Social Network Mining and Analysis

Link Prediction

Peng Wang

Networked World

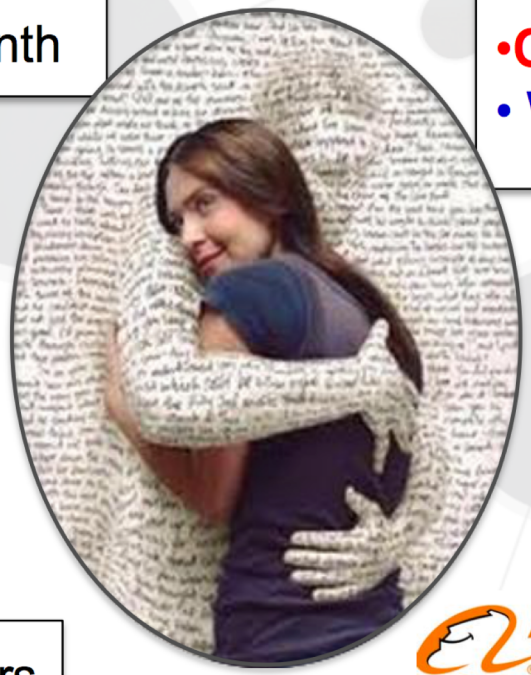
Real World---Map---World Wide Web

facebook

- **1.65 billion** MAU
- **2.5 trillion** minutes/month

WeChat

- **QQ: 800 million** MAU
- **WeChat: 800 million** MAU



twitter

- **320 million** MAU
- **Peak: 143K** tweets/s

新浪微博 weibo.com

- **360 million** users
- **influencing** our daily life

amazon.com

- **304 million** active users
- **14 billion** items/year

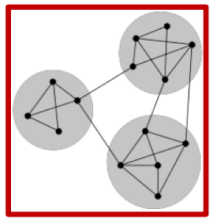
Alibaba Group 阿里巴巴集团

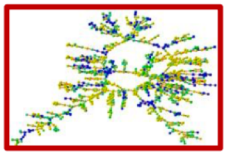
- **~700 million** trans. (alipay)
- **120.7 billion** on 11/11

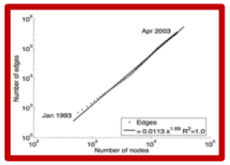
History of Social Network Analysis

Computational Social Science [Giles] — 2012

Computational Social Science [Lazer et al.] — 2009







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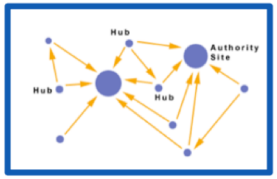
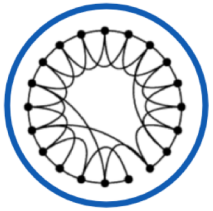
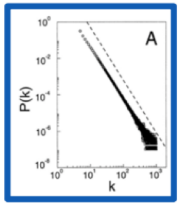
Scale Free [Barabási, Albert & Faloutsos et al.] — 1999

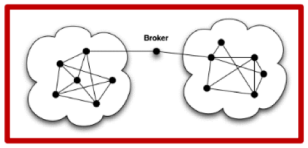


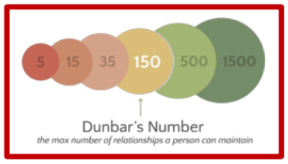




Small World [Watts, Strogatz] — 1998

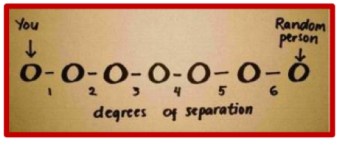
HITS [Kleinberg]&PageRank [Brin&Page] — 1997





1995 — Structural Hole [Burt]

1992 — Dunbar's Number [Dunbar]

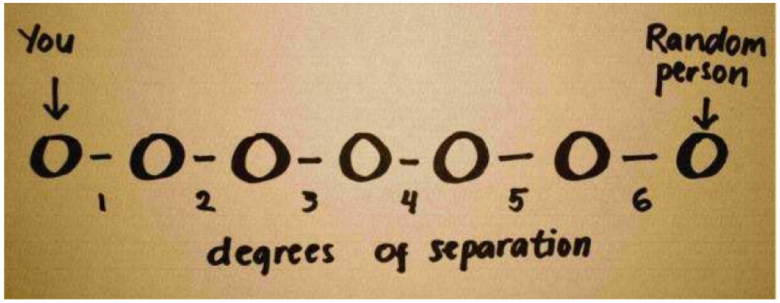


1973 — Weak Tie [Granovetter]

1967 — Six Degrees of Separation [Milgram]

1967: Six Degrees of Separation

- "Given two individuals selected randomly from the population, what is the probability that the minimum number of intermediaries required to link them is 0, 1, 2, …, *k*?"
- Milgram "selected 296 volunteers and to distribute a mail to a stockholder living in Boston."
- "The average number of intermediaries in the mailing chains was 5.2."

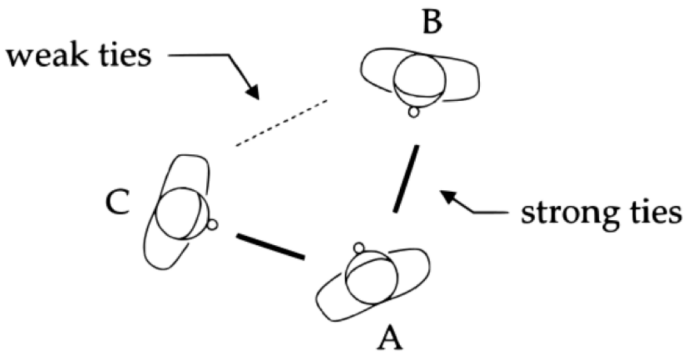


Stanley Milgram. The small world problem. *Psychology Today*, 2(1):60–67, 1967. Cited by 6967 (as of May 2016)

1995 Structural Hole [Burt]
1992 Dunbar's Number [Dunbar]
1973 Weak Tie [Granovetter]
1967 Six Degrees of Separation [Milgram]

1973: Weak Tie

- The **weak tie hypothesis** argues, if A is linked to both B and C, then there is a greater-than-chance probability that B and C are linked to each other.
- Essentially form "A friend's friend is also my friend"



Granovetter, Mark S. The strength of weak ties. *American journal of sociology* 78.6 (1973): 1360-1380. Cited by 43186 (as of April 2017)

1995 Structural Hole [Burt]
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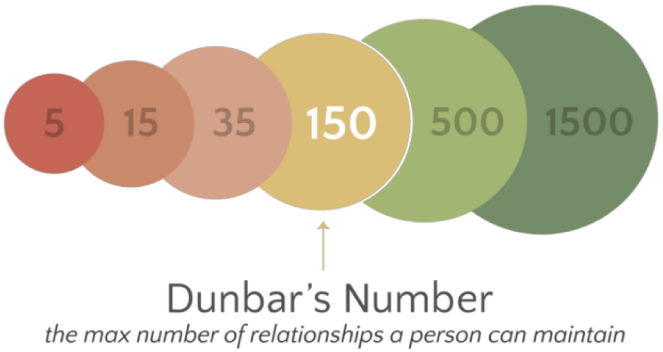
1973 Weak Tie [Granovetter]
1967 Six Degrees of Separation [Milgram]

1992: Dunbar's Number

- "**Dunbar's number** is a suggested cognitive limit to the number of people with whom one can maintain stable social relationships."
- Dunbar "proposed that humans can only comfortably maintain **150** stable relationships."



Robin I. M. Dunbar. Neocortex size as a constraint on group size in primates. *Journal of Human Evolution* 22 (6): 469–493. Cited by 1393 (as of May 2016)

1995 Structural Hole [Burt]
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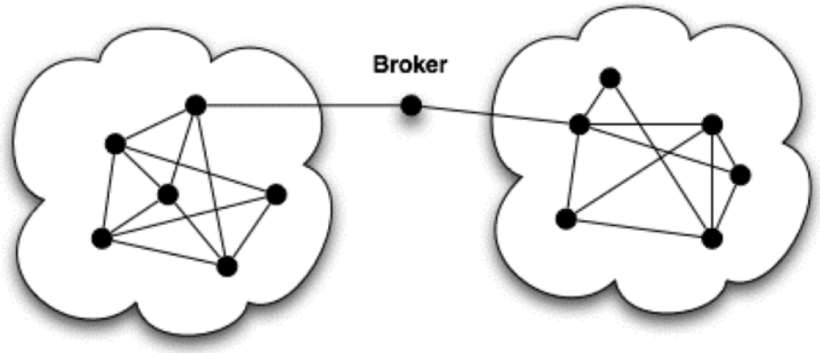
1995: Structural Holes

- "The position of a bridge between distinct groups allows him or her to transfer valuable information from one group to another."
- "The individual can combine all the ideas he or she receives from different sources and come up with the most innovative idea among all."



Ronald S. Burt. *Structural Holes: The Social Structure of Competition*. Cambridge: Harvard University Press. 1995. Cited by 20207 (as of May 2016)

1995 **Structural Hole [Burt]**
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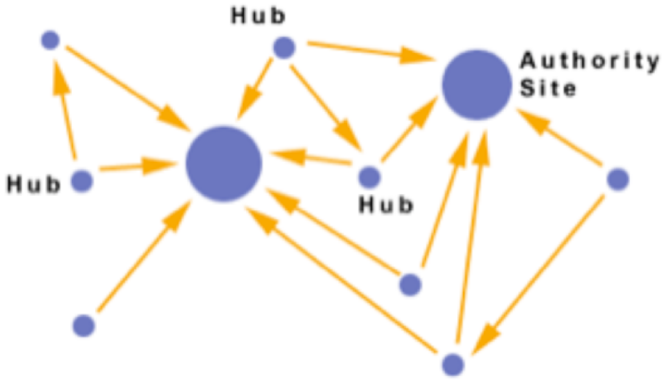
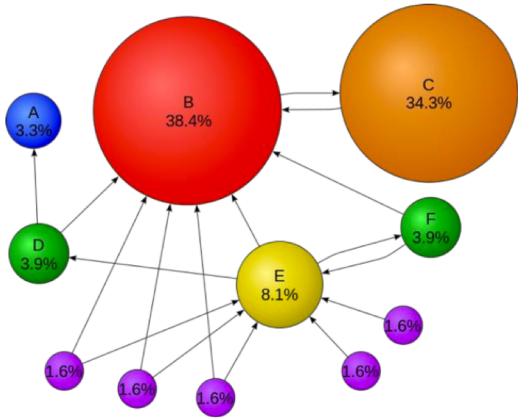
1997-1998: HITS and PageRank





Scale Free [Barabási,Albert & Faloutsos et al.]	1999
Small World [Watts, Strogatz]	1998
HITS [Kleinberg]&PageRank [Brin&Page]	**1997**

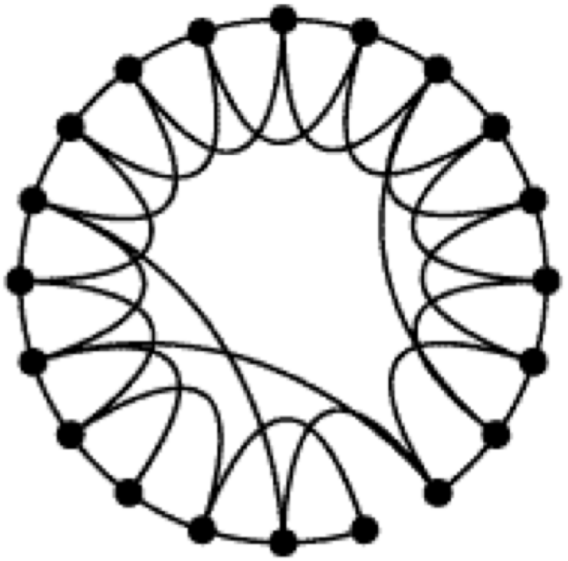
1. Jon M. Kleinberg. Authoritative sources in a hyperlinked environment. In ACM SODA, 1998. Extended version in Journal of the ACM 46 (1999). Also at IBM Research Report RJ 10076, May 1997. Cited by 9896 (as of May 2016)

2. Sergey Brin, Lawrence Page. The anatomy of a large-scale hypertextual Web search engine. In WWW'07, Pages 107-117,1998. Cited by 14618 (as of May 2016)

1998: Small World

Small-World Properties:

1. short average path lengths
2. high clustering coefficients



https://en.wikipedia.org/wiki/Small-world_network

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HITS [Kleinberg]&PageRank [Brin&Page] 1997

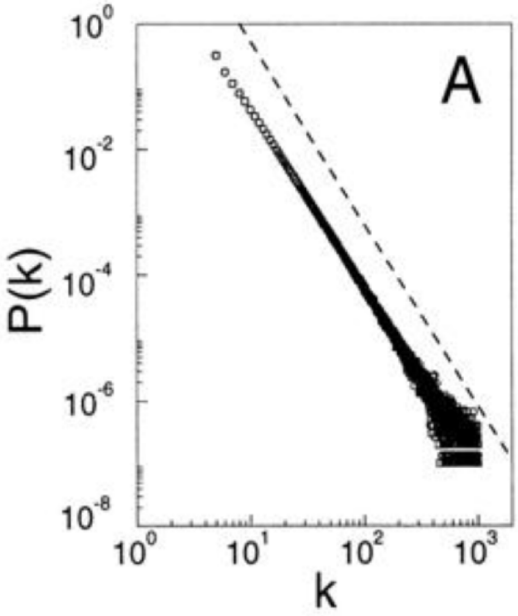
Duncan Watts, Steven Strogatz. Collective dynamics of 'small-world' networks. Nature 393 (6684): 440–442. Cited by 29044 (as of May 2016)

1999: Scale Free

- "A scale-free network is a network whose degree distribution follows a power law."
- The fraction $P(k)$ of nodes having k connections to other nodes:

$$\boldsymbol{P(k) \sim k^{-\gamma}}$$

where γ is a parameter whose value is typically in the range $2 < \gamma < 3$



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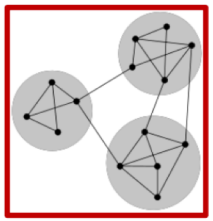
Albert-László Barabási, Réka Albert. Emergence of scaling in random networks, Science, 286:509–512, 1999. Cited by 25189 (as of May 2016)

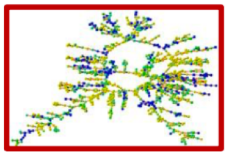
Michalis Faloutsos, Petros Faloutsos, Christos Faloutsos. On power-law relationships of the internet topology. In ACM SIGCOMM 1999. Cited by 5631 (as of May 2016)

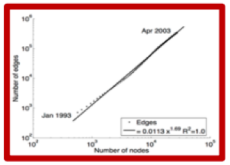
2002: Community Detection

- "The property of community structure, in which network nodes are joined together in tightly knit groups, between which there are only looser connections."

M. Girvan and M. E. J. Newman. Community structure in social and biological networks. *PNAS 99(12):7821-7826, 2002*. Cited by 8088 (as of May 2016)







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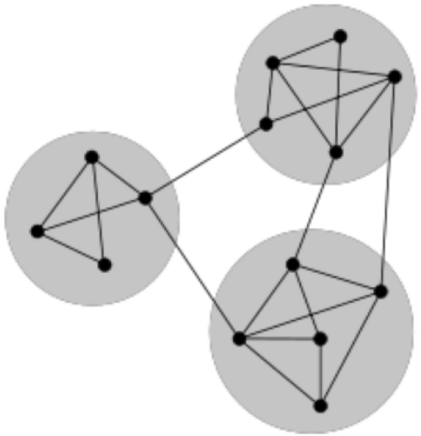
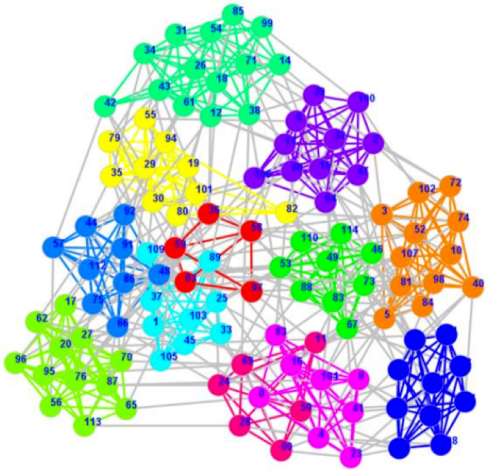
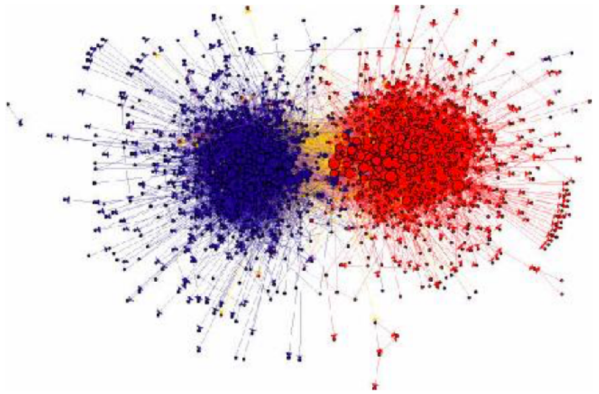


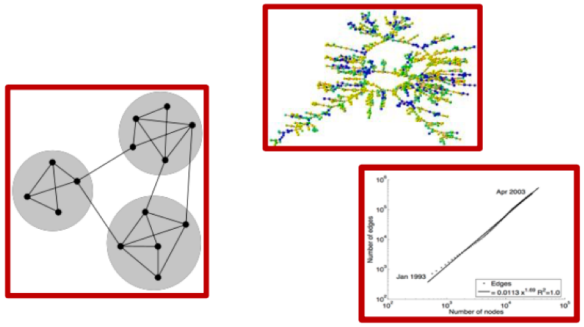




2003: Influence Maximization

- Minimize marketing cost and more generally to maximize profit, e.g., to get a small number of influential users to adopt a new product, and subsequently trigger a large cascade of further adoptions.

D. Kempe, J. Kleinberg, E. Tardos. Maximizing the Spread of Influence through a Social Network. In ACM KDD 2003. **Best Research Paper Award & Test of Time Paper Award**. Cited by 3513 (as of May 2016)



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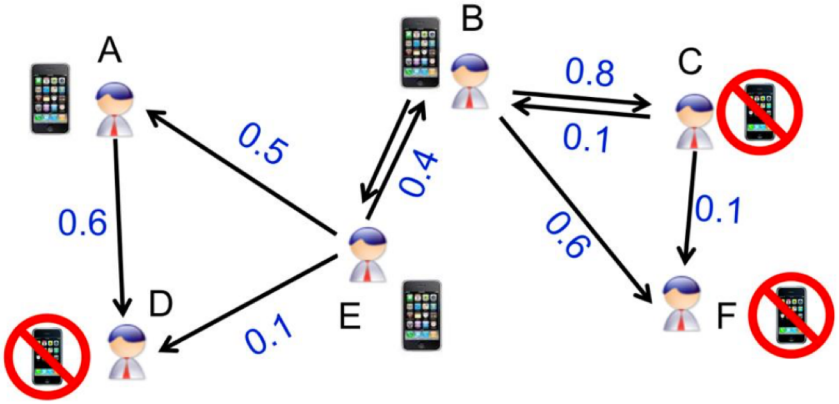
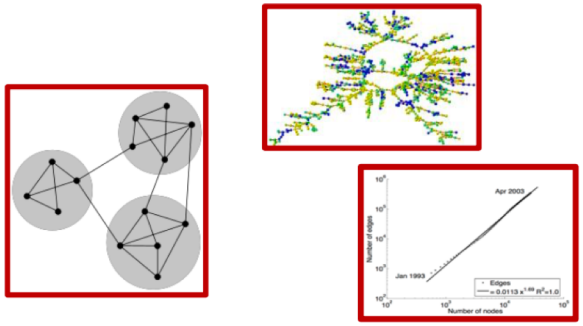


2003: Link Prediction

- "Given a snapshot of a social network at time *t*, we seek to accurately predict the edges that will be added to the network during the interval from time *t* to a given future time *t'* ."

D. Liben-Nowell, J. Kleinberg. The Link Prediction Problem for Social Networks. In ACM CIKM, 2003. Cited by 2616 (as of May 2016)



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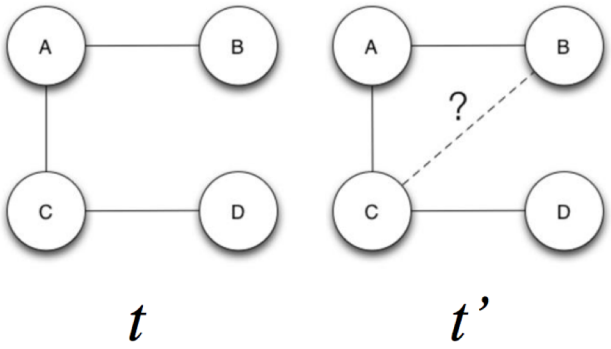
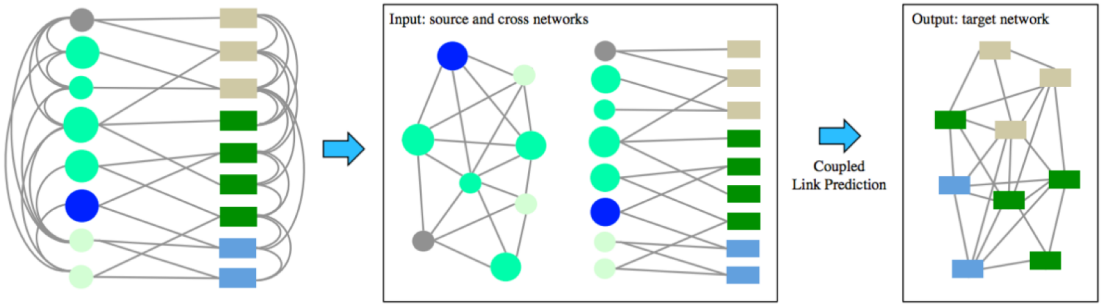
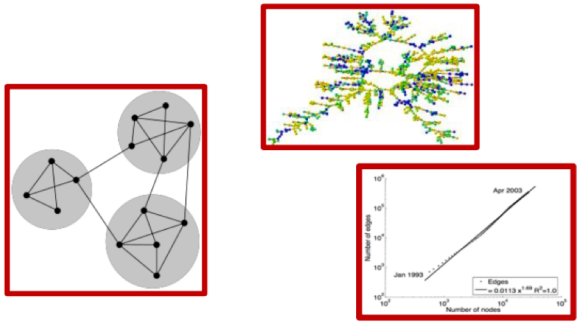




2005: Network Evolution

- "Most of graphs densify over time, with the number of edges growing superlinearly in the number of nodes."
- "The average distance between nodes often shrinks over time."

