Balancing Cooperation and Defection in a 2-agent grid-world game

The Malmö Collaborative AI Challenge

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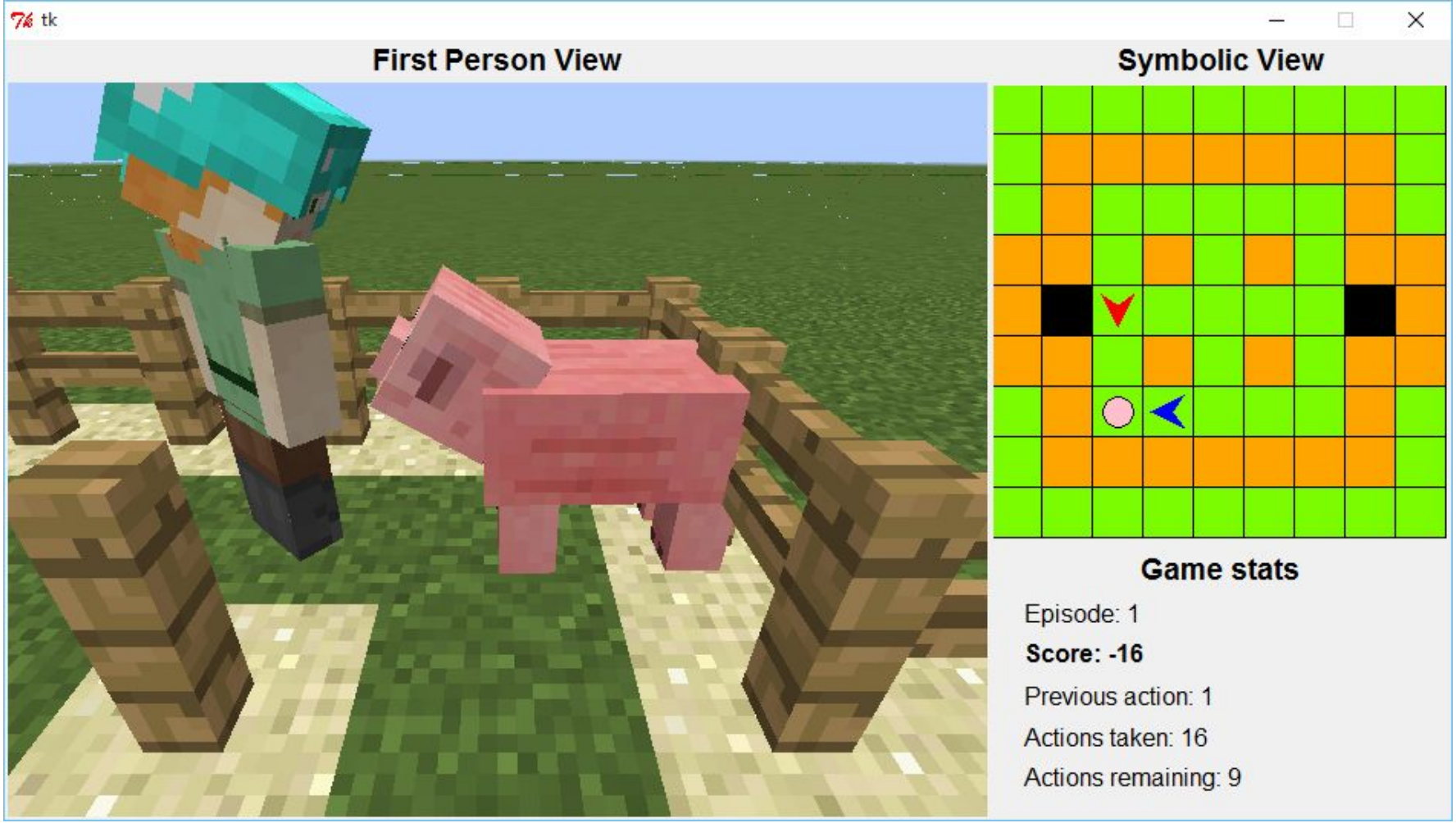


