On the Intrinsic Limits to Representationally-Adaptive
Machine-Learning

David Windridge
Department of Computer Science
School of Science and Technology, Middlesex University
The Burroughs, London, NW4 4B, UK
Email: d.windridge@mdx.ac.uk

Abstract
Online learning is a familiar problem setting within Machine-Learning in which data is presented serially in time to a learning agent, requiring it to progressively adapt within the constraints of the learning algorithm. More sophisticated variants may involve concepts such as transfer-learning which increase this adaptive capability, enhancing the learner’s cognitive capacities in a manner that can begin to imitate the open-ended learning capabilities of human beings.

We shall argue in this paper, however, that a full realization of this notion requires that, in addition to the capacity to adapt to novel data, autonomous online learning must ultimately incorporate the capacity to update its own representational capabilities in relation to the data. We therefore enquire about the philosophical limits of this process, and argue that only fully embodied learners exhibiting an a priori perception-action link in order to ground representational adaptations are capable of exhibiting the full range of human cognitive capability.

keywords: philosophy of machine learning, perception-action learning, online learning

1 Introduction
In the following, we aim to circumscribe the inherent conceptual limits implicit in the notion of open-ended machine learning - a key criteria for human-like cognition and intelligence - and to propose a strategy for building autonomous agents capable of operating at this extremity of capability. We first commence with a brief statement of the problem.

1.1 Conceptual Limits to Open-Ended Learning
In Putnams’s classical ‘brain in a vat’ philosophical thought experiment, a brain is attached via wires to a supercomputer that simulates all aspects of the real world, mediating this in terms of electrical signals sent down the wires in response to input signals from the brain in the form of nerve impulses. The thought experiment is thus intended to address notions of radical scepticism; could such a brain be justified in having true beliefs? (and would these be beliefs about objects existing within the simulated world or about the input/output characteristics of the electrical signals).

A variant of this thought experiment (in fact a subset of this thought experiment) might be the notion of a brain in a vat attached, from birth, only via its optic nerves to a video camera, in front of which pass, in a temporal sequence, all of the natural scenes of the world. The refined question is then ‘would such a brain represent the world in the same manner that a typical human would; one that is free to move and interact with the world’?

It is implicitly argued within this paper that this is not the case; indeed, it will be argued that such
fundamental human perceptual characteristics as the delineation of the world into discrete objects (i.e. the delineation of entities that are invariant under translation) would not occur to a non-embodied agent. Any such relational, non-essentialist notion of representation ([11]) has clear implications for artificial implementations of cognitive learning, which we shall explore in this paper.

In order to evolve this argument, we first consider the problem of how machine learning takes place in temporalized environments, and address the inherent limitations on this form of learning.

2 Limits to Standard Approaches to Adaptive Online Learning

Online learning ([2][3]) is a standard form of machine-learning induction in which data is presented serially in time, and in which learning generally takes place one instance at a time (it is thus the opposite of offline, or batch, learning). It is also inherently predictive, predicting the label values of data not yet presented to the system. Such a system is thus inherently adaptive; the degree of adaptation to new data will vary from on-line learner to on-line learner (sophisticated variants may incorporate notions such as transfer learning ([1][5]), anomaly detection ([6]), and active learning ([7][8])).

Despite this tendency towards increasing adaptivity, however, the majority of existing approaches typically assume an underlying consistency in the representational characteristics of the data; the datastream presented to an on-line learner is generally delineated in terms of a fixed set of classes, or a fixed set of features (for example, spatial interest points or texture-descriptors). Techniques exist that partially address these limitations, such as in online learners that incorporate Dirichlet processes to spawn novel clusters in relation to the requirements of the data ([9]), which are thus capable of expanding their representational characteristics to a certain extent. However, such a learner would not be capable of spontaneously carrying out as fundamental a data-driven representational shift as that involved in the transition from, say, a low-level feature-based representation of the world (delineated e.g. in terms of colored pixels) to an object-based representation of the world (delineated in terms of indexed entities with associated positions, orientations etc), unless a prior capacity for object representation had been incorporated into it.

Taking the notion of autonomous adaptation to serial data to its conceptual limit would thus require that both the representational capabilities of the learner as well its objective knowledge acquisition capabilities should be included in the autonomous learning process. Consider, for example, the case of an idealized autonomous online learning robot. Such an idealized online learner would thus be capable of spontaneously reparametrizing its representation of the world in relation to novel sensor data; i.e it must not just be capable of updating it’s model of the world, W, generated in terms of some particular representational framework, R, (written R[W]), it must also be able to find an appropriate transformation of its representational framework in order to ‘most effectively represent” the totality of the temporal data, W, via some appropriate criterion. It must thus perform the double mapping R[W] → R'[W'] (composed of the individual mappings R → R' and W → W’ ) such that the data W and W’ are guaranteed to both represent the same set of entities, as represented by a ‘noumenal equivalence’ predicate Equiv(R[W], R'[W']) or similar (we shall return to this point later).

