TEAM DECISION MAKING WITH SOCIAL LEARNING: HUMAN SUBJECT EXPERIMENTS

Joong Bum Rhim*

GroupM 498 7th Avenue, New York, NY 10018

ABSTRACT

We demonstrate that human decision-making agents do social learning whether it is beneficial or not. Specifically, we consider binary Bayesian hypothesis testing with multiple agents voting sequentially for a team decision, where each one observes earlier-acting agents' votes as well as a conditionally independent and identically distributed private signal. While the best strategy (for the team objective) is to ignore the votes of earlier-acting agents, human agents instead tend to be affected by others' decisions. Furthermore, they are almost equally affected in the team setting as when they are incentivized only for individual correctness. These results suggest that votes of earlier-acting agents should be withheld (not shared as public signals) to improve team decision-making performance; humans are insufficiently rational to innately apply the optimal decision rules that would ignore the public signals.

Index Terms— Bayesian hypothesis testing, distributed detection and fusion, human behavior, sequential decision making, social learning

1. INTRODUCTION

Social learning is the process of learning from publicly observable behaviors of others, which are often called *public signals*, before acting. Even though social learning causes agents acting in sequence to sometimes herd to the incorrect decision when the private signals are boundedly informative [1, 2],¹ it enables asymptotically perfect decision making otherwise [3].

While social learning is rational behavior that leads to better decisions (lower error probabilities) for individuals acting in sequence, it may not be good when agents form a team. In [4], we introduced a distributed binary hypothesis testing scenario in which decisionmaking agents sequentially observe the decisions of earlier-acting agents and private signals that are conditionally independent and identically distributed (i.i.d.) given the hypothesis, and their individual decisions are fused into a single team decision by a fixed symmetric rule. For Bayes risk minimization (a single common goal for all the agents), social learning becomes futile in the sense that the optimal behavior of an individual is to ignore the public signals produced by the earlier-acting agents. This is discussed in detail in [5,6], with some key insights reviewed in Section 2.2. Vivek K Goyal[†]

Boston University 8 St. Mary's Street, Boston, MA 02215

There is significant evidence that humans perform approximate Bayesian reasoning [7–11]. However, group decision making is more subtle [12, 13], and the difference between individualistic behavior ("I want to be correct") and team-oriented behavior ("I want to contribute optimally to the group decision") is even more subtle. This is evidenced, for example, by the fact that the futility of social learning result of [6] holds for conditionally i.i.d. private signals but not more generally for conditionally independent private signals. This seems beyond the limits of innate Bayesian reasoning.

In this paper, we study whether human agents are rational enough to ignore public signals when it is optimal for them to do so. We design two decision-making scenarios and conduct experiments with human subjects on Amazon Mechanical Turk. These experiments reveal that not only do human agents perform social learning in both individualistic and team decision making, but also their behaviors in these two settings are hardly distinguishable—which is significantly suboptimal behavior.

Section 2 specifies our binary decision-making framework with symmetric aggregation and reviews the optimal decision-making rules. Section 3 describes the experiments and discusses human behaviors observed from them. Section 4 concludes the paper.

2. INDIVIDUALISTIC AND TEAM GOALS

We consider a scenario of binary Bayesian hypothesis testing. There is a group of N agents who sequentially make a binary decision. They know the prior probability of the two hypotheses, H = 0 and H = 1. The Bayes risk of their decision \hat{H} is given by

$$c_{10}\mathbb{P}\{\hat{H} = 1, H = 0\} + c_{01}\mathbb{P}\{\hat{H} = 0, H = 1\}$$

= $c_{10}p_0\mathbb{P}\{\hat{H} = 1|H = 0\} + c_{01}p_1\mathbb{P}\{\hat{H} = 0|H = 1\},$ (1)

where $p_0 = \mathbb{P}\{H = 0\}$ and $p_1 = \mathbb{P}\{H = 1\} = 1 - p_0$ are the prior probabilities and c_{10} and c_{01} are the Bayes costs associated with Type I and II errors, respectively. We assume all agents have the same Bayes costs. Decision making that minimizes the Bayes risk is optimal.

Each agent observes a *private signal* Y_n that is dependent on the true hypothesis. The conditional distribution $f_{Y_n \mid H}(y_n \mid h)$ is i.i.d. across all agents.

As the agents sequentially make decisions, those decisions become available as public signals to all other agents. The first agent who makes a decision has a private signal only. The second agent has a private signal and a public signal from the first agent. The third agent has a private signal and two public signals from the first two agents, and so on. We will discuss how Nora, the *n*th decision maker, should make a decision in two cases.

^{*}The first author performed the work while with the Research Laboratory of Electronics, Massachusetts Institute of Technology.

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¹A signal Y generated under a state H is called *boundedly informative* if there exists $\kappa > 0$ such that $\kappa < f_{Y|H}(y|h) < 1/\kappa$ for all y and h.

