‘AI-Generated Inventions’: Time to Get the Record Straight?

This article attempts to clarify the notion of an ‘AI-generated’ invention, an issue which has triggered an intense debate on the future of patent law and policy. While there is a general consensus that such inventions are incompatible with the concept of human inventorship, it remains largely unclear to what extent concerns regarding ‘non-human’ ingenuity can be justified. Most uncertain is how AI ‘autonomously generates’ inventions, and in what way ‘AI-generated’ inventions differ from inventions developed with the aid of AI.

Drawing on the extensive literature review, this article depicts AI techniques as methods of computational problem solving. It emphasises that such methods should not be equated with a computer’s ‘cognitive autonomy’. Further, it clarifies that the types of AI that have been most debated in the patent law literature — artificial neural networks and evolutionary algorithms — essentially require detailed instructions that determine how the relation between inputs and outputs is derived through computation. Accordingly, it is argued that, as long as computers rely on instructions designed by humans as to how to solve a problem, the separation between human and non-human (algorithmic) ingenuity is, in itself, artificial. Ultimately, the article calls for a broader technical inquiry that would elucidate the relevance of the currently debated normative concerns over ‘non-human inventorship’ against the background of the technological state of the art.

The real danger of artificial intelligence is not that computers are smarter than us, but that we think [they] are.1

I. Introduction

The debate surrounding ‘AI-generated’ inventions continues to build momentum, reaching the agenda of policymakers at the international level2 as well as prompting numerous scholarly inquiries.3 On 21 December 2019, the European Patent Office (EPO) announced its refusal to examine two patent applications, designating an AI system DABUS as the inventor, on the formal ground of failure to fulfil the requirement of the European Patent Convention that ‘an inventor designated in the application to have been a human being, not a machine’.4 Shortly before this, the World Intellectual Property Organisation (WIPO) issued a call for comments raising, among others, the question of how patent law and policy should react to inventions ‘autonomously generated by AI’.5 That initiative was preceded by a request for comments by the U.S. Patent and Trademark Office (USPTO) addressing similar issues.6

Concerns were raised that under the current patent system third parties can indicate themselves as inventors of technologies generated by intelligent systems, and that the European Patent Office (EPO) announced its refusal to examine two patent applications, designating an AI system DABUS as the inventor, on the formal ground of failure to fulfil the requirement of the European Patent Convention that ‘an inventor designated in the application to have been a human being, not a machine’. Shortly before this, the World Intellectual Property Organisation (WIPO) issued a call for comments raising, among others, the question of how patent law and policy should react to inventions ‘autonomously generated by AI’. That initiative was preceded by a request for comments by the U.S. Patent and Trademark Office (USPTO) addressing similar issues. Concerns were raised that under the current patent system third parties can indicate themselves as inventors of technologies generated by intelligent systems, and that the
grant of such rights would impose an unjustified welfare loss on the society.7 Proposals were made as to how the patent system should be adjusted in the wake of artificial ingenuity, if not ‘abolished altogether’.8

Yet, it remains largely unclear: What do we mean by AI-generated inventions? How do we define computer autonomy during the inventive process? The amount of legal writing highlighting the incompatibility9 of the existing patent system with ‘artificial inventions’ appears to be in stark contrast with the seeming non-existence of technical inquiries on the very source of concerns – the phenomenon of ‘autonomous generation of inventions’ by computers.10 It is remarkable that, when raising the fundamental question of how patent law needs to be adjusted in the advent of ‘artificial inventions’, policymakers neither provide an operative technical definition of such inventions, nor clarify how they differ from AI-aided inventions, nor review the technological state of the art.11 Patent law literature on this topic refers to a handful of examples12 without providing or referencing a technical analysis, which could explain how the ‘intelligent systems’ were designed, and how the overall computational process leading to an invention was set up. Rather, the existence of ‘artificial’ inventions is taken as a premise13 for legal and policy discussions.

AI is often portrayed as yielding inventions with a wave of a magic wand – or a magic click,14 or simply by asking15 – autonomously from humans. However, researchers in the field of automatic programming acknowledge that the aspiration to make computers perform tasks by giving orders in a high-level language without specifying how they should be accomplished is ‘unrealistic, at least in the foreseeable future’.16 Moreover, experts in AI and robotics caution that characteristics such as ‘autonomous’, ‘unpredictable’ and ‘self-learning’ are ‘based on an overvaluation of the actual capabilities of even the most advanced robots, a superficial understanding of unpredictability and self-learning capacities [...]’, a robot perception distorted by Science-Fiction and a few recent sensational press announcements’.17 While it is highly uncertain when Artificial General Intelligence (‘Strong AI’)18 can be achieved, the mean average, according to a survey conducted among prominent researchers in the field of AI, is predicted to be the year 2099.19 Meanwhile, the anthropomorphic rhetoric in relation to AI – while being ‘helpful when explaining complex models to audiences with minimal background in statistics and computer science’20 – was criticised for being ‘misleading and potentially dangerous’.21

Such views should, at a minimum, raise curiosity as to what legal and policy discussions mean by ‘autonomously generated’ inventions. A more plausible scenario is, perhaps, where AI is applied as computational methods in the course of solving problems in various fields of research and development.22 In such situations, however, it appears unclear what degree of AI involvement should be considered to be prejudicial for recognising a human as an inventor, especially, given that the use of problem-solving tools and methods has not been a material factor from an inventorship perspective. (Otherwise, we should also be concerned about situations where microorganisms are used in research and development of biotechnological inventions, as they appear more viable candidates to act as ‘autonomous agents’ having consciousness of their own.23)

7 See eg WEF (in 2) 9 (stating that ‘more patents, resulting from AI-generated inventions, will increase social costs and monopolies, and stifle the entry of new ventures, thereby hampering innovation’); Craglia Massimo and others, Artificial Intelligence: A European perspective (Publications Office of the European Union 2018) 66-67 (https://ec.europa.eu/digital-single-market/en/news/trends-and-developments-artificial-intelligence-challenges-ethical-property-rights> accessed 3 March 2020 (doubting ‘whether incentives are needed [for AI-generated inventions], especially in cases where the investment cost is low, and what consequences such rights might have on the market, including on creations or inventions made by humans’); Yanisky-Ravid and Liu (n 3) 2221 (pointing out that autonomy and creativity of AI systems ‘make justifications such as personality theories and incentive/efficiency arguments irrelevant’).
8 Yanisky-Ravid and Liu (n 3) 2215, 2222 (stating that ‘[the traditional patent law has become outdated, inapplicable and irrelevant with respect to inventions created by AI systems’ and arguing for ‘abolishing patent protection of inventions by AI altogether’).
9 See eg Hattenbach and Glucox (n 3) 32 (‘The coming wave of computer-generated material is on a collision course with our patent laws’; Vertinsky and Rice (n 3) 575 (envisioning that ‘machines will perform the majority of the work in the invention process and originate novel solutions not imagined by their human operators, transforming the invention process in ways not easily accommodated within the current U.S. patent system’).
10 The search conducted by the author could not identify any expert assessment report on this topic. The subject, however, has been discussed in blogs and internet publications. See eg Angela Chen, ‘Can an AI Be an Inventor? Not yet.’ (MIT Technology Review, 8 January 2020) <https://www.technologyreview.com/s/615020/ai-inventor-patent-dabus-intellectual-property-uk-european-patent-office-law/> accessed 3 March 2020 (stating that ‘[a] more fundamental problem is that we’re nowhere near general artificial intelligence, so few people will believe that the AI is truly the inventor’); Rose Hughes, ‘The first AI inventor – IPKat searches for the facts behind the hype’ (IPKat, 15 August 2019) <http://ipkatblogspot.com/2019/08/the-first-ai-inventor-ipkat-searches.html> accessed 3 March 2020 (pointing out that ‘[b]y the legal questions are considered, it is important to note that evidence demonstrating the capabilities of the inventive algorithm has not yet been provided’).
11 For an overview of policy inquiries on this subject, see below at II.1.2 See below at II.2.
12 See eg WEF (n 2) 6 (‘The fact that patents have already been granted for inventions created by AI [...] raises concerns [...]’ (emphasis added)); ‘WIPO Conversation on IP’ (n 2) 3 (stating that ‘it would now seem clear that inventions can be autonomously generated by AI’ (emphasis added)).
13 See eg Feldman and Thieme (n 3) 77 (‘picturing the process as follows: an AI [...] takes as input a topic (“toothbrushes”) and after a button press, spits out a new product (novel toothbrush bristle designs)’ (emphasis added)). In his book with the telling title ‘Gene in the Machine’, Robert Plotkin contemplates that ‘the role of human inventors in the Artificial Intelligence Age [will be] to formulate high-level descriptions of the problem to be solved, not to work out the details of the solution [...] Once given this problem description (wish), the artificial invention software (gene) produces a design for a concrete product [...] that solves the stated problem.’, Plotkin (n 3) 3.
14 See eg Ryan Abbott, ‘Everything Is Obvious’ 66 U.C.L.A. Law Review 1, 29 (2018) n 154 (stating that ‘a user could ask a computer to design a new battery with certain characteristics’).
15 Michael O’Neill and Lee Spector, ‘Automatic Programming: The open issue?’ Genetic Programming and Evolvable Machine (11 September 2019) (emphasis added) <https://doi.org/10.1007/s10710-019-09364-2> accessed 3 March 2020.
16 ‘Open Letter of to the European Commission. Artificial Intelligence and Robotics’ para 2 <http://www.robotics-openerletter.eu/> accessed 3 March 2020 (emphasis added).
17 Artificial General Intelligence is commonly understood as being on par with the human that ‘[h]orizontal intelligences are consider-
18 Martin Ford, Architects of Intelligence: The truth about AI from the people building it (Pact Publishing 2018) 258.
19 David Watson, ‘The Rhetoric and Reality of Anthropomorphism in Artificial Intelligence’ 29 Minds & Machines 417-440, 434 (2019).
20 ibid.
21 On the applications of artificial neural networks and evolutionary algorithms in solving engineering and scientific problems, see below (n 43-44).
22 J Shashi Kiran Reddy and Contzen Pereira, ‘Understanding the Emergence of Microbial Consciousness’ 16(1) J Integr Neurosci. 27 (2017). See also below (n 72) and the accompanying text.
The main objective of this paper is to highlight the need for a further inquiry into the technical underpinnings of ‘artificial inventions’ and to identify the starting points in the relevant technical literature. Part II frames the issue: it reviews recent inquiries on patent policy and AI, lists instances of reported ‘artificial inventions’, points out the distinction between automation and autonomy, and formulates the legal uncertainty regarding implications for inventorship in the absence of autonomously acting computers. Part III synthesises insights gained from the literature review on computational problem solving and sketches out a basic understanding of how inventive process is automated through computational methods such as artificial neural networks (ANNs) and evolutionary algorithms (EAs). Part IV argues that the design of the overall procedure, which determines how the given inputs are transformed into the intended outputs, plays the decisive role in computational problem solving. It highlights that, as long as instructions on the derivation of the input-output relation are provided by a human, the delineation between human and non-human (algorithmic) ingenuity is pointless. Part V concludes by reinforcing the point that, without an in-depth inquiry into the technological state of the art, challenges to patent law and policy cannot be identified adequately.