In general, ‘this most effective’ representation criterion will be efficiency based - i.e. we will seek the mapping R[W] → R'[W'] that minimizes complexity (via e.g an MDL ([10]) or Occam’s Razor -like criterion). A motivation for this efficiency of representation criterion can be found in Biosemantics ([11]) - humans have adapted over millions of years for efficiency of their representational capability (in terms of either the overall neuronal budget or the total energy of processing). However, there are other aspects to this natural selection of representative capabilities that must be considered (see section [13])

Certain machine learning paradigms are inherently capable of the reparameterization R[W] → R'[W'],
for example, manifold learning techniques ([12]) and non-linear dimensionality reduction techniques ([13]). The technique adopted is not significant for our wider discussion; the key point is that following the process we arrive at both a reparameterization framework $R'$ (such as an orthonormal basis in manifold or sub-manifold coordinates) and a revised data set description $W'$ in the representational framework (e.g. following projection into the manifold coordinates).

Typically, reparameterization will also involve a reduction in the number of parameters required to represent the data - i.e. the determination of some data-derived sub-manifold $M_s$ necessarily implicates the existence of a projection operator such that the full range of data in the original domain, $W \subset M$, can be mapped into $M_s$ - for instance, by collapsing data points along the orthogonal complement, $W^\perp$ ($M$ is thus the original sensory manifold, and $M_s$ the remapped representational framework if equipped with a suitable basis).

Criteria for applying such a reductive reparameterization are many and varied: we might use a stochastically-motivated $2\sigma$ Eigenvalue cut-off in Principle Component Analysis to eliminate noise, for instance, or (more generically), we might use a model selection criterion such as the Akaike information criterion in order to arrive at a principled way to determine the allocation of manifold parameters in relation to the characterization of out-of-model data (the latter is related to minimum-description length (MDL) approaches, which in turn may be considered approximations of the ‘intrinsic’ (incomputable) Kolmogorov Complexity of the observed data set).

Whilst there might thus exist an intrinsic parameterization of any given dataset when considered only in terms of the efficiency of representation, the ideal choice of representation will also, of necessity, depend on the purpose to which the data set is put. Thus, there will always be meta-reasons for the favoring of a particular data parameterization, a particular representational framework. In fact, efficiency of representation is just such an extrinsic meta-reason; Kolmogorov Complexity is thus not in this sense an intrinsic measure of the data, but rather a measure driven by just one among several (potentially infinite) competing requirements for data representation, of which efficiency is only one.

### 3 Identity Retention in Online Learning

However, the above relates to batch processing of the data, and therefore makes the implicit assumption that all data points are derived from the same source, with perhaps only an instrumentally-irrelevant temporal delay between the collection of data points (that are otherwise independently and identically distributed i.e. they are i.i.d). There is hence a strong assumption of ‘noumenal continuity’ implicit in non-online forms of learning.

This assumption however, becomes complicated when considering an adaptive online learning, in which both the data and the data representation both have a temporal component. For instance, to give perhaps the simplest instance of this problem, in Simultaneous Location and Mapping (SLAM) robotics ([14], [15]), the robotic agent’s model of the world necessarily depends upon its calculation of its own position and orientation in the world (i.e. it must factor its own perspectival world-view into the world model). However, this positional calculation is itself dependant on (is relative to) the agent’s model of the world (i.e. the agent describes its own position and orientation in relation to the world model). A SLAM agent will therefore position itself in the world (perhaps using active learning ([16]) in order to minimize model ambiguity) by leveraging its own, uncertain model of the world. Interconnected ambiguities are thus always present in both the agent’s self-model (of its location/orientation) and its model of the world; the hope of SLAM robotics is that, following full exploration of the environment, these ambiguities converge to within some manageable threshold.

In general, the SLAM problem is not soluble unless certain a priori assumptions are made. A key such assumption is that the environment remains reasonably consistent over time. If an environment were to undergo some arbitrary spatial transformation at each iteration of the SLAM algorithm, then no convergence would be possible (and in fact there would
be no meaning to the concept of world model). However, much milder perturbations of the spatial domain would be sufficient to ensure non-convergence of the algorithm.

A further key *a priori* assumption, one that shall be particularly important in the following, but which is often overlooked, relates to the robotic agent’s *motor capabilities*. The robotic agent’s motor capability may, in this case, be considered as *that which initiates the change of perspective/change of representation*. However, as such, it cannot in itself be doubted (unlike the world model), and must thus be assumed *a priori*. Colloquially, the agent might thus doubt its location, or its world model, but it cannot, if it is to work at all, doubt the fact that a specific motor impulse has taken place (for instance, a ‘move forward’ or ‘turn left’ command). The agent cannot converge on a world model if, for instance, motor impulses to the actuators underwent arbitrary permutation. Even non-arbitrary permutation would not be distinguishable, even in principle, from a corresponding non-arbitrary permutation of the world space. (This non-distinguishability of perceptual manipulations from motor manipulations is absolutely fundamental, and has important consequences in our later argument).

