Approximations for Explanations of Inconsistency in Partially Known Multi-Context Systems*

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Abstract. Multi-context systems are a formalism to interlink decentralized and heterogeneous knowledge based systems (contexts), which interact via (possibly nonmonotonic) bridge rules. Inconsistency is a major problem, as it renders such systems useless. In addition, it is likely that complete knowledge about all system parts is unavailable and cannot be obtained, for instance in applications where confidentiality or trust are prohibitive. We therefore aim at explaining reasons for inconsistency in multi-context systems without having an omniscient view of the whole system. To this end we propose a representation for partial knowledge about contexts, and define over- and underapproximations for existing notions characterizing inconsistency in multi-context systems. Furthermore, we discuss query selection strategies for improving approximations in situations where a limited number of queries can be posed to a partially known context.

1 Introduction

In recent years, there has been an increasing interest in interlinking knowledge bases, in order to enhance the capabilities of systems. Based on McCarthy's idea of contextual reasoning [1], the Trento School around Giunchiglia and Serafini has developed multi-context systems in many works, in which the components (called contexts) can be interlinked via so called bridge rules for information exchange, cf. [2, 3]. Generalizing this work, Brewka and Eiter [4] presented nonmonotonic multi-context systems (MCSs) as a generic framework for interlinking possibly heterogeneous and nonmonotonic knowledge bases.

Typically, an MCS is not built from scratch, but assembled from components which were not specifically designed to be part of a more complex system. Unintended interactions between contexts thus may easily arise and cause inconsistency, which renders an MCS useless.

To make bridge rules defeasible, similarly as in [5], may help to avoid inconsistency; this cures faults in silent service, but underlying reasons for inconsistency

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may remain unnoticed. Therefore, to help the user analyze, understand and eventually repair inconsistencies, suitable notions of consistency-based diagnosis and entailment-based explanation for inconsistency were introduced in [6]. However, an omniscient view of the system was assumed, where the user has full information about all contexts including their knowledge bases and semantics. In real world scenarios, full information may not be available [7]; a context may be a black box with hidden internal knowledge base and semantics, which are not disclosed (e.g., due to intellectual property or privacy issues). Partial behavior of such contexts may be known, however querying the contexts might be limited, e.g., by contracts or costs. This calls for explaining inconsistency in an MCS with *partial knowledge* about contexts, which raises the following issues:

- how to represent partial knowledge about the system, and
- how to obtain reasonable *approximations* for explanations of inconsistency in the actual system (under full knowledge), ideally in an efficient way.

The first issue depends on the nature of this knowledge, and a range of possibilities exists. The second issue requires an assessment method to determine such approximations. We tackle these issues and make the following contributions.

• We develop a representation of partially known contexts, which is based on context abstraction with Boolean functions. Partially defined Boolean functions [8, 9] are then used to capture partially known behavior of a context for specific inputs.
• We exploit these representations to determine *over*- and *underapproximations* of diagnoses and explanations for inconsistency according to [6] in the presence of partially known contexts. The approximations target either the whole set of diagnoses, or one diagnosis at a time; analogously for explanations.
• For scenarios where partially known contexts can be asked a limited number of queries, we consider query selection strategies.
• Finally, we briefly discuss computational complexity. In contrast to semantic approximations for efficient evaluation, our approximations provide methods for handling incompleteness, which usually increase complexity. However, they do not incur higher computational cost than in the case of full information.

Our results extend methods for inconsistency handling in MCSs to more realistic settings. This allows to identify reasons for inconsistency even if it is impossible to obtain full system knowledge, without increasing computational cost.

2 Preliminaries

A heterogeneous nonmonotonic MCS [4] consists of *contexts*, each composed of a knowledge base with an underlying *logic*, and a set of *bridge rules*

A logic $L = (\mathbf{KB}_L, \mathbf{BS}_L, \mathbf{ACC}_L)$ is an abstraction, which allows to capture many monotonic and nonmonotonic logics, e.g., classical logic, description logics, default logics, etc. It consists of the following components:

– $\mathbf{KB}_L$ is the set of well-formed knowledge bases of L. We assume each element of $\mathbf{KB}_L$ is a set of "formulas".
– $\mathbf{BS}_L$ is the set of possible belief sets, where a belief set is a set of "beliefs".
– $\mathbf{ACC}_L : \mathbf{KB}_L \rightarrow 2^{\mathbf{BS}_L}$ is a function describing the semantics of the logic by assigning to each knowledge base a set of acceptable belief sets.

Each context has its own logic, which allows to model heterogeneous systems.

A *bridge rule* models information flow between contexts: it can add information to a context, depending on the belief sets accepted at other contexts. Let $L = (L_1, \ldots, L_n)$ be a tuple of logics. An L_k-bridge rule r over L is of the form

$$(k : s) \leftarrow (c_1 : p_1), \ldots, (c_j : p_j), \mathbf{not}\ (c_{j+1} : p_{j+1}), \ldots, \mathbf{not}\ (c_m : p_m). \quad (1)$$

where $1 \leq c_i \leq n$, p_i is an element of some belief set of L_{c_i}, and k refers to the context receiving formula s. We denote by $hd\,(r)$ the formula s in the head of r.

Definition 1. *A multi-context system $M = (C_1, \ldots, C_n)$ is a collection of contexts $C_i = (L_i, kb_i, br_i)$, $1 \leq i \leq n$, where $L_i = (\mathbf{KB}_i, \mathbf{BS}_i, \mathbf{ACC}_i)$ is a logic, $kb_i \in \mathbf{KB}_i$ a knowledge base, and br_i is a set of L_i-bridge rules over $(L_1, \ldots, L_n)$. By $IN_i = \{hd\,(r) \mid r \in br_i\}$ we denote the set of possible* inputs *of context C_i added by bridge rules, and by $br_M = \bigcup_{i=1}^{n} br_i$ the set of all bridge rules of M.*

In addition, for each $H \subseteq IN_i$ we must have $kb_i \cup H \in \mathbf{KB}_{L_i}$.

The following running example involves policies and trust information which are often non-public and distributed [7], and thus demonstrates the necessity of reasoning under incomplete information. For more examples of MCSs see [4, 6].

