RIO: Minimizing User Interaction in Debugging of Knowledge Bases

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Abstract
The best currently known interactive debugging systems rely upon some meta-information in terms of fault probabilities in order to improve their efficiency. However, misleading meta information might result in a dramatic decrease of the performance and its assessment is only possible a-posteriori. Consequently, as long as the actual fault is unknown, there is always some risk of suboptimal interactions. In this work we present a reinforcement learning strategy that continuously adapts its behavior depending on the performance achieved and minimizes the risk of using low-quality meta information. Therefore, this method is suitable for application scenarios where reliable prior fault estimates are difficult to obtain. Using diverse real-world knowledge bases, we show that the proposed interactive query strategy is scalable, features decent reaction time, and outperforms both entropy-based and no-risk strategies on average w.r.t. required amount of user interaction.

1 Introduction
Efficient debugging is a prerequisite for successful evolution, maintenance and application of knowledge-based systems. In a standard application scenario a debugger deals with a faulty knowledge base (KB) \( \mathcal{O} \) which fails to meet predefined quality criteria \( \mathcal{R} \) such as consistency. The task of debugging aims at modifying \( \mathcal{O} \) in that a (subset-)minimal set of axioms \( \mathcal{D} \subseteq \mathcal{O} \), termed diagnosis, is deleted in order to restore compliance of the KB with \( \mathcal{R} \), whereas a set of axioms \( \text{EXD} \) is inserted to \( \mathcal{O} \) to preserve designated entailments which might have been broken by the removal of \( \mathcal{D} \). Usually, a large number of competing diagnoses exist for a faulty \( \mathcal{O} \). Without additional information, there is no means to decide which \( \mathcal{D} \) to prefer. In many practical scenarios, however, there is some kind of meta information available, for example in terms of (1) logs of prior debugging sessions, (2) common faults or fault patterns occurring in logical formulas, or (3) a subjective guess of the involved user based on their experience. Given such data, one can extract a-priori fault probabilities and use them to guide the search for diagnoses. For example, one could use a uniform cost strategy to find the most probable diagnosis w.r.t. fault probabilities, see e.g. [Kalyanpur, 2006]. However, only in the best case, if the fault probabilities are perfectly adjusted for the particular case, this will lead the search to the desired diagnosis the deletion of which enables to formulate a KB compliant with the requirements defined by the user.

Interactive debugging systems such as [Shchekotykhin et al., 2012] [Siddiqi and Huang, 2011] tackle this issue by letting an oracle take action during the debugging session by answering queries. In case of KBs a debugger asks about entailments and non-entailments of the desired \( \mathcal{O}_t \), called test cases [Shchekotykhin et al., 2012]. These pose constraints to the validity of diagnoses and thus help to sort out incompliant diags and update the probabilities of remaining ones step-by-step. However, often a debugger can find many alternative queries for a set of diagnoses. Selection of the “best” query, an answer to which allows to obtain maximum information, is very important since it affects the total number of queries required to localize the fault. In their seminal work [de Kleer and Williams, 1987] proposed two query selection strategies: split-in-half and entropy-based. The latter strategy can make optimal profit from exploiting properly adjusted initial fault probabilities, whereas it can completely fail in the case of weak prior information. The split-in-half manifests constant behavior independently of the probabilities given, but lacks the ability to leverage appropriate fault information. Selection of the best strategy is problematic, since one has to decide about the quality of the prior fault probabilities without knowing the desired solution. Our evaluation shows that selection of an inappropriate strategy can result in a substantial increase of more than 2000% w.r.t. number of queries.

The contribution of this paper is a new RIsk Optimization reinforcement learning method (RIO). Compared to existing strategies RIO allows to minimize user interaction in the average case for any quality of meta information. By virtue of its learning capability, our approach is optimally suited for debugging of KBs where only vague or no meta information is available. Moreover, RIO uses the acquired information to adapt its learning strategy. On the one hand, our method takes advantage of the given meta information as long as good performance is achieved. On the other hand, it gradually gets more independent of meta information if suboptimal behavior is measured. Experiments on two datasets of faulty ontologies show the feasibility, efficiency and scalability of RIO. The evaluation will indicate that, on average, RIO is the best choice of strategy for both good and bad meta information...
with savings as to user interaction of up to 80%.

