Sensing And Decision Making In Social Networks

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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)

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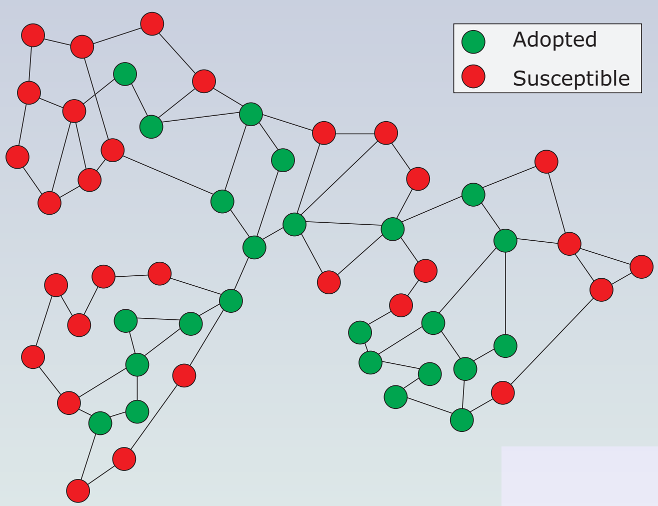
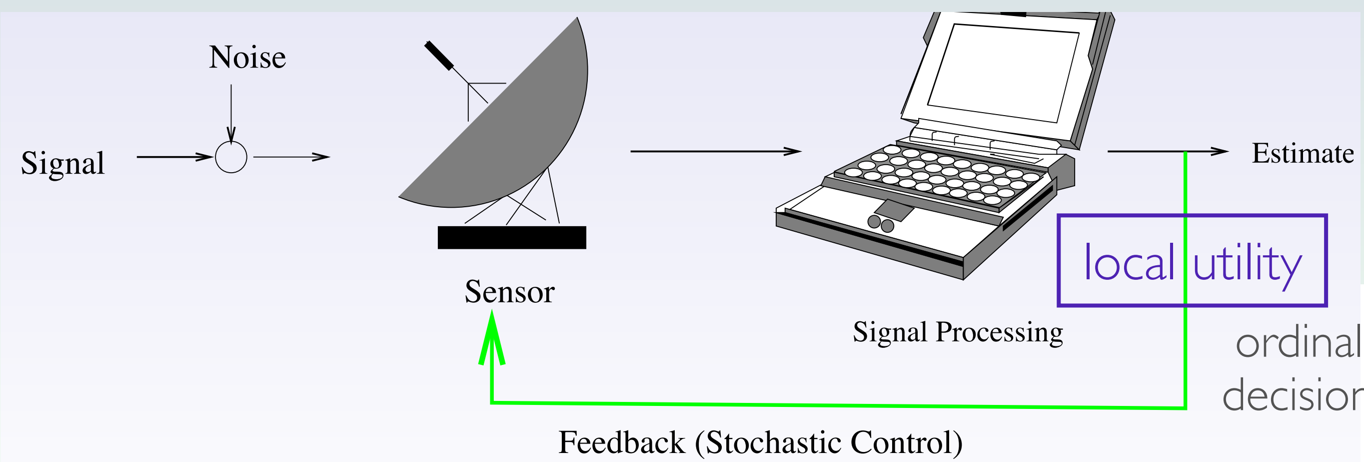
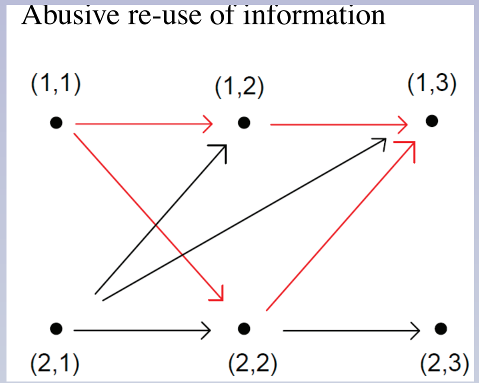


1. Social Sensors influence each other over a network
2. Social Sensors have dynamics: learn from past decisions and decisions of others
3. Social Sensors reveal quantized decisions (privacy) and are ordinal.
4. Social sensors go beyond physical sensors.

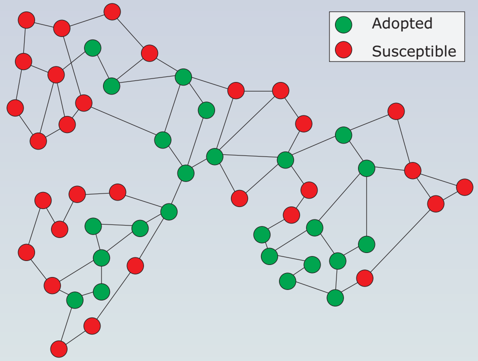


Outline

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.



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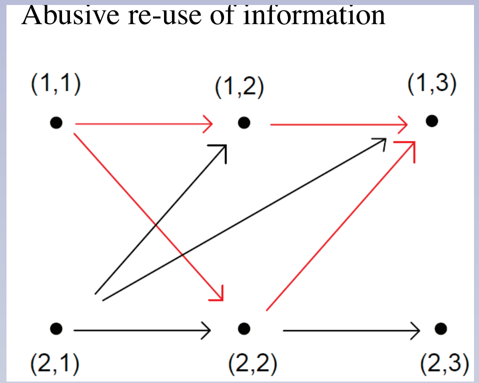

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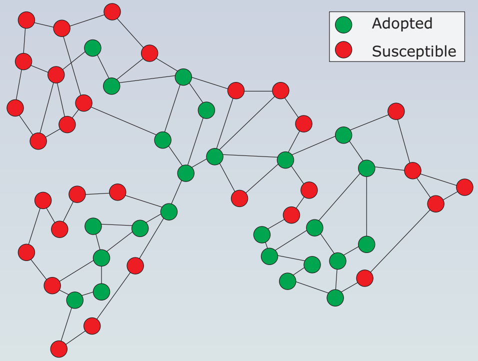

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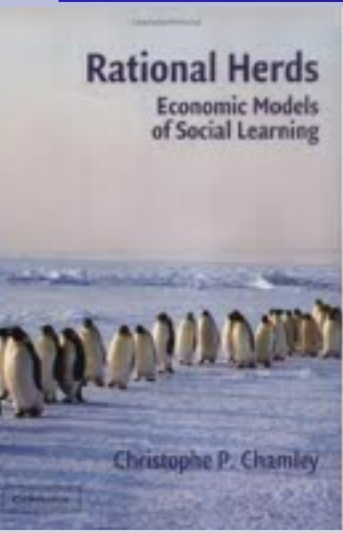
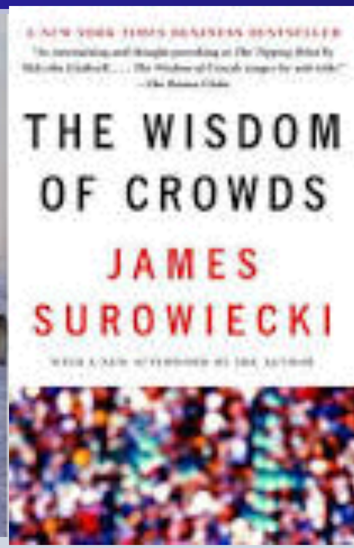
Unifying Theme: Interaction of dynamical sensors
Interaction of local and global decision makers.
Non-standard information patterns.

PART 1: SOCIAL LEARNING FOR SENSING





Learning from the Behavior of Others: Conformity, Fads, and Informational Cascades

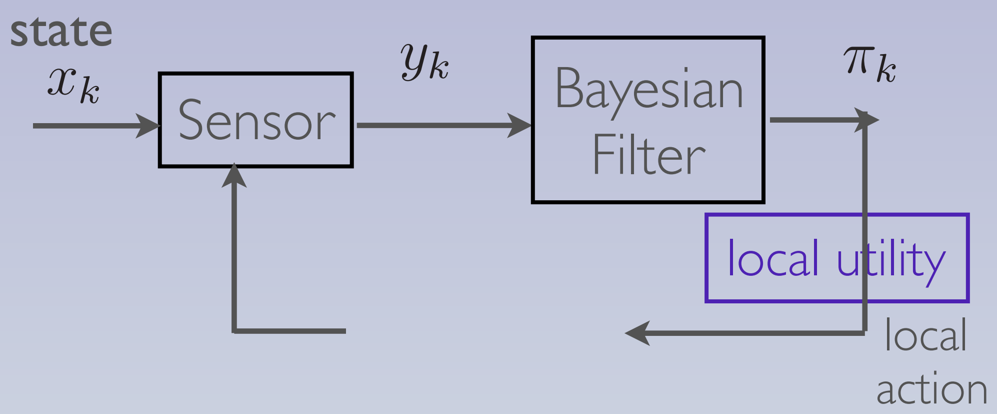
Sushil Bikhchandani, David Hirshleifer and Ivo Welch
The Journal of Economic Perspectives
Vol. 12, No. 3 (Summer, 1998), pp. 151-170

psychology, economics, sociology (groupthink), computer science, signal processing

OUTLINE for Part I

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

1.1 GLOBAL SENSING WITH SOCIAL LEARNING



The social sensor

Examples:

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

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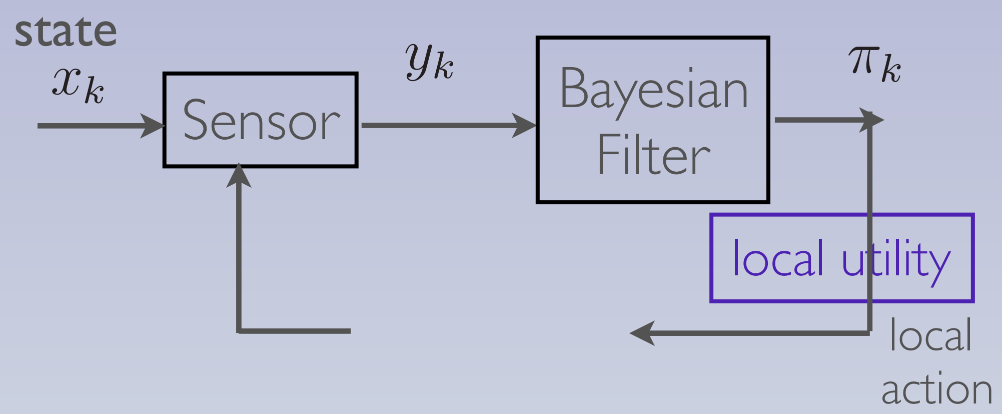

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Some perspective on "vanilla" social learning ...