II. ‘AI-generated’, or aided by AI?

1. The lack of technical definitions in policy inquiries

Notably, while raising the questions of how patent law and policy should respond to ‘autonomously generated’ inventions, none of the reviewed policy documents provides a technical definition of such inventions. For instance, the WIPO draft issues paper states that ‘it would now seem clear that inventions can be autonomously generated by AI’. While no explicit reference is provided in support, it is worth noting that, only recently, this scenario was considered by WIPO to be a ‘science fiction’. The World Economic Forum white paper assumes that ‘AI is no longer “just crunching numbers” but is generating works of a sort that have historically been protected as “creative” or as requiring human ingenuity’. However, no technical literature but only legal sources are referenced.

Somewhat puzzlingly, the request for comments initiated by the USPTO uses the term ‘AI inventions’ to refer to both inventions that utilise AI and inventions developed by AI. It is assumed that both types can comprise elements such as ‘the application of AI, the structure of the database on which the AI will be trained and will act; the training of the algorithm on the data; the algorithm itself; the results of the AI invention through an automated process’. (This view, however, requires further precision. For instance, if machine learning is applied in the process of drug discovery and development, the AI technique involved in that process would not be part of the resulting drug claimed as an invention.) Further, the document deliberates that, in both cases, a natural person can contribute to the conception of an invention, including by ‘designing the algorithm and/or weighting adaptations, structuring the data on which the algorithm runs, running the AI algorithm on the data and obtaining the results’. This suggests that, in the USPTO’s view, the development of an invention ‘by AI’ can still involve human input, which raises a critical question as to where to draw the line between situations where AI ‘develops’ an invention and where it is used as a tool (i.e. as a problem-solving technique).

2. Examples of ‘artificial inventions’

Legal narratives of AI-generated inventions often refer to almost the same set of examples: the Oral-B toothbrush and other accomplishments of the ‘Creativity Machine’ designed by Stephen L. Thaler, the NASA antenna, achievements in the field of genetic programming reported by John Koza, and AI applications in drugs discovery and development. More recently, the project ‘Artificial Inventor’ presented several inventions attributed to the connectionist system DABUS, a method for constructing and simulating artificial neural networks, a food container, and devices and methods for attracting enhanced attention.

None of the reviewed legal sources, however, provide a technical explanation of how the computational process...

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24 ‘WIPO Conversation on IP’ (n 2) 1.
25 The text refers to ‘several reported cases of applications for patent protection in which the applicant has named an AI application as the inventor’ (supposedly, inventions developed by the connectionist system DABUS). See also below (n 37-38).
26 WIPO. (n 2) 6.
27 SCP 30/5 para 55 (WIPO, 28 May 2019).
28 ibid (in particular referencing Fraser (n 3), Vertinsky and Rice (n 3), Hattenbach and Glucott (n 3)).
29 USPTO (n 6) para 1.
30 ibid.
31 On a sharper delineation between AI-generated, AI-assisted inventions (i.e where AI is applied as a tool to invent), and AI-implemented inventions (i.e where AI is implemented as part of the invention), see Jesse Drexl and others, ‘Comments of the Max Planck Institute for Innovation and Competition of 11th February 2020 on the Draft Issues Paper of the World Intellectual Property Organization on Intellectual Property Policy and Artificial Intelligence’ para 10 <https://pure.mpg.de/de/item/item_3193085_1/component/file_3193086/content> accessed 3 March 2020.
32 USPTO (n 6) para 2.
33 Stephen L. Thaler, ‘Creativity Machine ̶ Paradigm’ in Elias G Carayannis (ed), Encyclopedia of Creativity, Innovation, Entrepreneurship (Springer 2013) 447, 451.
34 John Bluck, ‘NASA “Evolutionary” software automatically designs antenna’ (NASA, 14 June 2004) <https://www.nasa.gov/mission_pages/evolutionary/marsproject/ver_5-media/04-55AR.html> accessed 3 March 2020.
35 Homepage of John R Koza <http://www.genetic-programming.com/johnkoza.html> accessed 3 March 2020 (stating that ‘genetic programming may produce a result that is equivalent to an invention that was patented in the past or that is patentable today as a new invention’). See generally John R Koza, ‘Human-competitive Results Produced by Genetic Programming’ 11 Genet. Program. Evolvable Mach. 251 (2010); Matthew J Streeter, Martin A Kearne and John R Koza, ‘Routine Duplication of Post-2000 Patented Inventions by Means of Genetic Programming’ in James A Foster and others (eds), Genetic Programming 5th European Conference, EuroGP 2002, Kinsale, Ireland, April 2002 Proceedings (Springer 2002) 26.
36 ibid (n 3) 60 (providing few other examples).
37 The Artificial Inventor Project <http://artificialinventor.com/> accessed 3 March 2020.
38 Artificial Inventors <http://artificialinventor.com/dabus/> accessed 3 March 2020.
39 U.S. Patent No 5,852,815. According to Ryan Abbott, Stephen Thaler, who was designated as the inventor, claimed that ‘the Creativity Machine invented the patent’s subject matter’. See Ryan Abbott, ‘I Think, Therefore I Invent: Creative Computers and the Future of Patent Law’ 57 B. C. L. Rev. 1079, 1085 (2016).
40 European Patent Application No 18275163.6.
41 European Patent Application No 18275174.3.
was set up.42 Without such understanding, it does not appear straightforward in what way the allegedly 'AI-generated' inventions differ from AI-aided inventions. In this regard, it is worth mentioning that AI techniques such as EAs and ANNs have been applied in various domains of science and engineering for decades,43 including in life sciences,44 molecular modelling and drug design,45 aerospace engineering,46 mechanical engineering,47 civil engineering,48 etc.49 Yet, one does not find in these accounts the language that would refer to inventions generated by 'autonomous entities'. Rather, they depict processes of designing computational systems and applying computational approaches as instances of computer-aided problem solving, design, and engineering.50 In contrast to the legal narratives claiming that computers generate inventions 'autonomously',51 technical literature usually uses the term 'automated'.52

3. Automation vs. autonomy

Automation means that a task can be carried out by a device without the human participation during the performance of a function.53 The term automation can be equally used with regard to physical labour (robotics) and cognitive phenomena and functions, such as problem solving.54 Machine learning, for instance, is defined as 'field of computer science that studies algorithms and techniques for automating solutions to complex problems that are hard to program using conventional programming methods'.55 Automation should not be equated with autonomy. While autonomy implies self-determination or self-rule,56 it is doubtful whether computers can, at all, be autonomous from humans and perform computation 'on their own'. The impossibility to reproduce a self-organising

42 Among the reviewed sources, the book by Robert Plotkin presents a relatively detailed account of how the process of inventing becomes automated. Plotkin (n 3) 52 ff.

43 See generally Mitsuo Gen and Lin Lin, ‘Evolutionary Techniques for Automation’ in Shimon Nof (ed), Springer Handbook of Automation (Springer 2009) 487-502; David E Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning (Addison-Wesley Reading, 1989); Prabhjot Hajela, ‘Genetic Search – An Approach to the Nonconvex Optimization Problem’ 28(7) AIAA Journal 1205-1210 (1990); Dianpang Dasgupta and Zbigniew Michalewicz (eds), Evolutionary Algorithms in Engineering Applications (Springer 1997).

44 See eg Maxwell W Lobbrecht and William S Noble, ‘Machine Learning Applications in Genetics and Genomics’ 166(6) Nat. Rev. Genet. 321 (2015).

