A Robot’s Sense-making of Fallacies and Rhetorical Tropes.
Creating Ontologies of What Humans Try to Say

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Abstract

In the design of user-friendly robots, human communication should be understood by the system beyond mere logics and literal meaning. Robot communication-design has long ignored the importance of communication and politeness rules that are ‘forgiving’ and ‘suspending disbelief’ and cannot handle the basically metaphorical way humans design their utterances. Through analysis of the psychological causes of illogical and non-literal statements, signal detection, fundamental attribution errors, and anthropomorphism, we developed a fail-safe protocol for fallacies and tropes that makes use of Frege’s distinction between reference and sense, Beth’s tableau analytics, Grice’s maxim of quality, and epistemic considerations to have the robot politely make sense of a user’s sometimes unintelligible demands.

Keywords: social robots, logical fallacies, metaphors, reference, sense, maxim of quality, tableau reasoning, epistemics of the virtual.

在人性化機器人的設計中，系統應該超越邏輯和字面的意思來理解人類的交流，長期以來，機器人的通信設計忽略了溝通和禮貌規則的重要性。這些規則被稱為是“體諒”和“暫時放下的懷疑”，這種設計的缺失導致了機器人無法理解人類話語中隱晦的含義。通過分析不符合邏輯和非文字表述的心理原因、信號檢測、基本歸因謬誤和擬人化，我們開發了一種針對謬誤和比喻的故障安全協議，利用Frege對引用和感覺的區別、Beth的圖表分析、Grice的質量準則和認知方面的考慮，讓機器人禮貌地理解用戶時難以理解的需求。

關鍵字：社交機器人，邏輯謬誤，隱喻，參考，感覺，質量準則，表論推理，虛擬的認知
1. Introduction

There is this cartoon by Randy Glasbergen, saying “I want a computer that does what I want it to do, not what I tell it to do!” Computer users sometimes mean something different from what they put into the computer while the computer executes commands literally, much to the user’s aggravation. What if we could teach a computer to check what the user means if it encounters a command that would go against the ontology it knows the user normally keeps? That would lay the foundation of a robot that does not blindly execute commands nor tell the user wrong but deals with mistakes, fallacies, and figurative language from a position of understanding what it is that its user tries to convey.

In the current paper, we explain why user mistakes in logics happen and how the robot should deal with them (Figure 1). We also address how a robot may deal with non-literal comparisons such as metaphors (A is B) and similes (A is like B). The exploration of faulty and non-literal utterances starts with a discussion of two modes of information processing in the human brain, which are responsible for producing fallacies and similes.

In Figure 1, the brain is thought to run two modes of processing in parallel: reflective and affective (Konijn & Hoorn, 2017). The reflective mode relates to the neocortex and is more rational; the affective mode mainly concerns the limbic system and is more emotional. Both are always in function but one mode may take precedence over the other. The limbic, affective process, solves problems that demand immediate action: fight, flight, freeze, or positive approach (e.g., to make up). Its tactic is reflexive, taking things at face value (wysiwyg) and trading accuracy for speeded decisions. The reflective, cortical system, controls the limbic system so that on second thought, mistakes are corrected or emotions are regulated. The reflective mode is more concerned with logics and reasoning but also with association and creative problem solving (Pfenniger, 2001, p. 91).

Figure 1 shows that when fear and joy arise from the affective process, the reflective process interferes to channel those emotions into the right direction. The anger of a reasonable person should not lead to a fist fight but to a discussion. However, sometimes the affective process takes precedence and reflection may not be absent but is backgrounded at the least. At that point, mistakes easily happen as accuracy is traded for rash action. In terms of signal-detection theory, the number of false alarms (i.e. seeing something that is not there) and missed signals (i.e. overlooking something that is there) is likely to increase.

In the current paper, we argue that signal-detection faults may give rise to specific types of logical fallacies as well as to metaphors and similes, dependent on the problem-solving strategy of the reflective process. We argue that false alarms in combination with reasoning activities likely produce ex-consequentia fallacies (A \( \rightarrow \) B, B, \( \rightarrow \) A). False alarms in combination with creativity lead to false-positive or Fp-type of metaphors (e.g., ‘Juliet is the sun’ or ‘Humans are robots’). Missed signals combined with reasoning likely produce reverse errors (A \( \rightarrow \) B, \( \neg \)A, \( \rightarrow \) \( \neg \)B) and in combination with creativity to false-negative or Fn-type of metaphors (e.g., ‘This planet is Venus’ or ‘Robots are human too’).

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1 https://s-media-cache-ak0.pinimg.com/736x/95/16/d2/9516d292f976ef8c5b060d5499767903.jpg
Figure 1. Robot’s sense-making of fallacies and rhetorical tropes.
The four types of literally false statements (Figure 1, dashed box) may result into so-called fundamental attribution errors (Ross, 1977). People are inclined to think that someone’s actions (e.g., late at a meeting) express what internally goes on inside that person (i.e., indifferent person) and tend to overlook external explanations such as a person being forced by circumstances (e.g., a traffic jam). Reversely, people tend to attribute successes (e.g., win tennis match) to their own qualities whereas failure is blamed on the circumstances (e.g., bad court). With respect to robots, people make two types of attributions: When missing the cues to being a robot (e.g., a synthetic voice), people apply human-like qualities to the machine, disregarding that the robot may be operated by human hand. This is what is called anthropomorphism (e.g., Epley, Waytz, & Cacioppo, 2007). While seeing more than meets the eye, false alarms result into detecting robots everywhere, framing even fellow humans as such in disregard of their organic origins (‘He acts like a robot’). This is what may be coined robotomorphism, applying schemas and templates from machine performance onto human conduct.

How should a robot deal with utterances of its user that are literally false (Figure 1, dashed box)? We propose a four-pronged approach, that involves the way a robot updates its ontology about the user, the logics and communication rules it applies, and the epistemic system that attributes ‘believe’ or ‘empirical plausibility’ to unintelligible user statements. To do so, we work from Frege’s (1892) distinction between reference and sense. We apply Beth’s (1955) tableau analytics to prove a statement is false, yet keep the robot from telling its user wrong by introducing an intensional operator under Grice’s (1975) Maxim of Quality. We end with Hoorn’s (2012) knowledge theory that can make sense of fictitious, imaginative, and possible worlds to update the robot’s ontology about its user again. Like this, we hope the robot might one day reply to its illogical user that speaks with rhetorical tropes: “I understand what you try to say.”

2. Reflexive, Reflective

The limbic system plays a pivotal role in the first assessment of the situation an organism is in. It specializes in unconscious, reflexive responses to react fast to, in particular, threatening situations. The limbic system takes things at face value. If a twig on the ground looks like a snake it will respond to it as if it were a snake from a heuristic of ‘better safe than sorry.’ Because social interaction is crucial to survival for humans, recognition of facial expressions (angry, sad, happy) also goes through the limbic system first.

In their Experiment 1, Appel and Richter (2010) found that with high need for affect, people are transported easily into a story that is relevant to their beliefs so that the fictional narrative actually becomes influential for those believes. If people are lonely and the robot is framed as a companion, a lover, a grandchild, or something else that is relevant to the user’s believes, people easily go along with the doll play and their beliefs are impacted by their play act. Make-believe impacts beliefs about reality (Appel & Richter, 2010).

Konijn and Hoorn (2016; 2017) explain that emotions lend “realness” to the object of emotion such as a robot, signaling the user that something of “real” importance is going on. The observer interprets his or her personal physiological change as proof of reality and it influences the perception of the object that evokes the emotion. When the affordances of a robot, the things you can do with it, are relevant to user objectives, the evoked emotions
‘prove’ to the limbic system that the robot has genuine traits (‘It likes me!’), even if this is manifestly not so programmed.