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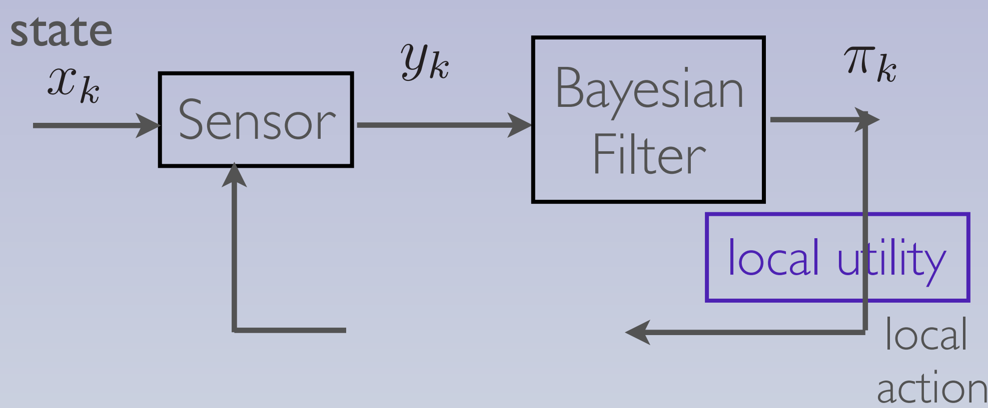

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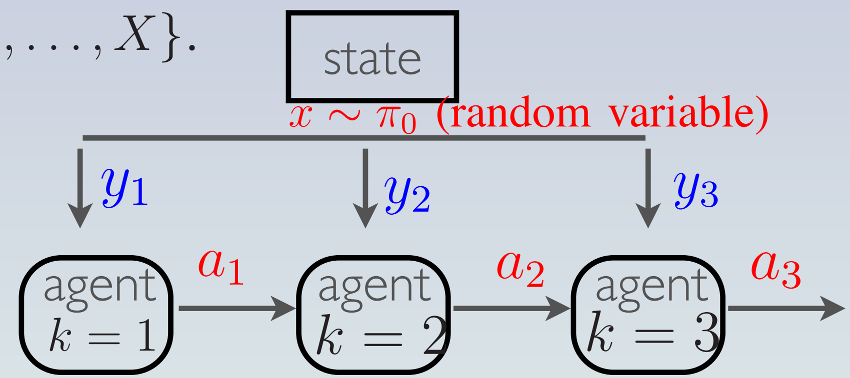

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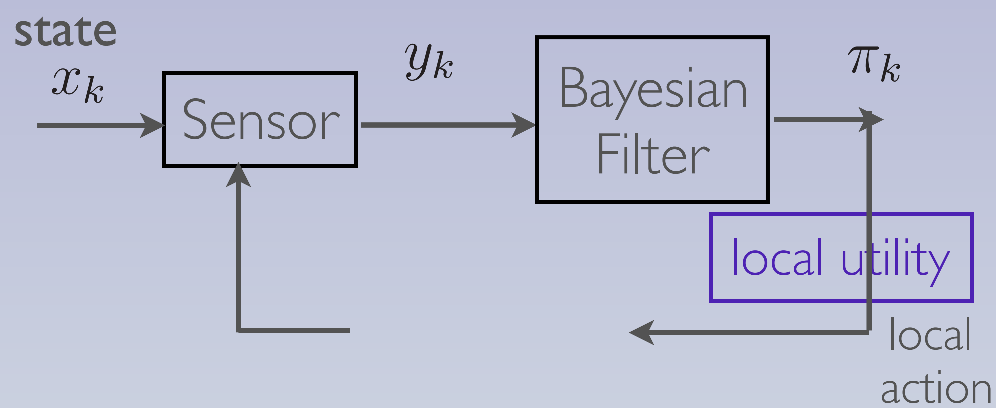

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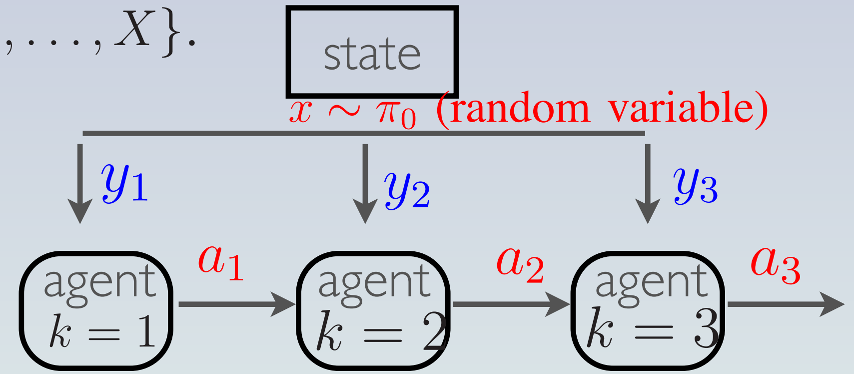

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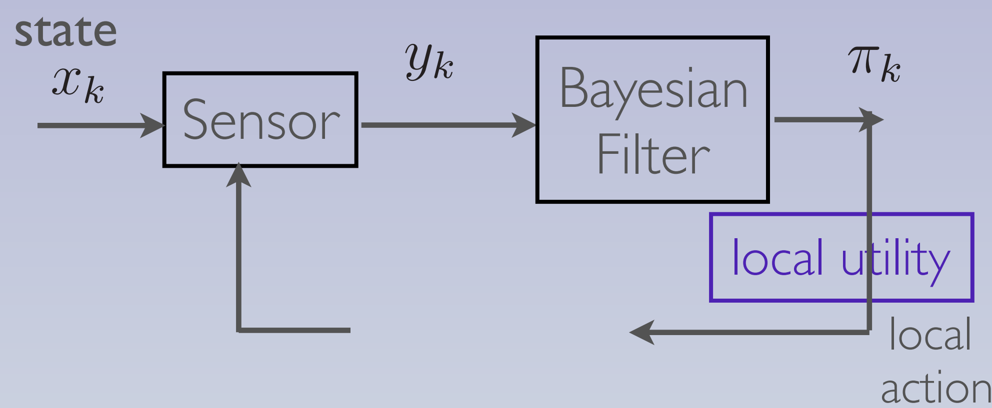

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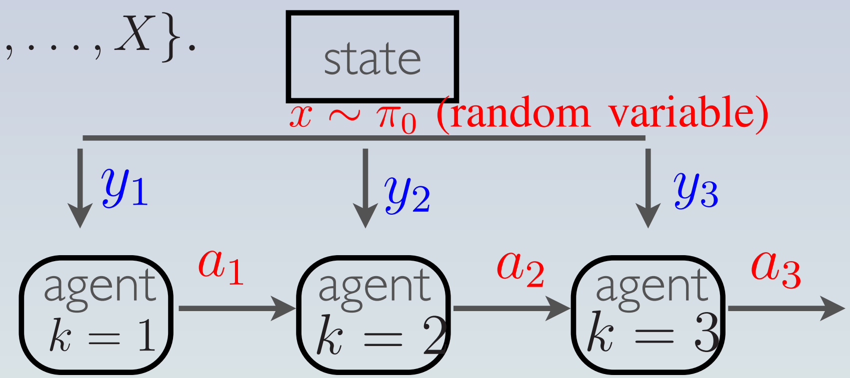

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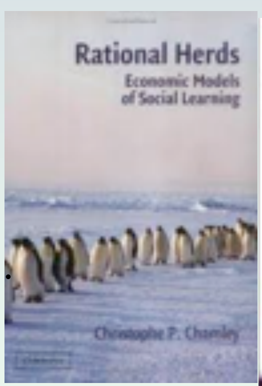
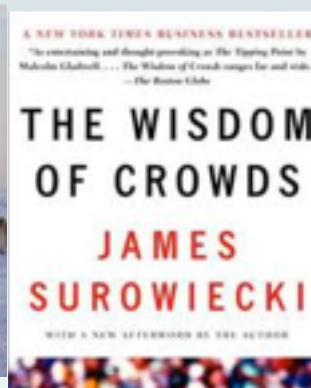
Theorem: [Bhikchandani, J. Political Economy, 1992; Cover & Hellman, 1970].
Agents eventually choose same action (information cascade, herd).
Social learning stops w.p.1 for finite k.





Acemoglu & Ozdaglar [2010,...]: General communication graphs.

