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Virtual Reality in Biology: Can We Become Virtual Naturalists?

Authors list: Juliano Morimoto[1,2,*], Fleur Ponton[1]

Author's affiliations:

1 - Department of Biological Sciences, Macquarie University, NSW 2109, North Ryde, Australia

2 – School of Biological Sciences, University of Aberdeen, Zoology Building, Tillydrone Ave, Aberdeen AB24 2TZ, United Kingdom

*To whom correspondence should be addressed:

Juliano Morimoto

School of Biological Sciences, University of Aberdeen, Zoology Building, Tillydrone Ave, Aberdeen AB24 2TZ, United Kingdom, e-mail: juliano.morimoto@gmail.com

Abstract

Technological advances made Virtual and Mixed Reality (VMR) accessible at our fingertips. However, only recently VMR has been explored for the teaching of biology. Here, we highlight how VMR applications can be useful in biology education, discuss about caveats related to VMR use that can interfere with learning, and look into the future of VMR applications in the field. We then propose that the combination of VMR with Machine Learning and Artificial Intelligence can provide unprecedented ways to visualise how species evolve in self-sustained immersive virtual worlds, thereby transforming VMR from an educational tool to the centre of biological interest.

Keywords : evolutionary biology / education / immersive reality

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Introduction

With increasing computational power, technologies that were costly or impossible to implement in the past have now become accessible in laptops and mobile phones [1,2]. These technologies are now revolutionising the ways we interact with the world, how we learn, and how we teach [3]. Virtual and Mixed Reality (VMR) is one of these technologies. Throughout the text, we use the term VMR to include all virtual types of applications, from Augmented Reality (AR), Mixed Reality (MR) through to Virtual Reality in its strict sense (see Box 1). VMR can be defined as an alternate world filled with computer-generated entities that interact with human sensory and motor systems to cause a sense of 'presence' or 'immersion' in the subject [4]. Despite its highly technological nature, VMR has been around for decades, and it thought to have its origin when, in the 1960s, Morton Heilig created one of the first immersive multi-sensory simulator that included stimuli such as sound, scent, wind and vibration (called 'Sensorama') [5,6]. Ever since, VR technology has advanced significantly to the point that today there exists many platforms for creating as well as experiencing VMR applications [e.g., [7-9]].

In the last decade, the use of VMR in teaching and learning has increased dramatically, and spans across a variety of subjects [10-13], including biology [14,15]. A meta-analysis of sixteen studies has shown that VMR surgical simulators decrease the time to complete surgical procedures, suggesting a more efficient surgical skill acquisition [16]. Furthermore, VMR improves the learning of tasks that require spatial and visual memory, observation, as well as control of emotional responses in stressful conditions [17]. Importantly, autistic children have been described as having positive engagement with VMR applications in educational settings [18], suggesting that VMR can be used in a wide range of contexts and function as an inclusive tool for the education of students with special needs. Therefore, VMR has the potential to become an important educational tool in our century [10]. But, what is the true power of VMR in teaching and learning in biology? What can future developments in VMR teach us about nature?

Here, we highlight the power and applicability of VMR by providing an overview of how VMR applications are changing teaching and learning in biology. Next, we discuss the potential caveats associated with VMR applications and discuss how VMR use can hinder (rather than help) teaching and learning. Lastly, we look into the future of VMR technology and discuss the directions in which future VMR developments can teach us about important principles of nature, in which VMR can act as an independent, self-sustained virtual experimental world. Having said that, we hope that this paper will help guide future developments in VMR applied to biology in a constructive manner.

VMR uses in Biology education

VMR has been used in both secondary and tertiary education biology courses [13,19-21]. A number of VMR applications attempt to reproduce the laboratory environment to students with otherwise no access to laboratory facilities, with demonstrated benefits over traditional lectures [see e.g., Labster [22]]. Other VMR applications were designed to give the students an immersive experience of more specific biological processes such as the cell structure [23], spatial orientation [24], and vision formation in animals [25]. Students report higher engagement and learning outcomes with immersive experiences offered by VMR applications, which is encouraging for the use of VMR in biology education [11,13,14,26,27] (Fig 1). For example, [24] designed an immersive interactive VMR platform for visualisation and teaching of conformation and geometry of protein crystallographic structures, whereby the test group was able to identify characteristics and regions in the samples that were obfuscated in non-immersive programs [24]. Thus, innovative curricula that harness the power of new technologies can provide significant benefits to the teaching and learning of biology [28,29].

