Finding Counterfactual Explanations through Constraint Relaxations

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Abstract

Interactive constraint systems often suffer from infeasibility (no solution) due to conflicting user constraints. A common approach to recover infeasibility is to eliminate the constraints that cause the conflicts in the system. This approach allows the system to provide an explanation as: “if the user is willing to drop out some of their constraints, there exists a solution”. However, one can criticise this form of explanation as not being very informative. A counterfactual explanation is a type of explanation that can provide a basis for the user to recover feasibility by helping them understand which changes can be applied to their existing constraints rather than removing them. This approach has been extensively studied in the machine learning field, but requires a more thorough investigation in the context of constraint satisfaction. We propose an iterative method based on conflict detection and maximal relaxations in over-constrained constraint satisfaction problems to help compute a counterfactual explanation.

Introduction

In the long-standing history of constraints, an explanation often strives to interpret the reasons for an infeasible scenario. This interpretation mostly depends on the identification of minimal conflicts (or minimal unsatisfiable subsets). Conflicts have been studied extensively in areas such as model-based diagnosis, Boolean satisfiability, product configuration, solving logic puzzles, interactive search, etc., where the user constraints play an important role (Gupta, Genç, and O’Sullivan 2021). For instance, in the context of model-based diagnosis, if an observed outcome is not what was expected, then the goal is to provide an explanation to help understand which sets of conditions led to that unexpected outcome. Similarly, when solving a scheduling problem, an explanation can provide insights to why the given problem is not feasible under the provided sets of background and foreground constraints, and removing which set of constraints can provide a relaxation to the problem such that one can find a feasible solution. However, it is important to note here that these explanations are not always produced for the user, but sometimes produced for speeding up the search or debugging for the developer.

Recently, the need for user-centered explanations in AI has substantially increased due to several important factors such as the black-box nature of complex AI applications, the right to explanation of a decision in the EU’s General Data Protection Regulations (Parliament and Council of the European Union), and the development of Trustworthy AI for building trust between AI and the society (High-Level Expert Group on AI 2019). To address this issue, Wachter et al. proposed to use counterfactuals from philosophy, and adapt them to the AI domain to explain algorithmic decisions (Wachter, Mittelstadt, and Russell 2017, 2018). They describe a counterfactual explanation as a statement that explains the minimal change to the system that results in a different outcome. By providing counterfactual explanations, it is expected to improve the understandability of the underlying model, and support decision-making process of the user.

A counterfactual explanation seeks to provide a minimal explanation to a question of the form: “Why is the outcome X and not Y?” (Wachter, Mittelstadt, and Russell 2018). To illustrate, consider a constraint system that aims to solve the course timetabling problem at a university. The dedicated admin staff runs the timetabling system to obtain a feasible timetable. However, a lecturer, who is used to teaching their assigned course on Mondays, asks the admin: “Why is my Course A scheduled to Friday instead of Monday? I cannot attend lectures on Fridays due to travel.”. In order to accommodate this user constraint, which was not a part of the system before, the admin can add this new information to the system as a background constraint to ensure it is not violated. However, adding the new constraint may cause an infeasible state in the system. To recover from this situation, the admin can follow a traditional conflict elimination mechanism, which involves finding a set of constraints to relax so the conflicts in the problem are removed. Alternatively, the system can provide a counterfactual explanation that explains: “If you move Course B from Monday to Tuesday, you can schedule Course A on Friday.”. Note that, if the user’s request does not cause an infeasibility, alternative explanations can be considered such as: “Given the new constraint, an alternative schedule can be found at an extra cost of X.”.

Counterfactual explanations have recently been adapted to optimization problems (Korikov, Shleyfman, and Beck 2021). We discuss relevant work in more detail in the Re-
lated Work section. We then propose a new approach to finding a counterfactual explanation based on identifying conflicts and maximal relaxations, demonstrate our model on a configuration problem, and conclude with a discussion and identification of some future directions.

Related Work

Our work focuses on explanations in the constraint satisfaction branch of AI working with a multi-point relaxation system. Infeasibility in constraint systems may cause an enormous cost at an industrial level, which includes customer dissatisfaction. Hence, explanation generation has been a very active and interesting topic. The existing work on this topic has mostly focused on identification conflicts in the constraint satisfaction literature and also other relevant areas such as Boolean satisfiability (Gupta, Genc, and O’Sullivan 2021, Marques-Silva and Mencl 2020). In this paper, we propose to adapt counterfactual explanations to constraint-based systems. Up to date, counterfactual explanations are mostly studied under the XAI branch of machine learning systems and attracted a lot of attention.

