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## Pursuing Actionable Interpretations of Non-Literal Language

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### Abstract

This paper describes the approach to treating non-literal language in the OntoAgent cognitive architecture. It makes three claims: treating non-literal language cannot be postponed in agent systems that are designed to interact with people; orienting around actionability rather than perfection makes processing non-literal language feasible in the near- to mid-term; and the runtime treatment of non-literal language can and should be threaded with the agent's lifetime learning of the lexicon. Argumentation in support of these claims will be followed by a description of our microtheory of non-literal language. The paper suggests that developers of language-endowed agent systems can integrate non-literal language support into their systems right away, since achieving a useful interpretation of many inputs containing non-literal language is far less daunting than might be imagined.

### 1. Introduction

Endowing intelligent agents with near-human-level natural language understanding (NLU) capabilities represents a long-term challenge for the artificial intelligence community. A key to making associated programs of R&D viable is showing useful intermediate progress as we work toward a comprehensive solution. This paper describes our approach to operationalizing the treatment of two types of non-literal language in the OntoAgent cognitive architecture: metaphors and similes. Although similes are easy to define – they are comparisons using *as* or *like* – metaphors are not. In fact, the literature on metaphors often sidesteps a formal definition, which is not surprising since it is, in fact, not always clear whether a given non-literal meaning (a) is dynamically computed from some literal sense, or (b) already exists as a full-fledged, remembered sense. Moreover, in the latter case, the metaphorical meaning might strongly resonate with its non-metaphorical source, or the historical link might be lost to some or all speakers. In the spirit of practicality that inspires our work, we will not linger on formally defining metaphors, instead allowing our functional definition to become clear through the narrative and examples.

The intelligent agents we develop attempt to compute the full semantic and pragmatic meaning of inputs, but when this is not possible, they determine whether the analyses they *can* generate are actionable – i.e., sufficient to support reasoning about action. Actionability is not simply a stopgap engineering strategy (though its strategic utility given the current state of the art is clear). Instead, it holds a proper place in a human-inspired cognitive model of NLU since people far from always extract full and confident meaning from every utterance. So, although agents' interpretations and confidence levels will, in many cases, not equal those of people, all human and non-human agents must be able to successfully operate in a space of communicative imprecision.

Our R&D in the realm of non-literal language follows the same pattern as for any linguistic phenomenon: We develop a microtheory that elucidates and classifies the potential manifestations of the phenomenon, and then formulate heuristic-supported algorithms for detecting and treating as many of these manifestations as possible. All microtheories are, at all times, under development, since the linguistic problems at hand are formidable. But the big idea remains: We are trying to enable agents to function as competently as possible, as soon as possible, under the real-world necessity of not artificially constraining what people say or how they say it.

This paper makes three claims: (1) treating non-literal language cannot be postponed in agent systems that are designed to interact with normal people; (2) orienting around actionability rather than perfection makes processing non-literal language feasible; and (3) the runtime treatment of non-literal language can and should be threaded with the agent’s lifetime learning of the lexicon. These claims are supported by argumentation in Section 2. Section 3 describes how we are operationalizing the interpretation of non-literal language, which is visually summarized in Figure 2. Section 4 presents plans for future work – of which there is quite a lot.

The main point is that there is no need to exclude non-literal language from the purview of natural language understanding systems, no matter how limited a system’s capabilities, since many manifestations of non-literal language can be easily identified and treated. In short, although natural language is full of all kinds of monstrosities, as least from the perspective of computer systems, *monstrous* is not a necessary feature of non-literal language.

This paper focuses on the conceptual, rather than system-building, aspects of our non-literal language microtheory. We think that the description of the microtheory – even in its current, rather preliminary state – could serve as a guide for other system builders, who might choose to implement and expand upon the ideas in parallel with our continued work on this topic. Before moving on to the body of the paper, let us first present some brief background about NLU in the OntoAgent cognitive architecture, as well as comparisons with past work by others.

## 1.1 Background on NLU in OntoAgent

Intelligent agents developed within the OntoAgent architecture (McShane and Nirenburg, 2012) have the typical cognitive capabilities of perception, reasoning and action. Channels of perception apart from natural language can include interoception generated from a physiological model (Nirenburg, McShane and Beale, 2008), robotic vision (Nirenburg et al., 2018), and others. Language understanding follows the theory of Ontological Semantics, whose initial statement is presented in (Nirenburg and Raskin, 2004).

The goal of OntoAgent text analysis is to automatically generate fully specified, disambiguated, ontologically-grounded text meaning representations (TMRs) from unconstrained natural language inputs. Translation into the ontologically-grounded metalanguage of a TMR focuses on the content of its message rather than its form. For example, the TMR for the input *You need to apply pressure to the wound* is as follows.<sup>1</sup>

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<sup>1</sup> For reasons of space, we exclude extensive metadata, e.g., which word of text is being analyzed, which lexical sense was used to generate each frame, inverse frames unless they include additional properties, etc.

<b>REQUEST-ACTION-1</b>	<b>PRESS-1</b>
AGENT            HUMAN-1 ; <i>the speaker</i>	AGENT            HUMAN-2 ; <i>the interlocutor</i>
THEME            PRESS-1	THEME            WOUND-INJURY-1
BENEFICIARY    HUMAN-2 ; <i>the interlocutor</i>	

This TMR is headed by a numbered instance of the concept REQUEST-ACTION, which is the interpretation of “you need to”.<sup>2</sup> The AGENT of this action is the HUMAN speaker and its THEME (what is requested) is an instance of PRESS. The PRESS event instance is further specified, in its own frame, as having the HUMAN interlocutor as its AGENT and an instance of WOUND-INJURY as its THEME. This instance of WOUND-INJURY will be coreferred with an earlier instance (explaining the article *the*) when the full context is analyzed.

The concepts referred to in TMRs are not merely symbols in an upper-case semantics. They are grounded in a 9,000-concept, property-rich ontology developed to support semantically-oriented NLP, script-based simulation, and overall agent reasoning (McShane and Nirenburg, 2012). For example, PRESS is the child of APPLY-FORCE. Among its property-value pairs are case-roles that support lexical disambiguation, including (AGENT ANIMATE), (INSTRUMENT LIMB, DEVICE), (THEME PHYSICAL-OBJECT). A prerequisite for automatically generating TMRs is our highly specified lexicon, which includes syntactic and semantic descriptions linked by variables. Consider, for example, the first two verbal senses for *address*, shown in Table 1 using a simplified formalism. Syntactically, both senses expect a subject and a direct object in the active voice, filled by \$var1 and \$var2, respectively.<sup>3</sup> However, in *address-v1*, the meaning of the direct object (^\$var2; ‘^’ indicates ‘the meaning of’) is constrained to a HUMAN or, less commonly, ANIMAL, whereas in *address-v2* the meaning of the direct object is constrained to an ABSTRACT-OBJECT. The constraints appear in italics because they are virtually available – the analyzer accesses them from the ontology at runtime. This difference in constraints permits the analyzer to disambiguate: if the direct object is abstract, as in *He addressed the problem*, then *address* will be analyzed as CONSIDER; by contrast, if the direct object is human, as in *He addressed the audience*, then *address* will be analyzed as SPEECH-ACT.

