Deep Learning

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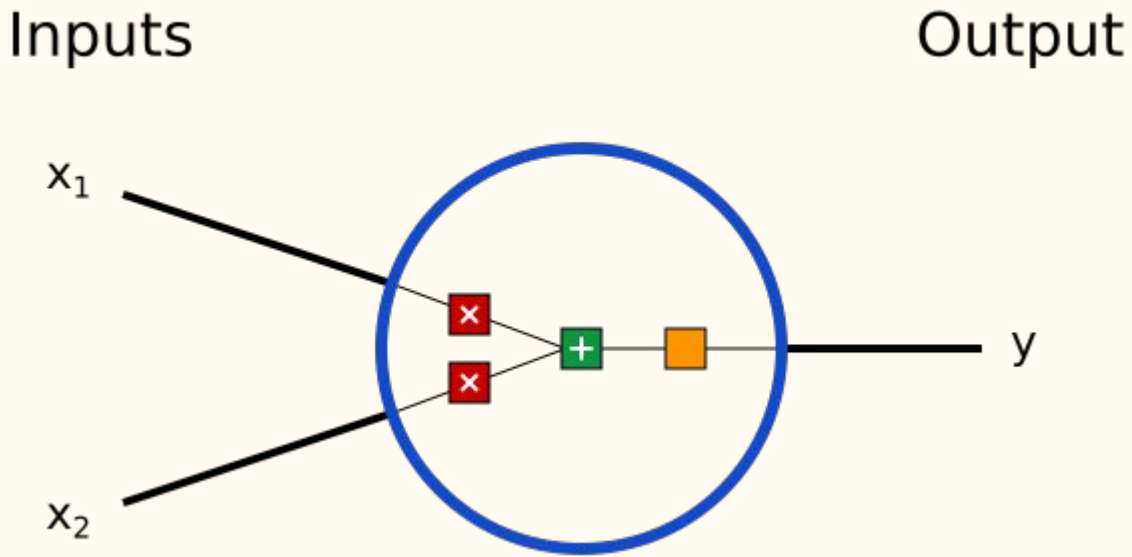
Let’s get Started

Topics

To learn and Understand!

- **Artificial Neural Networks**
- **Convolutional Neural Networks**
- **Recurrent Neural Networks**

Introduction to Neural Networks



$$x_1 \rightarrow x_1 * w_1$$

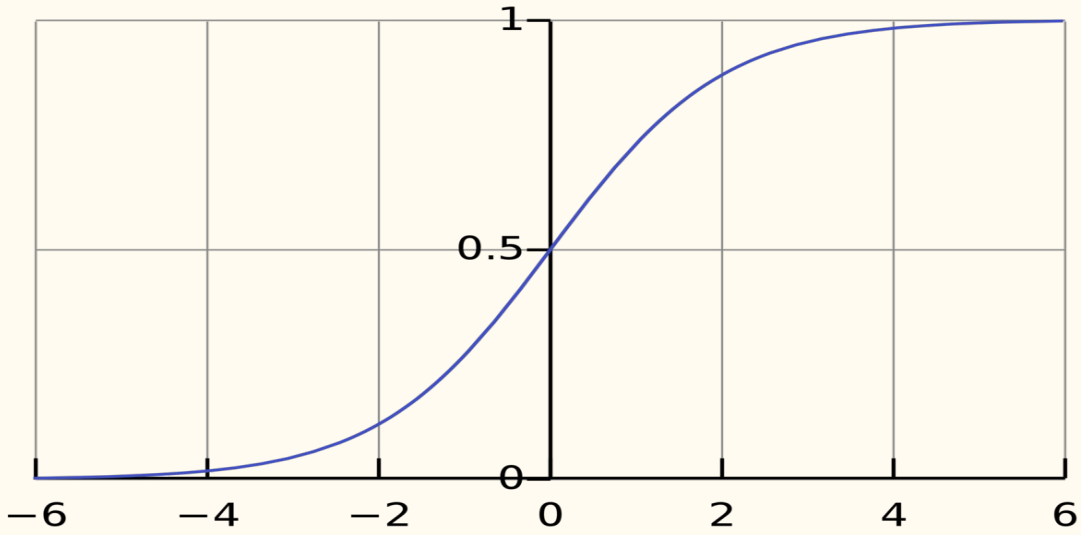
$$x_2 \rightarrow x_2 * w_2$$

$$(x_1 * w_1) + (x_2 * w_2) + b$$

$$y = f(x_1 * w_1 + x_2 * w_2 + b)$$

The activation function is used to turn an unbounded input into an output that has a nice, predictable form. A commonly used activation function is the sigmoid function.

Sigmoid Function



The sigmoid function only outputs numbers in the range (0,1). You can think of it as compressing (−∞,+∞) to (0,1) — big negative numbers become ~0, and big positive numbers become ~1.

Feed Forward

Assume we have a 2-input neuron that uses the sigmoid activation function and has the following parameters:

W = [0,1], b=4

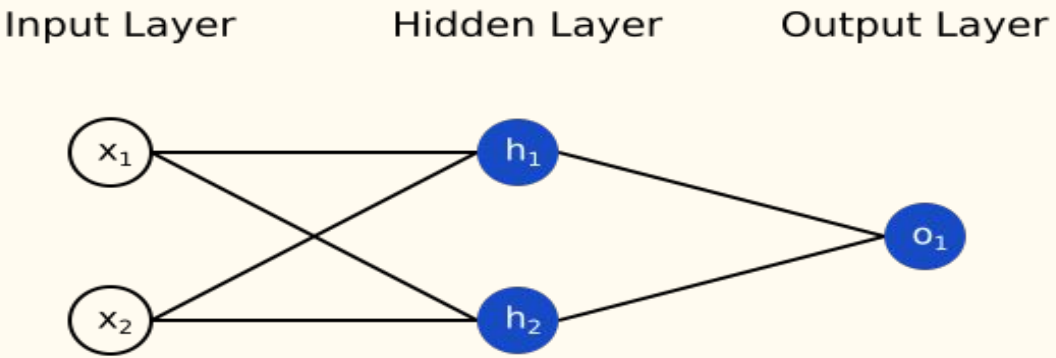
w=[0, 1] is just a way of writing $w1$=0, $w2$=1 in vector form. Now, let's give the neuron an input of x=[2, 3]. We'll use the dot product to write things more concisely:

$$\begin{aligned}(w \cdot x) + b &= ((w_1 * x_1) + (w_2 * x_2)) + b \\ &= 0 * 2 + 1 * 3 + 4 \\ &= 7\end{aligned}$$

$$y = f(w \cdot x + b) = f(7) = \boxed{0.999}$$

Combining Neurons into Neural Networks

A neural network is nothing more than a bunch of neurons connected together. Here's what a simple neural network might look like:



This network has 2 inputs, a hidden layer with 2 neurons ($h1$ and $h2$), and an output layer with 1 neuron ($o1$). Notice that the inputs for $o1$ are the outputs from $h1$ and $h2$ — that's what makes this a network.

Loss

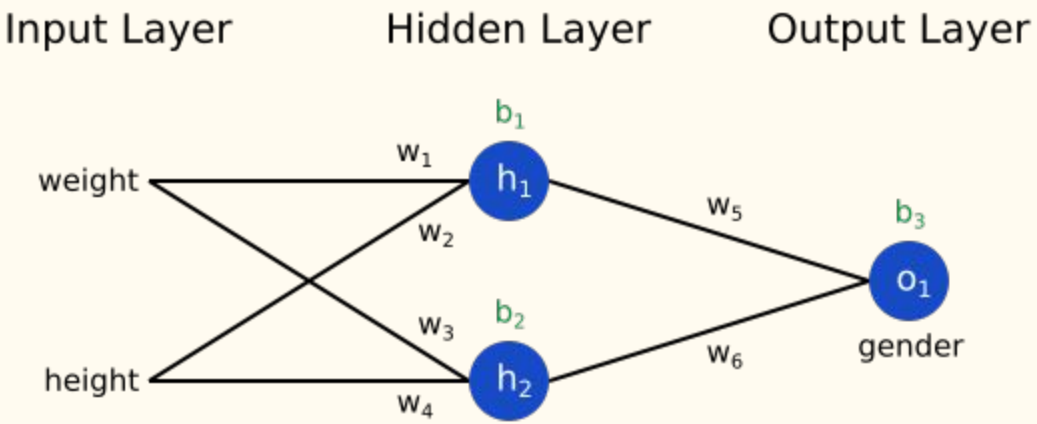
Before we train our network, we first need a way to quantify how "good" it's doing so that it can try to do "better". That's what the **loss** is.

We'll use the **mean squared error** (MSE) loss:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_{true} - y_{pred})^2$$

($y\_true - y\_pred$)^2 is known as the **squared error**. Our loss function is simply taking the average over all squared errors (hence the name *mean* squared error). The better our predictions are, the lower our loss will be!

Another way to think about loss is as a function of weights and biases. Let's label each weight and bias in our network:



Then, we can write loss as a multivariable function:

$$L(w_1, w_2, w_3, w_4, w_5, w_6, b_1, b_2, b_3)$$

$$\boxed{\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y_{pred}} * \frac{\partial y_{pred}}{\partial h_1} * \frac{\partial h_1}{\partial w_1}}$$

This system of calculating partial derivatives by working backwards is known as **backpropagation**, or “backprop”.

$$w_1 \leftarrow w_1 - \eta \frac{\partial L}{\partial w_1}$$

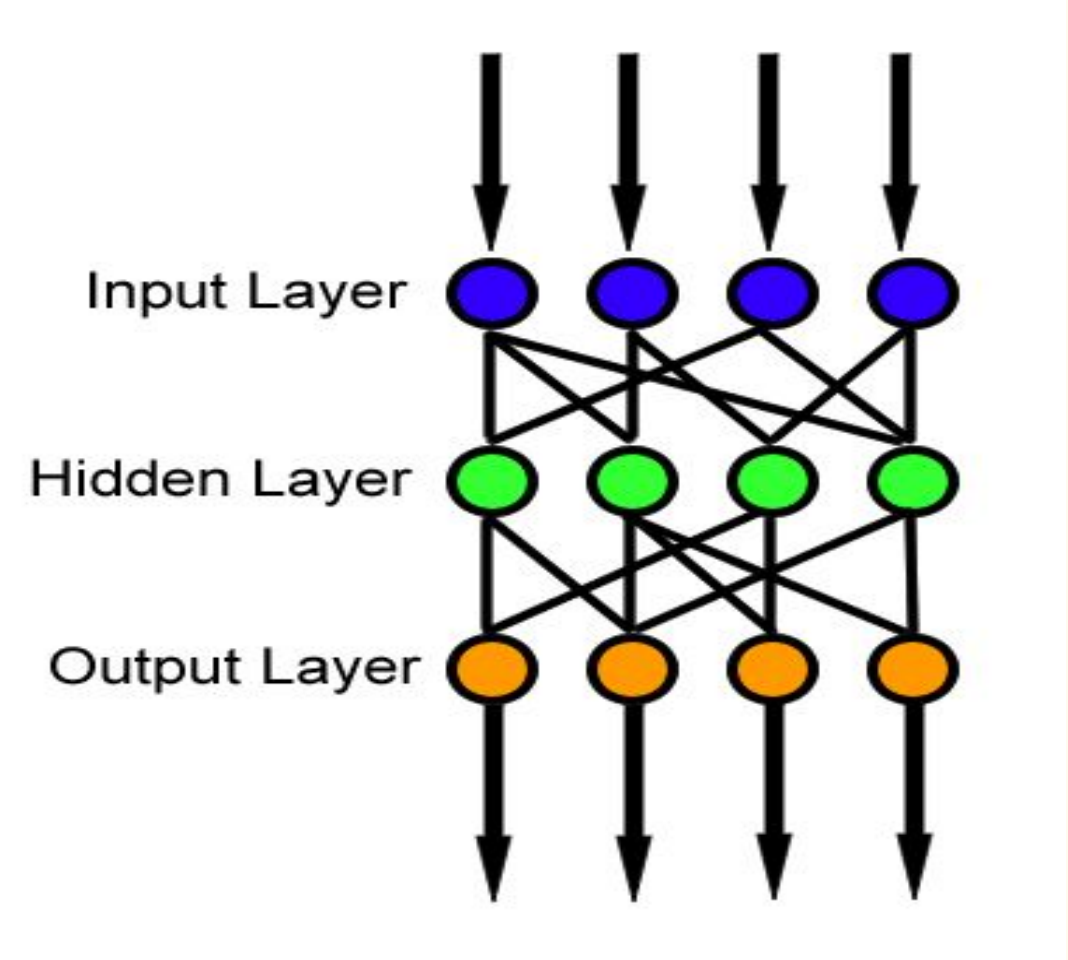
stochastic gradient descent (SGD) that tells us how to change our weights and biases to minimize loss. It’s basically just this update equation:

Artificial Neural Networks

An Artificial Neuron Network (ANN), popularly known as Neural Network is a computational model based on the structure and functions of biological neural networks. It is like an artificial human nervous system for receiving, processing, and transmitting information in terms of Computer Science.

There are 3 Different Layers in ANN

1. Input Layer (All the inputs are fed in the model through this layer)
2. Hidden Layers (There can be more than one hidden layers which are used for processing the inputs received from the input layers)
3. Output Layer (The data after processing is made available at the output layer)



The figure Depicts the Three different Layers present in a Neural Network.

The First Layer is Input Layer, the Second Layer is Hidden Layer and the Output Layer.

The Input Layer

The Input layer communicates with the external environment that presents a pattern to the neural network. Its job is to deal with all the inputs only. This input gets transferred to the hidden layers which are explained below. The input layer should represent the condition for which we are training the neural network. Every input neuron should represent some independent variable that has an influence over the output of the neural network

The Hidden Layer

The hidden layer is the collection of neurons which has activation function applied on it and it is an intermediate layer found between the input layer and the output layer. Its job is to process the inputs obtained by its previous layer. So it is the layer which is responsible extracting the required features from the input data. Many researches has been made in evaluating the number of neurons in the hidden layer but still none of them was successful in finding the accurate result.

Also there can be multiple hidden layers in a Neural Network. So you must be thinking that how many hidden layers have to be used for which kind of problem. Suppose that if we have a data which can be separated linearly, then there is no need to use hidden layer as the activation function can be implemented to input layer which can solve the problem. But in case of problems which deals with complex decisions, we can use 3 to 5 hidden layers based on the degree of complexity of the problem or the degree of accuracy required.

That certainly not means that if we keep on increasing the number of layers, the neural network will give high accuracy! A stage comes when the accuracy becomes constant or falls if we add an extra layer! Also, we should also calculate the number of neurons in each network. If the number of neurons are less as compared to the complexity of the problem data then there will be very few neurons in the hidden layers to adequately detect the signals in a complicated data set. If unnecessary more neurons are present in the network then Overfitting may occur.

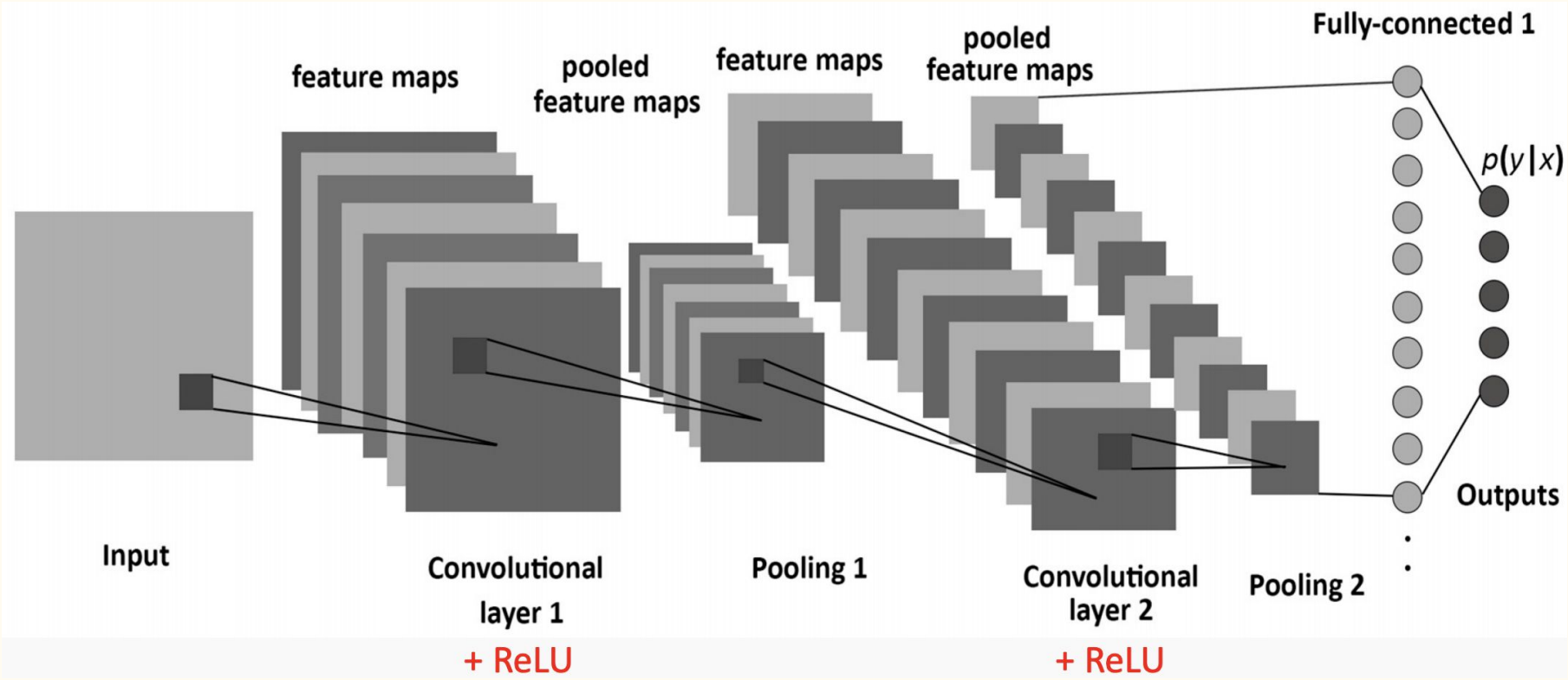
Output Layer

The output layer of the neural network collects and transmits the information accordingly in way it has been designed to give. The pattern presented by the output layer can be directly traced back to the input layer. The number of neurons in output layer should be directly related to the type of work that the neural network was performing. To determine the number of neurons in the output layer, first consider the intended use of the neural network.

