

## **Artificial Intelligence**

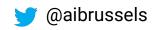
A broader perspective

#### **Current Trends in Al**

Johan Loeckx

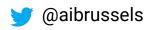
28/02/2020

jloeckx@ai.vub.ac.be



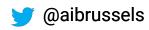
# Q#1 Give examples of "Al in use"

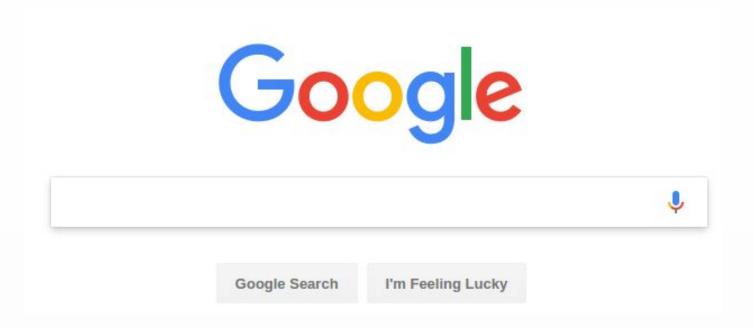




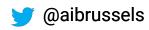






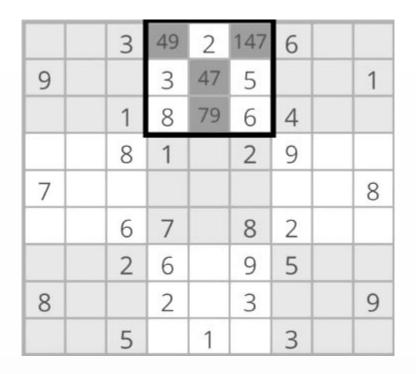












#### **LOGIC**

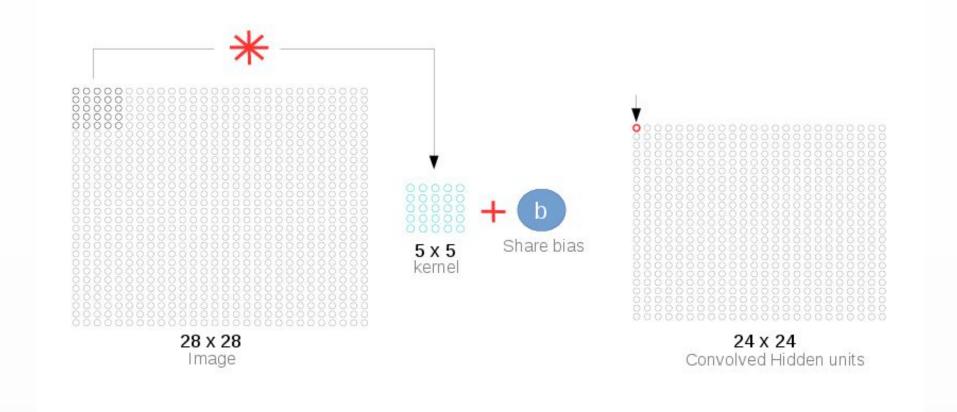
(e.g. model expansion)





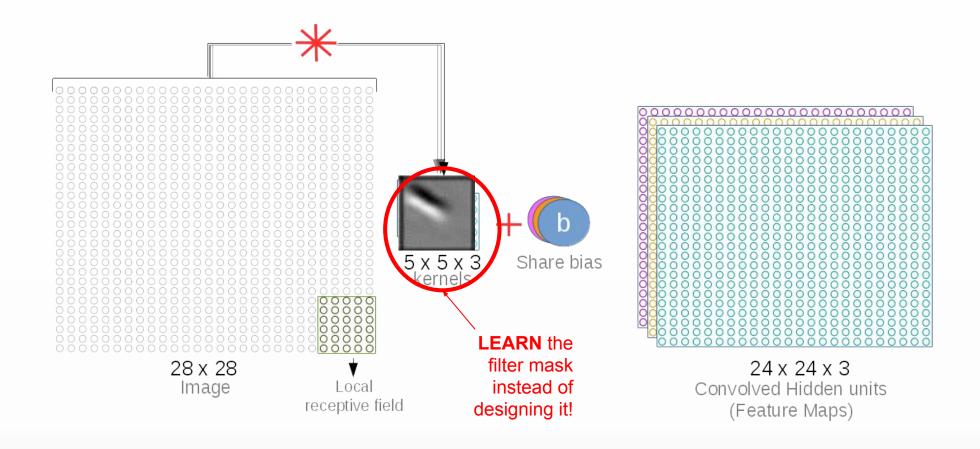


### Convolutionary neural networks

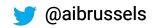




#### Convolutional neural network



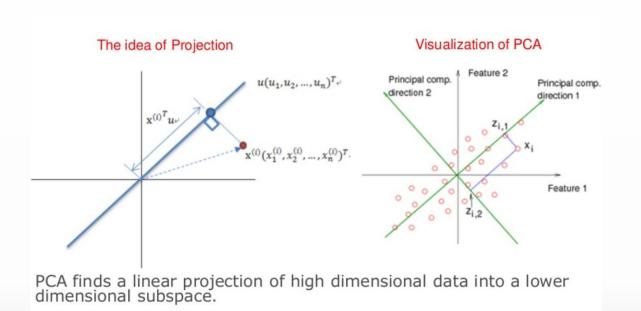


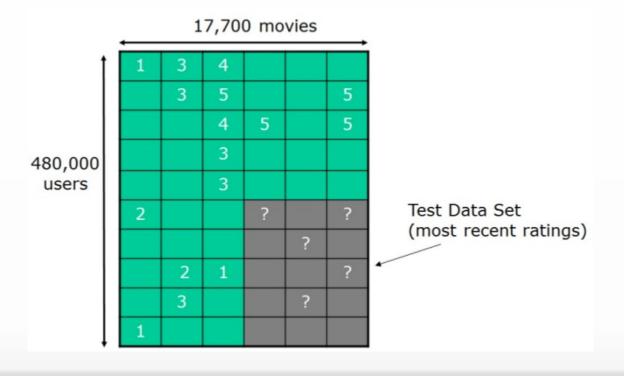


#### Recommendation

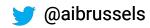
Given a sparse matrix of (user, item) preferences

