بنام خداوند جان و خرد

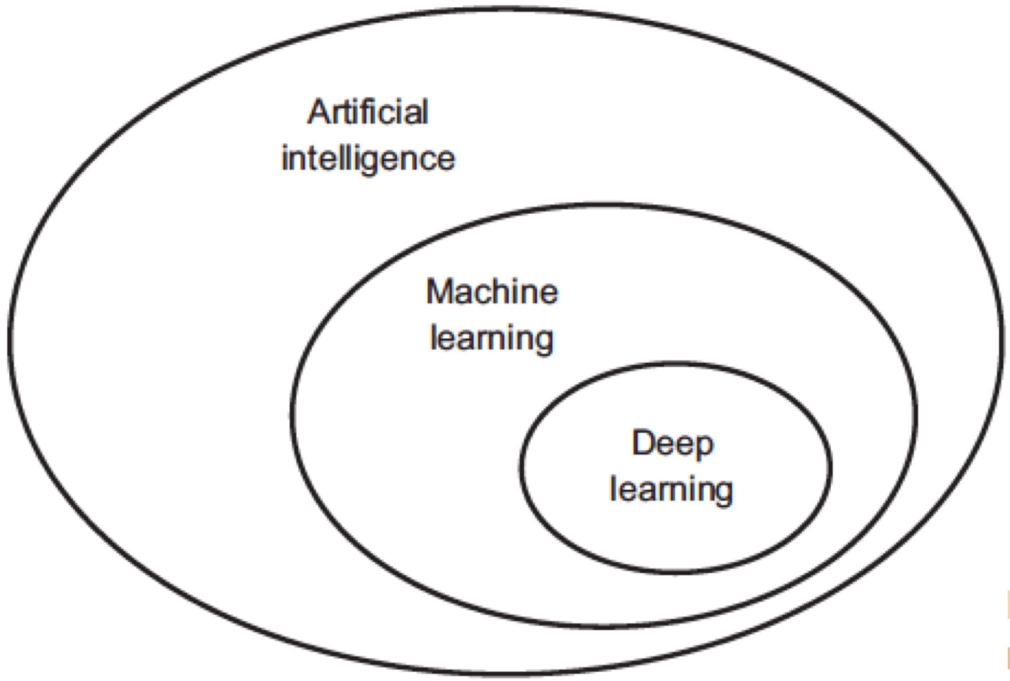
What is deep learning?

Mohammad Taher Pilehvar

Introduction to Artificial Intelligence, 97

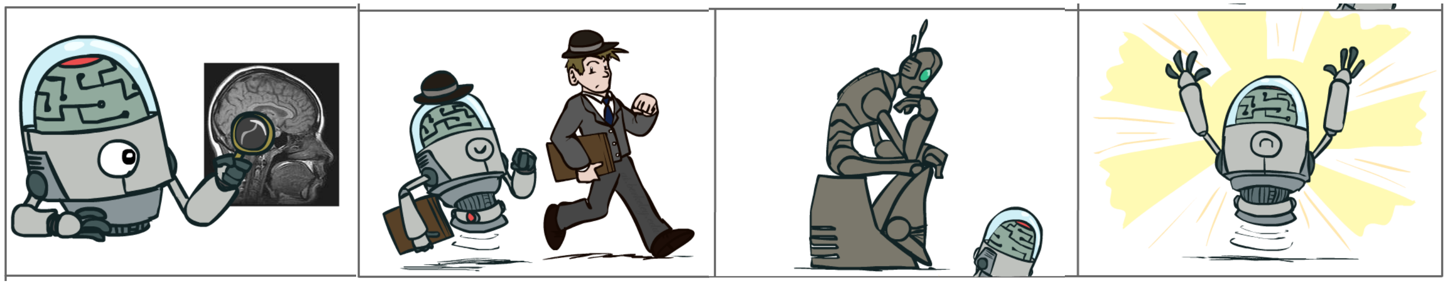
http://iust-courses.github.io/ai97/

AI, ML, and DL



Artificial Intelligence

- The effort to automate intellectual tasks normally performed by humans

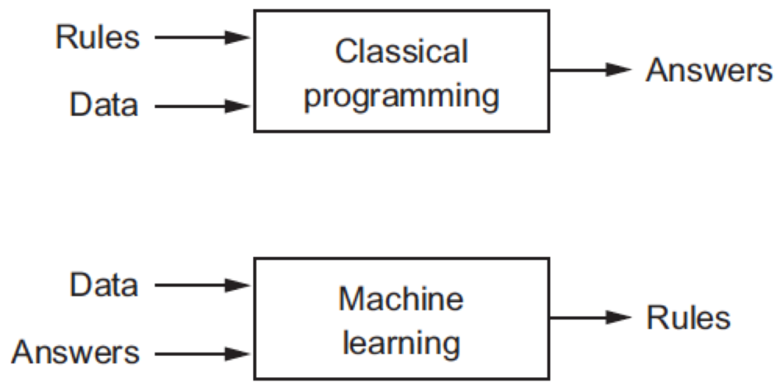


  - Not necessarily through Machine Learning or Deep Learning
    - For instance, early chess programs with hardcoded rules
    - Symbolic AI, dominant from 1950s to 1980s

Machine Learning vs. symbolic AI

- Symbolic AI: humans input rules (a program) and data to be processed according to these rules, and out come answers.

- Machine learning: input data as well as the answers expected from the data, and out come the rules.
  - These rules can then be applied to new data to produce original answers.



Machine Learning

A machine-learning system is **trained** rather than explicitly **programmed**.

It's presented with many examples relevant to a task

- It finds statistical structure in these examples that eventually allows the system to come up with rules for automating the task.

Machine Learning example: Sentiment Analysis

انبر قفلی ایران پتک مدل HB 1010 سایز 10 اینچ

Iran Potk HB 1010 Locking Pliers 10 Inches

برند : ایران پتک   دسته‌بندی : انبر

گارانتی اصالت و سلامت فیزیکی کالا

فروشنده: سارامون

رضایت خرید : ۸۸ %

آماده ارسال

۵۸,۹۰۰ تومان

یکی از بهترین انبر قفلی هایی هست که توی بازار در دسترس هست و با توجه به کیفیت با این قیمت ارزش خرید بالایی دارد

در مقام مقایسه یک پله از انبر قفلی آمریکایی به دلیل بالاتر بودن کیفیت فک های انبر آمریکایی پایین تر است

نمیشه گفت محصول کارامدی نیست ،...

ولی برای من با اولین پیچ 2تا دندونش صاف شد....

حالا شاید من درست کار نکردم باهاش ،

ولی فشاری که من وارد کردم اصلا در حد صاف شدن این دندونه ها نبود .....

موفق باشید

ایران پتک با کیفیترین اجناس,رو تولید میکنه قیمتش بخاطر کیفیتشه حققشه ازش حمایت شه

ایران پتک برند خوبیه

برای انبر قفلی خوب باید آلیاژ کروم وانادیوم یا کروم مولیبدن باشه ولی این آلیاژ نیست فقط فورج یا همان آهنگری قدیم می باشد که اصلاً جواب نمیده

از اینکه تولید داخل هست وباید از تولید داخل حمایت کرد شکی نیست ولی کاش سازنده ان برای اطمینان بهتر وفروش بیشتر گارانتی میدادن .کیفیتش خوبه .افتخار واسه ایران هست ولی مثل جنیوس نمیشه .عیب اجناس ایرانی اینه که تا بازار فروش خوب شد کیفیت پایین میارن

Machine Learning example:
Machine Translation

(src)="13"> But on the other side of that , though , we were big readers in our house .
(trg)="13"> هر چند ، اما از طرف دیگه تو خونه ما زیاد کتاب می خوندیم .

