A framework for step-wise explaining how to solve constraint satisfaction problems

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(Joint work with Emilio Gamba, Jens Claes, and Tias Guns)

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- "There Are No CNF Problems" (P.J. Stuckey)
- Adopt a (simple) high-level modeling language

BEYOND SATISFIABILITY

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- Structural information of the problem visible
- E.g., symmetry breaking

 $\forall p[Pigeon] \exists h[Hole] : In(p,h)$ $\forall h[Hole], p_1p_2[Pigeon] : In(p_1,h) \land In(p_2,h) \Rightarrow p_1 = p_2.$

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Choice ... fragmentation ... ASP, CP, SMT, ...

BEYOND SATISFIABILITY: THIS TALK

- ► Algorithms: SAT level
- Explanation: first-order level



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LOGIC GRID PUZZLES

- Set of clues
- Sets of entities that need to be linked
- Each entitity is linked to exactly one entity of each other type (bijectivity)
- ► The links are consistent (transitivity)

LOGIC GRID PUZZLES: EXAMPLE

- The person who ordered capellini paid less than the person who chose arrabiata sauce
- > The person who ordered tagliolini paid more than Angie
- The person who ordered tagliolini paid less than the person who chose marinara sauce
- Claudia did not choose puttanesca sauce
- The person who ordered rotini is either the person who paid \$8 more than Damon or the person who paid \$8 less than Damon
- The person who ordered capellini is either Damon or Claudia
- ► The person who chose arrabiata sauce is either Angie or Elisa
- ► The person who chose arrabiata sauce ordered farfalle

2019 HOLY GRAIL CHALLENGE: LOGIC GRID PUZZLES

- Parse puzzles and translate into CSP
- Solve CSP automatically
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2019 HOLY GRAIL CHALLENGE: LOGIC GRID PUZZLES

- Parse puzzles and translate into CSP
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We won the challenge... out of two participants



- Automatically generated constraint representation from natural language (no optimization of the constraints for the explanation problem)
- No modifications to the underlying solvers (we do not equip each propagator with explanation mechanisms)
- demo: https://bartbog.github.io/zebra/pasta/



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- Formalize the step-wise explanation problem
- Propose an algorithm (agnostic of actual propagators, consistency level, etc.)
- Propose heuristics for guiding the search for explanations
- Experimentally demonstrate feasibility

PRELIMINARIES/NOTATION

- Propositional vocabulary Σ
- (partial) interpretation *I*: consistent set of literals over Σ Slightly abusing notation: set of (unit) clauses
- Propositional theory T (set of constraints over Σ)
 Slightly abusing notation: set of constraints = conjunction

▶ Notation $T \land I \models I'$



▶ Given *T* and *I*, let *I*_{end} denote the maximal set of literals such that

$$T \land I \models I_{end}$$

Explain in simple steps how to derive *I*_{end}

Our focus: single steps (not optimizing entire sequence yet)

Let I_{i-1} and I_i be partial interpretations such that $I_{i-1} \land T \models I_i$. We say that (E_i, S_i, N_i) explains the derivation of I_i from I_{i-1} if the following hold:

- ▶ $N_i = I_i \setminus I_{i-1}$ (i.e., N_i consists of all newly defined facts),
- ► $E_i \subseteq I_i$ (i.e., the explaining facts are a subset of what was previously derived),
- ▶ $S_i \subseteq T$ (i.e., a subset of the clues and implicit constraints are used), and
- ► $S_i \wedge E_i \models N_i$ (i.e., all newly derived information indeed follows from this explanation).

We call (E_i, S_i, N_i) a non-redundant explanation of the derivation of I_i from I_{i-1} if it explains this derivation and whenever $E' \subseteq E_i$; $S' \subseteq S_i$ while (E', S', N_i) also explains this derivation, it must be that $E_i = E', S_i = S'$.

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Observation: computing non-redundant explanations of a single literal can be done using Minimal Unsat Core (MUS) extraction:

Theorem

There is a one-to-one correspondence between \subseteq -minimal unsatisfiable cores of $I_i \land T \land \neg \ell$ and non-redundant explanations of $I_i \cup \{\ell\}$ from I_i (given T).

