

Artificial Intelligence

Intro to Machine Learning (ML)

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ML - Introduction

- ML?
 - Machine Learning
 - Predictive Analytics
 - Statistical Learning
- Subjects
 - Computer Science
 - Statistics
- ML = extracting knowledge from data
- Examples
 - Recommender systems
 - Which music to listen to (Spotify)
 - Which videos to watch (Netflix)
 - Data-driven research
 - Astronomy (finding planets)
 - DNA analysis



ML - contrast

- Early A.I. systems
 - "Expert" systems
 - Hardcoded rules
 - Feasible
 - When humans have a good understanding of the process
 - Very specific
 - The logic required is specific to a single domain and task
 - Examples where it might work:
 - Fighting email spam with blacklists
 - ?
 - Examples where it will fail
 - Detecting human faces in photos
 - In general, processes where it is very hard to identify a set of rules and/or where the whole is more than the sum of its parts
- ML is "learning by example"
 - With enough examples, a solution for the task arises



Supervised ML

- Assist on decision-making by generalization from examples
- Supervised learning
 - Algorithms that learn from supervised (input, desired output) pairs
 - Researcher provides pairs (input, desired output)
 - For example, pictures with animals and the label "dog", for some
 - For example, a list of emails and the label "spam" for some
 - Algorithm automatically finds how to reach the output, from the input
 - In particular, for never seen inputs
 - The algorithm does "predictions" with a level of probabilistic certainty
 - The "supervision" (creating the dataset) is hard work
 - Well understood
 - Measurable performance



Supervised ML - more examples

- Handwritten digits recognition
 - Inputs: scans of handwritten digits
 - Outputs: their correct values
 - To create a dataset for building a ML model: collect, collect...
- Medical diagnosis from images
 - Is a tumor benign or not?
 - Inputs: images of tumors
 - Outputs: the correct classification of the tumors
 - To create a dataset for building a ML model: database of medical images + assessment by experts
- Detecting fraud in financial transactions
 - Inputs: records of financial transactions
 - Outputs: their classification as "fraud", or not
 - To create a DB for building a ML model: logs + the users' reports

Supervised ML - classification concepts

- Samples are examples of something
- Samples have "features", which are measurements of properties/attributes in them
- A collection of samples is a "dataset"
- If, for every sample, there is a label available
 - Then, the dataset is a "labelled dataset" that can be used for "supervised learning"
- The idea is to create a function F that, receiving a [new] sample, can assign it a classification
 - $F(\text{sample}) = \text{classification}$
 - $F(X) = y$



Supervised ML - train and test sets

- There are known examples, AKA "samples"
 - They capture what is known, observed
- Do NOT use them all for training a model
 - Select some samples, say 75%, of all the available data
 - This is the "training set"
- Reserve some samples, say 25%, of all the data
 - To test the accuracy of the model
 - The accuracy is a measure of how correct the model is expected to be with new samples
 - The test samples, because they are not used in training, are like "new samples", although their correct classification is known



