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Multiple Constraint Acquisition

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Abstract
QUACQ is a constraint acquisition system that assists a non-expert user to model her problem as a constraint network by classifying (partial) examples as positive or negative. For each negative example, QUACQ focuses onto a constraint of the target network. The drawback is that the user may need to answer a great number of such examples to learn all the constraints. In this paper, we provide a new approach that is able to learn a maximum number of constraints violated by a given negative example. Finally we give an experimental evaluation that shows that our approach improves on QUACQ.

1 Introduction
Constraint programming is a powerful paradigm for modeling and solving combinatorial problems. However, it has long been recognized that expressing a combinatorial problem as a constraint network requires significant expertise in constraint programming [Freuder, 1999]. To alleviate this issue, several techniques have been proposed to acquire a constraint network. For example, the matchmaker agent [Freuder and Wallace, 2002] interactively asks the user to provide one of the constraints of the target problem each time the system proposes an incorrect (negative) solution. In [Beldiceanu and Simonis, 2012], Beldiceanu and Simonis have proposed MODELSEEKER, a system devoted to problems with regular structures, like matrix models. Based on examples of solutions and non-solutions provided by the user, CONACQ.1 [Bessiere et al., 2005; 2015] learns a set of constraints that correctly classifies all the examples given so far. As an active learning version, CONACQ.2 [Bessiere et al., 2007; 2015] proposes examples to the user to classify (i.e., membership queries). In [Shchekotykhin and Friedrich, 2009], the approach used in CONACQ.2 has been extended to allow the user to provide arguments as constraints to converge more rapidly.

QUACQ is a recent active learning system that is able to ask the user to classify partial queries [Bessiere et al., 2013]. QUACQ iteratively computes membership queries. If the user says yes, QUACQ reduces the search space by removing all constraints violated by the positive example. If the user says no, QUACQ focuses onto one, and only one, constraint of the target network in a number of queries logarithmic in the size of the example. This key component of QUACQ allows it to always converge on the target set of constraints in a polynomial number of queries. However, even that good theoretical bound can be hard to put in practice. For instance, QUACQ requires the user to classify more than 8000 examples to get the complete Sudoku model.

An example can be classified as negative because of more than one violated target constraint. In this paper, we extend the approach used in QUACQ to make constraint acquisition more efficient in practice by learning, not only one constraint on a negative example, but a maximum number of constraints violated by this negative example. Inspired by the work on enumerating infeasibility in SAT (Minimal Unsatisfiability Subsets [Liffiton and Sakallah, 2008]), we propose an algorithm that computes all minimal scopes of target constraints violated by a given negative example.

2 Background
The constraint acquisition process can be seen as an interplay between the user and the learner. For that, user and learner need to share a same vocabulary to communicate. We suppose this vocabulary is a set of $n$ variables $X = \{x_1, \ldots, x_n\}$ and a domain $D = \{D(x_1), \ldots, D(x_n)\}$, where $D(x_i) \subset \mathbb{Z}$ is the finite set of values for $x_i$. A constraint $c_S$ is defined as a pair where $S$ is a subset of variables of $X$, called the constraint scope, and $c$ is a relation over $D$ of arity $|S|$. A constraint network is a set $C$ of constraints on the vocabulary $(X, D)$. An assignment $c_Y$ on a set of variables $Y \subseteq X$ is rejected by a constraint $c_S$ if $S \subseteq Y$ and the projection $c_S$ of $c_Y$ on the variables in $S$ is not in $c$. An assignment on $X$ is a solution of $C$ if and only if it is not rejected by any constraint in $C$. The set of solutions of $C$ is denoted by $\text{sol}(C)$.

