Understanding and Common Sense: Two Sides of the Same Coin?

Kristinn R. Thórisson[1,2] & David Kremelberg[1]

[1] Icelandic Institute for Intelligent Machines, Reykjavik, Iceland
[2] CADIA, School of Comp. Sci., Reykjavik University
Reykjavik, Iceland

Abstract. The concept of “common sense” (“commonsense”) has had a visible role in the history of artificial intelligence (AI), primarily in the context of reasoning and what’s been referred to as “symbolic knowledge representation.” Much of the research on this topic has claimed to target general knowledge of the kind needed to ‘understand’ the world, stories, complex tasks, and so on. The same cannot be said about the concept of “understanding”; although the term does make an appearance in the discourse in various sub-fields (primarily “language understanding” and “image/scene understanding”), no major schools of thought, theories or undertakings can be discerned for understanding in the same way as for common sense. It’s no surprise, therefore, that the relation between these two concepts is an unclear one. In this review paper we discuss their relationship and examine some of the literature on the topic, as well as the systems built to explore them. We agree with the majority of the authors addressing common sense on its importance for artificial general intelligence. However, we claim that while in principle the phenomena of understanding and common sense manifested in natural intelligence may possibly share a common mechanism, a large majority of efforts to implement common sense in machines has taken an orthogonal approach to understanding proper, with different aims, goals and outcomes from what could be said to be required for an ‘understanding machine.’

1 Introduction

Common sense (“commonsense knowledge”, “common sense reasoning”) has been deemed an important topic in AI by many authors since the field’s inception (Lenat et al. 1990, Liu and Singh 2004, McCarthy 1959, 1963, Minsky 2006, Panton et al. 2006). Following its use in our everyday language, the term has typically been used broadly in the AI literature, incorporating a large portion of human experience relating to the spatial, physical, social, temporal, and psychological aspects of everyday life (Liu and Singh 2004). Used in this way, the term refers to a vast body of knowledge assumed to be common to most humans. It is also used to refer to modes of reasoning and argumentation, as much of everyday planning involves the usage of standard forms of deduction, induction and abduction (e.g. “strong winds may blow rain through an open window so don’t leave your books on the windowsill”).

* Sponsored in part by the School of Computer Science at Reykjavik University and by a Centers of Excellence Grant from the Science & Technology Policy Council of Iceland.

The relation of common-sense and understanding is an unclear one. What can be said with some certainty is that in the AI literature, common sense has almost always been aligned with human common sense – that is, the knowledge that defines human common sense, with numerous attempts having been made to imbue machines with this same knowledge (Cambria et al. 2012, Lenat et al. 1990, Liu and Singh 2004, McCarthy 1959, Panton et al. 2006, Poria et al. 2014). The best known example is the Cyc project of Lenat's Cycorp Inc. (Lenat 1995), whose database currently consists of seven million axioms, 630,000 concepts and 38,000 relations between those concepts. [1]

Common sense may intuitively seem closely related to the concept of understanding. This seems to have been the opinion of Minsky and Papert, among others, who in 1970 wrote, when discussing one of Aesops fables: "The usual test of understanding is the ability of the child to answer questions like Did the Fox think the crow had a lovely voice? The topic is sometimes classified as natural language manipulation or as deductive logic, etc. These descriptions are badly chosen. For the real problem is not to understand English; it is to understand at all." (Minsky and Papert 1970:38). This text appeared in the section with the heading 'Narrative, Microworlds, and "Understanding" ' (quotes by the authors), throughout which the terms *understanding* and *meaning* are always in quotes when referred to in the context of machines, indicating a certain distrust towards the possibility of infusing them into machines in any real sense; why the authors did not aim for "real" understanding and "real" meaning may be because these concepts were not—at that time—very well understood (no pun intended). The authors conclude that a good body of knowledge is equally necessary for common sense as are reasoning rules to understand stories such as that of Aesop's crow, and predicting that "less than a million statements" (Minsky and Papert 1970:40) would be needed for such a knowledge base to work for that purpose. In the 40 years since this text was written, this heavy emphasis on background knowledge - which in their case at least seems synonymous with common sense - has only grown, and the terms have been used largely interchangeably (Lenat et al. 1990, Liu and Singh 2004, Panton et al. 2006).