45 See eg Vasundhara Devi, Sva Sathya and Mohane Selvargar Coumaran, ‘Evolutionary Algorithms for De Novo Drug Design – A survey’ 27 Applied Soft Computing 543 (2015); Eric Wubbio Lameijer and others, ‘Evolutionary Algorithms in Drug Design’ 4 Natural Computing 177 (2005); James Devillers, Genetic Algorithms in Molecular Modeling (Academic Press 1996). On application of ANN-based methods in drug discovery and development, see eg Matthew A Sellowood and others, ‘Artificial Intelligence in Drug Discovery’ 10(17) Future Medicinal Chemistry 2025 (2018) (noting that AI has been used in different forms and to a varying extent in the search for novel molecules and structure-activity correlations since the 1960s).

46 See eg Markus Olhofer and others, ‘Aerodynamic Shape Optimisation using Evolution Strategies’ in Ian Parne and Prabhjot Hajela (eds), Optimization in Industry (Springer 2002); Alfredo Arias-Montano, Carlos A Coello Coello and Efren Mezura-Montes ‘Multiobjective Evolutionary Algorithms in Aeronautical and Aerospace Engineering’ 16(5) IEE Transactions on Evolutionary Computation 662 (2012).

47 Joulin Lampinen, ‘Cam Shape Optimisation by Genetic Algorithms’ 35 Computer-Aided Design 727 (2003).

48 Janusz Kłosow and Moncef Krarti, ‘Genetic-algorithm Based Approach to Optimize Building Envelope Design for Residential Buildings’ 45(7) Building and Environment 1574 (2010).

49 For an overview of domain applications of EAs, see eg Gabor Renner and Aniko Eka, ‘Genetic Algorithms in Computer Aided Design’ 35(8) Computer-Aided Design 709 (2003); David J Munk, Gareth A Vio and Grant P Steven, ‘Topology and Shape Optimization Methods Using Evolutionary Algorithms: a review’ 52 Struct. Multidisc. Optim. 613 (2015); David Greiner and others, ‘Evolutionary Algorithms and Metaheuristics: Applications in Engineering Design and Optimization’ Mathematical Problems in Engineering 1 (2018); Christopher Tong and Duvvuru Srinivasan (eds), Artificial Intelligence in Engineering Design (Academic Press 1992) (a three-volume collection surveying applications of AI techniques in various areas including in civil, chemical, electrical, and mechanical engineering). See also Gabor Renner, ‘Genetic algorithms in CAD’ 35 Computer-Aided Design 707, 798 (2003) (summarising that ‘the number of applications of genetic algorithms in engineering design is extremely large and continuously increasing’). For an overview of computational methods of scientific discovery, see Peter D Sozou and others, ‘Computational Scientific Discovery’ in Lorenzo Magnani and Tommaso Russo (eds), Springer Handbook of Model-Based Science (Springer 2017) 719.

50 Sellowood and others (n 45) 2025 (‘AI is often seen as a magic button that can be pressed at will to produce the perfect output, often regardless of the input. AI is not the tool that solved the theory challenge, it is the tool that if used correctly can help to augment current understanding and drive new discoveries’ (emphasis added)); Siddhivinayak Kulikarni, Machine Learning Algorithms for Problem Solving in Computational Automation (Springer 2012) xvi (observing that components of machine learning are used to solve real world problems). See generally Lampinen (n 47), Renner and Eka (n 49); Renner (n 49).

51 Ryan Abbott, ‘I think, Therefore I invent’ (n 3) 1083 (stating that ‘[c]omputers have been autonomously creating inventions since the twentieth century’).

52 A representative example is the space antenna developed by NASA scientists. See Abbott (n 15) 29 (stating that ‘NASA recruited an autonomously invention machine to design an antenna’ (emphasis added)). But see the account by NASA scientists: Gregory S Hornby and others, ‘Automated Antenna Design with Evolutionary Algorithms’ American Institute of Aeronautics and Astronautics (American Institute for Aeronautics and Astronautics, 2006) <https://arc.aiaa.org/doi/pdf/10.2514/6.2006-7242> 1 (‘Whereas the current practice of designing antennas by hand is severely limited because it is both time and labor intensives and requires a significant amount of human knowledge, evolutionary algorithms can be used to search the design space and automatically find novel antenna designs that are more effective than would otherwise be developed. Here we present automated antenna design and optimization methods based on evolutionary algorithms’ (emphasis added)). For another example, see Fraser (n 3) 318-319 (claiming that ‘so-called robot scientists are systems that integrate AI algorithms with physical laboratory robots to physically conduct an experiment’ (emphasis added), and that such ‘technology represents a marked step towards autonomous scientific discovery over the status quo where humans are primarily responsible for these functions’ (emphasis added) (referencing Ross D King and others, ‘Functional Genomic Hypothesis Generation and Experimentation by a Robot Scientist’ 427 Nature 247 (2004)). But see the original paper by King and others, referring throughout the text to the automation of research and automatic systems.

53 Shimon Nof, ‘Automation: What It Means to Us Around the World’ in Nof (n 43) 14 (‘Automation involves machines, tools, devices, installations, and systems that are all platforms developed by humans to perform a given set of activities without human involvement during those activities.’).

54 George A Schilling, ‘Automation’ in Carl Mitcham (ed), Encyclopedia of Science, Technology, and Ethics (Macmillan Reference 2005) 146, 146 (referring to automation as a process, which is implemented by utilising a device ‘as a substitute for human physical or mental labor’).

55 Cospinath Rehula, Ajay Ravi and Sathy Churuvula, An Introduction to Machine Learning (Springer 2019) 1 (emphasis added). See also Nof (n 53) 22 (pointing out that the significant advantage of AI is that ‘it can function automatically, i.e., without human intervention during its operation/function’ (emphasis added)); Wolfgang Ertel, Introduction to Artificial Intelligence (Springer 2017) 8 (defining AI as ‘a practical science of thought mechanization [that] could […] only begin once there were programmable computers’); Ivan Jureta, The Design of Requirements Modelling Languages (Springer 2013) 18 (noting that the use of AI in problem solving is equal to ‘making languages and algorithms that can automate specific […] problem solving tasks’).

56 Online Etymology Dictionary, ‘Autonomy’ <https://www.etymonline.com/word/autonomy> accessed 3 March 2021. See also Sara Governing, ‘Autonomy’ in Sara Governing (ed), The Oxford Encyclopedia of Science and Society (Oxford University Press 2012) 153, 155 (noting that the concept of autonomy, ‘like freedom, combines two aspects: the negative condition of freedom from external constraints and the positive condition of a self-determined will’).
system is considered to be the fundamental limitation of automation.57 For any operation to be run on a computer, it needs to be programmed58 (even in the case of self-improving software59). Put figuratively: ‘Programmers are the hand that feeds AI. It’s improbable that they’ll get bitten anytime soon.’60

Admittedly, one does come across the terms ‘autonomous’ and ‘automated’ being used interchangeably in the technical literature. However, unlike in legal scholarship, ‘autonomous’ is used (rather inaccurately) as a synonym of automation i.e. referring to processes executed without the human intervention.61 (Implications of this distinction for inventorship are further discussed in Section II.5. and Part IV of this paper.)

4. No ‘genie in the machine’

While AI is sometimes portrayed as the ‘genie in the machine’ capable of fulfilling human wishes for new inventions,62 this allegory does not correspond to reality (yet). The design of systems, which would respond to commands given in a high-level language without any instructions as to how to perform a task, has been a research aspiration in the field of genetic programming.63 Yet, researchers acknowledge that such aspiration is ‘unrealistic, at least in the foreseeable future’,64 and that ‘[t]he mere possibility of recursively self-improving software remains unproven’.65

57 Richard D Patton and Peter C Patton, ‘What Can Be Automated? What Cannot Be Automated?’ in NoF (n 43) 305, 305 (stating that, even though it would be ‘a brilliant act of creating a new form of life (ie, a self-organizing system), [...] that is certainly not what automation is all about’). Further, they note that ‘the mechanistic model lacks the system’s inherent capability for self-organization.’ ibid 308.

58 John P Sullins III, ‘Artificial Intelligence’ in Mitcham (n 54) 111, 112 (pointing out that a computer needs to be programmed in order to ‘display advanced levels of intelligence’).

59 See below (n 64-65) and the accompanying text.

60 Niarm Reed, ‘Artificial Intelligence and the Future of Programming’ (2017) 61 Datafloq https://datafloq.com/article/artificial-intelligence-future-of-programming/5124 accessed 3 March 2020.

61 Dilip Kumar Pratihar and Lakhmi C Jain, ‘Towards Intelligent Autonomous Systems’ in Dilip Kumar Pratihar and Lakhmi C Jain (eds), Intelligent Autonomous Systems: Foundations and Applications (Springer 2010) 1 (defining an autonomous system as a system that can ‘perform the assigned task without continuous human guidance’); NoF (n 53) 22 (stating that ‘the reliance on a process that can proceed successfully to completion autonomously, without human participation and intervention, is an essential characteristic of automation’ (emphasis added)). In the context of policymaking, ‘autonomous driving’ is a prime example. See eg European Commission, ‘Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee, the Committee of the Regions “On the road to automated mobility: An EU strategy for mobility of the future”’ COM (2018) 283 final (17 May 2018) (primarily referring to automated (mobility, vehicles) throughout the document but, at times, using automated interchangeably with autonomous (driving, systems). Notably, when defining the levels of automation, the Communication uses the classification of the Society of Automotive Engineers-SAE, which defines full automation as where a ‘system can cope with all situations automatically in a defined use case’.

62 Plotkin (n 3).

63 O’Neill and Spector (n 16) 1 (stating that genetic programming has been described as an ‘invention machine’ that is capable of generating human-competitive solutions).

