Commonsense Interpretation of Triangle Behavior

Andrew S. Gordon
Institute for Creative Technologies
University of Southern California
12015 Waterfront Drive
Los Angeles, California 90094 USA
gordon@ict.usc.edu

Abstract

The ability to infer intentions, emotions, and other unobservable psychological states from people's behavior is a hallmark of human social cognition, and an essential capability for future Artificial Intelligence systems. The commonsense theories of psychology and sociology necessary for such inferences have been a focus of logic-based knowledge representation research, but have been difficult to employ in robust automated reasoning architectures. In this paper we model behavior interpretation as a process of logical abduction, where the reasoning task is to identify the most probable set of assumptions that logically entail the observable behavior of others, given commonsense theories of psychology and sociology. We evaluate our approach using Triangle-COPA, a benchmark suite of 100 challenge problems based on an early social psychology experiment by Fritz Heider and Marianne Simmel. Commonsense knowledge of actions, social relationships, intentions, and emotions are encoded as defeasible axioms in first-order logic. We identify sets of assumptions that logically entail observed behaviors by backchaining with these axioms to a given depth, and order these sets by their joint probability assuming conditional independence. Our approach solves almost all (91) of the 100 questions in Triangle-COPA, and demonstrates a promising approach to robust behavior interpretation that integrates both logical and probabilistic reasoning.

Introduction

In an early study of human social perception, psychologists Fritz Heider and Marianne Simmel (1944) presented subjects with a short animated film depicting the movements of two triangles and a circle in and around a box with a hinged opening. Asked what they saw in the film, subjects each responded with similar narratives that anthropomorphized the moving shapes as intentional characters with beliefs, goals, emotions, and social relationships. The simplicity of the film was in sharp contrast with the richness of the subjects' narratives, highlighting the role of knowledge and personal experience in the process of interpretation. In his influential book, *The Psychology of Interpersonal Relations* (1958), Heider argued that the interpretation of intentional behavior was driven by commonsense theories of psychology and sociology, and was the basis of human social interaction.

Artificial Intelligence researchers have sought to model people's abilities for commonsense social reasoning in software-based cognitive systems, directing their efforts toward three fundamental challenges. First, researchers have worked to represent commonsense knowledge of human psychology and social interaction as formal theories for use in automated reasoning systems. Steady progress continues on the logical formalization of commonsense knowledge, both in the formalization of specific domain theories of commonsense psychology and sociology (Davis and Morgenstern 2005; Gordon and Hobbs 2011) as well as general commonsense knowledge (Panton et al. 2006). Second, other researchers have focused on the challenge of designing the cognitive architectures for automated reasoning, and have increasingly worked to apply these architectures to social reasoning problems (Meadows, Langley, and Emery 2014; Pynadath, Rosenbloom, and Marsella 2014). The third challenge is the evaluation of automated social reasoning systems, which has received comparably little attention. Natural-language commonsense reasoning evaluations are becoming increasingly popular (Levesque, Davis, and Morgenstern 2012; Roemmele, Bejan, and Gordon 2012), but the gap between formal theories of social interaction and the lexical semantics of these evaluations make them difficult to use for benchmarking current approaches. Needed are integrative approaches that incorporate rich representations of commonsense theories in practical reasoning systems that demonstrate their effectiveness in comprehensive evaluations.

In this paper we describe our efforts to overcome all three challenges (representation, reasoning, and evaluation) in a computational model of behavior interpretation using commonsense theories of psychology and sociology. To make progress in each of these areas, we restrict the scope of the reasoning challenge to the domain of Heider and Simmel's original film, depicting the actions of two triangles and a circle around a box with a hinged door. Although this narrative setting is constrained, interpreting the behavior of moving shapes in a humanlike manner required us to formalize hundreds of commonsense axioms concerning actions, intentions, emotions, and social relationships, among others. Using these axioms, we identify possible interpretations of action sequences via logical abduction, backchaining to distinct sets of assumptions that logically entail the observations. We then order these sets of assumptions by computing their joint probability assuming conditional independence. We evaluate our approach using the Triangle-COPA set of 100 challenge problems, each one describing a situation in the domain of the original Heider-Simmel film. Our approach solves almost all (91) of the 100 questions in Triangle-COPA, and demonstrates a promising approach to robust behavior interpretation that integrates both logical and probabilistic reasoning.

