Sensing And Decision Making In Social Networks

Vikram Krishnamurthy
Cornell University
Electrical & Computer Engineering

from a statistical signal processing/stochastic control viewpoint
SOCIAL (HUMAN) SENSORS

- Social sensor: Provides information about environment to a social network after interaction with other agents.
- Examples: Twitter posts, Facebook status updates, ratings on online reputation systems (Yelp, TripAdvisor)
Social (Human) Sensors

- Social sensor: Provides information about environment to a social network after interaction with other agents.
- Examples: Twitter posts, Facebook status updates, ratings on online reputation systems (Yelp, Tripadvisor)

1. Social Sensors influence each other over a network
2. Social Sensors have dynamics: learn from past decisions and decisions of others
3. Social Sensors reveal quantized decisions (privacy) and are ordinal.
4. Social sensors go beyond physical sensors.

Sensor-Adaptive Signal Processing

Statistical signal processing: Extract signal from noise

Sensor-Adaptive Signal Processing: Dynamically manage sensor resources.

Feedback (Stochastic Control)
**Part 1.** How do agents learn from observations and actions of other agents? 
*Social Learning:* Herds and Data incest occur.

**Part 2.** How does information propagate in a large scale social network? Mean Field Dynamics of sensing over a random graph.
**Part 1.** How do agents learn from observations and actions of other agents? 
*Social Learning*: Herds and Data incest occur.

**Part 2.** How does information propagate in a large scale social network? Mean Field Dynamics of sensing over a random graph.

**Unifying Theme:** Interaction of dynamical sensors 
Interaction of local and global decision makers. 
Non-standard information patterns.
Learning from the Behavior of Others: Conformity, Fads, and Informational Cascades

Sushil Bikhchandani, David Hirshleifer and Ivo Welch

*The Journal of Economic Perspectives*

Vol. 12, No. 3 (Summer, 1998), pp. 151-170

**OUTLINE for Part 1**

- Bayesian model for Social Learning
- Global Sensing with Social Learning
- Data Incest in Social Learning

**psychology, economics, sociology (groupthink), computer science, signal processing**
1.1 Global Sensing with Social Learning

The social sensor

**Examples:**
- sentiment sensing in microblogs
- High Frequency Trading [Quant Finance]
The social sensor

Examples:
- sentiment sensing in microblogs
- High Frequency Trading [Quant Finance]

Some perspective on “vanilla” social learning ...
Agents $k = 1, 2, \ldots$ act sequentially to estimate $x \in \{1, 2, \ldots, X\}$.

**Social Learning**: Given prior $\pi_k = P(x|a_1, \ldots, a_k)$ and observation $y_{k+1}$ from a finite set

- Agent $k + 1$: picks local action $a_{k+1} = f(y_{k+1}, \pi_k)$
  
  $a_{k+1} = \arg\min_{a \in A} \mathbb{E}\{c(x, a)|a_1, \ldots, a_k, y_{k+1}\}$

- Broadcast local action (ordinal decision)

- Other agents update public belief
  
  $\pi_{k+1} = P(x|a_1, \ldots, a_{k+1}) \propto \sum_y P(a_{k+1}|y, \pi_k)P(y|x)\pi_k$
1.1 Global Sensing with Social Learning

The social sensor

Examples:
- sentiment sensing in microblogs
- High Frequency Trading [Quant Finance]

Agents $k = 1, 2, \ldots$ act sequentially to estimate $x \in \{1, 2, \ldots, X\}$.  

Social Learning: Given prior $\pi_k = P(x|a_1, \ldots, a_k)$ and observation $y_{k+1}$ from a finite set

- Agent $k + 1$: picks local action $a_{k+1} = f(y_{k+1}, \pi_k)$  
  $a_{k+1} = \arg\min_{a \in A} \mathbb{E}\{c(x, a)|a_1, \ldots, a_k, y_{k+1}\}$

- Broadcast local action (ordinal decision)

- Other agents update public belief  
  $\pi_{k+1} = P(x|a_1, \ldots, a_{k+1}) \propto \sum_y P(a_{k+1}|y, \pi_k)P(y|x)\pi_k$
A. The Multi-agent Social Learning Model

