Human-interpretable input for Machine Learning in Tactical Air Traffic Control

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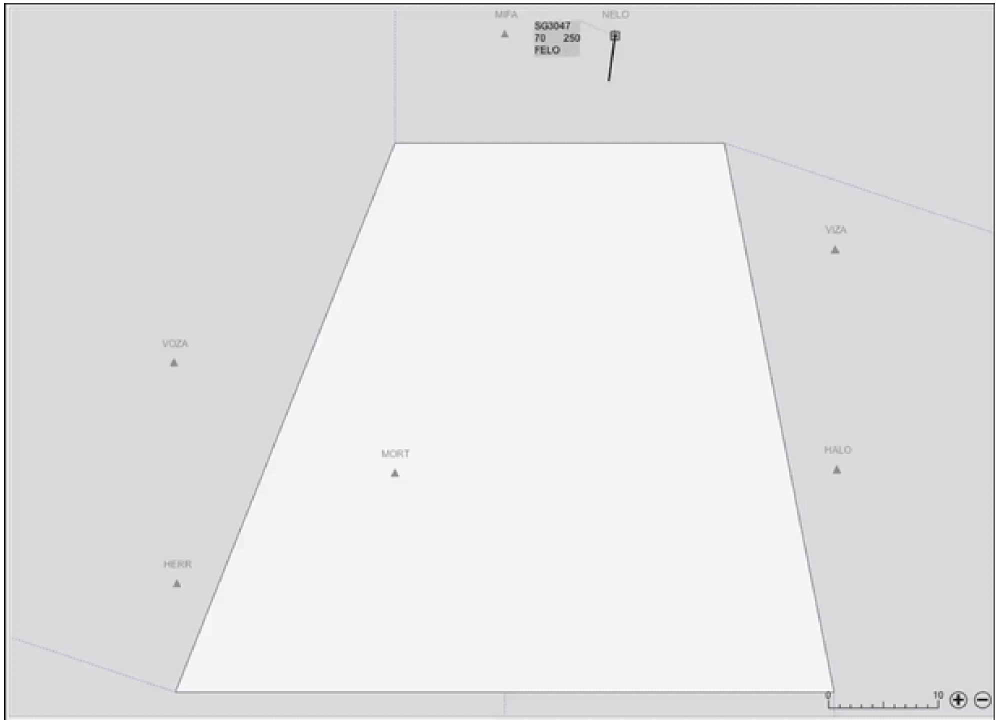
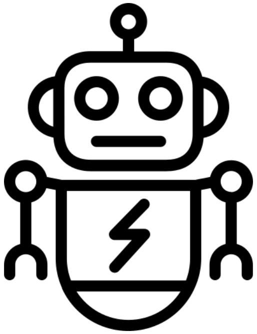
Automation acceptance in ATC

Acceptance



Authority and autonomy



How to build ML?

A simple but profound question: *Should we build automation that is CONFORMAL or TRANSPARENT?*

Conformance— does automation seem to match human strategies?
Transparency— is automation's inner process explainable to human?

		TRANSPARENCY	
		Low	High
CONFORMANCE	Low	**Stupid automation:** *"It's doing a strange thing, and I don't understand why…"*	**Peculiar automation:** *"It's doing a strange thing, but I understand why…"*
	High	**Confusing automation:** *"It's doing the right thing, but I don't understand why…"*	**Perfect automation:** *"It's doing the right thing, and I understand why…"*

Objectives

- Create / integrate / demonstrate a **hybrid ML capability** for detecting/resolving ATM conflicts

  Hybrid ML model for CD&R via
  - Supervised Learning (SL)– deep learning– to detect / classify conflicts
  - Reinforcement Learning (RL)– rule based– to resolve conflicts