Algorithms and Properties

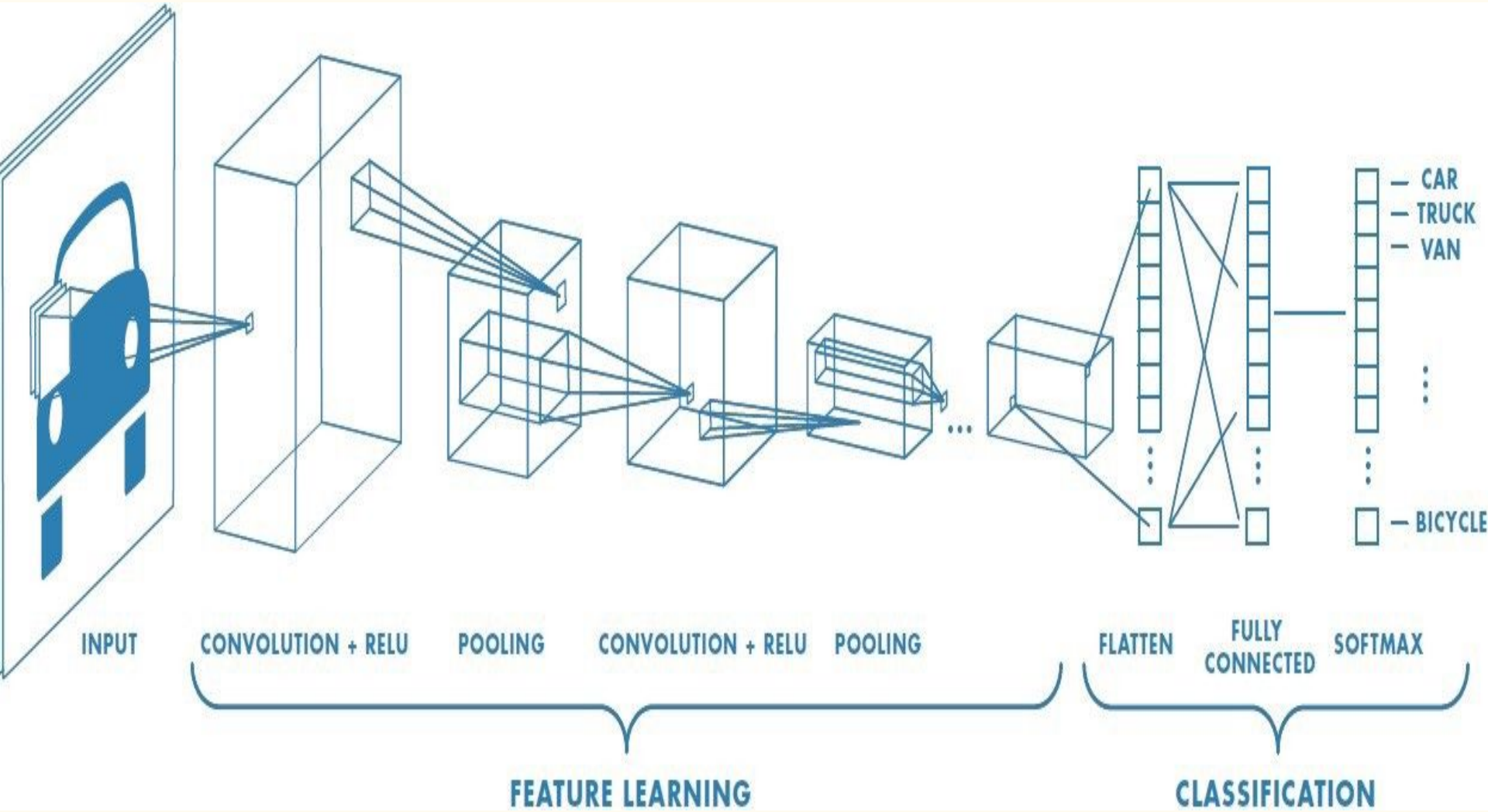
Algo	Type	Tolerance number features	Parametrization	Memory size	Minimal required quantity	Com m	Overfitting Tendency	Difficulty	Time for Learning	Time for predicting
Linear Regression	R	Weak	Weak	Small	Small	++	Low	Weak	Weak	Weak
Logistic Regression	C	Weak	Simple	Small	Small	++	Low	Weak	Weak	Weak
Decision Tree	R & C	Strong	Simple / intuitive	Large	Small	+++	Very high	Weak	Weak	Weak
Random Forest	R & C	Strong	Simple / intuitive	Very Large	Large	++	Average	Average	Costly	Costly
Boosting	R & C	Strong	Simple / intuitive	Very Large	Large	+	Average	Average	Costly	Weak
Naive Bayes	C	Weak	No params.	Small	Small	++	Low	Weak	Weak	Weak
SVM	C	Very strong	Not intuitive	Small	Large	--	Average	High	Costly	Weak
Neural Network (NN)	C	Very strong **	Not intuitive	Inter	Large	---	Average	Very high	Costly	Weak
Deep Neural Network	C	Very strong **	Not intuitive	Very Large	Very Large	---	High	Very high	Very costly	Weak
K-Means	CL*	Strong	Simple / Intuitive		Small	+		High	Weak	
One class SVM	A	Very strong	Not intuitive	Weak	Large	--	Average	High	Costly	Weak

Convolutional Neural Networks



Introduction

Convolutional neural networks are neural networks used primarily to classify images (i.e. name what they see), cluster images by similarity (photo search), and perform object recognition within scenes. For example, convolutional neural networks (ConvNets or CNNs) are used to identify faces, individuals, street signs, tumors, platypuses (platypi?) and many other aspects of visual data.

