Contrastive Explanations of Multi-agent Optimization Solutions

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Abstract

In many real-world scenarios, agents are involved in optimization problems. Since most of these scenarios are overconstrained, optimal solutions do not always satisfy all agents. Some agents might be unhappy and ask questions of the form "Why does solution S not satisfy property P?". In this paper, we propose MAOE, a domain-independent approach to obtain contrastive explanations by (i) generating a new solution S' where the property P is enforced, while also minimizing the differences between S and S'; and (ii) highlighting the differences between the two solutions. Such explanations aim to help agents understanding why the initial solution is better than what they expected. We have carried out a computational evaluation that shows that MAoE can generate contrastive explanations for large multi-agent optimization problems. We have also performed an extensive user study in four different domains that shows that, after being presented with these explanations, humans' satisfaction with the original solution increases.

Introduction

In many real-world scenarios, AI systems generate solutions for optimization problems involving multiple agents with conflicting preferences. Due to these conflicts and the overconstrained nature of the problems, satisfying all agents' preferences is often impossible, and AI decisions might lead to some agents being unhappy (Kraus et al. 2020). In such situations, it is natural that some agents question the decisions made by the AI system, since there is a mismatch between the proposed solution and the user's mental model (Chakraborti et al. 2017). Generating explanations for such questions may improve the AI system's transparency, facilitate human-computer collaboration, and increase human satisfaction (Bradley and Sparks 2009).

Generating explanations for such questions may improve the AI system's transparency, facilitate human-computer collaboration, and increase human satisfaction (Bradley and Sparks 2009). Studies in different areas ranging from Explainable AI (Krarup et al. 2021) to social sciences (Lim, Dey, and Avrahami 2009; Miller 2019) or marketing (Tomaino et al. 2022) show that users typically formulate "why?" questions when they are not happy with a

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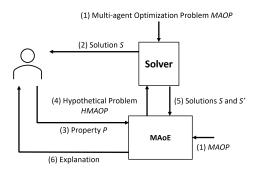


Figure 1: Schematic representation of MAoE.

given solution. These questions usually take the form of "Why does solution S not satisfy property P?". There exist two main approaches to answer these questions in the literature: counterfactual and contrastive explanations.

Counterfactual explanations (Wachter, Mittelstadt, and Russell 2017; Korikov, Shleyfman, and Beck 2021) try to provide explanations by constructing a hypothetical situation where the agent would have received its desired solution if its inputs were different. These explanations take the form of "solution S would have satisfied property P if your input to the system had been Y' rather than Y''. Counterfactual explanations have two main benefits: (i) they allow agents to interpret the underlying AI mechanism by comparing the original and the hypothetical situations; and (ii) they provide agents with actionable recourses that they could use to achieve their desired solutions in future runs of the algorithm. However, these benefits might vanish in many scenarios where the world is non-stationary (Upadhyay, Joshi, and Lakkaraju 2021), solutions are generated in a one-shot fashion, or it is not realistic to apply the actionable recourses in practice.

Another alternative to answering "why?" questions focuses on contrastive explanations (Lipton 1990; Miller 2021). In this case, the focus is purely on understanding why the solution returned by the AI system was a better choice than the one the human agent who requested the explanation had in mind. Inspired by (Krarup et al. 2021), in this paper we present Multi-Agent optimization problems Explanations (MAOE), a novel domain-independent approach to

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generate local contrastive explanations for multi-agent optimization problems. Figure 1 depicts MAoE.

First, the solver generates a solution S for the original Multi-Agent Optimization Problem (MAOP) and presents it to the user. Then, the user formulates a question asking why solution S does not satisfy property P. This is passed to MAOE, which generates a new hypothetical MAOP (HMAOP) that forces property P to be satisfied. The hypothetical problem suggested by the user might lead to a new solution which is very different to the original one. This is often not desirable, since (i) the new solution should be plausible in the real world, i.e., it should be similar to the one generated by the solver; and (ii) a large number of changes between the original and new solutions would entail longer explanations that could frustrate users. Therefore, HMAOP not only encapsulates property P, but also modifies the original problem to minimize the number of changes between the original solution S and the new solution S'. The Solver sends these two solutions to MAOE, which finally generates an explanation by computing their differences. This process is iterative, as the user can ask further questions until the explanation is satisfactory, also gaining a better understanding of the decision-making process followed by the Solver at each iteration.

The main contributions of this paper are: (i) the definition of hypothetical MAOP; (ii) the automated generation and solving of HMAOP that yields contrastive explanations; (iii) a computer-based evaluation of several MAOP tasks; and (iv) an extensive user-study in four domains with more than 200 users that shows the value and user acceptance of those explanations.

The rest of the paper is organized as follows. We first formalize MAOPs. Then, we introduce our novel approach to generate contrastive explanations of solutions to these problems. After that, we evaluate MAOE on four well-known MAOPs, showing how it generates explanations in a similar time as the one needed to solve the original problem. Later, we present the results of an extensive user study in four well-known MAOPs with more than 200 users. After being presented with these explanations, humans' satisfaction with the original solution increases and their desire to complain decreases. Finally, we draw our main conclusions and outline future work.

Multi-Agent Optimization Problems

Multi-Agent Optimization Problems (MAOPs) are solved by finding an optimal solution that minimizes (or maximizes) a given objective function from a set of alternatives taking into account a set of constraints referring to a set of agents. We focus on MAOPs where the decision-making is centralized, i.e., a central entity solves the optimization problem by considering the agents' preferences and constraints. Many real-world scenarios lie under this framework, such as nurse shift scheduling, task or resource allocation, or logistics planning.

MAOPs are formally defined as follows:

Definition 1 A Multi-Agent Optimization Problem (MAOP) is a tuple MAOP = $\langle A, X, C, f, m \rangle$ where A is a set of agents, X is a domain of feasible points subject to the

set of constraints C, f is the objective function, and m is the goal function which is either min or max.