Example 1. Consider an MCS M consisting of a permission database $C_1 = C_{\mathbf{perm}}$ and a credit card clearing context $C_2 = C_{\mathbf{cc}}$, and the following bridge rules:

$$\begin{aligned}
r_1 &: (\mathbf{perm} : \mathit{person}(\mathit{Person})) && \leftarrow \top. \\
r_2 &: (\mathbf{cc} : \mathit{card}(\mathit{CreditCard})) && \leftarrow (\mathbf{perm} : \mathit{person}(\mathit{Person})), \\
& && \quad\ \mathbf{not}\ (\mathbf{perm} : \mathit{grant}(\mathit{Person})), \\
& && \quad\ (\mathbf{perm} : \mathit{ccard}(\mathit{Person}, \mathit{CreditCard})). \\
r_3 &: (\mathbf{perm} : \mathit{ccValid}(\mathit{CreditCard})) && \leftarrow (\mathbf{cc} : \mathit{valid}(\mathit{CreditCard})).
\end{aligned}$$

Here r_1 defines a set of persons which is relevant for permission evaluation in $C_{\mathbf{perm}}$; r_2 specifies, that if some person is not granted access, credit cards of that person have to be validated; and r_3 translates validation results to $C_{\mathbf{perm}}$.

The MCS formalism is defined on ground bridge rules, which are in the following denoted by $r_{i,<constants>}$, e.g., $r_{2,moe,cnr2}$ denotes r_2 with $\mathit{Person} \mapsto \mathit{moe}$ and $\mathit{CreditCard} \mapsto \mathit{cnr2}$. Unless stated otherwise, we assume that bridge rules are grounded with $\mathit{Person} \in \{\mathit{nina}, \mathit{moe}\}$ and $\mathit{CreditCard} \in \{\mathit{cnr1}, \mathit{cnr2}\}$.

We next describe the context internals: $C_{\mathbf{perm}}$ is a datalog program with the following logic: $\mathbf{KB}_{\mathbf{perm}}$ contains all syntactically correct datalog programs, $\mathbf{BS}_{\mathbf{perm}}$ contains all possible answer sets, and $\mathbf{ACC}_{\mathbf{perm}}$ returns for each datalog program the corresponding answer sets. The knowledge base $kb_{\mathbf{perm}}$ is as follows:

$$\begin{array}{lll} \mathit{group}(\mathit{nina}, \mathit{vip}). & \mathit{ccard}(\mathit{nina}, \mathit{cnr1}). & \mathit{ccard}(\mathit{moe}, \mathit{cnr2}). \\ \mathit{igrant}(\mathit{Person}) & \leftarrow \mathit{person}(\mathit{Person}), \mathit{group}(\mathit{Person}, \mathit{vip}). & \\ \mathit{grant}(\mathit{Person}) & \leftarrow \mathit{igrant}(\mathit{Person}). & \\ \mathit{grant}(\mathit{Person}) & \leftarrow \mathit{ccValid}(\mathit{CreditCard}), \mathit{ccard}(\mathit{Person}, \mathit{CreditCard}). & \end{array}$$

Context $C_{\mathbf{cc}}$ is a credit card clearing facility, which typically is neither fully disclosed to the operator, nor can it be queried without significant cost. $C_{\mathbf{cc}}$ accepts $\mathit{valid}(\mathit{CreditCard})$ for valid cards that are present as atoms $\mathit{card}(\mathit{CreditCard})$. We only know the behavior of $C_{\mathbf{cc}}$ for empty input: $\mathbf{ACC}_{\mathbf{cc}}(kb_{\mathbf{cc}}) = \{\emptyset\}$. □

Equilibrium semantics selects certain belief states of an MCS $M = (C_1, \ldots, C_n)$ as acceptable. A *belief state* is a sequence $S = (S_1, \ldots, S_n)$, s.t. $S_i \in \mathbf{BS}_i$. A bridge rule (1) is *applicable* in S iff for $1 \leq i \leq j$: $p_i \in S_{c_i}$ and for $j < l \leq m$: $p_l \notin S_{c_l}$. Let $\mathit{app}(R, S)$ denote the set of bridge rules in R that are applicable in belief state S.

Intuitively, an equilibrium is a belief state S, where each context C_i takes into account the heads of all bridge rules that are applicable in S, and accepts S_i.

Definition 2. *A belief state $S = (S_1, \ldots, S_n)$ of M is an equilibrium iff, for $1 \leq i \leq n$, the following condition holds: $S_i \in \mathbf{ACC}_i(kb_i \cup \{\mathit{hd}(r) \mid r \in \mathit{app}(br_i, S)\})$. By $\mathrm{EQ}(M)$ we denote the set of equilibria of M.*

Example 2 (ctd). Assume that M_1 is the MCS M with just $\mathit{person}(\mathit{nina})$ present at $C_{\mathbf{perm}}$. As *nina* is in the *vip* group there is no need to verify a credit card, and M_1 has the following equilibrium (we omit facts, that are present in $kb_{\mathbf{perm}}$): $(\{\mathit{person}(\mathit{nina}), \mathit{igrant}(\mathit{nina}), \mathit{grant}(\mathit{nina})\}, \emptyset)$. □

Inconsistency in an MCS is the lack of an equilibrium. No information can be obtained from an inconsistent MCS. Therefore we analyze inconsistency in order to explain and eventually repair it.

Explanation of Inconsistency. We use the notions of consistency-based *diagnosis* and entailment-based *inconsistency explanation* in MCSs [6], which aim at describing inconsistency by sets of involved bridge rules.

Given an MCS M and a set R of bridge rules, by $M[R]$ we denote the MCS obtained from M by replacing its set of bridge rules br_M with R (in particular, $M[br_M] = M$ and $M[\emptyset]$ is M with no bridge rules). By $M \models \bot$ we denote that M is inconsistent, i.e., $\mathrm{EQ}(M) = \emptyset$, and by $M \not\models \bot$ the opposite. For any set of bridge rules A, $\mathit{heads}(A) = \{\alpha \leftarrow \mid \alpha \leftarrow \beta \in A\}$ are the rules in A in unconditional form. For pairs $A = (A_1, A_2)$ and $B = (B_1, B_2)$ of sets, the pointwise subset relation $A \subseteq B$ holds iff $A_1 \subseteq B_1$ and $A_2 \subseteq B_2$. We denote by $S|_A$ the projection of all sets X in set S to set A, formally $S|_A = \{X \cap A \mid X \in S\}$.

Definition 3. *Given an MCS M, a* diagnosis *of M is a pair (D_1, D_2), $D_1, D_2 \subseteq br_M$, s.t. $M[br_M \setminus D_1 \cup \mathit{heads}(D_2)] \not\models \bot$. $D^{\pm}(M)$ is the set of all such diagnoses. $D^{\pm}_m(M)$ is the set of all pointwise subset-minimal diagnoses of an MCS M.*

A diagnosis points out bridge rules which need to be modified to restore consistency; each rule can either be deactivated, or added unconditionally. We assume that context knowledge bases are consistent if no bridge rule heads are added, so restoring consistency is always possible. For more background and discussion of this notion, we refer to [6]. We next give an example of an inconsistent MCS and its diagnoses.