Technical preliminaries are provided in Section 2. Section 3 explains the suggested approach and gives implementation details. Evaluation results are described in Section 4. Section 5 concludes.

2 Preliminaries

In order to make the paper self-contained we provide a short introduction to description logic (DL), which is a knowledge representation and reasoning system (KRS) used in the paper. Of course, the approach suggested in this work is not limited to DL and can be applied to any KRS for which there is a sound and complete reasoning method and the entailment relation is extensive, monotone and idempotent.

Description logic [Baader et al., 2003] is a family of knowledge representation languages with a formal logic-based semantics that are designed to represent knowledge about a domain in form of concept descriptions. The syntax of a language $\mathcal{L}$ is defined by its signature (vocabulary) and a set of constructors. A signature in this case corresponds to a (disjoint) union of sets $N_C$, $N_R$ and $N_I$, where $N_C$ contains all concept names (unary predicates), $N_R$ comprises all role names (binary predicates) and $N_I$ is a set of individuals (constants). Each concept and role description can be either atomic or complex. The latter ones are composed using constructors defined in the particular language $\mathcal{L}$. A typical set of DL constructors includes conjunction $\land$, disjunction $\lor$, negation $\neg$, existential $\exists r.A$ and value $\forall r.A$ restrictions, where $A, B \in N_C$ and $r \in N_R$.

A DL ontology $\mathcal{O}$ is defined as a tuple $(T, A)$, where $T$ (TBox) is a set of terminological axioms and $A$ (ABox) a set of assertional axioms. Each TBox axiom is expressed by a general concept inclusion $A \sqsubseteq C$, a form of logical implication, or by a definition $A \equiv C$, a kind of logical equivalence, where $C$ is an atomic or complex concept. ABox axioms are used to assert properties of individuals in terms of the vocabulary defined in TBox, e.g. concept $A(x)$ or role $r(x, y)$ assertions, where $x, y \in N_I$.

The semantics of DLs is given in terms of interpretations $I = (\Delta_I^C, \Delta_I^R)$ consisting of a non-empty domain $\Delta_I$ and a function $\cdot^I$ that maps each concept to a subset of $\Delta_I$, each role to a subset of $\Delta_I \times \Delta_I$ and each individual to some value in $\Delta_I$. An interpretation $I$ is a model of $\mathcal{O}$ iff it satisfies all TBox and ABox axioms. $\mathcal{O}$ is unsatisfiable iff it has no model. A concept $A$ (role $r$) is satisfiable w.r.t. $\mathcal{O}$ iff there is a model $I$ of $\mathcal{O}$ with $A^I \neq \emptyset$ ($r^I \neq \emptyset$). A TBox is incoherent iff there exists an unsatisfiable concept or role.

Usually description logic systems provide sound and complete reasoning services to their users. In addition to verification of coherence and consistency of $\mathcal{O}$, the reasoners also perform classification and realization. Classification is a subsumption algorithm that determines most specific (general) concepts that subsume (are subsumed by) a certain concept. Realization computes for each individual $x$ a set of most specific concepts $\{C_1, \ldots, C_n\}$ such that $\mathcal{O} \models C_i(x)$ for all $i = 1, \ldots, n$. Note, when we speak of entailments below, we address (only) the output computed by the classification and realization services of a DL-reasoner.

Ontology debugging, given an ontology $\mathcal{O}$, aims at approximating the so-called target ontology $\mathcal{O}_t$ by $\mathcal{O}^*$, where $\mathcal{O}_t$ is some correct and complete ontology that satisfies all requirements to the knowledge-based application it is used for. $\mathcal{O}^*$ must satisfy all explicitly stated requirements and is thus termed complying ontology. It results from modifications to $\mathcal{O}$ in terms of (1) deleting axioms $D$ and (2) inserting axioms $EX_D$. We call $D = \mathcal{O} \setminus \mathcal{O}^*$ a diagnosis.