The Mixed Integer Programming (MIP) formulation of MAOPs is based on an algebraic specification of a set of feasible alternatives, as well as the objective criterion for comparing alternatives. This is achieved by: (i) introducing discrete and/or continuous decision variables; (ii) expressing the criterion as a function of variables; and (iii) representing the set of feasible alternatives as the solutions to a conjunction of constraints described as equations and inequalities over the variables. Therefore, MIP provides a general framework for modeling a large variety of MAOPs such as scheduling, planning, task assignment, network design, etc. A general MIP formulation of a MAOP is defined below:

$$\begin{array}{ll} \min & f(x) \\ \text{s.t.} & g_i(x) \geq 0 \quad i = 1,...,q \\ & h_j(x) = 0 \quad j = 1,...,p \end{array}$$

where $x \in X \subseteq \mathbb{R}^n$ represents an n-variable decision vector subject to a feasible set X. Let $a(x) \subseteq x$ refer to the subset of decision variables involving agent $a \in A$. The objective function f(x) is composed of two sub-terms: $f_A(x)$, a function over the subset of decision variables involving agents' inputs; and $f_G(x)$, a function over the subset of decision variables not involving any agents' input.

The feasible set X is given by the set of constraints in C. These constraints are represented as inequalities (g_i) or equalities (h_j) of functions over the decision vector x.

Finally, a maximization problem can be modelled as a minimization problem by multiplying the objective function by (-1). We denote the quality of a solution to a MAOP as q(f(x)). An optimal solution is represented as x^* . In the rest of the paper, we will always refer to optimal solutions when we talk about solutions of MAOPs.

Running Example: the Knapsack Problem Let us introduce a Knapsack Problem (KP) as the running example throughout the paper. In KP, each agent from a set of agents owns a few items. Each item occupies a different space, and each agent assigns a different utility value to each item, i.e., how much they appreciate their items. The agents share a common depot with a limited capacity where items can be included. The problem is determining the items to be included in the depot so that the total utility is maximized, while satisfying the depot's capacity and considering some fairness issues. A formal MIP formulation of a KP is shown below. The objective function to optimize is:

$$\max \sum_{a \in A, i \in I} x_{a,i} \times \text{UTILITY}(a,i) + \text{minItems}$$
 (1)

subject to the following constraints:

$$\sum_{a \in A, i \in I} x_{a,i} \times \text{SPACE}(i) \le \text{depotCapacity}$$
 (2)

$$\sum_{i \in I} x_{a,i} \ge \min \text{Items} \tag{3}$$

$$x_{a,i} \in \{0,1\} \tag{4}$$

$$minItems \in \mathbb{Z} \tag{5}$$

There is one binary decision variable $x_{a,i}$ for each agent $a \in A$ and item $i \in I$. These variables will take a value of 1 if item i from agent a is included in the depot. Integer decision variable minItems keeps track of the number of items belonging to the agent with the least number of items included in the depot (Constraint 3). The objective function maximizes the utility of the included items, and the number of items belonging to the agent with the least number of items included in the depot. Constraint 2 ensures that the maximum capacity of the depot is not exceeded.

In this case, the first term of the objective function corresponds to $f_A(x)$, i.e., variables explicitly associated with agents' inputs, while the second term corresponds to $f_G(x)$, i.e., other variables not involving agents' inputs.

MAOE: Generating Contrastive Explanations

Given that most MAOPs are over-constrained, optimal solutions do not always satisfy all agents, who might be unhappy and ask questions about the solution. In this paper, we focus on generating local contrastive explanations for questions that take the form of "Why does solution S not satisfy property P?". The next sections describe how MAOE works: (i) it builds a hypothetical MAOP; and (ii) it generates explanations from the comparison of the solutions returned by the original and the hypothetical MAOP.

Building a Hypothetical MAOP

To generate these explanations, we build a hypothetical optimization problem where property P is forced to be satisfied. This hypothetical problem might generate a solution that is very different from the original one. To prevent this, we further modify the original problem to minimize the number of changes between the original and new solution, S and S'.

We first define how to compute the differences between two solutions. In many scenarios, the set of decision variables x used to model MAOPs includes some auxiliary variables that are used to help the modeling process or improve the efficiency when solving the problem. We refer to the subset of decision variables in a MAOP that actually represent a solution as $S \subseteq x$. These are the variables considered when computing the differences between two solutions. Going back to our KP running example, while $x_{a,i}$ and minItems are the decision variables of the problem (x), only $x_{a,i}$ variables would be in S, since they are the only ones representing a solution.

We formally define a Hypothetical Multi-Agent Optimization Problem (HMAOP) as an extension of the original MAOP as follows:

Definition 2 A Hypothetical Multi-Agent Optimization Problem (HMAOP) is a tuple HMAOP = $\langle A, X', C', f, m, S, P \rangle$, where A is a set of agents, X' is an updated domain of feasible points subject to the new set of constraints C', f and m remain as in the original OP, S is a solution to the original MAOP, and P is the hypothetical property to be enforced.

We extend the original set of constraints C with a new set of constraints that enforce that the hypothetical property P is satisfied. From now on, we assume HMAOP is solvable,

i.e., enforcing the hypothetical property P might affect quality but not solvability. We also extend the original decision vector x with a new set of decision variables z(S) that will compute the differences between the solution to the original MAOP (S) and a solution to the new HMAOP (S'). The value of these new variables is ensured by a set of constraints Z, i.e., $C' = C \cup P \cup Z$. Finally, we also modify the original objective function to reason at the same time about the quality of the solution, f(x), and the number of changes between the original and the hypothetical solution, z(S). A general MIP formulation of a HMAOP is defined as:

where $x' \in X'$ represents the new decision vector subject to the feasible set X'. We introduce two parameters (weights) in HMAOP's objective function, α and β . By modifying these parameters, we will generate solutions that prioritize either maximizing the quality of the hypothetical MAOP solution or minimizing the number of changes between the original $(S \subseteq x)$ and the hypothetical $(S' \subseteq x')$ MAOP solutions. In scenarios where we maximize quality, the solution to the HMAOP problem might be arbitrarily different from the original solution, thus yielding very long explanations. However, minimizing the number of changes between the original $(S \subseteq x)$ and the hypothetical $(S' \subseteq x')$ MAOP solutions leads to shorter and more concise explanations.

