Influence diffusion dynamics and influence maximization in complex social networks

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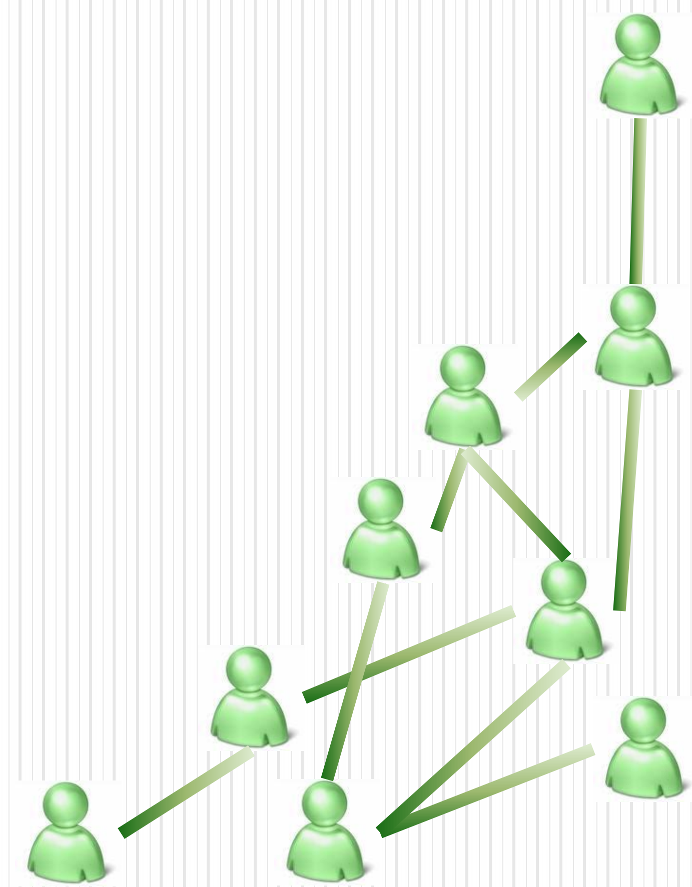


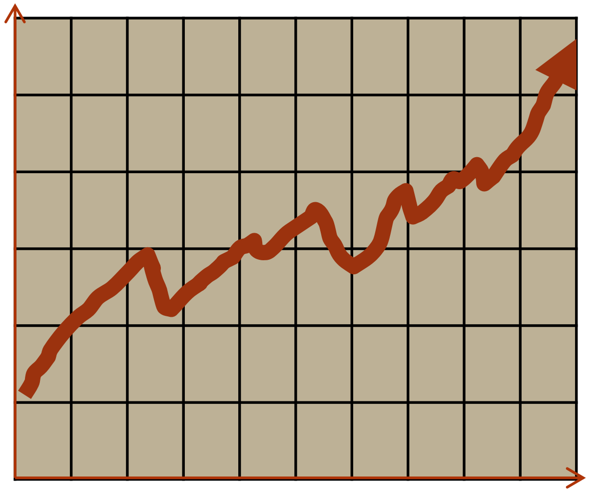
Social influence (人际影响力)

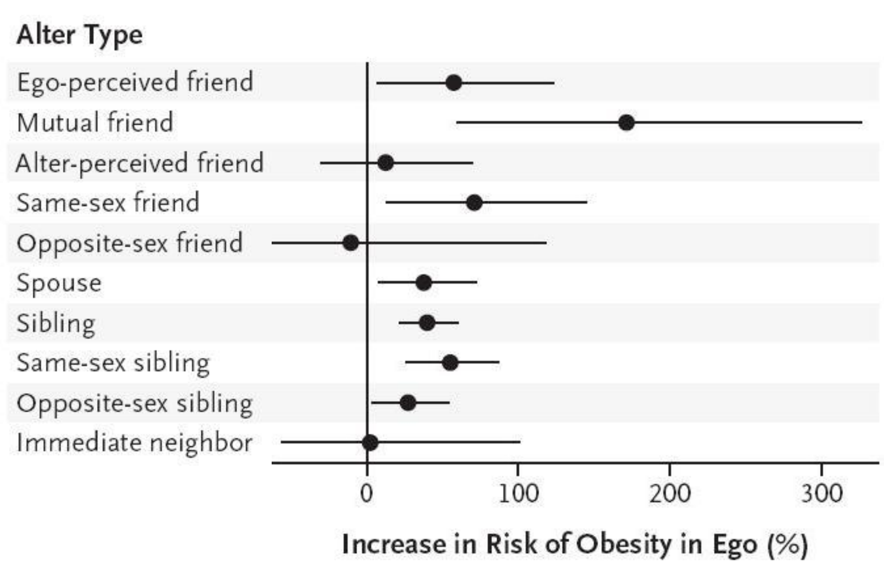
- **Social influence** occurs when one's emotions, opinions, or behaviors are affected by others.