In addition to the vocabulary, the learner owns a language $\Gamma$ of bounded arity relations from which it can build constraints on specified sets of variables. Adapting terms from machine learning, the constraint bias, denoted by $B$, is a set of constraints built from the constraint language $\Gamma$ on the vocabulary $(X, D)$, from which the learner builds the constraint network. A concept is a Boolean function over $D^X = \Pi_{x_i \in X} D(x_i)$, that is, a map that assigns to each example $e \in D^X$ a value in $\{0, 1\}$. We call target concept the concept $f_T$ that returns 1 for $e$ if and only if $e$ is a solution of the problem the user has in mind. In a constraint program-
A membership query $ASK(e)$ is a classification question asked to the user, where $e$ is a complete assignment in $D^X$. The answer to $ASK(e)$ is “yes” if and only if $e \in sol(C_T)$. A partial query $ASK(e_Y)$, with $Y \subseteq X$, is a classification question asked to the user, where $e_Y$ is a partial assignment in $D^Y = \Pi_{x \notin Y} D(x)$. A set of constraints $C$ accepts a partial assignment $e_Y$ if and only if there does not exist any constraint $c \in C$ rejecting $e_Y$. The answer to $ASK(e_Y)$ is “yes” if and only if $C_T$ accepts $e_Y$. A classified assignment $e_Y$ is called a positive or negative example depending on whether $ASK(e_Y)$ is “yes” or “no”. For any assignment $e_Y$ on $Y$, $\kappa_B(e_Y)$ denotes the set of all constraints in $B$ rejecting $e_Y$. We now define convergence, which is the constraint acquisition problem we are interested in. We are given a set $E$ of (partial) examples labelled by the user as positive or negative. We say that a constraint network $C$ agrees with $E$ if $C$ accepts all the examples labelled as positive in $E$ and does not accept those labelled as negative. The learning process has converged on the learned network $C_L \subseteq B$ if $C_L$ agrees with $E$ and for every other network $C' \subseteq B$ agreeing with $E$, we have $sol(C') = sol(C_L)$. If there does not exist any $C_L \subseteq B$ such that $C_L$ agrees with $E$, we say that we have collapsed. This happens when $C_T \subseteq B$.

Finally, we introduce the notion of minimal scope, which is similar to the notion of MUS (Minimal Unsatisfiable Subset) in SAT [Liffton and Sakallah, 2008].

**Definition 1 (Minimal Scope).** Given a negative example $e$, a minimal scope is a subset of variables $U \subseteq X$ such that $ASK(e_U) = \text{no}$ and for all $x_i \in U$, $ASK(e_{U \setminus \{x_i\}}) = \text{yes}$.

## 3 Multiple Constraint Acquisition

In this section, we propose **MULTIACQ** for Multiple Acquisition. **MULTIACQ** takes as input a bias $B$ on a vocabulary $(X, D)$ and returns a constraint network $C_L$ equivalent to the target network $C_T$ by asking (partial) queries. The main difference between **QUACQ** and **MULTIACQ** is the fact that **QUACQ** learns and focuses on one constraint each time we have a negative example, whereas **MULTIACQ** tries to learn more than one explanation (constraint) of why the user classifies a given example as negative.

### 3.1 Description of **MULTIACQ**

**MULTIACQ** (see Algorithm 1) starts by initializing the $C_L$ network to the empty set (line 1). If $C_L$ is unsatisfiable (line 3), the acquisition process will reach a collapse state. At line 4, we compute a complete assignment $e$ satisfying the current learned network $C_L$ and violating at least one constraint in $B$. If such an example does not exist (line 5), then all the constraints in $B$ are implied by $C_L$, and we have converged. Otherwise, we call the function **findAllScopes** on the example $e$ (line 8). If $e$ is negative, **findAllScopes** returns the set $MSes$ of minimal scopes of $e$. As each minimal scope in $MSes$ represents the scope of a violated constraint that must be learned, the function **findC** is called for each such minimal scope (line 10). It returns a constraint from $C_T$ with the given minimal scope as scope, that rejects $e$. We do not give the code of function **findC** because it is implemented as in [Bessiere et al., 2013]. If no constraint is returned (line 11), this is a second condition for collapsing as we could not find in the bias $B$ a constraint rejecting the negative example. Otherwise, the constraint returned by **findC** is added to the learned network $C_L$ (line 12).