KP running example. Now, agent "Alice" asks why item "bed" has not been included in the optimal MAOP's solution x^* . We build the associated HMAOP as follows. First, we enforce the agent's property by adding the following constraint, which ensures that the bed is included in the depot. Then we generate a new set of z(S) variables by duplicating the decision variables used to represent the original solution. In this case, we add one $z_{a,i}$ variable for each original $x_{a,i}$ variable. We also add the following constraints to ensure that the z variables capture the changes of the new solution with respect to the original one:

$$x'_{a,i} - x_{a,i} \le z_{a,i}, \qquad x_{a,i} - x'_{a,i} \le z_{a,i}, \qquad z_{a,i} \ge 0$$

Finally, we update the objective function:

$$\max \alpha \Big(\sum_{a \in A, i \in I} x_{a,i} \times \text{utility}(a,i) + \min \text{Items} \Big) - \beta \sum_{a \in A, i \in I} z_{a,i}$$

In the following, we focus on two main variations of MAOE: Q-MAOE, which prioritizes quality by making $\alpha \gg \beta$; and C-MAOE, which prioritizes the number of changes by making $\beta \gg \alpha$. Both variations still reason about both terms.

The complexity of the new HMAOP compared to that of the original MAOP relates to how many new constraints and variables need to be added. The number of constraints and variables to add depends on (i) the number of decision variables used to represent a solution in the original MAOP; and (ii) the hypothetical property P to be enforced. HMAOP's objective function is more complex since it also reasons about z(S) variables. However, as we will see later, the hypothetical property P tends to constrain the solution space so that HMAOPs can be efficiently solved in practice.

Generating Explanations from MAOP and HMAOP Solutions

The next step of MAOE is to generate explanations by computing the differences between the solution to the original MAOP S, and the solution to the HMAOP S'. We envision generating two types of explanations, depending on the level of abstraction we want.

Abstract Explanation. The explanation only refers to the difference in the quality of both solutions.

Quality Diff =
$$q(f(x)) - q(f(x'))$$
 (6)

Full Explanation. The explanation refers to the specific changes between S and S', grouping them by agents. Algorithm 1 outlines how this computation is performed. The

Algorithm 1: Full Explanation Generation

```
Require: HMAOP = \langle A, X', C', f, m, S, P \rangle, S'
Ensure: \mathcal{E}
   1: \mathcal{E}_{\mathcal{I}} \leftarrow \emptyset
   2: \mathcal{E}_{\mathcal{D}} \leftarrow \emptyset
  3: \mathcal{I} = \text{COMPUTEINCREASES}(S, S')
  4: \mathcal{D} = \text{COMPUTEDECREASES}(S, S')
   5: for a \in A do
               \mathcal{I}_a = a(\mathcal{I})
               \mathcal{D}_a = a(\mathcal{D})
   7:
               \mathcal{E}_{\mathcal{I}} \leftarrow \mathcal{E}_{\mathcal{I}} \cup \{\langle i, q(f(i)) \rangle \mid i \in \mathcal{I}_a\}
   8:
               \mathcal{E}_{\mathcal{D}} \leftarrow \mathcal{E}_{\mathcal{D}} \cup \{\langle d, q(f(d)) \rangle \mid d \in \mathcal{D}_a\}
10: end for
11: \mathcal{E} \leftarrow \mathcal{E}_{\mathcal{I}} \cup \mathcal{E}_{\mathcal{D}}
12: return \mathcal{E}
```

algorithm receives as input the HMAOP and the solution to the new problem (HMAOP already contains the solution to the original problem). First, the algorithm computes the subset of decision variables representing a solution whose value has either increased or decreased between the original and the hypothetical solution. This is done by the COMPUTEIN-CREASES and COMPUTEDECREASES functions, which return the set of increase (\mathcal{I}) or decrease (\mathcal{D}) changes, respectively. Then, the algorithm iterates over the set of agents, computing the subset of increases and decreases where agent a was involved (lines 6 and 7). After that, it computes the contribution of these changes to the objective function and updates the sets of increases and decreases (lines 8 and 9). Finally, the algorithm returns the explanation \mathcal{E} , which is the union of all the decision variables in the solution that either increased or decreased their value in the new solution S'with respect to the original solution S.

KP running example. Let us assume that the only change between solutions S and S' is Bob removing his bed (with a utility of 4) in favour of Anna's bed (with a utility of 2). The Abstract Explanation would be that doing so would mean a loss of 2 utility units. The Full Explanation would be: $\mathcal{E}_{\mathcal{I}} = \{\langle x_{\text{Alice,bed}}, 2 \rangle\} \cup \mathcal{E}_{\mathcal{D}} = \{\langle x_{\text{Bob,bed}}, 4 \rangle\}.$

Computational Evaluation

Although our formalization is general to any MAOP described as a MIP, we run experiments using Mixed Integer Linear Programs (MILP) for which optimal solutions

are easier to compute. We evaluate our approach by providing explanations in simulated scenarios in four well-known MAOPs that can be formulated as MILPs. Below we provide a brief description of each domain. A formal definition of their associated MILPs can be found in Appendix A.

- **Knapsack Problem (KP)**. A variation of our KP running example where the objective function only optimizes the total utility of the items included in the depot.
- Task Allocation Problem (TAP). A set of tasks need to be allocated to a set of agents. Each agent has a maximum workload. Each agent assigns a different utility value to each task. The goal is to assign all the tasks, while maximizing the total utility of the assignment and respecting agents' workload.
- Wedding Seating Problem (WSP). A set of agents need to be seated at a set of tables with different capacities. Each pair of agents has an associated affinity value, i.e., how much they would like to be seated at the same table. The AI system's problem is determining the allocation of agents to tables so that the total affinity is maximized while satisfying the tables' capacities.
- Capacitated Vehicle Routing Problem (CVRP). A set of agents (vehicles) with heterogeneous capacities have to visit a set of points distributed on a map. The number of points a vehicle can visit is given by its capacity. All agents start and end in a depot. Each pair of points has an associated distance. The AI system needs to determine the route of vehicles so that the total traveled distance is minimized while satisfying the vehicles' capacities.