64 ibid 2. See also Sai Sumathi, Thiag Hamsapriya, Paneerselvan Surekha, Evolutionary Intelligence: An Introduction to Theory and Applications (Springer 2008) 172 (pointing out that ‘the idea of a computer automatically programming itself is a very old, desirable and elusive goal’, that ‘it is as difficult to get a computer to program as it is to get it to do anything else’, and that ‘when early attempts at automating the programming largely failed to deliver what they promised, people began to […] stay away from the subject’).

65 Roman V Yampolskiy, ‘On the Limits of Recursively Self-Improving AGI’ in Jordi Bieger, Ben Goertzel and Alexey Potapov (eds), Artificial General Intelligence. AGI 2015, vol 9205 (Springer 2015) 394, 395. For an overview of currently self-improving computer programs and the challenges of creating software capable of writing new software, see generally Roman V Yampolskiy, ‘Analysis of Types of Self-Improving Software’ in Bieger, Goertzel and Potapov (this note) 384.

Thus, ‘machine intelligence’ appears to be the function of designing computational systems and programming computers and, hence, an expression of human intelligence.66 More so, the fundamental limitation of computational systems to perform cognitive operations is seen in that such operations can be reproduced through computer programs to the extent, to which human designers of computational systems understand the underlying intellectual mechanisms.67

5. Does the use of AI as a problem-solving technique pose a legal uncertainty regarding inventorship?

As far as the allocation of the inventor entitlement is concerned, patent law, in principle, does not discriminate between inventions that might simply occur to the inventor’s mind and those that might be developed with the help of problem-solving techniques and instruments.68 Neither does it matter whether an invention came into being by sheer chance69 or through the intentional process of trial and error. Instead, this factor,70 as well as the means of problem solving71 can be relevant for the definition of a person skilled in the art in the context of the inventive step assessment. Even more so, any legal constraints on the use of problem-solving techniques would be at odds with the very rationale of patent law to promote the diffusion of knowledge. The use of the problem-solving tools has not been prejudicial to the allocation of the inventor entitlement to a natural person, even where they may surpass human capabilities (e.g. optical instruments), or where biological organisms – that, unlike computers, are self-organising might be involved in research.72

General Intelligence. AGI 2015, vol 9205 (Springer 2015) 394, 395. For an overview of currently self-improving computer programs and the challenges of creating software capable of writing new software, see generally Roman V Yampolskiy, ‘Analysis of Types of Self-Improving Software’ in Bieger, Goertzel and Potapov (this note) 384.

66 See Massimo Mentielfa and Alfredo Paternoster, ‘Models and Mechanisms in Cognitive Science’ in Magnani and Bertolotti (n 49) 929, 930 (pointing out that, certain aspects of cognitive processes and phenomena (such as perception, language understanding, reasoning, etc.) can be reproduced in computational artifacts, such as computer programs, to the extent, to which they can be captured by computational modelling).

67 See John McCarthy, ‘What is Artificial Intelligence’ (Stanford University, 12 November 2007) 4 <http://www.formal.stanford.edu/~mcc/whatisai.pdf> accessed 3 March 2020 (noting that ‘[w]henver people do better than computers on some task or computers use a lot of computation to do as well as people, this demonstrates that the program designers lack understanding of the intellectual mechanisms required to do the task efficiently’).

68 Drexel and others (n 31) para 13 (pointing out that ‘[o]ne needs first to consider why the patent system has never required disclosure of how an invention came into being – not of least importance is the reason that such a requirement might simply be unfeasible to apply and enforce’).

69 For instance, in a 1929 U.S. case, the invention at issue resulted from an observation that a cutting machine with ‘a wrong set of gearing [could] cut a double thread screw instead of a single thread’. Townsend v Smith 36 F.2d 292 (1929) 293.

70 For instance, under the EPO approach, routine trial-and-error experiments lack inventive step. Case T 0104/92 (Oriented film/Grace) of the EPO, ‘Guidelines for Examination in the European Patent Office’ 71 EPO, ‘Guidelines for Examination in the European Patent Office’ (EPO 2019) Part G – ch VII-1 (defining the person ordinarily skilled in the art as the one, who has ‘the means and capacity for routine work and experimentation which are normal for the field of technology in question’).

72 Danielle N Harris, ‘Use of Microorganisms as Analytical Tools’ 27(11) Analytical Chemistry 1630 (1955).
Perhaps the main concern arising with regard to the application of AI techniques in the inventive process is that they automate cognitive functions, such as problem solving and data and information processing. On the one hand, one may doubt whether the contribution to the inventive process by a natural person can be deemed to be sufficient to give rise to the inventor entitlement. On the other hand, one can question whether it is possible, at all, to distinguish between the roles of a human and an 'intelligent system', given that the latter is designed by the former. Assuming that fully autonomous AI systems – i.e. systems capable of performing tasks in the absence of any instructions – are not on the horizon yet, AI can be applied as problem-solving techniques during the inventive process. The question arises: Can automation of problem solving through such techniques reach an extent, which would no longer fit the concept of human inventorship, and what qualifying criteria can, or should, be applied to assess the sufficiency of such contribution?

As far as the normative criteria are concerned, we may not find explicit specific provisions under existing patent laws. The rules on co-inventorship appear to be rather inapplicable to the human-machine interaction. Yet, the underlying principle that there should be a substantial contribution to the development of an invention, as a qualifying factor for the inventor entitlement, can still be valid in situations where a technical solution might be found by applying AI. For instance, most would probably agree that merely switching on a computer, or giving a computer a command in a natural language – ‘Solve this’, or ‘Design a new product!’ – cannot be deemed as a sufficient human contribution. While this scenario is not yet realistic, the question is whether there are interim steps performed by a computer that might be more decisive for solving a problem and outweigh the human contribution. For that, we need to take a closer look at the human-computer interaction in the process of developing an invention.

III. Automation of inventive process: A basic understanding

In view of an invention as a technical solution for a technical problem, this section situates AI applications in the context of literature on computational methods enabling (partial) automation of problem solving.

1. Computational paradigm of problem solving

While a problem is generally defined as a goal that is not ‘immediately attainable’, problem solving refers to a process of achieving the goal, starting from the initial state, through a sequence of actions. Such view, essentially, reflects the concept of computation as a process of deriving the intended output from the given inputs. More so, problem solving is compared to calculating a mathematical function, whereby x values are transformed into y values.

Computations connect computer science and cognitive science. Computational approaches – including those that are often called ‘AI’ – are also known as computational intelligence, computational thinking, and intelligent computing. Even though the extent to which the analogy with computation can be applied to cognition is disputable, computational modelling is regarded to be

76 The classical definition by the mathematician George Polya holds that solving a problem means ‘to search consciously for some action appropriate to attain some clearly conceived but not immediately attainable aim’. George Polya, Mathematical Discovery (Wiley 1992, first published in 1942) 117.
77 Kenneth J Gilhooly, ‘Human and Machine Problem Solving. Toward a Comparative Cognitive Science’ in Kenneth J Gilhooly (ed), Human and Machine Problem Solving (Springer 1989) 3.
78 Nir Fresco, Physical Computation and Cognitive Science (Springer 2014) 4. See also Eugene Charniak, Artificial Intelligence Programming, 2nd ed, Psychology Press (2014) 332 (observing that ‘any computing activity may be thought of as directed toward solving some problem’, while a problem can be defined as ‘a state of affairs to be brought about starting from a given initial state’); Hector Zenil and Nicolas Gauvrit, ‘Algorithmic Cognition and the Computational Nature of the Mind’ in Robert A. Meyers (ed), Encyclopedia of Complexity and Systems Science (Springer 2nd ed, Springer 2018) <https://doi.org/10.1007/978-3-642-27737-5_707-2> accessed 3 March 2020 (defining computability as a ‘theory that studies the problems that can be solved by algorithmic means with, for example, digital computers’); Marsha C Lovett, ‘Problem Solving Intermediate’ in Lynn Nadel (ed), Encyclopedia of Cognitive Science (Wiley Online Library 2006) <https://doi.org/10.1002/0470018860.s00045> (noting that research on problem-solving ‘has made much theoretical progress in developing and testing computational models’).
79 Paolo Ferragina and Fabrizio Luccio, Computational Thinking, First Algorithms, Then Code (Springer 2018) 3.
80 See Fresco (n 78) 1-31.
81 Computational intelligence is defined as ‘a broad and diverse collection of artificial intelligence-inspired computational methodologies and approaches and tools and techniques that are meant to be used to model and solve complex real-world problems in various areas of science and technology in which the traditional approaches based on exact and well-defined tools and techniques, […] are either not feasible or not efficient’. It comprises ‘all kinds of connectionist systems and […] learning systems [such as] fuzzy logic, (artificial) neural networks, and evolutionary computation’. Janusz Kacprzyk and Witold Pedrycz, ‘Introduction’ in Janusz Kacprzyk and Witold Pedrycz (eds), Springer Handbook of Computational Intelligence (Springer 2015) 1-2.
82 See eg Youngsoek Lee and Jungwon Cho, ‘Knowledge Representation for Computational Thinking Using Knowledge Discovery Computing’ in Ifi Technol Manag 15, 16 (2020) (defining computational thinking as ‘the ability of solving problems through automated techniques by recognizing and abstracting problems [based on] the basic concepts and principles of computational technology’ (emphasis added)). For an overview of definitions, see Karl Beecher, Computational Thinking – A Beginner’s guide to problem-solving and programming (BCS Learning & Development Limited 2017).
83 See eg Mathew Kuruvilla and Isaac Byju, ‘Survey of Intelligent Computing in Case Studies’ in Isaac Byju and Israr Nauman (eds), Intelligent Computing: Achievements and Trends (CRC Press 2014) 1-16.
84 See eg Anthony Freeman, ‘Consciousness’ in Mitcham (n 54) 411 (observing that ‘[t]he question of whether and when a conscious mind itself is computational, that is, completely describable mathematically and therefore in determinist terms, is hotly disputed’). For a summary of research on this topic, see eg William J Rapaport, ‘Cognitive science’ in Edwin D Reif and Anthony Rolnick (eds), Digital Innovation: An Introduction to Computer Science (4th ed, John Wiley & Sons 2003) <https://search.ece.doreference.com/content/entry/encyclopedia/cognitive_science/0?institutionId=4759> accessed 3 March 2020.
‘a definitional factor’ of cognitive science\textsuperscript{85} and a key methodology for understanding cognitive phenomena.\textsuperscript{86}

