Exact Learning of \mathcal{ELI} Queries in the Presence of DL-Lite-Horn Ontologies

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Abstract

Learning, in Angluin's framework of exact learning, a query in the presence of a description logic ontology often involves as a crucial (iterated) step the generalization of a hypothesis query. This may be achieved, for example, by constructing a least general generalization of the hypothesis and a counterexample that was provided by the oracle. In this research note, we observe that it may pay off to resort to a more liberal construction that uses the counterexample as a guide to produce a generalization of the hypothesis while not necessarily achieving a generalization of the counterexample. We use this approach to show polynomial time learnability of \mathcal{ELI} concept queries (ELIQs) in the presence of ontologies which are formulated in a mild restriction of $DL-Lite_{form}^{\mathcal{F}}$.

Keywords

Exact Learning, Least General Generalizations, DL-Lite-Horn

1. Introduction

Various forms of learning description logic (DL) concepts, ontologies, and queries have been studied in the literature, including PAC learning [1, 2, 3], the construction of the least common subsumer (LCS) and the most specific concept (MSC) [4, 5, 6, 7, 8], and learning from labeled data examples [9, 10, 11, 12, 13, 14]. In this research note, we consider Angluin's framework of exact learning where a learner interacts in a game-like fashion with an oracle [15, 16]. The main aim is to find an algorithm that enables the learner to construct the target object in polynomial time based on queries that they pose to the oracle, even when the oracle does not answer the queries in the most informative way.

The interest in exact learning in DLs started with an investigation of ontology learning in (the conference version of) [17], see also [18, 19] and the survey [20]. This was complemented by studies of exactly learning DL concepts and queries: learning \mathcal{ELI} concept queries (ELIQs) without ontologies is considered in [21] while [22] studies learning \mathcal{EL} concept queries (ELQs), ELIQs, and restricted forms of conjunctive queries (CQs) in the presence of \mathcal{EL} and \mathcal{ELI} ontologies. Very recently, [23, 24] has investigated learning ELIQs in the presence of ontologies formulated in the DL-Lite dialects DL-Lite^{\mathcal{H}} and DL-Lite^{$\mathcal{F}-$} where the '-' indicates a restriction on the use of inverse functional roles.

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To explain the contribution of this article, let us introduce exact learning of queries in the presence of DL ontologies. Learner and oracle both know and agree on the ontology \mathcal{O} and they also agree on the target query q_T to use only concept and role names from \mathcal{O} . There are two kinds of queries that the learner may pose to the oracle. In a *membership query*, the learner provides an ABox \mathcal{A} and a candidate answer \bar{a} and asks whether $\mathcal{A}, \mathcal{O} \models q_T(\bar{a})$; the oracle faithfully answers "yes" or "no". In an *equivalence query*, the learner provides a hypothesis query q_H and asks whether q_H is equivalent to q_T under \mathcal{O} ; the oracle answers "yes" or provides a counterexample, that is, an ABox \mathcal{A} and tuple \bar{a} such that $\mathcal{A}, \mathcal{O} \models q_T(\bar{a})$ and $\mathcal{A}, \mathcal{O} \not\models q_H(\bar{a})$ (*positive counterexample*) or vice versa (*negative counterexample*). Then, *polynomial time learnability* means that there is a learning algorithm that constructs $q_T(\bar{x})$, up to equivalence w.r.t. \mathcal{O} , such that at any given time, the running time of the algorithm is bounded by a polynomial in the sizes of q_T , \mathcal{O} , and the largest counterexample given by the oracle so far. A weaker requirement is *polynomial query learnability* where only the sum of the sizes of the queries posed to the oracle up to the current time has to be bounded by such a polynomial.

We next describe, on an informal level, how a typical learning algorithm works. The described strategy has been used, e.g., to learn CQs and mappings in database theory [25, 26], LTL formulas [27], as well as ontologies and queries in a DL context [17, 22, 24]. The algorithm constructs a sequence

$$q_0 \subseteq_{\mathcal{O}} q_1 \subseteq_{\mathcal{O}} q_2 \subseteq_{\mathcal{O}} \cdots$$

of increasingly general hypothesis queries, where $\subseteq_{\mathcal{O}}$ denotes query containment under the ontology \mathcal{O} . It maintains the invariant that $q_i \subseteq_{\mathcal{O}} q_T$ for all $i \ge 0$ where q_T is the target query to be learned (only known to the oracle). As the initial hypothesis q_0 , one constructs a very strong query which implies any possible q_T . If, for example, the query language is unary CQs and the ontology \mathcal{O} does not express any disjointnesses between concept and role names, then this query might be the single-variable query that has atoms A(x) and r(x, x) for all concept names A and role names r. If a more restricted query class such as ELIQs is used or the ontology expresses disjointness constraints, then the construction of the initial hypothesis might be more subtle and also involve interaction with the oracle, see [22, 24].

To move from hypothesis q_i to q_{i+1} , the algorithm repeatedly employs a suitable generalization strategy, which may be viewed as the heart of the learning algorithm. In the literature, one finds two main such strategies. To describe them, assume that the class of target queries Q is a class of CQs such as all CQs or all ELIQs.

When query and ontology language are sufficiently restricted, it may happen that the set of all possible least general generalizations of the current hypothesis q_H can be computed in polynomial time. Then, membership queries to the oracle can be used to identify a generalization that implies the target, and the algorithm does not need to use equivalence queries at all. This strategy has been used, for example, to learn ELIQs in the presence of ontologies formulated in *DL-Lite*^{\mathcal{H}} and DL-Lite^{$\mathcal{F}-$} [21, 24], but it already fails for learning ELIQs under *DL-Lite*_{horn} ontologies [24]; recall that the \cdot_{horn} subscript indicates the presence of conjunction. The second strategy is to pose the current hypothesis as an equivalence query to the oracle, and to then construct a least general generalization of the hypothesis q_H and the returned counterexample (\mathcal{A}, \bar{a}), which must be positive since the hypothesis is contained in the target. What we mean here is a Q-LGG, that is, a query p such that $q_H \subseteq_{\mathcal{O}} p$, $q_A \subseteq_{\mathcal{O}} p$ where q_A is A viewed as a CQ with answer variables \bar{a} , and $p \subseteq_{\mathcal{O}} p'$ for every $p' \in Q$ with $q_H \subseteq_{\mathcal{O}} p'$ and $q_A \subseteq_{\mathcal{O}} q'$. This approach has been used to learn unrestricted CQs without ontologies [21] and to learn syntactically restricted CQs under \mathcal{EL} ontologies [22].

