Learning in Repeated Interactions on Networks

Wanying (Kate) Huang[1] Philipp Strack[2] Omer Tamuz[1]

[1] Caltech

[2] Yale University

Motivation and Question

- People learn by interacting with others.
- E.g., what is the most healthy diet?
- You observe your friends' past choices and pick your diet today.
- This influences by your friends' future choices.
- Repeated interactions are hard to model tractably.
- This paper:
  - constant stream of information
  - social network
  - repeated interactions
  - rational framework
- Question: How efficient is the aggregation of information?

Motivation and Question

- People learn by interacting with others.
- E.g., what is the most healthy diet?
- You observe your friends' past choices and pick your diet today.
- This influences by your friends' future choices.
- Repeated interactions are hard to model tractably.
- This paper:
  - constant stream of information
  - social network
  - repeated interactions
  - rational framework
- Question: How efficient is the aggregation of information?

Motivation and Question

- People learn by interacting with others.
- E.g., what is the most healthy diet?
- You observe your friends' past choices and pick your diet today.
- This influences by your friends' future choices.
- Repeated interactions are hard to model tractably.
- This paper:
  - constant stream of information
  - social network
  - repeated interactions
  - rational framework
- Question: How efficient is the aggregation of information?

Motivation and Question

- People learn by interacting with others.
- E.g., what is the most healthy diet?
- You observe your friends' past choices and pick your diet today.
- This influences by your friends' future choices.
- Repeated interactions are hard to model tractably.
- This paper:
  - constant stream of information
  - social network
  - repeated interactions
  - rational framework
- Question: How efficient is the aggregation of information?

Motivation and Question

- People learn by interacting with others.
- E.g., what is the most healthy diet?
- You observe your friends' past choices and pick your diet today.
- This influences by your friends' future choices.
- Repeated interactions are hard to model tractably.
- This paper:
    - constant stream of information
    - social network
    - repeated interactions
    - rational framework
- Question: How efficient is the aggregation of information?

Motivation and Question

- People learn by interacting with others.
- E.g., what is the most healthy diet?
- You observe your friends' past choices and pick your diet today.
- This influences by your friends' future choices.
- Repeated interactions are hard to model tractably.
- This paper:
  - constant stream of information
  - social network
  - repeated interactions
  - rational framework
- Question: How efficient is the aggregation of information?

Motivation and Question

- People learn by interacting with others.
- E.g., what is the most healthy diet?
- You observe your friends' past choices and pick your diet today.
- This influences by your friends' future choices.
- Repeated interactions are hard to model tractably.
- This paper:
  - constant stream of information
  - social network
  - repeated interactions
  - rational framework
- Question: How efficient is the aggregation of information?

Motivation and Question

- People learn by interacting with others.
- E.g., what is the most healthy diet?
- You observe your friends' past choices and pick your diet today.
- This influences by your friends' future choices.
- Repeated interactions are hard to model tractably.
- This paper:
  - constant stream of information
  - social network
  - repeated interactions
  - rational framework
- Question: How efficient is the aggregation of information?

Motivation and Question

- People learn by interacting with others.
- E.g., what is the most healthy diet?
- You observe your friends' past choices and pick your diet today.
- This influences by your friends' future choices.
- Repeated interactions are hard to model tractably.
- This paper:
  - constant stream of information
  - social network
  - repeated interactions
  - rational framework
- Question: How efficient is the aggregation of information?

Motivation and Question

- People learn by interacting with others.
- E.g., what is the most healthy diet?
- You observe your friends' past choices and pick your diet today.
- This influences by your friends' future choices.
- Repeated interactions are hard to model tractably.
- This paper:
  - constant stream of information
  - social network
  - repeated interactions
  - rational framework
- Question: How efficient is the aggregation of information?

Motivation and Question

- People learn by interacting with others.
- E.g., what is the most healthy diet?
- You observe your friends' past choices and pick your diet today.
- This influences by your friends' future choices.
- Repeated interactions are hard to model tractably.
- This paper:
  - constant stream of information
  - social network
  - repeated interactions
  - rational framework
- Question: How efficient is the aggregation of information?

Motivation and Question

- People learn by interacting with others.
- E.g., what is the most healthy diet?
- You observe your friends' past choices and pick your diet today.
- This influences by your friends' future choices.
- Repeated interactions are hard to model tractably.
- This paper:
  - constant stream of information
  - social network
  - repeated interactions
  - rational framework
- Question: How efficient is the aggregation of information?

Model

- A fixed binary state of the world: $\Theta \in \{\mathfrak{g}, \mathfrak{b}\}$ with a uniform prior.
- A finite set of agents: $i \in N = \{1, 2, \ldots, n\}$.
- Discrete time: $t \in \{1, 2, \ldots\}$.
- Social network: i's network neighbors are $N_i \subseteq N$.
- Strongly connected network: observation path from each i to each j.
- Private signal conditional distributions $\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}} \in \Delta(\Omega)$, finite Ω.
- In every period t, agent i
  - observes the past actions of her neighbors $H_t^i = (a_s^j)_{s<t, j \in N_i}$;
  - receives a conditionally independent private signal;
  - chooses an action $a_t^i \in \mathcal{A} = \{\mathfrak{g}, \mathfrak{b}\}$;
  - gets payoff function $u(a_t^i, \Theta) = \mathbb{1}(a_t^i = \Theta)$.
- Agent i maximizes expected discounted utility:

$$(1-\delta)\sum_{t=1}^{\infty} \delta^{t-1} \mathbb{E}[\mathbb{1}(a_t^i = \Theta)]$$

- Solution concept: Nash equilibrium.

Model

- A fixed binary state of the world: $\Theta \in \{\mathfrak{g}, \mathfrak{b}\}$ with a uniform prior.
- A finite set of agents: $i \in N = \{1, 2, \ldots, n\}$.
- Discrete time: $t \in \{1, 2, \ldots\}$.
- Social network: i's network neighbors are $N_i \subseteq N$.
- Strongly connected network: observation path from each i to each j.
- Private signal conditional distributions $\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}} \in \Delta(\Omega)$, finite Ω.
- In every period t, agent i
  - observes the past actions of her neighbors $H_t^i = (a_s^j)_{s<t, j \in N_i}$;
  - receives a conditionally independent private signal;
  - chooses an action $a_t^i \in \mathcal{A} = \{\mathfrak{g}, \mathfrak{b}\}$;
  - gets payoff function $u(a_t^i, \Theta) = \mathbb{1}(a_t^i = \Theta)$.
- Agent i maximizes expected discounted utility:

$$(1-\delta)\sum_{t=1}^{\infty} \delta^{t-1} \mathbb{E}[\mathbb{1}(a_t^i = \Theta)]$$

- Solution concept: Nash equilibrium.

Model

- A fixed binary state of the world: $\Theta \in \{\mathfrak{g}, \mathfrak{b}\}$ with a uniform prior.
- A finite set of agents: $i \in N = \{1, 2, \ldots, n\}$.
- Discrete time: $t \in \{1, 2, \ldots\}$.
- Social network: i's network neighbors are $N_i \subseteq N$.
- Strongly connected network: observation path from each i to each j.
- Private signal conditional distributions $\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}} \in \Delta(\Omega)$, finite Ω.
- In every period t, agent i
  - observes the past actions of her neighbors $H_t^i = (a_s^j)_{s<t, j \in N_i}$;
  - receives a conditionally independent private signal;
  - chooses an action $a_t^i \in \mathcal{A} = \{\mathfrak{g}, \mathfrak{b}\}$;
  - gets payoff function $u(a_t^i, \Theta) = \mathbb{1}(a_t^i = \Theta)$.
- Agent i maximizes expected discounted utility:

$$(1-\delta)\sum_{t=1}^{\infty} \delta^{t-1} \mathbb{E}[\mathbb{1}(a_t^i = \Theta)]$$

- Solution concept: Nash equilibrium.

Model

- A fixed binary state of the world: $\Theta \in \{\mathfrak{g}, \mathfrak{b}\}$ with a uniform prior.
- A finite set of agents: $i \in N = \{1, 2, \ldots, n\}$.
- Discrete time: $t \in \{1, 2, \ldots\}$.
- Social network: i's network neighbors are $N_i \subseteq N$.
- Strongly connected network: observation path from each i to each j.
- Private signal conditional distributions $\mu_\mathfrak{g}, \mu_\mathfrak{b} \in \Delta(\Omega)$, finite Ω.
- In every period t, agent i
  - observes the past actions of her neighbors $H_t^i = (a_s^j)_{s<t, j \in N_i}$;
  - receives a conditionally independent private signal;
  - chooses an action $a_t^i \in \mathcal{A} = \{\mathfrak{g}, \mathfrak{b}\}$;
  - gets payoff function $u(a_t^i, \Theta) = \mathbb{1}(a_t^i = \Theta)$.
- Agent i maximizes expected discounted utility:

$$(1-\delta)\sum_{t=1}^{\infty} \delta^{t-1} \mathbb{E}[\mathbb{1}(a_t^i = \Theta)]$$

- Solution concept: Nash equilibrium.