2.1. Optimal Individualistic Decision Making

The first case is when the agents are optimizing only for the accuracy their own decisions [14]. In other words, Nora makes her decision \hat{H}_n to minimize her Bayes cost:

$$c_{10}p_0\mathbb{P}\{\hat{H}_n = 1 \mid H = 0\} + c_{01}p_1\mathbb{P}\{\hat{H}_n = 0 \mid H = 1\}.$$
 (2)

Before making a decision, she observes public signals $\hat{H}_1, \ldots, \hat{H}_{n-1}$ —the decisions of her preceding agents—and a private signal Y_n . She can learn some information about the true hypothesis from these signals. Her decision rule should be the likelihood ratio test that compares the likelihood of all private and public signals on each hypothesis:

$$\frac{f_{Y_{n},\hat{H}_{1},...,\hat{H}_{n-1}\mid H}(y_{n},\hat{h}_{1},...,\hat{h}_{n-1}\mid 1)}{f_{Y_{n},\hat{H}_{1},...,\hat{H}_{n-1}\mid H}(y_{n},\hat{h}_{1},...,\hat{h}_{n-1}\mid 0)} \overset{\hat{H}_{n}=1}{\underset{\hat{H}_{n}=0}{\overset{c}{\overset{c}}} \frac{c_{10}p_{0}}{c_{01}p_{1}}.$$
 (3)

Conditioned on H, her public signals are independent of her private signal. Thus, the decision rule can be rewritten as

$$\frac{f_{Y_n \mid H}(y_n \mid 1)}{f_{Y_n \mid H}(y_n \mid 0)} \stackrel{\hat{H}_n=1}{\underset{\hat{H}_n=0}{\overset{\sim}{\sim}}} \frac{c_{10}q_n}{c_{01}(1-q_n)},$$
(4)

where

$$q_{n} \triangleq p_{0} \times \frac{p_{\hat{H}_{1},\dots,\hat{H}_{n-1}|H}(\hat{h}_{1},\dots,\hat{h}_{n-1}|0)}{p_{\hat{H}_{1},\dots,\hat{H}_{n-1}}(\hat{h}_{1},\dots,\hat{h}_{n-1})} = p_{H|\hat{H}_{1},\dots,\hat{H}_{n-1}}(0|\hat{h}_{1},\dots,\hat{h}_{n-1}).$$
(5)

This optimal decision rule suggests that Nora use her public signals to update the prior probability to a posterior probability—which is often called *belief update*—and determine the optimal threshold of the likelihood ratio of her private signal. The process of belief update is discussed with more detail in [14, 15].

2.2. Optimal Team Decision Making

The second case is when the agents are optimizing for the accuracy of a team decision. Like in Section 2.1, agents still make decisions sequentially and can observe all decisions made before them along with their own private signals. Now, decisions are fused by a symmetric *L*-out-of-*N* rule: If *L* or more agents choose 1, then the team decision is $\hat{H} = 1$; otherwise $\hat{H} = 0$.² The following Bayes risk is applied to everyone:

$$R = c_{10} p_0 \mathbb{P}\{\sum_{n=1}^{N} \widehat{H}_n \ge L \mid H = 0\} + c_{01} p_1 \mathbb{P}\{\sum_{n=1}^{N} \widehat{H}_n \le L - 1 \mid H = 1\}.$$
 (6)

Intuitively, the improvement of individual decisions would drive the improvement of the team decision. It has been shown, however, that optimal individual decisions can harm the team decision making in some cases. What is easily overlooked here is that, effectively, the fusion rule is changing as the agents act in sequence. Once the first agent chooses $\hat{H}_1 = 1$, for example, the effective fusion rule for the remaining agents is the (L-1)-out-of-(N-1) rule, i.e., L-1more votes for 1 among N-1 will determine the team decision to be 1. It is proven in [6] that agents need to do both belief update and fusion rule evolution for optimal decision making, and in the case of conditionally i.i.d. private signals, they end up with the same decision rule as when they do not have any public signal,

$$\frac{f_{Y_n \mid H}(y_n \mid 1)}{f_{Y_n \mid H}(y_n \mid 0)} \stackrel{H_n=1}{\underset{\widehat{H}_n=0}{\gtrsim}} \frac{c_{10}p_0}{c_{01}p_1}.$$
(7)

Belief update encourages an agent to agree with earlier-acting agents. The less intuitive aspect, as stated in [6]: "a good agent does not take lightly the disenfranchisement of later-acting agents."

3. PRACTICAL HUMAN DECISION MAKING

We have shown that social learning is optimal behavior in individualistic decision making but not necessarily in team decision making. In practice, human agents deviate from optimality in various ways. Our goal is to test the following two hypotheses through experiments:

Hypothesis 1 *Human agents are affected by public signals in team decision making.*

Hypothesis 2 Human agents are less affected by public signals in team decision making than they are in individualistic decision making.

