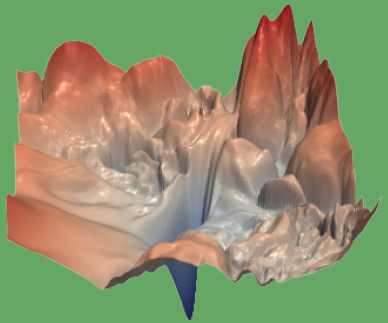
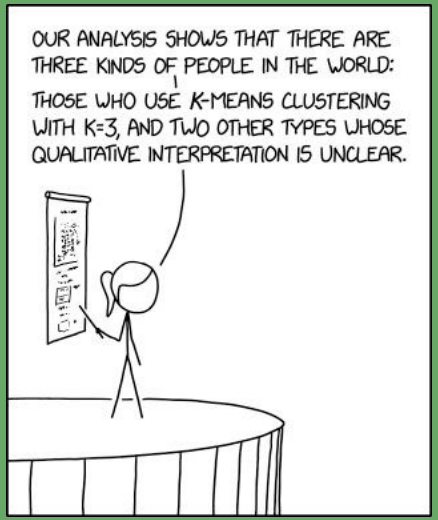
Deep Learning



AAKASH GHOSH
19MS129

Presentation made for the completion of Course MA5115

Traditional ML



Traditional Machine learning

The older/traditional way of applying machine learning consisted of the following steps:

- **Feature Extraction**: Features which can be used to discriminate between classes is captured. This step usually requires in-field knowledge about the problem.

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- **Cross-validation/Tested**: The model is tested/cross-validated on with held data

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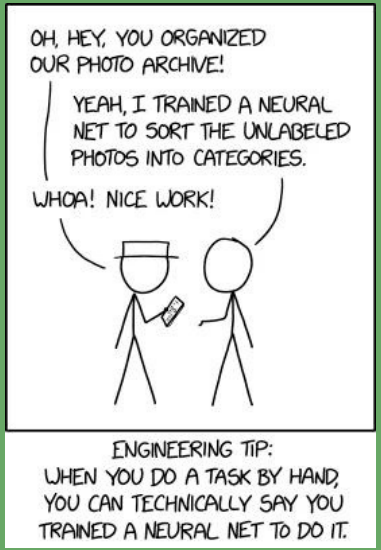
- **Unorganized Data**: Feature extraction is hard in unorganized data (such as a literary works).

The idea behind deep learning



Ideas behind a neural network

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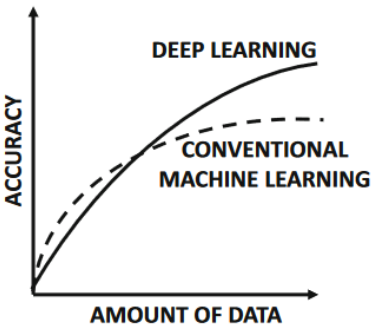
- **Overview**: We make a perceptron, which is essentially the digital analog of a neuron. We connect multiple neurons together(similar to our brain) and look at what pattern and amount of activation leads to best result.

A practical comparison with traditional ML



Comparision based on amount of data features.
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- Traditional ML models show better prediction when the amount of features involved is small. Features can be individually engineered and interpreted.

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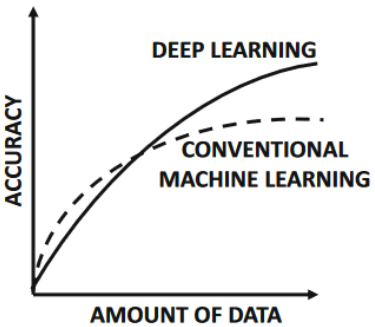

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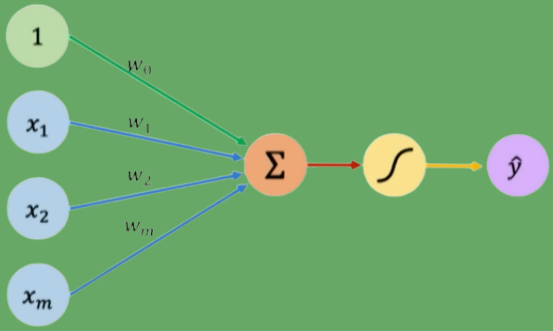
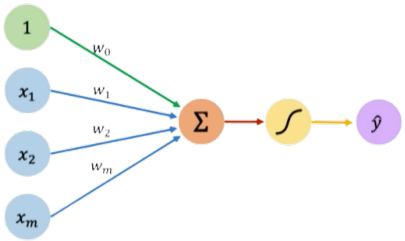
- Traditional ML models show better prediction when the amount of features involved is small. Features can be individually engineered and interpreted.
- Deep learning models are better when data is unstructured or there are a lot of features which need to be considered. With proper construction and training almost any decision boundaries can be learned.

