Counterfactual explanations for Workforce Scheduling and Routing Problems

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DecisionBrain™
Smarter Decisions. Better Results.

Plan

1. Introduction
2. Related works
3. Mathematical model of the WSRP
4. Generating counterfactual explanations
5. Conclusion

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   - Use case
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Motivations

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 by **non-expert people**.

↪ End-users may experience a **black box feeling**.

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

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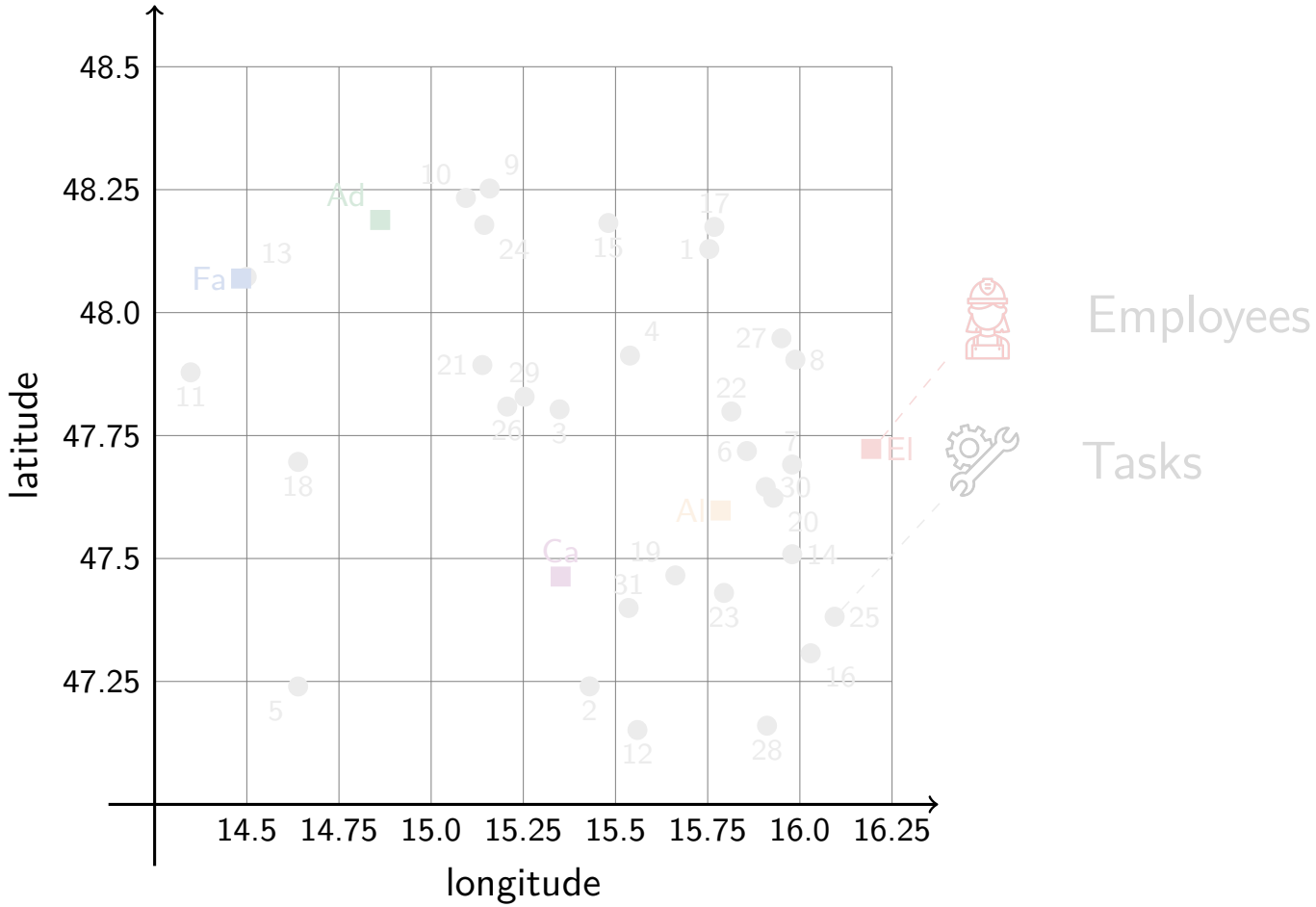
Use case - (1) CO problem

Workforce Scheduling and Routing Problem (WSRP):



