On Expert Behaviors and Question Types for Efficient Query-Based Ontology Fault Localization

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Abstract. We challenge existing query-based ontology fault localization methods wrt. assumptions they make, criteria they optimize, and interaction means they use. We find that their efficiency depends largely on the behavior of the interacting expert, that performed calculations can be inefficient or imprecise, and that used optimization criteria are often not fully realistic. As a remedy, we suggest a novel (and simpler) interaction approach which overcomes all identified problems and, in comprehensive experiments on faulty real-world ontologies, enables a successful fault localization while requiring fewer expert interactions in 66% of the cases, and always at least 80% less expert waiting time, compared to existing methods.

1 Introduction, Discussion and Approach

Motivation. As Semantic Web technologies have become widely adopted in, e.g., security and health applications, the quality assurance of the knowledge underpinning these applications is a critical requirement. At the core of semantic technologies, ontologies are a means to represent knowledge in a formal, structured and human-readable way, with a well-defined semantics. Due to high ontology complexity, expressive logics used, or distributed, collaborative and tool-supported development processes pursued, faults in ontologies are frequent [8, 15]. Among those, faults that affect the ontology’s semantics are of particular concern, e.g., a medical system could suggest a wrong therapy for a patient. Since manual quality assurance is virtually infeasible for present-day on-

malities often are not fully realistic. As a remedy, we suggest a novel (and simpler) interaction approach which overcomes all identified problems and, in comprehensive experiments on faulty real-world ontologies, enables a successful fault localization while requiring fewer expert interactions in 66% of the cases, and always at least 80% less expert waiting time, compared to existing methods.

Challenges and Goals. Since expert consultancies are costly, query-based debuggers pursue the following goals: (G1) Find the actual diagnosis (G2) with the least effort and (G3) with the least waiting time for the interacting user. The following influencing factors determine how well these goals can be approached: (F1) The way of interacting with the expert (how to define a query?), (F2) the expert behavior (how will the expert answer queries?), (F3) the criterion to be optimized (how to measure the expert’s effort?), and (F4) the used algorithm for query computation (how to compute the best query?).

Existing Approaches. We now discuss how existing query-based methods address these questions: (F1) A (normal) query is a set of axioms \( Q = \{a_1, \ldots, a_n\} \) (this definition is natural for algorithmic and computational reasons, cf. [1] for details). Showing the expert \( Q \) means asking them whether or not the query-axioms are (not) entailed by the intended ontology. (F2) The (query-based) expert is viewed as a function that maps queries to either true or false, where true (false) means that each (some) query-axiom is (not) entailed by the intended ontology. Clearly, to answer positively, the expert must examine each query-axiom; as opposed to the negative case, where it suffices to know some non-entailed query-axiom. So, whether (and how much) information beyond the mere answer false (i.e., that some undefined query-axiom is non-entailed) is obtained depends on the expert at hand. To study the impact of different answering behaviors on fault localization efficiency, we complement the (existing) notion of the query-based expert with the one of an axiom-based expert, i.e., a function which maps query-axioms to either true or false. While query-based and axiom-based experts are equally-behaving in the affirmative case, we can conceive of various axiom-based sub-
types in the negation case, e.g., the minimalist (classifies one query-axiom by false), the pragmatist (classifies query-axioms one-by-one, until and including the first negative one that is encountered), and the maximalist (classifies each query-axiom). Note that each (negative) axiom-based answer is strictly more informative than a query-based one, i.e., an axiom-based answering strategy means better diagnoses elimination and less cost. (F3) Most often, the number of queries (#Q) is used to quantify fault localization cost. Because the (global) minimization of #Q is NP-hard, query selection heuristics [11, 13, 18] are employed for choosing the best query in each iteration based on a (local) one-step-lookahead assessment (how favorable is the expected situation after a query is answered?). However, these heuristics do not take into account the number of axioms (#Ax) an expert has to classify, although the size of different queries in terms of the included axioms can vary considerably. Hence, we argue that #Ax is a more realistic measure to evaluate the expert’s effort. Moreover, a query defined as a set of axioms, see (F1), coupled with the fact that heuristics perform a binary (true vs. false) query-analysis, yields a dilemma. For, if the interacting expert is not query-based, this binary analysis is only an approximation as there are exponentially many possible axiom-based expert answers (each query-axiom can be true/false/unanswered), and an exact analysis is impractical since exponential. (F4) State-of-the-art methods [4] can efficiently compute queries that are informative wrt. the minimization of #Q under the assumption of a query-based expert, but they do neither (primarily) consider the expert’s effort for query answering nor the contingency of an axiom-based expert interacting with the system.

