# Hybrid strategies and meta-learning: an inquiry into the epistemology of artificial learning

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**Abstract.** The problem of developing artificial learning systems cannot be confined in the realm of computer science and researchers in this field are called to face an ambitious question reverberating on several disciplines. A deeper investigation in this sense reveals an intriguing parallelism between conceptual theories of knowledge and mathematical models of intellect. Hybridisation strategies and meta-learning approaches are discussed in conformity with the indications of a comprehensive epistemological inquiry into artificial intelligence.

## 1 Introduction

The progress attained in artificial learning in the last few decades gave rise to the rapid proliferation of several applications, some of them exhibiting commercial software facets. Also, the oncoming development of new branches of research and the continuous broadening of application environments favoured the machine learning appealing to a new generation of young scientists and specialists. However, if we refer to the very ultimate goal of the research in artificial intelligence (AI), addressing the thorough emulation of human capabilities, a still long route remains to be covered. In this direction, it makes sense, at least in an academic perspective, to investigate theoretical models of intellect, in order to deepen our understanding of human and artificial cognitive mechanisms.

This work takes part in the epistemological debate around the validity of artificial learning methods, not only in terms of contingent performance results, but also considering the theoretical assessment of their inherent foundation. Moving from the classical debates about the human intellect, we propose a critical inquiry to highlight the strict connection existing between philosophical constructions and scientific approaches to artificial learning. Putting emphasis on the twofold character of human thought, combining apriority and adaptivity, we analyse the typical conceptual schemes which formalise the common reasoning mechanisms. It should not come as a surprise the resort to the speculative investigations for tackling questions pertaining to the computer science sphere of activity. Actually, it has been observed that the scientific progress would grow faster if the close relationship between mathematical and philosophical concepts is properly understood and esteemed [1]. Bearing in mind this guideline, we draw up a survey of the various concepts of human intellect, steering our research in the realm

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of artificial learning. The resulting epistemological analysis is helpful to show connections among the ideas developed by thinkers and scientists far separated in time and space. Particularly, the problem of learning is tackled in the article, by establishing an extensive definition of learning by induction which is involved with the Hume's predicament concerning the plausibility of generalisations [2]. In the context of AI system development, we underline how the mechanism of hybridisation could produce a synthesis among adaptivity and apriority (similarly to what happened in particular moments of the philosophical debate). Moreover, to escape the riddle of induction, we propose a peculiar epistemological approach, claiming the possibility for inductive processes to justify themselves. In this way, we address the field of *meta-learning* as a promising research direction to vitalize the studies in artificial intelligence. By the end of the paper, we shall be able to briefly illustrate also a particular meta-learning framework developed according to the indications provided by the epistemological inquiry.

## 2 The quest for a theory of knowledge

Since from the ancient times, philosophers tried to find a rationale behind the processes of knowledge acquisition and the mechanisms of learning. A first relevant construction of a theory of knowledge could be traced back to Plato. The Greek philosopher emphasised the inadequacy of human senses, stating that the ability to think is founded on a priori concepts embedded into the human mind, namely the *Ideas* [3]. These abstract concepts are endowed with complete worthiness and possess true and eternal existence. This is the reason why the Platonic philosophical establishment is also referred to as *realism*, indicating the reality of a priori Ideas, opposed to the unreality of experience. Engaging in controversy with the Platonic realism, a different conceptual perspective called *nominalism*, related to the Cynic school of philosophy, stated the impossibility of grasping the universal concepts without the recourse to sensible experience. In this way, the Ideas lose any existential connotation and are regarded only as labels indicating ensembles of objects.

The realism and the nominalism have represented the keystones of the philosophical debates in the subsequent centuries. On the one hand, Platonic realism advocates committing to apriorism for grounding a theory of knowledge, that should always start from a base of eternal immutable universal concepts. On the other hand, nominalism considers the sensible experience as the only source of knowledge, thus resorting to adaptivity for adequately tackling the natural plurality. Plato's principle of apriority provide for an answer about the possibility of knowledge, but it does not suffice to approach another fundamental question concerning intellect: how is *learning* possible? This kind of inadequacy was quite soon identified as a "leak" into the Platonic construction: Aristotle recognised that Plato's formulation cannot generate any form of learning, since Ideas are detached from the world where the universal concepts become incarnate. To solve this problem, the Aristotelian theory is based on the assumption that the communication of Ideas with the physical world is resolved in the meeting between form and matter [4]. The Aristotelian forms are characterised by an a priori universal reality and represent the formative principle in human learning. However, forms possess also a dynamic nature, being able to originate all the extraordinary variety of the physical world, during their encounter with matter. Aristotle's construction can be seen as the first attempt to approach the debate about the theory of knowledge by combining apriority with adaptivity of mind.

