A Taste of Deep Learning

You can do it !

Class 0 - Q1 - 2016


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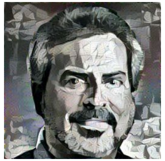
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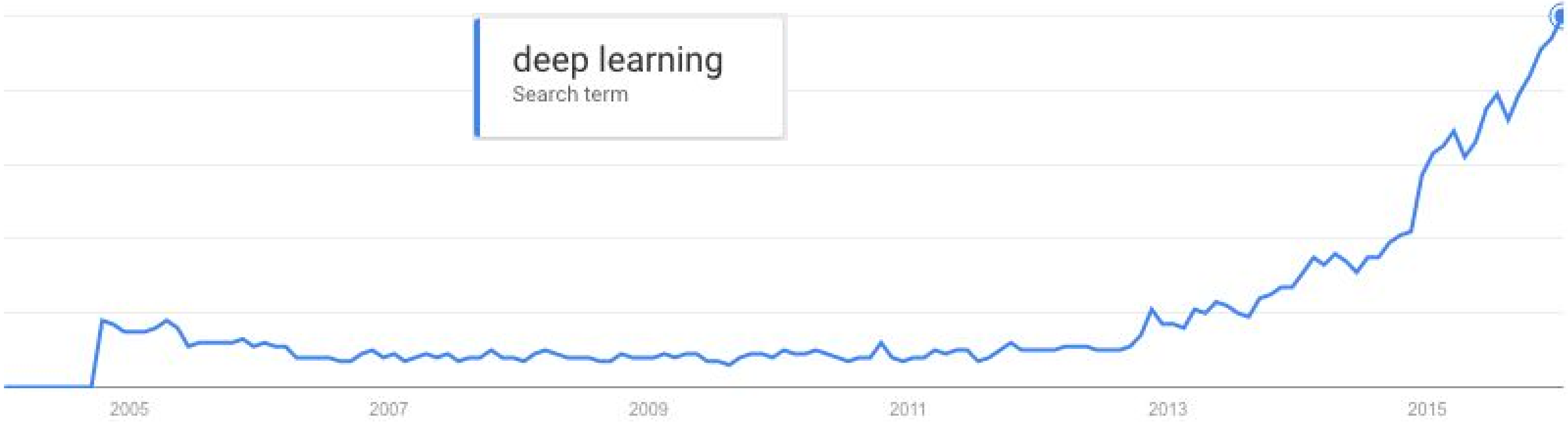
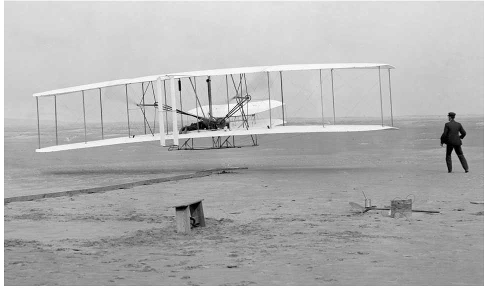
The Big Bet

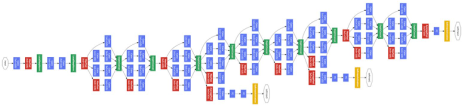


Credit: Google Trends

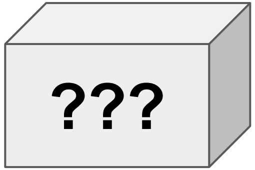
Why we are Bullish about the Future



...100 years...



...10 years...



...100 years?...

Projections

McKinsey projects $50T by 2025

- Knowledge work: big data, smart assistants, marketing, sports…
- Finance, health care, genomics, law, insurance...
- IoT: smart appliances, sensors, cameras, wearables
- Robots, autonomous vehicles, drones, manufacturing

… so VCs are pouring money into Deep Learning companies.

A Brief History of Artificial Intelligence

How to define Artificial Intelligence?

Easy for People (intelligence)

Vision, speech, understanding language

Planning, common sense

Having a conversation

Reading emotions

Translating Russian to English

Playing Chess, Go

Proving math theorems

Easy for Machines (stamina)

Multiplying huge matrices

Searching large databases

Sorting a trillion records

Finding a path in a huge maze

Hard for People and Machines

Predicting the weather

Predicting the winning lottery ticket

First AI Winter

1973 — **Lighthill Report**

Minsky and Papert — 1969

ELIZA, first chatterbot (*) — 1966

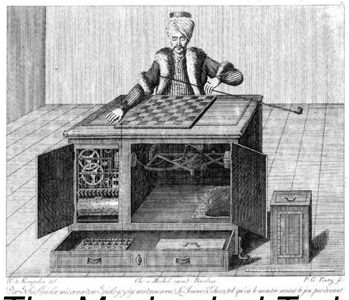
1958 — *LISP*

1957 — *Perceptrons, Frank Rosenblatt*

Dartmouth Conference — $$$ 1956

Checkers-playing program

1950 — **The “Turing Test”**



The Mechanical Turk — 1770

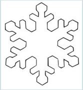
— **“Magic”**

Hand-written digits recognition — 1998 — Google

Deep Blue vs Kasparov — 1997 — BabelFish

1995 — AltaVista

1991 — http://www



Second AI Winter

1989 — Expert systems disappoint, end of 5th gen

```
(#$isa #$BarakObama #$USPresident)
(#$genls #$Tree-ThePlant #$Plant)
...
```

Cyc — 1984

1982 — Connection Machine

$$$

1981 — 5th Generation Computing, Japan

Expert systems — 1980

TensorFlow

Google Photos

2015

Text breakthrough — 2013 — Deep Mind plays Atari games

Google Brain — 2012 — Image breakthrough

2011 — IBM Watson wins at Jeopardy

2010 — Personal Assistant (Siri, Angie)

Voice breakthrough — 2009 — The Unreasonable Effectiveness of Data

2006 — Fundamental DL technique cracked!

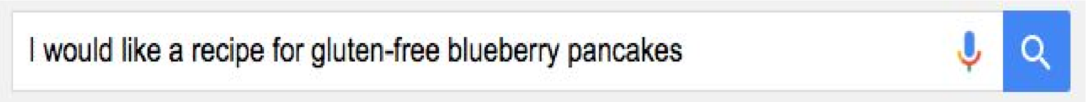
Project DAVE autonomous robot — 2004

So what did we learn?

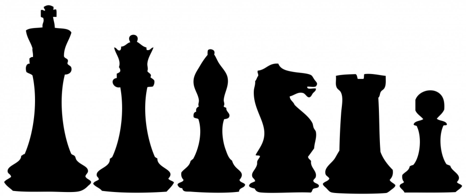
Lesson: People are easy to fool!

```
I am the psychotherapist.  Please, describe your problems.  Each time
you are finished talking, type RET twice.

my cat hates me

Why do you say cat hates you?

because of the way she looks at me

Are you sure that is the real reason?

no, she believes I like the dog more
```

Eliza: 100% smoke and mirrors. Addictive.



No real 'understanding", lots of data, lots of computing power

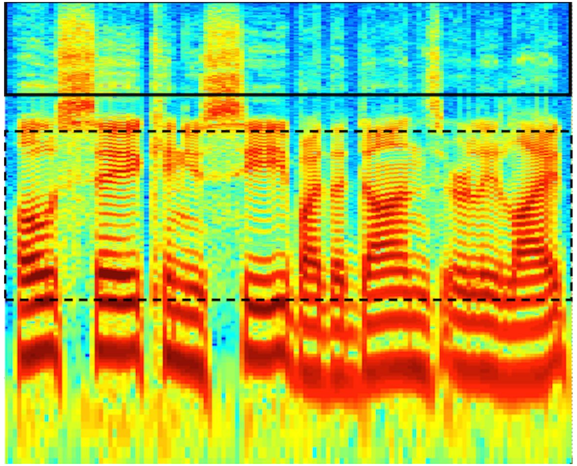


Chess: large-scale search

Wikipedia, tricks, fast search

Lesson: Some Things are Particularly Hard to Code

Vision



Speech

He said that she replied that they could not agree. But she was wrong.

Natural Language

Use Rules? Use Data?

Option 1: **Write a set of rules**

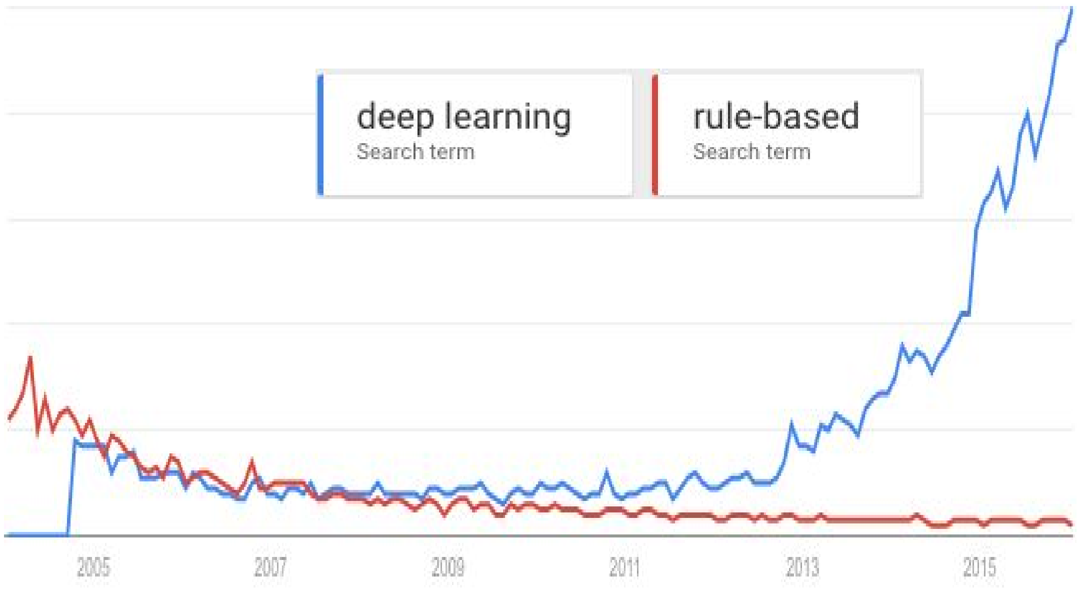
- Use **logic** and **heuristics** to assemble **hand-coded rules**
- The real world is messy and **changes** all the time
- This approach won't scale, and it's **expensive** (people)
- (We don't have a symbol-manipulation engine in our heads)

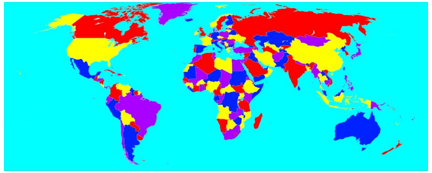
Option 2: **Learn from data**

- Uses examples to **find patterns automatically**: the more data, the better!
- Automatically **adapts** to new data
- This approach scales, and it's **cheap** (computing power)

Conclusion?

MORE DATA AND
COMPUTING POWER
ALWAYS BEAT
FANCY ALGORITHMS!





Lesson: Some Problems are AI-Complete

"...I got a .45 and a shovel..."

Lesson: Some Problems are AI-Complete

“...I got a .45 and a shovel...”