(src)="14"> And if the TV was on , we were watching a documentary .
(trg)="14"> و اگر تلویزیون روشن بود فیلمهای مستند نگاه می کردیم .

(src)="15"> And my dad is the most voracious reader I know .
(trg)="15"> پدرم حریص ترین کتابخونی بود که می شناسم .

(src)="16"> He can read a novel or two a day .
(trg)="16"> روزی یک یا دو تا رمان می خوند .

(src)="17"> But when I was little , I remember , he would kill flies in our house with my BB gun .
(trg)="17"> یادمه وقتی بچه بودم ، علاقه داشت که مگس های تو خونه را با تفنگ بادی من بکشد .

(src)="18"> And what was so amazing to me about that -- well he would be in his recliner , would holler for me to fetch the BB gun , and I 'd go get it .
(trg)="18"> وقتی پدرم رو صندلیش داد می زد که تفنگ بادیش رو ببرم-- خیلی ذوق می کردم و براش می بردم

(src)="19"> And what was amazing to me -- well it was pretty kickass ; he was killing a fly in the house with a gun -- but what was so amazing to me was that he knew just enough how to pump it .
(trg)="19"> کشتن پشه تو خونه با تفنگ بادی برام خیلی سرگرم کننده بود اما خیلی جالب بود که می دونست چقدر پمپ تنفنگ رو باد کنه .

(src)="20"> And he could shoot it from two rooms away and not damage what it was on because he knew how to pump it just enough to kill the fly and not damage what it landed on .
(trg)="20"> از دوتا اتاق اونور تر شلیک می کرد بدون اینکه به چیزی آسیب بزنه ، برای اینکه می دونست برای کشتن پشه چقدر باید پمپ رو باد کنه و به چیزی آسیب نمی رسوند .

(src)="21"> So I should talk about art .
(trg)="21"> مثله اینکه قراره در مورد هنر حرف بزنم .

(src)="22"> Or we 'll be here all day with my childhood stories .
(trg)="22"> همه روز را می توانیم با قصه های بچگی می بگذرانیم .

(src)="23"> I love contemporary art , but I 'm often really frustrated with the contemporary art world and the contemporary art scene .
(trg)="23"> من عاشق هنر معاصر هستم اما گاهی اوقات ، از هنر معاصر دنیا و نمایش هنر معاصر خسته میشم .

Learning Representations

To do machine learning, we need three things:

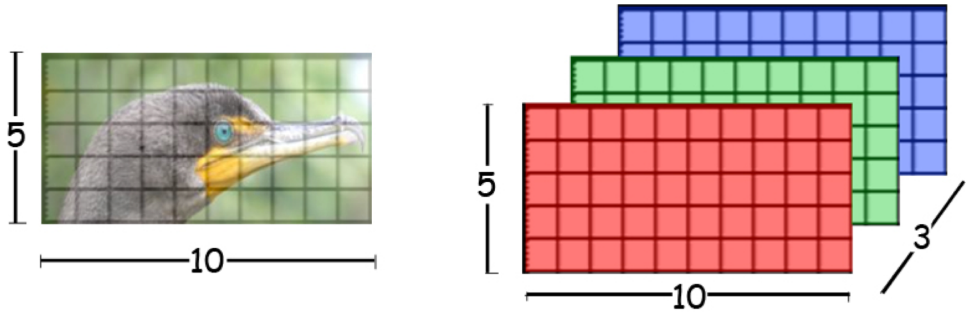
- Input data points
- Examples of expected output
- A way to measure whether the algorithm is doing a good job

- A machine-learning model **transforms** its input data into meaningful outputs, a process that is "learned" from exposure to known examples of inputs and outputs.

- The central problem in machine learning and deep learning:
  meaningfully transform data
  - In other words, to learn useful representations of the input data at hand, representations that get us closer to the expected output

What's a representation?

A different way to look at data, to represent or encode data



Original Color Image

Matlab RGB Matrix

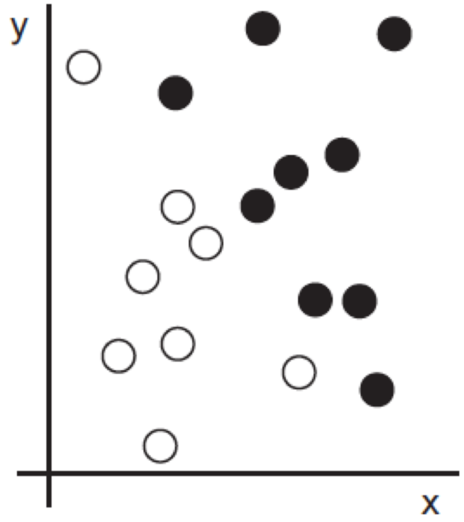
Some tasks are easier to be done on some representations, for instance, detecting red parts of picture

Image from Wikipedia

What's a representation?

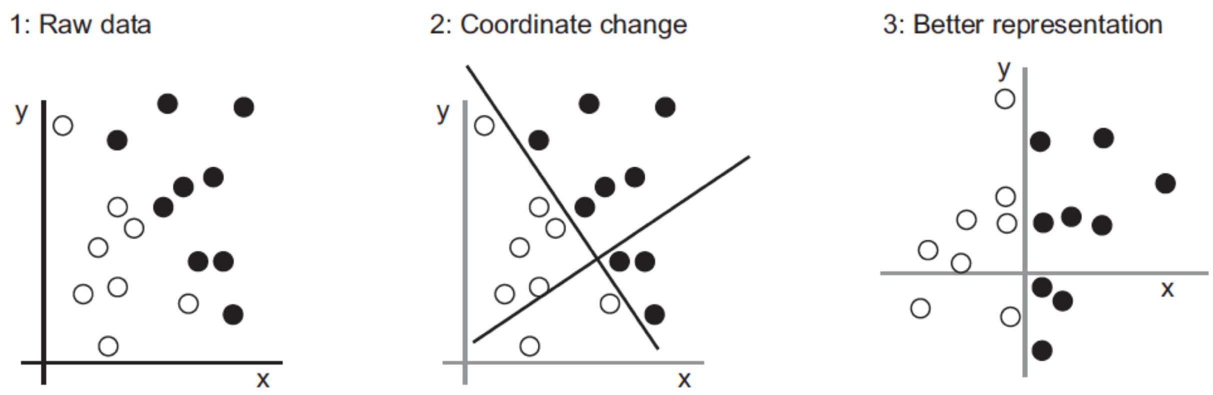
Develop an algorithm that can take the coordinates (x, y) of a point and output whether that point is likely to be black or to be white

- The inputs are the coordinates of our points.
- The expected outputs are the colors of our points.
- A way to measure whether our algorithm is doing a good job could be, for instance, the percentage of points that are being correctly classified.



What's a representation?

