Machine Learning

IMPORTANT

> There is more information than needed for the exam on here, because I wanted to make my take on an introduction to AI, doing it my way. Be careful with that. I tried to summarize what is important for the exam whenever there is a TDLR (Too Long Didn't Read). Read this with the slides on the side, to compare information. This serves as an explanation for the theory. Keep in mind that the long practice exercise is a Decision Tree. If you have questions/suggestion/critiques write to me. Un beso. - *Tomi*

Explicit instructions are at the core of nearly every algorithm that we use, if we want a loop that generates the Fibonacci numbers, we know exactly how to do it. We give the computer the instructions in the form of python code and it gives out exactly what we asked.

This is not the case in Machine Learning, the instructions that these algorithms use are not explicit, the algorithms themselves learn them.

They improve their performance after observations about the world, that is, they improve by using data. They can evaluate their performance at a given time and change their internal parameters accordingly.

There are several reasons for using Machine Learning (ML from now on):

- Unexpected future situations; capacity of generalization
- Manual knowledge coding: hard and time consuming Task
- Adaptation
- When there is no solving method

There are three main types of learning, they are usually called paradigms:

- Supervised

  > with a teacher (learning from pairs of input-output, the desired outcomes)

- Unsupervised

  > without a teacher (only learning from inputs)

- Reinforcement

  > agent acting, there are reward/penalties for actions executed

All of these will be explained. We are also going to look at Neural Learning, which it is not a learning paradigm. It is a type of model architecture, it indicates how an AI model is build, not how it learns. This architecture can be used in the main tree learning paradigms.

The opposite concept of Neural Learning is symbolic learning, another model "architecture" which we are going to look also (e.g. decision trees).

Explanation-based Learning (EBL)

To describe ML models we also need to take into account the existence of prior knowledge. The main type of training that uses this concept to the maximum is Explanation-based Learning.

These models require a perfectly defined domain. We can take chess as an example, where there are perfectly define rules and game states, there is no ambiguity. We call it a perfect o complete domain, a domain that has all information needed to answer any question regarding the domain.

An EBL system can take a perfect domain, and with just a single example of a state with a label (e.g. "forced loss of black queen in two moves"), deduce all the features or characteristics that that particular state has.

We only need 4 types of information to create an EBL system:

1. The set of all possible conclusions (e.g. all game states)
2. Axioms about the domain (e.g. the rules of chess)
3. Training examples (e.g. examples of a *jaque mate*)
4. Criteria for determining which features in the domain are efficiently recognizable. Which features are directly detectable by sensors (e.g. if a white piece can "kill" a black one)

These models are notably used in NLP, to form a grammar/syntax tree (i.e. what is the Subject and the Predicate of a sentence). They can perform the syntax parsing of a language.

TLDR:

> With perfect information about a game/domain we can use an EBL system to find a way to deduce the features of each training example. With these features learned the model can deduce the best move.

Supervised Learning

Very often we can rely on datasets that are labeled. Imagine that we want to make a model that recognizes images of cats, to build it (i.e. trained) we can use a dataset of cat images. By showing the model many many examples of cat images, it can be able to learn how to recognize them.

The learning is done with a teacher in the sense that the model has guidance, it knows if it gave the correct answer. Our cat recognizer, can have a binary output:

- Cat
- No cat

The dataset consists of pairs of information, an image and a label for that image. During training an image is given as input to the model, that outputs a label (e.g. `cat`). By giving the model images from the dataset, we can compare the outputs to the label and adjust the parameters of the model accordingly. The specific methods to do this are going to be explained in the neural learning part.

The key concept behind these types of models is that it learns from examples that we have information about (we have labels). During the training the model gets positive and negative examples and learns from them.

In the case of our cat recognizer, we are going to give it a bunch of images of cats, and another bunch of no-cats. Keep in mind that is a very simple model that in practice does not make sense (see this 1min video to know what I mean).

By using this learning paradigm, the model is able to predict outputs of unseen inputs (e.g. recognize a cat from an image that has never seen during training).

To generalize, we can say that we give as input a vector of attributes. It can be text, images... Furthermore there can be two main types of output:

- Discrete (e.g. classification task `no cat` / `cat`), it is a boolean value
- Continuous (e.g. regression task for predicting temperature)

This can be tricky and I do not consider is a good way to explain things because the usual way to output is with probabilities. If, with discrete outputs, we can only use booleans. Then there will not be discrete models, 95% of all models are going to be continuous because the outputs are expressed in probabilities (e.g. the model "says" *"I am 83% confident that in this image there is a cat"*). Anyways, learn what the slides/Pedro say.

Regression vs Classification

In a classification task, the goal is to assign inputs to predefined categories or classes, with the output being categorical. Examples include spam detection and image classification. If the output is the form of probabilities, it is a continuous value. For more complex tasks these is the case.

In a regression task, the goal is to predict a numerical value based on input data, with the output being continuous. Examples include predicting house prices and estimating temperature.

TLDR: Classification is discrete and regression is continuous, but there are cases with classification that this is not true.

- Discrete (e.g. classification task `no cat` / `cat`), it is a boolean value

- Continuous (e.g. regression task for predicting temperature)

Types of datasets

In a supervised learning case, a big dataset is divided into 3 smaller ones:

- Training set (to perform training)
- Validation set (to perform validation)
- Test set (to assess model performance)

The largest one of the 3 is the training set, often there is a 80/20 between the training and test ones. The validation one is used for what we call hyperparameter tuning (i.e. changing the architecture of the model).

The main takeaway is the the train and test datasets cannot have duplicates of the data. This is done in order to ensure generalization of the model:
Imagine that the training set consists of an unusual high number of black cats, the model is going to get particularly good at recognizing black cats, but when seeing one that is orange it may struggle a bit. The test dataset is used to check that this is not the case. We use it to ensure accuracy in the "wild", with never before seen examples of the data.

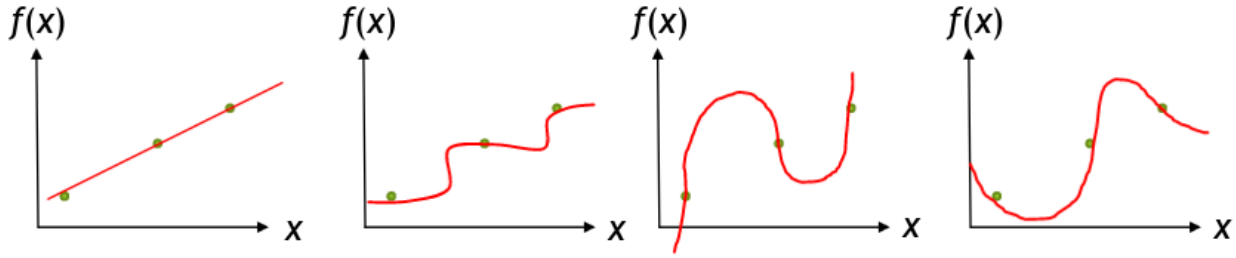
If you want to learn a bit more or there is something that is not quite clear, please check out this website it has wonderful explanation of this 3 types of datasets.

Example: Hypothesis function

- Training set consistent of paint of inputs x_i and outputs y_i called datapoints:

$$(x_{1,}, y_{1,}), (x_2, y_2), \cdots, (x_n, y_n)$$

- Unknown function $f(x) = y$ that describes the datapoints
- We look for a function h called hypothesis, such that h approximates f:



- To validate the h function we use the test set, a sample of datapoints (x_i, y_i) different from the training. With this dataset we assess if h is valid for our application.

Inductive learning

The key idea behind inductive learning is to figure out a general rule from a sample of specific examples.

This is closely related with Rule-based machine learning, where rules presented in the form of `{IF:THEN} expression` are often used. For example: `{IF 'red' AND 'octagon' THEN 'stop-sign'.

As you can imagine, decision trees play an important part in this types of algorithm because, we can work with a clear set of rules where there is no ambiguity.

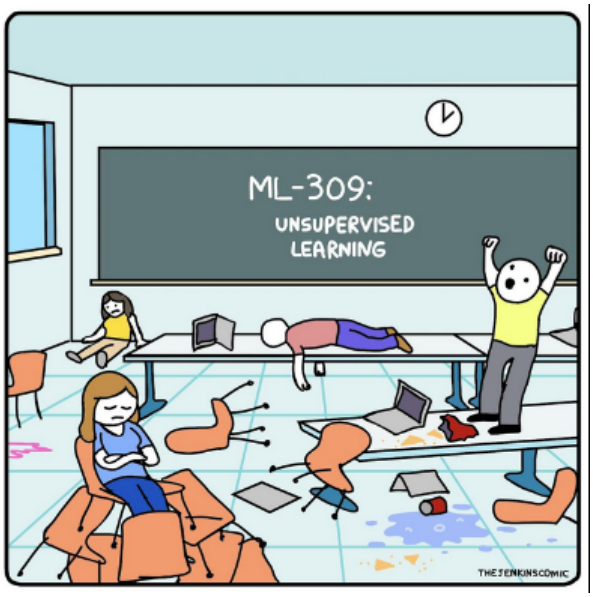
Do not give much though to inductive learning, it seems a term more used in cognitive psychology than in ML. Just relate the Inductive Learning to decision trees.

For a example of a decision tree, please look up the practice exam (Google Drive) that we did in class.

Unsupervised Learning

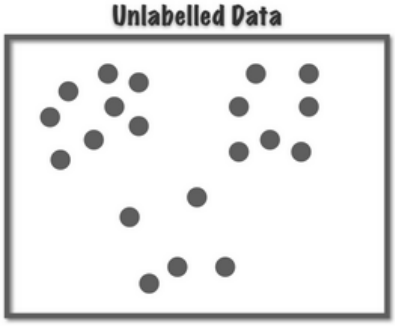
> *But what if we do not have labels in our data???* - You, probably right now

Then, we just use unsupervised learning:



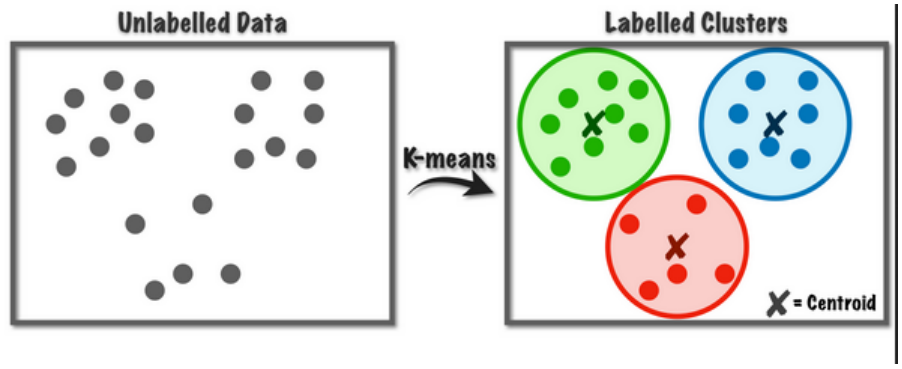
The training is performed without a teacher, the model does not evaluate their performance from labels in the training or test datasets. The models learn patterns exclusively from unlabeled data.