VMR applications could help learning and teaching of ecology by simulating field expeditions in which students have to identify plants and/or animals in virtual reality, as in non-immersive virtual field trips developed previously [e.g., [30,31]]. Students have in fact reported that non-immersive virtual field trips provide a useful complement to the real field trip and could be a powerful tool to prepare and revise real field trips (Spicer and Stratford 2001). This could also complement units of taxonomy of plants and animals as well as provide virtual field experience to the student prior to the real task, thereby amalgamating students' learning experience. In VMR, immersive scenarios could include representative environments from different ecosystems (e.g., Amazon rainforest, tundra, desert) in which the aim is to identify the greater number of plant species as well as the morphological traits that are shared amongst species.

It is important to mention that virtual systems have been developed to explore all aspects of biology education. For instance, pervious digital material has been designed for teaching and learning of astrobiology [for instance in the *Habitable Worlds* platform [15]], although not yet in the fully immersive platform of VMR. *Habitable Worlds* allows students to experience a inquiry-driven learning environment designed to enhance students' learning outcomes on science through observation and modelling of virtual systems [15]. The results are promising as more than 70% of students had grades average or higher, and student engagement significantly increased compared to benchmark [15]. As such, *Habitable Worlds* provides some guidelines for the design of digital platforms that could be transferable to VMR systems, including automated feedback tailored to the students' needs and student-educator interactions (both in real-time and in forums) [15]. It will be interesting for future developments of *Habitable Worlds* to expand the educational content from astrobiology to other subjects within biology, as well as to include VMR experience and compare the performance of students with traditional *versus* immersive platforms.

The potential misuses of VMR

As for any new technology, we are still discovering the limitations of VMR applications as educational tools. VMR applications are attractive because they contain a wide variety of sensory stimuli that give the participant a sense of immersion (presence). However, too many stimuli – such as colours, shapes, characters, movement – can distract the participant and have detrimental effects on learning, a phenomenon that has been acknowledged in the literature and commonly referred to as *cognitive overload* [32]. A recent study has shown that university students learned less and experienced higher cognitive overload when they experienced a science lab in a fully-mounted VMR headset as oppose to the VMR scenes played on 2D displays, in spite of higher feeling of presence (i.e., immersion) in the VMR scene as opposed to the 2D screen display [27]. This suggests that, in some cases, the very same attributes that make VMR attractive can make VMR applications ineffective. Other negative effects of VMR applications are motion sickness and dizziness caused by the immersive experience [33-35], which can preclude appropriate understanding of the material. Given the negative effects of VMR, guidelines are urgently needed to minimise VMR misuses. Recent literature provides comprehensive lists of fundamental characteristics of 3D virtual environments and general features that can be adjusted to increase students' engagement and learning in virtual systems [see e.g., [36-38]]. Here, our point is to reiterate the importance of careful design and testing of new VMR applications prior to implementation in the classroom in order to mitigate cognitive overload and/or motion sickness, which could significantly hamper VMR's educational potential [36]. Research is only beginning to uncover the positive and negative aspects of VMR applications; future studies will provide more detailed evidence-based guidelines to build effective VMR applications that maximise educational potential while minimising negative effects of VMR misuse [39,40].

The future: Can VMR teach us Biology?

The use of VMR technology in teaching and learning will very certainly be part of the future of education across all disciplines, and the formulation of evidence-based guidelines for the creation of VMR educational material is urgently needed. While we can teach and learn Biology using VMR applications, a key question is 'can VMR teach us anything about Biology?' We believe – as described below – that the answer is 'Yes'. It is important to clarify that we are not criticising previous work in the field but instead aimed at conceptualising a new way of harnessing the power of new technologies such as VMR to biology teaching and learning.

