Abstract. Theoretical analysis of machine intelligence (MI) is useful for defining a common platform in both theoretical and applied artificial intelligence (AI). The goal of this paper is to set canonical definitions that can assist pragmatic research in both strong and weak AI. Described epistemological features of machine intelligence include relationship between intelligent behavior, intelligent and unintelligent machine characteristics, observable and unobservable entities and classification of intelligence. The paper also establishes algebraic definitions of efficiency and accuracy of MI tests as their quality measure. The last part of the paper addresses the learning process with respect to the traditional epistemology and the epistemology of MI described here. The proposed views on MI positively correlate to the Hegelian monistic epistemology and contribute towards amalgamating idealistic deliberations with the AI theory, particularly in a local frame of reference.

Keywords: epistemology, ontology, artificial intelligence, computational theories of learning, intelligent systems, tests of machine intelligence

1. Introduction

Epistemology, or colloquially the theory of knowledge, is relatively a modern term although its roots can be traced to the scholastic philosophy (Everson 1990). As such epistemology is one of the core areas of philosophy. It is concerned with the nature, sources and limitations of knowledge (Dancy 1991). The term itself was coined by the Scottish philosopher James Frederick Ferrier in the 19th century. The most important question that epistemology addresses is "What is knowledge?". This fundamental question is in focus of human thought for millennia, perhaps since the birth of a human mind capable of sapient abstract thinking. In this respect, epistemology of MI should address the question “What is machine knowledge?”.

The acronym machine is used in the paper to describe software or hardware of any artificial system, e.g. a computer information system. Another term for machine is system.

It is also important to note that the meaning of the term MI, as used here in the article, differs from the meaning of the term AI. MI will only describe the intelligence of machine under observation, and AI will pertain to the respective field of computer science (CS). The intent of such an approach is to circumvent ambiguities in the definition of general intelligence, mutual relationship between strong and weak AI, and in the resulting consequences.

Nevertheless, it is plausible to speculate about expanding the meaning of the term machine and, for example, use it to encompass biological entities as well, but such considerations are not within the scope of this particular paper.

Intelligence is defined by many different sources (Sternberg et al. 2000), and although as yet there is no unambiguous and mathematically formal definition of intelligence (Pfeifer and Scheier 2001), in order to achieve a better understanding and advancements in AI fields, it is necessary to take a broader look at the theory of knowledge, i.e. the foundations of intelligent behavior.

2. Setting the stage

The relationship between intelligent behavior and machine characteristics can be symbolically described in the following Venn diagram (Fig. 1):
There are six sets in this diagram:
1. Observed Intelligent Machine Characteristics (OIMC)
2. Observed Machine Characteristics (OMC)
3. Intelligent Machine Characteristics (IMC)
4. Intelligent Behavior (IB)
5. Machine Characteristics (MC)
6. Classification of Machine Characteristics (CMC)

Mutual relationships between these six sets can formally be written as follows:
\[ IMC \subseteq IB; IMC \subseteq MC \]
\[ IB \cap MC = IMC \]
\[ OMC \subseteq MC \]
\[ OIMC \subseteq IMC; OIMC \subseteq OMC \]
\[ IMC \cap OMC = OIMC \]
\[ CMC \notin IB; CMC \notin MC \]

The set OIMC is an intersection of three sets. It is a subset of OMC and IMC. Also, OIMC is a subset of OMC and IMC, which is an intersection of IB and MC. Finally, the set CMC is detached from the first five sets. The diagram in Fig. 1, and the accompanying theory, can be aptly named elementary epistemology of machine intelligence.

The set IB encompasses every type of intelligent behavior, not just that manifesting itself in some particular method or field of AI. The set MC represents every attribute of the machine under observation, while OMC represents every perceived machine’s attribute. This epistemology makes clear distinction between what exists in reality and what is observed. Reality isn’t relative. It is unchangeable by the machine or the observer which can only draw from the reality. In this epistemology the reality is represented by three sets: IB, MC and CMC. All other sets are intersections of these three or demand subjective observation.

OIMC is, epistemologically, the most important set, which holds all machine characteristics noticed by an observer and labeled as intelligent. Establishing definitions of intelligence recognition and observing processes are not the primary goal of this article. For elementary considerations it is sufficient to presume the existence of an independent observer who is able to annotate machine’s features and discriminates between intelligent and unintelligent characteristics. The lack of an infallible observer will introduce errors in these processes, but all theoretical principles described here will be unaffected.

