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Authorship in the Age of Machine Learning and Artificial Intelligence

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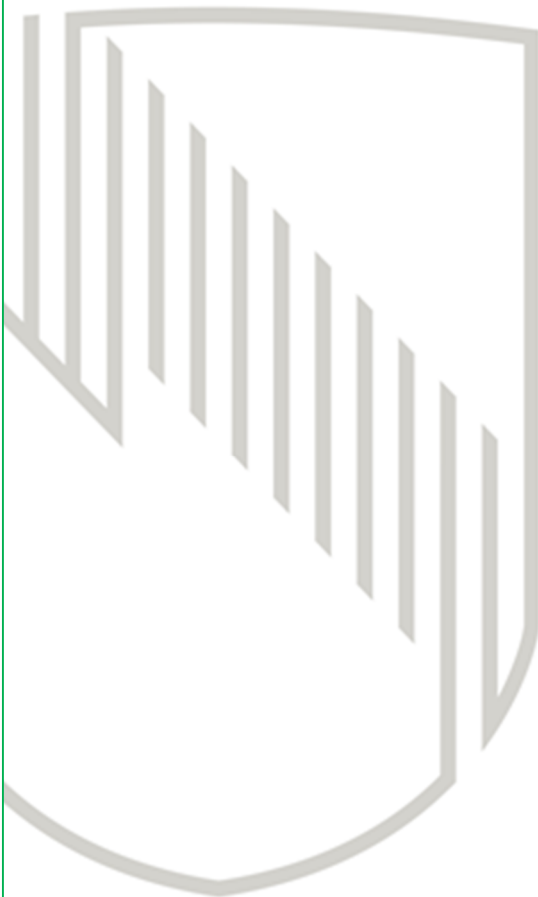
IN THE AGE OF MACHINE LEARNING

AND ARTIFICIAL INTELLIGENCE

Jean-Marc Deltorn

—

Franck Macrez



Authorship in the Age of Machine learning and Artificial Intelligence

Jean-Marc Deltorn,
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New generations of algorithmic tools have recently become available to artists. Based on the latest development in the field of machine learning - the theoretical framework driving the current surge in artificial intelligence applications -, and relying on access to unprecedented amounts of both computational power and data, these technological intermediaries are opening the way to unexpected forms of creation. Instead of depending on a set of man-made rules to produce novel artworks, generative processes can be automatically learnt from a corpus of training examples. Musical features can be extracted and encoded in a statistical model with no or minimal human input and be later used to produce original compositions, from baroque polyphony to jazz improvisations. The advent of such creative tools, and the corollary vanishing presence of the human in the creative pipeline, raises a number of fundamental questions in terms of copyright protection. Assuming AI generated compositions are protected by copyright, who is the author when the machine contributes to the creative process? And, what are the minimal requirements to be rewarded with authorship?

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1. Introduction

Mentions of artificial intelligence (AI) producing musical compositions rivalling human creations have flourished in the past years. YouTube sensation Taryn Southern's latest album, aptly titled "I AM AI" was claimed to be "the first of its kind to be fully composed with and totally produced by AI"¹. A year before, "Daddy's Car" a pop song generated in the style of The Beatles by Sony's FlowMachine software had hit the radios and concert halls². What may seem as another fad exploiting the current AI hype may actually hide a deeper undercurrent. For, beyond the overt sensationalist statements, new tools are becoming available to the musical community that are already changing the creative palette that musicians, professionals and amateurs alike, can resort to. As a consequence, new forms of algorithmic compositions are being developed that integrate, at the core of the creative process, automation tools based on the latest computer-science developments.

1.1 Procedural Creations

This should not come as a surprise: amongst all artistic fields, music is certainly leading the way in embracing the latest technological innovations as soon as they become available. From the early electroacoustic experiments of Maurice Martenot and Leo Theremin or Beauchamp and Rickenbacker's 1930s electronic guitar pick ups that took advantage of the development of vacuum tubes amplifiers³ to Raymond Scott's Clavivox keyboard synthesizer⁴ and Robert Moog's Voltage-Controlled Electronic Music Modules⁵ in the 1950s and 1960s, the inclusion of technical advances has been the source of new sounds, of new expressive forms and has often led the way to the development of brand new musical genres.

The computer has participated in this process as early as the late fifties⁶, where productions started to emerge based on compositional rules expressed in algorithmic

¹ <https://www.digitaltrends.com/music/artificial-intelligence-taryn-southern-album-interview/>.

² Daddy's car by Benoît Carré, François Pachet (2016) <http://www.flow-machines.com/ai-makes-pop-music/>.

³ Sean M. O'Connor, *Patented Electric Guitar Pick-Ups and the Creation of Modern Music Genres*, 23 Geo. Mason L. Rev., 1007 (2016).

⁴ Thom Holmes, *Electronic and Experimental Music: Technology, Music, and Culture*, 5th ed., Routledge, (2015).

⁵ See *Id.*

⁶ Donald J. Grout and Claude V. Palisca, *A History of Western Music*. 5th ed., W. W. Norton & Company: New York (1996).

language⁷. During the 1980s composers attempted to expand upon the limitations of these first generations of procedural creations (where the computer followed a set of rules set out in advance by the musician) by integrating techniques derived from the budding field of machine learning.⁸ These statistically grounded approaches allow to learn directly from data and solve specific problems (from classifying spam email to recognising images, speech or ... music) without requiring an explicit and often painstaking elicitation of the rules required to do so. These techniques excel when, as Rebecca Fiebrink and Baptiste Caramiaux put it: “the desired application is too complex to be described by analytical formulations or manual brute force design”,⁹ a characterisation certainly representative of the musical creative process. Neural network architectures, one of the early leading candidates for the machine learning techniques, were thus soon applied to the production of musical compositions¹⁰ and used to improvise beats and melodies as part of a jazz band¹¹.

1.2 Deep Neural Architectures

However, in spite of this enticing début, the practical difficulties associated with training neural networks severely curbed their widespread applications and confined them to the realm of fringe experiments. Interesting as they may be, they had mostly “failed to capture global musical structure”¹² and had fallen short of delivering on their early promises. This, however, changed radically in the last years. Many of the hurdles that had initially plagued the development of large-scale neural networks have been indeed—at least partially—lifted with the concurrent development of novel algorithmic training protocols (spearheaded by an ever-growing ecosystem of deep learning techniques)¹³, the access to an unprecedented amount of computational power and the

⁷ The Illiac suite, composed in 1957, (Lejaren Hiller and Leonard Isaacson, *Experimental Music: Composition With an Electronic Computer*. McGraw-Hill (1959)) or Iannis Xenakis’ “Morsima-Amorsima” (1962) are but a few of these experiments.

⁸ Machine learning techniques, by identifying statistical correlations present in a training set (e.g. formed of musical compositions) can model the characteristic features inherent to the training data. These models can then be used to produce novel musical works that express the same features.

⁹ Rebecca Fiebrink and Baptiste Caramiaux, *The machine learning algorithm as creative musical tool*, arXiv:1611.00379v1 (2016).

¹⁰ Peter M. Todd, *A connectionist approach to algorithmic composition*, 13 *Computer Music Journal*, no. 4, 27 (1989). Jamshed J. Bharucha, and Peter M. Todd, *Modeling the perception of tonal structure with neural nets*, 13 *Computer Music Journal*, no. 4, 44 (1989). C. Stevens and J. Wiles, *Representations of tonal music: A case study in the development of temporal relationship.*, in, *Proceedings of the 1993 Connectionist Models Summer School*, 228 (1994).