Thus, both the world-model and the agent’s (orientation/position-based) self-model are inherently posited *relative* its motor impulses, which can be considered to represent the agent’s *intentions* in the sense that the existence of a specific intention is necessarily not itself open to doubt to the agent, however uncertain its perceptual outcome. Model convergence on a complete world model occurs when the outcome of all actions leads to predictable perceptual consequences (to within some given threshold). The agent has thus obtained a complete odometry of the environment (in human terms, we have ‘paced-out’ the domain). We can thus consider the world model as being mapped on to a grid of motor impulses such that, in a sense, the agent’s active capabilities provide the *metric* for its perceptual data (cf also (17, 18, 19)).

In short, where there exists the capacity for updating the representational capacity of an agent in relation to perceptual data that it has sought *on the basis of its original representation*, then we need some mechanism for guaranteeing that there is either sufficient *a priori* noumenal knowledge of the external world, or else sufficient *a priori* assumptions made regarding the process (e.g. movement) that initiates new data acquisition, in order for the representation-updating procedure to converge. Although this is problematic in SLAM, the problem is much more acute in fully open-ended learning scenarios where whole new *categories* of perception can be generated.

Of course, in dealing with *a priori* requirements for perception in an empirical setting, the relevant philosopher is Kant - we now look more closely at this issue in Kantian terms.

### 3.1 The Kantian Perspective on Cognitive Agency

We are essentially, in the above, asking the question of how, in an adaptive online learning context, is it ever possible for us to empirically validate a proposed change to our representative capability (how is it, in a Popperian sense, possible to *falsify* a proposed representational update). Falsification of a *world model* is, by comparison, straightforward in a standard autonomous robotic system, in that a world model typically constitutes a set of proposed haptic *affordances* (20, 21) gathered at-a-distance by a vision system. Thus, the visual model typically denotes a set of object hypotheses that may be verified via haptic contact (22, 23).

Haptic contact is thus typically considered to be prior to vision, or at least *a priori* less prone to ambiguity than vision. This is also experienced to an extent in human terms; we tend to consider something that we can touch, but not see (for example, a ‘force field’) as intrinsically having substance, whereas something that we can see occupying volumetric space but which we cannot verify by touch as being intrinsically illusory (a holographic image, for instance).

However, in a hypothetical automaton where there exists complete representational fluidity, such that a completely novel sensorium could be developed (for instance by combining sonar data with visual data in some hybrid world description), then we cannot *a pri-
ori favor one group of senses/sensors over another in order to delineate hypotheses about the world. Moreover, there is no immediately obvious way to form hypotheses about the most appropriate representational framework to adopt.

In order to address this, we borrow a key insight from Kant; namely that object concepts constitute orderings of sensory intuitions ([24]). Objects, as we understand them do not thus constitute singular perceptions, but rather synthetic unities built upon an a priori linkage that must be assumed between sensory intuitions and the external noumenal world (these a priori links cannot be in doubt since the are a condition of empirical validation for synthetic unities). Implicit in this is the notion that actions can be deployed to test the validity of these synthetic unities (which being synthetic rather than analytic are only contingently true, and therefore falsifiable through experience). Actions are thus causally initiated by the agent and serve to bring aspects of the synthetic unities to attention (within the a priori strata of space and time) in a way that renders them falsifiable.

For Kant, assuming that spatiality and temporal causality are a priori, means that they are assumed by the agent in order to have falsifiable perceptions at all; in principle, other ordering approaches to sensory data may be possible. However, it would be impossible for the agent to retain the continuity and falsifiability of object representation across such a fundamental transition of representation (it would also be impossible for a self-conscious agent to retain its identity – or ‘synthetic unity of apperception’– across such a fundamental representational chasm). This is the problem of ‘noumenal continuity’ that we identified earlier; how can an agent that undergoes a change of representation framework at time $t_0$ ever be sure that the objects delineated at $t_0-1$ were the same objects as those delineated at $t_0+1$ (indeed, would the number of objects even be preserved?) A cognitive agent might, for instance, hypothesize a perceptual change in which the independent perceptual axes of color-awareness and shape-awareness were combined in a single-dimension unity, such that only one color was allowed per shape, with the corresponding inability to discriminate all of the objects previously discriminated. An online learner would therefore appear to be severely limited in the extent to which it could utilize data across representational changes; in short the agent would no longer be a strictly online learner, but rather a serial batch-learner.

However, there is one way in which novel representational changes can be made while retaining an agent’s ability to falsify both these as well as any object hypotheses (synthetic unities) formed in terms of these representational changes and, moreover, do so while retaining online continuity of object identity (when extended in perception-action terms -see below). This is when representational changes are built hierarchically.