The sets IB and CMC are independent upon the existence, and intrinsic attributes, of a machine, whereas all other sets (IMC, MC, OMC and OIMC) are dependent upon the machine and its attributes.

Going further with the examination of elementary epistemology of MI it is possible to define MI tests. In this respect, we can say that all tests of machine intelligence are functions that monitor manifestations of intelligent, and also unintelligent, machine behavior. The tests watch for observable machine’s characteristics and class them according to their properties as intelligent or unintelligent. Their intrinsic functions map perceptible and perceived elements of MC into CMC.

In other words, every test of MI is a non-injective non-surjective function \( f_{it} \) whose domain is the set OMC and codomain set CMC (Fig. 2).

\[ f_{it}: OMC \rightarrow CMC \]
The function $f_{ti}$ has to map every element in domain $OMC$ to exactly one element in codomain $CMC$, and for every element in codomain there are one or more elements in domain. It is very important to emphasize that a perfect intelligence test has the entire $IMC$ as its domain. Such imaginary and absolute test detects every single instance of intelligent behavior. $OIMC$ is a subset of $IMC$, and a realistic intelligence test works only with a part of $IMC$’s elements.

3. Quality measure of machine intelligence tests

Using cardinalities of the sets described in the previous chapter it is possible to define efficiency coefficient $\eta$ of an intelligence test as in Eq. 3.

Efficiency coefficient is a dimensionless value that describes how well a test of intelligence uses observed machine’s characteristics, i.e. its domain space, to interpret intelligent behavior. Essentially, efficiency coefficient describes relation between four sets: $OIMC$, $IMC$, $OMC$ and $MC$. If $OIMC \equiv IMC$ and $OMC \equiv MC$ the efficiency of MI test is maximal, but only an ideal test can reach 1 (100%) on this notional scale. For convenience if either set, $IMC$ or $MC$, is empty ($\emptyset$) $\eta$ equals zero.

Now going further, let’s for a moment assume that we have access to an infallible test of intelligence and let’s denote it by $f'_{ti}$. This test will always give correct classifications of observed machine’s characteristics. Now we can compare every intelligence test $f_{ti}$ with $f'_{ti}$ and calculate its accuracy. If it is possible to assign subtraction operator $-$ and modulo function $| \cdot |$ to $CMC$, we can define accuracy coefficient $c_a$ of an intelligence test (see Eq. 4). Accuracy coefficient explains how precise a test of intelligence is in classification of a machine’s characteristics. As a test makes more errors in classification, the coefficient diminishes.

Measure of intelligence is either a scalar, e.g. a decimal number such as the intelligence coefficient (IQ) (Bartholomew 2004), or a categorical (i.e. nominal) variable which classifies data into classes, e.g. descriptive grades of intelligence (Sternberg et al. 2000). Since categorical variables can be transformed to numeric, in principle it should always possible to define subtraction and modulo functions for $CMC$.

Accuracy and efficiency coefficients together define quality measure $Q$ of an intelligence test. Measure of quality is a unified pair $Q = \{c_a, \eta\}$. Two intelligent tests can be compared through modulo of their respective quality measures (Eq. 5). Therefore, given a set of intelligent tests with the same domain and codomain, the best test is the one with the greatest $Q$. The numerical variable $s_e$ holds the summation of all errors that $f_{ti}(x)$ has made for each $x \in OMC$.

If necessary, it is also possible to count the number of errors $N_e$ an intelligence test has made while classifying machine’s observable characteristics (Eq. 6).

By having at disposition a perfect intelligence test we can neatly avoid a formal definition of intelligence, of what constitutes an intelligent behavior, and how exactly to recognize it. This know-how will undoubtedly change and also, qualitatively and quantitatively, improve over time. Therefore, a formal definition, i.e. an algorithm or pseudo code in CS terms, of a perfect intelligence test will have to change as well. The approach taken here encompasses that process.
In a real world situation the perfect intelligence test can be substituted with a domain expert, or it should be possible to use competitive selection to iteratively process out the optimum available intelligence test.

4. Elementary epistemology of intelligence

Going further with the model in Fig. 1, we expand it to provide a single comprehensive picture of relative relationships between the world’s characteristics (WC), observed world’s characteristics (OWC) and intelligent behavior. The set WC exists autonomously and OWC depends upon it. See Error! Reference source not found. The intelligence is also a function. It is denoted by $f_i$. In the model above it is assumed that a hypothetical intelligent entity observes the world and tries to comprehend it. This implies the existence of intelligence. OWC is the set of all events or phenomena in the world, i.e. the universe, which have been noticed, or observed, by the hypothetical entity.