Hypothesis 1 argues that human agents are irrational because they are supposed to ignore public signals in team decision making. However, they may be rational enough to rely less on public signals in team decision making than in individual decision making as suggested by Hypothesis 2.

3.1. Design of Experiments

We conduct two experiments. Experiment A is designed to measure human decision rules at a fine scale. Experiment B is designed with a simpler setting to reconfirm the results of Experiment $A.^3$

Most parts of the two experiments are identical: both experiments assume a game show where one basket is presented and contestants guess which of two baskets it is. The basket is randomly chosen between Basket A, which has 70 red and 30 blue balls, and Basket B, which has 30 red and 70 blue balls. The prior probability of each basket is 0.5, and all contestants are made aware of this. Seven contestants make decisions by the following procedure:

- 1. The order of decision making is determined.
- 2. The first contestant comes out, draws from the basket, and replaces drawn balls.
- 3. He/she guesses whether the basket is A or B and announces his/her answer. In the meantime, other contestants cannot see the balls but can hear the answer.
- 4. Repeat (2) and (3) until the last contestant.

The contestants get a private signal in step (2) and public signals in step (3).

Each experiment has two versions of evaluating the answers. In version 1 (individualistic goal), each contestant who gives the right

 $^{{}^{2}}L$ -out-of-N rules generalize the common use of majority rule in human decision making, where $L = \lceil \frac{N+1}{2} \rceil$. Rules requiring unanimity are given by L = 0 and L = N. Optimal decision fusion is discussed in [16].

³Before starting these experiments, the authors have passed a training course on human subjects research to accommodate MIT regulation. The experiments have been approved by the Committee on the Use of Humans as Experimental Subjects (COUHES): COUHES Protocols No. 1310005949 and 1403006285, respectively.



Fig. 1: Thresholds of human decision rules. (a) Human agents' average thresholds and optimal thresholds for various public signals (sorted in increasing order of optimal threshold for the individualistic goal). (b) Distribution of thresholds for individualistic goal when the public signal is $(A \rightarrow A \rightarrow A \rightarrow B)$. (c) Distribution of thresholds for team goal with the same public signal.

answer wins a prize. In version 2 (team goal), all seven contestants win a prize if the majority is right and otherwise no one wins a prize. We can verify Hypothesis 1 from the result of version 1 and Hypothesis 2 by comparing the results of versions 1 and 2. All winning contestants get an equal prize to prevent competition among them.

Amazon Mechanical Turk workers living in the U.S. participated in these experiments. Each worker was randomly assigned to either version without even knowing the existence of the other version. We intentionally hide it because otherwise they may think that they should behave differently. Furthermore, each worker could participate in at most one experiment.

Regardless of the version, we present each test subject with a number of situations with various decision-making positions and various public signals.⁴ For each situation, the subjects are to answer their decision thresholds—i.e., the minimum number of red balls in the private signal to cause them to choose Basket A. We make it clear that the prior probability of each basket is 0.5 because human agents are not likely to correctly incorporate a different prior. The rational behavior without a public signal is to choose Basket A if the participant draws more red balls than blue balls and Basket B otherwise.

Every worker gets paid a fixed amount of base reward upon completion of the experiment. In addition, we offer a bonus up to three times of the base reward depending on the worker's decisionmaking performance in order to encourage them to think carefully and thoroughly. The workers participating in version 1 get a bonus depending on how close to optimal their answers are; the workers participating in version 2 get a bonus depending on how much their answers improve team decisions.

3.2. Experiment A: Complex Private Signal

The difference between experiments A and B is the number of balls drawn as a private signal. In Experiment A, each agent draws 9 balls from the basket as the private signal in order for us to finely monitor the decision rules of human agents.

In total 200 Amazon Mechanical Turk workers have participated in Experiment A; half in A-1 and the other half in A-2. Each subject is asked the same 29 situations of various public signals regardless of the version.

Fig. 1 summarizes the results of Experiment A, dashed curves for Experiment A-1 and solid curves for Experiment A-2. It is notable that human decision makers do not change their decision rules based on the different goals (individual vs. team), unlike the optimum behavior.

Fig. 1a shows the thresholds—the minimum number of red balls in a private signal that is required to choose A. The threshold of human agents drawn in Fig. 1a is the average of thresholds answered by 100 subjects in each version.

Human agents with the individualistic goal seemingly learn from public signals and alter their thresholds accordingly. The alteration, however, is weaker than optimal. For example, when the fourth agent observes all three preceding agents have chosen Basket A, the agent should choose A even if the private signal has just three red balls. Average human decision makers, however, choose Basket A if their private signal has at least four red balls.