However, this hardwired reflexive response does not stand on its own because it may be fast but it is not too accurate. The snake may be just a twig, the smile of the alpha male does not mean happiness but frustration, and a robot does not have feelings. Therefore, the reflexive and affect-oriented limbic system is kept in check by a more cognitive-reflective thinking mode to keep the affective assessment from making critical mistakes.

The neocortex has several problem-solving strategies in store that are more sophisticated than merely attack, embrace, flee, or sit still. It may rely on intelligence to reason logically from the givens to a conclusion: Snakes are not of wood. The twig consists of wood. Therefore, the twig is not a snake. Its solution may come from creativity when information is scarce and problems are underdetermined (Figure 1): To ward off my enemies, I make a snake from this twig. Although affective and reflective processes run in parallel, sometimes the reflective mode is strongly suppressed when something is acute (e.g., a car accident), when in fear (e.g., during a robbery), or in joy (e.g., when being love-struck).

3. Signal Detection

Taking a twig for a snake is an example of a ‘false alarm’ or ‘false positive’ in signal-detection theory. Likewise, the statement ‘that man behaves like a robot’ also is a false alarm, expressed in a simile. Under emotional circumstances, the signal-to-noise ratio deteriorates (Figure 2). Signal in our case is the difference between a human and a robot, the noise being the variability in robots and humans showing resemblance (e.g., in appearance or intelligence).

Detection theory looks into the difference between the response distribution to something exceptional (the signal: a snake, robot) relative to the response distribution to everything normal (the noise: a twig, human beings). This difference often is expressed as the distance \( d' \) between the top of the two normal distributions of internal responses for, in the case of the human as robot, “Human” (the noise) and “Robot” (the signal plus noise). Distance \( d' \) is estimated with the standardized difference (\( z \)-scores) between the right-tail probabilities \( p \) on the normal distributions, where

\[
d' = z_{\text{false alarms}} - z_{\text{hits}} = \frac{p - M}{SD}
\]

Index \( d' \) indicates personal sensitivity to the difference between, in our case, robots and humans (Figure 2). Higher values for \( d' \) mean more sensitivity to the difference and less overlap between the distributions. There is better stimulus discrimination. Thus, the more signals (cues to a robot) amount on top of the noise (everything is human), the more the distribution for “Robot” moves to the right and distance \( d' \) increases (you see better it is a robot).

In a cognitive reflective mode, which is slower and more accurate, people are more critical to detail so that sensitivity to the difference is higher (\( d' \) increases). In reflective mode, people evaluate whether the signal-noise ratio is large enough to conclude that the difference (distance \( d' \) ) is not due to chance. In their minds, hypothesis H1 states that robots differ from humans whereas H0 says that what you see is mere variability in humans and that you cannot tell that there is a robot around (cf. Turing Test). There should be enough cues to a robot to decide for “robot” and not for just another human being (perhaps someone with dyspraxia).
In signal detection, the null hypothesis stands for true negatives: There is no signal; there is nothing at hand (Figure 2).

In reflective mode, people maintain a conventional level of confidence that their observations are correct. They may say that ‘It is not so that humans and robots do not differ (reject H0) but I might be wrong about it.’ Put differently, they may say that ‘Humans and robots do differ (accept H1) and I am for 95% sure of it’ (so the probability they are wrong is about 5%, $p < .05$). If people cannot reject the H0, the agency is just another human being. The alternative explanation is that the observer cannot prove that this one agency actually is a robot, for instance, because it has passed the Turing Test (Hoorn, Konijn, & Pontier, 2018).

![Signal-detection account for observing a robot. Emotions make the distributions overlap more.](image)

**Figure 2.** Signal-detection account for observing a robot. Emotions make the distributions overlap more.

In an affective reflexive mode, which is fast and imprecise, sensitivity $d'$ decreases (Figure 2). Distinctions are not that clear any more, the two distributions grow together, they ‘blur,’ and mistakes occur in the overlapping area.

People sometimes fear the introduction of robots for dehumanizing care or expected job loss. Although the data fearful people perceive may suggest otherwise, from a concept-driven perspective they see the influence of robots everywhere: People may fear that robots are taking over and that Artificial Intelligence (AI) will outsmart us all, that ‘AI is our biggest existential threat’ (Elon Musk in Cellan-Jones, 2014, January 2). When in fear, people tend to make Type I errors (Figure 2), rejecting H0 when in fact they sound a false alarm: There is no signal, no cue to a robot around.
When in fear, people’s heuristic is to be better safe than sorry and look for confirmation of their (perhaps illusory) ideas. They are convinced of their right and look for conceptual confirmation of beliefs, accepting any cue that hinges on robot presence. Because their confidence is high, criterion in Figure 2 shifts left, (e.g., $p < .1$ as measured from the right tail). This means that people in fear do not care too much about counter-evidence and are eager to accept the H1 (and reject the H0). They focus on abnormality. Strange things are happening! Which increases Type I errors.

Reversely, people sometimes welcome the introduction of robots for easing their loneliness or for doing household chores. When in joy, people easily make Type II errors, willing to accept the H0 (no signal) when in fact there is something the matter. There may be cues that indicate the presence of something robotic. However, because the robot fulfills a need and its functions are relevant to personal concerns, the user happily ignores the robotic side of the helper and feels the robot is like a human friend (cf. Computers Are Social Actors theory, Nass & Moon, 2000).

Because in joy, people are more relaxed, accepting, and open to explore, they do not exclude new information from known categories so quickly but are willing to change their ideas and accept new category members although those may be peripheral, not prototypical. When joyful, people care less about the soundness of their beliefs but focus on the experience itself that makes them happy. Therefore, criterion in Figure 2 shifts right, (e.g., $p < .0001$ as measured from the right tail). This means that people in a positive mood focus on sameness and togetherness rather than difference and alienation. They are not eager to accept the H1 (therefore, $p < .0001$) but desire the H0 to be true: Humans treat robots as if they were other humans (cf. Media Equation). There is nothing strange to loving a robot, which increases Type II errors.

In all, when the intensity of negative emotions is high, beliefs are willingly confirmed, and people tend to make Type I errors or call out for ‘false alarms.’ They do not look into the data but project their conceptualizations onto the world. What the majority thinks reality is about, fearful people say is all a fiction (Figure 2). When positive emotions are dominant, it does not matter that the robot disconfirms beliefs because it fulfills a relevant need. People tend to make Type II errors or allow ‘misses’ because they pay no attention or lack the sensitivity to detect the distinction, taking fiction for real (Figure 2). Obviously, however, what is real, not real, true or false all depends on one’s conception of ‘reality.’ This issue we will address in the section entitled Epistemics of the Virtual.

4. **Result: Logical Fallacies and Rhetorical Tropes**

Although false alarms may arise from negative emotions and signal misses from positive ones, the limbic system still is into contact with the neocortex and is reflected upon. As said, there are two main streams of problem-solving strategies of a reflective kind: logical reasoning or ‘intelligence’ and associative combination-making or ‘creativity.’