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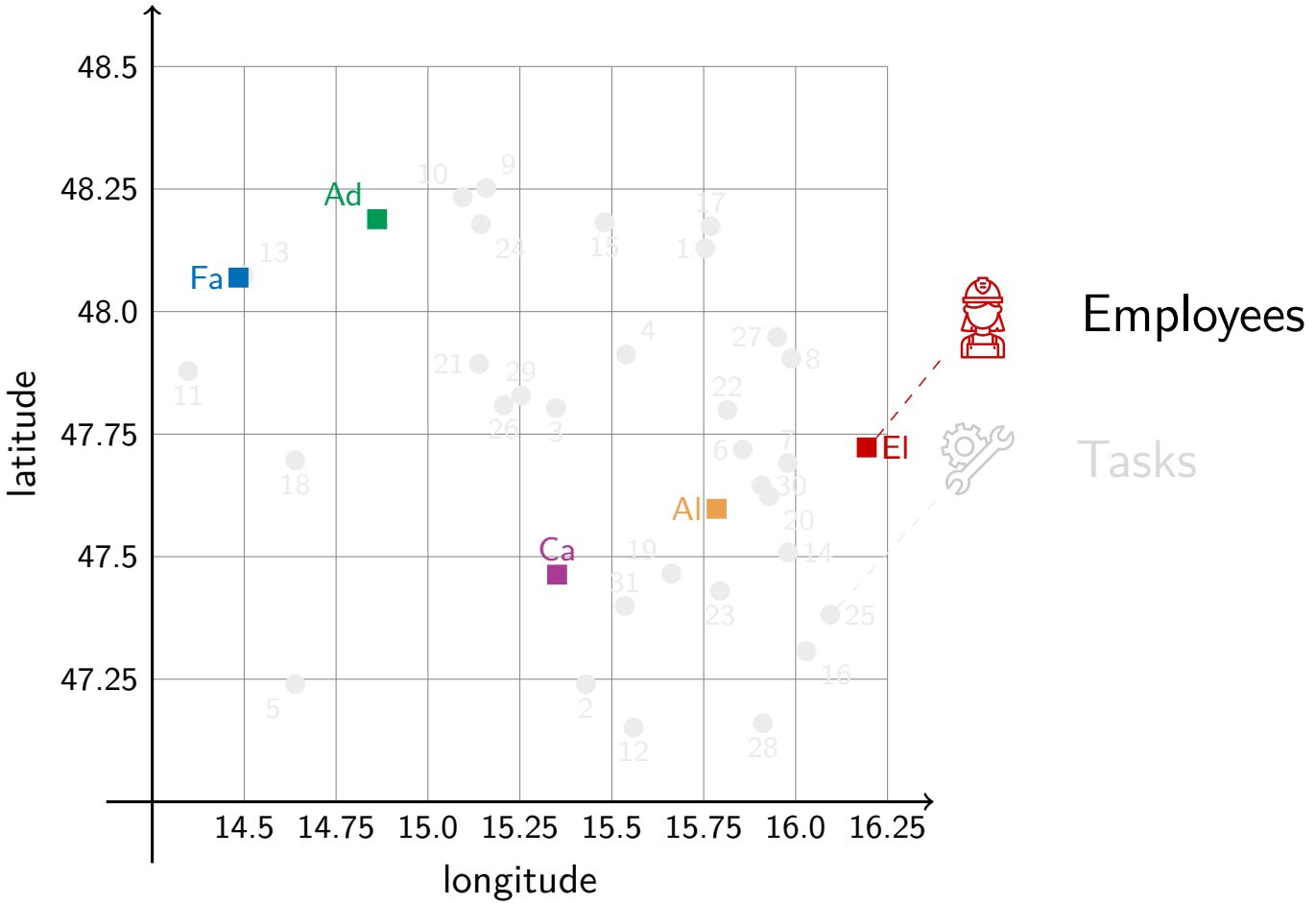

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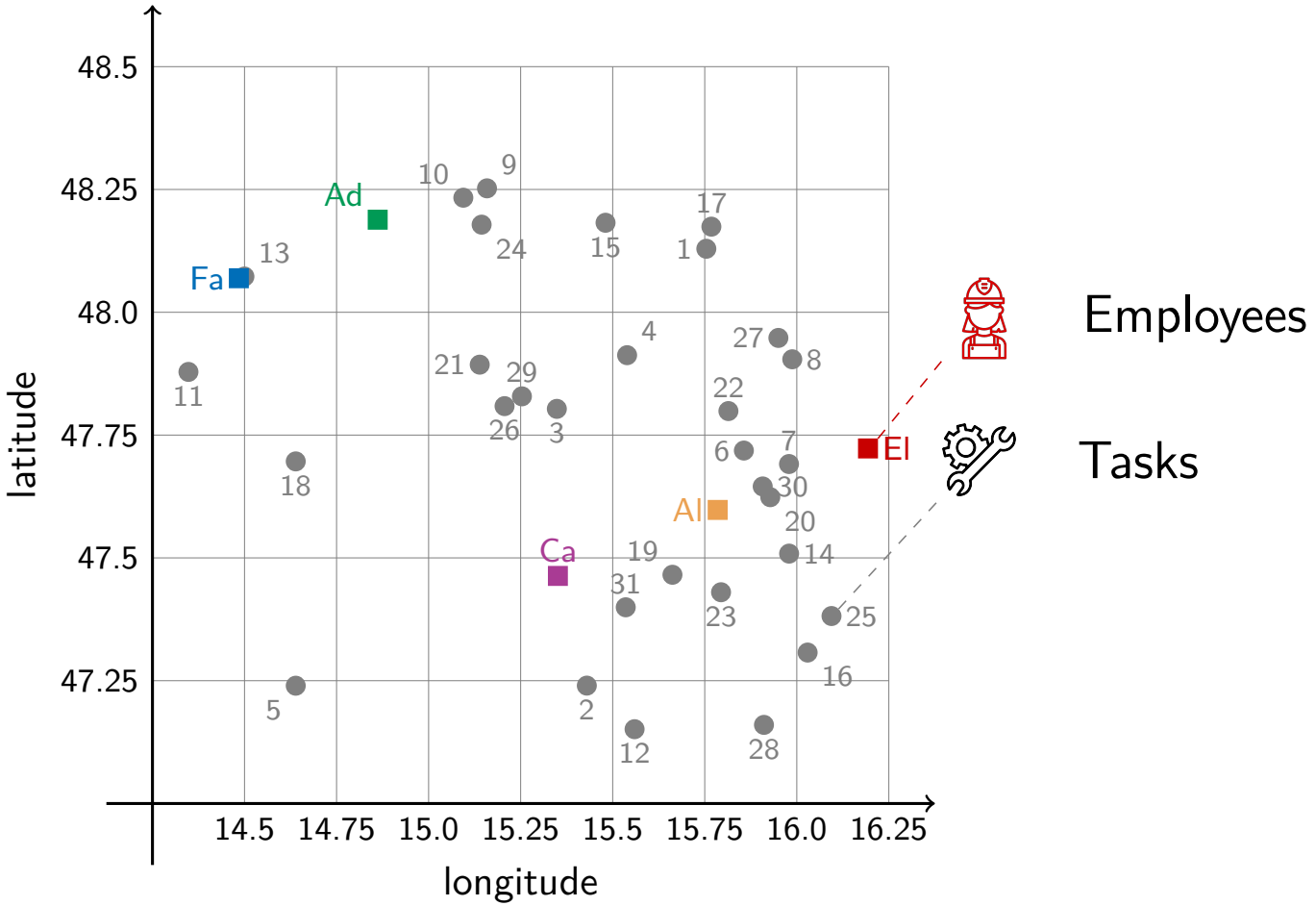

