Abstract

Recently, the D3WA system was proposed as a paradigm shift in how complex goal-oriented dialogue agents can be specified by taking a declarative view of design. However, it turns out actual users of the system have a hard time evolving their mental model and grasping the imperative consequences of declarative design. In this paper, we adopt ideas from existing works in the field of Explainable AI Planning (XAIP) to provide guidance to the dialogue designer during the model acquisition process. We will highlight in the course of this discussion how the setting presents unique challenges to the XAIP setting, including having to deal with a different user persona as the domain modeler rather than the end-user of the system, and consequently having to deal with the unsolvability of models in addition to explaining generated plans.

Introduction

The state of the art (Sreedhar 2018) in the design of sophisticated goal-directed conversational agents – e.g. for applications such as customer support – requires the dialogue designer to either manually specify the entire dialogue plan (e.g. Google Dialogue Flow or Watson Assistant) or train end-to-end systems from existing logs of conversation. The former, of course, becomes intractable pretty soon which means conversational agents of any reasonable sophistication are still comfortably out of reach (Computer Generated Solutions 2018); while the latter provides no control over the emergent behavior of the agent, as seen in the infamous deployment of “Tay” (Metz 2018), and are thus unusable in the enterprise scene where customer experience has to be guaranteed to a reasonable certainty.

The topic of making the design of conversational agents easier for the dialogue designers – especially the task of making the specification of the conversation flow more tractable – remains of immense interest (Amazon 2019; Google 2019) to the AI community, and consequently to the world of automated planning as well due to its unique value proposition in the declarative specification of agents and the composition of higher order behavior from it. For example, recently authors of (Muise et al. 2019a; Botea et al. 2019) proposed a planning-based approach to bring down the effort in specification of such agents. These works present a paradigm shift in how goal-directed conversational agents can be designed using automated planning technology, demonstrating a tight synergy of symbolic and non-symbolic AI techniques to achieve a fully functional embodiment of reasoning, learning, and natural language processing under the same roof. We build on this work here and hence start with a brief description of the same below.

A Brief History of D3WA

At the core of the declarative specification proposed in (Muise et al. 2019a) is an agent-centric view of the world – the dialogue designer specifies “capabilities” that are available to an agent and lets a non-deterministic planner generate (Muise, McIlraith, and Beck 2012) and execute (Muise et al. 2019b) the composed dialogue plan in the background. The authors of that work demonstrated in ICAPS 2019 (Chakraborti et al. 2019b) how this can lead to exponential scale-up from the size of the specification to the complexity of the composed agent, as an illustration of the exciting fusion of planning based technologies (especially non-deterministic planning) and the design of dialogue agents. This is especially useful in the design of certain kinds of conversations, especially ones with an underlying process – e.g. a business process (Anonymous 2020) – that drives the conversation. However, it turns out that while this provides a powerful tool for an experienced domain writer with expertise in planning, and declarative programming in general, for the uninitiated it presents too steep a learning curve. In particular, since the designers no longer explicitly compose the dialogue plan, they lose control over the composed agent if they do not grasp the imperative consequences of their declarative specification.

In this paper, we thus build on this work with the aim of making the core domain authoring engine more amenable to dialogue designers who are usually outside the planning community and do not readily subscribe to the declarative mental model. In order to do so, we build upon recent techniques from the explainable AI planning (XAIPI) community (Hoffmann and Magazzini 2019) to bridge the gap with the end user. Before we get to the specific contributions of this paper, we start with a brief introduction to D3WA so as to make the rest of the presentation self-contained.
Actions, Outcomes and Context Variables  The original system D3WA is illustrated in Figure 1. The interface surfaces two key elements to the dialogue designer: 1) context variables that model the agent’s world; and 2) actions that are defined in terms of these variables. For a dialogue agent, these actions model the different capabilities available to it in terms of dialogue actions towards the end user, or internal system actions such as API calls or logical inferences.

