Argumentation and Data-oriented Belief Revision: On the Two-Sided Nature of Epistemic Change

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Abstract. This paper aims to bring together two separate threads in the formal study of epistemic change: belief revision and argumentation theories. Belief revision describes the way in which an agent is supposed *to change his own mind*, while argumentation deals with persuasive strategies employed *to change the mind of other agents*. Belief change and argumentation are two sides (cognitive and social) of the same epistemic coin. Argumentation theories are therefore incomplete, if they cannot be grounded in belief revision models – and vice versa. Nonetheless, so far the formal treatment of belief revision widely neglected any systematic comparison with argumentation theories. Such lack of integration poses severe limitations to our understanding of epistemic change, and more comprehensive models should instead be devised. After a short critical review of the literature (cf. 1), we outline an alternative model of belief revision whose main claim is the distinction between data and beliefs (cf. 2), and we discuss in detail its expressivity with respect to argumentation (cf. 3): finally, we summarize our conclusions and future works on the interface between belief revision and argumentation (cf. 4).

1 BELIEF REVISION WITHOUT ARGUMENTATION

Following the seminal work in [10], belief revision has recently become an extremely active area of research at the confluence between AI, logic, cognitive science, and philosophy. Notwithstanding the impressive amount and quality of studies devoted to this topic, belief revision has been mainly addressed in a rather single-minded fashion, isolating the issue of belief change from other related features of cognitive processing. As remarked in [15], current theories of belief revision have been put forward and discussed in a sort of epistemological vacuum, without providing a more comprehensive account of epistemic states and dynamics. Moreover, the process of belief change has been usually conceived as an isolated activity, neglecting obvious connections with other cognitive tasks: e.g. inferential reasoning, communication, argumentation. On the contrary, we claim that belief revision should be investigated as a specific function (albeit a crucial one) in the cognitive processing of epistemic states, integrating formal models of belief change in a comprehensive epistemological theory, with systematic connections with related cognitive tasks.

1.1 Limitations of current theories

The AGM paradigm [10] has been the most influential model of belief revision so far, serving as a frame of reference for both refinements and criticisms of the original proposal. Roughly summarizing (see [14] for further discussion), this model was first conceived as an idealistic theory of rational belief change: belief states were characterized as sets of propositions (infinite and deductively closed), three basic types of change were described (expansion, contraction, revision), and rationality was expressed by a set of postulates binding these operators. To decide between different outcomes of the revision process (i.e. different sets of propositions consistent with the rationality postulates), an ordering criterion was introduced in the original belief state, ranking propositions for their importance (epistemic entrenchment).

This approach to belief revision fails to integrate with argumentation theories for two reasons: (1) it does not make any predictions or assumptions about how and why some propositions come to be believed, rather than others; (2) there is a deliberate lack of structural properties in the characterization of epistemic states. Argumentation theories capture the ways in which a desired change in the audience's beliefs is brought about by the arguer: therefore, without an explicit theory of *the reasons to believe something*, the whole point of argumentation is lost. AGM-style approaches to belief revision simply lack the necessary internal structure to describe argumentative strategies.

In this respect, the so called *foundation theories* of belief revision fare better than AGM, since they provide a precise account of the reasons supporting a given belief, e.g. using truth maintenance systems [5]. Similar proposals have also been advanced in the field of multi-agent systems [6, 8, 9].

Nevertheless, none of these theories explicitly address argumentation, and the structural properties of epistemic states are restricted to factual supports for the agent's beliefs, in order to ensure an accurate weighting of unreliable and/or contrasting sources of information. Although such structures are essential to integrate belief revision and argumentation, they are not enough: a fairly rich picture of argumentative strategies must also include motivational and emotional features [4, 11, 12], not only factual credibility. We also claim that belief revision is affected by similar considerations, so that a more comprehensive cognitive model of epistemic change must be devised (cf. 2.1-2.4; see also [7, 9, 15]).

2 DATA-ORIENTED BELIEF REVISION (DBR): AN ALTERNATIVE MODEL FOR COGNITIVE AGENTS

The following sections provide a short outline of an alternative model of belief revision, i.e. *Data-oriented Belief Revision (DBR)*: for further details, see [3, 14].

