Seeing is "Behaving":

Using Revealed-Strategy Approach to Understand Cooperation in Social Dilemma

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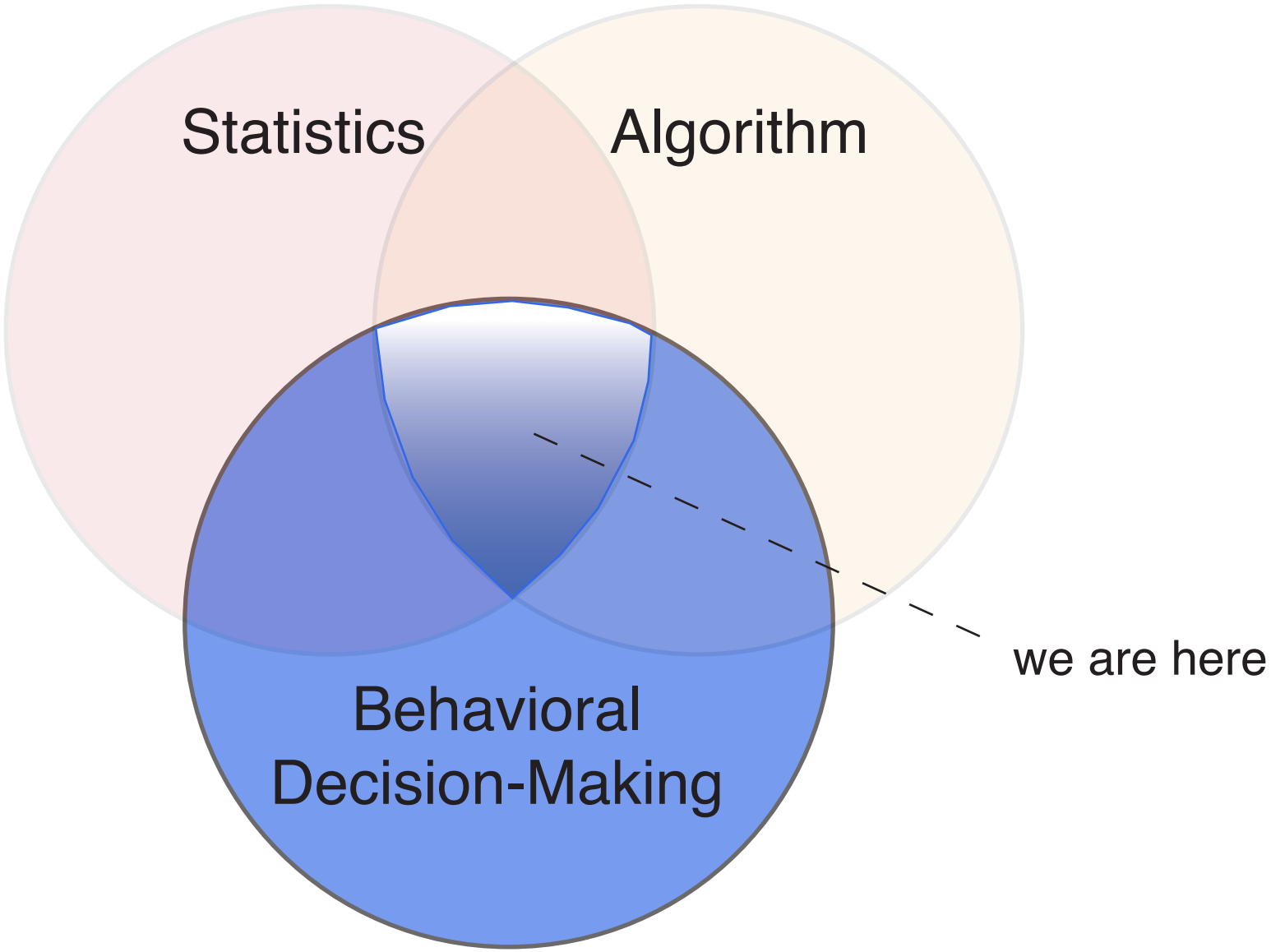
Positioning



Motivation

"The most important discovery was the evidence on the pervasiveness of heterogeneity and diversity in economic life... the long-standing edifice of the representative consumer was shown to lack empirical support."

—— James Heckman (2001, *p674*)

Traditionally: $$Y = m(X) + \varepsilon,$$

where we impost a functional form on $\mathbf{var}(\varepsilon|x)$

to capture heterogeneity.

Motivation

For example: Cooperation among self-interested individuals in social dilemma. How people make cooperation decisions?

- International environment treaty;
- global counter terrorism strategy;
- patent sharing of technology innovation;
- neighborhood security watching.

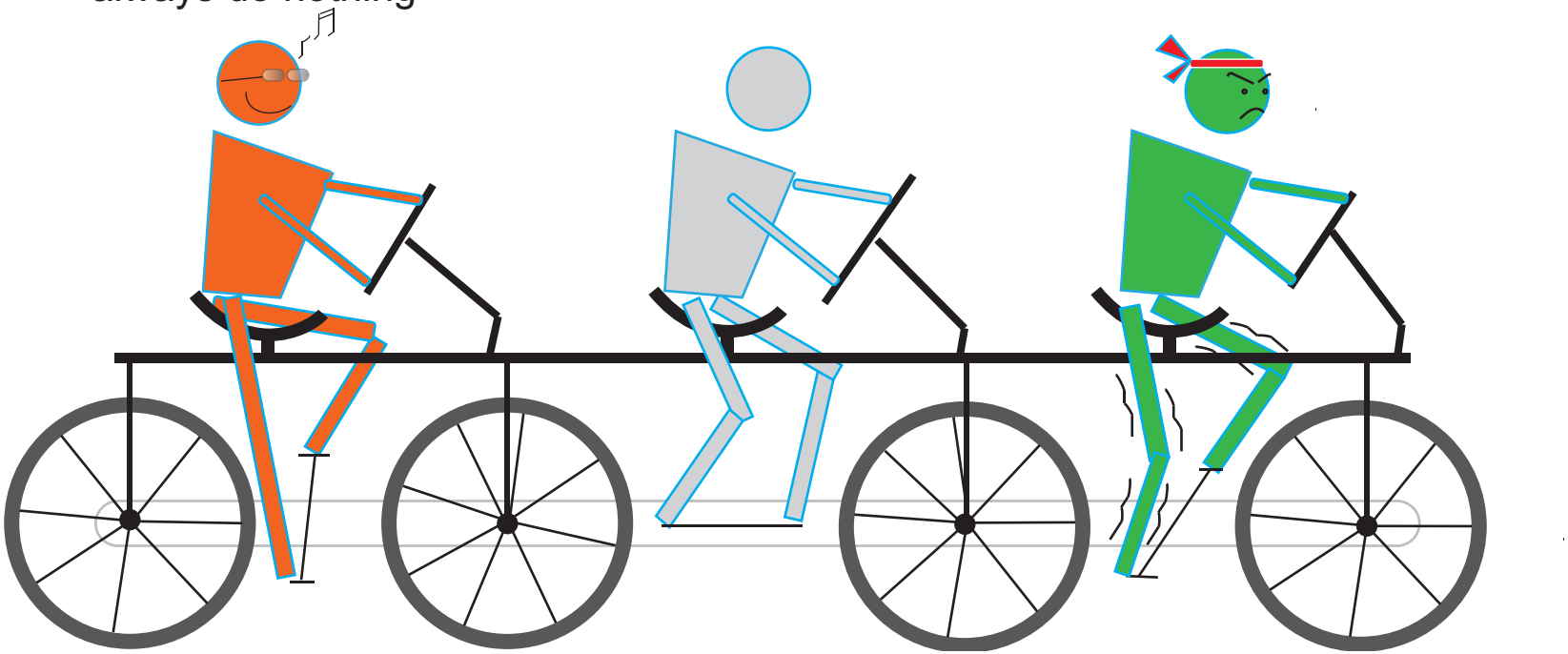
On a tandem: how hard would you try?

From the literature:

Free-rider:
always do nothing

Conditional cooperator:
we know little about them

Strong cooperator:
always try hard



Motivation

- A wide range of terms have been used to describe heterogeneous behavioral patterns in cooperation.