Search is another fundamental concept that relates problem solving, computation, and AI.\textsuperscript{87} Computational problem solving underlies Herbert Simon’s theory that conceptualises the process of problem solving as the search through a problem space.\textsuperscript{88} Machine learning algorithms reflect this idea.\textsuperscript{89}

Attempts to automate problem solving processes have been pursued in the field of computer science and AI for decades.\textsuperscript{90} Computational problem solving represents an area of interdisciplinary research and integrates approaches of cognitive science, mathematics, logic, computer science, neuroscience, biology, and psychology among others. The notion of computation is a junction point where these disciplines intersect.\textsuperscript{91}

It is important to distinguish between ‘computational’ and ‘computer-implemented’ problem solving. The former is a broader concept and implies ‘abstracting’ away from the material details of the device [used] to make the calculations, be it an abacus, pen and paper, or [a] programming language and processor.\textsuperscript{92}

For the purpose of understanding the human-computer interaction in the process of developing an invention, it is helpful to outline the main stages of computational problem solving.

| Activity | Description |
|----------|-------------|
| Problem formulation | The identification of the problem to be solved through computation |
| Abstraction and modelling | The reduction of a problem to the elements and relations that are necessary for understanding and solving it and their representation in a formal structure (e.g. a computational model) |
| The design of an algorithm (or the adjustment of the pre-existing algorithm) | The specification of a sequence of steps that can transform given inputs into the intended output |
| Programming | The coding of an algorithm in a way it can be executed on a physical computer |
| Data manipulation | The preparation of the selected data to be used during computation |
| Execution | The execution of an algorithm on a computer |
| Interpretation and communication of results | The analysis of the results of computation and their representation in a way they can be communicated |

Let us take a closer look at those components that are most closely related to the design of the problem-solving mechanism.

2. Abstraction and computational modelling

For a problem to be solved by computational methods, it needs to be represented in ‘the right abstraction’.\textsuperscript{94} Abstraction constitutes the ‘essence of computational thinking’.\textsuperscript{95} It involves the reduction of a phenomenon of interest – e.g. an object, system, or a process – ‘to a set of essential characteristics for a particular modelling purpose’,\textsuperscript{96} and the encoding of the key mathematical,
logical or symbolic relations between its constituting elements.⁹⁷

Computational modelling refers to the conception and the formal representation of how the input-output relation can be derived.⁹⁸ While computational modelling integrates approaches from various disciplines (among others: computer science, engineering, mathematics and physics⁹⁹), mathematical principles, rules and tools – e.g. different types of equations¹⁰⁰ – play a crucial role in determining the way in which computation proceeds.¹⁰¹ A computational model captures the relations between inputs and outputs by ‘map[ping] them into appropriate mathematical expressions [such as a set of equations]’.¹⁰² In this sense, it essentially represents a causal mechanism connecting the inputs and the desired outcome through the sequence of states.¹⁰³

Computational models vary greatly as to their purposes,¹⁰⁴ types,¹⁰⁵ and complexity.¹⁰⁶ They are considered to be powerful tools applied in problem solving across the fields of science¹⁰⁸ and engineering.¹⁰⁹ What enables such broad deployment of computational approaches is that many problems across disciplines (including biology, physics, chemistry, engineering, etc.) can be ‘cast as optimization problems and thereby benefit from [...] the reservoir of knowledge of mathematical optimization [...] numerical analysis, computational methods, and other branches of mathematics’.¹¹⁰ Notwithstanding their diversity and complexity, computational methods of problem solving, at their basis, serve one purpose: to transform the given inputs into the desired output by way of executing the given instructions.

3. Designing an algorithm and programming

In order to address a problem with a computer, any executed operation needs to be specified ‘with absolute precision [...] at least with the machines we have access to today’.¹¹¹ While the search for a problem solution can be viewed as a sequence of states, an algorithm specifies instructions that determine the transitions between the states. By definition, an algorithm is ‘an effective procedure to solve a given problem, that is, a finite sequence of elementary and totally explicit (= well defined and not ambiguous) instructions’.¹¹² An algorithm and a code ‘together indicate how to organize and describe a series of actions to achieve a desired result: the algorithm constitutes the stage of designing and evaluating the strategy on which to build single actions, while coding reflects the operational phase that leads to the execution of those actions on a particular computing device, such as a PC’.¹¹³ In itself, programming language does not ‘offer any approach to problem solving beyond a means of formulating algorithms’.¹¹⁴ After all, ‘programming isn’t hard when you know how to solve the problem’.¹¹⁵

Thus, nothing ‘esoteric’ is going on when computational models are executed by a computer.¹¹⁶ Notwithstanding a model’s complexity, computers contribute to problem solving by ‘crunching numbers’¹¹⁷ obediently, and it is by ‘brute force computation¹¹⁸ that they can outperform humans.

⁹⁷ Dietmar P F Moeller, Mathematical and Computational Modelling and Simulation. Fundamentals and Case Studies (Springer 2004) iv. See also Government Office of Science (n 96) 14-15; Wing (n 94) 3717 (pointing out that numeric representation is a type of a symbolic notation).
⁹⁸ Trillas (n 96) 250-251. See also Michaelson (n 93) 51-52 (summarising that ‘theory and practice of computations [...] involves making models of reality from information structures and algorithms, and then animating the models on computers’). Formalism refers to the representation in a particular notation system. For instance, mathematical models are defined as ‘symbolic and abstract representation of the problem at hand [that capture] variables, parameters, data, and relationships such as equations and inequalities or (in logic) other predicates’. Tony Hürlimann, Mathematical Modelling and Optimization. An Essay for the Design of Computer-Based Modeling Tools (Springer 1999) 24-25.
⁹⁹ Moeller (n 97) 5.
¹⁰⁰ Ibid 12-13 (referring among others to linear, non-linear, integral, differential, and stochastic equations).
¹⁰¹ On the role of mathematics in AI, see eg Angel Garrido, ‘The Emergence of Artificial Intelligence, Two Branches of the Same Tree’ 2(2) Procedia – Social and Behavioral Sciences 1133, 1134 (2010) (‘The problems in AI can be classified in two general types, Search Problems and Representation Problems. Then, we have Logics, Rules, Frames, Nets, as interconnected models and tools. All them are very mathematical topics. [Furthermore,] AI techniques implement representations such as categories, objects, properties, relations, etc. – all of which are connected to mathematics’ (emphasised in the original)). On mathematical foundations of AI, see generally Roumazis Ilieva, Kiriél Anguelov, and Yotó Nikolov, ‘Mathematical Algorithms for Artificial Intelligence’ 2172 AIP Conference Proceedings 110015-1 (2019).
¹⁰² Moeller (n 97) 5.
¹⁰³ David Davenport, ‘The Two (Computational) Faces of AI’ in Vincent Müller (ed), Philosophy and Theory of Artificial Intelligence (Springer 2013) 43, 49. See also Rod Stephens, Essential Algorithms: A Practical Approach to Computer Algorithms (John Wiley & Sons 2013) 3 (defining an algorithm as ‘a recipe for performing a certain task’).
¹⁰⁴ Such as illustration or visualisation, deriving a prediction, forecast future scenarios, informing decision making, understanding and explaining a theory, Government Office of Science (n 96) 17.
¹⁰⁵ For instance, numerical or symbolic, analytic or simulation, determinist or stochastic, linear or nonlinear models. For an overview, see Hürlimann (n 98) 67-71.
¹⁰⁶ See Ameet V Joshi, Machine Learning and Artificial Intelligence (Springer 2013) 17 (pointing out that the complexity of functions and computational models can vary greatly from a linear regression to large nonlinear functions that ‘approximate the nonlinear characteristics of the data’. Examples of nonlinear models are: neural networks, decision trees, probability models that are based on nonlinear distributions, ibid.
¹⁰⁷ Moeller (n 97) 1.
¹⁰⁸ See generally Magnani and Bertolotti (n 49).
¹⁰⁹ See above (n 43-49) and the accompanying text.
4. Soft computing

ANNs and EAs – two subfields of AI, which gave rise to the recent discussions on patent policy and AI-generated inventions – represent the so-called soft computing approaches. Such methods are applied to problems characterised by high uncertainty and complexity. A detailed explanation of how soft computing works goes beyond the scope of this paper. From the inventorship perspective, the most relevant aspect is: What determines the way computation is performed when methods based on ANNs or EAs are run on a computer?

