



Machine Learning in Interaction: Tool, Material, Culture

Baptiste Caramiaux

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Machine Learning in Interaction

Tool, Material, Culture

Baptiste Caramiaux

Habilitation à Diriger des Recherches (HDR), Université Paris-Saclay, 2023

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Introduction

This Habilitation is about machine learning in situated interaction. Machine learning is a field of research, a technology boosting innovation, the representation of resource exploitation (data, labour, energy), and the algorithms bringing artificial intelligence to ‘life’. Situated interaction is the recognition that technology is not detached from its development, deployment and uses context, and it is part of a network of interdependencies between actors and users.

Given the extent to which machine learning has become part of our digital ecosystems, and our collective imagination, notably through the ambiguous use of artificial intelligence, our interactions with this technology have become complex and troubling. By “our”, I mean different actors. First, I mean the users of systems embedding machine learning. These users are not machine learning savvy. They can be experts in their domain or maintain a practice of some sort. Users can be artists, scientists, activists, domain experts and laypeople. Second, I mean developers, engineers and scientists working on machine learning and artificial intelligence algorithms and infrastructures, either in public institutions or private corporations. These actors deal with increasingly complex networks of computation and data, triggering increasing questions about moral and ethical values. Third, I mean researchers, including me, studying machine learning in various research fields. These actors may consider machine learning as an object of study, or involve machine learning in their scientific practice. With regard to these actors, of which we are one, it is needed to ask what characterises our interaction with machine learning. Have we identified the entire space of possibilities? Do we have a point of view to put forward in a socio-technical context where machine learning is omnipresent? Do we have a responsibility as researchers vis-à-vis these technologies to which we contribute? How to integrate these questions into a research program focused on the design, development and study of interactive systems integrating machine learning?

This manuscript is an academic text that stands at the intersection of Human-Computer Interaction, Design Research, and Science and Technology Studies. Its HCI anchorage comes from the object of study: I am not simply interested in the machine learning technique, nor in the psychology of users, but in the phenomena

generated by the method in interaction with the practice. Its anchorage in Design Research comes from the methodologies used and the resulting epistemology: I am interested in creating knowledge through the design of interactive systems and their integration into the field. These can have a utilitarian or speculative function. Finally, its anchorage in science and technology studies comes from the contextual framing I would like to give to my research: I choose to extract my discourse from the applicative contributions but to focus on the cultural, social and political consequences of working with machine learning in various application domains, and, as we will see, especially in the creative and artistic disciplines.

Finally, since I will unfold a standpoint about machine learning from my research experience conducted in various sociocultural contexts, I would like to position myself. I was born in France, in the northern countryside. I am a tenured researcher at the National Centre for Scientific Research (CNRS), physically located at the Institute of Intelligent Systems and Robotics, part of Sorbonne Université in Paris. I situate my research within the field of Human-Computer Interaction. I have a background in applied mathematics and hold a PhD in Computer Music. I worked in (and was a consultant for) a start-up company in London as a senior researcher, designing deep-learning methods for audio.

Structure of the manuscript

I have chosen to articulate my position on machine learning in interaction from three interrelated perspectives: as a *tool*, *material*, and *cultural object*. As such, I have also selected specific research projects conducted with PhD students, post-doctoral researchers and colleagues that allowed me to construct a narrative across these three themes. Through this selection process, some of my previous research projects will therefore not appear in this manuscript, but this is not to diminish their importance in the construction of my position as a researcher and, thus, my argument along this manuscript and my future research project, which I will outline in the general discussion of the manuscript.

The three perspectives on machine learning in interaction structure this manuscript into three parts. Each Part is organised as follows. I will start by situating machine learning within the context of the theme, and I will then present my work that illustrates, explains and questions this perspective. The selected works from my research are called *foci* in the text.

In Part 1, I consider machine learning as a tool, the most apparent perspective given its use in the computer science and robotics communities: a technique made to perform a well-defined task. In this Part, I propose to analyse the following questions: What does it mean to consider machine learning as a tool, in the same way as a physical tool that one would usually handle? And, what are the limitations arising from such a machine learning perspective? I propose to start with theoretical

works on tool use, from the field of cognitive science to human-computer interaction. These works will highlight that tool use implies situated actions, which means actions performed in response to some contextual changes due to the previous actions performed and due to prior decisions made. These actions underlying the use of a given tool are not entirely determined before a task is performed with that tool.

As a result, we can observe situations where a tool is *re-purposed* according to the context, which means that a tool is used in a way that was not originally intended. I argue in this first Part that this also applies to machine learning. Machine learning can be considered a tool only when it is also situated. I am presenting two foci to illustrate my point. First, I describe some of my work using machine learning as a tool for inquiry in studies of human perception. Second, I present previous studies where machine learning is a creative tool in music performance. The creative use of machine learning shows the limit of this perspective and calls for an ampler view of machine learning in interaction.

In Part 2, I propose an alternative and broader view of machine learning beyond its use as a tool. This new perspective allows me to explain interaction phenomena when machine learning algorithms are designed to achieve a given task. In these cases, the technology is not fixed, and the technology evolves through the design stages and prompts the exploration of various algorithmic behaviours. In this Part, machine learning is presented as a material. I show the theoretical elements that characterise digital materiality, a notion stemming from the community of Design Research and Human-Computer Interaction. I argue that working with this material, akin to craft, is ubiquitous with machine learning, even in the machine learning research community.

Moreover, highlighted in a creative context, machine learning also has a material expression that helps to understand the basis on which a material is chosen for inclusion in the creative process. Appropriating the material expression of machine learning is, however, not easy and requires crafting the data and the model. I illustrate this in two foci. The first takes up the research work in the creative community and explicitly highlights the elements that constitute the materiality of this technology. The second presents work in pedagogy where the materiality of machine learning is put forward to transmit with greater ease the underlying concepts of this technology to novice audiences. This research shows that the work of the material, a craft, is at the heart of the interaction with machine learning but is not perceived as such by specific communities who emphasise the automatism of the underlying algorithms, increasing the opacity of the developed technology and its material expression. These points raise epistemological and cultural questions that constitute the trope of the following Part.

In Part 3, interactions with machine learning are considered from the perspective of the cultural and political object. The work of artists and creatives with machine learning has brought to light an additional phenomenon in the interaction with this

technology that has to do with its cultural agentivity, which is in tension with the positions of the artists who use it. Through ambiguous terminology related to artificial intelligence, and already present in terms of machine *learning*, the technology has been promoted using a normative view of how intelligence and artificiality are understood. This view is part of a dominant discourse that polarises what is natural, as opposed to artificial, what is an object, as opposed to a subject. In this Part, I articulate and highlight how this discourse can be deconstructed to imagine more exciting and rich narratives related to the interactions with machine learning. In particular, I explore this alternative narrative through artistic practice that helps to imagine new perspectives on technology, free from the epistemological framing of machine learning research. As a first focus, I return to the work presented in the previous Part, where visual artists use machine learning in their practice. I show how they make this dominant culture in machine learning and artificial intelligence explicit and discuss its limitations. As a second focus, I present an artistic performance that I contributed to that questions the role of artificial intelligence in contemporary algorithmic societies and how this role prompts violent behaviours.

Finally, I conclude this manuscript by presenting conclusions of this research work. This Part indicates the link between the three perspectives that define the abovementioned parts. The fact that I have created three parts separates them into three independent points of view; however, they are, by definition, interdependent. In conclusion, I propose highlighting how this work and reasoning defines rich and interdisciplinary research directions shaping my future research project.

Few technical things to know about machine learning

Before starting the first part of this manuscript, this section aims to give the necessary elements to understand the main notions behind the term *machine learning* in this manuscript. Readers who are already familiar with the technique can skip this section.

I start with a working definition. Machine learning is a set of techniques designed to extract patterns from data sets (which can be of any type, such as images, sounds, text or tabular data) according to an objective given a priori. Objectives may be to classify input data into categories, to predict values associated with input data, to find the most similar input data and group them together, to synthesize new data based on the input data, among some examples.

If, for instance, the aim is to assign a category (a label) to a given input data (for example, an image), a machine learning algorithm will identify what in the data relates to the provided labels. What is identified depends on the method chosen. For example, convolutional neural networks will identify spatial features at different scales (from local to global) related to the label. This task is called *classification*, and to achieve it, a classification algorithm is trained on examples of pairs of data inputs

and their corresponding labels (for instance, pair of images and tags). Since the algorithm has access to the description of each element in the dataset (through labels for example), this task is a *supervised* learning task. The labels associated with each image in the training set entirely condition the information the algorithm will extract from data inputs (for instance, images).

Once the patterns have been identified, a machine learning algorithm could perform inference which means taking as input a data point that the algorithm has not used for training and inferring likelihoods over a set of possible categories (or labels). Figure 1 (left) illustrates this task, where the dataset comprises images of paintings with their authors. The classification will be useful in this manuscript in the creative context where we will be interested in the recognition of gestures in real time for the interactive control of sounds.

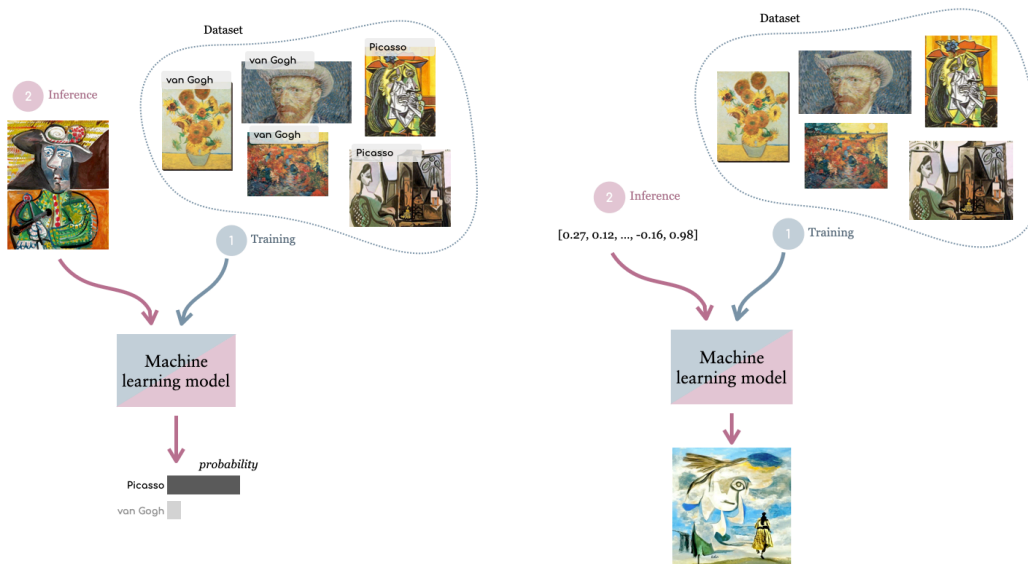


Figure 1. Illustration of machine learning tasks. On the left panel, the figure illustrates classification, an example of a supervised machine learning task. On the right panel, the figure illustrates generation, an example of an unsupervised machine learning task.

Machine learning algorithms are, therefore, data-driven computational techniques and various objectives are used to define machine learning tasks based on a given dataset. As we saw before, one goal can be to assign a label to an input. Another goal can be to provide a value to a given input, for instance, an estimation of the price for each painting. This task is called *regression*. Regression algorithms are trained beforehand on datasets, including examples of data and their corresponding output values. Their task is to learn the function from the input to these values, with the task to be as close as possible to the ones provided in the training set. Like classification, regression is a supervised learning task. As for classification, regression will be used, in this manuscript, to make the link between input motion data and output sound control parameters.

Now, one can provide the model with a data set without supervision (labels or associated values). In this case, the objective is to learn how to synthesise new data that looks like the input data. This task is called *generation*, a form of *unsupervised* learning (depicted in Figure 1 (right)). A generation task will be important in this manuscript when I present artists' work with machine learning, especially in visual arts. At the heart of generative machine learning models is an abstract space (sometimes called latent space or distribution space). In the case of image generation, each point in the latent space corresponds to an image generation. A "point" can be described abstractly by coordinate values in multidimensional space. Navigating through this space generates a series of images that interpolate, and to some extent extrapolate, the images used for training.

I presented three machine learning tasks (classification, regression, and generation) which correspond to three objectives given to the algorithm and a dataset. However, there are many other possible tasks: clustering, detection, transcription, translation, or probability estimation. In addition, I presented machine learning paradigms that rely on fixed datasets, including or not supervision signals. Another type of learning, *reinforcement learning*, works through interactions with an environment. In this paradigm, the algorithm implements an agent to perform actions in an environment that will affect this environment. The agent observes these effects. If they are positive (positive rewards), the action taken was appropriate, knowing the agent's current state. But, the action taken was not the right choice if they were negative (i.e. negative rewards or no rewards). By exploiting the rewarding actions and exploring those that have never been used, an algorithm can learn a policy, a strategy that would tell which action to take depending on the agent's state.

Tool

Generally, a tool allows us to act upon our environment to achieve a desired goal. A tool could be anything: an object, a device, a computer program, a word, or an expression. What makes it a tool is the function we attribute to it by using it to act on things in our environment. From this perspective, machine learning algorithms can also be seen as tools used to act in an environment composed of digital objects such as data. They are used to classify digital objects, associate them with other objects, or generate new objects. The questions are: What does it mean to consider machine learning as a tool in the same way as a physical tool that one would usually handle? And, what are the limitations arising from such a machine learning perspective?

The perspective of machine learning as a tool was predominant in the research I conducted at the end of my PhD at IRCAM in 2012 and during my first positions as a post-doctoral researcher. I saw machine learning algorithms as tools, which strongly influenced how they were subsequently integrated into my research and how they affected that research and forced an epistemology. I propose to begin by recalling this period of my academic work to contextualise the approach taken in this chapter. I then present a set of theoretical notions and contributions to understanding digital tools and their use. From there, I propose to illustrate the perspective of machine learning as a tool through two scientific projects involving the study of human perception, followed by the presentation of projects using machine learning as a creative tool for music creation. Reflecting on the status of technology in this set of previous works allows me to draw positive lessons in the context of human-computer interaction, as well as to point out that the narrow view of technology-as-a-tool is too limited to fully capture the relationship between researchers, other stakeholders, and technology in practice.

A preamble on the study of gesture-sound relationships

In 2012, I completed my PhD in computer music at IRCAM in Paris. During my doctoral work, I investigated the *relationships* between sounds and movements. The

scenario, from the beginning of the introduction of my PhD, describing the main objective of the work, was as follows:

“Let us imagine the situation where we listen to a piece of music. We sensitively experience the sound, which arouses sensations, emotions, memories, etc. While listening, we start to move our arms to the music, like a conductor, but without mimicking the gestures of the orchestra. Ours are personal, not codified; our intentions are diverse. Let's imagine now that as we listen and move along during this listening, the music becomes played by our movements. That is, the movements take control of the music. This does not simplify or impoverish the music. It becomes alive.”

On the one hand, I wanted to understand better which movements people associate with sounds while listening to them. If I perform a movement while listening to the sound of a wave, am I gesturally imitating the wave? On the other hand, I wanted to use these fundamental results to steer the design of gesture-*to*-sound mappings that could be integrated into musical performances and new musical instruments mediated by technology. Through this approach, called mapping-through-listening (Caramiaux, Françoise, *et al.*, 2014), I developed a method that brings back the perception–action loop as a fundamental design principle. One could build gesture-sound interactions that capture personal experiences of sounds and the imaginary associated with sounds.

Embodied music cognition provided a theoretical framework for studying listening in a musical context and the link between music perception and human actions (Leman, 2007). Machine learning provided us with the required tools to realise such scenarios. Gesture-sound interaction design scenarios are usually best defined from high-level gesture and acoustic descriptions, which cannot generally be easily programmed with other techniques. Machine learning techniques allow one to set the gesture–sound relationships from examples. The listening step allows for collecting training data to feed a gesture classification or gesture-to-sound regression model. After training, the system could use the gesture data as input for the models and synthesise sounds accordingly. That is how ML became an important asset in my research agenda (which will be further detailed in the following sections).

This research was also facilitated by the technological context in which it was rooted. First, the 2010s were an exciting time for those experimenting with movement-based interaction in the creative domain. It was when several companies released affordable movement-capture systems, primarily designed for video gaming but more largely usable as controllers in various ways. For instance, Nintendo released

the Wii Remote¹ (2006-2017), capturing movement rotations and dynamics. Microsoft released the Kinect² (2010-), which captures the positions of a silhouette's skeleton from video cameras. A Canadian start-up, Thalmic, released the Myo Armband (2013-2018), allowing for gesture recognition through muscle activations. Finally, a last example was Leap Motion Inc. which released the leap capture system (2012-2019) capturing hand movements with high fidelity. These technologies enabled the design of many creative scenarios, such as the ones we were interested in at IRCAM: controlling sounds through body movements. But they were also valuable assets for experimental research on human movement. We could perform motion capture in less controlled settings (than the lab) and study movement responses to sound in various contexts.

Second, it was an exciting time for those interested in applied machine learning. Few of us were applying this technology in movement-based interactive performance, but there was a growing interest within the community of creative computing and HCI. The deep learning breakthrough was around the corner, and machine Learning research was already very active. In our work, we borrowed models from other fields. We were typically interested in probabilistic models such as Hidden Markov Models (HMMs) and Gaussian Mixture Models (GMMs) because that was used in temporal sequence modelling such as speech.

In summary, through affordable movement capture systems, we were able to capture data, and this data represented the behaviour that we wanted to study and use in our interactive system. Machine Learning became the centre of our attention as a *tool* to make sense of these data.

Contextualising tools in digital technology

In the previous section, I presented the personal trajectory that led me to the use of machine learning as a tool to build gesture-sound interactions and perform movement analysis. I propose further articulating the notion of tool and tool use to understand how they apply to digital objects such as machine learning components (data, models, parameters, etc.). Therefore, this section aims to step back from the specific application of musical interaction and to ground the analysis of machine learning as a tool in fundamental research on tool and tool use.

¹ https://en.wikipedia.org/wiki/Wii_Remote

² <https://en.wikipedia.org/wiki/Kinect>

In this section, I will particularly emphasise the notion of tool *use* to understand the tool in interaction with the person using it and with the objects to which it is applied.

Tool use: From cognitive science to HCI

In human and animal cognition research, using tools mediates the interaction between the tool user and the environment. The environment is usually considered what is ‘outside’ the user’s body, which does not necessarily mean beyond the body’s physical limits. Tool use, therefore, engages the manipulation of some objects that have an action upon other objects or organisms in the environment (the elements on which a tool can act are diverse and can cover a wide range of *things* from microbes to buildings through digital information). In the physical world, these interactions can take the form of physical alteration of the environment, such as hitting a surface with a hammer held in one hand. The alteration is felt by the person handling the tool, for example, through a resistance felt by the hand to the contact of the hammer with the surface.

Tool use traditionally refers to manipulating hand-held objects. Consider the use of Japanese saws in manufacturing wood joints, for instance. Think of the scalpel in a surgeon’s hands when operating. Regularly using such tools makes them feel like they are an extension of the body. In that sense, Gibson wrote:

“When in use, a tool is a sort of extension of the hand, almost an attachment to it or a part of the user’s own body, and thus is no longer a part of the environment of the user. But when not in use, the tool is simply a detached object of the environment, graspable and portable, to be sure, but nevertheless external to the observer” (Gibson, 1979), pp.35.

This property of body extension through tool use extends our perception and cognition as it has been developed in embodied cognition (Noë, 2004; Kirsh, 2013). In embodied cognition, how agents communicate, infer concepts from elements perceived in the world, and reason about these elements, are body-dependent (Lakoff and Johnson, 2008; Varela, Thompson and Rosch, 2017). Furthermore, tools that agents have learned to use can become an extension of the body and, therefore, may constrain and inform the creation of concepts stemming from the agent acting within an environment.

Having introduced these concepts, we can observe that tool use remains related to hand-held objects operating on external objects. However, this view greatly restricts the spectrum of what tools can be. According to this view, digital tools cannot be considered as such because they are not tangible objects that can be manipulated directly. Digital tools may be buttons on an interface, sliders, documents, numbers, video streams, algorithms, etc. By nature, these tools are not tangible and cannot be taken in hands per se, as physical tools can. They can, however, be manipulated to some extent and they can be combined to create more complex tools. In response to

this problem, the definition of tool use has recently been extended to include the case where a tool is not directly manipulated and, therefore, is not simply a “detached object”. To that end, St Amant and Horton have proposed to define tool use as follows:

“the exertion of control over a freely manipulable external object (the tool) with the goal of (1) altering the physical properties of another object, substance, surface or medium (the target, which may be the tool user or another organism) via a dynamic mechanical interaction, or (2) mediating the flow of information between the tool user and the environment or other organisms in the environment” (St Amant and Horton, 2008).

These concepts have been of vast influence in designing user interfaces where analogies with the physical world help users interact with digital objects such as files, menus, data tables, or images. Furthermore, *interaction styles* establish how users interact with these digital objects. A notorious example is *direct manipulation*, where objects support actions on themselves and offer immediate, usually continuous, feedback to users while they perform the actions. Such interaction style can give the users the sense of manipulation as they would have done in the physical world, minimising the learning curve. Going beyond direct manipulation, Jacob and colleagues have proposed the concept of *reality-based interaction* where designing interaction with the digital object would rely on naïve physics and environment awareness and skill from users (Jacob *et al.*, 2008). Both of these approaches, however, do not allow for leveraging the computational capacity of technology, which may involve behaviours unrelated to what we experience in the physical world.

One example is copying and pasting, which is not an action that a tool can perform in the physical world as easily as in the virtual world³. More advanced computations, such as the ones at play in machine learning (clustering or loss optimisation, for instance), do not have a direct analogy in the physical world either. Leveraging both experiences in the physical and digital worlds, Jetter and colleagues (Jetter, Reiterer and Geyer, 2014) proposed the notion of *blended interaction* as a framework to understand when users perceive a user interface as “natural” (or not). However, a limitation resides in the fact that searching for naturalness in the user interface, such as minimising the learning curve or increasing the adoption of a given system, is often irrelevant. Many physical objects we use in the physical world may also be

3

“unnatural” (we could think of a violin, for instance), which makes this concept not really useful.

Finally, the concept of tool use has found an echo in HCI through the notion of instrumental interaction, as introduced by Beaudouin-Lafon (Beaudouin-Lafon, 2000; Beaudouin-Lafon and Mackay, 2018). The main idea is to focus on *domain objects*, which can be text, data, or images, and design *instruments* acting on those objects. Instruments can be activated or selected by users and can become themselves domain objects on which other instruments could act, pretty much as a tool in the physical world (e.g. a knife) can become the object on which a tool is acting (e.g. sharpening machine). Interestingly, the concept of instruments does not involve the notion of naturalness or intuitiveness. It could be intuitive if the instrument implements an analogy from the physical world, but it could also be abstract and adapted to some domain-specific, such as machine learning.

(Re-)purposing digital tools

When situated, tools in the physical world may be interchangeable if they share the same mechanical properties useful to achieve a task. For instance, if I have to drive a nail into a piece of wood, and I do not have a hammer in my possession, but I happen to be surrounded by stone, I can use a large enough stone as a tool for this task. Does this analogy apply to digital tools?

In the context of Miguel Renom’s doctoral thesis (Renom, 2022), which I co-supervised with Michel Beaudouin-Lafon, we studied the extent to which the principles of human tool use can be unfolded to understand digital tool use. In particular, we based our research on the *technical reasoning hypothesis* (Osiurak *et al.*, 2009), which posits that humans engage in physical tool use by reasoning about mechanical interactions among objects. For instance, if someone would like to cut an apple in half, the action of cutting is made possible by using a *tool* whose mechanical properties are *hard* and *sharp*, because they know that, on the contrary, a critical mechanical property of an apple is its *softness*. Therefore, a sharp object in contact with an object would cut it. This process of matching object properties with technical principles is what technical reasoning describes (Osiurak, Jarry and Le Gall, 2010). Therefore, any object can become a tool as long as its mechanical properties match the objective one is aiming at. And by modelling the use of objects as tools based on their abstract properties, this theory explains how tools can be re-purposed beyond their assigned function.

