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DIRECT LEARNING

Information for learning lawfully emerges from the cycle of perception and action

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DIRECT LEARNING

Information for learning lawfully emerges from the cycle of perception and action

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The theory of direct learning (Jacobs & Michaels, 2007) can be interpreted as a corollary of James Gibson's theory of direct perception (Gibson, 1979; Michaels & Carello, 1981). Direct perception asserts that perception is based on information. Without the need for inferential processes or cognitive enrichment, information specifies the environment to observers, who are therefore in direct epistemological contact with their surroundings. Direct learning builds upon this rationale and claims that learning, too, can be based on information, albeit of a different sort. Information for learning specifies not the current environment of the observer, but potential changes in the setup of his or her perceptual-motor system (Jacobs et al., 2009). This information can be used to optimize performance. As a consequence, progress in performance with practice is the result not of internal processing but of the detection and integration of information for learning. The theory of direct learning was developed as a response to the long-standing critique that ecological psychology lacked a principled account of learning (Michaels & Beek, 1995). It formalized a methodological doctrine for the study of learning in the same way that direct perception had established a doctrine for the study of perception (Turvey, 2001). But even though direct learning was intended to explain a broad range of learning phenomena, the studies following this doctrine appeared to focus more on perceptual attunement than on the acquisition of perceptual-motor skills (see Jacobs et al., 2012; Michaels et al., 2017, for exceptions). One of the reasons for this somewhat narrow interpretation of direct learning may be that earlier descriptions of the theory (Jacobs & Michaels, 2007; Jacobs et al., 2009) did not sufficiently emphasize the reciprocity of perception and action and the related fact that behavior is an emergent phenomenon (Warren, 2006), which has vast implications for any theory of learning. As such, our aim in this chapter is to more clearly position direct learning as a general theory of perceptual-motor learning, rather than a theory of perceptual attunement only. To do so, we revisit examples of applications of the theory in the past two decades, with an emphasis on research about the control of action. We start, however, by examining the cycle of perception and action, which constitutes the indispensable foundation of direct learning.

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The cycle of perception and action

In the performance of everyday activities, the processes of perception and action are intimately related. They form, as it were, two sides of the same coin (Gibson, 1979). The control of our actions, from locomotion to manipulation and beyond, cannot occur without a proper perception of the environment. Take the example of cycling down a crowded street in Amsterdam, a city known for its busy traffic. Navigating through the turmoil of passing cars and crossing pedestrians requires a continuous detection of information. Information about the motion of oneself, one's current speed and heading direction, but also information about the motion of other road users in relation to oneself. According to Gibson's theory of direct perception, such information is available in the energy arrays that surround the observer (Gibson, 1979). These can be optical, acoustical, or even chemical, but in any case the information residing in them needs to be detected by the observers to control their actions. The information detection is not a passive process of stimulus and response. It is an active process of organisms exploring their environment (Gibson, 1966). Cyclists in Amsterdam continuously scan their environment by moving their eyes, turning their head, and perhaps even leaning over to see whether there are any pedestrians crossing the street. As such, a proper perception of the environment cannot occur without the cyclist's action of exploring the available information. At the same time, the flow of information in the energy arrays is *a function of* the cyclist's movements. It is dependent not only on transformations that occur in the environment but also on transformations of oneself. This gives the processes of perception and action a mutual dependency that is characteristic of human behavior. In the words of Gibson: "We must perceive in order to move, but we must also move in order to perceive" (Gibson, 1979, p. 223). As it turns out, this reciprocity has repercussions for perceptual-motor learning, the likes of which we will address in this chapter.

The control of action

In the past 50 years, empirical work has revealed numerous informational variables that reside in the energy arrays surrounding an observer. A prominent example of this is τ, an optical variable that specifies the time remaining for an observer to be in contact with an approaching object (Lee, 1976). Formally, τ is defined as the optical angle of the object divided by its rate of expansion. If the speed of the object relative to the observer's point of view remains constant, this variable is invariant across different speeds, sizes, and shapes of the object. Due to this invariance, τ can be used for the visual control of various activities (Lee et al., 2009). Studies have suggested that τ, or its derivative $\dot{\tau}$, may indeed be involved in the control of braking a car (Lee, 1976), hitting a falling ball (Lee et al., 1983), timing an attacking drive in table tennis (Bootsma & van Wieringen, 1990), grasping an approaching ball (Savelsbergh et al., 1991), and reaching to grasp an object (Zaal & Bootsma, 1995). The identification of invariants such as τ has given rise to the notion of a control law (Warren, 2006). A control law is a mathematical formalization of the regulation of action on the basis of detectable information. The most general form of a control law is given by:

$$A = f(I).$$

In this equation, A is an (set of) action parameter(s) that is relevant to the outcome of the performance. It can be a force exerted by the organism on the environment but also the organism's center of pressure in the occasion of postural control or the position of the hand in the case of catching a ball. Later in this chapter we will also see an example of making perceptual judgments (Jacobs et al., 2009). In that case, the action constitutes a judgment, which is likewise hypothesized to be regulated by information. The variable *I* is an (set of) informational variable(s) that is presumedly detected and used for the control of the action. It can constitute an invariant such as τ, but it can also consist of other variables such as the object's optical size or rate of expansion. The examples presented in this chapter will exclusively consider optical variables, but information for action is by no means restricted to optics (e.g., Abney & Wagman, 2015). Lastly, *f* is the function that relates the detected information to the action. Given a particular informational variable, a well-defined function *f* allows one to determine the value of the action parameter.

