

Generating explanations of various types for end-users of optimization systems

Application to the workforce scheduling and routing problem

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ROADEF

21 February 2023

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- 3 Generating explanations
- 4 Example or demo
- 5 Conclusion

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- Use case
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3 observations:

- (1) Real-world situations modeled as **Combinatorial Optimization (CO) problems** (e.g. workforce management);
- (2) CO problems solved using **optimization systems** that are developed by experts (e.g. DecisionBrain);
- (3) Optimization systems are used as **black boxes** by **non-expert people** to make decisions.
 - End-users may experience a **lack of trust and confidence**.

Let see (1), (2) and (3) in our use case.

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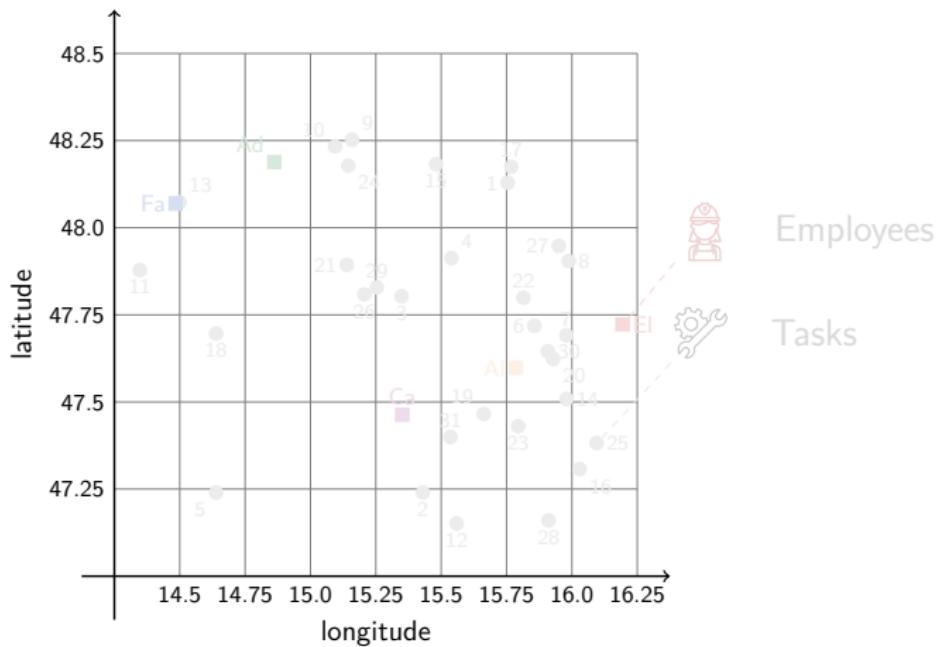
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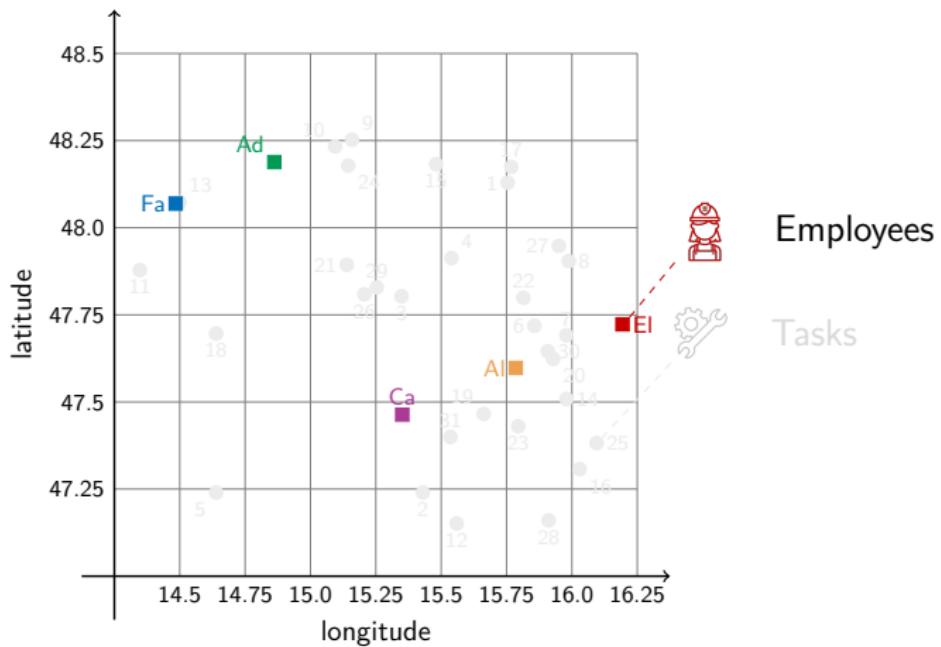
Use case - (1) CO problem

