Deep Learning for Computer Vision

Hao CHEN
hao.chen@inria.fr

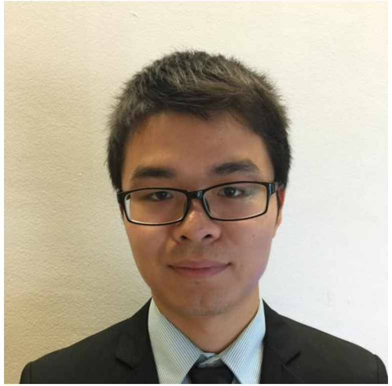
About me

Hao CHEN

Home page: chenhao2345.github.io

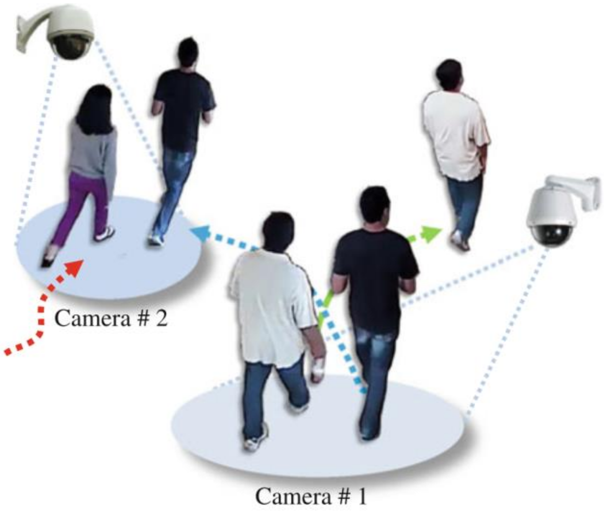
I’m a PhD student at Inria Stars Team.

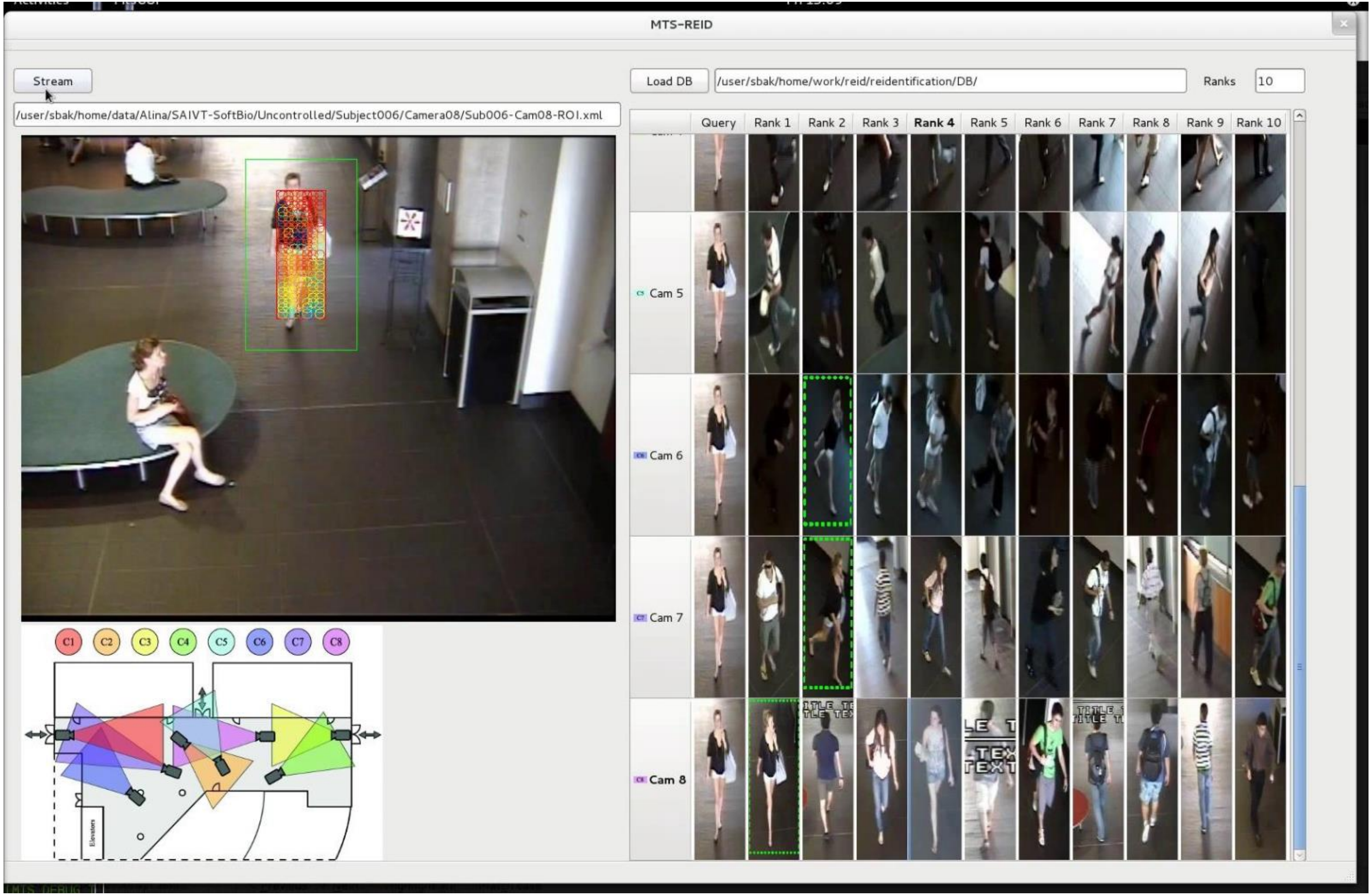
My research topic is “Person Re-identification using Deep Learning”, which can be used in surveillance system projects for smart city, such as “cashierless stores” and “traffic flow modelling”.



