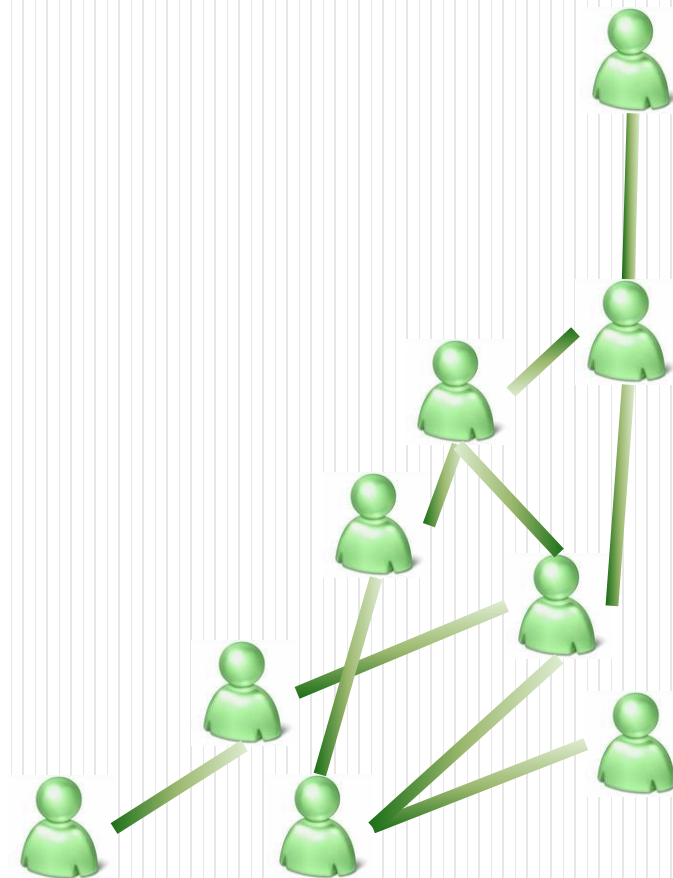


Computational Social Influence

Wei Chen

陈卫

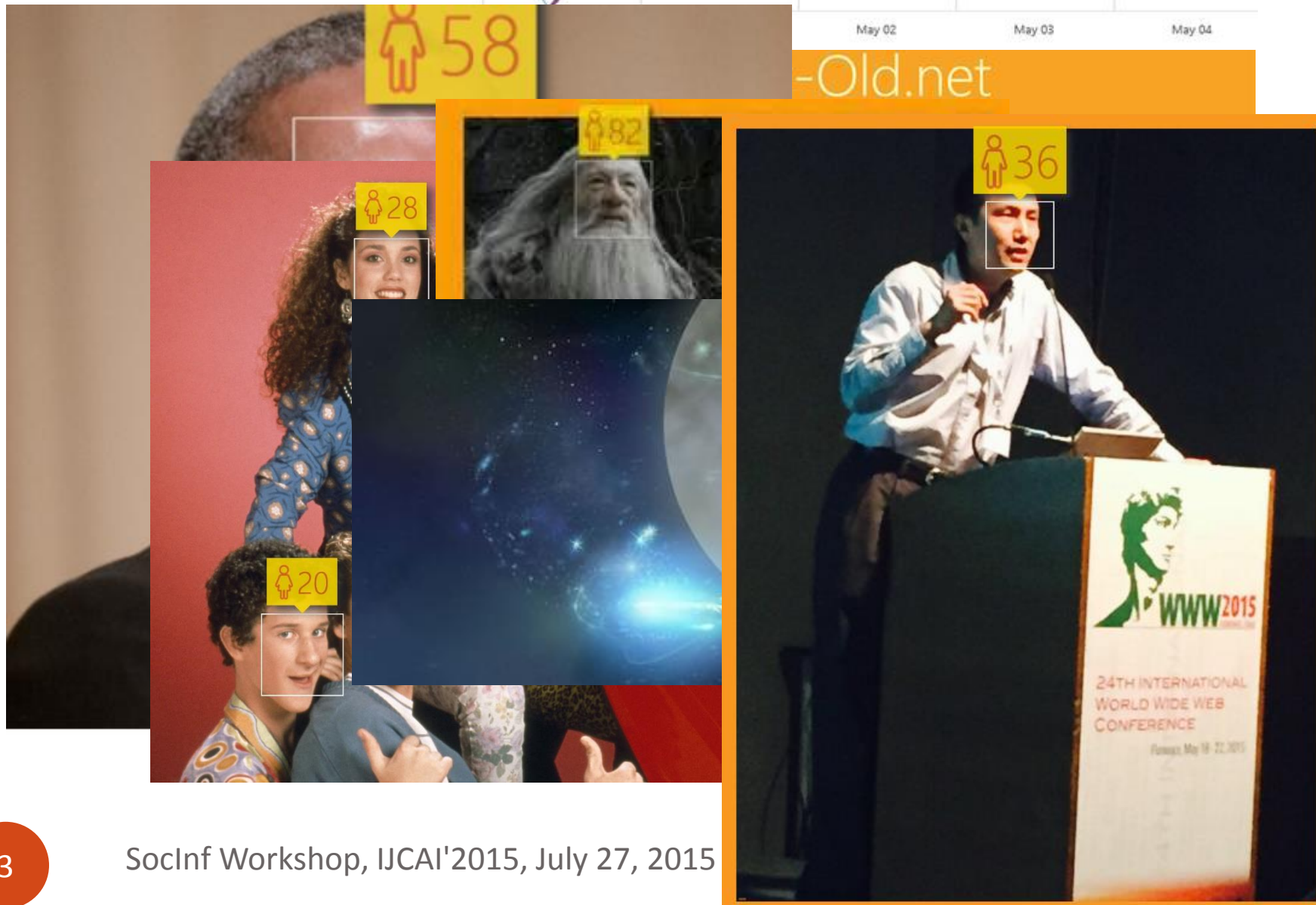
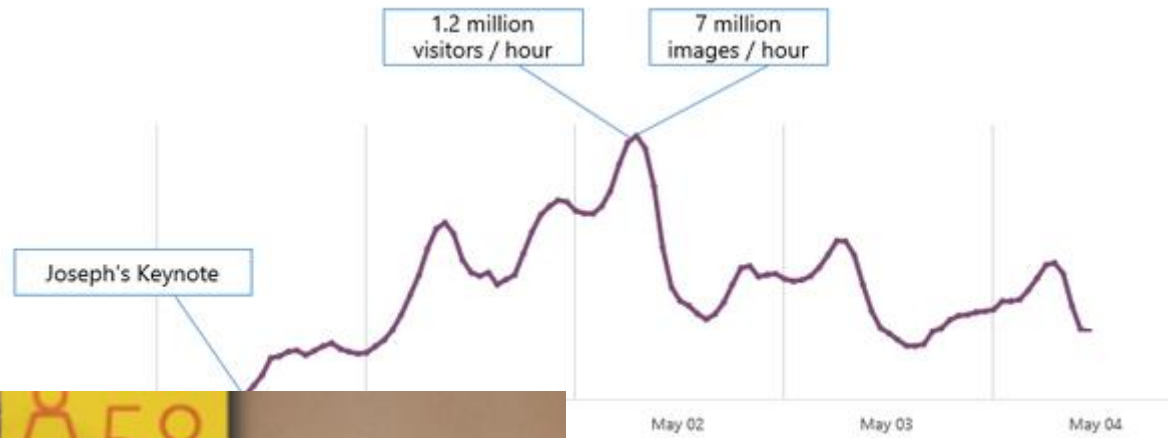
Microsoft Research Asia



Social influence

- **Social influence** occurs when one's emotions, opinions, or behaviors are affected by others.