2.1 Data and beliefs: properties and interaction

Two basic epistemic categories, *data* and *beliefs*, are put forward in this model, to account for the distinction between pieces of information that are simply *gathered and stored* by the agent (data), and pieces of information that the agent considers *reliable bases for action, decision, and specific reasoning tasks*, e.g. prediction and explanation (beliefs). Clearly, the latter are a subset of the former: the agent might well be aware of a datum that he does not believe (i.e. he does not consider reliable enough); on the

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other hand, the agent should not be forced to forget (i.e. to lose as a datum) a piece of information which he temporarily rejects as a belief [3]. Moreover, a rejected piece of information retains significant epistemic properties (e.g. its own unreliability, and the reasons for it) that will often be crucial in future revisions and should be preserved by a formal model of belief change [6, 15].

The distinction between data and beliefs yields a number of relevant consequences for the formal study of epistemic dynamics: to start with, it leads to conceive *belief change as a two-step process*. Let us consider external belief change (cf. 2.3), by way of example. Whenever a new piece of evidence is acquired, either through perception or communication, it affects *directly* the agent's data structure, and only *indirectly* his belief set. More precisely, the effects (if any) of the new datum on the agent's beliefs depend (1) on its effects on the other data, and (2) on the process of belief selection applied by the agent over such data (cf. 2.2). The resulting multi-layered architecture of belief change has been christened as Data-oriented Belief Revision (DBR) in [14].

In DBR, data are selected as beliefs on the basis of their properties, i.e. the possible *cognitive reasons to believe* such data. Our model accounts for four distinct properties of data [2, 3, 14]:

I. *Relevance*: a measure of the pragmatic utility of the datum, i.e. the number and values of the (pursued) goals that depends on that datum.
II. *Credibility*: a measure of the number and values of all supporting data, contrasted with all conflicting data, down to external and internal sources;
III. *Importance*: a measure of the epistemic connectivity of the datum, i.e. the number and values of the data that the agent will have to revise, should he revise that single one;
IV. *Likeability*: a measure of the motivational appeal of the datum, i.e. the number and values of the (pursued) goals that are directly fulfilled by that datum.

The assessment of credibility and importance is discussed in 2.3, while the assessment of relevance and likeability is detailed in [14]. In DBR, credibility, importance and likeability determine the outcomes of belief selection, i.e. whether a candidate data is to be believed or not, and with which strength (cf. 2.2), while relevance is crucial in pre-selecting the sub-set of active data (focusing), i.e. determining which data in the agent's data base are useful/appropriate for the current task, and should therefore be taken in consideration as candidate beliefs (more in-depth discussion on focusing is given in [14]). While relevance and likeability depend on a comparison between data and goals, credibility and importance basically *depend on structural relations between data* [6]. In fact, in DBR data bases are highly structured domains, best conceived as *networks*: data are represented as *nodes*, interconnected through characteristic functional relations (cf. 2.3), i.e. *links* in the network.

The agent's beliefs emerge from his data base through the selection process (cf. 2.2). Beliefs are characterized by *strength*, which reflects their implicit ordering. Strength is determined by the selection process from the values of credibility, importance, and relevance of the corresponding datum. Beliefs are organized in *ordered sets*, rather than networks [10, 14].

The basic distinction between data and beliefs yields a rich picture of epistemic dynamics (Table 1). From a computational viewpoint, such distinction opens the way for *blended approaches to implementation* [14]: data structures present remarkable similarities with Bayesian networks and neural networks, while belief sets are a well-known hallmark of AGM-style belief revision [10]. Moreover, data and beliefs in DBR are conceived as *different stages, roles, and functions in the processing of internal epistemic states*, to be accounted for in the agent architecture [14].