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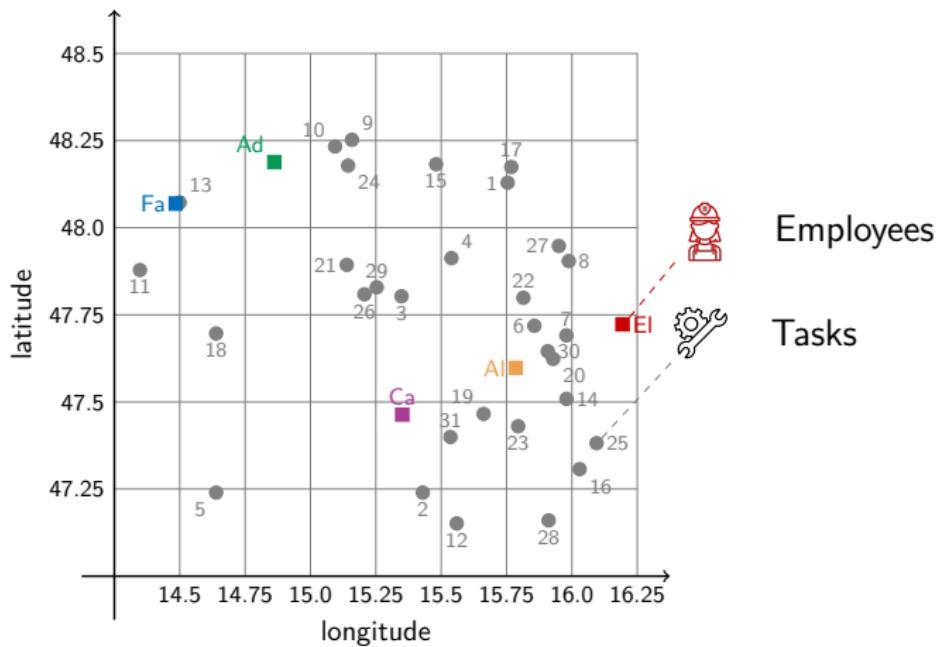
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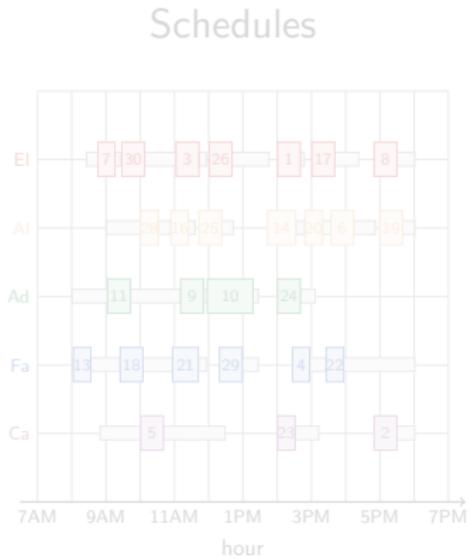
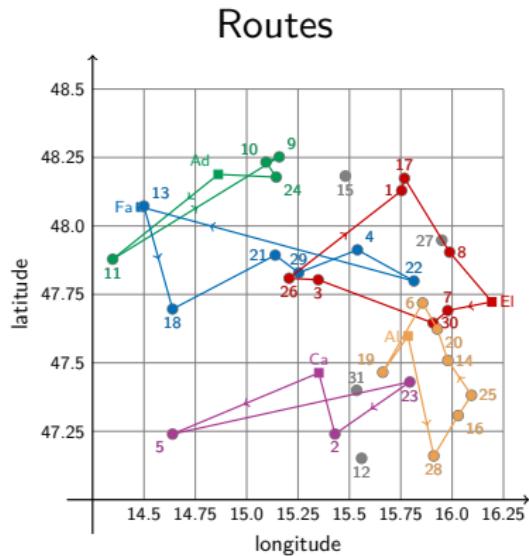
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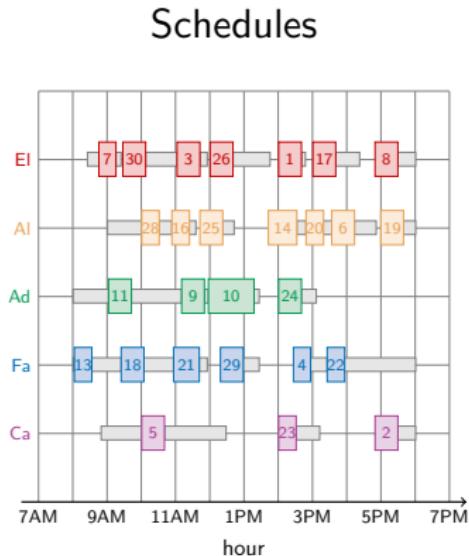
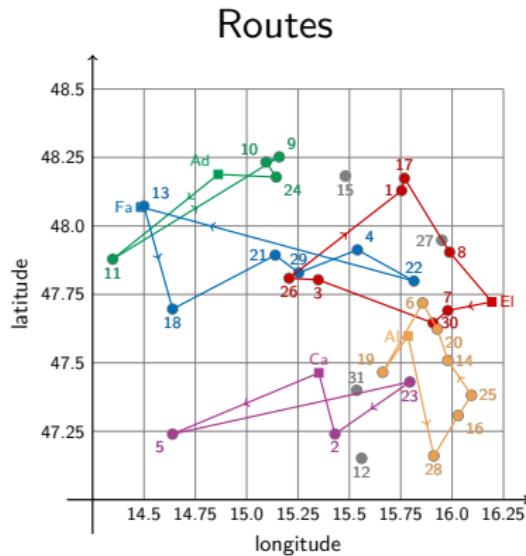
Use case - (1) CO problem

