It is Just a Machine that Learns

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Outline

Elon Musk
"With Artificial Intelligence, we are summoning the demon"

Andrew Ng
"Fearing a rise of killer robots is like worrying about overpopulation on Mars"

Jeff Hinton
"Whether or not it turns out to be a good thing depends entirely on the social system, and doesn't depend at all on the technology"

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OpenAI's transformer-based model

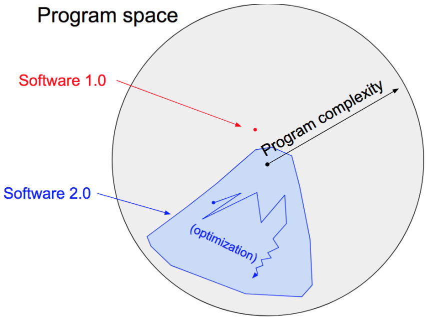
OpenAI on GPT-2

"We've trained a large-scale unsupervised language model which generates coherent paragraphs of text, achieves state-of-the-art performance on many language modeling benchmarks, and performs rudimentary reading comprehension, machine translation, question answering, and summarization—all without task-specific training."

"Due to concerns about large language models being used to generate deceptive, biased, or abusive language at scale, we are only releasing a much smaller version of GPT-2 along with sampling code. We are not releasing the dataset, training code, or GPT-2 model weights."

- **PR Focus** - reporters were given early information
- **Gatekeeping** - malicious uses were hypothesized and we have no way of testing
- **Misdirected** - not releasing affects researchers more than malicious actors due to the model price
- **Dual use** - OpenAI did not discuss dual-use technology

AI from the perspective of software development



Just a machine that learns

Machine learning emerged from AI - **build a computer system that automatically improves with experience**

- application is too complex for a manually designed algorithm
- application needs to customize its operational environment after it is fielded

A well-posed learning problem

A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E

Historically, ML is "just" part of the **industrial age's efforts towards perfecting task automation**

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Humanities research meets machine learning

As a consequence of the data surge, we are (also) "jumping the automation bandwagon"

– plus theoretical innovations that rely on ML/DL (e.g., lexical $\rightarrow$ compositional semantics)

Inherent challenges in our data and users

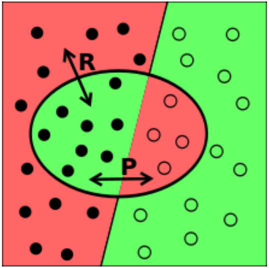
– data are unstructured, heterogeneous, need normalization, low resource varieties

– users lack of computational literacy, ++gab between technology and domain knowledge

Types of problems solved by ML:

– initially ML was the solution to a(-ny) research problem

– increasingly, ML solves auxiliary tasks related to automation



← `relevant objects` (e.g., ham)

→ `irrelevant objects` (e.g., spam)

⬭ objects classified with relevant class label

ERROR

CORRECT

Precision: fraction of retrieved instances that are relevant

$$P = \frac{TP}{TP + FP} \tag{1}$$

Recall: fraction of relevant instances that are retrieved

$$R = \frac{TP}{TP + FN} \tag{2}$$

P and *R* are inversely related. Identify balance through a Precision-Recall curve.

Impossibility results

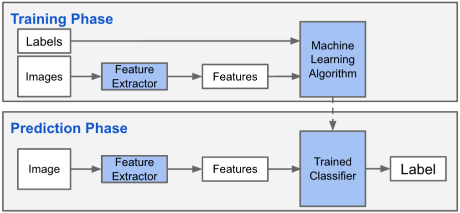
Assume differing base rates, $Pr_a(Y = 1) \neq Pr_b(Y = 1)$, and an imperfect learning algorithm, $C \neq Y$, then you cannot simultaneously achieve:

- **Precision parity**: $Pr_a(Y = 1 \mid C = 1) = Pr_b(Y = 1 \mid C = 1)$
- **True positive parity**: $Pr_a(C = 1 \mid Y = 1) = Pr_b(C = 1 \mid Y = 1)$
- **False positive parity**: $Pr_a(C = 1 \mid Y = 0) = Pr_b(C = 1 \mid Y = 0)$

"Suppose we want to determine the risk that a person is a carrier for a disease Y, and suppose that a higher fraction of women than men are carriers. Then our results imply that in any test designed to estimate the probability that someone is a carrier of Y, at least one of the following undesirable properties must hold: (a) the test's probability estimates are systematically skewed upward or downward for at least one gender; or (b) the test assigns a higher average risk estimate to healthy people (non-carriers) in one gender than the other; or (c) the test assigns a higher average risk estimate to carriers of the disease in one gender than the other. The point is that this trade-off among (a), (b), and (c) is not a fact about medicine; it is simply a fact about risk estimates when the base rates differ between two groups"

