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Non-Axiomatic Logic Modeling of English Texts for Knowledge Discovery and Commonsense Reasoning

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Featured Application: This work proposes a working set of rules for translating English sentences into the formal language of non-axiomatic logic (NAL). The proposed translation takes advantage of several linguistic tools for pre-processing and can be used for commonsense reasoning via non-deductive inferences formalized in NAL.

Abstract: Non-axiomatic logic (NAL) is a term-based, non-monotonic, multi-valued logic with evidence-based formal semantics. All those characteristics position NAL as an excellent candidate for modeling natural language expressions and supporting artificial agents while performing knowledge discovery and commonsense reasoning tasks. In this article, we propose a set of rules for the automatic translation of natural language (NL) text into the formal language of non-axiomatic logic (NAL). Several free available tools are used to support a previous linguistic analysis, and a common sense ontology is used to populate a background knowledge base that helps to delimit the scope and the semantics of logical formulas translated. Experimentation shows our set to be the most comprehensive NL-to-NAL translation rule set known so far. Furthermore, we included an extensive set of examples to show how our proposed set of rules can be used for translating a wide range of English statements with varying grammatical structures.

Keywords: non-axiomatic logic; computational linguistics; commonsense reasoning; knowledge discovery

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1. Introduction

Endowing artificial agents with the ability to understand natural language in a way similar to humans is a task in which artificial intelligence has not yet made enough progress [1–3]. Even the most advanced connectionist and generative models, trained with gigabytes of examples and on large-scale high-performance clusters, perform poorly when faced with the task of commonsense reasoning based on the contents of natural language texts [4,5]. From the symbolic perspective, modeling natural language with logic has also yielded poor results, but it is believed that those poor results are a consequence of the low expressive power of the logics used for modeling [6,7]. When predicate logic (PL) or any of its subsets have been used, poor results are also attributed to the mathematical orientation of those logics as well as their inability to model everyday concept acquisition and processing [8,9]. If a radically different logic is used, it may be possible to obtain better results, and that is exactly the case with non-axiomatic logic (NAL), a formal language designed to model the process of an agent pragmatically learning its environment [10,11]. As such, NAL offers several advantages over other symbolic logics [12,13], such as the ability to define higher-order expressions and use a variety of inference models besides deduction.

Although similar studies have been published using different logics, and even some of them have used the exact same logic (NAL), in all of them the core problem is the same:

translating natural language expressions into a formal language. Previous efforts in other logics have focused on formulating syntactic methods for identifying grammatical structure and semantic roles, but since we believe there is no clear, universal and deterministic way of doing so, in this research, we proceed the other way around. We use linguistic analysis tools to provide the grammatical and semantic elements needed for constructing an equivalent logic expression and provide context for each concept by using a general purpose ontology (WordNet). The main contributions of this paper can be summarized as follows:

1. We reverse the traditional process of tackling the problem of natural language translation into formal language by selecting some linguistic analysis tools as a guide for constructing logic expressions with approximately the same semantics as the natural language sentences being translated.
2. We use a logic that has features that other classic logics lack: subject–predicate sentences, experience-grounded semantics and syllogistic inference rules [14].

In contrast with the other representations of NL in NAL, our proposal have the following novelties:

1. We predefined some NAL terms (concepts), as well as some NAL term relations, for representing grammatical and semantic relations commonly found in English sentences.
2. We propose a set of NL-to-NAL translation rules general enough to cover the great majority of English universal dependencies use cases and provide a full set of examples.
3. We include not only grammatical properties of the translated sentences but semantic elements too.
4. Finally, we glimpse into the possible use of the proposed translation rules for supporting commonsense reasoning tasks [15].

The rest of this article is organized as follows: In Section 2, (Related Work) we briefly mention some previous related works that are relevant in understanding our contribution, either because of the similarity of the ideas used or because of the opposite. In Section 3, (Theoretical Foundations and Required Background Knowledge) the fundamental basic concepts of NAL are presented, as well as a brief listing of the linguistic tools used in this research. Section 4 (Proposal) details our proposal for translating English sentences into NAL expressions, including the predefined terms and their semantics, as well as the predefined relations used during the translation process. Section 5 (Experiments and Results) shows a large table of examples, helping to verify that all the intended use cases are indeed covered by the proposed translation rules set. In Section 6, (Commonsense Reasoning) we present a simple but illustrative example of how the translated expressions could be used to perform commonsense reasoning. Finally, in Section 7 (Discussion), we make some final remarks, draw some conclusions and speculate about future directions of the research.

2. Related Works

The task of computationally representing and processing natural language using some formal language has been a highly sought goal since the birth of the discipline of artificial intelligence. When it became clear that predicate logic (PL) did not have the expressiveness necessary to model some of the inference mechanisms that humans use on a daily basis, many efforts in that direction were abandoned. With that motivation, new logics aiming to capture new aspects of representation and reasoning closer to human common sense emerged, such as modal logics, fuzzy logics, temporal logics, paraconsistent logics, etc. These logics have been widely used in applications involving natural language, such as [16], which overviews means of description logics for representing knowledge contained in natural language texts, or [17], which uses a temporal logic for expressing natural language goals.

Non-axiomatic logic (NAL) brings together several features that other logics lack, such as subject–predicate sentences (as a result of being a *term* logic), experience-grounded semantics and syllogistic inference rules [18]. Those features have made NAL useful in diverse applications such as [19], which detects anomalies in a smart city domain, or [20], where a robotic manipulator arm learns about its environment. As for natural language, ways of appropriate translation to NAL, for different purposes, have been widely discussed; however, attempts to make a well-defined method are very scarce.

Among the few known works relating natural language and NAL are [21,22]. In [21], some guidelines for representing natural language in NAL are discussed, mainly through examples, whereas in [22], a small set of translation rules are proposed. Those rules are included in the implementation of OpenNARS for Applications, a NAL-based reasoning system. Unfortunately, [21] does not describe any methodology for the translation, nor does it propose any way to automate the process. On the other hand, the set of rules in [22] is very small and is only useful for simple sentences. Particularly, those rules create logical relationships from phrases using prepositions. Furthermore, those rules have some problems identifying named entities and a somewhat unstable handling of clauses. As an example, consider the sentences:

- You gave me the important manual
- You gave the important manual to me
- The important manual was given to me by you

Although all these sentences have different structures, they all have the exact same semantics. Therefore, it would be desirable for all of them to be translated in exactly the same way, regardless of their linguistic particularities.