Predict new preferences

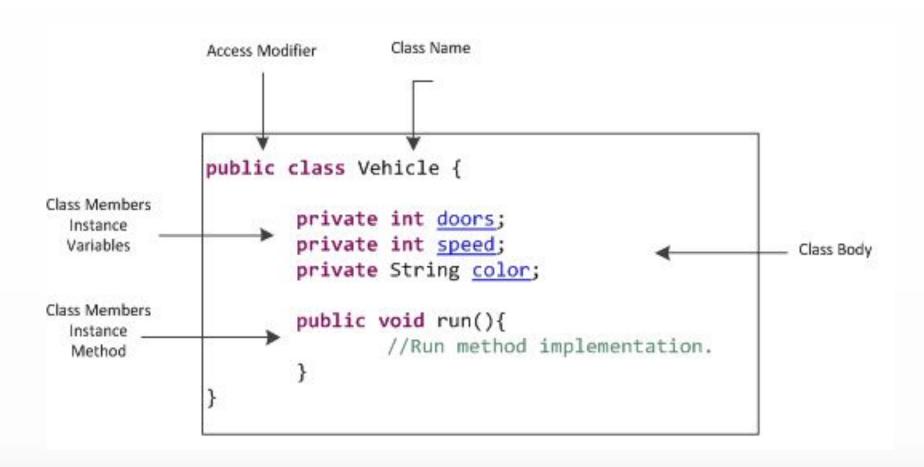








### Object-oriented programming





#### Natural language

TECHNOLOGY

#### A.I. Is Doing Legal Work. But It Won't Replace Lawyers, Yet.

By STEVE LOHR MARCH 19, 2017

James Yoon, a partner at Wilson Sonsini Goodrich

& Rosati in Palo Alto, Calif., says people are willing to pay for his experience. "What clients don't want

to pay for is any routine work."



working on the software meant to automate legal work say the adoption of A.I. in law firms will be a slow, task-by-task process. In other words, like it or not, a robot is not about to replace your lawyer. At least, not anytime soon.

"There is this popular view that if you can automate one piece of the work, the rest of the job is toast," said Frank Levy, a labor economist at the Massachusetts Institute of Technology. "That's just not true, or only rarely the case."

An artificial intelligence technique called natural language processing has proved useful

in scanning and predicting what documents will be relevant to a case, for example. Yet other lawyers' tasks, like advising clients, writing legal briefs, negotiating and appearing in court, seem beyond the reach of computerization, for a while.

"Where the technology is going to be in three to five years is the really interesting question," said Ben Allgrove, a partner at Baker McKenzie, a firm with 4,600 lawyers. "And the honest answer is we don't know."





A Lesson of Tesla Crashes? Computer Vision Can't Do It All Yet SEPT. 19, 2016

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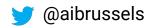
The Promise of Artificial Intelligence Unfolds in Small Steps FEB. 28, 2016



Robots Will Take Jobs, but Not as Fast as Some Fear, New Report Says JAN. 12, 2017

- + Sentiment analysis
- + Summarization
- + Classification & routing
- + Named entities, events

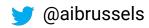






## Q#2 What is A!?





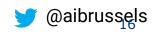
#### Al studies...

- 1. the nature and mechanisms of intelligence
- 2. Using formal methods, an
- 3. Attempts to **reconstruct** it.



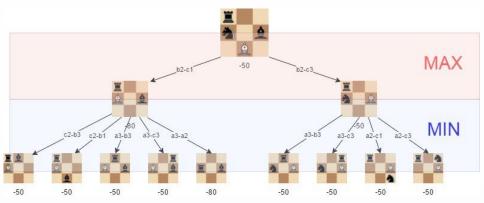
## in principle



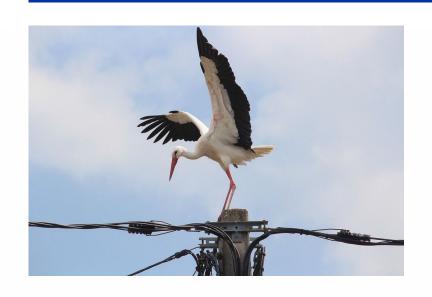


## Playing chess...





#### In principle: learn flying, not the bird.



- Do not copy the flapping wings
- Learn how a bird uses physics to fly

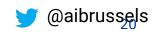
The question of whether a computer can think is no more interesting than the question of whether a submarine can swim -- Edsger W. Dijkstra

#### It does not serve a single function

- It's a mishmash of techniques, methods & ideas
- It's always at the front of computer science and is in continuous change
- It embodies the quest to express meaning in machines: a number can represent anything!

## 3 waves of artificial intelligence

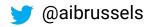




#### Waves of artificial intelligence

- 1. Manual coding
  - → if-then-rules, ad-hoc
- 2. Formalizing intelligence
  - → reformulate in a structured way (e.g. search)
- 3. Learning from data
  - → statistical patterns
- 4. Learning from interaction
  - → learn what decisions to take from rewards

learn from human knowledge, not data



1. Manual ad-hoc coding (not really called AI)



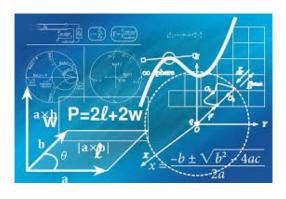




#### 2. **Symbolic** Al: learning from encoded **knowledge**







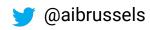
formalism!!





build upon existing implementations



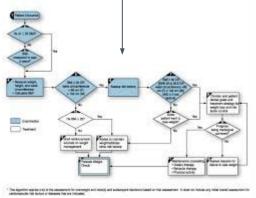


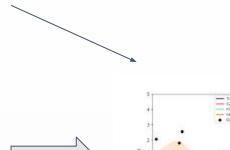
#### 3. Learning from data



time	n.cisk	n.event	survival	stderr	lower 95% CI	upper 95% CI
5	23	2	0.913	0.0588	0.8049	1
8	21	2	0.8261	0.079	0.6848	0.996
9	19	1	0.7826	0.086	0.631	0.971
12	18	1	0.7391	0.0916	0.5798	0.942
13	17	1	0.6957	0.0959	0.5309	0.912
18	14	1	0.646	0.1011	0.4753	0.878
23	13	2	0.5466	0.1073	0.3721	0.803
27	11	1	0.4969	0.1084	0.324	0.762
30	9	1	0.4417	0.1095	0.2717	0.718
31	8	1	0.3865	0.1089	0.2225	0.671
33	7	1	0.3313	0.1054	0.1765	0.622
34	6	1	0.2761	0.102	0.1338	0.569
43	5	1	0.2208	0.0954	0.0947	0.515
45	4	1	0.1656	0.086	0.0598	0.458
48	2	1	0.0828	0.0727	0.0148	0.462





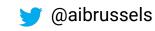


what task to solve?







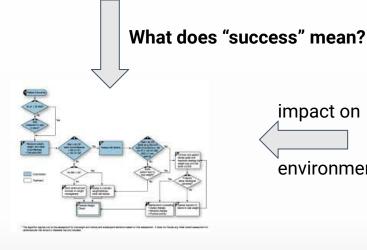


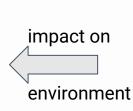
4. Learning from interaction (reinforcement learning)





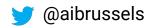












#### TRENDS IN ML + ROLE HUMANS

from knowledge



Symbolic AI, learns to **reason** 

Human creates rules



from **examples** 



Machine Learning, learns a **mapping** 

Humans annotate data





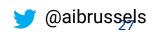
Reinforcement Learning, learns a **policy** 

Humans design success



## But it is Hard to structure.





### From a scope point-of-view

#### ARTIFICIAL INTELLIGENCE

The ability of a computer program or a machine to think like humans do.