4.1 **Ex-consequentia**

When fear causes false alarms that are addressed through logics, *ex-consequentia* reasoning may ensue (Figure 1). The problem with an *ex-consequentia* fallacy is that it draws a conclusion by affirming the consequent:
If A then B
B
Then A

People tend, for example, to infer external threats from internal psychological states. They believe: “If I feel anxious, there must be danger” (Engelhard & Arntz, 2005):

If there is danger, I feel anxious
I feel anxious
Therefore, there must be danger

More specifically:

If AI is dangerous, I fear it
I fear AI
Therefore, AI must be dangerous

When a robot falls of a table, is dropped, or is maltreated by its user, people tend to feel sorry for the machine (Konijn & Hoorn, 2016):

If an agency has pain, it says ‘ouch’
Robot says ‘ouch’
Therefore, the robot is in pain

Personal feelings and individual impressions often are used as signals to infer intrinsically ‘real’ psychological states, also in virtual others. Konijn, Walma van der Molen, and Van Nes (2009) found that viewers assumed genuine emotional states in soap characters because the viewers themselves were moved by the scene: “If I feel, it must be real.” Translating this finding into ex-consequentia format:

If I see real emotions, I feel them too (empathy)
I feel emotions
Then the emotions I see must be real (misplaced empathy)

That ex-consequentia is a fallacy is shown by raising counter-examples. With respect to the fear of AI, for instance, it may be that AI is not dangerous but that bad people are misusing it (i.e. people misuse other tools as well). The fear may not be induced by AI itself but by dystopic misrepresentations in Hollywood media fare. It may be that the fear is not induced by the AI but that AI is misinterpreted as its source.

Ex-consequentia may follow from false alarms, trying to infer the cause from the effect. For example, you blow your nose, so you have a cold (false alarm). You sound synthetic so you must be a robot (but it was Stephen Hawking, Cellan-Jones, 2014, January 2). Fear may lead to false alarms and ex-consequentia rhetoric.

4.2 Fp-type metaphor

When false alarms are used creatively, metaphors of the form ‘Juliet is the sun’ occur, which, for lack of better words, we name an Fp-type of rhetorical trope after ‘false positive.’ To
understand a metaphor or simile such as ‘Juliet is the sun’ or ‘This man is like a robot,’ we should look into Frege’s (1892) distinction between reference and sense.

The reference of a word is to something existing in the real world (according to the observer’s beliefs). The ‘sense’ of the word is its presentation form. The famous example is that the second planet from the sun may be called ‘Venus’ as well as ‘the morning star’ and ‘the evening star’ (although it is not a star at all). All three expressions are synonyms for that one particular planet. The ‘sense’ of a word emphasizes a particular aspect of the entity it refers to, conjuring up an image, a ‘mock thought’ or ‘Scheingedanke’ about that entity.

With ‘Juliet is the sun,’ something similar happens. Presupposing that the proper name refers to a girl (that once lived), ‘sun’ is the image, the ‘mock thought’ that highlights an aspect of the girl that the speaker admires (e.g., Juliet is bright). Juliet (supposedly) has reference to an entity, whereas with regard to the features of that entity, ‘sun’ has sense alone. In the case of an Fp-type of metaphor or simile (This man acts like a robot), the topic or focus of the comparison coincides with the reference (a specific man), while the imaginative part coincides with the sense (inflexible person):² The noise is supplemented by a fake signal (Figure 2).

4.3 Inverse error

Apart from false alarms that come out of fear, misses may occur as well, perhaps because a person was overwhelmed by joy. A logical fallacy that likely may arise from missed signals is the fallacy of the inverse (Figure 1). The fallacy of the inverse or inverse error denies the antecedent while inferring the inverse from its original statement:

If A then B
Not A
Then not B

For example:

If I see machine-like features, the agency is a robot
I do not see any machine-like features (missing the signal)
Then the agency is not a robot

To its conclusion, one can raise counter examples to show that an inference is a fallacy: The robot has autonomous systems that simulate human behavior very well. There may be an operator in the background that handles the machine. Forwarding counter-examples shows that there is a need for an ontology or knowledge base to draw the examples from. We will return to this issue later in the section Reference - sense.

4.4 Fn-type metaphor

When missed signals are used creatively, metaphors transpire such as ‘Venus is a planet’ and ‘Robots are human too.’ These we will call Fn-type of tropes after ‘false negative.’ Different

² In metaphor theory, many names address the same thing: Dependent on the theory, ‘topic’ may be called ‘primum comparandum,’ ‘principal subject,’ or ‘tenor’ and the imagery is sometimes called ‘secundum comparandum,’ ‘secondary subject,’ ‘marginal meaning,’ or ‘vehicle,’ etc.
from Fp-type, Fn-type of expressions focus on the word that carries sense alone as the topic (Venus, robot) and compare that to the word that has reference to the observer’s conception of reality (planet, human beings): The missed signal is filled up with noise (Figure 2).

5. Fundamental Attribution Errors

In the previous, we discussed four expressions that are non-literal and false, two coming from detection faults combined with flawed reasoning (ex-consequentia and inverse error) and two from creativity (Fp- and Fn-type metaphors). In this section, we argue that these four allow for fundamental attribution errors that people make with respect to their fellow humans as well as to robots, avatars, and autonomous AI.

Suppose a user is treated courteously by her robot. The user is delighted by the well-mannered robot and tends to attribute the robot’s behavior to its ‘personality,’ like people do to other people. She may believe the robot really likes her and has a friendly character. That user does not think that the robot merely follows protocol, implemented by a skilled programmer, and that it knows politeness nor friendliness. When the robot does not look at her during conversation, that user will not think the robot runs out of power, has a broken camera eye, or that the video overheated its CPU. It is just that the robot ‘does not feel like it today.’

If someone points out to that user that s/he makes a mistake, s/he will likely excuse him or herself by saying s/he never had any education, s/he was distracted by the TV, or that the retailer suggested it had advanced AI inside. Hardly ever will a user admit s/he does not have a clue and lacks the knowledge or even the intelligence to understand what a robot is about. People tend to believe that what the robot does reveals what goes on inside while ignoring external factors that explain its behaviors (such as a person that has the machine in remote control). This is what social psychologists call a ‘fundamental attribution error’ (Ross, 1977), inferring internal qualities from external cues.

Fundamental attribution errors are related to signal detection in that misses and false alarms both facilitate their occurrence albeit of a different kind. Imagine a user in a Turing Test with an avatar on screen, half the trials of which are handled by a human being and the other half by an AI. On certain trials, participants are sitting across a human being although they think they interact with the AI (false alarm, it is a confederate). However, all scripts and schemas of computers and machines become active. In that situation, the participant attributes internal robot qualities (rigid, cold) to the human confederate as based on the external performance of the avatar. In other words, false alarms to robot cues lead to fundamental attribution errors derived from the (non-social) schemas of machines. That the user makes such mistakes is likely denied. They may seek the cause in the drop-down menus of the interface, which avoided human emotional behavior of the confederate to come to full expression.

On other trials during that Turing Test, participants sit across an AI but believe they interact with a human being (miss, it is an AI). All scripts and schemas for human interaction remain active (cf. Nass & Moon, 2000). Thus, the participant attributes human qualities to that robot (kind, warm) as based on the external performance of the avatar. Missing the cues to a robot leads to fundamental attribution errors drawn from human social schemas and templates. Users will likely believe they are excused for their mistakes, for example, because no one told them when they would talk to a machine or not (which is the very idea of a Turing Test).
6. Anthropomorphism, Robotomorphism

Humans are inclined to attribute human emotions to animals in order to understand their behavior (Darwin, 1875/2002). This tendency to project human characteristics to living as well as non-living, virtual as well as real entities is called anthropomorphism (Anzalone, Boucenna, Ivaldi, & Chetouani, 2015).

