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The direct learning theory: A naturalistic approach to learning for the post-cognitivist era

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Abstract

Di Paolo, Buhrmann, and Barandiarán (2017) proposed a list of criteria that post-cognitivist theories of learning should fulfill. In this article we describe the direct learning theory, developed under the ecological approach, and review research performed in this theoretical framework. We argue that the theory of direct learning fulfills most of the criteria put forward by Di Paolo et al. In this sense, the tools and concepts of the direct learning theory can be useful to other post-cognitivist theories of learning. Direct learning holds that improvements with practice in perception and perceptually-guided action are driven by information for learning. Such information can be found in the dynamic interaction of the organism that performs the action and the environment in which the action is performed. The theory formally describes information for learning as a vector field that spans a space that includes all perception-action couplings that may be used to perform the action. Being located at a point of such a space means using a specific perception-action coupling. Changes in perception-action couplings due to learning can be represented as paths across the space, and can be explained with the vector field of information for learning. Previous research in the direct learning framework considered actions that were best understood with single perception-action couplings. To conclude the article, and inspired by the criteria of Di Paolo et al., we discuss an extension of the theory to actions that are best understood with multiple perception-action couplings.

Keywords: 4E, Learning theories, Ecological psychology, Enactivism, Direct learning

The Direct Learning Theory: A Naturalistic Approach to Learning for the Post-Cognitivist Era

Post-cognitivist approaches to psychology are a heterogeneous group of theories brought together by their shared rejection of the central assumptions of cognitivism: the poverty of the stimulus doctrine, the representational basis of the mind, and the computer metaphor of the brain. Their origin can be traced back to the early days of cognitive psychology in the 1940s-1950s. Since then, post-cognitivist approaches have independently proliferated on their opposition to the hegemonic cognitivist framework. As a result, the theoretical landscape in psychology has been enriched with a variety of alternative theories of cognition (Calvo & Gomila, 2008).

The cognitivist approach claims that cognition is based on mental representations, that is, symbolic intermediates between the observer and the world. As a consequence, the digital computer is considered as the best model to understand the operations of the mind, and information theory as the best tool to analyze it. In this computational portrait of cognition, perception is a process of enrichment and inference upon the ambiguous sensory stimulation to produce a representation of the most likely state of affairs of the world. Unsurprisingly, the mental operations that bring about veridical perception within the cognitivist explanation are abstract computations over abstract mental representations. Perception is considered, therefore, to be indirect. A practical consequence is that the focus of research in cognitivism is on perceptual errors that might reveal the cognitive processes underlying these errors.

Despite the particularities of the different post-cognitivist approaches, they share crucial commitments (Gonzalez-Grandón & Froese, 2018). The term “4E cognition” refers to embodied, embedded, enacted, and extended, as the expression of these commitments (Rowlands, 2010, p. 3). The 4E approach to cognition eschews the metaphor of the brain as a processor of information and considers that the agent-environment relation is central to understand cognition. Haugeland (1998) highlighted that the terms embodied and embedded emphasize that “mind, therefore, is not incidentally but intimately embodied and intimately embedded in its world" (p. 237). In addition, enaction emphasizes the importance of what the agent does to perceive meaning and extendedness implies that cognition spans beyond the body, including parts of the environment.

The original formulation of the 4E approach to cognition did not include the ecological theory of perception among its defining members (Gonzalez-Grandón & Froese, 2018; Haugeland, 1998; Kiverstein & Clark, 2009; Rowlands, 2010). However, the main commitments that characterize the 4E approach (the non-representationalism; the extended, embodied, and embedded nature of cognition; and the active role of the agent) are fundamental assumptions of ecological psychology since its inception in the middle of the twentieth century (Gibson, 1979; Michaels & Carello, 1981). In addition, the ecological approach to perception has a record of more than sixty years of empirical research on perception across the different modalities, on the active role of the perceiver through the perception-action coupling and the analysis of exploratory actions, on motor control including anticipation, and on learning. In sum, we think that the naming of the approach would be equally appealing and more encompassing under the label "5E cognition", with the fifth E standing for ecological.

The absence of ecological psychology in the original 4Es maybe the related to the fact that the 4E notion itself emerged in close relation to philosophical questions. One of the main aims of this article is to help bridge the gap between disciplines to foster interdisciplinary cross-pollination. Ecological psychologists are, first and foremost, experimental psychologists. This primacy of experiments is responsible for our bias toward explanations grounded in real situations with ecological validity. We do appreciate the formal elegance of models, but if one aims to explain cognition as an activity of life, models should refer to actual experiments with real organisms or other situations with ecological validity. Said in other words, abstract models whose equations, symbols, and graphs do not refer to aspects of real actions of organisms in environments are less common and less appreciated in ecological psychology.

Among the different perspectives included under the umbrella of 4E cognition, enactivism is the approach that has moved most from theoretical toy models to more tangible and applied psychological research. Noteworthy examples of experimental psychology performed from an enactive perspective can be found in the field of sensory substitution (Auvray, Hanneton, & O'Regan, 2007; Bermejo, Di Paolo, Hüg, & Arias, 2015; Froese, McGann, Bigge, Spiers, & Seth, 2012; Lenay, Gapenne, Hanneton, Marque, & Genouëlle, 2003; Visell, 2009; cf. Díaz, Barrientos, Jacobs, & Travieso, 2012). As a consequence, we think that enactivism is the most appropriate member of the 4Es for an empirically informed dialogue with the ecological approach. The general relation between ecological psychology and enactivism has extensively been discussed in Fultot, Nie, and Carello (2016) and the associated open peer commentaries (cf. Mossio & Taraborelli, 2008).

The specific focus of the present article is on learning. For the classic cognitive approach, theories of learning are often enrichment theories. Such theories may suppose, for example, that improvements with practice are to be found in the process of stimulus enrichment with inferences using previous knowledge. Under the 4E umbrella, interesting steps toward an account of learning have been made by Di Paolo, Buhrmann, and Barandiarán (2017; cf. Baggs, 2018, for an ecologically-inspired review of this book). Di Paolo and colleagues indicate that sensorimotor learning is a crucial but neglected aspect of the sensorimotor approach. Among other things, they discuss general principles that a theory of learning should fulfill. To facilitate the interdisciplinary interaction among post-cognitivist approaches, we describe the ecological theory of direct learning (Jacobs & Michaels, 2007) and argue that this theory fulfills many of the requirements on learning theories that were identified by Di Paolo and collaborators.

Our article is organized as follows. The first section provides a brief introduction to ecological psychology and enactivism, discussing their theoretical relation. In the second section, we present criteria for theories of learning derived from Di Paolo et al. (2017). The third section reviews the direct learning theory and two exemplar studies that were performed under this theory. The fourth section discusses direct learning from the perspective of the criteria identified by Di Paolo and collaborators. Finally, the last section presents an extension of the theory of direct learning that aims to solve some issues for its application to a more general domain.

Ecological Psychology and Enactivism

In 1979, James Gibson culminated his development of the theory of ecological psychology with the book “The ecological approach to visual perception” (Gibson, 1979). Gibson challenged, among other things, traditional conceptions about the object of perception and the appropriate level of analysis to study perception. During the first half of the twentieth century, perceptual theories often defined the object of perception at the level of physical units, characterized by absolute measurements of distance, volume, mass, or force. Gibson defined a new level of analysis, the ecological scale, which contains the organism-environment systems that psychology should be concerned about. A related departure of ecological psychology from classic theories is the use of the concept of information instead of the one of stimulus. The doctrine of stimulus poverty implies an elementaristic, passive, local, and instantaneous concept of the stimulus. For ecological psychology, in contrast, information is to be found in dynamic patterns of environmental energy. Any such pattern is a candidate informational variable that an organism can potentially use to control an intended action. Complex ambient energy patterns that extend over substantial time and space intervals are referred to as higher-order informational variables.

Some informational variables in environmental energy arrays are specific to properties of the environment that are relevant to the organism. Such informational variables and the specified ecological properties are bound by a one-to-one relation. This means that detecting the informational variable equals perceiving the ecological property. In this sense, the notion of information in the ecological theory is not akin to the correlational/probabilistic notion of information theory. The portrayal of perception as active information pickup is typically referred to as direct perception, because representational intermediates and mental processes are not necessary for perception to occur (Michaels & Carello, 1981). To reiterate this fundamental notion, the specificity between properties or processes of the organism-environment system and informational variables allows perception to be direct, that is, to be based on the detection of information (in the ecological sense).