In a work led by Miguel (Renom, Caramiaux and Beaudouin-Lafon, 2022), we studied the relevance of technical reasoning to digital tool use. In other words, we wanted to observe if people, when asked to perform a given task in a digital environment (in this case a text editing environment, see Figure 2), could use tools that may not be usual for the task at hand but which have the “mechanical” properties to allow them to achieve it. In this work, people will have to use an

unusual tool-object association for the task, i.e. they will have to repurpose the digital tools to the task at hand.

The task was to indent the first sentence of the paragraph with the length indicated by the guideline. A rather simple task in any common text editing software. The interesting part of the study was to incrementally deactivate the commands that were used to achieve the task. For instance, if a user would use the space bar to indent the text, in the next trial, the space bar was deactivated and they had to find another option. This process was repeated until they gave up. Our goal was to observe if people manage to re-purpose digital tools, the same way one would do in a physical environment, and to correlate people's capacity to do so with creativity traits and expertise in text editing.

We found that creativity enhances the re-purposing performance of participants, meaning that creative people are more prompt to reason about objects beyond their assigned functions but based on their “mechanical” properties. This work was then extended to introduce *interaction knowledge* as the “mechanical” knowledge of digital environments (Renom, Caramiaux and Beaudouin-Lafon, 2023). In this work, although people were prepared to interact with a certain type of digital object (text or image), they showed that they could adapt the tools according to the task (and thus how the environment reacted to their actions), even if some clung to their habits.

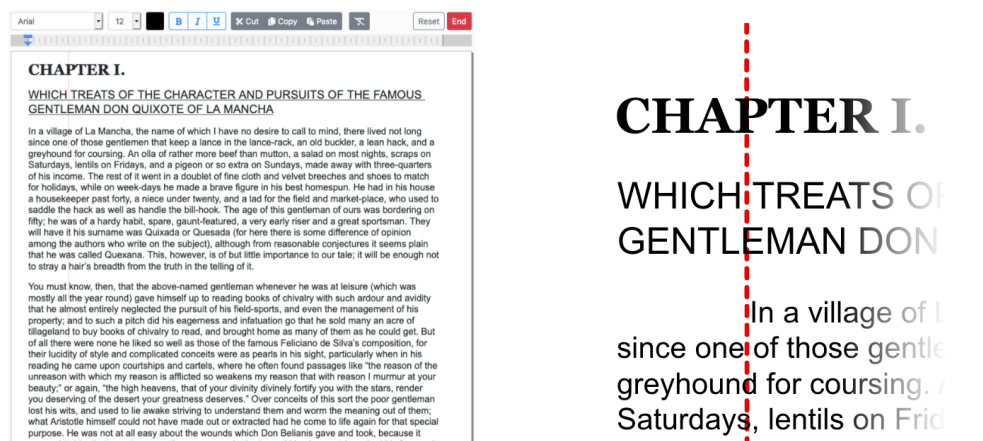


Figure 2 Description of the digital environment. On the left, the editor is in its initial state. On the right, the goal state shows the indentation of the first sentence of the paragraph with the length indicated by the guideline. Image adapted from the article (Renom, Caramiaux and Beaudouin-Lafon, 2022).

These theoretical works help us understand the way we reason with tools: the way we can sometimes adapt tools to our own objectives, or the way we can sometimes lock ourselves into using a few tools that we are used to practising, even if they are not the best for the task at hand. On the one hand, the latter can refer to functional fixedness (Duncker and Lees, 1945), bias from knowledge of the assigned functions

of tools when facing a novel task requiring the creative use of a familiar object. On the other hand, it can also positively refer to our ability to develop skills with a tool that alleviates its inherent limitations.

In addition, these works helped us to understand that, even if people could plan to perform a certain sequence of actions to perform a task in a digital environment, the imposed constraints would make them change their strategy. In other words, the use of tools is situated in the context of the environment we developed, and situated, also, within the experimental context of the study.

“the position to be taken – and the one that I will adopt here – could be that, however planned, purposeful actions are inevitably situated actions.”
(Suchman, 1987)

In this quote taken from the foreword of her book on *situated actions*, Lucy Suchman challenges that we can plan actions beforehand, out of context. On the contrary, by situated, she wants to emphasise that these actions are taken in the context of concrete circumstances. Even if, in order to achieve a specific objective, a plan of action to be carried out is put in place, the concrete effects of these actions, when carried out, will lead to an adaptation of these actions, not to a modification first of the plan and then of the actions. Similarly, what we found illustrates Suchman situated knowledge principle in digital tools and their use. In carrying out a task involving a series of actions with some given tools, it will be inevitable to change the pattern of actions as the task unfolds, as circumstances and constraints dictate.

Summary

This section provides the foundation to interpret how machine learning refers to a tool in the works I am about to present. The first contention of this chapter is that machine learning algorithms become tools when situated, which is related to people's ability to re-purpose these tools to suit their objectives in relation to the objects to which the tools apply. Therefore, I believe that machine learning methods cannot refer to tools when used on decontextualized objects, such as fixed benchmark datasets. They become tools when situated and, therefore, when an algorithm is thought of as a means of responding to the circumstances and constraints arising from completing a task in a given context.

Focus • Metric learning as a tool for inquiry

Machine learning tasks such as recognition, clustering, or regression, can help advance scientific knowledge by providing a way to analyse high-dimensional data and therefore provide new insights on fundamental questions, e.g. in the field of neuroscience (Kell *et al.*, 2018; Richards *et al.*, 2019).

In this first *focus*, I illustrate the way I used machine learning as a tool for inquiry in scientific research. I will present two examples taken from my own research. The two examples use the same tool, which is a *metric learning* algorithm, in two unrelated problems: understand music perception from sound similarity measures and study motor learning through human annotations of the similarity between learners' movements and target movements. Figure 3 illustrates the general problem of these examples. In these two examples, a scientific question about perception is described by a stimulus and measures of stimulus similarity. A metric learning process aims to mimic this similarity measure and thereby provide information about the mechanisms of perception.

The objective of the first focus is to show how the same tool has been designed for a given problem and re-purposed for a second problem.

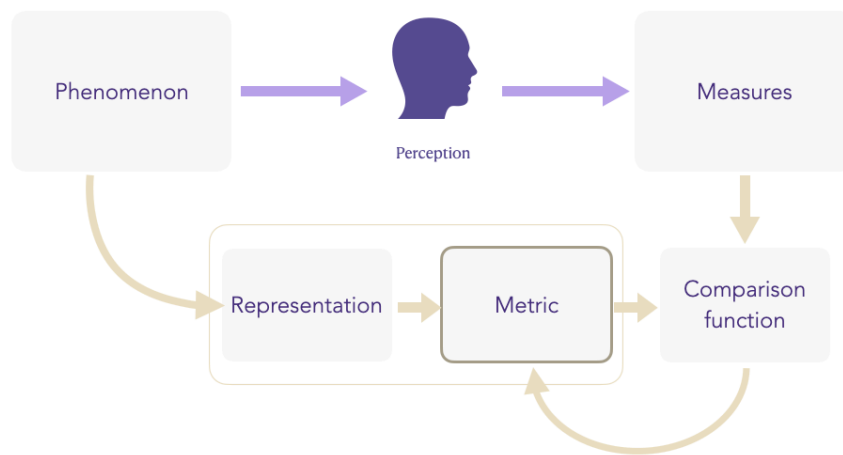


Figure 3 General description of the two examples involving metric learning as a tool for scientific inquiry. In these two examples, a perception question is described by a stimulus and measures of similarity. A metric learning process intends to mimic this measure of similarity and through this, provides insights into the mechanisms of perception.

Learning metrics to reveal the perception of musical instrument timbre

In 2016-2017, I was a Marie Skłodowska-Curie research fellow at McGill University, joint between the Department of Music and the Department of Psychology. Etienne Thoret, a post-doctoral researcher in the same department, with Philippe Depalle and Steve McAdams, both professors in Music Technology, were working on musical instrument timbre perception. Steve McAdams had recently gathered a collection of 17 datasets including sounds and perceptual dissimilarity measures obtained experimentally from historical studies, conducted between 1977 and 2016. These datasets were comprising a wide range of sound stimuli and dissimilarity measures, ranging from recorded notes to synthesized and hybrid musical sounds.

Having in hand this rich corpus, the objective was to investigate if we could apply metric learning to mimic human dissimilarity perception and thereby extract knowledge that helped us to better understand timbre perception.

My intention in this section is not to get into the details of the study, nor into the technical aspects of the algorithm used (the interested reader could refer to the corresponding Nature Human Behaviour article (Thoret *et al.*, 2021)), but rather to give a sense of how we use the algorithmic tool for this problem.

First of all, let us place the project in its scientific context on the perception of timbre. The human auditory system processes acoustic information through several levels of increasing complexity. At the first levels, transformations of the physical vibrations into neural activity conveyed by the peripheral auditory system are reasonably well known (Moore, 2012). However, nonlinear transformations carried out at higher cortical levels are less understood, especially when considering the perception of complex and rich sounds such as those from musical instruments. Musical instrument sounds have perceptually salient properties such as loudness (perceived energy), pitch (perceived frequency), and timbre (related to their “sound quality”). Although the first two properties are well understood, the timbre of musical instrument sounds remains complex and ill-defined (Siedenburg and McAdams, 2017). The fundamental question is: Wherein lies the difference between the sounds produced by two musical instruments playing the same pitch at the same loudness?

The standard methodology of timbre perception studies involves participants (listeners) that are asked to rate the dissimilarity between pairs of sounds from which relevant perceptual dimensions of a timbre space can be extracted. This data-driven approach is typically using Multidimensional Scaling (MDS). MDS produces a low-dimensional parametric space (typically with two or three dimensions) in which sounds are assigned coordinates, and the distances between sounds within this lower-dimensional space reflect their perceptual dissimilarities. Relevant dimensions of these timbre spaces are then correlated with audio descriptors computed from the sound signal, enabling a psychoacoustic interpretation of musical timbre perception. Based on this approach, previous works have found that two descriptors best explain the dissimilarity measures as projected by MDS: the attack time and the spectral centroid, which can be thought of as the brightness of the sound (see for instance (Krumhansl, 1989; McAdams *et al.*, 1995)).

However, this approach suffers from severe limitations that are explained in the article (Thoret *et al.*, 2021). One important limitation is that by reducing timbre spaces to two main dimensions, the subtle differences between musical instrument timbres are lost. Our question, therefore, became: Can we find a tool operating in a more complex, high-dimensional sound space, in which the subtleties of musical timbre lie, such as mimicking human dissimilarity measures?

With Etienne, we designed a distance that assigns a weight to each dimension, based on the Mahalanobis distance. This approach was not new: we borrowed a distance

metrics used in a previous paper on the musical timbre representation (Patil *et al.*, 2012). In this, the machine learning method was used to perform sound classification. In our case, we wanted to use the distance metric between sounds to mimic perceptual dissimilarity rather than the perceptual classification of sounds. Therefore, we had to adapt the learning objective to our aim. We used a correlation coefficient between the distances computed with the metric and the perceptual dissimilarity values provided experimentally. If the correlation is high, the metric behaves in the same way as the perceptual dissimilarities. The learning procedure was to adapt the weights of the distance such as maximizing this correlation, and therefore, fitting human perceptual distance. The dimensions with a higher weight are those that are considered to be less used in perceptual sound dissimilarity.

Putting the tool into practice followed a conventional machine learning workflow: running many training-testing trials while varying the parameters used. For instance, we could change the weights' initial values, affecting convergence. We could change the number of iterations in the optimization procedure, which affects performance and the time needed to obtain the results (that directly impacts the number of tests we can practically do). All these parameters shaped our tool. Finding the right set of parameters was eventually the most time-consuming part of the project, and when to stop shaping our tool was not planned. We decided to stop when we thought we could not go higher than a given performance (a global correlation between the computed dissimilarities and the perceptual dissimilarities). At this moment, we could use the tool to answer the research questions, and the resulting scientific contributions of this research project were significant for the field of timbre perception.

Interestingly, developing the tool used to achieve this inquiry certainly took more time in the project than interpreting the results on timbre perception. Undoubtedly, the development of the tool made us understand the data more in-depth than if we were using an off-the-shelf technique. However, none of these aspects was made apparent in the final paper.

Re-purposing metric learning to investigate motor learning

The past project made me think that metric learning in the context of understanding human perception is an intriguing tool that would be worth exploring further. As

part of ANR⁴-funded projects, ARCOL⁵ and ELEMENT⁶, focusing on movement learning facilitated by technology, I proposed to explore the same methodology in a different context. Borrowing the terminology related to tool use introduced in the first sections of this chapter, I proposed to *re-purpose* the metric learning tool to investigate another problem of human perception. This work was led by Antoine Lorientte, post-doctoral researcher on the project, and supervised by Frédéric Bevilacqua and myself. I refer the interested reader to the paper to find all the necessary details about this work (Lorientte *et al.*, 2023).

As above, I propose to begin by placing the project in its scientific context on motor skill learning. Motor skill learning is defined as the ability to perform a movement better, according to some given criteria such as speed or accuracy, in comparison to a reference movement (Wolpert, Ghahramani and Flanagan, 2001; Schmidt *et al.*, 2018). Metrics used to assess motor learning usually rely on error-rates or movement variability measures (Shmuelof, Krakauer and Mazzoni, 2012). However, such measures do not necessarily reflect the way humans perceive movement improvements: people might instead focus on specific movement features or aggregate several criteria established qualitatively. The goal was to use perception-driven metric learning in order to describe human perception of movement improvement during motor learning or adaptation processes. In other words, we propose to collect movement dissimilarity measures from participants observing movements and use metric learning on movement data in order to mimic the collected dissimilarity measures.

This approach was not totally new in the field of movement perception. For body pose and movement perception, metric learning has been applied with human comparison of still images from datasets containing skeleton data. Harada *et al.* (Harada *et al.*, 2004) optimised the correlation between a weighted sum of joint distances and human ratings to show that wrist, neck and head were the most important joints for explaining body pose similarity. Marinoiu *et al.* (Marinoiu, Papava and Sminchisescu, 2016) derived a metric from data (using Relevant Component Analysis) using the way humans reproduced poses they had seen on videos before analysing how it differed from standard Euclidean distance. As movement is dynamic, previous work also looked at ways to take movement temporal structure into account. Krüger *et al.* (Krüger *et al.*, 2011) explored the

⁴ ANR stands for French National Agency for Research (Agence Nationale de la Recherche in French)

⁵ ARCOL is an individual ANR-funded project <https://arcol.isir.upmc.fr/>

⁶ ELEMENT is collaborative ANR-funded project between IRCAM, Université Paris-Saclay and Sorbonne Université <https://element-project.ircam.fr/>

effect of different input features on the correlation of a Dynamic Time Warping (DTW) metric (representing the cost of temporal alignment between two examples), with similarity ratings produced by humans based on videos. However, metric learning was not investigated in the context motor learning.

We base our research on an existing dataset, which was initially collected to study how users learn long gesture sequences from videos, over several days (Liu *et al.*, 2022). In other words, we had the stimuli but we were lacking the dissimilarity measures, contrary to the previous project. We collected the measures in an experimental setting among the authors of the paper. Then we set out to learn a distance metric on human movements that maximises the correlation with human annotations. The goal was to transfer the tool, and the related practice, from one study (presented above) to another. Not that we could seamlessly take the code from project 1 and apply it to the data from project 2, but the metric learning approach has been successfully re-purposed from a timbre perception problem to a human movement perception problem. The generic machine learning algorithm used became a tool because it was situated in the scientific context of human perception study.

Focus • Machine learning as a creative design tool

I started this chapter by recalling the research agenda I was carrying out at the end of my PhD and pursued after that at Goldsmiths College, University of London. I carried out this research in labs where computing systems meet creative practices. Such a research environment gathers academics from different backgrounds, such as computer science, music, social sciences and artists whose practices vary widely from each other. In this context, the research culture does not emphasize technical innovations but does focus on what a given technical tool could bring to the creation and art making. Artistic and creative practices engage with technological objects and tools from a different perspective that can create an epistemology and innovations. By doing so, technological objects can be used in ways that were not obvious initially. Like a tangible object or a tool that can be re-purposed in a physical world, technological objects can also be re-purposed to alternative objectives situated within various contexts, creating new opportunities for reflection, understanding and innovation.



Figure 4. Atau Tanaka performs live with biosensors and gesture-based recognition systems used to control sounds in real time. (Photo: Martin Delaney)

In this second *focus*, I am focusing on machine learning as a design tool in a creative context, with a particular focus on my research around motion-sound interaction design. Here machine learning is used to create interactions from examples: by providing gestural inputs and desired associated outputs, machine learning models can create the program to map inputs to outputs. The machine learning tools used in this research were gesture recognition systems situated in artistic performance and installations.

Creating movement-based musical interactions from examples

The design of motion-based interactions using machine learning in the creative context relies on creating such interactions from data examples rather than programming. Machine learning algorithms are inductive machines that can generate a program from data inputs and some given specifications that will configure the task at the end (classification, regression, or clustering). In other words, it is a tool to build computer programs without explicitly writing the program but rather by providing data examples illustrating the task that the program should achieve. The main idea is to *teach* a computer (or any computational system like a robot) to perform specific tasks by demonstrating how to perform these tasks. A human user typically provides demonstrations (sometimes called an operator in the context of human-robot interaction). Figure 5 presents the conceptual difference between an

inductive machine (allowed by machine learning) and a hypothetic-deductive machine, more conventionally used in programming.

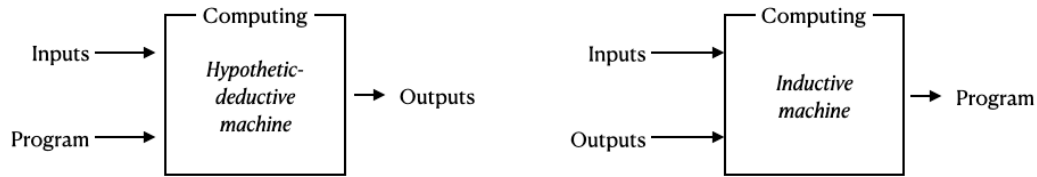


Figure 5. Hypothetic-deductive machine (left): both inputs and the program are provided to the machine which computes the outputs. Inductive machine (right): both inputs and outputs are provided to the machine which computes (or “learns”) the program. This figure is adaptive from (Cardon, Cointet and Mazières, 2018), courtesy of the authors.

This approach, called *programming-by-examples*, or sometimes *programming-by-demonstration*, has a long history in Human-Computer Interaction (Halbert, 1984; Lieberman, 2001) and Human-Robot Interaction (Billard *et al.*, 2008; Calinon, 2009). In particular, programming by demonstration has found significant resonance in human-robot interaction, where an operator can program a robotic arm by manipulating it or demonstrating the task at hand. Programming such robotic arms, which have many dependent actuators, is tedious, and showing how to do the task has, therefore, many advantages. In this context, many recent approaches use machine learning at their core (Billard *et al.*, 2008; Argall *et al.*, 2009; Hussein *et al.*, 2017; Ravichandar *et al.*, 2020)⁷.

The idea of programming a system by demonstrating what it has to do or how it has to behave has made its way into interaction design, supporting creative and artistic practices, because non-experts in machine learning could realise their own designs by the mean of demonstrations. During her PhD, Rebecca Fiebrink formalised using supervised learning for designing data-driven interactions with sounds (Fiebrink, 2011). One of her seminal work goals was to make supervised learning algorithms usable tools for computer music practitioners, helping them work efficiently (where the notion of *efficiency* is often subjectively assessed) and enabling new forms of art through these systems. One of the key findings of this research has been to show the importance of user interactions and the non-utilitarian assessment of artist-users of machine learning models. In other words, artists will use data and machine

⁷ For instance, one can demonstrate a trajectory that the robotic arms must follow. A model of this trajectory can then be built and used by the robot, for instance, using Hidden Markov Models (HMM) or any sequence modelling technique (Lee and Xu, 1996).

learning models to achieve their creative goals, often through exploration and iteration. Then, assessing such models through accuracy and other *objective* measures computed on benchmark datasets, as is usually done in machine learning research, is insufficient for models deployed in creative practices (and other application domains involving open-ended design objectives). The way artists will qualitatively assess the model, depending on their own purposes, can be as important as the model's accuracy.

Together with Rebecca Fiebrink, we further formalized the approach in a co-authored book chapter entitled "*The Machine Learning Algorithm as Music Creative Tool*" (Fiebrink and Caramiaux, 2018), providing examples of musical instrument making that make use of the machine learning-based inductive design process described above. Starting with the presentation of Machine Learning tasks, we exposed machine learning as an interface, highlighting the importance of understanding user interactions with this interface. In addition, we highlighted the affordances offered by machine learning algorithms, i.e. the actions that users may perceive as allowed when interacting with these algorithms, which is particularly interesting when designing motion-based interactions through this technology.

Jules François has formalised the use of machine learning algorithms more specifically to infer movement-sound interaction from examples in his doctoral work (François, 2015) and in later work on motion-sound mapping through interaction (François and Bevilacqua, 2018). These works are part of a larger set of works which include: (Bevilacqua *et al.*, 2009; Fiebrink, Cook and Trueman, 2011; François *et al.*, 2014; Gillian and Paradiso, 2014; Bullock and Momeni, 2015; Visi and Tanaka, 2021). The approach relying on machine learning inference is particularly suitable for the design of movement-based interaction with sounds. First, movements are not easily 'expressible' in computational terms (Höök, 2010; Rivière *et al.*, 2018; Gillies, 2019): what features to choose in order to describe body movements? how to compute these features for real-time music performance? A machine learning algorithm could extract these salient features from examples of movements. Second, artists, musicians and performers do not necessarily have the technical knowledge to implement such interactions on a computer. Artists and creatives may prefer to use known (or their own) content (images, sounds, texts, etc.) instead of trying to break the barrier of learning a programming language in order to explore a system that is meant to support their practice. Finally, the creative process involved in building musical interactions is evolving, non-stationary, and iterative. The exploration through iterative processes is typically what creates meaning and knowledge in art making. Implemented relationships between movements and sounds must therefore not be fixed and static but rather adaptable and malleable.

Gesture recognition

Figure 6 illustrates the general scenario where movement-sound examples are provided to a machine learning algorithm that induces the relationships between both modalities. This process is typically occurring in real-time while interacting with the system. Machine learning by demonstration in movement-based interaction includes various machine learning approaches (from classification to regression). Here, I am using the specific example of gesture recognition to illustrate an implementation of machine learning as a creative design tool in the context of music performance. The general technical objective was to propose an algorithm to recognise gestures during a performance (musical or dance) and to associate these gestures with composed sound treatments: recognised gestures could trigger sounds, and gestural execution could continuously process sounds.

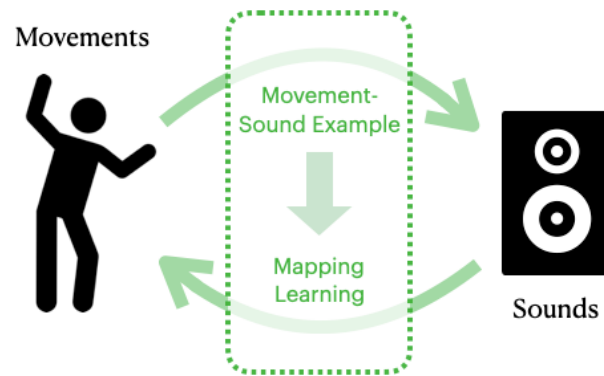


Figure 6 General interaction scenario in the use of machine learning as a design tool for movement-based interaction. A performer or an artist is listening to sounds while moving. The system learns the mapping between the executed movements and the sounds. The performer can then re-interpret the sounds with variations of their movements.

At the time of this research, previous works had developed toolkits in addition to more conceptual works on programming by demonstration through machine learning (Fiebrink and Cook, 2010; Gillian and Paradiso, 2014; Bullock and Momeni, 2015). These toolkits involved algorithms that were designed to recognise gestures as static objects (e.g. postures). Such algorithms were, however, not able to model the temporal structure of gestural execution and movement qualities, and therefore not able to take into account the dynamics of body movements that convey expressivity and emotions (Pelachaud, 2009). Frédéric Bevilacqua proposed in 2009 a tool that goes beyond static gesture recognition. This tool was able to recognise and temporally follow a gesture by modelling its temporal structure. The tool was called *Gesture Follower* (Bevilacqua *et al.*, 2009).

