Towards Semantic Analysis of Training-Learning Relationships within Human-Machine Interactions

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Abstract— **In this article First-Order Predicate Logic (FOL) is employed for analysing some relationships between human beings and machines. Based on FOL, we will be conceptually and logically concerned with semantic analysis of training-learning relationships in human-machine interaction. The central focus is on formal semantics and its role in the 'relationship' between human beings and machines. The analysed relationships between a human being and a machine will support our thoughts on and contemplations over the HowNess of establishing formal semantics within human-machine interaction.**

Keywords: **Semantics; Training-Learning Relation; Human-Machine Interaction; Predicate Logic.**

I. INTRODUCTION AND MOTIVATION

Machine Learning is a subfield of Artificial Intelligence and Computer Science. A machine learning approach attempts to develop appropriate procedures and techniques that allow machines to improve the productivity of their performances concerning a given goal, see [8]. In [2], we have focused on conceptual analysis of human-machine interactions and we have provided a conceptual and epistemological junction between human beings' minds and machines' knowledge bases. According to [6], and relying on our epistemological approach, the multilevel interactions between a human being (as a trainer) and a machine (as a metaphorical learner) could be seen as a radical constructivist account of human cognition, realisation and comprehension. Let me bring up some fundamentals in order to clarify our conception and way of thinking about the metaphorical use of 'learning'. In the expression 'machine learning', the word 'learning' has been utilised as a binary predicate with the word machine. Learning as a binary predicate has been asserted to be a role that is being performed by a machine. Thus, the act of 'learning' for a machine could be interpreted as a reflection of the [human] learning phenomenon in machines. In fact, machine learning is a metaphor that attempts to simulate the learning phenomenon with regard to the ingredients, components and concepts that are concerned with effective and successful learning processes in the real world. Let me bring the notion 'concept' into our explanation and be more specific on this research's objectives. 'Machine concept learning' approaches try to provide appropriate realisable logical descriptions for a human being's constructed concepts and their interrelationships after being transformed (from a human's mind into a machine's knowledge base) with regard to their structures and to their interrelationships to the world. Note that 'concept' is a complicated term. We see a concept as a linkage between a human's mental images of parts of reality (as things/phenomena), on the one hand, and a human's linguistic expressions and statements concerning those things/phenomena on the other hand, see [4]. In [2], we have explained that concepts are transformed in order to be represented and expressed within a machine's knowledge base. For instance, concepts can be reflected in order to be represented in the form of the entities as classes of individuals and objects. In other words, a concept is understood and is seen as an idea that can be transformed into a hypothesis in order to correspond to a distinct entity [and, respectively, to a group of entities] or to its [and their] essential attributes, features, characteristics and properties. The hypotheses can describe multiple theories based on terminologies and world descriptions. Accordingly, they support inferential and reasoning processes and satisfy multiple conditions for definitions of truth with regard to interpretation functions.

In this article, we will employ First-Order [Predicate] Logic in order to focus on relationships between human beings and machines. FOL allows us to make arbitrarily complex relationships between different objects of a system. Based on FOL we will be conceptually and logically concerned with semantic analysis of training-learning relationships in human-machine interactions. We shall stress that our main focus is on the semantics of the 'relationships' between human beings and machines. The analysed relationships between a human being and a machine will support our thoughts about the HowNess of establishing a [formal] semantics concerning human-machine interactions. According to [3], semantics is the study of the meanings, and the relation of signs to the objects to which the signs are applicable.

In the following sections you will be offered the following: (III) The Logical Specification of the Notion of Hypothesis, (IV) Preliminaries: Predicate Logic and Semantics in FOL, (V) Formal Representation and Semantic Analysis of 'Training-Learning' and (VI) Conclusions and Future Work.

II. THE LOGICAL SPECIFICATION OF THE NOTION OF HYPOTHESIS

Based on Predicate Logic and focusing on Description Logics [1], an unary predicate is supposed to be logically equivalent to a concept. For instance, we can consider the unary predicate *Set* as a concept in order to employ it in concept learning (concept expression) processes. Additionally, a concept can be logically described by a hypothesis, see [5][8]. For instance, the concept *Set* can be described as *a collection of the distinct things* in order to provide a foundation for a hypnosis. And, for instance, {a , 5, Science, ∞ , Σ } and {Book, ●} could be the positive (constructive) examples of the proposed hypothesis, and '{3 , T' and 'Y' could be the negative examples of the proposed hypothesis. In our opinion, (*i*) analysing the supportive inferential processes on a hypothesis, and (*ii*) focusing on world descriptions using generated hypotheses relying on defined terminologies, could collectively determine the applications of predicates, and, subsequently, the applications of terms and statements. Conceptually and logically the hypotheses focus on describing the predicates. Then they are expected to describe the same attributes, characteristics and properties. According to [8], a hypothesis as a logical description of a concept, arises during a machine learning process. Actually, it is a tentative explanation of why the objects are members (or non members) of the concept. A characteristic feature of most concept learning approaches is the use of background knowledge. In concept learning with background knowledge, a machine, with regard to the given set of training examples and background knowledge, will focus on hypothesis generation.