¹¹ Masako Nishijima and Kazuyuki Watanabe, *Interactive music composer based on neural networks*, 29 *Fujitsu scientific and technical journal*, no. 2, 189, (1993).

¹² Douglas Eck and Juergen Schmidhuber, *A first look at music composition using lstm recurrent neural networks*, *Istituto Dalle Molle Di Studi Sull Intelligenza Artificiale*, 103 (2002).

¹³ Geoff E. Hinton, Simon Osindero, and Yee-Whye Teh, *A fast learning algorithm for deep belief nets*, 18, *Neural computation*, 7, 1527 (2006). Yoshua.Bengio, *Learning deep architectures for AI*. 2, *Foundations*

accumulation of large quantities of digitised training data. In fact, the versatility of deep neural architectures, capable, almost out of the box, to learn complex representations that capture high-level abstractions from their training set, makes them now the de facto standard on which a new generation of creative musical tools is being built.

What can these new tools do that makes them so special? How about generating artworks in the style of an ancient master at the click of a button? What was deemed of the realm of the thought experiment has been recently accomplished by a team of institutions in the Netherlands who used machine learning techniques to capture Rembrandt's style and create a portrait that could have been painted by the Dutch master himself. The same principles can be applied to musical creations. Daniel Johnson, for example, trained a neural network on compositions from classical composers ranging from Joseph Haydn to Claude Debussy, to produce surprisingly polished results with minimal human input¹⁴. Overall, neural networks, have now been successfully applied to the generation of a vast range of musical genres, including polyphonic music¹⁵, Johann Sebastian Bach-inspired piano pieces¹⁶, blues¹⁷ or Irish folk songs¹⁸. Other architectures, such as DeepMind's WaveNet, have recently been shown to produce aesthetically pleasing compositions.¹⁹

1.3 New Kinds of Interactions

But deep learning techniques are not limited to mimicking the styles of pre-existing composers, they can also be used to mix and combine multiple sources, from a variety of styles, in novels and often surprisingly believable syncretic compositions. Amongst the most notable productions, the creations of Sony's FlowMachine certainly stand out. Based on a vast corpus of about 13000 lead sheets from a diversity of sources (ranging from jazz to pop and Brazilian music), the machine learning system is capable

and trends in Machine Learning, no. 1, 1 (2009).

¹⁴<http://www.hexahedria.com/2015/08/03/composing-music-with-recurrent-neural-networks/>. The code is available at: <https://github.com/hexahedria/biaxial-rnn-music-composition>.

¹⁵ Nicolas Boulanger-Lewandowski, Yoshua Bengio and Pascal Vincent, *Modeling Temporal Dependencies in High-Dimensional Sequences: Application to Polyphonic Music Generation and Transcription*, in: Proceedings of the 29th International Conference on Machine Learning (ICML-12), 1159 (2012).

¹⁶ I-Ting Liu and Bhiksha Ramakrishnan, *Bach in 2014: Music Composition with Recurrent Neural Network*, arXiv:1412.3191 (2014).

¹⁷ Douglas Eck and Juergen Schmidhuber, *Finding temporal structure in music: Blues improvisation with LSTM recurrent networks*, in: Neural Networks for Signal Processing, 2002. Proceedings of the 2002 12th IEEE Workshop on, 747 (2002).

¹⁸ Florian Colombo et al., *Algorithmic Composition of Melodies with Deep Recurrent Neural Networks*, arXiv:1606.07251 (2016).

¹⁹ Li-Chia Yang et al. *MidiNet: A convolutional generative adversarial network for symbolic-domain music generation*, arXiv preprint arXiv:1703.10847 (2017).

of generating rich melodies that match and merge a variety musical genre.²⁰ Even further, different classes of neural architectures can now separate an underlying artistic style learned from a training corpus and apply it to secondary work. These generative engines are then capable of exploring questions such as “what would it sound like if a musical piece by ensemble/artist A was performed by ensemble artist B?”²¹ or of converting, for example, “a Mozart symphony performed by an orchestra to an audio in the style of a pianist playing Beethoven”²².

Undoubtedly, these new techniques open the way to uncharted territories in terms of creative explorations, not only to the experienced composer but, also, to the untrained amateur. As a matter of fact a growing number of companies, such as Jukedeck, Amper, Orb, Hexachord, already offer digital tools that allow anybody, with minimal musical background, to create pleasing compositions to the point that “AI music composers may inspire millions of music consumers to start creating their own songs”²³. The automation of the creative process opens the way to the production of artworks en masse, beyond the capabilities of the most prolific human composers. J.-S. Bach’s thousand cantatas would pale in comparison to the 50 000s folk pieces produced by Bob Sturm’s “The Endless folk-rnn Traditional Music Session”²⁴ or to the database of a billion unique songs generated automatically by Melomics 109, the music generation program developed by the University of Malaga in Spain.²⁵

Furthermore, far from being restricted to the sole function of automating the creative process, the same algorithmic platforms also offer new modalities of musical production, either by giving access to untapped sources of inspiration or by promoting different forms of dialogue between the musician and the machine. On the 27th of September 2016, Mark d’Inverno Quintet session at the Vortex Jazz Club in London was based on compositions written by a deep neural network. Highlighting the potential of new kinds of interactions between algorithmic creations and human interpretation,

²⁰ It was used to help produce “Daddy’s Car”, a pop song in the style of The Beatles, that was part of a set presented at the Gaîté Lyrique concert hall in Paris the 27th of October 2016.

²¹ Shaun Barry and Youngmoo Kim.: “Style” transfer for musical audio using multiple time-frequency representations, Open submission to the 6th International Conference on Learning Representations (2018).

²² Noam Mohr, Adam Polyak Wolf and Yaniv Taigman, *A Universal Music Translation Network*, arxiv 1805.07848 (2018).

²³ Joe Dysart, *Give me that AI Rock and Roll*, Communications of the ACM (3 July 2018).

²⁴ Available at: <http://www.eecs.qmul.ac.uk/~sturm/research/RNNIrishTrad/index.html>. A description of the corresponding generative process is presented in: Sturm, Bob, Joao Felipe Santos, and Iryna Korshunova. “Folk music style modelling by recurrent neural networks with long short term memory units.” In 16th International Society for Music Information Retrieval Conference. 2015.

²⁵ Carlos Sánchez Quintana et al., *Melomics: A Case-Study of AI in Spain*, 34, *AI Magazine*, no. 3, 99 (2013). The scale of such productions may then well jeopardize the status quo in terms of the economy of musical productions. As David Pogue puts it : “What is art’s value when there’s no longer any effort involved in its creation, or scarcity to limit its ownership?” (David Pogue, *A Compendium of AI-Composed Pop Songs*, *Scientific American* (2018), <https://www.scientificamerican.com/article/a-compedium-of-ai-composed-pop-songs/>).

d'Inverno noted: "Even if you don't think machines can be creative by themselves, they can potentially be creative friends. You can imagine a situation when you're having a conversation with a machine offering prompts as a critical, creative accomplice."²⁶

1.4 Deep Learning and New Creative Tools: Copyright Issues

These new algorithmic tools, by offering new avenues for creation of musical works, be it in the studio²⁷ or live²⁸, certainly raise fundamental questions in terms of the protection regime under which these productions may fall. Since a common denominator of "AI" systems is to "emulate intelligent behaviour in terms of computational processes"²⁹ some of the cognitive and—in the present instance—creative choices of the natural person could originate from the algorithm. This take over by the automata of the creative process could directly affect the personal contribution of the musician or composer to the final work.

