APPLICATIONS OF SOCIAL DIFFUSION AND INFLUENCE ALGORITHMS IN TENCENT GAMES

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INFORMATION DIFFUSION MEETS INVITATION MECHANISM

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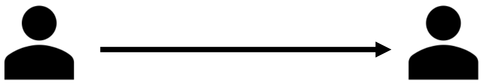
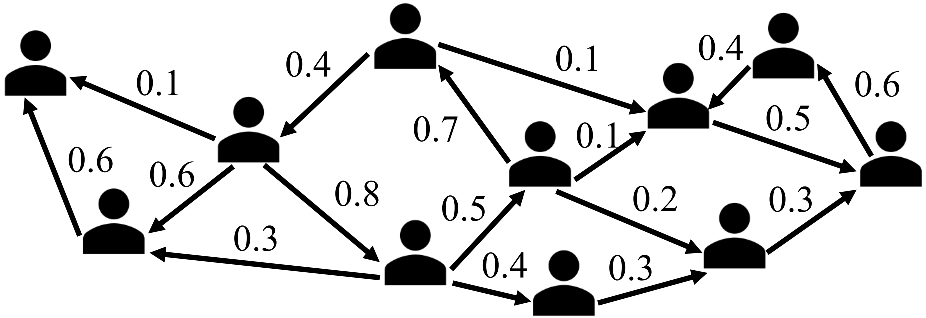
INVITATION MECHANISM

- Invitation is also everywhere in Tencent games
- The invitation behavior can cascade

HOW TO MODEL INFORMATION DIFFUSION VIA INVITATION MECHANISM?



IC model:
u independently influences
v with probability $p_{u,v}$



social network

- Traditional diffusion models ignore the conversion funnel in invitation mechanism.

CONVERSION FUNNEL

- A distillation of a user’s journey
- Describe how user behavior changes in multiple stages