For example, I ask you to cluster (make groups) out of this data points:



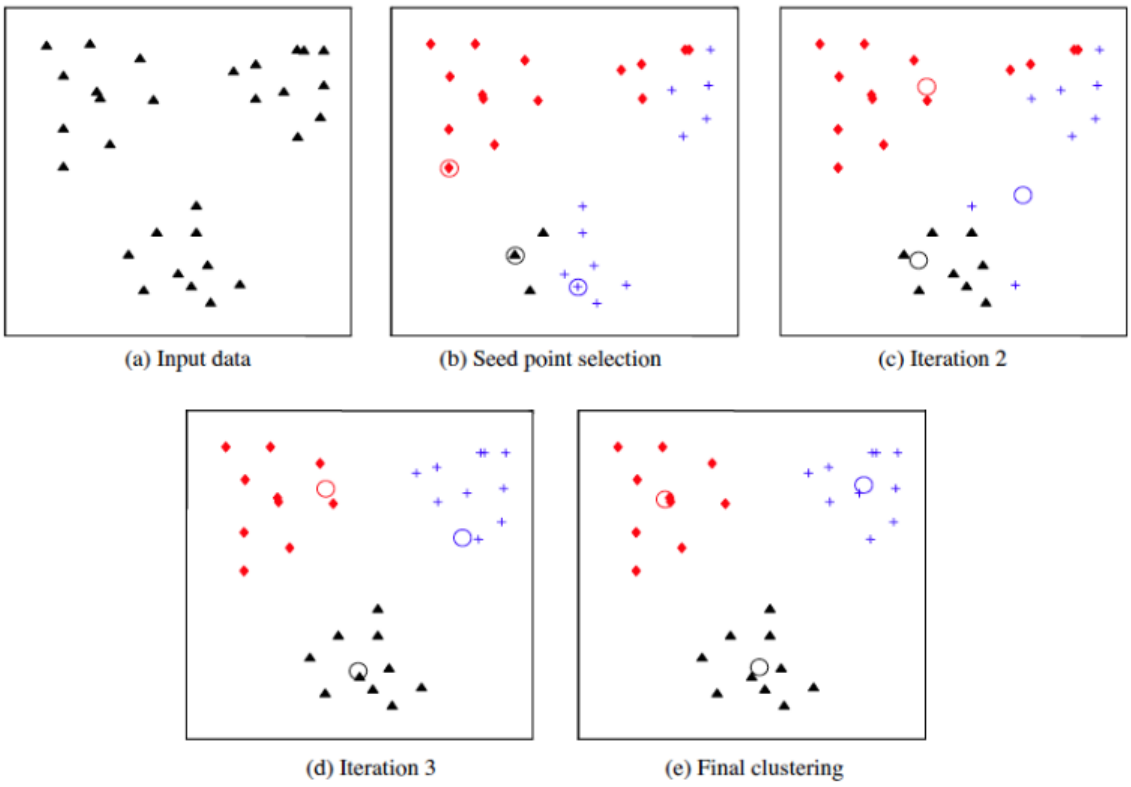
You are probably able to form the clusters in your head, without any additional knowledge of the data. It turns out that computers with the help of unsupervised learning are able to do so.

The main algorithm for these types of tasks (clustering) is k-means. It is able to cluster data points based on clusters formed from centroids:

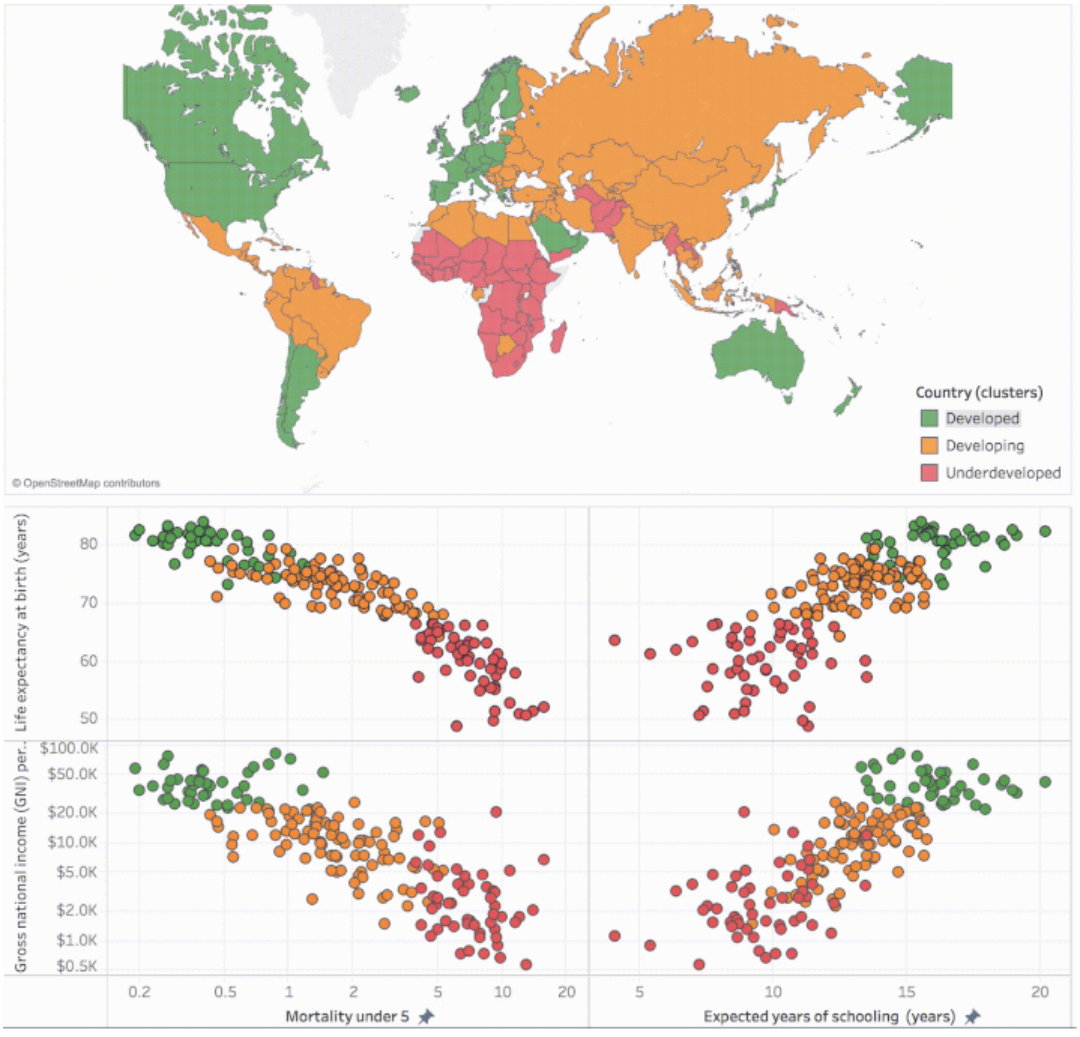


The centroids are just the centers of each cluster, from them we can define the cluster using a radius.

The parameters of the model (position of the centroid and their radius) are learned by iteration:



Here there is a practical quick example of clustering done to classify countries based on their "development" status. Note how different charts (therefore parameters) play a role in the clustering.



Reinforcement Learning

The key idea behind RL is that an AI can be an agent. In other words, that it can be a "player" in a environment that can makes actions depending on the current state of the environment. These are algorithms based on trial and error.

To teach the agent what are the right actions, we use a reward function. This is the goal of the agent, maximize the function. We can also add penalties.

Imagine that we want an AI that plays Mario Bros, the reward is a functions that indicates the agent to go to the right of the screen (i.e. advance in the game). The additional penalty that we add is that their performance decreases if the agent does not move, thus, the agent will try to complete the game as fast as possible. Reference Video of AI playing Mario Bros

You can see how time plays a crucial role in RL, we do not want our agent to stay still. Moreover, keep in mind that the feedback that we give the agent is delayed, we cannot punish/reward if the consequences of their actions are not finish (e.g. in the middle of a jump).

Also it is easy to see how this are "online algorithms", they affect the environment, their actions determine the subsequent data it receives.

RL is the learning algorithm behind many evolutionary AIs which are mainly used to play videogames due to their fast adaptation. This YT channel is full of examples.

On the slides there is also this maze solver via RL (keep in mind that it is not evolutionary).

Neural Learning

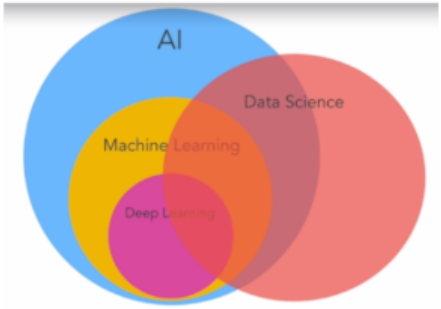
> You can skip this introduction but here I clarify some things about vocabulary and give some extra information about the current state of Deep Learning (DL). Go to the Neural Networks section if you want to skip it.

How the most important part, we are talking and talking about rewards, functions, actions, images, text, clustering and whatever. But how does all of this work?

The answer, as always, is **Linear Algebra and Calculus**. However, we are going to call these things, Neural Networks (NNs) and Backpropagation (Backprop), respectively. You will see what I mean.

When we talk about Neural Networks we are refereeing to the architecture of an AI model. How the data is transformed and treated. This type of architecture is just a bunch of matrices and vectors. That is why I say that NNs are Linear Algebra.

Keep in mind that NNs are ***just a type*** of AI models. Not all AI models are NNs and not all AI models use Machine Learning:



(NNs = Deep Learning, for the purpose of simplicity, but this is *not* entirely true). Read more here.

When we talk about optimization or machine learning with respect to this architecture, we are talking about Backpropagation, the algorithms that makes the NNs learn. This is just a bunch of partial derivatives. That is way I say that Backprop is Calculus.

Deep Learning is just NNs taken to the extreme. All relevant AIs today, the ones that you hear in the news/you use, are Deep Learning models. Here there are some examples:

- GPT-4 (OpenAI) `multimodal generation (text and images)`
- Gemeni (Google) `multimodal generation (text and images)`
- ChatGPT/GPT-3 (OpenAI) `text generation`
- **MIXTRAL (Mistral)** **`text generation`**
- Bard/LaMDA (Google) `text generation`
- **Phi2** (Microsoft) `text generation`
- **Stable Diffusion (Stability AI)** **`image generation`**

- DALL·E 3 (OpenAI) `image generation`
- **LLAMA (Meta/Facebook)** `text generation`
- Siri, Google Assistant, Alexa... `virtual assistants`
- Tesla Autonomous Driving Beta (Tesla) `coches que van solos`
- **Whisper (OpenAI)** `speech to text`
- GitHub Copilot (Microsoft/OpenAI) `coding companion`
- AlphaCode (Google) `code generation`
- **AlphaFold (Google)** `protein structure`
  I just list them so you now, the company that makes the models are in (parentheses). The ones in bold are open source.

You need to keep in mind how a company names their model and their product: ChatGPT **is a product**, the model behind it (the free version) is GPT-3.5-turbo.