According to Epley, Waytz, Akalis, and Cacioppo (2008) and Epley, Waytz, and Cacioppo (2007), anthropomorphism is a means to make inferences about an unknown entity by applying knowledge from known agencies. In our terms, the missed signal is filled up with noise. To do so, people should have the motivation (e.g., have fun), have a need (cf. loneliness), or the unknown entity should show certain similarities (cf. humanoids).

People attribute internal human qualities to other humans as based on external behaviors of the other, which we call a fundamental attribution error. When people attribute internal human qualities to objects, concepts, or non-human agencies (real or virtual) as based on the external behaviors of those entities, then we have a fundamental attribution error coming from poor signal detection, particularly missing the cue to non-humanness, leaving the schemas of human social behavior intact. This we call an anthropomorphism, which is a specific fundamental attribution error as it applies to non-human entities and is based on missing (perhaps deliberately ignored) signals to non-humanness.

When based on false alarms, schemas of machine behaviors become active (possibly internalized from film and other media fare) and ‘the other humans’ are alienated by assuming internal non-human, non-social, mechanisms and automated behaviors in them (cf. bureaucrats and technocrats). This we may coin ‘robotomorphism.’

Taken in unison, false alarms regarding cues to robots produce ex-consequentia fallacies and Fp-type of metaphors that activate behavioral schemas and scripts reminiscent of machinery that then are attributed falsely to humans: robotomorphism (Figure 1). Missed cues to robots produce inverse errors and Fn-type of metaphors so that current human behavioral scripts are not deactivated, which then are attributed falsely to robots: anthropomorphism (Figure 1).

7. How to Tell a Robot: A Four-pronged Approach

Robots are systems that basically run on logics. Humans run on psycho-logics. Human instructions, then, should one way or the other be brought back to logical statements for a robot to be executable. This is why people invented programming languages (i.e. Fortran) and graphical interfaces (‘click’) but during natural-language interactions between humans and robots, it may not work that way. How should a robot deal with emotionally aroused users that make logical mistakes or use rhetorical tropes such as metaphors and similes? Should the robot tell its user wrong all the time? Add to the anger? Spoil the joy?

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3 Robot developers tend to design robots after humans (‘humanoids’) from the presumption that people like them better and treat them better that way (cf. Złotowski, Proudfoot, Yogeeswaran, & Bartneck, 2015). For instance, human-like robots were punished less and praised more than robots that were less human-like (Bartneck, Reichenbach, & Carpenter, 2006). Human-likeness does not just pertain to outer appearance but also to the robot’s autonomy, communication, (emotional) behavior, intelligence, and predictability (Zlotowski et al., 2015).
One moral demand is that a social robot ought to tell the truth (deontics). That means that the
robot should point out mistakes to its user. Then again, a communication demand is that the
robot is polite and tactful. Sometimes, these demands are at odds. Internally, a robot needs
logical language to execute its tasks but attribution errors are often based on logically invalid
reasoning and detection wrongs. How to avoid that the user becomes lectured by its robot as
Doctor McCoy was by Mr. Spock: “I find your arguments strewn with gaping defects in
logic” (*Star Trek II: Wrath of Khan*).

We propose four measures for a robot to deal with logical fallacies and figures of speech. For
its ontology, it needs to discern reference from sense (Frege, 1892) (Section Reference -sense).
To prove an argument is false, it may apply tableau reasoning (Beth, 1955) (Section Tableau
reasoning). To keep the robot from responding ‘error’ and to suspend its disbelieve,
it should assess its user’s non-literal and false utterances under an intensional operator that is
authorized by Grice’s (1975) Maxim of Quality (see the section Maxim of Quality). To deal
with the imaginative world, mock thought, or ‘Scheingedanke’ conjured up by the user’s
fallacies and tropes, the robot should run two times an ‘Epistemics of the Virtual’ (Hoorn,
2012), once for its user and once for itself (see the section Epistemics of the Virtual).

### 7.1 Reference – sense

Philosophically, an ontology is the study of what is and is not in the world, what entities exist
(God, Martians, dark matter), what not, and what categories they are a member of. Each
ontology is observer-dependent. Translated into a computer system, an ontology is a formal
knowledge base, representing entities (objects, concepts) and their relationships that describe
some part of reality (e.g., the user’s family). With an ontology installed, the robot can make
inferences about the composition of that domain, for example, if A is the child of a man’s
sister, he must be A’s uncle.

For a robot to grasp the semantics of fallacies and rhetorical tropes, the ontology it works
with should be structured in categories (e.g., animals), exemplars (e.g., snakes), and features
(e.g., head, long, tail, no legs). As soon as a category mismatch happens (Juliet is an
exemplar in human beings but star is not), the robot knows that one of the terms has reference
(within category) and that the other probably has sense alone (out of category). This way, the
robot knows it is dealing with a non-literal utterance.

However, ontologies are observer-dependent. The robot’s ontology \(O_R\) is just one of two
ontologies that are matched against each other. The other is the ontology of the human \(O_H\),
which may differ from that of the robot. For instance, the robot may hold numbers for
physical features of objects, whereas the human classifies them under ideas. Or the human
classifies ‘robots’ under the category of human beings whereas the robot does not. The robot
may believe that ghosts do not exist ‘but my user does.’ Like this, the robot can work with
more perspectives or world views. Thus, each item in the ontology has a probability attached
that indicates the strength of belief that the agency thinks something is true. Thus, the robot
holds one ontology \(O_R\) for itself, containing the things the robot believes in and it holds one
ontology \(O_H\) for its user, containing the things the robot believes that the user believes in.
Like this, the robot has ‘theory of mind.’
Next, the robot determines whether it deals with a fallacy and for the robot to analyze whether the user went wrong, it may use tableau reasoning. Tableau reasoning is a predicate logic to (dis)prove a conclusion based on the ontology or knowledge base of an individual (Beth, 1955; 1956). The aim of tableau analysis is to prove that statements imply other statements (implications) in view of the rules of meaning of the statements’ connectives or quantifiers in first-order logic.

Through tableau reasoning, the analyst proves a statement by refutation of the contrary (i.e. for A to be true, not-A must be false). For every single statement, then, the possibilities of alternative truths are tested, trying to prove the falsehood of the implications (i.e. the negation of the ensuing statements). The semantics of the ontology may be, for example, that the category of human beings has Juliet as an exemplar but not robots. There also is a certain belief attached to each entity in the ontology. Certain entities are more probable (e.g., human beings have hands) than other (e.g., human beings have purple spots). The semantics of that ontology then transforms the list of alternative truths into a tree of simpler statements so to find a contradiction for each branch. To arrive at the simpler statements, reasoning rules apply (Figure 3). If contradictions are found between branches, it may be concluded that the original statements and the negation of their implications cannot be true all at once so that it follows that the original statement indeed implies its conclusions.

| Splitting rules (∨) | Non-splitting rules |
|---------------------|---------------------|
| rule 1              | rule 5              |
| X ∨ Y               | ¬(X ∧ Y)            |
| ¬X ¬Y               | X → Y               |
| X ↔ Y               | X ∧ Y               |
| ¬(X ∨ Y)            | ¬(X → Y)            |
| ¬¬X ¬¬Y             | ¬¬X ¬¬Y             |
| ¬¬X ¬¬Y             | ¬¬X ¬¬Y             |

Figure 3. Rules of tableau analytics.