What we need here is a new representation of our data that cleanly separates the white points from the black points.



Learning, in the context of machine learning, describes an automatic search process for better representations.

What’s a representation?

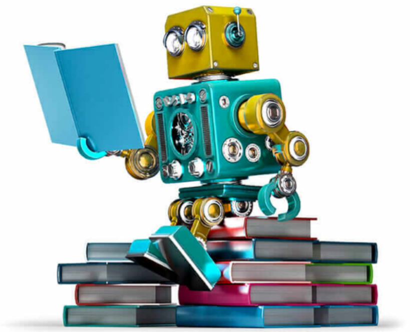
All machine-learning algorithms consist of automatically finding such transformations that turn data into more-useful representations for a given task

- Coordinate changes, linear projections (which may destroy information), translations, nonlinear operations, etc.

Machine-learning algorithms aren’t usually creative in finding these transformations

- They’re merely searching through a predefined set of operations, called a *hypothesis space*.

Machine Learning



Searching for

useful representations of some input data,

within a predefined space of possibilities,

using guidance from a feedback signal.

Deep Learning?

A specific subfield of machine learning

Not necessarily a deeper understanding! Rather the idea of successive layers of representations.

Other approaches to machine learning tend to focus on learning only one or two layers of representations of the data

- Hence, they're sometimes called *shallow learning*.

Deep learning and neural networks

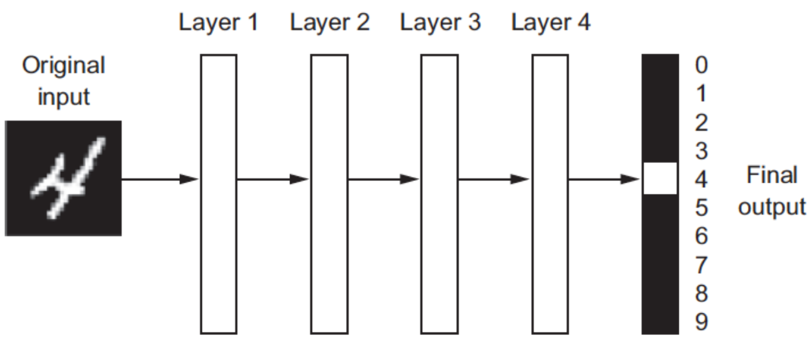
- In DL, layered representations are (almost always) learned via models called neural networks

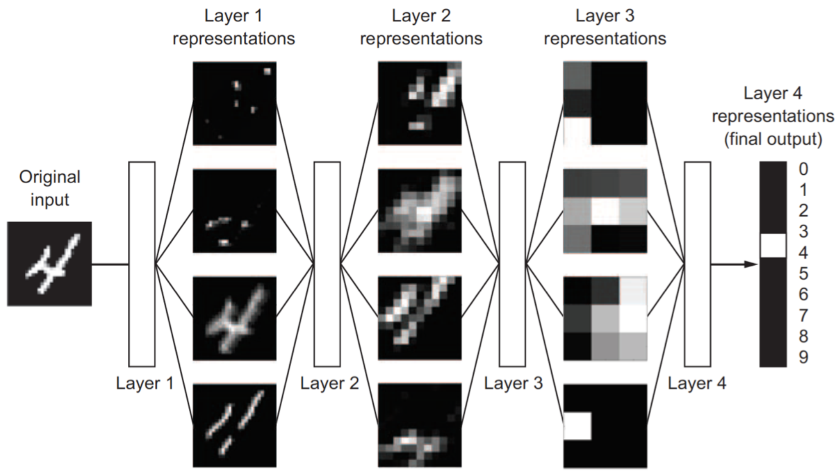
- Deep-learning models are not models of the brain!

- Deep learning is a just mathematical framework for learning representations from data

Deep learning: Representations

- What do the representations learned by a deep-learning algorithm look like?

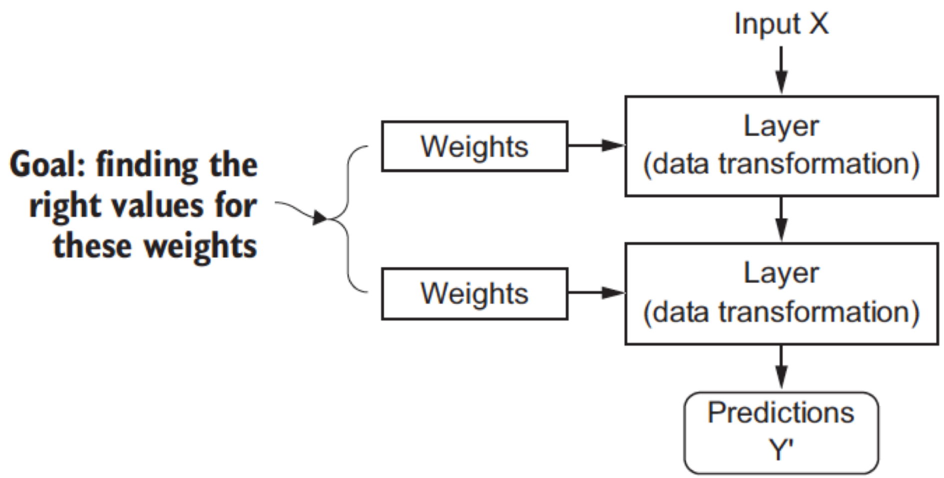




- The network transforms the digit image into representations that are increasingly different from the original image and increasingly informative about the final result.

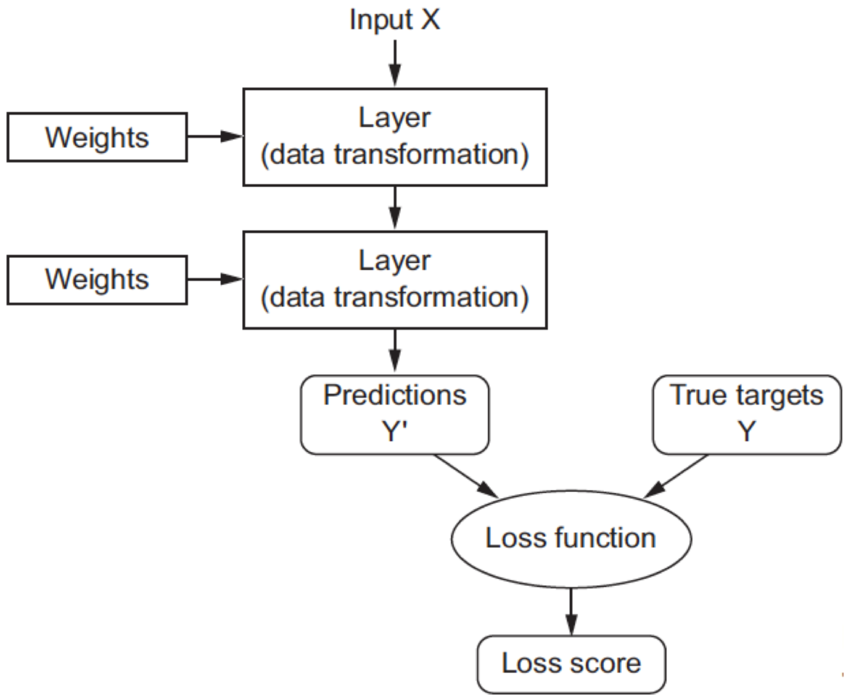
How deep learning works?

