Introducing Deep Learning

Dr. Eran Raviv

July 2022

A warm welcome

Agenda for today

- Introduction + logistics

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- Deep learning overview and examples

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- Deep learning simple first steps

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- Introduction + logistics
- Deep learning overview and examples
- Deep learning simple first steps
- Basic concepts and terminology

A bit about myself

Trained by:

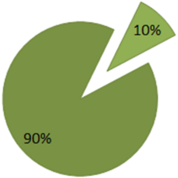
Here:

tinbergen institute

Erasmus University Rotterdam

Work for: apg

And for



Business Data Science

More on my personal blog

About this course

→ Understanding the fundamental building blocks of deep learning methods

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- –> Understanding the fundamental building blocks of deep learning methods
- –> Understand different DL architectures

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—> Understanding the fundamental building blocks of deep learning methods
—> Understand different DL architectures
—> Gain familiarity with advanced architectures ideas and concepts
—> Gain familiarity with DL programming frameworks
—> Ability to apply and judge DL models and performance

Logistics

- You can script in whichever language you feel comfortable with

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- Social event

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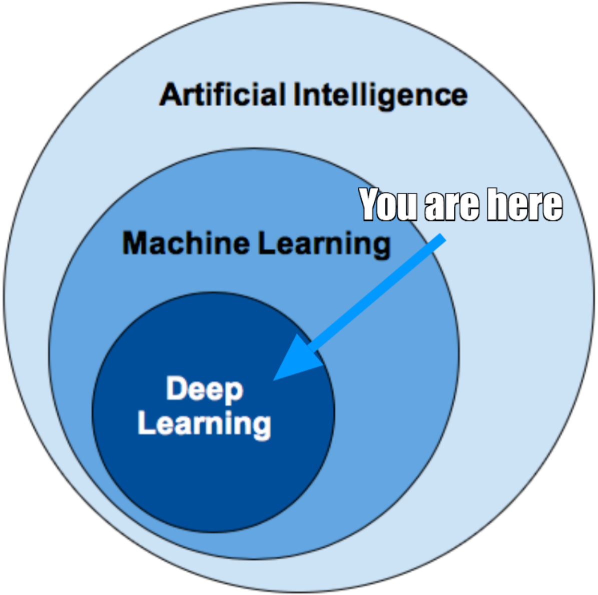
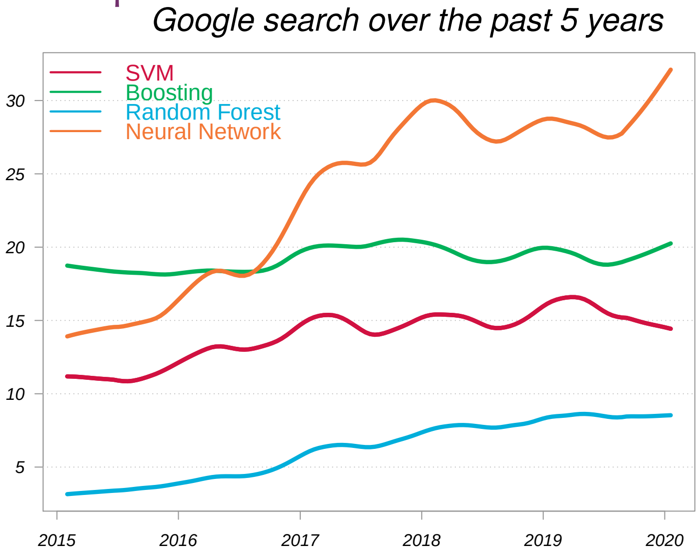
- You can script in whichever language you feel comfortable with
- Social event
- Graduation?