- Develop a control model and **UI** to foster transparency

  Build a UI to foster transparency & understandability of ML solutions

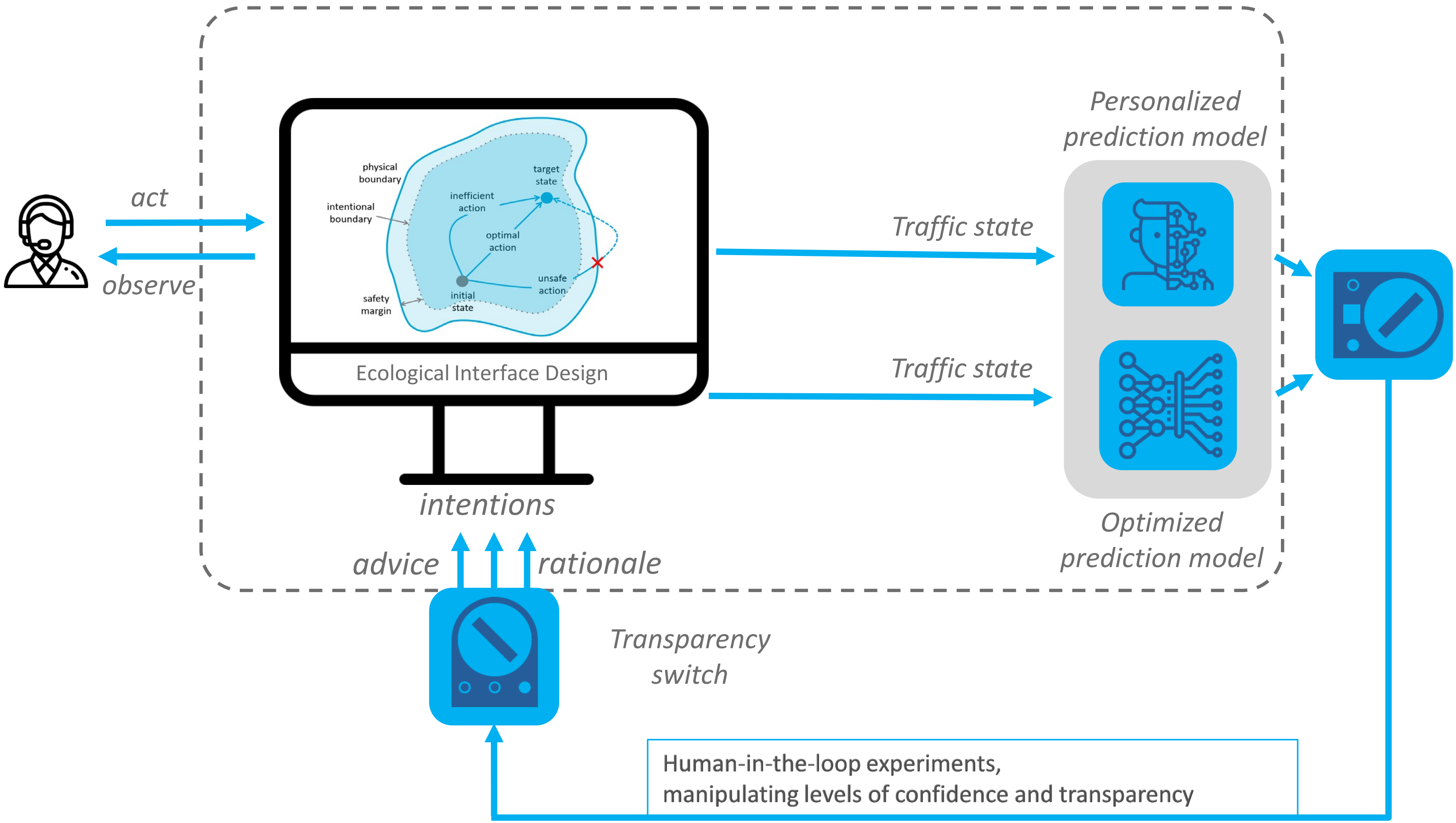
- Experimentally **evaluate impact** of conformance and transparency on performance

  HITL sims: How do Conformance, Transparency, Complexity impact trust, acceptance, etc of ML solutions?

- Define **framework** to guide development of AI systems

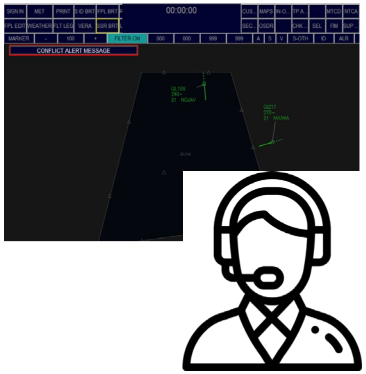
  Lessons learnt: How to build ML for ATM?