Triangle-COPA

Several AI researchers have viewed Heider and Simmel's original 1944 film as a challenge problem, where the objective is to construct software systems capable of generating interpretations similar to those of Heider and Simmel's subjects. Thibadeau (1986) takes a symbolic approach, representing the coordinates of each object in each frame of original film, which are matched to defined action schemas, such as opening the door or going outside the box. Pautler et al. (2011) follows a related approach, beginning with object trajectory information from an animated recreation of the Heider-Simmel film. An incremental chart parsing algorithm with a hand-authored action grammar is then applied to recognize character actions as well as their intentions.

These attempts highlight several problems for the use of the original Heider-Simmel film as a challenge problem by automated reasoning researchers. First, any system must overcome the difficult challenge of recognizing actions in the visual scenes, for example by first extracting quantitative trajectory information from the image data. Contemporary gesture recognition methods may be suitable for this task, using models trained on copious amounts of annotated examples. However, the effort involved in applying these techniques shifts research attention away from the central automated reasoning task of interpretation. Second, the original Heider-Simmel film provides a compelling input as a challenge problem, but the correct output is unspecified. Precisely because the input is "open to interpretation" it is difficult to compare the relative performance of two competing approaches, or even of the same approach as it develops over time.

The "Triangle Choice of Plausible Alternatives" (Triangle-COPA) set of one hundred challenge problems is a recent attempt to overcome these two problems with the original Heider-Simmel movie (Maslan, Roemmele, and Gordon 2015)[1]. Each of the one hundred questions in this problem set describes, in English and in first order logic, a short sequence of events involving the characters of the original Heider-Simmel film: two triangles and a circle moving around a box with a hinged opening. This description ends with a question that requires the interpretation of the action sequence, and provides a choice of two possible answers, also in both English and logical form. The task is to select which of the two options would be selected by a human, where the correctness of the choice has been established by perfect agreement among multiple human raters. Three examples of Triangle-COPA questions are as follows:

- Question 44: The triangle opened the door, stepped outside and started to shake. Why did the triangle start to shake?
  (and (exit' E1 LT) (shake' E2 LT) (seq E1 E2))
  a. The triangle is upset.
  (unhappy' e3 LT)
  b. The triangle is cold.
  (cold' e4 LT)
- Question 58: A circle and a triangle are in the house and are arguing. The circle punches the triangle. The triangle runs out of the house. Why does the triangle leave the house?
  (and (argueWith' E1 C LT) (inside' E2 C) (inside' E3 LT) (hit' E4 C LT) (exit' E5 LT) (seq E1 E4 E5))
  a. The triangle leaves the house because it wants the circle to come fight it outside.
  (and (attack' e6 C LT) (goal' e7 e6 LT))
  b. The triangle leaves the house because it is afraid of being further assaulted by the circle.
  (and (attack' e8 C LT) (fearThat' e9 LT e8))
- Question 83: A small triangle and big triangle are next to each other. A circle runs by and pushes the small triangle. The big triangle chases the circle. Why does the big triangle chase the circle?
  (and (approach' E1 C LT) (push' E2 C LT) (chase' E3 BT C) (seq E1 E2 E3))
  a. The big triangle is angry that the circle pushed the small triangle, so it tries to catch the circle.
  (angryAt' e4 BT C)
  b. The big triangle and circle are friends. The big triangle wants to say hello to the circle.
  (and (friend' e5 BT C) (goal' e6 e7 BT) (greet' e7 BT C))