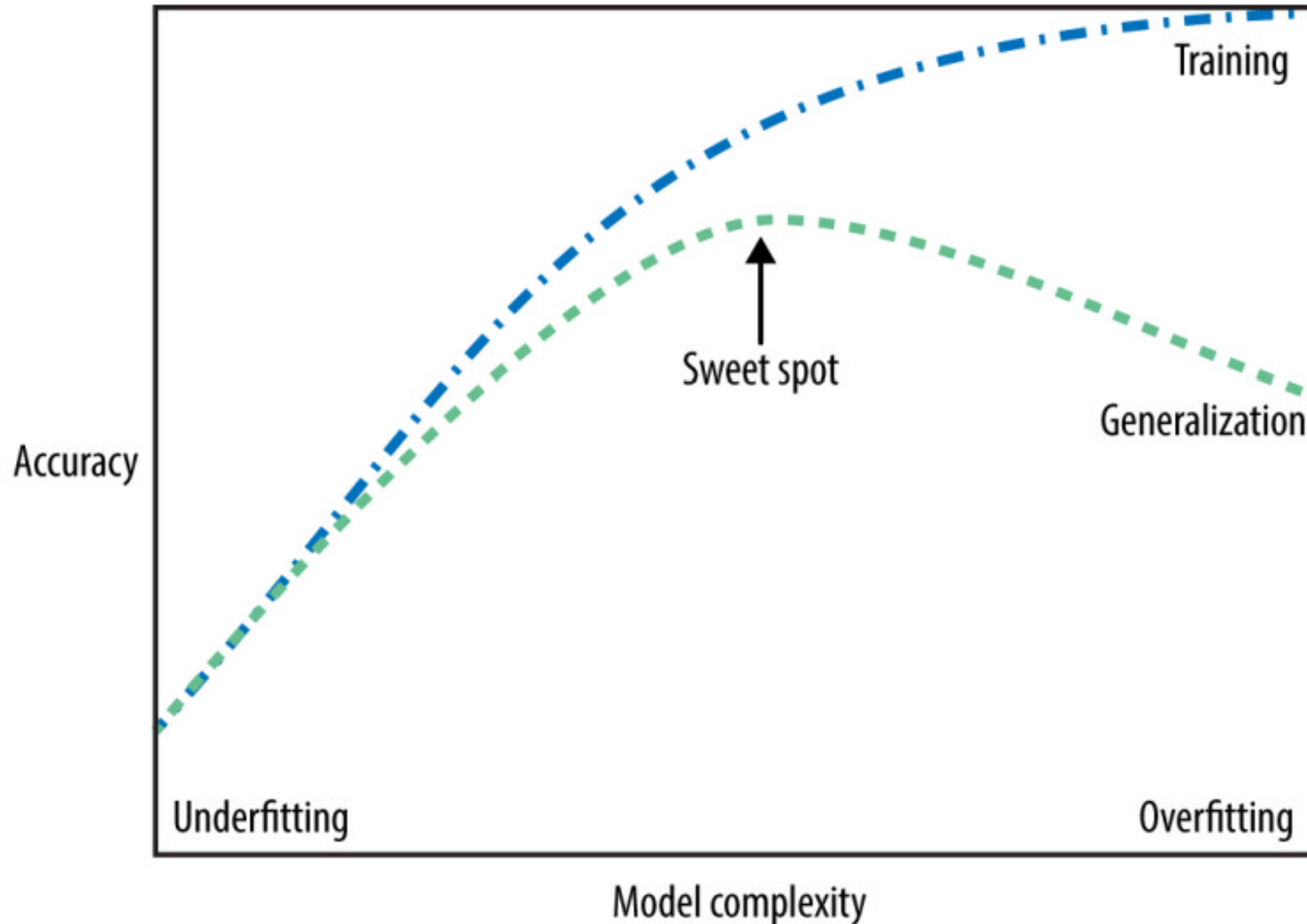
Supervised ML - some concepts

- Overfitting?
 - Model too complex, for the amount of available data
 - Fits great the available data
 - Predicts great, on the training set
 - But if it does so with too many rules, too much complexity...
 - It will, probably, not generalize well, to new data
- Underfitting?
 - Model too vague, for the amount of available data
- Ideal?
 - A balance between fitting the training set, without "gluing" to less represented samples, so it has opportunity to generalize to new samples



Supervised ML - balancing C/A/G

- Balancing complexity / accuracy, for generalization



Supervised ML using Keras

- In Python, Keras provides easy access to many datasets
 - `import tensorflow.keras.datasets.mnist as mnist`
 - `import tensorflow.keras.datasets.fashion_mnist as fashion_mnist`
 - `import tensorflow.keras.datasets.cifar10 as cifar10`
 - `import tensorflow.keras.datasets.cifar100 as cifar100`

- Take a peek at a them using the code snippet:

```
tupleForTraining, tupleForTesting = mnist.load_data()  
displayRandomNImagesFrom(  
    tupleForTraining[0],  
    tupleForTraining[1]  
)
```