Each action – as shown in Figure 1 – has a set of NEEDs (or preconditions) and a set of OUTCOMEs which house a set of non-deterministic UPDATEs to a variable. The outcomes within an action are mutually exclusive. For example:

1. Dialogue Action: If the agent wants to ask the user their name, the corresponding dialogue action would have one outcome when the user responds with their name, and another one that models a digression in the conversation.

2. System Action: In order to make an API call, the agent would require as NEEDs, access to the link and the relevant payload. Two possible outcomes of the call may be a successful response (in which case the agent updates the values of the relevant variables it was looking for) or a 404 error (in which case the agent gets nothing).

A non-deterministic planner receives this specification, plans for all possible outcomes, and generates the resulting dialogue plan in Figure 2e. This offline approach has two advantages: it allows the dialogue designer to inspect and sign off on the agent to be deployed, while also being able to support complex dialogues without having to plan and replan in real time. For more details on D3WA, and on how this specification is compiled to a planning problem in the background, we refer the reader to (Muise et al. 2019a).

Proposal: D3WA+

The proposed “explainable” version of D3WA – henceforth referred to as D3WA+ – provides a suite of debugging tools on top of the core model acquisition framework aimed to make the dialogue designer more self-sufficient when they are faced with modeling errors. Specifically, based on difficulties observed during preliminary internal testing, we tackle two core issues faced frequently by dialogue designers grappling with the declarative paradigm:

- **Specification cannot be solved by the planner.** This is the case when the graph in Figure 2e does not appear at all, and the dialogue designer is left with an inscrutable “no solution found” message and nothing else to work with. Our goal here is to surface features from the current specification back to the designer so that they can fix the root cause of the unsolvability.

- **Solution does not match expectations.** Here, the problem is solvable but the solution does not match the designer’s expectations – i.e. the graph in Figure 2e looks nothing like what they were aiming for. The goal here for us is to be able to respond to questions from the designer such as Why is this a solution? and Why is this not a solution?, so that they can modify the specification accordingly until they are satisfied with the outcome.

Some of these questions might look familiar with the line of investigation in (Smith 2012; Fox, Long, and Magazzeni 2017; Cashmore et al. 2019). However, the setting here involves the domain designer and not an end user. Thus the suite of challenges not only include the unsolvability question, not addressed in those works, but also the explanatory dialogue here is geared towards the model acquisition task rather than the exploration of the decision making process.

Contributions

- We formalize the XAIP problem for the model acquisition scenario and illustrate the salient challenges involved on a tool for the design of goal-directed conversational agents.

- To this end, we motivate how the XAIP framework must also consider the unsolvability problem in addition to the explanation of generated plans, as has been mostly focused on in existing literature.

- We build on recent work in explaining unsolvability of classical planning problems (Sreedharan et al. 2019) and extend it to handle non-determinism as required by the particular tool under consideration.

- We demonstrate the usefulness of the approach via illustrations and empirical evaluations.

Note that, while unsolvability has been explored before, such as in the generation of excuses (Göbelbecker et al. 2010) (which focus on counterfactuals that are not necessarily useful for the domain acquisition task) or in the generation of certificates(Eriksson, Röger, and Helmert 2017) (which are mostly only machine consumable), here we are concerned primarily with assisting a domain writer who needs an easily understandable explanation of unsolvability rather than a certificate for verification or an excuse that does not provide any insight on how to fix their specification.

**XAIP for Model Acquisition**

We now formalize the notion of explainable planning in the context of model acquisition, particularly extended to non-deterministic planning used by the tool in our case study.
Planning Problems

A planning problem $\Pi : \mathcal{M} \mapsto \{\pi\}$ takes in as input a model $\mathcal{M} = (\mathcal{F}, \mathcal{A}, \mathcal{I}, \mathcal{G})$ where $\mathcal{F}$ is a set of propositions that describe the state of the world and we will use $\mathcal{S}$ to represent the set of possible states that can be constructed from $\mathcal{F}$, $\mathcal{A}$ is a set of operators or actions available to an agent and produces a set of states $\pi$ that transform the initial state $\mathcal{I} \subseteq \mathcal{F}$ to the goal state $\mathcal{G} \subseteq \mathcal{F}$.