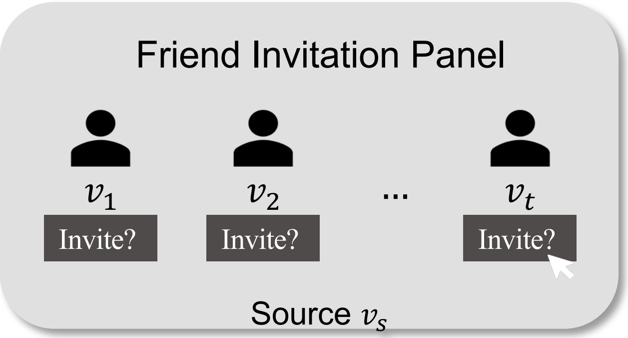
Awareness: business outreach

Adoption: platform activeness

Action: e-commerce revenue

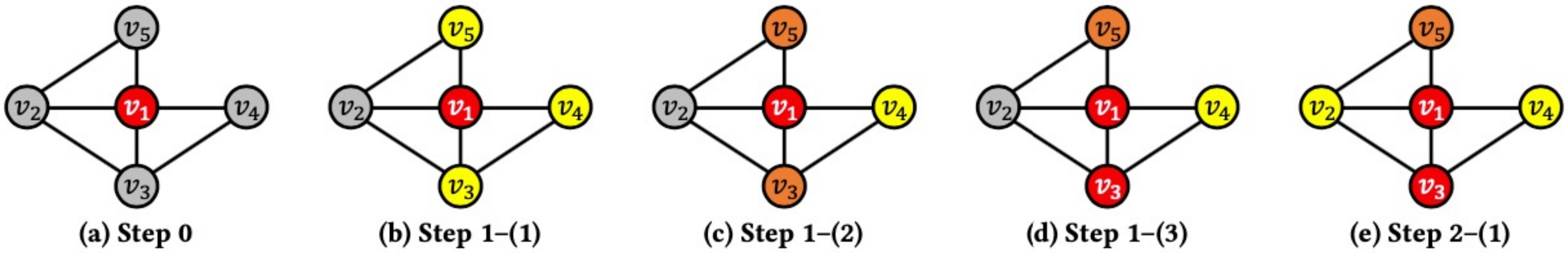
EVERY STAGE MATTERS

INVITATION CONVERSION FUNNEL



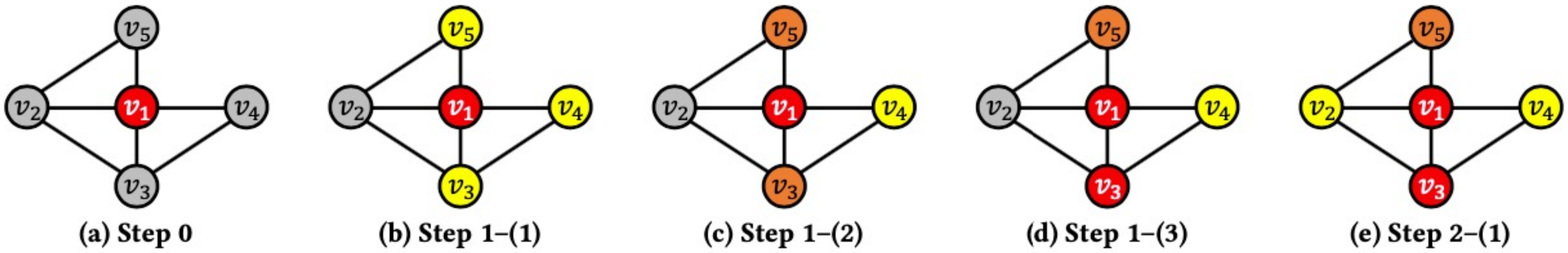
- Conversion funnel of a user

ICI: INDEPENDENT CASCADE WITH INVITATION MODEL



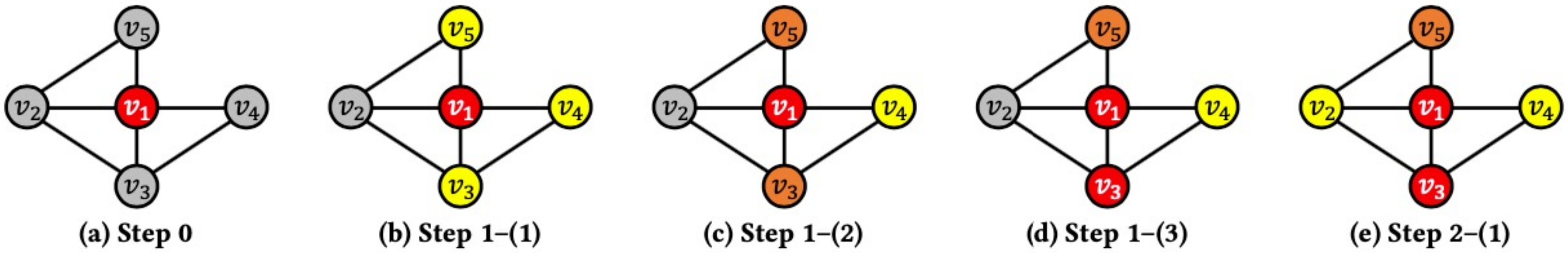
- User roles:
  - Inactive state: uninformed (grey)
  - Active states: inviter (red), invitee (yellow), acceptor (orange)

ICI: INDEPENDENT CASCADE WITH INVITATION MODEL



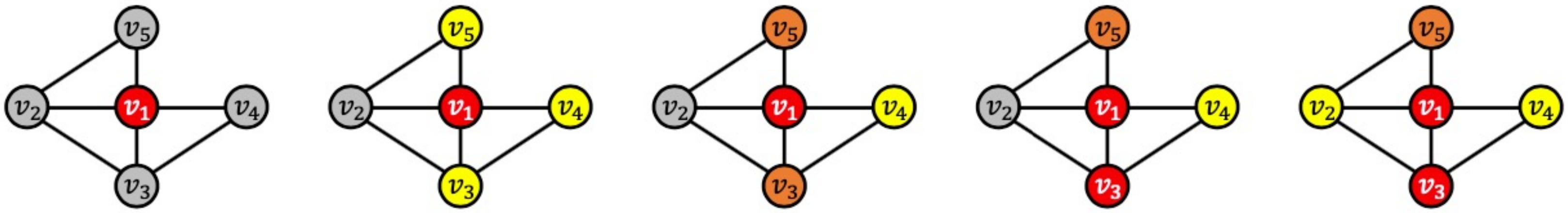
- Given the seeds, a diffusion instance unfolds in discrete steps
  - At step 0
    - all seeds → initial inviters
    - others → uninformed

ICI: INDEPENDENT CASCADE WITH INVITATION MODEL



- Given the seeds, a diffusion instance unfolds in discrete steps
  - At the subsequent step
    - new inviter v_i has a probability $p_{i,j}$ to invite the uninformed friend v_j
    - if v_j becomes an invitee, it has a probability β to be an acceptor
    - if v_j becomes an acceptor, it has a probability γ to be an inviter

ICI: INDEPENDENT CASCADE WITH INVITATION MODEL



(a) Step 0 **(b) Step 1–(1)** **(c) Step 1–(2)** **(d) Step 1–(3)** **(e) Step 2–(1)**

- Given the seeds, a diffusion instance unfolds in discrete steps
  - Stops when no new inviters exist

APPLICATION: CASCADE ESTIMATION

- Objective:
  - Estimate the number of influenced users from a given seed set S
- Solution:
  - Given a diffusion model M, estimate the average number of influenced users from S under M by T simulations
- Model M
  - Our proposal: ICI (treat acceptors as influenced users)
  - 6 competitors: IC, CT-IC, IC-N, LT, LT-C, F-TM (by defaults)

APPLICATION: CASCADE ESTIMATION

Table 1: Dataset statistics ($K = 10^3$, $M = 10^6$).