**Social Learning:** Given prior $\pi_k = P(x|a_1, \ldots, a_k)$ and observation $y_{k+1}$ from a finite set

- Agent $k + 1$: picks local action $a_{k+1} = f(y_{k+1}, \pi_k)$
  $a_{k+1} = \arg\min_{a \in A} \mathbb{E}\{c(x, a)|a_1, \ldots, a_k, y_{k+1}\}$
- Broadcast local action (ordinal decision)
- Other agents update public belief
  $\pi_{k+1} = P(x|a_1, \ldots, a_{k+1}) \propto \sum_y P(a_{k+1}|y, \pi_k) P(y|x) \pi_k$

**Theorem:** [Bikhchandani, J. Political Economy, 1992; Cover & Hellman, 1970]. Agents eventually choose same action (information cascade, herd).
Social learning stops w.p.1 for finite $k$.

Acemoglu & Ozdaglar [2010,...]: General communication graphs.
Agents \( k = 1, 2, \ldots \) act sequentially to estimate \( x \in \{1, 2, \ldots, X\} \).

**Social Learning:** Given prior \( \pi_k = P(x|a_1, \ldots, a_k) \) and observation \( y_{k+1} \) from a finite set

- Agent \( k + 1 \): picks local action \( a_{k+1} = f(y_{k+1}, \pi_k) \)
  \( a_{k+1} = \arg\min_{a \in A} \mathbb{E}\{c(x, a)|a_1, \ldots, a_k, y_{k+1}\} \)
- Broadcast local action (ordinal decision)
- Other agents update public belief
  \( \pi_{k+1} = P(x|a_1, \ldots, a_{k+1}) \propto \sum_y P(a_{k+1}|y, \pi_k) P(y|x) \pi_k \)

**Examples:**
- sentiment sensing in microblogs
- High Frequency Trading [Quant Finance]

-When I see others taking umbrellas, I take an umbrella without checking the weather forecast. I assume their private info is accurate. [Rational Herds]

**The social sensor**

- state \( x_k \)
1.1 Global Sensing with Social Learning

Agents $k = 1, 2, \ldots$ act sequentially to estimate $x \in \{1, 2, \ldots, X\}$.

**Social Learning:** Given prior $\pi_k = P(x|a_1, \ldots, a_k)$ and observation $y_{k+1}$ from a finite set

- Agent $k + 1$: picks local action $a_{k+1} = f(y_{k+1}, \pi_k)$
  $a_{k+1} = \arg\min_{a \in A} \mathbb{E}\{c(x, a)|a_1, \ldots, a_k, y_{k+1}\}$

- Broadcast local action (ordinal decision)

- Other agents update public belief
  $\pi_{k+1} = P(x|a_1, \ldots, a_{k+1}) \propto \sum_y P(a_{k+1}|y, \pi_k)P(y|x)\pi_k$

The social sensor

**Examples:**
- sentiment sensing in microblogs
- High Frequency Trading [Quant Finance]

In 1995, management gurus Treacy & Wiersema secretly bought 50,000 copies of their own book. Made NY times best seller list. How to cope with malicious agents?
Social learning results in herding.

Q1. How do Local and Global Agents Interact in decision making?

Q2. How to optimize Social Learning to delay herding?

Q3. How to price a product?
Q1. How do local & global decision makers interact?

Example: Multiagent Quickest Change Detection
Example: Multiagent Quickest Change Detection

Observations $y_k \sim \begin{cases} B_1(\cdot) & k \leq \tau^0 \\ B_2(\cdot) & k > \tau^0 \end{cases}$, where $\tau^0 =$ change time (usually geometric)

**Aim:** Compute time $\tau$ to announce change: Minimize $\mathbb{E}_{\pi_0}^{\mu} \{ d|\tau - \tau^0|^+ + f \, I(\tau < \tau^0) \}$

**Classical:** Given posterior $\pi_k = P(\text{change}|y_1, \ldots, y_k)$: 
Optimal decision policy is threshold. [Shiryaev 1950s].
Example: Multiagent Quickest Change Detection

Observations $y_k \sim \begin{cases} B_1(\cdot) & k \leq \tau^0 \\ B_2(\cdot) & k > \tau^0 \end{cases}$, where $\tau^0 = \text{change time} \ (\text{usually geometric})$

**Aim:** Compute time $\tau$ to announce change: Minimize $\mathbb{E}_{\pi_0}^\mu \{d|\tau - \tau^0|^+ + f I(\tau < \tau^0)\}$

**Classical:** Given posterior $\pi_k = P(\text{change}|y_1, \ldots, y_k)$: Optimal decision policy is threshold. [Shiriyaev 1950s].

