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CONCEPT REPRESENTATION ANALYSIS IN THE CONTEXT OF HUMAN-MACHINE INTERACTIONS

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ABSTRACT

This article attempts to make a conceptual and epistemological junction between human learning and machine learning. I will be concerned with specifying and analysing the structure of concepts in the common ground between a concept-based human learning theory and a concept-based machine learning paradigm. I will focus on (*i*) humans' conceptual representations in the framework of *constructivism* (as an educational theory of learning and a proper model of knowing) and *constructionism* (as a theory for conceptualising learning) and (*ii*) concept representations in the framework of *inductive concept learning* (as an inductive machine learning paradigm). The results will support figuring out the most significant key points for constructing a conceptual linkage between a human learning theory and a machine learning paradigm. Accordingly, I will construct a conceptual ground for expressing and analysing concepts in the common ground of human and informatics sciences and in the context of human-machine interplays.

KEYWORDS

Concept, Human Learning, Machine Learning, Constructivism, Constructionism, Inductive Concept Learning.

1. MOTIVATION

Regarding a very general definition, the act [and the role] of learning can be identified as related to acquiring new or modifying existing knowledge. Often, the ability to acquire knowledge is seen as a sign of, or even a prerequisite for, intelligent behaviour. I shall stress the fact that *knowledge* is a very complicated and sensitive term that must be used with caution. Considering the structures of human and information sciences and their interrelationships, I need to focus on specifying knowledge and on analysing the phenomenas that we can use under the label of 'knowledge'. It seems quite important to investigate what the term 'knowledge' stands for (and can stand for) to be assumed and to be comprehensible in various frameworks of learning within different systems. This article attempts to construct a conceptual and epistemological linkage between human learning and machine learning and to analyse the structure and description of concepts in the common ground between a theory (and a philosophy) in the framework of human learning and a paradigm in the framework of machine learning. Before getting into the details, I contemplate the term 'Machine Learning'. Later on, I focus on knowledge to provide a proper background for my desired contributions.

Machine Learning has been recognised as a subfield of Artificial Intelligence and Computer Science. According to [Mitchell (1997)], "A machine learning approach attempts to develop strong algorithms that allow machines to improve [the productivity of] their performances on a given goal [and on an objective function]". In machine learning, the word 'learning' has been utilised as a binary predicate for machine. Learning as a binary predicate describes a role that is being performed by a machine. It is important to focus on the term 'learning' within the context of the analysis of knowledge. My main goal is figuring out the most significant key points for building a conceptual link between humans and machines.

In order to analyse knowledge I take Bloom's taxonomy [1] into consideration. This taxonomy is a framework for classifying pedagogical objectives, which could be interpreted as the statements of what teachers [, tutors and mentors] expect their learners to have learned, see [Furst (1956), Krathwohl (2002)]. Consequently, knowledge has a strong relationship with recognition of materials, ideas, methods, processes, structures and settings. Bloom's taxonomy divides a body of knowledge into multiple classes like, e.g., knowledge of terminologies, knowledge of ways and means, knowledge of trends and sequences, knowledge of classifications and categorisations, knowledge of methodologies, knowledge of universals and abstractions, knowledge of principles and generalisations, knowledge of theories and structures. Later on, [Krathwohl (2002)] has proposed a knowledge dimension in the revised version of Bloom's taxonomy. The revised taxonomy consists of four categories: (1) Factual Knowledge (e.g., terminological knowledge), (2) Procedural Knowledge (e.g., knowledge of methods and algorithms), (3) Conceptual Knowledge (e.g., knowledge of theories, models and structures) and (4) Metacognitive Knowledge (e.g., contextual knowledge, conditional knowledge). According to this categorisation I can say that "knowledge acquisition consists of a sort of transformation of functions from reality into the sets and categories of facts, procedures, concepts and contexts". The human being has this ability to deal with multiple classes of facts, procedures, concepts and contexts and can transform them into her/his mind. Transformations can be interpreted as the outcomes of self-involvement in increasing knowledge about a subject matter. In human systems a learner is someone who intentionally attempts to know more about something in order to construct her/his knowledge about that thing. Any human has a background knowledge and tackles to carry on constructing knowledge over her/his existing knowledge. This consideration conduces me to observe and to interpret human knowledge acquisition (and human learning) as the *activity of construction*. Any person tackles to develop her/his constructed knowledge constructions and to gain an opportunity to attain deeper comprehensions, realisations and understandings. Also, human's deeper understandings support her/his greater motivations. Here I feel the need to concentrate on *conceptualisations* in order to provide a supportive analysis of realisation and understanding. In my opinion, "a conceptualisation is an uniform specification of separated understandings. A conceptualisation provides a global manifestation of local understandings in the context of a human's thoughts". Additionally, a human's grasp of concepts provides a proper foundation for generating her/his own conceptualisations. Also, the personal conceptualisation could be identified as the action or the process of forming a concept with regard to the basis that has been provided by the individual realisation.