Actually, the divergences between Aristotle and Plato were minimised by the thinkers of the years to come and the lack of clarity in Aristotelian theory contributed to the mediaeval controversy involving the sustainers of nominalism and realism. The theory of knowledge evolved through a debate strongly biased by the role played by theological thinking. The famous "Occam's razor", denying any resort to universal a-priori concepts to attain knowledge of the world, founded the problem of knowledge on direct experience and encouraged the scientific research and the development of the coming philosophy of empiricism.

The epistemological problem assumes the connotation of the "specific problem" of the modern philosophy: rationalism and empiricism can be seen as means to grasp the reality outside the mind. These means share the awareness of mental representations and external reality, but differ in their approaches. Rationalism answers the question of knowledge by highlighting the misleading nature of sensitivity and by proposing a metaphysical construction to bridge the gap between mental representations and external reality. Empiricism underlines the revealing character of sensitivity, trying to learn external reality by questioning our senses (denying any apriority for our mental representations). Again, the opposition between intellectual apriorism and natural adaptivity stands out, with a reprise of the dualism of realism and nominalism. As concerning the problem of learning, the empirical perspective is based on inductive approaches affirming the foundation of the knowledge of the world on simple sensible data. Particularly, Hume stressed the empirical tendencies by examining possibilities and limitations of human cognitive experience. In [2], the Scottish thinker faced the causality problem and, in his argumentations, the idea of a necessary connection cause-effect is ruled out both in aprioristic sense and in relation to any source of experience. In this way, the causality principle is spoiled of necessity, loosing epistemological justification: only habit is responsible of human generalisations. This consideration is pregnant of significance in our inquiry, since it asserts that induction is not a valid form of reasoning and, consequently, a criticism is raised with regard to the scientific method that aims at generalisation.

Similarly to Aristotle, Kant tried to solve the problem of knowledge composing the breach between rationalism and empiricism. In [5] it is shown how, although knowledge cannot transcend experience, nevertheless it is partly characterised by an a priori component that is not inductively inferable from experience. The novel epistemological argumentation asserts that science is based on synthetic judgements a priori that, even if can be evoked by experience, should be founded on a very solid base that induction could never offer to a general law. Again, the keystone of a unifying theory consists in its effort of combining apriority with adaptivity of mind. In the following, we start an analysis of formal

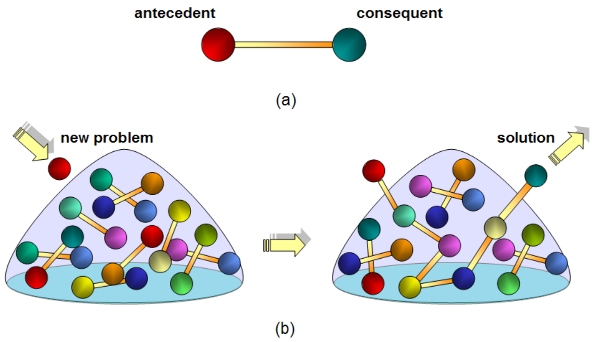


**Fig. 1.** The working mechanism of a rule-based artificial intelligent system.

modelling of intellect to underline the connection existing among mathematical concepts and philosophical positions.

## 3 Mathematical concepts of intellect

When dealing with logical reasoning, a concept can be thought as a rule by which an instance domain is partitioned into a subset of instances satisfying the rule, and another subset whose instances do not satisfy the rule. The process that allows to advance from general concepts to particular rules is referred to as *deduction*. If we intend to design an AI system working on the basis of deductive reasoning, then we should pay attention in providing it with a priori knowledge, namely a database of general concepts and rules, useful for tackling world problems. Deductive approach can be easily brought back to the Platonic realism: the role of a priori principles is emphasised in the knowledge construction process and experience of sensible world is just an afterthought.

When the reasoning process allows us to advance from particular observations to general concepts, then the logical inference performed is referred to as *induction*. An AI system, designed to reason in terms of inductive inferences, needs no a priori content: its action will be driven by the observation of real objects and the consequent generalisation processes. Induction could be related to the nominalistic approach: the role of universal principles is underestimated and general concepts become names, assigned to classes of similar objects.

The deductive inference is characterised by an additive, demonstrative, non-ampliative nature, which is able to preserve truthfulness. On the other hand, inductive learning preserves falsity and does not preserve truthfulness, thus showing a non-additive, non-demonstrative nature. Moreover, induction helps to go beyond deductive attainments, since inductive conclusions entail more information contents than those embedded into the premise concepts.

