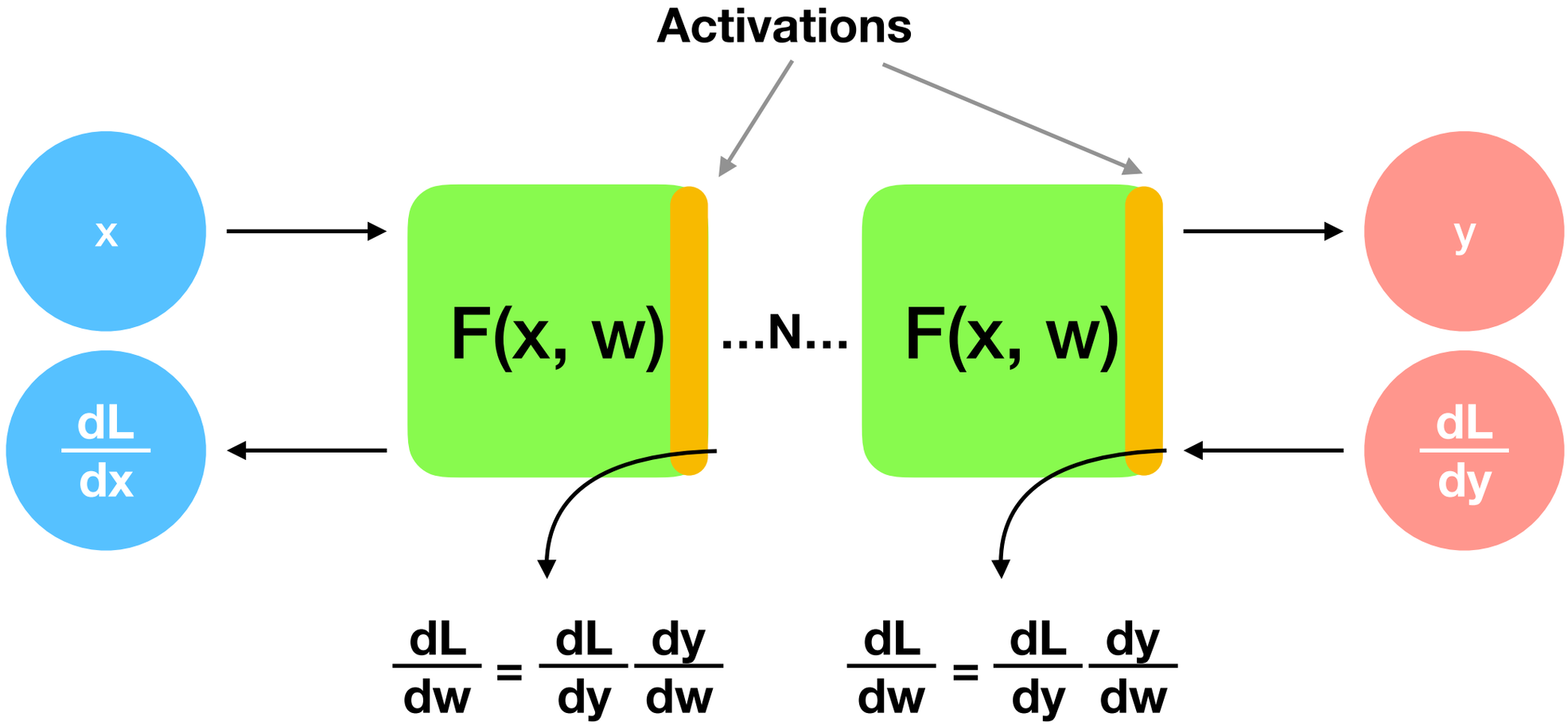
Neural Networks

Backward

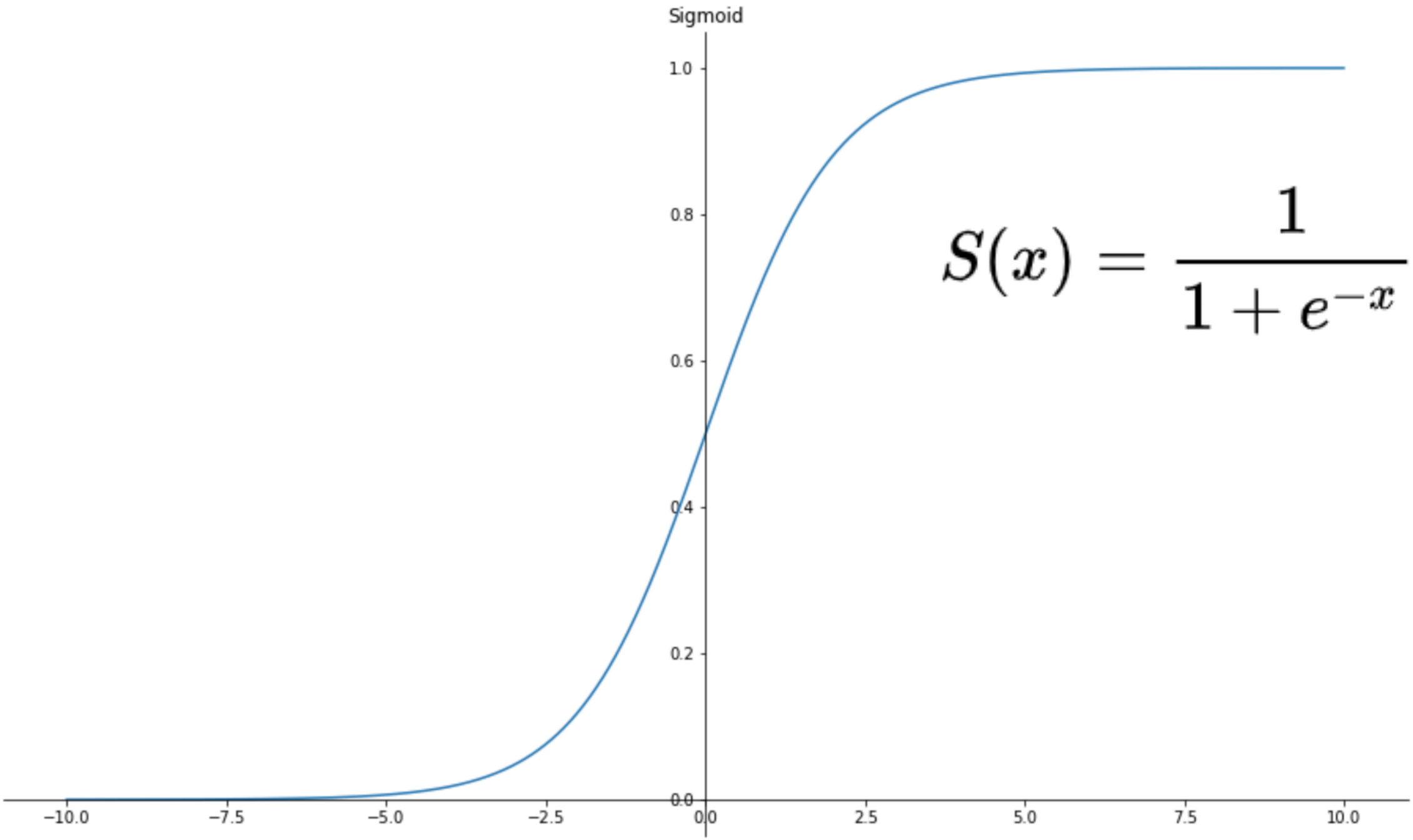


Neural Networks

Backward

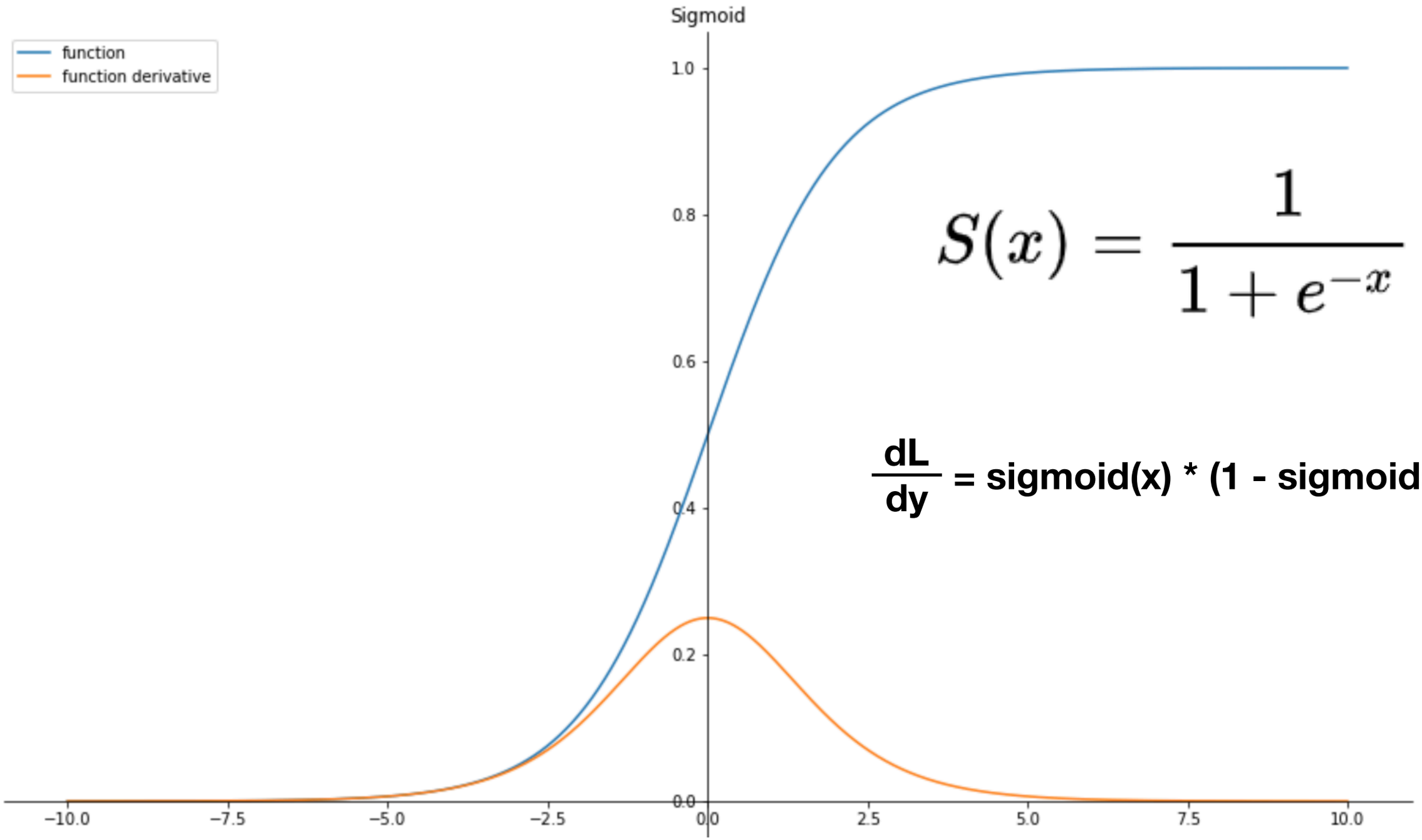


Sigmoid



$$S(x) = \frac{1}{1 + e^{-x}}$$

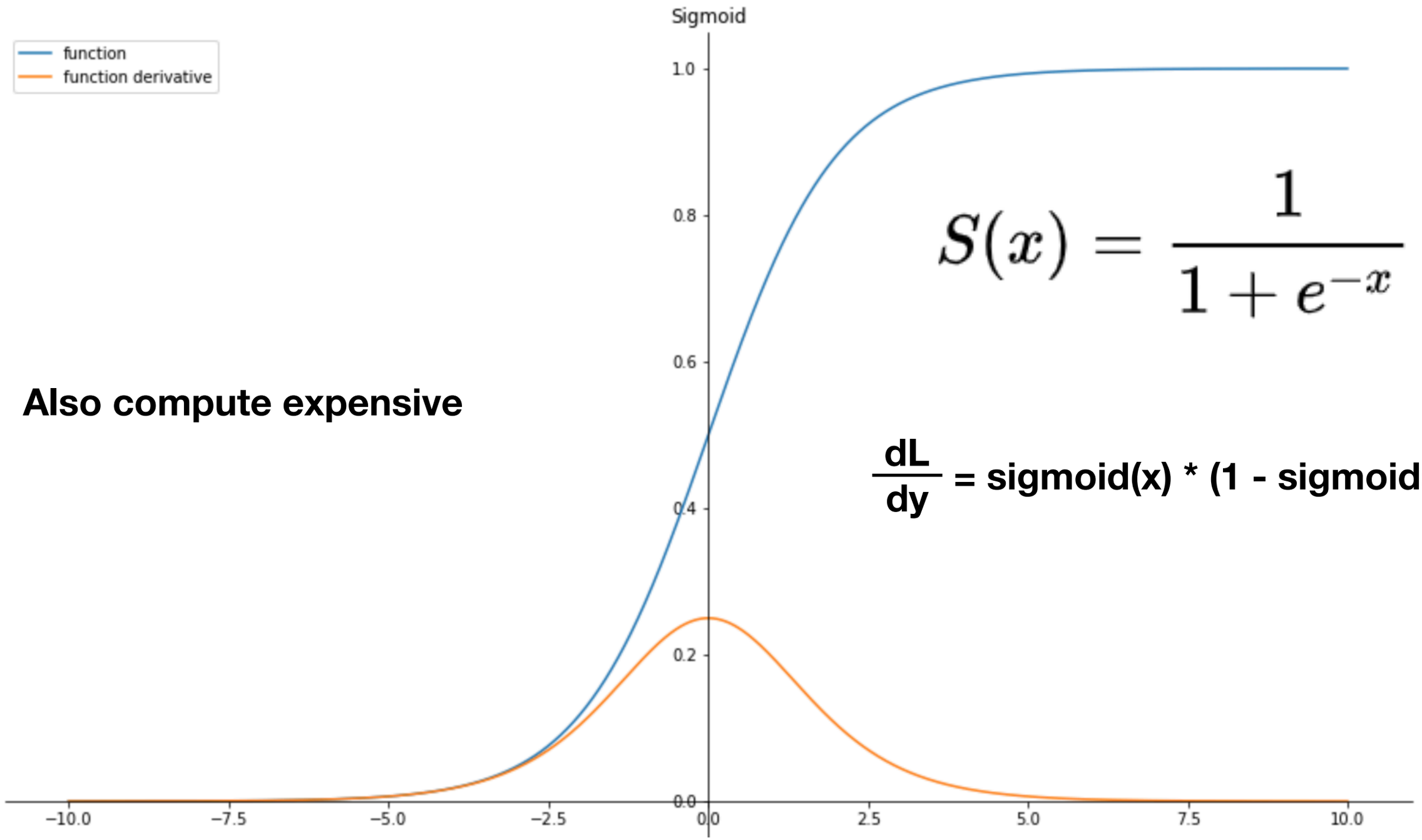
Sigmoid



$$S(x) = \frac{1}{1 + e^{-x}}$$

$$\frac{dL}{dy} = \text{sigmoid(x) * (1 - sigmoid(x))}$$

