Opponent Modelling in Persuasion Dialogues

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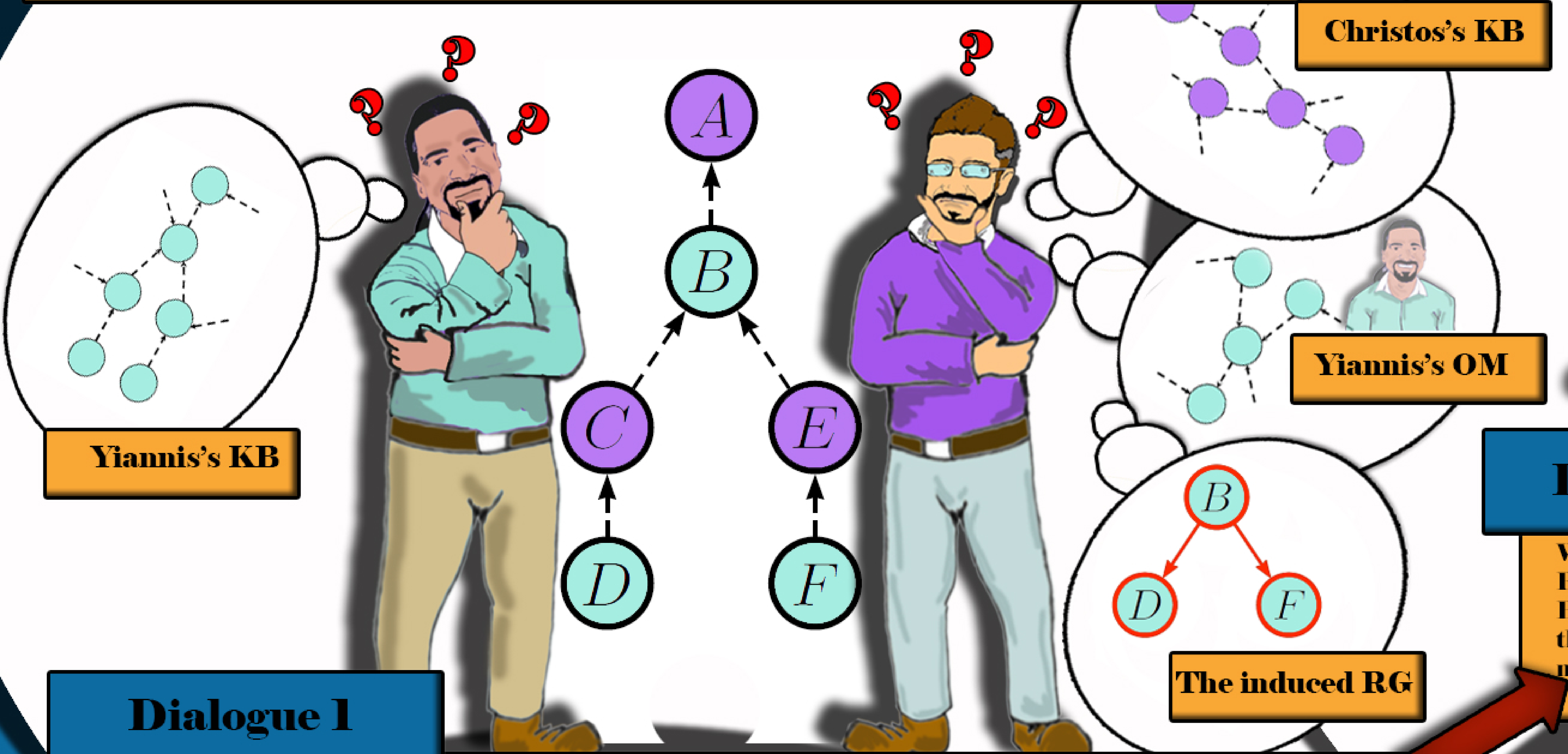
IJCAI-13

PROBLEM DESCRIPTION: This work deals with opponent modelling in dialogue games. Generally, in these games participants strategise relying on opponent models (OM). In most cases, such OMs fail to utilise an agent's general dialogue experience in an effective way, as they are built through previous dialogue interactions solely concerned with the opponent at hand.