*Table 1.* Two verbal senses for the word *address*. The symbol ^ indicates “the meaning of”.

<b>address-v1</b> anno definition “to talk to” example “He addressed the crowd.” syn-struct subject     \$var1 v         \$var0 directobject \$var2 sem-struct SPEECH-ACT AGENT        ^\$var1 ( <i>sem HUMAN</i> ) BENEFICIARY ^\$var2 ( <i>sem HUMAN</i> ) ( <i>relaxable-to ANIMAL</i> )	<b>address-v2</b> anno definition “to consider, think about” example “He addressed the problem.” syn-struct subject     \$var1 v         \$var0 directobject \$var2 sem-struct CONSIDER AGENT        ^\$var1 ( <i>sem HUMAN</i> ) THEME       ^\$var2 ( <i>sem ABSTRACT-OBJECT</i> )
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<sup>2</sup> The obligative modality indicated by *need to* is interpreted as a request for action when addressed to the interlocutor.  
<sup>3</sup> Variables are written, by convention, as \$var followed by a distinguishing number. Variables permit the language analyzer to map textual content from the input to elements of the syn-struct, and then link each syn-struct element with its semantic realization in the sem-struct.

These examples highlight several aspects of our lexicon. First, it supports the combined syntactic and semantic analysis of texts. Second, the metalanguage for describing meaning in the sem-strucs is the same one used in the ontology. Third, fixed and variable constructions of any complexity are readily supported. Finally, the sem-strucs—and, often, the associated syn-strucs—from the lexicon for one language can be ported into the lexicon of another language with minimal modification, which greatly enhances the multilingual applicability of the OntoAgent suite of resources.



Figure 1. Stages of processing representing vertical incrementality.

We model language understanding using two types of incrementality: *horizontal* incrementality involves treating elements of input as they become available in the speech or text stream; vertical incrementality involves applying up to six increasingly sophisticated analysis modules (shown in Figure 1) to the given fragment of input. For a discussion of incrementality, see McShane, Nirenburg, and English (2018).

For each TMR produced, the analyzer generates a value of the *confidence* parameter, which reflects the degree to which the interpretation deviates from the expectations of the supporting knowledge bases and algorithms. In collaborative human-agent applications, confidence levels help agents decide whether to act upon their understanding of a language input. Deciding whether to act on an interpretation is a practical halting condition for language analysis inspired by human behavior.

The OntoAgent microtheories that operationalize the treatment of linguistic phenomena are developed and improved over time, starting with the most readily and confidently treatable cases and progressing to the more difficult ones. Key to all processing is computer-tractable heuristics, which involve static knowledge, rule sets, and various types of reasoning. When an agent encounters an instance of a phenomenon, such as a simile or suspected metaphor, it attempts to arrive at a high-scoring, high-confidence analysis. If an instance falls outside of its current capabilities, the agent asserts this both via the actual content of the meaning representation (which would typically be underspecified) and its associated confidence score.<sup>4</sup>

## 1.2 Comparisons with Others

The topic of metaphor has been addressed from a broad variety of premises and in different contexts: in rhetoric since Aristotle, in literary criticism (e.g., Skulsky, 1986), semiotics (e.g., Eco, 1979), a variety of schools in linguistics (e.g., Lakoff, 1993; Steen, 2007), psychology (e.g., Bowdle and Gentner, 2005), psycholinguistics (e.g., Glucksberg, 2003), philosophy (e.g., Bayler-Jones, 2009; Lepore and Stone, 2010), neuroscience (e.g., Goldstein et al., 2012), and even statistical NLP, primarily using supervised machine learning supported by corpus annotation.

The distinction between conventional metaphors and novel metaphors has been firmly established in linguistics (e.g., Nunberg, 1987). Bowdle and Gentner (2005) argue that metaphors conventionalize and lose their metaphoricity over time. Most metaphors discussed within the popular conceptual metaphor theory (e.g., Lakoff, 1993) are actually conventional and, therefore,

<sup>4</sup> Our decision to make the agent accountable for identifying the instances it can treat confidently contrasts with mainstream NLP’s preference for creating task specifications that involve the manual selection of treatable instances (so-called “markables”), thus absolving systems from having to make this determination.

presumably exist in a native speaker’s lexicon. In a recent survey of work on metaphor in computational linguistics Shutova states: “Much of the metaphor processing work has focused on conventional metaphor, though in principle capable of identifying novel metaphor as well” (2015, p. 582).

One psychologically-grounded approach to analyzing metaphor interpretation is Gentner’s Structure-Mapping Theory (SMT), which relies on analogical reasoning (Gentner, 1983; Gentner & Markman, 1997). Gentner and colleagues provide psychological evidence that metaphor is a type of analogy and is processed as mapping between two disparate concepts. SMT defines an analogical mapping between source and target as a process of one-to-one structural alignment between properties of the source and properties of the target. For example, Gentner and Maravilla (2018; p. 186) present the example “Mitochondria are the furnace (or powerhouse) of the cell”, explaining that both objects produce energy in some form (furnaces: heat, vs. mitochondria: ATP) by consuming fuel of some type (furnaces: fuel, vs. mitochondria: glucose).

SMT has served as the basis for the computer modeling of analogical reasoning, as reported, e.g., in Gentner and Forbus (2011) and Forbus et al. (2017). However, the goals, foci, and scope of these computer implementations are quite different from ours. Since Forbus et al.’s systems take an existing theory as the substrate, they invoke the single analysis method licensed by that theory: analogical reasoning. Although this approach maximizes human-inspired plausibility in cognitive modeling, it also represents the most demanding approach to implementing metaphor analysis, since the system must somehow select the salient points of comparison from a potentially very large number of properties, which themselves must be available in a machine-tractable knowledge base. This is hard, so achieving high-quality results in fully automatic mode<sup>5</sup> for a large variety of examples does not appear imminent. We, by contrast, frame the problem rather differently, focusing on what we can enable agents to achieve in the near term as we continue to work on the how to process the most difficult cases over time.