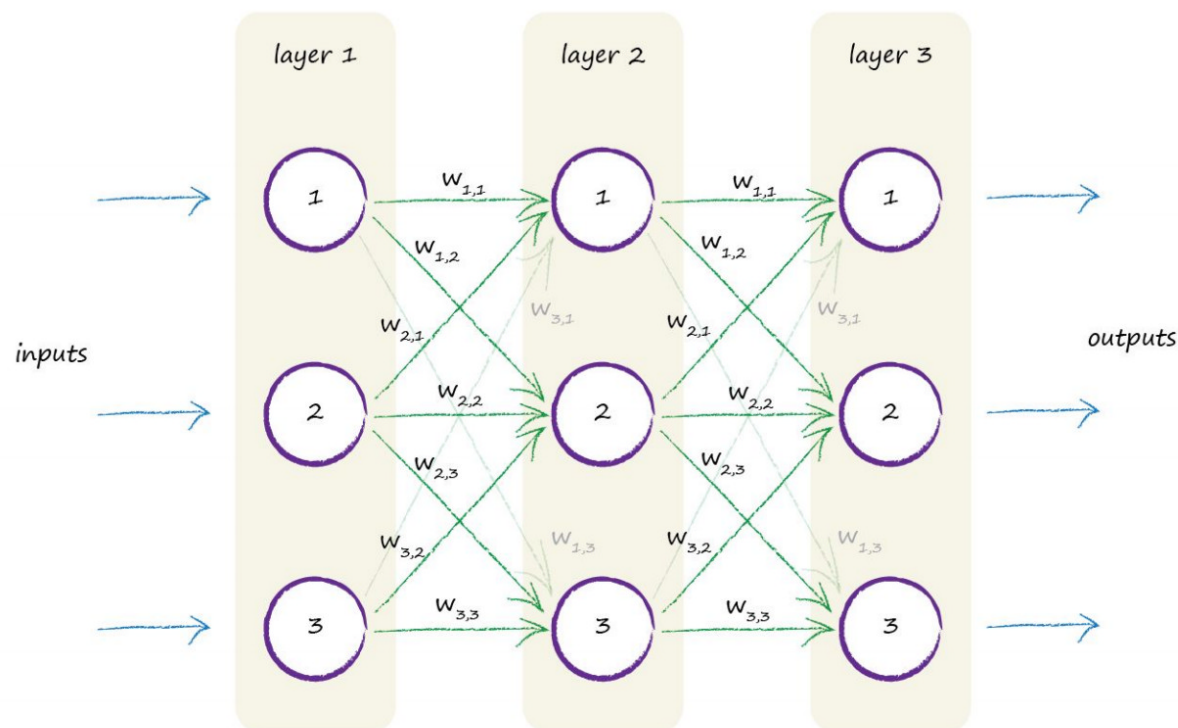
One Hot Encoding

- In coding for classification problems, it is usual to use the "one hot encoding" technique to represent the possible classes
- For example, in the hand written digits classification problem, there will be 10 classes (0 to 9)...
- ...that can be encoded as vectors with a single 1 for the right switch
- [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.] #class 0
- ...
- [0. 0. 0. 0. 0. 0. 0. 0. 0. 1.] #class 10
- The above representation is when using numpy.ndarray objects, which are arrays of floats