Example 3 (ctd). Let M_2 be the MCS M with just $person(moe)$ present at $C_{\mathbf{perm}}$, and assume the following full knowledge about $C_{\mathbf{cc}}$: all credit cards are valid.

M_2 is inconsistent: *moe* is not in the *vip* group, card verification is required by $r_{2,moe,cnr2}$, and $C_{\mathbf{cc}}$ accepts $valid(cnr2)$. This allows $C_{\mathbf{perm}}$ to derive $grant(moe)$, which blocks applicability of $r_{2,moe,cnr2}$. Therefore, M_2 contains an unstable cycle and is inconsistent.

Two $\subseteq$-minimal diagnoses of M_2 are then as follows: $(\{r_{2,moe,cnr2}\}, \emptyset)$ (do not validate *cnr2*), and $(\emptyset, \{r_{2,moe,cnr2}\})$ (always validate *cnr2*).[1] This points out r_2 as a likely culprit of inconsistency. Indeed, r_2 should intuitively contain $igrant(Person)$ in its body instead of $grant(Person)$. □

In this work we develop an approach which is able to point out a problem in r_2, without requiring complete knowledge.

3 Information Hiding

In this section, we introduce an abstraction of contexts which allows to calculate diagnoses and explanations. We generalize this abstraction to represent partial knowledge, i.e., contexts C_i, where either kb_i, or $\mathbf{ACC}_i$ is only partially known.

Context Abstraction. We abstract from a context's knowledge base kb_i and logic L_i by a Boolean function over the context's inputs IN_i (see Definition 1) and over the context's *output beliefs* OUT_i, which are those beliefs p in $\mathbf{BS}_i$ that occur in some bridge rule body in br_M as "$(i{:}p)$" or as "**not** $(i{:}p)$" (see also [6]).

Recall that a Boolean function (BF) is a map $f : \mathbb{B}^k \rightarrow \mathbb{B}$ where $k \in \mathbb{N}$ and $\mathbb{B} = \{0, 1\}$. Such a BF can also be characterized either by its true points $T(f) = \{\vec{x} \mid f(\vec{x}) = 1\}$, or by its false points $F(f) = \{\vec{x} \mid f(\vec{x}) = 0\}$.

Given a set $X \subseteq U = \{u_1, \ldots, u_k\}$, we denote by $\vec{x}_U$ the characteristic vector of X wrt. U (i.e. $\vec{x}_U = (b_1, \ldots, b_k)$, where $b_i = 1$ if $u_i \in X$, 0 otherwise). If understood, we omit U. Using this notation we characterize sets of bridge rule heads $I \subseteq IN_i$ and sets of output beliefs $O \subseteq OUT_i$ by vectors $\vec{\imath}_{IN_i}$ and $\vec{o}_{OUT_i}$, respectively. For example, given $O = \{a, c\}$, and $OUT_i = \{a, b, c\}$, we have $\vec{o} = (1, 0, 1)$.

Example 4 (ctd). We use the following (ordered) sets for inputs and output beliefs: $IN_{\mathbf{cc}} = \{card(cnr1), card(cnr2)\}$, and $OUT_{\mathbf{cc}} = \{valid(cnr1), valid(cnr2)\}$. □

Definition 4. *The unique BF $f^{C_i} : \mathbb{B}^{|IN_i|+|OUT_i|} \rightarrow \mathbb{B}$ corresponds to the semantics of context C_i in an MCS M as follows:*

$$\forall I \subseteq IN_i, O \subseteq OUT_i : f^{C_i}(\vec{\imath}, \vec{o}) = 1 \text{ iff } O \in \mathbf{ACC}_i(kb_i \cup I)\big|_{OUT_i}.$$

Example 5 (ctd). With full knowledge (see Example 3), $C_{\mathbf{cc}}$ has as corresponding BF the function $f^{C_{\mathbf{cc}}}(X, Y, X, Y) = 1$ for all $X, Y \in \mathbb{B}$, 0 otherwise. □

[1] Other $\subseteq$-minimal diagnoses of M_2 are $(\{r_{1,moe}\}, \emptyset)$, $(\{r_{3,cnr2}\}, \emptyset)$, and $(\emptyset, \{r_{3,cnr2}\})$.

If a context accepts a belief set O' for a given input I, we obtain the true point $(\vec{\imath}, \vec{o})$ of f with $O = O' \cap OUT_i$. Similarly, each non-accepted belief set yields a false point of f. Due to projection, different accepted belief sets can characterize the same true point.

Consistency Checking. Context abstraction provides sufficient information to calculate *output-projected equilibria* of the given MCS. Hence, it also allows for checking consistency and calculating diagnoses and explanations.

Given a belief state $S = (S_1, \ldots, S_n)$ in MCS M, the *output-projected belief state* $S' = (S'_1, \ldots, S'_n)$, $S'_i = S_i \cap OUT_i$, $1 \leq i \leq n$, is the projection of S to the output beliefs of M. In the following, we implicitly use the prime "$'$" to denote output-projection.

Definition 5 (see also [6]). *An output-projected belief state $S' = (S'_1, \ldots, S'_n)$ of an MCS M is an* output-projected equilibrium *iff, for $1 \leq i \leq n$, it holds that $S'_i \in \mathbf{ACC}_i(kb_i \cup \{hd\,(r) \mid r \in app(br_i, S')\})\big|_{OUT_i}$.*
By $\mathrm{EQ}'(M)$ we denote the set of output-projected equilibria of M.

Since $app(br_i, S) = app(br_i, S')$, a simple consequence is:

Lemma 1 ([6]). *For each equilibrium S of an MCS M, S' is an output-projected equilibrium; conversely, for each output-projected equilibrium S' of M there exists at least one equilibrium T of M such that $T' = S'$.*

Checking consistency is therefore possible using output-projected equilibria only. The representation of a context by a BF provides an input/output oracle, projected to output beliefs. As only output beliefs are relevant for bridge rule applicability, the BF is sufficient for calculating output-projected equilibria, and due to Lemma 1 also for checking consistency.

An MCS where a context is represented by a BF f is denoted as follows.

Definition 6. *Given MCS $M = (C_1, \ldots, C_n)$, BF f and index $1 \leq i \leq n$. We denote by $M[i/f]$ the MCS M where context C_i is replaced by a context $C(f)$ which contains the set br_i of bridge rules, a logic with a signature that contains $IN_i \cup OUT_i$, and $kb_{C(f)}$ and $\mathbf{ACC}_{C(f)}$, such that $f^{C(f)} = f^{C_i}$.*

For instance, $C(f)$ could be based on classical logic or logic programming, with $kb_{C(f)}$ over $IN \cup OUT$ as atoms encoding f by clauses (rules) that realize the correspondence.