The aim of this note is to introduce a variation of the second approach to generalization, and to demonstrate its usefulness by devising a polynomial time learning algorithm for ELIQs in the presence of DL-Lite $_{horn}^{\mathcal{F}-}$ ontologies. In theory, a natural way to construct a Q-LGG of the hypothesis q_H and counterexample \mathcal{A} is to build the universal models of q_H (viewed as an ABox) and of \mathcal{A} under the ontology \mathcal{O} , and to then take their direct product.¹ If we interpret 'universal model' as meaning homomorphism universal,² then such models are infinite and thus the described construction cannot be used in a learning algorithm. But homomorphism universality is not strictly required to obtain a Q-LGG when Q is not the class of all CQs. We may then use Q-universal models which only require that for every query q in the target query language Q, the answers to q on \mathcal{A} under \mathcal{O} coincide with the answers to q on the universal model. Sometimes, it is possible to construct finite Q-universal models, an approach that has been used successfully to learn a restricted form of CQs in the presence of \mathcal{EL} ontologies [22]. To learn ELIQs under DL-Lite ontologies, however, this approach fails since finite ELIQ-universal models are not guaranteed to exist (even for non-branching ELIQs).

Example 1. Let $\mathcal{O} = \{\top \sqsubseteq \exists r. \top\}$ and $\mathcal{A} = \{A(a)\}$. The homomorphism-universal model of \mathcal{A} and \mathcal{O} is \mathcal{A} extended with an infinite r-path $r(a, a_1), r(a_1, a_2), \ldots$. Any ELIQ-universal model also needs such a path, and thus the only chance to obtain a finite ELIQ-universal model is to reuse individuals on the path. But such a model cannot be ELIQ-universal: if $a_n = a_m$, with n < m, then a is an answer to the ELIQ $\exists r^m . \exists (r^-)^n . A$ on the universal model, but not on \mathcal{A} under \mathcal{O} .

Of course, there could potentially be ways to construct a Q-LGG other than taking the direct product of Q-universal models. In the presence of DL-Lite ontologies, though, the Q-LGG is not guaranteed to exist when Q is the class of CQs or the class of non-branching ELIQs extended with reflexive role atoms. For non-extended ELIQs, the existence of Q-LGGs remains open.

Example 2. Let $\mathcal{O} = \{ \exists r^- . \top \sqsubseteq \exists r . \top, \exists r^- . \top \sqsubseteq \exists s . \top \}$. Consider the unary CQs

$$p(x) = \exists y \exists z \, r(x, x) \land s(x, y) \land s(z, y) \land r(z, z) \land A(z) \quad and \quad q(x) = \exists y \, A(x) \land r(x, y).$$

We claim that no ELIQ-LGG of p and q exists, and thus also no Q-LGG for any query class Qthat contains all ELIQs. To see this, assume that the $CQ \hat{q}(x)$ is an ELIQ-LGG of p and q, and consider all ELIQs of the form $q_{n,m} = \exists r^n . \exists s . \exists s^- . \exists (r^-)^m . A$ with $n, m \ge 1$. It is easy to see that $p \subseteq_{\mathcal{O}} q_{n,m}$ and $q \subseteq_{\mathcal{O}} q_{n,m}$ if and only if n = m, thus $\hat{q} \subseteq_{\mathcal{O}} q_{n,m}$ if and only if n = m. For all $i \ge 1$, take a homomorphism h_i from $q_{i,i}$ to the homomorphism universal model \mathcal{U} of \hat{q} (viewed as an ABox) and \mathcal{O} ; this model is defined in detail in Section 2. If for some i, h_i maps two distinct variables in the $\exists r^i$ prefix of $q_{i,i}$ to the same element of \mathcal{U} , then an easy pumping argument shows that $\hat{q} \subseteq_{\mathcal{O}} q_{j,i}$ for some j > i, a contradiction. Otherwise, there is some $i \ge 1$ such that h_i chooses as the s-successor required by the $\exists s'$ infix in $q_{i,i}$ an element of \mathcal{U} that was

¹This may yield a CQ that does not fall within Q, but there are strategies for the learning algorithm to deal with this. ²that is, a universal model of an ABox A and O admits a homomorphism into every model of A and O.

generated by an existential quantifier, that is, it is in the tree-shaped 'anonymous' part of \mathcal{U} . Since $q_{i,i}$ is rooted, the h_i -homomorphic image of the ' $\exists r^i$ ' prefix of $q_{i,i}$ enters the anonymous part from the same non-anonymous element y where it also leaves it to eventually reach an element that satisfies A (there are no such elements in the anonymous part). Thus y is reachable in \hat{q} from x along an r-path and x reaches an instance of A along an r-path, which means that $\hat{q} \subseteq_{\mathcal{O}} \exists r^k A$ for some $k \geq 1$. But this contradicts $p \subseteq_{\mathcal{O}} \hat{q}$.