In 2017, Wachter et al. proposed to use counterfactual explanations as a way to provide a minimal amount of information capable of altering a decision without understanding the internal logic of a model (Wachter, Mittelstadt, and Russell 2017, 2018). In a recent survey paper on counterfactuals in XAI, Keane et al. (2021) presented a detailed analysis of 100 distinct counterfactual methods and their overall evaluation and shortcomings along with a roadmap to improvement. They highlighted that only a few of these approaches are supported by user evaluations. Similarly, Miller argued that in explainable AI, a ‘good explanation’ is usually defined by the researchers, but the social science dimension to this definition is not explored well (Miller 2019). Miller characterised explanations as contrastive, selected in a biased manner, social (i.e. transferring knowledge), and not completely based on probabilities (the most likely explanation is not necessarily the best explanation).

Explanation generation in constraint satisfaction is usually achieved by identification of minimal conflicts (or minimal unsatisfiable subsets), or maximal relaxations (Junker 2001, Lifitton and Sakallah 2005, O’Sullivan et al. 2007). Despite the long-standing history of explanation generation in constraint satisfaction, the notion of counterfactual explanations is a relatively new and interesting topic. However, there exist a few relevant studies that discuss related notions such as contrastive and abductive explanations in Boolean satisfiability. As an example, Ignatiev et al. have a number of studies at the intersection of ML and SAT (Ignatiev et al. 2018, 2020). Their work discusses different types of explanations, such as local abductive (answering “Why prediction X?”) and contrastive explanations (answering “Why not?”). More specifically, the authors discuss how recent approaches for computing abductive explanations can be exploited for computing contrastive(counterfactual) explanations. Their findings highlight an important property that the model based local abductive and contrastive explanations are related by minimal hitting set relationships (Ignatiev et al. 2020). More recently, Cooper and Marques-Silva investigate the computational complexity of finding a subset-minimal abductive or contrastive explanation of a decision taken by a classifier (Cooper and Marques-Silva 2021). The authors define the explanation notions analogous to Ignatiev et al. (Ignatiev et al. 2020).

In parallel, Cyras et al. present an extensive overview of various machine reasoning techniques employed in the domain of XAI, in which they discuss XAI techniques from symbolic AI perspective (Cyras et al. 2020). The authors classify explanations into three categories. These are namely attributive, contrastive, and actionable explanations. Subsequently, they discuss the links between these explanation notions and the existing notions in symbolic AI by covering many different topics such as abductive logic programming, answer set programming, constraint programming, SAT, etc. They discuss that contrastive explanations can be achieved via counterfactuals and define a counterfactual contrastive explanation as “making or imagining different choices and analysing what could happen or could have happened”. On the other hand, they define an actionable explanation as one that aim to answer “What can be done in order for a system to yield outcome o, given information i?”.

Explanation generation is also quite important for predictive models for they must provide justification for their decision along with alternative solutions specifically solutions which are closest to the user requirements. There have been some recent novel work on generating the nearest counterfactual explanation; Amir-Hossein Karimi et al. present a model agnostic, data type agnostic and distance agnostic algorithm which is able to generate plausible and diverse counterfactual explanations for any sample data. Their model generates counterfactuals at more favourable distances compared to recent optimization based approaches and also informs system administrators about the potential unfair dependence of the model on certain protected attributes (Karimi et al. 2020).

To the best of our knowledge, the most relevant study to our work has recently been conducted by Korikov et al., in which the authors extend the notion of counterfactual explanations to optimisation-based decisions by using inverse optimisation (Korikov, Shleifer, and Beck 2021). They assume that the user is interested in an explanation of why a solution to an optimisation problem does not satisfy a set of additional user constraints that were not initially expressed by the user. In their work, the authors define counterfactual explanations analogous to those of Wachter et al. (Wachter, Mittelstadt, and Russell 2018). They aim to find the nearest counterfactual explanation, which corresponds to finding a set of changes on the features such that the new solution is as close to the previous one as possible. The authors also highlight that the links between conflict-detection mechanisms in constraint satisfaction and counterfactual explanations is not clear. Subsequently, Korikov and Beck generalize their work to constraint programming and show that counterfactual explanations can be found using inverse constraint programming using a cost vector (Korikov and Beck 2021). Karimi (Karimi et al. 2020) along with Korikov (Korikov, Shleifer, and Beck 2021) have a similar goal to generate the
optimal counterfactual explanations for classifiers. Karimi however does not take into account decisions taken by explicit optimization models as opposed to Korikov.

