Introduction to Artificial Intelligence

Lecture 1

Nina Gierasimczuk

About the Lecturer: **Dr. Nina Gierasimczuk**

Associate Professor
DTU Compute, AlgoLoG
website: http://www.ninagierasimczuk.com/

Some relevant credentials:

MA Degree in Mathematical Logic 2005 (University of Warsaw)

PhD in Computer Science 2010 (University of Amsterdam)

Some larger research projects:

- Reasoning about quantum interaction (GRO 2011-12)
- The logical structure of correlated information change (AMS 2012-14)
- Learning from each other: formal analysis of MAL (AMS/CPH 2014-18)
- Social models of semantics learning (WAW/CPH 2016-19)

Some relevant current activities:

- Programme Committee of International Joint Conference of AI
- Board of The Association for Logic, Language and Information
  (FoLLI: ESSLLI, NASSLLI, JoLLI, and The Beth Prize in Logic)
- Visiting at the Institute for Logic, Language and Computation (AMS)

Teaching Assistants

- Erik Kristian Gylling (s173896@student.dtu.dk)
- Deina Kellezi (s174258@student.dtu.dk)
- Panagiotis Papadamos (s205637@student.dtu.dk)
- Oliver Ahlmann Sande (s174032@student.dtu.dk)
- Serdar Tunçkol (s192277@student.dtu.dk)

02180: Class Schedule

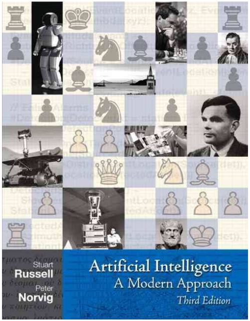
Unless announced otherwise we will follow this weekly class schedule:

- 8:15-10:00: Lecture on Zoom
- 10:15-12:00: Exercise session on MS Teams

  (a link to an appropriate room will be provided to you)

In the course we will mainly use the textbook:

Artificial Intelligence: A Modern Approach
(third edition)
by S. Russell and P. Norvig (R&N)



02180: Course content

WEEK	TOPIC	READING
1	Introductory lecture	R&N, Ch 1
2	Uninformed search	R&N, Ch 3: 3.1-3.4
3	Informed search	R&N, Ch 3: 3.5-3.6
4	Non-determinism and partial observability	R&N, Ch 4: 4.3-4.4
5	Adversarial search I	R&N, Ch 5: 5.1-5.6
6	Adversarial search II	slides, tba
7	TBA	
8	Logical agents	R&N, Ch 7: 7.1-7.4
9	Inference in propositional logic	R&N, Ch 7: 7.5-7.8
10	Belief revision I	slides and lecture notes, tba
11	Belief revision II	slides and lecture notes, tba
12	Extending to first order logic	R&N, Ch 8
13	Closing Lecture	R&N, Ch 26

The course will be assessed by:

- two group assignments, and
- a final two-hour online multiple choice exam.

The first group assignment, on search
start: March 1; end: March 29
The second group announcement, on logic
start: April 19; end: May 17

The course will be evaluated as a whole
with the two assignments weighing approximately 20% each,
and the final exam weighing approximately 60%.

02180: In the context of other courses at DTU

Advanced search methodologies (Ch. 3–4 of R&N)

- 02282 Algorithms for Massive Data Sets
- 42137 Optimization Using Metaheuristics

Operations Research (Ch. 4, 6 of R&N)

- 42101 Introduction to Operations Research
- 42114 Integer Programming
- 42142 Recent Research Results in Operations Research

Advanced logical methods in AI (Ch. 7–9 of R&N)

- 02156 Logical Systems and Logic Programming
- 02287 Logical Theories for Uncertainty and Learning

Automated planning (Ch. 10–11 of R&N)

- 02285 Artificial Intelligence and Multi-Agent Systems

Image processing (Ch. 24 of R&N)

- 02502 Image Analysis
- 02506 Advanced Image Analysis
- 02504 Computer Vision

02180: In the context of other courses at DTU

Knowledge-based reasoning (Ch. 12 of R&N)

- 02287 Logical Theories for Uncertainty and Learning (partly)

Probabilistic reasoning and learning (Ch. 13–21 of R&N)

- 02417 Time Series Analysis
- 02450 Introduction to Machine Learning and Data Mining (general intro)
- 02460 Advanced Machine Learning
- 02582 Computational Data Analysis
- 02456 Deep Learning
- 02287 Logical Theories for Uncertainty and Learning

Natural language processing (Ch. 22–23 in R&N)

- 02456 Deep Learning (partly)

Robotics (Ch. 25 of R&N)

- 31385 Autonomous Robot Systems
- 31388 Advanced Autonomous Robots
- 31389 Advanced Topics in Robotics and Autonomous Systems

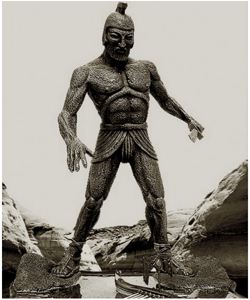
It is very hard to come up with a fundamental, general definition of the field.