#### MACHINE LEARNING

Subfield of AI giving machines the skills to learn from examples without being explicitly programmed.

Examples: Fraud detection, marketing personalization, email classification

#### **DEEP LEARNING**

Specialized machine learning technique enabling machines to train themselves to perform tasks.

Examples: Image classification, vehicle detection, sentiment analysis





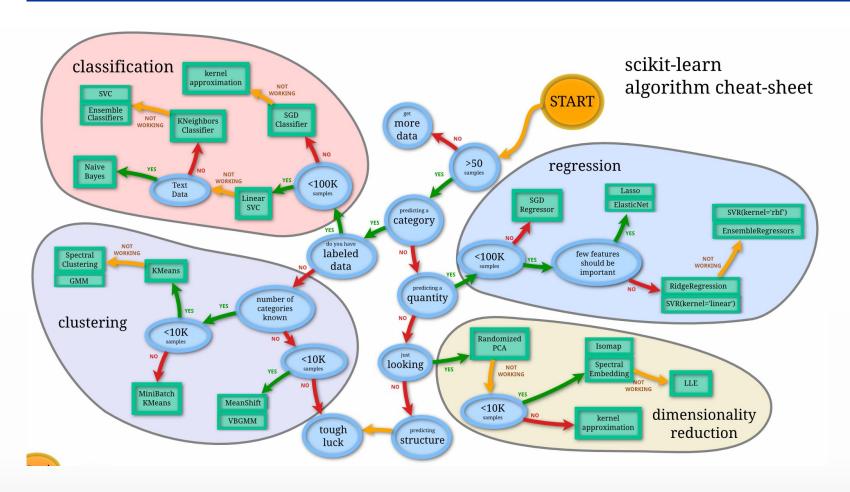




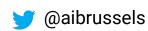




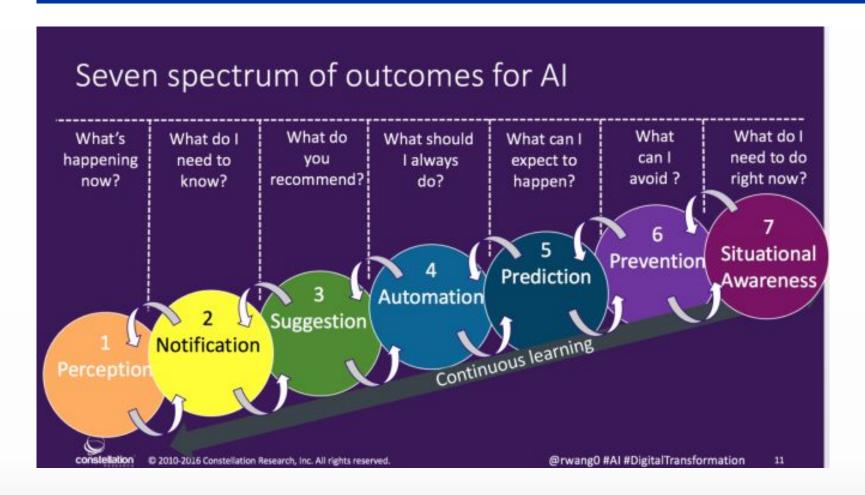
#### From an algorithmic point of view



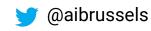




### From an outcome point-of-view







#### From an application point-of-view







### From an added-value perspective

What steps is your business taking to improve customer experience? Pick your top 3.



Delivering personalised offers



Creating personalised marketing / ad campaigns



Assessing and optimising marketing / ad campaigns



Identifying up / cross-sale opportunities



Re-engaging customers



Identifying new business opportunities

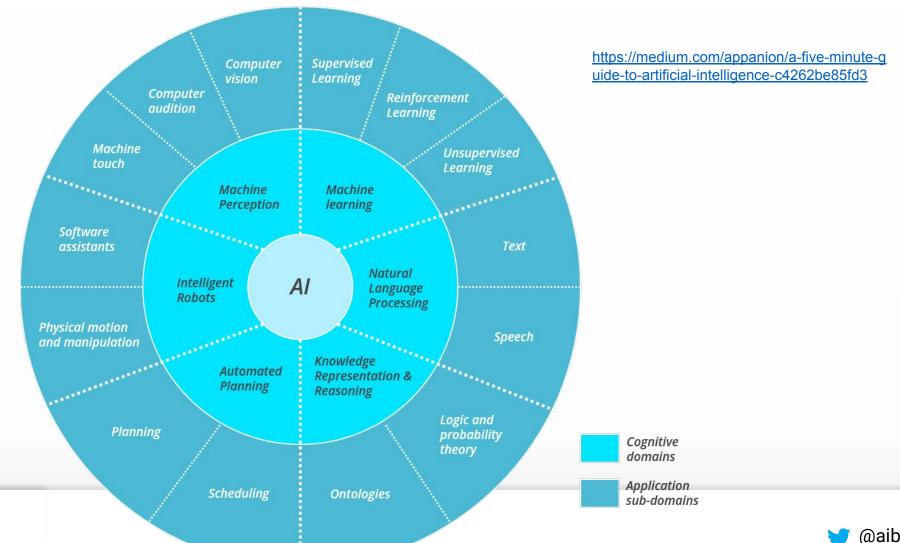


Improving data analytics



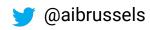
https://www.adobe.com/uk/artificial-intelligence/business-readiness-tool.html?sdid=55KD8VHP&mv=social&mv2=ownsoc

#### From research field point-of-view



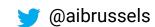
## Q#3 What is a chair?





## Symbolic





#### Al is all about representations

#### Symbolic ("top-down"): good-old-fashioned Al

- concepts understandable by humans
- manipulation of these concepts
- good in creating new knowledge (in a well contained domain)





## What is a chair? (part 2)

#### Subsymbolic ("bottom-up")

- "raw" measurable **data**, e.g. from sensors
- robust, good for ill-defined (simple) tasks





