25 Years of Collaborations in *IEEE Intelligent Systems*

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This article looks at IEEE Intelligent Systems' 25-year history and studies the evolution of scientific collaboration among IS authors through coauthorship network analysis.

In the past 25 years, *IEEE Intelligent Systems* (also named *IEEE Expert* from 1986 to 1997 and *IEEE Intelligent Systems and Their Applications* from 1997 to 2000) has witnessed the change in AI research topics and the rapid development of the field.¹ These changes happened under a joint effort

of international researchers. Previously, Daniel O'Leary examined the key contributors of *IS* from 1998 to 2008.² This article looks at the entire 25-year history and focuses on studying the evolution of scientific collaboration among *IS* authors through coauthorship network analysis. The analyses are conducted at researcher, institution, and country levels.

Data Set and Methodology

We downloaded the metadata for *IS* articles from the Institute for Scientific Information (ISI) Web of Science, an online academic citation index provided by Thomson Reuters (www.isiknowledge.com). Because this database did not record the *IS* articles published in 1986, we collected such papers from IEEE Xplore (<http://ieeexplore.ieee.org>). Our data set covers articles from 1986 (vol. 1, issue 1) to 2010 (vol. 25, issue 2).

IS magazine covers a wide range of information. To investigate scientific collaborations among researchers, we used only research reports such as paper submissions from authors and recommended by conferences as well as special issue guest editor introductions (which usually review the special issue's subject area). We did not include other articles, such as book, database, hardware, and software reviews; news; corrections; letters; interviews; notes; biographical items; and EIC editorials, in our analysis. The final data set contains 1,870 research articles.

We adopted a social network analysis approach and studied the collaborations among *IS* researchers via their coauthorship networks. This approach has been widely used in previous studies on scientific collaboration.³⁻⁸ In this article, we examine the collaborations at researcher, institution, and country and territory levels. In the researcher-level coauthorship network, each

Table 1. Topics (and classification codes) in three time periods

Rank	Period I	Period II	Period III
1	Computer software, data handling, and applications (723)	Computer software, data handling, and applications (723)	Computer software, data handling, and applications (723)
2	Automatic control principles and applications (731)	Computer systems and equipment (722)	Mathematics (921)
3	Industrial engineering and management (912)	Information science (903)	Information science (903)
4	Engineering profession (901)	Mathematics (921)	Automatic control principles and applications (731)
5	Light, optics, and optical devices (741)	Automatic control principles and applications (731)	Computer systems and equipment (722)

Table 2. Network topological measures for researcher-level coauthorship network.

Measure*	1986–1993	1986–2004	1986–2010
<i>N</i>	655	2282	3232
<i>L</i>	660	3476	5464
Δ	0.003	0.001	0.001
<i>NC</i>	303	780	970
<i>N_G</i> (%)	17 (2.6%)	254 (11.1%)	579 (17.9%)
$\langle d \rangle$	2.015	3.046	3.381
<i>C</i>	0.442	0.595	0.636
<i>l</i>	1.434	6.840	6.954
<i>D</i>	6	18	15

**N* is the number of nodes, *L* is the number of links, Δ is the network density, *NC* is the number of components, *N_G* is the number of nodes in the giant component, $\langle d \rangle$ is the average degree, *C* is the clustering coefficient, *l* is the average shortest path length, and *D* is the network diameter.

node corresponds to an *IS* author, and each link between two authors represents that they have coauthored in *IS*. To construct the institution- and country-and-territory-level coauthorship networks, we aggregated researcher-level coauthor relations. The link between two nodes indicates researchers from the corresponding institutions (or countries and territories) have coauthored in *IS*. This study treated all networks as undirected graphs.