Dataset	$\lvert\mathcal{V}\rvert$	$\lvert\mathcal{E}\rvert$	$\lvert\mathcal{S}\rvert$	Spread	Type
TXG-A	$153.0K$	$2.3M$	$10.3K$	$12.8K$	Invitation
TXG-B	$155.5K$	$2.5M$	$4.9K$	$12.6K$	Invitation
TXG-C	$155.9K$	$2.5M$	$4.4K$	$11.0K$	Invitation
TXG-D	$133.9K$	$2.1M$	$12.2K$	$76.4K$	Invitation
Diggs	$279.6K$	$1.5M$	$0.6K$	$8.1K$	Vote
Twitter	$456.6K$	$12.5M$	$27.0K$	$38.7K$	Retweet

Table 2: The RMSE of estimating overall spreads ($\times 10^3$).

Model	***TXG-A***	***TXG-B***	***TXG-C***	***TXG-D***	***Diggs***	***Twitter***
IC	40.6	32.7	32.7	39.7	40.9	13.2
CT-IC	*20.9*	*8.3*	*8.1*	*22.9*	30.8	42.0
IC-N	23.4	14.8	14.9	23.8	*22.0*	*76.7*
LT	97.1	100.0	101.7	88.6	59.6	227.4
LT-C	69.6	71.9	73.6	63.2	42.7	161.1
F-TM	103.1	112.0	113.4	92.2	120.6	241.6
ICI	**11.2**	**1.7**	**2.1**	**13.4**	**7.2**	**37.1**

- ICI outperforms all competitors across all test datasets in terms of RMSE

APPLICATION: DIFFUSION PREDICTION

- Objective:
  - Predict if each user is (directly/indirectly) influenced by a given seed set S
- Solution:
  - Given a diffusion model M, prediction is

$$\hat{y}_i = \frac{\text{\# times that } v_i \text{ is influenced from S under M over T}}{\text{T simulations}}$$

- Model M
  - Our proposal: ICI (treat acceptors as influenced users)
  - 6 competitors: IC, CT-IC, IC-N, LT, LT-C, F-TM (by defaults)

APPLICATION: DIFFUSION PREDICTION

Table 3: The AUC (%) and MAP (%) of different models in diffusion prediction.

Model		IC	CT-IC	IC-N	LT	LT-C	F-TM	IC+	ICI
TXG-A	**AUC**	82.11±0.08	79.30±0.10	82.36±0.10	78.29±0.03	77.77±0.07	77.32±0.17	*82.58±0.12*	**83.36±0.06**
	MAP	20.07±0.13	18.35±0.08	20.34±0.12	16.51±0.23	16.15±0.19	18.99±0.19	*20.69±0.05*	**20.71±0.12**
TXG-B	**AUC**	81.96±0.05	80.76±0.05	83.06±0.11	74.17±0.04	73.98±0.10	75.95±0.17	*83.30±0.15*	**84.43±0.10**
	MAP	19.48±0.06	20.13±0.06	21.05±0.11	12.41±0.12	12.37±0.14	16.10±0.24	*21.54±0.18*	**22.05±0.15**
TXG-C	**AUC**	82.26±0.09	81.23±0.07	83.35±0.13	73.56±0.06	73.28±0.07	75.06±0.17	*83.56±0.13*	**84.90±0.08**
	MAP	18.82±0.12	19.42±0.08	20.43±0.16	11.10±0.21	10.89±0.09	13.83±0.20	*20.81±0.11*	**21.41±0.09**
TXG-D	**AUC**	78.20±0.04	74.30±0.11	78.47±0.08	78.12±0.04	77.11±0.08	75.57±0.21	*78.35±0.06*	**78.98±0.07**
	MAP	20.04±0.04	16.43±0.06	20.03±0.03	20.03±0.08	19.14±0.18	20.01±0.14	*20.08±0.04*	**20.11±0.02**
Diggs	**AUC**	86.65±0.03	82.03±0.04	87.58±0.06	87.82±0.02	87.83±0.03	**90.18±0.05**	88.06±0.03	*89.67±0.06*
	MAP	10.19±0.02	7.25±0.01	11.52±0.12	11.85±0.08	12.02±0.06	**26.21±0.14**	12.23±0.03	*15.95±0.22*
Twitter	**AUC**	70.39±0.04	72.37±0.04	72.88±0.03	69.91±0.03	69.29±0.05	68.80±0.06	*76.62±0.04*	**77.97±0.04**
	MAP	15.97±0.03	19.12±0.04	18.27±0.06	14.35±0.04	14.59±0.06	15.40±0.04	*21.17±0.03*	**22.40±0.05**

- ICI outperforms all competitors on all test datasets but Diggs

APPLICATION: FRIEND RANKING

- Objective: recommend existing friends for players to improve engagement
- Solution:
  - Compute each friend's influence spread under IC/ICI model
  - Rank friends based on their spread in descending order
  - Select the top k friends to recommend
- Competitor: Intimacy
  - Rank friends based on the number of historical interactions with the player
  - Select the top k friends to recommend

APPLICATION: FRIEND RANKING

- Performance on social lottery events of one Tencent RPG game

Metrics	**ICI**	**IC**	**Intimacy**
Invitation Rate	**9.60%**	6.24%	7.98%
Pay Rate	**35.15%**	32.91%	26.71%