Find a set of values for the weights of all layers in a network, such that the network will correctly map example inputs to their associated targets.



How deep learning works?

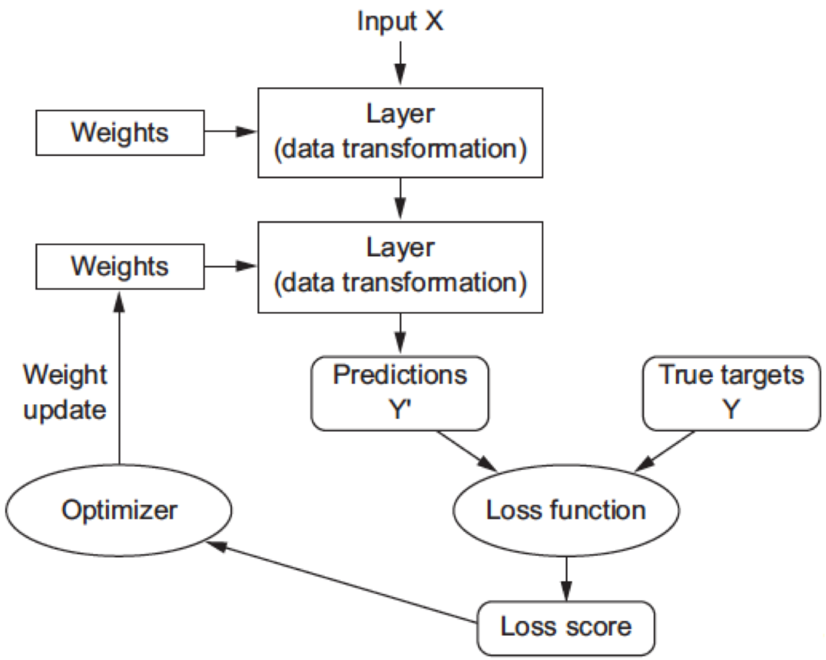
- Loss function (objective function): measures how far the output is from what you expected



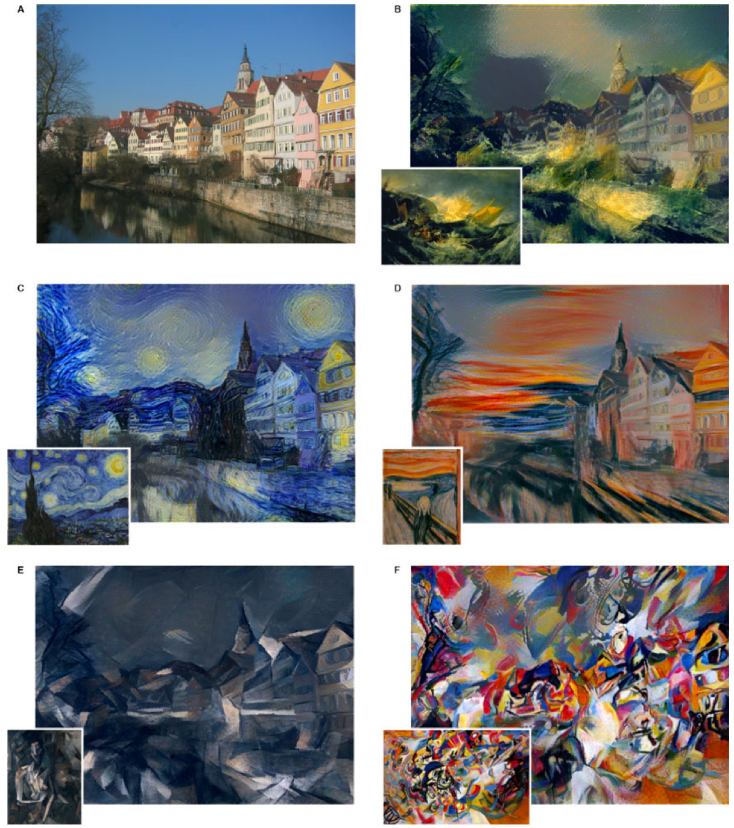
How deep learning works?

- Use the loss score as a feedback signal to adjust the value of the weights a little, in a direction that will lower the loss score for the current example

- Optimizer
- Backpropagation



What deep learning has achieved so far?



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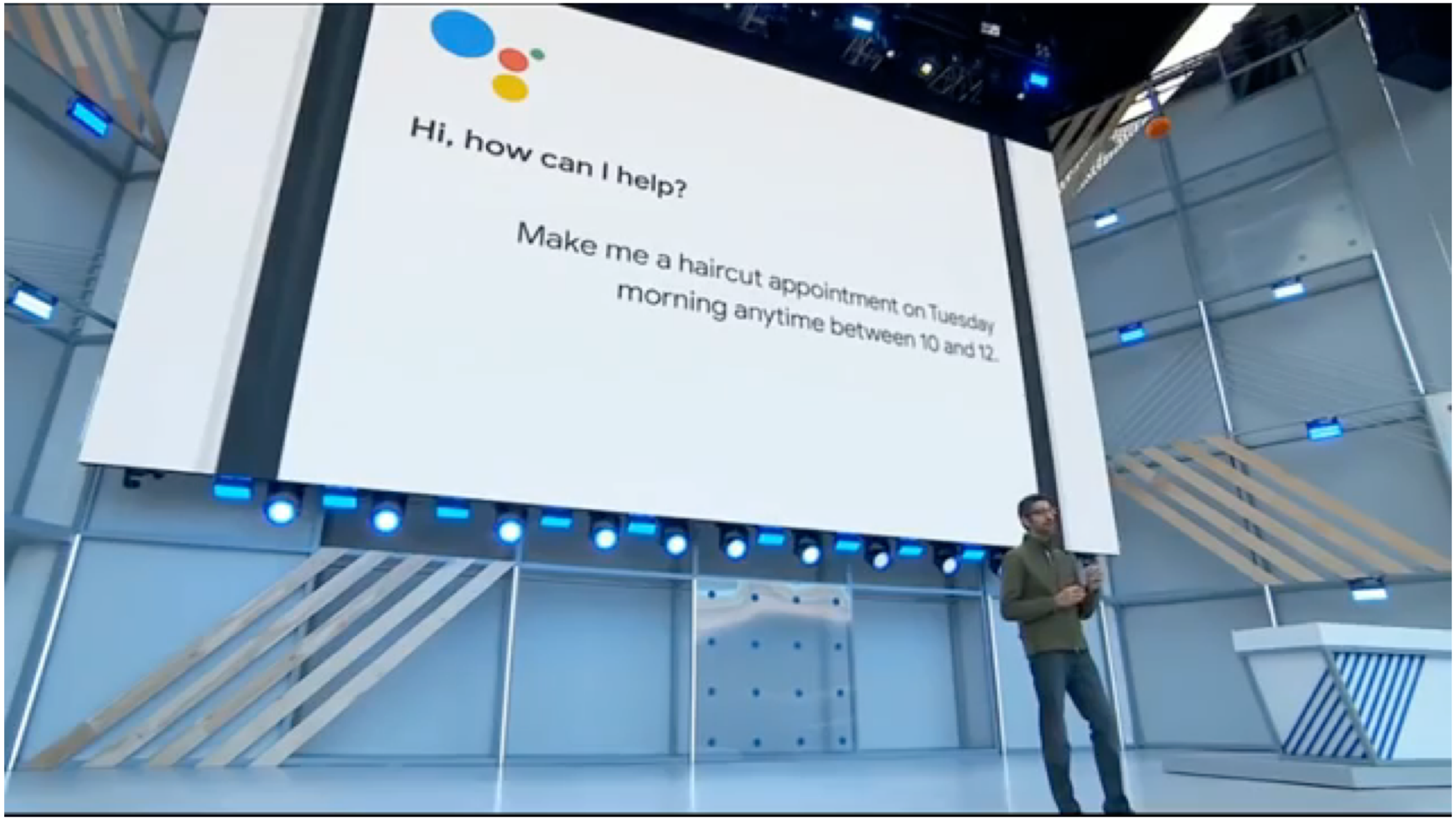

