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► **To cite this version:**

Sylvain Boulmé, Alexandre Maréchal. A Coq Tactic for Equality Learning in Linear Arithmetic. 2017.
hal-01505598v1

HAL Id: hal-01505598

<https://hal.science/hal-01505598v1>

Preprint submitted on 11 Apr 2017 (v1), last revised 20 Jul 2017 (v2)

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A Coq Tactic for Equality Learning in Linear Arithmetic ^{*}

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Abstract. COQ provides linear arithmetic tactics like `omega` or `lia`. Currently, these tactics let the current goal unchanged when they can not prove it. We propose to improve this behavior: when the goal is not provable in linear arithmetic, we inject in hypotheses new equalities discovered from the linear inequalities. These equalities may help other COQ tactics to discharge the goal. The paper describes how we have implemented this idea in a new COQ tactic, dealing with linear arithmetic over rationals. It also illustrates that equality learning allows our tactic to interact with other COQ tactics.

Keywords: Linear Programming, Clause Learning, Skeptical Approach

1 Introduction

Several COQ tactics prove goals containing linear (in)equalities: `omega` and `lia` on integers; `fourier` or `lra` on reals and rationals [7,1]. This paper provides yet another tactic for proving such goals. This tactic – called `vp1`¹ – is currently limited to rationals. It is built on the top of the *Verified Polyhedra Library* (VPL), a COQ-certified abstract domain of convex polyhedra [4]. Its main feature appears when it *can not prove* the goal. In this case, whereas above tactics let the goal unchanged (they fail), our tactic “simplifies” the goal. In particular, it injects as hypotheses a *complete* set of linear equalities that are deduced from the linear inequalities in the context. Then, many COQ tactics – like `congruence`, `field` or even `auto` – can exploit these equalities, even if they can not deduce them from the initial context by themselves. By simplifying the goal, our tactic both improves the user experience and proof automation.

Let us illustrate this feature on the following – almost trivial – COQ goal, where `Qc` is the type of rationals on which our tactic applies.

Lemma `ex1 (x:Qc) (f:Qc → Qc): x ≤ 1 → (f x) < (f 1) → x < 1.`

^{*} This work was partially supported by the [European Research Council](#) under the European Union’s Seventh Framework Programme (FP/2007-2013) / ERC Grant Agreement nr. 306595 “[STATOR](#)”.

¹ Coq plugin available on <http://github.com/VERIMAG-Polyhedra/Vp1Tactic>.

This goal is valid on `Qc` and `Z`, but both `omega` and `lia` fail on the `Z` instance without providing any help to the user. Indeed, since this goal contains an uninterpreted function `f`, it does not fit into the pure linear arithmetic fragment. On the contrary, this goal is proved by two successive calls to the `vp1` tactic. As detailed below, equality learning plays a crucial role in this proof: the rewriting of a learned equality inside a non-linear term (because under symbol `f`) is interleaved between deduction steps in linear arithmetic.

In short, this paper provides three contributions. First, we provide a COQ tactic with equality learning, which seems a new idea in the COQ community. Second, we provide a new algorithm which learns these equalities from conflicts between strict inequalities detected by a linear programming solver. This algorithm can be viewed as a special but optimized case of “*conflict driven clause learning*” – at the heart of modern DPLL procedures [6]. On most cases, it is strictly more efficient than the naive equality learning algorithm previously implemented in the VPL [4]. In particular, our algorithm is cheap when there is no equality to learn. At last, we have implemented this algorithm in an OCAML oracle, able to produce *proof witnesses* for these equalities. The paper partially details this process, and in particular, how the *proof* of the learned equalities are computed in COQ by reflection from these witnesses.

Specification of the Oracle. Let us now introduce the specification of the `vp1` tactic. As mentioned above, the algorithmic core of the tactic is performed by an oracle programmed in OCAML, and called `reduce`. This oracle takes as input a *convex polyhedron* P and outputs a *reduced polyhedron* P' such that $P' \Leftrightarrow P$ and such that the *number of constraints* in P' is lower or equals to that of P .

Definition 1 (Convex Polyhedron). A (convex) polyhedron² on \mathbb{Q} is a conjunction of linear (in)equalities of the form $\sum_i a_i x_i \bowtie b$ where a_i, b are constants in \mathbb{Q} , where x_i are variables ranging over \mathbb{Q} , and where \bowtie represents a binary relation on \mathbb{Q} among $\geq, > =$.

A polyhedron may be suboptimally written. In particular, one of its constraints may be implied by the others: it is thus *redundant* and can be discarded. Moreover, a set of inequalities can imply *implicit* equalities, such as $x = 0$ that can be deduced from $x \geq 0 \wedge -x \geq 0$. Definition 2 characterizes polyhedra without *implicit* equalities.

Definition 2 (Complete set of linear equalities). Let E be a set of linear equalities and I be a set of linear inequalities. E is said *complete w.r.t. I* if any linear equality deduced from the conjunction $E \wedge I$ can also be deduced from E alone. Formally, E is complete iff – with t_1 and t_2 ranging over linear terms –

$$\text{for all } t_1 \ t_2, \quad (E \wedge I \Rightarrow t_1 = t_2) \text{ implies } (E \Rightarrow t_1 = t_2) \quad (1)$$

Definition 3 (Reduced Polyhedron). A polyhedron P is *reduced* iff it satisfies the following condition.

² Dealing only with convex polyhedra on \mathbb{Q} , we often omit the adjective “convex”.

- If P is unsatisfiable, then P is a single constant constraint like $0 > 0$ or $0 \geq 1$. In other words, its unsatisfiability is checked by one comparison on \mathbb{Q} .
- Otherwise, P contains no redundant constraint and it is syntactically given as a conjunction $E \wedge I$ where polyhedron I contains only inequalities and where polyhedron E is a complete set of equalities w.r.t. I .

Having a reduced polyhedron ensures that any provable linear equality admits a pure equational proof which ignores the remaining inequalities. We shall show further (in Lemma 1) that this also happens for a larger class of equalities.