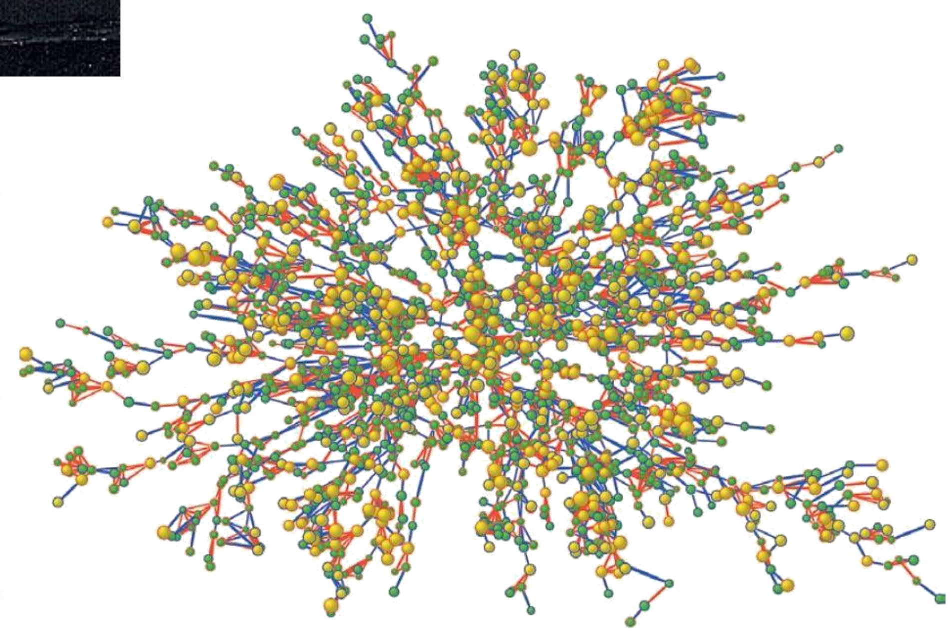
- **Social influence** is when the actions or thoughts of individual(s) are changed by other individual(s).


PSY
GANGNAM
STYLE


northern rock

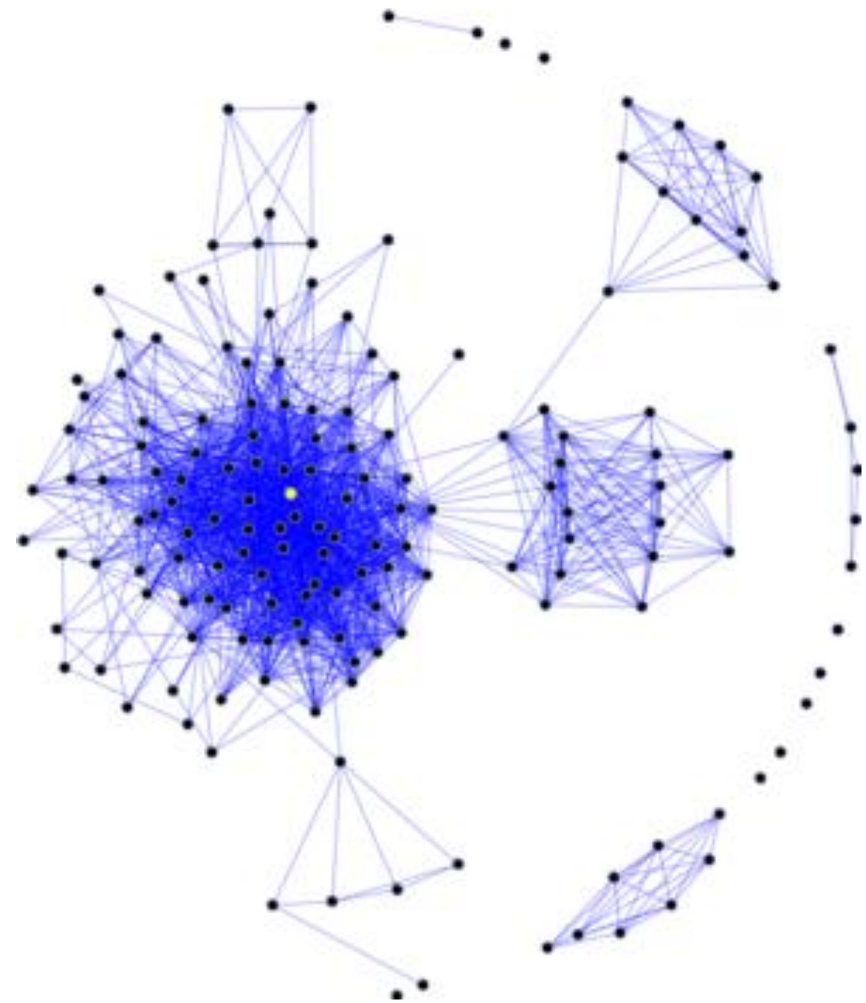






[Christakis and Fowler, NEJM'07,08]

Booming of online social networks



Opportunities on online social influence research and applications

- massive data set, real time, dynamic, open
- help social scientists to understand social interactions, influence, and their diffusion in grand scale
- help identifying influencers
- help health care, business, political, and economic decision making

Examples of recent studies

- Influential and susceptible members of social networks [Aral & Walker, Science'2012]
  - installing a facebook app and automatic notification to friends
  - men are 49% more influential than women, women influence men 46% more than they influence other women
  - younger users are more susceptible than older users
  - influential people are likely to be clustered
- 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

Challenges on the research of online social networks

- Data mining and modeling: mining large-scale social network data, and building realistic models of social influence diffusion patterns, both macro level and micro level
- Algorithm: Scalable algorithm design on influence computation, influencer ranking, and influence maximization
- System: Graph-based data storage and processing, for both offline and online data analysis