The entity’s function of intelligence $f_i$ maps OWC into IB (Fig. 3):

$$f_i: OWC \rightarrow IB$$

The function $f_i$ is a non-injective surjective function. One or more elements in OWC correspond to one or more elements in IB. An ideal $f_i$ will use all elements of both sets, whereas a less than perfect $f_i$ will use only a subset of domain OWC.
Intelligence has numerous definitions, however, it is clear that intelligence as – *the ability to acquire and apply knowledge and skills* (Sternberg et al. 2000; Weiner and Simpson 1991) – or by a different definition – *the skill necessary for acquiring a wide range of domain-specific knowledge* (Legg and Hutter 2007) – is related to the learning process.

5. Foundations of learning

Learning process is an enlargement of a system’s knowledge. By learning a system (machine) enhances its procedural and declarative knowledge.

A fact can be described as knowledge if and only if it is an objectively true belief. If one believes in a claim that is not true this is only individual or shared belief. Therefore, knowledge can also be called “Justified true belief”. The justification process is very important. To put it briefly, there are several reasons why a fact might seem true but in actuality is false. To begin with, the premises which logically imply the fact as their consequence can be untrue, they might be incomplete, or even the premises may, partially or completely, pertain to a different problem. Finally, even though all premises can be true and fully related to the specific area, the logical process (deductive or inductive) which leads to the consequence might be invalid. Venn’s diagrams, as the one in Fig. 5, are used to illustrate mathematical and logical relationships between sets; radius of a set is positively correlated to its cardinality, and distance between sets is negatively correlated to their combined cardinality.

When using epistemological arguments one has to be careful not to expose ontological paradoxes or other amphibolies. The modern philosophy recognizes various arguments why “justified true belief” cannot account as knowledge. The Gettier problem (Lycan 2006) and other similar problems (Ferré 1998) can be considered esoteric, but in a general frame of reference they are valid arguments. This is why the extent of the epistemology of MI proposed in this article is described conservatively. The most appropriate way to use this epistemology of MI is locally, within a certain scope and for a given problem. A local ontological frame of reference will ensure the least ambiguities and nondeterminism. These issues and the chosen knowledge representation model (Baral and Gelfond 1994) will decide if and to what extent it is possible to achieve determinism or decidability.

By using the paradigm of Venn’s diagrams it is possible to define three methods to increase the knowledge, i.e. the coincidence between belief and truth. These methods are:
1. Acquirement
2. Filtering
3. Specialization

The first and the most obvious learning method is the enlargement of the belief. This can be illustrated as an increase in the cardinality of
the belief set. The method can be named “Acquirement” (Fig. 6):

![Fig. 6 Acquirement method](image)

The second method discards unjustified belief and retains only those facts that constitute knowledge. In set diagrams this is manifested by the decreases in the cardinality of the belief set and in the distance between the belief and the truth. This method can be referred to as “Filtering” (Fig. 7):

![Fig. 7 Filtering method](image)

The third, and the last, method of knowledge augmentation is to shrink the truth set. This is done by pruning the problem domain and focusing only on the most important facts in the truth and the belief. The appropriate term for this method is “Specialization” (Fig. 8):

![Fig. 8 Specialization method](image)

As can be seen, these three methods cover all means that can increase the knowledge subset: i) enlarge belief, ii) draw closer together belief and truth, and iii) reduce truth.

After defining these learning methods in general, i.e. within the traditional epistemology, it is easier to apply them to a more specific issue of MI. Looking at Fig. 5 one cannot fail to notice a semantic analogy with the diagram in Fig. 1. In regard to the mutual relationship of the sets, their ability to change cardinality and their respective meanings it can be concluded that \( IB \) is analogous to the truth set and \( MC \) to the belief. The subset of knowledge is similar (i.e. approximately equal) to the subset \( IMC \):

\[
IB \cong \text{Truth} \\
MC \cong \text{Belief} \\
IMC \cong \text{Knowledge}
\]  

Thus we can define an ontologically simplified, or truncated, variant of MI epistemology with regard to the learning process (Fig. 9):

![Fig. 9 Epistemology of MI with respect to the learning process](image)

Following this line of inductive reasoning it is possible to define the same three procedures described before, but this time with the goal of enhancing MI.