Definition 1 (Complying Ontology, Diagnosis Problem)

Let $\mathcal{O}$ be an ontology, $B$ a background KB, $R$ a set of requirements to $\mathcal{O}$, $P$ and $N$ respectively a set of positive and negative test cases, where each test case $p \in P$ and $n \in N$ is a set of axioms. Then an ontology $\mathcal{O}^*$ is called complying ontology iff all the following conditions hold:

$$\forall r \in R : \mathcal{O}^* \cup B \models r$$
$$\forall p \in P : \mathcal{O}^* \cup B \not\models p$$
$$\forall n \in N : \mathcal{O}^* \cup B \not\models n$$

The tuple $\langle \mathcal{O}, B, P, N \rangle_R$ defines a diagnosis problem instance (DPI).

Often $R := \{\text{coherence, consistency}\}$ is assumed.

Definition 2 (Diagnosis)

$\mathcal{D} \subseteq \mathcal{O}$ is called diagnosis for a DPI $\langle \mathcal{O}, B, P, N \rangle_R$ if there is a set of axioms $EX_D$ such that $(\mathcal{O} \setminus \mathcal{D}) \cup EX_D$ is a complying ontology. A diagnosis $\mathcal{D}$ assumes that all $ax_1 \in \mathcal{D}$ are faulty and all $ax_j \in \mathcal{O} \setminus \mathcal{D}$ are correct. A diagnosis $\mathcal{D}$ is minimal if there is no $\mathcal{D}' \subset \mathcal{D}$ s.t. $\mathcal{D}'$ is a diagnosis. MD denotes the set of minimal diagnoses of a DPI.

Note that MD is usually used to approximate the set of all diagnoses of a DPI. The identification of $EX_D$, accomplished e.g. by some learning approach, is a crucial part of the ontology repair process. However, the complete formulation of $EX_D$ is outside the scope of this work where we focus on computing diagnoses. As suggested in [Shchekotykhin et al., 2012], we approximate $EX_D$ by the set $\bigcup_{p \in P} p$. Given a DPI $\langle \mathcal{O}, B, P, N \rangle_R$, if the set of axioms $\mathcal{O} \cup \bigcup_{p \in P} p$ is not a complying ontology then there is no diagnosis $D = \emptyset$, i.e. some axioms in $\mathcal{O}$ must be modified.

Example 1: Consider $O := \mathcal{O}_1 \cup \mathcal{O}_2 \cup \mathcal{M}_{12}$ with TBox $T$:

$$O_1 : ax_1 : PhD \sqsubseteq Researcher$$
$$ax_2 : Researcher \sqsubseteq DeptEmployee$$

$$O_2 : ax_3 : PhDStudent \sqsubseteq Student$$
$$ax_4 : Student \sqsubseteq \neg DeptMember$$

$$\mathcal{M}_{12} : ax_5 : PhDStudent \sqsubseteq PhD$$
$$ax_6 : DeptEmployee \sqsubseteq DeptMember$$

and ABox $A = \{\text{PhDStudent}(s)\}$, where $\mathcal{M}_{12}$ is an automatically generated set of semantic links between $O_1$ and $O_2$. The given ontology $O$ is inconsistent since it describes $s$ as both a department member and not. Let the DPI be defined as $(T, A, \emptyset, \emptyset)_{\text{(coherence)}}$, where $A$ is correct and thus added to the background theory and both sets $P$ and $N$ are empty. For this DPI $MD = \{D_1 : [ax_1], D_2 : [ax_2], D_3 : [ax_3], D_4 : [ax_4], D_5 : [ax_5], D_6 : [ax_6]\}$. To compute MD we employ a combination of HS-Tree [Reiter, 1987] and QuickXPlain [Junker, 2004] algorithms as suggested by [Friedrich and Schekotykhin, 2005].

