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Artificial Intelligence

Is more than data

Ann Nowé

AI lab
Vrije Universiteit Brussel



ai.vub.ac.be

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Everything smart

Smart phones

Smart TV's

Smart washing machines

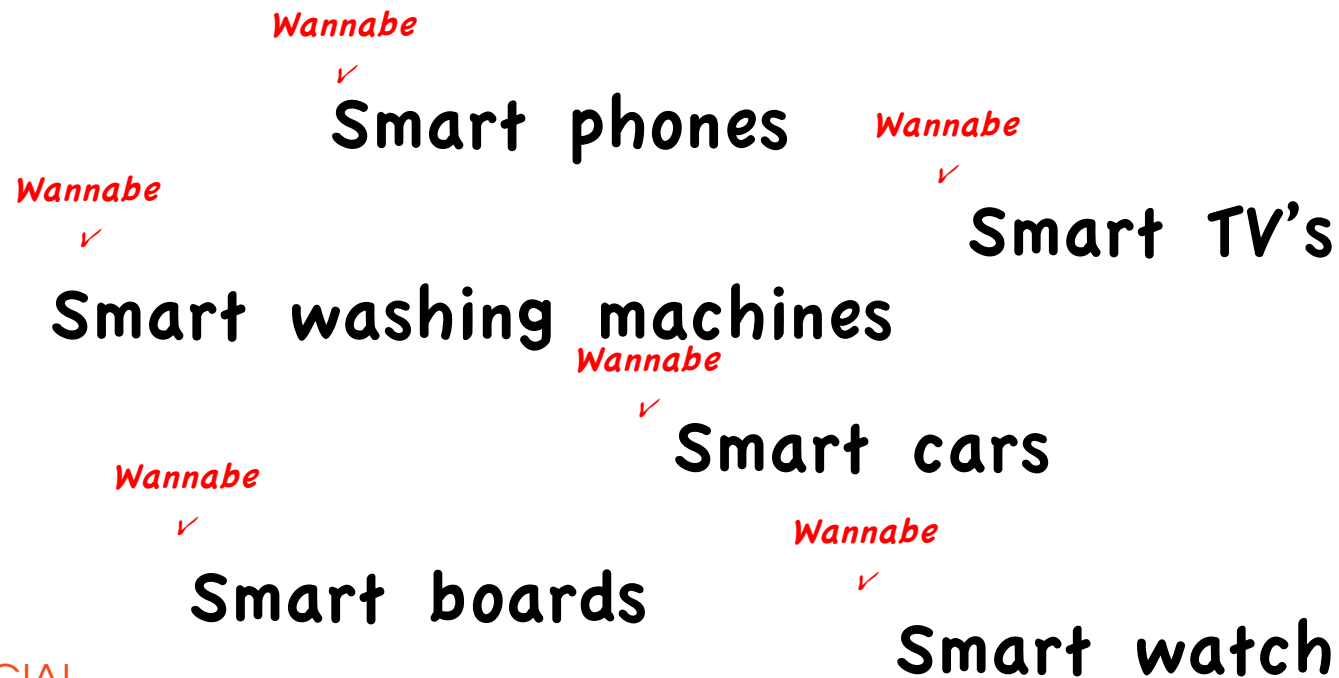
Smart cars

Smart boards

Smart watch

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Everything smart



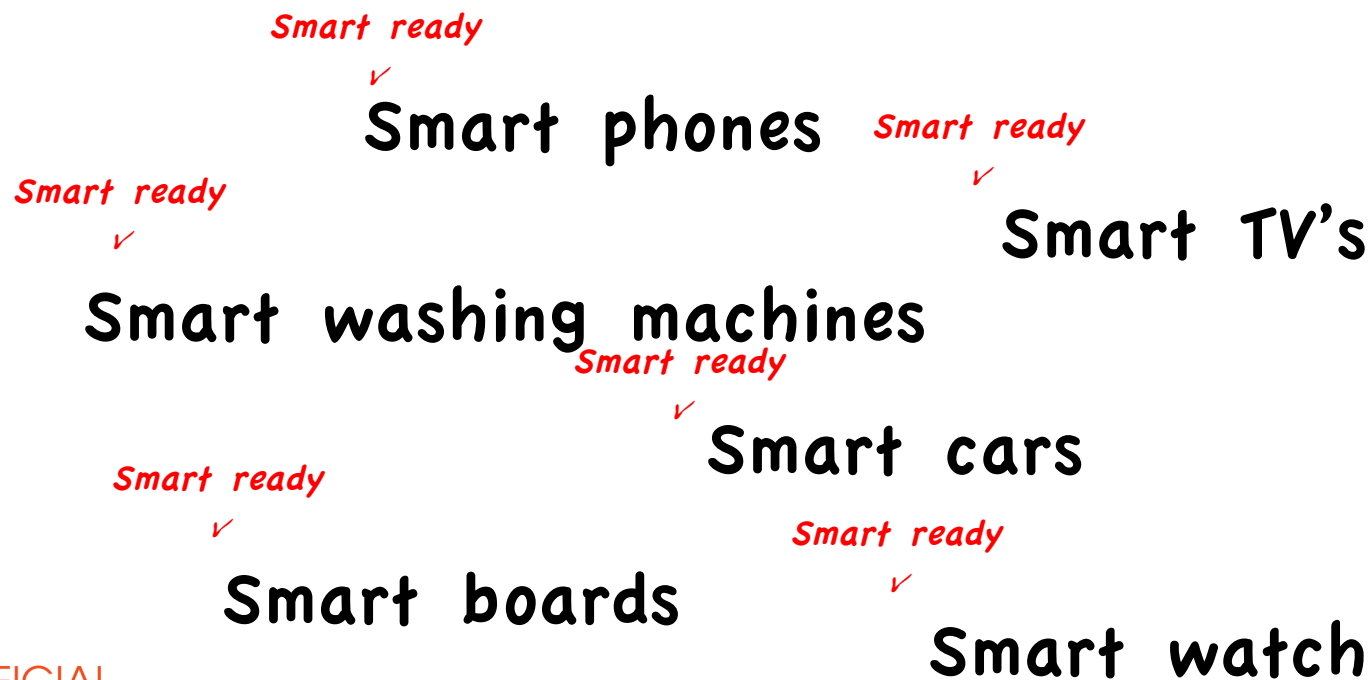
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The birth of AI



We propose that a 2 month, 10 man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of **intelligence can in principle be so precisely described that a machine can be made to simulate it.** An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer."



John McCarthy



Marvin Minsky



Nathaniel Rochester



Claude Shannon

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Brief history on AI



2 month, 10 man

"We propose be carried out in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer."



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Brief history on AI



learning

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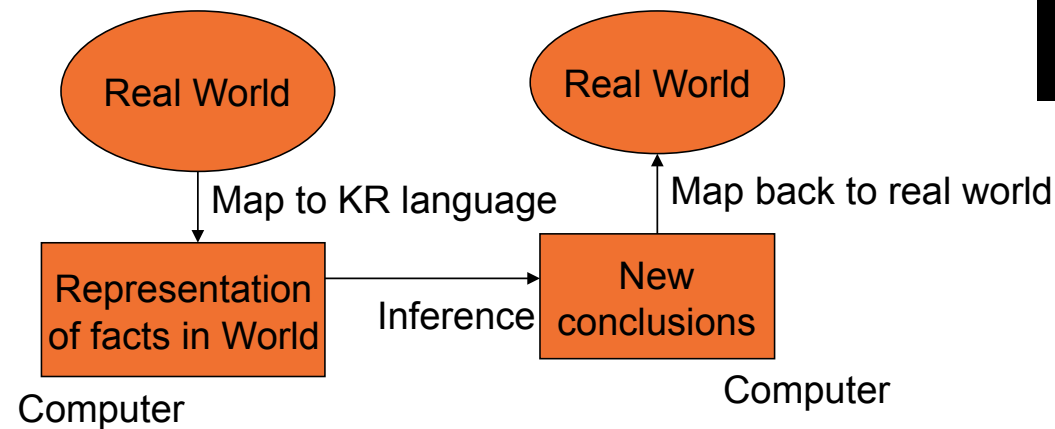
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The symbolic approach

Knowledge representation and state space search

- Knowledge representation languages should have precise syntax and semantics.
- You must know exactly what an expression means in terms of objects in the real world.



