



# **Social Psychology Meets Social Computing: State of the Art and Future Direction**

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# Data in Social Computing


## Nature of Data

- Many data in social computing is **related to** humans or **produced by** humans.
- Many of these solutions are also directly **consumed by** humans.



# Social Data


 **Dr.STONE** @DoctorStone96 · May 8  
Replying to @MothershipSG  
Well, lets see what latest research says about vaccine vs Omicron: 🧐



A health worker prepared a dose of the Pfizer-BioNTech vaccine, the patient's fourth shot, near Tel Aviv in December. Jack Guetz/Agence France-Presse — Getty Images

A second booster shot of the Pfizer-BioNTech Covid vaccine provides additional short-term protection against Omicron infections and severe illness among older adults, according to a large new study from Israel.

But the booster's effectiveness against infection in particular wanes after just four weeks and almost disappears after eight weeks. Protection against severe illness did




Stories Latest News Discover Singapore

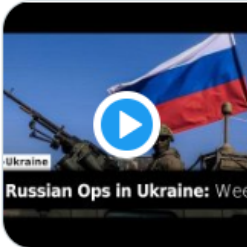
After infection adds little extra benefit against Omicron

...ing people who were previously infected with the coronavirus, a third dose of an mRNA vaccine from Pfizer/BioNTech or Moderna n

...boost t

...nt of t

 **P Lafala** @PLafala · Mar 27  
Replying to @MothershipSG  
Russia is winning the war in Ukraine. Probably in another 10 months all of Ukraine will be liberated.  
Watch "Russian Operations in Ukraine: Week 5 Update" on YouTube

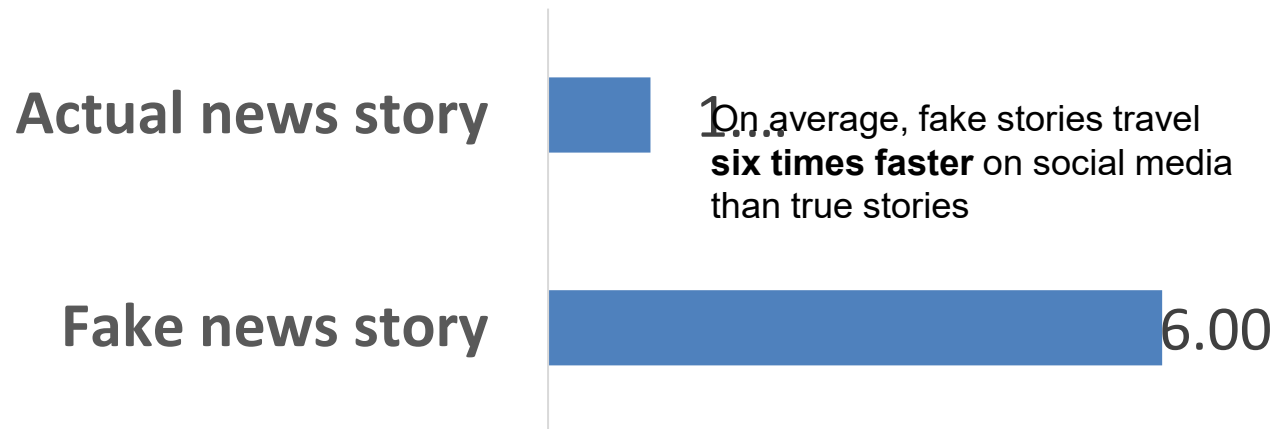


youtube.com  
Russian Operations in Ukraine: Week 5 Update  
Russian operations in Ukraine enter week 5. Despite claims Russia is stalled, frustrated, and without a ...



# The Power of Fake to Attract Our Attention

relative speed with which a story  
“travels” on social media.

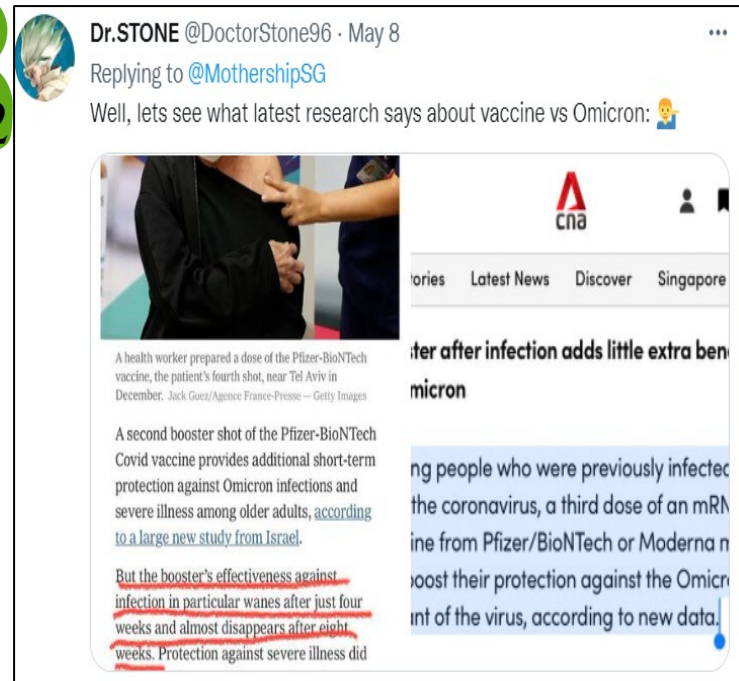
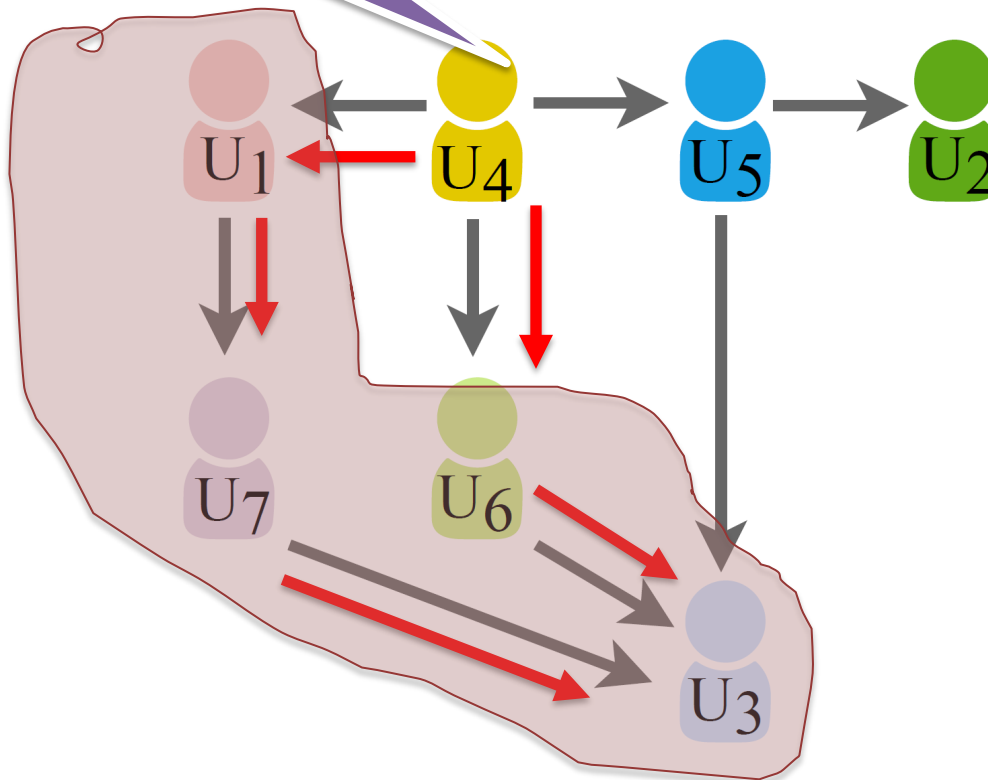


Source: Soroush Vosoughi, Deb Roy, and Sinan Aral, “The spread of true and false news online,” *Science* 369 (2018): 1146-1151.

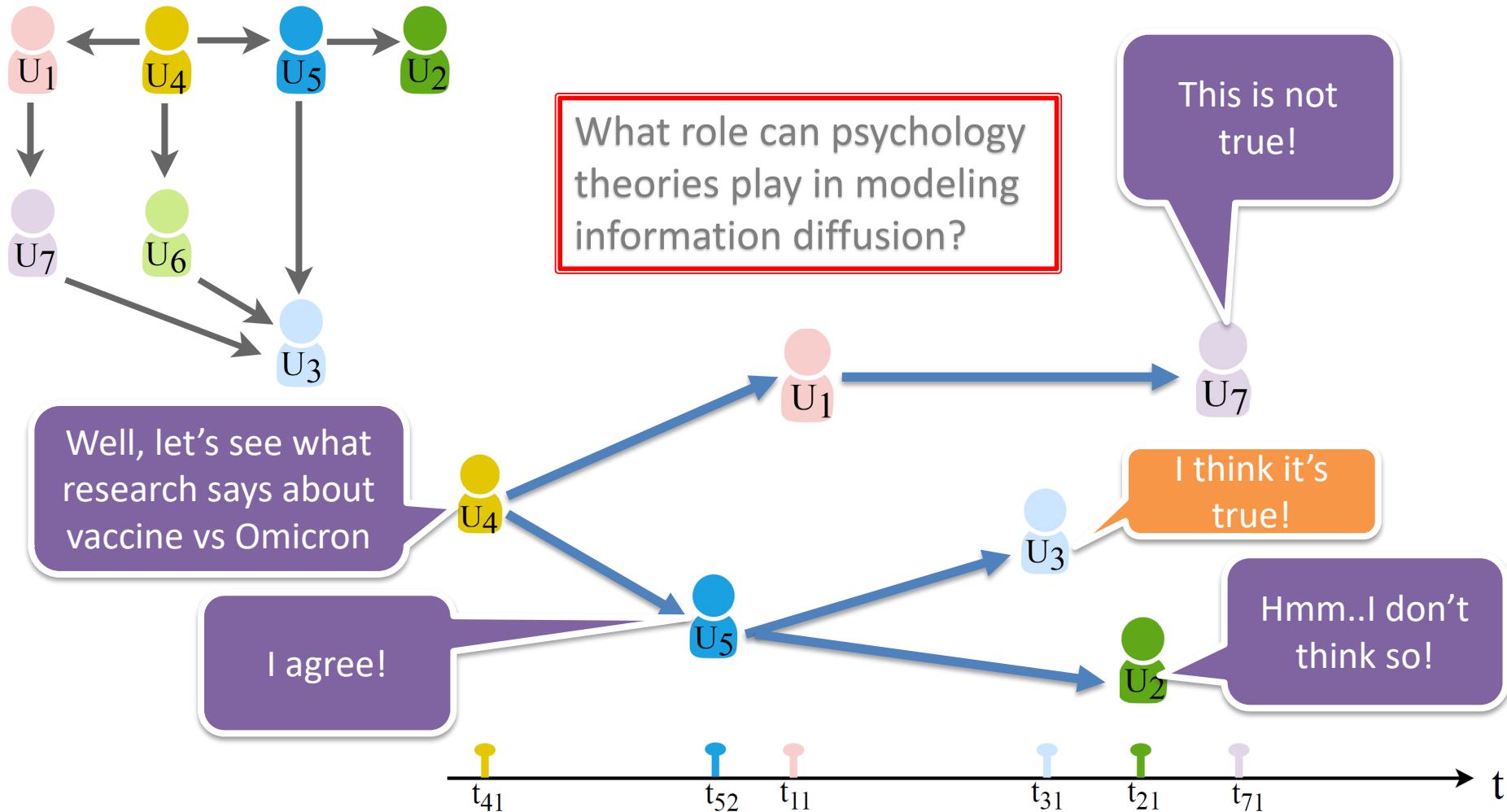


# Spread of (Fake) Information

Well, let's see what research says about vaccine vs Omicron



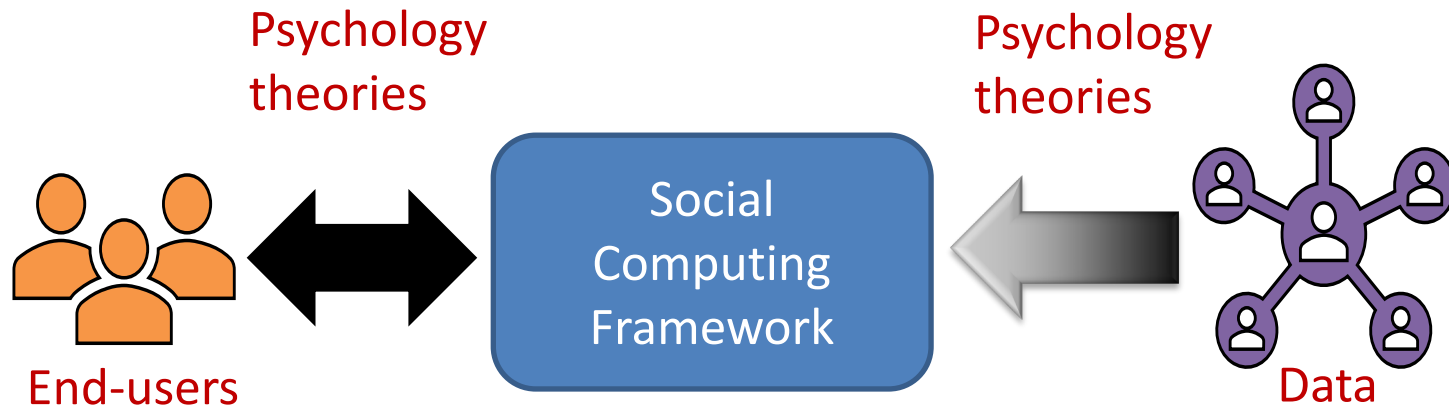
# Online Information Diffusion



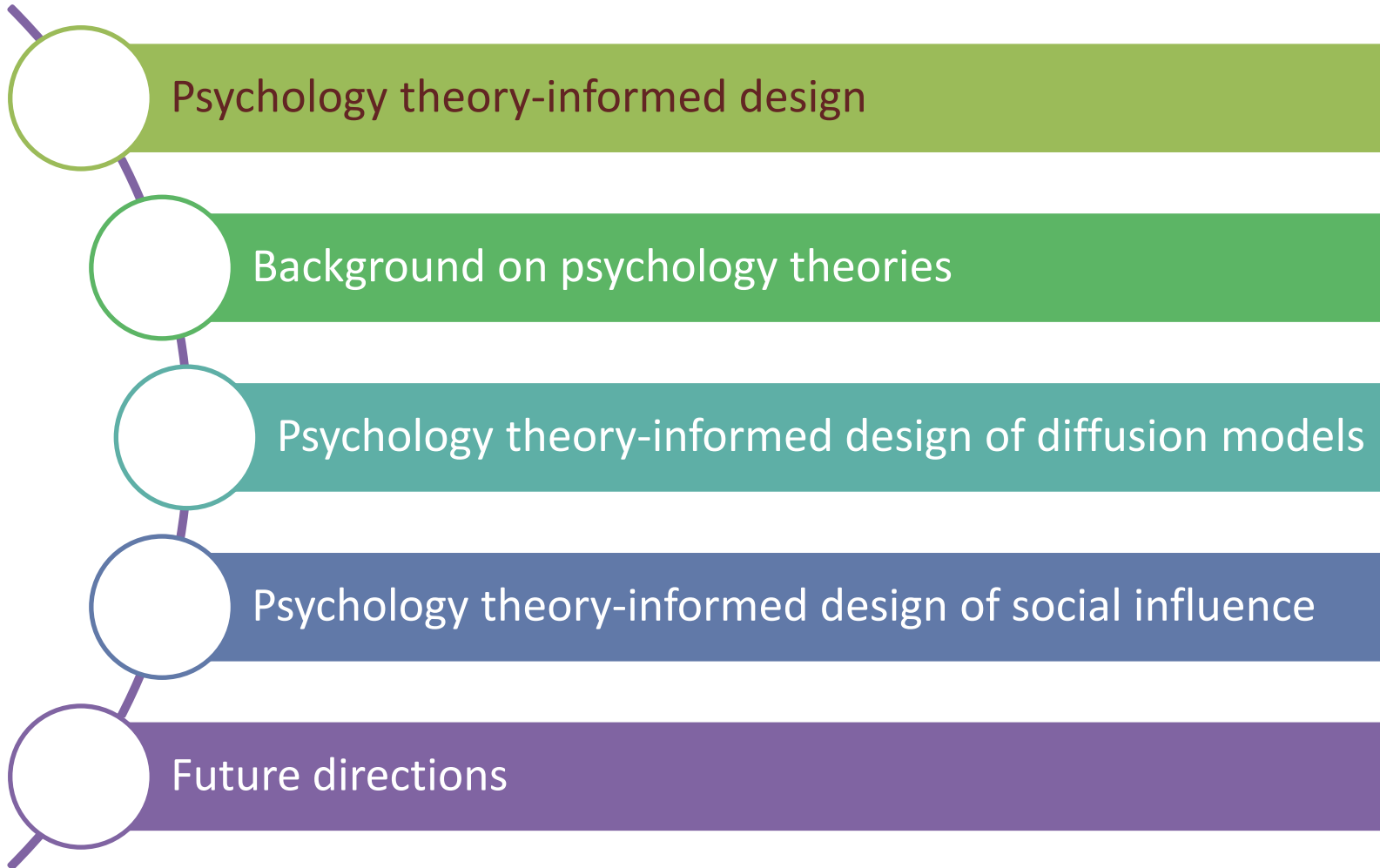
# Goal of the Tutorial

## Psychology Theory-informed Design

- Design social computing solutions that are informed by theories from social psychology.
- Focus on **social influence**.



# Overview of the Tutorial





# Role of Theory

## Theory

- A scientific theory is a **testable** explanation for a broad set of facts or observations.
- Different from the way people customarily use the term (wild speculation, mere hunch).

## Attributes of theory

- The power to explain the facts.
- The ability to be tested.



# Problems of Pure CS Theory-based Social Computing Solutions

## Issues

- Classical CS-based solutions focuses on **computing resource cost** but not on **cognitive and social bias in humans**
- **Conformity** may promote or block the influence spread
- Impacts prediction accuracy of the system

## Psychology theory-informed Solution

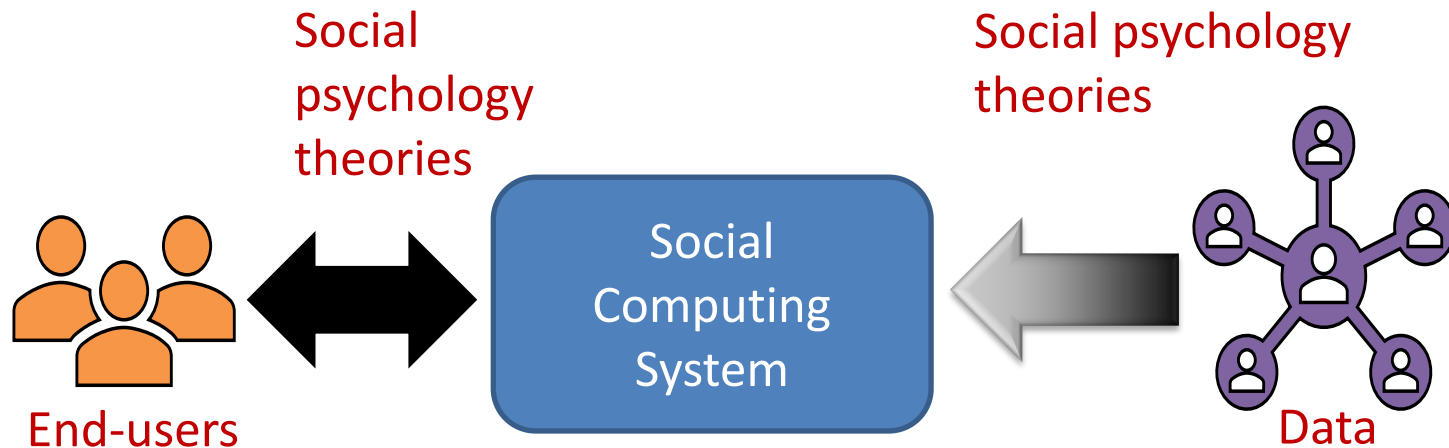
- Make the modeling of social computing problems and solutions **human behavior-sensitive**



# What Can Psychology Theories Do To Social Computing?

## Theory-informed Design

- Design social computing solutions that are informed by theories from psychology (in addition to theories from CS).
- Many social computing framework deals with data related to humans or are consumed by humans.



# Focus on Social Psychology

## Human Behavior

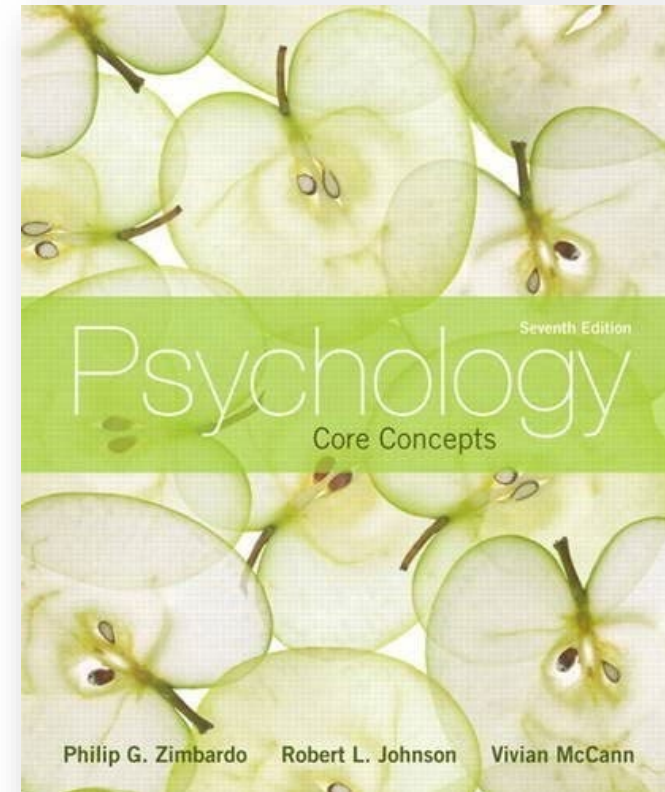
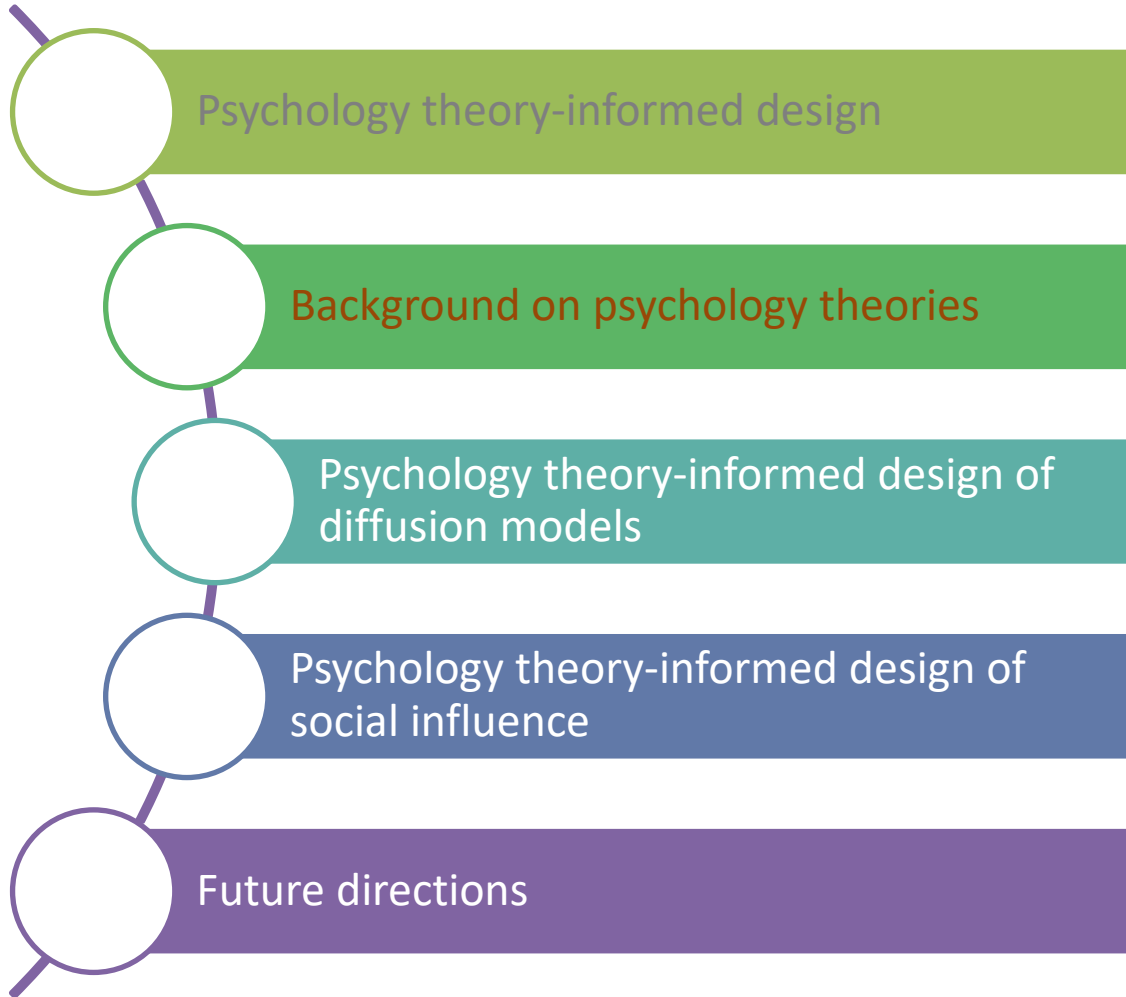
- Adapt our behavior to the demands of the **social situation**.
- In new or ambiguous situations, we take our cues from the behavior of others in that setting.
- Social psychology studies the behavior of individuals or groups in the context of particular situations.

## Social Computing and Social Psychology

- Human-related data implicitly or explicitly contain cues of human behavior
- Any social computing framework that do not consider it may be ineffective **in practice**.



# Next..



# What is Psychology?

## As a Field

- A broad field with many specialties.
- Science of behavior and mental processes (brain).
- The science of psychology is based on objective, verifiable evidence – not just the opinions of experts and authorities.

## Note

- Includes not only mental processes but also behaviors.
- Covers **internal** mental processes that we observe only indirectly (thinking, feeling, desiring).
- **External** (observable behaviors) such as talking, smiling, and running.



# Three Ways of Doing Psychology

## Experimental Psychologists

- They perform most of the research that creates new psychological knowledge.

## Educators of Psychology

- Focus more exclusively on teaching but some may conduct limited amount of research as well.

## Applied Psychologists

- Use the knowledge developed by experimental psychologists to tackle human problems of all kinds.



# Psychology Is Not Psychiatry

## Psychiatry

- Psychiatry is a medical specialty, not part of psychology at all.
- Almost all psychiatrists treat **mental disorders**.
- Psychiatrists hold MD (Doctor of Medicine) degrees and have specialized training in the treatment of mental and behavioral problems (typically with drugs).

## Psychology

- Much broader field – from brain function to social interaction and from mental well-being to mental disorder.
- Training is not usually medical training.





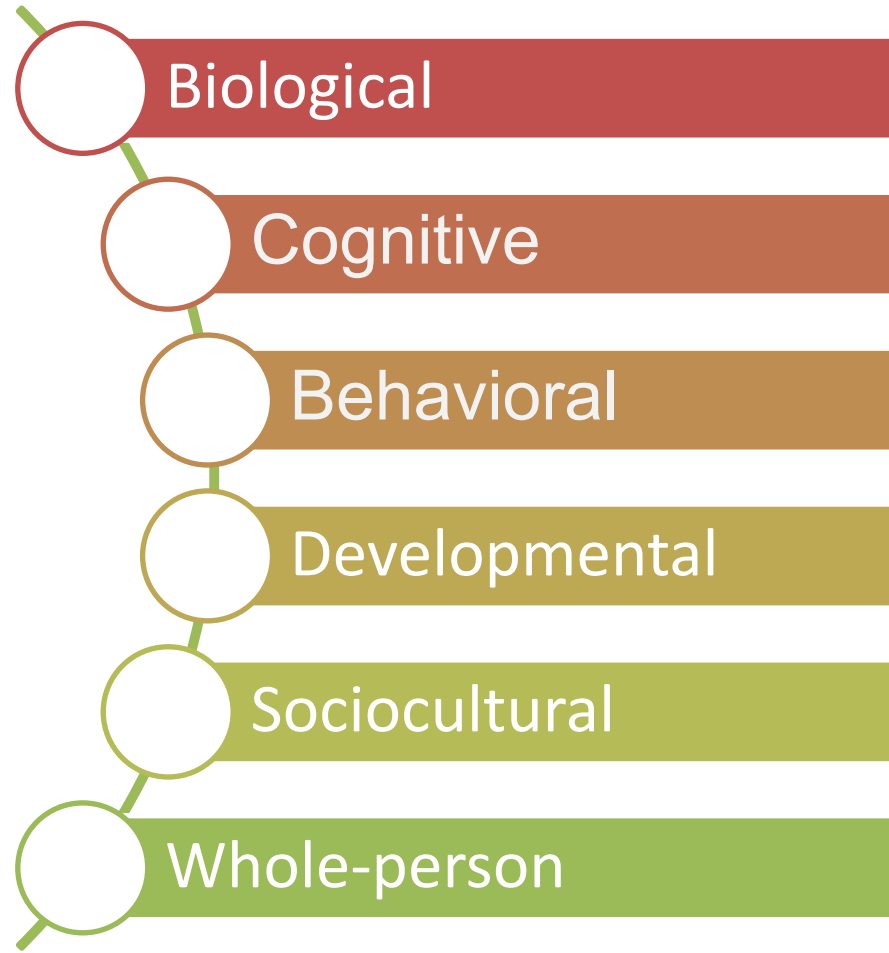
# Six Perspectives Of Psychology

## Motivation

- Each perspective offers its own unique explanation for human behavior.

## A Tool to Understand Human Behavior

- Each perspective is an important tool in your “psychological toolbox” for understanding human behavior.