**Social Learning:** Public belief $\pi_{k-1} = P(\text{change}|a_1, \ldots, a_{k-1})$.

- Agent $k$: Observes $y_k \sim P(y|x)$
- Broadcasts action $a_k = \arg \min_a \mathbb{E}\{c(\text{state}, a)|a_1, \ldots, a_{k-1}, y_k\}$.
- Other agents update public belief (social learning filter)

$$\pi_k = P(\text{change}|a_1, \ldots, a_k) \propto \sum P(a_k|y, \pi_{k-1})P(y|x) \times \text{(social learning filter)}$$

---

**Diagram:**

- **Global decision policy**
  - Declare change
  - No change

- **Posterior probability of change**
  - Declare change
  - No change

---
Define Bayesian Quickest-Time Change Detection likelihood ratio dominance, then Lattice programming Stochastic dynamic programming to compute Bayesian Quickest-Time Change Detection m = ldimertmonomerp antirbodymttragventm.

Agent T Update public belief Agent a

\[ | \{z\} = \arg \max_\pi \pi_k | \{z\} \] where m and \( \pi \) increasing in l

\[ \text{Minimize } \mathbb{E}_{\pi_0} \{ |\tau - \tau^0 + f I(\tau < \tau^0) \} \]

Classical: Given posterior \( \pi_k = P(\text{change}|y_1, \ldots, y_k) \). Optimal decision policy is threshold. [Shiryaev 1950s].

Social Learning: Public belief \( \pi_{k-1} = P(\text{change}|a_1, \ldots, a_{k-1}) \).

- Agent k: Observes \( y_k \sim P(y|x) \)
- Broadcasts action \( a_k = \arg \min_a \mathbb{E}\{c(\text{state}, a)|a_1, \ldots, a_{k-1}, y_k\} \).
- Other agents update public belief (social learning filter)

\[ \pi_k = P(\text{change}|a_1, \ldots, a_k) \propto \sum P(a_k|y, \pi_{k-1})P(y|x) \times (\)\]

When should global decision-maker declare change?

\[ \text{multi-threshold} \]

posterior probability of change

\[ \text{global decision policy} \]

\[ \text{no change} \]

\[ \text{declare change} \]
Example: Multiagent Quickest Change Detection

Observations $y_k \sim \begin{cases} B_1(\cdot) & k \leq \tau^0 \\ B_2(\cdot) & k > \tau^0 \end{cases}$, where $\tau^0 = \text{change time (usually geometric)}$

Aim: Compute time $\tau$ to announce change: Minimize $\mathbb{E}_{\pi_0}^{\mu} \left\{ d|\tau - \tau^0|^+ + f \ I(\tau < \tau^0) \right\}$

Classical: Given posterior $\pi_k = P(\text{change}|y_1, \ldots, y_k)$: Optimal decision policy is threshold. [Shiryaev 1950s].

Social Learning: Public belief $\pi_{k-1} = P(\text{change}|a_1, \ldots, a_{k-1})$.

- Agent $k$: Observes $y_k \sim P(y|x)$
- Broadcasts action $a_k = \arg\min_a \mathbb{E}\{c(\text{state, a})|a_1, \ldots, a_{k-1}, y_k\}$.
- Other agents update public belief (social learning filter)
  $$\pi_k = P(\text{change}|a_1, \ldots, a_k) \propto \sum P(a_k|y, \pi_{k-1}) P(y|x) \times (\cdot)$$

When should global decision-maker declare change? Stopping set is non-convex

---

Q1. How do local & global decision makers interact?