In this paper, our goal is to find a counterfactual explanation to a given constraint problem by using conflicts and constraint relaxation, and address the question that Korikov et al. raised related to the connection between conflicts and counterfactuals (Korikov, Shleyfman, and Beck [2021]). To achieve this, we use a relevant work from Ferguson and O’Sullivan as the foundation of our proposed method, in which the authors generalize conflict-based explanations to Quantified CSP framework (Ferguson and O’Sullivan [2007]). Their approach extends the famous QUICKXPLAIN algorithm (Junker [2004]) by allowing relaxation of constraints instead of their removal from the constraint set. We also demonstrate how this mechanism based on identification of maximal relaxations can be used to find counterfactual explanations in constraint-based systems.

Methodology

First, we define some important notions existing in the Constraint Programming literature on explanations, define counterfactual explanations, and discuss the relation with a counterfactual explanation and constraint relaxation. Consequently, we present our proposed model to find a counterfactual explanation and demonstrate it on a sample item configuration problem.

Preliminaries

A constraint satisfaction problem (CSP) is defined as a 3-tuple \( \phi := (\mathcal{X}, \mathcal{D}, \mathcal{C}) \) where \( \mathcal{X} := \{x_1, x_2, \ldots, x_n\} \) is a finite set of variables, \( \mathcal{D} := \{D(x_1), D(x_2), \ldots, D(x_n)\} \) denotes the set of finite domains where the domain \( D(x_i) \) is the finite set of values that variable \( x_i \) can take, and a set of constraints \( \mathcal{C} := \{c_1, c_2, \ldots, c_m\} \). More specifically, a problem \( \phi \) in Constraint Programming can be defined using two sets of constraints \( \mathcal{B} \) representing the background constraints and \( \mathcal{F} \) representing the foreground constraints (or user requirements/constraints) in the context of configuration problems or other interactive settings. Using this alternative representation, a problem is noted as \( \phi := (\mathcal{X}; \mathcal{D}, \mathcal{C}) \), where \( \mathcal{C} := \mathcal{B} \cup \mathcal{F} \). In order to increase readability, we sometimes refer to a problem as \( P := (\mathcal{B}, \mathcal{F}) \). A set of constraints is called inconsistent (or unsatisfiable) if there is no solution. In this case, the problem is said to be infeasible. If the problem has at least one solution, the set of constraints is said to be consistent (or satisfiable), and the related problem is referred to as feasible. We assume that the set of background constraints are consistent, but the user constraints may introduce infeasibility. We define below a number of relevant definitions existing in the literature.

**Definition 1 (Conflict [Junker 2004]).** A subset \( C \) of \( \mathcal{F} \) is a conflict of a problem \( P := (\mathcal{B}, \mathcal{F}) \) iff \( \mathcal{B} \cup C \) has no solution.

**Definition 2 (Minimal Conflict [Junker 2004]).** A conflict \( C \) of \( \mathcal{F} \) is minimal (irreducible) if each proper subset of \( C \) is consistent with the background \( \mathcal{B} \) (or if no proper subset of \( C \) is a conflict).

**Definition 3 (Relaxation [Junker 2004]).** A subset \( R \) of \( \mathcal{F} \) is a relaxation of \( P := (\mathcal{B}, \mathcal{F}) \) iff \( \mathcal{B} \cup R \) has a solution.

**Definition 4 (Maximal Relaxation [O’Sullivan et al. 2007]).** A subset \( R \) of \( \mathcal{F} \) is a maximal relaxation of a problem and there is no \( \{c\} \in \mathcal{F} \setminus R \) such that \( \mathcal{B} \cup R \cup \{c\} \) also admits a solution.

A problem is said to be over-constrained if it contains an exponential number of conflicts and an exponential number of relaxations. Based on the definition of a maximal relaxation, the complementary notion of minimal exclusion set can be defined.

**Definition 5 (Minimal Exclusion Set [O’Sullivan et al. 2007]).** Given a problem \( P := (\mathcal{B}, \mathcal{F}) \) that is inconsistent, and a maximal relaxation \( R \subseteq \mathcal{F}, E = \mathcal{F} \setminus R \) denotes a minimal exclusion set.

