Comparative Analysis of NARS and Qualitative Representations

Yi Qu

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1. Abstract:

This proposed research is expected to present a comparative analysis of NARS (Non-Axiomatic Reasoning System) and Qualitative Representations (QR), two approaches to artificial general intelligence that address uncertainty and dynamic change from different perspectives. NARS emphasizes flexible, resource-bounded reasoning with a focus on variable unification, symbolic inference, and probabilistic rule application. In contrast, QR leverages structural mapping and qualitative simulation to model real-world processes without relying on precise numerical data. The analysis highlights how each system manages ambiguity and changes and discusses potential avenues for integrating the strengths of both approaches to enhance overall reasoning capabilities.

2. Relevant Works

Wang, P. (2013) [3] This work lays out the theoretical foundation of NARS and explains how reasoning under uncertainty and limited resources is achieved through flexible, weighted inference. It's an essential reference for understanding the principles and applications of NARS. Forbus, K. D. (1983) [4] This paper introduces key ideas behind qualitative reasoning and how processes can be represented without relying on exact numerical data. It forms the basis for many qualitative simulation systems. Kuipers, B. (1994) [5] This book comprehensively treats qualitative reasoning, including the theoretical and practical aspects of modeling dynamic systems when precise quantitative information is not available. Gentner, D. (1983) [6] Although not solely focused on qualitative reasoning, this article introduces the structure-mapping framework that underpins many approaches (like QR's SME) for drawing analogies and abstracting relational structures, which is relevant to QR's design.

3. Background:

Qualitative Representations (QR) follows the representationalism principle in AGI. It is a framework and methodology used to describe, reason, and simulate the world with continuous changes, which serves as an important role in natural language and visual semantics. It abstracts continuous numerical data into qualitative categories (e.g., low, medium, high) and qualitative trends (e.g., increasing, decreasing, steady). This mirrors how humans often reason about everyday phenomena without performing exact numerical calculations. On top of that, when people derive hypotheses from their experiences, the qualitative features help them reason in partial causal knowledge by omitting unimportant numerical details, which provides the basis for both commonsense reasoning and expert reasoning.

QR abstracts relational representations (observations) using a structure mapping engine (SME) and stores them in a knowledge base using a sequential analogical generalization engine (SAGE)[1]. Russian psychologist and philosopher Lev Vygotsky pointed out that much of our knowledge is learned through interactions with other people. Inspired by this, QR tries to become a software social organism that works with people using natural modalities (natural language, sketch, vision, speech).

Analogy and Analogical Reasoning borrow the idea of assimilation and accommodation from psychology, especially in the constructive theory of knowing. [9] An analogy is a comparison between two objects, or systems of objects, that highlights respects in which they are thought to be similar. Analogical reasoning is any type of thinking that relies upon an analogy. Analogical reasoning is fundamental to human thought and, arguably, to some nonhuman animals as well. Historically, analogical reasoning has played an important, but sometimes mysterious, role in a wide range of problem-solving contexts. The explicit use of analogical arguments, since antiquity, has been a distinctive feature of scientific, philosophical and legal reasoning. [7]. Analogical reasoning is wildly used in qualitative representations. It is performed under the assumption that people learn new concepts by comparison with the most similar ones they already know. For example, assume that you do not know trapezoids. The first time you see Figure 1, you may name it quasi-parallelogram, or something else. What happens in your mind is that, when new concepts come in, it keeps looking for the similarities to your acquired concepts and encapsulates them into your knowledge base. Analogical reasoning finds a short-cut in your knowledge base. It serves as an efficient method to do data incrementation and inspectable learning.

Structure Mapping Theory, developed by Dr. Dedre Gentner, is a theory of analogical reasoning aiming to improve upon previous theories of analogy by distinguishing analogy from literal similarity [8]. Literal similarity represents the attributes used to describe nones. Whereas structure mapping theory pointed out that analogy maps the similarity in the relationships between nones. Attributes are predicates with One argument, whereas relationships are predicates with two or more arguments. For example, the K5 planetary system is like the Solar System, which is literal similarity because the attributes of K5 are compared with which of the sun, the planetary system is compared with our solar system. However, the atom is like the Solar System is an analogy. This statement does not compare the attributes of an atom with the sun (e.g., the size of the atom cannot be comparable with the sun). However, the higher-order relationships (e.g., the motion of electrons) are compared with the solar system.