Workforce Scheduling and Routing Problem (WSRP):



Use case - (1) CO problem

Workforce Scheduling and Routing Problem (WSRP):



Our use case - (2) Optimization system

WSRP-solving system:

e.g DecisionBrain's Dynamic Scheduler

DecisionBrain DASHBOARD JOBS ASSIGN JOB ENGIN > 01-04-2019 1 / 101 9 h 4.04 47.84 mi 72 Daniel Godard

J100402 - HULL SPRING BANK AP0914 Air Conditioning RM W100403 105 min

0 modified planned jobs 0 unassigned planned jobs SAVE CLOSE

Search Engineers X Only compatible engineers

Mon 1 Apr 2019

	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00
Engineer 5	W100403	W100577	W100574	W100575	W100576	W100578	W100579	W100580			
Engineer 13		W100578	W100579	W100580	W100581						
Engineer 3											
Engineer 17	W100577	W100578	W100579	W100581	W100581	W100582	W100583	W100584			
Engineer 20	W100585	W100586	W100587	W100588	W100589	W100590	W100591	W100592			
Engineer 8	W100594	W100595	W100596	W100597	W100598	W100599	W100600	W100601			
Engineer 21	W100602	W100603	W100604	W100605	W100606	W100607	W100608	W100609			
Engineer 16											
Engineer 22	W100630	W100631	W100632	W100633	W100634	W100635	W100636	W100637			
Engineer 4	W100640	W100641	W100642	W100643	W100644	W100645	W100646	W100647			
Engineer 23	W100648	W100649	W100650	W100651	W100652	W100653	W100654	W100655			

Jobs

ID	Type	Craft	Work order	Contract	Site name	Post code	Due Date
J100576	RM	Air Conditioning	W100577		WAKEFIELD	LS26	01-04-2019 10:00
J100574	RM	Air Conditioning	W100575		LINCOLN WRAGBY	LN2	02-04-2019 17:30
J102689	PPM	Air Conditioning	W102411		THORPE MARSH DONCASTER	DN3	05-04-2019 23:59
J100577	RM	Air Conditioning	W100578	PONTERFRACT (999 Park Rd)	WFB	03-04-2019 23:59	
J100402	RM	Air Conditioning	W100403	HULL SPRING BANK AP0914	HUS	01-04-2019 17:30	

Map Satellite

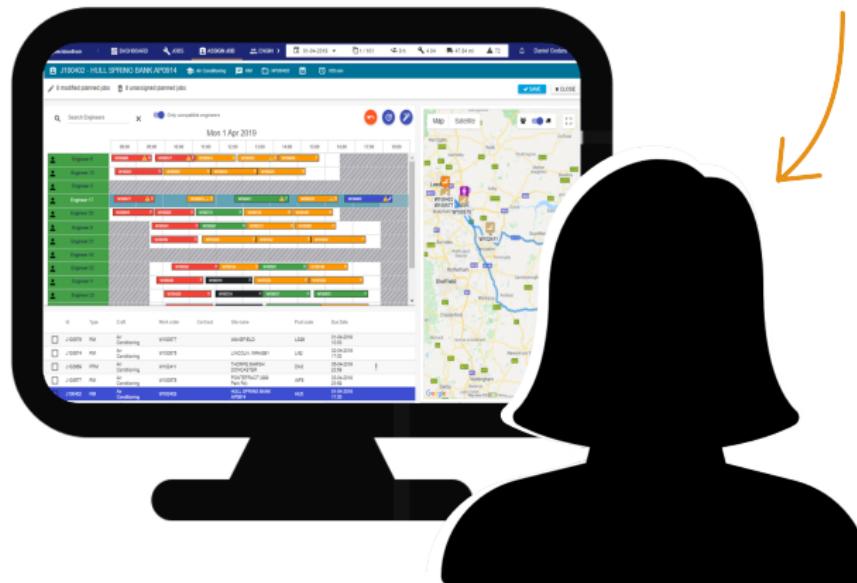


Leeds W100403 W100577 Wakefield W100578 W102411 Scunthorpe W100575 North Hykeham W100675

Map Data ©2019 Google Terms of Use Report a map error

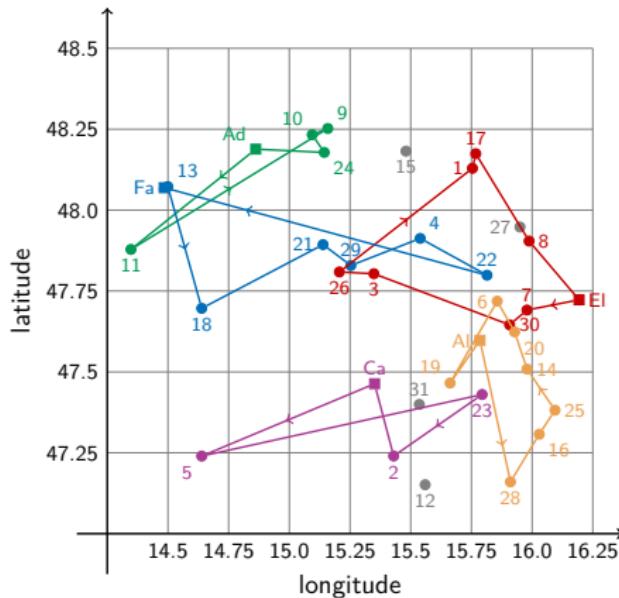
Use case - (3) Non-expert end-user

Planner:



Our use case - (3) Non-expert end-user

A problematic situation for a planner:



“Ellen is not performing task 15 in addition to the tasks of her route...”