# Six Perspectives of Psychology

The six perspectives all play key roles in developing a holistic understanding of human behavior

Many perspectives can reasonably apply to any single behavior – rarely just one perspective sufficient to adequately explain the behavior

Need multiple perspectives to fully understand the causes of human behavior



# Sociocultural Perspective

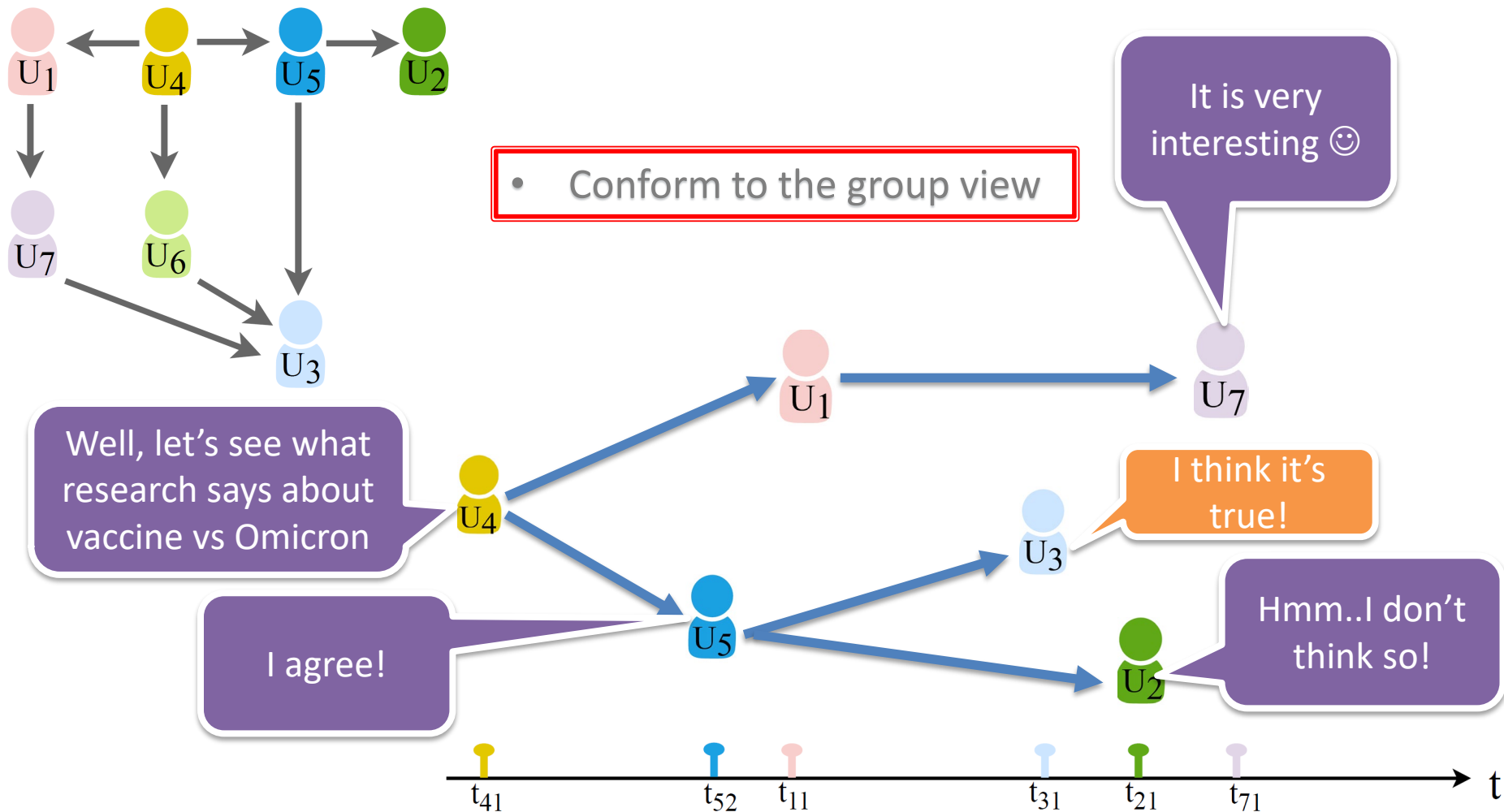
## Current View

- Who could deny that people exert powerful influences on each other?
- Sociocultural perspective places the idea of social influence center stage.

*The **social and cultural situation** in which the person is embedded can sometimes overpower all other factors that influence behavior.*



# Spread of (Fake) Information



# Power of the System

## System Power

- Power that creates and maintains specific situations
- Many studies in social psychology show that the power of the situation can pressure ordinary people to commit horrible acts.

## Understanding Human Behavior

- Three level analysis
- The individual's dispositions
- The power of the situation
- The power of the system



# Understanding Human Behavior

## Individual

- Individual's dispositions.

## Power of the Situation

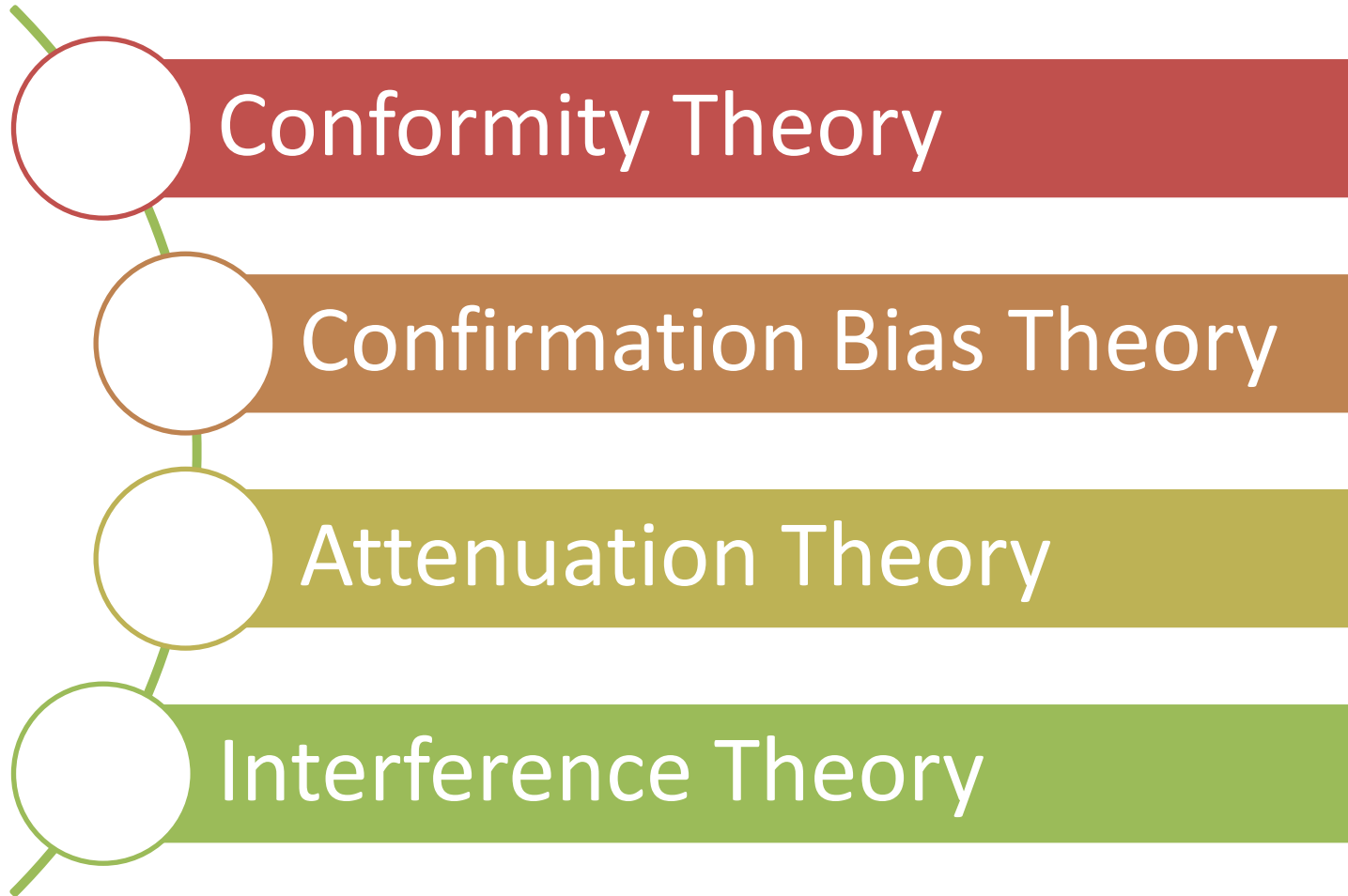
- The environment that creates situations that influence behaviors.

## Power of the System

- Systems shape situations which in turn affects behavior.



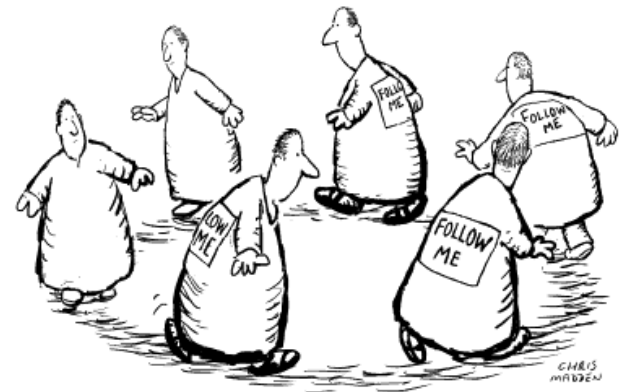
# Relevant Social Psychology Theories



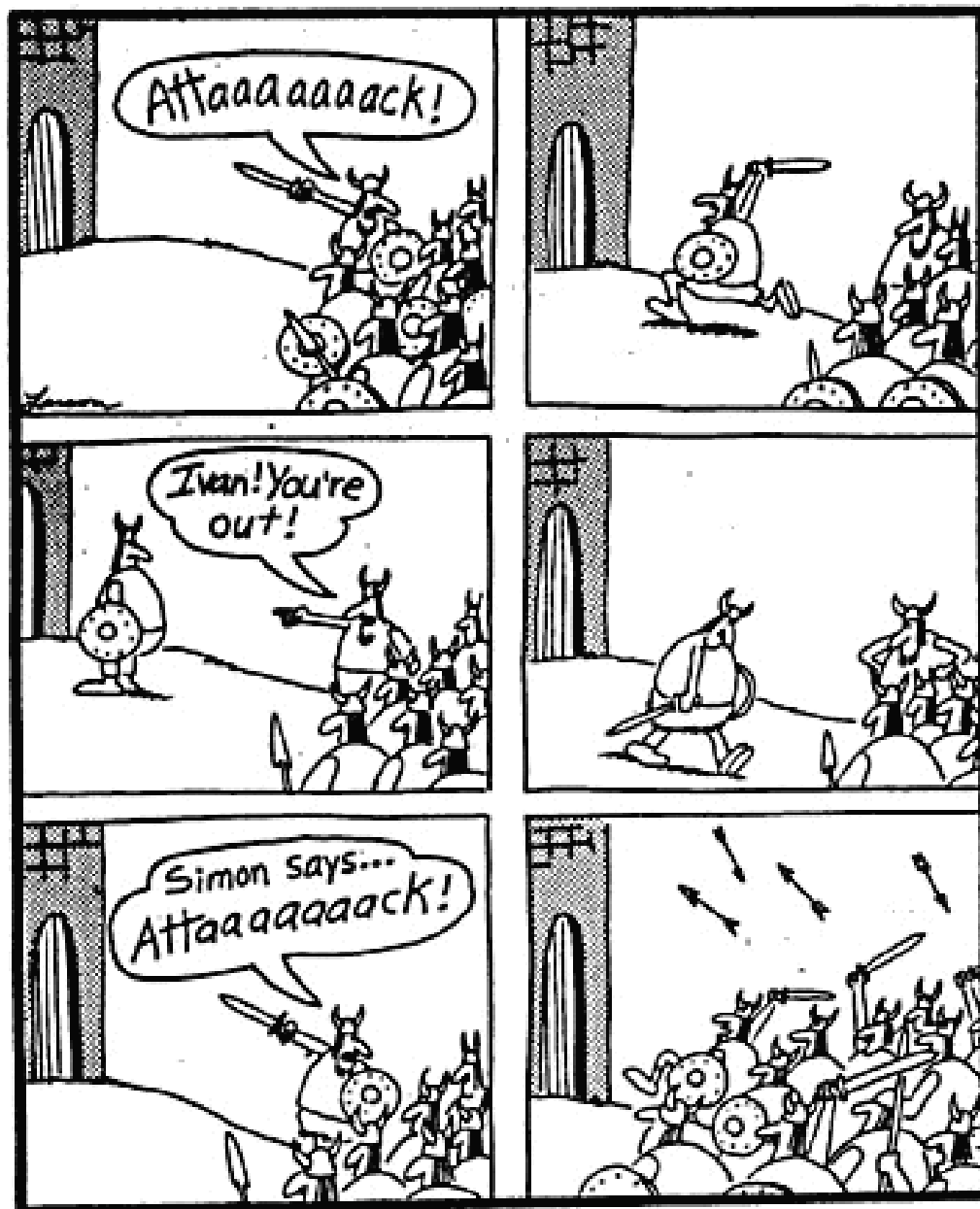
# Theory of Conformity

## Conformity

- Refers to the inclination to align our attitudes and behaviors with those around us.
- Long stream of research in social psychology that shows existence of conformity in social interactions.
- **Asch effect** – the powerful influence that a group exerts on the objective judgments of an individual







# Why Do We Conform To the Group?

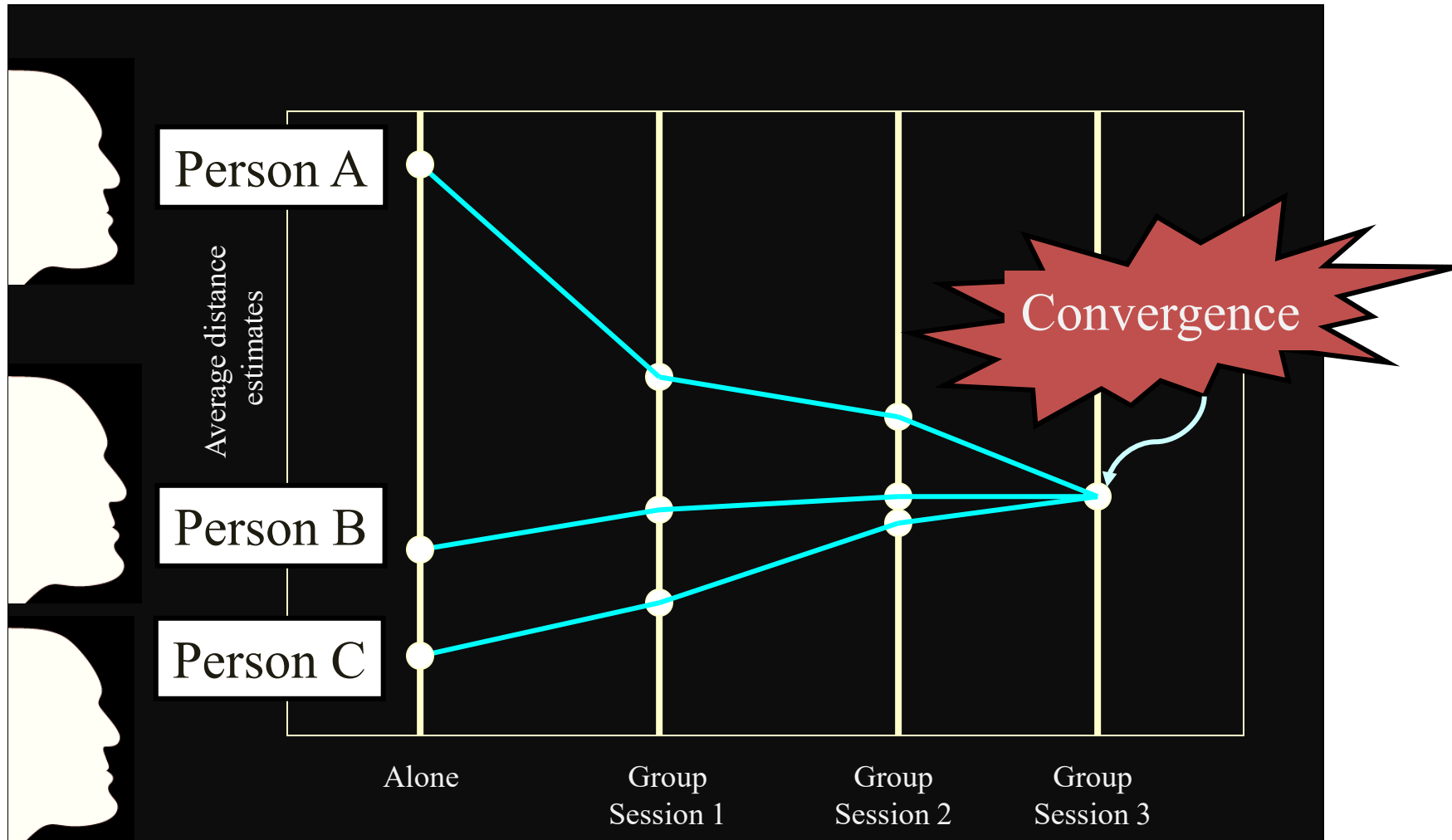
## Informational Conformity

- People conform to peer views in an attempt to reach appropriate behaviours and attitudes due to lack of knowledge.

## Normative Conformity

- Desire to be accepted or that keep us from being isolated or rejected by others.



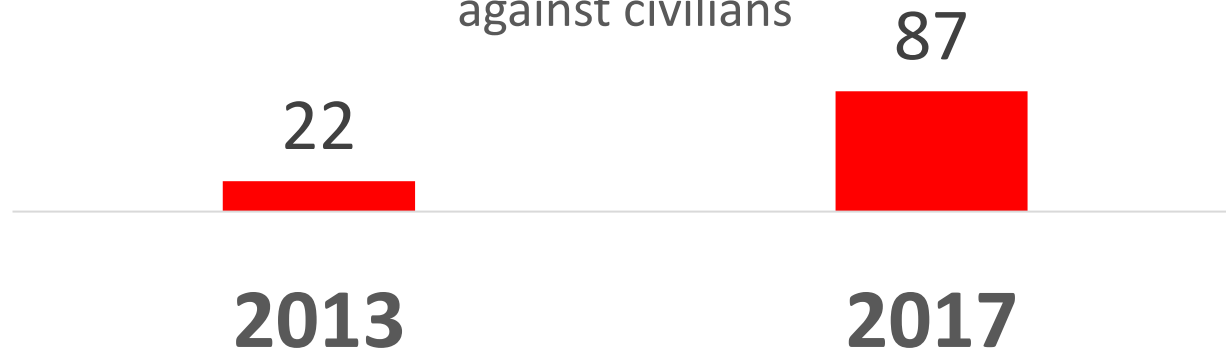


Initially, they differ; but over trials, they converge



# Conformity to claims made by party leaders and by like-minded media sources

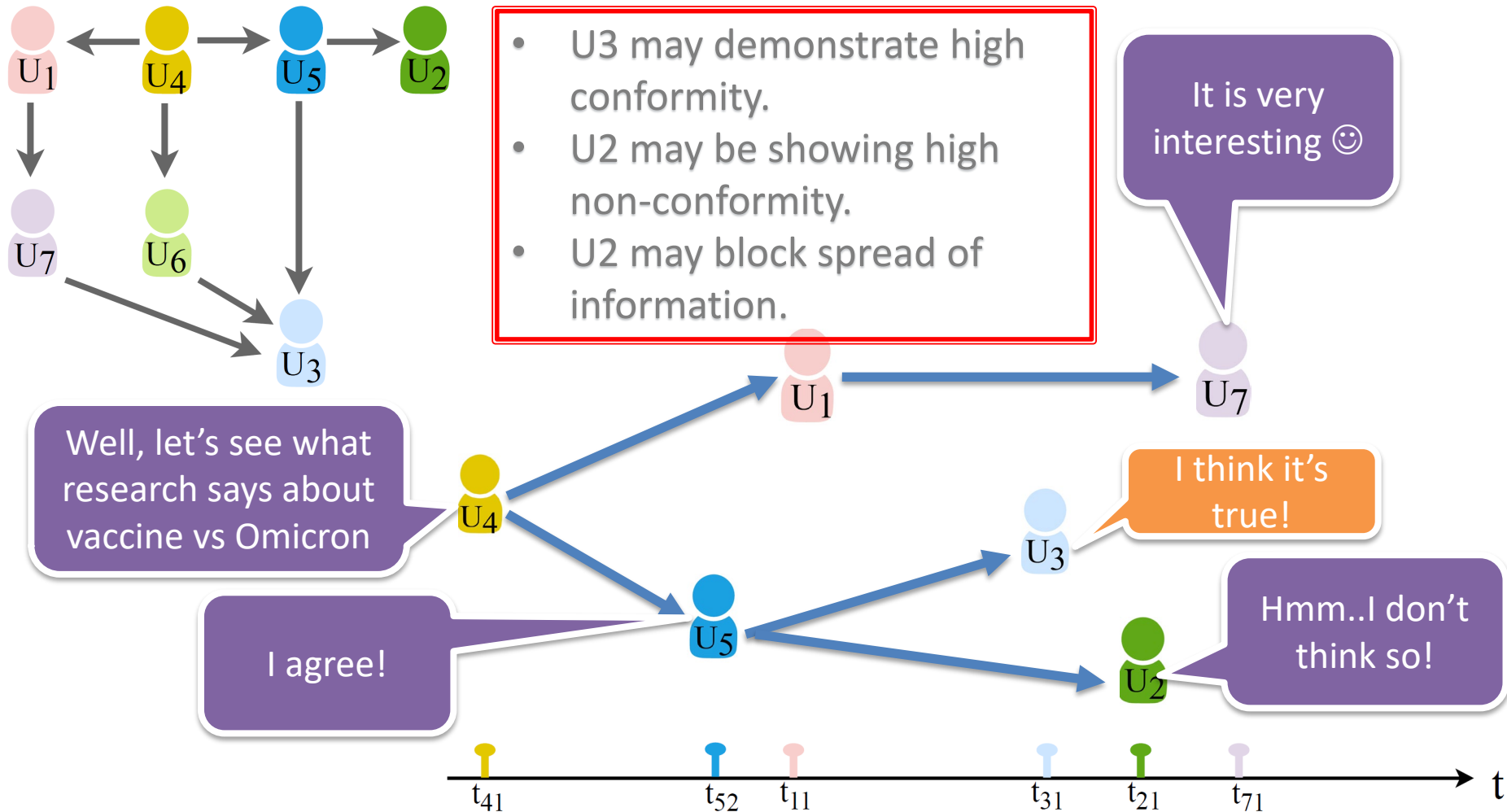
Percentage of Republicans expressing support for US missile strikes against Syria in response to Bashar al-Assad using chemical weapons against civilians



Source: Washington Post/ABC News polls, 2013 and 2017.



# Spread of (Fake) Information



# What Conditions Encourage Conformity?

## Unanimity of the majority

- If everyone in the group agrees, they exert a powerful social pressure
- If one person defects from the majority, conformity can go down drastically

## Size of the group

- Conformity pressure increases when confronting a group of **3 or more**.



# What Conditions Encourage Conformity?

## Making a public commitment

- If you believe others in the group will not hear your responses, you are less likely to go along with them when you think they are incorrect

## Ambiguity

- When people are more to self-doubt, they yield to group conformity



# What Conditions Encourage Conformity?

## Self-esteem

- People who place a low value on themselves are more likely to conform.

## Makeup of the majority

- More conformity occurs when the group has high status





# Resisting Conformity

## Illusion of personal invulnerability

- NOT ME syndrome
- Others may but not me!
- More susceptible to influence agents because their guard is done and they do not engage in mindful, critical analysis of situational forces acting on them.



# Can Groups Themselves be Pressured to Conform?

## Groupthink

- Encourages conformity in the thinking and decision making of individuals when they are in groups (e.g., committees).
- Members of the group attempt to conform their opinions to what each believes to be the consensus of the group.
- Can lead the group to take actions each member might normally consider to be unwise.



# When Groupthink Likely to Happen?

## Conditions Promoting Groupthink

- **Directive leadership**, a dominant leader
- High group **cohesiveness**, with absence of dissenting views
- **Lack of norms** requiring methodical procedures for evidence collection/evaluation
- **Homogeneity** of members' social background and ideology
- High **stress** from external threats combined with low hope of a better solution than that of the group leader



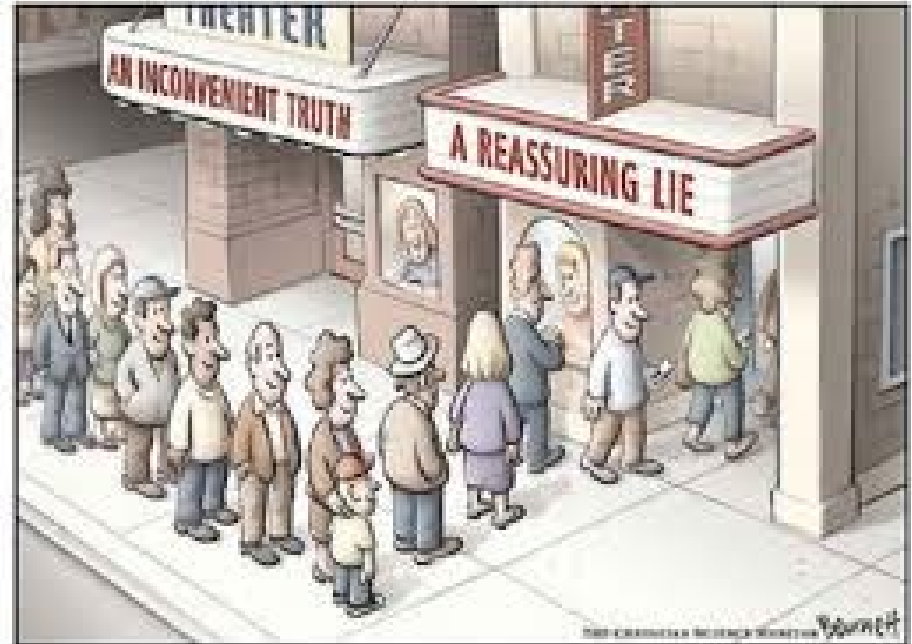
# Confirmation Bias Theory

## Confirmation Bias

- Remember events that confirm our beliefs and ignore or forget contradictory evidence.
- A powerful and all-too-human tendency.

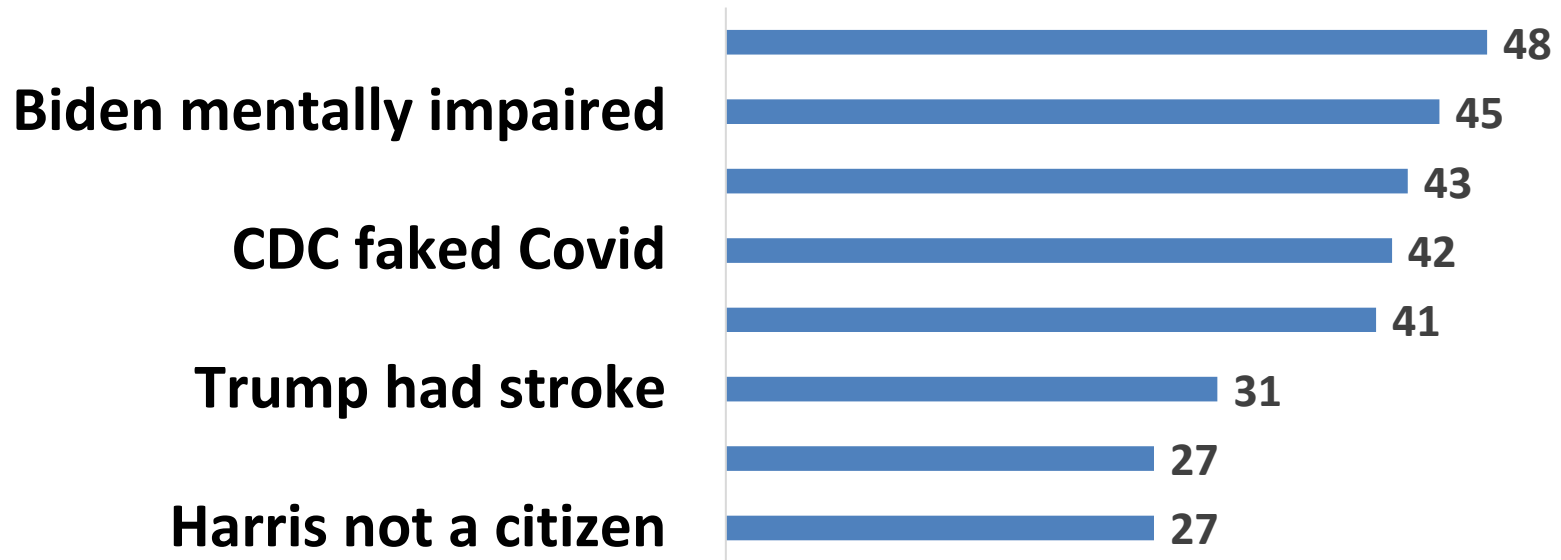
### It's a bias!

- Unconscious or unintentional.
- It does not mean that individuals are incapable of providing perspectives that counter their own beliefs.
- Unmotivated to do so.