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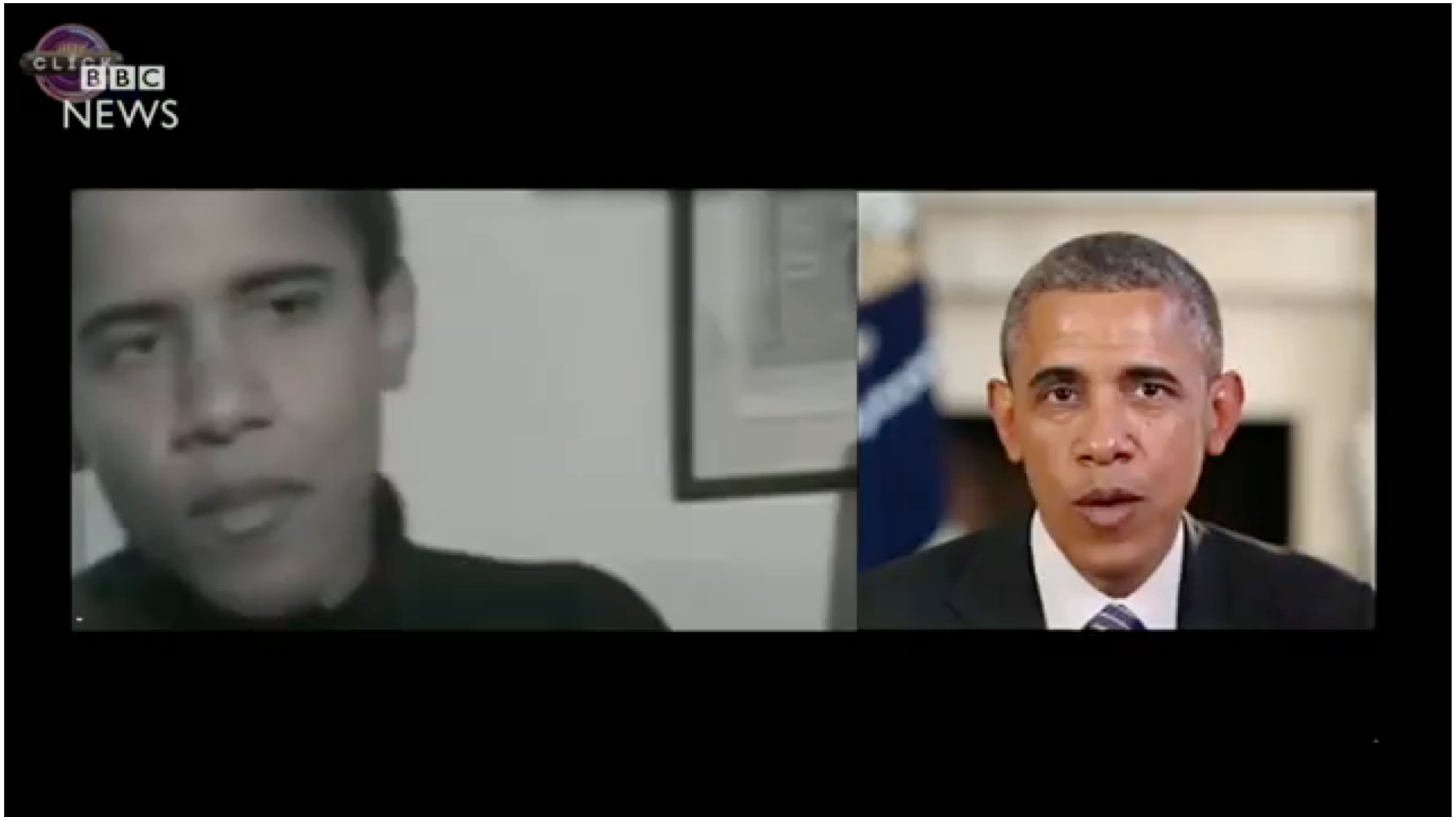


Deep learning hype

- Human-level general intelligence shouldn't be taken too seriously
  - The risk with high expectations for the short term is that, as technology fails to deliver, research investment will dry up, slowing progress for a long time.

- This has happened before.
- Marvin Minsky
  - 1967: "Within a generation … the problem of creating 'artificial intelligence' will substantially be solved."
  - 1970: "In from three to eight years we will have a machine with the general intelligence of an average human being."
  - As of 2018, still far from possible

- As these high expectations failed to materialize, researchers and government funds turned away from the field, marking the start of the first *AI winter*

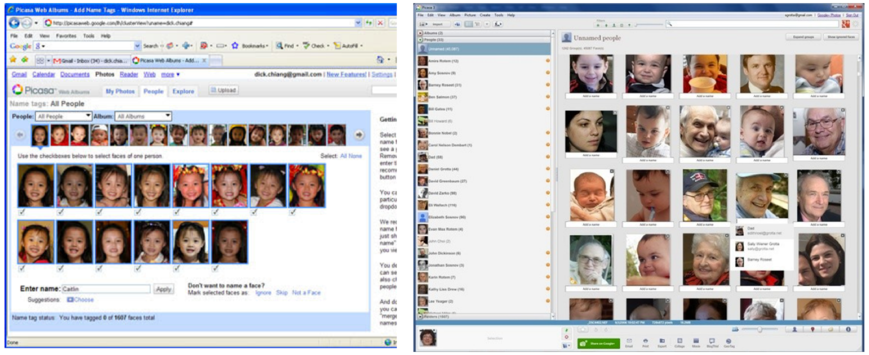
Promise of AI

- Don’t believe the short-term hype, but do believe in the long-term vision
  - AI is coming!