Specification of the Tactic. Roughly speaking, a COQ goal corresponds to a sequent $\Gamma \vdash T$ where context Γ represents a conjunction of hypotheses and T a conclusion. In other words, this goal is logically interpreted as the meta-implication $\Gamma \Rightarrow T$. The tactic transforms the current goal $\Gamma \vdash T$ through three successive steps:

1. First, the goal is rewritten equivalently as $\Gamma', \llbracket P \rrbracket(m) \vdash T'$ where P is a polyhedron and m an assignment of P variables. For example, the `ex1` goal is rewritten as $\llbracket P_1 \rrbracket(m_1) \vdash \mathbf{False}$, where

$$P_1 := x_1 \leq 1 \wedge x_2 < x_3 \wedge x_1 \geq 1$$

$$m_1 := \{ x_1 \mapsto \mathbf{x}; x_2 \mapsto (\mathbf{f} \ \mathbf{x}); x_3 \mapsto (\mathbf{f} \ 1) \}$$

Hence, $\llbracket P \rrbracket(m)$ corresponds to a conjunction of inequalities on \mathbb{Q} that are *not necessarily* linear, because m may assign variables of P to arbitrary COQ terms on \mathbb{Q} . Actually, $\llbracket P \rrbracket(m)$ contains at least all (in)equalities on \mathbb{Q} that appear as hypotheses of Γ . Moreover, if T is an inequality on \mathbb{Q} , then an inequality equivalent to $\neg T$ appears in $\llbracket P \rrbracket(m)$ and T' is proposition `False`.³ This step is traditionally called *reification* in COQ tactics.

2. Second, the goal is rewritten equivalently as $\Gamma', \llbracket P' \rrbracket(m) \vdash T'$ where P' is the *reduced polyhedron* computed from P by our `reduce` oracle. For instance, polyhedron P_1 found in the `ex1` goal is reduced into

$$P'_1 := x_1 = 1 \wedge x_2 < x_3$$

3. At last, if P' is unsatisfiable, then so is $\llbracket P' \rrbracket(m)$, and the goal is finally discharged. Otherwise, given E the complete set of equalities in P' , equalities of $\llbracket E \rrbracket(m)$ are rewritten in the goal. For example, on the `ex1` goal, our tactic rewrites the learned equality “`x=1`” into the remaining hypothesis. In summary, a first call to the `vpl` tactic transforms the `ex1` goal into

$$\mathbf{x}=1, (\mathbf{f} \ 1) < (\mathbf{f} \ 1) \vdash \mathbf{False}$$

A second call to `vpl` detects that hypothesis `(f 1) < (f 1)` is unsatisfiable and finally proves the goal.

In the description above, we claim that our transformations on the goals are equivalences. This provides a guarantee to the user: the tactic can always be applied on the goal, without loss of information. However, in order to make the COQ proof checker accept our transformations, we only need to prove implications, as detailed in the next paragraph.

³ Here, $T \Leftrightarrow (\neg T \Rightarrow \mathbf{False})$ because comparisons on \mathbb{Q} are decidable.

The COQ Proof Built by the Tactic. The tactic mainly proves the two following implications which are verified by the COQ kernel:

$$\Gamma', \llbracket P \rrbracket(m) \vdash T' \Rightarrow \Gamma \vdash T \quad (2)$$

$$\forall m, \llbracket P \rrbracket(m) \Rightarrow \llbracket P' \rrbracket(m) \quad (3)$$

Semantics of polyhedron $\llbracket \cdot \rrbracket$ is encoded as a COQ function, using binary integers to encode variables of polyhedra. After simple propositional rewritings in the initial goal $\Gamma \vdash T$, an OCAML oracle provides m and P to the COQ kernel, which simply computes $\llbracket P \rrbracket(m)$ and checks that is syntactically equals to the expected part of the context. Hence, verifying implication (2) is mainly syntactical.

For implication (3), our `reduce` oracle actually produces a COQ AST, that represents a *proof witness* allowing to build each constraint of P' as a non-negative linear combination of P constraints. Indeed, such a combination is necessarily a logical consequence of P . In practice, this proof witness is a value of a COQ inductive type. A COQ function called `reduceRun` takes in input a polyhedron P and its associated witness, and computes P' . A COQ theorem ensures that any result of `reduceRun` satisfies implication (3). Thus, this implication is ensured by construction, while – for the last step of the tactic described above – the COQ kernel computes P' by applying `reduceRun`.

Overview of the Paper. Section 2 illustrates our tactic on a non-trivial example. It also explains how it collaborates with other COQ tactics through equality learning. Section 3 details the certificate format produced by our oracle, and how it is applied in our COQ tactic. At last, Section 4 details the algorithm we developed to produce such certificates.

2 Applications of the `vp1` Tactic

This section illustrates the applications of the tactic, in particular when it can not prove the goal. Section 2.1 details the following completeness result – which is a consequence of the Lemma 1 given below.

Our tactic removes the need to consider inequalities on goals of the form “ $P \Rightarrow t_1 = t_2$ ” when P is a polyhedron and t_1, t_2 are first-order terms of an *equational extension of linear rational arithmetic* (see Definition 5).

Section 2.2 provides a detailed example which illustrates such equality proofs and how they may appear inside a larger proof.

2.1 Application to equality proofs

Definition 4. We note $\mathbb{Q}_{1, \geq, >}[\vec{X}]$ the first-order theory (with congruence) of linear arithmetic over \mathbb{Q} . This theory syntactically distinguishes \mathbb{Q} constants from other \mathbb{Q} terms: each \mathbb{Q} constant is considered as a distinct function symbol. On \mathbb{Q} terms, this theory axiomatizes addition, linear multiplication, and orders using axioms of totally ordered vector spaces – where vectors are \mathbb{Q} terms and scalars are \mathbb{Q} constants.

Definition 5. We call equational extension of linear rational arithmetic a *first-order theory that extends* $\mathbb{Q}_{1,\geq,>}[\vec{X}]$ with axioms that are only equational Horn clauses. Such an axiom is of the following form (where t_i and t'_i are first-order terms, and \vec{x} ranges over all the variables of the axiom):

$$\forall \vec{x}, (t_1 = t'_1 \wedge \dots \wedge t_n = t'_n) \Rightarrow t_{n+1} = t'_{n+1}$$

For example, equational extensions of linear rational arithmetic are closed under extensions with uninterpreted function symbols. Indeed, for these new symbols, we only add congruence axioms, which are equational Horn clauses.