Introduction to Deep Learning

Coordinates



Hot topic



Google search over the past 5 years
SVM
Boosting
Random Forest
Neural Network
30
25
20
15
10
5
2015
2016
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2018
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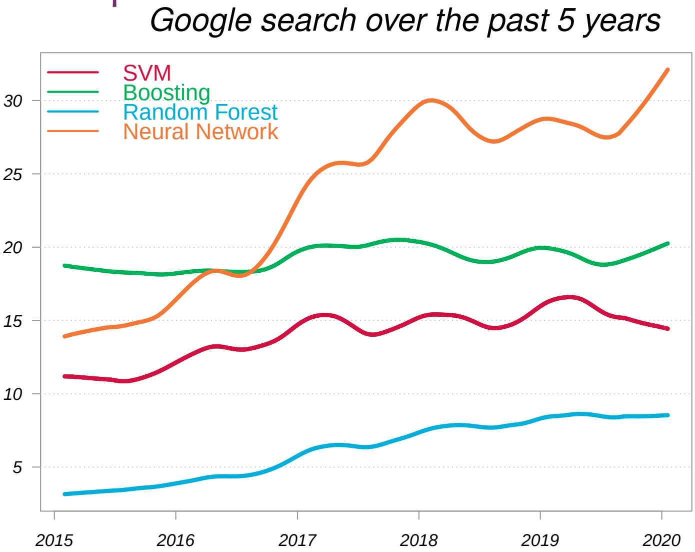
2020

Hot topic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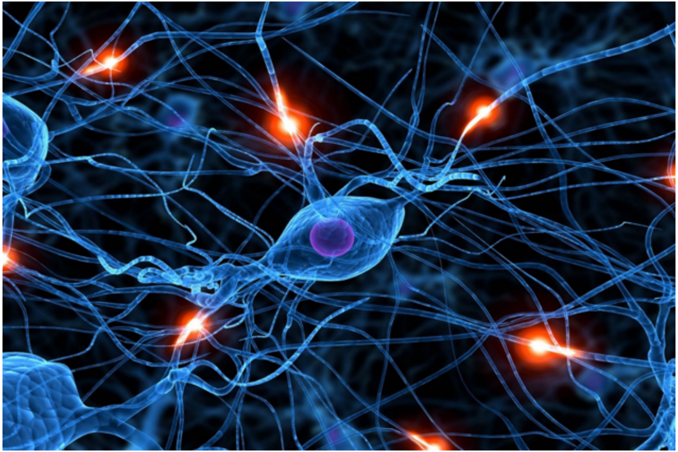
- More!

Loosely inspired by the human brain

Sensors sends information/signal. If it is strong (enough), the neuron is activated and transmitting the signal to the next neuron.



Take the basic regression setup for example

- We have the pair $(\mathbf{x}_i, y_i) \quad i = \{1, \ldots, m\}$ and $\mathbf{x}_i$ is $d \times 1$ vector of features, y_i is simply the target.

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- We need to "find" good (best, in some sense) $\mathbf{w}$ such that the (quadratic in this case) risk of the loss $\mathcal{L}_i = (y_i - \widehat{y}_i)^2$ is minimal.

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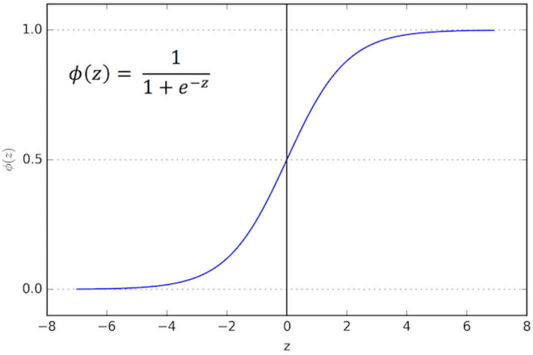
- We create a mapping $\mathbf{y} = f(\mathbf{x}; \mathbf{w})$, and $f(\cdot)$ is called the activation function.
- So a neural network with a linear activation function is simply a linear regression model.