In this paper, we propose to replace Q-LGGs by a more liberal construction, which still achieves a generalization of the hypothesis, though not necessarily of the counterexample. In fact, we use the counterexample only as a guide to identify in polynomial time a generalization of the hypothesis that is contained in the target query. In contrast to the construction of Q-LGGs via products, our construction is asymmetric in that it treats the hypothesis differently from the counterexample. We use our construction as a central ingredient to prove polynomial time learnability of ELIQs in the presence of DL-Lite $_{horn}^{\mathcal{F}-}$ ontologies. For the type of learning algorithm that we pursue, there is a 'natural ensemble' of lemmas that one may use to prove correctness and termination in polynomial time [21, 22]. Whenever possible, we establish these lemmas in a general version, namely for rooted CQs in place of ELIQs and for \mathcal{ELIF} ontologies in place of DL-Lite $_{horn}^{\mathcal{F}-}$ ontologies. This serves to highlight the places where we crucially rely on ELIQs and DL-Lite $_{horn}^{\mathcal{F}-}$, and in addition it is potentially useful for future proofs where the lemmas that admit a general formulation do not need to be reproved.

Missing proof details will be provided in the long version of the paper.

2. Preliminaries

Ontologies and ABoxes. Let N_C , N_R , and N_I be countably infinite sets of *concept*, *role* and *individual names*. A *role* R is a role name r or the inverse r^- of a role name, and R^- denotes r when $R = r^-$. A *basic concept* B is of the form \top , A, or $\exists R$ where A ranges over N_C and R over roles. A *DL-Lite*^{$\mathcal{F}}_{horn}$ *ontology*is a set of*concept inclusions*(*CIs* $) <math>B_1 \sqcap \cdots \sqcap B_n \sqsubseteq B$, *concept disjointness constraints* $B_1 \sqcap \cdots \sqcap B_n \sqsubseteq \bot$, *role disjointness constraints* $R_1 \sqcap R_2 \sqsubseteq \bot$, and *functionality assertions* func(R) where B_i , B range over basic concepts and R_1 , R_2 , R over roles. In a *DL-Lite*^{\mathcal{F}}_{horn} ontology, we additionally require that if $\exists R$ occurs on the right-hand side of a CI, then func(R^-) $\notin \mathcal{O}$ [24].</sup>

An \mathcal{ELI} concept is an expression C that is built according to the rule $C ::= \top |A| |C \sqcap C|$ $\exists R.C$ where A ranges over concept names and R over roles. An \mathcal{ELIF} ontology \mathcal{O} is a finite set of concept inclusions (CIs) $C \sqsubseteq D$, emptiness constraints $C \sqsubseteq \bot$, role disjointness constraints $R_1 \sqcap R_2 \sqsubseteq \bot$, and functionality assertions func(R) where C, D range over \mathcal{ELI} concepts and R_1, R_2, R over roles. The basic concept $\exists R$ is a different way to write the \mathcal{ELI} concept $\exists R.\top$. Note that every DL-Lite^F_{horn} ontology is an \mathcal{ELIF} ontology. An \mathcal{ELIF} ontology (and thus also a DL-Lite^F_{horn} ontology) is in normal form if all concept inclusions in it are of the form $A \sqsubseteq C$ or $C \sqsubseteq A$, where A is a concept name. Every DL-Lite^F_{horn} ontology \mathcal{O} can be transformed in polynomial time into a DL-Lite^F_{horn} ontology \mathcal{O}' in normal form such that \mathcal{O}' is a conservative extension of \mathcal{O} , and the same is true for \mathcal{ELIF} ontologies.

An ABox \mathcal{A} is a finite set of concept assertions A(a) and role assertions r(a, b) with A a concept name or \top , r a role name, and a, b individual names. We use $ind(\mathcal{A})$ to denote the

set of individual names used in A. We admit concept assertions $\top(a)$ in order to represent interpretations and ABoxes in a uniform way.

The semantics is defined as usual in terms of *interpretations* \mathcal{I} , which we define to be a (possibly infinite and) non-empty set of concept and role assertions. We use $\Delta^{\mathcal{I}}$ to denote the set of individual names in \mathcal{I} and set $A^{\mathcal{I}} = \{a \mid A(a) \in \mathcal{I}\}$ for all $A \in \mathsf{N}_{\mathsf{C}}$ and $C^{\mathcal{I}}$ for compound concepts C in the usual way [28]. Note that every ABox is a finite interpretation and, vice versa, every finite interpretation is an ABox. An interpretation \mathcal{I} satisfies a concept inclusion $C \sqsubseteq D$ if $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$, a constraint $C \sqsubseteq \bot$ if $C^{\mathcal{I}} = \emptyset$, a functionality assertion $\mathsf{func}(R)$ if $R^{\mathcal{I}}$ is a partial function, a concept assertion A(a) if $a \in A^{\mathcal{I}}$, and a role assertion r(a, b) if $(a, b) \in r^{\mathcal{I}}$. An interpretation is a *model* of an \mathcal{ELIF} ontology or an ABox if it satisfies all concept inclusions, constraints, and assertions in it. We write $\mathcal{O} \models C \sqsubseteq D$ if every model of the ontology \mathcal{O} satisfies the concept inclusion $C \sqsubseteq D$ and $\mathcal{A}, \mathcal{O} \models B(a)$ if every model of \mathcal{A} and \mathcal{O} satisfies the concept assertion R(a). An ABox \mathcal{A} is satisfiable w.r.t. an \mathcal{ELIF} ontology \mathcal{O} if \mathcal{A} and \mathcal{O} have a common model. We use $\mathcal{I}_1 \times \mathcal{I}_2$ to denote the *direct product* of two interpretations $\mathcal{I}_1, \mathcal{I}_2$.

A signature is a set of concept and role names, uniformly referred to as symbols. For a syntactic object O such as an ontology, we use sig(O) to denote the symbols used in O and ||O|| to denote the size of O, that is, the length of a representation of O as a word in a suitable alphabet.