As another example, consider an extension of $\mathbb{Q}_{1,\geq,>}[\vec{X}]$ embedding the ring theory of $\mathbb{Q}[\vec{X}]$, and that provides an axiom – for any rational constant c – linking linear multiplication (noted below \cdot) to unrestricted multiplication (noted below \times) given by

$$\forall x, c \times x = c \cdot x$$

This theory is an equational extension of linear rational arithmetic.

As a counter-example, field theory $\mathbb{Q}(\vec{X})$ can not be encoded with only equational Horn clauses. Intuitively, a field must provide an axiom for inverse like $x \neq 0 \Rightarrow x \times x^{-1} = 1$, which is not an equational Horn clause.

Lemma 1 (Extended Completeness). We assume E and I two polyhedra satisfying property (1) when t_1 and t_2 are linear terms (i.e. range over $\mathbb{Q}_1[\vec{X}]$). Property (1) is also satisfied when t_1 and t_2 range over first-order terms of any equational extension of linear rational arithmetic.

Proof. By induction on a cut-free proof of $t_1 = t_2$. There are two cases. Either we have applied an axiom corresponding to an equational Horn clause, and we conclude by induction hypotheses. Otherwise, we are on a pure equality of $\mathbb{Q}_1[\vec{X}]$ which can be deduced from E . \square

For example, property (1) ensures that we have a complete tactic for solving goals of the form “ $P \Rightarrow t_1 = t_2$ ” – where P is a polyhedron and where t_1 and t_2 are polynomials in $\mathbb{Q}[\vec{X}]$ – by first applying our tactic and then applying the `ring` tactic. We can extend this completeness result when t_1 and t_2 contain uninterpreted symbols by also applying congruence closure.

When t_1 and t_2 are fractions of $\mathbb{Q}(\vec{X})$, we can not have such a completeness result. For example, $x = y \wedge y \geq 1 \Rightarrow x \times y^{-1} = 1$ is a tautology whereas $x = y \Rightarrow x \times y^{-1} = 1$ is false when $x = y = 0$. However, if denominators appearing in t_1 and t_2 are themselves linear, then we can still discharge goals of the form “ $P \Rightarrow t_1 = t_2$ ” by combining our tactic with the `field` tactic. This is illustrated in the following example.

2.2 A Detailed Example

This section illustrates the main aspects of the tactic on a single example. This goal contains two uninterpreted functions `f` and `g` such that `f` domain and `g`

codomain are the same uninterpreted type A . As we will see below, in order to prove this goal, we need to use its last hypothesis – of the form “ $g(\cdot) \triangleleft g(13)$ ” – by combining equational reasoning on g and on Qc field. Of course, we also need linear arithmetic on Qc order.

```

Lemma ex2 (A:Type) (f:A → Qc) (g:Qc → A) (v1 v2 v3 v4: Qc):
  6*v1 - v2 - 10*v3 + 7*(f(g v1) + 1) ≤ -1
  → 3*(f(g v1) - 2*v3) + 4 ≥ v2 - 4*v1
  → 8*v1 - 3*v2 - 4*v3 - f(g v1) ≤ 2
  → 11*v1 - 4*v2 > 3
  → v3 > -1
  → v4 ≥ 0
  → g((11 - v2 + 13*v4) / (v3+v4)) <> g(13)
  → 3 + 4*v2 + 5*v3 + f(g v1) > 11*v1.

```

The `vp1` tactic reduces this goal to the equivalent one given below (where typing of variables is omitted).

```

H5 : g((11 - (11 - 13*v3) + 13*v4) / (v3+v4)) = g 13 → False
vp1 : v1 = 4 - 4 * v3
vp10 : v2 = 11 - 13 * v3
vp11 : f (g (4 - 4 * v3)) = -3 + 3 * v3
----- (1/1)
0 ≤ v4 → (3#8) < v3 → False

```

Here, three equations `vp1`, `vp10` and `vp11` have been learned from the goal. Two non-redundant inequalities remain in the hypotheses of the conclusion – where $(3\#8)$ is the COQ notation for $\frac{3}{8}$. The bound “ $v3 > -1$ ” had disappeared because it is implied by “ $(3\#8) < v3$ ”. By taking $v3 = 1$, we can build a model satisfying all the hypotheses of the goal – including $(3\#8) < v3$ – except `H5`. Thus, using `H5` is necessary to prove `False`.

Actually, we provide another tactic called `vp1_post` which automatically proves this goal. This tactic combines equational reasoning on Qc field with a bit of congruence.⁴ Let us detail how it works on this example. First, in backward reasoning, `H5` is applied to eliminate `False` from the conclusion. We get the following conclusion (where previous hypotheses have been omitted).

```

----- (1/1)
g((11 - (11 - 13*v3) + 13*v4) / (v3+v4)) = g 13

```

Here, backward congruence reasoning reduces this conclusion to

```

----- (1/1)
(11 - (11 - 13*v3) + 13*v4) / (v3+v4) = 13

```

Now, the `field` tactic reduces the conclusion to

```

----- (1/1)
v3+v4 <> 0

```

⁴ It is currently implemented on the top of `auto` with a dedicated basis of lemma.

Indeed, the `field` tactic mainly applies ring rewriting on `Qc` while generating subgoals for checking that denominators are not zero. Here, because we have a linear denominator, we discharge the remaining goal using the `vp1` tactic again. Indeed, it gets the following polyhedron in hypotheses – which is unsatisfiable.

$$v4 \geq 0 \ \wedge \ v3 > \frac{3}{8} \ \wedge \ v3 + v4 = 0$$

Let us remark that since lemma `ex2` is provable on \mathbb{Q} , it is also valid when the codomain of `f` and types of variables `v1` . . . `v4` are restricted to \mathbb{Z} . However, both `omega` and `lia` fail on this goal without providing any help to the user.