Metrics	**ICI**	**IC**	**Intimacy**
Invitation Rate	**17.89%**	16.85%	16.15%
Pay Rate	**30.91%**	24.53%	29.80%

APPLICATION: KOL SELECTION

- Objective: identify k influencers to maximize the event outreach
- Solution:
  - Treat IC/ICI as the diffusion model
  - Invoke the greedy algorithm of influence maximization to select k seeds
- Competitor: degree
  - Select k players with the largest degree centrality

APPLICATION: KOL SELECTION

- Performance on viral marketing events of one Tencent battle royale game

Metrics	ICI	IC	Degree
Spread Increment	**2286**	1923	843
Invition Rate	**46.20%**	39.64%	32.44%

SUMMARY

- ICI: a new diffusion model considering invitation mechanism
- Better performance on cascade estimation and diffusion prediction
- Have been deployed to friend ranking and KOL selection on Tencent gaming platforms

CAPACITY CONSTRAINED INFLUENCE MAXIMIZATION IN SOCIAL NETWORKS

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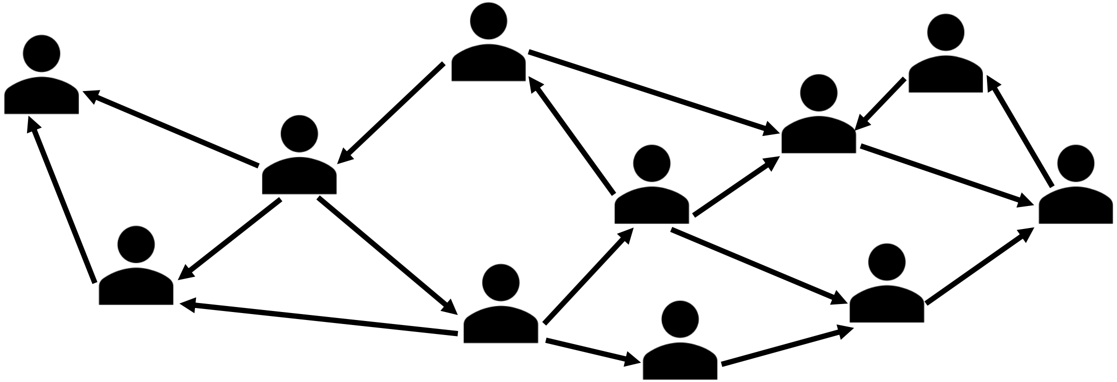
INFLUENCE MAXIMIZATION (IM)

followee can influence follower

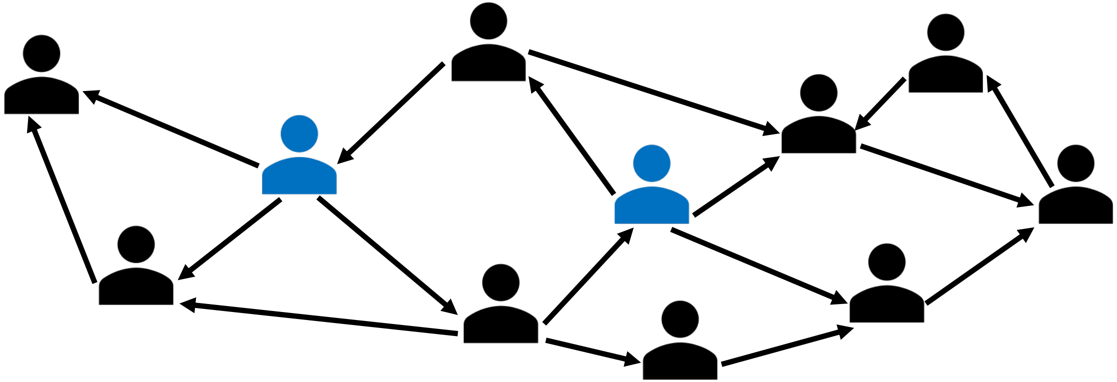


social network

- Motivated by viral marketing in social networks

INFLUENCE MAXIMIZATION (IM)

initial adopter:
paid by the merchant

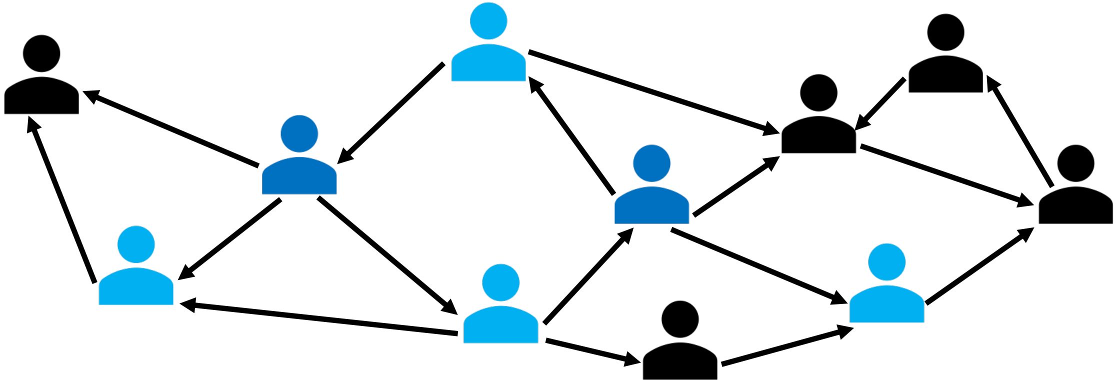


social network

- Motivated by viral marketing in social networks
  - pay *k* individuals

INFLUENCE MAXIMIZATION (IM)