We see the relationship between understanding and common sense as being far from settled, especially in light of the seemingly long road still ahead for reaching "true AI" (artificial general intelligence) and ask,

- *Can common sense exist without understanding?*

Are they perhaps two sides of the same coin? If so, what coin is that? Put another way, for any subject X, can a state of knowledge exist, and be held by an agent, that is deemed "common sense" with respect to X while the knowledge cannot be said to contain "understanding" of X? The question can of course be turned around, and this brings out the second question,

- *What is the relationship between 'common sense' and 'understanding'?*

To answer these questions one must look more deeply at the concepts themselves, and perhaps consider their usage and relation to some real-world examples. We look at the relevant literature and examine systems built to implement common-sense reasoning. The rest of this review paper is organized as follows: a discussion of common sense as it has been treated and previous attempts to implement it in systems along with

[1] *http://www.cyc.com/platform/*, accessed Apr. 29 2017.

a review of how this relates to our theory of understanding, the limitations seen in systems which have attempted to implement common sense, followed by a discussion contrasting understanding and common sense, and followed finally by our conclusions.

2 Common Sense & Understanding

To date, common sense has been viewed in a narrow way within the AI literature, generally being conceptualized as consisting of a body of facts or information. Accordingly, systems intended to demonstrate common-sense reasoning have generally tried to imbue common sense through pre-programming of vast amounts of knowledge. Few if any definitions of the term can be found, forcing us to rely on our general common sense of commonsense.

Broad, consistent knowledge about everyday things allows us humans to "flexibly understand and react to novel situations" (Panton et al. 2006). Analogously, if we could imbue machines with such broad and consistent knowledge the same should hold for machines. In 1990 the authors of Cyc argued that vast amounts of common sense knowledge would be required to produce an AI (Lenat et al. 1990). The argument goes that a large, general knowledge base enables consistent, efficient, and correct reasoning about everyday things with relatively simple and few rules (Minsky and Papert 1970), and a system with broad knowledge about facts and relations could thus be successful in completing tasks that require common sense (Panton et al. 2006). Without such knowledge and reasoning ability, however, systems will remain idiots savants (Panton et al. 2006).

Liu and Singh (2004) discuss ConceptNet, a commonsense knowledge base and natural language processing toolkit whose knowledge representation is semi-structured English. The commonsense knowledge contained within their database include spatial, physical, social, temporal, and psychological aspects of everyday life. The authors argue, however, that while some success has been found when using keyword-based and statistical approaches with respect to areas such as information retrieval, data mining, and natural language processing, it appears that these approaches provide too shallow of an understanding for all practical purposes, and that larger amounts of semantic knowledge are required in order to allow software to have a deeper understanding of text, echoing other authors' call for larger, more extensive knowledgebases.

These "common-sense" systems have numerous aspects in common: A knowledge-base (database + rules for how to use the data + metadata + network of relationships between the data) built on the same rules as typical databases in computer science, using hand-written rules authored along the same way as regular software is written. Relations between data are somewhat different from regular business rules in e.g. a bank or IT company, the principles for running such systems are very close to those governing operating systems and IT networks.

Understanding, which on the face of it seems highly related to common sense, takes up much less space than the concept of common sense in the AI literature, at least as an independent phenomenon or process, and when discussed seems to be considered largely synonymous with it, or even a less precise way of talking about common sense. Discussions of understanding proper have been mainly limited to the field of philosophy, which has been somewhat dominated by a language-centric viewpoint that aligns well with the symbolic approach to common sense, where knowledge is defined as "true, justified belief" (cf. Grimm 2014, Potter 1994, Grimm 1988).