In this research I will mainly focus on concepts, conceptions and concept representations. I have believed that the main focus of process of knowledge acquisition (and learning) is on concepts and concept representations in the ground of conceptualisations. Knowledge acquisition based on concepts can be based on the following definition. This definition draws out the key elements, which have individual and social implications for intelligent learners, see [Watkins (2002)]. Knowledge acquisition is the reflective activity which enables the learner to draw upon her/his previous experiences (and her/his background knowledge) to conceptualise (and, respectively, understand) and evaluate the present, so as to build up and shape future actions and to construct (and develop) new knowledge.

Let me go back to machines and machine learning. A machine program is said to learn from an experience if (i) there is a set of tasks for machine and (ii) there is a machine's performance measure, and also if (iii) the machine's performance at those tasks, as measured, improves with its experiences. Here I present a problem in human learning to make a comparison between human learning and machine learning. This example can clarify what the afore-mentioned concepts in a machine learning problem are. Suppose we think of the problem that focuses on students' mathematical problem solving. Considering this problem, the most significant task of a student is to find proper solutions for mathematical problems. Then the set of tasks must consist of the student's tasks and obligations for solving mathematical problems. Also, the performance measure could be known as the percentage of correctly solved problems. Additionally, the experience could consist of the existing transformations and alterations between observed problems and solved problems. Hence, a student can improve her/his ability in performing proper solutions for different mathematical problems after further experiments (experiencing more transformations). Subsequently, this student will have a better capability and more qualified competences in solving mathematical problems when more transformations (experiences) are provided for her/him. Providing more transformations for a student could

[1] www.icels-educators-for-learning.ca

be achievable by showing and providing her/him with more positive (sample) and negative (non sample) examples of the solved mathematical problems.

Here I shall claim that the word ‘learning’ in ‘machine learning’ is a *metaphorical image* and is a reflection of human knowledge acquisition and learning in machines and artificial agents. Let me express that machine learning is a metaphor that describes what ingredients and concepts are concerned with effective knowledge acquisition and learning within reality. Through my lenses, the most important concepts in a machine learning problem (e.g., problem, experience, task, performance, ability, learning) are *conceptual reflections*. They are some mappings from reality into usable and applicable labels.

In the following sections I will focus on (*i*) humans’ conceptual representations in the framework of constructivism (as an educational theory of learning and a proper model of knowing) and constructionism (as a theory for conceptualising learning that could be identified as a complement for constructivism) and on (*ii*) hypothesis generation and concept representation in the framework of inductive concept learning (as a supervised machine learning paradigm). Accordingly, the main contribution of this research is figuring out the most significant key points for constructing a conceptual and epistemological linkage between a [concept-based] human learning theory and a [concept-based] machine learning paradigm. I will analyse the structural and logical specifications of concepts and conceptual representations and will analyse a common ground for expressing and analysing concepts in the context of human-machine interplays. I will also relate my specifications with Kantian account of schemata (and schemata-based concepts). Consequently, I will provide a list of the most significant transformations (from human into machine) and reflections (of human in machine) that make conjunctions between human learning and machine learning.

2. CONCEPTUAL REPRESENTATION

In this section I focus on (*i*) human conceptual representation in the framework of constructivism and constructionism and on (*ii*) hypothesis generation in the framework of inductive concept learning.

2.1 Constructivism and Constructionism

Constructivism is a philosophy that appears in a variety of guises, some of them pedagogical, some epistemological and some in complex combinations, see [Phillips (1995)]. In this research I see constructivism as a model of knowing with roots in philosophy, psychology and cybernetics that could support constructivist learning. In my opinion, the successful theories of learning are always getting supported by strong models of knowing, and thus, constructivism as a learning philosophy and as a theory of learning is highly dependent on constructivism as a model of knowing. According to these characteristics, it's possible to say that a successful theory of knowledge and an effective learning science may be constructed and developed based on the proper foundation that is provided by constructivism. Jean Piaget, the originator of constructivism, argued that all learning was mediated by the construction of mental objects that he called *schemata*. Schemata gradually develop into more conceptual mental entities, see [Bartlett (1932), Parker (2008)]. Let me explain the schemata in more detail. In constructivist learning the human’s mental structures manifest themselves in the form of schemata. The schemata demonstrate the human’s realisation of the world. They conceptually represent the constituents of human’s thoughts for knowledge acquisition with regard to her/his realisation of the world. Anyhow, in the framework of constructivism, a human being with respect to her/his pre-structured knowledge and her/his preconceptions attempts to develop the construction of knowledge. The most significant objective of constructivism is producing one’s own understanding of the world, see [Husen (1989), Keith Sawyer (2014), McGawand (2007)] for more detailed information.