Sigmoid

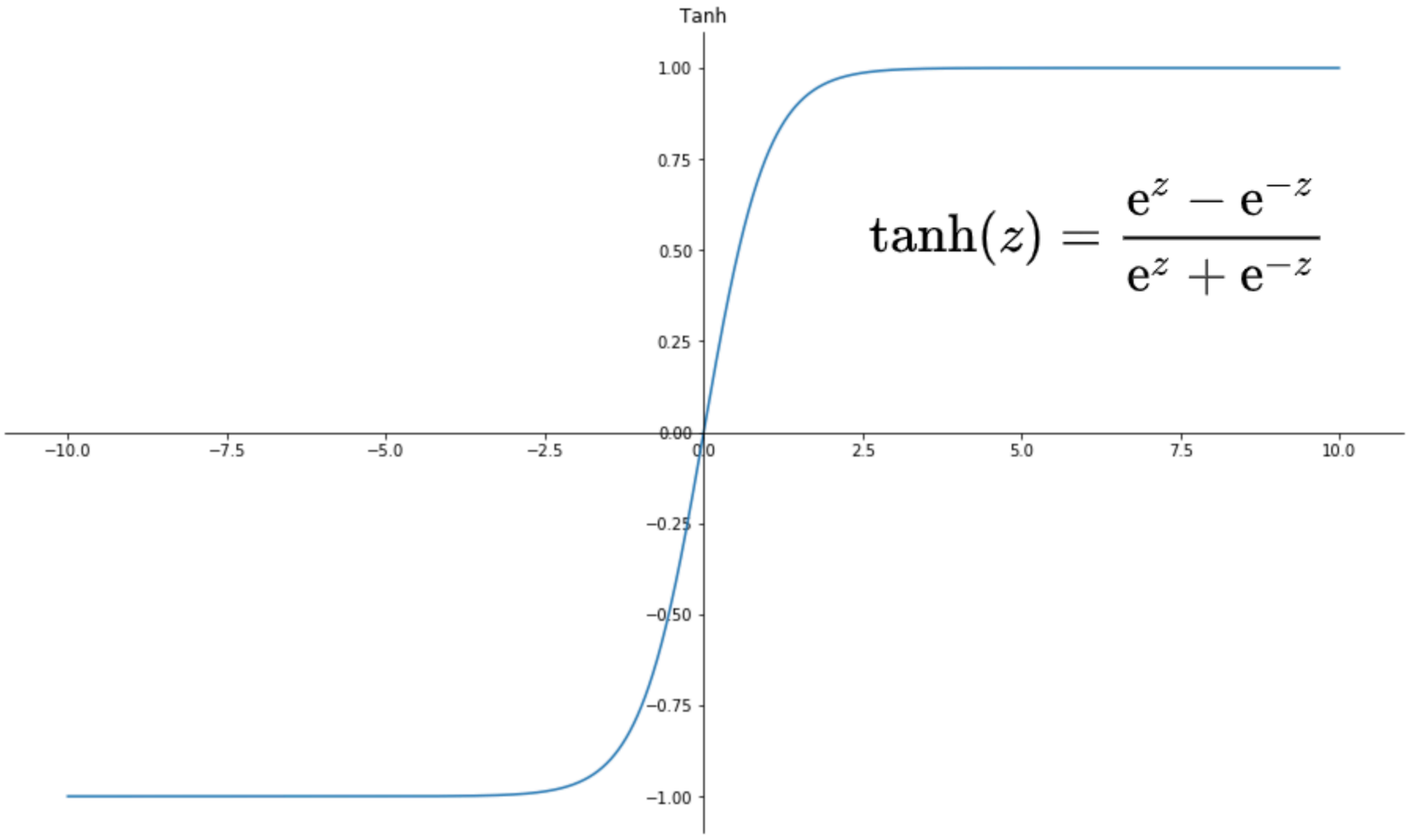


$$S(x) = \frac{1}{1 + e^{-x}}$$

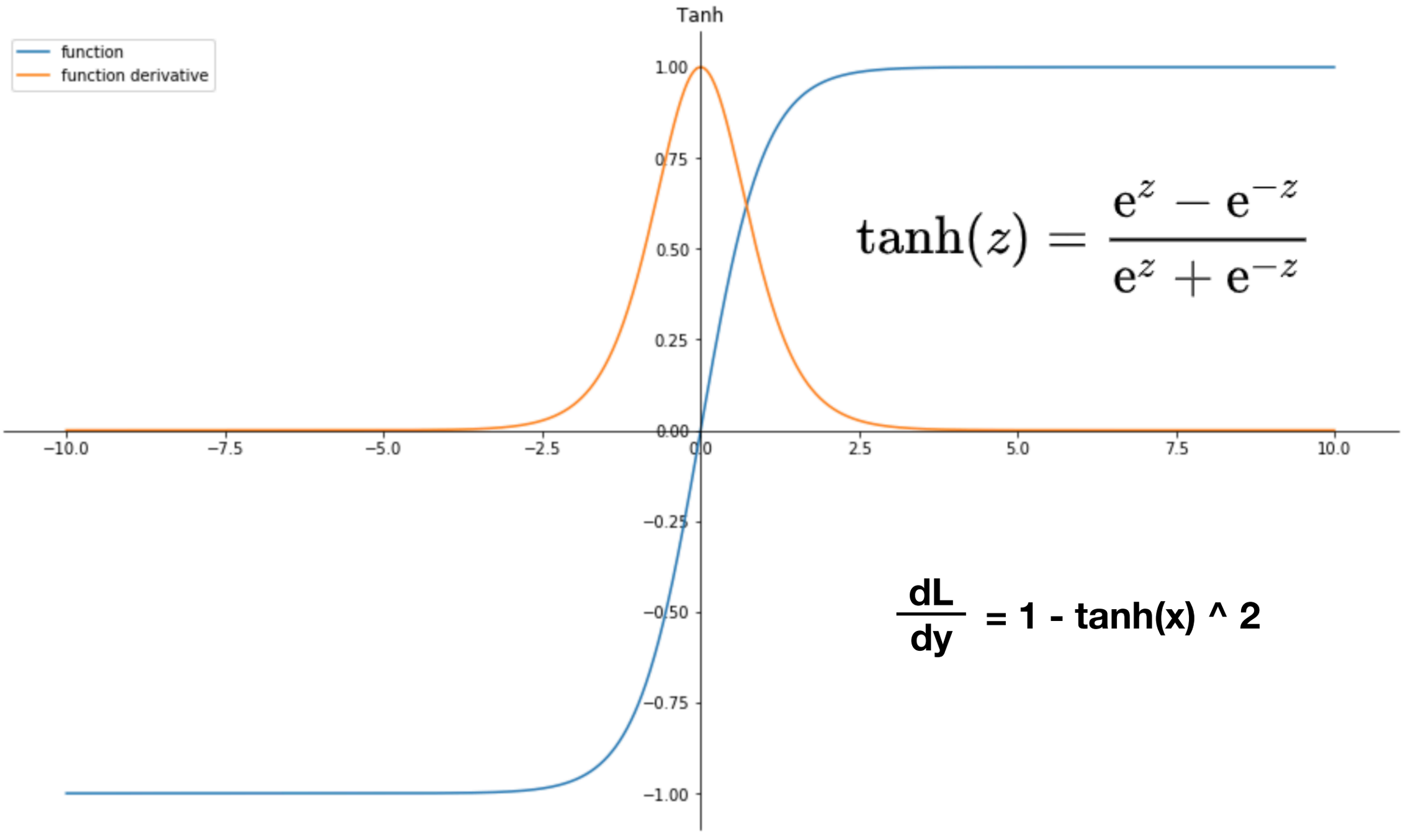
Also compute expensive

$$\frac{dL}{dy} = \text{sigmoid(x) * (1 - sigmoid(x))}$$

Tanh


Tanh
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
$\tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$