### 3.2 Description of the function **findAllScopes**

The recursive function **findAllScopes** (see Function 1) takes as input a complete example $e$ and a subset of variables $Y$ ($X$ for the first call). Function **findAllScopes** returns $true$ if and only if there exists a minimal scope of $e$ in $Y$. But the real aim of function **findAllScopes** is to fill the set $MSes$ with all the minimal scopes of $e$. Function **findAllScopes** starts by checking if the subset $Y$ is already reported as a minimal scope (line 1). If this occurs, we return $true$. As we assume that the bias is expressible enough to learn $C_T$, when $\kappa_B(e_Y) = \emptyset$ (i.e., there is no violated constraint in $B$ to learn on $Y$), it implies that $ASK(e_Y) = \text{yes}$ and we return $false$ (line 2). As a third check (line 3), we verify if we have not reported a subset of $Y$ as a minimal scope. If that is the case, we are sure that $ASK(e_Y) = \text{no}$ and we get into the main part of the algorithm. If not, at line 4, we ask the user to classify the (partial) example $e_Y$. If it is positive, we remove from $B$ all the constraints rejecting $e_Y$ and we return $false$ (lines 5-6). If $ASK(e_Y) = \text{no}$, this means that there exist minimal scopes in $Y$ and in what follows, we try to report them. For that, we call **findAllScopes** on each subset of $Y$ built.
by removing one variable from $Y$ (lines 8-9). If any sub-call to $\text{findAllScopes}$ returns $true$, the Boolean $flag$ will be set to $true$, which means that $Y$ itself is not a minimal scope (line 10) and we return $true$ at line 11. Otherwise, when all the sub-calls of $\text{findAllScopes}$ on $Y$ subsets return $false$, this means that $Y$ is a minimal scope (line 10) so we add it to the set $\text{MSES}$.

### 3.3 Analysis

We analyze the correctness (i.e., soundness and completeness) of $\text{findAllScopes}$. We also give a complexity study of $\text{MULTIACQ}$ in terms of the number of queries it can ask of the user.

**Lemma 1.** If $ASK(e_Y) = yes$ then for any $Y' \subseteq Y$ we have $ASK(e_{Y'}) = yes$.

*Proof.* Assume that $ASK(e_Y) = yes$. Hence, there exists no constraint from $C_T$ violated by $e_Y$. For any $Y'$ subset of $Y$, the projection $e_{Y'}$ also does not violate any $C_T$ constraint (i.e., $ASK(e_{Y'}) = yes$).

**Lemma 2.** If $ASK(e_Y) = no$ then for any $Y' \supseteq Y$ we have $ASK(e_{Y'}) = no$.

*Proof.* Assume that $ASK(e_Y) = no$. Hence, there exists at least one constraint from $C_T$ violated by $e_Y$. For any $Y'$ superset of $Y$, $e_{Y'}$ also violates at least the constraint violated by $e_Y$ (i.e., $ASK(e_{Y'}) = no$).

**Theorem 1.** Given a bias $B$ and a target network $C_T$ representable by $B$, function $\text{findAllScopes}$ is correct.

*Proof. Soundness.* Assume that we have a complete assignment $e_X$. We show that any subset $Y$ added to $\text{MSESs}$ by $\text{findAllScopes}$ is a minimal scope. If $Y$ is added to $\text{MSESs}$ (line 10), this means that $flag = false$, and either there exists $M \subseteq Y$ in $\text{MSESs}$ or $ASK(e_Y) = no$ (lines 3 and 4 to avoid line 6). As $flag = false$, all sub-calls of $\text{findAllScopes}$ (line 9) on subsets of $Y$ of size $|Y| - 1$ returned $false$. Hence, there does not exist any $M \subseteq Y$ in $\text{MSESs}$. Thus, $ASK(e_Y) = no$. In addition, the fact that $\text{findAllScopes}$ returns $false$ when called on any $Z \subseteq Y$ implies that $ASK(e_Z) = yes$ or $\kappa_B(e_Z) = \emptyset$. As the target network is representable by the bias $B$, $\kappa_B(e_Z) = \emptyset \Rightarrow ASK(e_Z) = yes$. As a result, all the sub-calls of $\text{findAllScopes}$ on the subsets of $Y$ return $false$ because $\forall x_i \in Y$, we have $ASK(e_{Y\setminus\{x_i\}}) = yes$. Then, knowing that $ASK(e_Y) = no$ implies that $Y$ is a minimal scope (Definition 1).