Model

- A fixed binary state of the world: $\Theta \in \{\mathfrak{g}, \mathfrak{b}\}$ with a uniform prior.
- A finite set of agents: $i \in N = \{1, 2, \ldots, n\}$.
- Discrete time: $t \in \{1, 2, \ldots\}$.
- *S*ocial network: i's network neighbors are $N_i \subseteq N$.
- Strongly connected network: observation path from each i to each j.
- Private signal conditional distributions $\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}} \in \Delta(\Omega)$, finite Ω.
- In every period t, agent i
  - observes the past actions of her neighbors $H_t^i = (a_s^j)_{s<t, j \in N_i}$;
  - receives a conditionally independent private signal;
  - chooses an action $a_t^i \in \mathcal{A} = \{\mathfrak{g}, \mathfrak{b}\}$;
  - gets payoff function $u(a_t^i, \Theta) = \mathbb{1}(a_t^i = \Theta)$.
- Agent i maximizes expected discounted utility:

$$(1-\delta)\sum_{t=1}^{\infty} \delta^{t-1} \mathbb{E}[\mathbb{1}(a_t^i = \Theta)]$$

- Solution concept: Nash equilibrium.

Model

- A fixed binary state of the world: $\Theta \in \{\mathfrak{g}, \mathfrak{b}\}$ with a uniform prior.
- A finite set of agents: $i \in N = \{1, 2, \ldots, n\}$.
- Discrete time: $t \in \{1, 2, \ldots\}$.
- *S*ocial network: i's network neighbors are $N_i \subseteq N$.
- Strongly connected network: observation path from each i to each j.
- Private signal conditional distributions $\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}} \in \Delta(\Omega)$, finite Ω.
- In every period t, agent i
  - observes the past actions of her neighbors $H_t^i = (a_s^j)_{s<t, j \in N_i}$;
  - receives a conditionally independent private signal;
  - chooses an action $a_t^i \in \mathcal{A} = \{\mathfrak{g}, \mathfrak{b}\}$;
  - gets payoff function $u(a_t^i, \Theta) = \mathbb{1}(a_t^i = \Theta)$.
- Agent i maximizes expected discounted utility:

$$(1-\delta)\sum_{t=1}^{\infty} \delta^{t-1} \mathbb{E}[\mathbb{1}(a_t^i = \Theta)]$$

- Solution concept: Nash equilibrium.

Model

- A fixed binary state of the world: $\Theta \in \{\mathfrak{g}, \mathfrak{b}\}$ with a uniform prior.
- A finite set of agents: $i \in N = \{1, 2, \dots, n\}$.
- Discrete time: $t \in \{1, 2, \dots\}$.
- Social network: i's network neighbors are $N_i \subseteq N$.
- Strongly connected network: observation path from each i to each j.
- Private signal conditional distributions $\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}} \in \Delta(\Omega)$, finite Ω.
- In every period t, agent i
  - observes the past actions of her neighbors $H_t^i = (a_s^j)_{s<t, j \in N_i}$;
  - receives a conditionally independent private signal;
  - chooses an action $a_t^i \in \mathcal{A} = \{\mathfrak{g}, \mathfrak{b}\}$;
  - gets payoff function $u(a_t^i, \Theta) = \mathbb{1}(a_t^i = \Theta)$.
- Agent i maximizes expected discounted utility:

$$(1-\delta)\sum_{t=1}^{\infty} \delta^{t-1} \mathbb{E}[\mathbb{1}(a_t^i = \Theta)]$$

- Solution concept: Nash equilibrium.

Model

- A fixed binary state of the world: $\Theta \in \{\mathfrak{g}, \mathfrak{b}\}$ with a uniform prior.
- A finite set of agents: $i \in N = \{1, 2, \ldots, n\}$.
- Discrete time: $t \in \{1, 2, \ldots\}$.
- *S*ocial network: i's network neighbors are $N_i \subseteq N$.
- Strongly connected network: observation path from each i to each j.
- Private signal conditional distributions $\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}} \in \Delta(\Omega)$, finite Ω.
- In every period t, agent i
  - observes the past actions of her neighbors $H_t^i = (a_s^j)_{s<t, j\in N_i}$;
  - receives a conditionally independent private signal;
  - chooses an action $a_t^i \in \mathcal{A} = \{\mathfrak{g}, \mathfrak{b}\}$;
  - gets payoff function $u(a_t^i, \Theta) = \mathbb{1}(a_t^i = \Theta)$.
- Agent i maximizes expected discounted utility:

$$(1-\delta)\sum_{t=1}^{\infty} \delta^{t-1}\mathbb{E}[\mathbb{1}(a_t^i = \Theta)]$$

- Solution concept: Nash equilibrium.

Model

- A fixed binary state of the world: $\Theta \in \{\mathfrak{g}, \mathfrak{b}\}$ with a uniform prior.
- A finite set of agents: $i \in N = \{1, 2, \dots, n\}$.
- Discrete time: $t \in \{1, 2, \dots\}$.
- $\mathcal{S}$ocial network: i's network neighbors are $N_i \subseteq N$.
- Strongly connected network: observation path from each i to each j.
- Private signal conditional distributions $\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}} \in \Delta(\Omega)$, finite Ω.
- In every period t, agent i
  - observes the past actions of her neighbors $H_t^i = (a_s^j)_{s<t, j \in N_i}$;
  - receives a conditionally independent private signal;
  - chooses an action $a_t^i \in \mathcal{A} = \{\mathfrak{g}, \mathfrak{b}\}$;
  - gets payoff function $u(a_t^i, \Theta) = \mathbb{1}(a_t^i = \Theta)$.
- Agent i maximizes expected discounted utility:

$$(1-\delta)\sum_{t=1}^{\infty} \delta^{t-1}\mathbb{E}[\mathbb{1}(a_t^i = \Theta)]$$

- Solution concept: Nash equilibrium.

Model

- A fixed binary state of the world: $\Theta \in \{\mathfrak{g}, \mathfrak{b}\}$ with a uniform prior.
- A finite set of agents: $i \in N = \{1, 2, \ldots, n\}$.
- Discrete time: $t \in \{1, 2, \ldots\}$.
- Social network: i's network neighbors are $N_i \subseteq N$.
- Strongly connected network: observation path from each i to each j.
- Private signal conditional distributions $\mu_\mathfrak{g}, \mu_\mathfrak{b} \in \Delta(\Omega)$, finite Ω.
- In every period t, agent i
  - observes the past actions of her neighbors $H_t^i = (a_s^j)_{s<t, j\in N_i}$;
  - receives a conditionally independent private signal;
  - chooses an action $a_t^i \in \mathcal{A} = \{\mathfrak{g}, \mathfrak{b}\}$;
  - gets payoff function $u(a_t^i, \Theta) = \mathbb{1}(a_t^i = \Theta)$.
- Agent i maximizes expected discounted utility:

$$(1-\delta)\sum_{t=1}^{\infty} \delta^{t-1}\mathbb{E}[\mathbb{1}(a_t^i = \Theta)]$$

- Solution concept: Nash equilibrium.

Model

- A fixed binary state of the world: $\Theta \in \{\mathfrak{g}, \mathfrak{b}\}$ with a uniform prior.
- A finite set of agents: $i \in N = \{1, 2, \dots, n\}$.
- Discrete time: $t \in \{1, 2, \dots\}$.
- *S*ocial network: i's network neighbors are $N_i \subseteq N$.
- Strongly connected network: observation path from each i to each j.
- Private signal conditional distributions $\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}} \in \Delta(\Omega)$, finite Ω.
- In every period t, agent i
  - observes the past actions of her neighbors $H_t^i = (a_s^j)_{s<t, j \in N_i}$;
  - receives a conditionally independent private signal;
  - chooses an action $a_t^i \in \mathcal{A} = \{\mathfrak{g}, \mathfrak{b}\}$;
  - gets payoff function $u(a_t^i, \Theta) = \mathbb{1}(a_t^i = \Theta)$.
- Agent i maximizes expected discounted utility:

$$(1-\delta)\sum_{t=1}^{\infty} \delta^{t-1} \mathbb{E}[\mathbb{1}(a_t^i = \Theta)]$$

- Solution concept: Nash equilibrium.

Model

- A fixed binary state of the world: $\Theta \in \{\mathfrak{g}, \mathfrak{b}\}$ with a uniform prior.
- A finite set of agents: $i \in N = \{1, 2, \dots, n\}$.
- Discrete time: $t \in \{1, 2, \dots\}$.
- *S*ocial network: i's network neighbors are $N_i \subseteq N$.
- Strongly connected network: observation path from each i to each j.
- Private signal conditional distributions $\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}} \in \Delta(\Omega)$, finite Ω.
- In every period t, agent i
  - observes the past actions of her neighbors $H_t^i = (a_s^j)_{s<t, j \in N_i}$;
  - receives a conditionally independent private signal;
  - chooses an action $a_t^i \in \mathcal{A} = \{\mathfrak{g}, \mathfrak{b}\}$;
  - gets payoff function $u(a_t^i, \Theta) = \mathbb{1}(a_t^i = \Theta)$.
- Agent i maximizes expected discounted utility:

$$(1-\delta)\sum_{t=1}^{\infty} \delta^{t-1} \mathbb{E}[\mathbb{1}(a_t^i = \Theta)]$$

- Solution concept: Nash equilibrium.

Model

- A fixed binary state of the world: $\Theta \in \{\mathfrak{g}, \mathfrak{b}\}$ with a uniform prior.
- A finite set of agents: $i \in N = \{1, 2, \ldots, n\}$.
- Discrete time: $t \in \{1, 2, \ldots\}$.
- Social network: i's network neighbors are $N_i \subseteq N$.
- Strongly connected network: observation path from each i to each j.
- Private signal conditional distributions $\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}} \in \Delta(\Omega)$, finite Ω.
- In every period t, agent i
  - observes the past actions of her neighbors $H_t^i = (a_s^j)_{s<t, j \in N_i}$;
  - receives a conditionally independent private signal;
  - chooses an action $a_t^i \in \mathcal{A} = \{\mathfrak{g}, \mathfrak{b}\}$;
  - gets payoff function $u(a_t^i, \Theta) = \mathbb{1}(a_t^i = \Theta)$.
- Agent i maximizes expected discounted utility:

$$(1-\delta) \sum_{t=1}^{\infty} \delta^{t-1} \mathbb{E}[\mathbb{1}(a_t^i = \Theta)]$$

- Solution concept: Nash equilibrium.