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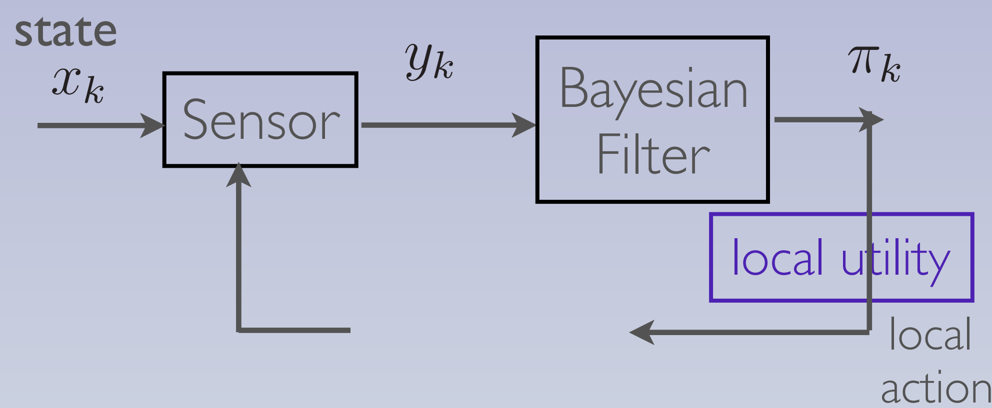

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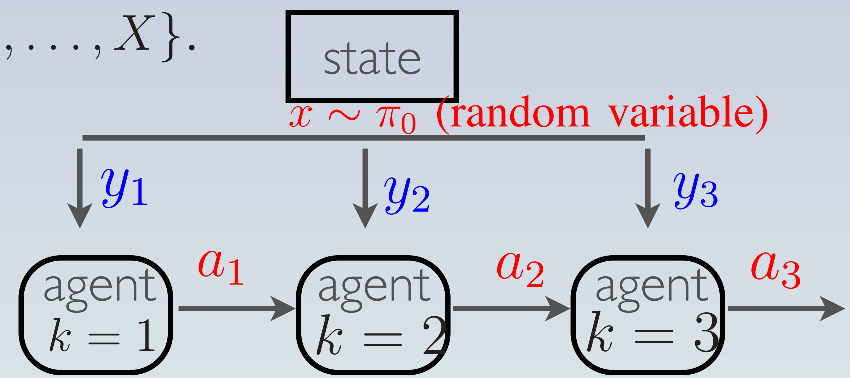

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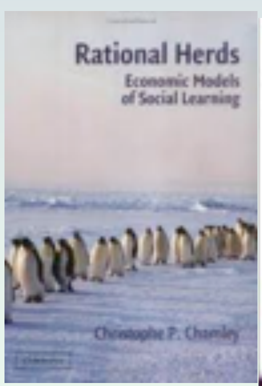

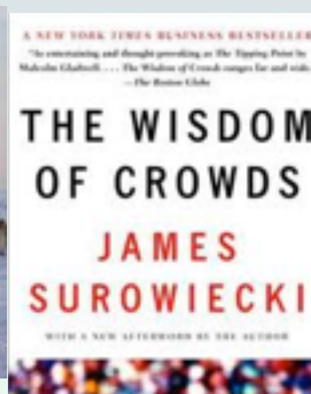

- When I see others taking umbrellas, I take an umbrella without checking the weather forecast. I assume their private info is accurate. *. Rational Herds*

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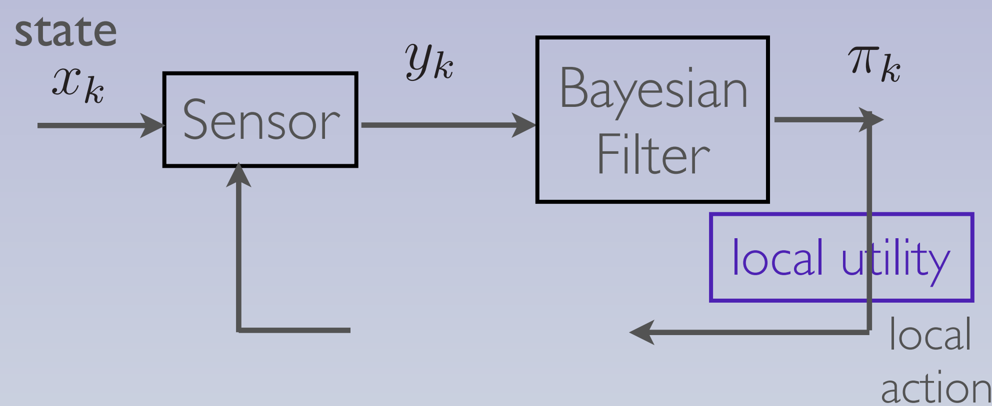

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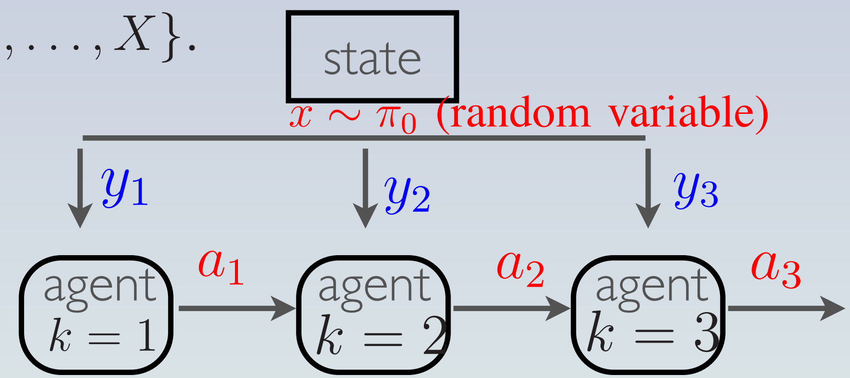

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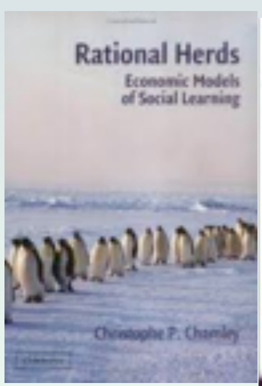
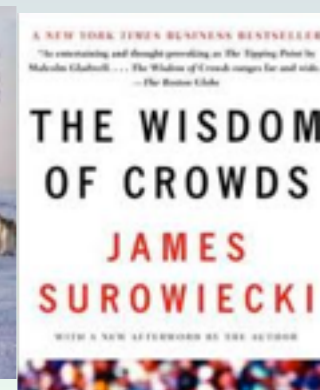




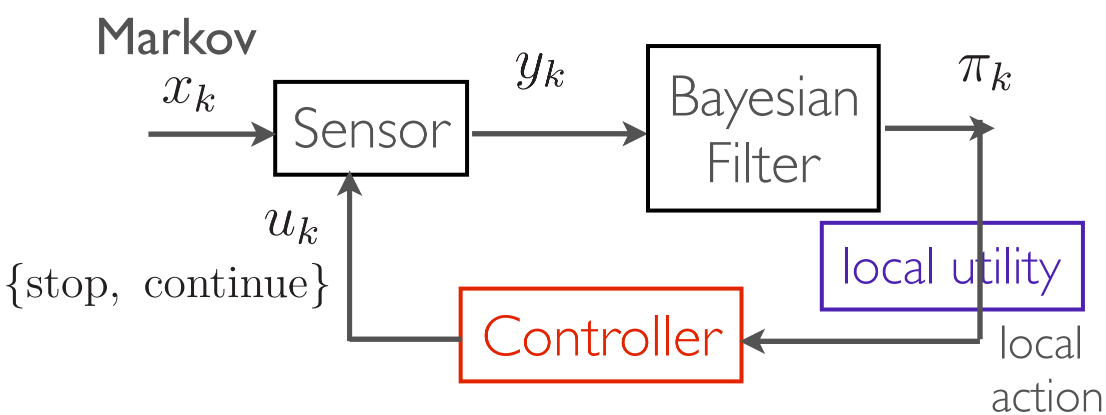
In 1995, management gurus Treacy & Wiersema secretly bought 50,000 copies of their own book. Made NY times best seller list. How to cope with malicious agents?

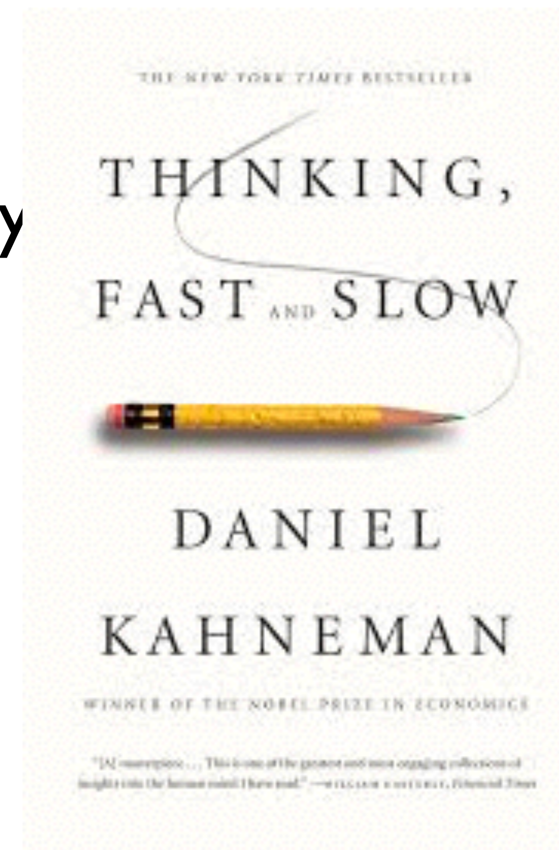
Social learning results in herding.

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?





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Example: Multiagent Quickest Change Detection

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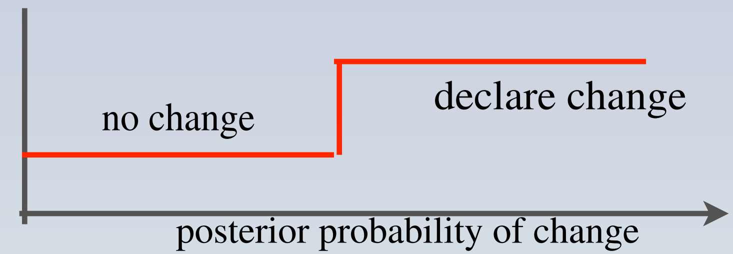
Classical: Given posterior $\pi_k = P(\text{change}|y_1, \ldots, y_k)$: Optimal decision policy is threshold. [Shiriyaev 1950s].



