

# Discovering Strategic Behaviors for Collaborative Content-Production in Social Networks

Yuxin Xiao, Adit Krishnan, Hari Sundaram  
University of Illinois at Urbana-Champaign

**Yash Saboo**  
**Tai-Ying Chen**

# ABSTRACT

- **Setting:** There are always individuals who obtain greater rewards and reputation than their peers on social networking sites, no matter if the reward is transparent or opaque.
- **Challenge:** Identify the rationality behind their actions due to factors like the combinatorial strategy space, inability to determine payoffs, and resource limitations faced by individuals.
- **Problem the Paper addresses:** Can resource-limited individuals discover strategic behaviors associated with high payoffs when producing collaborative/interactive content in social networks?

# ABSTRACT

- **Proposed Solution:** Dynamic Dual Attention Networks (DDAN)
  - models individuals' content production strategies through a generative process, under the influence of social interactions involved in the process
- **Findings:**
  - Different strategies give rise to different social payoffs;
  - The best performing individuals exhibit stability in their preference over the discovered strategies, which indicates the emergence of strategic behavior; and
  - The stability of a user's preference is correlated with high payoffs.

# Related Work

- **Aim:** Find if individuals can successfully discover strategies with high payoffs in social networks
- Herbert A Simon (1972). “Theories of bounded rationality”
  - Introduced the idea of bounded rationality—that human beings use limited resources to make decisions.
  - Previous lectures: D. Kahneman, "A perspective on judgment and choice: Mapping bounded rationality." and Papadimitriou, C. H. and Yannakakis, M. (1994), "On complexity as bounded rationality"

# Related Work

- Anderson, A., Huttenlocher, D., Kleinberg, J., and Leskovec, J. (2013), “Steering user behavior with badges”
  - Online social networks typically have an explicit mechanism that allocates rewards (usually points) that vary with users’ behaviors;
  - for example,
    - StackOverflow (explicit)
    - Twitter(implicit)
- Thodoris Lykouris, Vasilis Syrgkanis, and Éva Tardos (2016). “Learning and efficiency in games with dynamic population”
  - when agents play repeated games with strategies that guarantee low-adaptive regret, high social welfare is ensured. But the question arises that does this still hold in practice?

# Problem Formulation

- Authors ask:

Are resource-limited individuals in social networks able to discover content-production strategies that yield high payoffs?

- **Resource-limited:** limited time, attention
- **Content:** blog post, academic paper, question-answer forum (e.g., StackExchange)
- **Payoffs:** citations (academic paper), in-links (blog posts), up votes (QA forum)

# Novelty

- Previous work was on:
  - theoretical concepts only
  - no attempt to identify strategic behaviors from data
- 1st attempt to identify strategic behaviors from empirical data
- Strong experimental findings:
  - Different strategies result in different payoffs.
  - Stability of preference is correlated with high payoffs.

**Let's Brainstorm,  
shall we?**



As a researcher, where  
would you publish?

High prestige  
conference



Low prestige  
conference

The Sixth IEEE International Conference  
on  
Multimedia Big Data



Where should David Dobrik publish his next video?

D.A.V.I.D.S  
V.L.O.G

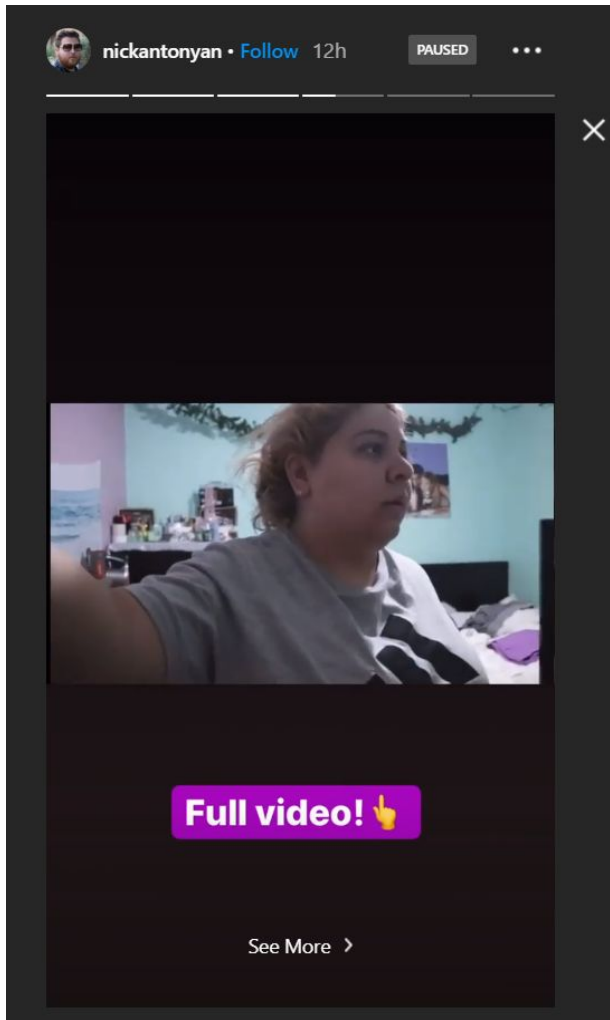
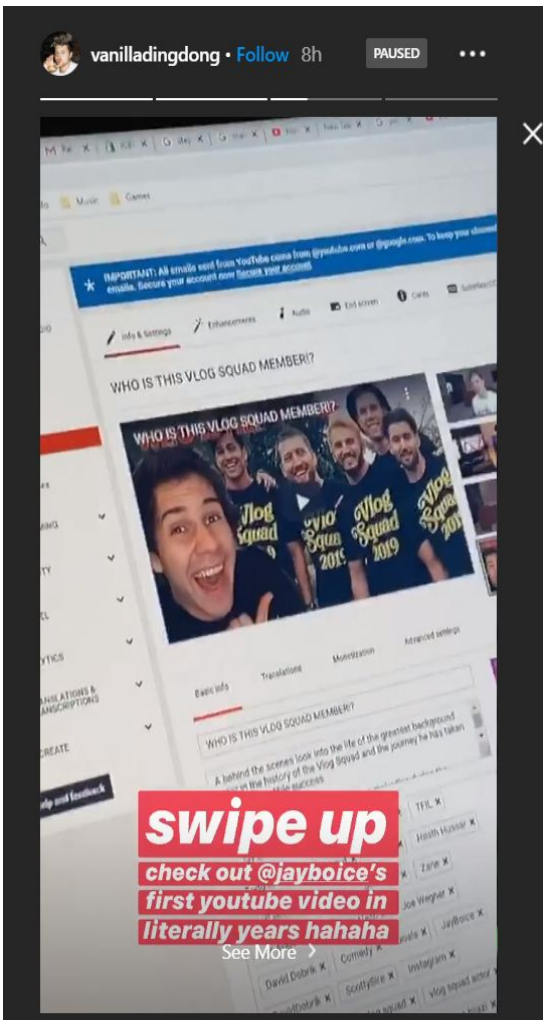