Table 1. Data and beliefs in DBR: an overview

	Basic properties	Organization principle	Internal dynamics	Interaction principle
DATA	*Relevance, credibility, importance, likeability*	*Networks*	*Updates, propagation*	*Belief selection*
BELIEFS	*Strength*	*Ordered sets*	*Inferential reasoning*	*Feedback mapping*

2.2 Belief selection in DBR

Once the informational values of the available data are assessed (cf. 2.3), a selection over such data is performed, to determine the subset of reliable information (i.e. beliefs) and their degree of strength. Every time new information is gathered by the agent, modifying his data network, the belief selection takes place anew, possibly (but not necessarily) changing the agent's belief set.

This process of belief selection in DBR regulates the interaction from data to beliefs, determining (1) what data are to be believed, given the current informational state, and (2) which degree of strength is to be assigned to each of them. The outcome of belief selection is determined by the informational values of the candidate data (credibility, importance, likeability) and by the specific nature of the agent's selection process.

In this model, the agent's belief selection is represented by a mathematical system, including a *condition C*, a *threshold k*, and a *function F*. Condition and threshold together express the minimal informational requirements for a datum to be selected as belief. The function assigns a value of strength to the accepted beliefs. Both C and F are mathematical functions with credibility and/or importance and/or likeability as their arguments, but they do not need to be identical. Given a datum $\square$, $c^{\square}$, $i^{\square}$, $l^{\square}$ are, respectively, its credibility, importance, and likeability. Let $\boldsymbol{B}$ represents the set of the agent's beliefs, and $B^{s}\square$ represents the belief $\square$ with strength s. Hence the general form of the selection process is:

if $C(c^{\square}, i^{\square}, l^{\square}) \leq k$ then $B^{s}\square\square\,\boldsymbol{B}$

if $C(c^{\square}, i^{\square}, l^{\square}) > k$ then $B^{s}\square\square\,\boldsymbol{B}$ with $s^{\square} = F(c^{\square}, i^{\square}, l^{\square})$

The setting of C, F and k is an individual parameter, which might vary in different agents (cf. 2.4). Examples are given in [14].

2.3 Information update and data assessment

Belief revision is usually triggered by *information update* either on a fact or on a source: the agent receives a new piece of information, rearranges his data structure accordingly, and possibly changes his belief set, depending on the belief selection process. Information update specifies the way in which new evidences are integrated in the agent's data structure. We define *external belief selection* the process of epistemic change triggered by information update, in contrast to *internal belief revision*, i.e. belief change initiated by inferring a new piece of information through reasoning (on internal belief revision, see [14]).

Data structures are conceived as networks of nodes (data), linked together by characteristic relations. For the purposes of the present discussion, it will suffice to define three different types of data relations: support, contrast, and union.

I. *Support*: □ supports □ (□□ □) iff c^□ µ c^□, the credibility of □ is directly proportional to the credibility of □.
II. *Contrast*: □ contrasts □ (□□□) iff c^□ µ 1/c^□, the credibility of □ is conversely proportional to the credibility of □.
III. *Union*: □ and □ are united (□ & □) iff c^□ and c^□ jointly (not separately) determine the credibility of another datum □

New external information generates not only a datum concerning its *content*, but also data concerning *source attribution* and *source reliability*, and the *structural relations* among them. More precisely, information update brings together:

I. a datum concerning the content (object datum, *O-datum*);
II. a datum identifying the information source (*S-datum*);
III. a datum concerning the reliability of the source (*R-datum*).

These data are closely related, since the credibility of the new information depends on the jointed credibility of the other two data: i.e. the union of the S-datum and the R-datum supports the O-datum (Fig. 1). Once an agent has been told by *x* that □ holds, his confidence in □ will depend on the reliability he assigns to *x*, provided he is sure enough that the source of □ was indeed *x*. The environmental input is characterized by a content □ (e.g. its propositional meaning), a source *x* (e.g. another agent), and a noise *n* (affecting both source identification and content understanding)[1].

