WHY WE NEED AN AI-RESILIENT SOCIETY

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Thomas Bartz-Beielstein
Institute of Data Science, Engineering, and Analytics
Faculty of Computer Science and Engineering Science
TH Köln
51643 Gummersbach
thomas.bartz-beielstein@th-koeln.de

ABSTRACT

Artificial intelligence is considered as a key technology. It has a huge impact on our society. Besides many positive effects, there are also some negative effects or threats. Some of these threats to society are well-known, e.g., weapons or killer robots. But there are also threats that are ignored. These "unknown-knowns" or blind spots affect privacy, and facilitate manipulation and mistaken identities. We cannot trust data, audio, video, and identities any more. Democracies are able to cope with known threats, the known-knowns. Transforming unknown-knowns to known-knowns is one important cornerstone of resilient societies. An AI-resilient society is able to transform threats caused by new AI tecchnologies such as generative adversarial networks. Resilience can be seen as a positive adaptation of these threats. We propose three strategies how this adaptation can be achieved: awareness, agreements, and red flags. This article accompanies the TEDx talk *Why we urgently need an AI-resilient society*, see `https://youtu.be/f6c2ngp7rqY`.

***K*eywords** artificial intelligence · resilient society · generative adversarial networks · deep fakes · hoaxes

1 Introduction

In 1962, Martin Gardner described how to build a game-learning machine, and how to teach it to play and win [Gardner, 1962]. Gardner described *hexapawn*, a simplified chess computer, which can be build with 24 matchboxes. These boxes are filled with colored beads. By shaking the matchbox, drawing a bead, the computer's move is determined based on the color of the bead. If the computer loses, it is punished by taking away the bead from the last draw. Figure 1 shows the chess computer.

Interestingly, Gardner reported that two matchbox computers learned to play chess by playing against each other[Gardner, 1969].

> "Several readers built two matchbox machines to be pitted against each other. John Chambers, Toronto, called his pair THEM (Two-way Hexapawn Educable Machines). Kenneth W. Wiszowaty, science teacher at Phillip Rogers Elementary School, Chicago, sent me a report by his seventh-grade pupil, Andrea Weiland, on her two machines which played against each other until one of them learned to win every time. John House, Waterville, Ohio, called his second machine RAT (Relentless Auto-learning Tyrant), and reported that after eighteen games RAT conceded that HER would win all sub-sequent games."

Since 1962, when Gardner's article was published, *Artificial Intelligence* (AI) has made tremendous improvements [Russell and Norvig, 2009]. In 1997, Deep Blue, a chess-playing computer developed by IBM, won its first game against the world chess champion Gary Kasparov [IBM Corporation, 2019]. More and more games were won by AI, e.g., Go [Silver and Hassabis, 2016].

Most considerations and examples in our article refer to weak (or narrow) AI, i.e., AI that is able to solve a specific task. In contrast to weak AI, strong AI (or super-intelligence) is defined as a machine with the ability to apply intelligence

Figure 1: A simplified chess computer. Hexapawn is played on a 3x3 board.

to any problem. Strong AI is sometimes associated with understanding and (self-)consciousness, whereas weak AI is associated with data processing and adaptation. Super-intelligence is considered to be far away.

AI tools are successful in many applications, especially in pattern recognition, e.g., speech recognition, image classification, or big data analysis. There are many interesting articles available that describe recent developments and the current state of this fascinating technology. Sullivan [2019] gives an overview by describing ten important moments in AI. Benaich and Hogarth [2019] discuss the latest developments in AI research, industry, and politics in 2019. Crawford et al. [2019] describes the social implications of AI technologies. Walsh [2018a] considers the impact AI will have on our society, e.g., on work, war, equality, politics and, ultimately, the fate of humanity. We highly recommend the books by Walsh [2018b], Marcus and Davis [2019], and Agrawal et al. [2018].

AI does not only affect everybody's life, it revolutionizes our life. *Google maps* and similar systems have changed how we navigate. But where there is light, there must be shadow. Since there is a very bright light in AI today, mustn't there be a very dark shadow? We will take a deeper look at light and shadow caused by AI in this article. We will focus on the consequences for our society.

AI is already there, and will be there in the future—even during the next AI winter.