As a benchmark set of challenge problems for automated reasoning systems, Triangle-COPA has a number of attractive characteristics. By providing first-order logic representations as inputs and outputs, Triangle-COPA focuses the efforts of competitors specifically on the central interpretation problem. At the same time, it places no constraints on the particular reasoning methods that are actually used to select the correct answer, affording comparisons between systems that use radically different knowledge resources and reasoning algorithms. The relational vocabulary of Triangle-COPA literals are fixed (see Maslan et al. 2015), but the semantics of these predicates are not tied to any one ontology or theory. The correct answers of Triangle-COPA are randomly sorted, so the quality of any given system can be gauged between that of random guessing (50%) and human performance (100%).

Etcetera Abduction

Triangle-COPA problems can be viewed as a choice between two alternative interpretations of a sequence of observable

[1] Available at https://github.com/asgordon/TriangleCOPA

actions. Hobbs et al. (1993) demonstrated that interpretation in natural language processing can be cast as problems of logical abduction, and solved using automated abductive reasoning technologies. Abduction, as distinct from logical deduction or induction, is a form of logical reasoning that identifies a hypothesis that, if it were true, would logically entail the given input. Abduction is not a sound inference mechanism in standard first-order logic; asserting the truth of an antecedent given an observable consequent is a logical fallacy, "affirming the consequent." Still, automated abductive reasoning is a natural fit for many commonsense reasoning problems in artificial intelligence (Ng and Mooney 1992; Bridewell and Langley 2011; Meadows, Langley, and Emery 2014).

Automated abductive reasoning requires two mechanisms: a means of generating sets of hypotheses that entail the input, and a scoring function for the preferential ordering of these hypotheses. Hobbs et al. (1993) described "Weighted Abduction," where hypotheses are generated by backchaining from the given input using the implicature form of knowledge base axioms, unifying literals across different antecedents wherever possible. The process generates an and-or proof graph similar to that created when searching for first-order proofs by backchaining, but where every solution in the and-or graph identifies a set of assumptions that, if true, would logically entail the given observables. Weighted Abduction orders these hypotheses by computing the combined cost of all assumed literals (those without justification), through a mechanism of propagating initial costs to antecedents during backchaining. Maslan et al. (2015) demonstrated how Weighted Abduction can be used to solve Triangle-COPA problems by searching for the least-cost set of assumptions that entailed the literals in one of the two alternatives.

In our own work, we devised a new probabilistic reformulation of Weighted Abduction, which we call Etcetera Abduction. Several researchers have previously pursued probabilistic reformulations of Weighted Abduction, eschewing the use of ad-hoc weights for probabilities that might be learned from empirical data. Ovchinnikova et al. (2013) and Blythe et al. (2011) describe two recent probabilistic reformulations, each casting the and-or proof graph as a Bayesian network whose posterior probabilities can be calculated using belief propagation algorithms for graphical models. These efforts help to position abductive reasoning among current approaches to uncertain inference, and to take advantage of recent advances and tools for reasoning with Markov Logic networks (Richardson and Domingos 2006). However, a simpler formulation of probabilistic abduction may be more appropriate when the task is only to rank possible hypotheses.

As in other probabilistic reasoning tasks, the calculation of the joint probability of a set of events is trivially easy if we assume that they are all conditionally independent: the joint probability of the conjunction is the product of their prior probabilities. If we know the prior probabilities of all assumed literals in an abductive proof (those without justification), then the naive estimate of their joint probability is simply their product (Poole 1991). This calculation can be applied to any solution in an and-or graph created by backchaining from the given input, giving us a convenient means of ranking hypotheses.

This approach allows us to use standard first-order logic and familiar technologies of lifted backchaining instead of belief propagation in graphical models. However, by using logical inference (rather than uncertain inference) we require that the consequent of an implication is always true when the antecedent holds, where the probability of the consequent given the antecedent is always one. Hobbs et al. (1993), building on McCarthy's (1980) formulation of circumscription, describes how defeasible first-order axioms can be authored by the inclusion of a special etcetera literal (etc) as a conjunct in the antecedent. These literals are constructed with a unique predicate name that appears nowhere else in the knowledge base, and therefore can only be assumed (via abduction), never proved. The arguments of this predicate are all of the other variables that appear in the axiom, restricting its unification with other etcetera literals of the same predication that may be assumed in the proof.