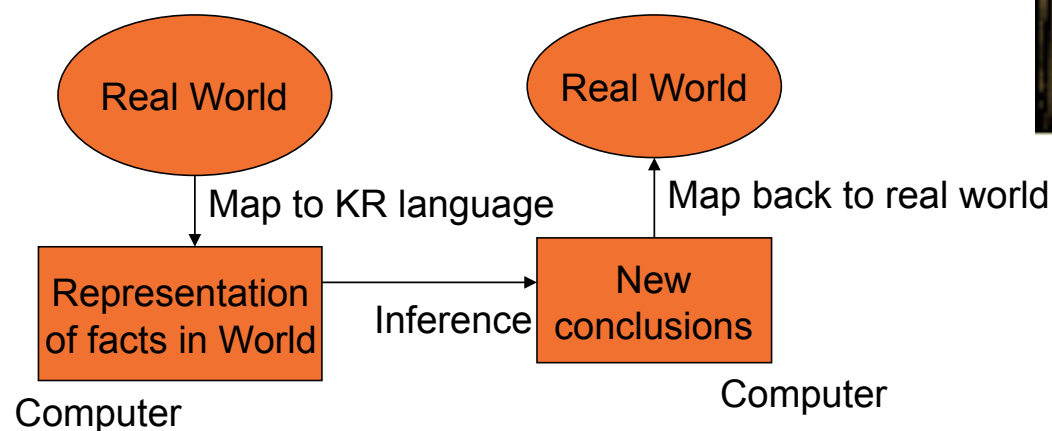
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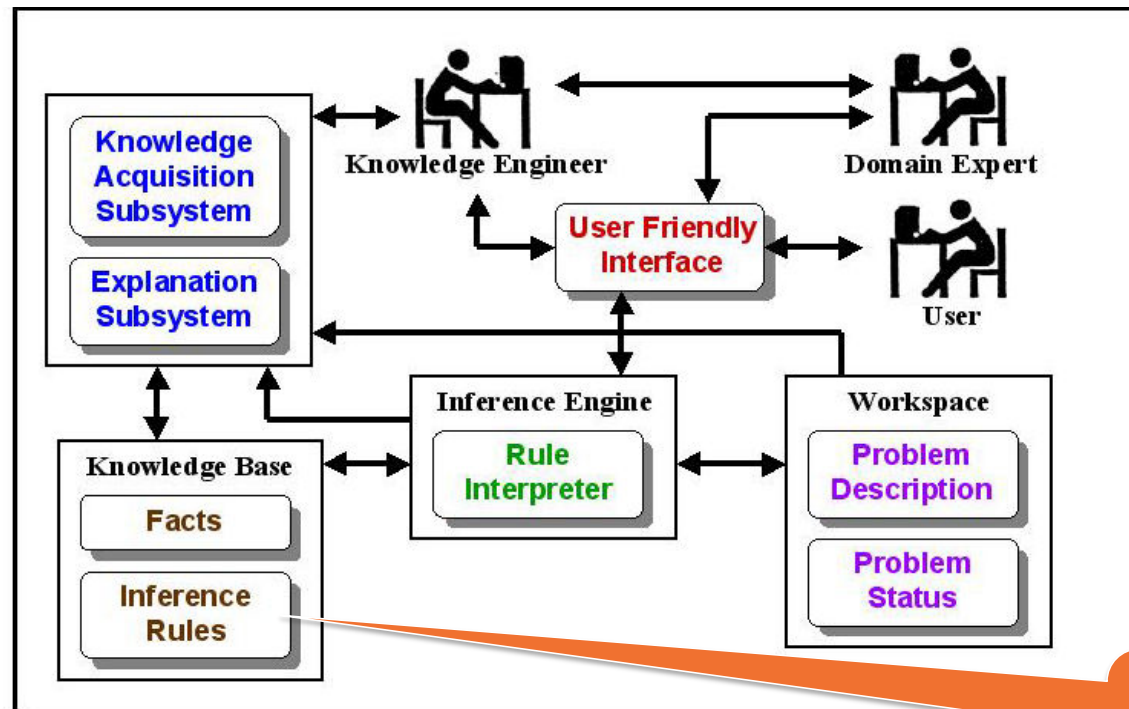
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The symbolic approach



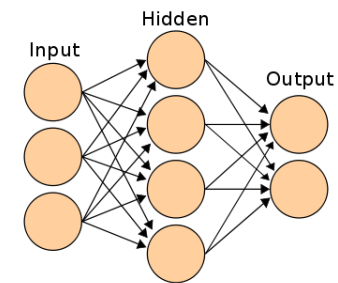
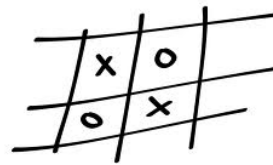
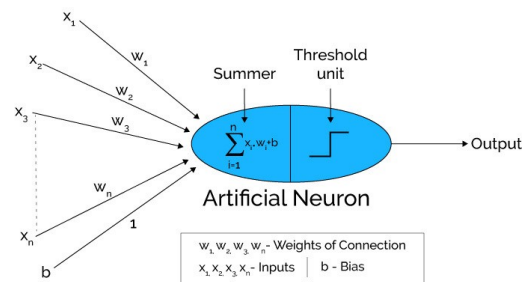
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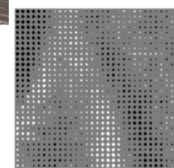
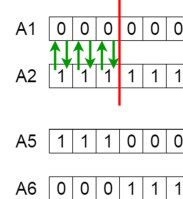
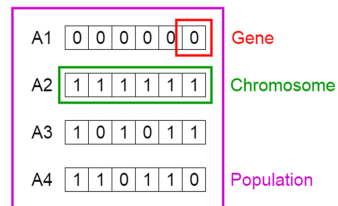
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Sub-symbolic approach



