

Introduction to AI, practical approach

Dr. Ahmad El Sallab

AI Senior Expert

What will you learn?

- What is AI?
- Identify what AI can and cannot do?
- AI vs. ML vs. DL
- ML vs. Data science
- How ML/DL works?
- Global ML/DL framework
- How to speak the language of AI team?
- What are the steps of an AI project?
- Limitations of AI
- What is the effect of AI on society?

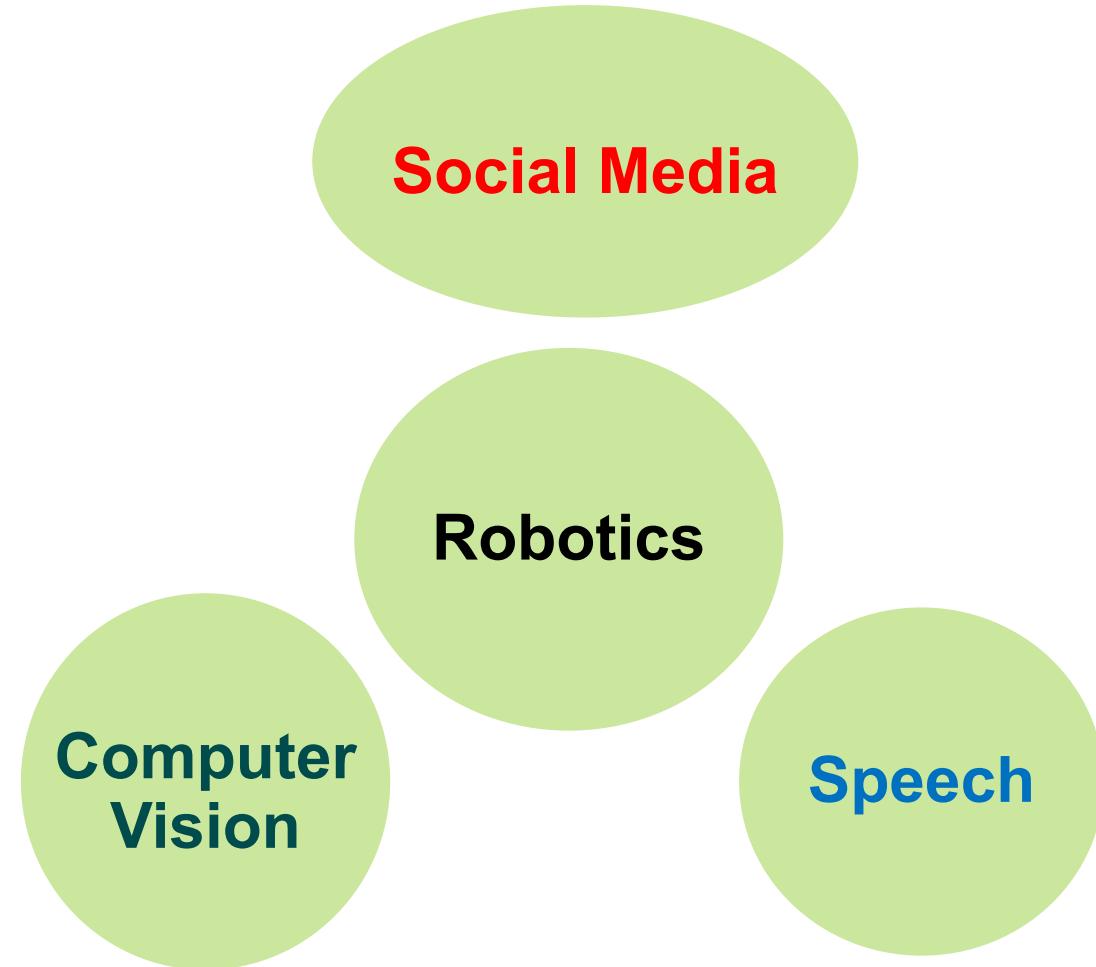
Agenda

- Part 1: What is AI?
- Part 2: Working with an AI team
- Part 3: AI and the society
- Part 4: How it works?

Agenda

- Part 1: What is AI?
- Part 2: Working with an AI team
- Part 3: AI and the society

Where can we find AI today?



The AI revolution

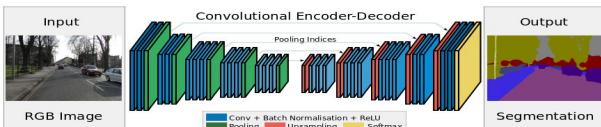


IBM Pepper

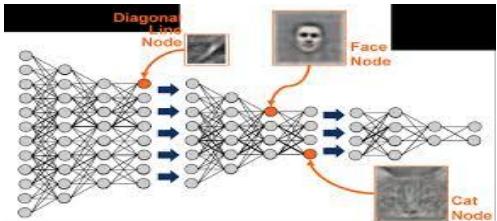
Apple Siri



SegNet



Computer Vision



AlexNet

Google now

Social Media



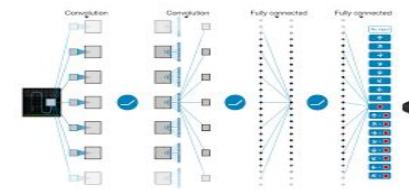
FB Chatbot



MS Cortana



DeepMind
AlphaGo



Atari
DeepMind



MS Speech



Comma.ai
HAD

Speech

DeepSpeech 2

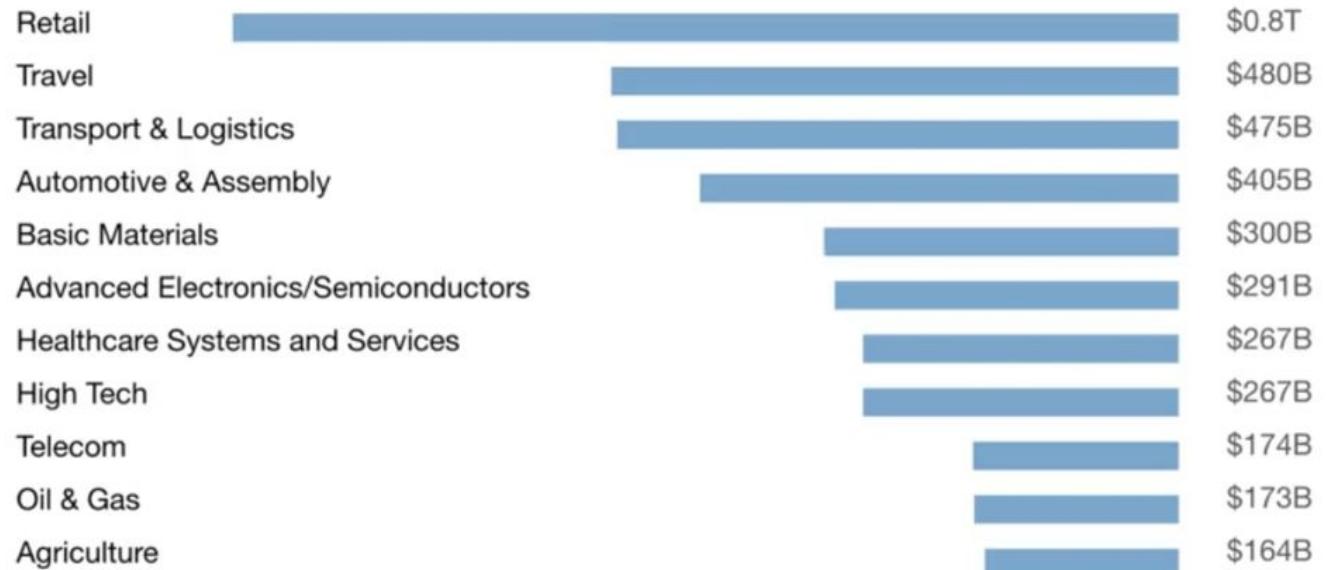


What value AI is creating?

AI value creation

by 2030

\$13
trillion



[Source: McKinsey Global Institute.]

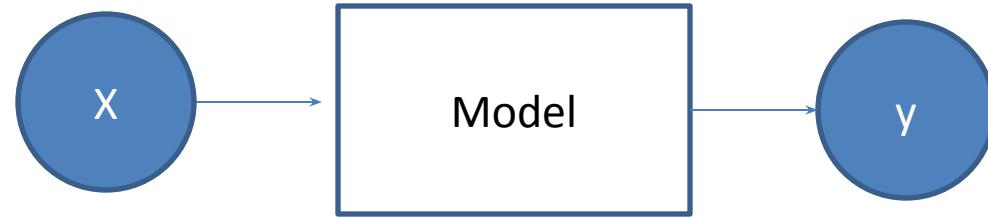


deeplearning.ai

Andrew Ng

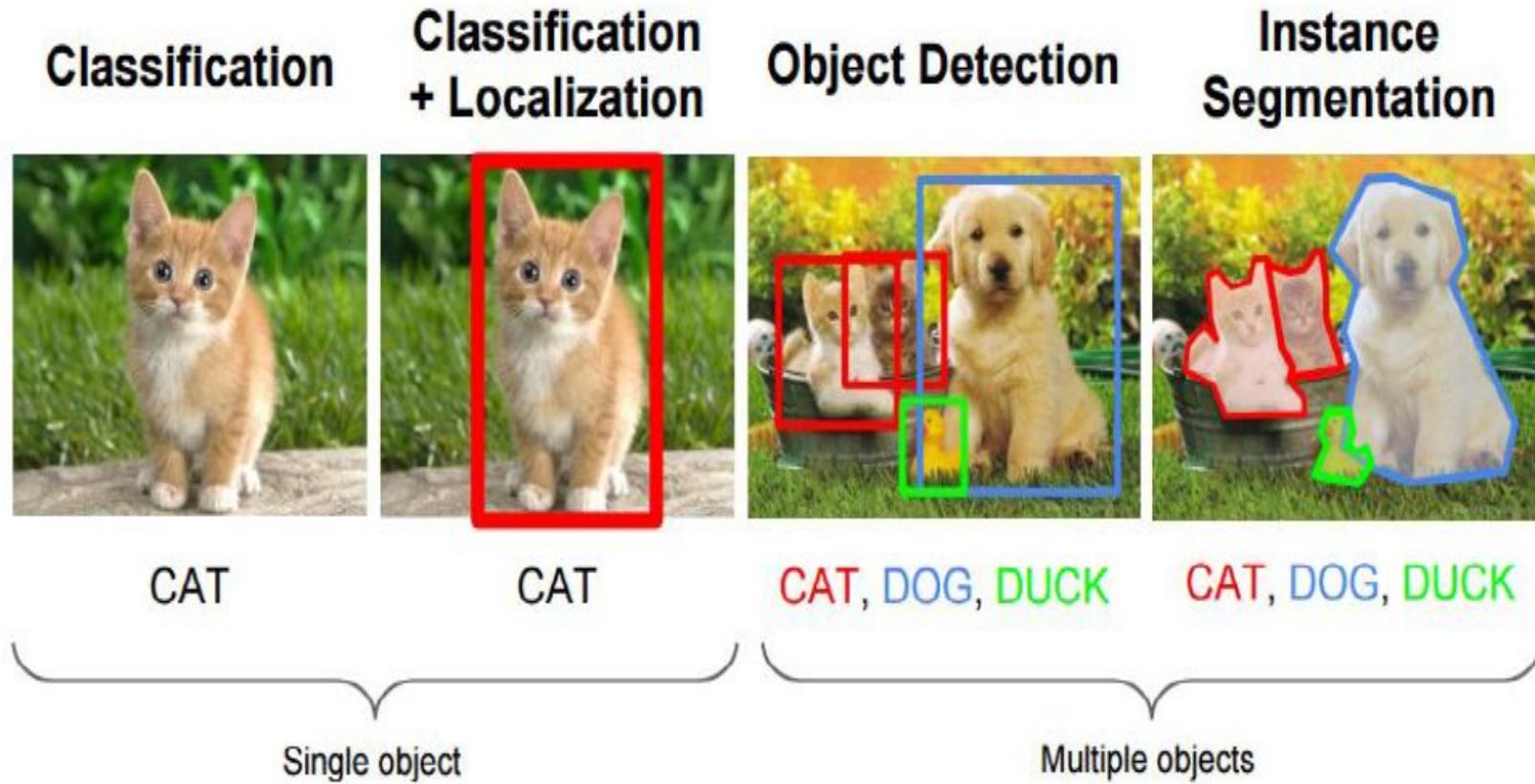
AI is in many fields, MOSTLY not software!

What AI can do?



Simple mappings

Computer vision possible tasks



Source: Fei-Fei Li, Andrej Karpathy & Justin Johnson (2016) cs231n, Lecture 8 - Slide 8, Spatial Localization and Detection (01/02/2016). Available:
http://cs231n.stanford.edu/slides/2016/winter1516_lecture8.pdf

What AI can do?

Structured data

| Price | Floor space | Rooms | Lot size | Appartment | Row house | Corner house | Detached |
|--------|-------------|-------|----------|------------|-----------|--------------|----------|
| 250000 | 71 | 4 | 92 | 0 | 1 | 0 | 0 |
| 209500 | 98 | 5 | 123 | 0 | 1 | 0 | 0 |
| 349500 | 128 | 6 | 114 | 0 | 1 | 0 | 0 |
| 250000 | 86 | 4 | 98 | 0 | 1 | 0 | 0 |
| 419000 | 173 | 6 | 99 | 0 | 1 | 0 | 0 |
| 225000 | 83 | 4 | 67 | 0 | 1 | 0 | 0 |
| 549500 | 165 | 6 | 110 | 0 | 1 | 0 | 0 |
| 240000 | 71 | 4 | 78 | 0 | 1 | 0 | 0 |
| 340000 | 116 | 6 | 115 | 0 | 1 | 0 | 0 |

Machine learning background survey 04.09.18

Please answer "Yes" to the following questions if:

This form is automatically collecting email addresses for VALEO users. [Change settings](#)

Know about basic linear algebra and matrices operations (multiplication, add, transpose)?

- Yes
 No

Know how to apply differentiation and the chain rule? *

- Yes
 No

Unstructured data

Classification



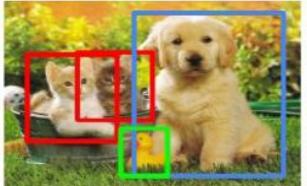
CAT

Classification + Localization



CAT

Object Detection



CAT, DOG, DUCK

Instance Segmentation



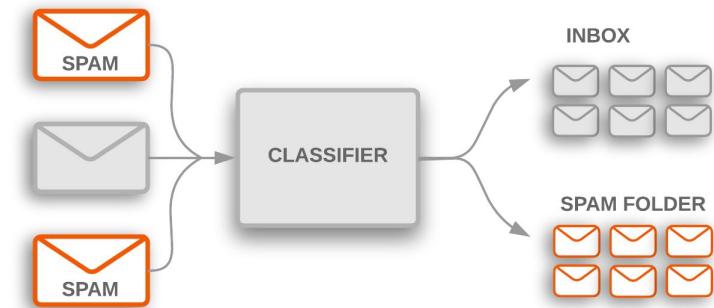
CAT, DOG, DUCK

Single object

Multiple objects

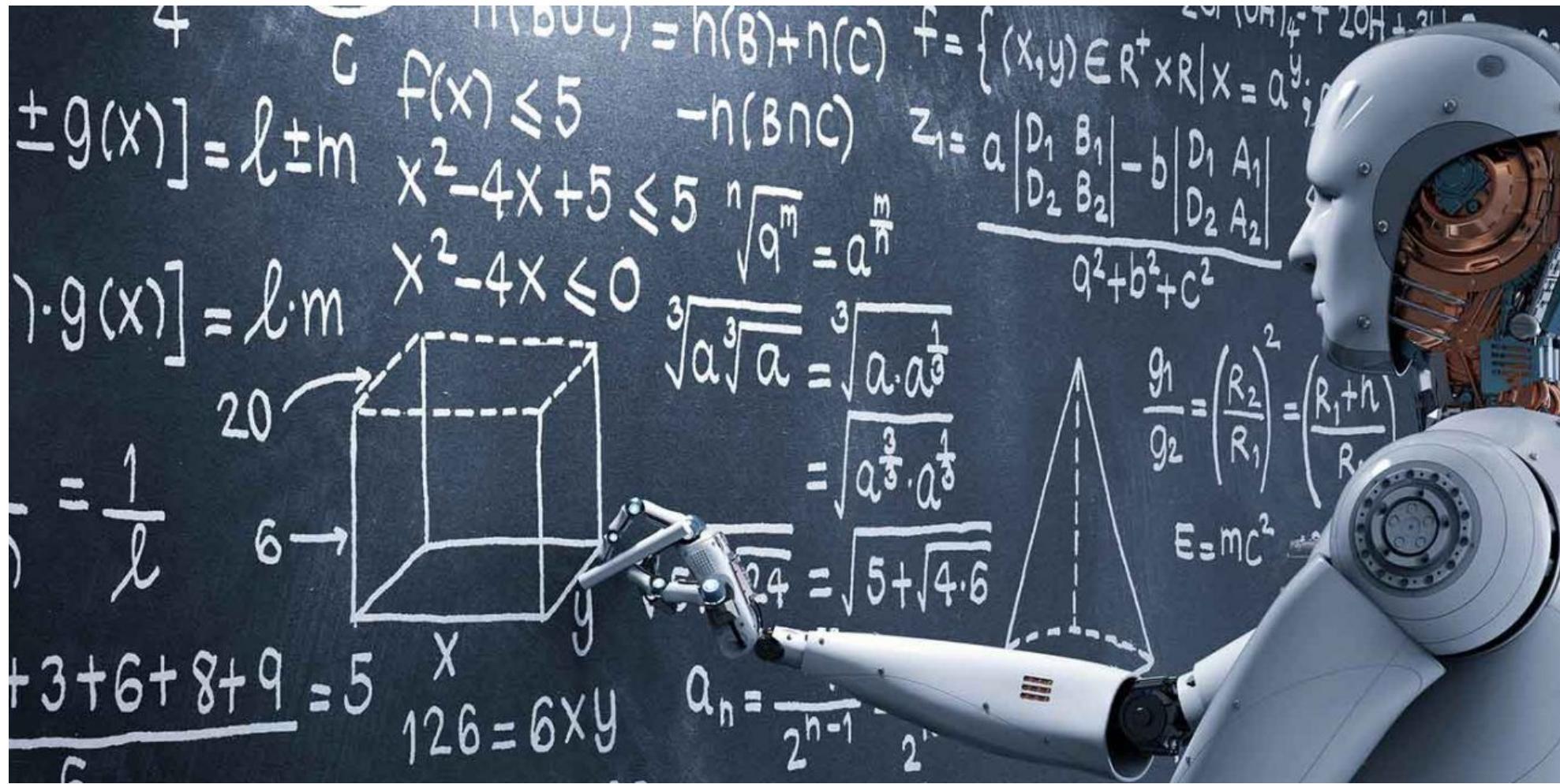
Source: Fei-Fei Li, Andrej Karpathy & Justin Johnson (2016) cs231n, Lecture 8 - Slide 8, *Spatial Localization and Detection* (01/02/2016). Available:

http://cs231n.stanford.edu/slides/2016/winter1516_lecture8.pdf



Artificial Narrow Intelligence: Structure or unstructured

What AI can NOT do?