J. Leskovec, J. Kleinberg, C. Faloutsos. Graphs over Time: Densification Laws, Shrinking Diameters and Possible Explanations. In KDD, 2005. **Best Research Paper Award & Test of Time Award**. Cited by 1492 (as of May 2016)



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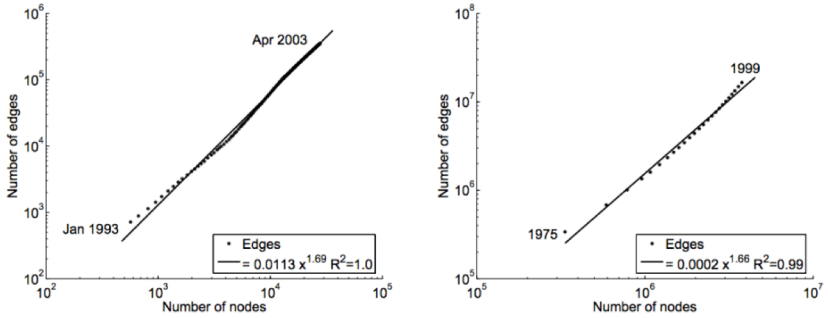
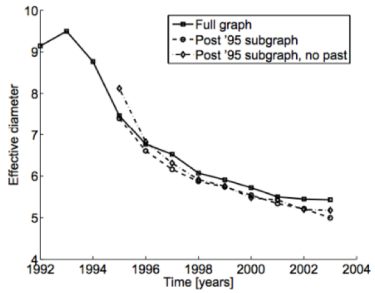
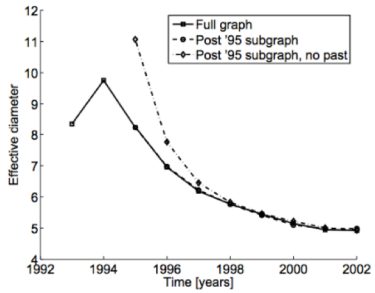


Densification

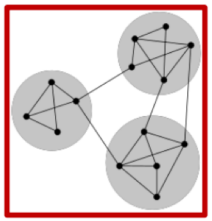


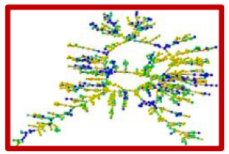


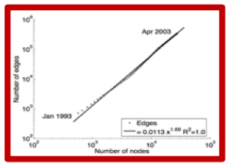
Shrinking Diameters

2007: Diffusion and Influence

1. Nicholas Christakis, James Fowler. The Spread of Obesity in a Large Social Network Over 32 Years. The New England Journal of Medicine 357 (4): 370–379, 2007. Cited by 3335 (as of May 2016)
2. Nicholas Christakis, James Fowler. The Collective Dynamics of Smoking in a Large Social Network. The New England Journal of Medicine 358 (21): 2249–2258, 2008. Cited by 1232 (as of May 2016)
3. James Fowler, Nicholas Christakis. The Dynamic Spread of Happiness in a Large Social Network. British Medical Journal 337 (768): a2338, 2009. Cited by 1178 (as of May 2016)







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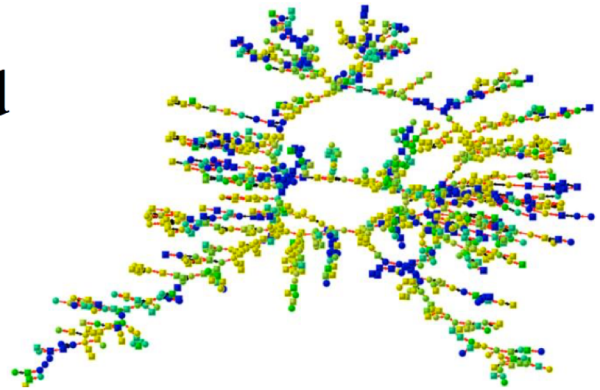
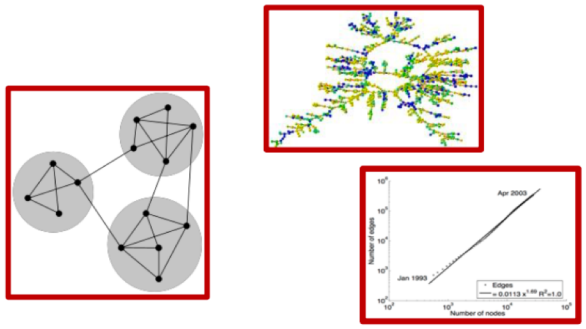
"If the husband became obese, the likelihood that his wife would become obese increased by **37%**."
—by tracking 10,000+ people for 32 years



2009: Social Influence Analysis

- "Social influence is a prevalent, complex and subtle force that governs the dynamicsof all social networks."

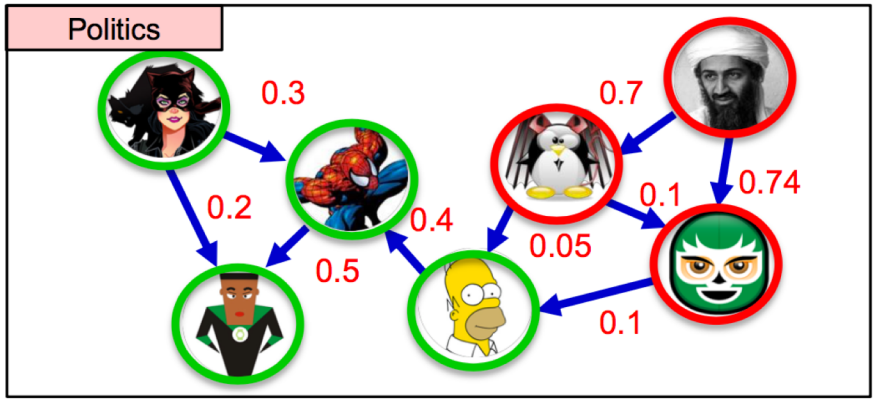
Jie Tang, Jimeng Sun, Chi Wang, and Zi Yang. Social Influence Analysis in Large-scale Networks. In KDD'09, pages 807-816. **Top cited paper in KDD'09**. Cited by 624 (as of April 2017)



2009	**Social Influence Analysis [Tang, Sun]**
2007	Spread of Obesity, Happiness [Christakis, Fowler]
2005	Densification [Leskovec, Kleinberg, Faloutsos]
2003	Link Prediction [Liben-Nowell, Kleinberg] Influence Maximization [Kempe, Kleinberg, Tardos]
2002	Community Detection [Girvan, Newman]

"How to quantify the *social influences* from different topics"

—Topical Affinity Propagation (TAP), an efficient model



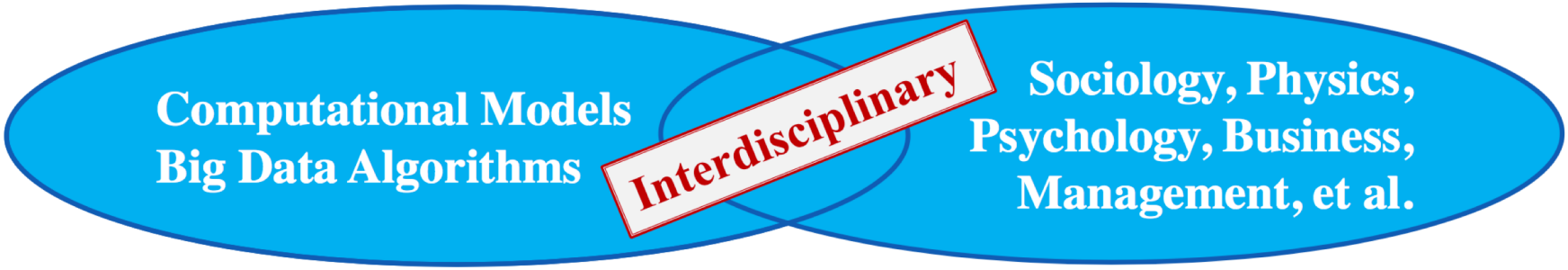
Computational Social Science

Computational Social Science [Giles] 2012

Computational Social Science [Lazer et al.] 2009

"A field is emerging that leverages the capacity to collect and analyze **data at a scale** that may reveal patterns of individual and group behaviors."

David Lazer, Alex Pentland, Lada Adamic, Sinan Aral, Alber-Laszlo Barabasi, et al. from *Departments of Sociology, Computer Science, Physics, Business, Government*, etc. at *Harvard, MIT, Northeastern, Northwestern, Columbia, Cornell, etc*.

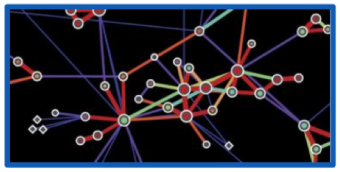


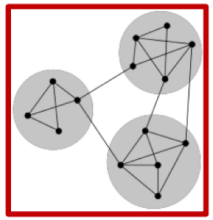
1. **David Lazer et al. Computational Social Science. *Science* 2009.**
2. James Giles. Computational Social Science: Making the Links. **Nature** 2012.

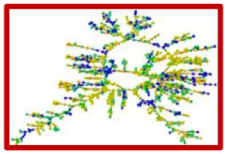
History of Social Network Analysis

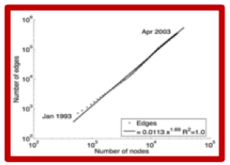
Computational Social Science [Giles] 2012

Computational Social Science [Lazer et al.] 2009









2009 Social Influence Analysis [Tang, Sun]

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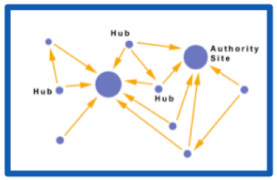
2003 Link Prediction [Liben-Nowell, Kleinberg]
Influence Maximization [Kempe, Kleinberg, Tardos]

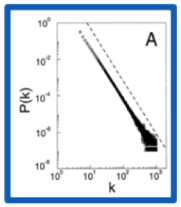
2002 Community Detection [Girvan, Newman]

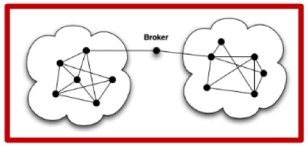
Scale Free [Barabási, Albert & Faloutsos et al.] 1999

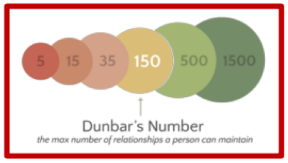
Small World [Watts, Strogatz] 1998

HITS [Kleinberg]&PageRank [Brin&Page] 1997







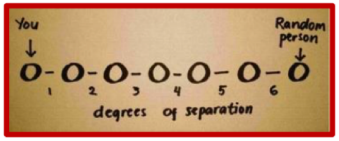


1995 Structural Hole [Burt]

1992 Dunbar's Number [Dunbar]

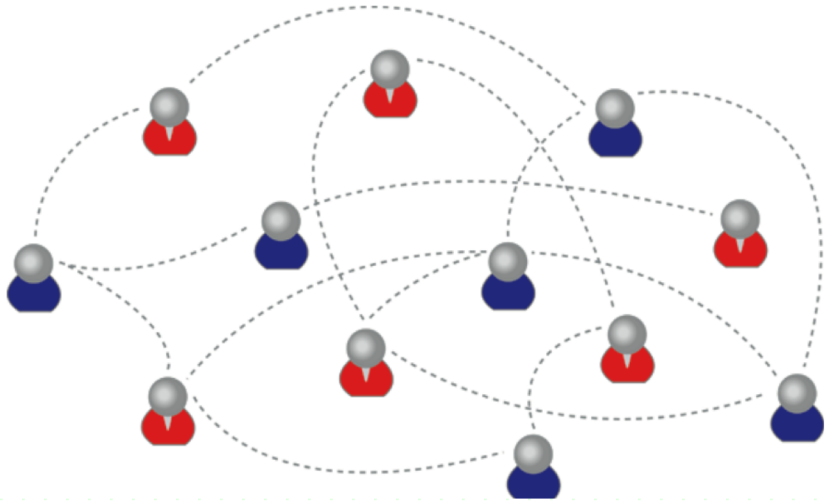
1973 Weak Tie [Granovetter]

1967 Six Degrees of Separation [Milgram]



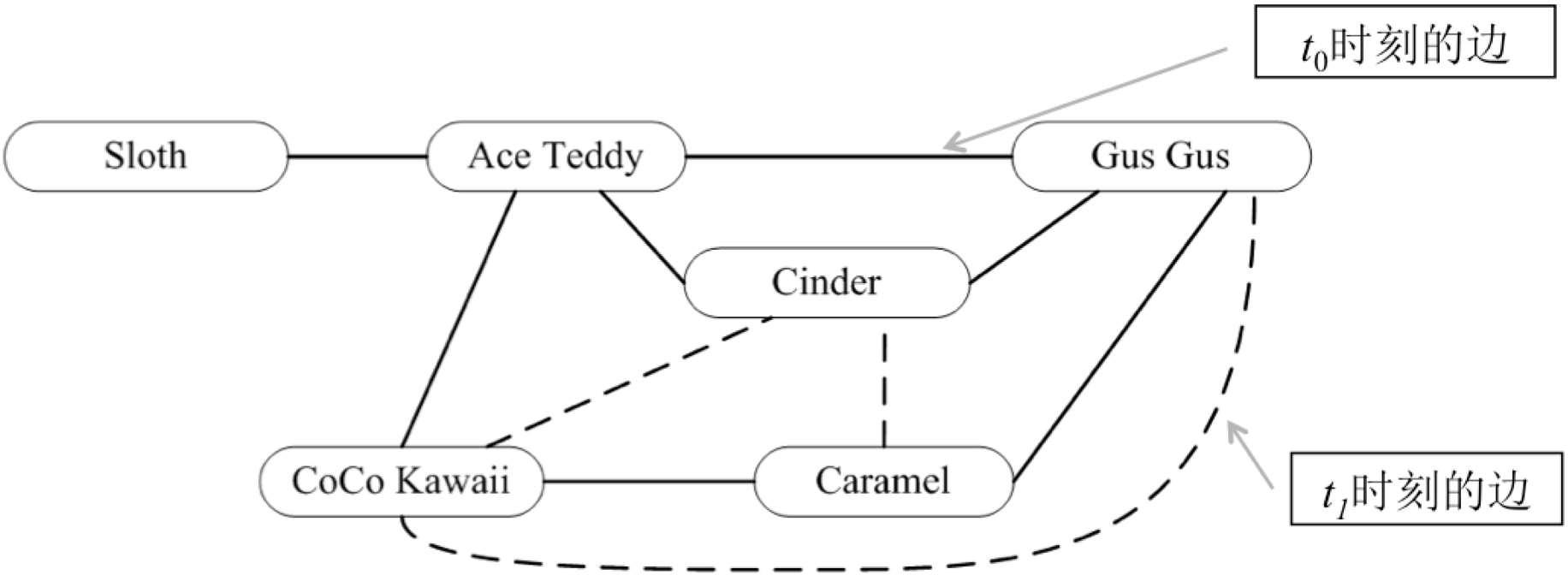
What is a social network?

- A social network is:
  - a **graph** made up of :
  - a set of **individuals**, called “nodes”, and
  - tied by one or more **interdependency**, such as friendship, called “edges”.



What is Link Prediction

Link Prediction: Given a network in t_0, predict new links in future $t_1(t_1>t_0)$, or find missing and unseen links。



Wang P, *et al.* *Sci China Inf Sci* January 2015 Vol. 58 011101:2

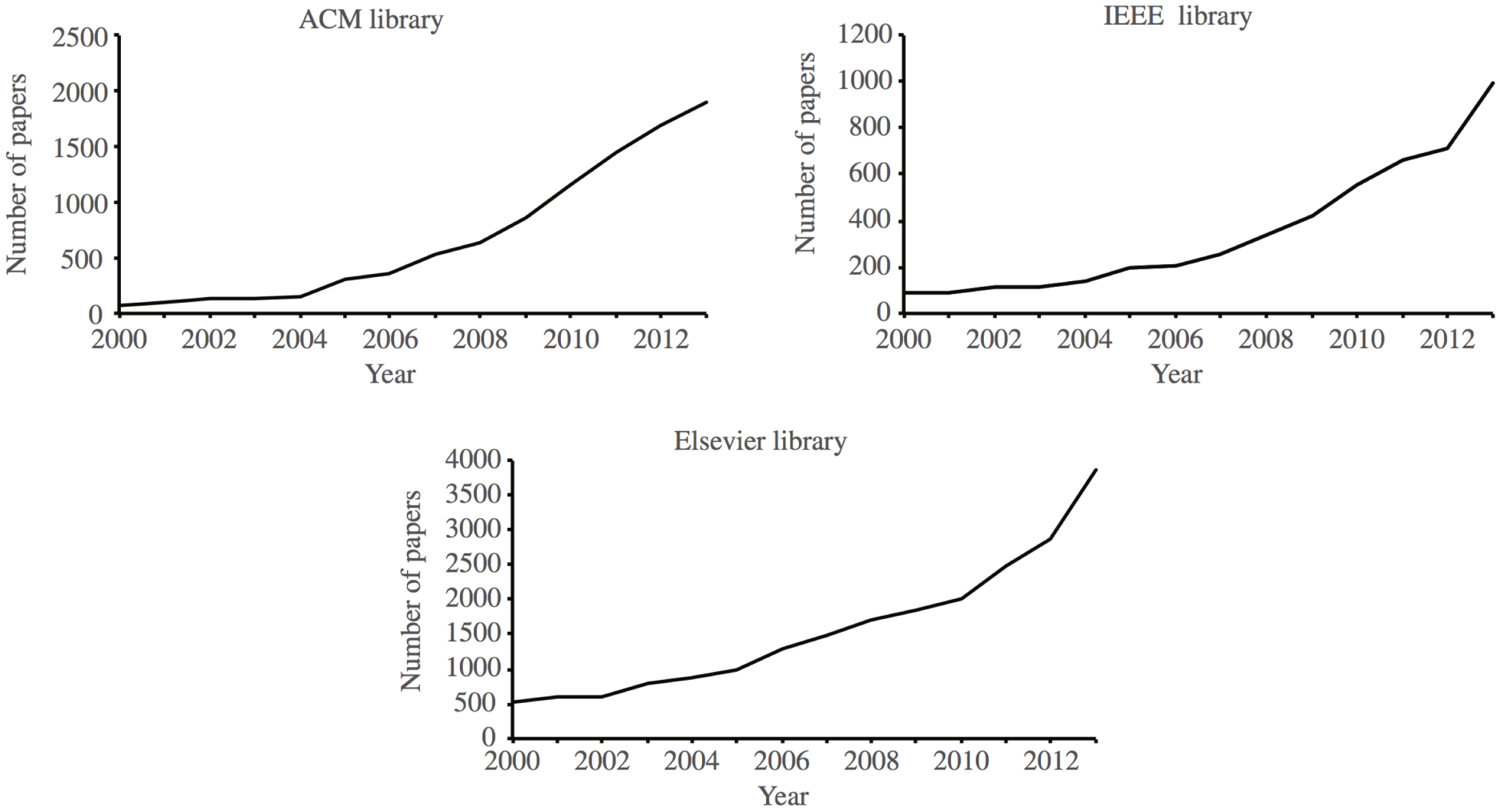


Figure 1 Published papers related to link prediction problem on ACM, IEEE, and Elsevier libraries.

Link prediction framework

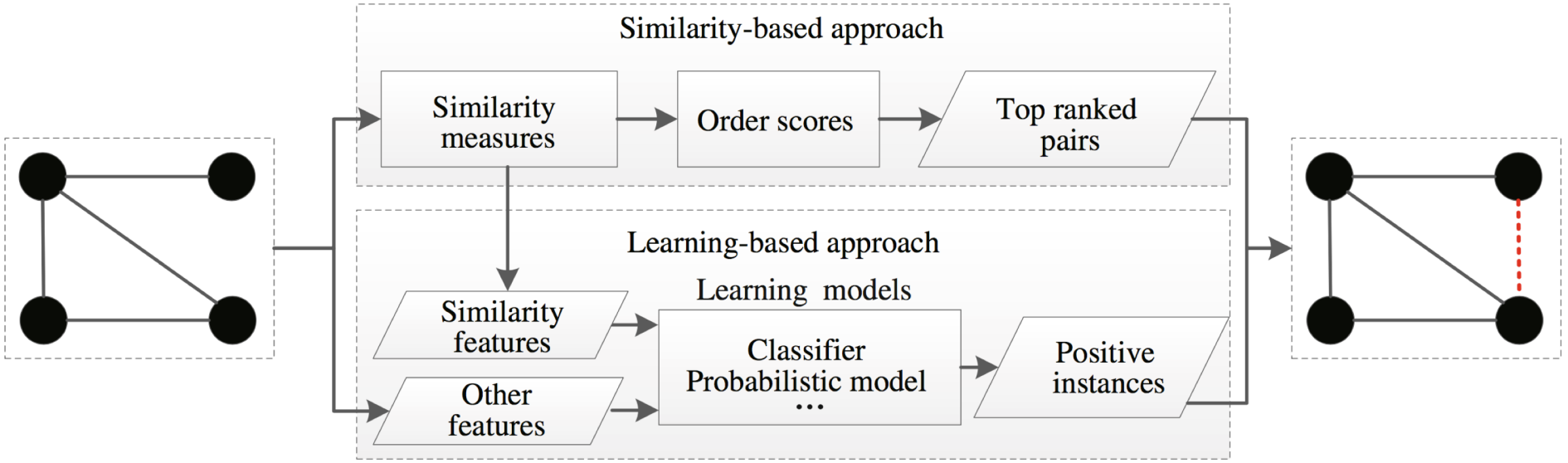
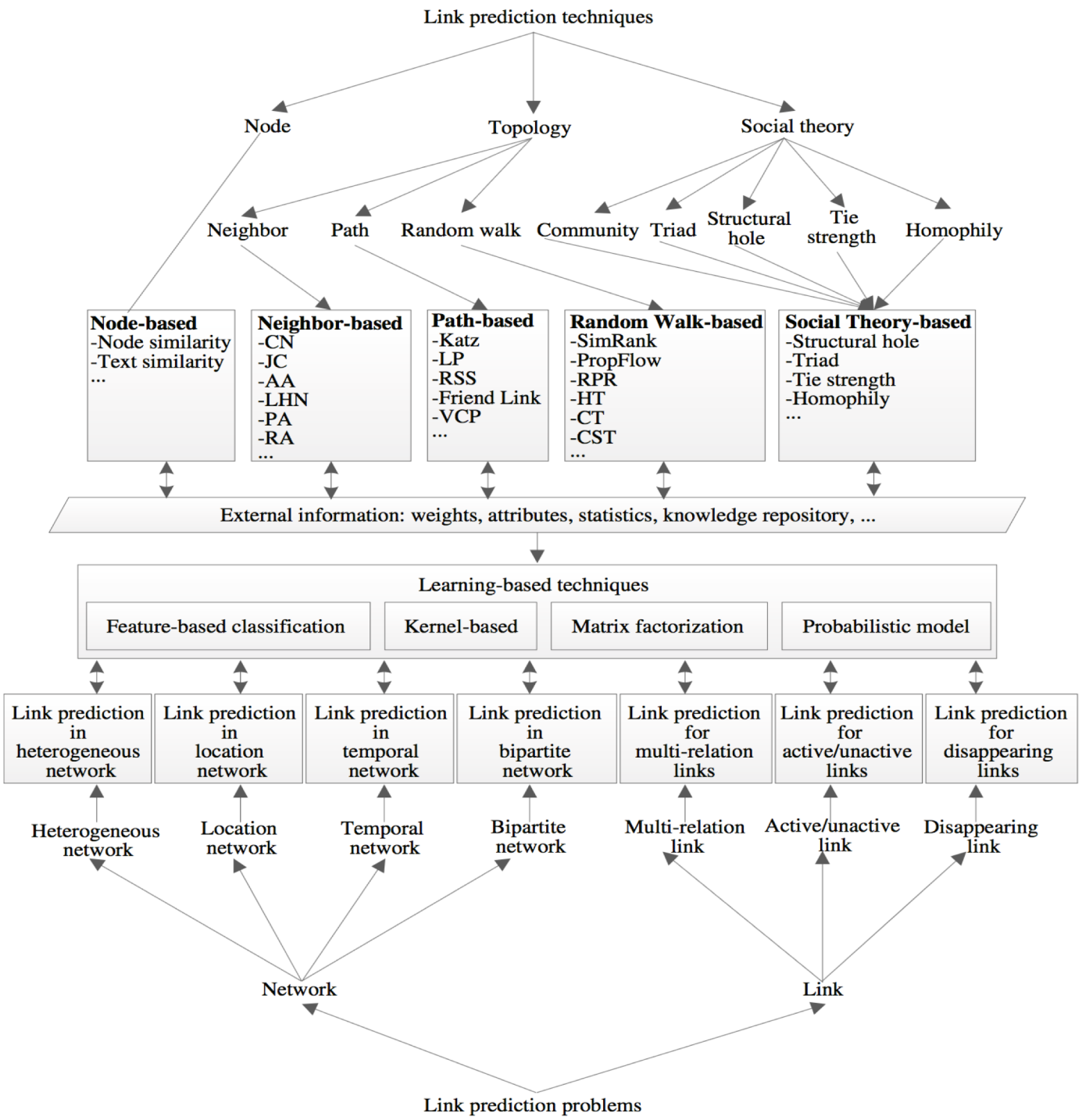


Figure 7 The generic link prediction framework.