I am focusing on the Gesture Follower because it plays an important role in my own research at that time (detailed below) and because it illustrates the way gesture recognition translates from algorithm to tool. Technically, the gesture follower was trained by providing one gesture example per gesture class to recognise, which made it trainable quickly and in real-time. Once each class has been defined through its example, a new gesture could be executed and the algorithm provides real-time recognition information in addition to a time progression value that indicated where in the recognised model the current observation of the executed gesture corresponded. In other words, the gesture follower could follow the performed gesture on the basis of the example provided.

By recognising and following the gestures performed by the musicians, a composer could compose synthesized sounds associated with the performance, an augmented score. Florence Baschet used the tool in her piece called *StreicherKreis* involving a string quartet (Figure 7 right) where each instrumentalist's gesture was captured using a worn inertial sensor (Figure 7 left). This model has then been used in various music pieces (Kimura *et al.*, 2012) or dance installations (Bermudez *et al.*, 2011; Bevilacqua, Schnell and Alaoui, 2011). The gesture follower has been a success in that it has enabled new forms of interaction through continuous, real-time tracking of gestures, which have been of interest in several examples of artistic work. In this sense, the gesture follower has become, in its context of use, a tool that some artists have been able to apply to the various objects ("gesture" data), in order to achieve an artistic intention.



Figure 7 Pictures from 'StreicherKreis' by Florence Baschet. On the left, the inertial sensor is placed on the performers' wrists. On the right, is a picture of the quartet interpreting the piece. (Pictures courtesy of IRCAM).

Besides recognising and following a gesture in real-time, previous gesture recognition algorithms could not leverage complex variations of executed gestures. In collaboration with Nicola Montecchio, I developed an extension of the *Gesture*

Follower that can recognise gestures in real-time as well as their variations during execution. For instance, the algorithm would be able to recognise the gesture that is being performed and estimate if it is being performed slower, faster, or with more amplitude. The objective was to augment the gesture follower by affording additional expressive controls in interaction.

We called this algorithm *Gesture Variation Follower* algorithm (GVF) (Caramiaux, Montecchio, *et al.*, 2014) as a way to mark the lineage with the *Gesture Follower* developed by Frédéric Bevilacqua (Bevilacqua *et al.*, 2009) and presented above. Technically, the algorithm used a different approach than the gesture follower. It implemented an algorithm which allowed to sample a given number of possible variations of the current gesture. The number of possible variations was arbitrary (for instance 1000). This number was a parameter of the model that regulated the speed at which the algorithm could adapt to gesture variations. By estimating possible variations in real-time, the algorithm could recognise gesture invariant to these variations. In other words, the estimation of the variations was initially intended only to improve the performance of the algorithm. Eventually, they became in practice the key output features of the algorithm as the algorithm could output the likelihood of the current template under a given variation, and the values of the variation features (for instance speed, amplitudes, orientation, ...).

Gesture recognition in design practice

The development of GVF was in principle an academic success: it achieved better performance than the state-of-the-art and has been consequently published and released as a software library. But can it perform the role it has been assigned in practice?

During my post-doctoral research at Goldsmiths College in 2015, I was involved in the supervision of Alessandro Altavilla's PhD thesis, with Professor Atau Tanaka. Together, we developed the idea of using GVF as a tool that enables designers to build rapid prototypes of gesture-sound interactions, without requiring technical skills. Designers could train the model on-the-fly and choose which sound parameters to control with the estimated gesture variations. We imagined a workshop where participants, primarily designers, would start from sounds from their own everyday experiences, as a way to trigger design ideas and rich movement-based interactions. These sounds would then be taken as objects to interact with. Designers would have to find movements to manipulate these sonorous objects. In order to make such a movement-to-sound interaction design process possible, we use GVF. I describe briefly the outcomes of this research below and more details can be found in the dedicated published article (Caramiaux *et al.*, 2015).

We designed and conducted a series of participatory design workshops that focus on participants' memory and direct experience of sound in the everyday. We used a two-phase structure, *Ideation* followed by *Realization*, as a way to move from the

description of an affective experience to the elaboration of a functioning interactive sound prototype. I will specifically focus on the Realization phase here, to illustrate how the machine learning-based tool GVF was used by participants during the workshops. In the realization phase, each breakout group chose one scenario from their group to be developed into a functioning prototype. They first created a realizable interaction scenario by storyboarding it, describing actions, sounds and interactions. They then recorded or searched online databases for sounds that approximated the sound they wanted to work with from their own personal experience. With this, they authored a movement/sound interaction using our hardware/software toolkit. The toolkit included gesture sensors and software tools for motion data processing, mappings and sound synthesis (Caramiaux *et al.*, 2022). Despite the potential difficulty of working with interactive sound software, the high-level abstractions and workflow of our software toolkit were generally well understood by the participants. During all the workshops, the participants were highly independent and asked for help from us only when they wanted a software feature that was not included in the toolkit, for instance, a sound synthesis engine such as sine wave generator. This was facilitated by the modular architecture of the toolkit and also by working in breakout groups (Figure 8 left).



Figure 8 Pictures from the workshops “Form Follows Sound” where participants had to imagine gestural interactions with sounds from the everyday life, and realise these interactions using the gesture recognition tool called GVF.

During the workshop, participants were mostly using machine learning to perform gesture recognition among a set of self-defined gesture classes. The algorithm was used as a label-producing tool operating on the input data streamed from the sensors. Limitations and constraints of such a tool arise from the difficulty to assess the gestures taken as inputs to the algorithm. In other words, the tool was operating on an ill-defined object (gesture), from the perspective of the participants. In that sense, participants were tactful in working around the limitations and constraints of the

technology. For example, in one prototype, participants transformed the physical space, creating an obstacle course to walk through to more clearly send distinct foot gestures and slowing down the user's walk to aid the GVF module (performing the gesture recognition) of the toolkit in distinguishing gestures to trigger different floor crackling sounds (Figure 8 right). In this way, input gestures were constrained in order to be handled by the gesture recognition system.

Note that this lack of transparency in the properties of gesture-objects to be handled by the gesture recognition system made the participants iterating on them. In other words, the recognition algorithm became a tool for participants to reflect on the gestures taken as templates. By iterating on the definition of these templates, they incrementally defined more appropriate gestures for the type of interaction they were envisioning⁸.

Discussion

This chapter addresses the use of machine learning algorithms as tools to achieve pre-defined tasks on data objects. Like tools that inhabit our everyday life, algorithms can also be seen as tools in their own right, although their actions impact digital objects instead of physical ones. Algorithms act on data, and their actions are transformative because they usually change the state of the objects to which they are applied. In addition, algorithms can be re-purposed in the same way as a conventional (physical) tool when the actions performed with it are not initially associated with that tool.

I chose to present two *foci* from my own research. I considered machine learning algorithms as tools in two contexts: used to conduct a data-driven investigation of human perception in music and movement learning, and to build interactive systems, creating bridges between movement and sound spaces and applied to interaction design. In the first case, the objects were sound representations and similarity measures. Such a tool aimed to take sound representations as input and generate estimates that resembled similarity measures. As when using a bubble level to set up planar elements with respect to a reference, we adapted the representations (by learning weights on their dimensions) to be faithful to a perceptual reference. In the second case, the objects were data streams representing gestural executions during a live performance, and the tool had to associate classes to them as well as variations

⁸ In the next chapter, I will go further in the consideration of machine learning as a design material, by detailing the notion of materiality of digital information, often seen as immaterial.

from a reference gesture representing the class. When to classify an input gesture was dictated by a scenario (or a score in the case of music performance).

When all you have is gesture recognition, everything looks like a gesture

During my stay at Goldsmiths College, University of London, I started to collaborate on an artistic project with artist and PhD student Marco Donnarumma. Marco's practice involves body performance where music, light and technology are assembled together with body movements in a composition that redefined body configurations. As part of his practice, Marco developed a muscle sensor capturing the mechanical activity of the muscle (Donnarumma, 2011). The goal of our collaboration was to involve real-time *gesture* recognition in his piece, where gestures were internal (as a manifestation of muscle activity) as opposed to external (as a manifestation of visually perceivable body movements).

We began by experimenting with his sensors, capturing the mechanical activity of the muscle. We organised sessions of data capture and post-analysis, but it became quickly clear that the data captured dynamic transitions between muscle contractions and the resulting trajectories calculated by gesture recognition system did not make sense. We added a second sensor based on a different technology (electromyogram (EMG)), which measures the electrical discharges activating the muscle. Here a new problem emerged, following Donnarumma's feedback about the resulting movement-sound interaction: controlling EMG trajectories was not aesthetically convincing, for it could not allow a highly dynamic mode of interaction, one of our main musical goals. Therefore, there was no reason to use gesture recognition. Based on this failure in using gesture recognition, we started exploring the design of a computational music system that would not be tied to conventional mapping techniques, but instead would reflect, through sound, levels of effort intensity, movement abruptness and degree of complexity of particular body configurations (a more thorough description of our collaboration can be read in a dedicated article (Caramiaux and Donnarumma, 2021)). The terminology also changed: "configuration" was preferred to "gesture".

This story highlights that the technological tool we were forcing ourselves to use with physiological data did not work as intended. The gestures we aimed to recognise were challenging the algorithm's capacity and failing the use of the algorithm in the piece. This failure made us understand that what we considered as *gestures* (from the performance perspective) were not *gestures* (from the technology perspective). There was a semantic gap between the objects handled by the tools and the objects involved in the performance.

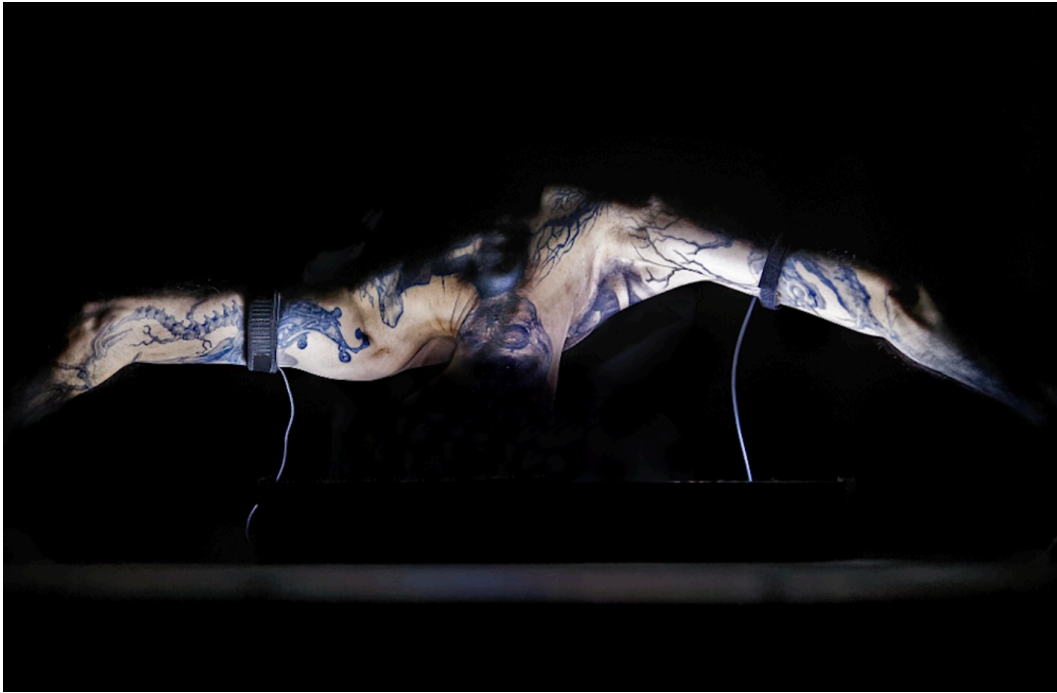


Figure 9 Corpus Nil by Marco Donnarumma, an interactive piece on which I collaborated with the artist on capturing gesture expressivity from bio-signals. Levels of effort intensity, movement abruptness and degree of complexity of particular body configurations were translated into sounds and lights during the performance.

What does it tell us about machine learning algorithms as tools in this context? When all you have is gesture recognition, does everything look like a gesture? First, once built, there seems to be a process by which a tool detaches from the human intentions and values it has stemmed from. This process of detachment creates an object that has the appearance of the whole, embodied by its function. The tool is a “pure assembly of matter, devoid of any real meaning, and having only a utility”, as put by Simondon (Simondon, 1980). And the extent of this function is not questioned. If this tool allows recognising gestures from data stream input, it is its function. I can take it for granted and use it. We know that this approach is not always valid, especially when we are both the creator and the user, but there is always a desire to follow this path.

Where does the problem lie then? On the one hand, it is due to our understanding of the properties of the objects on which a tool is applied, which was explained under the notion of *technical reasoning* above. Understanding the compatibility of the “mechanical” properties of the tool and the object to which the tool applies may require training and explanations. On the other hand, I would say that in the very specific and niche case of the projects I presented above, it has been partially driven by my personal will to show that the tool I have created is generic enough to be used in art-making and, more generally, in the design of movement-based interactive systems. It is what I call the creator’s bias, where it is harder to accept failures than to believe in magic.

The forgotten materiality

The perspective highlighted in this chapter regarding machine learning algorithms as tools is surely the most common one when dealing with this technology. The way this technology is designed to achieve tasks reveals a utilitarian view of this technology, where performance, as computed by accuracies, is what the algorithm should maximise. A machine learning algorithm should perform classification with the highest performance possible, and the same for regression or generation. When does it become a tool? What do we make of the process put in place to build the tool and the decisions made while building it?

During the first project, we spent a large amount of time adapting the tool to the problem. We had to understand how to deal with high-dimensional objects in a reasonable amount of time. We had to deal with overfitting (the model learns too much, which means basically noise), or underfitting (the model does not learn much). The design of the tool was instructive to understand the objects of study, and iterating on the design made us get closer to these objects and be able to slowly create a discourse about them. Importantly, we needed to understand when to end the design phase of the tool and use it for its intended overall purpose. This question of when stopping the improvement of a tool is fundamental and difficult. And I think it does not respond to prescribed criteria, given in advance, but to arbitrary decisions made in view of the circumstances of a given context. Has a higher correlation been achieved compared to the baseline? Has the model been trained to recognise gestures satisfactorily for the performance's needs?

This process describes the forgotten materiality and culture of technology that, altogether, made up the tool of inquiry. However, in the final paper, we reported the final results as is tradition, and we set aside the design aspects. When he was a PhD student in psychology and cognitive science working on sound perception and affordances (whether people could hear the property and material of struck wood and metal), Bill Gaver wrote:

“Writing up the study, I used the canonical structure for reporting experiments. I set the scene both theoretically and in terms of related work, using that to motivate a set of hypotheses, describing my methods, stimuli and procedure, and then reported the data and discussed how they reflected on my initial hypotheses. What I did not do—of course!—was talk about all the work done to achieve the final data set: the shopping I did in specialist hardwood stores, the improvising of foam mounts that would let the bars sound when struck, the ways I tried to get participants to listen to the right things, and so on. Instead, I told the story the way I had been taught, as a linear narrative from theory to experiment to data and back to theory, in which each step was logically connected to the previous ones and to those that followed.” (Gaver, 2014)

The forgotten materiality and culture occult the staging created in order to achieve scientific results. The way results are reported about the use of machine learning as a tool may be too often seen as a “linear narrative from theory to experiment to data and back to the theory”. But the narrative is usually not linear.

In the second focus I presented, we were deliberately within a non-linear narrative from research question to results. Tools were made to explore and create. Here the tension was too high, we felt that the tool alone could not explain the phenomena observed in practice (either in workshops or performance). The gesture recognition algorithms that we presented remain tools but there were also used to explore gestural possibilities and body configurations. The goal of recognising gestures is blurred with other goals, more exploratory, less focused on (model) performance, and more prone to serendipity. The objectives were more “nebulous”, as Gaver put it when talking about his research-through-design project (Gaver, 2014). Creative practice with technology makes clear that technological objects need to be understood beyond the notion of tools, and embrace their materiality.

In this manuscript, I want to tell a more complete story about how technology has contemporary modes, and the tool is only one of these modes.

Material

In 2012, the machine learning community experienced an event that challenged its beliefs. A team led by Geoffrey Hinton from the University of Toronto presented a method at one of the leading conferences in the field that showed performance dramatically better than anything that had existed before and beyond anything the community had imagined possible. On an image classification task, where the goal is to predict the correct class to assign to an image among 1000 classes, the approach obtained an error rate of 15%, while the best results obtained by others so far were 26% error (Krizhevsky, Sutskever and Hinton, 2012). Such a difference is a qualitative gap in this scientific domain, where improvements are more likely to be counted in tenths of a percent. The proposed method used a neural network architecture, which was not innovative for the machine learning community and had already been proposed several years earlier (LeCun and Bengio, 1995). But its presentation at the conference marked the birth of Deep Learning for the world. When this story was related and analysed by Dominique Cardon and colleagues from the point of view of the sociology of science and technology, they reported the comments of researchers in the field. In one of these interviews, conducted with a pioneer of deep learning in France (anonymous in the paper), we can read:

“The thing they did was to remove all the feature extraction and take the raw image. The guys who did that with Hinton are crazy because it's one thing to reproduce, but to go like that and explore! They made systems of a complexity that we didn't imagine, and they were able to make them work. You take a paper from these people; you look at it, I'm scared, I'm too old! The guys talk to you as if they were almost programming. They don't make a description with three equations that make sense to me. But in 5 lines, they're going to describe a hypercomplex thing. So, that means that he made an architecture in which he put 100 elements together, and for each one, you have ten possible choices to link them. He played with that to make it work. He's a hacker; it's a hacker's job.” (translated from the French version presented in (Cardon, Cointet and Mazières, 2018))

When reading this quote from Cardon's paper, I thought that what Hinton's students have achieved could be considered technological and design innovations. Neural

Networks (especially Convolutional Neural Networks used in the method proposed by Hinton's team) were well-known in the field. They achieved a technological innovation to make such a model architecture work at scale through graphics processing units and programming mastery. But in addition, they achieved design innovation by using the existing pieces (neural layers, training mechanisms, ...) as material to build something that works. They assembled the pieces by intuition, technical skills, and exploration of hundreds of iterations until finding the configuration that would give good results, hopefully better than the state-of-the-art.

Eventually, machine learning (and deep learning) has extended far beyond the research community in machine learning. But how this technology is used remains unchanged: the datasets shape the behaviour of the model, the model is assembled from unitary elements (layers, activation functions, etc.) in such a way as to make it more expressive, and finally, a decision has to be taken on when to end the training. In this chapter, I describe how these elements constitute the materiality of machine learning and how this materiality becomes explicit when one (engineer, designer, researcher, artist, laypeople) becomes involved in the training process.

I illustrate this point through the work I have done as supervisor of Téo Sanchez's doctoral work and as a collaborator of Hugo Scurto while they were doing their PhD.

Material Expression of Machine Learning

Digital information is often seen as an entity without materiality. What we see on the screen, or what we think occurs behind it, feels intangible and immaterial, as opposed to elements in the physical world that we can touch, grasp or displace. But, since we are able to design and build things with digital information (e.g. through programming), it seems reasonable to imagine that the notion of materiality extends to things within the digital world, especially to machine learning.

In HCI research, the community has brought the concept of materials and materiality to the foreground, providing definitions and properties of the digital (or computational) materiality (Redström, 2005; Vallgård and Redström, 2007; Vallgård and Sokoler, 2010), building frameworks and methodologies of practice (Gross, Bardzell and Bardzell, 2014; Wiberg, 2014; Giaccardi and Karana, 2015), or understanding digital materiality through the feminist theory lens (Fors, 2011). Building on this work in HCI, in this section, I will review the concepts of digital materiality and, in particular, highlight the idea of material expression that has been discussed for digital material. My goal is to extrude the digital materiality of machine learning, in particular in the context of design and creation.

Digital materiality

There are at least two ways to articulate digital materiality. One approach is to consider the materiality of digital information in terms of the infrastructures that create and sustain it. This has been documented in science and technique studies, where previous research has looked at what lies behind the scene in terms of the invisible human labour (Denis and Pontille, 2012), the process of digitization (Camus and Vinck, 2019), and the infrastructures at play (Star, 1999). Digital materiality is pipes, cables, standards, protocols, machines, and labour. The interaction between operators and matters shapes digital information over interlocking operating chains. This view of digital materiality as components of underlying infrastructures helps to ground digital information in reality, as opposed to an idealistic viewpoint, which promotes the digital as an abstract entity devoid of materiality. And this process helps highlight the various relationships between socio-economical groups, technical substrates, and services.

In the specific context of machine learning, and artificial intelligence (AI), Kate Crawford explores such a perspective in her book “Atlas of AI” (Crawford, 2021). The author discusses the several elements in play for machine learning to exist, such as the rare minerals at the core of the batteries and screens of computing systems like mobile phones structuring the infrastructural grid. Or the electricity consumed to power these computation resources within the grid. In joint work with researcher Vladan Joler, they proposed a visualization of these infrastructures and interdependencies called the *Anatomy of an AI system*. The result is a high-definition visual artwork (see Figure 10) that depicts the anatomy map of the infrastructure underlying AI (through the specific example of Amazon Echo): human labour, data, and planetary resources.

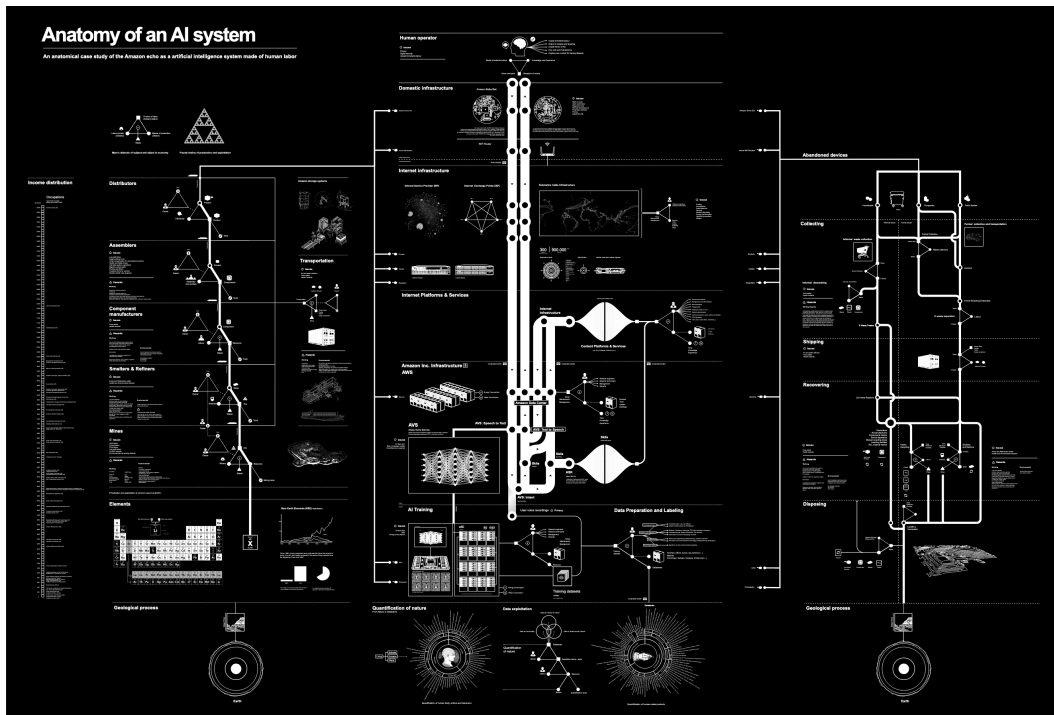


Figure 10. *Anatomy of an AI* by Kate Crawford and Vladan Joler. Courtesy of the artists. High-resolution version of the map can be found at <https://anatomyof.ai/img/ai-anatomy-map.pdf>

A second approach to understanding digital materiality can be from a design perspective: in a digital environment, materiality relates to the things that can be used to make stuff⁹. This view imparts materiality to the entities created of digital information (computer programs, data, algorithms, graphical interfaces, etc.) used to build new digital entities. Digital materiality is embodied in many ways: it can be combined with physical material to create heterogenous artefacts (an automatic gate can be seen as a composite material where a moving physical part is operated by an electronic and digital part), or it can be embodied in ‘purely’ digital artefacts (visualisation tools can be seen as a digital artefact created through digital materiality made of data, algorithms, and graphical components). Furthermore, digital materiality can be envisaged at a different scale of “granularity”: from bits that can be composed and wired to computational abstractions that can be programmed graphically (*Max/MSP* for music or *Scratch* for pedagogy are good examples) through hardware building blocks that can be assembled (*Arduino* is an example). It is this view that I will detail and illustrate in this chapter. In particular, the

⁹ Here, I am using Ingold’s informal way of defining material (Ingold, 2007) to provide an immediate sense of what I mean by digital materiality from a design perspective. Further details on materials will be provided in the following section.

consideration of digital materiality through digital entities that constitute and construct it follows a set of recent research in HCI and Design Research.