Outline of this talk

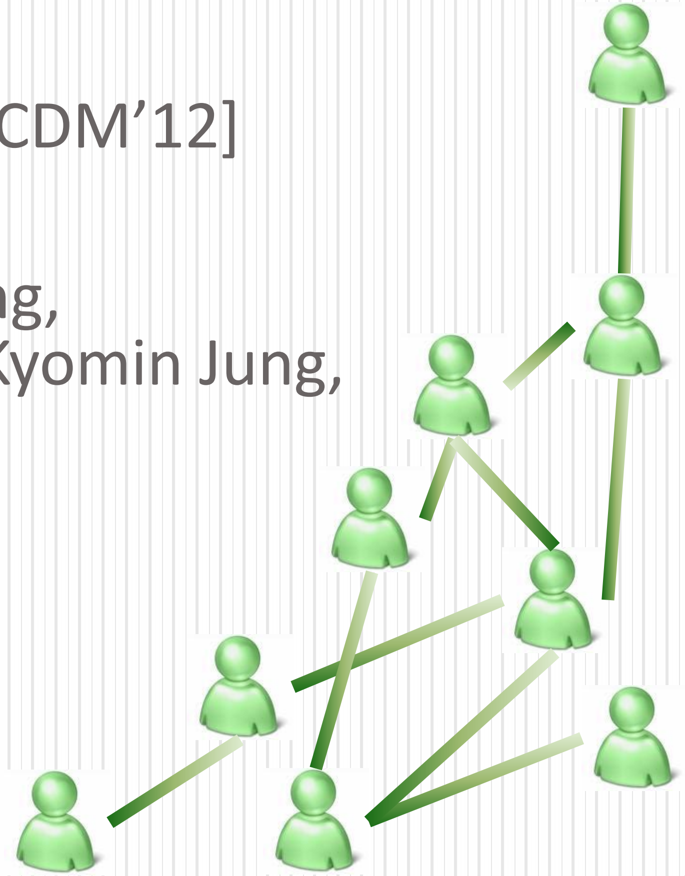
- Scalable influence maximization
- Competitive influence dynamics and influence blocking maximization

Scalable Influence Maximization in Social Networks

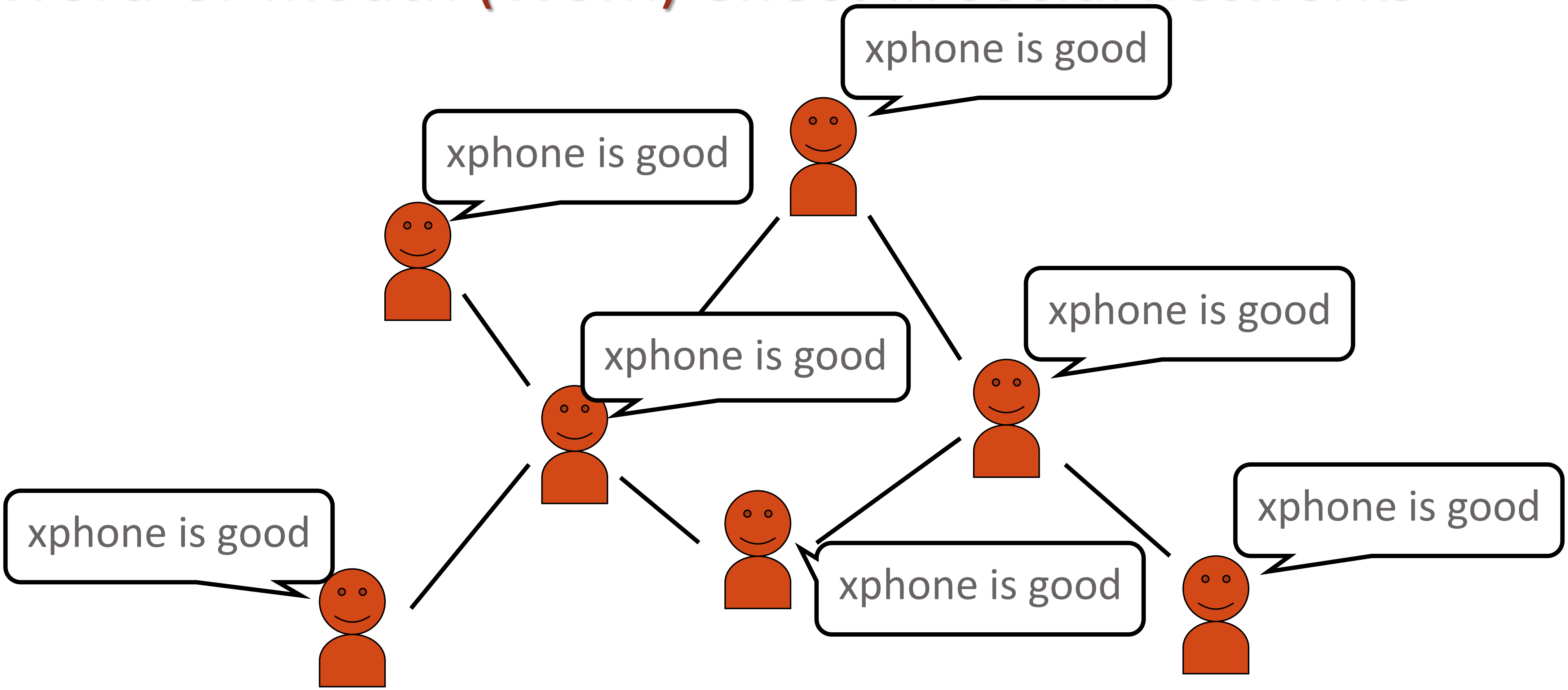
[KDD'09, KDD'10, ICDM'10, AAAI'12, ICDM'12]