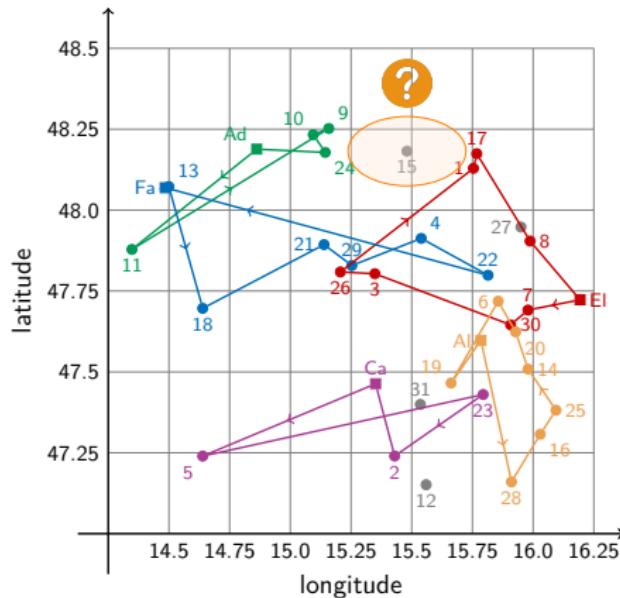
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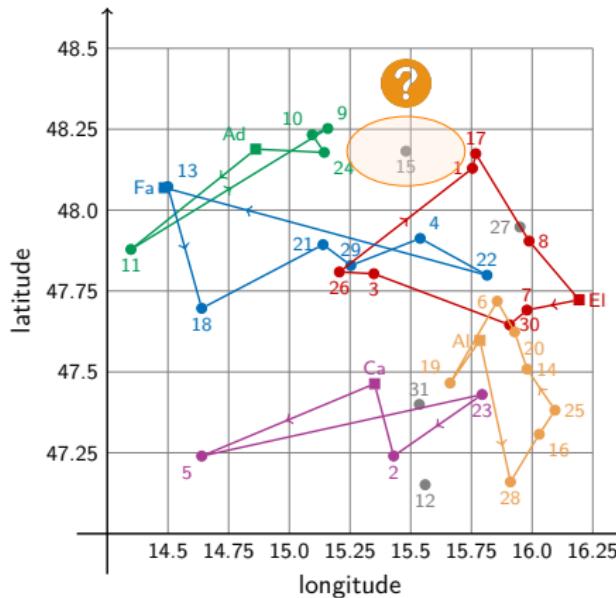
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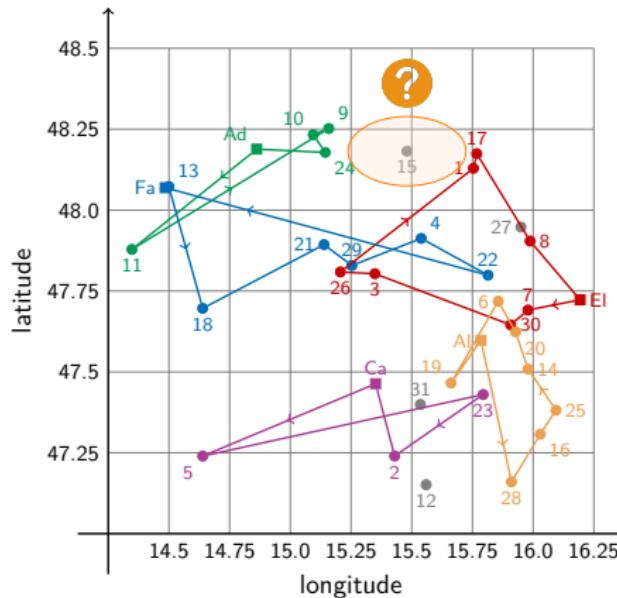
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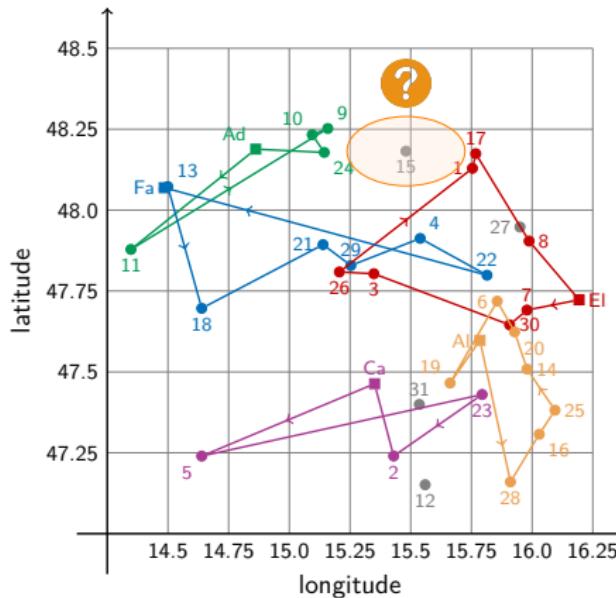
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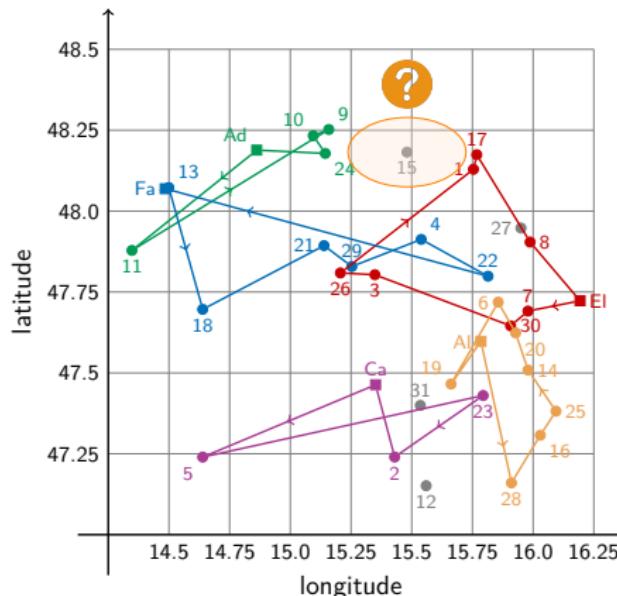
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- Explanations in Artificial Intelligence
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Literature on eXplainable Artificial Intelligence (XAI):