---

Multi-threshold decision policy

---

Social Learning

---

Bayesian Quickest-Time Change Detection
Example: Multiagent Quickest Change Detection

Observations $y_k \sim \begin{cases} B_1(\cdot) & k \leq \tau^0 \\ B_2(\cdot) & k > \tau^0 \end{cases}$, where $\tau^0 =$ change time (usually geometric)

**Aim:** Compute time $\tau$ to announce change: Minimize $\mathbb{E}_\pi^\mu \{d|\tau - \tau^0| + f I(\tau < \tau^0)\}$

**Classical:** Given posterior $\pi_k = P(\text{change}|y_1, \ldots, y_k)$: Optimal decision policy is threshold. [Shiryaev 1950s].

**Social Learning:** Public belief $\pi_{k-1} = P(\text{change}|a_1, \ldots, a_{k-1})$.

- Agent $k$: Observes $y_k \sim P(y|x)$
- Broadcasts action $a_k = \arg\min_a \mathbb{E}\{c(\text{state, } a)|a_1, \ldots, a_{k-1}, y_k\}$.
- Other agents update public belief (social learning filter)

$$\pi_k = P(\text{change}|a_1, \ldots, a_k) \propto \sum P(a_k|y, \pi_{k-1})P(y|x) \times \pi_k$$

When should global decision-maker declare change?

**Summary:** Global Decision making using local decisions is non-monotone!
Q2: How to optimize Social Learning?

Social Learning: Choose local decision greedily: $a_k = \min_a \mathbb{E}_{\pi_{k-1}, y_k} \{c(x, a)\}$. Results in herding. Posterior $\pi_k = P(x|a_1, \ldots, a_k)$ freezes.
Q2: How to optimize Social Learning?

Social Learning: Choose local decision greedily: 
\[ a_k = \min_a \mathbb{E}_{\pi_{k-1}, y_k} \{ c(x, a) \} \].
Results in herding. Posterior \( \pi_k = P(x|a_1, \ldots, a_k) \) freezes.

Socialistic Learning: [More Sophisticated Protocol] To estimate \( x \sim \pi_0 \)

\[ I \text{ choose my local decision to sacrifice my local utility so that my action provides useful information to subsequent agents} \]
Benevolent agents choose local decision by minimizing social welfare cost:
Q2: How to optimize social learning?

Social Learning: Choose local decision greedily: $a_k = \min_a \mathbb{E}_{\pi_{k-1}, y_k} \{c(x, a)\}$. Results in herding. Posterior $\pi_k = P(x|a_1, \ldots, a_k)$ freezes.

Socialistic Learning: [More Sophisticated Protocol] To estimate $x \sim \pi_0$

I choose my local decision to sacrifice my local utility so that my action provides useful information to subsequent agents

Benevolent agents choose local decision by minimizing social welfare cost:

$$a_k = \mu^*(\pi_{k-1}, y_k) \in \{y_k(\text{reveal}), a_{k-1}(\text{herd})\}, \quad \mu^* = \arg\min_{\mu} \mathbb{E}_{\pi_0}^{\mu} \left\{ \sum_{k=1}^{N} c(x, a_k) \right\}$$

global decision
Q2: How to optimize Social Learning?

Social Learning: Choose local decision greedily: $a_k = \min_a \mathbb{E}_{\pi_k, y_k} \{ c(x, a) \}$. Results in herding. Posterior $\pi_k = P(x|a_1, \ldots, a_k)$ freezes.

Socialistic Learning: [More Sophisticated Protocol] To estimate $x \sim \pi_0$

*I choose my local decision to sacrifice my local utility so that my action provides useful information to subsequent agents*

Benevolent agents choose local decision by minimizing social welfare cost:

$$a_k = \mu^*(\pi_{k-1}, y_k) \in \{ y_k(\text{reveal}), a_{k-1}(\text{herd}) \}, \quad \mu^* = \arg \min_{\mu} \mathbb{E}_\pi^{\mu} \{ \sum_{k=1}^N c(x, a_k) \}$$

Partially Observed Stochastic Control Problem.
**Q2: How to Optimize Social Learning?**

**Social Learning:** Choose local decision greedily: $a_k = \min_a E_{\pi_{k-1}, y_k} \{c(x, a)\}$. Results in herding. Posterior $\pi_k = P(x|a_1, \ldots, a_k)$ freezes.