Collaborators:

Yajun Wang, Siyu Yang, Chi Wang,
Yifei Yuan, Li Zhang, Wei Lu, Ning Zhang, Kyomin Jung,
Wooram Heo



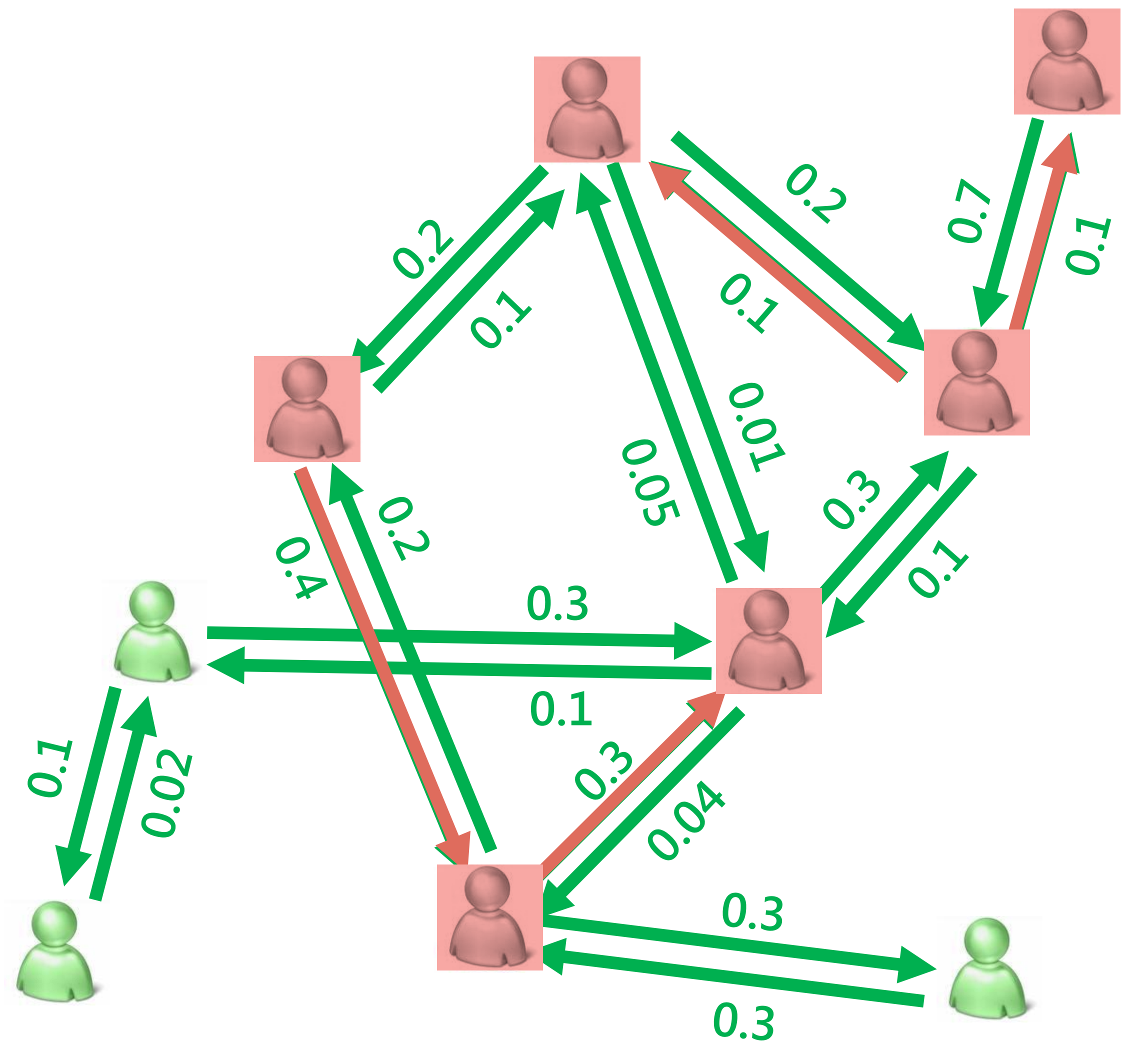
Word-of-mouth (WoM) effect in social networks



- Word-of-mouth effect is believed to be a promising advertising strategy.
- Increasing popularity of online social networks may enable large scale WoM marketing

The Problem of Influence Maximization

- Social influence graph
  - vertices are individuals
  - links are social relationships
  - number p(u,v) on a directed link from u to v is the probability that v is activated by u after u is activated
- Independent cascade model
  - initially some *seed* nodes are activated
  - At each step, each newly activated node u activates its neighbor v with probability p(u,v)
- Influence maximization:
  - find *k* seeds that generate the largest expected influence