“Let’s see: a .45 is a gun, and a shovel is used to dig holes. A father is usually very protective of his daughter, and he looks intensely at the daughter's date when he says that.
Most likely interpretation: if anything happens to his daughter (accident, pregnancy), he will kill the guy with the gun and bury him with the shovel. It’s a threat, but it can’t be serious, this is illegal, and he is talking in front of his daughter; so it’s a funny threat, a warning. The guy will still understand that the dad means business and expects him to take good care of his daughter.”

...

Let’s have a quick chuckle, and on to the next line…

Examples of AI-Complete Tasks

Vision

Natural Language Understanding

- Say: “Wreck a nice beach”
- Now: “Recognize speech”

Automated Translation

Virtual Assistant (Personal Assistant)

Holding a conversation

Truly summarizing text

Dealing with the real world

- Navigation
- Planning
- Adapting to new environments

Lesson: Don’t be afraid to Experiment

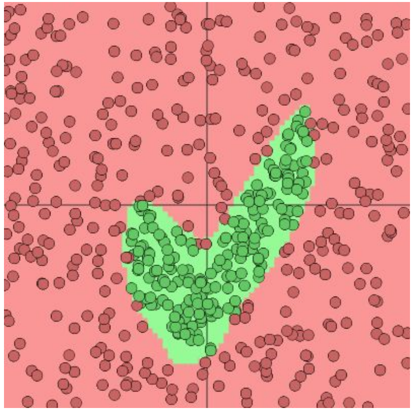
As we’ll learn: turn everything into numbers, mix them happily!

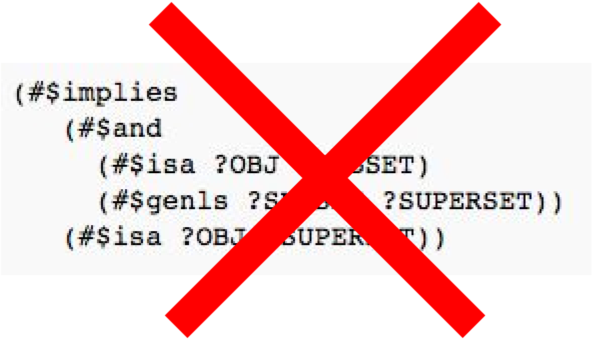
Don’t try to follow rigorously what is going on!

Don’t expect a mathematical proof for everything!

If you remember only one thing...

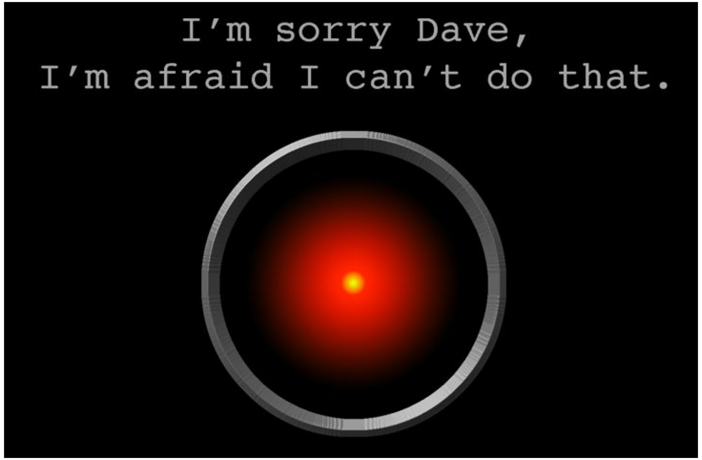
The approach that won: learn from the data!

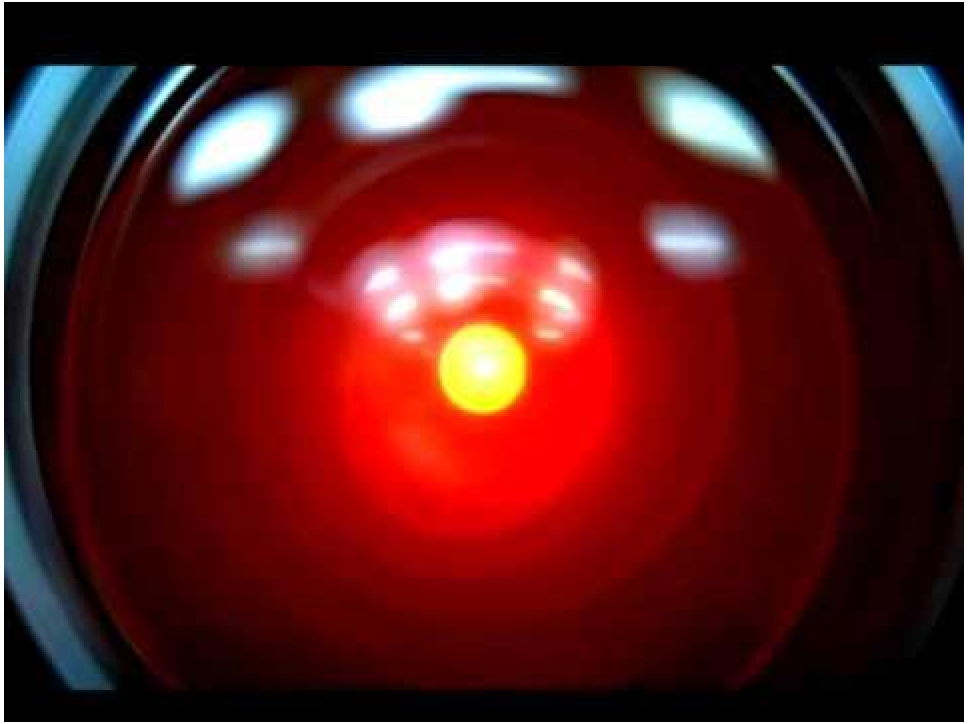




Interlude: A.I. Movies and Memes

2001 - A Space Odyssey



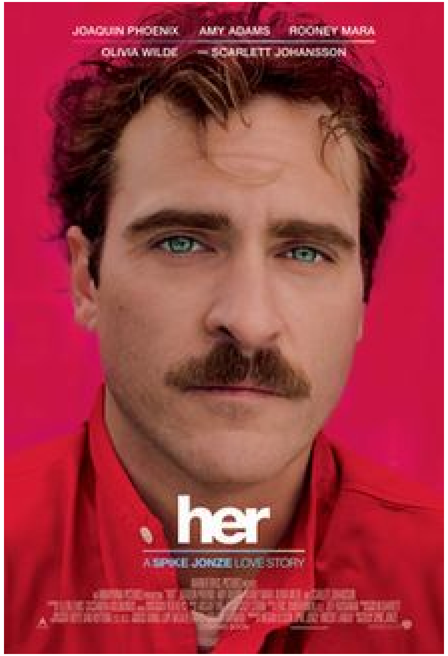


Terminator


QUT

Sarah - Eureka

Her


JOAQUIN PHOENIX AMY ADAMS ROONEY MARA
OLIVIA WILDE SCARLETT JOHANSSON
her
A SPIKE JONZE LOVE STORY


TRAILER
HD

Transcendence

Ex Machina


domhnall gleeson alicia vikander and oscar isaac
ex machina
what happens to me if i fail your test?
coming soon
FILM4
A24


OFFICIAL TRAILER HD

1/ Artificial Narrow Intelligence (ANI) = Weak IA
2/ Artificial General Intelligence (AGI) = Strong IA
3/ Artificial SuperIntelligence (ASI) = 12k IQ

Art & Conception of AI

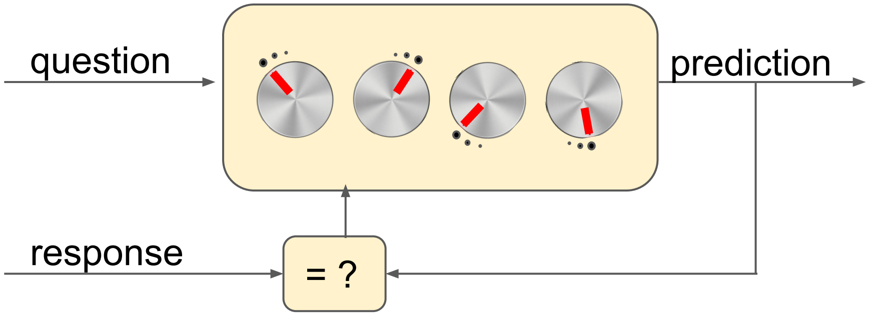
Today, computers are not smart, all the ingenuity of the designers in AI is to make you think they are reproducing human thought patterns.

The Future of AI: What if We Succeed?

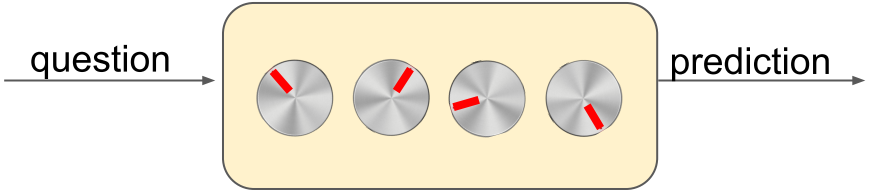
Take a Break!

A Taste of
Deep Learning

What is Machine Learning?



1. Training a model



2. Using the trained model

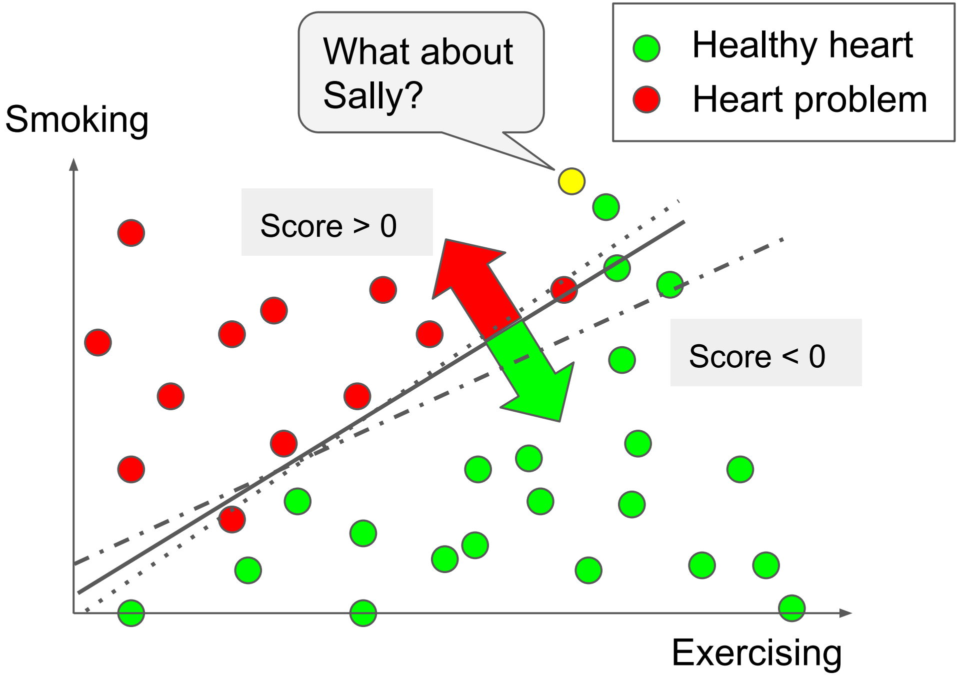
(Supervised learning)

Let’s do a (totally fake) Clinical Study

Patient id	#packs per day	#hours exercise per day	heart problem
1	.5	2	0
2	2	0	1
3	3	6	1
4	0	5	0
5	1	0	1
6	1.5	5	0

Can we **learn** a pattern? Can we use it to **predict** outcome of new patients?