Using the set of translation rules proposed in [22], those sentences are translated in three different ways. However, even worse is that some of the resulting expressions in NAL completely lose their original semantics.

Instead, the herein proposed set of translation rules identifies the semantics independently from the sentence structure and translates all three sentences in the exact same way.

Nowadays, connectionist models and methods have gained popularity for natural language processing tasks. However, in order to obtain acceptable experimental results, complex architectures and huge amounts of training data are required. Furthermore, although some research has been carried out on the semantics and explainability of those models, as in [23,24], it seems quite evident that the most popular connectionist applications today have severe problems with basic reasoning tasks, and their generalization capacity is in serious doubt, as discussed in [25–27].

Those discussions have motivated the formulation of some neuro-symbolic methods [28], which in addition to incorporating symbolic knowledge to reinforce semantics, have been able to yield better experimental results, and simple reasoning benchmarks have also been proposed [29,30]. However, we strongly believe that symbolic methods should not be relegated exclusively to representational tasks, as they can prove indispensable for logical and commonsense reasoning tasks, which can naturally be modeled with formal systems. It is therefore very important to note that the proposed representation in this paper is not intended to be used as input to any kind of neural network or connectionist architecture, and therefore cannot be compared with representations that do have that purpose. On the contrary, the logical representation herein presented was designed with the aim of integrating a complete reasoning module able to use all of the NAL inference rules. As an example of this type of vision, consider [31], where OpenNARS for Applications acts as an oracle for ChatGTP-4.

3. Theoretical Foundations and Required Background Knowledge

3.1. Non-Axiomatic Logic

Non-axiomatic logic (NAL) [14,18,32] is a non-monotonic and multi-valued term logic developed in order to model everyday thinking as well as the process of an artificial agent learning its environment and adapting to it. NAL is not an agent logic in the modern computational sense but only a formal language that serves as a sufficiently expressive knowledge representation tool and as a reasoning guide for an agent who must always operate under the *Assumption of Insufficient Knowledge and Resources* (*AIKR*). This assumption implies that the agent can never assume that it has neither complete knowledge of any situation nor infinite time and/or processing resources to obtain it. Furthermore, to operate under *AIKR* implies that there is no constraint defined on the content of the experience the agent may have. Most notably, the classic monotonic-reasoning restriction of many other logics is not present in NAL.

As a non-monotonic logic, in NAL, it is not required for each new formula just learned to be consistent with all formulas previously known. This characteristic allows us to better model the flow of a text in natural language [33]. As a multi-valued logic, the truth values of formulas in NAL are not limited to be either *true* or *false*. This enables the grading of truth based not on predefined axioms but strictly on the account of evidence supporting each formula in the agent's experience. Lastly, being a term logic means that formulas do not adhere to the mathematical predicate logic syntax and semantics. NAL formulas are more closely related to Aristotle's logic, where each formula is composed of two *terms* (called *subject* and *predicate*) related by a relational operator (called *copula*). A *term* is either a constant labeling a specific concept within the *universe of discourse* (also called *domain*) or a quantified variable that represents a subset of concepts within the same domain and which are still to be determined [34].

Since *Götlob Frege* first defined predicate logic [35], he claimed that its crucial advantage over term logics was its capability for expressing any conceivable relation between concepts, while a term logic can only represent a finite and small number of relations depending on the copulas defined. NAL has only five native copulas defined (see Table 1), and although these five copulas are evidently not enough to match the expressive power of predicate logic, that handicap is compensated by NAL's capabilities to express *compound terms*, and *user-defined relations*.

Table 1. Native NAL copulas.

Copula	Formula Structure	English Meaning	Example
Inheritance	$S \rightarrow P$	S is a type of P	$canary \rightarrow bird$ (Canaries are a type of bird)
Similarity	$S \leftrightarrow P$	S is similar to P	$tweety \leftrightarrow birdy$ (Tweety is similar to Birdy)
Instance	$\{S\} \rightarrow P$	S is an instance of P	$\{tweety\} \rightarrow canary$ (Tweety is a canary)
Property	$S \rightarrow [P]$	S has property P	$canary \rightarrow [yellow]$ (Canaries are yellow)
Instance–property	$\{S\} \rightarrow [P]$	Instance S has property P	$\{tweety\} \rightarrow [yellow]$ (Tweety is yellow)

Compound terms are constructed using some set theory operators (union, intersection, and difference), while user-defined relations are constructed by associating a compound term, including all related terms, with a new term that names the relation among them. This last extension is what really helps to harness the expressive power of NAL, and it is a crucial modeling element of the proposed method. Tables 1 and 2 summarize basic compound term capabilities in NAL.

Table 2. Compound terms and relations definition in NAL.

Term Connector	Term Structure	English Concept	Example
$\cup$ Set Union	$T1 \cup T2$	Any element of concept T1 or concept T2	$(bird \cup [yellow])$
$\cap$ Set Intersection	$T1 \cap T2$	An element of concept T1 and of concept T2	$(bird \cap [yellow])$
$-$ Asymmetric Set Difference	$T1 - T2$	An element of concept T1 but not of concept T2	$(bird - [yellow])$
$\ominus$ Symmetric Set Difference	$T1 \ominus T2$	An element with properties of T1 but no properties of T2	$(canary \ominus bird)$
$\times$ Relation	$(\times T1, \ldots, Tm) \rightarrow Tn$	Terms T1 to Tm are related by a Tn relation	$(\times cat, bird) \rightarrow chase$

The element that notably highlight the distinction between NAL and other symbolic logics are the truth values of formulas. However, in order to correctly define truth values in NAL, it is first necessary to understand how to account for *positive* and *negative* evidence for a logical expression. Since NAL has *experience-based* semantics, *positive* and *negative* evidence depends on the occurrence of specific statements in the agent's experience (i.e., its knowledge base). For example, if an agent perceives a flying bird (identified as *bird-1*), it may add to its knowledge base the expressions: *bird-1* $\rightarrow$ *bird* and *bird* $\rightarrow [flying]$ to represent the learned facts that "entity *bird-1* is a *bird*" and "*Birds* can *fly*". Each new flying bird observed by the agent will add to the *positive evidence* of the latter expression. However, at any moment, the agent may observe a penguin, an ostrich or a kiwi, which are non-flying birds. Then, each of those experiences add to the *negative evidence* of the knowledge that "*Birds* can *fly*", so the truth value of the expression *bird* $\rightarrow [flying]$ will change to reflect the new balance of evidence.