Image from the official challenge repository

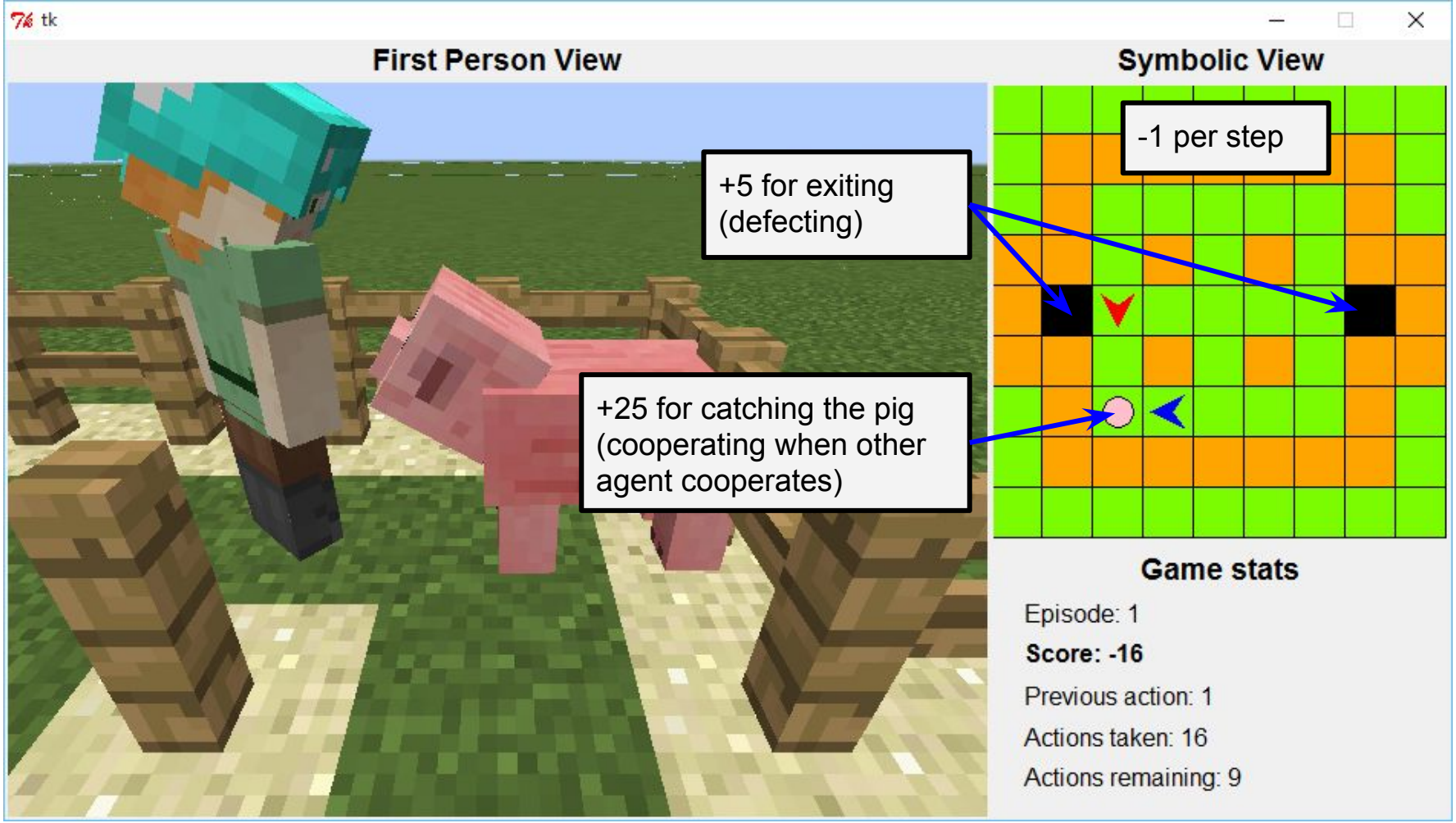


Image from the official challenge repository

Inferring other agent's strategy

- Define a set of basic strategies
  - Focused: go towards the pig as fast as possible
  - Random: Take an uniformly random action