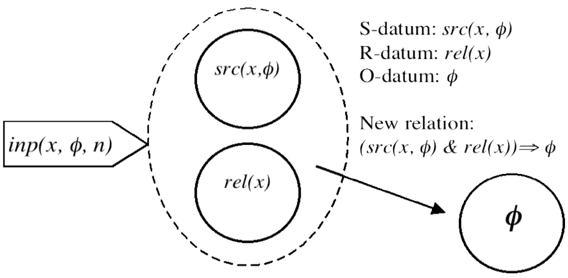

Figure 1. Information update: integrating new external data

While pragmatic relevance and emotional likeability of a datum are further discussed in [3, 14], here we focus on credibility and importance. The credibility of a given datum depends on the credibility of its supports, weighted against the credibility of its contrasts [3, 8, 15]. Each agent must be equipped with a specific algorithm to determine such value. Although this algorithm is an individual parameter (different agents can use different heuristics for data assessment), it must obey the general definition of support and contrast relations. This is an example of *credibility algorithm*[2]:

c^□ = (1 - □ □□ S□ (1 - c^□)) □□ □□ K□ (1 - c^□)
with S□ = the set of all data supporting □
K□ = the set of all data contrasting □

Support and contrast determine the credibility of one *relatum* in terms of the credibility of the other. Union takes in account the credibility of both *relata* at the same time, in order to assess the credibility of a third datum – either supported or contrasted. An example is given by information update (Fig. 1): the credibility of the O-datum depends on the credibility of the union of S-datum and R-datum. Therefore we need to specify a *union algorithm* for each agent [14]: i.e. a procedure to assess the credibility of *(□ & □)*, given the credibility of □ and □. For instance:

c^□ & □ = min(c^□, c^□)

Now we have enough elements to provide a quantitative description of information update, and not only a qualitative one. The credibility of the O-datum will depend on the credibility of the union of the S-datum (here with $c = 1$, assuming noiseless communication by hypothesis) and the R-datum, weighted against the credibility of all contrasting evidences (if any), according to the credibility algorithm of that particular agent. The assessment of source reliability is thoroughly discussed in [3, 8, 14].

Importance assessment in DBR is formally similar to credibility assessment, although different features of the datum are considered here: importance measures the *connectivity* of the datum (i.e. its epistemic value: how many data explains and are explained by that datum), therefore it depends on the number and credibility of all related data – without distinction between supports and contrasts. An *importance algorithm* (determining the agent's general strategy in evaluating importance) and a *threshold* (ranged in **[0, 1]**, selecting which data are good enough to influence the importance estimate) are defined for each agent, and they are both individual parameters (cf. 2.4). In addition, importance assessment requires also to specify a certain *depth*, i.e. the number of steps (forward or backward) in data networks considered by the agent in assessing importance. Provided that data are typically inserted in chains of sequential supports (e.g., □□ □□ □□ □□ □ etc.), not all data in the chains will be relevant to assess the importance of each node, although they are all related to each other: the number of nodes actually considered depends on the depth parameter (in DBR, a positive integer) characteristic of that particular agent. An example of parametrical setting for importance evaluation is the following:

□ < 5 *i^□ = □/5 □ (1 – □ □□ N□ (1 – c^□))*
□ ≥ 5 *i^□ = 1 – □ □□ N□ (1 – c^□)*
with N□ = the set of all data related to □ in depth □
□ = the number of data in N□ with c^□ ≥ *w*

Threshold *w* = 0.3
Depth □ = 2

In this case, the agent will apply his importance algorithm to all related active data within two steps in the data network (depth) and with credibility equal or greater than 0.3 (threshold). Different settings of these parameters can be used to express different individual attitudes in importance assessment (cf. 3.5).

2.4 Individual variation in DBR: principles and parameters

The DBR model is based on a conceptual distinction between *principles* and *parameters* [14]. Principles are *general* and *qualitative* in nature, defining the common features which characterize epistemic processing in every agent. Parameters, instead, are *individual* and *quantitative*, specifying in which fashion and measure each agent applies the universal principles of DBR. The cognitive and social framework of the model is captured by its principles, while individual variation is represented through parametrical setting.

[1] More sophisticated models (e.g. [8]) might take in account also the degree of certainty over the content expressed by the source, allowing agents to communicate information with different shades of confidence.

