

# An Integrated Approach for Generating Arguments and Rebuttals and Understanding Rejoinders

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**Abstract.** This paper describes an integrated approach for interpreting a user's responses and generating replies in the framework of a WWW-based Bayesian argumentation system. Our system consults a user model which represents a user's beliefs, inferences and attentional focus, as well as the system's certainty regarding the user's beliefs. The interpretation mechanism takes into account these factors to infer the intended effect of the user's response on the system's argument. The reply-generation mechanism focuses on the identification of discrepancies between the beliefs in the user model and the beliefs held by the system that are relevant to the inferred interpretation.

**Keywords:** argumentation, Bayesian networks, plan recognition, discourse planning.

## 1 Introduction

An ideal interactive system would allow a user to request additional explanations, express doubt about the system's recommendations, and present his/her own views to the system. The interaction with such a system could continue indefinitely. In this paper, we present a first installment in the development of such a system. This is a WWW-based *Bayesian Interactive Argumentation System* (BIAS), which generates arguments, allows the user to question these arguments, and generates rebuttals to the user's rejoinders. In particular, we focus on the requirements placed by these capabilities on the system's user modeling component.

BIAS' active components are: (1) a WWW interface, (2) an inference mechanism, (3) an argument-generation mechanism, and (4) a rebuttal-generation mechanism. The interaction with BIAS starts with the presentation of background information regarding a particular scenario, which the user can explore further through the WWW interface. At any point the user can ask BIAS to present its argument regarding the goal proposition in this scenario; this argument is produced by the generation mechanism. The user can then accept this argument, explore the scenario further or pose a rejoinder. After receiving the user's rejoinder, BIAS activates the inference mechanism to recognize the user's intent, and then uses the rebuttal-generation mechanism to produce a rebuttal which takes into account the information in the rejoinder. The user can then continue exploring the scenario or generate another rejoinder, and so on.

In the next section, we present BIAS' WWW interface and the scenario used in our current implementation. In Section 3, we discuss our knowledge representation formalism and our user model. We then describe our procedure for inferring a user's line of reasoning, followed by our algorithm for rebuttal generation. In Section 6, we review related work, followed by concluding remarks.

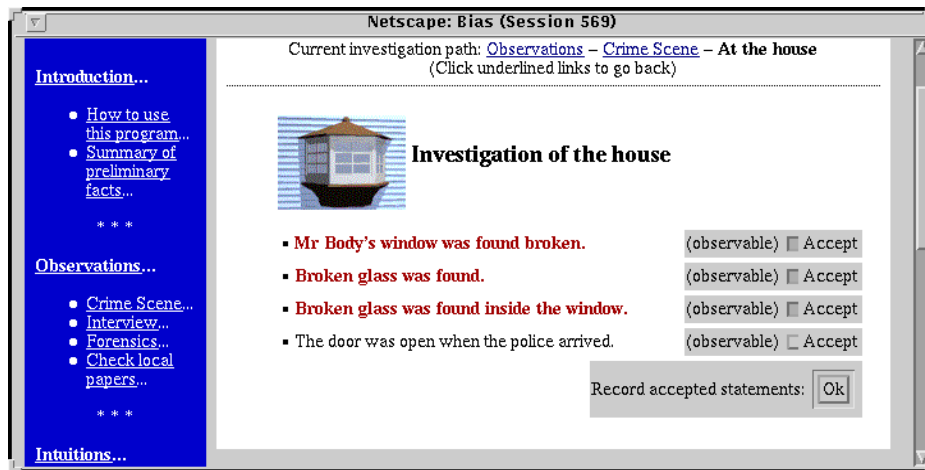


Fig. 1. Sample screen of the WWW interface

## 2 WWW Interface and Sample Scenario

Our experimental set up is designed to model a situation where the user and the system are “true” partners (contrary to the usual mode of operation, where the system is omniscient). In our set up, both the user and the system start with the same amount of information, and both can obtain additional information from the “world”.<sup>1</sup> Our experimental set up is realized by means of a “murder scenario”, where BIAS and the user are partners in solving a crime. At the beginning of the interaction, the WWW interface presents a preamble that describes the preliminaries of the case. The following preamble is used for the interaction described in this paper:

*Mr Body was found dead in his bedroom, which is in the second story of his house. Bullets were found in Mr Body’s body. A gun was found on the premises, and fingerprints were found on the gun. In addition, inspection of the grounds revealed footprints in the garden and circular indentations in the ground outside the bedroom window.*

After receiving the preamble, the user can use a WWW interface to gather additional information about the world, e.g., from witnesses or the crime scene, or to post his/her intuitions about unobservable propositions, e.g., *Mr Green had a motive to kill Mr Body*. Figure 1 shows a screen where the user investigates the victim’s house. The first three propositions (in red in the interface) have been accepted by the user, while the last proposition (in black) was seen (but not accepted) by the user.<sup>2</sup> The information in the preamble, the seen and accepted facts and the intuitions entered by the user are stored in the user model. The investigated propositions and the preamble are also stored in BIAS’ model of the world. In addition, during argument generation, BIAS investigates the world to obtain information necessary for argument formulation.

<sup>1</sup> At present, the relation between the system and the user is still asymmetrical, since the system is aware of all the information accessed by the user, while this is not the case for the user.

<sup>2</sup> A user may forget to indicate explicit acceptance of a proposition, or may decide not to click the acceptance boxes in order to expedite the interaction.

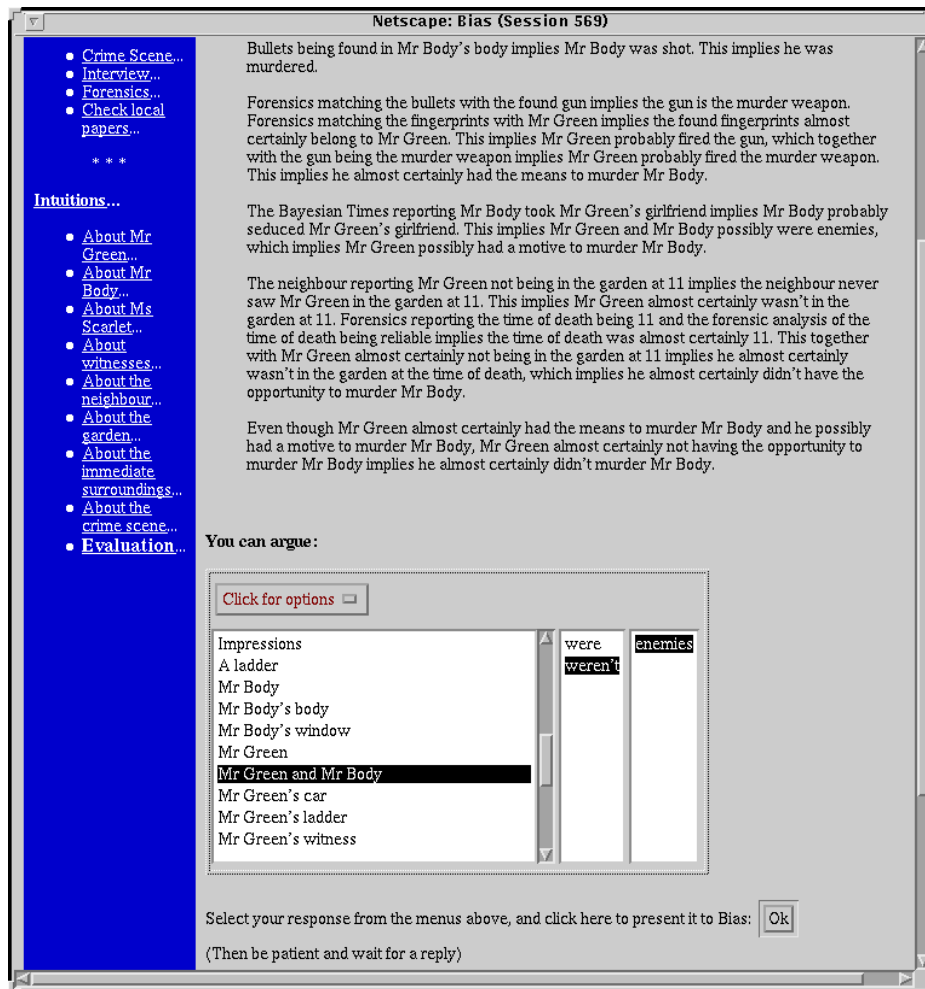


Fig. 2. Sample argument generated by BIAS

When the user asks for BIAS' opinion about the case, BIAS calls a Bayesian argument generator [9] to produce an argument for the goal proposition, which in our scenario is either *Mr Green is guilty* or *Mr Green is innocent* (whichever is most likely). The argument generator is given a desired level of belief for this goal. Initially, this level of belief is moderate so that the generator produces a preliminary argument which presents the system's "initial thoughts" about the case. If possible, our argument generator produces an argument that is compatible with both BIAS' beliefs about the world and the user's presumed beliefs. If this is not possible, BIAS' beliefs take precedence. Figure 2 shows the initial argument generated by BIAS in light of the above preamble and information gathered from the world.

The user can now continue investigating the world or s/he can pose a rejoinder. This is done by selecting the type of the rejoinder (*but* or *consider*) from a drop-down menu,

Actually, it is quite likely that Mr Green and Mr Body were enemies. This is for the following reason. A blue car being here last week and Mr Green having a blue car implies Mr Green's car was almost certainly here last week, which implies Mr Green almost certainly visited Mr Body last week. The neighbour reporting Mr Green arguing with Mr Body last week together with Mr Green almost certainly visiting Mr Body last week implies he almost certainly argued with Mr Body. The Bayesian Times reporting Mr Body took Mr Green's girlfriend implies Mr Body probably seduced Mr Green's girlfriend. This together with Mr Green almost certainly arguing with Mr Body implies Mr Green and Mr Body probably were enemies. Let's now go back to the main argument. Mr Green and Mr Body probably being enemies implies it is more likely that Mr Green had a motive to murder Mr Body, making it rather likely. This implies it is only slightly more likely that Mr Green murdered Mr Body.