We now show that a BF representation of a context is sufficient for calculating output-projected equilibria. We denote by $M[i_1, \ldots, i_k/f_1, \ldots, f_k]$ the substitution of pairwise distinct contexts $C_{i_1}, \ldots, C_{i_k}$ by $C(f_1), \ldots, C(f_k)$, respectively.

Theorem 1. *Let $M = (C_1, \ldots, C_n)$ be an MCS, and let $f_{i_1}, \ldots, f_{i_k}$ be BFs that correspond to $C_{i_1}, \ldots, C_{i_k}$. Then, $\mathrm{EQ}'(M) = \mathrm{EQ}'(M[i_1, \ldots, i_k/f_{i_1}, \ldots, f_{i_k}])$.*

Proof (sketch). Let $M^\star = M[i_1, \ldots, i_k/f_{i_1}, \ldots, f_{i_k}]$. By construction $M^\star = (C^\star_1, \ldots, C^\star_n)$, such that $C_i = C^\star_i$ for non-substituted contexts, and $br_i = br^\star_i$ for $1 \leq i \leq n$. The latter also implies $IN_i = IN^\star_i$ and $OUT_i = OUT^\star_i$, for $1 \leq i \leq n$.

By Definition 5, $\mathrm{EQ}'(M) = \mathrm{EQ}'(M^\star)$ if the following condition (i) holds: for each pair $(C_i = ((\mathbf{KB}_i, \mathbf{BS}_i, \mathbf{ACC}_i), kb_i, br_i),\ C_i^\star = ((\mathbf{KB}_i^\star, \mathbf{BS}_i^\star, \mathbf{ACC}_i^\star), kb_i^\star, br_i^\star)$ of contexts, and for all $H \subseteq IN_i$: $\mathbf{ACC}_i(kb_i \cup H)|_{OUT_i} = \mathbf{ACC}_i^\star(kb_i^\star \cup H)|_{OUT_i}$.

This trivially holds for non-substituted contexts. So let $C_i^\star = C(f_i)$ be an arbitrary substituted context. By construction it holds that $f^{C_i^\star} = f_i$. Furthermore, each f_i corresponds to its respective C_i, so $f_i = f^{C_i}$. Thus, $f^{C_i^\star} = f^{C_i}$. Since f^{C_i} is defined in a 1–1 relationship to $\mathbf{ACC}_i(kb_i \cup H)|_{OUT_i}$ for all $H \subseteq IN_i$ (see Definition 4), we obtain that (i) holds for all substituted contexts. □

Partially Known Contexts. As the BF representation concerns only output beliefs, by simply using this abstraction we already hide a part of the context, while we are still able to analyze inconsistency. Now we generalize the BF representation to *partially defined Boolean functions* (pdBFs) (cf. [8, 9]), to represent contexts where we have only partial knowledge about their output-projected behavior.

In applications, existence of such partial knowledge is realistic: for some bridge rule firings one may know an accepted belief set of a context, but not whether other accepted belief sets exist. Similarly one may know that a context is inconsistent for some input combination, but not whether it accepts some belief set for other input combinations.

Formally, a pdBF pf is a function from $\mathbb{B}^k$ to $\mathbb{B} \cup \{\star\}$, where $\star$ stands for undefined (cf. [8]). It is equivalently characterized by two sets [9]: its true points $T(pf) = \{\vec{x} \mid pf(\vec{x}) = 1\}$ and its false points $F(pf) = \{\vec{x} \mid pf(\vec{x}) = 0\}$. We denote by $U(pf) = \{\vec{x} \mid pf(\vec{x}) = \star\}$ the *unknown points* of pf. A BF f is an *extension* of a pdBF pf, formally $pf \leq f$, iff $T(pf) \subseteq T(f)$ and $F(pf) \subseteq F(f)$.

We connect partial knowledge of context semantics and pdBFs as follows.

Definition 7. *A pdBF $pf : \mathbb{B}^k \rightarrow \mathbb{B} \cup \{\star\}$ is compatible with a context C_i in an MCS M iff $pf \leq f^{C_i}$ (where f^{C_i} is as in Definition 4).*

Therefore, if a pdBF is compatible with a context, one extension of this pdBF is exactly f^{C_i}, which corresponds to the context's exact semantics.

Example 6 (ctd). Partial knowledge as given in Example 1 can be expressed by the pdBF $pf_{\mathbf{cc}}$ with $T(pf_{\mathbf{cc}}) = \{(0,0,0,0)\}$ and $F(pf_{\mathbf{cc}}) = \{(0,0,A,B) \mid A, B \in \mathbb{B}, (A,B) \neq (0,0)\}$. (See Example 4 for the variable ordering.) □

In the following, a *partially known MCS* (M, i, pf) consists of an MCS M, where context C_i is partially known, given by pdBF pf which is compatible with C_i.

4 Approximations

In this section, we develop a method for calculating under- and overapproximations of diagnoses and explanations, using the pdBF representation for a partially known context C_i. For simplicity, we only consider the case that a single context in the system is partially known (the generalization is straightforward).

Diagnoses. Each diagnosis is defined in terms of consistency, which is witnessed by an output-projected equilibrium. Such an equilibrium requires a certain set of output beliefs O to be accepted by the context C_i, in the presence of certain bridge rule heads I. This means that f_{C_i} has true point $(\vec{\imath}, \vec{o})$. For existence of an equilibrium where C_i gets I as input and accepts O, no more information is required from f_{C_i} than this single true point.

We can approximate the set of diagnoses of M as follows:

- Completing pf with false points, we obtain the extension $\underline{pf}$ with $T(\underline{pf}) = T(pf)$. The set of diagnoses witnessed by $T(pf)$ contains a *subset* of the diagnoses which actually occur in M, therefore we obtain an *under*approximation.
- Completing pf with true points, we obtain the extension $\overline{pf}$ which contains the largest set of true points in an extension of pf. The set of diagnoses witnessed by this extension contains a *superset* of the diagnoses which actually occur in M, providing an *over*approximation. Formally,

Theorem 2. *Given a partially known MCS* (M, i, pf)*, the following holds:*

$$D^{\pm}(M[i/\underline{pf}]) \subseteq D^{\pm}(M) \subseteq D^{\pm}(M[i/\overline{pf}]).$$

Proof (sketch). $D^{\pm}(M[i/\underline{pf}]) \subseteq D^{\pm}(M)$ is proved as follows: each diagnosis $(D_1, D_2) \in D^{\pm}(M[i/\underline{pf}])$ induces a consistent MCS $M^{\star}$ by removing bridge rules D_1 and making bridge rules D_2 unconditional. Since (D_1, D_2) is a diagnosis, $M^{\star}$ has at least one witnessing output-projected equilibrium S'. At context C_i, S' contains a certain set of output beliefs $O = S'_i$, furthermore the set of active bridge rule heads at C_i is $I = app(br_i, S')$.