- Amazing progress in the past years

- But little of this progress has made its way into the products and processes that form our world
  - Your doctor doesn’t yet use AI
  - Neither does your accountant

Promise of AI

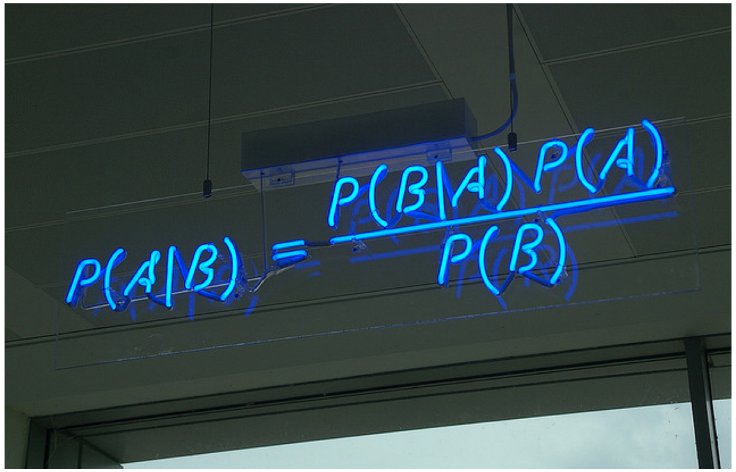


Before deep learning

- Deep learning isn't always the right tool for the job
  - Sometimes there isn't enough data for deep learning to be applicable, and sometimes the problem is better solved by a different algorithm.

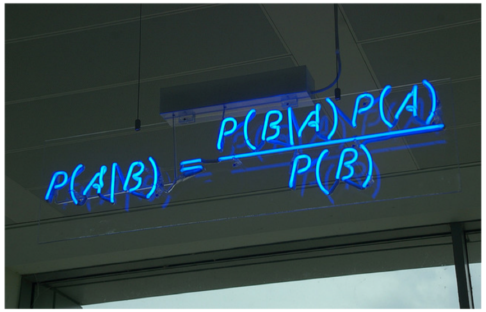
Naïve Bayes

- A type of machine-learning classifier based on applying Bayes' theorem while assuming that the features in the input data are all independent



Naïve Bayes: example, gender classification

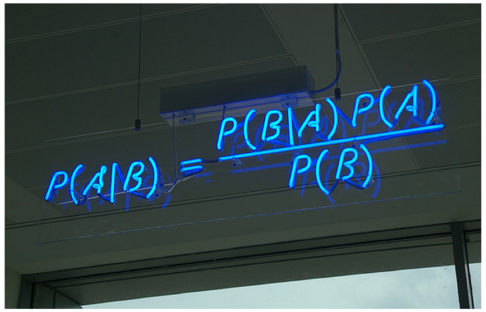
Person	height (feet)	weight (lbs)	foot size(inches)
male	6	180	12
male	5.92 (5'11")	190	11
male	5.58 (5'7")	170	12
male	5.92 (5'11")	165	10
female	5	100	6
female	5.5 (5'6")	150	8
female	5.42 (5'5")	130	7
female	5.75 (5'9")	150	9



Person	mean (height)	variance (height)	mean (weight)	variance (weight)	mean (foot size)	variance (foot size)
male	5.855	$3.5033*10^{-2}$	176.25	$1.2292*10^{2}$	11.25	$9.1667*10^{-1}$
female	5.4175	$9.7225*10^{-2}$	132.5	$5.5833*10^{2}$	7.5	1.6667

Naïve Bayes: example, gender classification

Person	height (feet)	weight (lbs)	foot size(inches)
sample	6	130	8

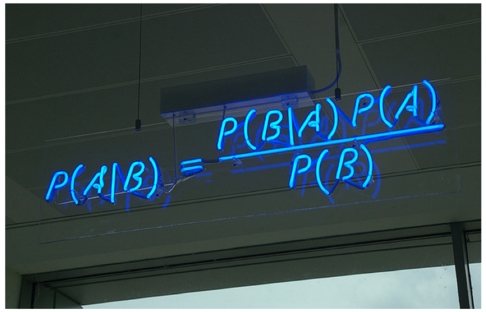


$$\text{posterior (male)} = \frac{P(\text{male})\, p(\text{height} \mid \text{male})\, p(\text{weight} \mid \text{male})\, p(\text{foot size} \mid \text{male})}{evidence}$$

$$\text{posterior (female)} = \frac{P(\text{female})\, p(\text{height} \mid \text{female})\, p(\text{weight} \mid \text{female})\, p(\text{foot size} \mid \text{female})}{evidence}$$

$$\begin{aligned}\text{evidence} = {} & P(\text{male})\, p(\text{height} \mid \text{male})\, p(\text{weight} \mid \text{male})\, p(\text{foot size} \mid \text{male}) \\ & + P(\text{female})\, p(\text{height} \mid \text{female})\, p(\text{weight} \mid \text{female})\, p(\text{foot size} \mid \text{female})\end{aligned}$$

Naïve Bayes: example, gender classification



$$P(\text{male}) = 0.5$$

$$p(\text{height} \mid \text{male}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-(6-\mu)^2}{2\sigma^2}\right) \approx 1.5789,$$

$$p(\text{weight} \mid \text{male}) = 5.9881 \cdot 10^{-6}$$

$$p(\text{foot size} \mid \text{male}) = 1.3112 \cdot 10^{-3}$$

$$\text{posterior numerator (male)} = \text{their product} = 6.1984 \cdot 10^{-9}$$

$$P(\text{female}) = 0.5$$

$$p(\text{height} \mid \text{female}) = 2.2346 \cdot 10^{-1}$$

$$p(\text{weight} \mid \text{female}) = 1.6789 \cdot 10^{-2}$$

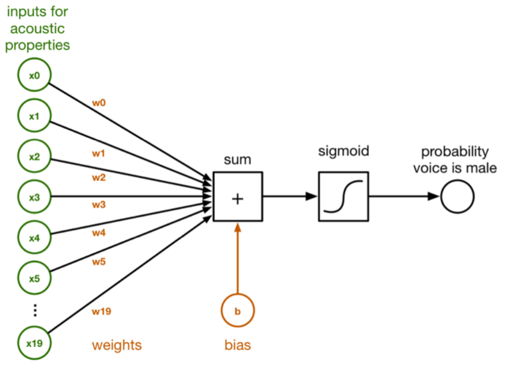
$$p(\text{foot size} \mid \text{female}) = 2.8669 \cdot 10^{-1}$$

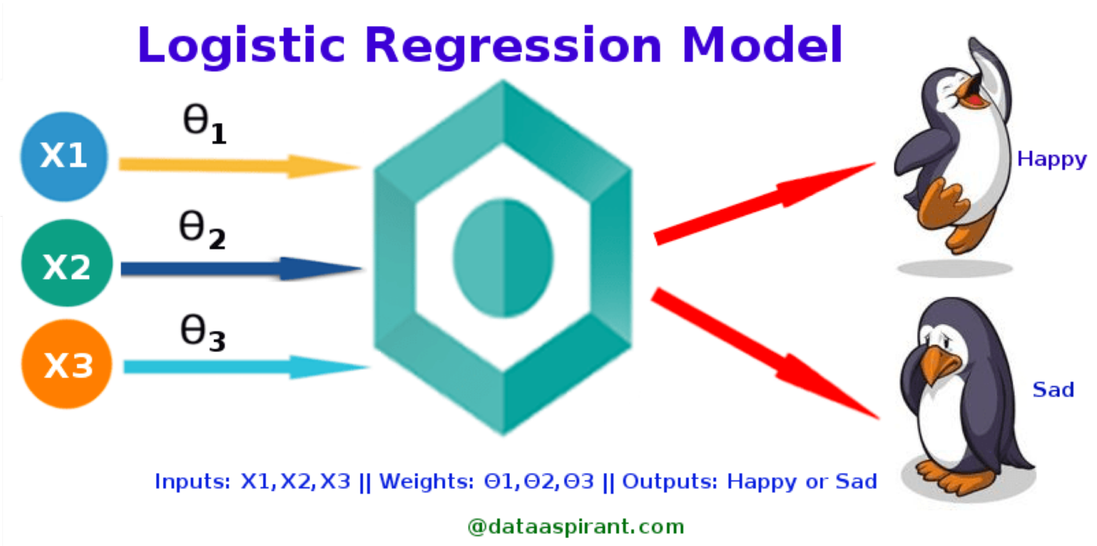
$$\text{posterior numerator (female)} = \text{their product} = 5.3778 \cdot 10^{-4}$$

- Since posterior numerator is greater in the female case, we predict the sample is female.

