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Insight

Preference elicitation for horizontal collaborations in transport operations

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Outline

- The LOGISTAR project
  - Goals
  - Our role in the project - University College Cork (UCC)
- Preference learning for horizontal collaborations in transport operations
  - Evaluation of collaborative journeys
  - The preference model considered
  - Preference learning observing the user decisions

LOGISTAR

- Warehouse operations optimisation
  - Precise time of arrival prediction
  - incident detection and efficient re-optimisation

- Routing improvement of multimodal transport modes
  - Reduce cost of logistic operations
  - Infrastructure optimisation

- Horizontal collaborative planning
  - Share costs
  - Reduce emissions and empty kilometers

LOGISTAR - UCC

- Predictions
  - Task: Predictions of timings of typical events in logistic transportation
  - Goal: reducing the waiting time for operations in the warehouse
  - Example - for a given location and specific time of the day:
    - predict the arrival time of a truck
    - predict the time spent to load/unload goods
- Preferences
  - Task: Estimation of the preferences of the users over some KPIs
  - Goal: computation of personalized solutions
  - Example - trade-offs between:
    - Cost
    - Distance
    - CO_2 emissions

Preference learning for horizontal collaborations

Evaluation of collaborative journeys

#	Stakeholder	Type	Delivery Nr.	From	To	Pallets	Weight
1	Nestlé		0866095128	SHW -	-	13	27210.0 kg
2				SHW -	TSY 07:00 - 07:00	13	
3	Nestlé		0866095128	-	TSY 07:00 - 07:00	18	27210.0 kg
4	pladis		CUST86213196	MIDLANDS_DC 08:59 - 09:30	-	11	5805.0 kg
5				MIDLANDS_DC 08:59 - 09:30	POUNDLAND LTD 08:59 - 09:30	6	
6	pladis		CUST86213196	-	POUNDLAND LTD 08:59 - 09:30	6	5805.0 kg
7	pladis		CUST86213198	MIDLANDS_DC 10:29 - 11:00	-	2	5768.0 kg
8	pladis		CUST86213197	MIDLANDS_DC 11:29 - 12:00	-	12	5875.0 kg
9				MIDLANDS_DC 11:29 - 12:00	POUNDLAND LTD 11:29 - 12:00	14	

KPI	Collaborative	Non collaborativ
Distance [km]	343.06	331.81
Empty running [%]	59.25	54.67
Time [h]	8.66	7.63
Fill rate (pal) [%]	0.69	0.30
Fill rate (FP) [%]	0.63	0.36
Cost [MU]	242.92	192.05

Estimated non-collaborative KPIs

Suppose we have two orders N1 and N2 from Nestle, and two orders P1 and P2 form Pladis

Estimated non-collaborative KPIs

Suppose we have two orders N1 and N2 from Nestle, and two orders P1 and P2 form Pladis

Collaborative solution

C1

KPIs(C1) = [100euro, 25kg]

C2

KPIs(C2) = [110euro, 30kg]

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Estimated non-collaborative KPIs

Suppose we have two orders N1 and N2 from Nestle, and two orders P1 and P2 form Pladis

Collaborative solution

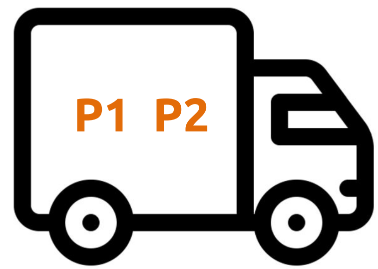
C1

KPIs(C1) = [100euro, 25kg]

Non-collaborative solution

NC1

KPIs(NC1) = [130euro, 37kg]



NC2

KPIs(NC2) = [115euro, 32kg]

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Estimated non-collaborative KPIs

Suppose we have two orders N1 and N2 from Nestle, and two orders P1 and P2 form Pladis

Collaborative solution

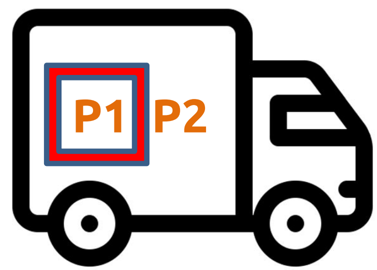
C1

KPIs(C1) = [100euro, 25kg]

Non-collaborative solution

NC1

KPIs(NC1) = [130euro, 37kg]



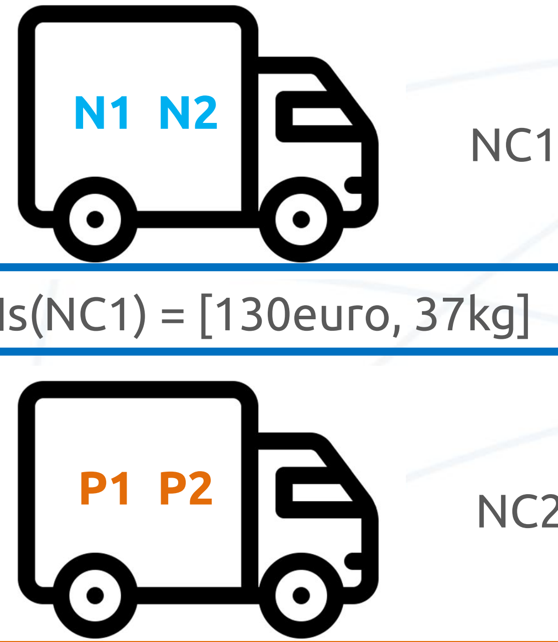
NC2

KPIs(NC2) = [115euro, 32kg]

Estimated non-collaborative KPIs

Suppose we have two orders N1 and N2 from Nestle, and two orders P1 and P2 form Pladis