Tanh

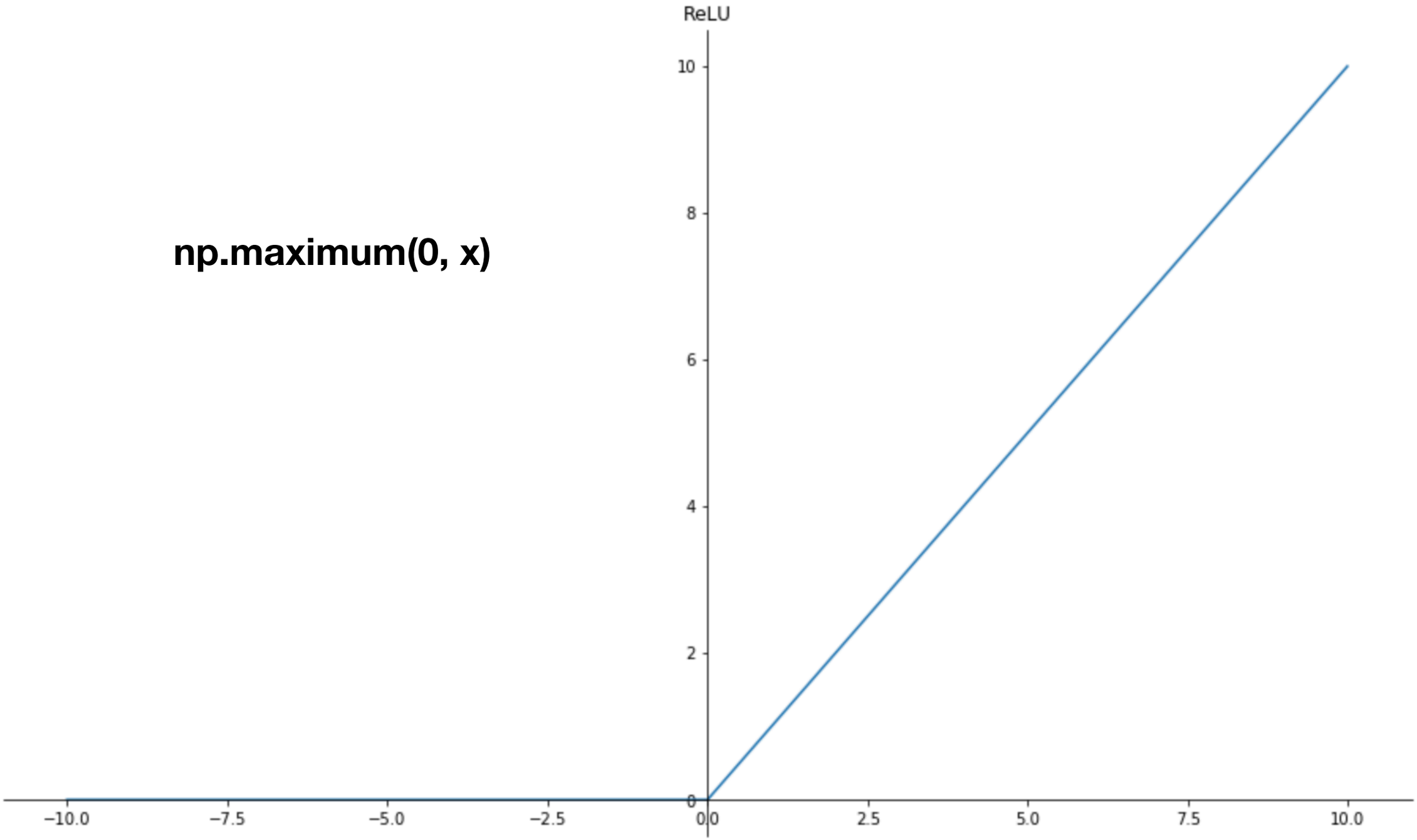


$$\tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

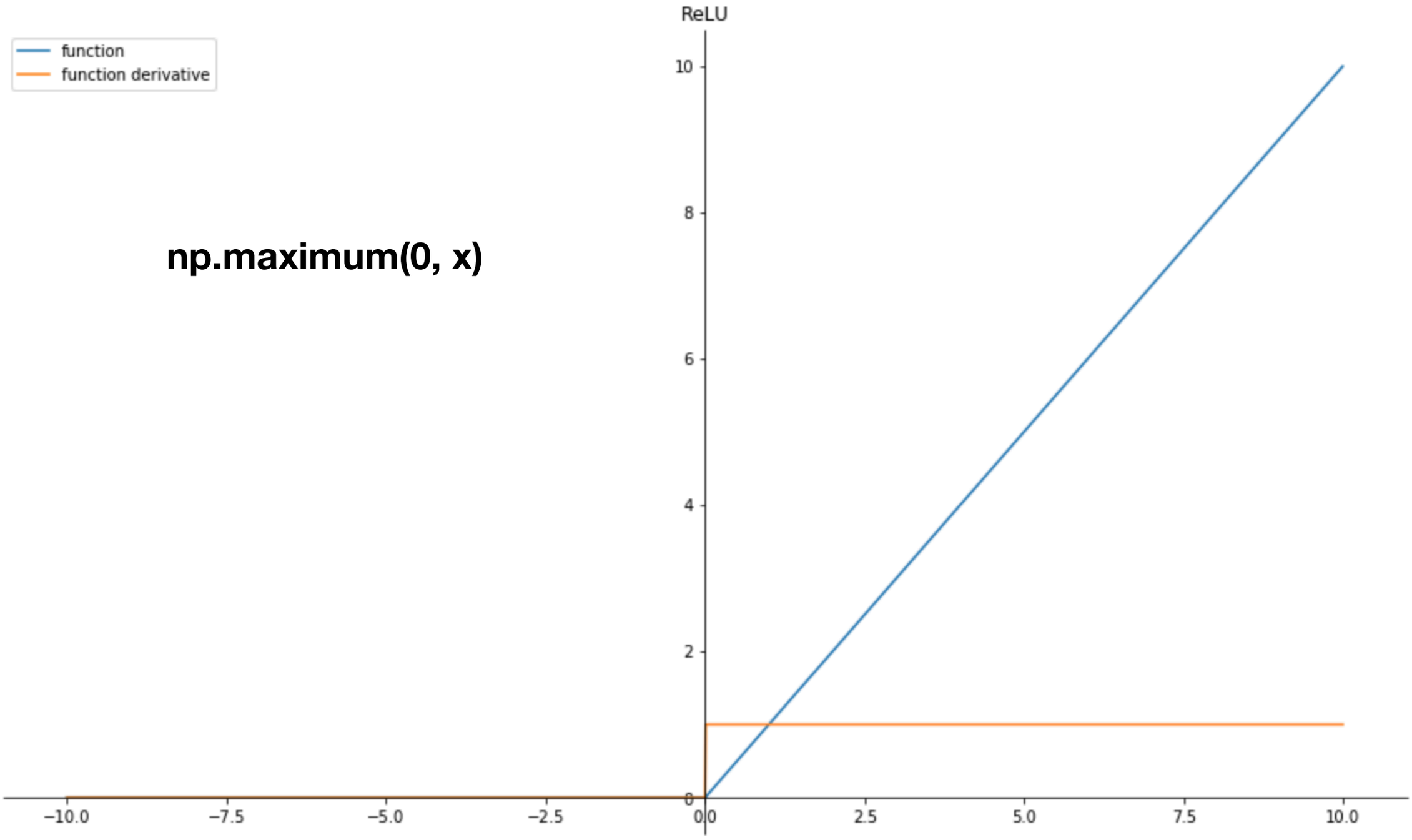
$$\frac{dL}{dy} = 1 - \tanh(x) \wedge 2$$

ReLU

np.maximum(0, x)

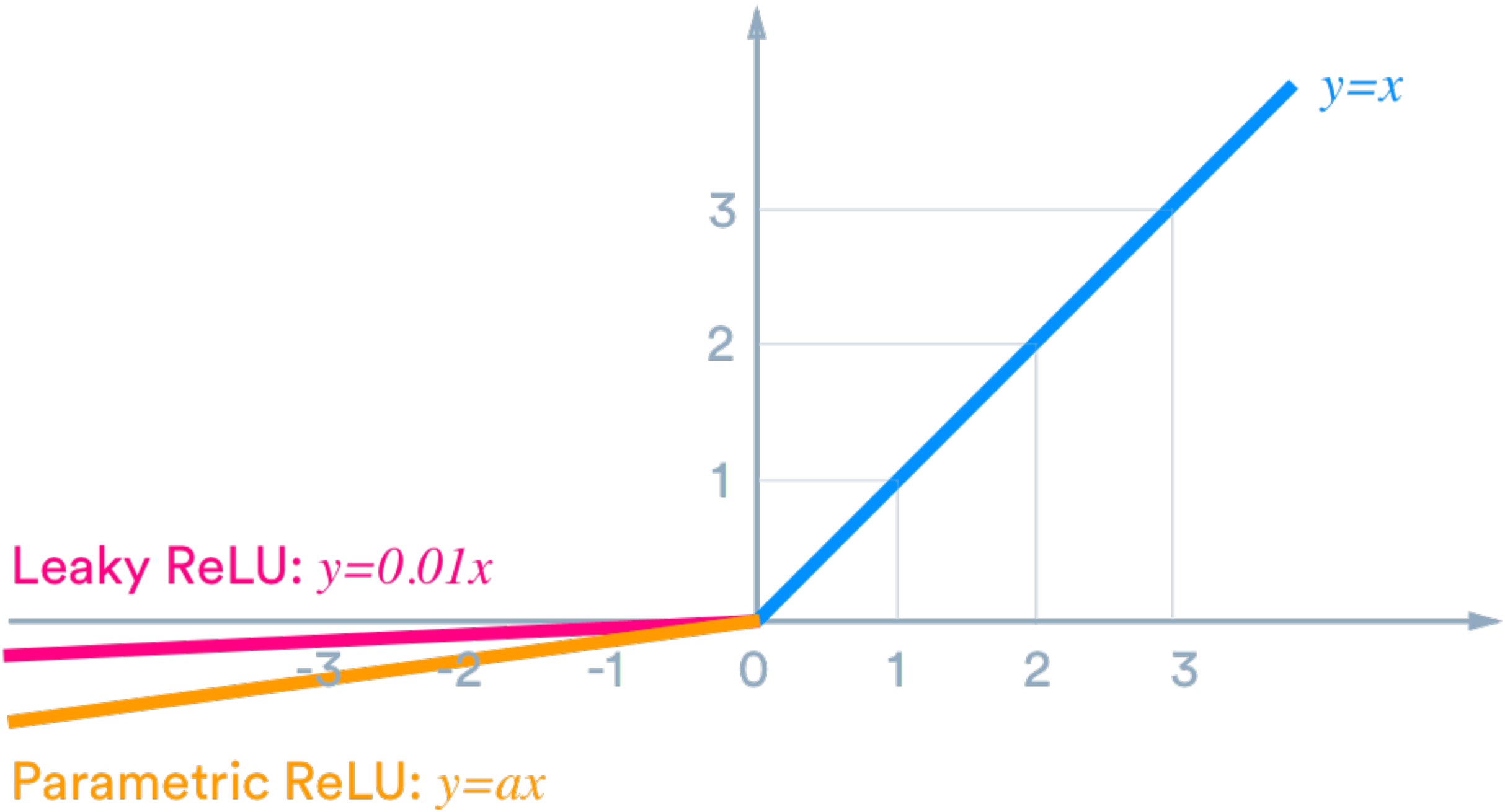


ReLU

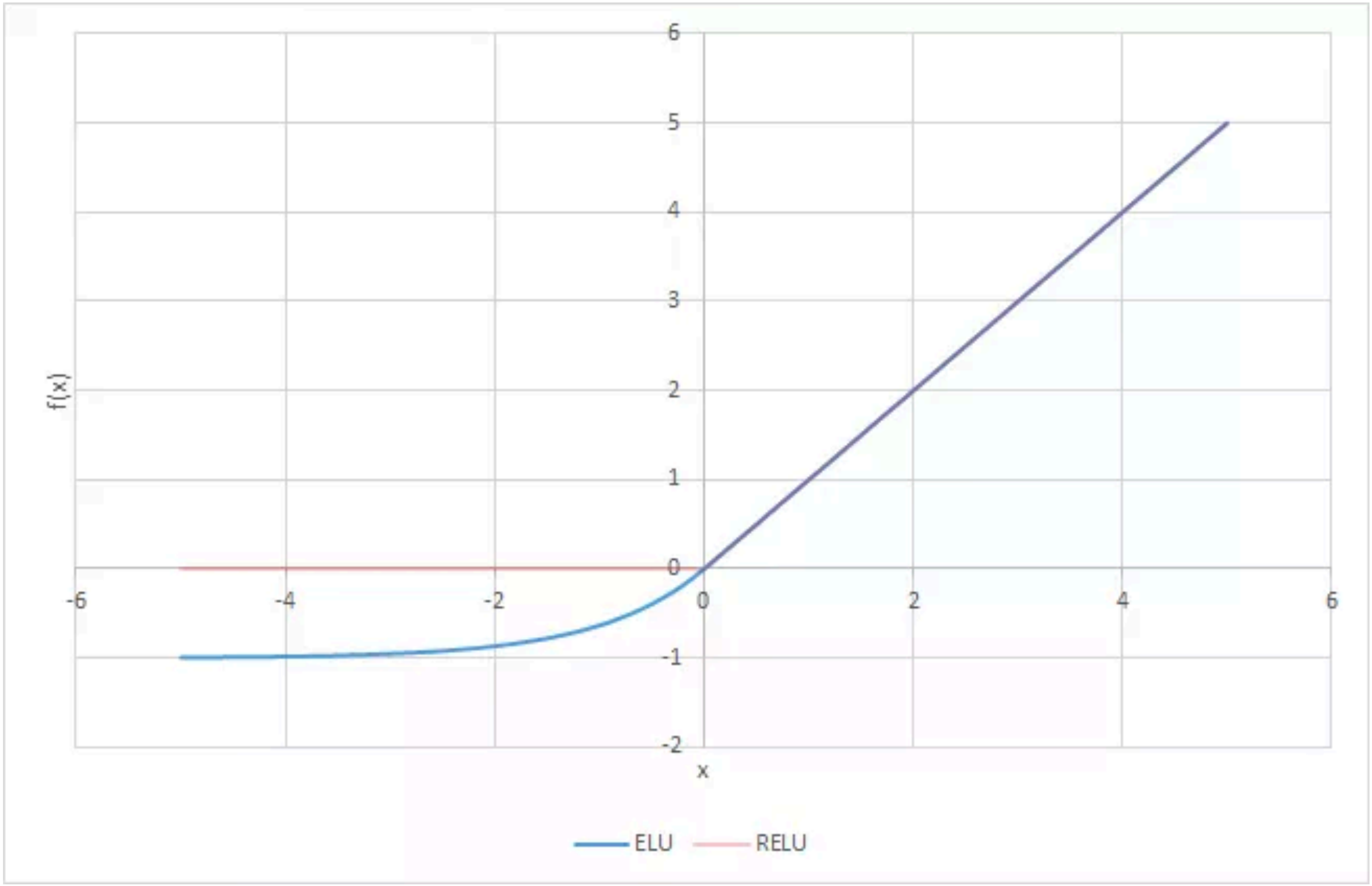


np.maximum(0, x)