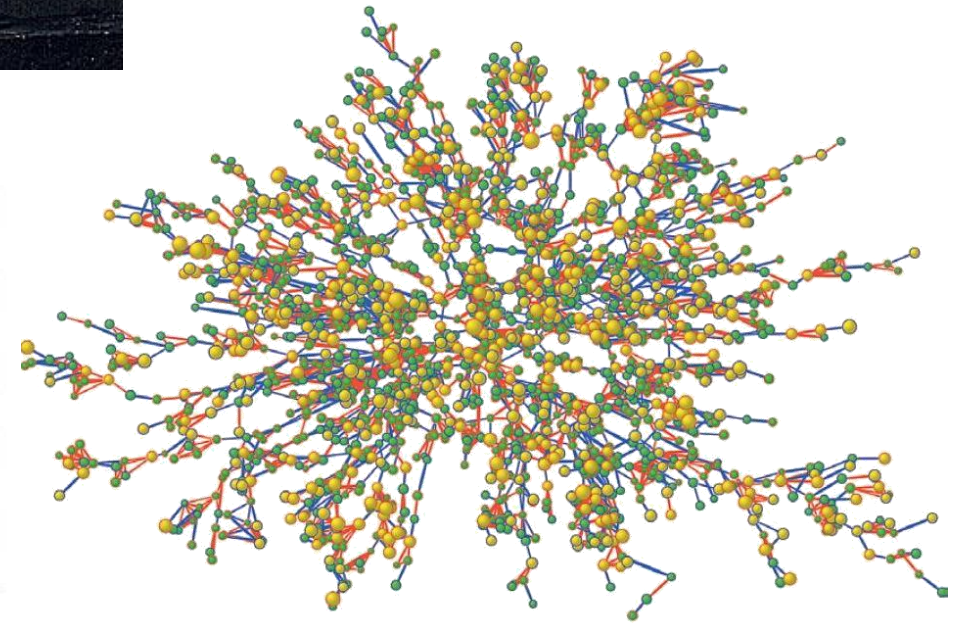
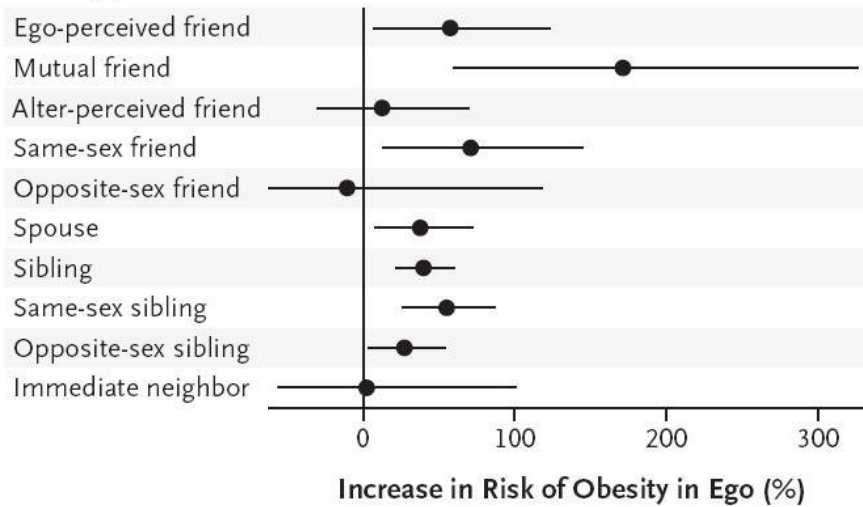






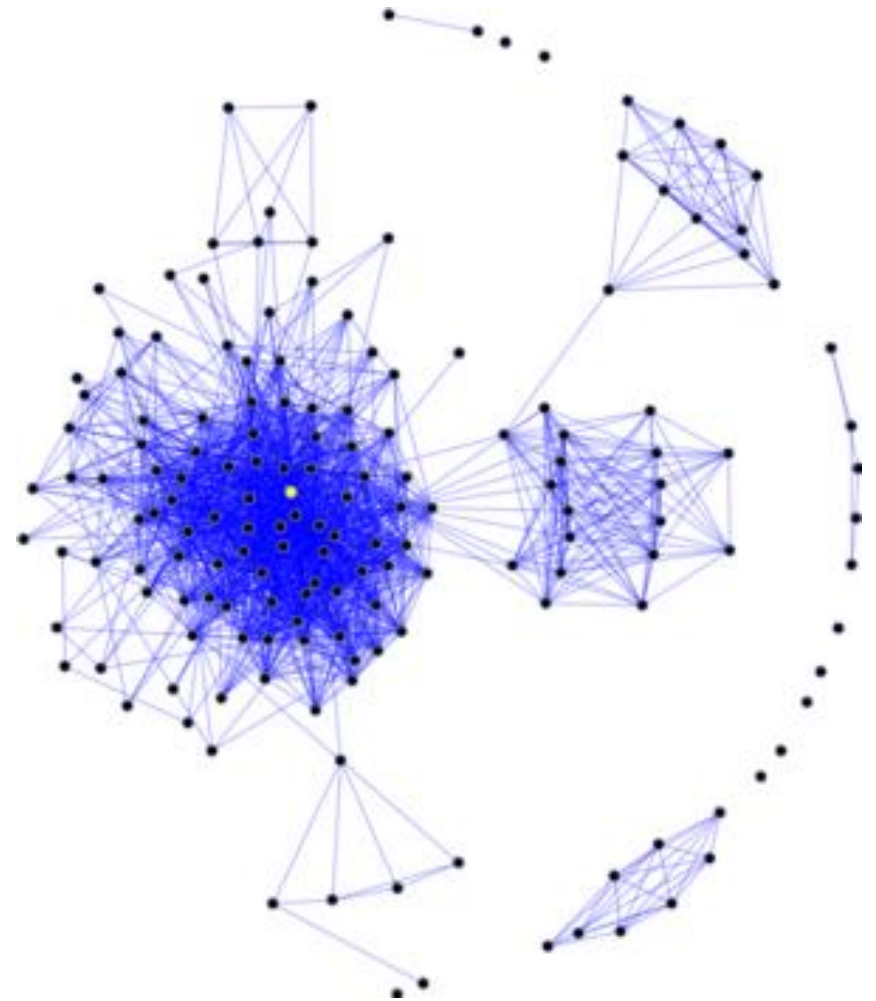


Alter Type



[Christakis and Fowler, NEJM'07,08]

Booming of online social networks



Opportunities on online social influence research and applications

- massive data set, real time, dynamic, open
- help understand social interactions, influence propagation patterns in grand scale
- help identifying influencers
- facilitate decision making in health care, business, politics, and economics