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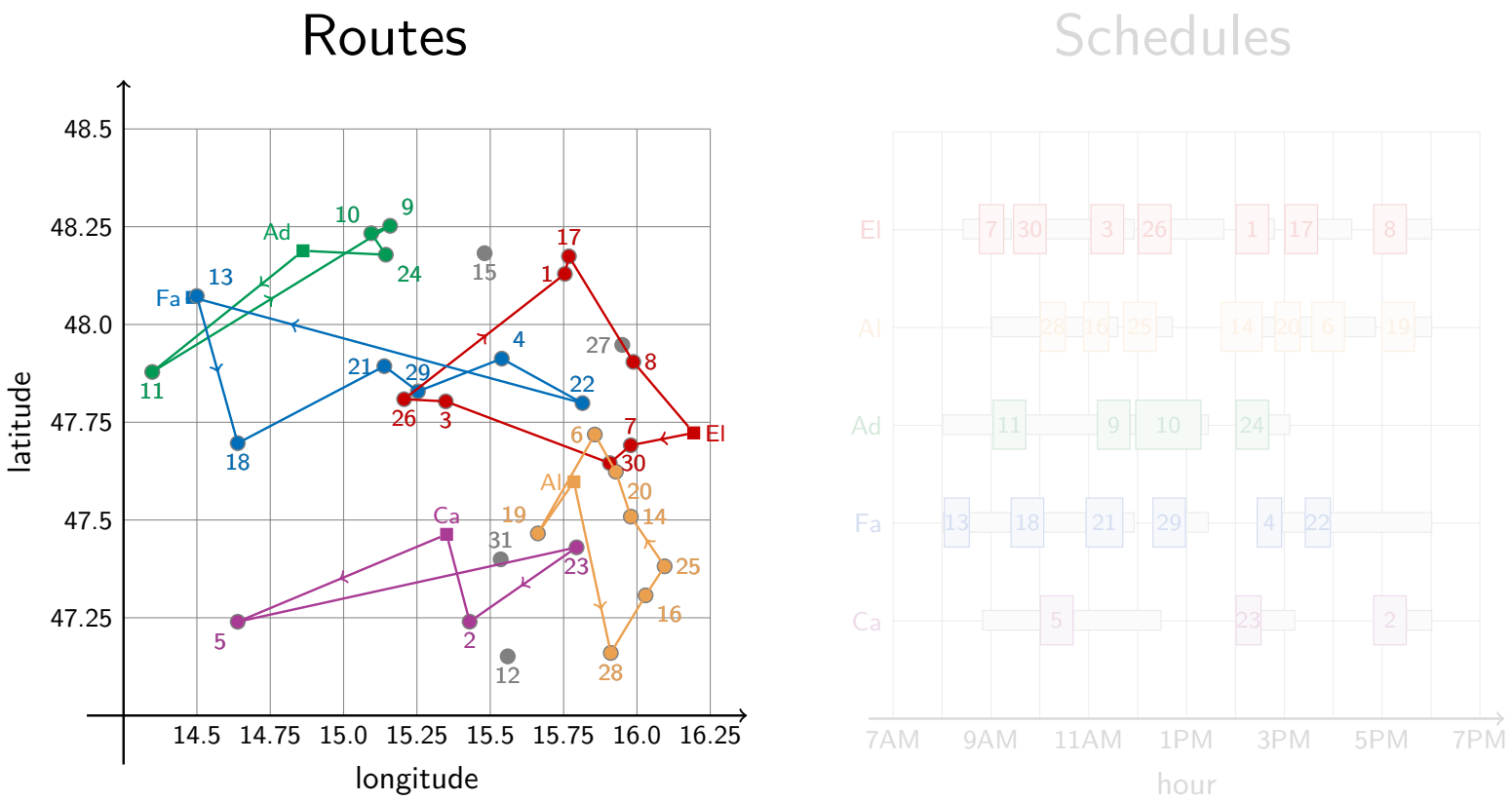

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Workforce Scheduling and Routing Problem (WSRP):

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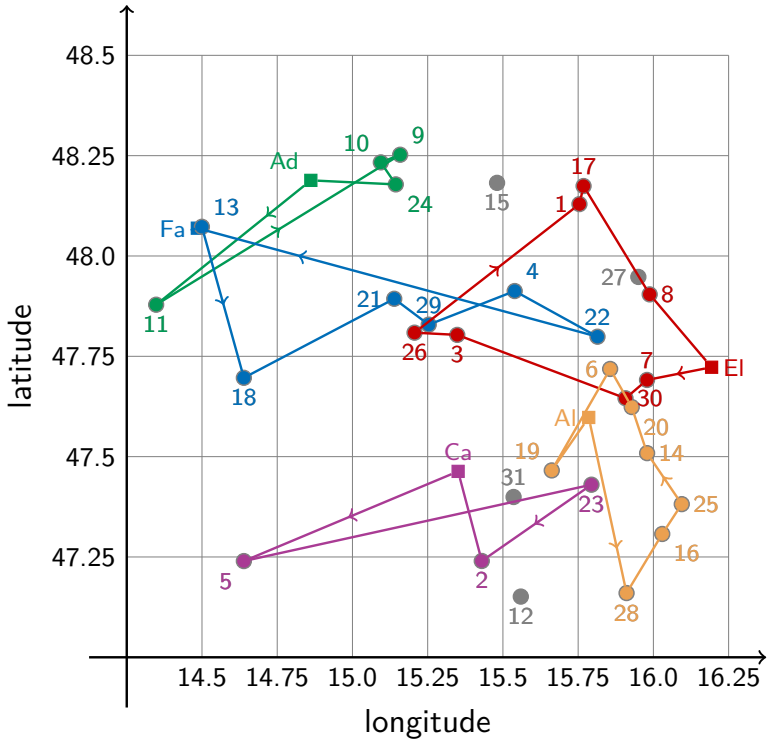
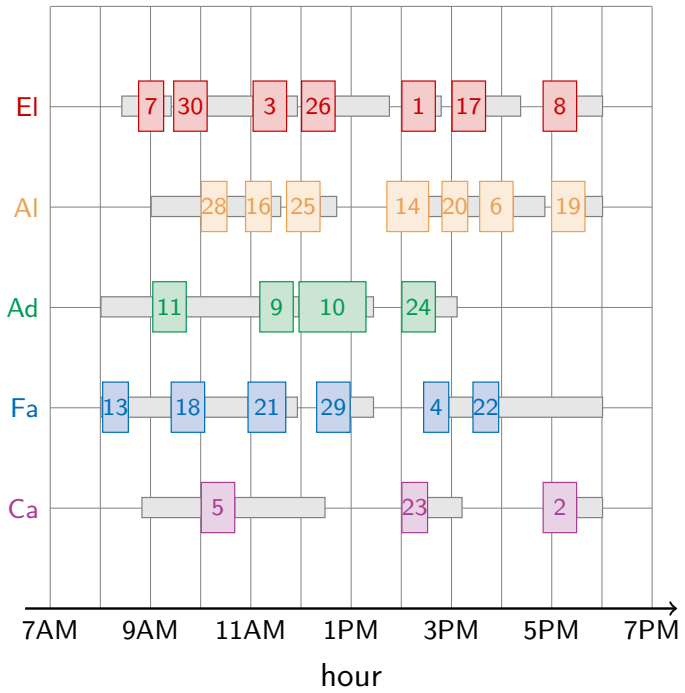