AI is the field devoted to building artificial 'intelligent creatures', i.e., building artificial correlates of the non-artificial intelligent beings the human race has been able to encounter so far: animals of the non-human variety, and humans.

Some cultural precursors

The dream of creating such beings is often encountered in culture, e.g.:

- In Greek mythology, Talos, was a giant automaton made of bronze to protect Europa in Crete from pirates and invaders, circling the island's shores three times daily.
- Frankenstein's monster is a thinking creature created in a scientific experiment by a young scientist Victor Frankenstein, in an 1818 novel written by English author Mary Shelley.




Is Artificial Intelligence possible?

Can machines think?

Can machines think?

FIGURE: Alan Turing

Turing Test

HARD QUESTION:
Can machines think?

Turing Test

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STRONG ANSWER:
Yes, machines can have minds **just as** humans do (STRONG AI)

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Instead:

SOFTER QUESTION:
Can machines pass a behavioural intelligence test?

Alan Turing, 'Computing Machinery and Intelligence' (1950)

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STRONG ANSWER:
Yes, machines can have minds **just as** humans do (STRONG AI)

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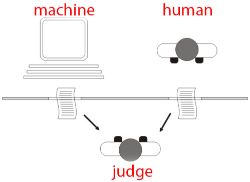

SOFTER ANSWER:
Yes, machines can behave **as if** they are intelligent (WEAK AI)

Turing Machines and Church-Turing Thesis

Alan Turing's theory of computation,

combined with elements of mathematical logic,

suggests that a machine operating in on binary numbers
(Turing Machine, digital computer),

could simulate any conceivable formal reasoning.

(Church–Turing Thesis)

The official birth of the field of AI

Workshop at Dartmouth College in 1956.

Participants included: Allen Newell (CMU), Herbert Simon (CMU), John McCarthy (MIT), Marvin Minsky (MIT), and Arthur Samuel (IBM).

(This is also where AI and Cybernetics parted ways.)

Definition by John McCarthy:

> *'Artificial intelligence is the* **science** *and* **engineering** *of making* **intelligent machines**, *especially* **intelligent computer programs**.*'*

Since Turing's conceptualisations
a lot of energy in technology is put to engineering intelligent designs
which would match/outperform/mimic/complement
the behaviour of non-artificial agents (most importantly, humans).

The goal of AI: matching human performance?

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the behaviour of non-artificial agents (most importantly, humans).

Since intelligence is displayed in problem solving the field got fragmented into different subdomains with flagship/benchmark problems for AI to defeat.

Example achievements of AI research: narrow intelligence

1991 **US Defence planning system** employed in Gulf War logistics.

1994 **Driverless car** drives 1000 km on public roads in France.

1997 IBM chess computer **Deep Blue** beats world champion Gary Kasparov.

2011 IBM Jeopardy computer **Watson** beats the Jeopardy world champions.

2011 Apple releases its intelligent personal assistant **Siri**.

2015 **Google DeepMind** teaches itself to play Atari games with above human level on most games.

2016 **Google AlphaGo** reaches world-class level in the game of Go.

AI (narrowly) attacks the domain of Art

2015 V. van Gogh vs Neural Networks, compare:

AI (narrowly) attacks the domain of Art

2015 V. van Gogh vs Neural Networks, compare:

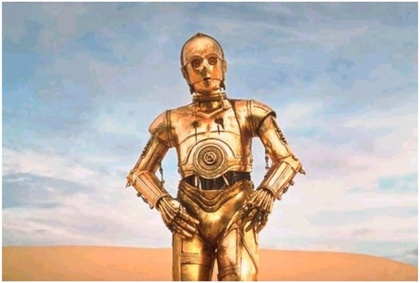
2016 J.S. Bach vs Flow Machines, compare:

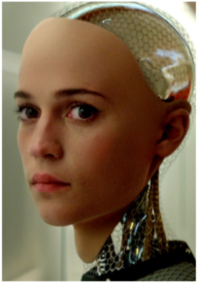
play 1

play 2

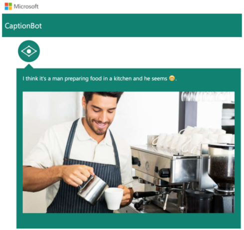
To vote go to www.menti.com and use the code 75 62 37 7

AI in Science Fiction: towards total human experience





Yet another level: Everyday AI



CaptionBot image recognition

Siri on iPhone

Google driverless car

Current features of AI

- **Specialised systems** that solve well-defined, clearly delimited problems.
- **No magic wand**: progress requires huge computing and human resources.
- **Advantage due to computational power and data**, rather than the development of fundamentally new algorithms.