Genetic Algorithms



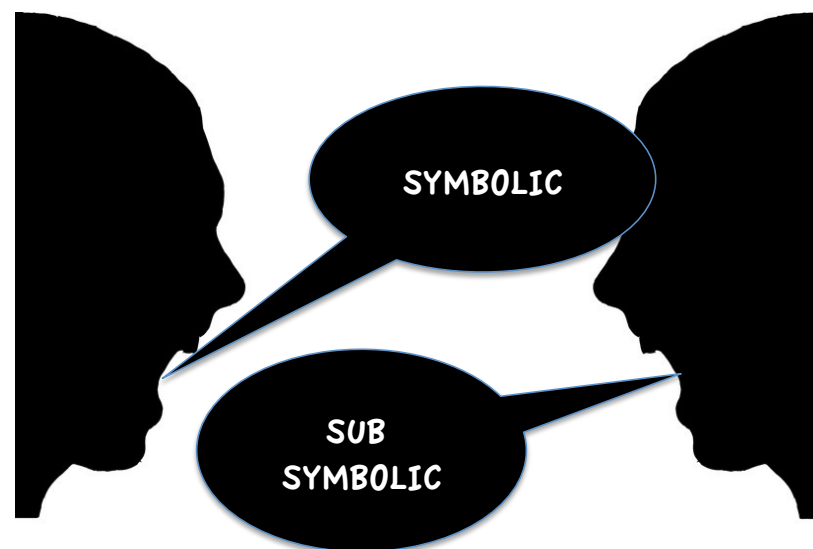
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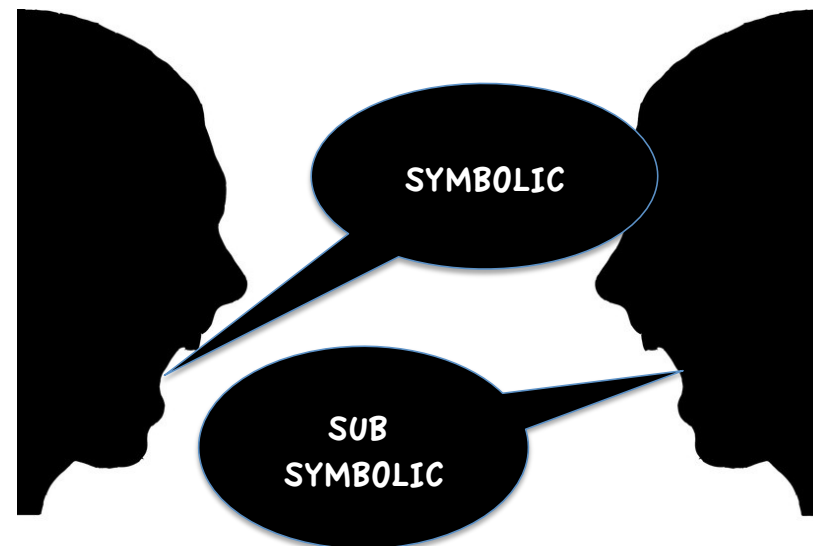
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1988 AAAI Symposium on Parallel Models of Intelligence



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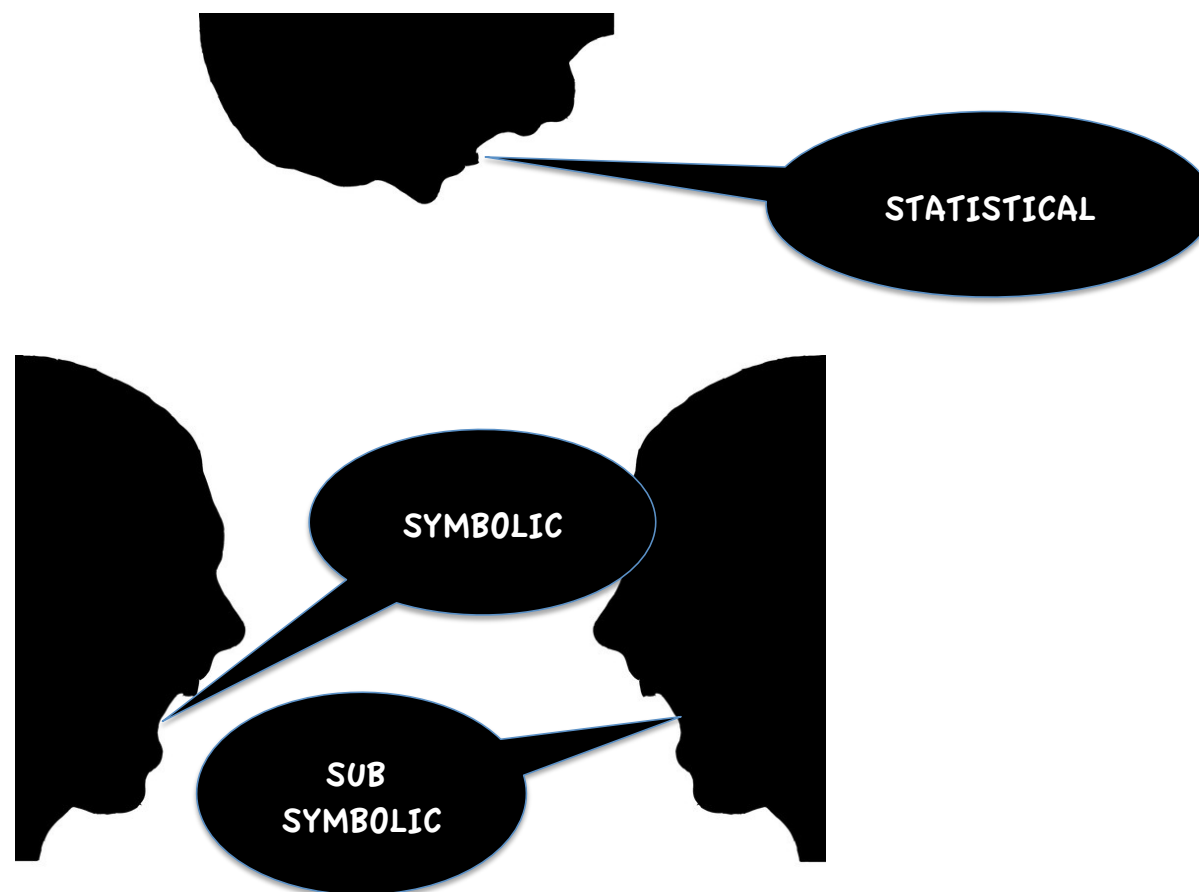
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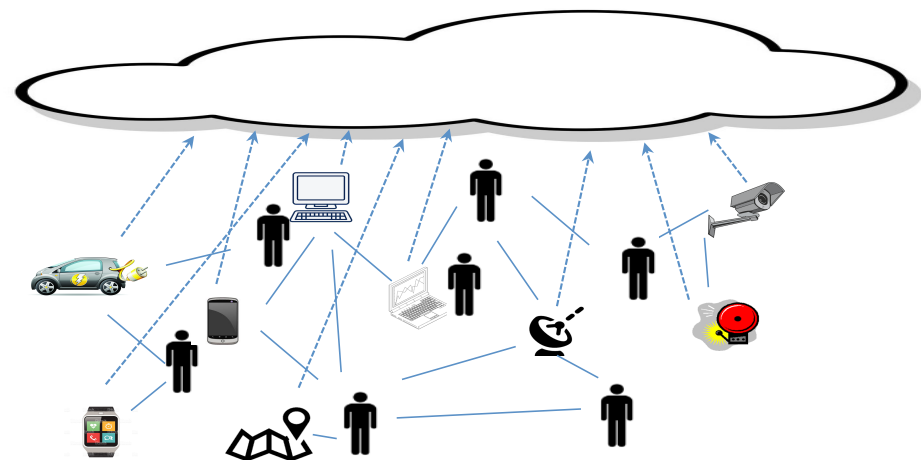
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From data to big data



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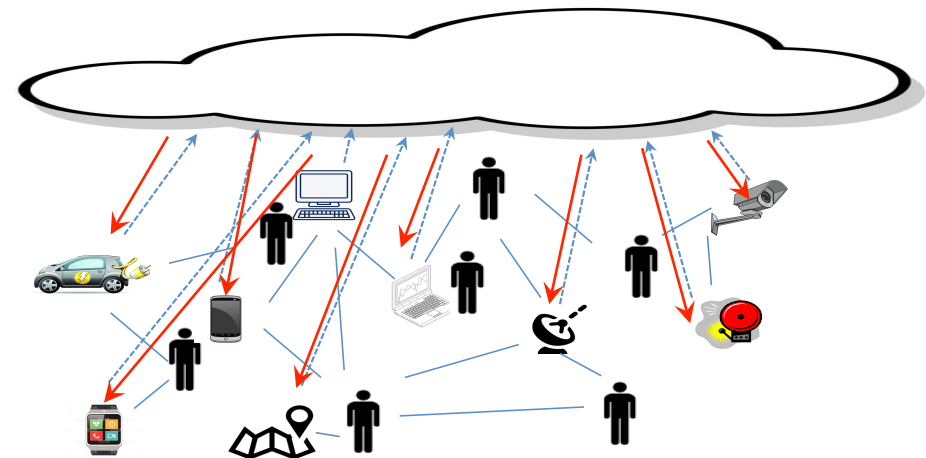
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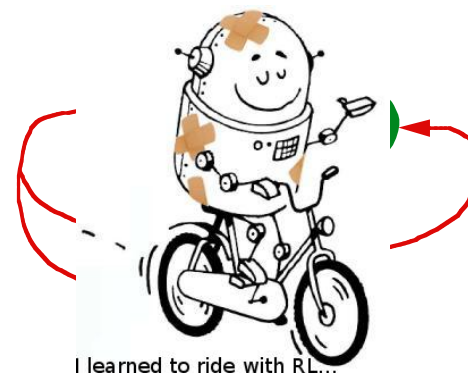
Reinforcement Learning

What is it?