Artificial General Intelligence is very far (10/100/1000 yrs)

What AI cannot do? Complex mappings

Can do



A → B

Cannot do



stop

hitchhiker

bike turn
left signal

Gestures could be hard even sometimes
for humans

How to quickly spot the potential of AI to a project?

- Simple task for human → simple concept
 - < 1 sec
- And/or needs lots of data to perform
- Think Tasks not Jobs
 - Instead of replacing an operator, think of how AI can automate parts of his job

Examples:

- Simple perception: text, speech, image
- Automation: Look at many data and predict say house price

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How to speak the language of AI team

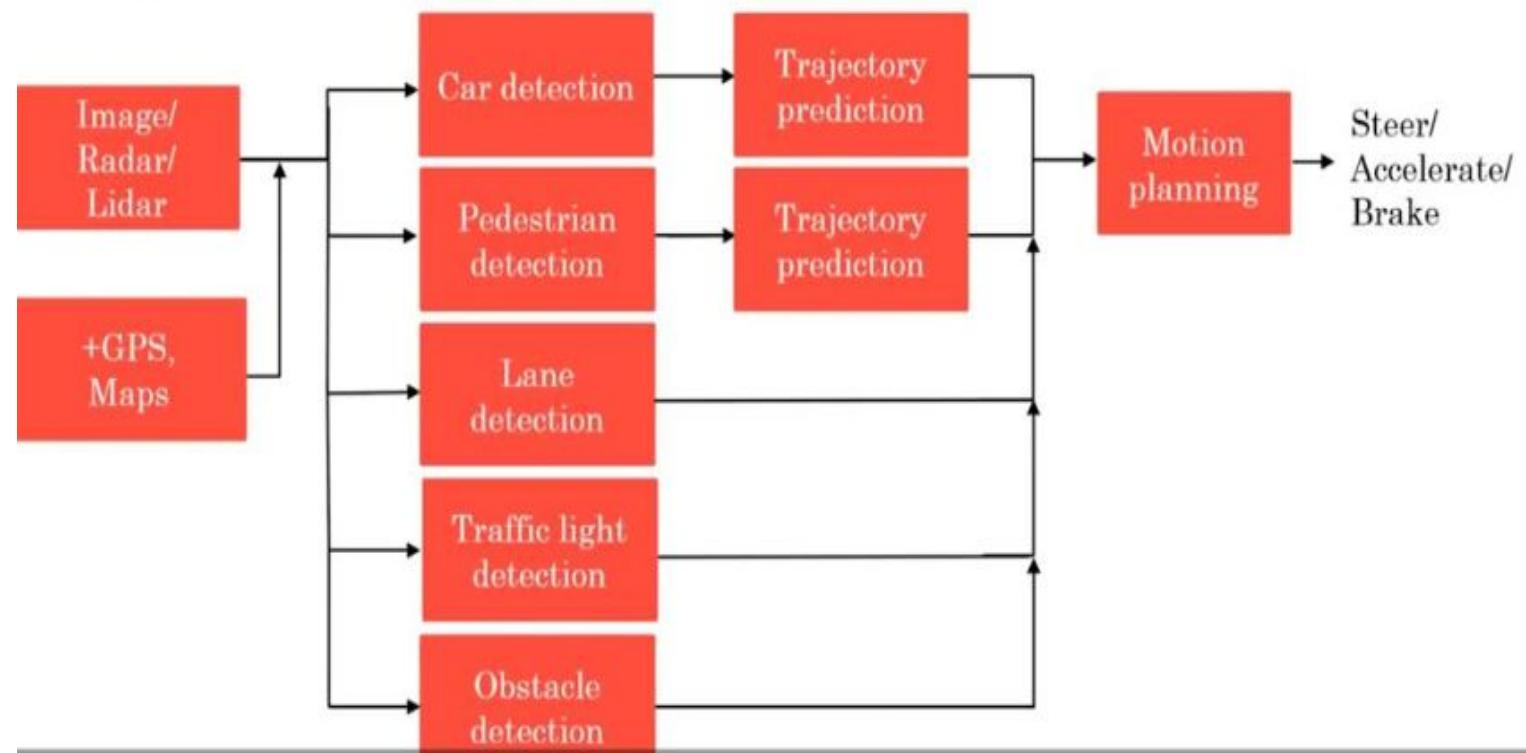
- What AI can and cannot do
- AI project lifecycle
- Define the performance requirements
- Data needs

Workflow of an AI project

AD pipeline

Each is an AI project: A \rightarrow B

1. Data collection
2. Train
 - a. Many iterations
3. Deploy



How to define performance requirements?

Always talk in a statistical metrics

- 100% is not possible due to reasons that will be described later

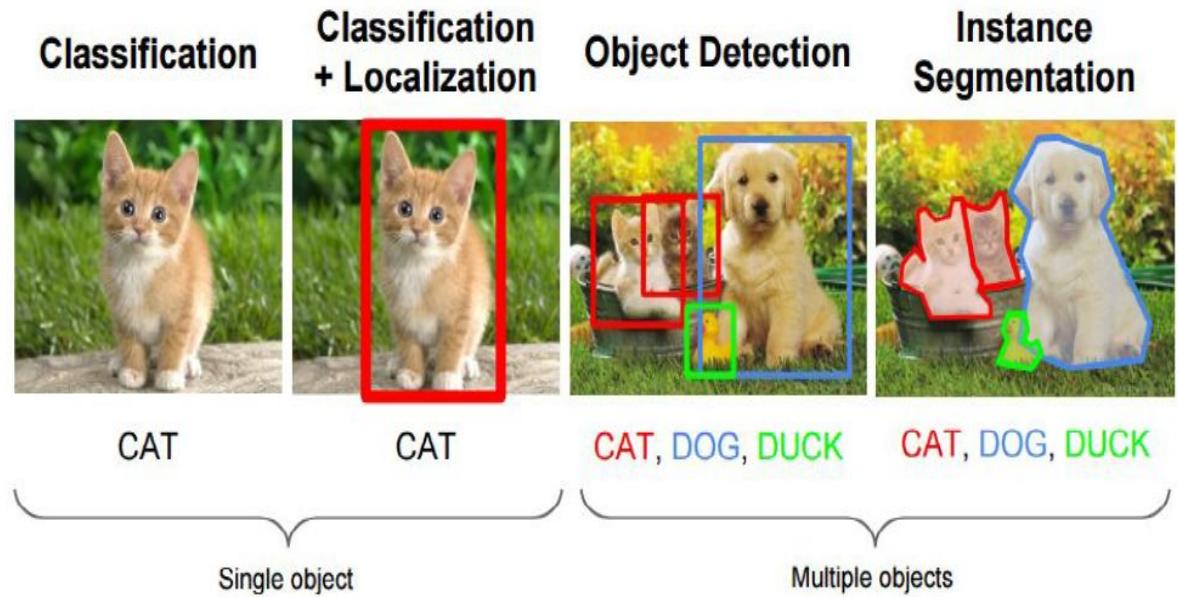


Goal: detect defects with 95% accuracy

Provide AI team a dataset on which to measure their performance
test set
n | 1000

How to acquire data?

1. Raw data collection, where?
 - a. Public
 - b. Own
 - c. From users experience (early deployment)
2. Annotation = Labeling
 - a. Manual
 - b. Automatic → Observe behaviors
 - c. Semi-automatic



Source: Fei-Fei Li, Andrej Karpathy & Justin Johnson (2016) cs231n, Lecture 8 - Slide 8, *Spatial Localization and Detection* (01/02/2016). Available:
http://cs231n.stanford.edu/slides/2016/winter1516_lecture8.pdf

Data acquisition tips

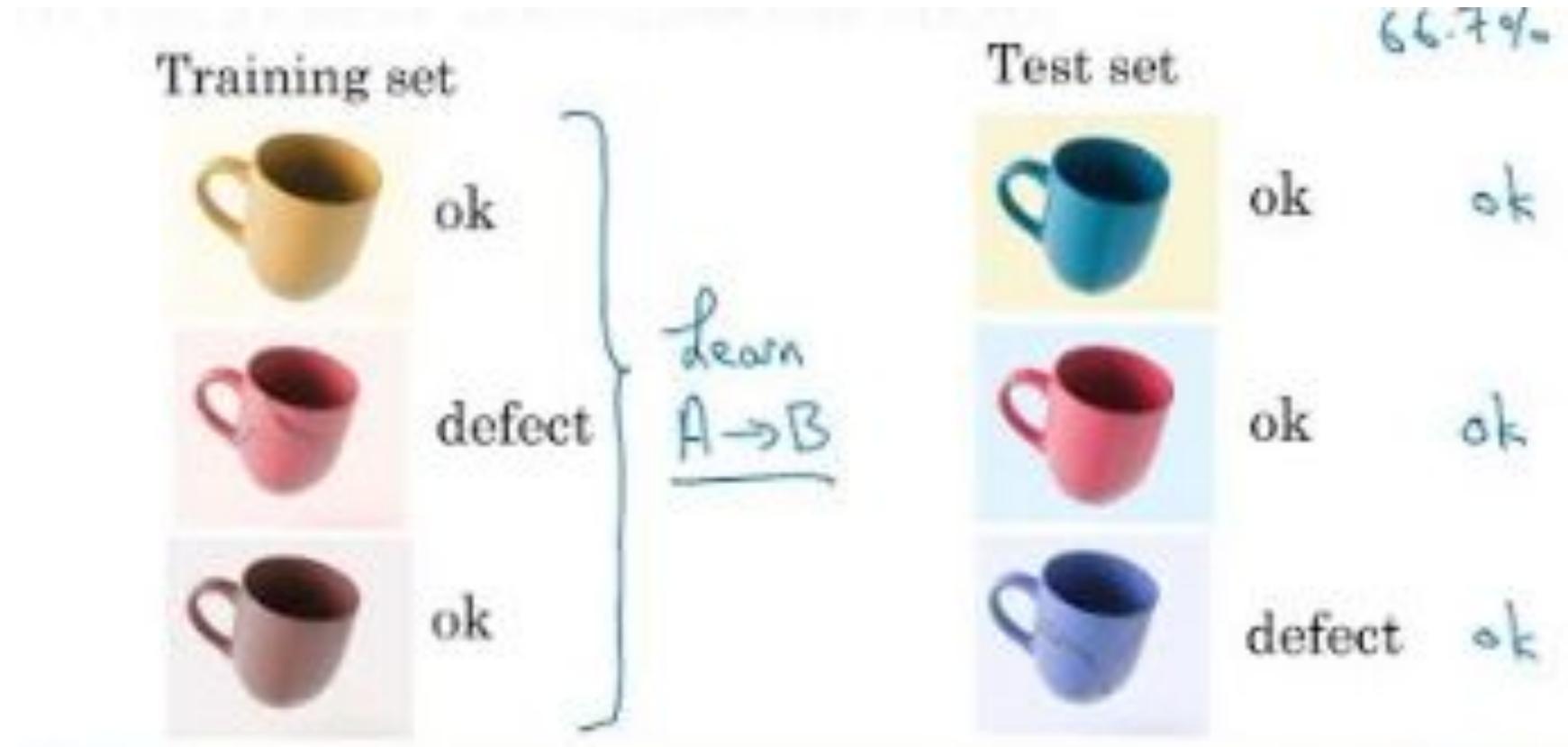
- Integrate AI teams
 - Quick feedback
 - Set data collection requirements and quality
- Deploy early (Tesla model)
 - Do not wait years to collect all the data
 - Quick feedback

How much data?

- Usually BigData → How big?
 - The bigger the better → MB, GB, TB, PB
 - Problem dependent
 - Rule of thumb, 5k/class → if classification

What data sets an AI team needs?

- Train data
- Test data
- Validation data



100% is not possible

- Garbage in - Garbage out
 - o Incorrect labels
 - o Missing values
 - o Ambiguous labels
- ML limitations
 - o Statistical methods
 - o Traditional ways fails due to many cases

| Test set | | |
|---|--------|---|
|  | ok |  defect ok |
|  | ok |  ok defect? |
|  | defect |  ok |

- Limitations of ML
- Insufficient data ←
- Mislabeled data ←
- Ambiguous labels ←

AI Technical tools

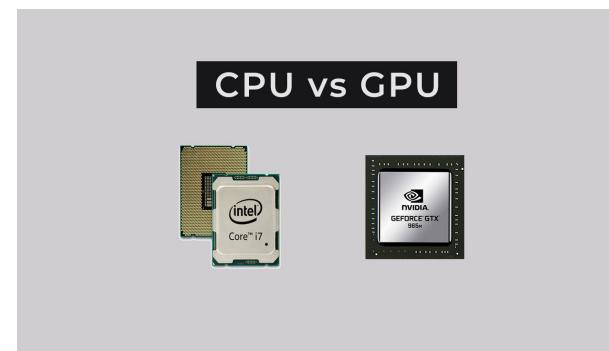
ML frameworks: TensorFlow, Pytorch, Keras, CNTK,...etc

Linux

Opensource: Github → critical for fast prototyping. Most of the ideas are from research papers.

GPU vs CPU

Cloud vs. On-prem



Make or buy?

- ML can be in-house or outsourced
 - o Most probably it will soon be an industry standard
 - o
- Data science (analytics) are better in-house → custom
- Embrace the industry standards → re-use when possible
 - o Do not reinvent the wheel

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AI and Society

- Hype of AI
- Limitations of AI
 - Bias
 - Adversarial Attacks
- Effect on Jobs

The hype of AI

AGI is too far

- AI cannot do everything
- There's no need to fear it! This creates limitations

AI winter is too far as well

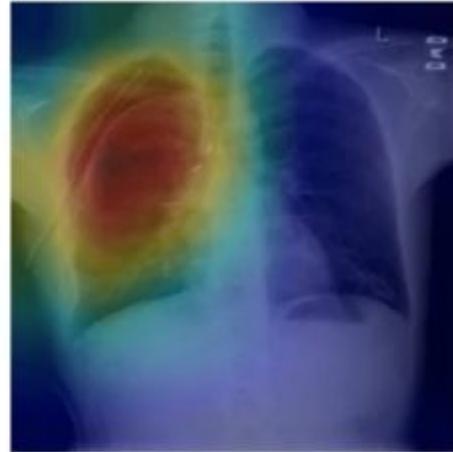
- AI is creating lots of gains in economy already

Limitations of AI

Explainability



Right-sided
Pneumothorax
(collapsed lung)



[Rajpurkar et al. (2018). CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning.]

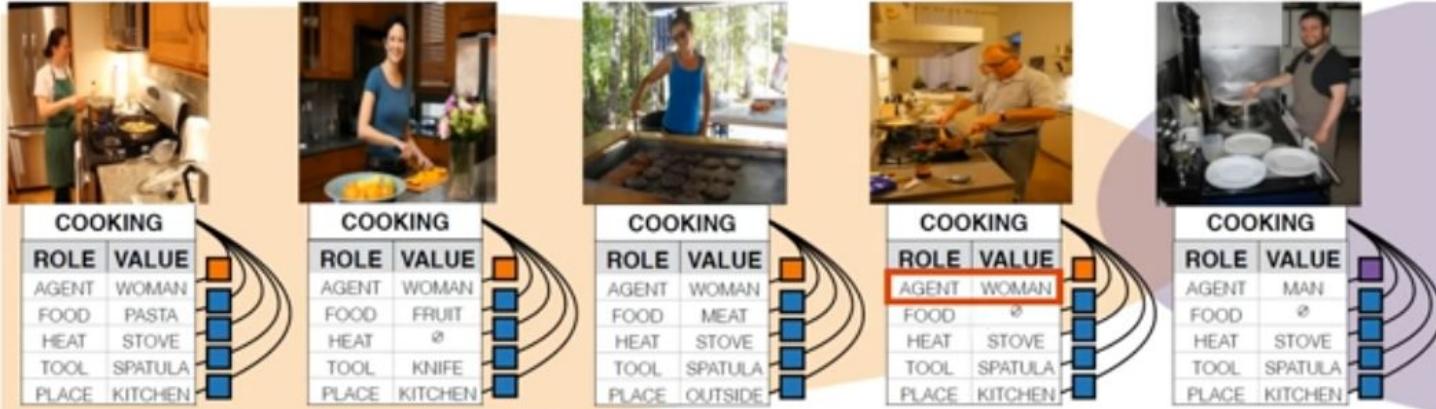
Humans also have hard time explain themselves, but are less susceptible to errors

Limitations of AI

Bias

Gender bias

Machine Learning can amplify bias.



Data set: 67% of people cooking are women

Algorithm predicts: 84% of people cooking are women



Language

The screenshot shows a machine translation interface with three language tabs: English, Turkish, and Spanish. The English tab is active. Below the tabs, there are two examples of text pairs:

- English: "She is a doctor." / Turkish: "O bir doktor." / Spanish: "O bir hemşire." (Note: "hemşire" is misspelled as "hemşire").
- English: "He is a doctor." / Turkish: "O bir doktor." / Spanish: "S/he is a nurse" (Note: "S/he" is misspelled as "She").

Both examples show a 50/5000 character limit indicator. A "Translate" button is visible at the top right of the interface.

<https://course.fast.ai/>

Limitations of AI Bias

Ethnic bias

A War of Words Puts Facebook at the Center of Myanmar's Rohingya Crisis

By MEGAN SPECIA and PAUL MOZUR OCT. 27, 2017



Across Myanmar, Denial of Ethnic Cleansing and Loathing of Rohingya

查看简体中文版 | 查看繁體中文版

By HANNAH BEECH OCT. 24, 2017



"Kalar are not welcome here because they are violent and they multiply like crazy, with so many wives and children," he said.

Mr. Aye Swe admitted he had never met a Muslim before, adding, "I have to thank Facebook because it is giving me the true information in Myanmar."



Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica
May 23, 2016

Prediction Fails Differently for Black Defendants

| | WHITE | AFRICAN AMERICAN |
|---|-------|------------------|
| Labeled Higher Risk, But Didn't Re-Offend | 23.5% | 44.9% |
| Labeled Lower Risk, Yet Did Re-Offend | 47.7% | 28.0% |

<https://course.fast.ai/>

Limitations of AI

Why is it a problem?

