Introduction to Neural Networks

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January 30, 2020

Outline

Introduction

Apparently easy problems that are difficult

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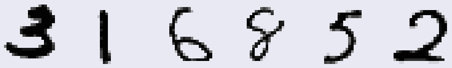
Handwritten numbers recognition



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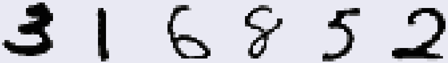

Cat or dog

Apparently easy problems that are difficult

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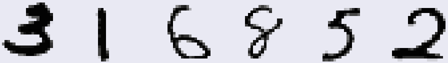
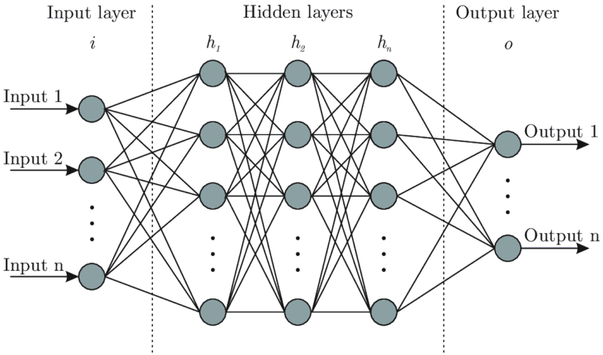


Cat or dog

How can we program a computer to perform these tasks?

What is a neural network?



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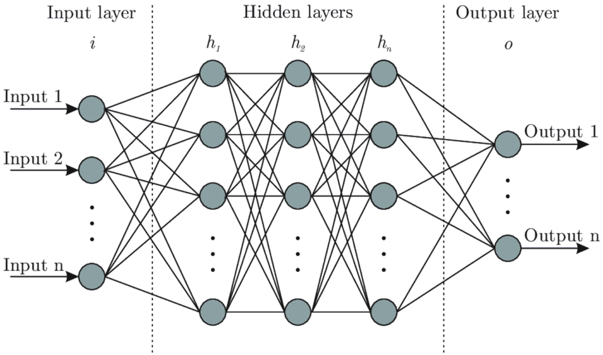

We can think of different pairs of input and output:

- Pixels in an image → Number that the image represents.
- State of a chess game → What should be the next move.
- Text → Audio of a person reading that text.

Single neuron example

Processing the input

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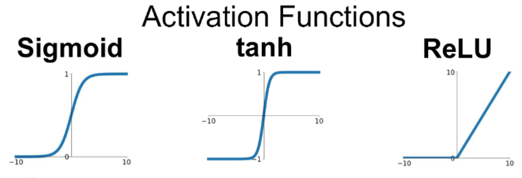
- The input is moved to the neuron by multiplying by a weight **w** and adding a bias **b**.
- The obtained value $\mathbf{x} \cdot \mathbf{w} + \mathbf{b}$ is evaluated by an activation function. This simulates the firing or not of the neuron.



$\sigma(x) = \frac{1}{1+e^{-x}}$ $\tanh(x)$ $\max(0, x)$

The obtained output will be Activation$(x \cdot w + b)$

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- Correction of the parameters $\rightarrow$ Backpropagation

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- We can define a function as our criterion of how far is the **output** from the true **target** (loss function).

$$\mathrm{MSELoss}(\mathrm{output}, \mathrm{target}) = (\mathrm{output} - \mathrm{target})^2 \tag{1}$$