Examples:

strong cooperators;	conditional cooperators;
weak cooperators;	imperfect cooperators;
strong free-riders;	imperfect conditional cooperators;
week free-riders;	hump-shaped cooperators,
strategic cooperators;	noise makers.....

Motivation

- To date, we have not found a method that can systematically and comprehensively identify the existing (and the hypothesized) behavioral types scattered in this literature.

- Instead of pre-specify the agent types, we need to uncover heterogeneous behavior patterns from the data.

Motivation

Research Goal: We propose a data-driven approach to uncover behavioral patterns in social dilemma.

1). How to systematically describe strategy patterns?

2). How different patterns dynamically interact with each other?

Experiment: public goods

Experiment

- Linear public goods game.

- 18 participants in a session, 6 people were randomly assigned into a group.

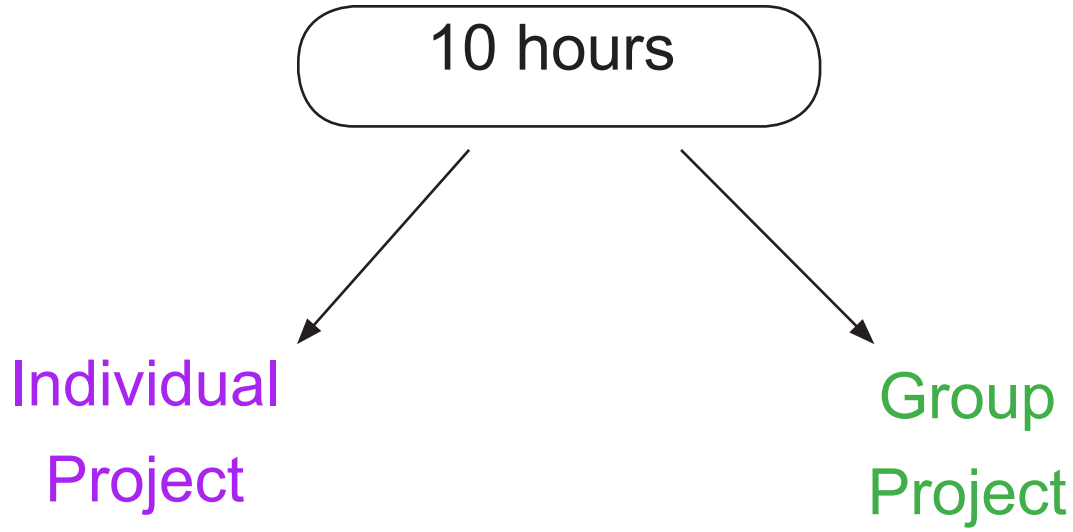
- Each session took approximately 60 minutes. In total 252 undergraduate students (14 sessions). Incentivized decisions.

- All the sessions were conducted with computer-based materials, programed using z-tree.

- Context: weekend time allocation

Experiment

- Endowment: 10 hours
- Decision: time allocation



Experiment

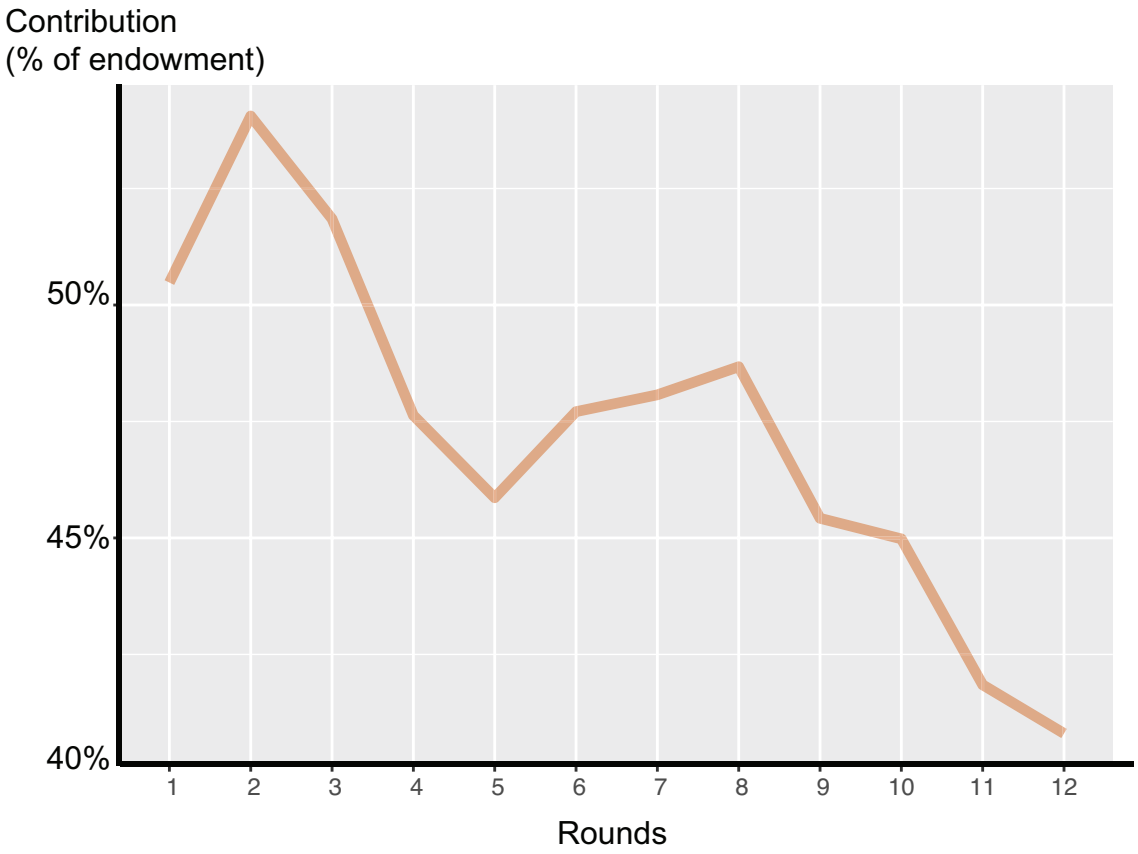
- Individual project: Every hour yields 20 game points;
- Group project: every hour yields 40 game points.
- At the end of each round, all participants in the same group receives an **equal share** from the group project.

$$\pi_i = 10 - C_i + \frac{1}{3}\sum_{j=1}^{6} C_j$$

Experiment

- Repeated game, random-match;
- Seeing the group average as a "Signal" at the end of each round;
- Random end mechanism (at least 12 rounds).

The Contribution Decayed Overtime



Behavior Profile

A person's **Behavior Profile** — a reliable tendency of how one makes decisions in interactive,dynamic settings — should be revealed by analyzing a series of observed decisions.

Behavior Profile

"Behavior is a product of the **person** and the **environment**." *Lewin (1943)*

A **behavior profile** will at least consist of two pieces of information:

- unconditional behavior
- conditional behavior

Behavior Profile

- In a public goods game with certain rules (i.e., parameters and context), a behavioral profile should capture a participant's behavioral pattern that:

  1. How she makes decisions on her own and,

  2. How she make decisions in response to others' behaviors.

Behavior Profile

- **Behavior Profile**:

  1. First-round contribution (unconditional decision)

  2. Contribution to signal ratio (conditional decision)

     — average ratio over 12 period
     (capture how one respond to external influence)

     — variance of the ratio
     (capture the stability of the strategy.)

Behavior Profile

- Formally, we use

$$B_k^i = \{b_1^i, b_2^i, ..., b_k^i\}$$

to denote a player i's behavior profile, which contains *k* components.

- Here, we make a week assumption that each participant's strategy profile could be characterized by:

$$B_3^i = \{b_1^i, b_2^i, b_3^i\}$$

where: b_1^i is first-round contribution;
b_2^i is average ratio over time;
b_3^i is variance of the ratio.

Behavior Profile

- Suppose every participant have her own reasoning and therefore, a unique behavior-profile, which strategy-profiles are similar enough to be considered as the same "type"?

- For individual *i*, let consider the behavior-profile as a vector. Operationally, we use the Euclidean distance between the vectors to determine the similarity between the profiles.