Enactivism was proposed by Varela, Thomson, and Rosch (1991) as a general theory of cognition and psychological experience that considers cognition as the result of a dynamic organism-environment interaction. Nowadays, the enactive approach encompasses several flavors of the original formulation that share the principle of cognition as organism-environment interaction, but diverge on their preferred location along the organism-environment dipole, which is to say, on their respective emphasis on the organism or the environment (Barandiarán, 2017). The original formulation of enactivism defined cognitive systems as autonomous and operationally closed systems (Varela, Thomson, & Rosch, 1991). This notion of autonomy was inherited from the theory of autopoietic systems (Maturana & Varela, 1987), a biological precursor of enactivism.

Autopoietic systems are the result of a self-sustaining closed network of interactions that constitute the identity of the system as a whole, that is, the autopoietic organization (Maturana & Varela, 1987). The behavior of autopoietic systems is not determined by natural forces, it is the product of the internal agenda of the autopoietic system. An autopoietic system takes advantage of natural causation to fulfill its internally defined goals. In this sense, autopoietic systems are considered autonomous: their interiors are complex enough to bring about a characteristic way of using energetic and material environmental perturbations while perpetuating their organization. In contraposition, the behavior of natural systems is passive-reactive against the laws of nature.

Foundational enactivism considers the nervous system as operationally closed and autonomous and hence focuses on neural dynamics in their explanation of behavior (Varela et al., 1991). The nervous system interfaces sensory and motor tissues in order to provide an adaptive coupling to the environment, but there is nothing of essential interest to be found outside of the closed network of neural interactions other than perturbations. In response to this solipsistic perspective of cognition, and to further reduce the appeal to representationalism, contemporary enactivism has evolved away from the strong internalism of the enactivism of Varela and colleagues (Barandiarán, 2017). This is clear, for example, in the emphasis of some contemporary enactivists on sensorimotor contingencies and on the dynamic role of the external environment that furnishes those contingencies (e.g., O'Regan & Noë, 2001).

Historically, the interaction between ecological psychology and enactivism has not been particularly fluent. Autopoietic enactivism has rejected direct perception since its initial proposal for two reasons. First, it is argued that direct perception overemphasizes the importance of the environment (Varela et al., 1991). Relatedly, the use of the word *information* in the ecological approach is considered by autopoietic enactivism as implying instructive interactions with the environment, thus breaking the principle of operational closure of the organism. Second, enactivism argues that the ecological approach is a form of a physicalism. Such claims remain common in the work of contemporary enactivists (e.g., Di Paolo et al., 2017, p. 81). The examples throughout this article will illustrate that these claims, rather than being faithful with the ecological tradition, highlight a problem of communication between (and understanding of) approaches with different philosophical backgrounds (cf. Baggs, 2018).

Nowadays, researchers can crudely be divided in three different positions regarding the relation between ecological psychology and enactivism (Fultot et al., 2016). The first position holds that the theoretical differences are irreconcilable. Cariani (2016), for example, argues that ecological psychologists defend a direct realism and claim that meaning is in the environment, whereas enactivists defend perspectivist ontologies and claim that meaning is in the head of the agent. A second position is that the theories complement each other at different levels of analysis. In this sense, Heras-Escribano (2016) proposes that the approaches can be reconciled in a shared research program in which enactivism accounts for the subpersonal processes via neurodynamics and ecological psychology explains the agential level through direct perception (cf. McGann, 2016). A third position holds that there are already bridges between the theories. Stapleton (2016), for example, points to research that joins the ecological concept of affordance and the process of sense-making from enactivism.

Despite the theoretical differences, many points of agreement become obvious if one considers the approaches in the context of specific perceptual-motor problems. Let us illustrate this with two examples. First, walking to a target, which is a rather simple action for humans and other animals. A variable that specifies the direction of motion in the temporal changes of the visual field, the optic flow, is the focus of expansion (Warren, Kay, Zosh, Duchon, & Sahuc, 2001). If we change our walking direction, we modify what is at the focus of expansion. If we move orthogonally with regard to the direction of a target, the target will not be at the focus of expansion. Walking to a target can be achieved by keeping the focus of expansion at the target. This means that the focus of expansion may used to control locomotion by correcting deviations from the intended direction.

This perceptually-guided behavior can easily be incorporated in an enactive description. Visual expansions are the result of a sensorimotor loop that can be enacted (we can turn right and left and control the focus of expansion). Moreover, its detection does not specify the effect on the organism (it is not instructive) and, therefore, does not break the operational closure principle. In addition, an agent can use the mastery of this sensorimotor contingency. On the other hand, the focus of expansion is a higher-order variable at the ecological scale (it is contained in the time evolution of a substantial part of the optic array). Its behavior is lawful, and it is so because of the laws of optics. It is useful for the prospective control of locomotion and, at the same time, it requires the relative movement of the perceiver, which in the ecological approach is achieved through the perception-action coupling.

As a second example, consider the muscle-based perception through wielding (Turvey & Carello, 1995). Perceiving properties of objects by wielding is a daily activity, as when handling utensils. Individuals can perceive properties such as the length and width of hand-held objects or whether the objects are bent or not. To do so, inertial properties are explored. During wielding, forces and torques are applied, and spatial translations and rotations are obtained as a consequence. For linear movements, the mass of an object is the relation between the total force that is applied and the acceleration that is produced as a result. For rotational movements in three dimensions, a higher-order quantity captures the relation between the rotational forces (i.e., torques) and accelerations: the inertia tensor. The inertia tensor is a nine-dimensional quantity (i.e., a 3×3 matrix) that is based on the distribution of mass along the object (Solomon & Turvey, 1988). Despite its apparent complexity, the inertia tensor describes the relation between forces and movements. As such, the components of the inertia tensor can be detected through wielding, which is to say, by applying forces and observing their relation to the movements.

As indicated in the previous paragraph, wielding objects allows the detection of multiple candidate variables. Later in this article, we will need more precise definitions of three of those variables: mass (M), static moment (SM), and the first principal moment of inertia (I_1; i.e., a main component of the inertia tensor). The following expressions of these variables indicate their close linkage:

$$I_1 = \int \rho(s)\, \delta(s)^2\, \mathrm{d}V, \tag{1}$$

$$SM = \int \rho(s)\, \delta(s)\, \mathrm{d}V, \text{ and} \tag{2}$$

$$M = \int \rho(s)\, \mathrm{d}V. \tag{3}$$

In these equations, $\rho(s)$ is the mass-density function of the wielded object, $\delta(s)$ the distance to a given axis of rotation, and V the volume of the wielded object over which $\rho(s)$ and $\delta(s)$ are integrated (Jacobs, Silva, & Calvo, 2009). The mass of an object can be detected through linear exploratory movements or by holding the object still against the effect of gravity. The static moment of an elongated object, such as a rod, can be detected by suspending it horizontally from a single grip and noting the rotational force that is generated. As mentioned above, active exploration with rotational movements allows the detection of the components of the inertia tensor, including the first principal moment.

The fundamental notions required to understand the muscle-based perception through wielding, typically studied from the ecological perspective, are laws that connect a motor component (the forces) to a sensory component (the resulting movements). Such notions can easily be accommodated in an enactive account. Consider, for example, the similarities between muscle-based perception and the enactive portrayal of the perception of softness through exploration of a sponge:

> Having the sensation of softness consists in being aware that one can exercise certain practical skills with respect to the sponge: one can, for example, press it, and it will yield under the pressure. The experience of softness of the sponge is characterized by a variety of such possible patterns of interaction with the sponge, and the laws that describe these sensorimotor interactions we call, following MacKay (1962), laws of sensorimotor contingency (O'Regan, Myin, & Noë, 2005).

General Principles for 4E-Inspired Theories of Learning

The goal of this section is to explicitly formulate a list of requirements that should ideally apply to any theory of learning that falls under the umbrella of 4E cognition. Without aiming to be exhaustive, our hope would be to obtain a tentative list on which different contributors of the 4E approach may agree. We will first describe requirements that are implied by the 4E concept itself. Following those, we describe requirements that were selected from chapter 4 of Di Paolo et al. (2017)—which we believe to be the main attempt so far from the enactive approach to formalize a learning theory. A final requirement in our list is taken from the ecological approach. In subsequent sections of this article, we will use the obtained list of requirements to assess the contributions of the theory of direct learning.

The most obvious requirements are the ones implied by the name of the 4E approach. That is, a theory of learning from the approach should be consistent with the commitments to describe cognition, and hence learning, as an *embodied*, *embedded*, *enacted*, and *extended* process. Relatedly, a learning theory in the 4E approach should be *non-representational*. This means that learning cannot be portrayed as an improvement in syntactic operations or computations on symbolic representations. Less obviously, the processes that are responsible for the improvements with learning should not be based on such computations and representations either.

We next consider elaborations of and additions to these requirements that were formulated by Di Paolo et al. (2017). One of the requirements that these authors mention is that learning should *transform perception* rather than construct perception out of previous processes other than perception. In their words, "the starting point from which perception develops is always already a form of perception" (p. 79). With regard to their specific theory, they claim that the process "starts always from an existing sensorimotor organization" and that it "develops from there into novel forms, differentiated forms, forms that become extinct and replaced by others, and so on" (p. 79).