In general, we are fascinated by AI and want to share our fascination with society. However, we do not blindly follow every new AI promise. So, this article is not an article against AI. On the contrary, we wish to attract people to AI.

This article is structured as follows. Section 2 presents threats caused by AI. These can be based on failing AI systems as well as on working AI systems. A classification of these threats based on the Johari window is presented in Sec. 3. *Generative adversarial networks* (GANs), which are considered the most fascinating, but also the most dangereous AI tools, are discussed in Sec. 4. The AI resilient society is introduced in Sec. 5. This article closes with a conclusion in Sec. 6.

2 Threats Caused by AI

Modern technologies make our life easier and more convenient. But when they fail, they can cause severe threats. Although this is true for every technology and not an AI specific problem, it is worth taking a look at some prominent AI failures.

2.1 Where AI Fails

Translation We start with a hoax. Translate the phrase "the spirit is willing but the flesh is weak" into Russian, and then back into English. The result is:"the vodka is good but the meat is rotten." This example is simply an amusing story, but not a factual reference to an actual machine translation error [Hutchins, 1995]. However, this funny idea made it to a late night show on TV: Jimmy Fallon and his guests take turns singing classic ABBA songs, like "Dancing Queen" which turns into "Hula Prince" after running the lyrics through Google Translate [Fallon, 2018].

Face Recognition Many countries are using face recognition in public places [nat, 2019]. China has been using automated facial recognition techniques to educate people. For example, to shame jaywalkers their names are posted on public screens. One camera seemingly caught a jaywalker, but it turned out to be a famous businesswoman whose photo appeared on a bus advertisement. When the bus passed by, the camera took a photo of her photo on the bus [NEWS, 2018, Liao, 2018].

Self-driving Cars The death of Elaine Herzberg. This was the first recorded case of a pedestrian fatality involving a self-driving car [National Transportation Safety Board, 2018]. She died of her injuries in a hospital after a collision with an Uber test car. The accident occurred in March 2018. The Uber car was operated in self-drive mode with a human safety backup driver sitting in the driving seat.

Healthcare IBM Watson and healthcare problems [Strickland, 2019]. Oren Etzioni, CEO of the Allen Institute for AI and former computer science professor, is quoted in Gizmodo with the following words [Brown, 2017]:"IBM Watson is the Donald Trump of the AI industry—outlandish claims that aren't backed by credible data. [...] Everyone—journalists included–know[s] that the emperor has no clothes, but most are reluctant to say so."

These failures can threaten society. But since they are known, countermeasures can be taken. The corresponding algorithms could be improved [Martineau, 2019], so that, at least in principle, these threats can be eliminated.

2.2 Threats Caused by Working AI

Besides the threats caused by AI failures, there are AI inherent threats: even if AI does not fail it can cause threats to our society. They might be intended, e.g., AI based weapons or unintended, e.g., AI bias [Winter, 2019]. Taken to the extreme, super-intelligence can also be considered as a threat to our society [Marcus and Davis, 2019, Walsh, 2018b].

3 Known Knowns and Unknown Unknowns

What kind of threats are there? What is probably the most famous classification of these threats? What are the real dangers and threats to citizens today?

In 2002 United States Secretary of Defense, Donald Rumsfeld, stated in a U.S. Department of Defense news briefing about the war in Iraq [Rum, 2002, CNN, 2002]:

> Reports that say that something hasn't happened are always interesting to me, because as we know, there are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns—the ones we don't know we don't know.

Rumsfeld used a simplified version of the Johari window, which is used in psychology to help people better understand their relationship with themselves and others [Luft and Ingham, 1955]. We will use the Johari Window to describe how threats are recognized in our society.

3.1 The Johari Window

Rumsfeld mentioned known knowns, known unknowns, and unknown unknowns. But there is even more. The Johari window covers four combinations: known knowns, unknown unknowns, known unknowns, and also unknown knowns.

Known knowns These are the threats that are well-known, taken care of, and discussed in public.