Software used in Deep Learning:

- **PyTorch (Meta/Facebook)** `python library for DL`
- **TensorFlow (Google)** `python library for DL`
- **scikit-learn (open source)** `python library for ML in general`
- Hugging Face (Hugging Face) `community to share DL models and datasets`

PyTorch is the Python library that we are going to use in the future, scikit-learn is also **very much** important. Look into it to get a peek of what we are going to do in 2nd/3rd year.

sry for not including links, sometimes im lazy

Videos to understand a Neural Network

just watch them and you can skip the next section and just go to the Deep Learning one.

Neural Networks

I am going to try to explain a bit more than necessary, hope is not too much.

The neuron or perceptron

What are the two simplest operations that you can do to data? Multiplication and Sum.

These are the two operations that an artificial network performs, combining them into what we call a *weighed sum*. It can be understood as a vector-vector multiplication, a scalar product:

$$\boldsymbol{x} \cdot \boldsymbol{w} = x_1 w_1 + x_2 w_2 + \cdots + x_n w_n$$

Where $\boldsymbol{x}$ and $\boldsymbol{w}$ are two real valued vector with the same size n.

$\boldsymbol{x}$ is a input vector (the data), and $\boldsymbol{w}$ has the weights that multiple the elements of $\boldsymbol{x}$. You can clearly see how each element has its own weights.

We say that the weights are the parameters of the neuron/perceptron. Easy.

Usually the operation $\boldsymbol{x} \cdot \boldsymbol{w}$ is expressed as:

$$\boldsymbol{x} \cdot \boldsymbol{w} = \sum_{i=1}^{n} x_i w_i$$

But this is not all, in a neuron there is another parameter that we call bias, usually represented by b, it just sums the previous operation:

$$b + (\boldsymbol{x} \cdot \boldsymbol{w}) = b + \sum_{i=1}^{n} x_i w_i$$

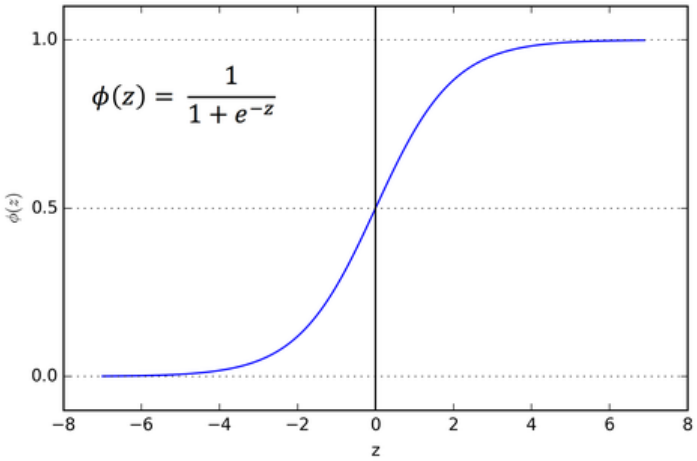
It is clear that b is just a real number, because we know by definition that the output of the scalar product/weighted sum is a also a real number.

The output of a neuron/perceptron is just a number. We give a vector as input, and returns a number. The weights and the bias are the parameters of the neuron.

However, there is a final thing, an activation function.

Do you see how the previous operation is a linear function (represented by two vectors and a number). This is no good, because with the neurons we want to form a very complex operation (the NN). If the neurons are just a vector-vector multiplication, no matter how much of them we have, we can just simplifying all the neurons to one. This is the same principle behind the matrix multiplication, if you have many matrices multiplying, they turn out to be just one matrix.

Thus, we need to add a non-linear function to the neuron to add complexity. We can for example use the sigmoid function:



There is something peculiar about this function also, the outputs are between 0 and 1, thus, they are normalized. If we use this activation function, the outputs of the each neuron are going to be a number between 0 and 1.

There are several activation function that are used. Here there is a list.

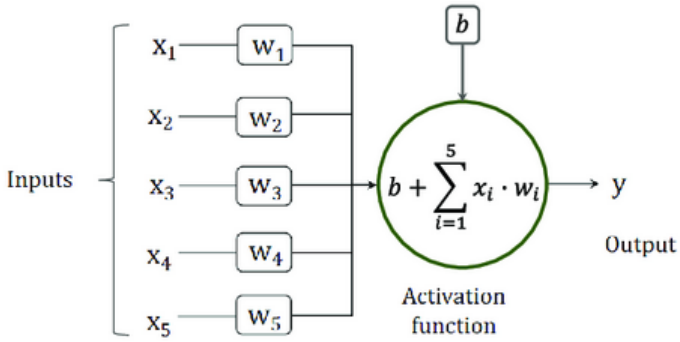
We can also use the binary step one, as Pedro points out in the slides:

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

The normalization of the output depends on the activation function used.

TLDR: We use a non-linear function on the neuron to add complexity to the operation and normalize its output.

Example for neuron with a 5 element input vector:



The activation function is applied to the $b + (\boldsymbol{x} \cdot \boldsymbol{w})$. Easy.

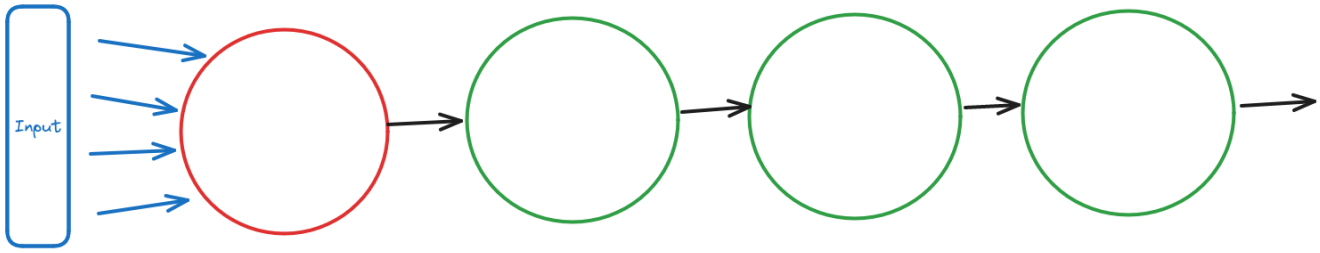
To summarize, what a neuron does is:

$$\sigma\Big(b + (\boldsymbol{x} \cdot \boldsymbol{w})\Big) = \sigma\left(b + \sum_{i=1}^{n} x_i w_i\right)$$

Where σ is the activation function and n is the size of the input vector.

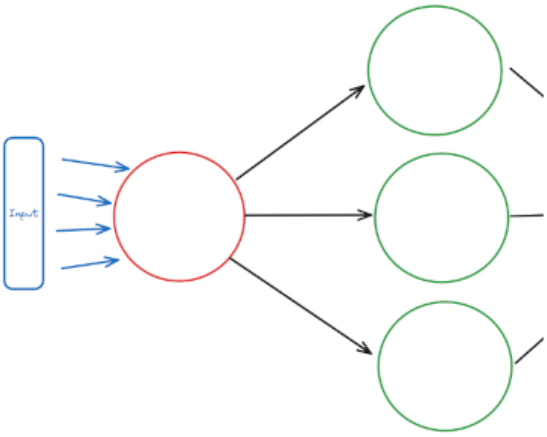
Layers

Before, I mentioned that we need to have many neurons together to form a more complex operation/function. The output of one neuron is input of the next one. Thus, we can make a chain of neurons concatenating them:



You can see that there is an input vector in blue, that goes into the red neuron. However, the neuron only outputs one number (black arrow), thus the following neurons only output one number also. This is not very efficient, we take a 4-element vector and turn it into a number. There is a huge loss of information.

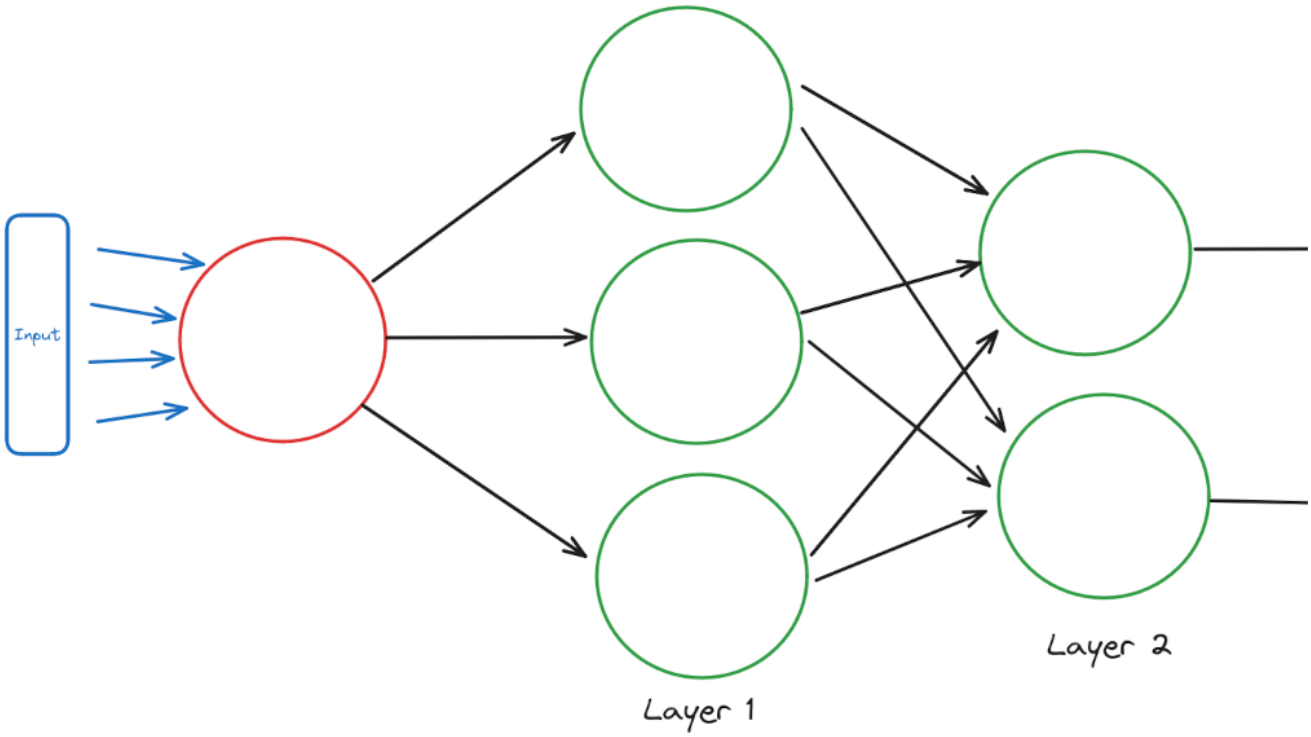
We can remediate this problem by doing a network of neurons, not a chain. The input of the red neurons can go to three of the green ones, for example:



Note that is the same input in all three, the same number goes into each one.

We call the trio of green neurons a layer.