Behavior Profile

- Specifically, the Euclidean distance between two vectors B_3^i, B_3^j is measured by:

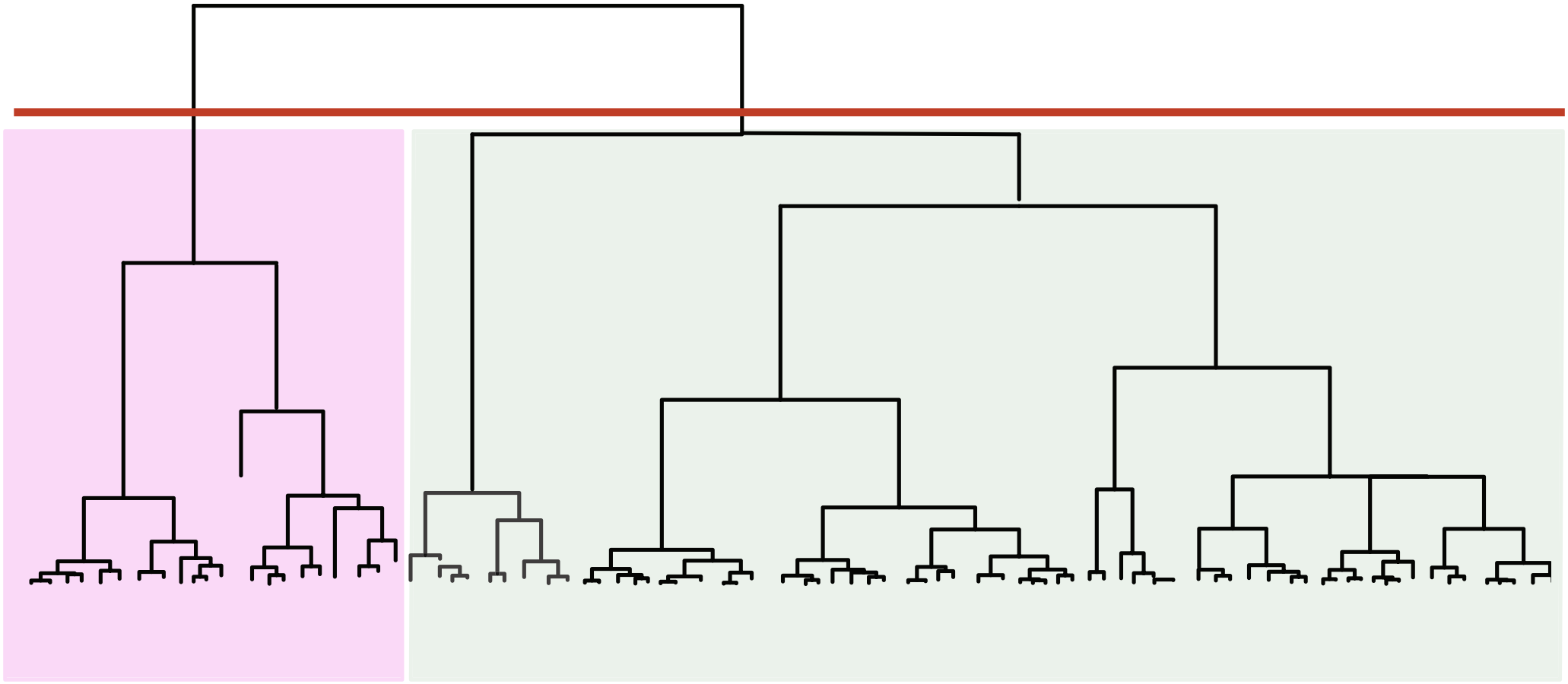
$$d(B_3^i, B_3^j) = \sqrt{(b_1^i - b_1^j)^2 + (b_2^i - b_2^j)^2 + (b_3^i - b_3^j)^2}$$

- Based on this distance measure, we then apply hierarchical clustering method to divide individuals into different types.