Interactive ontology debugging iteratively incorporates a user’s knowledge about $O_t$, thereby differentiating between diagnoses in MD. The overall procedure is as follows:
Compute a set of at most \( n \) leading diagnoses \( D \subseteq MD \) that serve as an approximation of all minimal diagnoses MD. Restricting the computation of MD to a predefined number \( n \) helps to overcome exponential explosion of HS-Tree. Preference criteria such as most probable or minimum cardinality diagnoses are used to specify \( D \) within MD. (2) Exploit \( D \) to compute/select a query which is posed to the user. (3) Incorporate the user’s answer to prune the search space for diagnoses. Go to (1) until a predefined stop criterion is met by a set of constructors available in the used knowledge representation language, e.g. \( \{\forall, \exists, \subseteq, \cup, \cap\} \subseteq CT(OWL) \) [Grau et al., 2008]. These fault probabilities \( p_i \) are assumed to be independent and used to calculate fault probabilities of axioms \( ax_k \) as \( p(ax_k) = 1 - \prod_{t \in CT} (1 - p_t)^{n(t)} \) where \( n(t) \) is the number of occurrences of construct type \( t \) in \( ax_k \). The probabilities of axioms can in turn be used to determine fault probabilities of diagnoses \( D_i \in D \) as
\[
p(D_i) = \prod_{ax \in D_i} p(ax) \prod_{ax \notin D_i} (1 - p(ax)) \quad (4)
\]

ENT selects the query \( X_j \in X_D \) with highest expected information gain, i.e. which minimizes \( sc_{ent}(X_j) \) defined as:
\[
\sum_{u \in \{t,f\}} p(u_j = a) \sum_{D_i \in D} -p(D_k | u_j = a) \log_2 p(D_k | u_j = a)
\]
where \( p(u_j = t) = \sum_{D_i \in D} p(D_i) \frac{1}{2} p(D_i^0) \), \( p(D_i^0) = \sum_{D_j \in D} p(D_j) \) and \( u_j = a \) is used to update probabilities \( p(D_k) \) according to the Bayesian formula, yielding \( p(D_k | u_j = a) \). The result of the evaluation in [Shchekotykhin et al., 2012] shows that ENT reveals better performance than SPL in most of the cases. However, SPL proved to be the best strategy in situations when misleading prior information is provided, i.e. the target diagnosis \( D^* \) has low probability. So, one can regard ENT as a high risk strategy with high potential to perform well, depending on the already unknown quality of the given fault information. SPL, in contrast, can be seen as a no-risk strategy without any potential to leverage good meta information. Therefore, selection of the proper combination of prior probabilities \( \{p_t | t \in CT(L)\} \) and query selection strategy is crucial for successful diagnosis discrimination and minimization of user interaction.

### 3 Risk Optimization for Query Selection

The proposed Risk Optimization Algorithm (RIO) extends ENT strategy with a dynamic learning procedure that learns by reinforcement how to select optimal queries. The behavior is determined by the achieved performance in terms of diagnosis elimination rate. Good performance means similar behavior to ENT, whereas aggravation of performance leads to a gradual neglect of the given meta information. Like ENT, RIO continually improves the prior fault probabilities based on new knowledge obtained through queries to a user.
RIOD learns a “cautiousness” parameter $c$ whose admissible values are captured by the user-defined interval $[\underline{c}, \overline{c}]$. The relationship between $c$ and queries is as follows:

**Definition 4 (Cautiousness of a Query)** We define the cautiousness $c_q(X_i)$ of a query $X_i$ as follows:

$$c_q(X_i) := \min \left\{ \left\{ \frac{|D^P|}{|D|}, \frac{|D^N|}{|D|} \right\} \mid 0 \leq \frac{|D^P|}{|D|} \right\} =: [\underline{c}_q, \overline{c}_q]$$

A query $X_i$ is called braver than query $X_j$ iff $c_q(X_i) < c_q(X_j)$. Otherwise $X_i$ is called more cautious than $X_j$. A query with maximum cautiousness $\overline{c}_q$ is called no-risk query.

