Interview CR CNRS for the Competition 06/02

Mohamed Siala

Insight, Centre for Data Analytics, University College Cork, Irlande

Keywords: Constraint Programming, Combinatorial Optimisation, Machine Learning, Artificial Intelligence

March 20, 2018

Plan

1. Curriculum Vitae
2. Research Paper: Two Clause Learning Approaches for Disjunctive Scheduling, Mohamed Siala, Christian Artigues, and Emmanuel Hebrard, CP'15
3. Research Project: Explainable Combinatorial Optimisation via Constraint Reasoning and Machine Learning
4. Conclusion

Academic Career

- **December 2011 to May 2015:**
  - PhD in Computer science, LAAS-CNRS, INSA Toulouse, France
  - Funding: CNRS, Google, Midi-Pyrénées
- **Since June 2015:**
  - Post Doctoral Researcher, Insight, Centre for Data Analytics, University College Cork, Ireland.
  - Funding: Science Foundation Ireland 90% and UCC-UTRC 10%.

Research Areas & Applications

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- **Constraint programming:** [CP'12, IJCAI'13, CPAIOR'14, Constraints'14, CP'15, EAAI'15, CPAIOR'16, Constraints'16, CP'17, IJCAI'17, CPAIOR'17, CPAIOR'18]

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- **Boolean SAT:** [CPAIOR'14, CP'15, CP'17, CPAIOR'17]

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Applications

- **Scheduling & Sequencing Problems:** [CP'12, IJCAI'13, CPAIOR'14, Constraints'14, CP'15, EAAI'15, Constraints'16]
- **Matching under Preferences:** [CPAIOR'16, CP'17, IJCAI'17, ICTAI'17, COCOA'17]

Achievements and Other Research Activities

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- PC member for: IJCAI, ECAI, CP, etc.
- Reviewing for journals: Artificial Intelligence, JAIR, Constraints, etc

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- Declarative approach for combinatorial problems
- Large spectrum of real world applications: space exploration, music, verification, etc
- Excellent trade-off between efficiency, flexibility, and re-usability

Definitions & Notations

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Constraint Satisfaction Problem (CSP)

- Variables $x_1, x_2, ..$
- Domains
- Constraints

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- Nogood: a conjunction of literals that makes the problem unsatisfiable
- Clause: a disjunction of literals

Modern Constraint Solvers: Example

$$
\begin{aligned}
&x_1 + x_7 \geq 4 \wedge \\
&x_2 + x_{10} \geq 11 \wedge \\
&x_3 + x_9 = 16 \wedge \\
&x_5 \geq x_8 + x_9 \wedge \\
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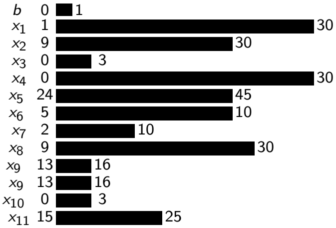

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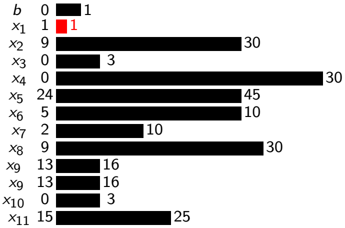

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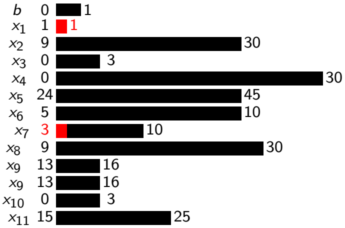

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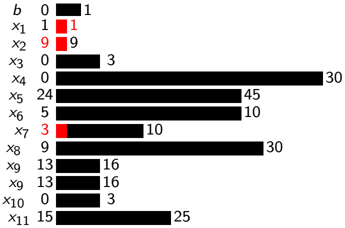

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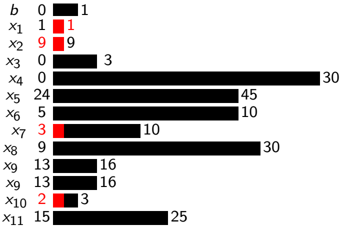

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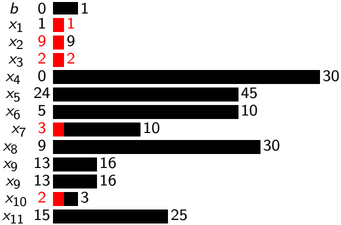