By way of example, consider how, as humans we typically represent our environment when driving a vehicle. At one level, we internally represent the immediate environment in metric-related terms (i.e. we are concerned with our proximity to other road users, to the curb and so on) ([25]). At a higher level, however, we are concerned primarily with navigation-related entities (i.e how individual roads are connected). That the latter constitutes a higher hierarchical level, both mathematically and experientially, is guaranteed by the fact that the topological representation subsumes, or supervenes upon, the metric representation; i.e. the metric-level provides additional ‘fine-grained’ information to the road topology: the metric representation can be reduced to the topological representation, but not vice versa. In robotics, when goals and sub-goals are explicitly delineated at each level, this is known as a subsumption hierarchy ([26]).

In a fully adaptive online learner, it is thus possible to provide a grounded approach to representational induction by adopting a correspondingly hierarchical approach. Thus, on the assumption of the existence of an a priori means of validating low-level hypotheses (for example via haptic contact), it is possible to construct falsifiable higher-level representational hypothesis provided that these subsume the latter. Thus, for instance, an embodied autonomous robotic agent might, following active experimentation, spontaneously conceive a high-level concept of affordance, or schema ([27]), such as that of container. Clearly, in this case, the notion container subsumes the concept
of haptic contact.

Continuity of noumenal identity is thus guaranteed by the lowest level of the hierarchy, with the higher hierarchical levels constituting progressive abstractions and enrichments of the lower level representations. An embodied autonomous robotic agent might therefore initially represent the world in terms of (hypothetical) volume elements such as voxels or 3d meshes (the a priori bootstrap representation), but, following extensive experimentation, might then go on to generate an enriched representation of its world at a higher level in which containers and non-containers are delineated. (Note that the original representation of the world in volumetric terms is thus still present).

Falsifiability of the representational concept ‘container’ is thus guaranteed, just as it is possible to guarantee the falsifiability of the hypothesis of the existence of any specific container, by exploiting the fact that these hypotheses are grounded throughout the hierarchy. Thus, in the former case, the hypothesis of the existence of a specific container is rendered falsifiable by haptic contact (and its higher level corollaries); i.e. the agent can test whether the proposed container-entity is, in fact, capable of containing another object.

On the other hand, the high-level representational concept ‘container’ is rendered falsifiable by the fact that it is conceived along with a corresponding high-level action e.g. ‘placing an object into a container’ which necessarily subsumes lower-level concepts such as ‘haptic contact’ etc. Thus, the representational concept is rendered falsifiable on the basis of its utility and compressibility.

To see how this works, suppose that an autonomous agent, on discovering by chance exploratory activity (e.g. motor babbling (28)), or via activity driven by lower-level action imperatives, that the previously defined concept ‘object’ yields an exception that allows for objects to be placed co-extantly in the same location as another object. Thus, if there were only a single container in the world, or if it were not possible to train an accurate classifier for containers in general, then it would be unlikely to constitute a useful description of the world; it would likely be more efficient simply to retain the existing concept of object without modification. However, when the world is in fact constituted of objects for which it is an efficient compression of the agent’s action capability to instigate such a modification of the object concept, then it is appropriate for a representationally-autonomous agent to spontaneously form a higher level of its representational hierarchy. (For an example of this approach utilizing first-order logic induction see (29)).

Very often compressibility will be predicated on the discovery of invariances in the existing perceptual space with respect to randomized exploratory actions. Thus, for example, an agent might progress from a pixel-based representation of the world to an object-based representation of the world via the discovery that certain patches of pixels retain their relative identity under translation, i.e. such that it becomes far more efficient to represent the world in terms of indexed objects rather than pixel intensities (though the latter would, of course, still constitute the base of the representational hierarchy). This particular representational enhancement can represent an enormous compression (30); a pixel-based representation has a parametric magnitude of \( P^n \) (with \( P \) and \( n \) being the intensity resolution and number of pixels, respectively), while an object-based representation typically has a parametric magnitude of \( \sim n^o \), where \( o \) is the number of objects.
In positing this hierarchical approach to representational adaptation, we have thus outlined a framework in which complete representational-autonomy for an embodied machine learner becomes feasible, one in which representations are empirically validatable, and in which the ‘noumenal continuity’ of identified entities can be assumed across representational transformations.

A key aspect of this falsifiability is the requirement that the spontaneous generation of higher-level perceptions in the agent’s representational hierarchy correlates directly with higher level actions. We now look more closely at this perception-action connection, and consider the low-level a priori guarantees of representational falsifiability.

4 Perception-Action Learning

Perception-Action learning is a novel paradigm in robotics that aims to address significant deficits in traditional approaches to embodied computer vision ([31]). In particular, in the conventional approach to autonomous robotics, a computer vision system will typically be employed to build a model of the agent’s environment prior to the act of planning the agent’s actions within the domain. Visual data arising from these actions will then typically be used to further constrain the environment model, either actively or passively (in active learning the agent actions are driven by the imperative of reducing ambiguity in the environment model).