Learning from interaction

Learning about, from, and
while interacting with an external environment

Learning what to do—how to map situations to actions—
so as to maximize a numerical reward signal



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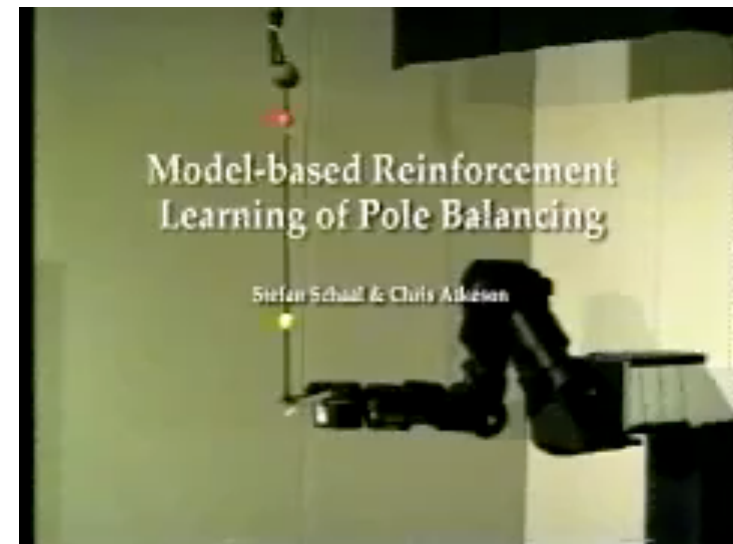
Reinforcement Learning

Trial and error but not random

Performance is gradually improving

Domain knowledge can be incorporated
to speed up learning

Theoretical guarantees on convergence



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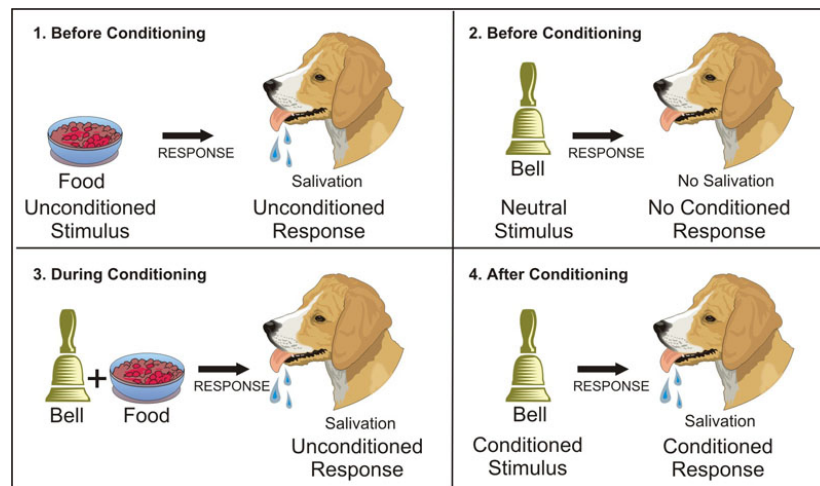
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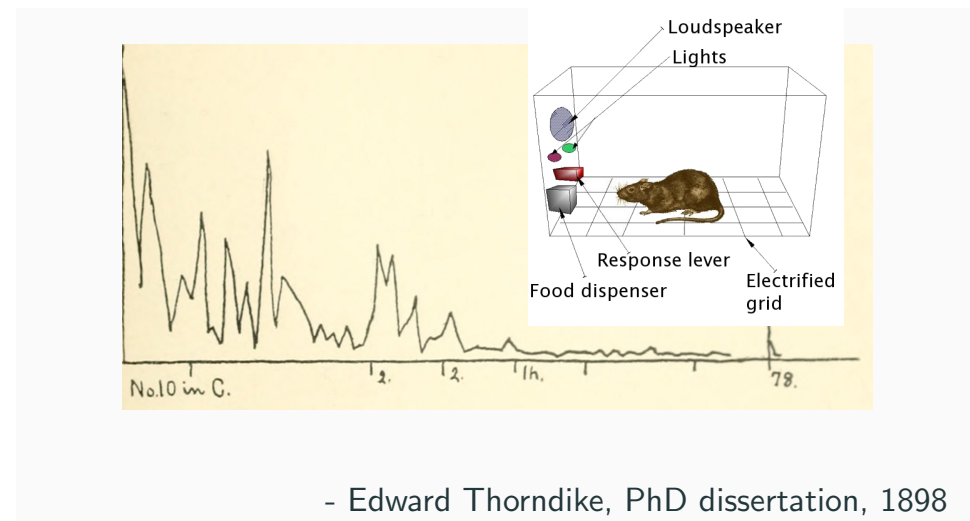
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Reinforcement Learning

Inspired by Reinforcement Learning known in psychology.



Classical Conditioning



- Edward Thorndike, PhD dissertation, 1898

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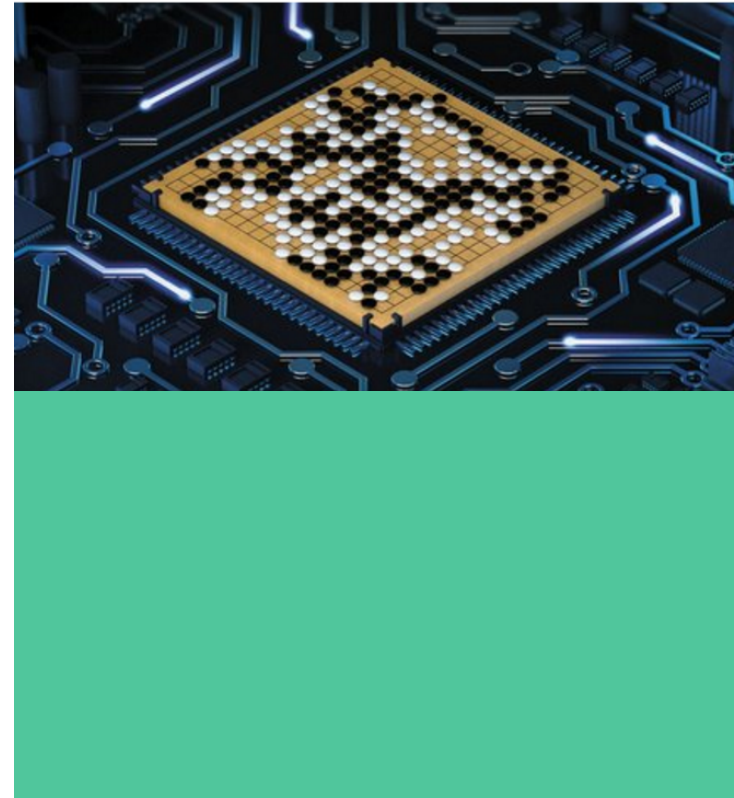
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Where is AI today?