Link prediction techniques
Node
Topology
Social theory
Neighbor
Path
Random walk
Community
Triad
Structural hole
Tie strength
Homophily
Node-based
-Node similarity
-Text similarity
...
Neighbor-based
-CN
-JC
-AA
-LHN
-PA
-RA
...
Path-based
-Katz
-LP
-RSS
-Friend Link
-VCP
...
Random Walk-based
-SimRank
-PropFlow
-RPR
-HT
-CT
-CST
...
Social Theory-based
-Structural hole
-Triad
-Tie strength
-Homophily
...
External information: weights, attributes, statistics, knowledge repository, ...
Learning-based techniques
Feature-based classification
Kernel-based
Matrix factorization
Probabilistic model
Link prediction in heterogeneous network
Link prediction in location network
Link prediction in temporal network
Link prediction in bipartite network
Link prediction for multi-relation links
Link prediction for active/unactive links
Link prediction for disappearing links
Heterogeneous network
Location network
Temporal network
Bipartite network
Multi-relation link
Active/unactive link
Disappearing link
Network
Link
Link prediction problems

Solutions

- **1. Based on node properties**
  - ✓ **Similarity between node properties**

- **2. Based on topology**
  - ✓ **Based on common neighbors**

  CN,JC,AA,PA,RA,LHN,HP,HD,PD,SI,SC,…
  - ✓ **Based on paths**

  Katz, LP, RSS, VCP, …
  - ✓ **Based on random walk**

  SimRank, Rooted PageRank, PropFlow,…

Solutions

- **3. Based on social theory**
  - ✓ community, triadic closure, strong and weak ties, homophily, and structural balance
- **4. Based on machine learning**
  - ✓ Feature-based classification
  - ✓ Probabilistic graph model
  - ✓ Matrix factorization
  - ✓ Deep learning

Topology based methods

Common Neighbors (CN): The CN metric is one of the most widespread measurements used in link prediction problem mainly due to its simplicity [30]. For two nodes, x and y, the CN is defined as the number of nodes that both x and y have a direct interaction with. A bigger number of the common neighbors make it easier that a link between x and y will be created. This measure is defined as following formula.

$$\mathrm{CN}(x, y) = |\Gamma(x) \cap \Gamma(y)|. \tag{1}$$

Since CN metric is not normalized, it usually reflects the relative similarities between node pairs. Therefore, some neighbor-based metrics consider how to normalize the CN metric reasonably.

Jaccard Coefficient (JC): Jaccard coefficient normalizes the size of common neighbors. It assumes higher values for pairs of nodes which share a higher proportion of common neighbors relative to total number of neighbors they have. This measure is defined as:

$$\mathrm{JC}(x, y) = \frac{|\Gamma(x) \cap \Gamma(y)|}{|\Gamma(x) \cup \Gamma(y)|}. \tag{2}$$

Topology based methods

Sørensen Index (SI): This metric is defined as formula (3). Besides considering the size of the common neighbors, it also points out that lower degrees of nodes would have higher link likelihood.

$$\mathrm{SI}(x,y) = \frac{|\Gamma(x) \cap \Gamma(y)|}{|\Gamma(x)| + |\Gamma(y)|}. \tag{3}$$

Salton Cosine Similarity (SC): SC is a common cosine metric for measuring the similarity between two nodes x and y. It is defined as:

$$\mathrm{SC}(x,y) = \frac{|\Gamma(x) \cap \Gamma(y)|}{\sqrt{|\Gamma(x)| \cdot |\Gamma(y)|}}. \tag{4}$$

Topology based methods

Adamic-Adar Coefficient (AA): The AA metric was proposed by Adamic and Adar for computing similarity between two web pages at first [35], subsequent to which it has been widely used in social networks. The AA measure is formulated related to Jaccard's coefficient. But here, common neighbors which have fewer neighbors are weighted more heavily. It is defined as:

$$\mathrm{AA}(x,y) = \sum_{z \in \Gamma(x) \cap \Gamma(y)} \frac{1}{\log |\Gamma(z)|}. \tag{9}$$

Preferential Attachment (PA): The PA metric indicates that new links will be more likely to connect higher-degree nodes than lower ones [12]. It is defined as:

$$\mathrm{PA}(x,y) = |\Gamma(x)| \cdot |\Gamma(y)|. \tag{10}$$

Resource Allocation (RA): This metric is proposed by Zhou et al. [32], and is motivated by the physical processes of resource allocation. RA metric has a similar form like AA. They both suppress the contribution of the high-degree common neighbors. However, RA metric punishes the high-degree common neighbors more heavily than AA. Therefore, AA and RA have very close prediction results for the networks with small average degrees, but RA performs better for the networks with high average degrees. In addition, RA and AA not only use direct neighbors, but also consider neighbors of neighbors. This is different with other metrics. RA is defined as:

$$\mathrm{RA}(x,y) = \sum_{z \in \Gamma(x) \cap \Gamma(y)} \frac{1}{|\Gamma(z)|}. \tag{11}$$

Topology based methods

Local Path (LP): LP metric [37] makes use of information of local paths with length 2 and length 3. Unlike the metrics that only use the information of the nearest neighbors, it exploits some additional information of the neighbors within length 3 distances to current node. Obviously, paths of length 2 are more relevant than paths of length 3, so there is an adjustment factor α applied in the measure. α should be a small number close to 0. The metric is defined as following formula (12). Here, A^2 and A^3 denote adjacency matrices about the nodes having 2 length and 3 length distances, respectively. Therefore, LP is also an adjacency matrix which describes the node pairs with length 2 and 3 distances.

$$\mathrm{LP} = A^2 + \alpha A^3. \tag{12}$$

Katz: Katz metric [38] is based on the ensemble of all paths, and it counts all paths between two nodes. The paths are exponential damped by length that can give more weights to the shorter paths. This measure is defined as follows, where $\mathrm{path}_{x,y}^{l}$ is the set of all paths from x to y with length l, $\beta > 0$ and the very small β will cause Katz metric much like CN metric because paths of long length contribute very little to final similarities.

$$\mathrm{Katz}(x,y) = \sum_{l=1}^{\infty} \beta^l \cdot |\mathrm{path}_{x,y}^{l}| = \beta A + \beta^2 A^2 + \beta^3 A^3 + \cdots \tag{13}$$

Topology based methods

SimRank: SimRank metric [46] is defined in a self-consistent way, according to the assumption that two nodes are similar if they are connected to similar nodes. There is a parameter γ that controls how fast the weight of connected nodes decrease as they get farther away from the original nodes.

$$\text{simRank}(x,y) = \begin{cases} 1, & x = y, \\ \gamma \cdot \frac{\sum_{a \in \Gamma(x)} \sum_{b \in \Gamma(y)} \text{simRank}(a,b)}{|\Gamma(x)| \cdot |\Gamma(y)|}, & \text{otherwise.} \end{cases} \tag{20}$$

The SimRank score can be explained in terms of the random surfer-pairs model: $\text{simRank}(x,y)$ measures how soon two random surfers are expected to meet at the same vertex if they individually start at vertices x and y, and randomly walk through edges on the reverse graph.

The computation complexity of SimRank is $O(n^4)$ at the worst time where n is the number of vertices. Such a high computation cost limits its wide usage for large scale networks.

Rooted PageRank (RPR): Rooted PageRank [19] is a modification of PageRank, which is the core algorithm used by search engine to rank search results. The rank of a node in graph is proportional to the probability that the node will be reached through a random walk on the graph. In addition, there is a factor ϵ that specifies how likely the algorithm is to visit the node's neighbors than starting over. Let D be a diagonal matrix with $D_{i,i} = \sum_j A_{i,j}$. The measure is defined as:

$$\text{RPR} = (1-\epsilon)(I - \epsilon D^{-1} A)^{-1}. \tag{21}$$

Learning based methods

Let $x, y \in V$ be nodes in the graph $G(V, E)$ and $l^{(x,y)}$ be the label of the node pair instance (x, y). In link prediction, each non-connected pair of nodes corresponds to an instance includes the class label and features describing the pair of nodes. Therefore, a pair of nodes can be labeled as positive if there is a link connecting the nodes, otherwise, the pair is labeled as negative. The label of x and y is defined as follows:

$$l^{(x,y)} = \begin{cases} +1, & \text{if } (x, y) \in E, \\ -1, & \text{if } (x, y) \notin E. \end{cases} \tag{24}$$

This is a typical binary classification problem and many supervised classification learning models can be used to solve it. For instance, decision tree, support vector machines, naïve Bayes, and so on.

Learning based methods

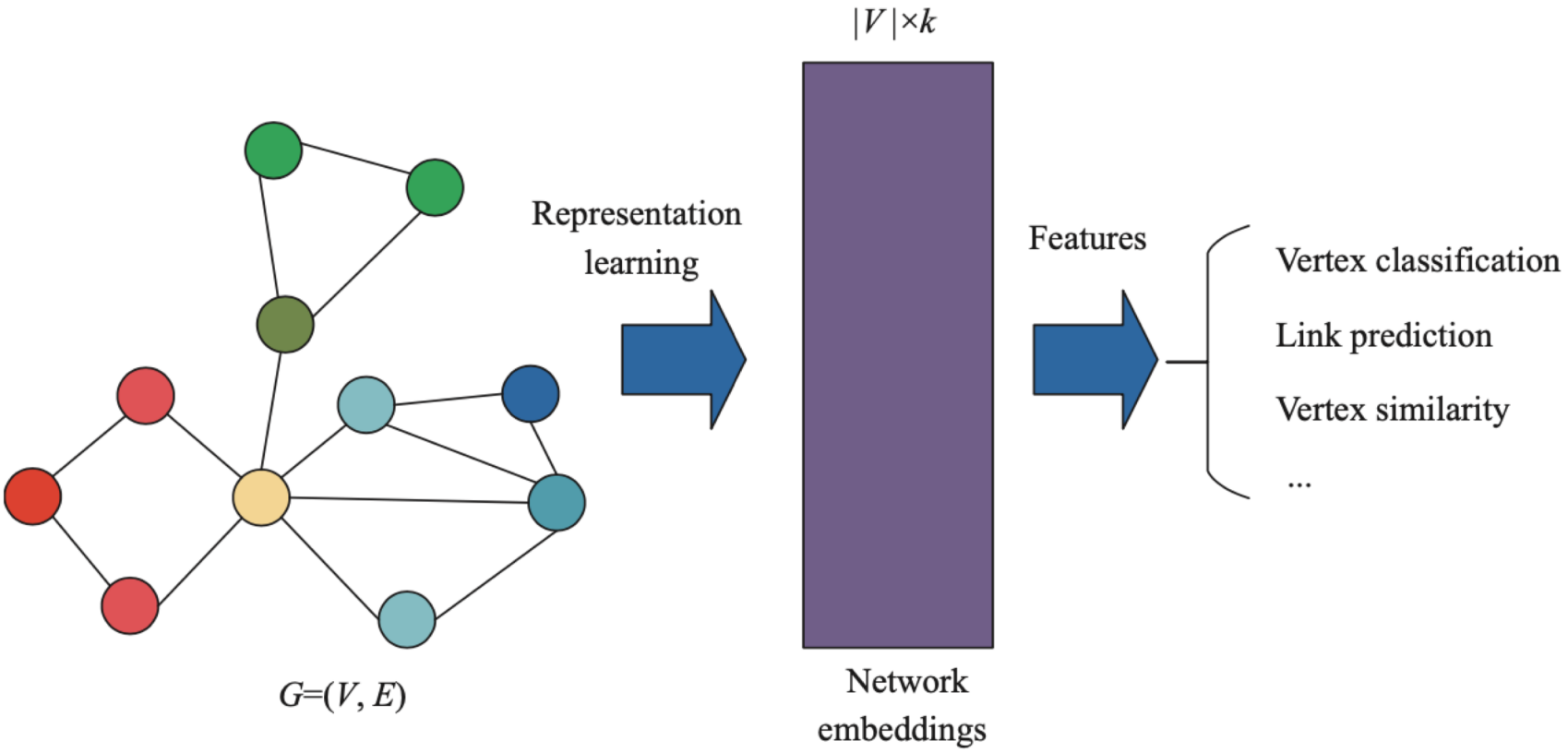


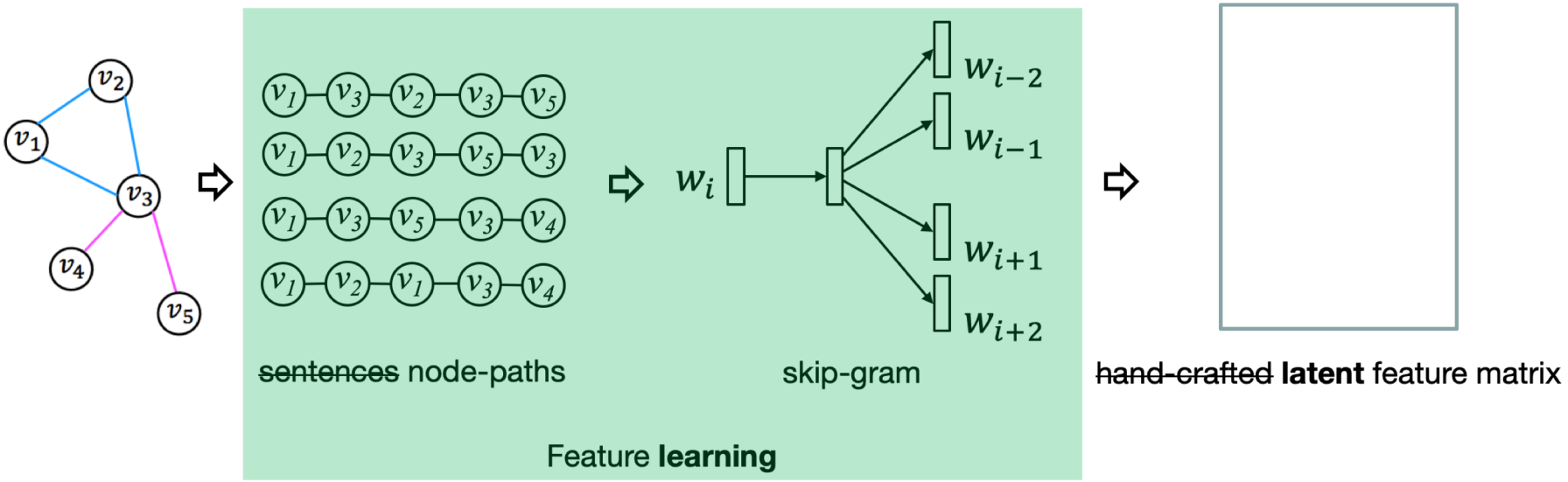
图 1 (网络版彩图) 网络表示学习流程图

Figure 1 (Color online) The flow chart of NRL

Learning based methods

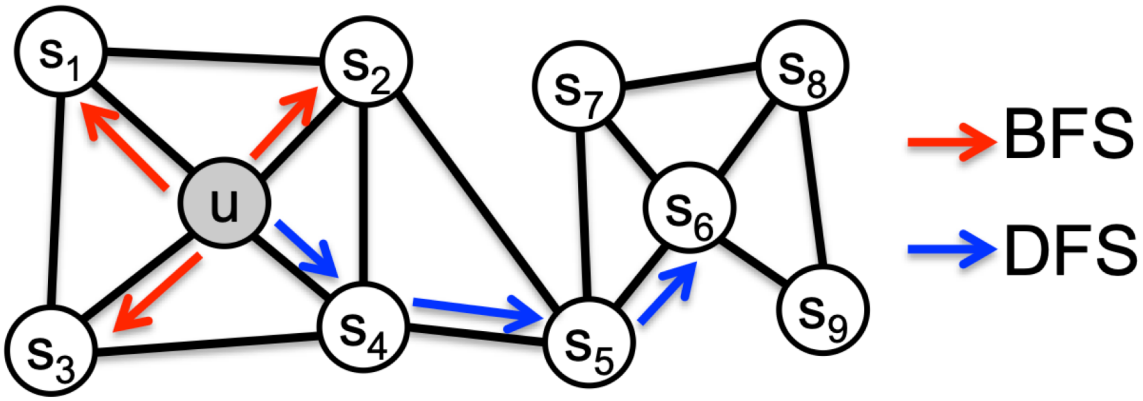
Network embedding: DeepWalk

- Input: a network $G = (V, E)$
- Output: $\boldsymbol{X} \in R^{|V| \times k}, k \ll |V|$, k-dim vector $\boldsymbol{X}_v$ for each node v.