In prior work we proposed a theory of understanding that rests on the idea that a learner that acquires understanding is in fact building a model that captures causal and other relations in the phenomenon being thus understood (Thórisson et al. 2016). Isolating causal relations is necessary in order to commit intervening actions that will produce predictable results. Modeled causal relations can be manipulated through the application of ampliative reasoning (cf. Wang 2012) due to the hypothetico-deductive nature embedded in macro-scale causality. Without causality, in fact, not much can be done – committing to a behavior with the aim to achieve a certain outcome for thing Y by manipulating X is not successful when the two are only correlated but not causally related.

In our approach, causal-relational models must be micro-malleable: to take into account any new fact or piece of knowledge that changes some of the assumptions already incorporated, however large or small, without having to re-structure all of the knowledge from scratch.[2] "Common sense" is generally thought to be common among humans (hence the name), while commonalities relating to experience should generalize more broadly, in such a way that if the system experienced an environment vastly different from a human environment it should still have common sense. Such a system as we describe must be able to produce models, on its own, in which rules are induced through observation and experience. Given an agent A with models M of a phenomenon Φ—M_{Φ}—we have proposed the following definition of understanding:[3] A's *understanding* of phenomenon Φ made up of sub-parts $\varphi \in \Phi$, depends on the accuracy of its models M_{Φ} with respect to Φ. Understanding is a (multidimensional) gradient from low to high levels, determined by the quality (correctness) of two main aspects in M_{Φ} relative to Φ:

U1 The *completeness* of the *set* of elements $\varphi \in \Phi$ represented by M_{Φ}.
U2 The *accuracy* of the *relevant* elements φ represented by M_{Φ}.

We also suggest that understanding can be tested for in the following ways:

(1) To *predict* Φ; (2) To *achieve goals* with respect to Φ;
(3) To *explain* Φ; and (4) To *(re)create* Φ.

This approach has been implemented in a system called AERA/S1, which demonstrates cognitive mechanisms very different from both classical symbolic systems such as Cyc and ConceptNet, reinforcement learners, and artificial neural net systems such as deep and recurrent neural nets (ANNs) (Nivel et al. 2014). S1 has been shown to be able to learn very complex spatio-temporal tasks from observation when given only a tiny amount of information up front, including a few top-level goals it should achieve. It does not require enormous hand-coding like (most) symbolic approaches, and neither does it require the tens of thousands of data and training iterations of ANNs. It can handle a vastly greater number of variables than the most sophisticated reinforcement learners to date, and it can handle inconsistencies and contradictions. It also learns cumulatively and continuously – on the job (Nivel et al. 2013, Nivel et al. 2014).

[2] This bears a relation to McCarthy's (1998) concept of "elaboration tolerance": Micro-malleability is a way to imbue causal-relational models with elaboration tolerance.
[3] For a thorough overview of this theory see Thórisson et al. (2016).

3 Some Limitations Observed in Commonsense Systems To Date

When looking at the performance, capabilities and state of commonsense/expert systems to date, three things jump out. First, no system so far has demonstrated automatic acquisition of commonsense knowledge. Second, very few have been provided with more than a few thousand axioms/rules/knowledge-nodes/facts – the main exception being Cyc, which contains over seven million axioms.[4] And thirdly, they all demonstrate a level of brittleness evident in frequent and unexpected errors and failures whose source, while not too difficult to trace in each case, is virtually impossible to foresee.

With respect to systems focusing on common-sense reasoning, while little has been written explicitly addressing their brittleness, this is a common concern that has been raised not only by critics of the approach but also by the authors of such systems (cf. Panton et al. 2006:22). However, when brittleness has been addressed by the developers of such systems it is often in the context of arguing that more rules are needed, hypothesizing that while programs lacking commonsense reasoning are brittle, those with sufficiently large databases will not be (Panton et al. 2006; Lenat et al. 1990). Examples of brittleness have been provided in the way of expert systems which break down in the face of contradictions and in areas outside their domain (Lenat et al. 1990). Pratt (1994) provides one of the more illuminating analyses of brittleness—in his case with Cyc—where numerous failures of an actual demonstration of the system were exposed in routine interaction.[5] Other publications do not present very strong evidence to anything contrary, with Lenat et al. stating in 2006 that Cyc fails to produce correct facts more often than 50 percent of the time, when searching the World Wide Web was used as a resource (Panton et al. 2006:22). All in all, "common-sense" systems seem still to fall short of their main goal when it comes to real-world performance.

