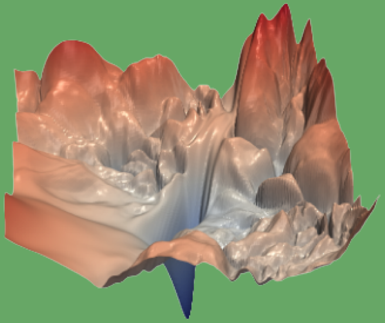
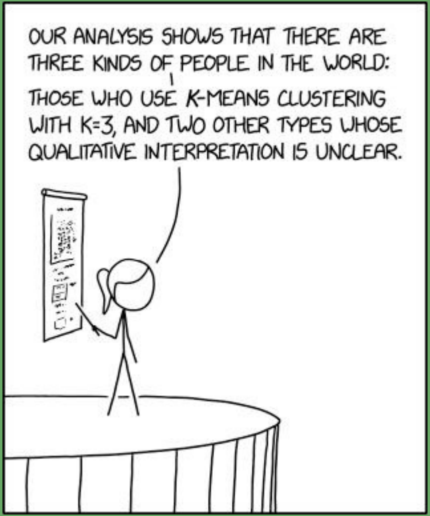
Deep Learning



AAKASH GHOSH
19MS129

Presentation made for the completion of Course MA5115

Traditional ML



Traditional Machine learning

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- **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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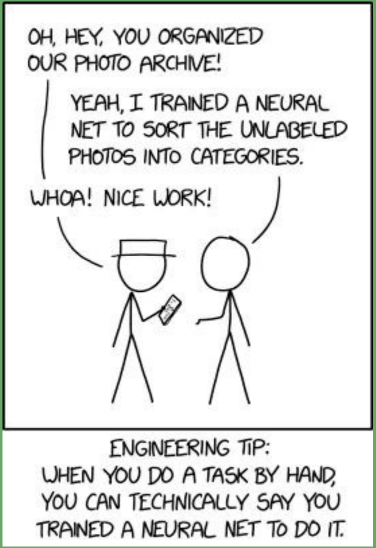
- **Amount of Data**: In the current era, the amount of data sometimes is simply so large that meaningful features are hard to extract
- **Unorganized Data**: Feature extraction is hard in unorganized data (such as a literary works).

The idea behind deep learning



Ideas behind a neural network

- **Pattern recognition**: Almost all the problems with traditional Ml lies in proper feature selection. We now take a different approach: We train the machine to learn what the necessary patterns/features are.

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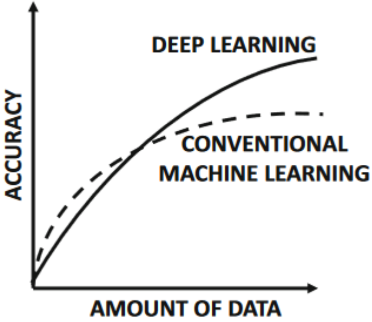
- **Overview**: We make a perceptron, which is essentially the digital analog of a neuron. We connect multiple neurons together(similar to our brain) and look at what pattern and amount of activation leads to best result.

A practical comparison with traditional ML



Comparision based on amount of data features.
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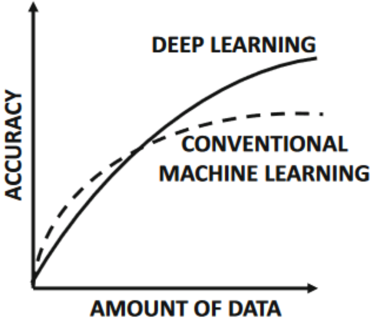

