

Towards Explainable Recommendations of Resource

Allocation Mechanisms in On-Demand Transport Fleets

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Context and motivation

On-Demand Transport

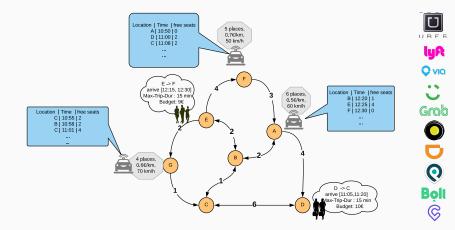


Figure 1: Dial A Ride Problem (DARP)



Existing approaches

Centralized dispatching

- · Requests are centralized in a portal
- Linear/ Mixed integer program models \Rightarrow NP-Hard problem, lack of scalablity
- · Continuous access to the portal
 - \Rightarrow expensive with a critical bottleneck

Decentralized allocation

· Decentralized autonomous decisions

 \Rightarrow need for conflict detection and avoidance protocols

• peer-to-peer (P2P) communication

 \Rightarrow need for scalable communication model to ensure best information sharing

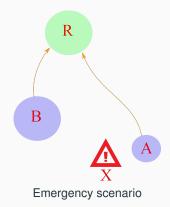


$= \sum_{\substack{i \in I \\ i \in I \\ i \in I \\ i \in I}} \sum_{i \in I \\ i $	
	2

About the Need for Explainability



Demand distribution at rush hours





Contribution

A generic model to ODT's dynamic resource allocation problem Extends the Online Localized Resource Allocation (OLRA) [Zargayouna et al., 2016] by considering Autonomous Vehicle (AV) fleets with communication constraints

 $\left\langle \mathcal{R},\mathcal{V},\mathcal{G},\mathcal{T}\right\rangle$

- \mathcal{R} : a dynamic set of requests
- \mathcal{V} : a fleet of *m* vehicles
- $\mathcal{G}:$ a graph defining the road network
- \mathcal{T} : the problem's time horizon



Communication range and direct connectivity

Vehicles communicate within limited communication range

 $\texttt{d_ctd}: \mathcal{V} \times \mathcal{V} \times \mathcal{T} \rightarrow \{0,1\}$

defines if two vehicles are connected directly to each other

$$\texttt{d_ctd}(i, j, t) = \begin{cases} 1, & \text{if } \textit{distance}(\texttt{loc}_i^t, \texttt{loc}_j^t) \leq r : r = \textit{min}(\textit{rng}_i, \textit{rng}_j) \\ 0, & \text{otherwise} \end{cases}$$



Transitive connectivity

To maximize their connectivity, two vehicles can be connected transitively

$$\mathtt{ctd}: \mathcal{V} \times \mathcal{V} \times \mathcal{T} \to \{0,1\}$$

generalizes the d_ctd with the transitive connectivity.

$$\mathtt{ctd}(i,j,t) = \begin{cases} 1, & \text{if } \mathtt{d_ctd}(i,j,t) \text{ or } \exists k : \mathtt{ctd}(i,k,t) \& \mathtt{ctd}(k,j,t) \\ 0, & \text{otherwise} \end{cases}$$



Connected sets

A connected set is a set of entities that are connected directly or by transitivity.

$$\textit{CS}: \mathcal{V} \times \mathcal{T} \rightarrow 2^{\textit{V}}$$

$$CS(i, t) = \{j \in \mathcal{V} | ctd(i, j, t)\}$$

The connected sets are dynamic entities; they are created, split, merged at run-time based on the vehicles' movement.

A vehicle v may communicate at time t only with the members of its connected set by directed or broadcast messages.

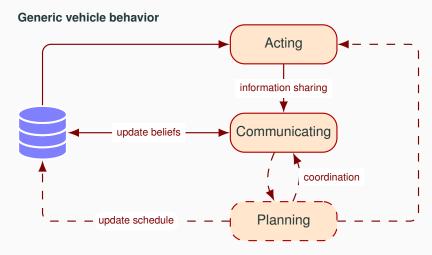


Vehicle communication (cont.)