Room for learning

The control law provides a parsimonious way to study the control of action. It allows the researcher to investigate how informational variables, invariant or not, are used to regulate actions without presupposed mediation of internal models or programs for action. At the same time, the control law may create the false impression of an infallible and static perceptual-motor system (Sims & Fajen, 2007). Human agents, in contrast, are fallible and highly dynamic. We detect informational variables in the ambient arrays that are non-specific to the property we intend to perceive (Withagen, 2004), such that inaccuracies in our performance emerge. We have trouble calibrating our perceptual-motor system, such that we time our actions too early or too late, often with serious consequences. We move with too much force, or with too little, and perhaps we control one action parameter while we ought to control another. There is, however, also an upside to this story: Human agents have the admirable ability to *learn*. Whenever we practice a task, we tend to improve our performance. Whereas we may fail on the short timescale of the action itself, we tend to succeed on the longer timescale of learning (Jacobs & Michaels, 2002). To mention two well-studied improvements, we attune to the informational variables that specify the to-be-perceived property, such that our performance becomes more accurate, and we calibrate our perceptual-motor system, such that the information-action relationship becomes more adequate (Gibson & Gibson, 1955; Jacobs & Michaels, 2007). In other words, we adapt the control law or perception-action coupling that governs our behavior. The question that is at the core of understanding learning is *how* we manage to do so. But before we address this question and thereby lay out the theory of direct learning, let us consider some of the empirical evidence for attunement and calibration in the control of action.

Evidence for attunement and calibration

The first evidence for attunement in visually controlled action was provided by Smith et al. (2001) via a ball-hitting paradigm. Participants in this study released a simulated pendulum with the aim of making it collide at the appropriate place and time with a ball that approached at a constant speed (Figure 19.1). In a series of experiments, Smith and colleagues varied the speed and size of the approaching ball and measured the timing of the release. This allowed them to study whether participants would use variables such as the invariant τ, introduced earlier in this chapter, to control their action. They observed that participants initially released the pendulum too early for slow balls and for large balls. This

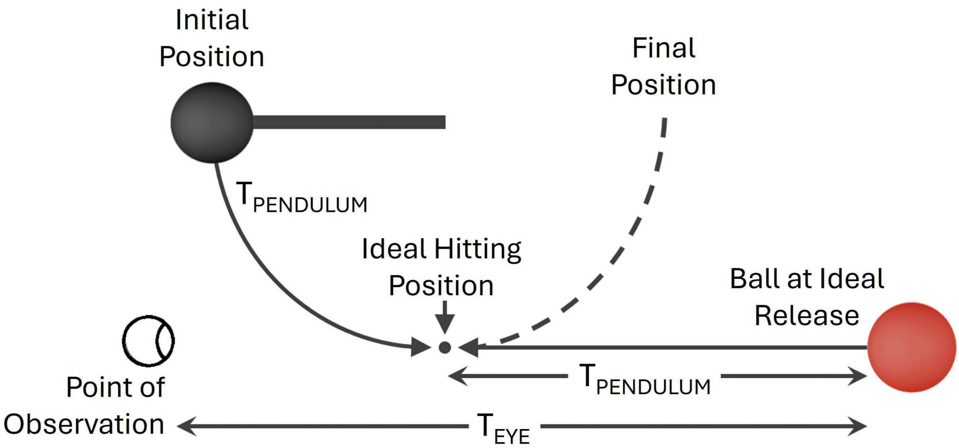

Figure 19.1 Schematic representation of the experimental setting of Smith et al. (2001). Participants released a falling pendulum so that it collided with an approaching ball at the ideal hitting position. Adapted from Smith et al. (2001).

suggested that participants did not rely on τ, but on the rate of expansion of the ball, given that this latter variable varied with speed and size while τ remained invariant. With practice, participants strongly improved their performance, and they came to hit the balls for all types of approaches, including the slower and larger ones. This suggested that participants came to rely on a τ-like strategy, based on a combination of optical size and expansion rate. To confirm whether this was indeed the case, Smith et al. designed follow-up experiments that included transfer tests. One group of participants trained with slow balls and then transferred to faster ones, whereas another group trained with fast balls and transferred to slower ones. As it turned out, practice with slow balls helped participants to discover the τ-like strategy, and participants in this condition were highly successful in the transfer to faster balls. Conversely, practice with fast balls did not help participants to discover the τ-like strategy. According to the authors, participants in this condition came to rely predominantly on the optical angle of the approaching ball. As a result, performance with slower balls in the transfer test was weak. Taken together, the experiments reported by Smith et al. showed that practice under the right conditions can push participants to rely on informational variables that are better suited to the visual control of their actions.