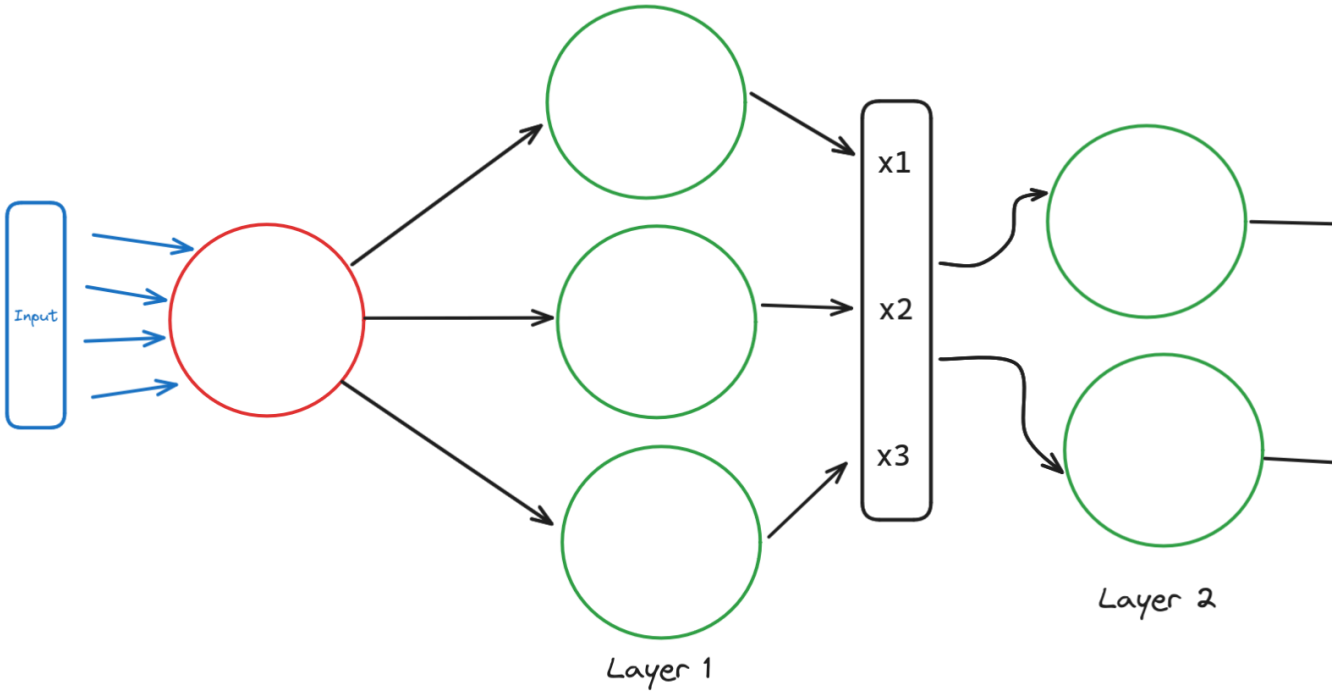
Now we can expand the Network further by adding an additional layer:



Now things get really interesting, the output of each neuron in layer 1 goes to each neuron in layer 2. Thus the latter ones have 3 inputs each.

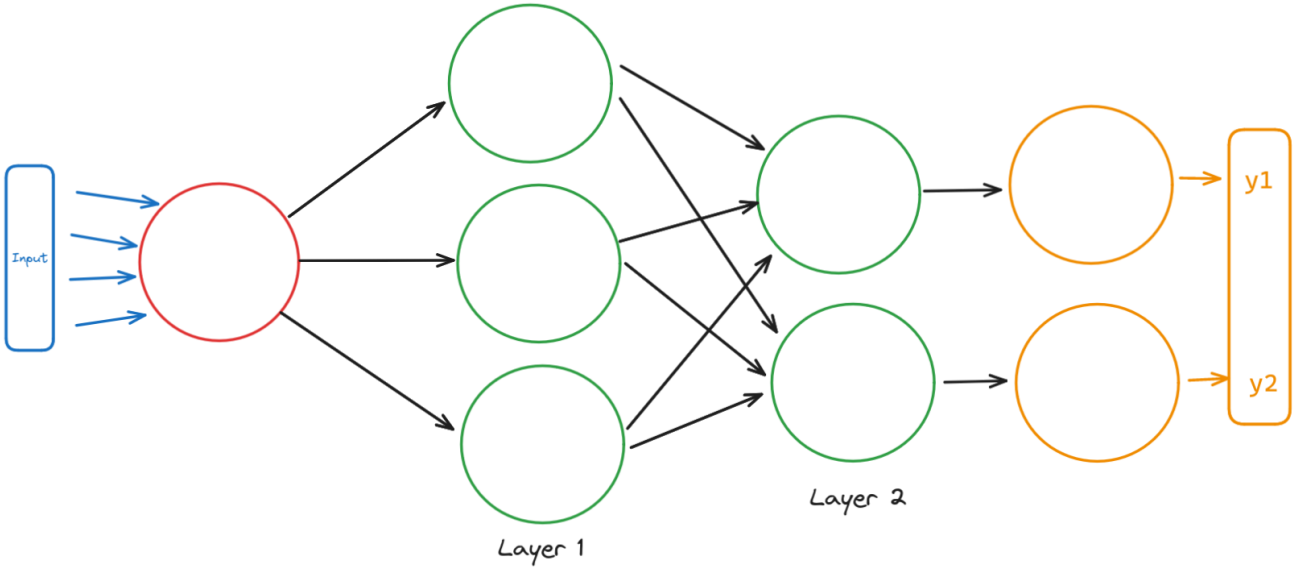
Before going further into the explanation, do you see how there are vectors everywhere?

The output of layer 1 is a 3-element vector. And the neurons on the second one get as input the same 3-element vector:

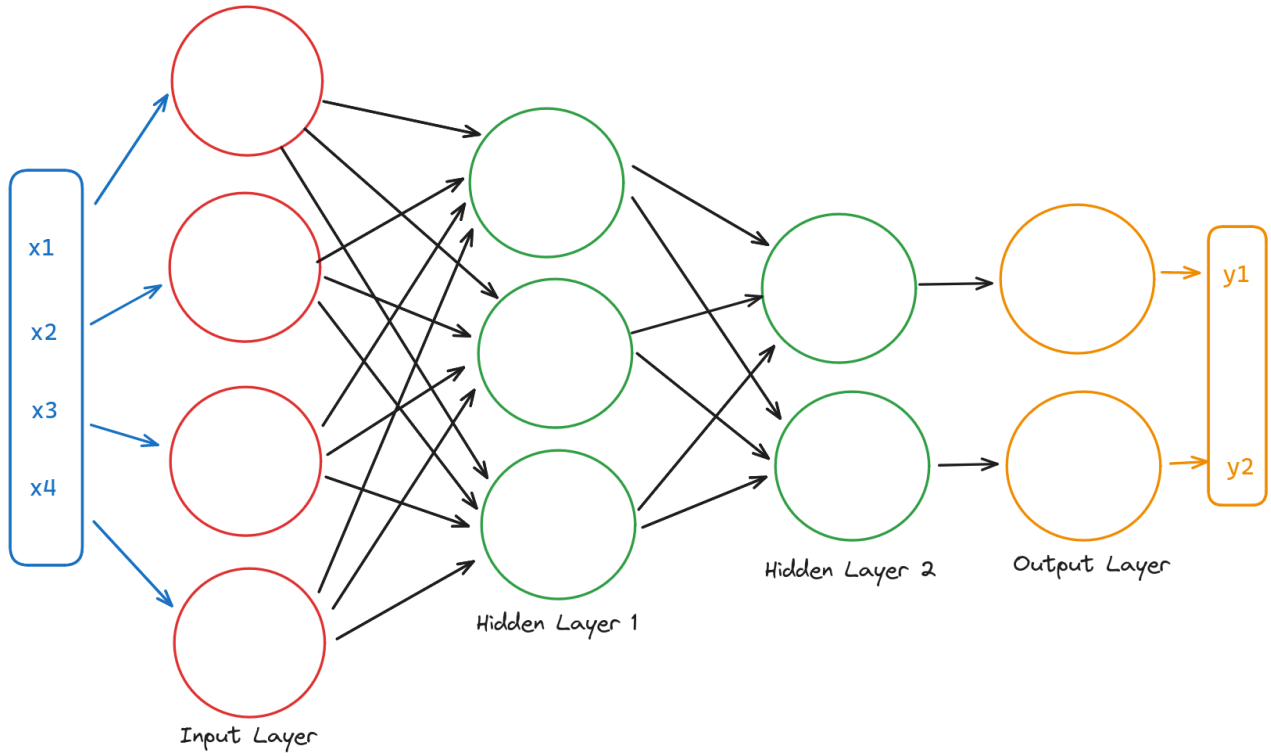


I told you was all linear algebra!

Finally, we put two more neurons that make the output vector (marked in yellow):



You can see how clearly the neurons of different color have different purposes. We have the greens that are in between the input and output, we call this the hidden layers. The red one is the input layer, and the yellow/orange the output layer:



I lied to you a bit before, usually, each element of the input vector has its own neuron, that why how the input layer has 4 neuron, one for each number in the vector.

TLDR:

> There are 3 types of layers in a NN:
>
> - input
> - hidden
> - output
>
> We give a vector as input and receive another one has output. The layer pass a vector of their outputs to the next layer. Each output comes from a neuron.

The neural networks are just many layers with many neurons each one connected between them:

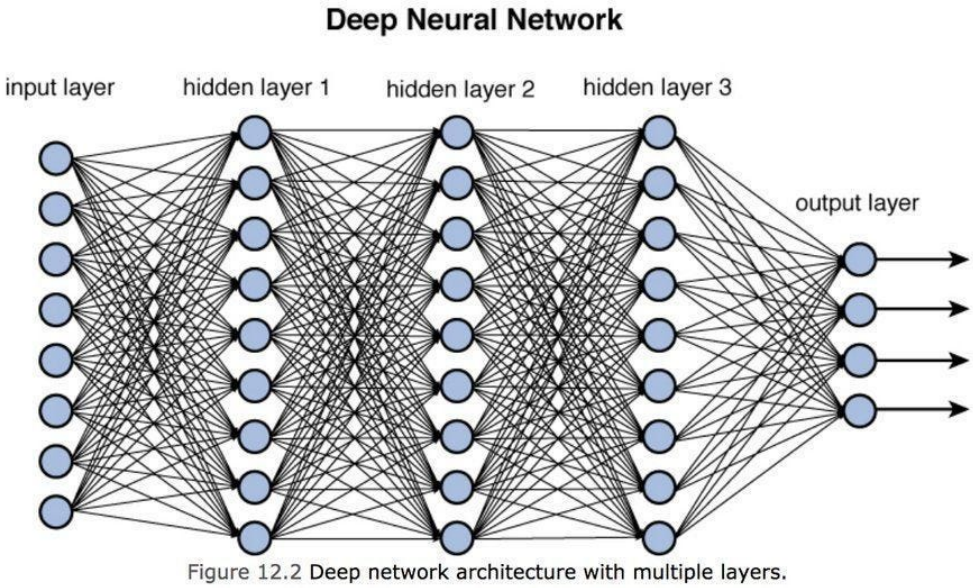


Figure 12.2 Deep network architecture with multiple layers.

What we call Deep Learning is just a NN with a large number of layers. It is somewhat of an ambiguous term.

How my question is: Do you see how NNs are like Lego? There a bunch a different types of pieces that you can arrange in several ways to form vastly different NNs.

But wait.. "you said that there are several types of pieces", does that mean that there are several types of neurons? - You probably now.