Can such automated creations be protected under copyright? If so, who is the author when the machine contributes to the creative process? What are the rules to delineate the perimeter of ownership in deep-generative art? What is then the minimal requirement to be rewarded with authorship? Do all automatically or semi-automatically musical compositions warrant copyright protection? Examining whether the presence of the author resists to the intermediation of the generative algorithms will require first to examine the conditions of protection, in particular, the expression of an imprint, of the creators' intent in the expressed musical form. The question is especially complex since it is not to be limited to the analysis of pure computer-generated creations, but focuses on those situations where the computer helps create alongside humans. Indeed, when the artwork emerges through an "algorithmic pipeline", it can be all the more difficult to identify "who created what" as these new technical intermediaries blur the lines between the contributions of the human and those of the machine. Disentangling the inputs of the human creator from those of the AI automaton is essential for copyright assignment, where authorship results from an original contribution of a natural person. It is therefore appropriate to examine, firstly, the essential rules of assignment of copyright as applied

²⁶ James Vincent, *A night at the AI Jazz Club*, The Verge, <http://www.theverge.com/2016/10/12/13247686/ai-music-composition-jazz-club-london-deep-learning> (12 Oct. 2016).

²⁷ The team behind FlowMachine has released a new album including collaborations with known artists under the name Skygge.

²⁸ Shimon, the marimba-playing robot from Georgia-Tech is interacting live with human counterparts (<http://www.news.gatech.edu/2017/06/13/robot-uses-deep-learning-and-big-data-write-and-play-its-own-music>), Rebecca Fiebrink is modulating a neural network model in real time to produce music in front of an audience: see Rebecca Fiebrink, and Baptiste Caramiaux, *The machine learning algorithm as creative musical tool*, in *The Oxford Handbook of Algorithmic Music*, Roger T. Dean and Alex McLean eds., 181 (2016).

²⁹ Robert J. Schalkoff, *Artificial Intelligence: An Engineering Approach*, McGraw-Hill (1990).

to musical creations resulting from the machine learning (2). Secondly, the analysis being extremely casuistic, we will specify, through examples, what can be the role of the human in the framework of this type of creative processes (3).

2. Authorship and the protection of deep musical creations

2.1 Assignment to Nobody

The first assumption is that in which no copyright cannot be awarded, because of insufficient originality or lack of identification of a human author.

2.1.1 Originality and the Need of a Human Author

Article 2 § 1 of the Berne Convention does not set any limitations to the protection of artistic works and has left to national jurisdictions the freedom to specify the minimum threshold that a copyrightable work must meet.³⁰ A common standard state that a copyrightable work should originate from an author's creative effort, and not be the mere copy of a pre-existing work. This principle forms the basis of an essential condition for a work to be protected by copyright: the requirement for originality. In the absence of any positive definition in the national laws, the interpretation of this notion has been left to the courts. More generally, it seems logical that when the Berne Convention speaks of "author" or "authorship", it refers to a human author³¹. This analysis is consistent with the fact that intellectual property is now considered as a fundamental right³².

In Europe (as a whole), there is no harmonized provision defining originality. But the important European Court of Justice (ECJ) Infopaq decision ruled that the protection is granted if the work (or the element of the work) expresses "the author's own intellectual creation"³³, with a clear intention to unify the concept of originality in Europe. To do so, the ECJ extended to the whole of copyright the definition of originality contained into

³⁰ Article 2 §1 of the Berne Convention allows for the protection of "every production in the literary, scientific and artistic domain, whatever may be the mode or form of its expression", no other criteria such as merit or destination being taken into account. Article 2 §2 grants national legislations the freedom to prescribe whether or not an artworks shall be "fixed in some material form" in order to be protected.

³¹ Sam Ricketson, *People or Machines: The Berne Convention and the Changing Concept of Authorship*, 16 Columbia-VLA Journal of Law & the Arts, 1 (1991).

³² Id., p.34: "The human-centered notion of authorship presently enshrined in the Berne Convention embodies a fundamental human right, namely that of the creator over the work he or she creates."

³³ Infopaq International A/S v Danske Dagblades Forening (C-5/08) EU:C:2009:465 (2012) at 48.

three specific EU Directives concerning computer programs³⁴, databases³⁵ and photographs³⁶. The Court of Justice of the European Union further clarified the condition of originality by underlying that: “an intellectual creation is an author’s own if it reflects the author’s personality. That is the case if the author was able to express his creative abilities in the production of the work by making free and creative choices.”³⁷ This definition is usually interpreted as requesting that the author be a natural person. Laws from EU member States confirm this interpretation: art. L.111-1 of the French Intellectual Property Code refers to copyrighted work as a “creation of the mind”. Similarly, section 7 of the German Copyright act states that “the rights holder is the creator of the work”.

In the U.S., the Supreme Court held in a 1991 decision that copyright protection could only be granted to “works of authorship” that possess “at least some minimal degree of creativity”³⁸. However, as the Court added, “the requisite level of creativity is extremely low; even a slight amount will suffice. The vast majority of works make the grade quite easily, as they possess some creative spark.”³⁹ Although the definition of originality varies between national legislation, the imprint of an individual’s “personality” or “creative spark” is commonly required as a minimum threshold to allow protection under copyright. The requirement of a human author is made explicit in U.S. copyright law in the context of artwork generated through automated processes: the U.S. Copyright Office has indeed now taken the position that “in order to be entitled to copyright registration, a work must be the product of human authorship. Works produced by mechanical processes or random selection without any contribution by a human author are not registrable.”⁴⁰

The creator is, as a consequence, unambiguously required to be a human being. The difficulty will therefore lie in identifying the putative author when an algorithmic process that mimics or augments some of the creative attributes of human artists participate in the production of an artwork.

³⁴ Council Directive 91/250/EEC of 14 May 1991 on the legal protection of computer programs (OJ 1991 L 122, p. 42), codified by Directive 2009/24/EC of 23 April 2009.

³⁵ Directive 96/9/EC of the European Parliament and of the Council of 11 March 1996 on the legal protection of databases, OJ, 27 March 1996, L 77.

³⁶ Directive 2006/116/EC of the European Parliament and of the Council of 12 December 2006 on the term of protection of copyright and certain related rights (OJ 2006 L 372, p. 12).

³⁷ Painer v. Standard Verlags GmbH, Case C145/10, 2012, ECDR 6, at 89 and at 94. Similarly: Infopaq International v. Danske Dagblades Forening, Case C-5/08 2009, ECDR 16; Football Dataco Ltd and others v. Yahoo! UK Ltd and others, Case C-604/10, 2012, ECDR. This principle is, similarly, reflected in article 6 of the E.U. Copyright Term Directive (2006/116/EC).

³⁸ Excluding thereby the attribution of a copyright on the sole justification of labour (the “sweat of the brow”).

³⁹ Feist Publications v. Rural Telephone Service, 499 U.S. 340, 345 (1991).

⁴⁰ Compendium of U.S. Copyright Office Practices, Third Edition (December 22, 2014), section 313.2 “Works that lack human authorship”.

2.1.2 Unlikely Assignment

Works generated by or with the help of automation tools will be subjected to the same rules. Since some of the prerogative traditionally allocated to human creators may now be delegated to an algorithmic layer, the presence of an original contribution in the final musical work could well be attenuated. The fact that deep creations rely on a training phase, where man-made examples serve to train a model, would, in most cases, incorporate a necessary human component in the generative process. However, this may not suffice if no recognizable imprint of any composition used during training is present in the final work. Similarly, in the absence of any other contribution, “clicking on a button” to produce a new work would certainly not justify the attribution of authorship. Conversely, the use of powerful generative models may not be equated to a systematic decrease of the “creative spark”. Indeed, as discussed above, these new tools can very well be the media through which the personality of an author is expressed.