As concerns points of comparison for NLU overall – i.e., without a special focus on non-literal language – the most relevant ones date back over two decades, from before the statistical revolution, as described, with extensive references, in Nirenburg and McShane (2016a). The most relevant *current* points of comparison are cognitive systems that include NLU, while not (as far as we can tell) claiming it as their main contribution (e.g., Lindes and Laird, 2016; Scheutz et al., 2017).

## 2. Main Claims

We motivate the microtheory of non-literal language processing to be presented in Section 3 with three main claims.

**Claim 1: Treating non-literal language cannot be postponed in agent systems that are designed to interact with normal people.** By some accounts, English speakers produce a unique

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<sup>5</sup> Different systems reported by Forbus et al. feature different levels of automaticity. They report that in some implementations candidate sets were created manually whereas in others they were created automatically. The 2011 paper lists four stages of processing – retrieval, mapping, abstraction, and rerepresentation – but skips over the first in presenting deep analyses, making it unclear how step one of the process was carried out. We are, by the way, fully in favor of working toward automation in stages that involve manual interventions. However, our current interest in processing non-literal language prioritizes full automation.

metaphor for every 25 words uttered (Graesser, Long, and Mio, 1989).<sup>6</sup> Past attempts to force people to constrain how they express themselves have proven futile, as shown by the history of work on controlled languages (for an overview, see McShane and Nirenburg, 2012). So, as with all other difficult language phenomena, agents must be prepared to muddle through all kinds of input the best they can, *without imposing unnatural constraints on their human collaborators*.

This tenet is counter to the decision of most agent system developers, who constrain the domain and inventory of utterances allowed by human participants. This methodology is perfectly reasonable, as it supports the important goal of integrating language processing with other agent functionalities. However, domain-specific approaches are unlikely to evolve into more generic ones because they avoid key issues, such as lexical disambiguation, unexpected input (e.g., fractured, non-canonical utterances), and – key to our discussion – non-literal language. Therefore, we consider non-literal language, along with all of these other difficult issues, within purview immediately. An important addendum to this claim is the observation that not every case of non-literal language is a worst-case scenario (though worst-case scenarios tend to be the focus of discussions in scientific writings).

**Claim 2: Orienting around actionability rather than perfection makes processing non-literal language feasible.** Like most scientists, linguists put a premium on building elegant theories, streamlined accounts, and perfect rule sets. This stance has led, not surprisingly, to the widespread use of “wastebaskets” to accommodate examples that just don’t fit, under the assumption that there must exist something outside of the theory that can account for the renegades without marring the theory’s intrinsic elegance. This preoccupation with perfection is also seen, interestingly enough, in some aspects of mainstream NLP – namely, competition-oriented task specifications. In a nutshell, when a linguistic phenomenon (e.g., coreference resolution, named entity recognition, word sense disambiguation) is selected for treatment, only its more readily computable manifestations are considered within the purview of the task description. For all the positive aspects of this machinery, one downside is that it makes such tasks look much simpler than they actually are, since the difficult cases are never seen by developers and are not included in counts of precision and recall.

Given the challenges of messy and often unwieldy language, it makes sense to orient around *actionable* rather than *perfect* interpretations of language inputs. An actionable interpretation is one that is understood with sufficient completeness and confidence to support the agent’s reasoning about action. Actionability is in play when an agent compares its interpretation of an input, along with its interpretation of other percepts (e.g., visual stimuli), with its current understanding of the situation (its own goals, those of its interlocutor, etc.). This means that an actionable interpretation could be many things, such as: (a) a high-confidence interpretation of a question that the agent knows how to answer, embedded in a much longer utterance that it only partially understands; (b) a poor understanding of an utterance that includes many unknown words, but that the agent confidently ignores because it identifies the utterance as part of expected off-topic conversation among its human collaborators; (c) a moderate-confidence hypothesis that the utterance is an indirect speech act indicating a request, in a context in which fulfilling that request – even if not intended – carries no negative consequences. For example, in a collaborative furniture assembly application the human might say, “We’re going to have to tighten these screws more” with the idea

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<sup>6</sup> Pollio & Pollio’s (1974) data on the development of figurative language in children suggests that children are able to use figurative language well before they can explain the exact nature of the relationship linking elements of the non-literal trope.

that they will do it later. If the agent immediately starts to act upon the task, there is no problem, the person can follow up with “I didn’t mean now” or something of that sort – exactly as would happen in human-human collaboration. Clearly, to make use of the idea of actionability, the agent must be endowed with metacognition to assess its own confidence in the quality of its language analyses (for related discussion, see McShane, Beale and Nirenburg, 2019).

**Claim 3: The runtime treatment of non-literal language can and should be interleaved with the agent’s lifetime learning of the lexicon.** Many instances of metaphorical language reflect conventional metaphors – i.e., ones that belong to the lexical stock of native speakers of a language. These frequently continue to evoke the mental image of their metaphorical roots, but they focus on one or more specific properties. *Which* properties is often not predictable. Consider, for example, that *rock* can be used to describe a person who is a reliable source of support, as in “You are my rock!” This metaphorical extension of *rock* focuses on stability and support, but that choice of salient properties is historically idiosyncratic. *Rock* could as easily have come to mean that the person in question was a burden, weighing one down. How do people learn which properties of *rock* are salient when it is metaphorically applied to a person? As always, through context. If someone thanks a friend saying, “You are my rock!” this is, at a minimum, a positive thing; additional details from the given context, or others encountered at different times, would then highlight the implications of stability and support, allowing for the fundamental learning of this word sense.

Whereas the metaphorical use of *rock* relies on a physical object whose properties all speakers will know, many locutions that are, historically, metaphors have etymologies unknown to the speakers who use them. For example, how many speakers know that *by and large* and *in the offing* are of nautical origin, that *flash in the pan* is from old artillery practice, or that *by the skin of one’s teeth* comes from Job 19:20? Even though these might conjure images of some sort, the link between the images and the meanings they have come to convey is much more distant.