Because S' is an output-projected equilibrium, we have that $O \in \mathbf{ACC}_i(kb_i \cup I)|_{OUT_i}$, so $\underline{pf}$ has a true point at $(\vec{\imath}, \vec{o})$. Since pf is compatible with C_i, some extension of pf is equal to f^{C_i}. Moreover, every true point of $\underline{pf}$ is a true point of pf, therefore every true point of $\underline{pf}$ is a true point of f^{C_i}. Consequently, C_i accepts some S for input I where $O = S \cap OUT_i$, which proves that (D_1, D_2) is a diagnosis of M.

$D^{\pm}(M) \subseteq D^{\pm}(M[i/\overline{pf}])$ is proved similarly: no true point of f^{C_i} is a false point of pf, and thus neither of $\overline{pf}$. Consequently, all true points of f^{C_i} are true points of $\overline{pf}$. Hence, all accepted input–output "behaviors" of context C_i are accepted in the overapproximation, and therefore each diagnosis in $D^{\pm}(M)$ is in $D^{\pm}(M[i/\overline{pf}])$, as well. □

Example 7 (ctd). The extensions $\overline{pf}_{\mathbf{cc}}$ and $\underline{pf}_{\mathbf{cc}}$ are as follows:

$$T(\overline{pf}_{\mathbf{cc}}) = \mathbb{B}^4 \setminus F(pf_{\mathbf{cc}}), \qquad F(\overline{pf}_{\mathbf{cc}}) = F(pf_{\mathbf{cc}}),$$
$$T(\underline{pf}_{\mathbf{cc}}) = T(pf_{\mathbf{cc}}), \text{ and} \qquad F(\underline{pf}_{\mathbf{cc}}) = \mathbb{B}^4 \setminus T(pf_{\mathbf{cc}}).$$

The underapproximation $D^{\pm}(M_2[\mathbf{cc}/\underline{pf}_{\mathbf{cc}}])$ yields several diagnoses, e.g., $D_\alpha = (\{r_{1,moe}\}, \emptyset)$, $D_\beta = (\{r_{2,moe,cnr2}\}, \emptyset)$, and $D_\gamma = (\emptyset, \{r_{3,cnr2}\})$.

The overapproximation $D^{\pm}(M_2[\mathbf{cc}/\overline{pf}_{\mathbf{cc}}])$ contains the empty diagnosis $D_\delta = (\emptyset, \emptyset)$, because $M_2[\mathbf{cc}/\overline{pf}_{\mathbf{cc}}]$ is consistent; it has the following two equilibria: $(\{person(moe)\}, \emptyset)$ and $(\{person(moe)\}, \{valid(cnr1)\})$. □

Subset-minimality. If we approximate $\subseteq$-minimal diagnoses, the situation is different. Obtaining additional diagnoses may cause approximated minimal diagnoses to become smaller. Missing certain diagnoses can make approximated minimal diagnoses larger.

Therefore, the following holds for $\subseteq$-minimal diagnosis approximations.

Theorem 3. *Given a partially known MCS (M, i, pf), the following hold:*

$$\forall D \in D^{\pm}_{m}(M[i/\underline{pf}])\ \exists D' \in D^{\pm}_{m}(M) : D' \subseteq D \tag{2}$$

$$\forall D \in D^{\pm}_{m}(M)\ \exists D' \in D^{\pm}_{m}(M[i/\overline{pf}]) : D' \subseteq D \tag{3}$$

$$D^{\pm}_{m}(M[i/\underline{pf}]) \cap D^{\pm}_{m}(M[i/\overline{pf}]) \subseteq D^{\pm}_{m}(M) \tag{4}$$

Proof (sketch). (2) For a diagnosis $D \in D^{\pm}_{m}(M[i/\underline{pf}])$ by definition of $D^{\pm}_{m}$ we know that $D \in D^{\pm}(M[i/\underline{pf}])$. From Theorem 2 we infer that $D \in D^{\pm}(M)$. If D is $\subseteq$-minimal in $D^{\pm}(M)$, then (2) follows for $D' = D$, otherwise there exists a $D' \in D^{\pm}_{m}(M)$, such that $D' \subseteq D$, which also implies (2).

(3) This is proved by analogous arguments.

(4) $D \in D^{\pm}_{m}(M[i/\underline{pf}])$ implies $D \in D^{\pm}(M)$. From $D \in D^{\pm}_{m}(M[i/\overline{pf}])$, we infer that there is no $D' \subseteq D$ such that $D' \in D^{\pm}(M[i/\overline{pf}])$. Since $D^{\pm}(M) \subseteq D^{\pm}(M[i/\overline{pf}])$, it follows that there is no $D' \subseteq D$ such that $D' \in D^{\pm}(M)$. Taking into account that $D \in D^{\pm}(M)$, this proves $D \in D^{\pm}_{m}(M)$. □

Example 8 (ctd). Note that the diagnoses in Example 7 are in fact the $\subseteq$-minimal diagnoses of the under- and overapproximation, and that they are actual $\subseteq$-minimal diagnoses. Under complete knowledge (see Example 3), there are additional $\subseteq$-diagnoses which are not members of the underapproximation.

The overapproximation, on the other hand, yields a consistent system and therefore an empty $\subseteq$-minimal diagnosis D_{δ}. In Section 5 we develop a strategy for improving this approximation if limited querying of the context is possible. □

We can use the overapproximation to reason about the necessity of bridge rules in actual diagnoses: a necessary bridge rule is present in all diagnoses.[2]

Definition 8. *For a set of diagnoses $\mathcal{D}$, the set of* necessary bridge rules *is* $nec(\mathcal{D}) = \{r \mid \forall (D_1, D_2) \in \mathcal{D} : r \in D_1 \cup D_2\}$.

Proposition 1. *Given a partially known MCS (M, i, pf), the set of necessary bridge rules for the overapproximation is necessary in the actual set of diagnoses. This is true for both arbitrary and $\subseteq$-minimal diagnoses:*

$$nec(D^{\pm}(M[i/\overline{pf}])) \subseteq nec(D^{\pm}(M)),\ \textit{and}\ nec(D^{\pm}_{m}(M[i/\overline{pf}])) \subseteq nec(D^{\pm}_{m}(M)).$$

Proof (sketch). We first prove $nec(D^{\pm}(M[i/\overline{pf}])) \subseteq nec(D^{\pm}(M))$: from Theorem 2 we conclude that $D^{\pm}(M) \subseteq D^{\pm}(M[i/\overline{pf}])$. Thus, if a bridge rule is contained in all diagnoses of the latter set, it must also be contained in all diagnoses of the former.