Linear Regression



Compute a linear combination of

- p = # packs per week
- h = # hours of exercise per week

$$score = w1 * p + w2 * h + w3$$

Find w1, w2, w3 that best match the data. That's the **learning**.

if (score > 0) then **predict** heart problem.

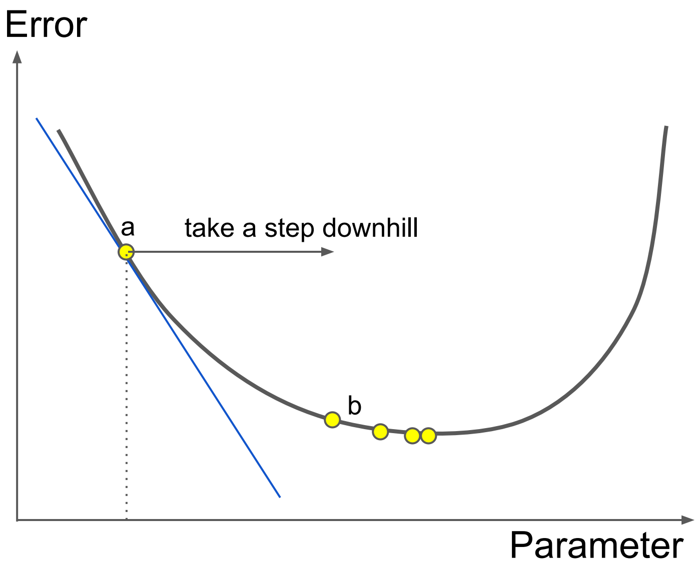
Simple statistics.

How to find the best values for w1, w2 and w3 ?

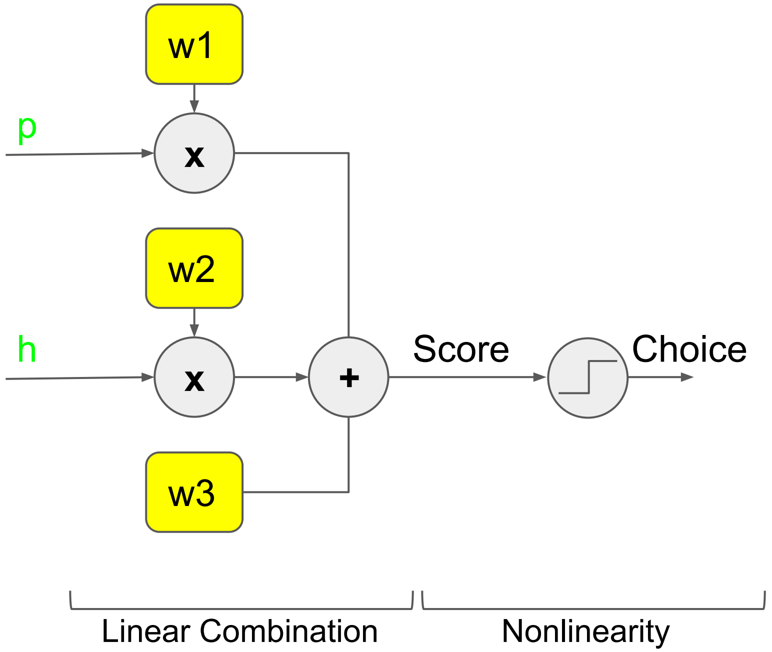
Define **error = |expected - computed|** ^{2}

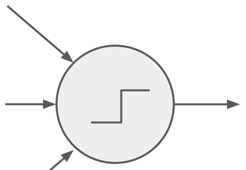
Find parameters that **minimize** average error.

Perform Gradient Descent: quality goes up.

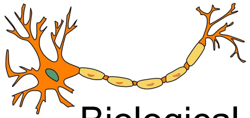


Why “neurons”?





Artificial Neuron

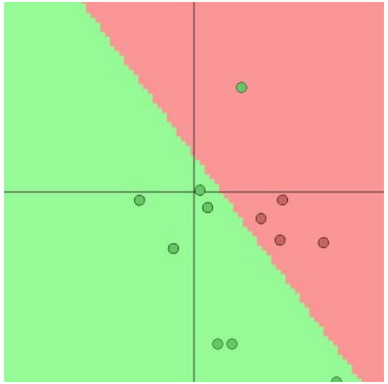


Biological Neuron

Demo: ConvNetJS

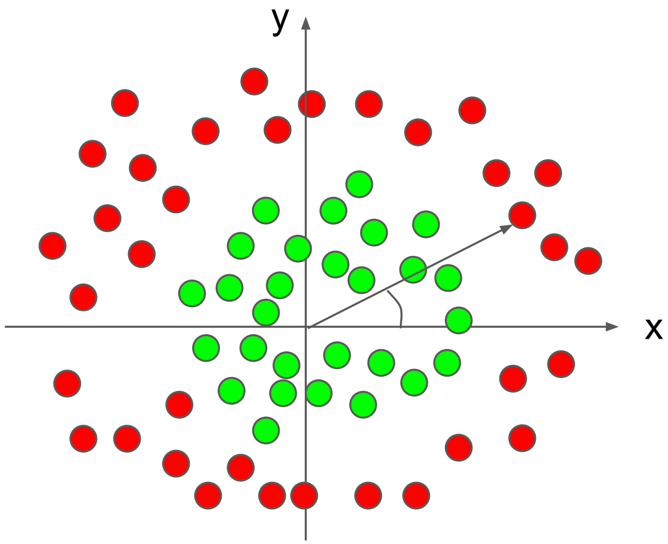
https://github.com/holbertonschool/deep-learning/tree/master/ConvNetJS

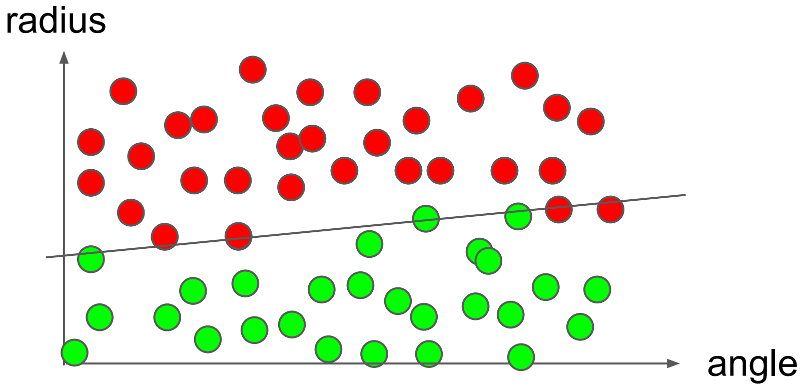
Credits and thanks to Andrej Karpathy, Stanford



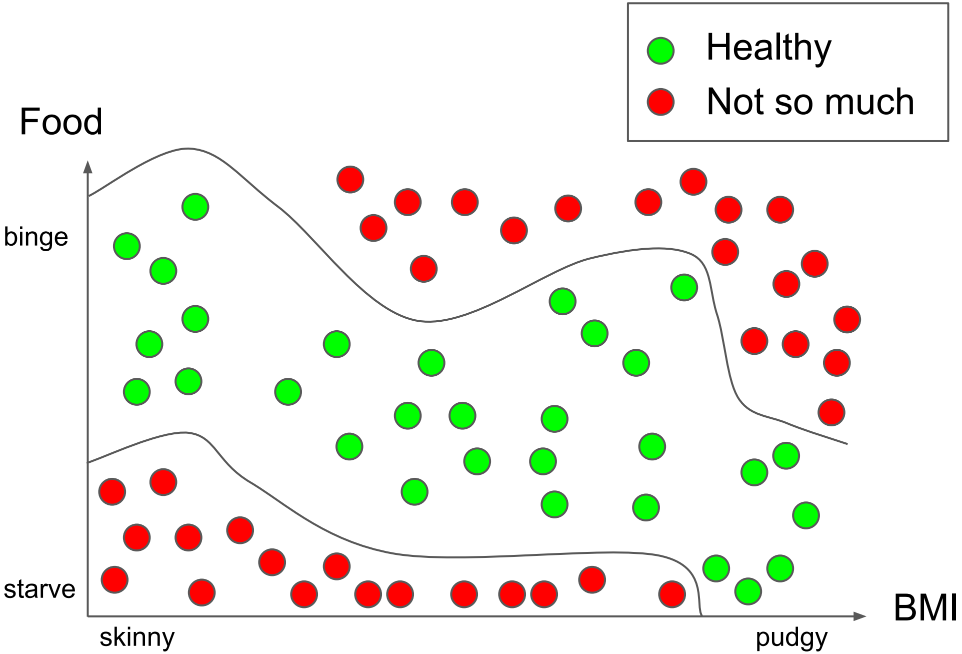

Congratulations!
You just trained your first model!

