Incremental preference elicitation for SRMP models: Application for autonomous drones

Arwa Khannoussi, Alexandru-Liviu Olteanu, Catherine Dezan, Jean-Philippe Diguet, Christophe Labreuche, Jacques Petit-Frère, Patrick Meyer

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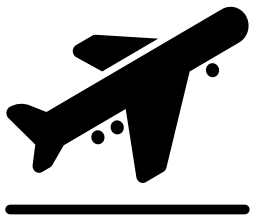
Outline

1. Context & Research questions
2. Simple Ranking Method using Reference Profiles (SRMP)
3. Heuristics for incremental learning of SRMP model
4. Experimental Results
5. Conclusion

Drone Context



1. Mission
   - **Military**
   - **Civilian**
   - **Specified by a set of waypoints and objectives**
2. Decision Making
   - **Make autonous decisions**
   - **Take into account multiple criteria to acheive the mission's objectives**
3. Confidence
   - **Guarantee a level of trust in the drone's behavior**
   - **The drone's decisions should be consistent with the priorities of the operator**

Research questions

1. Which MCDA model to integrate into the drone ?

2. How to learn the parameters of the MCDA model ?

RQ1 : Which model?

Real-world constraints

- Decisions related to high-level actions (like land, loiter, skip a waypoint, ...)

  $\rightarrow$ choose one alternative among all possible ones

- Guarantee a high level of trust in the drone's decision

  $\rightarrow$ integrate the preference model onboard of the drone

- The preference model and its consequences are presented to the operator in order to be validated

- Heterogeneous evaluation scales of the criteria:
  quantitative (energy, ...) and qualitative (risk, ...)

RQ1: Which model?

Proposal

- Ranking or choosing in the outranking paradigm

- Simple Ranking Method using Reference Profiles (SRMP) [Rolland 2013]

  ranking can be explained through a series of rules, understandable by the drone operator

RQ2 : How to learn the parameters of the model?

Real-world constraints

- Cognitive effort of the operator should be minimized
- The operator is not an expert of the decision model, and he is probably not able to fix the parameters of the model "directly"
- However : the operator is able to make a preferential choice between pairs of actions (in a simulated environment, with a given context)
- Not all decision actions are possible (existing database of possible pairs of actions, in a given context)

RQ2 : How to learn the parameters of the model?

Proposal

- Learn the SRMP model from pairwise comparisons of alternatives (indirect elicitation)
- Elicit the SRMP model incrementally
- Confront the operator with pairs of possible actions selected from an existing database of possible pairs

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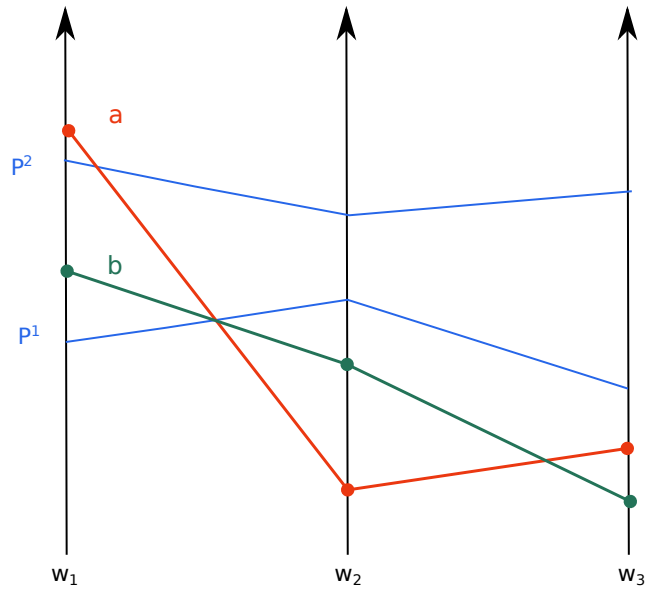
Simple Ranking Method using Reference Profiles (SRMP)

- Preference parameters of the decision maker:
  - k reference profiles: $p^1, \ldots, p^h, \ldots, p^k$
  - a lexicographic order σ on the reference profiles
  - criteria weights $w_1, \ldots, w_m$, with $w_j \geqslant 0$ and $\sum_{j \in M} w_j = 1$