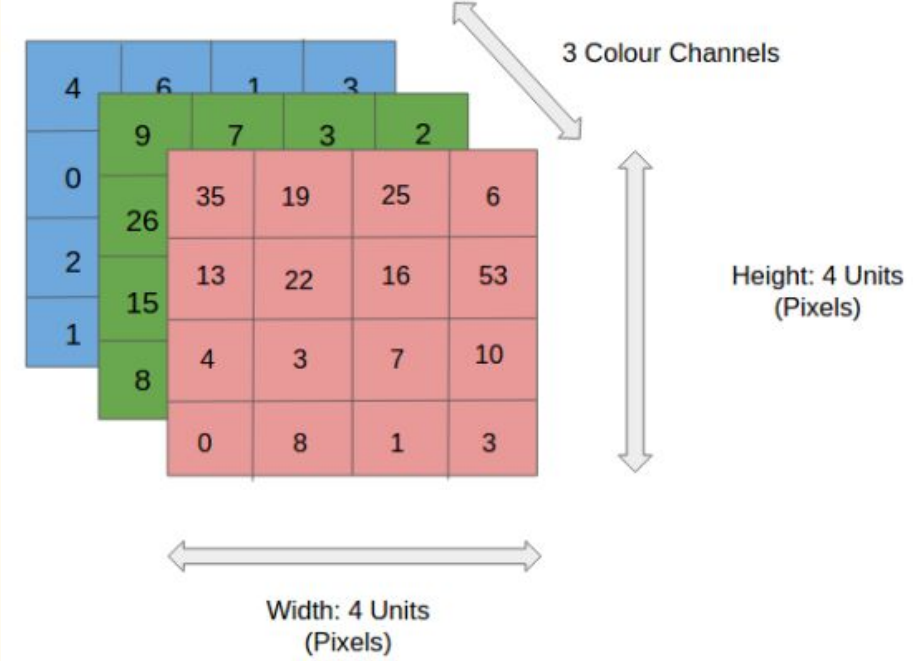

CAR
TRUCK
VAN
BICYCLE
INPUT
CONVOLUTION + RELU
POOLING
CONVOLUTION + RELU
POOLING
FLATTEN
FULLY CONNECTED
SOFTMAX
FEATURE LEARNING
CLASSIFICATION

The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.

The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlap to cover the entire visual area.

Why Conv Nets over Neural Nets ?

A ConvNet is able to **successfully capture the Spatial and Temporal dependencies** in an image through the application of relevant filters. The architecture performs a better fitting to the image dataset due to the reduction in the number of parameters involved and reusability of weights. In other words, the network can be trained to understand the sophistication of the image better.



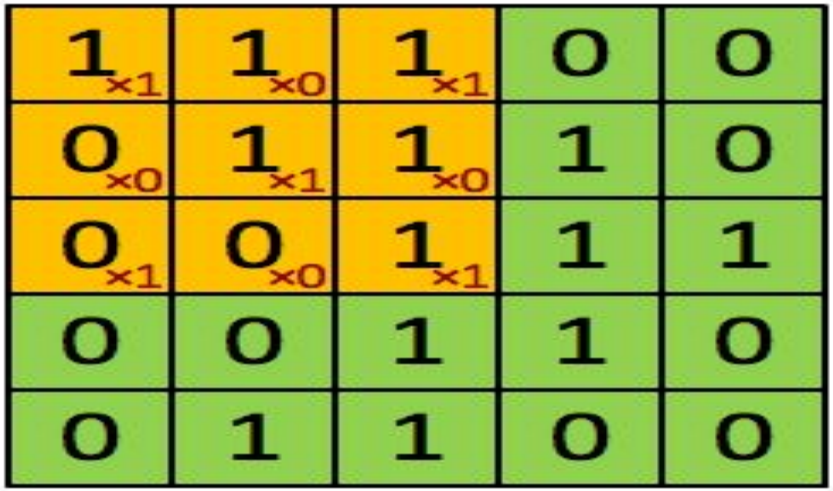
In the figure, we have an RGB image which has been separated by its three color planes — Red, Green, and Blue. There are a number of such color spaces in which images exist — Grayscale, RGB, HSV, CMYK, etc.

You can imagine how computationally intensive things would get once the images reach dimensions, say 8K (7680×4320). The role of the Conv Net is to reduce the images into a form which is easier to process, without losing features which are critical for getting a good prediction. This is important when we are to design an architecture which is not only good at learning features but also is scalable to massive datasets.

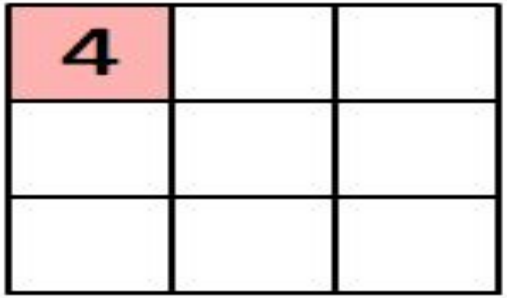
Layers in CNN

- Convolutional Layer
- Pooling Layer
  - Max Pooling Layer
  - Min Pooling Layer
  - Avg Pooling Layer
- Fully Connected Layer

Convolutional Layer



Image



Convolved Feature

Image Dimensions = 5 (Height) x 5 (Breadth) x 1 (Number of channels, eg. RGB)

In the above demonstration, the green section resembles our **5x5x1 input image, I**. The element involved in carrying out the convolution operation in the first part of a Convolutional Layer is called the **Kernel/Filter, K**, represented in the color yellow. We have selected **K as a 3x3x1 matrix.**

Strides

The Kernel shifts 9 times because of **Stride Length = 1 (Non-Strided)**, every time performing a **matrix multiplication operation between K and the portion P of the image** over which the kernel is hovering.