Works on explanations:

- Many in Machine Learning [Barredo Arrieta et al., 2020].
- Some in other AI fields including
 - Expert Systems, [Wick and Thompson, 1992],
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[Mohseni et al., 2021]
→ ≈ answering “What if ... ? Would it be ... ?” questions;
- **counterfactual**, i.e. presenting **alterations in inputs data** that would have resulted in a different outputs, such as an **end-user-specified outputs** [Wachter et al., 2018]
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- Observations about a solution
 - From observations to questions
 - From questions to computation
 - From computation to explanations

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List of possible observations:

We identify **16 possible observations** based on **templates**, about **various desired changes** in the solution:

- **adding** a task in an employee route;
e.g. “⟨employee i ⟩ is not performing ⟨task $j- ... just after ⟨task $k- ... in addition to the tasks of their route?”$$

- **swapping** two tasks outside - inside a route;
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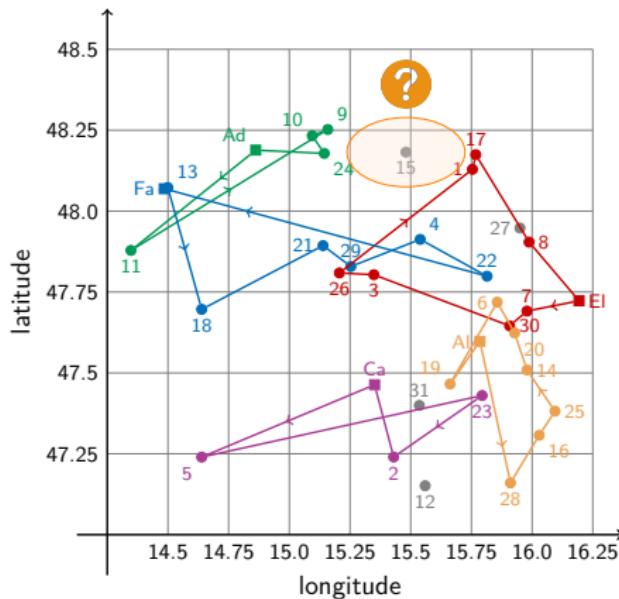
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A problematic situation for a planner:



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From 1 observation, 3 questions for the end-user:

From an observation, e.g. “ $\langle \text{employee } i \rangle$ is not performing $\langle \text{task } j \rangle$ in addition to the tasks of their route?”, we can build:

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“How to make $\langle \text{employee } i \rangle$ perform $\langle \text{task } j \rangle$ in addition to the tasks of their route?”

