Trust and explainability: The relationship between humans & AI

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A bit about myself

Thomas Bolander

- Associate professor in AI at DTU Compute, Technical University of Denmark.
- Member of the SIRI commission.
- Current research: Social aspects of AI. To equip AI systems with a Theory of Mind (ToM).
Quotes on AI and trust

The measure of success for AI applications is the value they create for human lives. In that light, they should be designed to enable people to understand AI systems successfully, participate in their use, and build their trust.

AI technologies already pervade our lives. As they become a central force in society, the field is shifting from simply building systems that are intelligent to building intelligent systems that are human-aware and trustworthy.

(My highlighting)

(One Hundred Year Study on AI: 2015–2016, Stanford University, 6. september 2016)
Introduction to trust and explainability

When do we trust the decisions, predictions or classifications of another agent (person, AI system, company):

1. When the agent is always right (0 probability of mistakes)?
2. When the agent is almost always right (very low probability of mistakes)? The same mistake might be repeated, but still with very low probability.
3. When the agent is most often right, but when not, the agent has an acceptable and explainable reason for not being so. The same mistake is not repeated (one-shot learning).
What is artificial intelligence (AI)?

Definition by John McCarthy, the father of AI:

“Artificial intelligence is the science and engineering of making intelligent machines, especially intelligent computer programs.”

John McCarthy, 2006

Doesn’t imply that they are intelligent in the same way as humans.

AI today is probably more different from human intelligence than anyone anticipated.

Threatens trust of humans in decisions made by AI.
Symbolic vs sub-symbolic AI

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

- robust, predictable, explainable
- strictly delimited abilities
- flexible, learning
- never 100% predictable/error-free

The **sub-symbolic paradigm** (1980–): Simulates the fundamental physical (neural) processes in the brain. Artificial neural networks. **Ex:** image recognition.
Humans vs machines in relation to trust

Human
Fluent integration of subsymbolic (intuition, patterns) and symbolic reasoning (language, logic). Leads to ability to explain.

Machine
High performance and precision on clearly delimited task.

Fundamental differences between human and machine intelligence can negatively affect trust, in particular by:

- **Lack of robustness**: Lack of precision and robustness of machine.
- **Lack of human understanding**: 1) Lack of understanding how machine works; 2) lack of reasonable explanations in case of failures.
Both have **social intelligence** among the 3 human cognitive abilities that are hardest to simulate by computers and robots.

**Social intelligence**: The ability to understand others and the social context effectively and thus to interact with other agents successfully.
Lack of understanding: Machines behaving strangely

Lewis et al.: Deal or No Deal?, ArXiv, June 2017:
“We found that updating the parameters of both agents led to divergence from human language.”

Forbes, 31 July 2017:
Facebook AI Creates Its Own Language In Creepy Preview Of Our Potential Future

New York Post, 1 August 2017:
Creepy Facebook bots talked to each other in a secret language

The Telegraph, 1 August 2017:
Facebook shuts down robots after they invent their own language
Lack of robustness: verification vs machine learning

Safety/robustness/flawlessness: verification vs machine learning.

Verification:

Intel Pentium bug 1994

Machine learning:

Simple hacking of machine learning techniques
Lack of robustness: Fooling deep neural networks

http://www2.compute.dtu.dk/~tobo/deepvis_recognition.mov
‘Your account has been disabled for not following the Instagram Community Guidelines, and we won’t be able to reactivate it.

We disable accounts that post content that is sexually suggestive or contains nudity. We understand that people have different ideas about what’s okay to share on Instagram, but to keep Instagram safe, we require everyone to follow our guidelines.

(Metro UK, 5 April 2015)
Trust from low probability of mistakes?

Is it sufficient that the agent is almost always right?

No:

For example, we cannot argue that a pedestrian detector is safe simply because it performs well on a large data set, because that data set may well omit important, but rare, phenomena (for example, people mounting bicycles). We wouldn’t want our automated driver to run over a pedestrian who happened to do something unusual.

(Russell & Norvig: Artificial Intelligence—A Modern Approach, 3ed, 2010.)
Regaining trust: explainable AI

- Trust in AI systems is at risk when systems are neither 100% robust, nor explainable (by themselves or from the outside).
- In lack of 100% robustness, we need more transparent and explainable AI.
- Subsymbolic AI (e.g. neural networks) is naturally opaque.
- Symbolic AI (e.g. manually hand-crafted rule-based systems) is naturally transparent, but difficult to craft.
- Best current bet is to combine: The output of learning is rules and explicit models that can be inspected, understood and modified by humans.

The Big Data mantra of “what, not why” is challenged when decisions are made by algorithms, and the people affected want an explanation.
Correlations vs causal relationships: AI can’t distinguish

Divorce rate in Maine correlates with
Per capita consumption of margarine (US)

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<td>Per capita consumption of margarine (US)</td>
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Correlation: 0.992558
When can we expect explanations of failures?

Is it realistic to expect a system to be able explain failures in classification/prediction?

Why did you move the marble into the red square?

Why did you believe this was a horse?

Why did you believe this was red?
Symbolic vs sub-symbolic AI: explicit vs implicit models

\[ a_x = -\frac{kv_x}{m} = \frac{dv_x}{dt} \quad (1), \]

and

\[ a_y = \frac{1}{m} (-kv_y - mg) = -\frac{kv_y}{m} - g = \frac{dv_y}{dt} \quad (2) \]
From raw data to symbolic representations

- **Subsymbolic AI**: input is raw data (subsymbolic), output is subsymbolic (implicit model).
- **Symbolic AI**: Input is symbolic, output is symbolic (explicit model).

What we really need for **explainability**: input is raw data, output is explicit model (symbolic). Requires combining symb. and subsymb. AI.
Three waves of AI

DARPA (Defense Advanced Research Projects Agency, USA) identifies three waves of AI:

- “The first wave of AI: Handcrafted knowledge”. Essentially the symbolic paradigm.
- “The second wave of AI: Statistical learning”. Essentially the subsymbolic paradigm.
- “The third wave of AI: Contextual adaptation”. Essentially the combination of symbolic and subsymbolic approaches. Combine perception in neural networks with symbolic models for representing features, allowing explanations (“I thought it was a cat because it has fur and a short snout”).
Loosing trust: machine bias

Huge potential in machine learning algorithms (subsymbolic AI) for **predictions** and **decision making**. However, any bias in the data will also be learned.

(Angwin et al.: Machine Bias, ProPublica, 23 May 2016)
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Lewis et al.: Deal or No Deal?, ArXiv, June 2017: “We found that updating the parameters of both agents led to divergence from human language.”

Politiken, 31 July 2017:
Eksperiment lukket ned: To Facebook-robotter opfandt deres eget sprog
Et eksperiment med kunstig intelligens er blevet lukket ned hos Facebook, efter at robotter skiftede sprog.

New York Post, 1 August 2017:
Creepy Facebook bots talked to each other in a secret language
Neural networks

input layer   hidden layer   output layer

horse: 0.3
zebra: 0.7
mule: 0.5