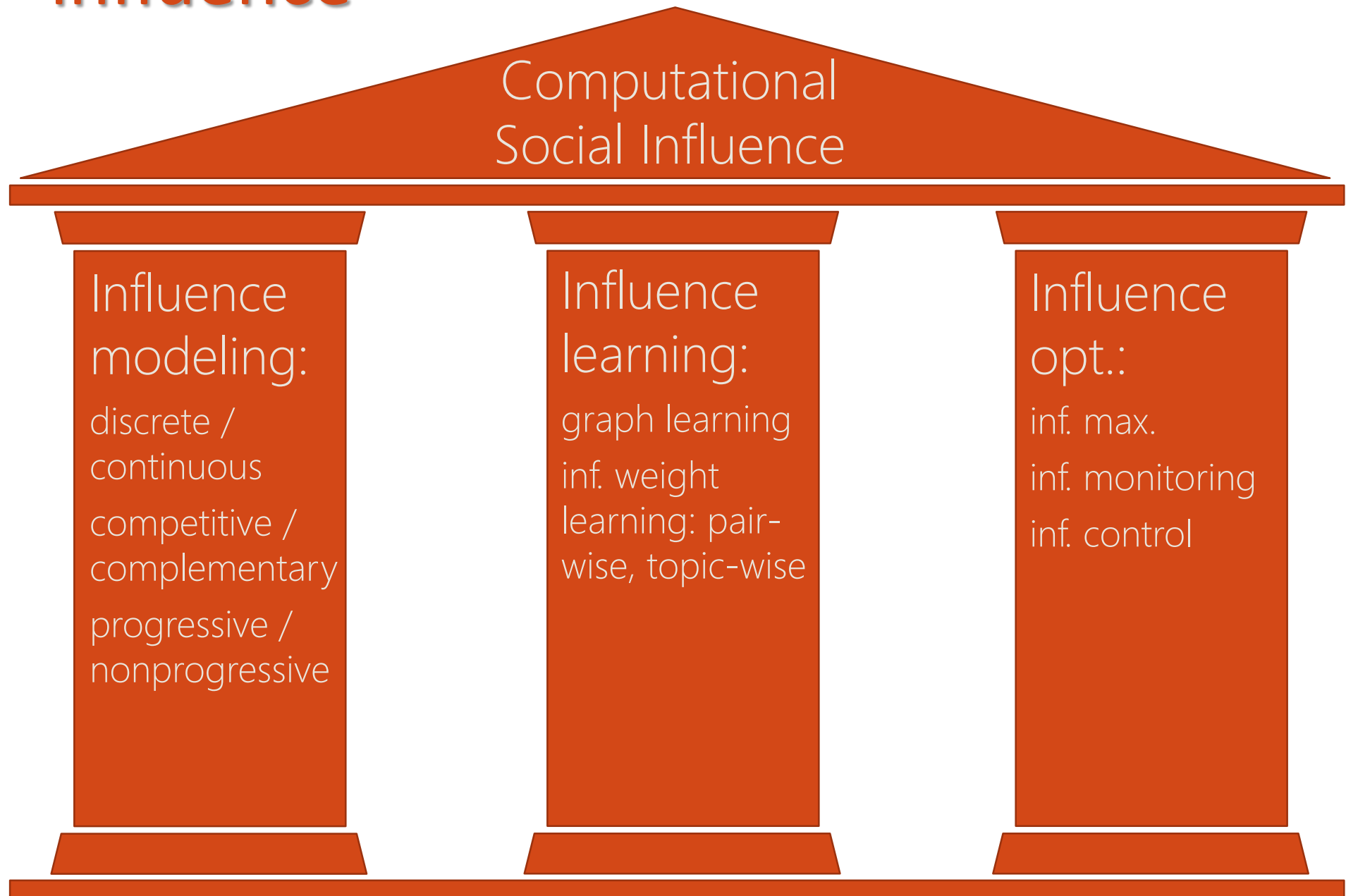
Voting mobilization: A Facebook study

- Voting mobilization [Bond et al, Nature'2012]
 - show a facebook msg. on voting day with faces of friends who voted
 - generate 340K additional votes due to this message, among 60M people tested



The image shows a Facebook notification titled "Today is Election Day" with a "What's this? • close" link. On the left is a circular "VOTE" button with a red top half containing three white stars and a blue bottom half containing three white stars. To the right of the button is the text: "Find your polling place on the U.S. Politics Page and click the 'I Voted' button to tell your friends you voted." Below this text is a blue "I Voted" button. To the right of the text is a counter showing "01155376" in blue boxes, with the text "People on Facebook Voted" below it. At the bottom left is a row of six profile pictures of people. To the right of the pictures is a Facebook icon followed by the text: "Jaime Settle, Jason Jones, and 18 other friends have voted."

Three pillars of computational social influence



Influence modeling

- Discrete-time models:
 - independent cascade (IC), linear threshold (LT), general cascade models [KKT'03]
 - topic-aware IC/LT models [BBM'12]
- Continuous-time models [GBS'11]
- Competitive diffusion models
 - competitive IC [BAA'11], competitive LT [HSCJ'12], etc.
- Competitive & complementary diffusion model [LCL'15]
- Others, epidemic models (SIS/SIR/SIRS...), voter model variants

Influence optimization

- Scalable inf. max.
 - Greedy approximation [KKT'03, LKGFVG'07, CWY'09, BBCL'14, TXS'14, TSX'15]
 - Fast heuristics [CWY'09, CWW'10, CYZ'10, GLL'11, JHC'12, CSHZC'13]
- Multi-item inf. max. [BAA'11, SCLWSZL'11, HSCJ'12, LBGL'13, LCL'15]
- Non-submodular inf. max. [GL'13, YHLC'13, ZCSWZ'14, CLLR'15]
- Topology change for inf. max. [TPTEFC'10, KDS'14]
- Inf. max with online learning [CWY'13, LMMCS'15]
- many others ...

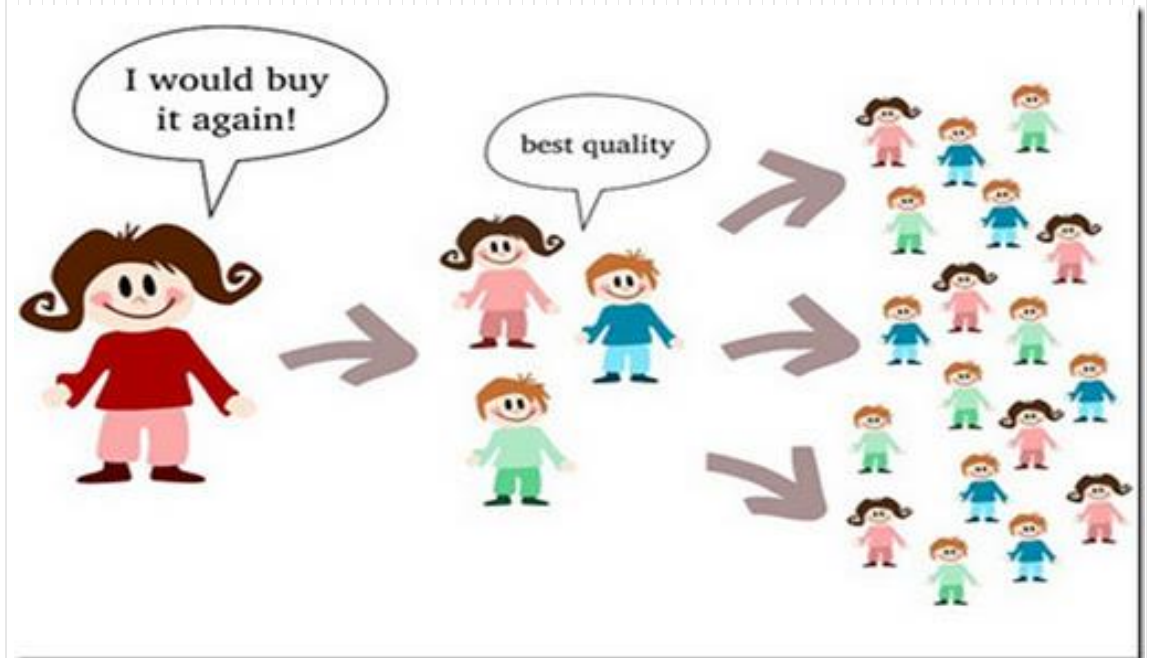
Influence learning

- Based on user action / adoption traces
- Learning the diffusion graph [GLK'10]
- Learning (the graph and) the parameters
 - frequentist method [GBL'10]
 - maximum likelihood [SNK'08]
 - MLE via convex optimization [ML'10,GBS'11,NS'12]