Person Re-identification

Matching a probe person against a set of gallery across a network of non-overlapping cameras




MTS-REID
Stream
/user/sbak/home/data/Alina/SAIVT-SoftBio/Uncontrolled/Subject006/Camera08/Sub006-Cam08-ROI.xml
Load DB
/user/sbak/home/work/reid/reidentification/DB/
Ranks
10
Query
Rank 1
Rank 2
Rank 3
Rank 4
Rank 5
Rank 6
Rank 7
Rank 8
Rank 9
Rank 10
Cam 5
Cam 6
Cam 7
Cam 8
C1
C2
C3
C4
C5
C6
C7
C8

Lecture 1: One Artificial Neuron

Objective

In the first lecture, you will see

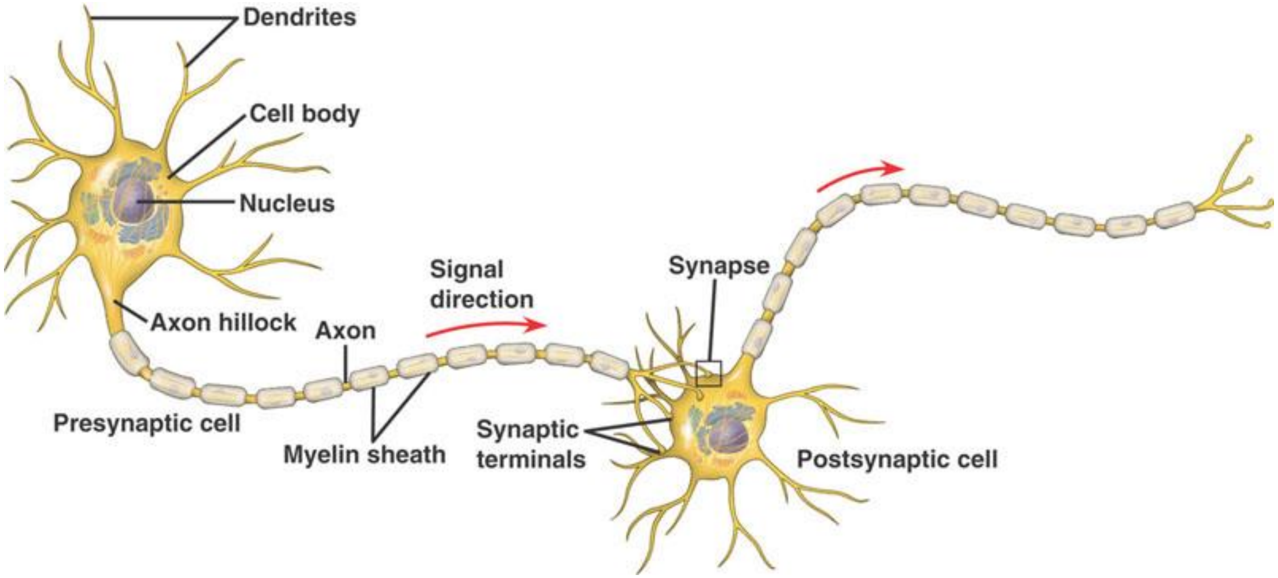
- The difference between a biological neuron and an artificial neuron
- Components of an artificial neuron
- How an artificial neural network works