Explicitly assigning material attributes to digital entities enriches interaction design practice and theory. First, digital entities are not only tools but materials that can lead to developing a dedicated practice. Highlighting digital materiality by making digital information material, for instance (e.g. through visualisation), fosters design inspiration because one can *see* and *feel* what we can do with this material, as mentioned in (Sundström *et al.*, 2011). Vallgård and Redström (Vallgård and Redström, 2007) add that computational materiality needs to be part of a composite with other materials (e.g. physical material) to be useful for design: “a computer is a material, but also that its computational property, in its raw form, is difficult (if not impossible) to exploit. The conclusion was that the computer needed to be part of a composite with other materials to become useful in design.” Through the idea of computational composites, the authors aim to introduce new material properties “to introduce the ability of digital computations together with tensile properties, optical properties, electrical properties, thermal properties and insulation, acoustic properties, deformations, deterioration, appearance and so forth.”.

Second, digital entities are not detached from the social and economic environment, and considering the materiality of digital information helps highlight sociocultural values, and personal meanings, embedded in the design of digital artefacts (Jung and Stolterman, 2012), “materiality is [...] about the relationship between people (user) and the material artifact in terms of how it is used out in the world.”

In line with this research, recent papers have started to write about “*machine learning as design material*” (Dove *et al.*, 2017; Yang, 2018; Benjamin *et al.*, 2021). The perspective adopted is that of designers of new interactions and applications, for whom shaping a rich user experience is one of their main objectives. Therefore, machine learning is seen as a way to create innovative and rich user experiences (UX) and user interfaces (UI). The advent of new machine learning methods, capable of performing more complex tasks on actual data (such as images and sounds), is a boon to innovation in user experience design. As some commentators have put it, “*AI is the new UI*”¹⁰ (where AI refers to artificial intelligence, with machine learning at its core). But, beyond promises and communication strategies, a shared finding of this research is that UX design with machine learning remains difficult (Dove *et al.*, 2017; Holmquist, 2017; Yang *et al.*, 2018). These articles have highlighted the challenge of working with machine learning in this context because designers struggle to understand what this technology is capable of. UX/UI designs are

¹⁰ <https://www.fastcompany.com/3047199/apple-finally-learns-ai-is-the-new-ui>

constrained by available data that are hard to get or to build and whose quality is challenging to assess. Moreover, even if designers know what machine learning is capable of, it is hardly possible to explain why and how machine learning does it, and it can manifest unexpected behaviours. Moreover, in real-world applications, it is still difficult to leverage the cost of a machine learning feature (in terms of data, computations, and development work) over the innovation gain that the feature will bring (Yildirim *et al.*, 2022).

The story described at the beginning of this chapter, where researchers assembled deep learning materials to create an algorithm capable of recognising images with great accuracy, is a challenging scenario to achieve. The elements defining the materiality of machine learning are data, model parts, parameterisation, performance criteria, visualisations, and computational infrastructure. However, the design process leads to describing machine learning with abstractions that are not immediately related to the computational material. But it seems to me essential to understand this material beyond its usefulness in the processing chain and in particular the aesthetic and experiential natures of the chosen machine learning materials before assembling its elements to produce innovative user experience and user interfaces.

Material expressions

Ingold defines materials as “the stuff that things are made of” (Ingold, 2007). And, in the absence of a further definition, Ingold writes that:

“a rough inventory might begin with something like the following, taken from the list of contents from Henry Hodges’s excellent little book *Artefacts* (Hodges, 1964): pottery; glazes; glass and enamels; copper and copper alloys; iron and steel; gold, silver, lead and mercury; stone; wood; fibres and threads; textiles and baskets; hides and leather; antler, bone, horn and ivory; dyes, pigments and paints; adhesives; some other materials”.

In this text fragment, Ingold lists several materials that speak to us through their properties because we have a direct relationship with them as they are used in many artefacts we manipulate daily. Although we may not learn the physics of materials, we experience them. Pottery is usually intricate (after being fired) but breakable if it falls on a hard floor. Wood is a relatively soft material that can be carved easily with hand-held tools. Glass is transparent and retains liquids, while several textiles are flexible and can be worn. The physical properties of materials are engaged in the design process: they are intrinsically related to the final function of an artefact. Undeniably, designers will pay particular attention to the properties of the material used to ensure specific mechanical characteristics of the created artefact.

But, design practice tends to also pay particular attention to the *material expressions* beyond the material properties themselves. I define material expressions as the distinctive features (in terms of aesthetics, culture or physical characteristic) that identify material and that will be put forward in the creation of the artefact. Let's take the example of designers and artists working with ceramics. They will choose a specific clay and glazes because they know that when fired in the kiln, their alliance will result in a desired expression of the selected materials. This expression can be revealed in terms of colours, asperities, etc.

The notion of material expression emphasises that the material *communicates* with its environment and primarily with the designer working with it. This communication is fundamental in the design practice. Designers are trained to try ideas with different materials to achieve their goals. The process is iterative and exploratory, involving one or several materials, not all used to create the final artefact. For instance, they may use paper to rapidly prototype or clay to model a form before deciding on its final material. In return, the material talks back to the designer, revealing limitations and surprises and allowing the formation of new ideas. This *conversation* between the maker and the material used to make is what Schön called *reflection in action* and *reflection on action* (Schön, 1983). *Reflection in action* means that a practitioner discovers an idea by doing and at the point of rendering it. And *reflection on action* means that a practitioner steps back to assess what they have made as they plan their next design move. Therefore, the material expressions enable this conversation between the maker and the material.

If we now look at the practice of designing interactions involving digital material, could we achieve such a reflecting conversation with a material made of bits? What would be the material expression of digital information? Characterising the expressions of such a material is a challenging task because, in the first place, it is the basis for a diversity of digital entities which would themselves have specific expressions. It results that material expressions of technology may be felt as nonexistent. But Johan Redström proposes that this expression is hidden rather than absent:

“Another reason for thinking further about the idea that the material expressions of technology are hidden rather than non-existent is that early examples of technology, particularly before devices are working perfectly, often have very strong expressions in themselves. In the early days of radio and television, for instance, signal transmission and reception were ‘expressed’ as noise and distortion of sound and image.” (Redström, 2005)

What is highlighted here is that the material expression of technology, as illustrated by the presence of noise in radio sound, tends to be erased by technological advances. Image and sound transmissions are improving, trying to avoid any kind of interference and offering higher quality. However, while technologists tend to erase

the expressions of digital material under the necessity of progress, artists and designers are well aware of this expression and use it in their creations. So is the general public: when users apply sepia effects to photos to give them a warm and old-fashioned expression, there is a re-enactment of a vanished technological material expression.

Does machine learning also have a material expression? In many ways, it does, and the most straightforward way to see it is to consider generative models. In this context, the observation made above about the fact that continuous progress tends to erase the artefacts of previous versions also applies to machine learning. For example, Figure 11 depicts the evolution of image generation using a specific generative model developed in computer vision called Generative Adversarial Network (GAN), proposed in 2014 (Goodfellow *et al.*, 2014). Over the years, several authors have brought “improvements” to the model, such as generating more realistic and larger images. However, one can ask if the 2014 version of GAN was not more convincing from a designer’s point of view, searching for the expression of the material than the 2018 version providing a photorealistic image that seems to be found on someone’s internet profile page. In this example, quality assessment is driven by the need to reach “realistic” image generation. However, realism may feel less expressive.



Figure 11. Evolution of the quality of Generative Adversarial Networks (GAN) from 2014 (the year of its invention) and 2018. Image adapted from (Cheng *et al.*, 2020)

What then constitutes the material expression of machine learning? From the previous example with GAN, the material term of this technology is illustrated by the generated images and depends firstly on the images used to train the model (black and white, low-resolution or high-resolution photos, etc.), secondly on the ability of the model to be able to represent the information present in the input information (notably via its architecture and parameters), thirdly on the loss function which would guide the model towards the relevant information to focus on, and finally on

the training itself involving decisions on stopping, quality and performance. As a designer, the question may not be what performance in the accuracy percentage I would like to obtain but what quality, in terms of expression of the technology involved, I would like to get.

Importantly, what makes these design materials explicit is their action during the development of the system, i.e. during learning. In a design and creative context, I argue that learning provides access to the materiality of machine learning and the expression of that materiality. To consider machine learning as a design material is to consider the interaction with the learning process of a machine learning model. This is well illustrated in the creative and artistic field, where artists develop interactive approaches to take advantage of learning. I will go into this in more detail, but first, I propose to emphasise the notion of interactivity.

Enabling Materiality through Interactivity

Similarly to working with tangible materials in a design process, working with machine learning elements implies enabling a high level of interactivity between the designers and these elements. As opposed to the scenario mentioned in the introduction of this chapter, such interactivity is usually limited for the designers and other end-users without expertise in machine learning. These people do not usually have access to the data used to train a model, the model's parameters, or other means allowing them to shape the system's behaviour. Saleema Amershi and colleagues described this point as follows (Amershi *et al.*, 2014):

“The applied Machine Learning workflow often involves long and complex iterations. The process starts with data provided by domain experts or specifically collected for the target application. Machine learning practitioners then work with domain experts to identify features to represent the data. Next, the practitioners experiment with different machine learning algorithms, iteratively tuning parameters, tweaking features, and sometimes collecting more data to improve target performance metrics. Results are then further examined both by practitioners and domain experts to inform the subsequent iteration. At the end of this long cycle, the model is updated in several ways and can be drastically different from the previous iteration. Furthermore, this iterative exploration of the model space is primarily driven by the machine learning practitioners, who rely on their understanding of machine learning techniques to make informed model updates in each iteration.”

I consider that this status quo, where the machine learning experts are those who have access to the information provided to the model, and thus to the framework imposed on the system delimiting what it can or cannot understand, limits the potential for design, creation and learning (without mentioning the political

implications of such a status quo, which will be further discussed in the following chapter). Providing interactivity to a vast panel of users has the power to expand this potential.

Looking into the literature on Human-Computer Interaction, several authors have investigated ways to enable interactivity with machine learning, where the elements of the machine learning pipeline are exposed to the users (machine learning experts, domain experts, or laypeople), allowing them to act upon the training phase of a learning algorithm (Ware *et al.*, 2001; Fails and Olsen Jr, 2003; Amershi *et al.*, 2014; Gillies *et al.*, 2016; Dudley and Kristensson, 2018). As put in (Amershi *et al.*, 2014): “In contrast [to conventional ML workflows], model updates in interactive machine learning are more rapid (the model gets updated in response to user input), focused (only a particular aspect of the model is updated), and incremental (the magnitude of the update is small; the model does not change drastically with a single update). This allows users to interactively examine the impact of their actions and adapt subsequent inputs to obtain desired behaviours.”

I illustrate the interaction workflows described in this quote in Figure 12. The figure depicts the interaction between users and a machine learning-based system without the mediation of an expert. It shows examples of inputs provided by users and examples of feedback returned by the model. This representation also highlights the interweaving of usage, development and testing processes, characterizing the interactive machine learning paradigm. Users can use the system, test it and re-train seamlessly by adapting the data inputs and starting model training when they see fit.

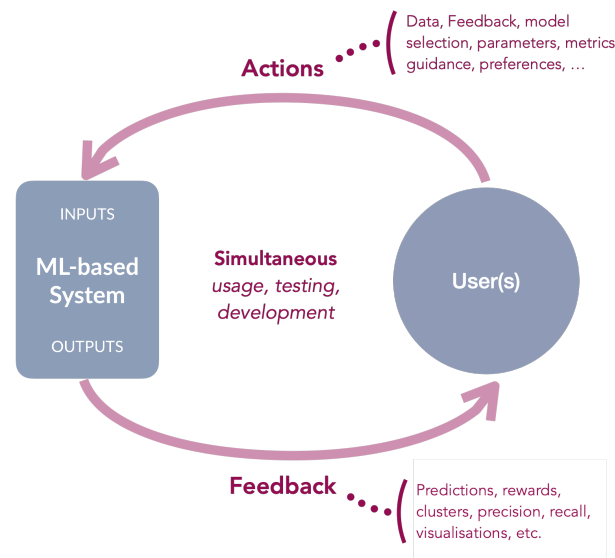


Figure 12. Interactivity in Machine Learning: users (not necessarily knowledgeable in ML and computer science) are engaged in the learning loop. Figure adapted from (Amershi *et al.*, 2014)

Such a paradigm's objectives were not initially linked to exposing machine learning materiality to designers and artists. A large body of previous work has found this approach to be a way of building more robust models than using fixed benchmark datasets, taking advantage of user expertise and insights through appropriate interaction techniques and visualisations (Talbot *et al.*, 2009; Wallace *et al.*, 2012; Berg *et al.*, 2019). Previous research has shown that it allows helping users (typically users who are experts in a domain) to efficiently convey expert knowledge to the system (Holzinger, 2016), which can have a critical impact in high-stake applications (for instance, in the medical field), but also for communities of practice and knowledge sharing specific expertise. Shaping the model behaviour through data and model edition also enables the personalisation of technology to a user's particular needs (Fiebrink, Cook and Trueman, 2011) or helps users better understand the caveats and strengths of a machine learning pipeline (Hohman *et al.*, 2020).

In light of what I have presented before on the notion of materiality in design and creative processes, I see the development of such interactivity with the machine learning pipeline as a method of uncovering this materiality in the context of machine learning-embedded design. Enabling such a level of interactivity transforms machine learning elements into materials that one can manipulate, assemble, modify, or replace to discover and explore innovative ways to use this technology. Although rarely stated in terms of materiality, there are existing works that emphasise interactivity with the objective of exploration and discovery, in particular in the creative and artistic domains (Fiebrink, 2011; Françoise, 2015; Scurto and Fiebrink, 2016; Scurto *et al.*, 2021; Visi and Tanaka, 2021). The previous chapter introduced some of these works focusing on the “tool mode” of machine learning. But, beyond the tool, I want to emphasise that the materiality of the technology is made apparent in these works through the enhancement of interactivity. The interactive machine learning paradigm, allowing for short cycles of interaction between actions and returns, establishes what we can call a *conversation* between the designer and the materials constituting the machine learning pipeline in a manner very similar to that evoked by Schön (Schön, 1983). This conversation allows the designer to discover an idea by exploring the capabilities of a model or a dataset and allows for downstream reflection to make the right design decisions based on the actions taken. In the following of this chapter, we will see that this possibility of conversation is not only theoretical and is applied to different tasks, starting from the artistic field and continuing with pedagogy and technology democratisation.

Focus • Material for creative and artistic practices

In the previous chapter, I presented machine learning as a tool in a creative and artistic context. Machine learning was used to design movement-to-sound interactions iteratively, with application examples in interaction design and artistic performance. Eventually, I showed the limitations of this tool-oriented perspective.

While remaining in an artistic and creative context, I suggest emphasising the case where the algorithm is perceived less for the task it can accomplish than for its use as a material in the creative process and the expression it conveys. In the resulting practice, artists actively participate in the processes constituting a machine learning pipeline. They find ways to orient the model to their needs and aesthetics and escape the technology determinism inferred by off-the-shelf models and pipelines.

I present two cases from my own research. We designed a system to assist exploration and sound creation in the first case. The originality is to use the machine's learning mechanisms as an interface for exploration, exposing the consequences of each user action on the model and thus its materiality. In the second, we interviewed visual artists whose practice involves machine learning-based generative models. The analysis of these interviews shed light on the materiality of machine learning in a very pragmatic way, including how to curate datasets and shape model training.

Creative exploration through data-driven insights

The first example I focus on is the design of an interactive machine-learning system that could support human creative exploration through data-driven insights provided by users. This work stems from the doctoral thesis of Hugo Scurto (Scurto *et al.*, 2021), on which I collaborated, where we addressed this question in the specific application domain of sound design.

In sound design, practitioners typically face the challenge of exploring high-dimensional, parametric sound spaces through complex interfaces, including many controls on the sound synthesis engine. Although this formulation could sound like a search for a problem-solving technological solution (and a creative one), the project started with hardly a technology but a type of machine learning. We were interested in exploring *reinforcement learning*, a machine learning paradigm where an artificial agent learns by performing actions within the sound space and receives rewards (sound designer's preferences) accordingly. In other words, an agent would start a random exploration of the sound space, incrementally receive positive or negative feedback about its current progression, and converge towards the zone the designer is interested in. Figure 13 depicts the interface of the prototype used in the study, where participants could provide several types of data-driven insights: positive or negative feedback on the trajectory taken by the agent in the sound space, positive or negative feedback on the zone in general, examples of parameter configuration desirable, etc.



Figure 13 Co-Explorer Interface (image adapted from (Scurto et al., 2021)). On the top left, the interface depicts the user feedback controls (such as 'like' or 'don't like', or 'change zone'). At the top centre, a user could manipulate directly the parameters structuring the design space. At the bottom, a timeline shows the progression of the learning phase and depicts the previous interactions (e.g. a green bar refers to positive feedback from the user).

We were interested in the strategies sound designers devised to achieve interesting sounds, their experience of the system and how it might be integrated into their practice. From a methodological point of view, we proposed a design approach centred on expert sound designers. This method allowed us to conceptualise exploration in this context by analysing the preferences provided by the designers on the system's behaviour, as well as their qualitative feedback on their experience. This was done through workshops including 12 professional users (Figure 14, left). Participants ranged from sound designers, composers, musicians and artists to music researchers and teachers. The workshop was divided into two tasks: (1) explore to discover and (2) explore to create. In the first task, sound designers had to shape the model by discovering the design space and producing 5 sounds they liked. In the second task, sound designers had 4 images to create a sound for each image through the same interface. Figure 14 (right) shows one participant performing the second task with the four images next to him. Group discussion was carried out at the end of the workshop to let participants exchange views on parameter space exploration.



Figure 14 Images of the workshops conducted for the evaluation of the co-explorer (adapted from the journal article (Scurto et al., 2021)).

From the elicited experience of the users, we were able to assess the suitability of the proposed interaction for the discovery task (finding 5 sounds in the design space). For this task, three participants wished that the system reacted more quickly to feedback concerning the task: “I would really like to feel the contribution of the agent, but I couldn’t”, one participant said. Also, another participant highlighted the difficulties in giving evaluative feedback in the considered task: “without a context, I find it hard”, he analysed. Despite this, all participants wished to spend more time teaching the system by carefully customising the parameter space with user feedback. For example, five participants wanted to slow the speed of the agent during autonomous exploration to be able to give more precise guidance feedback. And three participants wanted to express more material-oriented feedback: “There, I am going to guide you about the colour of the spectrum. [...] There, I’m going to guide you about, I don’t know, the harmonic richness of the sound, that kind of stuff...”, one participant imagined.

We were also able to assess the suitability of the proposed interaction for the creative task (having set an objective through images) and the usage they could make in their practice when dealing with real commissions. Indeed, all participants were able to describe additional features for the system to be usable in their real-world professional work environments. For instance, sound designers mentioned connecting the model to other sound spaces, memory transfer from one space to another, multiple agent memory management or data exportation. Half of the participants were enthusiastic about exploiting the temporal trajectories as actual artefacts of their creation. For instance, a participant said, “What I would find super interesting is to be able to select the sequences corresponding to certain parameter evolution or playing modes. [...] Selecting and memorising this evolution would be great, rather than just a small sonic fragment”. In general, they found using the system for the creative task more relevant than for the discovery task. They appreciated that the creative process did not rely on analysing the design space (the parameters defining the structure of this space) but instead relied on listening.

These results highlight the potential of using machine learning processes as an interface to enable the exploration (and exploitation) of the materiality of ML in a creative task. In this case, sound designers had few agencies on the model itself but could focus on providing the model with data-driven insights to craft its behaviour. This approach was successful in general. And, while ML materiality was not elicited by sound designers, which is not surprising given that they were not familiar with such a task (and ML in general), their approach was indeed to consider some features of the learning mechanisms (e.g. model temporal trajectories) as material for design.

Crafting data and models in artistic practices

The second example takes a step back from a particular system and looks at an artistic practice of machine learning, particularly the use of generative models in the visual arts.

Let me first give some examples of artists and artworks that illustrate this ongoing and ever-dynamic practice. In visual arts, Video work by Memo Akten explores how images generated by deep learning models trained on large data sets push us to reflect on our collective representations of the world (Akten, Fiebrink and Grierson, 2019). Memo Akten was one of the first artists to use deep generative models in “*all watched over by machines of loving grace*” (Akten, 2015), together with Mike Tyka (Mordvintsev, Olah and Tyka, 2015; Tyka, 2015). Both used the Deepdream algorithm, which conveys a strong expression recognisable among many generative algorithms (see Figure 15, showing artwork by Mike Tyka).

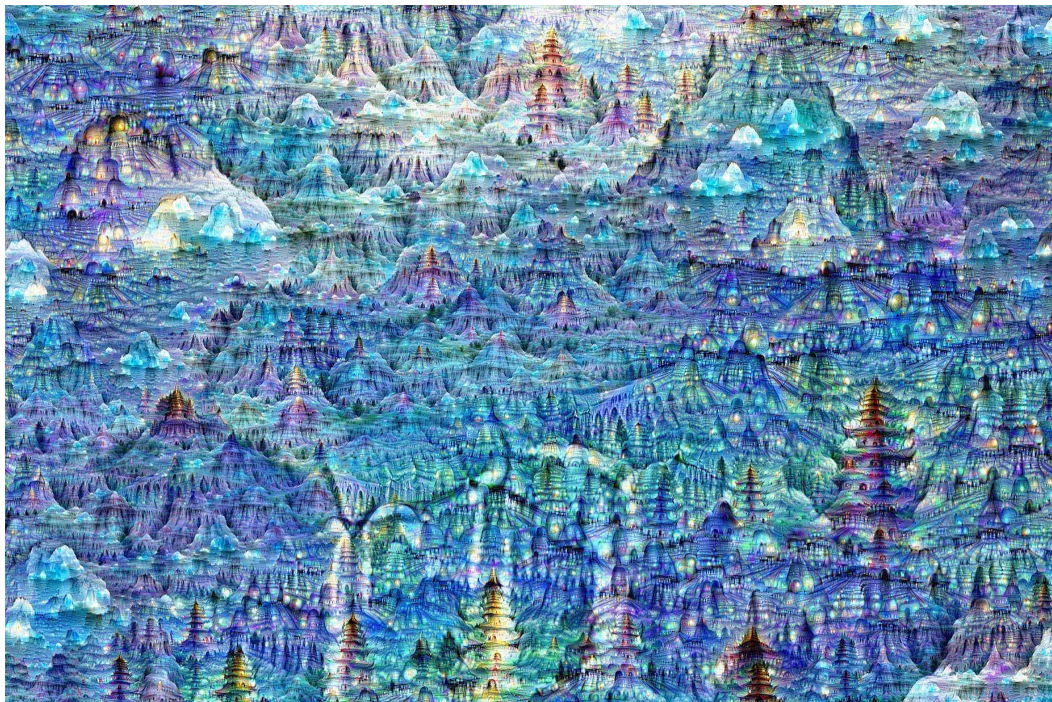


Figure 15. “Ground still state of God’s original brigade” by Mike Tyka. Neural net, Archival print, 60"x48", SOLD. 2016. Photo courtesy of the artist Mike Tyka. Title generated by LSTM by Ross Goodwin.