Model

- A fixed binary state of the world: $\Theta \in \{\mathfrak{g}, \mathfrak{b}\}$ with a uniform prior.
- A finite set of agents: $i \in N = \{1, 2, \ldots, n\}$.
- Discrete time: $t \in \{1, 2, \ldots\}$.
- Social network: i's network neighbors are $N_i \subseteq N$.
- Strongly connected network: observation path from each i to each j.
- Private signal conditional distributions $\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}} \in \Delta(\Omega)$, finite Ω.
- In every period t, agent i
  - observes the past actions of her neighbors $H_t^i = (a_s^j)_{s<t, j \in N_i}$;
  - receives a conditionally independent private signal;
  - chooses an action $a_t^i \in \mathcal{A} = \{\mathfrak{g}, \mathfrak{b}\}$;
  - gets payoff function $u(a_t^i, \Theta) = \mathbb{1}(a_t^i = \Theta)$.
- Agent i maximizes expected discounted utility:

$$(1-\delta) \sum_{t=1}^{\infty} \delta^{t-1} \mathbb{E}[\mathbb{1}(a_t^i = \Theta)]$$

- Solution concept: Nash equilibrium.

Model

- Info available to i at time t is $(s_1^i, \cdots, s_t^i, H_t^i)$.
- Agents do not observe payoffs, only signals and neighbors' actions.
- But can think of private signals as payoff + noise.
- Each agent learns the state in the long run.
- How fast do they learn?
- Do they even learn at the same speed?

Model

- Info available to i at time t is $(s_1^i, \cdots, s_t^i, H_t^i)$.
- Agents do not observe payoffs, only signals and neighbors' actions.
- But can think of private signals as payoff + noise.
- Each agent learns the state in the long run.
- How fast do they learn?
- Do they even learn at the same speed?

Model

- Info available to i at time t is $(s_1^i, \cdots, s_t^i, H_t^i)$.
- Agents do not observe payoffs, only signals and neighbors' actions.
- But can think of private signals as payoff + noise.
- Each agent learns the state in the long run.
- How fast do they learn?
- Do they even learn at the same speed?

Model

- Info available to i at time t is $(s_1^i, \cdots, s_t^i, H_t^i)$.
- Agents do not observe payoffs, only signals and neighbors' actions.
- But can think of private signals as payoff + noise.
- Each agent learns the state in the long run.
- How fast do they learn?
- Do they even learn at the same speed?

Model

- Info available to i at time t is $(s_1^i, \cdots, s_t^i, H_t^i)$.
- Agents do not observe payoffs, only signals and neighbors' actions.
- But can think of private signals as payoff + noise.
- Each agent learns the state in the long run.
- How fast do they learn?
- Do they even learn at the same speed?

Model

- Info available to i at time t is $(s_1^i, \cdots, s_t^i, H_t^i)$.
- Agents do not observe payoffs, only signals and neighbors' actions.
- But can think of private signals as payoff + noise.
- Each agent learns the state in the long run.
- How fast do they learn?
- Do they even learn at the same speed?

Model

- Info available to i at time t is $(s_1^i, \cdots, s_t^i, H_t^i)$.
- Agents do not observe payoffs, only signals and neighbors' actions.
- But can think of private signals as payoff + noise.
- Each agent learns the state in the long run.
- How fast do they learn?
- Do they even learn at the same speed?

Learning Speed

- What is the probability of mistake $\mathbb{P}[a_t^i \neq \Theta]$?
- Explicit calculation seems hopeless, even in special cases.
- Classical result in statistics and probability:
  - Single agent:
  $$\mathbb{P}[a_t \neq \Theta] \approx \exp(-r_1 \cdot t),$$
  where r_1 can be explicitly calculated given μ_Θ.
  - n agents + **public signals / optimal aggregation**:
  $$\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-nr_1 \cdot t).$$
- Define the **speed of learning** of agent i as the exponential rate at which she converges to the correct action:
$$r = \liminf_{t\to\infty} -\frac{1}{t} \log \mathbb{P}[a_t^i \neq \Theta].$$
- If this limit exits and is equal to r, then $\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-r \cdot t)$.
- $r_1 \leq r \leq nr_1$.
- Tractable. Asymptotic, no welfare implications.

Learning Speed

- What is the probability of mistake $\mathbb{P}[a_t^i \neq \Theta]$?
- Explicit calculation seems hopeless, even in special cases.
- Classical result in statistics and probability:
  - Single agent:
  $$\mathbb{P}[a_t \neq \Theta] \approx \exp(-r_1 \cdot t),$$
  where r_1 can be explicitly calculated given μ_Θ.
  - n agents + **public signals / optimal aggregation**:
  $$\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-nr_1 \cdot t).$$
- Define the **speed of learning** of agent i as the exponential rate at which she converges to the correct action:
$$r = \liminf_{t\to\infty} -\frac{1}{t} \log \mathbb{P}[a_t^i \neq \Theta].$$
- If this limit exits and is equal to r, then $\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-r \cdot t)$.
- $r_1 \leq r \leq nr_1$.
- Tractable. Asymptotic, no welfare implications.

Learning Speed

- What is the probability of mistake $\mathbb{P}[a_t^i \neq \Theta]$?
- Explicit calculation seems hopeless, even in special cases.
- Classical result in statistics and probability:
  - Single agent:
  $$\mathbb{P}[a_t \neq \Theta] \approx \exp(-r_1 \cdot t),$$
  where r_1 can be explicitly calculated given μ_Θ.
  - n agents + **public signals / optimal aggregation**:
  $$\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-nr_1 \cdot t).$$
- Define the **speed of learning** of agent i as the exponential rate at which she converges to the correct action:
$$r = \liminf_{t \to \infty} -\frac{1}{t} \log \mathbb{P}[a_t^i \neq \Theta].$$
- If this limit exits and is equal to r, then $\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-r \cdot t)$.
- $r_1 \leq r \leq nr_1$.
- Tractable. Asymptotic, no welfare implications.

Learning Speed

- What is the probability of mistake $\mathbb{P}[a_t^i \neq \Theta]$?
- Explicit calculation seems hopeless, even in special cases.
- Classical result in statistics and probability:
  - Single agent:

    $$\mathbb{P}[a_t \neq \Theta] \approx \exp(-r_1 \cdot t),$$

    where r_1 can be explicitly calculated given μ_Θ.
  - n agents + **public signals / optimal aggregation**:

    $$\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-nr_1 \cdot t).$$

- Define the **speed of learning** of agent i as the exponential rate at which she converges to the correct action:

$$r = \liminf_{t\to\infty} -\frac{1}{t} \log \mathbb{P}[a_t^i \neq \Theta].$$

- If this limit exits and is equal to r, then $\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-r \cdot t)$.
- $r_1 \leq r \leq nr_1$.
- Tractable. Asymptotic, no welfare implications.

Learning Speed

- What is the probability of mistake $\mathbb{P}[a_t^i \neq \Theta]$?
- Explicit calculation seems hopeless, even in special cases.
- Classical result in statistics and probability:
  - Single agent:
$$\mathbb{P}[a_t \neq \Theta] \approx \exp(-r_1 \cdot t),$$
    where r_1 can be explicitly calculated given μ_Θ.
  - n agents + **public signals** / **optimal aggregation**:
$$\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-nr_1 \cdot t).$$
- Define the **speed of learning** of agent i as the exponential rate at which she converges to the correct action:
$$r = \liminf_{t \to \infty} -\frac{1}{t} \log \mathbb{P}[a_t^i \neq \Theta].$$
- If this limit exits and is equal to r, then $\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-r \cdot t)$.
- $r_1 \leq r \leq nr_1$.
- Tractable. Asymptotic, no welfare implications.

Learning Speed

- What is the probability of mistake $\mathbb{P}[a_t^i \neq \Theta]$?
- Explicit calculation seems hopeless, even in special cases.
- Classical result in statistics and probability:
  - Single agent:
  $$\mathbb{P}[a_t \neq \Theta] \approx \exp(-r_1 \cdot t),$$
  where r_1 can be explicitly calculated given μ_Θ.
  - n agents + **public signals / optimal aggregation**:
  $$\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-nr_1 \cdot t).$$
- Define the **speed of learning** of agent i as the exponential rate at which she converges to the correct action:
$$r = \liminf_{t\to\infty} -\frac{1}{t} \log \mathbb{P}[a_t^i \neq \Theta].$$
- If this limit exits and is equal to r, then $\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-r \cdot t)$.
- $r_1 \leq r \leq nr_1$.
- Tractable. Asymptotic, no welfare implications.