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Furthermore, we assume existence of a cost function $f(E_i, S_i, N_i)$ that quantifies the interpretability of a single explanation

Given a theory T and initial partial interpretation I_0 , the explanation-production problem consist of finding a non-redundent explanation sequence

$$(I_0, (\emptyset, \emptyset, \emptyset)), (I_1, (E_1, S_1, N_i)), \dots, (I_n, (E_n, S_n, N_n))$$

such that some aggregate over the sequence $(f(E_i, S_i, N_i))_{i \le n}$ is minimised.

Algorithm 1: ONESTEP(T, f, I, I_{end})

- 1 $X_{best} \leftarrow nil;$
- 2 for $\ell \in \{I_{end} \setminus I\}$ do
- 3 $X \leftarrow MUS(T \land I \land \neg \ell);$ 4 if $f(X) < f(X_{best})$ then
- 5 $X_{best} \leftarrow X;$
- 6 end
- 7 end
- 8 return X_{best}

MUS-BASED GENERATION NOT SUFFICIENT

- ► MUS guarantees non-redundancy ...
- ... does not guarantee quality

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- ECAI paper: MUS-based workaround (heuristic): do not use full *T*, but approximate
- ▶ No details in this talk.

IMPLEMENTATION (ECAI PAPER)

- Visual explanation interface
- Logic Grid puzzle cost function:
 - Single implicit axiom: very cheap
 - Single constraint + implicit: less cheap
 - Multiple constraints: very expensive

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"The person who ordered capellini is either Damon or Claudia".

 $\exists p : ordered(p, capellini) \land (p = Damon \lor p = Claudia).$

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SMUS: #-minimal (still not sufficient...)

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- ► MUS: ⊆-minimal
- SMUS: #-minimal (still not sufficient...)
- ► New problem OUS

Let T be a formula, $f : 2^T \to \mathbb{N}$ a cost function. We call $S \subseteq T$ an OUS of T (with respect to f) if

- ▶ S is unsatisfiable,
- ▶ all other unsatisfiable $S' \subseteq T$ satisfy $f(S') \ge f(S)$.

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Q: How to compute OUSs?

Algorithm 2: ONESTEP(T, f, I, I_{end})

- 1 $X_{best} \leftarrow nil;$ 2 for $\ell \in \{I_{end} \setminus I\}$ do 3 $\mid X \leftarrow OUS(T \land I \land \neg \ell);$ 4 $\mid if f(X) < f(X_{best})$ then 5 $\mid X_{best} \leftarrow X;$ 6 \mid end
- 7 **end**
- 8 return X_{best}

BEYOND OUS-BASED EXPLANATIONS

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- ► The different iterations (for loop line 2)... very similar
- Can we exploit this?
- Essentially, the task at hand is: find a single unsatisfiable subset of

$$T \wedge I \wedge \bigvee_{\ell \in I_{end} \setminus I} \neg \ell$$

that:

- ▶ Is optimal w.r.t. f
- Contains exactly one literal $\neg \ell$ with $\ell \in I_{end} \setminus I$ (example!)

Let T be a formula, $f : 2^T \to \mathbb{N}$ a cost function and p a predicate $p : 2^T \to \{\mathbf{t}, \mathbf{f}\}$. We call $S \subseteq T$ an OCUS of T (with respect to f and p) if

S is unsatisfiable,

▶ p(S) is true

▶ all other unsatisfiable $S' \subseteq T$ with $p(S') = \mathbf{t}$ satisfy $f(S') \ge f(S)$.

OCUS-BASED EXPLANATION GENERATION

Algorithm 3: EXPLAIN-ONE-STEP-OCUS (T, f, I, I_{end})

1 $p \leftarrow$ exactly one of $\overline{I_{end} \setminus I}$ 2 return OCUS $(T \land I \land \overline{I_{end} \setminus I}, f, p)$

Hitting set-based algorithms: used for MaxSAT and SMUS

Theorem

A set $S \subseteq T$ is a MCS of T iff it is a minimal hitting set of MUSs(T). A set $S \subseteq T$ is a MUS of T iff it is a minimal hitting set of MCSs(T).