IGTV  
(12M)



YouTube  
(16.6M)





**Do you think  
people “have  
gamed the  
system”?**



chiaraferragni

Following



12,721 posts 19.2m followers 1,088 following

Chiara Ferragni

Love fiercely (and don't forget to stop along the way to take photos) Founder @chiaraferragnicollection. WATCH @chiaraferragniunposted ON PRIME VIDEO [www.gofundme.com/f/coronavirus-terapia-intensiva](http://www.gofundme.com/f/coronavirus-terapia-intensiva)

Followed by isbellamaddiex, colette.s96, briannacyz + 3 more



Best of Leo 2



Business



Best of Leo



Documenta...



Lancomez...



Mini Leo

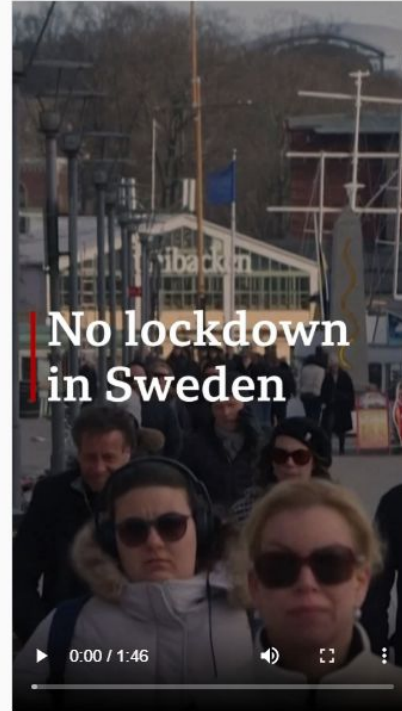
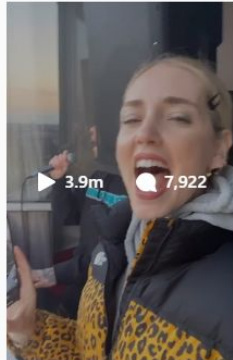
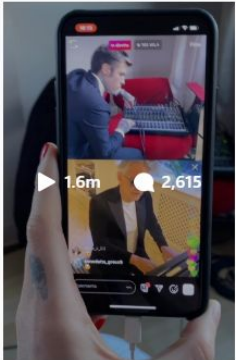


Wedding

POSTS

IGTV

TAGGED



bbcnews



bbcnews No lockdown in Sweden

While swathes of Europe's population endure lockdown conditions in the face of the coronavirus outbreak, one country stands almost alone in allowing life to go on much closer to normal. After a long winter, it's just become warm enough to sit outside in the Swedish capital and people are making the most of it. #Coronavirus #Covid19 #Sweden #BBCNews

5m



cla\_udiya Was machst du, wenn ich plötzlich nackt in deinem Zimmer schlafe?

5m Reply



15,697 views

5 MINUTES AGO

Add a comment...

Post



# Ronaldo

IS A QUARANTINE THIRST TRAP



SWIPE UP  
for video

See More >



imdb • Following



imdb @PixarSoul Trailer 🎬

Everybody has a soul. Joe Gardner is about to find his. Watch the new trailer for #PixarSoul starring @iamjamiefoxx and #TinaFey.

3w



Ooskar Damn Pixar is going to make me cry again



3w 44 likes Reply

— View replies (1)



ckkyang That sound at the beginning though, my friend thought I was watching something else



192,501 views

MARCH 12



Add a comment...