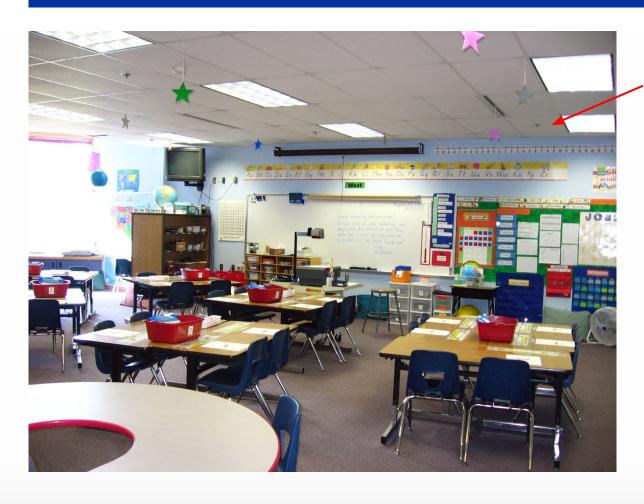


## Sub-symbolic example





## Example: meeting room occupation

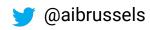


temperature IR sensor

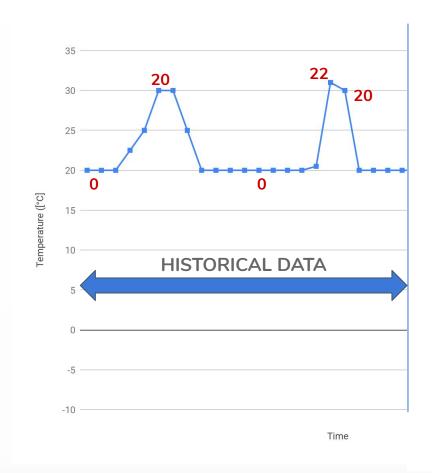
We want to detect automatically when the classroom is occupied.

⇒ Set up an experiment to learn the relation!





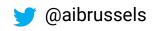
### First look at sensor data



Nice: we can use AI to learn the #persons in the room.

#### **Used for decision making:**

Rooms with <20 users/day will be discarded.

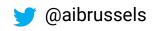


### First look at sensor data

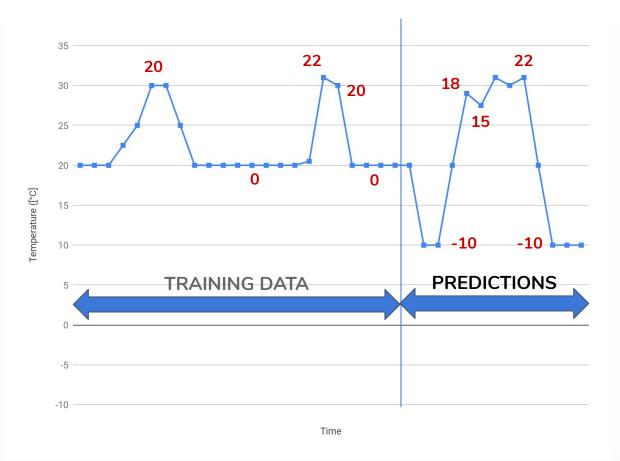


The board decides to **cut down energy.** What will happen to the predictions?





## Energy saving ⇒ A/C off at night



Negative #persons?! What is the consequence?

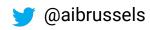
The model **overgeneralized**.

Room will be discarded as the sum < 20.

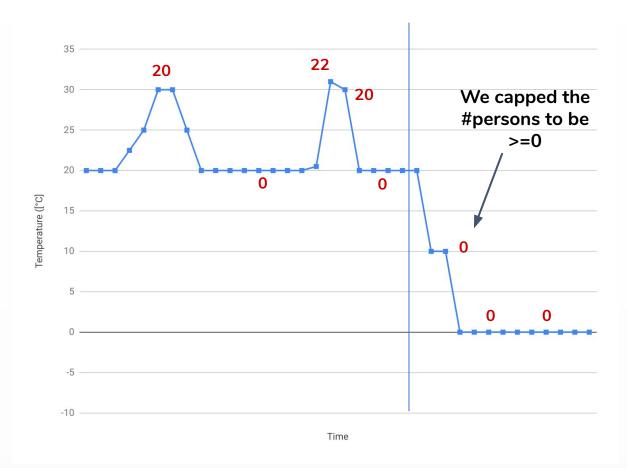
## AHA!

## We know that the #persons cannot be negative.





## Strange... what happens here?

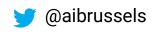


Room no longer in use? Very cold outside?

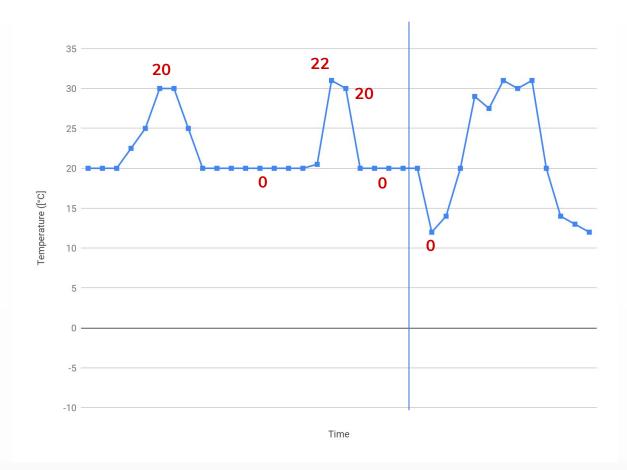
The **sensor** input was **blocked** and outputs 0.

Room will be discarded.



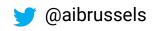


### Then summer comes...



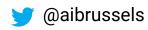
A/C is shut off in summer. 20 °C is no longer a reference.

We know the sensor is just a proxy to measure t° increase by human presence



# Algorithms have no idea of the context, unless you tell them so.





## Data are a projection of reality

Which representation do you prefer to calculate a route?

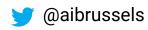




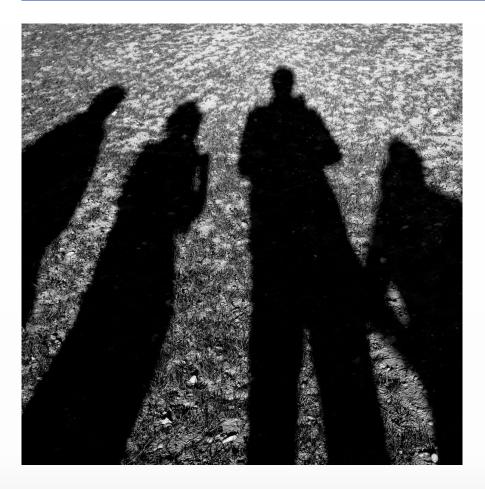


# Q#4 When did Al start? What are the roots, foundations?





## Plato



Reality

... how we represent / think about it

... and how we perceive it

## Aristotle, Descartes, Leibniz

- We can represent reality as symbols
- And reasoning can represent our thinking
- Machines can perform reasoning

### Ada Lovelace



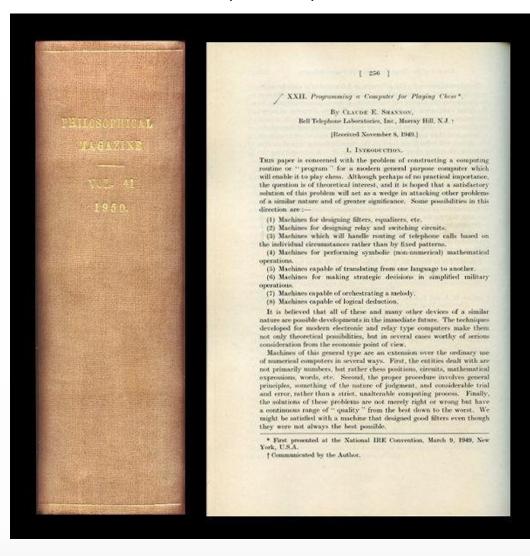
[The Analytical Engine] might act upon other things besides *number*, were objects found whose mutual fundamental relations could be expressed by those of the abstract science of operations...