Note that, the definitions above are defined under two-point relaxation spaces. A two-point relaxation space either allows to have the constraint in the constraint set, or not. In this paper, we work under multi-point relaxation spaces, which correspond to replacing a constraint with any weaker one (Ferguson and O’Sullivan 2007; Mehta, O’Sullivan, and Quesada 2015). To illustrate this, consider the user constraint in Equation [1] between two variables.

\[
x_1 \in \{1, 2, 3\}, x_2 \in \{3, 4\}, \{x_1 > x_2\}
\]

Equation [1] is an inconsistent constraint. Assuming that all remaining constraints are consistent, one can remove this constraint from the constraint set to recover consistency in a two-point relaxation space. Alternatively, in a multi-point relaxation space, this constraint can be relaxed to Equation [2], which evaluates to \( \text{true} \) as there exist satisfying values: \( x_1 = 3, x_2 = 3 \). We say that Equation [1] is a tighter version of Equation [2] and the Equation [2] is a relaxed version of the former.

\[
x_1 \in \{1, 2, 3\}, x_2 \in \{3, 4\}, \{x_1 \geq x_2\}
\]

**Finding a counterfactual explanation in CSP**

We define a counterfactual explanation by adapting the definitions from Wachter et al. (2018) and Korikov et al. (2021). We aim to find an explanation to the user with minimal changes to her constraints that informs the user on how to recover from an infeasible state. In other words, given a problem \( P := (\mathcal{B}, \mathcal{F}) \), and a user constraint \( \{c\} \notin \mathcal{F} \) and \( \mathcal{P}' := (\mathcal{B}, \mathcal{F} \cup \{c\}) \) is infeasible, we define a counterfactual explanation as a set of constraints that explain the minimal set of changes in \( \mathcal{F} \) so that the problem \( \mathcal{P}' \) with the updated constraints becomes feasible. In Definition 6 we formally define to a counterfactual explanation based on maximal relaxations in CSP.

**Definition 6.** Define two CSPs as \( P := (\mathcal{B}, \mathcal{F} \cup \{c\}) \) that is inconsistent and \( P' := (\mathcal{B} \cup \{c\}, \mathcal{F}') \) that is consistent, where a constraint \( \{c\} \notin \mathcal{B} \cup \{c\}, \mathcal{F}' \) that is consistent, and \( \mathcal{F}' \) corresponds to a minimal set of changes applied to \( \mathcal{F} \) such that \( \mathcal{P}' \) becomes consistent. A counterfactual explanation, denoted by \( \mathcal{E} \), corresponds to a minimal set
of changes required on user constraints to change the state of the problem, where \( E = \mathcal{F}^f \setminus \mathcal{F} \).

Observe that, this system can be generalized to any infeasible problem \( P := (\mathcal{B}, \mathcal{F}) \) to explain how to recover feasibility without requiring any counterfactual user constraint.

Our method assumes the existence of a multi-point relaxation space defined by the knowledge engineer for each variable in the problem. The relaxation space of a feature may take different characterisations, such as a partially ordered set, lattice, hierarchical ordering, etc. Using these structures pave the way to have comparable or incomparable relaxation states. A top element \( T \) must be defined for each relaxation space, which corresponds to maximally relaxing the relevant constraint (eliminating from the constraint set). Similarly, a bottom element \( \bot \) denotes an infeasible state for a given constraint. To illustrate, Figure 1 can be considered as a multi-point relaxation space for equality or inequality constraints that deal with numerical variables. For instance, given an equality constraint such as \( x = 5 \), the constraint can be relaxed to \( x \leq 5 \) or \( x \geq 5 \), where the two states are incomparable on the partially ordered set of states. For the sake of notation, we denote comparable states as \( \{ T \} \subseteq \{ \leq \} \subseteq \{ = \} \subseteq \{ \bot \} \), where \( \{ T \} \subseteq \{ \leq \} \) is read as state \( \{ T \} \) dominates state \( \{ \leq \} \).