3 The Witness Format and its Interpreter in the Tactic

Section 3.3 below presents our proof witness format in COQ to build a reduced polyhedron P' as a logical consequence of P . It also details the implementation of `reduceRun` and its correctness property, formalizing property (3) given in introduction. In preliminaries, Section 3.1 recalls the Farkas operations of the VPL, at the basis of our proof witness format, itself illustrated in Section 3.2.

3.1 Certified Farkas Operations on Linear Constraints

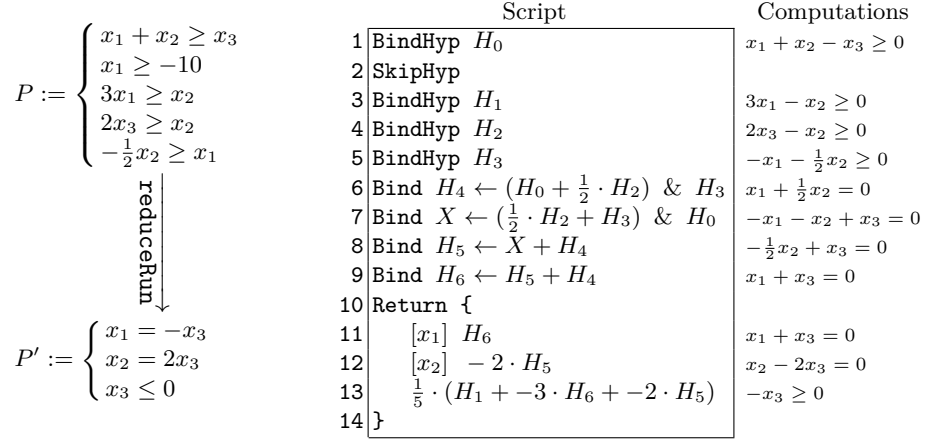
The tactic uses the linear constraints defined in the VPL [3], that we recall here. Type `var` is the type of variables in polyhedra. Actually, it is simply defined as type `positive`, the unbounded binary positive integers of COQ. Module `Cstr` provides an efficient representation for linear constraints on `Qc`, the COQ type for \mathbb{Q} . Type `Cstr.t` handles constraints of the form “ $t \bowtie 0$ ” where t is a linear term and $\bowtie \in \{=, \geq, >\}$. Hence, each input constraint “ $t_1 \bowtie t_2$ ” will be encoded as “ $t_1 - t_2 \bowtie 0$ ”. Linear terms are themselves encoded as radix trees over `positive` with values in `Qc`.

The semantics of `Cstr.t` constraints is given by predicate `(Cstr.sat c m)`, `(sat c m)` expressing that model `m`: `var` \rightarrow `Qc` satisfies constraint `c`. Module `Cstr` provides also the following operations:

- $(t_1 \bowtie_1 0) + (t_2 \bowtie_2 0) \triangleq (t_1 + t_2) \bowtie 0$ where $\bowtie \triangleq \max(\bowtie_1, \bowtie_2)$ for the total increasing order induced by the sequence $=, \geq, >$;
- $n \cdot (t \bowtie 0) \triangleq (n \cdot t) \bowtie 0$ assuming $n \in \mathbb{Q}$ and, if $\bowtie \in \{\geq, >\}$ then $n \geq 0$;
- $(t \geq 0) \ \& \ (-t \geq 0) \triangleq t = 0$.

It is easy to prove that each of these operations returns a constraint that is satisfied by the models of its inputs. For example, given `c1` and `c2` such that `(sat c1 m)` and `(sat c2 m)`, then `(sat (c1+c2) m)` holds. When invoked on a wrong precondition, these operations actually return “ $0 = 0$ ” which also is satisfied by any model. Still, this precondition violation only appears if there is a bug in the `reduce` oracle. These operations are called *Farkas operations*, in reference to Farkas lemma recalled on page 11.

In the following, we actually handle each constraint with a proof that it satisfies a given set `s` of models (encoded here by its characteristic function). The type of such a constraint is `(wcstr s)`, as defined below.

Fig. 1. Example of a Proof Script and its Interpretation by `reduceRun`

```

Record wcstr (s : (var → Qc) → Prop) :=
{ rep : Cstr.t; rep_sat : ∀ m, s m → Cstr.sat rep m }.

```

Hence, all the Farkas operations are actually lifted to type $(\text{wcstr } s)$, for all s .

3.2 Example of Proof Witness

We introduce our syntax for proof witnesses on Figure 1. Our oracle detects that P is satisfiable, and thus returns the “proof script” of Figure 1. This script instructs `reduceRun` to produce P' from P . By construction, we have $P \Rightarrow P'$.

This script has three part. In the first part – from line 1 to 5 – the script considers each constraint of P and binds it to a name, or skips it. For instance, $x_1 \geq -10$ is skipped because it is redundant: it is implied by P' and thus not necessary to build P' from P . In the second part – from line 6 to 9 – the script builds intermediate constraints: their value is detailed on the right hand-side of the figure. Each of these constraints is bound to a name. Hence, when a constraint – like H_4 – is used several times, we avoid a duplication of its computation.

In the last part – from line 10 to 14 – the script returns the constraints of P' . As further detailed in Section 4, each equation defines one variable in terms of the others. For each equation, this variable is explicitly given between brackets “[.]” in the script of Figure 1, such as x_1 at line 11 and x_2 at line 12. This instructs `reduceRun` to rewrite equations in the form “ $x = t$ ”.

3.3 The HOAS of Proof Witnesses and its Interpreter

Our `reduceRun` function and its correctness are defined on Figure 2. In this COQ code, the input polyhedron of `reduceRun` is given as a list of constraints 1 of

```

Definition pedra := list Cstr.t.
Definition [[1]] m := List.Forall (fun c => Cstr.sat c m) l.
Definition answ (o: option pedra) m
  := match o with Some l => [[1]] m | None => False end.

Definition reduceRun (l: pedra)(p: ∀ v, script v): option pedra
  := scriptEval (s:=[[1]]) (p _) l (* ... *).
Lemma reduceRun_correct l m p: [[1]] m → answ (reduceRun l p) m.

