# Social Learning with Questions

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## CCS CONCEPTS

• **Theory of computation → Convergence and learning in games**; *Social networks*; *Algorithmic mechanism design*.

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## 1 INTRODUCTION

In social networks, agents use information from (a) private signals (knowledge) they have, (b) learning past agents actions (observations), and (c) comments from contactable experienced agents (experts) to guide their own decisions. With fully observable history and bounded likelihood ratio of signal, *Information Cascade* occurs almost surely when it is optimal for agents to ignore their private signals for decision making after observing the history. Though individually optimal, this may lead to a socially sub-optimal outcome. Literature studying social learning, i.e., making socially optimal decisions, is mainly focused on using channels (a) and (b) above for Bayes-rational agents by either relaxing the assumption of bounded signal strength or allowing the distortion of the history. In this work, we enable a limited communication capacity to let Bayes-rational agents querying their predecessors, motivated by the real-world behavior that people usually consult several friends before making decisions. We allow each Bayes-rational agent to ask a single, private and finite-capacity (for response) question of each among a subset of predecessors. Note that the Maximum Aposteriori Probability (MAP) rule is still individually optimally and will be used by each agent for her decision. With an endowed communication capacity, we want to answer the following two questions: 1) *What is the suitable framework to model the help that questions provide on information aggregation?* 2) *Can we construct a set of questions that will achieve learning by querying the minimum set of agents with the minimum capacity requirements (in terms of bits)?*

## 2 PROBLEM FORMULATION

We consider a binary states of the world $\Omega = \{A, B\}$ with equal priors and a countable number of Bayes-rational agents, each taking a single action sequentially and indexed by $n \in \{1, 2, \ldots\}$. At each time slot $n$, agent $n$ shows up and chooses an action $X_n = \{\bar{A}, \bar{B}\}$ with the goal of matching the true state of the world, i.e., $u_n(\omega, \bar{\omega}) = 1, \omega \in \Omega$, and 0 otherwise.


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Before agent $n$ takes her action, she receives an informative but not revealing private signal $s_n$ through a binary symmetric channel (BSC) with a time-invariant crossover probability $1-p$, where $p \in (0.5, 1)$, $s_n \in \{A, B\}$ for all $n$. The full history of actions taken by her predecessors is observable for agent n, $H_n \in \{\bar{A}, \bar{B}\}^{n-1}$.

Then, agents' communication is modeled by a directed acyclic graph $G(\mathbb{N}, E)$. On each such edge, agents are allowed to transmit information (asking questions) up to pre-determined $K$ bits. We allow agents to decide questions she is going go query **after** observing the history and receiving her private signal.

## 3 QUESTIONS AND INFO-SET PARTITION

The main novelty and contributions of this work is figuring out how questions help gather information and how the capacity constraints limit the (lossless) information aggregation. To begin, let $T_n$ be the set of sequences of private signals from agent 1 to $n-1$, $T_n \ni (s_i)_{i=1}^{n-1}$. The information space of agent $n$, corresponding to a observed history $H_n$ and the question guidebook $Q$, is the set of all feasible sequences $T_n^*(Q, H_n) \subseteq T_n$. The questions assigned to agent $n$ help her to update her posterior belief of the true state by partitioning $T_n^*$ into information sets $I_n(Q, H_n)$ and telling agent $n$ the set that she is in. For simplicity of notation, we denote the collection of information sets $I_n(Q, H_n)$ by $\mathcal{I}_n(Q, H_n)$.

Given the finite-bit constraint, losing (a part of) information is the nature of the scheme and it will limit the (feasible) partition in the information space. Once a set of private signal sequences are always at the same information set $I_n$ under $H_n$ for any questions queried by agent $n$, then this set of private signal sequences will stay indivisible when future agents $m > n$ queries agent $m$.

By viewing question as an information set partition tool, studying the transition from $\mathcal{I}_m(Q, H_m)$ to $\mathcal{I}_n(Q, H_n)$ while $m \in \mathcal{B}_n$ can help us understand how information aggregates. A well-known approach to analyze this class of problems systematically is by mapping these information-set transitions to Markov chains with transition matrices. To formulate the mapping, we associate a QGB with a sequence of sets of Markov chains sharing the same state space. Denote $(G, (\mathcal{M}_n))$ to be a sequence of sets of Markov chains, where $G$ is the state set and $\mathcal{M}_n$ is the set of Markov chains at time $n$. To represent all distinguishable information sets, an inequality $|G| \geq \sup_{n, H_n \in \mathcal{H}, s_n} |\mathcal{I}_n(Q, H_n)|$ is required for the corresponding $(G, (\mathcal{M}_n))$. Since state space $G$ is shared by all $\mathcal{M}_n$.

## 4 ACHIEVE LEARNING VIA QUESTIONS

To exhibit how designing QGBs can achieve learning, we provide an design achieve asymptotic learning in a directed line graph. In such a graph, besides observing the actions in history, the only source for an agent to get additional information is asking finite-bit questions to her immediate predecessor. We show that one-bit question is enough to avoid information cascade, aka, achieve (asymptotic) learning and the result can be generalized to finite signal spaces. The full version is available at https://arxiv.org/abs/1811.00226.