Post

**Thanks for  
attending Social  
Influencing Class  
101**

# Deep Dive into Paper's Aim

- Can individuals with limited resources discover content production strategies with high payoffs in social networks? Let's disintegrate it:
  - 1. Does the preference order among strategies for authors stabilize over time, indicating the emergence of strategic behavior?
  - 2. If the preference order is stable, does the preference order maximize utility?
- Things to note:
  - 1. preference order stability does not imply high payoffs.
  - 2. the stability may arise due to other factors such as social norms.

It's a non-trivial problem to solve.

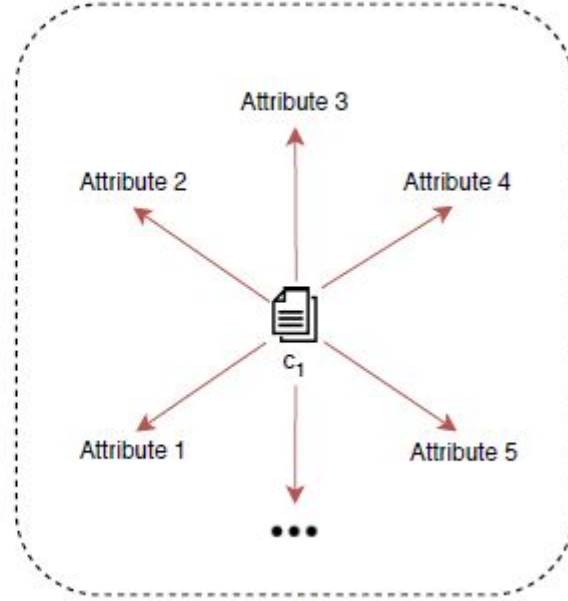
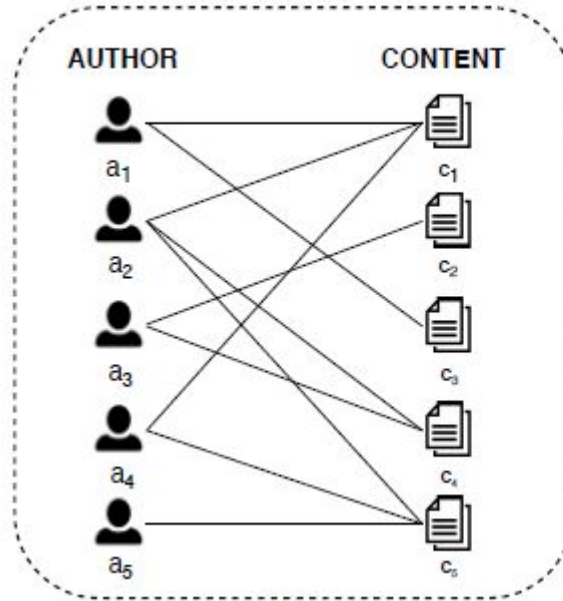


# Technical Insight

- **Assumption:** Set of strategies is common to all, but each individual adopts a mixed-strategy over the set of different strategies.
- **Proposition:** Use bipartite graph (set of graph vertices decomposed into two disjoint sets such that no two graph vertices within the same set are adjacent) to conceptualize content production, where
  - Node: individuals and contents
  - Many to One relation between them: content may have multiple authors

# Data Model

- set of individuals =  $A$ 
  - Authors may either collaborate or work alone
- piece of content =  $c$ 
  - content could be a blog, post, an academic paper, or when a group attempts on a answering Stack-Exchange question.
- construct an undirected bipartite graph where,
  - $V = A \cup C$ ,
  - $E = \{(a, c) \mid a \in A, c \in C, a \text{ is an author of } c\}$ ,
- each content  $c \in C$  may have multiple attributes



# Data Model

- attributes of  $c$  = venue of publication; time of publication; content topic; links to other entities including contents and authors.
- Author picks the attribute values strategically. Let every author use the same strategy space.
  - Strategy space =  $S$ , where  $|S| = m$
- However, each author randomizes over them strategies independently.
  - When a group of authors collaborate, we assume that they negotiate and develop a consensus strategy.
- $a$ 's strategy distribution at time  $t = D_a(t)$ 
  - Authors assume that the author's past strategy  $D_a(t-1)$  and her co-authors' strategy at time  $t$  influence  $D_a(t)$ . Authors call this as **Strategy distributions assumption**.

# Data Model

Notation	Description
$G(t)$	Snapshot of the author-content graph at time $t$
$C_a(t)$	Set of contents created by $a$ at time $t$
$\tilde{\mathcal{A}}'(t)$	Set of authors with over 5 active contents at time $t$
$h_a(t)$	Embedding vector of $a$ at time $t$
$F_a(t)$	Field vector of $a$ at time $t$
$D_a(t)$	Strategy distribution of $a$ at time $t$
$r(a   c)$	$a$ 's contribution to $c$ 's strategy distribution
$\mu_a(t, k)$	Utility received by $a$ with $D_a(t)$ over $k$ time units
$\hat{\mu}_a(t - k)$	Normalized total utility received by $a$ with $D_a(t - k)$
$\bar{\mu}_g(t, S)$	The global expected normalized utility for strategy $S$

**Table 1: Notation table.**

# Data Model

- time-varying utility for content  $c = \mu_c(k)$
- time of publishing the content =  $t$
- time passed since content has been published =  $k$
- utility after  $k$  time units (i.e  $t+k$ ) = papers receive citations; up/down votes
  - Since each author contributes to a different extent to produce  $c$ , we assume

utility that flows back to author  $\propto$  author's contribution

$$\mu_{a|c}(k) \propto (\mu_c(k) \times r(a|c))$$

Authors call this as **Utility calculation assumption**.

$$\mu_a(t, k) = \sum_{c \in C_a(t)} \mu_c(k) \cdot r(a|c)$$

# Refresh Paper's Aim

- Authors asks 2 questions:
  - How to determine the strategy distribution  $D_c$  for content  $c$ , jointly authored by a set of authors  $A_c$ ?
  - Determine how the prior strategy distribution  $D_a(t - 1)$  and the strategy distributions of the co-authors of  $a$  influence the strategy distribution  $D_a(t)$ .