Underlying a user’s statement is a certain belief in $O_H$ of which the statement is a logical consequence. The robot tests if the statement as logical consequence of the user’s beliefs is true given the information in the ontology $O_H$. In making use of the rules in Figure 3, the robot then divides the logical formula that contains that knowledge into different components with their logical consequences. Each logical sequence is transformed into an NNF (negation normal form) in which a negation sign is placed in front of the statement under scrutiny. This is done to check if all the components from $O_H$ are in contradiction with all the components of the logical sequence. When all sub-components of $O_H$ and the logical consequence are in contradiction, the robot regards the logical consequence as proven true.

Next, we illustrate the procedure with an example. It is an ex-consequentia reasoning structure, coming from a false alarm in detection (Figure 1). Suppose the user says: “I feel
anxious, so there must be danger” (Engelhard & Arntz, 2005). Translated into logics, the robot holds that:

\[ a = \text{anxiety} \]
\[ d = \text{danger} \]

\[ \text{anxiety} \rightarrow \text{danger} \]

From the \( O_H \) that the robot also keeps, the robot knows that the user knows that the reverse is true as well: Being in danger causes anxiety.

\[ \text{danger} \rightarrow \text{anxiety} \]

Based on \( O_H \), the epistemic logics of the robot is that this human knows that danger causes anxiety but that the user inversed that relationship. Let:

\[ B = \text{Believes} \]
\[ K = \text{Knows} \]
\[ O = \text{Ontology ('knowledge base')} \]
\[ R = \text{Robot} \]
\[ H = \text{Human} \]

and let \( O_R \) contain:

\[ B(R) \supseteq B(H(\text{danger})) \rightarrow K(H(\text{anxiety})) \quad (1) \]

Equation (1) is the world view that the robot holds as ‘standard,’ the one most agencies in its community share. From the user’s statement, however, the robot observes that this human also seems to believe that anxiety is causing danger:

\[ B(R) \supseteq K(H(\text{anxiety})) \rightarrow B(H(\text{danger})) \quad (2) \]

Statement (2) seems a deviant thought compared to (1) and may now be tested through tableau analytics.

The robot works from \( O_R \) and starts out from assuming its truth. The logical consequence of (2) contains the ontology from the current \( O_H \); it is a new ‘hypothesis’ of which the robot is unsure about its truth. With the rules of tableau reasoning installed (Figure 3) (Beth, 1955; 1956), the robot may try to solve the \textit{ex-consequentia} fallacy the user apparently makes in (2).

**Logical consequences**

\[ (O_R) \quad B(R) \supseteq B(H(\text{danger})) \rightarrow K(H(\text{anxiety})) \quad X \rightarrow Y \quad r3 \]

\[ \neg B(R) \lor (B(H(d)) \rightarrow K(H(a))) \quad \neg X \lor Y \]

\[ \neg B(R) \lor (\neg B(H(d)) \lor K(H(a))) \quad \neg X \lor (\neg y_1 \lor y_2) \]

\[ (O_H) \quad B(R) \supseteq K(H(\text{anxiety})) \rightarrow B(H(\text{danger})) \quad X \rightarrow Y \quad r3 \]
\[-B(R) \lor K(H(a) \rightarrow B(H(d))) \quad \neg X \lor Y\]
\[-B(R) \lor (\neg K(H(a)) \lor B(H(d))) \quad \neg X \lor (\neg y_2 \lor y_1)\]
\[-(\neg B(R) \lor (\neg K(H(a)) \lor B(H(d)))) \quad \text{NNF} \quad (\neg X \lor (\neg y_2 \lor y_1))\]

Proving or disproving the consequence

\((O_R)\)

1. \(-B(R) \lor (\neg B(H(d)) \lor K(H(a)))\) from 1 \(-B(R)\)
2. \(-B(H(d)) \lor K(H(a))\) from 3 \(-B(H(d))\)
3. \(-B(R) \lor (\neg B(H(d)) \lor K(H(a)))\) from 1 \(-B(R)\)
4. \(-B(R) \lor (\neg B(H(d)) \lor K(H(a)))\) from 1 \(-B(R)\)
5. \(-B(R) \lor (\neg B(H(d)) \lor K(H(a)))\) from 1 \(-B(R)\)
6. \(-B(R) \lor (\neg B(H(d)) \lor K(H(a)))\) from 1 \(-B(R)\)
7. \(-B(R) \lor (\neg B(H(d)) \lor K(H(a)))\) from 1 \(-B(R)\)
8. \(-B(R) \lor (\neg B(H(d)) \lor K(H(a)))\) from 1 \(-B(R)\)
9. \(-B(R) \lor (\neg B(H(d)) \lor K(H(a)))\) from 1 \(-B(R)\)
10. \(-B(R) \lor (\neg B(H(d)) \lor K(H(a)))\) from 1 \(-B(R)\)

Note: ‘No contradiction’ is proof of fallacy

\(\neg B(R) \lor (\neg B(H(d)) \lor K(H(a)))\)

\(-B(R)\)

\(-B(H(d))\)

\(K(H(a))\)

\(\neg B(H(d))\)

Figure 4. Tableau analysis of an ex-consequentia fallacy \((T = \text{true}, F = \text{false})\).
Because through tableau analysis (Figure 4), the robot does not find a contradiction in all cases, it cannot conclude that (2) $B(R) \supseteq K(H(\text{anxiety})) \rightarrow B(H(\text{danger}))$ is true based on (1) $B(R) \supseteq B(H(\text{danger})) \rightarrow H(\text{anxiety})$. The robot has not found proof to accept the human statement and knows that the human drew an incorrect conclusion (i.e. *ex-consequentia*). In conventional systems, an error message would be outputted (ID10T).

With respect to the *inverse error*:

If A then B
Not A
Then not B.

If ‘cues to machine’ then agency is a robot
No cues to machine detected (miss)
Then agency not a robot

Let in the same ontology $O_R$ as before:

$A = \text{Agency}$
$cm = \text{cues to machine}$

Then,

Logical consequences apply

\[
(O_R) \quad B(R) \supseteq B(H(\text{cues_to_machine})) \rightarrow B(H(\text{Agency=Robot})) \quad X \rightarrow Y \quad r3
\]

\[
\neg B(R) \lor (B(H(cm)) \rightarrow B(H(A=R))) \quad \neg X \lor Y \quad r3
\]

\[
\neg B(R) \lor (\neg B(H(cm)) \lor B(H(A=R))) \quad \neg X \lor (\neg y_1 \lor y_2)
\]

Given its ontology $O_R$, the robot now tests whether it believes it is true that ‘when a human does not believe that there are cues to a machine, an agency is not a robot’ (Figure 5).

\[
(O_{R1}) \quad B(R) \supseteq \neg B(H(cm)) \rightarrow \neg B(H(A=R))) \quad X \rightarrow Y \quad r3
\]

\[
\neg B(R) \lor (\neg B(H(cm)) \rightarrow \neg B(H(A=R))) \quad \neg X \lor (\neg y_1 \rightarrow \neg y_2) \quad r3
\]

\[
\neg B(R) \lor (B(H(cm)) \lor \neg B(H(A=R))) \quad \neg X \lor (y_1 \lor \neg y_2)
\]

\[
\neg (\neg B(R) \lor (B(H(cm)) \lor \neg B(H(A=R)))) \quad \text{NNF} \quad \neg (\neg X \lor (y_1 \lor \neg y_2))
\]

\[
\neg (B(R) \lor \neg (B(H(cm)) \lor \neg B(H(A=R)))) \quad X \lor \neg (y_1 \lor \neg y_2)
\]

\[
\neg (B(R) \lor \neg B(H(cm)) \lor B(H(A=R))) \quad X \lor \neg y_1 \lor y_2
\]

