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Learning Generalized Unsolvability Heuristics for Classical Planning

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Abstract
Recent work in classical planning has introduced dedicated techniques for detecting unsolvable states, i.e., states from which no goal state can be reached. We approach the problem from a generalized planning perspective and learn first-order-like formulas that characterize unsolvability for entire planning domains. We show how to cast the problem as a self-supervised classification task. Our training data is automatically generated and labeled by exhaustive exploration of small instances of each domain, and candidate features are automatically computed from the predicates used to define the domain. We investigate three learning algorithms with different properties and compare them to heuristics from the literature. Our empirical results show that our approach often captures important classes of unsolvable states with high classification accuracy. Additionally, the logical form of our heuristics makes them easy to interpret and reason about, and can be used to show that the characterizations learned in some domains capture exactly all unsolvable states of the domain.

1 Introduction
For solving planning tasks efficiently via search it is often crucial to detect unsolvable states, i.e., states from which the goal cannot be reached [Junghanns and Schaeffer, 1998; Kolobov \textit{et al.}, 2012; Muise \textit{et al.}, 2012; Cserna \textit{et al.}, 2018]. In classical planning, unsolvable states have traditionally only been recognized implicitly, as a byproduct of the computation of heuristics designed to estimate the cost of reaching the goal from a given state. Most of the standard heuristics are safe unsolvability estimators too, in that a state with an infinite heuristic value is guaranteed to be unsolvable. In recent years, there has been a renewed interest in unsolvability detection methods [Bäckström \textit{et al.}, 2013; Hoffmann \textit{et al.}, 2014; Lipovetzky \textit{et al.}, 2016; Ståhlberg, 2017; Eriksson \textit{et al.}, 2017; Steinmetz and Hoffmann, 2017], as witnessed by the 2016 Unsolvability International Planning Competition [Muise and Lipovetzky, 2016; Seipp \textit{et al.}, 2016; Torralba, 2016]. Many of these methods incorporate a preprocessing phase that computes an unsolvability heuristic tailored to the particular instance at hand.

In this paper, we approach the problem of unsolvability detection from a generalized perspective, and learn characterizations of unsolvable states for entire planning domains. Although this is obviously not easier than characterizing the unsolvable states of a single instance of the domain, the advantage is that the learned knowledge can be used for many instances. Although deciding unsolvability for a single instance is in general PSPACE-complete, many standard domains have relatively simple descriptions of what constitutes an unsolvable state, which we aim to capture with our approach.

We frame this problem in terms of a standard self-supervised binary classification task, where training data and labels are generated by exhaustive exploration of a few small instances of the planning domain. The features our classifiers use are derived automatically from the first-order predicates and constants that describe the domain, avoiding the need for manual feature engineering. Our approach thus follows the footsteps of recent works that learn logic-based domain control knowledge from the observation of a few instances of the domain [Bonet \textit{et al.}, 2019; Francès \textit{et al.}, 2021]. Whereas these works aim at obtaining general policies, here we focus squarely on characterizing unsolvability.

We present three different learning algorithms that learn simple formulas in disjunctive normal form (DNF) over the domain features. The three approaches differ in the guarantees they provide and in their computational demands. We show that the resulting functions are concise and hence fast to evaluate. Our experiments also confirm that some domains have simple characterizations of unsolvable states that our approaches capture successfully. Furthermore, we leverage the interpretability of the learned formulas in order to show that some of them are sound and complete characterizations for the entire domain.

2 Background
In this section, we review classical planning, description logic and its use in classical planning.

2.1 Classical Planning
We consider deterministic, fully-observable planning problems represented in a fragment of PDDL [Haslum \textit{et al.},...
2019]. Namely, we consider ground PDDL planning problems defined as a tuple \( P = \langle \sigma, A, s_0, \gamma \rangle \). The function-free vocabulary \( \sigma \) consists of a set of constant symbols (also called PDDL objects) and a set of predicate symbols. We assume w.l.o.g. that \( \sigma \) contains only predicates with arity at most two; higher-arity symbols can be compiled into multiple binary predicates in the standard manner. PDDL types can also be compiled into unary predicates. The set of states \( S_P \) of problem \( P \) contains all possible sets of ground atoms over \( \sigma \). We write \( S \) when \( P \) is clear from context. We call \( s_0 \in S \) the initial state of the problem and \( \gamma \) the (conjunctive) goal. A state \( s \in S \) is a goal state if \( \gamma \subseteq s \). Each action \( a \) in the set of ground actions \( A \) has a precondition \( pre(a) \), an add list \( add(a) \) and a delete list \( del(a) \), each of which is a set of ground atoms over \( \sigma \).