Now with logistic regression

The logistic distribution function:

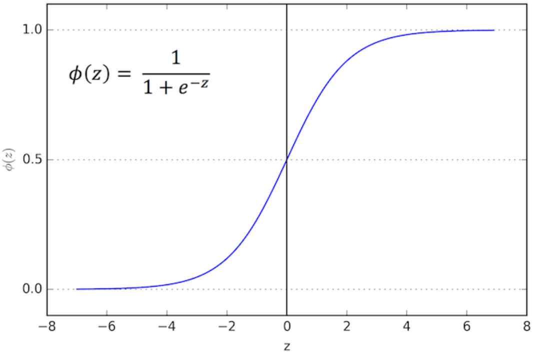
- Instead of taking the linear combination as is, we map it back to the $[0, 1]$ interval.



Now with logistic regression

The logistic distribution function:

- Instead of taking the linear combination as is, we map it back to the $[0, 1]$ interval.
- Hence, sometimes it is also referred to as a "squashing" activation function.



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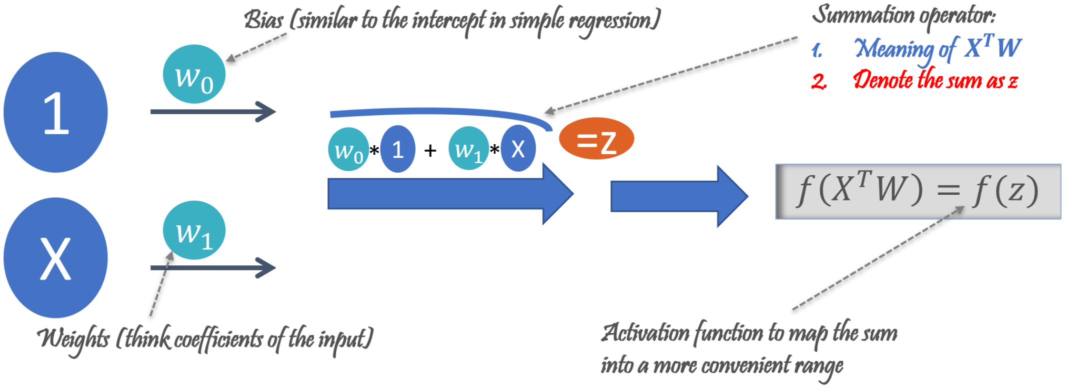
- So a (one-layer) neural network with a logistic activation function (aka sigmoid function) boils down to simply a logistic regression model.

Now with the DL jargon



What is the difference between supervised learning and unsupervised learning

What is the difference linear model, general linear model and nonlinear model?

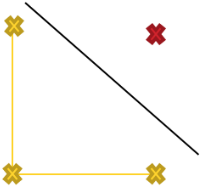
What is the main difference between traditional statistics and Machine Learning/ modern statistics?

What is meant by nonlinearity?

What are nonlinear problems?

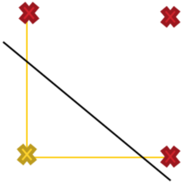
AND gate

x1	x2	Y
1	1	1
0	0	0
1	0	0
0	1	0



OR gate

x1	x2	Y
1	1	1
0	0	0
1	0	1
0	1	1



Exclusive (XOR): OR & !AND

x1	x2	Y
1	1	0
0	0	0
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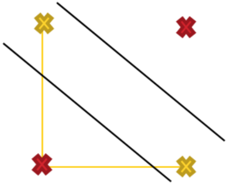
0	1	1



Machine learning and deep learning

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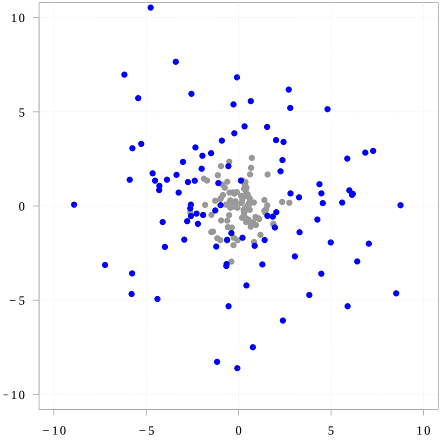
- Many of existing machine learning algorithms could be represented as shallow neural network.
- The main power of deep learning models is the ability to create a **flexible**, **expressive** models.
- Let's see what does that mean