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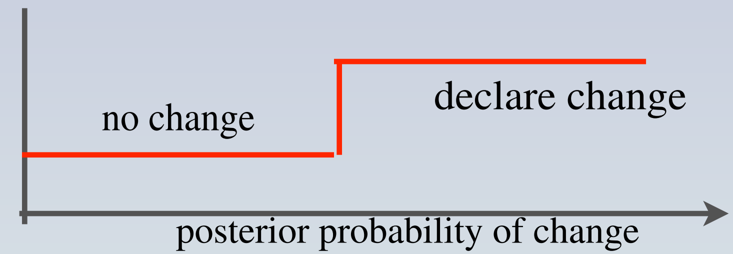

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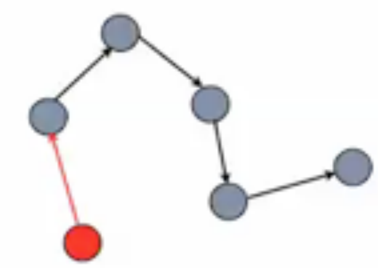
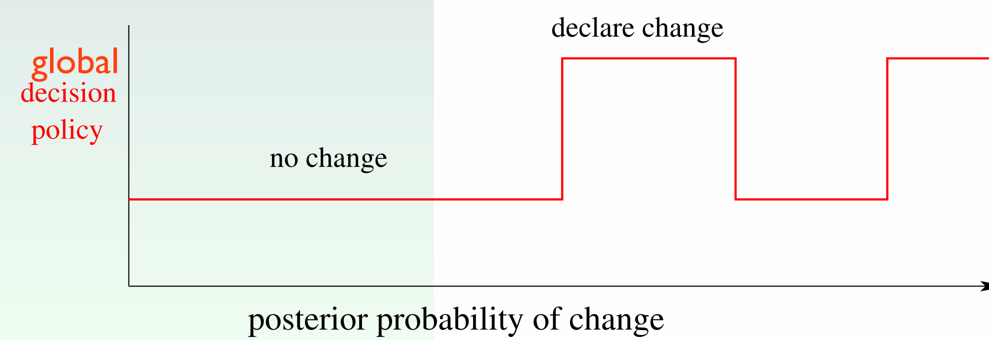
update





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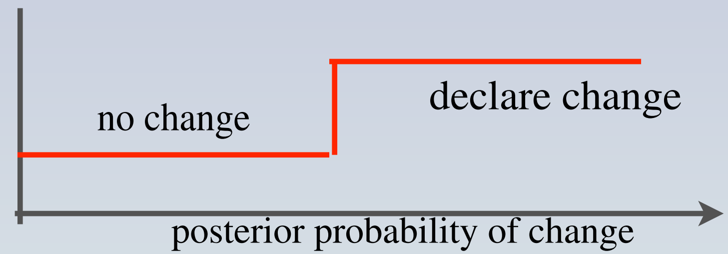

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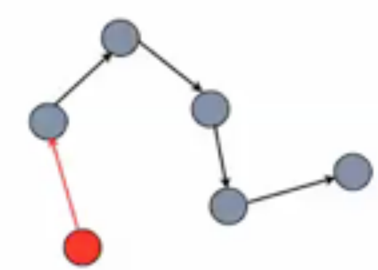
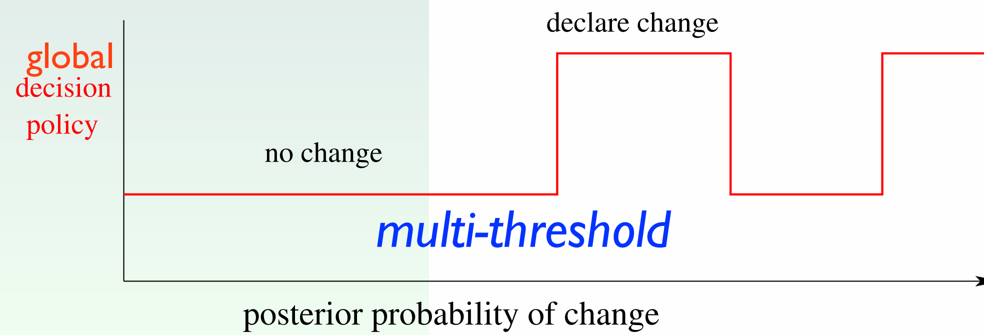


When should global decision-maker declare change?



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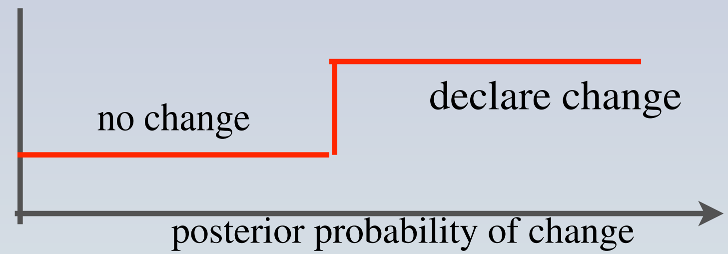

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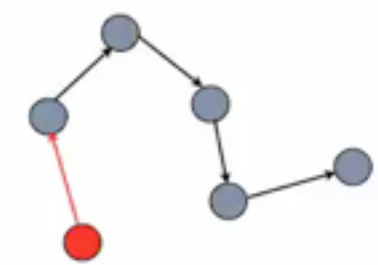

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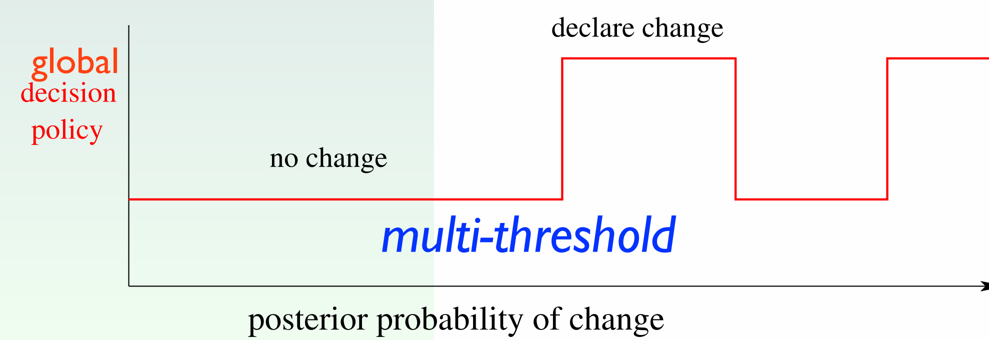
.Stopping set is non-convex



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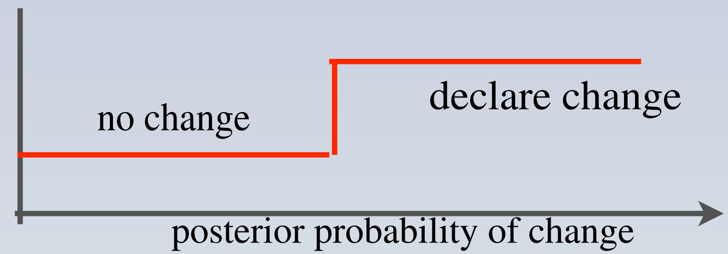

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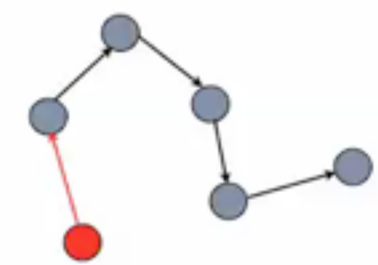
predictor update



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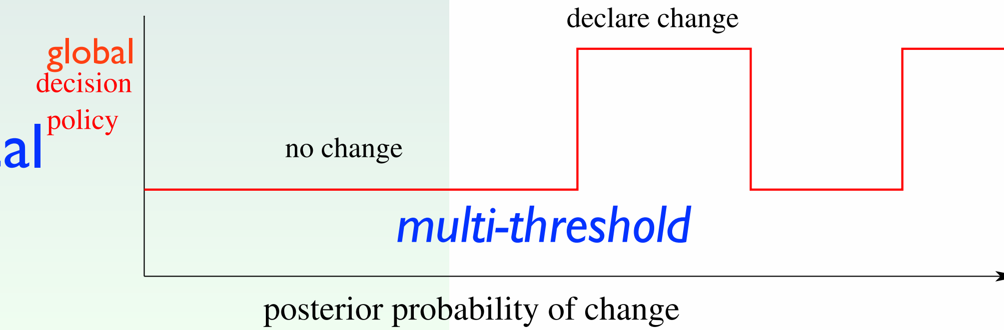

Summary: Global Decision making using local decisions is non-monotone!

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.

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

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

Benevolent agents choose local decision by minimizing *social welfare* cost:

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Partially Observed Stochastic Control Problem.

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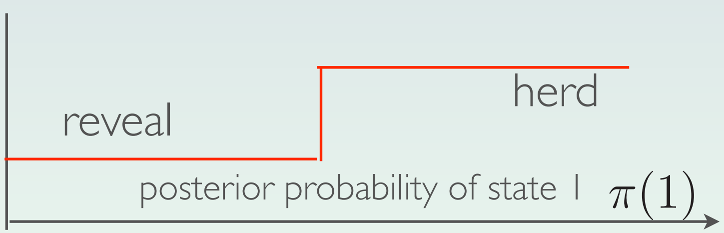
Can show: [IEEE Trans. Info. Theory, 2011]

- Under supermodular assumptions global decision policy is threshold.



- Global decision policy: Initially socialistic then capitalistic.
- Privacy vs Reputation

Q3: □ Price □ High □ Or □ Low?