MAHALO Overview

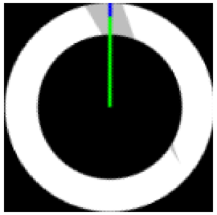


Supervised Learning model

Sector X ATC simulator



Conflict scenarios



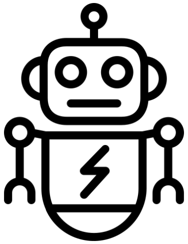
Solution Space Diagram

Human conflict resolutions

Supervised Learning Model

Training a model

AI-supported ATM system



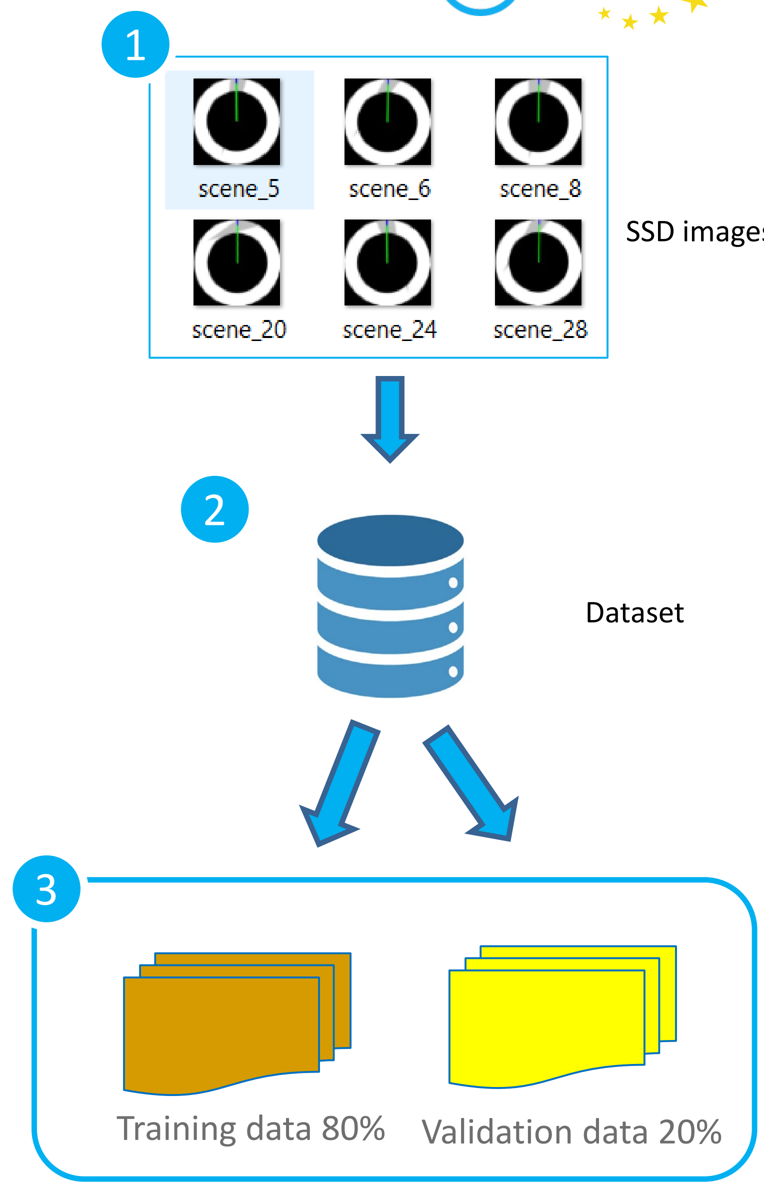
Heading advisories

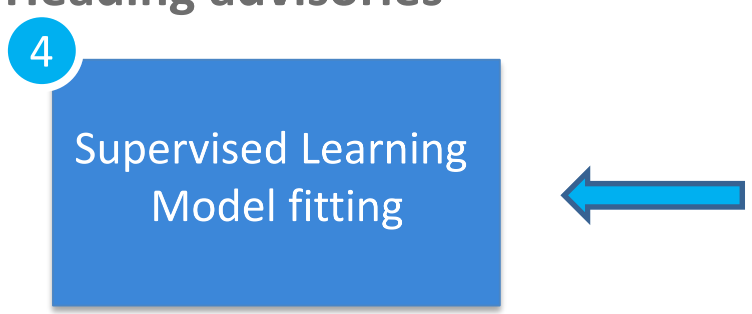
Human AI collaboration

Supervisory controller

Our approach

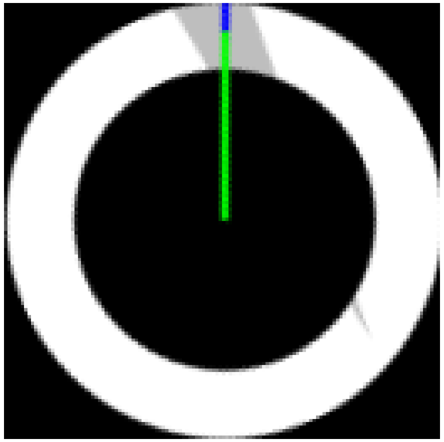
- Train a model on multiple conflicts and ATCO resolutions
- SectorX ATC research simulator
- AI sees what the human sees (same information/situation)
  - Solution space diagram (SSD)
  - Images from the radar screen
  - Heading advisories





Our approach

- Google Tensorflow
  - SSD input -> Heading advisories
- Convolutional neural network
- Data from ATCO students (Sim1)
- Training pipeline



Rooijen, S. J. Van, Ellerbroek, J., Borst, C., & Kampen, E.-J. Van. (2019). Conformal Automation for Air Traffic Control using Convolutional Neural Networks. In Thirteenth USA/Europe Air Traffic Management Research and Development Seminar (pp. 1–10), Vienna.

Q-Learning for MVP

- MVP = Modified Potential Value