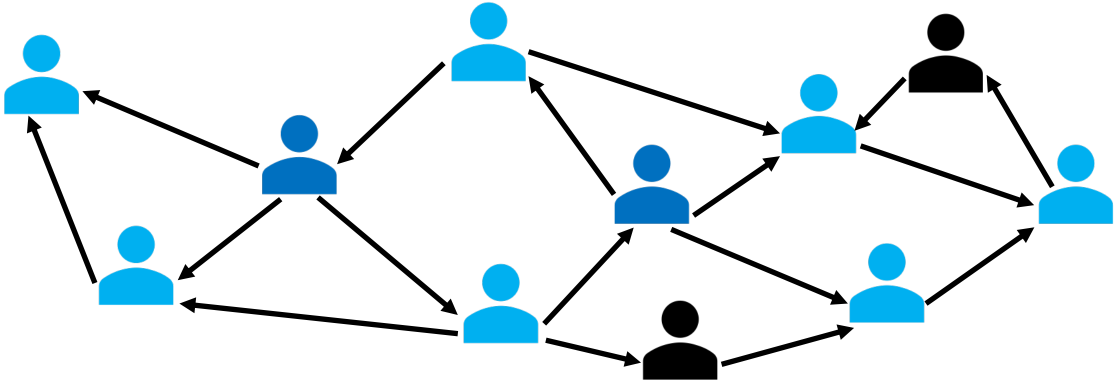
subsequent adopter:
influenced by friends



social network

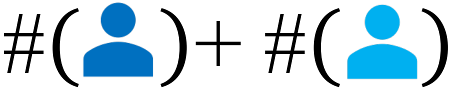
- Motivated by viral marketing in social networks
    - hope word-of-mouth promotes the given product

INFLUENCE MAXIMIZATION (IM)

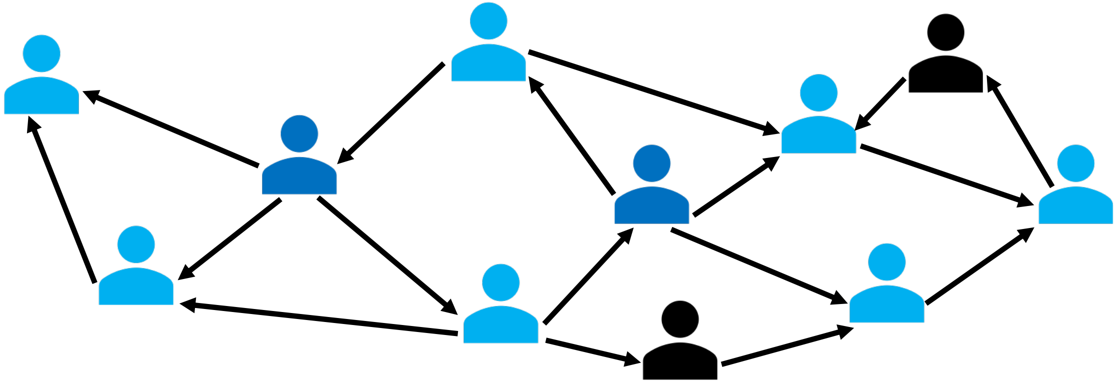


- Motivated by viral marketing in social networks
  - hope word-of-mouth promotes the given product
  - create a *cascade of influence*

INFLUENCE MAXIMIZATION (IM)



influence spread

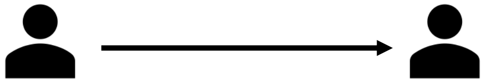


social network

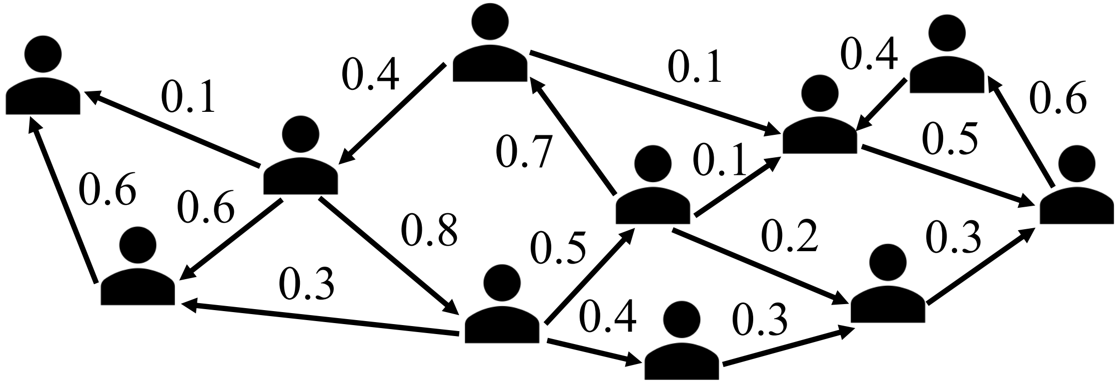
- Problem: how to pick *k* individuals for the merchant such that the eventual influence spread is maximized?