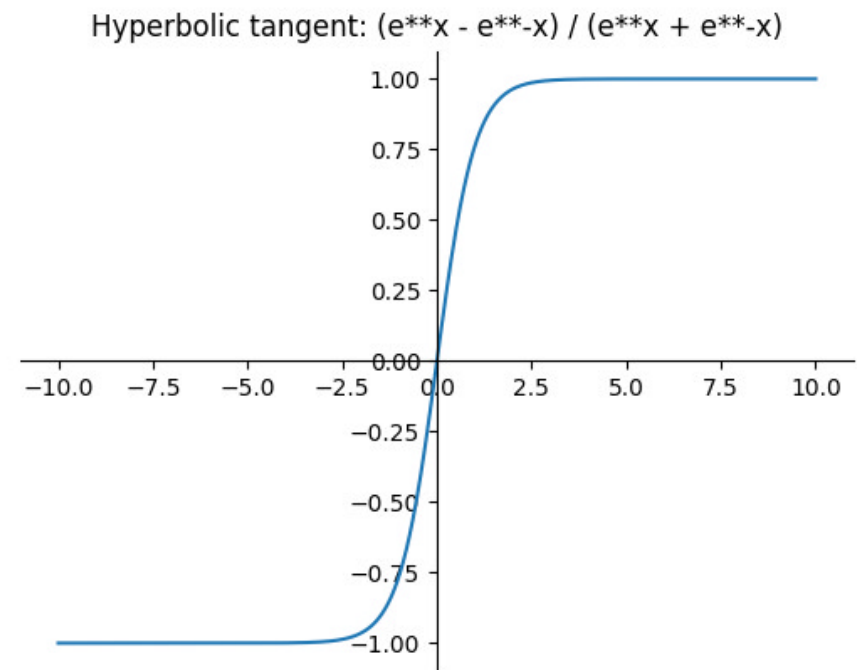
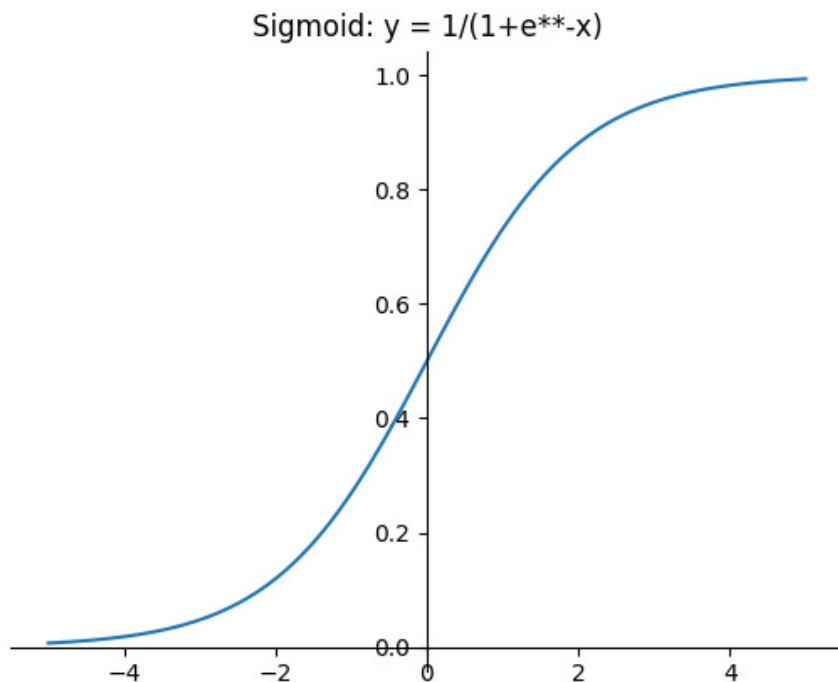
Neural Networks can have billions of nodes

- A neuron "fires" a signal to the "next" neuron
 - Different signals (inputs) are subject different to "intensities"
- Think of "layers" of nodes
 - Each signal that is input to a node is "weighted"
 - All the weighted inputs are summed and subjected to an activation function, which returns an output, input to all the next



Brain neurons as an approach

- A bio-neuron does not behave as a linear function
 - output-via-axon-terminals \neq constant * input-via-dendrites + bias
 - Output is suppressed, until it reaches a level when it then triggers an output
 - Threshold
 - A function that takes inputs and returns outputs taking into account some threshold is an "activation function"; e.g.: sigmoid aka logistic, h-tangent



Neural Networks for Classification in ML

- A computational solution to find the optimal W and b
- Plain algebra could be used
- But there is noise and unknown data
- The theoretical function is actually UNKNOWN
 - Probably not linear at all
- The challenge is:
 - Find the values for W and b
 - That best FIT the data that is actually available
- Find an approximate function that maps inputs to outputs, as closely as possible
 - But that does NOT just memorize the example mappings
 - This is an optimization problem



Matrices multiplication

- Matrix multiplication is
 - a binary operation (means 2-operands) that takes a pair of matrices and returns another matrix
 - NOT commutative (order of operands is relevant)
- The standard way to multiply matrices is called "row by column" multiplication
 - The element at the i -th row and j -th column of the resulting matrix is calculated by multiplying each element of the i -th row of the first matrix by the corresponding element of the j -th column of the second matrix and adding the results.
 - Done for all combinations of rows from the first matrix and columns from the second matrix.
 - The number of columns in the first matrix must be equal to the number of rows in the second matrix. If the first matrix is of dimension $m * n$, and the second matrix is of dimension $n * p$, then the resulting matrix will be of dimension $m * p$.