[2] It is convenient to range credibility in the close interval **[0, 1]**, but this does not necessarily lead to probabilistic accounts of epistemic dynamics. Probabilities can be handy for implementation (e.g. Bayesian networks), without being used as a general paradigm for the modeling of knowledge.

For instance, the overall two-step dynamic of belief revision is a universal principle, while the mathematical nature of the selection process is an individual parameter. Credibility assessment will always be positively affected by supporting evidence and negatively affected by contrasting data, but the credibility algorithm might vary from one agent to another. All agents perform inferential deduction at the level of beliefs, but the specific axioms applied are a matter of individual variation – and so on. A mathematical sketch of parametrical setting is given in 3.5, to illustrate part of their impact over argumentation.

3 ARGUMENTATION AND DBR

This section is devoted to highlight several connections between DBR and argumentation theories [1, 4, 11, 13, 16]: the impact of rhetorical arguments over the audience's beliefs (cf. 3.1), the different stages in Toulmin's model of argumentation (cf. 3.2), the treatment of defeasible reasoning (cf. 3.3), the role of contradictions in arguments (cf. 3.4), and the effects of individual parameters over argumentation strategies and outcomes (cf. 3.5).

3.1 Rhetoric and audience's beliefs

Aristotle's definition of rhetorical argument characterizes it as being especially focused on the *audience's beliefs*, rather than general acceptability. This definition is usually referred to in formal studies of rhetorical argumentation, e.g. [11], where the need for a model of belief revision (and more generally belief processing) is quite self-evident. However, as far as cognitive agents are concerned, even the most general and uncontroversial argument requires a process of belief revision in the mind of the audience: it is not the fact that *p* follows from *q* and *q* is the case which makes me believe *p*, but rather my beliefs that "*p* follows from *q*" and "*q* is the case". An integrated framework naturally emphasizes that any form of argumentation (including strictly logical ones) must be strongly focused on the audience's beliefs.

In our model, a crucial factor in determining whether a new piece of information will be accepted or rejected as belief is its *importance* [10, 14], i.e. the degree of connectivity (integration) of the new datum in the audience's data structure (cf. 2.3). An effective argument not only presents new information to the audience, but also provides the relevant connections with data already available to (and possibly believed by) that audience. Such connections vouch for the *plausibility* of the new datum [3] and are crucial in persuading the audience to accept it. In data networks, we distinguish two cases of argumentation through plausibility:

I. *Self-evident data*: the new datum is presented as following from what the audience already knew – the datum had not yet been inferred, but it might have been, and the audience is likely to remark: «Sure! Of course! Obviously!» etc.;
II. *Explanatory data*: the new datum is presented as supporting and explaining data already available – since such explanation was missing so far, it produces reactions like: «Now I see! That's why! I knew it!» etc.

This distinction is easily represented by a structured data-domain: in DBR, self-evident data are data with a high number of supports, while explanatory data in turn support many other data (Fig. 2). Different degrees of self-evidence and explanatory power are expressed by epistemic importance (cf. 2.1).

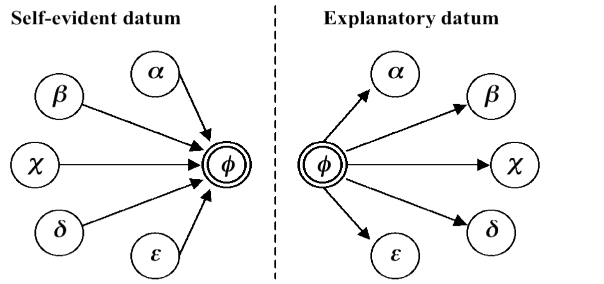

Figure 2. Two plausibility arguments: self-evident and explanatory data

3.2 Toulmin revis(it)ed

One of the most influential account of argumentation is the so called Toulmin's model [16], which analyzes six features of an argument: data, claim, warrant, backing, qualifier, rebuttal. The *data* are the facts (e.g. John loved his wife) which support the arguer's *claim* (e.g. John did not murder her), while the *warrant* ensures the connection between data and claim (e.g. people do not murder the ones they love), on the basis of some *backing* (e.g. murderers hate their victims); the *qualifier* specifies to what extend the warrant applies to the claim (e.g. usually), and the *rebuttal* describes special conditions which undermine the warrant (e.g. John is in bad need of money and will benefit from her insurance).