What is Learned in deep learning? (example)

Cartesian Coordinates

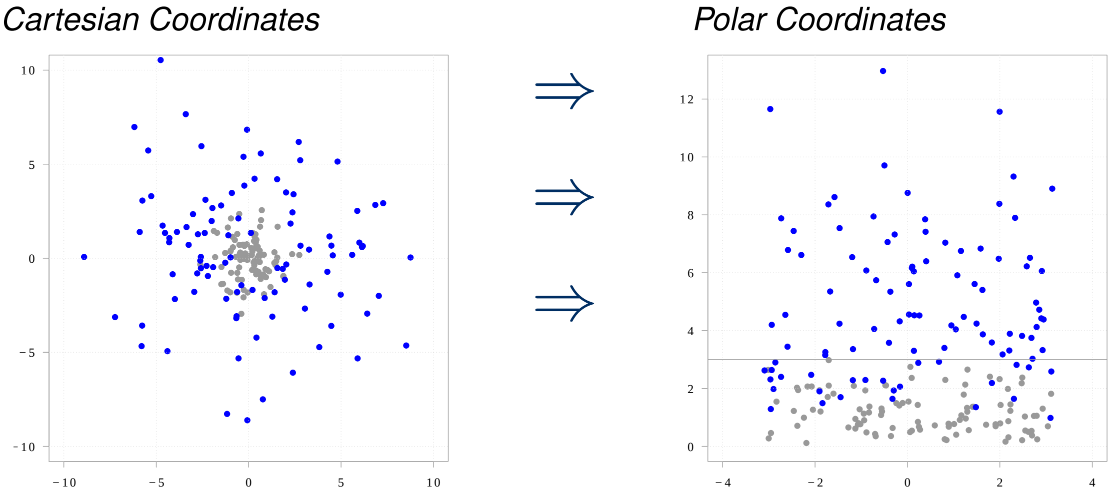


$\Rightarrow$

$\Rightarrow$

$\Rightarrow$

What is Learned in deep learning? (example)



But we want and "automatic" procedure for these transformations.

What did we do before deep learning?

- We highly valued models with a good story/rationale

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- We designed feature by hand

What did we do before deep learning?

- We highly valued models with a good story/rationale
- We designed feature by hand
- We had much less expressive machine learning algorithms

General concepts and formulation

In general terms

We define a predictor for the output $\mathbf{y}$ given input $\mathbf{X} = (\mathbf{x}_1, \ldots \mathbf{x}_d)$. The output could be continuous or discrete.

We learn a mapping $F : \mathbf{X} \rightarrow \mathbf{y}$, and the prediction is

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$f_l^{W,b} := f_l \left(\sum_{j=1}^{N_l} \mathbf{w}_{lj} \mathbf{x}_j + \mathbf{b}_l \right) = f_l \left(\mathbf{W}_l \mathbf{X}_l + \mathbf{b}_l \right), \quad 1 \leq l \leq L$ and the overall prediction function is

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$\hat{\mathbf{y}}(\mathbf{X}; \theta) := F(\mathbf{X}; \theta) = \left(f_1^{\mathbf{W}_1, \mathbf{b}_1} \circ \ldots \circ f_L^{\mathbf{W}_L, \mathbf{b}_L} \right) (\mathbf{X})$ where $\theta = \{\mathbf{W}, \mathbf{B}\}$ represents the entire collection of parameters (bias parameters included).

What is so deep about deep neural networks?