Another set of requirements on a learning theory mentioned by Di Paolo et al. (2017) is that such a theory should be *action-based* and *world-involving*. With regard to the action-based part, they state that "adaptations only occur in the context of active, personal effort in remastering the visual world" (p. 79). However, it is not the activity of the learner as such that is claimed to be important. Rather, it is the dynamic interaction of the learner with the world. Di Paolo formulate this world-involving part of their requirement by saying that learning "involves a relation to the dynamics of the world beyond the mere supply of sensory input" (p. 80). More passive learning situations would lack "a chance to engage the world and attune to a new form of coupling with it" (p. 80).

Di Paolo et al. (2017) also mention that a theory of learning requires *adaptive mechanisms*, which may be based on a *normative evaluation* that provides the agent with feedback to evaluate if his or her current state of functioning is appropriate in a concrete situation. Related to the requirements of adaptive mechanisms and normative evaluation, Di Paolo et al. write:

> an agent can also learn from the way she fails. *Directed learning* [emphasis added] could rely, for instance, on gradients in the normative evaluation ... or on details of perturbations encountered in failed assimilation attempts (p. 103).

As we will illustrate in subsequent sections, we believe that this quote—including the wording used to refer to the learning processes—is indicative of the relevance of the direct learning framework to parts of the approach to learning sketched by Di Paolo et al.

Another pair of requirements on theories of learning that we have selected from the chapter by Di Paolo et al. (2017) relate to the fact that *learning never ends*. In the words of Di Paolo et al., for learners "this requires that they never reach strictly stable equilibrium" and that they "must retain a residue of dynamic criticality without which they would simply be unchangeable automatisms" (p. 102). A related requirement is that learning processes are *open-ended*. According to Di Paolo et al., this implies that learning does not have an end point, meaning that novel and un-anticipated perception-action solutions can be arrived at through learning (p. 78 and p. 98).

This brings us to the final requirement of our list, which was anticipated in the introduction. Many theories in the 4E approach agree that the formal aspects of dynamic models can usefully be applied to the understanding of cognitive processes. The theory sketched by Di Paolo et al. (2017) and the direct learning framework are no exceptions. A final requirement for a theory of learning, inspired by common practice within the ecological approach, is that the dynamic models that are inspired by the theory and that aim to illustrate the theory should be formulated *at the ecological scale*, meaning that they should refer to tangible aspects of real-world actions. Let us consider two purposefully simplified models to illustrate this requirement.

First, let *S* refer to an organism-environment system that includes all possible perception-action couplings in which the organism can engage. Note that *S* can be high dimensional. Given that learning implies a change in the organism-environment system and its perception-action couplings, we can refer to learning as the derivative of *S*. Second, let *O* be an organism with two action possibilities: it may be at rest or move at a constant speed. In this second case, learning may be portrayed as, say, a change in the rules, or probabilities, by which the organism chooses to move or not.

However simple these models are, they might have some virtues. With respect to the first model, one may argue that it is not wrong in the sense that all types of learning will eventually be some further specification of the model. With regard to the second model, one may argue (or demonstrate) that its behavior has some similarities with human behavior, and hence that the model exemplifies how the considered behavior may arise. Despite these arguments, however, the points, spaces, trajectories, vectors, gradients, etc., that illustrate such models do not refer to tangible aspects of real world actions. Hence, if one accepts the requirement that models are ideally formulated at the ecological scale, one should be suspicious about the contribution of such models to learning theories in the 4E approach.

Di Paolo et al. (2017) state that “several of these principles are already present in other approaches” (p. 103). We believe that the theory of direct learning, not mentioned in the chapter, is a good candidate in this regard. The next section provides a summary of the direct learning theory, including two examples of actions that have been used to elaborate the theory.

Direct Learning

The direct learning theory has been developed under the principles of the ecological approach (Jacobs & Michaels, 2007; cf. Jacobs, 2001). With the theory, the authors aimed to respond to the criticism that the ecological approach, at that time, did not provide a sufficiently detailed understanding of learning (Michaels & Beek, 1995). The direct learning approach considers two levels of analysis: the one of perceiving and acting and the one of learning (aiming for a theory that is consistent as well with the level of analysis of ecological realism; Jacobs & Michaels, 2002). The processes that are implied by perceiving, acting, and learning are conceived as multiple continuous and concurrent processes that occur at different timescales. The main research strategy of the direct learning approach is to scrutinize the traditional ecological principles, which were developed to understand perceiving and acting, and to explore how these principles may be interpreted or modified to be applicable to processes at the longer time-scale of learning.

Crucial among those principles, and giving rise to the name direct learning, is the claim of the traditional ecological approach that perceiving and acting are direct or information-based rather than inferential processes. Analogously, direct learning claims that learning is information-based. As does the traditional ecological approach at the level of perceiving and acting, the direct learning approach considers the directness of learning as a methodological doctrine. This means that, rather than aiming to prove or disprove the claim, the approach takes the methodological doctrine as its starting point and asks what else must be true if the doctrine is true. This search has led to a sequence of concepts, ideas, and empirical studies that, we believe, are useful to many members of the 4E approach.

In the framework of direct learning, the level of learning includes at least three processes: the education of intention, the education of attention, and calibration. With regard to the first process, the education of intention, one should realize that many actions are possible in any given situation. If a ball approaches, one may be able to catch the ball, dive away to avoid the ball, or try to hit the ball. The intention of an agent determines which action he or she aims to perform. The *education of intention*, then, refers to the process by which agents improve in choosing which action they aim to perform (or what property they aim to perceive). Assuming an intention is indispensable in the direct learning approach, and in the ecological approach in general, because it allows one to evaluate the environment and the performance of the agent in terms of the goals of the agent. This is related to the normative evaluation often mentioned by proponents of the enactive approach (Hutto, 2005; Di Paolo et al., 2017). A more detailed consideration of intentions and changes therein and their place in the direct learning framework can be found in Arzamarski, Isenhower, Kay, Turvey, and Michaels (2010; cf. Shaw & Kinsella-Shaw, 1988).

To give an example of the need for the concept of intention in the direct learning theory, note that assuming a particular intention is indispensable to evaluate the usefulness of informational variables. Variables that specify the property that an agent intends to perceive or act upon are useful whereas variables that are unrelated to that property, even though they may specify other properties, are not. Empirical evidence shows that, with practice, individuals graduate from the use of less useful variables to the use of more useful variables (e.g., Jacobs, Runeson, & Michaels, 2001). This gradual process of convergence toward specifying information, even if the intention of the agent is assumed to remain constant, is known as the *education of attention* (Gibson, 1979). The third process at the level of learning that is considered in the direct learning framework is *calibration*. This process refers to changes in how the informational variable that is operative at a particular moment is carried into perception or action.

To provide a more formal interpretation of these learning processes, needed to outline subsequent aspects of the theory, let us consider the following equation:

$$F = f(I), \tag{4}$$

in which I is the informational variable that is used at a particular moment, F refers to a particular action parameter (e.g., a force exerted by the action system; when studying perception, F is substituted for a perceptual parameter, P), and f is the single-valued function that describes how information is carried into perception or action. The equation describes how an action system functions at a particular moment. An intention determines that the system acts the way it does, and therefore sets up the equation as a whole. Even with a constant intention, however, the equation that best describes the functioning of a system changes with practice. In line with our previous description, the education of attention corresponds to changes in the informational variable I and calibration to changes in the single-valued function f.

Equation 4 is essentially the same as the traditional ecological concept of *control law* (Warren, 2006), which has frequently been used to formalize aspects of the ecological approach at the level of perceiving and acting. Changes in the equation over time, formalized by the temporal derivatives of f and I, provide a foot into the door of the direct learning theory. To describe further aspects of the theory we need to advance from the disembodied description of Equation 4, without reference to a particular action, to action-related and thereby falsifiable interpretations of the concepts that are implied by the equation. To do so, we have selected two empirical studies on direct learning that we consider particularly relevant to members of the 4E approach.

Learning as continuous movement through a space: The pole-balancing example

Jacobs, Vaz, and Michaels (2012) analyzed learning using a cart-pole task (Figure 1). The task of participants was to keep the unstable pole on the cart balanced for 30 s. Performing this action requires practice: participants needed between 22 and more than 150 trials to maintain the pole balanced for three consecutive trials. Participants control the force, $F(t)$, that they apply to the cart. In line with the ecological approach, and the concept of control law, Jacobs et al. assumed that the applied force is a function of information detected a short time interval before exerting the force. What information was used? And, what function related that information to the applied force?