**Fig. 3.** Rebuttal for the rejoinder *But Mr Green and Mr Body weren't enemies*

and composing a sentence using three dynamic menus (Figure 2).<sup>3</sup> In this example, the rejoinder is *but Mr Green and Mr Body weren't enemies*. Rejoinders that begin with “but” correspond to an expression of doubt [2], which intends to undermine the system's argument. Rejoinders that begin with “consider” constitute requests for the consideration of the effect of a proposition on the argument.

After receiving a rejoinder, BIAS tries to determine the line of reasoning intended by the user. For the sample rejoinder in Figure 2, BIAS postulates that the user's rejoinder is aimed at increasing the belief in Mr Green's innocence through the following line of reasoning: *Mr Green and Mr Body not being enemies implies that Mr Green less probably had a motive to murder Mr Body, which implies that Mr Green less probably murdered Mr Body*. BIAS then generates the rebuttal in Figure 3, which presents a stronger sub-argument against the rejoinder proposition than that presented in the original argument.

### 3 Knowledge Representation and User Model

We have chosen Bayesian networks (BNs) as our main representational formalism owing to their ability to represent normatively correct reasoning under uncertainty. BIAS uses BNs to represent the information about the world, the system's beliefs about the world, and the user's presumed beliefs. The world-BN contains the nodes and links which represent the characters and props in a murder case and the relations between them. Different instances of a murder case may be created by instantiating particular observable facts, e.g., *The neighbour reports that Mr Green was in the garden*. BIAS' BN and the user-model BN contain subsets of the world-BN, which represent BIAS' and the user's current beliefs about the murder case, respectively. These subsets are dynamically expanded using information obtained from the world-BN when the user investigates the murder case, when generating and presenting arguments and rebuttals, and when interpreting a user's rejoinders.

BIAS' BN and the user-model BN are used in different ways to perform these tasks. The interpretation process is performed in the context of the user model, since BIAS tries to “make sense” of what the user is saying relative to the system's view of the user's beliefs. In contrast, the processes for generating the initial argument and the rebuttals

<sup>3</sup> Dynamic menus are used in order to avoid dealing with words and propositions not known by the system. The acceptance of free-form input is the subject of future research.

consult the user model and BIAS' model. When generating the initial argument, BIAS tries to rely on beliefs held by both BIAS and the user if possible [9], while during rebuttal generation, BIAS focuses on the discrepancies between the user-model BN and BIAS' BN [6].