Queries. Every \mathcal{ELI} concept C can be viewed as an \mathcal{ELI} query (ELIQ). An individual $a \in \operatorname{ind}(\mathcal{A})$ is an answer to C on an ABox \mathcal{A} w.r.t. an ontology \mathcal{O} , written $\mathcal{A}, \mathcal{O} \models C(a)$, if $a \in C^{\mathcal{I}}$ for all models \mathcal{I} of \mathcal{A} and \mathcal{O} . We shall often view ELIQs as unary conjunctive queries (CQs) and also consider CQs that are not ELIQs. A CQ takes the form $q(\bar{x}) = \exists \bar{y} \phi(\bar{x}, \bar{y})$ with ϕ a conjunction of concept atoms A(x) and role atoms r(x, y) where $A \in \mathsf{N}_{\mathsf{C}}$ and $r \in \mathsf{N}_{\mathsf{R}}$. We call the variables in \bar{x} answer variables. The arity of q is the length $|\bar{x}|$ of \bar{x} , and a query is Boolean if it has arity 0. We use $\mathsf{var}(q)$ to denote the set of variables that occur in q. We may view q as a set of atoms whenever convenient and may write $r^-(x, y)$ in place of r(y, x). A CQ is rooted if in its Gaifman graph $G_q = (\mathsf{var}(q), \{\{y, z\} \mid r(y, z) \in q\})$ every variable is reachable from some answer variable. It is well-known that ELIQs are in 1-to-1 correspondence with rooted, unary CQs whose Gaifman graph is a tree and that contain no self-loops and multi-edges. We use \mathcal{A}_q to denote the ABox obtained from CQ q by viewing variables as individuals and atoms as assertions. A CQ q is satisfiable w.r.t. ontology \mathcal{O} if \mathcal{A}_q is. For any CQ q and set $U \subseteq \operatorname{var}(q)$,

The semantics of CQs is given in terms of homomorphisms as usual. As for ELIQs, we will write $\mathcal{A}, \mathcal{O} \models q(\bar{a})$ if the tuple \bar{a} is an answer to $q(\bar{x})$ on \mathcal{A} w.r.t. \mathcal{O} . For CQs q_1 and q_2 and an \mathcal{ELIF} ontology \mathcal{O} , we say that q_1 is contained in q_2 w.r.t. \mathcal{O} , written $q_1 \subseteq_{\mathcal{O}} q_2$, if for all ABoxes \mathcal{A} and \bar{a} from ind(\mathcal{A}), $\mathcal{A}, \mathcal{O} \models q_1(\bar{a})$ implies $\mathcal{A}, \mathcal{O} \models q_2(\bar{a})$. We call q_1 and q_2 equivalent w.r.t. \mathcal{O} , written $q_1 \equiv_{\mathcal{O}} q_2$, if $q_1 \subseteq_{\mathcal{O}} q_2$ and $q_2 \subseteq_{\mathcal{O}} q_1$.

Universal Model. Query answering and query containment w.r.t. $DL-Lite_{horn}^{\mathcal{F}}$ ontologies can be conveniently characterized using universal models. Let \mathcal{O} be an $DL-Lite_{horn}^{\mathcal{F}}$ ontology in normal form and \mathcal{A} an ABox that is satisfiable w.r.t. \mathcal{O} . For a set M of concept names, we write $\prod M$ as a shorthand for $\prod_{A \in M} A$. For $a \in ind(\mathcal{A})$, M, M' sets of concept names, and R a role, we write $a \rightsquigarrow_{\mathcal{A},\mathcal{O}}^{R} M$ if $\mathcal{A}, \mathcal{O} \models \exists R. \prod M(a)$ and M is maximal with this condition. We write $M \rightsquigarrow_{\mathcal{O}}^{R} M'$ if $\mathcal{O} \models \prod M \sqsubseteq \exists R . \prod M'$ and M' is maximal with this.

A trace for \mathcal{A} and \mathcal{O} is a sequence $t = aR_1M_1R_2M_2...R_nM_n$, $n \ge 0$ where $a \in ind(\mathcal{A})$, $R_1, ..., R_n$ are roles in sig(\mathcal{O}), and $M_1, ..., M_n$ are sets of concept names in sig(\mathcal{O}), such that

- (i) $a \rightsquigarrow_{\mathcal{A},\mathcal{O}}^{R_1} M_1$ and there is no $b \in ind(\mathcal{A})$ with $R_1(a,b) \in \mathcal{A}$,
- (ii) $M_i \rightsquigarrow_{\mathcal{O}}^{R_{i+1}} M_{i+1}$ and $R_{i+1} \neq R_i^-$, for $1 \le i < n$.

The set **T** of all traces for \mathcal{A} and \mathcal{O} forms the domain of the universal model $\mathcal{U}_{\mathcal{A},\mathcal{O}}$, defined as

$$\mathcal{U}_{\mathcal{A},\mathcal{O}} = \mathcal{A} \cup \{A(a) \mid \mathcal{A}, \mathcal{O} \models A(a)\} \cup \{A(tRM) \mid tRM \in \mathbf{T} \text{ and } A \in M\} \cup \{R(t, tRM) \mid tRM \in \mathbf{T}\}.$$

For a CQ q, we usually write $\mathcal{U}_{q,\mathcal{O}}$ instead of $\mathcal{U}_{\mathcal{A}_q,\mathcal{O}}$. The following property of $\mathcal{U}_{\mathcal{A},\mathcal{O}}$ is crucial for our technical development.

Observation 3. Let \mathcal{O} be a DL-Lite^{\mathcal{F}}_{horn} ontology in normal form, \mathcal{A} an ABox, and $\mathcal{I} = \mathcal{U}_{\mathcal{A},\mathcal{O}} \setminus \mathcal{A}$. Then for every role R, $R^{\mathcal{I}}$ is a partial function.