**Completeness.** Given a complete example $e_X$, if $ASK(e_X) = yes$, there is no minimal scope of $e$ to find. Suppose that $ASK(e_X) = no$ with a minimal scope $M$ to find. The three conditions at lines 1, 2 and 4 are not satisfied ($X \notin \text{MSESs}$ because $M \subseteq X$, $\kappa_B(e_X) \neq \emptyset$, and $ASK(e_X) = no$). Hence, function $\text{findAllScopes}$ is called on all the subsets $X'_i \subseteq X$ such that $X'_i = X \setminus \{x_i\}, x_i \in X$. As $M \subseteq X$ is a minimal scope of $e$, $ASK(e_M) = no$ and $\forall Y \subseteq X\setminus M, ASK(e_{M,Y}) = no$ (Lemma 2). Hence, any call of $\text{findAllScopes}$ on a superset of $M$ will behave exactly as on $X$. By induction, there will be a call of $\text{findAllScopes}$ on $M$. As $M$ is a minimal scope, for any subset $M' \subset M$ we have $ASK(e_{M'}) = yes$ (Definition 1). Thus, $M$ is added to $\text{MSESs}$ by $\text{findAllScopes}$ at line 10.

**Theorem 2.** Given a bias $B$ built from a language $\Gamma$ of bounded arity constraints, and a target network $C_T$, $\text{MULTIACQ}$ uses $O(|C_T| \cdot (|X| + |\Gamma|) + |B|)$ queries to prove convergence on the target network or to collapse.

*Proof.* We first show that the number of queries asked by $\text{findAllScopes}$ is bounded above by $|C_T| \cdot |X| + |B|$. Let us start with the number of queries asked by $\text{findAllScopes}$ and classified as negative by the user. By definition, a query on $e_Y$ where $Y$ is a subset of $X$ is classified as negative if and only if there exists a minimal scope $M$ of $e$. $M \subseteq X$. Hence, given a minimal scope $M \subseteq X$, each time $\text{findAllScopes}$ asks a query on a superset $Y$ of $M$, it is classified as negative and $\text{findAllScopes}$ reduces the size of $Y$ by one. Thus, the number of negative queries asked by $\text{findAllScopes}$ to go from $X$ to $M$ is bounded above by $|X| - |M|$. The worst case is when $|M| = 1$ where we will have $|X| - 1$ negative queries. Once $M$ is found, the use of Lemma 2 at lines 1 and 3 of $\text{findAllScopes}$ ensures that we will never ask again a query on a superset of $M$. With the fact that the total number of minimal scopes is bounded by $|C_T|$, we have that the total number of negative queries asked by $\text{findAllScopes}$ is bounded above by $|C_T| \cdot |X|$. We now show that the number of queries asked by $\text{findAllScopes}$ and classified as positive by the user is bounded above by $|B|$. Let us take two subsets $Y$ and $Y'$ where $\kappa_B(e_{Y'}) \subseteq \kappa_B(e_Y)$. If an $ASK$ on $Y$ is classified as positive, we remove $\kappa_B(e_{Y'})$ from $B$ (line 5) and therefore $e_{Y'}$ will be discarded without any query because $\kappa_B(e_Y)$ became empty (line 2). The worst case is when we remove, at each time, only one constraint from $B$ (i.e., $|\kappa_B(e_Y)| = 1$). In this case, $\text{findAllScopes}$ asks $|B|$ positive queries.