```

Fig. 2. Definition of reduceRun and its Correctness

```

Inductive fexp (v: Type): Type :=
| Var: v → fexp v (* name bound to [Bind] or [BindHyp] *)
| Add: fexp v → fexp v → fexp v
| Mul: Qc → fexp v → fexp v
| Merge: fexp v → fexp v → fexp v.

Fixpoint fexpEval {s} (c: fexp (wcstr s)): (wcstr s) :=
  match c with
  | Var c => c
  | Add c1 c2 => (fexpEval c1) + (fexpEval c2)
  | Mul n c => n.(fexpEval c)
  | Merge c1 c2 => (fexpEval c1) & (fexpEval c2)
  end.

```

Fig. 3. Farkas Expressions and their Interpreter

type `pedra`. Its output is given as type `(option pedra)` where a `None` value corresponds to the case where `l` is unsatisfiable.

Given a value `l: pedra`, its semantics – still noted `[[1]]` – is a predicate of type $(\text{var} \rightarrow \text{Qc}) \rightarrow \text{Prop}$ which is defined from `Cstr.sat`. This semantics is extended to type `(option pedra)` by the predicate `answ`. Lemma `reduceRun_correct` thus formalizes property (3) of page 4 with a minor improvement: when the input polyhedron is unsatisfiable, a proof of `False` is directly generated.

The proof witness in input of `reduceRun` is a value of type $\forall v, \text{script } v$. Here, `script` – defined at Figure 5 – is the type of a Higher-Order Abstract Syntax (HOAS) parameterized by the type `v` of variables. A HOAS avoids the need to handle explicit variable substitutions when interpreting binders: those are encoded as functions, and variable substitution is delegated to the COQ engine. The universal quantification over `v` avoids exposing the representation of `v` – used by `reducedRun` – in the `p` proof witness.

The bottom level of our HOAS syntax is given by type `fexp` defined at Figure 3 and representing “Farkas expressions”. Each constructor in this type corresponds to a Farkas operation, except constructor `Var` that represents a constraint name which is bound to a `Bind` or a `BindHyp` binder (see Figure 1). The function `fexpEval` computes any such Farkas expression `c` into a constraint

```

Inductive pexp (v: Type): Type :=
| Bind: fexp v → (v → pexp v) → pexp v
| Contrad: (fexp v) → pexp v
| Return: list ((option var) * (fexp v)) → pexp v.

Fixpoint pexpEval {s} (p: pexp (wcstr s)): option pedra :=
match p with
| Bind c bp ⇒ pexpEval (bp (fexpEval c))
| Contrad c ⇒ contrad c
| Return l ⇒ Some (ret l nil)
end.

Lemma pexpEval_correct s (p: pexp (wcstr s)) m:
s m → answ (pexpEval p) m.

```

Fig. 4. Polyhedral Computations and their Interpreter

```

Inductive script (v: Type): Type :=
| SkipHyp: script v → script v
| BindHyp: (v → script v) → script v
| Run: (pexp v) → script v.

Fixpoint scriptEval {s} (p: script(wcstr s)) (l: pedra):
(∀ m, s m → [[1]] m) → option pedra := (* ... *)

Lemma scriptEval_correct s (p: script(wcstr s)) m: ∀ l: pedra,
(∀ m, s m → [[1]] m) → s m → answ (scriptEval p l) m.

```

Fig. 5. Script Expressions and their Interpreter

of type $(wcstr\ s)$ – for some given s – where type v is itself identified with type $(wcstr\ s)$.

Farkas expressions are combined in order to compute polyhedra. This is expressed through “polyhedral expressions” of type `pexp` on Figure 4 which are computed by `pexpEval` into $(option\ pedra)$ values. Type `pexp` has 3 constructors. First, constructor $(Bind\ c\ (\mathit{fun}\ H\ \Rightarrow\ p))$ is a higher-order binder of our HOAS: it computes an intermediate Farkas expression c and stores the result in a variable H bound in the polyhedral expression p . Second, constructor $(Contrad\ c)$ returns an *a priori* unsatisfiable constant constraint, which is verified by function `contrad` in `pexpEval`. At last, constructor $(Return\ l)$ returns an *a priori* satisfiable reduced polyhedron, which is encoded as a list of Farkas expressions associated to an optional variable of type `var` (indicating a variable defined by an equation, see example of Figure 1).

Finally, a witness of type `script` first starts by naming useful constraints of the input (given as a value $l: pedra$) and then runs a polyhedral expression in this naming context. This semantics is given by `scriptEval` specified at Fig-

ure 5. On a script (`SkipHyp p'`), function `scriptEval` simply skips the first constraint by running recursively (`scriptEval p' (List.tl l)`). Similarly, on a script (`BindHyp (fun H => p')`), `scriptEval` pops the first constraint of `l` in variable `H` and then run itself on `p'`. Technically, `scriptEval` assumes the following precondition on polyhedron `l`: it must satisfies all models `m` characterized by `s`. As shown on Figure 2, (`reduceRun l p`) is a simple instance of (`scriptEval (p (wcstr s)) l`) where `s:= $\llbracket 1 \rrbracket$` . Hence, this precondition is trivially satisfied.

4 The Reduction Algorithm

The specification of the `reduce` oracle is given in introduction of the paper: it transforms a polyhedron P into a reduced polyhedron P' with a smaller number of constraints and such that $P' \Leftrightarrow P$. Sections 4.4 and 4.5 describe our implementation. In preliminaries, Section 4.1 gives a sufficient condition, through Lemma 4, for a polyhedron to be reduced. This condition leads to learn equalities from conflicts between strict inequalities as detailed in Sections 4.2 and 4.3. In our proofs and algorithms, we only handle linear constraints in the restricted form “ $t \bowtie 0$ ”. But, for readability, our examples use the arbitrary form “ $t_1 \bowtie t_2$ ”.

4.1 A Refined Specification of the Reduction

Definition 6 (Echelon Polyhedron). *An echelon polyhedron is written as a conjunction $E \wedge I$ where polyhedron I contains only inequalities and where E is written “ $\bigwedge_{i \in \{1, \dots, k\}} x_i - t_i = 0$ ” such that each x_i is a variable and each t_i is a linear term, and such that the two following conditions are satisfied. First, no variable x_i appears in polyhedron I . Second, for all integers $i, j \in \{1, \dots, k\}$ with $i < j$ then x_i does not appear in t_j .*

Intuitively, in such a polyhedron, each equation “ $x_i - t_i = 0$ ” actually defines variable x_i as t_i . As a consequence, $E \wedge I$ is satisfiable iff I is satisfiable.