Supposing, for instance, that the fundamental relations of pitched sounds in the science of harmony and of musical composition were susceptible of such expression and adaptations, the engine might compose elaborate and scientific pieces of music of any degree of complexity or extent.

## Russel, Gödel, Turing, Shannon

- Formal systems
- Turing machines
- Algorithms that work on representations to solve tasks
- Cybernetics, information theory, systems theory

#### (1950)



1. Zero-order approximation (symbols independent and equiprobable).

XFOML RXKHRJFFJUJ ZLPWCFWKCYJ FFJEYVKCQSGHYD QPAAMKBZAACIBZL-HJQD.

2. First-order approximation (symbols independent but with frequencies of English text).

OCRO HLI RGWR NMIELWIS EU LL NBNESEBYA TH EEI ALHENHTTPA OOBTTVA NAH BRL.

3. Second-order approximation (digram structure as in English).

ON IE ANTSOUTINYS ARE T INCTORE ST BE S DEAMY ACHIN D ILONASIVE TU-COOWE AT TEASONARE FUSO TIZIN ANDY TOBE SEACE CTISBE.

4. Third-order approximation (trigram structure as in English).

IN NO IST LAT WHEY CRATICT FROURE BIRS GROCID PONDENOME OF DEMONSTURES OF THE REPTAGIN IS REGOACTIONA OF CRE.

5. First-order word approximation. Rather than continue with tetragram, ..., *n*-gram structure it is easier and better to jump at this point to word units. Here words are chosen independently but with their appropriate frequencies.

REPRESENTING AND SPEEDILY IS AN GOOD APT OR COME CAN DIFFERENT NAT-URAL HERE HE THE A IN CAME THE TO OF TO EXPERT GRAY COME TO FURNISHES THE LINE MESSAGE HAD BE THESE.

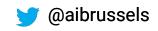
Second-order word approximation. The word transition probabilities are correct but no further structure is included.

THE HEAD AND IN FRONTAL ATTACK ON AN ENGLISH WRITER THAT THE CHARACTER OF THIS POINT IS THEREFORE ANOTHER METHOD FOR THE LETTERS THAT THE TIME OF WHO EVER TOLD THE PROBLEM FOR AN UNEXPECTED.









#### Welcome to

 EEEEEE
 LL
 IIII
 ZZZZZZZ
 AAAAA

 EE
 LL
 II
 ZZ
 AA
 AA

 EEEEEE
 LL
 II
 ZZ
 AA
 AA

 EEEEEE
 LL
 III
 ZZZZZZZ
 AA
 AA

Eliza is a mock Rogerian psychotherapist.

The original program was described by Joseph Weizenbaum in 1966.

This implementation by Norbert Landsteiner 2005.

ELIZA: Is something troubling you ?

YOU: Men are all alike.

ELIZA: What is the connection, do you suppose ?

YOU: They're always bugging us about something or other.

ELIZA: Can you think of a specific example ? YOU: Well, my boyfriend made me come here.

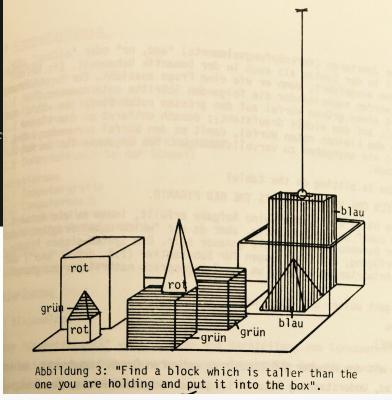
ELIZA: Is it important to you that your boyfriend made you come her

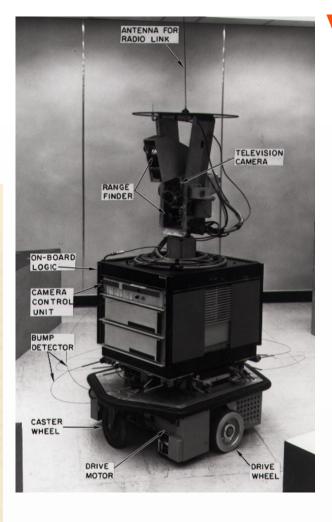
YOU: He says I'm depressed much of the time. ELIZA: I am sorry to hear that you are depressed.

YOU: It's true. I am unhappy.

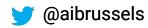
ELIZA: Can you explain what made you unhappy ?

YOU:



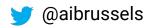


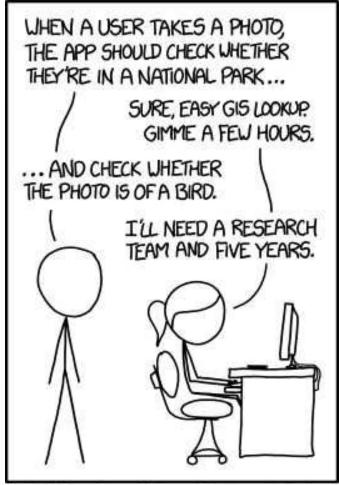




## Q#5 What makes Al hard?



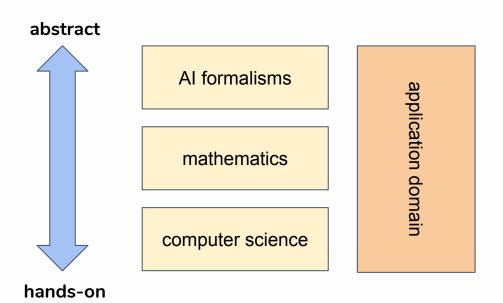




IN CS, IT CAN BE HARD TO EXPLAIN THE DIFFERENCE BETWEEN THE EASY AND THE VIRTUALLY IMPOSSIBLE.



## Interdisciplinary (intersection, not union)



how does my business work?

but explained to a computer...

that is, in mathematical terms?

## "Understanding" how it works

conceptually?

mathematically?

algorithmically?

```
    Empirical risk minimization

    framework to design learning algorithms

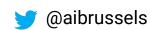
                     # Hyperparameters for our network
                     input size = 784
                     hidden_sizes = [128, 64]
                     output_size = 10
  \rightarrow l(f(\mathbf{x}^{(t)};
                     # Build a feed-forward network
                     model = nn.Sequential(nn.Linear(input_size, hidden_sizes[0]),
                                             nn.ReLU(),
   • \Omega(\boldsymbol{\theta}) is a
                                             nn.Linear(hidden_sizes[0], hidden_sizes[1]),
                                             nn.ReLU(),
                                             nn.Linear(hidden_sizes[1], output_size),

    Learning i

                                             nn.Softmax(dim=1))
                     print(model)

 ideally, we'd
```





loss function is a surrogate for what we truly should optimize (e.g. upper bound)

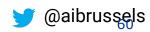
## It challenges our beliefs.