Symbolic vs sub-symbolic AI

The symbolic paradigm (1950–): Simulates human symbolic, conscious reasoning. Search, planning, logical reasoning, e.g.: chess computer.

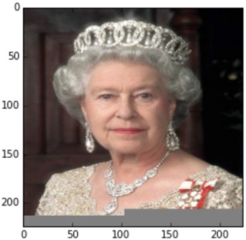
- Advantages: robust, predictable, explainable;
- Disadvantages: strictly delimited abilities.

The sub-symbolic paradigm (1980–): Simulates the fundamental physical (neural) processes. Artificial neural networks, e.g.: image recognition.

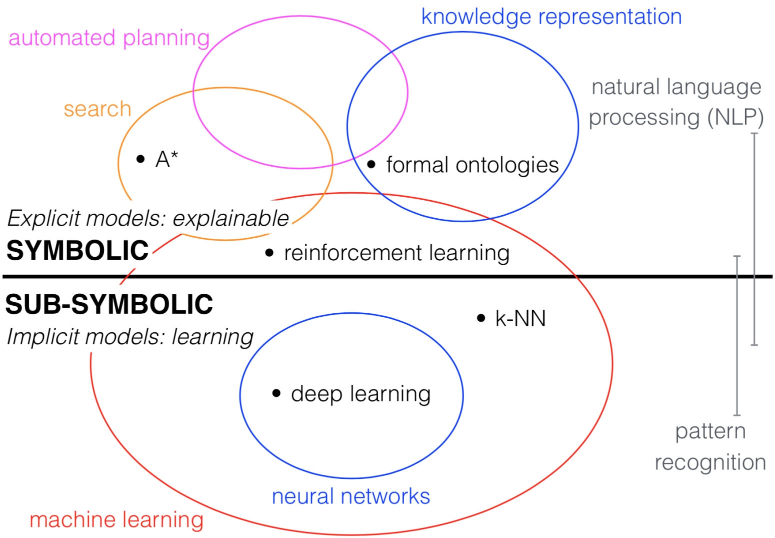
- Advantages: flexible, adjustable;
- Disadvantages: never 100% predictable/error-free.

Challenges in sub-symbolic AI


```
class: 793
label: n04209133 shower cap
certainty: 99.7%
```



Symbolic and sub-symbolic AI



Intelligent agents

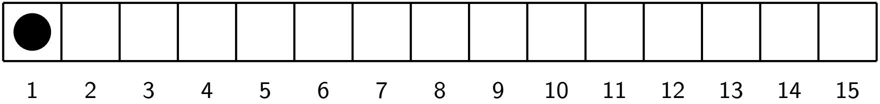
> *An agent is anything that can be viewed as perceiving its* **environment** *through* **sensors** *and acting upon that environment through* **actuators***.*
>
> *(Russell & Norvig, Chapter 2)*

So in the design of agents (AI systems), what becomes central is:

1. What kind of **environment** is the agent supposed to act in?
2. What is **inside** the agent: how does it process its perceptions and decide what to do?

Agents and problem solving: Race Game

Consider the following two-player game **Race Game**. Initially there is a token on cell 1. The two players take turn to move the token 1, 2 or 3 cells to the right. The one who moves the token into cell 15 has won.



At home: Play the game a few times with a friend.
Questions:

1. What is the best strategy for the first player?
2. How did you come up with it?
3. How can we make AI to play such a game?

Three levels of AI in the Race Game

1. **Hardcoded strategy**: a human finds the optimal strategy and codes it into a computer program.
2. **Search for a strategy**: a human implements a search algorithm (backwards induction/minimax algorithm), and the computer uses this search algorithm to find the optimal strategy.
3. **Develop strategy from scratch**: no insights about games in general or the particular game are provided to the computer. The rules of the game could be known or unknown.

Deductive reasoning (valid or invalid):

1. All men are mortal.
2. Socrates is a man.
3. **Therefore, Socrates is mortal.**

Inductive reasoning (strong or weak):

1. All biological life forms that we know of depend on liquid water to exist.
2. **Therefore, if we discover a new biological life form it will probably depend on liquid water to exist.**

Inductive Inference
is where logic meets probability and where reasoning meets learning.