Outline of Lecture 1

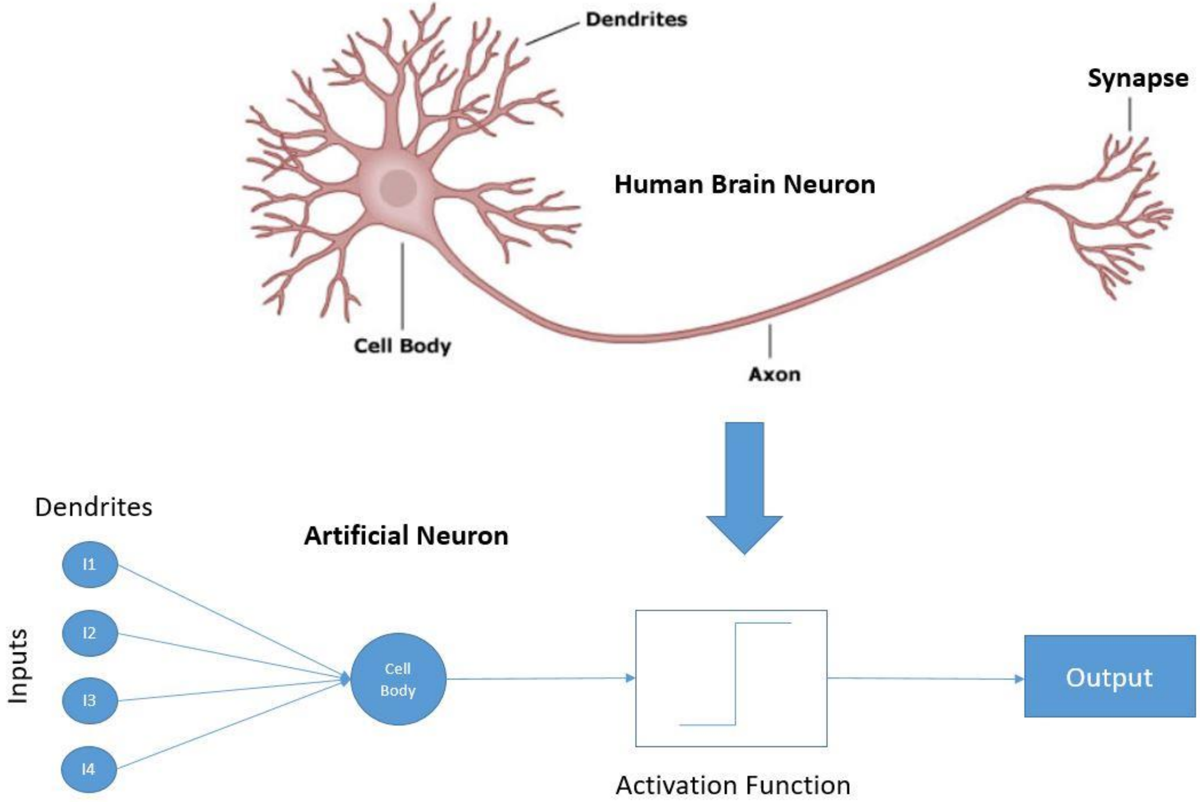
- Artificial neuron
- Logistic regression
- Cost function
- Gradient descent