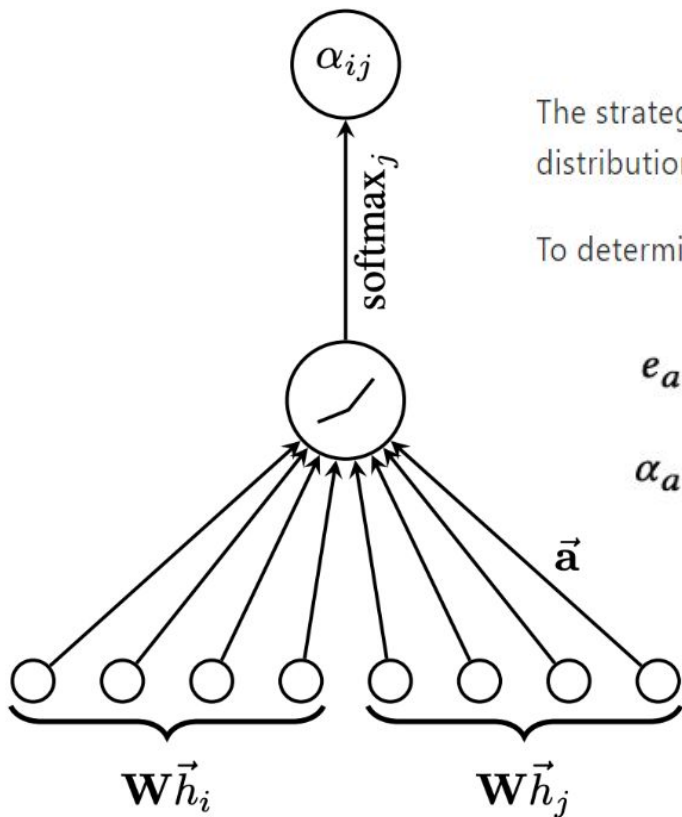
# Assumptions

- Vertex representation:
  - node embedding vector for content  $c = h_c \in \mathbb{R}^F$  and
  - node embedding vector for author  $a$  at time  $t = h_a(t) \in \mathbb{R}^F$ 
    - a time-dependent embedding vector for an author, by treating the same author at different times as separate nodes when embedding the network.
- Network snapshots:
  - Since the graph  $G = (V, E)$  grows over time, we divide the graph into snapshots.
  - If an author appears for the first time in snapshot  $t$ , we draw the prior strategy distributions  $D_a(t-1)$  from a *flat Dirichlet distribution* and use an all zero vector as the prior embedding  $h_a(t-1)$ .

# Dynamic Dual Attention Networks (DDAN)



# Determining strategy for production of single content



The strategy distribution  $\mathbf{D}_c$  of content  $c$  created at time  $t$  is affected by the strategy distribution  $\mathbf{D}_a(t)$  of all authors  $a \in \mathcal{A}_c$

To determine the contribution  $\alpha_{a|c}$  of a specific author  $a$  towards  $\mathbf{D}_c$

$$e_{a|c} = \sigma(\phi_{c,a}^\top \cdot [\mathbf{W}_{c,a}\mathbf{h}_c \parallel \mathbf{W}_{c,a}\mathbf{h}_a(t)]),$$

$$\alpha_{a|c} = \text{softmax}_a(e_{a|c}) = \frac{\exp(e_{a|c})}{\sum_{a' \in \mathcal{A}_c} \exp(e_{a'|c})},$$

# Determining strategy for production of single content

Since  $\alpha_{a|c}$  is  $a$ 's contribution to the determination of  $\mathbf{D}_c$ , set  $r(a|c) = \alpha_{a|c}$

$$\mathbf{D}_c = \xi \left( \sum_{a \in \mathcal{A}_c} \alpha_{a|c} \cdot \mathbf{D}_a(t) \right).$$

- $\xi$ : tanh nonlinear activation
- L1 normalization to ensure  $\mathbf{D}_c$  is a valid strategy distribution

# Determining an author's strategy

An author's strategy  $\mathbf{D}_a(t)$  depends on the strategy adopted for each content she authors at time  $t$  as well as her past strategy distribution  $\mathbf{D}_a(t-1)$ .