PROPOSED SOLUTION: We rely on an agent's general experience to define a mechanism for augmenting an OM with information likely to be dialectally related to information already contained in it, aiming to increase a strategy's efficiency.

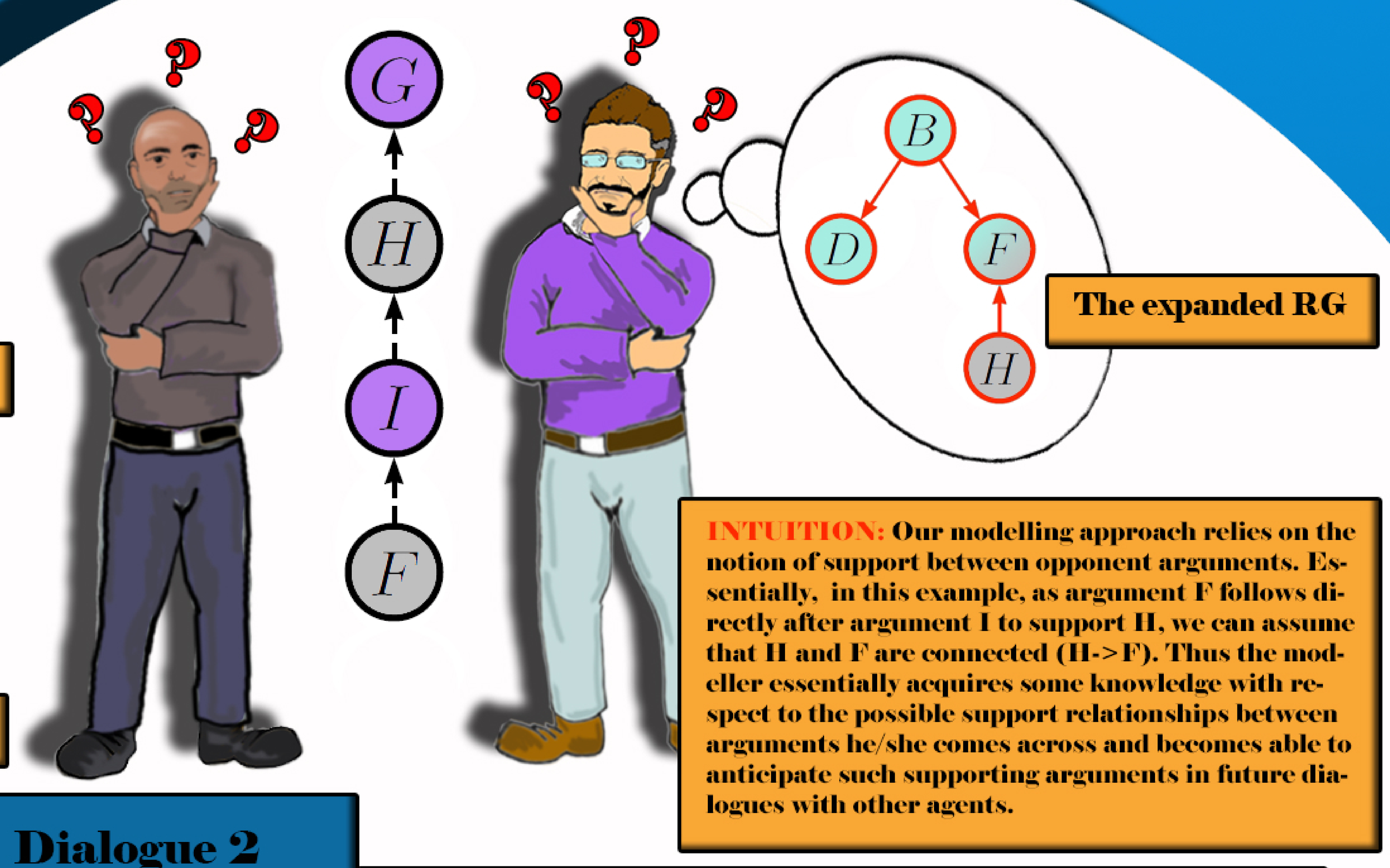


Dialogue 1

AGENT KNOWLEDGE BASE (KB): We assume each participant to maintain a KB in the form of abstract argumentation frameworks (AF). Such frameworks are expressed as directed graphs where the nodes are arguments linked with attack relationships (e.g. Christos's KB or Yiannis's KB).