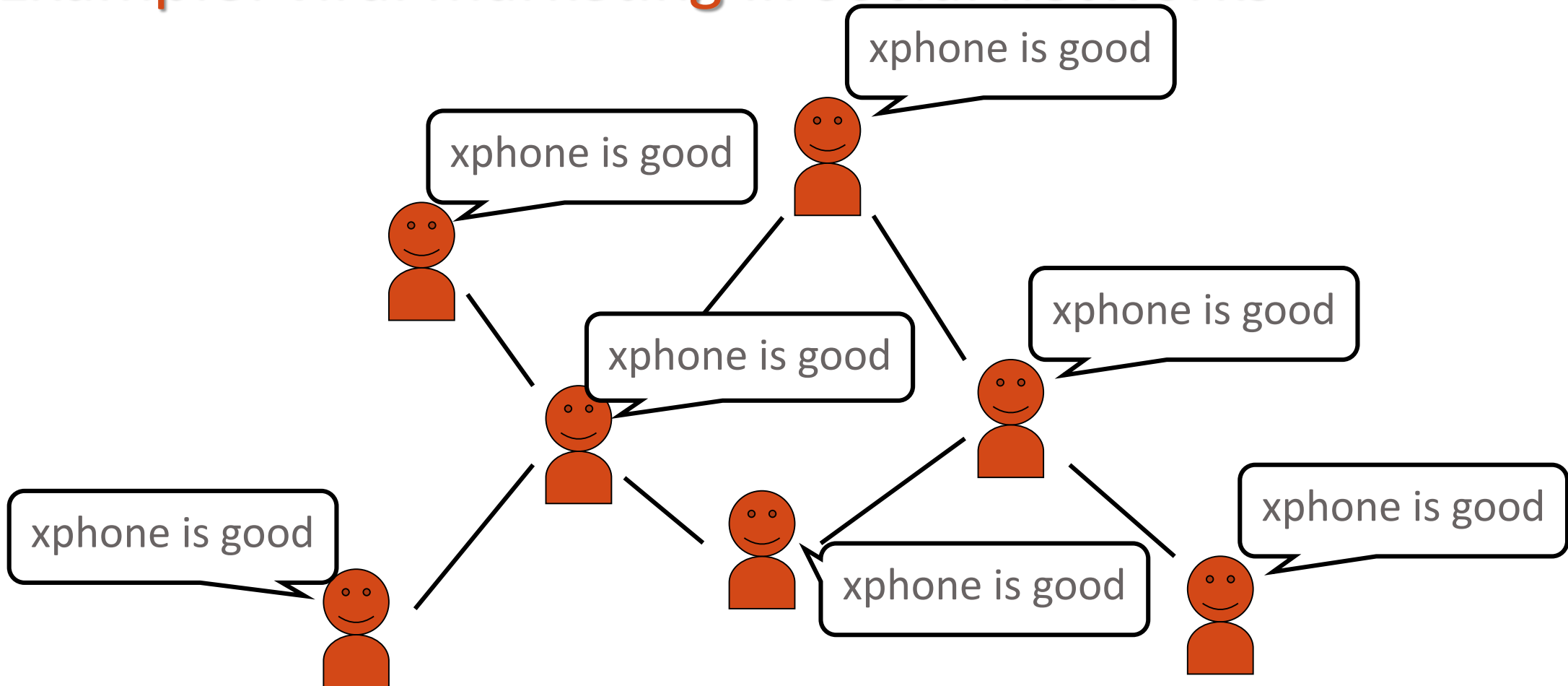
Rest of this talk

- Quick review of influence model and maximization
- Amphibious influence maximization
- Comparative influence diffusion --- from competition to complementarity

Quick Review of Influence Model and Maximization



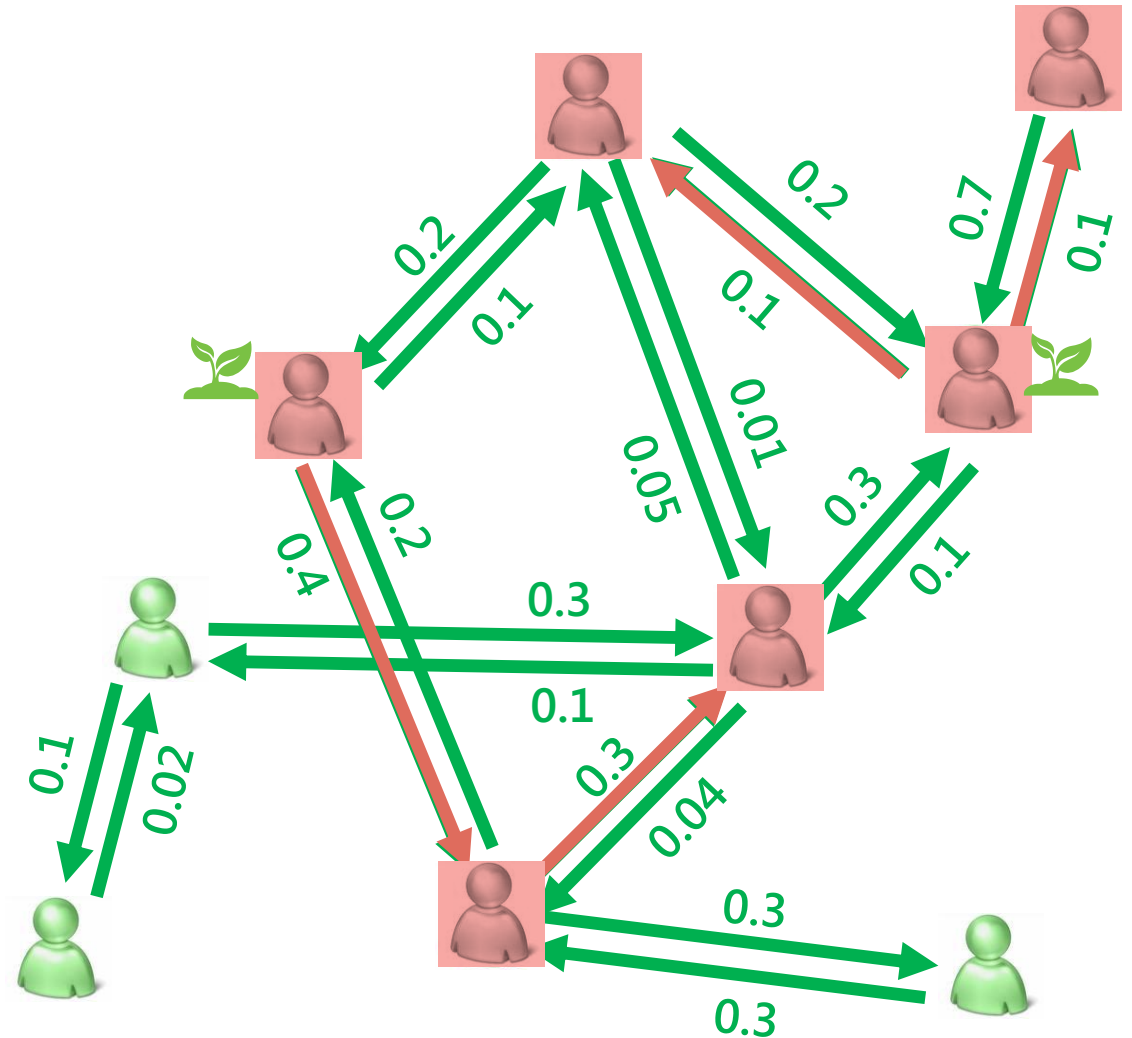
Example: viral marketing in social networks



- Viral (word-of-mouth) marketing is believed to be a promising advertising strategy.
- Increasing popularity of online social networks may enable large scale viral marketing

Influence diffusion model

- Directed graph $G = (V, E)$
 - V : set of nodes, representing users
 - E : set of directed edges, representing influence relationships
- Influence probabilities on edges
 - $p(u, v)$: the probability that u activates v
- Independent cascade model
 - Initially nodes in a seed set S are activated
 - At step t , each node u activated at step $t - 1$ has one chance to activate each of its out-going neighbor v , with success probability $p(u, v)$
 - influence spread $\sigma(S)$: expected number of active nodes when S is the seed set

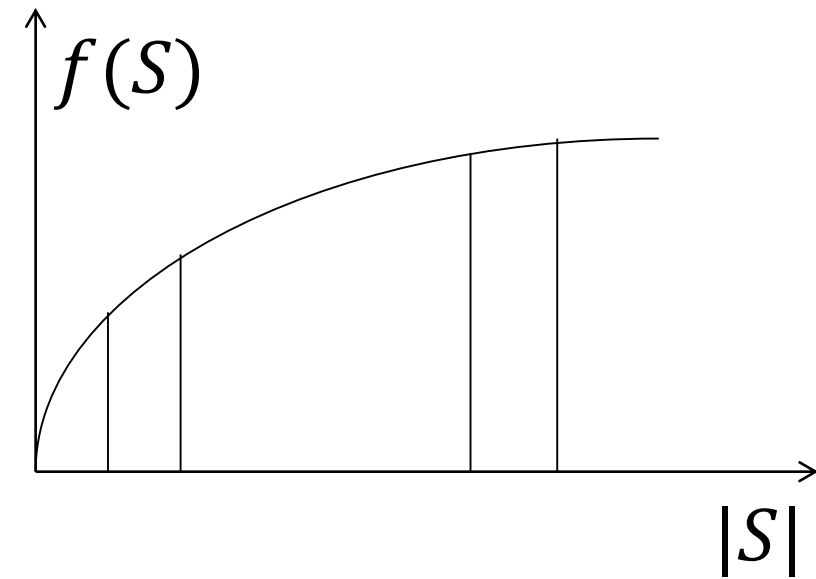


Influence maximization

- Given a social network, a diffusion model with given parameters, and a number k , find a seed set S of at most k nodes such that the **influence spread of S , $\sigma(S)$, is maximized.**
- Many possible variants
 - non-uniform cost, minimize seed set size, etc.
- NP hard