Learning Speed

- What is the probability of mistake $\mathbb{P}[a_t^i \neq \Theta]$?
- Explicit calculation seems hopeless, even in special cases.
- Classical result in statistics and probability:
  - Single agent:
  $$\mathbb{P}[a_t \neq \Theta] \approx \exp(-r_1 \cdot t),$$
  where r_1 can be explicitly calculated given μ_Θ.
  - n agents + **public signals / optimal aggregation**:
  $$\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-nr_1 \cdot t).$$
- Define the **speed of learning** of agent i as the exponential rate at which she converges to the correct action:
$$r = \liminf_{t\to\infty} -\frac{1}{t}\log \mathbb{P}[a_t^i \neq \Theta].$$
- If this limit exits and is equal to r, then $\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-r \cdot t)$.
- $r_1 \leq r \leq nr_1$.
- Tractable. Asymptotic, no welfare implications.

Learning Speed

- What is the probability of mistake $\mathbb{P}[a_t^i \neq \Theta]$?
- Explicit calculation seems hopeless, even in special cases.
- Classical result in statistics and probability:
  - Single agent:
    $$\mathbb{P}[a_t \neq \Theta] \approx \exp(-r_1 \cdot t),$$
    where r_1 can be explicitly calculated given μ_Θ.
  - n agents + **public signals / optimal aggregation**:
    $$\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-nr_1 \cdot t).$$
- Define the **speed of learning** of agent i as the exponential rate at which she converges to the correct action:
  $$r = \liminf_{t\to\infty} -\frac{1}{t} \log \mathbb{P}[a_t^i \neq \Theta].$$
- If this limit exits and is equal to r, then $\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-r \cdot t)$.
- $r_1 \leq r \leq nr_1$.
- Tractable. Asymptotic, no welfare implications.

Learning Speed

- What is the probability of mistake $\mathbb{P}[a_t^i \neq \Theta]$?
- Explicit calculation seems hopeless, even in special cases.
- Classical result in statistics and probability:
  - Single agent:
    $$\mathbb{P}[a_t \neq \Theta] \approx \exp(-r_1 \cdot t),$$
    where r_1 can be explicitly calculated given μ_Θ.
  - n agents + **public signals / optimal aggregation**:
    $$\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-nr_1 \cdot t).$$
- Define the **speed of learning** of agent i as the exponential rate at which she converges to the correct action:
$$r = \liminf_{t \to \infty} -\frac{1}{t} \log \mathbb{P}[a_t^i \neq \Theta].$$
- If this limit exits and is equal to r, then $\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-r \cdot t)$.
- $r_1 \leq r \leq nr_1$.
- Tractable. Asymptotic, no welfare implications.

Learning Speed

- What is the probability of mistake $\mathbb{P}[a_t^i \neq \Theta]$?
- Explicit calculation seems hopeless, even in special cases.
- Classical result in statistics and probability:
  - Single agent:
$$\mathbb{P}[a_t \neq \Theta] \approx \exp(-r_1 \cdot t),$$
    where r_1 can be explicitly calculated given μ_Θ.
  - n agents + **public signals / optimal aggregation**:
$$\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-nr_1 \cdot t).$$
- Define the **speed of learning** of agent i as the exponential rate at which she converges to the correct action:
$$r = \liminf_{t\to\infty} -\frac{1}{t} \log \mathbb{P}[a_t^i \neq \Theta].$$
- If this limit exits and is equal to r, then $\mathbb{P}[a_t^i \neq \Theta] \approx \exp(-r \cdot t)$.
- $r_1 \leq r \leq nr_1$.
- Tractable. Asymptotic, no welfare implications.

Related Literature

- Bikhchandani, Hirshleifer and Welch 1992, Banerjee 1992.
  - 10,000,000 citations.
- DeGroot (1974), Bala and Goyal (1998), Molavi et al., (2018), Golub and Jackson (2010)
  - Social network
  - Bounded rationality
- Mossel et al. 2014, 2015.
  - Social network
  - One signal
- Harel et al. 2021.
  - Repeated signals
  - Complete network
  - Myopic agents

Related Literature

- Bikhchandani, Hirshleifer and Welch 1992, Banerjee 1992.
  - 10,000,000 citations.
- DeGroot (1974), Bala and Goyal (1998), Molavi et al., (2018), Golub and Jackson (2010)
  - Social network
  - Bounded rationality
- Mossel et al. 2014, 2015.
  - Social network
  - One signal
- Harel et al. 2021.
  - Repeated signals
  - Complete network
  - Myopic agents

Related Literature

- Bikhchandani, Hirshleifer and Welch 1992, Banerjee 1992.
  - 10,000,000 citations.
- DeGroot (1974), Bala and Goyal (1998), Molavi et al., (2018), Golub and Jackson (2010)
  - Social network
  - Bounded rationality
- Mossel et al. 2014, 2015.
  - Social network
  - One signal
- Harel et al. 2021.
  - Repeated signals
  - Complete network
  - Myopic agents

Related Literature

- Bikhchandani, Hirshleifer and Welch 1992, Banerjee 1992.
  - 10,000,000 citations.
- DeGroot (1974), Bala and Goyal (1998), Molavi et al., (2018), Golub and Jackson (2010)
  - Social network
  - Bounded rationality
- Mossel et al. 2014, 2015.
  - Social network
  - One signal
- Harel et al. 2021.
  - Repeated signals
  - Complete network
  - Myopic agents

Related Literature

- Bikhchandani, Hirshleifer and Welch 1992, Banerjee 1992.
  - 10,000,000 citations.
- DeGroot (1974), Bala and Goyal (1998), Molavi et al., (2018), Golub and Jackson (2010)
  - Social network
  - Bounded rationality
- Mossel et al. 2014, 2015.
  - Social network
  - One signal
- Harel et al. 2021.
  - Repeated signals
  - Complete network
  - Myopic agents

Related Literature

- Bikhchandani, Hirshleifer and Welch 1992, Banerjee 1992.
  - 10,000,000 citations.
- DeGroot (1974), Bala and Goyal (1998), Molavi et al., (2018), Golub and Jackson (2010)
  - Social network
  - Bounded rationality
- Mossel et al. 2014, 2015.
  - Social network
  - One signal
- Harel et al. 2021.
  - Repeated signals
  - Complete network
  - Myopic agents

Related Literature

- Bikhchandani, Hirshleifer and Welch 1992, Banerjee 1992.
  - 10,000,000 citations.
- DeGroot (1974), Bala and Goyal (1998), Molavi et al., (2018), Golub and Jackson (2010)
  - Social network
  - Bounded rationality
- Mossel et al. 2014, 2015.
  - Social network
  - One signal
- Harel et al. 2021.
  - Repeated signals
  - Complete network
  - Myopic agents

Related Literature

- Bikhchandani, Hirshleifer and Welch 1992, Banerjee 1992.
  - 10,000,000 citations.
- DeGroot (1974), Bala and Goyal (1998), Molavi et al., (2018), Golub and Jackson (2010)
  - Social network
  - Bounded rationality
- Mossel et al. 2014, 2015.
  - Social network
  - One signal
- Harel et al. 2021.
  - Repeated signals
  - Complete network
  - Myopic agents

Related Literature

- Bikhchandani, Hirshleifer and Welch 1992, Banerjee 1992.
  - 10,000,000 citations.
- DeGroot (1974), Bala and Goyal (1998), Molavi et al., (2018), Golub and Jackson (2010)
  - Social network
  - Bounded rationality
- Mossel et al. 2014, 2015.
  - Social network
  - One signal
- Harel et al. 2021.
  - Repeated signals
  - Complete network
  - Myopic agents

Related Literature

- Bikhchandani, Hirshleifer and Welch 1992, Banerjee 1992.
  - 10,000,000 citations.
- DeGroot (1974), Bala and Goyal (1998), Molavi et al., (2018), Golub and Jackson (2010)
  - Social network
  - Bounded rationality
- Mossel et al. 2014, 2015.
  - Social network
  - One signal
- Harel et al. 2021.
  - Repeated signals
  - Complete network
  - Myopic agents

Related Literature

- Bikhchandani, Hirshleifer and Welch 1992, Banerjee 1992.
  - 10,000,000 citations.
- DeGroot (1974), Bala and Goyal (1998), Molavi et al., (2018), Golub and Jackson (2010)
  - Social network
  - Bounded rationality
- Mossel et al. 2014, 2015.
  - Social network
  - One signal
- Harel et al. 2021.
  - Repeated signals
  - Complete network
  - Myopic agents

Related Literature

- Bikhchandani, Hirshleifer and Welch 1992, Banerjee 1992.
  - 10,000,000 citations.
- DeGroot (1974), Bala and Goyal (1998), Molavi et al., (2018), Golub and Jackson (2010)
  - Social network
  - Bounded rationality
- Mossel et al. 2014, 2015.
  - Social network
  - One signal
- Harel et al. 2021.
  - Repeated signals
  - Complete network
  - Myopic agents

Related Literature

- Bikhchandani, Hirshleifer and Welch 1992, Banerjee 1992.
  - 10,000,000 citations.
- DeGroot (1974), Bala and Goyal (1998), Molavi et al., (2018), Golub and Jackson (2010)
  - Social network
  - Bounded rationality
- Mossel et al. 2014, 2015.
  - Social network
  - One signal
- Harel et al. 2021.
  - Repeated signals
  - Complete network
  - Myopic agents

Main Result

- For every pair of conditional signal distributions $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$ define

$$M = 2 \sup_{\omega \in \Omega} \left| \log \frac{\mu_{\mathfrak{g}}(\omega)}{\mu_{\mathfrak{b}}(\omega)} \right| \tag{1}$$

  This is twice the maximal log-likelihood ratio induced by any signal realization.

Theorem 1

Fix $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$. In any equilibrium, on any social network of any size, and for any discount factor $\delta \in [0, 1)$, the speed of learning is at most M.

- Adding more agents (thus more info) in the network cannot improve the learning speed without bound.