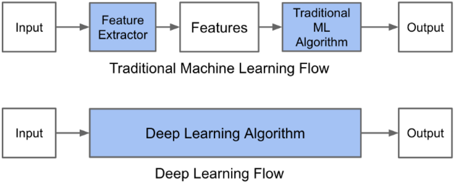
Kleinberg J., S. Mullainathan, & M. Raghavan (2016), Inherent Trade-Offs in the Fair Determination of Risk Scores, arXiv:1609.05807

Basic supervised pipeline



Machine Learning Phases

The emergence of deep learning



Neurons

Basic computational unit of a neural network

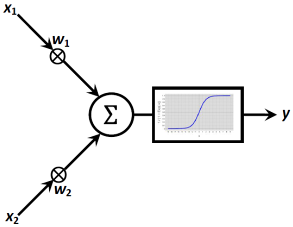


Figure 1: A neuron takes inputs, x_1, x_2, does *some math on them*, and generates an output, y

The input is weighted

$$x_1 \to x_1 \times w_1$$
$$x_2 \to x_2 \times w_2$$

then added with a bias

$$(x_1 \times w_1) + (x_2 \times w_2) + b$$

and finally passed through an activation function

$$y = f(x_1 \times w_1 + x_2 \times w_2 + b)$$

A word on the activation functions

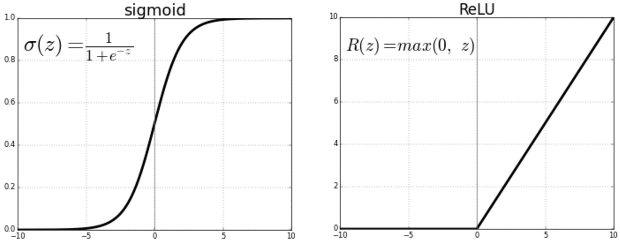


Figure 2: The sigmoid activation function "squashes" an unbounded $(-\infty, +\infty)$ to a bounded $(0, 1)$ set. Computationally simpler activation functions, such as rectifiers, are starting to replace sigmoids.

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Example

cat/dog classifier where x_1 "has fur" and x_2 "barks" and we are generally more likely to encounter dogs, so when "it has fur and barks", then:

$$
\begin{aligned}
w &= [0, 1] \\
b &= 2
\end{aligned}
$$

$$
\begin{aligned}
(w \cdot x) + b &= ((w_1 \times x_1) + (w_2 \times x_2)) + b \\
&= 1 \times 0 + 1 \times 1 + 2 \\
&= 3
\end{aligned}
$$

$$f(w \cdot x + b) = f(3) = \frac{1}{1 + e^{-}3} = 0.953$$

Neurons in a network

An artificial neural network is just a set of neurons wired together (typically) in a layered structure.

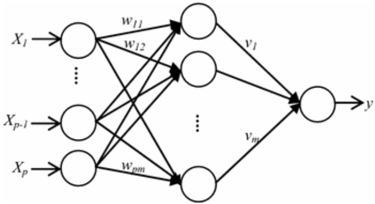

Figure 3: Feedforward neural network with one hidden layer of size *m*. A hidden layer is any layer between the input and output. Hidden layers perform transformations on the input or previous hidden layers. A network can have many hidden layers.

A neural network can have any number of neurons and layers. *Deep* in deep learning just refers to representations learned in multi-layered (deep) structures. The core idea is to propagate input forward through the transformations of the hidden layers in order to get an output.

Example

continue example from before (cat/dog), with one hidden layer and two hidden units, $w = [0, 1]$, $b = 0$, and $x = [0, 1]$:

$$\begin{aligned} h_1 = h_2 &= f(w \cdot x + b) \\ &= f((0 \times 0) + (1 \times 1) + 0) \\ &= f(1) \\ &= 0.731 \end{aligned}$$

$$\begin{aligned} o_1 &= f(w \cdot [h_1, h_2] + b) \\ &= f((0 \times h_1) + (1 \times h_2) + 0) \\ &= f(0.731) \\ &= 0.675 \end{aligned}$$

Training the model

It is impossible to compute the perfect weights for a neural network. Instead learning becomes an optimization problem and algorithms are used to run through the space of possible weights that the model can use to make a good prediction.

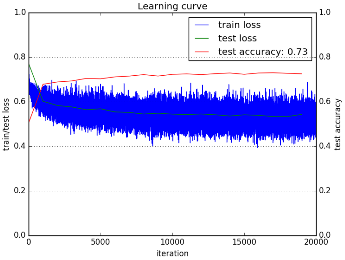

Figure 4: Training is an optimization problem: minimizing loss function & maximize test accuracy

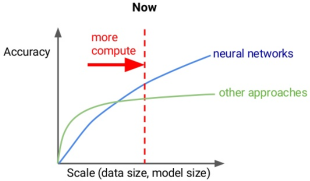

Figure 5: Currently there seems to be no upper limit on performance - except for the perfect classifier

– Training consists of iteratively adjusting the weights in order to minimize a loss function.