The Perceptron



Non-Linearity is the key



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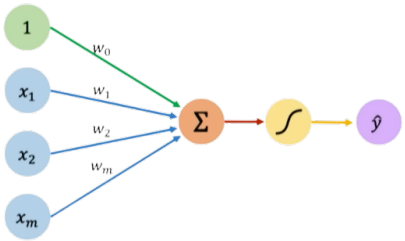

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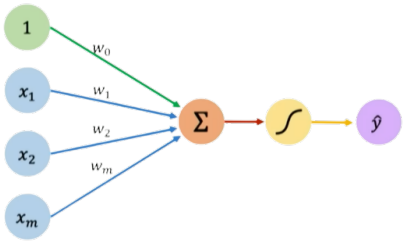

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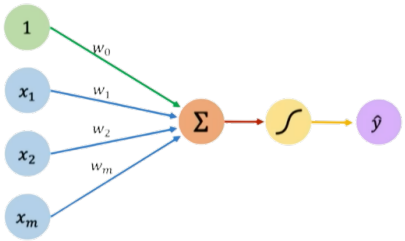

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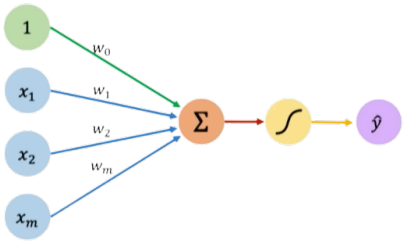

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- At the very core, Machine Learning works by constructing proper decision boundaries.
- A very simple calculation shows if σ is linear then the decision boundary is also linear. It therefore makes sense to use non-linear σ.

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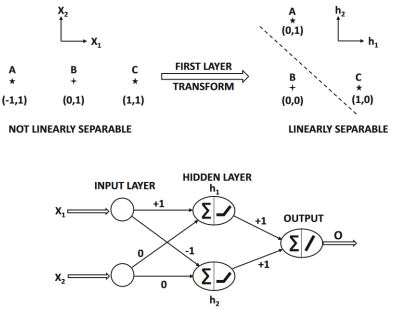

Non-linearity in action
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- As shown in the figure on left, classes which can't be separated by linear boundaries can be separated by non-linear functions.(Think SVM but the kernals are learned.)

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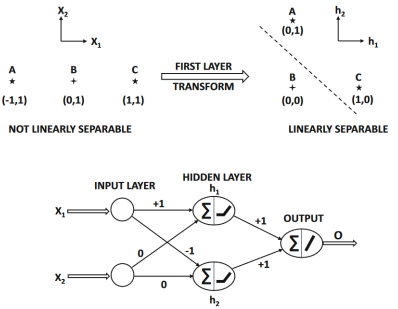

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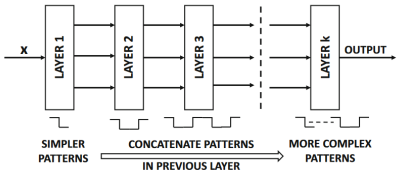
- It can be theoretically shown that almost all boundary function can be separated by a 2 layered neural network.

Increasing depth



Why is depth needed
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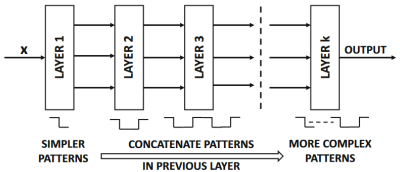

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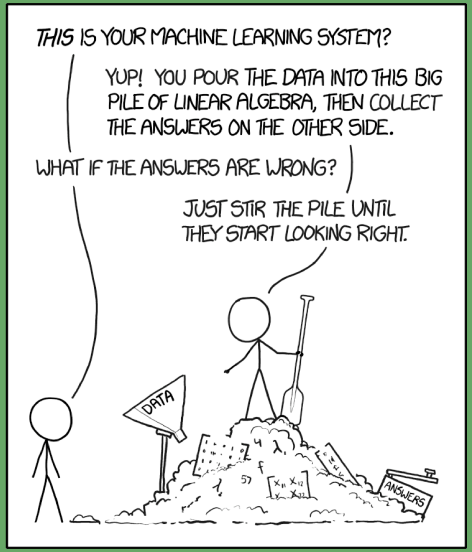
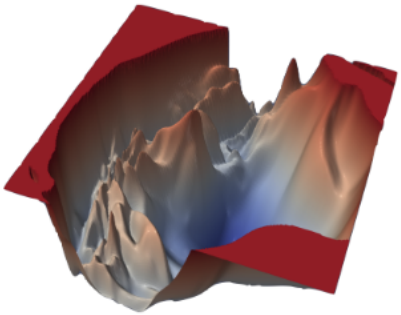
- It should be noted how non-linearity discussed above plays an important role: Irrespective of number of layers, composition of linear functions is linear. On the other hand compositions of non-linear function can lead to richer families of functions. (*Ref: https://www.desmos.com/-calculator/m645ggyl2i*)

Training a neural network

Loss functions,Backpropagation, Reversemode Auto-Diff, Practical problems and hardware considerations



Loss Function



A slice of the loss landscape of resnet-110 with no skip connections
Src: Visualizing the Loss Landscape of Neural Nets, Hao Li, Zheng Xu, Gavin Taylor, Christoph Studer, Tom Goldstein

