How Action Understanding can be Rational, Bayesian and Tractable

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Abstract
An important aspect of human sociality is our ability to understand the actions of others as being goal-directed. Recently, the now classic rational approach to explaining this ability has been given a formal incarnation in the Bayesian Inverse Planning (BIP) model of Baker, Saxe, and Tenenbaum (2009). The BIP model enjoys considerable empirical support when tested on ‘toy domains’. Yet, like many Bayesian models of cognition, it faces the charge of computational intractability: i.e., the computations that the model postulates may be too resource demanding for the model to be scalable to domains of real-world complexity. In this paper, we investigate ways in which the BIP model can possibly parry the charge. We will show that there are specific conditions under which the computations postulated by the model are tractable, despite the model being rational and Bayesian.

Keywords: goal inference, inverse planning, computational complexity, intractability, NP-hard, fixed-parameter tractability

Introduction
Imagine a mother and her son, sitting in the same room, when she hears his stomach rumble. She sees her son get up, walk to the kitchen and start searching for something. At first he finds a sour apple, which he discards in search of something else. Then the mother sees her son finding a delicious candy bar. When he starts to eat it she realizes her son is trying to still his hunger and at the same time wanting to eat something sweet. In this scenario, the son goes through a process of planning, choosing his actions to achieve his goals. The mother observes the actions of her son and based on her observations infers the goals she thinks her son is trying to achieve. This process is called goal inference.

In line with a long tradition of explaining the human ability to understand actions as goal-oriented (Dennett, 1987; Charniak & Goldman, 1991; Csibra, Gergely, Biró, Kóós, & Brockbank, 1999; Cuijpers, Schie, Koppen, Erlhagen, & Bekkering, 2006), Baker, Saxe, and Tenenbaum (2009) have proposed that goal inference can be seen as a form of inverse planning, just as vision is a form of inverse graphics. Baker et al. go beyond existing psychological approaches by providing a precise formalization of ‘inverse planning’ in the form of a Bayesian inference model. We will refer to this model as the BIP model of goal inference (where BIP stands for Bayesian Inverse Planning). The BIP model has been tested in several experiments, and Baker et al. (2007, 2009) observed that it can account for the dynamics of goal inferences made by human participants in several different experimental settings.

According to the BIP model, observers assume that actors are ‘rational’ in the sense that they tend to adopt those actions that best achieve their goals. Given the assumption of rationality, and (probabilistic) knowledge of the world and how actions are affected by it, one can compute the probability that an agent performs an action given its goals, denoted

$$P(\text{action} | \text{goal}, \text{environment}) \quad (1)$$

When observing a given action, the probability in (1) can be inverted using Bayes’ rule to compute the probability of a given goal:

$$P(\text{goal} | \text{action}, \text{environment}) \propto P(\text{action} | \text{goal}, \text{environment})P(\text{goal} | \text{environment}) \quad (2)$$

Of all the possible goals that an observer can (or does) entertain, the goal that maximizes the probability in (2) best explains why the observed action was performed and is the goal that is inferred.¹

Given that the BIP model belongs to the class of (rational) Bayesian inference models—and Bayesian inference is known to be intractable if no additional constraints are imposed (e.g. Chater, Tenenbaum, and Yuille (2006); see also Kwisthout (2009))—the question arises if the computations that it postulates can scale to situations of everyday complexity. As Gigerenzer and colleagues put it:

The computations postulated by a model of cognition need to be tractable in the real world in which people live, not only in the small world of an experiment with only a few cues. This eliminates NP-hard models that lead to computational explosion, such as probabilistic inference using Bayesian belief networks … including its approximations. (Gigerenzer, Hoffrage, and Goldstein (2008) p. 236)

Although we share the stance of Gigerenzer et al. (2008) towards intractable (NP-hard) models of cognition, we are not as pessimistic about the viability of Bayesian models. In our view, the key to understanding the computational feasibility of a Bayesian (or any cognitive) model lies in studying domain-specific constraints that hold in the model’s domain of application (e.g., action understanding or vision) and investigating if and how such constraints may render the computations postulated by the model tractable for its domain,

¹In other words, in the BIP model, goal inference is conceptualized as a form of probabilistic inference to the best explanation, a.k.a. abduction (e.g. Charniak and Shimony (1990)).
Computational Models

Baker et al. (2009) propose three different versions of Bayesian Inverse Planning (M1, M2 and M3) to account for data gathered in several maze experiments. These two-dimensional maze experiments, based on earlier work (Gergely, Nádasdy, Csibra, & Biro, 1995; Schultz et al., 2003), were designed to assess subjects’ inferences about the goals of a planning agent. Subjects were shown videos of agents moving in a maze, such as those in Fig. 1, and under different timing and information conditions had to infer the goal of the agent. In these experiments changes in location were considered actions and the location of the agent was considered its state. Specific locations (A, B and C) were possible goals.