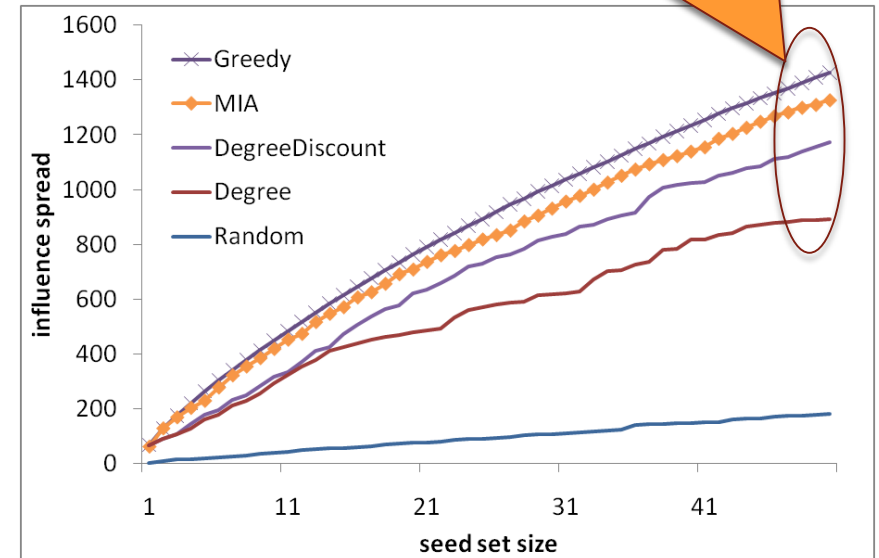
Greedy approximation framework

- influence spread $\sigma(S)$ is **submodular**:
 - for all $S \subseteq T \subseteq V$, all $v \in V \setminus T$,
$$\sigma(S \cup \{v\}) - \sigma(S) \geq \sigma(T \cup \{v\}) - \sigma(T)$$
 - diminishing marginal return
- Submodular function maximization
 - Greedy algorithm: iteratively finding the next seed with the largest marginal influence spread
 - $1 - 1/e$ approximation

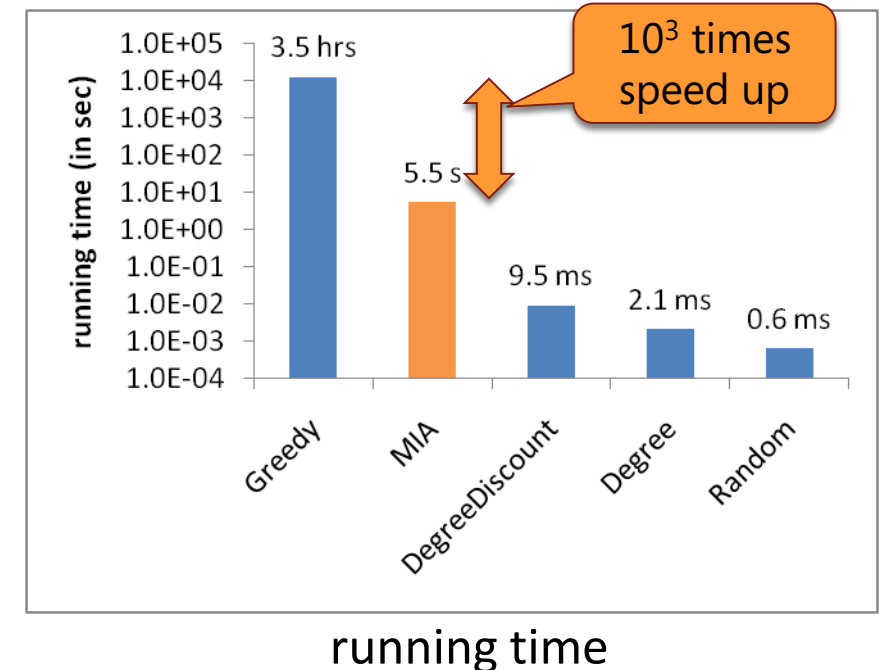


Fast MIA heuristic

- Pure greedy algorithm is very slow
- MIA uses local tree structure to replace general influence computation
- 1000 fold speedup with similar seed quality
- new algorithms available