However, it is apparent that there exists in this approach, a very wide disparity between the visual parameterization of the agent’s domain and its action capabilities within it ([32]). For instance, the parametric freedom of a front-mounted camera will typically encompass the full intensity ranges of the Red, Green and Blue channels of each individual pixel of the camera CCD, such the the range of possible images that might be generated in each time-frame is of an extremely large order of magnitude (of course, only a minuscule fraction of this representational space is ever likely to be experienced by the agent). On the other hand, the agent’s motor capability is likely to be very much more constrained (perhaps consisting of the possible Euler angle settings of the various actuator motors). This disparity leads directly to the classical problems of framing ([33]) and symbol grounding ([34]) (note that this observation is not limited purely to vision based approaches - alternative modalities such as LIDAR and SONAR would also exhibit the same issues).

Perception-Action (P-A) learning aims to overcome these issues by adopting as its motto, ‘action precedes perception’ ([35], [36]). By this it is meant that, in a strict sense (to be defined), actions are conceptually prior to perceptions; i.e. that perceptual capabilities should depend on action capabilities and not vice versa.

Thus, a Perception-Action learning agent proceeds by randomly sampling its action space (‘motor babbling’). For each motor action that produces a discernible perceptual output in the bootstrap representation space $S$ (consisting of e.g. camera pixels), a percept $p_i \in S$ is greedily allocated. The agent thus progressively arrives at a set of novel percepts that relate directly to the agent’s action capabilities in relation to the constraints of the environment (i.e. the environment’s affordances); the agent learns to perceive only that which it can change. More accurately, the agent learns to perceive only that which it hypothesizes that it can change - thus, the set of experimental data points $\bigcup_i p_i \subset S$ can, in theory, be generalized over so as to create a percept-manifold that can be mapped onto the action space via e.g. the bijective relation $\{actions\} \rightarrow \{percept_{initial}\} \times \{percept_{final}\}$ (i.e. such that each hypothesizable action has a unique, discriminable outcome) [29], [37], [38].

When such a perceptual manifold is created (representing a generalization over the tested space of action possibilities), this then permits an active sampling of the perceptual domain - the agent can propose actions with perceptual outcomes that have not yet been experienced by the agent, but which are consistent with its current representational model (again, this guarantees falsifiability of the perceptual model). It is in this way that Perception-Action learning constitutes a form of active learning: randomized selection of perceptual goals within the hypothesized perception-action manifold leads more rapidly to the capture of data that might falsify the hypothesis than
would otherwise be the case (i.e. if the agent were performing randomly-selected actions within the original motor domain). Thus, while the system is always 'motor babbling' in a manner analogous to the learning process of infant humans, the fact of carrying out this motor babbling in a higher-level P-A manifold means that the learning system as a whole more rapidly converges on the correct model of the world.

Of course, this P-A motor-babbling activity can take place in any P-A manifold, of whatever level of abstraction; we may thus, by combining the idea of P-A learning with the notion of hierarchical representation presented above, conceive of the notion of a hierarchical Perception-Action learner (39), in which a vertical representation hierarchy is progressively constructed for which randomized exploratory motor activity at the highest level of the corresponding motor hierarchy would rapidly converge on an ideal representation of the agent’s world in terms of its affordance potentialities. Such a system would thus converge upon both a model of the world, and an ideal strategy for representation of that world in terms of the learning agent’s action capabilities within it.

Perceptual goals thus exist at all levels of the hierarchy, and the subsumptive nature of the hierarchy means that goals and sub-goals are scheduled with increasingly specific content as the high-level abstract goal is progressively grounded through the hierarchy. (Thus, as humans, we may conceive the high-level intention ‘drive to work’, which in order to be enacted, involves the execution of a large range of sub-goals with correspondingly lower-level perceptual goals e.g. ‘stay in the center of the lane’, etc).

We finally now look at how such a system for representational updating might have spontaneously evolved in humans, and how the wider question of representational fluidity fits into a biological context.

5 The Biophilosophical Perspective

Biosemantics, as a sub-branch of Biophysics, was proposed by Millikan (11) as an attempt to subsume certain philosophical questions of representation and perception within the purview of biology, and in particular, the contingencies that arise from consistency with respect to natural selection.

We have indicated earlier that a key notion of Biosemantics lies in motivating an efficiency of representation criterion; organisms are naturally-selected for efficiency of their representational capability in terms of either overall neuronal budget or total energy of processing.