In NAL each formula is assigned a truth value, which is a vector $\langle f, c \rangle$, where [14]:

- *Frequency* (f) is a real number in the interval [0, 1] computing the ratio of positive evidence (w^+) for the formula over the total available evidence (W, the sum of positive and negative evidence) about it; therefore, $f = w^+/W$.
- *Confidence* (c) is another real number in [0, 1) computing the ratio of currently available evidence (W) for the formula over the total amount of evidence expected to exist ($W + k$), so $c = W/(W + k)$, where the k variable is a constant expressing the system's learning speed, and it is usually set at $k = 1$.

The above quantification system is similar, although not exactly equivalent, to some commercial product ranking systems that rely on users' opinions. When a potential new buyer queries for a product, he/she looks for two elements: the average rating assigned by users and the number of users that have rated it. The first element (the product's average rating) is expressed as a ratio of the received rating over the maximum allowed rating, for example: 3 1/2 stars out of 5 possible stars. However, for that measure to make sense, it is also necessary to look at how many users have rated the product. If that number is very small, there is *little evidence* of the quality rating of the product, whereas if that number is high, there is *much evidence* that the average rating of the product is most likely the real one.

According to the semantics of NAL expressions, the evidence supporting each judgement can only come from the agent's experience (i.e., the contents of its memory). Therefore, each time a new English sentence is read and has to be translated to NAL, if it is the first contact of the agent with the terms involved in that sentence, then it is the first and only piece of evidence supporting that sentence in the agent's experience (i.e., $W = 1$, and $w+ = 1$). Therefore, it should be assigned a frequency value of 1.0. As for the confidence of such a new judgement, *Pei Wang* justifies in [14] that a value of 0.9 expresses that the agent has *almost* all the available evidence but without ruling out the possibility that some other new evidence might be encountered in the near future. Therefore, each time the agent learns a new, not seen before, judgement, its truth value is set to <1.0, 0.9>.

On the other hand, if new evidence supports *inconsistent* judgements with the ones included in the current database, the agent must *generalize* and *summarize* its experiences by applying *local* inference rules, specifically *revision* and *choice*. Please refer to [14,18] for a detailed description of these inference rules and their use.

Because of this process, NAL truth values do not express a coincidence between a particular judgement and the current state of the universe of discourse, unlike other axiomatic logics. Furthermore, agents with different experiences will assign different truth values to the same facts.

Finally, NAL, as with almost all predicate logic variants, also has *variables*. Variables in NAL formulas are terms representing another term whose value has not been defined yet. It is not necessary to ground variables when performing inference since an adequate structure of the conclusion formula does not depend on the value of variables. Syntactically, all variables start with a '#' character followed by a name written in italic font. Furthermore, we named variables with the grammatical element that the variable represents in each formula, so you can find variables as #*Whomever* or #*Whatever*.

3.2. Linguistic Tools

In order to properly define rules for NL-to-NAL translation, it is first necessary to obtain the linguistic structure of the NL text. Particularly, *dependency parsing*, *part of speech tagging*, *named entity recognition*, and *search for hypernyms* are the more relevant linguistic analyses needed.

Dependency parsing [36] is a linguistic analysis that identifies the grammatical structure of sentences and constructs a dependency tree that represents such a structure. This process finds sets of related words within a sentence, as well as the specific type of each one of those relations. Found relationships are called *dependencies*, and *universal dependencies* [37] is a representative set of dependencies designed to cover a great majority of use cases in all languages (see Tables 3 and 4).

Part of Speech Tagging (PoS tagging) [38] is a process that marks each word in a sentence with a tag that indicates its grammatical role in that sentence. PoS tags include the eight classic categories (noun, verb, participle, article, pronoun, preposition, adverb, conjunction) as well as other related subcategories. Both dependency parsing and part of speech analysis are used to define the type of terms and the hierarchical structure of the NAL expressions defined, and the Stanford typed dependencies module of the Stanford Parser is used for this process [39].

Named entity recognition [40] involves the identification and categorization of certain words or parts of sentences considered as key information or entities. An entity is basically anything that is consistently talked about or referred to in the text. Named entities include persons, geographic locations, dates, ages, addresses, phone numbers, organizations, companies, etc. The Stanford Named Entity Recognizer [41] is used for this process with only Person, Organization, and Location labels.

Lastly, *hypernyms* are words with a more general meaning than another word with a related but more specific meaning. We *search for hypernyms* to establish and enrich the context of each concept used in the NL text being translated (i.e., each *term* modeled in an NAL expression). Hypernyms and their opposite hyponyms define a hierarchy of concepts extremely similar to that defined by the *intension and extension calculus* definitions, which are the basic ideas that conform the formal semantics in NAL expressions. WordNet [42] is used for finding chains of related hypernyms (i.e., the *intension* of a term).

A summary of the linguistic analysis performed with the software tools used is included in Table 5.

Table 3. Universal dependencies: table of core, non-core and nominal dependencies used in this article.

	Nominals	Clauses	Modifiers	Function Words
Core Arguments	nominal subject object indirect object	clausal subject clausal complement open complement		
Non-core Dependents	oblique nominal expletive	adverbial cl modifier	adverbial modifier	copula marker
Nominal Dependents	nominal modifier appositional mod numeric modifier	clausal modifier	adjectival modifier	determiner case marking

Table 4. Universal dependencies: table of other dependencies used in this article.

Coordination	Multi Word Expression	Special
conjunct coordinating conjunct	fixed flat compound	goes with

Table 5. Table of linguistic analysis made before application of rules, with software and outputs used.

Linguistic Analysis	Software	Output
Named entity recognition	Stanford Named Entity Recognizer, v. 4.2.0	Tagged entities in text
Dependency parsing	Stanford Parser, v. 4.2.0	Universal dependencies
PoS tagging	Stanford Parser	Penn Treebank PoS Tags
- [1]	WordNet, v. 3.0	Hypernyms of nouns and verbs in text
Semantic dependency parsing	- [2]	VerbNet roles

[1] Here we obtain hypernyms for concepts in the text, which is not a linguistic analysis per se. [2] See the note in Section 7.1, in the last bullet point.

4. Proposal

Linguistic analysis tools facilitate the identification of concepts and relationships expressed in an NL text. However, in order to decrease the amount of background knowledge necessary for an agent to reason with the generated logical formulas, on the logic side, it is required to establish some previous concepts. Therefore, the core of our proposal is the definition of a group of NAL terms with pre-established semantics, a group of user relationships with predefined structure and semantics and an informal convention on the use of NAL variables. These fundamental definitions provide a solid basis for simplifying the translation process as well as a common base for performing inference tasks with the generated NAL formulas.