- MVP has some tunable parameters:
    - Lookahead distance
    - Safety Margin
- A Q-Learning agents learns the optimal parameters for the MVP method given a certain conflict scenario
- A conflict scenario is classified by:
    - Conflict angle
    - Time to closest point of approach (tCPA)
    - Distance at closest point of apporach (dCPA)

MVP

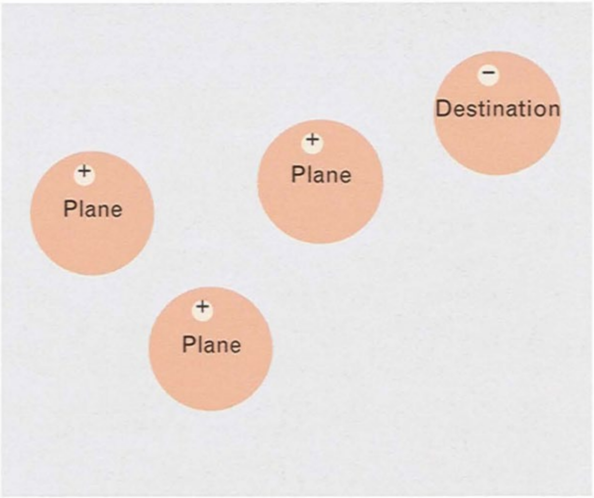


FIGURE 2. Air traffic model based on voltage potential fields. The model exhibits two critical features of successful ATC: aircraft (positively charged particles) tend to maintain separation between each other (because of mutual repulsion) while moving toward their destination (because of attraction to the opposite charge).

From: Eby, M. S. (1994). A Self-Organizational Approach for Resolving Air Traffic Conflicts. Lincoln Laboratory Journal.

Deep Q-Learning from Demonstrations (DQFD): why use demonstrations?

RL tends to be data inefficient

Cumbersome data collection process. Requires a lot of interaction with environment

RL has bad initial performance

Dangerous to use at the beginning of training (if done online in a physical environment)

Q: How do we make a RL agent that is **data efficient** and has a **decent initial performance**?