- For a deterministic model, each action produces a single next state: $A \ni a : S \rightarrow S$. The solution to a deterministic problem are plans represented as a sequence of actions.
- The execution of a non-deterministic action $A \ni a : S \rightarrow \{S\}$ can result in more than one possible state. The solution to a non-deterministic planning problem $\Pi$ is thus a contingent plan which induces a set of plans. The behavior of the agent is described by one of those plans depending on which outcomes occur at the time of execution.

Since we are primarily concerned here with goal-directed agents (e.g. goal-directed conversations), we consider the space of behaviors represented by $\Pi(\mathcal{M})$ as the solution space. The discussion generalizes to a “space of plans” enabled by a domain in the absence of a goal or initial state. Throughout the paper, we will refer to a non-deterministic problem as having a plan if a weak solution exists (Cimatti et al. 2003) – i.e., there is some sequence of actions and outcome selections that achieves the goal.

Transformations on $\mathcal{M}$

We now introduce a few operations in the space of models that we will deploy later to tackle the various challenges in model space reasoning for XAIP and model acquisition.

Model Edits  
Model edits $\delta : \mathcal{M} \mapsto \mathcal{M}'$ (Keren et al. 2017; Chakraborti et al. 2017) change one or more conditions in the model to generate a new model. For example, this could involve adding or removing a condition from the initial or goal state or from the set of preconditions and effects of an action. Search in the space of models propagates by the application of one or more such model edits. The size of a model edit is denoted by $|\delta|$.  

Abstractions  
Abstractions $\text{Abs} : \mathcal{M} \times \mathcal{P} \mapsto \mathcal{M}'$, on the other hand, simulate a collection model edits together that change one or more features of the model (Clarke et al. 2000). Here $\mathcal{P}$ is the set of variables that can be projected away. For example, authors in (Sreedharan, Srivastava, and Kambhampati 2018) use this technique of syntactic state variable projection to determine the right level of abstraction to present explanations in, while in (Sreedharan et al. 2019) authors use the same technique to explain unsolvability. We build on the latter in this paper, particularly extended in service of non-deterministic planning used in the tool under study. We will go into more details of this later.

Determinisation  
Determinisation is the process of turning a non-deterministic model $\mathcal{M}$ into a deterministic one $\text{Det}(\mathcal{M})$ – e.g. an “all-outcomes” determinisation scheme (Yoon, Fern, and Givan 2007) transforms an action $a : S \rightarrow \{S_i\}$ into a set of actions $\forall i a_i : S \rightarrow S_i$ so that all the outcomes of an action with non-deterministic effects can be realized in the determined model. With the fairness assumption (Cimatti et al. 2003), a solution to $\text{Det}(\mathcal{M})$ is also a valid behavior for $\mathcal{M}$, i.e. $\Pi(\text{Det}(\mathcal{M})) = \Pi(\mathcal{M})$.

Plan Preservation  
The model transformation $\text{Obs} : \mathcal{M} \times \{\pi\} \mapsto \mathcal{M}'$ receives a model and a (partial) sequence of actions (equivalent to a set of possible plans) and produces a compiled model where this sequence must be preserved, i.e. $\{\pi\} \subseteq \Pi(\mathcal{M}')$. In the past, such techniques have been used in the compilation of the goal recognition task into a classical planning problem (Ramírez and Geffner 2009) or in the construction of partial foils from the end user for the purposes of explanation (Sreedharan, Srivastava, and Kambhampati 2018). In the preservation technique used here for deterministic models, we allow for partial observation of non-determinism as well, in addition to the usual partial plans, in order to account for the specific needs of the tool under study. This means that an action may be specified in a plan but its outcome may be left unspecified.

The xMAS Problem

Explanations in the context of the model acquisition task provide a unique twist to a well known framework in XAIP – model reconciliation (Chakraborti et al. 2017). There, the task is to compute, given the agent model, the mental model, and a plan to explain, a set of updates that when applied to the mental model would render the given plan optimal (and hence without any foil) in the updated mental model.