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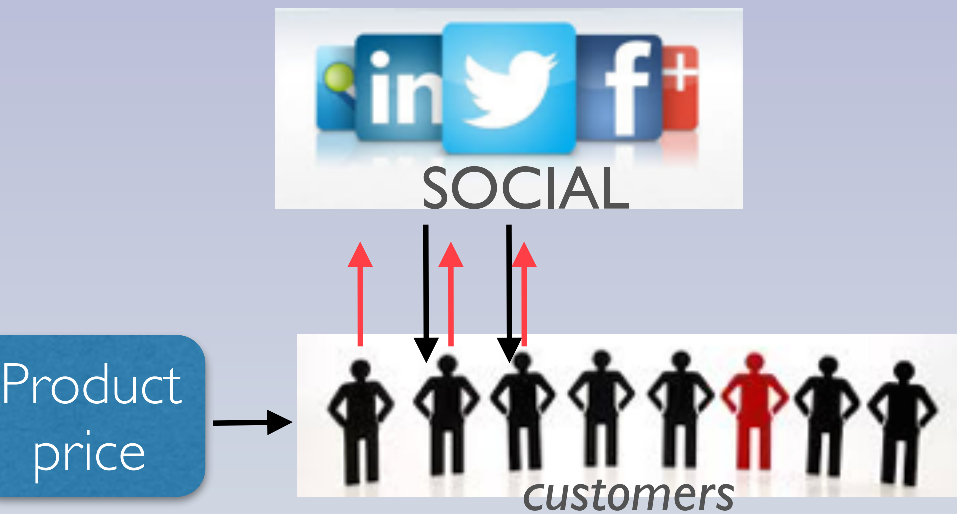
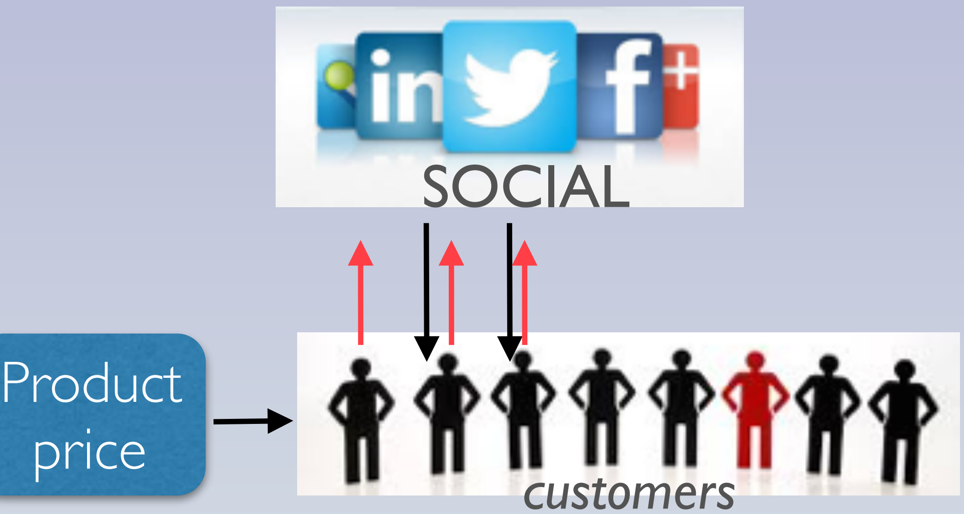


Each Sale to a customer

- Brings in money
- Customers perform social learning on the product

How should the product price be chosen over time?

Q3: □ Price □ High □ Or □ Low?



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

Agent: $y_k \sim p(\cdot|x),\ x \sim \pi_0.$
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Public belief: $\pi_k = T(\pi_{k-1}, a_k)$

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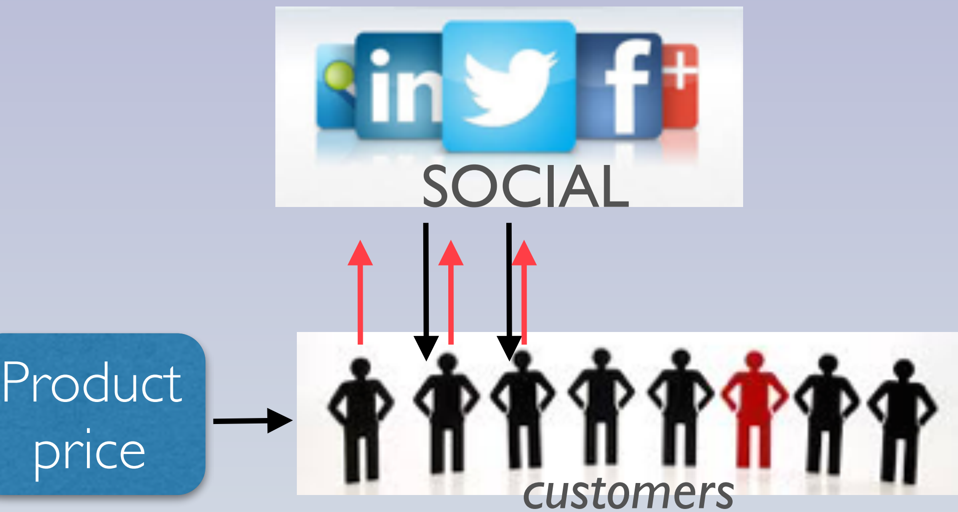

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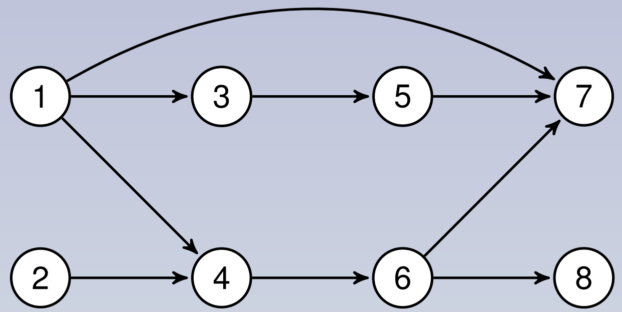
``***Optimal soln***'': *Price high initially; build elite customer base; then gradually decrease prices.*

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]

DISCUSSION □ FOR □ PART □ 1: □ SOCIAL □ LEARNING

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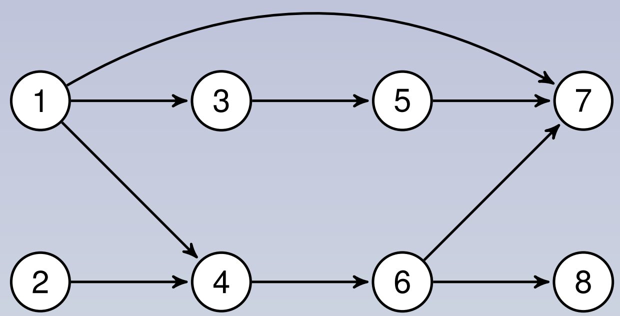

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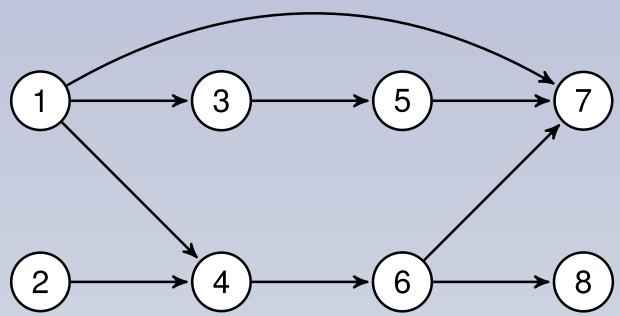

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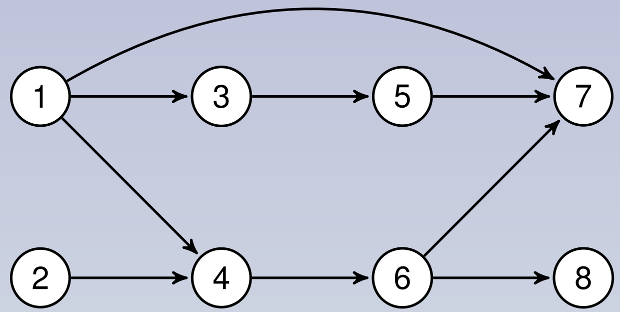
$$a_k = \arg\min_a \mathbb{E}_{\pi_{k-1},y_k}\{c(x,a)\} \quad \longrightarrow \quad a_k = \arg\min \mathcal{R}_{\pi_{k-1},a_k}\{c(x,a)\}$$

Example: $a_k = \underset{a\in\mathcal{A}}{\operatorname{argmin}}\{\mathrm{CVaR}_\alpha(c(x_k,a))\}$ (Rockafellar & Uryasev, 2000)

- ***Decisions are ordinal in belief and observation***
- ***Risk averse agents herd more frequently at cheaper costs and therefore compromise state estimate.***

DISCUSSION FOR PART 1: SOCIAL LEARNING

1. Data Incest + Herding in social learning over general graphs



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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

High reputation

Good reputation

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

No reputation

Low reputation

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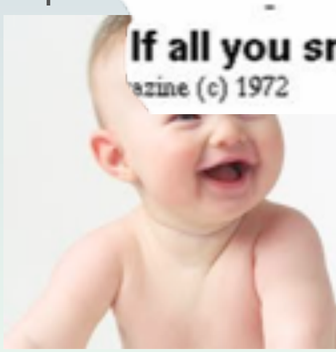

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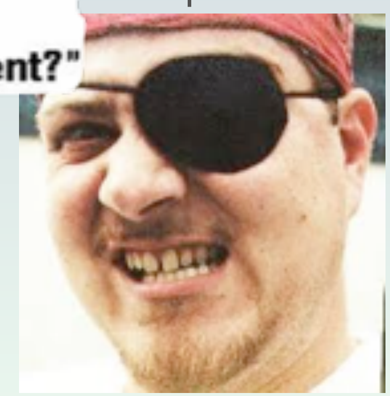

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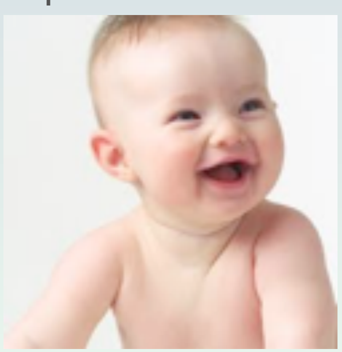
Anderson & Kilduff, Berkeley Hass School, 2009.