Pre-defined terms delimit the scope of some fundamental concepts *implicit* in the NL text that would require human-level knowledge and experience to grasp, such as those expressed by the question words *when* or *where*. We highlight these terms, writing them in italic font and always ending with a '*' character. Table 6 shows the pre-defined NAL terms and their semantics.

Table 6. Pre-defined terms and their semantics.

Pre-Defined Term	Semantics
*where**	Term for expressing the location of something or of an event. See example 1. Nominal subject, case (e)
*when**	Term for expressing when something occurred or to indicate that two events happened at the same time. See example 7. Oblique nominal, case (b)
*but**	Term for expressing concession between two events. See example 9. Adverbial clause modifier, case (c)
*purpose**	Term for expressing that an event is the purpose of another. See example 9. Adverbial clause modifier, case (e)
*reason**	Term for expressing that an event is the reason for another. See example 9. Adverbial clause modifier, case (f)
*how**	Term for expressing that an event modifies the manner in which another occurred. See example 9. Adverbial clause modifier, case (h)

Pre-defined relations, on the other hand, allow logical formulas to mimic the grammatical structure of NL sentences. Notably, we use a pre-defined four-term relation to express the grammatical relation between a subject and its direct and indirect objects with the verb in an NL sentence. As these elements are not always *explicit* in a sentence, we also defined the special term '_' (underscore), playing the role of an anonymous variable whose value is not explicitly included in the sentence but is not needed for its understanding or processing. Table 7 shows the pre-defined relations with their structure and semantics.

Table 7. Pre-defined relations and their semantics.

Pre-Defined Relation	Semantics
$(\times, subject, object, recipient) \rightarrow verb$	*subject* (actor, agent or experiencer as in [43]) makes *verb* (an action), the direct object (not a recipient) of *verb* is *object*, and *recipient* is the recipient. See example 1. Nominal subject, case (a) or 3. Indirect object, case (a)
$(\times, argument1, argument2) \rightarrow$ *pre-defined term*	*argument1* and *argument2* are related under the semantics of the *pre-defined term*. See example 1. Nominal subject, case (e) or 7. Oblique nominal, case (b)
$(\times, argument1, argument2) \rightarrow adjective$	*argument1* and *argument2* are related following the semantics of *adjective*. See example 6. Open clausal complement, case (b) or 7. Oblique nominal, case (e)
$(\times, argument1, argument2) \rightarrow comparative$	*argument1* and *argument2* are related following the semantics of *comparative*, which represents a comparative or superlative adjective. See example 6. Open clausal complement, case (b) or 7. Oblique nominal, case (e)

Table 7. *Cont.*

Pre-Defined Relation	Semantics
$(\times, argument1, argument2) \rightarrow equality$	*argument1* and *argument2* are related following the semantics of *equality*, which represents an equality comparison. See example 9. Adverbial clause modifier, case (g) or 15. Adjectival modifier, case (c)

Translation Rules

The proposed set of NL-to-NAL rules was designed to cover all universal dependencies (see Tables 3 and 4), with a few exceptions [44]. The rules are grouped into four different sets:

- **Entity rules**: Rules that only require as input the result of the named entity recognition analysis. These rules ground some of the logical terms and establish some of the context judgements. With these rules, the words "Bill Gates" will be translated to a single term $\{\text{Bill-Gates}\}$ and the judgment $(\{\text{Bill-Gates}\} \rightarrow \text{person})$
- **Term rules**: These rules take as input the lemmatization of the text, dependency parsing and PoS tagging results of the text. This type of rule obtains some compound and non-compound terms that will be used in the translation—for example, the words "the manual", "chasing" and "important" will be mapped to the terms $\{\textit{the-manual}\}$, *chase* and $[\textit{important}]$
- **Hypernym rules**: As the name suggests, these rules take as input hypernyms of concepts in the text via WordNet. The output of these rules is judgments representing "is a" context, for example $(\text{canary} \rightarrow \text{bird})$
- **Text rules**: Their input consist of the dependency parsing of the text, PoS tagging results and hypernyms of some of the concepts in the text. Establishing judgements that involve defined terms and express the content of the text is the main goal of this group of rules. Suppose the sentence "Ana writes poems" is in the text, then these rules will obtain the judgment $(\{Ana\}, poem, \_) \rightarrow write$.

Figure 1 shows the data flow for applying the proposed set of rules. Parallelograms indicate the specific group of rules applied in each case and shaded rectangles indicate the type of NAL formulas yielded. A thorough example of the application of rules is shown below, and Section 5 contains a list of examples in the translation of all universal dependencies used.

Example 1. *Consider the sentence:*

"The important manual was reluctantly given to Bill Gates by Ford".

Following the diagram in Figure 1, first, a named entity recognition analysis is made, and it should state that Bill Gates and Ford are entities—the first one is a person, and the second one is an organization; hence, the application of entity rules will give as the result:

$$\{\text{Bill-Gates}\} \rightarrow \text{person} \quad \%\textit{Bill Gates is a person}$$
$$\{\text{Ford}\} \rightarrow \text{organization} \quad \%\textit{Ford is an organization}$$

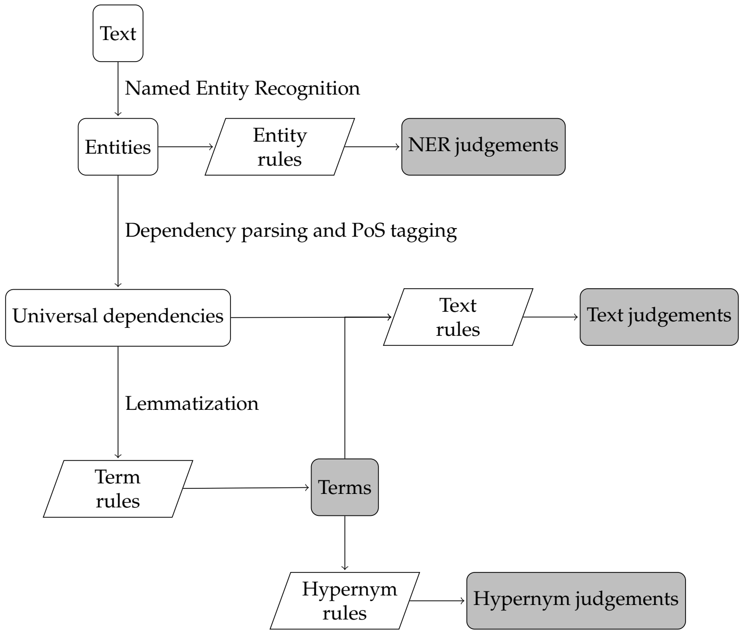
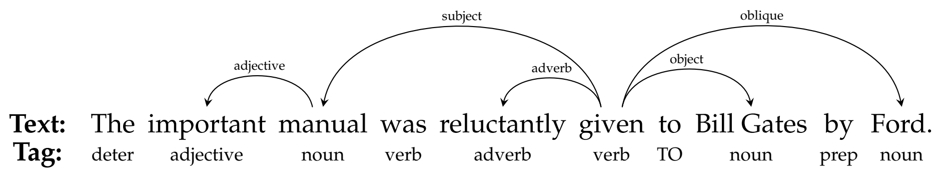


Figure 1. Translation process.