A ground action \( a \in A \) is applicable in state \( s \in S \) if \( pre(a) \subseteq s \). In that case, applying \( a \) to \( s \) results in the successor state \( s[a] = (s \setminus del(a)) \cup add(a) \). A sequence of actions \( \pi = (a_1, \ldots, a_n) \) is applicable in a state \( s \) iff for all \( i \), \( a_i \) is applicable in state \( s[a_1] \cdots [a_{i-1}] \). We write \( s[\pi] \) for the state that results from applying \( \pi \) to \( s \). State \( s' \) is reachable from state \( s \) if there is a sequence \( \pi \) such that \( s[\pi] = s' \). We say that a state is reachable in \( P \) if it is reachable from the initial state \( s_0 \). A state \( s \) is solvable if there is a goal state that is reachable from \( s \). The solution to the planning task, i.e., a plan, is a sequence of actions \( \pi = (a_1, \ldots, a_n) \) that is applicable in the initial state \( s_0 \) and leads to a goal state, i.e., \( \gamma \subseteq s_0[\pi] \).

Note that each state \( s \in S \) represents a first-order interpretation \( I(s) \) that assigns a truth value to all formulas over \( \sigma \). We write \( s \models \varphi \) if formula \( \varphi \) is true under \( I(s) \).

**Planning domains.** In this paper we refer to a generalized planning domain as a set \( Q \) of planning problems whose vocabularies all have the same predicate symbols, and possibly share some of the constants symbols. A typical instantiation of such a domain is given in PDDL domain files.

### 2.2 Description Logics

Description logics are a family of knowledge representation formalisms based on tractable fragments of first-order logic [Baader et al., 2004]. They build on the notions of concepts, classes of objects that share some property, and roles, relations between these objects. Several description logics exist in the literature; we describe the one we use next.

**Syntax.** Compound concepts and roles are defined inductively starting from a given set of primitive concepts and roles. Primitive concepts are unary predicates, whereas primitive roles are binary predicates. Each primitive concept is a concept, and each primitive role is a role. The universal concept \( \top \) and the bottom concept \( \bot \) are also concepts. Let \( C \) and \( C' \) be concepts, and \( R \) and \( R' \) roles. The negation \( \neg C \), the union \( C \cup C' \), the intersection \( C \cap C' \), the existential restriction \( \exists R.C \), the universal restriction \( \forall R.C \), and the role-value-map \( R = R' \) are also concepts. If \( \{ a \} \) is a constant symbol, the nominal \( \{ a \} \) is a concept. The inverse role \( R^{-1} \) and the (non-reflexive) transitive closure role \( R^+ \) are also roles.

**Semantics.** The semantics of concepts and roles are defined relative to a given universe of discourse \( \Delta \). A model \( \mathcal{M} \) maps each constant symbol \( a \) to an element \( a^\mathcal{M} \in \Delta \), each primitive concept \( C \) to a subset \( C^\mathcal{M} \subseteq \Delta \), and each primitive role \( R \) to a subset \( R^\mathcal{M} \subseteq \Delta \times \Delta \). \( \mathcal{M} \) extends to compound concepts and roles as follows:

\[
\begin{align*}
\top^\mathcal{M} & = \Delta, \\
\bot^\mathcal{M} & = \emptyset, \\
(C \cup C')^\mathcal{M} & = C^\mathcal{M} \cup C'^\mathcal{M}, \\
(C \cap C')^\mathcal{M} & = C^\mathcal{M} \cap C'^\mathcal{M}, \\
(\exists R.C)^\mathcal{M} & = \{ a \mid \exists b : (a, b) \in R^\mathcal{M} \land b \in C^\mathcal{M} \}, \\
(\forall R.C)^\mathcal{M} & = \{ a \mid \forall b : (a, b) \in R^\mathcal{M} \to b \in C^\mathcal{M} \}, \\
(R^\mathcal{M})^\mathcal{M} & = \{ (b, a) \mid (a, b) \in R^\mathcal{M} \}, \\
(R^-)^\mathcal{M} & = \{ \{ a_0, a_n \} \mid \exists a_1, \ldots, a_{n-1} : (a_{i-1}, a_i) \in R^\mathcal{M} \text{ for all } 1 \leq i \leq n \}.
\end{align*}
\]

**Complexity.** The complexity \( \mathcal{K}(C) \) of a concept or role \( C \) is defined as the number of nodes of the parse tree used to represent it.

### 2.3 Use of Description Logics in Classical Planning

We follow several works in the literature on learning for planning that use description logics or similar formalisms as the foundation of first-order features useful for the design of generalized features and policies [Martín and Geffner, 2004; Fern et al., 2006; Francès et al., 2019; Francès et al., 2021]. The connection between a planning problem \( P \) and a corresponding description logic language \( DL(P) \) is straightforward. The unary and binary predicates of \( P \) are taken to be primitive concepts and roles, respectively, and the universe of discourse \( \Delta \) contains all constants in the problem, which we always consider to denote themselves. Hence, each state \( s \in S_P \) can also be seen as a model for \( DL(P) \), where \( C^s = \{ a \mid I(s) \models C(a) \} \) for primitive concepts \( C \), and \( R^s = \{ (a, b) \mid I(s) \models R(a, b) \} \) for primitive roles \( R \).

The description language \( DL(P) \) is usually enriched with goal modalities \( p_G \) of those predicates \( p \) that are used to define the goal of the problem [Khardon, 1999]. These, are, to all effects, additional primitive concepts and roles, whose denotation is fixed in all states \( s \) by the atoms appearing in the goal conjunction. We also limit nominal concepts in \( DL(P) \) to PDDL-level constants, which are those PDDL objects that by definition appear in all instances of the domain. Because of this, all problems of a same planning domain share the same description language, and we sometimes speak of the description language of a domain.

**Example.** Take as example the Spanner domain, where an agent moves along a corridor, and can pick up single-use spanners that are scattered along the corridor. These spanners are needed at the end of the corridor, where several nuts have to be tightened. The corridor is one-way, hence as soon as the agent leaves sufficiently many spanners behind, the problem becomes unsolvable. The PDDL encoding has a unary predicate tightened and a binary predicate at, representing the status of nuts and the position of the agent, spanners and nuts within the corridor, respectively. The PDDL types of
the original encoding can be compiled into unary predicates. The description language corresponding to this domain will hence have primitive concepts man, nut, spanner and tightened, and a primitive role carrying. The interpretation of these in a given state \( s \) represents sets of objects (for concepts) or object pairs (for roles) that satisfy some property in \( s \). Compound concepts allow us to represent complex sets of objects. The concept 3\( \text{at}^{-1}.\text{man} \), for instance, represents the set of all corridor locations with an agent in them, whereas tightened\(_{C} \cap \neg\text{tightened} \) represents the nuts that need to be tightened in the goal, but are not tightened in the current state. Both concepts have syntactic complexity 4.

3 Generalized Unsolvability Heuristics

We are interested in functions that take any state \( s \) of any instance in a given class \( Q \) of planning problems, and predict whether \( s \) is unsolvable. The next definition generalizes the one by Hoffmann et al. [2014]:

**Definition 1.** A generalized unsolvability heuristic for a class \( Q \) of planning tasks is a function \( h : \cup_{Q \in Q} sP \to \{0, \infty\} \). We say that \( h \) is safe whenever \( h(s) = \infty \) if \( s \) is unsolvable, and perfect whenever \( h(s) = 0 \) iff \( s \) is unsolvable.