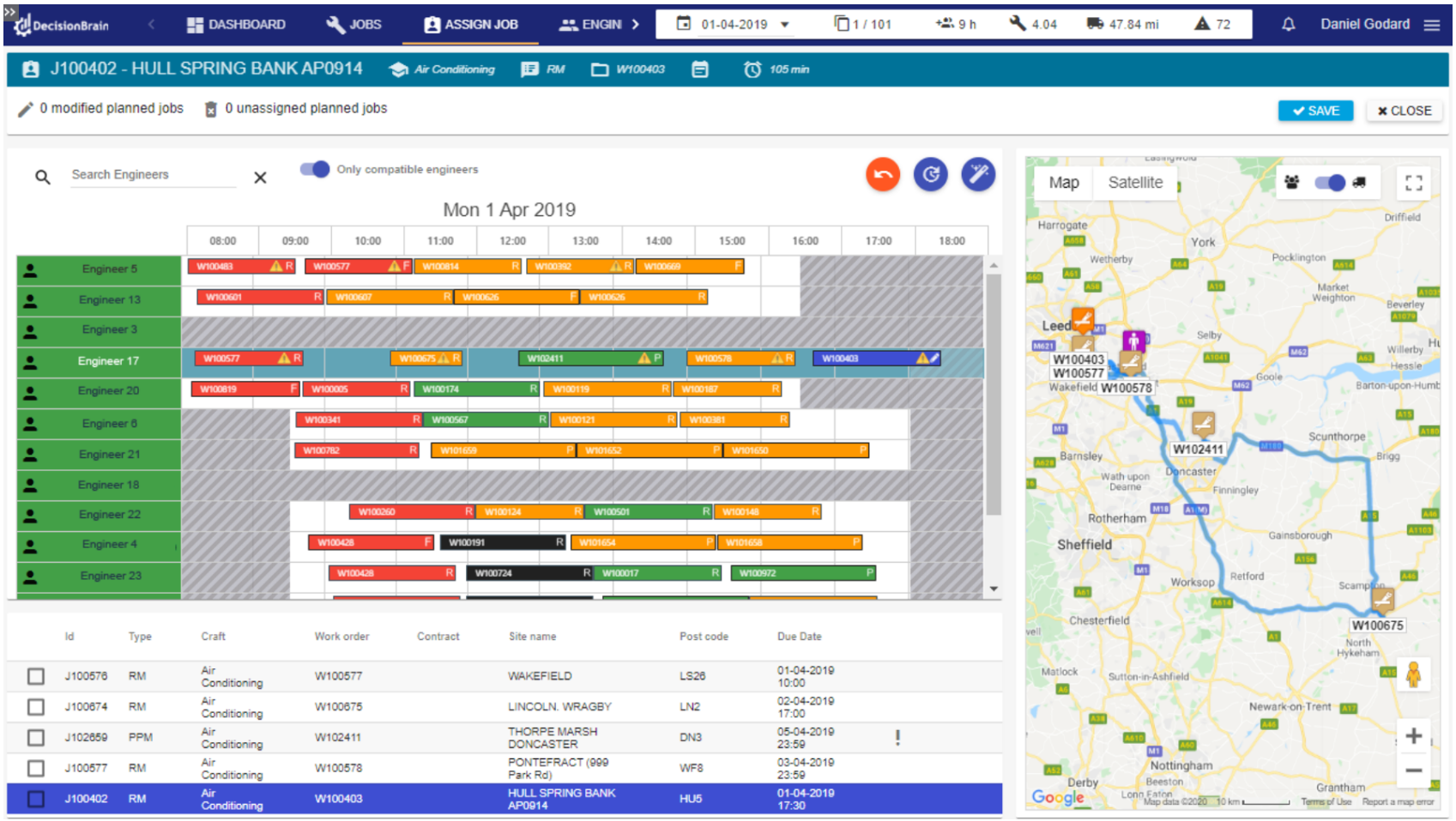
Schedules



Our use case - (2) Optimization system

WSRP-solving system:

e.g DecisionBrain's Dynamic Scheduler



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

Planner:

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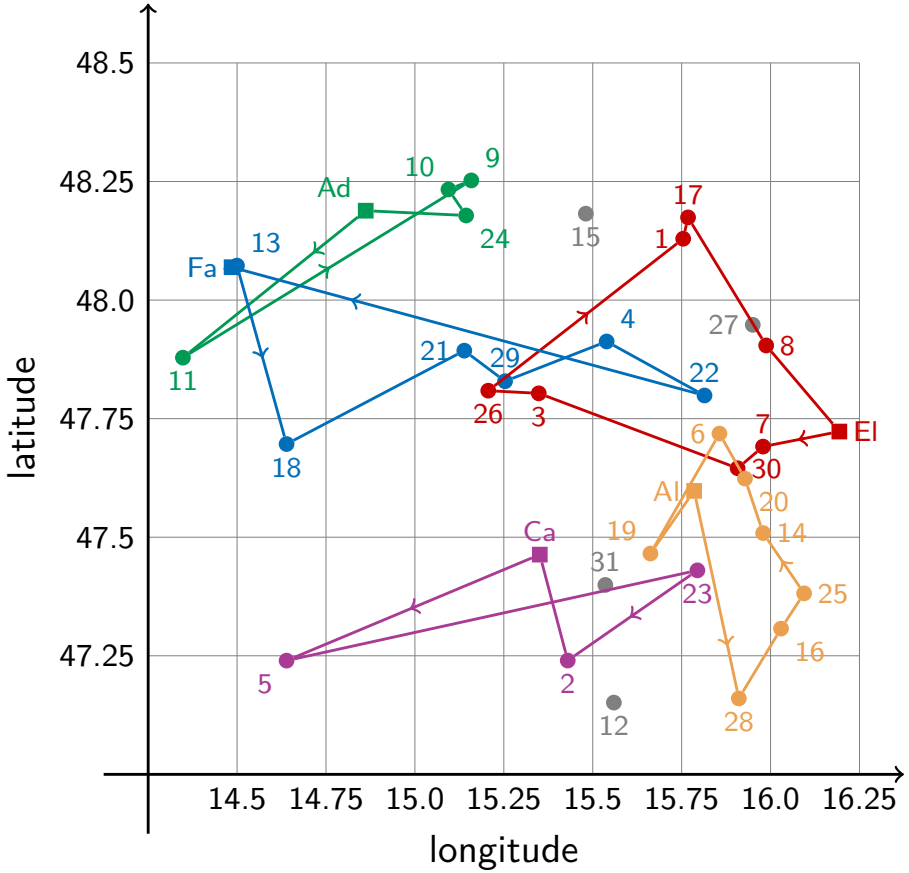

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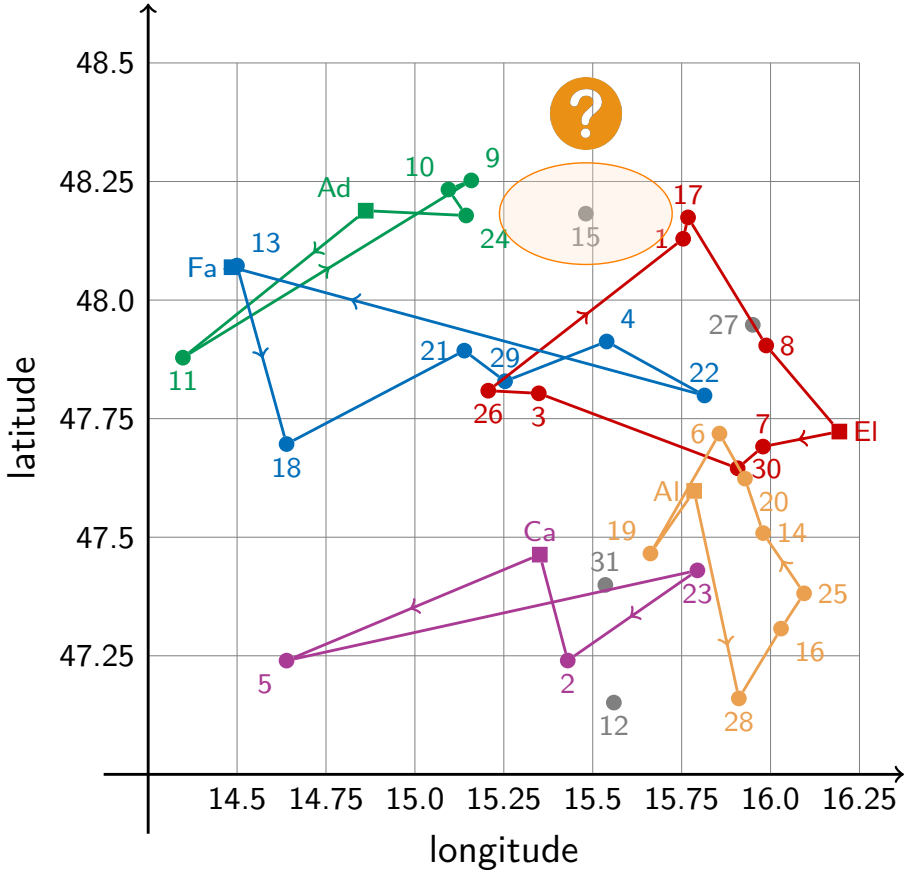

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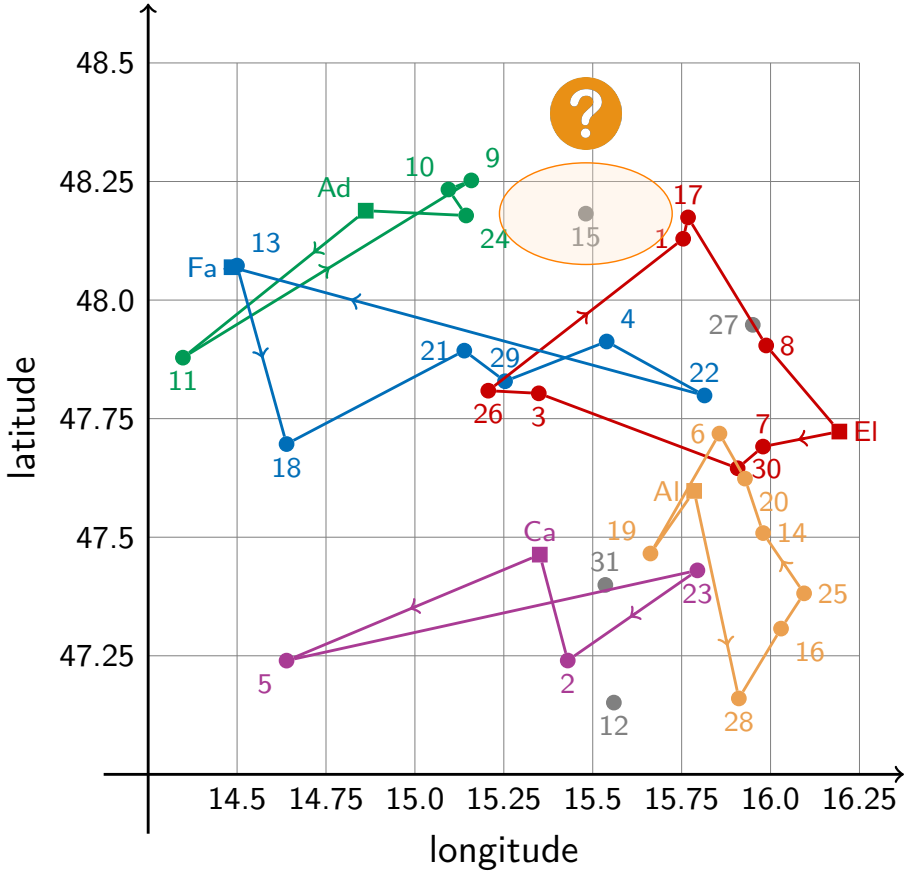