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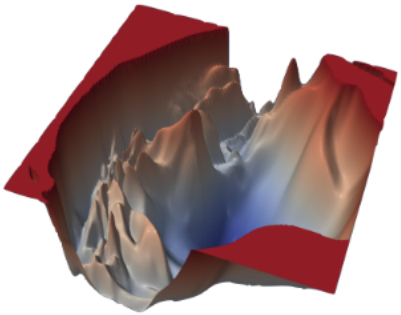

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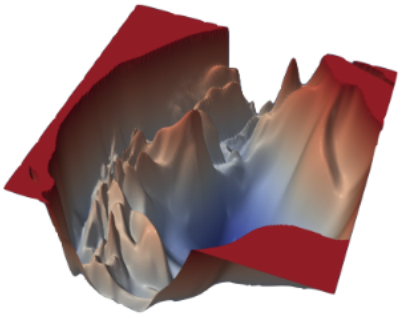

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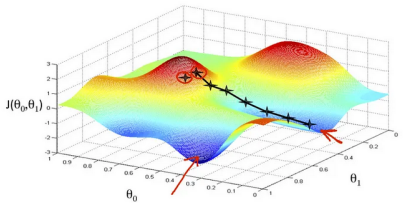
- Common choices of $\mathcal{L}$ include MSE for continuous variables and cross-loss entropy for categorical variables.

Gradient descent



Gradient descent
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- To find the correct set of weights, we use a greedy approach. We check the surrounding landscape of the weight(i.e. calculate the gradient) and take a step in the direction which leads to maximum decrease in $\mathcal{L}$. Mathematically, we have:

$$w_i = wi - \eta \frac{\partial \mathcal{L}}{\partial w_i}$$

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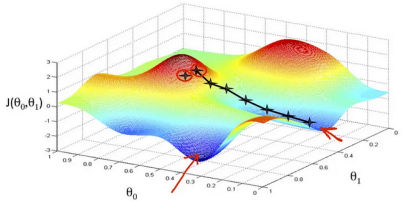

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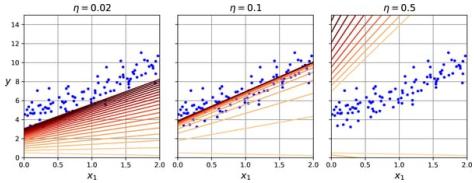
- η is known as the learning rate.

Learning Rate



Variations in learning rates
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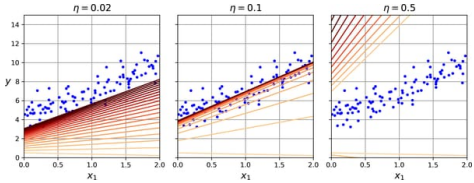

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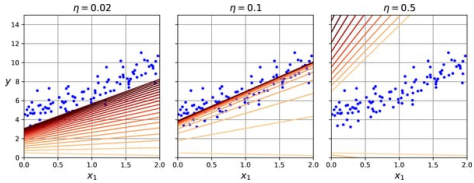

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- Fixing η is quite tricky.
- If η is small we get stuck at local minima
- If η is large we overshoot our targets and never converge.
- The best way to do things is to use a adaptive learn rate. Some methods(parametric, non-parametric and hybrid are discussed later, once we cover backpropagation)

Backpropagation

Consider a neural network to be an acyclic directed graph

- We want to calculate the partial derivative of a node with respect to the other.

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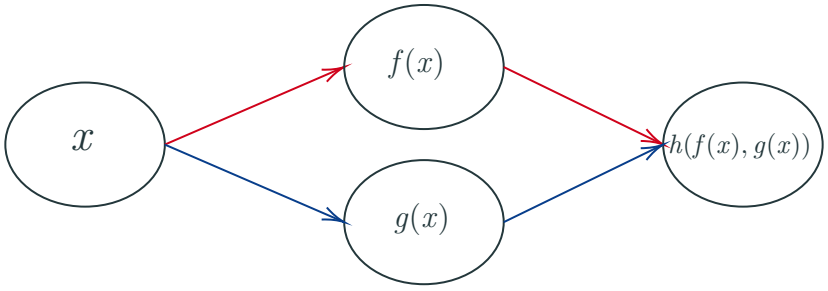
- We want to calculate the partial derivative of a node with respect to the other.
- The way to do this is to use the chain rule
- When we use the chain rule, we sum the partial derivative along all the paths joining the two nodes
- It is easy to see that the computation needed explodes as the depth increases
- The way to navigate this problem is to use dynamic programming.



$$\frac{\partial h}{\partial x} = \frac{\partial h}{\partial f} \cdot \frac{\partial f}{\partial x} + \frac{\partial h}{\partial g} \cdot \frac{\partial g}{\partial x}$$

Backpropagation

Roughly, the alogirithm works as follows:

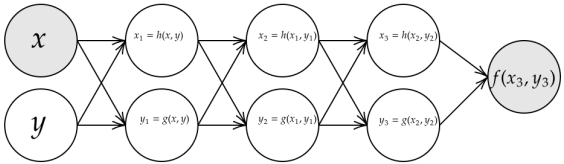
- Initialize the weights

Backpropagation

Roughly, the alogirithm works as follows:

- Initialize the weights
- Calculate $\mathcal{L}$. Note, that this step occurs from the input towards the output and is known as the forward phase.
- Calculate gradient. This process occurs from the output towards the input and is known as the backward phase.