After this, dependency parsing and PoS tagging should be carried out. The result of this analysis should be similar to the following:



Applying term rules, the terms {*the-manual*} (the manual is an instance), [*important*] (important is a property), [*reluctantly*] (reluctantly is a property) and *give* (give is an atomic term) will be obtained.

With the information from WordNet and the Hypernym rules, the following judgements will be added to the translation as context:

{the-manual} → manual %*The manual is a manual*
manual → handbook %*Manuals are handbooks*
handbook → book %*Handbooks are books*

person → organism %*Persons are organisms*
organism → living-thing %*Organisms are living things*

organization → social-group %*Organizations are social groups*
social-group → group %*Social groups are groups*

give → transfer %*Giving is transferring*

Lastly, applying the text rules, the following judgements are obtained:

% Ford, the manual, and Bill Gates are related under the relation of giving reluctantly
$(\times, \{\text{Ford}\}, \{\text{the-manual}\}, \{\text{Bill Gates}\}) \rightarrow \text{give} \cap [\text{reluctantly}]$
% the manual has the property of being important
$\{\text{the-manual}\} \rightarrow [\text{important}]$

Every judgment obtained will be assigned an initial truth value of $\langle 1.0, 0.9 \rangle$, a value that corresponds to a verified positive example of the related statement, as discussed in Section 3.1.

The final set of NAL judgements will show two important characteristics:

1. Every concept appearing in the text will be implicitly represented and its meaning extended with the help of auxiliary background judgements from the WordNet ontology.
2. NAL is a non-monotonic logic, an agent wielding that logic can always *learn* new concepts and receive new information, consequently adding new formulas to its knowledge base, even when such new formulas seem like contradictory information.

5. Experiments and Results

Experiments per Case

This section shows some examples of natural language sentences translated into NAL formulas. The examples follow Table 3, with the exception of function words (last column), and are labeled accordingly to facilitate their identification and association with the corresponding dependency cases. Each case shows an example sentence and the translated NAL formula we obtain by applying the proposed methodology.

1. **Nominal subject**
(a) **Active voice with a verb as root and nominal core arguments**
Clinton defeated Dole
$(\times, \{\text{Clinton}\}, \{\text{Dole}\}, \_) \rightarrow \text{defeat}$
(b) **Passive voice with a verb as root and nominal core arguments**
Dole was defeated by Clinton
$(\times, \{\text{Clinton}\}, \{\text{Dole}\}, \_) \rightarrow \text{defeat}$
(c) **Adjective as root**
This toy is red
$\{\text{this-toy}\} \rightarrow [\text{red}]$
(d) **Nominal as root and no case dependency**
Roses are flowers
$\text{rose} \rightarrow \text{flower}$
(e) **Nominal as root and case dependency**
We are in the barn
$(\times, \{\text{we}\}, \{\text{the-barn}\}) \rightarrow \textit{where}^*$
(f) **Copular sentence with clausal complement (outer)**
The important thing is to keep calm
$\{\text{the-thing}\} \cap [\text{important}] \rightarrow ((\times, \#\textit{Whoever}, \text{calm}, \_) \rightarrow \text{keep})$

2. **Object**
(a) **Active or passive voice with a verb as root**
Ana teaches Logic
$(\times, \{\text{Ana}\}, \text{logic}, \#\textit{To-whomever}) \rightarrow \text{teach}$

3.	**Indirect object**
(a)	**Active or passive voice with a verb as root** Ana teaches the students Logic $(\times, \{\text{Ana}\}, \text{logic}, \{\text{the-students}\}) \to \text{teach}$

4.	**Clausal subject**
(a)	**Active voice with a verb as root** Taking a nap will relax you $(\times, ((\times, \#\textit{Whoever}, \{\text{a-nap}\}, \_) \to \text{take}), \{\text{you}\}, \_) \to \text{relax}$
(b)	**Passive voice with a verb as root** That she lied was suspected by everyone $(\times, \#\textit{everyone}, ((\times, \{\text{she}\}, \#\textit{Whatever}, \#\textit{To-whomever}) \to \text{lie}), \_) \to \text{suspect}$
(c)	**Adjective as root** Taking a nap is relaxing $((\times, \#\textit{Whoever}, \{\text{a-nap}\}, \_) \to \text{take}) \to [\text{relaxing}]$
(d)	**Nominal as root and no case dependency** What she said is a proverb $((\times, \{\text{she}\}, \#\textit{Whatever}, \#\textit{To-whomever}) \to \text{say}) \to \text{proverb}$
(e)	**Copular sentence with clausal complement (outer)** To hike in the mountains is to experience nature $((\times, \text{hike}, \{\text{the-mountains}\}) \to \textit{where}^*) \to ((\times, \#\textit{Whoever}, \text{nature}, \_) \to \text{experience})$

5.	**Clausal complement**
(a)	**Active or passive voice with a verb as root and the explicit subject of the complement** He says you like flowers $(\times, \{\text{he}\}, ((\times \{\text{you}\}, \text{flower}, \_) \to \text{like}), \#\textit{To-whomever}) \to \text{say}$
(b)	**Active or passive voice with an adjective as root and the explicit subject of the complement** Ana is delighted that you could help $(\times, \{\text{Ana}\}, ((\times, \{\text{you}\}, \#\textit{Whatever}, \#\textit{To-whomever}) \to \text{help})) \to \text{delighted}$
(c)	**Active or passive voice with a verb as root and not specified subject of the complement** The boss said to start digging $(\times, \{\text{the-boss}\}, ((\#\textit{Whoever}, \text{dig}, \_) \to \text{start}), \#\textit{To-whomever}) \to \text{say}$