To dissect this a bit further, one of the failures of expert systems in particular, and the classical symbolic approach in general, is the often-referenced mistake by a medical diagnosis system to diagnose a rusty car as "having measles". Such errors are due to lack of contextual knowledge. Another source of brittleness stems from the human ability to handle alternative background assumptions - a popular example being this exchange between father and child: Child: Do knights slay fire-breathing dragons? Father: Yes. Child: Do fire-breathing dragons exist? Father: No. The ability to humans to seemingly freely alter the assumptions on which reasoning is done, without losing track of the context, allow us to talk about imaginary things, hypothetical things, uncertainty, and numerous other things that are difficult to program in an automatic reasoning engine based on augmented first-order logic. Other sources of difficulty in commonsense reasoning are, for instance, unusual usage of the rich experience-based knowledge that humans have about the world (e.g. a rock being used as a table – a table with no legs), and when we use analogies (e.g. "The woods are his home away from home"). Another source of brittleness relates to a lack of contextual flexibility. While humans have many domains and resources to draw from, programs fail when situations exceed their limitations (Lenat et al. 1990).

---

[4] *http://www.cyc.com/platform/*, accessed Apr. 29 2017.

[5] In a demo given of Cyc to one of the authors of this paper (Thórisson) in 1998 (around 200 images instead of 20), unexplained inconsistencies surfaced, albeit different ones from those reported by Pratt (1994).

Some have argued that overcoming brittleness requires broad knowledge, and that a certain breadth is necessary and sufficient to begin to integrate new knowledge automatically (Lenat et al. 1990). The Cyc database is one of a few serious efforts to test this hypothesis. The original number predicted as necessary and sufficient for the system to start learning more or less on its own was 1 million rules (Lenat 1995).[6]

4 Why Understanding is Not Common Sense

Judging from the preceding literature review, it would seem that an overemphasis on the concept of commonsense in AI has resulted in the relegation of the broader concept of *machine understanding* to the sidelines. In the example of Cyc, the creators hypothesized that with respect to common-sense knowledge acquisition, one million axioms relating to basic (human experience) facts would be foundationally sufficient for the system to begin reading text authored by humans and acquiring the embedded knowledge mostly automatically, with one million axioms being an "inflection point" of sorts. When one million axioms did not produce adequate performance, the minimum was increased to two million; still, Cyc continued to display similar issues in performance - unexpected brittleness and failures. Interestingly, the Cyc project continued and is now at seven million axioms. This expected minimum might be sufficient, finally, but we have not seen any evidence thereof. We suspect that other factors are at play than simply the size of the knowledge base.

This raises important questions. For example: Is the representation method chosen in symbolic expert systems a good one for supporting automatic knowledge acquisition? Is first- (or second-) order logic a proper foundation for achieving robust results for the purposes these systems are built? Is a database with hand-written rules and relations a good foundation for machines to acquire and reach "common sense"?

A related question relates to the very definition of common sense – and also one that directs our attention to the anthropocentrism of the data these systems have been based on. Is the fact that "the third president of country X was Y really what we mean by the term "common sense"? Perhaps there are more fundamental aspects of the physical world that must be represented correctly and acquired autonomously by the correct mechanisms that must be present such that the system can learn such facts autonomously. Most importantly, are there other things, besides or instead of the reasoning methods employed, that enable such systems to acquire knowledge autonomously?