Logistic Regression

- “hello world” of modern machine learning



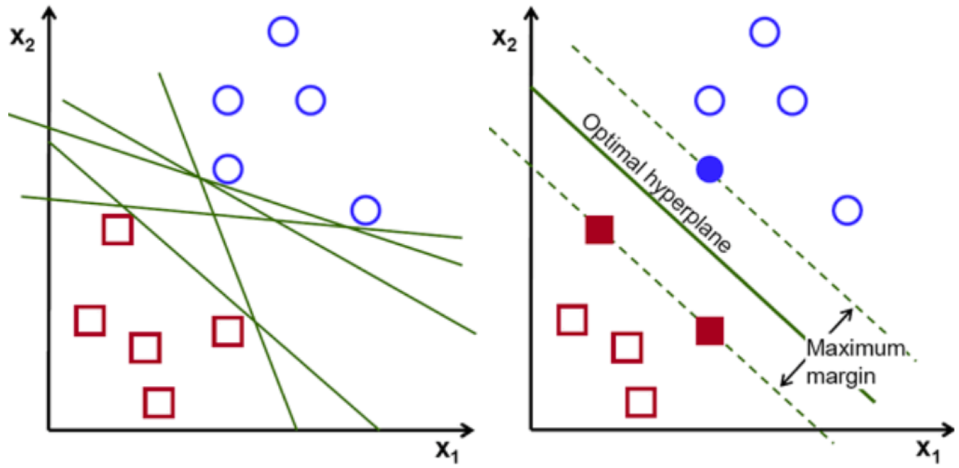


Kernel methods: SVM

Support Vector Machines

1. Data mapped to a new high-dimensional representation where the decision boundary can be expressed as a hyperplane

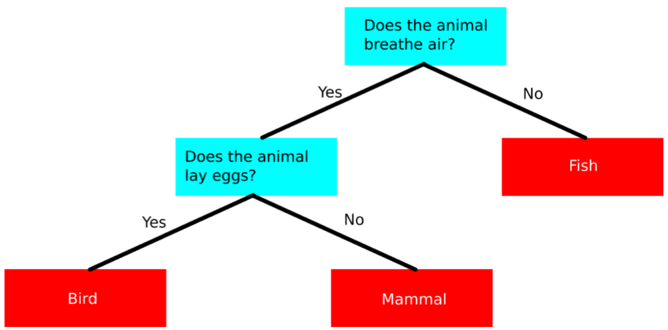
2. Maximizing the margin: a good decision boundary (a separation hyperplane) is computed

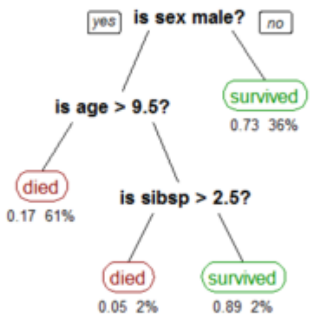


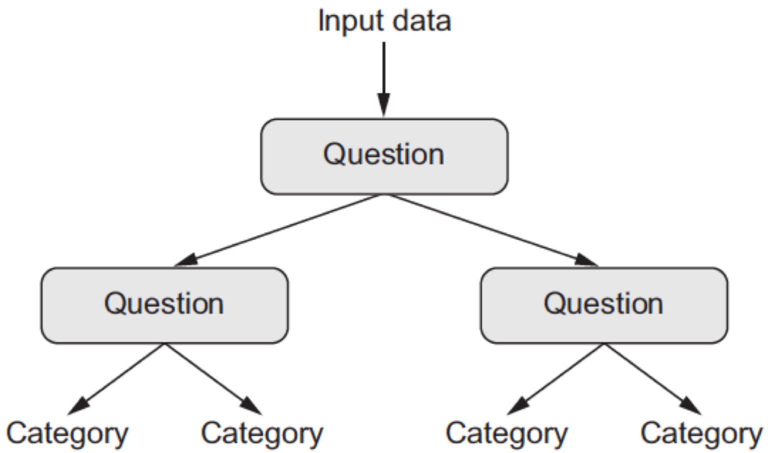
Kernel trick: you can directly compute the distances between pairs of points in a new space using Kernel function (without needing the explicit computation)

Decision Trees

- Flowchart-like structures that let you classify input data points or predict output values given inputs
- Easy to visualize and interpret

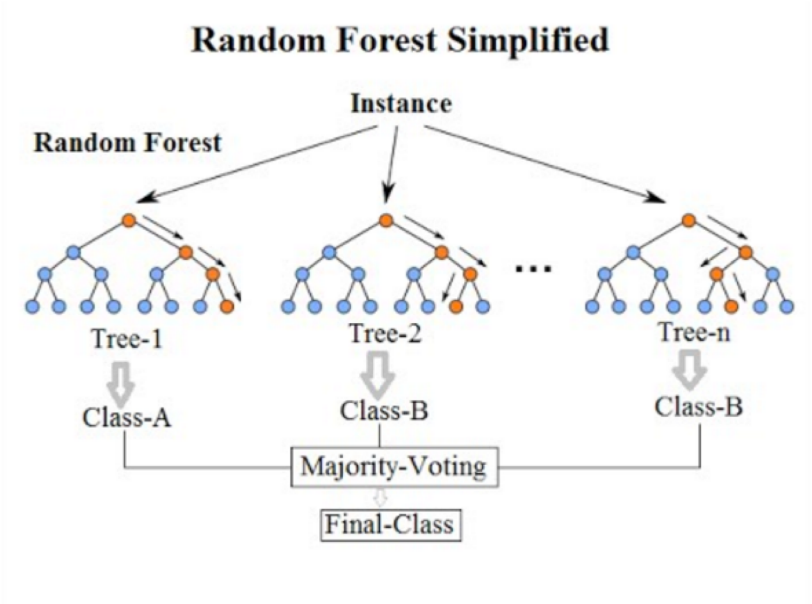






Random Forest

- Build a large number of specialized decision trees and then ensemble their outputs.



Return of neural networks

IMAGENET

Very difficult; classifying high resolution color images into 1,000 different categories after training on 1.4 million images.