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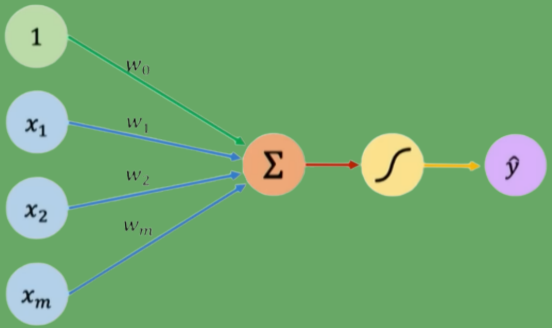
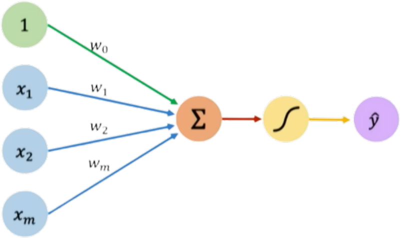
- Traditional ML models show better prediction when the amount of features involved is small. Features can be individually engineered and interpreted.
- Deep learning models are better when data is unstructured or there are a lot of features which need to be considered. With proper construction and training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

The Perceptron



Non-Linearity is the key



A perceptron
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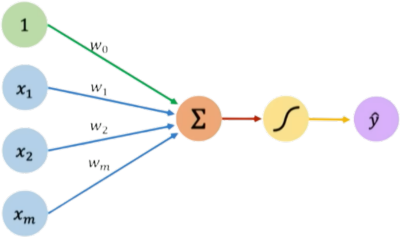

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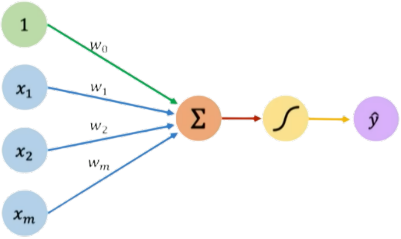

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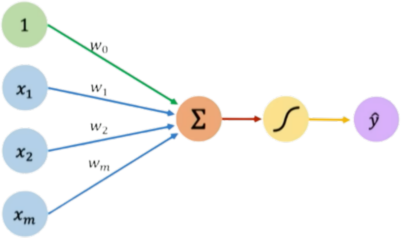

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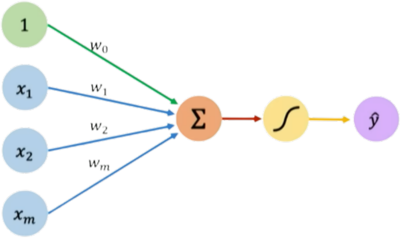

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- A very simple calculation shows if σ is linear then the decision boundary is also linear. It therefore makes sense to use non-linear σ.

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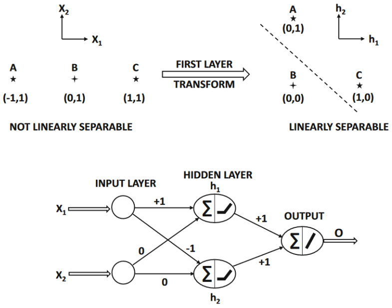

Non-linearity in action
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- As shown in the figure on left, classes which can't be separated by linear boundaries can be separated by non-linear functions.(Think SVM but the kernals are learned.)

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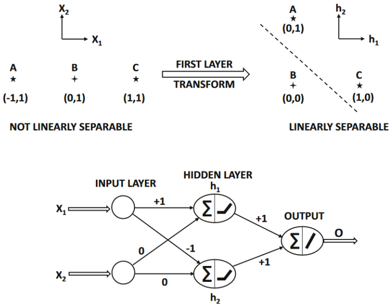

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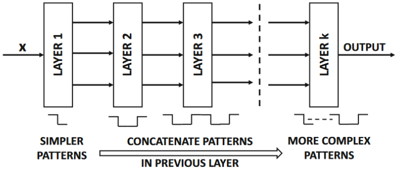
- It can be theoretically shown that almost all boundary function can be separated by a 2 layered neural network.