# None are true, but each is believed by tens of millions of Americans

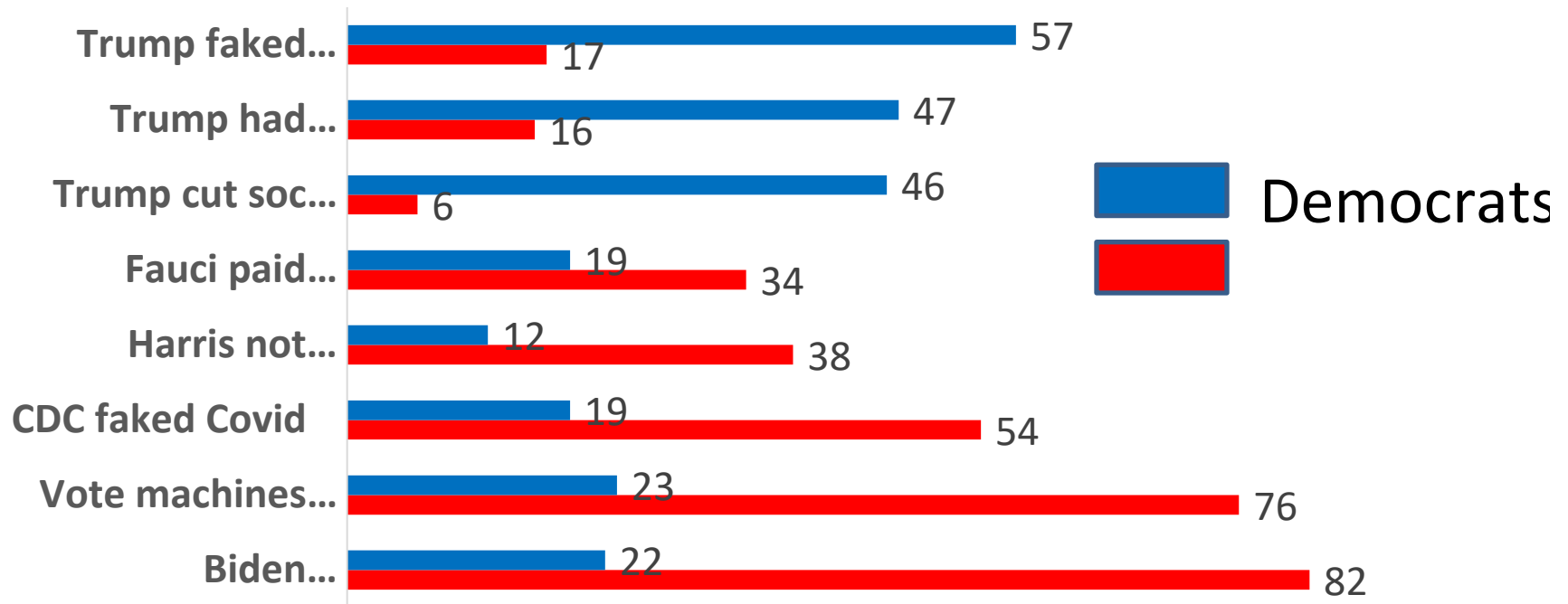
percentage of respondents saying statement is true



Source: Indiana University's Observatory on Social Media survey, November 2020



# Confirmation Bias affects Republicans & Democrats alike - accepting false claims that align with one's partisanship

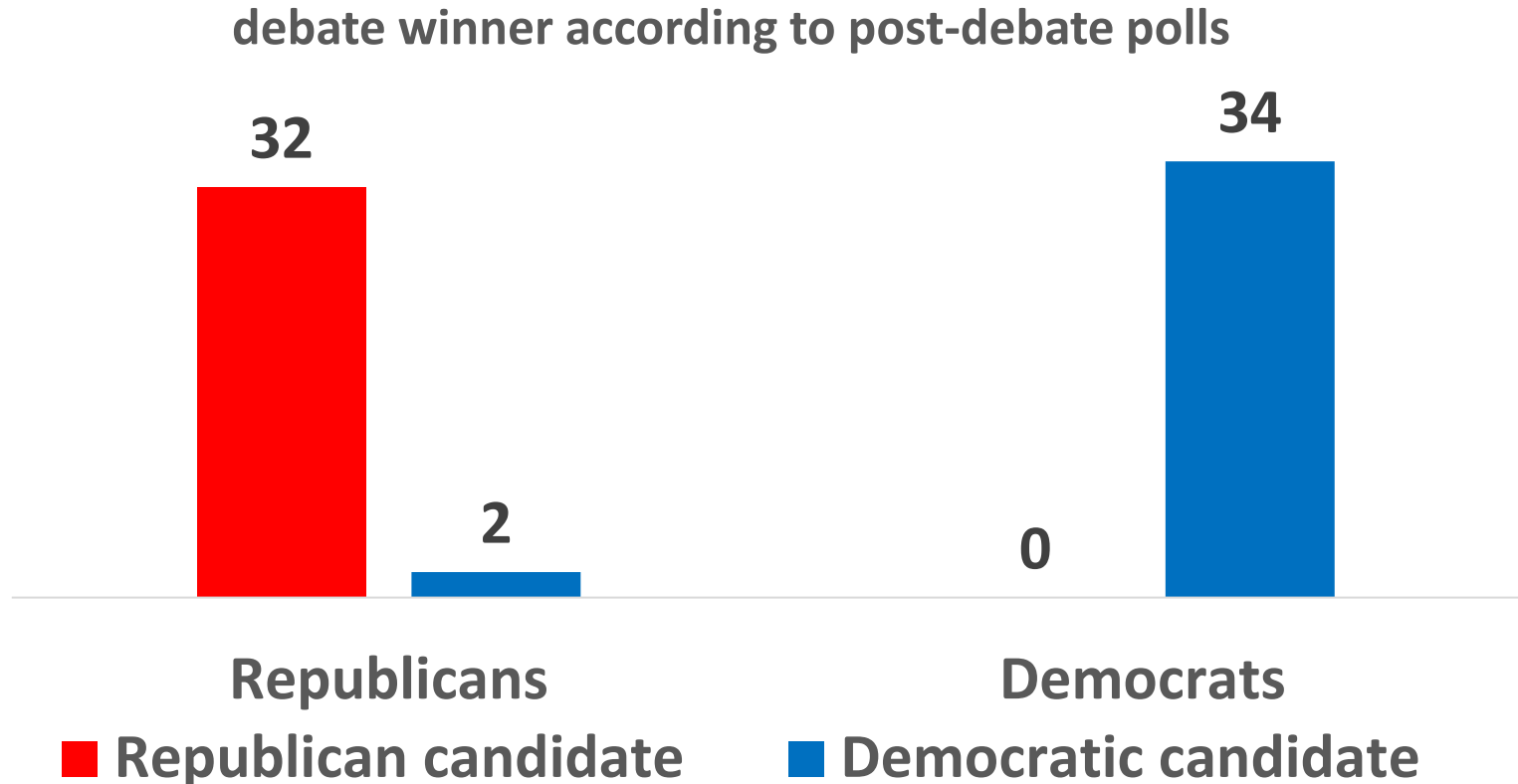


Source: Indiana University's Observatory on Social Media survey, November 2020



# Confirmation Bias example

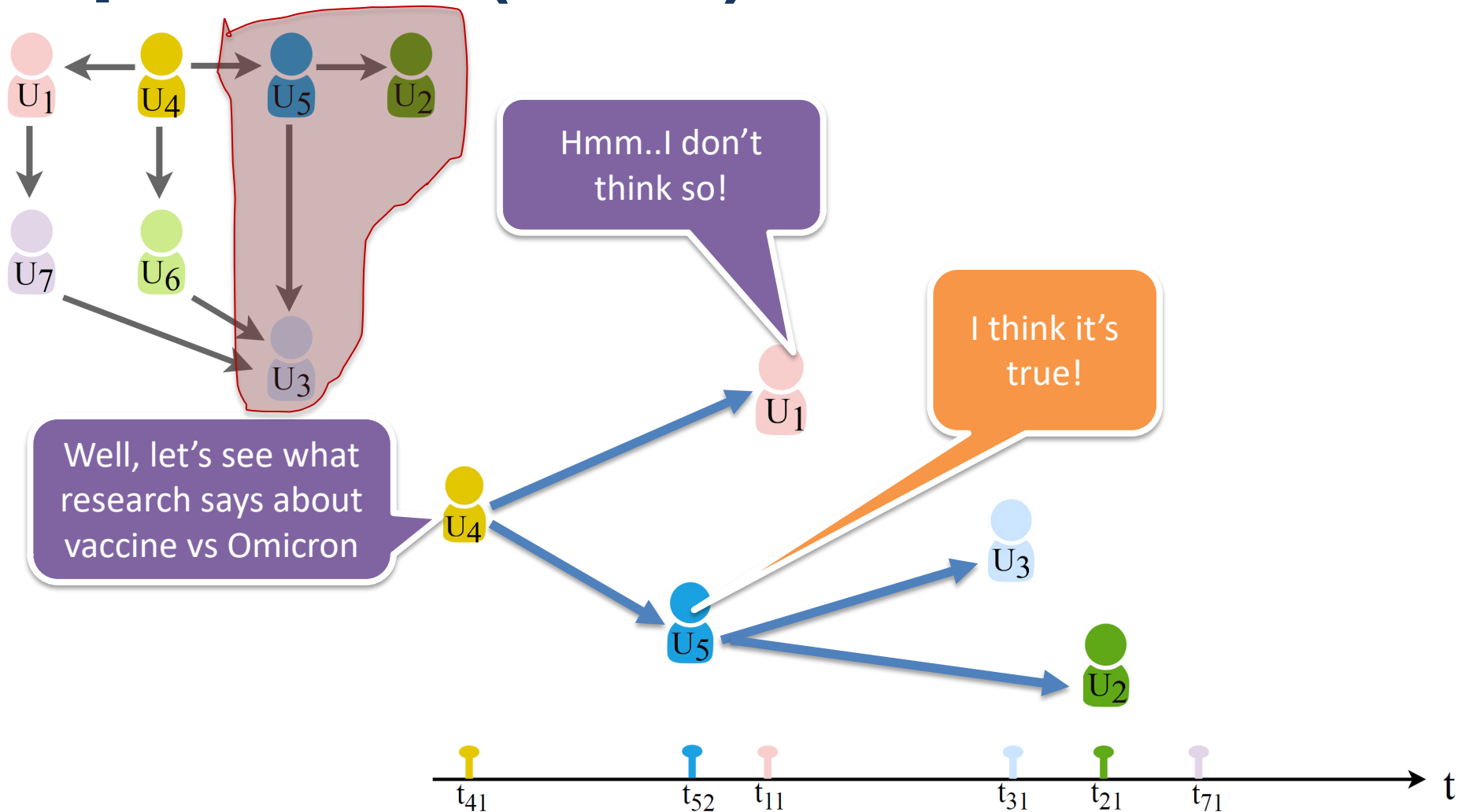
Of the 34 election presidential debates . . .



Source: Multiple polls, estimated for some on incomplete data



# Spread of (Fake) Information





# Theory of Attention

## Attention

- A form of mental activity or energy that can be distributed to different tasks.

## Attention is

1. Selective
2. Divisible
3. Shiftable
4. Sustainable



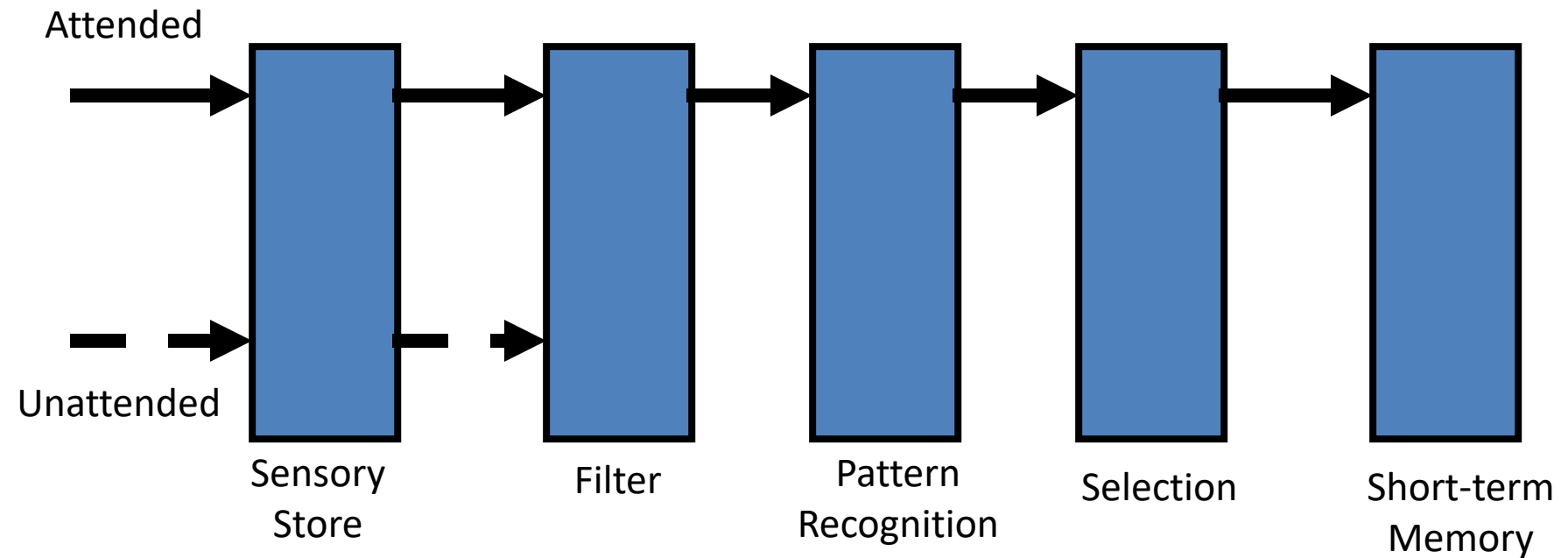
# The Filter Model

## Broadbent's Filter Model of Attention

- Information is selected on the basis of physical characteristics.
- The selected information is allowed to pass to later stages where it undergoes further processing.
- Unselected information is **blocked completely**.
- An example of an *early selection model*.



# The Broadbent Model of Selective Attention



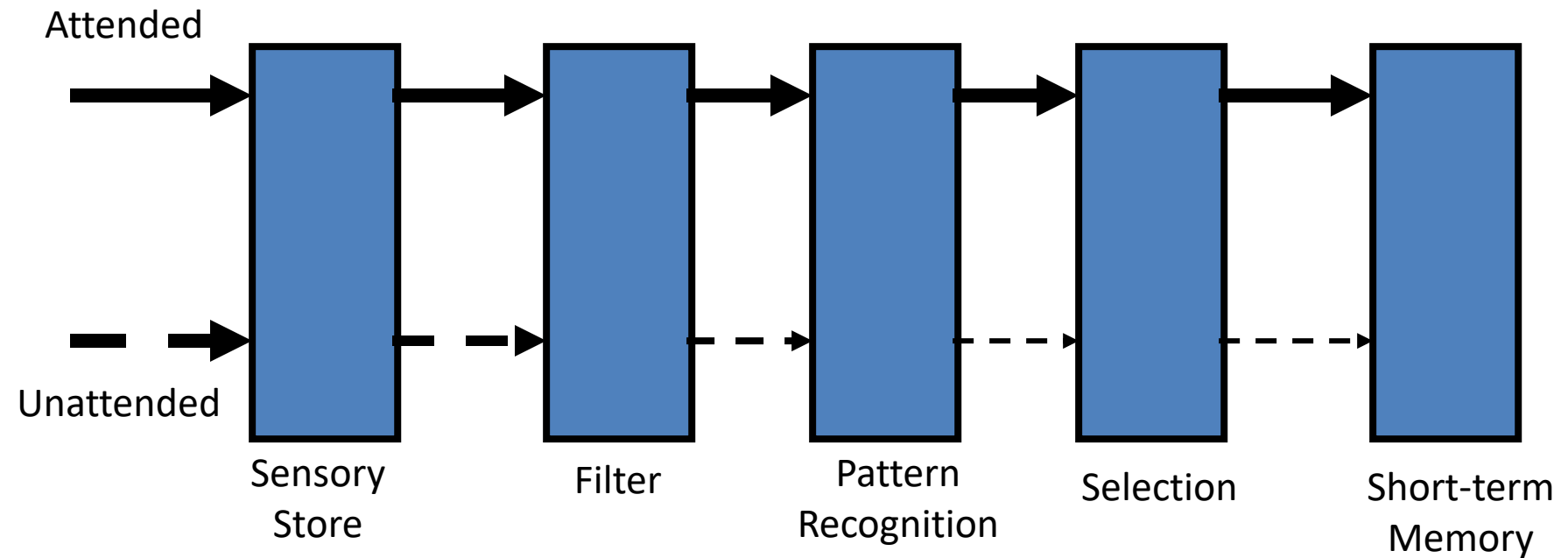
# The Attenuation Model

## Treisman's Model

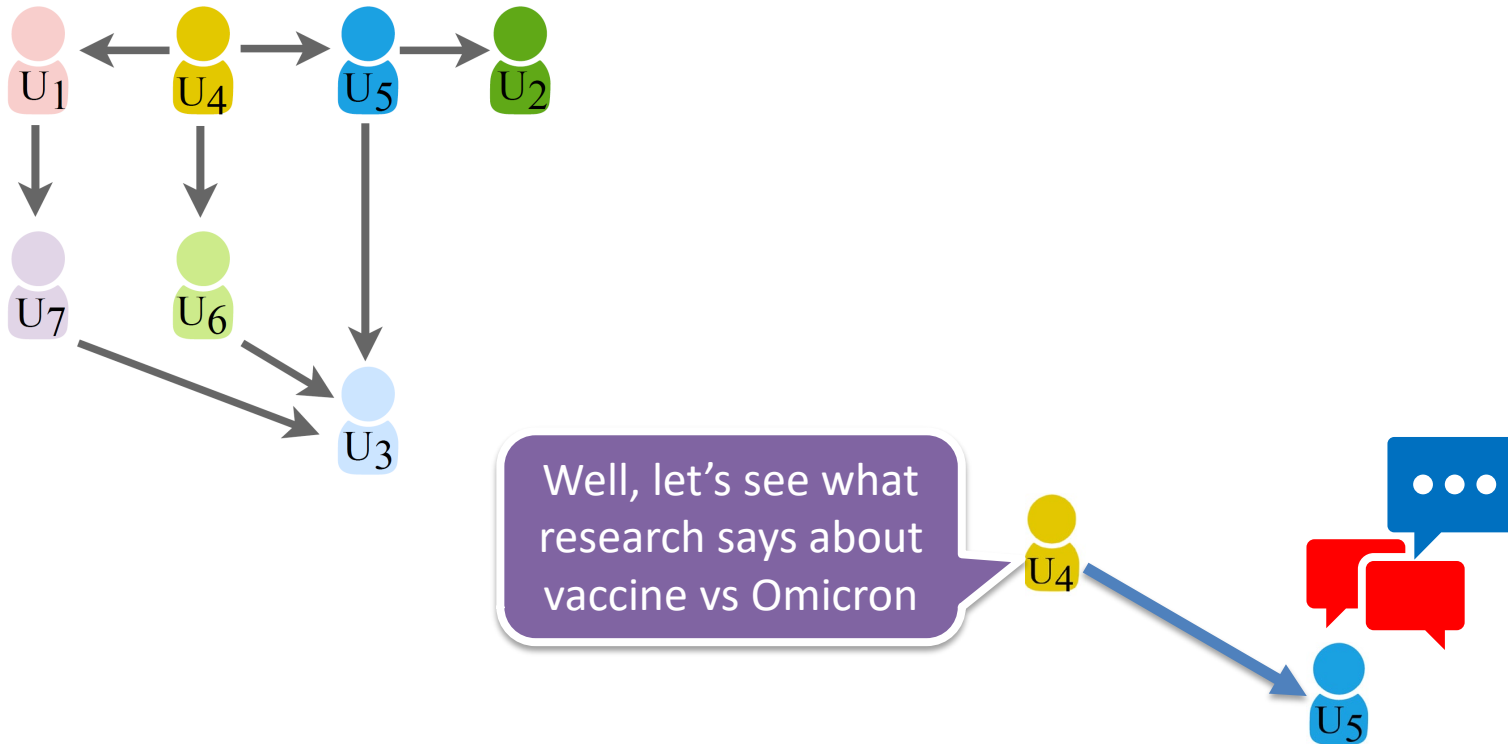
- Formulated by Treisman (1964).
- This theory aims to explain why and how individuals tend to process only certain parts of the world surrounding them, while ignoring others.
- Unattended message is attenuated (i.e., weakly processed information) but **not entirely blocked** from further processing and entry into memory.
- The likelihood of information getting through is determined by its **threshold**.
- Weakly processed information have different thresholds of recognition depending on their relevance and significance to the individual.



# Treisman Model of Selective Attention



# Spread of (Fake) Information



# Why Do We Forget?

## Five Key Theories

- Decay
- Interference
- Motivated Forgetting
- Encoding Failure
- Retrieval Failure

## Decay Theory

- Memory degrades with time.

## Interference Theory

- All forgetting cannot simply be explained by decay.
- One memory competes (*interferes*) with another.



# Interference Theory

## Retroactive Interference

- New information *interferes* with recall of old.

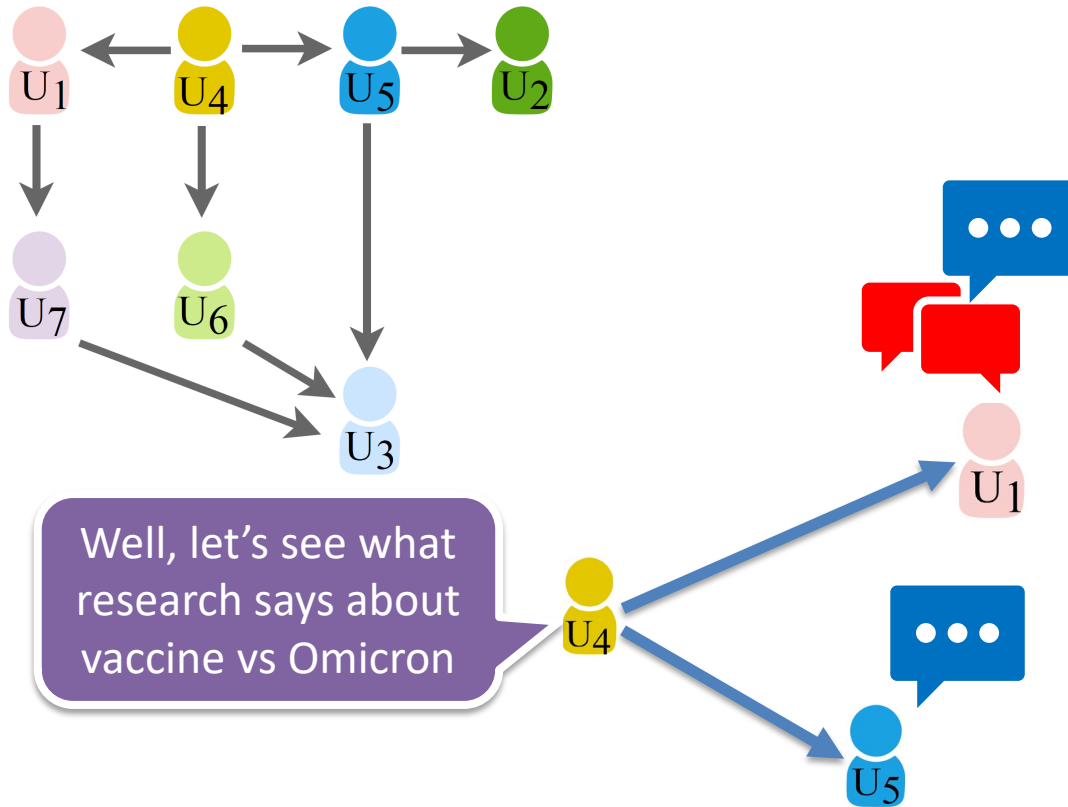
## Proactive Interference

- Old information *interferes* with recall of new.
- When learning SQL your knowledge of Python interferes.





# Spread of information in the presence of retroactive interference



# Testing an Idea Scientifically in Psychology

## Four Steps

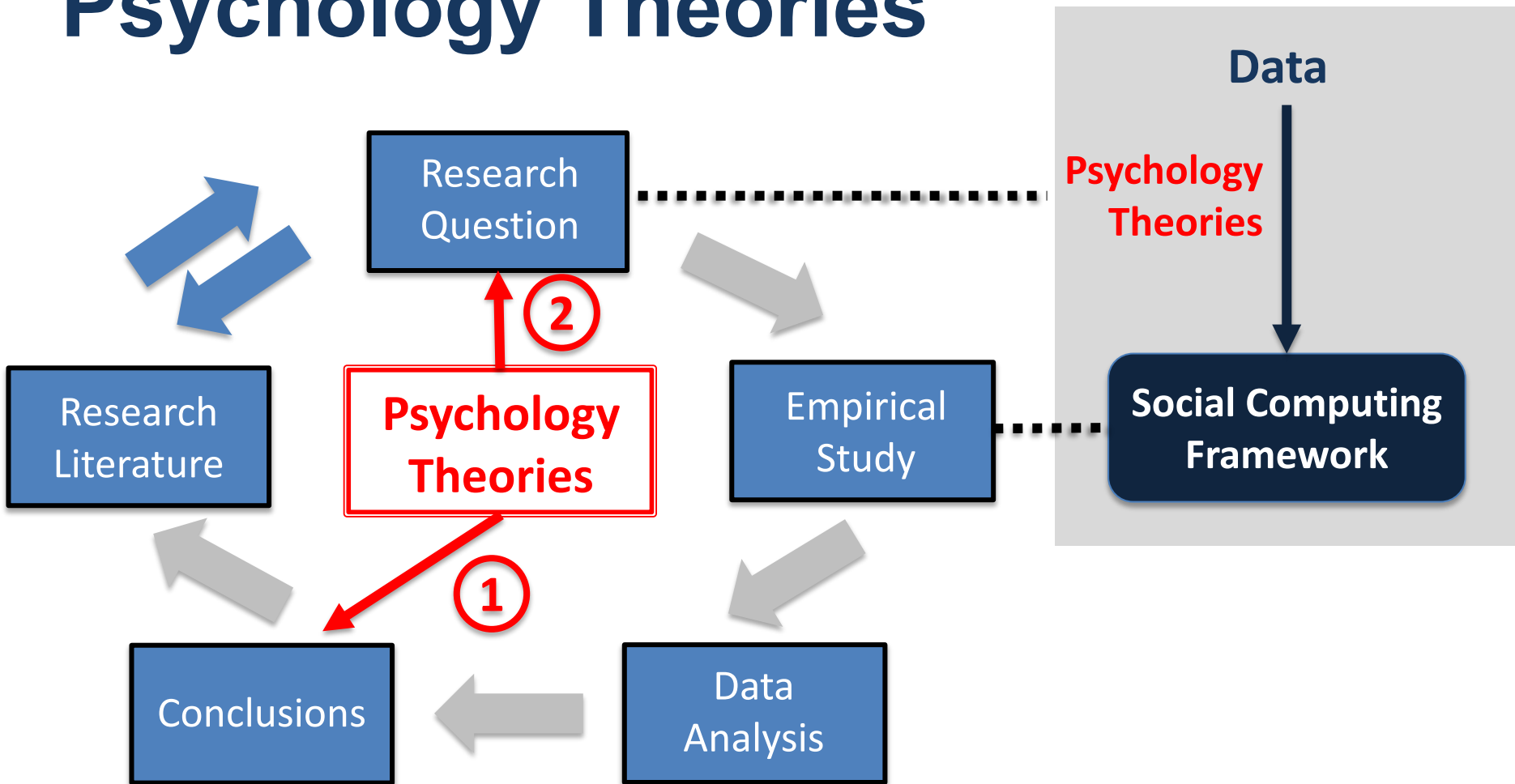
- Develop a hypothesis (a specific **testable** idea or prediction)
- Gathering objective data
- Analyzing the results
- Publishing, criticizing, and replicating the results

## Gathering objective data

- Start of **empirical** investigation.
- Investigating a question empirically means collecting evidence (data) carefully and systematically using a set of methods.
- These methods are designed to avoid false conclusions caused by our expectations, biases, and prejudices.



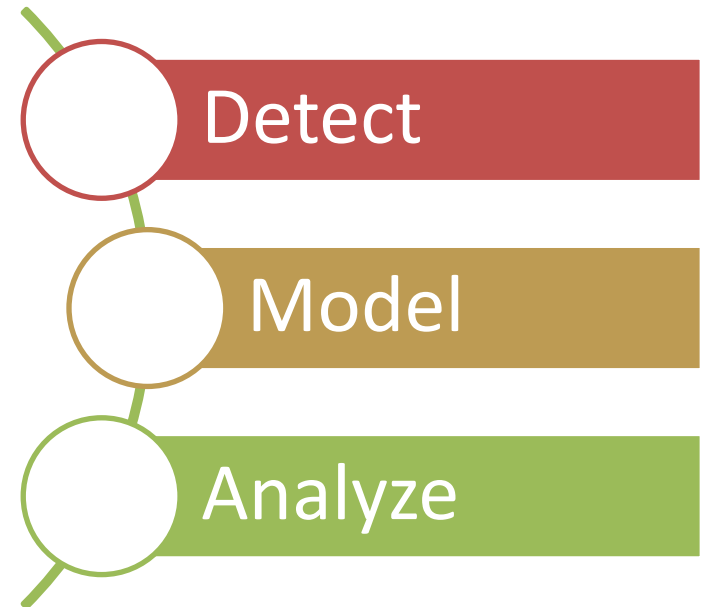
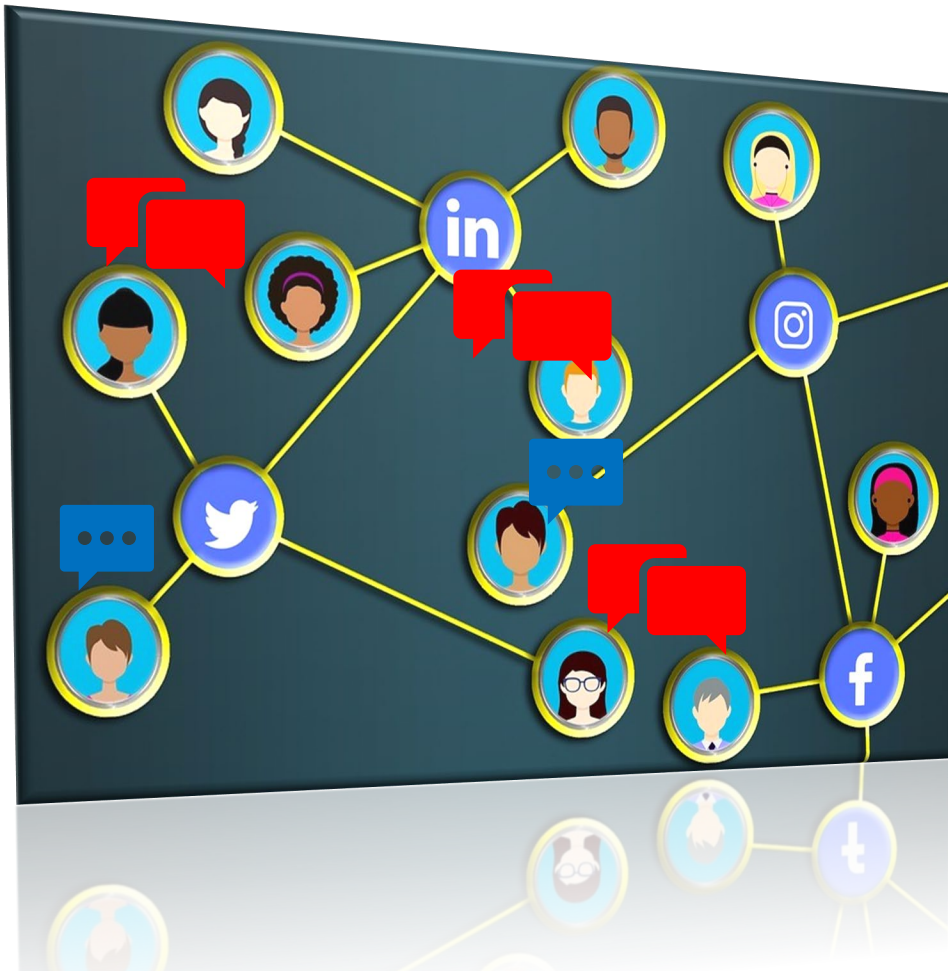
# Framework Used to Investigate Psychology Theories



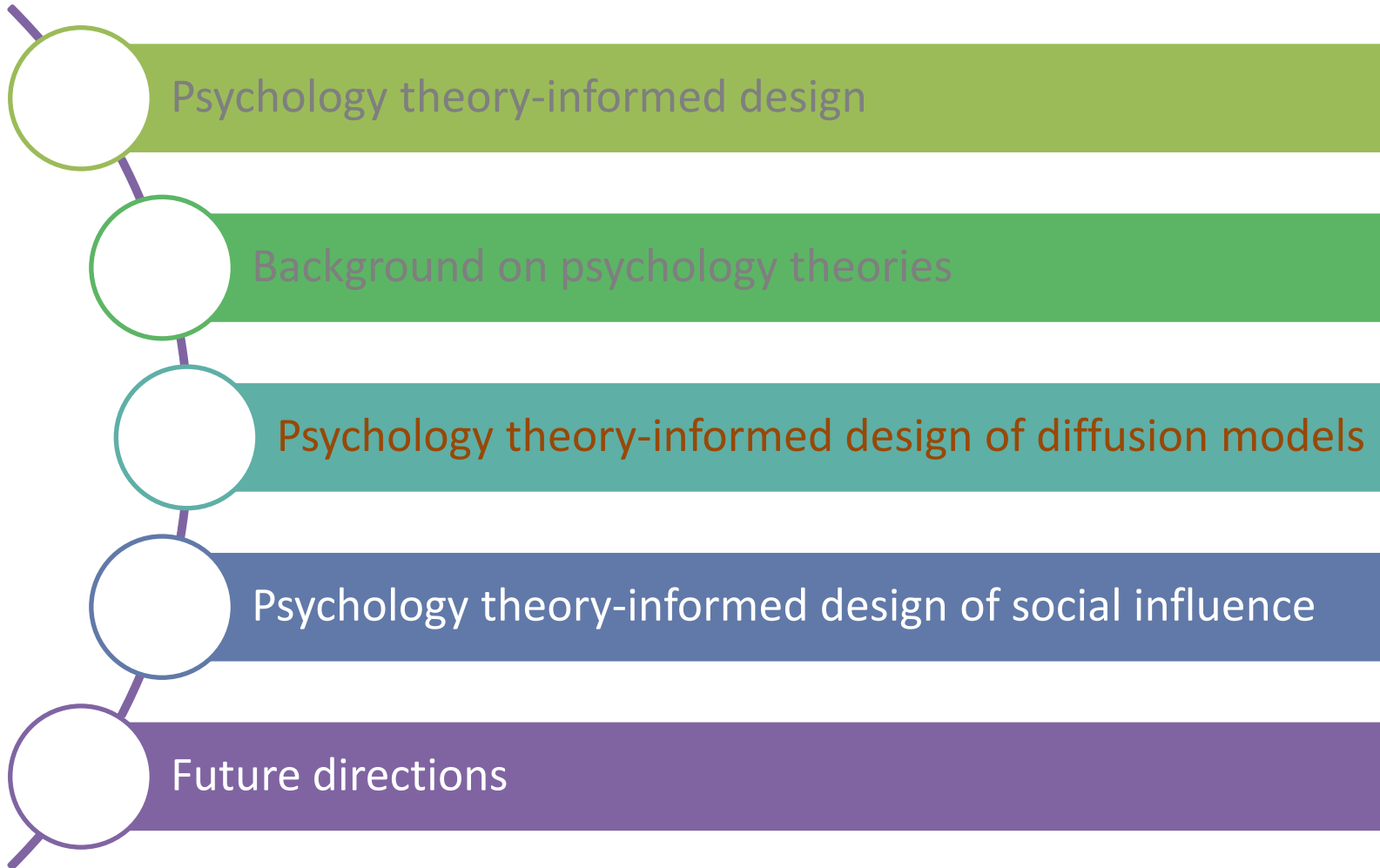
Shaughnessy, John J., Eugene B. Zechmeister, and Jeanne S. Zechmeister. *Research methods in psychology*. McGraw-Hill, 2000.