We recall below the Farkas lemma[2] which reduces the unsatisfiability of a polyhedron to the one of a constant constraint, like $0 > 0$ or $-1 \geq 0$. The unsatisfiability of such a constraint is checked by a simple comparison on \mathbb{Q} .

Lemma 2 (Farkas). *Let I be a polyhedron containing only inequalities. If I is unsatisfiable then there is an unsatisfiable constraint “ $-\lambda \bowtie 0$ ”, computable from a non-negative linear combination of constraints of I (i.e. using operators “+” and “.” defined at Section 3.1), and such that $\bowtie \in \{\geq, >\}$ and $\lambda \in \mathbb{Q}^+$.*

Proof. This standard lemma is proved by induction on the number of variables in I . In the inductive case, one variable is eliminated using Fourier-Motzkin’s elimination (i.e. by combining all pairs of inequalities in which this variable appears with an opposite sign). \square

From Farkas lemma, we derive the following auxiliary lemma which reduces the verification of an implication $I \Rightarrow t \geq 0$ to the verification of a syntactic equality between linear terms.

Lemma 3 (Implication Witness). *Let t be a linear term and let I be a satisfiable polyhedron written $\bigwedge_{j \in \{1, \dots, k\}} t_j \bowtie_j 0$ with $\bowtie_j \in \{\geq, >\}$.*

If $I \Rightarrow t \geq 0$ then there are $k + 1$ non-negative rationals $(\lambda_j)_{j \in \{0, \dots, k\}}$ such that $t = \lambda_0 + \sum_{j \in \{1, \dots, k\}} \lambda_j t_j$.

Proof. Let us assume that $I \wedge -t > 0$ is unsatisfiable.

By Farkas lemma, there is an unsatisfiable constant constraint $-\lambda_0 \bowtie 0$ such that $-\lambda_0 = (\sum_{j \in \{1, \dots, k\}} \lambda_j t_j) + \lambda_{k+1} \cdot (-t)$ with all λ_j being non-negative rationals. Actually, $\lambda_{k+1} > 0$. Otherwise, $-\lambda_0 \bowtie 0$ would be a proof that I is unsatisfiable. Thus, for all $j \in \{0, \dots, k\}$, $\frac{\lambda_j}{\lambda_{k+1}} \geq 0$ and $t = \frac{\lambda_0}{\lambda_{k+1}} + \sum_{j \in \{1, \dots, k\}} \frac{\lambda_j}{\lambda_{k+1}} t_j$. \square

Definition 7 (Strict Version of Inequalities). *Let I be a polyhedron with only inequalities. We note $I^>$ the polyhedron obtained from I by replacing each large inequality “ $t \geq 0$ ” by its strict version “ $t > 0$ ”. Strict inequalities of I remain unchanged in $I^>$.*

Lemma 4 (Completeness from Strict Satisfiability). *Let us assume an echelon polyhedron $E \wedge I$ without redundant constraints, and such that $I^>$ is satisfiable. Then, $E \wedge I$ is a reduced polyhedron.*

Proof. Obviously, because $I^>$ is satisfiable, then I is satisfiable and $E \wedge I$ also. Now, let us prove property (1) of Definition 3. Let t_1 and t_2 be two linear terms such that $E \wedge I \Rightarrow t_1 = t_2$. We aim to prove $E \Rightarrow t_1 = t_2$.

First, we rewrite equations of E into terms of the form $t_1 - t_2$. This gives a term t which does not contain variables x_i defined in E . Because variables defined in E do not appear in I and t , we deduce $I \Rightarrow t = 0$ from $E \wedge I \Rightarrow t_1 = t_2$.

By Lemma 3, because $I \Rightarrow t \geq 0$, we have $t = \lambda_0 + \sum_{j \in \{1, \dots, k\}} \lambda_j t_j$ where $\lambda_j \geq 0$ and $I = \bigwedge_{j \in \{1, \dots, k\}} t_j \bowtie_j 0$. Similarly, since $I \Rightarrow -t \geq 0$, we have $-t = \lambda'_0 + \sum_{j \in \{1, \dots, k\}} \lambda'_j t_j$ where $\lambda'_j \geq 0$.

Let us define $t' \triangleq (\lambda_0 + \sum_{j \in J} \lambda_j t_j) + (\lambda'_0 + \sum_{j \in J'} \lambda'_j t_j)$. Let m be an assignment of I variables such that $\llbracket I^> \rrbracket m$. By definition, $\forall j \in \{1, \dots, k\}, \llbracket t_j \rrbracket m > 0$. If there exists $j \in \{0, \dots, k\}$ such that $\lambda_j \neq 0$, then we have $0 < \llbracket t' \rrbracket (m) = \llbracket t - t \rrbracket (m) = 0$. This is impossible. Therefore, t is syntactically the constant 0. This actually proves $E \Rightarrow t_1 = t_2$, because $E \Rightarrow t_1 - t_2 = t = 0$. \square

In this proof, the model m of $I^>$ is a *witness* allowing to prove that E is complete. However, as noted in introduction, for our tactic, we do not need to formally prove in COQ that E is complete: we do not need to output m from our oracle.

Lemma 4 gives a strategy to implement the **reduce** oracle. If the input polyhedron P is satisfiable, then try to rewrite P as an echelon polyhedron $E \wedge I$ where $I^>$ is satisfiable. The next step is to see that on an echelon polyhedron $E \wedge I$ where $I^>$ is unsatisfiable, we can learn new equalities from a minimal subset of $I^>$ inequalities that is unsatisfiable. The inequalities in such a minimal subset are said “*in conflict*”.

4.2 Conflict Driven Equality Learning

Conflict Driven Clause Learning (CDCL) is a standard framework of modern DPLL SAT-solving [6]. Given a set of large inequalities I , we reformulate the satisfiability of I into this framework by considering each large constraint $t \geq 0$ of I as a clause $(t > 0) \vee (t = 0)$. Hence, our literals are either strict inequalities or equalities.