**Definition 5 (Elimination Rate)** Given a query $X_i$ and the corresponding answer $u_i \in \{t, f\}$, the elimination rate $e(X_i, u_i) = \frac{|D^N|}{|D|}$ if $u_i = t$ and $e(X_i, u_i) = \frac{|D^P|}{|D|}$ if $u_i = f$. The answer $u_i$ to a query $X_i$ is called favorable iff it maximizes the elimination rate $e(X_i, u_i)$. Otherwise $u_i$ is called unfavorable. The minimal or worst case elimination rate $\min_{u_i \in \{t, f\}} (e(X_i, u_i))$ of $X_i$ is denoted by $\epsilon_w(X_i)$.

So, the cautiousness $c_q(X_i)$ of a query $X_i$ is exactly the worst case elimination rate, i.e. $c_q(X_i) = \epsilon_w(X_i) = e(X_i, u_i)$ given that $u_i$ is the unfavorable query result. Intuitively, parameter $c$ characterizes the minimum proportion of diagnoses in $D$ which should be eliminated by the successive query.

**Definition 6 (High-Risk Query)** Given a query $X_i$ and cautiousness $c$, $X_i$ is called a high-risk query iff $c_q(X_i) < c$, i.e. the cautiousness of the query is lower than the algorithm's current cautiousness value $c$. Otherwise, $X_i$ is called non-high-risk query. By $\text{NHR}(X_D) = \emptyset$ we denote the set of all non-high-risk queries w.r.t. $c$. For given cautiousness $c$, the set of all queries $X_D$ can be partitioned in high-risk queries and non-high-risk queries.

**Example 2 (cont. Example 1):** Let the user specify $c := 0.3$ for the set $D$ with $|D| = 6$. Given these settings, $X_1 = \{\text{DeptEmployee}(s), \text{Student}(s)\}$ is a non-high-risk query since its partition $\langle \{P_{\text{Ph}}(s)\} \rangle$ with partition $\langle \{P_{\text{Ph}}(s)\} \rangle = 1/6 < 0.3 = c$ and $X_2 := \{\text{Ph}(s)\}$ is a high-risk query because $\epsilon_w(X_2) = 1/6 > 0.3 = c$. Given a user’s answer $u_1$ to a query $X_2$, the cautiousness $c$ is updated depending on the elimination rate $e(x_2, u_1)$ by $c \leftarrow c + c_{adj}$, where the cautiousness adjustment factor $c_{adj} := 2(\overline{c} - c)$. The scaling factor $2(\overline{c} - c)$ regulates the extent of the cautiousness adjustment depending on the interval length $\overline{c} - c$. More crucial is the factor $adj$ that indicates the sign and magnitude of the cautiousness adjustment.

$$adj := \left\lfloor \frac{|D|}{2} - \varepsilon \right\rfloor - e(x_2, u_1)$$

where $\varepsilon \in (0, \frac{1}{2})$ is a constant which prevents the algorithm from getting stuck in a no-risk strategy for even $|D|$. E.g., given $c = 0.5$ and $\varepsilon = 0$, the elimination rate of a no-risk query $e(x_2, u_1) = \frac{1}{2}$ resulting always in $adj = 0$. The value of $\varepsilon$ can be set to an arbitrary real number, e.g. $\varepsilon := \frac{1}{2}$.

**Algorithm 2: Risk Optimization Algorithm (RIO)**

Input: diagnosis problem instance $(C, B, P, N, \beta)$, fault probabilities of diagnoses $DP$, cautiousness $C = (c, \overline{c}, \underline{c})$, number of leading diagnoses $n$ to be considered, acceptance threshold $\sigma$.

Output: a diagnosis $D$.