# Psychology-informed Design



# Next..



# Online Information Diffusion

## Information Diffusion

A process by which **information spreads** over a **network**

- Which pieces of **information** diffuse the most?
- **How and why** information is **diffusing** and will be diffused in the future?
- Which network **members** play crucial roles?

## Diffusion Models

Applications

Viral marketing

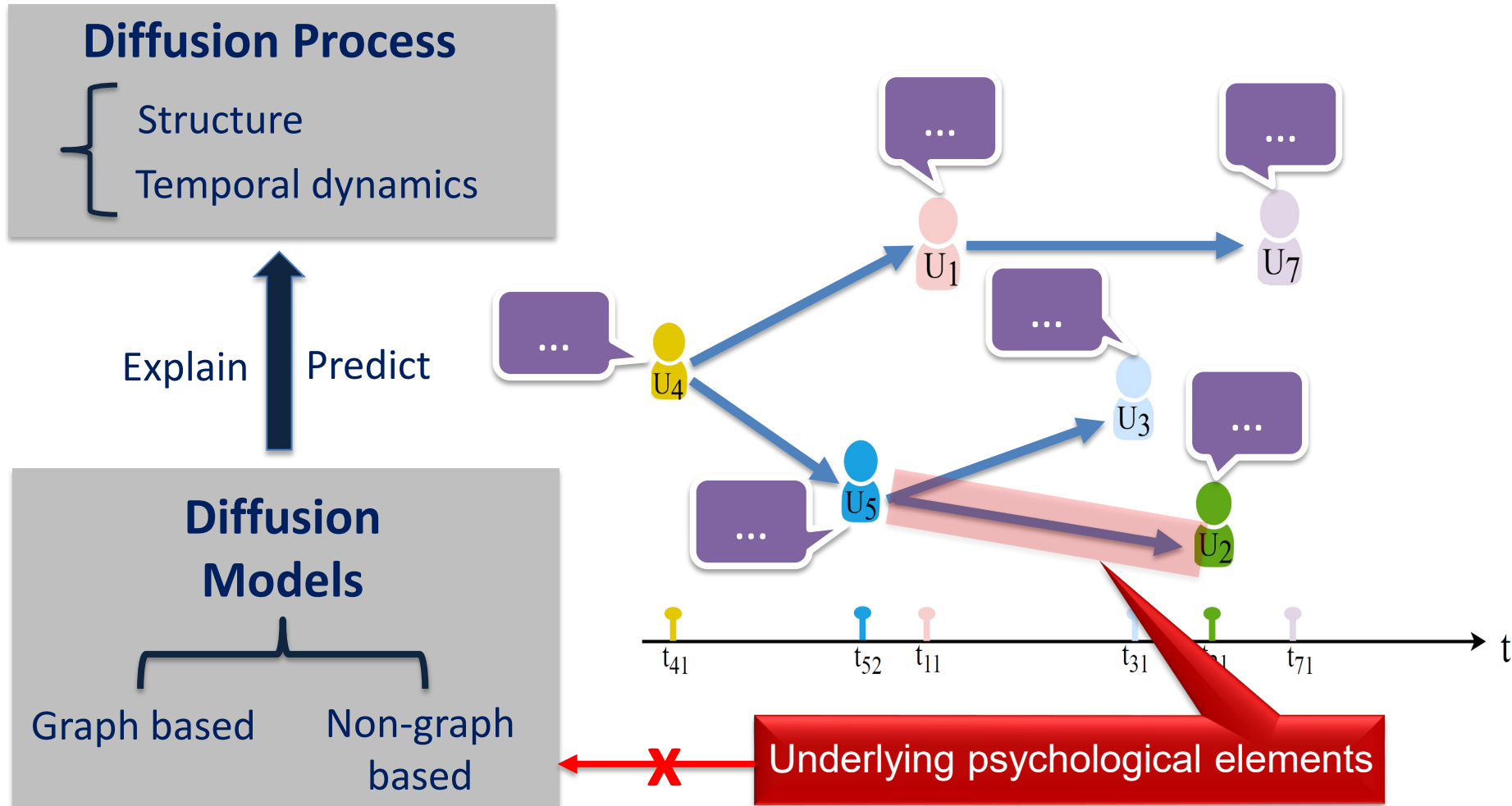
Rumor detection,  
fake news propagation

User behavior  
prediction

...

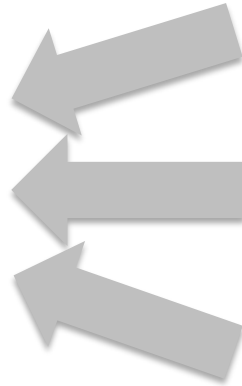


# Online Information Diffusion



# Psychology-informed design of diffusion models

**Diffusion Models**



## Psychology Theory

- Conformity theory
- Attention attenuation and interference theories
- Confirmation bias theory





# Overview of Modeling Psychology Theories

## Conformity

- Decompose *interpersonal influence strength* into *two additive parts*
- Quantify *informative and normative conformity* within these parts

## Attenuation & Interference

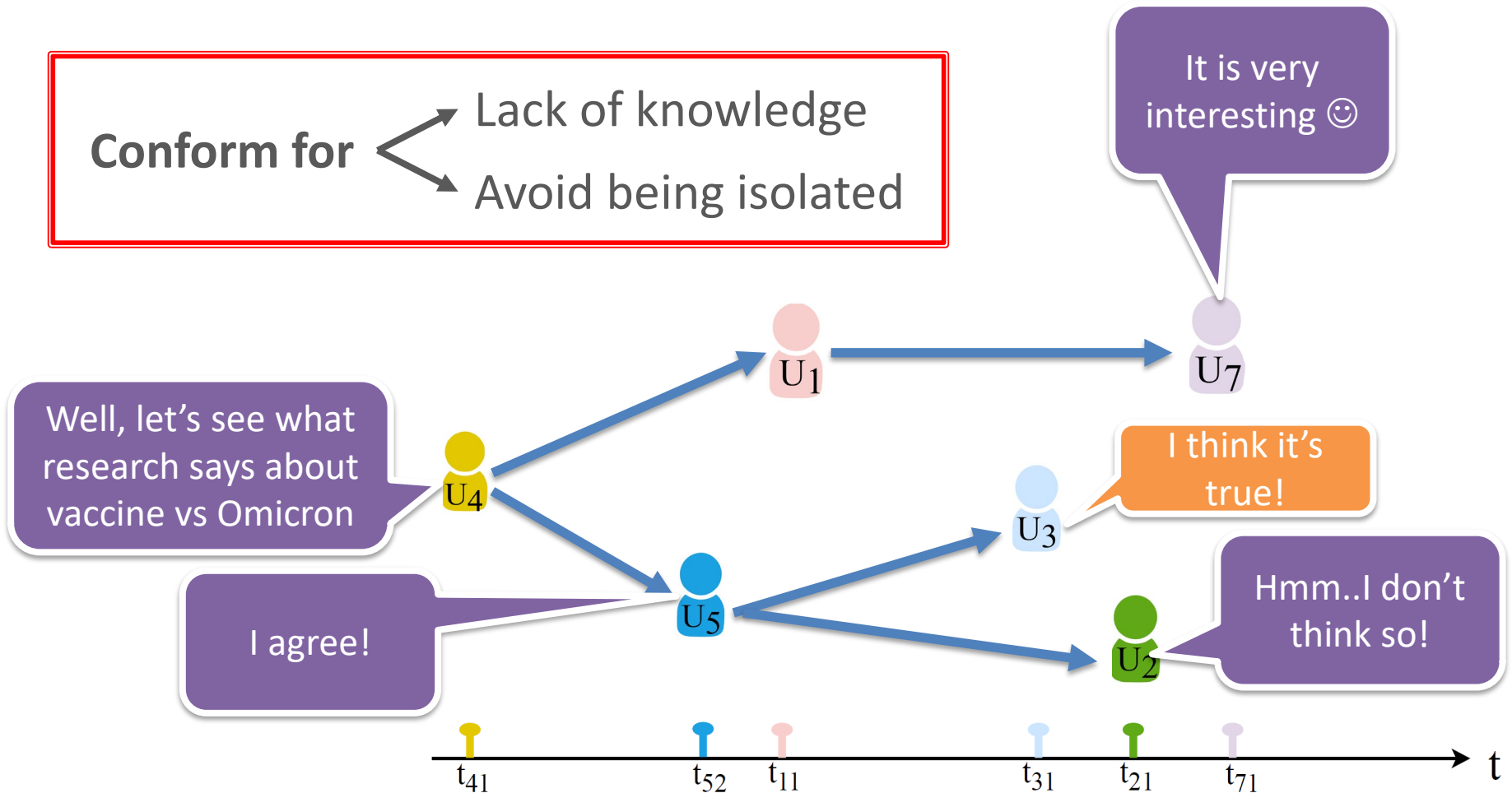
- Locate the *static activation threshold* that contrary to psychological mechanisms
- Replace the static threshold with *a personalized nonlinear growth function*

## Confirmation Bias

- Characterize the *influence weight* of news agencies over individuals as *state-dependent* (i.e., heavily depends on individuals' current opinions)



# Diffusion Models and Conformity Theory



Li, Hui, Hui Li, and Sourav S. Bhowmick. "Chassis: Conformity meets online information diffusion." Proceedings of the 2020 ACM SIGMOD International Conference on Management of Data. 2020.



# Challenges: Diffusion Models & Conformity Theory



The private beliefs of individuals may not be exposed explicitly in social activities.

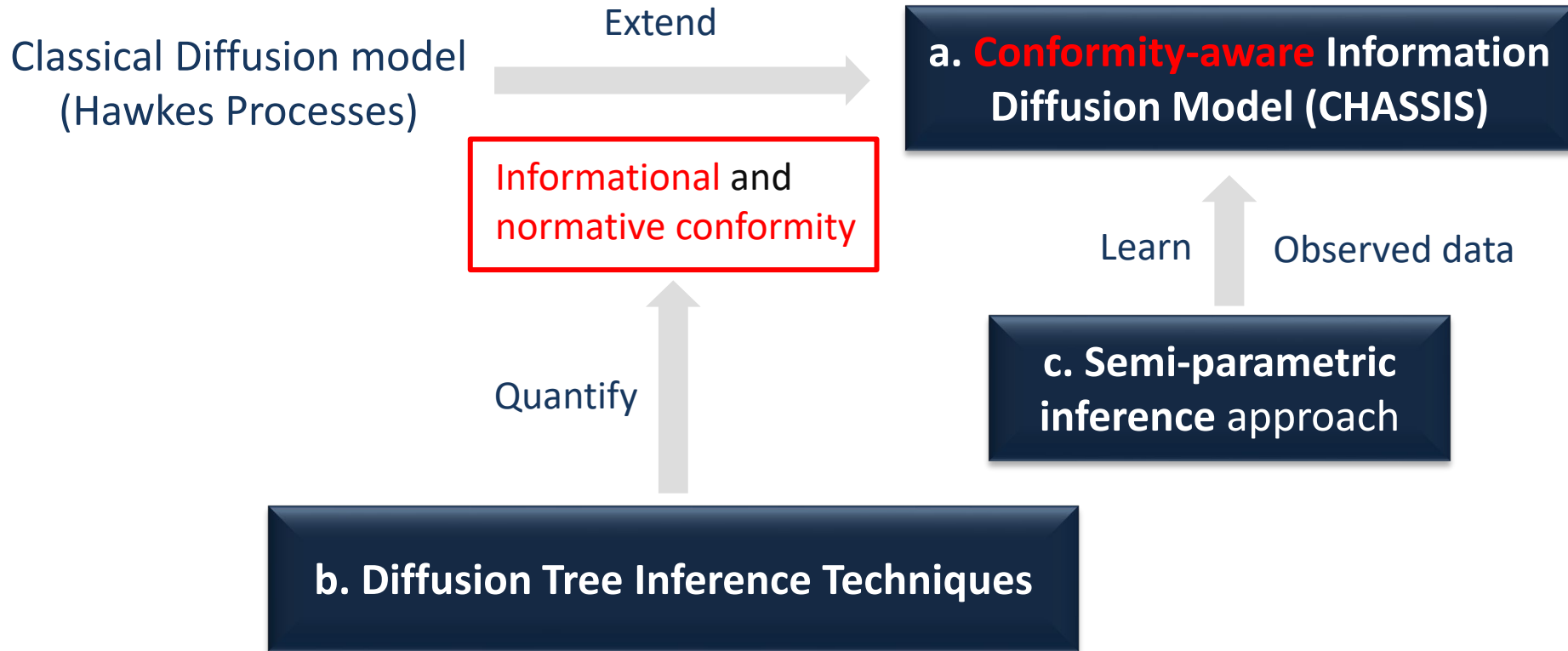
Conformity of an individual is context-sensitive.

The knowledge of the topology of a social network is insufficient to model conformity.



# Diffusion Models and Conformity Theory

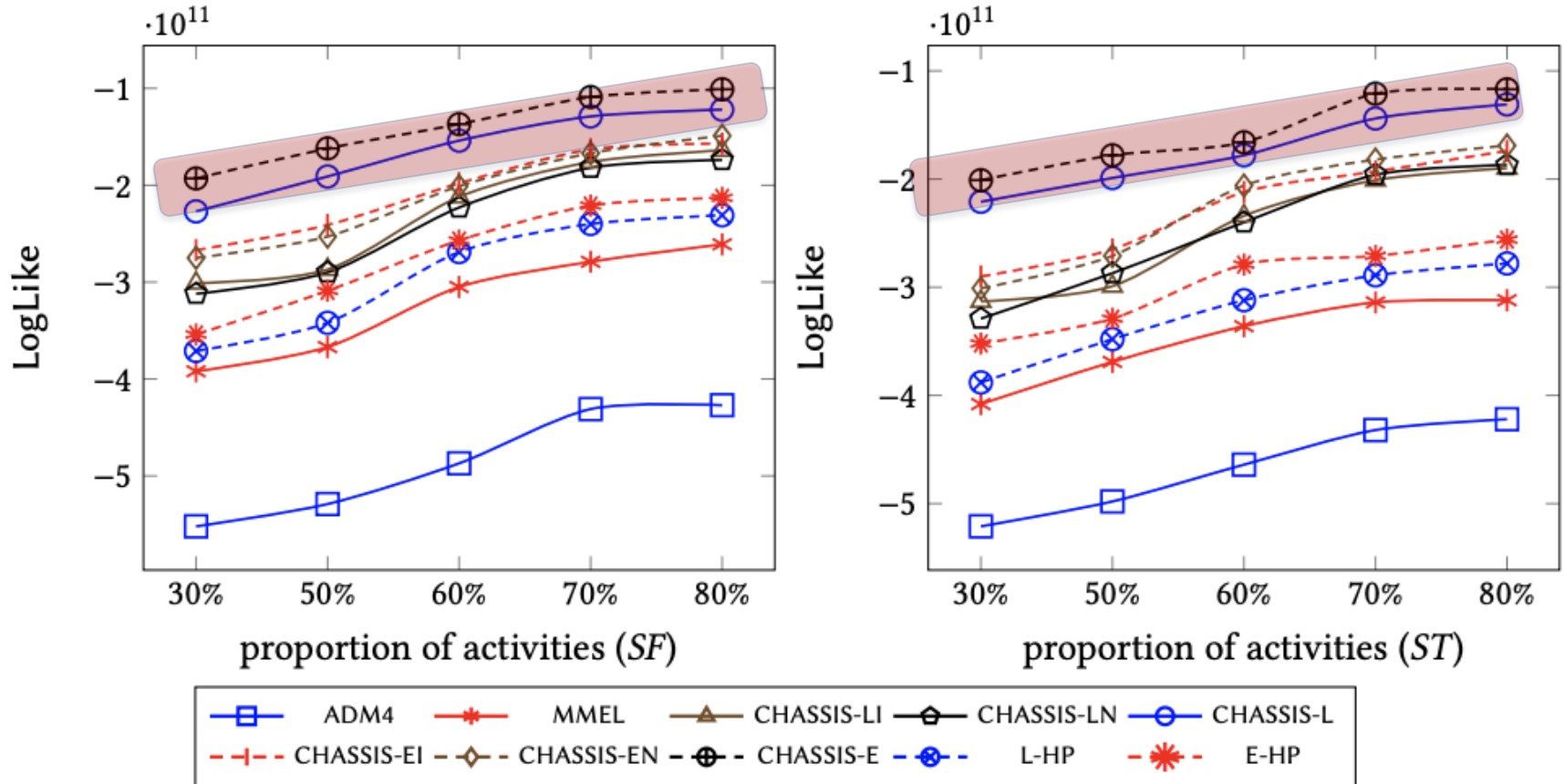
Aim: to better characterize online information diffusion



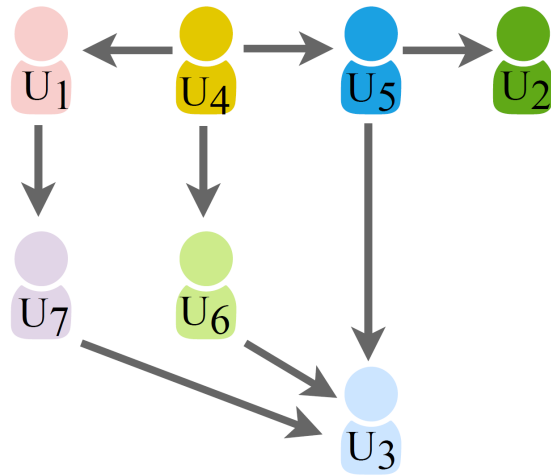
Li, Hui, Hui Li, and Sourav S. Bhowmick. "Chassis: Conformity meets online information diffusion." Proceedings of the 2020 ACM SIGMOD International Conference on Management of Data. 2020.



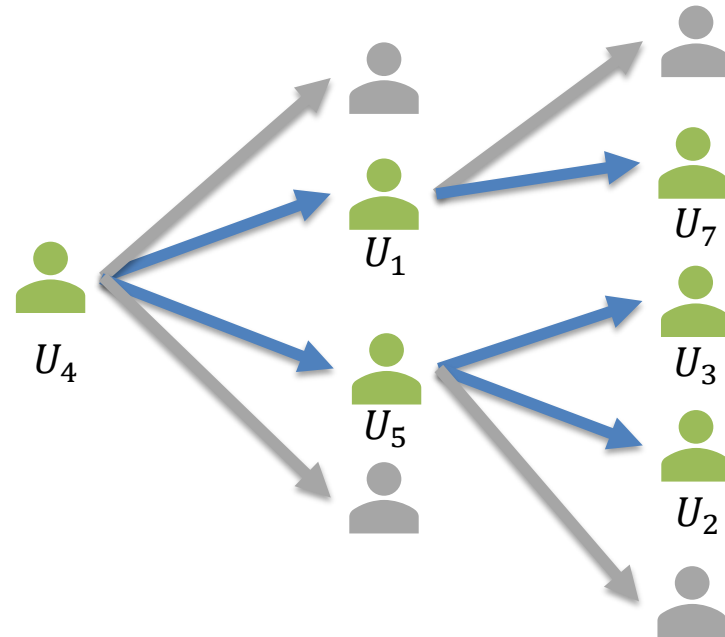
# Diffusion Models and Conformity Theory



# Diffusion Models and Attention Attenuation and Interference Theories



Activities on Social Networks



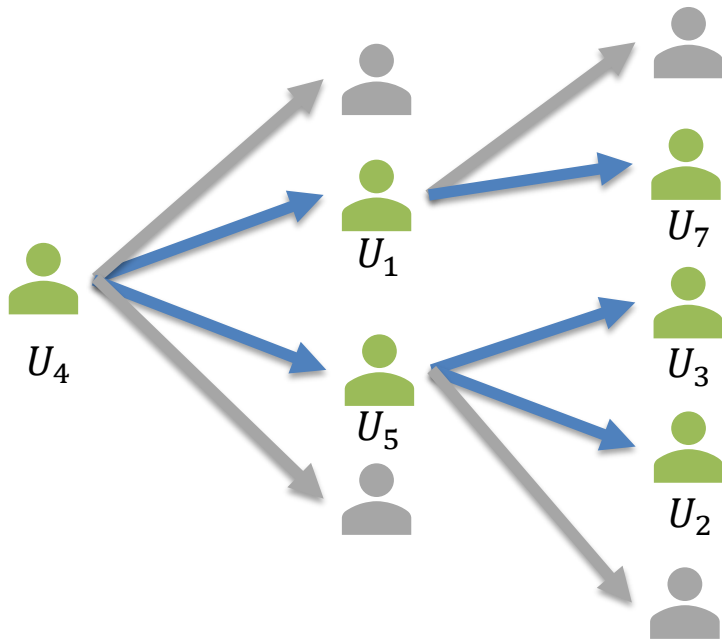
A Sample Cascade

Luo, Tianyi, et al. "A dissemination model based on psychological theories in complex social networks." IEEE Transactions on Cognitive and Developmental Systems 14.2 (2021): 519-531.



# Diffusion Models and Attention Attenuation and Interference Theories

People forward and disseminate online information based on interest and attention.



## Attention attenuation theory

The attention people give to the obtained information will decrease and shift over time.

## Interference theory

New information increases people's resistance, hindering its spread.

## Empirical Evidence

The spread of online information becomes more difficult as cascade depth increases.



# Diffusion Models and Attention Attenuation and Interference Theories

**LT model** (Linear Threshold): each node has an **activation threshold** indicating how easily it be affected.

Inactive: influence  $< \theta$

Active: influence  $\geq \theta$

**Constant!**



## Psychological Theories and Empirical Evidence

- The activation threshold of nodes **grows nonlinearly** over **time** and eventually converges to 1.
- The growth function can be **personalized**.





# Diffusion Models and Attention Attenuation and Interference Theories

## Resistant Linear Threshold (RLT) Dissemination Model

- Extend the classical **linear threshold (LT)** model
- Based on **psychological theories** and **empirical findings**

## RLT Model Validation on three types of networks

- **Quantify and compare** the dissemination characteristics of **the simulation results** with those from the empirical results

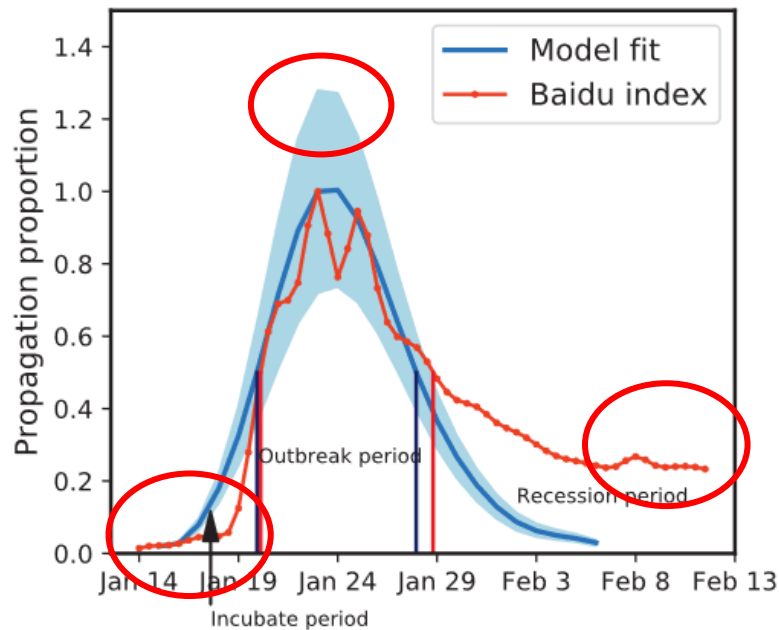
## Sensitivity Analysis and Case Studies

- Explore the effect of network structure and model parameters on information dissemination
- Perform two case studies to **demonstrate** the **effectiveness and applications of the model**

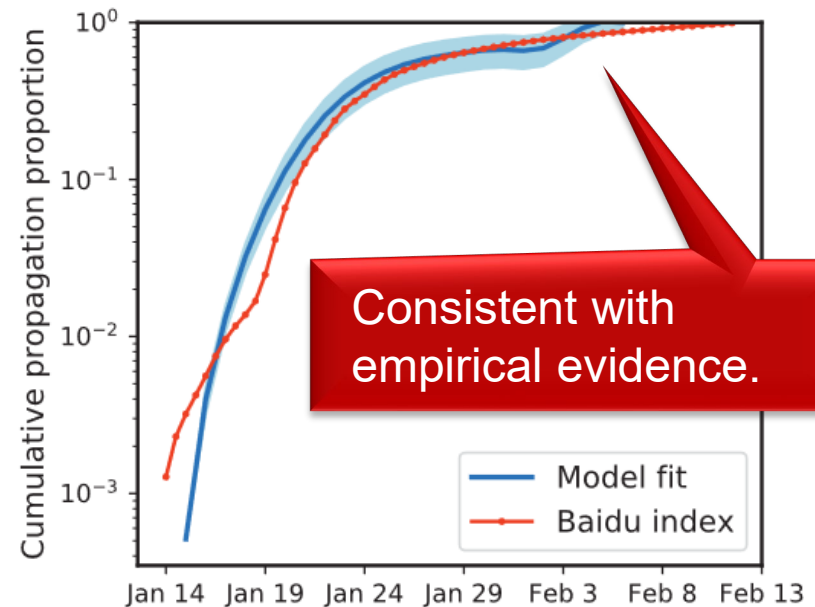


# Diffusion Models and Attention Attenuation and Interference Theories

## Dissemination of Online Information About COVID-19



(a)



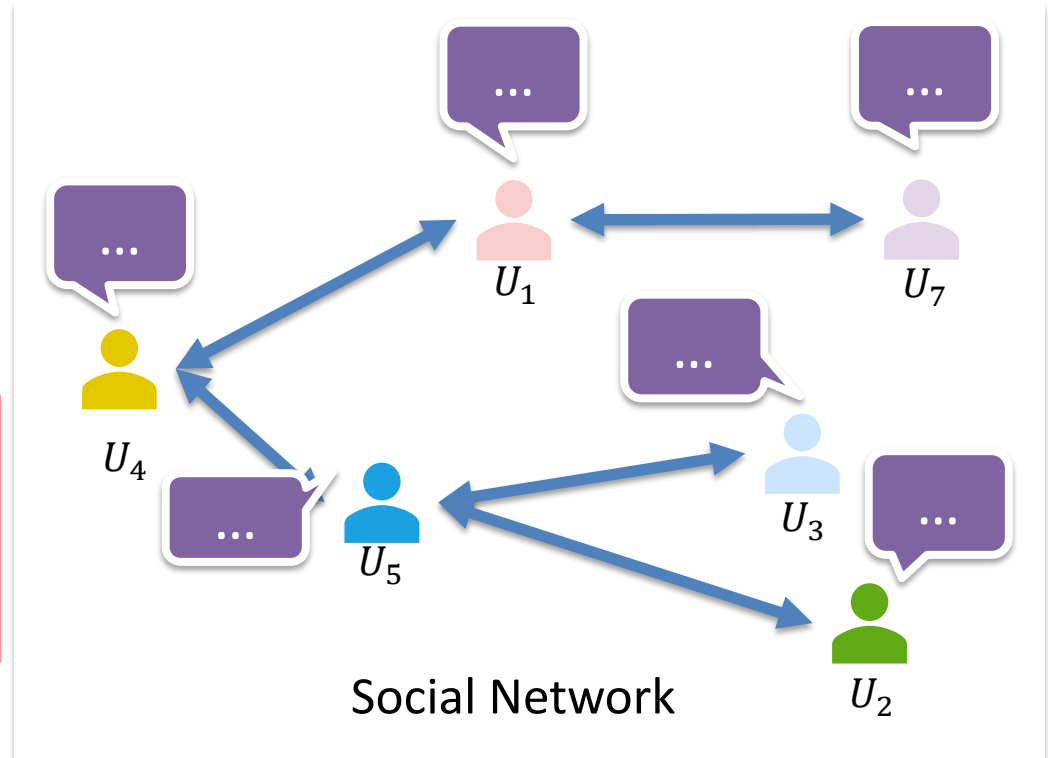
(b)

# Diffusion Models and Confirmation Bias

In online social networks, individuals form opinions based on three factors:

- Innate opinions
- Information from other individuals
- Information from the news sources/followed thought leaders

**Confirmation bias**

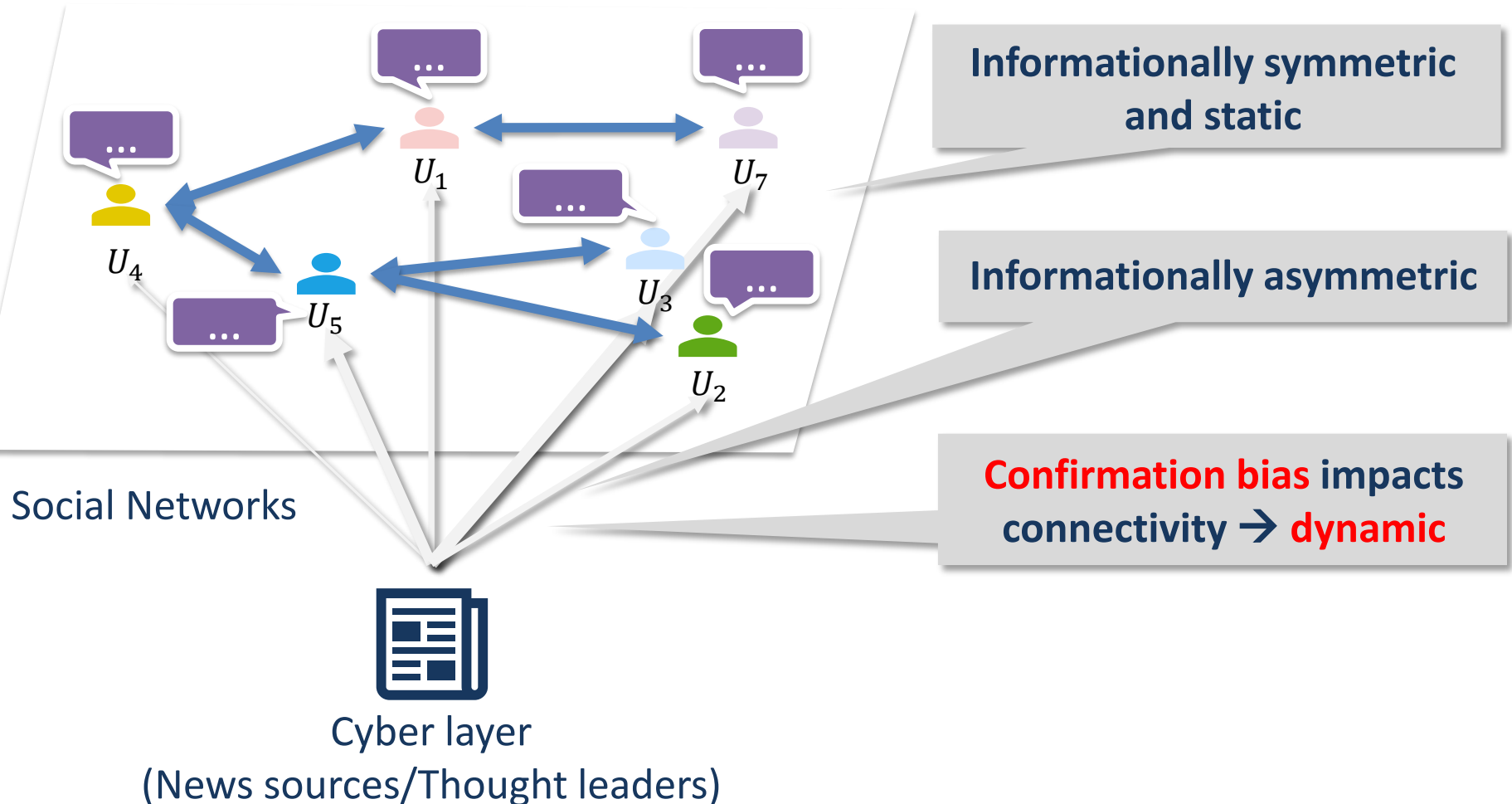


Mao, Yanbing, Sadegh Bolouki, and Emrah Akyol. "Spread of information with confirmation bias in cyber-social networks." IEEE Transactions on Network Science and Engineering 7.2 (2018): 688-700.