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From an observation, e.g. “ $\langle \text{employee } i \rangle$ is not performing $\langle \text{task } j \rangle$ in addition to the tasks of their route?”, we can build:

- a **contrastive** question,

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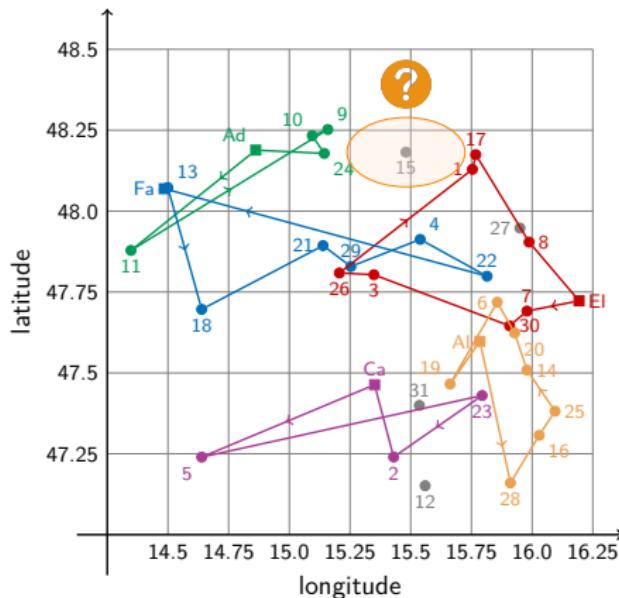
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A problematic situation for a planner:



“Ellen is not performing task 15 in addition to the tasks of her route...”

“Why is Ellen not performing task 15 in addition to the tasks of her route?”

“How to make Ellen perform task 15 in addition to the tasks of her route?”

- If no explanations, then lack of trust and confidence...

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Computation related to a contrastive question:

Consider a contrastive question, e.g. “Why is \langle employee i \rangle not performing \langle task j \rangle in addition to the tasks of their route?”

- Through their question, the end-user implicitly defines interesting **solutions neighboring the current one**, e.g. the solutions obtained by inserting j in the route of i and choosing a permutation of the tasks in this route.
- To answer the question, we must test if these solutions are **feasible and better** than the current one; **if not, extract information for why.**
- We build **algorithms for checking** solutions feasibility and improvement which are (depending on the question):
 - either **polynomial algorithms**,
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Consider a scenario question, e.g. “What if \langle changes in the instance parameters \rangle ? Would \langle employee i \rangle be performing \langle task j \rangle in addition to the tasks of their route?”

- The reasoning is the same as in the contrastive case: the user implicitly defines **solutions neighboring the current one**, but for an **instance** that is slightly **different**.
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Providing an explanation as a text:

We **ran the algorithm** associated with a question of any type.

We **fill explanation template texts** with values from the result.

Example of explanation text:

“How to make \langle employee i \rangle perform \langle task j \rangle in addition to the tasks of their route?”

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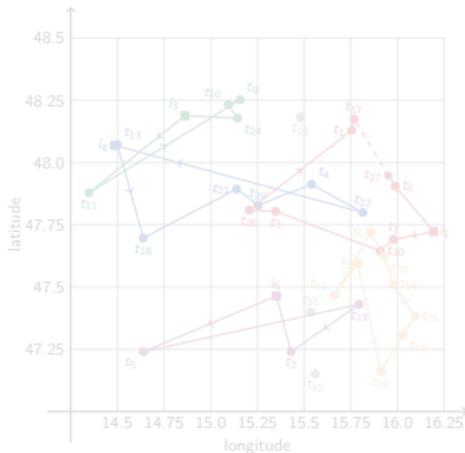
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Planner looking for explanations (1/3):

- Why is Ellen not performing t_{27} just after t_{17} ?
 - If Ellen performs t_{27} just after t_{17} , then she would end t_{27} at the earliest at 4:37PM while t_{27} is not available after 3:00PM.
Therefore Ellen is not performing t_{27} just after t_{17} .

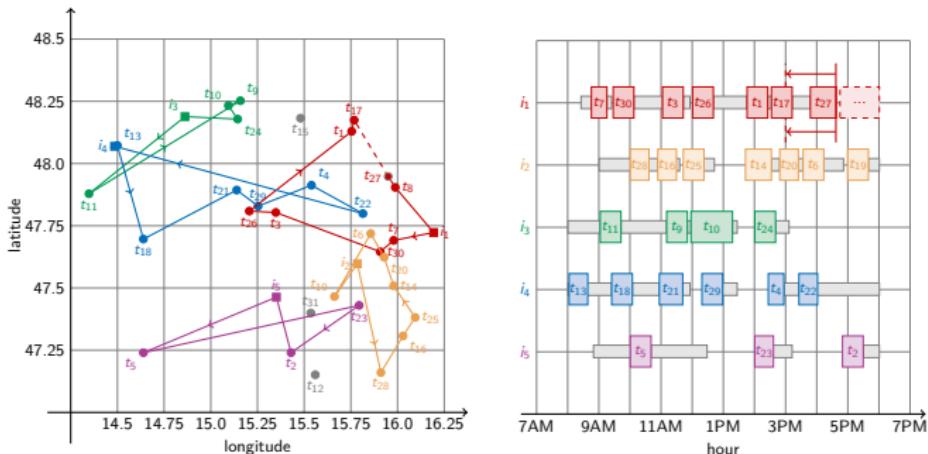
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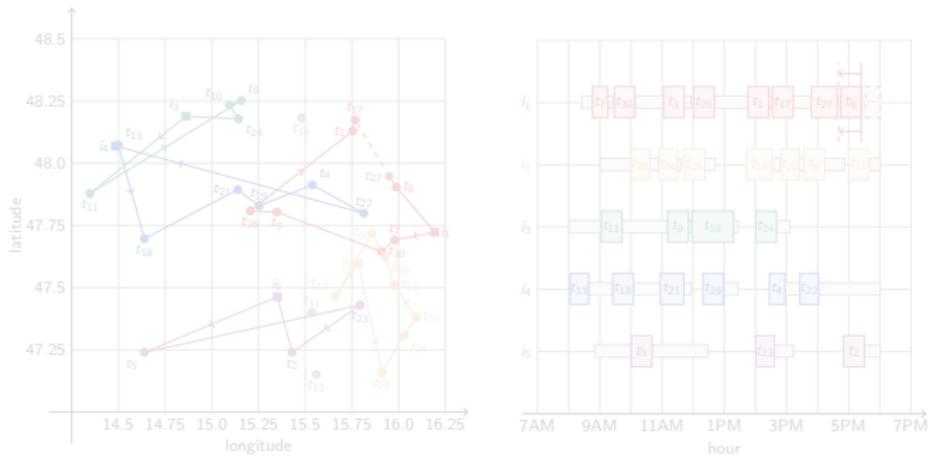
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Example or demo