- Alternatives are compared indirectly via reference profiles (p^h)
- $a \succsim_{p^h} b$ iff a outranks p^h more strongly than b
- Create a pre-order of the alternatives



SRMP: Parameters elicitation

- Preference elicitation : tune the parameters of the SRMP model
- In our practical context : indirect elicitation
  - Determine the parameters from holistic judgements of the decision maker on pairs of alternatives (*aPb* / *aIb*)
  - Mixed Integer Program (MIP) [Olteanu et al. 2018]
    Inputs : a set of pairwise comparisons of alternatives
    Outputs : values of the parameters of the SRMP model
- Our contribution :
  - Incremental learning to limit the number of learning example
  - Heuristics to select the learning examples

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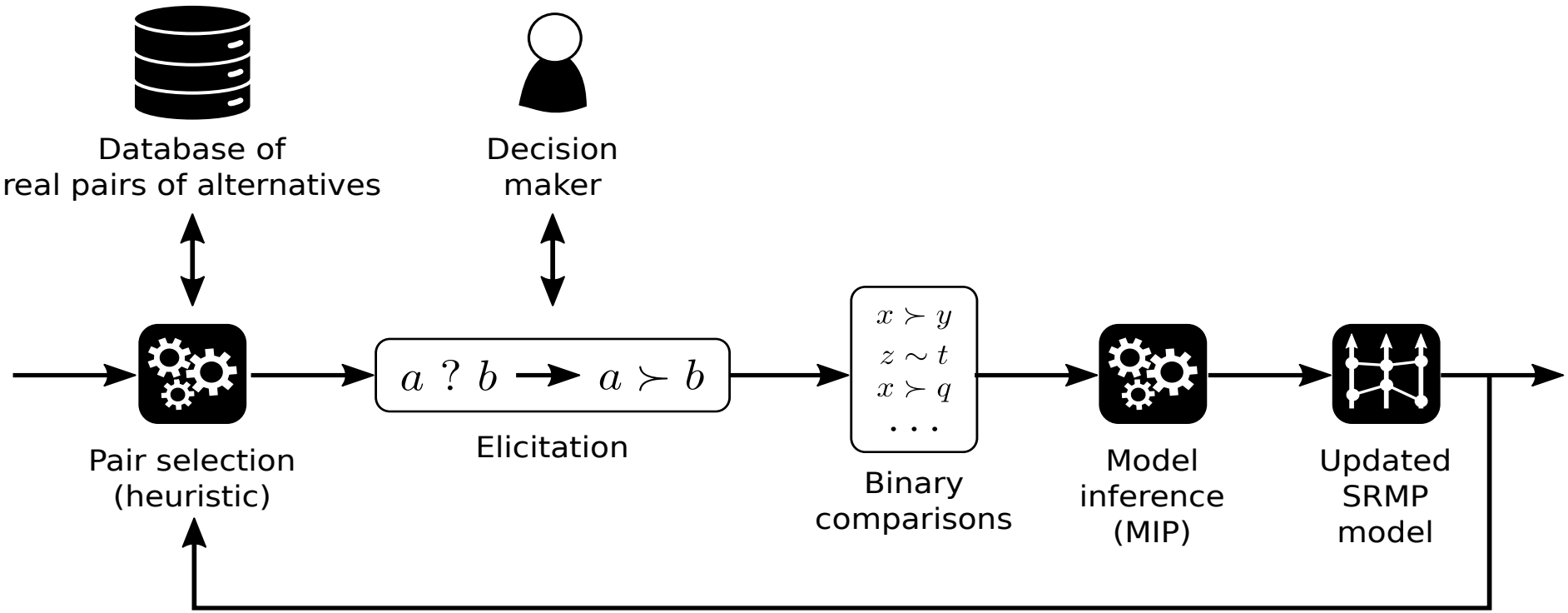
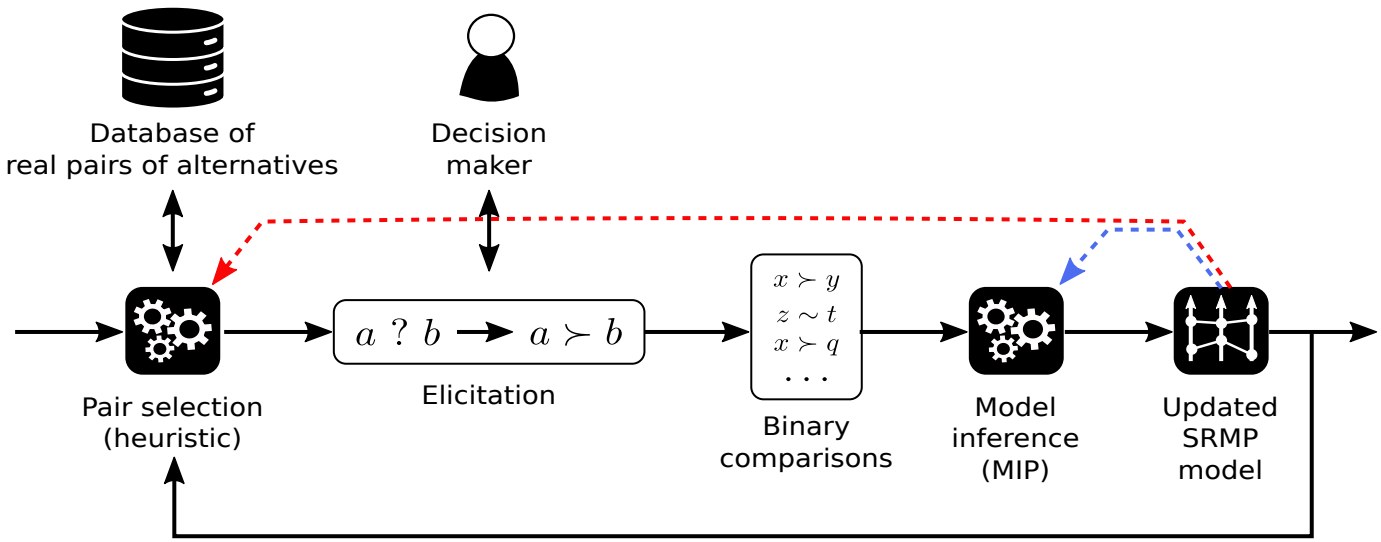
Incremental learning of the SRMP model