a) Artificial neural networks

ANNs comprise a variety of computational models with biologically motivated structures and form a subfield of machine learning, which is defined as “the study of methods for programming computers to learn” that evolved from computational learning theory and pattern recognition. What an algorithm ‘learns’ in the course of processing training data is how to correlate inputs (independent variables) with outputs (dependent variables) by inferring a function. While a function is sometimes playfully called ‘a magical artifact’ that turns inputs into outputs, ‘instead of using magic, [one] actually [uses] an instruction (algorithm) of how to transform the x to get the y, by using simpler functions such as addition, multiplication and exponentiation.’ Thus, in the course of learning, ‘the algorithm defines, refines, and executes a [...] function, which is always specific to the kind of problem being addressed by the algorithm.’ As each artificial neuron ‘solves a small piece of the problem, [...] using many neurons in parallel solves the problem as a whole.’ Ultimately, ANNs constitute nothing more than ‘long sequences of summations and multiplications.’

b) Evolutionary algorithms

Evolutionary (or genetic) algorithms represent a category of stochastic search algorithms that are applied to solving complex problems such as optimisation of multiple, potentially conflicting parameters of a system. In essence, evolutionary algorithms generate and evolve a set of candidate solutions (a population) through

Even though it is often said that machine learning techniques can perform tasks without being ‘explicitly’ programmed, this does not denote the absence of any instructions determining how the input-output relation is derived through computation. Instead of being ‘explicitly’ programmed in a conventional sense (i.e. by providing a workflow-type list of commands), machine learning leverages mathematical and statistical methods. Thus, the learning process is, on the one hand, ‘purely mathematical’, whereby computational operations are guided by formulas, equations, functions, etc. that constitute a part of an algorithm. On the other hand, it is ‘basically just a statistical matter of which variables are most correlated with the outcome.’ That being said, commentators argue that machine learning has ‘nothing to do with understanding’, and that a more suitable term for it would be ‘automated model fitting’ which would not sound cool enough to attract the same level of investment and innovation interest.

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120 Besides neural networks and evolutionary computing (genetic algorithms), other main soft computing methods are: fuzzy logic and probabilistic computing, Moeller (n 97) 311.
121 Oded Maimon and Lior Rokach, ‘Introduction to Soft Computing for Knowledge Discovery and Data Mining’ in Oded Maimon and Lior Rokach (eds), Soft Computing for Knowledge Discovery and Data Mining (Springer 2008) 1; Moeller (n 97) 3; Luigi Fortuna and others, Soft Computing. New Trends and Applications (Springer 2001) 261.
122 A considerable amount of literature for a non-technical audience exists on this subject. For a basic introduction of machine learning, see eg WIPO (n 74) 4-11; Josef Drexl and others, ‘Technical Aspects of Artificial Intelligence: An Understanding from an Intellectual Property Law Perspective’ Max Planck Institute for Innovation & Competition Law Perspective’ Max Planck Institute for Innovation & Competition Research Paper No 19-13 (2019) <https://www.ip.mpg.de/de/publikationen/details/technical-aspects-of-artificial-intelligence-an-understanding-from-an-intellectual-property-perspective.html> accessed 3 March 2020.
123 For an overview of ANN models, see generally Peter Tino, Lubica Benuskova and Alessandro Sperduti, ‘Artificial Neural Network Models’ in Kacprzyk and Pedrycz (n 8) 655.
124 Thomas G Dietterich, ‘Machine Learning’ in Nadel (n 78) 1.
125 Bin Shi and Sundaraja Sathirama Iyengar, Mathematical Theories of Machine Learning – Theory and Applications (Springer 2020) 13.
126 See also Nijenhuis, Introduction to Learning, From Logical Calculus to Artificial Intelligence (Springer 2018) 18.
127 ibid 18-19. See also Fortuna and others (n 121) 54 (‘The operations performed by the neurons are generally simple ones of addition, non-linear mapping, or thresholds.’).
128 Mueller and Massaron (n 116) 127.
129 ibid.
130 ibid 123.
reiterative modifications – mutation, recombination, selection – and reach the ‘best-scoring’ solution based on the principle of natural evolution that the fittest survives.\textsuperscript{143} EAs represent mathematical optimisation which derive optimal values to a given function (the objective function) subject to specific conditions (constraints).\textsuperscript{144}

While the term ‘stochastic’ implies randomness, it does not mean that a computer does something ‘out of the blue’: The application of stochastic local search algorithms requires a set of prerequisites that ultimately determine how computation is executed. In particular, components that need to be predefined are the search space, candidate solutions, neighbourhood relation, memory states, initialisation function, step function, and termination predicate.\textsuperscript{145} For instance, the initialisation function within an evolutionary algorithm ‘specifies the search initialisation in the form of a probability distribution over initial search positions and memory states’,\textsuperscript{146} while the step function ‘determines the computation of search steps by mapping each search position and memory state to a probability distribution over its neighboring search positions and memory states’.\textsuperscript{147}

To summarise, both ANNs and EAs rely on computational instructions – including functions and equations embedded in an algorithm – that determine how computation is executed.

\section*{IV. Implications for human inventorship}

\subsection*{1. The design of a computational method as the decisive factor of computational problem solving}

Of crucial importance from an inventorship perspective is an understanding of the extent to which the functioning of ‘intelligent systems’ can be attributed to the way they are designed and applied by humans. If we accept that problem solving ‘occurs when a problem solver determines how to solve a problem, that is, how to accomplish the goal’,\textsuperscript{148} in the case of computational problem solving, the ‘how’ refers to the conception of the overall computational procedure, which, besides an algorithm, can encompass multiple ingredients. In the case of ANNs, of particular importance is the selection of datasets. Collectively, such elements determine how the input-output relation is computed. In other words, the design of the overall computational method can be viewed as the conception of a problem-solving mechanism and, hence, an invention.

The reviewed literature suggests that the conception of a computational procedure occurs before an algorithm is encoded in a programming language and executed by a computer.\textsuperscript{149} The overall process of how the input-output relation can be derived through computation is conceptualised by a human\textsuperscript{150} and constitutes a causal mechanism embodied in an algorithm and a computer program.\textsuperscript{151} Notably, the characterisation of a problem is considered to be the ‘hardest part of problem solving’,\textsuperscript{152} which invokes the famous postulate that a well-stated problem is half-solved. Further, defining ‘the right abstraction is critical’\textsuperscript{153} for computational problem solving.\textsuperscript{154}

It is worth noting that algorithms vary in complexity and uniqueness: While routine tasks are performed by established algorithms, new algorithms can be designed for complex problems.\textsuperscript{155} Even though AI applications are, at times, portrayed in the legal scholarship as being able to ‘discover complex rules and patterns […] given only an abstract problem definition and simple rules for generating and evaluating possible solutions to the problem’,\textsuperscript{156} the simplicity of the given rules and the complexity of the derived rules ought not to be generalised. For instance, in the case of EAs, the definition of the fitness function is considered to be the most difficult part,\textsuperscript{157} which requires human judgement. More importantly, if a computer learns new rules based on the given rules, one cannot view such new rules as being generated by a computer autonomously, driven by ‘own will’.

Furthermore, the adjustment of an existing algorithm to a problem at hand should not be downplayed.\textsuperscript{158} Even where such adjustment concerns an algorithm, or a system designed to address a highly specific problem, it may not happen instantaneously, or effortlessly. The design of...
the NASA antenna is an apt example — it took the scientists about one month to adjust the system to the changed technical specifications of a mission’s parameters and to prototype the final antennat.239 (It is worth mentioning that NASA scientists had reportedly spent two years developing the evolutionary system for designing the antenna.240)

Moreover, it is important to emphasise that, even though AI is often characterised as a general purpose technology,241 and even claimed to be ‘a general-purpose method of invention’.242 there is no single ‘general-purpose’ algorithm, or a ‘general-purpose’ model capable of solving any problem.243 Quite to the contrary, scalability and generalizability are well-known problems of AI.244 Thus, computational problem solving is about designing ‘intelligent’ computational systems and algorithms, whereas ‘computers […] are incapable of formulating algorithms and even so-called “intelligent” systems rely on a human being to formulate the algorithm’.245 Notably, the future of AI is associated with the development of new algorithms.246 Thus, as long as an algorithm contains instructions that determine computational operations, and as long as computers are bound by such instructions, it would be unjustified to attribute ‘cognitive autonomy’ to an algorithm, or a software system, and to view ‘intelligent systems’ as ‘standalone’ problem-solvers and inventors. In light of the foregoing, the delineation between the human and non-human (algorithmic) contributions to an invention appears, in itself, artificial.247

2. What about ‘black-box’ models?

It is common to refer to some types of AI, especially deep neural networks, as ‘black box’ models.248 While such characterisation generally implies the limited explainability of models, it is worth noting that neither a universally accepted definition of explainability, nor a clear delineation between explainability and related terms – comprehensibility, transparency, interpretability – seems to exist.249 While all these qualities can be desirable and even indispensable for various regulatory reasons, the relevance of AI explainability for patent law has, at least, two distinct aspects. First, it matters for the fulfilment of the disclosure requirement, in particular, in cases where the claimed technical effect is enabled through the working of AI (akin to ‘computer-implemented’ inventions).250 Second, from an inventorship perspective, the question is whether the characterisation of a model as a ‘black box’ may denote certain decision-making autonomy of a computer as to how to perform computational operations.251

One can argue that, if it is unclear how exactly a problem is solved within a ‘black box’,252 a human cannot and should not be credited for finding the solution. However, it is important to clarify what exactly the ‘black box’ problem refers to, and what factors account for the limited explainability of ANN models. A ‘black box’ generally implies computational complexity, and the contributing factors include the non-linearity of a model,253 the complexity of data representation within a neural network (commentators note that, ‘even if [they] understand the underlying mathematical principles and theories, [ANN] models lack an explicit declarative representation of knowledge’254), the problem of data retrieval from a neural network,255 and a limited understanding of the operating algorithms cannot but reflect the intelligence embedded into such algorithmic procedures.256

See eg Cynthia Rudin, ‘Stop Explaining Black Box Machine Learning Models for High Stakes Decisions and Use Interpretable Models Instead’ 1 Nature Machine Intelligence 206 (2020) (defining a ‘black box’ model as a function that is too complicated for any human to comprehend). In other words, the ANN model is a ‘black box’ model, because it is impossible to represent the problem from a different perspective and provides a different meaning to explanation.257

A survey of Methods for Explaining Black Box Models’ 51(5) ACM Computing Surveys 93:2 (2018) (‘Different scientific communities studied the problem of explaining machine-learning decision models. However, each community addresses the problem from a different perspective and provides a different meaning to explanation.’).