Experimental Setting

We have generated problems in the four domains by fixing some inputs and general constraints of the problem: the depot's capacity in KP, the tables' capacity in WSP, the number of points and vehicles' capacity in CVRP, and the number of agents in TAP. For each configuration, we have generated 10 MAOPs with random utilities/affinities/distances depending on the domain. We optimally solved each problem and automatically computed all of the unsatisfied variables, i.e., those decision variables representing the solution with a value of zero. Then we randomly picked 10 of these unsatisfied variables in order to generate 10 hypothetical properties, i.e., agents' questions about the original solution. For example, in KP we get all of the items that were not included in the depot and generate 10 questions of the form "why was item x not included in the depot?". This yielded 100 HMAOPs to solve. We can solve each problem with either of the two variations of our approach: Q-MAOE or C-MAOE. For each problem, we report (i) the time needed to compute the solution for the MAOP and the HMAOP; (ii) the quality of the MAOP and the HMAOP; and (iii) the length of the explanation, i.e., the number of changes between the MAOP and HMAOP solutions.

MILP problems have been modeled using the PuLP Python library (Mitchell, OSullivan, and Dunning 2011) and solved using the CBC solver (Forrest and Lougee-Heimer 2005). Experiments were run in Intel(R) Xeon(R) CPU E3-1585L v5 @ 3.00GHz machines with 64GB of RAM and a

60s timeout, which includes the solving and model-building times.

Scalability Evaluation

We first evaluate the scalability of our approach by comparing the time (in seconds) needed to compute the original and the hypothetical solutions as we increase the complexity of the problem. In KP, we increase the complexity of the problem by increasing the number of agents and setting the depot's capacity to be a function of this number. In TAP, we fix the number of agents and increase the number of tasks to be assigned. In WSP, we also increase the number of agents, fixing the number of tables but varying their size to be able to accommodate all agents. Finally, in CVRP, we increase the number of points, fixing the number of vehicles but varying their capacity to be able to visit all points. All of these problems are solved using Q-MAOE. Execution times are similar for C-MAOE.

The results of this experiment are shown in Figure 2. As expected, increasing the complexity of the problems leads to longer solving times and explanation generation times in all domains. However, while generating explanations is notably faster than solving the problem in WSP and CVRP, the opposite occurs in KP and TAP. This is because these problems only have one type of decision variable and only a few types of constraints, while the other domains involve more constraints and interrelated decision variables.

We conclude that the time needed to generate an explanation compared to the time needed to generate a solution will vary depending on the problem to be solved and its formulation. However, this time difference does not usually exceed an order of magnitude and remains constant as problems become more complex. Therefore, our approach will generate explanations for any MILP for which a solution can be generated within reasonable time and memory bounds.

Solution Quality vs Explanation Length Trade-off

We analyze the trade-off between quality and explanation length by comparing our two approaches and measuring: (i) Explanation Length —the number of changes between the original and hypothetical solutions, $|\mathcal{E}|$; and (ii) Suboptimality Ratio —the quality of the original vs. the hypothetical solution, q(f(S))/q(f(S')). The results of this experiment are shown in Figure 3 for the smaller problems in all domains, i.e., 10 agents in KP, 10 tasks in TAP, 8 agents in WSP and 8 points in CVRP. Conclusions drawn from bigger problems are the same, and their results are shown in Appendix B.

As expected, optimizing the quality of solution S' first (Q-MAOE) yields solutions closer to the optimal one S (lower Suboptimality Ratios) at the expense of generating a new solution S' with more changes (higher Explanation Length). On the other hand, minimizing the number of changes between S and S' first (C-MAOE), generates shorter explanations at the expense of having slightly worse solutions in terms of quality.

Despite this trend, we often get the same Suboptimality Ratio and Explanation Length regardless of the approach used. From 100 problems generated for each domain, we obtain the same values in 67 problems in KP, 30 in TAP, 39 in WSP, and 9 in CVRP. When focusing on problems for which we obtain similar rather than exact values, there are 77 problems in KP, 30 in TAP, 49 in WSP, and 33 in CVRP for which the Suboptimality Ratio and Explanation Length values differ by less than 30%. These results show that, in most cases, there are no big differences in the solutions produced by both approaches.

User Study

We designed and implemented a between-subjects user study to validate MAOE. In the following subsections, we detail the setup, results and analysis.

Setup

We generated **abstract** and **full** explanations using Q-MAOE. We chose this variation given the similar results both approaches got in the previous section, while Q-MAOE generates solutions with slightly higher quality. We compared these explanations against a **baseline** explanation.

The objective of the baseline is to demonstrate that our explanation was the determining factor in the users' behavior, rather than simply providing any explanation. This is necessary based on the findings in (Kosch et al. 2023) that demonstrated the placebo effect in AI experiments. In particular, in this user study, we used "Sorry, this is what the algorithm generated" as a baseline explanation. We wanted to validate the following hypotheses:

Hp1: Explanations generated by MAOE improve humans' satisfaction with the decisions made by the AI system.

Hp2: Explanations generated by MAoE reduce humans' desire to complain about the decisions made by the AI system. **Hp3**: Humans prefer more detailed explanations.

Our experimental setting just focuses on assessing whether our contrastive explanations improve humans' satisfaction and decrease their desire to complain or not. We leave the evaluation of MAOE against other approaches as future work, as fairly comparing different explanation approaches becomes difficult. For example, counterfactual explanations (Korikov, Shleyfman, and Beck 2021) focus only on the individual asking the question, while contrastive explanations like the ones generated by MAOE, focus on the rest of the agents involved in the optimization problem.

By considering the four domains discussed in Section and the three types of explanation, we generated twelve scenarios. We force the original solution to be very unfavourable for the participants so they have a reason to complain. In each scenario, participants were asked (i) their *user satisfaction* for the solution generated by AI, and (ii) their *desire to make a complaint* regarding that solution. The answers to both questions were measured on a 5-point Likert scale, where 1 represents the lowest and 5 is the highest. Then, in each scenario, regardless of the level of satisfaction or their desire to complain, the participants were presented with one of the three different types of explanations.