Results

Cluster Dendrogram

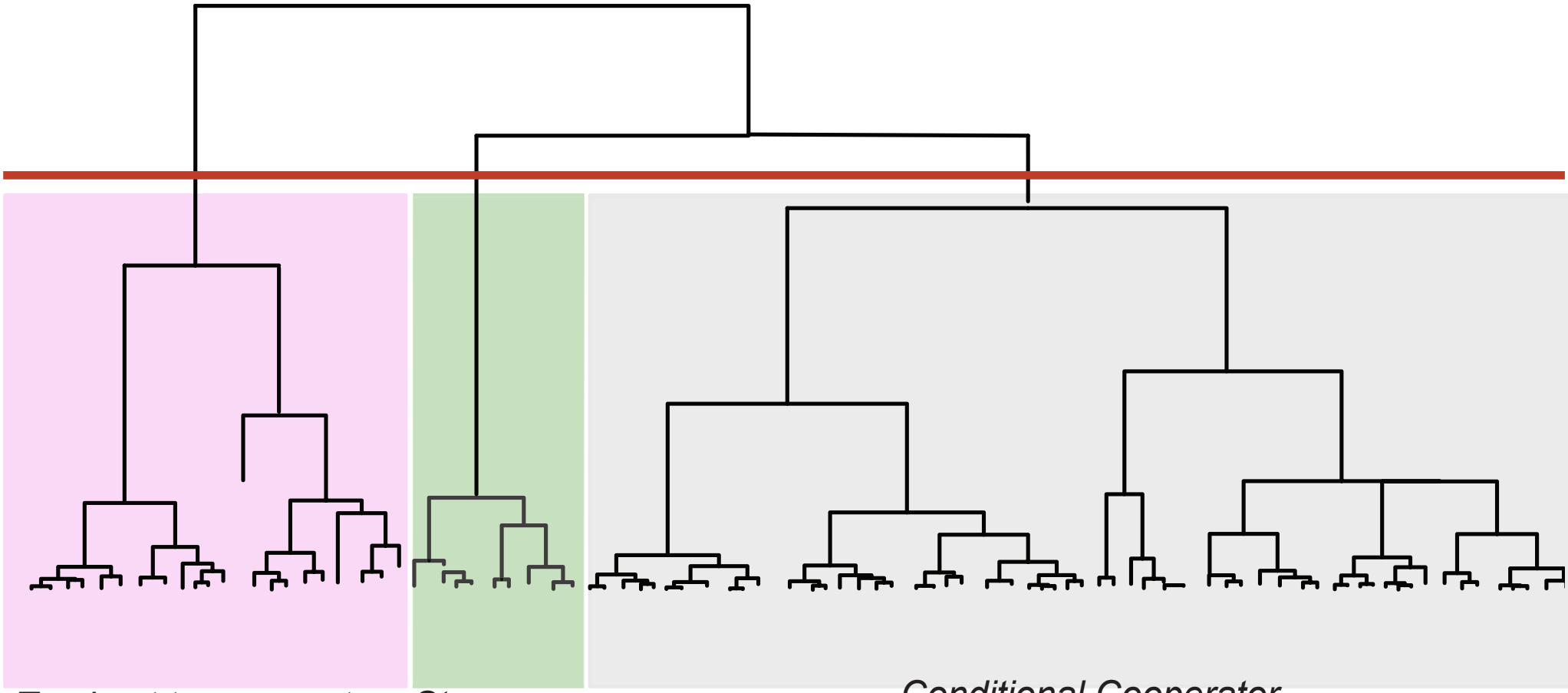
Cluster Dendrogram



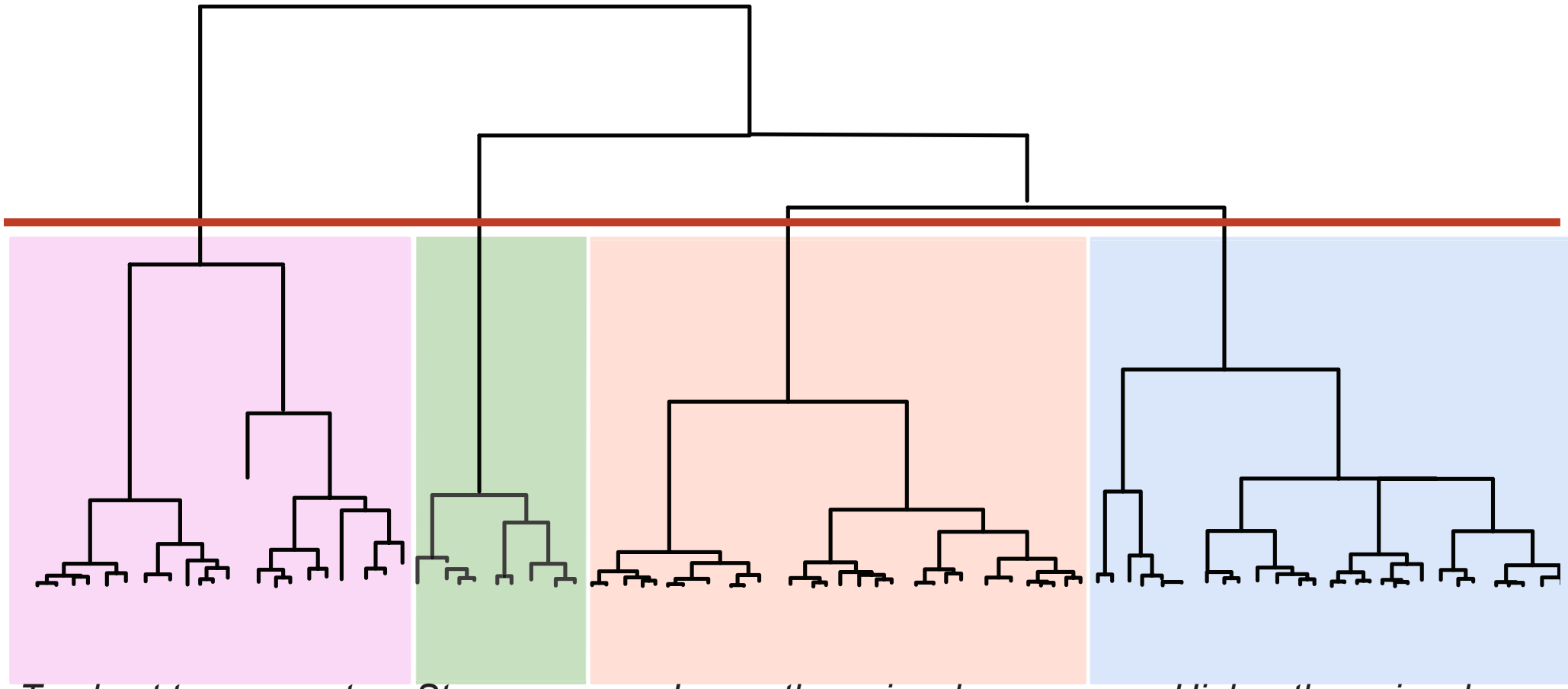
Tend not to cooperate

Tend to cooperate

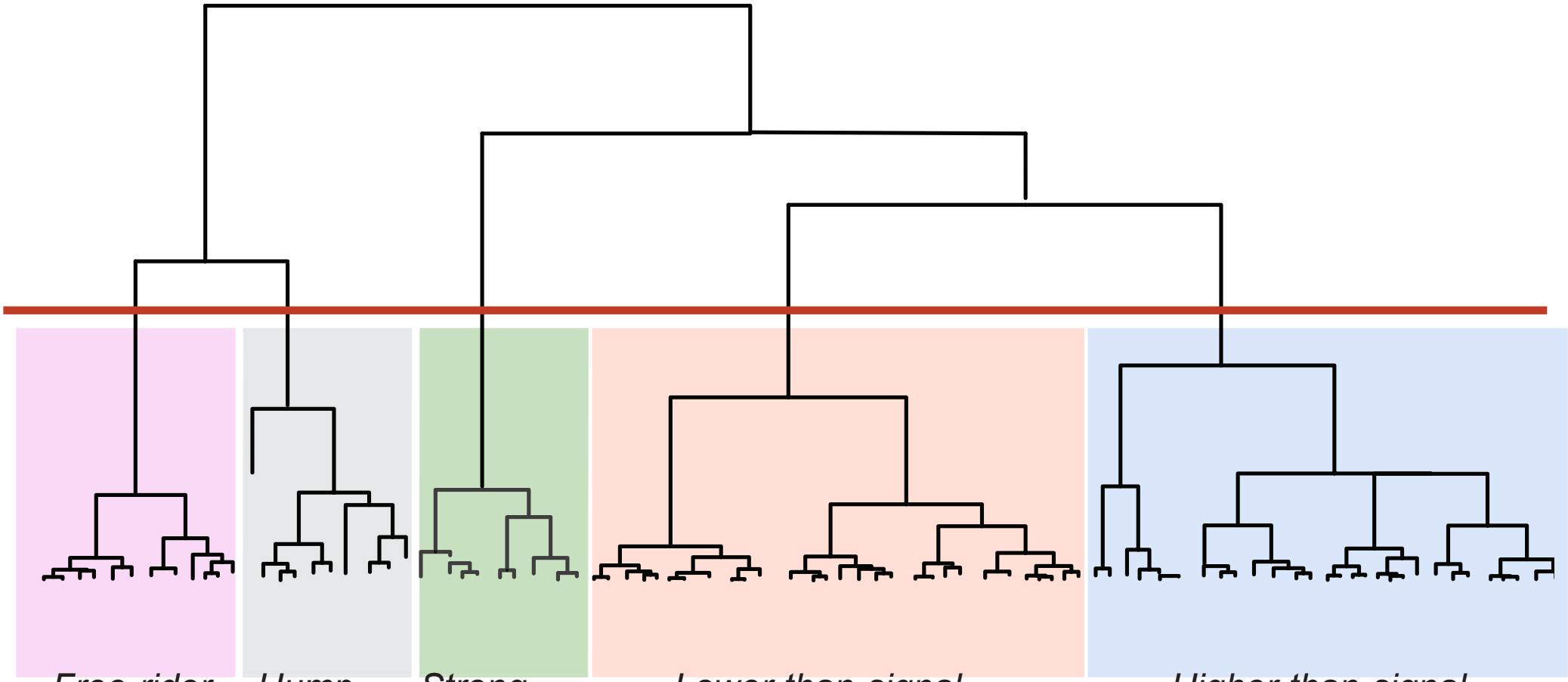
Cluster Dendrogram



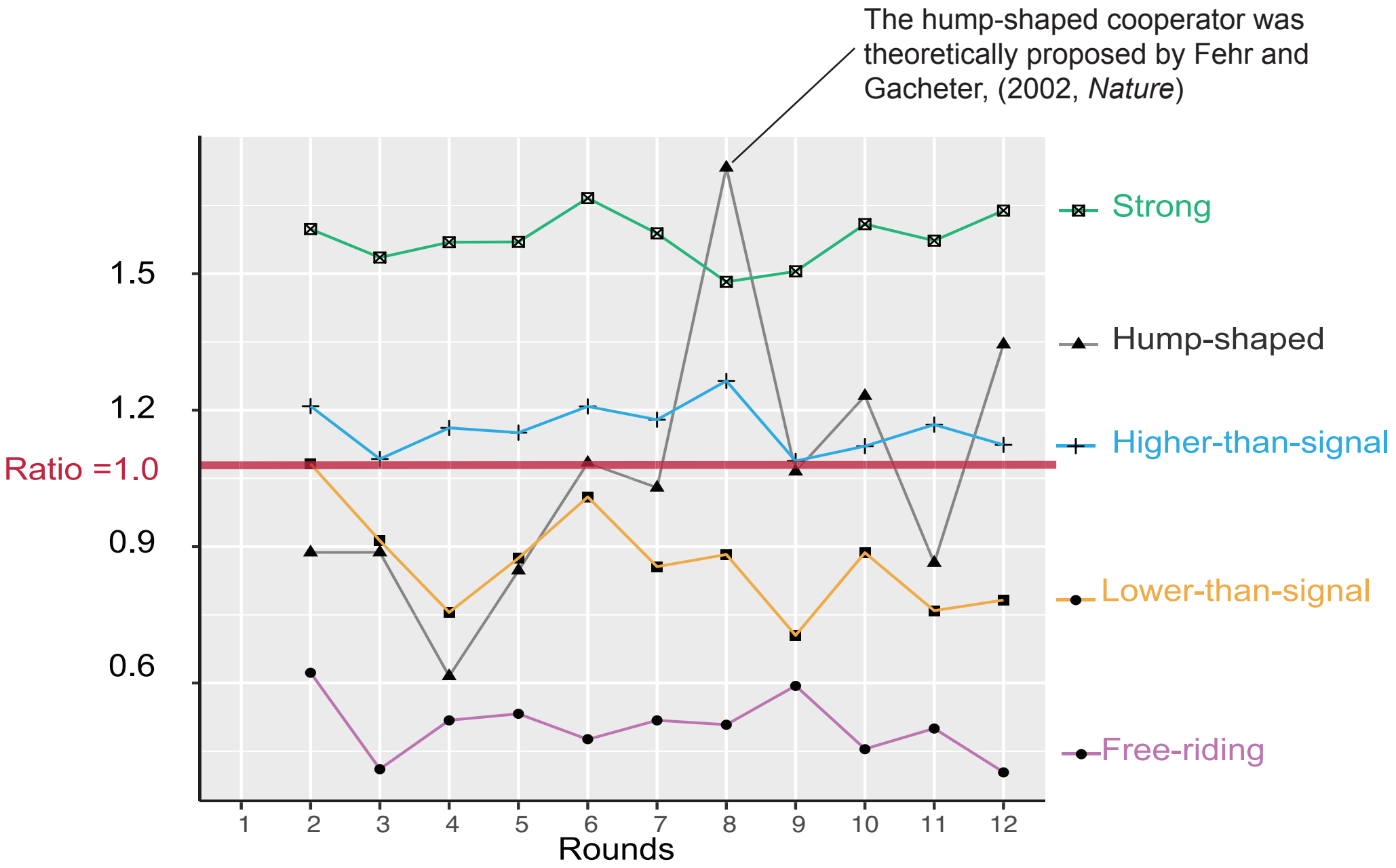
Cluster Dendrogram