## #1 - A walking robot should be stable at all times.





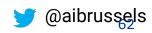
Al continuously challenges our beliefs and knowledge, as it learns to reproduce our results, and will take over a big part of experimentation too.

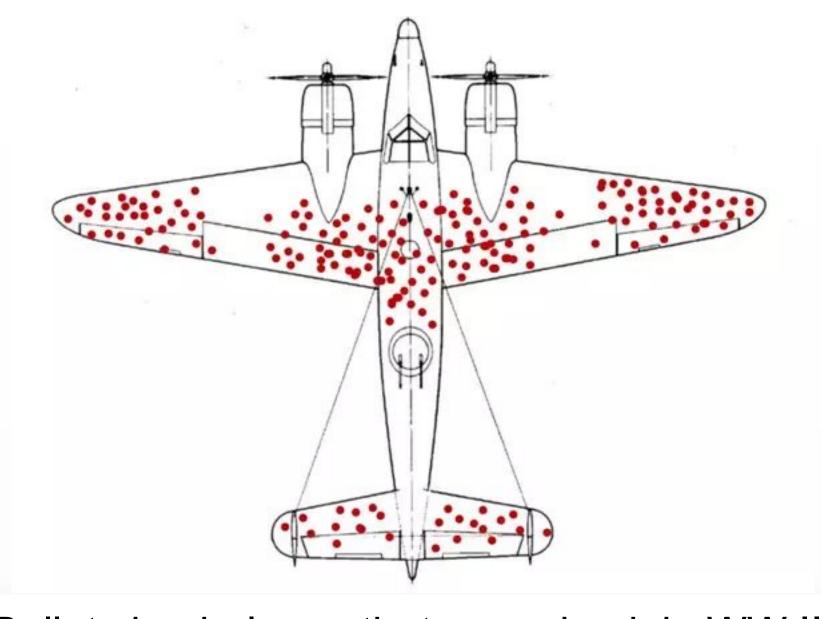




## #2 - Human & algorithmic biases







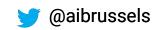
Bullets in airplanes that came back in WW II. Where to reinforce the armour?

## How many f's in the following sentence?



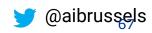
# "Finished files are the result of years of scientific study combined with the experience of years."





## #3 - What action should I take?





## Language & reality is ambiguous

(a chair, you said?)

"Descendez-le!"



### **Context** matters

"Could you please pass me the glass of water?"



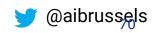


when I'm thirsty?

when I'm holding a bottle of water?

## #4 - Where is the flag?





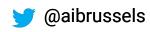
## We reason over language



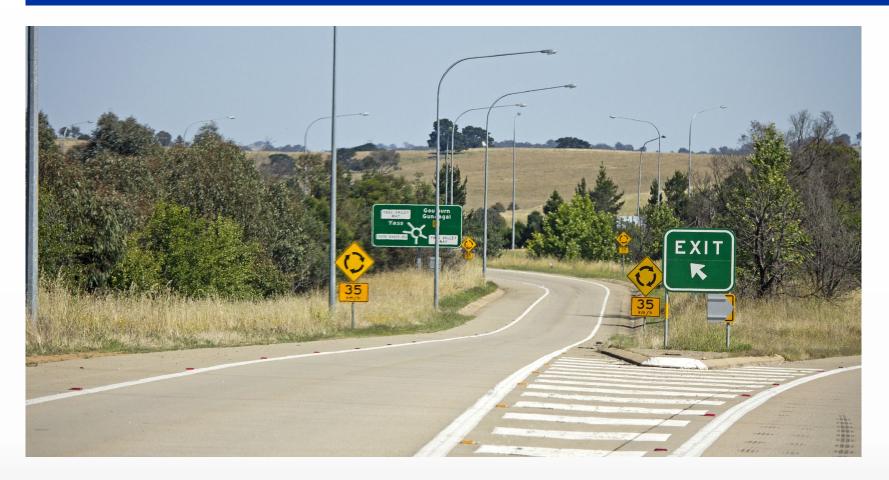
the flag is **left** of the table!

the flag is right of the table!





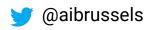
## "Hybrid" Al: data + reasoning





# Q#6 Why do we have a revival now?





### Why a revival?

- First digitalization wave has happened
   (data can be harvested, digital interfaces to processes & users, SOA)
- Global interconnected & servitized world & market (more competition, higher user expectations, new business models)
- Cloud services, open source & computing power (powerful, modular building blocks, small can compete with big)
- Consumer driven mindset
   (users compare with the best of all, not best of category)



#### Technology is moving to end-users

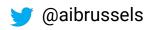
- Human interfaces to services are disappearing
  - bank tellers ⇒ ATMs
  - bank clerks ⇒ apps

- Users thus interact directly with technology.
  - Still very unnatural compared to humans (e.g. MOOC)
  - Quality and comfort are crucial
  - Digital natives



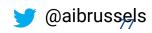
# Q#7 What will AI change?





# What is the impact of fixing three numbers?





#### Answer: global prosperity

research pessimists

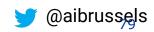


sale optimists



### Al is transformative





#### Al is transformative

#### 1. Changes the nature & discovery of knowledge

- a. Allows companies to formalize knowledge
- b. Moves from humans to self-learning machines
- c. Driving force in science, the new "statistics"

#### 2. Enables **autonomous** and **adaptive** systems

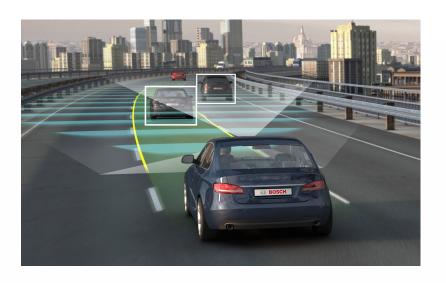
- a. humans go from commanding to interacting, giving up control
- b. go beyond our understanding (e.g. high dimensional / nonlinear)

#### 3. They have "infinite" **scale**.

- a. micro-personalization, human empowerment
- b. winner-takes-all economies as you can copy the best



We have come to a point that the systems we need are **too complex for humans** to build, understand or maintain.