To answer these questions, Jacobs et al. (2012) used a version of Equation 4 that is applicable to this particular action:

$$F(t) = k\,\theta^{(\alpha)}(t - d). \qquad (5)$$

In this equation, $\theta^{(\alpha)}$ is the fractional derivative[1] of order α of the angle of the pole (see Figure 1), d is the perceptual-motor delay, and k is a constant. The quantity $\theta^{(\alpha)}$ is the informational variable used in to control the action (I in Equation 4), α is a parameter that changes with changes in the education of attention, and k is a constant that changes with changes in calibration. Both the education of attention and calibration were formalized in ways that were considered as simple as possible to capture the relevant phenomena: both changes were portrayed as single-dimensional. Moreover, the calibration function f in Equation 4 was as simple as a multiplication by a constant. Note that, together with the equations of motion of the physical system, Equation 5 allows one to predict the performance of the agent-environment system as a whole.

We are now in the position to introduce another important aspect of the direct learning approach: learning processes are portrayed as continuous trajectories through a space. Most studies in the direct learning framework considered *information spaces*. Jacobs et al. (2012) instead used a combined *information-calibration space* (Figure 2). The coordinate axes of this space are the parameters that indicate the education of attention and calibration of an individual at a particular moment, which is to say, the parameters α and k in Equation 5. If one registers the movements of an individual that performs the action, one can determine the parameters α and k that best fit the

[1] Jacobs et al. (2012) reviewed the definition of fractional derivatives and discussed advantages of using that concept. To understand the following discussion it is sufficient to know that $\theta^{(\alpha)}$ is a detectable informational variable that depends on the parameter α.

performance, and hence localize the individual at a point in the space. A substantial number of empirical studies on direct learning show that learning, when analyzed this way, can be described as a process of convergence toward the more useful regions in such spaces (e.g., Michaels, Arzamarski, Isenhower, & Jacobs, 2008; cf. Abney & Wagman, 2015; Huet, Jacobs, Camachon, Missenard, Gray, & Montagne, 2011; Michaels & Romaniak-Gross, 2012).

For the pole-balancing task, this convergence toward the more useful regions in the space is illustrated in Figure 2 by the ellipses that summarize the empirically determined locations of the whole group of participants, at different phases of the experiment. Whereas the ellipse that indicates the initial performance (first quarter) is large, showing that individuals were widely distributed over the space, the ellipse indicating performance later in the experiment (fourth quarter) is small, showing that individuals by then had converged toward a more limited region in the space. Jacobs et al. (2012) further showed that the region on which individuals converged is indeed the most useful region. That is, an agent-cart-pole system remains well balanced if one uses the αs and *k*s from this region and simulates the performance of the system using the forces computed with Equation 5 together with the appropriate equations of motion.

So far, we have introduced the education of intention, the education of attention, and calibration, and we have seen how, in the context of particular actions, the latter two processes can be empirically tracked and analyzed as trajectories through information and information-calibration spaces. The claim that learning processes are information-based can now intuitively be understood as the claim that patterns in the dynamic agent-environment interaction that emerges while an agent is localized at a particular point in the space push the agent through the space. In the pole-balancing example, information for learning may be found, for example, in the particular ways that the pole remains balanced or falls down over multiple trails. We next provide more tangible illustrations of how the informational basis of the learning can be defined and analyzed.

Information for learning: A dynamic touch example

In the previous sections, we have introduced the central claim of the direct learning approach: learning processes are driven by information that emerges from the agent-environment interaction over some time. Whereas the previous section provided an example of how one may analyze and observe the changes due to learning, the present section concerns a study that provides a tangible example of information for learning: the muscle-based mass-perception study by Jacobs et al. (2009). Participants in that study were asked to freely wield unseen objects (called tensor objects) with their right hand and to judge the mass of those objects as compared to a reference object in their left hand. Instead of Equation 4, we now use the equation:

$$J = f(I) \,, \tag{6}$$

in which *J* is the mass judgment made on a particular trial and *I* the informational basis of that judgment, which is to be detected from the object through wielding.

For our current purpose, it is sufficient to analyze the education of attention. This means that we need an information space that allows us to track changes in the informational basis of performance (i.e., changes in *I*). The equation used by Jacobs et al. (2009) to describe that information space was:

$$I(x,y) = y\, I_3 + (1\text{-}y) \int \rho(s)\, \delta(s)^x \, dV \,. \tag{7}$$

It is crucial to understand that, in this equation, *I* is an informational variable that can be detected from the object through wielding and that the informational variable depends on two parameters: *x* and *y*. For a description of the general shape of the equation, and a motivation for using this one, we refer the reader to Jacobs et al. We provide the full equation here to emphasize that the direct learning theory has been worked out at the level of measurable quantities. Let us further mention, for completeness, that I_3 is the third principal moment of inertia and that the remaining terms are the same as in Equations 1 to 3.

With an informational variable, I, that depends on two parameters, x and y, we have obtained a two-dimensional information space. If x and y are both zero, the equation matches the one for mass (Equation 1). If $x = 1$ and $y = 0$, the equation matches the one for static moment (Equation 2). Other values of x and y correspond to other detectable informational variables. Jacobs et al. (2009) used this information space to track the information usage with learning of individuals in different experiments and conditions. The upper panel of Figure 3 presents the results for the pretest and posttest for a group of participants who received feedback based on mass. The lower panel presents analogous results for individuals who received feedback based on static moment. Consistent with the results from other studies in the direct learning paradigm, the figure shows that learning goes together with convergence toward the more useful informational variables.

For the relation between direct learning and other 4E theories, it is relevant to note that the informational variables represented by points in information spaces are actively picked up rather that detected in a passive manner. For muscle-based perception this is obvious: participants actively wield the to-be-perceived objects. Furthermore, and related to the traditional ecological claim that perceiving and acting are inseparable processes, the exploration that participants perform to detect the inertial informational variables depends on which variables they detect. To demonstrate this, Michaels and Isenhower (2011a; cf. Michaels & Isenhower, 2011b) determined the positions of participants who performed a muscle-based perception task in an information space and analyzed the way in which they wielded. Indeed, being localized at a certain point in the space went together with certain ways to explore (cf. Arzamarski et al., 2010). The continuous changes in what information is detected that are captured by the convergence in information spaces, therefore, should be hypothesized to go together with continuous changes in the exploratory movements that underlie the information detection.

Apart from this short aside on exploratory movements, being able to empirically track the learning of individuals as trajectories through a space allows us to proceed to a next step in the theory of direct learning: explaining the learning itself as an information-based process. As well-known from the theory of differential equations, trajectories through a space are specified by the temporal derivatives of the coordinates of the space at each point in the space. Those temporal derivatives define a vector field on the space. Along with the ellipses that describe the movements through the space with practice, Figure 3 gives vector fields that would predict such movements.

Now consider an individual who is localized at a particular point in the space, performing the wielding and making his or her judgments as determined by the information that is represented by that point in the space (in interaction with the world, or in this case the object that he or she happens to encounter). Such an individual would be predicted to move along the space according to the vector at his or her locus. The remaining question in the direct learning framework is: what informational pattern, detectable over multiple trials from the relation between the judgments, the resulting feedback, and other information detectable through the wielding, would specify the vector that indicates the observed movement at that locus? In the direct learning framework, a detectable informational quantity that specifies the movement through the space for all loci in the space and for all experimental conditions qualifies as *information for learning*.

The information for learning proposed by Jacobs et al. (2009) is described by the following equations:

$$x'(t) = -\, k_1\, covariance\{E, \mathrm{SM/M}\} \qquad (8)$$

and

$$y'(t) = -\ k_2\ covariance\{E, I_3\}. \tag{9}$$

In these equations, k_1 and k_2 are constants, E is the error as indicated by the feedback, and the other variables are as defined earlier in this article. Together, the temporal derivatives on the left hand side of the equations specify a vector in the space, as they should. Jacobs et al. showed that the vectors specified by the detectable quantities on the right hand side correspond reasonably well to the observed movements through the space. In fact, those vectors are the ones plotted in our Figure 3. With this example of detectable information for learning we have completed our description of the central claims of the direct learning theory.

Obviously, it is possible to accept or use some of the tools of the direct learning framework without accepting the entire theory. For example, our portrayal so far argued that learning trajectories are based on vectors, which means that learning is based on detected informational quantities that are as many dimensional as the space that is used to describe the learning. Even from within the framework of direct learning, however, we have tentatively explored the alternative view that learning may be based on single-dimensional potential functions on the space (Jacobs, Ibáñez-Gijón, Díaz, & Travieso, 2011). Figure 4 illustrates this type of analysis for the information space defined in Equation 7. The surface in the upper panel shows a detectable measure of the maximum level of performance that can be achieved by individuals who use the different loci in the space. The empirically-measured probability density functions shown in the lower panel of the figure indicate that, with practice, individuals move from the less useful to the more useful regions in the space. We cannot rule out that movements through information spaces are causally linked to usefulness functions rather than to vectors that represent information for learning.