OPPONENT MODELS (OM): OMs are also expressed in the form of AF's. Essentially they express an agent's assumptions about the beliefs of their opponents (e.g. Christos's OM of Yiannis).

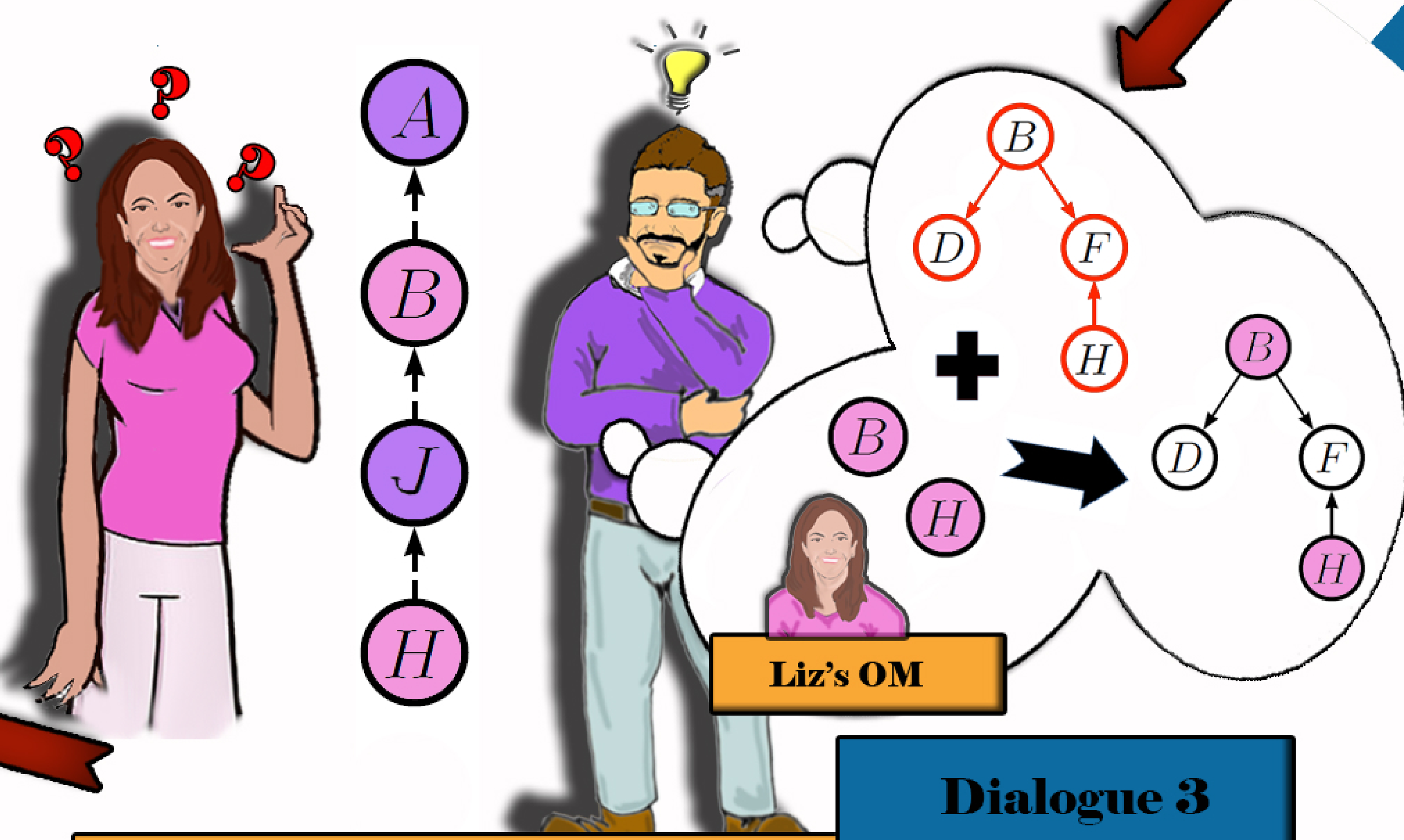
RELATIONSHIPS GRAPH (RG): A RG is also a directed graph with just opponent arguments as nodes, which is incrementally constructed through a series of dialogues. Two arguments B and D are linked (B->D) if they are found on the same dialogue path & D directly supports B (e.g. Christos's RG).



