

# Proving inconsistency: Towards a better Maltsev CSP algorithm

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In this lecture I will

- discuss the two main polynomial-time CSP algorithms,
- argue that one fails to meet the above criteria,
- offer a framework for a possible alternative.

# Motivating example

Fix a finite field  $F$ .

*Decision Problem:* **3-LIN**( $F$ )

## Inputs:

a finite list  $X = \{x_1, \dots, x_n\}$  of variables

a finite list  $\Sigma = \{\varepsilon_1, \dots, \varepsilon_m\}$  of linear equations in  $X$  over  $F$

– each equation involving **at most 3 variables**

**Question:** Does  $\Sigma$  have a solution (in  $F$ )?

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- Else,
  - ▶  $\Sigma$  is consistent, and
  - ▶ “backtracking” produces an explicit solution of  $\Sigma$ , which is itself a (very) “short proof” of consistency.
- Running time: essentially  $O(|\Sigma|n^2)$  arithmetic operations in  $F$ .

This is a *good algorithm*.

## Transition to CSP

Recall: an input to 3-LIN( $F$ ) is a pair  $(X, \Sigma)$  where

- $X = \{x_1, \dots, x_n\}$  is a finite list of variables.
- $\Sigma = \{\varepsilon_1, \dots, \varepsilon_m\}$  is a finite list of 3-variable equations over  $F$ .

Define

$$\mathbf{F} = (F, \{x - y + z\} \cup \{\lambda x + (1 - \lambda)y : \lambda \in F\}),$$

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**Observation:** if  $S$  is the set of solutions to a 3-variable linear equation  $\varepsilon$  over  $F$ , then  $S$  is a subuniverse of  $\mathbf{F}^3$ .

**Hence:** each equation  $ax_i + bx_j + cx_k = d$  can be expressed by the statement “ $(x_i, x_j, x_k) \in S$ ” for some  $S \leq \mathbf{F}^3$ .

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The **(fixed template) constraint satisfaction problem** generalizes 3-LIN( $F$ ) by permitting  $\mathbf{F}$  to be replaced by any idempotent algebra, equations by membership in named subpowers, and 3 by any fixed  $d \geq 2$ .

# Constraint Satisfaction Problem (CSP) definition

Formally, fix:

$\mathbf{A} = (A, \mathcal{F})$  – a finite *idempotent* algebra

$d \geq 2$

$\text{CSP}(\mathbf{A}, d)$  is the following decision problem:

**Inputs:**

a finite list  $X = \{x_1, \dots, x_n\}$  of variables [ranging over  $A$ ]

a finite list  $\Sigma = \{C_1, \dots, C_m\}$  of *constraints* on the variables:

Each constraint is a pair  $C = (J, R)$  where

- $J \subseteq X$  with  $1 \leq |J| \leq d$ ;
- $R \leq \mathbf{A}^J$ .

**Question:** Does  $\Sigma$  have a *solution*?

(I.e., a map  $\alpha : X \rightarrow A$  such that  $\alpha|_{J_t} \in R_t$  for all  $1 \leq t \leq m$ )



# CSP Algebraic Dichotomy Conjecture

## Conjecture (Bulatov, Jeavons, Krokhin)

Let  $\mathbf{A}$  be a finite idempotent algebra and  $d \geq 2$ .

If  $V(\mathbf{A})$  satisfies a nontrivial Maltsev condition, then  $\text{CSP}(\mathbf{A}, d)$  is in P.

Of course, every  $\text{CSP}(\mathbf{A}, d)$  is in NP:

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- “Short proofs” witnessing unsatisfiability (when  $\Sigma$  is unsatisfiable); they will put  $\text{CSP}(\mathbf{A}, d)$  in co-NP.
- Polynomial-time algorithm which decides  $\text{CSP}(\mathbf{A}, d)$  AND provides a solution or a short proof of unsatisfiability.