 \mathcal{O} -saturatedness and \mathcal{O} -minimality. Let \mathcal{O} be an \mathcal{ELIF} ontology. A CQ q is \mathcal{O} -minimal if there is no $U \subsetneq \operatorname{var}(q)$ such that $q \equiv_{\mathcal{O}} q|_U$. A CQ q is \mathcal{O} -saturated if $\mathcal{A}_q, \mathcal{O} \models A(y)$ implies $A(y) \in q$ for all $y \in \operatorname{var}(q)$ and $A \in \mathsf{N}_{\mathsf{C}}$. Every CQ (or ELIQ) can be converted into an equivalent \mathcal{O} -saturated one in polynomial time when an oracle for queries of the form " $\mathcal{A}, \mathcal{O} \models A(a)$?" is available. In DL-Lite^{\mathcal{F}}_{horn}, such queries can be answered in polynomial time [29] and thus \mathcal{O} -saturatedness can be established in polynomial time.

3. Guided Generalizations

Recall from the introduction that a CQ \hat{q} is a *least general* Q-generalization (Q-LGG) of CQs p, q under an ontology \mathcal{O} if $q \subseteq_{\mathcal{O}} \hat{q}, p \subseteq_{\mathcal{O}} \hat{q}$, and $\hat{q} \subseteq_{\mathcal{O}} q'$ for every $q' \in Q$ with $q \subseteq_{\mathcal{O}} q'$ and $p \subseteq_{\mathcal{O}} q'$. We consider the following weakening of Q-LGGs.

Definition 4. Let \mathcal{O} be an ontology and \mathcal{Q} a class of queries, and let p, q be CQs with $p \not\subseteq_{\mathcal{O}} q$. A $CQ \hat{q}$ is a p-guided \mathcal{Q} -generalization of q under \mathcal{O} if the following conditions are satisfied:

- 1. $q \subseteq_{\mathcal{O}} \widehat{q};$
- 2. $\widehat{q} \not\subseteq_{\mathcal{O}} q$;
- 3. $\widehat{q} \subseteq_{\mathcal{O}} q'$, for every $q' \in \mathcal{Q}$ with $q \subseteq_{\mathcal{O}} q'$ and $p \subseteq_{\mathcal{O}} q'$.

Conditions 1 and 3 match the first and the last condition in the definition of a Q-LGG. Intuitively, they mean that \hat{q} is a generalization of q (Condition 1) which preserves all common Q-consequences of p and q (Condition 3). Condition 2 weakens the second condition in the definition of an LGG: instead of requiring $p \subseteq \hat{q}$, we only want \hat{q} to strictly generalize q. In the context of learning, one may view p as orthogonal knowledge about how to imply the unknown target, and the goal of guided generalization is to incorporate some of that knowledge into \hat{q} . Thus, in contrast to LGGs, guided generalizations are an *asymmetric* notion in that the two queries p and q play different roles: q is the query to be generalized and p acts as the guide for doing so. We start with observing that p-guided Q-generalizations are not uniquely defined.

Example 5. Consider $q(x) = A(x) \wedge B(x) \wedge C(x)$ and p(x) = A(x). Then both $q_1(x) = A(x)$ and $q_2(x) = A(x) \wedge B(x)$ are p-guided ELIQ-generalizations of q under the empty ontology.

It is not by accident that in Example 5 the ELIQ-LGG of q and p (which is q_1) is also a guided ELIQ-generalization. In fact, it is not difficult to show that each Q-LGG of two CQs p, q under an ontology O is both a p-guided Q-generalization of q under O and a q-guided Q-generalization of p under O. The subsequent example shows that the converse direction is not true, that is, there are cases where a guided generalization exists, but LGGs do not.

Example 6. Consider again queries p and q and the ontology O from Example 2, and recall that there is no CQ-LGG for p, q. However, the query

$$\widehat{q}(x) = \exists y \exists y' r(x, y) \land r(x, y') \land A(y')$$

is a *p*-guided CQ-generalization of q under \mathcal{O} . To illustrate the asymmetry of the notion, observe that \hat{q} is not a *q*-guided CQ-generalization of *p* under \mathcal{O} , since it does not satisfy Condition 1.

We now give our main result, namely that guided ELIQ-generalizations of ELIQs under $DL-Lite_{horn}^{\mathcal{F}-}$ ontologies always exist and can be computed in polynomial time.

Theorem 7. Given a DL-Lite^{$\mathcal{F}-$}_{horn} ontology \mathcal{O} in normal form and ELIQs p, q such that p, q are satisfiable w.r.t. \mathcal{O} and q is \mathcal{O} -minimal,³ we can compute in polynomial time a p-guided ELIQ-generalization \hat{q} of q under \mathcal{O} such that \hat{q} is satisfiable w.r.t. \mathcal{O} .

Let $q(x_1), p(x_2)$ be ELIQs. We construct a *p*-guided ELIQ-generalization \hat{q} of q under \mathcal{O} in three steps as follows. We start with the query $\hat{q} = (\mathcal{U}_{q,\mathcal{O}} \times \mathcal{U}_{p,\mathcal{O}})|_{\{(x_1,x_2)\}}$, that is, the restriction of $\mathcal{U}_{q,\mathcal{O}} \times \mathcal{U}_{p,\mathcal{O}}$ to variable (x_1, x_2) , which will be the answer variable of \hat{q} . This query is then extended by first exhaustively applying rule (A1) below and then applying rule (A2).

- (A1) For every $(z,t) \in var(\hat{q})$ with $z \in var(q)$ and $t \in \Delta^{\mathcal{U}_{p,\mathcal{O}}}$, every atom R(z,z') in q, and every atom $R(t,t') \in \mathcal{U}_{p,\mathcal{O}}$, add the atom R((z,t), (z',t')), and all atoms A(z',t') such that $A(z') \in \mathcal{U}_{q,\mathcal{O}}$ and $A(t') \in \mathcal{U}_{p,\mathcal{O}}$.
- (A2) For every $(z,t) \in \operatorname{var}(\widehat{q})$ with $z \in \operatorname{var}(q)$ and $t \in \Delta^{\mathcal{U}_{p,\mathcal{O}}}$ and every role R such that $z \sim_{q,\mathcal{O}}^{R} M$ for some M and there is no atom of the form R(z, z') in q, add the atoms

$$R((z,t),\hat{z}), R(z',\hat{z})$$

with \hat{z} a fresh variable, and add a copy q' of q in which the copy of z is z'.