EXISTING SOLUTIONS FOR IM

- Adopt a stochastic model M to simulate the influence propagation
  - i.e., under what condition will a user be influenced
- Example: Independent Cascade (IC) model



IC model:
u independently influences v
with probability $p_{u,v}$



social network

EXISTING SOLUTIONS FOR IM

- Adopt a stochastic model M to simulate the propagation
  - i.e., under what condition will a user be influenced
- Generate samples of the social network based on M
- Identify k influencers by using
  - the samples to estimate the spread
  - and the greedy algorithm over samples

LIMITATION #1 OF IM

- Conventional IM
  - considers the cost factor
  - ignores individual's capacity for spending efforts on consuming the promoting content
- User's capacity
  - is crucial as it determines the adoption of the product
  - is limited on online platforms
    - e.g., while playing e-games with friends

LIMITATION #2 OF IM

- Conventional IM
  - assumes influencers unconditionally become initial adopters
- Observation from real-world scenarios
  - influencers tend to be the friends of initial adopters

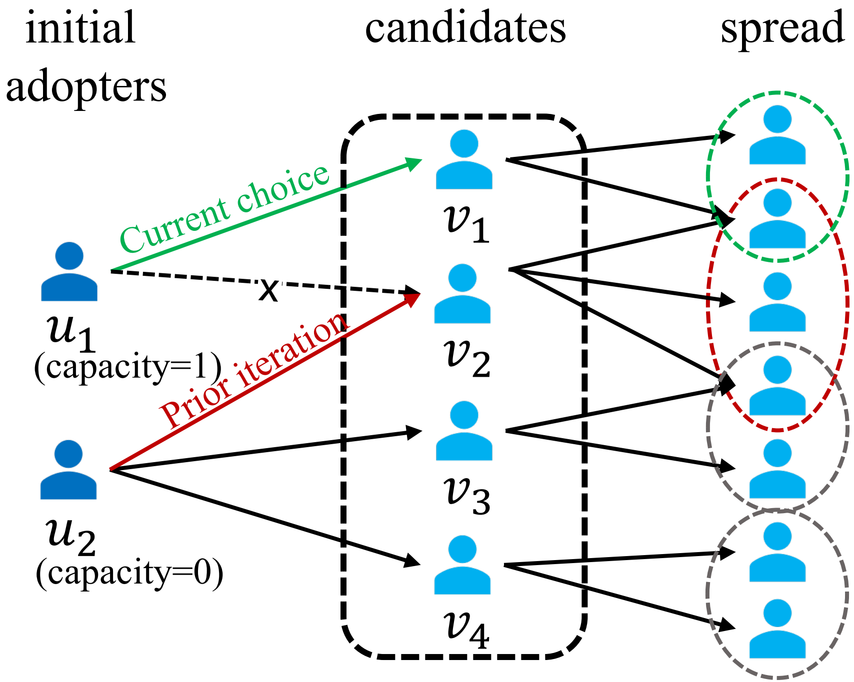
source: https://zootopia.fandom.com/wiki

CAPACITY CONSTRAINED IM (CIM)

- Input
  - social network G and stochastic model M
  - d initial adopters and capacity constant k
- Output
  - k influential friends (seeds) for each of d initial adopters
- Objective
  - maximize the spread of the set of all selected seeds
- CIM is NP-hard