What would happen then, when the work is deemed produced independently by an algorithmic process, without any significant human input? Most of the national copyright laws would consider the work in the public domain in the sense that it refers to categories of creations not protected by copyright law.

2.2 Assignment to Somebody

2.2.1 The User or the Programmer?

In the UK, a 1985 case concerned an automated process for the production of a sequence of letters for a game⁴¹. To the question as to whether assignment of copyright is possible when the object of protection is generated by a computer, Justice Whitford commented that, since “the computer was no more than a tool”, denying the possibility of authorship to (human) creators, “would be to suggest that, if you write your work with a pen, it is your pen which is the author of the work rather than the person who drives the pen”. The ruling hence stated unambiguously that computer-generated work could fall under copyright protection (something few would contest today) and suggested that the user (i.e. the “driver”) of the system could claim authorship to the output work.

Between the user of the generative process and the programmer, a clear rule for the assignment of authorship (or co-authorship) remains, however, undefined. For Annemarie Bridy, the doctrine of work made for hire could help resolve the apparent uncertainty: “With respect to works of AI authorship, treating the programmer like an employer—as the author-in-law of a work made by another—would avoid the problem of vesting rights in a machine and ascribing to a machine the ability to respond to copyright

⁴¹ Express Newspapers Plc v Liverpool Daily Post & Echo Plc [1985] 3 All E.R. 680.

incentives.”⁴² For Andres Guadamuz, the issue would be solved by identifying the person originating the production a new artwork: “[i]f the artificial agent is directly started by the programmer, and it creates a work of art, then the programmer is clearly the author in accordance to s 9 (3) CDPA. However, if a user acquires a program capable of producing computer-generated works, and uses it to generate a new work, then ownership would go to the user.”⁴³ Indeed, it is the person who uses the generative process who becomes entitled to authorship, irrespective of any other creative consideration. In this sense, the instantiation of an artwork is a sufficient condition for the attribution of authorship. Pamela Samuelson, following this thread, had already stated more than 30 years ago that assigning systematic ownership to the user of a computer-generated work could be justified on a doctrinal or policy standpoint: “there are several reasons it would make sense to designate the user of a generator program as the ‘author’ of its output, even when the user’s contribution is minimal. For one thing, the user will generally have already tithed to the owner of the program for rights to use it, either by purchase, lease, or license. This provides the programmer with some reward for the value of what he has created (that is, the program). It is not unfair in these circumstances to give some rights to a person who uses the work for its intended purpose of creating additional works.”⁴⁴ But is the argument of relative fairness (to the programmer, through contractual agreement, or to the user as the originator of the work) reason enough to allocate authorship on the production of new artworks, even when the sole contribution consists in “pressing a button”?

For Robert Denicola, this approach is all the more justified as it “aligns well with the incentive rationale for copyright protection. A computer-generated work will not come into existence unless a user is motivated to engage the machinery of its creation.”⁴⁵ The solution also fits neatly within the premises of British law, preventing that algorithmically generated works fall outside copyright protection for lack of an author (in the sense of section 178 [b] CDPA). Still, this framework clearly contrasts with the requirement of originality as set out in the EU Directive and in US case law. There, the threshold for allowing copyright protection relies on the exercise of personal choices as manifested in the final work, not solely on the initiation of an action leading to the creation of an artwork. As Jane Ginsburg clearly synthesises it: “[i]f the human intervention in producing these outputs does not exceed requesting the computer to generate a literary, artistic or musical composition of a particular style or genre, one may properly consider these works to be ‘computer-generated’ because the human users do not contribute sufficient ‘intellectual creation’ to meet minimum standards of authorship

⁴² Annemarie Bridy, *Coding Creativity: Copyright and the Artificially Intelligent Author*, 5 Stanford Tech. Law Rev., 23 (2012).

⁴³ Andres Guadamuz, *Do Androids Dream of Electric Copyright? Comparative analysis of originality in artificial intelligence generated works*, Intellectual Property Quarterly, 2 (2017).

⁴⁴ Pamela Samuelson, *Allocating ownership rights in computer-generated works*, 47 U. Pitt. L. rev., 1185 (1985). This position has been recently supported by other authors: see Robert C. Denicola, *Ex Machina: Copyright Protection for Computer Generated Works*, 69 Rutgers UL Rev., 251 (2016).

⁴⁵ See *Id.* at 282.

under the Berne Convention. Offline, merely giving a command does not make one an 'author': Pope Julius II may have commissioned the painting of the ceiling of the Sistine Chapel; from a Berne perspective (at the very least), the author of the frescos remains Michelangelo."⁴⁶

Furthermore, as clearly stated in another decision of the CJEU, since "[the] author expresses his creative ability in an original manner by making free and creative choices", the criterion of originality is not satisfied where the production of the work is only "dictated by technical considerations, rules or constraints which leave no room for creative freedom."⁴⁷ In this context, if the output of an automated creative process results directly from its internal logic, without influence (e.g. through the selection of parameters conducive to the modification of an internal state of the generative engine), then the creative role of the user is deemed null. While being the originator of a particular object, musical expression or composition, the user has no control on the output and, as such, cannot be granted all the prerogatives (economic and moral) associated with authorship in the sense of copyright or author's rights. For both the US and European legislation, the manifestation of a modicum of control over the generated output by a natural person appears therefore a necessary condition to the assignment of authorship and is thus incompatible with the premise of assigning copyright where "there is no human author of the work" as set out in sections 9 (3) and 178 (b) of UK CDPA.

2.2.2 UK Law: The Person Responsible for "Arrangement Necessary for the Creation"

However, this position is not universally accepted. In the case of strictly "computer-generated" works⁴⁸, defined as a work made "in circumstances such that there is no human author"; the Copyright, Designs and Patents Act 1988 (UK) (CDPA), provides indeed that "the author shall be taken to be the person by whom the arrangements necessary for the creation of the work are undertaken"⁴⁹. Under this provision, the author is not the creator (considered here to be the machine), but the individual responsible for "arrangements necessary for the creation of the work". Who

⁴⁶ Jane C. Ginsburg, *People Not Machines: Authorship and What It Means in the Berne Convention*, 49 International Review of Intellectual Property and Competition Law, no. 2, 131 (2018).

⁴⁷ C-604/10, *Football Dataco*, at 39.

⁴⁸ Section 178(b) of the UK Copyright, Designs and Patents Act states that " "computer-generated", in relation to a work, means that the work is generated by computer in circumstances such that there is no human author of the work."

⁴⁹ Copyright, Designs and Patents Act (United Kingdom), 1988, ch. 48, section 9(3), 178. Section 12(7) further states that, in the case of in computer-generated works, the copyright protection "expires after 50 years from the end of the calendar year in which the work was made". A few other jurisdictions (such as India, South Africa, Hong Kong or New Zealand) have opted for similar rules in relation to computer-generated works. See also, about the Irish copyright Act of 2000: Paul Lambert, *Computer-generated works and copyright: selfies, traps, robots, AI and machine learning*, EIPR, 12, 17 (2017).

that person may be is, still, left open to interpretation. Could it be the user of the deep neural network? The programmer who implemented that particular instance of a recurrent or convolutional neural network? The individual who selected the training set on which the internal weights were optimized? The investor who financed the development of the system? The scarcity of decisions applicable to the assignment of authorship to computer-generated artwork leaves indeed room for interpretation. One of the rare instances where such the subject was tackled by the court concerned the real-time generation of images in a video game. In this case, the court held that the player (i.e. the user of the system) could not be conceived as the author of the images, since no artistic contribution had been made to their creation. Although the sequence of images was dependent on the user's decisions, these choices were not considered sufficient to justify a creative input. Rather, the programmer, as the person who had initially "devised the appearance of the various elements of the game and the rules and logic by which each frame is generated and [...] wrote the relevant computer program" was deemed the sole author of the frames.⁵⁰

One can be skeptical on its compliance with EU standard of "intellectual creation"⁵¹. But the future Brexit may make this problem less significant. Be that as it may, beyond the difficulty to determine who undertakes the arrangements for the creation, the usefulness of this special copyright, limited to 50 years after the creation of the work⁵² and deprived of moral right⁵³, remains uncertain at this time.