In short, metaphorical meanings are far from always predictable based on compositional semantics and general reasoning; instead, they must be recorded in the lexicons of human and artificial agents. In a perfect world, there would already exist a computational lexicon that formally records the meanings of conventional metaphors so that agents, upon encountering “you are my rock”, would find an associated lexical sense and use it like any other to generate the correct overall analysis. However, a very large, well-stocked computational lexicon like this does not exist. (Of course, human-oriented lexicons do contain large numbers of conventional metaphors, but it takes work to covert their content into ontologically-grounded meaning representations.<sup>7</sup>) Moreover, it is unlikely that support for manually creating this type of lexicon will become available any time soon – not because this work is particularly hard or expensive (it is not), but because the manual creation of knowledge bases has not been fashionable for the past several decades.<sup>8</sup> This makes it a priority to enable our agents to learn new lexical senses as part of their normal operation. We are well into implementing associated capabilities of lifelong learning by reading, through dialog, and through experience (e.g., McShane, Blissett and Nirenburg, 2017; Nirenburg, Oates and English,

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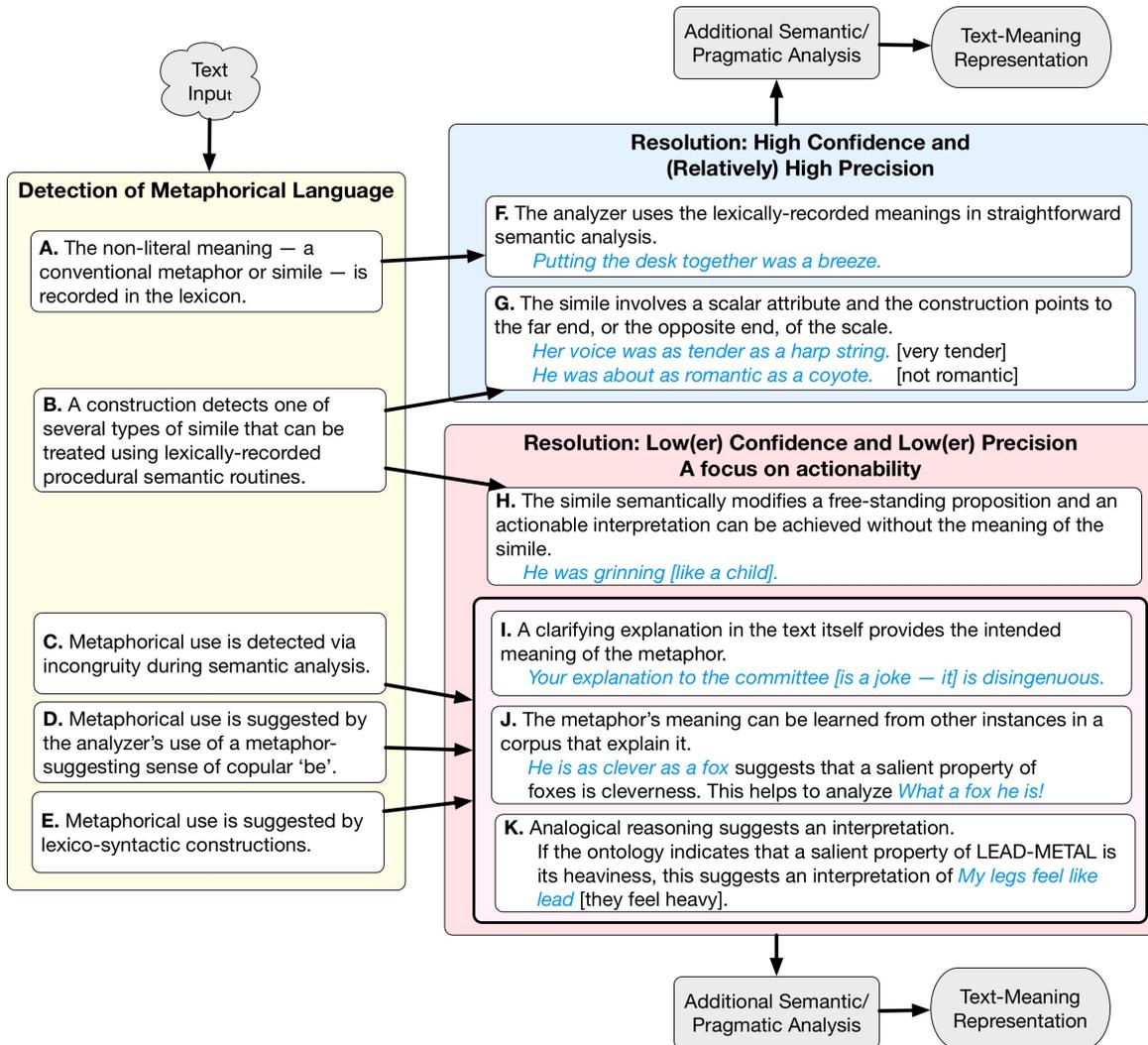
<sup>7</sup> The program of work on the work on machine-readable lexicons some 30 years ago showed just how problematic human-oriented lexical resources are for natural language processing systems (see, e.g., Ide and Véronis, 1993).

<sup>8</sup> As part of the statistical turn in NLP, manual resource acquisition has been deemed appropriate almost exclusively for corpus annotation in service of supervised machine learning.

2007; Nirenburg et al., 2018). Section 3 discusses specific angles of learning by reading that are relevant to the processing of non-literal language.

### 3. Operationalizing Non-Literal Language Interpretation

Operationalizing non-literal language processing involves two processes: detecting the non-literal use and interpreting its meaning. In some cases, our approach provides a joint solution to these problems (Section 3.1), whereas in other cases the detection process (Section 3.2) is carried out separately from the resolution process (Section 3.3). Figure 2 provides a visualization of the processing strategies to be discussed.



**Figure 2.** Detecting and resolving metaphors and similes during the process of semantic/pragmatic analysis by OntoAgents.

### 3.1 Methods that Cover Both Detection and Resolution

We have delineated two classes of non-literal language that are amenable to a combined method for detection and resolution. Note that most full-sentence examples are from the COCA corpus (Davies, 2008), hereafter referred to as simply COCA.

**Class 1: The non-literal meaning – a conventional metaphor or simile – is recorded in the lexicon.** (See Figure 2, boxes A and F). Many non-literal meanings make it into the lexical stock based not only on frequency but on semantic non-predictability. For example, just as the meaning of “*you are my rock*” is unpredictable and must be explicitly recorded in the lexicon, so are the meanings of *(sth.) is a breeze*, *(sth.) works like a dream*, *(s.o.) is like a sister to me*, and countless others. Moreover, some expressions have multiple non-literal meanings: e.g., *eat someone alive* can be used about someone being bitten by insects (*The mosquitos are eating me alive!*) or someone getting in trouble (*Your boss will eat you alive!*). When a non-literal sense is recorded in the lexicon, the agent uses its semantic description directly, like any other.