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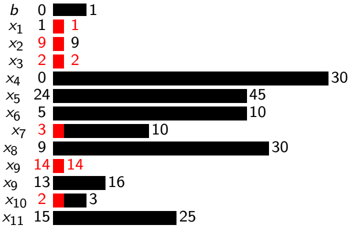

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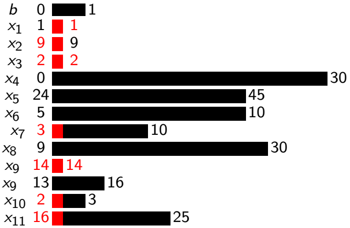

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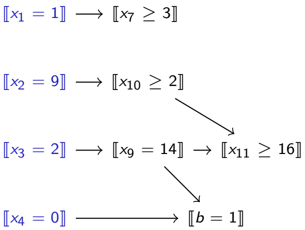

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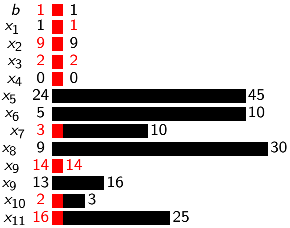

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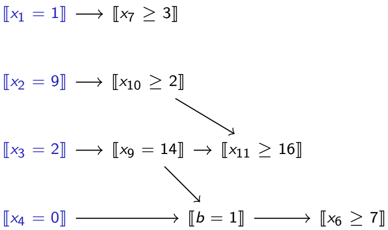

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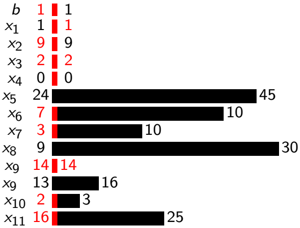

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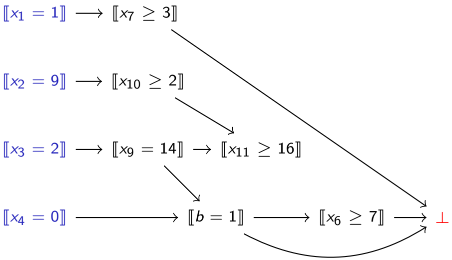

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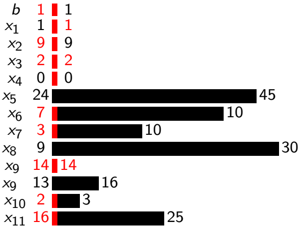

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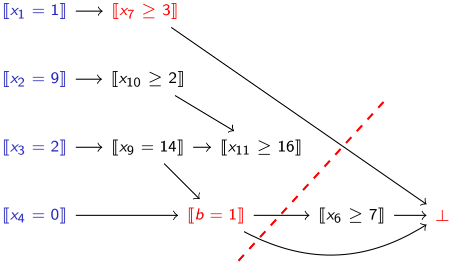

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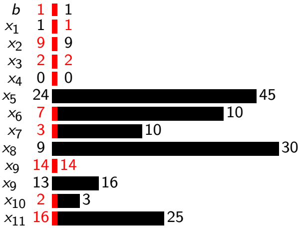

- Conflict analysis: $[\![b = 1]\!] \wedge [\![x_7 \geq 3]\!] \Rightarrow \perp$

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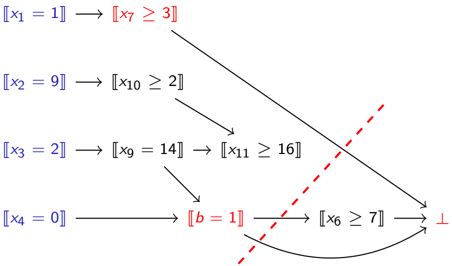

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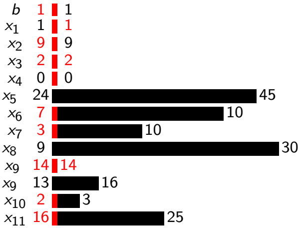

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- New clause: $[\![b \neq 1]\!] \vee [\![x_7 \leq 2]\!]$

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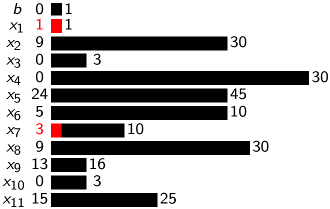
- New clause: $[\![b \neq 1]\!] \vee [\![x_7 \leq 2]\!]$
- Backtrack to level 1