Proving or disproving the consequence

\[
(O_R)
\]
1 \( \neg B(R) \lor (\neg B(H(cm)) \lor B(H(A=R))) \) \( \neg X \lor (\neg y_1 \lor y_2) \) \( r_1 \)

2\(\alpha\) from 1 \( \neg B(R) \) \( \neg X \)

3 \( \neg B(H(cm)) \lor B(H(A=R)) \) \( \neg y_1 \lor y_2 \) \( r_1 \)

4\(\alpha\) from 3 \( \neg B(H(cm)) \) \( \neg y_1 \)

5\(\alpha\) from 3 \( B(H(A=R)) \) \( y_2 \)

\((O_H)\)

6 \( B(R) \lor (\neg B(H(cm)) \lor B(H(A=R))) \) \( X \lor (\neg y_1 \lor y_2) \) \( r_1 \)

7\(\beta\) from 6 \( B(R) \) Contradiction with 2\(\alpha\) \( X \)

8 \( \neg B(H(cm)) \lor B(H(A=R)) \) \( \neg y_1 \lor y_2 \) \( r_1 \)

9\(\beta\) from 8 \( \neg B(H(cm)) \) No contradiction with 5\(\alpha\) \( \neg y_1 \)

10\(\beta\) from 8 \( B(H(A=R)) \) No contradiction with 4\(\alpha\) \( y_2 \)

Note: ‘No contradiction’
is proof of fallacy

\[\neg B(R) \lor (\neg B(H(cm)) \lor B(H(A=R)))\]

\[\neg B(H(cm))\] \[\neg B(R)\] \[\neg B(H(cm)) \lor B(H(A=R))\] \[B(H(A=R))\]

[2\(\alpha\)] [4\(\alpha\) from 3] [5\(\alpha\) from 3]

[7\(\beta\) from 6] [9\(\beta\) from 8] [10\(\beta\) from 8]

\(T\) \(F\)

\(F\)

Figure 5. Tableau analysis of an inverse error \((T = \text{true}, F = \text{false})\).

### 7.3 Maxim of Quality

As demonstrated in the above, humans use logical fallacies in their communication. Grice (1975) formulated a number of conversational maxims of which the Maxim of Quality is most useful to our purposes. Maxim of Quality approaches the speaker from the assumption that the user intends to speak the truth and provides honest evidence to support his or her statements. In the case of a fallacy, the speaker merely makes an error in the form, not in contents. Strictly speaking, with the Maxim of Quality the robot counters one fallacy with another. Maxim of Quality (MQ) is a fallacy \textit{ad ignorantiam} but pragmatically needed for the robot to ‘maintain the H0’ so that the user is ‘innocent until proven guilty.’ In applying an
With MQ activated, the robot then should check three things with its user. Robot should ask about the danger: “So it’s unsafe you think?” It should check the user’s anxiety: “You’re really anxious, aren’t you?” And it should verify the logical consequence: “Do you believe that your fear indicates a threat?” If all answers are ‘yes,’ the robot now believes \( B(R) \) that the user knows s/he is anxious \( K(H(a)) \) and that the user believes there is danger \( B(H(d)) \).

However, we suggest that after proving fallacy, the robot should not output an error message. Instead, the robot’s uncertainty whether the human really means that anxiety causes danger may be expressed under MQ as a special instantiation of the ‘possibly true’ operator \( \Diamond \) in intensional logics:

\[
B(R) \supset \Diamond_{MQ}(K(H(a)) \rightarrow B(H(d)))
\]

The robot then may update its knowledge about the user \( O_H \) such that:

If user senses anxiety \( B \)
And if \( B \) then \( A \) is necessarily \( \Box \) false to robot \( (false = F) \)
And Maxim of Quality \( (MQ) \) is possibly true
Then \( A \) (danger) is possibly true to user

\[
B(R) \supset \Box(B(H(d)) \rightarrow K(H(a))) \land \\
B(R) \supset \Diamond_{MQ}((K(H(a)) \rightarrow B(H(d))) \rightarrow \Diamond_{MQ}(B(H(d))))
\]

The fallacy fail-safe formula with epistemics and modalities in (4) says that robot believes it is necessary true that if user believes there is danger, then user senses (knows) s/he is anxious and robot also believes that possibly user is truthful if user knows s/he is anxious and wrongfully \( (F) \) infers danger from it, so that possibly the user believes there is danger.

The fallacy fail-safe formula also works for inverse error:

\[
\bar{B}(R) \supset \Diamond_{MQ}(-B(H(cm)) \rightarrow \neg B(H(A=R)))
\]

If user believes that there are no cues to a machine in some agency \( \neg A \)
And if \( \neg A \) then \( \neg B \) is necessarily \( \Box \) false to the robot
And Maxim of Quality is possibly true
Then \( \neg B \) (agency is no robot) is possibly true to user

\[
\bar{B}(R) \supset \Box(K(H(cm)) \rightarrow B(H(A=R))) \land \\
\bar{B}(R) \supset \Diamond_{MQ}((-B(H(cm)) \rightarrow \neg B(H(A=R))) \rightarrow \Diamond_{MQ}(\neg B(H(A=R)))
\]

With (6), the robot believes it is necessary true that if user knows there are cues to a machine in some agency, then the user believes the agency is a robot. Robot also believes that possibly user is truthful if user states s/he does not see cues to a machine and wrongfully infers the agency cannot be a robot. Thus, if the user believes there are no cues to a machine, then it is possible that the user believes that the agency is not a robot (and treats it as a human being).
7.4 Epistemics of the Virtual

With the introduction of the $\Diamond_{MQ}$ operator, the robot enters the realm of possibilities rather than applying rules to a known ontology with ‘historic’ information. Put differently, by inserting $\Diamond_{MQ}$, we actually demand from the robot to open up to a fictional or mistaken account of the world (cf. mock thoughts or ‘Scheingedanke’) (Figure 6, right). To understand the ‘sense’ of a message, the robot must assume that under certain conditions in a certain context with certain parameter settings, there are possible worlds in which an utterance may be true.

![Diagram of Reality (R) and Fiction (F)]

*Attribution of truth according to robot’s belief system or world view (e.g., scientific, religious, or cultural)

Figure 6. Epistemics of the Virtual.

In our lab, we develop a software called EpiVir, which is short for Epistemics of the Virtual (Figure 6, Hoorn, 2012). EpiVir is a system that builds up and changes an ontology, according to incoming information. EpiVir acknowledges that it deals with a representation of the physical world, which it calls ‘Reality’ (i.e. its own particular representation of the world). Within that specific Reality, EpiVir attributes a truth value to incoming information in the range [0-1] with possibilities for ‘partial truths’ [0.5, 0.3, etc.]. Truth is attributed to statements or observations, according to beliefs that are relatively stable (e.g., God exists, Martians do not. Superposition exists, quantum foam doesn’t). Truth values are not fixed but can change under the influence of new data. Information does not leave the system but lies at a higher or lower level of activation, depending on the goals and concerns of the agency. This

---

4 https://github.com/robopop/epistemics; https://github.com/robopop/docker/tree/master/epistemics
is how *EpiVir* builds up its database with probabilities on the ontological status of its contents (true, possible, false).

One segment of the database is categorized as Fiction (Figure 6, right). They are the entries in the database that range from [0.5-0], from possible to false. They may refer to motion pictures, theater acts, as well as exaggerations, mistakes, and plain lies. In Frege’s (1892) terms, it is the realm of sense rather than reference.