Fajen and Devaney (2006; cf. Fajen, 2008a, 2008b) built upon the work of Smith and colleagues (2001) and investigated attunement in an emergency braking paradigm. Participants in a virtual car waited until the last moment and then applied maximum braking pressure to stop at an indicated stop sign. In line with what had been reported by Smith et al. (2001), participants appeared to stop too early when the approach was slow or when the stop sign was large. This indicated, as expected, that participants initially controlled the braking on the basis of for this task non-specifying variables such as the sign's rate of expansion or 1/τ.[1] Performance improved with practice, suggesting that participants attuned to more suitable variables. However, the effects of speed and size did not disappear, meaning that participants did not come to rely on specifying invariants. The authors suggested that this may have been because the range of conditions used was too narrow in the experiments. In a follow-up experiment, approach speed and sign size were varied together instead of separately so as to increase the range of conditions. Intriguingly, this led to more substantial improvements in performance. Participants now seemed capable of exploiting variables such as a combination of τ and the ratio of the global optic flow rate of the ground plane, which specified the ideal deceleration. Together, these experiments demonstrate that the conditions of practice, also known as the local constraints (Jacobs et al., 2001), have a crucial role in the process of attunement. Only when the outcome of the behavior is unsatisfactory, and attunement is necessary, will people come to rely on the most relevant informational variables. If the behavioral consequences of relying on non-specifying variables are minor, participants may settle upon those variables without further adaptations.

The attunement to more relevant informational variables is not the only route to improving action control. Calibration of the perceptual-motor system is another way to enhance performance (Jacobs & Michaels, 2007). Evidence for this was reported by Jacobs and Michaels (2006), who used a lateral manual interception paradigm. Participants in this study intercepted balls that swung down on thin lines at a variable lateral distance from the participant. To identify the informational variables that may be used for the regulation of the interception, participants first judged the lateral distance of the balls. Comparison of the judgments to the actual distances suggested two things. First of all, participants improved

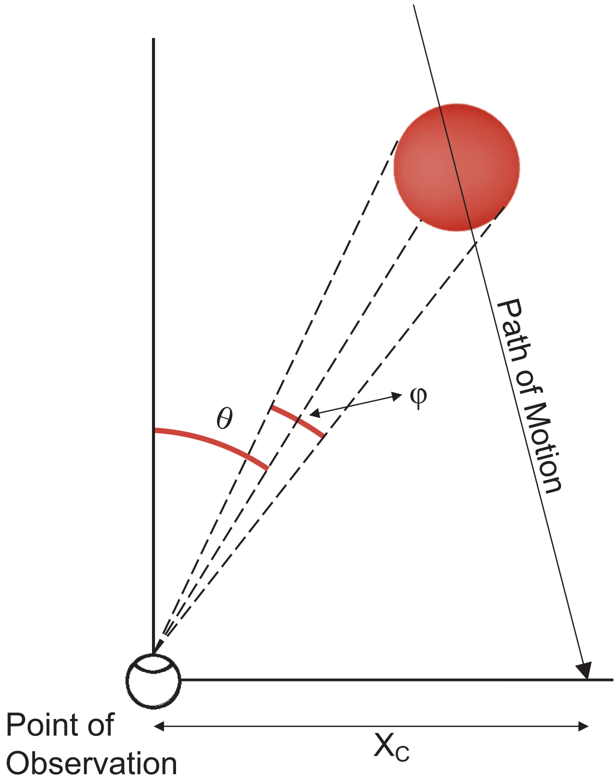

Figure 19.2 The experimental setting of Jacobs and Michaels (2006). X_C is the passing distance of the ball relative to the point of observation. φ is the optical angle subtended by the ball, and θ is the azimuthal angle, which equals the angle between the sagittal plane and a line from the eye to the center of the ball. Adapted from Jacobs and Michaels (2006).

in the accuracy of their judgments, implying a capacity to learn the task. And, second, they mostly attuned to the ratio between the rate of change of the azimuth angle and the rate of optical expansion (θ/φ), either in units of ball size ($\delta\times\theta/\varphi$) or not (Figure 19.2). For clarification, both of these variables comprised prospective information about the future passing distance of the ball, respectively, under a constant and varying ball size. In a second experiment, participants were instructed to intercept the balls rather than to only judge distance. Using an adapted version of a control law proposed by Peper et al. (1994), the authors simulated the hand trajectories for each of the earlier-identified variables and compared the simulated and actual hand trajectories. Again, the results pointed out that (1) participants improved in their interception performance and (2) they relied on either θ/φ (monocular condition) or $\delta\times\theta/\varphi$ (binocular condition). Somewhat to the surprise of the authors, however, the improvement in performance could not be attributed to an attunement to more relevant information, because the changes in variable use were modest. Instead, most of the learning could be attributed to the calibration of parameters in the control law.