**Socialistic Learning:** [More Sophisticated Protocol] To estimate $x \sim \pi_0$

I choose my local decision to sacrifice my local utility so that my action provides useful information to subsequent agents.

Benevolent agents choose local decision by minimizing social welfare cost:

$$a_k = \mu^*(\pi_{k-1}, y_k) \in \{y_k(\text{reveal}), a_{k-1}(\text{herd})\}, \quad \mu^* = \arg \min_{\mu} E_{\pi_0} \{ \sum_{k=1}^N c(x, a_k) \}$$

**Can show:** [IEEE Trans. Info. Theory, 2011]

- Under supermodular assumptions global decision policy is threshold.

- Global decision policy: Initially socialistic then capitalistic.

- Privacy vs Reputation
Q3: Which Price is High or Low?
Q3: Price High or Low?

Each Sale to a customer
- Brings in money
- Customers perform social learning on the product

How should the product price be chosen over time?
Q3: Price High or Low?

Each Sale to a customer
- Brings in money
- Customers perform social learning on the product

**How should the product price be chosen over time?**

**Optimal Pricing for Monopolist.**

Choose price $u_k = \mu(\pi_{k-1})$

Monopolist reward:

$$\text{Compute: } \sup_{\mu} J_\mu(\pi) = \mathbb{E}_{\pi}^{\mu} \left\{ \sum_{k=1}^{\infty} \rho^{k-1} I(a_k = \text{buy}) u_k \right\}$$

Agent:

$$y_k \sim p(\cdot|x), \ x \sim \pi_0.$$  
$$a_k = \arg\min_a c'_a, u_k, y_k \pi_{k-1}$$

Public belief:

$$\pi_k = T(\pi_{k-1}, a_k)$$
Q3: Price High or Low?

Each Sale to a customer
- Brings in money
- Customers perform social learning on the product

**How should the product price be chosen over time?**

**Optimal Pricing for Monopolist.**

Choose price \( u_k = \mu(\pi_{k-1}) \)

**Monopolist reward:**

Compute: 
\[
\sup_{\mu} J_{\mu}(\pi) = \mathbb{E}_{\pi} \left\{ \sum_{k=1}^{\infty} \rho^{k-1} I(a_k = \text{buy}) u_k \right\}
\]

**Agent:**
\[
y_k \sim p(\cdot | x), \ x \sim \pi_0. \quad a_k = \arg\min_a c'_{a,u_k,y_k,\pi_{k-1}}
\]

**Public belief:**
\[
\pi_k = T(\pi_{k-1}, a_k)
\]

``Optimal soln``: Price high initially; build elite customer base; then gradually decrease prices.
1. Data Incest + Herding in social learning over general graphs

Data incest results in overconfidence in estimate

• How to build unbiased reputation system?
• One-star increase in the Yelp rating maps to 5-9% revenue increase. [Harvard Business School, 2011]
1. Data Incest + Herding in social learning over general graphs

Data incest results in overconfidence in estimate
• How to build unbiased reputation system?
• One-star increase in the Yelp rating maps to 5-9 % revenue increase.[Harvard Business School, 2011]

2. Coherent Risk Measures instead of expected value.
1. Data Incest + Herding in social learning over general graphs

Data incest results in overconfidence in estimate

- **How to build unbiased reputation system?**
- One-star increase in the Yelp rating maps to 5-9% revenue increase.[Harvard Business School, 2011]

2. Coherent Risk Measures instead of expected value.

\[ a_k = \arg \min_a \mathbb{E}_{\pi_{k-1}, y_k} \{ c(x, a) \} \quad \text{and} \quad a_k = \arg \min \mathcal{R}_{\pi_{k-1}, a_k} \{ c(x, a) \} \]

**Example:**

\[ a_k = \arg \min_{a \in A} \{ \text{CVaR}_\alpha (c(x_k, a)) \} \quad (\text{Rockafellar & Uryasev, 2000}) \]

- **Decisions are ordinal in belief and observation**
- **Risk averse agents herd more frequently at cheaper costs and therefore compromise state estimate.**
1. Data Incest + Herding in social learning over general graphs

Borkar & Varaiya: 1982

Data incest results in overconfidence in estimate
- How to build unbiased reputation system?
- One-star increase in the Yelp rating maps to 5-9% revenue increase.[Harvard Business School, 2011]

2. Coherent Risk Measures instead of expected value.

3. Experimental Data: Collaboration with Department of Psychology UBC. In perceptual tasks, data incest patterns occurred 79% and caused individuals to modify actions 21% of the time.