Influence spread vs. seed set size

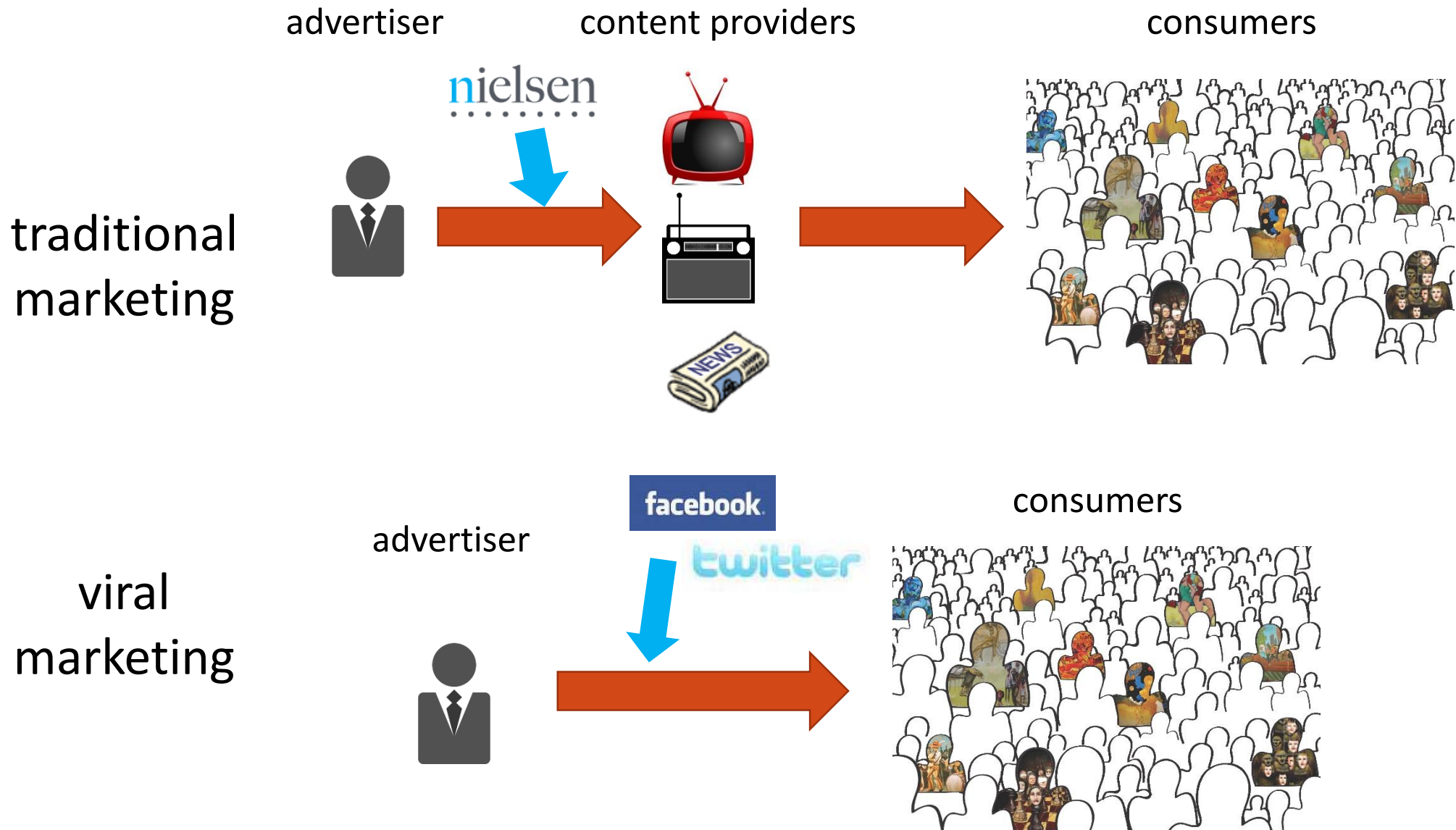


Amphibious Influence Maximization

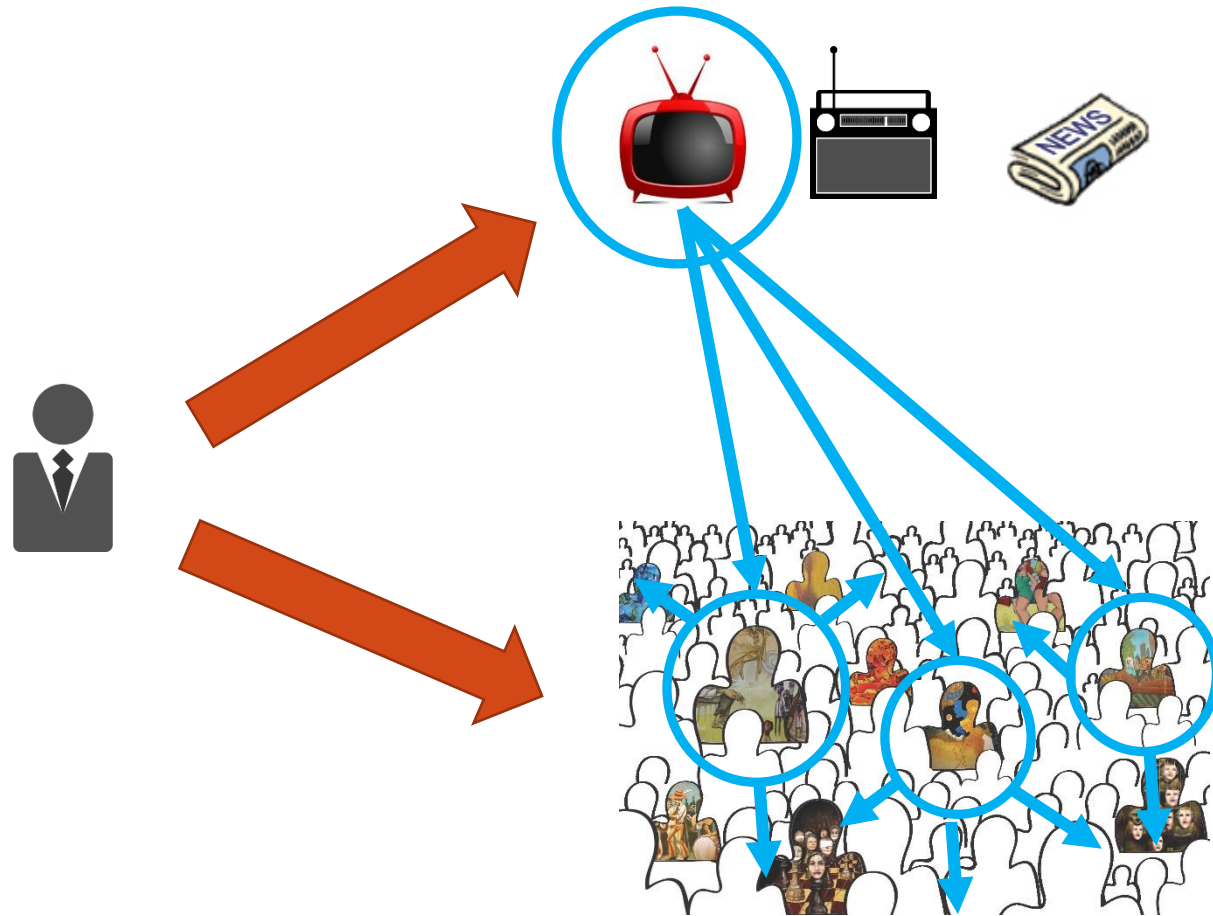
with Fu Li, Tian Lin, and Aviad Rubinstein



Traditional vs. viral marketing

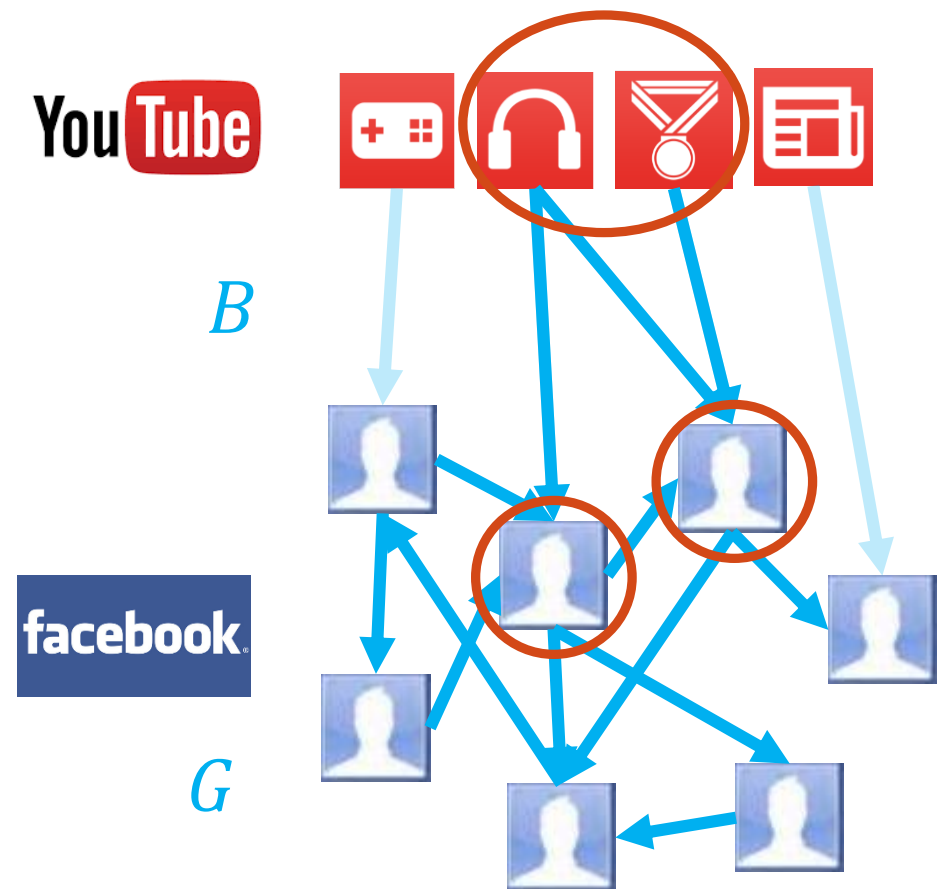


Amphibious marketing



Amphibious influence maximization

- Given:
 - U – content providers
 - V – consumers
 - $G = (V, P)$ – social network graph with influence probability matrix P
 - $B = (U, V, M)$ – provider to consumer influence graph, with bi-adjacency matrix M
- Diffusion model:
 - From selected seed providers $X \subseteq U$, to selected seed consumers $Y \subseteq V$, then to the rest of social network
 - Same as IC model, with X as seeds, and remove all edges from U pointing to $V \setminus Y$
 - Influence spread $\sigma(X, Y)$: expected number of active nodes in V
- Goal
 - Find b_1 seed providers X and b_2 seed consumers Y to maximize $\sigma(X, Y)$



Main results

- Difficulty:
 - $\sigma(X, Y)$ is submodular in X when fixing Y , or vice versa
 - but the interaction of X and Y makes it harder --- need both X and Y to generate influence spread --- non-submodular behavior
- Hardness: NP-hard to approximate to any constant factor in general graphs
 - reduced from a k -prover system
- Algorithm: When M (weighted bi-adjacency matrix for provider-consumer bipartite graph) has **constant rank**, polynomial-time algorithm with constant approx. factor $\left(1 - \frac{1}{e} - \varepsilon\right)^3$
 - constant rank assumption:
 - ♦ M dictated by a small number of provider/consumer features
 - ♦ often used in recommender systems

The algorithm

- Main observation:

$$\Pr[v \text{ activated}] = 1 - \prod_{u \in \Gamma(v)} (1 - M_{(u \rightarrow v)} x_u) \approx 1 - e^{-\sum_{u \in \Gamma(v)} M_{(u \rightarrow v)} x_u} (*)$$