INTUITION: Our modelling approach relies on the notion of support between opponent arguments. Essentially, in this example, as argument F follows directly after argument I to support H, we can assume that H and F are connected (H->F). Thus the modeller essentially acquires some knowledge with respect to the possible support relationships between arguments he/she comes across and becomes able to anticipate such supporting arguments in future dialogues with other agents.

Dialogue 2

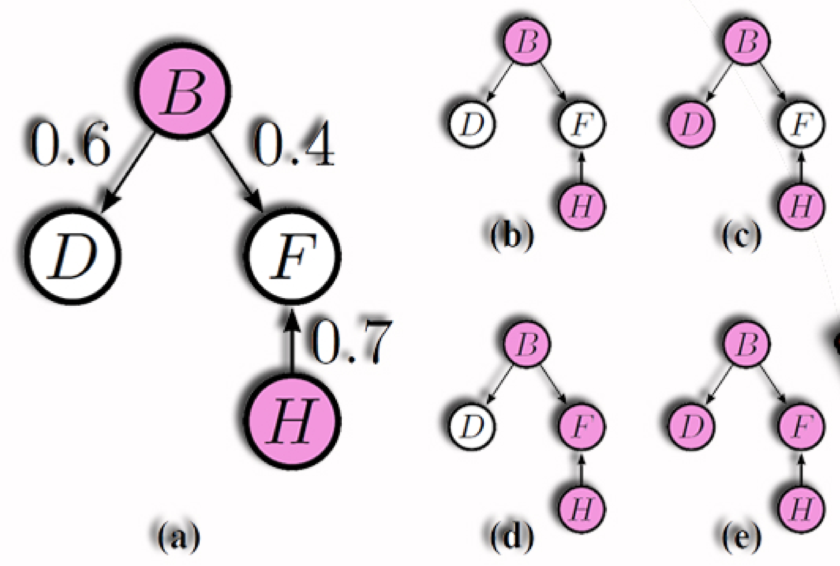
What we care to convey through this series of dialogues is the incremental process through which a RG can be constructed. Up to this point Christos's RG consists of three opponent arguments (B,D,F). Based on how they were encountered in Dialogue 1, we assume that there exist two links between them (B->D,B->F). Following on, as Christos engage's in another dialogue with Sanjay more arguments can be added into his RG and be linked with arguments already in it.



Dialogue 3

Let us then assume that Christos engages in a third Dialogue with Liz, in which he discovers that she is aware of arguments B and H. Christos is then able to build an initial OM for Liz including these 2 arguments in it. In addition though, by projecting the image of Liz's OM on the existing RG, Christos can also deduce possible supporting arguments to B and H which may also be known to Liz.

In the RG on the right the weights associated with the corresponding arcs are assumed to be computed over multiple dialogues and are not just based on those that appear on this poster...
This is necessary for meaningful conclusions to be drawn with respect to the relationship likelihood between arguments in the RG. Otherwise we encounter a COLD START PROBLEM!