# The two main CSP algorithms

## ① Local consistency (bounded width) algorithm

- ▶ Rather simple
- ▶ Works whenever  $V(\mathbf{A})$  is congruence  $SD(\wedge)$  [Barto & Kozik]

## ② Few subpowers algorithm

- ▶ Rather more complicated
- ▶ Works whenever  $V(\mathbf{A})$  is congruence modular [Barto? + IMMVW]
- ▶ The case when  $\mathbf{A}$  has a Maltsev operation is representative.

## Algorithm #1: Local consistency

Recall that constraints in an input to  $\text{CSP}(\mathbf{A}, d)$  have the form  $(J, R)$ :

- $J$  is a “small” subset of the set  $X$  of variables ( $|J| \leq d$ ).
- $R (\leq \mathbf{A}^J)$  restricts the values a solution may take on  $J$ .

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### Intuition:

For some fixed  $j < k$ , the system will permit deducing a  $\leq j$ -ary constraint from a collection of other  $\leq j$ -ary constraints, as long as:

- the deduction is correct (of course!), and
- the number of variables altogether is at most  $k$ .

**Example:** if  $(\mathbf{A}, d) = (\mathbf{F}, 3)$  and  $(j, k) = (3, 6)$ , then the system permits deductions of the following kind:

$$\begin{array}{rcl}
 \text{From} & x + y - u = 0 & \text{i.e., } (\{x, y, u\}, \text{graph}(+)) \\
 & y + z - v = 0 & (\{y, z, v\}, \text{graph}(+)) \\
 & u + z - w = 0 & (\{u, z, w\}, \text{graph}(+)) \\
 \hline
 \text{deduce} & x + v - w = 0 & (\{x, v, w\}, \text{graph}(+))
 \end{array}$$

Formally, the rules are (for some fixed  $j < k$ ):

① **Intersect**

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② **FictVar<sub>k</sub>** – add fictitious variables, up to  $k$  in total

$$\frac{(J, R)}{\therefore (K, (\text{pr}_{K \rightarrow J})^{-1}(R))}$$

for any  $J \subseteq K \subseteq X$ , provided  $|K| \leq k$ .

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③ **Project<sub>j</sub>** – projection to  $\leq j$  variables

$$\frac{(K, R)}{\therefore (J, \text{pr}_{K \rightarrow J}(R))}$$

for any  $J \subseteq K$ , provided  $|J| \leq j$ .

These rules give a formal notion of proof.

## Definition

Given an input  $(X, \Sigma)$  to  $\text{CSP}(\mathbf{A}, d)$ , a  $(j, k)$ -**proof from**  $(X, \Sigma)$  is a finite sequence  $(C_1, \dots, C_p)$  of constraints over  $X$  such that for all  $1 \leq i \leq p$ ,

- 1  $C_i \in \Sigma$ , or
- 2  $C_i$  is the result of applying **Intersect** to two constraints from  $\{C_1, \dots, C_{i-1}\}$ , or
- 3  $C_i$  is the result of applying **FictVar** <sub>$k$</sub>  or **Project** <sub>$j$</sub>  to a constraint from  $\{C_1, \dots, C_{i-1}\}$ .

I say that  $(C_1, \dots, C_p)$  is a  $(j, k)$ -**proof of**  $C_p$  **from**  $(X, \Sigma)$ .

**Note:** every solution to  $\Sigma$  also satisfies all  $C_i$  in a  $(j, k)$ -proof from  $(X, \Sigma)$ .

## Notation

Let's write  $(X, \Sigma) \vdash_{j,k} \emptyset$  if there exists a  $(j, k)$ -proof from  $(X, \Sigma)$  whose last constraint is *empty* (i.e., has the form  $(J, \emptyset)$ ).

**Remark:** if  $(X, \Sigma) \vdash_{j,k} \emptyset$ , then:

- $\Sigma$  is unsatisfiable.
- There exists a witnessing  $(j, k)$ -proof of length at most  $2^{|A|^k} \cdot |X|^k$ .  
(This is a good “short proof” of unsatisfiability.)