The filter moves to the right with a certain Stride Value till it parses the complete width. Moving on, it hops down to the beginning (left) of the image with the same Stride Value and repeats the process until the entire image is traversed.

Objective

The objective of the Convolution Operation is to extract the high-level features such as edges, from the input image. ConvNets need not be limited to only one Convolutional Layer. Conventionally, the first Conv Layer is responsible for capturing the Low-Level features such as edges, color, gradient orientation, etc. With added layers, the architecture adapts to the High-Level features as well, giving us a network which has the wholesome understanding of images in the dataset, similar to how we would.

Results of Padding

There are two types of results to the operation — one in which the convolved feature is reduced in dimensionality as compared to the input, and the other in which the dimensionality is either increased or remains the same. This is done by applying Valid Padding in case of the former, or Same Padding in the case of the latter.

Same Padding

When we augment the 5x5x1 image into a 6x6x1 image and then apply the 3x3x1 kernel over it, we find that the convolved matrix turns out to be of dimensions 5x5x1. Hence the name — **Same Padding**.

Valid Padding

if we perform the same operation without padding, we are presented with a matrix which has dimensions of the Kernel (3x3x1) itself — **Valid Padding**.

Pooling Layer

Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature. This is to **decrease the computational power required to process the data** through dimensionality reduction. Furthermore, it is useful for **extracting dominant features** which are rotational and positional invariant, thus maintaining the process of effectively training of the model.

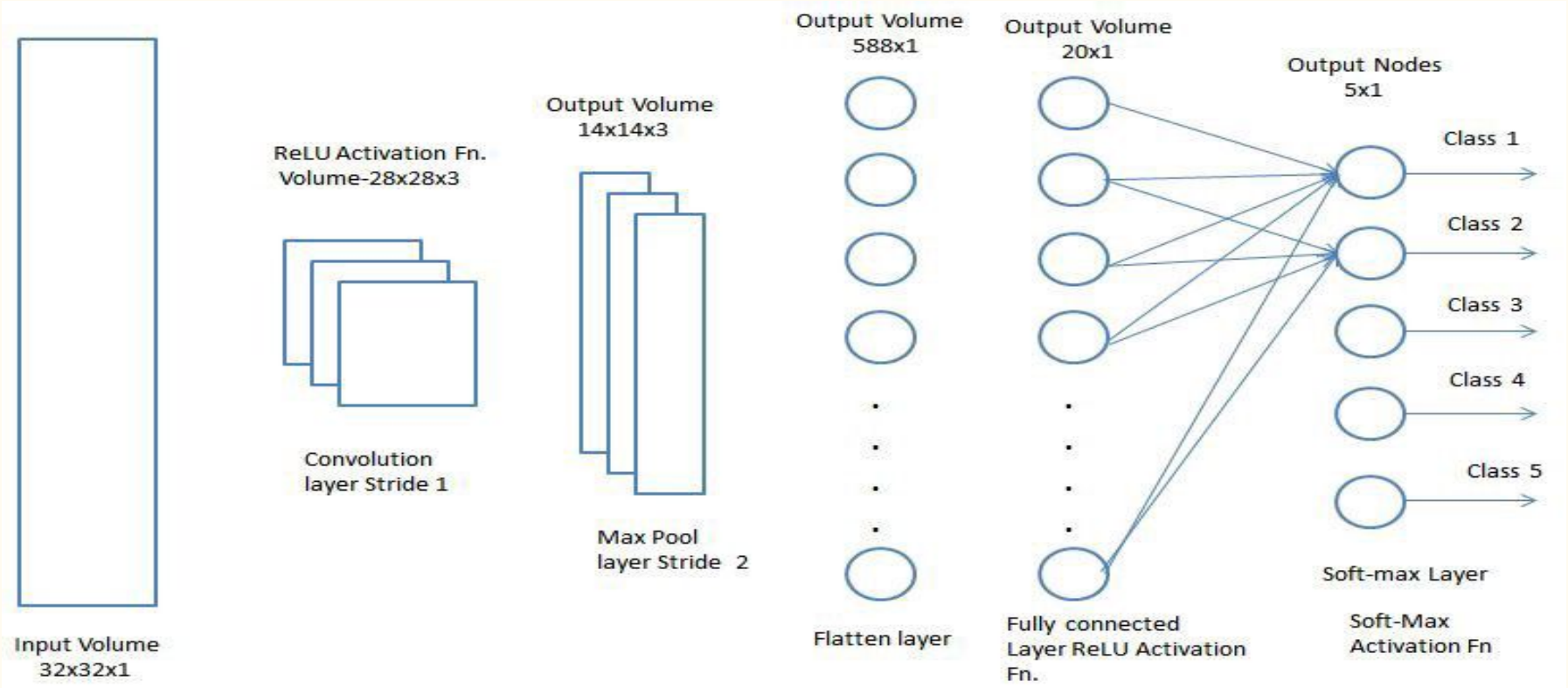
There are two types of Pooling: Max Pooling and Average Pooling. **Max Pooling** returns the **maximum value** from the portion of the image covered by the Kernel. On the other hand, **Average Pooling** returns the **average of all the values** from the portion of the image covered by the Kernel.

Max Pooling also performs as a **Noise Suppressant**. It discards the noisy activations altogether and also performs de-noising along with dimensionality reduction. On the other hand, Average Pooling simply performs dimensionality reduction as a noise suppressing mechanism. Hence, we can say that **Max Pooling performs a lot better than Average Pooling**.

The Convolutional Layer and the Pooling Layer, together form the i-th layer of a Convolutional Neural Network. Depending on the complexities in the images, the number of such layers may be increased for capturing low-levels details even further, but at the cost of more computational power.

After going through the above process, we have successfully enabled the model to understand the features. Moving on, we are going to flatten the final output and feed it to a regular Neural Network for classification purposes.