2.3 Assignment to the Machine?

What about the machine itself? If there is "*no human author of the work*" and since the generative process seems to be the source of the creative artefact, should it be considered the "author" even in the sense of copyright? Far from being rejected *ab initio* for lack of substance (the law, as we have seen, requires a human presence for the assignment of authorship), this question has occupied some of the doctrinal discussions for quite a long time⁵⁴. There was renewed interest in this idea, with a wider application,

⁵⁰ Nova Productions Ltd v Mazooma Games Ltd & Ors Rev 1 [2006] EWHC 24 (Ch) (20 January 2006), at 104, 105.

⁵¹ William Cornish, David Llewelyn and Tanya Aplin, *Intellectual Property: Patents, Copyright, Trade Marks and Allied Rights*, Sweet&Maxwell, 8th edition (2013).

⁵² CDPA 1988 ss. 12(7).

⁵³ Ss. 79(2), regarding the right to be identified as author of the work, and 81(2), regarding the right to object to derogatory treatment of the work.

⁵⁴ These questions were already examined more than 35 years ago: Timothy Butler, *Can a Computer be an Author? Copyright Aspects of Artificial Intelligence*, 4 Comm/Ent., 707 (1982); Pamela Samuelson, *Allocating Ownership Rights in Computer-Generated Works*, 47 University of Pittsburg Law review, 1185 (1986). They regained momentum recently with the advent of deep learning: Shlomit Yanisky-Ravid and Luis A. Velez- Hernandez, *Copyrightability of Artworks Produced by Creative Robots and Originality: a Formality-Objective Model*, 19 Minn. J.L. Sci. & Tech., 1 (2018). Russ Pearlman, *Recognizing Artificial Intelligence (AI) as Authors and Inventors Under U.S. Intellectual Property Law*, 24 Rich. J. L. & Tech., 2,

in the European Parliament's proposal for a legislative resolution⁵⁵, which intended to create "*a specific legal status for robots in the long run*"⁵⁶. It was finally abandoned, rightly so in our view. Capable of feats that were just a few years ago deemed beyond the capabilities of algorithmic expression (as in the case of AlphaGo and AlphaZero⁵⁷), it is easy to get caught in the assumption that the latest instances of deep neural architectures are showing some form of "creativity" or "autonomy". For some legal authors, "*creative robots as autonomous entities are capable of holding copyrights in artworks they produce.*"⁵⁸ For another, those denying AI authorship, "*fail to appreciate the independent creation of modern AI's that process information in ways much like human brains—well beyond simple mechanical devices using simple mathematical algorithms.*"⁵⁹ Still, current machine learning systems in their various instances (including the cornucopia of recent "deep" architectures) are nothing but the expression of "simple mathematical algorithms". As such, they simply encode the statistical properties (correlations or co-occurrences⁶⁰) of a collection of "experiences" (musical, for example) inscribed in a database. To this extent, these systems are dependent on a cohort of human decisions, from the choice of the training set to the training protocol, from the internal architecture in which the inference model is expressed to the objective function that will decide of its fate. The assumed "autonomy" and "creativity" should, at least on this basis, be put in perspective.

An example may help to illustrate this point. Let us build a simple (yet realistic) machine learning system that generates music. The first ingredient is data. For the purpose of this basic experiment, we could use some training set composed of sheet music encoded in MIDI format⁶¹, and extract only the one chord symbol per time interval (the same principle would also work for individual notes). A first sequence from the training set could look like: "G D Em G D Bm D G C E A etc."⁶² Based on a large number of these sequences, the system could learn to predict a chord based on the

(2018).

⁵⁵ European Parliament resolution of 16 February 2017 with recommendations to the Commission on Civil Law Rules on Robotics (2015/2103(INL)).

⁵⁶ See *Id.* at 59(f).

⁵⁷ David Silver et al., *Mastering the game of Go without human knowledge*, 550 *Nature*, no. 7676, 354 (2017).

⁵⁸ Yanisky-Ravid, *supra* note 54, focusing on an assignment of copyright and authorship based on an objective evaluation of the originality.

⁵⁹ Pearlman, , *supra* note 54.

⁶⁰ As another hurdle yet to be passed by deep neural networks, and as a rather unambiguous difference with the functioning of "human brains" (at least as we perceive it), the inherent incapacity of artificial neural architectures to represent causal relationships. Correlations without causation does not make intelligence in the human sense. It allows to excel at pattern recognition, the applicative field where statistical learning reigns supreme. For a recent discussion on the limitations of deep neural architectures, see: Gary Marcus, *Deep learning, a critical appraisal*, arXiv preprint arXiv:1801.00631 (2018).

⁶¹ For example from <http://www.midiworld.com/composers.htm>. Or, for J.S. Bach in particular, from the John Sankey MIDI collection: <http://www.jsbach.net>.

⁶² For the beginning of the Aria & variation 1 of the Goldberg Variations by J.S. Bach.

previous one. To do so, it would first compute the probability that a given chord follows another one. If chord "A" follows "Em" 4% of the time in the training corpus, we would encode this probability as $P(n_{i+1}=A|n_i=Em) = 0.04$. Similarly, if "D" follows "Em" with a probability of 1.5% we would record $P(n_{i+1}=D|n_i=Em) = 0.015$, and so on for all combinations of chords. This collection of values would then form a "probabilistic model" for chords sequences representative of the sheet music composing the input dataset. Then, to produce a new piece, a starting seed chords would be picked at random (e.g. "Em") and the system, in the generative mode this time, would pick the following chord based on the probability distribution learnt during training (i.e., using the example above, it could select "A" with probability 4% or "Em" with probability of 1.5%). Even with such an elementary process, a new sequence would then be created that could well evoke some of the melodic attributes of the original source compositions. This automatically generated tune could even pass for human-made.

Still, would this be enough reason to consider such a system "creative"? Should this "probabilistic chord model" (which would in practice amount to just a few lines of code) be considered an author-in-law? Albeit more technically involved, and capable of extracting richer structures capturing longer temporal dependencies, the functionalities of deep neural networks (or of any other member of the machine learning communities) would follow the same logic⁶³. And, as James Grimmelmann reminds us using the analogy of "Mozart's Dice Game" (a music composition game based on rolling a dice to pick a note), "[t]his suggestion [considering the generative process as the author] is essentially fallacious, the solution a mirage. No one, to my knowledge, has ever seriously entertained the idea that the *Musikalisches Würfelspiel* dice or the box they came in was the author of the resulting minuets. Why should it matter that in 'Mozart's Dice Game' the dice-rolling algorithm is implemented on a computer? Dice are not authors and neither are programs. It is only the novelty and seeming strangeness of computers that have encouraged people to think otherwise."⁶⁴ In fact, for Maria Elisabeth Reicher: "Identifying the computer as a composer is the only option of the ones mentioned above that can be ruled out immediately. Given that a computer does not make decisions but just conducts algorithms determined by the programmer and/or user, the computer cannot be the author of anything."⁶⁵ From a technical, as much as from a legal point of view, this seems reasonable.