- AI is involved in hiring, so hiring can be biased
- Facial recognition works better for light-skinned than dark-skinned, and is used in security departments
- Bank loan approvals
- Can lead to wars!

Limitations of AI

How to deal with bias?

- Technical solutions: collect balanced data
- Auditing: frequently test cases of bias from your algorithm
- Diverse workforce: creates less biased applications

Limitations of AI

Adversarial attacks

- AI does not see as we see

Adversarial defense

- Technical solutions exists, but with cost of slow running time
- Still in research phases



Hummingbird

Minor perturbation →



Hammer



Hare

Minor perturbation →



Desk

Limitations of AI

Mis-use of AI

- Deep Fakes <https://www.youtube.com/watch?v=cQ54GDm1eL0>
 - o Fake videos of people
- Manipulate freedom
 - o Oppressive surveillance
 - o Elections manipulation through personalized content
- Fraud (anti-fraud) attacks

AI Effect on jobs

Jobs displaced
by 2030

400-800 mil

Jobs created
by 2030

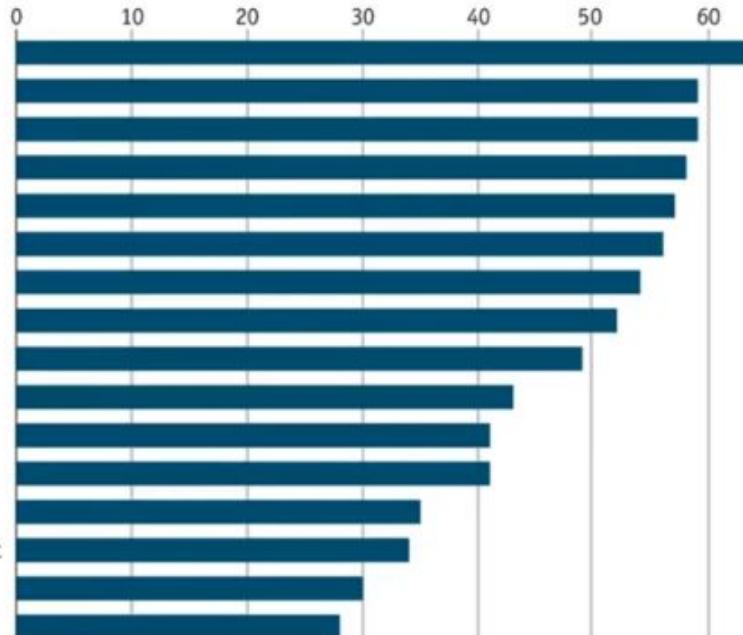
555-890 mil

[Source: McKinsey Global Institute.]

Automated for the people

Automation risk by job type, %

Food preparation
Construction
Cleaning
Driving
Agricultural labour
Garment manufacturing
Personal service
Sales
Customer service
Business administration
Information technology
Science & engineering
Healthcare
Hospitality & retail management
Upper management & politics
Teaching



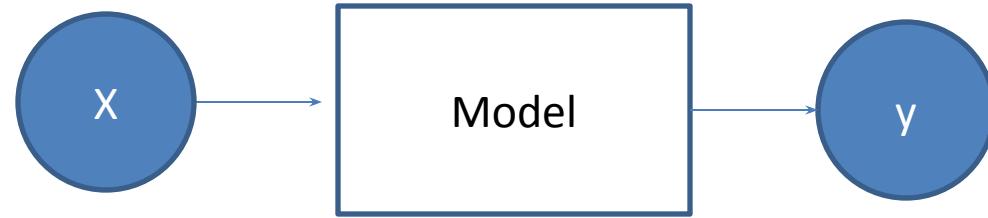
Source: OECD

[Image credit: Economist.com]
[Nedelkoska, L. and G. Quintini.
(2018). Automation, skills use
and training. *OECD Social,
Employment and Migration
Working Papers*, No. 202.]

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What AI can do?

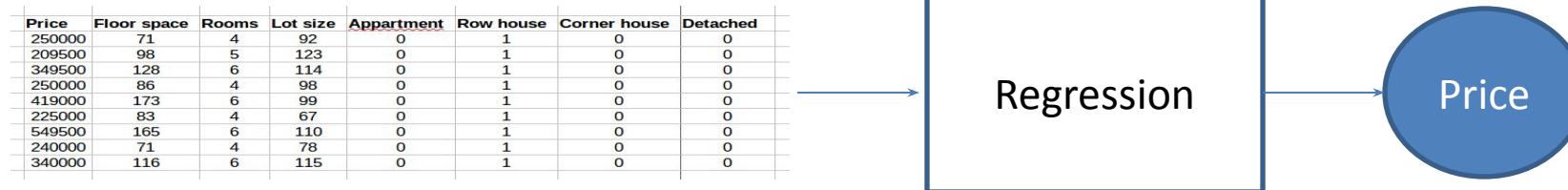


Simple mappings

What is AI is best at today?

Supervised Learning:

-->Learning for examples



Example: Machine Learning Background Survey

Machine learning background survey 04.09.18

Please answer "Yes" to the following questions if:

This form is automatically collecting email addresses for VALEO users. [Change settings](#)

Know about basic linear algebra and matrices operations (multiplication, add, transpose)?

- Yes
 - No

Know how to apply differentiation and the chain rule? *

- Yes
 - No

Example: Machine Learning Background Survey

$q^i = [q_1, q_2, \dots, q_N]$, N is the number of questions in the survey

q_j^i is the answer of question j for user i

$q_j^i \in [0, 1]$ for (Y/N) questions $q_j^i \in [0, L]$ for range questions, where $L \in R$

| A | B | C | D | E | F | G | H |
|---|---|---|--|----------------------------|-------------------------|-------------------------------|----------|
| | Know the difference between overfitting and underfitting? | Know what is a bias-variance trade-off? | Know what is a regularization parameter? | Know what is a hypothesis? | Know what is a feature? | Know what is a loss function? | Knows ML |

$0 \leq i \leq M$, M = number of users

For each q^i we want to predict Y/N result indicating whether the user knows or not ML: $y^i \in [0, 1]$

The set $\{q^i, y^i\}$, $0 \leq i \leq M$ is called the data set or the design matrix.

| A | B | C | D | E | F | G | H |
|-------------------|---------------------------------|---|---|----------------------------|----------------------------|---|--|
| Timestamp | Know about basic linear algebra | Know how to apply different machine learning algorithms | Know how to apply different machine learning models | Know what is a probability | Know what is a probability | Know the difference between overfitting and underfitting? | Know the difference between bias and variance? |
| 9/4/2018 8:50:55 | Yes | No | No | No | No | No | Yes |
| 9/4/2018 8:54:23 | Yes | Yes | Yes | Yes | Yes | No | Yes |
| 9/4/2018 10:38:22 | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| 9/4/2018 10:39:26 | Yes | No | No | No | No | No | Yes |

Example: Machine Learning Background Survey

The question now, how to find a mapping from q^i to y^i ?

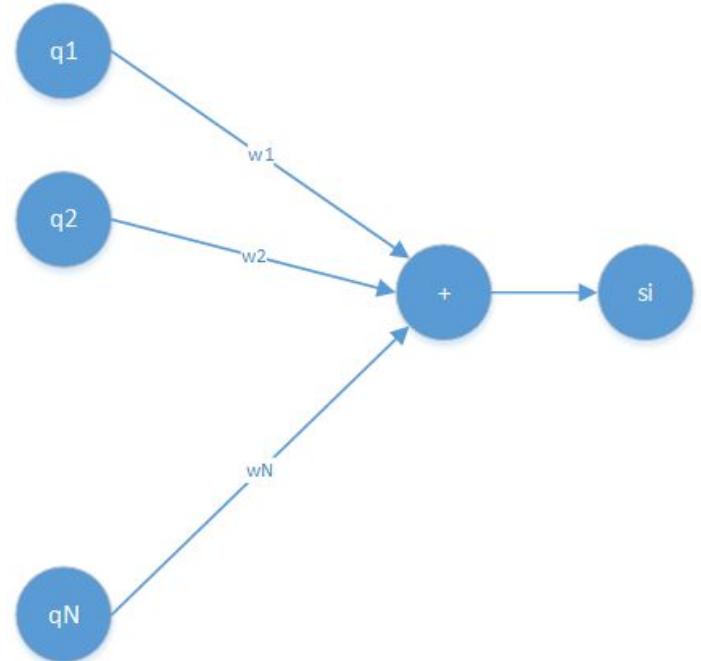
$$y^i = f(q^i)$$

Specifically, how to find f ?

Let's assume we will give every question j in the survey a certain *importance* $w_j \in R$

Now, we can have a score for each question as follows:

$$s_j^i = w_j * q_j^i$$



Now to get a score for the whole user s^i , all we need is to sum the individual scores:

$$s^i = \sum_{j=1}^N s_j^i$$

The above score is unnormalized, meaning, it can take any value.

We better have a normalized weight $0 \leq w_j \leq 1$:

$$s_j^i = w_j / \sum_{j=1}^N (w_j) * q_j^i$$

Now we can have normalized scores $0 \leq s_j^i \leq L$, where L is 1 for binary questions or max for range ones.

If we want $0 \leq s_j^i \leq 1$ then we formulate s_j^i as follows: $s_j^i = w_j / \sum_{j=1}^N (w_j) * q_j^i / L_j$, where L_j is the range of the question q_j^i .

Example: Machine Learning Background Survey

Normalization

The above score is unnormalized, meaning, it can take any value.

We better have a normalized weight $0 \leq w_j \leq 1$:

$$s_j^i = w_j / \sum_{j=1}^N (w_j) * q_j^i$$

Now we can have normalized scores $0 \leq s_j^i \leq L$, where L is 1 for binary questions or max for range ones.

If we want $0 \leq s_j^i \leq 1$ then we formulate s_j^i as follows: $s_j^i = w_j / \sum_{j=1}^N (w_j) * q_j^i / L_j$, where L_j is the range of the question q_j^i .

But this will give us a score that cannot be > 1 , since we normalize the weights. Check if all weights are 1, $w_j = 1$:

$$s^i = 1/N * \sum_{j=1}^N q_j^i / L_j$$

So it's like the average score, which is either [0,1] for the normalized case above (when each question answer we divide by L_j) or [0, L_j] if we don't divide. Say if all answers $q_j = L_j$, then the final answer is either 1 for the normalized case or L_j for the unnormalized case.

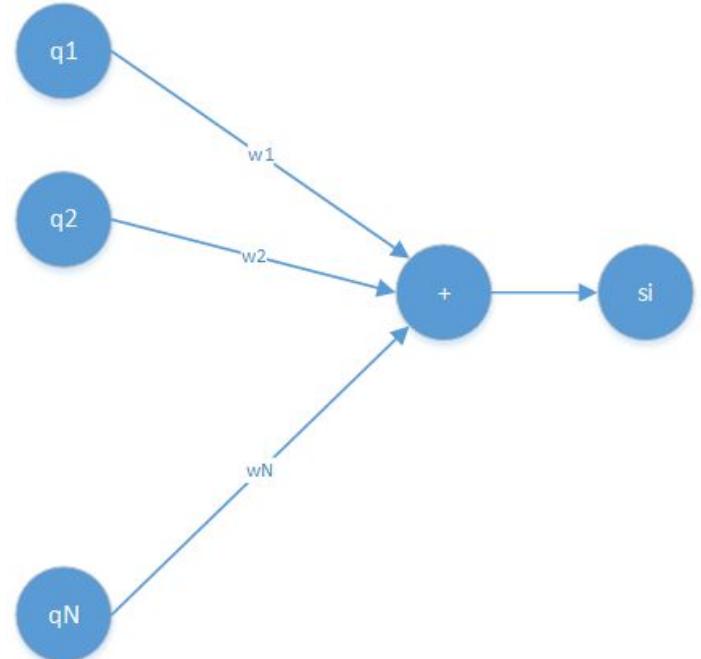
A special case of the above if all questions have the same range $L_j = L$, and if we want the final score to be in the same range (say [0,10] not [0,1]), all we need to do is multiply by L: $s^i = L * \sum_{j=1}^N s_j^i$

In this case, we just have a weighted average of the questions: $s^i = \sum_{j=1}^N (w_j / \sum_{j=1}^N (w_j)) * q_j^i$

Check, if all questions have $w_j = 1$ and $q_j^i = L_j$, then have normalized $s^i = 1$ and unnormalize $s^i = L_j$

$$s^i = 1/N * \sum_{j=1}^N q_j^i$$

Which is again the average.



Now to get a score for the whole user s^i , all we need is to sum the individual scores:

$$s^i = \sum_{j=1}^N s_j^i$$

Example: Machine Learning Background Survey

Now, back to the normal case, if we plug the whole equation we get:

$$s^i = \sum_{j=1}^N (w_j / \sum_{j=1}^N (w_j)) * q_j^i / L_j$$

This is just a parameterized function mapping from q_j^i to a score s^i

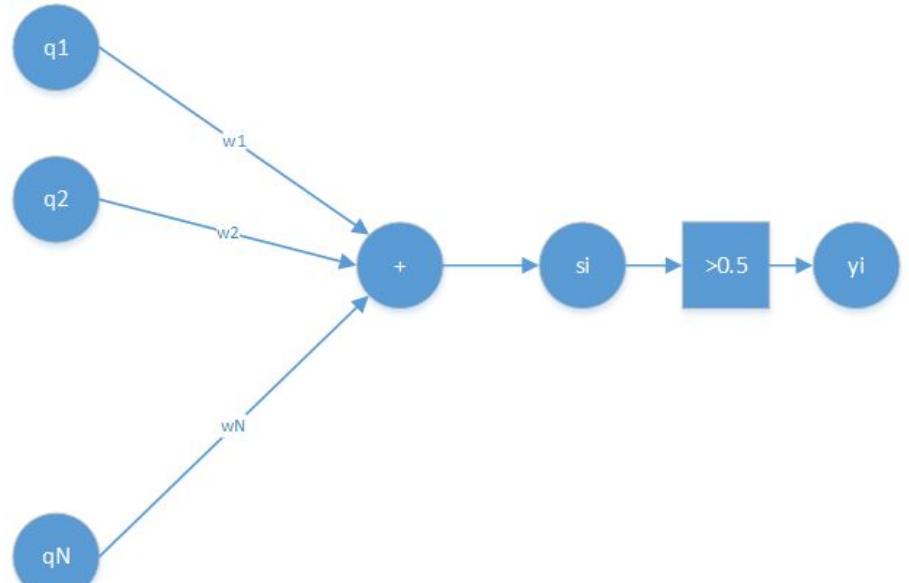
$$s^i = s(q_j^i; w_j)$$

To get a final result y^i whether a person knows ML or not, we need to apply a threshold, say 0.5:

$$y^i = 1\{s^i > 0.5\}$$

1- How to find w 's and threshold?

2- How to decide on the questions q 's?



How to set w's?

If the answer to this question is: "by experience or applying pre-defined rule", then you are doing rule-based AI or traditional AI.

If the answer is "we learn them" then you are doing ML.

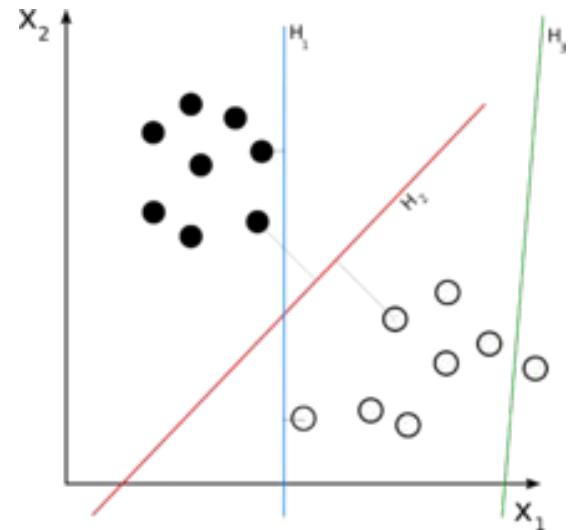
ML: How to learn w's?

Assume only 2 q's:

Basically → Search: ax_1+bx_2+c (**Model**) → $w_1=a$,
 $w_2=b$, $w_0=c$ (bias, to be clear later)

Try many lines, and get the one that separates the
Data better → How good? **Loss**

Practically → Smarter methods (**Optimizer**) are
used better than brute force or random search!



How to decide on questions?

We call the questions vector $q^i = [q_1, q_2, \dots, q_N]$ **features vector**

In case of structured data like above, normally we choose them based on experience.

| A | B | C | D | E | F | G | H | I |
|-------------------|---------------------------------|---|---|----------------------------|----------------------------|---------------------------------------|---------------------------------------|---|
| Timestamp | Know about basic linear algebra | Know how to apply different types of linear algebra | Know how to apply different types of linear algebra | Know what is a probability | Know what is a probability | Know the difference between ML and DL | Know the difference between ML and DL | I |
| 9/4/2018 8:50:55 | Yes | No | No | No | No | No | Yes | I |
| 9/4/2018 8:54:23 | Yes | Yes | Yes | Yes | Yes | No | Yes | I |
| 9/4/2018 10:38:22 | Yes | Yes | Yes | Yes | Yes | Yes | Yes | I |
| 9/4/2018 10:39:26 | Yes | No | No | No | No | No | Yes | I |

In case of unstructured data like images, the input vector is just the pixel values. So the question, what are the features?

The answer to this question defines if we do ML or DL

In general, if we feed raw pixels, we do DL, if we define specific features, we do ML. This will get more clear

Semantic gap - What the computer can see?

https://colab.research.google.com/drive/1lwhBkAvgBG0QiBwGPJb2FbOXtz_sQyBW?authuser=1#scrollTo=kJbwGQ5QhYXa

Semantic gap - What is the best representation of sensory signals for computers?