Increasing depth



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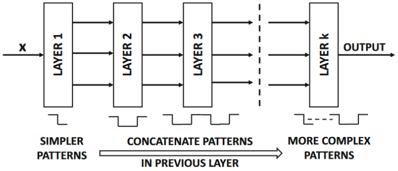

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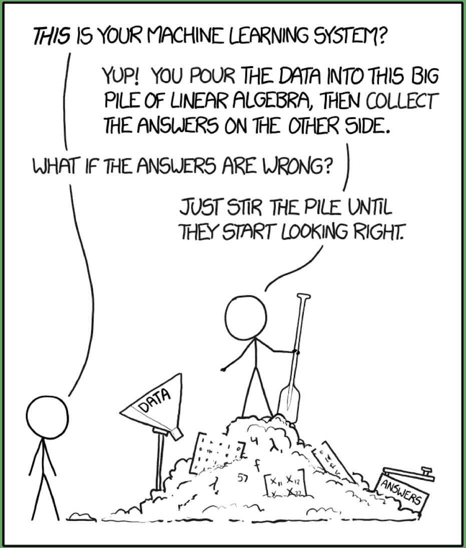
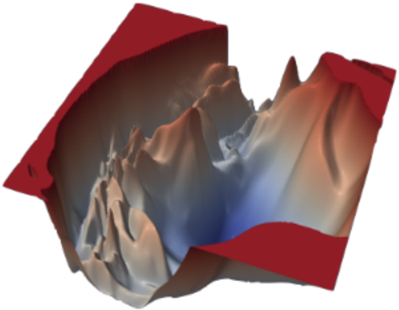
- While a single hidden layer is enough, making a deep neural network allows us to have more complex decision boundaries with relatively less number of nodes
- It should be noted how non-linearity discussed above plays an important role: Irrespective of number of layers, composition of linear functions 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

- We wish to calculate weights $w_i, 1 \leq i \leq n$ so that the predicted values $\hat{Y}$ are as close as possible(to an extent) to the actual values Y.

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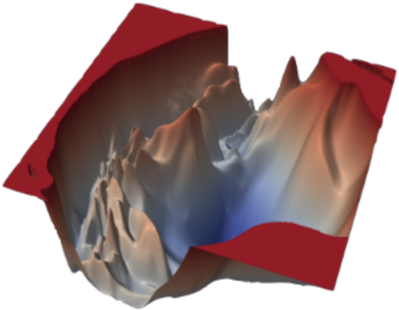

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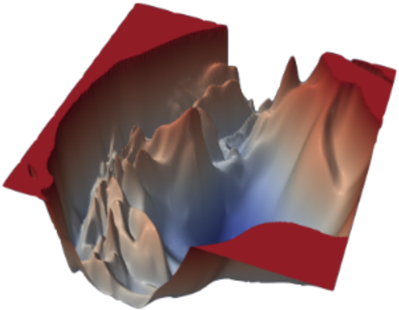

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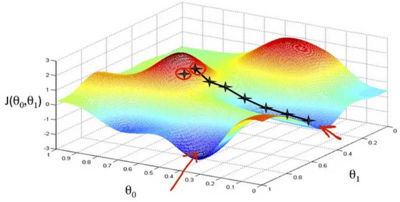
- Common choices of $\mathcal{L}$ include MSE for continuous variables and cross-loss entropy for categorical variables.

Gradient descent



Gradient descent
Src: https://towardsdatascience.com/an-intuitive-explanation-of-gradient-descent-83adf68c9c33

- 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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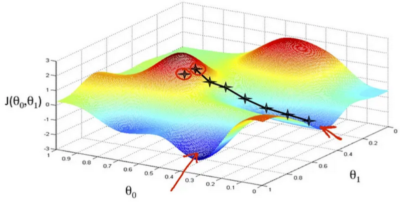

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- η is known as the learning rate.

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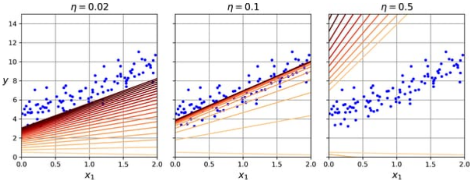

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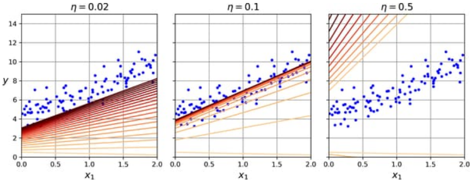

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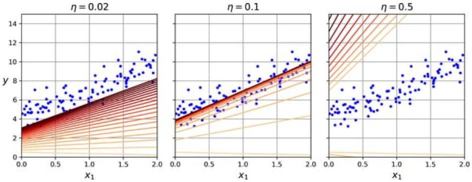