Moving in a learning space

The above examples demonstrate that learning to control an action can be understood as attuning to the right information *I* or calibrating the function *f* that couples the information to action. Another way of improving performance could be to change the action parameter *A* that is being controlled. Although learning may occasionally involve large transformations in behavior, these learning processes typically involve *gradual* adaptations in the setup of the perceptual-motor system. Instead of switching abruptly from one informational variable to another, learners attune gradually to the most relevant information. Likewise, learners do not change instantaneously from controlling one action variable to controlling another, but they progressively graduate to the most relevant ones.[2] To account for such continuity, the theory of direct learning proposes to frame learning as a movement through what we here refer to as *a learning space* (Jacobs & Michaels, 2007; cf. Pacheco et al., 2019). A learning space is a continuous space in which every locus represents a unique perception-action coupling (and thus a unique way to perform the action). Loci in the space that are close to each other correspond to ways to perform the action that are quite similar, whereas loci that are far apart correspond to ways that are substantially different. Gradual changes in performance over practice can therefore be represented as continuous trajectories through the space. The ultimate goal of direct learning is to explain such trajectories, which is to say, to explain the changes in the control law that governs the learner's perceptual-motor behavior.

The creation of a learning space is a difficult but important step in the methodology associated with direct learning. It often requires creativity on the part of the researcher. Ideally, the space should include all information-action couplings that are used by some individual at some phase of the learning process. This step is, of course, best illustrated with an example. We use the example of manual pole balancing (Jacobs et al., 2012). In this study, the authors created a compound information-calibration space to portray the process of learning. Bear in mind, however, that the methodology outlined in this study could in principle be generalized to any other type of learning space, such as an action space or an information-action space. Once one understands the principles that are illustrated by the example, it is easy to see that the information-calibration space proposed in Jacobs et al. falls under our definition of a learning space.

In the study of Jacobs et al. (2012), participants balanced an unstable cart-pole system by manually moving the cart attached to the pole along a steel rod. To be successful, they had to keep the pole upright for at least 30 seconds—a task that was far from easy to perform. To formalize the control of action in this setting, the authors proposed the following control law:

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

In this equation, the action parameter was given by $F(t)$, the time-dependent force exerted by the participant on the cart so as to control its motion. The information for the action was assumed to reside in the fractional derivative α of the pole angle θ (the deviation from the vertical). Crucially, α could take any value between 0 and 2, and the derivatives of θ thus constituted a continuum of variables. On this continuum, $\alpha = 0$ corresponded to the pole's angle, $\alpha = 1$ to the angular velocity, and $\alpha = 2$ to the angular acceleration. The authors assumed that participants could detect information corresponding to all values of α, including the non-integer ones. The control law was completed with calibration parameter k and a perceptual-motor delay ($d = 0.1$ s) between the detection of information and the implementation of action. Based on this law, Jacobs and colleagues created a two-dimensional information-calibration space with α on the x-axis and k on the y-axis (Figure 19.3). Any locus in this space corresponds to the detection of a particular informational variable in combination with a calibration parameter. Assuming the above-mentioned control

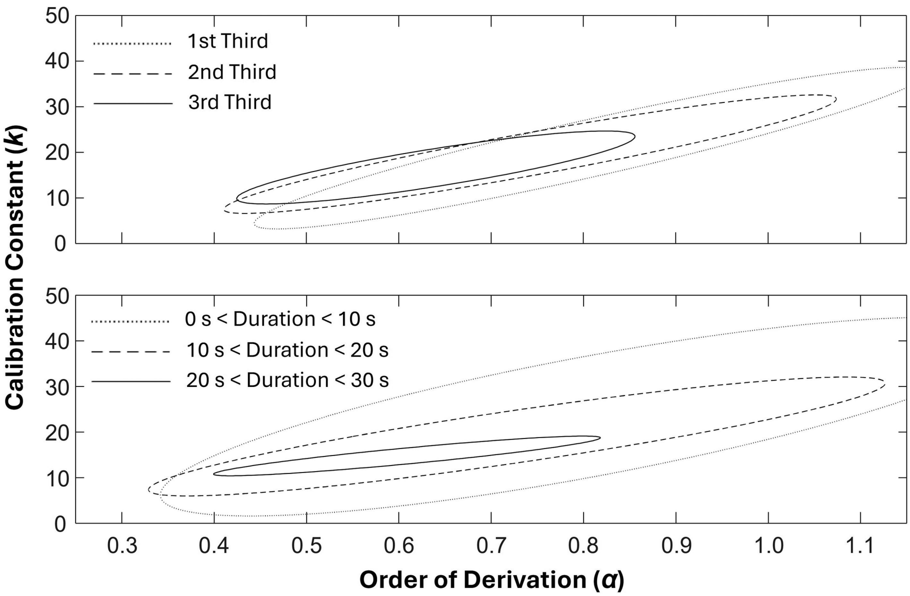

Figure 19.3 Average locations of participants in the information-calibration space from the first to the final third of practice (upper panel) and for trials with different durations (lower panel), indicated with standard error ellipses. The graph reveals that participants came to rely on a smaller and more useful section of the space. Adapted from Jacobs et al. (2012).

law, each point in the space in fact represents a perception-action coupling, making this information-calibration space a particular case of a learning space.

After having constructed the learning space, Jacobs et al. (2012) empirically tracked the trajectories of all participants over practice. They did so by determining each participant's locus, that is, each participant's perception-action coupling, in different phases of the experiment. The analysis revealed that the learners gradually moved to a preferred region in the learning space (Figure 19.3). Modeling of the cart-pole system showed that this region, corresponding to the use of an α around 0.64 and a calibration parameter k around 16.7, indeed resulted in a successful balancing of the pole. Thus, participants generally traversed to the most useful region in the learning space, indicating that they successfully adapted the control law underlying their behavior.