The probabilities of etcetera literals are straightforward if we interpret them as being an unspecified conjunction of all of the unknown factors of the world that must also be true for the antecedent to imply the consequent. Etcetera literals are true in exactly the cases where the remaining antecedent literals and the consequent are all true. As such, their prior probabilities are equal to the conditional probability of the consequent given the remaining conjuncts in the antecedent. Where there are no remaining conjuncts (a solitary etcetera literal implies the consequent), the prior probability of the etcetera literal is exactly equal to the prior probability of the consequent.

Commonsense Axioms

We hand-authored 136 axioms to encode commonsense knowledge in the domain of the Triangle-COPA question set, targeting the specific inferences necessary to infer the correct alternative for each question. Each of these axioms were written as first-order definite clauses in implicature form, and included a unique etcetera literal in each antecedent. For convenience, we encoded the prior probability of each etcetera literal as its own first argument, as a numeric constant. To encode the prior probabilities of predications in the Triangle-COPA domain, we authored an additional 116 axioms (one for each domain predicate) where the antecedent consisted of a solitary etcetera literal, again with its prior probability as the first argument. We expect that in the future it may be possible to automatically learn these probabilities from empirical data. However, in this work we assign probabilities to etcetera literals manually via commonsense intuition, knowing full well that such estimations may be systematically biased (Kahneman and Tversky 1982).

Each of the 136 commonsense axioms follows a common scheme, providing some possible explanation (the antecedent) for why a particular literal (the consequent) might be true. Three-fourths of the 136 commonsense axioms encoded possible explanations for observable actions, offering some reason that a given action might have been observed.

For example, four axioms provide possible reasons why one character would be chasing another:

- Chase 1: Maybe they are playing tag
  (if (and (playWith' e1 x y)
  (etcChase1 0.2 e1 x y))
  (chase' e x y))
- Chase 2: Maybe one is angry at the other
  (if (and (angryAt' e1 x y)
  (etcChase2 0.2 e1 x y))
  (chase' e x y))
- Chase 3: Maybe one is trying to rob the other
  (if (and (goal' e1 e2 x)
  (rob' e2 x y)
  (etcChase3 0.3 e1 e2 x y))
  (chase' e x y))
- Chase 4: Maybe one is trying to scare the other
  (if (and (goal' e1 e2 x)
  (afraid' e2 y)
  (etcChase4 0.5 e1 e2 x y))
  (chase' e x y))

Each of these four axioms provides a piece of some overall explanation for a situation that includes chasing, where the etcetera literals in each axiom each indicate the likelihood that the consequent is implied by the remaining conjuncts in the antecedent. Accompanying these four would be an additional axiom to encode the prior probability of observing such a chase:

- Chase 0: Maybe the conditions are right for chasing
  (if (etcChase0 0.01 e x y)
  (chase' e x y))

Note that despite its low probability (0.01), *etcChase0* would be the most-probable assumption that logically entailed the observation of one character chasing another, in the absence of other observations. While the prior for this assumption is less than those in the other four axioms, the probability of each of the other antecedents will also be a factor in their probability estimates, lowering their joint probability. It is only in combination with additional evidence that these other four explanations could be part of the most probable interpretation, where these antecedents could be unified with those of other observations as a common factor in the joint probability estimate.

The remaining commonsense axioms provide possible explanations for literals that cannot be directed observed (i.e. they appear as antecedents an action axiom like those above). These include possible explanations for emotional states (anger, excitement, relief), abstract social actions (helping, defending, disciplining), perceptions (hearing, seeing). The antecedents of these axioms typically include mental actions, emotions, and social relationships, most of which have no further explanations in the knowledge base.