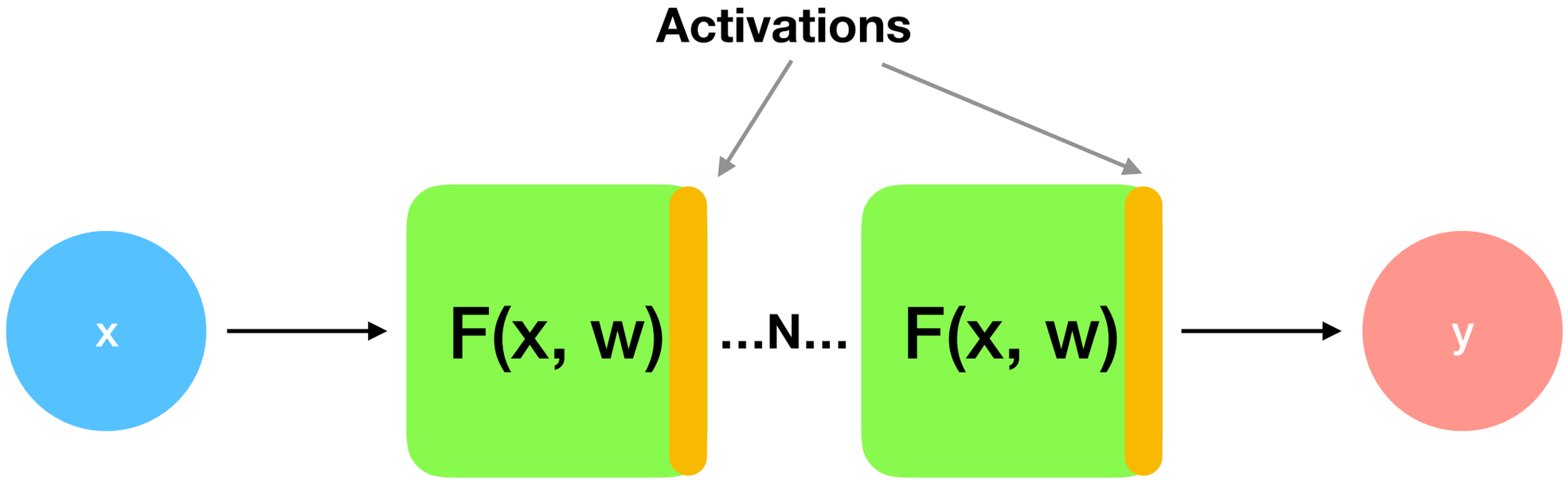
Leaky ReLU



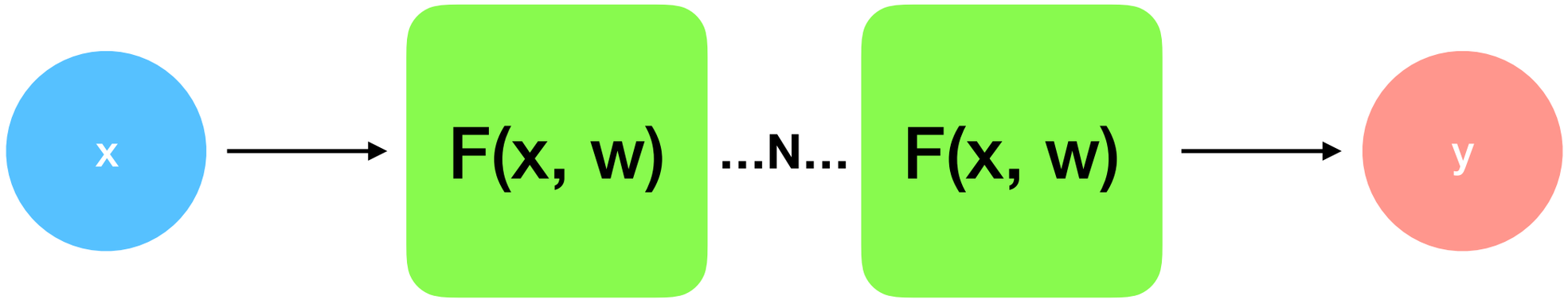
ELU



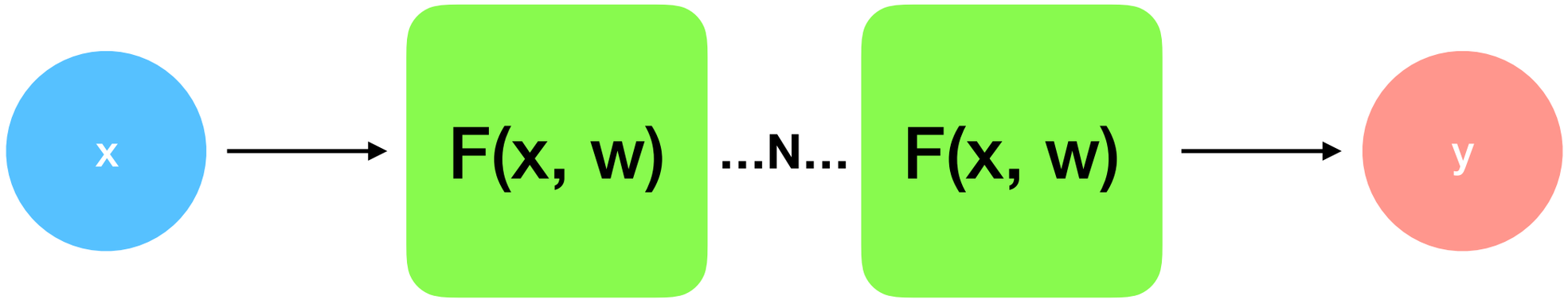
Neural Networks



Neural Networks



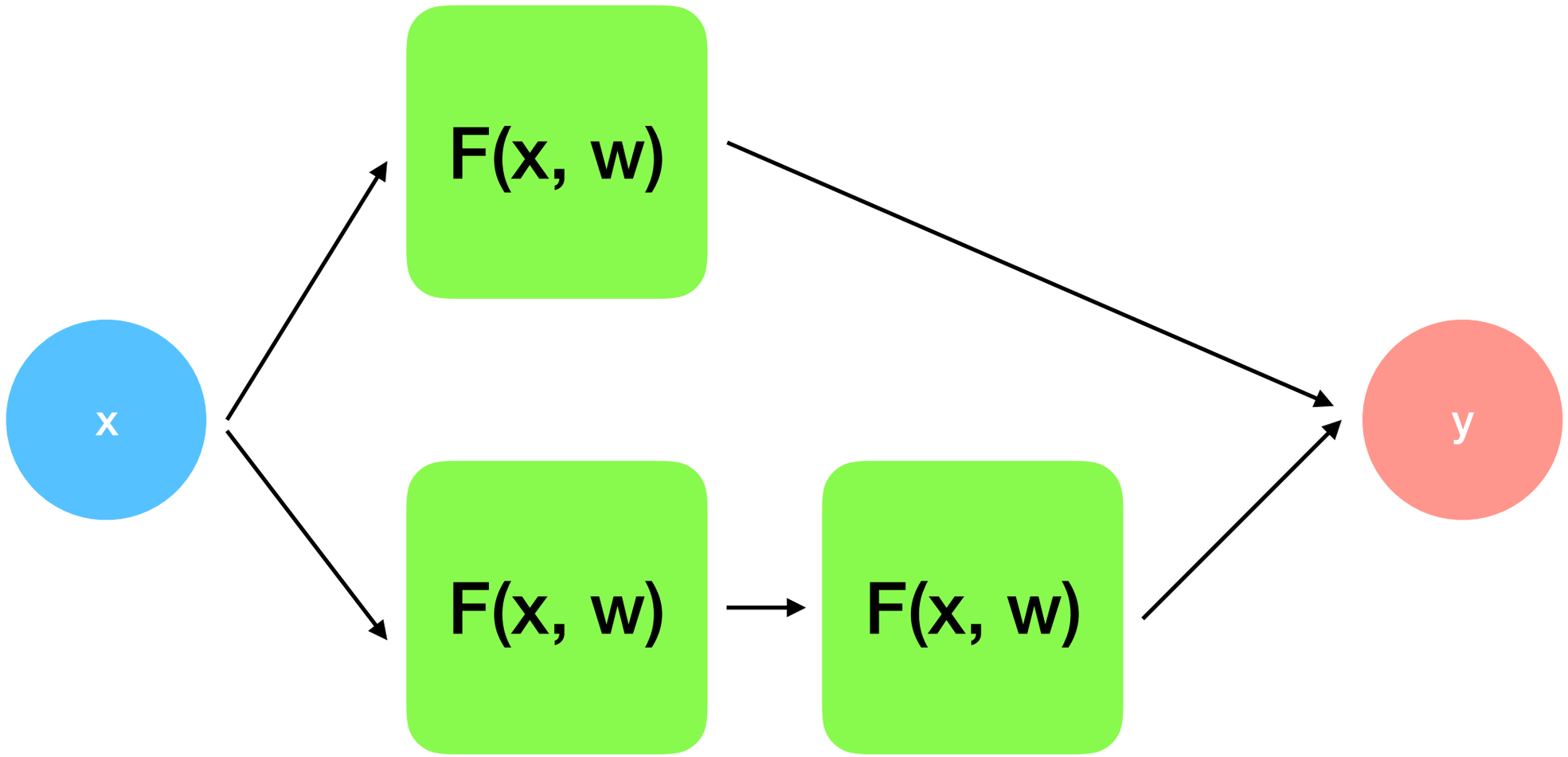
Neural Networks



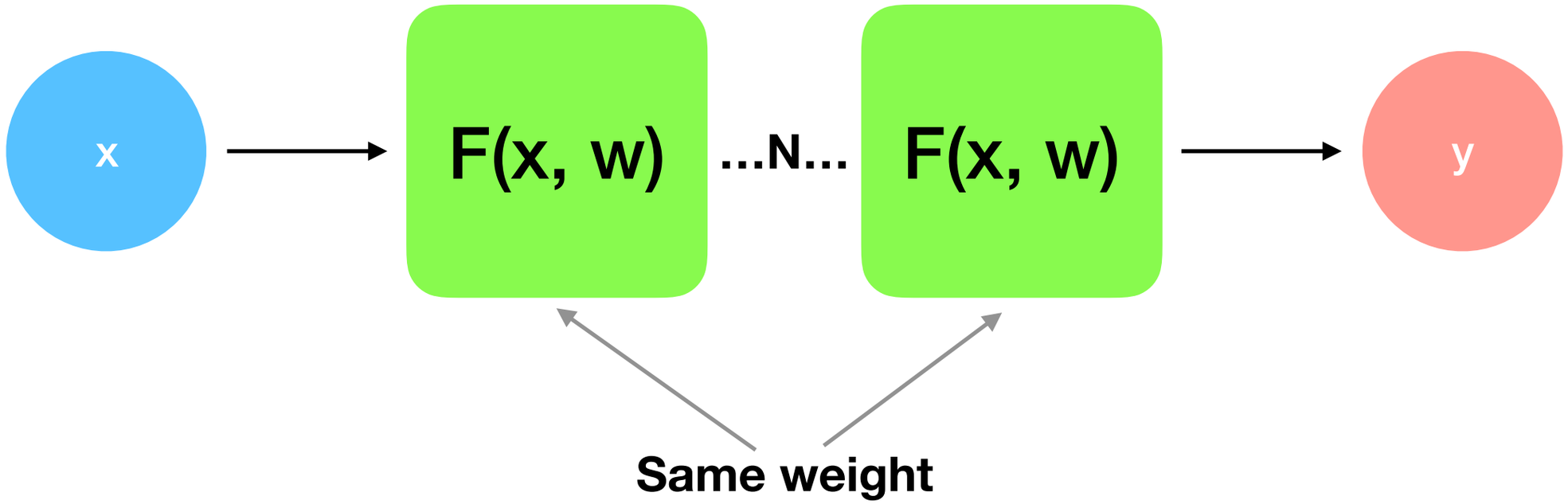
W1W2X = W3X

Neural Networks

It's a graph!