Matrices multiplication - examples

- $A(2,3) =$
a b c
d e f
- $B(2,3) =$
g h i
j k l
- AB can NOT be computed

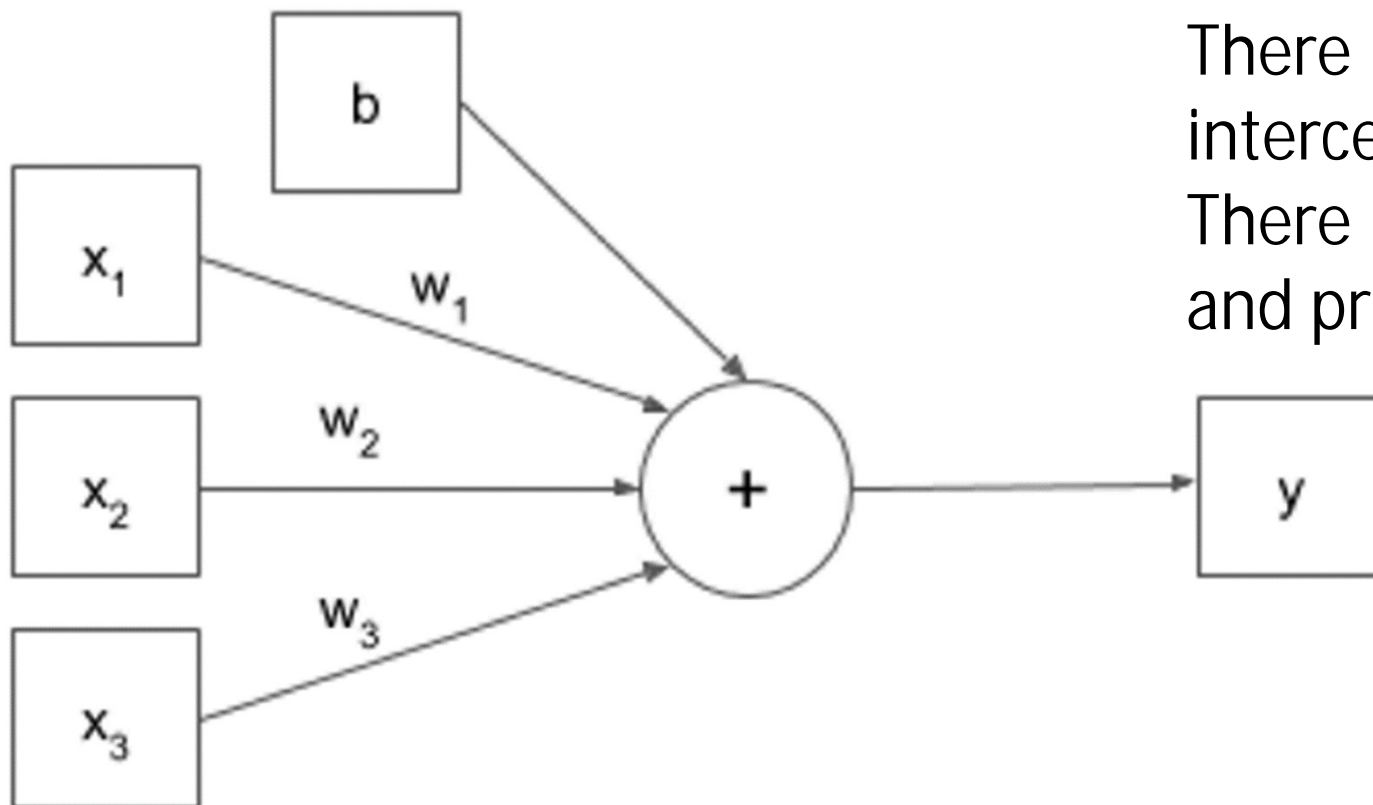
Matrices multiplication - examples

- $M1(3,3)$
- $a@(0,0)$ $b@(0,1)$ $c@(0,2)$
- $d@(1,0)$ $e@(1,1)$ $f@(1,2)$
- $g@(2,0)$ $h@(2,1)$ $i@(2,2)$
- $M2(3,3)$
- $j@(0,0)$ $k@(0,1)$ $l@(0,2)$
- $m@(1,0)$ $n@(1,1)$ $o@(1,2)$
- $p@(2,0)$ $q@(2,1)$ $r@(2,2)$