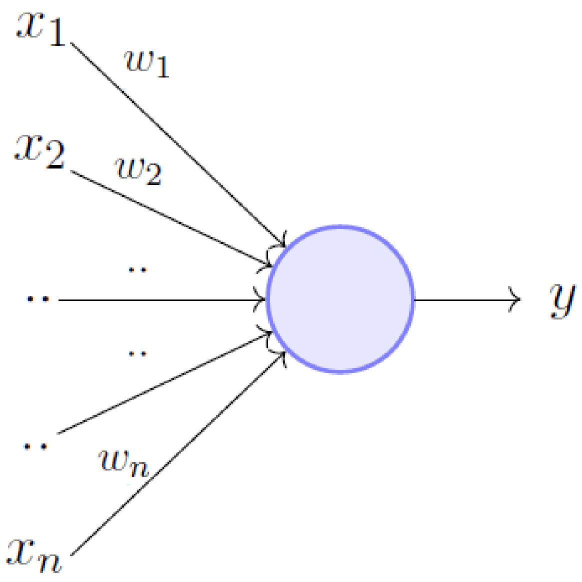
Neuron

Human brain is made of approximately 100 billion nerve cells, called neurons. Each neuron is connected to other neurons. Neurons gather and transmit electrochemical signals to send messages to each other.



Artificial Neuron





$$y = 1 \quad if \sum_{i=1}^{n} w_i * x_i \geq \theta$$
$$= 0 \quad if \sum_{i=1}^{n} w_i * x_i < \theta$$

Rewriting the above,

$$y = 1 \quad if \sum_{i=1}^{n} w_i * x_i - \theta \geq 0$$
$$= 0 \quad if \sum_{i=1}^{n} w_i * x_i - \theta < 0$$

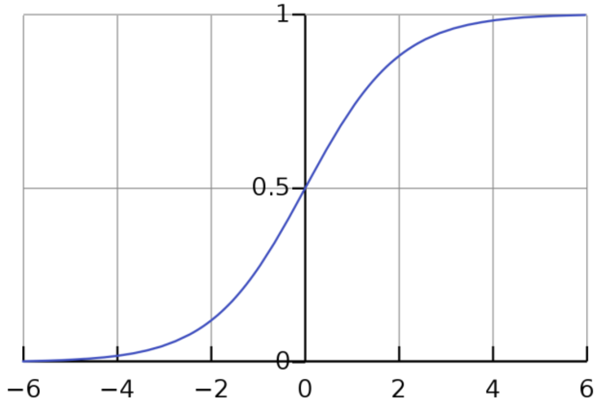
θ is the activation threshold.

In the previous example, the activation function is binary step function (also called Heaviside)

$$\sigma(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

Because it's not continuous at 0, in practice, we usually use sigmoid function (also called logistic)

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



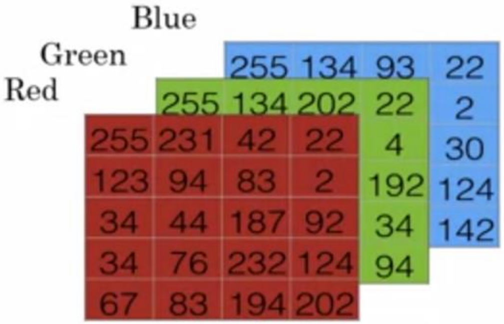
Reminder: image matrix

For image # i

$$y^{(i)} \in \{0, 1\}$$

For m training samples

$$\mathbf{y} = \begin{bmatrix} y^{(1)} & \dots & y^{(m)} \end{bmatrix}$$



$$x^{(i)} = \begin{bmatrix} 255 \\ 231 \\ 42 \\ \vdots \\ 142 \end{bmatrix}$$

$$\mathbf{x} = \begin{bmatrix} x^{(1)} & \dots & x^{(m)} \end{bmatrix} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,m} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,m} \end{bmatrix}$$

Recap

1. Each neuron can be regarded as a linear function.

$$\mathbf{z} = \omega^{\mathbf{T}}\mathbf{x} + b$$

1. Activation function make it possible to learn non-linear complex functional mappings. They introduce non-linear properties to our Network, which is important for solving complex visual tasks.

$$\mathbf{y} = \sigma(\mathbf{z}) = \sigma(\omega^{\mathbf{T}}\mathbf{x} + b)$$

Logistic Regression with Cost Function

From previous slide, we have a logistic regression model.

$$\hat{\mathbf{y}} = \sigma(\omega^{\mathbf{T}}\mathbf{x} + b), where\ \sigma(x) = \frac{1}{1+e^{-x}}$$

Given m samples,

$$\mathbf{x} = \begin{bmatrix} x^{(1)} & \dots & x^{(m)} \end{bmatrix}$$

$$\mathbf{y} = \begin{bmatrix} y^{(1)} & \dots & y^{(m)} \end{bmatrix}$$

We want to minimize the distance between the prediction and the ground truth,

$$\hat{y}^{(i)} \approx y^{(i)}$$

Logistic Regression with Cost Function

Define the distance with a loss function, for example, one half a square error

$$L(\hat{y}, y) = \frac{1}{2}(\hat{y} - y)^2$$

However, people don’t usually use this to learn parameters. In practice, we usually use the cross entropy loss to maximize the likelihood of classifying the input data correctly.