Structure Mapping Theory describes the psychological process of reasoning through analogies. Specifically, it describes how people generalize the familiar knowledge about a base domain to less familiar knowledge about a target domain. In QR, knowledge is represented in the tree structures. The mapping consists of three aspects: 1. correspondence between each tree. 2. numerical similarity scores that measure how similar those components are. 3. Candidate inference that aims to find the missing components with high similarity scores. Structure Mapping Theory is observed in a large body of psychological evidence.

4. Methodology:

4.1 NARS Methodology:

NARS is built on the principle of reasoning under the Assumption of Insufficient Knowledge and Resources (AIKR). Rather than presuming a complete, static knowledge base, NARS represents beliefs as weighted statements in a non-axiomatic logic, where each sentence carries a pair of truth values: frequency (how often it has been observed) and confidence (how reliable that evidence is). This allows NARS to operate under an open-world assumption: new information can always arrive, old beliefs can be revised, and no statement is ever taken as absolutely certain. Knowledge is stored in a dynamic memory network of concepts and terms, and inference is driven by a suite of generic syllogistic rules (deduction, induction, abduction, exemplification, and revisions) that apply to arbitrary term structures.

Reasoning in NARS proceeds as an iterative task-based cycle. At each step, incoming inputs (percepts, goals, questions) are framed as tasks and placed in a priority-driven task queue. The system selects a task, applies the inference rule(s) (deduction, induction, abduction, exemplification, and revisions) to produce new judgments or tasks, updates truth values via a revision rule when contradictions or redundancies arise, and then re-queues both the original and newly generated tasks according to their updated priorities. Over time, this multi-strategic strategy blending, coupled with resource-bounding mechanisms, enables NARS to perform learning, decision-making, and problem-solving robustly, even with partial knowledge and limited computational resources.

4.2 QR Methodology:

Instead of non-axiomatic, QR requires a comprehensive knowledge base that defines the reasoning system's basic concepts (nouns as facts, verbs as experiences). The knowledge is in a structural representation. Before starting the system, the users should specify a base case, which is a set of knowledge. The Structure Matching Engine (SME) is running to compare the similarity between the base and the target knowledge. MAC/FAC (magnitude accumulation components, force accumulation components) serves as the interface between the knowledge base and the other part of the system (QR focuses on physical world representations. However, it also supports commonsense reasoning). Figure 1 illustrates the overall view of the QR system.

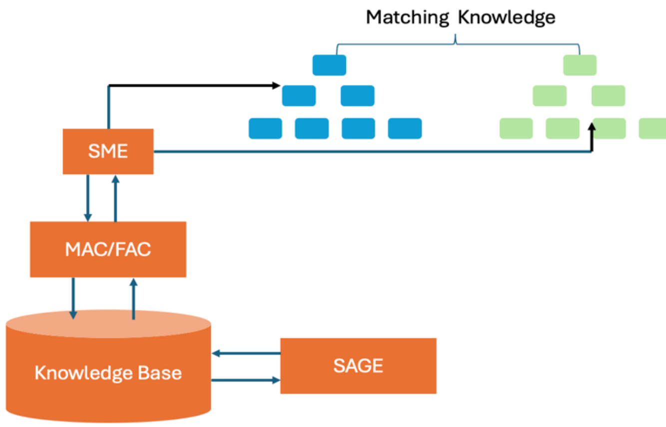

Figure 1: Overall view of Qualitative Representations

- MAC (Magnitude Accumulation Component):
  MAC essentially plays the role of integrating changes over time. It "accumulates" the effects of ongoing changes (for example, how a quantity increases or decreases gradually) without resorting to precise numerical integration. In a simulation, MAC is what lets the system predict that a variable is steadily moving toward a higher or lower qualitative state.
- FAC (Force/Forcing Accumulation Component):
  FAC deals with external or causal influences on the system. It captures how external "forces" impact the rate or direction of change. For instance, if an external input or disturbance acts on the system, FAC represents that sudden push or pull, modifying the trajectory produced by MAC.