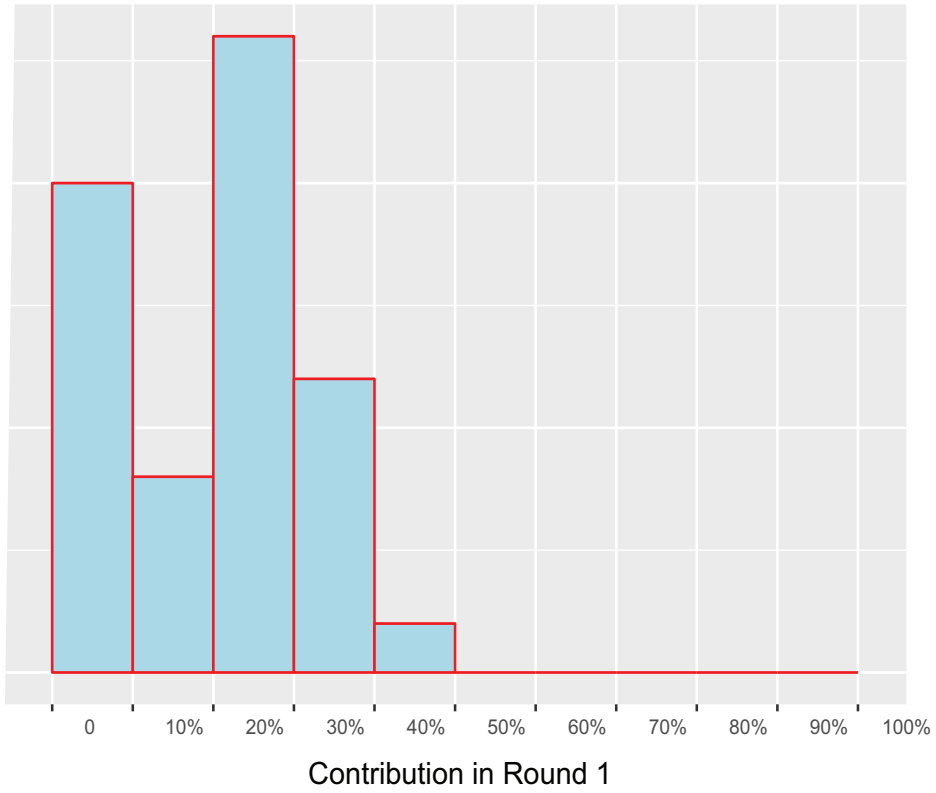
Cluster Dendrogram

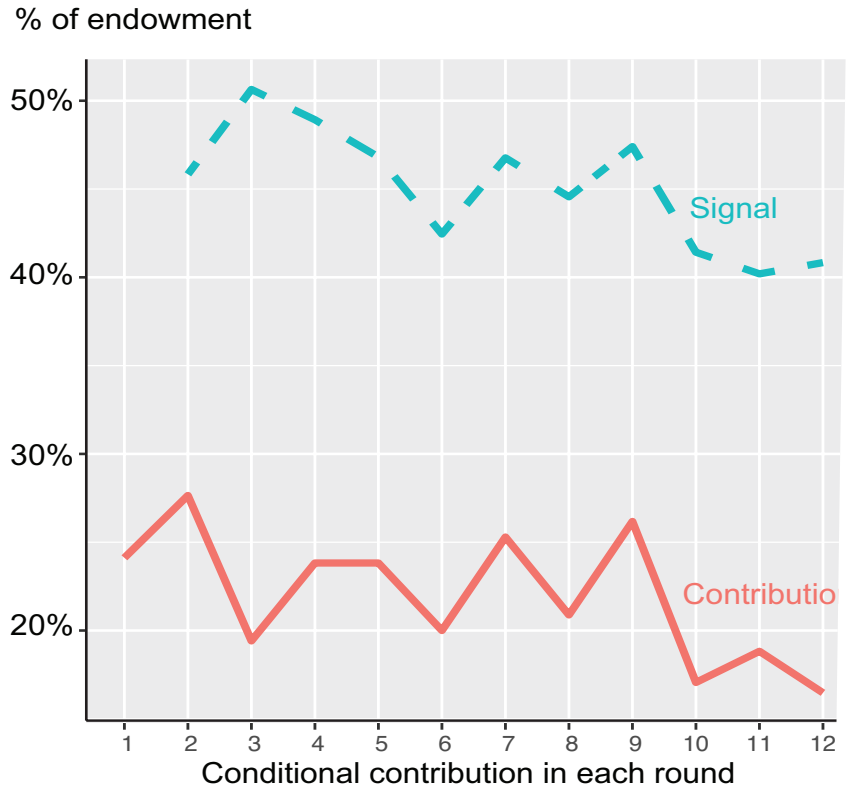


Results


The hump-shaped cooperator was theoretically proposed by Fehr and Gacheter, (2002, *Nature*)
1.5
1.2
Ratio =1.0
0.9
0.6
1
2
3
4
5
6
7
8
9
10
11
12
Rounds
Strong
Hump-shaped
Higher-than-signal
Lower-than-signal
Free-riding