Modern Constraint Solvers: Example

$\llbracket x_1 = 1 \rrbracket \longrightarrow \llbracket x_7 \geq 3 \rrbracket \longrightarrow \llbracket b = 0 \rrbracket$

- Conflict analysis: $\llbracket b = 1 \rrbracket \wedge \llbracket x_7 \geq 3 \rrbracket \Rightarrow \perp$
- New clause: $\llbracket b \neq 1 \rrbracket \vee \llbracket x_7 \leq 2 \rrbracket$
- Backtrack to level 1
- Propagate the learnt clause

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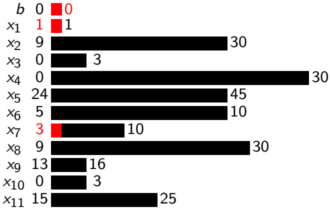
& b \rightarrow (x_6 + x_7 \leq 9) \wedge \\
& x_{11} \geq x_9 + x_{10}
\end{aligned}
$$



Modern Constraint Solvers: Example

$[\![x_1 = 1]\!] \longrightarrow [\![x_7 \geq 3]\!] \longrightarrow [\![b = 0]\!]$

- Conflict analysis: $[\![b = 1]\!] \wedge [\![x_7 \geq 3]\!] \Rightarrow \bot$
- New clause: $[\![b \neq 1]\!] \vee [\![x_7 \leq 2]\!]$
- Backtrack to level 1
- Propagate the learnt clause
- Continue exploration

$$
\begin{aligned}
& x_1 + x_7 \geq 4 \wedge \\
& x_2 + x_{10} \geq 11 \wedge \\
& x_3 + x_9 = 16 \wedge \\
& x_5 \geq x_8 + x_9 \wedge \\
& b \leftrightarrow (x_9 - x_4 = 14) \wedge \\
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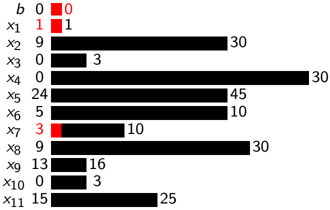

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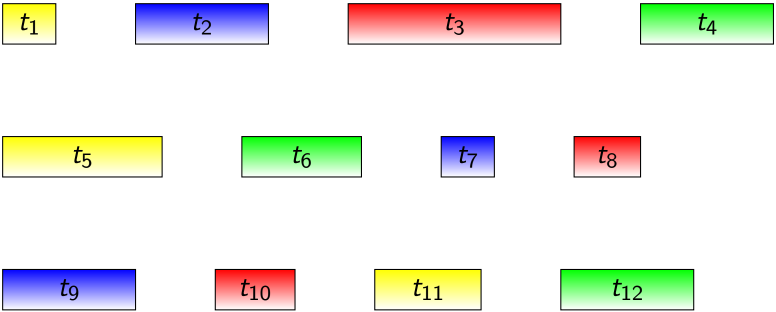

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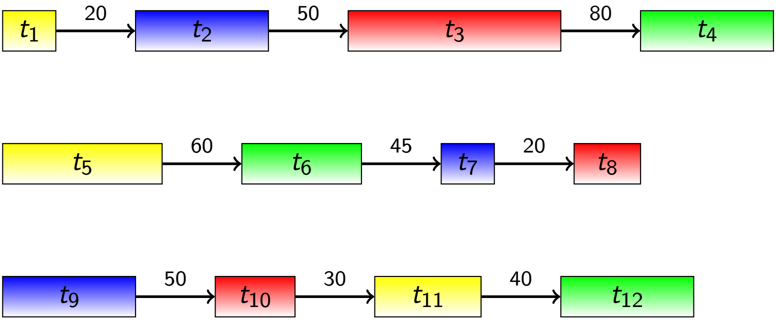

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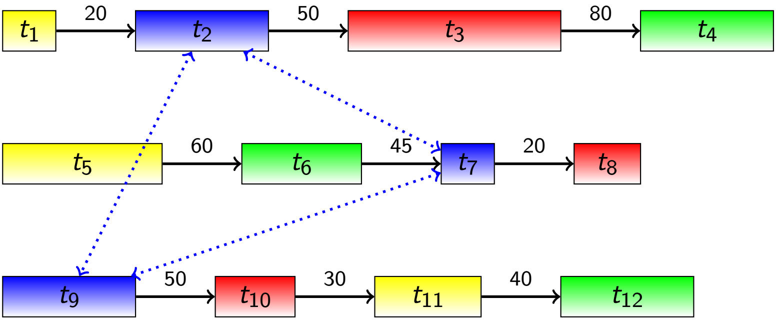