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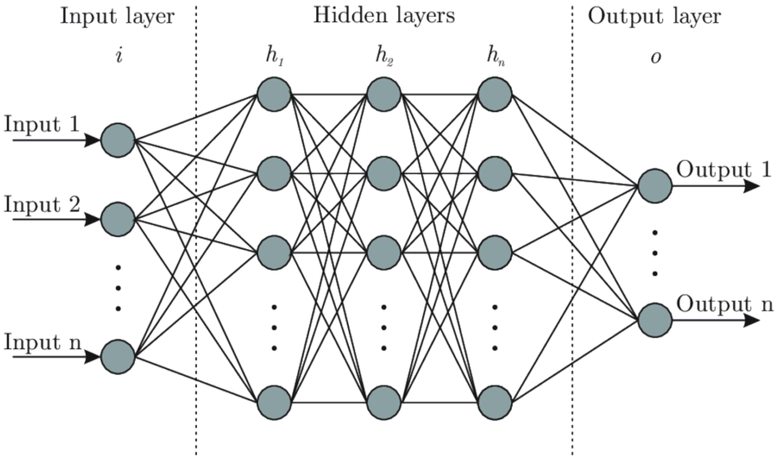
- We need a method for using the loss (L) obtained through the network to change the parameters in such a way that reduces the loss.
- $\Delta L \approx \frac{\partial L}{\partial w}\Delta w + \frac{\partial L}{\partial b}\Delta b \rightarrow \Delta w = -\eta \frac{\partial L}{\partial w}, \Delta b = -\eta \frac{\partial L}{\partial b}$
  $\eta \equiv$ learning rate

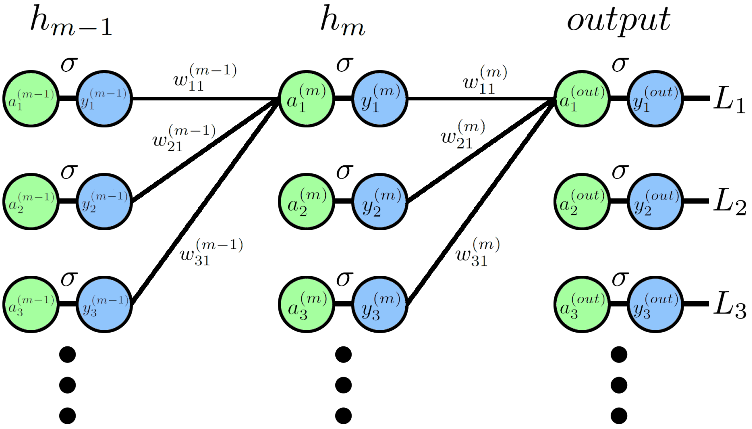
Neuron with PyTorch

Hidden layers

Structure of a neural network



Correcting the parameters of the neural network



Correcting $w_{11}^{(m)}$:

- $$\frac{\partial L_1}{\partial w_{11}^{(m)}} = \frac{\partial L_1}{\partial y_1^{(out)}} \frac{\partial y_1^{(out)}}{\partial a_1^{(out)}} \frac{\partial a_1^{(out)}}{\partial w_{11}^{(m)}}$$

Backpropagation example

For every layer k:

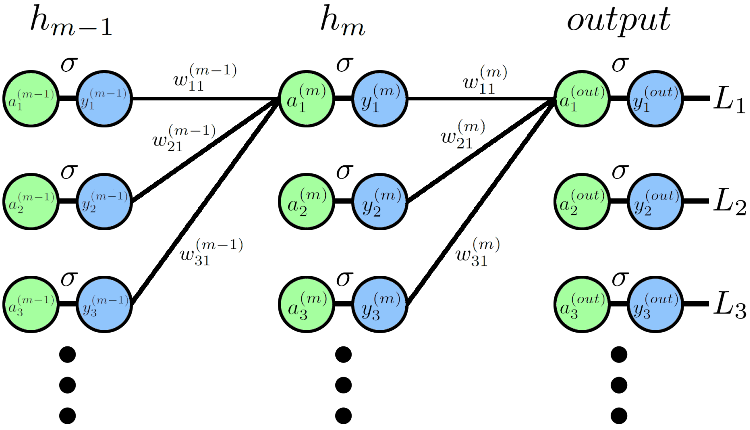
- $a_j^{(k)} = \sum_i w_{ij}^{(k)} y_i^{(k-1)} + b_j^{(k)}$, $y_j^{(k)} = \sigma(a_j^{(k)})$.
- $\sigma(x) \equiv$activation function.