All three models M1–3 can be seen as special cases of a more general BIP model, as depicted in Fig. 2, in which there is a goal structure template G that can encode different types of goal structures. The simplest goal structure is present in M1 where the observer assumes that the agent has one single goal that does not change over time (Fig. 3(a)). In M2 the model allows the observer to infer the agent has a different goal at any given time (Fig. 3(b)). This models the ability of people to infer changes in an agent’s goal over time. For instance, if someone is inspecting the contents of her fridge, you may infer she wishes to cook dinner, but when she closes the fridge, puts on her coat, and leaves the house, you may infer she is going to eat out. Finally, in M3 the goal structure encodes hierarchical goals (Fig. 3(c)), such that the observer can infer changes in the agent’s sub-goals, which are subserving a common high-level goal. For instance, when you see someone gathering kitchen utensils, each individual gathering can be a sub-goal but the high-level goal is to cook dinner.

Even though inference in Bayesian networks is hard in general, the BIP models proposed by Baker et al. are tractable. This tractability is in some sense an artifact of the simplified experiments for which these models were designed. In the experiments an agent never has more than one (high-level) goal at any given time. This property does not seem to hold in general, however. Reconsider, for instance, the scenario in our opening paragraph. There the mother infers that the son wants to satisfy his hunger and he wants to eat something sweet. This type of goal inference where multiple goals are inferred at the same time cannot be modelled by M1, M2 or M3. To accommodate for this observation, we propose an extension called MULTIPLE GOALS BIP or MGBIP. Fig. 4...

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2The authors are well aware of common claims of approximability of Bayesian inferences, and that approximation is generally believed to provide a way to overcome the intractability of Bayesian models. In this paper, we will depart from this standard viewpoint for two reasons. First, the claims of approximability seem at worst incorrect and at best unfounded; for instance it is known that approximating the most probable explanation in a Bayesian network is itself also intractable (Abdelbar & Hedetniemi, 1998). Second, we believe that there are other, better ways of dealing with the intractability of cognitive models, viz., by identifying model constraints that render otherwise intractable models tractable (van Rooij, 2008).

3In the original BIP models (M1, M2 and M3) Baker et al. used additional parameters to model the effect of noise (β), the probability of changing a goal in M2 (γ) and the probability of having sub-goals in M3 (κ) to fit the model to the experimental data. As these parameters are assumed constants, they can be safely ignored for the purposes of our analyses.

4For the formal proof of these claims we refer the reader to the Supplementary materials available online at http://tinyurl.com/suppl2010
Identifying Sources of Intractability

In order to find constraints on the input domain of MG-BIP that render the (restricted) model tractable, we adopt a method for identifying sources of intractability as described in (van Rooij, Evans, Müller, Gedge, & Wareham, 2008) (see also van Rooij and Wareham (2008)). The method works as follows.

First, one identifies a set of model parameters $K = \{k_1, k_2, \ldots, k_m\}$ in the model $M$ under study (for us, MG-BIP). Then one tests if it is possible to solve $M$ in a time that can grow excessively fast (more precisely: exponential or worse) as a function of the elements in $K$ yet slowly (polynomial) in the size of the input.\(^6\) If this is the case, then $M$ is said to be fixed-parameter (fp-) tractable for parameter set $K$, and otherwise it is said to be fp-intractable for $K$.

Observe that if a parameter set $K$ is found for which $M$ is fp-tractable then the problem $M$ can be solved quite efficiently, even for large inputs, provided only that the members

5Baker et al. (2009) also note, that the simplified models M1–3 unlikely suffice to model human action understanding in general and they argue that the models will need to be extended in various directions if they are to apply to real-world scenarios. Our extension can be seen as one such possible direction in which to extend the model. Other directions of extension are possible as well (see e.g. (Ullman, Baker, Macindoe, Goodman, & Tenenbaum, 2009)).