Learning based methods

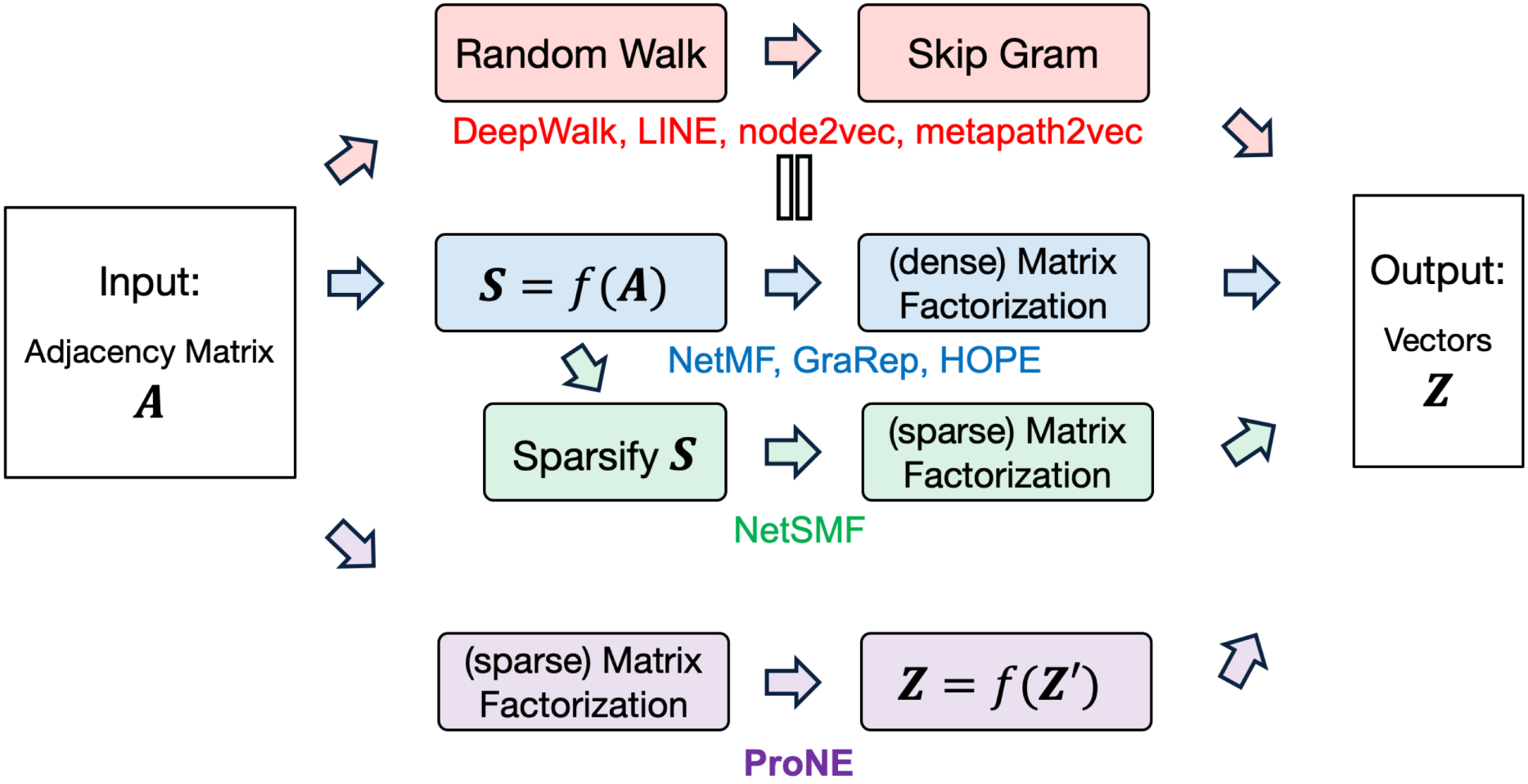
Network Embedding: node2vec



$$N_{BFS}(u) = \{s_1, s_2, s_3\}$$

$$N_{DFS}(u) = \{s_4, s_5, s_6\}$$

Learning based methods



Learning based methods

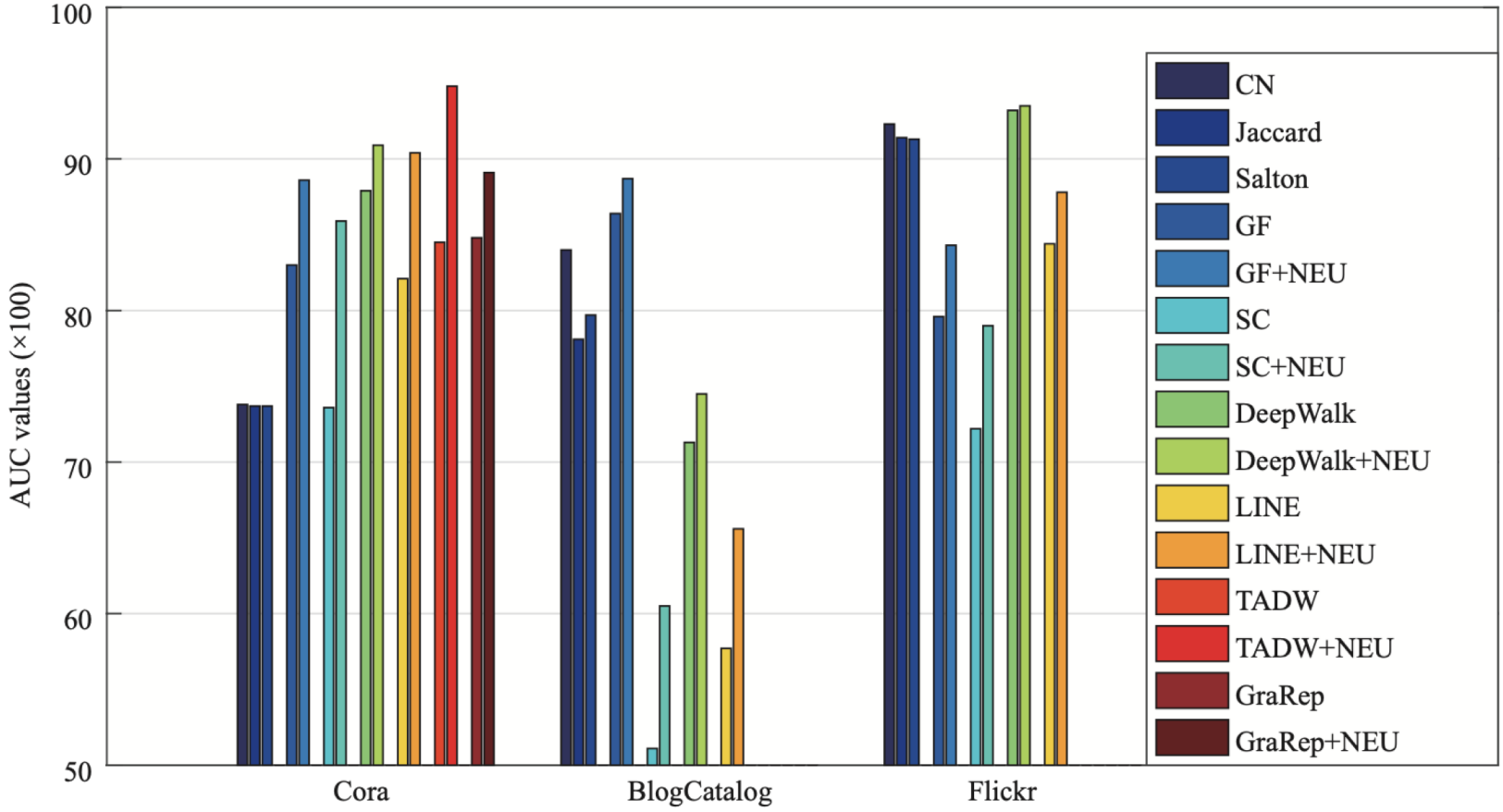
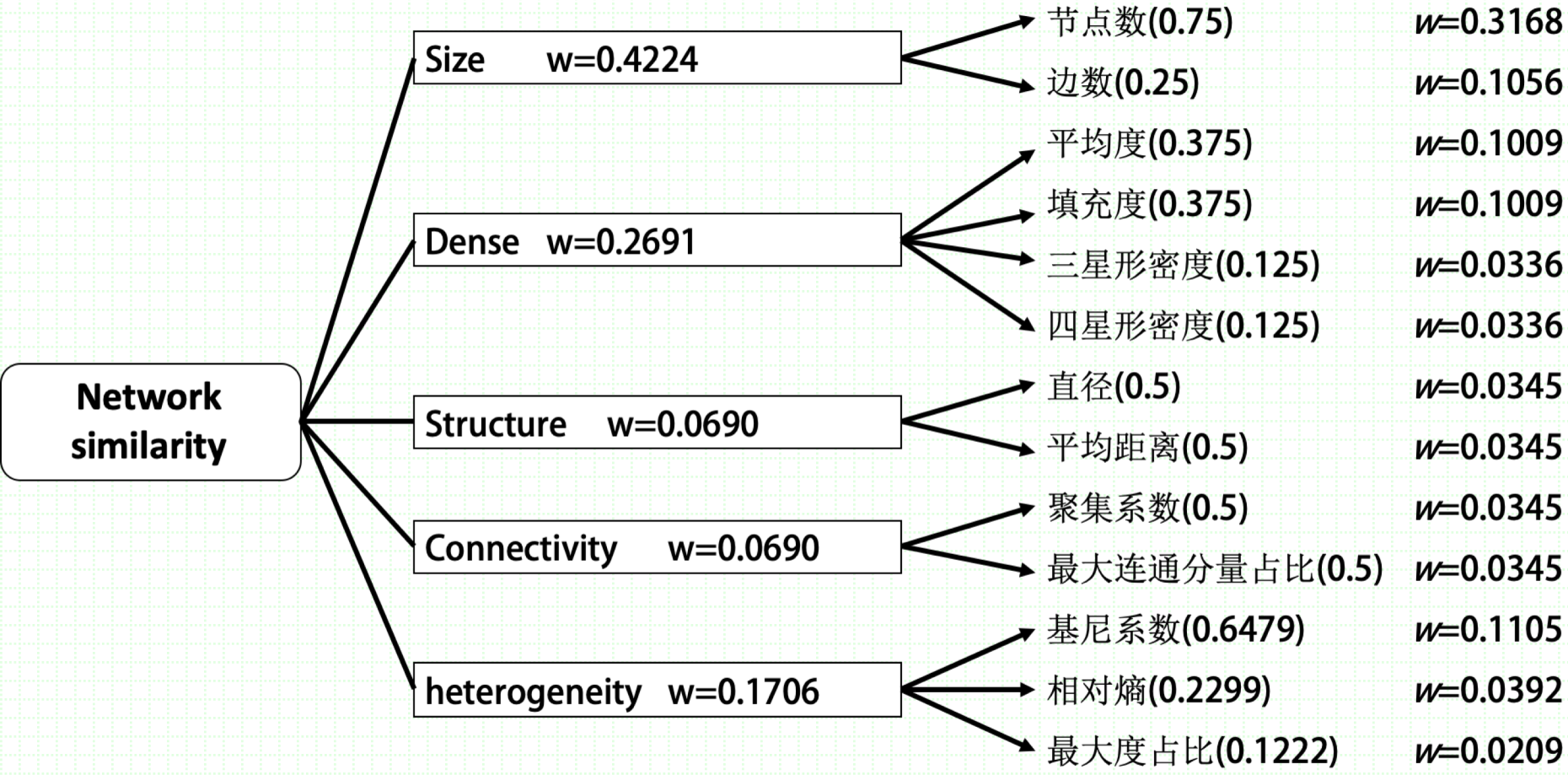


图 11 (网络版彩图) 链接预测实验结果

Figure 11 (Color online) Link prediction results

Link prediction evaluation: a benchmark methods



Link prediction evaluation: a benchmark methods

算法 1: 评测数据集筛选算法

Input: 各网络数据集网络拓扑结构属性矩阵, $M = (m_1, m_2, ..., m_k), m_i = (c_1, c_2, ..., c_t), i \in [1, k]$

Output: 评测数据集序号集合 $u = \{u_1, u_2, u_3, u_4\}$

队列 Q（初始只含一个成员 $\{1, 2, ..., k\}$，二叉树 B（初始只含根节点 $Root = \{1, 2, ..., k\}$），各数据集得分序列 $S = (s_1, s_2, ..., s_k)$;

while 队列 Q 不空 **do**

  Front = Q.front();

  寻找两个集合 P_1 和 P_2 使得 $P_1 \cup P_2 = Front$ 且 P_1 和 P_2 的距离最近;

  将 P_1 和 P_2 添加到二叉树 B 中;

  Q.push(P_1);

  Q.push(P_2);

  for $i \in P_1$ **do**

    $s_i = s_i + \frac{1}{Height(P_1)} \times \frac{|P_1|}{|Front|}$;

  end

  for $j \in P_2$ **do**

    $s_j = s_j + \frac{1}{Height(P_2)} \times \frac{|P_2|}{|Front|}$;

  end

end

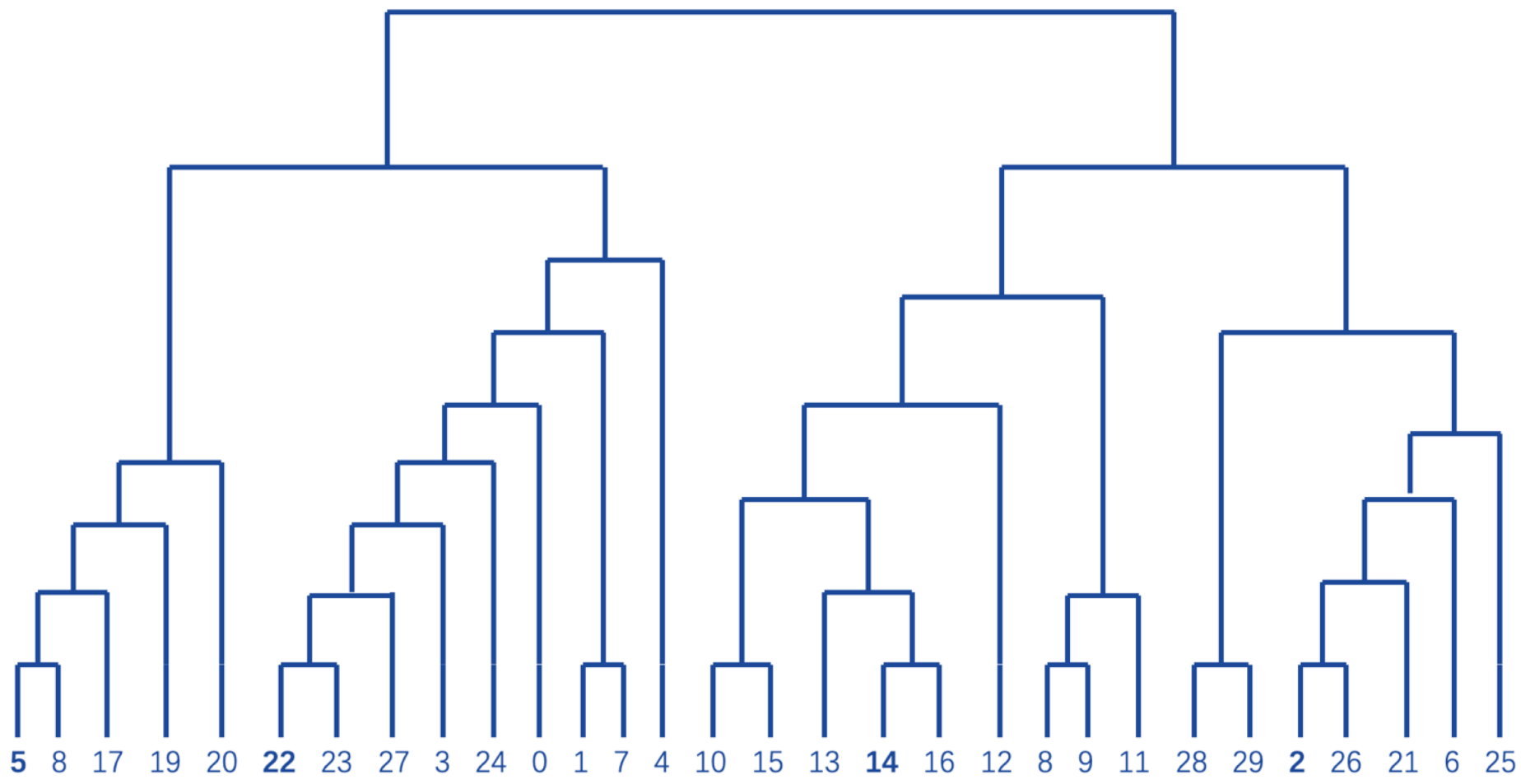
count = 0;

for $P \in B$ 且 $Height(P_2) = 2$ **do**

  u_{count} =S 中得分最高且对应下标属于 P 中的项对应的下标;

end

Link prediction evaluation: a benchmark methods

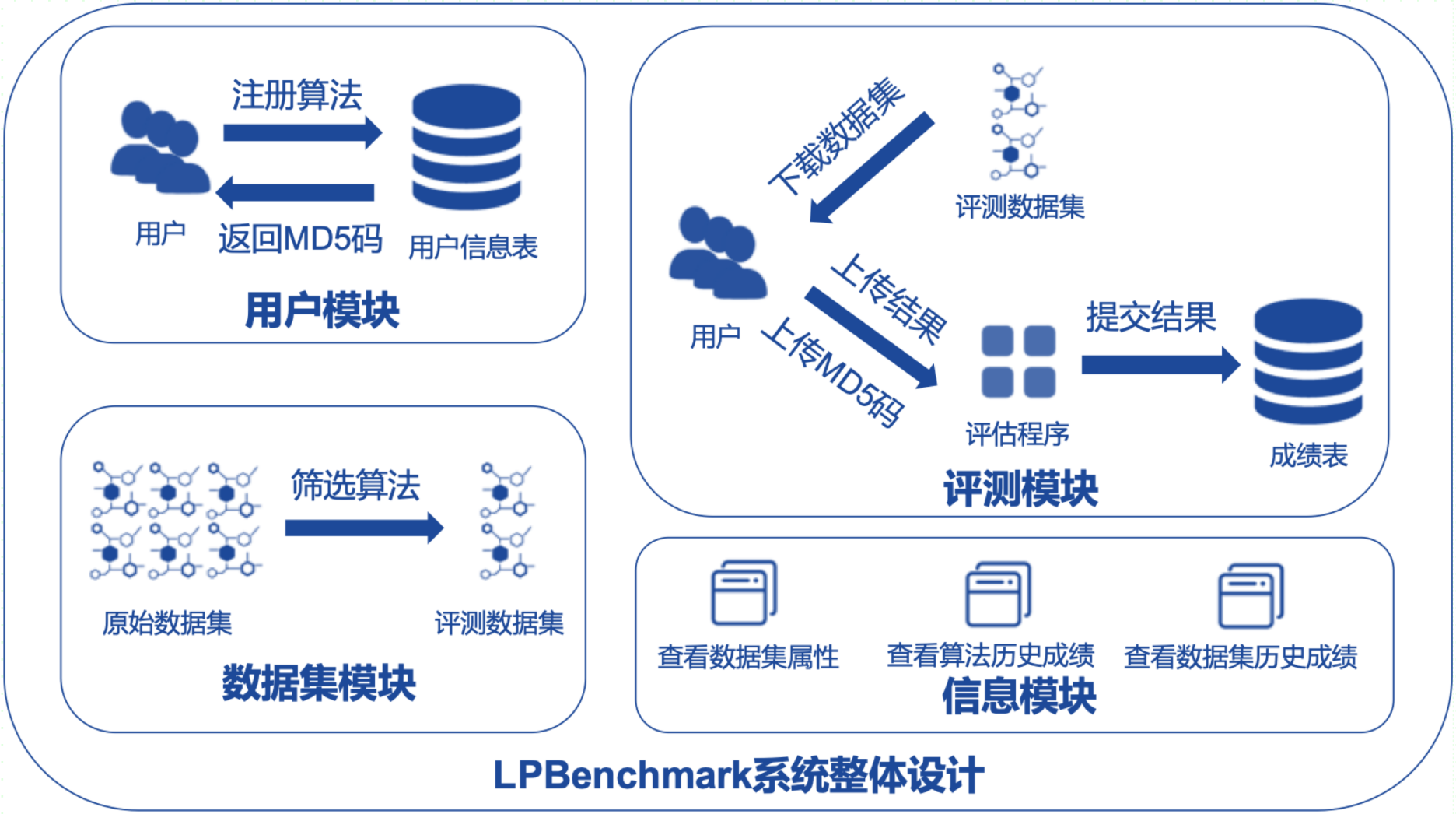


Link prediction evaluation: a benchmark methods

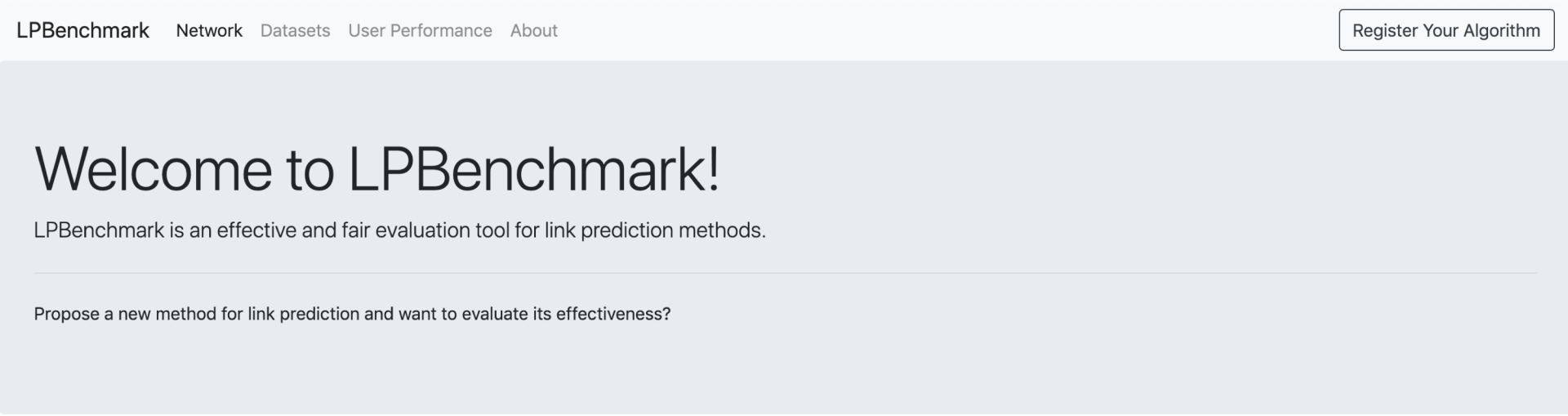
LPBenchmark Dataset

数据集名称	动态属性	节点数	边数	平均度	基尼系数
arXiv HepPh	动态网络	34546	421578	24.407	52.5%
Enron	动态网络	87273	1148072	26.31	90.8%
Manufacturing Emails	动态网络	167	82927	993.14	61.9%
Wikipedia talk,Portuguese	动态网络	541335	2424962	8.9589	76.3%
Berkeley/Stanford	静态网络	685230	7600595	22.184	65.9%
Blogs	静态网络	1224	19025	31.087	63.3%
CoraCitation	静态网络	23166	91500	7.8995	52.1%
Douban	静态网络	154908	327162	8.9589	69.4%

Link prediction evaluation: a benchmark methods



Link prediction evaluation: a benchmark methods



Link prediction evaluation: a benchmark methods

LPBenchmark Network Datasets User Performance About Register Your Algorithm

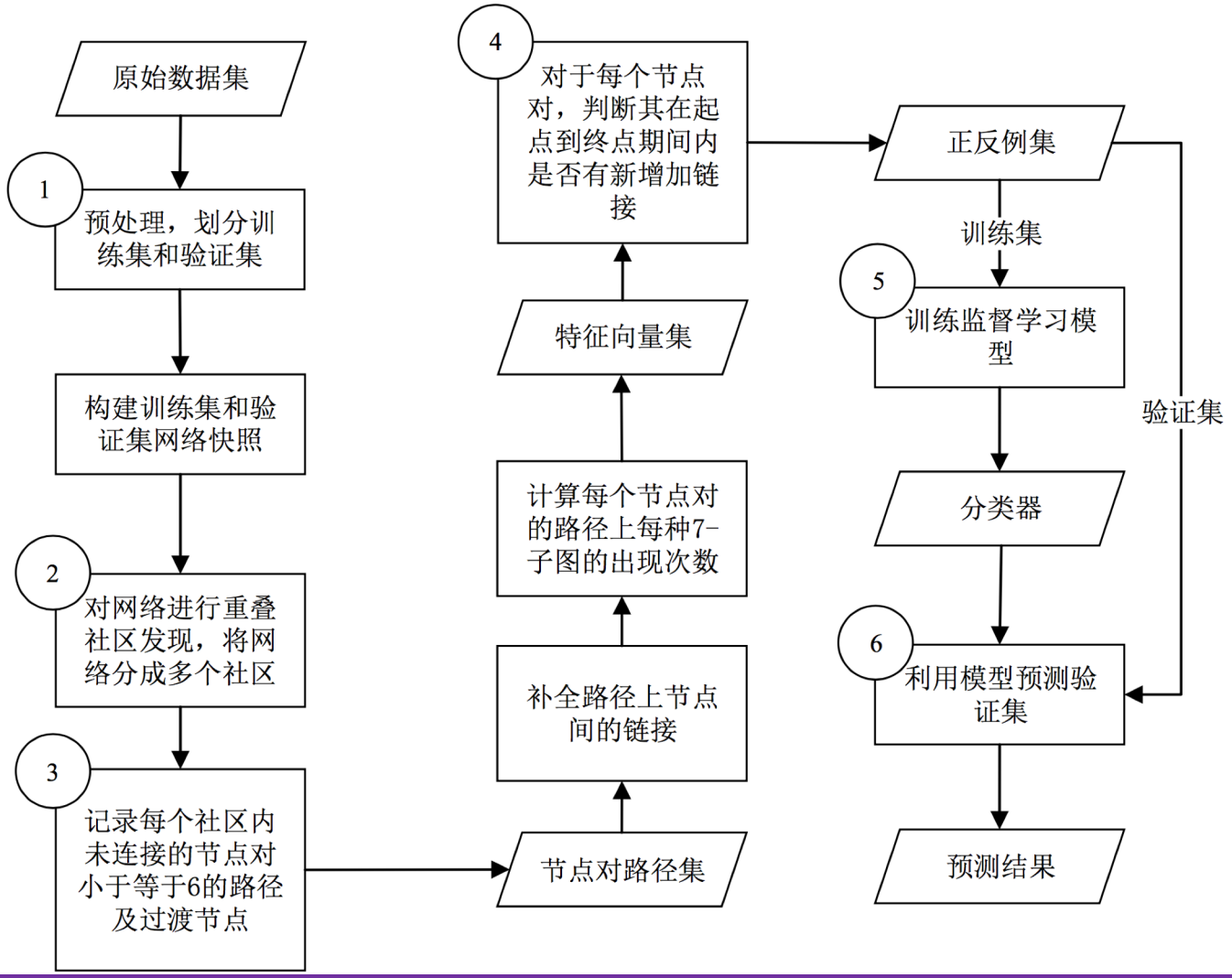
PropFlow

Southeast University

vincent shaw

Rank	Dataset Name	Dataset Type	Grade	AUC
1	Berkeley/Stanford	Temporal Network	0.9822	1.0412
2	Blogs	Temporal Network	0.8701	1.0359
3	Cora Citation	Temporal Network	0.8421	1.31
4	Douban	Temporal Network	0.9848	1.4458