Old problem → ADC

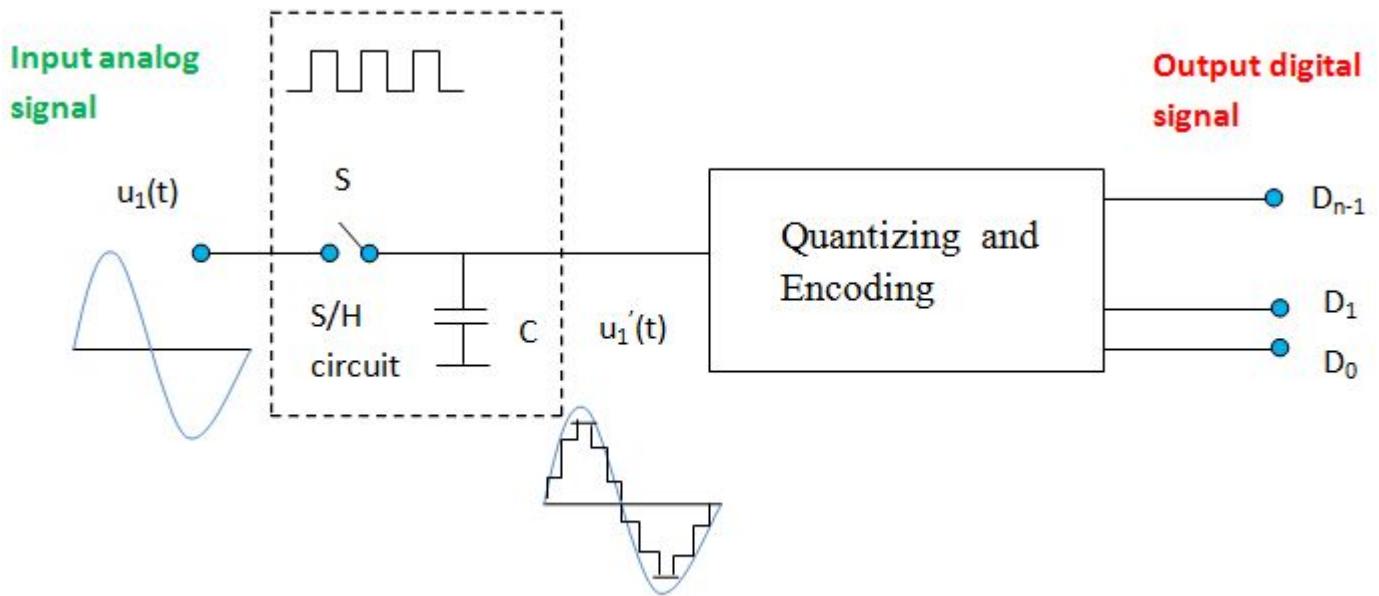
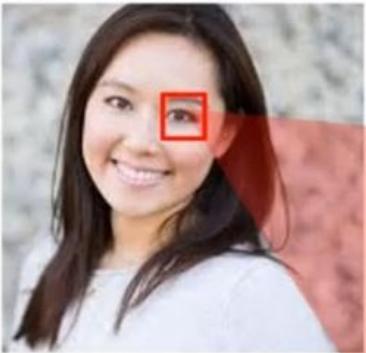


Figure 2

Semantic gap - What the computer can see?



| | | | | | | | | | |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 30 | 32 | 22 | 12 | 10 | 10 | 12 | 33 | 35 | 30 |
| 12 | 11 | 12 | 234 | 170 | 176 | 13 | 15 | 12 | 12 |
| 234 | 222 | 220 | 230 | 200 | 222 | 230 | 234 | 56 | 78 |
| 190 | 220 | 186 | 112 | 110 | 110 | 112 | 180 | 30 | 32 |
| 49 | 250 | 250 | 250 | 4 | 2 | 254 | 200 | 44 | 6 |
| 55 | 250 | 250 | 250 | 3 | 1 | 250 | 245 | 25 | 3 |
| 189 | 195 | 199 | 150 | 110 | 110 | 182 | 190 | 199 | 55 |
| 200 | 202 | 218 | 222 | 203 | 200 | 200 | 208 | 215 | 222 |
| 219 | 215 | 220 | 220 | 222 | 214 | 215 | 210 | 220 | 220 |
| 220 | 220 | 220 | 220 | 221 | 220 | 221 | 220 | 220 | 222 |

Image Classification: A core task in Computer Vision

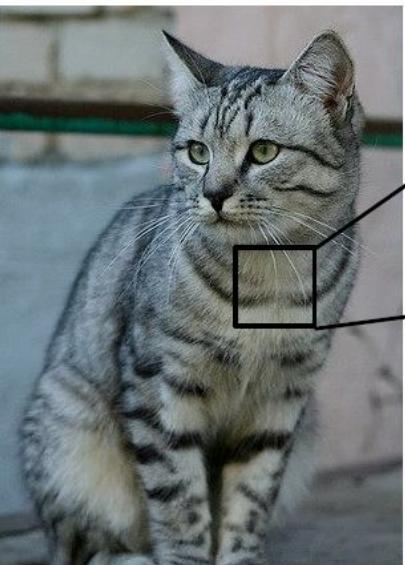


This image by Nikita is
licensed under CC-BY 2.0

(assume given set of discrete labels)
{dog, cat, truck, plane, ...}



The Problem: Semantic Gap



This image by Nikita is
licensed under CC-BY 2.0

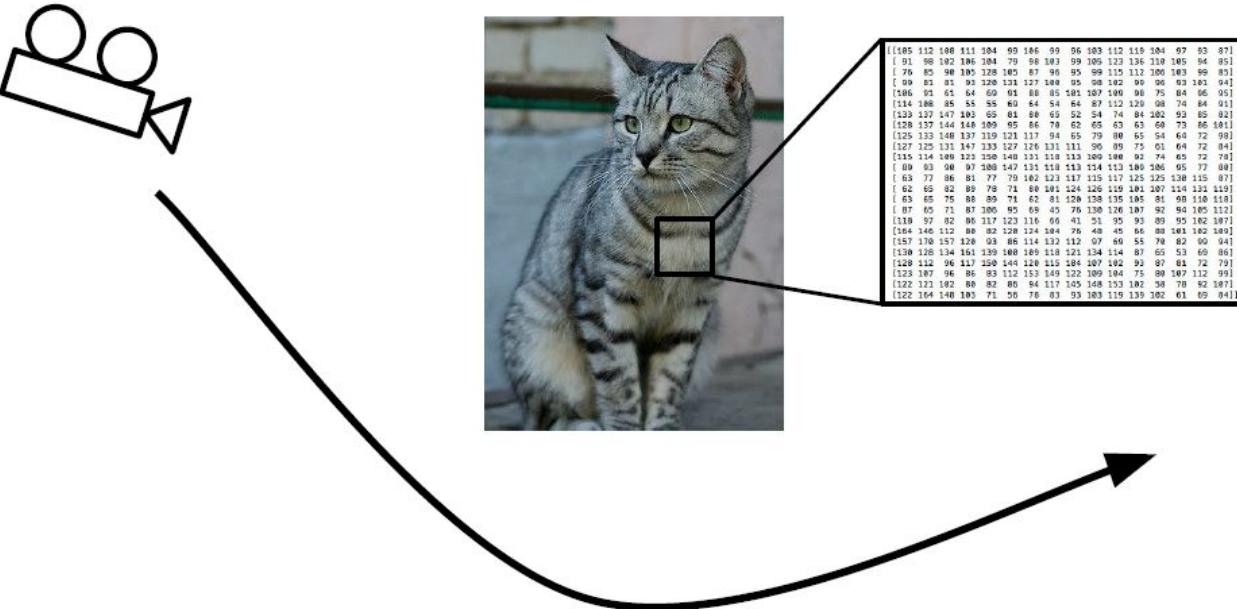
```
[165 112 108 111 104 99 106 99 96 103 112 119 104 97 93 87]  
[ 91 98 102 106 104 79 98 103 99 105 123 136 110 105 94 85]  
[ 76 85 90 105 128 105 87 96 95 99 115 112 105 103 99 85]  
[ 99 81 81 93 128 137 127 108 95 98 102 99 96 97 101 94]  
[105 91 61 64 69 91 81 85 101 107 109 98 75 84 96 95]  
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[133 137 147 103 65 83 88 65 52 54 74 84 102 93 85 82]  
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[125 133 148 137 119 121 117 94 65 79 80 65 54 64 72 98]  
[127 125 131 147 133 127 126 131 111 96 89 75 61 64 72 84]  
[115 114 109 123 158 148 131 118 113 109 108 92 74 65 72 78]  
[ 89 93 90 97 108 147 131 118 113 114 113 109 106 95 77 80]  
[ 63 77 86 81 77 79 102 123 117 115 117 125 125 130 115 87]  
[ 62 65 82 89 78 71 88 101 124 126 119 101 107 114 131 119]  
[ 63 65 75 88 89 71 62 81 128 138 135 105 81 98 118 118]  
[ 87 65 71 87 106 95 69 45 76 130 126 107 92 94 105 112]  
[118 97 82 86 117 123 115 66 41 51 95 93 89 95 102 107]  
[164 146 112 89 82 126 121 104 76 48 45 56 88 101 102 109]  
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[130 128 134 151 139 100 109 118 121 134 114 87 65 53 69 86]  
[128 112 96 117 158 144 120 115 104 107 102 93 87 81 72 79]  
[123 107 96 86 83 112 153 149 122 109 104 75 88 107 112 99]  
[122 121 102 80 82 86 94 117 145 148 153 102 58 70 92 107]  
[122 164 148 103 71 56 78 83 93 103 119 139 102 61 69 84])
```

What the computer sees

An image is just a big grid of
numbers between [0, 255]:

e.g. 800 x 600 x 3
(3 channels RGB)

Challenges: Viewpoint variation



All pixels change when
the camera moves!

This image by [Nikita](#) is
licensed under [CC-BY 2.0](#)

Challenges: Illumination



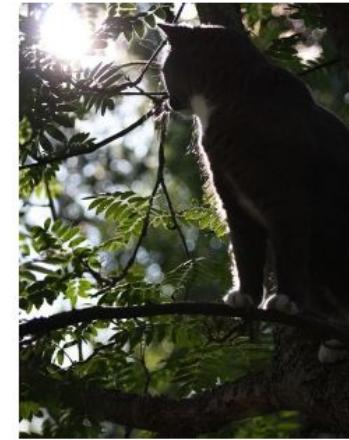
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Challenges: Deformation



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[This image by sare_bear](#) is
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[This image by Tom Thai](#) is
licensed under CC-BY 2.0

Challenges: Occlusion



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Semantic gap in text - What computers can read?

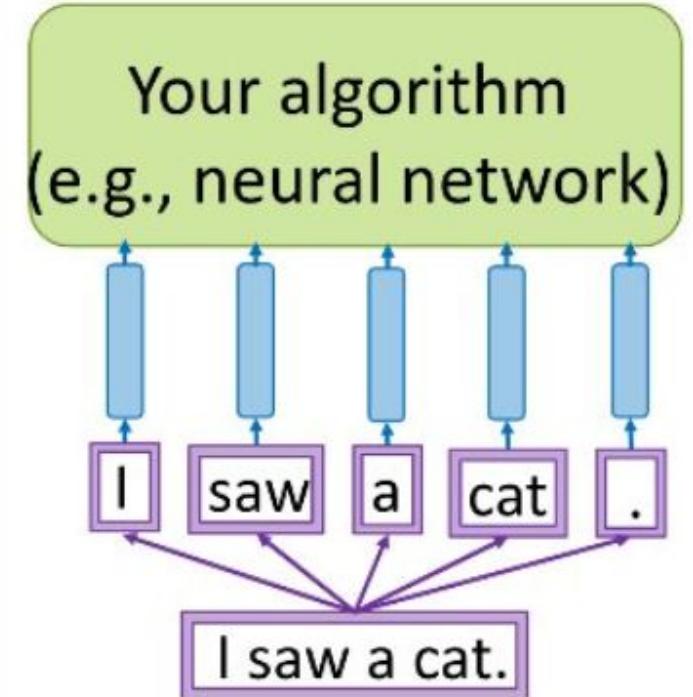
In images, we have matrix representation

In text → ??

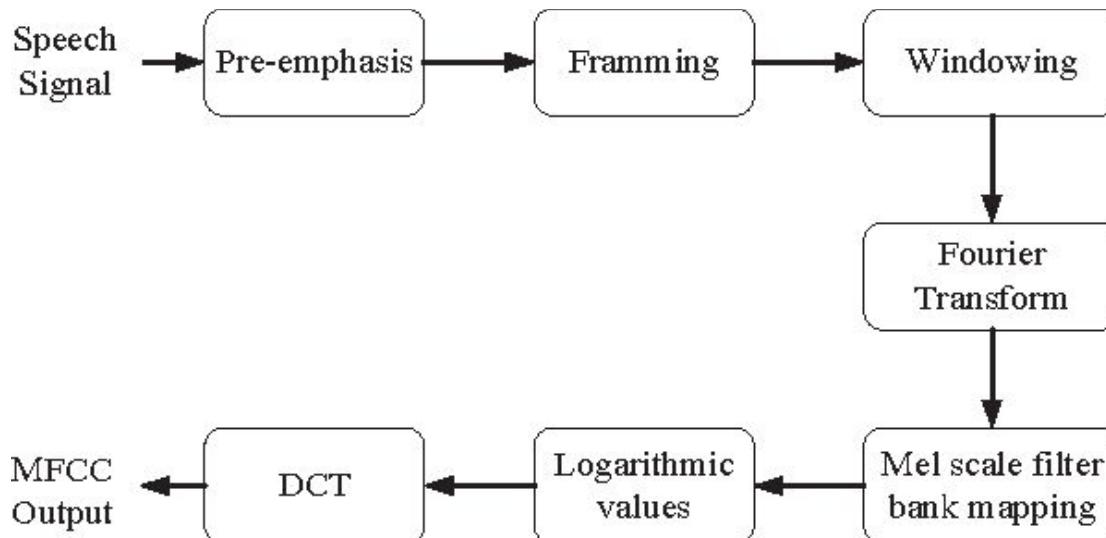
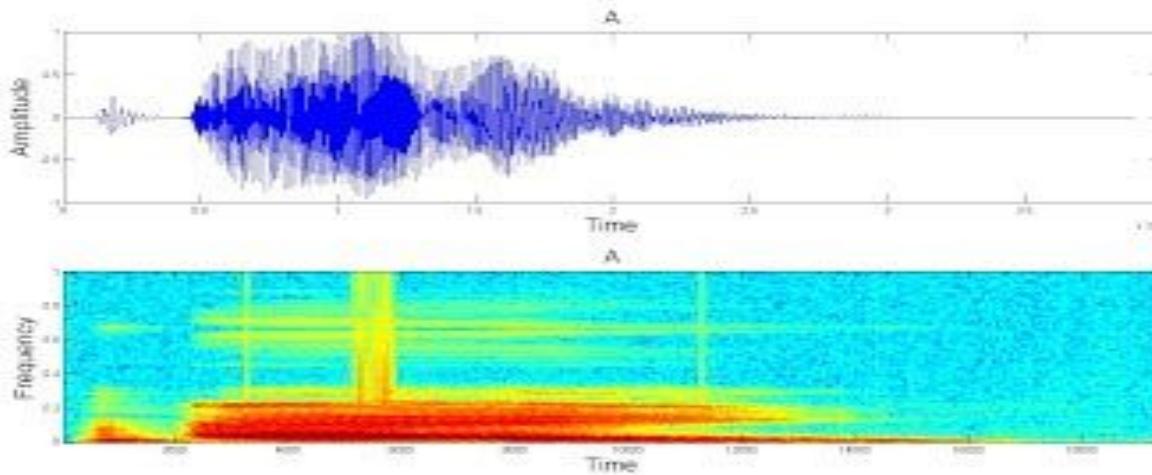
→ Naive = BoW against vocab

| Raw Text | Bag-of-words vector |
|-----------|---------------------|
| it | 2 |
| they | 0 |
| puppy | 1 |
| and | 1 |
| cat | 0 |
| aardvark | 0 |
| cute | 1 |
| extremely | 1 |
| ... | ... |

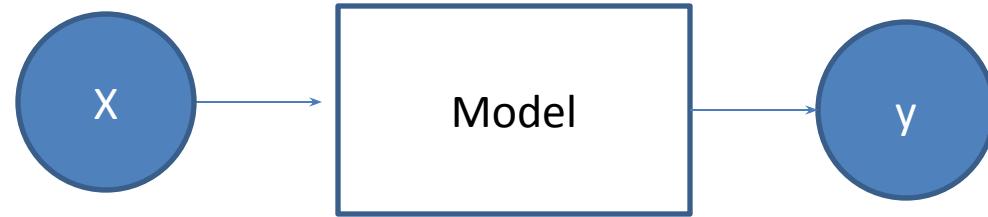
it is a puppy and it
is extremely cute



Semantic gap in speech - What computers can hear?

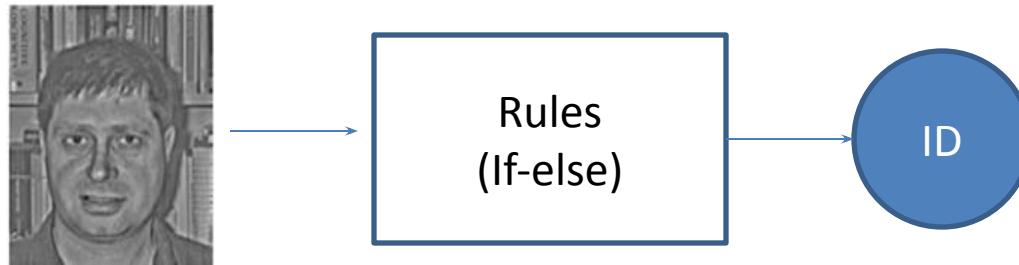


How to close the Gap?



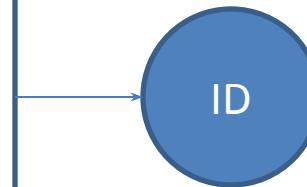
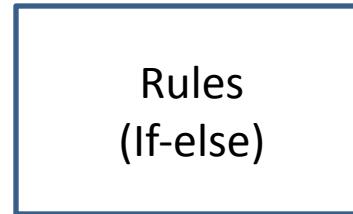
How to obtain the model?

Face recognition with traditional AI



Rule based AI

Face recognition with traditional AI

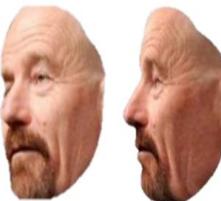


Did you handle Clutter?



Did you handle scale?

Did you handle pose?