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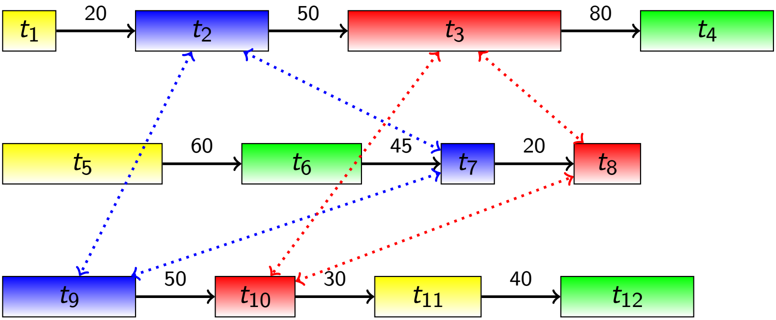

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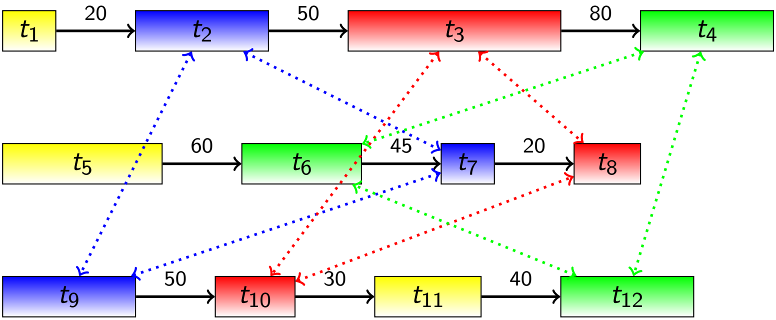

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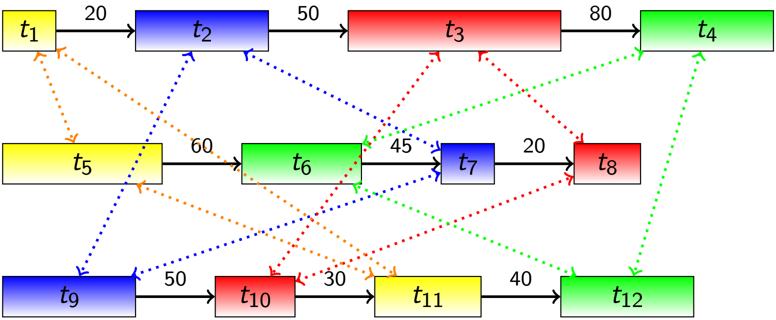

Context

- Scheduling in CP
  - Heavy filtering algorithms
  - Tailored search strategies

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- Scheduling in CP
  - Heavy filtering algorithms
  - Tailored search strategies
- Contribution: Focus on what can be learnt during search!

Modelling

Unary Resource Constraint

- $O(n^2)$ Boolean variables δ_{kij} $(i < j \in [1, n])$ per machine M_k.
- Decomposition using the following DISJUNCTIVE constraints:

$$\delta_{kij} = \begin{cases} 0 & \Leftrightarrow \quad t_{ik} + p_{ik} \leq t_{jk} \\ 1 & \Leftrightarrow \quad t_{jk} + p_{jk} \leq t_{ik} \end{cases} \tag{1}$$

Revisiting Lazy Atom Generation

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Domain Encoding: standard approach

1. Generate domain atoms: $a \leftrightarrow [\![x = d]\!]$, $b \leftrightarrow [\![x \leq d]\!]$
2. Generate domain clauses: $\neg[\![x \leq d]\!] \vee [\![x \leq d+1]\!]$, $\neg[\![x = d]\!] \vee [\![x \leq d]\!]$, etc
3. Scalability issue with large instances

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Lazy Atom Generation

1. Atoms and domain clauses are generated during conflict analysis
2. There is a redundancy issue
3. For a domain of size k, $k-2$ redundant clauses.

Avoiding redundancy via DomainFaithfulness

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Key Idea

- Use a single constraint responsible for the consistency of the domain.
- Whenever an atom is generated, we update the internal structure of the constraint

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Consistency of the domain

Can be enforced in constant amortized time complexity ($O(1)$) down a branch of the search tree

DISJUNCTIVE-based Learning

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- Allow decisions only on the Boolean variable δ_{kij}
- There exists an explanation for every bound literal $[\![x \leq u]\!]$ and $[\![x \geq l]\!]$

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Two phases:

1. Compute usual nogood
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Advantages:

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Advantages:

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- ⊕ Scheduling horizon does not manner in size

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- Well studied benchmarks in OR and CP (more than 2 decades)
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- State-of-art results with 7 new lower bounds.