MAC/FAC keeps an eye on the knowledge base, it fetches the target knowledge out of the knowledge base and feeds it into the SME to compare the similarity, and also updates the base knowledge according to the similarities.
For the knowledge base, there is another model called the Sequential Analogical Generalization Engine (SAGE), which incrementally produces generalizations in the knowledge base with the new information from MAC/FAC. SAGE only performs the similarities when generalizing the knowledge base, whereas SME computes the similarities while

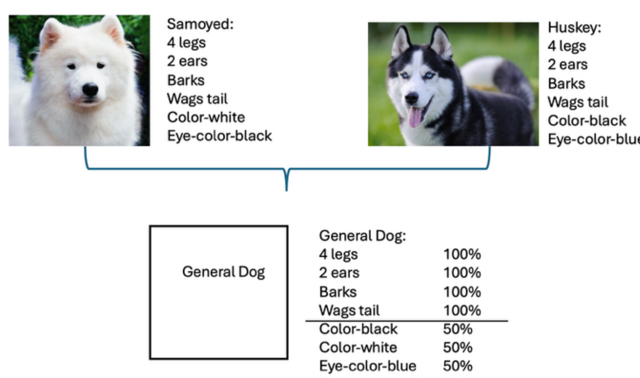

Figure 2: SAGE generalization process

reasoning about the inference cases. Figure 2 demonstrates the process of SAGE.

5. Comparative Analysis

In order to compare the performance of QR with NARS, the first thing to do is to merge the knowledge base from QR to NARS, since NARS knows nothing at the beginning. Figure 3 illustrates one example of the QR's knowledge base. It has four keywords: *isa*, *hasa*, *implies*, and *cause*. When translating the knowledge base to NARS, *isa, hasa,* and *implies* are straightforward, since we have a similar representation in NARS.

Figure 3: One example of QR's knowledge base

(isa A B) can be translated to <A --> B>. %1.00;0.90
(hasa A B) can be translated to <A --> [B]>, %1.00;0.90
(implies A B) can be translated to <A ==> B>. %1.00;0.90

However, for *cause*, NARS's representation requires an explicit causation to form the representation in our textbook

$$((\$a\ X\ \$b) \text{ -> } causation_i) \text{ <=> } ((\$a \text{ ==/> } \$b) \wedge (\$a\ X\ \$b) \text{ -> } criteria_i)$$

In QR's knowledge base, it is not necessary to explicitly mention the causation and criteria. Instead, I decided to translate *cause* into

(cause A B) can be translated to <(A ==/> B) ∧ ¬ (¬A ==/> B)>

With that in mind, I would like to compare the performance of QR and NARS in commonsense reasoning and physical world reasoning.

5.1 Commonsense Reasoning

Case 1 Deduction:

Input : <<robin --> bird> ==> <robin --> animal>>.
<<robin --> [flying]> ==> <robin --> bird>>.
Output: <<robin --> [flying]> ==> <robin --> animal>>. %1.00;0.81

NARS gives the above output in 19 iterations (roughly 3 seconds).

QR knowledge base is created as

(isa robin bird)
(isa robin animal)
(implies (isa robin bird) (isa robin animal))
(hasa robin flying)
(implies (hasa robin flying) (isa robin bird))

The QR output gives the following statement in less than 1 second.

(implies ((implies (hasa robin flying) (isa robin bird))) (isa robin animal))

Case 2 Abduction:

Input: <<robin --> bird> ==> <robin --> animal>>.
<<robin --> [flying]> ==> <robin --> animal>>. %0.80%
Output:<<robin --> bird> ==> <robin --> [flying]>. %1.00;0.39%
<<robin --> [flying]> ==> <robin --> bird>>. %0.80;0.45%

NARS gives the above output in 24 iterations (roughly 3 seconds)

QR knowledge base is created as

(isa robin bird)
(isa robin animal)
(implies (isa robin bird) (isa robin animal))
(hasa robin flying)
(implies (hasa robin flying) (isa robin animal))

The QR output gives the following statement in less than 1 second.

(implies (isa robin bird) (hasa robin flying))

However, it does not give us the inverse of the implication, which indicates that the implication rule is calculated by the mutual similarity.