Reverse Mode Auto Differentiation



$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial x_3} \cdot \frac{\partial x_3}{\partial x} + \frac{\partial f}{\partial y_3} \cdot \frac{\partial y_3}{\partial x}$$

$$= \frac{\partial f}{\partial x_3} \cdot \left(\frac{\partial x_3}{\partial x_2} \frac{\partial x_2}{\partial x} + \frac{\partial x_3}{\partial y_2} \frac{\partial y_2}{\partial x} \right) + \frac{\partial f}{\partial y_3} \cdot \left(\frac{\partial y_3}{\partial x_2} \frac{\partial x_2}{\partial x} + \frac{\partial y_3}{\partial y_2} \frac{\partial y_2}{\partial x} \right)$$

The whole idea relies on the fact that while calculating gradients, parts of the calculation are repeated.

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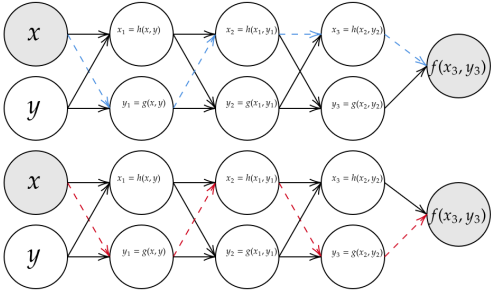

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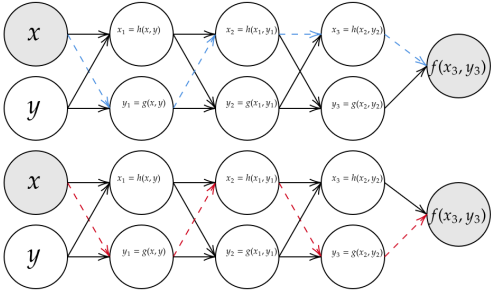
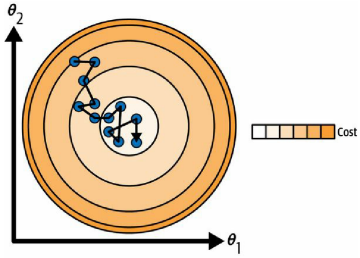


Sum is taken over the product along each path, over all the paths. It is trivial to note that parts of the paths are repeated.In the toy example on the left, the paths are essentially the same, varying only for the second to last node.

Gradient Descent Statergy-Stochastic Gradient Descent



Stochstic Gradient descent
Src:Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow Concepts, Tools, and Techniques to Build Intelligent Systems-O'Reilly Media, Inc, Aurélien Géron

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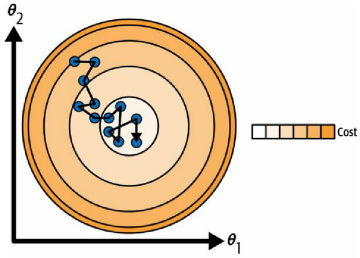

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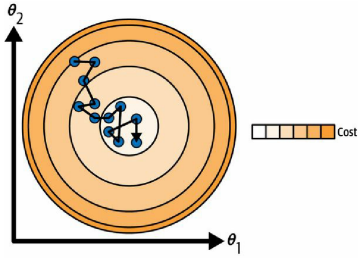

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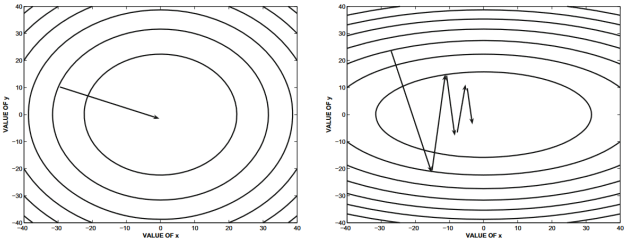
- Think instead of taking slower but confident steps, we take faster but less-confident steps.

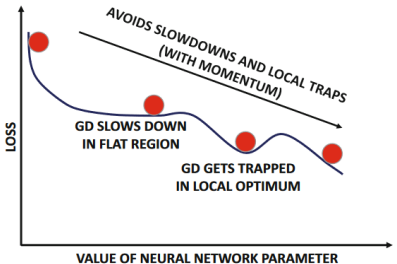
Gradient Descent Statergy- Normalization



Why normalize?
Src:Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow Concepts, Tools, and Techniques to Build Intelligent Systems-O'Reilly Media, Inc, Aurélien Géron

Normalizing features is a way to make the descent smoother. It essentially lowers the changes in direction orthogonal to the minima.