One should note that learning based on information that is as many dimensional as the space in which learning takes place, and that specifies a direction, is the more elegant formulation of the direct learning theory. This is so because it takes most advantage of the different time-scales of perception and action and of learning. If learning is slow, the processes of perceiving and acting can generate the learning vectors without noteworthy changes in the locus of the learner; in the extreme, the information for learning can be generated with the learner being located at a single point in the space. If the information for learning is a single-dimensional usefulness function, on the other hand, this function needs to be sampled from several nearby loci in the space to determine a direction of change. This sampling process necessarily mixes movements in the space, which are supposed to be slow, with the perceiving and acting that generates the information about the usefulness, which are supposed to be fast. However this may be, if one assumes that the information vector field is the gradient of a usefulness function, parts of the theory may be illustrated with usefulness functions as well as with information vectors, without bothering about which of the two is causally related to the learning. As such, we will make use of usefulness functions in the remaining part of this article. Note that this part of the direct learning theory shows similarities to the suggestion concerning *directed learning* by Di Paolo et al. (2017) that was quoted in the previous section.

Summarizing the main tenets of the direct learning theory, then, it is claimed that perceiving and acting are fast information-based processes that cause a dynamic interaction of the agent and its environment. In this interaction, the way that the agent perceives and acts at a particular moment has observable consequences. Information that drives the slower learning processes is claimed to be present in the rich higher-order structure over time of these observable consequences.

Direct Learning and Enactivist Principles for a Theory of Learning

As stated above, the aim of this article is to put forward the theory of direct learning as an empirically supported framework for post-cognitivist approaches to learning. In this section, we assess to what extent the direct learning theory fulfills the requirements that were derived from the analysis of Di Paolo et al. (2017).

The first set of requirements for such a theory is that it must comply with the basic commitments that characterize the 4E approach, that is, it should portray learning as an embodied, embedded, enacted, and extended process. We added to this general list an explicit commitment to non-representationalism and the need to formulate research questions at the ecological scale (that is, referred to aspects of real-world actions). Direct learning was developed within the ecological approach. In this sense, it assumes the basic tenets of the ecological approach, in particular: the directness of psychological processes that follows from a non-representational stance; the active nature of perception-action that parallels the enactive requirement; and the assumption that the ecological scale is the proper level of analysis for psychological phenomena, which incorporates embeddedness, embodiment, and extendedness at the root of the approach.

The first requirement derived from the analysis of Di Paolo et al. (2017) is that learning should transform perception, rather than to construct perception out of pre-existing non-perceptual processes. As explained in the previous section, the direct learning theory proposes information and calibration spaces and vector fields of information for learning to account for the changes in perception-action couplings. Every point in such spaces stands for a specific perception-action coupling. In other words, being at a certain point of an information-calibration space means using a specific informational variable, with a specific calibration, to control an action. As such, being at a certain point generates a specific interaction with the environment, which, in turn, contains information that allows the agent to modify its behavior at longer time-scales. This information in the loci-specific interaction with the environment can be formalized as a vector that indicates the direction and magnitude of change for a specific perception-action coupling. In sum, direct learning attempts to establish the laws by which perceiving and acting are transformed.

The next requirements are two intimately related notions: learning should be action-based and world-involving. This means that the actions of the learner or the mere sensory input that follows an action are not important per se. The relevance of action for learning only appears in relation to the dynamic interaction between the learner and the world. Note that this is what information for learning attempts to describe: how the dynamics of the current perception-action coupling constrain the evolution of the coupling itself. A clear example of world-involvedness can be found in Jacobs et al. (2012), who included the physical equations of motion of the cart-pole system as an essential part of their portrayal of learning (see their Equations 1 and 2).

Di Paolo et al. (2017) also highlighted that a post-cognitivist theory of learning requires adaptive mechanisms to determine the change of the current perception-action engagement. These adaptive mechanisms are assumed to be based on a source of normative evaluation that furnishes the agent with feedback to evaluate the appropriateness of its current state of functioning. One should observe that postulating such mechanisms may imply the risk to reintroduce traditional representational thinking in theories, because it may seem to require a traditional representational/inferential agent (or homunculus) that is responsible for the adaptive processes (i.e., for the mastery of sensorimotor contingencies; Noë & Noë, 2004). Warnings against reintroducing traditional representational thinking in this way can be found in Jacobs and Michaels (2007, p. 330; cf. Hutto, 2005, p. 392). As we have shown, however, the direct learning approach holds that processes such as normative evaluation and behavioral adaptation themselves can be accounted for at the ecological scale without appealing to representations or inferences. This, in fact, is why direct learning received this name: the adaptation due to learning is hypothesized to be information-based, which is to say, specified in the current agent-environment interaction.

The final set of requirements for a theory of learning identified by Di Paolo et al. (2017) are that learning never ends and must be open-ended. In line with these requirements, and with the Gibsonian view that perception itself is extended in time, Jacobs et al. claim that their theory "does not consider learning a process that has a beginning and an end. Learning does not start or stop" (p. 249). Illustrating this view, Michaels et al. (2008) designed a two-stage learning experiment. The structure of the feedback was changed from the first to the second stage of the experiment so as to modify the usefulness function and the information vectors. At each stage, a movement through the information space was observed that was compatible with the feedback, even though during the first stage near optimal performance was reached. Hence, the claim that learning never ends has always been present in the direct learning theory.

Open-endedness is accommodated to a certain degree. Depending on the particular learning environment, or on the feedback given in an experiment, different loci in information spaces are the more useful ones. It has been demonstrated empirically that learners converge toward those loci that are the most useful ones in their particular task environment, and hence that learning does not have a fixed end point (Huet et al., 2011; Jacobs et al., 2009; Michaels et al., 2008). For Di Paolo et al. (2017), however, open-endedness seems to go further. They claim that "the learning and refinement of perception and action skills in some cases, if not unbounded, seems to have no obvious predictable bounds" (p. 101), and that learning is seen as "the combinatorial construction of new patterns of sensorimotor coordination in a potentially ever-growing space of possibilities" (p. 104). They further argue that such open-endedness and lack of predictability requires some degree of randomness. In contrast to this requirement, the direct learning framework implies bounds on learning in the sense that learning cannot extend beyond the considered information and calibration spaces. Likewise, the direct learning framework, in its current state, does not provide an explicit and empirically demonstrated formulation of how randomness affects learning processes.

To summarize, we believe that the theory of direct learning fulfills the large majority of the criteria that post-cognitivist theories should fulfill. Our main claim in this article, therefore, is that the theory would be useful to members of the 4E approach as a starting point for further theorizing about learning. With regard to the criterion of open-endedness, it is fair to say that the direct learning theory encompasses fewer phenomena than the approach to learning that was sketched by Di Poalo et al. (2017). An important advantage that is related to having a less-encompassing theory, however, is that the direct learning theory has been formulated more precisely and has been developed in a much closer relation to empirical research with ecologically-valid tasks.

Finally, to demonstrate with an example that direct learning can be used as the starting point for further theorizing, we conclude this article with a speculative extension of the theory. Even though the theory presented so far is less in need of a representational homunculus that controls or supervises the learning than the to-be-presented extension, and better supported empirically, a few aspects related to open-endedness and randomness may be more easily incorporated in the extension. With this we aim to illustrate that extensions of the theory may be yet better suited to the criteria derived from the chapter by Di Paolo et al. (2017).

Direct learning and multiple perception-action couplings

Previous research on direct learning has addressed how experience with a particular task modifies and maintains a single perception-action coupling, or control law. Consider the example of displacing the hand with regard to the body with the aim to intercept an approaching object. Control laws that may be operative in this action have been studied extensively (e.g., Bootsma, Fayt, Zaal, & Laurent, 1997). To apply the direct learning framework, one would need to analyze the behavior of learners with an information-calibration space, a vector field that represents information for learning, and a usefulness function (cf. Jacobs & Michaels, 2006). Given that a single perception-action coupling is addressed, one would need one of each. For example, one would need only a single information-calibration space, independently of how many dimensions that space may have.

Some actions, however, are best described with several perception-action couplings (e.g., van Hof, van der Kamp, and Savelsbergh, 2006; cf. Lee, Young, Reddish, Lough, & Clayton, 1983, p. 343). Consider a hypothetical catching action in which the catcher separately controls three action components: (a) the timing of the initiation of the catch, (b) the displacement of the hand toward the ball, and (c) the timing of the grasp component of the catch. Three control laws may be used to describe this action.[2] If so, to study learning, one may also use three information-calibration spaces, usefulness functions, and quantities that serve as information for learning. The question that would be raised, we believe, is to what extent the learning of the different perception-action couplings would be independent. Said more precisely, the organism-environment interaction may only generate useful and detectable information for learning for one action component if the other action components are performed at least reasonably successfully.