**Reasoning for generation and interpretation – extending BIAS' BN and the user-model BN.** Different mechanisms are used to extend BIAS' BN and the user-model BN. BIAS' BN is extended by “looking over the user's shoulder” while the user is interacting with the WWW interface, and by accessing the world-BN directly during argument and rebuttal generation. This is done by considering propositions that are relevant to the goal, and if they are not directly observable, retrieving information about these propositions (i.e., their neighbouring nodes) from the world-BN. This process continues until the belief in the goal exceeds a particular threshold, which typically happens when BIAS retrieves observable propositions that have a large influence on the goal. For instance, in order to show that *Mr Green had a motive to kill Mr Body*, its neighbouring node in the world-BN, *Mr Green and Mr Body were enemies*, is retrieved. To determine the belief in this node, its two neighbours, *Mr Body seduced Mr Green's girlfriend* and *Mr Green and Mr Body argued last week* are retrieved, and so on [9]. Upon completion of this process, BIAS produces an argument in the form of a Bayesian sub-net, which is rendered in English and presented to the user (Figure 2).

The propositions in the user-model BN are obtained from a variety of sources: accepted propositions have been “clicked” by the user in the WWW-interface, while seen propositions have been shown to the user, but s/he has not indicated a belief in them. Propositions *arguedByUser* are mentioned in the user's rejoinder, while propositions *impliedByUser* are inferred from the rejoinder. Similarly, propositions in BIAS' arguments are *arguedByBIAS* or *impliedByBIAS*. These sources affect the system's certainty regarding the presence of the propositions in question in the user model. For instance, an *accepted* proposition is more likely to be believed by the user than a proposition *impliedByBIAS*. This certainty is represented by means of a numerical score, which is taken into account when interpreting the user's rejoinder (Section 4). The links in the user-model BN are obtained from the following sources: (1) BIAS' arguments and rebuttals, where they are presented by means of linguistic markers (e.g., *therefore* and *this implies*); (2) the interpretation of a user's rejoinders (links corresponding to the most likely interpretation or to the interpretation confirmed by the user); and (3) *accepted* propositions that are neighbours in the world-BN (e.g., *Mr Body's window was broken*, *broken glass was found* and *broken glass was found inside the window* in Figure 1).

**Modeling Attention.** As indicated above, during argument and rebuttal generation, BIAS obtains information from the world-BN about the nodes in BIAS' BN that are likely to be relevant to the goal. We use attentional focus as a partial model of relevance to determine which propositions in BIAS' BN to inspect. In addition, we postulate that the line of reasoning intended by a user in a rejoinder is likely to include propositions in his/her focus of attention. In order to determine whether a proposition is in the user's or BIAS' focus of attention, we use a model of attention represented by means of a semantic network (SN) which contains associative links (rather than causal or evidential links). Activation is spread throughout this network from salient propositions [1]. One SN is incorporated into the user model (linked to propositions in the user-model BN), and one into BIAS' model (linked to propositions in BIAS' BN).

## 4 Interpreting a User’s Rejoinder

The interpretation of a user’s rejoinder consists of inferring the reasoning path intended by the user in the context of the user model (augmented by the BN corresponding to the presented argument). This process is implemented by algorithm *IdentifyPath*, which receives two inputs: a linguistic clue (“but” or “consider”) and a rejoinder proposition (**R**) [8].

**Algorithm** *IdentifyPath*(*linguisticClue*, **R**)

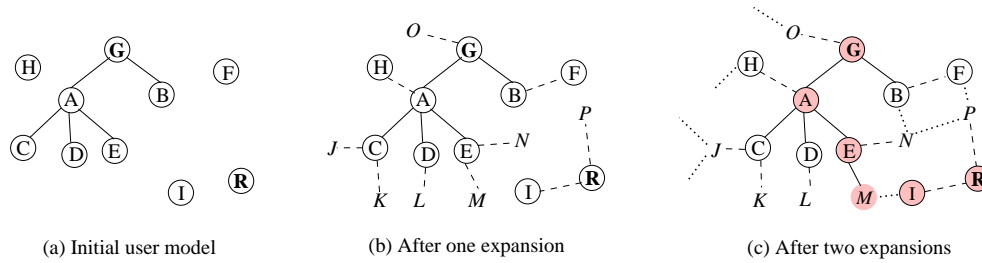
1. **Path construction** – Find paths that connect **R** to a proposition in the user model that is part of the argument-BN generated by BIAS.
2. **Path evaluation** – Compute a score for each path based on its effect on the argument, its presence in the user’s focus of attention, and BIAS’ confidence in it.
3. **Path selection** – Select the path with the highest score, or present promising paths to the user for confirmation if no single path is a clear winner.