- $M1 * M2$
- $a*j + b*m + c*p@(0,0)$ $a*k + b*n + c*q@(0,1)$ $a*l + b*o + c*r@(0,2)$
- $d*j + e*m + f*p@(1,0)$ $d*k + e*n + f*q@(1,1)$ $d*l + e*o + f*r@(1,2)$
- $g*j + h*m + i*p@(2,0)$ $g*k + h*n + i*q@(2,1)$ $g*l + h*o + i*r@(2,2)$

Linear Equations Representations

$$y = w_1x_1 + w_2x_2 + w_3x_3 + b$$



This is a graph representation of a linear equation

There are "weights" w_1, w_2, \dots, w_n

There are terms or "samples" x_1, x_2, \dots, x_n

There is a crossing point / intercept / "bias" b

There is a "node" doing a sum and producing an output y

Linear Equations Representations

Vectorized Implementation

$$Y = W \cdot X + b$$

Where $W = [w_1 \ w_2 \ w_3]$

and $X = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$

This is a vectored representation of a linear equation

There is the W matrix (1D array)

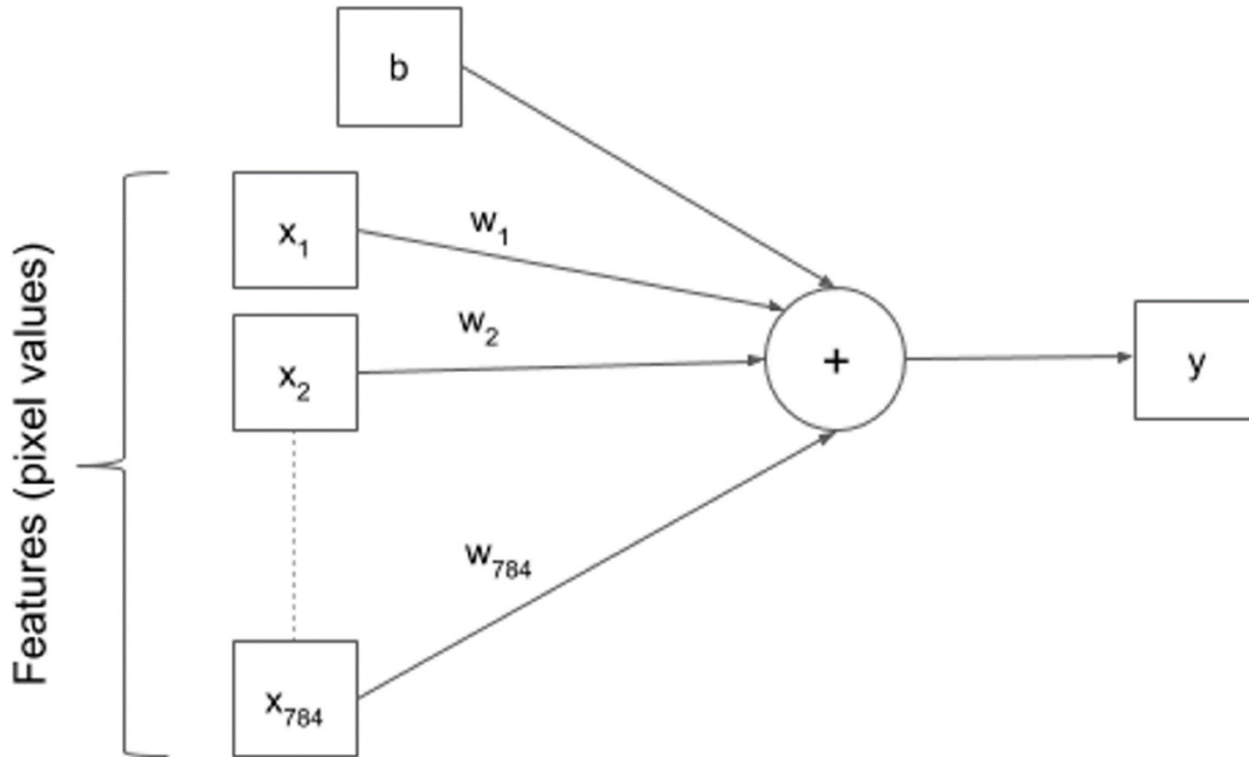
$$W = [w_1, \dots, w_n]$$

There is a single column samples matrix

$$X = [x_1, \dots, x_n]$$

There is a crossing point / intercept / "bias" b

If a problem can be modeled as a linear equation...



