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

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September 13, 2020 @ XLoKR20







Franz: "How tailored is this to CSP?"

- "CSP": any formalism that allows searching for models in the context of a finite domain (Model Expansion for FO, propositional logic, ASP, ...)
- Our step-wise ideas could also be applied to generate "simple first-order proofs" (to be explored)



- 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



> 2019 Holy Grail Challenge: Logic Grid Puzzles

- Parse puzzles and translate into CSP
- Solve CSP automatically
- Explain in a human-understandable way how to solve this puzzle
- ▶ More generic paper at ECAI 2020 [1]
- ► Journal version and follow-up conference paper under review.

WHAT WE WORKED ON ALREADY

- 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
- (unpublished) Nested explanations (conceptual extension)
- (unpublished) Incremental OMUS algorithms (efficiency bottleneck)

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)



- Automatically generated constraint representation from natural language (no optimization of hte 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/



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
- ► $S_i \cup E_i \models N_i$ (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 $I_i \land T \land \neg I$ and non-redundant explanations of $I_i \cup \{I\}$ from I_i .



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





- Greedy algorithm (max aggregate)
 - At each step, for each solution literal, find a MUS *
 - Pick the cheapest (cost-wise)
 - (some caching)
- Under the hood: IDP system [3]
- * single MUS call does not suffice
- Pruning based on optimistic approximation of cost
- * no guarantee of optimality
- * inefficient!

Algorithm 2: SINGLESTEPEXPLAIN(T, f, I)

1
$$BestVal \leftarrow \infty$$
;
2 for l such that $T \land I \models l$ and $l \notin I$ do
3 $| X \leftarrow OMUS(T \land I \land \neg l, f);$
4 $| if f(X) < BestVal$ then
5 $| BestVal \leftarrow f(X);$
6 $| Ibest \leftarrow T \cap X;$
7 $| Ibest \leftarrow I \cap X;$
8 $| lbest \leftarrow l;$
9 $| end$
10 end
11 return $(T_{best}, I_{best}, l_{best})$

LOGIC GRID PUZZLE

Visual explanation interface

Cost function:

- Single implicit axiom: very cheap
- Single constraint + implicit: less cheap
- Multiple constraints: very expensive

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

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



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

NEXT STEPS: NESTED EXPLANATION

- Idea: explanations at different levels of abstraction
- Explain hardest steps of the sequence
- Counterfactual reasoning/proof by contradiction
- See demo https://bartbog.github.io/zebra/pasta/

NEXT STEPS: OMUS COMPUTATION

- Algorithms to compute Optimal MUSs
- Based on hitting-set duality
- Combining existing SMUS (#-minimal) [6, 5] algorithms and MAXSAT [2] algorithms
- Incremental OMUS computation
- Constrained OMUS computation
- No experimental results yet

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MORE FUTURE WORK

- Learning the optimization function (from humans) Learning the level of abstraction
- Explaining optimization (different types of "why" queries); close relation to Explainable AI Planning [4]
- Scaling up (approximate algorithms; decomposition of explanation search)
- Incremental algorithms over different "why" queries

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