### 4.1 Path construction

Our path construction process copes with two types of inaccuracies in the user model: *incompleteness* (the user model does not represent all the user’s beliefs), and *high-granularity* (a one-step inference of the user corresponds to several links in the BN). This means that a path can be found between the rejoinder node and the argument-BN even if some nodes in this path do not appear in the user-model BN. Such *gaps* in the user model are filled during path construction by iteratively “growing” the user-model BN from two starting locations, **R** and the argument-BN, until **R** and the argument-BN become connected. Each iteration is similar to an argument-generation iteration in that the “horizon” nodes around **R** and around the argument-BN are passed to the world-BN in order to obtain information related to these nodes. However, in order to avoid the indiscriminate attribution of beliefs to the user, BIAS fills only small gaps (of at most two nodes). Since the path construction process often adds to the user model nodes that are not in the intended path, this process is performed in a *temporary user model*. The intended path is incorporated in the user model after path selection (Section 4.3).

To illustrate the path construction process, consider the user model in Figure 4(a), which contains an argument-BN (the tree whose root is the goal node **G**), the nodes investigated by the user through the interface (F, H, I), and the user’s rejoinder proposition **R**. After one expansion (drawn with dashed lines), propositions F, H and I become connected to **R** or to the argument-BN, and additional propositions from the world-BN, *J, K, L, M, N, O* and *P* (shown in italics in Figure 4(b)), are linked to **R** or to the argument-BN. After the second expansion (drawn with dotted lines), **R** becomes connected to the original argument-BN and the goal through several paths in the temporary user model, e.g., **R-I-M-E-A-G** (composed of grey nodes in Figure 4(c)).

The path construction process also takes into account the user’s bounded reasoning capacity in that it finds interpretations which are direct and involve relatively short “inferential leaps” between the rejoinder and the goal. For instance, if the user says “*But Mr Green was near the house at 11:15*” after the argument in Figure 2, BIAS infers that the user is implying that Mr Green had the opportunity to kill Mr Body. However, if the user had said “*But Mr Green owns a blue car*”, it is not reasonable for the system to postulate a convoluted inference between this rejoinder and the goal. BIAS achieves this behaviour by performing only three iterations when trying to connect **R** to the argument-BN, and by restricting the length of the paths being built.



**Fig. 4.** Path construction in a sample user-model BN

## 4.2 Path evaluation

The score of each path is a function of (1) the impact of **R** on BIAS’ argument along this path according to the user model, (2) whether the nodes in this path are in the user’s attentional focus, and (3) BIAS’ confidence regarding the nodes in this path.

**Impact of **R** along a path.** The impact of a rejoinder **R** on the nodes along a path is the change in the belief in these nodes due to **R**. This impact is moderated by the rejoinder’s linguistic clue. A felicitous expression of doubt contradicts a proposition in the interlocutor’s argument. Hence, its impact on a BN node is positive only when it moves the belief in this node in the “opposite” direction. In contrast, a request for consideration has no such negative connotations. Hence, it always has a positive impact.

When posing a rejoinder, a user may intend to affect the argument goal or another proposition in BIAS’ argument. Therefore, when assessing the impact of a rejoinder along a path, we focus on two propositions: the goal and the *highest-impact* proposition. This is the proposition in the argument-BN on which the rejoinder had the highest impact along this path. For instance, given the rejoinder *But Mr Green and Mr Body weren’t enemies*, the highest-impact proposition is *Mr Green had a motive to kill Mr Body*.

**Attentional focus.** When posing a rejoinder, the user usually makes a small inferential leap along the path between the rejoinder and the proposition s/he intends to affect. For instance, when saying “*But Mr Green and Mr Body weren’t enemies*”, the user implies a short reasoning chain to *Mr Green didn’t have a motive to kill Mr Body* and *Mr Green didn’t kill Mr Body*. We postulate that such an inferential leap is more likely if it includes propositions in the user’s focus of attention. The level of activation of the nodes along a path in the user model reflects their presence in the user’s focus of attention.