Let us run a CDCL SAT-solver on such a set of clauses I . First, let us imagine that the SAT-solver assumes all literals of $I^>$. Then, an oracle decides whether $I^>$ is satisfiable. If so, then we are done. Otherwise, by Farkas' lemma, the oracle returns an unsatisfiable constant constraint $-\lambda \bowtie 0$ such that $\lambda \geq 0$ and $-\lambda$ is written $\sum_{j \in J} \lambda_j t_j$ where for all $j \in J$, $\lambda_j > 0$ and $(t_j > 0) \in I^>$. The CDCL solver learns the new clause $\bigvee_{j \in J} t_j = 0$ equivalent to $\neg I^>$ under hypothesis I .

In fact, a simple arithmetic argument improves this naive CDCL algorithm by learning directly the conjunction of literals $\bigwedge_{j \in J} t_j = 0$ instead of the clause $\bigvee_{j \in J} t_j = 0$. Indeed, because $I \Rightarrow \bigwedge_{j \in J} t_j \geq 0$, we have – for all $j' \in J$ –

$$(I \wedge t_{j'} \neq 0) \Rightarrow 0 < \sum_{j \in J} \lambda_j t_j = -\lambda$$

Therefore, since $\lambda \geq 0$, we have $I \Rightarrow t_{j'} = 0$ for all $j' \in J$.

In the following, we learn equalities from conflicts between strict inequalities in an approach inspired from this naive CDCL algorithm. Whereas the number of oracle calls for learning n equalities in the naive CDCL algorithm is $\Omega(n)$, our additional arithmetic argument limits it to $\mathcal{O}(1)$ in the best cases.

4.3 Building Equality Witnesses from Conflicts

Let us now detail our algorithm to compute equality witnesses. Let I be a satisfiable inequality set such that $I^>$ is unsatisfiable. The oracle returns a witness combining $n + 1$ constraints of $I^>$ (for $n \geq 1$) that implies a contradiction:

$$\sum_{i=1}^{n+1} \lambda_i \cdot I_i^> \quad \text{where } \lambda_i > 0$$

We know that this witness represents a contradictory constraint $0 > 0$ and that each inequality I_i is large: otherwise, we would have a proof that I is unsatisfiable. Each inequality I_i is turned into an equality written $I_i^=$ – proved by

$$I_i \ \& \ \frac{1}{\lambda_i} \cdot \sum_{\substack{j \in \{1, \dots, n+1\} \\ j \neq i}} \lambda_j \cdot I_j$$

Hence, each equality $I_i^=$ is proved by combining $n + 1$ constraints. Proving $(I_i^=)_{i \in \{1, \dots, n+1\}}$ in this naive approach combines $\Theta(n^2)$ constraints.

We rather propose a more symmetric way to build equality witnesses which leads to a simple linear algorithm. Actually, we build a system of n equalities noted $(E_i)_{i \in \{1, \dots, n\}}$, where – for $i \in \{1, \dots, n\}$ – each E_i corresponds to the unsatisfiability witness where the i -th “+” has been replaced by a “&”:

$$\left(\sum_{j=1}^i \lambda_j \cdot I_j \right) \ \& \ \left(\sum_{j=i+1}^{n+1} \lambda_j \cdot I_j \right)$$

This system of equations is proved equivalent to $(I_i^=)_{i \in \{1, \dots, n+1\}}$ thanks to the following correspondence. This also shows that one equality $I_i^=$ is redundant,

because $(I_i^-)_{i \in \{1, \dots, n+1\}}$ contains one more equality than $(E_i)_{i \in \{1, \dots, n\}}$.

$$I_1^- = \frac{1}{\lambda_1} \cdot E_1 \quad \text{and} \quad I_{n+1}^- = -\frac{1}{\lambda_n} \cdot E_n \quad \text{and for } i \in \{2, \dots, n\}, I_i^- = \frac{1}{\lambda_i} \cdot (E_i - E_{i-1})$$

In order to use a linear number of combinations, we build $(E_i)_{i \in \{1, \dots, n\}}$ thanks to two lists of intermediate constraints $(A_i)_{i \in \{1, \dots, n\}}$ and $(B_i)_{i \in \{2, \dots, n+1\}}$ defined by

$$\begin{aligned} A_1 &:= \lambda_1 \cdot I_1 \quad \text{and for } i \text{ from } 2 \text{ up to } n, A_i := A_{i-1} + \lambda_i \cdot I_i \\ B_{n+1} &:= \lambda_{n+1} \cdot I_{n+1} \quad \text{and for } i \text{ from } n \text{ down to } 2, B_i := B_{i+1} + \lambda_i \cdot I_i \end{aligned}$$

Then, we build $E_i := A_i \& B_{i+1}$ for $i \in \{1, \dots, n\}$.

4.4 Illustration on the Running Example

Let us detail how to compute the reduced form of polyhedron P from Figure 1.

$$P := \{I_1 : x_1 + x_2 \geq x_3, I_2 : x_1 \geq -10, I_3 : 3x_1 \geq x_2, I_4 : 2x_3 \geq x_2, I_5 : -\frac{1}{2}x_2 \geq x_1\}$$

P is a satisfiable set of inequalities. Thus, we first extract a complete set of equalities E from constraints of P by applying the previous ideas. We ask to a Linear Programming (LP) solver for a point satisfying $P^>$, the strict version of P . Because there is no such point, the solver returns the unsatisfiability witness $I_1^> + \frac{1}{2} \cdot I_4^> + I_5^>$ (which reduces to $0 > 0$). By building the two sequences (A_i) and (B_i) defined previously, we obtain the two equalities

$$\begin{aligned} E_1 : x_1 + x_2 = x_3 \quad \text{proved by } & \underbrace{(x_1 + x_2 \geq x_3)}_{A_1: I_1} \& \underbrace{(x_3 \geq x_1 + x_2)}_{B_2: \frac{1}{2} \cdot I_4 + I_5} \\ E_2 : x_1 = -\frac{1}{2}x_2 \quad \text{proved by } & \underbrace{(x_1 \geq -\frac{1}{2}x_2)}_{A_2: I_1 + \frac{1}{2} \cdot I_4} \& \underbrace{(-\frac{1}{2}x_2 \geq x_1)}_{B_3: I_5} \end{aligned}$$