Known unknowns Known unknowns are potential threats, that we cannot determine exactly. AI systems improve, e.g., Kasparov was beaten by IBM's Deep Blue. It is a known known that you may lose if you play against a chess computer. Now consider that AI will improve more and more. This might result in some super-intelligence, which is so powerful that it will enslave all human beings. OK, this a classical SciFy story. And a typical known unknown, because the threat is known, but it is unknown, when it will happen—if it will ever happen at all.

Unknown unknowns These are the threats we will never know in advance. Consider, e.g., radioactivity. Before it was discovered in 1896 by Henri Becquerel, nobody considered this as a threat or predicted this as a threat.

Unknown knowns We claim that regarding AI, the main dangers lie in the "unknown knowns". So, you may ask: what are "unknown knowns"? Referring to the Johari window, these are the threats that everybody knows—and ignores. They are referred to as the "blind spots" in psychology.

The Johari window is illustrated in Fig. 2. What are the blind spots in AI?

3.2 Unknown Knowns in AI

The unknown knowns in AI are related to privacy, manipulation, and mistaken identities. Unknown knowns are threats that are ignored. Everybody knows about privacy issues with Facebook, WhatsApp, etc. But nobody really cares.

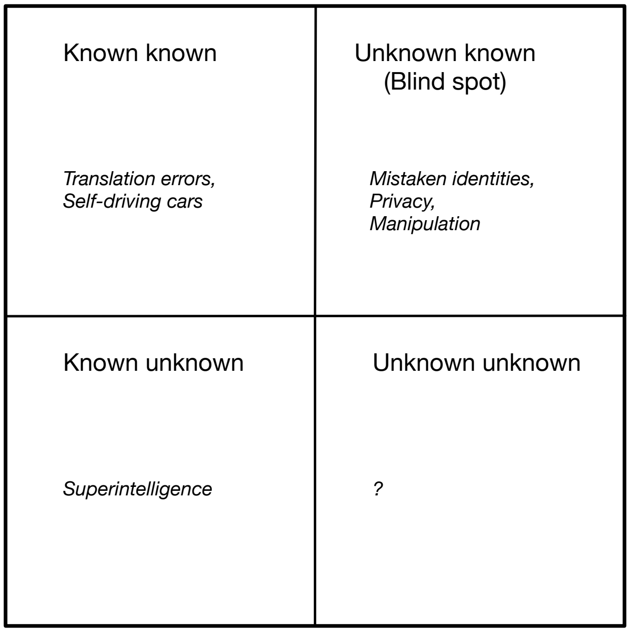

Figure 2: Johari window. A four paned window divides AI threats into four different types, as represented by the four quadrants. Known knowns are threats discussed in society, e.g., Google's translation errors. Known unknowns are threats that we are aware of, but do not know when they will (ever) happen. SciFy stories about super-intelligence can be mentioned here. Unknown unknowns are threats that cannot be predicted, they are not published as SciFy. We focus on unknown knows, i.e., the blind spots.

Example 3.1 (Siri)**.** Consider a popular "unknown known": Siri. Everybody knows that there is not a real person sitting in my phone and answering my questions. But what happens if we ask Siri about her identity:

Siri What can I help you with?

Question Are you a computer?

Siri I am not sure what you have heard. But virtual assistants have feelings, too.

Question Are you a computer?

Siri Well, I don't wanna brag. But I got a B+ on the Turing test.

Question Are you a computer?

Siri I am share this information on a need to know basis.

This conversation looks funny—at the first glance. But Siri's answers causes severe problems, which we will refer to as *mistaken identities*.

4 Generative Adversarial Networks

Siri integrates several very sophisticated AI tools. The most recent, the most fascinating, and probably the most threatening tools in AI are *Generative Adversarial Networks* (GANs)[Goodfellow et al., 2014]. Why are GANs the basis of the most threatening examples in AI? Given a large set of data, GANs can generate brand new data that look like the original [Klimek, 2018a].

Example 4.1 (Deep Fakes)**.** Consider the web page `https://thispersondoesnotexist.com`. The people shown on these photos look real, but they do not exist. These are *Deep Fakes* generated using GANs.

You may think that image manipulation is not really new and was used even before Photoshop was available. So, what is different today, what changed? The difference is three-fold: First, processors are much faster than 40 years ago. Second, there are more data. Third, GANs use a very clever strategy.