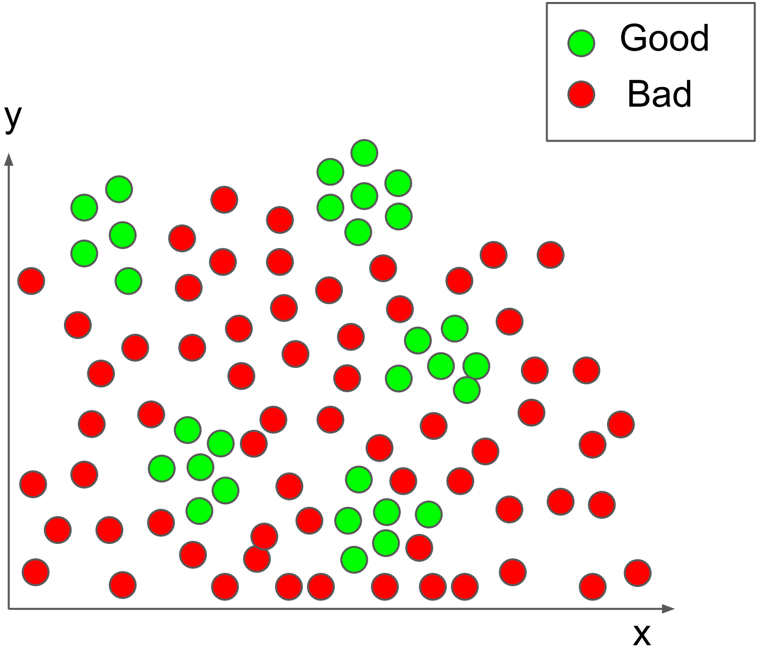
Feature Engineering



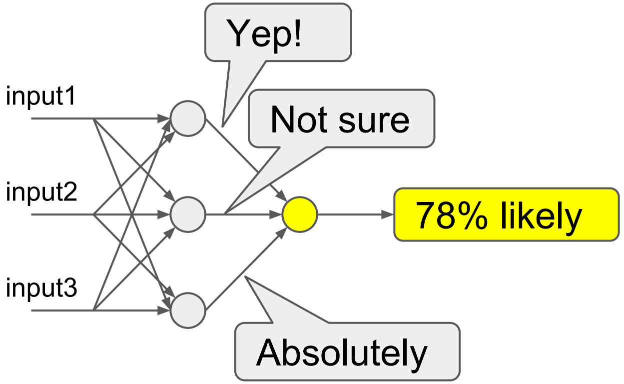


Limitations of a Linear Classifier

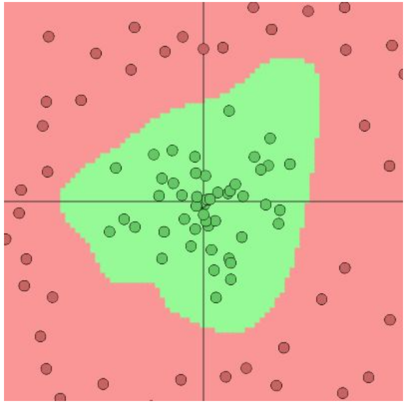




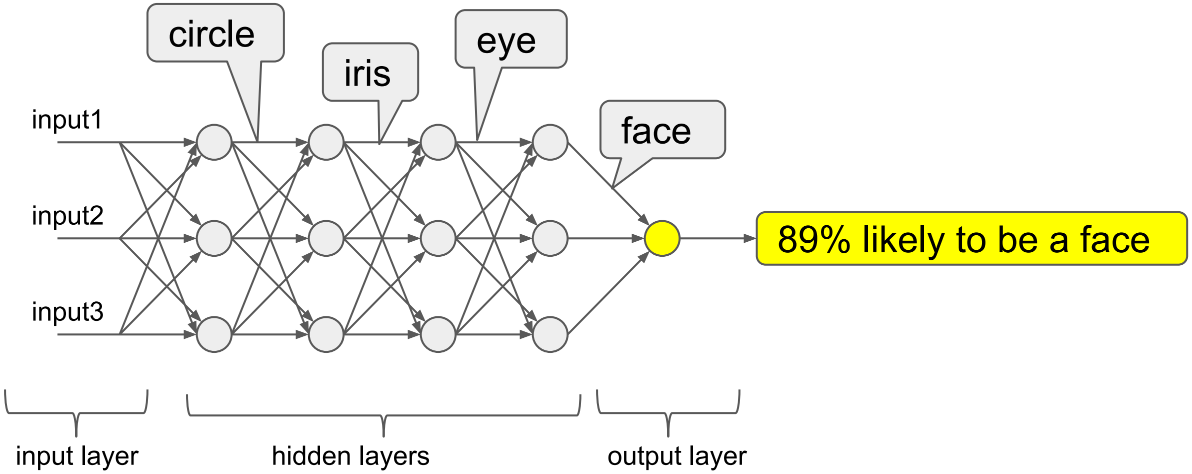
More Neurons



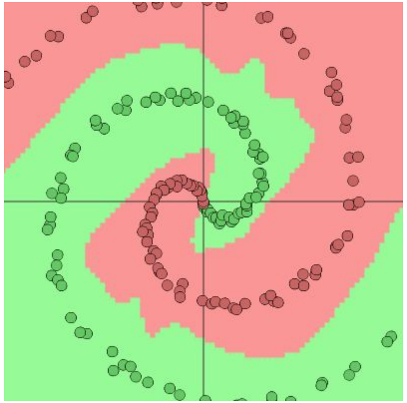
Demo: let's make an ensemble!



More Layers: Deep Learning



Demo: let’s go deep!




Holy Moly!
You just trained
your first deep model !!!

Why does this work?

Neural networks with at least one hidden layer can approximate any reasonably smooth function.

Large networks have lots of solutions (minima), most of them very good.

Gradient descent is very simple and very powerful.

Everyday examples of Deep Learning

Structured data: Netflix, Spotify and YouTube recommendations; Amazon suggestions; CC fraud detection

Text: Spam filtering; good spelling suggestions; matching ad to content; automated translation

Images: Google Photos; search by image; FaceBook face tagging; thumbnail for YouTube videos; OCR and handwriting recognition; surveillance videos