Deep Q-Learning from Demonstrations (DQFD): why use demonstrations?

A: Use **representative expert demonstrations**

Representative of the state-action space. Encompass diverse scenarios

A set of scenarios solved by a human expert or a simplified 'good-enough' algorithm

What is defined as a sample/demonstration?

↓

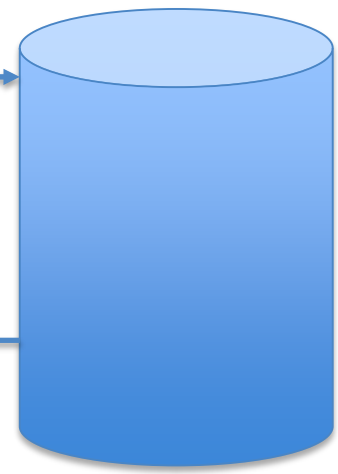
(s, a, r, s') Tuple

Deep Q-Learning from Demonstrations (DQFD): Pre-training

Collect demonstrations. Put them into the **replay buffer**

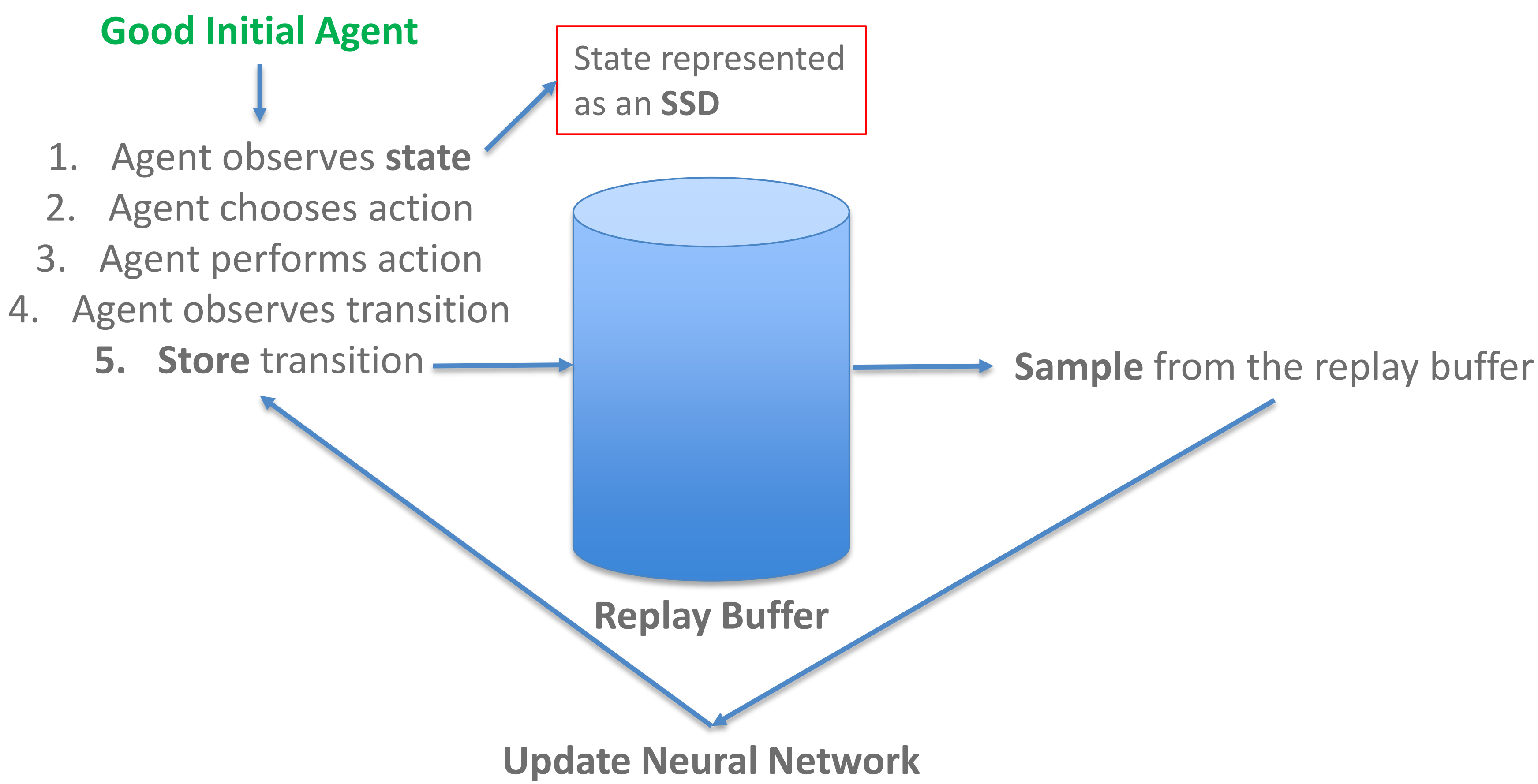
Pre training:
Agent learns by sampling from the demonstrations for *k* time-steps