Twenty-five years is not a short time in the history of computer science and AI. In this research, we examined the evolution of coauthorship networks by separating the data set into multiple time periods. Instead of arbitrarily choosing segmentations, we separated the data set according to the coherence of article topics. We used the Compendex Classification

Code provided by Engineering Village (www.engineeringvillage.com) as an abbreviated representation of the topics. We compiled time series vectors on the portion of articles for each classification code in each year. We applied two basic time series segmentation algorithms:

- the Nearest Neighbor Algorithm,⁹ which separates the time series at points with the largest topic differences between consecutive years, and
- the Bottom-Up Algorithm,¹⁰ which iteratively combines consecutive time segments according to their difference.

Both methods suggested that the most significant topic changes happened between 1993–1994 and 2004–2005. Thus, we separated the data set into

three periods: 1986–1993 (Period I), 1994–2004 (Period II), and 2005–2010 (Period III). We then inspected the collaboration at the end of each time period. Table 1 shows major research areas in each time period.

We applied topological analysis to unveil the overall collaboration patterns among *IS* researchers. We analyzed the degree distributions to describe node connectivity in co-authorship networks and inspected the growth of the giant component (the largest connected component) to show the network structure changes.^{11,12} Then we tested the small-world property and analyzed the change of the average shortest path lengths to investigate the networks’ knowledge diffusion efficiency.^{5,13} We identified the key collaboration facilitators through three measures in the coauthorship networks: degree, betweenness,¹⁴ and PageRank.¹⁵ We also adopted the Girvan-Newman algorithm to extract the major collaboration clusters in *IS*.¹⁶

In this research, we used the yEd Graph Editor toolkit (www.yworks.com/en/products_yed_about.html) and Netdraw (www.analytictech.com/netdraw/netdraw.htm) for visualization.

Collaborations among Researchers

Table 2 reports topological measures of the cumulative coauthorship networks formed at the end of each time period. There were 655 (660), 2,282 (3,476), and 3,232 (5,464) distinct nodes (links) at the end of Periods I, II, and III, respectively. The networks are generally sparse. The network densities at the end of Periods I, II, and III were 0.003, 0.001, and 0.001, respectively. We noticed that the network had a giant component and many small components.

Figure 1. Researcher-level collaboration network. Node size is proportional to number of publications. Node color indicates collaboration clusters.

The numbers of components NC were 303, 780, and 970, respectively. Because our research includes IS

articles, which cover a broad research area, it is not surprising to see sparse collaboration networks like these.

Figure 1 visualizes the researcher-level coauthorship network. We used three link colors to indicate the

collaborations that happened in the three time periods: blue for Period I, orange for Period II, and olive green for Period III. Node size is proportional to the number of articles published by a corresponding author. The figure clearly shows the network change, especially in the giant component. In Period I, collaborations were sparse and nodes were dispersed

into many small clusters. There were mainly small-scale collaborations. During Period II, a significant number of collaborations occurred, which connected small clusters to a chain structure. The major portion of the giant component was formed at this stage. After 2004 (Period III), more collaboration showed up and worked as shortcuts that further connect nodes in the giant component to a ring structure. The giant components contained 17, 254, and 579 nodes, which occupied 2.6, 11.1, and 17.9 percent of the entire network, respectively, for the networks at the end of the three time periods. This increasing trend shows that the interconnections among *IS* authors were getting stronger. The *IS* researchers were gradually forming a larger community.

In a coauthorship network, the average degree $\langle d \rangle$ indicates the average number of collaborators a node has in the network. It increased from 2.015 to 3.046 and 3.381 at the end of the three time periods. On average, there was an increasing trend in *IS* author collaboration. More researchers tended to work together on projects in AI fields. Figure 2 shows the degree distributions of the three networks. The degree distribution $p(k)$ of our network roughly follows

Figure 2. Degree distributions of the coauthorship networks.

a power-law distribution when degree is larger than six, which indicates that high degree authors have a higher probability to have future collaborations.