Prior work

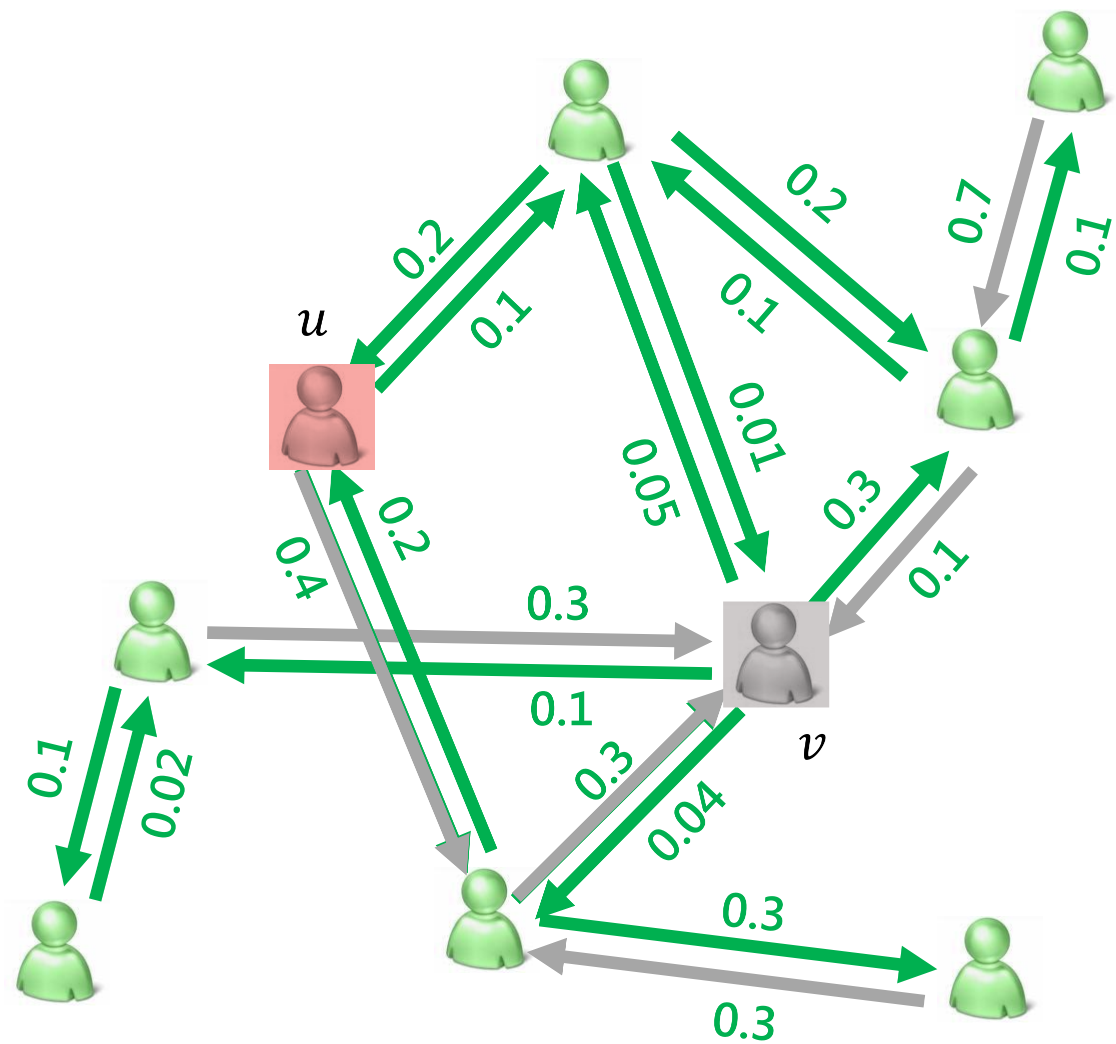
- Influence maximization as a discrete optimization problem proposed by Kempe, Kleinberg, and Tardos, 2003
  - Introduce Independent Cascade (IC) and Linear Threshold (LT) models
  - Finding optimal solution is provably hard (NP-hard)
  - Greedy approximation algorithm, 63% approximation of the optimal solution (based on submodularity)
    - select k seeds in k iterations
    - in each iteration, select one seed that provides the largest marginal increase in influence spread
- Several subsequent studies improved the running time
- Serious drawback:
  - very slow, not scalable: > 3 hrs on a 30k node graph for 50 seeds

Our work

- Exact influence computation is #P hard, for both IC and LT models --- computation bottleneck [KDD’10, ICDM’10]
- Design new heuristics
  - MIA for general IC model [KDD’10]
    - 10^3 speedup --- from hours to seconds
    - influence spread close to that of the greedy algorithm of [KKT’03]
  - Degree discount heuristic for uniform IC model [KDD’09]
    - 10^6 speedup --- from hours to milliseconds
  - LDAG for LT model [ICDM’10]
    - 10^3 speedup --- from hours to seconds
  - IRIE for IC model [ICDM’12]
    - further improvement with time and space savings
- Extend to time-critical influence maximization [AAAI’12]