1. $P \leftarrow \emptyset; N \leftarrow \emptyset; D \leftarrow \emptyset; n$.
2. repeat
3. $|D| \leftarrow \text{getDiagnoses}(D, n, C, B, P, N);$.
4. $DP \leftarrow \text{getProbabilities}(DP, D, P, N);$.
5. $X \leftarrow \text{generateQueries}(O, B, P, D);$.
6. $X \leftarrow \text{getMinScoreQuery}(DP, X);$.
7. if $\text{getQueryCautiousness}(X_i, D) < c$ then
8. $X_i \leftarrow \text{getAlternativeQuery}(X_i, X, DP, D);$.
9. if $\text{getAnswer}(X_i)$ then $P \leftarrow P \cup \{X_i\}$.
10. else $N \leftarrow N \cup \{X_i\}$.
11. $c \leftarrow \text{updateCautiousness}(D, P, N, X_i, c, \overline{c}, \underline{c})$.
12. until $(\text{aboveThreshold}(DP, \sigma) \text{ or eliminationRate}(X_i) = 0);$.
13. return $\text{mostProbableDiag}(D, DP);$.
Otherwise, GETALTERNATIVEQUERY selects the query $x_{alt} \in X_D$ ($x_{alt} \neq x_{sc}$) which has minimal score $sc_{ent}$ among all least cautious non-high-risk queries $L_c$. That is, $x_{alt} = \arg \min_{x_k \in L_c} (sc_{ent}(x_k))$ where $L_c := \{x_k \in NHR_c(X)p \mid v_{x_k} \in NHR_c(X) : c_q(x_k) \leq c_q(x_i)\}$. If there is no such query $x_{alt} \in X_p$, then $x_{sc}$ is selected.

Given the user’s answer $x_{sc}$, the selected query $x_{alt} \in \{x_{sc}, x_{alt}\}$ is added to $P$ or $N$ accordingly. In the last step of the main loop the algorithm updates the cautiousness value $c$ (function UPDATECAUTIOUSNESS) as described above.

Before the next query selection iteration starts, a stop condition test is performed. The algorithm evaluates whether the most probable diagnosis is at least $\sigma\%$ more likely than the second most probable diagnosis (ABOVETHRESHOLD) or none of the leading diagnoses has been eliminated by the previous query, i.e. GETELIMINATIONRATE returns zero for $x_{sc}$. If a stop condition is met, the presently most likely diagnosis is returned (MOSTPROBABLEDIAG).

4 Evaluation

Goals. This evaluation should demonstrate that (1) there is a significant discrepancy between SPL and ENT concerning number of queries where the winner depends on the quality of meta information, (2) RIO exhibits superior average behavior compared to ENT and SPL w.r.t. the amount of user interaction required, irrespective of the quality of specified fault information, (3) RIO scales well and (4) its reaction time is well suited for an interactive debugging approach.

Provenance of test data. As data source for the evaluation we used faulty real-world ontologies produced by automatic ontology matching systems (OMSSs) (cf. Example 1).

Definition 7 (Ontology matching) [Shvaiko and Euzenat, 2012] Let $Q(O) \subseteq S(O)$ denote the set of matchable elements in an ontology $O$, where $S(O)$ denotes the signature of $O$. An ontology matching operation determines an alignment $M_{ij}$, which is a set of correspondences between matched ontologies $O_i$ and $O_j$. Each correspondence is a 4-tuple $(x_i, x_j, r, v)$, such that $x_i \in Q(O_i)$, $x_j \in Q(O_j)$, $r$ is a semantic relation and $v \in [0,1]$ is a confidence value. We call $O_{iMj} := O_i \cup \sigma(M_{ij}) \cup O_j$ the aligned ontology for $O_i$ and $O_j$ where $\sigma$ maps each correspondence to an axiom.

Let in the following $Q(O)$ be the restriction to atomic concepts and roles in $S(O)$, $r \in \{\subseteq, \sqsubseteq, =\}$ and $\sigma$ the natural alignment semantics [Meilicke and Stuckenschmidt, 2009] that maps correspondences one-to-one to axioms of the form $x_i r x_j$. We evaluate RIO using aligned ontologies by the following reasons: (1) Alignments often cause inconsistence/incoherence of ontologies. (2) The (fault) structure of different ontologies obtained through matching generally varies due to different authors and matching systems involved. (3) For the same reasons, it is hard to estimate the quality of fault probabilities, i.e. it is unclear which existing query selection strategy to choose for best performance. (4) Availability of correct reference alignments.