6.	**Open clausal complement**
(a)	**Active or passive voice with a verb as root and the implicit subject of the complement** I consider her honest $(\times, \{\text{I}\}, (\{\text{she}\} \to [\text{honest}]), \_) \to \text{consider}$
(b)	**Adjective as root and implicit subject of the complement** Susan is liable to be arrested $(\times, \{\text{Susan}\}, \text{arrest}) \to \text{liable-to}$

7.	**Oblique nominal**
(a)	**Locational modifier dependent on a verb** The will arrive in Boston $(((\times, \{\text{they}\}, \_, \_) \to \text{arrive}), \{\text{Boston}\}) \to \textit{where}^*$
(b)	**Temporal modifier dependent on a verb** They will arrive on Friday $(((\times, \{\text{they}\}, \_, \_) \to \text{arrive}), \{\text{Friday}\}) \to \textit{when}^*$
(c)	**Element of the dative alternation dependent on a verb** Ana teaches Logic to the students $(\times, \{\text{Ana}\}, \text{logic}, \{\text{the-students}\}) \to \text{teach}$

(d) **Agent dependent on a passive verb**

The cat was chased by a dog

$(\times, \{\text{a-dog}\}, \{\text{the-cat}\}, \_) \rightarrow \text{chase}$

(e) **Dependent on an adjective**

He is afraid of sharks

$(\times, \{\text{he}\}, \text{shark}) \rightarrow \text{afraid-of}$

(f) **Adverbial modifiers**

The director is 65 years old

$\{\text{the-director}\} \rightarrow [\text{old}] \cap [\text{65-years}]$

8. **Expletive**

(a) **Existential there with an oblique modifier**

There is a ghost in the room

$(\times, \{\text{a-ghost}\}, \{\text{the-room}\}) \rightarrow \textit{where}^*$

(b) **"It" in extraposition constructions**

It is clear that we should decline

$((\times, \{\text{we}\}, \#\textit{Whatever}, \_) \rightarrow \text{decline}) \rightarrow [\text{clear}]$

(c) **Existential there without oblique modifiers**

There are children

$\#\textit{Some} \rightarrow \text{child}$

9. **Adverbial clause modifier**

(a) **Temporal modifier**

The accident happened as night was falling

$(\times, ((\times, \{\text{the-accident}\}, \_, \_) \rightarrow \text{happen}), ((\times, \text{night}, \_, \_) \rightarrow \text{fall})) \rightarrow \textit{when}^*$

(b) **Locational modifier**

They drove beyond where the city ends

$(\times, ((\times, \{\text{they}\}, \#\textit{Whatever}, \_) \rightarrow \text{drive}), ((\times, \{\text{the-city}\}, \_, \_) \rightarrow \text{end})) \rightarrow \textit{where}^* \cap [\text{beyond}]$

(c) **Concession modifier**

He is a teacher, although he no longer teaches

$(\times, (\{\text{he}\} \rightarrow \text{teacher}), ((\times, \text{he}, \#\textit{Whatever}, \#\textit{To-whomever}) \rightarrow \text{teach} \cap [\text{no-longer}])) \rightarrow \textit{but}^*$

(d) **Condition modifier**

If you know who did it, you should tell the teacher

$((\times, \{\text{you}\}, ((\times, \#\textit{Whoever}, \{\text{it}\}, \_) \rightarrow \text{do}), \_) \rightarrow \text{know})$
$\Rightarrow ((\times, \{\text{you}\}, \#\textit{Whatever}, \{\text{the-teacher}\}) \rightarrow \text{tell})$

(e) **Purpose modifier**

He talked to you in order to secure the account

$((\times, (\times, \{\text{he}\}, \#\textit{Whatever}, \{\text{you}\}) \rightarrow \text{talk}), ((\times, \#\textit{Whoever}, \{\text{the-account}\}, \_) \rightarrow \text{secure})) \rightarrow$
$\textit{purpose}^*$

(f) **Reason modifier**

I am in my house since I caught a cold

$((\times, (\times, \{\text{I}\}, \{\text{my-house}\}) \rightarrow \textit{where}^*), (\times, \{\text{I}\}, \{\text{a-cold}\}, \_) \rightarrow \text{catch})) \rightarrow \textit{reason}^*$

(g) **Comparison modifier**

John can speak English as fluently as his teacher can

$(\times, ((\times, \{\text{John}\}, \text{English}, \#\textit{To-whomever}) \rightarrow \text{speak}),$
$((\times, \{\text{his-teacher}\}, \text{English}, \#\textit{To-whomever}) \rightarrow \text{speak})) \rightarrow \text{as-fluent-as}$

(h) **Manner modifier**

He spent a lot of money as if he was rich

$(\times, ((\times, \{\text{he}\}, \text{money} \cap [\text{a-lot-of}], \_) \rightarrow \text{spend}), (\{\text{he}\} \rightarrow \text{rich})) \rightarrow \textit{how}^*$

10.	**Adverbial modifier**
(a)	**Adverbial modifying verb** Ana rarely drinks coffee $(\times, \{\text{Ana}\}, \text{coffee}, \_) \rightarrow \text{drink} \cap [\text{rarely}]$
(b)	**Adverbial modifying adjective** About 200 people came $(\times, [\text{about } 200] \cap \text{people}, \_, \_) \rightarrow \text{come}$
(c)	**Adverbial modifying adverb** Tom is almost always busy $\{\text{Tom}\} \rightarrow [\text{busy}] \cap [\text{almost always}]$
(d)	**Negation** Tom does not like Italian food $\neg((\times, \{\text{Tom}\}, [\text{Italian}] \cap \text{food}, \_) \rightarrow \text{like})$

11.	**Nominal modifier**
(a)	**Determiner modifying a noun or noun phrase** Some of the toys are red $\{\text{some toys}\} \rightarrow [\text{red}]$
(b)	**Noun modifying a noun or noun phrase** Toys for children are cute $\text{children-toys} \rightarrow [\text{cute}]$

12.	**Appositional modifier**
(a)	**Appositional modifier** Sam, my brother, arrived $((\{\text{Sam}\}, \_, \_) \rightarrow \text{arrive}) \wedge (\{\text{Sam}\} \rightarrow \{\text{my-brother}\})$

13.	**Numeric modifier**
(a)	**Numeric modifier** Sam spend forty dollars $(\{\text{Sam}\}, [40] \cap \text{dollar}, \_) \rightarrow \text{spend}$