6More formally, this would be a time on the order of $f(k_1, k_2, \ldots, k_m)n^c$, where $f$ is an arbitrary computable function, $n$ is a measure of the overall input size, and $c$ is a constant.
of $K$ are relatively small. In this sense the “unbounded” nature of $K$ can be seen as a reason for the intractability of $M$. Therefore we call $K$ a source of intractability of $M$.

The MGBIP model has several natural parameters, each of them a candidate source of intractability. In this paper we consider, five such parameters (see Table 1 for an overview and Fig. 5 for an illustration).

First consider parameters $T$, denoting the maximum number of observations the observer makes, and $1/T$, denoting the poverty of observations. Note that $T$ is small if few observations are made, and $1/T$ is small if many observations are made. Based on intuition one might think, the less information we have, the harder it is to understand actions. This makes $1/T$ a candidate source of intractability. However as $T$ grows, so does the size of the network and the necessary number of calculations and this also makes $T$ a likely candidate source of intractability.

Second, parameter $k$ is the maximum number of multiple goals that (the observer assumes) the agent can pursue. This parameter is also an excellent candidate source of intractability, because large $k$’s introduce an exponential number of combinations of possible multiple goals leading to a combinatorial explosion.

Third, the parameter $g$ is the maximum number of goal values per goal variable. As the number of possible values that a goal variable can take increases the necessary number of calculations, also $g$ is a candidate source of intractability.

Finally, the parameter $1 - p$ measures how far the most likely goal inference is from being completely certain (here $p$ is the probability of the most likely explanation). If $1 - p$ is small, this means that the most likely explanation is much more likely than any competitor explanation. If the value is large, it means that the most likely explanation has many competitor explanations of non-negligible probability (see e.g. Table 2). It seems intuitive that finding the most likely explanation is easier in the former case than in the latter case, and therefore also $1 - p$ can be considered a candidate source of intractability.

We have now reviewed five parameters that—on intuitive grounds—may be considered candidate sources of intractability in the MGBIP model. It is known, however, that human intuitions about what makes a computation tractable or intractable can be mistaken. Therefore it is necessary to verify such intuitions by means of mathematical proof.

**Results**

In this section we present our fp-(in)tractability results for the different parameters of the MGBIP model, and we explain how these results bear on the question ‘which constraints render the MGBIP model tractable?’.

![Figure 4: Graphical representation of the dynamic Bayesian network that describes MULTIPLE GOALS BIP (MGBIP).](image)

![Figure 5: Illustration of the Bayesian network and different parameters of the MGBIP model applied to the “mother observes son”-example.](image)

**Table 1: A list of parameters with short descriptions and their values based on the running example.**

<table>
<thead>
<tr>
<th>parameter</th>
<th>description</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T$</td>
<td>maximum observations</td>
<td>6</td>
</tr>
<tr>
<td>$1/T$</td>
<td>maximum observation poverty</td>
<td>1/6</td>
</tr>
<tr>
<td>$k$</td>
<td>maximum # multiple goals</td>
<td>2</td>
</tr>
<tr>
<td>$g$</td>
<td>maximum # goal values</td>
<td>3</td>
</tr>
<tr>
<td>$1 - p$</td>
<td>distance from certainty</td>
<td>0.4</td>
</tr>
</tbody>
</table>

**Table 2: Example probability distribution over the combinations of goal values. In this example $p = 0.6$ and $1 - p = 0.4$.**

<table>
<thead>
<tr>
<th>satisfy hunger</th>
<th>desire sweet</th>
<th>$P$</th>
</tr>
</thead>
<tbody>
<tr>
<td>big hunger</td>
<td>yes</td>
<td>0.05</td>
</tr>
<tr>
<td>medium hunger</td>
<td>yes</td>
<td>0.05</td>
</tr>
<tr>
<td>little hunger</td>
<td>yes</td>
<td>0.6</td>
</tr>
<tr>
<td>big hunger</td>
<td>no</td>
<td>0.3</td>
</tr>
<tr>
<td>medium hunger</td>
<td>no</td>
<td>0.0</td>
</tr>
<tr>
<td>little hunger</td>
<td>no</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Full details and proofs can
Bayesian models do not seem to make unrealistic assumptions about the computational powers of human minds/brains, even when operating on large networks of beliefs and observations. That being said, these models do seem to be theoretically problematic for a different reason: they are too specialized to count as models of goal inference in general.