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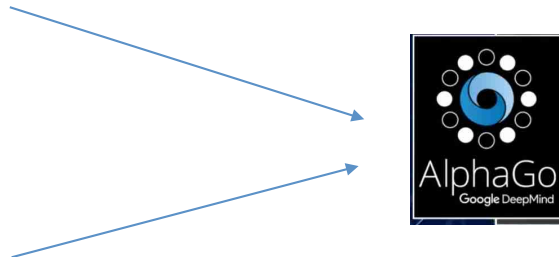
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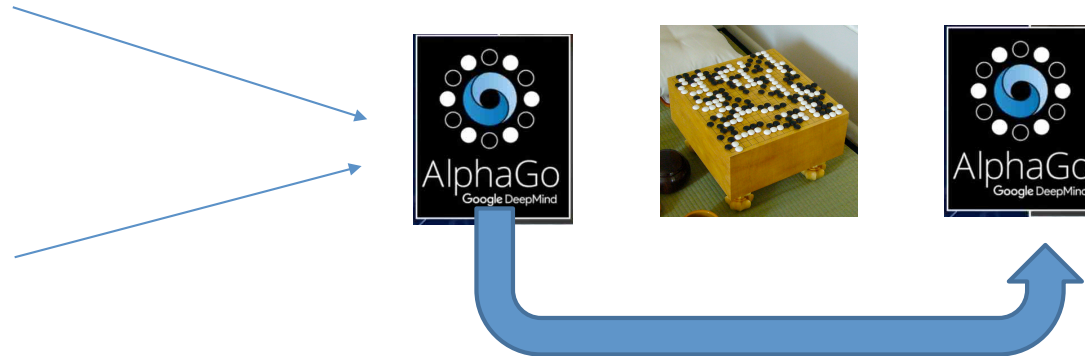
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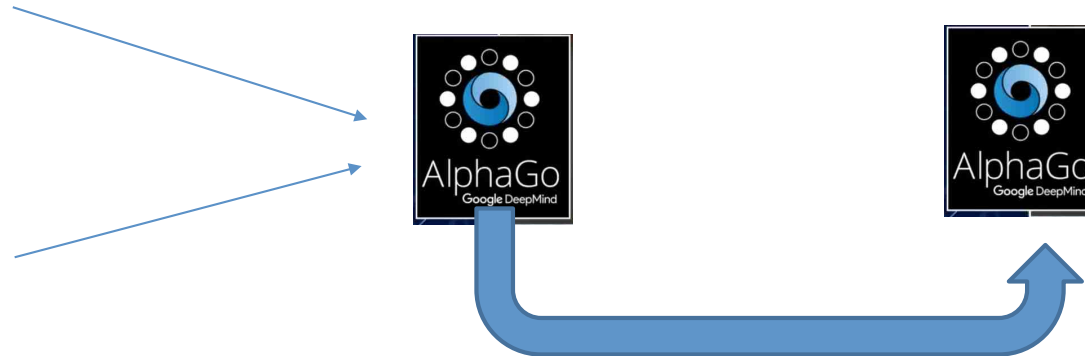
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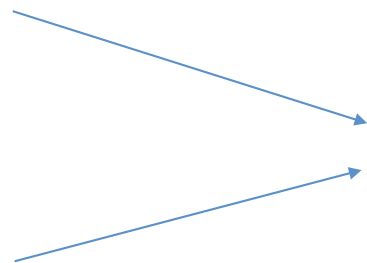
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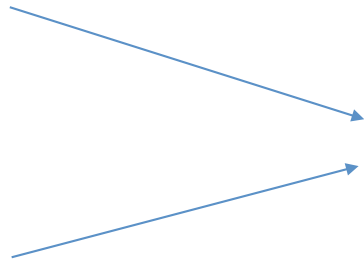
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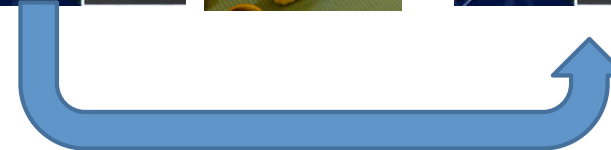
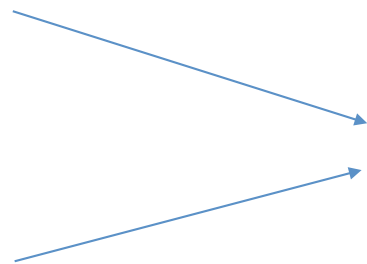
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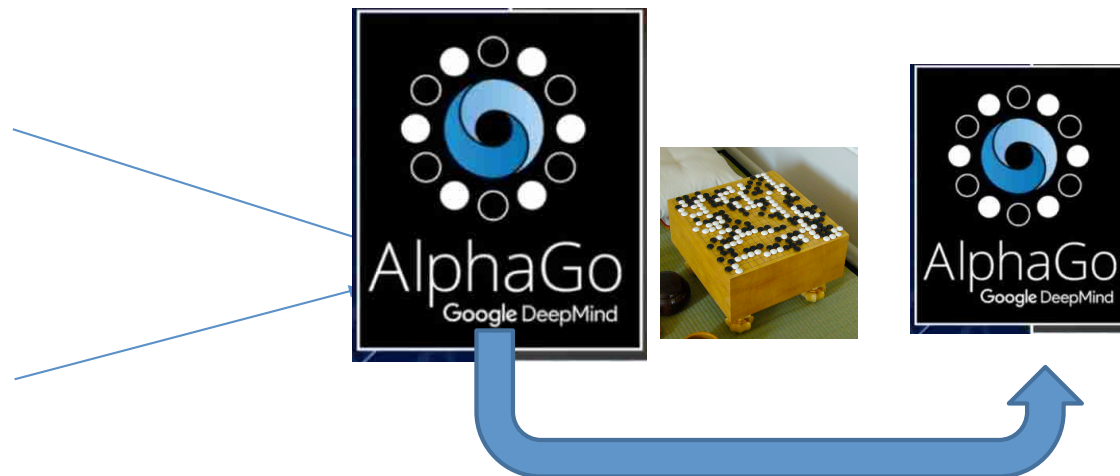
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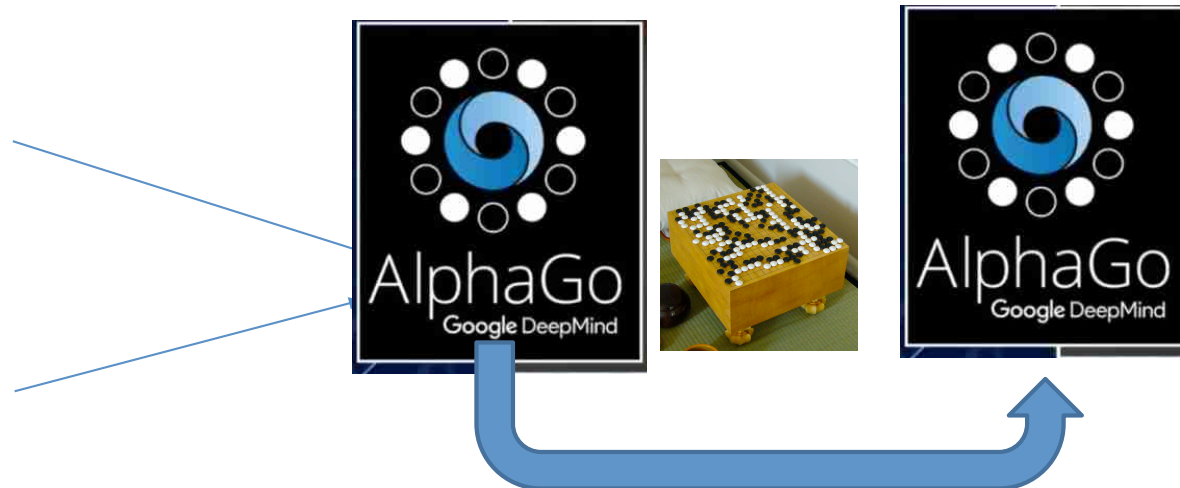
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Where is AI today?

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

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.

