Joint RL meeting

Gridworld implementation of Olivia's task

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Outline

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1. Implementation
2. Issues along the road
3. Results
4. Summary

Implementation

- RL concepts abstracted in high level functions :
  - `reset()`: reset the environment at the end of the episode
  - `reward()`: define in what conditions the agent get a reward and how much reward it gets
  - `is_terminated()`: define when the end of the episode has been reached
  - `step()`: execute the defined action in the current state

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new_state, reward, done = env.step(action, state)
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Implementation

- At each step, the agent gets a composite observation:

location	cue
{0,...,24}	North light
	South light
	Odor A
	Odor B

- Convenience functions to translate the movements between the grid positions and the states

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Implementation

- Wrapper environment to translate the human readable environment (composite states) into a suitable environment for the Q-learning algorithm (flat states)

```
state = {"location": 13, "cue": LightCues.South}
env.convert_composite_to_flat_state(state)
# => 38
```

```
state = 63
env.convert_flat_state_to_composite(state)
# => {"location": 13, "cue": <OdorID.A: 1>}
```

- Human readable objects

```
action = 0
Actions(action).name
# => "UP"
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Not enough states to solve the task

Pre odor - North light

0	1	2	3	4
5	6	7	8	9
10	11	12	13	14
15	16	17	18	19
20	21	22	23	24

Pre odor - South light

25	26	27	28	29
30	31	32	33	34
35	36	37	38	39
40	41	42	43	44
45	46	47	48	49

Post odor - Odor A

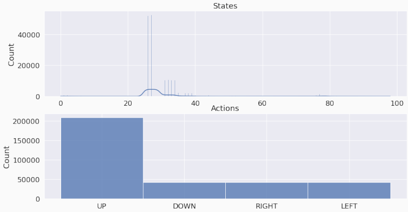
50	51	52	53	54
55	56	57	58	59
60	61	62	63	64
65	66	67	68	69
70	71	72	73	74

Post odor - Odor B

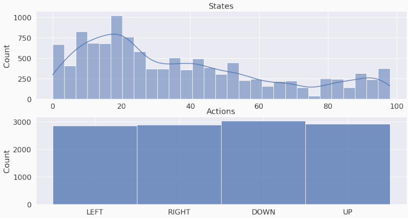
75	76	77	78	79
80	81	82	83	84
85	86	87	88	89
90	91	92	93	94
95	96	97	98	99

ϵ-greedy when Q-values are identical

Vanilla ϵ-greedy



Randomly choosing actions with the same Q-values



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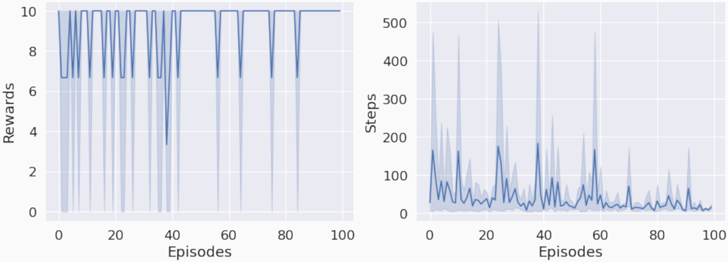

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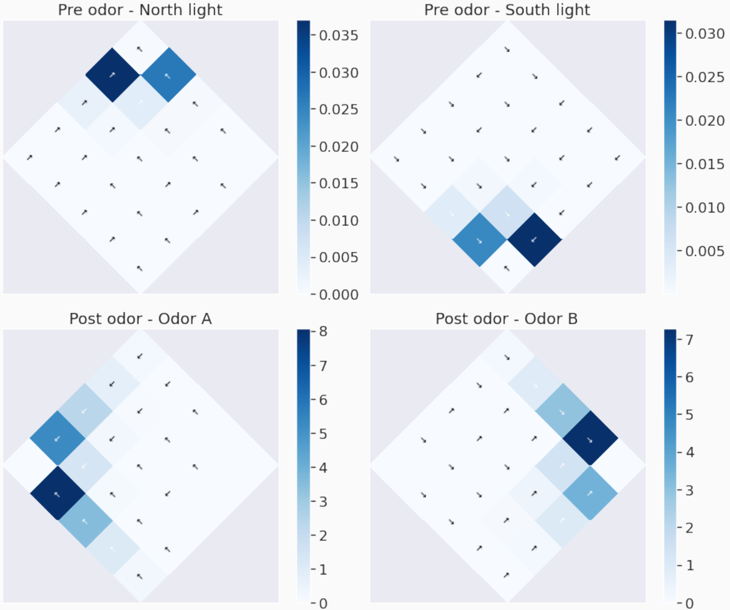
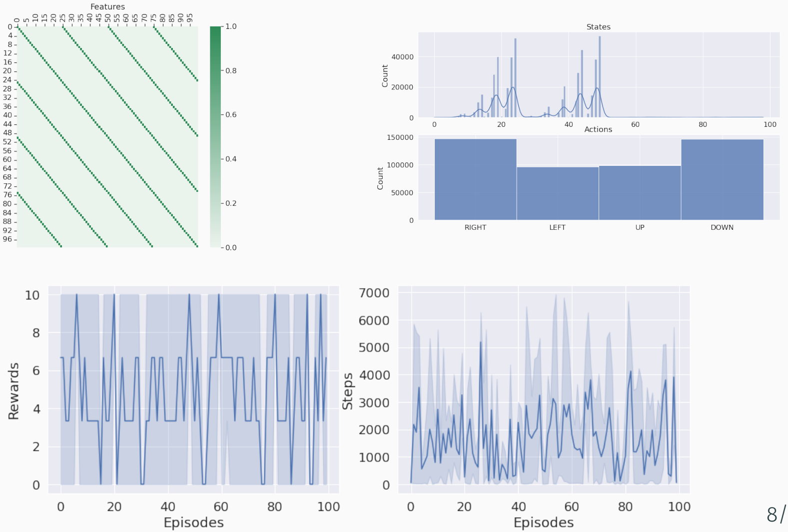


Q-learning with function approximation – allocentric environment – without joint representation



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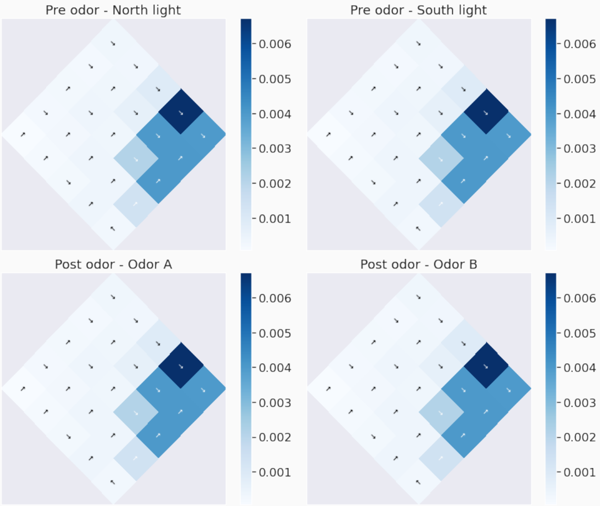

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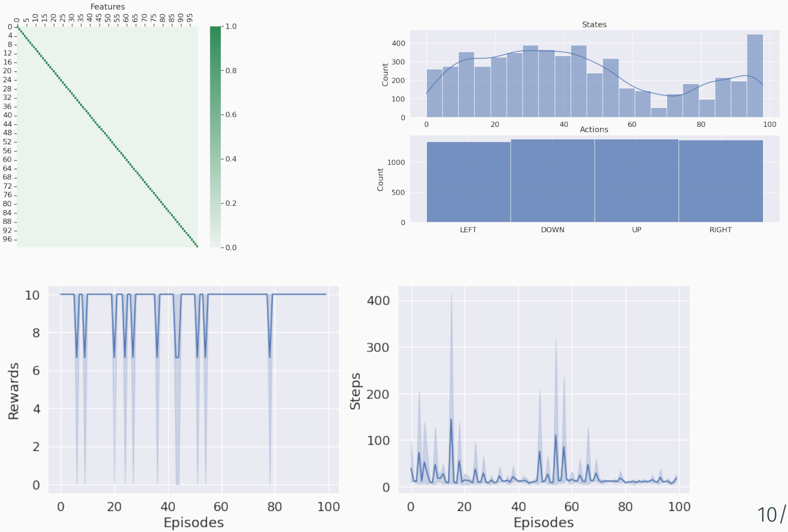