³We conjecture that, given an ELIQ, an equivalent \mathcal{O} -minimal ELIQ can be computed in polynomial time by extending the techniques for answering tree-shaped queries over *DL-Lite* knowledge bases in polynomial time [30] to *DL-Lite*^F_{horn} knowledge bases. For the purpose of this paper the statement in the theorem suffices.

Recall that $\mathcal{U}_{q,\mathcal{O}} \times \mathcal{U}_{p,\mathcal{O}}$, when viewed as an infinitary CQ, may serve as a CQ-LGG of p and q. Intuitively, the above construction may be viewed as producing an approximation of this product from below, in the sense that the product may be more general. It is easy to see that after having applied (A1) exhaustively, we have constructed exactly the restriction of the product $\mathcal{U}_{q,\mathcal{O}} \times \mathcal{U}_{p,\mathcal{O}}$ to the elements (t, t') that are reachable from the element (x_1, x_2) and satisfy $t \in var(q)$. We will show that this is a finite structure and even of polynomial size, which is essentially due to Observation 3 on the shape of universal models for DL-Lite $_{horn}^{\mathcal{F}^-}$ ontologies. What is missing is the infinite part of $\mathcal{U}_{q,\mathcal{O}} \times \mathcal{U}_{p,\mathcal{O}}$ determined by elements (t, t') where t is a proper trace, that is, t is not a variable from q. (A2) approximates this part by traveling the traces of $\mathcal{U}_{q,\mathcal{O}}$ (but not of $\mathcal{U}_{p,\mathcal{O}}$) for only one step and then adding copies of q as described. Note that for DL-Lite $_{horn}^{\mathcal{F}^-}$ ontologies \mathcal{O} , the first step into the traces of $\mathcal{U}_{q,\mathcal{O}}$ is enough to regenerate via \mathcal{O} the entire universal model $\mathcal{U}_{q,\mathcal{O}}$. Also note that for (A2) to produce a query that is satisfiable w.r.t. \mathcal{O} , we rely on the restriction to DL-Lite $_{horn}^{\mathcal{F}^-}$: the precondition of (A2) implies that $\exists R$ appears on the right-hand side of some concept inclusion in \mathcal{O} and thus R^- is not functional.

We demonstrate our construction on two examples that additionally illustrate (1) that (A2) is indeed needed and (2) that the result \hat{q} is not necessarily an ELIQ.

Example 8. (1) Consider the ontology $\mathcal{O} = \{X \sqsubseteq \exists r, \exists r \sqsubseteq X, \exists r^- \sqsubseteq \exists s\}$ and ELIQs

$$q(x_1) = B(x_1) \wedge X(x_1) \qquad p(x_2) = \exists x' \exists y \ X(x_2) \wedge r(x_2, y) \wedge r(x', y) \wedge B(x') \wedge X(x').$$

Note that p and q are O-saturated. The result of exhaustively applying Step (A1) is $\hat{q}_0(x) = X(x)$,⁴ which generalizes q, but is too general: the ELIQ

$$q_T(x) = \exists x' \exists y \exists y' \exists z \, r(x, y) \land s(y, z) \land s(y', z) \land r(x', y') \land B(x')$$

satisfies $\widehat{q}_0 \not\subseteq_{\mathcal{O}} q_T$, while $p \subseteq_{\mathcal{O}} q_T$ and $q \subseteq_{\mathcal{O}} q_T$. After additionally applying (A2), we obtain

$$\widehat{q}(x) = \exists x' \exists y \, X(x) \wedge r(x, y) \wedge r(x', y) \wedge B(x') \wedge X(x'),$$

which is a *p*-guided ELIQ-generalization of q under O.

(2) Consider the following queries p', q' and the empty ontology.

$$p'(x) = \exists y_1 \exists y_2 r(x, y_1) \land r(x, y_2) \land A(y_1) \land B(y_2)$$

$$q'(x) = \exists y \exists z r(x, y) \land r(z, y) \land A(y) \land B(y)$$

The result of (A1) is the direct product $q' \times p'$ of q' and p' which is $\hat{q}'(x) = \exists y_1 \exists y_2 \exists z r(x, y_1) \land r(x, y_2) \land r(z, y_1) \land r(z, y_2) \land A(y_1) \land B(y_2)$, which is not an ELIQ.

4. Exact Learning with Membership and Equivalence Queries

We apply the notion of guided generalizations to show that ELIQs are polynomial time learnable in the presence of DL- $Lite_{horn}^{\mathcal{F}-}$ ontologies using membership and equivalence queries. It is known that both kinds of queries are needed as otherwise polynomial time learnability fails (already without functional roles) [22]. Our learning algorithm follows the scheme detailed in the introduction. The main result is as follows.

⁴We have replaced the single answer variable (x_1, x_2) with x for the sake of readability.

Algorithm 1 Algorithm for learning ELIQs under DL-Lite $_{horn}^{\mathcal{F}-}$ ontologies

Input A *DL-Lite*^{\mathcal{F}_{hom}} ontology \mathcal{O} and a unary CQ q_H^0 satisfiable w.r.t. \mathcal{O} such that $q_H^0 \subseteq_{\mathcal{O}} q_T$ **Output** An ELIQ q_H such that $q_H \equiv_{\mathcal{O}} q_T$ $q_H := \text{extract-minimal-ELIQ}(q_H^0)$ **while** the equivalence query " $q_H \equiv_{\mathcal{O}} q_T$?" returns a counterexample (\mathcal{A}, a) **do** $q_D := \text{extract-minimal-ELIQ}(q_\mathcal{A})$ where $q_\mathcal{A}$ is \mathcal{A} viewed as a CQ with answer variable a $q'_H := a q_D$ -guided ELIQ-generalization of q_H under \mathcal{O} $q_H := \text{extract-minimal-ELIQ}(q'_H)$ **end while return** q_H

Theorem 9. ELIQs are polynomial time learnable under DL-Lite^{$\mathcal{F}-$}_{horn} ontologies using membership and equivalence queries.