– Neural network models are typically trained using the *gradient descent* optimization algorithm and weights are updated using the backpropagation (of error) algorithm

Loss function

Mean squared error loss:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_{true} - y_{pred})^2$$

– a good prediction lowers loss $\rightarrow$ training a network $\sim$ trying to mininmize loss

– iow: a loss function maps the networks output onto the "loss" associated with a prediction $\sim$ evaluated how well the neural network captures the data structure

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If the goal is to minimize loss of the network, the loss is a function of weights w and biases b. For a fully connected one-layered feedforward network $(2 \times 2 \times 1)$ then:

$$L(w_1, w_2, w_3, w_4, w_5, w_6, b_1, b_2, b_3)$$

Modifying w_1 then, will change L as $\frac{\partial L}{\partial w_1}$. Using the chain rule:

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y_{pred}} \times \frac{\partial y_{pred}}{\partial w_1}$$

Assume a simple binary classifier, $True : 1$, $MSE = (1 - y_{pred})^2$, then:

$$\frac{\partial L}{\partial y_{pred}} = \frac{\partial (1 - y_{pred})^2}{\partial y_{pred}} = -2(1 - y_{pred})$$

For $\frac{\partial y_{pred}}{w_1}$, let h_1, h_2, o_1 be the output of the neurons they represent, then:

$$y_{pred} = o_1 = f(w_5 h_1 + w_6 h_2 + b_3)$$

where f is the sigmoid activation function.

Because w_1 only modulates h_1 and not h_2:

$$\frac{\partial y_{pred}}{w_1} = \frac{\partial y_{pred}}{\partial h_1} \times \frac{\partial h_1}{\partial w_1}$$

and with the chain rule:

$$\frac{\partial y_{pred}}{\partial h_1} = w_5 \times f'(w_5 h_1 + w_6 h_2 + b_3)$$

Repeat procedure for $\frac{\partial h_1}{\partial w_1}$:

$$h_1 = f(w_1 x_1 + w_2 x_2 + b1)$$

$$\frac{\partial h_1}{\partial w_1} = x_1 \times f'(w_1 x_1 + w_2 x_2 + b1)$$

Compute the derivative of the sigmoid function:

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

$$f'(x) = \frac{e^{-x}}{(1 + e^{-x})^2} = f(x) \times (1 - f(x))$$

Put it all together and we can compute:

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y_{pred}} \times \frac{\partial y_{pred}}{\partial h_1} \times \frac{\partial h_1}{\partial w_1}$$

as:

$$-2(1 - y_{pred}) \times w_5 \times f'(w_5 h_1 + w_6 h_2 + b_3) \times x_1 \times f'(w_1 x_1 + w_2 x_2 + b1)$$

Backprobagation: The system of computing the partial derivatives by working backwards. Backpropagation in this form was derived by Stuart Dreyfus in 1962.

Dreyfus, S (1962). The numerical solution of variational problems. Journal of Mathematical Analysis and Applications. 5(1)

Training with Backprop

The most widely used training algorithm is *Stochastic Gradient Descent*, which is a set of formal steps for modifying weights and biases to minimize loss:

$$w_1 \leftarrow w_1 - \eta \frac{\partial L}{\partial w_1}$$

where the learning η rate controls the speed of training

- if $\frac{\partial L}{\partial w_1}$ is positive, then w_1 will decrease and L decrease
- if $\frac{\partial L}{\partial w_1}$ is negative, then w_1 will increase and L decrease

Algorithm 1 Gradient Descent

while $t < maxiter$ **do**
  for *all* i, j **do**
    $w_{ij} = w_{ij} - \eta \frac{\partial L}{\partial w_{ij}}$
  end for
end while

Underlying AI is just rather "dumb" system that improves its performance on a pre-specified task over time by **recursively sending the output of its computations backwards to the parent**.

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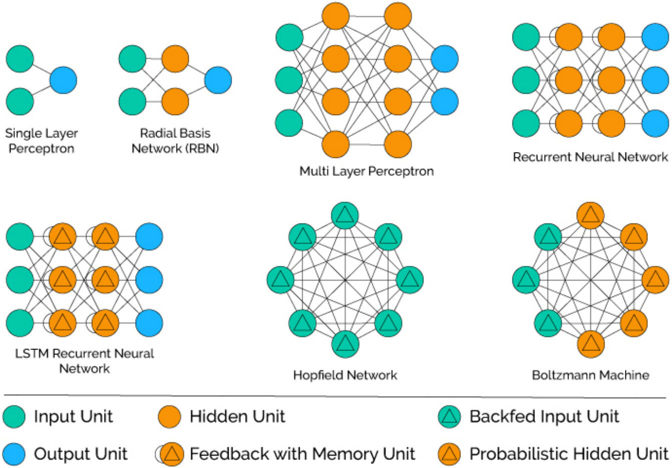
ANN architectures



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slides: http://knielbo.github.io/files/kln_fip19.pdf

& tak til

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