Hierarchical Common-Sense Interaction Learning

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Introduction

- The need for *coordination* among agents is inherent to the nature of multi-agent systems.

- Difficulty of predicting society-level phenomena on the grounds of local interactions suggests *learning* coordination strategies.

- Game-theoretic models widely used to model interaction situations at an abstract level (e.g. mechanism design, game-learning).

- However, little research focuses on agents learning something about the interaction *itself*.

- Idea: enable agents to develop a commonsense ("naive"?) understanding of the ongoing interaction.

- Our approach:
  - decompose the “coordination learning problem” in an intuitive way into several learning goals,
  - devise a hierarchical learning architecture to solve sub-problems and
  - integrate results.

- Identification of three *essential determinants* of interaction:
  1. **interdependence modalities**
  2. **opponent behaviour**
  3. **cooperation potential**

- Objective: construction of a *layered learning architecture* that integrates learning components for these (as an extension of the *InteRRaP* architecture).

- We concentrate on *learning* coordination in societies of purely *selfish* agents:
  - for abstract interaction situations (repeated n-player games),
  - without explicit communication and
  - without any prior knowledge of payoff functions, opponent strategies and opponent decision-making processes.

- Overview:
  1. Interaction Scenario
  2. Intuitive model of the "coordination problem"
  3. The LAYLA agent architecture
  4. Experimental Results
  5. Conclusions

Interaction Scenario

- n-person games in normal form with black-box payoff function (private knowledge of the *Simulation Engine*).

- Simulation procedure in round t:

  1. agents (players) $N = \{1, \ldots n\}$ communicate their action choices (taken from a joint strategy space $S = \times_{i \in N} S_i$) to the Simulation Engine (SE),

  2. SE computes all the resulting payoff $u_i(s_1, \ldots s_n)$ for every agent i,

  3. each agent is notified of the performed joint action $(s_1, \ldots s_n)$ and of the *private* payoff u_i it receives,

  4. round $t + 1$ is started.

- Repeated for a finite number of rounds which is *unknown* to the agents; no knowledge of the payoffs opponents receive.

Intuitive Model of the Coordination Problem

- Starting point: agents as individual utility-maximisers **but** problem of "egoist traps", esp. in the case of non-pareto-optimal Nash equilibria.

- *Socially coherent* behaviour can be defined as $OPT \subseteq S$ where

$$opt \in OPT \iff \text{$u(opt)$ is in the \textit{kernel} of the game}$$

- *What do agents need to know in order to converge to such behaviour?*

- Decomposition of learning problem into sub-problems corresponding to *essential determinants of interaction*

Interdependence Modalities:

- Denote *"what the interaction consists of"* i.e. in which way actors' actions affect each other.

- In repeated n-player games equivalent to learning the utility function.

$\Rightarrow$ Learning task: construct an explicit representation $\pi : S \rightarrow \mathbf{R}$ of agent i's private payoff function u_i

Opponent Behaviour Prediction:

- Important to predict others' future actions to plan strategically.

- Enables reasoning about what the interaction *will* be like (rather than what it *could* be like).

- Learning task: learn a function that can be used to predict any future opponent action sequence on the basis of past joint actions.

Cooperation Potential:

- Difference to opponent behaviour prediction: cooperation potential learning helps to *alter* opponent behaviour rather than only anticipate it.

- Learn to predict own action sequences that will "massage" the opponents into their most cooperative stance.

$\Rightarrow$ Clearly all three learning goals hardly achievable in the presented form, but valuable for defining the overall problem.

The LAYLA Agent Architecture

- Reasoning layers in the InteRRaP agent architecture correspond to the identified learning tasks.

- Idea of the **LAY**ered **L**earning **A**gent architecture: extend each InteRRaP layer by a learning component to attack (simplified versions of) the learning problems.

- Devise concrete learning algorithms for the layers for the specific problem of learning repeated games.

$\Rightarrow$ prototypical **Utility Engine**, **Strategy Engine** and **Social Behaviour Engine**

Utility Engine (L^{IM}): learn an approximation π of the actual payoff function u_i.