Thus, considering MSE as our loss function ($L = \sum_i (y_i^{(out)} - target_i)^2$):

- $\frac{\partial L_1}{\partial y_1^{(out)}} = 2(y_i^{(out)} - target_i)$
- $\frac{\partial y_1^{(out)}}{\partial a_1^{(out)}} = \sigma'(a_1^{(out)}) = \sigma(a_1^{(out)})(1 - \sigma(a_1^{(out)}))$ (For the sigmoid activation function)
- $\frac{\partial a_1^{(out)}}{\partial w_{11}^{(m)}} = y_1^{(m-1)}$

We can obtain the corrections $\Delta w_{ij}^{(m)} = -\eta \frac{\partial L_j}{\partial w_{ij}^{(m)}}$ for all the weights after the last hidden layer.

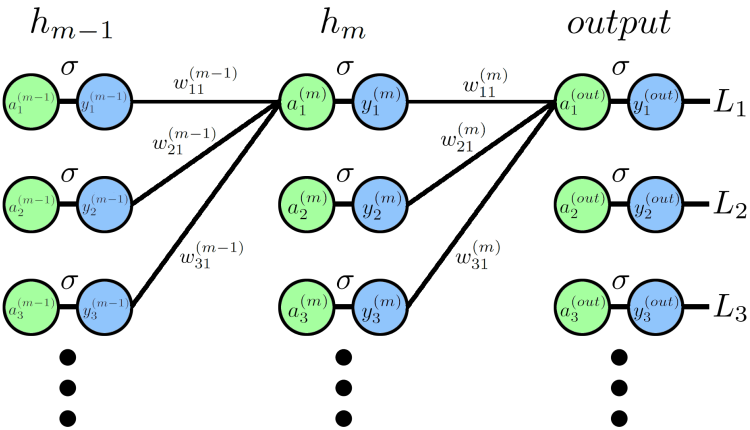
Correcting the parameters of the neural network



Correcting $w_{11}^{(m-1)}$:

- $$\frac{\partial L_1}{\partial w_{11}^{(m-1)}} = \frac{\partial L_1}{\partial y_1^{(out)}} \frac{\partial y_1^{(out)}}{\partial a_1^{(out)}} \frac{\partial a_1^{(out)}}{\partial y_1^{(m)}} \frac{\partial y_1^{(m)}}{\partial a_1^{(m)}} \frac{\partial a_1^{(m)}}{\partial w_{11}^{(m-1)}}$$