Algorithm 1 presents our proposed method CounterFactualXplain. This approach is an adaptation of the QUANTIFIEDXPLAIN algorithm that was proposed to solve Quantified CSPs following a set of different relaxation forms including single constraint relaxation, relaxation of existentially/universally quantified domain, quantifier relaxation, etc. [Ferguson and O’Sullivan 2007]. From the set of different relaxation forms they propose, we only adapt single constraint relaxations in our work. Our proposed method follows an iterative approach for identifying maximal relaxations of the problem. Note that, if the relaxation spaces are two-point (binary), then the algorithm becomes a version of Junker’s RePLAYXPLAIN algorithm that is an iterative approach to find a minimal conflict [Junker 2001].

The CounterFactualXplain admits a CSP \( \phi \) and the multi-point relaxation spaces of each constraint that can be relaxed, and returns a counterfactual explanation \( \mathcal{E} \) (a set of constraints that needs to be changed to restore feasibility) alongside a relaxed and feasible version of the constraint set of \( \phi \). If the given CSP is feasible, then the algorithm returns ‘no conflict’. Similarly, if there is no relaxation space defined for all foreground constraints, the algorithm returns ‘no relaxation’. For any other problem, the algorithm creates a copy CSP \( \phi' \) with the original set of variables and domains, but uses a constraint set \( C'^{\prime} \) that initially contains only the top elements of each relaxation space for each constraint in \( \mathcal{F} \). Then, the procedure iteratively attempts to tighten the maximal relaxation of each constraint until either the original user constraint is reached or an inconsistent set of constraints is formed. In this context, tightening a constraint \( c \) corresponds to adding a more restrictive form of \( c \) to the existing set of constraints. In the case of having incomparable states in the relaxation space, when tightening a constraint, first a path from the top element to the original constraint is found. Next, each path is explored from the most relaxed state to the tighter ones on the path.

**Demonstration**

Consider a small problem from the item configuration domain, in which a user wants to purchase a laptop. Assume there exist five different properties for each laptop: brand,
screen size, memory, battery life, and price. Table 2 lists all available laptops in the solution space. Also assume that the knowledge engineer defines the relaxation spaces as directions for the numerical values (screen size, memory, battery life, and price) for this problem, and the brand relaxation space consists of incomparable states. There are two directions for the numerical values: MIB (“more is better”) and LIB (“less is better”). Additionally, all brands are equally distant to each other. The users are allowed to express their preferences on the direction of numerical features. For demonstration purposes, assume there exists a user who initially expresses her preferred values for some of these properties. In Table 2, \(c_1, c_2, c_3, c_4\) correspond to the initial constraints of the user. The user is interested in finding a laptop with brand ‘Lenovo’, screen size of at least 15 inches, memory of at least 512 MB, and battery life of at least 10 hours. The constraint system solves the problem, and returns the solution (item) to the user: \{Lenovo, 15.0 inches, 512.0 MB, 10 hr, $2616.99\}. However, the user is not happy with the recommended item as she realises that the recommended item exceeds her budget. Therefore, she adds an extra constraint to the system by asking the question: “Why does the laptop recommended to me costs more than $2000? I need an alternative that costs at most $2000.”. This user constraint is captured as \(c_5\) in Table 2. Note that, we are interested in a solution that may not satisfy some user constraints but satisfies the counterfactual constraint. Therefore, we move the counterfactual constraint to the background constraints to avoid its relaxation by the COUNTERFACTUALXPLE algorithm.

As our relaxation spaces are defined as directions, we use an ordered list representation. Table 3 presents the relaxation spaces for all constraints, where features are ordered with respect to the user’s preference of direction. If the user does not have a preference, we assume the direction is the default direction provided by the knowledge engineer.

Table 4 lists all the steps performed by the COUNTERFACTUALXPLE algorithm to find a counterfactual explanation and a maximal relaxation to the given problem with the set of constraints \(S_0 = \{c_1, c_2, c_3, c_4\}\). Note that the given set of constraints \(C = S_0 \cup F\) is inconsistent. The algorithm initializes the set of constraints \(C' = \{T_1, T_2, T_3, T_4\}\). Let us introduce subsets of constraints denoted by \(S_i\) to represent the elements in \(C'\) at each iteration. The initial set is \(S_0 = C'\), and the subsequent subsets are identified by the iteration number in the table and are accumulated as \(S_i = S_{i-1} \cup r_j\), where \(r_j\) denotes the next tightening performed on the constraints.