However, a further aspect implicit in Biosemantics is the embodiment of the agent. Thus, the biological organism’s representational capability must, in addition to being maximally or near-maximally efficient, also be of utility to the organism in perpetuating it’s genetic code (i.e. it must be consistent with Natural Selection) if it is to be consistently propagated. In practical terms, this means that the organism must be able to discriminate those entities (food, predators, mates etc), that are key to its survival and reproduction (10). However, the biological agent will also have acquired, by Natural Selection, an active capability that is likewise evolved to maximize the organism’s ability to propagate its genetic code; i.e. its ability to interact with the environment is adapted to maximize its survival and reproductive capability; a lobster’s claws are evolved for opening shells etc. The perceptual and the active capabilities of most organisms have thus evolved in lock-step; the organism perceives only (since it must maximize efficiency of representation) that which is relevant to its survival and reproduction in addition to that which it is capable of interacting with so as to maximize its survival and reproductive capability.

However, this describes a biological entity with a fixed, evolved representational framework (whether in a natural or simulated environment (11)). Humans, however, have, to a larger degree than any other animal acquired the capacity to be able to reconfigure their neuronal and perceptual structure in relation to the environment in ways that go far beyond the immediate biological requirements. Thus, rather than both the organism’s representational framework, R, and the organism’s active capability, A, having being adapted to the world, w, over time, in humans beings, the representation framework is
capable of adapting directly to the world, \( w \). (Which is not to say that the possibility of reconfiguration does not serve our biological ends, simply that any particular reconfiguration occurs in relation to the biologically-experienced facts of the world, and is not itself naturally-selected for optimality with respect to the organism’s long-term capacity survival). These perceptual reconfigurations can be very abstract; we can thus, for instance perceive the world in terms of the interaction between socio-economic groups if we are an economist, or in aesthetic terms if we are an artist. (Note that we are not suggesting that humans are able to update all of their representative capacity, only some significant fraction of it).

This reconfigurability of human perceptual structure in relation to the environment makes it critically different from the more usual naturally-selected perceptual capability found amongst other organisms. There is, in particular, no immediate survival imperative attached to perceptual reconfiguration, other than by proxy (for instance there may be a constraint on the total neuronal/energy budget involved in the perceptual reconfiguration). However, such ‘budgetary’ proxies for the requirements of natural selection are not, in themselves, sufficient to motivate any particular reconfiguration of the human agent’s perceptual capability - for this we need an additional proxy criterion, one that leads to a ‘retention of active capability’ (if neuronal efficiency alone were the criterion for perceptual updating, then it would always be optimal to map increasing numbers of the original percepts on to a singular novel percept).

The two principle (non-naturally-selected) operative criteria for perceptual updating in humans are thus:

1. **Obtaining a maximally efficient representation of the environment**

in combination with:

2. **Ensuring the discriminability of the active capabilities of the agent, as well as key entities related to survival/reproduction/nutrition.**

By the ‘discriminability of the active capabilities’ in the latter constraint, we mean the ability to perceive the outcomes of intended actions undertaken by the agent i.e. an intentional action (or at least one initiated by the goal-setting aspect of the agent’s cognition), should be susceptible to the sensory determination of its having taken place as intended. (In straightforward terms we might say that an ‘intentional action’ is that which has a specific percept as its success criterion.)

It is thus clear, whether considered from an *a priori* Kantian, or an *a posteriori* Biophilosophical perspective, that perceptions and actions must retain a fundamental link in any representationally-adaptive online learning system capable of emulating human cognitive capabilities.

### 6 Conclusion

We have thus proposed hierarchical perception-action learning as the idealized form of adaptive online-learning, which, by virtue of its embodiment within the environment, is able to empirically validate both its model of the world and its representation of the world.

An important corollary of this approach is that, at no stage, is there any requirement for global hierarchical consistency of representation (thus, as humans, we do not carry around within us a set of exact Cartesian coordinate locations of the key elements of our native town; rather what we retain is a series of motor imperatives to be triggered in relation to key percepts: e.g. ‘turn left at the town-hall’). In a sense, in a Perception-Action learning agent, “the environment has become it own representation”, (\[12\]), which naturally represents a very significant compression of the information that an agent needs to retain.

This relates to the issue of symbol grounding, a seminal problem in the conceptual underpinning of the classical approach to machine learning (\[34\]). The problem arises when one attempts to relate an abstract symbol manipulation system (it was a common historical assumption that computational reasoning would center on first-order logic deduction) with the stochastic, shifting reality of sensor data. In hierarchical P-A learning the problem is eliminated by virtue of the fact that representations are *abstracted from the bottom-up* (\[36, 41, 43, 35\]). They are thus
always intrinsically grounded (indeed this grounding is the main guarantor of their falsifiability).

We finally note that motor-babbling at the top of the representation hierarchy would necessarily involve the spontaneous scheduling of perceptual goals and sub-goals at the lower level of the hierarchy in a way that would (as the hierarchy becomes deeper) necessarily look increasingly ‘intentional’ (a phenomenon that is readily apparent in the development of motor movement of human infants).