In pragmatic terms, the discussion over the computer generated artworks should therefore not crystallize over the hypothetical status of "the creative machine as an

⁶³ It might be noted here that the availability of libraries such as TensorFlow, Theano, Keras, Caffe, allow to greatly simplify the programming phase of, e.g., deep learning applications. Using these tools, a vanilla (deep) recurrent neural network could be written in a dozen lines of code.

⁶⁴ James Grimmelmann, *There's no such thing as a computer-authored work – and it's a good thing, too*, 39 Columbia Journal of Law & Arts, 403, 414 (2016).

⁶⁵ Maria Elisabeth Reicher, *Computer-generated Music, Authorship, and Work Identity*, Themes from Ontology, Mind, and Logic, Present and Past. Essays in Honour of Peter Simons, Edited by Sandra Lapointe, Grazer, 91 Philosophische Studien, no. 1, 107 (2015).

author” but should tackle instead in earnest the most pregnant issues centered on the role of the human authors in the creative pipeline. From finding the natural person source of the creative spark to determining those by whom the creation was made possible, whichever jurisdiction is concerned, the matter of copyright attribution to original works produced through deep machine learning architectures will rely in identifying the author(s) (authors-in-fact and/or authors-in-law). Since the intermediation of a complex, nonlinear, algorithmic process may blur the human contribution to the point where it is hardly discernible, this will entail a precise examination of the specific functionalities assigned to the computer system, as well as the possible interactions between the humans and generative model under consideration.

3. The Author’s Presence in the AI Musical Creation

As Sturm et al. remarks in relation to their deep recurrent model of Celtic music, the human presence remains essential to the production of musical composition: “*As they stand, these models are black boxes containing an agent that uses probabilistic rules to arrange tokens. Curation, composition and performance are required to make the generated transcriptions become music.*”⁶⁶ The roles of the humans, either as “curator”, “composer” or “performer”, and how they can, in these capacities, exercise deliberate choices over the creations produced with the generative engines will have to be examined. To flesh out some of the issues posed by these new creative tools, we will consider some novel applications of deep learning in the arts, where the technique has led to original applications: These will include the automated generation of musical compositions from a training corpus. New ways of interacting with neural generative processes and, finally, the possibilities to transfer stylistic components from a corpus to a new musical work.

3.1 The author as training set curator

3.1.1 Training the Machine

The recent “AI” revival is arguably attributable to the capacity of algorithmic engines to exploit and make sense of vast quantities of digitised sources. In the same manner as one may learn to recognise a rhythmic pattern or musical genre by listening

⁶⁶ Bob L., Sturm et al., *Music transcription modelling and composition using deep learning*, arXiv preprint arXiv:1604.08723 (2016).

to a set of audio sources characteristic of said rhythm or style, a “machine-learning model” is constructed by exposing the system to a large number of examples. During a training phase, based on a corpus of training data, an internal representation is thus created that captures the structures and variety of the sources it was presented with. In the case of deep neural architectures, the system would first learn to identify correlations present in the audio data (the probability that a given note follows another, the temporal separation between beats, etc.). Once captured and encoded in a neural network model, this information makes it possible to produce a new composition that conforms to the class of data used during training. The selection of a specific training set is therefore intimately related to the nature of the musical productions that can be derived from a machine learning models. When a corpus formed by the piano works of J.S. Bach is used to train a deep neural network, the system will be expected to produce compositions in the style of the baroque master.⁶⁷ Exposed to blues⁶⁸ or folk music⁶⁹, the model will generate compositions of the same genre (as long as the model was able to learn the specificities of the sources: what may be relatively easy with highly structured musical forms could prove unmanageable with more complex sources⁷⁰). Under which conditions could such productions justify the attribution of a copyright? Who would be the author of such a creation?

3.1.2 *Emily Howell*

Consider *Emily Howell*, the program created by David Cope⁷¹. *Emily Howell* produces musical composition based on the definition of a training corpus consisting in a unique selection of works by classical composers, David Cope’s own compositions, as well as a selection of previous hand-picked outputs from *Emily Howell* itself. The compositions that emanate from *Emily Howell*’s internal model, inasmuch as it has captured and encoded the specific mix of musical sources from which it has been constructed, are a direct reflection of these choices. Undoubtedly, this selection

⁶⁷ I-Ting Liu and Bhiksha Ramakrishnan, *Bach in 2014: Music Composition with Recurrent Neural Network*, arXiv:1412.3191 (2014). A more compelling work, based on modeling chorale works is Gaëtan Hadjeres, François Pachet and Frank Nielsen, *DeepBach: a Steerable Model for Bach Chorales Generation*, *Proceedings of the 34th International Conference on Machine Learning*, 70 PMLR, 1362 (2017).

⁶⁸ Douglas Eck and Juergen Schmidhuber, *Finding temporal structure in music: Blues improvisation with LSTM recurrent networks*, in *Proceedings of the 2002 12th IEEE Workshop on Neural Networks for Signal Processing*, 747 (2002).

⁶⁹ Bob Sturm, Joao Felipe Santos and Iryna Korshunova, *Folk Music Style Modelling by Recurrent Neural Networks with Long Short Term Memory Units*, presented at the 16th International Society for Music Information Retrieval Conference, late-breaking demo session (2015).

⁷⁰ As discussed in Hadjeres, supra note 67.

⁷¹ *Emily Howell* denomination is based on “EMI : Experiments in Musical Intelligence” the generative model described in: David Cope’s U.S. Patent No 7,696,426. “Recombinant music composition algorithm and method of using the same”. Keith Muscutt, *Composing with algorithms : An interview with David Cope*, 31 *Computer Music Journal*, no. 3, 10 (2007).

expresses David Cope's creative intent and the generated compositions, although filtered by an algorithmic process, constitute unique works that only David Cope could have produced. As such they "*reflect the author's personality*" and meet the condition of originality. Although distributed under the pseudonym of Emily Howell's⁷², David Cope is arguably the author of these compositions. The attribution of authorship through this training corpus selection may not always be so obvious. Take, the works of Daniel Johnson, for example⁷³. Johnson trained a recurrent neural network model based on a pre-existing corpus of compositions extracted from the "Classical Piano MIDI Page"⁷⁴. The results are compelling and, while musically interesting, are clearly a lesser reflexion of Johnson's personality than were *Emily Howell's* outputs imprinted with David Cope's specific choices. The question of the originality of Johnson's neural network creation could therefore be put to question and his authorship on the final compositions challenged. At the opposite end of the spectrum the use of a machine learning architecture to automate the generation of the works of a single composer (such as J.S. Bach⁷⁵ or Schubert⁷⁶), in the absence of any other inputs, could hardly be considered an "original" contribution.

3.1.3 A Derivative Work?

What about the presence of the original sources in the final piece? Could the work be considered a "derivative work" and joint authorship assigned to the authors of the training sources and of the final work (provided the latter meets the originality criterion)? Article 2 § 3 of the Berne Convention disposes that "[t]ranslations, adaptations, arrangements of music and other alterations of a literary or artistic work shall be protected as original works without prejudice to the copyright in the original work". This disposition is followed in most national jurisdictions (U.S. 1976 Copyright Act § 101; German Copyright Act, art. 3; French Intellectual Property Code, art. L.112-3). The wording of the Convention makes it clear that the consent of the author of the source work is required in order to alter it without infringing on the original work (a provision

⁷² Two albums have been distributed by Centaur Records under the name of Emily Howell "From darkness, light" (CRC 3023) in 2010 and "Breathless" (CRC 3255) in 2012.

⁷³ See: <http://www.hexahedria.com/2015/08/03/composing-music-with-recurrent-neural-networks/> the code for this project is available at <https://github.com/hexahedria/biaxial-rnn-music-composition>.