Here also, we have two models – the one currently specified by the domain writer or the revealed model, and the one that they wanted to specify or the mental model. Furthermore, similar to the case of model reconciliation process, here too we have model differences – the revealed model and the mental model do not match due to mistakes made by the domain writer. However, unlike in the case of explanations in the model reconciliation framework, the target here is for the explainable system to transform the revealed model to the mental model, and not update the mental model to agree with the revealed model as focused on traditionally in the model reconciliation framework.

This process is iterative with the human (domain writer) firmly in the loop. This is because, unlike in standard model estimation tasks where the features of the model are known, here the problem is open ended as the domain writer gradually builds their agent model. Thus, the model acquisition task is strictly not one of estimation of the mental model.

An Explainable Model Acquisition Setting  
$\text{XMAS}$ is defined by the tuple $\Psi = (\mathcal{M}, M^H)$ where $\mathcal{M}$ is the revealed model and $M^H$ is the mental model of the domain writer.

Since the eventual goal of writing a domain is to enable a desired set of behaviors, and there may be many ways to specify the same agent behavior, we condition the end goal of an $\text{XMAS}$ in terms of the space of plans afforded by the agent model that is being specified. The solution to $\Psi$ is a sequence of model updates $\Delta = (\delta_1, \delta_2, \ldots, \delta_n)$ such that:
The point here is to find the most complete simplification of the model where a solution exists and illustrate — for example, using VAL (Howey, Long, and Fox 2004) — to the user why that solution does not apply to M. The domain writer could also use this sample plan to explore where exactly a possible solution becomes invalid in the current specification, or even use it as a jumping off point to create more complex foils to investigate further.

3. Subgoals and Landmarks In addition to presenting the abstractions and an exemplary plan failure, we can further help the domain writer debug the problem by presenting them with a subgoal that is necessary for achieving the goal in the current specification but cannot be achieved. This is meant to serve as a prompt for the domain writer for a possible issue to focus on. We follow (Sreedharan et al. 2019) and use landmarks (Hoffmann, Porteous, and Sebastia 2004) for identifying such subgoals.

The earlier work constructs landmarks from models that are more abstract than the minimally unsolvable model but this can lead to less informed subgoals as it may not be considering many of the state factors. We will instead extract landmarks directly from the minimally unsolvable model using the following proposition:

**Proposition 1** If M is unsolvable, and Abs(M, P) is solvable while Abs(M, P ∪ {f}) is not, then either the delete relaxation of Abs(M, P ∪ {f}) is solvable or there must be an unmet landmark corresponding to f.

This follows from the fact that in the abstraction scheme we follow, when we consider the delete relaxation of Abs(M, P ∪ {f}) over that of Abs(M, P), the only possible differences can be that f may be part of preconditions and adds for an action. If this addition makes the delete relaxation unsolvable then that means that all relaxed plans for

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1Note that we cannot generate a plan from a minimal unsolvable abstraction since there are no solutions there. One possibility would be to choose a model more abstract than the minimally unsolvable one. Unfortunately, these models would ignore most model features and provide no useful plan for the user to debug.

2To improve the efficiency of the search, we will restrict the search for abstraction set over subsets of (F \ P_{min}) ∪ G (where P_{min} is minimum abstracting set). Since the abstraction techniques followed here guarantees that abstractions formed from supersets of P_{min} ∪ G will not result in solvable model. Moreover if P_{min} is the only subset of fluents leading to the unsolvability then (F \ P_{min}) ∪ G should automatically be a solvable domain. So we will start our search from (F \ P_{min}) ∪ G and will look at systematically relaxing the model until we get a solvable one. We evaluate this approximation against the exact approach in our evaluations.
**Q2. Why is this not a solution?**

This is the case when (for a set of plans \( \{ \pi \} \) presented by the domain writer): \( \{ \pi \} \subseteq \Pi(M^H) \) but \( \{ \pi \} \not\subseteq \Pi(M) \). This is really a special case of Q1 – we perform the following transformation to solve this:

Set: \( M \leftarrow \text{Obs}(M, \{ \pi \}) \)

If: \( \Pi(\text{Obs}(M)) \neq \emptyset \) (the compilation is solvable) then demonstrate to the user that for every \( \pi \in \Pi(\text{Obs}(M, \{ \pi \})) \):

\[
\text{cost}(\pi) > \text{cost}(\pi_i) \quad \forall \pi_i \in \{ \pi \}\]

this means that the foil is not better than anything else already in the solution. At this point, the user can ask Q3.