III. PRELIMINARIES: PREDICATE LOGIC

The Propositional Logic and its formulae (i.e., the formal and mathematical relationships or rules expressed in Propositional Logic's symbols) are constructed based on atomic objects. Note that the atomic objects, and, accordingly, the propositional formulae, could only be either true or false. First-order Predicate Logic (FOL) is constructed over propositional logic by seeing objects as the elements of sets and by applying universal and existential quantifications (restrictions). That's why some logicians and mathematicians see FOL as Quantification Theory, see [7] [9]. FOL allows us for making arbitrarily complex (specified) relationships between various objects. There are two kinds of symbols in FOL; (*i*) logical symbols and (*ii*) non logical symbols. The set of logical symbols in FOL is {Conjunction ($\wedge$), Disjunction ($\vee$), Negation ($\neg$), Implication ($\rightarrow$), Bi-conditional ($\longleftrightarrow$), Equality ($=$), Existential Restriction ($\exists$), Universal Restriction ($\forall$), Tautology ($\top$), Contradiction ($\bot$), Parentheses and brackets}. We shall stress that logical symbols always have the same meaning. It means that we are not allowed to interpret them and assign multiple values and definitions to them. The non logical symbols are represented in the following forms:

(i) *Constant Symbols.* For instance, *john*, *0* and *blue* are constant symbols.

(ii) *Unary Predicates.* In $P(x)$ and $Q(y)$, P and Q denote unary predicates. Also, x and y are variables (multiple constant symbols). These variables are the instances of P and Q. For instance, *Person*(*john*) denotes that 'John is a person'.

(iii) *Binary Predicates* (*Relations*). $R(m,n)$ is a binary predicate and makes a relation between two variables m and n. For example, *Equals*(m,n) can represent the 'equality between m and n' (i.e., m equals n).

(iv) *Function Symbols.* $f(x)$ is a function that operates the variable x. For example, *mother*(*john*) can represent the 'mother of john'.

At this point we shall draw your attention to the fact that the meanings of the non logical symbols are dependent on human being' interpretations. So, we need to interpret the non logical symbols to produce meanings and to clarify what we mean by them.

A. Semantics in FOL

In formal languages semantics is the study and analysis of the meanings of symbols and signifiers. Semantics focuses on the relationships between the signifiers of any language. In fact, the formal semantics employs the products of the human beings' interpretations in order to produce meanings. In fact, we need to consider the interpretation I that consists of (*i*) the domain of interpretation (that is a non empty set like D) and (*ii*) an interpretation function (like $\cdot^I$) that interprets the domain D in order to analyse the formal semantics of a term in FOL. For example, D = {Bob, Mary, Julian} could be interpreted (D^I) to represent the list of three PhD researchers in Metaphysics. Obviously, a meaning has been produced. Formally, the interpretation function assigns to every atomic unary predicate P (e.g., *Apple*, *Red*), a set like $P^I \subseteq D^I$. For instance, the interpretation of *Apple* ($Apple^I$) could express that "*Apple* is a Fruit and could be eaten". Also, the interpretation function assigns to every atomic binary predicate R (e.g., *Equals*) a binary predicate $R^I \subseteq D^I \times D^I$. For instance, the interpretation of *Equals* ($Equals^I$) could express that "*Equals* describes a kind of alignment between its right-hand side and its left-hand side".

Here we feel the need to describe the logical conception of equivalence relationship between two predicates. Two unary predicates (either atomic or non atomic) P and Q are equivalent ($P \equiv Q$), when for all interpretations I we have $P^I = Q^I$. On the other hand, they are not equivalent when there exists an (at least one) interpretation like J such that $P^J \neq Q^J$.

IV. TRAINING-LEARNING: FORMAL REPRESENTATION

In this section, the central focus is on conceptual and logical analysis of formal semantics within a training-learning relationship in the context of human-machine interactions. This research aims at investigating where the formal semantics come from and when it appears within a relationships between a human being and a machine. Considering the human being as the trainer and the machine as the metaphorical learner, accept the following axioms. These axioms focus on the non logical symbols of our formalism. They are the main building blocks of this research.

- The symbols h and m denote *human being* an *machine* respectively. They both represent constant symbols.