Incremental learning of the SRMP model



Pair selection (heuristic)

- Random pair
- Pair of most similar alternatives
- Pair of most dissmilar alternatives
- Pair close to previous model profile
- Pair that uses the biggest number of profiles to be discriminated by the previous model (indifference, k profiles, k-1 profile, ..., 1 profile)

Model inference (MIP)

- First feasible model
- Model closest to previous one
- Model centered inside search space

Heuristics: Experimental setting

- DM simulation: random SRMP model M_{DM} (fixed k profiles, m criteria)
- Artificial datasets (different n alternatives, m criteria, k profiles)
  - elicitation phase: 100 pairs of alternatives
  - test phase: 5000 alternatives
- At each iteration:
  - a pair of alternatives is selected by the heuristic
  - use M_{DM} to add new constraints to construct a new SRMP model M_i
- Rank the test data using M_{DM} and M_i, and then compare these rankings using *Kendall*'s rank correlation measure τ.
- Each SRMP model configuration (k profiles and m criteria) is experimented 100 times

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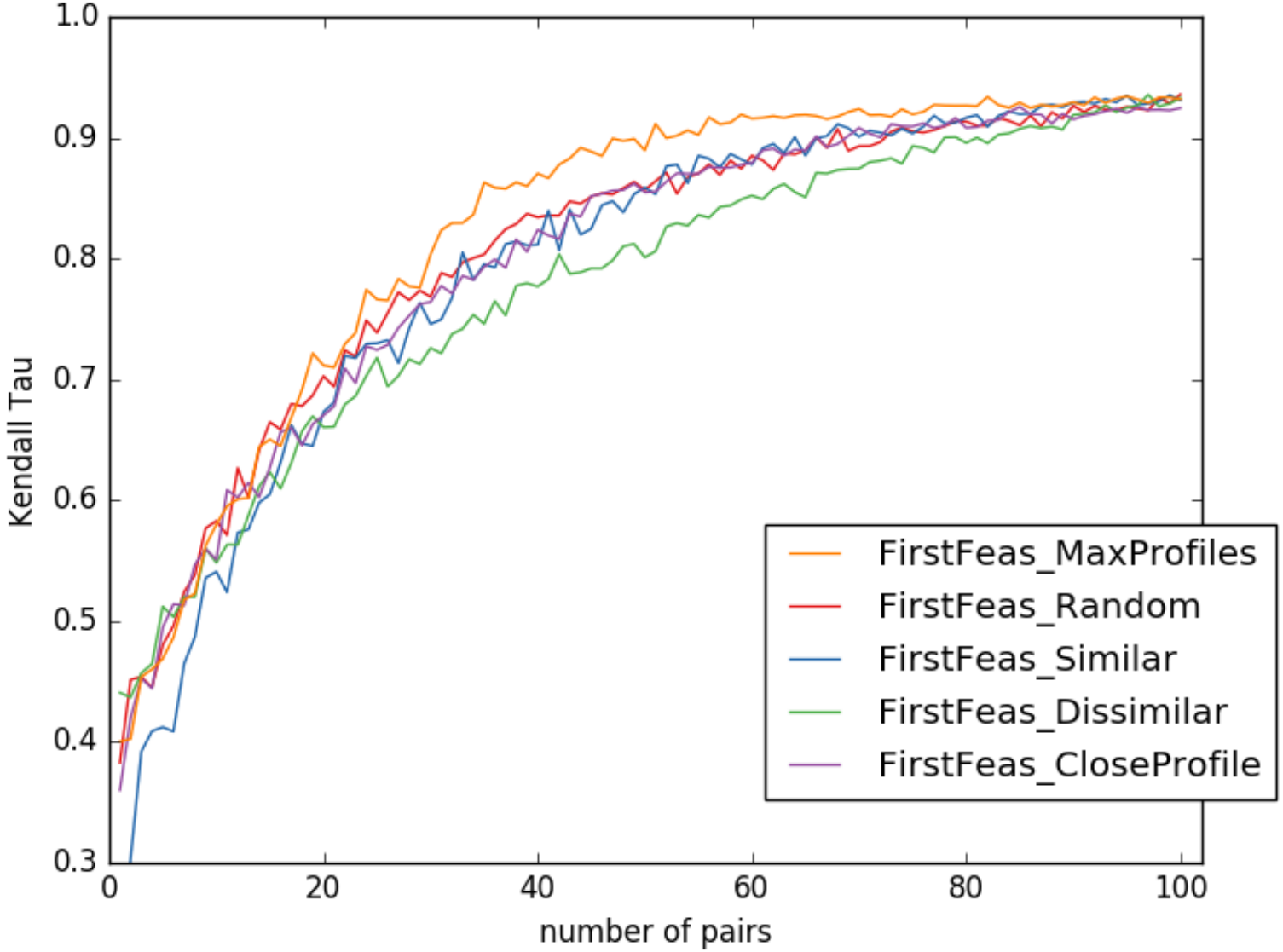
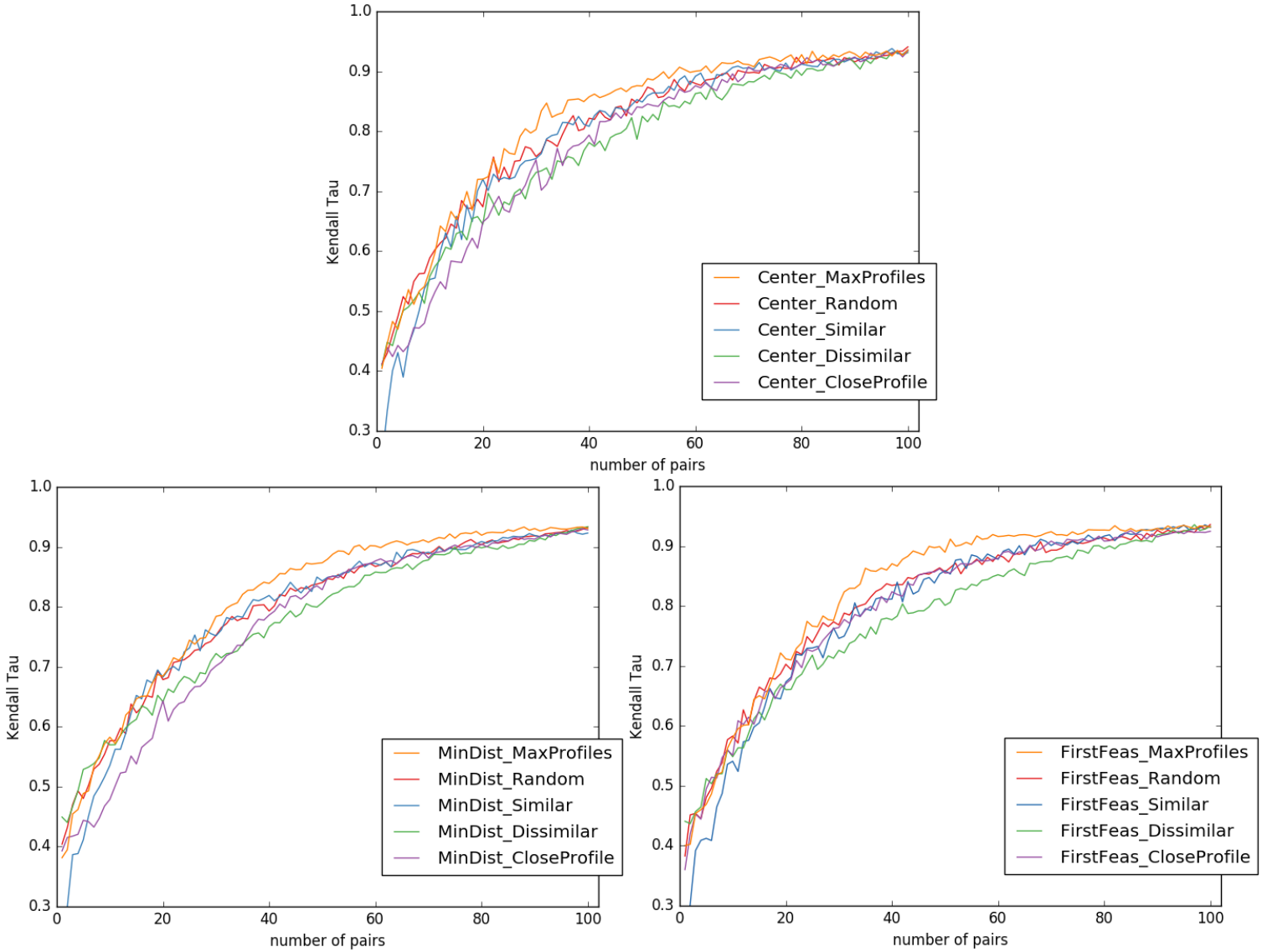
Experimental Results