Constructionism is a framework central to the learning sciences, and it posits that learners create their own knowledge by the construction of conceptual representations. Constructionism focuses on conceptualising learning and on learning how a human can learn. Papert’s constructionism focuses more on the art of learning and on the significance of making and producing things in learning. Papert is interested in how learners engage in a relationship with [their own or other’s] knowledge construction(s) and in how these relations ultimately facilitate the construction of new knowledge. Constructionism is a constructivist learning theory. It shares constructivism’s view of learning as ‘building knowledge structures’ through progressive internalisation of action, see [Spiro (1991), Ackermann (2002), Papert (1980)]. I may conclude that the main idea of constructionism is that human beings learn effectively through creating, constructing and developing things. Additionally, by adding experiences to the constructivism approach, constructionism attempts to conceptualise learning and to specify and analyse 'learning to learn'.

The most significant mutual objective of constructivism and constructionism is creating one's own knowledge by constructing conceptual representations. According to [Hampton (2003)], conceptual representations are arguably the most important cognitive functions in humans. They stand at the centre of the information processing flow, with input from perceptual modules of differing kinds. Also, the most important building block of constructivism and constructionism is schemata, see [Bartlett (1932)]. Schemata provide a proper background for the learner's concept (and conceptual) representations. They specify the learner's inferences and can satisfy various conditions for definitions of truth. We saw that everything is about concepts and conceptual representations. Conceptual representations attempt to investigate the origins of human's thought and roots of the constructed knowledge. In section 3 I will elaborate the description of schemata and will focus on structural and logical specifications of concepts as the key elements of the conceptual domains representation.

2.2 Inductive Concept Learning

Machine learning problems can be seen and analysed from different points of view and be divided into several categories. One categorisation could divide them into supervised, unsupervised, and reinforcement learning methods. In supervised learning method the pair (*input,output*) training examples are supplied by a trainer who is a human. So, the learner that is a machine searches for function mappings from the inputs into the outputs. In this research I am concerned with 'inductive learning from examples', which is a subfield of supervised machine learning. To induce means to infer general principles and rules from specific facts as the instances. I shall emphasise that these facts are different from the facts presented in the revised Bloom's taxonomy. All existing facts, procedures, concepts and contexts in Bloom's taxonomy could be captured as some principles (i.e. actuality, objectivity and reality) in machines. In Inductive Learning, we describe the main terminologies, axioms and rules by descriptive logical languages, e.g., First Order Predicate Logic (FOL) and Description Logics (DLs). *Inductive Concept Learning* (*ICL*) is a specified Inductive Learning. ICL attempts to logically describe concepts and their relationships. It employs the members (instances) and non-members of a concept that may be known as a class. A characteristic feature of most inductive learning approaches is the use of background knowledge. This feature supports more complicated and specific learning scenarios, because not only the factual description of the given examples can be used by the machine, but structurally rich knowledge representations can be taken into account as well, see [Mitchell (1997), Lehmann (2010)]. In parallel with [Lavrac (1994)], I focus on specification of concept learning with background knowledge. In concept learning with background knowledge, a machine with regard to the given set of training examples and background knowledge finds a *hypothesis*. A hypothesis can be expressible in concept description languages. Also, based on the background knowledge and given examples (to machine) a hypothesis can be complete and consistent, i.e. correct. So, one may assume that a hypothesis is generated based on ideas and can determine the applications of a term and a phrase. Furthermore, a hypothesis is a significant part in the use of reason and language. It has a very strong dependency to the background knowledge.