4. Human Interpretation of Data: Should two security guards look at one TV monitor and then discuss suspicious behavior? (with data incest and herding)

5. In which order should a panel of experts be polled? [Ottaviani & Sorenson, 2001]
Extension: Panel of Experts

In which order to poll agents? If senior agents talk first, they unduly affect junior agents.

High reputation

Good reputation

No reputation

Low reputation
Extension: Panel of Experts

In which order to poll agents? If senior agents talk first, they unduly affect junior agents.

High reputation

Good reputation

Seniority Rule?

Low reputation

No reputation

Extension: Panel of Experts

In which order to poll agents? If senior agents talk first, they unduly affect junior agents.
Extension: Panel of Experts

Seniority Rule?
Extension: Panel of Experts

For 94% of problems, the group’s final answer was the first answer suggested, and people with dominant personalities tend to speak first and most forcefully...

Extension: Panel of Experts

For 94% of problems, the group’s final answer was the first answer suggested, and people with dominant personalities tend to speak first and most forcefully...

Ottaviani, Sorensen, 2001. Information Aggregation in Debate: Who should speak first?
Social learning can result in herding and information cascades. Individuals end up blindly imitating others. **Groupthink**

- Group behavior may not be wise.
- Crowds reduce diversity & are misleading

Data incest results in bias
**Datasets are non-informative.**

*Rational inattention models* (Sims): ability of the human to absorb information is modeled via the information theoretic capacity of a communication channel
Social learning can result in herding and information cascades. Individuals end up blindly imitating others. **Groupthink**

- Group behavior may not be wise.
- Crowds reduce diversity & are misleading

Data incest results in bias
**Datasets are non-informative.**

*Rational inattention models* (Sims): ability of the human to absorb information is modeled via the information theoretic capacity of a communication channel

In complex settings, herding can result in interesting behavior: **Nobody goes there anymore … it is always too crowded (Yogi Berra)**
PART 2: INFORMATION DIFFUSION IN SOCIAL NETWORKS

Let \( N \) be a finite but large set of nodes (or agents) in a network with which it maintains direct connections. Each agent \( i \) can exist in one of two discrete states: 1. Susceptible (S) or 2. Adopted (A). In this state, the agent has the potential to infect any of its direct neighbors. Equivalently, the degree distribution depends on various parameters. We assume that network structure is also complex and is described only by its group of neighbors one another via links can communicate with one another. More specifically, each node only interacts with its fixed degree distribution which is the fraction of agents with degree \( k \) in the network that have exactly \( k \) neighbors.

In such a network, the population is large and the pattern of interactions between agents is a complex process whose solution is outlined in the Sec. III. Theorems (Mean field dynamics): Maximum likelihood classifier for plan (intent). Remarks: Incest arises since agent can infect neighbour, become susceptible and get reinfected by neighbour.

In this section, the network structure is defined together with the diffusion mechanism. Furthermore, the mean-field approximation is also provided in the form of a discrete-time difference equation. Finally, the social sensing mechanism is described as a noisy measurement of the rate of adoption in the network. This sets up a filtering field approximation is also provided in the form of a discrete-time difference equation. Finally, the social sensing problem whose solution is outlined in the Sec. III.

Fig. 1. An illustration of the diffusion of technology adoption over a social network.
**PART 2: INFORMATION DIFFUSION IN SOCIAL NETWORKS**

**Why?**


53% of people on Twitter recommend companies/products in tweets; 48% delivering on their intention to buy the product. ROI Research for Performance, 2010.