Called "policies" in RL, they define probability distribution over actions given a state

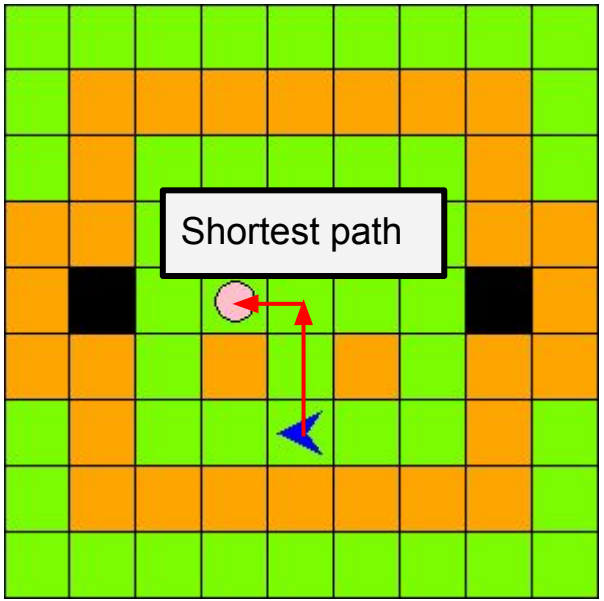
- Maintain a belief: probability of the other agent using each of the strategies

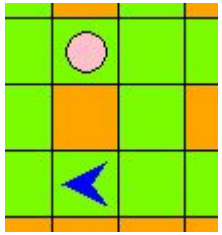
- Update using Bayes' theorem
  - Priors known

Specific case of Bayesian inference over a **parametrised family** of policies.

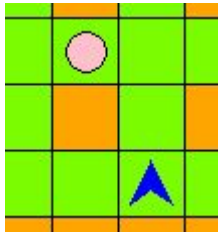
In this case there is only 1 parameter, which can have *n* discrete values for *n* base strategies.

Inferring other agent's strategy

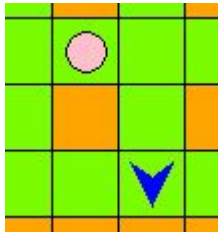




$$P(\uparrow \mid \text{focused}) = 0.01$$
$$P(\uparrow \mid \text{random}) = 1/3$$



$$P(\rightarrow \mid \text{focused}) = 0.98$$
$$P(\rightarrow \mid \text{random}) = 1/3$$



$$P(\leftarrow \mid \text{focused}) = 0.01$$
$$P(\leftarrow \mid \text{random}) = 1/3$$

Planning the optimal action

- UCT (Upper Confidence bounds for Trees), which is Monte-Carlo Tree Search with an exploration policy.
  - Default policy: if other agent cooperates, go to the place needed to catch pig; otherwise defect.

Other agent considered “environment”, its strategies sampled according to belief.

Could add stochastic model of pig moving but *we had no time.*

Exploration term

Avg. value

$$\bar{R}_j + 2c\sqrt{\frac{2\log n_j}{n_{\text{parent}(j)}}}$$

c=10 to compensate for R ∈ [-25, 25]

Evaluating metric: reward per step after 10 episodes.

Our algorithm: ~1.5 score, no training.

Tabular Q-learning baseline: ~0 score, 100k episodes training.

Takeaways

- Training not always needed
  - Especially in simple environments (where one can build model)
  - Especially in small-state-space environments

- Planning approaches easily adapt to new information as it comes
  - In this case, the last action of the other agent

- Learning in constrained domains very efficient
  - Learn other agent’s policy in 2-3 actions