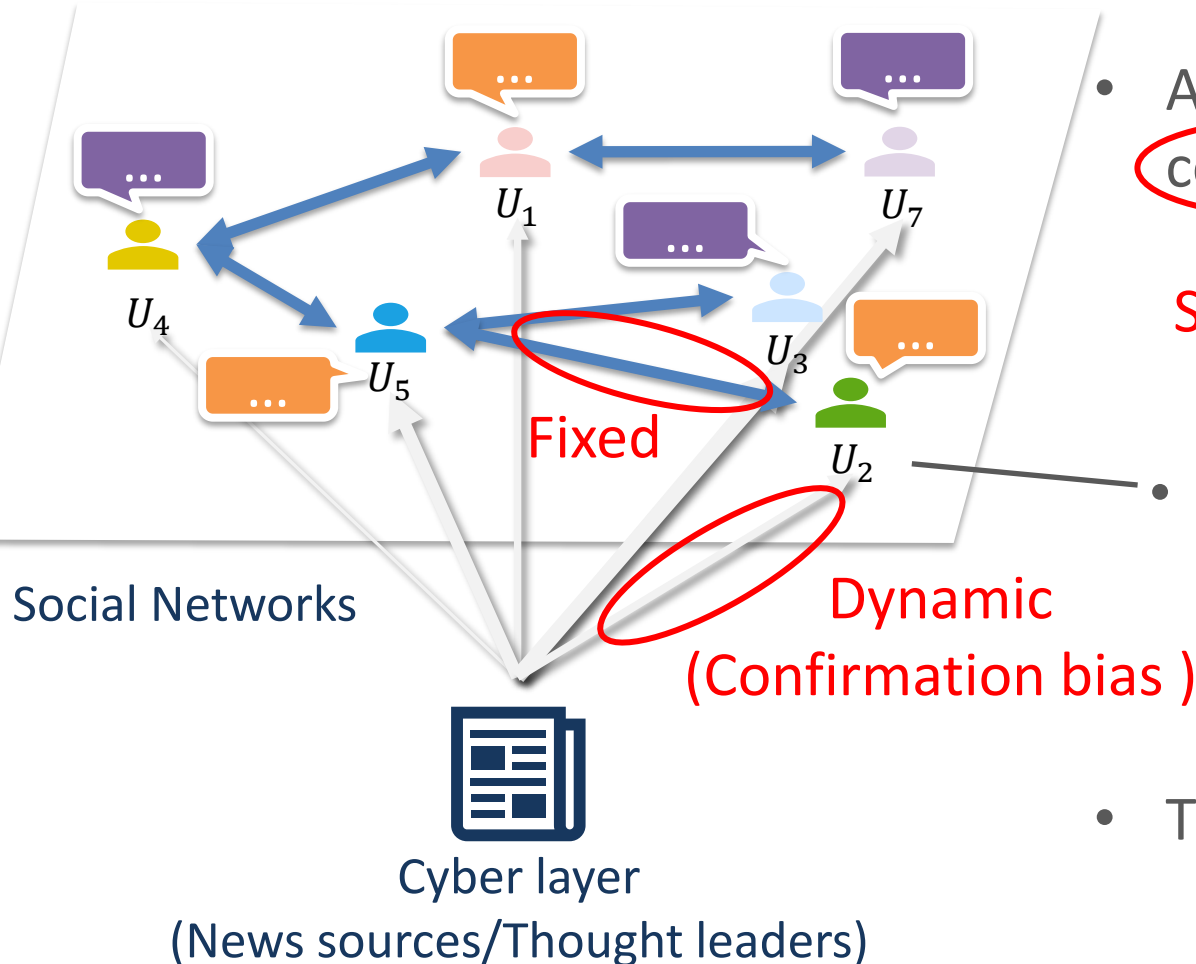
# Diffusion Models and Confirmation Bias

## A Dynamics of Cyber-social Networks



# Diffusion Models and Confirmation Bias

## Features of the New Opinion Dynamics Model



- All agents converge to the **consensus** (same state)  
Steady-state (equilibrium)
- Individual's opinion update mechanism
- The weight of influences

# Diffusion Models and Confirmation Bias

## Propose a Dynamics of Cyber-social Networks

Individual's **opinion update mechanism** is a convex combination of three factors

## Compute the Equilibrium Point of Proposed Dynamics

**Compute the equilibrium point** of the proposed dynamics under linear and nonlinear state-dependent weight functions

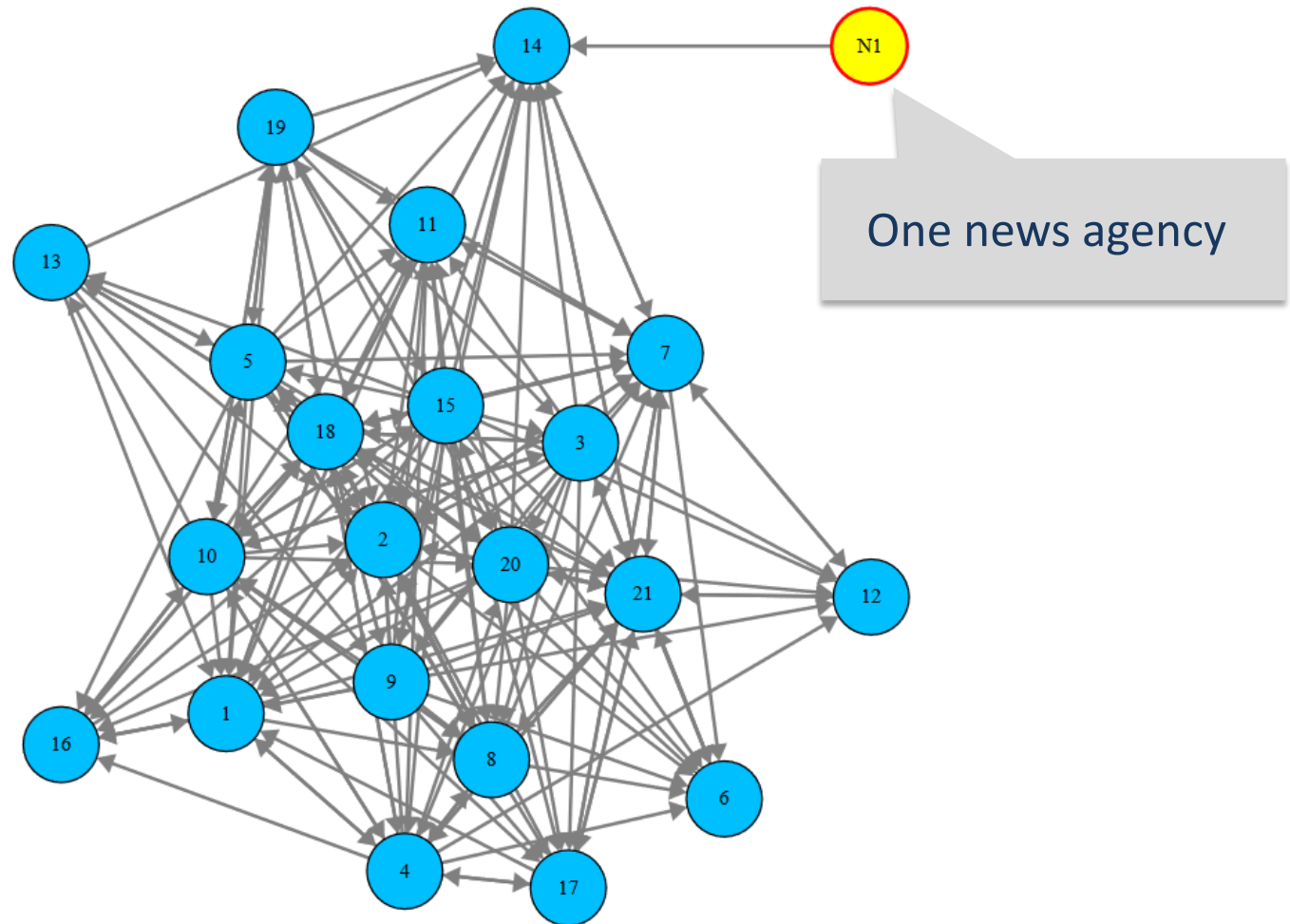
## Analyze the Impact of News Agencies Using Proposed Dynamics

Using the proposed dynamics to study **the effects** of the distribution of **news agencies'** opinions and the distance between polarized opinions of news agencies in **Krackhardt's advice network**



# Diffusion Models and Confirmation Bias

## Distribution of News Agency's Opinions



# Diffusion Models and Confirmation Bias

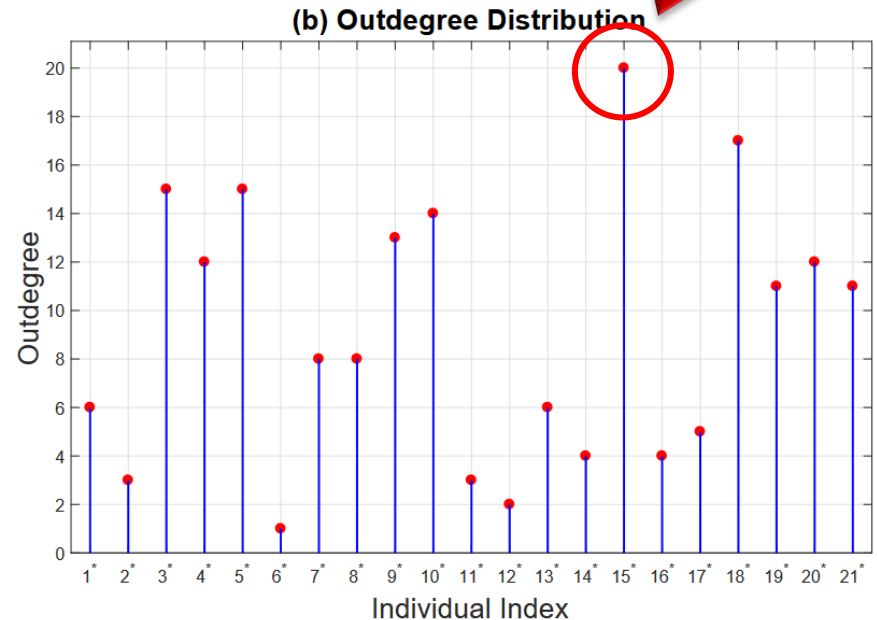
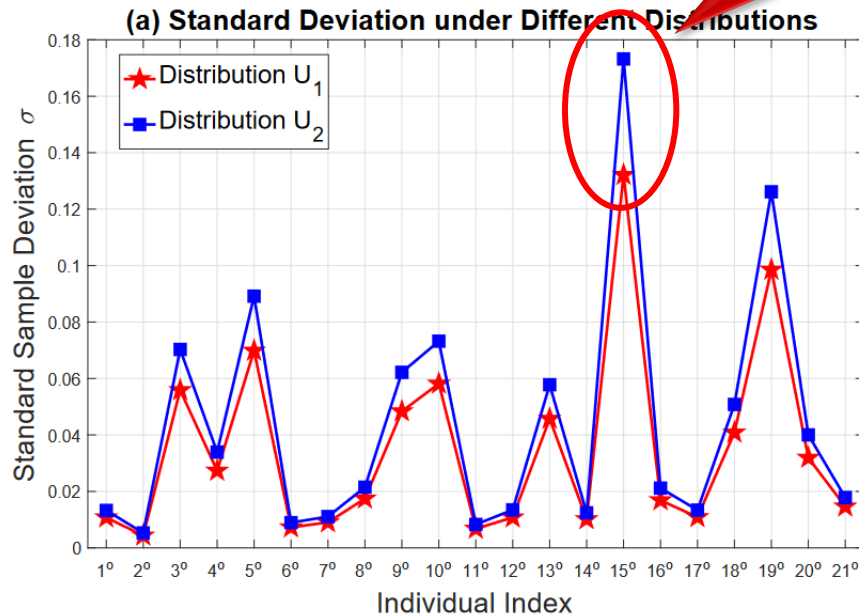
## Distribution of News Agency's Opinions

$$U_1: f(y) = \begin{cases} \frac{1}{0.8}, & y \in [0.1, 0.9] \\ 0, & \text{otherwise} \end{cases}$$

$$U_2: f(y) = \begin{cases} \frac{1}{0.4}, & y \in [0.1, 0.2] \cup [0.8, 1] \\ 0, & \text{otherwise} \end{cases}$$

U2 results in bigger sample deviation than U1

News agency influence critical individual



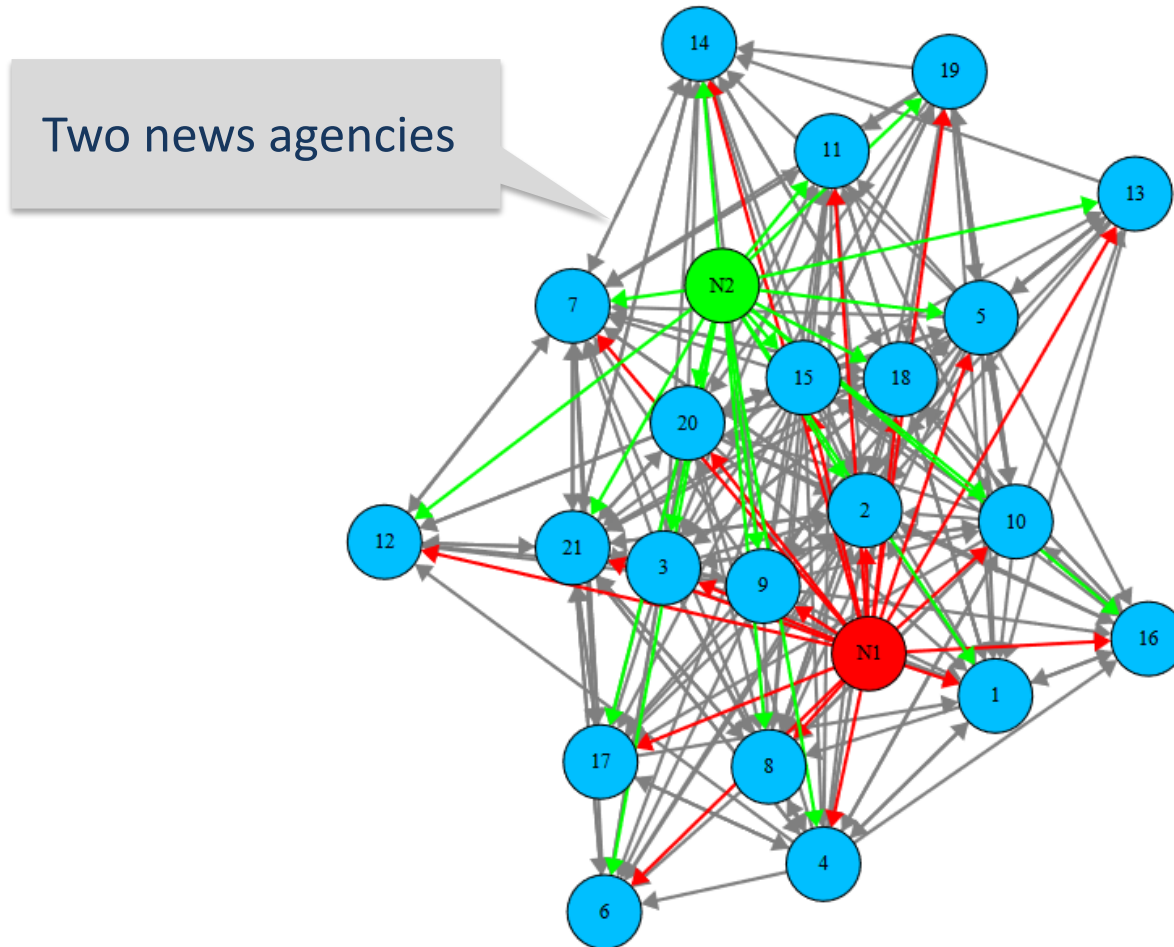
Individual index  $i^0$ : news agency  $N_1$  influences individual  $i$  solely





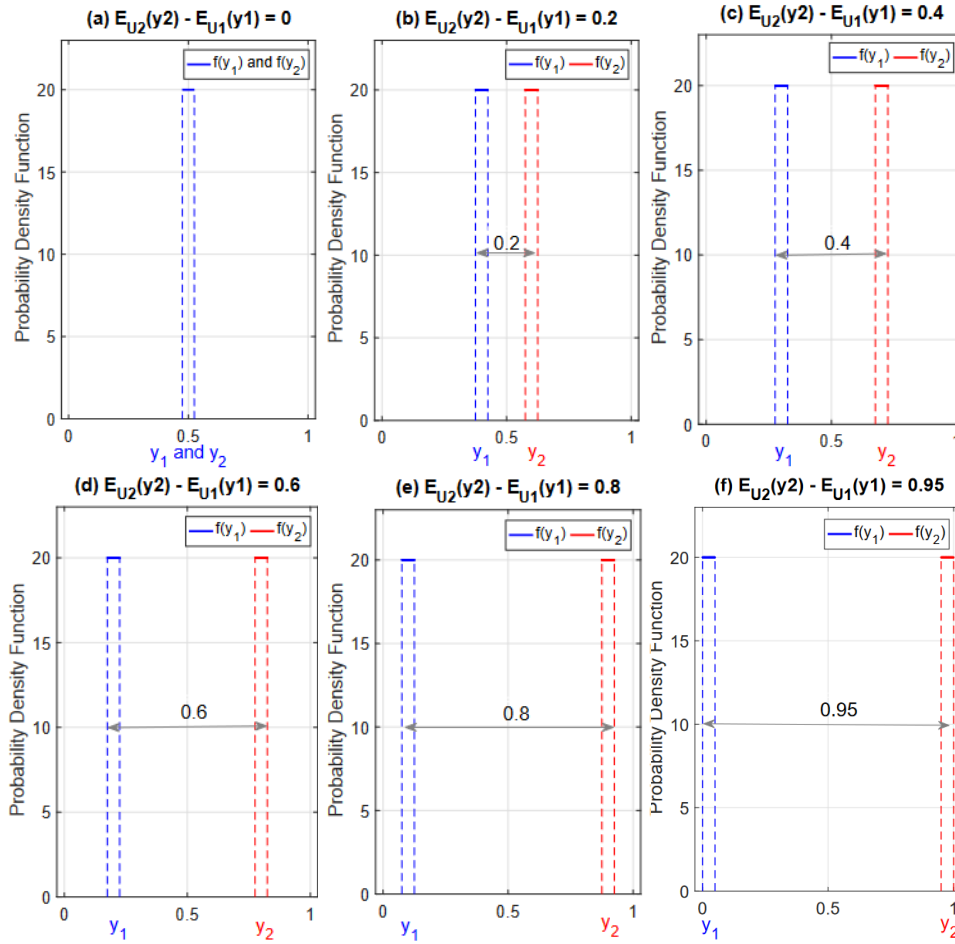
# Diffusion Models and Confirmation Bias

## Distance Between Polar Opinions

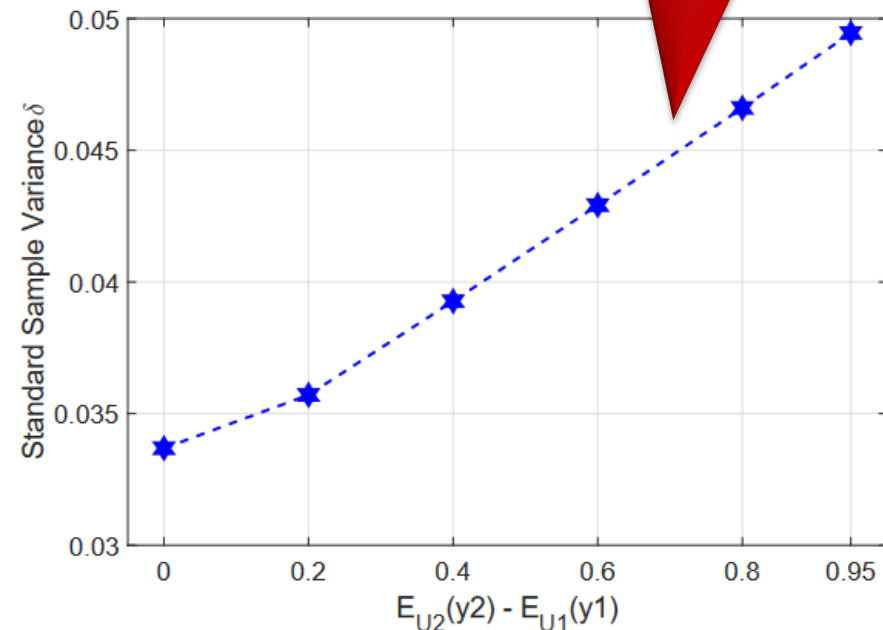


# Diffusion Models and Confirmation Bias

## Distance Between Polar Opinions



Longer distance between the means of polar opinions results in a larger sample variance



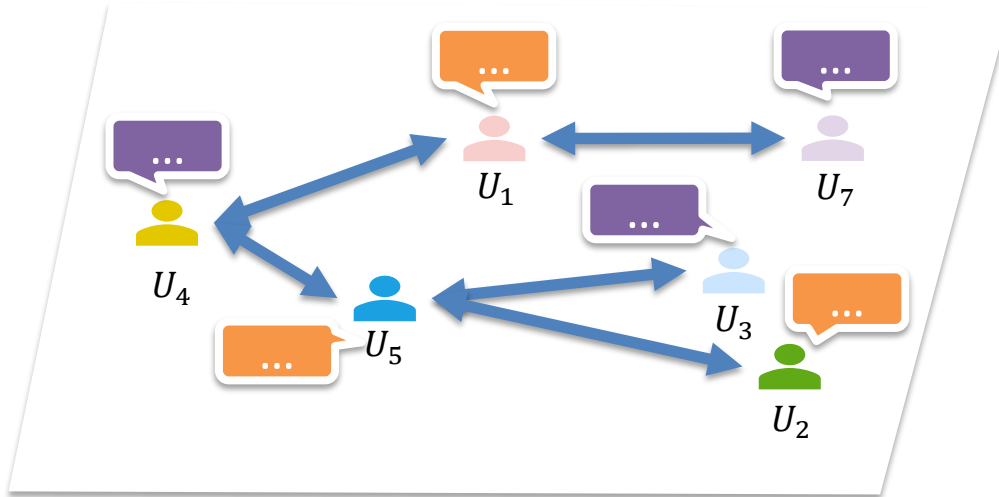
Six uniform distributions of N1 and N2



# Diffusion Models and Confirmation Bias

Competitive information spread on networks

- Misinformation spread
- Political polarization



Confirmation bias (CB) helps  
create “echo chambers”  
within networks



Not considered by  
prior works

Mao, Yanbing, and Emrah Akyol. "Competitive information spread with confirmation bias." 2019 53rd Asilomar Conference on Signals, Systems, and Computers. IEEE, 2019.

Mao, Yanbing, Emrah Akyol, and Naira Hovakimyan. "Impact of confirmation bias on competitive information spread in social networks." *IEEE Transactions on Control of Network Systems* 8.2 (2021): 816-827.