mean Kendall tau, 3 criteria, 2 profiles, 100 experiments

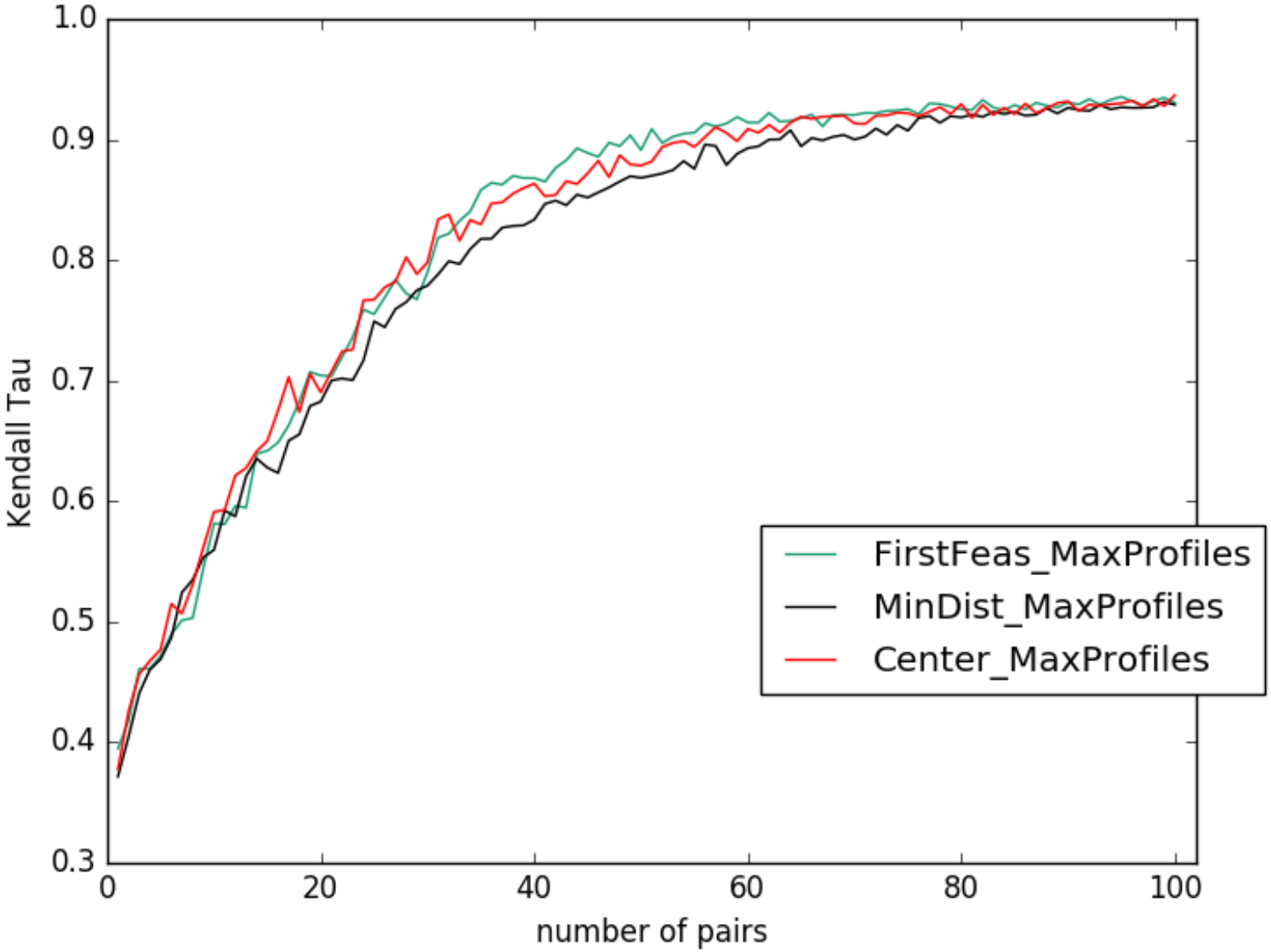


Experimental Results



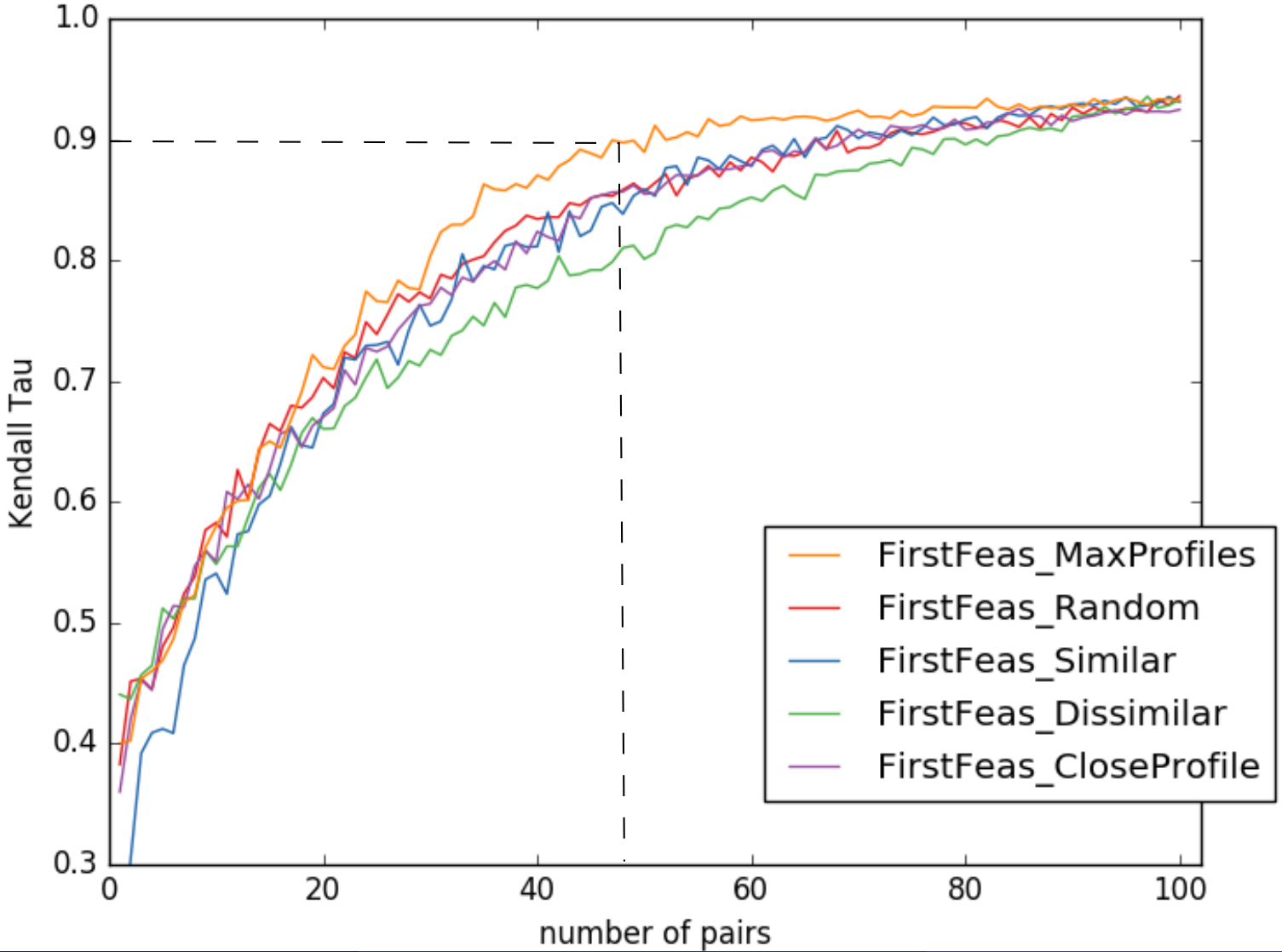
Mean Kendall Tau of 100 experiments for 2profiles 3 criteria

Experimental Results



Experimental Results

Determination of the number of pairs necessary to achieve a "good" preference model



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Conclusion

- The MaxProfiles heuristic dominates in the different MIP's configuration
- No clear difference between the MIP configurations
  Choice of the least-cost configuration in terms of computation time

- Future work :
  - Experiment new heuristics (Volume, MaxProfiles++, Alternate weights / profiles)
  - Input other preference information (typically the profiles)
  - Experiment other data configurations ((2 profiles, 7 criteria), (3 profiles, 5criteria), . . .)

    Computation time for 100 experiments: one week for 2 profiles and 3 criteria with all the different combination of heuristic and MIP's configuration. (200 cpu, 300GB RAM)
  - Integration of the learning algorithm in the drone simulator

References

Olteanu, A-L. et al. (2018). "Preference Elicitation for a Ranking Method based on Multiple Reference Profiles". working paper or preprint. URL: https://hal.archives-ouvertes.fr/hal-01862334.

Rolland, A. (2013). "Reference-based preferences aggregation procedures in multi-criteria decision making". In: *European Journal of Operational Research* 225.3, pp. 479–486. DOI: 10.1016/j.ejor.2012.10.013. URL: https://doi.org/10.1016/j.ejor.2012.10.013.