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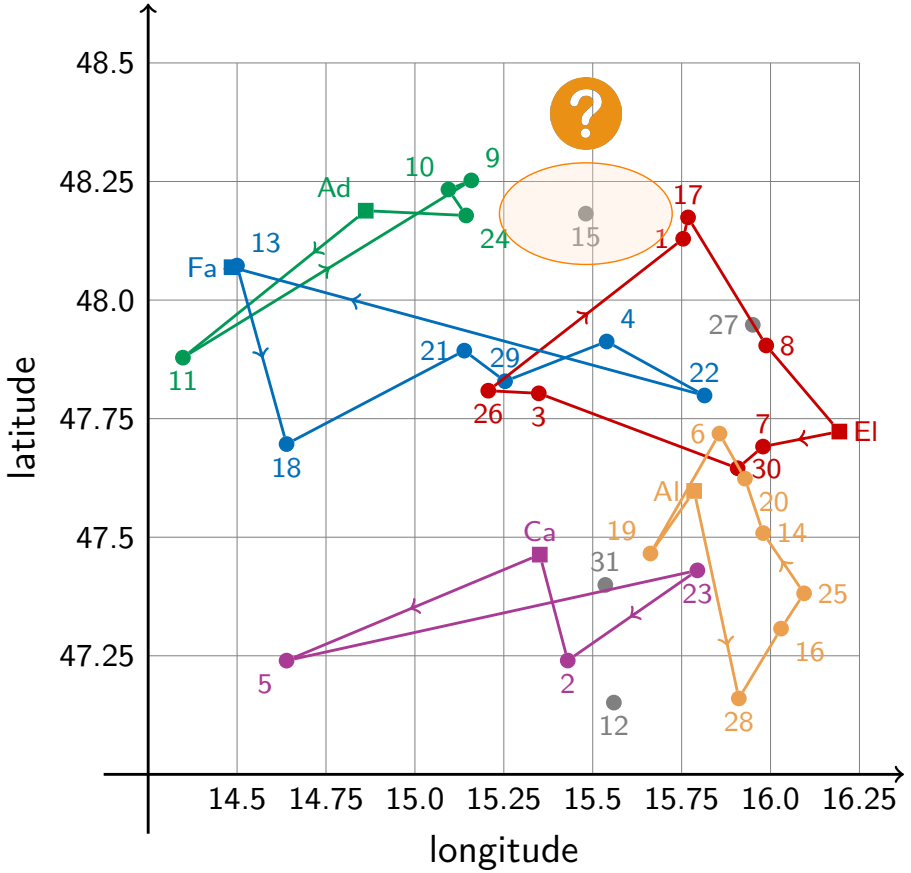

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Literature on eXplainable Artificial Intelligence (XAI):

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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↪ Survey **concepts about explanations** in AI fields other than CO and transpose them to CO.

[Barredo Arrieta et al., 2020] XAI: Concepts, taxonomies, opportunities and challenges toward responsible AI
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Some recurrent concepts in XAI methods:

Explanations are often:

- **local** [Wick and Thompson, 1992], *i.e.* focusing on a specific output generated by the system.
- **counterfactual** [Wachter et al., 2018], *i.e.* explanations which present alterations in the inputs that would have resulted in different outputs (*e.g.* end-user-specified one).
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Our proposition (with more details)

Tackling the black box feeling experienced by non-expert end-users solving WSRP instances, by generating **explanations** to help them better understand their WSRP solutions.

Generating **explanations** which are:

- focusing **on a given solution**,
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Mathematical model of the WSRP

Instance data:

- $\mathcal{E} = \{1, \ldots, n\}$ set of **mobile employees**,
  each employee i characterized by:
  - a **skill level** $ske_i \in \mathbb{N}$;
  - a working **time-window** $[lbe_i, ube_i] \subset [\![0, 1440]\!] \subset \mathbb{N}$;
  - a **location**.
- $\mathcal{T} = \{1, \ldots, m\}$ set of **tasks**,
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- **Travel duration** between two locations tr_{jk} with $(j, k) \in \mathcal{T}^2$.

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Bi-objective Integer Linear Program (ILP) model:

lex max (total working duration, −total traveling duration)

s.t.
- flow constraints
- skill constraints
- occurence constraints
- tasks availability constraints
- employees working hours constraints
- sequencing constraints

$U_{ijk} \in \{0,1\}$ whether or not i goes from j to k, $\forall i \in \mathcal{E},\ \forall (j,k) \in \mathcal{T}^2$

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Sequencing constraints:

$$\forall\ (j,k) \in \mathcal{T}^2,\ j \neq k,$$

$$T_j + \underbrace{dt_j}_{\substack{\text{duration}\\ \text{of } j}} + \sum_{i \in \mathcal{E}} U_{ijk}\ \underbrace{tr_{jk}}_{\substack{\text{travel}\\ \text{duration}\\ j \to k}} \leq T_k + \left(1 - \sum_{i \in \mathcal{E}} U_{ijk}\right) \underbrace{ubt_j}_{\substack{\text{upper}\\ \text{bound}\\ \text{of } j}}$$

↪ If there is an employee performing j then k,

$$T_j + dt_j + 1 \times tr_{jk} \leq T_k + 0 \times ubt_j$$

↪ Otherwise,

$$T_j + dt_j + 0 \times tr_{jk} \leq T_k + 1 \times ubt_j$$

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↪ If there is an employee performing j then k,

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Bi-objective Integer Linear Program (ILP) model:

lex max $\big($total working duration, $-$total traveling duration$\big)$

s.t.
- flow constraints
- skill constraints
- occurence constraints
- tasks availability constraints
- employees working hours constraints
- sequencing constraints