Link prediction based on OVCP structure



Link prediction based on OVCP structure

- **Representation of nodes**
  - ✓ **Limited subgraphs in *n*-size graph**

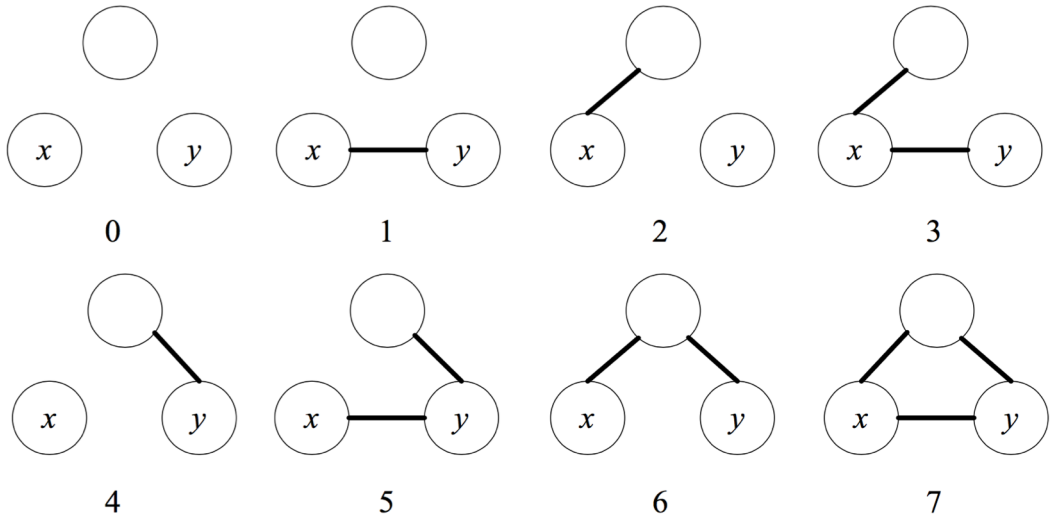


图 3.2 $n = 3$的所有可能子图

Link prediction based on OVCP structure

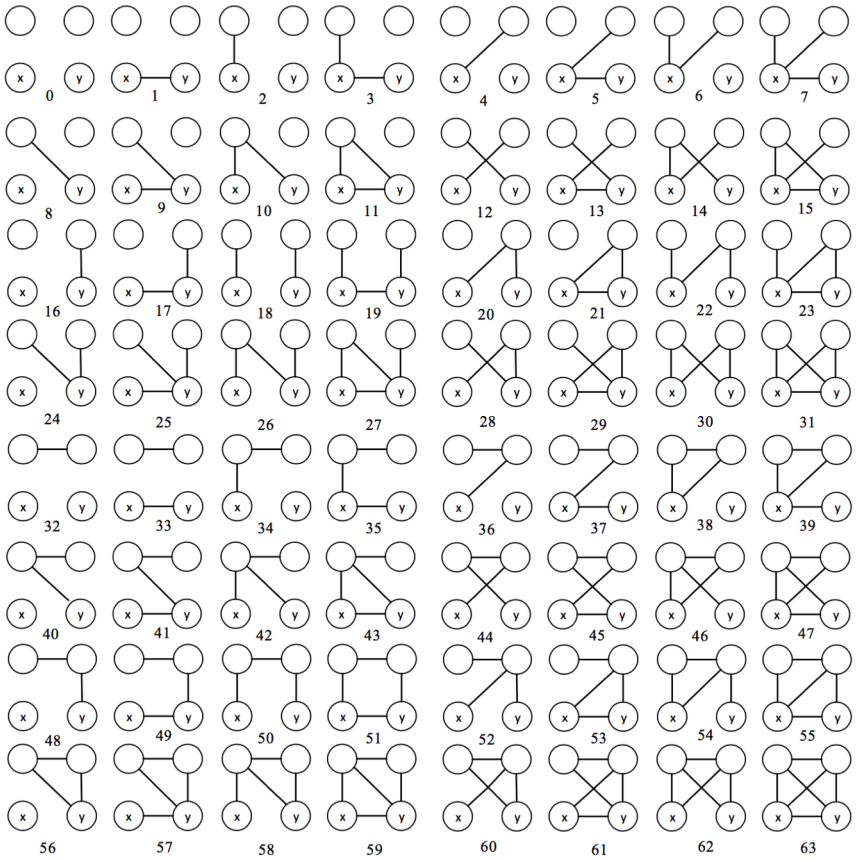


图 3.3 $n = 4$的所有可能子图

Link prediction based on OVCP structure

Representation of nodes

✓ Limited subgraphs in *n*-size graph

（子图位矩阵）对于无向n子图 $G(V,E)$，其位矩阵V是$n\times n$阶矩阵，设矩阵所有元素集为N，则V的定义如下

$$V_n=\left\{\left\{v_{ij}\in N \mid v_{ij}=\begin{cases}2^{\left(n(i-1)-\frac{1}{2}(i-1)(i+1)+j-2\right)} & if\ i<j\\ 0 & if\ i=j\\ 2^{\left(n(j-1)-\frac{1}{2}(j-1)(j+1)+i-2\right)} & if\ i>j\end{cases}\right\}\right\}$$

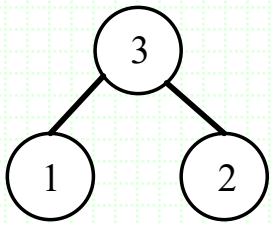
$$V_3=\begin{bmatrix}0 & 2^0 & 2^1\\ 2^0 & 0 & 2^2\\ 2^1 & 2^2 & 0\end{bmatrix}$$

$$V_4=\begin{bmatrix}0 & 2^0 & 2^1 & 2^2\\ 2^0 & 0 & 2^3 & 2^4\\ 2^1 & 2^3 & 0 & 2^5\\ 2^2 & 2^4 & 2^5 & 0\end{bmatrix}$$

Link prediction based on OVCP structure

（**子图地址**）对于n-子图G，将邻接矩阵与位矩阵做内积可以得到子图的地址，定义为

$$\Psi(G)=\sum_{i=1}^{n}\sum_{j=1}^{n}(v_{ij}\times d_{ij})$$



的邻接矩阵为 $\begin{bmatrix}0&0&1\\0&0&1\\1&1&0\end{bmatrix}$

地址为 $\begin{bmatrix}0&0&1\\0&0&1\\1&1&0\end{bmatrix}\cdot\begin{bmatrix}0&2^0&2^1\\2^0&0&2^2\\2^1&2^2&0\end{bmatrix}$

$$=0\times1+1\times2+1\times4+0\times1+1\times2+1\times4$$
$$=110_2\times2$$
$$=12$$

Link prediction based on OVCP structure

- **OVCP feature selection for nodes**
  - ✓ **Do not consider long path: six degrees separation**

We calculate that all subgraphs with the longest paths <6

Total: 78084 subgraphs

Link prediction based on OVCP structure

OVCP feature selection for nodes

✓ Transfer（*V*x,*V*y） to vector

定义 3.11（**7-子图的位矩阵**）具有 7 个节点的无权无向图 G，其位矩阵 V 是7×7阶矩阵，设矩阵所有元素集为 N，则 V 的定义如下

$$V=\left\{\left\{v_{ij}\in N \mid v_{ij}=\begin{cases}2^{\left(7(i-1)-\frac{1}{2}(i-1)(i+1)+j-2\right)} & if\ i<j\\ 0 & if\ i=j\\ 2^{\left(7(j-1)-\frac{1}{2}(j-1)(j+1)+i-2\right)} & if\ i>j\end{cases}\right\}\right. \tag{3-7}$$

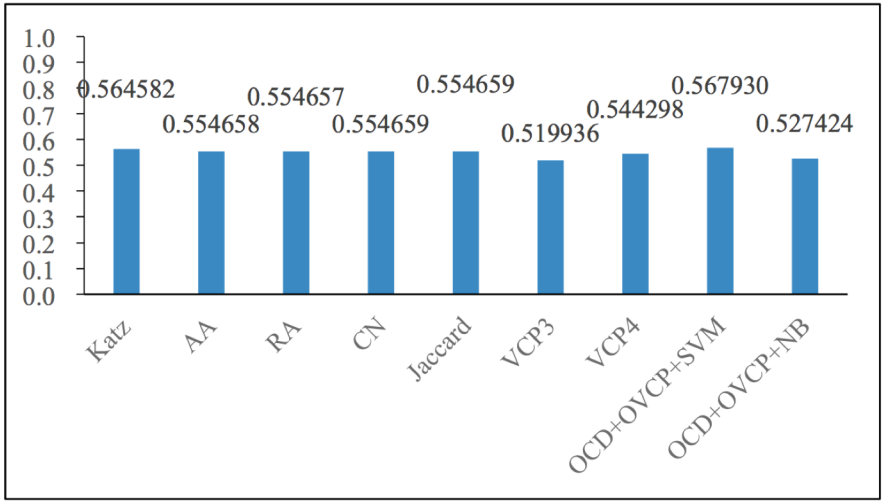
用另一种形式表示，$V=$

$$\begin{bmatrix}0 & 1 & 2 & 4 & 8 & 16 & 32\\ 1 & 0 & 64 & 128 & 256 & 512 & 1024\\ 2 & 64 & 0 & 2^{11} & 2^{12} & 2^{13} & 2^{14}\\ 4 & 128 & 2^{11} & 0 & 2^{15} & 2^{16} & 2^{17}\\ 8 & 256 & 2^{12} & 2^{15} & 0 & 2^{18} & 2^{19}\\ 16 & 512 & 2^{13} & 2^{16} & 2^{18} & 0 & 2^{20}\\ 32 & 1024 & 2^{14} & 2^{17} & 2^{19} & 2^{20} & 0\end{bmatrix}$$

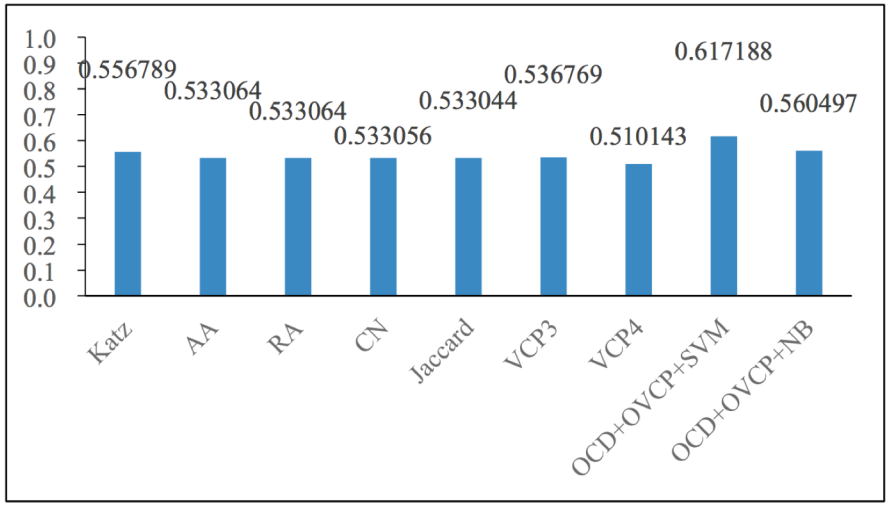
定义 3.12（**7-子图的地址**）7-子图 G 的地址可以用邻接矩阵与位矩阵做内积得到，即

$$\Psi(G)=\sum_{i=1}^{7}\sum_{j=1}^{7}(v_{ij}\times d_{ij}) \tag{3-8}$$

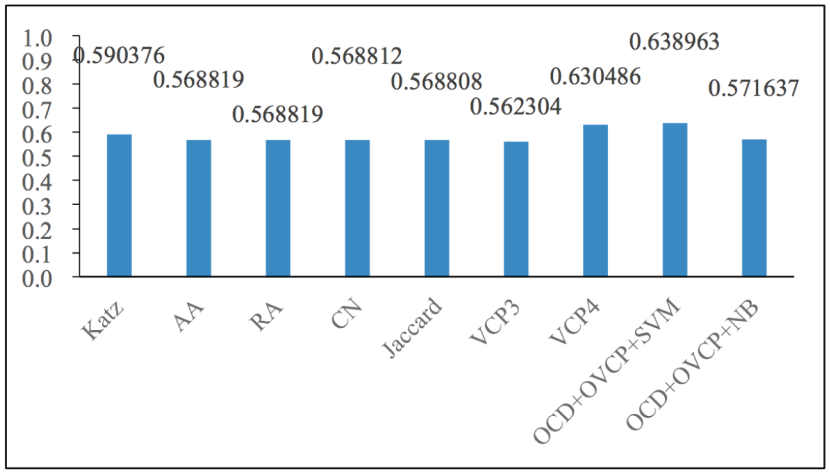
Link prediction based on OVCP structure



(a) DBLP 第一组数据集预测效果

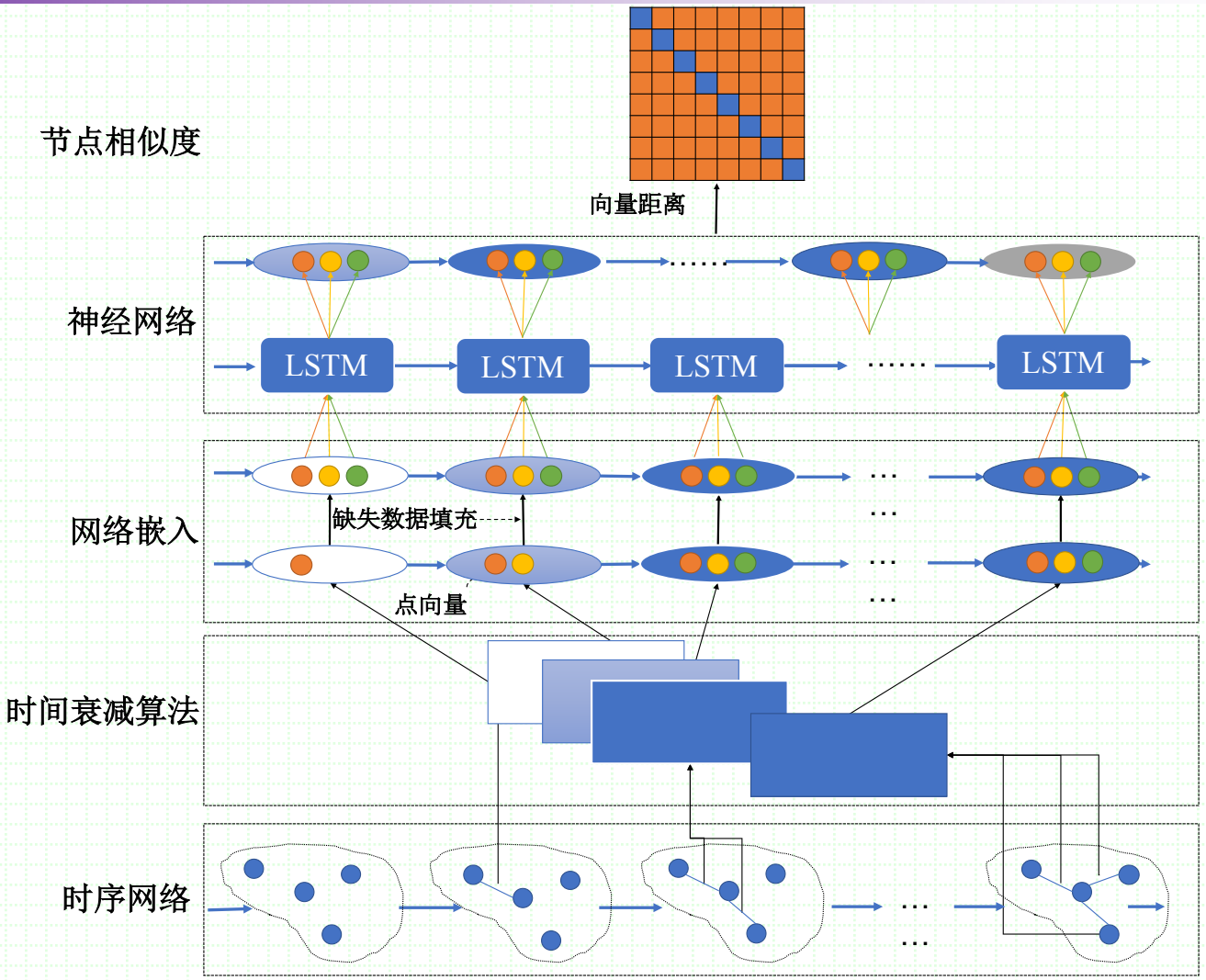


(c) Facebook Friendship 第一组数据集预测效果



(e) Facebook Wall 第一组数据集预测效果

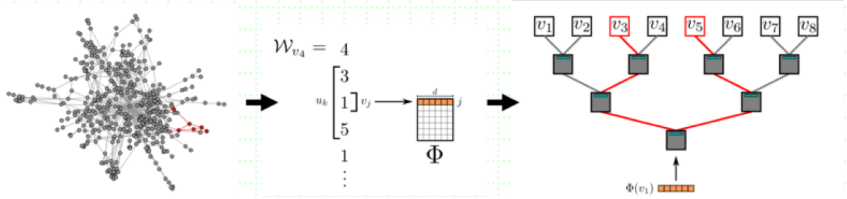
Temporal Link prediction based on DL



Temporal Link prediction based on DL

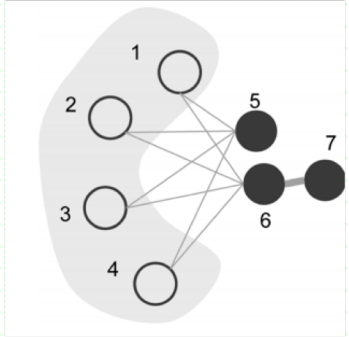
Network embedding

DeepWalk



$$Pr(u|v_j) = \frac{e^{\phi(v_j)\cdot\phi'(u)}}{\sum_{u\in W} e^{\phi(v_j)\cdot\phi'(u)}} \qquad J = -\sum_{u\in C(v_j)} logPr(u|v_j)$$

LINE



$$p_1(v_i, v_j) = \frac{1}{1 + e^{-u_i^T \cdot u_j}}$$

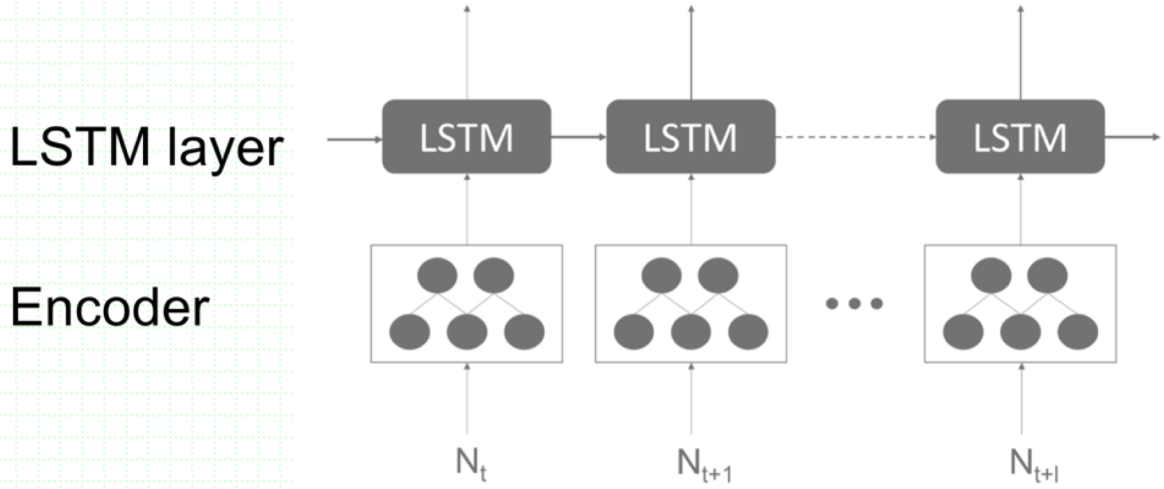
$$p_2(v_j|v_i) = \frac{e^{-u_j'^T \cdot u_i}}{\sum_{k=1}^{|V|} e^{-u_k'^T \cdot u_i}}$$

$$J = -\sum w_{ji} log p_1(v_j, v_i) - \sum w_{ji} log p_2(v_j|v_i)$$

只适用于无权网络

网络嵌入方法	上下文节点的来源	学习方法
DeepWalk	随机游走路径	带有分层 Softmax 的 Skip-gram
LINE	一阶相似度和二阶相似度	带有负采样的 Skip-gram

Temporal Link prediction based on DL



$$L_{t+l} = ||v'_{t+l+1} - v_{t+l+1}||^2 = ||f(v_t, ..., v_{t+l}) - v_{t+l+1}||^2$$

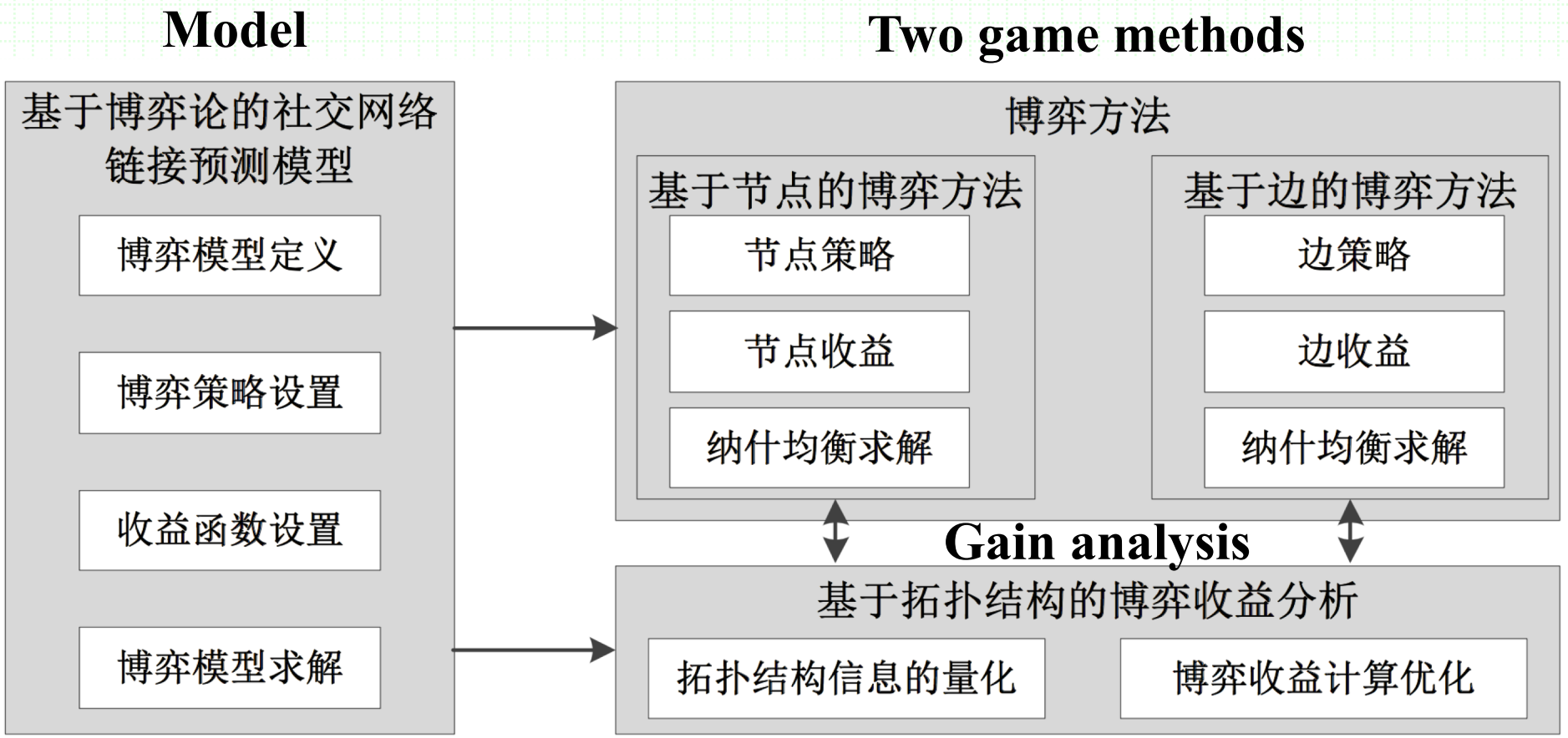
当使用单层LSTM时，前向传播：

$$v'_{t+1} = o_t * tanh(C_t) \qquad o_t = \sigma_t(W_{LSTM}[v'_t, v_t] + b_o)$$

利用梯度下降法优化：

$$\frac{\partial L_t}{\partial W} = [2(v'_{t+1} - v_{t+1})] \cdot [\frac{\partial f(V * W + b)}{\partial W}]$$

Link Prection based on Game Theory



Link Prection based on Game Theory

- **Current issues**
  - ✓ 预测结果的可解释性不强(interpretability)

无法精确捕获社交行为
无法有效捕获用户决策

  - ✓ 忽略了社交网络本身的“社会”特性(social features)