Else: Follow Q1 with \( M \).

Note that we cannot run VAL directly on the foil since: 1) It is very unlikely that the domain writer will provide full foils – this is largely due to the effort required in doing so but also uniquely infeasible for the current setting of dialogue design since internal system actions such as web calls and logical inferences are not part of logs that are used to stress test the design of the agent; and 2) in the case of a partial foil, \( \text{Obs}(M) \) may not have a solution to run VAL with.

**Q3. Why is this a solution?**

This is the case when (for a set of plans \( \{ \pi \} \) presented by the domain writer): \( \{ \pi \} \not\subseteq \Pi(M^H) \) but \( \{ \pi \} \subseteq \Pi(M) \). Here, the domain designer is surprised that a solution they considered valid for \( M \) is really a special case of \( M^H \) and there must exist an outcome \( o^a_i \) for \( a_i \) such that \( S_{i+1} = (S_i \setminus \text{dels}_{o^a_i}) \cup \text{adds}_{o^a_i} \). Then there must exist a corresponding transition \( \langle S_i \setminus \text{dels}_{o^a_i}, a_i, S_{i+1} \setminus \text{adds}_{o^a_i} \rangle \) that is valid for \( \text{Abs}(M, \{ \pi \}) \) with an outcome \( o^a_i \).

With these tools in place, we can generate explanations described in earlier sections by doing a search over the space of non-deterministic models. Though it would be easier if we could just focus on settings where we are testing solvability of classical planning model and extracting subgoals from these simpler models. We can in fact do this, by showing that all of our explanation generation procedures can be performed on the determinised version of the original non-deterministic model. Specifically, we will show that the abstraction of a determinised model is the determinisation of the abstracted non-deterministic model:

**Proposition 2** Given a non-deterministic model \( M \) and a set of fluents \( P \): \( \text{Det}(\text{Abs}(M, \{ \pi \})) = \text{Abs}(\text{Det}(M), \{ \pi \}) \).

The determinised model will contain an action for each possible outcome, i.e. \( \forall o^a_i, \text{Det}(M) \) contains an action \( a_n = \langle \text{prec}^a, \text{adds}_{o^a_i}, \text{dels}_{o^a_i} \rangle \). So the projection of this determinised action will be \( \langle \text{prec}^a \setminus \text{adds}_{o^a_i} \setminus P, \text{adds}_{o^a_i} \setminus P, \text{dels}_{o^a_i} \setminus P \rangle \), and you would get the same action if you were determining based on projected \( o^a_i \).

**Illustrations on D3WA+**

We will now illustrate each of the use cases covered above on our tool D3WA+. In the context of the design of dialogue agents using planning, each “solution” is a potential conversation path allowed by the agent design. Hence, the model acquisition process is one of the dialogue designer ensuring which conversations are allowed and which are not.

**Video link** – While we attempt to illustrate as much of the use cases as possible in the limited space available here, please refer to the video in the supplementary attachment for a more detailed walkthrough. The video is also accessible online at: https://bit.ly/2KE7sPx. (Duration: 7min 55sec excluding explanation generation time reported in Table 1)

**Car Inspection Bot** For purposes of illustration, we consider the design of a conversational agent tasked with helping in the inspection of a car. This domain is adapted from (Muise et al. 2019a) as a typical demonstration of the design of conversational agents using automated planning techniques. The final dialogue plan as seen in Figure 2e, has 63...
nodes and 272 edges and is thus quite comfortably out of scope for the state of the art in dialogue design. The declarative specification as seen in Figure 1, on the other hand, has just 8 variables and 7 non-deterministic actions. Let us consider the following dialogue in this domain:

Bot: Ready to record.
User: Break pads pass.
Bot: Ok, break pads pass.
User: What’s next? <-- initiative switch!
Bot: Check the spark plugs.
User: What are the options.
... Bot: Inspection complete!