This schema is liable of immediate implementation in our model of belief revision, since it defines a specific data structure (Fig. 3). The *union* of data and warrant *supports* the claim, and the warrant is in turn *supported* by its backing and *contrasted* by the rebuttal, i.e. *supports* to the rebuttal make the warrant less reliable. The qualifier is represented by the degree of *credibility* assigned to the claim by this data structure – while more sophisticated models of source integration might also distinguish between the claim's credibility and the confidence expressed by the arguer [8].

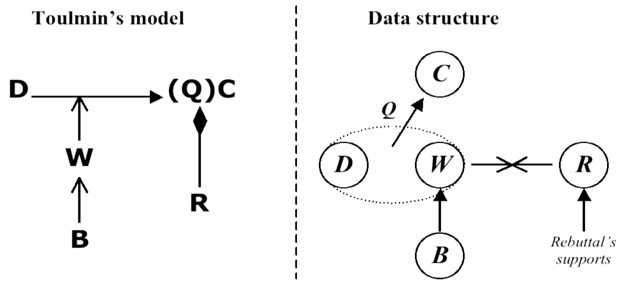

Figure 3. Toulmin's model in data structure

This convergence is not surprising, since our model is built over the intuition that epistemic processing requires "reasons to believe" [3, 5, 7], and indeed argumentation is mainly concerned with the manipulation of reasons in order to change the audience's beliefs. However, it is worth noticing that other theories of belief revision fail to incorporate Toulmin's model: e.g., in the AGM approach there is no way to capture similar argumentative structures, without undertaking major modification of the model.

3.3 Defeasible reasoning in data networks

Argumentation is often modeled in the formal framework of defeasible reasoning [1, 15], distinguishing between two kinds of defeaters (i.e. possible counterarguments against a reason-schema): *rebutting* vs. *undercutting defeaters*. Applying the terminology proposed in [16], a rebutting defeater is any reason which directly denies the claim of the argument, while an undercutting defeater is a reason which undermine the validity of the relevant warrant.

In our model, different defeaters target different nodes in the data network (Fig. 4): rebutting defeaters are data which contrast the claim-node (e.g. John has been seen shooting his wife), while undercutting defeaters are data contrasting the warrant-node (e.g. jealousy can make you kill the ones you love most). Moreover, a third category of defeaters can be expressed: *premise defeaters*, i.e. reasons which contrast the data-node (e.g. John did not love his wife). Undercutting and premise defeaters have similar function but different targets: the former attack the connection between data and claim, while the latter question the statement of fact which support the conclusion[3].

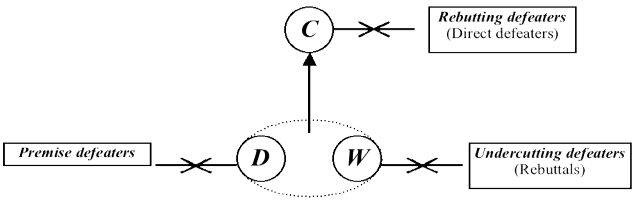

Figure 4. Defeasible reasoning in data structure

3.4 Revising contradictions in argumentation

AGM-style approaches to belief revision exclude contradictions in principle, assuming belief states to be fully consistent – an untenable assumption, as far as cognitive agents are concerned. On the contrary, argumentation theories have been quite successful in handling inconsistency and conflicts [1, 4, 15, 16], since the very idea of defeating an argument implies that such argument can be showed to be inconsistent with respect to a better one. Moreover, the AGM paradigm assumes belief states to be deductively closed, therefore infinite. This is not only a computational problem, but also a conceptual mistake: cognitive agents do not derive all the consequences from available data not only because they are resource-bounded [14], but mainly because they have no need to derive irrelevant consequences from accepted claims.