Hitting set-based algorithms: used for MaxSAT and SMUS

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We extended this to OCUS:

Algorithm 4: OCUS(*T*, *f*, *p*)

- 1 $\mathcal{H} \leftarrow \emptyset$
- 2 while true do
- $\mathcal{S} \leftarrow \text{COST-OPTIMAL-HITTINGSET}(\mathcal{H}, f, p)$
- 4 if $\neg SAT(S)$ then
- 5 return S

6 end

7 $\mathcal{S} \leftarrow \text{GROW}(\mathcal{S}, T)$

8
$$\mid \mathcal{H} \leftarrow \mathcal{H} \cup \{T \setminus S\}$$

🤋 end



Theorem

Let \mathcal{H} be a set of correction subsets of T. If S is a hitting set of \mathcal{H} that is f-optimal among the hitting sets of \mathcal{H} satisfying a predicate p, and S is unsatisfiable, then S is an OCUS of T. If \mathcal{H} has no hitting sets satisfying p, then T has no OCUSs.

- Incrementality: re-use previous computations in future calls
- Grow: Develop implementations of "grow" tailored for explanations

Algorithm 5: OCUS(T, f, p)

- $1 \hspace{0.1in} \mathcal{H} \leftarrow \ldots$
- 2 while true do
- $\mathcal{S} \mid \mathcal{S} \leftarrow \text{COST-OPTIMAL-HITTINGSET}(\mathcal{H}, f, p)$
- 4 if $\neg SAT(S)$ then
- 5 return *S*

6 end

- 7 $\mathcal{S} \leftarrow \text{GROW}(\mathcal{S}, T)$
- 8 $\mathcal{H} \leftarrow \mathcal{H} \cup \{T \setminus S\}$

🤋 end

When calling OCUS, the theory consists of

- 1. The original theory (constraints)
- 2. The current interpretation
- 3. The negation of literals in Iend
- ▶ What to take into account for GROW?
- What about the cost function?

T I_{end} I_{end} Implementation building on pysat + cpMpy

Q1 What is the effect of requiring optimality of the generated MUSs on the **quality** of the generated explanations?

Q2 Which domain-specific GROW methods perform best?

- Q3 What is the effect of the use of **contrainedness** on the time required to compute an explanation sequence?
- Q4 Does **re-use** of computed satisfiable subsets improve efficiency?

EXPERIMENTS: SOLUTION QUALITY



EXPERIMENTS: GROW STRATEGIES



EXPERIMENTS: PERFORMANCE





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- Some steps still quite difficult.
- Idea: explanations at different levels of abstraction
- Explain hardest steps of the sequence



	- FIEV				INCAL -			J				
	capellini	farfalle	tagliolini	rotini	4	80	12	16	angie	damon	claudia	elisa
the_other_type1		-										
arrabiata_sauce	-	✓	-	-	-					-	-	
marinara_sauce		•	•		-							
puttanesca_sauce		•									-	
angie	-		-				-	-				
damon		-		-				-				
claudia		•			[
elisa	-											
4		-	-									
8												
12												
16			-									

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- For which steps? Hardest step of the nested sequence simpler than the step to explain



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- Overview of a (relatively young) research project
 ⇒ Lots of open questions!
- Goal:Provide human-understandable explanations of inferences made by a constraint solver
- Our proposal: split in small comprehensible steps
- Explain them at different levels of detail (abstraction)
- Triggers novel algorithmic needs
- Demonstrated on logic grid puzzles



- Teach humans how to solve a certain problem
- Quantify problem difficulty
- "Help" button
- Interactive configuration/planning/scheduling

- Learning the optimization function (from humans) Learning the level of abstraction
- Explaining optimization (different types of "why" queries); close relation to Explainable AI Planning [2]
- Scaling up (approximate algorithms; decomposition of explanation search)
- Incremental algorithms over different "why" queries



- [1] Broes De Cat, Bart Bogaerts, Maurice Bruynooghe, Gerda Janssens, and Marc Denecker. Predicate logic as a modelling language: The IDP system. *CoRR*, abs/1401.6312v2, 2016.
- [2] Maria Fox, Derek Long, and Daniele Magazzeni. Explainable planning. *arXiv preprint arXiv:1709.10256*, 2017.