The answer is yes, there different types of layers and neurons. The type of neuron explained before is the most simple one. With this chart you can see how many types of neurons/layers/networks there are:

A mostly complete chart of

Neural Networks

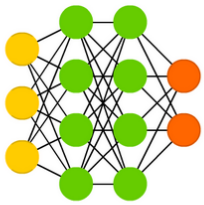
- Backfed Input Cell
- Input Cell
- Noisy Input Cell
- Hidden Cell
- Probablistic Hidden Cell
- Spiking Hidden Cell
- Output Cell
- Match Input Output Cell
- Recurrent Cell
- Memory Cell
- Different Memory Cell
- Kernel
- Convolution or Pool

Perceptron (P)

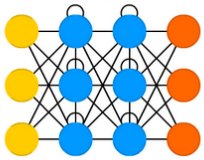
Feed Forward (FF)

Radial Basis Network (RBF)

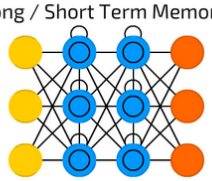
Deep Feed Forward (DFF)



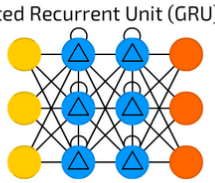
Recurrent Neural Network (RNN)



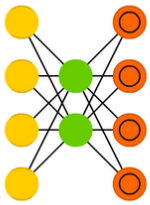
Long / Short Term Memory (LSTM)



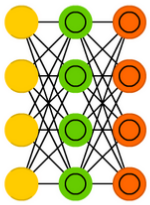
Gated Recurrent Unit (GRU)



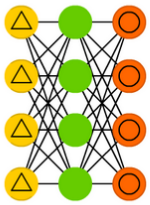
Auto Encoder (AE)



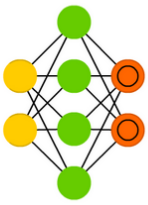
Variational AE (VAE)



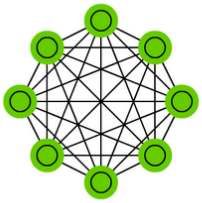
Denoising AE (DAE)



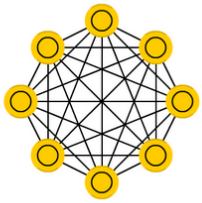
Sparse AE (SAE)



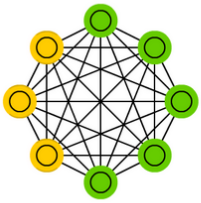
Markov Chain (MC)



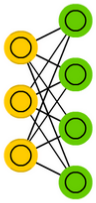
Hopfield Network (HN)



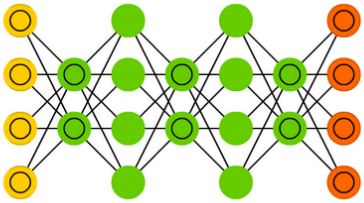
Boltzmann Machine (BM)



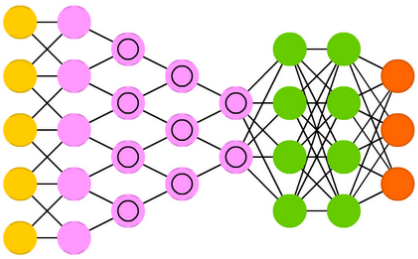
Restricted BM (RBM)



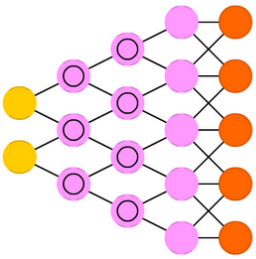
Deep Belief Network (DBN)



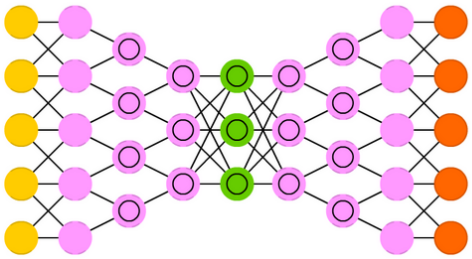
Deep Convolutional Network (DCN)



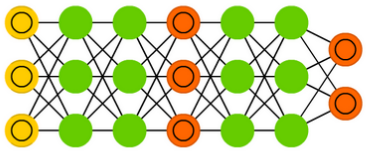
Deconvolutional Network (DN)



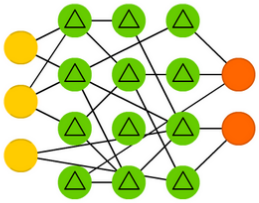
Deep Convolutional Inverse Graphics Network (DCIGN)



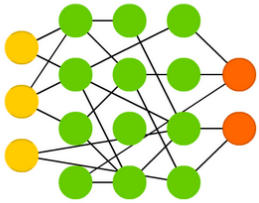
Generative Adversarial Network (GAN)



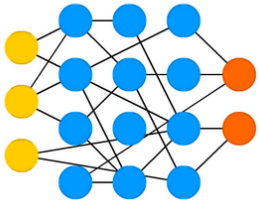
Liquid State Machine (LSM)



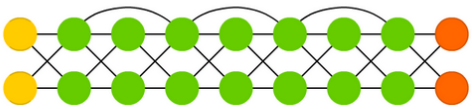
Extreme Learning Machine (ELM)



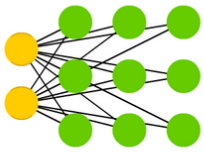
Echo State Network (ESN)



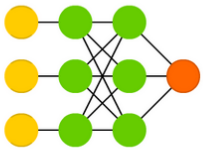
Deep Residual Network (DRN)



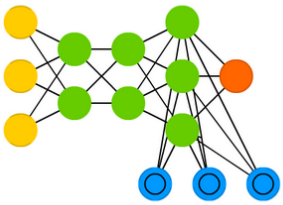
Kohonen Network (KN)



Support Vector Machine (SVM)



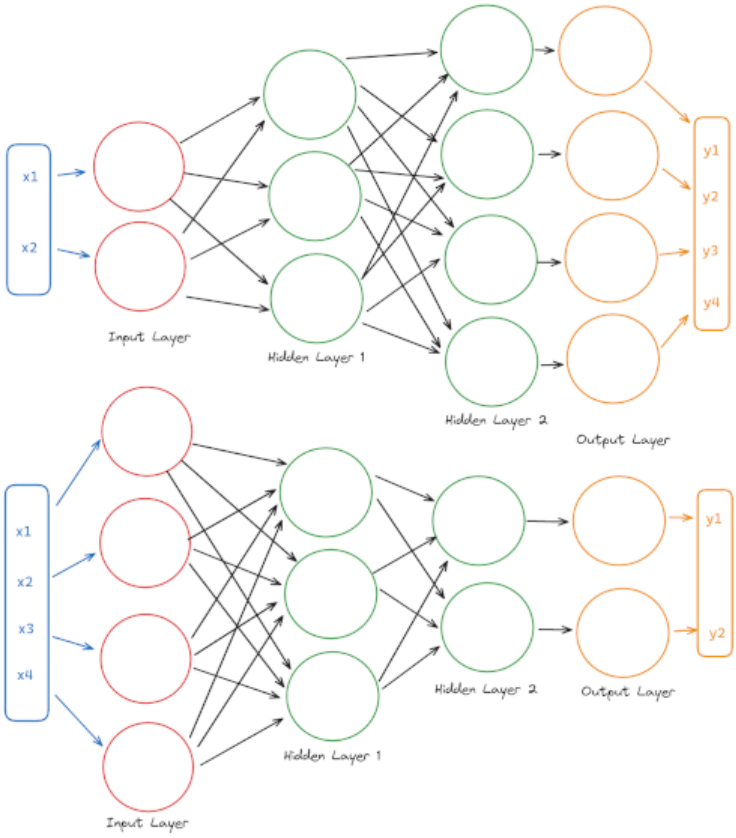
Neural Turing Machine (NTM)



Some of them are very important, other ones are outdated. The one that we have looked is the Deep Feed Forward network, also called fully connected network.

Take this chart as a reference for how to grasp the diversity of NNs that there is. If you want to know more go to the blogpost of the chart.

As final note, think about how the size of the input and outputs of a NN define its use. If the output is smaller than the input, that means that the NN is "compressing" the information in some way. If the output is larger, the NN is "adding complexity":



How you can think about how we can express these NNs in the form of matrix operations. Exercise left to the reader.

Backpropagation

> How are the NNs trained?/How do the NNs "learn"?

I have two answers to this question, a short one and a long one.

TLDR of Backpropagation (short one)

There is a function that we want to optimize with the NNs, it is called "loss" ($\mathcal{L}(\cdot)$). There are many types, the main one is Mean Squared Error (MSE):

$$\text{MSE}(\boldsymbol{x}, \boldsymbol{y}) = \frac{1}{m}\sum_{i=1}^{m}(y_i - x_i)^2 \qquad \boldsymbol{y}, \boldsymbol{x} \in \mathbb{R}^m$$

$\boldsymbol{y}$ is the ideal output, and $\boldsymbol{x}$ the one that we get from the NN.

Each parameter (weight and bias) of the NN is outdated via the gradient descend method. Taking the derivative of the loss function $\mathcal{L}(\cdot)$ with respect to the parameter:

$$\theta_i^{t+1} = \theta_i^t - \mu\frac{\partial\mathcal{L}(\boldsymbol{\theta})}{\partial\theta_i}$$

We just update the parameter via subtracting a small number that depends on the derivative ($\mu \approx 10^{-3}$). It is an iterative process.

To calculate each derivative we use backpropagation: The error directly depends on the output layer, thus we update the parameters of the output layer first.

The next layer to be optimize/updated is the directly connected to the output, thus, the last hidden layer. We use the error (derivatives) calculated before to calculate the ones of this layer. This is repeated until we reach the input layer.

We "backpropagate the errors" to update the parameters and optimize the loss function.

To do this we first need an output of the NN (to calculate the loss), thus each iteration step looks like:

1. Take an example of the dataset
2. Input it into the NN (forward pass). `Input -> Output`
3. Determine the error that the example "has" and update the parameters via backpropagation (backward pass).

The error is calculated by backprop process and the updating of the parameters are done by gradient descent. The backprop gives us the derivatives that gradient descent uses to optimize the NN.

These are repeated until we reach a minimum error or we exhaust our computing resources.

TLDR of the TLDR:

> - The error is `correct output - real output`.
> - Backpropagation is used to gradient descend in the parameter space
> - Gradient descent updates the parameters
> - The training is done by using many examples in an iterative procedure:
>   1. Take example
>   2. Execute `Input -> Output`
>   3. Determine error and update the parameters
>   4. Repeat until minimum error or exhausting resources.

This is all you need to know (**forget the math for the exam please, no math**).