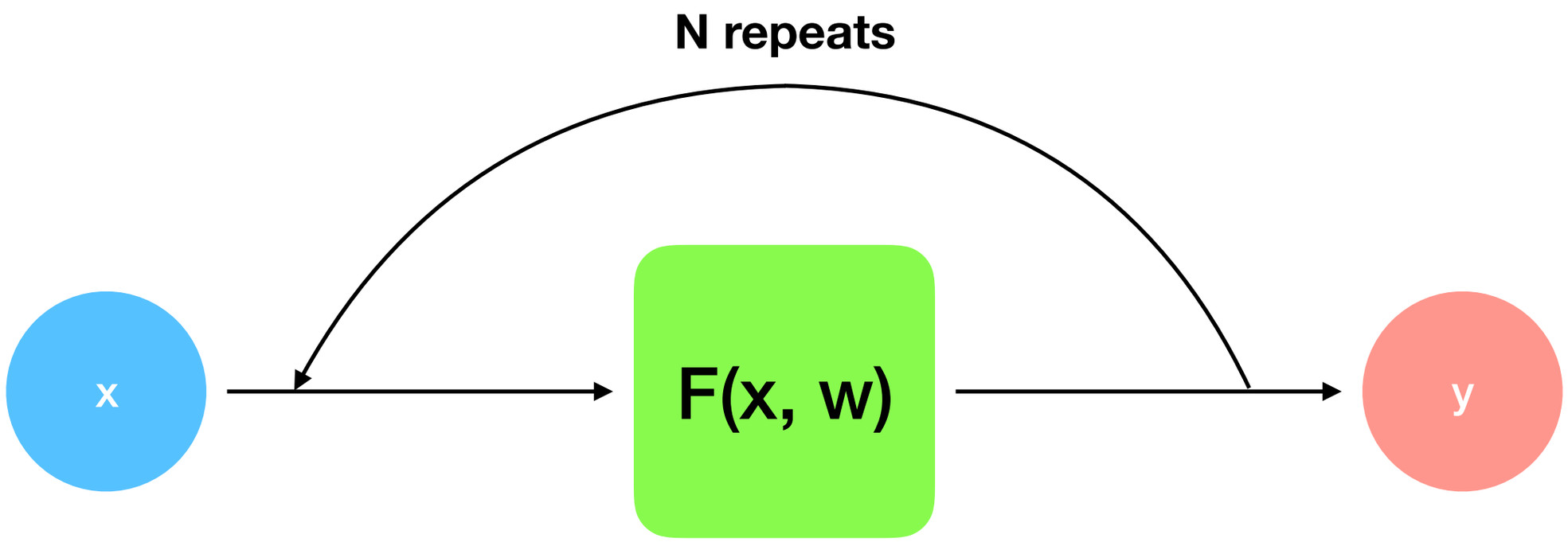


Neural Networks

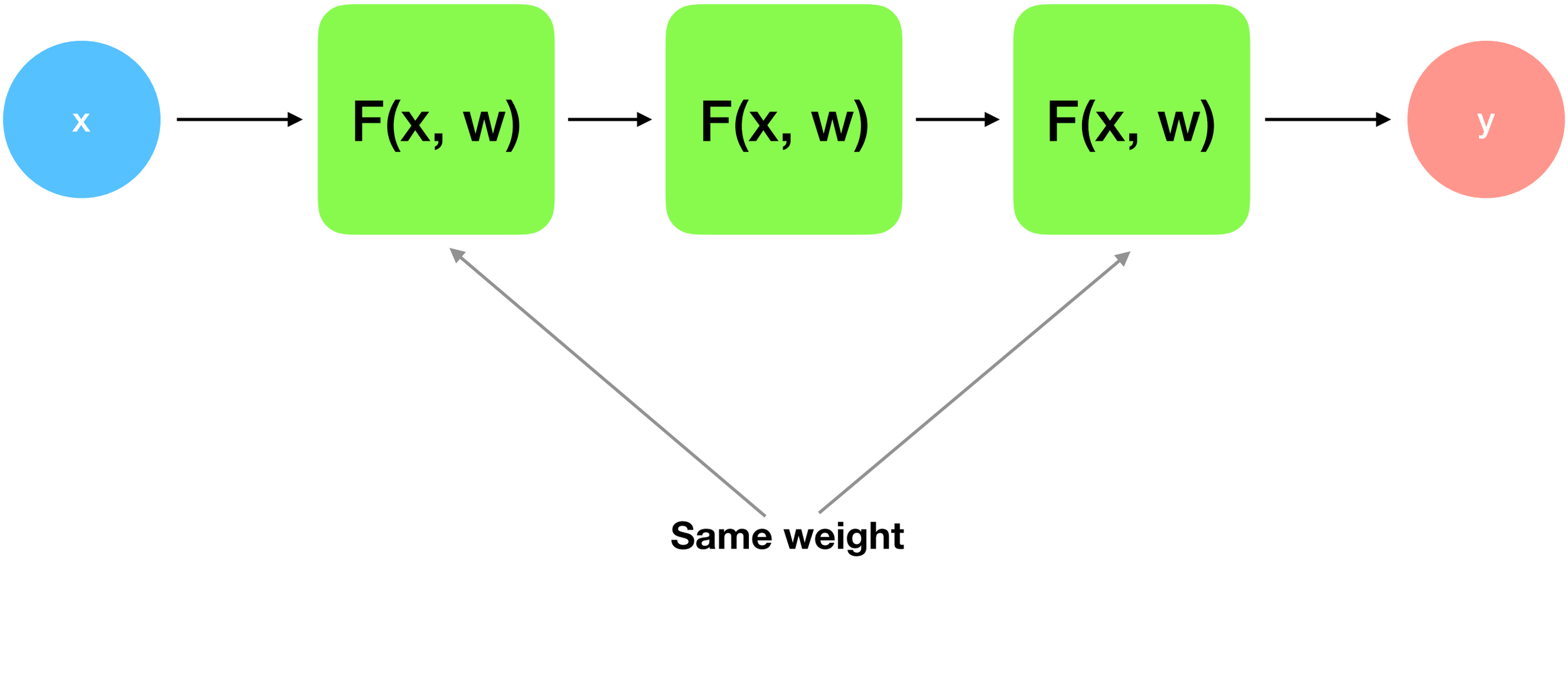


Neural Networks

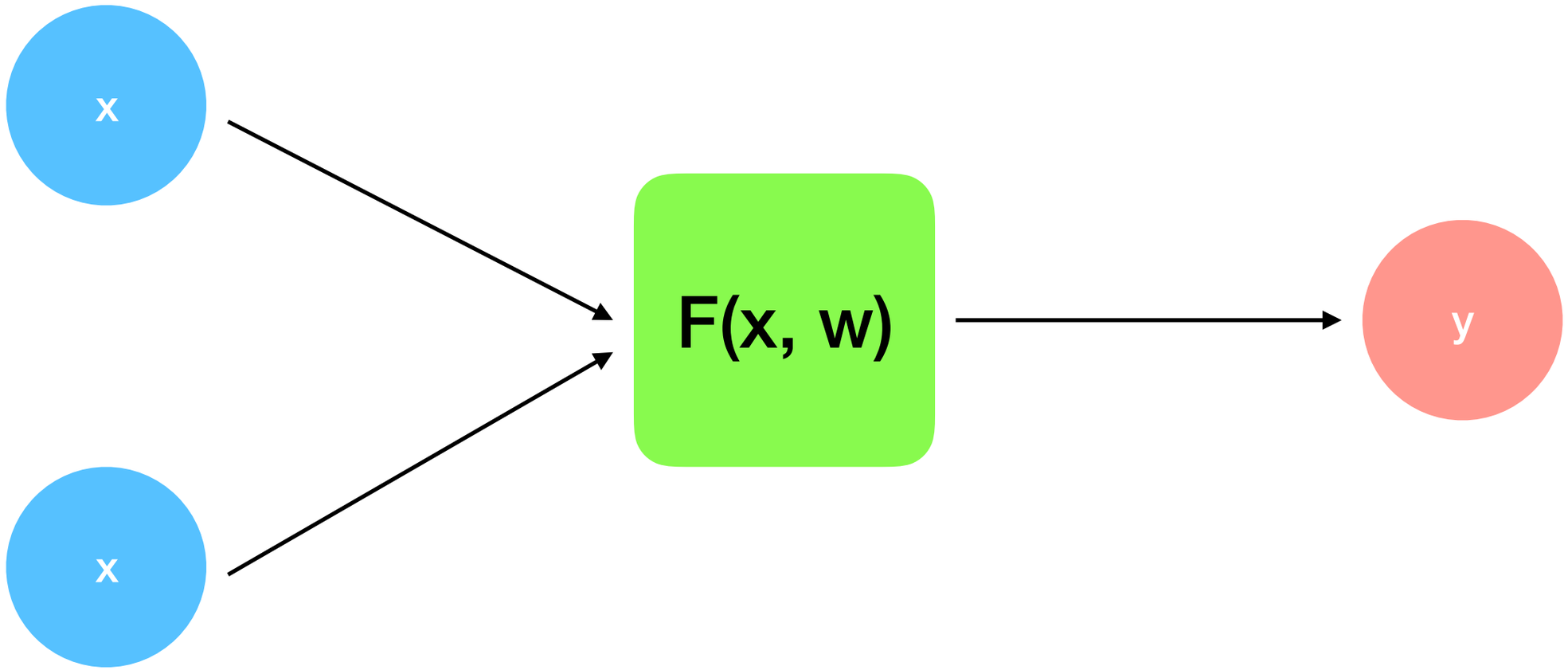
Recurrent



Neural Networks

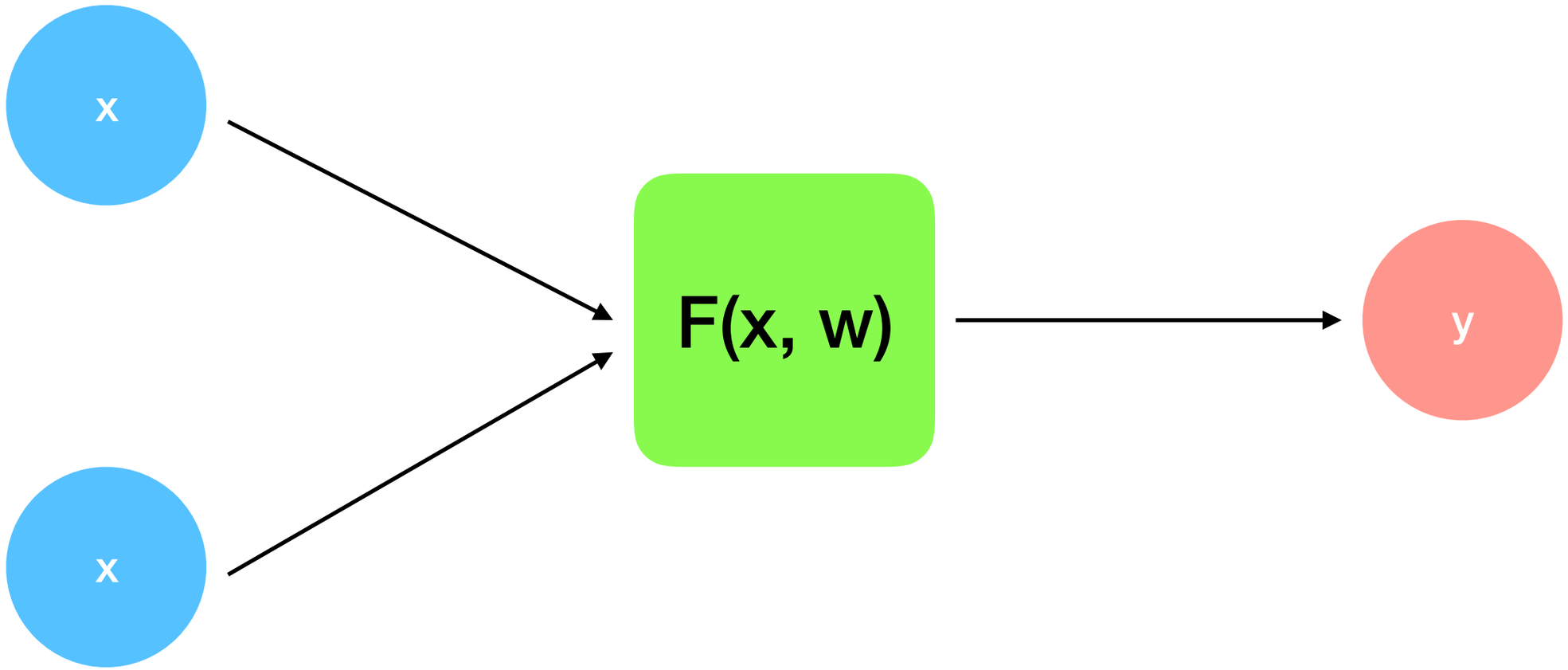


Neural Networks

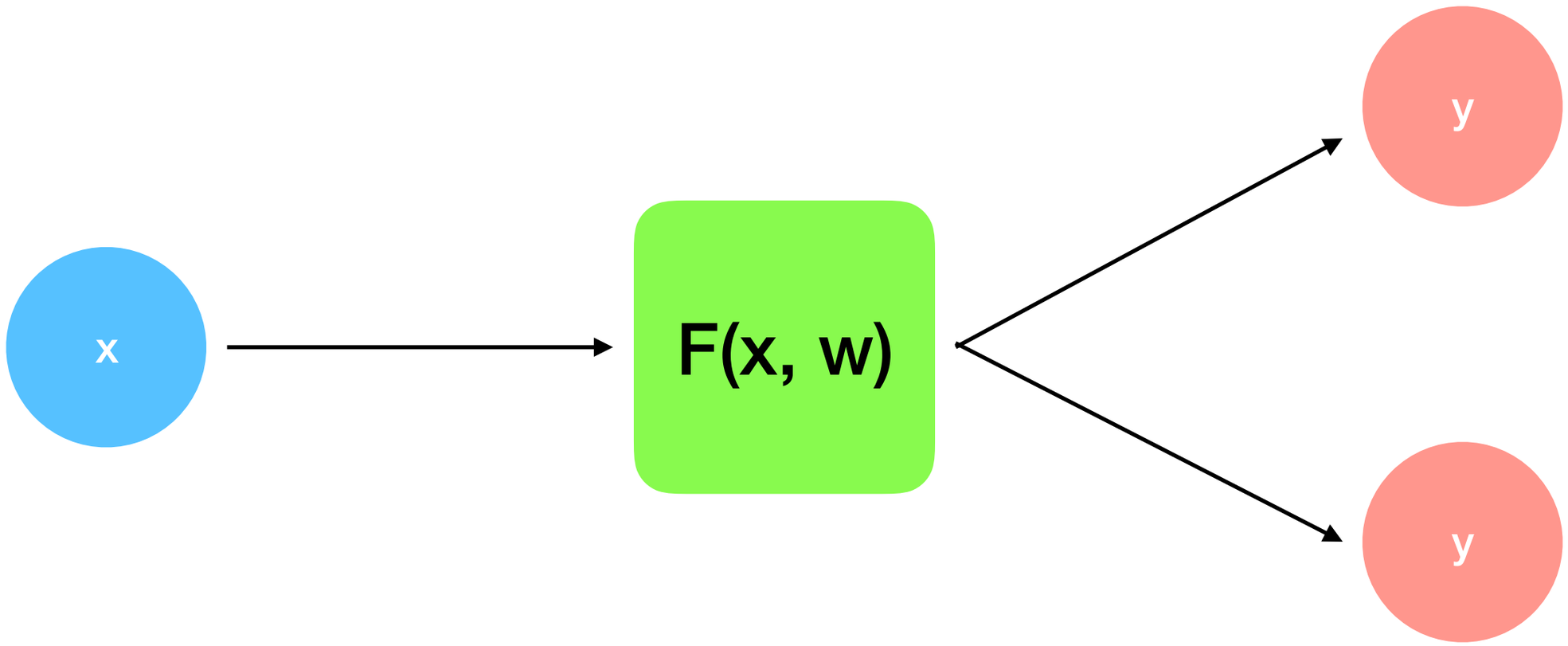


Neural Networks

e.g. qa

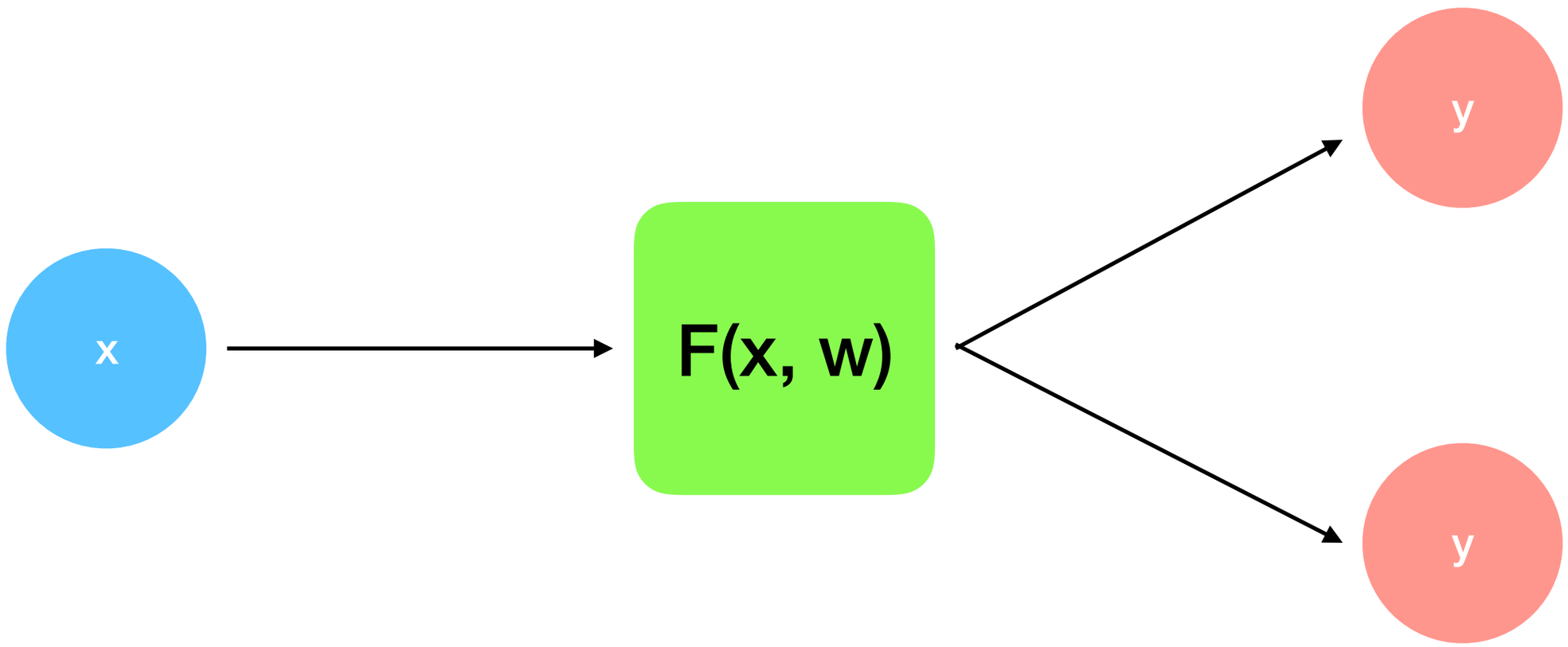