In our data set, the average shortest path lengths l are relatively small compared with a previously proposed empirical formula: $l = 0.35 + 2.06 \log(N)$.¹³ In addition, the networks' clustering coefficients C were 0.442, 0.595, and 0.636, which were many times larger than the expected values of the Erdos-Renyi random networks with the same size. The large values of C show that coauthors tend to work in clusters in the coauthorship network. These characteristics indicate that the *IS* researcher-level coauthorship networks possess the small-world property that has been observed in other coauthorship networks.⁵

Although the small-world phenomenon in general shows a certain level of knowledge diffusion efficiency, the fractions of giant components in the networks were small (2.6, 11.1, and 17.9 percent). The scope of possible knowledge diffusion is still limited. However, the steadily increasing number shows an evolving collaboration among AI researchers that is improving the knowledge diffusion efficiency in the field.

In *IS*' researcher-level coauthorship network, we also identified the key collaborators according to degree, betweenness, and PageRank algorithms (see Table 3). The degree measure shows the authors' number of collaborators in *IS*. A higher degree indicates a larger number of collaborators in *IS*. According to this measure, Robert R. Hoffman (Florida

Institute for Human and Machine Cognition), Fei-Yue Wang (University of Arizona and Chinese Academy of Sciences), and Hsinchun Chen (University of Arizona) have the largest numbers of collaborators. (Hoffman, Wang, and Chen have all served as department editors for *IS* and thus have published some department articles that cover many parts of the field rather than concrete methodologies.)

The betweenness measure helps us identify critical authors that bridge information flow among researchers.¹⁴ According to this measure, Craig A. Knoblock (University of Southern California), Qiang Yang (Hong Kong University of Science and Technology), Jeffrey M. Bradshaw (Florida Institute for Human and Machine Cognition), and Austin Tate (University of Edinburgh) are the top knowledge transmitters in the network.

PageRank helps us identify high-impact researchers in the network, given the assumption that the people who work with high-impact researchers will also have a relatively high impact.¹⁵ Table 3 shows that the high-impact researchers according to this measure are similar as the active researchers according to degree measure.

Table 3. Key collaborators.

Rank	Degree (active collaborator)		Betweenness (knowledge transmitter)		PageRank (high-impact collaborator)	
1	Robert R. Hoffman	43	Craig A. Knoblock	0.012154	Robert R. Hoffman	0.003023
2	Fei-Yue Wang	36	Qiang Yang	0.011382	Fei-Yue Wang	0.001888
3	Hsinchun Chen	29	Jeffrey M. Bradshaw	0.010773	Hsinchun Chen	0.001633
4	Jeffrey M. Bradshaw	29	Austin Tate	0.010007	Jeffrey M. Bradshaw	0.001460
5	Austin Tate	26	Li Li	0.009910	Qiang Yang	0.001366
6	Steve Chien	25	Fei-Yue Wang	0.009328	Austin Tate	0.001294
7	Daniel Zeng	24	William Swartout	0.009277	Craig A. Knoblock	0.001244
8	Craig A. Knoblock	23	Nigel Shadbolt	0.007758	Daniel Zeng	0.001237
9	Qiang Yang	20	James A. Hendler	0.005569	Stan Matwin	0.001130
10	Richard Doyle	18	Hsinchun Chen	0.005250	Rudi Studer	0.001065

We adopted the Girvan-Newman algorithm to identify the major clusters (collaboration groups) in the *IS* coauthor network.¹⁶ Figure 1 shows clustering result using different node colors, and also the four biggest clusters.

The largest cluster (Cluster I in Figure 1) contains 60 nodes and has three hubs—Tate, Knoblock, and Bradshaw. They facilitate the knowledge diffusion between the US and Europe. Cluster II contains 43 nodes, including Fei-Yue Wang and his colleague Daniel Zeng (from the University of Arizona and Chinese Academy of Sciences). Wang's collaborators were mainly from the US and China. One unique characteristic of this cluster is that most collaboration happened after 2000, making it a relatively new collaboration group. Cluster III and IV contain 42 nodes and 39 nodes. They are centered by Hsinchun Chen and Robert R. Hoffman, respectively.