In Table 4 the first iteration tightens \(c_1\) to ‘Lenovo’, which corresponds to the initial user constraint \(c_1\), and the set of constraints corresponding to this iteration \(S_1\) is consistent. Therefore, in the next iterations (from 2 to 4 inclusive), the constraint tightening is performed for the next constraint \(c_2\). As it is possible to tighten the \(c_2\) until the original user constraint, the fifth iteration tightens the next constraint, i.e. \(c_3\). Similarly, iterations 6 and 7 performs tightening on \(c_4\), where the seventh iteration with \(c_4 \geq 4.5\) makes the set of constraints inconsistent. Therefore, the tightest version of this constraint that is consistent is added to the explanation. Finally, the algorithm returns the maximal relaxation \(C' = S_6\), and the counterfactual explanation \(E = \{c_4 \geq 2.2\}\). The user-interface can inform the user with an explanation that is similar to: “If you change your constraint on battery life from 10 hr to 2.2 hr, you can find at least one solution that satisfies your remaining constraints”.

The relaxed CSP \(\phi' = (\mathcal{X}, \mathcal{D}, C')\) contains a single solution, which is \{Lenovo, 15.4 inches, 1024.0 MB, 2.2 hr, $1499.99\}. It is important to note here, one can argue that the item \{Lenovo, 14.0 inches, 512 MB, 4.5 hr, $1899\} is closer to the initial solution than the solution found by our approach by applying another metric. Our aim in this paper is to find a set of changes that can be applied to the system to change the outcome (feasibility state) of the system. At this stage, we discuss only preliminary research findings, and the relation

| Brand | Size (inches) | Memory (MB) | Life (hr) | Price   |
|-------|--------------|-------------|-----------|---------|
| Lenovo| 15.4         | 1024.0      | 2.2       | 1499.99 |
| Sony  | 11.1         | 1024.0      | 11.0      | 2349.99 |
| Lenovo| 15.0         | 512.0       | 10.0      | 2616.99 |
| HP    | 15.0         | 512.0       | 4.5       | 785.99  |
| Lenovo| 14.0         | 512.0       | 4.5       | 1899    |

Table 1: The set of all available laptops.

| \(c_i\) | Property | User Constraint | Preference |
|---------|----------|-----------------|------------|
| \(c_1\) | Brand    | Lenovo          | –          |
| \(c_2\) | Size (inches) | 15.0          | MIB        |
| \(c_3\) | Memory (MB)   | 512.0         | MIB        |
| \(c_4\) | Life (hr)     | 10.0          | MIB        |
| \(c_5\) | Price        | 2000           | LIB        |

Table 2: The list of user constraints (\(c_1, c_2, c_3, c_4\)) and the counterfactual constraint (\(c_5\)). The user preferences of directions are MIB ("more is better") and LIB ("less is better").

| \(i\) | Subset \((S_i)\) | \(S_i\) consistent\(^d\) | \(E\) |
|-------|-----------------|-------------------------|------|
| 1     | \(S_1 = S_0 \cup \{c_1 = ‘Lenovo’\}\) | true | \{\} |
| 2     | \(S_2 = S_1 \cup \{c_2 \geq 11.1\}\) | true | \{\} |
| 3     | \(S_3 = S_2 \cup \{c_3 \geq 14.0\}\) | true | \{\} |
| 4     | \(S_4 = S_3 \cup \{c_4 \geq 15.0\}\) | true | \{\} |
| 5     | \(S_5 = S_4 \cup \{c_5 \geq 512\}\) | true | \{\} |
| 6     | \(S_6 = S_5 \cup \{c_4 \geq 2.2\}\) | true | \{\} |
| 7     | \(S_7 = S_6 \cup \{c_4 \geq 4.5\}\) | false | \{\} |

Table 3: Relaxation spaces for every feature for our data set.

Table 4: The list of all iterations performed by the COUNTERFACTUALXPLE to find a counterfactual explanation given the background constraint set \(B = \{price \leq 2000\}\).
between system-based minimal changes vs. solution-based minimal changes needs to be studied further.

**Discussion and Future Work**

We propose a novel explanation type for constraint based systems by using the counterfactual explanation framework and identifying a maximal relaxation of the constraint set. Our proposed notion of counterfactual explanations aims to find a minimal set of changes for the set of user constraints using multi-point relaxation spaces that allows the user to find a solution. However, an important point to note here is that a minimal perturbation in the constraint set may not necessarily lead to minimal changes on the solution that was first presented to the user. As future work, we intend to further investigate the relation between minimal changes on the set of constraints and its effect on the solution. Our plan includes conducting a user study to also understand the social impact of it.

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