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An Experiment in Measuring Understanding

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Human-centric AI needs deliberative intelligence as well as reactive intelligence in order to achieve properties argued to be essential for human-centric AI [1], such as, (i) providing explanations comprehensible for humans, (ii) dealing with outliers, (iii) learning by being told, (iv) being verifiable and (v) seamlessly cooperating with humans [2]. Whereas reactive intelligence rests on directly applicable pattern-response pairs, deliberative intelligence rests on **rich factual models and inference**. Although many techniques exist to derive information once a rich model exists, the process of coming up with these models remains a serious issue. We intuitively call this process **understanding**. For example, when cooking a dish from a recipe, understanding amounts to identifying the ingredients and the food manipulations in sufficient detail to effectively cook the recipe [3] and possibly coming up with variations.

Understanding is hard because in real world problem situations inputs for making a model are often fragmented, multi-modal, underspecified, ambiguous and uncertain. These issues can only be tackled by integrating many possible knowledge sources: vision and pattern recognition, language parsing, ontologies, semantic memory, context models, mental simulation, real world action and episodic memory. Each of these knowledge sources is in turn incomplete, uncertain and not necessarily reliable. Moreover there can not be a linear progression where one knowledge source feeds its results into the next one, as is common in the pipelines of data-driven AI, because of a paradox known as the *hermeneutic circle*: To understand the whole we need to understand the parts but to understand the parts we need to understand the whole [4].

This paper reports on a way to measure progress in understanding. Such a measure is important for evaluating the performance of an understanding agent and can function as feedback signal for an agent that is learning to improve its understanding processes. **We frame the process of understanding in terms of a process of generating questions, reducing questions, and finding answers to questions.** The questions and answers form a network, called a *narrative network* (Figure 1). The proposed measures track the number of questions introduced by each knowledge source and the proposed answers.

Tracking is done with meta-level monitors which have been fully implemented and are demonstrated in the paper for a system that combines knowledge from language, ontologies, mental simulation and discourse memory to understand a cooking recipe

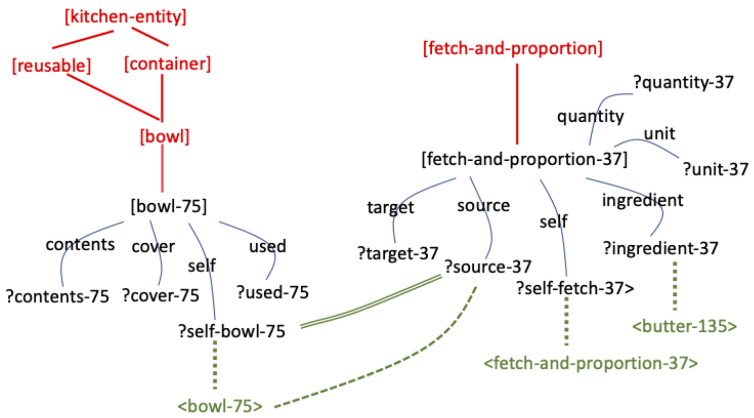

Figure 1. Small fragment of a narrative network built up for preparing an Almond Cookie Recipe. The questions are represented as symbols with a question mark, as in `?source-37`. Answers can be frames (with square brackets) or names of entities (with angular brackets) as in `<bowl-75>`. Links between questions and answers are in green.

phrased in natural language as developed by Katrien Beuls and Paul van Eecke https://ehai.ai.vub.ac.be/demos/recipe-understanding/. Figure 2 shows one way to visualize the measures, focusing on the percentage of questions answered and where the answers come from. In total 165 questions have been generated.

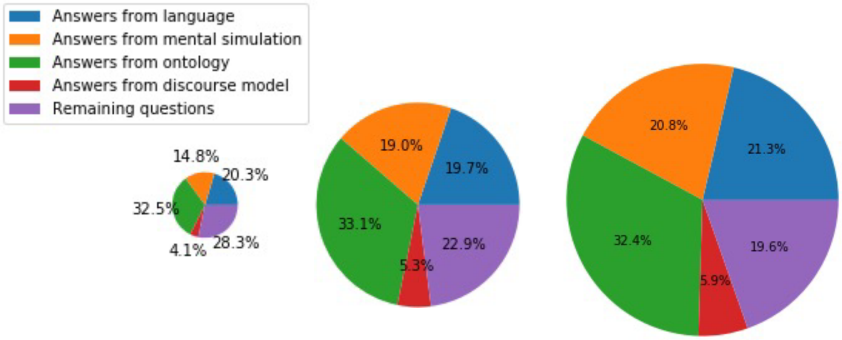

Figure 2. Three steps in the expansion of a narrative network for the cooking recipe. The size of the circle represents the total number of questions (scaled to the absolute maximum). The slices represent the percentage of questions answered through a particular knowledge source: blue for language, orange for mental simulation, green for the discourse model and red for the ontology.

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