[2] Note that we do not consider the dual notion of relevance, as it is trivial in our definition of diagnosis: all bridge rules are relevant in any $D^{\pm}(M)$.

Next, we prove $nec(D^{\pm}_{m}(M[i/\overline{pf}])) \subseteq nec(D^{\pm}_{m}(M))$: towards a contradiction assume $r \in nec(D^{\pm}_{m}(M[i/\overline{pf}]))$ and $r \notin nec(D^{\pm}_{m}(M))$. Then, there exists $D = (D_1, D_2)$, $D \in D^{\pm}_{m}(M)$, such that $r \notin D_1 \cup D_2$. By Theorem 3 (3), we conclude that there exists $D' = (D'_1, D'_2)$, $D' \in D^{\pm}_{m}(M[i/\overline{pf}])$, such that $D' \subseteq D$. Consequently, $r \notin D'_1 \cup D'_2$, a contradiction to $r \in nec(D^{\pm}_{m}(M[i/\overline{pf}]))$. □

While simple, this property is useful in practice: in a repair of an MCS according to a diagnosis, necessary bridge rules need to be fixed in any case.

Inconsistency explanations. So far we have only described approximations for diagnoses. Inconsistency explanations are a dual notion; they allow to separate independent sources of inconsistency. We first recall the definition from [6].

Definition 9. *Given an MCS M, an* inconsistency explanation *of M is a pair (E_1, E_2) s.t. for all (R_1, R_2) where $E_1 \subseteq R_1 \subseteq br_M$ and $R_2 \subseteq br_M \setminus E_2$, it holds that $M[R_1 \cup heads(R_2)] \models \bot$. By $E^{\pm}(M)$ we denote the set of all inconsistency explanations of M, and by $E^{\pm}_{m}(M)$ the set of all pointwise subset-minimal ones.*

An inconsistency explanation (in short 'explanation') points out bridge rules E_1 which suffice to ensure inconsistency, and bridge rules E_2 which must not be added unconditionally to sustain inconsistency.

Example 9. With complete knowledge as in Example 3, there is one $\subseteq$-minimal explanation: $(\{r_{1,moe}, r_{2,moe,cnr2}, r_{3,cnr2}\}, \{r_{2,moe,cnr2}, r_{3,cnr2}\})$. □

Explanations are defined in terms of non-existing equilibria, therefore we can use witnessing equilibria as counterexamples. From the definitions we get:

Proposition 2. *For a given MCS M and a pair $(D_1, D_2) \subseteq br_M \times br_M$ of sets of bridge rules, the following statements are equivalent:*

(i) *(D_1, D_2) is a diagnosis, i.e., $(D_1, D_2) \in D^{\pm}(M)$,*
(ii) *$M[br_M \setminus D_1 \cup heads(D_2)]$ has an equilibrium, and*
(iii) *$(R_1, R_2) = (br_M \setminus D_1, D_2)$ is a counterexample for all explanation candidates $(E_1, E_2) \subseteq (br_M \setminus D_1, br_M \setminus D_2)$.*

Furthermore, such pairs (D_1, D_2) characterize all counterexamples *that can exist for explanation candidates.*

Proof (sketch). Equivalence of (i) and (ii) is a straightforward consequence of Definition 3.

Equivalence of (ii) and (iii) follows from Definition 9. Suppose (ii) holds, and towards a contradiction assume that $(E_1, E_2) \subseteq (br_M \setminus D_1, br_M \setminus D_2)$ exists, such that $(E_1, E_2) \in E^{\pm}(M)$. Let $R_1 = br_M \setminus D_1$ and $R_2 = D_2$. Then, $E_1 \subseteq R_1 \subseteq br_M$ and $R_2 \subseteq br_M \setminus E_2$, and by Definition 9 it holds that $M[R_1 \cup heads(R_2)] \models \bot$. This contradicts (ii) since $M[R_1 \cup heads(R_2)] = M[(br_M \setminus D_1) \cup heads(D_2)]$, and by assumption the latter has an equilibrium. Therefore, (ii) implies (iii). On the other hand, (iii) implies that $M[R_1 \cup heads(R_2)]$ has an equilibrium, i.e., that $M[(br_M \setminus D_1) \cup heads(D_2)]$ has an equlibrium, proving (iii) implies (ii). □

As a consequence, it is possible to characterize explanations in terms of diagnoses.

Lemma 2. *Given an MCS M, a pair (E_1, E_2) with $E_1, E_2 \subseteq br_M$ is an inconsistency explanation of M iff there exists no diagnosis $(D_1, D_2) \in D^{\pm}(M)$ such that $(D_1, D_2) \subseteq (br_M \setminus E_1, br_M \setminus E_2)$.*

Proof (sketch). The only-if direction is a direct consequence of Definition 9. For the if direction suppose that there does not exist $(D_1, D_2) \in D^{\pm}(M)$ such that $(D_1, D_2) \subseteq (br_M \setminus E_1, br_M \setminus E_2)$, and assume that (R_1, R_2) is a counterexample for $(E_1, E_2) \in E^{\pm}(M)$. Then, $(br_M \setminus R_1, R2) \in D^{\pm}(M)$, a contradiction to our assumption since $br_M \setminus R_1 \subseteq br_M \setminus E_1$ and $R_2 \subseteq br_M \setminus E_2$. □

In fact we can sharpen the above by replacing $D^{\pm}$ with $D^{\pm}_m$.

Using this characterization, we can infer the following: a subset of the actual set of diagnoses characterizes a superset of the actual set of explanations. This is true since a subset of diagnoses will rule out a subset of explanations, allowing more candidates to become explanations. Conversely, a superset of diagnoses characterizes a subset of the explanations. Applying Theorem 2, we obtain:

Theorem 4. *Given a partially known MCS (M, i, pf), the following hold:*

$$E^{\pm}(M[i/\overline{pf}]) \subseteq E^{\pm}(M) \subseteq E^{\pm}(M[i/\underline{pf}])$$
$$\forall E \in E^{\pm}_m(M[i/\overline{pf}])\ \exists E' \in E^{\pm}_m(M) : E' \subseteq E$$
$$\forall E \in E^{\pm}_m(M)\ \exists E' \in E^{\pm}_m(M[i/\underline{pf}]) : E' \subseteq E$$

Proof (sketch). By the characterization of explanations in terms of counterexamples, this theorem follows from Theorems 2 and 3 and from Lemma 2 by the following set theoretic argument: if a family of counterexamples characterizes a family of sets by ⊆-inclusion (as in Lemma 2), a larger family of counterexamples characterizes a smaller family of sets and vice versa. □

Therefore, the extensions $\overline{pf}$ and $\underline{pf}$ allow to underapproximate and overapproximate diagnoses as well as inconsistency explanations.