Low reputation

No reputation



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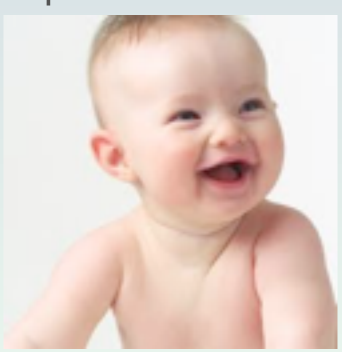
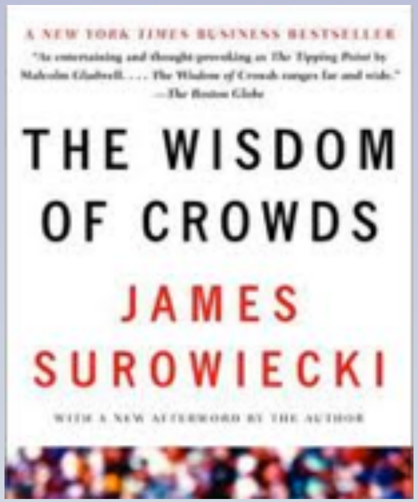


Ottaviani, Sorensen, 2001. *Information Aggregation in Debate: Who should speak first?*

Summary of Part 1

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

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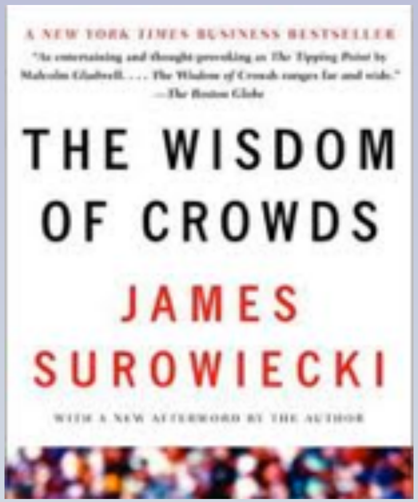

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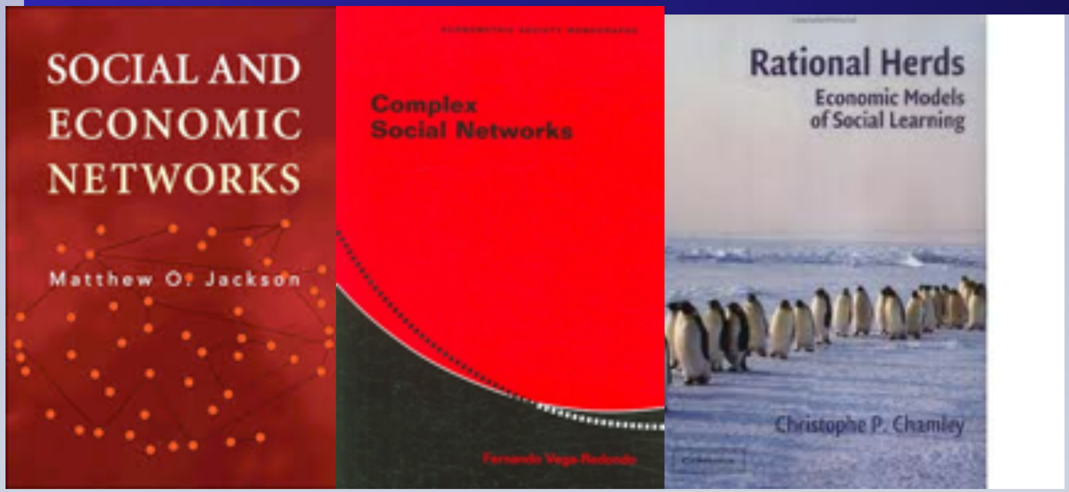
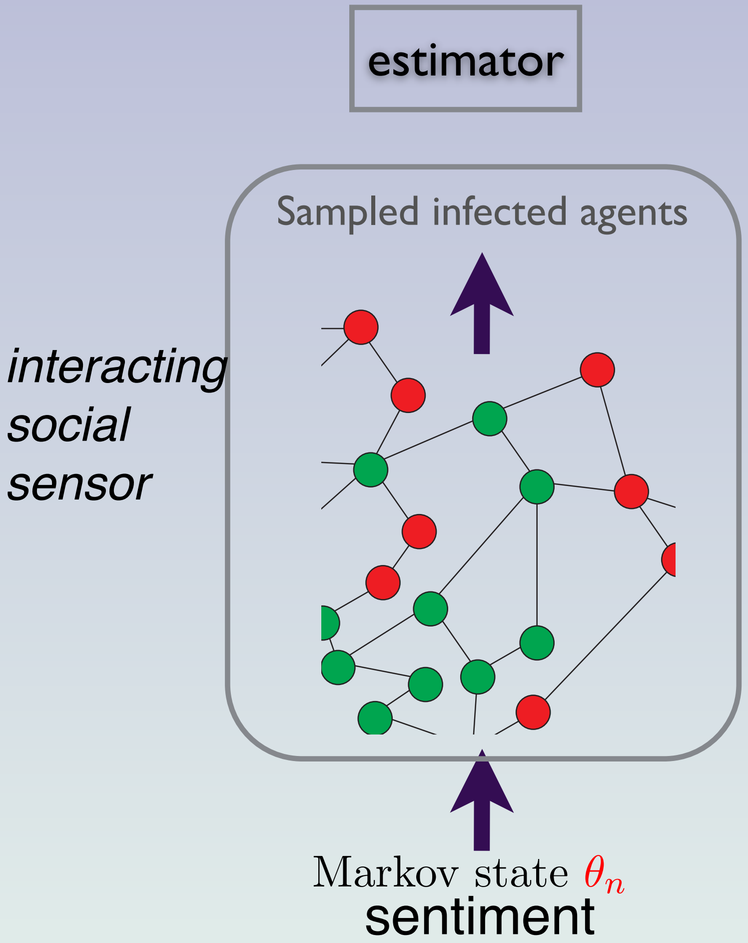
In complex settings, herding can result in interesting behavior:
Nobody goes there anymore … it is always too crowded (Yogi Berra)

PART 2: INFORMATION DIFFUSION IN SOCIAL NETWORKS





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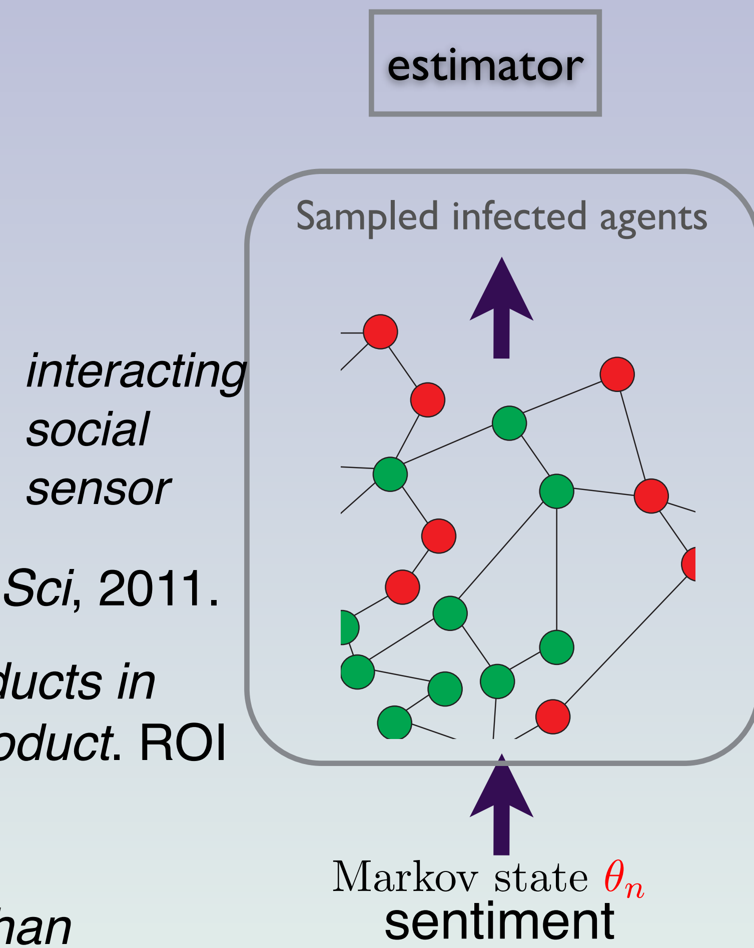


Why?