Test datasets. We used two datasets $D_1$ and $D_2$: Each faulty aligned ontology $O_{iMj}$ in $D_1$ is the result of applying one of four OMSs to a set of six independently created ontologies in the domain of conference organization. For a given pair of ontologies $O_i \neq O_j$, each system produced an alignment $M_{ij}$.

The average size of $O_{iMj}$ per matching system was between 312 and 377 axioms. $D_1$ is a superset of the dataset used in [Stuckenschmidt, 2008] for which all debugging systems under evaluation manifested correctness or scalability problems. $D_2$, used to assess the scalability of RIO, is the set of ontologies from the ANATOMY track in the Ontology Alignment Evaluation Initiative (OAEI) 2011.5 [Shvaiko and Euzenat, 2012], which comprises two input ontologies $O_1$ (11545 axioms) and $O_2$ (4383 axioms). The size of the aligned ontologies generated by results of seven different OMSs was between 17530 and 17844 axioms.

Reference Solutions. For dataset $D_1$, based on a manually produced reference alignment $R_{ij}$ for ontologies $O_i$, $O_j$ (cf. [Meilicke et al., 2008]), we were able to fix a target diagnosis $D^* := \sigma(M_{ij} \setminus R_{ij})$ for each incoherent $O_{iMj}$. In cases where $D^*$ represented a non-minimal diagnosis, it was randomly redefined as a minimum diagnosis $D^* \subset \sigma(M_{ij} \setminus R_{ij})$. In case of $D_2$, given ontologies $O_1$, $O_2$, matching output $O_{12}$, and the correct reference alignment $R_{12}$, we fixed $D^*$ as follows: We carried out (prior to the actual experiment) a debugging session with DPI ($\sigma(M_{12} \setminus R_{12})$, $O_1 \cup O_2 \cup \sigma(M_{12} \cap R_{12})$, $\emptyset$, $\emptyset$) and randomly chose one of the identified diagnoses as $D^*$. Note, it is common in OMS [Meilicke, 2011] that $D^*$ can be a subset of $D := (M_{ij} \setminus R_{ij})$ as there is no evidence based on coherence to classify any axia $\sigma(D \setminus D^*)$ as faulty.

Test settings. We conducted four experiments EXP-i ($i = 1, \ldots, 4$), the first two with dataset $D_1$ and the other two with $D_2$. In experiments 1 and 3 we simulated good fault probabilities by setting $p(ax_k) := 0.001$ for $ax_k \in O_i \cup O_j$ and $p(ax_{m}) := 1 - v_m$ for $ax_m \in M_{ij}$, where $v_m$ is the confidence of the correspondence underlying $ax_m$. Low quality fault information was used in experiments 2 and 4. In EXP-4 the following probabilities were defined: $p(ax_k) := 0.01$ for $ax_k \in O_i \cup O_j$ and $p(ax_{m}) := 0.001$ for $ax_m \in M_{ij}$. In EXP-2 we used probability settings of EXP-1, but fixed a completely unlikely target diagnosis in that we precomputed (prior to the actual experiment) the 30 most probable minimal diagnoses, and from these selected the one including the highest number of axioms $ax_k \in O_{iMj} \setminus \sigma(M_{ij})$ as $D^*$.