Hierarchical P-A learning would therefore seem the natural direction of progress in embodied adaptive online learning. The question then arises of how this would apply if the embodiment that guarantees the falsifiability of representational updating is in a domain that is not directly physical e.g. when the adaptive online learner is, for example, a web-crawling robot (indeed, what does ‘embodiment’ mean in this context?). Could such an agent spontaneously adapt to perceive high level concepts in, for example,html data while retaining the integrity of its underlying ‘motor space’?

The answer, in this case, hinges on the fact that the agent’s actions are the searching and indexing actions undertaken by the robot; it is embodied in so far as it has a location with respect to these action capabilities. At the lowest (a priori) level there is thus the basic ability to move between web-pages; this capability cannot, under any circumstances be altered by the agent. It is, however, quite free to spontaneously form higher level search and index capabilities built upon these, for example by meta-indexing documents in terms of discovered higher-level subject-matters. The agent is thus capable of complete flexibility of hierarchical representation with respect to the falsifiability constraints that we have outlined, and is thus a fully-constituted hierarchical P-A learner.

The proposed framework is thus one of very general applicability, and one which, we believe has the potential to address the fundamental conceptual deficits in standard notions of adaptive online learning that we have outlined.

References

[1] L. Wittgenstein, *Philosophical investigations : the German text with a revised English translation by Ludwig Wittgenstein*. Oxford : Blackwell, 2001.

[2] J.-B. Pothin and C. Richard, “Online learning with kernels a new approach for sparsity control based on a coherence criterion,” in *Machine Learning for Signal Processing, 2006. Proceedings of the 2006 16th IEEE Signal Processing Society Workshop on*, Sept 2006, pp. 241–245.

[3] J. Kivinen, A. Smola, and R. Williamson, “Online learning with kernels,” *Signal Processing, IEEE Transactions on*, vol. 52, no. 8, pp. 2165–2176, Aug 2004.

[4] S. J. Pan and Q. Yang, “A survey on transfer learning,” *Knowledge and Data Engineering, IEEE Transactions on*, vol. 22, no. 10, pp. 1345–1359, 2010.

[5] M. E. Taylor and P. Stone, “Transfer learning for reinforcement learning domains: A survey,” *The Journal of Machine Learning Research*, vol. 10, pp. 1633–1685, 2009.

[6] V. Chandola, A. Banerjee, and V. Kumar, “Anomaly detection: A survey,” *ACM Computing Surveys (CSUR)*, vol. 41, no. 3, p. 15, 2009.

[7] B. Settles, “Active learning literature survey,” *University of Wisconsin, Madison*, 2010.

[8] V. Koltchinskii, “Rademacher complexities and bounding the excess risk in active learning,” *The Journal of Machine Learning Research*, vol. 11, pp. 2457–2485, 2010.

[9] M. Hoffman, D. M. Blei, and F. Bach, “Online learning for latent dirichlet allocation,” *Advances in Neural Information Processing Systems*, vol. 23, pp. 856–864, 2010.

[10] J. Rissanen, *Minimum description length principle*. Springer, 2010.
[11] R. G. Millikan, *Language, Thought, and Other Biological Categories: New Foundations for Realism*. The MIT Press; Reprint edition, December 1987.

[12] Z. Zhang, J. Wang, and H. Zha, “Adaptive manifold learning,” *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 34, no. 2, pp. 253–265, 2012.

[13] M. Debruyne, M. Hubert, and J. Van Horebeek, “Detecting influential observations in kernel pca,” *Computational Statistics & Data Analysis*, vol. 54, no. 12, pp. 3007–3019, 2010.

[14] N. Engelhard, F. Endres, J. Hess, J. Sturm, and W. Burgard, “Real-time 3d visual slam with a hand-held rgb-d camera,” in *Proc. of the RGB-D Workshop on 3D Perception in Robotics at the European Robotics Forum*, Vasteras, Sweden, vol. 2011, 2011.

[15] H. Strasdat, J. Montiel, and A. Davison, “Scale drift-aware large scale monocular slam,” in *Proceedings of Robotics: Science and Systems (RSS)*, vol. 2, no. 3, 2010, p. 5.

[16] N. Fairfield and D. Wettergreen, “Active slam and loop prediction with the segmented map using simplified models,” in *Field and Service Robotics: Results of the 7th International Conference*, vol. 62. Springer, 2010, p. 173.

[17] J. Dewey, “The reflex arc concept in psychology,” *The Psychological Review*, no. 3, pp. 356–370, 1896.

[18] A. Glenberg, “What memory is for,” *Behavioral and Brain Sciences*, vol. 20, no. 1, pp. 1–55, 1997.

[19] G. Lakoff and M. Johnson, *Philosophy in the Flesh: The Embodied Mind and Its Challenge to Western Thought*. Harper Collins Publishers, 1999.

[20] J. J. Gibson, *The ecological approach to visual perception*. Boston: Houghton-Mifflin, 1979.