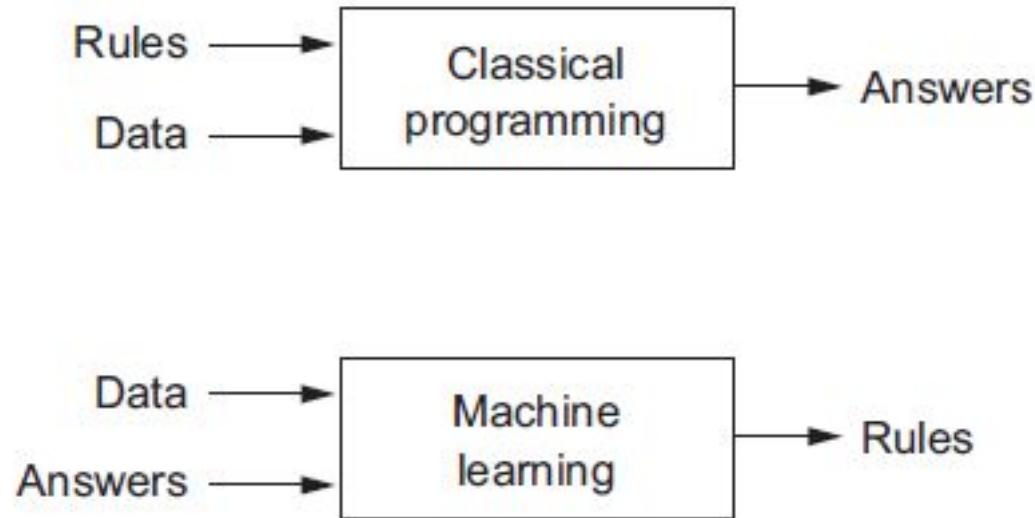
Did you handle colors?

Too many cases!!



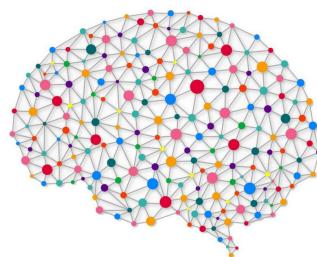
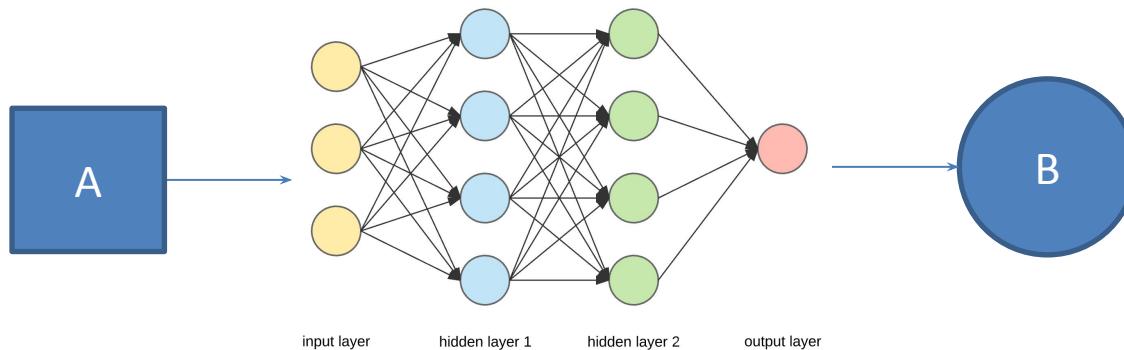
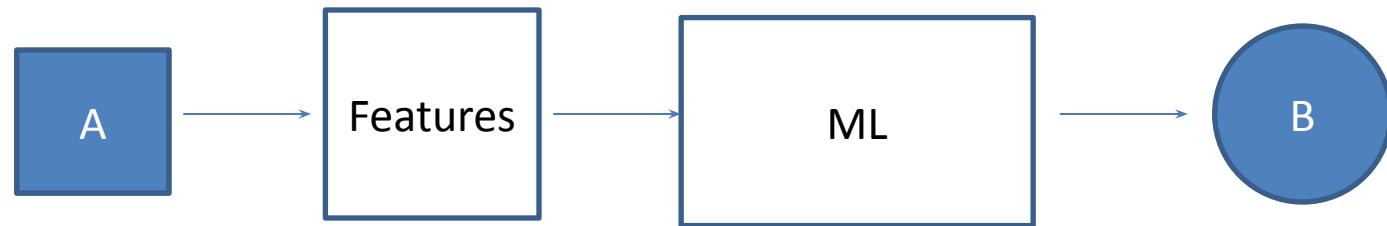
Let's Learn the rule!

Rule based AI vs. ML

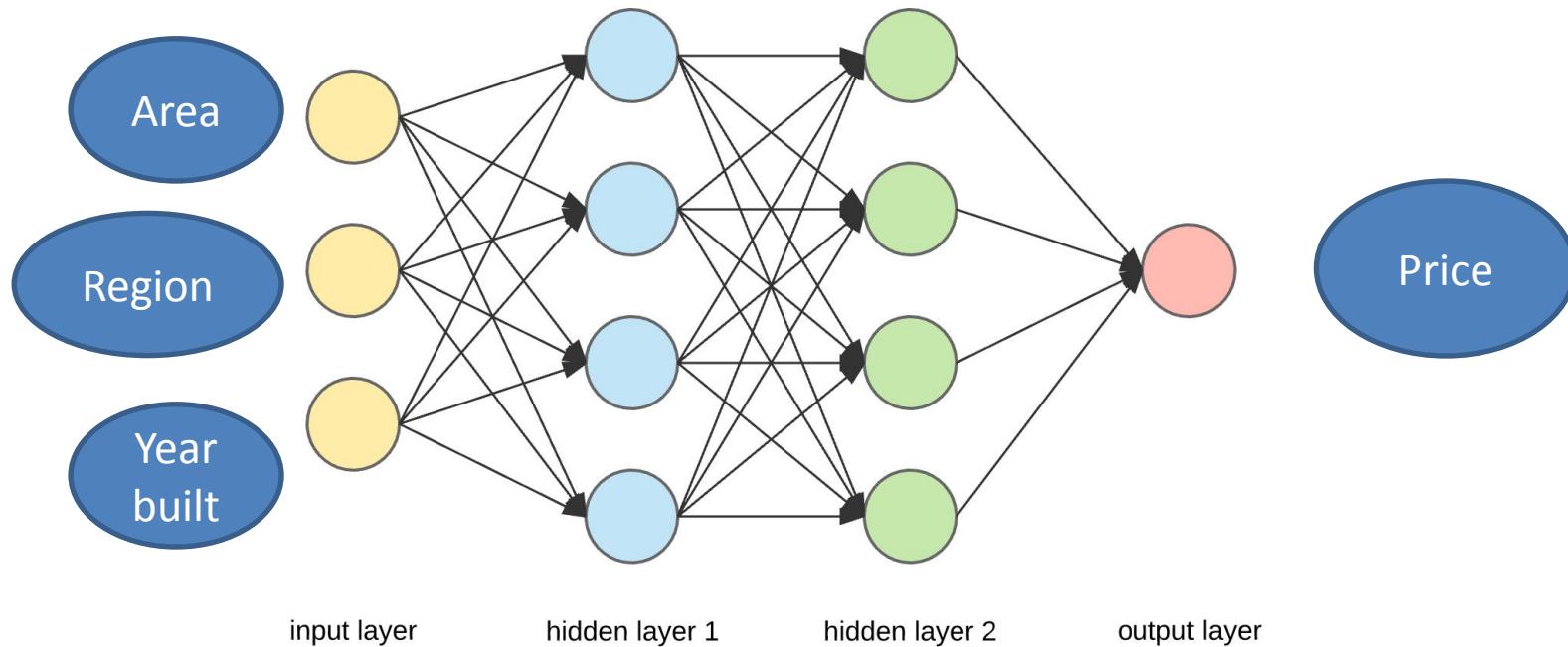


“Machine learning is the science of getting computers to act without being explicitly programmed”, Arthur Samuel 1959

Deep Learning vs. Machine Learning

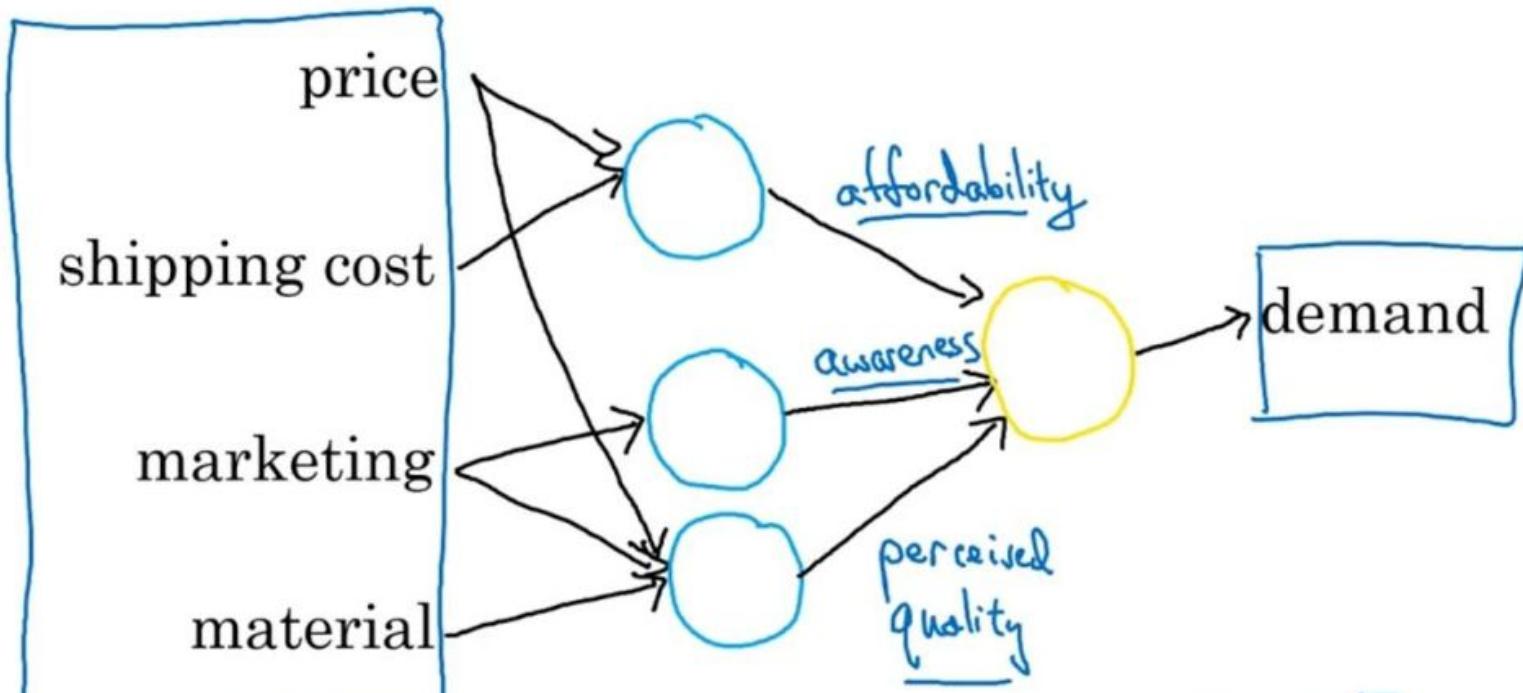


Deep Learning vs. Machine Learning



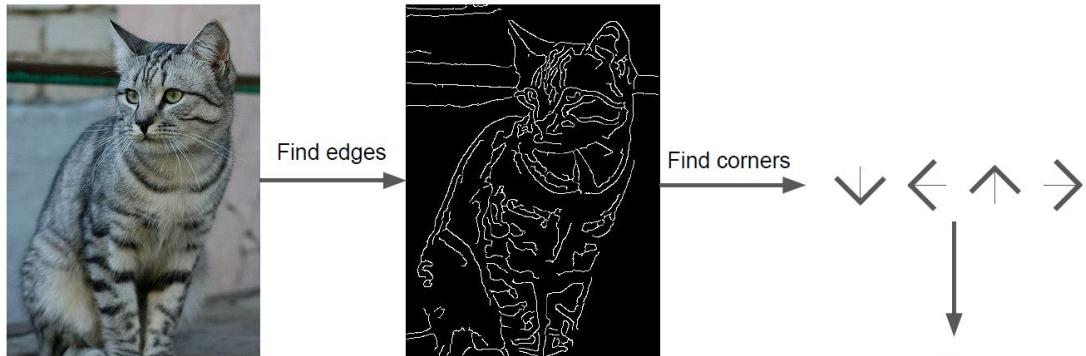
| Price | Floor space | Rooms | Lot size | Appartment | Row house | Corner house | Detached |
|--------|-------------|-------|----------|------------|-----------|--------------|----------|
| 250000 | 71 | 4 | 92 | 0 | 1 | 0 | 0 |
| 209500 | 98 | 5 | 123 | 0 | 1 | 0 | 0 |
| 349500 | 128 | 6 | 114 | 0 | 1 | 0 | 0 |
| 250000 | 86 | 4 | 98 | 0 | 1 | 0 | 0 |
| 419000 | 173 | 6 | 99 | 0 | 1 | 0 | 0 |
| 225000 | 83 | 4 | 67 | 0 | 1 | 0 | 0 |
| 549500 | 165 | 6 | 110 | 0 | 1 | 0 | 0 |
| 240000 | 71 | 4 | 78 | 0 | 1 | 0 | 0 |
| 340000 | 116 | 6 | 115 | 0 | 1 | 0 | 0 |

What neurons represent?



ML = manually engineered features vector But learn the weights

Attempts have been made

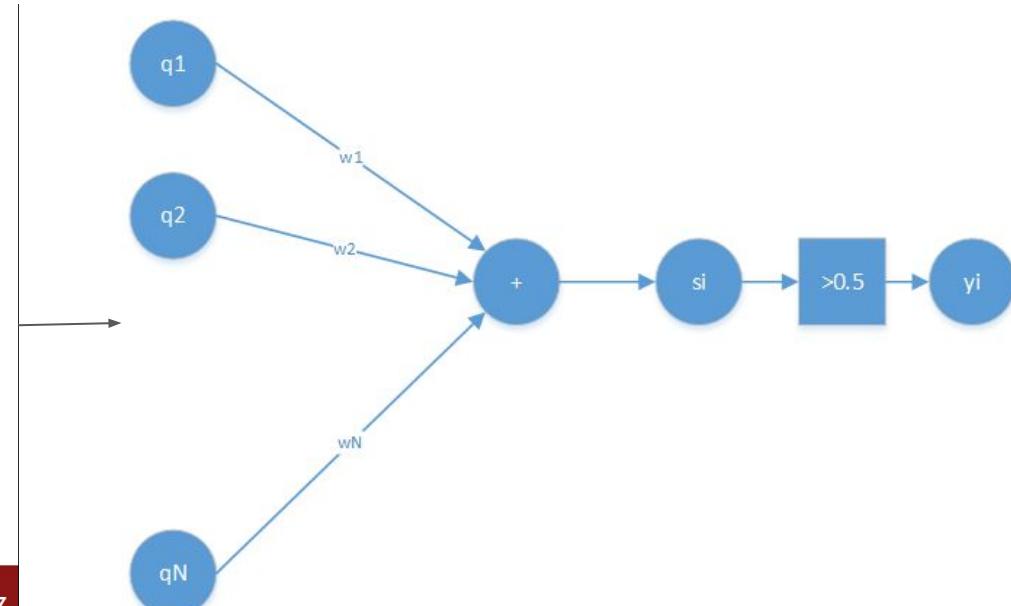


John Canny, "A Computational Approach to Edge Detection", IEEE TPAMI 1986

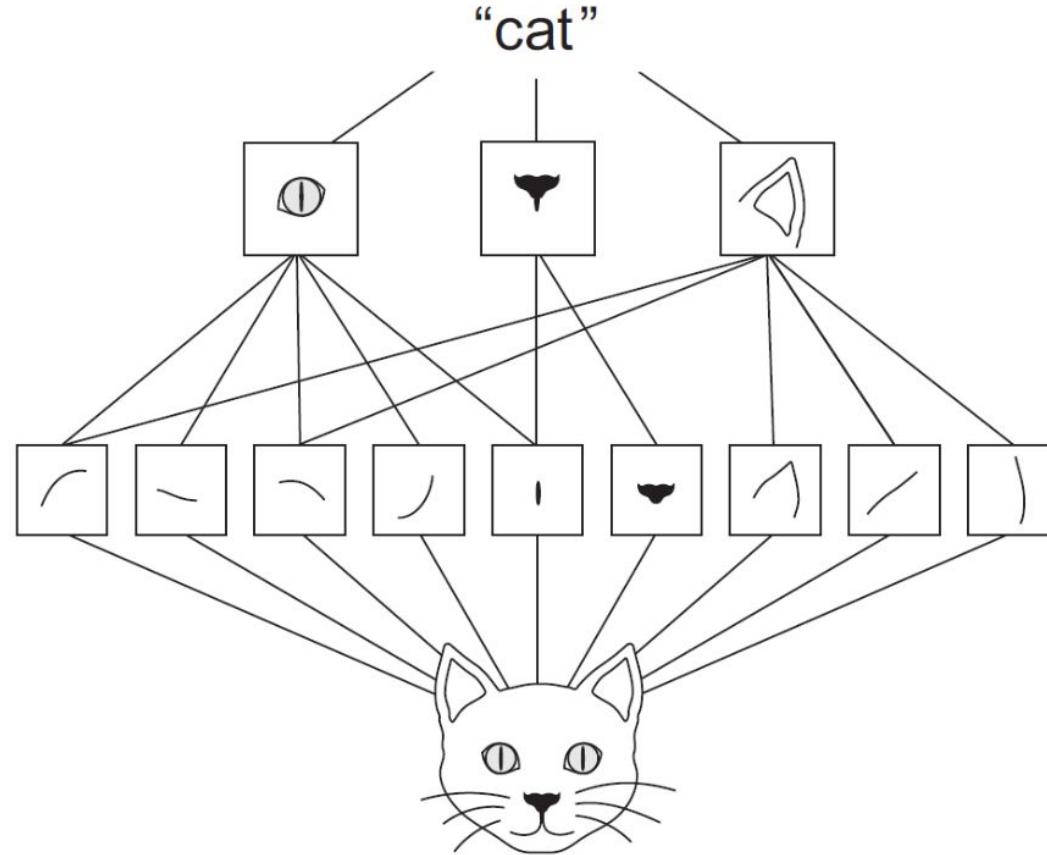
Fei-Fei Li & Justin Johnson & Serena Yeung