The over-specialization of M1, M2 and M3 is revealed when pondering the assumptions that these models make about the agent and the observer. For instance, all three models assume that (the observer assumes that) the agent can pursue at most one goal at a time. In the real-world, however, people often can and do act in ways so as to try and achieve two or more goals at the same time, and observers can also often understand what these simultaneous goals are from observing the actors behave in systematic ways. Recall, for example, the scenario from our Introduction where the son searches the kitchen for a candy bar. Under different circumstances, the mother may understand that her son has the goal to still his hunger (goal 1), to satisfy his craving for sweet (goal 2), to see how many bars are left (goal 3), to pretend that he did not hear his mom’s request to clean up his room (goal 4), to bring back a candy bar for his mom (goal 5), etc., or any combination of these goals.

To accomodate the fact that real-world goal inference is not restricted to one goal at a time, we defined a more general BIP model—having M1, M2 and M3 as special cases—which we refer to as MULTIPLE GOALS BIP, or MBG for short. Complexity Analysis of the MBG model revealed that it is computationally intractable (i.e., NP-hard), meaning that this model, in all its generality, does indeed make unrealistic assumptions about the computational powers of human minds/brains. We took this negative theoretical result to mean that—if the BIP model is to account for human goal inference at all—it must be the case that in those situations where humans are able to infer multiple simultaneous goals quickly and effortlessly, specific constraints apply that render the inferences under the MBG model tractable.

To investigate which types of constraints could render the MBG model tractable, we used a methodology for identifying sources of intractability in NP-hard computational models (e.g. van Rooij and Wareham (2008)) and derived several theoretical results. For instance, we ruled out the possibility of explaining speedy real-world (multiple) goal inferences by an appeal to small values of \( T \) (modeling situations when goals can be inferred using only few observations) or an appeal to large values of \( T \) (modelling situations where a lot of information is available on which to base a goal inference). Similarly, we ruled out that the speed of such inferences could be explained by an appeal to a small number of values per goal node. Besides these negative theoretical results, we also had two important positive results. For one, we established that as long as the number of goals that can be simulatenously pursued, \( k \), is not too large then goal inference is tractable under the MBG model. Secondly we have shown that goal inference is tractable under the MBG model whenever the probability

7See http://tinyurl.com/suppl2010
of the most likely combination of simultaneous goals, \( p \), is not too far from 1.

Whereas our negative theoretical results are useful to clarify that tractability is not a property that is trivially achieved (and often our intuitions about what constraints would render a model tractable can be wrong; cf. van Rooij et al. (2008)), our positive results show that a model of action understanding can nevertheless be rational, Bayesian, and tractable. Moreover, the nature of the constraints that need to be introduced to render the Bayesian Inverse Planning model of goal inference tractable yield new empirically testable predictions.

For instance, based on our results, we predict that human participants will be able to make quick and accurate goal inferences in the types of experimental set-ups such as used by Baker et al. (2007) (but see also Csibra et al. (1999)), but only if the number of simultaneous goals that the observed agents are pursuing is not too large, or the probability of the most likely combination of goals is not too small, or both. If both of these constraints were to be alleviated at the same time, we would predict that human performance on the goal inference task would deteriorate significantly. If our prediction were to be confirmed then this would provide corroborative support for the BIP model of goal inference, and validate that our theoretical results help explain the tractability of human goal inferences. If, on the other hand, the prediction were to be disconfirmed, then this would suggest that either the BIP model fails as an account of human goal inferences, or some constraint other than the ones we considered also suffices to render the BIP model tractable. The latter option may then be one that BIP modelers may be interested in pursuing further.

In closing, we remark that our approach can be seen as exemplary of a general strategy for dealing with intractability in Bayesian models, whether of action understanding or otherwise. Our approach reveals that—contrary to popular belief—Bayesian models can possibly scale to complex, real-world domains. To achieve this, Bayesian modelers need only identify constraints that apply in the real-world and suffice to render their models’ computations tractable. By restricting Bayesian models in this way these models also become better testable: the constraints required to guarantee tractability of the models yield new predictions (specifically, about the speed of inferences) that can be used to perform more stringent tests of such models.

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**References**