Collaborations between Institutions

Figure 3 visualizes the institution-level collaboration network following the similar schema as the researcher-level network. Table 4 reports topological measures of the networks. In institution level collaboration networks, there were 246 (60), 664 (422) and 921 (867) distinct nodes (links) at the end of Period I, II, and III, respectively.

The networks are sparse, with the network densities close to 0.002 at the end of each time period. However, the institution-level network shows a more interconnected pattern with a giant component occupying more than 40 percent of the nodes (until 2010). Similar to the researcher-level network, there were mainly local collaborations in Period I (nodes in the giant component were around Carnegie Mellon University). Starting from Period II, the giant component became much denser and bigger. The size of the giant component *NG* became 185. Several influential institutions, such as the University of Southampton, Chinese Academy of Sciences, University of West Florida (mainly contributed by Florida Institute for Human and Machine Cognition, which became an independent institute in 2002), and Hong Kong University of Science and Technology, joined in at this time. In Period III, collaborations further enforced the connections among existing and new institutions, such as the collaborations among the University of Arizona, and many new Asian universities. At the institution level, *IS* has been forming a close community in the past 25 years.

The average degree $\langle d \rangle$ of the institution-level network increased dramatically from 0.500 in Period I to 1.271 at the end of Period II. It continued to increase and reached

1.883 by the end of Period III. This observation further confirmed an increasing trend in interinstitution collaborations.

The institution-level networks also show a small-world phenomenon. They have small average shortest path lengths, 2.310, 4.506, and 4.575, respectively. The networks also have large clustering coefficients, 0.063, 0.205, and 0.279, respectively (compared to the expected values of the Erdos-Renyi random networks with the same sizes). The increasing trends of average degree and clustering coefficient indicate that the institution-level networks have become more clustered and the interinstitution collaborations became much more frequent.

We identified key institutions according to degree, betweenness, and PageRank algorithm (see Table 5). The most active institutions ranked by degree d are the University of Southern California (USC, $d = 32$), Carnegie Mellon University (CMU, $d = 30$), and University of Edinburgh ($d = 28$). USC and the University of Edinburgh had a close collaboration with each other through Craig A. Knoblock and Austin Tate. USC, the University of Edinburgh, CMU, and Massachusetts Institute of Technology (MIT) had a range of international collaborations with institutions from the US, Europe, and Asia.

Figure 3. Institution-level collaboration network. Node size is proportional to the number of publications. Node color indicates collaboration clusters.

According to the betweenness measure, CMU and USC are the top two knowledge transmitters in the institution-level collaboration network, with a much higher score than the other institutions. MIT, Stanford University, the University of Edinburgh, the Hong Kong University of Science and Technology, and the

University of Arizona also performed important roles as knowledge transmitters across the US, Europe, and Asia. CMU, USC, and Stanford University were ranked top three by PageRank, which indicated their high influence in worldwide research. Figure 3 highlights the three largest clusters extracted by the

Girvan-Newman algorithm. In Cluster I (50 nodes), Stanford University performed as the biggest hub. Instead of being led by several highly active authors, the collective contribution of all Stanford authors bring them to this significant role, such as researchers from the Knowledge Systems of the AI lab, the Stanford

Center for Biomedical Informatics Research, and many other labs and departments. In Cluster II (45 nodes), USC and MIT are major hubs with a large amount of international collaborations across the world. Both Cluster III and Cluster IV have 34 nodes. In Cluster III, there are a number of Chinese institutions around the University of Arizona and Chinese Academy of Sciences. In Cluster III, CMU and the University of Tokyo acted as two key hubs. Both Cluster III and IV contain numerous American-Asian collaborations.

Collaborations across Regions

In the past 25 years, researchers from 47 countries or territories have published in *IS*. Figure 4 visualized the country-and-territory-level collaboration network until 2010. In this network, seven countries and territories have a degree higher than 10: the US (27), England (16), Germany (15), Greece (15), France (14), Austria (13), and Japan (11). Most of the countries (39) are connected to the giant component. The small average shortest

Table 4. Network topological measures for institution-level coauthorship network.