It is a long story (long one)

Do not have much time to write, and there are smarter people than me that explain things better. Watch these two videos:

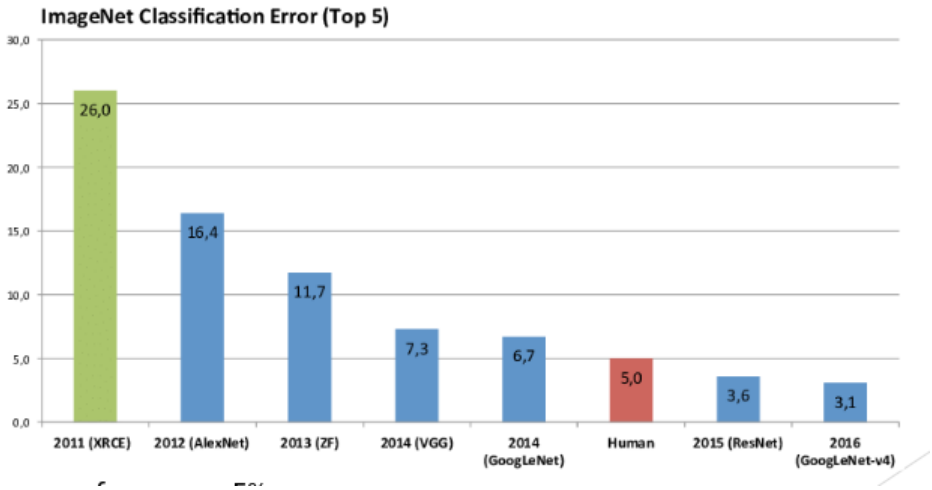
- Gradient Descent Explained
- Backpropagation Explained

Deep Learning

With all this information now can dive deeper into deep learning.

First of all note that all the recent advances in AI (at least the mainstream ones) have been due to DL. It all begin in 2012 when AlexNet (DL network) was submitted to a image classification competition (ImageNet Large Scale Visual Recognition Challenge). It performed 10% better than the last model to won the competition.

Since then, huge advances have been made in this field:



Graph with each winner of the competition from 2011 to 2016, there is also the average human performance. Pictured in green

is the performance of a non-DL model in the competition. Note that since 2012 (AlexNet), the improvement year over year has been pretty substantial. Since 2015 the models performed better than human. All the models in blue are DL.

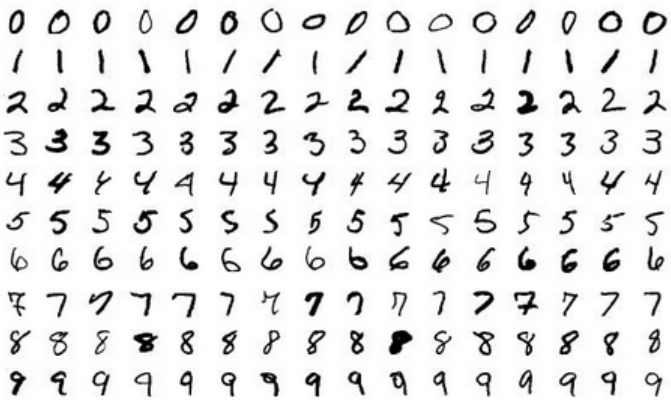
ANNs / FCNN

Artificial Neural Networks (name not used) or Fully Connected Neural Networks are the simplest type of neural networks that exists and are useful.

They have been already explained here, but there is a few things to point out still.

FCNN for Handwritten recognition

The MNIST dataset consists of 60k examples of images of handwritten digits with their respective labels:



Can we used this dataset to train a FCNN to recognize the digits? Yes.

If the images are of `20 x 20 pixels`, we transforms them into a `400` sized vector, on each element is a number between 0 and 1 that indicates the "color" of the pixel.

Now we can input this vector into an input layer of with `400` neuron, then we put a just a hidden layer with `300` neurons and finally the output layer with `10`. Thus, the output is a vector where is elements is the probability that a digit is recognized as a number.

If the vector has `0.82` in the position `2` therefore there is a probability of `82%` that the digit is a `2`. This is not entirely true, but for the sake of simplicity it is.

The idea to take into a account is that the output vector is of size 10, one element for possible category (0, 1, 2, 3, 4, 5, 6, 7, 8, 9).

TLDR:

> The input layer size matches the amount of pixels (1 neuron = 1 pixel)
> The output layer size matches the amount of categories to classify (1 neuron = 1 vector element = 1 category)

Learn more about this specific problem with this video.

You can clearly see how this is useful in automation of many tasks in post offices or banks.

Vanishing Gradient Problem

If we have a really deep FCNN, the gradients (derivatives) calculated by backprop start to get smaller and smaller as we go further into the network. This makes stall the training process, as the gradients are so small that they do not change the parameters like they should do.

This problem can vary with the type of activation functions that we choose, but sooner or later we encounter it.

Therefore, there is a limit to the size of this types of networks. We need to make new architectures that allow us to solve task with networks that are reasonable sized or do not encounter this problem.

This why we have many types of architecture, they are evolved and improved upon the FCNN. The rest of the document explains the new architectures.

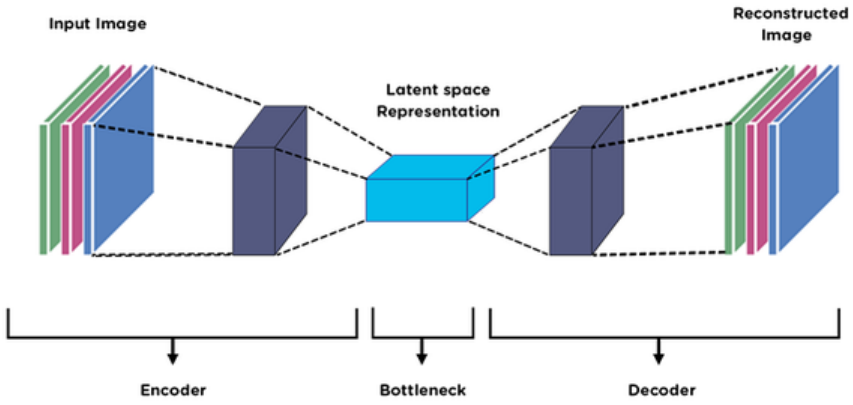
Autoencoders

Maybe the most relevant use of autoencoders, a type of neural networks that are able to learn efficient encoding of unlabeled data.

The model architecture consists of an encoder and decoder:

- Encoder: Takes input data (e.g. song, image...) and compressed it into a set of different features. They are abstract and learned by the model itself usually.
- Decoder: Takes the compressed data and tries to turn it into its original form (i.e. the input given).
  You can see how the model is trained without the labels (it is unsupervised), the relevant work done here is make as similar as possible the input data and the outputs. Reconstruct the compressed data into its original form.

The model architecture looks like funnel which gets narrower and then wider. The size of the input and output data match, of course, as we want them to be exactly the same:



The middle part, the compressed data, is called the latent space or the latent space representation of the data.

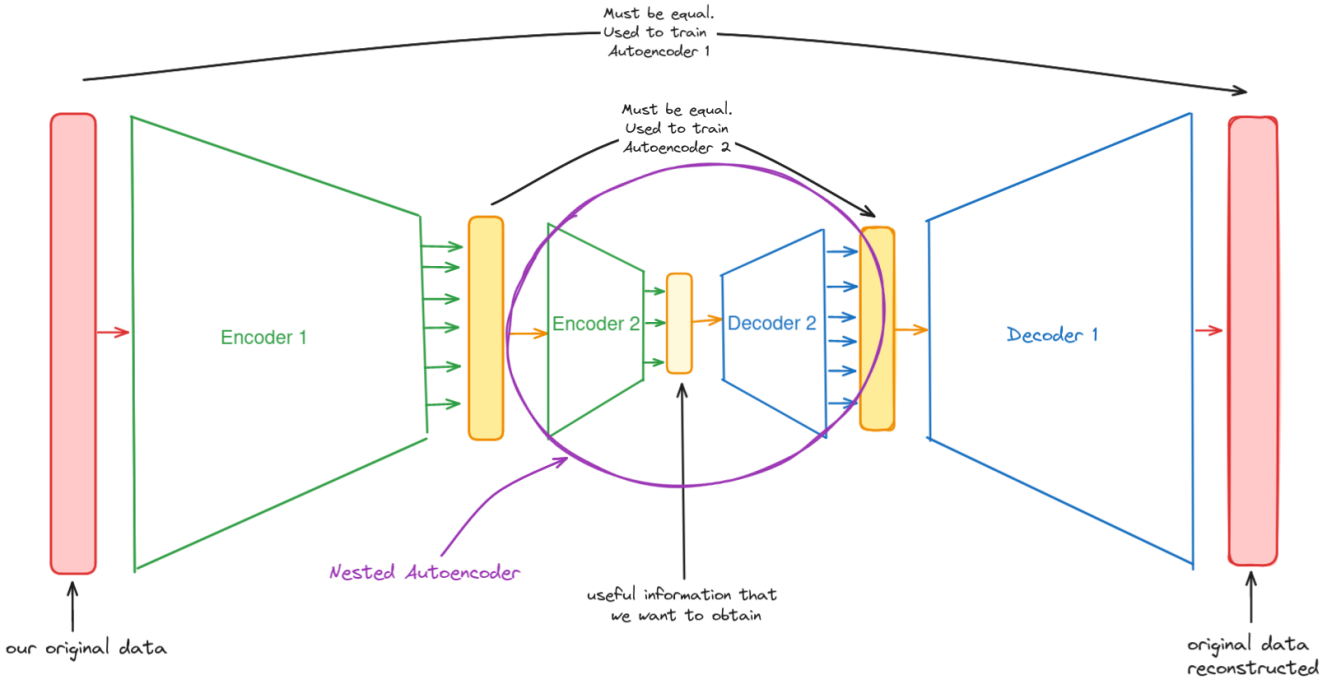
This representation of the data is "new" type of representation made by the model. It often identifies the characteristics of the problem and it is meaningful to our eyes, it captures meaning and relevant information. With unsupervised learning the features are automatically discovered!

Usually when the autoencoders finishes the training, the decoder is no longer useful, this depends of the application of the model.

Nested Autoencoders

Once we get a latent space representation we can give it as input to another autoencoder, thus we nest an autoencoder into another one. What happens here is that the smaller autoencoder (the nested one) can be trained with the representation that

the larger one has learned:



This can be possible because basically what an autoencoder does it so match the input and output data, without any labels. Therefore the data is much more easy to created, and can even be synthetic (created by an AI) like the nested autoencoders case.

We can keep nesting autoencoders util we find a the representation that is useful to our problem (in theory).

This approach allows us to train the models separately (they do not backpropagate into each other), therefore, we can build a model as larger as we can, without worrying about the Vanishing Gradient problem. Backprop problems do not happen.

> I did not find info about this last statement. *Creo que pedro se lo ha sacado de la chistera/sombrero.*

TLDR:

> The hidden layer of an autoencoder is the input layer of another autoencoder.
> We can keep doing this until we find useful representation of data.
> If we train one autoencoder at a time, the backprop problems do not happen.