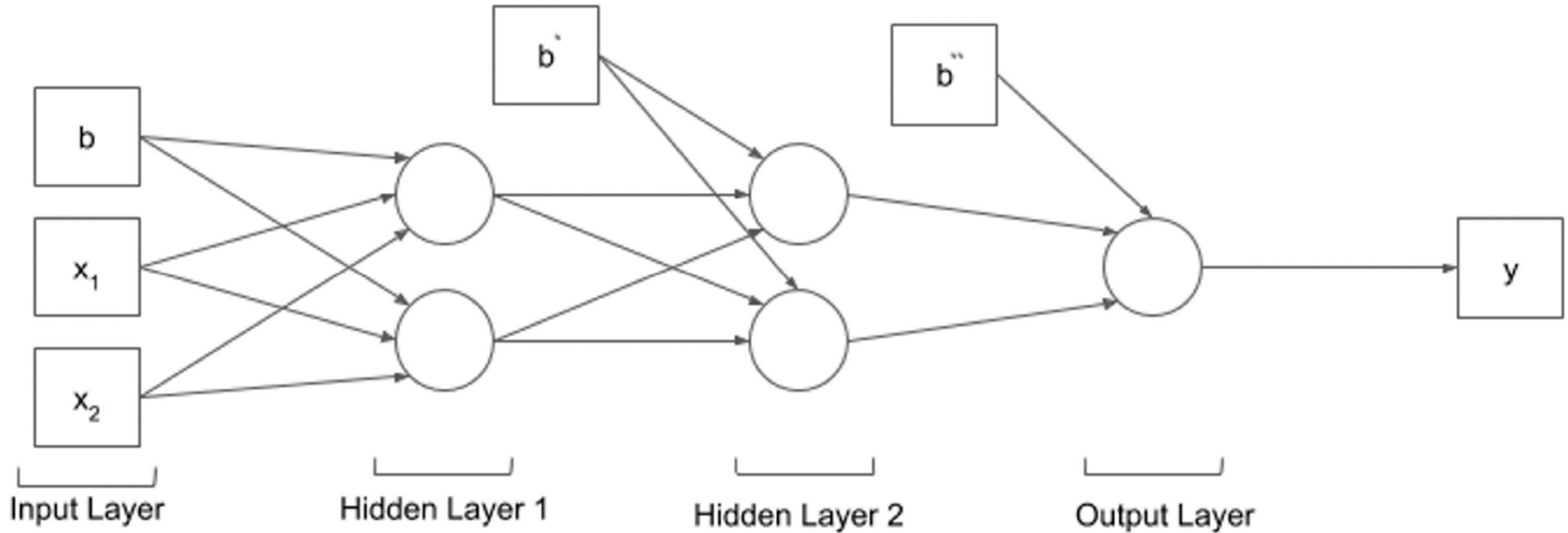
Each sample is an image
28 x 28 pixels = 784 pixels in total
Each pixel is a "feature", an attribute, of the image
Each feature is to be multiplied by a weight

The "Shape" of each example is 28x28

In the MNIST example project there are 60K samples for training + 10K samples for testing the training results

Each feature, each x , is a single pixel
Quite a long linear equation!