Main Result

- For every pair of conditional signal distributions $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$ define

$$M = 2 \sup_{\omega \in \Omega} \left| \log \frac{\mu_{\mathfrak{g}}(\omega)}{\mu_{\mathfrak{b}}(\omega)} \right| \tag{1}$$

  This is twice the maximal log-likelihood ratio induced by any signal realization.

Theorem 1

Fix $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$. In any equilibrium, on any social network of any size, and for any discount factor $\delta \in [0, 1)$, the speed of learning is at most M.

- Adding more agents (thus more info) in the network cannot improve the learning speed without bound.

Main Result

- For every pair of conditional signal distributions $(\mu_\mathfrak{g}, \mu_\mathfrak{b})$ define

$$M = 2 \sup_{\omega \in \Omega} \left| \log \frac{\mu_\mathfrak{g}(\omega)}{\mu_\mathfrak{b}(\omega)} \right| \tag{1}$$

  This is twice the maximal log-likelihood ratio induced by any signal realization.

Theorem 1

Fix $(\mu_\mathfrak{g}, \mu_\mathfrak{b})$. In any equilibrium, on any social network of any size, and for any discount factor $\delta \in [0, 1)$, the speed of learning is at most M.

- Adding more agents (thus more info) in the network cannot improve the learning speed without bound.

Main Result

- For every pair of conditional signal distributions $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$ define

$$M = 2 \sup_{\omega \in \Omega} \left| \log \frac{\mu_{\mathfrak{g}}(\omega)}{\mu_{\mathfrak{b}}(\omega)} \right| \tag{1}$$

  This is twice the maximal log-likelihood ratio induced by any signal realization.

Theorem 1

Fix $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$. In any equilibrium, on any social network of any size, and for any discount factor $\delta \in [0, 1)$, the speed of learning is at most M.

- Adding more agents (thus more info) in the network cannot improve the learning speed without bound.

Example

- Symmetric binary signals: $\mu_\theta(\theta) = 0.9$ for $\theta \in \{\mathfrak{g}, \mathfrak{b}\}$.
- a single agent's learning speed is $r_1 \approx 0.5$.
- $M = 2\log\frac{0.9}{0.1} \approx 4.5$
- So 4.5 is an upper bound to the learning speed in networks of **any size**.
- 10 agents with public signals achieve a speed of learning > 4.5.
- 1,000,000 agents who observe their neighbors' past actions never learns faster than 10 agents who share their private signals.
- More information loss in larger networks.

Example

- Symmetric binary signals: $\mu_\theta(\theta) = 0.9$ for $\theta \in \{\mathfrak{g}, \mathfrak{b}\}$.
- a single agent's learning speed is $r_1 \approx 0.5$.
- $M = 2\log\frac{0.9}{0.1} \approx 4.5$
- So 4.5 is an upper bound to the learning speed in networks of **any size**.
- 10 agents with public signals achieve a speed of learning > 4.5.
- 1,000,000 agents who observe their neighbors' past actions never learns faster than 10 agents who share their private signals.
- More information loss in larger networks.

Example

- Symmetric binary signals: $\mu_\theta(\theta) = 0.9$ for $\theta \in \{\mathfrak{g}, \mathfrak{b}\}$.
- a single agent's learning speed is $r_1 \approx 0.5$.
- $M = 2\log\frac{0.9}{0.1} \approx 4.5$
- So 4.5 is an upper bound to the learning speed in networks of **any size**.
- 10 agents with public signals achieve a speed of learning > 4.5.
- 1,000,000 agents who observe their neighbors' past actions never learns faster than 10 agents who share their private signals.
- More information loss in larger networks.

Example

- Symmetric binary signals: $\mu_\theta(\theta) = 0.9$ for $\theta \in \{\mathfrak{g}, \mathfrak{b}\}$.
- a single agent's learning speed is $r_1 \approx 0.5$.
- $M = 2\log\frac{0.9}{0.1} \approx 4.5$
- So 4.5 is an upper bound to the learning speed in networks of **any size**.
- 10 agents with public signals achieve a speed of learning > 4.5.
- 1,000,000 agents who observe their neighbors' past actions never learns faster than 10 agents who share their private signals.
- More information loss in larger networks.

Example

- Symmetric binary signals: $\mu_\theta(\theta) = 0.9$ for $\theta \in \{\mathfrak{g}, \mathfrak{b}\}$.
- a single agent's learning speed is $r_1 \approx 0.5$.
- $M = 2 \log \frac{0.9}{0.1} \approx 4.5$
- So 4.5 is an upper bound to the learning speed in networks of **any size**.
- 10 agents with public signals achieve a speed of learning > 4.5.
- 1,000,000 agents who observe their neighbors' past actions never learns faster than 10 agents who share their private signals.
- More information loss in larger networks.

Example

- Symmetric binary signals: $\mu_\theta(\theta) = 0.9$ for $\theta \in \{\mathfrak{g}, \mathfrak{b}\}$.
- a single agent's learning speed is $r_1 \approx 0.5$.
- $M = 2 \log \frac{0.9}{0.1} \approx 4.5$
- So 4.5 is an upper bound to the learning speed in networks of **any size**.
- 10 agents with public signals achieve a speed of learning > 4.5.
- 1,000,000 agents who observe their neighbors' past actions never learns faster than 10 agents who share their private signals.
- More information loss in larger networks.

Example

- Symmetric binary signals: $\mu_\theta(\theta) = 0.9$ for $\theta \in \{\mathfrak{g}, \mathfrak{b}\}$.
- a single agent's learning speed is $r_1 \approx 0.5$.
- $M = 2 \log \frac{0.9}{0.1} \approx 4.5$
- So 4.5 is an upper bound to the learning speed in networks of **any size**.
- 10 agents with public signals achieve a speed of learning > 4.5.
- 1,000,000 agents who observe their neighbors' past actions never learns faster than 10 agents who share their private signals.
- More information loss in larger networks.

Example

- Symmetric binary signals: $\mu_\theta(\theta) = 0.9$ for $\theta \in \{\mathfrak{g}, \mathfrak{b}\}$.
- a single agent's learning speed is $r_1 \approx 0.5$.
- $M = 2 \log \frac{0.9}{0.1} \approx 4.5$
- So 4.5 is an upper bound to the learning speed in networks of **any size**.
- 10 agents with public signals achieve a speed of learning > 4.5.
- 1,000,000 agents who observe their neighbors' past actions never learns faster than 10 agents who share their private signals.
- More information loss in larger networks.

Myopic and Strategic Behavior

- The posterior log-likelihood ratio is $L_t^i := \log \frac{\mathbb{P}[\Theta=\mathfrak{g}|s_1^i,\cdots,s_t^i,H_t^i]}{\mathbb{P}[\Theta=\mathfrak{b}|s_1^i,\cdots,s_t^i,H_t^i]}$.
- Myopically optimal action is

$$m_t^i := \arg\max_{a\in\mathcal{A}} \mathbb{P}[\Theta = a|s_1^i, \cdots, s_t^i, H_t^i] = \begin{cases} \mathfrak{g} & \text{if } L_t^i \geq 0, \\ \mathfrak{b} & \text{if } L_t^i < 0. \end{cases}$$

- If $\delta \in (0,1)$, there may be **strategic** incentive to **not** choose m_t^i.

Lemma 1 (Eventually Myopic)

(i) *In equilibrium, if for some time t it holds that $|L_t^i| \geq -\log(1-\delta)$ then $a_t^i = m_t^i$.*
(ii) *There exists a random time $T < \infty$ such that in equilibrium,* ***all*** *agents behave myopically after T, i.e. $t \geq T \Rightarrow a_t^i = m_t^i$ for all i almost surely.*

- Intuition: (i) as posterior belief becomes precise enough, not worthwhile behaving strategically; (ii) a stream of private signals → precise beliefs.

Myopic and Strategic Behavior

- The posterior log-likelihood ratio is $L_t^i := \log \frac{\mathbb{P}[\Theta=\mathfrak{g}|s_1^i,\cdots,s_t^i,H_t^i]}{\mathbb{P}[\Theta=\mathfrak{b}|s_1^i,\cdots,s_t^i,H_t^i]}$.
- Myopically optimal action is

$$m_t^i := \arg\max_{a\in\mathcal{A}} \mathbb{P}[\Theta = a|s_1^i, \cdots, s_t^i, H_t^i] = \begin{cases} \mathfrak{g} & \text{if } L_t^i \geq 0, \\ \mathfrak{b} & \text{if } L_t^i < 0. \end{cases}$$

- If $\delta \in (0,1)$, there may be **strategic** incentive to **not** choose m_t^i.

Lemma 1 (Eventually Myopic)

(i) *In equilibrium, if for some time t it holds that $|L_t^i| \geq -\log(1-\delta)$ then $a_t^i = m_t^i$.*

(ii) *There exists a random time $T < \infty$ such that in equilibrium,* ***all*** *agents behave myopically after T, i.e. $t \geq T \Rightarrow a_t^i = m_t^i$ for all i almost surely.*

- Intuition: (i) as posterior belief becomes precise enough, not worthwhile behaving strategically; (ii) a stream of private signals → precise beliefs.