Examine the effect of the strategy for the production of content  $c$  where she is a co-author in  $\mathcal{A}_c$ .

$$e_{c|a} = \sigma \left( \phi_{a,c}^1 \cdot [\mathbf{W}_{a,c} \mathbf{h}_a(t) \parallel \mathbf{W}_{a,c} \mathbf{h}_c] \right),$$

$$\alpha_{c|a} = \text{softmax}_c(e_{c|a}) = \frac{\exp(e_{c|a})}{\sum_{c' \in \mathcal{C}_a(t)} \exp(e_{c'|a})}.$$

$\alpha_{c|a}$ : content  $c$ 's contribution on author  $a$ 's strategy distribution  $\mathbf{D}_a(t)$

# Determining an author's strategy

To determine the contribution of  $a$ 's strategy distribution at time  $t - 1$  on her current strategy distribution.

$$\beta_a(t) = \text{sigmoid} \left( \boldsymbol{\phi}_{a,a}^\top \cdot [\mathbf{W}_{a,a} \mathbf{h}_a(t) \parallel \mathbf{W}_{a,a} \mathbf{h}_a(t - 1)] \right).$$

$a$ 's strategy distribution  $\mathbf{D}_a(t)$  at time  $t$  is the weighted sum of strategy distribution  $\mathbf{D}_c$  for  $c \in C_a(t)$  and  $\mathbf{D}_a(t - 1)$ .

$$\mathbf{D}_a(t) = \xi \left( \beta_a(t) \mathbf{D}_a(t - 1) + (1 - \beta_a(t)) \sum_{c \in C_a(t)} \alpha_{c|a} \cdot \mathbf{D}_c \right).$$

# Model for Rational Behavior

- An author engaged in rational behavior would be able to evaluate the utilities of all strategies and be able to identify the optimal strategy
- Ask:

Given the utility at time  $t$  of content co-authored by  $a$  at time  $t - k$ .

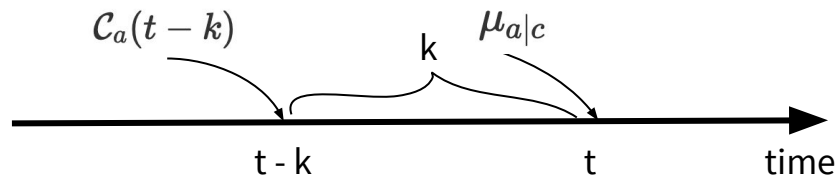
What is the utility of author  $a$  using strategies distribution  $\mathbf{D}_a(t - k)$ ?

where  $\mu_{a|c}(k)$  is the utility that flows back to  $a$  after  $k$  time

# Model for Rational Behavior

$$\hat{\mu}_a(t - k) = \underbrace{\frac{1}{k}}_{\text{time}} \times \frac{\sum_{c \in \mathcal{C}_a(t-k)} \mu_{a|c}(t - k)}{\underbrace{|\mathcal{C}_a(t - k)|}_{\text{count}}}$$

- $\hat{\mu}_a(t - k)$ : normalized utility due to the distribution  $\mathbf{D}_a(t - k)$
- $\mu_{a|c}(t - k)$ : relative utility
- $c \in \mathcal{C}_a(t - k)$ : participation in creation



# Experiments

# Datasets

- DBLP academic dataset [33, 36]
- Goal is to discover strategic behavior associated with two paper attributes
  1. Citations: Whom to cite?
  2. Publication Venue: Where to publish?

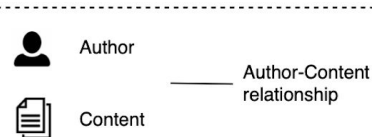
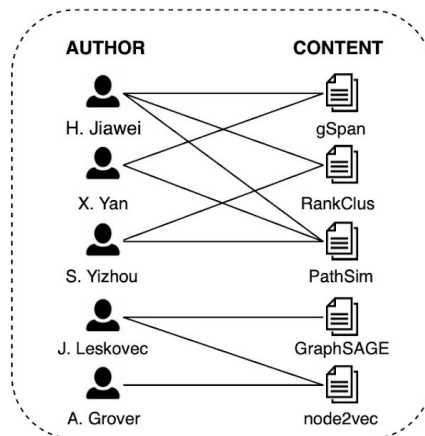
[33] Arnab Sinha, Zhihong Shen, Yang Song, Hao Ma, Darrin Eide, Bo-june Paul Hsu, and Kuansan Wang. 2015. An overview of microsoft academic service (mas) and applications. In Proceedings of the 24th international conference on world wide web. ACM, 243–246.

[36] Jie Tang, Jing Zhang, Limin Yao, Juanzi Li, Li Zhang, and Zhong Su. 2008. Arnet-Miner Extraction and Mining of Academic Social Networks. In KDD'08. 990–998.

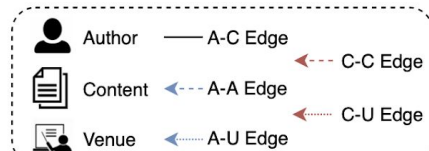
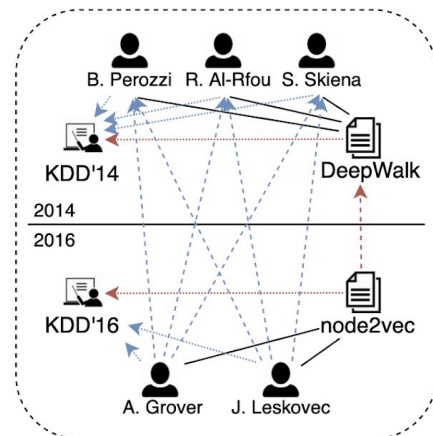