Gradient Descent Statergy- Mommentum



Need for momentum
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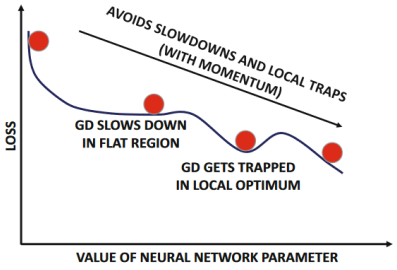

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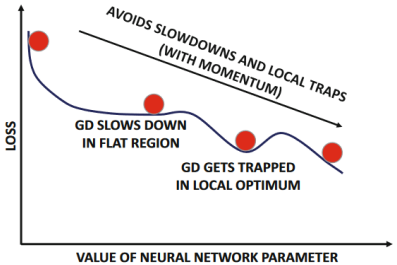

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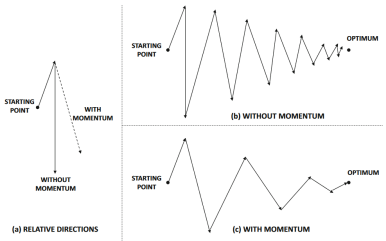

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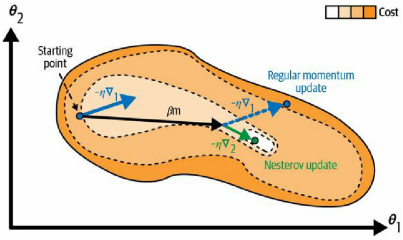
Gradient Descent Statergy- Nestov Mommentum



Nestov momentum
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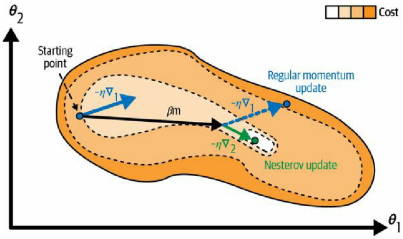

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- Nestov-momentum is similar to momentum with some scout ahead
- Knowing what's coming up ahead further helps in correcting the direction of descent.

Gradient Descent Statergy- Adaptive Learning Rates

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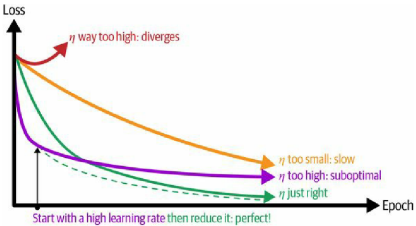
- We try to let different parameters have different learning rates.
- The idea is that parameters with large partial derivatives are often oscillating and zigzagging, whereas parameters with small partial derivatives tend to be more consistent but move in the same direction.
- Algorithms include AdaGrad, RMSProp and AdaDelta. Parametric algorithms combined with momentum considerations also exist: RMSProp with Nesterov Momentum, ADAM and it's variants like AdaMax, Nadam and AdamW. A quick comparison table is avilable at *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow Concepts, Tools, and Techniques to Build Intelligent Systems-O'Reilly Media, Inc by Aurélien Géron*

Gradient Descent Statergy- Learning Rate Scheduling



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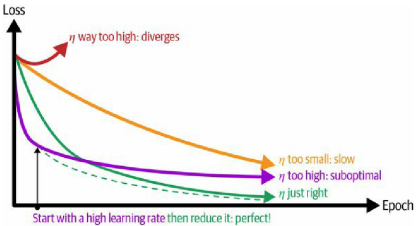

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- We have the learning rate high at first so that it gets a relative idea about where the minima lies, and then we lower it to find it with more accuracy

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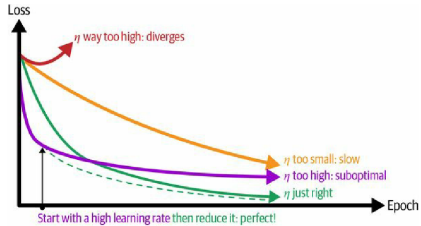

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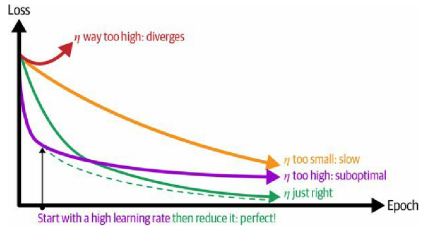

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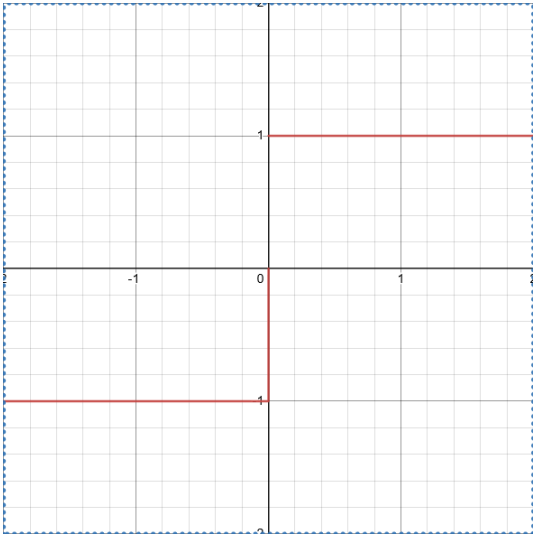
Gradient Descent Statergy- One cycle scheduling

- The basic idea behind one cycle scheduling is to start with a low learning rate, gradually increase it to a maximum value, and then decrease it again to a low value. This approach helps the network explore a wide range of learning rates, allowing it to quickly converge to a good solution and potentially escape from local minima.
- By using a cyclical learning rate schedule, one cycle scheduling aims to strike a balance between exploration and exploitation in the learning process. It enables the network to quickly explore a wide range of learning rates at the beginning and then gradually refine its weights as the learning rate decreases.

