Learning User Preferences in Interactive Constraint Programming

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Context & Related Work

Tough Decision, Nevertheless I Have a Taste

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- The variables are well defined
- The constraints are given
- The objective function is unknown: The user is non-expert in optimisation, aesthetic objective functions, dynamic environment, ..
- The user is able to rank the solutions according to her preferences
- Due to the exponential number of solutions, only a subset of solutions is iteratively proposed to the user

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- It dates back to 1988 (before?) with the notion of dynamic CSPs Dechter and Dechter [1988]
- A lot of developments since then and in particular in the past decade due to the proliferation of its applications in the real word
- Modern prescriptive decision making relies heavily on data, feedback loops, machine learning, and flexible solvers
- Different types of interactions:
  - Problem definition
  - Parameters approximation
  - Evolution of the model
  - Emerging Patterns
  - Explanations
  - ...

Related Work (Non Exhaustive)

- Dynamic Constraint-Networks (Dechter and Dechter [1988])
- The Inductive Constraint Programming Loop (Bessiere et al. [2016])
- Predict+optimise (Demirovic et al. [2019])
- Constraint acquisition (Bessiere et al. [2017])
- Specific classes of objective functions Toffano et al. [2022]; Benabbou and Lust [2019]
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Our Framework

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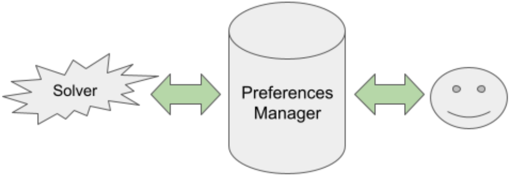
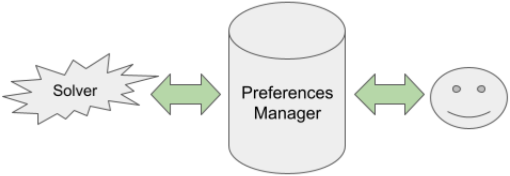
- Then at each iteration i, one additional solution is proposed. The user updates its ranking accordingly
- The purpose is to find the most preferred solutions in S within a bounded number of interactions



- Let S_i be the set of solutions that are ranked at iteration i
- The preferences manager build a ML model that predicts the ranking of the solutions in S by using S_i as a training data
- A solution with the best predicted rank is then proposed to the user at iteration $i+1$



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There is a Problem!

- Let $[1..k]$ be the labels associated to the solutions in S_i
- A solution that is better than all the solutions in S_i must have a label $k + 1$.
- **How does one build a model that predicts a label that is not used in the training ?**

Straightforward Approach

- One can build a model for each label $l \in [1..k]$ to predict whether a given solution has label l
- **Weakness: This approach can be useful to predict solutions with different labels than $[1..k]$. However, it does not capture the notion of preferences**

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Proposed Approach

- By reasoning about the order between the solutions instead of the ranking, the prediction model learns what makes a solution better than another
- We propose to build a prediction model (denoted by O) that takes as input a couple (s_1, s_2) and outputs 1 is s_1 is better than s_2, -1 if s_1 is worse than s_2, and 0 if they have the same rank

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- **Strategy** 1: pick a new solution that is predicted (according to O) to be better than most of the solutions that are already proposed. That is, one that maximizes $\sum_{s' \in S_i} O(s, s')$.
- **Strategy** 2: pick a new solution that is predicted to be better than most of the solutions that are not proposed. That is, one that maximizes $\sum_{s' \in S \setminus S_i} O(s, s')$.
- . . .

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$$\forall s_1, s_2, O(s_1, s_2) = -O(s_2, s_1)$$

Tough Challenge

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- There is a simple trick: train O only on couples that are ordered lexicographically. Then use the following prediction rule to answer the question "Is s_1 better than s_2 ?"
  - If $s_1 <_{lex} s_2$ then return $O(s_1, s_2)$
  - Otherwise, return $-O(s_2, s_1)$

Experimental Study

Stable Matching: Decision Version

- Two sets of agents (men, women)
- Each woman ranks the men in a strict order of preferences
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Objective Function

- Let M be a stable matching
- Let $Weight_w$ be the sum of the ranks of each woman's partner in M
- Let $Weight_m$ be the sum of the ranks of each man's partner in M
- **Balanced stable matching: minimize** $max(Weight_w, Weight_m)$

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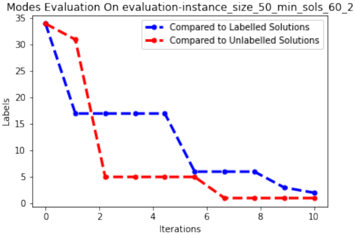
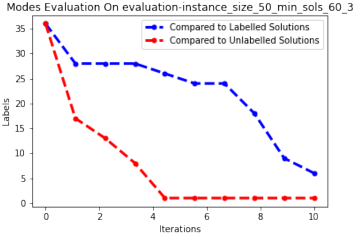
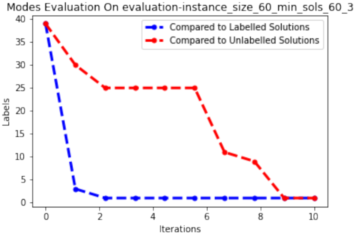
- The preferences manager in implemented in Python. It uses the latest version of CP-Optimizer and scikit-learn

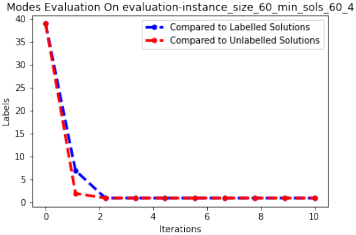
Evaluation of Instances of Size 50



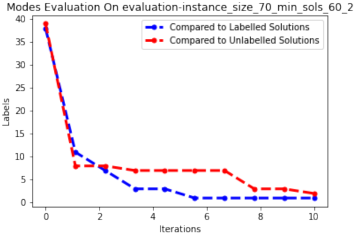


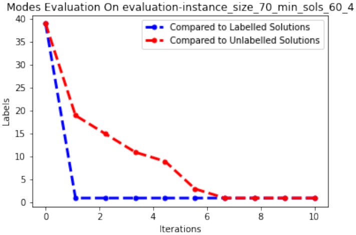
Evaluation of Instances of Size 60





Evaluation of Instances of Size 70





Conclusion

- New framework for interactive CP
- The interactions with the user are limited
- Only ranking queries
- No restriction on the objective function
- Flexible to be used in multiple scenarios
- A lot to explore
- ...

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https://www.cimi.univ-toulouse.fr/en/

Thank you!

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