JASON TASHEA SECURITY 04.17.17 7:00 AM

COURTS ARE USING AI TO SENTENCE CRIMINALS. THAT MUST STOP NOW

How Target Figured Out A Teen Girl Was Pregnant Before Her Father Did

The AI That Predicts Your Sexual Orientation Simply By Looking At Your Face



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Bernard Marr, CONTRIBUTOR
[FULL BIO](#) ✓

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Where is AI today?

Compas : AI model that predicts the risk of re-offending, used in the US, made by private company.



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Compas : AI model that predicts the risk of re-offending, used in the US, made by private company.

“Blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend”

“makes the opposite mistake among whites:

They are much more likely than blacks to be labeled lower-risk but go on to commit other crimes.”

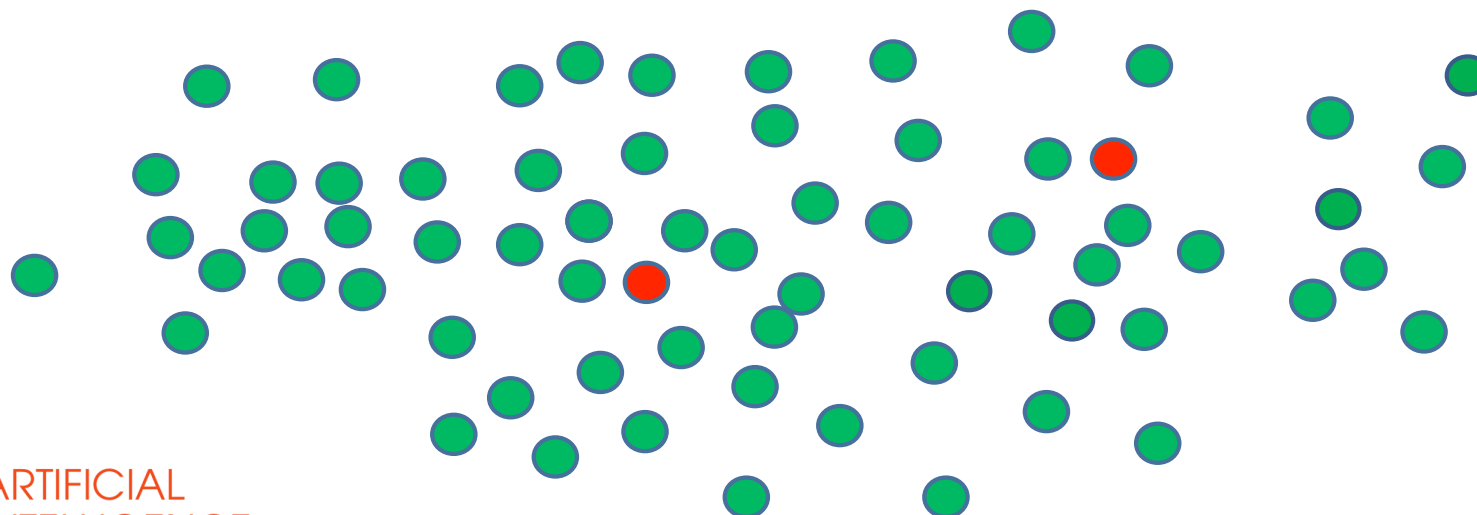
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Data mining requires expertise

Data set might be unbalanced

Unbalanced wrt the outcome class: for example rare diseases.

Always predict “healthy” high accuracy but not useful. Other performance measures are needed.



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Data mining requires expertise

Data set might be unbalanced

Some groups might be under represented. Amazon's AI recruitment tool

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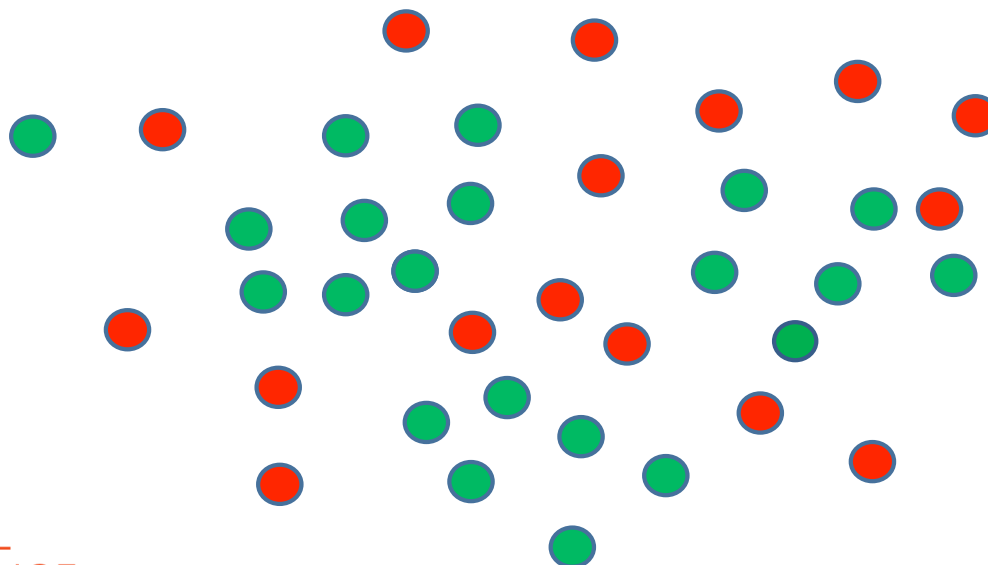
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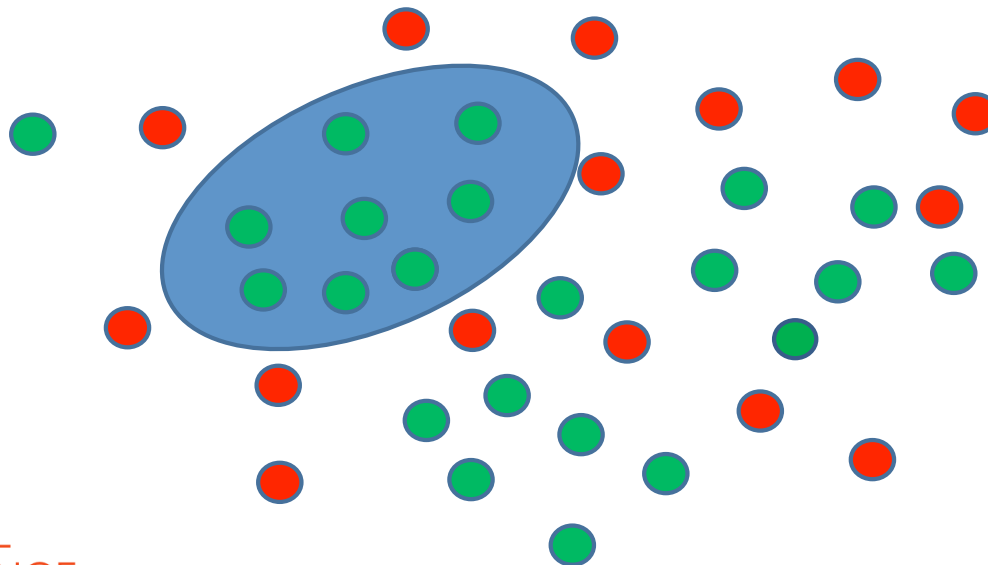
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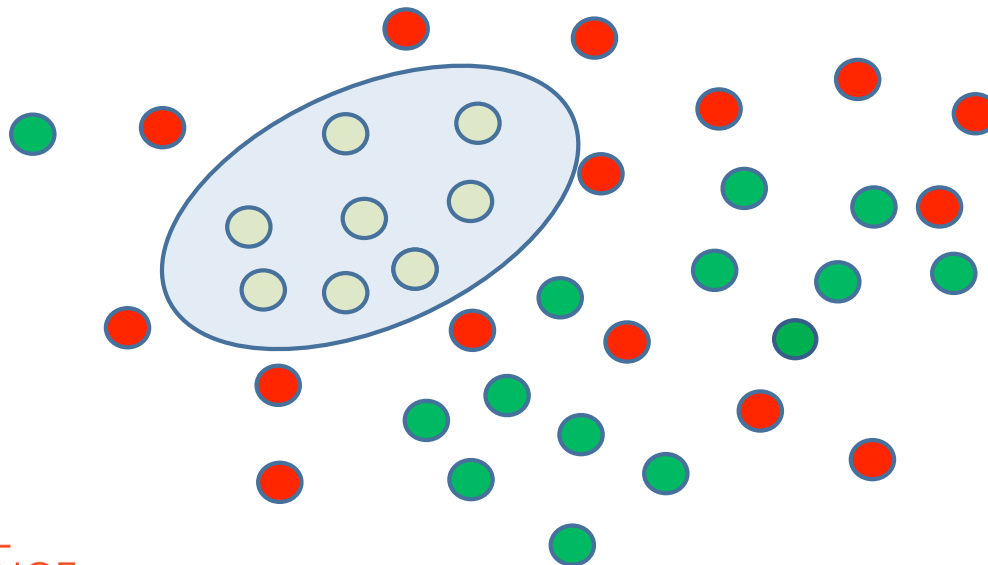
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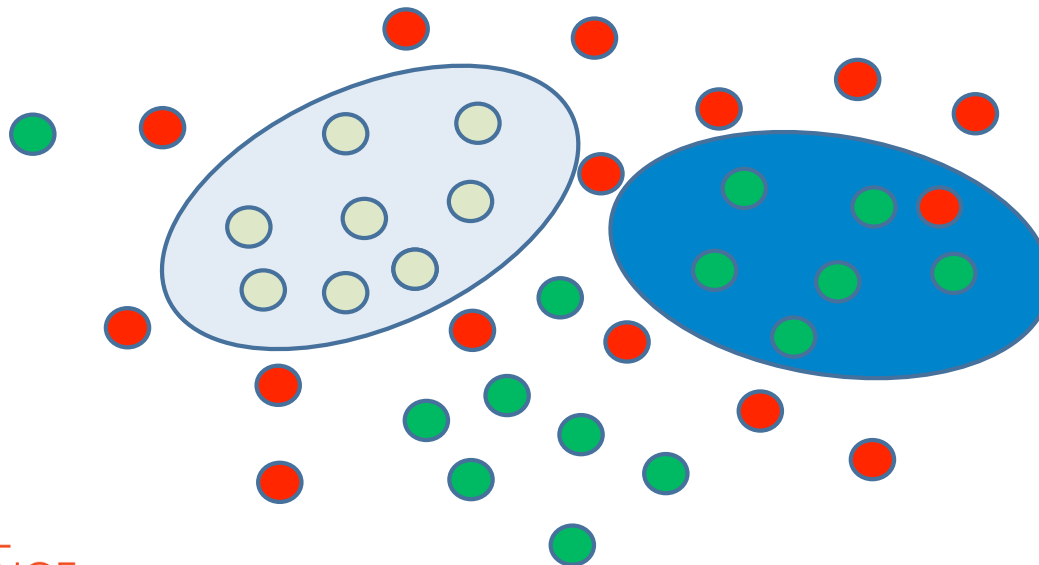
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Data mining requires expertise