3. CONCEPTS: STRUCTURAL AND LOGICAL SPECIFICATIONS

There has always been a general problem concerning the notion of 'concept', in philosophy, in linguistics, in psychology and in computer and information sciences. This research is focusing on knowledge acquisition and learning relying on concepts and concept representations. Thus I need to ascertain a realisable interrelationship between the description of concepts within human and information sciences. Actually, I am constructing a conceptual linkage between constructivism/constructionism and inductive concept learning. As mentioned, schemata provide proper backgrounds for the learner's concept (and conceptual) representations. In a simplified version of Kantian philosophy a non-empirical (pure) concept has been defined as a category. According to Kantian philosophy[2], schemata are the procedural rules by which a category is associated with a sense impression. Kant claimed that the schemata provide a reference to intuition in a way similar to the manner of empirical concepts. According to the Kantian account of schemata there are three types of concepts that employ schemata.

1. Empirical concepts[3]: For instance, the concept of *Spring* can describe a rule according to which human's imagination can visualise a general figure of '*a green season with beautiful trees and colourful flowers*' without being restricted and closed to any particular and specific shape produced by experience.

2. Pure mathematical concepts[4]: They are the construction or mental drawing of what is common to several geometrical figures. They can be concerned with numbers, algebras and arithmetics. I shall stress that these concepts are not based on objective visual images.

3. Pure concepts of the understanding[5]: They focus on characteristics, predicates, attributes, qualities or properties of an object, that are, also objects in general or as such.

The third employs transcendental schemata, see [Kant (1781,1790,1999)]. Here I focus on some specifications of concepts and then relate them to the Kantian philosophy. Concepts are the furniture of human beings' minds. A well furnished mind can be a source of successful knowledge acquisition and learning, see [Parker (2008)]. Concepts are realised (by some philosophers and psychologists) as representations of reality in mind. Regarding this grasp of concepts, they could be understood as some general objects and labels, where objects are the constituents of propositions that mediate between thought, language, and referents, see [Bartlett (1932)]. From these characteristics, I conclude that it's possible to say that concepts might be understood to be the representations of actualities and objectivities in humans' minds. The mental representations of actualities can affect the human's languages. More precisely, a concept is may be said to be a linkage between linguistic expressions (descriptions) and the mental images (e.g., representations of the world, representations of inner experiences) that a human being has in her/his mind, see [Götzsche (2013)]. Relying on logics and their descriptive features, a concept can be seen as an *idea* and the idea can be transformed into a hypothesis in order to correspond to a distinct entity (or even to a group of entities) or to its (their) essential features. The ideas determine the application(s) of terms and phrases. It's really important to say that any idea is a significant part in the use of reason and language. These characteristics and properties are being applied in order to support the metaphorical usages of concepts in machine applications. In fact the existing linkages between mental images and linguistic expressions can be mapped (be transformed) as multiple ideas into hypotheses in order to determine different applications in artificial systems. As mentioned, a concept can be expressible in some concept description languages and it's possible only in virtue of terminologies. In fact, various concepts and the relationships between them can be used to establish the fundamental terminologies adopted in a modelled conceptual domain regarding the hierarchical structures. According to the characteristics of human ideas, when a human being forms[6] an idea from its examples, s(he) gets to know more than just some definitions. This demonstrates the deep learning rather than superficial knowledge, see [Parker (2008)]. I shall emphasise that the human learner is the developer of her/his personal conceptions over the individually designed schemata. In my opinion, the relationships between 'Kantian account of schemata' and the 'empirical concepts' supports the human's mental representations of the objects. It also sees a 'pure concept of the understanding' as a characteristic and predicate of an object that can express what has been said about that object. The first one employs schemata and the second one employs transcendental schemata. In fact, this is how a learner deals with fundamental concepts within constructivist learning. Accordingly, the leaner employs inductive rules to expand her/his

[2] https://en.wikipedia.org/wiki/Schema_(Kant)
[3] http://kantwesley.com/Kant/EmpiricalConcepts.html
[4] http://plato.stanford.edu/entries/kant-mathematics/
[5] http://userpages.bright.net/~jclarke/kant/concept1.html
[6] http://teachinghistory.org/teaching-materials/teaching-guides/25184

general ideas into more specified ones. The generalisation of various specified hypotheses (based on ideas) supports the learner in discovering new hypotheses and generating new ideas. S(he) searches for and lists attributes and properties that can be used to distinguish exemplars (of various hypotheses) from non exemplars. But what s(he) really does is more than just specifying and generalising from different examples; S(he) is highly concerned with identifying and relating the induced examples. Let me be more specific. As mentioned in 2.2, a machine with regard to the given set of examples and its background knowledge finds hypotheses. The logical description of a concept, which arises during the knowledge acquisition and learning processes, is called a hypothesis, since it is a experimental explanation of why the objects are members (or non-members) of the hypotheses (concepts). Also, considering a concept as a hypothesis, if an example belongs to a hypothesis, we are able to conclude that the hypothesis covers the example. Then, the example has all features and characteristics of that concept, see [Baader (2003)].

