THE WEB CONFERENCE ACM

INFORMATION DIFFUSION MEETS INVITATION MECHANISM

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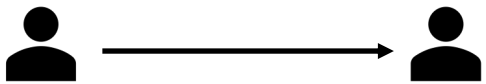
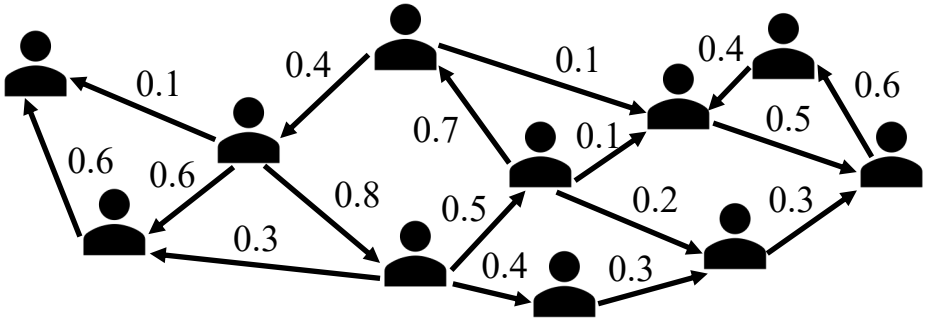
INVITATION MECHANISM

