ChatGPT

Modeling of *Human Group Coordination* (2022) – Summary

Objective and Approach

Purpose: Hornischer *et al.* (2022) investigate how humans coordinate in groups by combining controlled experiments with computational modeling [1]. The core question is whether simple, low-level decision rules can reproduce the emergent group behavior observed in humans [2]. In their experimental setup, ten human players move avatars on a virtual hexagonal grid towards goal locations (reward "fields") [3]. A *biased* minority of 2 players is privately told that one specific goal has a higher payoff, while the other 8 *unbiased* players know only that all goals give equal reward [4]. Crucially, the payoff for reaching a goal is multiplied by the number of co-players who also arrive there [4]. This incentivizes **goal-directed flocking**: individuals benefit from converging on the same goal field as a group [5]. However, players receive no instructions on *how* to coordinate beyond this reward structure, making any observed group coordination an emergent outcome of individual decisions [5].

Modeling methods: To explain the experimental results, the authors employ two complementary modeling approaches [6] [7]. First is a *"cognitive force"* model – a rule-based strategy in which each simulated agent at each step chooses the move that **maximizes its future movement options** [2]. In practice, the agent simulates many random walks (stochastic trajectories) from each possible next move and evaluates how many unique fields can be visited (with bonuses for reaching reward fields) [8] [9]. The agent then moves to the neighboring hexagon whose hypothetical walk covered the most territory [10] [11]. This **option-maximization heuristic** effectively encourages exploration and information gain, mimicking a strategy of "keeping one's options open." The second method is a standard **multi-agent reinforcement learning (RL)** approach: agents learn policies to maximize cumulative reward from past experience [2]. The authors formulate the game as a Markov game and use a state-of-the-art multi-agent RL algorithm (an actor-critic method with a centralized critic) to train agents' policies [12] [13]. This RL framework lets agents discover reward-maximizing behaviors through trial-and-error, while the cognitive force model uses a hand-crafted decision rule based on future possibilities.

Key Findings

Human vs model coordination: The two models were evaluated against 40 runs of the human experiment (400 total participants) [14]. The cognitive force simulation closely replicated human group behavior [15] [16]. In both humans and the cognitive model, the *biased* minority often successfully "led" the majority to the high-payoff field, resulting in most players converging on that target [17] [18]. This led to an **"all-or-nothing" group response** in many games: either almost all unbiased players followed the informed minority to the high-reward goal, or almost none did [18]. Quantitatively, the distribution of group sizes at a goal and the frequency of full-group coordination (8 or more people together) in the cognitive simulation matched the experimental data remarkably well [19] [20]. These results suggest that human group coordination may emerge from *nonspecific, information-based strategies* rather than explicit communication or complex planning [21]. In other words, humans might implicitly use a rule akin to maximizing future options or following simple local cues, as the cognitive force model encapsulates.

The multi-agent RL agents, in contrast, **underperformed** both the humans and the cognitive-force agents [22]. While the trained RL policy did capture some aspects of the task (e.g. agents learned to reach goals for reward), it did not consistently produce the high level of group alignment seen in the humans [22] [23]. The RL agents often failed to all converge on the same target, yielding only a partial group coordination effect [23]. Overall, the RL approach achieved lower rewards and a poorer match to human behavioral patterns than the simple option-maximization strategy [22]. The authors note that multi-agent RL is still an active research area and sometimes suffers from training instabilities, so its weaker performance here does not completely invalidate reward-driven decision-making as a model of human behavior [24]. However, the superior fit of the cognitive model indicates that human groups might be better described by strategies focusing on information and flexibility (exploration) rather than purely on learned reward optimization.

Integration of the *Fractal AI* Framework

A noteworthy aspect of the study is its use of the **Fractal AI** framework to inform the modeling. Fractal AI (Cerezo & Ballester 2018 [25]) is a theoretical framework for general intelligence that introduces new methods for decision-making by modeling information in a *fractal*, multi-scale manner. It addresses the classic exploration–exploitation dilemma in reinforcement learning by generating large numbers of high-quality exploratory trajectories, effectively turning reinforcement learning into a more supervised problem [25]. In this paper, Hornischer *et al.* explicitly cite Fractal AI as one of the inspirations for the **"option maximization" principle** underlying their cognitive force model [26]. In fact, their cognitive agents' behavior – simulating many random walks from each possible action and choosing the action that covers the most new ground – is very much in line with Fractal AI's idea of **maximizing informational gain** to guide decision-making. By exploring the environment through hypothetical roll-outs (not unlike a Monte Carlo tree search but with a stochastic, information-centric twist), the cognitive force agents ensure they retain as many future possibilities as possible. This resonates with Fractal AI's approach of building a database of top-performing action sequences with minimal computation, thereby efficiently solving exploration vs. exploitation [25].

In summary, the authors apply the general principle of maximizing future options – a concept grounded in prior work from physics, cognitive science, and AI (e.g. empowerment and Fractal AI) – to model human group coordination [26]. The successful replication of human-like collective behavior via this principle demonstrates how Fractal AI's **information-driven strategies** can be integrated into multi-agent simulations of social behavior. The study not only provides insight into human group dynamics but also exemplifies how Fractal AI's ideas of fractal information processing and exploratory action selection can inform practical modeling of complex, coordinated decision-making in groups.

Full Text Access: The complete paper *"Modeling of human group coordination"* by Hornischer *et al.* (Phys. Rev. Research **4**, 023037 (2022)) is published open-access under a CC BY 4.0 license. It can be accessed via the Physical Review Research journal (DOI: 10.1103/PhysRevResearch.4.023037) [27] [28] for further details.

References:

1. Hannes Hornischer *et al.*, *"Modeling of human group coordination,"* **Physical Review Research** 4, 023037 (2022) [2] [26].

2. Sergio H. Cerezo and Guillem D. Ballester, *“Fractal AI: A fragile theory of intelligence,”* arXiv:1803.05049 (2018) 25 .

---

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 26 27 28 (PDF)
Modeling of human group coordination
https://www.researchgate.net/publication/359910773_Modeling_of_human_group_coordination?_tp=eyJjb250ZXh0Ijp7InBhZ2UiOiJzY2llbnRpZmljQ29udHJpYnV0aW9ucyIsInByZXZpb3VzUGFnZSI6bnVsbH19

25 [1803.05049] Fractal AI: A fragile theory of intelligence
https://arxiv.org/abs/1803.05049