14.	**Clausal modifier of a noun**
(a)	**Modified noun as subject** My sister has a parakeet named Cookie $((\times, \{\text{my-sister}\}, \{\text{a-parakeet}\}, \_) \rightarrow \text{have}) \wedge ((\times, \#\textit{Whoever}, \{\text{Cookie}\}, \{\text{a-parakeet}\}) \rightarrow \text{name})$
(b)	**Modified noun as object** He is a teacher whom the students really love $(\{\text{he}\} \rightarrow \{\text{a-teacher}\}) \wedge ((\times, \{\text{the-students}\}, \{\text{a-teacher}\}, \_) \rightarrow \text{love})$

15.	**Adjectival modifier**
(a)	**Adjectival modifier** Canaries are yellow $\text{canary} \rightarrow [\text{yellow}]$
(b)	**Comparative adjective** Ana is taller than Tom $(\times, \{\text{Ana}\}, \{\text{Tom}\}) \rightarrow \text{taller}$
(c)	**Comparison "as … as"** Ana is as tall as Tom $(\times, \{\text{Ana}\}, \{\text{Tom}\}) \rightarrow \text{as-tall-as}$

(d) **Superlative adjective**	
	Ana is the tallest in the group
	$(\times, \{\text{Ana}\}, \$Whatever) \rightarrow \text{taller}$
	$\$Whatever \rightarrow \text{the-group}$

6. Commonsense Reasoning

Attempting to explain in sufficient detail the form and properties of commonsense reasoning is undoubtedly an extremely difficult task. Historically [6,7], commonsense reasoning deals with obtaining non-deductive logical consequences of the available data, and while *formal* reasoning systems are restricted to *deductive* inference, *commonsense* reasoning systems are more focused on other inference forms: *induction*, *abduction*, *analogy*, *exemplification*, etc. Furthermore, of course, the knowledge inferred by any of those forms cannot contradict or hinder in any way the formal deduction process. That is, *commonsense reasoning* must coexist with and support *formal reasoning*.

In NAL, there are ten different inference formulas (see [14] Appendix B), and while presenting and explaining all of them falls outside the scope of this paper, we will show here a brief but illustrative example. A reader interested in the details of NAL's inference rules should consult [10,14,18]. In addition to the obvious fact that there are no universally accepted characterizations of what constitutes commonsense reasoning, it is important to understand the following two aspects:

1. Inference formulas in NAL have both a syntactic component and an arithmetic component. The syntactic component shows how to combine the *terms* included in the initial premises to form a *conclusion*, while the arithmetic component shows how to compute the truth value of the conclusion from the truth value of the premises.
2. The conclusion expression, along with its truth value, must be translated back into natural language in order to complete the reasoning task. That translation involves the use of certain words to represent the numerical interval in which the values of both *frequency* and *confidence* in the truth value of the conclusion are found. This second translation process is also beyond the scope of this paper.

Lets analyze the following example:

Example 2. *We have the following sentences:*

- *Someone picked up some food for a snack at the supermarket.*
- *These ingredients were bought at the grocery store.*
- *Milk can be purchased at food markets.*

Using the translation method presented, the following judgments are obtained:

$$(\times, ((\times, \_, \text{snack-food}, \_) \rightarrow \text{pick-up}), \{\text{the-supermarket}\}) \rightarrow where^* \quad \langle 1, 0.9\rangle \tag{1}$$

$$(\times, ((\times, \_, \{\text{these ingredient}\}, \_) \rightarrow \text{buy}), \{\text{the grocery-store}\}) \rightarrow where^* \quad \langle 1, 0.9\rangle \tag{2}$$

$$(\times, ((\times, \_, \text{milk}, \_) \rightarrow \text{purchase}), \text{food-market}) \rightarrow where^* \quad \langle 1, 0.9\rangle \tag{3}$$

Please note that all three sentences were translated into higher-order NAL expressions. Furthermore, the context extraction process generates the following expressions extracted from WordNet:

$$\text{snack-food} \rightarrow \text{food} \ \ \langle 1, 0.9\rangle \tag{4}$$

$$\text{milk} \rightarrow \text{food} \ \ \langle 1, 0.81\rangle \tag{5}$$

$$\{\text{these ingredient}\} \rightarrow \text{food} \ \ \langle 1, 0.73\rangle \tag{6}$$

$$\text{pick-up} \rightarrow \text{buy} \ \ \langle 1, 0.81\rangle \tag{7}$$

$$\text{purchase} \leftrightarrow \text{buy} \ \ \langle 1, 0.9\rangle \tag{8}$$

$$\{\text{the supermarket}\} \rightarrow \text{food-market} \ \ \langle 1, 0.81\rangle \tag{9}$$

$$\{\text{the grocery-store}\} \rightarrow \text{food-market} \ \ \langle 1, 0.81\rangle \tag{10}$$

From the above expression, any *formal* reasoning system can perform *deduction*. Particularly, all the following conclusions can be obtained just by *deduction*:

From (1) and (4):

$$(\times, (\times, \_, \text{food}, \_) \rightarrow \text{pick-up}, \{\text{the-supermarket}\}) \rightarrow \textit{where}^* \langle 1, 0.81 \rangle \tag{11}$$

From (11) and (9):

$$(\times, (\times, \_, \text{food}, \_) \rightarrow \text{pick-up}, \text{food-market}) \rightarrow \textit{where}^* \langle 1, 0.65 \rangle \tag{12}$$

From (12) and (7):

$$(\times, (\times, \_, \text{food}, \_) \rightarrow \text{buy}, \text{food-market}) \rightarrow \textit{where}^* \langle 1, 0.59 \rangle \tag{13}$$

From (2) and (6):

$$(\times, (\times, \_, \text{food}, \_) \rightarrow \text{buy}, \{\text{the grocery-store}\}) \rightarrow \textit{where}^* \langle 1, 0.66 \rangle \tag{14}$$

From (14) and (10):

$$(\times, (\times, \_, \text{food}, \_) \rightarrow \text{buy}, \text{food-market}) \rightarrow \textit{where}^* \langle 1, 0.53 \rangle \tag{15}$$

From (3) and (5):

$$(\times, (\times, \_, \text{food}, \_) \rightarrow \text{purchase}, \text{food-market}) \rightarrow \textit{where}^* \langle 1, 0.73 \rangle \tag{16}$$

From (16) and (8):

$$(\times, (\times, \_, \text{food}, \_) \rightarrow \text{buy}, \text{food-market}) \rightarrow \textit{where}^* \langle 1, 0.66 \rangle \tag{17}$$