Artist Anna Ridler has explored crafting datasets by collecting thousands of pictures of tulips that have been annotated manually and then used to train a generative model (Ridler, 2018). The painting-like images by Mario Klingemann show the virtuosity, expressiveness and aesthetic sense that deep learning can generate, as shown in *Memory of Passerby I* (Klingemann, 2018). Robbie Barrat uses a deep generative model to create outfits from past fashion shows (Balenciaga) and plays with the absence of any contextual awareness of the functions of clothes, such as

whether a bag is “worn” or whether it differs in function from a background plant (Barrat, 2018). Sofia Crespo combines deep learning technology and biologically inspired productions, as seen in the piece “*This Jellyfish Does Not Exist*” (Crespo, 2020), shown in Figure 16. As a final example, Helena Sarin works on patterns found in nature and computational patterns. Her piece “leaves of manifold” is a book reporting two years-long work of training generative models on datasets of photos of flowering pear leaves, maple, and sweetgum leaves (Sarin, 2021)¹¹. Sofian Audry has recently compiled this practice in a book (Audry, 2021).



Figure 16. “*This Jellyfish does not Exist*” by Sofia Crespo, 2020. Photos courtesy of the artist.

Given that machine learning is designed as a technology to solve particular classification or content generation problems, how have artists been able to develop a practice with it? What is its specificity, and what perspective does this give on the technological object? To address these questions, and in particular to extract the materials used by artists in their creative workflow with machine learning, I recently conducted, in collaboration with Sarah Fdili Alaoui¹², a series of interviews of world-renown artists who pioneered the use of machine learning (the deep generative model in particular) in visual arts. We explore how machine learning shapes its creative endeavour through an interview study with five visual artists. The study not only sheds light on these particular uses of machine learning in art but also on critical

¹¹ This list is far from exhaustive, but it would be beyond the scope of this manuscript to describe the work of every visual artist using ML and AI. Here is a complementary list of artists: Daniel Ambrosi, Refik Anadol, Tega Brain, Sofia Crespo, Jake Elwes, Kyle McDonald, David Young.

¹² Although the study and analysis were done in collaboration with Sarah Fdili Alaoui, some of the interviews and transcripts were done with the help of Téo Sanchez and Siba Siddique.

aspects of how machine learning challenges notions of control and aesthetics, which led them to consider this technology as a creative material.

The five artists were as follows (and a sample of their artworks is depicted in Figure 17). **Memo Akten** is an artist, experimental filmmaker, musician and computer scientist. He works with emerging technologies and computation as a medium to create images, sounds, films, large-scale responsive installations and performances. **Jake Elwes** is a media artist. Their recent works explore their research into machine learning and artificial intelligence. Their practice looks for poetry and narrative in the success and failures of these systems while also investigating and questioning the code and ethics behind them. **Mario Klingemann** is an artist who uses algorithms and artificial intelligence to create and study systems. He is particularly interested in human perception of art and creativity, researching methods in which machines can augment or emulate these processes. **Kyle McDonald** is an artist crafting interactive installations, sneaky interventions, playful websites, workshops, and toolkits for other artists working with code. He explores possibilities of new technologies: to understand how they affect society, to misuse them, and build alternative futures, aiming to share a laugh, spark curiosity, create confusion, and share spaces with magical vibes. **Anna Ridler** is an artist and researcher who works with systems of knowledge and how technologies are developed to better understand the world. She is particularly interested in measurement and quantification and how this relates to the natural world. Her process often involves working with collections of information or data, particularly datasets, to create a new and unusual narrative.



Figure 17 Examples of artworks by each of the five artists interviewed in this article: A. *Journey through the layers of the mind* by Memo Akten [Photo Courtesy: Memo Akten], showing the poetry of what is happening inside the algorithm; B. *CUSP* by Jake Elwes [Photo Courtesy: Jake Elwes] where the machine learns qualities of different marsh birds; C. *Decontamination Chamber* by Mario Klingemann [Photo Courtesy: Mario Klingemann] showing machine ‘learning’ bodies and identities in order to reveal blurred shapes and colours; D. *Discrete Figures* by ELEVENPLAY, Rhizomatiks Research, MIKIKO, Daito Manabe, Motoi Ishibashi, and Kyle McDonald [Photo Courtesy: Kyle McDonald] explores the interrelationships between the performing arts and machine learning; E. *Mosaic Virus* by Anna Ridler [Photo Courtesy: Anna Ridler] shows a grid of continually evolving AI-generated tulips in bloom, bringing together ideas around capitalism, value, and collapse from different points in history.

We conducted interviews and analysed their transcripts in the methodological tradition of thematic analysis (Braun and Clarke, 2006). From this analysis, we have highlighted the importance of crafting in each artist’s creative process. Crafting appears at different levels of the machine learning process such as the way to handle model training or building a training dataset. Working with AI is approached by artists through a concrete experience of the algorithm’s behaviours rather than a theoretical understanding of its capabilities. Kyle McDonald said: “It starts with a technique, with the technology. And I kind of manipulate and explore that tech until I find something that is compelling to me, something that has a story that I’m interested in sharing or [...] that I want to pull back for other people as well.”

Therefore, starting from the technology's experience rather than its analytical understanding is essential in the artists' practice. This learning-by-doing approach leads them to develop specific skills related to the algorithms used. These skills do not refer to the ability to build better models in the sense of AI research (better accuracy, better data efficiency). Instead, they refer to the ability to better predict the system's behaviour so that it is more in line with their expectations. In other words, it is an ability to work with these materials for their expression. This specific set of skills is those of crafting, in the sense that artists favour a direct relationship with the algorithmic and data material (Torres, 2019). Mario Klingemann gave an example of crafting a model by understanding its behaviour when training an image generation model: "I usually never wait until the end, I constantly watch it, and while waiting, I learn about the process too [...]. After a few hours, I look at it and try to estimate if this goes where I want this to go".

Crafting also appears in how datasets are built to train a deep learning model. Anna Ridler makes an explicit link between the act of crafting and the creation of the training set, as opposed to the design of the algorithm: "I actually think that there are a lot of parallels between craft vs art and dataset vs algorithmic output. I think there are a couple of things like the relation between craft which is anonymous and less well regarded, and how it's repetitive versus art. And when you see dataset [...], the datasets are anonymous, and nobody talks or speaks about them. They are there, and people use them." In her work, crafting occurs explicitly when collecting and building the training set but also while training a model. Working with ML implies favouring the process over the outcome because it is difficult to anticipate the result of a specific model with a particular dataset. As Anna Ridler said, "I try to use it both as a process and a material".

In conclusion, artists invent new workflows. Despite being bound by what an AI-based system necessitates to process data, artists are finding freedom in curating the data, avoiding standardised measures of success and tweaking conventional steps of the process to get the desired outcome. They escape technology determinism that would impose an aesthetic on the produced artwork and criticise the trend of machine learning to normalise rather than diversify (see (Caramiaux and Fdili Alaoui, 2022) for more details).

The artists we interviewed built expertise from years of tweaking and playing with models. Although they do not have the technical backgrounds to invent ML algorithms that contribute to AI research, their experience in tweaking parameters and training models give them an acute expertise and sense of what the systems allow them to do and how to create a desired artefact out of it. The notion of crafting is critical here. Artists are engaged with the media through a close relationship with data and algorithmic material.

Focus • Material for pedagogy and democratization

The second focus in this section on the materiality of machine learning is about pedagogy and the democratisation of technology. Understanding the concepts underlying machine learning, or having more agency in developing machine learning systems, implies the need to provide interactions that encourage exploration (of models, data, outcomes). Exploration means iterations between users' actions and system feedback. Users need to discover the capacity of a model by trying out expected and unexpected input data or by acting on the model itself and re-iterating their tests. Therefore, what I have described above in how artists work with this machine learning can be transferred for the benefit of pedagogy and the democratisation of this technology in general. Focusing on the materiality of machine learning, as opposed to the final tasks, could thus help people to approach this technology and build an experiential knowledge of it.

In this section, I will articulate this perspective through Téo Sanchez's doctoral work, which I supervised with Wendy Mackay, investigating how novices teach machine learning algorithms. In this case, the model does not change, and newcomers discover its material expression interactively and shape it through data curation. Then I will present how this work led to creating a software solution, together with Jules Françoise and Téo Sanchez, that enables the design of interactive workflows with machine learning pipelines. This software was the basis for Teo's PhD work and was also used as a pedagogy for teaching interactive machine learning in graduate courses.

Novices' interaction with machine learning

The project originated from a collaboration with the *Association Traces*, a think-and-do, non-profit group based in Paris interested in science, its communication and its relationship with society. I had started a discussion with *Traces* shortly before this project, intending to take my research outside the lab and work with a different audience. In particular, I wanted to work with an audience with a diverse ML culture than the one that university students might have. At this time, *Traces* organised workshops and virtual sessions addressing a wide range of scientific topics for the general public. We (*Traces*, Téo Sanchez and myself) were interested in what "teaching an AI" might entail, including the concepts and values people might convey. This curiosity was the starting point of the collaboration.

Therefore, the interactive scenario involves teaching a model through data curation, which means deciding which data to use for training (or not). In this scenario, users have a direct experience of the effect of their data on model learning. This formalism, known as *machine teaching*, was at the core of Téo Sanchez's doctoral work, which investigated how novices in machine learning could handle the task of teaching a model some visual concepts (Sanchez, 2022). The objectives of this research were to highlight the strategies put in place by novice users to teach concepts to an algorithm,

to understand the knowledge they would acquire about ML through the act of model teaching, and to propose guidelines for helping the design of ML model development for a broader audience (tech democratisation) and designing through data material.

Our collaboration with Traces started with a workshop conducted at the *TurFu* festival in Caen and then through an online session of science outreach organised on the Twitch streaming platform (see Figure 18). The Twitch platform's live session was used as a pilot study to address our research questions. During this online session, people could try out the system and provide feedback in the chat. At both events, we proposed an application that allows people to train a classification model to recognise hand-drawn pictures using the computer mouse or trackpad.

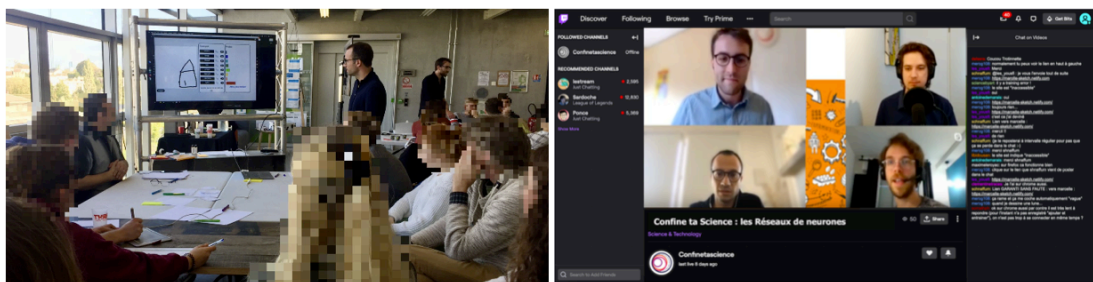


Figure 18 Pictures from the workshop during the *TurFu* Festival (on the left) and the Twitch session (on the right).

Three critical requirements steered the design of the application: (1) People should be able to produce their data to teach the system; (2) People should receive immediate feedback about the model's predictions and uncertainty; and (3) People should be able to use the application anywhere (without our intervention) and efficiently.

With the first requirement, we aim to involve users in generating and curating training examples. We use drawn sketches as inputs because sketching is a fairly common activity for people, and drawings are personal. Second, people need to be able to interpret the model's predictions, so we provide feedback on the recognised class but also how well this class is identified (or how confused the prediction is concerning the other classes). In addition, the model's predictions always embed uncertainty, which is also essential to convey to the users, especially the ambiguity of the predictions among the available classes. Third, our goal was to inspect novice users' real-world use of the system. As such, we brought particular attention to designing an application that can run online in any web browser that is easy to use.

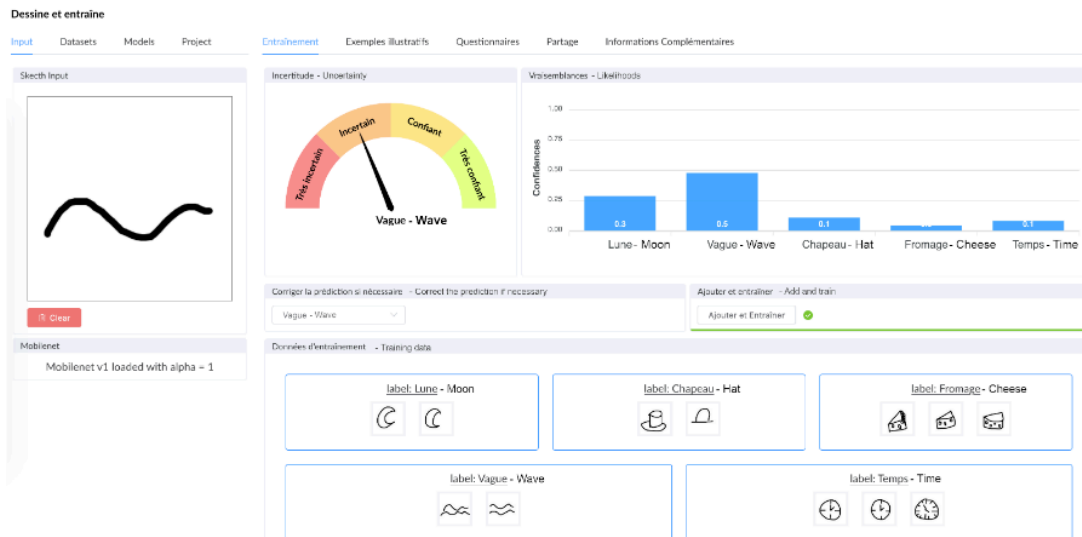


Figure 19 Interface of the sketch-based recognition application developed to study novices' ability to teach a deep learning model to recognise drawn sketches. The screenshot is adapted from the publication (Sanchez *et al.*, 2021).

The implementation of the scenario is illustrated in Figure 19 and was built using *Marcelle* (Françoise, Caramiaux and Sanchez, 2021) (more details are provided below). The left-side panel is dedicated to inputs. It exposes a white canvas where users can sketch drawings with the mouse. The right-side panel is dedicated to prediction, training and data visualisation. The workflow is as follows. The user draws a line ("sketch input") and releases the mouse button. Predictions are automatically updated (chart bars), as well as the prediction uncertainty (gauge). The user also receives feedback on the predicted label (drop-down menu below the indicator). If the user wants to correct the prediction, they can click on the drop-down menu, select the correct label, and then click on the button to update the training set and start training. Transfer learning makes model training fast (a few seconds)¹³. Once the training is done, the newly trained model automatically updates the prediction and uncertainty. The user can also choose not to add the drawing to the training set and keep adding elements to their drawings, inspecting the changes in predictions and uncertainty.

After the Twitch session, we chose to run further one-to-one sessions with participants, novices in ML and computer science. In each session, we use a think-

¹³ Transfer learning is based here on the use of a pre-trained model (MobileNet (Howard *et al.*, 2017)), which is used to extract well-calibrated features from a given image. The classification model trained in the application is the correspondence between the features provided by this model and the classes.

aloud protocol, a standard method for participants to describe what they are doing while they are doing it. In this way, we can interpret their actions on the data and the model qualitatively, using their terminology. The teaching task was similar to the Twitch workshop, teaching a classification algorithm from scratch to recognise hand-made drawings. The publication reports detailed results about novices' strategies and their understanding of machine learning. I would like to focus here on the results that I find interesting to reinterpret through the lens of ML materiality.

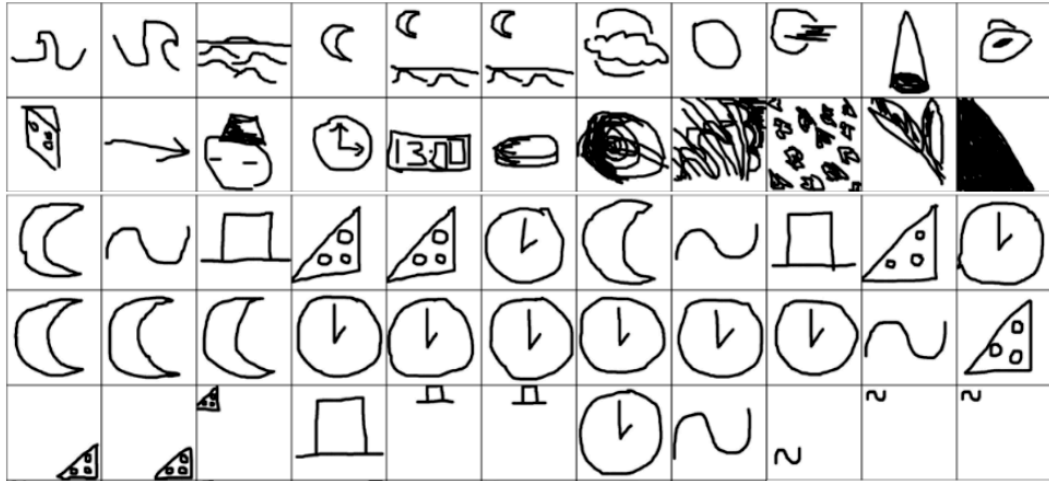


Figure 20. Examples of drawings provided by participants during the teaching task.

Data curation made participants explore the learning ability of the classification model, and this exploration was made possible through the immediate prediction for each drawing and the interactive model training. Through analysing the explanations provided while doing the task, we found that participants made explicit the properties of the data material. More precisely, they mentioned several properties that we divided into three categories: properties related to the *representation* of a drawn concept (shape, infilling, relief, etc.); properties related to the *execution* of a drawn concept (gesture); and properties related to the *operations* that would be relevant to apply to a drawn concept (translation, duplication, size, etc.). What I found interesting in this finding about materiality is that images, as graphical objects, have properties. Still, their situated use as a material applied to building a classification model alters (or enriches) the properties usually associated with images. For instance, “gesture” or “duplication” are properties that are not commonly associated with images.

In fact, images have properties that allow them to represent a concept, and people can operationally use them to create an image corresponding to the desired concept. But the agency of the image is the result of its interaction with the classification model and the person who interprets the model knowledge and infers the actions to do on the images. Suppose we interpret this finding through the lens of the Actor-

Network Theory (Latour, 1987). In that case, the images' agency is the effect of the network within which the images are situated, a network made (among other entities) of the deep learning model, the enabled interactivity, and the teacher.

Composing machine learning materials

Enabling interactivity with machine learning requires software solutions to mediate the interaction. These solutions have often been proposed according to the domain of applications or practice. Machine learning developers and researchers use tools to visualise their models' behaviour. Artists and designers use high-level solutions with hidden underlying learning mechanisms. This leads creative people with technical skills to create tools ad-hoc to their practice. I describe here a contribution of my research in this direction, which helps designers and creatives highlight this technology's materiality and work with it in their practice.

In collaboration with Jules Françoise and Téo Sanchez, we have initiated the development of a software library that allows designers and machine learning practitioners to compose interactions with machine learning pipelines and build dedicated interfaces for a wide range of users. In this section, I describe the library, called *Marcelle*, and then discuss its link with the materiality of machine learning technology. A full description of the library can be found in the published article (Françoise, Caramiaux and Sanchez, 2021).

We propose an architecture model that illustrates the way interactivity with machine learning materials has been thought of in the design of *Marcelle*. The model is based on five design principles enabling composing interactions with pipelines, and I describe three of them: components, custom workflows and composable interfaces.

First, we implemented a component-based architecture. Building interactive machine learning applications requires assembling interactions to facilitate the manipulation of machine learning objects. These objects of interest are highly heterogeneous and relate to various activities, as seen in the previous example reported above: curating data, training a model, deciding when to stop training, or changing the model's parameters. Therefore, users must operate upon various machine learning materials: data, algorithms, parameters, models, predictions, and explanations. The idea of the proposed architecture was to conceive building blocks for designing interactions that are components embedding data, computation, and interaction. Components enable granular interaction with specific elements of the machine learning pipeline. They can be flexibly composed to form higher-level interactions and workflows that support a wide range of activities. Components can typically be data sources (e.g. capturing images from a webcam, uploading files, recording user sketches as presented in Téo's work), data structures (e.g. a dataset used to store training examples), visualisations (e.g. to navigate through a dataset or to visualise predictions), computations (e.g. model training or prediction), or a combination. To

enable feedback and interaction, most components should also provide a graphical user interface that can be displayed on demand.

Second, we implemented customizable workflows. While in a typical machine learning setup, the workflow for training and testing might be standardized, enabling interactivity on machine learning pipelines involving custom workflows where the user can trigger various types of processing. For instance, a user can stop model training and add an image to a given class, automatically restarting training. It is essential to let developers create custom pipelines specifying complex relationships between the user's actions (e.g. capturing a new instance) and the resulting processing (e.g. adding it to a dataset, training a model, or updating predictions). Reactivity is critical to handle diverse workflows where streams of events of heterogeneous nature must be interconnected: streams of images, predictions, or parameters. Components operate streams of events and react to their changes. Altered streams of events outside components provide a powerful means for customizing the processing chain within machine learning pipelines.

Third, we implemented composable interfaces. Workflows encompass two main facets: the specification of reactive pipelines describing the relationships between various objects and actions, as described in the previous section, and the visual arrangement of components in the end-user interface. In their review of user interface design for interactive machine learning, (Dudley and Kristensson, 2018) underline that while common elements exist, the creation of interactive machine learning interfaces varies considerably according to the data and application. The proposed component specification includes an optional view allowing for visualization and enabling user interactions. However, how views are used in an application (e.g. where and when they are displayed) should not affect the logical relationships between components defined using reactive pipelines. We propose that components appear on demand. In practice, this means that multiple views could potentially be used to interact with the same components constituting the machine learning pipeline.

Marcelle allows us to build applications that enact various interactions with machine learning materials, such as data, parameters, model types, tasks, learning processes, and model explainers. Figure 21 depicts a mosaic of applications that are running online¹⁴. Each application is conceived as a set of components that structure the machine learning pipeline, and these components are linked together to shape the behaviour of the pipeline. Inputs can include webcam images, drawings, uploaded images, tabular data, and movement data.

¹⁴ <https://demos.marcelle.dev>

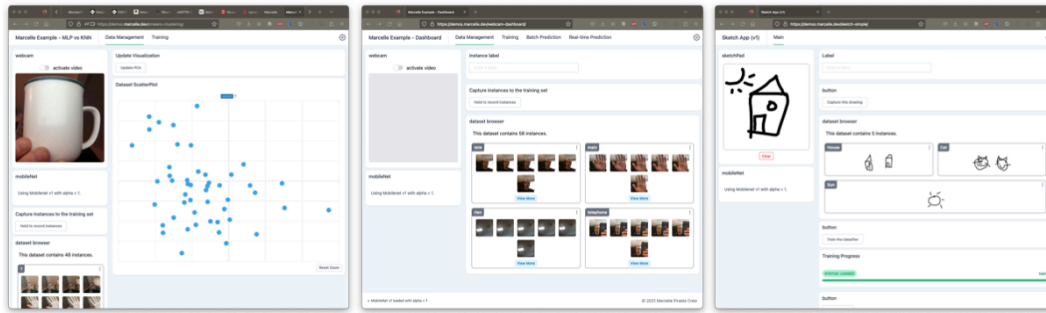


Figure 21 Mosaic of applications designed and implemented using Marcelle. These applications have various types of input data, visualisations and machine learning tasks.

Together with Jules Françoise, we teach Interactive Machine Learning as a graduate course. During this class, students build a scenario allowing the end-user (a designer, a domain expert, a creative practitioner, or a machine learning developer) to act on the elements of the machine learning pipeline to achieve a task contextualised in their practice. For instance, a scenario can help an application designer (novice in machine learning) build a robust model with limited but curated data.

To realise their scenario, students must investigate existing research and applications that address a similar use case. From there, they produce a mock-up of their scenario that will serve as a reference for the implementation. The implementation is realised using Marcelle. We observed that students use existing examples and demos to build their projects. By copying and pasting pieces of code, they efficiently create prototypes of their scenario. Each piece of code is often linked to interactive concepts between components of the machine learning pipeline: for instance, the code describes a new image from the webcam turned into an instance of a dataset and sent to a model for prediction.

```
input.$images
.map((image) => featureExtractor.process(image))
.map((features) => classifier.predict(features))
```

This code fragment describes the example described above. The goal is not to teach how to read this code. Instead, I want to illustrate how Marcelle allows working efficiently with elements of the machine learning pipeline through code reuse of behaviours. Code reuse enables users to think of their scenarios from a high-level perspective. Ultimately, this malleability of the programming practice provides a sense of crafting machine learning materiality.

