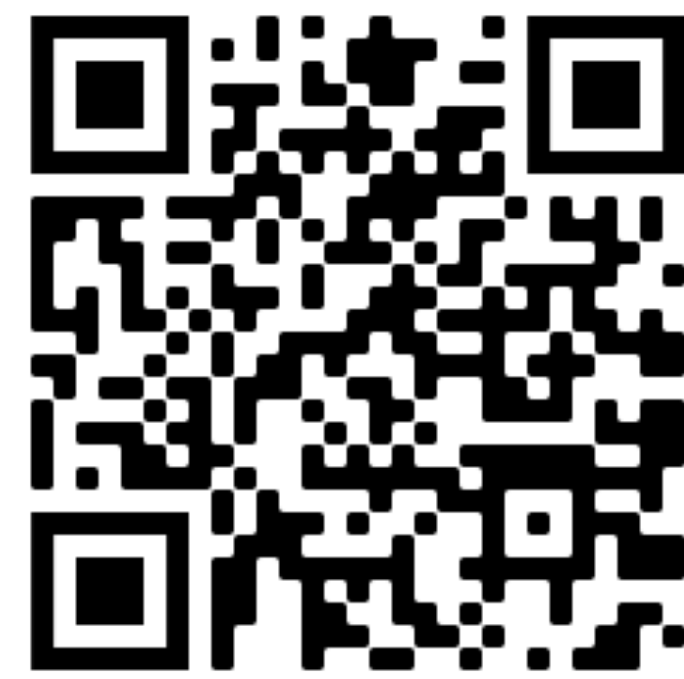
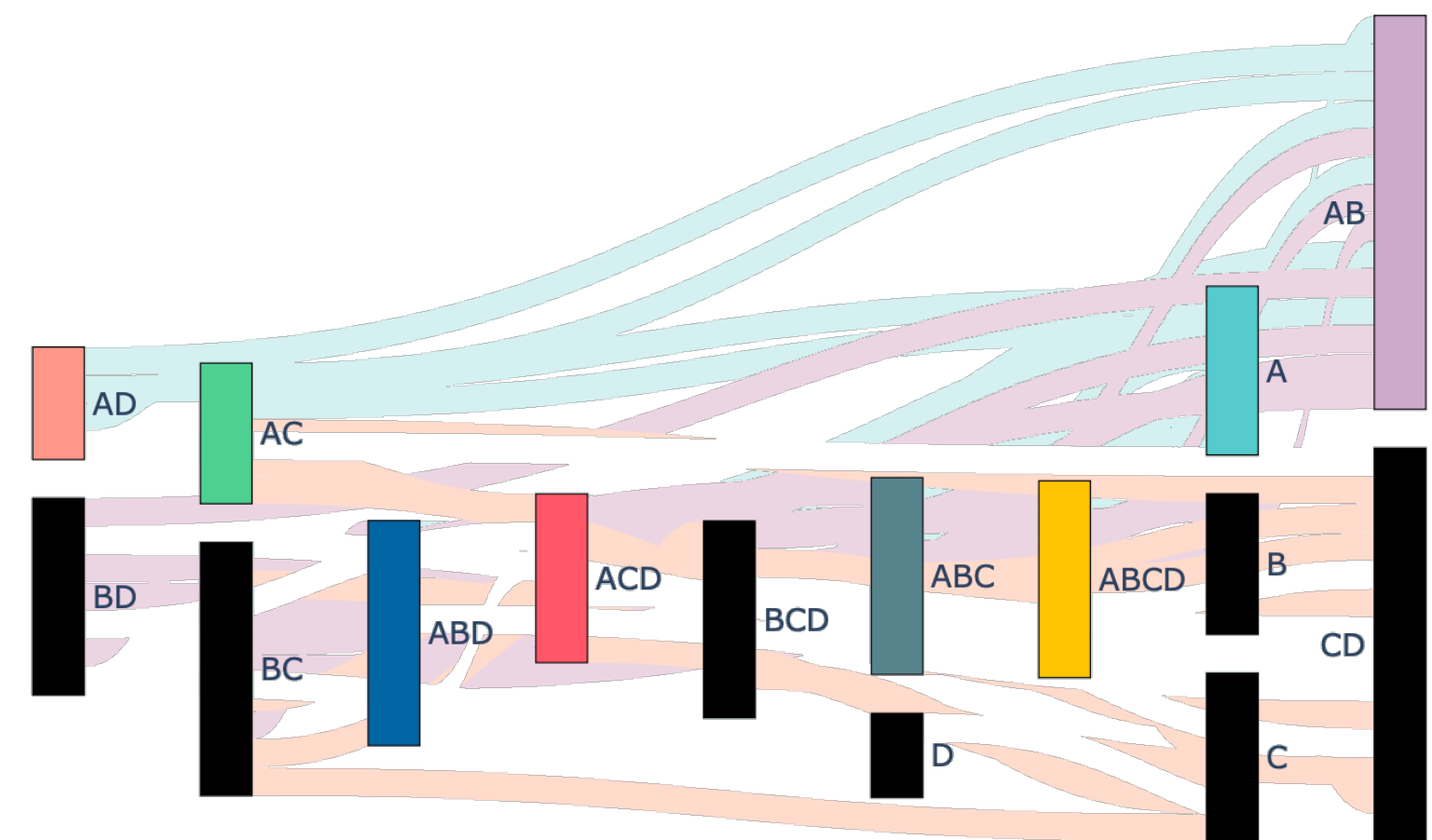