Neural Network - Model Example

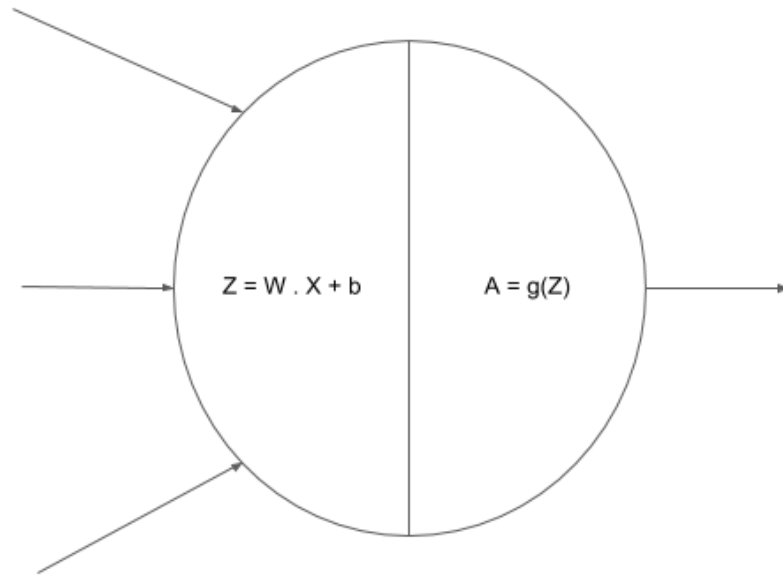


Graph: 784 inputs ; 10 possible outputs (Y); in-between sums and "activation functions" in HL
By cascading (and injecting non-linearity) to the linear sums, a much more complex function is possible

The difference (to a linear eq) is that not only the sum happens, but also an activation function
Activation function?

- bio (neuron) inspiration : takes the output signal from the previous cell and converts it to a form that can be taken as input to the next cell
- restricts values to controlled intervals
- adds non-linearity to the neural network
- contribute to change in W (the weights) to reduce loss, epoch (iteration) after epoch arturmarques.com

So, at each node of each HL



The linear equation (the sum $W \cdot X + b$)

The activation function (A)

There is an entire math field dedicated to the study of functions that can inject non-linearity and do so in a computationally efficient way.

Same A names:

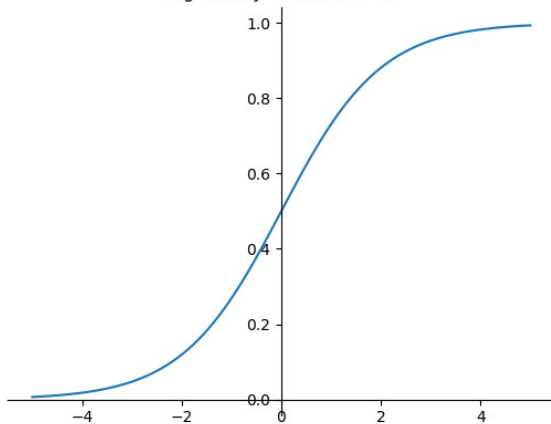
Sigmoid - Historical relevance, less used now.

Computationally expensive, non-zero centered output, derivative always in $0..0.25$

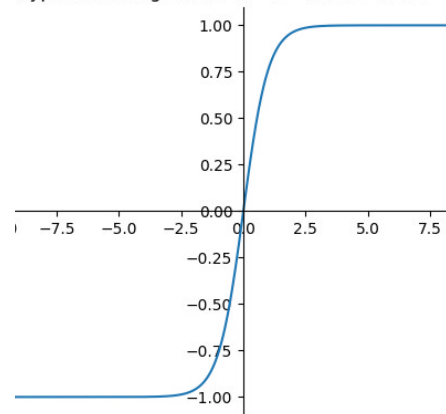
HTangent - a zero-centered ($f(0)=0$) sigmoid

ReLU - Rectified Linear Unit : $f(x) = \max(0,x)$

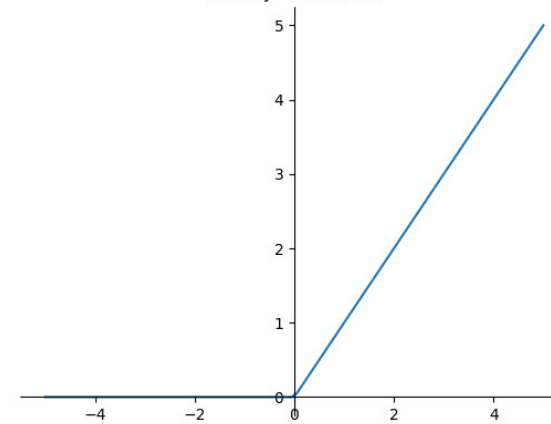
Sigmoid: $y = 1/(1+e^{-x})$



Hyperbolic tangent: $(e^{x} - e^{-x}) / (e^{x} + e^{-x})$



ReLU: $y = \max(0,x)$



References

- Free book on the math of ML:
 - <http://statweb.stanford.edu/~tibs/ElemStatLearn/>
- scikit-learn ML library
 - <https://scikit-learn.org/stable/>