**Example.** In the Spanner domain, a state is unsolvable iff the number of unused spanners that are carried by the agent or that can still be picked up is smaller than the number of nuts that still need to be tightened. Any function that returns \( \infty \) for a subset of these states is a safe unsolvability heuristic for the domain; any function that returns \( \infty \) exactly for these states is a perfect unsolvability heuristic.

3.1 Hypothesis Space

Because of their simplicity and interpretability, we focus on learning unsolvability heuristics represented by formulas in disjunctive normal form (DNF) over literals from a given language of the problem. When \( P \) is clear from context, we simply use \( \mathcal{F} \). Note that \( \mathcal{F} \) is well-defined for all domains represented in PDDL; the features it contains are tailored to the domain, but they are instance-independent, that is, well-defined in all states of all instances of the domain. This is key for generalization. Arithmetic comparison features such as \( |C| > |C'| \) and \( |C| = |C'| \) are a significant addition to the feature grammar used by Bonet et al. [2019] and in related work. In Spanner, for example, they could be used to compare the number of carried spanners with the number of nuts that need to be tightened.

3.2 Learning the Heuristics

We now present three different methods for learning unsolvability heuristics. All of them require two inputs: (1) a finite set \( \mathcal{F} \) of candidate features, and (2) a training set \( \mathcal{T} \) of states labeled as “solvable” or “unsolvable”. We denote with \( \mathcal{T}^+ \) the set of all states in \( \mathcal{T} \) that are unsolvable, and with \( \mathcal{T}^- \) the set of those that are solvable.

The \( \mathcal{T} \)-PERFECT Heuristic

We first consider a classifier that perfectly discriminates all unsolvable states from all solvable states in the training set \( \mathcal{T} \) with a DNF formula over literals from \( F \) that has minimum complexity. Here, we measure formula complexity as the sum of the complexities of all distinct features involved in the formula. Such a classifier might not exist if the features in \( F \) are not expressive enough. But when it does exist for a large enough training set, it is likely that it generalizes perfectly for the domain. We name this classifier \( \mathcal{T} \)-PERFECT, and call the DNF formula that it finds \( \varphi_{\mathcal{T} \text{-PERFECT}} \).

For fixed training set \( \mathcal{T} \) and candidate features \( F \), the computation of \( \mathcal{T} \)-PERFECT reduces to finding a set of features \( F^* \subseteq F \) with minimum complexity such that each pair of states \( s \in \mathcal{T}^+, \ t \in \mathcal{T}^- \) can be distinguished by at least one feature \( f \in F^* \) (that is, \( f^s \neq f^t \)). Formula \( \varphi_{\mathcal{T} \text{-PERFECT}} \) is then

\[
\varphi_{\mathcal{T} \text{-PERFECT}} \equiv \bigvee_{s \in \mathcal{T}^+} \bigwedge_{f \in F^*} L_{f,s},
\]

where \( L_{f,s} \) is the literal that describes the value of \( f \) in \( s \), i.e., the literal \( f \), if \( f \) is true in \( s \), and the literal \( \neg f \) otherwise.

We solve the problem of finding the set \( F^* \) with minimum complexity via a simple compilation to a Weighted Max-SAT problem \( \Phi(F, \mathcal{T}^+, \mathcal{T}^-) \). The problem \( \Phi(F, \mathcal{T}^+, \mathcal{T}^-) \) has a propositional variable \( \text{select}(f) \) for each candidate feature \( f \in F \), a soft clause \( \neg\text{select}(f) \) with weight equal to the complexity of \( f \) for each feature \( f \in F \), and a hard clause \( \bigvee_{f \neq f'} \text{select}(f) \) for each pair of states \( s \in \mathcal{T}^+, t \in \mathcal{T}^- \).
The resulting Max-SAT problem thus has $|F|$ variables and $|F| + |T^+| \cdot |T^-|$ clauses. Therefore, learning times grow in the worst case quadratically with the size of $T$ and exponentially with the size of $F$.

### 3.3 Learning Pipeline

To sum up, our learning pipeline consists of three steps: state labeling, feature generation, and heuristic learning.