Bio-inspired systems and the rise of artificial evolution

The parallels between natural and artificial evolutionary systems have long been recognised and explored. While few artificial life systems exist [41-43], perhaps the most famous example comes from the work of Thomas Ray and the 'Tierra' system [44]. The Tierra system simulates artificial life in self-replicating, evolving entities (aka 'algorithms') confined within virtual computer spaces, whereby the entities can be considered as uni- or multi-cellular entities that experience errors in replication analogous to mutations in biological reproduction [44-46]. Instead of solar energy and natural resources as in biological systems, artificial entities compete for central processing unit (CPU) and memory space [analogous to energy and spatial resource, respectively, as described in [44]]. As a result, artificial Tierra entities become progressively more adapted to exploit one another in order to gain advantage over the use of CPU and memory [44,47]. The outcome of this self-sustained virtual evolutionary world is remarkable given that the system evolves differences in entity sizes, ecological specialisation (e.g., parasites) and population dynamics processes (e.g., extinction) [44,46-48]. This provides an unprecedented study case to compare and understand how different shapes and forms emerge through evolutionary processes. However, visualisation of evolution in the Tierra system is not straightforward and largely inaccessible to a broader audience due to the highly technical language underlying the system. This poses a significant barrier to biologists with limited computational expertise and it is, to some extent, visually unappealing for students of biological sciences and related disciplines. Consequently, it is difficult (though not impossible) to use artificial model systems such as Tierra as an effective educational tool in the classroom while keeping the attention span and interest of students.

Can VMR and Artificial Intelligence (AI) revolutionise artificial evolutionary systems?

As discussed above, VMR is a powerful and appealing educational technology to teach biology. This is because students and educators respond rationally as well as emotionally to the educational material in the immersive experience, which can accentuate learning [21,22,31,49,50]. Thus, VMR can be an appropriate way to overcome accessibility problems of artificially evolving systems while increasing visual appealing to specialists and general audience.

The technological advances that allowed VMR to become an accessible tool has also allowed for powerful statistical models of Machine Learning and Artificial Intelligence (AI) to mushroom. Machine Learning are algorithms that process and learn with huge amounts of data in order to perform a task without necessarily being explicitly programmed to do so [51]. AI attempts to simulate human intelligence in machine systems; this includes machine learning but also (bio-inspired) robotics, ethics and philosophy associated with AI development [52]. Importantly, AI advances have recently demonstrated that machines can learn from data beyond human capabilities [53,54]. Furthermore, a new area on the interface between VMR and AI aims to integrate AI to entities in VMR [55-57]. As a result, a key question emerges: can we combine Machine Learning and AI with VMR to create a self-sustained evolving virtual world (a 'BioVR')? If so, why should we combine VMR with AI? The answer to the first question is, in our opinion, a sounding 'yes'. We strongly believe that future technological advances have the potential to create an immersive virtual world that reproduces the forces of evolution, which can allow us to visualise and measure how species have evolved, how ecosystems are formed, how species adapt to their environment, how we can anticipate effects of adverse climatic conditions across ecosystems in our changing world. In a sense, we could become 'virtual naturalists'. The learning benefits are unprecedented given that students can experience inaccessible and inhospitable environments, observe evolution, adaptation, trophic interaction, parasitism and many more biological processes without stepping outside the classroom. Furthermore, the freedom given to the students within these BioVRs forms the perfect ground for inquiry-based learning, where the students will observe and explore the environment, measuring and experiencing the virtual environment to inquiry about the underlying virtual biological phenomena [15]. The BioVR could then eliminate the need for complex computational expertise (at least from the users' point of view) and provide a fully immersive, artificial world upon which entities evolve following basic principles of biological evolution in our and other planets, while students can explore the environment and learn from their own virtual experience.

BioVR concept

We discuss here a series of possible steps upon which BioVR as we envisaged could be brought to (artificial) life, or at least inspire specialists in the field to further develop the ideas into a prototype of the concept. The steps are:

1. Simulate an artificial 'planet' whereby entities will interact, compete, and evolve. In this artificial planet, the 'biotic' rules are established, such as the basic environmental conditions (e.g., gravity) and resource distribution (e.g., marine vs terrestrial landscapes) [similar in concept to the 'soup' in Tierra [44] and the concept of virtual environments in [55]].
2. Design the ancestor entity, defining the rules of reproduction, mutation, and ecological interactions with the resources in the planet. The ancestor entity is the 'building block' for artificial life to evolve in BioVR and without it, the system does not have the evolving entity. The ancestor entity is equivalent to the ancestor species which gave origin to life on Earth, and is a common feature of artificial life systems [e.g., [46]]. In other words, without the ancestor entity to evolve, the system would resemble an immersive version of Google Earth [58].
3. Gather a large empirical dataset of environment–traits–species interactions as a basic starting-point for determining how different species evolve in different ecosystems (e.g., evolutionary convergences, divergences, character displacement) – we could call this 'rules of evolution'. One way in which evolutionary rules could be extracted from this dataset is using, for example, supervised learning models (see Box 2) to extract general rules as to how species evolve (morphologically and behaviourally) across different environments, commonality between functional traits across species in the same environments, as well as the number, distribution, and behaviour of

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different species within the same environment. Of course, this is optional as we may want to allow the system free to create its own evolutionary rules along time (iterations). Nonetheless, we believe that, if feasible, a good first proof-of-concept prototype should be based on empirical data. Once these rules of evolution are estimated (or guessed), they are applied to the ancestral entity which is allowed to evolve.

4. Ideally, BioVRs are self-sustained, and thus it would be interesting to have the changes and adaptations in one time point fed-back into the system for the next time point. For example, imagine that a species evolves a remarkable adaptation to convert virtual resource A into B. This transformation should be fed-back into the system so as to allow new evolutionary rules, perhaps favouring other species to adapt and utilise virtual resource B (which is being produced) instead of virtual resource A. Note that, over time, the ancestral entity will then evolve and adapt to different virtual resources and environments, thereby simulating evolution in a fully immersive system (Fig 2).
5. Given this self-sustained cycle of interaction between entities and the environments, and the iterative system that modulates virtual evolutionary rules, BioVR can become an artificial ecosystem, fully accessible for exploration through VMR in inquiry-based learning quests. This allows students and researchers to experience and study evolution in this immersive environment, comparing the outcomes of evolutionary forces within different environments within a BioVR and across BioVRs with different setups. Furthermore, since data visualisation is key for understanding biological processes [e.g., [59]] and is an essential component of affective learning [49,50], the use of VR to create BioVR worlds will allow VR to transcend the status of an educational tool that helps learning and teaching in Biology to become the main

technology for experiencing and learning about virtual biological phenomena. It is important to mention that BioVRs, have the potential to suffer from the same VMR misuses discussed above (e.g., cognitive overload) because the student and/or researchers can experience a highly immersive, dynamic and stimuli-rich virtual environment. One way that this could be minimised is by limiting the number of potential stimuli available at a given time; for instance, limit drastic changes in colour and texture of the scene simultaneously. Whether cognitive overload will affect BioVRs functionality remains contingent upon trials of first prototypes of the BioVR concept.

While the idea of BioVRs may seem allusive, attempts to merge the fields of VR, artificial life, and AI have been around for decades [55], with more recent efforts emerging from the astonishing 'boost' in computer power of our generation [60,61]. To our knowledge, concepts similar to the one of BioVR, as presented in this paper, have never been tested and thus remain subject of future developments in the field of statistics and computational biology. Nonetheless, we are aware that virtual environments, AI and semi-autonomous VR agents have been developed for other purposes such as direct or assist users into tasks [see e.g., [55]], and we are positive that future endeavours in this field will allow BioVRs to be available as an educational tool in biology.

Conclusion

VMR can be a powerful ally in biology education. The use of VMR has provided promising results for consolidating learning across secondary and tertiary biology education. With increasing technology, the combination of VMR with Machine Learning and AI has the potential to create a self-sustained evolving virtual world (BioVR) that allow us to uniquely explore how life as we know evolves and responds to extreme climatic conditions.

Conflict of interest

The authors have no conflict of interests to declare.