Autonomous Vehicle (AV) agents





A solution for AV-OLRA is defined for each connected set as an aggregation of the allocations of all vehicles in this set, avoiding all conflicts that could happen. Solution methods depend mainly on the adopted coordination mechanism (CM):

 $\mathit{CM} := \langle \mathit{DA}, \mathit{AC}, \mathit{AM} \rangle$

- DA: level of decision autonomy \Rightarrow centralized (C) / decentralized (D)
- AC: agents' cooperativeness level \Rightarrow sharing (S) / no-sharing (N)
- AM: the allocation mechanism ⇒ GREEDY / MILP / DCOP / AUCTIONS

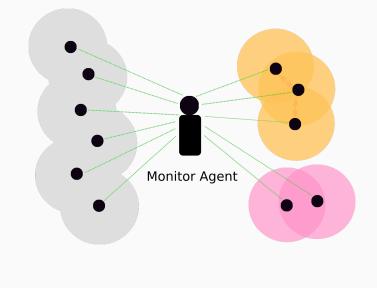


Implemented coordination mechanisms

- *Selfish*: (*D*, *N*,Greedy) [van Lon et al., 2012]
- Dispatching: $\langle C, S, MILP \rangle$ [El Falou et al., 2014]
- *Auctions*: (*D*, *S*,Auction) [Daoud et al., 2020]
- Cooperative: (D, S,DCOP) MGM-2 solver [Pearce and Tambe, 2007] DSA solver [Zhang et al., 2005]

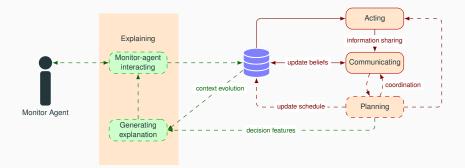


Monitor Agent (MA)



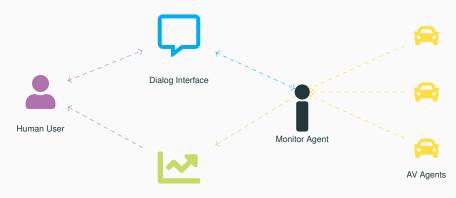


AV explaining sub-behavior





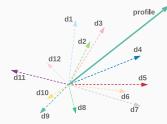
MA interaction model

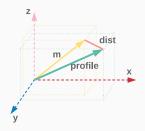


Simulation Statistics Interface



Computing the recommendations





$$dist(m, p) = \sqrt{\sum_{i=1}^{n} (m_i - p_i)^2}$$
$$sim(m, p) = \frac{1}{dist(m, p)}$$



Creating explanations

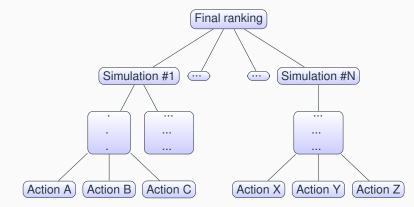
AV individual actions

- Whenever an AV take an explainable decision
- *AV* interpret his behaviors, justify the decisions with the social and technical reasons behind
- Interpretation are communicated to MA
- The set of explainable AV decisions depend mainly on the solution method adopted by AVs

Solution	DA	AC	AM	Explanation examples
Selfish	D	Ν	Greedy	Why prioritizing a specific request?
Dispatching	С	S	MILP	Which constraints are violated?
Market	D	S	Auctions	How winner determination computed?
				Why accepting some trade options?
Cooperative	D	S	DCOP	What are individual costs and utilities?



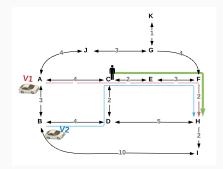
MA's aggregated decisions





Illustrative examples

Explaining AV individual actions with Auctions



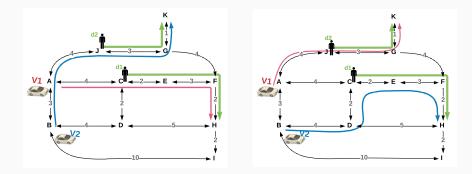
V1: "Serving d_1 costs 11 time units because reaching *C* from my current location *A* requires 4 time units, and reaching *H* from *C* requires at least 7"

V2: "Serving d_1 costs 13 time units because reaching *C* from my current location *B* requires 6 time units, and reaching *H* from *C* requires at least 7"

*V*1: "I win the auction because my offer has a lower cost than V_2 's. The lower the cost is, the better the *QoB* achieved."



Explaining AV individual actions with Auctions (cont.)



*V*1: "Abandoning d_1 in favor of V_2 decreases the global operational cost value by 1. It also decreases the accumulated waiting time by 1"



Abstract features

"greedy method favors closer requests with short distances, which means lower operational cost."