Non-collaborative solution



KPIs(NC1) = [130euro, 37kg]

KPIs(N1) = [60euro, 16kg]
KPIs(N2) = [70euro, 21kg]

KPIs(P1) = [50euro, 14kg]
KPIs(P2) = [65euro, 18kg]

KPIs(NC2) = [115euro, 32kg]

Estimated non-collaborative KPIs

Suppose we have two orders N1 and N2 from Nestle, and two orders P1 and P2 form Pladis

Collaborative solution

C1

KPIs(C1) = **[100euro, 25kg]**

Estimated_Non-Coll_KPIs(C1) =
KPIs(N1) + KPIs(P1) =
[110euro, 30kg]

Non-collaborative solution

KPIs(N1) = [60euro, 16kg]
KPIs(N2) = [70euro, 21kg]

KPIs(P1) = [50euro, 14kg]
KPIs(P2) = [65euro, 18kg]

How to split the KPIs – Shapley Value

- To split the KPIs of Journey among the corresponding orders, we consider the Shapley value based on the travelled distance

- Roughly speaking, the Shapley value of an order can be interpreted as the increase of total distance of the journey caused by the inclusion of the order itself

- Thus, the higher the Shapley value of an order is, the higher is the extra distance that a truck must travel to include the delivery of the order in the journey

- We compute then a weight for each order of the journey proportional to the corresponding Shapley value and we split the KPIs of the journey based on such weights

Preference elicitation

Preference model over KPIs

- –Suppose we want to minimise the KPIs values
  –We consider a value function representing the preferences of a user:

$$\alpha \text{ Is preferred to } \beta \Leftrightarrow v(\alpha) \leq v(\beta)$$
$$v(\alpha) = w_1\alpha_1 + \cdots + w_n\alpha_n$$

Where α and β are two KPIs vectors

–The parameter w is a non-negative and normalised weight vector defining the trade-offs of a decision-maker with respect to the KPIs

- Example of weights vector w for KPIs cost and CO2 emissions:
  - –(1, 0) focus on cost
  - –(0, 1) focus on CO2 emissions
  - –(0.6, 0.4) balanced weights vector

User decision and motivations

We learn preference information if the motivation for acceptance or rejection of a collaborative journey is related to the KPIs vectors:

- Collaborative KPIs VS estimated non-collaborative KPIs

We want to distinguish three scenarios with the selected motivation :

1. The decision was made considering the KPIs.
2. The decision was made considering mainly a specific KPI.
3. The decision was made for other reasons.

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Preference learning - example

- Suppose that the system shows to the user a collaborative solutions with:
  - Collaborative KPIs $\alpha = (110\ euro, 25kg)$
  - Estimated non-collaborative KPIs: $\beta = (100\ euro, 30kg)$

If the user accepts the collaboration selecting *better collaborative KPIs* as motivation, then we learn $v(\alpha) \leq v(\beta)$, i.e.:

$$110\, w_1 + 25\, w_2 \leq 100\, w_1, + 30\, w_2$$

Which is equivalent to $v(\alpha - \beta) \leq 0$, i.e.:

$$10\, w_1 - 5\, w_2 \leq 0$$

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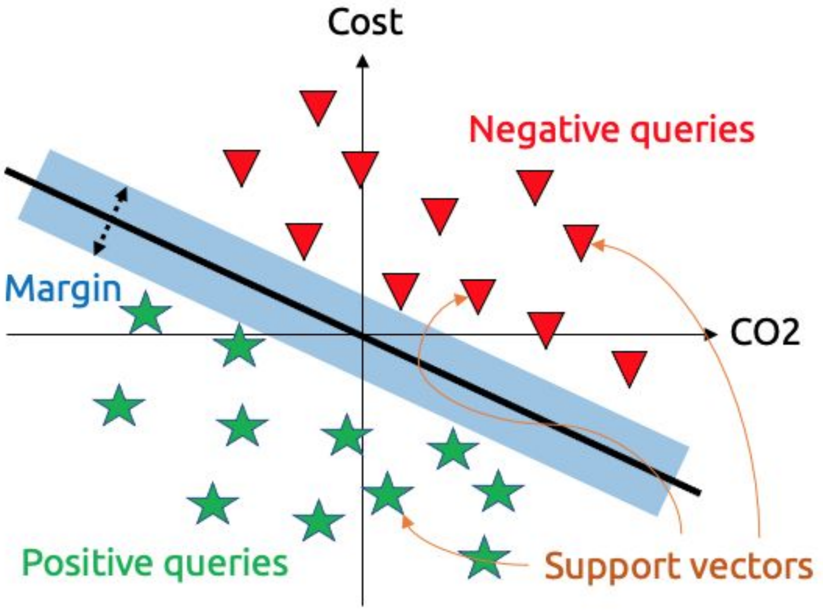
SVM

– Support Vector Machine (SVM)
  - It estimates the **hyperplane** that produces the largest margin from the boundary defined by two classes of support vectors

– In our context:
  - We want divide the queries $Q(\alpha, \beta)$: "Do you prefer KPIs α over KPIs β?" into two classes:
    - Positive queries (α is preferred to β): $(\alpha - \beta) \cdot w \leq 0$
    - Negative queries (β is preferred to α): $(\alpha - \beta) \cdot w \geq 0$
  - SVM learns a hyperplane that can be used to predict the user answer to a query $Q(\alpha, \beta)$
  - The normal vector w of the hyperplane represents the estimated user preferences



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Summary

–How to estimate the value of a collaborative journey

–A mathematical model representing the user preferences

–How to learn the user preferences