- The most significant unary predicates in our formalism are *Learner* and *Trainer*. Also, *Learner*(m) and *Trainer*(h) represent two unary predicate assertions (world descriptions over unary predicates). They demonstrate that the constant symbol m is an instance of the unary predicate *Learner* and the constant symbol h is an instance of the unary predicate *Trainer*. In other words, m is a *Learner* and h is a *Trainer*.

- Considering the unary predicates *Learner* and *Trainer*, the binary predicates *TrainerOf* and *LearnerOf* are defined. Consequently, *TrainerOf*(h,m) and *LearnerOf*(m,h) are two binary predicate assertions (or relation assertions, or world descriptions over binary predicates). The first relation describes that the human being h is the trainer of the machine m and the second one describes that the machine m is the learner of the human being h.

- Two functions *trainer*(m) and *learner*(h) are defined in order to represent the '*trainer of m*' and the '*learner of h*'.

A. Semantic Analysis

According to the proposed axioms and to the non logical symbols, we shall claim that the binary predicate *TrainerOf*(h,m) logically produces (implies) the equality *trainer*(m) = h. In fact,

$$\mathit{TrainerOf}(h,m) \qquad \textbf{(\textit{i})}$$
$$\Rightarrow\ \mathit{trainer}(m) = h\,. \qquad \textbf{(\textit{ii})}$$

The equation (ii) expresses the fact that the trainer of the machine m has been realised to be the person h. Note that this equality is produced with regard to our interpretation. In fact, it has been achieved based on the interpreted non logical symbols. Therefore, the equation (i) as a binary predicate, describes the interpreted relation between *trainer*(m) and h. We may claim that this equality is the root of the formal semantics within a training-learning relationship. The binary predicate equality describes that the meanings of its right-hand side and its left-hand side are the same. Consequently, the meaning of *trainer*(m) and h are the same. So, we shall emphasise that the achieved equality [as a binary predicate in FOL] aligns the meaning of *trainer*(m) and the meaning of h. Then we have:

$$\mathit{Equals}\ (\mathit{trainer}(m)\ ,\ h). \qquad \textbf{(\textit{iii})}$$

We shall maintain that the binary predicate (iii) has provided a supportive background for introducing the formal semantics. Considering this binary predicate, the function *trainer*(m) (as a non logical symbol) and the individual h (as a constant symbol) have been supposed to have the same meanings. Additionally, regarding the commutative laws, 'the trainer of m is h' and 'h is the trainer of m' are logically equivalent [and, thus, meaningfully, they are equal]. Consequently, 'the trainer of m implies h' and 'h implies the trainer of m'. Therefore:

$$\mathit{trainer}(m) = h\ \Rightarrow$$
$$(\ \mathit{trainer}(m) \rightarrow h\ )\ \wedge\ (\ h \rightarrow \mathit{trainer}(m)\ ). \qquad \textbf{(\textit{iv})}$$

The logical term (iv) is inherently equal to:

$$(\mathit{function} \rightarrow \mathit{constant}) \wedge (\mathit{constant} \rightarrow \mathit{function}). \qquad \textbf{(\textit{v})}$$

We have already deduced that the term '*a function symbol implies a constant symbol and a constant symbol implies a function symbol*' supports the analysis of our objective. Note that the term (iv) has been deduced based on the binary predicate *TrainerOf*(h,m) (or (i)). Then, there is a bi-conditional relation between (i) and (iv). Therefore:

$$\mathit{TrainerOf}(h,m)\ \longleftrightarrow$$
$$[\ (\ \mathit{trainer}(m) \rightarrow h\ ) \wedge (\ h \rightarrow \mathit{trainer}(m)\ )\ ]. \qquad \textbf{(\textit{vi})}$$

Equivalently:

$$\mathit{TrainerOf}(h,m)\ \rightarrow$$
$$[\ (\mathit{trainer}(m) \rightarrow h\ ) \wedge (\ h \rightarrow \mathit{trainer}(m)\ )\ ]$$
$$\text{AND}$$
$$[\ (\ \mathit{trainer}(m) \rightarrow h\ ) \wedge (\ h \rightarrow \mathit{trainer}(m)\ )\ ]\ \rightarrow$$
$$\mathit{TrainerOf}\,(h,m). \qquad \textbf{(\textit{vii})}$$

The logical term (vii) is structurally equal to:

$$\text{Relation}\ \rightarrow$$
$$[\ (\ \text{function} \rightarrow \text{constant}\ )\ \wedge\ (\ \text{constant} \rightarrow \text{function}\ )\ ]$$
$$\text{AND}$$
$$[\ (\ \text{function} \rightarrow \text{constant}\ )\ \wedge\ (\ \text{constant} \rightarrow \text{function}\ )\ ] \rightarrow$$
$$\text{Relation}. \qquad \textbf{(\textit{viii})}$$

In Figure 1, this logical conclusion has been figured out.