NAL also has rules to summarize judgments with the same sentence but different truth values, such as judgments (13), (15) and (17). One of these rules, called *revision*, produces the following judgment:

From (13), (15) and (17):

$$(\times, (\times, \_, \text{food}, \_) \rightarrow \text{buy}, \text{food-market}) \rightarrow \textit{where}^* \langle 1, 0.84 \rangle \tag{18}$$

Now, a *commonsense* reasoning system needs to infer non-deductive knowledge that may seem simpler but cannot be obtained by deduction. So, after performing all the above deductions, if the system receives a new piece of knowledge in the sentence: *I bought something at the supermarket*:

$$(\times, (\times, \{\text{I}\}, \text{something}, \_) \rightarrow \text{buy}, \text{food-market}) \rightarrow \textit{where}^* \langle 1, 0.9 \rangle \tag{19}$$

By applying the NAL induction rule, the system can infer:

$$\text{something} \rightarrow \text{food} \ \ \langle 1, 0.43 \rangle \tag{20}$$

Which represents the commonsense reasoning that whatever you bought at the supermarket is most probably food, because within the little experience available to the agent (Formulas (1) to (10) and confidence = 0.43 in the conclusion), all the evidence (frequency = 1) indicates that food is what is bought at supermarkets.

7. Discussion

Modeling a natural language with a formal language is always going to be an incomplete task. Part of the problem stems from the fact that logic formulas (in any symbolic logic) are purely declarative, while natural languages can express a variety of sentences besides declarative. It has been extensively argued that the lack of contextual or background knowledge in an artificial agent prevents any chance of communication or reasoning with unified semantics [45]. However, it seems quite evident that if artificial intelligence is going to have any chance of near-human behavior, it cannot depend on non-symbolic generative models for catching the true meaning of natural language expressions.

In this paper, we have shown a methodological return to the symbolic way, using linguistic analysis tools that identify the grammatical structure in a natural language sentence and reveal the various types of relations among words (dependencies, semantic role relations, etc.). Such an analysis provides sufficient evidence to identify concepts, instances of those concepts, properties and relations expressed by natural language sentences, which can then be translated into NAL formulas that not only preserve the original relations but also insert them in a multi-valued, non-monotonic, and higher-order logic with enough flexibility to later perform inference tasks [46,47].

Our approach has been to search for named entities and grammatical labels in order to define the *terms* (logical terms or concepts) on which the logical formulas will be based. Next, we used a commonsense ontology (WordNet) to construct a minimal background context for the selected terms. Finally, we took the table of universal dependencies as the landmark reference, maximizing a consistent covering of commonly used expressions and idioms, as well as their translation into NAL formulas. We would like to highlight the following linguistic/logic merits of our proposal:

- A nominal subject sentence (Examples, Nominal subject, cases (a) and (b)) gets translated to the exact same NAL formula, regardless of it being in an active or passive voice.
- A double object construction (Example, Indirect object, case (a)) and a prepositional construction (Example, Oblique nominal, case (c)) also got translated to the same NAL pre-defined relation formula.
- A careful use of NAL product terms allows the pre-defined relations to endow their related terms with a more semantic role than their syntactic analysis would suggest. For example, the two sentences *Ana teaches Logic* and *Ana teaches the students* have exactly the same dependency parsing but are translated to slightly different NAL formulas. The first one is translated into $(\times, \{\text{Ana}\}, logic, \#\textit{To-whomever}) \rightarrow teach$, while the second one is translated into $(\times, \{\text{Ana}\}, \#Whatever, \{\text{the-students}\}) \rightarrow teach$.
- Adjectives are not always translated into NAL properties. When appropriate, they can also be translated into relations, as can be seen in Examples, Table 15, Adjectival modifier, case (b), which is consistent with [48,49].

These characteristics, along with the broad coverage of universal dependencies, make our method more extensive and precise than the one implemented in [22] but still complying with the specifications in [21].

7.1. Limitations and Future Work

Some of the limitations of the proposed rule set are as follows:

- The rules are not capable of deciding if an adjective should be represented as a property or as a relation. This difference between adjectives can be clearly seen in possessive or predicative adjectives, as in [49]. Even more, their translation may depend on a specific context that could not be part of the current sentence.
- Some translations will not be useful to carry axiomatic reasoning. This can be clearly seen in the translation of numbers or unities, for example; consider the translation of the sentence *One apple plus two apples equals three apples* [50].

On another note, there are improvements to the proposal that can be integrated into future work, such as:

- Other linguistic analyses can be performed before the application of rules, such as word-sense disambiguation or anaphora resolution
- While all the variables considered in this work are *dependent variables* in NAL, this can be expanded so the rules also include independent variables.

Furthermore, the implementation could be improved if the following points were addressed:

- The implemented rules greatly depend in the linguistic software used. If an inadequate analysis is carried out before, the translation will also be erroneous.
- In addition to the previous point, the implementation is not connected to a semantic dependency parser to automatically obtain semantic roles in a sentence. Instead, Prolog predicates are used to denote locations, instruments, time, etc.

8. Conclusions

The contributions of this work can be summarized as follows:

- From the perspective of the symbolic paradigm, this work explores the possibility of extracting fundamental term relationships expressed in natural language to construct with them a representation in a formal language (NAL) previously known to be well adapted for reasoning tasks, and particularly commonsense reasoning.
- From the point of view of natural language processing and computational linguistics, this work proposes a way to use non-axiomatic logic as a minimum-loss formal representation of natural language sentences.
- Finally, from the point of view of artificial general intelligence, this work advances the first step required on the way to designing an agent with language understanding and commonsense reasoning capabilities.

Following the ideals of this research, the next step seems obvious, and by the time this paper is published, this next step will already have begun: to test the translated formulas in different inference tasks and dynamically extend the required background formulas to enable conversational and commonsense reasoning abilities in an artificial agent. However, since the first stage of translating natural language to NAL formulas has so many intricate details, we feel it is worth presenting it in its own dedicated paper. Undoubtedly, the task of building an artificial agent with commonsense reasoning skills is a colossal task. However, we firmly believe that the current trend of relying on generative connectionist models does not advance down the path of artificial general intelligence and fails to capture the essence of symbolic reasoning, much less commonsense reasoning. That is the reason that motivates and drives this research.

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Abbreviations

The following abbreviations are used in this manuscript:

NAL	Non-axiomatic logic
NL	Natural language
PL	Predicate logic
AIKR	Assumption of Insufficient Knowledge and Resources

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