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

The cost function on the m samples will be

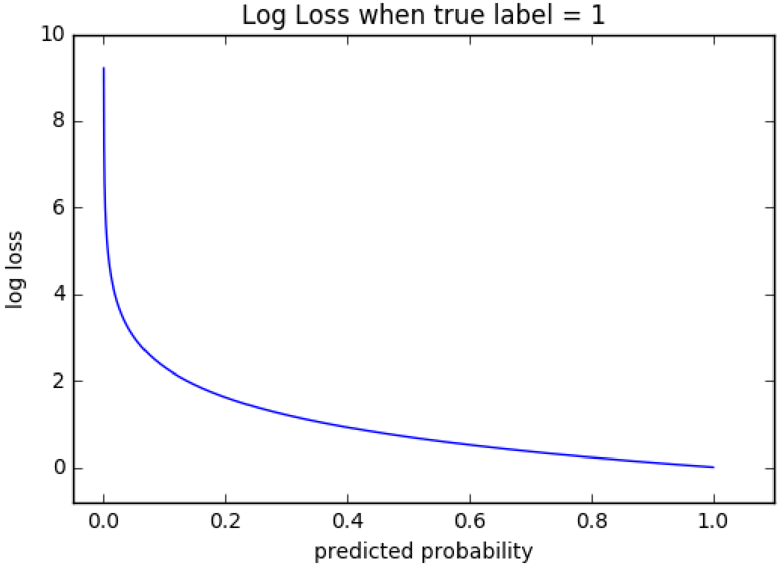
$$J(\omega, b) = \frac{1}{m} \sum_{i=1}^{m} L(\hat{y}, y)$$

Cross Entropy

Let’s look deeper into the cross entropy loss.

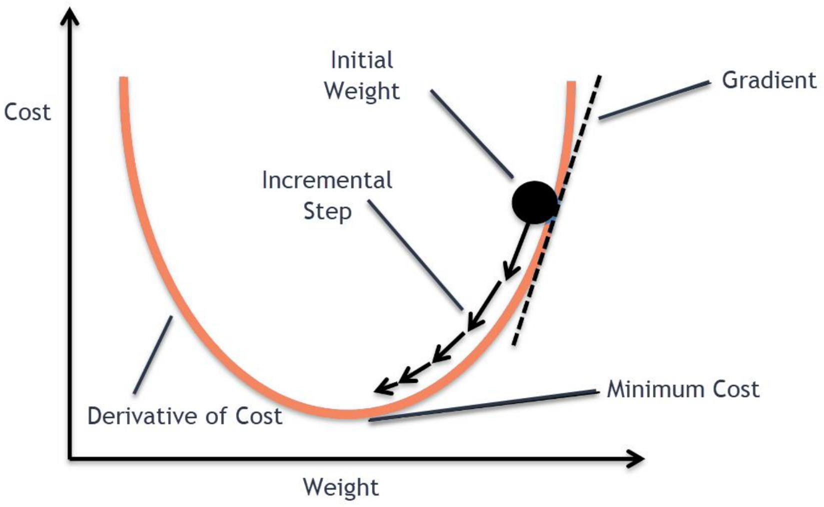
$$L(\hat{y}, y) = \begin{cases} -log(1-\hat{y}),\ if\ y = 0 \\ -log\hat{y},\ if\ y = 1 \end{cases}$$

When your prediction get further to the true label, your loss will grow exponentially.



Gradient Descent

Our objective is to find ω, b that minimize $J(\omega, b) = \frac{1}{m}\sum_{i=1}^{m} L(\hat{y}, y)$



Repeat $\begin{cases} \omega = \omega - \alpha \frac{\partial J(\omega,b)}{\partial \omega} \\ b = b - \alpha \frac{\partial J(\omega,b)}{\partial b} \end{cases}$

Reminder: $\frac{\partial J(\omega,b)}{\partial \omega}$ is the partial derivative of the cost with respect to ω, which gives the slope of the tangent line to the graph of the function at that point.