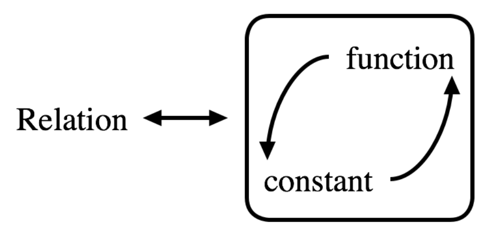

Fig.1. The General Structure of Semantics within Relationships Between Human Being & Machine

Conceptually, taking the afore-mentioned conclusions into consideration, we need to focus on four fundamental relationships: (**I**) The training relationship between human and machine (from human into machine), (**II**) The learning relationship between machine and human (from machine into human), (**III**) The iterative loops between human and machine (from human into machine and from machine into human), and (**IV**) The iterative loops between machine and human (from machine into human and from human into machine). Therefore, the formal semantics of training-learning relationship in the context of human-machine interactions is definable over four constructive implications:

I. Implying the 'iterative loops between human and machine' from the 'training relation between human and machine'. Then:

$$TrainerOf(h,m) \rightarrow [\,(\,trainer(m) \rightarrow h\,) \wedge (\,h \rightarrow trainer(m)\,)\,]. \qquad \textbf{(ix)}$$

II. Implying the 'iterative loops between machine and human' from the 'learning relation between machine and human'. Then:

$$LearnerOf\,(m,h) \rightarrow [\,(\,learner(h) \rightarrow m\,) \wedge (\,m \rightarrow learner(h)\,)\,]. \qquad \textbf{(x)}$$

III. Implying the 'training relationship between human and machine' from the 'iterative loops between human and machine'. This item is the inverse of the item (1). Then:

$$[\,(\,trainer(m) \rightarrow h\,) \wedge (\,h \rightarrow trainer(m)\,)\,] \rightarrow TrainerOf(h,m). \qquad \textbf{(xi)}$$

IV. Implying the 'learning relationship between machine and human' from the 'iterative loop between machine and human'. This item is the inverse of the item (2). Then:

$$[\,(\,learner(h) \rightarrow m\,) \wedge (\,m \rightarrow learner(h)\,)\,] \rightarrow LearnerOf(m,h). \qquad \textbf{(xii)}$$

Therefore:

- Fundamental **I** expresses: [(*Training Relation*) → (*Training Function* ⟷ *Learner Constant*)] .
- Fundamental **III** expresses: [(*Training Function* ⟷ *Learner Constant*) → (*Training Relation*)] .
- Fundamental **II** expresses: [(*Learning Relation*) → (*Learning Function* ⟷ *Trainer Constant*)] .
- Fundamental **IV** expresses: [(*Learning Function* ⟷ *Trainer Constant*) → (*Learning Relation*)].

According to the deduced results, we shall conclude that (**I**) the training relations (from human into machine) support the interrelationship between 'the act of training' and 'the machine', (**II**) the learning relations (from machine into human) support the interrelationships between 'machine learning' and 'human', (**III**) the interrelationship between 'the act of training' and 'the machine' support the training relation (from human into machine), and finally, (**IV**) the interrelationship between 'machine learning' and 'human' support the learning relation (from machine into human).

V. CONCLUSION AND FUTURE WORK

In this article, we have focused on First-Order formalisms in order to think of relationships between human beings and machines. The context of this research has been 'the training-learning relation between human and machine'. We have focused on logical description and logical analysis of the training-learning relations within human-machine interactions. The analysed relationships between human beings and machines have supported our thoughts about the HowNess of producing the formal semantics. This research has formed a building block of our PhD researches, which are dealing with Semantic Analysis of Constructivist Concept Leaning within Mentor-Learner-Machine Interactions. We have concluded four fundamentals that conceptualise meanings and express the structure of the formal semantics within relationships. Subsequently, we have concluded that the implications between 'relations' and 'the interrelationship of functions and constant symbols' support the formal semantics of the training-learning relationships. The conclusion of this research has prepared a strong backbone for our future research. In future research, we will focus on semantic analysis of human concept learning with regard to the semantics of her/his relationships with machines. We will also focus on the formal semantics of concept transformations from humans' minds into machine's knowledge bases with regard to our research in [10]. We will also work on semantic analysis of hypothesis generation. Human being generates a hypothesis in order to make it corresponded to a distinct entity or to its essential attributes, characteristics and properties. Semantically we will focus on an important form of HowNess: 'How do hypotheses determine the applications of the predicates?'

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