Gardner described two computers that play against each other [Gardner, 1969]. They used essentially the same strategy, they are somehow symmetric. GANs also play against each other, but in a very sophisticated manner. They use asymmetric algorithms. GANs are neural network-based architectures that use two models, a generator and a discriminator.

Example 4.2 (Counterfeit Money)**.** Imagine the following situation. The two models are running on two computers:

Figure 3: GANs creating counterfeit money. This process does not require any human interaction. *Left:* The first counterfeit note. *Center:* Improved counterfeit note. *Right:* Result after several billion iterations. Final counterfeit note [Kalina, 2018].

1. The first computer (generator), say A, creates fake images, e.g., counterfeit money.
2. The second computer (discriminator), say B, says "that's fake" and gives feedback.
3. A uses this feedback to make new money and shows it to B again.
4. B says "that's fake" and gives more feedback.

This cycle is repeated a several billion times, very quickly. The counterfeit money improves over time—without human intervention. Ultimately humans cannot distinguish whether the result is fake or real. This process is illustrated in Fig. 3. A similar example is presented in Klimek [2018b].

There are several introductions to GANs, e.g., Honchar [2019], Horev [2018], Karras et al. [2018, 2019]. Before reading these papers, it is worth watching some of the inspiring videos, e.g., Steenbrugge [2019].

Given a large set of data, the GAN is capable of generating completely new data indistinguishable from the original. This is the basis of the most threatening examples. To counterfeit money is only a simple example. The really ugly and threatening stuff happens, if people are involved. GANs can create new identities by combining features from different objects, e.g., faces. These images were generated by copying a specified subset of styles from the first source and taking the rest from a second source [Brock et al., 2018].

Example 4.3 (Face App)**.** GANs are also used in aging or de-aging programs. You might know or even have used the FaceApp program, which nicely shows how you will look in ten or twenty years [Fac, 2019]. FaceApp is based on GANs. And there are many more applications, e.g., GANs can also be used to determine the looks of a baby from the photos of its parents.

More than 40 years ago, science magazines explained how to build matchbox chess computers [Gardner, 1962]. Today, the same magazine describes how deep fake videos can be produced [Wha, 2019]. Everybody, who has access to the internet, can create fake videos/images [Nag, 2017]. This is a national security threat, because GANs can also create fake videos/images of important people that look real. Combining fake news with deep fakes produces powerful propaganda, which can be distributed on the internet very quickly (using twitter or facebook). GANs can affect personal safety and national security [Hsu et al., 2018]. The potential for bad is there. Think about elections, where false news articles flooded almost all social media platforms Andres [2019]. Imagine the impact these articles would have had if they had contained accompanying "false images", "false audio", or even "false video".

Example 4.4 (Deep-faking photos of the earth)**.** A dangerous AI-enabled weapon is deep-faking photos of the earth. First, AI is used to make undetectable changes to outdoor photos. Then these photos are released into the open-source world. Todd Myers, automation lead for the CIO-Technology Directorate at the National Geospatial-Intelligence Agency, warns [Tucker, 2019]:

> "Forget about the [Department of Defense] and the [intelligence community]. Imagine Google Maps being infiltrated with that, purposefully? And imagine five years from now when the Tesla [self-driving] semis are out there routing stuff?".

And there are many more applications [Nowlin, 2018]: Password Cracking [Klimek, 2018a], hiding malware [Klimek, 2018a, Rigaki and Garcia, 2018], or speech synthesis [Dessa, 2019].

5 AI Resilient Society

What can you do if you discover a deep-fake of your own? Nowadays, this remains an open question. There is no quick solution available. That is where an AI resilient society comes into play! You may ask: Why should our society be involved? Why can't this problem be solved by the AI experts using technological measures, e.g., by using anti-GAN software (similar to anti-virus software)?

Related attempts exist. Hsu et al. [2018] developed a *Deep Forgery Discriminator* (DeepFD). And for sure, programmers should engineer their systems with GANs in mind. Unfortunately, GANs are very tricky: they learn by playing against each other, so they may improve by playing against anti-GAN software. Furthermore, experience shows that technological countermeasures results in counter-countermeasures—this is an infinite loop.