## Definition

$(\mathbf{A}, d)$  has **width**  $(j, k)$  if, for every instance  $(X, \Sigma)$  of  $\text{CSP}(\mathbf{A}, d)$ ,

$$\Sigma \text{ unsatisfiable} \Leftrightarrow (X, \Sigma) \vdash_{j, k} \emptyset.$$

In other words,  $(\mathbf{A}, d)$  has width  $(j, k)$  if the formal system of  $(j, k)$ -proofs provides short proofs for all unsatisfiable instances to  $\text{CSP}(\mathbf{A}, d)$ .

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## Definition

$(\mathbf{A}, d)$  has **bounded width** if it has width  $(j, k)$  for some  $j < k$ .

## Local consistency algorithm

**Folklore:** For each  $j < k$  there is an algorithm (the “ $(j, k)$ -consistency algorithm”) which, given  $(\mathbf{A}, d)$  having width  $(j, k)$  and given an input  $(X, \Sigma)$  to  $\text{CSP}(\mathbf{A}, d)$ ,

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- If satisfiable, produces a solution.

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- decides whether  $(X, \Sigma)$  has a solution.
- If satisfiable, produces a solution.
- If unsatisfiable, produces a  $(j, k)$ -proof witnessing  $(X, \Sigma) \vdash_{j,k} \emptyset$ .
- Runs in polynomial time.

This is a *good algorithm*.

The extent of the local consistency algorithm:

Theorem (Larose & Zádori ( $\Rightarrow$ ); Barto & Kozik ( $\Leftarrow$ ))

Let  $\mathbf{A}$  be a finite idempotent algebra,  $d \geq 2$ , and assume the clone of  $\mathbf{A}$  is determined by its  $d$ -ary invariant relations. Then

$(\mathbf{A}, d)$  has bounded width  $\Leftrightarrow V(\mathbf{A})$  is congruence  $SD(\wedge)$ .

Unfortunately, if  $\mathbf{F}$  is the idempotent algebra corresponding to  $3\text{-LIN}(F)$ , then  $(\mathbf{F}, 3)$  does *not* have bounded width.

**Conclusion:** although Gaussian elimination is a form of “constraint” reasoning, it does not fall within the framework of local consistency proofs.

## Algorithm #2: Few subpowers

Recall that each input to  $\text{CSP}(\mathbf{A}, d)$  has the form  $(X, \Sigma)$  where

$$\Sigma = \{C_1, C_2, \dots, C_m\} \quad \text{with} \quad C_t = (J_t, R_t).$$

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For  $i \leq m$ , define  $B_i$  to be the set of solutions to the first  $i$  constraints:

$$\mathbf{A}^X = \mathbf{B}_0 \geq \mathbf{B}_1 \geq \mathbf{B}_2 \geq \dots \geq \mathbf{B}_m = \{\text{solutions to } (X, \Sigma)\}.$$

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The *few subpowers algorithm* (BD + IMMVW):

- is *not* based on reasoning with equations/constraints.
- instead, it successively computes *small generating sets* for each  $\mathbf{B}_t$ .
  - ▶  $(X, \Sigma)$  has a solution  $\Leftrightarrow$  the last generating set is nonempty.

## Special case: when $\mathbf{A}$ is Maltsev

(I.e., when  $V(\mathbf{A})$  is congruence permutable.)

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Based on the notion of *compact representations* of subsets of powers.

### Definition

Suppose  $A$  is a set and  $B \subseteq A^n$ .



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$$\text{Fork}(B) = \{(i, b, c) \in [n] \times A \times A : \exists \mathbf{u}, \mathbf{v} \in B \text{ with } u_j = v_j \text{ for all } 1 \leq j < i, \text{ and } (u_i, v_i) = (b, c)\}.$$

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**Exercise:** if  $T$  is a compact rep. for  $B \subseteq A^n$ , then  $|T| \leq n|A|^2$ .

## Key Fact (Bulatov, Dalmau)

If  $\mathbf{A}$  has a Maltsev term,  $\mathbf{B} \leq \mathbf{A}^n$ , and  $T$  is a compact representation of  $B$ , then  $T$  generates  $\mathbf{B}$ .