Data set might be unbalanced

Some groups might be under represented.



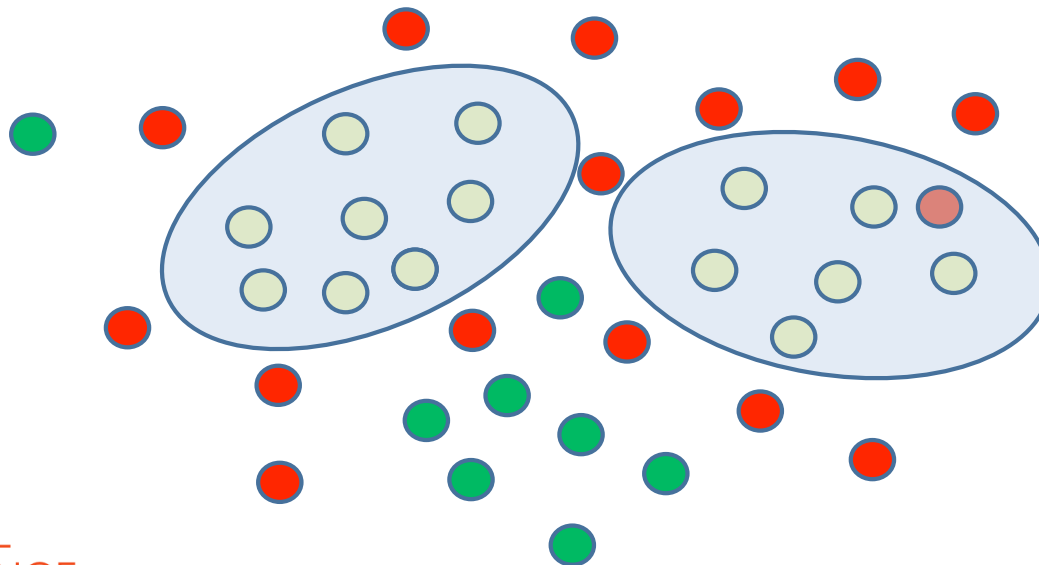
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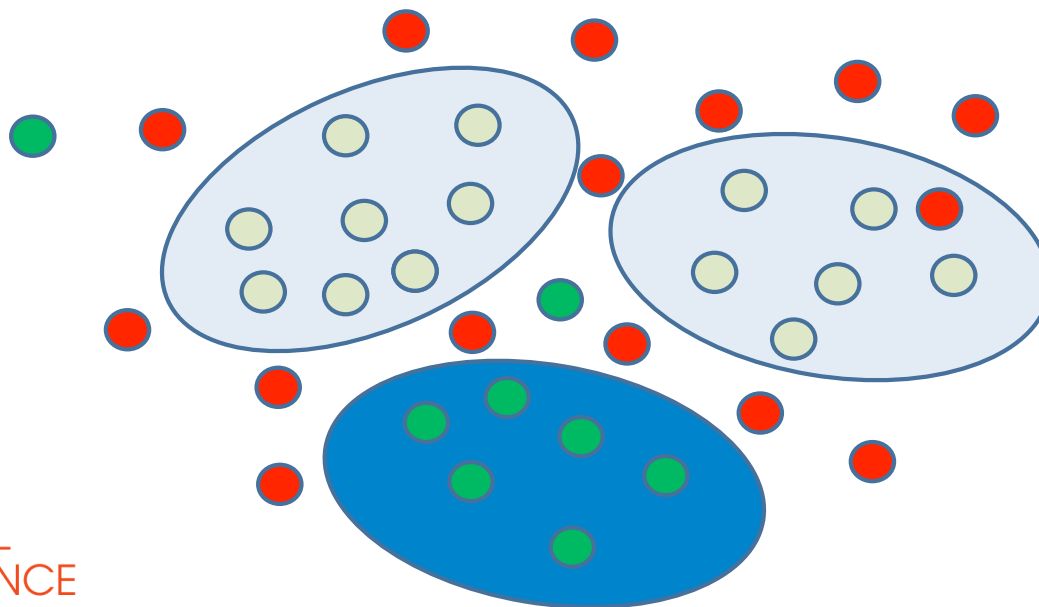
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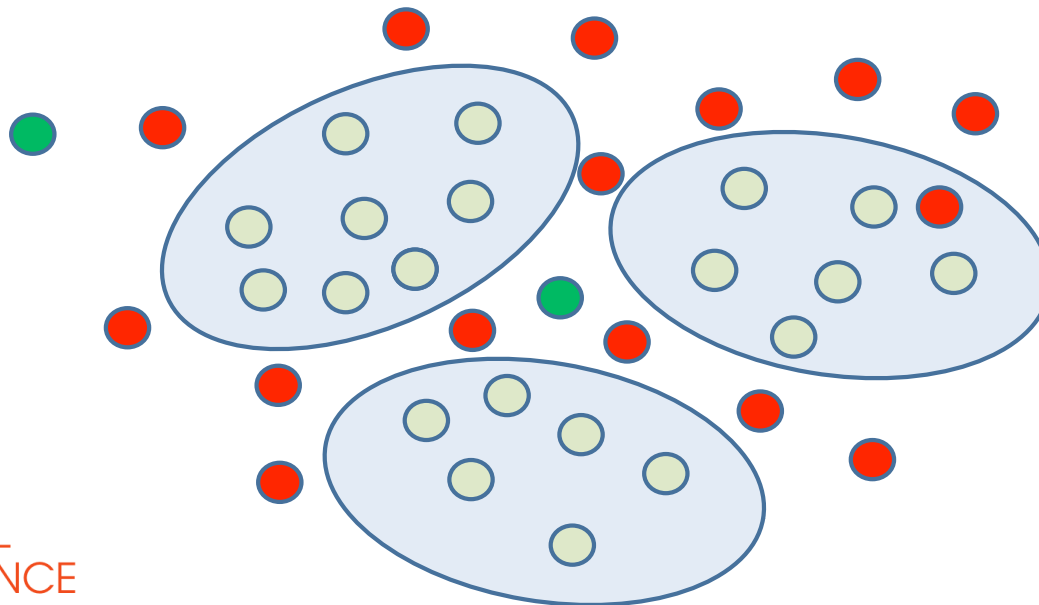
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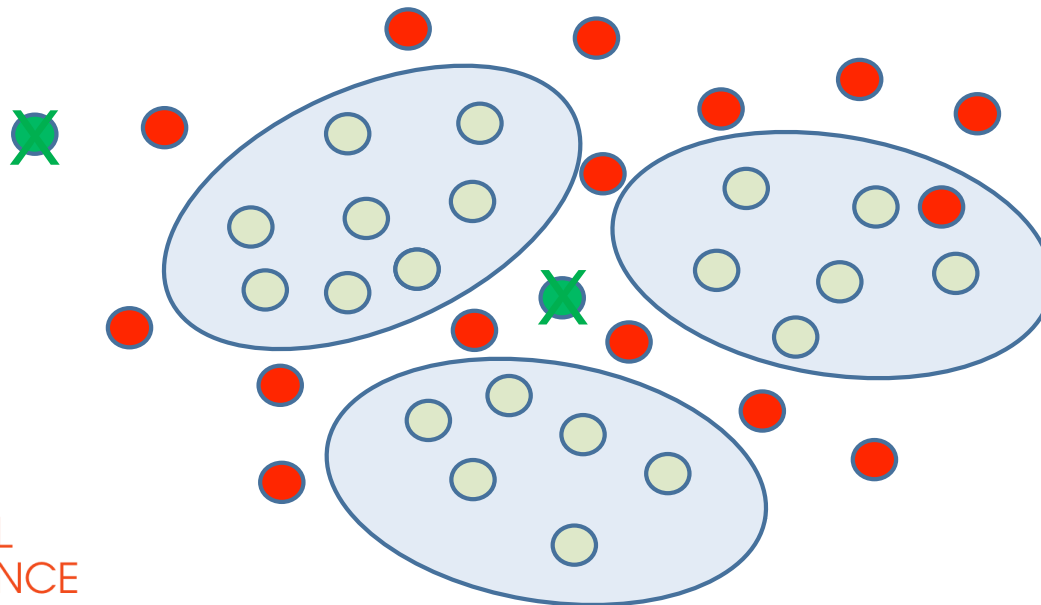
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Where is AI today?