5.2 Physical world Reasoning

I want to compare the performance on the case when a pendulum is at its leftmost point. A valid reasoning system will predict that the ball will move right. Therefore, in QR's knowledge base

(hasa ball mass)
(hasa ball gravity)
(isa ball left)
(isa ball right)
(hasa gravity left)
(hasa gravity right)
(hasa ball moving-left)
(hasa ball moving-right)
(implies (isa ball left) (hasa gravity right))
(implies (isa ball right) (hasa gravity left))
(implies (hasa gravity right) (hasa ball moving-right))
(implies (hasa gravity left) (hasa ball moving-left))

QR gives the output of the following in less than 1 second.

(implies (implies (isa ball left) (hasa gravity right)) (hasa ball moving-right))
(implies (implies (isa ball right) (hasa gravity left)) (hasa ball moving-left))

In NARS:

Input: <ball --> [mass]>.
<ball --> [gravity]>.
<ball --> left>.
<ball --> right>.
<gravity --> [left]>.
<gravity --> [right]>.
<ball --> [moving-left]>.

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        <ball --> [moving-right]>.
        <<ball --> [left]> ==> <gravity --> [right]>>.
        <<ball --> [right]> ==> <gravity --> [left]>>.
        <<gravity --> [left]> ==> <ball --> [moving-left]>>.
        <<gravity --> [right]>==> <ball --> [moving-right]>>.
Output:<<ball --> [left]> ==> <ball --> [moving-right]>>. %1.00;0.81%
        <<ball -->[moving-right]> ==> <ball --> [left]>>. %1.00;0.45%
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6. Discussion and Conclusion

Pioneered by Kenneth Forbus[2], QR focuses on modeling and reasoning about dynamic, real-world processes without relying on exact numerical data. In the physical world, we can set the direction left and right, the speed high and low, the weight heavy and light, depending on how accurate we want the system to be. For the output, QR gives out the whole sequence of similarity comparisons forming implications. Meanwhile, NARS always gives pairwise results, which are natural to the design of the truth-value system. For efficiency, QR is much faster than NARS in that QR seems more goal-oriented, whereas NARS sometimes gets distracted. In such simple testing cases, QR achieves comparative results to NARS, under the assumption of a closed world. However, in an open world, since the similarities are ubiquitous, the calculation of similarity (SME) cannot work very efficiently. Fairly speaking, NARS in the open world may suffer from getting more distracted.

Philosophically, analogical learning learns similarity, but it does not know that something is dissimilar. NARS naturally does not have such issues since the truth-value system guarantees antonymity. Since every quality is represented by categories, the dissimilarity is less represented in QR.

For the knowledge base, actually, with or without a knowledge base does not affect much in terms of the accuracy of the reasoning parts, at least in small testing cases. In the real world, a knowledge base may help the system initially. However, conflicts are more likely to arise when the system adapts new knowledge into the knowledge base. NARS gives the truth-value to each “observation”, which elegantly solves this issue.

To conclude, QR’s similarity + reasoning works more effectively under the closed-world assumption. It is designed for qualitative reasoning with partial knowledge and limitations of accuracy. In contrast, NARS’s pure reasoning can be more generalized in any case under AIKR.

Reference:

[1] https://www.qrg.northwestern.edu/ideas/smeidea.htm

[2] https://en.wikipedia.org/wiki/Ken_Forbus

[3] Wang, Pei. *Non-axiomatic logic: A model of intelligent reasoning*. World Scientific, 2013.

[4] *Qualitative Process Theory.* In *Proceedings of the 8th International Joint Conference on Artificial Intelligence (IJCAI-83)*, 406–412.

[5] *Qualitative Reasoning: Modeling and Simulation with Incomplete Knowledge.* MIT Press.
[6] *Structure-Mapping: A Theoretical Framework for Analogy. Cognitive Science, 7*(2), 155–170.

[7] Bartha, Paul, "Analogy and Analogical Reasoning", The Stanford Encyclopedia of Philosophy (Fall 2024 Edition), Edward N. Zalta & Uri Nodelman (eds.), https://plato.stanford.edu/archives/fall2024/entries/reasoning-analogy/

[8] https://en.wikipedia.org/wiki/Structure-mapping_theory

[9] https://en.wikipedia.org/wiki/Constructivism_(philosophy_of_education)