The easiest way to judge whether a non-literal meaning is conventional or novel is to check its frequency in a corpus, which can be done manually or automatically.<sup>9</sup> A higher frequency implies a greater likelihood that the expression is part of the lexical stock and should be recorded explicitly in the agent’s lexicon. E.g., COCA offers approximately 20 examples of *NP is a wizard at X*, in such collocations as *(someone) is a wizard at operations* <*at selling his students to Ivy League schools, at finding properties and investors, at securing federal funds, etc.*>. Similarly, for *NP is a giant among/in X*, COCA attests *(someone) is a giant in broadcasting* <*in the law, in conservation, in the field of telescopes, in the political arena*>; *(someone) is a giant among men* <*among world leaders, among home-run hitters, etc.*>. Given these examples, both expressions are good candidates to be recorded in the lexicon. Once recorded, they can be used in a straightforward manner in semantic analysis (Figure 2, box F).

**Class 2: A construction detects one of several types of simile that can be treated using lexically-recorded procedural semantic routines.** (See Figure 2, boxes B, G, H). Similes are easy to detect: they are comparisons using *as* or *like*. Three subclasses of similes are straightforward to resolve as well, albeit at the current state of the art only to an *actionable* degree, without capturing human-level semantic nuances.

The first subclass covers similes that involve scalar attributes; these typically point to the extreme end of the given scale (although they can also point to the opposite end of the scale, as covered by the next subclass). They are of the lexico-syntactic form *NP is/was as ADJ<sub>SCALAR</sub> as a/an N* and almost always mean “*very ADJ*”. Of course, such locutions conjure an image as well – e.g., *He is as tall as a giraffe* makes us think of a giraffe – but, for practical purposes, the related image is secondary to the core, actionable, meaning. Analysis of such constructions involves 3 procedures: (1) Each scalar adjective is analyzed as a point (or range) on its abstract {0,1} scale: e.g., *tall* is (HEIGHT .8), and *anxious* is (ANXIETY-ATTRIBUTE .8). These meaning representations are available in the OntoAgent lexicon. (2) The implied meaning, *very*, is captured by moving the scalar value by 0.1 to the extreme end of the scale; so *very tall* is (HEIGHT .9), and *very anxious* is (ANXIETY-ATTRIBUTE .9). (3) The image used in the simile is retained using the property RELATED-IMAGE, whose value is an ontological interpretation of the listed string (e.g., our giraffe example will have the property-value pair (RELATED-IMAGE GIRAFFE)). Below are some examples from COCA along with the ontological semantic interpretations of their simile-oriented portions.

<sup>9</sup> Psycholinguistic experiments could also assess this using reaction times, with a faster reaction time suggesting that the meaning is stored rather than dynamically computed.

**The corn is as high as an elephant’s eye.**

CORN-1  
 HEIGHT .9  
 RELATED-IMAGE EYE-1  
 EYE-1  
 PART-OF-OBJECT ELEPHANT

**The region’s cuisine is as complex as an intricately woven tapestry.**

CUISINE  
 RELATION REGION-1  
 COMPLEXITY .9  
 RELATED-IMAGE TAPESTRY-1  
 TAPESTRY-1  
 THEME-OF WEAVE-1  
 WEAVE-1  
 COMPLEXITY .9

**Her voice was soft, as tender as a harp string.**

VOICE  
 RELATION HUMAN-1  
 GENTLENESS .9  
 HUMAN-1  
 GENDER FEMALE  
 RELATED-IMAGE STRING-1  
 STRING-1  
 PART-OF-OBJECT HARP

**At night I am as anxious as a married lady.**

HUMAN-1  
 ANXIETY-ATTRIBUTE .9  
 RELATED-IMAGE HUMAN-1  
 HUMAN-1  
 GENDER FEMALE  
 MARITAL-STATUS MARRIED

Although this strategy works much of the time, it is important to recognize its challenges and limitations.

Challenge 1: The initial point of comparison can itself be metaphorical, at least as considered against the given state of the agent’s lexicon. This would be the case, for example, in *Her smile is as bright as an orange soda* [COCA] because our lexicon does not currently include a sense of *bright* that means ‘cheerful’ (although it should).

Challenge 2: In some cases the simile is – or might be – direct rather than metaphorical, which could lead to an inappropriate application of this metaphor resolution rule. The following COCA examples seem to reflect direct language use, since they suggest a specific context in which the literal interpretation is possible: *It’s difficult to get leverage when you’re as big as a basketball forward, especially playing inside. / However, the New Shepard is only capable of going to sub-orbital space, so it’s not traveling as fast or as high as a rocket going to orbit. / The 3-inch (8cm) stone was no match for the beam, which focused the equivalent of a million light bulbs onto an area as big as a pin, vaporizing that bit of the rock.* When it comes to the following COCA examples, however, we would have to ask an arachnologist and an antique clock expert, respectively, whether the following comparisons have a direct or metaphorical meaning: *Our guides cut down wild passion fruit for us to sample, pointed out spiders as big as a hand and chopped bamboo to whittle into cups.* [Can a spider be as big as a hand?] *The ancestral clock may have started out as simple as a sundial.* [If a clock is as simple as a sundial, then why it is called a clock?]

Challenge 3: The comparison might point to the opposite of the default connotation. For example, the COCA-attested “*shovels as big as a New York City studio apartment*” is intended to mean *extremely large shovels*, which follows our “extreme end of the scale” rule and would result in a

correct interpretation by the agent. However, it contradicts most people’s idea of the size of a NYC apartment, which is very small as apartments go. Still, the rule will recognize that the size comparison applies to shovels and not apartments, so that the intended meaning will be analyzed correctly.

Challenge 4: In still other cases, the opposite end of the scale is intended without a lexical flag making this clear (cf. the next section, in which lexical flags *do* make this clear). This is a rare eventuality, based on our corpus analysis to date, and combines simile processing with sarcasm detection: *Tears were wet on her cheeks and she was gulping for breath. Her eyes and nose were red, her hair was loose from its braids and straggling over her forehead. She looked as appetizing as a gutted herring, and he thought she was the most beautiful woman he'd ever seen [COCA].*

To summarize, it is easy and relatively reliable to extract the basic meaning of similes that indicate the extreme end of a scale. This level of understanding will be sufficient for (i.e., actionable in) many agent applications. In anticipation of future advances that might leverage the images invoked, we retain an ontological rendering of those images in the associated TMRs.