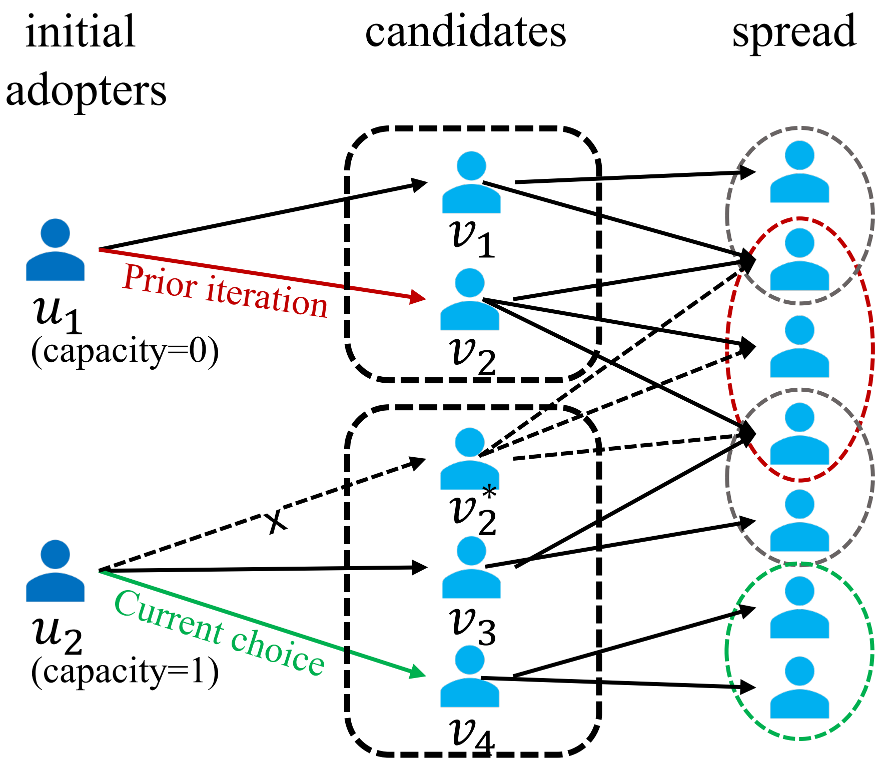
IDEA OF GREEDY ALGORITHMS

- MG-Greedy: select a user v from candidates as the next if
  - adding v to current seed set yields the largest lift
  - and, existing a v's friend in initial adopters that remains capacity
- $\frac{1}{2}$-approximate if known spread



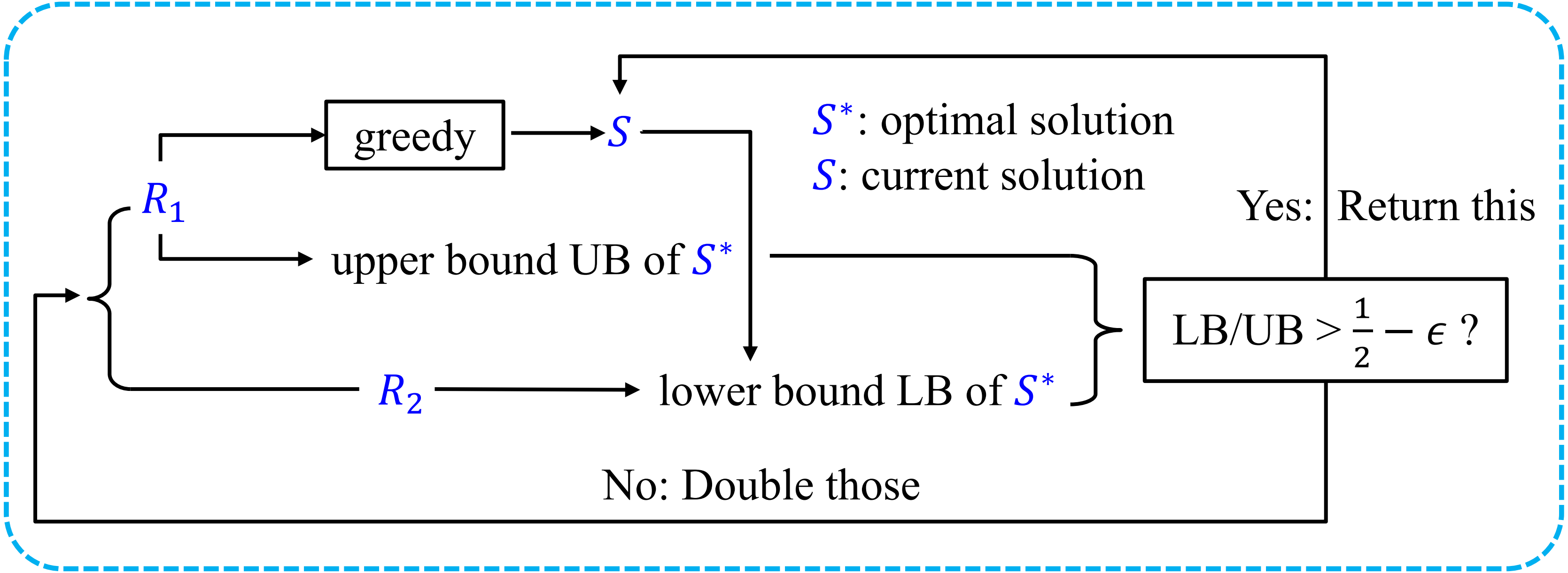
IDEA OF GREEDY ALGORITHMS

- RR-Greedy: select in a round-robin manner
  - choose an initial adopter u remaining capacity
  - select from u's candidates
  - add v to current seed set if yielding the largest lift
- $\geq \frac{1}{2}$-approximate if known spread



SCALABLE IMPLEMENTATIONS

- Borrow OPIM-C framework in SIGMOD’18
- Generate two equal-size sets of samples: R_1 and R_2



SCALABLE IMPLEMENTATIONS

- Borrow OPIM-C framework in SIGMOD'18
- Redesign each parameter by rigorous theoretical analysis
- Implementations:
  - MG-OPIM: greedy = MG-Greedy
  - RR-OPIM: greedy = RR-Greedy
  - RR-OPIM+: RR-OPIM with an optimized UB
- Result: $(\frac{1}{2} - \epsilon)$-approximate in near-linear running time