# Adaptive Dynamic Coalition Structure Generation

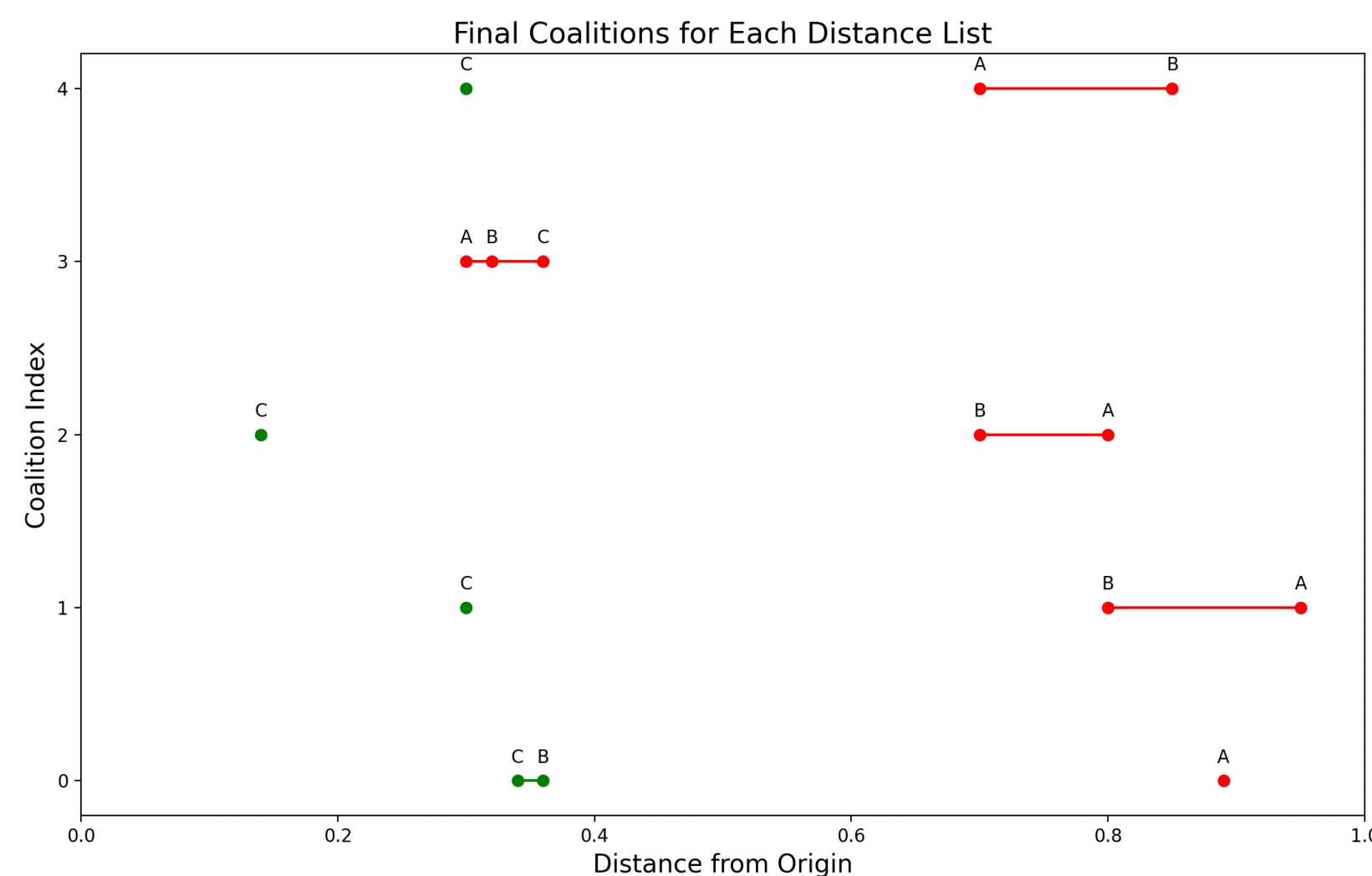


## Results

Coalition dynamics

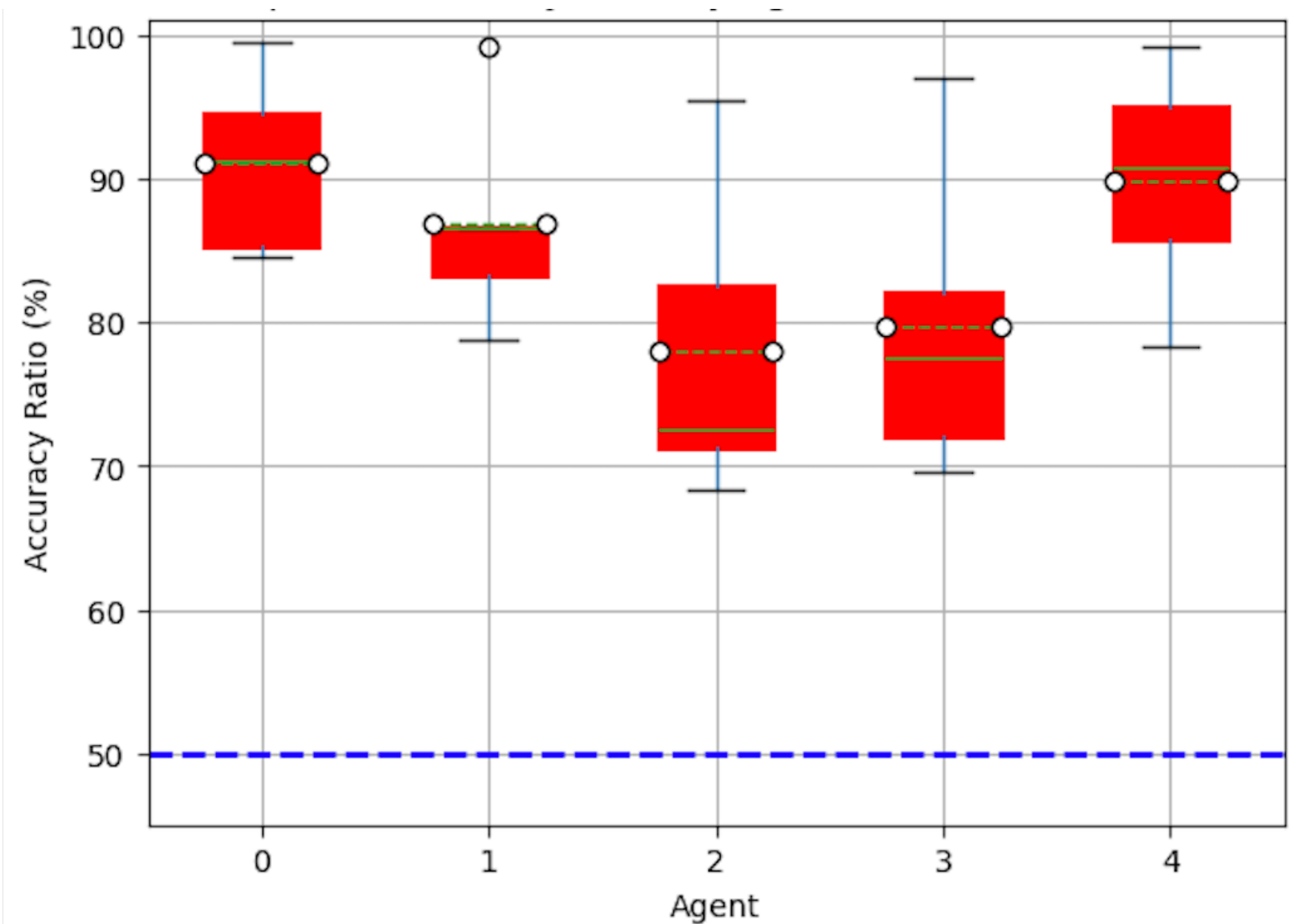


Generalization – Ridesharing game



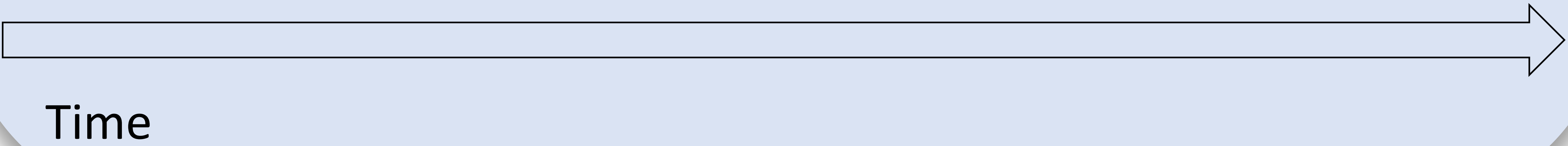
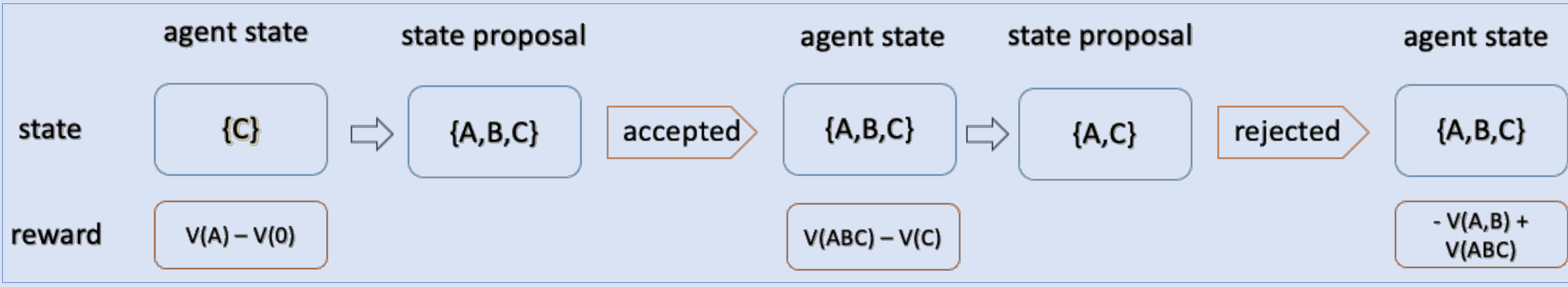
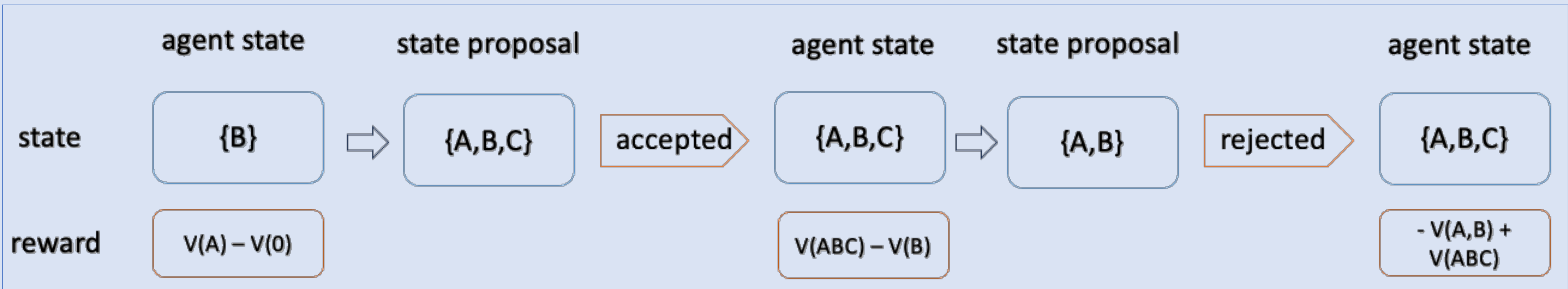
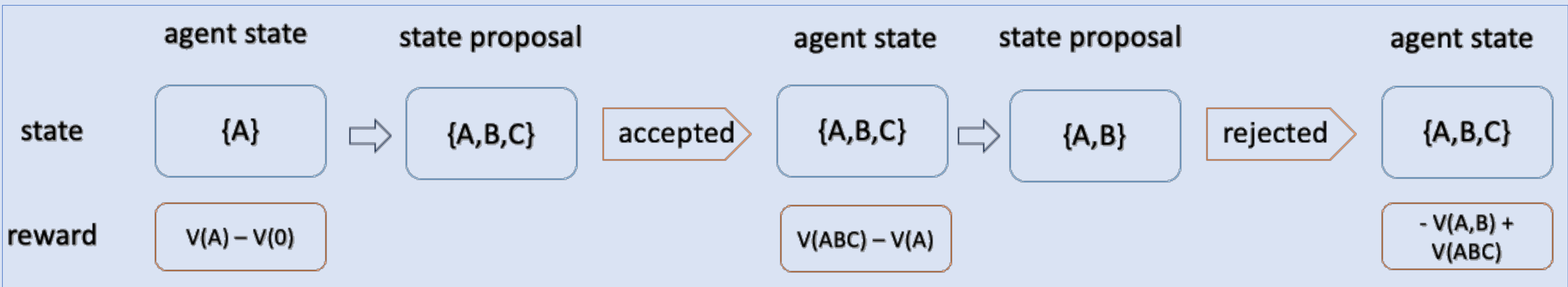
$$accuracy = \frac{\# \text{ correct actions}}{\# \text{ coalitions proposed}}$$

Accuracy of each agent’s policy across tasks (1 seed). The dashed line represents the accuracy of a random policy



## The Deal-or-No-Deal Game

### A Method to Obtain Socially Optimal Coalition Structures in a Dynamic Environment



## Motivation

- How to form coalitions of agents in a changing environment?
- Examples: ridesharing, wireless communications networks, ad-hoc teamwork, etc.
- Users/ agents are added or removed from the environment dynamically.

## How do we form coalitions in a changing environment?

- Brute force requires  $2^{N_t}$  computations every time the environment changes.
- Multi-agent approaches introduce non-stationarity of the environment

## Our Approach

- Method based on Deep RL for dynamic coalition games. Solved it as a single-agent problem. Each agent is trained using a deal-or-no-deal game
- Training with contextual data (such as distance matrix) achieves generalization.
- The **state** space is the  $2^N$  possible coalitions at any time. **Action** selection policy is to be able to identify the right coalition faster than exponential. The **Reward** is linked to the value of the selected coalition.
- **Objective** is to max Social Optimum. Reward encourages selection of good coalitions.