# Strategy Spaces

- One can create additional graphs using the attributes of each paper
  - $G_{a,c}$ : represents the content production, connecting authors to the content
  - $G_{a,a}$ : author-author citation graph
  - $G_{c,c}$ : paper-paper citation graph
  - $G_{c,u}$ : paper-location graph
  - $G_{a,u}$ : author-location graph



(b)



(d)

# Strategy Spaces

Identify four aspects

## 1. Popularity

- Preferential attachment: The probability of citing a past paper is proportional to its citations
- Uniform attachment

## 2. Similarity of field

- Preferring similar fields
- Preferring distinct fields

## 3. Familiarity

- Preferring nodes: Cite other papers based on authorship
- Preferring unfamiliar nodes

## 4. Time recency

- Preferring small time gaps
- Choose Random time gaps

Aspect	Strategy
Popularity	$s_{1,0}$ , preferential attachment
	$s_{1,1}$ , uniform attachment
Field	$s_{2,0}$ , preferring similar fields
	$s_{2,1}$ , preferring distinct fields
Familiarity	$s_{3,0}$ , preferring familiar nodes
	$s_{3,1}$ , preferring unfamiliar nodes
Time	$s_{4,0}$ , preferring small time gaps
	$s_{4,1}$ , choosing random time gaps

# Strategy Spaces

- Consider a paper  $c_1$  that cites  $c_2$  and is published at location  $u_1$ , explain directed edges  $(c_1, c_2)$  and  $(c_1, u_1)$
- Composite Strategies: Likelihood of the edge is a composite of each pure strategy
- $(c_1, c_2)$ : popularity, field, familiarity and time recency,  $2^4 = 16$  composite strategies
- $(c_1, u_1)$ : popularity, field, familiarity,  $2^3 = 8$  composite strategies
- Example of a citation strategy:  $S_4^c = s_{1,0} \times s_{2,0} \times s_{3,1} \times s_{4,0}$
- Example of a location strategy:  $S_6^l = s_{1,0} \times s_{2,1} \times s_{3,1}$

# DDAN Training & Optimization

- Consider loss function for graph  $G_{c,c}$

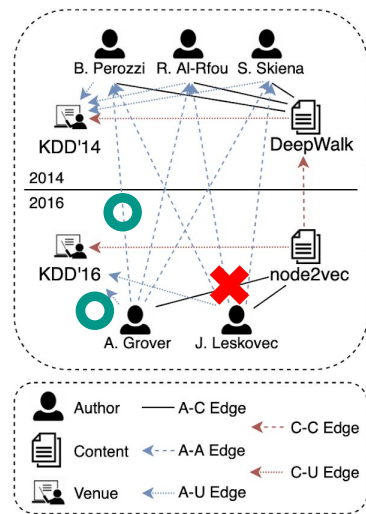
$$L_{c,c}(t) = \sum_{(c_i, c_j) \in \mathcal{E}_{c,c}(t)} -\log \sum_{S_i \in \mathcal{S}} P(S_i | D_{c_i}) \cdot \ell((c_i, c_j) | S_i).$$

- $P(S_i | \mathbf{D}_{c_i})$ : probability of picking strategy  $S_i$  given the distribution  $\mathbf{D}_{c_i}$  for content  $c_i$
- $\ell((c_i, c_j) | S_i)$ : likelihood of edge  $(c_i, c_j)$  given strategy  $S_i$
- Overall loss function

$$L(t) = L_{c,c}(t) + L_{c,u}(t) + L_{a,a}(t) + L_{a,u}(t)$$

# Experiment Settings

- Apply to the task of link prediction
- Identify the set of authors with over five new contents in the current snapshot and partition each author's contents for 5-fold cross validation
- Hide the author-content edges and model aims to recover the hidden attribute edges
- Baselines
  - Logistic Regression (LR)
  - Dirichlet Multinomial Mixture Model (DMM)
  - Topic Over Time (TOT)