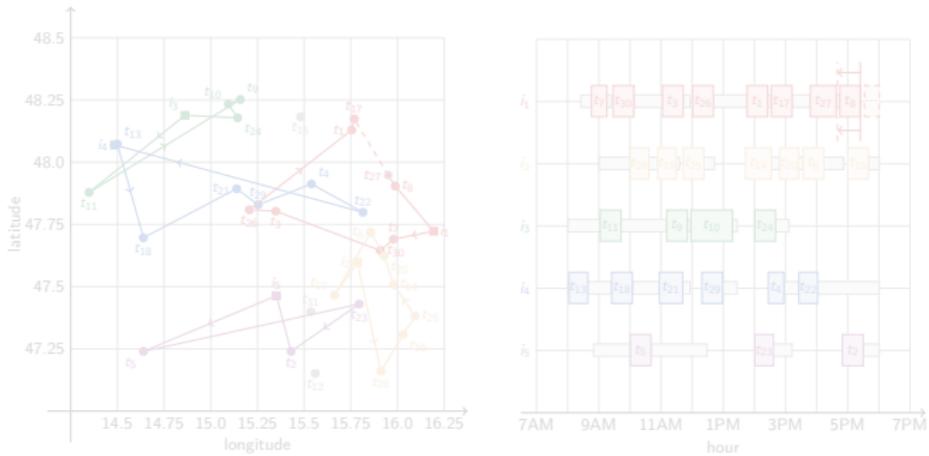
Planner looking for explanations (2/3):

- What if t_{27} was available up to 4:37PM (instead of 3:00PM)?
- If t_{27} was available until 4:37PM, then Ellen would be able to perform t_{27} during its availability time-window.
However, in the following steps of her route, Ellen would start t_8 at the earliest at 4:44PM while t_8 is not available after 4:40PM.
Therefore, it would still not make Ellen perform t_{27} just after t_{17} .



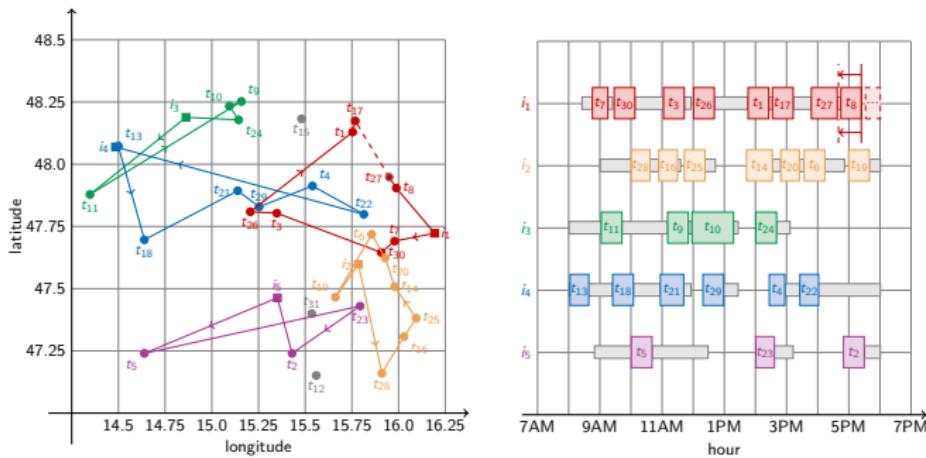
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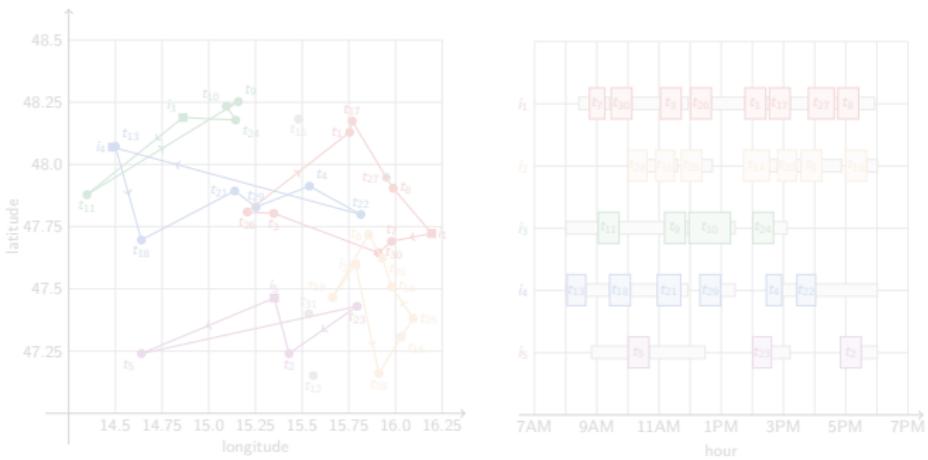
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- How to make Ellen perform t_{27} just after t_{17} ?
- If t_{27} was available until 4:37PM (instead of 3:00PM) and t_8 until 5:24PM (instead of 4:40PM), then it would make Ellen perform t_{27} just after t_{17} .