Voice: Android voice input; Nuance (Siri); transcription

Combo: Autonomous vehicles (soon); Virtual Assistant, Industrial robots

Other Forms of Machine Learning

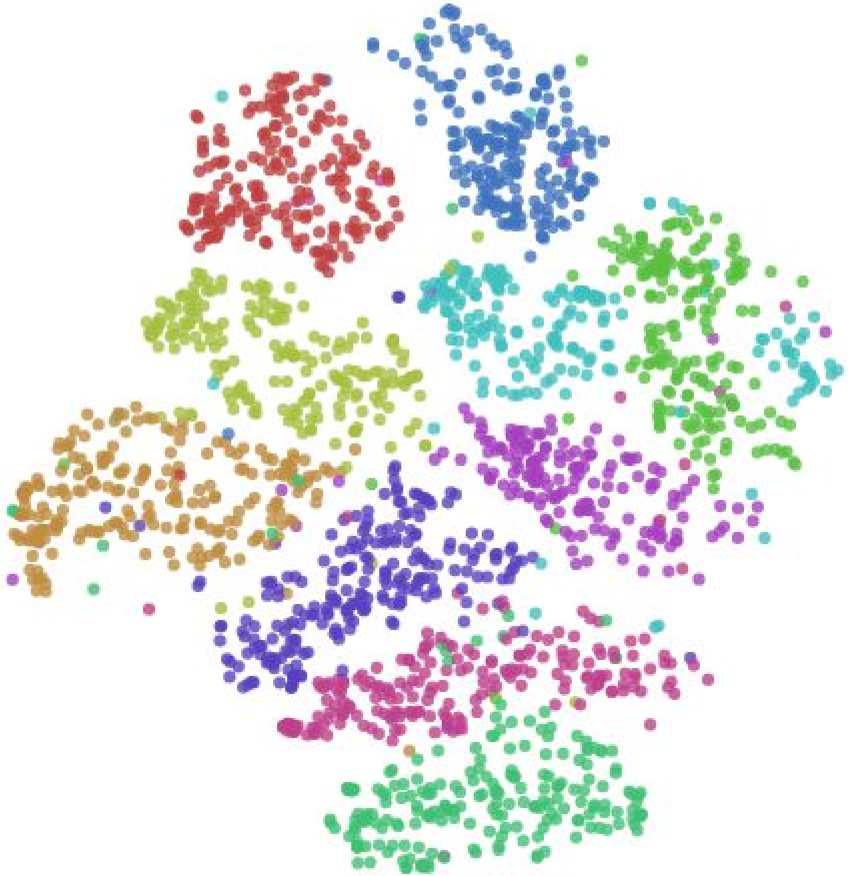
Unsupervised Learning

Automatically learn structure in data

Clustering

More compact representation

Semi-supervised learning

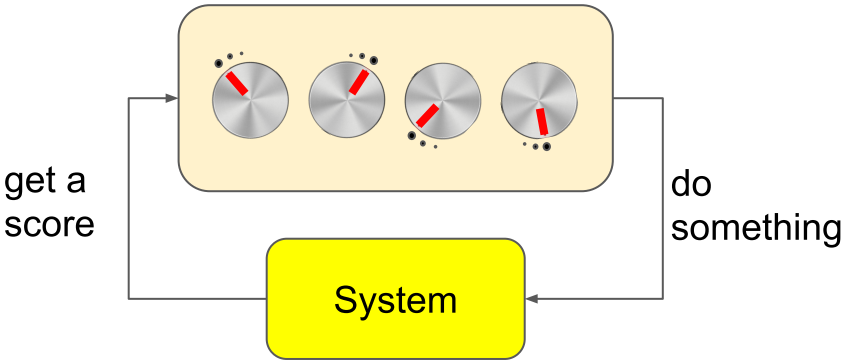


Credit: http://colah.github.io/posts/2014-10-Visualizing-MNIST/

Reinforcement Learning

Learn not from static data, but from **interacting** with a system

- playing a game
- flying a plane
- driving a car
- learning a task




Reinforcement Learning

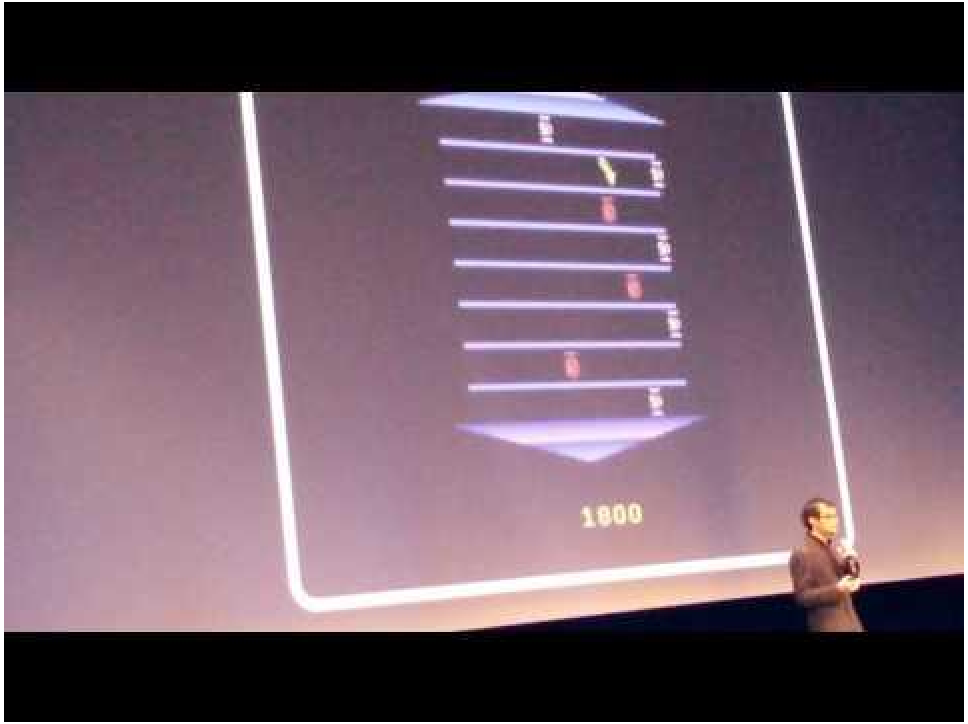
Learning to flip pancakes

Credit: Italian Institute of Technology

Stanford Helicopter - Andrew Ng

Driverless Car

Deep Mind plays Atari Games



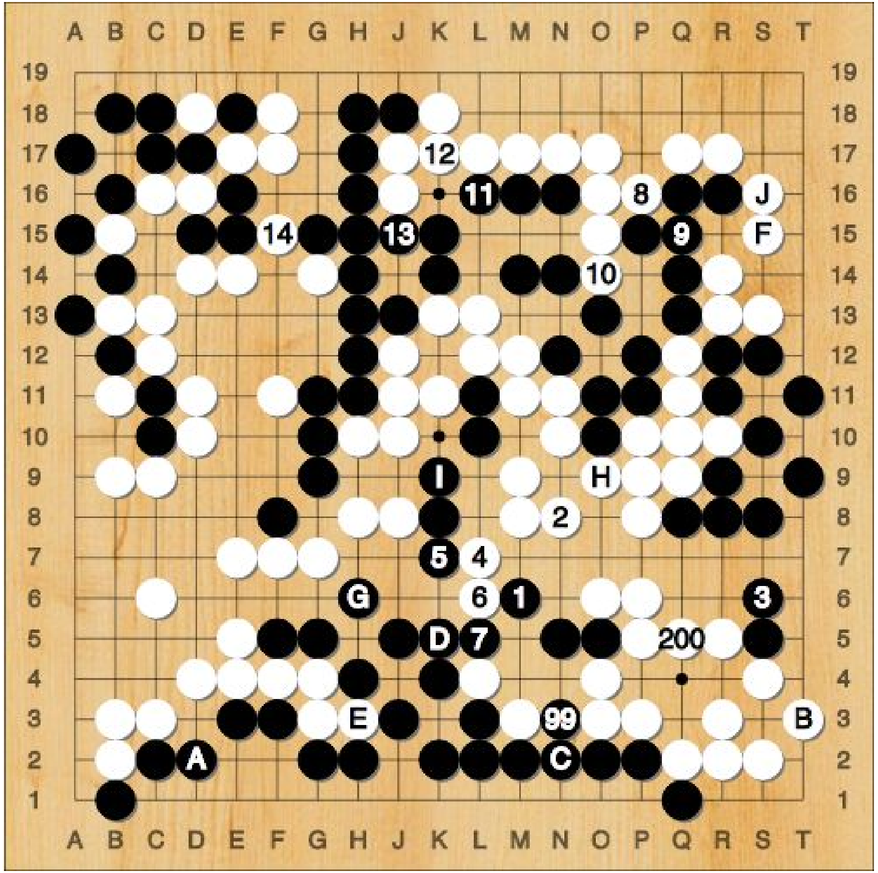
DeepMind AlphaGo

Go is much harder than chess

Oct 2015: AlphaGo beats Fan Hui, a top Go player

Jan 2016: paper comes out, world goes wild

Match with Lee Sedol, #1 player, in March 2016



If you remember only one thing...

We build a model from a set of examples.

It starts as a random set of parameters.

We measure how well the predictions match the truth.

We tweak the parameters to improve this match.

A good model will generalize to new data, making useful predictions.

What we will learn

How Deep Learning works, more precisely.

What all the terms mean. It’s a big zoo.

Using existing frameworks: TensorFlow, Torch...

Downloading, using, modifying existing models.

All the tricks to tune models.

Mapping a problem to an architecture.


Take a Break!

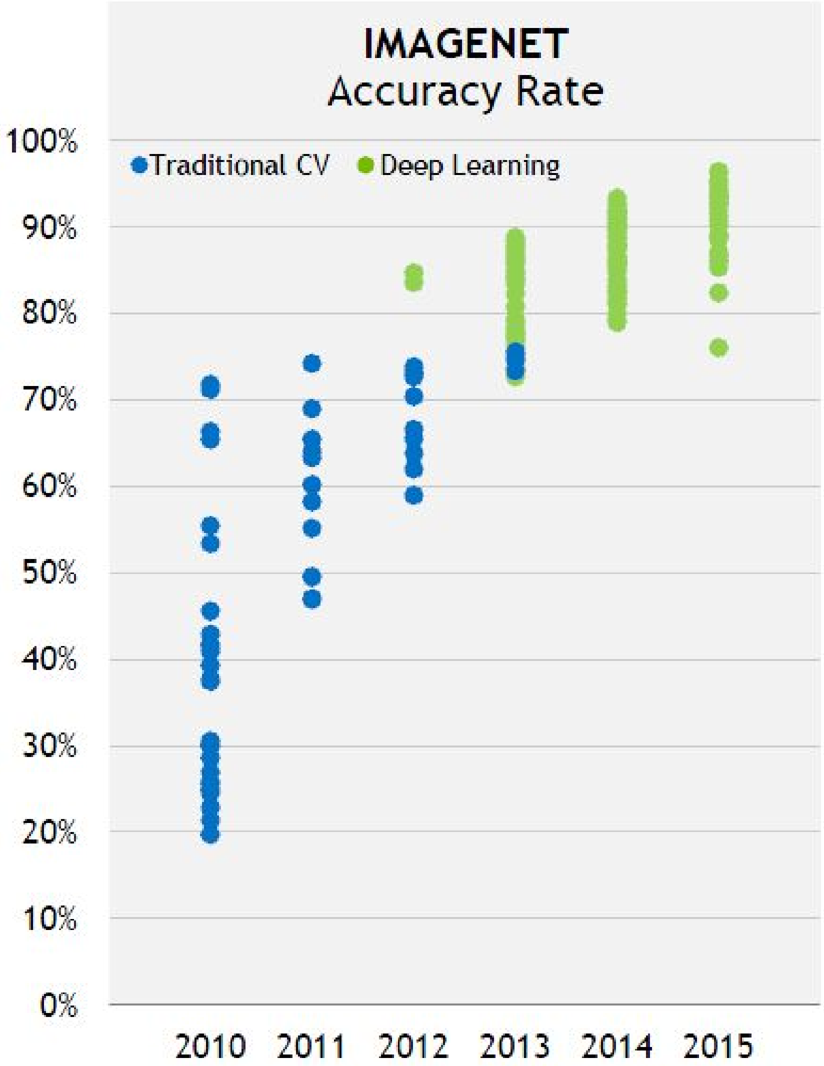
A Taste of
Deep Learning for Images

A Brief History of Visual Recognition

2012 - Annus Mirabilis for DL.

ImageNet contest.

Alex Krizhevsky, Ilya Sutskever, Geoffrey Hinton, University of Toronto



Why is Vision Hard?

Rules really don't work for vision

I'm asking you to describe cherry blossoms.
Please use precise features and rules!

"Well, white petals arranged in a circle. Unless some of the petals have fallen. With little white sticks and black dots arranged like this. Oh, except if seen from the side. Or if they overlap. Or if the sun is behind. Ignore the bee…"

Next task: a human face. <u>Any</u> human face.

Very slow progress, even with generations of graduate students.

Demo: Google Photos

Face Recognition

Maya Monier

Dec 12

Nov 10

Sep 10

Jul 23

Jul 20

Jul 19

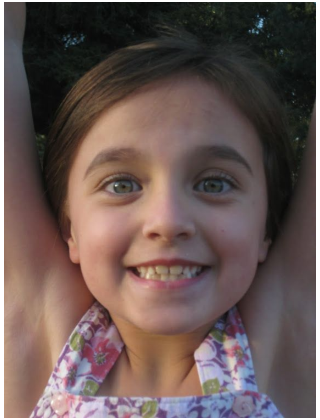
2014

2013

2012

2011

2010



2009

2008

2007

2006

2005

2004

2003


Glasses


Hat


Face paint


Eating


Tiny

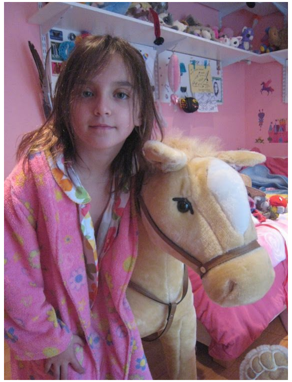

Overexposed


Sleeping

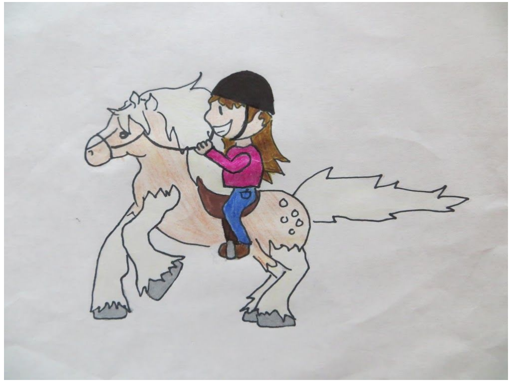
Demo: Google Photos

Entity Recognition


horse


horse


horse


horse


lake

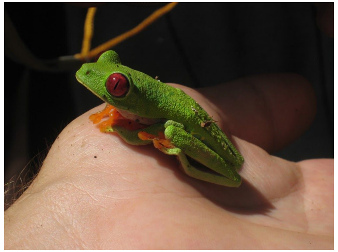

cup


cup


cup


boat


mushroom


frog


insect

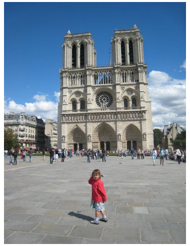

snail


helicopter


bed


chair


fountain


church


legos


bison


apple


apple


mouse


stuffed toy

Demo: Google Photos

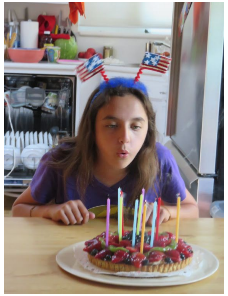
Scene Recognition


sunset


scuba


bowling


dancing


birthday


sleeping


halloween


birthday


drinking


formal wear


green

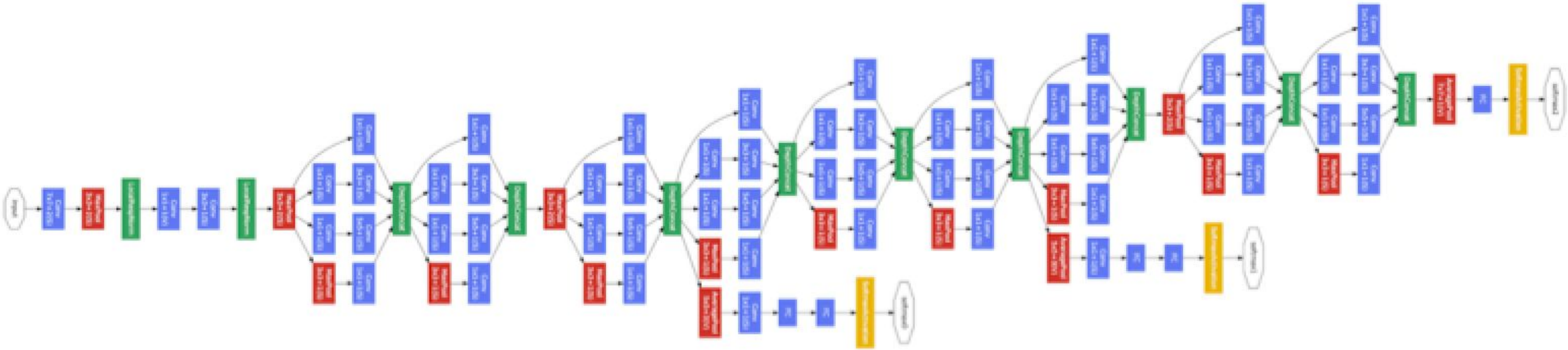

tennis


lunch


adventure


happiness

How did they do that?