An example would be a system for image recognition, a model that is true for ANN-based model.

See eg Wojciech Samek and Klaus-Robert Müller, ‘Towards Explainable Artificial Intelligence’ in Wojciech Samek and others (eds), Explainable AI: Interpreting, Explaining and Visualizing Deep Learning, Lecture Notes in Computer Science, vol 11700 (Springer 2019) 5, 17 (noting that ‘[a] theory of explainable AI, with a formal and universally agreed definition of what explanations are, is lacking’); Raccardo Guidotti and others, ‘A Survey of Methods for Explaining Black Box Models’ 51(5) ACM Computing Surveys 93:2 (2018) (‘Different scientific communities studied the problem of explaining machine-learning decision models. However, each community addresses the problem from a different perspective and provides a different meaning to explanation.’).

159 Gregory S Hornby, Jason D Lohn and Derek S Linden, ‘Computer-Automated Evolution of an X-Band Antenna for NASA’s Space Technology 5 Mission’ 19(1) Evolutionary Computation 1, 2 (2001).

160 Bluc (n 34).

161 WIPO Conversation on IP’ (n 2) 1.

162 Ian M Cockburn, Rebecca Henderson and Scott Stern, ‘The Impact of Artificial Intelligence on Innovation’, NBER Working Paper No 24449 (2018) 27.

163 In the words of Nick Bostrom, ‘It was a successful at its original goal, which all along has been not just to automate specific tasks but to replicate in machine substrates the general-purpose learning ability and planning ability that makes us humans smart, then that would literally be the last invention that humans ever needed to make’. Ford (n 19) 104. As observed by Andrew Ng, ‘Deep learning is limited, just like the internet is limited, and electricity is limited. Just because we invented electricity as a utility, it didn’t suddenly solve all of the problems of humanity. In the same way, backpropagation will not solve all the problems of humanity’. Ford (n 19) 192-193.

164 See eg Sullins (n 58) 111 (‘So far AI programs have not been able to succeed in solving problems outside of narrowly defined domains.’); O’Neill and Spector (n 16) 2 (‘While there have been many significant advances in the field of Genetic Programming, […] we have not solved the problem of automatic programming in any meaningfully scalable manner.’); Michael O’Neill and David Fagan, ‘The Elephant in the Room: Towards the Application of Genetic Programming to Automatic Programming’ in Wolfgang Banzhaf and others (eds), Genetic Programming Theory and Practice XVI, Genetic and Evolutionary Computation (Springer 2019) 179, 189 (‘Genetic Programming has a number of open issues which need to be addressed many of which have already been captured and include scalability and modularity, generalisation, context and complexity and usability and semantics.’); Davenport (n 103) 45 (noting that, while the connectionist approach ‘proved reasonably successful at simple low-level learning tasks, it struggled to demonstrate similar success at the higher levels where the symbolic approach had long held sway.’).

165 Backhouse (n 93) 4 (emphasis added).

166 In the words of Andrew Ng, while ‘there are a lot of limitations to the current generation of AI, […] one of the most exciting things yet to be invented will be other algorithms that are much better than backpropagation’. Ford (n 19) 195. See also Cathal Horan, ‘The Future Is Algorithms, Not Code’ (Hackerman, 19 March 2017) https://hackernoon.com/the-future-is-algorithms-not-code-64acca36eb982 accessed 3 March 2020.

167 Mueller and Massaron (n 116) 40 (‘Algorithms have become hard-coded in the intelligence of humans who devised them, and any machine learning system is called the model interpretability problem.’).

168 Andreas Holzinger and others, ‘Causality and Explainability of Artificial Intelligence in Medicine’ 9 WIREs Data Mining Knowl Discov 10 (2019).

169 Pat Langley, ‘Planning Systems and Human Problem Solving’ 7 Advances in Cognitive Systems 13, 19 (2018) (pointing out that, while humans can explain and justify actions retrospectively, few AI problem-solving systems retain records of ‘causal links among states, actions, and decisions’).
causality of the ‘learned’ statistical correlations. The latter factor can explain why the way a model has arrived at a prediction might not appear straightforward. In other words, it is often unclear whether the statistical correlations ‘learned’ from the training data actually reflect the genuine causality between the features. Yet, a limited understanding of data representations, or of the ‘learned’ correlations, do not denote a lack of understanding of how an ANN has been trained.

Furthermore, it might be interesting to ponder whether the factor of the explainability of how an invention might have come into being can, at all, be relevant for the question of the allocation of the inventor entitlement. Can we explain how thoughts and solutions occur and become perceptible to a human mind? History provides examples where great ideas were received in a dream state, or serendipitously, which might be more complex phenomena to explain compared to computational processes during the model training. What matters is that none of the above-mentioned factors of limited explainability of ANNs denote the absence of the causality between the instructions provided to a computer and the outcome of computation, irrespective of whether it can be (readily) interpreted or not.

3. What about the unpredictability of the solution?

Legal narratives about AI-generated inventions sometimes highlight ‘a surprising effect’ of AI applications. One can argue that, since a human could not imagine, or foresee the results, s/he cannot be deemed to be an inventor. Yet, this contention seems to be misplaced. First of all, the underlying premise that a solution should be known upfront is flawed, as it contradicts the very definition of problem solving – i.e. reaching an objective, which is not ‘immediately attainable’. For instance, in the case of inventions resulting from experimentation, it would be absurd to stipulate the foreseeability of the outcome as a prerequisite for the inventor entitlement.

Second, the task, for which an ANN model is trained, or to which an EA is applied, is always known upfront. What one perhaps cannot envisage is how exactly the function relating input and output variables will look like, since it is the interaction of an algorithm with training data that creates correlations (in the case of ANN). In this regard, the hypothetical that the solution could not have been imagined by a human is highly speculative: If a human, theoretically, can make the same calculations on paper – even if that would take a lifetime – s/he could eventually reach the same outcome.

Third, even less sophisticated methods, such as pattern recognition, can uncover relations that a human applying them may not foresee. However, irrespective of the level of complexity of computational methods, what matters from an inventorship perspective is that the problem-solving mechanism – i.e. the trajectory and the determinants of computational operations – is provided by a human. If so, there is seemingly no reason to consider an algorithm, which embodies such mechanism, to be an ‘autonomous problem solver’.

Curiously, one of the arguments raised by the applicants for patents designating the connectionist system DABUS as an inventor was that the computer ‘identified the novelty of its own idea before a natural person did’. Philosophy of AI is perhaps a better suited discipline to answer the question of whether computers can, at all, identify or conceive ideas. What can be reasonably assumed is that certain data representations, as a result of computational operations, can be formed within a computational system before they are perceived by a person using a computer to perform such operations. However, the case of data generated in the course of training is not unique in this regard. Likewise, one can argue that, when data is mined, a computer is first to ‘see’ a pattern, or microorganisms used as analytical tools are first to ‘discover’ certain biological phenomena, or a chemical reagent is first to ‘establish’ a chemical reaction. Thus, if such ‘priority’ factor were to be material for the allocation of the inventor entitlement to a natural person, it would need to be applied across the board. The question to what extent the human mind is independent in making discoveries might be a subject for an epistemological discussion. From a more practical perspective, the problem solver is the one who elaborates the steps of how a problem at hand can be solved. In the case of machine learning, as discussed earlier, the results obtained through the training of a model and its application are essentially determined by instructions provided

goals’ and, hence, such records cannot be retrieved ‘to support retrospective explanation of their decision making’.

Further, if one considers an algorithm, which embodies such mechanism, to be an ‘autonomous problem solver’, the factor of the explainability of how an invention might have come into being can, at all, be relevant for the question of the allocation of the inventor entitlement. Can we explain how thoughts and solutions occur and become perceptible to a human mind? History provides examples where great ideas were received in a dream state, or serendipitously, which might be more complex phenomena to explain compared to computational processes during the model training. What matters is that none of the above-mentioned factors of limited explainability of ANNs denote the absence of the causality between the instructions provided to a computer and the outcome of computation, irrespective of whether it can be (readily) interpreted or not.

176 Samek and Müller (n 169) 16 (noting that ‘some methods allow to visualize “first-order” information [revealing] which input features have been identified as being relevant for the prediction. However, the relation between these features, eg, whether they are important on their own or only when they occur together, remains unclear.’).

177 Ibid 5 (pointing out that the ‘nestted non-linear structure [of DNNs does] not provide[d] any information about what exactly makes them arrive at their predictions’ (emphasis added)).

178 ANN-based machine learning consists of two main steps: first, a model is trained; second, the trained model is applied to new data to derive a prediction.