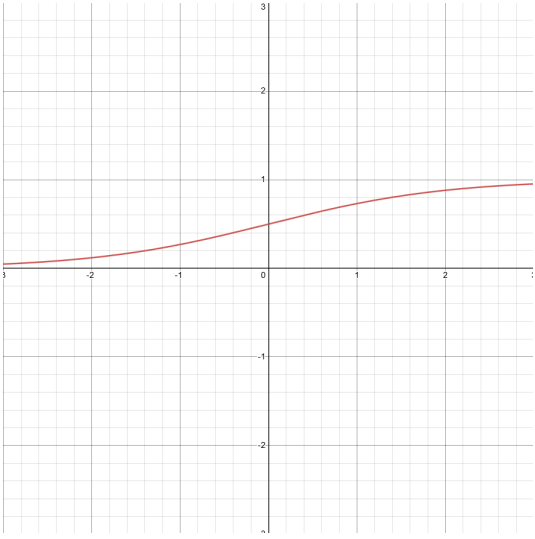
Gradient Descent Strategy- Choosing an activation function



$sgn(x)$

One of the first activation functions to be considered was $sgn(x)$ mostly because this was the function based on which our neurons operate.

Gradient Descent Strategy- Choosing an activation function



sigmoid

But soon better activation functions were found like the sigmoid function

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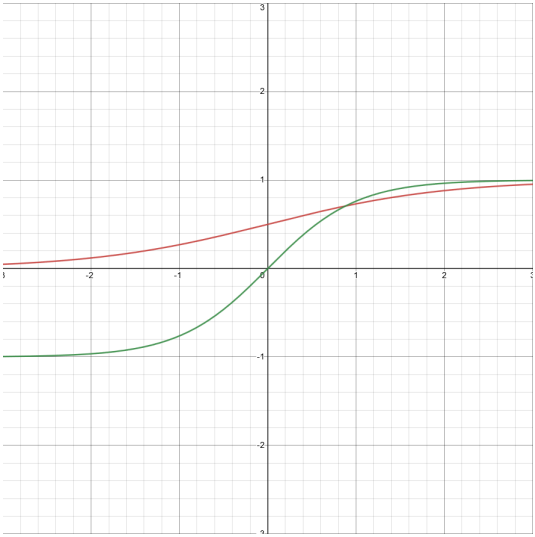

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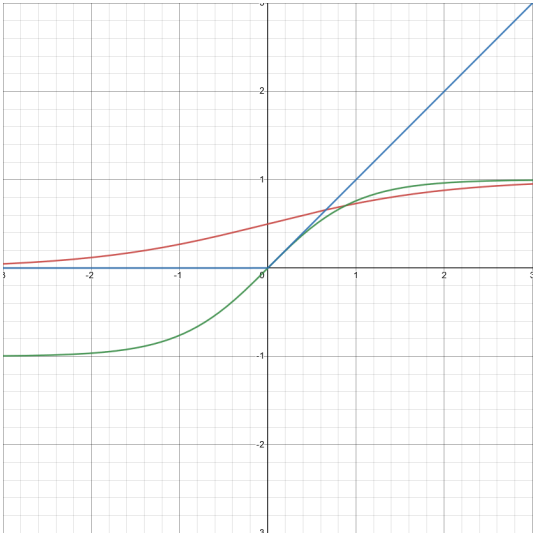

sigmoid, tanh, relu

But soon better activation functions were found like the sigmoid function, tanh function and relu function.

Gradient Descent Strategy- Dead Neurons and Vanishing & Exploding Gradients

sigmoid, tanh, relu

- Most activation function saturated. Therefore, high values meant no gradient ”propagated” forward. This leads to neurons which rarely activated and became ”dead”.

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- The effect of derivatives magnifies down the layers. If the order of magnitude is above 1(say 10) then it explodes(after 10 layers it will become 10^{10}).

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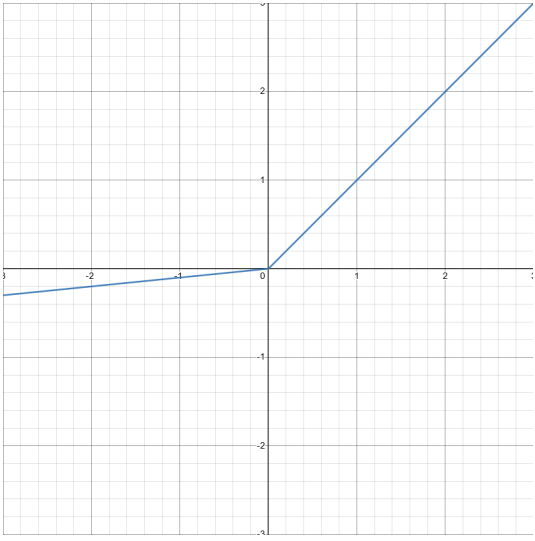
- The effect of derivatives magnifies down the layers. If the order of magnitude is below 1(say $1/10$) then it vanishes(after 10 layers it will become 10^{-10})
- From a more practical viewpoint, this might lead to overflow if the gradient explodes. If it is vanishing, then there might not be enough precision to handle the values.