**BIAS’ confidence in a path.** BIAS’ confidence in a path depends on its certainty regarding the user’s belief in each node along this path. This certainty is represented by the numerical score associated with the source from which a node was obtained (Section 3).

## 4.3 Path selection

Path selection consists of choosing the paths with the highest scores returned by the path evaluation step, and presenting them to the user for confirmation if no single path is a clear winner. The recognition process fails if BIAS could not find a path between the rejoinder proposition and the argument-BN during path construction, or too many paths with similar high scores were found (so they could not be presented for confirmation), or the user does not select any of the presented paths. In the future, our interface will ask the user to further specify his/her rejoinder in these situations.

**Table 1.** Conditions for the selection of a rebuttal strategy

	<b>R</b> is believed in BIAS' model and the user model	<b>R</b> is believed only in the user model
$\neg$ <b>R</b> is in the argument	N/A	Refute <b>R</b>
<b>R</b> has a strong effect on <b>G</b> in BIAS' model	Strengthen goal <b>G</b>	Refute <b>R</b>
<b>R</b> has a weak effect on <b>G</b> in BIAS' model	Dismiss Concede <b>R</b>	Dismiss Contradict <b>R</b>

*Actually, it is very improbable that the found gun is available only to Mr Green. However, even if it was available only to Mr Green, this would have only a small effect on the likelihood that Mr Green murdered Mr Body. This is for the following reason. The found gun being available only to Mr Green implies it is more likely that Mr Green fired the gun, making it almost certain. This implies it is more likely that he fired the murder weapon, making it almost certain, which implies it is even more likely that he had the means to murder Mr Body. This implies it is only slightly more likely that he murdered Mr Body.*

**Fig. 5.** Contradictory dismissal for *Consider that the found gun was available only to Mr Green*

## 5 Rebuttal Generation

Given a user's rejoinder proposition **R** and a *userPath* – the user's line of reasoning inferred by BIAS or selected by the user, we consider three main types of rebuttals: (1) *Refute R* – which argues against the user's belief in **R** (Figure 3); (2) *Strengthen G* – which presents a stronger argument for the original goal proposition **G**; and (3) *Dismiss userPath* – which shows how the user's reasoning path fails to achieve its intended effect. The selection of a rebuttal strategy depends on (1) the belief in **R** according to the user model and BIAS' model, (2) whether **R** was mentioned in BIAS' argument, and (3) the impact of **R** on the goal according to BIAS' model (the selection policy is summarized in Table 1). For instance, a rejoinder that contradicts directly a statement in BIAS' argument is always refuted. This is the case for the rejoinder in Figure 2. In contrast, a rejoinder that has a small impact on BIAS' belief in the goal is dismissed. We distinguish between two types of dismissals depending on whether BIAS and the user agree on **R**: *concessive* if they agree, and *contradictory* if they disagree. Figure 5 illustrates a contradictory dismissal for the rejoinder *Consider that the found gun was available only to Mr Green*. The dismissal denies the user's rejoinder proposition, and shows that its hypothetical effect on Mr Green's guilt is marginal.

Figure 6 shows simplified schemas for our rebuttal strategies. These strategies call our argument-generation mechanism [9] to generate sub-arguments. The refutation strategy includes a sub-argument which contradicts the user's rejoinder proposition, the goal-strengthening strategy includes sub-arguments which affect the belief in the goal proposition, and the dismissal strategy may include such sub-arguments. The last two strategies differ in that the goal-strengthening strategy looks for new information in support of BIAS' belief in the goal (BIAS changes its belief in the goal if it fails to find this information), while the dismissal strategy usually takes advantage of information that is already present in BIAS' model.