⁷⁴ <http://www.piano-midi.de>. Recurrent Neural Networks (RNN) are a particular architecture of neural networks designed to retain a "memory" of previous patterns and thus capable to capture dynamic temporal structures.

⁷⁵ Feynman Liang et al. *Automatic stylistic composition of bach chorales with deep LSTM*, in Proceedings of the 18th International Society for Music Information Retrieval Conference (ISMIR-17), Suzhou, China. (2017); Feynman Liang, *Bachbot: Automatic composition in the style of bach chorales*, masters thesis, University of Cambridge (2016).

⁷⁶ Stanislas Lauly, *Modélisation de l'interprétation des pianistes & applications d'auto-encodeurs sur des modèles temporels*, Masters thesis, University of Montréal (April 2010). Available at: <http://hdl.handle.net/1866/4426>.

explicitly stated in the U.S.: “protection for a work employing preexisting material in which copyright subsists does not extend to any part of the work in which such material has been used unlawfully.”⁷⁷), still, U.K. courts have ruled to the contrary, allowing that copyright may be granted to a derivative work even though it infringes on the source work.⁷⁸ The internal mechanics of the generative statistical engine rely on first decomposing the source materials in elementary elements (in the form of raw signal or audio features) before reassembling these building blocks into a new arrangement. The final work will not reflect any of the essential components of the initial sources (except in pathological cases of “over-fitting” where the training failed to reach sufficient generalisation). A “re-composition” rather than a mere copy or an audio collage, the final work will not—in most instances—be found “substantially similar” to any of the materials used to train the system.

Still a number of decisions have put the threshold for detecting such substantial similarities quite low, even in presence of significant alterations. For example, in *Bridgeport Music, Inc. v. Dimension Films*⁷⁹, the judges considered as infringing the sampling of a few seconds of audio (although the sound had been modified to the point of being hardly recognisable). A 2008 decision of the Federal Court of Justice of Germany stated that the “*smallest audio fragments*” are copyrightable and the sampling a few bars of a drum beat can be the basis for copyright infringement.⁸⁰ In France, a court decision in 2000 held that “*the personality of the author may transpire independently from the number of notes*”⁸¹. In such cases, machine learning generated products could qualify as a derivative work.

3.2 The Author as a Deep Model Composer

3.2.1 “Weights”

While being often referred to as autonomous, the music generative machine learning pipeline offers multiple entry points where the creator can interact and affect the musical outcome. A first, rather non-obvious, interaction consists in controlling the output from its very core: by modifying the neural network’s model itself. The model that encodes the musical structures learnt during training is made up of a set of parameters (namely, the “weights” that connect one neuron to others in the surrounding layers of the architecture and allow to balance and mix the information as it transits

⁷⁷ U.S. 1976 Copyright Act §103(a).

⁷⁸ *Redwood Music Ltd. v. Chappell & Co. Ltd.*, [Q.B. 1982] R.P.C. 109, 120.

⁷⁹ In *Bridgeport Music, Inc. v. Dimension Films*, 410 F.3d 792 (6th Cir. 2005).

⁸⁰ *Metall Auf Metall (Kraftwerk, et al. v. Moses Pelham, et al.)*, decision of the German Federal Supreme Court No. I ZR 112/06, November 20, 2008, at 56.

⁸¹ Tribunal de grande instance, Paris, 5 Jul. 2000. Com. comm. électr., March 2001, comm. n° 23, obs. C. Caron.

between input and output layers). These weights, if modified will affect the response of the system, thereby allowing to “play” the neural network model as one would play an instrument (tweaking parameters in the abstract space of the model instead of picking chords or pressing keys).

When Rebecca Fiebrink changes in real time the parameters of a pre-trained neural network, a sound is produced that depends on the current values of the weights.⁸² Even though the particular inflexion of the sound cannot be initially predicted (since the algorithm then reinterprets its generative repertoire based on the new parameters) the fact that R. Fiebrink adapts, according to the sound emitted, the variables of the system, is a manifestation of her choices. It is (at least) in this interactive adjustment of the parameters that the originality resides.

In the same spirit, the deepAutoController system⁸³ provides a user interface to control the generative process by modifying the input (selecting a particular seed source as an input), or by allowing to select (or deselect) the activation of a given unit in the artificial neural network. In both cases, the filtering of the intention of the author through the learning algorithm, although not fully predictable, will not prevent the artist to consciously influence the output sounds and to manifest elements of her personality.

3.2.2 User Interface and Multiple Parameters

Other parameters than the weights defining the neural model can control the final composition and that may contribute in assigning a sufficient level of “originality” to the final work. DeepBach, for example, not only learns to generate Bach chorales but includes an interface to allow user interaction: “[we] can generate a chorale from scratch, reharmonize a melody and regenerate a given chord, bar or part. We believe that this interplay between a user and the system can boost creativity and can interest a wide range of audience.”⁸⁴ Similarly, DeepJ, another deep learning model capable of composing polyphonic music conditioned on a mixture of multiple composer styles provides a graphical user interface including a set of tuneable parameters. “[This] ability to tune the properties of the generated music will yield more practical benefits for aiding artists, filmmakers, and composers in their creative tasks.”⁸⁵ The patent US 9715870 by IBM entitled “Cognitive music engine using unsupervised learning”⁸⁶ discloses an

⁸² Rebecca Fiebrink, Dan Trueman, et Perry R. Cook, *A metainstrument for interactive, on-the-fly machine learning*, Proc. of the International Conference on New Interfaces for Musical Expression (NIME), vol. 2, 101 (2009); Fiebrink, *supra* note 28.

⁸³ Andy M. Sarroff and Michael Casey, *Musical audio synthesis using autoencoding neural nets*, in Proceedings of the International Computer Music Conference, 14 (2014).

⁸⁴ Hadjeres, *supra* note 67.

⁸⁵ Huanru H. Mao, Taylor Shin and Garison Cottrell, *DeepJ: Style-specific music generation*, arXiv preprint arXiv:1801.00887 (2018).

⁸⁶ US 9715870 B2 “Cognitive music engine using unsupervised learning” by IBM Corp. (Inventors: Inseok Hwang, Jente B. Kuang and Janani Mukundan). Granted the 27th May 2017.

interface enabling users to “perturb a model”. This “perturbation” starts with a first tune generated by the network that is progressively modified to meet the constraints imposed by the user. To reach the desired outcome, the system combines a trained neural model with a rule-based mapping between the allowable parameters and some specific notes or chords. The notes corresponding to the selected parameters are then inserted in the first layer of the neural model thereby influencing the final composition: *“if the user intent was for a ‘happy’ output, the input vector would be perturbed by placing notes having an interval of a major third, fourth, fifth or sixth from an adjacent pitch in the vector. If the user intent was for a ‘sad’ output, the vector would be perturbed by inserting notes having an interval of a minor third or minor sixth to adjacent pitches in the input vector.”*⁸⁷ This last example gives us the opportunity to examine the particular inter-relation between the programmer (or the designer of the generative architecture) and the user, as well as their relative influence on the final composition. In this instance while the neural structure and associated generative process is arguably novel (and even inventive, having justified the grant of a patent), their inventors cannot anticipate the particular expression of the musical tunes it produces, since these depend on further interactions with a user. The “programmers” have essentially imparted on the system some technical functionalities and, with them, the potentiality to produce a musical output. They appear here at the same level as a craftsman building a musical instrument, or as evoked above by James Grimmelmann, the deviser of the *Musikalisches Würfelspiel*, who could not justify authorship over its outputs.