In DBR, epistemic states are both finite and deductively open, and there is no universal insurance against contradictions. Instead, we are able to capture two relevant distinction concerning inconsistency: *implicit* vs. *explicit contradictions*, and *data contrasts* vs. *beliefs contradictions*. Agents are likely to entertain a certain number of implicitly contradictory beliefs, i.e. beliefs from which a contradiction could be derived, although the agent has not yet done so. As long as the contradiction remains implicit, the agent has no problem in handling it. In fact, one of the most common strategy in argumentation consists in confronting the audience with their own contradictions, i.e. forcing them to draw contradictory conclusions from what they already believe.

In data structures, contrast relations capture contradictions between data (cf. 2.3). Such contradictions are actually beneficial to the agent, since they provide him with crucial information on the credibility of both *relata*. A contradiction needs to be solved *only if it arises at the level of beliefs*, i.e. if the selection process (cf. 2.2) accepts two contrasting data as beliefs. This is rare, since credibility plays a crucial role in belief selection, and the credibility of contrasting data is conversely proportional (cf. 2.3). However, under specific circumstances (e.g. a selection which emphasizes importance and likeability over credibility) it might happen that an agent is confronted with contradictory beliefs. In this case, the contradiction is solved through reasoning, applying an axiom to reject one of the contradictory beliefs, or both.

Contradiction management is further discussed in [14]. Here we want to emphasize that rational agents are not safe from contradictions for some benevolent 'law of nature': they are rather equipped *to handle contradictions efficiently*, e.g. exploiting the informational value of contrasting evidences. If we fail to acknowledge inconsistency in belief change, we miss the core of argumentation: weighting against each other contradictory claims.

3.5 Parameters and argumentation

In DBR, parameters (cf. 2.4) provides a computational description of individual variation [14]. They also have consequences over the treatment of argumentation, capturing the relevant distinction between *local* and *global persuasion*, and the *multi-layered nature of argumentative strategies*.

An argument can either aims to change single beliefs in the mind of the audience (local persuasion), or it might address the basic processes which define the outcome of belief revision for that audience (global persuasion). Whenever persuasive argumentation is a major issue (e.g. political campaigns, advertising, religious events), global persuasion is the key feature: it is not enough to change some specific beliefs, the arguer is basically trying *to make the audience accept a different way of thinking* – that is, different revision procedures, to be applied autonomously from now on.

Local and global strategies are grounded in our model, respectively, in *argumentation over data network* and *argumentation over parameters*. The examples discussed in 3.1-3.4 are instances of local persuasion, which attack or support nodes in the data structure. On the contrary, global persuasion questions the validity of individual parameters concerning belief revision, e.g. the selection process («You should not pay so much attention to explanatory power, otherwise you are prone to wishful thinking!»), the assessment of data values («Do not underestimate contrasting evidences, or you will be biased toward confirmation!»), the reliability assigned to new sources («Why do you trust so much somebody you does not know?») [14].

Perhaps the most famous instance of the interplay between belief revision parameters, argumentation and global persuasion is from the Gospels: that is, the incredulity of St Thomas. When Jesus, after his resurrection, appeared for the first time to the apostles, Thomas was not there. Once he had been told of the miracle by his companions, he refused to believe their account, claiming that "unless I see in his hands the print of the nails, and place my finger in the mark of the nails, and place my hand in his side, I will not believe" (St John, 20: 25). This bold statement was challenged when Jesus appeared again, and explicitly insisted that Thomas should probe Jesus' wounds with his incredulous finger. After that, the apostle was convinced and repentant, but Jesus was after a global persuasion, rather than a local one. Hence his final comment: "Have you believed because you have seen me? Blessed are those who have not seen and yet believe" (St John, 20: 29).

[3] Here we follow the terminology used in [15], but actually the expression 'rebutting defeater' is quite misleading, when compared with Toulmin's model. The rebuttal, as defined in [16], specifies the conditions which undermine the validity of the warrant, not of the claim – i.e. rebuttals are in fact undercutting defeaters. So the expression *direct defeaters* would be less ambiguous, to indicate defeaters which directly affect the claim.