To prove the theorem, it suffices to consider ontologies in normal form:

Lemma 10. If ELIQs are polynomial time learnable under DL-Lite $_{horn}^{\mathcal{F}-}$ ontologies in normal form using membership and equivalence queries, the same is true for unrestricted DL-Lite $_{horn}^{\mathcal{F}-}$ ontologies.

Our learning algorithm is listed in Algorithm 1. It takes as input a DL-Lite $_{horn}^{\mathcal{F}-}$ ontology \mathcal{O} in normal form and a seed query q_H^0 with $q_H^0 \subseteq_{\mathcal{O}} q_T$. A seed query can be obtained in several ways, depending on the type of disjointness constraints present in \mathcal{O} ; we refer to [24] for details. As explained in the introduction, the algorithm starts with the seed query and constructs a sequence of increasingly more general hypothesis queries. In each round, the learner asks whether the current hypothesis q_H is the target using an equivalence query. If not, they use the counterexample provided by the oracle as a guide to generalize q_H via the construction from the proof of Theorem 7. Since both the input to that construction and the queries posed as equivalence queries must be ELIQs, the algorithm relies on the subroutine extract-minimal-ELIQ to generalize a CQ q with $q \subseteq_{\mathcal{O}} q_T$ into an ELIQ q' with $q' \subseteq_{\mathcal{O}} q_T$ using membership queries. In order to attain polynomial running time, extract-minimal-ELIQ additionally ensures a strong minimality condition on q', namely that it is (q_T, \mathcal{O}) -minimal, which means that there is no $U \subsetneq var(q')$ with $q'|_U \subseteq_{\mathcal{O}} q_T$. Importantly, a (q_T, \mathcal{O}) -minimal query may have at most as many variables as q_T (provided that it is \mathcal{O} -saturated, a condition that we shall maintain at all times), and it is \mathcal{O} -minimal. We next detail the extract-minimal-ELIQ subroutine.

The extract-minimal-ELIQ subroutine takes as input a unary CQ q that satisfies $q \subseteq_{\mathcal{O}} q_T$. It computes an ELIQ q' with $q \subseteq_{\mathcal{O}} q' \subseteq_{\mathcal{O}} q_T$ by repeatedly attaining (q_T, \mathcal{O}) -minimality and increasing the length of cycles in q. A cycle in a CQ q is a sequence $R_1(x_1, x_2), \ldots, R_n(x_n, x_1)$ of distinct role atoms in q such that x_1, \ldots, x_n are distinct. Now, extract-minimal-ELIQ computes the \mathcal{O} -saturation p of q and then modifies p by exhaustively applying the following two rules:

Drop variable. Choose a variable $y \in var(p)$ and let $p' = p|_{var(p) \setminus \{y\}}$. If the response to the membership query $\mathcal{A}_{p'}, \mathcal{O} \models q_T(x)$ is positive, continue with p' in place of p.

Double cycle. Choose a role atom $r(x, y) \in p$ that is part of a cycle. Then add a disjoint copy

p' of p to p and let x', y' be the copies of x, y in p'. Remove the atoms r(x, y), r(x', y') and add the atoms r(x, y'), r(x', y).

We give preference to the first rule, that is, the second rule is only applied when the first one is not applicable. Clearly, if *Drop variable* is not applicable, then p is (q_T, \mathcal{O}) -minimal. Once no rule is applicable anymore, extract-minimal-ELIQ returns q' = p.

The following lemma collects the relevant properties of extract-minimal-ELIQ. All properties except termination are essentially consequences of the definition of the subroutine. The proof of termination after polynomially many steps relies on Theorem 13 below.

Lemma 11. Let q be a unary CQ with $q \subseteq_{\mathcal{O}} q_T$ that is satisfiable w.r.t. \mathcal{O} . Then, extract-minimal-ELIQ(q) terminates in time polynomial in $||\mathcal{O}|| + ||q|| + ||q_T||$ and returns an ELIQ q' that is \mathcal{O} -saturated, (q_T, \mathcal{O}) -minimal, and satisfies $q \subseteq_{\mathcal{O}} q' \subseteq_{\mathcal{O}} q_T$.

To show termination and correctness of our algorithm, we first formalize the notion of a 'sequence of increasingly general hypotheses which are all contained in q_T ,' which is underlying the general scheme described in the introduction.

Definition 12. Let q_T be a CQ and \mathcal{O} an ontology. A sequence q_1, q_2, \ldots of CQs is a generalization sequence towards q_T under \mathcal{O} if for all $i \ge 0$, $q_i \subseteq_{\mathcal{O}} q_{i+1} \not\subseteq_{\mathcal{O}} q_i$, $q_i \subseteq_{\mathcal{O}} q_T$, and $sig(q_i) \subseteq sig(\mathcal{O})$.

Let q_1, q_2, \ldots be the sequence of ELIQs that are assigned to q_H during the run of the algorithm. We show inductively that q_1, q_2, \ldots is a generalization sequence towards the target query q_T under \mathcal{O} . For the base case, note that extract-minimal-ELIQ (q_H^0) computes an initial q_H with $q_H^0 \subseteq_{\mathcal{O}} q_H \subseteq_{\mathcal{O}} q_T$. For the inductive step, let (\mathcal{A}, a) be a counterexample provided by the oracle to the equivalence query " $q_H \equiv_{\mathcal{O}} q_T$?". We may assume that \mathcal{A} uses only symbols from \mathcal{O} (we can simply drop all assertions mentioning other symbols). Since $q_H \subseteq_{\mathcal{O}} q_T$, the counterexample is positive and thus $q_\mathcal{A} \not\subseteq_{\mathcal{O}} q_H$. The subroutine extract-minimal-ELIQ generalizes $q_\mathcal{A}$ into a query q_D , hence $q_D \not\subseteq_{\mathcal{O}} q_H$. Since q'_H is a q_D -guided ELIQ-generalization of q_H , we have $q_H \subseteq q'_H$ (Condition 1 of Definition 4), $q'_H \not\subseteq q_H$ (Condition 2), and $q'_H \subseteq_{\mathcal{O}} q_T$ (Condition 3). It remains to note that extract-minimal-ELIQ preserves these conditions.