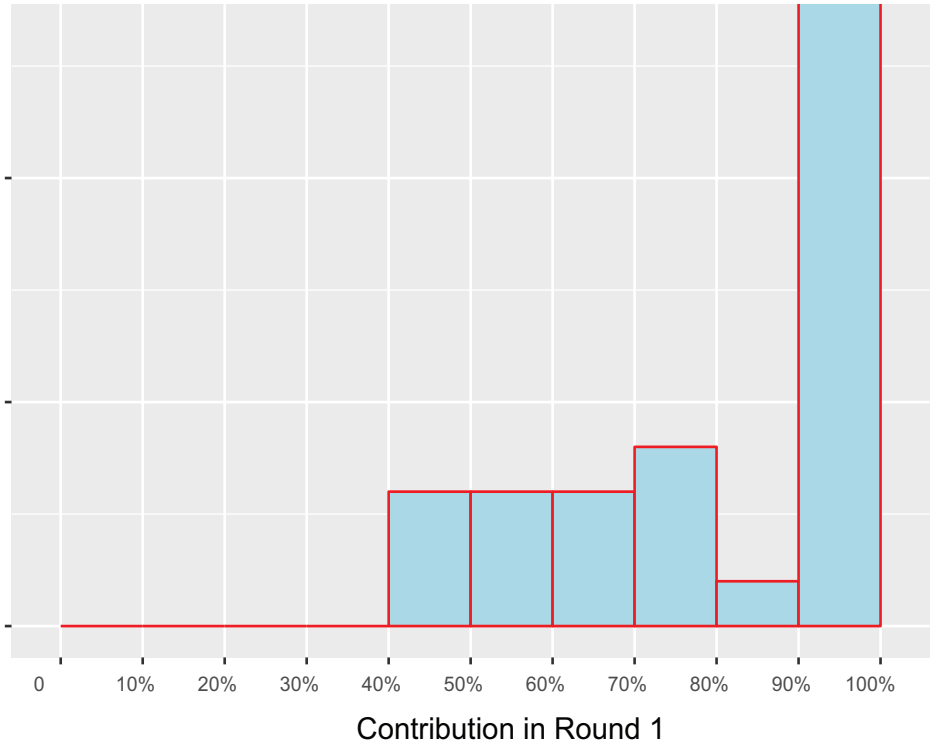
Free-riders

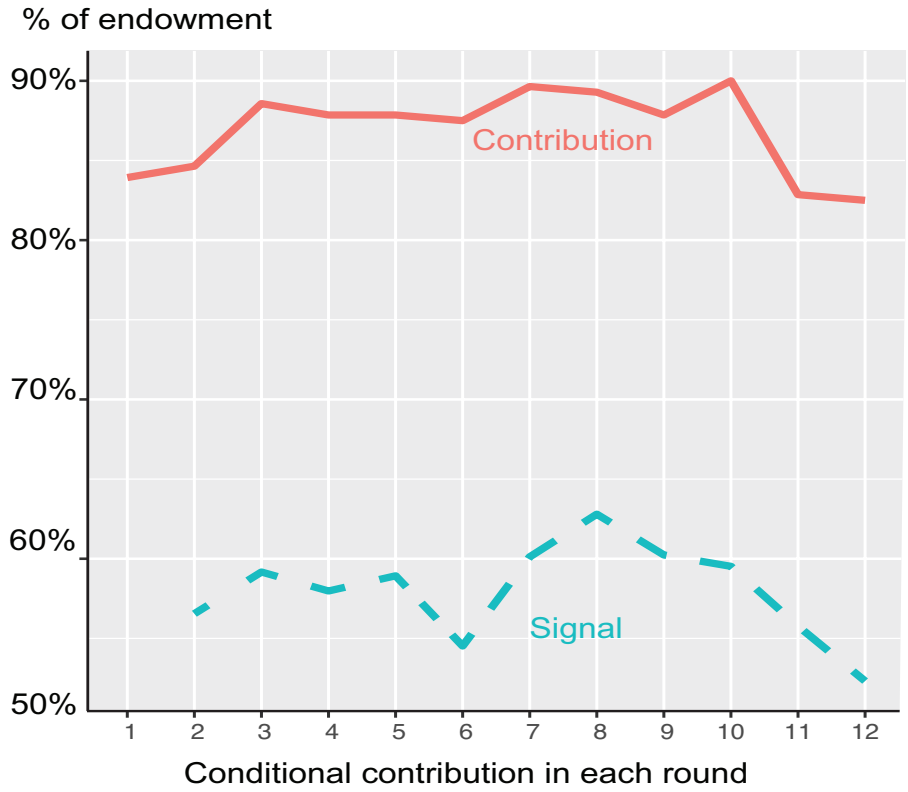




Example reasoning: "selfish is part of human nature, let's do the rantional thing."

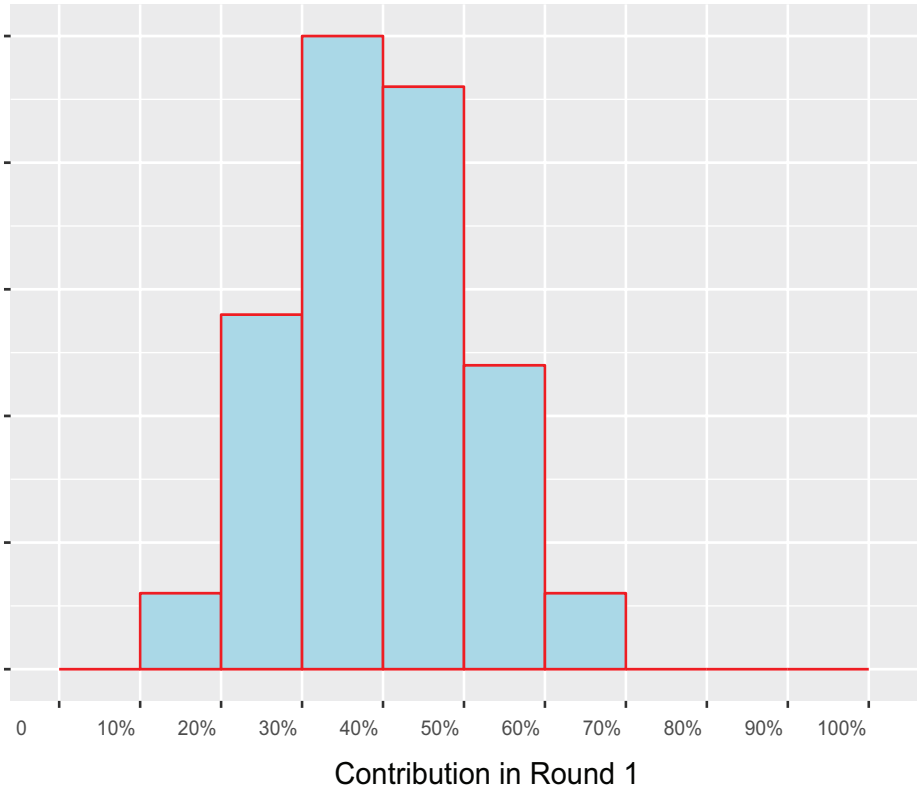
Strong cooperators

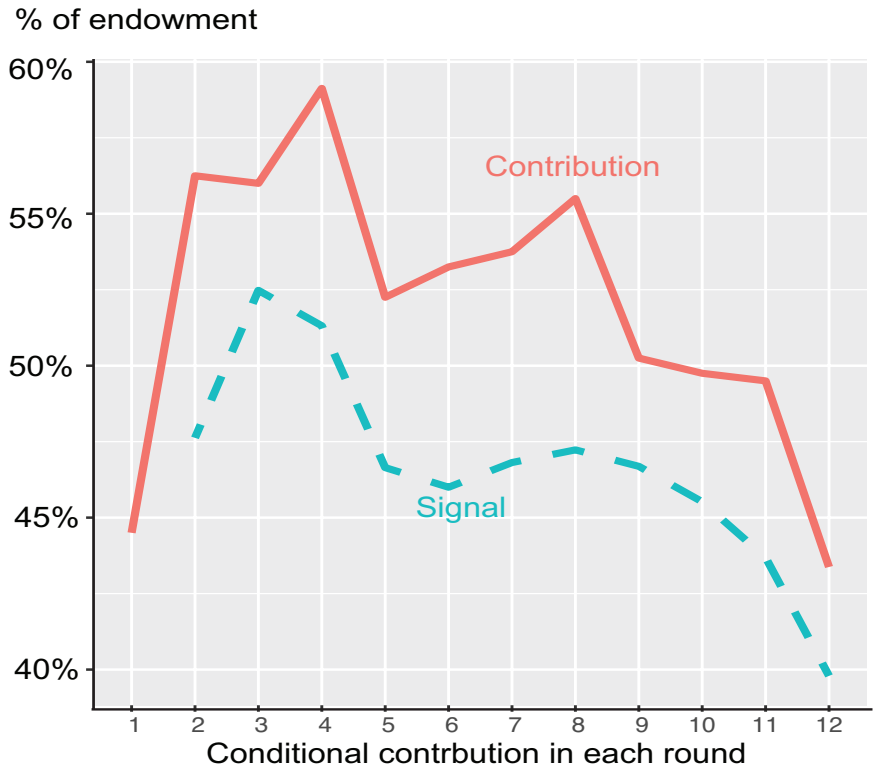




Example reasoning: "Loyalty never give up!"