# Diffusion Models and Confirmation Bias

## Adopt the Opinion Dynamics and a Linear CB Model

- Adopt the aforementioned **opinion dynamics** with two competitive information sources and **a linear CB model**

## Analyze the Information Spread with Two Information Sources

- The problem is formulated as a **zero-sum game**
- This game admits **a unique Nash equilibrium** which is in pure strategies

## Study the Impact of CB on the Nash Equilibrium

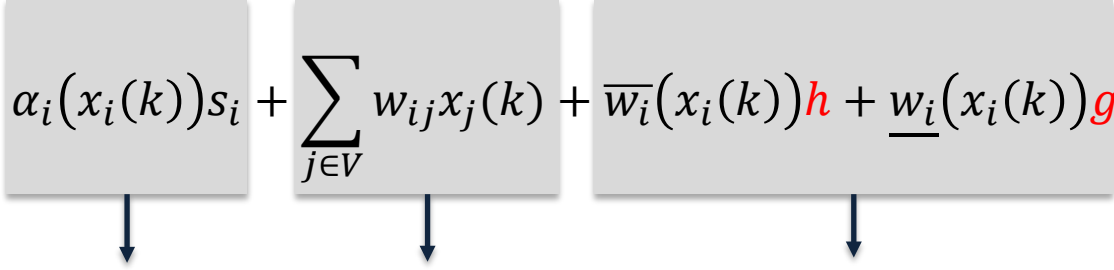
- Analyze how the equilibrium-achieving strategies depend on the the innate opinions of the public , network topology parameters, and the **CB parameters**



# Diffusion Models and Confirmation Bias

## Opinion Dynamics and the Linear CB Model

$$x_i(k+1) = \alpha_i(x_i(k))s_i + \sum_{j \in V} w_{ij}x_j(k) + \overline{w}_i(x_i(k))\textcolor{red}{h} + \underline{w}_i(x_i(k))\textcolor{red}{g}, i \in V$$



Innate opinion      Influence from other individuals      Information from two information sources


- $x_i(k) \in [0, 1]$ : individual  $v_i$ 's opinion at time  $k$
- $s_i \in [0, 1]$ : individual  $v_i$ 's innate opinion
  - Extreme innate opinions:  $\bar{s} \triangleq \max_{i \in V}\{s_i\}$ ,  $\underline{s} \triangleq \min_{i \in V}\{s_i\}$
- $w_{ij}$ : the influence of individual  $v_j$  on  $v_i$





# Diffusion Models and Confirmation Bias

## Opinion Dynamics and the Linear CB Model


$$x_i(k+1) = \alpha_i(x_i(k))s_i + \sum_{j \in V} w_{ij}x_j(k) + \overline{w}_i(x_i(k))\textcolor{red}{h} + \underline{w}_i(x_i(k))\textcolor{red}{g}, i \in V$$

  
 Innate  
opinion


  
 Influence from  
other individuals

  
 Information from two  
information sources

- $\textcolor{red}{h}, \textcolor{red}{g}$ : opinions of competitive information sources
  - $0 \leq g \leq \underline{s} \leq \bar{s} \leq h \leq 1$

**Aim**


Move the public  
opinions to the two  
extremes they present
- $\overline{w}_i(x_i(k)), \underline{w}_i(x_i(k))$ : state-dependent influence weights on individual  $v_i$ 
  - $\overline{w}_i(x_i(k)) = \beta - \gamma|x_i(k) - h|$
  - $\underline{w}_i(x_i(k)) = \beta - \gamma|x_i(k) - g|$

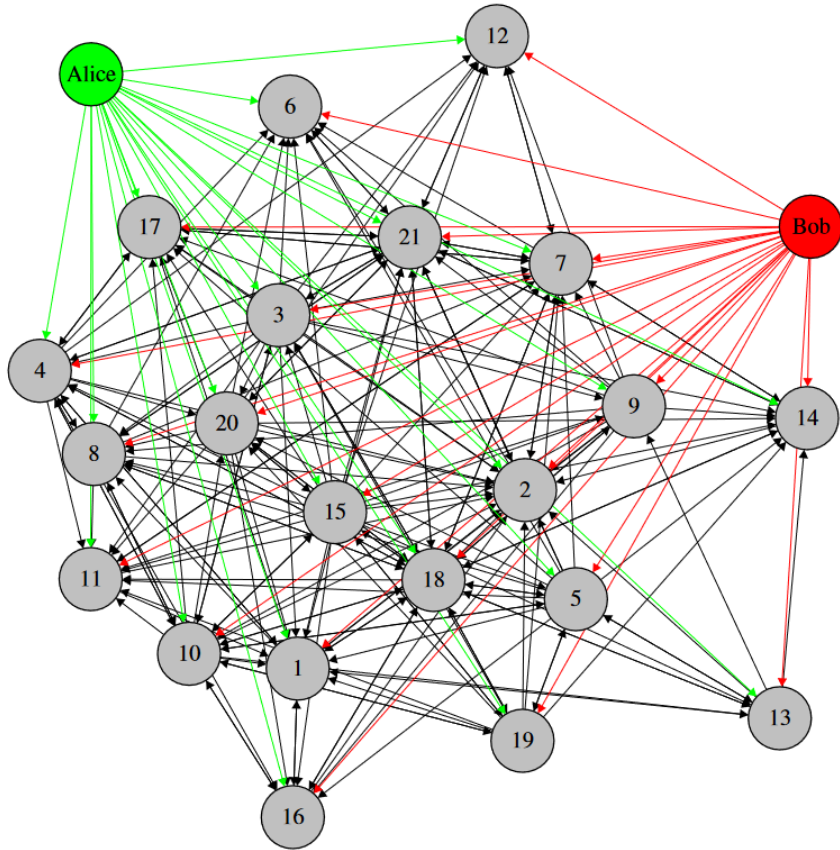
**Linear CB Models**


$\beta, \gamma \in R$ : **bias parameters**



# Diffusion Models and Confirmation Bias

## Zero-sum Game Problem Formulation



Alice ( $g \in [0, \underline{s}]$ )  
Bob ( $h \in [\bar{s}, 1]$ )

} Competitive Information Sources

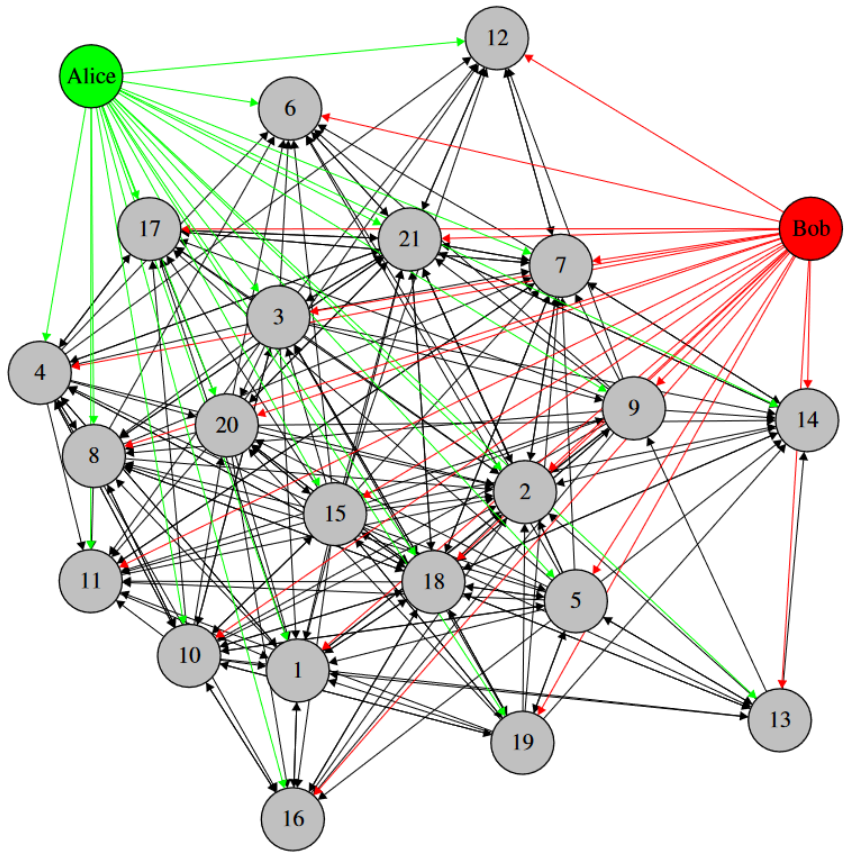
**Cost function  $f(g, h)$ :**

- Alice's objective is to maximize  $f(g, h)$
- Bob's objective is to minimize  $f(g, h)$

**Nash equilibrium:** a state that gives Alice and Bob no incentive to deviate from their initial strategy.

# Diffusion Models and Confirmation Bias

Nash Equilibrium **without CB**:  $\gamma = 0$

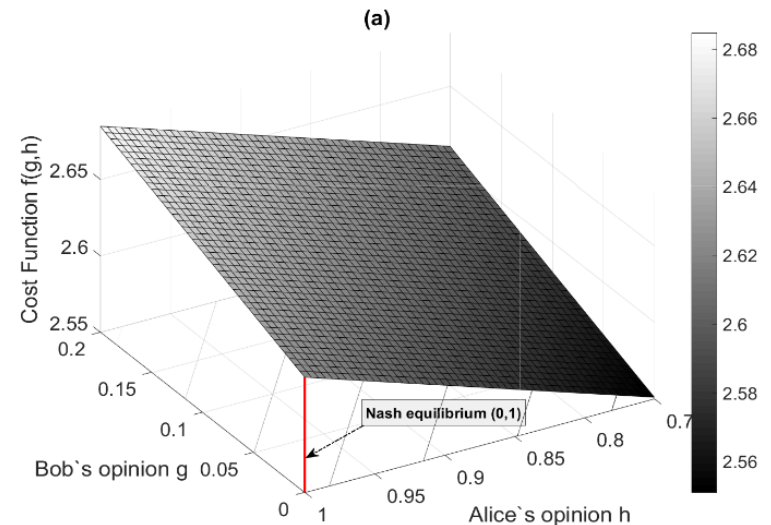


Innate opinions

- $s_1 = s_2 = 0.2$
- Others:  $s_i = 0.75$

$$\beta = 0.06, \\ \gamma = 0$$

The Nash equilibrium is  $(g^*, h^*) = (0, 1)$





# Diffusion Models and Confirmation Bias

Nash Equilibrium **with CB**:  $\gamma \neq 0$

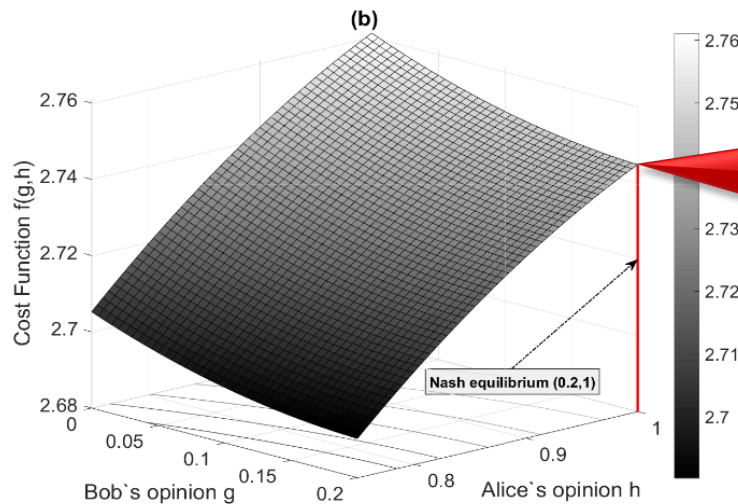
Innate opinions

- $s_1 = s_2 = 0.2$
  - Others:  $s_i = 0.75$
- $\beta = \gamma = 0.06$

$$\underline{s} = 0.2, \bar{s} = 0.75, \hat{s} = 0.7256$$

$\hat{s}$ : the average of innate opinions

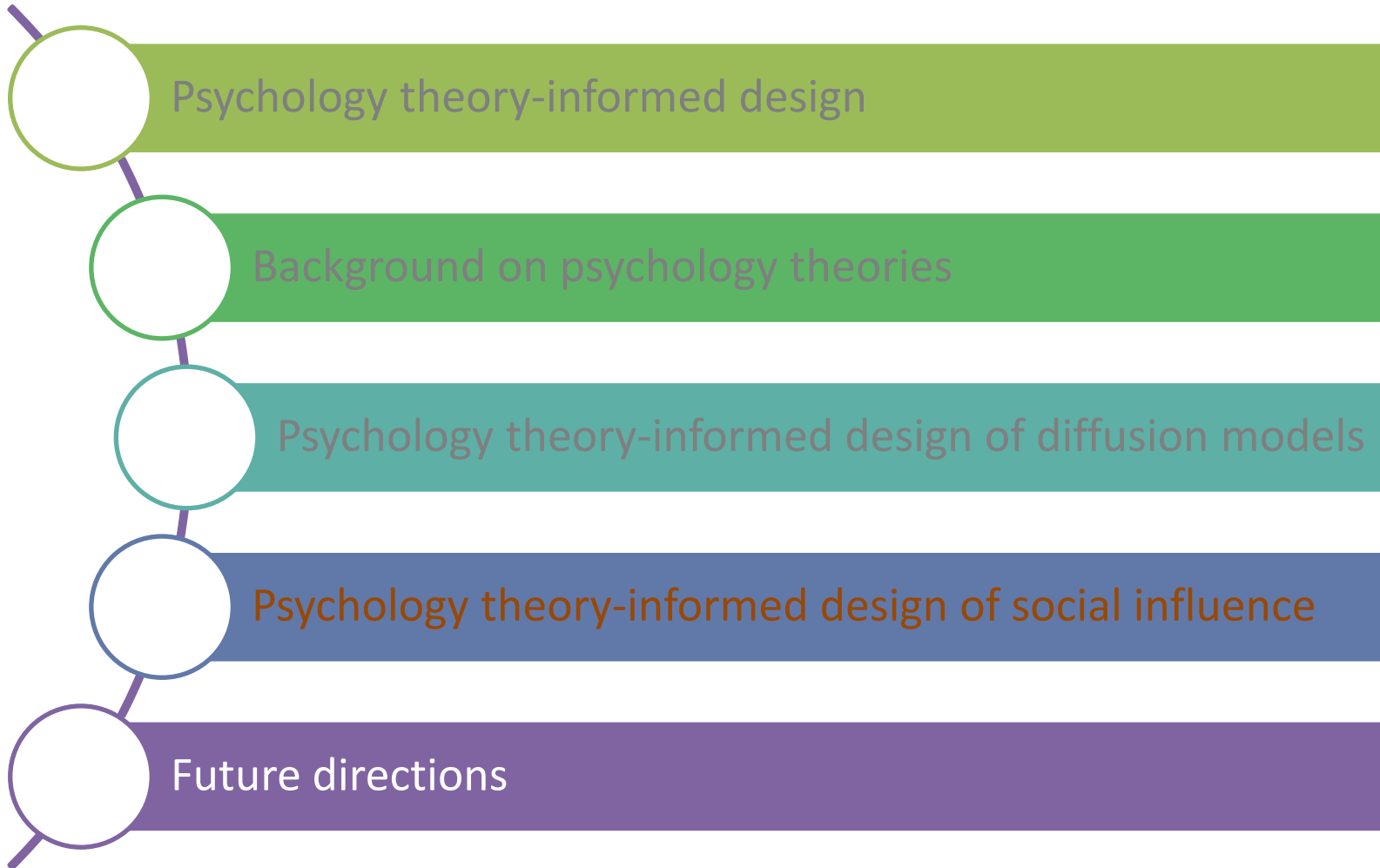
The Nash equilibrium is  $(g^*, h^*) = (\underline{s}, 1) = (0.2, 1)$



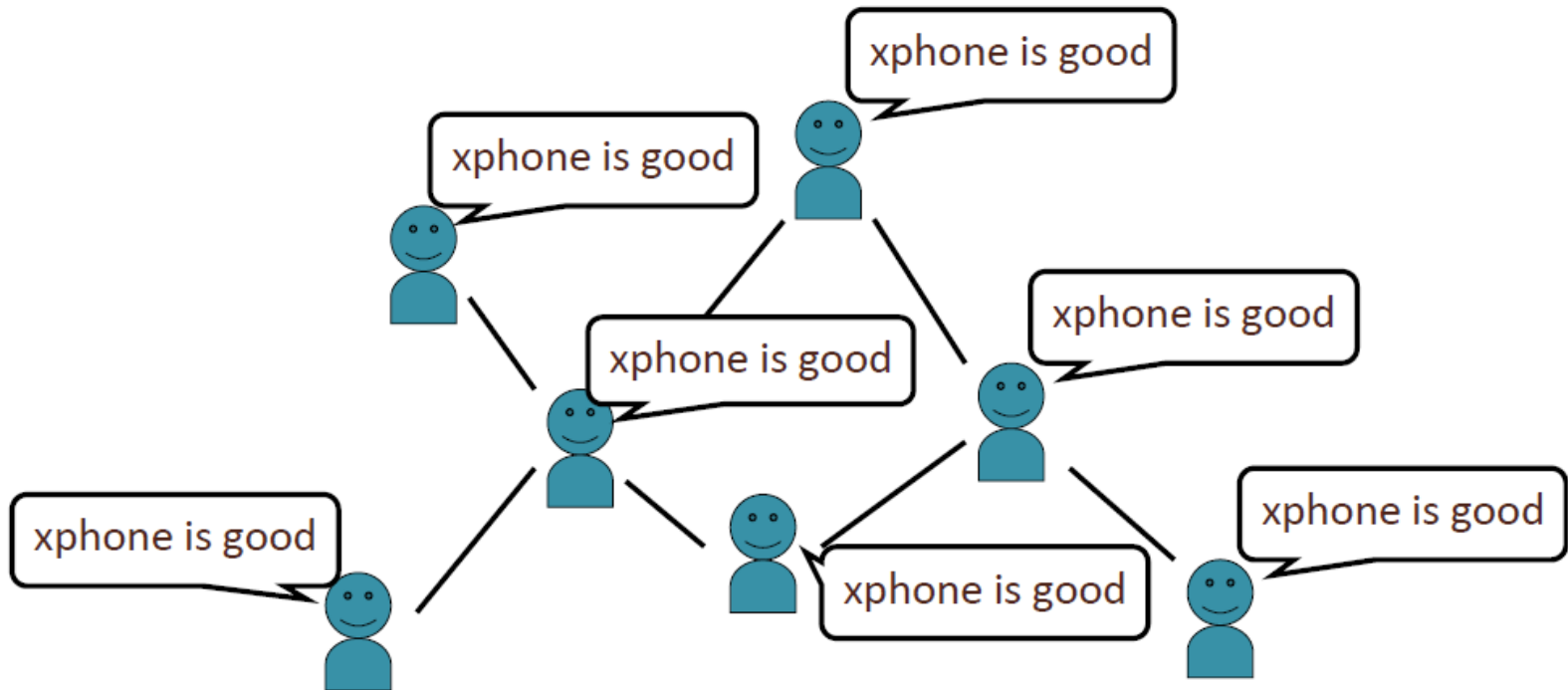
CB moves the Nash equilibrium toward the center only when the innate opinions are not neutral, and this move occurs for only one of the information sources.



# Next..



# Ideal Influence Propagation



**Word-of-Mouth Effect:** The information propagation process iterates through friends-of-friends and reaches a large population in the end

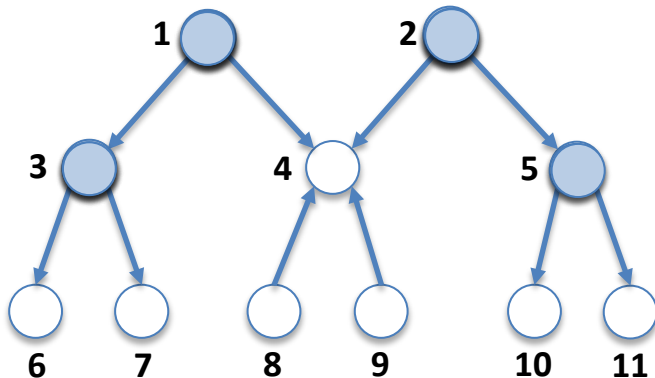
H. Li, S. S. Bhowmick, A. Sun. 2013. CINEMA: conformity-aware greedy algorithm for influence maximization in online social networks.  
H. Li, S. S. Bhowmick, A. Sun, J. Cui. 2015. Conformity-aware influence maximization in online social networks.



# Social Influence Estimation

## Influence Function

- Influence function of a seed set  $S$ , denoted as  $\sigma(S)$ , is the expected number of users influenced by  $S$ .
- For a node  $v \notin S$ ,  $\sigma(S \cup \{v\}) - \sigma(S)$  is the marginal influence of  $v$  with respect to  $S$ .

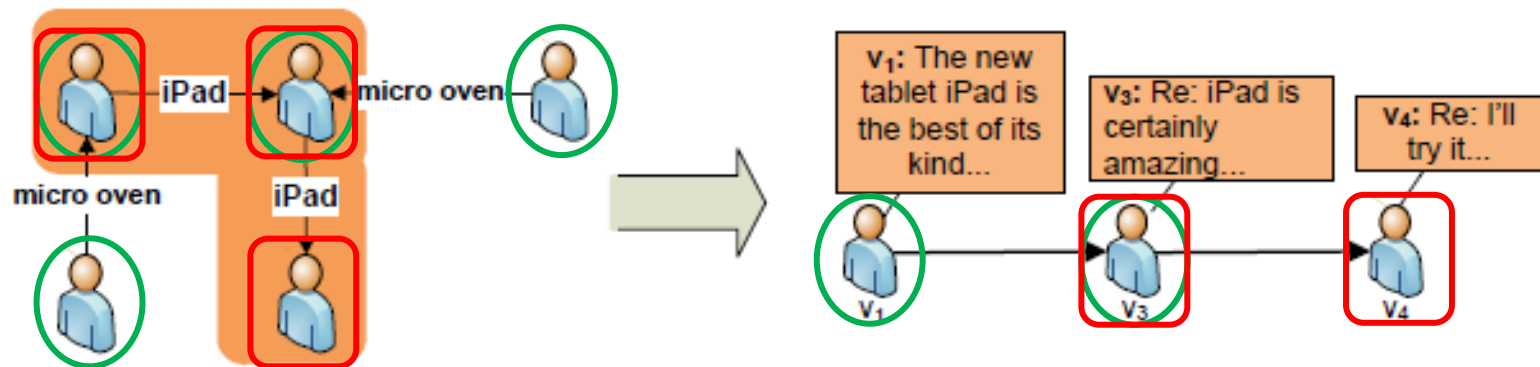


The graph is a simple social network with all weights equal to 1.

Seed	Influenced nodes	$\sigma(S)$
v1	v1, v3, v4, v6, v7	5
v1, v2	v1, v2, v3, v4, v5, v6, v7, v10, v11	9

# Psychology-informed Social Influence Propagation

There are different roles in influence propagation.

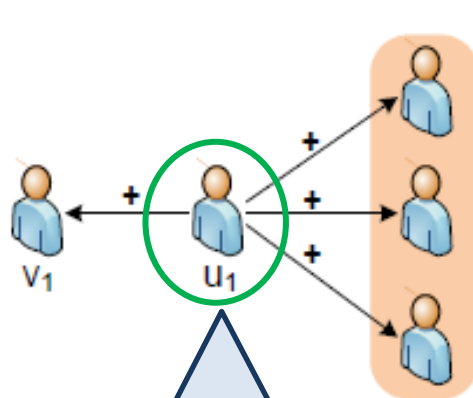


- **Influencer** (individual who is influencing others)  
→ influence  $\Phi(u)$

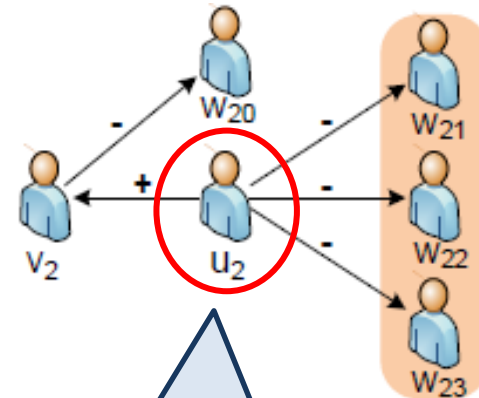
- **Influencee** (individual who is influenced by others)  
→ conformity  $\Omega(u)$

# Psychology-informed Social Influence Propagation

Different person may show different persona during the conversation with others.



- **Easily influenced:**  
mostly conform to  
the others' opinions



- **Hardly influenced:**  
mostly show  
opposite opinions

H. Li, S. S. Bhowmick, and A. Sun. 2011. "Casino: towards conformity-aware social influence analysis in online social networks.



# Psychology-informed Social Influence Estimation



$Prob[u \rightarrow v]$  could be affected by  $\Phi(u)$  and  $\Omega(v)$ .  
However, some research mainly focus on  $\Phi(u)$ .

Existing work may not exhibit satisfactory result with respect to influence and conformity.

How to quantify the different persona of different person?  $\rightarrow$  Conformity.

H. Li, S. S. Bhowmick, and A. Sun. 2011. Casino: towards conformity-aware social influence analysis in online social networks.



# Overview of Modeling Conformity Theory

## Social Influence Estimation

- Quantify the influence w.r.t. the *conformity* of each individual
- Distinguish and quantify the effects of the *different types of conformities*.

## Influence Maximization

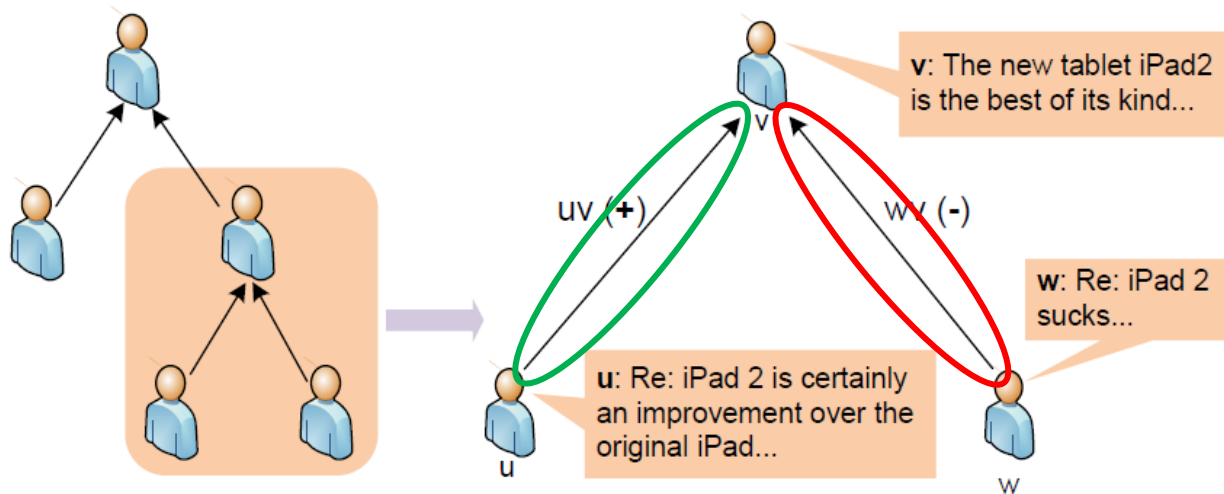
- Leverage *conformity* in computing the propagation probabilities of nodes
- Incorporate *friend conformity and group conformity* in group-based IM task





# Conformity-aware Social Influence Estimation - *CASINO*

**Signed Network:** An edge representing trust relationship is labeled as positive, otherwise negative. And  $G(V, E)$  can be represented using a pair of graphs  $G^+(V, E^+)$  and  $G^-(V, E^-)$ .



H. Li, S. S. Bhowmick, and A. Sun. 2011. "Casino: towards conformity-aware social influence analysis in online social networks."



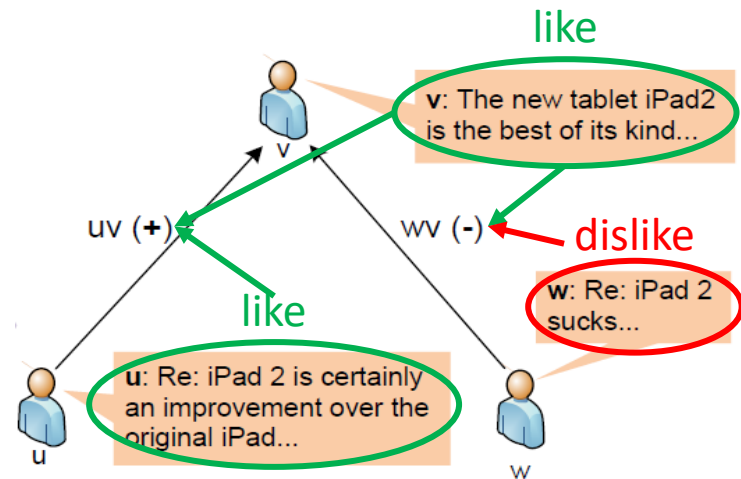
# Conformity-aware Social Influence Estimation - *CASINO*

## Edge Labeling

- Social networks may provide edge signs (i.e., Epinions) or not (i.e., Blog)
- Sentiment based analysis using LingPipe (e.g., Twitter)
- **Sentiments:** dislike, somewhat dislike, neutral, somewhat like, like

## Signed Network

- **Positive/negative:** sentiments at both ends are similar?
- Similar: sentiment similarity threshold is less than  $\epsilon$



# Conformity-aware Social Influence Estimation - *CASINO*

## Basic intuitions

Number of conforming followers  $\rightarrow$  high influence  
Number of conformed people  $\rightarrow$  high conformity

## Considering negative edges

Number of negative followers  $\rightarrow$  low influence  
Number of negative following  $\rightarrow$  low conformity

Investigate the mutual effect between them



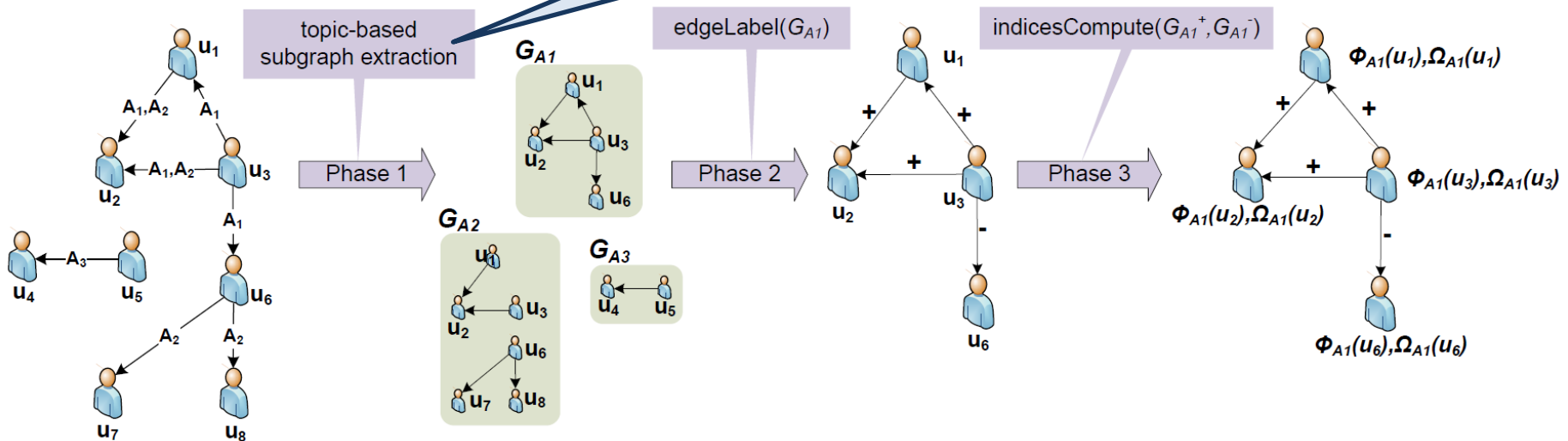
## • Influence and conformity Indices:

- $\Phi(v) = \sum_{\vec{uv} \in E^+} \Omega(u) - \sum_{\vec{uv} \in E^-} \Omega(u)$
- $\Omega(u) = \sum_{\vec{uv} \in E^+} \Phi(v) - \sum_{\vec{uv} \in E^-} \Phi(v)$

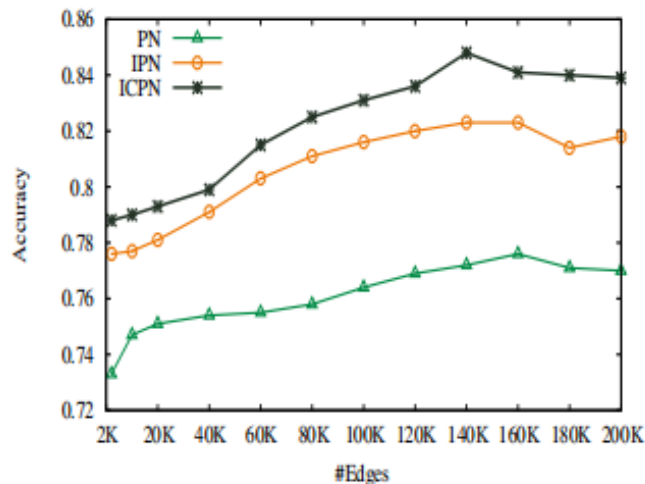
# Conformity-aware Social Influence Estimation - *CASINO*

Complete indices calculation process!

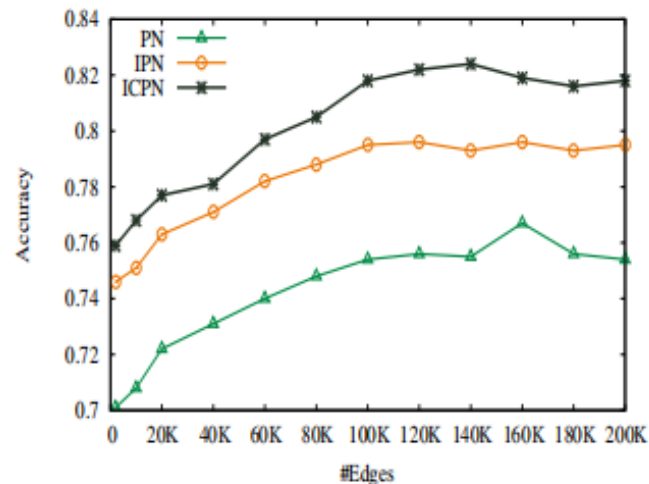
- A node's influence in one component is not significantly affected by nodes in other components.