In our approach, the ability to understand—or more precisely to deepen/broaden one's understanding—must involve a capacity for automatic knowledge acquisition, as opposed to axioms hand-coded by humans. The conceptualization of common sense embodied in symbolic approaches relying on human-authored knowledge seem too simple and too human-centric, lacking the generalizability needed to achieve human-like understanding. Our own approach involves a representation of concepts that is built up of peewee-size models, that when brought together to model a particular phenomenon will predict its behavior under various conditions. These models can be shared between concepts – in fact, rather than being "made up of" such models, concepts in our ap-

[6] This number may have originated from the MIT AI lab (Minsky and Papert 1970), however, its origin or argumentation for why *this* number and not some other is not provided in the respective publications.

proach are dynamically constituted by the system on the fly, based on experience, by assembling appropriate models for a particular computation that must be done. General or "common sense concepts" are then dynamic model assemblies that have happened to be useful a number of times for the system that generated them (i.e. the machine, not a human). Understanding in our conception, then, is the application of such model assemblies for modeling causal and other relations between sensed phenomena, and for guiding goal-driven planning in realtime.

We have experimented with systems built in this way and compared them with other cognitive architectures (Thórisson and Helgason 2012). The results, which are explained in some detail in Nivel et al. (2013) and Nivel et al. (2014), have demonstrated robust sequence learning - robust in the sense of acquiring complex patterns correctly in a very short period of time, as well as having a potential to model its own limitations and thus learn to avoid situations in which it will not perform above a certain threshold, which can be either given to the system beforehand or any time during its learning.

With respect to classical symbolic systems, the application of our definition of the process acquiring understanding produces at best a set of questions or at worst a void: neither understanding nor the capacity to acquire it appears to be obviously present within these types of systems. While it could be argued that such a system may be able to create largely complete and accurate models of phenomena, fitting our definition of understanding, this would fall apart when this understanding was then tested for. Such a knowledge database type of system has not, and would not be expected to, perform well with regard to predicting a phenomenon, achieving goals, explanations, or recreating a phenomenon (Bieger et al. 2017).

A critical piece missing from symbolic systems is some foundational grounding: essentially, they are simply more sophisticated versions of "good old-fashioned" AI - "symbol" manipulators, where the "symbols" are simply augmented tokens[7]. A (human-like) concept cannot be adequately represented by token(s), or even by extended token(s). This lack of a foundation or basic framework precludes these types of systems from building understanding, as we have defined it.

Additionally, systems taking the classical symbolic approach have difficulties searching for the reasons behind inconsistencies in their knowledge; limitations arise by being unable to go below a certain level. This, along with its simple pipeline reasoning method, the choice of a single ontology, and inability to choose between reasoning methods, may be factors behind the brittleness found in Cyc and similar systems. In other systems, such as AERA and NARS, levels of plausibility exist, while there is never absolute certainty. Additionally, the level of granularity of one symbol or token per idea does not allow for concepts to be represented at lower levels of granularity; this reification of concepts may preclude the flexibility required for understanding as well as deepening and broadening understanding.

All of the above leads us to field the following hypotheses:

Hypothesis 1: *Fine-grained representation of concepts, and fine-grained (and ampliative) methods to reason over these, is necessary to realize mechanisms for understanding acquisition.* To robustly understand, for instance, that something can be pulled

[7] The "symbols" in such systems have no meaning for its manipulator, and can thus only be considered a token in a simulator whose meaning can only be discerned by its human author.

by a string but not pushed by a string (Minsky 2006), one needs a reasonably good representation of how matter behaves under various conditions. A classical symbolic approach, as some of those reviewed above, might represent the concept of "string" as a node in a knowledge network whose neighbor nodes are pretty much at that same level. It is not clear how one would infuse such systems with information of the type that could model how strings woven in various manners might behave differently, and that for instance a string made of extra stiff (yet bendable) plastic might be used to push something if the stub is short enough. Or how one would represent the knowledge that should you dip a string into superglue it may harden enough to become stick-like, in which case you can push something with it. (Is it still a "string" in this case? If not, how would this be represented? If yes, is it a different kind of string?). This kind of lower-level knowledge can be found for virtually any example of human-level knowledge.