- Straightforward supervised learning problem: given joint-action/payoff pairs, approximate the payoff function.

- Employ standard multi-layer feed-forward neural networks that are trained with samples of the form
$$\left\langle \beta(s^{(t)}), \frac{u_i^{(t)}}{\max_{t' \leq t} u_i^{(t')}} \right\rangle$$

- Learning success satisfactory, but disadvantage: neural network design choices handcrafted.

Strategy Engine (L^{OBP}): learn an action-value function $m : S_i \rightarrow [0;1]$ to approximate the expected utility of actions.

- Uses a combination of genetic algorithms and nearest-neighbour learning.

- Trained by using pairs of consecutive opponent action pairs parametrised by the reasoning agent's own action

$$s_{-i}^{(t-1)} \xrightarrow{s_i^{(t-1)}} s_{-i}^{(t)}$$

- Fitness values of individuals depend on their validity with respect to past experience.

- Standard one-point crossover and mutation, wildcard bits; $|S_i|$ populations, one for each action of agent i

- Nearest-neighbour heuristic used to predict next opponent action depending on the previous action.

- Reduction of L^{OBP} to a one-step lookahead.

- By making use of the utility function approximator π a function
$$m(s_i) = \frac{\pi(\tilde{s}_{-i}, s_i)}{\sum_{s_i \in S_i} \pi(\tilde{s}_{-i}, s_i)}$$
can be calculated in each step (given the previous opponent action $\tilde{s}_{-i}$).

$\Rightarrow$ Ideally, m is maximal iff s_i is the (greedy) *best response* to the predicted next opponent action.

Social Behaviour Engine (L^{CP}):

- Learn peer preference structures, the "value" of peers for the agent.

- Use the learned to concepts to approximate the opponent's reasoning mechanism.

- Developed special algorithm for L^{CP} based on *gain models*.
  Idea: approximate two-player payoff dependencies within n-player interactions by

  1. combining worst-case and best-case payoffs for action combinations (s_i, s_j) and

  2. considering the overall *risk* of action s_i.

- *Probabilistic Ordering Models* are used for the approximation of the peer's gains.

- Recursive reasoning down to "level 3".

- Line of social reasoning:

  1. Assess the value of "help" that is provided to i by peer j by particular strategies of j and vice versa.

  2. Use 1. to compute the probability with which j will play any s_j if i plays any s_i.

  3. Use 2. to determine the *expected gain* $g_i(s_i)$ of every action s_i.

  4. Construct the set of *socially feasible actions*

     $L_j = \{s_i | m(s_i) + \gamma \cdot g_i(s_i) > max_{s_i'} m(s_i')\}$
     (*compromise factor* $\gamma \in [0; 1]$).

  5. Repeat 1.-4. for every peer j in a neighbourhood $N_i \subseteq N - \{i\}$.

  6. Construct the union of all socially feasible action sets $L = \bigcup L_j$.

     If empty, play according to m_i.

     Else choose that $s_i \in L$ that (allegedly) maximises opponents' expected gains.

- No built-in cooperativeness, but ability to detect cooperation potentials and notion of reciprocity.

- Integration of learning layers:

  - *downward commitment*:

    whenever compromise is possible, greedy choices are overruled;

    Utility Engine exploration action choices can be overruled by the Strategy Engine;

  - *upward activation*:

    learning of super-layer does not start until sub-layer makes sufficient progress;

    the Utility Engine and Strategy Engine perform supervised learning, so current errors can be measured
    $\Rightarrow$ use of thresholds

Experimental Results

- Application scenario:

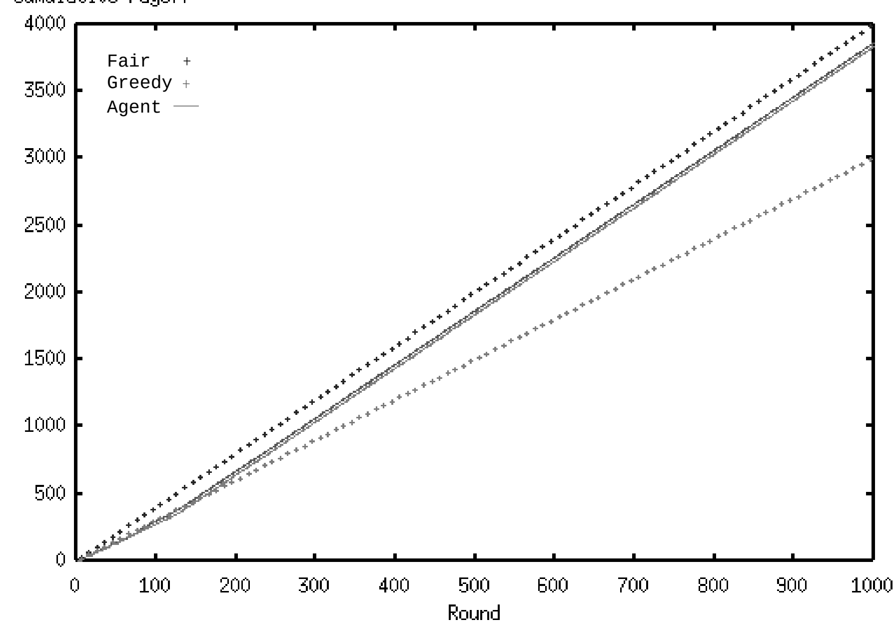
  resource-load balancing

- Special properties:

  1. A single strict Nash equilibrium that is not collectively rational ("greedy" action combination).

  2. Several "fair" resource allocation strategies, that provide higher payoffs to *all* agents than the equilibrium

- Tests in two-player two-resource, ten-player five-resource and fifty-player five-resource settings.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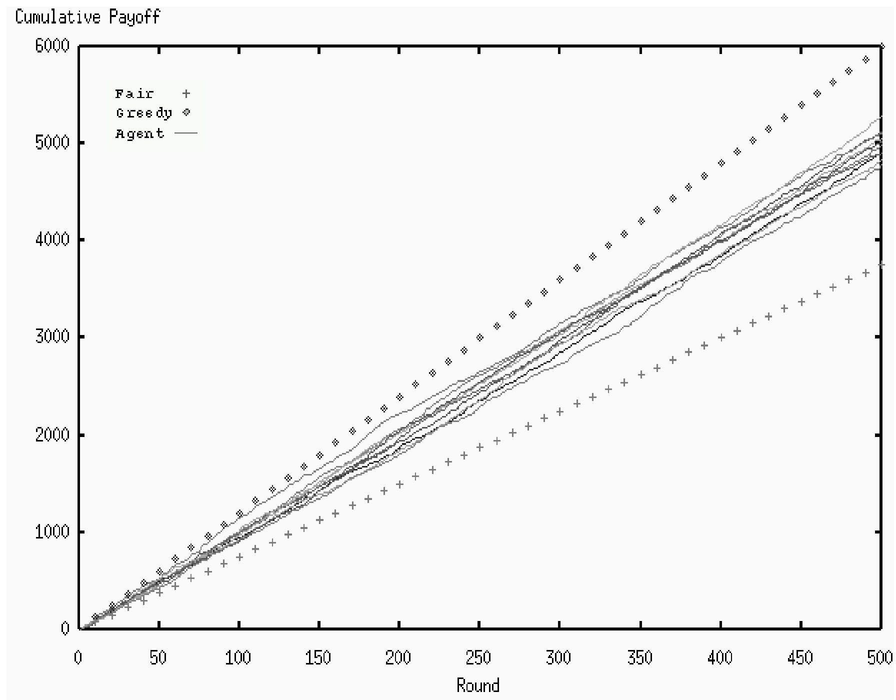
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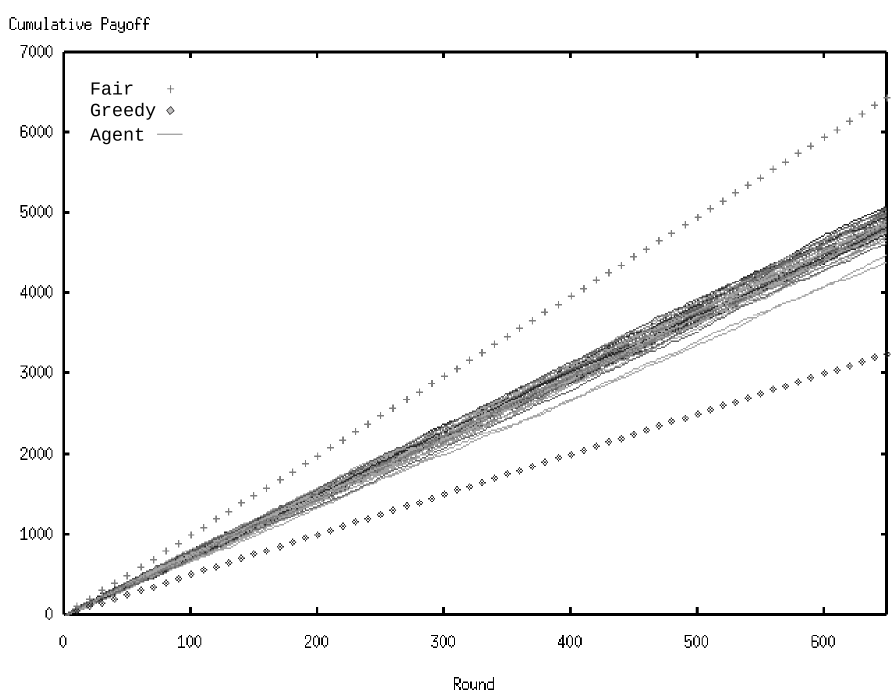
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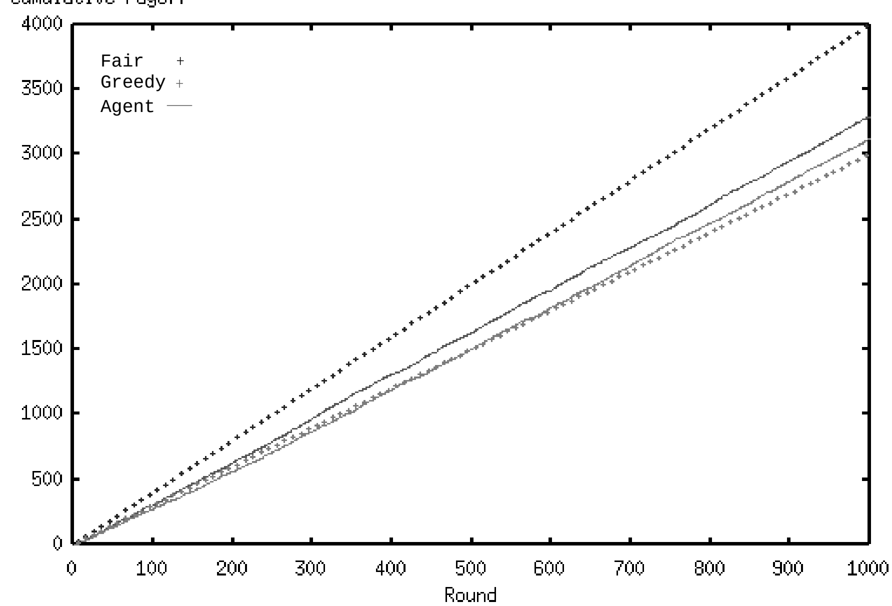
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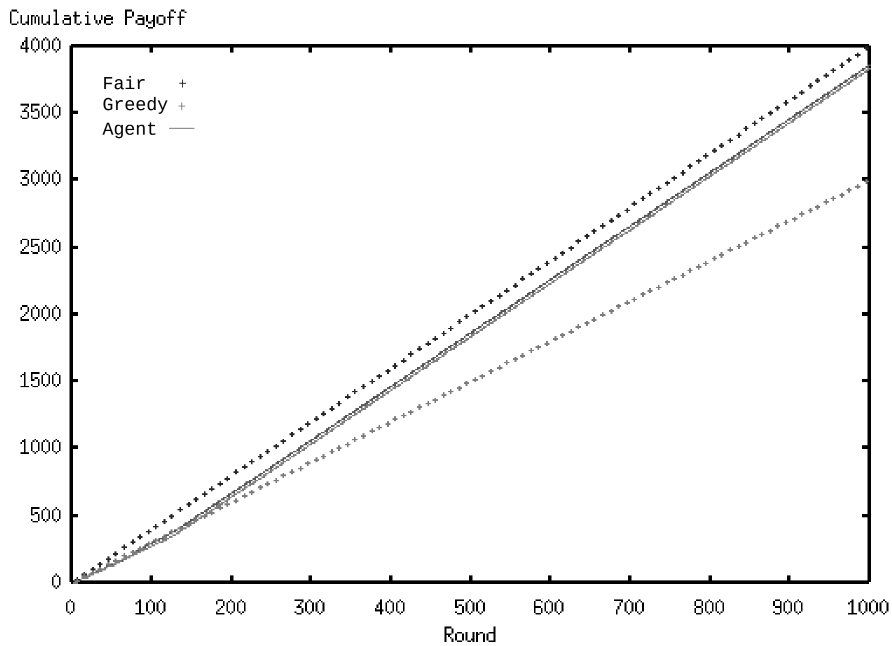
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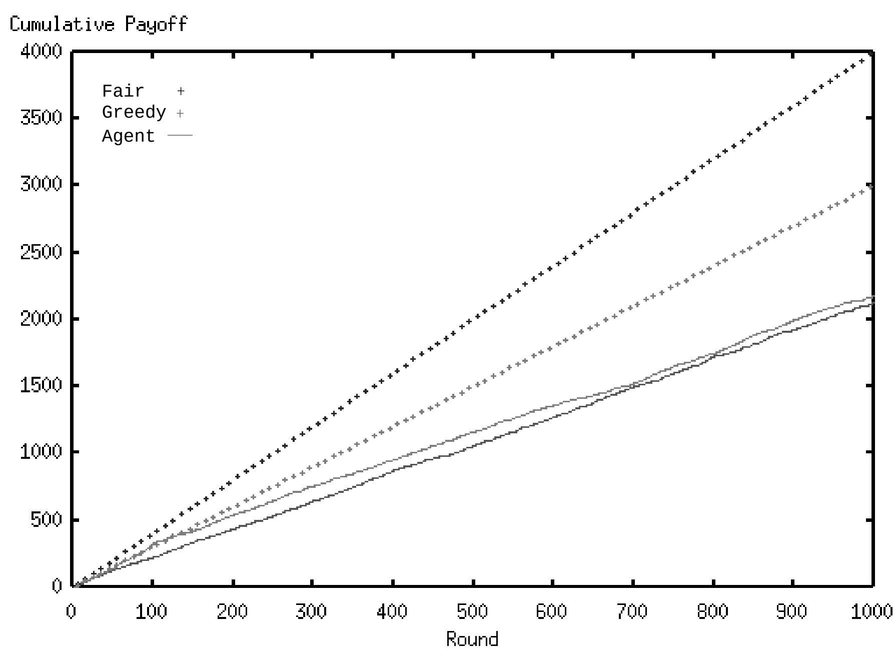
Cumulative Payoff
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Conclusions

- Selfish agents *can* learn to behave cooperatively
  - in games in which it is tempting to defect,
  - without being able to communicate,
  - with very little prior knowledge and
  - (although things get harder) even in games with *vast* strategy spaces.

- Layered learning offers the possibility to decompose hard problems into simpler ones but
  - the decomposition itself was not "learned",
  - the architecture is only relevant in the context of repeated games and
  - learning algorithms were tuned to match the needs of the application scenario.

- Drawbacks:
  - dependence of success on appropriate choice of compromise factor γ,
  - lack of meta-reasoning capabilities,
  - lack of dependable multi-agent learning and layered learning theory to compare our results with and
  - high complexity.
- Open issues:
  - Extensive form games,
  - non-game-theoretic interaction models
  - use of communication and
  - meta-learning.