The representations learned by the NNs can be very abstract sometimes:

(I do not know what is exactly going on here, I just copied from the slides. I think it is a GAN, idk)

Convolutional Neural Networks (CNNs)

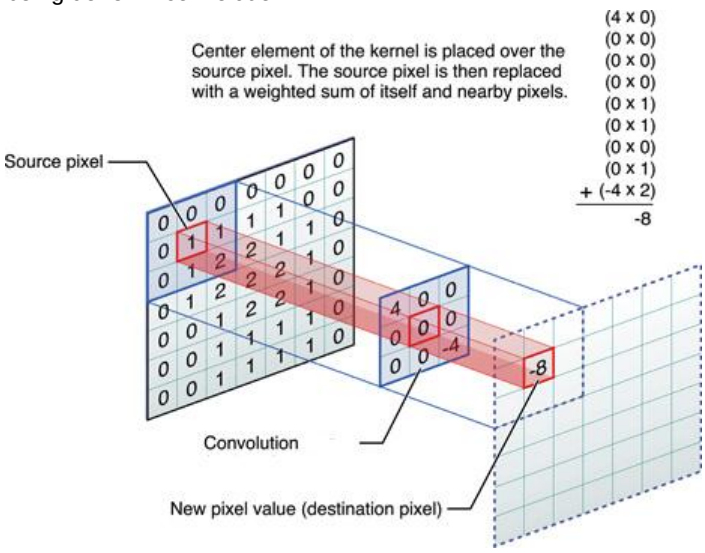
One of the most important NN architectures of the 2010s is the Convolutional NN. Known for its excellent performance on image classification (the famous AlexNet from 2012 is a CNN).

Convolution

The main idea with behind this architecture is a convolution, defined as:

> A mathematical operation on two functions that produces a third functions. It expresses how the shape of one is modified by the other.

Seems complicated, forget about the definition. Consider what happens when you blur an image digitally, what is the process being done? A convolution!



What a convolutions regarding an image means is just multiply the image by a tiny matrix called kernel or filter. It is an iterative process, every pixel is multiplied one by one.

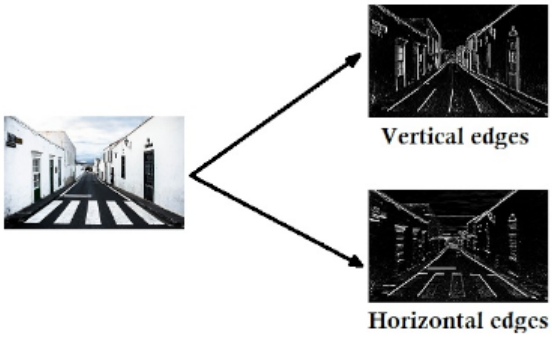
We take an input pixel and multiply its neighbors and it by kernel, thus we are using a function/matrix to transform the data. We can transform images in many ways using different types of kernel.

To blur an image usually this kernel is used:

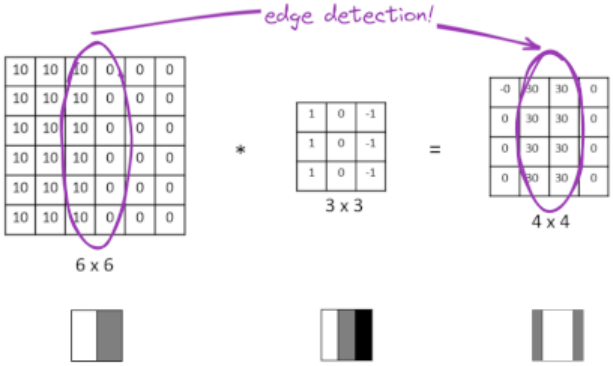
$$\begin{bmatrix} 4 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -4 \end{bmatrix}$$

Look at this GIF to see an animation performing a convolution.

Changing the kernel we can change the purpose of the convolution, here is an example for edge detection:



See how the edge between the 10s and 0s on the source image is represented with the 30s on the result of the convolution:

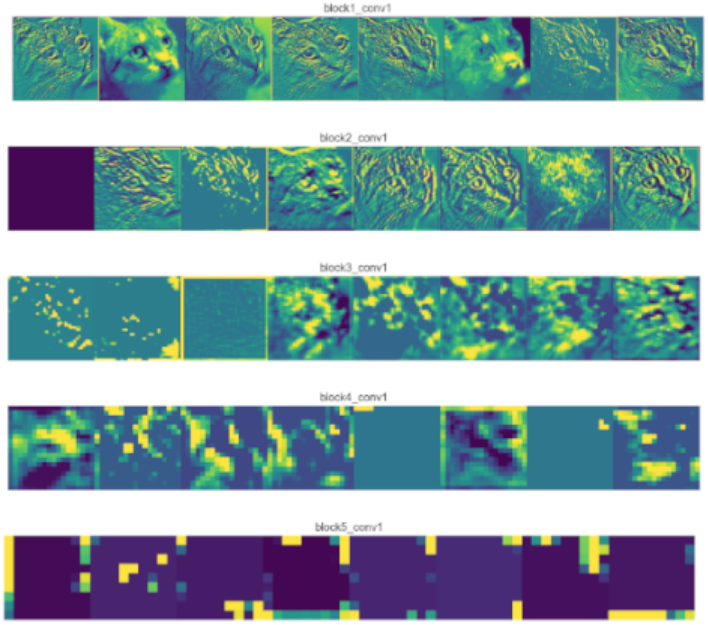


(This kernel is for vertical edge detection)

The key idea in a CNN is to train the kernels (e.g. the weights of the model are the numbers in the kernel). The network itself learn what transformations to apply to the source data.

What we are going with several convolutions chained together is transforming the source image over and over again, doing this we can extract information from it. More importantly we can extract features from it that have relevant meaning.

This is done with several kernels at the same time, look at this CNN with an input image of a cat:



The images are just the results of the convolutions, they are not the kernels. What we are seeing is hot the input image is changes as it goes deeper into the CNN.
Each row represents a different layer. Look at how we cannot longer recognize the cat as it goes deeper into the CNN, as always it is difficult to interpret the internal process of a NN.

The features that the CNN extract are from its own interpretation, it may not make sense to us, but this features can help in an image classification process. However, we know that as it goes deeper into the CNN more complex features are extracted.

TLDR:

> Feature extraction is performed by the multiplication of the image source by a kernel/filter. The features learned are used to better classify the images for example.
> We call the kernel multiplication a Convolution.

Architecture of a CNN

A layer inside a CNN that performs a convolutions is the Convolutional layer. They are combined with another type called the pooling layer. Their job is to take the results from the different types of convolution that combine them into one. They consolidate the features discovered by the kernels.

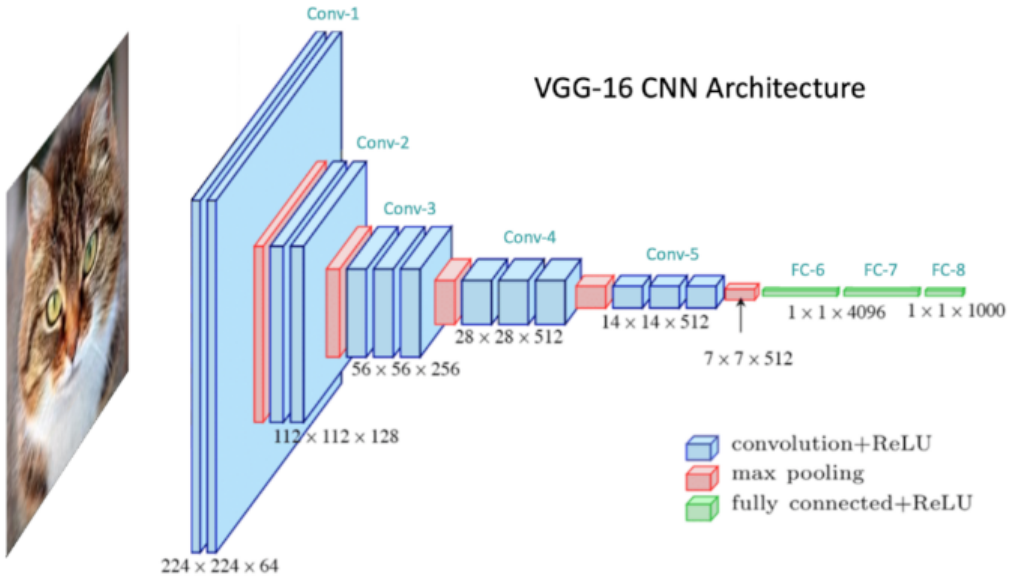
This two types of layers are the building blocks of CNNs:

- Convolutional Layers (feature extraction)
- Average/Max Pooling layers (feature consolidation)

Explanation of the different types of Pooling using an animation

Notice in the cat example how the images are getting smaller with time? This is because of the pooling being done. Without this layers, the results of the convolution are going to have the same size.

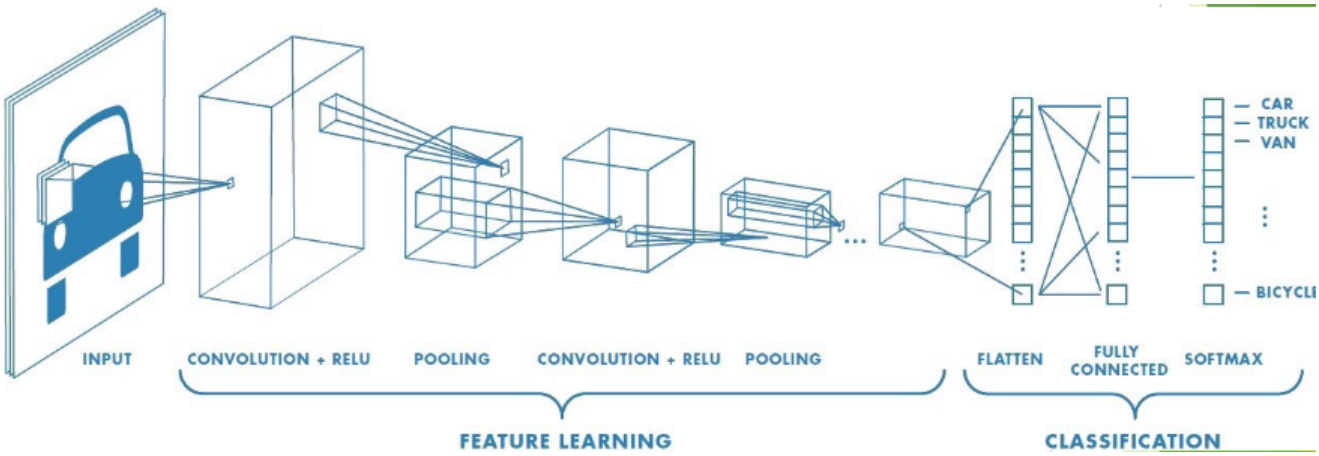
Combining this types of layers we can form the CNN:



Here are pictured the different types of layers (included a fully connected layer). ReLU (rectified linear unit) is just a type of activation function equal to $f(x) = \max(0, x)$. Note how on the final Convolutional layer there are 512 different types of filters. (`pixels x pixels x number neurons/kernels in layer`, if the layer is `1x1xN` that means the image has being transformed into a single number).

Learn more about this specific model (VGG-16) in this blog.

Image used in the slides:



Generative Adversarial Networks (GANs)

Lets look at the name for a bit and see what it means:

- Generative (it generates stuff)
- Adversarial (there is a competition)
- Networks (is a NN, obviously)

What I mean by competition is one between two different model. We need to teach a **generator** how to generate the images, and it needs help, cannot do it alone. The help comes from a discriminator.

These two models compete with each other. Think about them as art (or money) forgers (*falsificadores*) and police. These two groups are in a "arm race" to create the best possible false art and to detect which art is false from the real ones.