Hypothesis 2: *To ground knowledge acquisition and understanding, a system must be able to do experiments in the domain that is the target of its learning.* A system that builds models of its own experience over time will produce a wealth of data about how the world works. Add to that an ability to do induction and the system can begin to generalize its data and create meta-rules about its experience. Such models will at any and all points in time have inconsistencies and incomplete knowledge - and this is not only something that any such system must be able to live with, it must be able to use it to improve its knowledge. However, without the ability to test knowledge against the real world this may be difficult; it is difficult to imagine how a machine that can only access human-level tokens can ever grow to properly validate or invalidate its knowledge.

Hypothesis 3: *Understanding is necessary for common sense.* In our conceptualization, understanding is the process by which one can acquire reliable, useful knowledge that can be used to predict, intervene, achieve goals, and explain. This seems to us to be the proper foundation for common sense, much more so than the human-centric one that most approaches have taken to common sense so far. Insofar as many of these do not aim for general intelligence but rather some practical tools or other ends, this criticism is of course not justified. Yet even on that end results seem to be slow in coming.

Hypothesis 4: *Symbolic approaches are brittle because they lack proper mechanisms to acquire understanding.* If concepts exist as a set of dozens or hundreds finer-grained pee-wee models, as we hypothesize, then using a symbolic approach in order to capture common-sense will not be successful, as a) it prevents the ability for the system to automatically select viewpoints on the knowledge that are relevant to each goal, and b) it removes the ability of the system to be truly grounded, and that type of experiential grounding cannot reasonably be manually written or programmed.

Hypothesis 5: *Symbolic approaches are brittle because they lack mechanisms to resolve logical inconsistencies in their own knowledge introduced by their human programmers.* Because their knowledge is human-centric and human-generated, inconsistencies must be resolved at this level. But their knowledge is fixed at this level, and deeper, more fundamental knowledge and experience does not exist in their knowledgebase to dig into underlying causes. Moreover, their reasoning ability is limited by targeting this kind of knowledge only; a more integrative ampliative reasoning—which unifies deduction, induction, and abduction—in a flexible manner (Wang 2006) seems necessary, preferably in part learned by the system through experience. However, since this is missing in such systems, this requirement falls flat.

Taken together, if all five hypotheses are valid, this should place rather particular and notable constraints on AGI research. Whether they hold up to scrutiny, presenting promising paths for further experimentation, calls for deeper investigation. We can only hope that we are honing in on something worthwhile, rather than having come to one junction out of a thousand or a million. On that question, our interesting result with peewee-granularity knowledge representation so far (Nivel et al. 2014) should certainly not be a deterrent.

5 Conclusion

While classical symbolic systems capture some aspects that are needed for common-sense reasoning, the approaches taken to date seem to a) put an undue emphasis on common-sense reasoning when it should be emphasizing understanding, b) place the machine within a human-centric framework by grounding the concept of common sense in human experience, and c) attempt to teach the system about common sense in a way that is practically impossible, i.e. pre-programming facts. If such systems can be said to understand, then why is their performance so brittle? We argue that a certain minimum level of performance is required in order to show understanding. With respect to approaches to AGI, we have argued that the classical symbolic approaches reviewed (and similar ones) cannot produce understanding or common sense due to their inability to represent concepts at finer granularity, their inability to automatically resolve logical inconsistencies, and that the approach prevents the ability for a system to automatically select viewpoints on the knowledge that are relevant to each goal, and removes the ability of the system to be truly grounded. Brittle systems cannot cope with new ideas, new experiences, new sights and sounds: without this ability, systems can hardly hope to go beyond their current state in any meaningful way.

References

Bieger, J., Thórisson, K. R., & Steunebrink, B. (2017). Evaluating understanding. Accepted to *IJCAI Workshop on Evaluating General-Purpose AI*. Melbourne, Australia.

Cambria, E., Olsher, D., & Kowk, K. (2012). Sentic activation: A two-level affective common sense reasoning framework. *Proceedings of the Twenty-Sixth Conference on Artificial Intelligence*. Toronto, Canada: AAAI.