Step-1

AUGMENTATIONS: For deciding which of Liz's neighbouring arguments (D,F) should be included into her OM, we simply have to compute the likelihood of all the possible expansions of Liz's OM on the RG. We refer to these possible expansions as augmentations.

WEIGHTS: For computing these augmentations we rely on the weights found on RG's acs (r). These weight values (e.g. w_BF) represent the relationship likelihood of an argument B with an argument F. They are essentially a normalisation that allows us to compute a probability value Pr(r_BF) = w_BF for arc r_BF. We simply count the number of agents that have used, in dialogues, argument B followed by F, and we put them against the total number of agents that have simply put forth argument B in dialogues.

$$
\begin{aligned}
Pr(F) &= Pr(r_{HF} \cup r_{BF}) \\
&= Pr(r_{HF}) + Pr(r_{BF}) - Pr(r_{BF} \cap r_{HF}) \\
&= w_{HF} + w_{BF} - w_{BF} \cdot w_{HF} = 0.82
\end{aligned}
$$

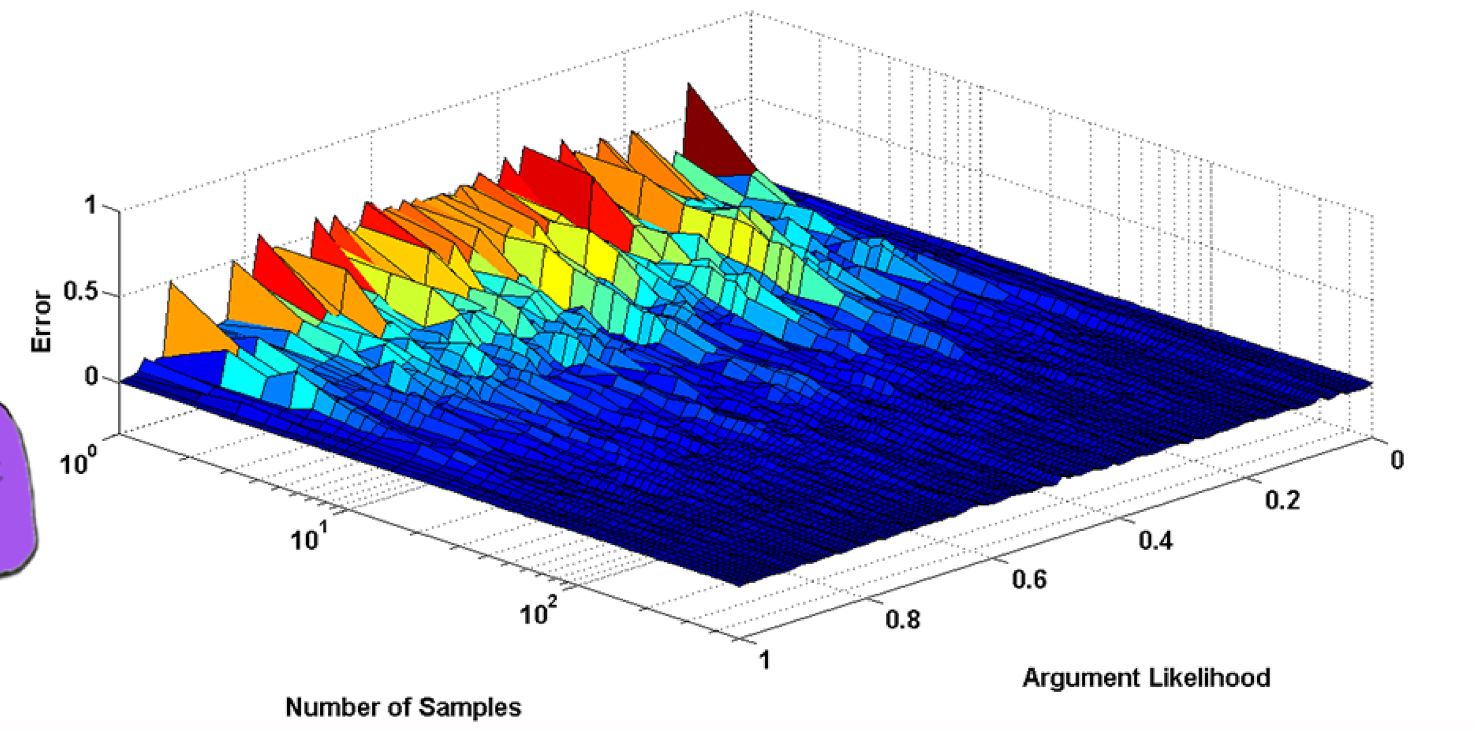
$$
Pr(\mathcal{A}'_F) = Pr(F)(1 - Pr(D)) = Pr(F)(1 - w_{BD}) = 0.328
$$