Proof idea.

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Thus  $(i, a_i, b) \in \text{Fork}(B)$



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Applying the Maltsev term, we get  $(a_1, \dots, a_{i-1}, a_i, \dots) \in \langle T \rangle_{\mathbf{B}}$ . □

**The BD Algorithm:** Let  $(X, \Sigma)$  with  $\Sigma = (C_1, \dots, C_m)$  be an input to  $\text{CSP}(\mathbf{A}, d)$  with  $\mathbf{A}$  Maltsev. Linearly order  $X = \{x_1, \dots, x_n\}$ , identify  $A^X$  with  $A^n$ , and recall the descending chain of subpowers given by  $C_1, \dots, C_m$ :

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**Key task:** For each  $(i, a, b) \in [n] \times A \times A$ , we need to decide whether  $(i, a, b) \in \text{Fork}(B_t)$  and, if "yes," we must find a witnessing pair  $\mathbf{u}, \mathbf{v} \in B_t$ .

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Finding a candidate  $\mathbf{u}$  is not too hard. To find  $\mathbf{v}$ , construct a new chain  $(\dagger)$  of subpowers in the special case, starting from  $\mathbf{B}_{t-1}$ , using  $u_1, \dots, u_{n-1}$ .

## The few subpowers algorithm and its extent

- A necessary feature of the BD algorithm is that  $\exists$  polynomial  $p(x)$  such that every  $\mathbf{B} \leq \mathbf{A}^n$  has a generating set of size at most  $p(n)$ .

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- The Bulatov-Dalmau algorithm generalizes to algebras having a cube term (IMMVW); called the *few subpowers algorithm*.
- With Barto's recently announced result, we know that (assuming  $\mathbf{A}$  is determined by its  $d$ -ary relations),

$\mathbf{A}$  has a cube term  $\Leftrightarrow V(\mathbf{A})$  is congruence modular.

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**Problem:** Are we stuck with it? Can we find a better algorithm?

# An idea for a new type of “short proof” of unsatisfiability

**Motivating example:** again  $3\text{-LIN}(F)$

**The sad fact:** Unsatisfiable instances of  $3\text{-LIN}(F)$  cannot be proved to be unsatisfiable by local consistency.

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**The happy fact:** Unsatisfiable instances of  $3\text{-LIN}(F)$  *can* be proved to be unsatisfiable by local consistency. . . provided one is permitted the **introduction of new variables**.

Suppose an instance  $(X, \Sigma)$  of 3-LIN( $F$ ) is given.

Suppose some new variables  $u_1, \dots, u_L$  are “introduced” (i.e., defined) by  $\leq 3$ -variable equations, say

$$u_1 := ax_5 + 1$$

$$u_2 := bx_3 + cx_6$$

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Let  $U$  be the set of new variables and let  $\Gamma$  be the set of defining equations.

Clearly  $(X, \Sigma)$  is satisfiable if and only if  $(X \cup U, \Sigma \cup \Gamma)$  is satisfiable.

## Theorem

Suppose  $(X, \Sigma)$  is an instance of 3-LIN( $F$ ), with  $|X| = n$  and  $|\Sigma| = m$ . If  $\Sigma$  is unsatisfiable, then there exists

- $L \leq mn(m + n)$ ,
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**Proof hint: Simulate Gaussian elimination.**

Linearly order  $X = \{x_1, x_2, \dots, x_n\}$ ; run GE. For each “complete” equation  $a_1x_1 + \dots + a_nx_n = b$  occurring in the GE computation, introduce  $n$  new variables representing the partial sums of the left-hand side:

$$u_1 := a_1x_1, \quad u_2 := u_1 + a_2x_2, \quad \dots, \quad u_n = u_{n-1} + a_nx_n. \quad (\text{Gives } U, \Gamma.)$$

Show that for each such equation,  $(X \cup U, \Sigma \cup \Gamma) \vdash_{3,6} “u_n = b.”$  □

## Formalize and Generalize:

Fix  $j < k$  and **A**. Also fix  $l_0, l_1$  satisfying  $l_0 \leq j$  and  $l_0 + l_1 \leq k$ .