To sum up, existing works tackle (F1)–(F4) in a way that (i) fault localization efficiency depends on (the behavior of) the interacting expert, (ii) finding of best queries might be inefficient or only approximative, and (iii) optimized criteria appear to be not fully realistic.

New Approach. To remedy these issues, we suggest to use so-called singleton queries instead of normal ones. A singleton query (SQ) is a query which includes exactly one axiom (cf. the example query above). Albeit pretty simple, the SQ-approach solves all problems we discussed. In particular, SQs have exactly two outcomes, entail a (necessarily) unique expert behavior (all expert types coincide), and imply #Ax = #Q (unequivocal optimization criterion). Further immediate advantages are: Each computed SQ-query-axiom depends on all so-far acquired expert inputs (better informed computations), worst-case search costs for best SQ are less than for best normal query (smaller search space), heuristic query evaluation is always exact and plausible for SQs, concepts (e.g., heuristics [11, 13, 18], UIs [10]) for normal queries are directly reusable for SQs (computability), with SQs there is no need to instruct experts (on how to operate for best results), to ascertain the expert’s type a-priori, or to adapt algorithms to different experts (simpler computation and optimization process), and SQs mean an equally or more informative feedback per asked axiom (all queried axioms are indeed answered).

Hence, the SQ-technique addresses (F1)–(F3) in an elegant way, in that queries are defined as SQs (F1), which directly answers, and thus obviates the need to care about, (F2) and (F3). Solely, regarding (F4), there is a hitch related to the (per-se favorable) smaller search space for SQs, in that a more sophisticated query search is required to ensure that the output is indeed an SQ. Whereas the conception of an efficient general algorithm for SQs is an open research question, we were able to develop a polynomial time and space algorithm to find, wrt. a given set of diagnoses, the best SQ among those of the form \( Q = \{ ax \} \) where \( ax \) is an element of the ontology.

2 Evaluation Results and Concluding Remarks

Evaluation. We conducted extensive experiments on faulty real-world ontologies to study normal queries in combination with the discussed expert types and to compare them with SQs. In the tests, we used only queries \( Q \subseteq O \) for each ontology \( O \). Focus of the investigations were the discussed goals (G1)–(G3). Specifically, we examined the following questions: (Q1) Does the expert answering behavior make a difference (wrt. fault localization cost)? Answer: For normal queries, yes. We observed significant differences (overheads of up to 140%) between the distinct expert types (in terms of both #Q and #Ax). For SQs, trivially no, as all expert behaviors coincide. (Q2) Which strategy is the best to answer normal queries? Answer: Wrt. #Ax: The pragmatist always performed superior (on avg.) to all others. Wrt. #Q: It was not clear-cut, but overall the pragmatist tended to be the best as well. Hence, when relying on normal queries, we should advise experts to pursue the pragmatist answering approach. (Q2) Which strategy is the best to answer normal queries? Answer: Wrt. #Ax: SQs led to less expert effort in two thirds of the tested cases. Wrt. #Q: Interestingly, SQs were mostly the better choice as well. (Q4) Which approach (query type and answering strategy) is computationally most efficient (wrt. the expert’s waiting time)? Answer: SQs. Time savings against normal queries were substantial (always larger than 80%), which can be attributed to the smaller search space.

Conclusion. Singleton queries represent an elegant solution to all discussed problems of existing query-based fault localization methods, and moreover enable a successful determination of the faulty axioms while proving more efficient on avg. than existing techniques in terms of both expert interaction effort and expert waiting time.

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