Gradient Descent Strategy- Better Activation Functions



leaky ReLu

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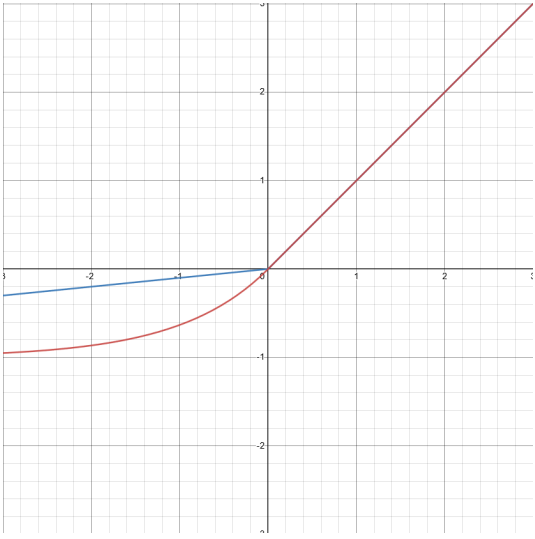
- Leaky ReLu $(\max(\alpha z, z))$

Gradient Descent Strategy- Better Activation Functions



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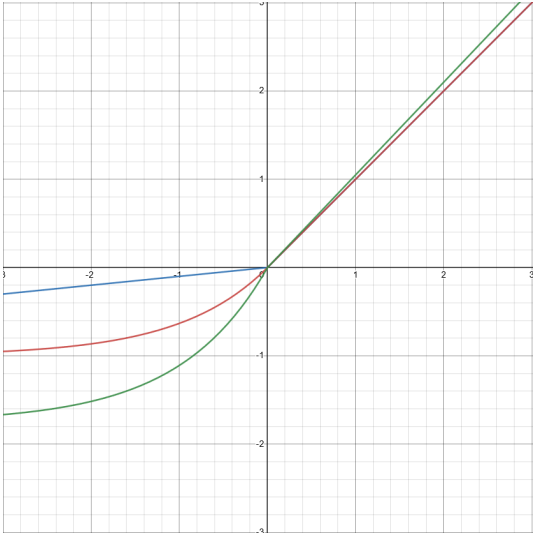

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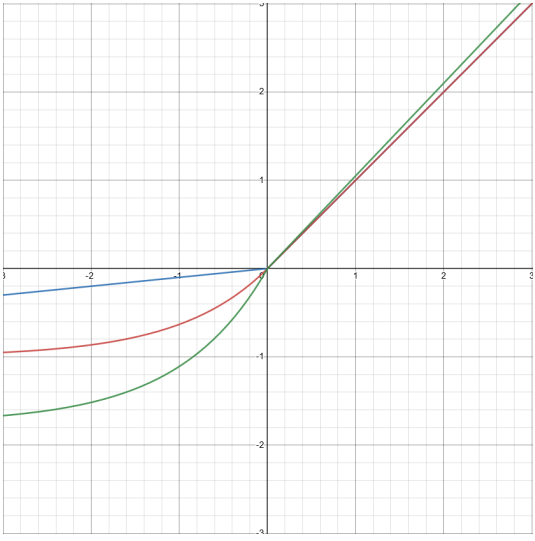

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One can also treat α as a parameter to be learned by back prop.

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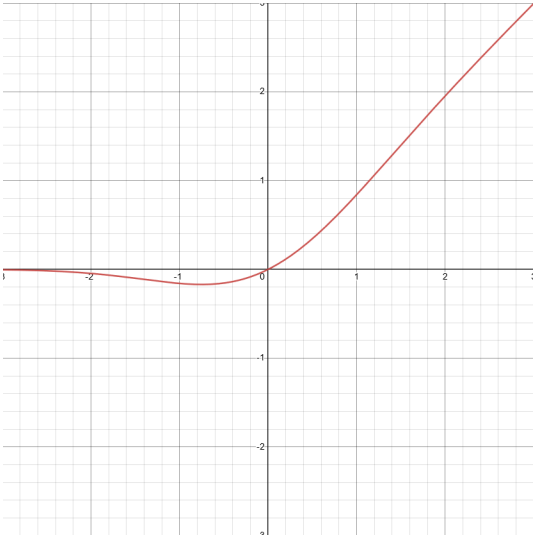

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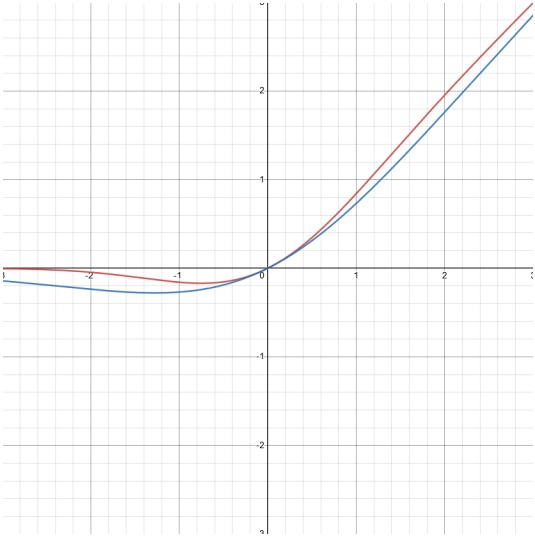