Afterward, the same set of questions was repeated in order to compare the participants' satisfaction and desire to complain before and after receiving the explanation. Each user

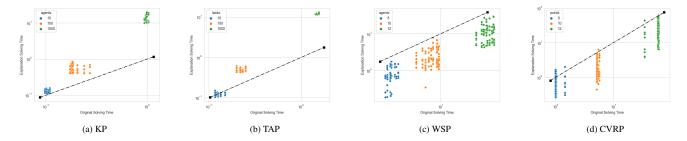


Figure 2: Time (seconds) in log scale needed to compute the original and hypothetical MAOP as we increase the complexity of the problem. Points below the diagonal line represent problems for which producing the explanation takes less time than solving the original problem.

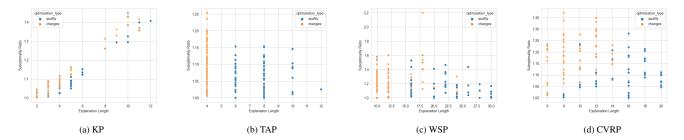


Figure 3: Trade-off between Explanation Length and Suboptimality Ratio when solving the HMAOP with Q-MAOE (blue points) or C-MAOE (orange crosses).

was asked to rate their satisfaction with the explanation on a Likert scale. Finally, we asked a domain-related question to verify the users' comprehension of the domain; e.g. in KP, asking what the goal of the AI algorithm was.

We recruited 207 computer science students, 75 females (36%) and 132 males (64%). The average age was 24.75 (StD=3.54).

Each participant was shown two or three scenarios randomly, but making sure that no domain or explanation type was repeated. The scenarios where users answered the verification question incorrectly (34 scenarios) were discarded, leading to a total of 100, 85, 76 and 84 scenarios examined for the KP, WSR, CVRP and TAP domains, respectively. We used repeated measures ANOVA (General Linear Model) for each domain separately.

Human Satisfaction & Desire to Complain

In the first part of the user study, we evaluate Hp_1 and Hp_2 . Table 1 shows the number of users (N) who participated in each scenario (distinct pairs of domain and explanation type). Further, it presents the mean and standard deviation of user satisfaction with the solution and their desire to complain. Based on the table, in all domains, the initial satisfaction of the users with the solution was similar among all users with different explanations (p>0.05). This is a good indication of our randomized distribution of the users between all sessions since, at the initial stage, no explanation was presented to the users.

Based on ANOVA analysis, in all domains, we found a *main effect* of satisfaction with the solution after an expla-

nation was presented. This means there was a change in the mean of satisfaction from the solutions before and after presenting an explanation. The main effect was statistically significant in all domains; KP (F(1) = 41.26, p < 0.01), WSP (F(1) = 95.70, p < 0.01), CVRP (F(1) = 12.16, p < 0.01) and TAP (F(1) = 15.49, p < 0.01), where the p-value was less than 0.05. An interaction effect between the change in satisfaction with the solution and the type of explanation was found in all domains. The interaction effect represents whether the changes in satisfaction with the solution were different based on different types of explanations. The F-scores and p-values were: KP (F(2) = 10.48,p < 0.01), WSP (F(2) = 11.29, p < 0.01), CVRP (F(2) =6.89, p < 0.01) and TAP (F(2) = 2.62, p = 0.08). In all domains, the p-value indicated a strong significance, except in the TAP domain which was close to significant.

From a post-hoc analysis with correction for multiple measurements in all domains, the level of satisfaction after receiving the explanation is still low. This is because the original solution was very unfavourable for the participants, and MAOE just tries to explain the outcome rather than changing it.

However, the increase in satisfaction was significantly greater following the *abstract* and *full* explanations compared to the *baseline* explanation. The results presented in this table confirm Hp1, i.e. the explanations generated by MAOE improve humans' satisfaction regarding decisions made by the AI system.

Similarly, in all domains, we found a *main effect* of decrease on the desire to complain following an explanation.

Table 1: Satisfaction and desire to complain ('mean (std)') about the original solution before and after participants are presented with MAoE's explanations in the four domains. N represents the number of participants per session.

		Domains											
Status Exp.		KP		TAP		WSP		CVRP					
		Satisfaction	Desire to Complain	N	Satisfaction	Desire to Complain	N	Satisfaction	Desire to Complain	N	Satisfaction	Desire to Complain	N
Before Exp.	-	1.52 (0.89)	4.32 (1.07)	100	1.79 (1.25)	3.82 (1.35)	84	1.14 (0.46)	4.42 (0.97)	85	2.14 (0.97)	3.89 (0.95)	76
	Baseline	1.58 (0.84)	4.11 (1.11)	36	1.63 (0.72)	4.00 (1.23)	30	1.40 (0.75)	4.15 (1.19)	32	2.04 (0.93)	3.64 (1.22)	25
After Exp.	Abstract	2.20 (0.98)	3.79 (0.90)	29	2.70 (1.06)	2.67 (1.30)	27	2.18 (1.00)	3.77 (1.08)	27	2.63 (1.09)	3.29 (1.16)	24
Aitti Exp.	Full	2.77 (0.94)	2.97 (1.04)	35	2.59 (0.97)	2.89 (1.08)	27	2.54 (0.99)	3.42 (1.14)	26	2.92 (0.87)	2.85 (1.06)	27
	Total	2.18 (0.92)	3.62 (1.01)	100	2.30 (0.92)	3.18 (1.20)	84	2.04 (0.91)	3.78 (1.14)	85	2.53 (0.97)	3.26 (1.14)	76

Table 2: User's satisfaction ('mean (std)') with each explanation in the four domains. N represents the number of participants per session.