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- Fixing η is quite tricky.
- If η is small we get stuck at local minima
- If η is large we overshoot our targets and never converge.
- The best way to do things is to use a adaptive learn rate. Some methods(parametric, non-parametric and hybrid are 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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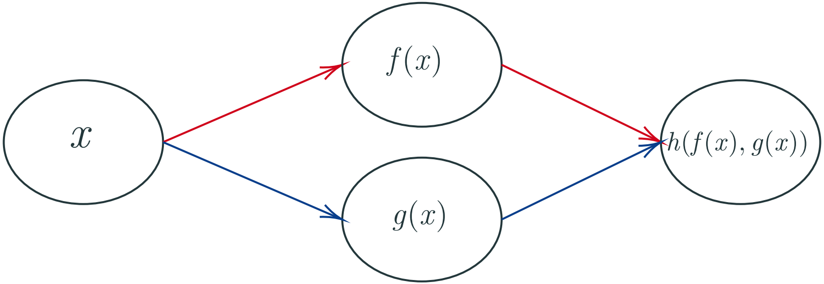
- The way to do this is to use the chain rule
- When we use the chain rule, we sum the partial derivative along all the paths joining the two nodes
- It is easy to see that the computation needed explodes as the depth increases
- The way to navigate this problem is to use dynamic programming.



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

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Roughly, the alogirithm works as follows:

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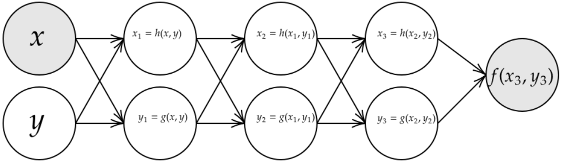
- Calculate $\mathcal{L}$. Note, that this step occurs from the input towards the output and is known as the forward phase.
- Calculate gradient. This process occurs from the output towards the input and is known as the backward phase.

Reverse Mode Auto Differentiation



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

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

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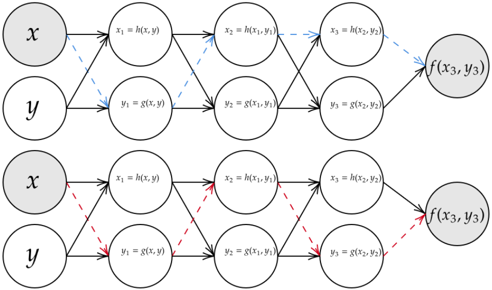

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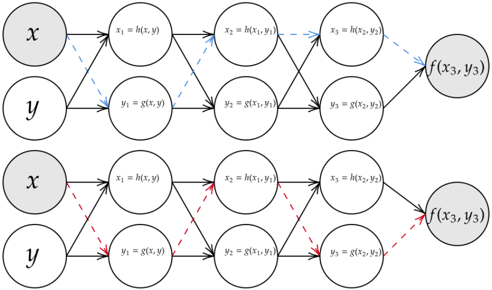
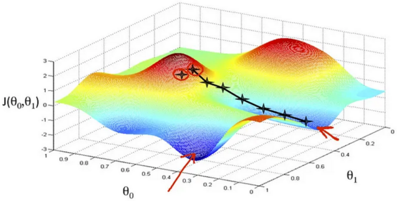


Sum is taken over the product along each path, over all the paths. It is trivial to note that parts of the paths are repeated.In the toy example on the left, the paths are essentially the same, varying only for the second to last node.

Stochastic Gradient Descent



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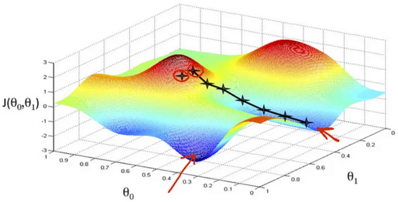

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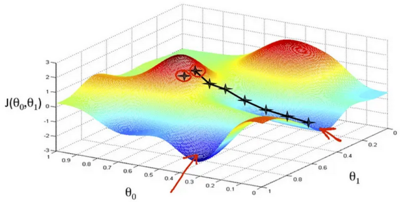

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