Information for learning

So far, we have established (1) that perceptual-motor learning may involve several processes, such as attunement, calibration, and changes on the side of the action and (2) that any of these processes can, in principle, be portrayed as a continuous movement in a learning space. The question that remains is: How can the movement in the space be explained? In the majority of the frameworks about skill acquisition (e.g., Schmidt, 1975; Wolpert et al., 2011), the dynamic nature of human functioning and our tendency for change is explained through internal computations, memory-based algorithms, probabilistic state transitions, and the like. The theory of direct learning, with its roots in Gibson's theory of direct perception, provides an ecological account of our tendency for change (Jacobs & Michaels, 2007; cf. Fowler & Turvey, 1978). According to this theory, the learning of perception and action is information-based. In the same way that perception and action themselves are based on information that resides in the ambient arrays, so is *the improvement* in perception and action based on the pickup of information. This information must be of a different sort, because the timescales of the processes differ. Whereas perception and action are fast and occur on a short timescale, the learning of perception and action is slow and occurs on a longer timescale (Jacobs & Michaels, 2002). As such, it seems reasonable to assume that information for learning reveals itself over a longer period of time, extended over multiple loops of the perception-action cycle (Figure 19.4). But what could such information entail?

As a starting point, let us assume that information for learning is indeed generated over multiple loops of the perception-action cycle on a timescale compatible with learning. Think, for instance, about a sequence of strokes in swimming or about a series of trials in catching a ball. Each of these repetitions is produced through a particular coupling of perception and action, and each of them has *a rich pattern of observable consequences* in the behavior that emerges. If the swimming stroke is effective, it leads to a strong push-off and an experience of fast gliding through the water, among a myriad of other bodily sensations. If not, the swimmer's forward acceleration in the pool will be low, and the stroke is unsuccessful. Similarly, if the catching movement is well controlled, it leads to a catch. If not, the catcher will miss the ball, and it will land somewhere else, either close by or far away. In practicing swimming or catching, each stroke or trial leads to new observable consequences. It is within the pattern of observable consequences over multiple cycles that information for learning resides (Jacobs et al., 2009). Detecting the appropriate information for learning from the pattern of consequences of perception and

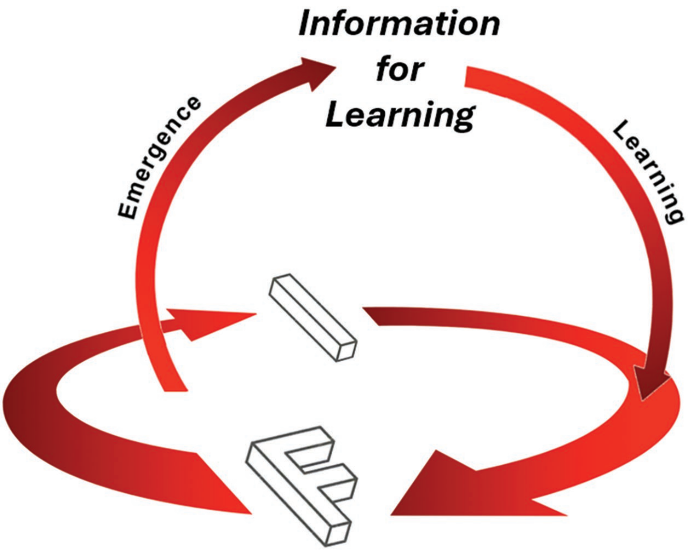

Figure 19.4 Lawfully coupled cycles of perception and action (horizontal cycle) and learning (vertical cycle). The theory of direct learning holds that the cycle of learning on the longer timescale modifies the coupling of perception and action on the shorter timescale. The perception-action coupling is represented by the arrow from the information for action (I) to the exerted force (F).

action allows the optimization of the coupling between the two. In other words, the fast perception-action cycle slowly generates the information for learning that drives the cycle of learning (Figure 19.4). If detected and used, this information for learning in the long run educates the learner about how to perform a particular task, what to see, what to hear, and what to do to be successful.

Information for learning as a vector field

As we have seen, direct learning asserts that information for learning is available in the energy arrays that surround the active learner. The information for learning is assumed to *specify* a movement in the learning space. Given that moving in the learning space means changing the perception-action coupling, we may say that information for learning specifies a change in the perception-action coupling. Let us consider this statement more carefully. Imagine a learner at a specific locus in the learning space, performing the action with the perception-action coupling corresponding to that locus. The information for learning that can be detected from the emerging behavior ought to specify a direction and speed of the movement in the space. This means that the information for learning at that locus can be visualized as a vector. The same is true for the other loci in the space. Given that information for learning can be represented with a vector at each locus in the space, it can be represented as a vector field on the space. The main assertion of direct learning, which is reflected in the name of the theory, can now be formulated in two ways. In the actual world, the change in the perception-action coupling (or, said with more precision, the change in the biological tissue that underlies the perception-action coupling) is hypothesized to be specific to detected information for learning. Likewise, in the learning space, the trajectory of the learner is hypothesized to follow the vectors that represent the information for learning.