There is a continuous loop, checking new input against known categories. This is a rough, low-level template check for continuity, whether stored concepts are still in line with sensor data, whether the ontology is still up to date. If information enters that differs too much from the template in terms of signal detection, a validation process becomes more highly activated. This is an effort-intense, precise, and detailed epistemic appraisal of the deviant stimulus. Ontological classification is concept-driven, whereas epistemic appraisal is more data-driven. Both processes run in parallel but one may be at a higher activation level than the other.

From this, a number of assessments is made with respect to the ontological status of the information in the database. Information may be more or less true, is part of fiction or reality, and seems more or less realistic. This way, the system can deal with someone staring out of the window [Reality], saying “It may be true but I can’t believe my eyes” [unrealistic]. Or someone watching a soap series on TV [Fiction], saying “Yes, I know this is not true, but such is life” [realistic].

When the robot encounters a logical fallacy, it initially will place a syllogism such as (2) in the area of ‘false,’ an unrealistic fictitious assessment of reality at the most. By using a fallacy fail-safe formula such as (4), the robot now may move the ‘contained’ fallacy into the area of truth and reality because the robot’s rendition is correct that its user believes the user’s rendition is correct although in the robot world, the user’s rendition is not.

When the robot encounters a metaphor or simile, it should accept a proposition that is not literally true, which means that the robot should be capable of dealing with possible worlds. In Epistemics of the Virtual (Hoorn, 2012), the fiction module is opened through ‘suspension of disbelief’ (cf. ◊MQ), where uncertain propositions are tested for truth through empirical scrutiny (called ‘epistemic appraisal’). Such propositions happen when we say ‘suppose that,’ ‘assume that,’ or ‘imagine a possible world in which…’

A creative proposition such as a metaphor (e.g., a human is a machine) is counterintuitive but not implausible: Owing to topological invariance, a donut can be transformed into a coffee mug (i.e. homeomorphism) (e.g., Hung, 2016). An orange looks like the sun because both are spheres. A chair is a table with part of the tabletop put upright. Gravity can be folded together with acceleration. Because of their disc-like shape, a coin may function as a button on a sleeve. In the same vein do people have all kinds of machine-like qualities such as the autonomous nervous system that automatically runs its programs. There are psychological scripts and social rituals that people follow as if they were programmed to do so. Moreover, humanoid robots look and behave like humans because indeed they are supposed to imitate humans.
A creative proposition comprises a conditional and intensional category attribution error (i.e. a human is not a machine, a girl is not a mermaid) from which an (over)generalization follows (i.e. all humans are machines). In Fiction $\mathcal{F}$, however, such an utterance is considered not necessarily false (Figure 7).

\[
\text{Reality (R) \quad 1 \quad 0}
\]
\text{possibly true}
\text{not necessarily false}

Figure 7. Truth continuum with probabilities of truth as related to reality and fiction judgments.

As a creative proposition, the statement that a simile such as ‘a human is like a robot’ or ‘a robot is like a human’ makes, is:

\[
\text{If it is possible that organisms are not machines and that if there is an organism (e.g., a human) the form of which partly resembles the form of a machine (e.g., a robot) then imagine as if it is not necessarily false that a human belongs to the machines from which follows that organisms can be like machines.} \quad (7)
\]

To formalize (7), let $X$ refer to the category of Organisms and $Y$ to the category of Machines and let $i$ ($t$ and $i$ combined) designate ‘topological invariance’ then (7) can be rewritten like (8) and then generalized to (9). This procedure may be used to keep a robot from responding ‘error’ to a user’s creative utterances:

\[
\text{If } \diamond ((\text{Organisms } \neq \text{ Machines}) \land \{ \exists x \in X \mid i \text{ Human } \approx i \text{ Robot} \}) \rightarrow \text{as if}
\]
\[
\text{(-\Box_{MQ}-(\text{Human } \in \text{ Machines}) \rightarrow (\text{Organisms } \approx \text{ Machines}))} = 1 \quad (8)
\]

\[
\text{If } \diamond ((X \neq Y) \land \{ \exists x \in X \mid i \, x_i \approx i \, y_j \}) \rightarrow \mathcal{F}(-\Box_{MQ}-(x_i \in Y) \rightarrow (X \approx Y)) = 1 \quad (9)
\]

In (9), there are three conditions that underlie the acceptance of a creative proposition:

i) $X \neq Y$, as tested by concepts of reality, beliefs, or world knowledge in EpiVir

ii) $\{ \exists x \in X \mid i \, x_i \approx i \, y_j \}$, which is tested by: ‘Through topological invariance, I can demonstrate that a human is like a robot (or a robot is like a human): For instance, both have arms, legs, etc., and execute scripted behaviors.’

iii) The category-attribution error $x_i \in Y$ and the consequential (over)generalization $X \approx Y$ should be saved from rejection with the $\mathcal{F}$ predicate that indicates as if. The condition before the $\mathcal{F}$ predicate refers to statements about Reality $\mathcal{R}$ with a certain probability of being true (intensional operator $\diamond$). After the $\mathcal{F}$ predicate, an imaginative world is proposed (‘suppose that…’) in which statements have a probability of not ($\neg$) necessarily (intensional operator $\Box_{MQ}$) being false under the Maxim of Quality (also see truth continuum Figure 7).

This is the way the robot may deal with metaphors, similes, and other creative propositions. The $\mathcal{F}$ predicate may be activated by the robot when running into a logical fallacy, category mismatch, recognition of the genre or genre attribution, for instance, when going to the movies, being in a VR environment, or hearing someone’s dreams. The topological similarity of forms provides the opportunity to transgress conventional boundaries between reality and
fiction and make a justifiable category-attribution error. The robot does not tell its user wrong. Instead, the category-attribution error is the impetus to the special metaphor-identification process (Hoorn, 2012, p. 106), which leads the robot to finding similarity in meaning, for example, that both human and robot are associated with agency, intelligence, and autonomy.

The overgeneralization sets up an ontology that contains fictional elements, forming the background against which subsequent utterances can be evaluated. If socially accepted, the overgeneralization may install a field of conventional metaphors (cf. Lakoff & Johnson, 2003). For instance, ‘humans are like robots’ may become generalized to Organisms are Machines.

8. Fail-safe Protocol for Fallacies and Tropes

These are the steps the robot should take when encountering a logical fallacy or a category-attribution error (which occur in metaphors):

I. Run Epistemics of the Virtual (EpiVir) on (OH) and (OR)
II. Observe mismatches between a user statement and the ontology of the user (OH) and/or the ontology of the robot (OR)
III. Apply Maxim of Quality and suspend disbelief (start timer, set duration)
IV. Do tableau reasoning. Can tableau be closed?
   - If yes, no fallacy. Go to VI
   - If no, contain fallacy through (4) or (6). Go to VI
V. Do creative-proposition analysis with (8) and (9)
   - If statement is a category-attribution error, classify as literally false/unrealistic in OR(Ḟ), figuratively true/realistic in OR(Ṙ). Go to VI
   - If not, return error but do not output ‘nonsense.’ Go to VII
VI. Respond you understand, do not tell wrong, close disbelief-suspension timer
VII. Respond you do not understand, do not tell wrong, ask clarification, do not close disbelief-suspension timer

For a robot to produce an analytic tableau or creative-proposition analysis, it should maintain a knowledge base through EpiVir for itself and for its user. It should have fallacy rules in place and know how to apply tableau reasoning. It also needs a logical ontology created from the statements of its user (logical consequence). Grice’s Maxim of Quality functions as an intentional probability operator to account for uncertainty about the user’s statements. Tableau reasoning lets the robot decide if the human conclusions are true. Creative-proposition analysis tells the robot not to take an utterance literally. In its output, the robot may state the truthfulness it attaches to the user’s conclusions but only if the user so requests. If the analyses of fallacies and tropes are correctly programmed, the robot may also state which logical fallacy led to the wrongly stated conclusion or what rhetorical trope the user applied but by default, the robot does not do so (politeness rule).

