Non-Linearities

Recap: A Simple Example



Linear models

A linear model cannot distinguish paws from background

Deep Networks





Non-Linearities

Rectified Linear Unit (ReLU)

 $\operatorname{ReLU}(x) = \max(x, 0)$







A Simple Example - Why?

Intuition

- first layer learns the color categories of the paw (white, black, grey)
- second layer classifies color as paw or not

How?



$$\operatorname{ReLU}(x) = \max(x, 0)$$



A Simple Example - Why?

Intuition

- first layer learns the color categories of the paw (white, black, grey)
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$$egin{aligned} f(x) &= ext{ReLU}igg(x-rac{1}{2}igg) + ext{ReLU}igg(rac{1}{2}-xigg) - rac{1}{4} \ &= igg|x-rac{1}{2}igg|-rac{1}{4} \end{aligned}$$



$$\operatorname{ReLU}(x) = \max(x, 0)$$



Deep Networks

Alternates linear and non-linear layers



Deep Networks

Model: $f_{ heta}: \mathbb{R}^n o \mathbb{R}^c$

:

Parameters: $heta = (\mathbf{W}_1, \mathbf{b}_1, ..., \mathbf{W}_N, \mathbf{b}_N)$

Computation:

 $egin{aligned} \mathbf{h}_1 &= \mathrm{ReLU}(\mathbf{W}_1\mathbf{x} + \mathbf{b}_1) \ \mathbf{h}_2 &= \mathrm{ReLU}(\mathbf{W}_2\mathbf{h}_1 + \mathbf{b}_2) \end{aligned}$

$$egin{aligned} \mathbf{h}_{N-1} &= \mathrm{ReLU}(\mathbf{W}_{N-1}\mathbf{h}_{N-2} + \mathbf{b}_{N-1}) \ f_{ heta}(\mathbf{x}) &= \mathbf{W}_N\mathbf{h}_{N-1} + \mathbf{b}_N \end{aligned}$$



What Is a Layer?

Largest computational unit that remains unchanged throughout different architectures





How Many Layers Does a Deep Network Have?

We only count linear layers





Universal Approximation Theorem

Universal Approximation Theorem

A two-layer deep network can approximate any continuous function.

- Constructing is inefficient
- Deep learning exploit structure in data to find efficient approximations



Non-Linearities - TL;DR

Deep networks are stacks of alternating linear and non-linear layers

Deep networks belong to a class of continuous functions that can approximate **any** continuous function!