Example 10 (ctd). From $\underline{pf}_{\mathbf{cc}}$ as in Example 7 we obtain one ⊆-minimal explanation: $E_\mu = (\{r_{1,moe}, r_{2,moe,cnr2}\}, \{r_{3,cnr2}\})$. This explanation is a subset of the actual minimal explanation in Example 9. □

5 Limited Querying

Up to now we used existing partial knowledge to approximate diagnoses, assuming that more information is simply not available. However, in practical scenarios like our running example, one can imagine that a (small) limited number of queries to a partially known context can be issued. Therefore we next aim at identifying queries to contexts, such that incorporating their answers into the pdBF will yield the best guarantee of improvement in approximation accuracy.

Given a partially known MCS (M, i, pf), let $D^{\pm}_{\Delta}(M, i, pf) = D^{\pm}(M[i/\overline{pf}]) \setminus D^{\pm}(M[i/\underline{pf}])$ (in short: $D^{\pm}_{\Delta}(pf)$ or $D^{\pm}_{\Delta}$) be the set of *potential diagnoses*, which are possible from the overapproximation but unconfirmed by the underapproximation.

A large set of potential diagnoses provides less information than a smaller set. Therefore we aim at identifying unknown points of pf which remove from $D^{\pm}_{\Delta}$ as many potential diagnoses as possible. To this end we introduce the concept of a *witness*, which is an unknown point together with a potential diagnosis that is supported by this point if it is a true point.

Definition 10. *Given a partially known MCS* (M, i, pf)*, a* witness *is a pair* $(\vec{x}, D)$ *s.t.* $\vec{x} \in U(pf)$ *and* $D \in D^{\pm}(M[i/f_{\vec{x}}]) \cap D^{\pm}_{\Delta}$*, where* $f_{\vec{x}}$ *is the BF with the single true point* $T(f_{\vec{x}}) = \{\vec{x}\}$*. We denote by* $W_{(M,i,pf)}$ *the set of all witnesses wrt.* (M, i, pf)*. If clear from the context, we omit subscript* (M, i, pf)*.*

Based on W we define the set $wnd(\vec{x}) = \{D \mid (\vec{x}, D) \in W\}$ of potential diagnoses witnessed by unknown point $\vec{x}$, and the set $ewnd(\vec{x}) = \{D \in wnd(\vec{x}) \mid \nexists \vec{x}' \neq \vec{x} : (\vec{x}', D) \in W\}$ of potential diagnoses exclusively witnessed by $\vec{x}$. These sets are used to investigate how much the set of potential diagnoses is reduced when adding information about the value of an unknown point $\vec{x}$ to pf.

Lemma 3. *Given a partially known MCS* (M, i, pf)*, and* $\vec{x} \in U(pf)$*, let* $pf_{\vec{x}:0}$ *(*$pf_{\vec{x}:1}$*) the pdBF that results from pf by making* $\vec{x}$ *a false (true) point. Then* $D^{\pm}_{\Delta}(pf_{\vec{x}:1}) = D^{\pm}_{\Delta}(pf) \setminus wnd(\vec{x})$*, and* $D^{\pm}_{\Delta}(pf_{\vec{x}:0}) = D^{\pm}_{\Delta}(pf) \setminus ewnd(\vec{x})$*.*

Note that $ewnd(\vec{x}) \subseteq wnd(\vec{x}) \subseteq D^{\pm}_{\Delta}$. If $\vec{x}$ is a true point, $|wnd(\vec{x})|$ many potential diagnoses become part of the underapproximation; otherwise $|ewnd(\vec{x})|$ many potential diagnoses are no longer part of the overapproximation. Knowing the value of $\vec{x}$ therefore guarantees a reduction of $D^{\pm}_{\Delta}$ by $|ewnd(\vec{x})|$ diagnoses.

Proposition 3. *Given a partially known MCS* (M, i, pf)*, for all* $\vec{x} \in U(pf)$ *such that the cardinality of* $ewnd(\vec{x})$ *is maximal, the following holds:*

$$\max_{u \in \mathbb{B}} \left| D^{\pm}_{\Delta}\left(pf_{\vec{x}:u}\right) \right| \leq \min_{\vec{y} \in U(pf)} \max_{v \in \mathbb{B}} \left| D^{\pm}_{\Delta}\left(pf_{\vec{y}:v}\right) \right|. \tag{5}$$

Proof (sketch). Given (M, i, pf) and $\vec{x}$ such that $|ewnd(\vec{x})|$ is maximal among $\vec{x} \in U(pf)$, (5) expresses the following: regardless of whether we obtain that $\vec{x}$ is a true or a false point of context C_i, we have a guaranteed reduction of the set of potential diagnoses, and no other $\vec{x}' \in U(pf)$ can guarantee a greater reduction.

Acquiring information about unknown point $\vec{x}$ has two possible outcomes: (i) $\vec{x} \in T(pf)$ and the reduction is $wnd(\vec{x})$; or (ii) $\vec{x} \in F(pf)$ and the reduction is $ewnd(\vec{x})$ (see Lemma 3). As $ewnd(\vec{x}) \subseteq wnd(\vec{x})$ (Definition 10), the guaranteed reduction in size is $|ewnd(\vec{x})|$. The proposition follows, since $\vec{x}$ is chosen s.t. $|ewnd(\vec{x})|$ is maximal. □

Proposition 3 suggests to query unknown points $\vec{x}$ where $|ewnd(\vec{x})|$ is maximum. If there are more false points than true points (e.g., for contexts that accept only one belief set for each input), using *ewnd* instead of *wnd* is even more suggestive.

If the primary interest are necessary bridge rules (cf. previous section), we can base query selection on the number of bridge rules which become necessary if a certain unknown point is a false point. Let $nwnd(\vec{x}) = nec(\overline{D^{\pm}} \setminus ewnd(\vec{x})) \setminus nec(\overline{D^{\pm}})$, where $\overline{D^{\pm}} = D^{\pm}(M[i/\overline{pf}])$, then $|nwnd(\vec{x})|$ many bridge rules become necessary if $\vec{x}$ is identified as a false point.