Notably, this set of axioms, hand-authored specifically for the Triangle-COPA question set, includes very few representations for concepts that have traditionally been the focus of formal knowledge representation research, such as time, space, sets, scales, and physics. Causality is only implicitly represented in the schema of each axiom, where the antecedent is seen as a causal explanation for the consequent.

Solving Triangle-COPA Problems

To automatically solve Triangle-COPA questions using our hand-authored set of axioms, we implemented Etcetera Abduction and used it to determine which of the two alternatives for each question was entailed by a more probable set of assumptions. Our software implementation[2] accepts the knowledge base and a conjunction of observations as input, and generates all possible sets of assumptions that logically entail the given observations, ranked by their joint probability estimate assuming conditional independence. This search begins by generating and-or trees of entailing assumptions for each input literal by backchaining on knowledge base axioms to a specified depth (an input parameter), where the set of solutions in the tree each identify a set of etcetera literals that logically entail one observed literal. The Cartesian product of these sets-of-sets is then computed, identifying sets of assumptions that logically entail all of the observed conjuncts. For each of these assumption sets, we then identify all possible ways that etcetera literals could be unified by substitutions of universally quantified variables. For each candidate, we compute the joint probability as the product of each etcetera literal's prior probability, and output a rank-ordered list.

First-order logical abduction is a quintessential combinatorial search problem, leaving few opportunities for optimization. We avoid some of the costs of computing all possible unifications by only considering assumption sets if the best-case joint probability would place it into a running n-best list, where n is an additional input parameter. By keeping the backchaining depth parameter low (e.g. below 5) and the n-best list short (e.g. 10 solutions), our implementation is able to exhaustively search through millions of assumption sets for each Triangle-COPA problem in seconds.

Each of the ordered n-best assumption sets logically entail the given observations. That is, asserting the truth of the etcetera literals and exhaustively forward-chaining on knowledge base axioms will produce the input literals as logical consequents. Also entailed are all of the literals that constitute a structured interpretation, namely the intermediate inferences between assumptions and the given observations the resulting proof-graph. We use these intermediate inferences as the basis for selecting between alternatives in the Triangle-COPA questions. In some cases, the literals of correct alternative to a Triangle-COPA problem are a subset of the intermediate inferences entailed by the most-probable interpretation of the question's given literals. In other cases, the correct answer can be found further down the n-best list, or not at all. Our implementation answers Triangle-COPA questions by finding both alternatives in the n-best list, and selecting the one with a higher probability.

Figure 1 shows an example proof-graph for Triangle-COPA question 83 (above). Here ovals represent the set of assumptions (etcetera literals), displayed only as their prior

[2] Available at https://github.com/asgordon/EtcAbductionPy

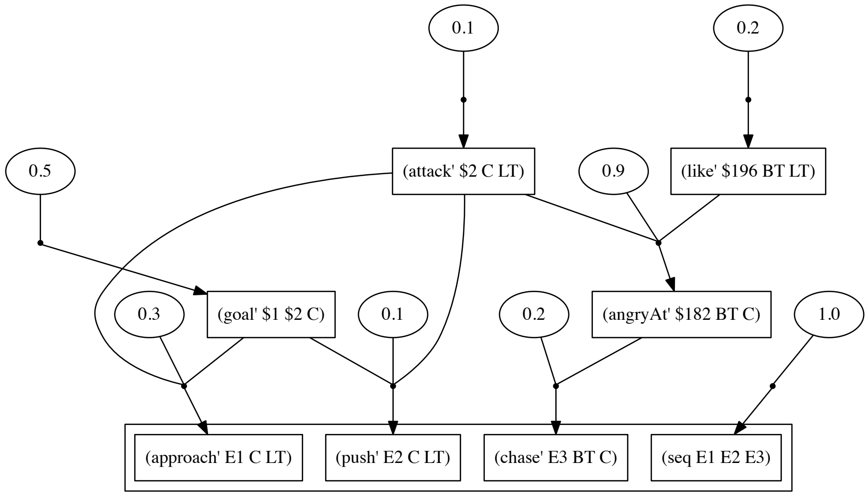

Figure 1: The most-probable proof of Triangle-COPA question 83.

probabilities. Rectangles represent entailed inferences, produced by exhaustively forward-chaining on knowledge base axioms, represented using arrows. Arguments with dollar signs (e.g. $196) represent Skolem constants that ground universally quantified variables. The four literals at the bottom, enclosed by a rectangle, are the given observations of the question.