Correcting the parameters of the neural network

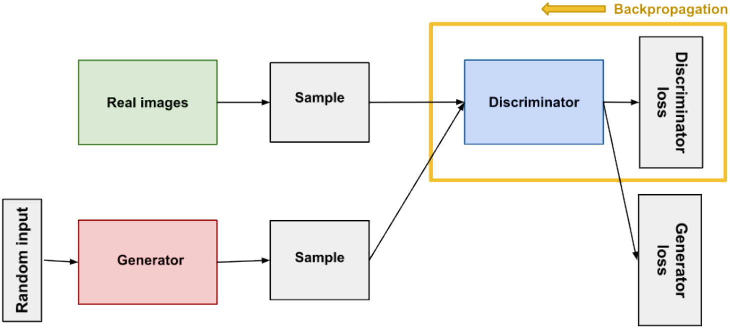


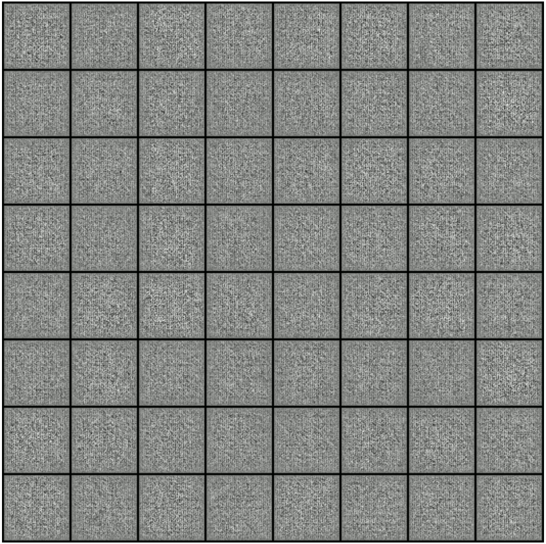
Obtaining the corrections for the parameters of the neural network requires simple calculations.

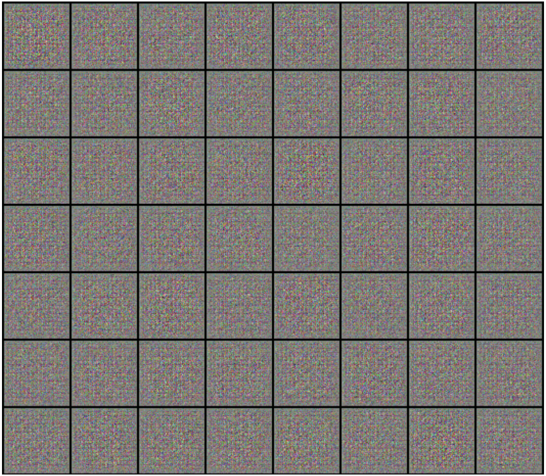
MNIST image recognition

Generative Adversarial Networks (GANs)

GANs structure







Summary

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- We have learned the very basics of neural networks.

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- We have seen the basics of how to use PyTorch to define perform the training of a neural network.

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Other examples

- We have learned the very basics of neural networks.
- We have seen the basics of how to use PyTorch to define perform the training of a neural network.
- Neural networks can have different forms that allows them to perform different tasks.

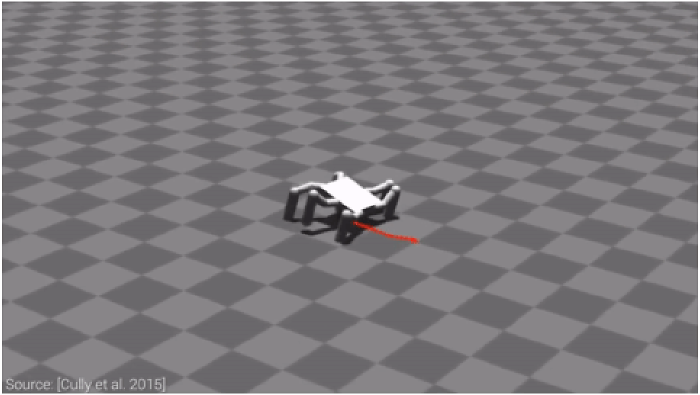
Go

Configuration and strength[62]

Versions	Hardware	Elo rating	Date	Results
AlphaGo Fan	176 GPUs,[53] distributed	3,144[52]	Oct 2015	5:0 against Fan Hui
AlphaGo Lee	48 TPUs,[53] distributed	3,739[52]	Mar 2016	4:1 against Lee Sedol
AlphaGo Master	4 TPUs,[53] single machine	4,858[52]	May 2017	60:0 against professional players; Future of Go Summit
AlphaGo Zero	4 TPUs,[53] single machine	5,185[52]	Oct 2017	100:0 against AlphaGo Lee 89:11 against AlphaGo Master
AlphaZero	4 TPUs, single machine	N/A	Dec 2017	60:40 against AlphaGo Zero

Silver, D. et al. "Mastering the game of go without human knowledge." Nature, 550(7676), 354-359.

Teaching robots how to walk



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Thanks for your attention!