Discussion

In the previous Part, the creative and artistic context showed the limitations of seeing machine learning technology as a tool. In particular, it made apparent how machine learning is crafted before becoming a stabilised tool used in practice. Here we proposed a perspective where we think of interaction design with machine learning as assemblages between its constitutive elements, such as data, models, or visualisations. These assemblages were made possible by enabling the materiality of the technology. I grounded this view in the past and ongoing research on digital materiality in design research and human-computer interaction. I also showed that machine learning materiality is enabled through interactivity.

This position was illustrated with two foci from my research, conducted with PhD students, post-doctoral researchers and collaborators. As a first focus, I took the case of machine learning as creative design material in sound design and visual art-making. I explicitly showed how interactive training through human feedback can be used to explore and create sounds in a high-dimensional sound space. The importance is then given to the trajectory the algorithm takes in the learning process rather than the final model obtained. This was further investigated through interviews of visual artists using machine learning in their practice. Materiality became explicit in data curation, model training (and the decision made when stopping the model's training), serendipity in the outcomes, and the acquisition of experiential skills of machine learning (as opposed to technical skills).

As a second focus, I took the case of pedagogy, in particular, providing novices with interactive machine learning systems performing image classification, which they can train according to their own success criterion. By allowing interactivity with the algorithm's training phase, we made the machine learning materiality apparent to the participants who could develop strategies, through data curation mainly, to shape the model's behaviour. We showed that images acquired agency due to their interaction with the classification model and the person who interprets the model knowledge and infers the actions to do on the images. The agency of the material is the effect of the situated context made of its different actors. Such systems used in the research were built with a software library that allowed compositing interactive machine learning pipelines and tailored interfaces. The library implements several machine learning and visualisation components that can be linked and interacted with, producing a malleability in developing machine learning systems and applications.

The learning process: an interface for machine learning materiality

The common thread in the work I have presented in this Part has been to consider users (artists or novices) in interaction with the learning mechanisms of the algorithms. Considering machine learning as a material (or a set of materials) means that the person interacting with this material must deal with the changes due to the

algorithm's learning. These changes orient the subsequent actions performed by this person. Sound designers send their preferences to the algorithm to steer towards the zone of interest in the sound space. Novices vary their sketches in such a way that they can explore the blind spots of the model. Visual artists are literally watching the model training to understand it and decide how to influence it in the way they are interested.

The actions taken by users during the learning process are therefore situated within the interactive learning procedure. What does this imply in terms of machine learning materiality? First, I argue that this materiality is exposed to the users during this situated interaction because users can experience the properties of the different materials of machine learning through their influence on the model's behaviour (and, therefore, the system they are building). Second, I believe that this also exposes the agency of this material. As discussed above, within the project of machine teaching of a sketch recognition system, the agency of sketch results from its contextualisation as an image used to train a neural network-based recognition algorithm by a novice in machine learning in the situation of experimental research practice. In other words, human and material agencies are redrawn in context or reconfigured (Suchman, 2007).

Studying interactions between users and the machine learning process also creates epistemological difficulties. While in machine learning research, a novel algorithm is assessed through fixed benchmark datasets, the assessment of a machine learning algorithm in interaction cannot be dissociated from user interaction. User actions and machine learning changes are interdependent. In the first study presented, sound designers guided a reinforcement learning-based algorithm within a parametric sound space. This example shows that the most interesting phenomena resulting from the interaction between sound designers and the artificial agent are occurring in the exploration of the sound space mediated by the optimisation mechanisms used by the algorithm under the hood. The model cannot be assessed in isolation, and the user's actions depend on the algorithm changes. However, this might not be what one expects from a machine learning system, often seen as a problem solver. When we submitted this work to one of the leading journals in the field of HCI, we received the following review:

“The paper does not provide proof that training the Reinforcement Learning-agent produces meaningful policies. For instance, a perceptual comparison between the sounds produced from random parameters and the parameters suggested by participant-guided policies could have been conducted at the end of the workshop. I understand that policy learning is not the focus of this work but showing proof that users successfully guided the agent towards the desired goal would definitely strengthen the paper.”

Indeed, in the study, we let sound designers train a model without caring about the produced policy. But what would a “trained” model mean in this case? And more fundamentally, when can we consider that we should stop training a model? I have started to discuss this point in the previous Part. Here the question becomes more pressing as we are explicitly looking at the interaction with the learning mechanisms. In the different projects I have mentioned, very few eventually considered the trained model.

The hidden craft

I began this chapter by recalling the history of the deep learning breakthrough through the presentation of a seminal paper at a machine learning conference in 2012. Taken from an article in the sociology of science and technology by Dominique Cardon and colleagues (Cardon, Cointet and Mazières, 2018), this story was used to highlight both the technical and design innovation behind the breakthrough. In addition, the purpose of starting with this story was to show the ubiquity of the practice of craft in machine learning and this outside of creative and artistic contexts. Machine learning practice in technical fields is heavily based on iterative processes, trial-and-error, and intuition, which lead to conversations with digital materiality. However, it is not presented as such. The notion of craft is rarely put forward in the community, where we can find specific cases related to particular machine learning problems, such as crafting adversarial examples in deep learning security (Papernot *et al.*, 2016). In general, the notion of craft is hampered by a discourse of machine learning that emphasises the automatic and autonomous nature of this technology, disembodied from its socio-technical context of development.

Visual artist Anna Ridler criticises this posture that hides craft over something nobler. We mentioned in the text the way she discussed the distinction between craft and art-making and the distinction between dataset creation and model design. When talking about the piece she did that required the annotation of thousands of pictures of tulips, she said:

“Yes, I took 10,000 pictures of tulips. I labelled them as well. It’s insane, it’s driven me crazy, but it’s also like, one of the things through the process of doing it. [...] It reminded me of the early computing history in the 1940s [...] You’ve got all of these hidden histories: a lot of the early programmers were women and did the calculations by hand and as it became more professionalized it became a more male industry, but [earlier] it was a heavily feminized industry of lots of women doing very boring jobs by.”

In summary, the point I would like to make here is that the materiality of machine learning and the crafting of these technologies that it underpins is, in fact, a practice that exists beyond the creative and artistic contexts. These contexts allow us to

expose such materiality and crafting practice. But, although these practices may exist, they are often hidden at the expense of a dominant discourse that reflects a culture and politics, which I propose to analyse in the following lines.

Culture

*“Caterpillars extract nutrients which are then converted into butterflies.
People have extracted billions of nuggets of understanding and GPT-4¹⁵ is
humanity’s butterfly”*

Geoffrey Hinton’s Tweet, March 14th, 2023

In recent years, I have been involved in several European endeavours to investigate the opportunities, challenges and risks of using artificial intelligence in the creative and cultural sectors. Artificial intelligence, technically implemented as a set of machine learning techniques, has entered the sectors of music, visual arts, fashion, museum and cultural heritages, film, publishing and writing, and architecture. It is used in content generation, forecasting, artist identification, assisting decision-makers, personalisation and customer services with the following objectives: reducing cost, improving decision-making, engaging the audience or inspiring creation. Artificial intelligence has become needed in the face of the increasing digitisation of cultural artefacts. As a result, cultural and artistic actors are torn between the desire to experiment with this technology within their practice and the desire to avoid the pitfall of techno-positivism that would not correspond to their needs and habits.

The formal outcome of this collective effort has been to deliver white papers and cultural policy recommendations. In these reports, we have captured the problems that artificial intelligence could address and the need for stakeholders to have a say in how this technology should be used in their sector, if at all. We had many informal discussions on machine learning and artificial intelligence from a cultural

¹⁵ GPT-4 (Generative Pre-Trained Transformer 4) is a multimodal language model developed by OpenAI.

perspective. I attended meetings between researchers, archivists, artists, art and museum curators and activists. During these meetings, I could hear a generally critical tone, not necessarily about the technology itself but its cultural representation within mainstream media, which was (and still is) presenting artificial intelligence in normative ways. As an illustration, if I were doing a simple web search with the keyword ‘artificial intelligence’ on my laptop computer, I would obtain the result reported in Figure 22, showing a consistent representation of the term as humanoid robots, typically surrounded by a blue background contributing to the decontextualisation of artificial intelligence (no here and now). The results were similar if I used the keyword ‘machine learning’. During these meetings, we discussed pragmatically the de-mystification of artificial intelligence, which involved the diversification of representations of the technology through alternative cultural references to humanoid robots.

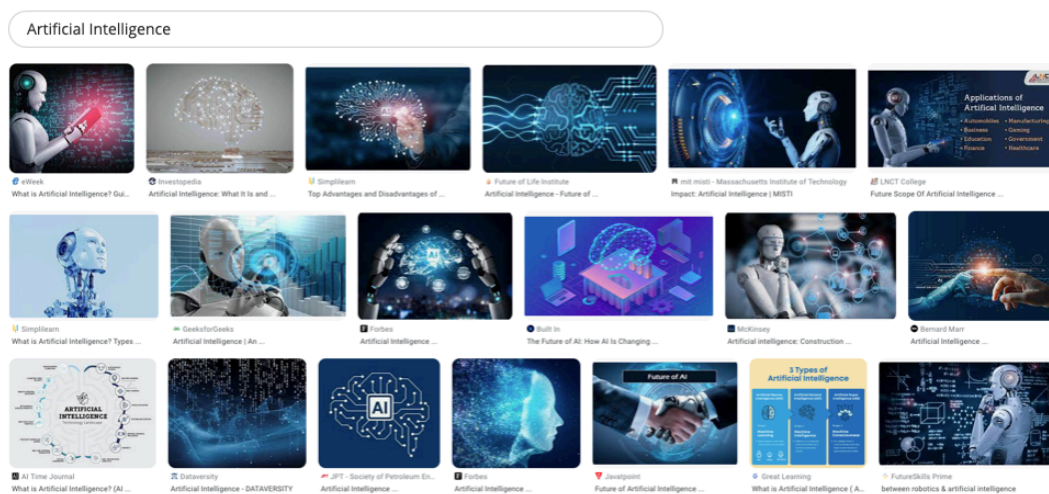


Figure 22. Web search results from the query "artificial intelligence" on a popular engine.

In the previous chapters of this manuscript, I presented machine learning as a tool performing a task and then as a material used to design the tool, instrument or application. I have shown machines capable of learning things or classifying concepts. However, I have not discussed what terms like “learning” or tasks like “classifying concepts” can trigger as imaginary for the user. And I have not highlighted how these imaginaries are also shaped by those who develop the technology. In this chapter, I articulate a cultural perspective on machine learning (and artificial intelligence) regarding the references taken by the “machine learning makers” to communicate about this technology. I argue that this view is prescriptive and normative and propose deconstructing it to imagine alternative interactions with this technology. I highlight examples of these alternative interactions through artistic stances on the subject.

A normative standpoint

Machine learning algorithms are data-driven. These algorithms rely on data collections and often annotated descriptions of these data that are culturally and politically imbued content (Pasquale, 2015; O’neil, 2017; Eubanks, 2018; Noble, 2018; Benjamin, 2020; Crawford, 2021). Take the example of image recognition tasks. Images are the visual representation of a concept, which will be annotated to be described with words. The way images are collected (the socio-cultural and socio-political contexts of data collection, often performed by companies through little-qualified and low-paid labour (Tubaro and Casilli, 2019)) and the terms used to describe its content are necessarily subject to biases due to the situated context within which this process is performed.

However, the cultural representation of machine learning does not convey the idea of a situated technology whose weaknesses and biases are acknowledged. On the contrary, machine learning communicates a normative standpoint, which I can summarise as more rational and faster than humans. And this is reinforced by the ambiguity of the terminology through the use of ‘artificial intelligence’. My position is to challenge a normative viewpoint communicated as technological determinism. Machine learning deserves its successes and the imaginary that goes with it, i.e. its vision and fantasy. However, it becomes problematic when one viewpoint becomes dominant.

In this section, I start by presenting the twist in terminology between machine learning and artificial intelligence. This will lead me to present the ideology of artificial intelligence as a disembodied and rational intelligent agent. This ideology is reinforced by its immersion in cultural codes such as games and creativity.

Terminological twist and anxieties

Over the last decade, there has been a shift in terminology from machine learning to artificial intelligence. While the former is usually associated with the technique able to extract structure from data and makes a prediction based on it, the latter is multifaceted and does not only refer to the underlying technologies involved. The former remains within academic disciplines interested in creating techniques able to perform more complex tasks better, finding ways to interact efficiently with it, or exploiting its discursive power. The latter spreads over academia, industry and culture through media such as images, films, and articles. In a recent article, Meredith Whittaker recalls the deep learning breakthrough that occurred in 2012 (that I also highlighted in the introduction to the second chapter of this manuscript) and the change in terminology that followed (Whittaker, 2021). She wrote:

“The year 2012 showed the commercial potential of supervised machine learning and the power of the term AI as a marketing hook. Tech companies quickly (re)branded machine learning and other data-

dependent approaches as AI, framing them as the product of breakthrough scientific innovation. Companies acquired labs and start-ups, and worked to pitch AI as a multitool of efficiency and precision, suitable for nearly any purpose across countless domains.”

Artificial intelligence, as a term, is not new but was invented after the second world war. And it is grounded in a large body of cultural and artistic works, especially literary works of science fiction. Western culture imagined very early on other types of intelligence and how human-made techniques can automate the tasks we have to do. In a recent UNESCO report (Kulesz, 2018), Kulesz mentioned that in the Iliad, “*there were mentions of automatic tripods, fashioned by the god Hephaestus to carry out his tasks*”. More recently, creating artificial life was shown in famous works such as Metropolis, Frankenstein and Terminator. The word Robot comes from the play R.U.R (Rossum’s Universal Robots) by the Czech writer Karel Čapek, where robots mean slaves, rebelling against humans at the end of the piece.

In the way it is communicated for marketing purposes, the term artificial intelligence conveys an image that goes beyond the one of a significant technological breakthrough but intends to highlight humanity’s power over nature (including humanity itself). If humans can build machines that are more intelligent than themselves, it means that they dominate nature. Knowledge and Science bring us to this state of affairs, where a machine can now compete with humans in many fields and is pitched as “suitable for nearly any purpose across countless domains” (Whittaker, 2021).

This terminology twist from machine learning to artificial intelligence brings anxiety to observers and researchers. While machine learning, although technical, seemed better defined, artificial intelligence remains deliberately vague. This has been commented upon in relation to a related concept, algorithms, in the anthropology of science and technology. In his article “*Algorithms as culture*”, Nick Seaver writes that algorithms, which were seen as well-defined by humanities scholars, were in fact “*something of a modern myth*” (Barocas, Hood and Ziewitz, 2013), “*to which great importance and power are ascribed, but whose properties are ill-defined*” (Seaver, 2017). The algorithms in question referred to technological solutions deployed by large companies capable of processing large amounts of data and producing a service in return. That is to say, something quite close to what we call artificial intelligence in this Part.

Seaver writes that humanist scholars studying algorithms might not have understood what algorithms are because this concept, through its ambiguous terminology, has somehow slipped through their fingers. This ambiguity in terminology can create *anxieties* for researchers about dealing with a concept that is initially thought to be well described but ultimately not. In his view, these terminological anxieties are an essential characteristic of critical algorithm studies: “*it is because terminological anxieties are first and foremost anxieties about the boundaries of*

disciplinary jurisdiction, and critical algorithm studies are, essentially, founded in a disciplinary transgression.” Then it becomes interesting not to provide a general definition of this terminology but to study its existence in various communities of practice.

In a simple analogy, it is also fruitful to study its existence and enactments in various communities of practice. So, how is artificial intelligence enacted in machine learning and artificial intelligence research communities, the communities that are technically contributing to it?

The ideology of artificial intelligence

In the machine learning research community, artificial intelligence means designing and implementing algorithms capable of simulating *human intelligence* in terms of perception or decision-making. This definition is helpful in that we understand that we are talking about something that is evaluated against human capabilities (further detailed below) and that we are talking about something that is computational.

With this in mind, I would like to discuss the terms. Intelligence is a broad concept, which is likely to find a different definition depending on the social group within which this notion takes shape. Furthermore, the term artificial is also problematic. Understood as technical, through machines, this term is constructed in opposition to what is considered natural. However, what is natural intelligence? Isn't the observed or designated intelligence in someone also the result of social and material interactions with the environment? My position here is to argue that the culture of machine learning, through the term artificial intelligence, does not explore the complexity and diversity of the concept behind “intelligence” and “artificiality” but takes the disembodied form of efficient, rational thinking.

To illustrate this point, let's focus on games. Games, such as chess or go, often culturally associated with the figure of the genius, have been often considered benchmarks for human intelligence and, as such, are the basis for the assumption that if machines can beat humans on this field, machines are on the path to exhibiting '*artificial intelligence*'. As Crawford said, “Unlike everyday life, games offer a closed world with defined parameters and clear victory conditions. The historical roots of AI in World War II stemmed from military-funded research in signal processing and optimization that sought to simplify the world, rendering it more like a strategy game” (Crawford, 2021), p.213.

This culture has been perpetuated until now. A first and famous example that occurred before the deep learning breakthrough was the win of Deep Blue in 1997 against the world's best chess player Garry Kasparov. Then, DeepMind, a private company owned by Google, focused its communication on the fact that it is developing artificial intelligence technologies capable of competing with (and beating) humans (even the world's best players) at games. They initially focused their strategy on combining the power of deep learning and reinforcement learning. As a

result, they achieved several breakthroughs showing above-human performance in Atari (Mnih *et al.*, 2015) and Go game (Silver *et al.*, 2016, 2017). In the film retracing the story of AlphaGo, the software based on reinforcement learning that won against one the best Go players in the world, the firm's CEO says: "The number of combinations of the [Go] board is more than the number of atoms in the universe. So even if you took all the computers in the world and ran them for a million years, that wouldn't be enough computing power to calculate all the possible variations. If you ask a great Go player why they played a particular move, sometimes they just tell you it felt right." Therefore, creating an algorithm capable of playing Go is perceived as going beyond a technical feat, which amounts to constructing an algorithm that will not try all combinations but will react in the best way to a particular situation. Such an algorithm, if possible, is imbued with intuition.

However, these games are based on logic, bounded by possibilities, evolving in a finite world free from complex interactions. Note that I do not underestimate the conceptual and technical progress of the research carried out by the DeepMind teams, research that has had significant consequences in other fields, such as bioinformatics (Jumper *et al.*, 2021). My goal is to highlight and bring a critique of a dominant culture of artificial intelligence as it is highlighted here: a form of disembodied rational intelligence.

In this sense, I am joining similar critiques that can be found among other researchers and commentators (Broussard, 2018; Crawford, 2021)). In particular, I am taking a quote by Neville-Neil highlighting the fact that intelligence could not be solely understood as disembodied:

"We have had nearly 50 years of human/computer competition in the game of chess, but does this mean that any of those computers are intelligent? No, it does not, for two reasons. The first is that chess is not a test of intelligence; it is the test of a particular skill or the skill of playing chess. If I could beat a Grandmaster at chess and yet not be able to hand you the salt at the table when asked, would I be intelligent?" (Neville-Neil, 2020), pp.247

This culture carries a cognitive ideology of artificial intelligence as strategic engineering. I am using the term ideology on purpose to emphasise the predefine character of the prism through which intelligence is analysed and assigned to an artificial being.

Creativity and the unexpectedness

In the example of Go introduced previously, the moves designated as creatives were those to which the observers (and players) paid the most attention: they were waiting that the algorithm would make unexpected moves because such moves would be perceived as a sign of intelligence. As Lee Sedol, the professional Go player who lost

against DeepMind’s algorithm, said: “I thought AlphaGo was based on probability calculation and that it was merely a machine. But when I saw this move, I changed my mind. Surely, AlphaGo is creative.”

Creativity and art-making are among the characteristics that are often considered exclusive to the human species. It is, therefore, hardly surprising that creativity and art-making have been taken up as an additional challenging benchmark for machine learning and artificial intelligence methods in human’s quest to compete with nature (understood as what is there but beyond the socio-cultural constructions of human beings). The machine learning research community and companies have quickly placed a strategic focus on creative applications. As an example in visual arts, when the first artistic experiments with neural networks appeared, particularly when using the Inceptionism algorithm (Mordvintsev, Olah and Tyka, 2015), companies such as Google set up exhibitions and artist residencies. Companies pushed and incentivised the cultural appropriation of the technologies they were developing.

Several creative and artistic projects have involved machine learning algorithms in the process. However, when mainstream culture has picked them up through online media, podcasts or television, they have often been communicated by the terminological twist described above, i.e. celebrating the victory of artificial intelligence over human creativity and artistic creation. This was the case in many creative and cultural sectors¹⁶, for which, in these mainstream media, we could read “the first {painting/movie/song} created by an AI”.

In cinema, the short movie “Sunspring” screenplay was generated (and curated) thanks to the text generation algorithm written by Ross Goodwin. It was not surprising to see it communicated as “*a short science fiction movie written entirely by AI*”¹⁷. The music album “Hello World”, released in 2018 in France, has been composed using Flow Machines, a set of tools that generate musical arrangements. The album was then recorded in a studio and curated by SKYGEE, a (human) composer, and communicated as the first music album composed with artificial intelligence¹⁸. More recently, in 2022, the cover image of a general public magazine was made using a text-to-image generative algorithm (Dall-E2 based on Dall-E (Aditya et al., 2021)) and announced as the first magazine cover made by artificial intelligence. The magazine went even further by crediting the generative algorithm

¹⁶ In 2019, I co-edited a white paper for a European institution on the implication of machine learning technologies in the creative and cultural sectors with Fabien Lotte and Joost Geurts. We could show their ubiquity and the challenges they pose (Caramiaux *et al.*, 2019).

¹⁷ <https://arstechnica.com/gaming/2021/05/an-ai-wrote-this-movie-and-its-strangely-moving/>

¹⁸ <https://www.helloworldalbum.net/>

in its title as the creator of the cover: “*The World’s Smartest Artificial Intelligence Just Made Its First Magazine Cover*”¹⁹.

I have given three examples, taken among a wide range of cultural artefacts where machine learning was involved in their creation but communicated by mainstream media in a way that highlights artificial intelligence as a provocation against humans. This communication shows that artificial intelligence is now intelligent enough to create artwork and fast enough to do it. This narrative is similar to the one conveyed in the cultural realm of games, such as go or chess, described in the previous section. We can read in it an intention to put us (humans) in competition with technology and to challenge us on our identity as humans endowed with intelligence and creativity. We can read that our intelligence and creativity may not be so unique and could be replicated.

But, the challenger remains an entity that is never defined and perceived as disembodied, immaterial and super-intelligent (according to the axes of efficiency and performance).

Summary

I have tried in this section to articulate the dominant perspective of what artificial intelligence, boosted by underlying data-driven machine learning techniques, conveys. I used the word ‘perspective’ in this summary but used the term ‘ideology’ previously. The word ‘ideology’ might feel strong, but I think it conveys the fact that the dominant view is based on beliefs that are not meant to be put into question. These beliefs are constituted of a set of results on understanding human intelligence and a conception of the artificial. I acknowledge this standpoint and consider it one way to see artificial intelligence. But, as we shall see, there is no one truth, no matter how well it is communicated. The problem arises when one view is promulgated as the norm. As result, is there only one way to conceive our interaction with artificial intelligence? In what follows, I propose to deconstruct this norm to provide a vision where a diversity of standpoints coexist, and I focus on the domain of HCI, which seems to me to be the appropriate domain to provide a framework and operational tools to implement these alternative perspectives, with the help of artists and other actors from the cultural sectors.