$U_{ijk} \in \{0,1\}$ whether or not i goes from j to k, $\forall i \in \mathcal{E},\ \forall (j,k) \in \mathcal{T}^2$

$T_j \in \mathbb{N}$ start time of j, $\forall j \in \mathcal{T}$

Plan

1. Introduction
2. Related works
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Explanations requested through questions

List of end-user questions:

We propose **16 template questions** about **various topics**:

- **inserting** a task in an employee's route
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We selected these questions as they satisfy some **assumptions**:

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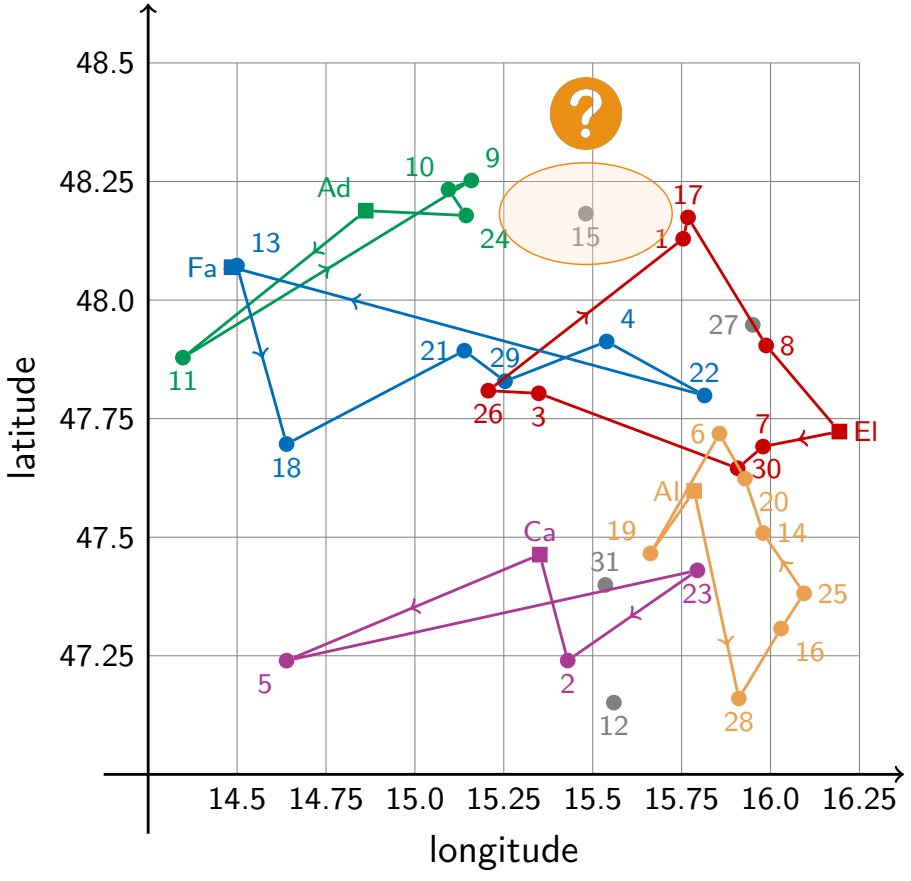
Reminder | Our use case - (3) Non-expert end-user

A problematic situation for a planner:



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

↪ If no explanations, then black box feeling...

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From questions to mathematical programming

General principle:

Each question q is **mapped** to a **multi-obj. ILP model** which:

- aims at finding **how to alter the instance parameters** s.t.:
  1. we obtain a solution satisfying the *desideratum*;
  2. we minimize the **alterations** (**magnitude** and **number**);
  3. we optimize the solution quality.
- is based on the WSRP model with **adaptations**:
  - focus on only one employee's route;
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Multi-objective ILP model on an example of question:

Let q be a question based on "How to make ⟨employee i^*⟩ perform ⟨task j^*⟩ in addition to the tasks of their route?"

Some preliminary remarks:

- We can work with a **reduced set of tasks** $\mathcal{T}^* = \{j \text{ performed by } i^* \text{ in solution}\} \cup \{j^*\}$.
- We assume that the user wants to alter only **task time parameters** (dt_j, lbt_j, ubt_j) within some acceptable ranges.
- We introduce new **decision variables** including:
  - ΔDT_j, decrease of dt_j, for all $j \in \mathcal{T}^*$;
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lex min $\Big(T^{lb}_{j^*} - T^{ub}_{j^*}, \quad \sum_{j \in \mathcal{T}^*} \Delta DT_j, \quad \Delta T_{max}, \quad$ nb of alterations, total traveling duration$\Big)$

s.t.
- adjusted flow constraints
- adjusted occurence constraints
- adjusted tasks availability constraints
- adjusted working hours constraints
- adjusted sequencing constraints
- constraints on altering variables like ΔDT_j

$U_{i^*jk} \in \{0,1\}$	whether or not i^* goes from j to k,	$\forall\ (j,k) \in (\mathcal{T}^*)^2$
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Sequencing constraints:

$$\forall\ (j,k) \in \mathcal{T}^2,\ j \neq k,$$

$$T_j + \underbrace{dt_j}_{\substack{\text{duration}\\ \text{of } j}} + \sum_{i \in \mathcal{E}} U_{ijk}\ \underbrace{tr_{jk}}_{\substack{\text{travel}\\ \text{duration}\\ j \to k}} \leq T_k + \left(1 - \sum_{i \in \mathcal{E}} U_{ijk}\right) \underbrace{ubt_j}_{\substack{\text{upper}\\ \text{bound}\\ \text{of } j}}$$

↪ If there is an employee performing j then k,

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↪ Otherwise,

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Sequencing constraints with altering variables:

3 groups of constraints instead of 1:

- $\forall\ (j,k) \in (\mathcal{T}^* \setminus \{j^*\})^2,\ j \neq k,$

$$T_j + dt_j - \Delta DT_j + U_{i^*jk}\ tr_{jk} \leq T_k + \left(1 - U_{i^*jk}\right) ubt_j$$

- $\forall\ k \in \mathcal{T}^* \setminus \{j^*\},$

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- $\forall\ j \in \mathcal{T}^* \setminus \{j^*\},$