Fully Connected Layer



Adding a Fully-Connected layer is a (usually) cheap way of learning non-linear combinations of the high-level features as represented by the output of the convolutional layer. The Fully-Connected layer is learning a possibly non-linear function in that space.

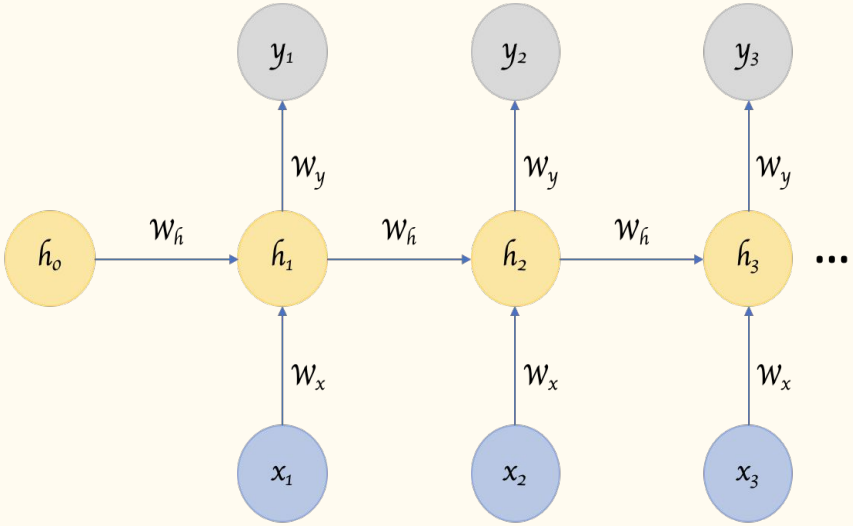
Now that we have converted our input image into a suitable form for our Multi-Level Perceptron, we shall flatten the image into a column vector. The flattened output is fed to a feed-forward neural network and backpropagation applied to every iteration of training. Over a series of epochs, the model is able to distinguish between dominating and certain low-level features in images and classify them using the **Softmax Classification** technique.

CNN Architectures

- **LeNet**
- **AlexNet**
- **VGGNet**
- **GoogLeNet**
- **ResNet**
- **ZFNet**

Recurrent Neural Networks

Recurrent Neural Networks (RNNs) add an interesting twist to basic neural networks. A vanilla neural network takes in a fixed size vector as input which limits its usage in situations that involve a ‘series’ type input with no predetermined size.



Recurrent Neural Network remembers the past and it's decisions are influenced by what it has learnt from the past. Note: Basic feed forward networks "remember" things too, but they remember things they learnt during training. For example, an image classifier learns what a "1" looks like during training and then uses that knowledge to classify things in production.

While RNNs learn similarly while training, in addition, they remember things learnt from prior input(s) while generating output(s). It's part of the network. RNNs can take one or more input vectors and produce one or more output vectors and the output(s) are influenced not just by weights applied on inputs like a regular NN, but also by a "hidden" state vector representing the context based on prior input(s)/output(s). So, the same input could produce a different output depending on previous inputs in the series.

In summary, in a vanilla neural network, a fixed size input vector is transformed into a fixed size output vector. Such a network becomes “recurrent” when you repeatedly apply the transformations to a series of given input and produce a series of output vectors. There is no pre-set limitation to the size of the vector. And, in addition to generating the output which is a function of the input and hidden state, we update the hidden sate itself based on the input and use it in processing the next input.

Parameter Sharing

If we don’t share parameters across inputs, then it becomes like a vanilla neural network where each input node requires weights of their own. This introduces the constraint that the length of the input has to be fixed and that makes it impossible to leverage a series type input where the lengths differ and is not always known.

But what we seemingly lose in value here, we gain back by introducing the “hidden state” that links one input to the next. The hidden state captures the relationship that neighbors might have with each other in a serial input and it keeps changing in every step, and thus effectively every input undergoes a different transition!

Deep RNNs

While it's good that the introduction of hidden state enabled us to effectively identify the relationship between the inputs, is there a way we can make a RNN "deep" and gain the multi level abstractions and representations we gain through "depth" in a typical neural network?

Ways to add Depth

(1) Perhaps the most obvious of all, is to add hidden states, one on top of another, feeding the output of one to the next.

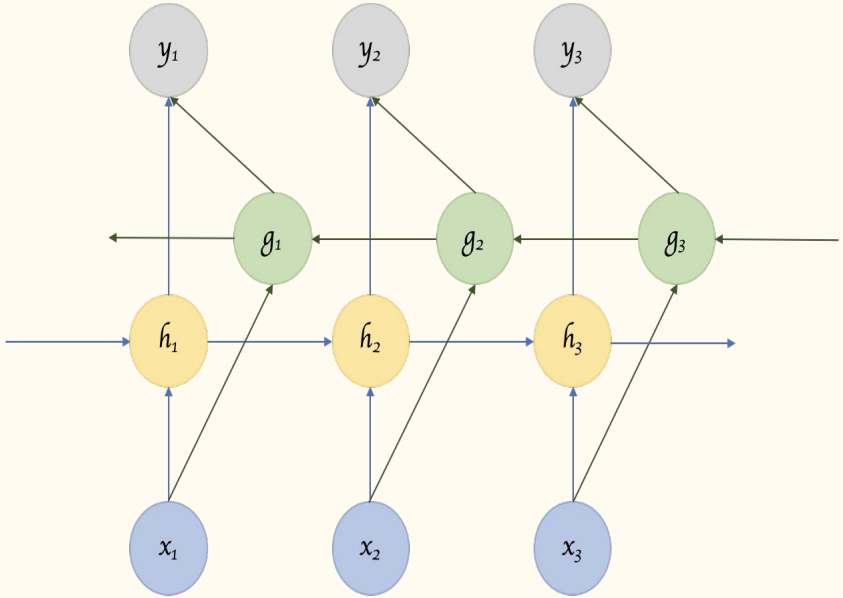
(2) We can also add additional nonlinear hidden layers between input to hidden state

(3) We can increase depth in the hidden to hidden transition

(4) We can increase depth in the hidden to output transition.