3.2.3 User as the Author

The sole authorship would then rest, under condition of originality, on the user. It remains, then, to be seen whether the setting of, for example, one or two parameters would qualify as *“free and creative choices”*. With due accounts to the minimal current threshold of originality it seems that as long as a *choice* is made (by a human actor), a case for originality may be made (in the absence of any such choice, however, when the final work is determined solely by the functionalities of the system it emanates from, no such authorship would be granted). One may even take, with Maria Elisabeth Reicher, a further step: *“the creation of a musical work by selecting a score for presentation is certainly a limiting case of authoring, just as the authoring of ready-mades in the fine arts. But if one accepts ready-mades as works (as seems common nowadays in the art world), then there is no principled reason to deny this status to selected computer-generated scores. Analogously, if one accepts Marcel Duchamp as the author of the famous Bottle Rack, there is no principled reason to deny a user who selects a computer-generated score for presentation the status of an author.”*⁸⁸

⁸⁷ See *Id.*

⁸⁸ Maria Elisabeth Reicher, *Computer-generated Music, Authorship, and Work Identity*, 91 Grazer

This, however, remains to be evaluated by the courts and in the absence of a harmonised conception of the originality criterion, and in spite of an overall low standard of originality, results may vary. The case of *Nova Productions Ltd v Mazooma Games Ltd* in the UK showed that mere control of video games was not sufficient to impart authorship over the scene depicted therein (the creation was deemed indeed computer-generated in the sense of section 178 [b] CDPA). Changing a known setting in a pre-set environment (e.g. the theme colour, or the background music, for the game) would certainly lead to the same result. In practice, simply due to the heterogeneity and the variety of uses of the growing cohort of “AI” tools catering the creative crowd, sorting out the assignment of authorship will likely require a case-by-case analysis. As Margot Kaminski puts it: *“the central question of algorithmic authorship will likely be a factual one: whether the algorithm looks more like a tool, or whether the algorithm’s programmers look more like co-authors”*⁸⁹.

The interaction between the neural network and the musician can also consist of a form of dialogue where the user can input a melody and where the system responds by either following up and continuing the priming musical sequence until the human counterpart takes over again⁹⁰, or by providing in return a variation on the initial proposed theme, that the musician can then select, discard, or build upon⁹¹. This interactive creation is certainly at the core of Sony’s Flow Machine creative process: *“In a typical session with Flow Machines, users first select a set of scores (lead sheets) that they want to take inspiration from. These scores determine the style of the scores generated by Flow Machines. Then they select a set of audio recordings that determine the sound textures of the audio stems generated by Flow Machines. Users can go back and forth between the generation of scores and the generation of audio renderings using an interactive interface, until they get a result they are satisfied with.”*⁹² A particular expression of such a dialogue can take the form of co-improvisation between performers and the responses generated live (and adaptively) by an algorithmic process.⁹³ In some instances the system not only bounces back on the improvisation of

Philosophische Studien, no. 1, 107 (2015).

⁸⁹ Margot E. Kaminski, *Authorship, Disrupted: AI Authors in Copyright and First Amendment Law*, 51 UCDL Rev., 589 (2017).

⁹⁰ Elliot Waite, Douglas Eck, Adam Roberts, and Dan Abolafia. Project Magenta: Generating long- term structure in songs and stories, 2016. <https://magenta.tensorflow.org/blog/2016/07/15/lookback-rnn-attention-rnn/>; Hang Chu, Raquel Urtasun, and Sanja Fidler. *Song from PI: A musically plausible network for pop music generation*, arXiv preprint arXiv:1611.03477 (2016).

⁹¹ Adam Roberts et al., *Interactive musical improvisation with Magenta*, in Proc. Neural Information Processing Systems (2016).

⁹² <https://www.helloworldalbum.net/about-hello-world/>

⁹³ Mason Bretan et al., *Deep Music: Towards Musical Dialogue*, in Proc. of AAAI, pp. 5081 (2017); Oliver Bown, Benjamin Carey and Arne Eigenfeldt. *Manifesto for a Musebot Ensemble: A platform for live interactive performance between multiple autonomous musical agents*, in Proceedings of the International Symposium of Electronic Art. (2015); Marco Scirea et al. *Primal-improv: Towards co-evolutionary musical improvisation*, in Computer Science and Electronic Engineering (CEEC), 172 (2017).

the human musicians but learns to predict their contribution, "*anticipating the rhythmic pulse of an ensemble that one musician will play a solo, or the best dynamic to enhance the collective sound*"⁹⁴. Lastly, beyond the strict confines of academic or fringe experiments, a growing number of ready-made applications and services based on the machine learning techniques are now available for the musicians to experiment with⁹⁵. Not just the musicians in fact, interfaces such as Amper⁹⁶, AlgoTunes⁹⁷, and Jukedeck⁹⁸, to name a few, allow individuals without any background in music whatsoever to experiment and create. In these instances, as long as the user can manifest some control in the form of a choice over the created composition (selecting several parameters, iteratively guiding the selection the output itself) it is conceivable that she could be granted authorship thereover.

4. Conclusion

The issue of copyright / authors' rights protection of computer-generated creations and machine learning output warrants a two-pronged approach.

De lege lata, it is necessary to analyze the existing law to assess whether it allows the protection of such creations. Basically, the rule is that it is a human person who can be the cause of copyrightable creation. This leads to denying the protection to pure computer-generated creations. This also mandates a case-by-case analysis to analyze the degree of human intervention associated with an original contribution. However, others consider that such a lack of protection should be remedied⁹⁹.

⁹⁴ Charles P. Martin, Kai Olav Ellefsen and Jim Torresen, *Deep Predictive Models in Interactive Music*, arXiv preprint arXiv:1801.10492v2 (2018).

⁹⁵ Hexachords (<http://www.hexachords.com>) and Orb Composer (<https://www.orb-composer.com>) are two examples of such powerful tools. Both can produce a piece of music with a specified genre, intensity, length. An intuitive graphical user interface allows to drag and drop the desired elements of style and gives control on the properties of the music thus created (enabling to change or redistribute the instruments, modify the tonal structure or the orchestration, etc..).

⁹⁶ <https://www.ampermusic.com>.

⁹⁷ As the company's website mentions: "anyone can signup to generate music of their preferred mood and style with the push of a button. The music is composed instantly in a few seconds by AlgoTunes' web app, and available for download as WAV or MIDI files" (<https://www.algotunes.com/generate-music/>).

⁹⁸ <http://jukedeck.com>.

⁹⁹ Lambert, *supra* note 49; Julia Dickenson, Alex Morgan and Birgit Clark, *Creative machines: ownership of copyright in content created by artificial intelligence applications*, 39 EIPR, no. 8, 457 (2017), stating that "[i]t is possible that the developments that stretch AI legislation will eventually become necessary" (at 457).

De lege ferenda, the first question to be asked is whether an expansion of protection to strict computer-generated works is consistent with the rationale and objectives of copyright. On the one hand, the rationale formulated in terms of natural law, present in the Berne Convention, seems to exclude such a broadening. On the other hand, the incentive to create and invest, highlighted mostly by the common law systems and not totally ignored Berne, could justify the extension.

The second question that needs to be asked is whether such an expansion is really useful, especially if it is thought of as an investment right. As a matter of fact, the creator of the algorithm has protection of its software implementation by copyright and, possibly, of its functionalities by patents. In Europe, protection by the sui generis right on databases can also be obtained¹⁰⁰. Furthermore, other legal mechanisms such as competition law can effectively protect the outputs of automated creative tools when no original human contribution is manifested in the artwork, without the need to modify the existing copyright regime or extend it to non-human authors.

¹⁰⁰ Ginsburg, *supra* note 46.