## 6 Related Research

Our research builds on the system described in [9], which generated arguments from BNs, and the follow-on system described in [10], which enabled a user to explore the



<p><b>Refute R:</b></p> <ol style="list-style-type: none"> <li>1. Deny the belief in <b>R</b> stated by the user.</li> <li>2. Present a sub-argument for BIAS' belief in <b>R</b>.</li> <li>3. If <b>R</b> was not mentioned in BIAS' argument, or the belief in <b>R</b> as a result of the sub-argument differs from that originally stated by BIAS, then follow the effect of <b>R</b> along <i>userPath</i>.</li> </ol>
<p><b>Strengthen G:</b></p> <ol style="list-style-type: none"> <li>1. Acknowledge the user's belief in <b>R</b>.</li> <li>2. While the belief in <b>G</b> is not as intended by BIAS, inspect each proposition <math>P_i</math> along <i>userPath</i> (starting from <b>R</b> towards <b>G</b>). <ol style="list-style-type: none"> <li>(a) Generate a sub-argument for BIAS' belief in <math>P_i</math>.</li> <li>(b) If this sub-argument yields a significant change in <math>P_i</math> then store it for presentation, and propagate its effect on the beliefs in BIAS' model.</li> </ol> </li> <li>3. Present the line of reasoning along <i>userPath</i> with the planned sub-arguments.</li> </ol>
<p><b>Dismiss <i>userPath</i>:</b></p> <ol style="list-style-type: none"> <li>1. Acknowledge/Contradict the user's belief in <b>R</b>.</li> <li>2. Generate a sub-argument for each proposition that accounts for the discrepancy between the user's beliefs and BIAS' beliefs along <i>userPath</i>. These propositions (1) are directly connected to <i>userPath</i>, (2) have different beliefs according to the user model and BIAS' model, and (3) have a significant effect on the belief in a proposition on <i>userPath</i>. (It is possible that no such propositions are found, as shown in the example in Figure 5).</li> <li>3. Follow the line of reasoning along <i>userPath</i> from <b>R</b> to <b>G</b> according to BIAS' model (this line is hypothetical for a contradictory dismissal).</li> </ol>

**Fig. 6.** Rebuttal Strategies

impact of different propositions on an argument by requesting the system to perform changes to this argument. Neither of these systems recognized a user's intentions from rejoinders or generated rebuttals that take into account these intentions, which BIAS does.

Quilici (1992) and Carberry and Lambert (1999) used a plan-based approach for argumentation. Quilici's system recognized the justification for a user's proposal and provided its own justifications in plan-related arguments. However, the rebuttals generated by this system were based on a single strategy: applying backwards chaining using a set of justification rules. This strategy is a special case of the more general rebuttal schemas presented here. Carberry and Lambert's system recognized a user's intentions during expert-consultation dialogues. Like BIAS, their system combined linguistic and contextual knowledge to recognize a user's intentions from rejoinders. However, it differed from BIAS in several respects: it covered a wider range of linguistic phenomena than those handled by BIAS, but it did not generate rebuttals, and it handled conversational turns in the context of interactions where each participant utters one or two propositions (compared to BIAS' complex arguments and rebuttals).

BNs have been used in several predictive tasks related to user modeling, e.g., [3–5]. BIAS resembles Gertner *et al.*'s system in that both systems use BNs for belief representation and plan recognition. However, the systems differ in the manner in which the BNs are obtained and in the usage of the BNs. Heckerman and Horvitz used a BN to infer a user's software assistance requirements from his/her input. Charniak and Goldman used BNs and marker passing (a form of spreading activation) for plan recognition during story understanding. However, neither of these two systems used BNs as a formalism for synthesis and analysis, as described in this paper.

## 7 Conclusion

We have offered a WWW-based interactive argumentation system which generates probabilistic arguments, recognizes a user's intentions from short-form rejoinders, and generates rebuttals to these rejoinders. The system consults a user model which represents a user's beliefs and inferences, the source from which these beliefs were obtained, and the user's attentional focus. The recognition mechanism, which is robust with respect to certain types of inaccuracies in the user model, connects the user's response with the system's argument. The rebuttal-generation process selects a rebuttal strategy on the basis of the beliefs in the user model and BIAS' model, and the impact of the user's rejoinder on the beliefs in BIAS' model. A preliminary evaluation of our interpretation mechanism indicates that people found BIAS' interpretations appropriate [8]. The rebuttal-generation mechanism will be evaluated in the near future.

## 8 Acknowledgments

The author thanks Sarah George, Nathalie Jitnah and Richard McConachy for writing the software for this project.

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