Good Initial Agent



Replay Buffer

Deep Q-Learning from Demonstrations (DQFD): Training



Deep Q-Learning from Demonstrations (DQFD): Handling Demonstrations

- **Prioritized sampling** is used for the Demonstrations.
- Samples are replaced by newer ones on a **FIFO** basis.
- Should demonstrations be replaced?

- A1: Yes, replaced the same way as other transitions
- A2: No, demonstrations are always kept

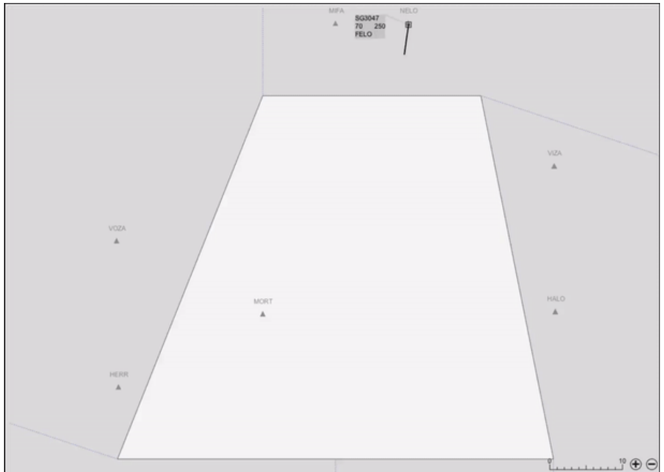
Reward function

- In RL a reward function is used to *define* objective optimality

- An optimal policy maximizes the expected sum of future rewards

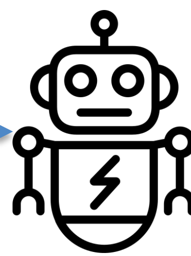
- How to design this reward function???
    - Collision avoidance
    - Extra distance flown
    - Extra time used
    - Fuel usage
    - Workload
    - Etc.

Resulting automation



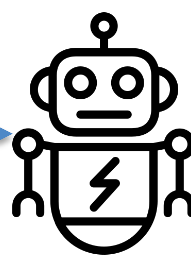
Observe

Conformal



Suggestion coherent with **previous solutions** by the ATCO

Optimal



Suggestion based on **best performance**

Results

- Current results relate to the development of the different ML agents, interfaces and presentation within SectorX
- Proof of concept simulation (Sim1) successfully performed
- Sim 2a currently underway (experiment involving ATC professionals)

Results: Preliminary findings

- Sim 2a pre-test underway:
  - ATCOs find the traffic scenarios complex and a bit unrealistic without being artificial
  - ATCOs gave additional feedback on the interface
  - No boredom reported so far

Conclusions

- Article presented an overview of the current approach being taken by the MAHALO team
- A combination of SL and RL agents are used to achieve conformal and “optimal” performance, respectively
- Main focus is to study effects of conformance and explainability on acceptance
- A Human-Interpretable input is used for the ML agents
- Currently in the HITL stage of the project

Future Work

- Surpassing current limitations:
    - Larger action space
    - More complex traffic scenarios and resolutions (ALT+HDG+SPD)
    - Inclusion of adverse weather
    - Expansion of work to other interfaces (Travel space representation, for example)

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