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Figure captions

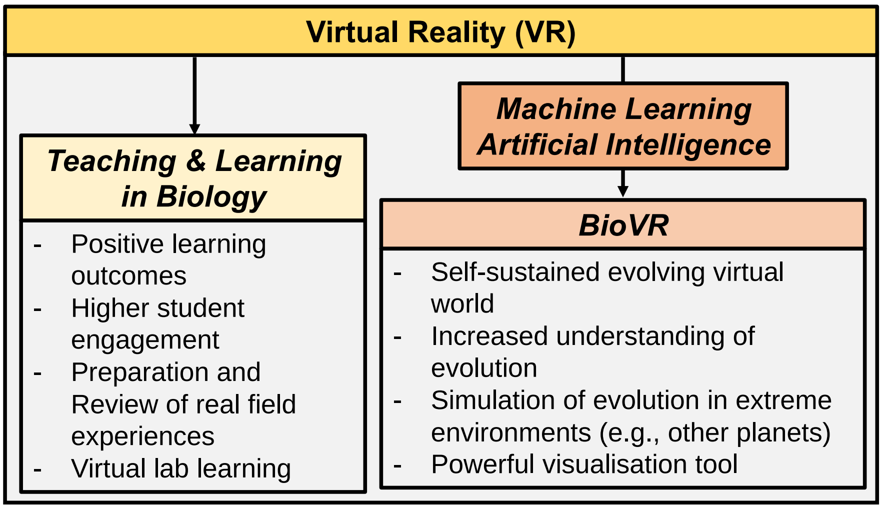

Fig 1 – Schematic overview of the potential for VMR to impact Biology. On one hand, VMR has increasingly been used for teaching of a variety of topics within Biology. As technology advances, it may be possible to combine other cutting-edge technologies such as Machine Learning and Artificial Intelligent to create a self-sustained evolving virtual world (BioVR) that allows us to gain insights into biological processes.