Four commonsense axioms are employed in this interpretation. When someone has the goal to attack someone else, he will approach her (Pr=0.3), and he will push her (Pr=0.1). Therefore, we assume that the Circle (C) has the goal of attacking the Little Triangle (LT). When someone is angry at someone else, he will chase her (Pr=0.2). Therefore, we assume that the Big Triangle (BT) is angry at the Circle (C). When someone likes a second person that is attacked by a third person, he will be angry at the third person (Pr=0.9). Therefore, we assume that the Circle (C) attacked someone that the Big Triangle (BT) likes. Substituting variables via unification, we can assume that the person the Big Triangle (BT) likes is the Little Triangle (LT). In this interpretation, four literals are entailed by solitary etcetera literals (the goal, the attack, the liking emotion, and the sequence of events), each with their own prior probabilities (Pr=[0.5, 0.1, 0.2, 1.0]). The joint probability of this interpretation assuming conditional independence of etcetera literals is the product of these priors (Pr=0.000054). This is the most-probable interpretation for question 83, and it logically entails the correct answer: the Big Triangle (BT) is angry at the Circle (C).

Results

Our approach correctly solves 91 of the 100 Triangle-COPA problems. In 56 cases, the correct answer is entailed in the most-probable interpretation, not just higher on the n-best list than the incorrect alternative. A backchaining depth of 3 was sufficient in all but 1 question, where a depth of 4 was necessary. An n-best list length of 10 was sufficient in all but 1 question, where a length of 27 was necessary.

When assessing this result, it is important to remember that Triangle-COPA was designed as a *development* test set, not as a held-out test set for use in competitive evaluations. Our strong performance on this set demonstrates that Etcetera Abduction is a viable approach, but our success owes much to the labor of hand-crafting the axioms necessary to solve these specific questions. Accordingly, the most interesting findings are in the nine incorrect answers, where we could not find a straightforward means of inferring the correct alternative using our approach.

Seven of these nine incorrect answers involved the emotional consequences of the interpreted situation, not the situation itself (questions 54, 65, 72, 79, 81, 89, and 93). For example:

- Question 65. A circle and small triangle are hugging. A big triangle approaches and pulls the small triangle away. How do the circle and small triangle feel? (answer: unhappy).

The necessary commonsense knowledge is not difficult to articulate as an axiom: people might be unhappy when forcibly separated from their friends. However, this knowledge does not help explain an *observed* event appearing in the logical representation, one that would enable the system to backchain on this axiom for use in an interpretation. The only indication that the emotional consequence is of concern in this problem is in its English-language description, not in the logical formalization authored by Maslan et al. (2015). One solution would be to explicitly encode the question as a observation to be interpreted, analogous to the way that *Answer* literals are used in resolution-based question-answering systems (Green 1969), for example by asserting that the Circle and Little Triangle feel *something* and letting abduction resolve the ambiguity.

Two of the nine incorrect answers (questions 100 and 93, again), involve the interpretation of inaction, which is also not explicitly represented in the question formalizations. For example:

- Question 100. A circle knocks on the door. A triangle goes to the door, but hesitates to open it. Why does the triangle hesitate to open the door? (answer: the triangle feels conflicted).