Neural Networks



Neural Networks

e.g. multi-task

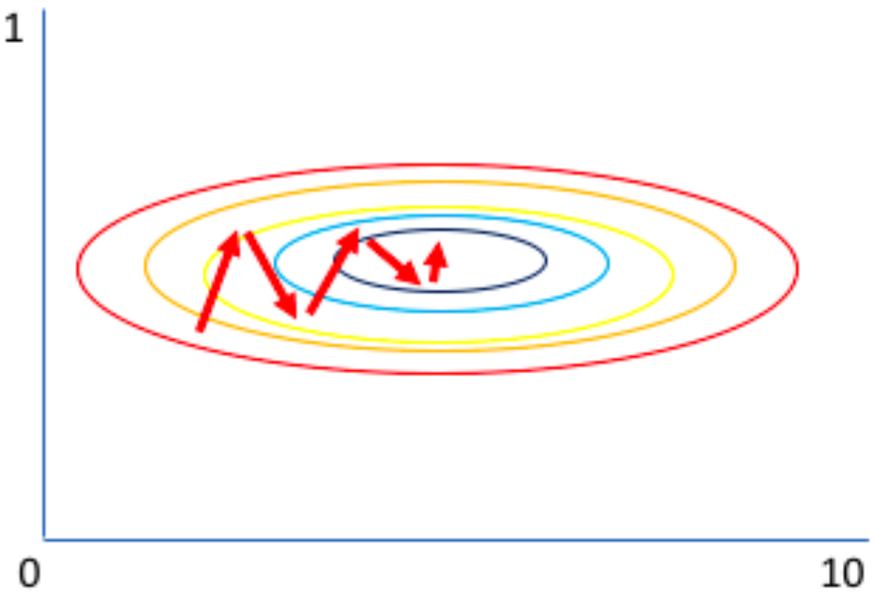


Important things

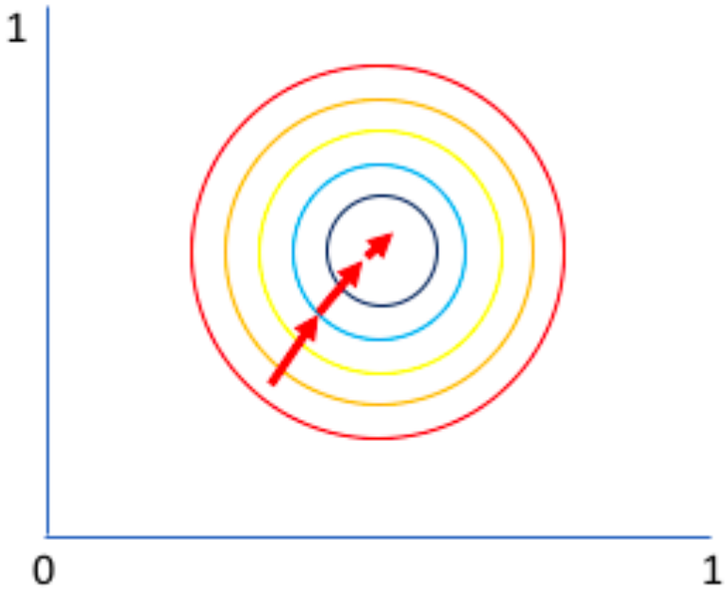
- Don’t use sigmoid as inner activation in MLP
- But then we talk about how you can use sigmoid as inner activation
- Normalize your data
- Early stopping

Important things

Why normalize?