与社会理论成果结合不深
没有考虑社交用户——人的理性和自私

human sense

Link Prection based on Game Theory

- **Our novel model**

基于博弈的社交网络链接预测模型

✓ 博弈参与者(Player)：

社交网络中的用户

✓ 博弈策略(Strategy)：

如何构造博弈策略

✓ 博弈收益(Playoff)：

如何使收益最大化

博弈求解：纳什均衡，时间复杂度NP-Hard

Link Prection based on Game Theory

- **Node based game: NGLP**

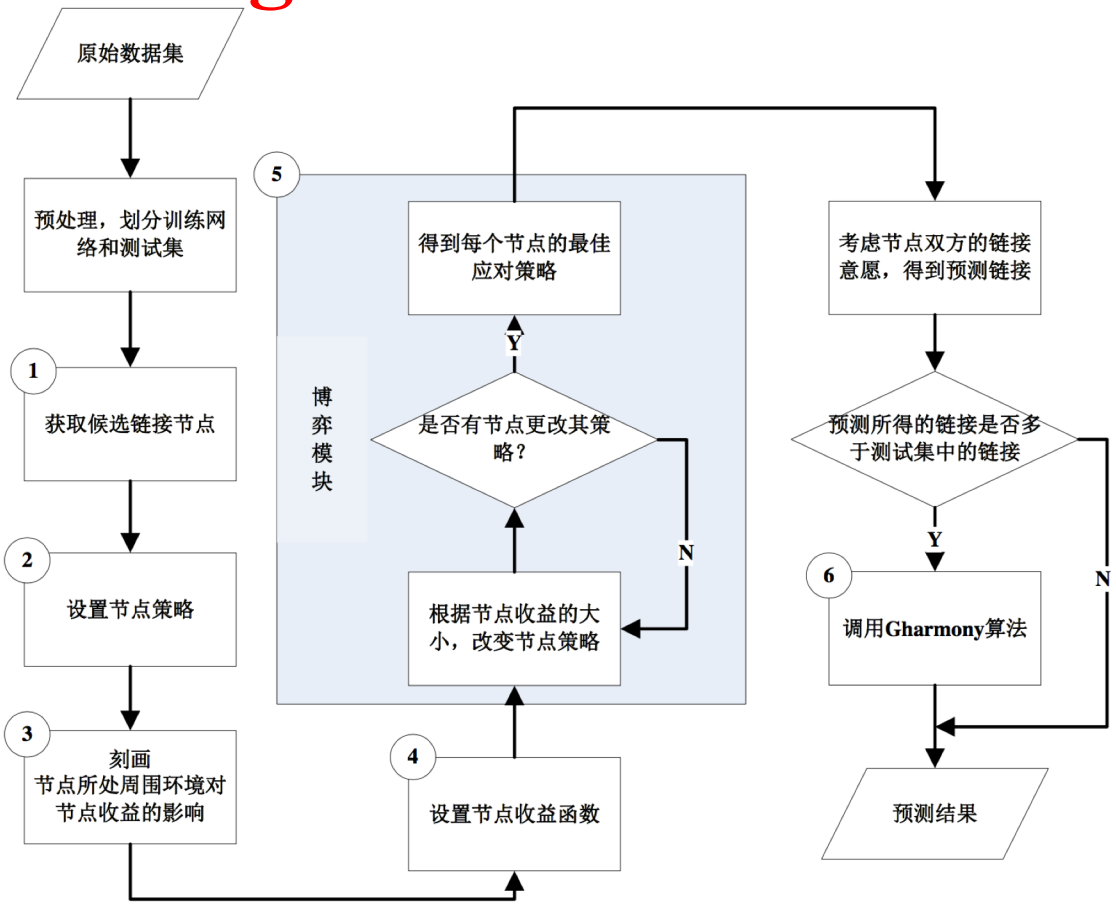


图 3-1NGLP 方法的流程图

Link Prection based on Game Theory

- **Node based game: NGLP**

Most new links have small length

绝大部分新链接形成与距离2-3的节点之间

表 3-1 社交网络中的路径距离对链接形成的影响

	$\delta=2$	$\delta=3$	$\delta=4$	$\delta=5$	$\delta=6$	$\delta\succ 6$
Jazz	100%	0	0	0	0	0
Hamsterster	95.43%	2.52%	0.60%	0.06%	0.00%	1.39%
Email	71.43%	18.50%	5.86%	0.73%	0.00%	3.48%
Enron	90.96%	2.40%	0.20%	0.07%	0.01%	6.36%
Facebook	99.65%	0.22%	0.00%	0.01%	0.00%	0.01%
CA-GrQc	83.16%	2.48%	0.97%	0.00%	0.83%	11.25%
CA-HepTh	81.85%	3.76%	2.13%	1.20%	0.97%	10.09%
CA-HepPh	96.56%	1.23%	0.48%	0.22%	0.12%	1.39%
Twitter	99.08%	0.47%	0.00%	0.00%	0.00%	0.45%
Weibo	46.82%	16.28%	5.00%	0.00%	0.00%	31.90%

Link Prection based on Game Theory

Node based game: NGLP

Node strategy

节点策略：选择距离2-3的节点作为候选链接节点

定义 3-2(节点策略)：给定一个社交网络 $G(V,E)$，对于 $\forall i \in V$，节点 i 的策略 s_i 为节点 i 的链接候选节点的子集

$$s_i \subset \{t \mid t \in cNode(i)\} \tag{3-2}$$

此时节点策略方法的时间复杂度和空间复杂度均为 $O(2^{|cNode|})$，其中，$0 \le |cNode| < N - \bar{d}$，$|cNode|$ 表示网络的平均链接候选节点个数。可以发现，当网络达到一定规模时，我们仍然很难在多项式时间和空间内给出所有的节点策略。

策略复杂度的解决：；去除重复策略，且每次只选择一个最佳策略

Link Prection based on Game Theory

Node based game: NGLP

Node gain

节点收益：利用节点所处拓扑结构进行收益量化分析

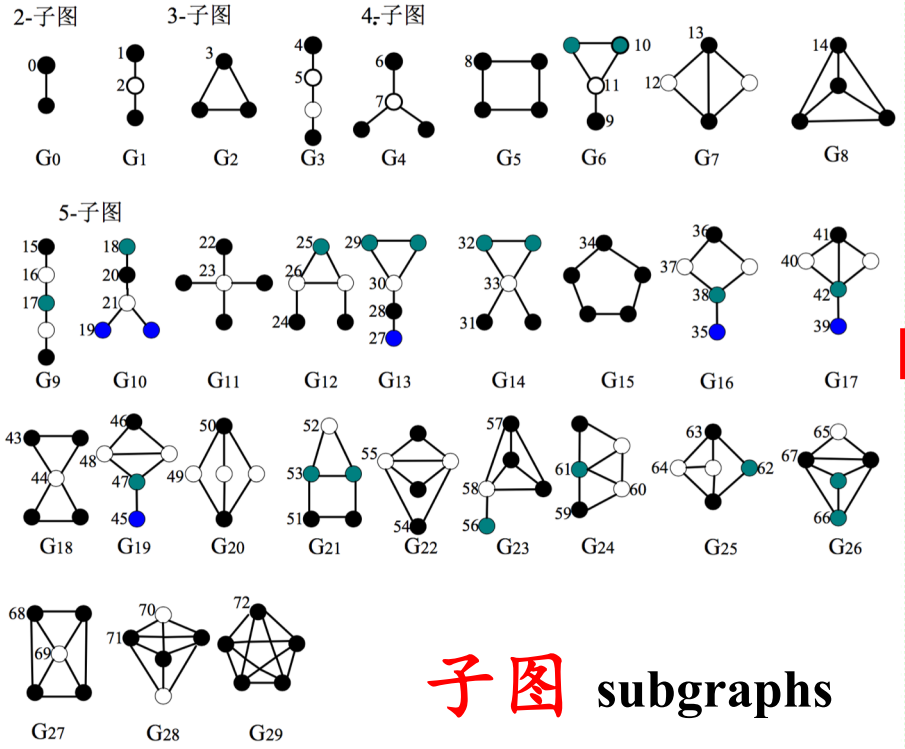


图 3-6 由 2,3,4,5 节点组成的所有子图(Graphlet)

子图 subgraphs

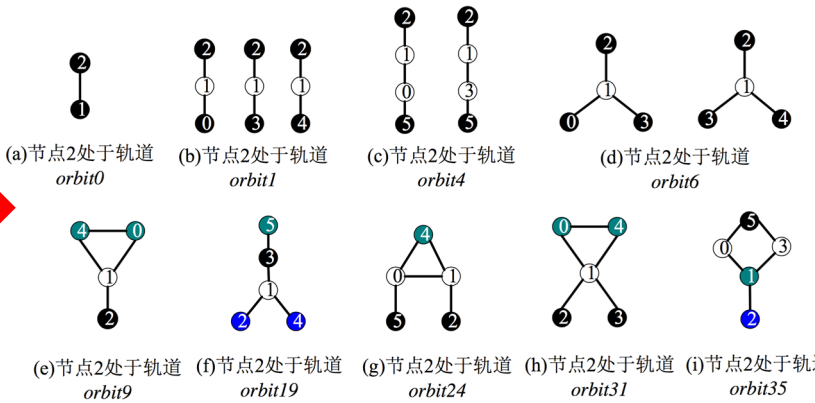


图 3-7 节点 2 与其他节点组成的所有子图

Orbit vector **轨道向量**

Link Prection based on Game Theory

Node based game: NGLP

轨道向量：量化表示节点在特定拓扑结构下的收益情况

定义 3-12(权力向量)：给定社交网络 $G(V,E)$，以及任意轨道 *orbitx* 的轨道占比 $ratio(x)$。我们称网络 $G(V,E)$的权力向量为各个轨道对节点收益的影响权重，

$$powerVector = (powerVector(0), powerVector(1),..., powerVector(k)) \quad (3\text{-}10)$$

其中 $powerVector(x)$为轨道 *orbitx* 的权力参数，表明轨道 *orbitx* 对节点收益的影响。 k 表示轨道的个数。

Link Prection based on Game Theory

Node based game: NGLP

收益函数 $Payoff_i(s) = GainNode_i(s) - LossNode_i(s)$

定义 3-14(福利函数——$GainNode_i(s)$)：给定社交网络 $G(V,E)$以及网络的当前策略组合 $s=(s_i,s_{-i})$，令节点 i 的福利为 特定拓扑结构中获得的福利

$$GainNode_i(s) = orbitVector(i) \times powerVector^T \quad (3\text{-}12)$$

维持链接需要付出成本（例如脚踏两只船、一心二用）

定义 3-15(损失函数——$LossNode_i(s)$)：给定社交网络 $G(V,E)$以及网络的当前策略组合 $s=(s_i,s_{-i})$，节点 i 的损失开销为

$$LossNode_i(s) = d(i) \times c \quad (3\text{-}13)$$

Link Prection based on Game Theory

Node based game: NGLP

算法复杂度优化：

1、若节点 i 利用 **Join** 操作，往其最佳应对策略 s_i 中加入一个链接候选节点 j，生成新策略 s_i'。那么，节点 i 选择新策略下所处的周围拓扑结构环境中将出现一条新边 $\langle i, j \rangle$

2、节点 i 利用 **Leave** 操作，从其最佳应对策略 s_i 中移除一个节点 j，生成当前策略 s_i'。那么，节点 i 选择当前策略下所处的周围拓扑结构环境中的边 $\langle i, j \rangle$ 被移除。

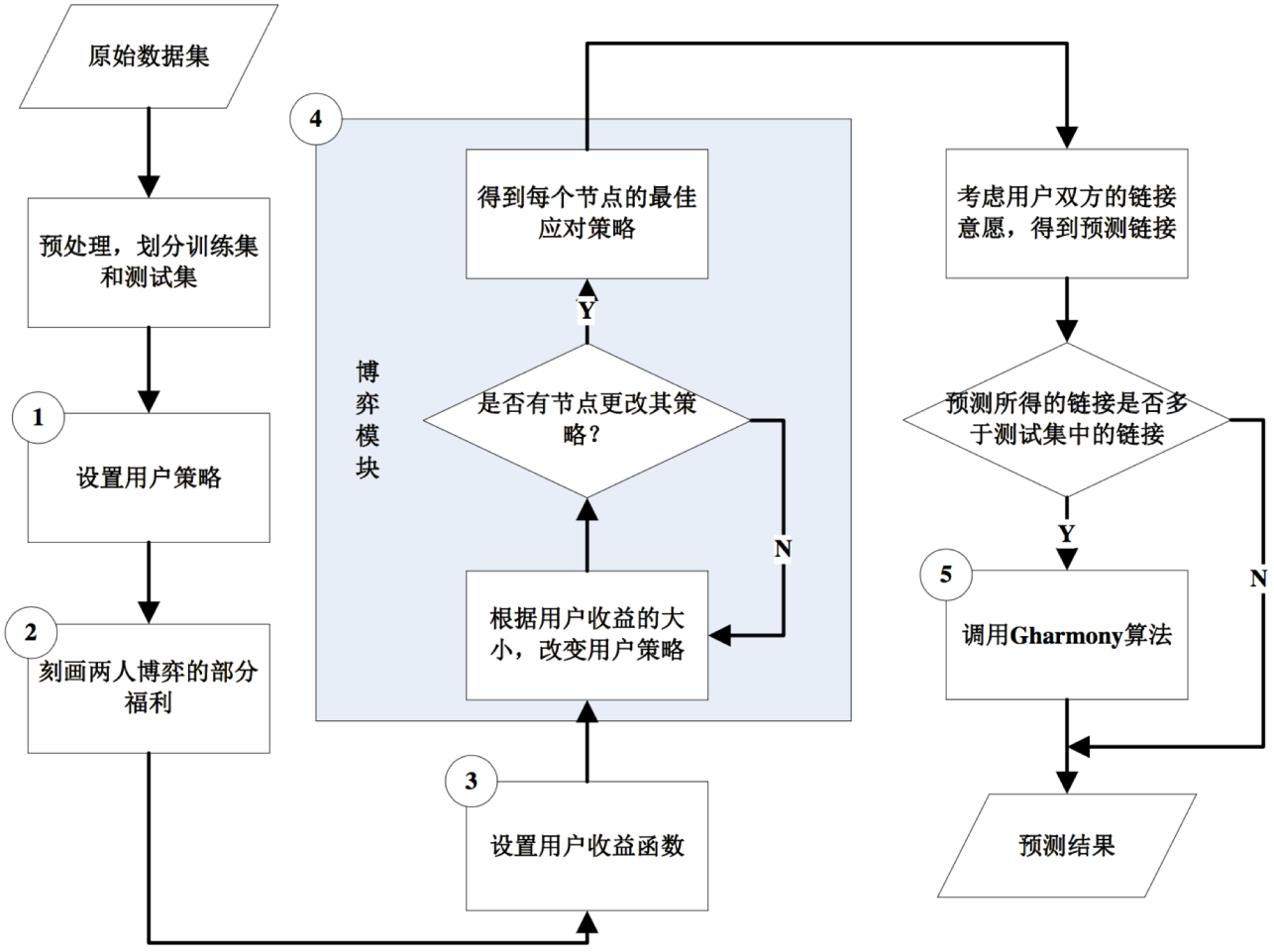
纳什均衡求解：

定理 3-1：在一定条件下，NLGP 博弈为潜能博弈，存在纯策略纳什均衡解。

博弈结果过滤：

Link Prection based on Game Theory

- **Edge based game: NGLP**



Link Prection based on Game Theory

- 实验评估：数据集

表 5-1 各数据集的网络拓扑信息

数据集	节点数	边数	平均度	平均聚集系数	直径
Jazz	198	2742	27.7	0.6174	6.0
Hamsterster	2426	16631	13.71	0.5376	10
Email	1133	5451	9.62	0.2202	8
Enron	36692	183831	10.02	0.4970	11
CA-GrQc	5242	14496	5.53	0.5296	17
CA-HepTh	9877	25998	5.26	0.4714	17
CA-HepPh	12008	118521	19.74	0.6115	13
Facebook	4039	88234	43.69	0.6055	8
Twitter	81306	1768149	43.49	0.5653	7
Weibo	135623	276739	4.08	0.0958	4.0

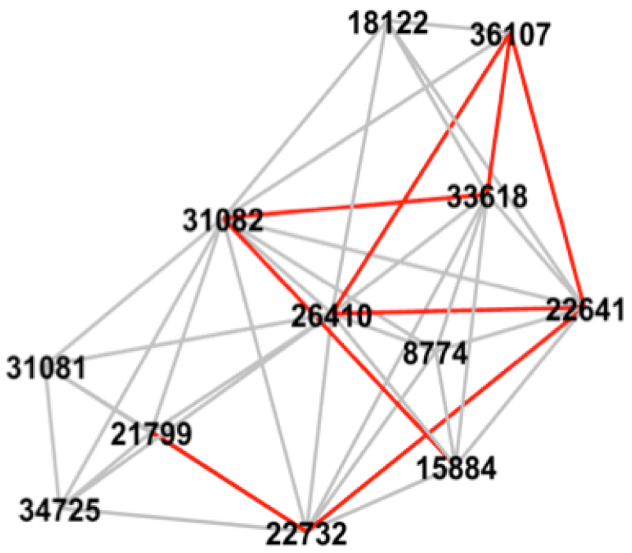
表 5-3 各个链接预测方法在多个数据集上的预测效果

		NGLP	EGLP	RA	PF	KZ	CN	AA	JC	PA	RPR	VCP
Jazz	F1	0.549	0.549	**0.567**	0.385	0.483	0.516	0.552	0.534	0.123	0.36	0.218
	AUC	**0.59**	0.591	0.549	0.279	0.471	0.498	0.552	0.509	0.082	0.269	0.175
Hamsterster	F1	0.332	0.325	**0.343**	0.297	0.198	0.202	0.257	0.232	0.046	0.243	0.127
	AUC	**0.36**	0.328	0.293	0.245	0.142	0.146	0.194	0.199	0.029	0.194	0.149
Email	F1	**0.17**	0.166	0.157	0.059	0.135	0.145	0.168	0.068	0.024	0.048	0.031
	AUC	**0.239**	0.161	0.101	0.03	0.106	0.114	0.124	0.033	0.012	0.026	0.048
Enron	F1	0.217	0.214	0.328	0.167	**0.334**	0.133	0.155	0.001	0.032	0.133	0.049
	AUC	0.22	0.231	0.271	0.139	**0.897**	0.096	0.114	0.011	0.019	0.106	0.057
CA-GrQc	F1	0.409	0.39	**0.543**	0.326	0.344	0.363	0.464	0.349	0.049	0.159	0.207
	AUC	0.474	0.436	**0.515**	0.252	0.315	0.327	0.449	0.26	0.037	0.125	0.331
CA-HepTh	F1	0.286	0.274	**0.346**	0.189	0.201	0.233	0.335	0.142	0.003	0.155	0.094
	AUC	**0.306**	0.291	0.3	0.137	0.164	0.184	0.284	0.099	0.002	0.127	0.172
CA-HepPh	F1	0.521	0.573	**0.778**	0.276	0.477	0.503	0.585	0.565	0.256	0.15	0.186
	AUC	0.608	0.657	**0.805**	0.216	0.465	0.492	0.577	0.533	0.233	0.099	0.197
Facebook	F1	0.352	0.364	**0.452**	0.186	0.315	0.317	0.334	0.323	0.055	0.17	0.141
	AUC	**0.412**	0.409	0.411	0.119	0.255	0.259	0.275	0.249	0.024	0.126	0.108
Twitter	F1	0.246	N/A	**0.296**	0.128	0.066	0.197	0.231	0.077	0.014	0.134	0.057
	AUC	**0.282**	N/A	0.233	0.136	0.044	0.14	0.169	0.032	0.008	0.09	0.046
Weibo	F1	0.043	N/A	0.027	0.012	**0.05**	0.049	0.04	0	0.015	0.012	0.001
	AUC	**0.036**	N/A	0.021	0.023	0.034	0.032	0.026	0	0.009	0.007	0.003

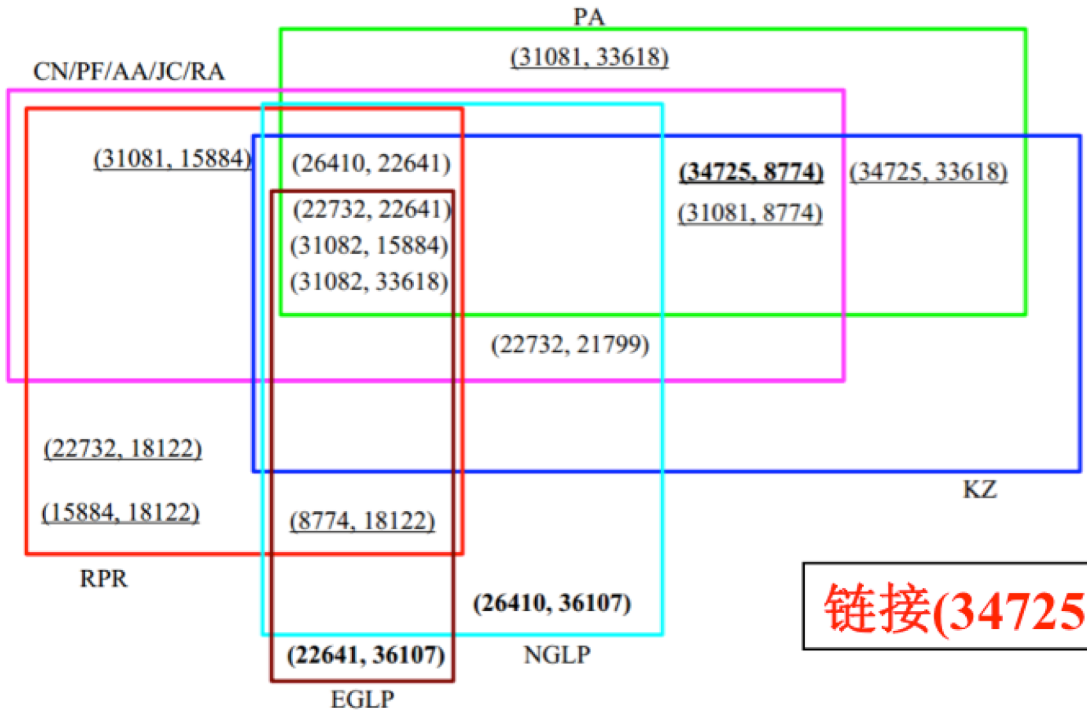
Link Prection based on Game Theory

- **Advantage 1:**

能过滤掉一些节点之间相似度较高的错误的链接



Enron数据集的
一个连通子图

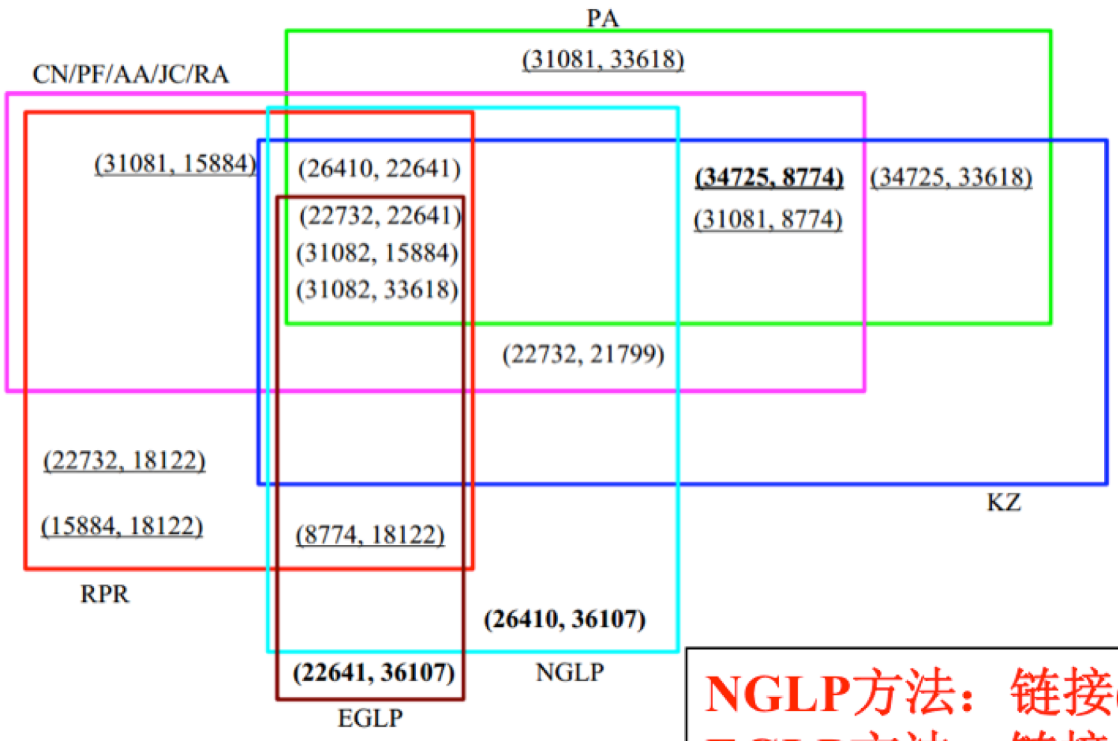


链接(34725,8774)