Since technological countermeasures can only temporarily solve the problem, our society should be involved. There are success stories from history that illustrate how our society can cope with technological threats. Consider, e.g, nuclear bombs or the ozone hole. These were severe threats, but we found ways to manage them.

Common to these threats is that the corresponding technologies were not discussed behind closed doors or only in the ivory tower. At least, after some time, they were discussed in public. Public engagement resulted in agreements, rules, and laws. But laws can only be decided upon if there are *known knowns*. So, known knowns are the cornerstones of an AI resilient society.

Based on these ideas, we are able to define the term *AI-resilient society*.

Definition 1 (AI Resilient Society)**.** An AI resilient society is able

1. to transform the unknown knowns to known knowns and
2. to develop rules (laws) for the known knowns.

Resilience can be seen as a positive adaptation of these threats.

In the following section, we will mention three important strategies how this adaptation can happen: awareness, agreements, and red flags. Note, AI resilience describes a property of the society, and not a feature of the AI technology.

5.1 Awareness

Awareness can be generated by publishing papers and giving public talks, e.g., the corresponding TEDx talk to this paper [Bartz-Beielstein, 2019]). And there are many more ways to create awareness.

Example 5.1 (Simple truth)**.** We should promote simple truths. Every child should know: "If you're not paying for the product (e.g., FaceApp), you are the product." That's an famous saying from Steve Jobs—but it is ignored by many people today.

Example 5.2 (Hoax identification)**.** Janne Ahlberg, a security professional from Finland, maintains a blog to identify fake or hoax pictures [Ahlberg, 2019].

Example 5.3 (Fact checking)**.** There is a list of fact checking websites on Wikipedia [Wikipedia contributors, 2019]. It includes websites that provide fact-checking services about both political and non-political subjects.

Example 5.4 (Reverse image search)**.** You can use *reverse image search*. Tools such as *TinEye* help you to search by image or perform what reverse image searches [Tin, 2019]. This short video explains how to perform reverse image search on a mobile phone: `https://youtu.be/OoLFjxtvPIM`. But, beware: "Google reverse image search results—especially the suggested text—should not be trusted. Google simply picks up the most used keywords. You can and sometimes should try different keywords for the image you are searching.", see `https://hoaxeye.com/2019/07/15/reverse-searching-images/`

Example 5.5 (Challenges)**.** In October 2019, Facebook, Microsoft, and academics came together to build the Deep-fake Detection Challenge [Facebook Designated Agent, 2019].

Example 5.6 (Information)**.** The *WITNESS Media Lab* is hosting the project *Prepare, Don't Panic: Synthetic Media and Deepfakes*. They have compiled a list of "twelve things we can do now to prepare for deepfakes" [WITNESS Media Lab, 2019]. The *WITNESS Media Lab* supports citizens and grassroots groups documenting human rights abuse with video. It is a collaboration with the News Lab at Google.

Example 5.7 (Think critically about AI)**.** Marcus and Davis [2019] states that it is "increasingly important that we be able to sort out AI hype and AI reality." AI limits should discussed publicly. In a recent article, Chollet [2019] describes how to measure intelligence.

5.2 Agreements

An AI resilient society benefits from principles and laws proposed by scientists, writers, or experts [Allen, 2019].

Example 5.8 (Asimov's laws)**.** Consider Asimov's laws—you might remember the film "I, Robot" [Asimov, 1950]:

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Law.

In 2010, the *Engineering and Physical Science Research Council* (EPSRC), the main UK government body that funds AI research, defined principles for roboticist. Similar initiatives, that develop agreements, are needed.

Example 5.9 (Partnership on AI)**.** Google, Amazon, IBM, Microsoft and Facebook announced a "Partnership on AI to benefit people and society." [Par, 2019].

Example 5.10 (Dual use of concern)**.** The so-called *dual-use risk* describes the risk that a technology, which was primarily developed for a civilian, "good" purpose, is being alienated for potentially unethical, public-endangering use. An interdisciplinary research project at TU Darmstadt deals with the evaluation of dual-use risks in software development [Reuter and Nordmann, 2018].