Another possible criterion for selecting queries can be based on the likelihood of errors, similar to the idea of *leading diagnoses* [10]. Although a different notion of diagnosis is used there, the basic idea is applicable to our setting as follows: if multiple problematic bridge rules are less likely than single ones, or if we have confidence values for bridge rules (e.g., some rules were designed by an expert, others by a less experienced administrator), then we can concentrate on trying to confirm or discard diagnoses that have a high probability. If we have equal confidence in all bridge rules, this amounts to using *cardinality-minimal* potential diagnoses for determining witnesses and guiding the selection of queries.

Example 11 (ctd). In our example, the set of potential diagnoses is large, but the cardinality-minimal diagnosis is the empty diagnosis, which has the following property: bridge rule input at $C_{\mathbf{cc}}$ is $\{card(cnr2)\}$, and $C_{\mathbf{cc}}$ either accepts $\emptyset$ or $\{valid(cnr1)\}$ (the unrelated credit card). Therefore, points $(0,1,0,0)$ and $(0,1,1,0)$ are the only witnesses for D_δ, and querying these two unknown points is sufficient for verifying or falsifying D_δ. (Note that $pf_{\mathbf{cc}}$ has 12 unknown points, the four known points (one true and three false points) are $(0,0,X,Y)$ s.t. $X,Y \in \mathbb{B}$.)

After updating pf with these points (false points, if all credit cards are valid), the overapproximation yields the $\subseteq$-minimal diagnoses; this result is optimal. □

So far we considered membership queries which check whether $O \in \mathbf{ACC}(kb \cup I)$ for given $(\vec{\imath}, \vec{o})$. Alternatively, one could use stronger queries that provide the *value* of $\mathbf{ACC}(kb \cup I)$ for a given $\vec{\imath}$. On the one hand this allows for a better query selection, roughly speaking because combinations of unknown points together witness more diagnoses exclusively than they do individually. On the other hand, however, considering such combinations increases computational cost.

Another possible extension of limited querying is the usage of meta-information, e.g., monotonicity, or consistency properties, of a partially known context.

6 Discussion

Approximation Quality. In the previous section, we related unknown points to potential diagnoses. This correspondence allows to obtain an estimate for the quality of an approximation, simply by calculating the ratio between known and potential true (resp., false) points: a high value of $\frac{|T(pf)|}{|T(pf)|+|U(pf)|}$ indicates a high underapproximation quality, while a low value indicates an underapproximation distant from the actual system. This is analogous for overapproximation, exchanging $T(pf)$ with $F(pf)$. These estimates can be calculated efficiently and prior to calculating an approximation; a decision between under- and overapproximation could be based on this heuristic.

Even if nothing is known about the behavior of some context C, the overapproximation accurately characterizes inconsistencies that do not involve C.

Complexity and Computation. Since our approximation methods deal with incomplete knowledge, it is important how their computational complexity compares to the full knowledge case. For the latter setting, the following results were established in [6], depending on the complexity of output checking for contexts C_i, which is deciding for C_i, $I \subseteq IN_i$ and $O \subseteq OUT_i$ whether $O \in \mathbf{ACC}(kb_i \cup I)|_{OUT_i}$. With output checking in $\mathbf{P}$ (resp., $\mathbf{NP}$, $\mathbf{\Sigma^P_k}$), recognizing correct diagnoses is in $\mathbf{NP}$ (resp., $\mathbf{NP}$, $\mathbf{\Sigma^P_k}$) while recognizing minimal diagnoses and minimal explanations is in $\mathbf{D^P}$ (resp., $\mathbf{D^P}$, $\mathbf{D^P_k}$); completeness holds in all cases.

Let us first consider the case where some contexts C_i are given by their corresponding BF f_i (in a representation such that $f_i(\vec{\imath}, \vec{o})$ can be evaluated efficiently). As we know that context C_i accepts only input/output combinations which are true points of f, we simply guess all possible output beliefs O_i of all contexts and evaluate bridge rules to obtain I_i; if for some C_i as above, $f_i(\vec{\imath}_i, \vec{o}_i)$=0 we reject, otherwise we continue checking context acceptance for other contexts. Overall, this leads to the same complexity as if all contexts were total. Thus, detecting explanations of inconsistency for an MCS M, where some contexts are given as BFs, has the same complexity as if M were given regularly.

Approximations are done on an MCS where a pdBF pf is given instead of a BF f, in a representation such that the value of $pf(\vec{\imath}, \vec{o})$ can be computed efficiently. This implies that the extensions $\underline{pf}$ and $\overline{pf}$ can be computed efficiently as well. Hence, approximations of diagnoses and explanations have the same complexity as the exact concepts. Dealing with incomplete information usually increases complexity, as customary for many nonmonotonic reasoning methods. Our approach, however, exhibits no such increase in complexity, even though it provides faithful under- and overapproximations.

Learning. To learn a BF seems suggestive for our setting of incomplete information. However, explaining inconsistency requires correct information, therefore pac-learning methods [8] are not applicable. On the other hand, exact methods [11] require properties of the contexts which are beneficial to learning and might not be present.[3] Furthermore, contexts may only allow membership queries, which are insufficient for efficient learning of many concept domains [11]. Furthermore, partially known contexts may not allow many, even less a polynomial number of queries (which is the target for learnability).

Most likely it will thus not be possible to learn the complete function. Hence learning cannot replace our approach, but it can be useful as a preprocessing step to increase the amount of partial information.

7 Related Work and Conclusion

To the best of our knowledge, explaining inconsistency in multi-context systems with partial specification has not been addressed before. Weakly related to our work is [12], who aimed at approximating abductive diagnoses of a single knowledge base. They replaced classical entailment with approximate entailment of [13], motivated by computational efficiency. However, there is no lack of information about the knowledge base or semantics as in our case.

[3] Note that, even if a context's logic is monotonic (resp., positive) this does not imply that the BF corresponding to the context is monotonic (resp., positive).

Our over- and underapproximations of $D^{\pm}$ and $E^{\pm}$ are reminiscent of lower and upper bounds of classical theories (viewed as sets of models [14]), known as cores and envelopes. The latter also were used for (fast) sound, resp. complete, reasoning from classical theories.

The limited querying approach is related to optimal probing strategies [15]. However, we do not require probing to localize faults in the system, but to obtain information about the behavior of system parts, which have a much more fine grained inner structure and more intricate dependencies than the systems in [15]. (Those system parts have as possible states 'up', and 'down', while in MCSs each partially known context possibly accepts certain belief sets for certain inputs.)

Ongoing further work includes an implementation of the approach given in this paper, and the usage of metainformation about context properties to improve approximation accuracy. The incorporation of probabilistic information into the pdBF representation is another interesting topic for future research.

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