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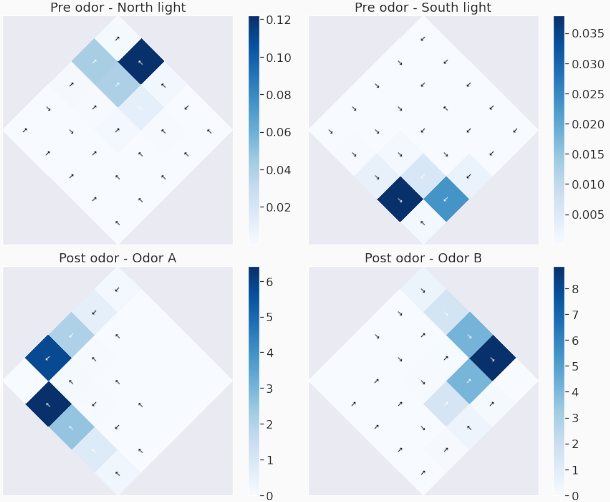
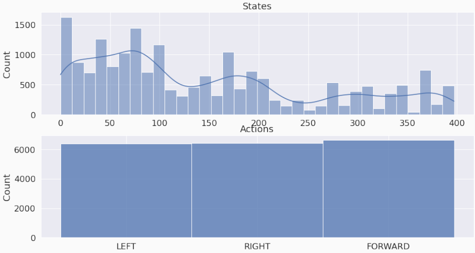
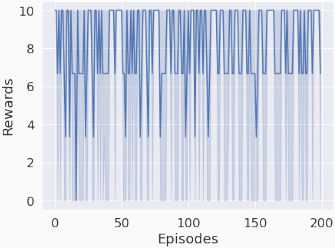
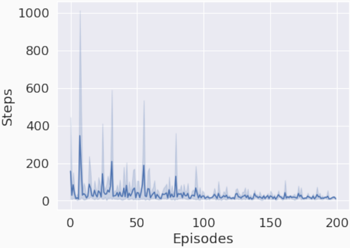


Standard Q-learning – egocentric environment







Q-learning with function approximation – egocentric environment

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- Standard Q-learning can learn the task in the egocentric environment in ~100 episodes
- Niloufar's results with function approximation on the allocentric environment are reproducible :
    - The agent is not able to learn the task without having a place-odor joint representation
    - With a place-odor joint representation, the agent is able to learn the task in ~60 episodes

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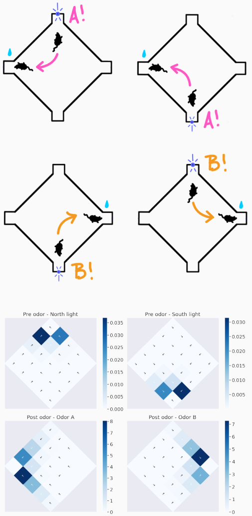
Main differences with Niloufar's model

- The environment is closer to the real experiment → ports are in the corners of the arena, not in the middle of the walls
- Code is clean, readable, and abstracted in high level functions/concepts



Next steps

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- Replace the manually crafted features matrix by an artificial neural network, which should learn the necessary representations to solve the task from scratch

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Questions ?