An analysis of mathematical models of intellect can be focused in the field of artificial intelligence, in particular reviewing rule-based models and connectionist systems. Assuming that a priori knowledge has to be embedded into a

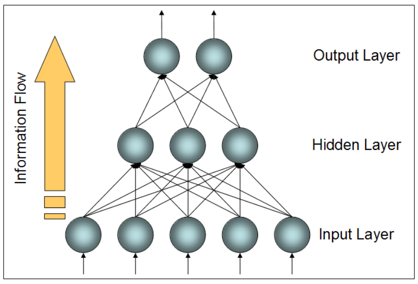


**Fig. 2.** The structure of an ANN composed by two unit layers, plus an input layer.

machine, an AI system can be endowed with a base of logical rules, similar to the high-level cognitive concepts utilised by a human in conscious decision-making processes. The mathematical formalisation of this concept of intellect makes use of name variables, rather then numbers, and logical inferences represent the basis of reasoning and knowledge acquisition. This direction in the theory of intellect has been usually referred to as *rule-based AI* or, with a misnomer, *symbolic AI* [6, 7]. The basic working plan of a rule-based system follows the reasoning process of a human expert to solve a real-world problem. All the possible situations in a particular environment are codified in a number of rules of the typical form: "IF *antecedent* THEN *consequent*". The necessary relationship between *antecedent* and *consequent* formalises in a logical form the knowledge of the expert (as sketched in figure 1(a)). When the system has to face a particular problem, the real occurrence is translated into a logical form, consistent with the knowledge base, and a concatenation of inferences produces the final solution, as depicted in figure 1(b). The question about the possibility of learning is re-proposed in rule-based AI, since the deductive inferences operated by logical systems do not prove to build up a model of intellect with actual knowledge enlargement capabilities. Moreover, combinatorial complexity undermines the foundation of rule-based AI. Actually, systems of logical rules are doomed to perform well in limited domains, since the amount of concepts to be formalised is not prohibitive.

Artificial neural networks (ANN) are computational models that, loosely motivated by biological systems, exhibit some of the properties of the brain [8, 9]. They are composed by a number of simple processors (neurons) working in parallel, without any centralised control. The neurons are arranged into a particular structure (usually organised in layers), where a system of weighted connections guarantees the information flow through the network (see figure 2). Neural networks are commonly regarded as learning machines that work solely on the basis of empirical data. The only means for acquiring knowledge about the world in a connectionist system come from observational instances and there are no a priori designed conceptual patterns that could lead the learning process. The lack of any kind of conceptual cognition and the resort to data for developing knowledge let us review the connectionist approach as an empirical attitude in the context of the theory of intellect. Neural networks have shown their effectiveness in a number of applications, however they exhibited also a variety of problems that in many cases limit their profitable employment. In particular, the most relevant difficulties are related to the lack of transparency of neural networks (that represents also an obstacle for the a priori knowledge exploitation), and the number of training samples required for learning (that could be prohibitive when dealing with large, complex real-world problems).

## 4 Complexity, hybrid strategies and fuzzy logic

The conducted analysis would suggest that every attempt to develop a comprehensive mathematical model of human intellect could be frustrated by a combinatorial complexity explosion. In fact, methods based on adaptivity are subjected to combinatorial explosion of the training process. On the other hand, approaches related to apriority have to face combinatorial explosion of the knowledge base complexity. A lesson can be derived from those remarks: the matter of combining adaptivity and apriority assumes paramount relevance in artificial intelligence, similarly to what happens in the debates for understanding human intelligence. As already pointed out, Aristotle perceived that the lack of adaptivity would have doomed the Platonic theory of ideas to cut off every kind of learning capacity. Correspondingly, the Kantian construction of a theory of knowledge, based on synthetic judgements a priori, implicitly expressed the urge for a combination of the aprioristic contents of intellect with its adapting capabilities. Also in recent lines of inquiry, related to the field of philosophy of science, the mechanism of hybridisation has been appraised as a more correct attitude for developing consistent research in the AI field [10]. Hybridisation, in fact, appears to be a much more effective practice to produce successful models, in place of the abused appeal to "paradigms" (that disorderly evolve in a quite exaggerated number in AI contexts, with respect to what happens in more consolidated sciences, such as physics).