**State labeling.** Taking as input a PDDL domain and some PDDL problems for the domain, we explore the (reachable part of the) state space of each instance by running a breadth-first search from its initial state. We add all visited states to the training set $T$, and label them as solvable if a goal state is reachable from them, and unsolvable otherwise.

**Feature generation.** Taking as input a PDDL domain, the set $T$, and two constants $k$ and $n$, we first generate up to $n$ description logic concepts with syntactic complexity at most $k$, prioritizing concepts with lower complexity. Then, we generate the set $F$ of all Boolean features in our feature space that can be derived from those concepts and also have syntactic complexity of at most $k$.

**Unsolvability heuristic learning.** Taking the features in $F$ and the labeled states in $T$, we compute a DNF formula over atoms in $F$ with one of the algorithms described above.

The entire pipeline is automated, and domain knowledge is only required for generating or selecting the problem instances that are taken as input to the first pipeline step. We describe this process in the next section.

### 4 Datasets

Before our empirical analysis, we describe the datasets used in our experiments. These are a contribution in their own right and were designed with the goal of being useful for other researchers. To generate the datasets, we need to select domains, problems from each domain, states from each problem, and then compute feature valuations for these states.

**Domains.** We consider six domains from previous International Planning Competitions (IPC): Barman, Childsnack, Hiking, Nомystery, Spanner and Woodworking. We use these domains because they contain unsolvable states and there are PDDL generators to create new instances of controlled size for them. Two of the domains, Hiking and Nомystery, contain predicates with arity 3. While it would be possible to reformulate the domain, we choose to simply ignore these predicates.

**Problems.** To label the states, we need instances that are (1) small enough to be explored completely with a breadth-first search, and (2) are as diverse as possible, to maximize the chances of generalization. Since IPC tasks are usually too large for (1), we use PDPL generators to generate new tasks. We choose suitable sets of (low) parameter values for
Table 1: Training and test sets. \( |F| \) is the number of generated features, \( k \) is the maximum feature complexity attained. For both sets, \( |P|, |T^+| \) and \( |T^-| \) show, resp., the number of instances used to generate the set, and the number of unsolvable and solvable states.

|         | \( |F| \) | \( k \) | \( |P| \) | \( |T^+| \) | \( |T^-| \) | \( |P| \) | \( |T^+| \) | \( |T^-| \) |
|---------|--------|------|------|------|------|------|------|------|
| Barman  | 83081  | 10   | 16   | 4110 | 4836 | 16   | 500  | 500  |
| Childsnack | 80617 | 12   | 13   | 2630 | 2542 | 12   | 500  | 500  |
| Hiking  | 75638  | 13   | 22   | 457  | 318  | 18   | 163  | 500  |
| Nomystery | 71719 | 16   | 24   | 677  | 24    | 24   | 500  | 500  |
| Spanner | 68417  | 15   | 18   | 74   | 318  | 18   | 163  | 500  |
| Woodworking | 40749 | 9    | 41   | 4954 | 4482 | 41   | 163  | 500  |

5.1 Experiment Setup

The methods \( T\text{-PERFECT} \) and \( T\text{-SAFE} \) use the Open-WBO Weighted Max-SAT solver [Martins et al., 2014] and the DECISIONTREE algorithm uses the Scikit-learn machine learning library [Pedregosa et al., 2011]. For all domains, we limit the feature complexity by \( k=16 \) and the number of concepts by \( n=80K \) in the feature generation step (see Section 3.3). We give each method a maximum of five hours to learn an unsolvability heuristic. We run \( T\text{-SAFE} \) as an anytime algorithm, but it only reaches the time limit for Barman and Nomystery. All source code, benchmarks and datasets are available online.\(^1\)

5.2 Domain-Independent Heuristics

The main focus of our work is to find out whether we can learn domain-dependent unsolvability heuristics that accurately characterize unsolvable states over whole domains. However, apart from this theoretical question, we are also interested in evaluating how such heuristics compare to existing domain-independent heuristics. The left part of Table 2 shows the recall on our test dataset for some heuristics from the literature: the causal graph heuristic \( h^{CG} \) [Helmert, 2004], the context-enhanced additive heuristic \( h^{CEA} \) [Helmert and Geffner, 2008], the state-equation heuristic \( h^{SEQ} \) [Bonet, 2013], the \( h^m \) heuristic for \( m \in \{1, 2, 3\} \) [Haslum and Geffner, 2000], and \( k\)-consistency [Bäckström et al., 2013] for \( k \in \{1, 2, 3\} \). Except for \( h^{CG} \) and \( h^{CEA} \), these heuristics are safe and hence guaranteed to have precision 1. Since the two unsafe heuristics have precision 1 on our test set, we only report recall for all of these heuristics.