The interesting part is the potential for initiative switch during the conversation – either the user can go through all the parts by themselves or hand over control to the bot to guide them, or a combination of both. 3 The salient feature of the specification is thus: there is a catch-all dialogue action to respond to the user when they have initiative and a set of actions to ask the user for information when the bot has initiative. There is one outcome in all these actions that

3The complete specification is provided both as a supplementary file and online at: https://bit.ly/2NYHgRU.

switch initiative based on what the user has said, while the other outcomes update the state of the inspection by logging the correct variables based on the user utterance. Next, we follow the designer’s journey to get to this specification.

Q1. Why is there no solution? In our user story, the designer has forgotten to add a few critical domain conditions – the OUTCOME for the initiative switch is missing in the catch-all action while the UPDATE for spark plugs is also missing in the corresponding OUTCOME (refer back to the introduction to D3WA for a refresher of this modeling artifacts). As a result the model has become unsolvable – there is no way for either the inspector or the bot to drive the initiative and visit all the parts. In Figure 2a the user is presented with the minimal abstraction where the model is unsolvable. They fix this simpler specification to arrive at the solution in Figure 2b. The fix – adding the UPDATE for spark plugs – when applied to the original specification takes the designer from Figure 2c to 2e. This interaction with D3WA+ allowed the user to find a fix for an unsolvable model by inspecting a much simpler model.

Q2. Why is this not a solution? However, the missing OUTCOME for the initiative switch in the catch-all action
is still missing. As a result, all solutions right now only involve the user driving the conversation and the resulting solution in Figure 2c looks different from what the designer was expecting – i.e. it does not contain any conversation flow where the bot has initiative. The domain writer expects the sample conversation to be possible but do they know it’s unsolvable, at all? In the spirit of XMAS, the domain writer gets to query D3WA+ with this foil – see Figure 3. The system again responds with a minimal abstraction to fix, along with a sample plan and an unachieved landmark in the maximally solvable abstraction illustrating why that foil fails in the current model. This not only explains the unsolvability but also provides powerful directive to fix the model.

Empirical Evaluations

We empirically investigate the properties of XMAS in terms of the size of the abstractions relative to the size of the original specifications, and the time taken to generate them. We focus on Q1 here since the properties of the solutions to Q2 are derived from Q1 while, as we mentioned before, Q3 is already quite well understood in existing literature.

Test Domains To test out the empirical properties of our approach, we use two new domains, in addition to the car inspection domain used in the illustrative examples. The first of them – Data Doppelganger – is an assistant chat-bot that helps a user perform variety of data science tasks, such as plotting a graph, given a data set. The last domain – Credit Card Recommendation – is again adopted from (Muise et al. 2019a), and takes the user through choices of credit cards and their features until the user makes a selection.

To evaluate the effectiveness of XMAS, we needed to evaluate the systems on plausible mistakes on these test domains. For Table 1, we tried to create unsolvable problems for the first three domains by removing three model conditions at random. Specifically, we deleted adds and initial states from the model. Unfortunately, for the credit card domain randomly removing a subset of model components weren’t yielding unsolvable problems. So instead, we went with a unique domain-specific mistake for each of the five cases. Each mistake was centered around the domain author missing adds for a specific outcome or initial state for a specific proposition. After identifying a reason for unsolvability, we further delete two additional adds per unsolvable instance. The solvability of the determinized problems was tested using FastDownward (Helmert 2006) implementation of A* and LM-Cut (Helmert and Domshlak 2009). The landmarks were extracted using FastDownward implementation of (Keyder, Richter, and Helmert 2010) with m = 1. All experiments had a timeout of 60 mins.