Link Prection based on Game Theory

- **Advantage 2：**

能够预测到其他方法预测不到的链接。



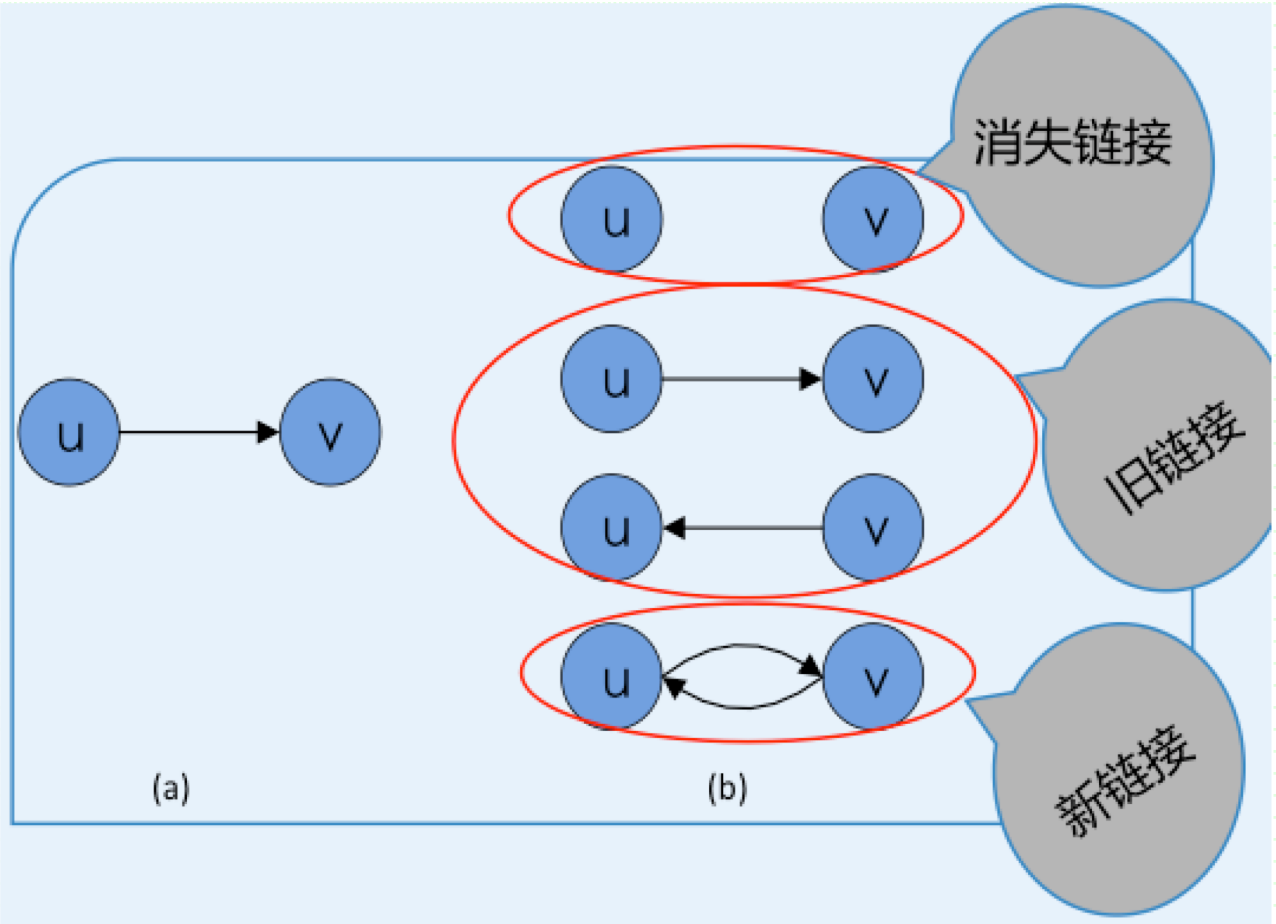
链接(26410,22641)

新链接的形成对网络节点策略选择的影响

NGLP方法：链接(26410,36107)
EGLP方法：链接(22641,36107)

The predictability of disappearing links

- **Problem**



The predictability of disappearing links

- 消失链接现象实证分析 empirical analysis

链接比例分布

各符号表示含义：

- E_1和E_2----子网络G_1和G_2共有节点链接集合
- S_{Dis} ----消失链接集合
- S_{new}----新链接集合
- S_{Old}----旧链接集合

消失链接比例（*ratio_dis*）

$$ratio\_dis = \frac{|S_{Dis}|}{|E_1|}$$

新链接比例（*ratio_new*）

$$ratio\_new = \frac{|S_{New}|}{|E_2|}$$

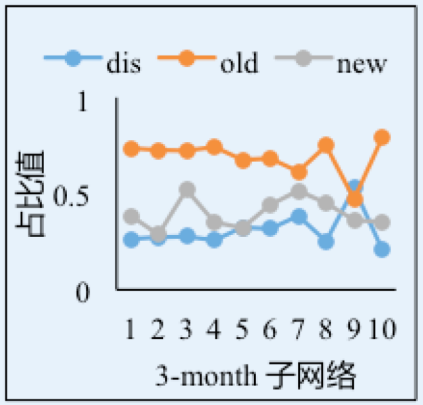
继续存在链接比例（*ratio_old*）

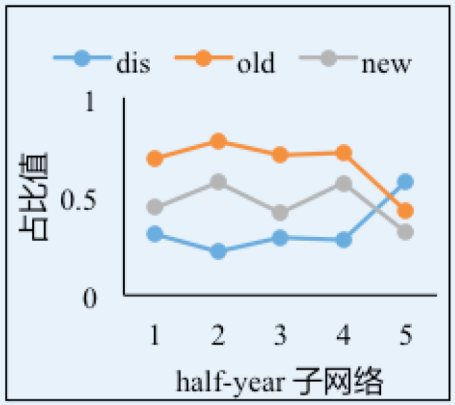
$$ratio\_old = \frac{|S_{Old}|}{|E_1|}$$

The predictability of disappearing links

- 消失链接现象实证分析 empirical analysis

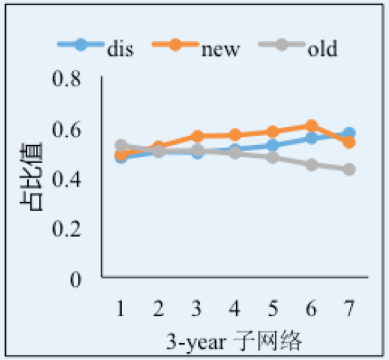
Enron

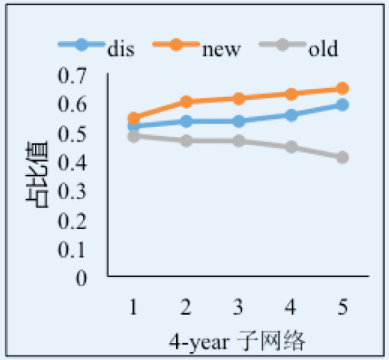


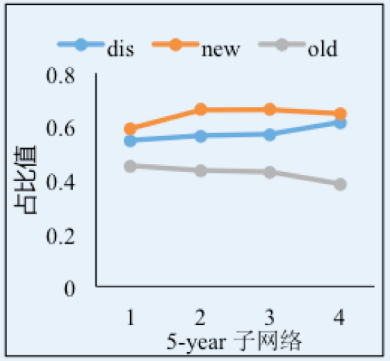


真实社交网络中的消失链接现象普遍存在

DBLP







The predictability of disappearing links

- 消失链接现象实证分析 empirical analysis

互惠性

嵌入性

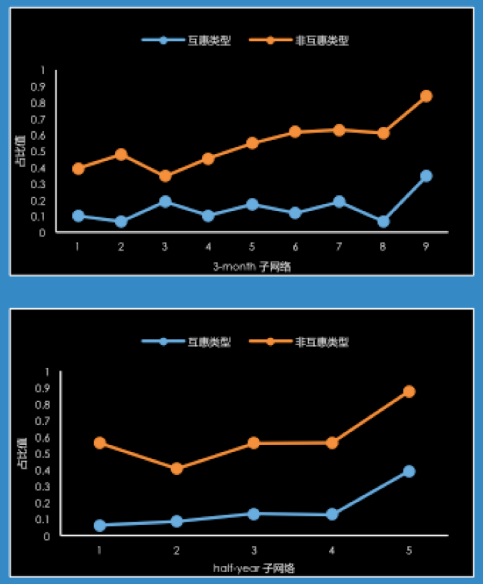
互动频率

时间属性

Enron实验结果：满足互惠性质的链接消失的可能性明显小于不满足互惠性质的情况

互惠性：有向网络，具体表现为两节点之间链接的双向性。

Enron数据集



The predictability of disappearing links

- 消失链接现象实证分析 empirical analysis

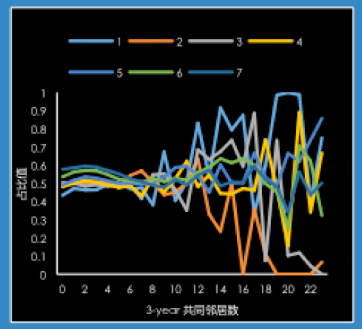
互惠性

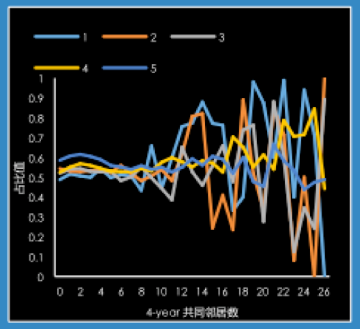
嵌入性

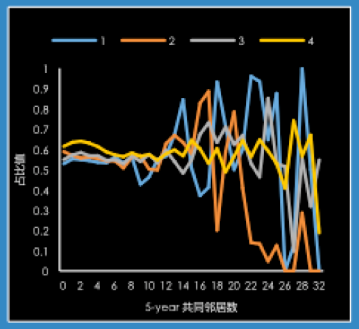
互动频率

时间属性

DBLP







嵌入性：定义为两节点的共同邻居数

DBLP:嵌入性链接的消失预测作用不明显

The predictability of disappearing links

- 消失链接现象实证分析 empirical analysis

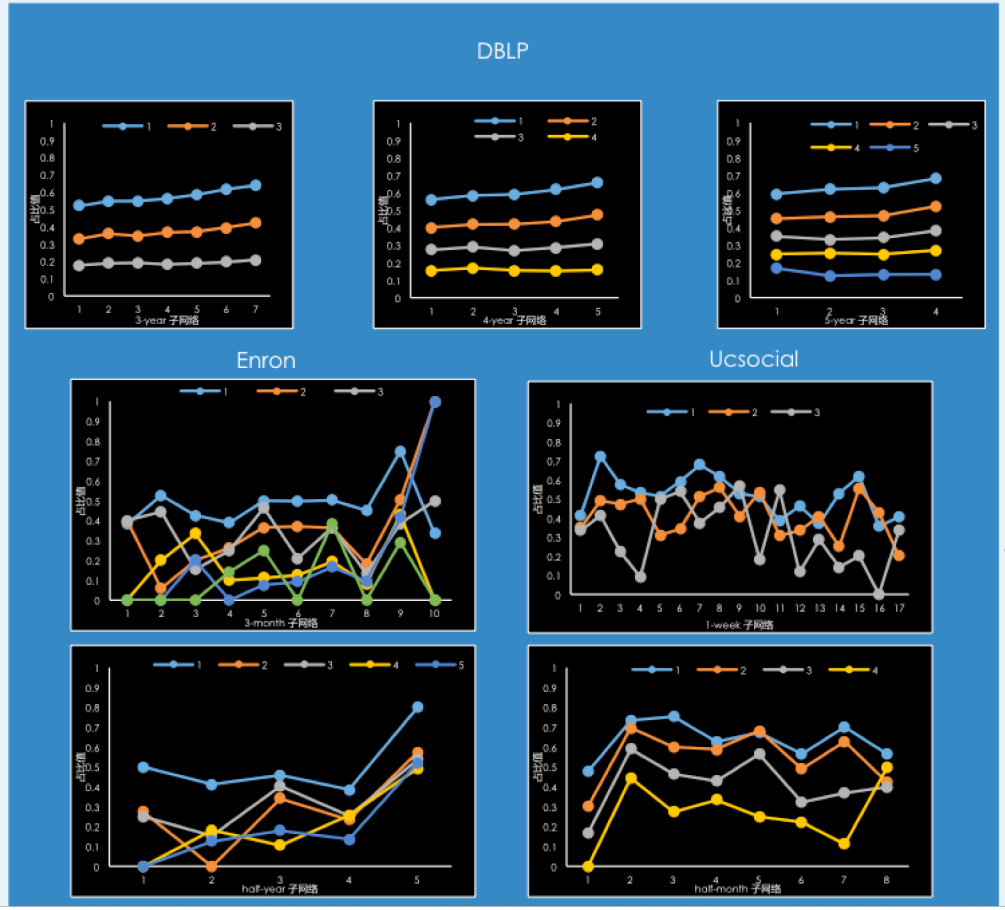
互惠性

嵌入性

互动频率

时间属性

互动频率：相互交流的次数衡量



实验结果：
链接互动频率的增加可以减小消失的概率。

The predictability of disappearing links

- 消失链接现象实证分析 empirical analysis

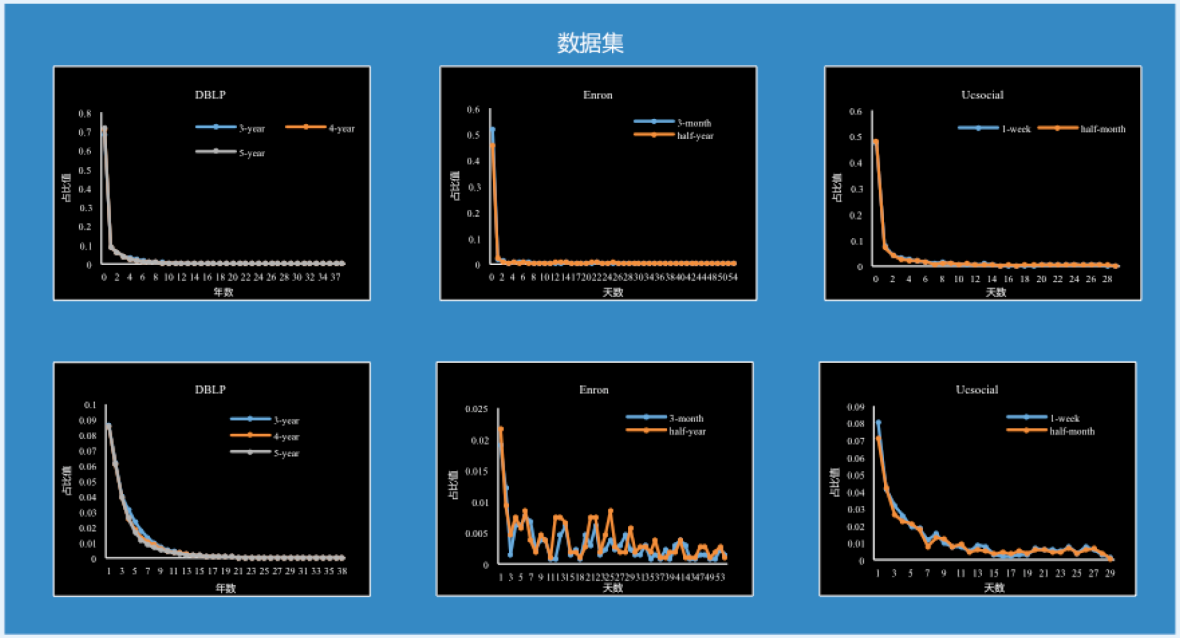
互惠性

嵌入性

互动频率

时间属性

时间属性：链接生存时间



实验结果表明：

网络中的时序信息对于实验结果有着显著的影响，特别是当链接的生存时间小于某一阈值时，其消失概率随着生存时间的增加显著减小；当其生存时间大于某一阈值时，链接的消失概率同生存之间不在具有显著的相关性

The predictability of disappearing links

- 消失链接预测方法 Prediction methods

无向无权网络

同质性

优先连接

三度影响力

社会比较理论

子图转移概率矩阵

链接联系强度

基于同质性理论的相似性指标

- CN指标： $s_{xy}=|\Gamma(x)\cap\Gamma(y)|$
- Salton指标： $s_{xy}=\frac{|\Gamma(x)\cap\Gamma(y)|}{\sqrt{k_x k_y}}$
- Jaccard指标： $s_{xy}=\frac{|\Gamma(x)\cap\Gamma(y)|}{|\Gamma(x)\cup\Gamma(y)|}$
- Sorenson指标： $s_{xy}=\frac{2\times|\Gamma(x)\cap\Gamma(y)|}{k_x+k_y}$
- HPI指标： $s_{xy}=\frac{|\Gamma(x)\cap\Gamma(y)|}{\min\{k_x,k_y\}}$
- HDI指标： $s_{xy}=\frac{|\Gamma(x)\cap\Gamma(y)|}{\max\{k_x,k_y\}}$
- LHN-I指标： $s_{xy}=\frac{|\Gamma(x)\cap\Gamma(y)|}{k_x k_y}$
- AA指标： $s_{xy}=\sum_{z\in\Gamma(x)\cap\Gamma(y)}\frac{1}{\log k_z}$
- RA指标： $s_{xy}=\sum_{z\in\Gamma(x)\cap\Gamma(y)}\frac{1}{k_z}$

各符号表示含义：

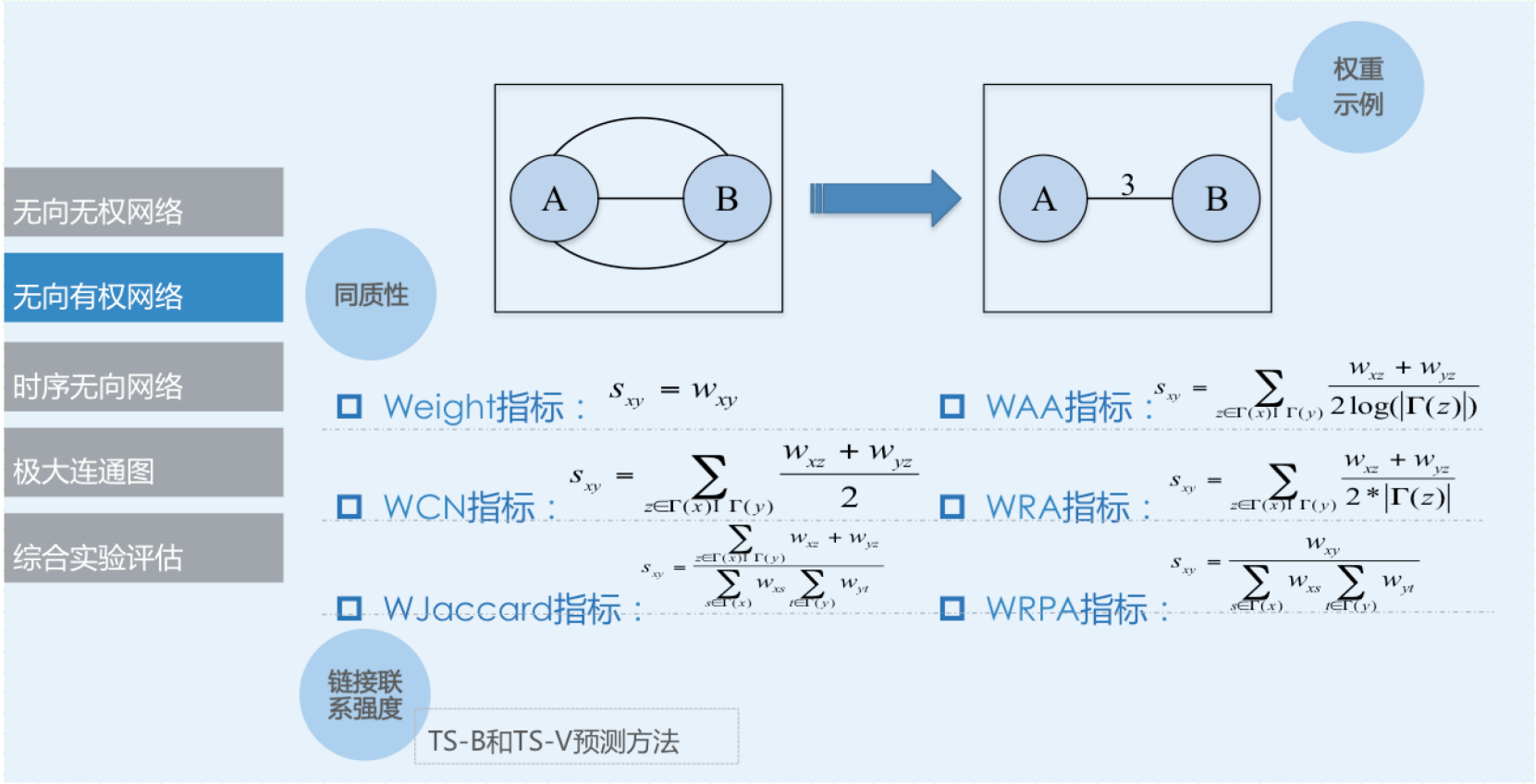
- $\Gamma(x)$---节点 v_x 邻居节点集合
- k_x ----节点 v_x 度数值