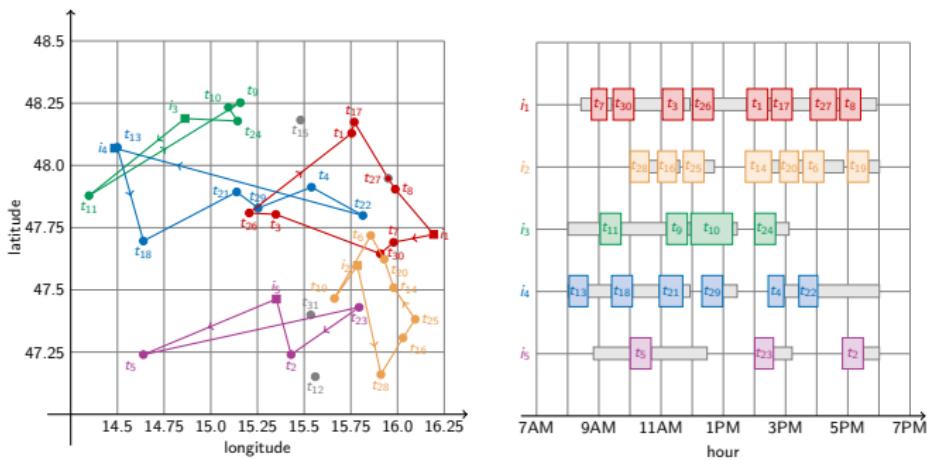


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Achieved work:

Approach for **generating explanations** that:

- is thought for an end-user of a system solving a **WSRP**;
- starts from **observations** about a solution;
- handles **contrastive, scenario** or **counterfactual questions**;
- is (often) based on **mathematical programming**;
- outputs **texts** thanks to templates;

to prevent the end-user from loosing **trust and confidence**.

Work in progress:

- Evaluate how explanations influence **end-users' trust**.
- Perform an exhaustive study for assessing **computational efficiency** of explanations generation.

Perspectives:

How much **generic** is our approach?

Can we transpose it to **other optimization problems**?

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Thank you for your attention!

[Barredo Arrieta et al., 2020] Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., and Herrera, F. (2020).

Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI.

Information fusion, 58:82–115.

[Chakraborti et al., 2020] Chakraborti, T., Sreedharan, S., and Kambhampati, S. (2020).

The emerging landscape of Explainable AI Planning and Decision Making.

In *Proceedings of the twenty-ninth International Joint Conference on Artificial Intelligence*, pages 4803–4811. IJCAI Organization.

[Junker, 2004] Junker, U. (2004).

Quickxplain: Preferred explanations and relaxations for over-constrained problems.

In *Proceedings of the ninetieth Association for the Advancement of Artificial Intelligence Conference on Artificial Intelligence*, page 167–172. AAAI Press.

References III

[Korikov et al., 2021] Korikov, A., Shleyfman, A., and Beck, C. (2021).

Counterfactual explanations for optimization-based decisions in the context of the GDPR.

In *Proceedings of the thirtieth International Joint Conference on Artificial Intelligence*, pages 4097 – 4103. IJCAI Organization.

[Krarup et al., 2021] Krarup, B., Krivic, S., Magazzeni, D., Long, D., Cashmore, M., and Smith, D. E. (2021). Contrastive explanations of plans through model restrictions.

[Lipton, 1990] Lipton, P. (1990).

Contrastive explanation.

Royal Institute of Philosophy Supplement, 27:247–266.

[Mohseni et al., 2021] Mohseni, S., Zarei, N., and Ragan, E. D. (2021).

A multidisciplinary survey and framework for design and evaluation of Explainable AI systems.

ACM Transactions on Interactive Intelligent Systems, 11(3–4).

[Wachter et al., 2018] Wachter, S., Mittelstadt, B., and Russell, C. (2018).

Counterfactual explanations without opening the black box: Automated decisions and the GDPR.

Harvard Journal of Law & Technology, 31.

[Wick and Thompson, 1992] Wick, M. and Thompson, W. (1992).

Reconstructive Expert System explanation.

Artificial Intelligence, 54:33–70.