- Nothing (I am so sorry about this..). There is nothing deep going on. It is a highly non-linear transformation of the inputs, but it is simple. E.g.: $f(\mathbf{x}) = f^{(3)}(f^{(2)}(f^{(1)}(\mathbf{x})))$

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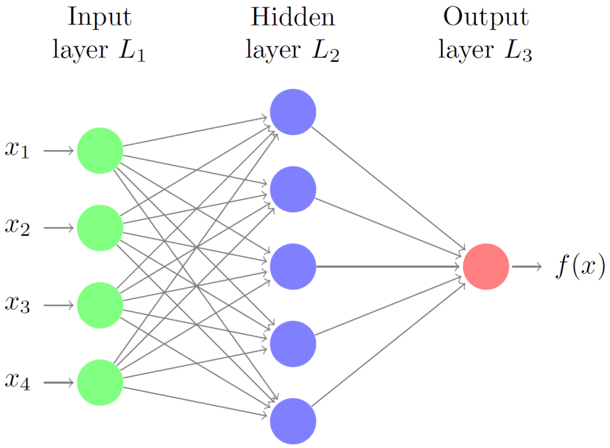
- $f^{(l)}$ is the lth layer.
- The last layer is called the output layer.

Schematic basic neural networks



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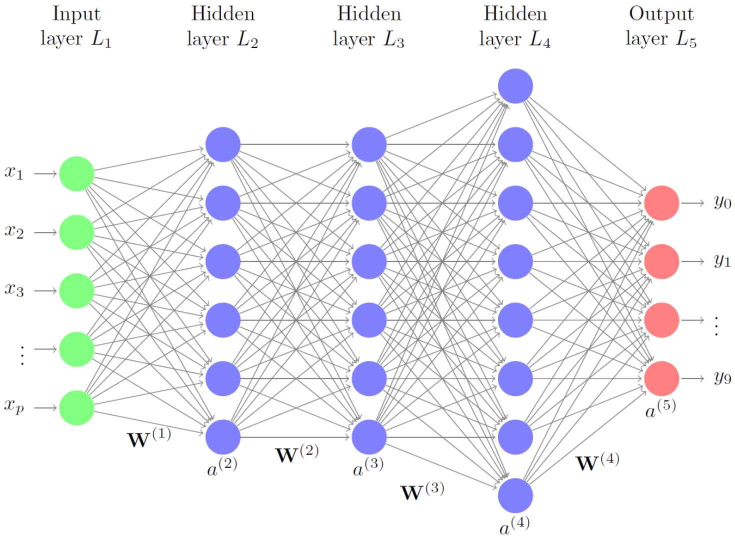

Historical example: The Perceptron

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- Takes input through connections with weights (while synapses pass information to other neurons)

Neurons communicate with one another at junctions called synapses

There are many other activation functions

* Heaviside step function, aka unit step function, aka binary step function:

$$h(x) = \begin{cases} 0, & x < 0, \\ 1, & x \geq 0. \end{cases}$$

* Sigmoid function, aka logistic function:

$$s(x) = \frac{1}{1 + e^{-x}} = \frac{e^x}{e^x + 1}$$

More activation functions

* Tanh function, aka tangent hyperbolic function:

$$t(x) = \frac{sin(x)}{cos(x)} = \frac{e^x - e^{-x}}{e^x + e^{-x}} = 2sigmoid(2x) - 1$$

* Hard Tanh

$$ht(x) = \begin{cases} -1 & : x < -1 \\ x & : -1 \leq x \leq 1 \\ 1 & : x > 1 \end{cases}$$

More activation functions

* Rectified linear units (ReLU):

$$r(x) = \max(0, x)$$

* Leaky ReLU:

$$lr(x) = \begin{cases} x & \text{if } x > 0 \\ 0.01x & \text{otherwise} \end{cases}$$

* Leaky ReLU is a special case of parametric ReLU.
* Exponential ReLU, aka scaled exponential:

$$elu(x) = \begin{cases} x & \text{if } x > 0 \\ a\,(e^x - 1) & \text{otherwise} \end{cases}$$

More activation functions

* Linear:

$$l(x) = ax \qquad \text{e.g. } a = 1$$

* Swish:

$$sw(x) = x sigmoid(x)$$

* There are more.
* More are coming.