Grimm, S. R. (1988). The value of understanding. *Philosophy Compass 7*(2): 279-299.

Grimm, S. R. (2014). Understanding as knowledge of causes. In A. Fairweather (Ed.), *Virtue Epistemology Naturalized*. New York City: Springer.

Lenat, D. B. (1995). Cyc: A large-scale investment in knowledge infrastructure. *Communications of the ACM 38*(11): 33-38.

Lenat, D. B., Guha, R. V., Pittman, K., Pratt, D., et al. (1990). Cyc: Toward programs with common sense. *Communications of the ACM 33*(8): 30-49.

Liu, H., & Singh, P. (2004). ConceptNet - a practical commonsense reasoning tool-kit. *BT Technology Journal 22*(4): 211-226.

McCarthy, J. (1959). Programs with common sense. *Proceedings Symposium on Mechanization of Thought Processes*. London: Her Majesty's Stationary Office.

McCarthy, J. (1963). Situations, actions, and causal laws. Stanford Artificial Intelligence Project, Memo No. 2.

McCarthy, J. (1998). Elaboration Tolerance. Common-Sense 98.

Minsky, M. (2006). *The Emotion Machine*. New York: Simon and Schuster.

Minsky, M. & Papert, S. (1970). Proposal to ARPA For Research on Artificial Intelligence at M.I.T., 1970-1971. Artificial Intelligence Memo No. 185. Massachusetts Institute of Technology A.I. Lab.

Nivel, E., Thórisson, K. R., Steunebrink, B. R., Dindo, H., et al. (2013). Bounded recursive self-improvement. Reykjavik University School of Computer Science Technical Report, RUTR-SCS13006 / arXiv:1312.6764 [cs.AI]

Nivel, E., Thórisson, K. R., Steunebrink, B. R., Dindo, H., et al. (2014). Autonomous acquisition of natural language. *Proc. IADIS International Conference on Intelligent Systems and Agents 2014 (ISA-14)*. Lisbon, Portugal: IADIS Press.

Nivel, E., Thórisson, K. R., Steunebrink, B., & Schmidhber, J. (2015). Anytime bounded rationality. *Proc. 8th International Conference on Artificial General Intelligence (AGI-15)*. New York City: Springer.

Panton, K., Matuszek, C., Lenat, D., Schneider, D., et al. (2006). Common sense reasoning - From Cyc to intelligent assistant. In Y. Cai & J. Abscal (Eds.), *Ambient Intelligence in Everyday Life*. Berlin, Germany: Springer.

Poria, S., Gelbukh, A., Cambria, E., Hussain, A., et al. (2014). EmoSenticSense: A novel framework for affective common-sense reasoning. *Knowledge-Based Systems 69*: 108-123.

Potter, V. G. (1994). *On Understanding Understanding: A Philosophy of Knowledge*. New York: Fordham University Press.

Pratt, V. (1994). CYC Report. Accessed Apr. 29, 2017 http://boole.stanford.edu/cyc.html

Thórisson, K. R., Kremelberg, D., Steunebrink, B. R., & Nivel, E. (2016). About understanding. *Proc. 9th International Conference on Artificial General Intelligence (AGI-16).* Cham, Switzerland: Springer International Publishing.

Thórisson, K. R. & Helgason, H. P. (2012). Cognitive architectures and autonomy: A comparative review. *Journal of Artificial General Intelligence, 3*(2): 1-30.

Thórisson, K. R. & Nivel, E. (2009). Achieving artificial general intelligence through peewee granularity. *Proc. of the Second Conference on Artificial General Intelligence (AGI-09)*. Paris, France: Atlantis Publishing.

Wang, P. (2006). From NARS to a thinking machine. Artificial General Intelligence Research Institute Workshop, Washington DC, May 2006.

Wang, P. (2012). *Non-Axiomatic Logic - A Model of Intelligent Reasoning*. Hackensack, NJ: World Scientific Publishing Co., Inc.