Myopic and Strategic Behavior

- The posterior log-likelihood ratio is $L_t^i := \log \frac{\mathbb{P}[\Theta=\mathfrak{g}|s_1^i,\cdots,s_t^i,H_t^i]}{\mathbb{P}[\Theta=\mathfrak{b}|s_1^i,\cdots,s_t^i,H_t^i]}$.
- Myopically optimal action is

$$m_t^i := \arg\max_{a \in \mathcal{A}} \mathbb{P}[\Theta = a | s_1^i, \cdots, s_t^i, H_t^i] = \begin{cases} \mathfrak{g} & \text{if } L_t^i \geq 0, \\ \mathfrak{b} & \text{if } L_t^i < 0. \end{cases}$$

- If $\delta \in (0,1)$, there may be **strategic** incentive to **not** choose m_t^i.

Lemma 1 (Eventually Myopic)

(i) *In equilibrium, if for some time t it holds that $|L_t^i| \geq -\log(1-\delta)$ then $a_t^i = m_t^i$.*

(ii) *There exists a random time $T < \infty$ such that in equilibrium,* ***all*** *agents behave myopically after T, i.e. $t \geq T \Rightarrow a_t^i = m_t^i$ for all i almost surely.*

- Intuition: (i) as posterior belief becomes precise enough, not worthwhile behaving strategically; (ii) a stream of private signals → precise beliefs.

Myopic and Strategic Behavior

- The posterior log-likelihood ratio is $L_t^i := \log \frac{\mathbb{P}[\Theta=\mathfrak{g}|s_1^i,\cdots,s_t^i,H_t^i]}{\mathbb{P}[\Theta=\mathfrak{b}|s_1^i,\cdots,s_t^i,H_t^i]}$.
- Myopically optimal action is

$$m_t^i := \arg\max_{a\in\mathcal{A}} \mathbb{P}[\Theta = a|s_1^i, \cdots, s_t^i, H_t^i] = \begin{cases} \mathfrak{g} & \text{if } L_t^i \geq 0, \\ \mathfrak{b} & \text{if } L_t^i < 0. \end{cases}$$

- If $\delta \in (0,1)$, there may be **strategic** incentive to **not** choose m_t^i.

Lemma 1 (Eventually Myopic)

(i) *In equilibrium, if for some time t it holds that $|L_t^i| \geq -\log(1-\delta)$ then $a_t^i = m_t^i$.*

(ii) *There exists a random time $T < \infty$ such that in equilibrium,* ***all*** *agents behave myopically after T, i.e. $t \geq T \Rightarrow a_t^i = m_t^i$ for all i almost surely.*

- Intuition: (i) as posterior belief becomes precise enough, not worthwhile behaving strategically; (ii) a stream of private signals $\rightarrow$ precise beliefs.

Myopic and Strategic Behavior

- The posterior log-likelihood ratio is $L_t^i := \log \frac{\mathbb{P}[\Theta=\mathfrak{g}|s_1^i,\cdots,s_t^i,H_t^i]}{\mathbb{P}[\Theta=\mathfrak{b}|s_1^i,\cdots,s_t^i,H_t^i]}$.
- Myopically optimal action is

$$m_t^i := \arg\max_{a\in\mathcal{A}} \mathbb{P}[\Theta = a|s_1^i, \cdots, s_t^i, H_t^i] = \begin{cases} \mathfrak{g} & \text{if } L_t^i \geq 0, \\ \mathfrak{b} & \text{if } L_t^i < 0. \end{cases}$$

- If $\delta \in (0,1)$, there may be **strategic** incentive to **not** choose m_t^i.

Lemma 1 (Eventually Myopic)

(i) *In equilibrium, if for some time t it holds that $|L_t^i| \geq -\log(1-\delta)$ then $a_t^i = m_t^i$.*

(ii) *There exists a random time $T < \infty$ such that in equilibrium, **all** agents behave myopically after T, i.e. $t \geq T \Rightarrow a_t^i = m_t^i$ for all i almost surely.*

- Intuition: (i) as posterior belief becomes precise enough, not worthwhile behaving strategically; (ii) a stream of private signals → precise beliefs.

Myopic and Strategic Behavior

- The posterior log-likelihood ratio is $L_t^i := \log \frac{\mathbb{P}[\Theta=\mathfrak{g}|s_1^i,\cdots,s_t^i,H_t^i]}{\mathbb{P}[\Theta=\mathfrak{b}|s_1^i,\cdots,s_t^i,H_t^i]}$.
- Myopically optimal action is

$$m_t^i := \arg\max_{a\in\mathcal{A}} \mathbb{P}[\Theta = a|s_1^i, \cdots, s_t^i, H_t^i] = \begin{cases} \mathfrak{g} & \text{if } L_t^i \geq 0, \\ \mathfrak{b} & \text{if } L_t^i < 0. \end{cases}$$

- If $\delta \in (0,1)$, there may be **strategic** incentive to **not** choose m_t^i.

Lemma 1 (Eventually Myopic)

(i) *In equilibrium, if for some time t it holds that $|L_t^i| \geq -\log(1-\delta)$ then $a_t^i = m_t^i$.*

(ii) *There exists a random time $T < \infty$ such that in equilibrium, **all** agents behave myopically after T, i.e. $t \geq T \Rightarrow a_t^i = m_t^i$ for all i almost surely.*

- Intuition: (i) as posterior belief becomes precise enough, not worthwhile behaving strategically; (ii) a stream of private signals $\to$ precise beliefs.

Myopic and Strategic Behavior

- The posterior log-likelihood ratio is $L_t^i := \log \frac{\mathbb{P}[\Theta=\mathfrak{g}|s_1^i,\cdots,s_t^i,H_t^i]}{\mathbb{P}[\Theta=\mathfrak{b}|s_1^i,\cdots,s_t^i,H_t^i]}$.
- Myopically optimal action is

$$m_t^i := \arg\max_{a\in\mathcal{A}} \mathbb{P}[\Theta = a|s_1^i,\cdots,s_t^i,H_t^i] = \begin{cases} \mathfrak{g} & \text{if } L_t^i \geq 0, \\ \mathfrak{b} & \text{if } L_t^i < 0. \end{cases}$$

- If $\delta \in (0,1)$, there may be **strategic** incentive to **not** choose m_t^i.

Lemma 1 (Eventually Myopic)

(i) *In equilibrium, if for some time t it holds that $|L_t^i| \geq -\log(1-\delta)$ then $a_t^i = m_t^i$.*

(ii) *There exists a random time $T < \infty$ such that in equilibrium,* ***all*** *agents behave myopically after T, i.e. $t \geq T \Rightarrow a_t^i = m_t^i$ for all i almost surely.*

- Intuition: (i) as posterior belief becomes precise enough, not worthwhile behaving strategically; (ii) a stream of private signals $\rightarrow$ precise beliefs.

Common Learning Rate

Lemma 2 (All Agents Learn at the Same Rate)

(i) *If agent i can observe agent j, i.e., $i \in N_i$, then in equilibrium i learns at a (weakly) higher rate, i.e., $r_i \geq r_j$.*

(ii) *All agents learn at the same rate, i.e., $r_i = r_j$ for all i, j, in any strongly connected network.*

- We call this common rate *the equilibrium speed of learning.*
- Intuition: the imitation principle.

Common Learning Rate

Lemma 2 (All Agents Learn at the Same Rate)

(i) *If agent i can observe agent j, i.e., $i \in N_i$, then in equilibrium i learns at a (weakly) higher rate, i.e., $r_i \geq r_j$.*

(ii) *All agents learn at the same rate, i.e., $r_i = r_j$ for all i, j, in any strongly connected network.*

- We call this common rate *the equilibrium speed of learning.*
- Intuition: the imitation principle.

Common Learning Rate

Lemma 2 (All Agents Learn at the Same Rate)

(i) *If agent i can observe agent j, i.e., $i \in N_i$, then in equilibrium i learns at a (weakly) higher rate, i.e., $r_i \geq r_j$.*

(ii) *All agents learn at the same rate, i.e., $r_i = r_j$ for all i, j, in any strongly connected network.*

- We call this common rate *the equilibrium speed of learning.*
- Intuition: the imitation principle.

Common Learning Rate

Lemma 2 (All Agents Learn at the Same Rate)

(i) *If agent i can observe agent j, i.e., $i \in N_i$, then in equilibrium i learns at a (weakly) higher rate, i.e., $r_i \geq r_j$.*

(ii) *All agents learn at the same rate, i.e., $r_i = r_j$ for all i, j, in any strongly connected network.*

- We call this common rate *the equilibrium speed of learning.*
- Intuition: the imitation principle.

Common Learning Rate

Lemma 2 (All Agents Learn at the Same Rate)

(i) *If agent i can observe agent j, i.e., $i \in N_i$, then in equilibrium i learns at a (weakly) higher rate, i.e., $r_i \geq r_j$.*

(ii) *All agents learn at the same rate, i.e., $r_i = r_j$ for all i, j, in any strongly connected network.*

- We call this common rate *the equilibrium speed of learning.*
- Intuition: the imitation principle.

The Imitation Principle

(i) Imitation Principle for Myopic Agents if i observes j, then i's actions are not worse than j's:

$$\mathbb{P}[a_t^i \neq \Theta] \leq \mathbb{P}[a_{t-1}^j \neq \Theta],$$

since i can always imitate j.

(ii) Imitation Principle for Strategic Agents in equilibrium, i's actions are never much worse than j's, even though i may choose myopically sub-optimal actions:

$$\mathbb{P}[a_t^i \neq \Theta] \leq \frac{1}{1-\delta}\mathbb{P}[a_{t-1}^j \neq \Theta].$$

- Intuition: i can imitates j's action at $t-1$ forever (from t onward), but this cannot be a profitable deviation in eqm.
- Similar ideas in Smith and Sorensen (1996), Sorensen (1996), Gale and Kariv, (2003) Golub and Sadler (2017)

The Imitation Principle

(i) Imitation Principle for Myopic Agents if i observes j, then i's actions are not worse than j's:

$$\mathbb{P}[a_t^i \neq \Theta] \leq \mathbb{P}[a_{t-1}^j \neq \Theta],$$

since i can always imitate j.