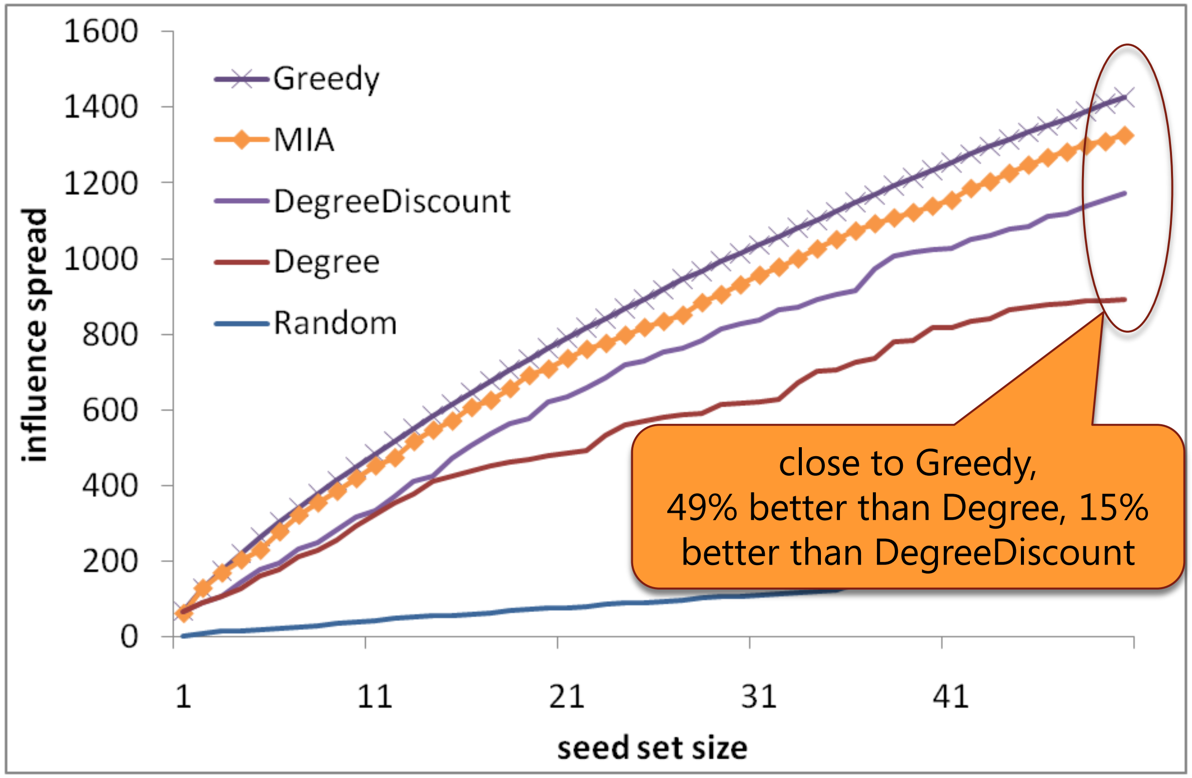
Features of Maximum Influence Arborescence (MIA) heuristic

- Based on greedy approach
- Localize computation
- Use local tree structure
  - easy to compute
- linear batch update on marginal influence spread

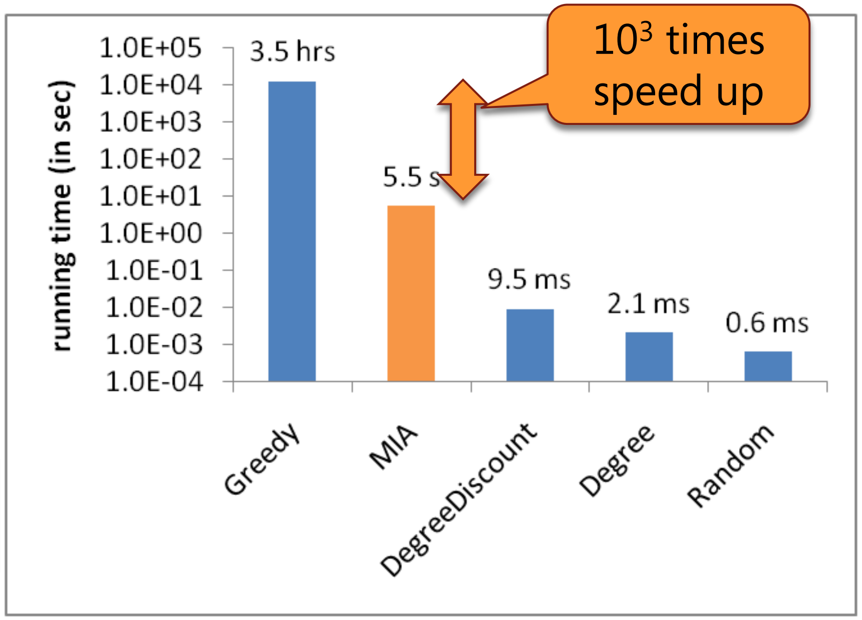


Experiment results on MIA heuristic

Influence spread vs. seed set size



running time



Experiment setup:

- 35k nodes from coauthorship graph in physics archive
- influence probability to a node v = 1 / (# of neighbors of v)
- running time is for selecting 50 seeds

Summary

- Scalable influence maximization algorithms
  - MixedGreedy and DegreeDiscount [KDD’09]
  - PMIA for the IC model [KDD’10]
  - LDAG for the LT model [ICDM’10]
  - IRIE for the IC model [ICDM’12]: further savings on time and space
  - MIA-M for IC-M model [AAAI’12]: include time delay and maximization within a short deadline
- PMIA/LDAG have become state-of-the-art benchmark algorithms for influence maximization

Competitive Influence

[SDM'11, SDM'12, others under submission]