"centralized dispatching requires continuous communication between vehicles and the dispatching portal, this consumes bandwidth in dynamic settings"



Scenario evolution

Example : QoS oscillation during a specific time slot

"At the specified time slot, 70% of vehicles were carrying passengers on the route to their far destinations, only a low number of requests is satisfied, meaning low values of QoS for a while; when these long trips ended one by one, the number of satisfied requests increases rapidly causing the peak in QoS."



Conclusion

Our contribution

- · A multi-agent model of explainable ODT system
- · A generic model for solution methods
- · Extension with agent behavior interpretation
- · Tree shaped aggregation of explanation for flexible interaction granularity
- · Implementation guidelines for the explainable recommender system



Thank you!





References



Cashmore, M., Collins, A., Krarup, B., Krivic, S., Magazzeni, D., and Smith, D. (2019).

Towards Explainable AI Planning as a Service.

arXiv:1908.05059 [cs]. arXiv: 1908.05059.



Cordeau, J.-F. and Laporte, G. (2007).

The dial-a-ride problem: models and algorithms.

Annals of Operations Research, 153(1):29-46.



Daoud, A., Balbo, F., Gianessi, P., and Picard, G. (2020). Ornina: A decentralized, auction-based multi-agent coordination in odt systems.

AI Communications, pages 1-17.



References (cont.)

Daoud, A., Balbo, F., Gianessi, P., and Picard, G. (2021). A generic multi-agent model for resource allocation strategies in online on-demand transport with autonomous vehicles.

In Proceedings of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), page 3.

El Falou, M., Itmi, M., El Falou, S., and Cardon, A. (2014).
On demand transport system's approach as a multi-agent planning problem.

In 2014 International Conference on Advanced Logistics and Transport (ICALT), pages 53–58, Tunis, Tunisia. IEEE, IEEE.

Goodman, B. and Flaxman, S. (2017).

European union regulations on algorithmic decision-making and a "right to explanation".

Al magazine, 38(3):50-57.





Lipton, Z. C. (2018).

The mythos of model interpretability.

Commun. ACM, 61(10):36–43.



Liu, Y., Li, Z., Liu, J., and Patel, H. (2016).

A double standard model for allocating limited emergency medical service vehicle resources ensuring service reliability.

Transportation Research Part C: Emerging Technologies, 69:120–133.



Mualla, Y. (2020).

Explaining the Behavior of Remote Robots to Humans: An Agent-based Approach.

PhD thesis, University of Burgundy - Franche-Comté, Belfort, France. 2020UBFCA023.



- Pearce, J. P. and Tambe, M. (2007).

Quality guarantees on k-optimal solutions for distributed constraint optimization problems.

In Proceedings of the 20th International Joint Conference on Artificial Intelligence, IJCAI'07, page 1446–1451, San Francisco, CA, USA. Morgan Kaufmann Publishers Inc.

Ronald, N., Thompson, R., and Winter, S. (2015). Simulating demand-responsive transportation: A review of agent-based approaches.

Transport Reviews, 35.



Schilde, M., Doerner, K., and Hartl, R. (2011).

Metaheuristics for the dynamic stochastic dial-a-ride problem with expected return transports.

Computers & Operations Research, 38(12):1719–1730.





Schofer, J. L., Program, T. C. R., and Board, N. R. C. U. S. . T. R. (2003). *Resource Requirements for Demand-responsive Transportation Services.* Transportation Research Board.

Google-Books-ID: RG9wnNBKCy4C.



Singh, R., Dourish, P., Howe, P., Miller, T., Sonenberg, L., Velloso, E., and Vetere, F. (2021).

Directive explanations for actionable explainability in machine learning applications.

arXiv preprint arXiv:2102.02671.



- van Lon, R. R., Holvoet, T., Vanden Berghe, G., Wenseleers, T., and Branke, J. (2012).

Evolutionary synthesis of multi-agent systems for dynamic dial-a-ride problems.

In Proceedings of the fourteenth international conference on Genetic and evolutionary computation conference companion - GECCO Companion '12, page 331, Philadelphia, Pennsylvania, USA. ACM Press.

Zargayouna, M., Balbo, F., and Ndiaye, K. (2016). Generic model for resource allocation in transportation. application to urban parking management.

Transportation Research Part C: Emerging Technologies, 71:538 – 554.



Zhang, W., Wang, G., Xing, Z., and Wittenburg, L. (2005). Distributed stochastic search and distributed breakout: properties, comparison and applications to constraint optimization problems in sensor networks.

Artificial Intelligence, 161(1):55 – 87. Distributed Constraint Satisfaction.