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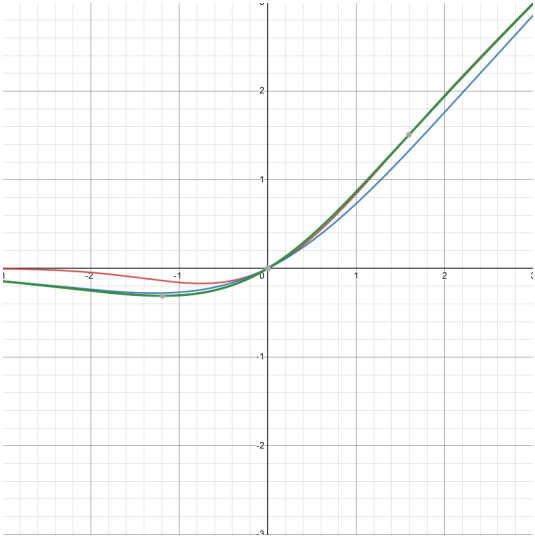

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- MISH $(z\tanh(\ln(1+exp(z))))$where σ is the sigmoid function.

Gradient Descent Strategy- Weight Initialization

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- Other methods include normalizing the whole vector with respect to a norm.

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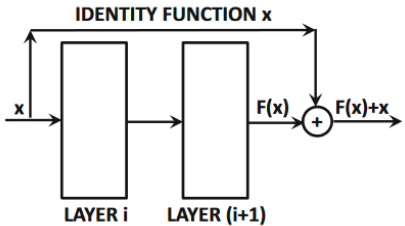
- If activation functions are not combined properly then there might be presence of local minimas

Aspects of a deep neural network-skip connections



Skip connections
Src:Neural Networks and Deep Learning: A Textbook, Charu C. Aggarwal

- We might allow nodes from deeper layers to have direct access to nodes from shallower layers while *skipping* the intermediate layers.

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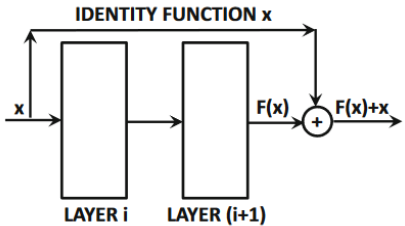

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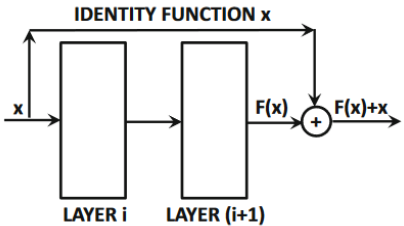
- We might allow nodes from deeper layers to have direct access to nodes from shallower layers while *skipping* the intermediate layers.
- This provides a kind of highway for the deeper layers to access simpler features.

Aspects of a deep neural network-skip connections



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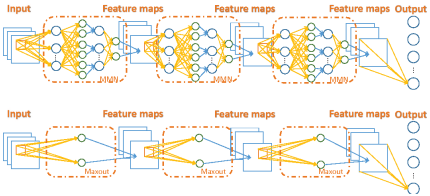
- We might allow nodes from deeper layers to have direct access to nodes from shallower layers while *skipping* the intermediate layers.
- This provides a kind of highway for the deeper layers to access simpler features.
- This is especially used in CNNs.

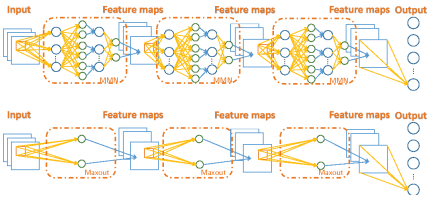
Aspects of a deep neural network-maxout networks



Max-out connections
Src:Improving deep neural networks with multilayer maxout networks, Weichen Sun, Fei Su, Leiquan Wang

- In a certain sense this is type of ensemble method.

Aspects of a deep neural network-maxout networks



Max-out connections
Src:Improving deep neural networks with multilayer maxout networks, Weichen Sun, Fei Su, Leiquan Wang

- In a certain sense this is type of ensemble method.
- Two sets of weights W_1, W_2 are trained for each input.
- The activation is set to $\sigma\left(\max(W_1 \cdot X_{in}, W_2 \cdot X_{in}) + b_0\right)$

Aspects of a deep neural network-navigating the loss landscape

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- Deeper networks have a harder time converging.

Aspects of a deep neural network-navigating the loss landscape

- Generally, as far as decision boundaries are concerned, adding depth gives ore bang for the buck than adding more nodes in a single layer.But depth comes with its own share of problems.
- Deeper networks have a harder time converging.
- If activation functions are not combined properly then there might be presence of local minimas

References