Thus, P is rewritten into $E \wedge I$ with

$$\begin{aligned} E &:= \{E_1 : x_1 + x_2 = x_3, E_2 : x_1 = -\frac{1}{2}x_2\}, \\ I &:= \{I_2 : x_1 \geq -10, I_3 : 3x_1 \geq x_2\} \end{aligned}$$

To be reduced, the polyhedron must be in echelon form, as explained in Definition 6. This implies that each equality of E must have the form $x_i - t_i = 0$, and each such x_i must not appear in I . Here, let us consider that E_1 defines x_2 . To be in the form $t = 0$, E_1 is rewritten into $x_2 - (x_3 - x_1) = 0$. Then, x_2 is eliminated from E_2 , leading to $E'_2 : x_1 + x_3 = 0$. In practice, our oracle goes one step further by rewriting x_1 (using its definition in E'_2) into E_1 in order to get a reduced echelon system E' of equalities:

$$E' := \{E'_1 : x_2 - 2 \cdot x_3 = 0, E'_2 : x_1 + x_3 = 0\}$$

Moreover, the variables defined in E' (i.e. x_1 and x_2) are eliminated from I , which is rewritten into

$$I' := \{I'_2 : -x_3 \geq -10, I'_3 : -x_3 \geq 0\}$$

The last step is to detect that I'_2 is redundant w.r.t. I'_3 with a process which is indicated in the next section.

For simplicity, construction of proof witness is omitted on the pseudo-code. In other words, the result of `reduce` is

- either “`Contrad(c)`” where c is a contradictory constraint
- or “`Reduced(P')`” where P' is a satisfiable reduced polyhedron.

```

function reduce( $E \wedge I$ ) =
  ( $E, I$ )  $\leftarrow$  echelon( $E, I$ )
  match is_sat( $I$ ) with
  | Unsat( $\lambda$ ) -> return Contrad( $\lambda^T \cdot I$ )
  | Sat( $_$ ) ->
    loop
      match is_sat( $I^>$ ) with
      | Unsat( $\lambda$ ) ->
        ( $E', I'$ )  $\leftarrow$  learn( $I, \lambda$ )
        ( $E, I$ )  $\leftarrow$  echelon( $E \wedge E', I'$ )
      | Sat( $m$ ) ->
         $I \leftarrow$  rm_redundancies( $I, m$ )
        return Reduced( $E \wedge I$ )

```

Fig. 6. Pseudo-code of the `reduce` oracle

4.5 Description of the Algorithm

The pseudo-code of Figure 6 describes the `reduce` algorithm. The input polyhedron is assumed to be given in the form $E \wedge I$, where E contains only equalities and I contains only inequalities. First, polyhedron $E \wedge I$ is echeloned: function `echelon` returns a new system $E \wedge I$ where E is an echelon system of equalities without redundancies (they have been detected as $0 = 0$ during echeloning and removed) and without contradiction (they have been detected as $1 = 0$ during echeloning and inserted as a contradictory constraint $-1 \geq 0$ in I). Second, the satisfiability of I is tested by function `is_sat`. If `is_sat` returns “`Unsat(λ)`”, then λ is a Farkas witness allowing to return a contradictory constant constraint written $\lambda^T \cdot I$. Otherwise, I is satisfiable and `reduce` enters into a loop to learn all implicit equalities.

At each step of the loop, the satisfiability of $I^>$ is tested. If `is_sat` returns “`Unsat(λ)`”, then a new set E' of equalities is learned from λ and I' contains the inequalities of I that do not appear in the conflict. After echeloning the new system, the loop continues.

Otherwise, `is_sat` returns “`Sat(m)`” where m is a model of $I^>$. Geometrically, m is a point in the interior of polyhedron I . Point m helps function `rm_redundancies` to detect and remove redundant constraints of I , by a ray-tracing method described in [5]. At last, `reduce` returns $E \wedge I$, which is a satisfiable reduced polyhedron because of Lemma 4.

5 Conclusion and Related Works

This paper describes a COQ tactic that learns equalities from a set of linear inequalities. It uses a simple algorithm – implemented in the new VPL – that follows a kind of conflict driven clause learning. This equality learning algorithm only relies on an efficient SAT-solver on inequalities able to generate non-negativity witnesses. Hence, it seems generalizable to arbitrary polynomials. We may also hope to generalize it to totally ordered rings like \mathbb{Z} .

The initial implementation of the VPL [4] also reduces polyhedra as defined in Definition 3. It implements equality learning in a more naive way: for each inequality $t \geq 0$ of the current (satisfiable) inequalities I , the algorithm checks whether $I \wedge t > 0$ is satisfiable. If not, equality $t = 0$ is learned. In other words, each learned equality derives from one satisfiability test. Our new algorithm is more efficient, since it may learn several equalities from a single satisfiability test. Moreover, when there is no equality to learn, the new algorithm performs only one satisfiability test, whereas the previous version checks all inequalities.

We have implemented this algorithm in an OCAML oracle, able to produce *proof witnesses* for these equalities. The format of these witnesses is very similar to the one of micromega [1], except that it provides a bind operator which avoids duplications of computations (induced by rewriting of learned equalities). In the core of our oracle, the production of these witnesses follows a lightweight, safe and evolutive design, called *polymorphic LCF style*⁵. This style makes the implementation of VPL oracles much simpler than in the previous VPL implementation. Our implementation thus illustrates how to instantiate “polymorphic witnesses” of polymorphic LCF style in order to generate COQ abstract syntax trees, and thus to prove the equalities in COQ by computational reflection.

The previous COQ frontend of the VPL [3] would also allow to perform such proofs by reflection. Here, we believe that the HOAS approach followed in Section 3.3 is simpler and more efficient than this previous implementation.

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⁵ See our paper *Certification for Free!* submitted to ICFP’2017.