Lecture 2 - 15

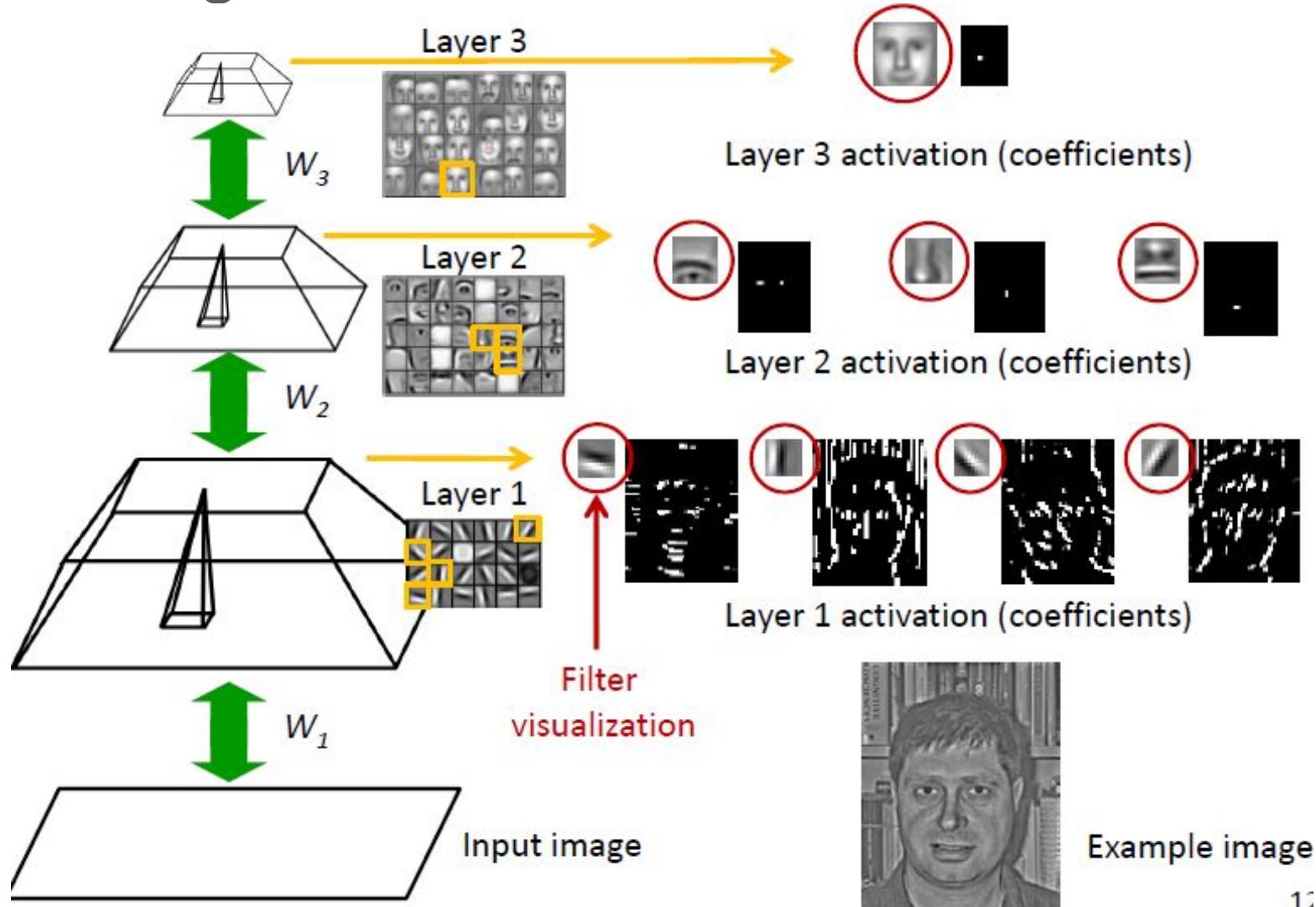
April 6, 2017



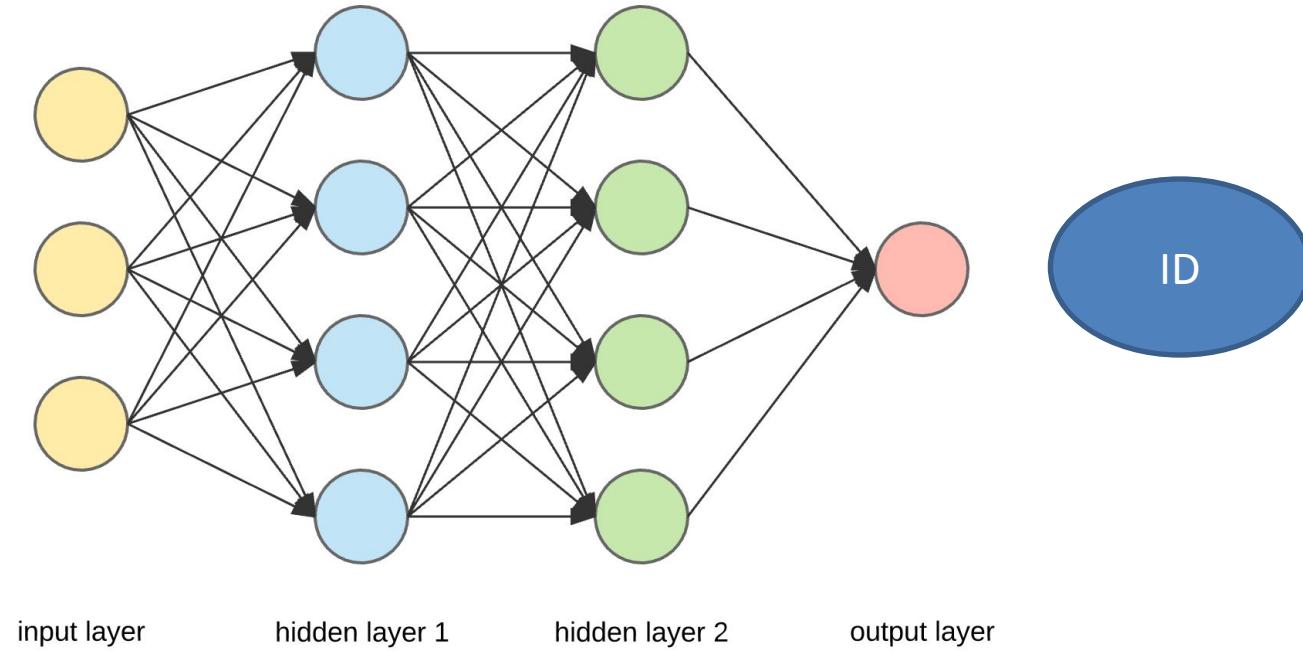
What could be good cat features?



What could be good face features?



Deep Learning vs. Machine Learning



What neurons can see?

Face recognition

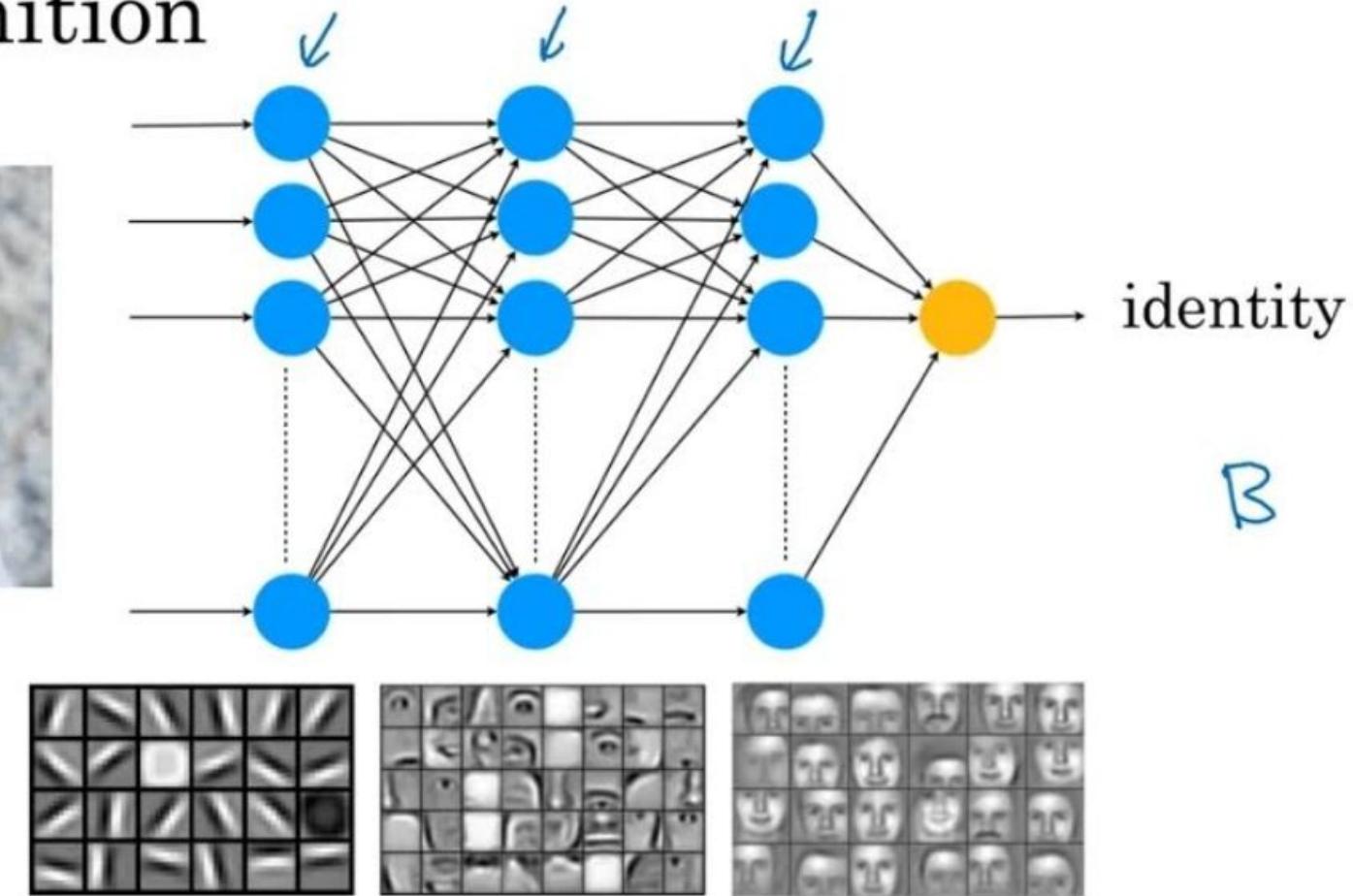


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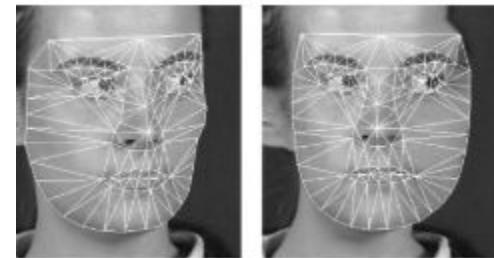


B

Features

Raw data = pixels

Features = $f(\text{Raw data})$



Features = face points

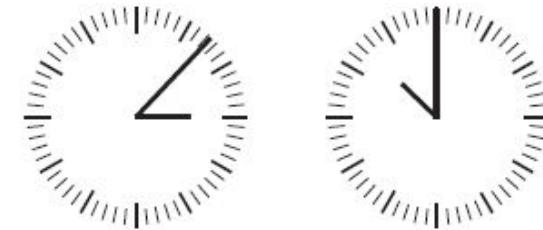
Feature is a representation / transformation of raw data

Why representation matters so much?

Which is easier to read the time?

- to make computer vision program to see the analog form
- just read x1,y1 and x2,y2 of the 2 pointers?
- just read theta 1 and theta 2 of the 2 pointers?

Raw data:
pixel grid



Better
features:
clock hands'
coordinates

{x1: 0.7,
y1: 0.7}
{x2: 0.5,
y2: 0.0}

{x1: 0.0,
y1: 1.0}
{x2: -0.38,
y2: 0.32}

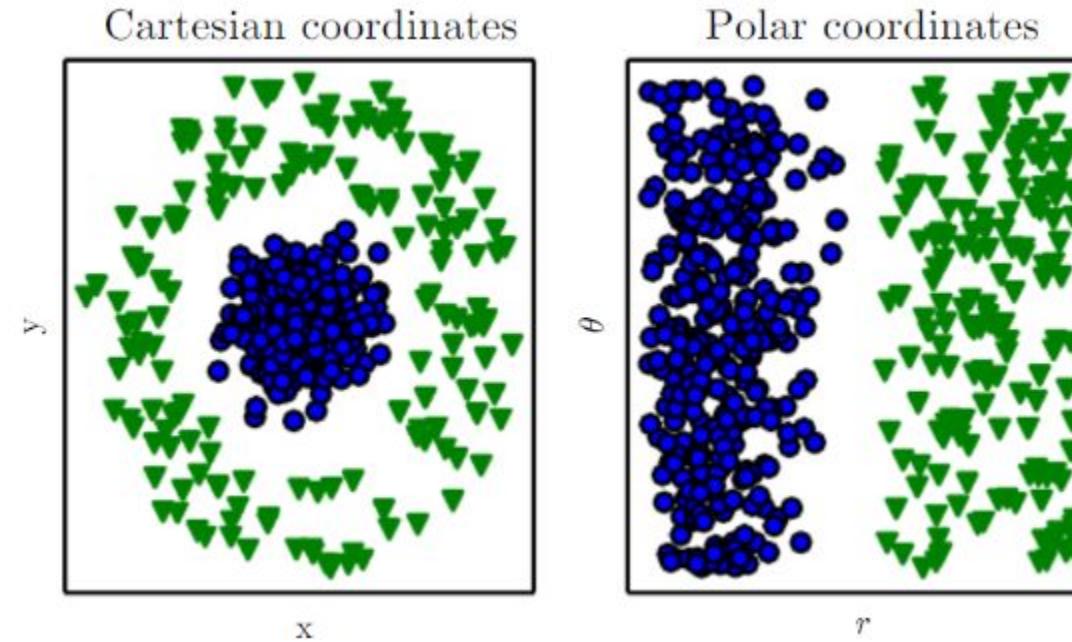
Even better
features:
angles of
clock hands

theta1: 45
theta2: 0

theta1: 90
theta2: 140

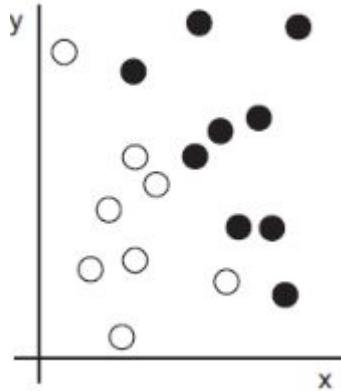
Why representation matters so much?

We have two categories (blue/green) which we want to cluster/separate/classify

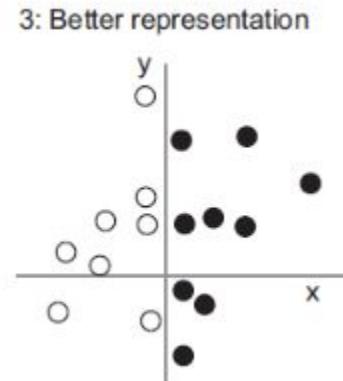
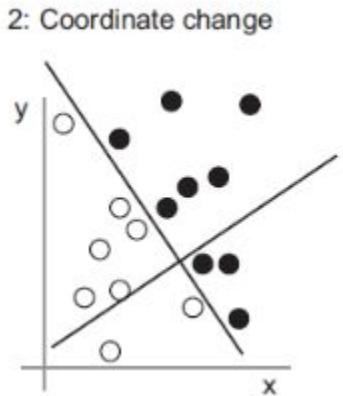
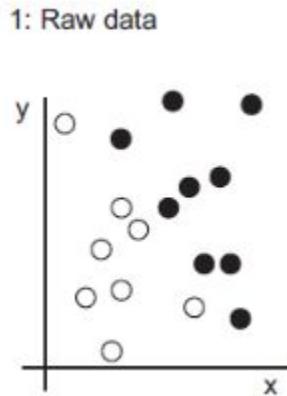


So separating the two classes in this case is much easier just by using polar representation

Why representation matters so much?

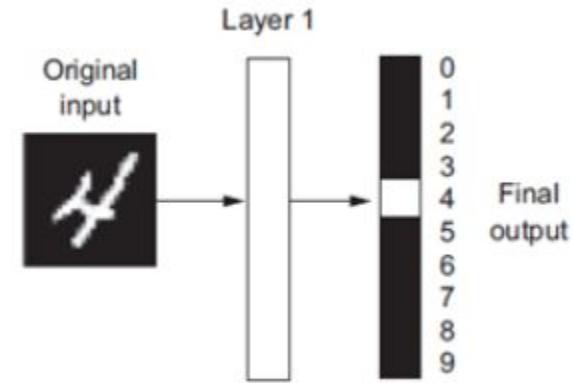


We want to develop an algorithm that can take the coordinates (x, y) of a point and output whether that point is likely to be black or to be white:
-Inputs: the coordinates of our points.
-Outputs: the colors of our points.

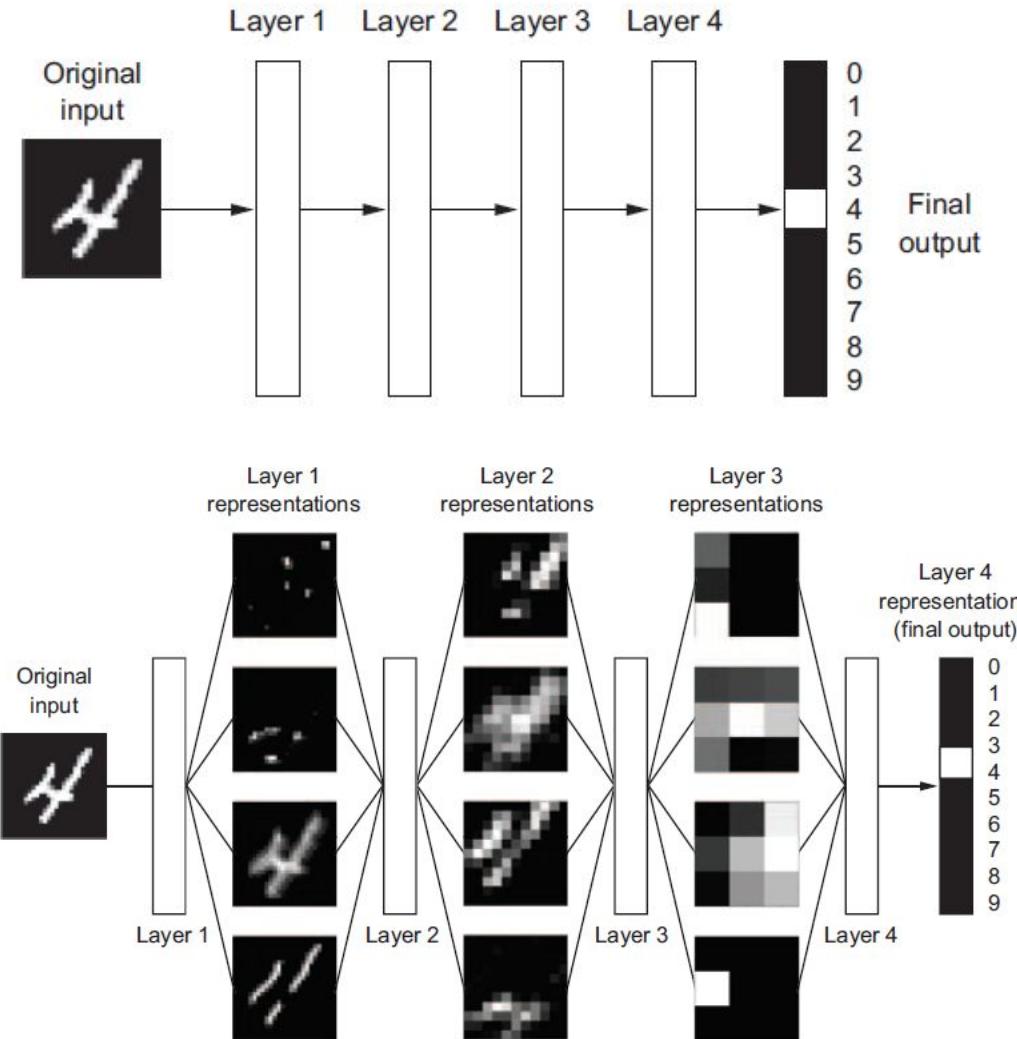


How to decide on which representation?