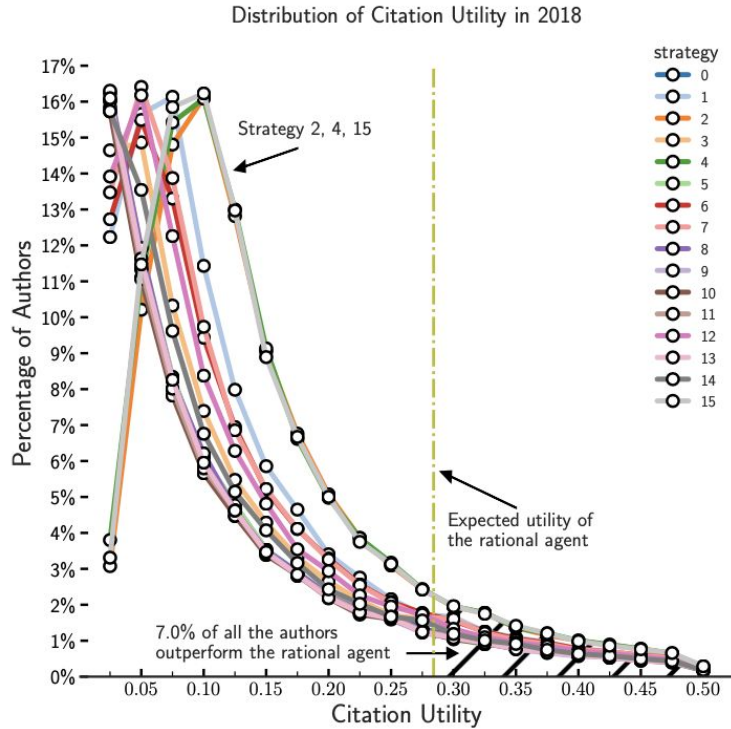
# Experiment Results

Year	Strategies	LR [13]	DMM [45]	TOT [41]	DDAN
2000	Citation	0.72	0.72	0.73	<b>0.74</b>
	Publication	0.71	0.70	0.73	<b>0.75</b>
2005	Citation	0.69	0.69	0.70	<b>0.71</b>
	Publication	0.69	0.69	0.72	<b>0.73</b>
2010	Citation	0.67	0.67	0.68	<b>0.69</b>
	Publication	0.71	0.71	0.73	<b>0.74</b>
2015	Citation	0.67	0.67	0.68	<b>0.69</b>
	Publication	0.72	0.72	0.74	<b>0.75</b>
2018	Citation	0.67	0.67	0.68	<b>0.69</b>
	Publication	0.76	0.75	0.77	<b>0.78</b>

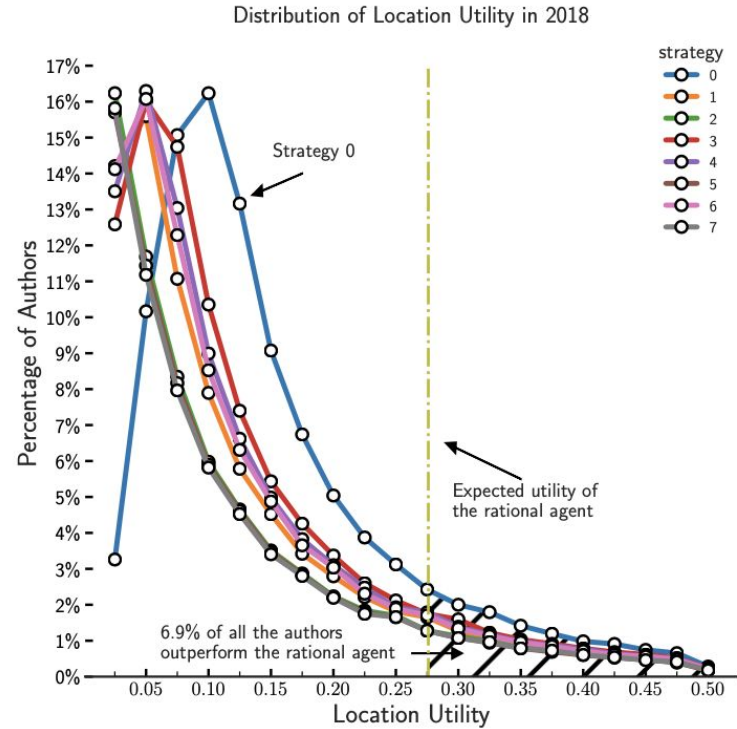
**Table 4: Experiment results using Mean Average Precision (MAP) as the evaluation metrics. DDAN achieves the highest scores for both strategies in all testing snapshots.**

# Qualitative Analysis

# Do strategies matter?



(a)

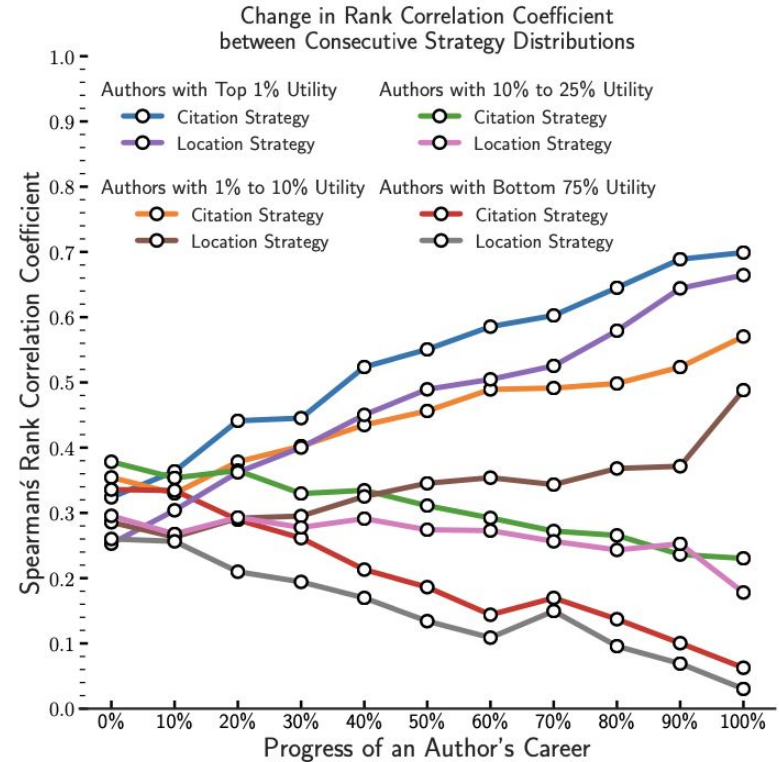


(b)