二者关系： $k_x=|\Gamma(x)|$

The predictability of disappearing links

- 消失链接预测方法 Prediction methods

无向有权网络



The predictability of disappearing links

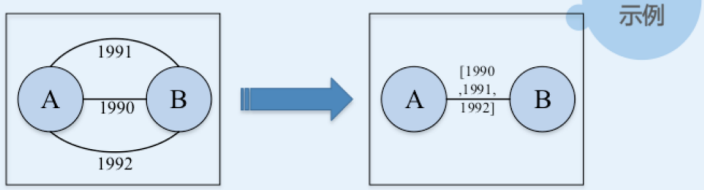
- 消失链接预测方法 Prediction methods

无向时序网络

无向无权网络
无向有权网络
时序无向网络
极大连通图
综合实验评估

预测指标

时序示例



- FirstLast(FL)指标：主要衡量的是链接存在的时间长度；本文认为，该链接的存在时间越长，则该链接的稳定性越高；其中$First(x,y)$表示的是链接(x,y)首次出现的时间，$Last(x,y)$表示的是链接(x,y)最新出现的时间。定义为

$$T_{xy} = Last(x,y) - First(x,y)$$

- ActiveMulti(AM)指标：主要通过链接两端节点的最近活跃时间去度量链接的活跃程度；本文认为该链接两端的节点越活跃，则该链接的稳定性越高；其中，T 表示当前时间，$last(x)$表示的是节点 v_x的最近活跃时间。为了使得分母不为0，故加1处理。定义为

$$T_{xy} = \frac{1}{(T - last(x) + 1)(T - last(y) + 1)}$$

- TimeList(TL)指标：主要是通过引入影响因子去衡量不同的时序信息对整个链接的存在稳定性的作用；本文认为链接两端节点的合作时间越近，则对当前链接的稳定性影响程度越大；其中 $\alpha \in [0,1)$为影响因子，$[t_1,t_2,\mathrm{L}$ 为网络中的当前链接的时序信息列表。定义为

$$T_{xy} = \sum_{t \in [t_1,t_2,\mathrm{L}]} (1-\alpha)^{(T-t)}$$

The predictability of disappearing links

Factor analysis

- 消失链接预测因素的相关性分析

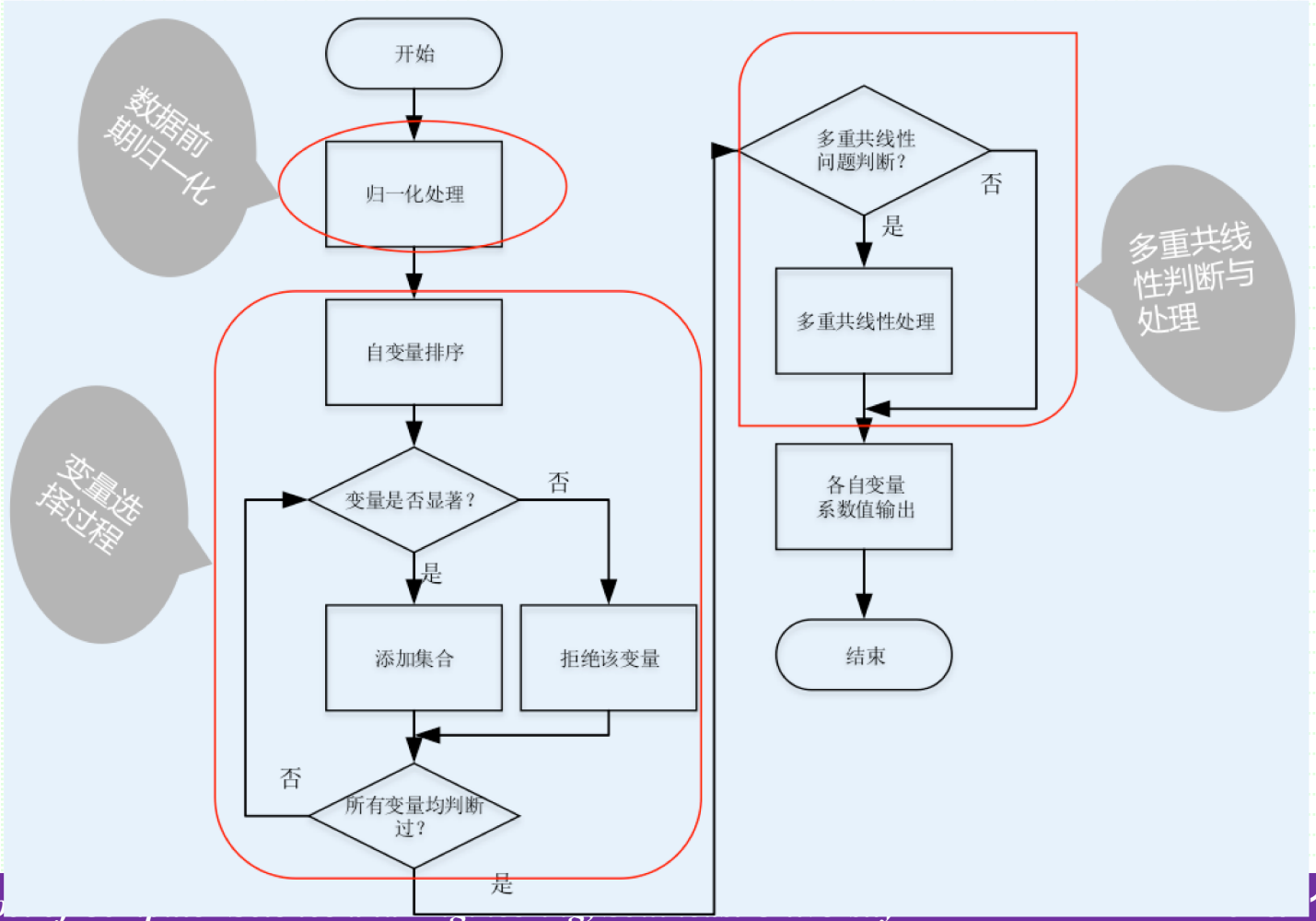
拓扑结构度量	符号/定义	含义
节点数	n	描述网络中节点总数
链接数	m	描述网络中链接总数
最大度	$k_{\max}$	描述所有节点中度数最大值
平均度	$< k >$	描述网络中节点的平均链接数
密度	D	衡量网络稀疏程度
聚集系数	C	描述节点的平均聚集程度
网络效率	E	描述网络连通性能
锲形数目	s	描述2-星数目
爪形数目	z	描述3-星数目
三角数目	t	描述三元闭包的数目
幂律	λ	节点度分布幂律值
相关链接分布熵	H_{er}	网络中度分布的等价程度
同配系数	r	描述链接形成的偏好性

The predictability of disappearing links

Factor analysis

- 消失链接预测因素的相关性分析

多元线性相关性分析过程



The predictability of disappearing links

Factor analysis

消失链接预测因素的相关性分析

主要工作一：无向无权网络

- 基于无向网络中各拓扑结构和预测指标效果值之间的多元相关性分析结果，经过数据归一化、变量选择和多重共线性处理，得到最后结果，分析并得出结论。

主要工作二：最大连通图

- 基于最大连通图中各拓扑结构和预测指标效果值之间的多元相关性分析结果，经过数据归一化、变量选择和多重共线性处理，得到最后结果，分析并得出结论。

主要工作四：综合结果

- 综观所有结果，选择显著影响的拓扑特征

主要工作三：有向网络

- 基于有向网络中各拓扑结构和预测指标效果值之间的多元相关性分析结果，经过数据归一化、变量选择和多重共线性处理，得到最后结果，分析并得出结论。

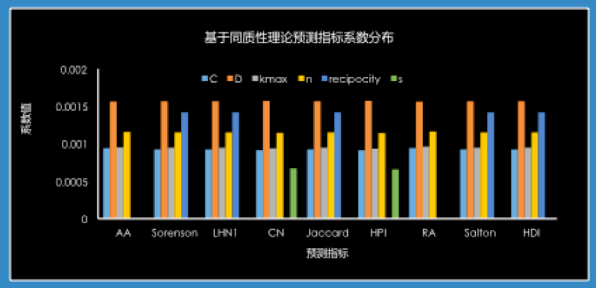
The predictability of disappearing links

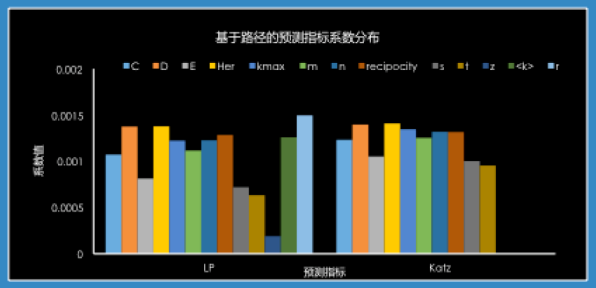
Factor analysis

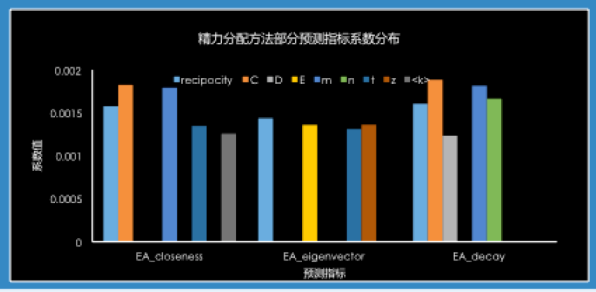
消失链接预测因素的相关性分析

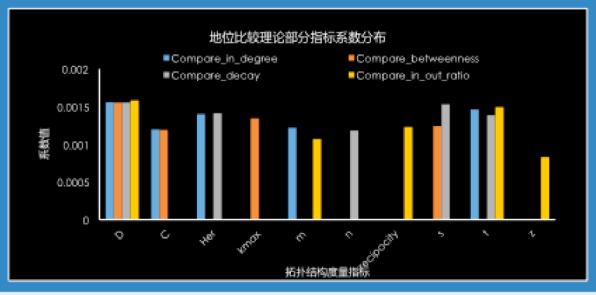
- 消失链接现象
- 链接预测方法
- 相关性分析
- 网络演化模型

Ucsocial









实验结果表明

- 有向无权Ucsocial网络中经岭回归方法处理后可知C和D度量方式对各指标综合影响最深。

Evolution model for disappearing links

描述

前提：初始状态为n_0个节点构成的完全网络G_0，网络G_t在下个时间步$t+1$，将以不同的概率发生下列的三种事件，且每个时间步有且仅有一种事件发生。

1）**新节点添加：**

以概率p_a发生该事件。事件描述为：将一个新节点添加到网络中，以偏好概率

$$P_{t+1}[u]=\frac{d_t(u)}{\sum_{w\in V_t} d_t(w)}=\frac{d_t(u)}{2m_t}$$

同网络中已有节点之间建立c_1条链接。

Evolution model for disappearing links

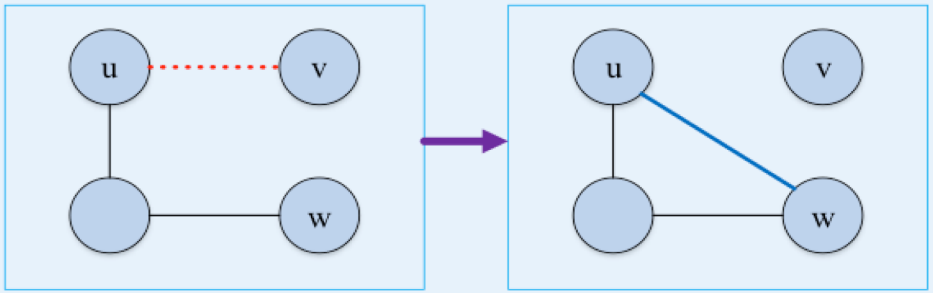
描述

2) 链接重连：

以概率 p_b 发生该事件。事件描述为：以反偏好概率

$$P_{t+1}[u] = \frac{n_t - d_t(u)}{n_t^2 - 2m_t}$$

选择节点，同时在节点的邻居节点中以反偏好概率选择节点 ，删除二者之间的连线；再以偏好概率在网络中选择节点同该节点建立链接。此事件重复发生 c_2 次。



3） 旧节点消失：

以概率 $p_c = 1 - p_a - p_b$ 发生该事件。事件描述为：以反偏好概率选择节点删除，同时将该节点相关链接删除。

Evolution model for disappearing links

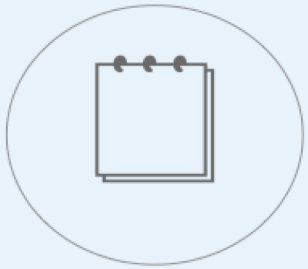
证明目标：LWBA模型中节点数、链接数、平均节点度等特征如何变化？LWBA模型中**度分布**是否符合幂律分布？

证明思路

节点数

- 同新节点添加事件；旧节点消失事件有关
- 表示为：

$$n_t = (p_a - p_c)t$$



链接数

- 同新节点添加事件；旧节点消失事件有关
- 表示为：

$$E[m_t] = \frac{c_1 p_a}{1+\left(\frac{2p_c}{p_a - p_c}\right)}t$$

平均节点度

- 同节点数和链接数相关，表达式：

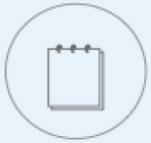
$$\bar{d}_t = \frac{2m_t}{N_t} = \frac{\left[\frac{2c_1 p_a}{1+\left(\frac{2p_c}{p_a - p_c}\right)}t\right]}{(p_a - p_c)t} = \frac{2c_1 p_a}{p_a + p_c}$$

Evolution model for disappearing links

LWBA模型中度分布证明思路： $P[k]=\lim_{t\to+\infty}\frac{N_{k,t}}{N_t}$

新节点添加

- 新节点的影响：分为 $k=c\downarrow 1$ 和 $k\neq c\downarrow 1$
- 已有节点的影响：节点度数为 k 和 $k-1$ 的情况



链接重连

- 链接消失相关节点影响：节点度数为 k 和 $k+1$ 的情况
- 链接新生相关节点影响：节点度数为 k 和 $k-1$ 的情况

旧节点消失

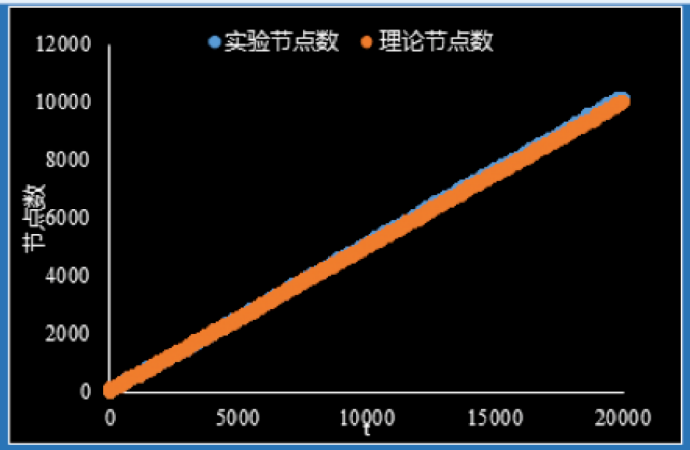
- 消失节点的影响：节点度数为 k
- 消失节点相关邻居节点：节点度数为 k 和 $k+1$ 的情况

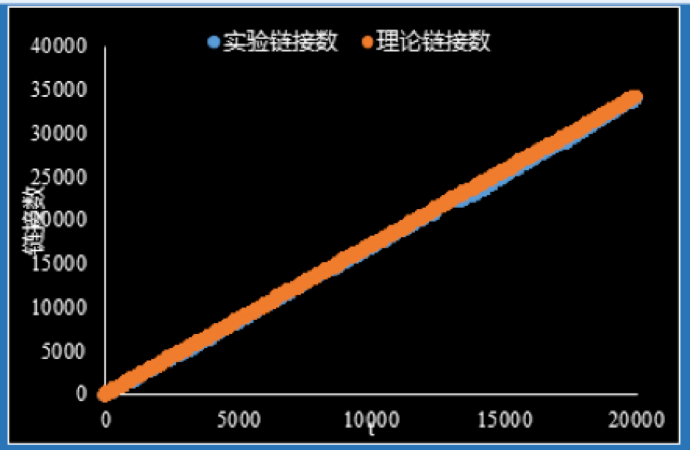
度分布结果为：$p[k]: k^{-1-\left[\frac{-2c_1p_ap_a}{2c_1p_ap_c-(p_ac_1+p_bc_2)(p_a+p_c)}\right]}$

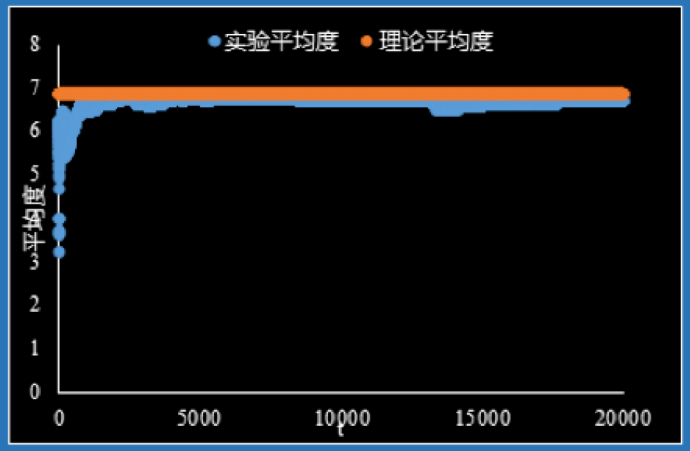
需要注意的是当 $p_a=1, p_b=p_c=0$ 时，整个模型退化为BA模型

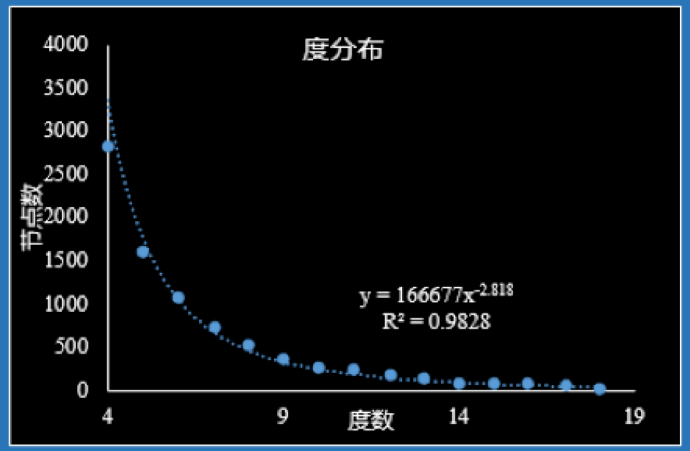
Evolution model for disappearing links

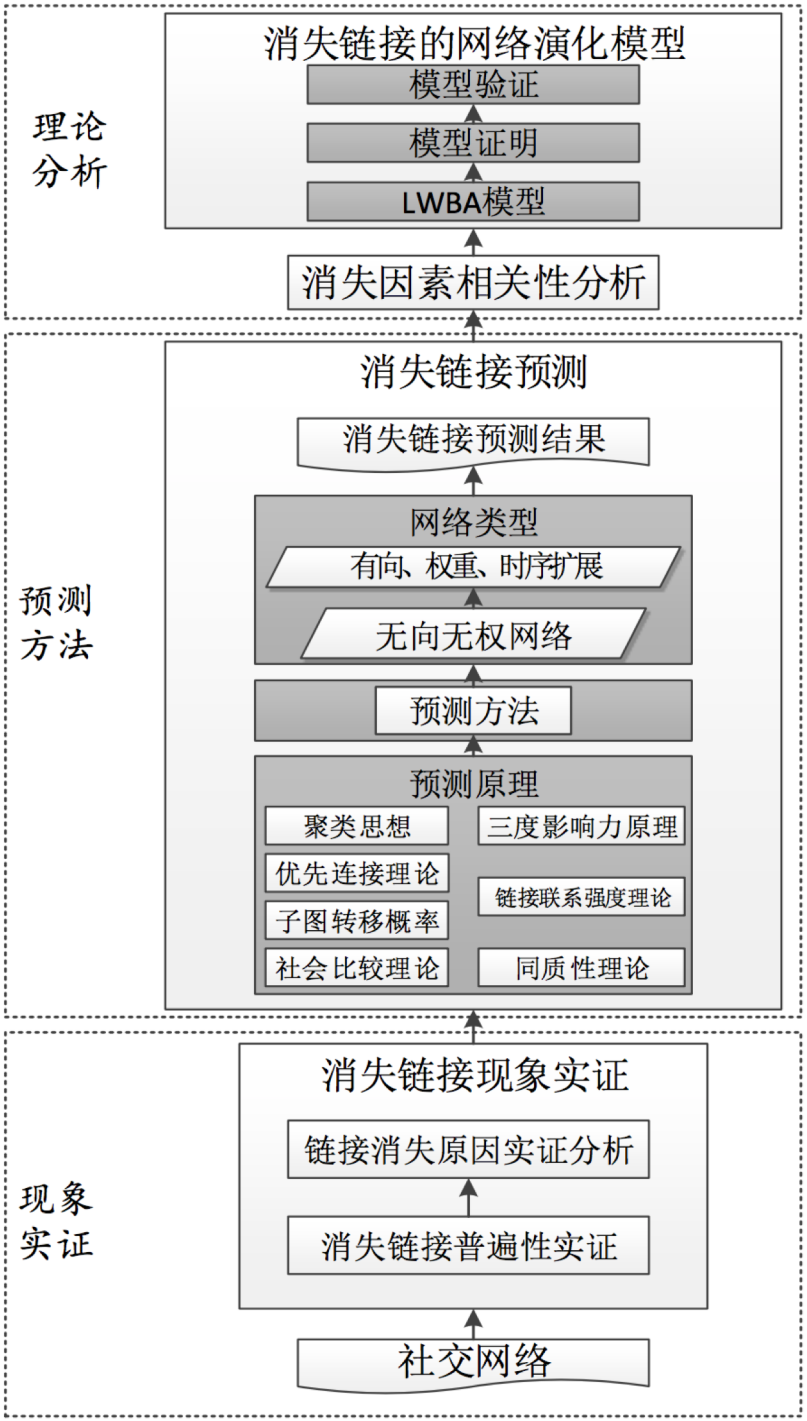
- 正常情况 case2:Pa=0.6,pb=0.3,pc=0.1: 度分布-2.78



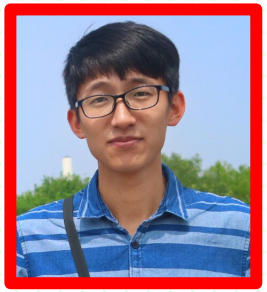







理论分析
消失链接的网络演化模型
模型验证
模型证明
LWBA模型
消失因素相关性分析
预测方法
消失链接预测
消失链接预测结果
网络类型
有向、权重、时序扩展
无向无权网络
预测方法
预测原理
聚类思想
三度影响力原理
优先连接理论
链接联系强度理论
子图转移概率
社会比较理论
同质性理论
现象实证
消失链接现象实证
链接消失原因实证分析
消失链接普遍性实证
社交网络

Some KGCode members in the above work



ASSIGNMENT

Link Prediction in Social Networks

- Goal
  - Implement at least 3 classical link prediction methods for social networks
  - Use network embedding (Deepwalk, LINE, node2vec) for link prediction
  - Baseline: CN, AA, and RA
- Datasets
  - Social Networks: http://snap.stanford.edu/data/ego-Facebook.html
  - Others: SNAP http://snap.stanford.edu/data/index.html

Link Prediction in Social Networks

- Paper writing: a team paper can be collaborated written including:
  - abstract / problem definition / approach overview
  - details of algorithms / experiments / related works / reference
  - LNCS template with latex
  - PPT
- References

[1] Liben-Nowell D, Kleinberg J M. The link-prediction problem for social networks. J Am Soc Inf Sci Technol, 2007, 58: 1019–1031

[2] Wang, Peng, et al. "Link prediction in social networks: the state-of-the-art." *Science China Information Sciences* 58.1 (2015): 1-38.

[3] Cui, Peng, et al. "A survey on network embedding." *IEEE Transactions on Knowledge and Data Engineering* 31.5 (2018): 833-852.

धन्यवाद
Hindi

多謝
Traditional Chinese

ขอบคุณ
Thai

Спасибо
Russian

Gracias
Spanish

شكرا
Arabic

Thank You
English

Obrigado
Brazilian Portuguese

Danke
German

Grazie
Italian

多谢
Simplified Chinese

Merci
French

நன்றி
Tamil

ありがとうございました
Japanese

감사합니다
Korean

Email: pwang@seu.edu.cn