- 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 $p_{u,v}$

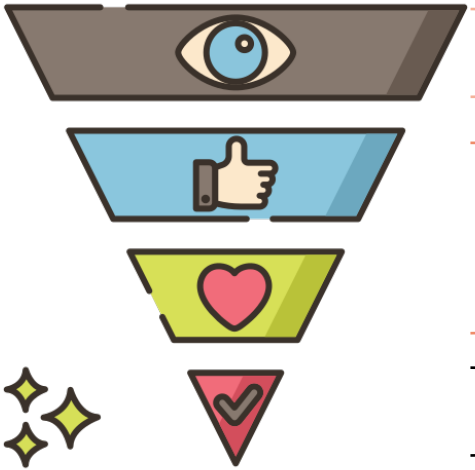


social network

- 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



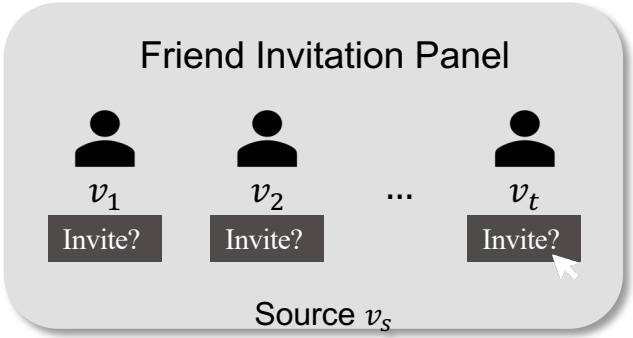
Awareness: business outreach

Adoption: platform activeness

Action: e-commerce revenue

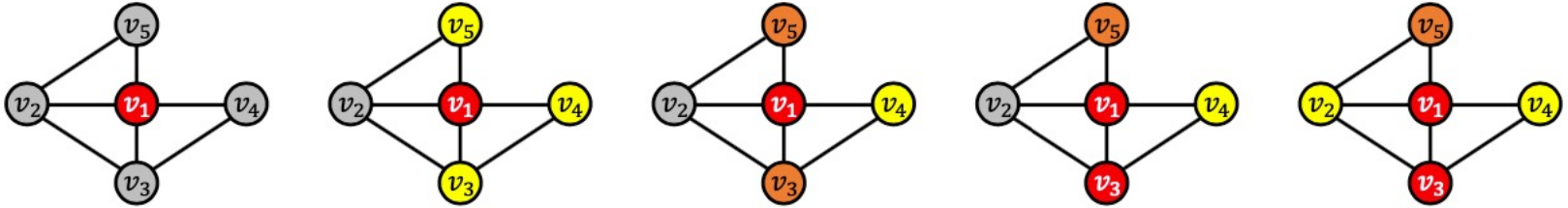
EVERY STAGE MATTERS

INVITATION CONVERSION FUNNEL



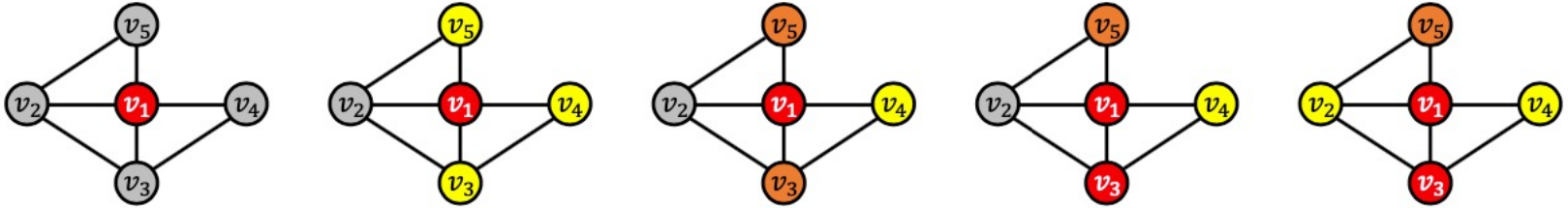
- Conversion funnel of a user

ICI: INDEPENDENT CASCADE WITH INVITATION MODEL



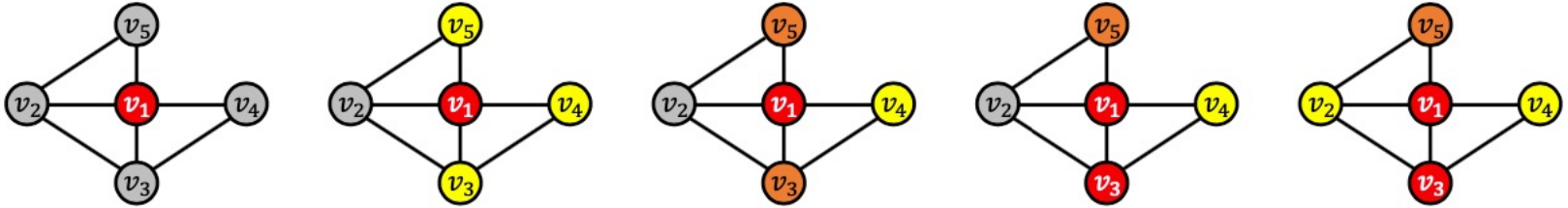
- User roles:
  - Inactive state: uninformed (grey)
  - Active states: inviter (red), invitee (yellow), acceptor (orange)

ICI: INDEPENDENT CASCADE WITH INVITATION MODEL



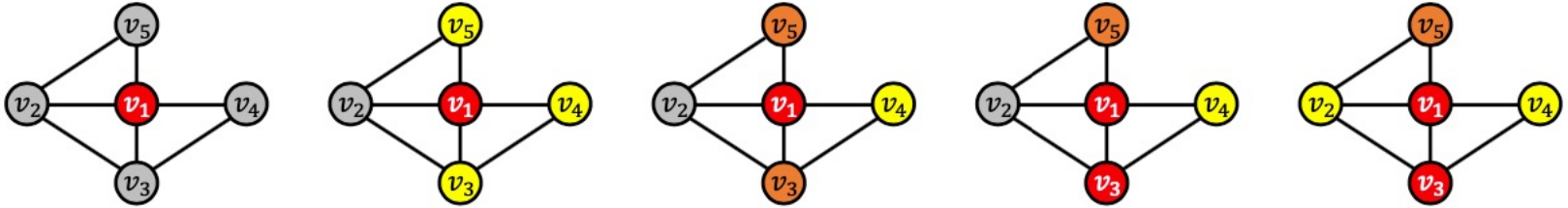
- Given the seeds, a diffusion instance unfolds in discrete steps
  - At step 0
    - all seeds → initial inviters
    - others → uninformed

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



- 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

THANK YOU!