Intro to Deep Learning

Big Data y Machine Learning para Economía Aplicada

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Agenda

- 1 Single Layer Neural Networks
- 2 Activation Functions
- 3 Output Functions
- 4 Training the network

Deep Learning: Intro

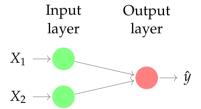
- Linear Models may miss the nonlinearities that best approximate $f^*(x)$
- ► Neural networks are simple models.
- ► The model has **linear combinations** of inputs that are passed through **nonlinear activation functions** called nodes (or, in reference to the human brain, neurons).

Deep Learning: Intro

▶ Let's start with a familiar and simple model, the linear model

Deep Learning: Intro

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Single Layer Neural Networks

A neural network takes an input vector of p variables

y = f(X) + u

► The Single layer NN model has the form

$$f(X) = f^{(output)}(g(X))$$

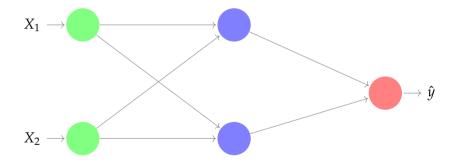
- where g is the activation function in the hidden unit
- ightharpoonup the second layer, $f^{(output)}$ is the output layer of the network

(1)

(2)

(3)

Single Layer Neural Networks

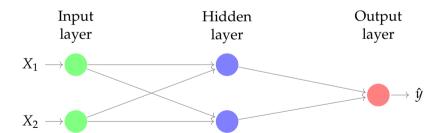


Single Layer Neural Networks

► NN are made of **linear combinations** of inputs that are passed through **nonlinear** activation functions

- ▶ 2 Predictors: p = 2, $X = (X_1, X_2)$
- ▶ 2 Nodes: K = 2, $A_1(X)$ and $A_2(X)$
- Non-linear activation function $g(z) = z^2$
- ▶ Want to predict a number $\in \mathbb{R}$: identity output function ($f^{(output)} : \mathbb{R} \to \mathbb{R}$ such that $f^{(output)}(x) = x$)

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$$f(X) = \beta_0 + \sum_{k=1}^{2} \beta_k \left(w_{k0} + \sum_{j=1}^{2} w_{kj} X_j \right)^2$$
 (5)



Why not linear activation functions?

Worked Example II: The "Exclusive OR (XOR)" Function

- ► The exclusive disjunction of a pair of propositions, (p, q), is supposed to mean that p is true or q is true, but not both
- ► It's truth table is:

q	p	y
0	0	0
0	1	1
1	0	1
1	1	0

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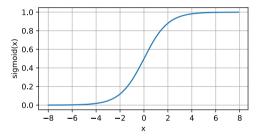
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Sigmoid Function (Logit)

- ▶ The sigmoid function transforms its inputs, for which values lie in the domain \mathbb{R} , to outputs that lie on the interval (0, 1).
- ► For that reason, the sigmoid is often called a squashing function: it squashes any input in the range (-inf, inf) to some value in the range (0, 1):

$$sigmoid(x) = \frac{1}{1 + \exp(-x)}.$$

Sigmoid Function (Logit)



When attention shifted to gradient based learning, the sigmoid function was a natural choice because it is smooth and differentiable.

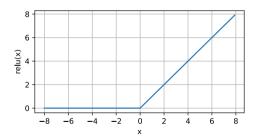
ReLU Function

► ReLU Function

- ▶ The most popular choice, due to both simplicity of implementation and its good performance on a variety of predictive tasks, is the rectified linear unit (ReLU).
- ▶ ReLU provides a very simple nonlinear transformation. Given an element *x*, the function is defined as the maximum of that element and 0:

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

- ▶ ReLU function retains only positive elements and discards all negative elements by setting them to 0.
- ► It is piecewise linear.



Neural Networks: Activation Functions

- ► Sigmoid(x) = $\frac{1}{1 + \exp(-x)}$
- $ightharpoonup \operatorname{ReLU}(x) = \max\{x, 0\}$
- ► Among others (see more here)
- ► Hidden unit design remains an active area of research, and many useful hidden unit types remain to be discovered

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Output Functions

- ▶ The choice of output unit is related to the problem at hand
 - Regression
 - Classification
 - ► Binary
 - Multiclass

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► El objetivo es

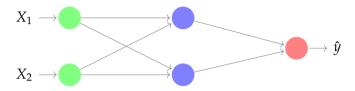
$$\hat{f} = \underset{f}{\operatorname{argmin}} \left\{ \sum_{i=1}^{n} L(y, f(X; \Theta)) \right\}$$
 (6)

► SNN

$$f(X, \beta, w) = f \left[\beta_0 + \sum_{k=1}^K \beta_k g \left(w_{k0} + \sum_{j=1}^p w_{kj} X_j \right) \right]$$
 (7)

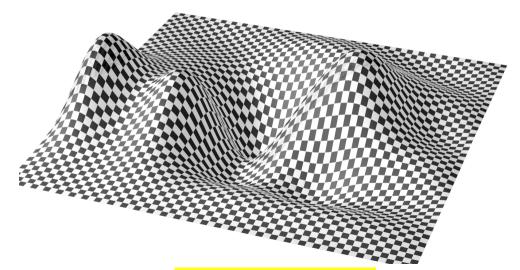
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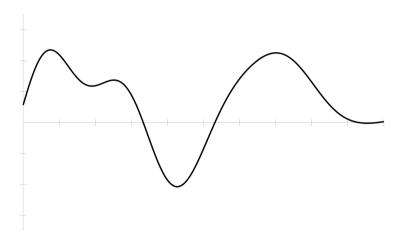
Example: House Prices



- Equations
 - ► Hidden Layer sigmoid (logistic):
 - $A_1 = \sigma(w_{11} \cdot X_1 + w_{12} \cdot X_2 + w_{10})$
 - $A_2 = \sigma(w_{21} \cdot X_1 + w_{22} \cdot X_2 + w_{20})$
 - Output Layer, identity output function:
 - $\hat{y}_i = \beta_0 + \beta_1 \cdot A_1 + \beta_2 \cdot A_2$
- ► Loss Function \Rightarrow MSE: $\frac{1}{n} \sum_{i=1}^{n} (y_i \hat{y}_i)^2$

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Example: House Prices