The second readily treatable subclass of similes is like the first but includes the modifiers *only* or *about as*, resulting in the constructions *NP is only <about> as ADJ as a(n) N*, which predictably point to the opposite end of the named scale. The formal treatment of these is similar to the examples above, except for switching the end of the scale pointed to. Some examples from COCA: *Zave was about as romantic as a coyote [he was unromantic], and besides, we were just friends. / But the idea of delivering a computer virus so potent it instantly disables an entire interstellar space fleet is, well, about as realistic as a light sabre [it is unrealistic]. / Broom, who likes to search for fossils in the nude, is called “about as honest as a poker player” [he is dishonest] and is twice banned from his own research site. With this class, we encounter the same kinds of challenges as for the previous one. For example, the simile can actually have a direct rather than a metaphorical meaning, as in *That part in your real ear is only as big as a grain of rice. / Hadlock's trenches had been only as wide as a shovel blade, and he easily could have missed crucial evidence. / The hall shrank to a circle of light only as big as a watch face..... / Some sections of the outer banks are only as wide as a couple of football fields.* It would take deep domain knowledge to arrive at the conclusion that these comparisons were literal. However, note that even if the agent misinterprets them as non-literal, the results could still be useful. E.g., ‘only as big as grain of rice’ will be interpreted as ‘very small’, which is true, though less precise than the original input. The same reduction of specificity applies to the other examples as well.*

In some cases, the surrounding context corroborates the interpretation of the simile, thus increasing the agent’s confidence in it. Consider, e.g., *The junk you've been writing is about as funny as a dead baby. It's not funny, it's not new. It's not sexy.* [COCA] “About as funny as a dead baby” will be analyzed as (HUMOR-ATTRIBUTE .1).<sup>10</sup> This is corroborated by the next clause which presents a paraphrase with a very similar analysis: (HUMOR-ATTRIBUTE .2).

The third subclass of readily treatable simile involves similes that semantically modify propositions. In the examples we have presented so far, the meaning of the whole proposition relied on the analysis of the simile: e.g., in *Zave was about as romantic as a coyote*, there is no proposition without the simile. However, in other cases, a simile modifies an otherwise free-standing

<sup>10</sup> If we were manually writing TMRs for inputs, we would make the value of HUMOR-ATTRIBUTE here 0. But we are not: we are using a rule that works quite well for the general case. Here, *funny* is lexically described as HUMOR-ATTRIBUTE .8. The lexeme *about as* shifts this to the opposite end of the scale: .2. And then the simile shifts the value by .1 toward the extreme of that scale, ending at HUMOR-ATTRIBUTE .1.

proposition, serving as an image-rich flourish rather than a meaning that is essential to an agent’s reasoning about action: *Then, grinning like a devil that seizes lost souls, he got to his feet. / He was grinning like a child with a secret he was dying to tell. / Sam perched himself on the only bare corner of my desk, grinning like a gapped-toothed Jack-O-Lantern. / Crying like a woman won’t help* [COCA]. We must emphasize that we are not suggesting that these comparisons lack meaning: *grinning like a devil that seizes lost souls* implies forthcoming evil action, whereas *grinning like a child with a secret to tell* is vastly more benign. What we are suggesting is that, although for the foreseeable future intelligent agents will not be able to compute all of the implicatures, or appreciate all of the nuances, that a person would, they can compute *actionable* interpretations – i.e., those that are sufficient to support their reasoning about action. As with earlier examples, the meaning representations for these inputs will retain the RELATED-IMAGE in expectations of it being useful for reasoning in the future.

Predictable exclusions from this category involve verbs that require – at least in one sense – a complement headed by *like*, such as *look like*, *act like*, *behave like*, *feel like*, and *sound like*: *Holidays were tough, but Linda was right. It was time she started acting like a big girl. / This is really crazy. He’s behaving like a lunatic. / You know, you’re acting like a thug*. In all of these cases, there is no propositional meaning if the simile is omitted.

To summarize this subsection, we have shown that many instances of non-literal language can be detected and resolved using lexical senses that support both of those tasks together. In some cases, a lexical sense explicitly records the needed semantic interpretation (Figure 1, boxes A & F). In other cases, a construction-oriented lexical sense points to a procedural semantic routine that can compute such an analysis (Figure 1, boxes B & G). In still other cases, a construction-oriented lexical sense indicates that “resolution” involves *not* incorporating the meaning of certain strings into the text meaning representation, since they are deemed to be not required for achieving an actionable interpretation (Figure 2, boxes B & H). We must emphasize that choosing not to reflect the meaning (nuances, implicatures, etc.) of some textual elements in a text meaning representation reflects language-oriented reasoning: the agent does not randomly ignore elements of input.

### 3.2 Methods for Detection that Do Not Incorporate Resolution

We currently have three methods for detecting instances of non-literal language that are not integrated with resolution strategies. Follow-up resolution strategies are described in Section 3.3.

**Method 1. Metaphorical use is detected via incongruity during semantic analysis.** (See Figure 2, box C).<sup>11</sup> The observation that semantic incongruity suggests non-literal language dates back to at least Wilks (1978), who presents the now-classic example “My car drinks gasoline”. Nirenburg and McShane (2016b) classify dependency incongruities as a type of “unexpected input anomaly” (whose other manifestations include, e.g., humor and hyperbole). The idea is that there is no ontologically licensed dependency between the available meanings of a head (here, the verb *drink*) and the dependent(s) (here, *my car* as the external argument and *gasoline* as the internal one). When processing such inputs, the agent assigns a low score to its incongruous interpretation, which serves as a flag to seek an indirect interpretation. It must be emphasized that a challenge in using selectional constraint violations to detect non-literal language is that often a non-literal meaning parallels a literal one with the same constraints: e.g., *hit* can mean to physically assault or to have a strong non-physical negative impact on. We discuss the issue of this and similar semantic problems in McShane, Beale, and Nirenburg (2019).

<sup>11</sup> Although here we focus on metaphors, metonymies and other tropes can also be detected this way.

**Method 2. Metaphorical use is detected by the analyzer’s use of a metaphor-suggesting sense of copular<sup>12</sup> ‘be’.** (See Figure 2, box D.) In the OntoAgent lexicon, the verb ‘be’ has dozens of senses, many of which cover different semantic classes of copular constructions. For example, HUMAN {be} SOCIAL-ROLE means HUMAN (HAS-SOCIAL-ROLE SOCIAL-ROLE); so *John is a doctor* is analyzed as (HUMAN (HAS-NAME John) (GENDER male) (HAS-SOCIAL-ROLE PHYSICIAN)). Similarly, OBJECT {be} {ontological hypernym of OBJECT} means OBJECT (SUBCLASS-OF {ontological hypernym of OBJECT}); so *Cuapacu is a fruit* is analyzed as (CUAPACU (SUBCLASS-OF FRUIT)). The agent always prefers more semantically specific interpretations of an input to more generic ones, which will lead to the correct interpretations of the examples above. However, there is also a default copular sense of “be” that is used when none of the more specific ones fit. That sense (a) sets up a generic RELATION between the meanings of the noun phrases, and (b) calls a procedural semantic routine that will attempt to further specify that RELATION if any domain-specific or situational knowledge can be brought to bear. That routine leverages, among other things, the metaphor resolution strategies described in Section 3.3.