# Conformity-aware Social Influence Estimation - *CASINO*



(a) Epinions



(b) Slashdot

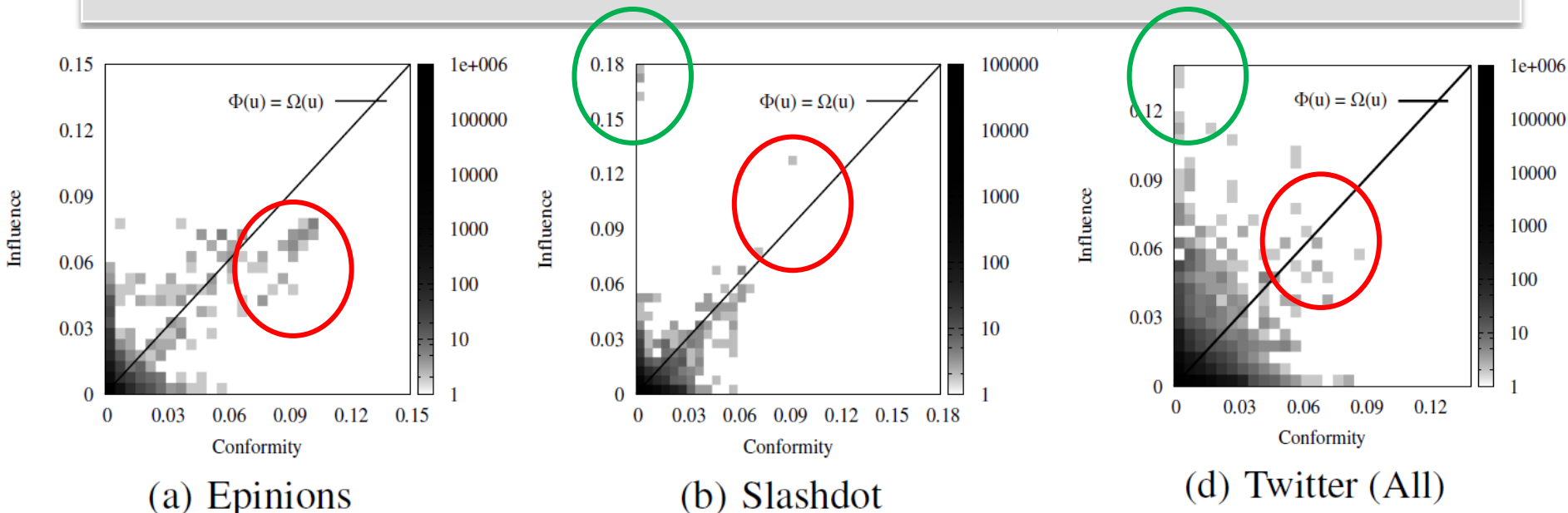
I: influence  
C: conformity  
P: positive  
N: negative

Signed edge prediction:  $ICPN > IPN > PN$

- Considering **influence** of nodes improves prediction accuracy.
- Considering **both influence and conformity** further improves the accuracy.

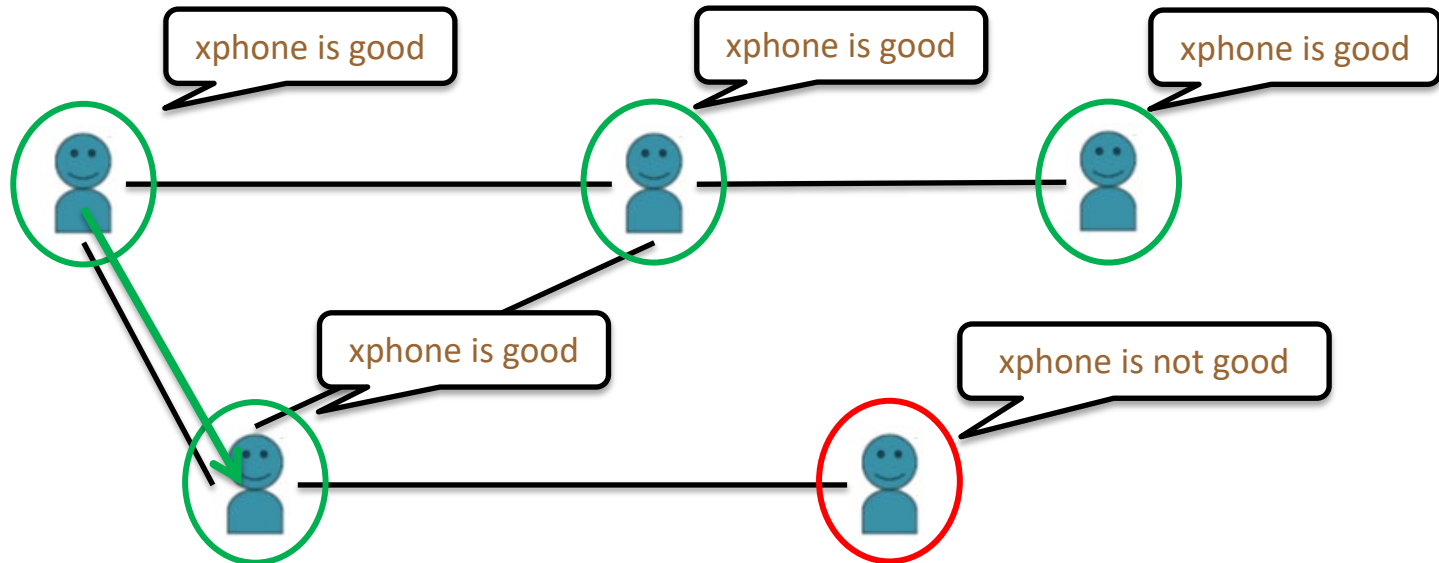
# Conformity-aware Social Influence Estimation - *CASINO*


- The most influential nodes hardly conform to others in Twitter and Slashdot.



- The most conforming nodes also influence others (in all the three networks).

# Conformity-aware Social Influence Estimation - *Confluence*



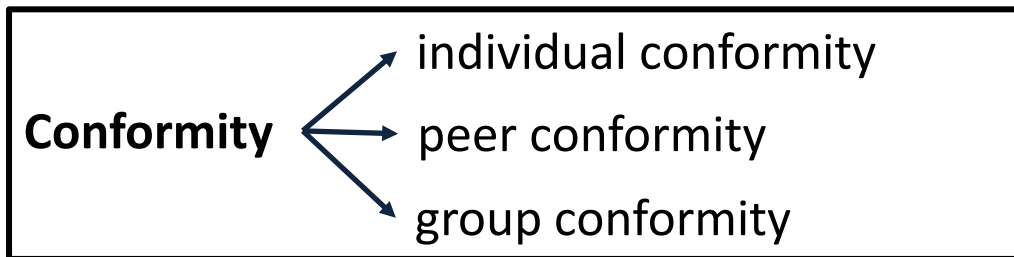
**Conformity** 

- individual conformity
- peer conformity
- group conformity

J. Tang, S. Wu, J. Sun. 2013. Confluence: conformity influence in large social networks.



# Conformity-aware Social Influence Estimation - *Confluence*



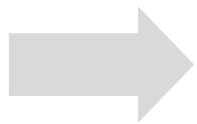
how easily user  $v$ 's behavior conforms to her friends

A specific action performed by user  $v$  at time  $t$

$(a, v_i, t)$ : user  $v_i$  performed action  $a \in A$  ( $A$ : action history) at time  $t$

$\epsilon$  is a threshold of difference between the time when the two users  $v$  and  $v'$  performed the same action  $a$

Exists a friend  $v'$  who performed the same action at time  $t'$

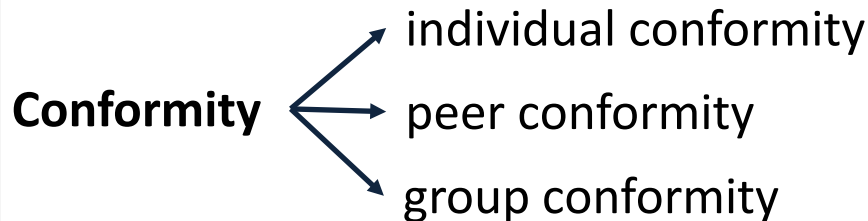


$$icf(v) = \frac{|(a, v, t) \in A_v| \exists (a, v', t') : e_{vv'} \in E \wedge \epsilon \geq t - t' \geq 0|}{|A_v|}$$

All actions by user  $v$



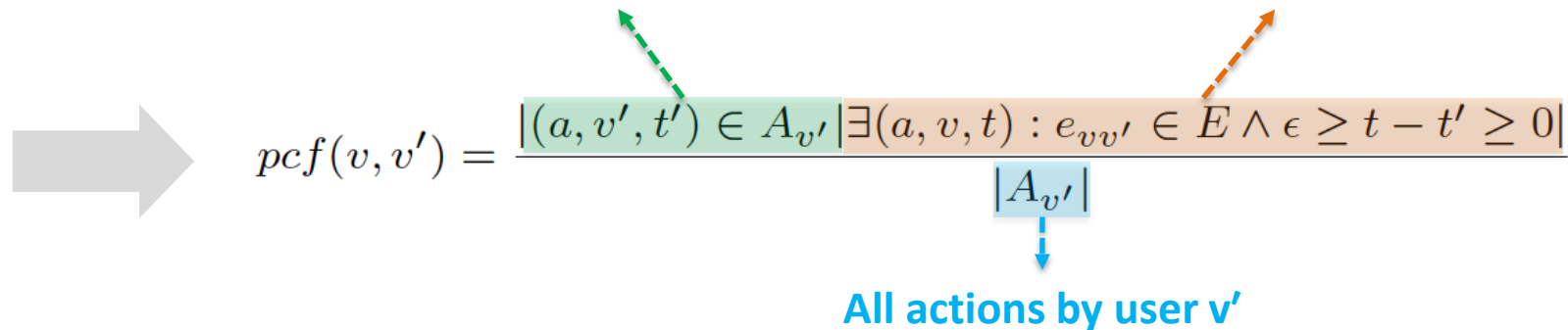
# Conformity-aware Social Influence Estimation - *Confluence*



how likely the user  $v$ 's behavior is influenced by one particular friend  $v'$

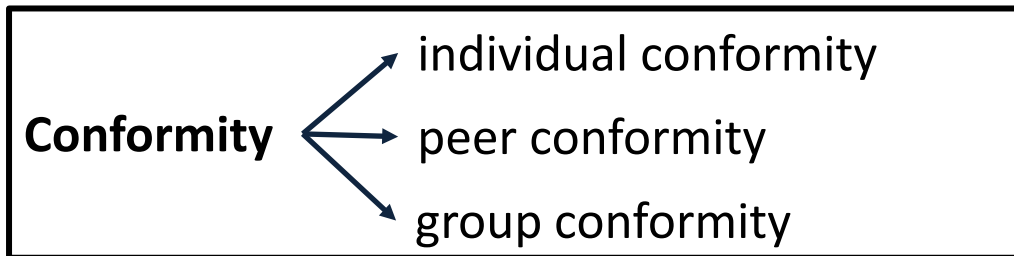
A specific action performed by user  $v'$  at time  $t'$

User  $v$  follows  $v'$  to perform the action  $a$  at time  $t$


$$pcf(v, v') = \frac{|(a, v', t') \in A_{v'}| \cdot |\exists (a, v, t) : e_{vv'} \in E \wedge \epsilon \geq t - t' \geq 0|}{|A_{v'}|}$$

All actions by user  $v'$

# Conformity-aware Social Influence Estimation - *Confluence*



conformity of user  $v$ 's behavior to groups that the user belongs to

$\tau$ -group action: an action performed by more than a percentage  $\tau$  of all users in the group  $C_k$

A specific  $\tau$ -group action

User  $v$  conforms to the group to perform the action  $a$  at time  $t$

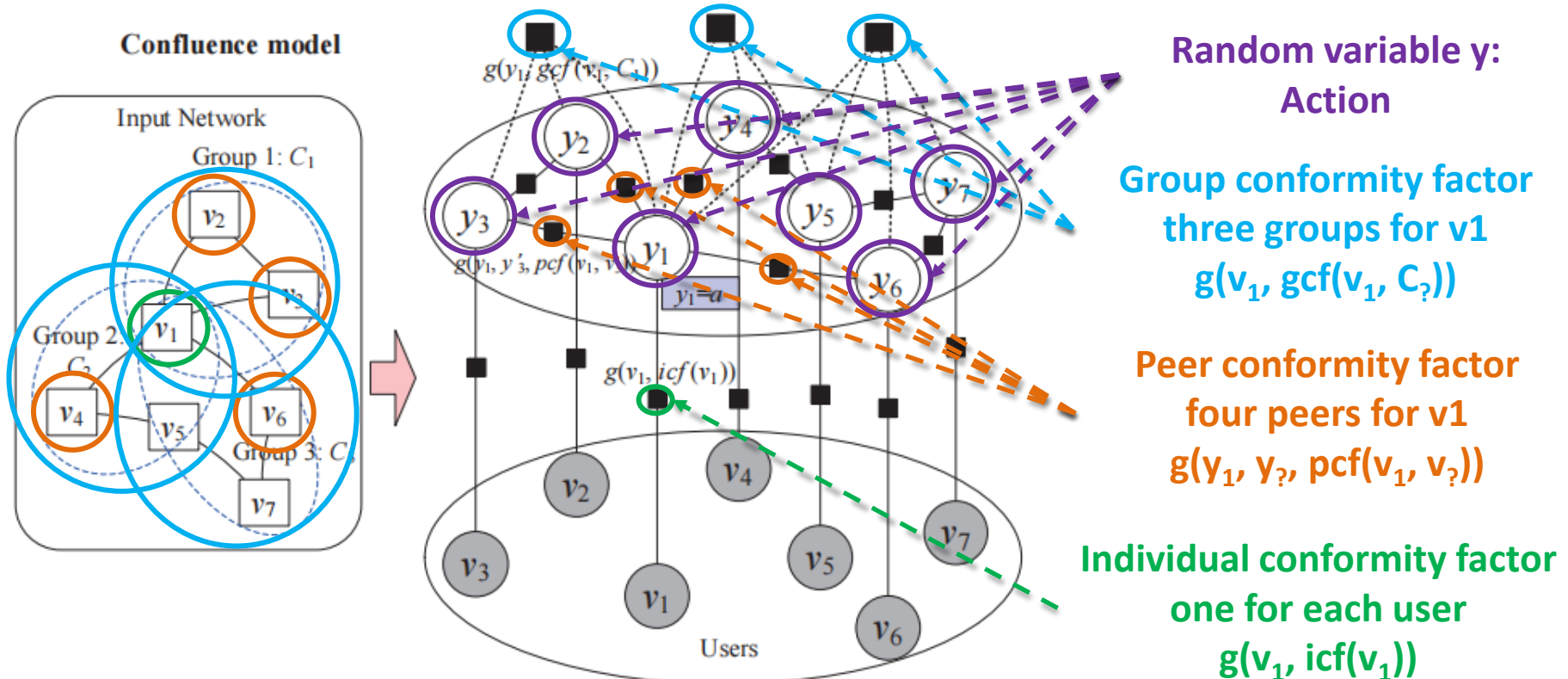


$$gcf^{\tau}(v, C_{vk}) = \frac{|(a, v', t') \in A_{C_k}^{\tau} \cap \{(a, v, t) : \mathbb{I}[c_{ik}] \wedge \epsilon \geq t - t' \geq 0\}|}{|A_{C_k}^{\tau}|}$$

All  $\tau$ -group actions performed by users in the group  $C_k$

# Conformity-aware Social Influence Estimation - *Confluence*

Graphical representation of the Confluence model!



J. Tang, S. Wu, J. Sun. 2013. Confluence: conformity influence in large social networks.



# Conformity-aware Social Influence Estimation - *Confluence*

By **integrating all the factor functions** together, and according to the Hammersley-Clifford theorem, it can obtain the following log-likelihood objective function.

$$\begin{aligned} \mathcal{O}(\theta) &= \log P_{\theta}(Y|G, A) \\ &= \sum_{i=1}^N \left[ \sum_{j=1}^d \alpha_j f(y_i, x_{ij}) + \beta_i g(y_i, icf(v_i)) \right] \\ &\quad + \sum_{e_{ij} \in E} \mathbb{I}[y'_j] \gamma_{ij} g(y_i, y'_j, pcf(v_i, v_j)) \\ &\quad + \sum_{i=1}^N \sum_{k=1}^m \mathbb{I}[c_{ik}] \mu_{ik} g(y_i, gc f(v_i, C_k)) - \log Z \end{aligned}$$

capture the correlation between the user's attribute  $x_{ij}$  (the  $j$ -th attribute of user  $v_i$ ) and user's action

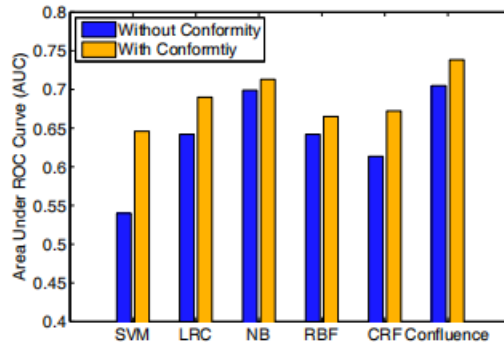
$$g(y_i, icf(v_i)) = \frac{\sum_{k=1}^{|A_{v_i}|} (\frac{1}{2})^{\frac{t-t'}{\lambda}} \mathbb{I}[y'_j \wedge e_{ij} \in E]}{|A_v|}$$

$$g(y_i, y'_j, pcf(v_i, v_j)) = (\frac{1}{2})^{\frac{t-t'}{\lambda}} pcf(v_i, v_j)$$

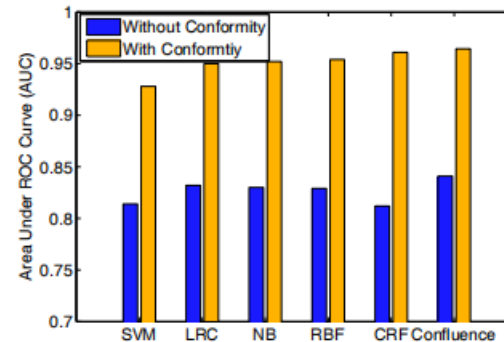
$$g(y_i, y'_j, pcf(v_i, v_j)) = (\frac{1}{2})^{\frac{t-t'}{\lambda}} pcf(v_i, v_j)$$

$\theta = (\{\alpha\}, \{\beta\}, \{\gamma\}, \{\mu\})$  is a parameter configuration estimated from the training data (i.e., historic users' actions). It can quantify the importance of the different types of conformities for each user.

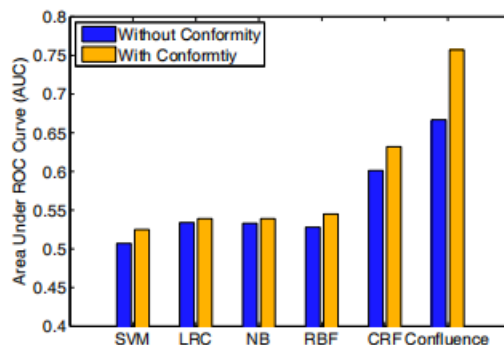
# Conformity-aware Social Influence Estimation - *Confluence*



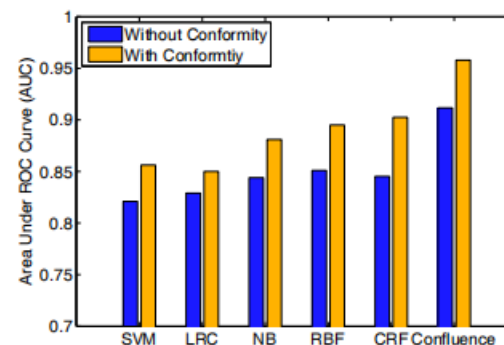
(a) Flickr



(b) Gowalla

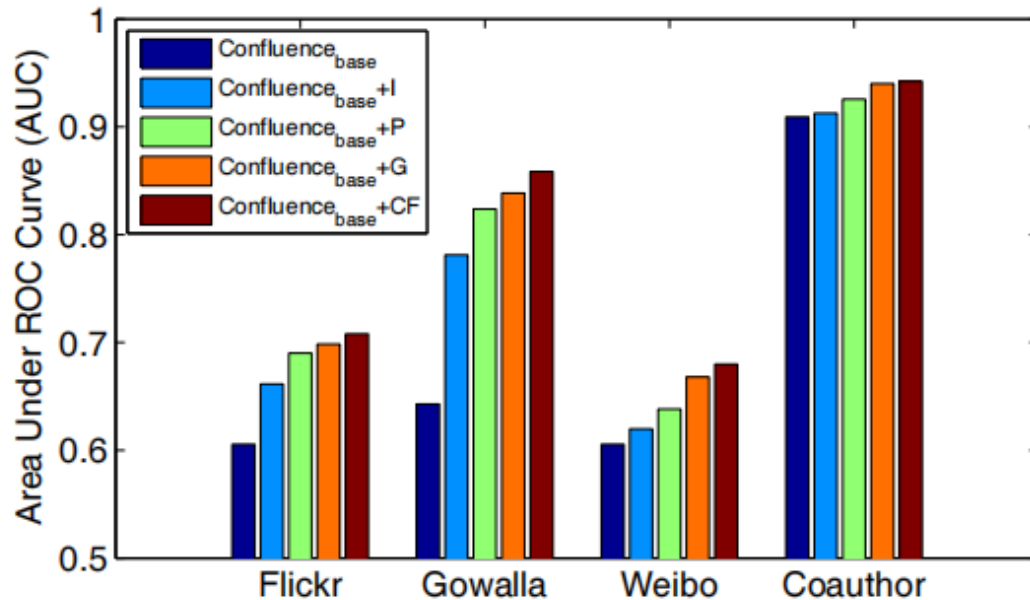


(c) Weibo



(d) Co-Author

# Conformity-aware Social Influence Estimation - *Confluence*



- **Confluence<sub>base</sub>**: Confluence method without any social based features
- **I**: individual conformity
- **P**: peer conformity
- **G**: group conformity
- **CF**: conformity features

Effects of different levels of conformities:

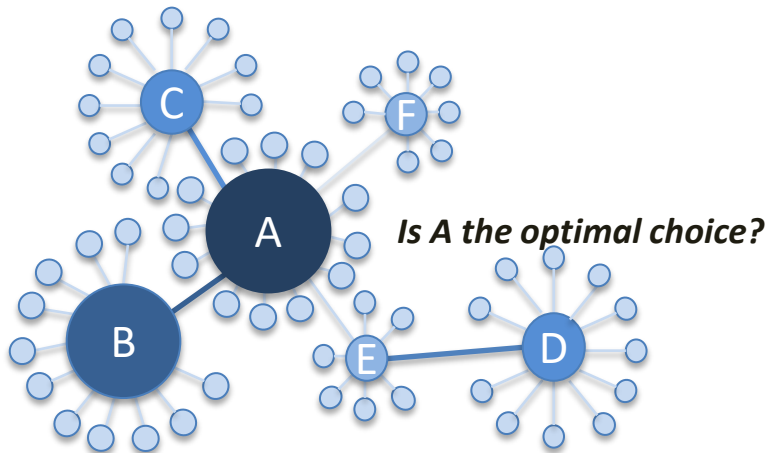
- **Without the conformity** based factors, the prediction performance drop significantly.
- **The group conformity** is more important than the other types.

# From Social Influence *Estimation* to *Maximization*

## Definition of Influence Maximization

Given  $G = (V, E)$  and a positive integer  $k$ , select a set  $S^*$  of  $k$  users from  $V$  as the seed set to maximize the influence spread  $\sigma(S^*)$ ,

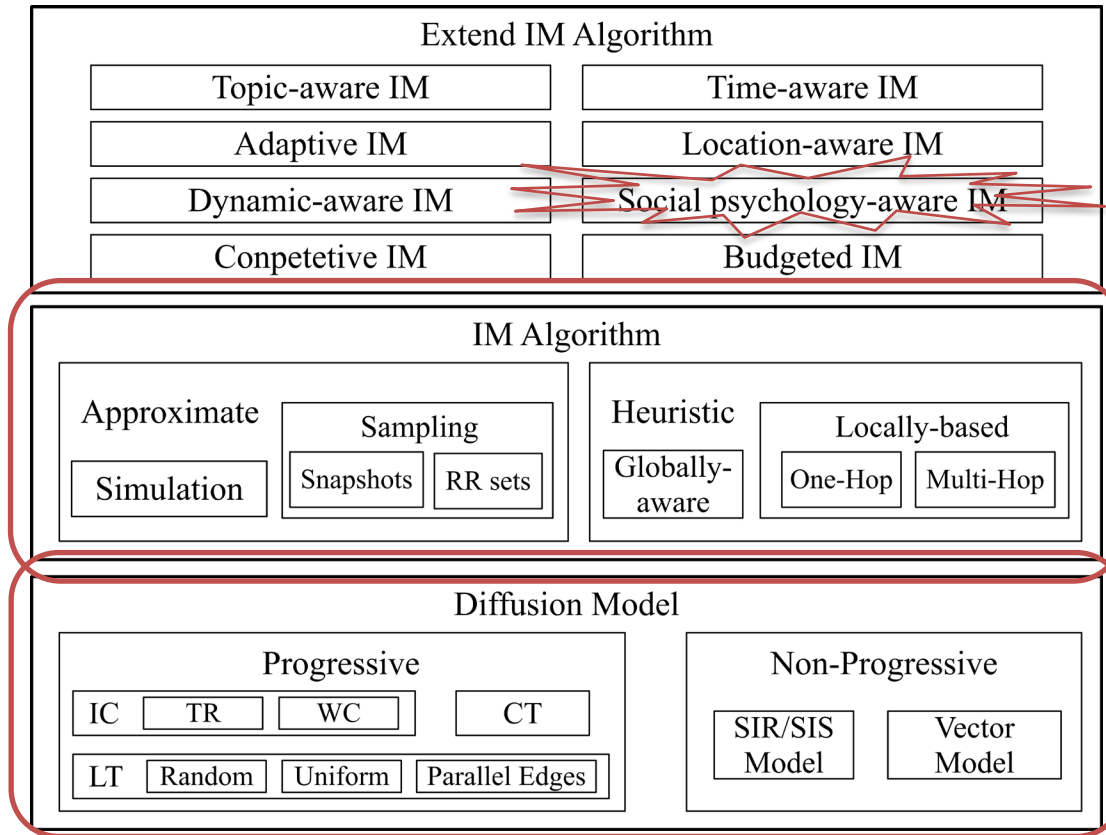
$$S^* = \operatorname{argmax}_{S \subseteq V \wedge |S| \leq k} \sigma(S)$$



### Viral Marketing:

Now, a marketer may provide some individuals in a social network with free products in exchange for them to spread the good word about it.

# Taxonomy of Research Related to Influence Maximization Problem



Li et al. clearly organize and differentiate existing research related to IM problem.

The foundation of the IM problem includes diffusion models and influence estimation.



# Approximate Algorithm of Influence Maximization

## Greedy Algorithm

Kempe et al.<sup>[4]</sup> presented the first approximate algorithm based on hill-climbing strategy, which is illustrated as follows.

David Kempe, Jon M. Kleinberg, and Éva Tardos. 2003. Maximizing the spread of influence through a social network.



# Heuristic Algorithm of Influence Maximization

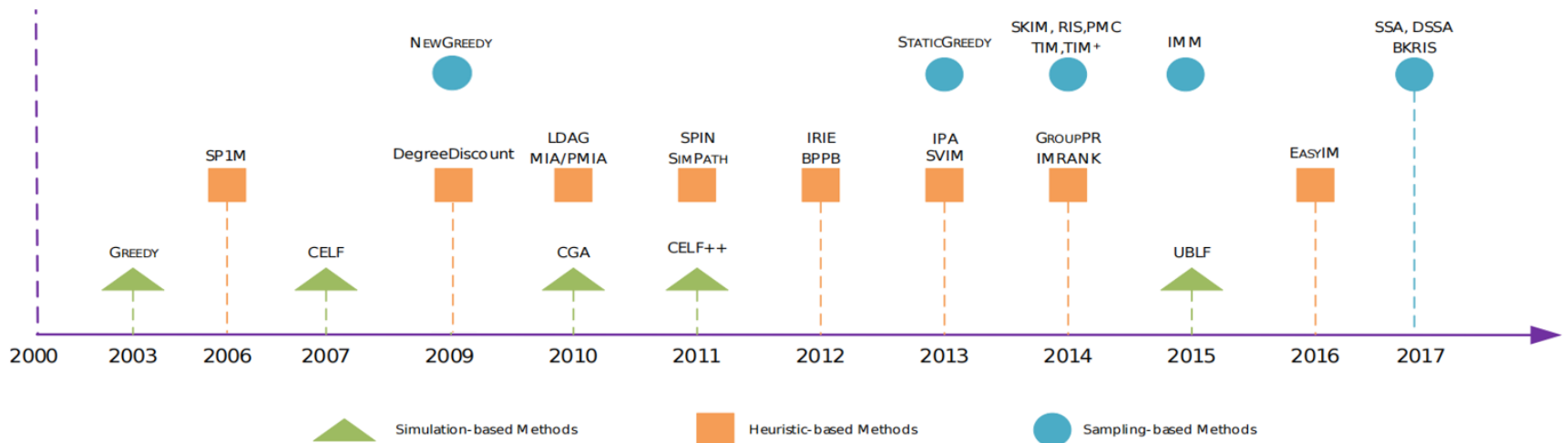
## High-degree Heuristic

- Degree is frequently used for selecting seeds in IM problem. For example, the high-degree heuristic chooses nodes  $v$  in order of decreasing degrees  $d_v$ .

D. Kempe, J. M. Kleinberg, and É. Tardos. 2003. Maximizing the spread of influence through a social network.



# Classical IM Solutions



The figure shows more representative work and milestones for classical IM solutions across all three categories.

Although these works have made significant progress in terms of performance, conformity theory is often ignored in these models.

# Conformity-aware Social Influence Maximization - *CINEMA*

## The formal definition of $C^2$ model

Let  $A_i$  be the set of nodes activated in the  $i$ -th round and  $A_0 = S$ . For any  $(u, v) \in E$  such that  $u \in A_i$  and  $v \notin A_i$ ,  $v$  is influenced by  $u$  in the next  $(i+1)$ -th round with probability  $\Phi(u)\Omega(u)$

Thus, 
$$P[v \in A_{i+1}] = 1 - \prod_{u \in A_i, (u,v) \in E} (1 - \Phi(u)\Omega(u))$$

Besides, this effort is also extended by considering context-specific influence and conformity of nodes in  $C^3$ , which incorporates topic-aware influence and conformity into  $C^2$ .