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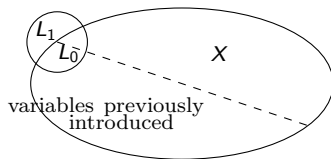
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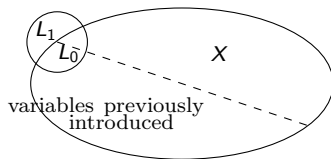
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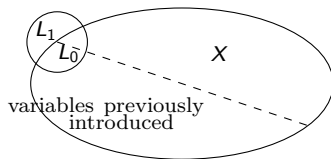
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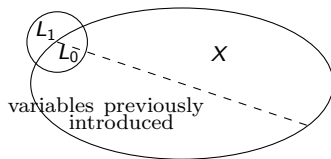
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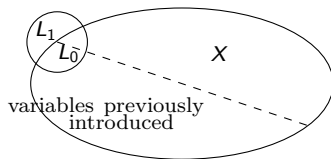
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Using these four rules, we get a notion of “ $(j, k; \ell_0, \ell_1; \mathbf{A})$ -proof.”

## Notation

If  $(X, \Sigma)$  is an instance of  $\text{CSP}(\mathbf{A}, d)$ , let's write

$$(\mathbf{A}, X, \Sigma) \Vdash_{j,k;\ell_0,\ell_1}^N \emptyset$$

if there exists a  $(j, k; \ell_0, \ell_1; \mathbf{A})$ -proof from  $(X, \Sigma)$  whose last constraint is empty, and which introduces at most  $N$  new variables.

Using these four rules, we get a notion of “ $(j, k; \ell_0, \ell_1; \mathbf{A})$ -proof.”

## Notation

If  $(X, \Sigma)$  is an instance of  $\text{CSP}(\mathbf{A}, d)$ , let's write

$$(\mathbf{A}, X, \Sigma) \Vdash_{j,k;\ell_0,\ell_1}^N \emptyset$$

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## Definition

$(\mathbf{A}, d)$  has **VI-width**  $(j, k; \ell_0, \ell_1)$  if  $\exists$  polynomial  $p(x)$  such that for every instance  $(X, \Sigma)$  of  $\text{CSP}(\mathbf{A}, d)$  with  $|X| = n$ ,

$$(X, \Sigma) \text{ is unsatisfiable} \Leftrightarrow (\mathbf{A}, X, \Sigma) \Vdash_{j,k;\ell_0,\ell_1}^{p(n)} \emptyset.$$

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$(\mathbf{A}, d)$  has **bounded VI-width** if it has VI-width  $(j, k, \ell_0, \ell_1)$  for some  $j, k, \ell_0, \ell_1$ .

**Fact:** if  $(\mathbf{A}, d)$  has bounded VI-width, then

- $\text{CSP}(\mathbf{A}, d)$  is in  $\text{NP} \cap \text{co-NP}$ .
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$(\mathbf{A}, d)$  has **strongly bounded VI-width** if for some  $j, k, \ell_0, \ell_1$ :

- $(\mathbf{A}, d)$  has VI-width  $(j, k; \ell_0, \ell_1)$ , and
- there exists a polynomial-time algorithm solving  $\text{CSP}(\mathbf{A}, d)$  and which, for unsatisfiable instances, returns a  $(j, k; \ell_0, \ell_1, \mathbf{A})$ -proof of an empty constraint. (Such an algorithm is *good*.)

**Thus:** if  $(\mathbf{A}, d)$  has strongly bounded VI-width then  $\text{CSP}(\mathbf{A}, d)$  is in P.

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- 3 Same question for any finite idempotent Maltsev algebra  $\mathbf{A}$ .

## Speculations

- ④ Is there a polynomial-time “strong bounded VI-width” algorithm for  $\text{CSP}(\mathbf{A}, d)$ , when  $\mathbf{A}$  is Maltsev, which is “essentially” local consistency + Gaussian elimination?

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**Thank you!**