Remember that the action that emerges at a given moment is a function not only of the control law but also of the environment in which the action takes place. The usefulness of loci in the learning space is thus co-dependent on the surroundings of the learner. As such, the vectors in the information field and the trajectories of the learners are not determined in advance but emerge from the cycle of perception and action *within* the encountered conditions. The fast emergence of action drives the slow emergence of learning, but both are emergent processes. This emergent character implies that predictions concerning the learning trajectories can be made only with sufficient knowledge of the constituent practice conditions.[3,4]

In the body of work on direct learning, there are no empirical examples of information for learning in action tasks. The best examples of information for learning as portrayed by a vector field can be found in studies on perceptual judgments, such as dynamic touch (Michaels et al., 2008; Jacobs et al., 2009). In Jacobs et al., participants judged the mass of an unseen tensor object by wielding the object freely. Earlier research revealed several informational variables that may be used to perceive the objects' mass, ranging from static moment to the first and third principal moments of inertia (Turvey & Carello, 2011). To create a learning space, these variables were transformed into a *continuum*. To do so, the following equation was proposed:

$$I(x, y) = yI_3 + (1 - y)\int \rho(s)\delta(s)^x \, \mathrm{d}V.$$

In this equation, ρ stands for the mass-density function of the tensor object, δ for the distance of a point s to the axis of rotation, and V for the volume of the object. More relevantly, $I(x, y)$ defines a two-dimensional space that includes all the aforementioned informational variables (Figure 19.5). At (0, 0) we find mass M, at (1, 0) static moment SM, at (2, 0) the first principal moment of inertia I_1, and at (0, 1) the third principal moment of inertia I_3. Other loci comprise non-integer values of x and y, which nonetheless have the status of information for perception. In an experiment, participants practiced to judge the mass of a set of tensor objects with varying masses and mass distributions. One group received feedback on the object's mass, whereas another group received feedback on its static moment. As illustrated in Figure 19.5, participants in the first group traversed to (0, 0) over practice, the locus that specified M. Participants in the second group moved toward (1, 0), the locus specifying SM. This confirmed that the learning space was adequate for capturing learning.[5]

The next step of Jacobs et al. (2009) was to identify information for learning. To do so, they carefully considered the consequences of being at a particular locus, that is, of making judgments on the basis of a particular variable. Participants who pick up SM, so they realized, tend to overestimate tensor objects that have a mass far from the axis of rotation, because SM in these objects is relatively large. This implies a positive relationship between judgment error E and the distance of the mass to the axis of rotation. Given that this distance is related to the ratio of SM over M, information for learning resides in the covariation between E and SM/M. To formalize the learning process, Jacobs et al. equated the covariation between E and SM/M, multiplied by a parameter k_1,

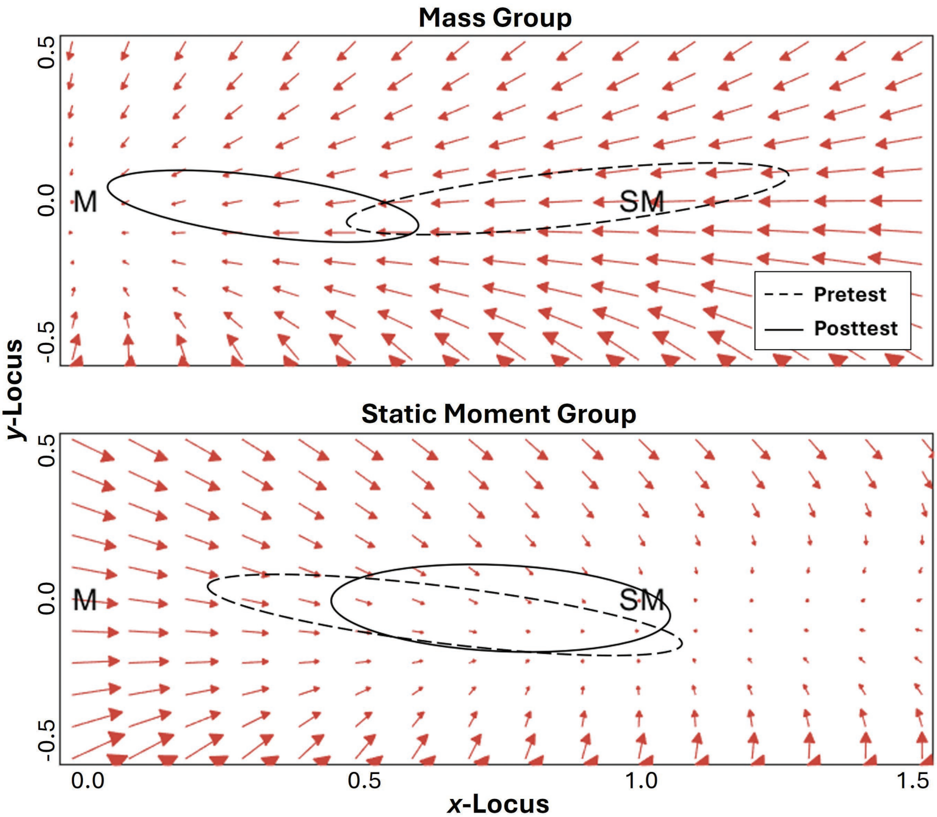

Figure 19.5 The two-dimensional information space of Jacobs et al. (2009). Participants in the upper panel received feedback on mass and moved toward (0, 0). Participants in the lower panel received feedback on static moment and moved toward (1, 0). The vector fields correspond to the information for learning available to both groups. Adapted from Jacobs et al. (2009).