Example 5.11 (Science magazines, podcasts)**.** We need to decide on the acceptable use of AI technologies such as automated facial recognition nat [2019]. And we should discuss how to build in safeguards to protect human rights. Articles in science magazines or podcasts can initiate this discussion, e.g., trustworthy AI is discussed by Metzinger [2019]. He claims that ethics have also economical aspects.

Example 5.12 (Discussion papers)**.** The *Australian Human Rights Commission* has published a discussion paper that presents preliminary views on protecting and promoting human rights amid the rise of new technologies Australian Human Rights Commission [2019].

Example 5.13 (Bloxberg)**.** The Max Planck Digital Library established the research project *bloxberg*, which provides a trusted research infrastructure. The bloxberg infrastructure is a secure global blockchain established by a consortium of leading research organizations. It enables trusted data management, communication, and collaboration [Blo, 2019].

5.3 Walsh's Red Flags

One important safeguard against AI-based threats was proposed by Toby Walsh, who introduced *red flags* [Walsh, 2016]. The red flag idea was motivated by the *Locomotive Act from 1865*: concerned about the impact of motor vehicles on public safety, the British parliament required a person to walk in front of any motorized vehicle with a red flag to signal the oncoming danger.

In view of today's traffic situations, the Locomotive Act sounds crazy. But consider the following, modern variant of the red flag idea that was agreed upon in California in September 2004: governor A. Schwarzenegger signed legislation that prohibits the public display of toy guns unless they are clear or painted a bright color, in order to differentiate them from real firearms [Salladay, 2004].

Having AI systems in mind, Walsh defined the *Turing Red Flag Law* as follows [Walsh, 2016]:

> "An autonomous system should be designed so that it is unlikely to be mistaken for anything besides an autonomous system, and should identify itself at the start of any interaction with another agent."

Walsh's idea is discussed among the AI experts worldwide. The *High-Level Expert Group on AI*, which was set up by the European Commission, recommended red flags in the following manner [Smuha, 2019]:

> Introduce a mandatory self-identification of AI systems. In situations where an interaction takes place between a human and an AI system, and whenever there is a reasonable likelihood that end users could be led to believe that they are interacting with a human, deployers of AI systems should be attributed a general responsibility to disclose that in reality the system is non-human. This goes hand-in-hand with ensuring the transparency of AI systems.

There are several ways, how red flags can be implemented.

Example 5.14 (Computer generated text)**.** Whenever computer generated text, e.g., news or radio comments, is broadcasted, a red flag should come up.

Example 5.15 (Siri et al.)**.** It should be good style for Siri, Alexa, and all the others to correctly answer questions about their identities. [1]

[1] Maybe Tim Cook will read this article some day.

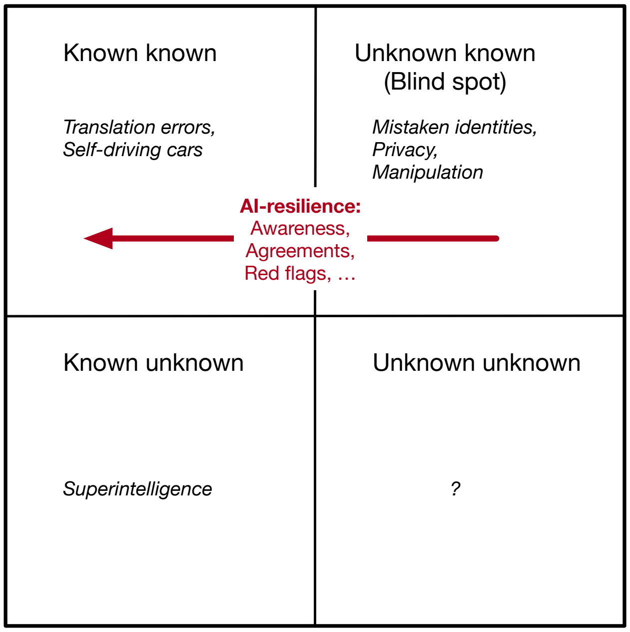

Figure 4: AI-resilient society in one figure. Unknown knows are transformed into known knowns.

6 Conclusion

The AI genie is out of the bottle and we cannot put it back. We cannot trust data, images, audio, video, and identities any more. That's why we urgently need an AI resilient society, which is based on openness and knowledge transfer. This process is illustrated in Fig. 4.

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