Here the key event is that the triangle hesitated to open the door, but the represented sequence events for this question ends with the last observable action: the triangle approaches the door. We believe that this problem will be harder to solve than the emotion consequent problems (above), because the triangle's hesitation is itself part of the interpretation of the situation. However, if the question explicitly represented the triangle's hesitation, it could be easily explained with the commonsense knowledge that conflicted feelings lead to hesitation in action.

One question (number 68) was simply too large for our system to handle. The unique qualities of this problem yield a combinatorial search space that is too large to explore in a reasonable amount of time (hours) using our implementation.

- Question 68. A big triangle, small triangle, and circle are in the house. The big triangle and the circle each kiss the small triangle, wave, and then leave the room. How are the shapes related? (answer: the big triangle and the circle are the parents of the small triangle)

The conceptual knowledge required to solve this problem is rich, but not insurmountable: people kiss and wave when they depart, married couples depart together, parents visit the homes of their (adult) children, etc. However, combining this knowledge requires backchaining with some reasonable depth (maybe 4 or 5 steps). Additionally, the given observations in this problem are represented by 11 literals, the most of any Triangle-COPA problem. Worse still, five of these literals have the same predicate as one of the remaining six, leading to explosions in the sets of possible unifications that must be considered when searching for a minimal (and most-probable) set of assumptions. Solving this problem in reasonable time will require more sophisticated methods for optimizing the search than used in our implementation of Etcetera Abduction.

Discussion

Future AI systems will require a robust capability for inferring the plans, goals, beliefs, and emotional states of the humans with which they interact. In this paper we demonstrate a solution to the mind-reading problem in a limited domain, based on an influential film created by social psychologists Fritz Heider and Marianne Simmel. The 100 challenge problems in the Triangle-COPA set involve only three characters and a fixed set of disambiguated actions, but require a rich capacity for commonsense reasoning to select correct answers. The requisite knowledge base contains hundreds of hand-authored axioms and probability estimates for everyday concepts in commonsense psychology and sociology, and provides a template for future knowledge bases that target open-domain commonsense reasoning.

Our approach is to view the reasoning task as an interpretation problem, and to follow Hobbs et al.'s (1993) proposal for solving interpretation problems with logical abduction. Logic-based approaches are common in several areas of AI, but evaluation-driven research in recent years has favored machine learning approaches, particularly where gold-standard training data is abundant. For many problems, it is easier to learn the implicit correlations between input features and output labels than to articulate this knowledge as explicit rules. Triangle-COPA provides no such training data, and we doubt that such a data set could be curated of sufficient size and inter-rater agreement, precisely because the output labels are *open to interpretation*. Hand-authoring the requisite logical axioms was laborious, but tractable.

Our probabilistic formulation of logical abduction, Etcetera Abduction, greatly facilitated the authoring of axioms. The necessary quantitative information could be intuitively understood as prior and conditional probabilities associated with etcetera literals. Using logical inference (rather than probabilistic inference) and assuming conditional independence of etcetera literals, we gain some of the benefits of contemporary probabilistic reasoning approaches without giving up on the useful notions of logical entailment, unification of quantified variables, and first-order model theory. Likewise, by only backchaining on first-order definite clauses, we avoid the brittleness of resolution theorem proving and other logic-based automated reasoning architectures, with respect to incomplete or contradictory formalizations in the knowledge base. Etcetera Abduction only identifies sets of assumptions that logically entail the given observations, whatever the state of the knowledge base.

At its core, logical abduction is a search through the space of combinations of associations, looking for the most parsimonious sets of antecedents for each of the given input literals. First-order logical abduction is a quintessential combinatorial search problem, requiring both the enumeration of a Cartesian product of sets of justifications and the possible ways that each resulting set could be reduced through unification. From an engineering perspective, we see the need for optimizations and approximate solutions that will enable the use of logical abduction with larger sets of input literals, larger knowledge bases, and greater depth of backchaining. From a cognitive science perspective, we wonder if the human brain engages in an analogous search when faced with commonsense interpretation problems. Do we unconsciously explore the space of combinations of associations to find the most parsimonious interpretation of our perceptions?

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