179 See eg T Great Examples of Scientific Discoveries Made in Dreams’ (Famous Scientists, not dated) (https://www.famousscientists.org/?great-examples-of-scientific-discoveries-made-in-dreams) accessed 3 March 2020.

180 On serendipity in problem solving, see Steven Johnson, Where Good Ideas Come From (Penguin 2010) 99 ff.

181 As pointed out earlier, computers follow algorithms obediently, while algorithms need to specify computational procedures precisely. See above Wang (n 87) 31; Ferragina and Lucchi (n 79) 12.

182 Vertinsky and Rice (n 3) 757 (assuming that ‘machines will […] originate novel solutions not imagined by their human operators, transforming the invention process in ways not easily accomplished within the current U.S. patent system’); Plotkin (n 3) 80 (‘Artificial invention technology [can] discover complex rules and patterns that its human programmer never imagined.’).

183 Polya (n 76) 117.

184 Taulli (n 132) 49.

185 For an overview of methods applied in pattern recognition models, see eg Jun-Hai Zhu, Su-fang Zhang and Xu-zhao Wang, ‘An overview of pattern classification methodologies’ Proceedings of Fifth International Conference on Machine Learning and Cybernetics (Dalian, 13-16 August 2006) (https://ieeexplore.ieee.org/document/4028622) accessed 3 March 2020.

186 Uncovering patterns in medical data is an apt example. See eg Ruchi Caruana and others, ‘Intelligible Models for Healthcare: Predicting Pneumonia Risk and Hospital 30-day Readmission’ KDD15: Proceedings of the 21st ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (2015) 1721 (https://doi.org/10.1145/2783258.2788613) accessed 3 March 2020 (reporting cases where ‘high-performance generalized addictive models with pairwise interactions uncovered surprising patterns in medical data’).

187 EPO, ‘Summary of the relevant facts and submissions’ (n 4) para 5 (emphasis added).

188 Harris (n 72).
by a human.\textsuperscript{189} Furthermore, it is important to emphasise that, as such, data representations or ‘learned’ statistical correlations do not constitute a readily applicable solution to a problem. The issue of interpretability of ANNs is a prima facie evidence that computational outcomes can be transformed into meaningful, actionable and communicable knowledge only when they are interpreted by a human.

4. Towards a broader dialogue

The view presented here based on the literature review is that computational methods of problem solving – including ANNs and EAs – essentially rely on the instructions that determine how inputs are mapped into output through computation. Thus, as long as a computer is bound by an algorithm, there is no reason to assign to it ‘cognitive’ autonomy, irrespective of the complexity of the computational process. As an operative test to prove the decisive role of such instructions, it is suggested to run a counterfactual where a computer would need to solve a problem in their absence.

As computational techniques are inevitably becoming more and more sophisticated, questions that needs to be explored with experts in computer science on a broad basis are: Under what conditions can a computer deviate from the algorithm provided by a human? Under what conditions might it be possible that a computer can derive the relation between inputs and outputs without instructions, provided upfront by a human, of how this should be done?

Distilling an adequate understanding of the capabilities of computational systems can be challenging due to the significant divergence in opinions as to how far the developments in automation of cognitive functions can reach.\textsuperscript{290} Automation of scientific research can be an apt example. Some commentators envisage that ‘the next logical step in laboratory automation’ is where Robot Scientists are able to ‘automate all aspects of the scientific discovery process’\textsuperscript{\cite{731}} generate hypotheses from a computer model of the domain, design experiments to test these hypotheses, run the physical experiments using robotic systems, and then analyse and interpret the results.\textsuperscript{\cite{290}} Other researchers argue that, even though computational methods of scientific discovery ‘are an increasingly important tool in science[,] the role of the human scientist remains, for the foreseeable future, essential’.\textsuperscript{\cite{290}}

Furthermore, the diversity of scenarios of problem solving through computational techniques needs to be further examined, especially, where multiple contributors are involved in the design of a computational model. The eclectic nature of computational techniques can have implications for the allocation of the inventor entitlement. For instance, in some cases, not only the designer of the original algorithm, but also the user who adjusts (‘tweaks’) it to the problem at hand can be viewed as equal contributors to problem solving. In other cases, a standard algorithm can be applied, but the choice and the handling of data by a data scientist might play a decisive role. This aspect can be explored through case studies, as constellations can be as diverse as the problems solved through computational techniques. However, while the scenarios may vary greatly, they might not pose new legal uncertainties and can eventually be resolved under the rules on co-inventorship. This issue is not covered within the scope of this paper, as the focus here lies mainly on the human-computer interaction in the context of the inventive process and its implications for the concept of inventorship.

V. Concluding remarks

This paper highlights that the ongoing policy inquiries and the recent legal scholarship on the topic of ‘AI-generated’ inventions demonstrate the lack of a comprehensive technical basis, as well as tend to underappreciate the distinction between ‘autonomous’ and ‘automated’ systems. Paraphrasing the opening quote, there might be a profound disconnect between the questions raised by policymakers concerning ‘non-human inventorship’ and the technological state of the art.

The article has shown that AI techniques represent computational methods of problem solving enabling partial automation of inventive activity. As such, the application of such techniques cannot be prejudicial for the allocation of the inventor entitlement to a natural person. As long as a human specifies instructions that determine how the input-output relation is derived through computation, and as long as computers are bound by such instructions, there is seemingly no reason why AI-aided – allegedly ‘AI-generated’ – inventions should be treated under patent law differently than inventions assisted by other types of problem-solving tools and methods as far as inventorship is concerned. Instead, the use of such techniques should be a matter of the assessment of inventive step.\textsuperscript{\cite{299}}

As we do not personify the laws of physics or chemistry, neither should we attribute a mystic personality to computational processes carried out according to the laws of mathematics and statistics. Even though it became common to use the language that anthropomorphises algorithms, such tendency was viewed as ‘an obstacle to properly conceptualizing’ legal and societal challenges posed by AI techniques,\textsuperscript{\cite{298}} as well as misleading the policy priorities.\textsuperscript{\cite{295}} If computers only execute the problem-solving mechanism – defined in this paper as instructions as to how the input-output relation should be derived through

\textsuperscript{189} Above (n 181).
\textsuperscript{190} See generally Ford (n 19).
\textsuperscript{191} Andrew Charles Sparkes and others, ‘Towards Robot Scientists for Autonomous Scientific Discovery’ 2(1) Automated Experimentation 1-12 (2010).
\textsuperscript{192} Sozou and others (n 48) 731. See also Langley (n 158) 231, 234 (noting that ‘the more common perspective is that [computational] discovery systems should aid scientists rather than replace them’).
\textsuperscript{193} Peter Blok, ‘The Inventor’s New Tool: Artificial intelligence – how does it fit in the European patent system?’ 39(2) E.I.P.R. 69 (2017) (pointing out that ‘an artificial intelligence application should be seen as a tool, and that inventions made with that tool are patentable as long as the artificial intelligence application is not a tool the average skilled person would use routinely’).
\textsuperscript{194} Watson (n 20) 417.
\textsuperscript{195} In the words of Yann LeCun, the concerns that one day ‘...artificial general intelligence, and that we’ll create a human-level intelligence that will escape our control [is] a bit like we haven’t invented the internal combustion engine yet and we are already worrying that we’re not going to be able to invent the brake and the safety belt’. Ford (n 19) 135-136.
computation – the distinction between human and ‘non-human’ (algorithmic) ingenuity is simply pointless.

While the views on the human-machine interaction in the process of problem solving presented here are not claimed to be conclusive, this paper calls for an in-depth inquiry that would elucidate under what conditions a computer is able to solve technical problems ‘on its own’. Not only the potential of such techniques, but also the time horizon need to be clarified. Prospects that automatic programming would threaten the very existence of IP rights have been discussed in legal literature at least since 1970s.\textsuperscript{196}

Yet, neither at that time,\textsuperscript{197} nor more recently have concerns regarding artificial entities endowed with cognitive autonomy materialised.\textsuperscript{198} If the advent of Artificial General Intelligence is as uncertain and distant as AI designers currently predict,\textsuperscript{199} it appears to be more beneficial to turn attention to more pertinent issues arising in relation to IP law as it applies to AI techniques,\textsuperscript{200} and to examine more comprehensively its actual role in AI innovation.

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\textsuperscript{196} Timothy L Butler, ‘Can a Computer be an Author? Copyright Aspects of Artificial Intelligence’ 4 Hastings Comm. & Ent. L.S. 707 (707) (1981) (cautioning that computer software that is ‘capable of automatic programming, inductive analysis and knowledge-based problem solving will soon challenge the legal concepts of authorship and originality’); Karl F Milde, ‘Can a Computer be ‘An Author’ or an ‘Inventor?’ 51 J. Pat. Off. Soc’y, 378 (1969).
\textsuperscript{197} Charles Rich and Richard C Waters, ‘Automatic Programming: Myths and Prospects’ 21(8) Computer 40 (1988).
\textsuperscript{198} Above at II.4. See also Mueller and Massaron (n 87) 15 (‘Intelligent machines, robots, cyborgs, and so on are favourite themes of all forms of science fiction. [Although science fiction] has very often inspired scientists in AI and other areas, […] it may give a mistaken picture of what is actually happening in current research.’).
\textsuperscript{199} See above (n 19) and the accompanying text.
\textsuperscript{200} See Drexl and others (n 31) para 6 (pointing out the need to shift the focus from AI-generated output and to examine ‘the applicability of the existing IP framework to AI as a tool and its constituting elements [in order to] gain a more detailed understanding of how AI interacts with IP law’).
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