Note that the data in Table 2 is obtained on small problem instances. Some of the heuristics are impractical to be used for larger tasks. For example, \( h^3 \) is very expensive to evaluate and rarely used in practice. We defer the comparison with more sophisticated unsolvability heuristics to a stage where we can directly compare their pruning power in a search on larger instances. This is because some of these heuristics, such as clause learning [Steinmetz and Hoffmann, 2017], are online learning approaches, while others, such as those based on abstraction heuristics [Seipp et al., 2016; Torralba et al., 2016], would yield perfect results on our small instances.

5.3 Domain Analyses

The right part of Table 2 presents the precision and recall of our methods on the test states, together with the size and maximum feature complexity of the DNFs. We next discuss the results for some of the domains.

Barman. In the Barman domain, a robot barman prepares cocktails with the help of shot glasses and a shaker. Unsolvable states in this domain are related to incorrect combinations of drinks in the shaker, which prevent the barman from preparing the right cocktail and, somewhat counterintuitively, prevent it from emptying the shaker as well. Of the standard heuristics that we test, \( h^2 \) and \( h^3 \) capture all unsolvable states in our test set, \( h^1 \) and \( h^{CEA} \) capture 88% of them, and the rest have low or zero recall. Among our heuristics, \( T\text{-PERFECT} \) is

\(^{1}\) https://doi.org/10.5281/zenodo.4740386
Unable to obtain a formula in less than five hours, and \( \mathcal{T} \)-SAFE computes a formula that does not generalize correctly, showing imperfect precision. Although \( \mathcal{T} \)-SAFE has no guarantees of being safe on the training set, it finds a classifier with both high precision and recall.

**Childsnack.** In the Childsnack domain, sandwiches need to be prepared for a number of children, some of which are allergic to gluten. The key for that is to reserve enough gluten-free ingredients to serve the gluten-allergic children. It is easy to forecast a gluten allergy. The key for that is to reserve enough gluten-free ingredients to serve the gluten-allergic children. It is easy to forecast a gluten allergy.

The formula says that a state is unsolvable iff the number of loose nuts is larger than the number of spanners that is usable (i.e., has not yet to be tightened). Since both sets are always disjoint, \( \varphi \) will evaluate to true if the number of loose nuts is larger than the number of spanners that is usable (i.e., has not yet been discarded) and reachable. The formula can be proven a perfect characterization of all unsolvable states in the domain. This result and the simplicity of the formula are in stark contrast with the fact that Spanner is consistently hard for all the heuristic approaches in the left part of Table 2. Only \( h^3 \) captures a significant fraction of the unsolvable states in our test set (31\%), whereas the other approaches capture only between 0 and 13\%. This is no surprise, as Spanner is a well-known example showing the limitations of delete-relaxed heuristics in problems with consumable resources [Haslum and Geffner, 2001]. The accuracy of our methods illustrates the advantages of a first-order approach.

### 6 Conclusions

We studied the problem of learning unsolvability heuristics that work for entire classes of planning problems, from the exploration of a few small instances of that class. Our heuristics are simple logical and arithmetical combinations of features that are defined in the same language that is used to specify the planning task and can be generated without manual intervention through the exhaustive application of a standard description-logics grammar. We presented three different algorithms, each with different properties regarding optimality, classification power and learning time. Our evaluation of these algorithms on a number of standard domains shows that the logical characterizations of unsolvability that they learn not only often have strong predictive power, but in some cases can be proven perfect for the entire domain. This is remarkable, as many of the existing heuristics fail to detect many unsolvable states in our dataset.

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