with the derivative of x. Analogously, the covariation between E and I_3, multiplied by parameter k_2, was equated with the derivative of y. This resulted in the following set of differential equations:

$$\dot{x}(t) = -k_1 \text{ covariance } \{E, SM / M\},$$

and

$$\dot{y}(t) = -k_2 \text{ covariance } \{E, I_3\}.$$

Such equations are to learning what control laws are to action. The right-hand sides define information for learning as detectable quantities. The left-hand sides indicate the change that is affected by the learning, which can be interpreted as a vector field on the space. A comparison between the vector fields and the empirically tracked movements through the space confirmed that the trajectories were indeed (partly) explained by the identified information for learning. In mathematical terms, this means that the trajectories are solutions of the set of equations.

Information for learning in action tasks

As anticipated, we are not aware of empirical examples of information for learning as described by a vector field in studies with an emphasis on action. Fully worked out examples of the direct learning methodology only apply to studies with an emphasis on perception. Even so, the line of reasoning that was set out in the previous sections seamlessly fits the action side as well. Given the reciprocity of perception and action, we would even argue that *all* motor learning is, in fact, perceptual-motor learning. Every action comes with perception, just as every perception comes with action. This brings us back to the example of cycling through Amsterdam. Anyone who has ever been to this city would agree that this activity requires an extensive process of learning. While experienced cyclists navigate fluently through the whirlwind of cars and pedestrians, inexperienced cyclists experience serious trouble in this dynamic environment. So how can a task such as cycling, for which perception and action are both required, be learned? What could be *the information for learning* in this situation?

Put up front, information for learning is expected to be as complex as the environment from which it arises. Thus, for a researcher, it is not likely to be easy to identify. Allow us, however, to speculate on some of its components, inspired by the studies discussed in this chapter. The cyclist is confronted with different traffic users. These include fast cars but also slow pedestrians. Imagine that the cyclist uses the optical rate of expansion of the road users for the control of braking to avoid colliding with them. As we have seen in the work of Smith et al. (2001) and Fajen and Devaney (2006), reliance on this non-specifying variable probably results in braking too early for slow road users and braking later for faster ones. Braking early for pedestrians is thus *an observable consequence* of the suboptimal detection of information. Hence, when braking early occurs a number of times, and only for pedestrians and not for cars, a pattern emerges from the cycle of perception and action. The covariation between the type of traffic user and braking early (or not) constitutes information for learning that may drive the cyclist to the use of a τ-related invariant. The covariation is only available on the longer timescale of learning, and it does not require updates of internal models. This, of course, is only one component of a set of complex perceptual-motor skills that are required to cycle through Amsterdam. Nevertheless, it serves as a demonstration that information for learning is not merely an abstract construct. Rather, it is detectable for the learner as well as identifiable for the researcher.

As becomes clear from this illustration, learning in daily life typically occurs *during* an ongoing activity. We learn to navigate *while* we are cycling, because we are continuously informed by the cycle of perception and action that governs our actions. As such, it is surprising that most of the experimental learning paradigms use discrete tasks, such as pushing a button on a keyboard, without consequences that resemble those in real life. To identify information for learning in ecologically relevant settings (and possibly even to allow direct learning to occur), it is necessary to investigate the continuous looping of perception and action. An example of an experimental task that may permit this is the recently introduced manual ball-and-beam paradigm (Hafkamp et al., 2023, 2024). In this paradigm, participants control a ball rolling back and forth between two targets on a handheld beam. To do so, they continuously adjust the inclination angle of the beam so that the ball hits the targets as often as possible in a given timespan. This paradigm requires a considerable amount of practice for the learner to be successful (Hafkamp et al., 2024). Different informational variables can be detected for the control of the beam's inclination angle, and the observable consequences of relying on a particular variable emerge during the ongoing action. That is, the sequence of undershoots and overshoots of the ball, together with more complex aspects of the ball's movement, constitutes a rich pattern of information for learning. It is in this way that we envision information for learning to emerge in the flow of our day-to-day lives as well.

On individual differences and methodological doctrines

The direct learning approach has been criticized for not sufficiently taking individual differences in learning into account (Pacheco et al., 2019; Withagen & van Wermeskerken, 2009; cf. Higueras-Herbada et al., 2019). We think, however, that the framework described in this chapter provides new ways to understand such differences. In the first place, every individual starts the learning process at a unique locus in the learning space, corresponding to a unique perception-action coupling. This starting locus depends on many factors, including the history of the individual with similar tasks. In the second place, the information for learning that emerges during the performance depends on the anatomical makeup of the learner *and* on the environment that is encountered. Given that it is unlikely that these aspects are identical for different learners, one should expect differences in the learning trajectories even if learners would initially be at nearby loci. Finally, it is possible that different learners have different capabilities of detecting and integrating the information for learning. Whereas some may detect the relevant observable consequences of their perceptual-motor behavior, others may fail to do so. Consequently, some may be guided toward the more useful regions in the learning space, whereas others may be stuck at suboptimal task solutions. In line with the above-mentioned critique on the approach, however, previous work in the context of direct learning did not consider this last type of individual differences. The reason for this is as follows.