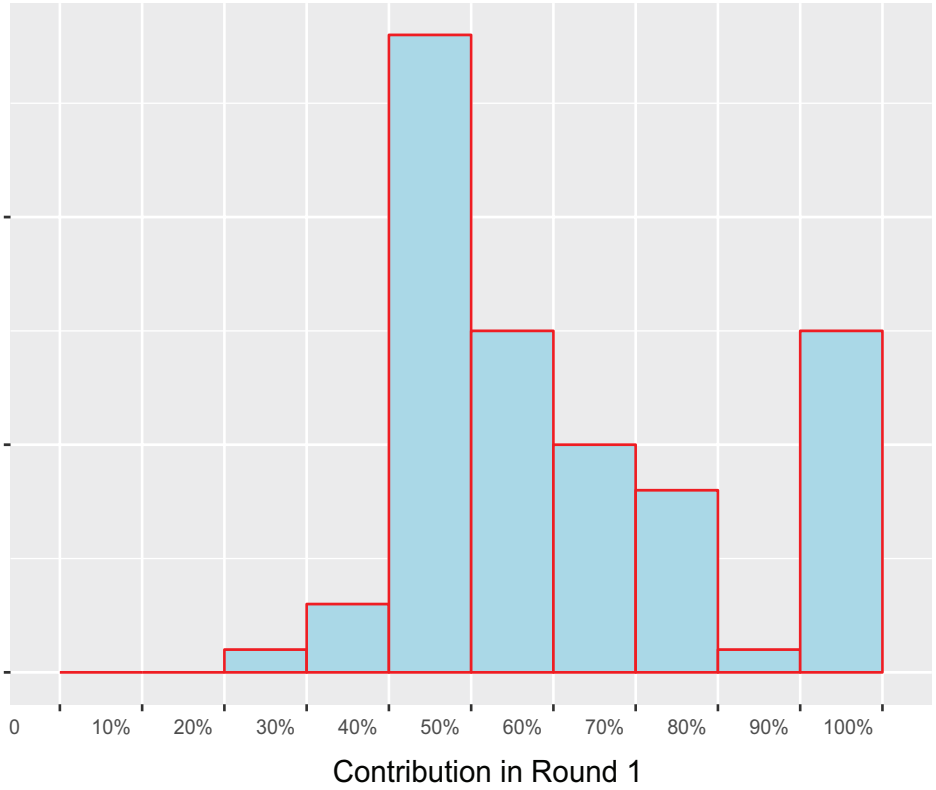
Higher-than-signal cooperators

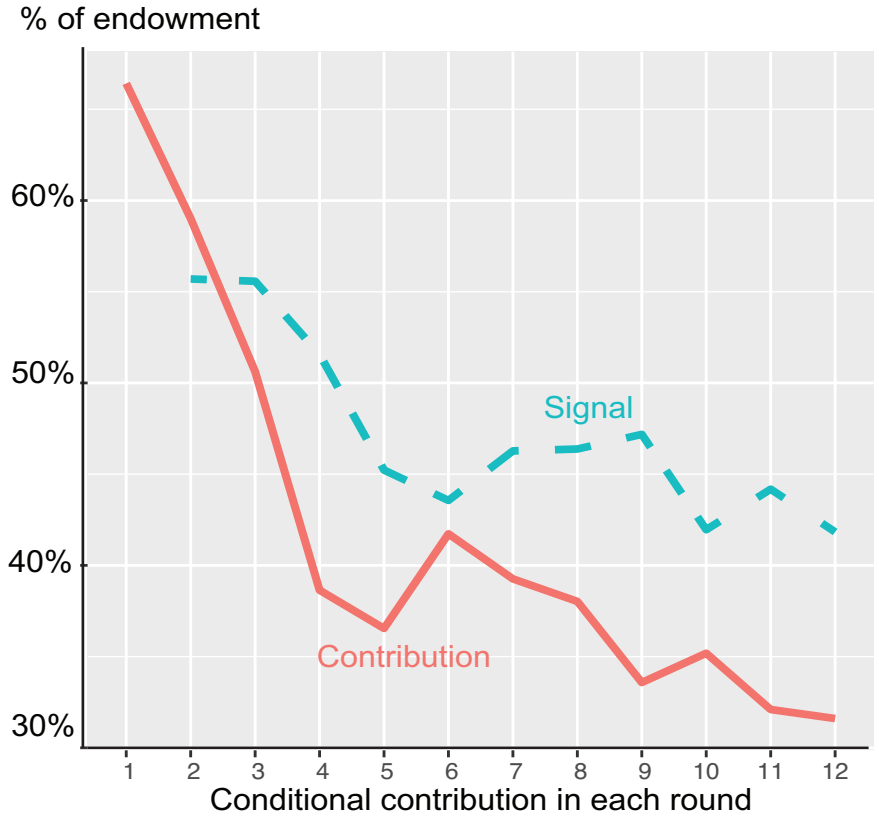




Example reasoning: "I try to lead people do the right thing, but I donna want to be a fool."

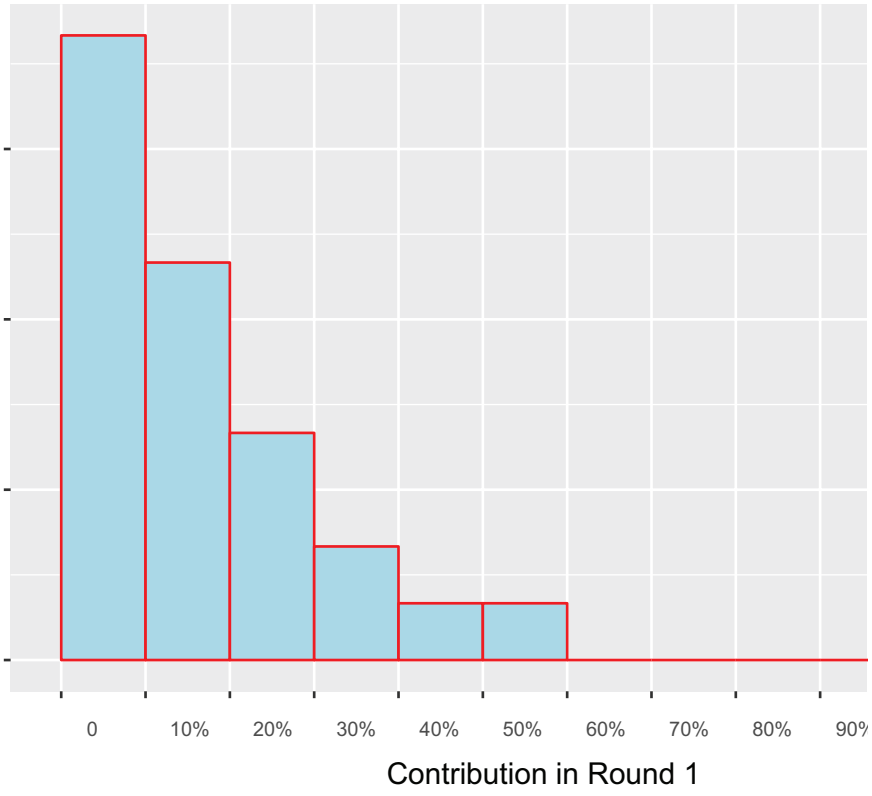
Lower-than-signal cooperators

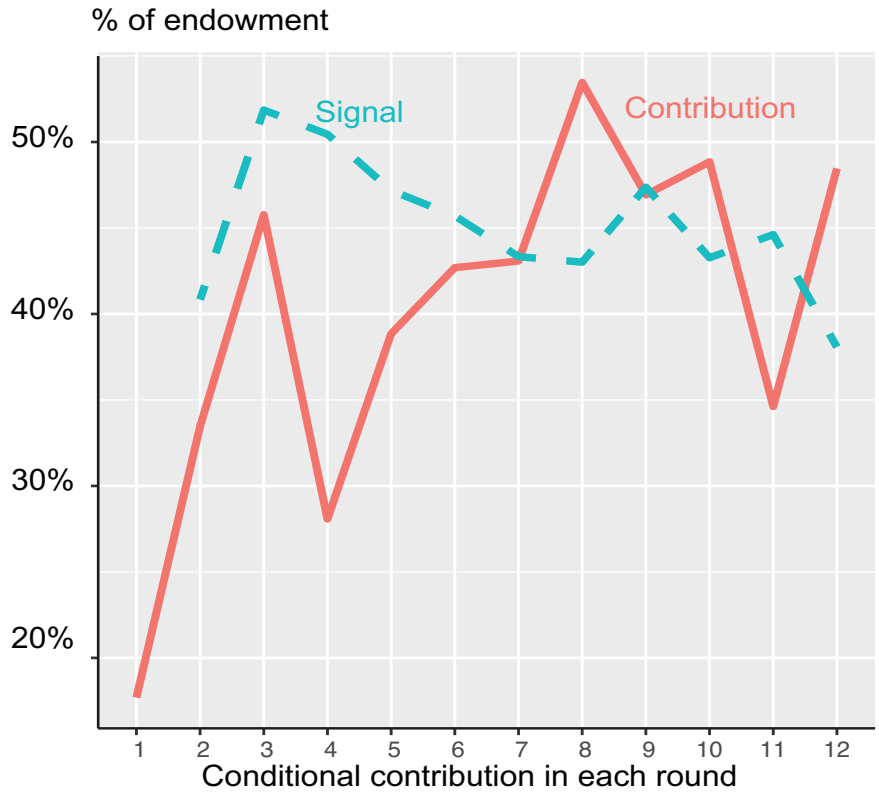




Example reasoning: "I do a little less than the average, so that I did my part, and won't loss money"

hump-shaped cooperators





Example reasoning: "I trick other people contribute a lot, then I can enjoy the benefit."