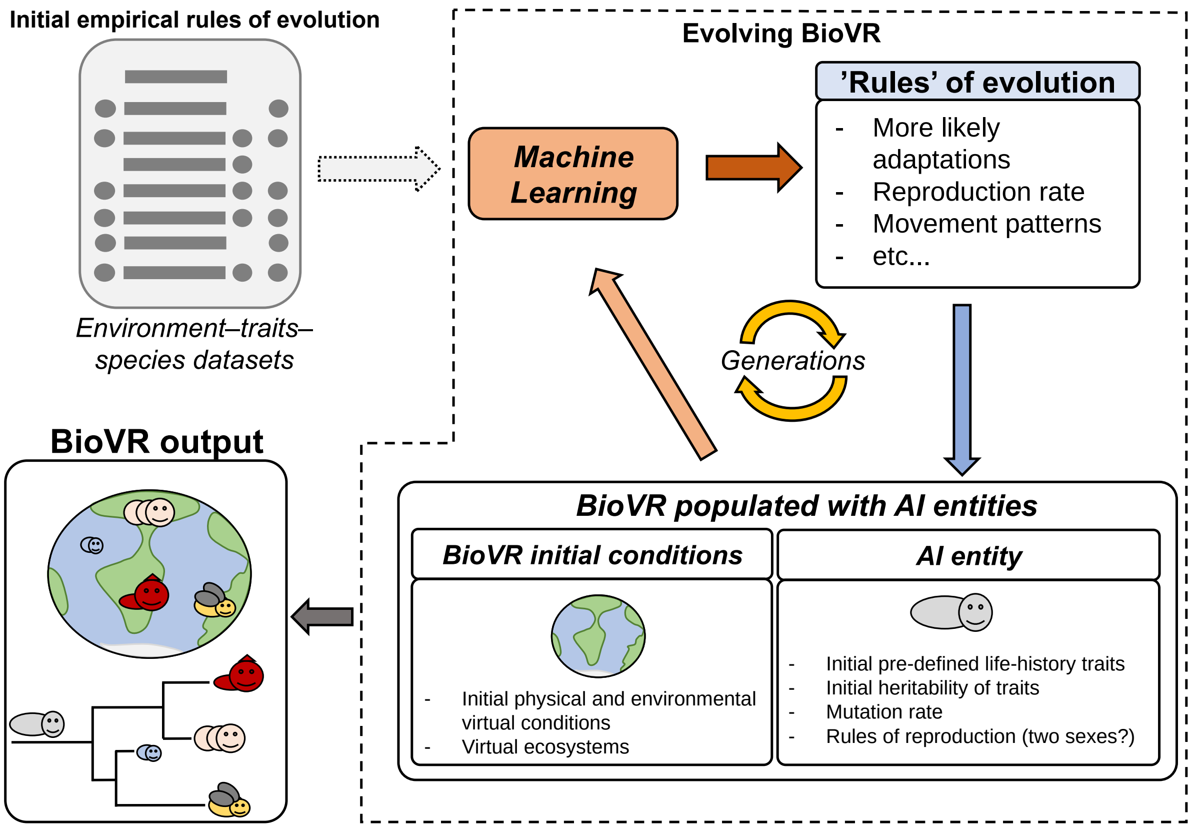

Fig 2 –Conceptual overview of the steps to build a BioVR. A supervised machine learning algorithm is implemented to empirical environment-trait-species datasets in order to extract the patterns (or 'rules') of evolution across environments. Meanwhile, the initial settings for the BioVR world and the ancestral AI entity are also set. The settings include physical and environmental conditions, as well as patterns of lifespan, movement, and reproduction of the AI entity. Next, the 'rules of evolution' are incorporated into the BioVR and AI entity with original settings, and the BioVR is allowed to evolve. Note that the evolution patterns in the BioVR are then fed-back to the machine learning model, which is updated. This way, the only input from empirical data is at the initial states, and BioVR are allowed to evolve independently afterwards. As a result, we can measure and visualise species evolution as it happens, in an immersive experience of the BioVR.

Boxes

Box 1 – The reality-virtuality continuum

In a highly influential paper, [62] proposed the reality-virtuality continuum (see Fig 3) to classify VMR technology and applications. On one side of the spectrum is the real world (reality) and, on the other side of the spectrum, the fully virtual world (virtuality) where Virtual Reality (VR) in its strict sense resides. In between the extremes, stands Augmented Reality (AR) – which relies mostly on real world elements but with the addition of virtual entities; the best known (and controversial) example of AR has been Pokemon Go! [63,64] – and Augmented Virtuality (AV) with the opposite of AR, that is, mostly virtual world but with the addition of 'real' entities [62]. AR and AV are cases of Mixed Reality (MR), where real and virtual elements are intertwined within the application (see Fig 3). For the purpose of

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this paper and for simplicity, we refer to AR, AV, and VR all as virtual and mixed reality (VMR) applications because they all have some degree of virtuality.

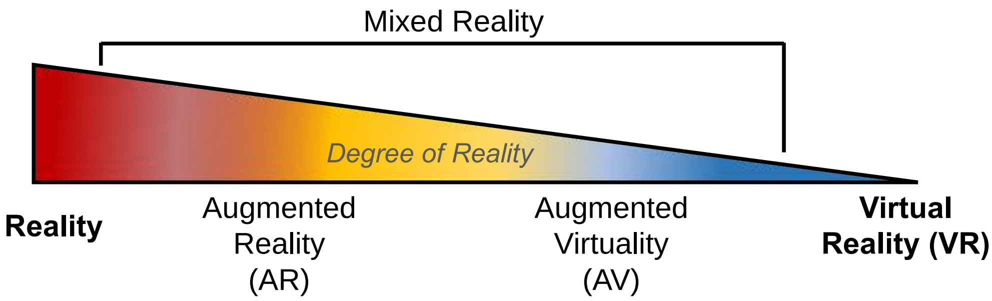

Fig 3 – The reality-virtuality continuum. AR – augmented reality; AV – augmented virtuality; VR – virtual reality (based on Milgram et al., 1995).

Box 2 – Supervised and unsupervised machine learning.

Machine learning models can be broadly classified into *supervised* or *unsupervised* learning algorithms, depending on the structure of the data [65] (Note: there are intermediate cases called *semi-supervised learning* which we will not consider here, see e.g., [66] for details). Unsupervised learning algorithms use data in which the outcome is not yet labelled or identified, and therefore the algorithm cannot 'know' the outcomes in advance. The algorithm then learns how to classify and predict the outcome from new observations based on the inherent structure of the data at hand. An example of unsupervised learning is the clustering of groups within a dataset (Fig 4a). Conversely, supervised learning algorithms uses data in which the outcome is known, and the algorithm learns how to predict the outcome of future observations based on what was learnt from the information and outcomes obtained from previous data. An example of supervised learning is the classification (or prediction, in the case of regression models) of a new observation between two categories based on n number of characteristics or variables (Fig 4b).