Measure	1986–1993	1986–2004	1986–2010
N	240	664	921
L	60	422	867
Δ	0.002	0.002	0.002
NC	190	378	421
N_G (%)	16 (6.7%)	185 (27.9%)	380 (41.3%)
$\langle d \rangle$	0.500	1.271	1.883
C	0.063	0.205	0.279
l	2.310	4.506	4.575
D	6	13	12

path length l (2.108), diameter D (4), and large clustering coefficient C (0.424) show that it is a small-world network, which supports efficient knowledge transfer. Further inspections show that most of the international collaborations appeared after 1994. After then, the average degree $\langle d \rangle$, average shortest path length l , and clustering coefficient C increased significantly, indicating a fast growth of cross-country collaborations.

We ranked countries and territories according to degree, betweenness, and PageRank algorithm (see Table 6). The US holds an overwhelming lead according to all the measures, showing that the US dominated the AI research in *IS* in the past 25 years. Next, several other countries and

territories, such as England, Greece, Germany, Austria, and France, have similar scores, in different lists. They were the second batch of major knowledge diffusion facilitators in international AI research.

In this article, we analyzed the researcher-, institution-, and country-and-territory-level collaboration networks in *IS* publications. We segmented the data into three time periods according to the coherence of topics to study the network evolutions. We found that the collaborations have become denser over the past 25 years and there is a small-world property at all network levels. We identified the key collaborators according

Table 5. Key institutions.

Rank	Degree (active collaborator)		Betweenness (knowledge transmitter)		PageRank (high-impact collaborator)	
1	University of Southern California (USC)	32	Carnegie Mellon University (CMU)	0.054917	CMU	0.011668
2	CMU	30	USC	0.053396	USC	0.010602
3	University of Edinburgh	28	Massachusetts Institute of Technology (MIT)	0.026234	Stanford University	0.009531
4	University of Arizona	25	Stanford University	0.023416	University of Arizona	0.009217
5	MIT	25	University of Edinburgh	0.023304	MIT	0.009071
6	Stanford University	23	Hong Kong University of Science and Technology	0.022065	University of Edinburgh	0.008697
7	Chinese Academy of Sciences	20	University of Arizona	0.02015	University of Southampton	0.007581
8	University of Southampton	18	University of Southampton	0.018265	University of Maryland	0.007141
9	University of West Florida	17	University of West Florida	0.017551	Stanford University	0.006953
10	University of Maryland	16	University of Maryland	0.016167	Chinese Academy of Sciences	0.006181

Figure 4. Country- and territory-level collaboration network.

to degree, betweenness, and PageRank algorithm. They were also hubs of collaboration clusters identified by the Girvan-Newman algorithm. Institutional analysis shows that CMU, USC, MIT, Stanford University, the University of Edinburgh, the University of Arizona, and the Chinese Academy of Sciences were the key

knowledge diffusion facilitators. At the country and territory level, the US played a dominant role in international collaborations in *IS*. ■

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Table 6. Key countries and territories.

Rank	Degree (Active collaborator)		Betweenness (Knowledge transmitter)		PageRank (High impact collaborator)	
1	US	27	US	0.245896	US	0.099289
2	England	16	England	0.096154	England	0.059336
3	Greece	15	Austria	0.082786	Greece	0.052017
4	Germany	15	Netherlands	0.074191	Germany	0.051195
5	France	14	Greece	0.059073	France	0.048922
6	Austria	13	Japan	0.046451	Austria	0.048596
7	Japan	11	Germany	0.038003	Japan	0.040859
8	Ireland	9	France	0.035878	Netherlands	0.037881
9	Italy	9	Spain	0.025794	Spain	0.033235
10	Netherlands	9	Australia	0.015203	Italy	0.032384

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