Alex Collins, Rachel Cummings, Te Ke, Zhenming Liu, David Rincon, Xiaorui Sun, Yajun Wang, Wei Wei, Yifei Yuan, Xinran He, Guojie Song, Qingye Jiang, Yanhua Li, Zhi-Li Zhang

Competitive influence diffusion

- Exogenous competition: rival products compete for social influence in the social network
  - CLT model and CLDAG algorithm for influence blocking maximization [SDM'12]
- Endogenous competition: bad opinions about a product due to product defect competes with positive opinions
  - IC-N model and MIA-N algorithm [SDM'11]
- Influence diffusion in networks with positive and negative relationships
  - voter model in signed networks with exact inf. max. algorithm

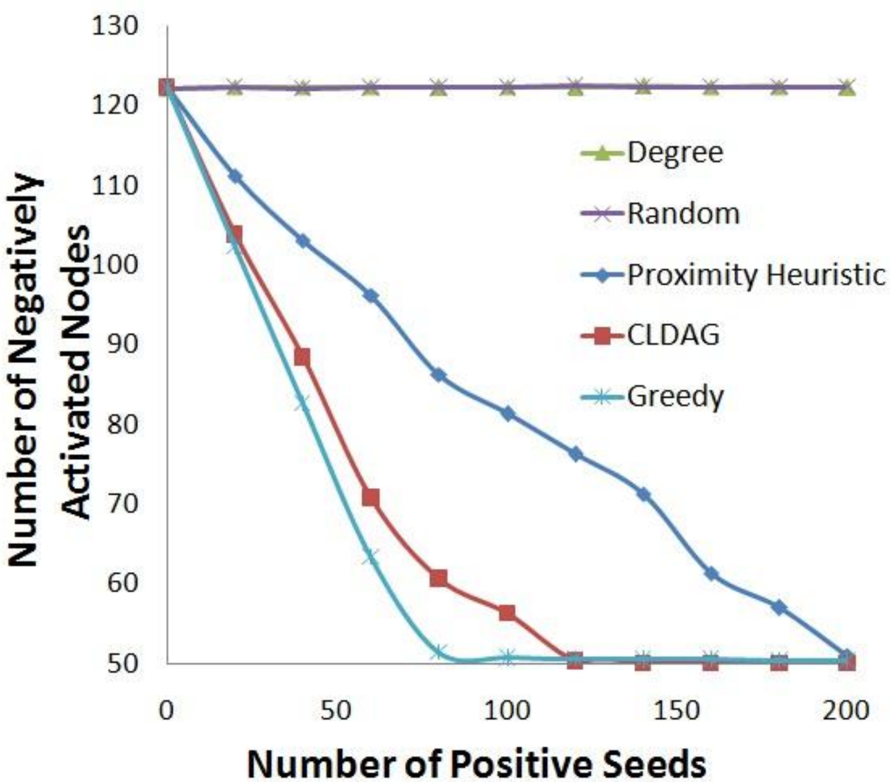
Exogenous competition

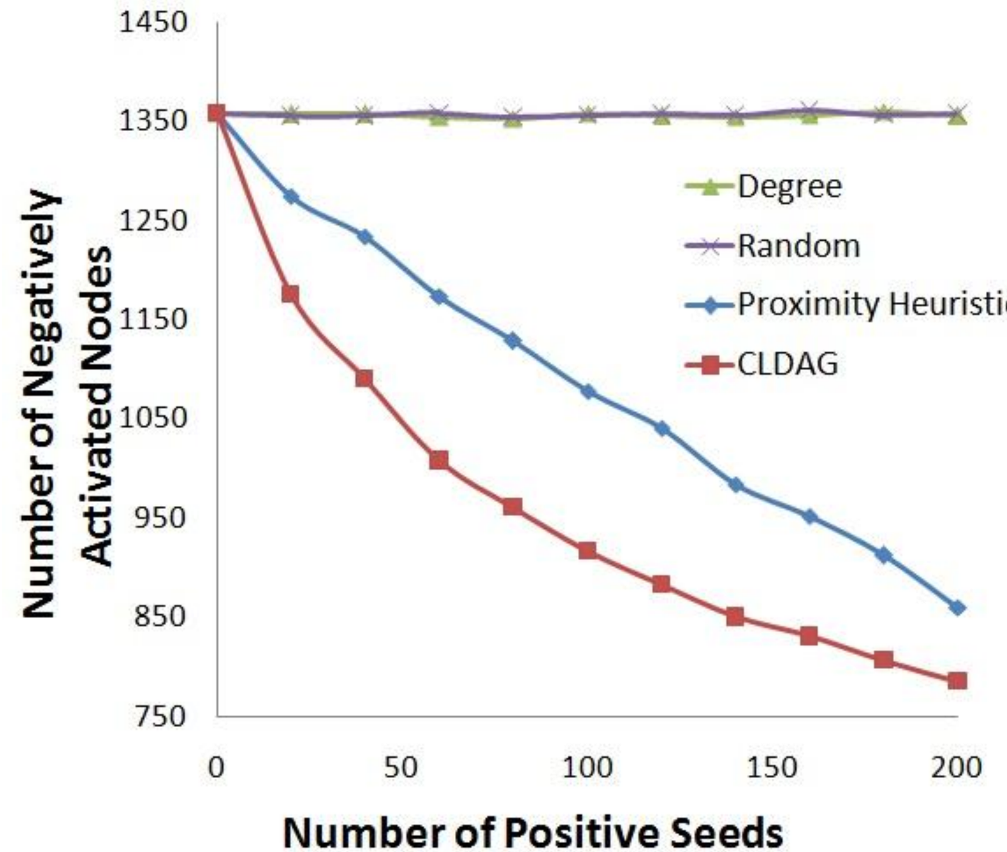
- Competitive linear threshold model
  - positive and negative influence each follows LT model
  - when competing on a node at the same step, negative influence wins with a fixed probability
- Influence blocking maximization
  - Given the negative activation status
  - find k positive seeds
  - minimize the further negative influence, or maximize the expected number of "saved" or "blocked" nodes from negative influence --- *negative influence reduction*
  - application: rumor control