In ecological psychology, the claim that perception and action rely on invariants that specify to-be-perceived properties is often used as a methodological doctrine. If individuals seem to detect non-specifying variables or seem to differ in which variables they use, then the methodological doctrine spurs scientists to keep searching for an alternative information usage rather than accepting the absence of specification (Turvey, 2001). This can be done by using more ecologically relevant tasks or by reconsidering the available information in the agent-environment system. Direct learning, in contrast, uses individual differences at the level of perception and action as one of its starting points. As such, the approach undermines the original methodological doctrine. To offer an alternative, Jacobs and Michaels (2007) suggested searching not for information for perception and action but for information *for learning*. If different learners seem to use information for learning differently, then the new methodological doctrine motivates scientists to make an effort in searching for lawfulness, perhaps by using more ecologically relevant tasks, by creating different learning spaces, or by reconsidering the available information for learning. In our view, adopting this doctrine strengthens the direct learning approach. Nevertheless, the majority of concepts and methodological tools of the approach can also be used by scientists who prefer not to use the doctrine.[6]

Direct and indirect approaches

Let us return once more to the cyclist in Amsterdam and imagine that he or she sees someone running toward a tram station. The cyclist may *infer* that the runner wants to catch a tram even before a tram can be seen or heard. In this situation, there is not only a direct perception of the runner but also an indirect inference about the runner's situation (e.g., a tram will arrive). Although the process of inferring is not typically addressed by ecological psychologists, we argue that direct perception is not necessarily inconsistent with cognitive processes that may be based on, co-occur with, or precede the information detection (Runeson, 1977; cf. Heft, 2001, p. 49). What ecological psychology aims to do, however, is to understand as many phenomena as possible without falling back on representational schemes, using direct perception as a methodological doctrine. In a similar way, we think that direct learning is not inconsistent with indirect forms of learning. Learning to swim, for example, is difficult without explicit instructions from a coach and may require more cognitive processes on the part of the learner. Yet, in our view, at least some aspects of the change that occurs with learning will always be specific to patterns of information that are generated in the organism-environment interaction, which is to say, some aspects of learning will always be direct. As a research agenda, we therefore suggest investigating how far explanations on the basis of direct learning can be pushed. At the same time, we think that the main message of this chapter is relevant to *all* approaches to learning, including non-ecological ones. Although information for learning may be of different sorts and may be used in different ways, indirect approaches need some type of information for learning as well. A coach needs information to give instructions, just like a more cognitive learner who needs information to decide what to try next. Without information for learning, there is no learning. And without the perception-action cycle, information for learning does not come into existence.

Summary and conclusions

This chapter described the theory of direct learning with a focus on perceptual-motor learning, rather than on perceptual attunement only. Through examples of studies about information-based action, we presented the hypothesis that learning involves the detection and integration of information for learning, without the need for inferential processes. Information for learning emerges as a consequence of the cycle of perception and action and gradually drives the learner toward better performance. In this approach, learning is portrayed as a movement in a learning space. Within the learning space, information for learning corresponds to a vector field. In addition to their key roles in the theory of direct learning, we believe that the perception-action cycle and the therefrom emerging information for learning should be crucial concepts in other approaches to learning too. In fact, it may very well be that all understanding of learning requires a thorough understanding of information for learning.

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Notes

1 In emergency braking experiments with trial-to-trial variation in the approach speed, one should not start braking at a fixed time to contact with respect to the stop sign. This means that τ alone (or its inverse alone) does not specify the ideal moment to start braking.
2 It may be relevant to note at this point that all the changes with learning that are considered in this chapter assume that the intention of the learner to perform a certain task does not change. Within the framework of direct learning, in contrast to the changes that are addressed in this chapter, changes in intention have been portrayed as discontinuous jumps in a space (Arzamarski et al., 2010).
3 An extensive body of ecologically-inspired work on learning with a strong emphasis on emergence can also be found in the context of the constraint-led approach (Newell, 1986; cf. Araújo et al., 2006).
4 The dependence of information for learning on the practice conditions explains why some conditions have different effects on learning than others. Huet et al. (2011) used this idea to provide an explanation for the difference between constant and variable practice conditions.
5 Interestingly, Arzamarski et al. (2010) showed that every locus in an information space for dynamic touch corresponded to a specific pattern of wielding the object (cf. Michaels & Isenhower, 2011a, 2011b). This means that detecting a particular variable is accompanied with a particular form of exploratory action.
6 In the case of perceptual learning, additional reasons to adopt the methodological doctrine of direct learning can be derived from the interplay among direct perception, direct learning, and direct realism, via the idea of having an attractor on specifying invariants for all individuals and in all situations (Jacobs & Michaels, 2002; Jacobs et al., 2009).

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