*Consumer reviews are trusted nearly 12 times more than descriptions from manufacturers. eMarketer, 2010.*

*myYearbook: 81% of respondents recede advice from friends related to product purchase, 74% found advice to be influential in decision to buy. ClickZ, 2010.*
PART 2: INFORMATION DIFFUSION IN SOCIAL NETWORKS

OUTLINE for Part 2 (very brief)

- Mean Field Dynamics for Sentiment
- How to Sample Social Network?
How to build a tractable model for information flow in large scale social networks to estimate sentiment?
Information diffusion in random graph is asymptotically equivalent to ordinary differential (difference) equation. Estimating sentiment is a Bayesian filtering problem.

\[ \frac{d\rho(k)}{dt} = F(\rho(k), \rho(k^-), \theta_t), \quad \theta_t \sim Q \]

fraction of infected nodes of degree \( k \)

Measurement process:
\[ Y_t = \int_0^t \lambda(\theta_t) dt + w_t \]

Sampled infected agents

Markov state \( \theta_n \)

sentiment
Information diffusion in random graph is asymptotically equivalent to ordinary differential (difference) equation. Estimating sentiment is a Bayesian filtering problem.

\[ \frac{d\rho(k)}{dt} = F(\rho(k), \rho(k^-), \theta_t), \quad \theta_t \sim Q \]

Fraction of infected nodes of degree \( k \)

Measurement process: \( Y_t = \int_0^t \lambda(\theta_t)dt + w_t \)

Sampling network

estimator

Markov state \( \theta_n \)

Sampled infected agents

sentiment
Information diffusion in random graph is asymptotically equivalent to ordinary differential (difference) equation. Estimating sentiment is a Bayesian filtering problem.

\[ \frac{d\rho(k)}{dt} = F(\rho(k), \rho(k-), \theta_t), \quad \theta_t \sim Q \]

\[ Y_t = \int_0^t \lambda(\theta_t)dt + w_t \]

References:
- Benaim, Econometrica, 2003
- Sun, Modeling Contagion Through Facebook News Feed, AAAI Conf Social Media, 2009
- Sakaki, Earthquake shakes twitter users: Real time event detection using social sensors, 2010.
HOW TO SAMPLE SOCIAL NETWORK
• Intent Polling: who will you vote for?
• Expectation Polling: who do you think will win?

Intuitively: expectation polling is more accurate.
Expectation polling can be biased

• Intent Polling: who will you vote for?
• Expectation Polling: who do you think will win?

Intuitively: expectation polling is more accurate.

Expectation polling can have higher variance
Expectation polling can be biased

Expectation polling can have higher variance

weight samples inversely proportional to their degree - then unbiased
Expectation polling can be biased

Expectation polling can have higher variance

weight samples inversely proportional to their degree - then unbiased

• Intent Polling: who will you vote for?
• Expectation Polling: who do you think will win?
  Intuitively: expectation polling is more accurate.

• Mean number of friends are smaller than mean number of friend of friends (Feld 1991 - friendship paradox).
• Respondent Driven Sampling: snowball MCMC sampling method for marginalized populations in social networks.

US Centers for Disease Control and Prevention: HIV drug users.

This presentation is highly simplified and omits several important areas:
Dynamic Coherent Risk Measures
Homophily vs Contagion
Dynamics of viral marketing:
Revealed Preferences: Are humans utility maximizers?
**SUMMARY**


This presentation is highly simplified and omits several important areas:

- **Dynamic Coherent Risk Measures**
- **Homophily vs Contagion**
- **Dynamics of viral marketing:**
- **Revealed Preferences:** Are humans utility maximizers?

Part 2. Diffusion in Large Scale Networks. Mean field dynamics: infected degree distribution satisfies differential equation
Sampling: Expectation Polling, Respondent Driven Sampling

This presentation is highly simplified and omits several important areas:
Dynamic Coherent Risk Measures
Homophily vs Contagion
Dynamics of viral marketing:
Revealed Preferences: Are humans utility maximizers?
This talk

- Krishnamurthy and Hoiles, Social Learning, Data Incest and Revealed Preferences, *IEEE Journal Computational Social Systems*, 2015
- Krishnamurthy, Quickest Detection POMDPs with Social Learning, *IEEE Trans Information Theory*, 2012
This talk

- Krishnamurthy and Hoiles, Social Learning, Data Incest and Revealed Preferences, *IEEE Journal Computational Social Systems*, 2015
- Krishnamurthy, Quickest Detection POMDPs with Social Learning, *IEEE Trans Information Theory*, 2012