Inductive Inference: Card Game

What is the rule behind this sequence of cards?

Inductive Inference: Card Game

What is the rule behind this sequence of cards?

A♠

Inductive Inference: Card Game

What is the rule behind this sequence of cards?

A♠ Q♠

Inductive Inference: Card Game

What is the rule behind this sequence of cards?

A♠ Q♠ 3♠

Inductive Inference: Card Game

What is the rule behind this sequence of cards?

A♠ Q♠ 3♠ A♠

Inductive Inference: Card Game

What is the rule behind this sequence of cards?

A♠ Q♠ 3♠ A♠ Q♠

Inductive Inference: Card Game

What is the rule behind this sequence of cards?

A♠ Q♠ 3♠ A♠ Q♠ 4♡

Inductive Inference: Card Game

What is the rule behind this sequence of cards?

A♠ Q♠ 3♠ A♠ Q♠ 4♡ . . .

How many different abstract scenarios?

Assume we have at our disposal unlimited amount of playing cards.

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1. How many different (kinds of) playing cards do we have?

How many different abstract scenarios?

Assume we have at our disposal unlimited amount of playing cards.

1. How many different (kinds of) playing cards do we have?
2. How many different beginnings of length 1?

Assume we have at our disposal unlimited amount of playing cards.

1. How many different (kinds of) playing cards do we have?
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3. How many different beginnings of length 2?

How many different abstract scenarios?

Assume we have at our disposal unlimited amount of playing cards.

1. How many different (kinds of) playing cards do we have?
2. How many different beginnings of length 1?
3. How many different beginnings of length 2?
4. How many different infinite sequences?

1.	A♠	A♠	A♠	A♠	A♠	A♠	. . .
2.	A♣	A♣	A♣	A♣	A♣	A♣	. . .
3.	A♡	A♡	A♡	A♡	A♡	A♡	. . .
4.	A♢	Q♠	3♠	8♡	2♡	5♠	. . .
5.	A♠	Q♠	7♠	J♠	5♠	5♠	. . .
. . .							
m.	A♣	A♡	A♣	A♡	A♣	A♢	. . .
. . .							

The Infinities of Inductive Inference

1.	A♠	A♠	A♠	A♠	A♠	A♠	...
2.	A♣	A♣	A♣	A♣	A♣	A♣	...
3.	A♡	A♡	A♡	A♡	A♡	A♡	...
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...							
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m.	A♣	A♡	A♣	A♡	A♣	A♢	...
...							

The Infinities of Inductive Inference

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...							

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...								

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...								
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...								

...

How many possible rules are there?

1. In principle...

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1. In principle...
2. Rule written down on a piece of paper.
3. Rule expressed by a natural language sentence.
4. Rule described by a theory that fills a 300 pages book.

How many possible rules are there?

1. In principle...
2. Rule written down on a piece of paper.
3. Rule expressed by a natural language sentence.
4. Rule described by a theory that fills a 300 pages book.
5. Rule encoded by a Turing Machine program.

Descriptions are finite, and there are countably many of them.

How many sequences comply to one rule?

1. The sequence has solely A♠-cards.

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2. The sequence has solely ♠-cards.

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3. The sequence has ♡-cards on even places.

How many sequences comply to one rule?

1. The sequence has solely A♠-cards.
2. The sequence has solely ♠-cards.
3. The sequence has ♡-cards on even places.
4. The sequence is definable in first-order logic.
5. etc...

Different Hypothesis Spaces

What can we know and how can we know it?

1. $\{(\text{all cards are } \spadesuit), (\text{all cards are } \diamondsuit)\}$
2. $\{(\spadesuit \text{ at the 4-th position}), \neg(\spadesuit \text{ at the 4-th position})\}$
3. $\underline{\{(\text{exactly } n \text{ cards are } \heartsuit) \mid n \in \mathbb{N}\}}$
4. $\{(\text{exactly } n \text{ cards are } \heartsuit) \mid n \in \mathbb{N}\} \cup \{(\infty \text{ cards are } \heartsuit)\}$

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A♠ Q♠ 3♠ A♠ Q♠ 4♡

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A$\spadesuit$ Q$\spadesuit$ 3$\spadesuit$ A$\spadesuit$ Q$\spadesuit$ 4$\heartsuit$ Q$\spadesuit$ Q$\heartsuit$...

The Game of Learning in the Limit: Learner and Nature

- A class of possible worlds (known by both players).
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Her success depends on her skills and on the problem.

THE END OF LECTURE 1