¹⁹ <https://www.cosmopolitan.com/lifestyle/a40314356/dall-e-2-artificial-intelligence-cover/>

Deconstructing the normative standpoint

The main argument of the previous section is to show that, through a terminological twist, where machine learning becomes artificial intelligence, we enter a cultural realm dominated by disembodied rational intellect and the opposition between artificial and natural. This narrow but dominant view of the matter is problematic in many ways I am describing here, taking as theoretical foundations previous works in feminist theory and social inquiry of science and technology. Based on these theoretical foundations, I am refocusing the issue of machine learning as a disembodied form of knowledge promoting objectivity from the perspective of Human-Computer Interaction to rethink interactions with technology.

When culture meets nature

“I would like to insist on the embodied nature of all vision and so reclaim the sensory system that has been used to signify a leap out of the marked body and into a conquering gaze from nowhere. This is the gaze that mythically inscribes all the marked bodies, that makes the unmarked category claim the power to see and not be seen, to represent while escaping representation. This gaze signifies the unmarked positions of Man and White, one of the many nasty tones of the word ‘objectivity’ to feminist ears in scientific and technological, late-industrial, militarized, racist, and male-dominant societies, that is, here, in the belly of the monster, in the United States in the late 1980s. I would like a doctrine of embodied objectivity that accommodates paradoxical and critical feminist science projects: Feminist objectivity means quite simply situated knowledges.” (Haraway, 1988), pp. 581

In this text fragment from her essay “*Situated Knowledges: The Science Question in Feminism and the Privilege of Partial Perspective*”, Donna Haraway rejects the idea of objectivity in science that would lead to ‘universal truths’, brought by disembodied scientists looking at decontextualized facts. In this idea of objectivity, there is the myth of purity, where objects of interest are detached from the scientist’s subjectivity, the influence of the social forces in the laboratory, or the political context within which the science is enacted. Objectivity is seen as a means of hierarchizing knowledge by separating what belongs to nature (beyond humans) and culture (within humans), the object from the subject, the individual from the group, and other equivalent binarities.

In contrast, knowledge is situated and embedded in social and political contexts. And this also applies to technological knowledge and innovation. Haraway’s famous figure of the Cyborg (Haraway, 1985) brings forward the idea of an entity that cannot be assigned to a category and transcends polarized views (artificial-natural, female-male, etc.). To this view, objectivity is seen as a reductionism, a simplification

designed to maintain existing power relations by those whose values and interests are aligned with the conditions of objectivity (typically white, Western-cultured men).

The concept of objectivity, as highlighted by Haraway, has also been rejected by other humanists of science and feminist theorists of science, more or less at the same time. Bruno Latour also underlined the danger of the idea of purity in science, which is said to be exempt from the context in which its practice takes place (Latour, 1984). For him, the scientific practice is a staging between the scientists and the studied objects, mediated by instruments and techniques (Latour, 1987). There is no such thing as Science (with capital S) as an objective inquiry for truth. The scientific practice has its own mode of existence (Latour, 2012), meaning its mode of veracity, depending on its condition of development in the laboratory or the field, just as other fields have their mode of veracity (such as justice or politics, for example). And the problem arises when one mode of veracity becomes hegemonic and encroaches on the others, for example, when the scientific mode of veracity becomes synonymous with truth by the facts it studies and wants to apply them to politics or justice, for example (Latour, 2012).

Karen Barad, in her famous book “Meeting the Universe Halfway” (Barad, 2007), explores the concept of diffraction, introduced by Haraway, that rejects the idea of one truth but emphasises that several approaches, texts, or traditions need to be dialogically read “through one another”. Her book’s title is evocative: it is not a question of discovering an objective and immutable nature but of finding it halfway, where our instruments lead us and where nature reveals itself. The phenomenon resulting from their meeting (or intra-action) is the source of knowledge. Beyond these examples, a large body of work addresses this and related issues concerning the state of knowledge and practice, where different perspectives and the intersections between these perspectives from social, cultural, economic or political groups need to be taken into account (Crenshaw, 1989).

Returning to artificial intelligence, I aim to deconstruct the dominant standpoint described above with the help of these theories. As promulgated within the community that technically contributes to its development, this technology takes the form of a disembodied authority. This posture is similar to that attributed to science and challenged by sociologists and feminist theorists, whose point of view has been briefly introduced above. Artificial intelligence, as is often said, is presented as an immaterial and disembodied entity: it is not made of matter. It has no tangible, visible form in the physical world. And artificial intelligence was a long time seen (and sometimes still) as neutral because of technical. The theoretical literature presented above helps us to deconstruct a normative view that is too often promulgated in specific communities of research practice related to machine learning. The problem is not that this community focuses on technical aspects of the technology. Technological research, innovation and development have their own *mode of existence* (to borrow Latour’s words) that leads to knowledge creation.

The problem begins when an ideology is put forward and alienates other standpoints.

So, why is the culture of disembodied, decontextualised artificial intelligence problematic? First, it conveys that there is only one way to conceive artificial intelligence and machine learning, based on an enormous amount of aggregated knowledge through data scraped from the Internet without curation and little moderation. This point of view is part of an economic and political agenda where data are resources, as is the computing power offered by clusters of computers, and where machine learning is envisaged as an instrument to exploit these resources. This view is proposed by corporations who have built their business models based on an ecosystem and infrastructures that make them the only ones with the computing and data resources to effectively develop machine learning.

Second, and related to the first point, this culture of artificial intelligence de facto excludes any other kind of “intelligence” or “artificiality”. There are many ways of looking at intelligence and artificiality, which can foster alternative practices that promote efficiency, rationality, performance and competition. Diversity in visions can lead to implementing an alternative design for the technology. These alternative views may come from marginalised groups and various communities of practice. One of these is artists with whom I have worked and to whom I will return in more detail later in this chapter. As Harding showed (Harding, 2004), any production of knowledge and technology that is detached from a marginalised, or less represented, community’s daily experience is more compatible with a group whose needs are already met, as opposed to disadvantaged groups, for whom these needs have not been met. Indeed, the involvement of communities of practice and marginalised groups will surely redistribute the cards in the design, architecture and deployment of this technology.

The standpoint of Human-Computer Interaction

Since the field of Human-Computer Interaction is interested in phenomena related to when human users and technology meet, the area is in a position to help explore alternative views and interaction design principles between human users and machine learning.

As a matter of fact, HCI has enriched the set of possible interactions that humans can have with machines beyond an objective, cognitivist view of interaction that marks the first wave of HCI (Bødker, 2006). In the field’s history, third-wave HCI has shown the rise of embodiment in interaction design (Dourish, 2001), promoting body-driven methodologies as opposed to rationality-driven ones (Höök, 2018). Third-wave HCI also showed the rise of affective computing (Picard, 2000), which makes a significant place for emotions in interaction, and user experience (McCarthy and Wright, 2004). In other words, the field of HCI has embraced other perspectives

where interactions are co-constructed between the users acting in the environment and the things with which they interact.

In this context, the feminist theory of science has made its way to HCI with authors such as Bardzell (Bardzell, 2010; Bardzell and Bardzell, 2011; Rode, 2011). Shaowen Bardzell wrote (Bardzell, 2010):

“As computers increasingly become a part of everyday life for ever increasing populations in the world—from the rise of domestic computing in the West to the rise of ICTs for developing countries—the stakes have never been higher. Digital interactions mediate people’s relationships with friends and loved ones, with society, and with culture itself. As we aspire to develop more pervasive, ubiquitous, and universal technologies, we inevitably also must engage in the increasing moral and intellectual complexity of our professional activities.”

The goal of the feminist agenda in HCI is to design interactive systems that enable agency, equity, empowerment, social justice, and diversity. It prompts the need for socio-technical theory in HCI (to escape the utilitarian view of social science and ethnography as a way to generate implications for design (Dourish, 2006)). The theoretical groundings come from feminist theories of science such as the works of Donna Haraway (Haraway, 1985, 1988), Karen Barad (Barad, 2003, 2007), Sandra Harding (Harding, 2004), or Judith Butler (Butler, 2002) (among others).

Feminist theories and methodologies have given rise to a rich body of research in design and interaction design, an exhaustive list of which is beyond the scope of this manuscript. As cherry-picked examples, feminist theories in HCI led to address questions regarding women’s health (Talhouk *et al.*, 2016), the gender-related binarity embedded in the technological infrastructure (Spiel, 2021), or intersectional studies on race and gender (Schlesinger, Edwards and Grinter, 2017). This has led to a rethinking of HCI in terms of a new wave of entanglements between humans and technological beings, where we, as HCI researchers, no longer design computational systems that are interactive but we design interactions with systems that are entangled with our individual and social lives but are invisible, immaterial, and intelligent (Comber, Lampinen and Haapoja, 2019; Frauenberger, 2020). However, this last point of view seems to take for granted that intelligent infrastructures are themselves objectified, leaving little space for a co-construction with the users of these. AI infrastructures are spreading but they are not immutable.

Feminist theory of science has emerged in opposition to the culture promulgated by research and innovation in machine learning technologies. This culture, which I highlighted in the previous sections, gave rise to several systems that demonstrated racist, sexist, and discriminatory biases against marginalised communities, to which there was a need for a theoretical and methodological response. In particular, in algorithm fairness and transparency, intersecting research in machine learning and

social science and humanities, questions about the position of marginalised communities regarding machine learning technology are critical (Hanna *et al.*, 2020). Strategies have been to organise events in conferences, discussing, for instance, the positionality of machine learning, similarly that one has their own partial view (Kaeser-Chen *et al.*, 2020). The authors wrote: “Every perspective has its limits – there is no view from nowhere. Without an awareness of positionality, the current debate on bias in machine learning is quite limited: adding more data to the set cannot remove bias”. In a recent study, Klumbyté and colleagues went further and organised workshops where students in ML and HCI were invited to think through the lens of critical algorithm studies and feminist theories about machine learning and artificial intelligence (Klumbyté, Draude and Taylor, 2022). In general, the movement is still in its infancy. In my work, in collaboration with Hugo Scurto and Frédéric Bevilacqua, we initiated the formalisation of diffractive methods to inform art practice with machine learning (Scurto, Caramiaux and Bevilacqua, 2021).

Summary

Seminal works in the feminist theory of science and science and technology studies provided the grounding to rethink our interactions with machine learning in a way that allows *meeting halfway* with the technology. HCI and related fields at the intersection with machine learning have recently involved these critical concepts in operationalizable actions. I want to enrich this work by promoting artistic practice and research-creation as a means to further this agenda. In particular, I first give the floor to artists working with artificial intelligence to understand their perspective on this technology and how they move away from a dominant culture emanating from the field. Second, I am presenting an artwork I made in collaboration with a Berlin-based artist collective. This dance-theatre piece features humans and non-humans, including artificial intelligence. It deals with the inherent entanglements between species and the resulting violence and empathy, reflecting current issues in Western society.

Focus • What are AI artists saying about AI?

This focus examines cultural issues related to machine learning from the perspective of artistic creation. I choose to focus on artistic practice because it allows for an alternative view to the conventional narrative put forward by the actors of the technology, and in the case of machine learning, by the community contributing to it technically. Being freed from the normative constraints of research in this field opens up new readings of technology, questioning its rational, disembodied and exploitative nature.

Machine learning, or artificial intelligence, can become an object of artistic interest. For example, Hito Steyerl developed the visual and spatial installation “This is the

Future”, a speculative future represented by plants or animal forms generated by a machine learning based algorithm. The artwork also criticises humanity’s desire to control what is yet to come. Another example is the work “G5” by Rocio Berenguer, where representatives of the 5 types of entities on earth (vegetal, mineral, animal, human, and artificial) are meeting to address fundamental questions of living together. In my work in collaboration with artists Marco Donnarumma and Margherita Pevere, we explored AI as an actor in the performance, which will be further detailed in the next section.

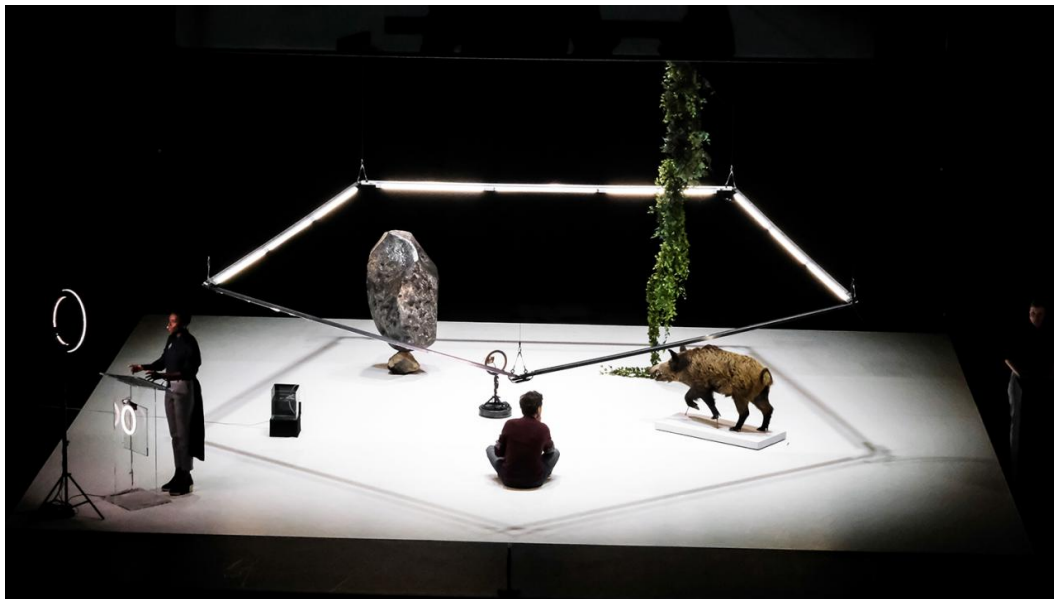


Figure 23. "G5" by Rocio Berenguer, describes an imaginary meeting between a representative from the five species on earth: mineral, vegetal, animal, human, and artificial. Photo courtesy of the artist.

Machine learning can be used in creative and artistic practice as a tool, a material and a cultural object. In the previous chapter, I presented a work conducted with Sarah Fdili Alaoui (Caramiaux and Fdili Alaoui, 2022), in which we interviewed five world-renowned visual artists about their use of machine learning in their creative process, with a focus on how artists highlighted the materiality of this technology. The second part of the findings of this study focused on the politics behind the use of machine learning in the artists’ work and how they are aware of and make these explicit. I propose to present the second part of these results in this chapter, echoing the above theoretical elements on questioning a normative discourse of artificial intelligence, leading to technological determinism, which was seen as disembodied and objective.

As a reminder, the five artists that we interviewed were: Memo Akten, Mario Klingemann, Anna Ridler, Jake Elwes and Kyle McDonald. A snapshot of their work is reported in Figure 17. At the time of the interviews, most of these artists were using a widely used generative machine learning model called Generative Adversarial

Networks (or GAN) (Goodfellow *et al.*, 2014), which was state of the art in generative models from 2014 to around 2020 (Creswell *et al.*, 2018). Two were residents at the Google Arts & Culture Institute in Paris.

I mentioned in the introduction of this section that artists have the freedom to escape from the values of artificial intelligence research culture. From our interviews, the artists expressed that they do not abide by the epistemological values dominant in artificial intelligence technology and are defined by the constraints, goals and standards of researchers, engineers and big corporations. Even if they use the same computational methods (such as GANs), they express their freedom from the underlying constraints resulting from AI culture's values, such as accuracy, productivity and performance.

For instance, Anna Ridler opposed the epistemological values of AI research by reconciling the distinction that has been made between data and model, particularly the distribution of visibility and power between the ones developing the models and the ones producing the datasets:

“In all of the big scientific papers that come out (ICML, NeurIPS, etc.) the scientists are known but the person who put together the datasets [or created the labels] is not known. The datasets are anonymous, and nobody talks or speaks about them, they just sit there and people use them. [...] I think there could be something interesting to unpack and explore there.”

The field of machine learning has very few examples of datasets whose authors have been acknowledged. One example is ImageNet (Deng *et al.*, 2009), which has enabled the development of deep learning and has brought forward underlying critical problems with large datasets, such as the temptation of cumulating always more data, computational construction of meaning and making part of the underlying work invisible (Denton *et al.*, 2021). While scientific progress in AI constrains the evaluation of the models on specific datasets, the artists grant themselves the freedom to choose the data to use, avoiding the standardised mappings between content and annotations. Mario Klingemann pointed out this by saying: “I can use materials that they [research scientists] might not be able to use. For example, when I collect training data, I do really just pick anything. And if you are doing scientific research, you are limited to ImageNet, for instance.” In other words, AI then conveys a different meaning: it is no longer a model that has to achieve the highest performance on fixed standardised tasks but a material fused with data, producing meaning and representations for artists and audiences.

Second, the power dynamics existing when working with artificial intelligence are concrete and made clear by the artists. Artists expressed that crafting AI is a challenging and exclusive task that only some can access, either for lack of skills or computational power. In AI research, we typically witness that the models are released. Still, the data are not, and the artist may not have access to enough

computational power to train the models anyways. In this context, Kyle McDonald reported that the main challenge is to make these technologies more inclusive: “sometimes that means taking something very complex and technical and sharing it with other people in a way that gives them access to something they wouldn’t have access to otherwise. Sometimes that means tool building. Sometimes that means storytelling in a way that gives you like a direct experience of something that’s happening behind the scenes.” According to him, making AI more inclusive is particularly challenging because the design of this technology is on purpose “*opaque*”, reinforcing how the power of understanding and developing them is retained among the few researchers and corporations that release them. In his words:

“They’re designed generally to, like I said, reinforce power rather than question power. And they resist our attempts to open them up actually. [...] there’s just certain kinds of curtains we cannot pull back. You know, we can kind of see what’s on the surface and like dissect that a little bit. But then at some point we hit a wall. We can’t look inside Google, we can’t look inside Facebook. We can’t look at their algorithms. We can maybe read the research papers that they publish sometimes because it turns out that the current iteration of machine learning, which is deep learning, has been very open about the research process. But even when we read those papers, like ultimately, we don’t have access to the data that they use, we don’t have access to the computing resources that they use.”

Not having all the ingredients leading to the creation of the final tool is a way to keep some mystery about the system’s capabilities, to put forward a discourse centred on magic rather than practical explanation, and a lesson centred on ideology rather than materialism.

Third, and finally, we found that the artists engage with ethical questions regarding their responsibility regarding how they use AI, which does not obviously occur with other technology. For instance, Jake Elwes said, “it’s your responsibility [as an artist] to not necessarily explain the technology, getting people to think slightly deeper of what this stuff is capable of, and convey a bit of a message about it”. This does not mean an artwork produced with machine learning must convey a message about the technology. But the status of AI in Western culture is such that the use of this type of technology will surely trigger an emotional response in the audience. Jake Elwes expressed regret for the specific use of “AI to kind of bamboozle the public”. His way of using it ethically is by being “very honest about it [AI] because I think there is far too much miscommunication around it [AI]”.

As mentioned in the previous sections, AI has been widely used in the (mainstream) media and the academic world to refer to a wide variety of techniques but rather specific values. These definitions and scope delimitations have an inherent ethical agenda. For example, in the previous section, I mentioned the arbitrary binarity

between nature and culture and between artificial and natural intelligence. Kyle McDonald shared his thought on that:

“There’s the obvious understanding of what artificial is, a kind of artificial as opposed to natural, that we have a sort of natural intelligence in humans. I don’t find that to be a super helpful distinction personally because of the fact that I see intelligence as very collective and hybrid itself. [...] What do you call a crowd of people working together? Is that a natural intelligence or is it kind of artificially created out of their relationships? I’m not sure. [...] I think that there’s also artificial for me ties back to a very long history of basically anybody in power abusing their power to diminish those that they deem kind of lesser. [...] this idea of distinguishing between the natural and artificial, for me, it connects to other kinds of classifications that have been used to reinforce power. And that’s disturbing to me. I think we have to be careful about using those kinds of terms.”

This quote illustrated what I mentioned early in this chapter about the alternative views of “intelligence” and “artificiality”. These alternative views help reflect on technology and culture. The artists acknowledge that working with artificial intelligence is not neutral. This inspires them to develop a critical discourse in their artworks about the politics and ethical pitfalls behind this specific technology. As a technology fundamentally designed to analyse massive amounts of data, there has been a high incentive for surveillance applications. In the piece entitled “*Learning to See: Hello World!*” Memo Akten involved elements of reflection on the link between artificial intelligence and surveillance. The work uses a CCTV camera that captures images of the exhibition hall. It then feeds the artificial intelligence model that ultimately recreates a vision based on what it has learned to see, cf. Figure 24 (left). In “*Exhausting a Crowd*”, Kyle McDonald explicitly involves crowd surveillance, where an online audience is invited to tag human activity from CCTV images from a public space, cf. Figure 24 (right).

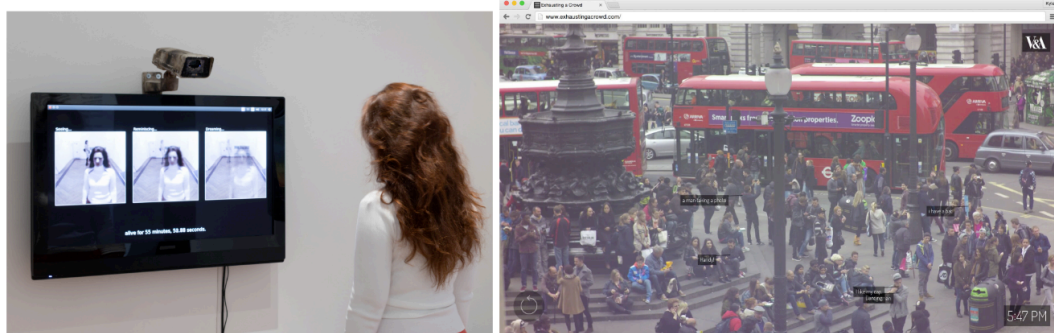


Figure 24. (left panel) “*Learning to See: Hello World!*”, 2017, by Memo Akten [Photo Courtesy: Memo Akten]; (right panel) “*Exhausting a Crowd*”, 2015, by Kyle McDonald [Photo Courtesy: Kyle McDonald]

In conclusion, by analysing these artists' practices, I have highlighted how political issues related to artificial intelligence are made explicit. Through different forms of art, the artists question the dominant position of the algorithm over the data. The algorithm is compared to the art, while data is compared to craft and hidden. This dichotomy keeps the technologies developed opaque, which leads to a disembodied technology that escapes us. This is also made clear by artists who question the notion of artificiality as opposed to the natural. This change in discourse is, therefore, there, but still not made apparent enough. Importantly, these views are then enacted into artworks conveying alternative experiences and narratives.

Focus • Humane Methods

This second *focus* examines the question of artificial intelligence as a cultural and political object in an artistic performance that I developed in collaboration with artists from the Berlin-based Fronte Vacuo collective²⁰. *Humane Methods*, a dance-theatre production, involves human and non-human performers, including artificial intelligence. The piece was initiated in 2019 and premiered in 2022.

Through the presentation of the *Humane Methods* and the process of its creation, I seek to show how the play enacts a performative realisation of the theoretical aspects mentioned above, including the critique of a disembodied technology, the power relations between human and non-human entities, and the critique of the arbitrary separation between natural and artificial, object and subject, and individual and group.

Research-creation methodology

Humane Methods is a dance-theatre production that began with a long-term collaboration with artist Marco Donnarumma with whom I have already worked on a piece presented in the first chapter of this manuscript. Humane Methods inherits from these past collaborations, where machine learning, involved in both works, evolved from a tool to perform gesture recognition to a political object, an actor of the performance. Elements of this evolution were described in a dedicated article

²⁰ Fronte Vacuo is a collective of artists based in Berlin, Germany. Like a fungus, then, Fronte Vacuo started growing underground, soon ramifying itself through an extended network of artists and researchers with diverse backgrounds and interests, ranging from stage design, wearable sculpture, engineering, architecture, computer science, cultural studies, curatorial practices and cultural production. <http://frontevacuo.com>

(Caramiaux and Donnarumma, 2021), where we implemented a research-creation methodology.

Research-creation is an interdisciplinary methodology where artistic practice intersects with experimental research practice to provide new insights on topics of inquiry (Springgay, Irwin and Kind, 2005). A particularity of the method involves an experimental procedure that cannot be determined in advance and usually relies on speculations. Sarah Truman discusses research-creation as “situated speculations” (Truman, 2023), where an artist-researcher speculates about aimed potentialities that unfold during the creation process while being situated in the larger context unique to the researcher through their subjective positionality. Similarly, Erin Manning highlights that research-creation involves being “speculatively pragmatic” (Manning, 2016), which means being interested in “the pragmatic force of the conditions of the here and now, while simultaneously remaining oriented to the as-yet-unknown”.