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Sequencing constraints with altering variables:

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From questions to mathematical programming

Multi-objective ILP model on an example of question:

lex min $\big(T^{lb}_{j^*} - T^{ub}_{j^*}, \quad \sum_{j \in \mathcal{T}^*} \Delta DT_j, \quad \Delta T_{max}, \quad$ nb of alterations, total traveling duration$\big)$

s.t.
- adjusted flow constraints
- adjusted occurence constraints
- adjusted tasks availability constraints
- adjusted working hours constraints
- adjusted sequencing constraints
- constraints on altering variables like ΔDT_j

$U_{i^*jk} \in \{0,1\}$	whether or not i^* goes from j to k,	$\forall\ (j,k) \in (\mathcal{T}^*)^2$
$T_j \in \mathbb{N}$	start time of j	$\forall\ j \in \mathcal{T}^*$
$T^{ub}_{j^*}, T^{lb}_{j^*} \in \mathbb{N}$	bounds on the start time of j^*	
$\Delta DT_j \in \mathbb{N}$	decrease of the duration of j	$\forall\ j \in \mathcal{T}^*$
...		
$\Delta T_{max} \in \mathbb{N}$	greatest value of time alterations	

Plan

1. Introduction
2. Related works
3. Mathematical model of the WSRP
4. Generating counterfactual explanations
   - Explanations requested through questions
   - From questions to mathematical programming
   - From mathematical programming to explanations
5. Conclusion

From mathematical programming to explanations

3 cases of explanations:

Assume that the multi-objective ILP model has been solved.

1. $T_{j^*}^{lb} - T_{j^*}^{ub} = 0$ and $\Delta T_{max} > 0$
   ↪ The *desideratum* is obtained **thanks to alterations**.

2. $T_{j^*}^{lb} - T_{j^*}^{ub} = 0$ and $\Delta T_{max} = 0$
   ↪ The *desideratum* is obtained **without any alterations**.

3. $T_{j^*}^{lb} - T_{j^*}^{ub} > 0$
   ↪ Alterations ranges are **not enough** to get the *desideratum*.

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From mathematical programming to explanations

Explanation text in case 1.:

"By ⟨applying the alterations of the instance parameters given by positive values of altering variables like ΔDT_j⟩,
⟨the *desideratum*⟩ would be possible;
in this case, the solution would be ⟨the one deduced from the ILP optimal result⟩."

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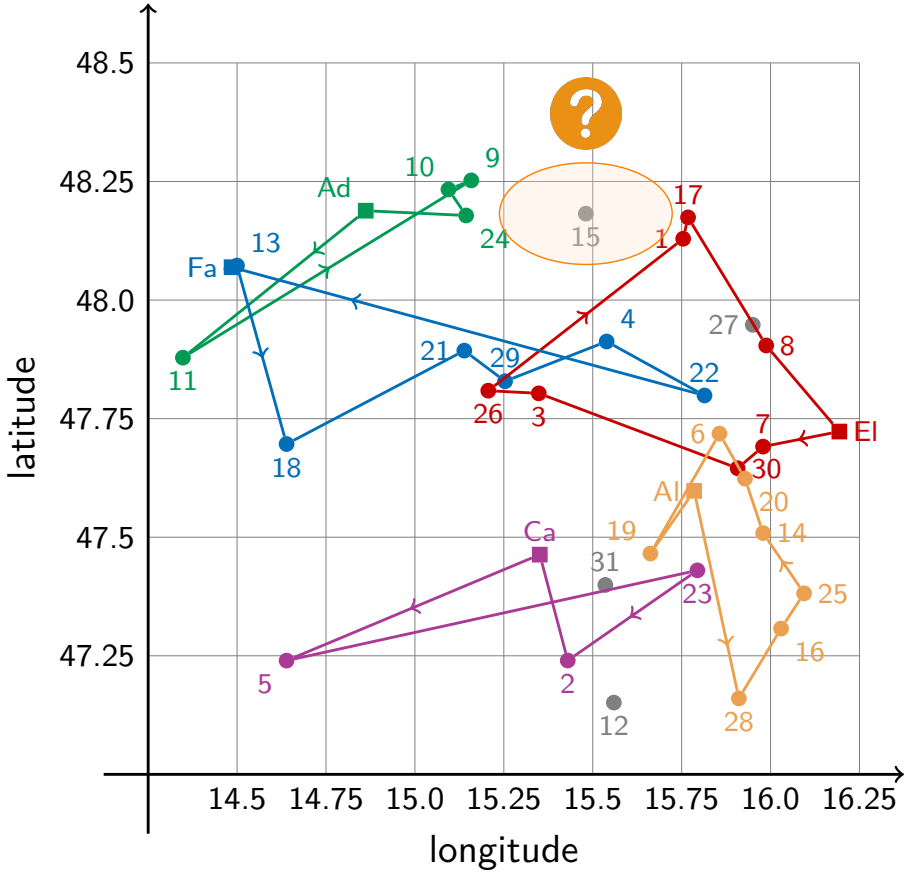
Reminder | Our use case - (3) Non-expert end-user

A problematic situation for a planner:



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

↪ If no explanations, then black box feeling...

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"By changing the opening time of task 17 to 12:29PM (instead of 12:30PM in the current input data),
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in this case, the solution would be the one obtained by changing Ellen's sequence of performed tasks to [30, 7, 8, 1, 17, 15, 26, 3]."

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Conclusion

Achieved work in this article:

Approach for generating **counterfactual explanations** that:

- is thought for an end-user of a system solving a **WSRP**;
- starts from user **questions** about various *desiderata*;
- is based on **mathematical programming**;
- ends on explanations given as **texts**.

Related work:

Approach for generating **contrastive explanations**:

[Lerouge et al., 2022] Explaining solutions stemming from optimization systems solving the Workforce Scheduling and Routing Problem to their end-users (Working paper).

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Work in progress:

- Perform an exhaustive study for assessing **computational efficiency**.
- Evaluate how explanations influence **end-users' trust**.
- Design an explanation system handling **various types of explanations** (contrastive, scenario and counterfactual).

Perspectives:

How much **generic** is our **approach**? Can we transpose it to other optimization problems?

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Thank you for your attention!

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