Deep Neural Networks

Years of Google Images, tagged by users, as training set

Face recognition is a special thing

Demo: FaceYou

Demo: ParotAI

NeuralTalk Video

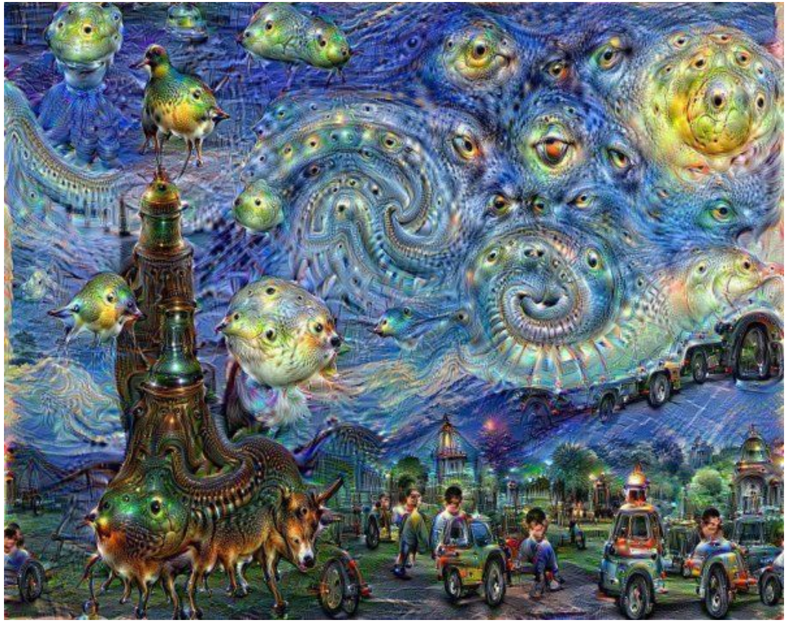
Running it in Reverse

Credit: http://arxiv.org/pdf/1511.06434v2.pdf

Credit: https://github.com/Newmu/dcgan_code

Credit: https://twitter.com/vintermann/status/675599478494208000

Deep Dream by Google



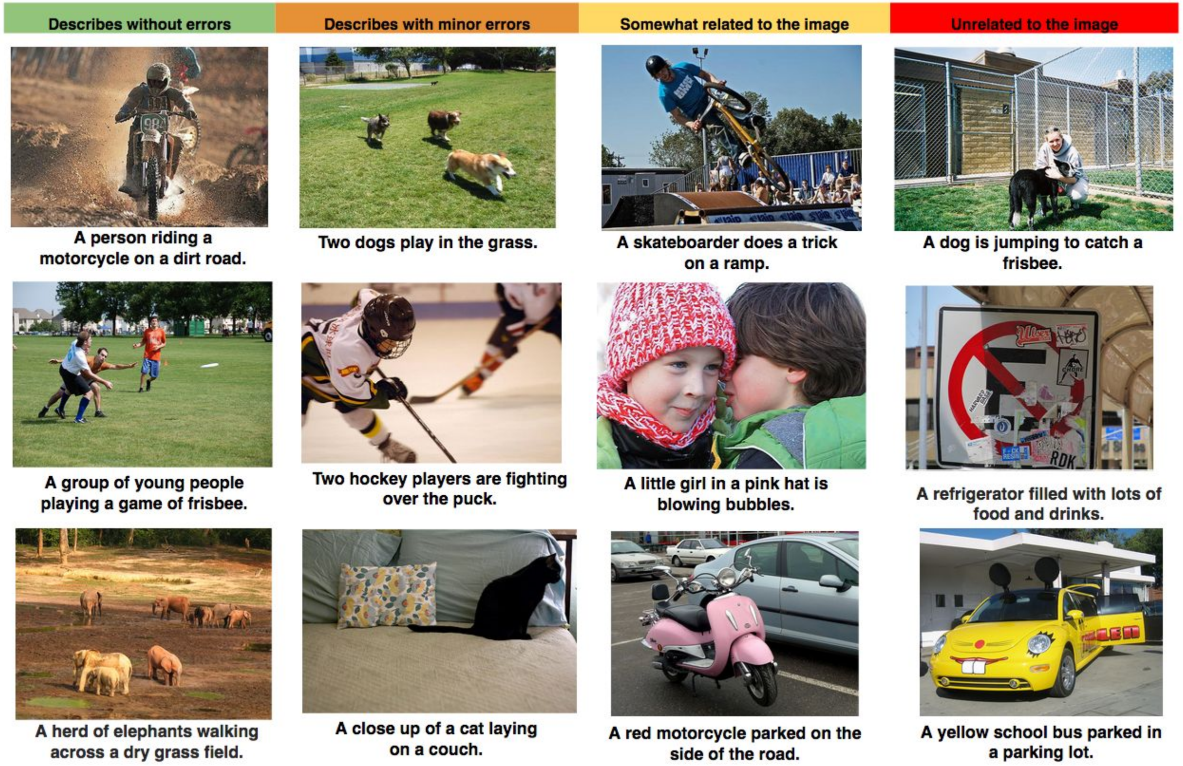
An Amazing Coincidence...

Credit: http://arxiv.org/pdf/1508.06576v1.pdf

Demo: Deep Art live


example 2

Image Captioning



Source : http://googleresearch.blogspot.com/2014/11/a-picture-is-worth-thousand-coherent.html

What we will learn

Convolutional Neural Networks (ConvNets)

Adapting existing models

If you remember only one thing...

Vision is not a task that can be reduced to simple rules.

Immense progress since modern ConvNets and GPUs, ~2012.

Many real-life applications today.

Expect a lot more.


Take a Break!

A Taste of
Deep Learning for Text

Natural Language Processing (NLP)

Parsing words

Spell checking

Finding synonyms

Part of Speech (POS) Tagging

Classification
- Encoding and language detection
- Sentiment analysis
- Spam detection
- Matching ad to content

Extracting entities (people, places…)

Full-text Search

Summarization

Automated Translation

Question Answering

Virtual Assistant
- Siri, Watson, Alexa, … QA
- Her, HAL, Sarah, … Empathy & Emotion

What is so hard about Natural Language Processing?

Understanding H2H Communication

Source : https://mishahlini1996.wordpress.com

Languages are Complex - Ambiguity

Jaguar or Jaguar ?

Languages are Complex - Context

“The Jaguar eats his prey” => predator => big cat

“The Jaguar eats the road” => image => car

Also: idioms, technical lingo, slang, humor, sarcasm, poetry, emotions...

Unsaid, but implied

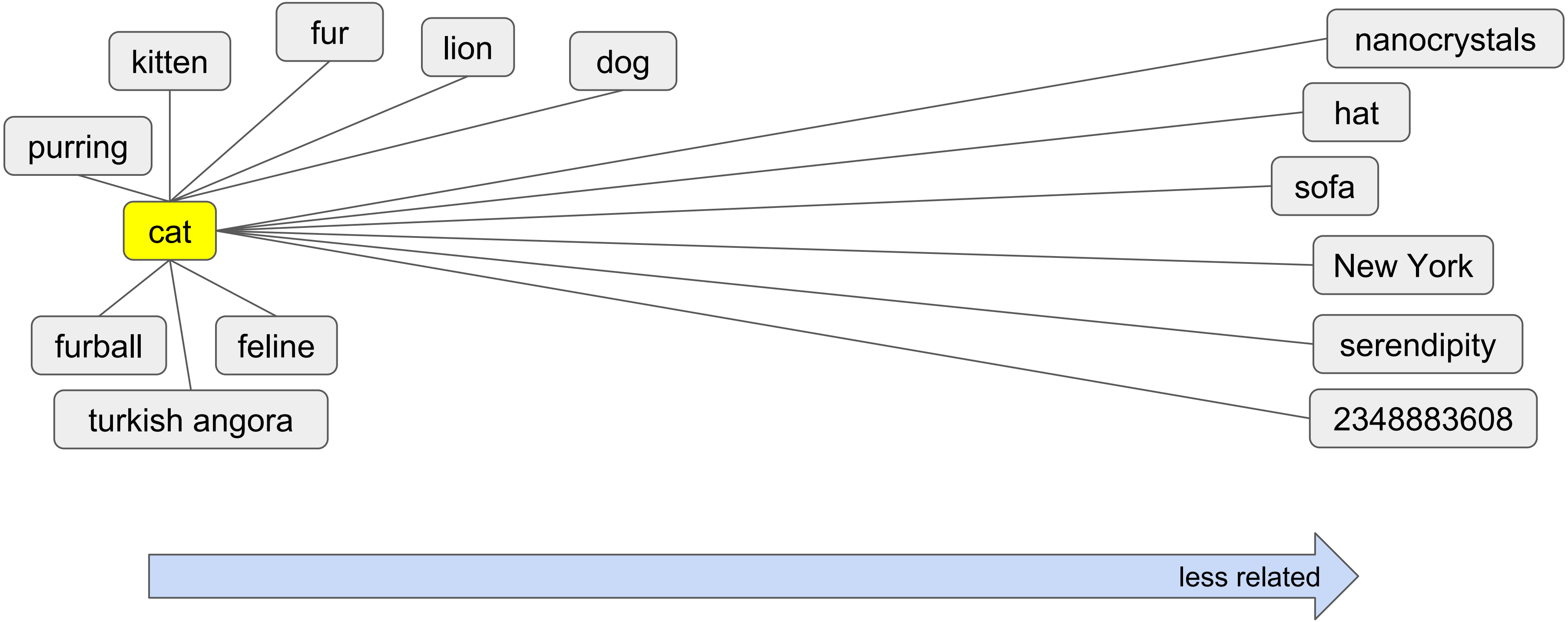
“The baby looks happy!”

...

“Where are the cookies?”