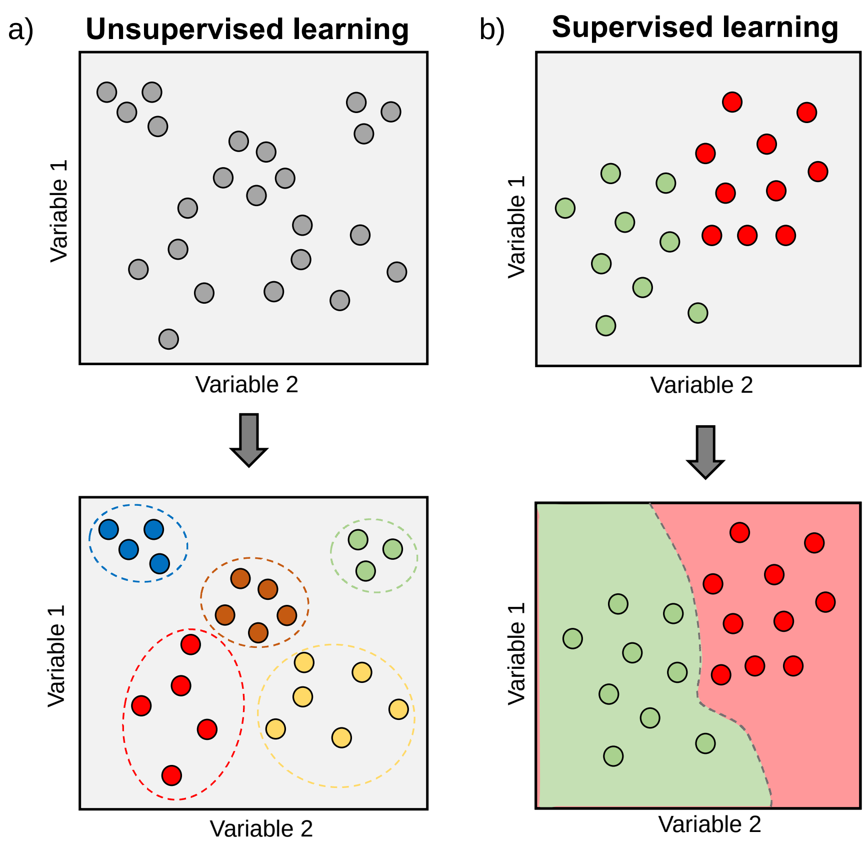

Fig 4– Supervised and unsupervised machine learning. a) Schematic representation of an unsupervised learning model. Unlabelled data is used in unsupervised learning algorithms for clustering. b) Schematic representation of a supervised learning model. Labelled data are used in supervised learning algorithms for classification.

Biographical narrative

Juliano Morimoto is a Research Fellow in the School of Biological Sciences at the University of Aberdeen. He obtained his BSc in Biological Science (Brazil) during which he was an undergraduate fellow at the Italian Synchrotron in Trieste. Dr Morimoto obtained his DPhil (PhD) in Zoology at the University of Oxford, and completed two postdocs at the University of Sydney and Macquarie University in Australia before his current appointment. Dr Morimoto is coordinator and author of the upcoming book Poetic Geometry, funded by the Brazilian National Research Council (CNPq), which is an initiative to disseminate scientific contents to high school children of low-income schools in Brazil. Dr Morimoto's research is focused on behavioural ecology of invertebrates, particularly Diptera. He uses Machine Learning and other statistical tools to model animal foraging behaviour and decision-making in nutritional environments, and the life-history implications of these choices to individuals and populations. **Fleur Ponton** is a Senior Lecturer in the Department of Biological Sciences at Macquarie University. The primary goal of her research is to describe and understand the network of interactions that defines the relationships between nutrition, infection, and host fitness. The framework and methods originated from Dr Ponton's research has opened a new avenue in the study of insect-symbiont interactions, and have been applied across disciplines including nutritional sciences and ecology, animal behaviour, as well as agricultural health. Dr Ponton is coordinates teaching units with more than 450 students on the essential skills students should acquire to continue their studies in Biology, and is fascinated in developing new tools to increase teaching effectiveness.