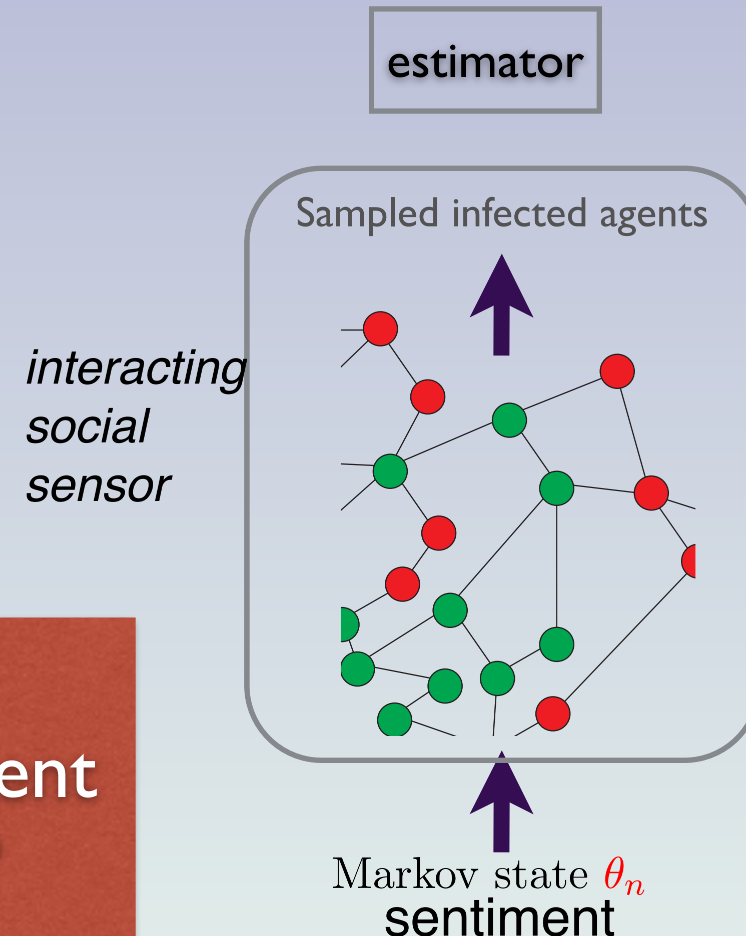
Twitter mood predicts stock market, *J. Computational Sci*, 2011.

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.

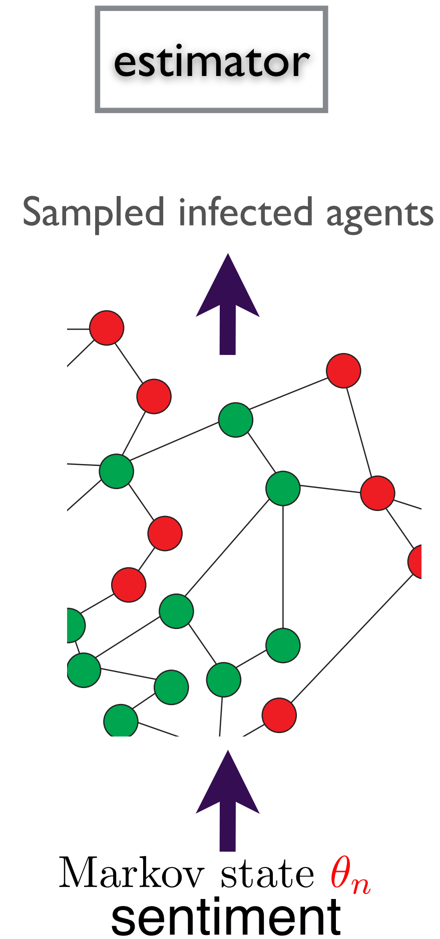
Part 2: Information Diffusion in Social Networks



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?



Mean Field Dynamics For Sensing

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

estimator

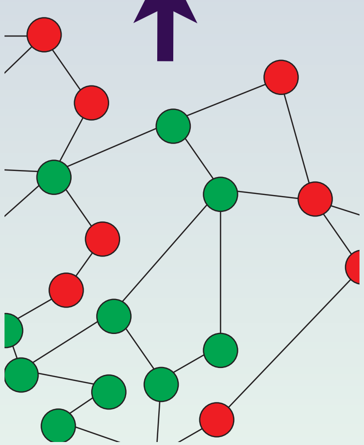
$$\frac{d\rho(k)}{dt} = F(\rho(k), \rho(k-), \theta_t), \quad \theta_t \sim Q$$

fraction of infected nodes of degree k

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

sampling network

Sampled infected agents



Markov state θ_n
sentiment

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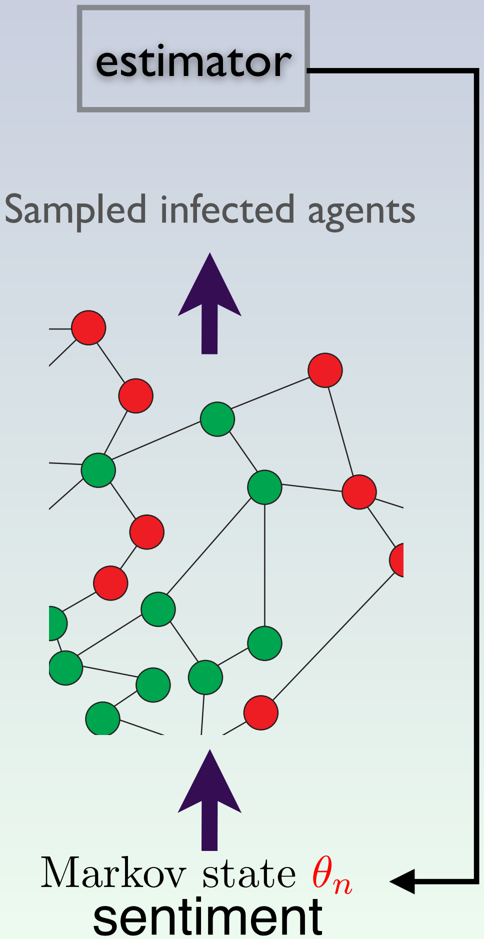

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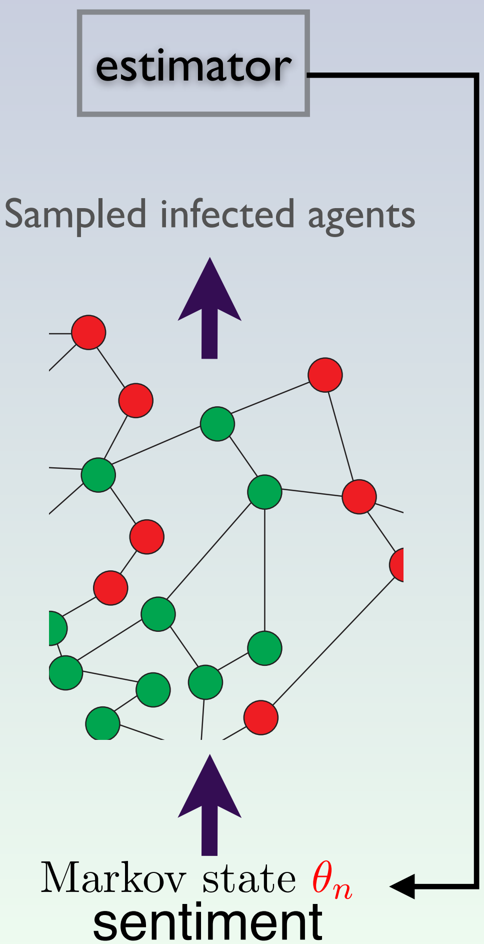

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References:

- Benaim, Econometrica, 2003
- Pastor-Satorrras, Epidemic spreading in scale free networks, Physical Review Letters, 2001
- D. Lopez-Pintado, Diffusion in complex social networks, Games & Economic Behavior, 2008.
- 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

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.

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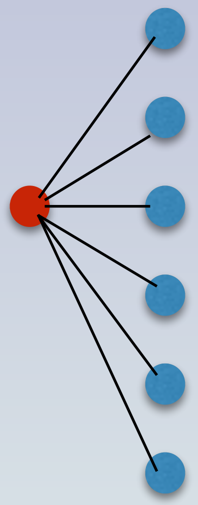
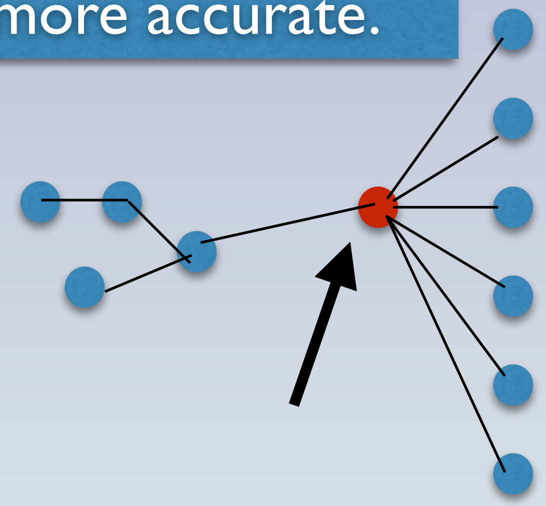


Expectation polling can be biased



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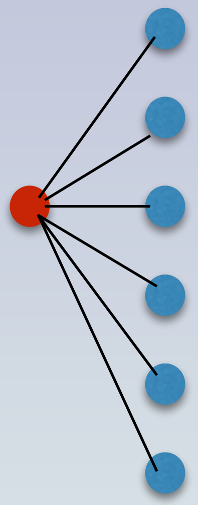

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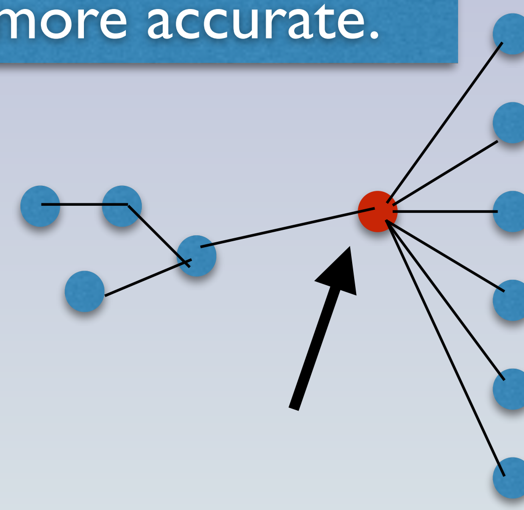

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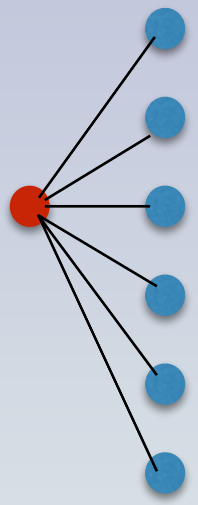

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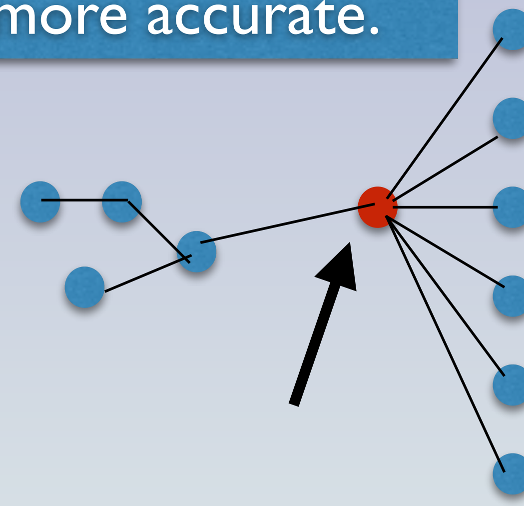

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- Mean number of friends are smaller than mean number of friend of friends (Feld 1991 - friendship paradox).
- Respondent Driven Sampling: snowball MCMC sampling method for marginalized populations in social networks.