Therefore, in research-creation, we start with ideas and speculations but we avoid setting up fully planned objectives. The researcher’s positionality (their “situatedness”) is part of the research practice, which means that the researcher is not investigating the object of interest from a detached perspective (the objective vision criticized by Haraway and other theorists in science and technology studies). Still, the researcher is part of the investigation (so does their subjectivity). Research-creation represents a relevant framework for exploring art and science coupling, for it generates knowledge from action, self-reflection and empirical experimentation (Biggs, 2004).

Research-creation has been used in human-computer interaction, where art practice intersects with computer science and social science. In this sense, research-creation is intrinsically linked to art-led research, research-through practice, and performance-led research. One of the objectives of implementing such methods in HCI is to leverage the creative nature of artists to study alternative use of technologies. As Steve Benford put it: “artists’ uses of emerging technologies are often highly innovative and unusual, stretching the technology in unforeseen ways, highlighting new design values and approaches that are sometimes contrary to received wisdom in HCI (e.g., ambiguity or discomfort [...]), and opening up new areas of application.” (Benford *et al.*, 2013).

Using art-making as the drive of the research inquiry allows for studying alternative uses of technology that would not have been made apparent otherwise, leading to new knowledge in HCI. The methodology has found an echo in dance performances by conducting interviews of artists on stage as well as members of the audience (Fdili Alaoui, 2019; Correia *et al.*, 2021), showing emergent relationships between dance, media and interaction as well as the tensions and negotiations that emerged from integrating technology in art. In music performances involving machine learning technology, Fiebrink and Sonami have reflected on their long-term researcher-artist

relationship through mutual interviews, highlighting how machine learning became part of the artist's practice in a way that was not predictable (Fiebrink and Sonami, 2020). In my research, I have used a research-creation approach to document and reflect on the use of machine learning in music making and performance (Caramiaux and Donnarumma, 2021), through my collaboration with Marco Donnarumma, which I detail below.

Creation, production, termination

The Humane Methods project is a collaborative endeavour that involves, aside from the collaboration between myself and artist Marco Donnarumma, a shared authorship between Margherita Pevere and video artist Andrea Familiarì, who form the Fronte Vaccuo collective. In particular, the artistic concept for the piece was jointly created by Pevere and Donnarumma and then furthered through close collaboration with the others like myself. I collaborated with the collective from the initial idea in 2019, the design of the machine learning software and research, until the premiere in 2022²¹. The original idea of the creative work was to work on the violence generated by the polarisation of opinions in the social and political spheres, accentuated by the increasing part played by algorithmic methods in our access to and communication of information. The play is set in the context of our contemporary Western societies, in which we grew up and were educated.

The play initially involved two performers dressed in grey cloth. These performers were not talking and started in a world not identifiable in space and time. The world was filled with vegetal, organic forms and cables. The piece included an additional presence embodied on stage through lights and sounds. In the background, an algorithm we built controlled these two media. This initial version of the algorithm was desperately trying to optimise a function that had no meaning. By trial and error, the algorithm slowly converges to the solution before being reset at a specific interval.

In June 2019, we had the opportunity to collect subjective feedback from the audience during an open rehearsal at the Centre des Arts Enghien les Bains (CDA). Our encounter with the audience in France was significant, for it allowed us to open our aesthetics and research to a general public, most of whom had little or no familiarity with the ongoing project or our previous works. We found that several

²¹ I should mention that the COVID-19 pandemic has slowed down the creation and production process. In fact, this period was very difficult for artists worldwide. In France and Germany, Culture was one of the last sectors considered by the governments. Several theatre and concert venues, but also museums, remained closed for months after the end of the first lockdown.

spectators did not realise that music and light were driven by an algorithm. This feedback confirmed our intuition about the challenges of making artificial intelligence perceivable to a public audience. Our algorithm only manifests indirectly through lights and music without a physical embodiment. But this was a choice we made to reinforce our critical stand on the impact of artificial intelligence in society; this technology is pervasive and ubiquitous while simultaneously invisible and implicit, integrated seamlessly as they are in institutional structures and interpersonal lives. “Our AI” was designed with this in mind and is therefore omnipresent and unobservable.

As a second step, the Humane Methods project expands into a series of dance-theatre artworks: ΔNFANG, ŪR, ΣXHALE, δISSOLUTION. Each one is called a rhizome of the Humane Methods project, which follows the initial task of exploring the multi-layered nature of today’s violence in our societies. The communicated project description was that “the project departs from the assumption that through the physical and psychological brutalization of people and non-human beings, the combination of digital technologies and the capitalistic urge has driven the natural ecosystem towards impending destruction. The project then aims to dissect the violence of algorithmic societies, where power structures, knowledge creation, and normative criteria become means of manipulation.”

I will focus on ΣXHALE, the ‘rhizome’ in which I have been the most involved. The piece starts with an ecosystem of catharsis, a biome not meant to be situated in time and space, similar to the play’s first version. But now, the audience sits in greenhouses, creating a physical separation between their space and the world of the piece (Figure 25 shows a part of the stage with the greenhouses in the background). The greenhouses are made of transparent and semi-transparent materials, which allow the audience to see what is happening outside. And it will allow performers to interact with the audience during the unfolding of the piece.

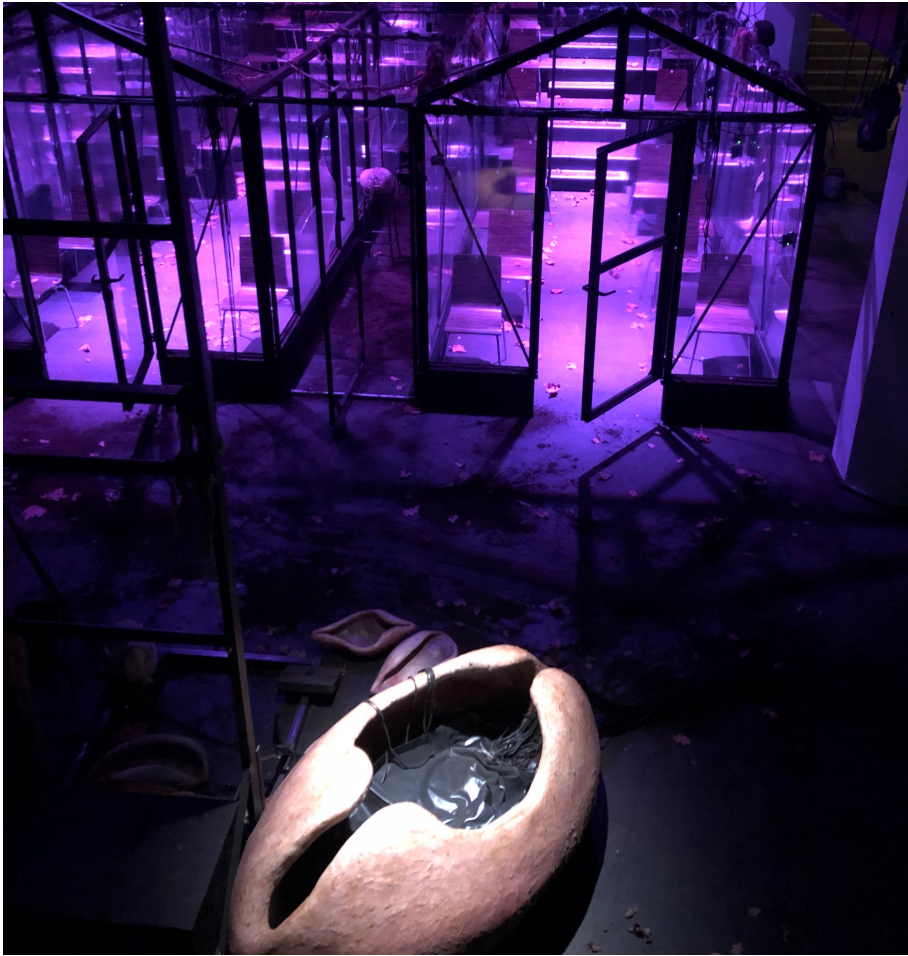


Figure 25. Picture of the scenography before the beginning of the performance. The audience is sitting in the greenhouses and watching the performance through the transparent windows. The stage is filled with organic shapes, cables, and plants.

Outside, the stage is filled with human and non-human beings, including plant specimens and fungi growing on costumes, uncompleted or destroyed architectural structures, and silicon-based beings – such as artificial intelligence algorithms running on computers and visualised on screens. Six human performers are on stage, dressed in grey cloth, and their faces are initially hidden. They move slowly among cables and organic forms.

From the original version of the piece, we kept the structure in loops, where performers repeat some actions to learn what the world is made of. At the beginning of each loop, they return from where they come from. At the end of each loop, they reach a point always further. Conceptually, each loop involves humans who dictate instructions through actions, and algorithms pick up instructions and repeat them in their own way. The other living things suffer instructions and capital increases. Then it repeats: humans dictate, algorithms repeat, living things suffer, and capital increases. It is an intricate network of relations, entanglements, a continuous loop of

actions and consequences, where everyone has a responsibility (humans and non-humans).



Figure 26. Photo courtesy of Giada Spera. Picture from a live performance of *Humane Methods* at RomaEuropa Festival. Portrayed is one of the iterations of the ritual at the core of the performance. It is possible to observe in detail the lighting generated by the AI.

In the piece, the overwhelming authority of humans is put into question. They try to dictate but feel dictated from the audience's perspective. Seedlings, fungi and custom-made artificial intelligence software (<dmb>) are co-creators. <dmb>, the "AI performer", orchestrates rhythm, music and lights in response to the actions of the other performers. This new version of the algorithm sees through video cameras that are sometimes fixed and sometimes hand-held by performers. The algorithm learns what it sees and reconstructs it endlessly in a "brute force" way. The results are projected onto screens (see Figure 25 (left)) dispatched in the greenhouses.

ΣXHALE puts into question the viewpoint of the audience. Placed in the greenhouse, the audience feels safe and detached from this world that it does not understand but whose violence is perceived. As the loops continue, the performers interact with the audience through the semi-transparent windows. The audience, which initially had an outside view of the stage, is now part of it. During the performances, we saw people engaged and affected by these interactions and others trying to avoid them. The audience had to think about their position in this world of violence and ritual. But, a striking moment is when the piece ends. The greenhouses open while the performance continues, slowly but unchanged. The audience is free to leave. And so, there is no clear ending. There is a continuity between the moment of the performance and the moment of their reality outside. There is no moment for applause, so there is no clear break between fiction and reality. The audience leaves still feeling the experience of the play. This is a vital element of the piece that clarifies this idea of a continuous interplay between entities and situations. Polarities are erased.

Discussion

This chapter addresses the perspective of machine learning as a cultural object, which means the representations technology takes on when it is removed from its purely technical character. I am talking about visual representations, as illustrated at the beginning of this chapter, but also, and especially, conceptual ones. First, machine learning took the form of a broader concept termed ‘artificial intelligence’. Ill-defined and culturally loaded, the term triggers cultural imaginations borrowed from a Western history of science and technology: a disembodied, rational, efficient agent in competition with humans. The problem I tried to highlight is that this view alienates others, and there is a lack of constructive discourse on its underlying beliefs.

To explore fruitful ways to interact with machine learning, and artificial intelligence, I proposed deconstructing the dominant standpoint through the feminist theory of science and previous related work in science and technology studies. This theoretical work helps bring a perspective where polarisation and binarities are avoided to give space to mutual and transformative agencies between the different actors situated in their context. The idea is not to consider artificial intelligence as this disembodied and rational entity that competes with us but as an alternative form of intelligence in an alternative form of materiality.

In this endeavour, I believe that creative and artistic approaches give a fruitful voice, which I showed through the testimonies of visual artists on their use of artificial intelligence, as well as through a dance-theatre piece on which I collaborated criticising the power taken by artificial intelligence in our Western algorithmic society and depicting how it is part of a network of entangled entities (humans and non-humans). This is a personal reflection and an academic work in progress that I wish to nourish and pursue, as explained in the future perspectives at the end of this manuscript.

Some critics and answers

The task of highlighting the cultural and political tenants of technology exposes, by rebound effect, my subjectivity and cultural baggage that allows me to hold this discourse. The exercise is, therefore, risky and can lead to critics. Here I present some of the critics, gathered through feedback, and propose a response.

For some readers, the call to deconstruct the dominant view of artificial intelligence might seem idealistic. I am aware that part of the problem with the widespread view of artificial intelligence, as described above, stems from marketing strategies related to corporate objectives for developing and exploiting this technology. And proposing to deconstruct their communication of artificial intelligence will not change it. However, this deconstruction can inspire other actors, such as those in the creative and cultural sectors, and help them imagine different perspectives, applications and designs using artificial intelligence. The products of these sectors may help demystify

and decolonise artificial intelligence and, in turn, affect the communication of the leading players in the machine learning field. Peter Drucker said, “culture eats strategy at breakfast”. This saying refers to innovation and entrepreneurship strategy but can, in my opinion, be applied here to illustrate that culture here enables artificial intelligence adoption. Note that culture refers here to what Simondon defines as “a basis of meaning, means of expression, justifications and forms. A culture establishes a regulating communication between those who possess it” (Simondon, 1980). Eventually, there is a cultural battle between AI corporations, pushing their agenda, and a local, diversified, dynamic, and non-structured counter-power made of people and creative and cultural actors.

Second, to emphasize the disembodied nature of artificial intelligence technology, I presented examples of techniques used in games and creativity without mentioning the fact that, behind the scene, there was a myriad of people operating the various levers of the machine learning pipeline to make them work (engineers, designers, scientists, experts, marketers, policymakers, micro-workers, and more). Artificial intelligence is, therefore, not detached from human actions and agency. However, the argument I intended to make was not to say that artificial intelligence requires human labour. We actually know it does. In the AlphaGo movie, there is particular care to demonstrate the team’s collective effort, including their anxiety a few days before the match, as the algorithm did not look as good as expected. Still, they had no time to run any more training sessions. The film did an excellent job of showing the collective human emotion during the construction of this entity. We know that artificial intelligence is, eventually, a collective human effort (with its apparent inequalities). The narrative is that collective human effort creates machines able to compete and overcome their creators. And what remains is the outcome of this effort.

Conclusions

“Not a given, it’s ongoingly and actively constituted and reproduced.”

Lucy Suchman

Machine learning is widely discussed in many academic fields and beyond academia. So, why did we need another text on the matter? Because machine learning lacks articulated perspectives as a situated object in interactions with people, infrastructures, and contexts of development and use. Machine learning is “ongoingly and actively constituted”, to use Suchman’s words, due to these heterogeneous situated interactions. Whether it is used to perform a data analysis task by scientists in the context of an experimental study; used by an artist to build a body-based musical instrument in rehearsal rooms or live on stage; used to reflect on our contemporary societies by a humanist scholar; or used to build a state-of-the-art image classification model by a machine learning expert; machine learning is in interaction with people, within a context situated in time and space. Then its use in any project is subject to neither neutral nor obvious decisions. One of the contributions of this Habilitation was to make this point explicit through theory and focused examples, contextualised in Human-Computer Interaction, and shed light on what it means to say that machine learning is “used”.

Three contemporary views

I chose to focus my Habilitation on *machine learning in interaction* to have the opportunity to bring together three views: that of a tool, a material, and a cultural (and political) object. Like many decisions, this one is motivated by a subjective position linked to my research object and the context of my research practice.

Working with machine learning as a tool has advantages, as I have shown in studies of human perception or in the movement-sound interaction design, where machine learning was used for gesture recognition. The process starts by isolating a problem and then formalising it in a way compatible with the tasks handled by the machine learning algorithms. However, this view obscures other rich phenomena in the interaction, especially during exploration and hesitation in the tool’s design. This is

demonstrated in creative and artistic applications, where iterative processes are critical. Looking at it as a design material helped me enrich the picture. The tool now has a materiality that can be used as such. Machine learning can be crafted, its crafting practice can be described and analysed, and its expressiveness as a material can be exhibited. But, the decisions made while using the machine learning tool or while crafting this material are imbued with the cultural representation we (designers, artists, scientists) had of the technology. The terminology used plays a critical role, as well as the vision and fantasy triggered by what is feasible with this technology. Considering the representations machine learning conveys and its associated values make it possible to complete the analysis.

Having said that, I wish to add that these perspectives (tool, material and culture) were not born with this manuscript. These perspectives have existed heterogeneously and fragmentedly in the fields of human-computer interaction, design research and the literature on science and technology studies. As I mentioned in the first part of this manuscript, machine learning users often refer to technology as a tool to help them perform tasks, whether functional or creative. Indeed, in the art world, it is not uncommon for an artist to compare generative algorithms to a new tool, augmenting the possibilities of a medium, such as a computer. Similarly, several academics have written about machine learning as a design material in design research, particularly intending to create interactions that enhance the user experience. In a recent event addressing the use of artificial intelligence in the cultural and creative sectors, a theme that I have been involved in over the past years, a researcher in AI Ethics was giving a talk with the following structure: AI as an instrument, AI as an infrastructure, AI as an ideology. The similarity with the chosen perspectives in this manuscript was striking, even if the content was, for her, about law and justice.

Being situated in these different socio-cultural and socio-economic research contexts, I am also inspired by and infused by this previous work. Here I participate in this effort by combining the tool, the material and the cultural object in the same text and putting them into interaction. I presented these three perspectives in three separate chapters of this manuscript. But this was not motivated by the desire to separate them. Their separation was artificial insofar as it was staged to show the interdependencies between the first and the second, the second and the third and the first and the third. These perspectives are contemporary and not separable.

Future perspectives

My research activity so far has primarily focused on studying and developing machine learning-based systems to support creativity, human learning and pedagogy. However, more recently, I have been increasingly attentive to considering the social, political and cultural framework of academic research projects involving machine learning. A first reason was to avoid the pitfall of carrying an uninteresting and dangerous normative discourse, as illustrated in the third Part of this manuscript. A

second reason was to guide the design and evaluation of systems to reflect a scientific approach that promotes people’s agency, equity, empowerment, social justice and diversity.

This interest has taken shape through ongoing research projects. These projects increasingly involve collaborative settings and situated interactions. For example, we recently explored how a group of users collaboratively taught an image classification system in a project led by Behnoosh Mohammadzadeh and supervised by Jules Françoise, Michelle Gouiffès and myself. In this preliminary study, the task was to train a system to recognise dance styles from images. Each participant could upload images through a web application, train a classification model locally and then share the data and the model with the rest of the group. Participants could also share insights with their collaborators via a chat. The application worked online, accessible from a phone, tablet or computer, whether at home, on the move or at work. Participants’ data were secured. Figure 27 depicts a snapshot of the application that we developed in the context of this research project.

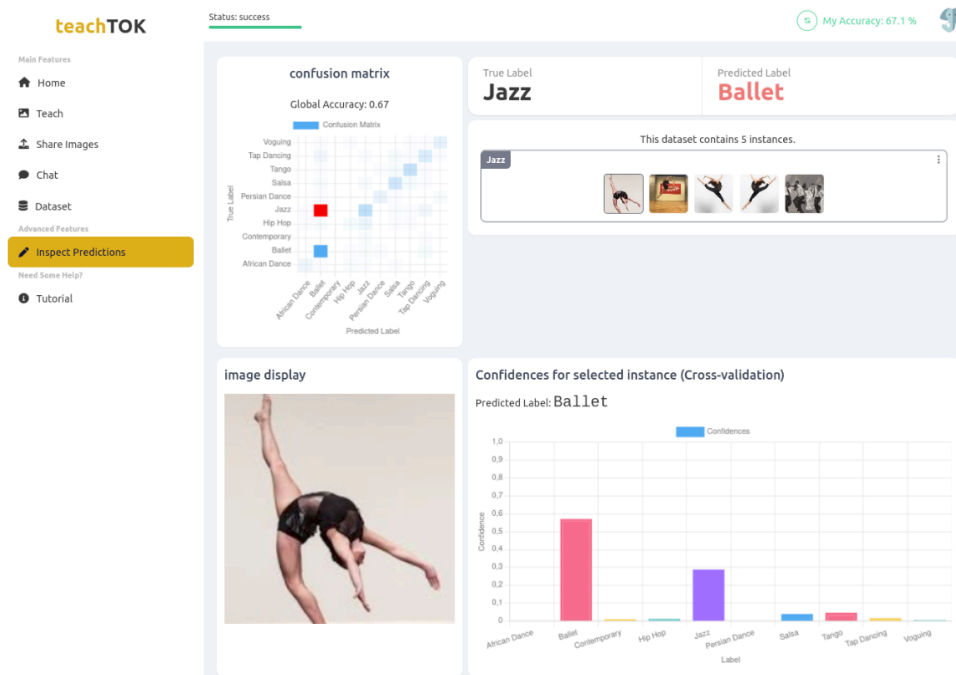


Figure 27. Screenshot of the application developed by Behnoosh Mohammadzadeh and Jules Françoise in the context of the project investigating collaborative teaching strategies of an image-based classification system.

What do we expect to achieve with this work? We believe that inspecting collaborative strategies developed by the participants can have significant impacts. First, collaborative teaching can help mitigate bias in machine learning-based systems. Having multiple ‘machine teachers’ helps bring diverse opinions to a topic and develop a plan to reduce biases. These strategies could subsequently be

operationalised in other contexts and at other scales. Second, collaborative teaching can help generate knowledge about the application domain (here, dance) and the underlying technologies. The critical element in this type of application, and which has come up throughout this manuscript, is users' access to the different stages of machine learning, particularly the learning loop.

A second example I would like to report is an ongoing project with Necker Hospital in Paris. In this project, we design and develop an application to assist tracheal intubation in the context of pediatric surgery. The project involves developing an application that relies on clinical data to make a recommendation dedicated to the anaesthetist. The anaesthetist can consult this recommendation and correct it if needed, continuously feeding the database. The surgeons and the anaesthetists can train the model. Interpretable indicators need to be implemented to help them decide when and how to train the model. That being said, our approach in this project was not to deliver a solution where machine learning becomes a problem solver. We are trying to co-construct the infrastructure with the actors of the field (surgeons and anaesthetists), which implies understanding the socio-technical framework of deployment.

These two projects illustrate what my research programme will look like. I am willing to implement a programme structured on the study of situated interactions with machine learning and artificial intelligence technologies, involving multiple actors through various application areas. I will ensure to strengthen this effort by the theoretical means of critical concepts inspired by feminist theorists and science and technology studies. These means will help me to develop methodologies that consider the positionalities of human and non-human stakeholders, including environmental considerations. These methodologies will lead to concrete design actions and software implementations that reflect, as best I can, this approach and intention.

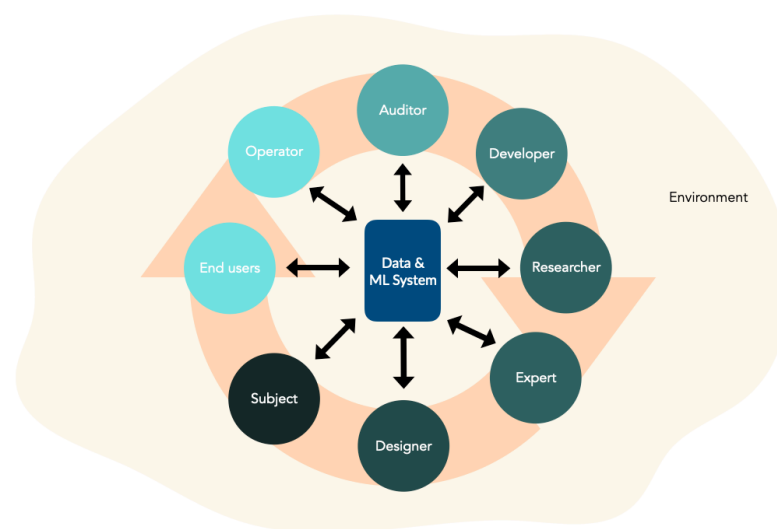


Figure 28. Illustration of the socio-technical and socio-cultural networks involving data-driven machine learning technology.

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