Bidirectional RNNs

Sometimes it's not just about learning from the past to predict the future, but we also need to look into the future to fix the past. In speech recognition and handwriting recognition tasks, where there could be considerable ambiguity given just one part of the input, we often need to know what's coming next to better understand the context and detect the present.



This does introduce the obvious challenge of how much into the future we need to look into, because if we have to wait to see all inputs then the entire operation will become costly. And in cases like speech recognition, waiting till an entire sentence is spoken might make for a less compelling use case. Whereas for NLP tasks, where the inputs tend to be available, we can likely consider entire sentences all at once. Also, depending on the application, if the sensitivity to immediate and closer neighbors is higher than inputs that come further away, a variant that looks only into a limited future/past can be modeled

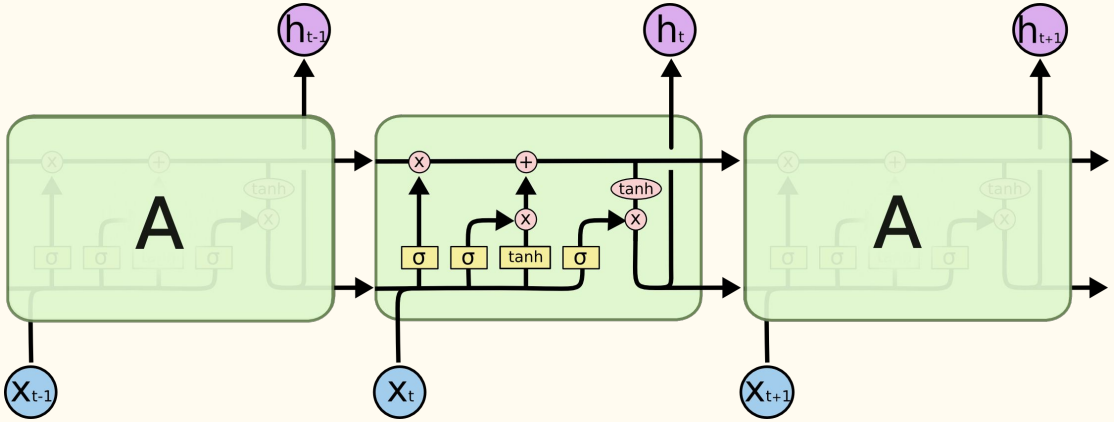
LSTMs

Long Short Term Memory networks – usually just called “LSTMs” – are a special kind of RNN, capable of learning long-term dependencies. They were introduced by Hochreiter & Schmidhuber (1997), and were refined and popularized by many people in following work.1 They work tremendously well on a large variety of problems, and are now widely used.

LSTMs are explicitly designed to avoid the long-term dependency problem. Remembering information for long periods of time is practically their default behavior, not something they struggle to learn!

All recurrent neural networks have the form of a chain of repeating modules of neural network. In standard RNNs, this repeating module will have a very simple structure, such as a single tanh layer.

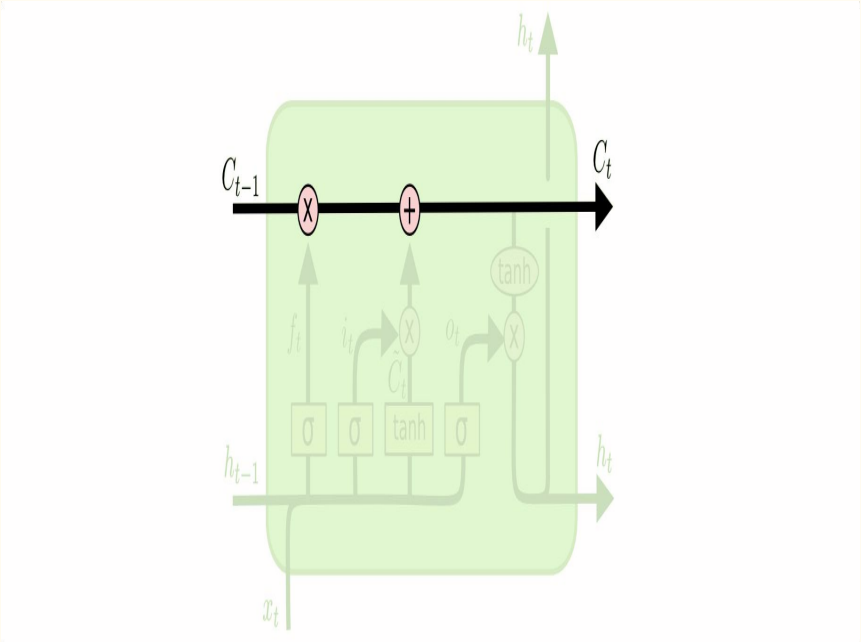
LSTMs also have this chain like structure, but the repeating module has a different structure. Instead of having a single neural network layer, there are four, interacting in a very special way.



Idea behind LSTMs

The key to LSTMs is the cell state, the horizontal line running through the top of the diagram.

The cell state is kind of like a conveyor belt. It runs straight down the entire chain, with only some minor linear interactions. It's very easy for information to just flow along it unchanged.



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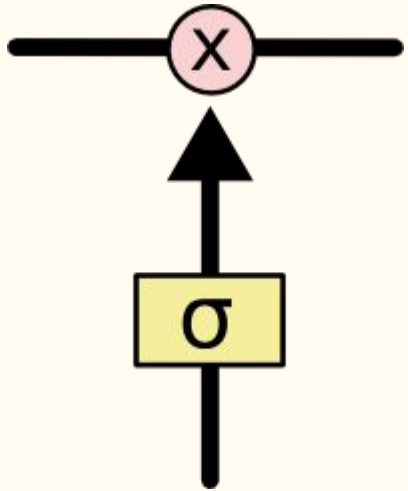

The sigmoid layer outputs numbers between zero and one, describing how much of each component should be let through. A value of zero means “let nothing through,” while a value of one means “let everything through!”

An LSTM has three of these gates, to protect and control the cell state.

Thank you