As a result, the total number of queries asked by $\text{findAllScopes}$ is bounded above by $|C_T| \cdot |X| + |B|$. Function $\text{findC}$ uses $|\Gamma|$ queries to return a constraint from $C_T$ [Bessiere et al. 2013] and thus $|C_T| \cdot |\Gamma|$ queries to return all the constraints. Therefore, the total number of queries asked by $\text{MULTIACQ}$ to converge to the target network is bounded above by $|C_T| \cdot |X| + |B| + |C_T| \cdot |\Gamma|$.

From this complexity analysis we can see that $\text{MULTIACQ}$ converges on a constraint of the target network in a number of queries linear in the size of the example whereas QUACQ converges on a constraint in a logarithmic number of queries. We will show that this decay in theoretical complexity does not prevent a good experimental behavior.

### 4 Strategies

Given a negative example, function $\text{findAllScopes}$ asks partial queries to compute the set of minimal scopes of constraints that explain why the user said no. Function $\text{findAllScopes}$ needs to explore, in the worst case, a search space containing $2^{|X|}$ candidate scopes. Hence, generating a
query in `findAllScopes` can be time-consuming. We analyze the behavior of `findAllScopes` on a sample problem. Based on this analysis, we propose strategies of exploration of the search space to get the best tradeoff between time-consumption and number of queries.

4.1 Analyzing the behavior of `findAllScopes`

We take the Radio Link Frequency Assignment Problem described in Section 5 as sample problem.

In Figure 1, we report the time needed to compute queries and minimal scopes using `findAllScopes` on a negative example. The first observation we make is that the time needed to compute queries and minimal scopes follows an exponential scale. Generating a query and computing a minimal scope becomes more and more time-consuming as minimal scopes are found. The increasing cost of generating minimal scopes is due to the fact that `findAllScopes` returns quickly most of the minimal scopes just by exploring the first branch (90% of the minimal scopes are found in the first branch for our sample problem). The few remaining minimal scopes are found by exploring the whole remaining branches.

The second observation is that the two curves are almost parallel. Thus, the number of minimal scopes increases quasi-linearly with the number of queries. Hence, the increasing cost of finding minimal scopes is not due to an increasing number of queries required to find a minimal scope. It is due to the increasing cost of generating queries. The increasing cost of generating queries is because during search, `findAllScopes` will apply more and more Lemmas 1 and 2, avoiding to ask question on many branches.

4.2 Heuristics

It is not satisfactory, in an interactive process, to let the human user wait too long between two queries. We then use the observations made in the previous subsection to propose a combination of heuristics to maintain a good trade-off between number of queries and waiting time.

Our first heuristic is merely to use a cutoff on the waiting time between two queries. As a result, we guarantee that the user will not wait too long between two queries. However, if the cutoff is too short, we will not be able to explore the fast branches of the search for minimal scopes, those branches including the last variables.

We combine the cutoff technique with a second heuristic based on reordering the variables. Given a call to `findAllScopes` on a `complete` (negative) example `e`, after triggering the cutoff for the first time, we call again `findAllScopes` on the same complete example `e`, but on a reverse order of the variables. If a second cutoff is triggered, we come back to MULTIACQ, generate a new example and make a shuffle on the variable order. To ensure termination of MULTIACQ, we force `findAllScopes` to return at least a minimal scope before cutting off.

We implemented this combination of heuristics in `findAllScopes` and tested it on our sample problem. The cutoff on the time between two queries has been set to 5 seconds. This is an acceptable waiting time for a human user.

Figure 2(a) shows a comparison on #queries and #minimal scopes (#MS) computed over time by `findAllScopes` with and without heuristics. Without heuristics (grey lines), `findAllScopes` returns its set of minimal scopes on only one negative example generated by MULTIACQ. But the time needed per minimal scope grows during search, as already observed in Figure 1. With heuristics (multicolored lines), `findAllScopes` will cut off the search, reverse the variables, restart, cut off again, and take a new negative example generated by MULTIACQ. This is marked in the figure as 1st negative example, 2nd negative example, and so on. We observe that for a same amount of time, the number of minimal scopes found with heuristics increases and thus, the total time needed to return the whole set of minimal scopes decreases (from 36 minutes without heuristics to 139 seconds with heuristics).