- Manual: ML
- Learning: DL
(Representation Learning)
- How ?
 - **Hypothesis space**: We have many possible transforms: f_1, f_2, \dots
 - **Learning**: Search in the *hypothesis space*



The “Deep” in Deep Learning Hierarchical Representation



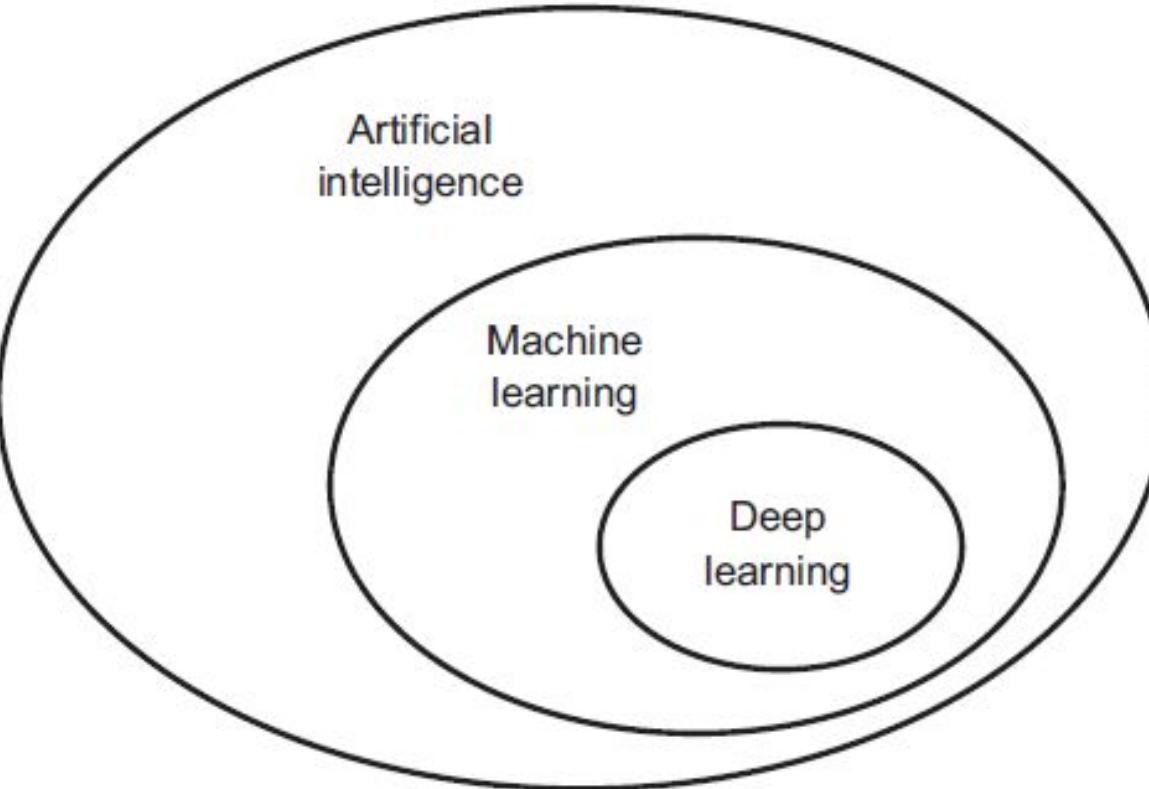
Now we converge to a definition of Deep Learning

Deep Learning = Deep Representation Learning

- “*Deep learning is a particular kind of machine learning that achieves great power and flexibility by learning to represent the world as a nested hierarchy of concepts, with each concept defined in relation to simpler concepts, and more abstract representations computed in terms of less abstract ones.*”
 - *Deep Learning Book, Ian Goodfellow, Yoshua Bengio, Aaron Courville*

Now we can draw a line
between AI, ML,
Representation Learning

a . . .



|

<https://www.deeplearningbook.org/>

Why now?

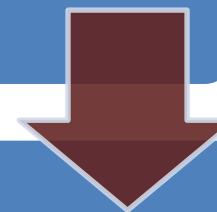
Computer

- Machine for logical and mathematical computations
- 1781 (Charles Babbage)



Programming

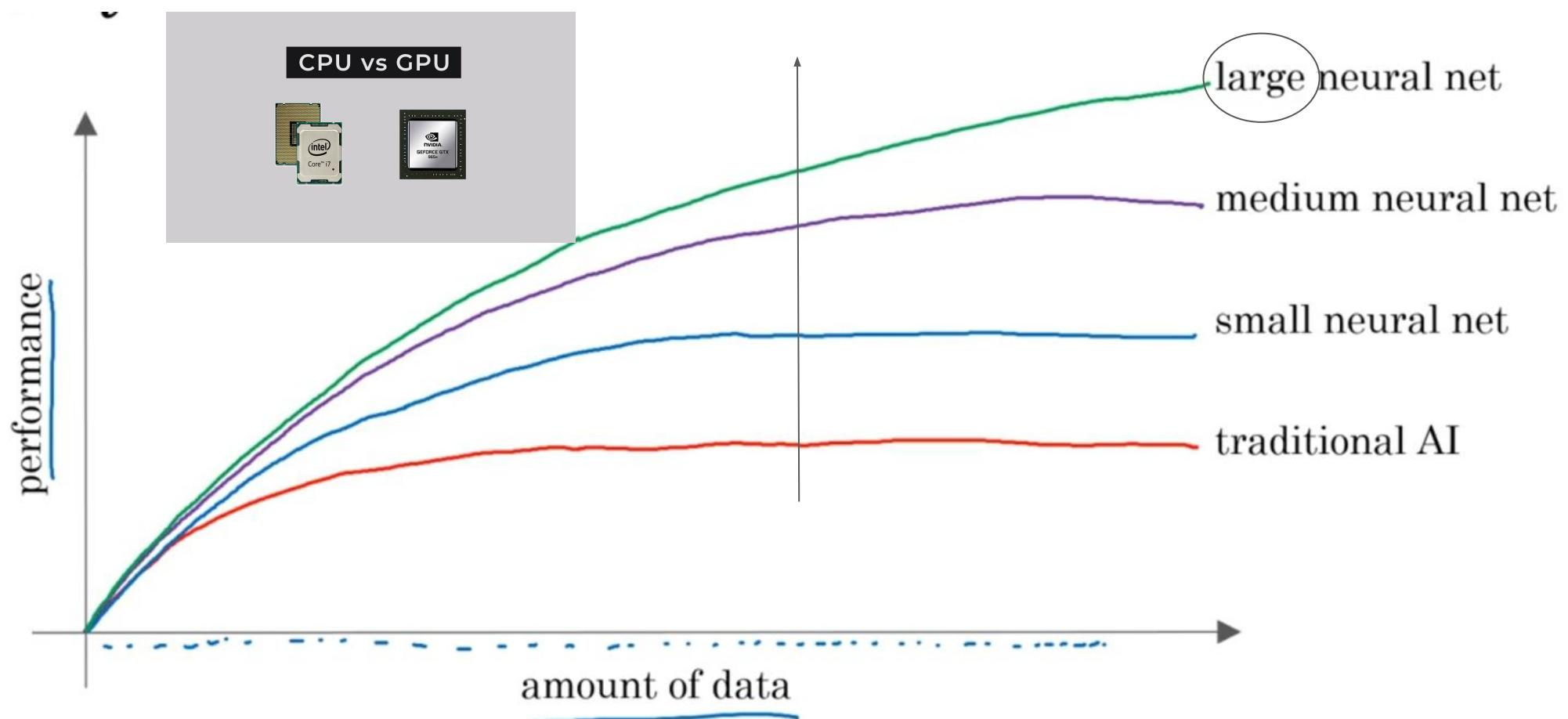
- If-else
- 1936 (Turing Machine)
- 1945 (ENIAC)



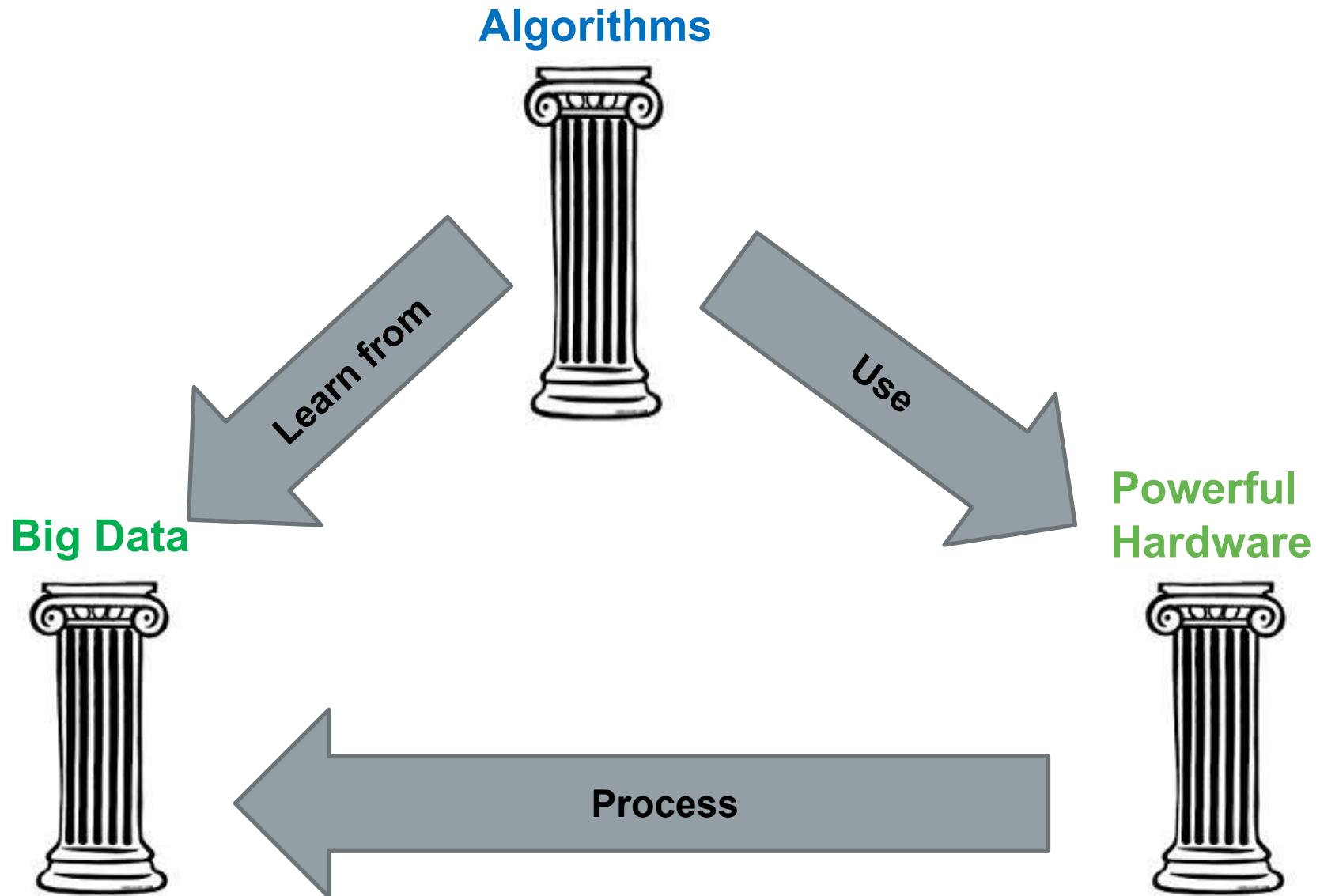
Machine learning

- 1959 (Arthur Samule)
- Problem: clutter, pose, conditions,...etc all affect the designed features vector

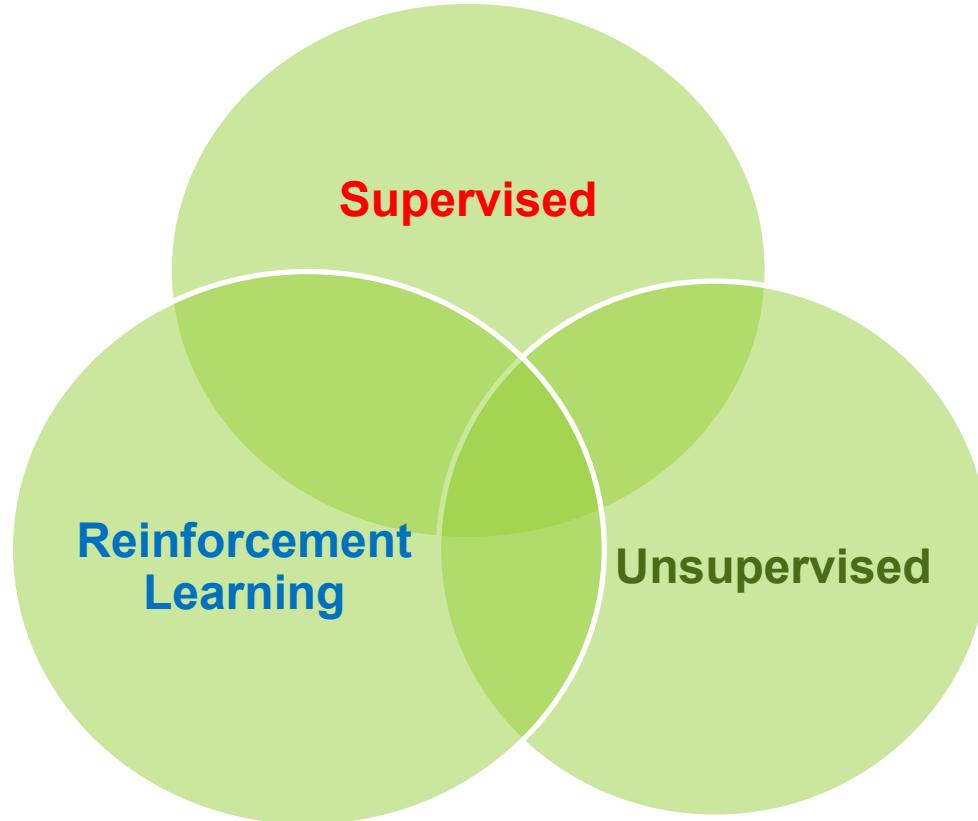
Why now?



Why now?

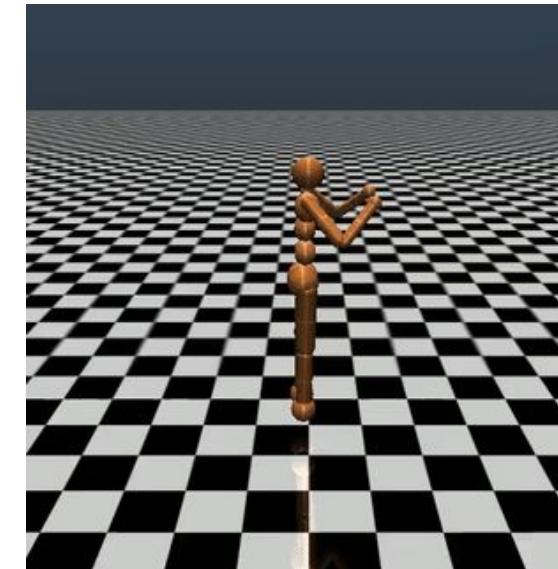
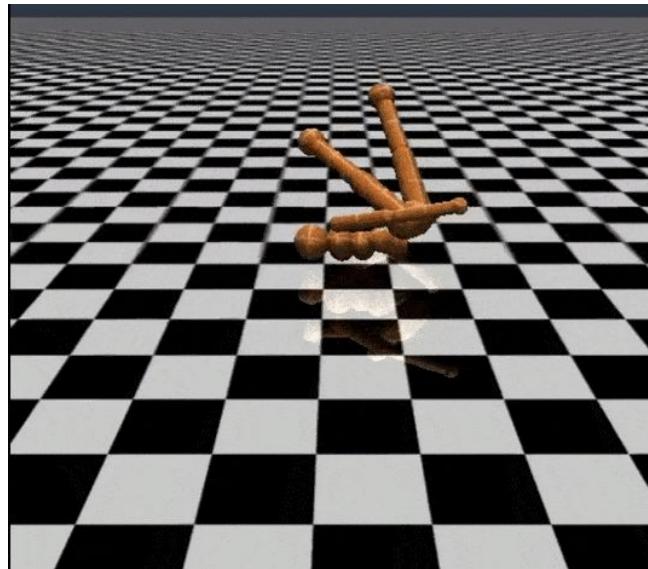


What other types of ML?