Among the situations, we specifically examine when the fifth agent observes public signals of three A's and one B: $(A \rightarrow A \rightarrow A \rightarrow B)$, $(A \rightarrow A \rightarrow B \rightarrow A)$, $(A \rightarrow B \rightarrow A \rightarrow A)$, or $(B \rightarrow A \rightarrow A \rightarrow A)$. These public signals should be differently interpreted according to who has answered B. When an earlier-acting agent answers B, it is likely a wrong answer due to an unlikely private signal, which thus is

⁴E.g., what is your decision rule when you are the third agent and observe $(A \rightarrow B)$ as a public signal?



Fig. 2: Behavior of human agents when they observe various public signals. (a) Individual decision-making. (b) Team decision-making.

reversed to A by following agents. On the contrary, when a lateracting agent answers B, it should be considered more seriously as the agent should have had a private signal strong enough to counteract preceding agents' decisions. Therefore the optimal threshold is 2.5 for public signal ($B \rightarrow A \rightarrow A \rightarrow A$) but 4.5 for ($A \rightarrow A \rightarrow A \rightarrow B$).

It turns out that human agents use 3.5 as their threshold in all four situations. One of our interpretations is that human agents do not believe that other people are fully rational—they may think the agent who has chosen B is wrong. Another interpretation is that they do not care about the order in which the decisions are made but simply process the public signal as three A's and one B.

Considering the team decision-making, the average threshold of human agents is similar to that in individual decision-making. Humans take into account the public signals when they have a team goal as much as when they have an individualistic goal, even though the optimal behavior is to ignore the public signals in the former case.

For a more precise comparison, we ran two-sample Kolmogorov– Smirnov tests of the distributions of 100 thresholds between individualistic and team goals. The test accepts the null hypothesis—the two distributions are the same—in all cases but one with probability greater than 0.05; in half of the cases with probability greater than 0.9. For example, Fig. 1b and Fig. 1c compare the distributions of human agents in individual and team decision-making cases with respect to their decision thresholds when $(A \rightarrow A \rightarrow A \rightarrow B)$ is the public signal. The two-sample Kolmogorov–Smirnov test accepts they are the same distribution with probability of 0.96. Interested readers may see [5] for the comparison in all 29 situations. As a result, we accept Hypothesis 1 but reject Hypothesis 2.

3.3. Experiment B: Simple Private Signal

We have found out that human agents are not fully rational in the sense that they do not learn from public signals as much as they should for the individualistic goal and they learn from public signals while they should not for the team goal. However, the private signal consisting of nine balls may be too complicated for the agents to correctly process. Therefore, Experiment B was designed with a simple private signal: each contestant draws only one ball. Everything else is the same between experiments A and B.

A hundred Amazon Mechanical Turk workers have participated in Experiment B; half in B-1 and the other half in B-2. Each subject is asked 18 situations of various public signals. We asked subjects their choice when the private signal is a red ball and when it is blue.

Fig. 2 depicts the most common behavior of the subjects in each

situation. The behavior is summarized as either *Not Herding* (NH)—ignoring public signals and following private signals—or *Herding toward A* (HA)—following public signals and ignoring private signals.

Most subjects in individualistic decision making correctly ignore or follow public signals, depending on the particular public signal. Subjects in team decision making, however, still follow public signals although they should not. In fact, they show the same behavior in both individual and team decision-making except one situation—when $(A \rightarrow A)$ is the public signal.

This experiment with simple private signals again supports our conclusions in Section 3.2. First, human agents do not seem to understand that optimal decision-making as a team is different from individualistic decision-making. Second, they seem rather rational when they are deciding to meet the individualistic goal, even though they are limited in their processing abilities when working with complex private signals.

4. CONCLUSION

We have conducted experiments to test if human agents adopt optimal decision rules by using public signals in individualistic decision making and by not using them in team decision making. It is worth evaluating human rationality especially because the optimal decision rule for the team case is counterintuitive. Our experiments have revealed that human agents are not fully rational when they observe public signals.

With public signals, human agents do social learning. They can interpret public signals and adjust their decision thresholds accordingly for the individualistic goal. That being said, we could observe two limitations from human agents. First, they seem incapable of perfectly tuning decision rules to complex private signals. Second, they fail to draw correct inferences from the order of public signals. They do not differentiate between the cases when the minority public signal is produced by an earlier-acting or later-acting agent.

Furthermore, it turns out that human agents behave very similarly for a team goal and for an individualistic goal, though this is suboptimal. They seem to use all information available to them in decisions. This suggests a simple design prescription for a crowdsourcing platform or online poll that aids human team decision making: it is better to hide irrelevant information that may lead to a suboptimal decision. This observation emphasizes the importance of design of voting rules that can enhance humans' rationality and optimal opinion aggregation.

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