Influence blocking maximization under CLT

- Negative influence reduction is submodular
- Allows greedy approximation algorithm
- Fast heuristic CLDAG:
  - reduce influence computation on local DAGs
  - use dynamic programming for LDAG computations

Performance of the CLDAG

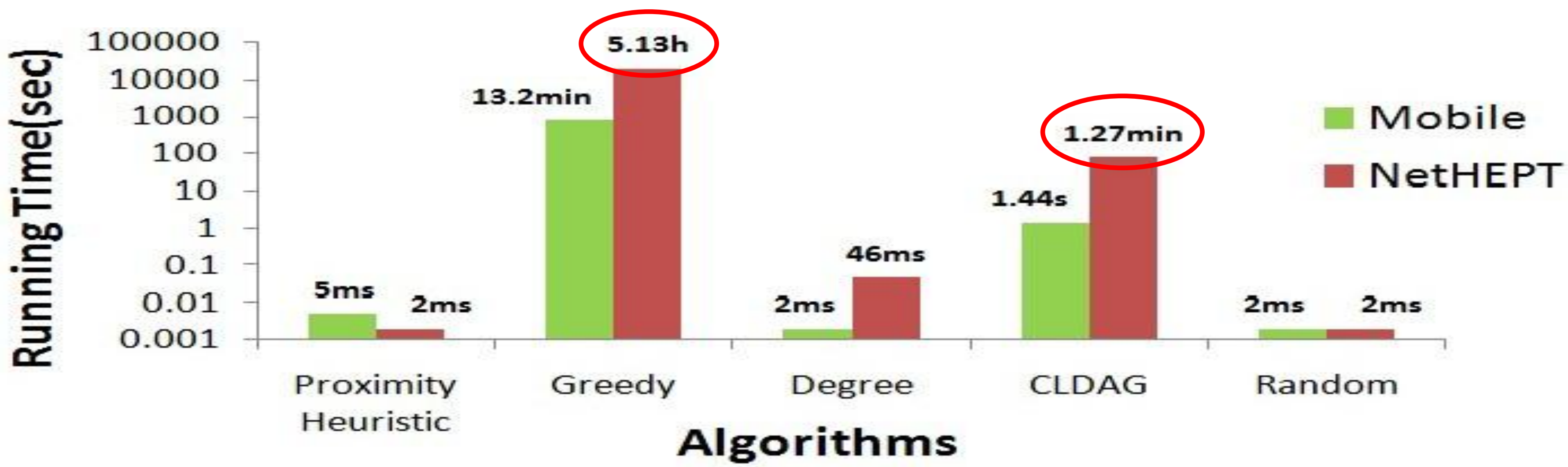




- with Greedy algorithm
- 1000 node sampled from a mobile network dataset
- 50 negative seeds with max degrees

- without Greedy algorithm
- 15K node NetHEPT, collaboration network in arxiv
- 50 negative seeds with max degrees

Scalability—Real dataset



Scalability Result for subgraph with greedy algorithm

Ongoing and future research directions

- Model validation and influence analysis from real data
- Even faster heuristic algorithms
- Fast approximation algorithms
- Online and adaptive algorithms
- Game theoretic settings for competitive diffusion
- Incentives for information / influence diffusions

Grand challenge

- Understand the true viral diffusion scenarios, online and offline
- Apply social influence research to explain, predict, and control viral phenomena
- New focus of network science in the next decade

Acknowledgments

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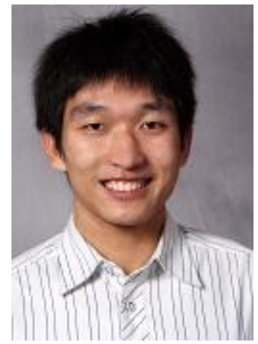

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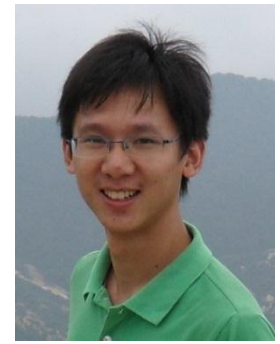

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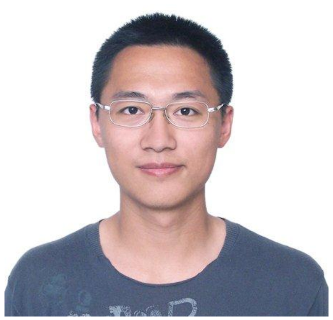

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Questions?

Additional materials on my homepage:

Search “Wei Chen Microsoft”

- KDD’12 tutorial on influence spread in social networks
- my papers