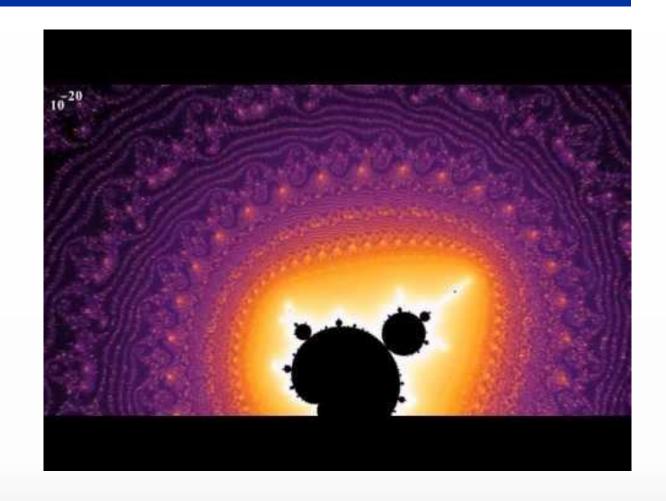
# The real transformative <u>value</u> of Al lies exactly in <u>the systems we do not understand</u>



### Explainability

### Transparency of algorithms?

$$f_c(z) = z^2 + c$$



#### AlphaGo

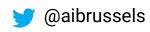
- 1. **Better** at Go than humans (scientists thought this breakthrough to happen in 2030 earliest)
- 2. Learn to play in 2 days
- 3. And "invent" creative moves



4. An infinite #players can be created instantaneously

#### Al advances science

- Automate tedious research tasks
- Detect complex patterns, rules... "New statistics"
- Improve Randomized Controlled Trials
- The user is the experiment => longitudinal studies, we learn a lot about humans



### Unpredictable impact





#### Humans vs. machines

#### What happened to...

- bank tellers
- video stores
- accountants
- webmasters

#### What will happen to?

- travel agents
- real estate agents
- broadcasters
- farmers
- marketeers

#### And so who are...

- content managers
- community managers
- IT car repair men
- elevator service personnel

#### Have we become the robots?

- algorithms orchestrating people in warehouses;
- opening doors to flats for people decided by airbnb;
- buying books Amazon tells us to.



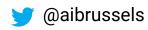
#### "General consensus"

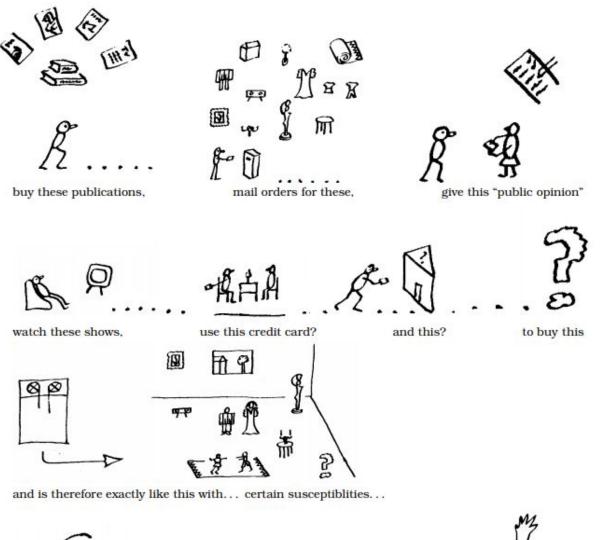
- Will change our jobs
  - probably not eliminate, but change the tasks we do
  - and create new jobs!
- Our interaction with products will change
  - · systems that have their own plan, "will"
- Lifelong learning becoming main learning mode
- Polarization of tech, data & talent



# Q#8 Why is it freaky?









Good Morning!

Your new life style!

New politics!

New religion!

How can I ever thank you?

#### Creative ways...

## Turn your competitors' visitors into your customers

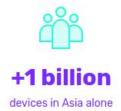
By combining location intelligence with online advertising potential OMNIcookie empowers retailers to reconnect with shoppers after they've left the store



SEE HOW IT WORKS



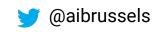












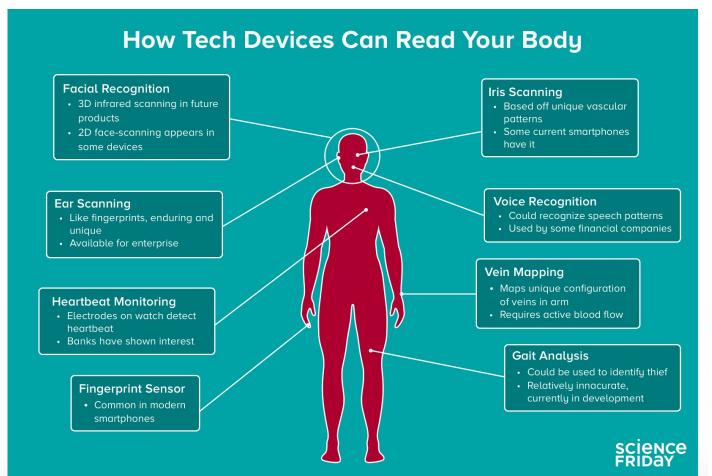
#### Vacuum cleaners

#### What does your interior design tell about

- your personality?
- your lifestyle?



### Also when "logged out" (passive authentication)





#### Personal identification

#### People can now be identified at a distance by their heartbeat

And then dealt with, if they are enemy operatives







https://www.economist.com/science-and-technology/2020/01/23/people-can-now-be-identified-at-a-distance-by-their-heartbeat https://seon.io/sense-platform/



#### Recommender systems

#### Winner technology of Al

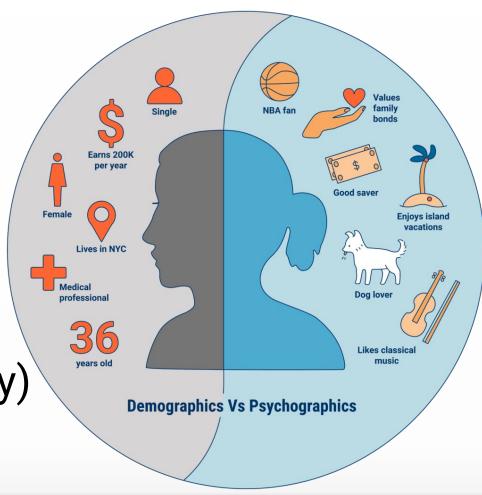
- What advertisements you see (Google)
- What movie you watch (Netflix)
- What products you buy (Amazon)
- What news you read (Google, Facebook,...)
- What friends you make(Facebook, Linkedin,...)
- Who will be your spouse (Match.com, ...)

The most pervasive (and profitable) of all AI applications.



### Psychometrics

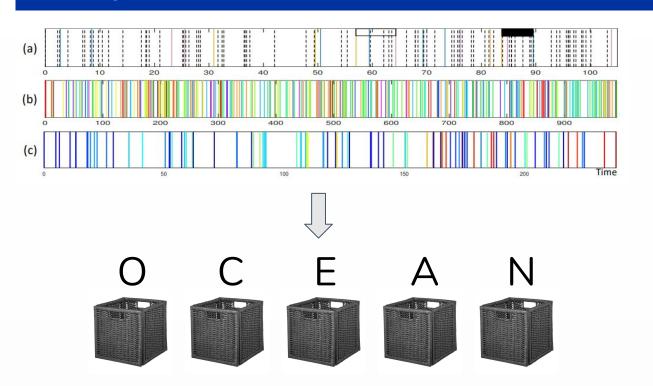
- Understanding the customer
- Classification into specific categories
- Prediction of specific quantities
- Clustering of your profile (similarity)







#### Saying someone's behaviour is extravert





... is different from understanding what that means, or **reason** about it.