Why so many? What are the advantages/disadvantages of each?

Cost- loss-, error-, objective-, and risk-function

Sometimes different definitions for different purposes. Here we use the following:

- Loss function, or error function is the a function of a single error:

$$\mathcal{L}(\widehat{y}_i, y_i) = \mathcal{L}(\widehat{y}_i - y_i) = \mathcal{L}(e)$$

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- Cost function is used to describe the entire cumulative error for the entire sample:

$$\mathcal{J}(\mathbf{w}) = \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}(\widehat{y}_i, y_i)$$

Cost- loss-, error-, objective-, and risk-function

- Risk is the expectation of the cost function. It is a "theoretical" quantity, which we estimate from the data.

$$\mathcal{R}(\mathbf{w}) = \mathrm{E}\left(\mathcal{J}(\mathbf{w})\right)$$

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- The risk function is a type of objective function. Objective function is a general term describing what you would like to optimize for.

Recap

What have we covered today?

- DL are pure-prediction algorithms

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Multinomial logistic regression

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  It would perhaps be better to call the softmax function “softargmax”, but the current name is an entrenched convention.

Multinomial logistic regression

$$P(y = k|x, W) = \text{softmax}_k(Wx) = \frac{\exp\left(w_k x\right)}{\sum_{j=1}^{j=k} \exp\left(w_j x\right)}$$

$$J(W) = -\left[\sum_{i=1}^{m} \sum_{k=1}^{k} 1 \left\{y^{(i)} = k\right\} \log \frac{\exp(w_k x)}{\sum_{j=1}^{j=1} \exp\left(w_j x\right)}\right],$$

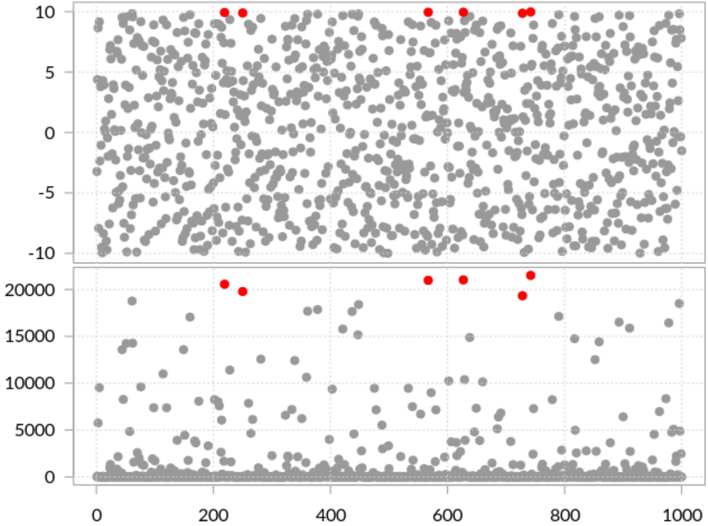
$$\mathcal{I}\left\{y^{(i)} = k\right\} = \begin{cases} 1, & \text{if } y^{(i)} = k \\ 0, & \text{otherwise} \end{cases}$$

$$w := w - \eta \Delta w$$

$$\Delta w_k = \frac{\partial}{\partial w_j} J(w) = -\sum_{i=1}^{m} \left[x^{(i)} \left(1 \left\{y^{(i)} = k\right\} - P\left(y^{(i)} = k|x^{(i)}, W\right)\right)\right]$$

Softmax

What does the softmax function do?



Cross entropy loss

$$J = -\sum_i p_i \log q_i$$

where you can think of q_i as the observable of category i and p_i is the calculated probability for that category.

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- Classification error is a crude measure. Disregard level of confidence.
- Still, two competing models could have opposite ranking of the cross entropy loss and classification error.
- Sometimes it is useful to look at both.

Now Let's code!

References

Deep Learning - main textbook

Deep Learning: A Practitioner's Approach

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