Word and Sentence Similarity

Semantic Distance for Words



Not to scale :)

Terms similar to ***Champagne***

french champagne, cognac, champagne's, champagnes, veuve clicquot, cremant, louis roederer, rosé, taittinger, fine champagne, champagne wine, sparkling wines, dom pérignon, dom perignon, pol roger, vintage champagne, bubblies, pommery, rose wine, pink wine, blancs, french wine, cliquot, beaujolais nouveau, sancerre, sparkling, burgundy, chateau, chablis, cognacs, pink champagne, domaine, moët, methode champenoise, burgundy wines, apéritif, armagnac, chandon, champenoise, beaujolais, heidsieck, marnier, wine, bourgogne, aperitif, chateau margaux, demi-sec, moelleux, champagne cocktail, crémant, half-bottle, cuvée, brut, ruinart, champagne flute, st emilion, white wine, loire valley, wine cocktail, veuve, drinking champagne, french wines, blanc, chardonnay wine, champagne glass, cuvées, mauzac, roederer estate, laurent-perrier, puligny, negociant, prosecco, rose wines, gloria ferrer, red wine, musigny, coteaux, corton-charlemagne, fine wine, dessert wine, bordeaux, champagne glasses, cheval blanc, champagne flutes, cuvees, champange, four wines, montlouis, rémy martin, primeur, fine wines, lirac, d'yquem, burgundy wine, red bordeaux, brandy, cuvee, white burgundy, chardonnay, chambolle-musigny, cheverny, great vintages, yquem, special wines, wonderful wines, burgundies, half bottles, grand marnier, grand cru, primeurs, sauterne, minervois, pouilly-fuissé, sauternes, chambertin, white bordeaux, vougeot, epernay, vin gris, chalonnaise, quaffer, loire, sweet white wine, d'aunis, côtes, gevrey-chambertin, limoux, english wine, chateaux, château haut-brion, blanche, pinot meunier, six glasses, mâconnais, épernay, bourbon, sparkler, volnay, white wines, chassagne-montrachet, burgundys, vin jaune, claret, beaune, grande champagne, white grapes, bordeaux wine, dessert wines, crème de cassis, pinot noir grapes, chardonnay grapes, armand de brignac, select wines, calvados, country wine, muscadet, leflaive, reisling, cointreau, own wine, caveau, clos de vougeot, inexpensive wines, vosne-romanée..., expensive wines, red burgundy, barsac, delicious wine, wine flight, puligny-montrachet, rousanne, châteauneuf-du-pape, liqueur, schramsberg, touraine, montrachet, arbois, lanson, vintage wine, chateauneuf, blanquette, non-vintage, orange wine, three wines, wine.the, banyuls, merlot wine, vendange, red table wine, sweet wines, santenay, languedoc, moscato d'asti …

Terms similar to ***Brad Pitt***

angelina jolie, george clooney, cameron diaz, julia roberts, leonardo dicaprio, matt damon, tom cruise, nicole kidman, reese witherspoon, charlize theron, jennifer aniston, halle berry, kate winslet, jessica biel, ben affleck, bruce willis, scarlett johansson, uma thurman, matthew mcconaughey, jake gyllenhaal, sandra bullock, oscar winner, gwyneth paltrow, sean penn, demi moore, naomi watts, colin farrell, mickey rourke, orlando bloom, bradley cooper, natalie portman, jennifer garner, tom hanks, dicaprio, jessica chastain, robert de niro, julianne moore, leo dicaprio, channing tatum, kirsten dunst, jessica alba, emily blunt, salma hayek, ryan gosling, mark wahlberg, renee zellweger, drew barrymore, renée zellweger, gerard butler, hilary swank, ryan phillippe, john malkovich, nicolas cage, kate hudson, sharon stone, sienna miller, *new movie*, kim basinger, robert downey jr, keira knightley, ryan reynolds, johnny depp, jennifer connelly, edward norton, emma stone, don cheadle, marisa tomei, jason statham, eva mendes, kate beckinsale, *oscar-winner*, katie holmes, kelly preston, denzel washington, zac efron, clive owen, *oscar-winning*, forest whitaker, penelope cruz, ashton kutcher, sigourney weaver, rachel weisz, billy bob thornton, catherine zeta-jones, benicio del toro, keanu reeves, *new film*, ewan mcgregor, jeremy renner, hugh grant, liam neeson, scarlett johannson, jude law, russell crowe, jodie foster, harrison ford, meryl streep, justin theroux, john travolta, christian bale, emile hirsch, adrien brody, jonah hill, nick nolte, dennis quaid, liv tyler, kate bosworth, *hollywood star*, amber heard, javier bardem, robert deniro, evan rachel wood, helen mirren, milla jovovich, blake lively, james franco, vince vaughn, joaquin phoenix, diane kruger, *upcoming movie*, robert pattinson, michael douglas, courteney cox, richard gere, daniel craig, sylvester stallone, *latest movie*, rachel mcadams, josh brolin, jennifer lawrence, brangelina, *oscar winners*, hugh jackman, zoe saldana, *oscar nominee*, dakota fanning, josh hartnett, annette bening, mila kunis, emma watson, david fincher, megan fox, quentin tarantino, ben stiller, a-lister, kristen stewart, charlie sheen, christoph waltz, christopher walken, michelle pfeiffer, phillip seymour hoffman, thandie newton, amanda seyfried, ethan hawke, liam hemsworth, morgan freeman, robert downey, owen wilson, olivia wilde, costars, paula patton, casey affleck, kevin costner, clooney, clooneys, andrew garfield …

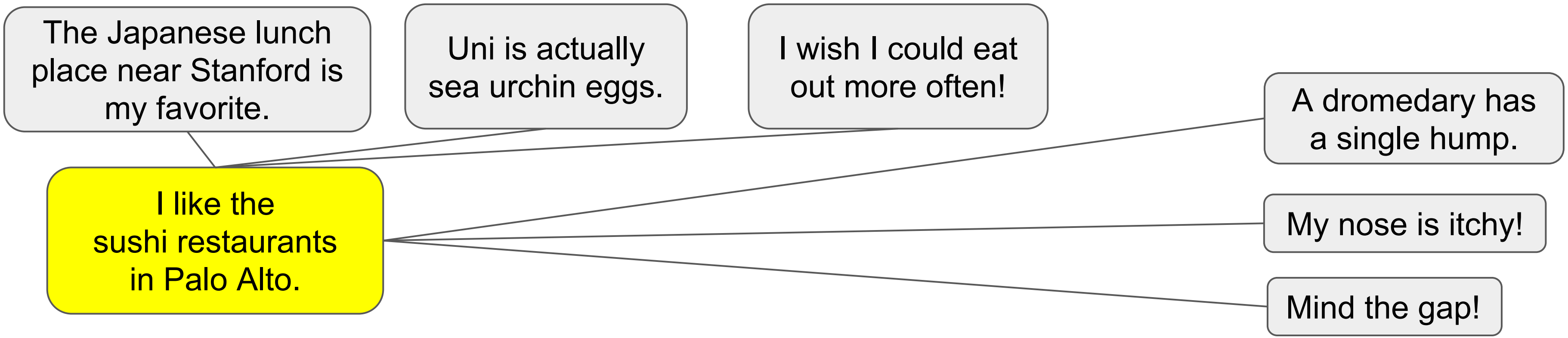
Terms similar to ***greenish***

bluish, pinkish, yellowish, reddish, brownish, purplish, grayish, yellow-green, orange-yellow, yellow-brown, yellowish green, reddish brown, orange-red, pale green, whitish, reddish-brown, greenish yellow, mottled, pale yellow, greenish-brown, greenish-yellow, yellow-orange, orangish, red-brown, bluish-green, dark brown, greyish, yellowish-green, bluish-black, reddish-orange, orange-brown, yellowish-orange, yellowish-white, brownish red, pale orange, bright yellow, deep yellow, blue-green, paler, brownish-red, bluish-grey, blueish, green-brown, pinkish-brown, golden yellow, blotches, yellowish-brown, brownish-yellow, golden-yellow, pale, grayish-white, coppery, creamy yellow, greyish-white, pale gray, purple-brown, olive-green, pale brown, blackish, brownish yellow, tinge, dark purple, light yellow, red-orange, dark red, rusty brown, brownish black, purplish-red, mottling, bluish-gray, yellowish brown, greyish-green, dull red, dark green, creamy white, purple-black, yellow brown, pinkish red, greenish-blue, reddish purple, bright red, reddish-purple, grayish-green, greenish-white, pale cream, creamy-white, brownish-gray, white spots, silvery, dark grey, dark orange, purplish-black, grayish-blue, purple-blue, greenish-black, yellow spots, bluish-white, purple-red, pure white, light brown, various shades, grey-brown, pale grey, orange-pink, brownish-black, brick-red, purplish-brown, olive-brown, brown colour, speckling, pale blue, brownish gray, deep orange, grayish-brown, blue-black, darker spots, brown-red, yellow patches, gray-black, coloration, reddish color, bluish-purple, green patches, pale red, chestnut-brown, brown streaks, yellow green, lemon yellow, pinkish-red, flecks, dark reddish brown, black spots, grey-black, lemon-yellow, pinkish-white, deep red, brownish-grey, dull black, purple spots, darker green, red spots, blue-grey, splotches, grey-green, pink-purple, greenish-gray, violet-blue, silvery grey, chocolate-brown, yellowish color, cream-coloured, orange brown, small white spots, light orange, brown-grey, violaceous, dark-brown, streaked, green veins, olive brown, olive green, brown markings, gray-green, pale pink, dark blotches, light green, grey-white, dark markings, brilliant red, light violet, blackish-brown, greyish-brown, color ranges, brown-black, orange red, yellow colour, yellow color, red brown, orange markings, small black spots, veined, brick red …

Terms similar to ***worse***

even worse, far worse, very bad, horrible, terrible, awful, horrendous, bigger problem, suffer, things worse, horribly, unfortunate, better, worst, bad, complain, real problem, after all, unfortunately, no good, too, lousy, atrocious, even less, even so, very poor, far more serious, miserable, intolerable, terribly, serious problem, trouble, worrying, bothering, blame, no better, worsened, bother, worse off, dreadful, hardly, horrid, big problem, real concern, fortunately, main problem, sooner, major problem, hopeless, excuse, serious problems, way worse, complaining, horrendously, abysmal, better off, worried, inevitable, wrong, marginally, even, rid, frankly, anymore, bothered, bothers, worry, uglier, sadly, even more, worsen, severe, serious, unacceptable, badly, nasty, different story, worse problems, main reason, worst thing, far less, go away, hurt, obviously, seriously, serious trouble, hurting, gotten, anyone else, worse.it, anyway, happen, worst cases, *say nothing*, appalling, main concern, somehow, obvious reason, troubling, simple fact, unbearable, problematic, huge problem, worst one, exacerbated, afraid, tired, blaming, painfully, suffers, much, ironically, do anything, embarrassing, worse things, inevitably, same problems, bad problems, anything, real reason, everyone else, atrociously, unpleasant, thing, worse again, apparent reason, needlessly, ignore, seemed, horrifically, worth noting, biggest problem, real issue, even more serious, dreadfully, worsening, useless, even though, probably more, some people, pitiful, worrisome, far more, because, deplorable, point out, but, stupid, admittedly, pudgenet, worst part, less so, little improvement, grossly, make things, unnecessarily, too bad, crap, bad thing, laughable, problem, might, trying, exaggerating, pretty much, lot, doing anything, ridiculous, little reason, misguided, exact opposite, worse not better, even when, weren't, inconsequential, simple reason, expect, avoided, something wrong, counter-productive, dismal, appallingly, far more likely, ugly, almost everyone, shame, wonder why, less, polfbroekstraat, worse here, plagued, worse though, honestly, bad situation, nobody, pathetic, certainly, plain wrong, almost nothing …

Semantic Distance for Sentences



Demo: Sentence Similarity

Demo: Translation

USA a Rusko strácajú s Ukrajinou trpezlivosť

#USA #Ukrajina #Rusko #Minské dohody

ta, Pravda | 19.01.2016 08:51

Minské dohody, konkrétne ich realizácia, boli koncom minulého týždňa predmetom šesťhodinových rusko-amerických rozhovorov v Kaliningradskej oblasti. Nedávno sa na nich dohodli počas návštevy Moskvy šéf diplomacie USA John Kerry a jeho ruský rezortný kolega Sergej Lavrov. A tak Kerryho námestníčka Victoria Nulandová a Vladislav Surkov, poradca ruského prezidenta Vladimira Putina, rokovali za zatvorenými dvermi a prvé reakcie hovoria o novej cestovnej mape či dokonca rusko-americkom pakte. Po tom, čo Paríž a Berlín ako hlavní garanti nedokázali pohnúť z miesta realizáciu dohôd známych ako Minsk 2 a Kyjev v tomto smere rovnako zatiaľ nič neurobil, v Moskve aj vo Washingtone stratili trpezlivosť.