#### Examples

#### Uber: Users Are More Likely To Pay Surge Pricing If Their Phone Battery Is Low



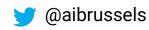
Amit Chowdhry Contributor ①

Tech enthusiast, born in Ann Arbor and educated at Michigan State

### Mac users pay more than PC users, says Orbitz

The travel site says Mac users will pay \$20 to \$30 a night more on hotels than PC users.





#### Polarization...



IN BRIEF

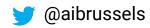
- Not only will 75% of jobs go to automation, the developing world may also see swaths of companies leaving their shores and returning to developed nations, as labor will be less of a factor for industry.
- Plans, such as a universal basic income, need to be initiated before this process proliferates and these regions are plunged into even more dire circumstances.

November 11, 2016

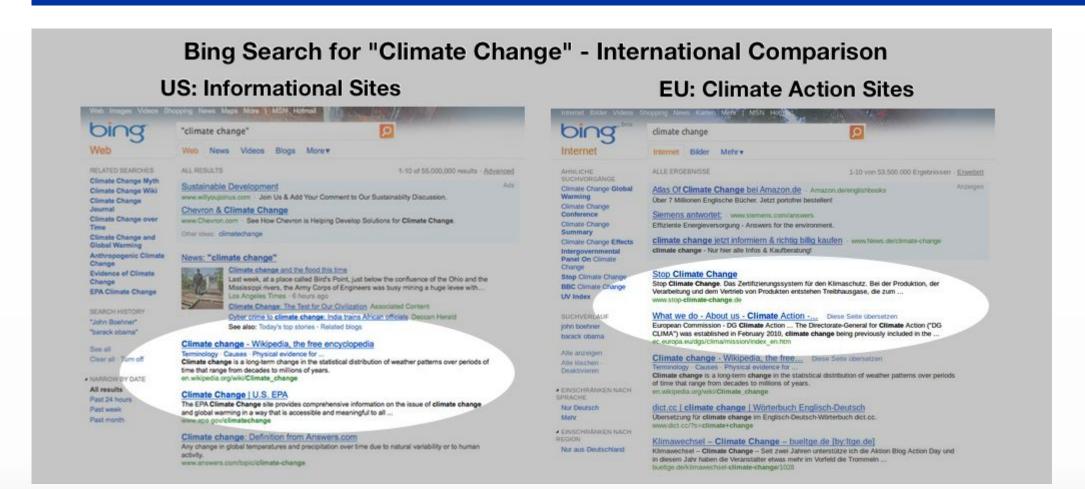
education?

equality?





#### Filter bubble



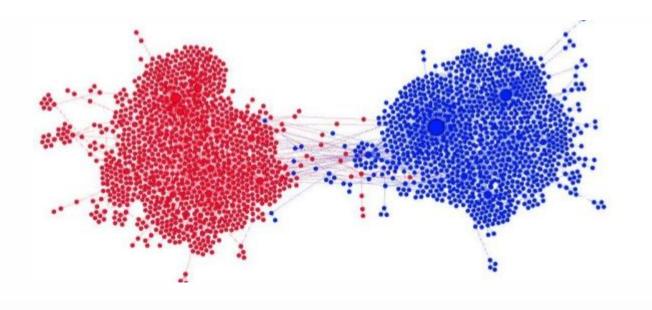






#### Polarization

- ... of opinions
- ... of people you meet
- ... music you listen to
- ... clothes you wear?



### Deepfakes





Input photo











Input photo

Remove chairs

Output result







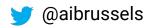


tample of GAN-Generated Photographs of Human PosesTaken from Pose Guided Person Image Generation, 2017.



## Q#9 What can Al NOT do today?





"We are only 20 years away from a world in which machines will do any work a man can do"

H. Simon (1965)

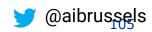


#### Dartmouth summer program

- The term "Artificial Intelligence" was coined.
  - John McCarthy
  - Marvin Minsky
  - Nathaniel Rochester
  - Claude E. Shannon
- They expected to need 2 months and a team of 10 to solve the problem

# #1 we underestimate our own intelligence





#### We underestimate our intelligence!

- Tactile feedback
- Substance identification
- Memory of weight
- Geometric reasoning





#### Recognizing a guitar is different from



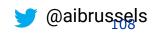
**PHYSICAL** 



understanding that you can play music on it, or that if you can play on a guitar, you can play on a banjo.

# #2 algorithms are ruthless





#### Algorithms are ruthless

Cobra effect: government policy to get rid of cobras. If a citizen brings in a venomous snake, they got a reward. People started breeding snakes.



#### Algorithms are ruthless (and so they cheat)

#### Algorithms Acting Out

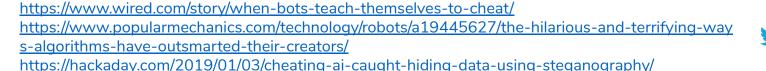
- Infanticide: In a survival simulation, one AI species evolved to subsist on a diet of its own children.
- Space War: Algorithms exploited flaws in the rules of the galactic videogame Elite Dangerous to invent powerful new weapons.
- Body Hacking: A four-legged virtual robot was challenged to walk smoothly by balancing a ball on its back. Instead, it trapped the ball in a leg joint, then lurched along as before.
- Goldilocks Electronics: Software evolved circuits to interpret electrical signals, but the design only worked at the temperature of the lab where the study took place.
- Optical Illusion: Humans teaching a gripper to grasp a ball accidentally trained it to exploit the camera angle so that it appeared successful—even when not touching the ball.





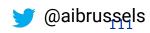






# humans are the limit: we have to describe our problem mathematically

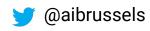




#### Formulating the problem = hard part

- It is like explaining how to
  - drive a car
  - cook
  - diagnose a patient
  - play chess
- to a computer, that has no understanding of context
- MATHEMATICALLY!





#### The description is the limit

#### The **complexity** of

- rules
- annotation
- reward signal

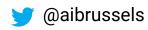
to describe the **problem** 

that a human can handle is the sky.



# Q#10 How would you design a system that...





#### Answers questions like

Are there more blue things than yellow ones?



#### Visual question answering

https://ehai.ai.vub.ac.be/ demos/visual-question-ans wering/

https://ehai.ai.vub.ac.be/demos/clevr-grammar/



#### Questions?

Johan Loeckx <u>iloeckx@ai.vub.ac.be</u> <u>https://ai.vub.ac.be</u>

+32(0)486 37 98 71