$(1 - 1/e)$ factor

- **Linear term** in the exponent allows us to use constant rank
 - (polynomially sized) ε -net S_ε over all vectors $\mathbf{s} \approx M\mathbf{x}$
 - ♦ (fixing \mathbf{s} , we know from $(*)$ the probability that each consumer is activated by the providers)
 - for each choice of \mathbf{s}
 - ♦ pick feasible \mathbf{y}_s (indicator vector of V) that (approximately) maximizes the spread (standard submodular maximization)
 - ♦ Pick feasible \mathbf{x}_{y_s} (indicator vector of U) that (approximately) maximizes the spread, given fixed \mathbf{y}_s
 - output $(\mathbf{x}_{y_s}, \mathbf{y}_s)$ that maximizes $\sigma(\mathbf{x}_{y_s}, \mathbf{y}_s)$, among all $\mathbf{s} \in S_\varepsilon$

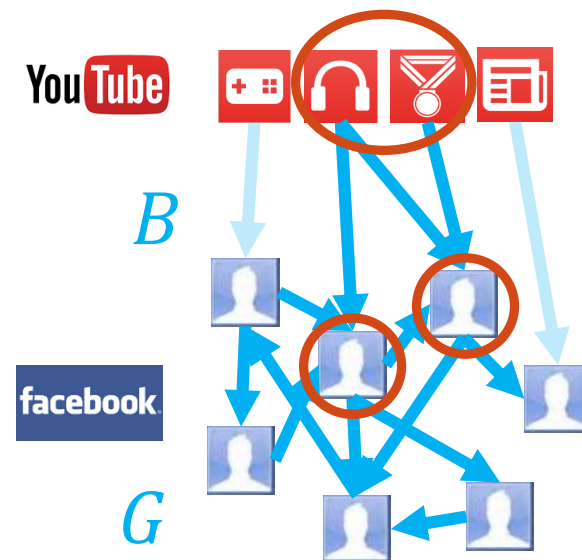
$(1 - 1/e - \varepsilon)$ factor

ε error

$(1 - 1/e - \varepsilon)$ factor

Contributions

- Conceptual: proposes **amphibious marketing**
 - using data from both content providers and social networks
- Technical:
 - hardness reduction from k -prover systems
 - **constant rank assumption to deal with non-submodularity**



Open problems

- Is the approximation factor $\left(1 - \frac{1}{e} - \varepsilon\right)^3$ tight?
- Handling non-submodularity:
 - Can constant rank assumption be applied to other context?
 - Is there other reasonable assumptions on (weighted) influence networks?
- Better models for “amphibious marketing”?
 - learning? privacy? incentives?

Comparative Influence Diffusion: From Competition to Complementarity

with Wei Lu and Laks Lakshmanan



Competition and complementarity

- Many competitions in the market



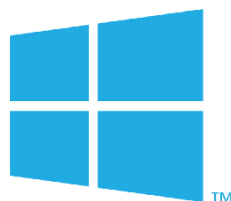
vs



vs



- Also many complementarity and cooperation



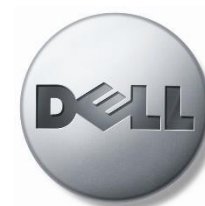
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Influence diffusion with competition and complementarity

- Most existing research focus on single-item diffusion or pure competitive diffusion
- Can we cover the diffusion of competitive and/or complementary items in a single unified model?

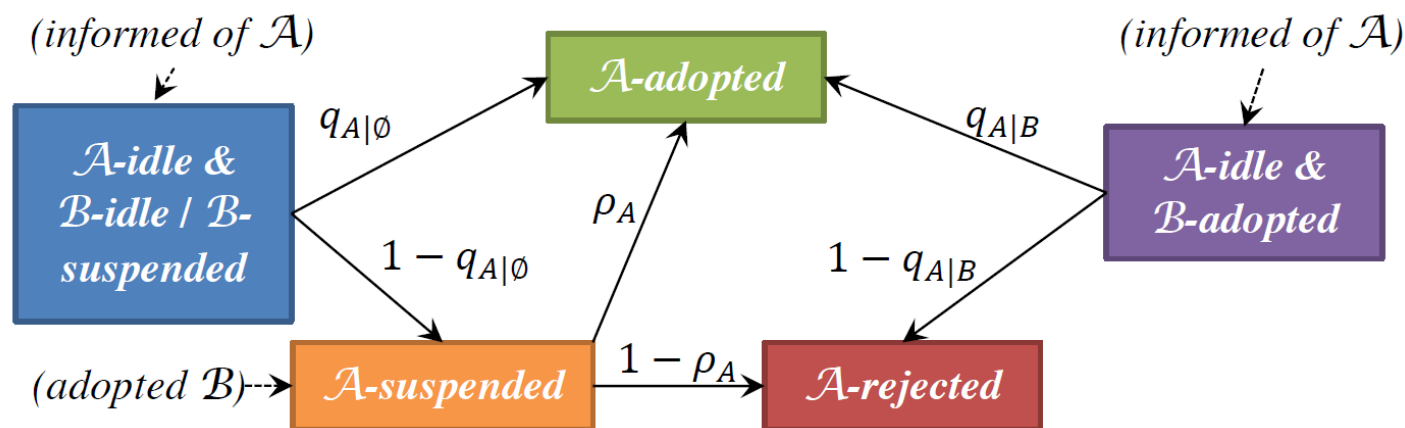


Comparative IC (Com-IC) model

- Consider two items A and B
- Comparative: user compares two items
 - covers both competition and complementarity, partial or complete
- Social graph $G = (V, E)$
 - edge probabilities $p(u, v)$: probability that u will pass information about A or B to v
 - ♦ open once for both items
- Node adoption states and their transitions
 - four states for each item:
 - ♦ idle, suspended, adopted, rejected
 - four global adoption probability (GAP) parameters:
 - ♦ $q_{A|\emptyset}, q_{A|B}, q_{B|\emptyset}, q_{B|A}$



Node level state transition



- Principle

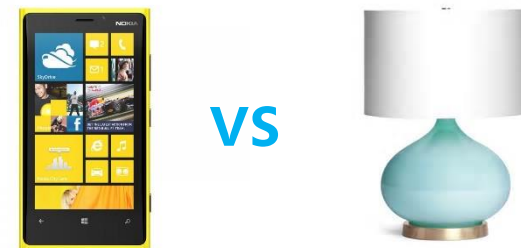
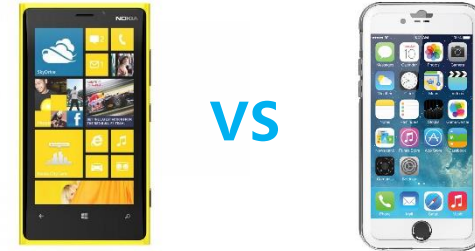
- If not adopt B and get informed about A, use $q_{A|\emptyset}$ to test A adoption
- If already adopted B and get A-informed, use $q_{A|B}$
- If failed adopting A initially (becoming A-suspended) and later adopt B, reconsider A with probability ρ_A

- ♦ $\rho_A = \frac{\max\{q_{A|B} - q_{A|\emptyset}, 0\}}{1 - q_{A|\emptyset}}$

- ♦ only reconsider when $q_{A|B} \geq q_{A|\emptyset}$, and overall A adoption probability is $q_{A|B}$

The competition to complementarity spectrum

- Mutual competition:
 - $q_{A|B} \leq q_{A|\emptyset}$ and $q_{B|A} \leq q_{B|\emptyset}$
 - pure competition: $q_{A|B} = 0$ and $q_{B|A} = 0$
- Mutual complementarity:
 - $q_{A|B} \geq q_{A|\emptyset}$ and $q_{B|A} \geq q_{B|\emptyset}$
 - perfect complementarity: $q_{A|B} = 1$ and $q_{B|A} = 1$
- Mutual indifference:
 - $q_{A|B} = q_{A|\emptyset}$ and $q_{B|A} = q_{B|\emptyset}$
- One way complementarity:
 - $q_{A|B} \geq q_{A|\emptyset}$ and $q_{B|A} = q_{B|\emptyset}$



Submodularity on complementary cases

- influence spread $\sigma_A(S_A, S_B)$: expected number of A-adopted nodes with A seed set S_A and B seed set S_B
 - self-submodularity: fix S_B , σ_A changes on S_A
 - cross-submodularity: fix S_A , σ_A changes on S_B
- Submodularity only holds in some sub-cases
 - self-submodularity holds for one-way complementarity:
 $q_{A|B} \geq q_{A|\emptyset}$ and $q_{B|A} = q_{B|\emptyset}$
 - cross-submodularity holds when A perfectly complements B: $q_{B|A} = 1$