Najčítanejšie dnes včera 3 dni

1 USA a Rusko strácajú s Ukrajinou trpezlivosť
2 Slota havaroval, odmietol sa podrobiť dychovej skúške
3 Samson: Visegrádske štáty zabodovali
4 Rusi očakávajú jeden z najťažších rokov
5 Prieskum: Smer prvý, do parlamentu by sa dostala aj SMK
6 Bratislava je zlatá realitná baňa
7 Tusk: Ak nevyriešime migračnú krízu za dva mesiace, Schengen skončí
8 Do štrajku sa zatiaľ hlási zlomok učiteľov
9 Odsúdili pilota, ktorý pri havárii vrtuľníka prišiel o syna
10 Pred desiatimi rokmi havarovalo vojenské lietadlo pri obci Hejce

Kvety.Pravda.sk

USA and Russia are losing patience with Ukraine

#usa #Ukrajina #Rusko # Minsk Agreement

the, Truth | 01/19/2016 08:51

Minsk agreement, namely their implementation were late last week subject to six-hour Russian-American talks in the Kaliningrad region. Recently they agreed upon by Moscow during the visit of US Foreign Minister John Kerry and his Russian counterpart Sergei Lavrov. So Victoria Nuland Kerry's Deputy Vladislav Surkov and, Advisor to Russian President Vladimir Putin discussed behind closed doors and the first reactions speak of a new road map or even a US-Russia pact. After Paris and Berlin as the main guarantor could not move from the place of execution of agreements known as 2 Minsk and Kiev in this direction as well while nothing is done, Moscow and Washington had lost patience.

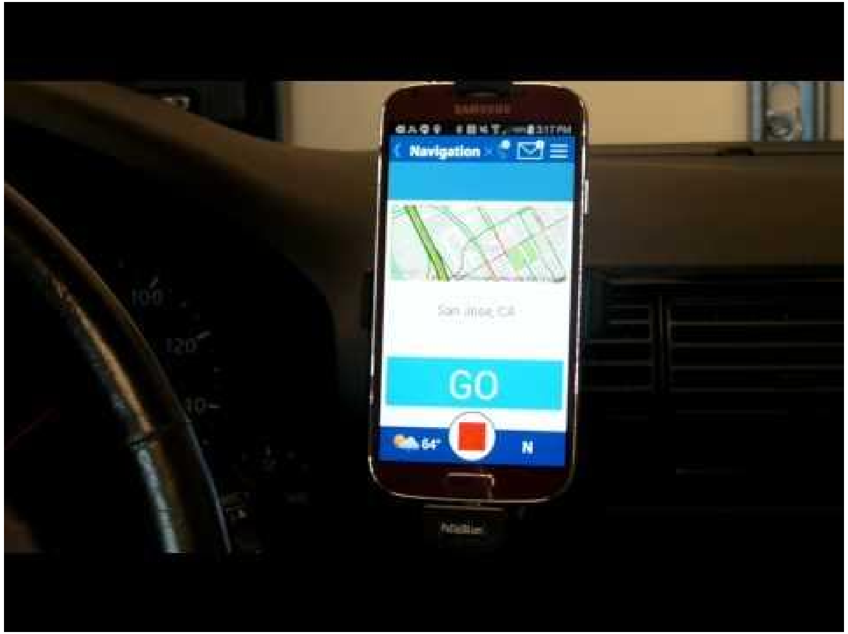
Most Popular today yesterday 3 days

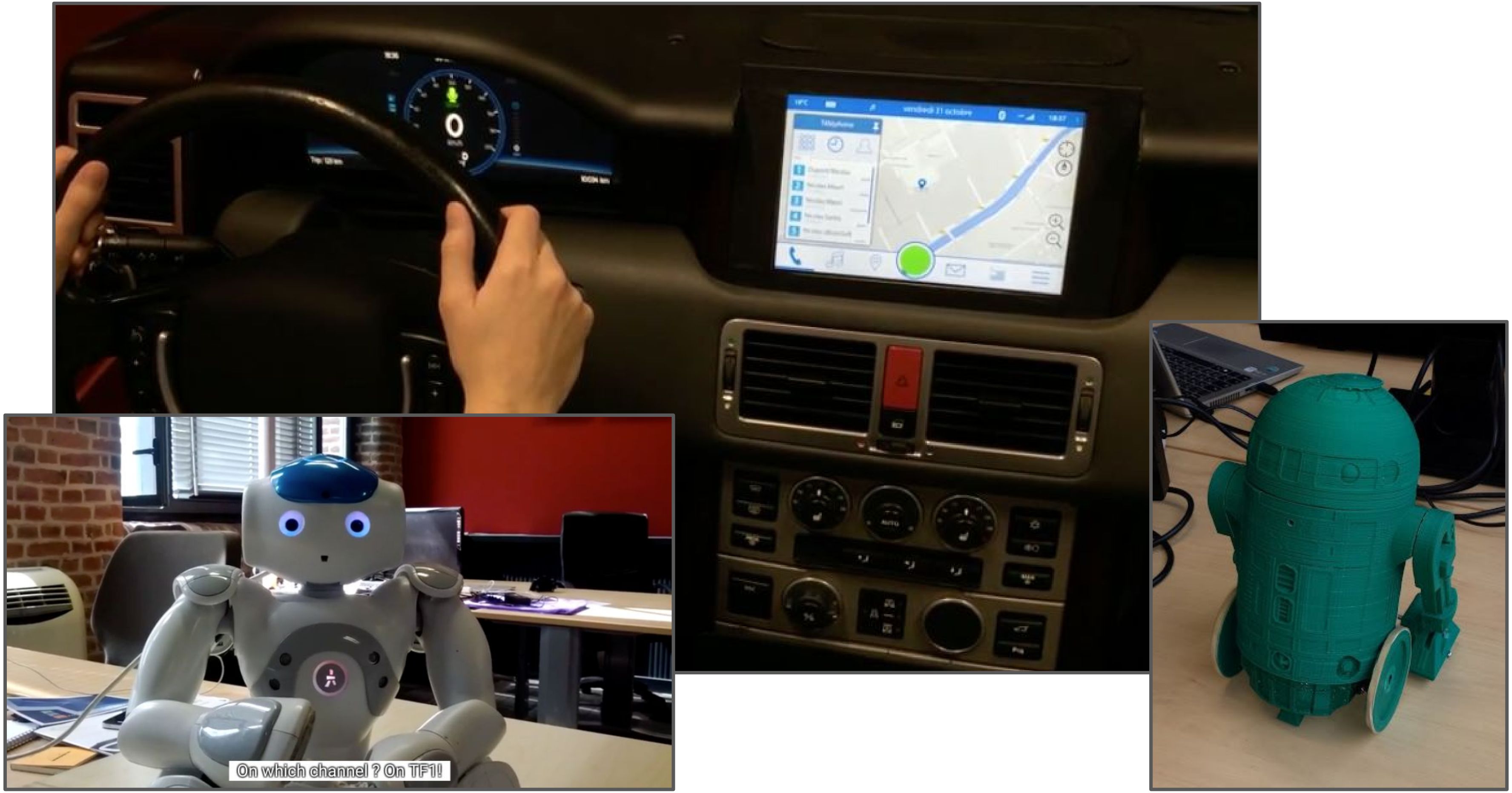
1 USA and Russia are losing patience with Ukraine
2 Slota crash, refused to submit to a breath test
3 Samson: Visegrad states scored
4 Russians expect one of the toughest years
5 Survey: As a first, the parliament would get the SMK
6 Bratislava is a gold mine estate
7 Tusk: If we do not solve migration crisis for two months, Schengen ends
8 The strike has not yet reported the fraction of teachers
9 condemned pilot who crash the helicopter arrived on son
10 Ten years ago warplane crashed near the village Hejce

char-nn
by Andrej Karpathy

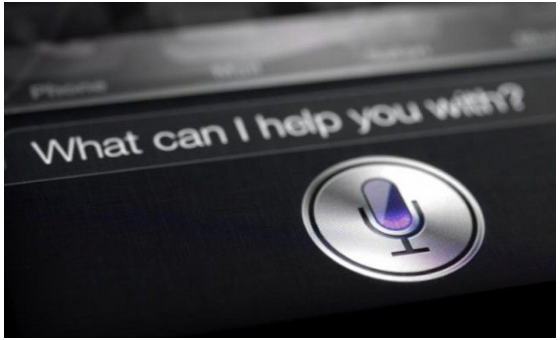
```
PANDARUS:
Alas, I think he shall be come approached and the day
When little srain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:
They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:
Well, your wit is in the care of side and that.

Second Lord:
They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

Clown:
Come, sir, I will make did behold your worship.

VIOLA:
I'll drink it.
```

Virtual Assistant : Car, Appliance, Robot, IoT, VR, ...




On which channel ? On TF1!

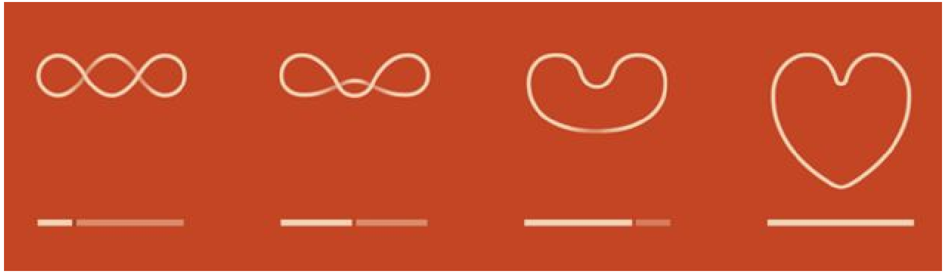
Content Centric → People Centric



Siri, Cortana, Alexa, ...

- Content Centric
  - Question - Answering
  - Light dialog
- Context Sequence(s)
- Knowledge or Actions

Far from the Human communication



HER, Sarah, HAL (or not ;p)

- People (person) Centric
  - Human like dialog
  - Empathy & Emotion
- Global Context
- Concept Learning

Human emotional communication

What we will learn

How to to acquire large corpora and solve common NLP tasks.

The **nltk** and **gensim** libraries, in Python.

Vector representation for text (Embeddings).

Different examples of text classification.

The Deep Neural Networks that perform best on text: LSTM, GRU…

Generative models.

If you remember only one thing...

NLP is hard, but traditional techniques work pretty well.

Nice progress since 2012, we are getting our hands on “semantic proximity”.

Rapid progress on classification, translation.

But no true “understanding” yet.


Take a Break!

How is this Relevant to You?

Do it with Ethic. Always!

Problem solving ?!?

Imagine how to solve one of your daily problems through Deep Learning