Compas : AI model that predicts the risk of re-offending, used in the US, made by private company.

“Blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend”

“makes the opposite mistake among whites:

They are much more likely than blacks to be labeled lower-risk but go on to commit other crimes.”

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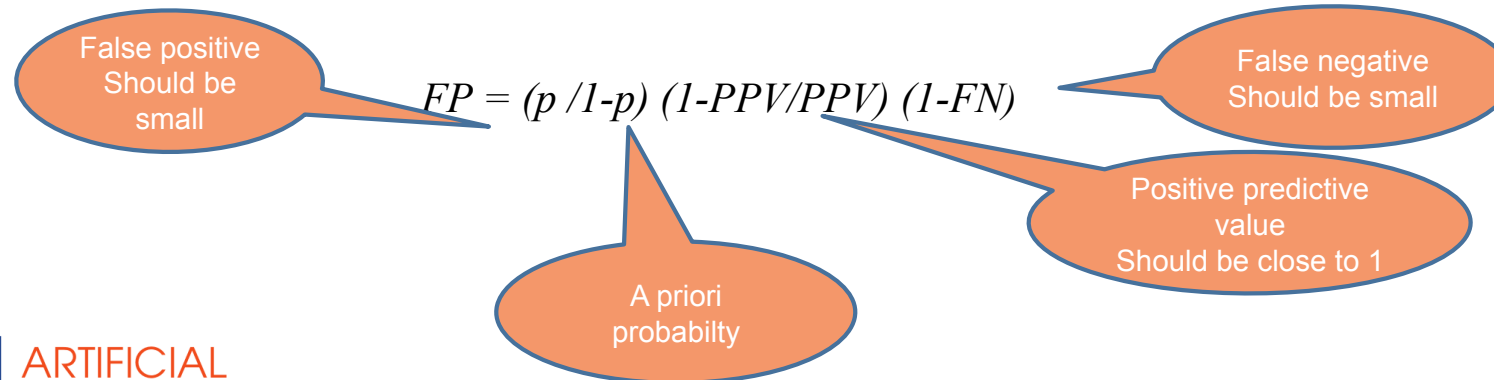
Where is AI today?

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Applies to
First
subgroup

$$FP = (p / 1-p) (1-PPV/PPV) (1-FN)$$

$$FP_1 = (p_1 / 1-p_1) (1-PPV_1/PPV_1) (1-FN_1)$$

Applies to
Second
subgroup

$$FP_2 = (p_2 / 1-p_2) (1-PPV_2/PPV_2) (1-FN_2)$$

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Model is fair if

$$FP_1 = FP_2$$

$$FN_1 = FN_2$$

$$PPV_1 = PPV_2$$

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Model is fair if

$$FP_1 = FP_2$$

$$FN_1 = FN_2$$

$$PPV_1 = PPV_2$$

= > $p_1 = p_2$ unless model is perfect

Explainable & Accountable AI

General Data Protection Regulation GDPR

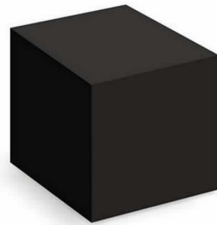
article 22, that will take effect in May 25 2018

all AI that has impact on human lives, will need to be explainable and accountable,

the interpretability of machine learning based models will be key
for the usage of these models.

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Accountable AI



Black box model
Often very performant
But can not explain itself

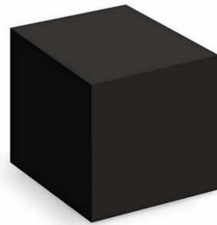


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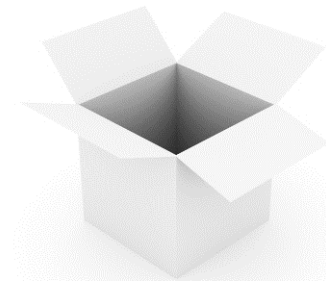
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Accountable AI



Black box model
Often very performant
But can not explain itself



White box
Interpretable model
Transparent model
Robust model

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