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

SUMMARY

Part 1. Social Learning. Learn from observations, past decisions and others [Psychology, Economics, CS,EE]
Herding and Data Incest yield non-informative datasets.

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?

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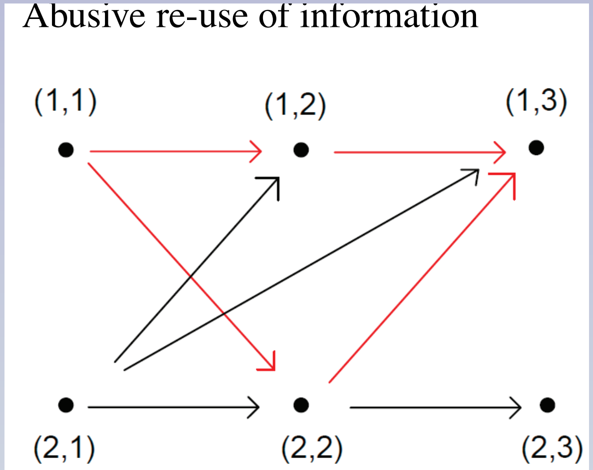

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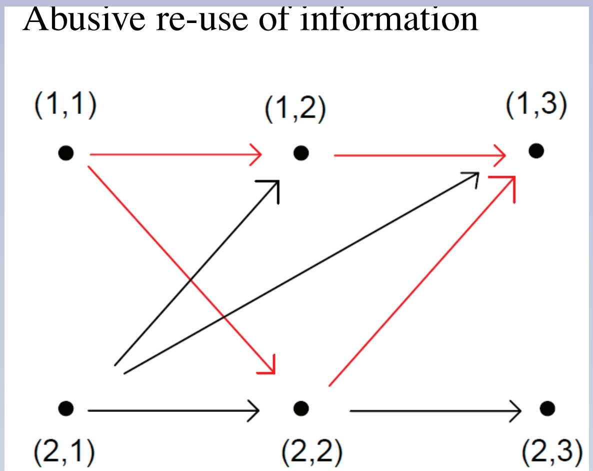
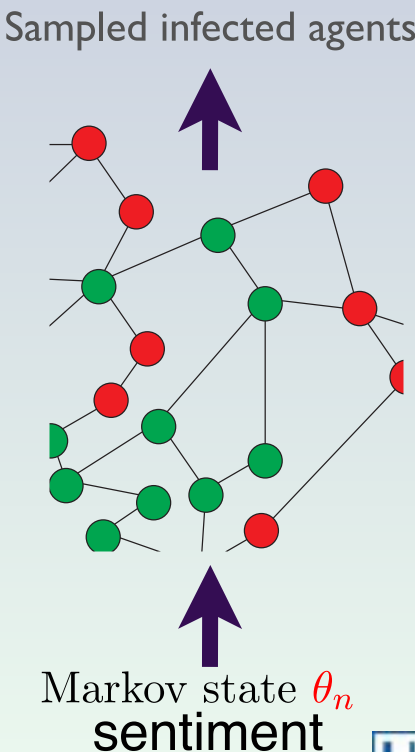


Part 2. Diffusion in Large Scale Networks.
Mean field dynamics: infected degree distribution satisfies differential equation
Sampling: Expectation Polling, Respondent Driven Sampling



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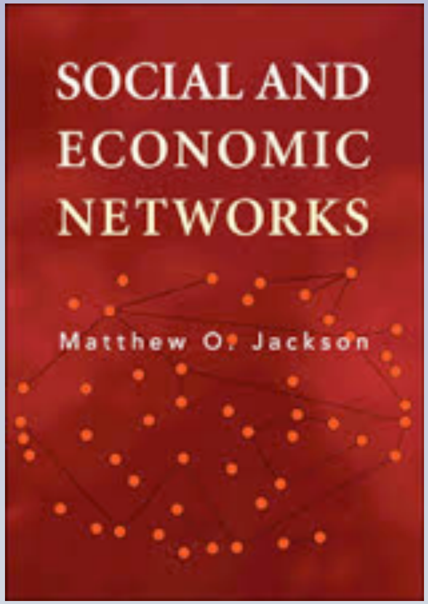

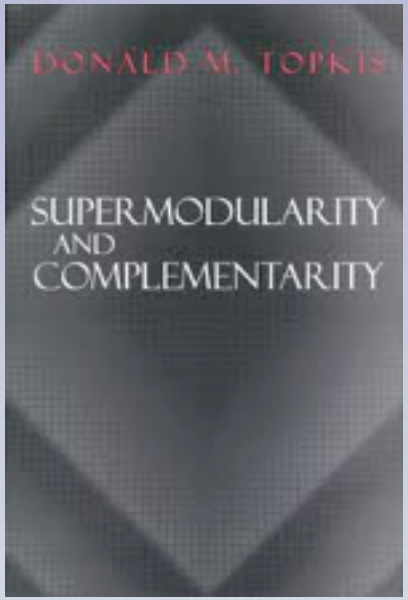

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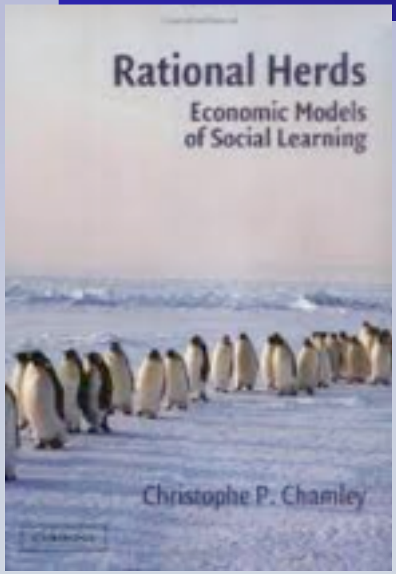
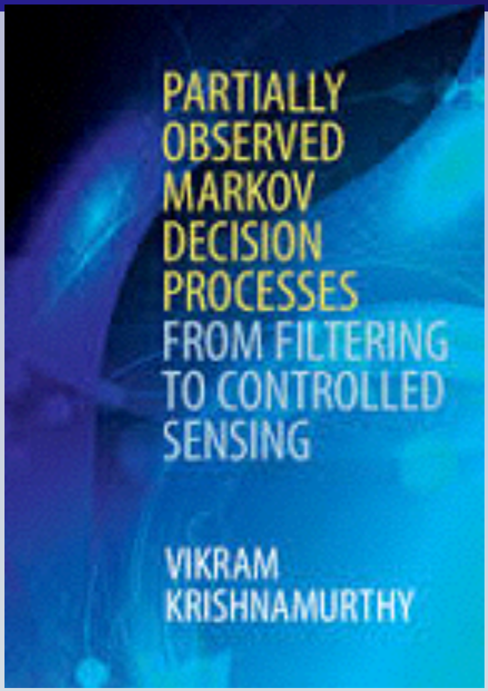
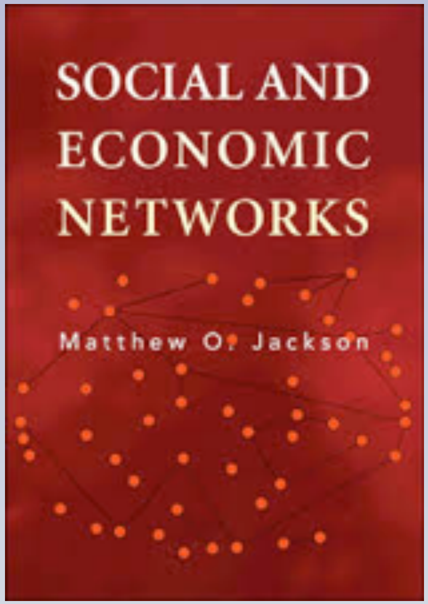
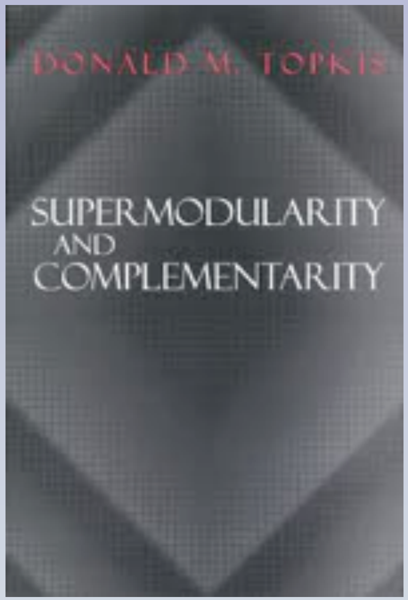
- Krishnamurthy & Yin, Tracking the Degree Distribution of Random Graphs, *IEEE Trans Information Theory*, 2014.
- Krishnamurthy, Bhatt, Sequential Detection of Market Shocks with Risk-Averse CVaR social sensors, *IEEE Journal Selected Topics Signal Proc, 2016*

References









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