Conclusions

- Alternative lazy (atom) generation approach avoiding a major redundancy issue
- Novel conflict analysis and learning mechanism
- Efficient in practice, specially for finding proofs

Plan

1 Curriculum Vitae

2 Research Paper: Two Clause Learning Approaches for Disjunctive Scheduling, Mohamed Siala, Christian Artigues, and Emmanuel Hebrard, CP'15

3 Research Project: Explainable Combinatorial Optimisation via Constraint Reasoning and Machine Learning

4 Conclusion

Explainable Artificial Intelligence (AI)

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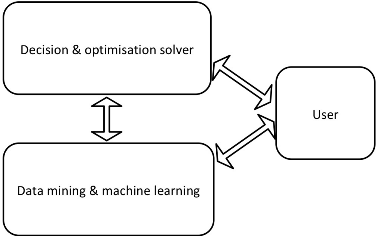
  - A nurse can ask why does the system put her in unfair situation with 5 nights shifts whereas her colleague is getting only one?
- Will be mandatory in crucial applications of AI (e.g., medical treatments and legal professions)
- Very little is done regarding explainable combinatorial optimisation!

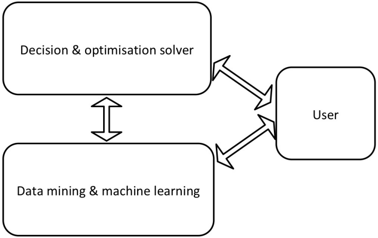
Research Project

- Title: **Explainable Combinatorial Optimisation via Constraint Reasoning and Machine Learning**
- In a nutshell:
  - How to make decision & optimisation solvers explainable?
  - How can we take into consideration the user's preferences towards explanations?

Interactive Combinatorial Optimisation

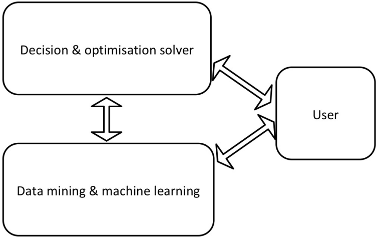


Interactive Combinatorial Optimisation



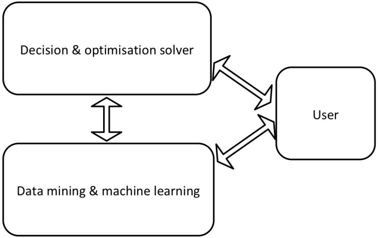
- **Decision & optimisation solver:**
  - solves combinatorial problems in an interactive way
  - is able to explain itself

Interactive Combinatorial Optimisation



- **User:**
  - asks for explanations
  - interacts with the "Data mining & machine learning" component in two ways:
    - gives preferences towards the explanations
    - changes data about the problem

Interactive Combinatorial Optimisation



- **Data mining & machine learning:**
  - handles data from the user about the problem
  - treats the preferences of the user towards explanations to learn and communicate the preferred explanations to the solver.

Challenges

- **Challenge 1:** From explaining a filtering algorithm to explaining a backtracking algorithm?
- **Challenge 2:** Making explanations understandable by humans?
- **Challenge 3:** Dealing with model updates: A minor change can have a huge impact on the hardness?

Roadmap

1. A uniform language for explanations based on queries
2. Develop efficient and reusable algorithms for computing explanations.
3. Machine learning modules to predict the impact of the interactive updates on
   - the hardness of solving the problem
   - the current solution

Plan

1. Curriculum Vitae
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Conclusion

- Next generation of interactive combinatorial optimisation
- Extremely challenging : both theoretically and practically
- Related to the theme "Data science : data and knowledge engineering, machine learning and reasoning"

Thank you for your attention

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Awards

- XCSP3 Solver Competition
- EurIA best thesis award, honourable mention
- CP'12 paper, honourable mention

Publications

- 3 Journals: Constraints (2), Engineering Applications of Artificial Intelligence (1)
- 11 International Conferences: IJCAI (2), CP (3), CPAIOR (4), ICTAI (1), COCOA (1) (+ since submission CPAIOR'18)

Research Project

- Explainable combinatorial optimisation
- Constraint reasoning meets machine learning for interactive decision making

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