At the beginning the police/discriminators are quite good at distinguishing the false from the real, so the forgers have to improve a lot. As they improve the police keeps getting better with their detection techniques. As that happens it forces the forgers to get even better techniques. This happens for a while until the real painting and the false ones are indistinguishable from each other, and the forgers/generators won.

The exact same thing happens with this two models, the discriminators forces the generator to get better and better as the training of the models progresses. This happens until a point in reach where the discriminator cannot tell what is real and what is not. **The generator tries to fool the discriminator.**

This two points are the important stuff:

Discriminator

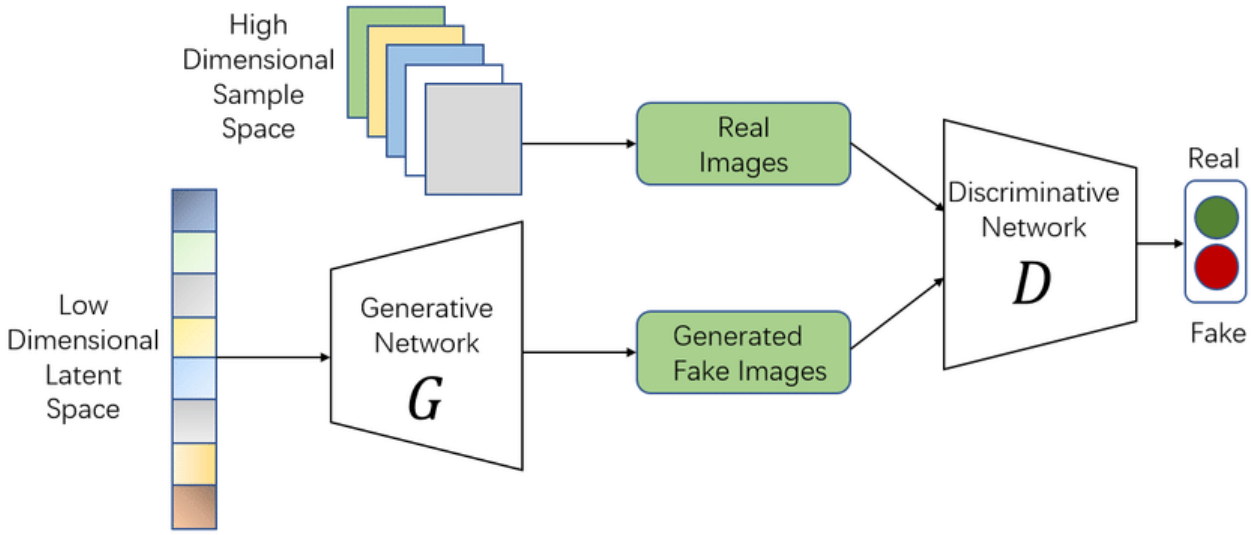
- Its trained on real and false images, with the goal of distinguishing between them
- It is connected to the generator to give "feedback"
- At the beginning of the training is very good at its job, but when the training ends, usually it is because the generator won, and the discriminator cannot detect which images are false.

Generator

- Computes synthetic images, trying to fool the discriminator
- Its input is noise to bring variety to the generated images.
- Usually it is just trained to generate a type of images (e.g. faces of images)

During the training, if the generator success, then backprop is done on the generator. When the training is finished we are only interested in the generator.

Schema explaining a bit the structure of the model:



We can put convolutional layers inside the models to make them perform better.

This types for networks are responsible for the famous deep fakes (remember the Obama video). See this website if you want to see some fake faces.

However, I need to mention that this types of networks are kind of outdated at the the moment. The best AI generated images come from Diffusion Models, if you have seen a popular AI image lately, most probably comes from this models. They work in a similar way to autoencoders, they are not Adversarial models. The architecture and inner workings are quite complicated. I just mention them so you now that they exits (and GANs are outdated).

Word Embedding

The basic task behind of a words embeddings it to give some text a number. Think about how easy it is to translates the images into number, the pixels are already numbers!

This is not the case with text, the language corpus are very large. To associate a vector to a words, it is possible to do it by meaning. The words are organized by for example semantic fields (e.g. a region of the vector space that has programming related words). Usually this embeddings are made with autoencoders, or embedding layers inside a larger NN, but other methods exists.

The most factor to take into account is the context around the word, that is extracted from the corpus. It sets how it is embedded on the vector space. This translates also into the context on the vector space, where the words are clustered by

meaning (sort of).

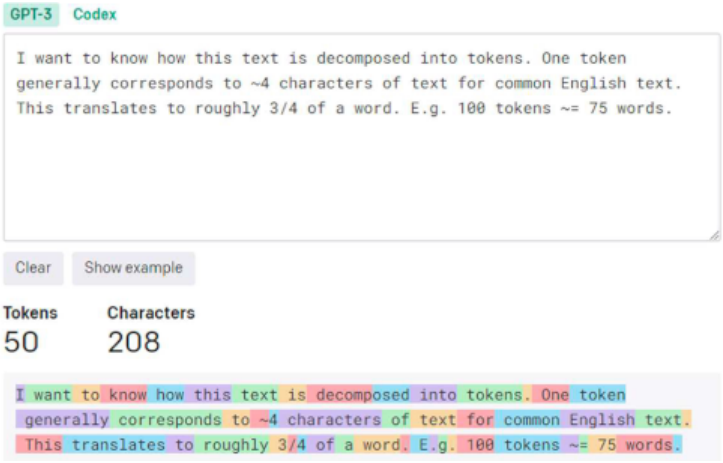
Relationships between the words can be represented by vector algebra (e.g. `king - man + woman = queen`)

Large Language Models (LLMs)

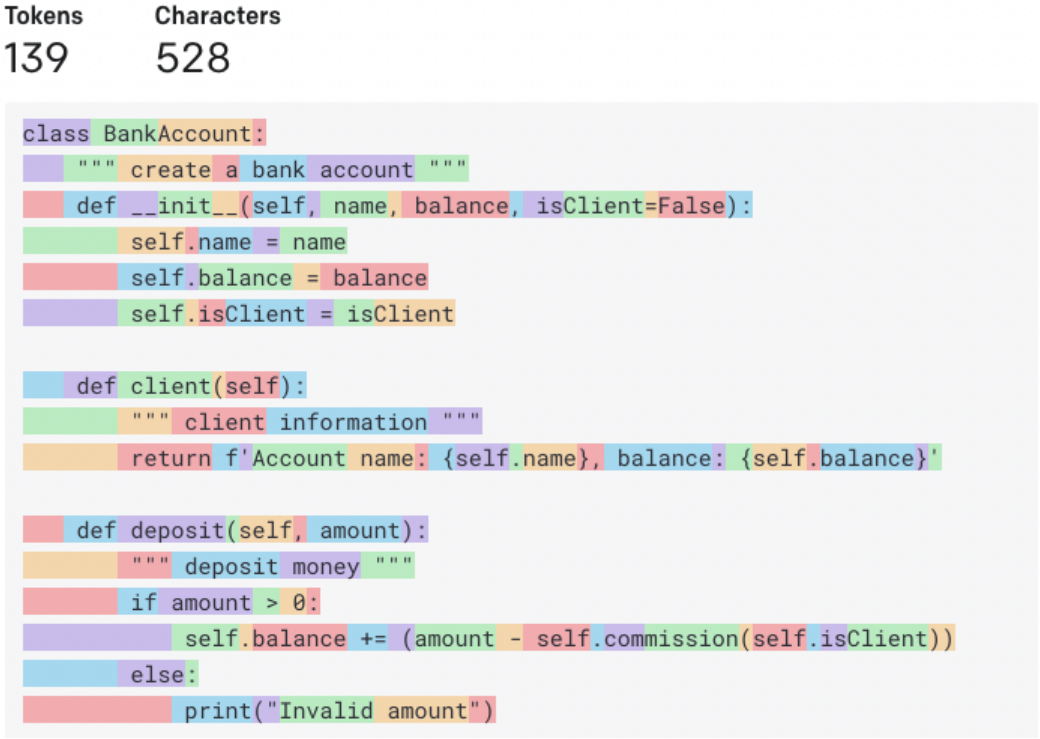
Tokenizer

First of all note that the input text given to this models are token, they are not words. Sometimes a words is not equal to the tokens that are expressed. A good example are the adverbs/*adverbios*, they can be divided between the core word (e.g. final) and the postfix (-ly): `final + ly = finally`. The same thing can be done on spanish: `final + mente = finalmente`. On these examples `final` is its own token, with `mente` or `ly` being another one. This is important because if you use an API, you pay for tokens used, not words.

Text examples



As another example see a bit of code:



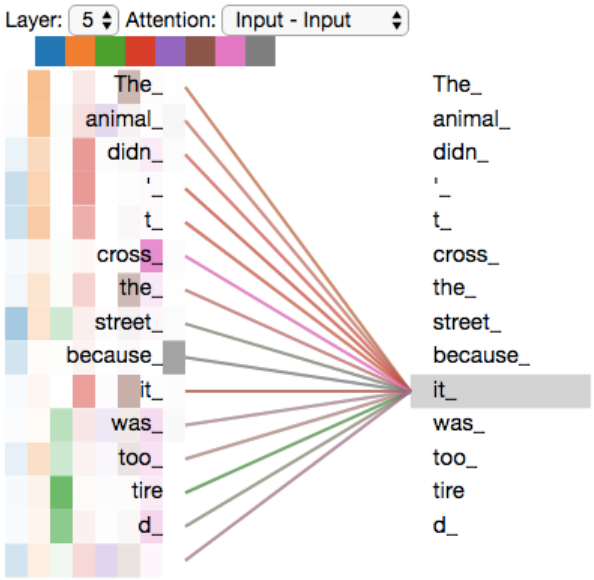
Pay attention of own some variables are divided: `self.isClient = self . is Client.`

LLMs architectures

- Recurrent Neural Networks (RNNs)
- Long short-term memory (LSTM) `~2005 first conceptualized on 1995`
- Transformers `2017-Present`

There was always the search for an architecture to work with sequential information (e.g. music, text...) which is a difficult task. There has to be some type of "memory" for the model to interpret text or generate. If you are writing something, you cannot forget what you wrote on the last paragraph, the same happens when you read text.

On 2017, the *Attention is all you need* paper was published, in which the Transformer architecture was introduced. It is responsible for all the great large language models that we have today (e.g. GPT-`X` from OpenAI). What transformers do is bring attention into the text. This is the "memory" that the models has:



A word is predicted based on the previous important words. *As we are encoding the word "it" [...], part of the attention mechanism was focusing on "The Animal", and baked a part of its representation into the encoding of "it".* Taken from this blog.

They are tasked with word prediction, given a text keep complete it. If we give an answer, they respond. All that they do is answer the question of "What is the next word?"

The follows the following process:

1. The prompt (input) is tokenized
2. Tokens are translated into a word embedding
3. The models predicts the text word (with attention)

Usually this models are pretrained (GPT = Generative pretrained transformer), they are trained on huge amounts of data (e.g. the whole Wikipedia), a wide corpus of unsupervised text.
Now, with the pretraining done, we can fine-tune them, doing more training for an specific task with smaller labeled datasets.

As a final non-important note: Transformers are the current best architecture. In the following couple of years will see if we can keep using them to make better models (at time of writing the best is `GPT-4-turbo`) or we are going to leave transformers behind and use state machines (e.g. mamba) will take their place.