9. Conclusions/Discussion

A robot should do what a user wants it to although what the user says is not always what s/he intends. Yet, the robot should stay polite and not return an error. We looked into the reasons why users make such mistakes and how they come to use figures of speech.
The root cause lies in the psychophysiological architecture of the brain in which all information runs through the limbic system, which basically responds with actions pertaining to joy (positive) and fear (negative). The neocortex has a more reflective and control function and may modulate the limbic responses through reasoning or solving problems creatively.

Whether in joy or fear but signal detection worsens when humans are emotionally excited. In fear, people are biased to the detection of abnormality; they are quick to see cues to danger, giving rise to many ‘false alarms.’ If the neocortex responds to false positives through reasoning, *ex-consequentia* fallacies emerge. If approached creatively, the ‘False positive’ (Fp) type of metaphor occurs (e.g., ‘Humans are robots’). With an aversion to robots, behavioral schemas and scripts reminiscent of machines are activated and attributed falsely to humans: We coined this phenomenon ‘robotomorphism.’

When in joy, people care less about detecting abnormality; they miss out on cues to apparent robotic presence, leading to many ‘false negatives.’ From a reasoning viewpoint, dealing with false negatives produces *reverse errors*. Dealt with creatively, the ‘False negative’ (Fn) type of metaphor occurs (‘My robot is my human partner’). In both cases, the normal human behavioral scripts are not deactivated, which then are attributed falsely to robots, resulting into anthropomorphism.

In an attempt to let a robot make sense of a user’s logical fallacies and rhetorical tropes, we analyzed how to neutralize *ex-consequentia* reasoning and *reverse errors* and how to handle non-literal utterances such as metaphor and simile. For that, we needed four pieces of theory: Frege’s distinction between reference and sense, Beth’s tableau reasoning, Grice’s communicative Maxim of Quality, and Hoorn’s Epistemics of the Virtual. Frege taught us that a word may be without reference but not without meaning. Beth showed how to proof fallacy of a syllogism while Grice inspired us to formulate the MQ operator to bear with the user’s illogical and non-literal statements. Epistemics of the Virtual made it possible to handle the fiction of possible worlds conjured up by illogical and non-literal communications.

These exercises let us formulate a fallacy fail-safe formula with epistemic and intensional operators as well as a creative-proposition analysis, packed together into a fail-safe protocol for fallacies and tropes, which may lead the way to a more polite handling by the robot of a user’s something unintelligible remarks and commands.

We took a small step into a direction that usually evades logical analysis: Making sense of fallacies and analyzing figurative speech. We realize, however, how small the step is. With our protocol, the robot hopefully is able to handle clear-cut cases of illogical and non-literal utterances but in real life, things usually are more convoluted. Next, we provide two examples of fallacy and metaphor that are so embedded that a robot still cannot make sense of them, we suppose.

We will start from reasoning. What our fallacy fail-safe cannot do yet is to quarantine fallacies that are embedded in locally logic constituents that together are fallacious. Certainly, robots may be able to recognize *modus ponens* (i) and deem the logic form correct:

If A then B
A
Then B
or (ii):

\[
\begin{align*}
\text{If } A & \text{ then } B \\
\text{If } B & \text{ then } C \\
A & \\
\text{Then } C.
\end{align*}
\]

For example:

“The development of full artificial intelligence could spell the end of the human race.”
“It would take off on its own, and re-design itself at an ever increasing rate.”
“Humans, who are limited by slow biological evolution, couldn’t compete, and would be superseded.” (Stephen Hawking in Cellan-Jones, 2014)

Brought back to (ii):

\[
\begin{align*}
\text{If AI is autonomous (A) } & \rightarrow \text{ it will redesign itself (B)} \\
\text{If redesigned (B) } & \rightarrow \text{ humans will be superseded (C)} \\
\text{If superseded (C) } & \rightarrow \text{ the human race will end (D)} \\
\text{If AI is autonomous (A) } & \rightarrow \text{ the human race will be superseded (C) and thus end (D)}
\end{align*}
\]

The fallacy outlined above has an embedded form. The constituents are logically sound but the overall reasoning is not. The elaborate *modus ponens* (ii) is used as a line of argumentation within a larger *ex-consequentia* structure:

\[
\begin{align*}
\text{If there is danger, I feel anxious} \\
\text{I feel anxious about AI (because A } \rightarrow \text{ B, B } \rightarrow \text{ C, C } \rightarrow \text{ D, A } \rightarrow \text{ D)}} \\
\text{Therefore, AI must be dangerous}
\end{align*}
\]

Counter examples against the fear of AI, for instance, may be that AI will not become completely autonomous because humans are not either, that humans may prevent it, that other AI may prevent it, that it is speculative that autonomy leads to self-redesign, that redesign does not necessarily lead to being superseded (perhaps there will be peaceful coexistence and collaboration), that being superseded will end the human race (perhaps we will merely serve but not become extinct, perhaps AI will protect us), and that most of these ideas may come from graphical Sci-Fi horror movies, not from deep knowledge about AI.

The next example is more creative and sketches a scenario in which metaphor is engrained in human conversation and has no simple A is B form. Suppose a little girl is on the plane with a cuddle robot in her arms. The robot has conversational AI and is used as a companion for the long flight and as a monitor for her safety. Right before take-off, the girl says: “Robot, I cannot put on my seat belt.” Robot infers: If seat belt is not fastened, the girl’s safety (goal) is at risk (negative outcome expectancies), she must fasten her seat belt. Then the girl explains: “I have no legs.” Robot internally responds: False. My OR tells me that this girl does have legs. The girl must be mistaken. At this point, the robot does not recognize the implicit metaphor because on the outer surface of the conversation, there is no category-mismatch; it is just the denial of a feature that manifestly is visible in the set.

We saw that in OR, within the larger conception of Reality R, entities that have sense rather than reference fall under the heading of Fiction F (Figure 6, right). In Fiction F, the girl’s
utterance should be taken as an ‘as if’ statement and the robot should have had knowledge that someone without legs cannot put on a seatbelt. Under $\mathcal{O}_{\text{MQ}}$, however, the nearest realistic interpretation to the girl’s hyperbole is that she means she is too small for the seatbelt to fit, which is something the robot cannot guess.

Then the metaphor arises. The girl says: “I am a mermaid.” The robot internally responds: False. My $\mathcal{O}_{R}$ tells me that this agency is a girl. Yet, the metaphor now is manifest at the surface level. While running $\textit{EpiVir}$, the robot keeps the fiction module $\tilde{F}$ active and starts the creative-proposition analysis. It searches for females without legs but should limit its search to this child’s knowledge base ($\mathcal{O}_{h}$). Then the robot should find a fitting item, mermaid, and conclude: She probably means ‘I am like a mermaid’ because in fairy-tales ($\mathcal{O}_{h}(\tilde{F})$) mermaids are girls with no legs, which she equals with her being too small in ($\mathcal{O}_{h}(\tilde{R})$). The robot has searched the child’s ontology to bring yet reference to the sign with sense alone (Figure 1).

With our fail-safe protocol for fallacies and tropes we may have contributed to better human-robot conversation but only for very clear and limited cases. Future research will focus on an implementation of the fail-safe protocol, running simulations, and conduct user tests to hopefully bring us to more advanced iterations of our present work.

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