Consider Figure 5. Imagine that the horizontal axis is an information space for the timing of the initiation of the catch. The continuous curve is a hypothetical usefulness function, such as the maximum percentage of correct catches that may be achieved on the basis of the informational variables that are represented in the space. If the other action components would not be controlled in a sufficiently close to optimal way, one could not catch 100% of the to-be-caught balls, not even if one initiates the catches on the basis of the most optimal informational variable. This is illustrated by the dashed usefulness function in Figure 5. In light of the direct learning theory, one should imagine that the lower usefulness function goes together with an information field with shorter and less precise information vectors.

The previous argument implies that a relatively successful control of the hand displacement and of the timing of the grasp may be necessary to guarantee the existence of information for learning for the initiation of the catch. Likewise, a to-some-extent successful initiation of the catch may be necessary to guarantee the information for learning for the other components. Imagine, then, a particular observer that performs each action component on the basis of an informational variable with a very low usefulness. The three usefulness functions related to such a situation might be as the approximately flat curves in Figure 6. To explain the left panel: even if the observer initiates the catch on the basis of a reasonably good variable, he or she will still catch only a few random balls

[2] We use this suggestion only as a convenient way to illustrate the theoretical point that we want to make in this section. With the example we do not aim to take side in the debate about how the initiation of catches, and the other action components, are actually controlled (cf. Bootsma et al., 1997, p. 1287).

as long as the control of the other components is insufficient. The question becomes: how can a learner get out of such a situation? If, as we have sketched, the overall situation is poor in information for learning, the answer to this question may require more than the direct learning theory as we have described it in earlier sections.

Given that the situation in Figure 6 is poor in information for learning, it invites some random behavior into the theory (and hence some individual differences in learning trajectories; cf. Withagen & van Wermeskerken, 2009). By trying out different informational variables (i.e., loci) at the initial stages of the learning process, the learner might create a situation in which some slight peaks start to emerge in one of the usefulness functions. These slight peaks may form the beginning of a more deterministic learning process that increases the peaks also in the other usefulness functions. The slowly increasing optimality of the different action components will then guarantee the existence of information for learning for the respective components, which, in turn, allows direct learning. If a certain level of performance is achieved, the different action components may flexibly keep each other in shape, achieving a system that is robust to a wide range of perturbations.

One may speculate that situations such as the one described in Figure 6, in which the percentages of correctly performed actions are very low and some random behavior seems to be required, are more characteristic for infant learning (e.g., van der Kamp, Oudejans, & Savelsbergh, 2003; cf. Kayed & van der Meer, 2007) than for the learning patterns shown by adults. Even for adults, however, some actions may initially be so cognitive/inferential, of such an exploratory nature, and/or so much based on instructions, that one might question the usefulness of the direct learning theory on itself for such actions (cf. Runeson, Juslin, & Olsson, 2000). One could think, for example, about learning to swim a particular stroke, which is even unlikely to occur only on the basis of practice. The theoretical sketch provided in this concluding section may therefore increase the scope of the theory also for adults.

References

Abney, D. H., & Wagman, J. B. (2015). Direct Learning in Auditory Perception: An Information-Space Analysis of Auditory Perceptual Learning of Object Length. *Ecological Psychology, 27(4)*, 335-356.

Arzamarski, R., Isenhower, R.W., Kay, B.A., Turvey, M.T., & Michaels, C.F. (2010). Effects of intention and learning on attention to information in dynamic touch. *Attention, Perception & Psychophysics, 72*, 721-735.

Auvray, M., Hanneton, S., & O'Regan, J. K. (2007). Learning to perceive with a visuo-auditory substitution system: Localisation and object recognition with 'The vOICe'. *Perception*, *36*(3), 416–430.

Baggs, E., (2018). A psychology of the in between? *Constructivist Foundations 13(3)*: 395–397.

Barandiarán, X. E. (2017). Autonomy and enactivism: Towards a theory of sensorimotor autonomous agency. *Topoi, 36*(3), 409-430.

Bermejo, F., Di Paolo, E. A., Hüg, M. X., & Arias, C. (2015). Sensorimotor strategies for recognizing geometrical shapes: a comparative study with different sensory substitution devices. *Frontiers in Psychology*, *6*, 1–20.

Bootsma, R. J., Fayt, V., Zaal, F. T. J. M., & Laurent, M. (1997). On the information-based regulation of movement: What Wann (1996) may want to consider. *Journal of Experimental Psychology: Human Perception and Performance*, *23*, 1282–1289.

Calvo, P., & Gomila, T. (2008). *Handbook of cognitive science: An embodied approach*. Elsevier.

Cariani, P. A. (2016). Learning of New Percept-Action Mappings Is a Constructive Process of Goal-Directed Self-Modification. *Constructivist Foundations, 11(2)*, 322-324.

Di Paolo, E., Buhrmann, T., & Barandiarán, X. (2017). *Sensorimotor life: An enactive proposal*. Oxford University Press.

Díaz, A., Barrientos, A., Jacobs, D. M., & Travieso, D. (2012). Action-contingent vibrotactile flow facilitates the detection of ground level obstacles with a partly virtual sensory substitution device. *Human Movement Science, 31*(6), 1571-1584. doi: 10.1016/j.humov.2012.05.006

Froese, T., McGann, M., Bigge, W., Spiers, A., & Seth, A. K. (2012). The enactive torch: A new tool for the science of perception. *IEEE Transactions on Haptics, 5*(4), 365-375.

Fultot, M., Nie, L., & Carello, C. (2016). Perception-Action Mutuality Obviates Mental Construction. *Constructivist Foundations*, *11*(2), 298-307.

Gibson, J. J. (1979). *The ecological approach to visual perception*. London: Routledge.

Gonzalez-Grandón, X., & Froese, T. (2018). Grounding 4E Cognition in Mexico: Introduction to special issue on spotlight on 4E Cognition research in Mexico. *Adaptive Behavior, 26*(5), 189-198.

Heras-Escribano, M. (2016). Embracing the environment: ecological answers for enactive problems. *Constructivist Foundations*, *11*, 309-312.

Haugeland, J. (1998). *Having thought: Essays in the metaphysics of mind*. Cambridge: Harvard University Press.

Huet, M., Jacobs, D.M., Camachon, C, Missenard, O., Gray, R. & Montagne, G. (2011). The education of attention as explanation of variability-of-practice effects: Learning the final approach phase in a flight simulator. *Journal of Experimental Psychology: Human Perception and Performance, 37*, 1841-1854.

Hutto, D. D. (2005). Knowing what? Radical versus conservative enactivism. *Phenomenology and the Cognitive Sciences, 4*, 389-405.

Jacobs, D.M. (2001). *On perceiving, acting, and learning: Toward an ecological approach anchored in convergence*. Utrecht, The Netherlands: Digital Printers Partners.

Jacobs, D.M., Ibáñez-Gijón, J., Díaz, A., & Travieso, D. (2011). On potential-based and direct movements in information spaces. *Ecological Psychology, 23*, 123-145.

Jacobs, D. M., & Michaels, C. F. (2002). On the apparent paradox of learning and realism.

Ecological Psychology, 14, 127-139.

Jacobs, D. M., & Michaels, C. F. (2006). Lateral interception I: Operative optical variables, attunement, and calibration. *Journal of Experimental Psychology: Human Perception and Performance, 32*, 443-458.

Jacobs, D. M., & Michaels, C. F. (2007). Direct learning. *Ecological psychology*, *19*(4), 321-349.

Jacobs, D. M., Runeson, S., & Michaels, C. F. (2001). Learning to perceive the relative mass of colliding balls in globally and locally constrained task ecologies. *Journal of Experimental Psychology: Human Perception & Performance, 27*, 1019-1038.

Jacobs, D. M., Silva, P. L., & Calvo, J. (2009). An empirical illustration and formalization of the theory of direct learning: The muscle-based perception of kinetic properties. *Ecological Psychology*, *21*(3), 245-289. doi: 10.1080/10407410903058302

Jacobs, D. M., Vaz, D. V., & Michaels, C. F. (2012). The learning of visually guided action: An information-space analysis of pole balancing. *Journal of Experimental Psychology: Human Perception and Performance*, *38*(5), 1215-1227. doi: 10.1037/a0027632

Kayed, N. S., & van der Meer, A. L. H. (2007). Infants' timing strategies to optical collisions: A longitudinal study. *Infant Behavior & Development*, *30*, 50–59. doi: 10.1016/j.infbeh.2006.11.001

Kiverstein, J., & Clark, A. (2009). Introduction: Mind embodied, embedded, enacted: One church or many? *Topoi, 28*(1), 1-7.