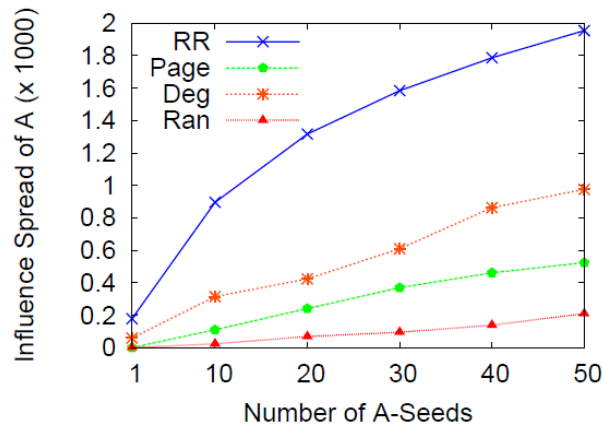
Influence maximization on complementary cases

- SelfInfMax: For a fixed set S_B , find S_A of size k to maximize $\sigma_A(S_A, S_B)$
- ComplInfMax: For a fixed set S_A , find S_B of size k to maximize $\sigma_A(S_A, S_B) - \sigma_A(S_A, \emptyset)$
- Our results:
 - for submodular cases: design fast approximation algorithm based on [Reverse-Reachable sets](#)
 - for non-submodular cases: find upper/lower bounded submodular cases, and [use sandwich approximation](#)

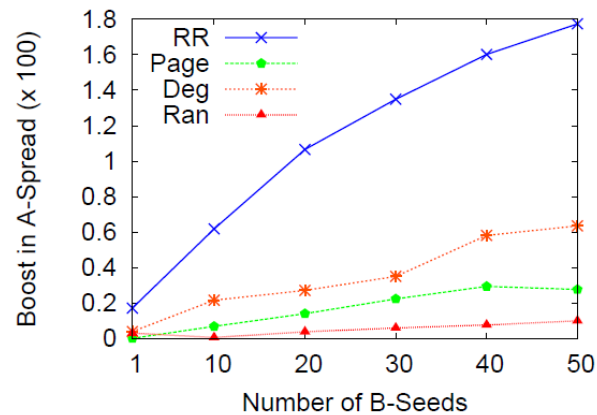
Experimental evaluation

\mathcal{A}	\mathcal{B}	$q_{\mathcal{A} \emptyset}$	$q_{\mathcal{A} \mathcal{B}}$	$q_{\mathcal{B} \emptyset}$	$q_{\mathcal{B} \mathcal{A}}$
<i>Monster Inc.</i>	<i>Shrek</i>	.88	.92	.92	.96
<i>Gone in 60 Seconds</i>	<i>Armageddon</i>	.63	.77	.67	.82
<i>Prisoner of Azkaban</i>	<i>What a Girl Wants</i>	.85	.84	.66	.67
<i>Shrek</i>	<i>Fast and Furious</i>	.92	.94	.80	.79

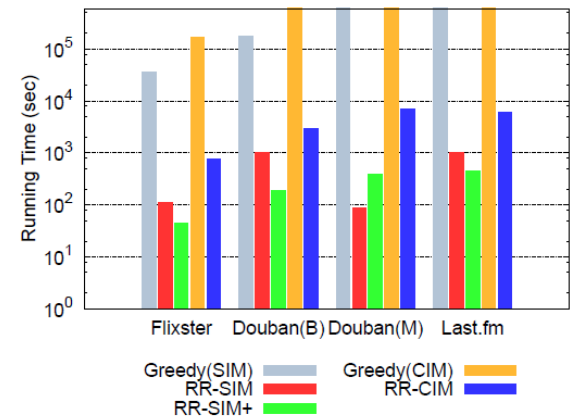
Table 2: Selected GAPs learned for movies from *Flixster*



SelfInfMax on Flixster

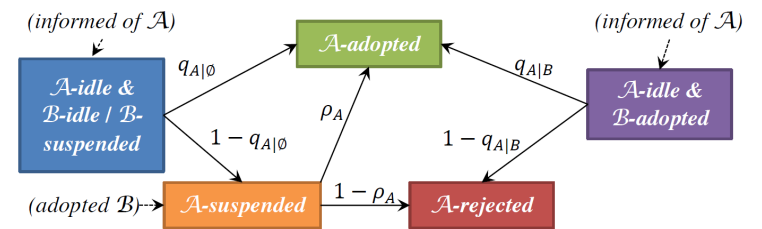


ComplInfMax on Flixster



Running time

Contribution



- Conceptual: propose a unified diffusion model covering both competition and complementarity
- Technical:
 - new problems arises from the new model
 - self- and cross-submodularity analysis
 - generalize RR-set approach and design fast approximation algorithms for SelfInfMax and ComplInfMax
 - sandwich approximation dealing with non-submodularity

Open problems

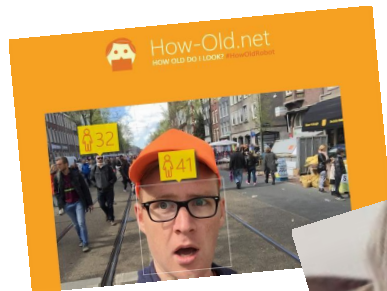
- Can SelfInfMax and ComplInfMax be made near-linear time?
- Can we fully characterize monotonicity and submodularity for the entire GAP space?
- Can we efficiently generalize Com-IC to multiple items?
- How to efficiently learn GAP parameters?
- What are other interesting problems in the Com-IC model?

Conclusion

CSI still in its early stage

- Many models and problems still need to be studied
 - non-binary, non-progressive models
 - dealing with dynamic graphs
- Influence analysis and learning is still a big challenge
 - data is still not big enough!
 - ◆ too sparse, too noisy, non-critical
 - need smart methods in learning influence model parameters
 - need robust optimization methods dealing with uncertainty in the model
 - combine online learning with influence maximization

Grand challenge

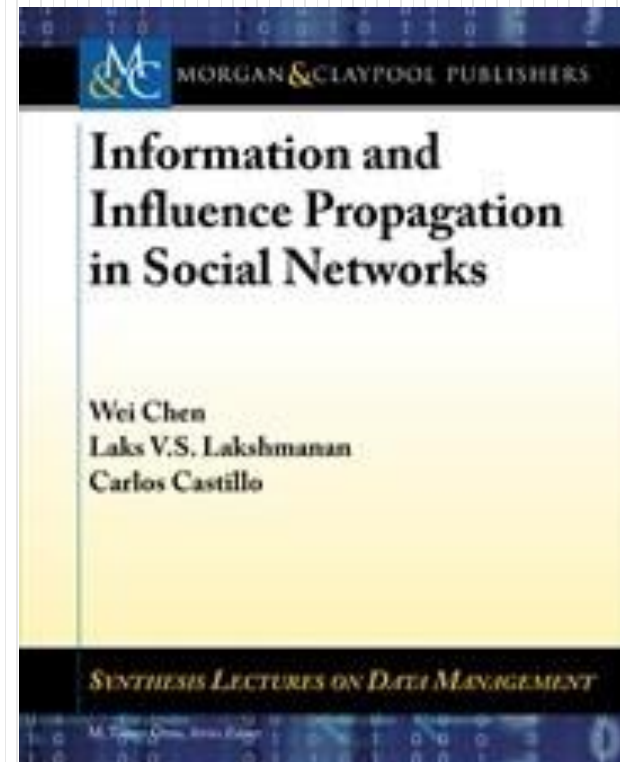


- Understand from data the true peer influence and viral diffusion scenarios, online and offline
- Apply social influence research to explain, predict, and control influence and viral phenomena
- Network and diffusion dynamics would be focus of network science in the next decade

Further resources

Search “Wei Chen Microsoft”

- Monograph: “Information and Influence Propagation in Social Networks”, Morgan & Claypool, 2013
- KDD’12 tutorial on influence spread in social networks
- my papers and talk slides



Acknowledgments to my CSI collaborators

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Thank you!