Nevertheless, the problem of complexity is deeply rooted in some kind of contradictions that can be highlighted once again by referring to the conceptual discussions of the past. Aristotelian logic hardly conciliates with the theory of forms: while the first describes laws governing definitive and eternal truths, the latter emphasises the dynamic and adaptive role of forms in a mutable world. In modern times, Kant operated a "Copernican revolution" to explain the modalities of the knowledge construction process. The novel epistemological assessment, while stating that it is impossible to know the *thing-in-itself* of the world reality, transfers the focus on the cognitive subject and her own peculiar ability of perceiving phenomena. This way of understanding reality could be hardly represented by the logical mechanisms, which seek for the absolute essence of the thing-in-itself. When the mature logical tradition of the early 1900s resolved to eliminate any uncertainty and subjectivity from the knowledge construction process, a definitive impediment disturbed the mathematical dream. Gödel theorems of incompleteness established that the price for the exactness is paid in terms of completeness. A different direction to resolve the Aristotelian contradiction, opposing rigid logical schemes to the plasticity of human thought, was undertaken by accepting uncertainty in reasoning process. Fuzzy logic invalidates the cornerstones of formal logic (namely, the law of excluded third and the principle of contradiction) and brings forward a form of approximate reasoning that, while renouncing exactness, fits better the vagueness of real world situations. Into the inherent nature of fuzzy logic, admitting a subjective capability of expressing different degrees of truth, it is possible to trace the echoes of the modern philosophical attitude toward the theory of knowledge, as expressed by Schopenhauer's words. "The world is my representation" [11] could be intended as the *ante litteram* statement of the novel conception of knowledge embedded in the fuzzy way of reasoning.

## 5 Learning through induction

As we have already pointed out, the problem of establishing a proper definition of learning has troubled thinkers and scientists for many times. We assume that learning occurs by increasing the amount of available knowledge, namely by enlarging the base of knowledge determined by a "deductive closure". In order to derive some new pieces of information, the "inductive leap" appears to be a necessary mechanism, therefore we concentrate on induction to properly discuss an epistemological assessment of learning practices.

It is straightforward to relate this kind of definition of learning, connected with induction, with the conceptual disputes dating back to Hume's argumentations about the generalisation plausibility. It should be noted that the intriguing unsafety of induction does not regard only the guarantee of generating correct conclusions: it is also doubtful whether the basic inductive mechanisms possess credibility, in any meaningful sense. The crux of the matter in Hume's argumentation relies in the inability to define a rationale behind inductive activities, since no finite number of observations could be enough reason to suppose anything general. This consideration ultimately prevents the support of any degree of confidence in any prediction. Following this line, only habit (namely, repeated observation of regularities) is responsible for the generalisation practice [2].

The problem of induction represents the starting point also for modern naturalism, suggesting a new attitude to tackle generalisation [12]. Moving from the observation of the defeat of traditional epistemology, that was not able to escape the stalemate of the Hume's predicament, the new claim of naturalism consists in reducing the human knowledge to a natural phenomenon, falling under the activity sphere of science. In this way, epistemological problems become scientific concerns, thus reducing the role of the theory of knowledge: an implicit reshaping of epistemology is applied, admitting the out-of-reach character of traditional investigations. Following the naturalistic view, inductive processes are endowed with the faculty of justifying themselves, and epistemological concerns address a higher conceptual level where basic learning practice leaves room for *meta-learning* investigations. In other words, the attention is shifted from mere justification of induction toward the problem of performing a suitable selection among inductive hypotheses. Of course, these aspects are intrinsically connected and their examinations cannot be conducted in a separate fashion. Nevertheless, it seems that an interesting approach could be grounded on a modified basic perspective. Instead of reviewing our mind activity as a process triggered off only by the experience of particular regularities in the world, we could think of our inductive mechanisms as a perpetual motion of the mind, which naturally generalises from observations along different lines, and progressively becomes skilled in tracing the correct directions.

In practice, artificial learning, recognised as the empirical science of inductive methods, provides a laboratory to develop and evaluate generalisation strategies. If inductive practices scatter in several directions, then producing successful generalisations is just a matter of defining the proper *bias* which helps to find the way in each circumstance. Meta-learning should be able to provide the necessary knowledge of the world and guidance for determining the proper direction in generalisation processes. The meta-learning activity should rely on the assumption that previously successful strategies of induction are supposed to generate hypotheses which can be generally considered better supported. In other words, predictive success provides one of the most powerful basis to assess inductive conclusions. Following this approach, where inductive practices are evaluated by resorting to induction, meta-learning strategies should be employed in the field of artificial learning, supported by the current directions of epistemological investigations. In the following we are going to take a closer look at the computational methods of artificial learning, briefly reviewing the limitations of common base-learning strategies and the potentialities of meta-learning approaches.