Lee, D. N., Young, D. S., Reddish, D. E., Lough, S., & Clayton, T. M. H. (1983). Visual timing in hitting an accelerating ball. *Quarterly Journal of Experimental Psychology: Human Experimental Psychology*, *35*(*A*), 333–346.

Lenay, C., Gapenne, O., Hanneton, S., Marque, C., & Genouëlle, C. (2003). Sensory substitution: Limits and perspectives. *Touching for knowing*, 275-292.

Maturana, H. R., & Varela, F. J. (1987). *The tree of knowledge: The biological roots of human* *understanding*. Boston, MA: New Science Library/Shambhala Publications.

McGann, M. (2016). Enactivism and Ecological Psychology: Divided by Common Ground. *Constructivist Foundations*, *11*, 312-315.

Michaels, C., & Beek, P. (1995). The state of ecological psychology. *Ecological psychology, 7*(4), 259-278.

Michaels, C. F., & Carello, C. (1981). *Direct perception*. Englewood Cliffs, NJ: Prentice-Hall.

Michaels, C. F., Arzamarski, R., Isenhower, R. W., & Jacobs, D. M. (2008). Direct learning in dynamic touch. *Journal of Experimental Psychology: Human Perception and Performance, 34(4)*, 944.

Michaels, C. F., & Isenhower, RW. (2011a). Information space is action space: Perceiving the partial lengths of rods rotated on an axle. *Attention, Perception, & Psychophysics, 73*, 160-171.

Michaels, C. F., & Isenhower, R.W. (2011b). An information space for partial length perception in dynamic touch. *Ecological Psychology, 23*, 37-57.

Michaels, C. F., & Romaniak-Gross, C.A. (2012) Geometric specification of dynamics: Learning to visually perceive kinetic quantities from static images. *Perception, 41*, 93-109.

Mossio, M., & Taraborelli, D. (2008). Action-dependent perceptual invariants: From ecological to sensorimotor approaches. *Consciousness and Cognition*, *17*, 1324-1340. doi: 10.1016/j.concog.2007.12.003

Noë, A., & Noë, A. (2004). *Action in perception*. MIT press.

O’Regan, J. K., Myin, E., & Noë, A. (2005). Skill, corporality and alerting capacity in an account of sensory consciousness. *Progress in brain research, 150*, 55-592.

O'Regan, J. K., & Noë, A. (2001). A sensorimotor account of vision and visual consciousness. *Behavioral and Brain Sciences*, *24*, 939-973. doi: 10.1017/S0140525X01000115

Rowlands, M. (2010). *The new science of the mind: From extended mind to embodied phenomenology*. Cambridge: MIT Press.

Runeson, S., Juslin, P., & Olsson, H. (2000). Visual perception of dynamic properties: Cue heuristics versus direct-perceptual competence. *Psychological Review, 107*, 525-555.

Shaw, R., & Kinsella-Shaw, J. (1988). Ecological mechanics: A physical geometry for intentional constraints. *Human movement science*, *7*(2-4), 155-200.

Solomon, H. Y., & Turvey, M. T. (1988). Haptically perceiving the distances reachable with hand-held objects. *Journal of experimental psychology: Human perception and performance, 14(3)*, 404.

Stapleton, M. (2016). Enactivism embraces ecological psychology. *Constructivist Foundations*, *11*, 325-327.

Turvey, M. T., & Carello, C. (1995). Dynamic touch. In: W. Epstein & S. J. Rogers (Eds.), *Perception of space and motion* (pp. 401–490). San Diego, CA: Academic.

Van der Kamp, J., Oudejans, R., & Savelsbergh, G. (2003). The development and learning of the visual control of movement: An ecological perspective. *Infant Behavior and Development, 26*(4), 495-515.

Van Hof, P., van der Kamp, J., & Savelsbergh, G. J. (2006). Three-to eight-month-old infants' catching under monocular and binocular vision. *Human Movement Science, 25*(1), 18-36.

Varela, F., Thompson, E., & Rosch, E. (1991). *The Embodied Mind: Cognitive Science and Human Experience*. MIT Press, Cambridge, Massachusetts.

Visell, Y. (2008). Tactile sensory substitution: Models for enaction in HCI. *Interacting with Computers, 21*(1-2), 38-53.

Warren, W. H. (2006). The dynamics of perception and action. *Psychological review*, *113*(2), 358.

Warren, W. H., Kay, B. A., Zosh, W. D., Duchon, A. P., & Sahuc, S. (2001). Optic flow is used to control human walking. *Nature neuroscience, 4*(2), 213.

Withagen, R., & Van Wermeskerken, M. (2009). Individual differences in learning to perceive length by dynamic touch: Evidence for variation in perceptual learning capacities. *Perception*

& Psychophysics, 71(1), 64-75.

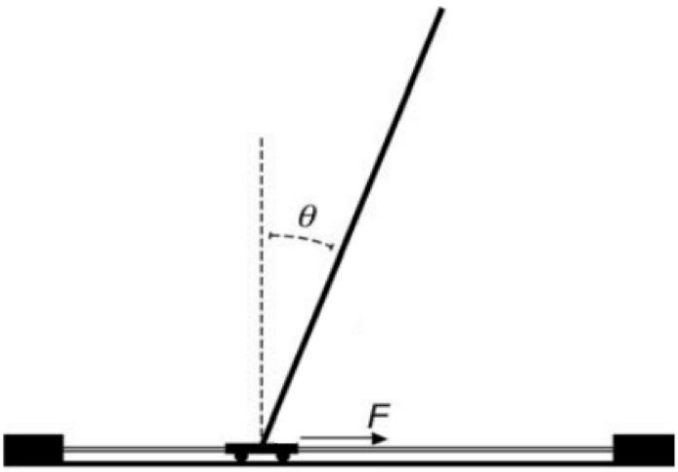

Figure 1. The cart-pole system. Participants moved the cart with their dominant hand along a steel rod with the aim to keep the pole balanced. Adapted form "The learning of visually guided action: An information-space analysis of pole balancing," by D. M. Jacobs, D. V. Vaz, and C. F. Michaels, 2012, *Journal of Experimental Psychology: Human Perception and Performance*, *38*, p. 1216. Copyright by American Psychological Association. Adapted with permission.

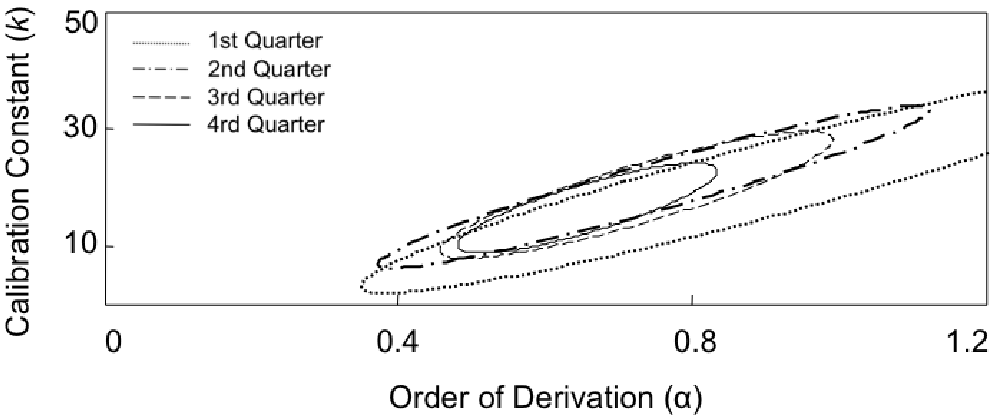

Figure 2. Information-calibration space used to study cart-pole balancing. The ellipses indicate the location of the group of participants in the space for each quarter of trials during the experiment. Adapted form "The learning of visually guided action: An information-space analysis of pole balancing," by D. M. Jacobs, D. V. Vaz, and C. F. Michaels, 2012, *Journal of Experimental Psychology: Human Perception and Performance*, *38*, p. 1220. Copyright by American Psychological Association. Adapted with permission.