DATASETS

- Various public datasets
  - *DNC*
  - *Blog*
  - *Twitch*
  - *Orkut*
  - *Twitter*
- Tencent game dataset
  - *TXG* (with ground-truth spread)

Dataset statistics ($K = 10^3, M = 10^6, B = 10^9$)

Name	**#nodes (n)**	**#edges (m)**
DNC	$0.9K$	$24.2K$
Blog	$10.3K$	$668.0K$
Twitch	$168.1K$	$13.6M$
TXG	$243.4K$	$11.8M$
Orkut	$3.1M$	$234.2M$
Twitter	$41.7M$	$2.9B$

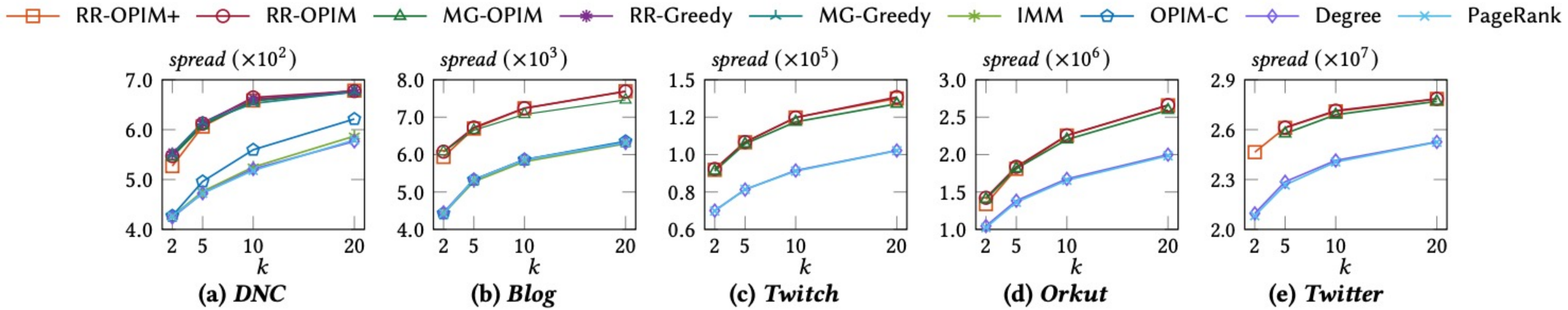
APPROACHES

- Local competitors: independently select k friends for each initial adopter
  - based on a heuristic score: Degree, PageRank
  - based on a SOTA IM solver: IMM, OPIM-C
- Greedy solutions
  - MG-Greedy, RR-Greedy
- Scalable implementations
  - MG-OPIM, RR-OPIM, RR-OPIM+

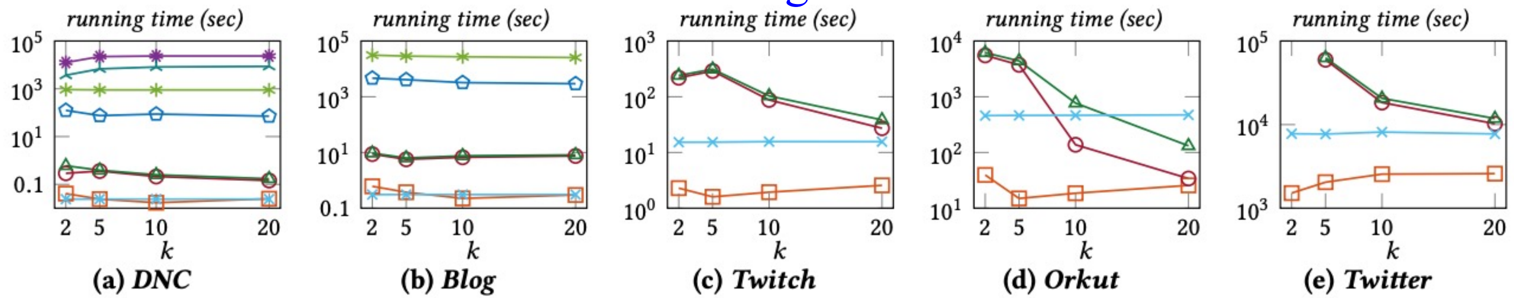
PERFORMANCE ON PUBLIC DATASETS

- Final solution RR-OPIM+ outperforms all solutions

Large spread



Low running time



ACTUAL SPREAD ON TENCENT GAME

- Final solution RR-OPIM+ outperforms
  - all solutions on TXG during offline evaluation

Solution	RR-OPIM+	MG-OPIM	RR-OPIM	Degree	PageRank
Spread	**1,632**	1,625	1,609	1,488	1,471

  - control group on a battle royale game during online deployment

Solution	Treatment	Control
Spread	**60.69K**	58.28K

SUMMARY

- CIM: a new problem for real-world viral marketing
- MG/RR-Greedy: effective greedy algorithms for CIM
- RR-OPIM+: scalable greedy implementation for CIM
- Have been deployed on Tencent gaming platforms

THANK YOU!