(ii) Imitation Principle for Strategic Agents in equilibrium, i's actions are never much worse than j's, even though i may choose myopically sub-optimal actions:

$$\mathbb{P}[a_t^i \neq \Theta] \leq \frac{1}{1-\delta}\mathbb{P}[a_{t-1}^j \neq \Theta].$$

- Intuition: i can imitates j's action at $t-1$ forever (from t onward), but this cannot be a profitable deviation in eqm.
- Similar ideas in Smith and Sorensen (1996), Sorensen (1996), Gale and Kariv, (2003) Golub and Sadler (2017)

The Imitation Principle

(i) Imitation Principle for Myopic Agents if i observes j, then i's actions are not worse than j's:

$$\mathbb{P}[a_t^i \neq \Theta] \leq \mathbb{P}[a_{t-1}^j \neq \Theta],$$

since i can always imitate j.

(ii) Imitation Principle for Strategic Agents in equilibrium, i's actions are never much worse than j's, even though i may choose myopically sub-optimal actions:

$$\mathbb{P}[a_t^i \neq \Theta] \leq \frac{1}{1-\delta}\mathbb{P}[a_{t-1}^j \neq \Theta].$$

- Intuition: i can imitates j's action at $t-1$ forever (from t onward), but this cannot be a profitable deviation in eqm.
- Similar ideas in Smith and Sorensen (1996), Sorensen (1996), Gale and Kariv, (2003) Golub and Sadler (2017)

The Imitation Principle

(i) Imitation Principle for Myopic Agents if i observes j, then i's actions are not worse than j's:

$$\mathbb{P}[a_t^i \neq \Theta] \leq \mathbb{P}[a_{t-1}^j \neq \Theta],$$

since i can always imitate j.

(ii) Imitation Principle for Strategic Agents in equilibrium, i's actions are never much worse than j's, even though i may choose myopically sub-optimal actions:

$$\mathbb{P}[a_t^i \neq \Theta] \leq \frac{1}{1-\delta}\mathbb{P}[a_{t-1}^j \neq \Theta].$$

- Intuition: i can imitates j's action at $t-1$ forever (from t onward), but this cannot be a profitable deviation in eqm.
- Similar ideas in Smith and Sorensen (1996), Sorensen (1996), Gale and Kariv, (2003) Golub and Sadler (2017)

The Imitation Principle

(i) Imitation Principle for Myopic Agents if i observes j, then i's actions are not worse than j's:

$$\mathbb{P}[a_t^i \neq \Theta] \leq \mathbb{P}[a_{t-1}^j \neq \Theta],$$

since i can always imitate j.

(ii) Imitation Principle for Strategic Agents in equilibrium, i's actions are never much worse than j's, even though i may choose myopically sub-optimal actions:

$$\mathbb{P}[a_t^i \neq \Theta] \leq \frac{1}{1-\delta}\mathbb{P}[a_{t-1}^j \neq \Theta].$$

- Intuition: i can imitates j's action at $t-1$ forever (from t onward), but this cannot be a profitable deviation in eqm.
- Similar ideas in Smith and Sorensen (1996), Sorensen (1996), Gale and Kariv, (2003) Golub and Sadler (2017)

Proof sketch

Theorem

Fix $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$. In any equilibrium, on any social network of any size, and for any discount factor $\delta \in [0,1)$, the speed of learning is at most M.

- Suppose speed of learning is $r > M$.
- Condition on $\Theta = \mathfrak{g}$.
- $a_t^j = \mathfrak{g}$ eventually.
- $\mathbb{P}[a_t^j \neq \mathfrak{g}] \approx \mathrm{e}^{-rt}$.
- Observing j provides a log-likelihood ratio

$$\log \frac{\mathbb{P}[\Theta = \mathfrak{g} | a_t^j = \mathfrak{g}]}{\mathbb{P}[\Theta = \mathfrak{b} | a_t^j = \mathfrak{g}]} \approx rt.$$

- t private signals provide a log-likelihood ratio in $[-Mt, Mt]$.
- So eventually imitation dominates any possible signal.
- Agents stop looking at their signals.
- But if no-one is looking at signals then learning stops.

Proof sketch

Theorem

Fix $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$. In any equilibrium, on any social network of any size, and for any discount factor $\delta \in [0,1)$, the speed of learning is at most M.

- Suppose speed of learning is $r > M$.
- Condition on $\Theta = \mathfrak{g}$.
- $a_t^j = \mathfrak{g}$ eventually.
- $\mathbb{P}[a_t^j \neq \mathfrak{g}] \approx \mathrm{e}^{-rt}$.
- Observing j provides a log-likelihood ratio

$$\log \frac{\mathbb{P}[\Theta = \mathfrak{g} | a_t^j = \mathfrak{g}]}{\mathbb{P}[\Theta = \mathfrak{b} | a_t^j = \mathfrak{g}]} \approx rt.$$

- t private signals provide a log-likelihood ratio in $[-Mt, Mt]$.
- So eventually imitation dominates any possible signal.
- Agents stop looking at their signals.
- But if no-one is looking at signals then learning stops.

Proof sketch

Theorem

Fix $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$. In any equilibrium, on any social network of any size, and for any discount factor $\delta \in [0, 1)$, the speed of learning is at most M.

- Suppose speed of learning is $r > M$.
- Condition on $\Theta = \mathfrak{g}$.
- $a_t^j = \mathfrak{g}$ eventually.
- $\mathbb{P}[a_t^j \neq \mathfrak{g}] \approx \mathrm{e}^{-rt}$.
- Observing j provides a log-likelihood ratio

$$\log \frac{\mathbb{P}[\Theta = \mathfrak{g} | a_t^j = \mathfrak{g}]}{\mathbb{P}[\Theta = \mathfrak{b} | a_t^j = \mathfrak{g}]} \approx rt.$$

- t private signals provide a log-likelihood ratio in $[-Mt, Mt]$.
- So eventually imitation dominates any possible signal.
- Agents stop looking at their signals.
- But if no-one is looking at signals then learning stops.

Proof sketch

Theorem

Fix $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$. In any equilibrium, on any social network of any size, and for any discount factor $\delta \in [0, 1)$, the speed of learning is at most M.

- Suppose speed of learning is $r > M$.
- Condition on $\Theta = \mathfrak{g}$.
- $a_t^j = \mathfrak{g}$ eventually.
- $\mathbb{P}[a_t^j \neq \mathfrak{g}] \approx \mathrm{e}^{-rt}$.
- Observing j provides a log-likelihood ratio

$$\log \frac{\mathbb{P}[\Theta = \mathfrak{g} | a_t^j = \mathfrak{g}]}{\mathbb{P}[\Theta = \mathfrak{b} | a_t^j = \mathfrak{g}]} \approx rt.$$

- t private signals provide a log-likelihood ratio in $[-Mt, Mt]$.
- So eventually imitation dominates any possible signal.
- Agents stop looking at their signals.
- But if no-one is looking at signals then learning stops.

Proof sketch

Theorem

Fix $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$. In any equilibrium, on any social network of any size, and for any discount factor $\delta \in [0,1)$, the speed of learning is at most M.

- Suppose speed of learning is $r > M$.
- Condition on $\Theta = \mathfrak{g}$.
- $a_t^j = \mathfrak{g}$ eventually.
- $\mathbb{P}[a_t^j \neq \mathfrak{g}] \approx \mathrm{e}^{-rt}$.
- Observing j provides a log-likelihood ratio

$$\log \frac{\mathbb{P}[\Theta = \mathfrak{g} | a_t^j = \mathfrak{g}]}{\mathbb{P}[\Theta = \mathfrak{b} | a_t^j = \mathfrak{g}]} \approx rt.$$

- t private signals provide a log-likelihood ratio in $[-Mt, Mt]$.
- So eventually imitation dominates any possible signal.
- Agents stop looking at their signals.
- But if no-one is looking at signals then learning stops.

Proof sketch

Theorem

Fix $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$. In any equilibrium, on any social network of any size, and for any discount factor $\delta \in [0,1)$, the speed of learning is at most M.

- Suppose speed of learning is $r > M$.
- Condition on $\Theta = \mathfrak{g}$.
- $a_t^j = \mathfrak{g}$ eventually.
- $\mathbb{P}[a_t^j \neq \mathfrak{g}] \approx \mathrm{e}^{-rt}$.
- Observing j provides a log-likelihood ratio

$$\log \frac{\mathbb{P}[\Theta = \mathfrak{g} | a_t^j = \mathfrak{g}]}{\mathbb{P}[\Theta = \mathfrak{b} | a_t^j = \mathfrak{g}]} \approx rt.$$

- t private signals provide a log-likelihood ratio in $[-Mt, Mt]$.
- So eventually imitation dominates any possible signal.
- Agents stop looking at their signals.
- But if no-one is looking at signals then learning stops.

Proof sketch

Theorem

Fix $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$. In any equilibrium, on any social network of any size, and for any discount factor $\delta \in [0, 1)$, the speed of learning is at most M.