Results

The Hump-shaped cooperators alter contribution conditional on the signal

Signal	*Average Ratio (for each type of players)*		
	Higher-than-signal cooperator	Lower-than-signal cooperator	Hump-shaped cooperator
0-20%	1.19	0.86	1.10
20%-30%			
30%-40%			
40%-50%			
50%-60%	1.05	0.83	0.78
60%-70%			
70%-80%			
80%-100%			

Application: Agent-based Model

Agent-Based Simulation

- Agent-based simulations are widely used in social science studies, especially in studying the dynamic of strategic interactions.

- A challenge task is to identify (and justify) the agent types.

- Instead of pre-specify the agent types, we can build the simulated agents based on the strategy-profiles being revealed from our experimental data.

Agent-Based Simulation

$$C_{i,t} = \begin{cases} first_i, & t = 1 \\ signal_t \times ratio_{i,t}, & t \geq 2 \end{cases}$$

Where:

$C_{i,t}$ denotes type i agent's contribution in round t;
$first_i$ denotes type i agent's first-round contribution;
$ratio_{i,t}$ denotes type i agent's ratio in round t;
$signal_t$ denotes the signal in round t.

Agent-Based Simulation

- In particular, we examine the effectiveness of policies that aim to change the perceived norm.

  Simulation 1: exactly the same as our laboratory setting;

  Simulation 2: Double the average contribution in round 1, and then send this modified signal to the agents for their deision in round 2.

Agent-Based Simulation

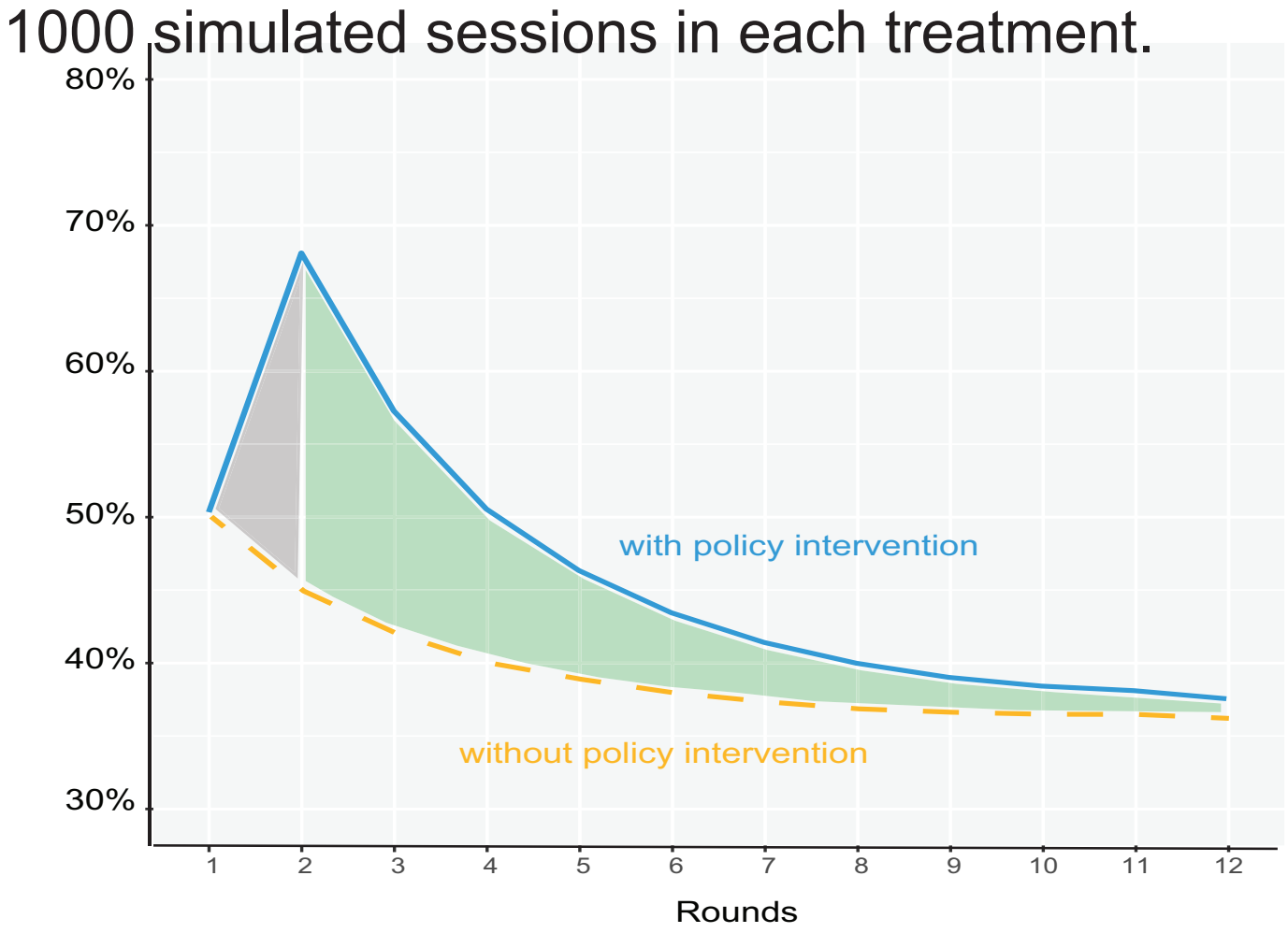


Figure 4. Policy intervention promote cooperation and social welfare

Agent-Based Simulation

The one-instance change in the signal improves social welfare

	WITHOUT Policy Intervention		**WITH** Policy Intervention		Changes in contribution	Changes in payoffs
	Average Contribution (% of endow.)	Average Earnings (Points)	Average Contribution (% of endow.)	Average Earnings (Points)		
FR	24%	2937	24%	3139	0%	+6.9%
LC	31%	2877	40%	2976	29%	+3.5%
HC	48%	2688	59%	2768	23%	+3.0%
HS	14%	3066	12%	3281	-14%	+7.0%
SC	87%	2239	87%	2433	0%	+8.7%

Discussion

- The **revealed-strategy approach** uncover complex manifestations in cooperation behaviors that have been overlooked.

- We found three sub-types of conditional cooperators: lower-than-signal, higher-than-signal, and hump-shaped cooperators.

- To our knowledge, we were the first to identify “hump-shaped” players in repeated public goods game with random matching.

Discussion

- This revealed-strategy approach could be applied to many other situations to look at the heterogeneous behaivoral patterns in dynamic interactions.

- We showed one possible application of the revealed-strategy approach: to build agent-based models and test the effectiveness of certain policies.

General Framework

Suppose we have a set of observed actions $\mathcal{A}$. We first use dimensionality reduction techniques to construct the decision-maker's **behavior profile** — a reliable tendency of how one behave in strategic interactions. Let's use $\mathcal{B}$ to denote the behavioral profile, then:

$$\mathcal{T}_1 : \mathcal{A} \to \mathcal{B}$$

After constructing the strategy profile, we then use unsupervised machine learning techniques to cluster individual behavior profiles into several different types, that is:

$$\mathcal{T}_2 : \mathcal{B} \to \mathbb{N}, \mathbb{N} \wedge I$$

Upon having the cluster results, we can then conjecture the motivations/preferences based on the properties of each type of players.

$$\mathcal{H} : \mathbb{N} \to \text{types}$$

In general, we propose the revealed-strategy approach as:

$$\mathcal{T} : \mathcal{A} \to \text{types},$$

$$\text{where: } \mathcal{T} = \mathcal{H} \circ \mathcal{T}_2 \circ \mathcal{T}_1$$