[21] J. McGrenere and W. Ho, “Affordances: Clarifying and evolving a concept,” in *Proceedings of Graphics Interface 2000*, Montreal, Canada, 2000, pp. 179–186.

[22] J. Saunders and D. C. Knill, “Visual feedback control of hand movements,” *J. of Neuroscience*, vol. 24, no. 13, pp. 3223–3234, 2004.

[23] E. J. Schlicht and P. R. Schrater, “Bayesian model for reaching and grasping peripheral and occluded targets,” *Journal of Vision*, vol. 3, no. 9, p. 261, 2003.

[24] I. Kant, *Critique of Pure Reason*, A. W. W. Paul Guyer, Ed. Cambridge University Press, 1999.

[25] D. Windridge, A. Shaukat, and E. Hollnagel, “Characterizing driver intention via hierarchical perception-action modeling,” *Human-Machine Systems, IEEE Transactions on*, vol. 43, no. 1, pp. 17–31, 2013.

[26] R. A. Brooks, “Intelligence without representation,” *Artificial Intelligence*, vol. 47, pp. 139–159, 1991.

[27] D. L. Hintzman, “Schema abstraction in a multiple-trace memory model,” *Psychological Review*, vol. 93, no. 4, pp. 411–428, 1986.

[28] J. Modayil and B. Kuipers, “Autonomous development of a grounded object ontology by a learning robot,” in *Proceedings of the national conference on Artificial intelligence*, vol. 22, no. 2. Menlo Park, CA; Cambridge, MA; London: AAAI Press; MIT Press; 1999, 2007, p. 1095.

[29] D. Windridge and J. Kittler, “Perception-action learning as an epistemologically-consistent model for self-updating cognitive representation,” in *Brain Inspired Cognitive Systems 2008*. Springer, 2010, pp. 95–134.

[30] J. G. Wolff, “Cognitive development as optimisation,” in *Computational Models of Learning*, L. Balc, Ed. Heidelberg: Springer-Verlag, 1987, pp. 161–205.
[31] H. Dreyfus, *What Computers Can’t Do*. New York: Harper and Row, 1972.

[32] C. L. Nehaniv, D. Polani, K. Dautenhahn, R. te Boekhorst, and L. Canamero, “Meaningful information, sensor evolution, and the temporal horizon of embodied organisms,” in *Artificial Life VIII*, B. Standish, Abbass, Ed. MIT Press, 2002, pp. 345–349.

[33] J. McCarthy and P. Hayes, “Some philosophical problems from the standpoint of artificial intelligence,” *Machine Intelligence*, no. 4, pp. 463–502, 1969.

[34] S. Harnad, “The symbol grounding problem,” *Physica D*, no. 42, pp. 335–346, 1990.

[35] G. Granlund, “Organization of architectures for cognitive vision systems,” in *Proceedings of Workshop on Cognitive Vision*, Schloss Dagstuhl, Germany, 2003.

[36] M. Felsberg, J. Wiklund, and G. Granlund, “Explanatory learning structures in artificial cognitive systems,” *Image and Vision Computing*, vol. 27, no. 11, pp. 1671–1687, 2009.

[37] D. Windridge and J. Kittler, “Epistemic constraints on autonomous symbolic representation in natural and artificial agents,” in *Studies in Computational Intelligence: Applications of Computational Intelligence in Biology*. Springer Berlin Heidelberg, 2008, vol. 122, pp. 395–422.

[38] D. Windridge, M. Felsberg, and A. Shaukat, “A framework for hierarchical perception-action learning utilizing fuzzy reasoning,” *Cybernetics, IEEE Transactions on*, vol. 43, no. 1, pp. 155–169, Feb 2013.

[39] M. Shevchenko, D. Windridge, and J. Kittler, “A linear-complexity reparameterisation strategy for the hierarchical bootstrapping of capabilities within perception–action architectures,” *Image and Vision Computing*, vol. 27, no. 11, pp. 1702–1714, 2009.

[40] J. Piaget, *Genetic Epistemology*. New York: Columbia University Press, 1970.

[41] M. Sipper, “An introduction to artificial life.” *Explorations in Artificial Life (special issue of AI Expert)*, pp. 4–8, September 1995.

[42] A. Newell and H. Simon, “The theory of human problem solving; reprinted in collins & smith (eds.),” in *Readings in Cognitive Science, section 1.3.*, 1976.

[43] D. Marr, *Vision: A Computational Approach*. San Fr.: Freeman & Co., 1982.

[44] P. Gärdenfors, “How logic emerges from the dynamics of information,” *Logic and Information Flow*, pp. 49–77, 1994.

[45] J. Modayil, “Bootstrap learning a perceptually grounded object ontology,” 2005, retr. 9/5/2005 http://www.cs.utexas.edu/users/modayil/modayil-proposal.pdf.