Figure 1: #queries and #minimal scopes (#MS) returned by `findAllScopes` on an RLFAP negative example.

Figure 2: `findAllScopes` with/without heuristics on RLFAP.
Figure 2(b) shows #minimal scopes over #queries with and without heuristics. With heuristics, we observe a clear decrease of the ratio #minimal scopes/#queries. The total number of queries increases from 500 to more than 800.

This example shows that the use of heuristics allows us to reduce the time needed to compute the total number of minimal scopes by a factor of 44 with an increase by a factor of almost 2 on the number of queries asked.

5 Experiments

We made experiments to evaluate the performance of MultiACQ and its findAllScopes function compared to QUACQ. We also evaluate the version using cut-offs, that we call MACQ-CO (i.e., MultiACQ with Cuts-Offs). Our tests were conducted on an 1.6 GHz Intel Core i5 with 4.0GB of RAM (1600 MHz DDR3). We first present the benchmark problems we used for our experiments.

5.1 Benchmark Problems

**Murder.** Someone was murdered last night. There are 5 suspects, each having an item, an activity and a motive for the crime. Under a set of additional clues, the problem is who was the murderer? The target network has the 20 variables we described (i.e., the 5 suspects and their items, activities and motives) with domains of size 5, and 53 binary constraints. We use a bias of 380 constraints based on the language $\Gamma = \{\neq\}$. The edge labels are all different. As an instance, we take 9 nodes and 15 edges. The target network contains 156 constraints (binary and ternary constraints). The bias that we use contains 4600 constraints of basic arithmetic (binary and ternary) constraints.

**Zebra problem.** The Lewis Carroll Zebra problem is formulated using 25 variables, with 5 cliques of $\neq$ constraints and 14 additional constraints. We use a bias of 4450 unary and binary constraints taken from a language with 24 basic arithmetic and distance constraints.

**Graceful Graphs.** (prob053 in [Gent and Walsh, 1999]) A graph of $m$ edges is graceful if all its nodes are assigned to a unique label from $\{0, \ldots, m\}$ and when each edge $xy$ is assigned to $(\text{label}(x) - \text{label}(y))$. The edge labels are all different. As an instance, we take 9 nodes and 15 edges. The target network contains 156 constraints (binary and ternary constraints). The bias that we use contains 4600 constraints of basic arithmetic (binary and ternary) constraints.

5.2 Results

Table 1 displays the performance of MultiACQ and QUACQ. We report the size $|C_L|$ of the learned network, the average time $T$ needed to generate a query in seconds, the standard deviation $\sigma_T$ of $T$, the total number of queries $\#q$, the average size $\bar{q}$ of all queries, the number of complete positive (resp. negative) queries $\#q^+_c$ (resp. $\#q^-_c$) and the number of partial positive queries $\#q^+_p$.

If we compare MultiACQ to QUACQ, the main observation is that the use of findAllScopes to find all minimal scopes of a negative example reduces significantly the number of queries required for convergence.

We take the Murder problem. MultiACQ exhibits a gain of 22% on the number of queries. The second observation that we make is the fact that MultiACQ reduces significantly the average size of the queries (52%), which is probably easier to answer by the user. Another point to stress is that MultiACQ needs only 3 complete negative examples instead of 52 for QUACQ. This is not surprising as MultiACQ is dedicated to return the entire set of minimal scopes of a negative example, where QUACQ focuses on one minimal scope each time we feed it with a negative example.

The same observations on the performance of Multi-
ACQ comparing to QUACQ are true on the other problem instances:

- Number of queries reduction (i.e., gain of 65% on Latin Square, 55% on Golomb Rulers and 73% on Sudoku).
- The average size of the queries (i.e., 71% on Latin-Square, 20% on Golomb Rulers and 90% on Sudoku).
- Obviously, we need less complete negative example (i.e., only one instead of 90 on Latin Square, 43 instead of 323 on Golomb Rulers and only one instead of 622 on Sudoku).