In all experiments, we set $|D| := 9$ which proved to be a good trade-off between computation effort and representativeness of leading diagnoses, $\sigma \approx 85\%$ and as input parameters for RIO $c := 0.25$ and $[\varepsilon, \bar{\varepsilon}] := [c_q, \frac{c_q}{2}]$. To let tests pose the highest challenge for the evaluated methods, the initial DPI was specified as $\{O_{iMj}, \emptyset, \emptyset\}_{\{\text{coherence}\}}$, i.e. the full search space was explored without adding parts of $O_{iMj}$ to $B$. In practice, given prior knowledge of correct axioms, adding those to $B$ can severely restrict the search space and greatly accelerate debugging. All tests were executed on a Core-i7 (3930K), 32GB RAM with Ubuntu 11.04 and Java 6.

Metrics. Each experiment involved a debugging session of ENT, SPL as well as RIO for each ontology in the respective dataset. In each session we measured the number of required queries ($q_i$) until $D^*$ was identified, the overall debugging time ($debug$) assuming that queries are answered instantaneously and the reaction time ($react$), i.e. the average time between

1http://oaei.ontologymatching.org
2See http://code.google.com/p/rmbd/wiki/ for code and details.
two successive queries. The queries generated in the tests were answered by an automatic oracle by means of the target ontology $O_t := O_{MAJ} \setminus D^*$. 

**Observations.** The difference w.r.t. number of queries per test run between the better and the worse strategy in \{SPL,ENT\} was absolutely significant, with a maximum of 2300% in EXP-4 and averages of 190% to 1145% throughout all experiments (Figure 2(c)). Moreover, results show that varying quality of fault probabilities in \{EXP-1,EXP-3\} compared to \{EXP-2,EXP-4\} clearly affected the performance of ENT and SPL (see first two rows in Figure 1(a)). This perfectly motivates why a risk-optimizing strategy is suitable.

Results of both experimental sessions, \{EXP-1,EXP-2\} and \{EXP-3,EXP-4\}, are summarized in Figures 2(a) and 2(b) respectively. The figures show the (average) number of queries needed by RIO, grouped by matching tools. The lower (upper) end of the whisker indicates the average $q$ needed by the per-session better (worse) strategy in \{SPL,ENT\}. Box-Whisker Plots presenting the distribution of overhead ($\Delta q := q_{w} - q_{b}$)\footnote{\[ \text{overhead} = \frac{\Delta q}{q_{b}} \times 100 \text{ (in %)} \] per debugging session of the worse strategy $q_w := \max(q_{SPL}, q_{ENT})$.} compared to the better strategy $q_b := \min(q_{SPL}, q_{ENT})$. Mean values are depicted by a cross.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1}
\caption{(a) Percentage rates in how many debugging sessions which strategy performed best/better w.r.t. the required user interaction, i.e. number of queries. EXP-1 and EXP-2 involved 27, EXP-3 and EXP-4 seven debugging sessions each. $q_{str}$ denotes the number of queries needed by strategy $str$ and $\min$ is an abbreviation for $\min(q_{SPL}, q_{ENT})$. (b) Average time (sec) for the entire debugging session (debug), average time (sec) between two successive queries (react), and average number of queries ($q$) required by each strategy.}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2}
\caption{(a) The bars show the average number of queries ($q$) needed by RIO, grouped by matching tools. The lower (upper) end of the whisker indicates the average $q$ needed by the per-session better (worse) strategy in \{SPL,ENT\}. (b) Box-Whisker Plots presenting the distribution of overhead ($\Delta q := q_{w} - q_{b}$)\footnote{\[ \Delta q := q_{w} - q_{b} \] (in %) per debugging session of the worse strategy $q_w := \max(q_{SPL}, q_{ENT})$} compared to the better strategy $q_b := \min(q_{SPL}, q_{ENT})$. Mean values are depicted by a cross.}
\end{figure}

5 Conclusions

We have shown problems of state-of-the-art interactive ontology debugging strategies w.r.t. the usage of unreliable meta information. To tackle this issue, we proposed a learning strategy which combines the benefits of existing approaches, i.e. high potential and low risk. Depending on the performance of the diagnosis discrimination actions, the trust in the a-priori information is adapted. Tested under various conditions, our algorithm revealed good scalability and reaction time as well as superior average performance to two common approaches in the field w.r.t. required user interaction.
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