	Domains							
Exp.	KP		TAP		WSP		CVRP	
	$\mu(std)$	N	$\mu(std)$	N	$\mu(std)$	N	$\mu(std)$	N
Baseline	1.64 (0.96)	36	1.97 (1.22)	30	1.65 (0.97)	32	2.16 (1.07)	25
Abstract	2.95 (1.15)	29	2.92 (1.35)	27	2.41 (1.22)	27	2.87 (1.29)	24
Full	3.17 (1.22)	35	3.00 (0.91)	27	3.23 (1.17)	26	3.63 (1.08)	27
Total	2.58 (1.11)	100	2.62 (1.16)	84	2.43 (1.12)	85	2.89 (1.15)	76

The main effect was statistically significant in all four domains: KP (F(1) = 27.45, p < 0.01), WSP (87.50, p < 0.01)p < 0.01), CVRP (F(1) = 27.02, p < 0.01) and TAP (F(1) = 24.66, p < 0.01), where the p-value was less than 0.05. Also, an interaction effect was found in all domains between the change in desire to make a complaint and the type of explanation . The F-scores and p-values for the four domains were: KP (F(2) = 5.3, p < 0.01), WSP (F(2) = 11.29, p < 0.01), CVRP (F(2) = 9.3, p < 0.07)and TAP (F(2) = 2.71, p = 0.07). In all domains, the pvalue indicated a strong significance except in the TAP domain, which was close to significant. Finally, from a posthoc analysis with correction for multiple measurements in all domains, the decrease in desire to complain was significantly greater following the abstract and full explanations compared to the baseline explanation. The results presented in this table confirm Hp2, that the generated explanations by MAOE decrease humans' desire to complain regarding decisions made by AI.

Length of Explanation

In this part of the study, we validate our third hypothesis, Hp_3 . The results in Table 2 present a between-subjects analysis comparing the satisfaction between the users in each of the explanation types, using Univariate Analysis of Variance. In all domains, we found an effect for the type of explanations on user's satisfaction. The F-score and p-value were; $KP(F(2) = 19.52, p \ll 0.01)$, WSP(F(2) = 14.62, $p \ll 0.01$), CVRP (F(2) = 10.64, $p \ll 0.01$) and TAP (F(2) = 6.9, p < 0.01). In general, in all domains, users reported higher satisfaction with the abstract and full explanations rather than the baseline explanation. In CVRP and WSP, users were significantly more satisfied with the full explanation in comparison to the abstract explanation. However, their satisfaction with the abstract and full explanations was much closer in the KP and TAP domains. We hypothesize this is because KP and TAP are much simpler

domains in comparison to CVRP and WSP. The results of Table 2 confirm Hp3 —users prefer a more detailed explanation. These results are aligned with previous works on social sciences and marketing (Ramon et al. 2021).

Summary of Results

The three hypothesis presented in Section were validated by a user study. The first part of the user study validates the first hypothesis, i.e., the explanations generated by MAOE improve humans' satisfaction with the decisions made by the AI system. Although the general satisfaction after receiving explanations is still low due to the solution being very unfavourable for the participants, the increase in satisfaction was significant following the abstract and full explanations compared to the baseline explanation. It also validated the second hypothesis, i.e., explanations generated by MAOE reduce humans' desire to complain. This decrease effect was significant across the four domains. Finally, the second part of the user study validates the third hypothesis, i.e., humans prefer more detailed explanations. We observed this behavior more clearly in more difficult problems (CVRP and WSP), where participants were significantly more satisfied with the *full* explanation in comparison to the *abstract* explanation.

Related Work

Most works on generating explanations for optimization models focus on explaining infeasibility, often through identifying a minimal (Parker and Ryan 1996; Chinneck 2007) or user preferred (Junker 2004) set of constraints that should be relaxed to get a solution. More recent works also cover optimality in their explanations using different approaches.

Korikov *et al.* (Korikov, Shleyfman, and Beck 2021; Korikov and Beck 2021) propose to use counterfactual explanations for OPs. Given a set of facts and a solution that does not satisfy some desired features, they solve an inverse optimization problem to generate explanations in the form of a

hypothetical set of facts that would have satisfied the users' characteristics. Their setting is similar to ours, allowing an individual to inquire about any change to a decision that can be represented with a constraint set on the original formulation. However, while their explanations involve hypothetical features or facts that would yield the user desired output, our explanations highlight the losses incurred in satisfying users' characteristics. Another difference is that their explanation focuses only on the individual asking the question, while our explanation focuses on the rest of the agents involved in the optimization problem. On the experimental side, they limit their evaluation to simulations in two well-known domains, but do not test the validity and usefulness of their explanations with user studies as we do here.

Other literature focuses on contrastive explanations. Cyras et al. (Cyras et al. 2019) explain schedules using argumentation frameworks. In order to provide the explanations, they manually generate the attack graphs, i.e., the relationship between the preferences and the assignments, while we do not need any external input other than the original model and the user's request. A key difference between these works and ours is that they are restricted to makespan scheduling problems with a limited number of preferences, while our approach can provide explanations for any MAOP. On the evaluation side, they do not report any experiments. Pozanco et al. (Pozanco et al. 2022) proposed the EXPRES framework, which also focuses on explaining why the original solution is better than one where the user inquiry is satisfied. However, they: (i) are restricted to linear programs where a totally ordered set of preferences is defined; (ii) need external inputs as in (Cyras et al. 2019); and (iii) only conducted experiments in a workforce scheduling domain, where they measured whether humans preferred explanations generated by other humans or those generated by EX-PRES. In this paper, we have conducted experiments in many different MAOPs, showing how humans' satisfaction with the original solution increased after receiving the explanations generated by MAoE.

Finally, our approach for providing explanations is inspired by works in the context of Explainable Planning (Fox, Long, and Magazzeni 2017). Eifler et al. (Eifler et al. 2020) focus on generating global contrastive explanations, i.e., universal answers determining shared properties of all possible alternative plans satisfying the users' given property. Closer to our approach is the work by Krarup et al. (Krarup et al. 2021), where the focus is on local contrastive explanations by generating a new plan that satisfies the given property, and answers the question based on comparing the original and the hypothetical plan. There exist two main differences between their work and MAOE. First, they focus on automated planning tasks, while we focus on OPs. Although planning techniques can be used to solve optimization problems and vice versa, the modeling and performance gap can be huge in many cases, leaving one of them as the most suitable approach. Second and more importantly, they do not focus on minimizing the number of changes (length of the explanation) between the original and the hypothetical plans, while this is a core feature in our approach.