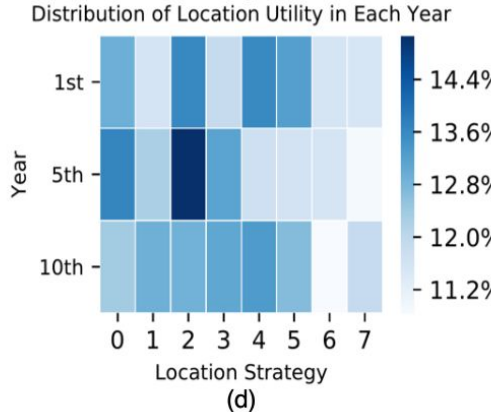
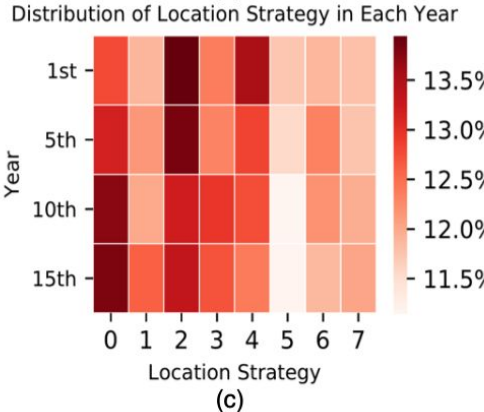
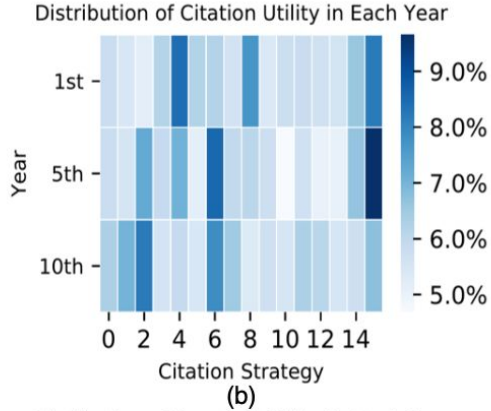
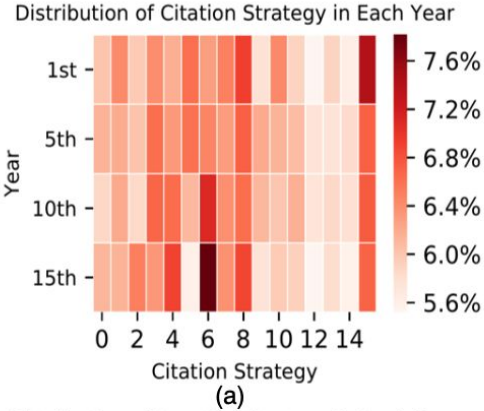
# Emergence of Order

- Compute the Spearman rank correlation coefficient
- The correlations **increase** for authors with the normalized utility in the top 10%

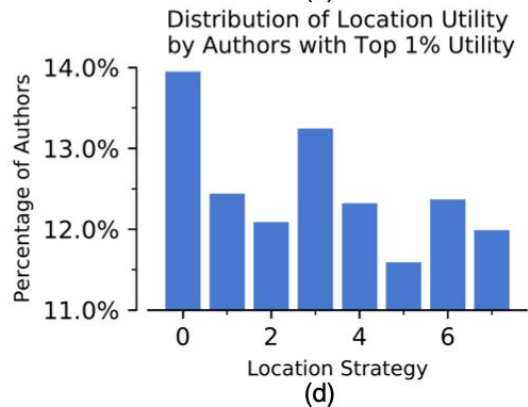
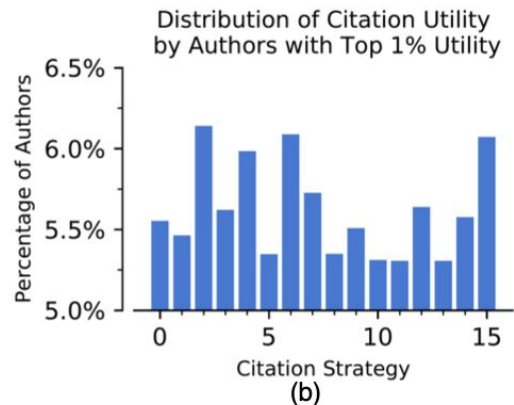
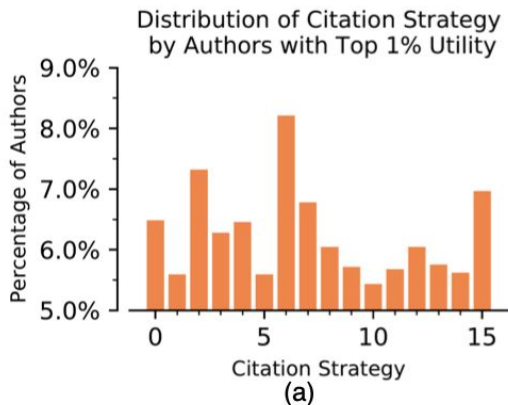


(c)

# Emergence of Order



# Stability and Payoffs



# Discussion

- Strengths
  - Conceptualize the observed behavior as a generative process
  - Encode hand-crafted strategies gives the opportunity to interpret the network
- Weaknesses
  - Come up with a complete strategy space is not trivial
  - Rational model is myopic
  - Lack of explanations on why resources such as social norm limited the model

# Questions