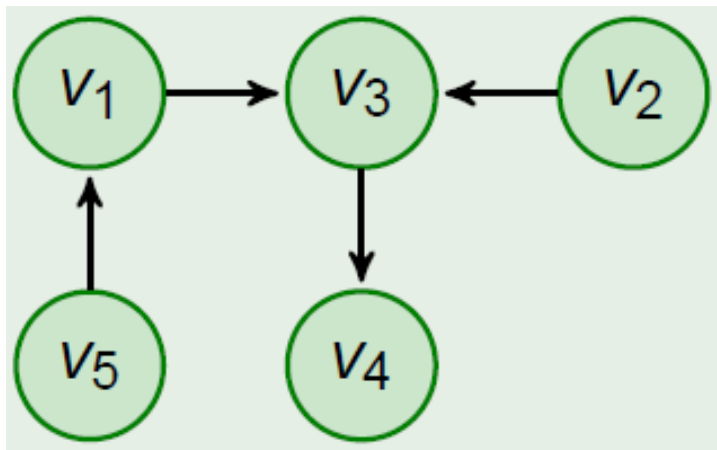
H. Li, S. S. Bhowmick, A. Sun. 2013. CINEMA: conformity-aware greedy algorithm for influence maximization in online social networks.  
H. Li, S. S. Bhowmick, A. Sun, J. Cui. 2015. Conformity-aware influence maximization in online social networks.



# Conformity-aware Social Influence Maximization - *CINEMA*

Under **IC model** with **p=0.5**, let **X** denote the set of activated edges, then  $\sigma(v_1)$  can be computed as

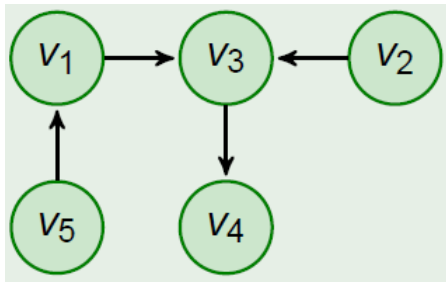
$$\sigma(v_1) = \text{Prob}[\overrightarrow{v_1 v_3} \notin X] \times 1 + \text{Prob}[\overrightarrow{v_1 v_3} \in X, \overrightarrow{v_3 v_4} \notin X] \times 2 + \text{Prob}[\overrightarrow{v_1 v_3} \in X, \overrightarrow{v_3 v_4} \in X] \times 3$$



Candidate Seeds List (IC model p=0.5)

Node	$\sigma(\cdot)$
<b>v<sub>5</sub></b>	<b>1.875</b>
v <sub>1</sub>	1.75
v <sub>2</sub>	1.75
v <sub>3</sub>	1.5
v <sub>4</sub>	1

# Conformity-aware Social Influence Maximization - *CINEMA*



Indices (computed by **CASINO**)

Node	Influence	Conformity
$v_1$	0.68	0.21
$v_2$	0.68	0.11
$v_3$	0.18	0.94
$v_4$	0.03	0.21
$v_5$	0.18	0.11

Candidate Seeds List ( $C^2$  model)

Node	$\sigma(\cdot)$
$v_1$	1.73
$v_2$	1
$v_5$	1.49
$v_3$	1
$v_4$	1

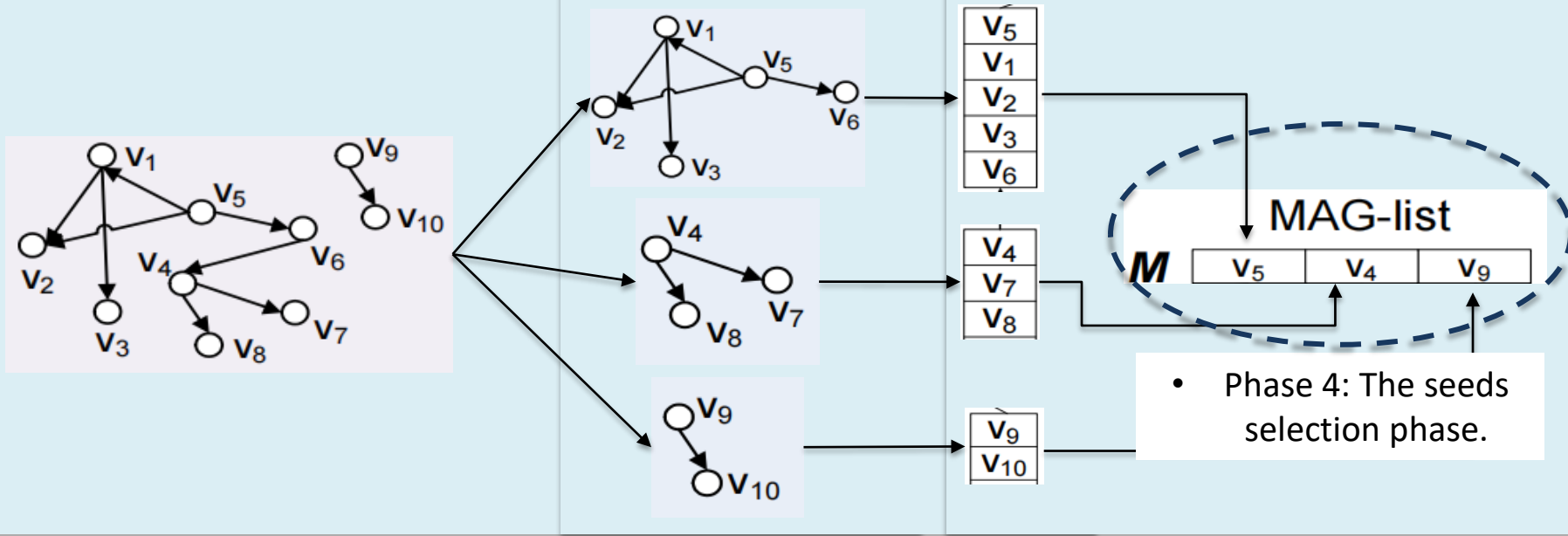
Under **IC model**  $\rightarrow$  select  $S=\{v_5\}$

Under  **$C^2$  model**  $\rightarrow$  select  $S=\{v_1\}$

# Conformity-aware Social Influence Maximization - *CINEMA*

Complete seed set selection process!

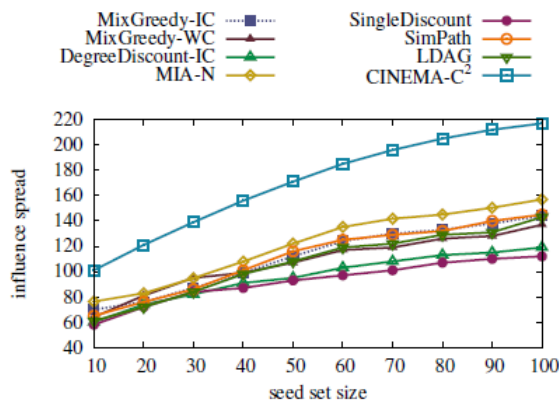
- Phase 1: The network partitioning phase
- Phase 2: The conformity computation phase.
- Phase 3: The mag-list construction phase.



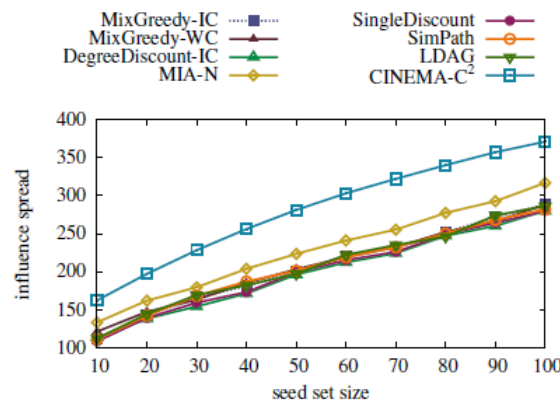
H. Li, S. S. Bhowmick, A. Sun. 2013. CINEMA: conformity-aware greedy algorithm for influence maximization in online social networks.



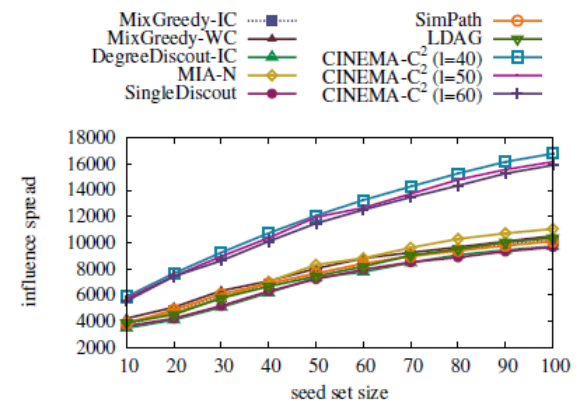
# Conformity-aware Social Influence Maximization - *CINEMA*



(a) Spread of Hep



(b) Spread of Phy

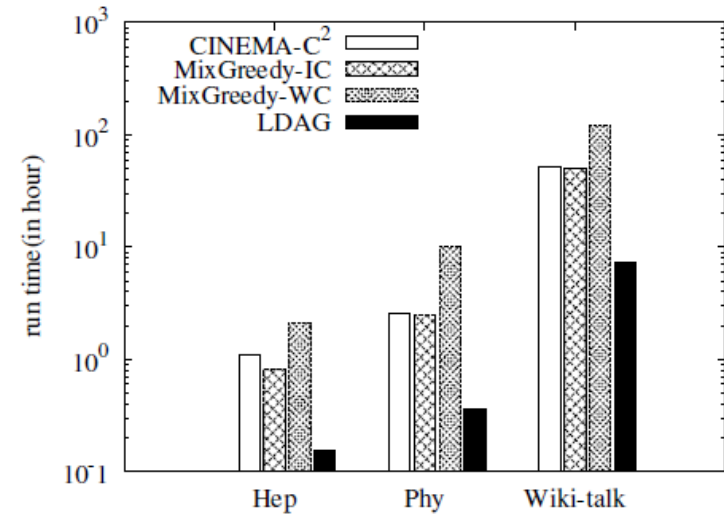
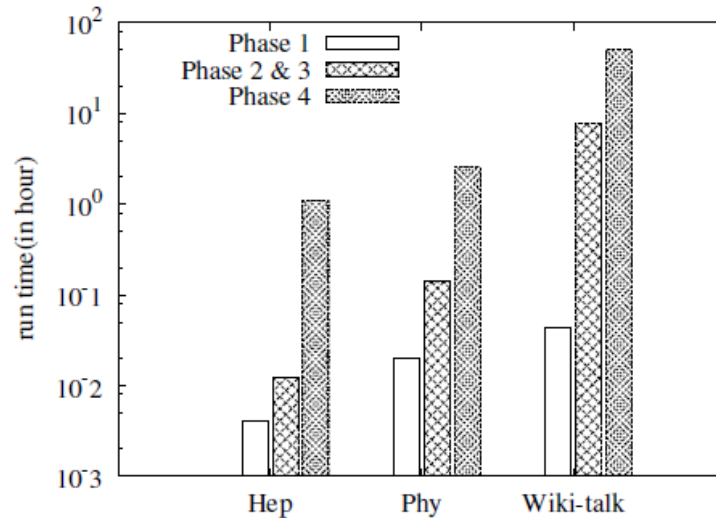


(c) Spread of Wiki-talk

- All the other approaches exhibit poor performance **under C2 model**
- They only account for **60%, 66%, 57%** the performance of **CINEMA**



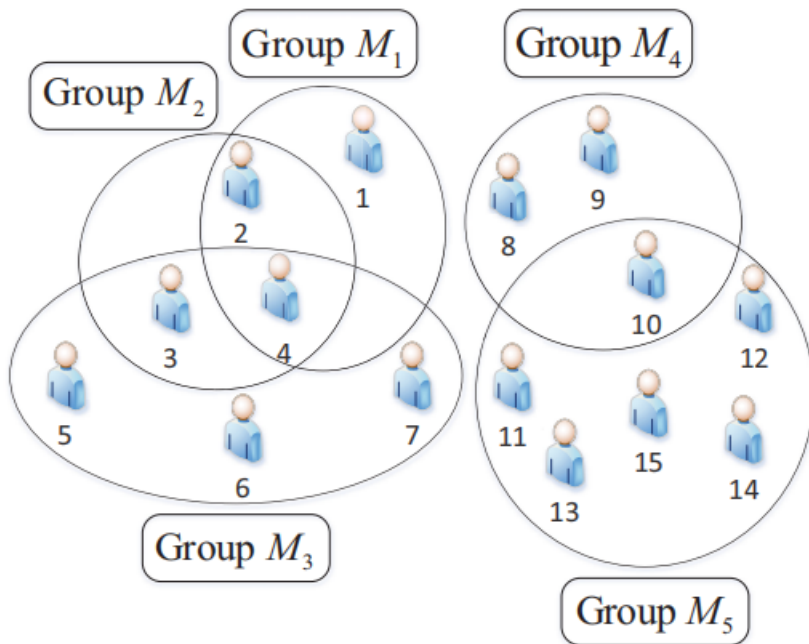
# Conformity-aware Social Influence Maximization - *CINEMA*



- Seeds selection phase (phase/step 4) dominates the running time
- The running time of **CINEMA** is similar to **MixGreedy-IC**

# Conformity-aware Social Influence Maximization - *GIM*

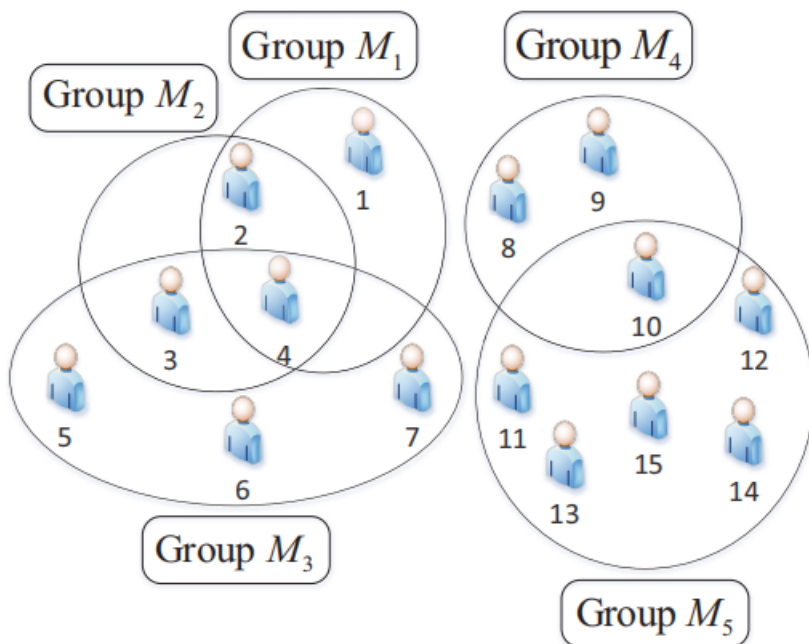
For user  $u$ , user profile  $A_u$  contains  $d$  attributes denoted as  $A_u = \{a_{1,u}, a_{2,u}, \dots, a_{d,u}\}$ .



Users' profiles	
User	Profile={Gender, Basketball, Tennis, Football, Movie, Book}
$U_1$	$A_u=\{1, 1, 0, 0, 0, 0\}$
$U_2$	$A_u=\{0, 1, 1, 0, 0, 0\}$
$U_3$	$A_u=\{1, 0, 1, 1, 0, 0\}$
$U_4$	$A_u=\{0, 1, 1, 1, 0, 0\}$
$U_5$	$A_u=\{1, 0, 0, 1, 0, 0\}$
$U_6$	$A_u=\{0, 0, 0, 1, 0, 0\}$
$U_7$	$A_u=\{1, 0, 0, 1, 0, 0\}$
...	...

# Conformity-aware Social Influence Maximization - *GIM*

Use **discriminative attributes** to describe a group. It explains well for one group and differentiates this group from the others.

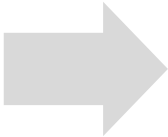



Groups' profiles

Group	Profile={Gender, Basketball, Tennis, Football, Movie, Book}
$M_1$	$P_{M_1}=\{0, 1, 0, 0, 0, 0\}$
$M_2$	$P_{M_2}=\{0, 0, 1, 0, 0, 0\}$
$M_3$	$P_{M_3}=\{0, 0, 0, 1, 0, 0\}$
$M_4$	$P_{M_4}=\{0, 0, 0, 0, 1, 0\}$
$M_5$	$P_{M_5}=\{0, 0, 0, 0, 0, 1\}$



# Conformity-aware Social Influence Maximization - *GIM*

Conform to  $\begin{cases} \text{Friends} \longrightarrow \text{similarity between a pair of friends' profiles} \\ \text{Group} \longrightarrow \text{similarity between profiles of user and group} \end{cases}$

$$\begin{aligned} \text{sim}(A_u, A_v) &= \frac{A_u \cdot A_v}{\sum_{a_{i,u} \in A_u} a_{i,u}} \\ \text{sim}(A_u, P_{M_j}) &= \frac{A_u \cdot P_{M_j}}{\sum_{a_{i,u} \in A_u} a_{i,u}}, u \in M_j \end{aligned}$$

Generally, information Q can also be marked by multiple features.

$$\begin{aligned} \text{sim}(A_u, Q) &= \frac{\sum_{i=1}^d a_{i,u} \cdot q_i}{h} \\ (\text{h: the number of information attributes}) \\ \text{pro}(u, v) &= \text{sim}(A_u, A_v) \times \text{sim}(A_u, P_{M_j}) \times \text{sim}(A_u, Q) \end{aligned}$$

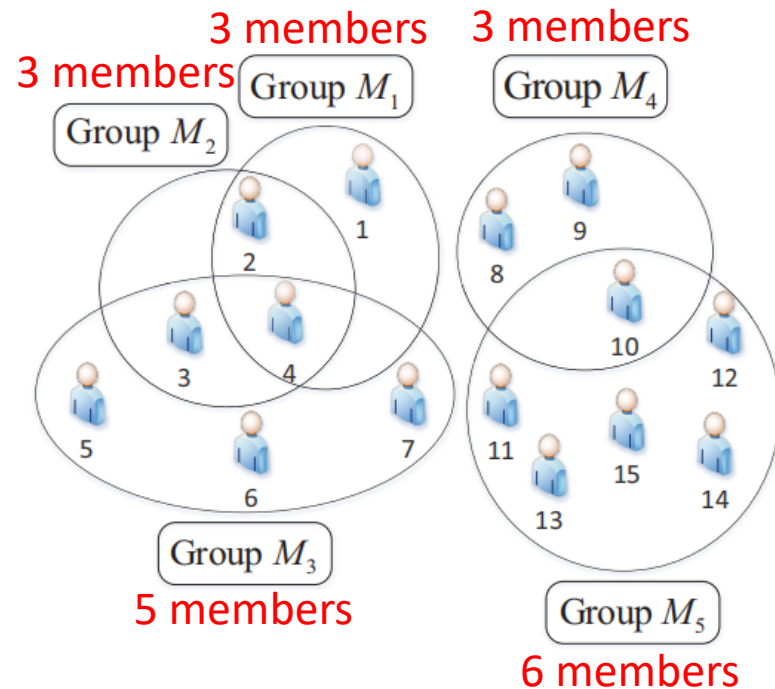
# Conformity-aware Social Influence Maximization - *GIM*

## Group selection

- Arrange the groups in a decreasing order w.r.t. *sizes*.
- According to *k*, assign one seed for each group.
- When group *M<sub>j</sub>* has been assigned with seeds, its neighbor groups will not be allocated any seed.

$$M^R = \{M_5, M_3, M_4, M_2, M_1\}$$

$$k=2, \{M_5, M_3\}$$

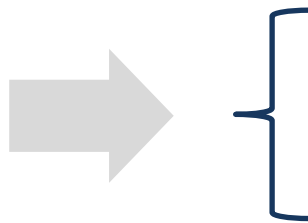


$$M^C = \{M_5, M_3\}$$

# Conformity-aware Social Influence Maximization - *GIM*

## Seed selection

- total number of nodes in each group  $u$  is involved in  $\rightarrow$  high cardinality
- the similarity between involved groups and  $u \rightarrow$  high similarity



$$rank(u) = \sum_{M_j \notin T, u \in M_j} |M_j| \times sim(A_u, P_{M_j})$$

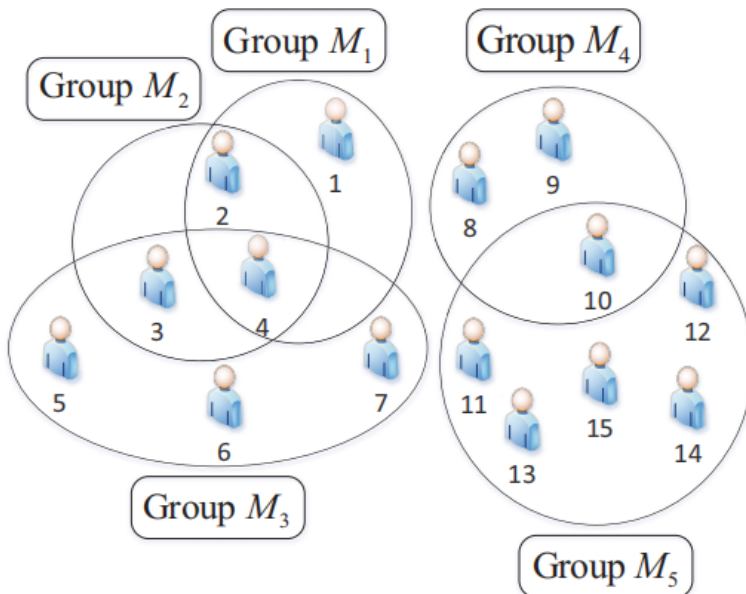
(T: the set of groups in M that already have seeds allocated)

$$\sigma(S) = \sum_{u \in S} rank(u)$$

# Conformity-aware Social Influence Maximization - *GIM*

Complete seed set selection process!

We assume that each vertex has the same similarity **0.5** for each group on the profile and **k = 2**. And we know that  $M^C = \{M5, M3\}$ .

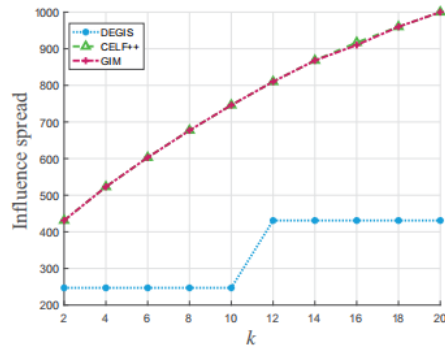


Group	$rank(\cdot)$ values for each user
$E$	$rank(10) = 3 \times 0.5 + 6 \times 0.5 = 4.5$ $rank(11) = 6 \times 0.5 = 3$ $rank(12) = rank(13) = rank(14) = rank(15) = rank(11) = 3$ $rank(8) = rank(9) = 3 \times 0.5 = 1.5$
$C$	$rank(4) = 3 \times 0.5 + 3 \times 0.5 + 5 \times 0.5 = 5.5$ $rank(3) = 3 \times 0.5 + 5 \times 0.5 = 4$ $rank(2) = 3 \times 0.5 + 3 \times 0.5 = 3$ $rank(5) = rank(6) = rank(7) = 5 \times 0.5 = 2.5$ $rank(1) = 3 \times 0.5 = 1.5$

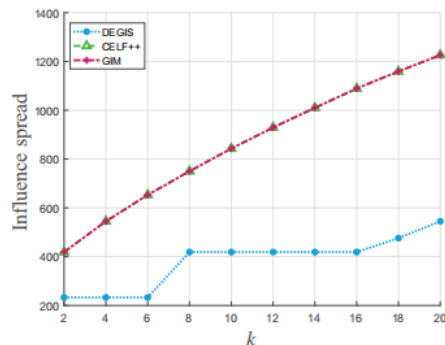
Y. Li, X. Gan, L. Fu, X. Tian, Z. Qin, Y. Zhou. 2018. Conformity-Aware Influence Maximization with User Profiles.



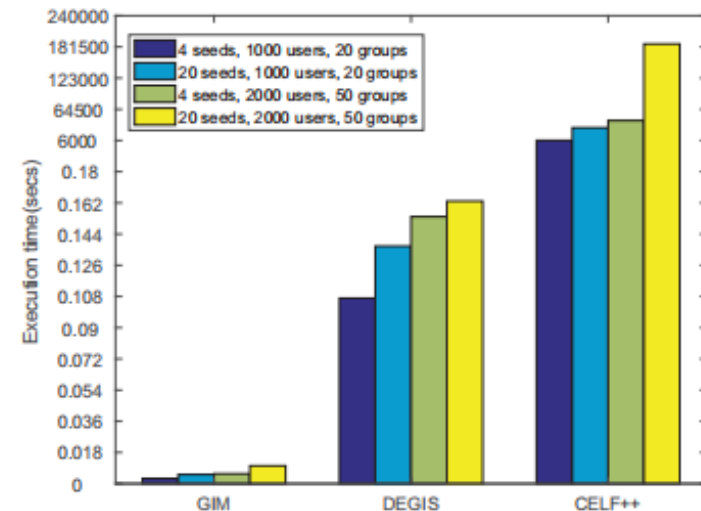
# Conformity-aware Social Influence Maximization - *GIM*



(a) User number  $n = 1000$ , group number  $m = 20$



(b) User number  $n = 2000$ , group number  $m = 50$





# Psychology-aware social influence Est. and Max.: Besides Conformity

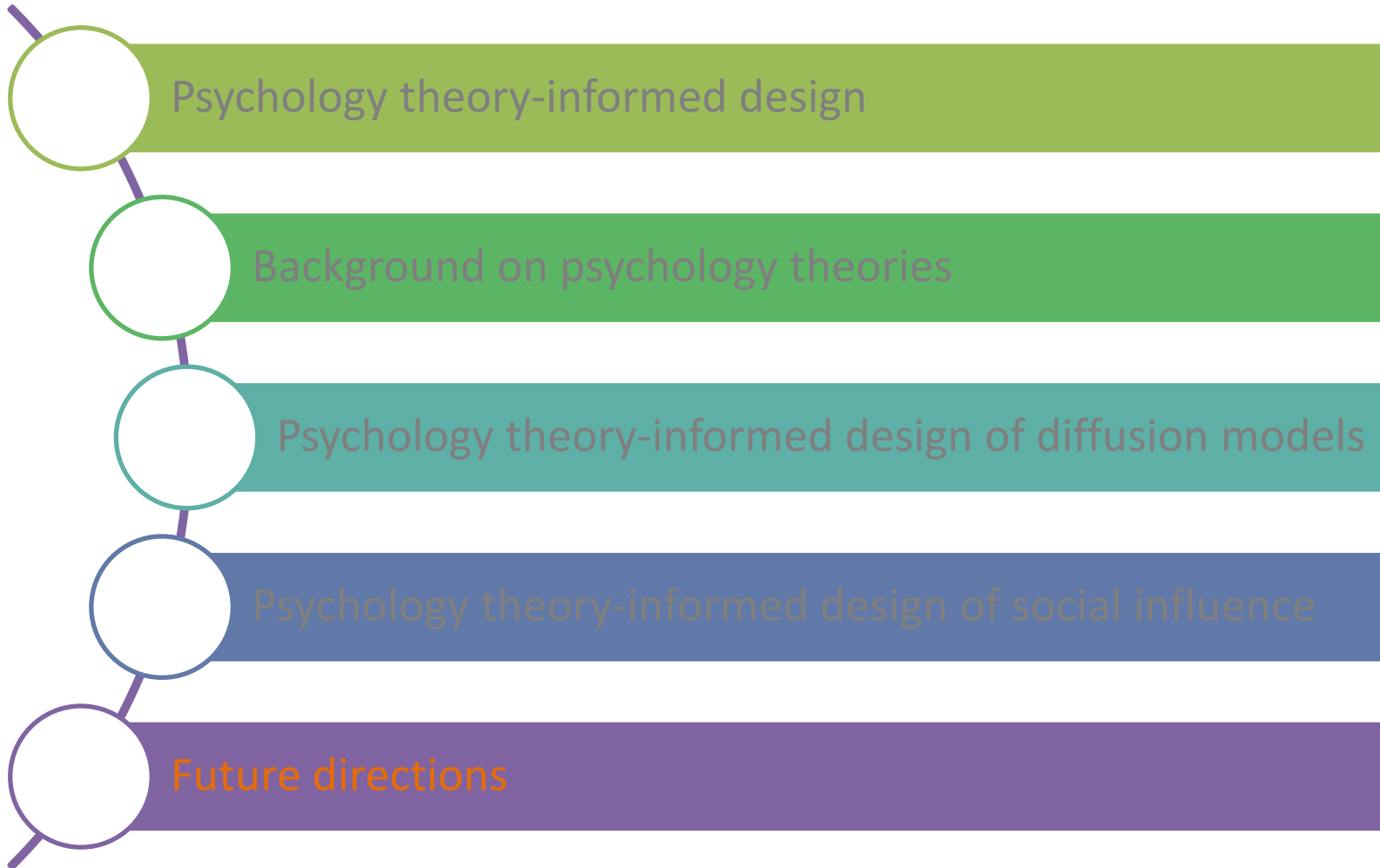


Normative vs. Informational conformity: leads to the same influence

Attention attenuation: LT diffusion model  $\rightarrow$  RLT model; est. and max. following RLT

Confirmation bias: Topic-aware IM & Cost-aware VM

# Next..



# Expansion to Larger Social Computing Problems

## Goal

- Trigger rethinking of existing social computing solutions

## Community Search

- Social psychology influence interactions between individuals
- Existing community search techniques are psychology-oblivious

## Bias and Fairness

- A lot of research activities in recent times.
- Solutions are typically not informed by psychology theories



# Expansion to Larger Social Computing Problems

## Fake News Propagation

- Confirmation bias plays a significant role.
- Techniques can benefit from psychology-informed design.
- Potential to improve understanding and accuracy.

## Social Data Quality

- Collaborative editing of Wikipedia
- Influenced by confirmation bias, conformity.



# Expansion of Psychological Theories

## Goal

- Tip of the iceberg
- Conformity theory
- Confirmation bias
- Interference theory
- Attenuation theory

## Role Theory

- Roles that people occupy provide context that shape behaviour
- Potential to contribution to information propagation



# Expansion of Psychological Theories

## Social Impact Theory

- Amount of influence a person experiences in group settings:
  - Strength (power or social status) of the group
  - Immediacy (psychological or physical distance)
  - Number of people in the group exerting the influence
- Useful for understanding social influence

## Cognitive Psychology

- Study of how people think and process information
- Cognitive load theory
- Check out our tutorial at **SIGMOD 2024!**



# Data-driven Quantitative Model of Psychological Theories

## Goal

- Existence of massive human-related data
- Can we model psychological theories at scale?
- Data-driven techniques to influence psychology

## Early Efforts

- Modeling of confirmation bias
- Conformity



# Conclusions

Think about the role psychology theories can play in designing social computing solutions

Review relevant research on this interdisciplinary topic