Conclusion and Future Work

We have introduced MAOE, a domain-independent approach to generating contrastive explanations of multi-agent optimization solutions. We generate explanations by building a hypothetical optimization problem that (i) forces the user's requested property to be satisfied; and (ii) minimizes the number of changes between the original and the hypothetical solution. Experimental results through a computational evaluation show how MAOE can scale in generating contrastive explanations for MAOPs. Finally, an extensive user study in different MAOPs shows that explanations generated by MAOE increase humans' satisfaction with the original solution and decrease their desire to complain.

Currently, we are only providing one explanation. However, HMAOPs often have a few optimal solutions. In future work, we would like to characterize each of these solutions to present a set of diverse explanations from which users could choose. Also, we would like to extend MAOE to consider agents' privacy or fairness when generating explanations.

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Appendix A

In this supplementary material, we present the MILP model of the KP, TAP, WSP and CVRP domains.

Knapsack Problem (KP)

To model the problem we have defined the binary variable $x_{a,i}$ for each agent $a \in A$ and item $i \in I$, where A and I represents a set of agents and items, respectively. These variables will take a value of 1 if item i from agent a is included in the depot.

$$\max \sum_{a \in A, i \in I} x_{a,i} \times \text{UTILITY}(a,i)$$

subject to the following constraint:

$$\sum_{a \in A, i \in I} x_{a,i} \times \text{SPACE}(i) \leq \text{depotCapacity}$$

$$x_{a,i} \in \{0,1\}$$

The utility of each item $i \in I$ for each argent $a \in A$ is given by UTILITY(a, i). In our experimental setup utility of each item was between 1 and 5 where 1 represents the lowest and 5 the highest importance. The objective function maximizes the utility of the included items.

Also the problem is subject to a constraint which ensures that the maximum capacity of the depot, depotCapacity, is not exceeded.

Task Allocation Problem (TAP)

To model the problem we have defined the binary variable $x_{a,t}$ for each agent $a \in A$ and task $t \in T$, where A and T represents a set of agents and tasks, respectively. These variables will take a value of 1 if task t is allocated to agent a.

$$\max \sum_{a \in A, t \in T} x_{a,t} \times \text{UTILITY}(a,t)$$

subject to the following constraints:

$$\begin{split} \sum_{t \in T} x_{a,t} &\leq \text{Workload}(a), \quad \forall a \in A \\ \sum_{a \in A} x_{a,t} &= 1, \quad \forall t \in T \\ x_{a,t} &\in \{0,1\} \end{split}$$

Similar to KP, in this problem the utility of each task $t \in T$ for each argent $a \in A$ is given by UTILITY(a,t). In our experimental setup utility of each item was between 1 and 10 where 1 represents the lowest and 10 the highest utility. The objective function maximizes the utility of the assigned tasks.

The problem is subject to a set of constraints which ensures that (i) the maximum workload of each agent, WORKLOAD(a), is respected; and (ii) each task is only allocated to one agent.

Wedding Seating Problem (WSP)

To model the problem, we have introduced set P which is a set of unique pairs of agents p. Each pair $p = (a_i, a_j)$ is consist of two agents $a_i, a_j \in A$, where $i, j \in |A|$ and i < j. AFFINITY(p) represents the affinity value of each pair $p \in P$ (i.e. how much each pair would like to be seated at the same table). Further, we have defined two binary variables $x_{p,t}$ and $y_{a,t}$ for each pair $p \in P$ or each agent $a \in A$ and each table $b \in T$. These variables will take a value of 1 if pair $b \in T$ or agent $b \in T$. These variables will take a value of 1 if pair $b \in T$ or agent $b \in T$.

$$\max \sum_{p \in P, t \in T} x_{p,t} \times \text{AFFINITY}(p)$$

subject to the following constraints:

$$\begin{split} &\sum_{t \in T} x_{p,t} = 1, \quad \forall p \in P \\ &\sum_{t \in T} y_{a,t} = 1, \quad \forall a \in A \\ &x_{p,t} \times 2 \leq \sum_{a \in \mathrm{PAIR}(p)} y_{a,t}, \quad \forall p \in P, \quad \forall t \in T \\ &\sum_{a \in A} y_{a,t} \leq \mathrm{Capacity}(t), \quad \forall t \in T \\ &x_{a,t} \in \{0,1\} \end{split}$$

The affinity of each pair of agents $p \in P$ is given by AFFINITY(p). In our experimental setup affinity of each pair was between 1 and 10 where 1 represents the lowest and 10 the highest affinity. The objective function maximizes the total affinity of pairs allocated to tables.

The problem is subject to a set of constraints. The first and second set of constraints ensure each pair and each agent is assigned to exactly one table. The third set of constraints, makes the connection between two set of binary variables in the problem, $x_{p,t}$ and $y_{a,t}$. PAIR(p) outputs the set of agents that form pair $p \in P$. The last set of constraints ensures the number of agents assigned to each table respects the capacity of each table, CAPACITY(t).

Capacitated Vehicle Routing Problem (CVRP)

To model the problem we have defined the binary variable $x_{i,j,v}$ for each point $i \in P$, $j \in P \setminus i$, and $v \in V$, where P is the set of the point representing the points on a map, and V is the set of vehicles that we are planing for. The variable $x_{i,j,v}$ gets value 1 if the vehicle v goes from point i to j. The distance between each two points i and j is given by DISTANCE(i,j). It is important to note that the distance between the points are not symmetric.

$$\min \sum_{i \in P, j \in P \setminus i, v \in V} x_{i,j,v} \times \text{distance}(i,j)$$

subject to the following constraints:

$$\sum_{j \in P \backslash i} x_{i,j,v} = \sum_{j \in P \backslash i} x_{j,i,v}, \quad \forall i \in P, \forall v \in V$$

$$\sum_{i \in P \backslash Depot} x_{i,b,v} = 1, \quad \forall p \in P \backslash Depot$$

$$\sum_{i \in P \backslash Depot} x_{Depot,i,v} = 1, \quad \forall v \in V$$

$$\sum_{j \in P \backslash Depot} x_{Depot,j,v} \leq \operatorname{Capacity}(v), \forall v \in V$$

$$\sum_{i \in \operatorname{Set}, j \in P \backslash \operatorname{Set}, v \in V} x_{i,j,v} \geq 1, \quad \forall \operatorname{Set} \in \operatorname{Subsets}(P \backslash Depot)$$

$$x_{i,j,v} \in \{0,1\}$$

The objective function minimizes the total traveled distance by all the vehicles. The first constraint ensures that all vehicles leave the points they visit. The second constraint ensures that each point is visited exactly once by any vehicle. The third constraints ensure all the vehicles start from the depot. The return of vehicles to the depot is ensured by the conjunction of the first and third constraints. The fourth constraint ensures that the capacity of the vehicle, i.e., the number of points a vehicle can visit is satisfied. Finally, the fifth constraint prevents the existence of subtours in the returned routes. This is done by precomputing all the subsets composed by the points in $P \setminus D$ epot.