Model Compression Table 1 shows the amount of compression offered by the abstraction, against the size of the full models, for five randomly generated unsolvable instances. Here the size of each possible model is reported in terms of the number of non-goal fluents that are part of it (|P|), the number of model conditions that are part of the problem (denoted as size in the table) and the percentage of model conditions remaining as compared to the original domain model (denoted as ‘size in %’ in the table). The larger the compression, the easier we make it for the domain writer.

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4We want to impress on the reader at this point that this discussion of “mistakes” or missing components are in hindsight – the target model does not exist until the domain designer gets there.

5p5 for credit card domain timed out (removed from Table 1).
to understand the cause of unsolvability, as has been established in existing literature (Sreedharan et al. 2019). Clearly, we are able to significantly reduce the size of the specification for this purpose using the proposed abstraction approach. For the credit card domain, where the original model contains close to 2k components, being able to focus on a subset containing only 5 conditions is a massive reduction.

**Maximal versus Minimal Abstractions** Table 1 also shows the difference in size of the plans in the minimal⁶ and maximal abstractions. As we mentioned before, this was a specific design choice made so as to ensure that the domain writer has a reference point while inspecting an unsolvable model – they can use this either to debug the current model or to explore newer foils. The point of computing this reference point in the maximal as opposed to the minimal model (as evident from Table 1) is to provide more helpful debugging information to the domain writer – XMAS is not just about explaining unsolvability but also completing the model acquisition task. The reference point uses the maximal model in order to make sure maximal number of model features are considered so that the generated foil is as close as possible to a plan the user might be looking for in \( M_H \).

In Table 1, we refer to generating maximal model by starting from abstraction corresponding to \( P \setminus P_{min} \) while the exact one refers to a systematic search starting from the most concrete domain to one where it is solvable. While search for maximal model was in general fast, we can see that the approximate method is much faster and finds models that are quite comparable to the exact minimal solution.⁷

**Model Evolution** In Table 2, we illustrate the evolution of the size of the abstractions as the domain writer progress-

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**Table 1: Empirical properties of XMAS in three typical conversational domains modeled in D3WA.**

<table>
<thead>
<tr>
<th>problem</th>
<th>maximal abstraction (approx)</th>
<th>maximal abstraction (exact)</th>
<th>minimal abstraction</th>
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<tbody>
<tr>
<td></td>
<td>size</td>
<td>time</td>
<td>plan</td>
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</table>

⁶Note that since the minimal model is also unsolvable, the plans used here for comparison are from the models that are one abstraction simpler than the minimal unsolvable model.

⁷An interesting course of investigation in the future would be adopting the considerable body of work in the determination of dead ends during planning (Steinmetz and Hoffmann 2017; Muise 2014; Kolobov, Mauam, and Weld 2010) for XMAS. While our motivation here is user facing and is thus quite different to those works – i.e. we want to use abstractions to facilitate explanations, particularly in the model acquisition task, rather than speed up planning – it would be interesting to explore whether those techniques can speed up the explanation generation step in the future.

**Table 2: Size of abstractions along the entire model reconciliation process during the model acquisition task.**

<table>
<thead>
<tr>
<th>problem</th>
<th># edits</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>p0</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>p1</td>
<td>2</td>
<td>47</td>
<td>49.477</td>
<td>51</td>
</tr>
<tr>
<td>p2</td>
<td>40</td>
<td>152.989</td>
<td>51</td>
<td>193.358</td>
</tr>
<tr>
<td>p3</td>
<td>40</td>
<td>184.747</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

**Conclusion**

In this paper, we formulated the explainable planning challenges in model acquisition tasks and demonstrated them in the context of a tool for the design of goal-oriented conversational agents using automated planning. Perhaps one of the most compelling aspects of our work is how powerful planning techniques and concepts themselves can be in helping with the acquisition of planning specifications to begin with. Going forward, we intend to evaluate the approach with a wide base of seasoned dialogue designers. This is a significant undertaking since one must design the interface carefully in order to separate confounds that can mix up whether the designers could grasp the declarative mental model or not with indicators of whether the explanations themselves proved to be useful during debugging. While we laid the theoretical foundations of XMAS here, UX design is out of scope for this work. We hope to report on the results of investigation in that direction in the future.