**Method 3. Metaphorical use is detected by lexico-syntactic constructions.** (Figure 2, box E.) Certain turns of phrase explicitly and with high confidence suggest the use of non-literal language: e.g., “as if”, “VERB like a NP”, “metaphorically speaking,” “so to speak”, etc. Examples from COCA include: *Soon we will kill again and then it will be as if nothing was ever wrong, as if destruction was a meal, maybe toast and honey. / ...I think you’d enjoy the chance to even the score. Metaphorically speaking, of course. / We’re the last of the guns for hire so to speak.* Constructions like these only point out the use of non-literal language, they give no guidance for its interpretation – which is what we turn to now.

### 3.3 Methods for Resolution Once the Non-literal Language Has Been Detected

We are currently exploring three methods of interpreting instances of non-literal language that are not covered by the methods described in Section 3.1. All of these integrate real-time analysis with lifelong learning: after all, expressions that are novel to the agent, based on its current lexical stock, might well be conventional metaphors whose meaning might not be completely predictable even given optimal dynamic reasoning. Note that we are manually exploring these methods quite extensively before setting upon implementing our nascent algorithms because we want to be quite sure that the kinds of information we would *like* to find in corpora – which will be needed by those algorithms – actually exist.

This caution is not without precedent, as can be seen from the example of learning ontological scripts from texts. One might expect that, as long as a system had sufficient NLU capabilities, it should be able to learn all manner of scripts from text corpora. However, it is well known that in their writing and conversations, people do not overtly describe how everyday events play out, from end to end, along with their options, defaults, and so on. So, although solid NLU capabilities are certainly a precondition for high-quality script learning, it is no less important – and challenging – to figure out how to detect and assemble the relevant bits and pieces from different sources.

Returning to our task of interpreting non-literal language, developing the reasoning capabilities to interpret novel (for the agent) non-literal language will require quite a lot of work, and this capability is competing for resources with many, many other capabilities. So we want to be sure

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<sup>12</sup> A copular verb links the subject of a sentence to a predicate, such as the word ‘is’ in the sentence “My dog is a chowhound.”

that methods which, on the surface, seem to hold promise actually do in the framework of the operation of a complete system.

**Method 1. A clarifying explanation in the text itself provides the intended meaning of the metaphor.** (See Figure 2, box I.) Often, the meaning of non-literal language is explained right there in the text. This is a boon not only for NLU but for people too – both those who are learning a language and those who are trying to understand what might be a strange and unexpected locution by a speaker. The most reliable detection method we have identified is the pattern “NP<sub>1</sub> is NP<sub>2</sub> {punct} PRO<sub>1</sub> ...”, in which the subscripts indicate coreference. In contexts like these, the main meaning of the input can be extracted by *skipping over* the metaphor and directly attaching the explanation to its target. The following rewrite rule captures this generalization, where the strikethrough indicates the portion to be skipped over: NP<sub>1</sub> is NP<sub>2</sub> {punct} PRO<sub>1</sub> VP → NP<sub>1</sub> ~~is NP<sub>2</sub> {punct}~~ PRO<sub>1</sub> VP.

The following COCA examples use the same strikethrough convention to convey how this rule will play out during runtime analysis: *Facebook ~~is a stew~~. It's an amalgam of all sorts of different things that are all given more or less equal weight. / Your explanation to this committee ~~is a joke~~. It is disingenuous. / No matter what their politics, people here think the Project on Community ~~is a joke~~. It's useless. It won't accomplish anything. / But a Corpsegrinder ~~is a parasite~~. It has no true identity of its own, so it constructs one from bits and pieces of everything that's unpleasant within you. / The snow ~~is a blanket~~. It protects them from the wind and keeps them warm until spring. / Financial aid ~~is a swamp~~. It looks incomprehensible from the outside. / A.J.'s office ~~is a closet~~. It has no windows, no pictures on the wall, no family photos on the desk, no knickknacks, no escape. / I've always been picky because my hair ~~is a mop~~. It's so big I've never even put pads in my helmet. / Physically, this galaxy ~~is a monster~~. It lies 120 million lightyears distant and measures a respectable 5.8' by 1.8' in our sky.* These modified inputs will then be subjected to full semantic and pragmatic analysis. The associated TMRs will retain a trace of the associated image, as shown in earlier examples (i.e., using the property RELATED-IMAGE).

This resolution strategy is not without its complications, which include the following (with examples from COCA). (1) The right-hand boundary of the explanation can be unclear – a problem common to all language analysis tasks that rely on discourse chunking: e.g., *That holding cell ~~is a nightmare~~. It smells. There's no privacy even for the toilet, and they took blood samples to test me for HIV and other diseases.* (2) Extended metaphors that involve multiple assertions can describe a metaphor using another metaphor: *I mean, this administration is a port-a-potty. It's full of crap. / Old sorrow is a thief. It picks your pocket. Or slips steel to your gut; your knees hit the ground, and you're breathless.* (3) The explanation might not be self-sufficient if certain aspects of the metaphor itself – such as its sentiment (positive vs. negative) – are not retained: *Her husband is a snake. He takes orders from my father at the tire company, yet uses his parking space. / For Kristen, the first week is a nightmare. She meets a cute guy at a beer blast, goes home with him, and is a victim of date rape.* (4) The semantic analysis of the explanation can be difficult to compute, given that the metaphor itself does not provide direct evidence: *This dish is a heartbreaker. It tastes great, but just look at it.* [The expression ‘Just look at it’ can be a request for action or an expression of disappointment.] (5) What is formally an explanation can be not very explanatory, even if it is not completely metaphorical itself (cf. point 2 above): e.g., *Narcissism is a liability. It's actually inside feeling very small and wounded and empty and you need to keep the world buttressed – bumping you up so you can feel OK and then you start to believe it.*

**Method 2. The metaphor’s meaning can be learned using other instances in a corpus that explain it.** (See Figure 2, box J.) As we just said, identifying metaphor-explaining contexts can

contribute to lifelong learning. However, it can also be leveraged when the agent encounters an example that is not locally explained. Rather than limit its analysis space to the text itself, the agent can search a corpus for examples that *are* explained and use those to inform the given analysis – in the spirit of lifelong learning. For example, the previous section cites sentences that describe *a joke* as disingenuous and useless. These, together, can be interpreted as the semantic space of ‘joke’ used metaphorically – in addition to whatever additional evidence can be found in a corpus using the same analysis methods. However, before setting an agent loose on learning of this kind, we need to precisely specify – through manual simulation of agent functioning – how such interpretations will be collated, generalized upon, and corroborated, since the learning process must yield not only a candidate interpretation, but also a confidence estimate in that interpretation.