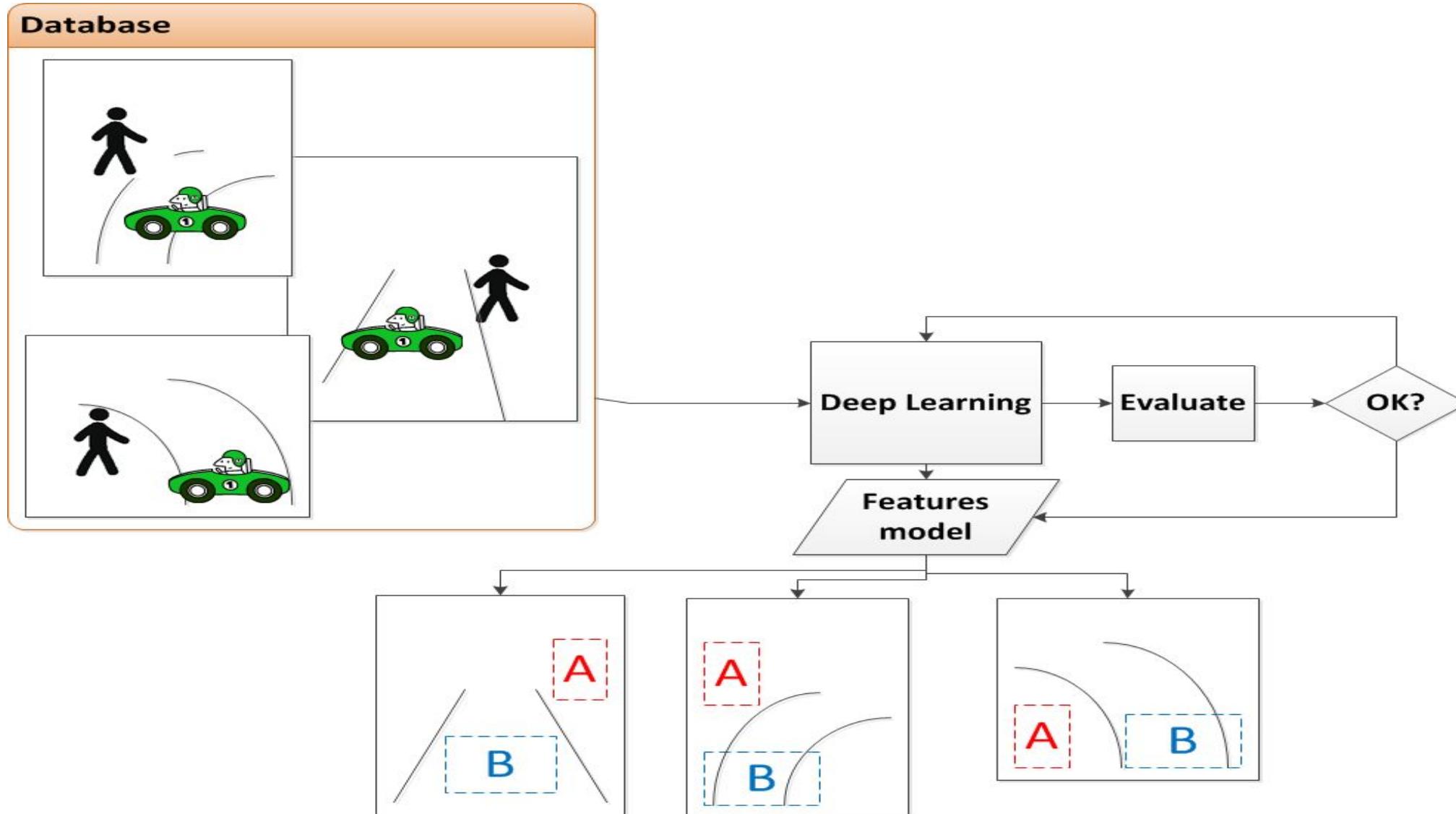
How it works? By interaction (Reinforcement)

Learning in mammals

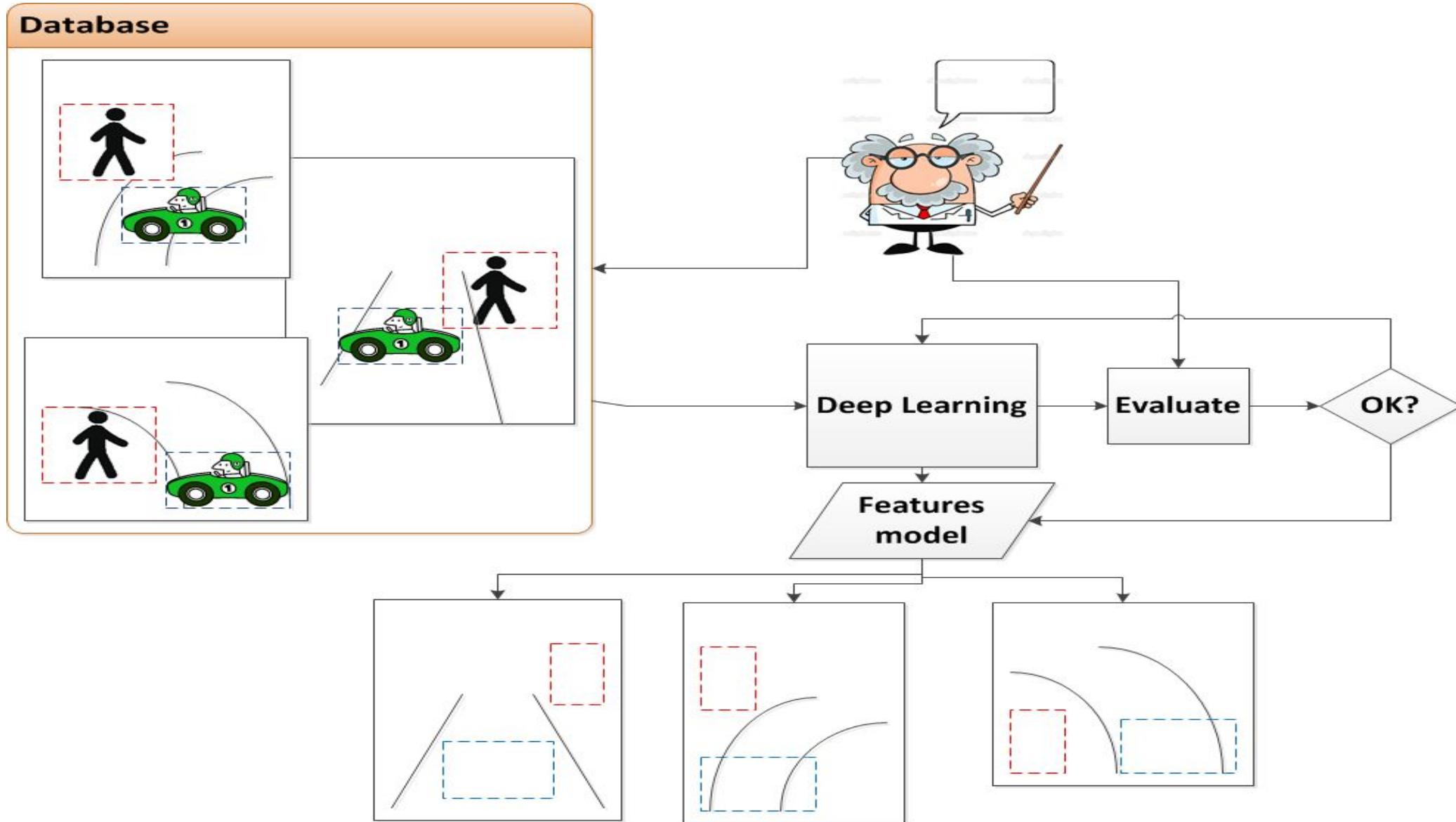


After many attempts

How it works? Unsupervised from big data



How it works? Supervised with a teacher



Transfer Learning

Car detection



100,000 images

Golf cart detection



100 images

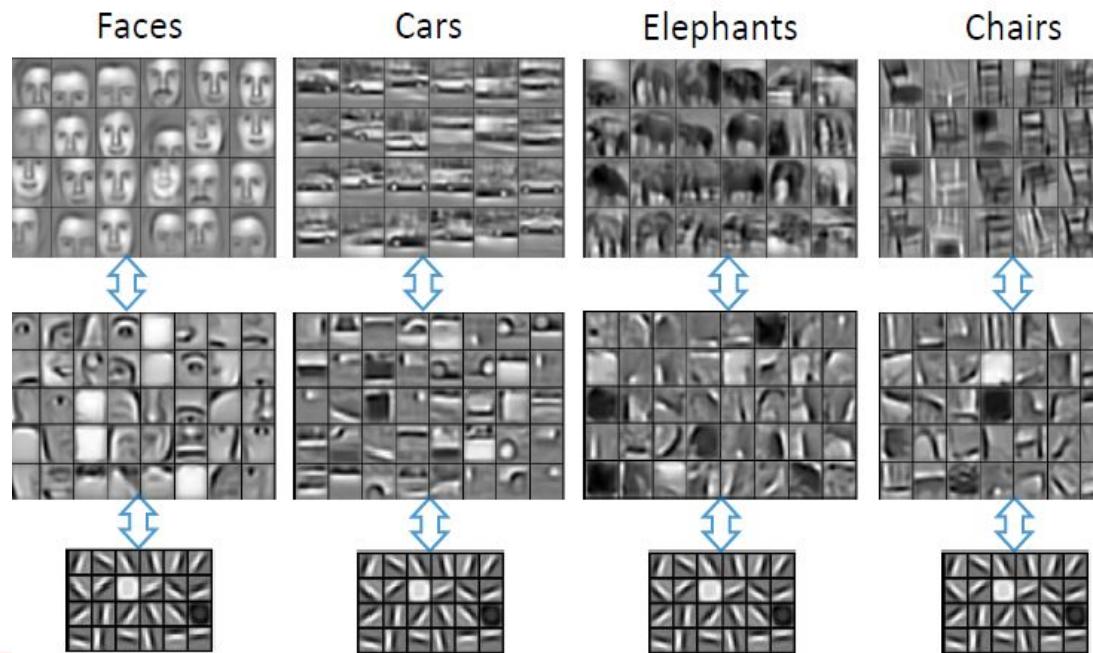
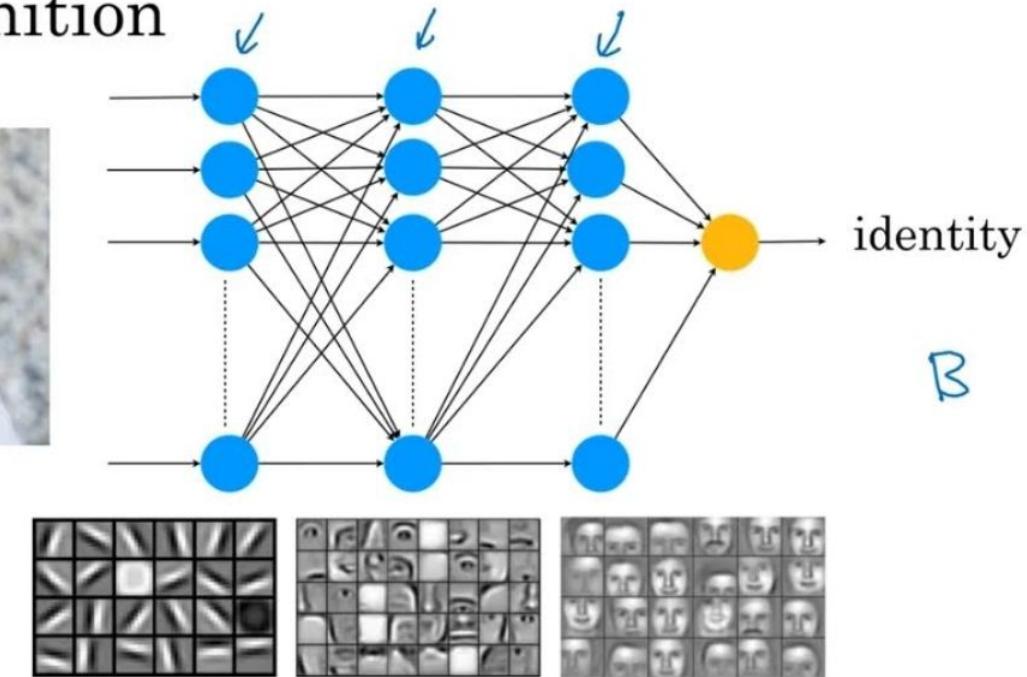
Learn from task A, and use knowledge to help on task B

Transfer Learning - How is it possible?

Face recognition

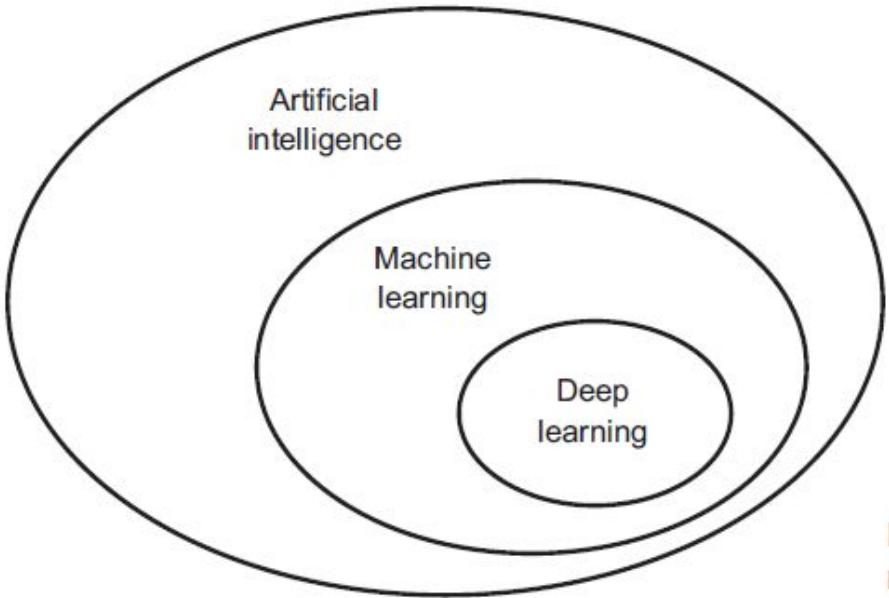


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Data science vs. Machine Learning

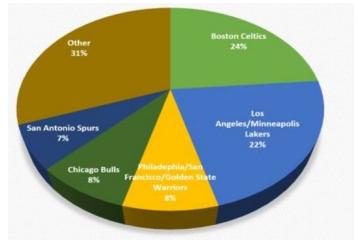
ML: “Make computers learn rather than explicitly programmed”, Arthur Samuel 1959



Output is software

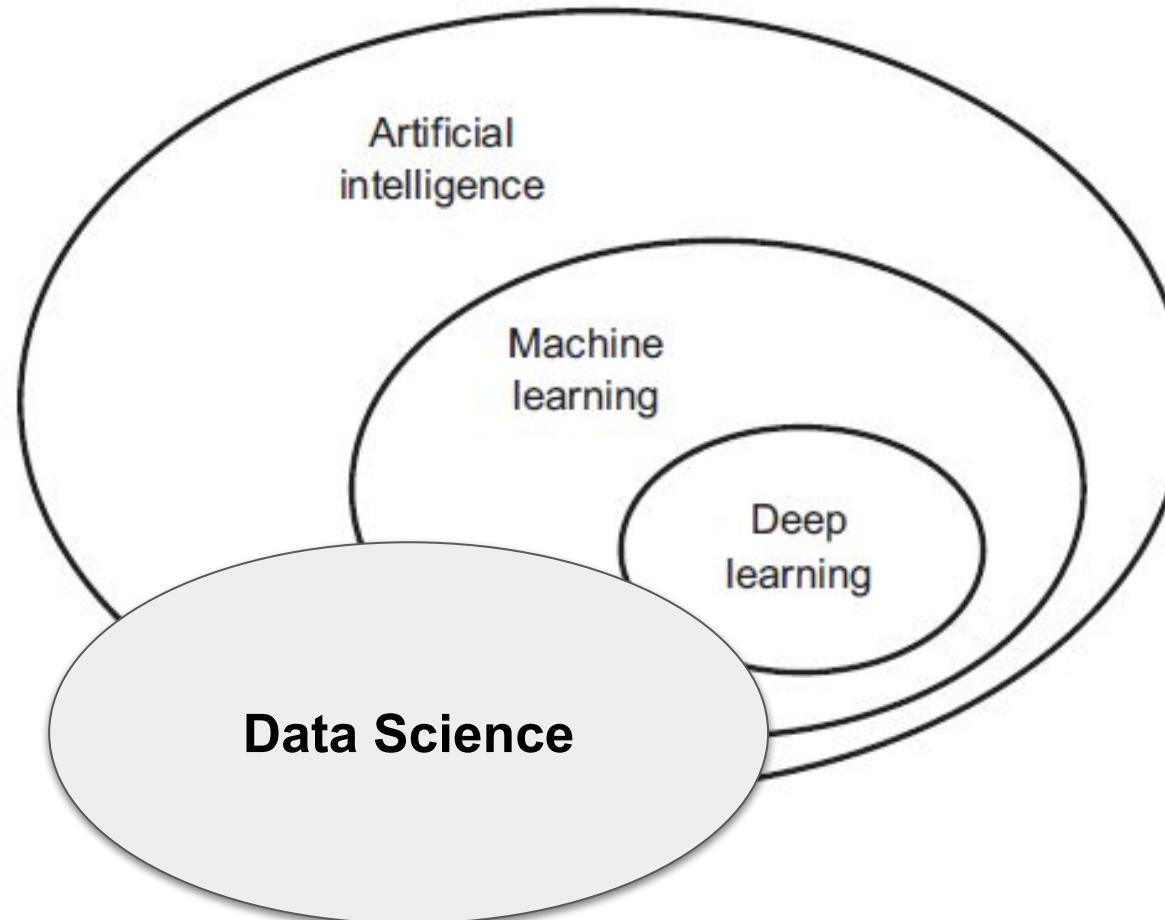
DS: “Science of extracting Knowledge and insights from data”

| Price | Floor space | Rooms | Lot size | Apartment | Row house | Corner house | Detached |
|--------|-------------|-------|----------|-----------|-----------|--------------|----------|
| 250000 | 71 | 4 | 92 | 0 | 1 | 0 | 0 |
| 209500 | 98 | 5 | 123 | 0 | 0 | 0 | 0 |
| 349500 | 128 | 6 | 114 | 0 | 1 | 0 | 0 |
| 250000 | 86 | 4 | 98 | 0 | 1 | 0 | 0 |
| 419000 | 173 | 6 | 99 | 0 | 1 | 0 | 0 |
| 225000 | 83 | 4 | 67 | 0 | 1 | 0 | 0 |
| 549500 | 165 | 6 | 110 | 0 | 1 | 0 | 0 |
| 240000 | 71 | 4 | 78 | 0 | 1 | 0 | 0 |
| 340000 | 116 | 6 | 115 | 0 | 1 | 0 | 0 |



Looking at market data, what is the best sales strategy?
Output = slide deck supporting decision making
“Speak with Data”

Data science vs. Machine Learning



Take away messages

ML is data driven

Global ML workflow

DL is more data driven + HW driven → Why now? GPU

AI is good at simple perception tasks and automation using analysis of tons of data

AI is not good at complex tasks. AGI is far.

Think statistical metrics. 100% is not possible.

AI Hype and Limitations: Bias, Attacks

References

<https://www.coursera.org/learn/ai-for-everyone>

<https://www.coursera.org/learn/machine-learning-projects>

<https://course.fast.ai/>

<https://www.deeplearningbook.org/>

QUESTIONS



**THANK
YOU**