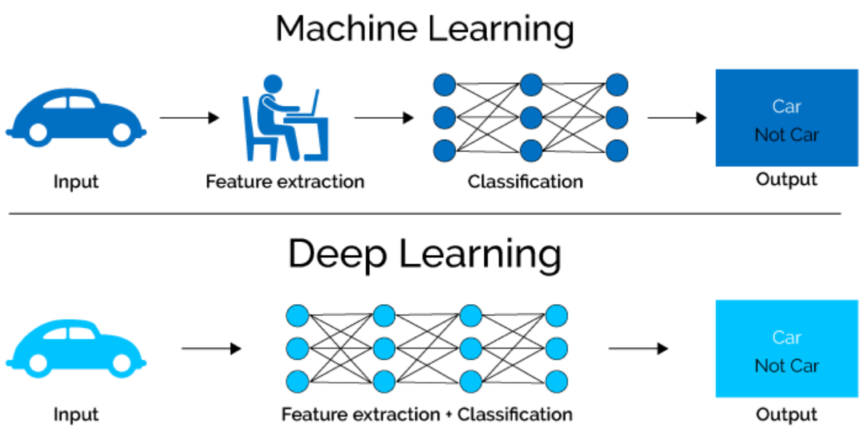
- 2011: classical approaches, 74.3%
- 2012: deep learning, 83.6% (huge breakthorough)
  - Since then, dominated by CNNs
- 2015: 96.4%
  - Completely solved

What makes deep learning different?

- Easier, because it completely automates the *feature engineering* stage

- Earlier machine learning techniques required manual engineering of good layers of representations for their data.

- Sophisticated multistage pipelines with a single, simple, end-to-end deep-learning model.



Source: XenonStack

Stacking shallow methods?

Could shallow methods be applied repeatedly to emulate the effects of deep learning?

- No, the deep model learns all layers of representation jointly
  - The optimal first representation layer in a three-layer model isn't the optimal first layer in a one-layer or two-layer model

- This is much more powerful than greedily stacking shallow models, because it allows for complex, abstract representations to be learned by breaking them down into long series of intermediate spaces (layers)

Modern ML landscape

kaggle

- A good way to see trending techniques
- Highly competitive
  - Some contests have thousands of entrants and milliondollar prizes

- Wide variety of machine-learning problems covered

Why deep learning? Why now?

- Many of the algorithms are old:
  - CNN and backpropagation: 1989
  - LSTM: 1997

- What changed?
  - Hardware
  - Datasets and benchmarks
  - Algorithmic advances

What changed? Hardware

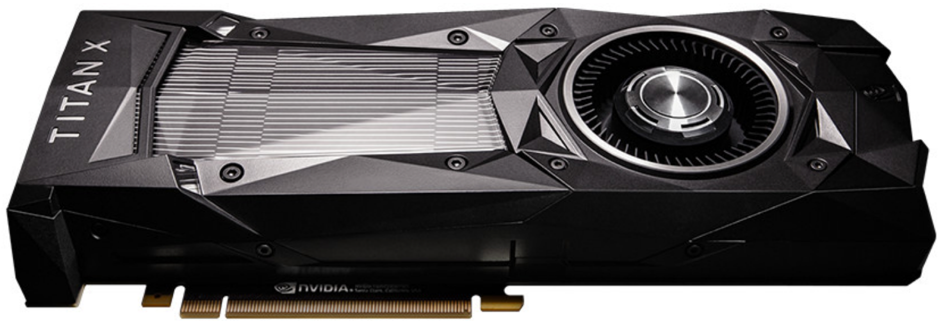
- Between 1990 and 2010, off-the-shelf CPUs became faster by a factor of approximately 5,000

- Nvidia and AMD: investing billions of dollars in developing fast, massively parallel chips (GPUs), mainly for games and 3D design

- 2007: Nvidia released CUDA, a programming interface for its line of GPUs

What changed? Hardware

Titan XP: 6.6 trillion float32 operations per second. That's about 350 times more than what you can get out of a modern laptop.



What changed? Hardware

Meanwhile, large companies train deep-learning models on clusters of hundreds of GPUs of a type developed specifically for the needs of deep learning

What changed? Data

- The exponential progress in storage hardware over the past 20 years
- The rise of the internet
  - Making it feasible to collect and distribute very large datasets for machine learning

What changed? Data

- ImageNet dataset
  - 1.4 million images that have been hand annotated with 1,000 image categories

- Yearly competition

What changed? Algorithms

- Until late 2000s, we were missing a reliable way to train very deep neural networks.

- Around 2009-10
  - Better *activation functions* for neural layers
  - Better *weight-initialization schemes*, starting with layer-wise pretraining, which was quickly abandoned
  - Better *optimization* schemes, such as RMSProp and Adam

Huge investments in deep learning

- In 2011, right before deep learning took the spotlight, the total venture capital investment in AI was around $19 million, which went almost entirely to practical applications of shallow machine-learning approaches.

- By 2014, it had risen to a staggering $394 million.
    - Google acquired the deep-learning startup DeepMind for a reported $500 million
    - Baidu started a deep-learning research center in Silicon Valley, investing $300 million in the project
    - The deep-learning hardware startup Nervana Systems was acquired by Intel in 2016 for over $400 million.

Deep learning toolsets

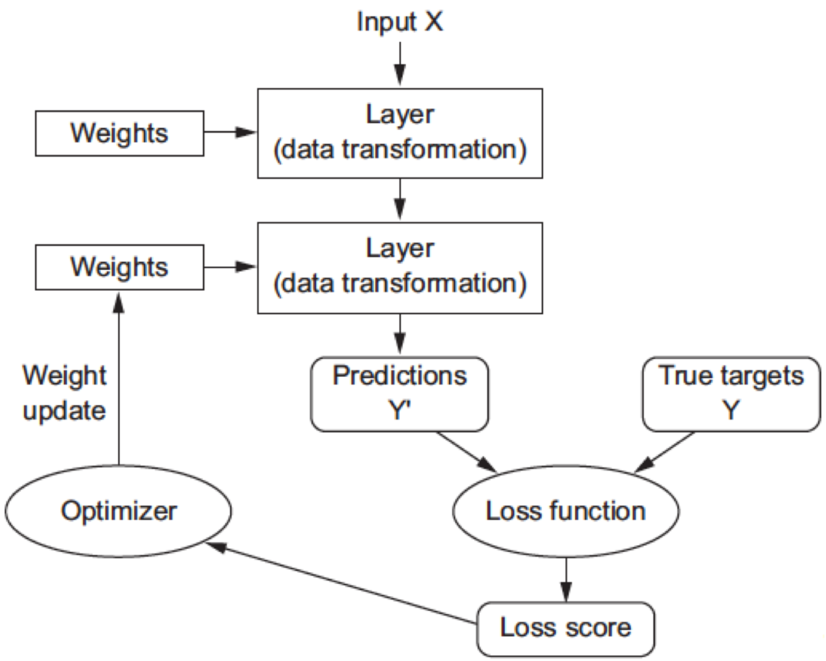
- Early days: C++ and CUDA
- Nowadays: Python scripting

TensorFlow theano Keras PYTORCH

Will it last?

- Simplicity - no need for feature engineering
- Scalability - highly parallelizable
- Versatility and reusability - can be trained on additional data without restarting from scratch
  - Repurposable and thus reusable: for instance, it's possible to take a deep-learning model trained for image classification and drop it into a video processing pipeline.

Questions?



Input X
Weights
Layer
(data transformation)
Weights
Layer
(data transformation)
Weight
update
Predictions
Y'
True targets
Y
Optimizer
Loss function
Loss score