### 5.1 Computational methods and induction: being MINDFUL when learning

The applied research in the field of artificial intelligent systems often deals with empirical evaluations of machine learning algorithms to illustrate the selective superiority of a particular model. This kind of approach, with multiple models evaluated on multiple datasets, is characterised by a "case study" formulation that has been recognised and criticised in literature [13, 14]. The selective superiority demonstrated by a learner in a case study application reflects the inherent nature of the so-called *base-learning* strategies, where data-based models exhibit generalisation capabilities when tackling a particular task. Precisely, base-learning approaches are characterised by the employment of a fixed bias, that is the ensemble of all the assumptions, restrictions and preferences presiding over the learner behaviour. This means a restricted domain of expertise for each learning model, and a reduction in its overall scope of application. The limitations of base-learning strategies can be theoretically established: the no free lunch theorems express the fundamental performance equality of any chosen couple of learners (when averaged on every task), and deny the superiority of specific learning models outside the case study dimension [15].

Obviously, if we want to perform pragmatic investigations of particular domains, base-learning approaches represent a quite satisfactory way of proceeding

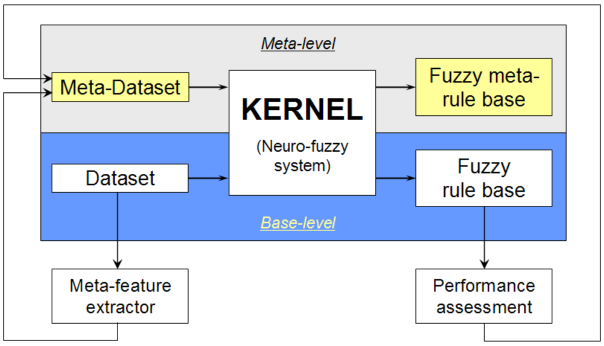


**Fig. 3.** The design of the MINDFUL system; the kernel of the system is represented by a neuro-fuzzy learning scheme.

to obtain adequate results. On the other hand, whenever we are interested in following a line of research with a broader scope, involving more general theoretical issues and some kind of cross-domain applications, the resort to somewhat different methodologies is advisable. By focusing the attention on the role of bias, we characterise the *meta-learning* approach as a dynamical search of a proper bias, that should be able to adapt the learner behaviour to the particular task at hand. The research field of meta-learning represents a novel approach aiming at designing artificial learners with enhanced capabilities, possibly capable of profiting from accumulated past experience [16, 17]. In this way, the formulation of the model evaluation could overcome the case study dimension and the limitations of the base-learning strategies.

The conducted epistemological inquiry, in the way it has been described in this paper, ultimately directed our investigation to design a particular meta-learning framework, namely the MINDFUL (Meta-INDuctive neuro-FUzzy Learning) system, which we are going to synthetically describe. (Obviously, the comprehensive presentation of the MINDFUL system, together with the discussion of its realisation and evaluation do not concern the scope of this article, see [18] for further details.) To compose the schism between aprioristic knowledge representations and adaptive fitting to data observations, our meta-learning methodology is centred on the integration of apriority and adaptivity, conjugating the expressiveness of a rule base with the effectiveness of a neural model. Moreover, this kind of hybridisation takes into account the problem of complexity, and aims at combining the neural network learning capabilities with the representational power of fuzzy logic. In this way, the learning framework is based on the employment of a neuro-fuzzy integration which provides the additional benefit of arranging the available knowledge in a comprehensible and manageable fashion. Actually, the neuro-fuzzy scheme had to be adapted to fulfil the meta-learning requirements. The important point here consists in consenting inductive practices to evaluate past experiences of induction and to project successful generalisations beyond the analysed situations. For this purpose, the MINDFUL system has been organised in order to employ the same neuro-fuzzy learning scheme both as base- and meta-learner (figure 3 depicts the general scheme of the system). In practice, base-level tasks are tackled following a consolidated approach which exploits neural learning for deriving from data a base of interpretable knowledge, useful for solving each specific problem at hand. At the same time, a meta-learning activity is brought forward, where the same knowledge-based methodology is adopted. In this case, a set of meta-features (describing the properties of tasks) is correlated with the bias configurations adopted during the base-level activity (different learning parameter settings are acknowledged as distinct biases of the system). In this way, the meta-learner provides an explicit meta-knowledge, in terms of fuzzy rules, representing a significant form of high-level information to direct the learning process of the base-learner in novel circumstances.

MINDFUL does not pretend to furnish a definitive solution to the meta-learning questions, neither to stand as an arrival point for our investigation. Nevertheless, it is an attempt toward a systematic study of meta-learning, where hybridisation issues and epistemological grounds are particularly emphasised.

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