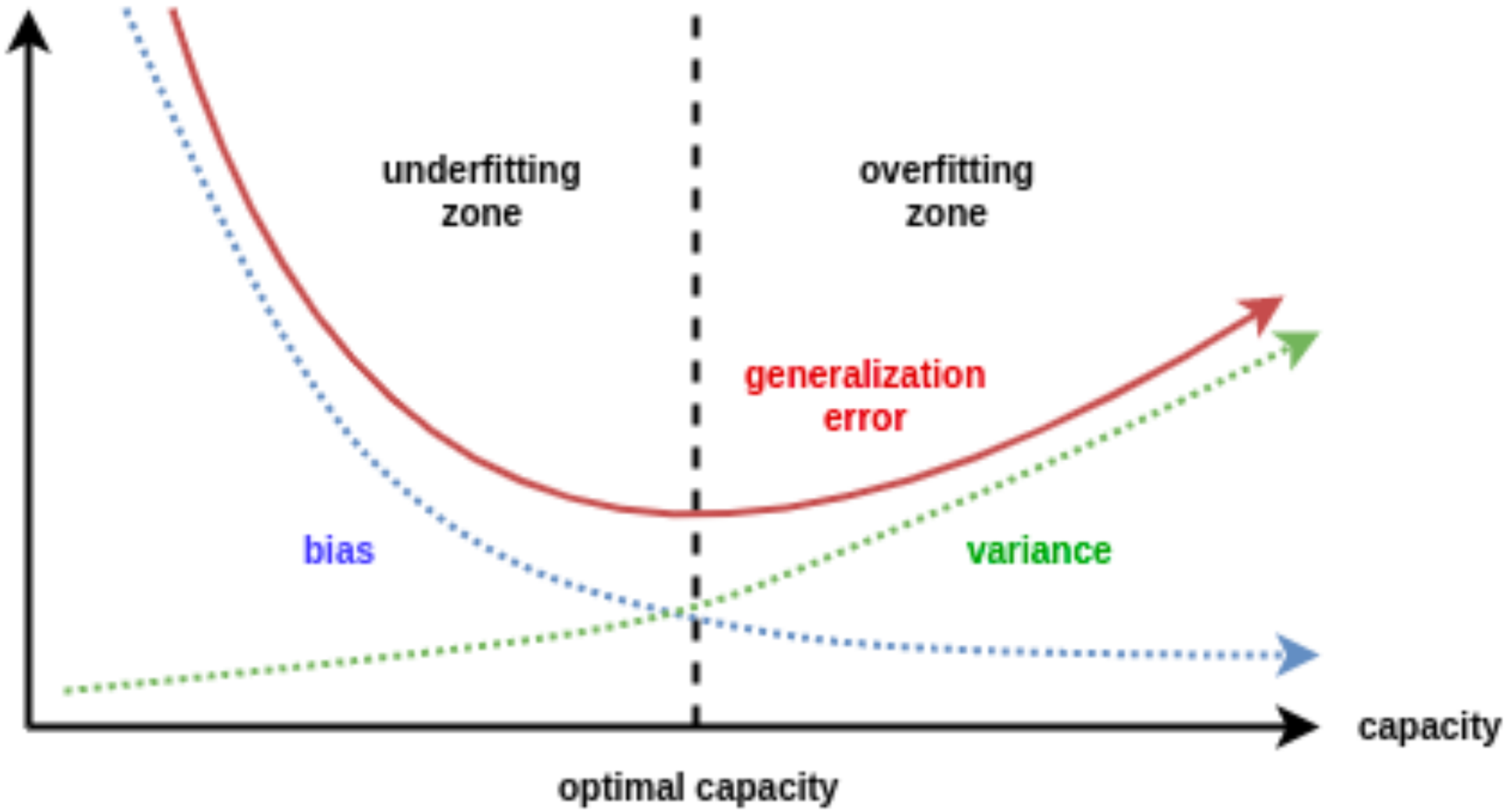


Gradient of larger parameter dominates the update

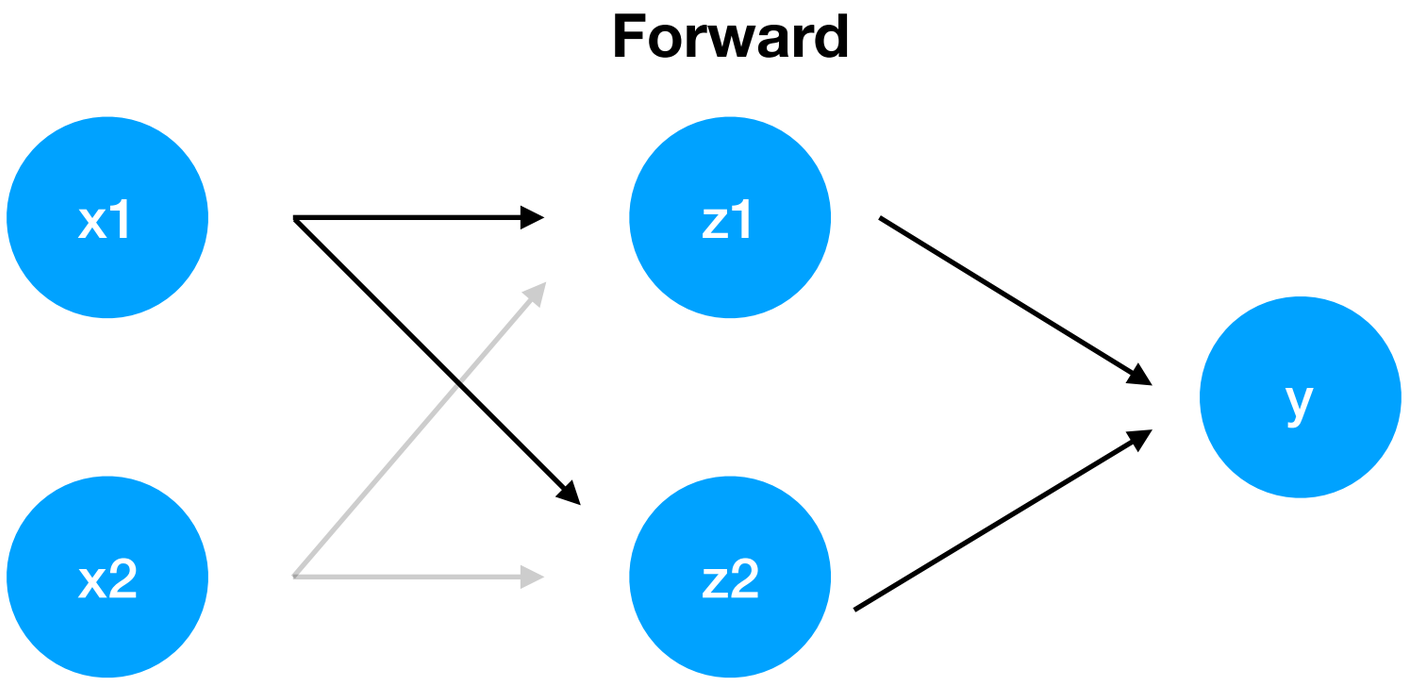


Both parameters can be updated in equal proportions

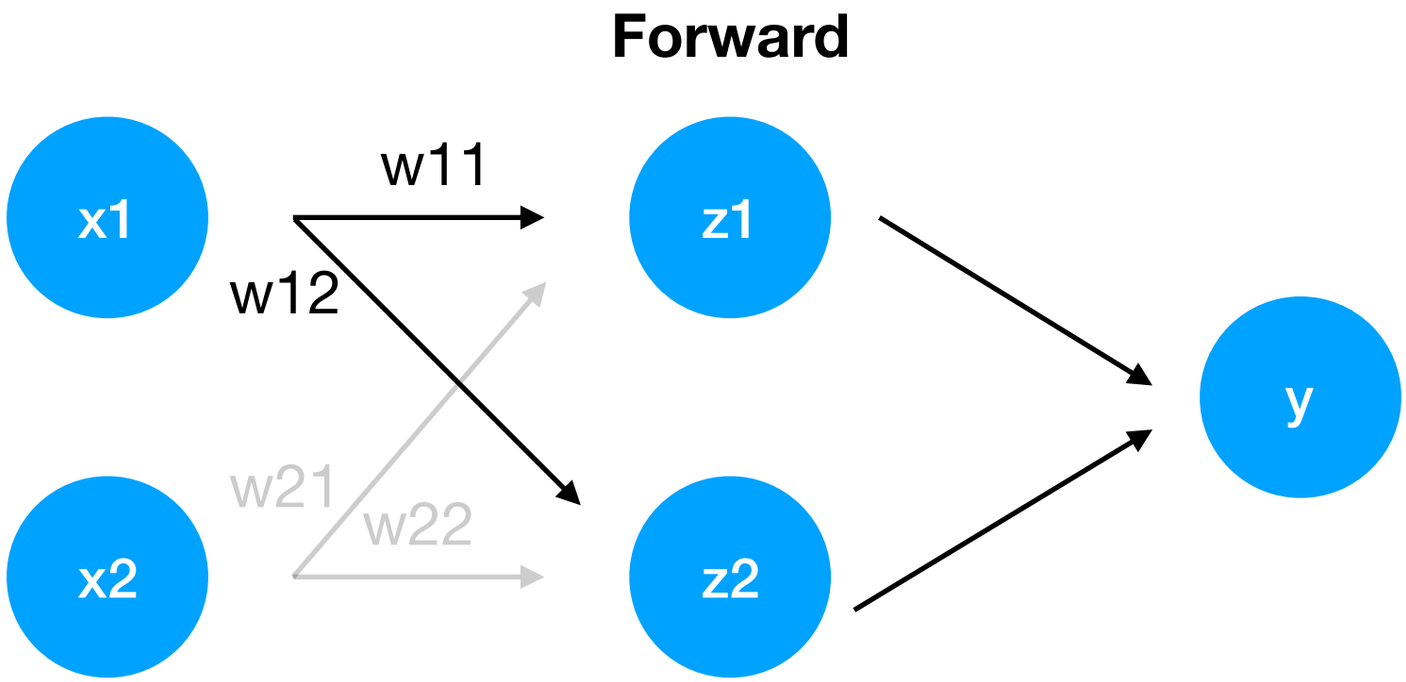
Early Stopping



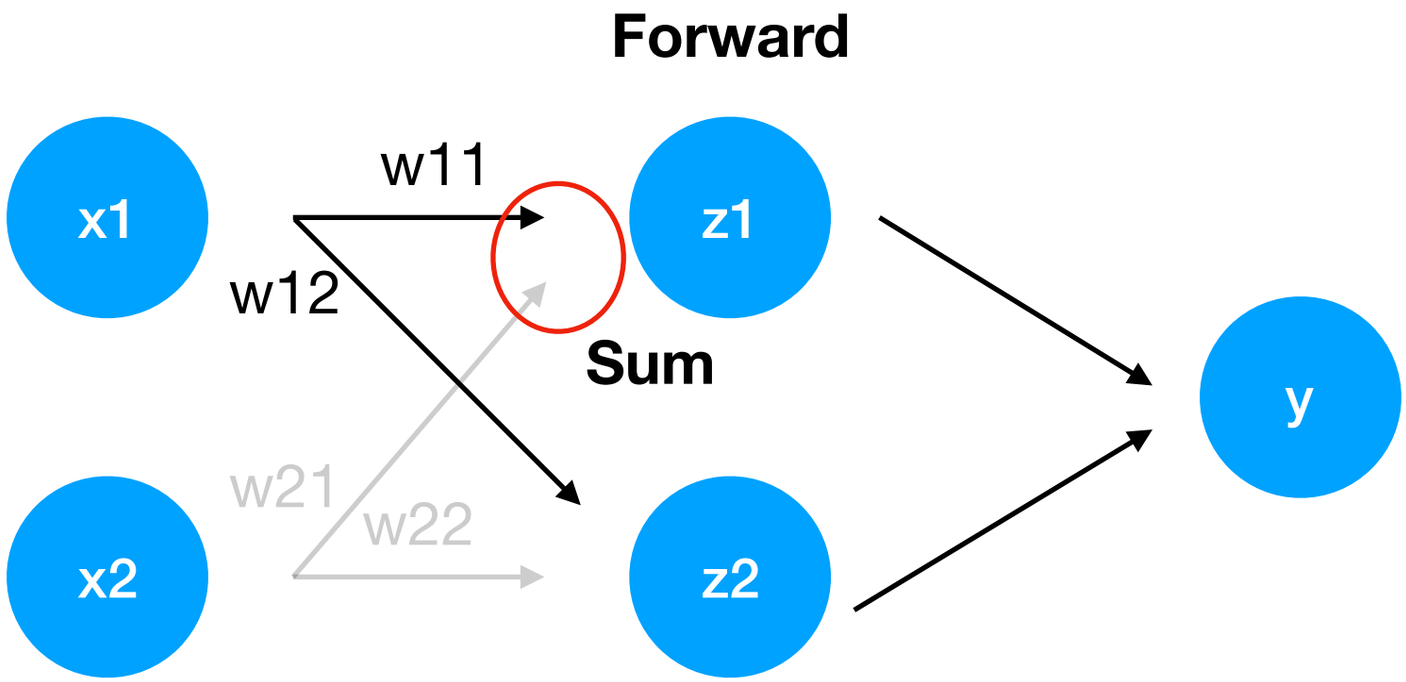
Chain Rule



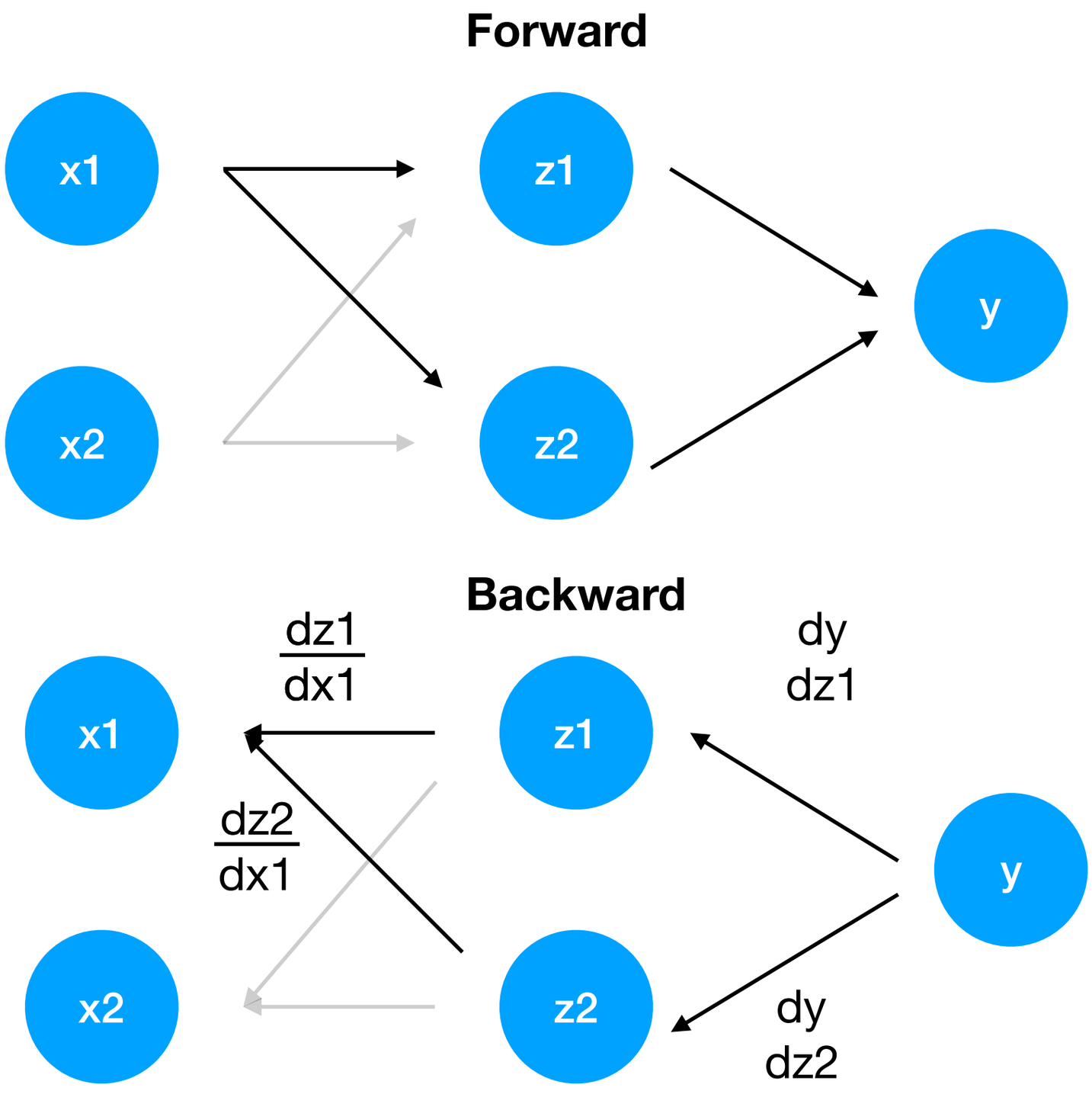
Chain Rule



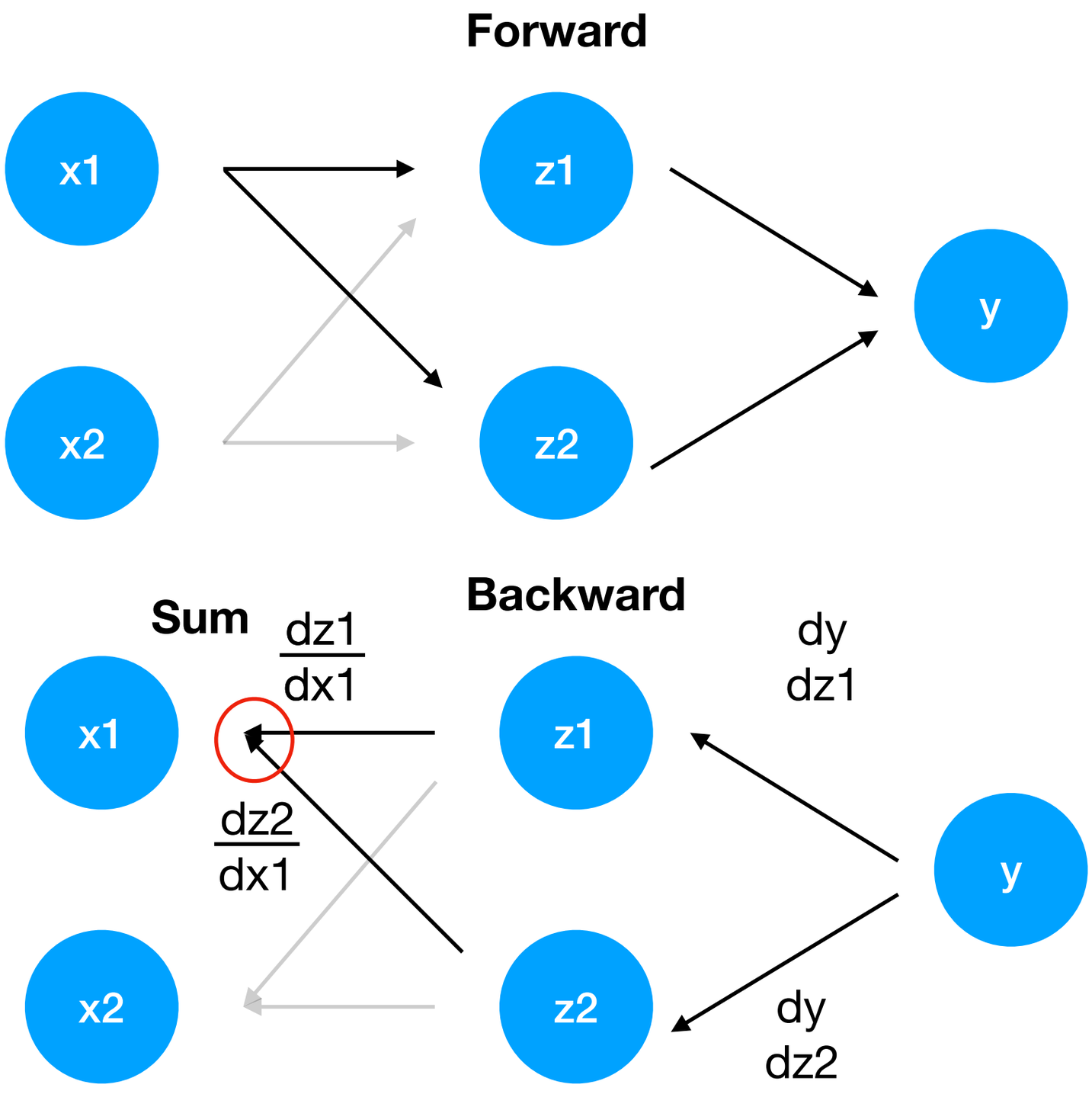
Chain Rule



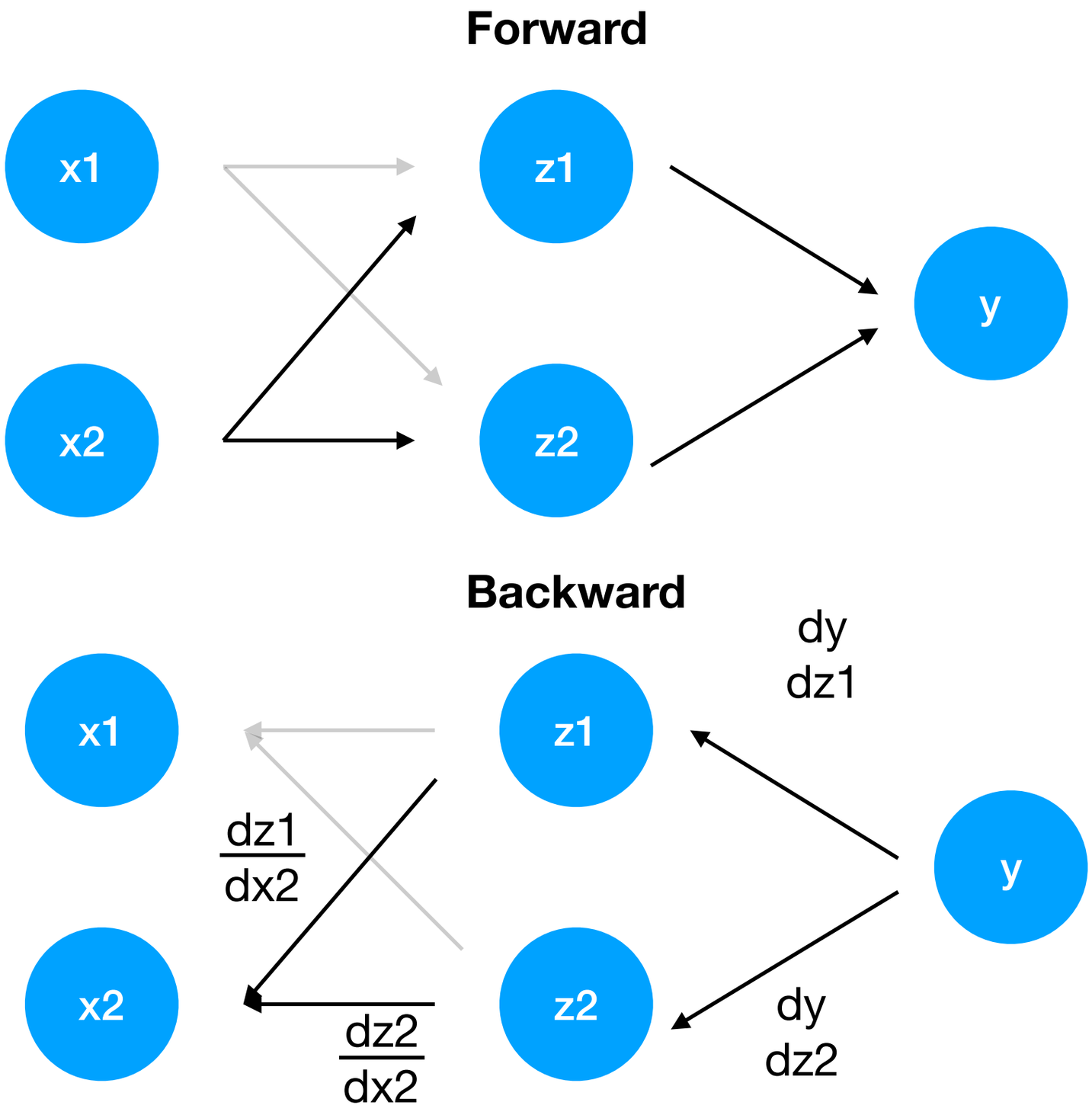
Chain Rule



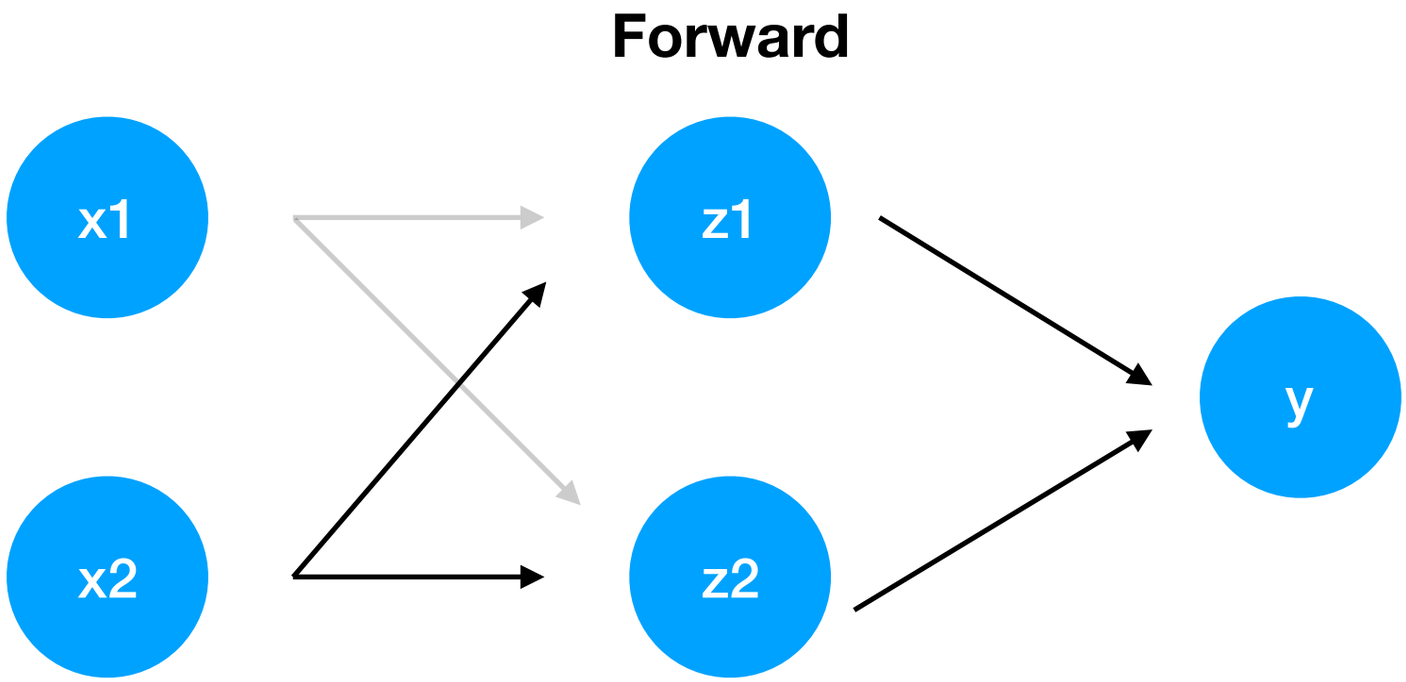
Chain Rule

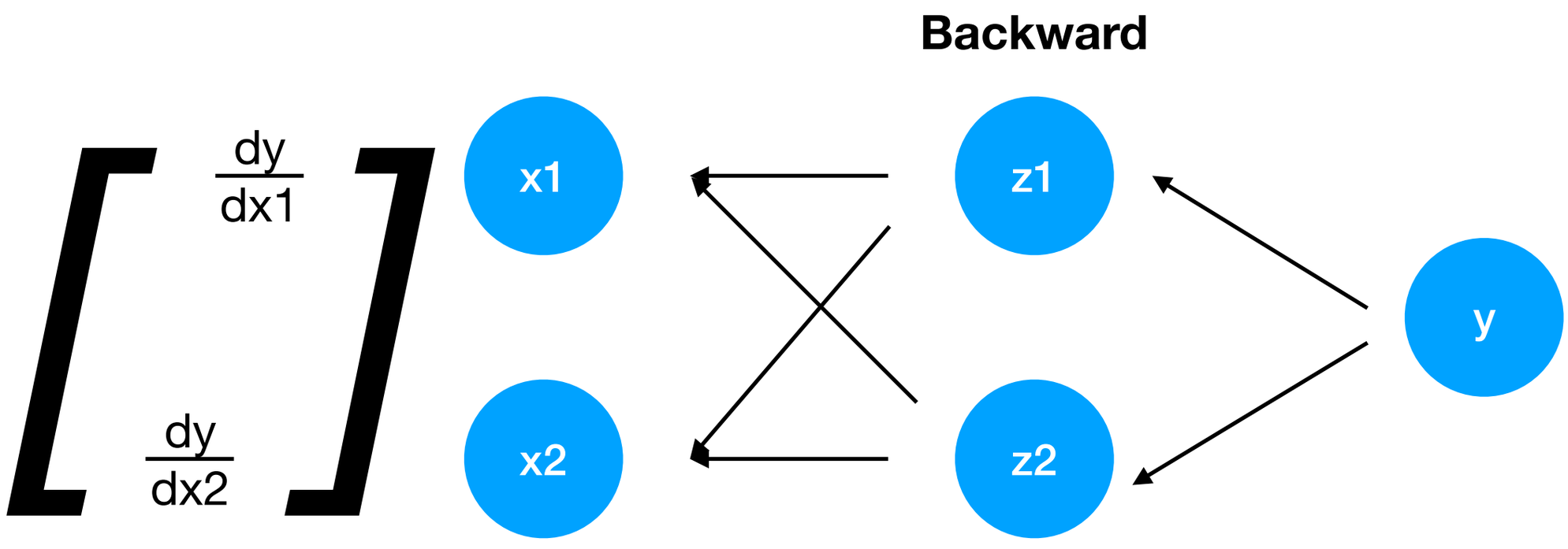


Chain Rule

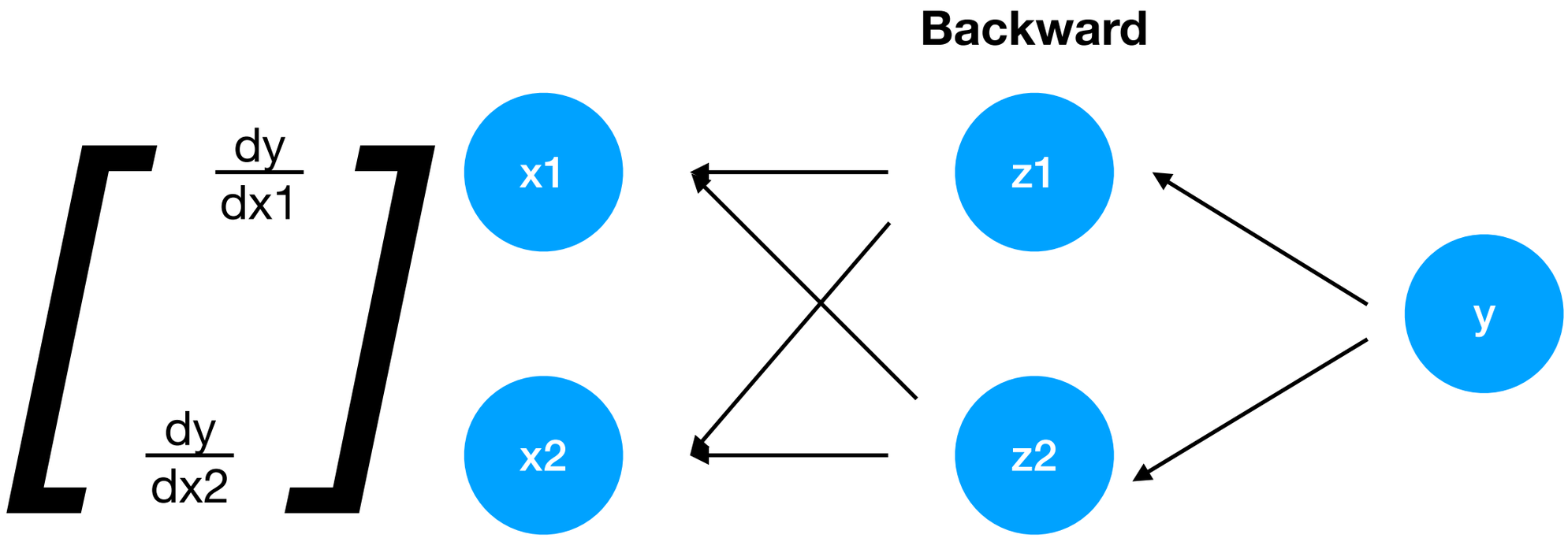

Forward
x1
x2
z1
z2
y
Backward
x1
x2
z1
z2
y
dz1
dx2
dz2
dx2
dy
dz1
dy
dz2

Chain Rule





Chain Rule



dx = np.dot(prev_grad, w.T)

dw = np.dot(x.T, prev_grad)

Homework

- N-layer neural network

Projects

- Chit-chat chatbot
  - Ranking
  - Generative
- Neural machine translation
- NER or another sequence tagging
- Image captioning
- Kaggle competition

Projects

- Transfer learning from scratch
- Paper implementation
  - ULMFiT
  - GPT
  - BERT
  - XLNet
  - Unsupervised Data Augmentation

Projects

- Question answering
- Low-resource Deep Learning
    - Few-shot learning
- Language modeling
- Transformer
    - Extensions
- Sentiment
- Distillation

Projects

- Long text classification
- Dialogue engines
- Summarization
- Transfer learning from metric learning (sentence embeddings)
- Slot filling
- Multi-task
- Your Project

https://paperswithcode.com/area/natural-language-processing

Thanks for your Attention!

Boris Zubarev

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