Appendix B

Solution Quality vs Explanation Length trade-off in the four domains.

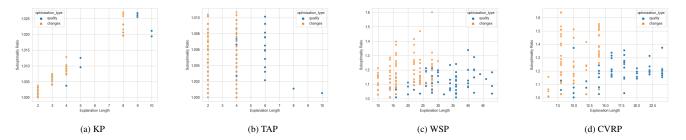


Figure 4: Trade-off between Explanation Length and Suboptimality Ratio when solving the HMAOP with Q-MAOE (blue points) or C-MAOE (orange crosses). Problems with 100 agents in KP, 100 tasks in TAP, 10 agents in WSP, and 10 points in CVRP.

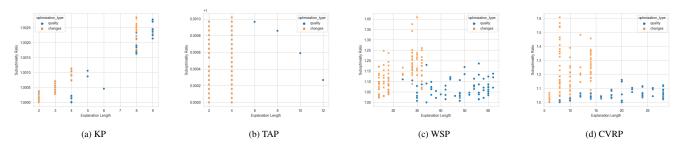


Figure 5: Trade-off between Explanation Length and Suboptimality Ratio when solving the HMAOP with Q-MAOE (blue points) or C-MAOE (orange crosses). Problems with 1000 agents in KP, 1000 tasks in TAP, 12 agents in WSP, and 12 points in CVRP.

Appendix C

Knapsack scenario used in our user study. The below scenario is shown in raw format and without any interactive component, while the user study was run in an interactive platform. Please refer to the main body of the paper for details on how experiments were run, i.e., explanations shown per user, how the scenario was introduced to the participants etc.

Scenario. Consider we have 7 people (Tal, Noam, Dagan, Bar, Gefen, Aviv and Ziv) that want to share a storage with space capacity of 55. Each person has the following items: bed, sofa, table, chair, lamp, books, computer, clothes, fridge, and fan. However, each item has a different utility for each person. The following table specifies the space required to include each item.

Item	Bed	Sofa	Table	Chair	Lamp	Books	Computer	Clothes	Fridge	Fan
Space	25	12	8	4	2	2	2	3	4	2

Table 3: Space required to include each item.

Optimal solution. We computed the optimal solution for this problem. The optimal solution would allow only the following items from each person to be in the storage:

• Tal: computer, fan

• Noam: chair, lamp, computer

• Dagan: lamp

• Bar: lamp, books, computer, fan

• Gefen: chair, computer

Aviv: lamp, books, computer, clothesZiv: table, lamp, books, fridge, fan

Question and Explanation. Imagine you are Tal and the utility of each item for you is shown below, where the higher the utility level indicates the higher importance of the item.

Item	Bed	Sofa	Table	Chair	Lamp	Books	Computer	Clothes	Fridge	Fan
Utility	4	2	2	1	1	1	1	1	1	1

Table 4: Tal's utility assigned to each item.

Considering that you are Tal, please mark the most accurate statement.

I'm dis-	I'm	I'm	I'm	I'm
satisfied	somewhat	neither	somewhat	satisfied
with the	dissatis-	satisfied	satisfied	with the
llocation	fied with	nor dis-	with the	allocation
	the	satisfied	allocation	
	allocation	with the		
		allocation		
\bigcirc	\bigcirc	\bigcirc	\bigcirc	\bigcirc
\sim	\sim	\sim	\sim	\sim

Please mark to what extent do you agree with the following statement:

I would like to make a complaint about my allocation.

Strongly	Disagree	Neutral	Agree	Strongly
disagree				agree
\bigcirc	\circ	\circ	\circ	\circ

We would like to present you with an explanation regarding the allocation that you (Tal) have received.

Considering that you (Tal) are dissatisfied with the allocation, you have asked: "Why is my bed not included in the optimal solution?"

Provided explanation.

Here is your explanation:

- Sorry, this is what the algorithm generated
- Total utility would decrease
- Total utility would decrease by 13 based on the following table:

Item	Tal	Dagan	Gefen	Aviv	Ziv
Removed items (utility)	Computer, Fan (2)	Lamp (1)	Chair (4)	Clothes(2)	Fridge, Table (8)
Added items (utility)	Bed (4)	-	-	=	-

Please mark the most accurate statement regarding your satisfaction with the explanation.

I'm dissatisfied with the explanation	I'm somewhat dissatis- fied with the expla- nation	I'm neither satisfied nor dis- satisfied with the explana-	I'm somewhat satisfied with the explana- tion	I'm satisfied with the explana- tion
		explana- tion		
\bigcirc	\bigcirc	\bigcirc	\bigcirc	\bigcirc

Considering the provided explanation, we would like to ask again, please mark the most accurate statement.

I'm dis-	I'm	I'm	I'm	I'm
satisfied	somewhat	neither	somewhat	satisfied
with the	dissatis-	satisfied	satisfied	with the
allocation	fied with	nor dis-	with the	allocation
	the	satisfied	allocation	
	allocation	with the		
		allocation		
\bigcirc	\bigcirc	\bigcirc	\bigcirc	\bigcirc

Please mark to what extent do you agree with the following staten

I would like to make a complaint about my allocation.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
\circ	\bigcirc	\bigcirc	\bigcirc	\circ