In this episode a whole attitude (skepticism) is stigmatized as inadequate within a given context (matters of faith), and the misbehaving agent is required for the future to apply different parameters to his processes of belief selection and change. The opposite attitude is exemplified by Mary Magdalene, who immediately believed in the resurrection of Jesus once he was told by him, although she was not able to distinguish his features and his voice: the testimony of a stranger standing next to the sepulcher of Jesus was enough for her to believe in the miracle. Both these attitudes can be captured (in a simplified form) within the framework of DBR, as the computational analogous of Mary Magdalene and St Thomas summarized in Table 2. In the DBR counterpart of the biblical episode, the argumentative strategy applied by Jesus on Thomas would aim to make him shift his parameters towards the ones of Mary, i.e. developing a more trustful epistemic attitude through several minor changes: e.g. a less pessimistic assessment of credibility value (the first two parameters), more refined processes for assessing importance (the third, fourth and fifth parameter), a less realistic process of belief selection (the sixth, seventh and sixth parameter), and more reliance in unknown sources of information (the last parameter listed in Table 2).

Table 2. Parameters in DBR and argumentation: Mary Magdalene vs. St Thomas

	TRUSTFUL (Mary Magdalene)	**SKEPTIC (St Thomas)**
Credibility alg.	*c□ = (1 - □ □□S□ (1 - c□)) □□ □□K□ (1 - c□)*	*c□ = pr□ □□ □□K□ (1 - pr□)* with □ □ *S* *c□ = 1 - □ □□S□ (1 - c□)* with □ □ *S*
Union alg.	*c□&□ = min(c□, c□)*	*c□&□ = c□ □ c□*
Importance alg.	*□ < 5, i□ = □/5 □ (1 - □ □□N□ (1 - c□))* *□ ≥ 5, i□ = 1 - □ □□N□ (1 - c□)*	*□ < 5, i□ = □/5 □ (1 - □ □□N□ (1 - c□))* *□ ≥ 5, i□ = 1 - □ □□N□ (1 - c□)*
Depth □	*2*	*1*
Consid. thres. w	*0.3*	*0.6*
Condition C	*c□ / (1 - i□)*	*c□*
Accept. thres. k	*0.6*	*0.8*
Function F	*c□ + i□ – (c□ □ i□)*	*c□*
Reliab. default	*0.7*	*0.3*

Finally, parameters play a crucial role in any instance of argumentation, since *the arguer is required to understand, at least partially, the parameters governing belief revision in his audience*. This reflects the multi-layered nature of argumentation: for the arguer to be effective, it is not enough to figure out the audience's beliefs (the data structure and the resulting belief set), but also the way in which beliefs are processed (the audience's parameters on belief revision, e.g. how they assess data values, how they select beliefs from data, etc.). Factual evidences are useless, if the audience do not care for credibility in belief selection; on the other hand, alluring picture of highly desirable states of things does not work with matter-of-fact types – and so on. Formal models of belief change which fail to account for individual variation are implying that every audience will have identical reactions to the same base of data: an highly untenable assumption [2, 4, 14, 16].

4 CONCLUSIONS AND FUTURE WORK

The integrated framework sketched here strongly supports a general methodological claim: a model of belief revision, in order to deal effectively with argumentation, must ensure *a proper degree of structural analysis* – i.e. it must emphasizes the relational properties which characterize epistemic processing, rather than its overall principles. Ordering criteria over propositions or sets, like in AGM-style approaches, are not expressive enough to model argumentation – nor belief revision.

In our future work we intend to refine the formal model of DBR (e.g. extending the computational treatment of data properties to motivational and emotional features, i.e. relevance and likeability [3, 12, 14]), provide more systematic connections with argumentation theories [1, 4, 7, 11, 13, 16], and move towards implementation in multi-agent systems, especially for agent-based social simulation [6, 9, 14]. We plan to use argumentation tasks as testing ground for belief revision algorithms, and vice versa. We want also to investigate a more radical hypothesis concerning the connection between belief revision and argumentation: namely, the idea of modeling the whole process of epistemic change as a form of *internal argumentation* [3, 15], as long ago suggested in developmental psychology by Jean Piaget and Lev Vygotsky.

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