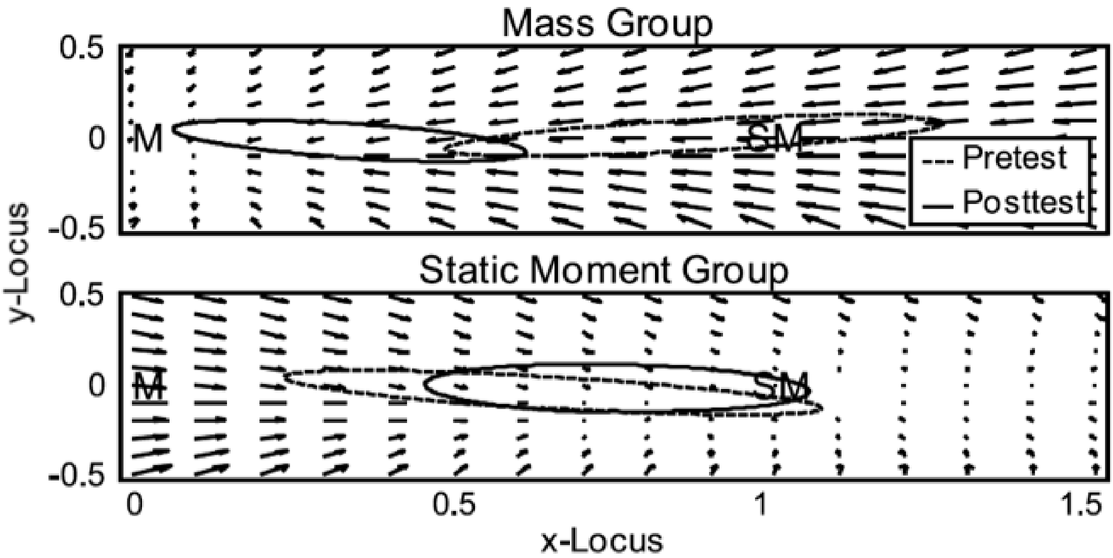

Figure 3. Ellipses that indicate the location of individuals in the information space defined by Equation 7, for groups of individuals with feedback on mass (upper panel) and static moment (lower panel), in the pretest (dashed outline) and posttest (continuous outline). The vector fields correspond to the information for learning defined in Equations 8 and 9. *M* = locus corresponding to mass. *SM* = locus corresponding to static moment. Adapted form "An empirical illustration and formalization of the theory of direct learning: The muscle-based perception of kinetic properties," by D. M. Jacobs, P. L. Silva, and J. Calvo, 2009, *Ecological Psychology*, *21*, p. 257. Copyright by Taylor & Francis Group, LLC. Adapted with permission.

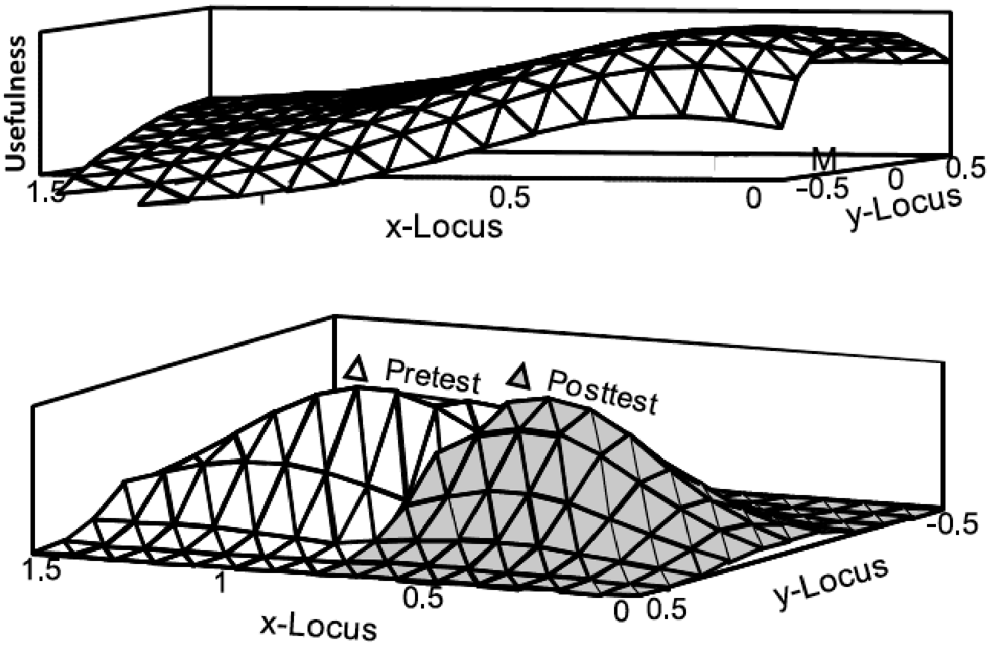

Figure 4. Upper panel: Usefulness function for the information space indicated by Equation 7 for a mass-estimation task (the *fast* condition of Experiment 2 of Jacobs et al., 2009). More useful variables are indicated by a higher surface. Lower panel: distributions functions that indicate the locations of the group of individuals before and after practice. Adapted form "An empirical illustration and formalization of the theory of direct learning: The muscle-based perception of kinetic properties," by D. M. Jacobs, P. L. Silva, and J. Calvo, 2009, *Ecological Psychology*, *21*, p. 269. Copyright by Taylor & Francis Group, LLC. Adapted with permission.

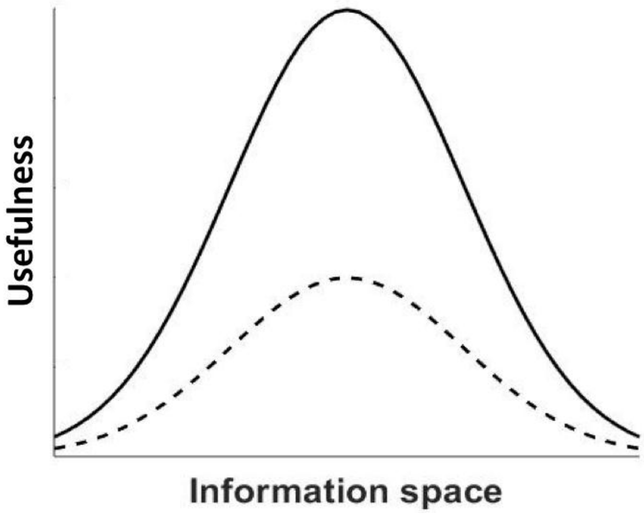

Figure 5. Hypothetical usefulness functions associated to an information space for one component of a multi-component action. The solid line stands for a situation in which the other components of the action are performed in a way that is sufficiently close to optimal. The dotted line stands for a situation in which this is not the case.

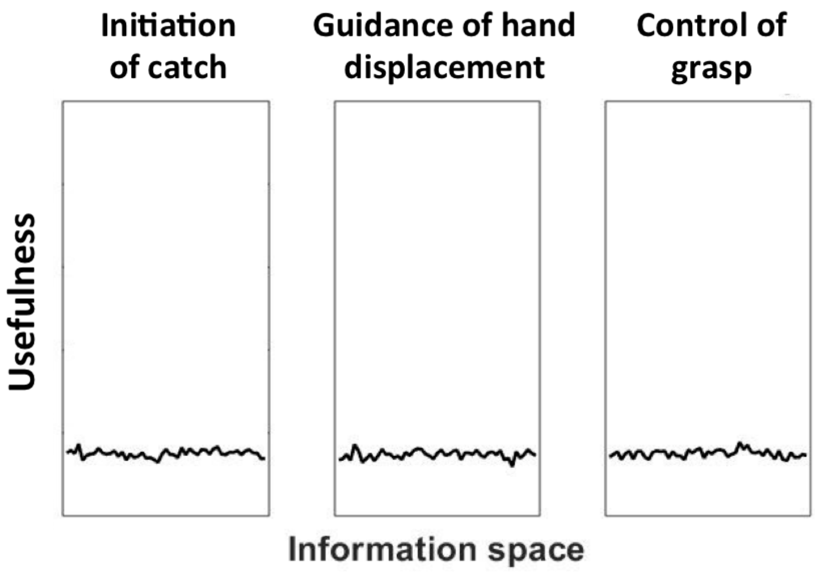

Figure 6. Flat usefulness functions that correspond to the components of a hypothetical catching action in which all components are performed in a way that is far from optimal.

Author Biographies

Alfredo Higueras-Herbada is Ph.D. aspirant in the Faculty of Psychology at the Universidad Autónoma de Madrid. His main research interests are sport science and ecological psychology. He is now combining research in anticipation in sport with direct learning theory to improve the understanding of learning in sport.

Carlos de Paz is Ph.D. student at the Universidad Autónoma de Madrid. His research focuses on how to design sensory substitution devices to allow users to perceive the affordances of the environment, such as the passability through apertures or grasping objects. He is also interested in perceptual learning, ecological psychology, sensorimotor contingencies and post-cognitive approaches.

David M. Jacobs, Ph.D., is Associate Professor (Profesor Contratado Doctor) at the Department of Psychology of the Universidad Autónoma de Madrid. His main theoretical contributions are formulated around an ecological theory of learning that he, with Claire F. Michaels, has named direct learning. His most recent empirical research aims to apply and advance ecological ideas about perception, action, and learning, in the fields of sensory substitution, aviation, and sports.

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Jorge Ibáñez-Gijón, Ph.D., is Postdoctoral Researcher at the Universidad Autónoma of Madrid, from the Talent Attraction program of the Autonomous Region of Madrid. His research interests encompass ecological and dynamical approaches to perception, action, and learning in a variety of tasks including sports, sensory substitution, and animal behavior.