It has been observed that already for ELIQs that do not use inverse roles and under the empty ontology, there is no elementary bound on the length of generalization sequences towards a given query q_T [31]. However, since Lemma 11 guarantees that all q_i are (q_T, \mathcal{O}) -minimal and \mathcal{O} -saturated, the next theorem implies that only polynomially many hypotheses are produced.

Theorem 13. Let q_T be a rooted CQ and \mathcal{O} an \mathcal{ELIF} ontology in normal form, and let q_1, q_2, \ldots be a generalization sequence towards q_T under \mathcal{O} such that q_1 is satisfiable w.r.t. \mathcal{O} . If all q_i are (q_T, \mathcal{O}) -minimal and \mathcal{O} -saturated, then the sequence has length at most $|var(q_T)|^3 \cdot |sig(\mathcal{O})|$.

It remains to show that the extract-minimal-ELIQ subroutine terminates after polynomially many steps. For this, consider the sequence p_1, p_2, \ldots of queries that *Double cycle* is applied to during a run of extract-minimal-ELIQ. All these queries are \mathcal{O} -saturated. By the preference imposed on rule application, they are also (q_T, \mathcal{O}) -minimal. Since an application of *Drop Variable* decreases the size of the query, there are at most polynomially many such applications between p_i and p_{i+1} . Thus, it suffices to show the following lemma and apply Theorem 13.

Lemma 14. The sequence p_1, p_2, \ldots is a generalization sequence towards q_T under \mathcal{O} .

We conclude the section with some comments regarding the (limits of) generality of the central Theorem 13. It has been shown that Theorem 13 holds for unrestricted CQs when one considers the restriction \mathcal{EL} of \mathcal{ELI} as ontology language [22] and we conjecture the same to be true also for many *DL-Lite* dialects, e.g., *DL-Lite*_{horn}^{\mathcal{F}}. However, the extension to unrestricted, that is, possibly non-rooted, CQs is not possible for \mathcal{ELI} . The subsequent example illustrates that it fails already for Boolean CQs with a single variable.

Example 15. Let X_i , $\overline{X_i}$ for $1 \le i \le n$ be concept names and r a role name. Let \mathcal{O} be an \mathcal{ELI} ontology that contains the following concept inclusions, for all i with $1 \le i \le n$:

$$\overline{X_i} \sqsubseteq \exists r.\top$$
$$\exists r^-.(X_0 \sqcap \cdots \sqcap X_{i-1} \sqcap \overline{X_i}) \sqsubseteq X_i \qquad \exists r^-.(X_0 \sqcap \cdots \sqcap X_{i-1} \sqcap X_i) \sqsubseteq \overline{X_i}$$
$$\exists r^-.\overline{X_i} \sqcap \overline{X_j} \sqsubseteq \overline{X_i} \qquad \exists r^-.X_i \sqcap \overline{X_j} \sqsubseteq X_i$$

Each subset of $\{X_i, \overline{X_i} \mid 1 \leq i \leq n\}$ containing exactly one of $X_i, \overline{X_i}$ for each *i* represents a number between 0 and $2^n - 1$ in an obvious way. Let q_i be the Boolean CQ that corresponds to number *i*. Clearly, all q_i are \mathcal{O} -saturated and (q_{2^n-1}, \mathcal{O}) -minimal. The sequence $q_1, q_2, \ldots, q_{2^n-1}$ is a generalization sequence towards q_{2^n-1} under \mathcal{O} , but its length is exponential in n.

5. Conclusions and Future Work

We have introduced a new form of generalizations and proved its applicability in the context of exact learning of ELIQs in the presence of DL-Lite $_{horn}^{\mathcal{F}-}$ ontologies. We believe it is worth investigating the new notion of guided generalizations more thoroughly. On the one hand, there are basic open questions such as whether there always exists a *least general* or *most general* p-guided ELIQ-generalization of q for all ELIQs p, q. On the other hand, we would like to understand whether Theorem 7 holds for other relevant combinations of query class and ontology language, e.g., ELIQs and DL-Lite $_{horn}^{\mathcal{F}}$, CQs and any DL-Lite dialect, ELIQs and DL-Lite $^{\mathcal{H}}$, that is, DL-Lite with role hierarchies. The latter will be challenging since there are no universal models that satisfy Observation 3. We note that Theorem 7 does not extend to ELIQs and \mathcal{ELI} ontologies: Our results imply that if we could compute in polynomial time using an oracle for queries of the form " $\mathcal{A}, \mathcal{O} \models A(a)$ ", guided ELIQ-generalization of ELIQs under \mathcal{ELI} ontologies, then ELIQs would be polynomial query learnable under \mathcal{ELI} ontologies which is known not to be the case [22]. In cases where guided generalizations are not guaranteed to exist, it would be interesting to study the induced existence and verification decision problems [7]. Finally, we are wondering whether guided generalizations have other applications, for example in learning from labeled data examples.

As we have shown, positive answers to (some of) these questions would directly lead to polynomial time learnability results. Here, interesting open (and challenging) questions are whether CQs are polynomial time learnable in the presence of DL-Lite^{\mathcal{F}}_{horn} (or even DL-Lite) ontologies, and whether ELIQs are efficiently learnable under DL-Lite^{\mathcal{F}}_{horn} or DL-Lite^{\mathcal{H}} ontologies.

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