- Suppose speed of learning is $r > M$.
- Condition on $\Theta = \mathfrak{g}$.
- $a_t^j = \mathfrak{g}$ eventually.
- $\mathbb{P}[a_t^j \neq \mathfrak{g}] \approx \mathrm{e}^{-rt}$.
- Observing j provides a log-likelihood ratio

$$\log \frac{\mathbb{P}[\Theta = \mathfrak{g} | a_t^j = \mathfrak{g}]}{\mathbb{P}[\Theta = \mathfrak{b} | a_t^j = \mathfrak{g}]} \approx rt.$$

- t private signals provide a log-likelihood ratio in $[-Mt, Mt]$.
- So eventually imitation dominates any possible signal.
- Agents stop looking at their signals.
- But if no-one is looking at signals then learning stops.

Proof sketch

Theorem

Fix $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$. In any equilibrium, on any social network of any size, and for any discount factor $\delta \in [0, 1)$, the speed of learning is at most M.

- Suppose speed of learning is $r > M$.
- Condition on $\Theta = \mathfrak{g}$.
- $a_t^j = \mathfrak{g}$ eventually.
- $\mathbb{P}[a_t^j \neq \mathfrak{g}] \approx \mathrm{e}^{-rt}$.
- Observing j provides a log-likelihood ratio

$$\log \frac{\mathbb{P}[\Theta = \mathfrak{g} | a_t^j = \mathfrak{g}]}{\mathbb{P}[\Theta = \mathfrak{b} | a_t^j = \mathfrak{g}]} \approx rt.$$

- t private signals provide a log-likelihood ratio in $[-Mt, Mt]$.
- So eventually imitation dominates any possible signal.
- Agents stop looking at their signals.
- But if no-one is looking at signals then learning stops.

Proof sketch

Theorem

Fix $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$. *In any equilibrium, on any social network of any size, and for any discount factor* $\delta \in [0, 1)$*, the speed of learning is at most* M.

- Suppose speed of learning is $r > M$.
- Condition on $\Theta = \mathfrak{g}$.
- $a_t^j = \mathfrak{g}$ eventually.
- $\mathbb{P}[a_t^j \neq \mathfrak{g}] \approx \mathrm{e}^{-rt}$.
- Observing j provides a log-likelihood ratio

$$\log \frac{\mathbb{P}[\Theta = \mathfrak{g} | a_t^j = \mathfrak{g}]}{\mathbb{P}[\Theta = \mathfrak{b} | a_t^j = \mathfrak{g}]} \approx rt.$$

- t private signals provide a log-likelihood ratio in $[-Mt, Mt]$.
- So eventually imitation dominates any possible signal.
- Agents stop looking at their signals.
- But if no-one is looking at signals then learning stops.

Proof sketch

Theorem

Fix $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$. In any equilibrium, on any social network of any size, and for any discount factor $\delta \in [0,1)$, the speed of learning is at most M.

- Suppose speed of learning is $r > M$.
- Condition on $\Theta = \mathfrak{g}$.
- $a_t^j = \mathfrak{g}$ eventually.
- $\mathbb{P}[a_t^j \neq \mathfrak{g}] \approx \mathrm{e}^{-rt}$.
- Observing j provides a log-likelihood ratio

$$\log \frac{\mathbb{P}[\Theta = \mathfrak{g} | a_t^j = \mathfrak{g}]}{\mathbb{P}[\Theta = \mathfrak{b} | a_t^j = \mathfrak{g}]} \approx rt.$$

- t private signals provide a log-likelihood ratio in $[-Mt, Mt]$.
- So eventually imitation dominates any possible signal.
- Agents stop looking at their signals.
- But if no-one is looking at signals then learning stops.

Proof sketch

Theorem

Fix $(\mu_{\mathfrak{g}}, \mu_{\mathfrak{b}})$. In any equilibrium, on any social network of any size, and for any discount factor $\delta \in [0, 1)$, the speed of learning is at most M.

- Suppose speed of learning is $r > M$.
- Condition on $\Theta = \mathfrak{g}$.
- $a_t^j = \mathfrak{g}$ eventually.
- $\mathbb{P}[a_t^j \neq \mathfrak{g}] \approx \mathrm{e}^{-rt}$.
- Observing j provides a log-likelihood ratio

$$\log \frac{\mathbb{P}[\Theta = \mathfrak{g} | a_t^j = \mathfrak{g}]}{\mathbb{P}[\Theta = \mathfrak{b} | a_t^j = \mathfrak{g}]} \approx rt.$$

- t private signals provide a log-likelihood ratio in $[-Mt, Mt]$.
- So eventually imitation dominates any possible signal.
- Agents stop looking at their signals.
- But if no-one is looking at signals then learning stops.

Conclusion

- Social learning in a
  - **rational** setting,
  - on **general** networks,
  - with **forward-looking**/strategic agents
  - who interact **repeatedly**.
- **speed of learning**:
  - Measure of efficiency of information aggregation.
  - Asymptotic.
  - Tractable.
- Main result: The speed of learning is **bounded above** by a constant, which depends only on the private signal structure.
- Aggregation is highly **inefficient**.

Thank You!

Conclusion

- Social learning in a
  - **rational** setting,
  - on **general** networks,
  - with **forward-looking**/strategic agents
  - who interact **repeatedly**.
- **speed of learning**:
  - Measure of efficiency of information aggregation.
  - Asymptotic.
  - Tractable.
- Main result: The speed of learning is **bounded above** by a constant, which depends only on the private signal structure.
- Aggregation is highly **inefficient**.

Thank You!

Conclusion

- Social learning in a
  - **rational** setting,
  - on **general** networks,
  - with **forward-looking**/strategic agents
  - who interact **repeatedly**.
- **speed of learning**:
  - Measure of efficiency of information aggregation.
  - Asymptotic.
  - Tractable.
- Main result: The speed of learning is **bounded above** by a constant, which depends only on the private signal structure.
- Aggregation is highly **inefficient**.

Thank You!

Conclusion

- Social learning in a
  - **rational** setting,
  - on **general** networks,
  - with **forward-looking**/strategic agents
  - who interact **repeatedly**.
- **speed of learning**:
  - Measure of efficiency of information aggregation.
  - Asymptotic.
  - Tractable.
- Main result: The speed of learning is **bounded above** by a constant, which depends only on the private signal structure.
- Aggregation is highly **inefficient**.

Thank You!

Conclusion

- Social learning in a
  - **rational** setting,
  - on **general** networks,
  - with **forward-looking**/strategic agents
  - who interact **repeatedly**.
- **speed of learning**:
  - Measure of efficiency of information aggregation.
  - Asymptotic.
  - Tractable.
- Main result: The speed of learning is **bounded above** by a constant, which depends only on the private signal structure.
- Aggregation is highly **inefficient**.

Thank You!

Conclusion

- Social learning in a
  - **rational** setting,
  - on **general** networks,
  - with **forward-looking**/strategic agents
  - who interact **repeatedly**.
- **speed of learning**:
  - Measure of efficiency of information aggregation.
  - Asymptotic.
  - Tractable.
- Main result: The speed of learning is **bounded above** by a constant, which depends only on the private signal structure.
- Aggregation is highly **inefficient**.

Thank You!

Conclusion

- Social learning in a
  - **rational** setting,
  - on **general** networks,
  - with **forward-looking**/strategic agents
  - who interact **repeatedly**.
- **speed of learning**:
  - Measure of efficiency of information aggregation.
  - Asymptotic.
  - Tractable.
- Main result: The speed of learning is **bounded above** by a constant, which depends only on the private signal structure.
- Aggregation is highly **inefficient**.

Thank You!

Conclusion

- Social learning in a
  - **rational** setting,
  - on **general** networks,
  - with **forward-looking**/strategic agents
  - who interact **repeatedly**.
- **speed of learning**:
  - Measure of efficiency of information aggregation.
  - Asymptotic.
  - Tractable.
- Main result: The speed of learning is **bounded above** by a constant, which depends only on the private signal structure.
- Aggregation is highly **inefficient**.

Thank You!

Conclusion

- Social learning in a
    - **rational** setting,
    - on **general** networks,
    - with **forward-looking**/strategic agents
    - who interact **repeatedly**.
- **speed of learning**:
    - Measure of efficiency of information aggregation.
    - Asymptotic.
    - Tractable.
- Main result: The speed of learning is **bounded above** by a constant, which depends only on the private signal structure.
- Aggregation is highly **inefficient**.

Thank You!

Conclusion

- Social learning in a
  - **rational** setting,
  - on **general** networks,
  - with **forward-looking**/strategic agents
  - who interact **repeatedly**.
- **speed of learning**:
  - Measure of efficiency of information aggregation.
  - Asymptotic.
  - Tractable.
- Main result: The speed of learning is **bounded above** by a constant, which depends only on the private signal structure.
- Aggregation is highly **inefficient**.

Thank You!

Conclusion

- Social learning in a
  - **rational** setting,
  - on **general** networks,
  - with **forward-looking**/strategic agents
  - who interact **repeatedly**.
- **speed of learning**:
  - Measure of efficiency of information aggregation.
  - Asymptotic.
  - Tractable.
- Main result: The speed of learning is **bounded above** by a constant, which depends only on the private signal structure.
- Aggregation is highly **inefficient**.

Thank You!

Conclusion

- Social learning in a
  - **rational** setting,
  - on **general** networks,
  - with **forward-looking**/strategic agents
  - who interact **repeatedly**.
- **speed of learning**:
  - Measure of efficiency of information aggregation.
  - Asymptotic.
  - Tractable.
- Main result: The speed of learning is **bounded above** by a constant, which depends only on the private signal structure.
- Aggregation is highly **inefficient**.

Thank You!