**Method 3. Analogical reasoning suggests an interpretation.** (See Figure 2, box K.) As described earlier, an analogy is a mapping of knowledge about one domain (the source) onto another domain (the target). A key open question in modeling analogical reasoning is how to determine the salient properties of the source and target being underscored by the analogy. This is largely determined by which properties are, by default, salient for different objects and events – information that is known by speakers of a language (and, no doubt, largely generalizable across languages). For example, whereas comparing one’s dog to a firefighter could plausibly focus on bravery or physical strength, it cannot serve to highlight that both are mammals. Since the saliency of objects and events is an aspect of knowledge, and agents, like humans, need this knowledge, an important aspect of operationalizing analogical reasoning is knowledge acquisition. We have been exploring two methods of knowledge acquisition that are faster and cheaper than setting knowledge engineers to the task: crowdsourcing and automatic learning by reading.

*Crowdsourcing.* Crowdsourcing has become a widely-used method of fast and inexpensive knowledge acquisition. It has been effectively used, e.g., to support the development of machine learning systems addressing such tasks image classification and sentiment analysis. Amazon’s Mechanical Turk is a web service widely used to crowdsource data and knowledge from an international group of paid, non-expert workers. Research indicates that crowdsourcing is a viable technique for accomplishing labor-intensive natural language processing tasks: e.g., Snow et al. (2008) showed that large linguistic labeling tasks can be viably carried out using Amazon’s Mechanical Turk, and Callison-Burch (2009) demonstrated the value of crowdsourcing as a method for evaluating translation quality. The well-understood limitation, however, is that tasks must be formulated in a simple and straightforward manner, and they must not require deep knowledge or complex analysis.

We hypothesize that we can use crowdsourcing to enhance our ontology with indications of the salient features of objects and events. The planned methodology is as follows. We will automatically extract candidate metaphors from a development portion of the COCA corpus, orienting around copular constructions whose predicate nominal represents the candidate metaphor (e.g., NP is a/an N). We will manually extract from these candidates the actual metaphorical usages, which are expected to represent a relatively small proportion of instances. We will group those into semantic classes (e.g., animals, machines) and add to each group additional members that could presumably be used metaphorically.<sup>13</sup> We will then randomize the ordering of this inventory and present it to Turkers along with the task of writing the most important two or three features of each one.

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<sup>13</sup> Widely unknown members of a class (e.g., the animals called Ili Pika and Grimpoteuthis) are hardly likely to be used metaphorically since people won’t know what features they represent.

We conducted a preliminary, exploratory exercise, which suggested the need for certain specific instructions – though our expectations that participants will follow them are modest. Misfires we would like to avoid include treating the task as a word association game (e.g., *capitalism* → *market*; *prison* → *system*) and indicating the superclass (which *is* a property, but not a useful one for analogical reasoning; e.g., *ostrich* → *bird*). Beyond these, and perhaps a few other rules of thumb, we will allow Turkers to express any features, in any way they choose, since having too many instructions is counterproductive for this knowledge acquisition methodology. For example, they can list the feature name with its value implied (e.g., *size*) or they can list the value itself (e.g., *large*); and they can use any paraphrase they want: e.g., *large*, *big*, *very large*, *it’s very big*, *it tends to be very big*. When given such minimal instructions for our trial-balloon exercise, multiple participants came up with each of the following, quite useful, responses: *rock* → *hard / can be thrown*; *ostrich* → *flightless / long legs / feathers*; *capitalism* → *wealth*; *window* → *transparent*. We will semi-automatically filter, and finally manually confirm, the collected data before adding the saliency information to the ontology.

*Automatic learning from corpus-attested metaphors.* Earlier we described how similes involving scalar attributes tend to serve as modifications to the basic meaning: *He is as clever as a fox*. Such similes assert the salient property of the entity and support learning of these properties by the agent. However, as always, this learning is far more confident if corroborated by multiple instances – after all, similes can be idiosyncratic, and they can be sarcastic, potentially corrupting the knowledge base if not detected.

Of course, the point of recording ontological knowledge about property-related saliency is to then use that knowledge in the analysis of metaphorical usages. As shown by the examples above, a given entity can be associated with multiple salient properties, one or all of which might be relevant to the context. The order of research, therefore, is to compile saliency information for a seed inventory of objects and events, identify contexts in which those are used metaphorically, and attempt to identify features of the context that can predictably serve as heuristics for zeroing in on the intended focus of comparison. Once the process has been fleshed out for the seed development set, it will be modified as needed and applied to a larger sample set.

#### 4 Closing Thoughts

This paper suggests a method of treating non-literal language that involves delineating a suite of individual problems, each of which offers different solutions with different associated confidence levels.

In the domain of non-literal language, we posit the same realistic goal as for all aspects of NLU: whittling away at the machine-tractable instances of phenomena over time, while preparing the agent to function acceptably in contexts in which it cannot arrive at a full interpretation of the input. This practical approach derives not only of general experience, but of the frequency of strange and unspecific metaphorical formulations that we humans come up with. Consider a couple of examples: the metaphor “Democracy is a pendulum” offers no direct feature-based comparison and requires quite a lot of real-world reasoning, including historical knowledge, to interpret; and the metaphor “The world of philosophy is a puzzle that can be solved but slowly, by constantly adding new questions” is too clever for its own good, piling ellipsis on top of a complex metaphor in an already-complex domain (the puzzle isn’t solved by new questions, but by *answering* those questions). People are marvelously adept at ignoring all kinds of things: incomprehensible utterances, things that aren’t important, things that they probably should understand but don’t, and so on. In order to function realistically in the imperfect communicative world of humans, agents

need these abilities as well. We consider it equally important to prepare agents to get by in situations they don't completely understand as to advance their core NLU capabilities.

In closing, this paper has combined a description of past and ongoing theoretical, descriptive and computational implementation work on non-literal language with a statement about our near-future plans. We have shown how our program of R&D invokes cognitive modeling in multiple ways. On the one hand, we are aiming toward near-human-level NLU using human-inspired methods. On the other hand, we are addressing the practical problem of not yet having achieved that long-term goal by endowing agents with additional human-inspired capabilities, including learning by reading and being able to function adequately even in the context of incomplete or imperfect understanding.

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