In order to ameliorate the intelligent behavior of a machine the cardinality of \( IMC \) has to be enlarged. This can be accomplished by the following machine learning (ML) methods (Fig. 10-12):
In specialization, the cardinality of the set $IB$ is reduced but the set remains independent from the machine, as is outlined in the second chapter. The learning method can make local reductions to $IB$, and create a localized set denoted by $IB^*$ (Fig. 12). The specialization ML method does not affect the set $IB$ itself. Filtering and specialization learning methods are not continuously linearly ascending with respect to the cardinality of $IMC$, while acquirement is. By using filtering and specialization the subset $IMC$ will grow to a point, and after that it will decrease. It is possible to construct a machine $m$ with only a handful of elements in $MC$ and a total alignment between $IB$ and $MC$. Therefore $|IMC_m|/|MC_m| = 1$ which makes such a machine perfectly intelligent. But although all machine’s characteristics are intelligent, it has only a few characteristics in total. Obviously, such a machine would be less intelligent than a machine $m'$ for which $|IMC_m'| > |IMC_m|$. In summary; in order to increase the intelligence of a machine, in the broadest ontological terms, it is possible to: i) acquire new relevant data, ii) filter existing data and discard false or irrelevant data, and iii) narrow the problem domain. See Table 1.

The phrase data is used here to denote declarative and procedural knowledge together. In a typical IT system information would be stored in a database and algorithms coded in a programming language as functions of a computer application. The term database in the table below is a reference to a generic data storage system that the machine uses to store data.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acquirement</td>
<td>Expand the machine’s database content or data model.</td>
</tr>
<tr>
<td>Filtering</td>
<td>Search and remove false or irrelevant data from the machine's database.</td>
</tr>
<tr>
<td>Specialization</td>
<td>Redesign the whole machine system and narrow its problem domain.</td>
</tr>
</tbody>
</table>

Table 1 – Description of machine learning methods

It is important to realize that the increase in machine’s intelligence does not necessarily cause the increase in the efficiency or accuracy of MI tests. Although these can be positively correlated, there is no causal connection between them. In order to make a particular intelligence test better, it should be modified to implement new features, paradigms or algorithms. The procedures of acquirement, filtering and specialization described previously will not necessarily improve the results of MI tests. The reason for this is that the relationship between the sets $OIMC$, $OMC$ and $CMC$ is not constant, but it rather varies with the characteristics of a particular intelligence test. Depending on the problem each intelligence test, or a class of tests, will define differently the relationship between $OIMC$, $OMC$ and $CMC$. In fact, according to the equation (3) if cardinality of $IMC$ is increased and the size of all other sets remains the same, the test’s efficiency coefficient $\eta$ will be reduced. If intelligence of a system increases the test of its intelligence has to be enhanced as well.

Finally, there is one important assumption incorporated in the three methods of learning and improvement of MI: the belief has to be a subset of the truth and moreover $MC$ has to be a subset of $IB$.

$$MC \subseteq IB$$  \hspace{1cm} (9)

Without this assumption it wouldn’t be possible to define MI learning method because the sets $MC$ and $IB$ would be inherently disjunctive. They could never be allowed to overlap and subsequently the set $IMC$ would be $\emptyset$, i.e. empty. However, the consequence of
this postulate goes beyond this immediate deliberation. The equation (9) is saying that everything that a machine or a system do, have done, or will do, no matter how complex or trivial, is comprehensible by, and exists in intelligent behavior, i.e. the intelligence itself. This ontological viewpoint on MI absolutely correlates with the postulates of the ontological monism by Georg Wilhelm Friedrich Hegel. The philosophic Hegelian idealistic views (Marcuse and Benhabib 1987) stipulate the existence of a single unitary principle that permeates the world, and the identity of the mind and the reality. The dialectic process is an objective characteristic of the mind and world alike. This stance overcomes the permanent duality, i.e. apory of duality, as a difference between a cognitive object and a cognizing subject. With the acceptance of the ontological monism, further deliberations, or in more technical terms of computer science – research, can dwell on the properties of this subject-object rather than on their relation.

6. Conclusion

This article is directed at helping subsequent research in characterization of artificial intelligence systems and their quantization through the MI tests. The considerations set out in the article are intended to be included in and encourage theoretical analysis and the development of AI. Arguments or thought experiments like the Chinese Room (Searle 1980) and Brain in a Vat (Searle 1990), are useful for examination of the essence and range of AI, as well as the definition and mutual relationship between weak and strong AI. The role of the paper should be viewed primarily in this light. The elementary property of the described MI epistemology is also reflected in the idealistic thesis lying in the center of the described theory. Further aggregations and pervasive nondeterminism are, naturally, possible and an issue for further work and ongoing improvement.

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8. References