3.1 Concepts in the Common Ground between Human Constructivist Learning and Machine ICL

Obviously, there is an important characteristic of concepts held in common ground. The concepts in the common ground are the images of the Idea transformations (the transformations from human being into machine). The mappings epitomise humans' conceptual representations and generate hypotheses. In the common ground a concept is a specialised or generalised experience. The concepts could be recognised by their instances that are other concepts as well and they all can be represented in different hierarchies. In human scientific approaches an experimental explanation of why some objects are the members of a concept may support learners in representing their own ideas and in providing ideal (and conceptual) representations. In fact, the quality and the modality of the concept representation is affected by observing 'empirical concepts' and the 'pure concept of understanding' with regard to a Kantian account of schemata and transcendental schemata. On the other hand, in machine learning approaches, a machine generates the represented concept from its given instances. In the common ground, an experimental and empirical explanation of WhyNess of existence of some 'concepts, ideas and hypotheses' as the instances of other 'concepts, ideas and hypotheses' can provide a strong background for improving the quality of conceptualisations. Here are a number of transformations (from human into machine) and reflections (of human in machine) that make a conceptual and epistemological connection between human learning and machine learning:

- Transformation of a human being's knowledge and knowings into multiple principles (and axioms) in machines that are mainly object-oriented. Accordingly, the human being's knowings get classified into the specified classes (and under the determined labels) in machine's knowledge base.

- Transformation of a human being's experimental and empirical achievements into various categories of positive and negative examples in machines. Thus the human being's experiments get divided into exemplars and non-exemplars of the specified classes with determined labels.

- Transformation of a human being's real 'problems', real 'tasks for solving problems' and real 'performances' into provided classes with the same labels (Problem, Task and Performance) in machines.

- The reflection of human learning and knowledge acquisition in machines and artificial agents. This reflection is equivalent to transforming a taken metaphorical image of learning and knowledge acquisition into machines and artificial agents.

- The reflection of human concepts in the hypotheses. The linkages between a human being's mental representations and linguistic expressions (and descriptions) are getting mapped as some ideas into hypotheses in machines. They correspond to multiple entities or to their essential features in order to express different significant parts in the use of reasons and languages.

- The reflection of humans' conceptual representations in hypothesis representations and representation of hierarchy of hypotheses in machines' knowledge bases.

4. SUMMARY AND CONCLUSIONS

In this article I have focused on a conceptual and epistemological linkage between concept-based human learning and concept-based machine learning. Regarding the structures of human oriented sciences and information sciences and according to the fact that human oriented sciences and information sciences support distinct types of frameworks, I have had to specify and to analyse knowledge, knowledge acquisition and learning from two separated points of view. In human systems, knowledge acquisition is a reflective activity that enables a human being to draw upon her/his experiences and background knowledge to understand, conceptualise and evaluate the present, so as to build up and shape her/his future actions and to construct and develop new knowledge. On the other hand, a machine program is said to learn (and acquire knowledge) from an experience if there is a set of tasks and a performance measure for it, and also if its performance at those tasks, as measured, improves with its given experiences. In this article, according to (*i*) constructivism as a model of knowing and a theory of learning and constructionism as a theory of conceptualising learning, and (*ii*) inductive concept learning as a supervised machine learning paradigm, I have focused on building a conceptual linkage between human learning and machine learning. The constructivist and constructionist theories of human learning and the inductive concept [machine] learning paradigm are all shaped based upon concepts. The first two are focusing on concepts and conceptual representations and the third one focuses on representing concepts in informations sciences within electronic systems for hypothesis representation and hypothesis generation. My main concern has been analysing concept representations in the mentioned frameworks and on their common ground. A concept can be seen as a linkage between linguistic expressions and the mental images that a human has in mind. It can be observed as an idea and be transformed into a hypothesis in order to be corresponded to entities or to their essential features. In fact, schemata provide proper backgrounds for the learner's concept (and conceptual) representations. A Kantian account of schemata sees the empirical concepts in the human's mental representation of the objects. It also sees a pure concept of the understanding as a characteristic and predicate of an object. It can express what has been said about a thing. The first one employs schemata and the second one employs transcendental schemata. In fact, this is how a learner deals with fundamental concepts within constructivist learning and transforms her/his concepts into multiple hypotheses in order to be applied by inductive concept learning frameworks in machines.

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