Learning rate decay

In the previous slide, α is called learning rate. To find the minimal, we need to gradually decrease the learning rate.

For example,

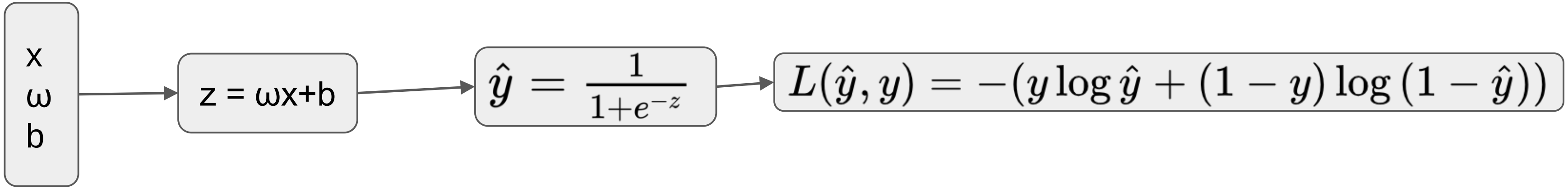
1. Multi-step learning rate

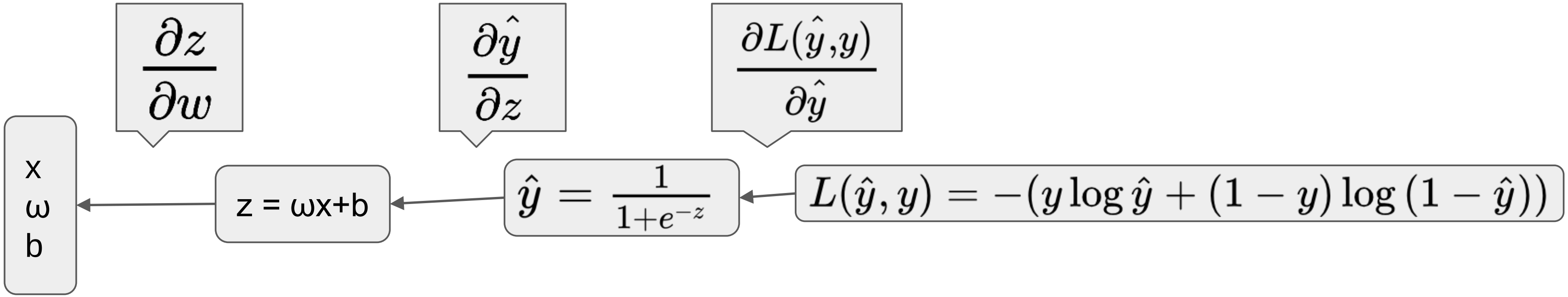
$$\alpha = \begin{cases} \alpha_0 & \text{if } \#epoch < 100 \\ 0.1 * \alpha_0 & \text{if } 100 < \#epoch < 200 \\ 0.01 * \alpha_0 & \text{if } 200 < \#epoch < 300 \end{cases}$$

1. Exponential learning rate

$$\alpha = \alpha_0 * decay\_rate^{\#epoch}$$

Let's put them together





ω get updated → $\omega = \omega - \alpha \frac{\partial L(\omega,b)}{\partial \omega}$

Derivative results

$$\frac{\partial L}{\partial \hat{y}} = \frac{\hat{y}-y}{\hat{y}(1-\hat{y})}$$

$$\frac{\partial \hat{y}}{\partial z} = \hat{y}(1-\hat{y})$$

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

$$\boxed{\frac{\partial L}{\partial w} = \frac{\partial L}{\partial \hat{y}}\frac{\partial \hat{y}}{\partial z}\frac{\partial z}{\partial w} = x(\hat{y}-y)}$$

Conclusion

1. An artificial neuron is composed by a linear transformation and an activation function.
2. To adjust parameters in an artificial neuron, we need to define a cost function. By decreasing the cost function with gradient descent, the parameters get updated step by step.

Practice-1

Estimate coefficients for a step function with logistic regression. You will need to implement:

1. Sigmoid function
2. Cross-entropy loss
3. Gradient for back propagation