Step-2

As illustrated in the above example, where we compute the likelihood of augmentation (d), it is first necessary to compute the likelihoods of all the arguments included in that augmentation. In this case, argument F.

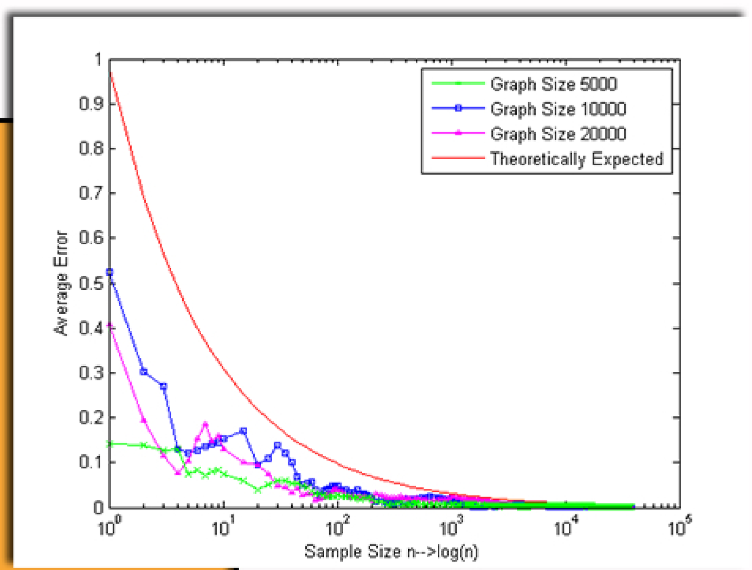
Computing the argument likelihood is done using the inclusion-exclusion probability over the incoming arcs.

PROBLEM: However, as the RG grows in size, and the incoming arcs of arguments increase in number, computing this probability becomes very expensive.



Step-3

In order to maintain the scalability of the proposed model, we developed and used a MONTE-CARLO method in order to estimate likelihoods of arguments in the RG. This method produces results of reasonable accuracy in a number of samples which is independent of the graph size.



ALGORITHM: The method we describe is as follows:

- Assume an RG and an OM
- We begin with the original OM
- For each argument Y of the OM we include the outgoing arcs to that argument with probability equal to their weights
- If an arc is included, we then add the end point argumnet of that arc in the OM'.
- At the end of the process OM' contains a possible 1-hop augmentation of OM.

By repeating this process multiple times we can infer the argument likelihoods by calculating the proportion of times they were added in augmentations OM' and thus choose high likelihood arguments to be augmented in the original OM.

Contributions

Through this work we have:

- Provided a general methodology for updating and augmenting an OM, based on an agent's experience obtained through dialogues.
- Provided a method for building a graph between related arguments asserted by a modeller's opponents, referred to a RG, and proposed an augmentation mechanism, enabling an agent to augment its current beliefs about its opponents beliefs by including additional information (arguments), that is of highlikelihood to be related to what the opponent is currently assumed to know.
- Thus, we enabled an agent to also account in its strategizing for the possibility that additional information may also be known to its opponents.
- Finally, we defined and analysed a MONTE-CARLO simulation which enabled us to infer the likelihood of those additional arguments in a tractable and efficient way.

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