We also observe that the number of constraints learned by MULTIACQ is always greater than or equal to the number of constraints learned using QUACQ (|CL| column). This can be explained by the fact that MULTIACQ can learn redundant constraints, which is not the case using QUACQ. Take three constraints c₁, c₂ and c₃ such that c₁ & c₂ → c₃. If we generate a negative example c₁ that violates the three constraints, MULTIACQ will return three minimal scopes corresponding to the three constraints. By contrast, QUACQ will return only one minimal scope, let us say the one of c₂. In a second iteration QUACQ learns c₁, c₃ is automatically satisfied in any next iteration and will never be learned by QUACQ.

A last observation we can make on Table 1 is related to the average time needed to generate a query. If we take the instances of Golomb Rulers and Sudoku, we observe that MULTIACQ respectively needs twice more time (1.20s instead of 0.53s) and three times more time (0.24s instead of 0.08s) than QUACQ. On these two instances, generating a query is starting to become time-consuming.

Table 1 does not report the results of MACQ-CO because it performs exactly the same as the basic version of MULTIACQ. The reason is that the average time (and standard deviation) needed to generate a query is significantly below the value of the cutoff (5s in our case).

Table 2 gives the results on four additional benchmark problems where MULTIACQ takes long in average to compute a query (more than 2 seconds for all four problems). Results are reported for QUACQ, MULTIACQ and MACQ-CO. The results displayed for MACQ-CO are the average over 10 runs because of the shuffle on the variables, which makes it non deterministic.

The observations made on Table 1 remain true on RLFA and Langford instances. The difference is in the average time needed to generate a query. Using MULTIACQ, the time increases significantly. For instance, on Langford, QUACQ takes 0.03 ± 0.13 seconds to generate a query whereas MULTIACQ takes 4.24 ± 23.03 seconds. On Zebra and Graceful Graphs instances, we observe the same behavior as on the previous two instances for the time to generate a query. However, as for the number of queries, QUACQ is better than MULTIACQ. This can be explained by the high number of partial positive queries asked by MULTIACQ (e.g., for Zebra we have |q_C⁺| = 592 with MULTIACQ against 255 with QUACQ). By definition, MULTIACQ has a trend to ask small queries and then, needs an important number of partial positive queries to reduce the bias and thus, to converge.

Comparing MULTIACQ and MACQ-CO in Table 2, we observe that MACQ-CO reduces drastically the time $T$ needed to generate a query as well as the standard deviation $σ_T$. However, MACQ-CO requires more queries than MULTIACQ to converge, asking almost twice more queries than MULTIACQ on RLFA and three times more on Langford. This is consistent with our analysis in Section 4. Surprisingly, MACQ-CO is better than MULTIACQ in number of queries on Zebra and Graceful Graphs. A possible explanation is the very low number of solutions of these problems that lead MULTIACQ to visit too many partial positive examples that MACQ-CO avoids thanks to the heuristics.

Let us now compare MACQ-CO vs QUACQ. The main observation is that MACQ-CO wins in number of queries on all four problems of Table 2. For instance, on RLFA we note a gain of 37%. Concerning the time to generate queries, we observe that MACQ-CO is quite competitive thanks to the use of cutoffs and its different heuristics.

### 6 Conclusion

We have proposed a new approach to make constraint acquisition more efficient in practice by learning a maximum number of constraints from a negative example. The QUACQ constraint acquisition system focuses on the scope of one target constraint each time it processes a negative example. Our proposed MULTIACQ, with the `findAllScopes` function, reports all minimal scopes of violated constraints. We have also proposed several heuristics, leading to the MACQ-CO version, to obtain a good trade-off between time and number of queries. We have experimentally evaluated the benefit of our algorithm and heuristics on some benchmark problems. The results show that MULTIACQ dramatically improves the basic QUACQ in terms of number of queries. The queries generated are often much shorter than those asked by QUACQ, so are easier to handle for the user. Finally, as MULTIACQ can take too long to generate queries on some problems, MACQ-CO appears as a good compromise between QUACQ and MULTIACQ in terms of time-consumption and number of queries.

### References


