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The Evolution of Turing Award Collaboration Network: Bibliometric-Level and Network-Level Metrics

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***Abstract*— The year of 2017 for the 50th anniversary of the Turing Award, which represents the top-level award in the computer science field, is a milestone. We study the long-term evolution of the Turing Award Collaboration Network, and it can be considered as a microcosm of the computer science field from 1974 to 2016. First, scholars tend to publish articles by themselves at the early stages, and they began to focus on tight collaboration since the late 1980s. Second, compared with the same scale random network, although the Turing Award Collaboration Network has small-world properties, it is not a scale-free network. The reason may be that the number of collaborators per scholar is limited. It is impossible for scholars to connect to others freely (preferential attachment) as the scale-free network. Third, to measure how far a scholar is from the Turing Award, we propose a metric called the Turing Number (TN) and find that the TN decreases gradually over time. Meanwhile, we discover the phenomenon that scholars prefer to gather into groups to do research with the development of computer science. This article presents a new way to explore the evolution of academic collaboration network in the field of computer science by building and analyzing the Turing Award Collaboration Network for decades.**

***Index Terms*— Bibliometric-level metrics, network dynamics, network-level metrics, Turing Award Collaboration Network, Turing Number (TN).**

I. Introduction

COMPUTER science is a diverse field full of academic activities, including plenty of partitions. There are many prizes to commemorate computer scientists who have made outstanding contributions to the computer science field. The ACM A. M Turing Award, established by the Computer Society (ACM), was awarded the title of Nobel Prize in the Computer Field and has far-reaching implications [1]. It is meaningful to study computer science from the perspective of the Turing Award. However, compared to the Nobel Prize, the research of the Turing Award is relatively incomprehensive. There exist several works devoted to studying relevant attributes of the Nobel Prize [2] and the Nobel Prize laureates [3], while the research of the Turing Award is particularly rare. As the highest prize in the field of computer science, we believe that the analysis of the Turing Award can highlight the important contributions of the Turing Award laureates. It is also beneficial to motivate the younger generation of computer scientists to fulfill their values [4], [5].

In order to analyze the Turing Award, we propose to study the collaboration network related to the Turing Award laureates. The study of scientific collaboration networks helps us to further understand knowledge production and innovation. Scientific collaboration networks have received growing attention in recent years [6]. Scientific collaboration is a key approach to promote the progress of computer science because it can gather data and resources to boost the collaborative development of knowledge production. The collaboration network is built from the list of published articles by treating the authors as connecting nodes if scholars write one or more articles jointly. In the view of a collaborative point, these networks have revealed some patterns of collaboration and research behaviors in different areas [6], [7].

In addition to the field of computer science, there is an important way to analyze collaborative networks. In the field of mathematics, scholars can adopt the Erdös Number (EN) to measure the distance from any mathematician to the far-reaching mathematician through a series of coauthors. It signifies mathematicians' nearness to the great scientist Erdös. Afterward, some authors analyze the pattern of the Erdös collaboration graph [8]. Inspirationally, we intend to form a collaboration network of the top-level authors of computer science to analyze the evolution process of the collaboration network. However, in the era of Turing, scientists are not as collaborative as current scholars. Based on the existing digital library, it is found that Turing had no collaborators on publishing articles so that no one can connect to him directly in the collaboration network. Therefore, we attempt to find a similar and alternative scientist. It is difficult to measure and find the most prestigious scientist in computer science. To this end, we can consider the Turing Award laureates as an alternative approach. We present the Turing Number (TN)

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to measure the distance of a given scholar to the Turing Award laureates in the network. Unlike the first two metrics, the apparent difference of our proposed metric is that we measure the distance from a certain scholar to the group of the Turing Award laureates, while the first two metrics are the distances to a specific person.

One of the most popular methods for analyzing network evolution is the bibliometric-level approach, which focuses on the quantitative and qualitative results of scientific research activities. The analysis of the bibliometric-level approach is usually based on measurable descriptions of scientific outcomes, including authorship, publications, and citations [9]. Subsequently, it has collected collaborative data to explore complex structures of contact in various fields.

The network-level analysis, extensively applied in collaboration network analysis, is another widely used method for researching the network [10]. Many studies propose several network-level metrics [11], such as the measure of degree, variety of centrality, and diameter. Some studies focus on describing structural properties through metrics, e.g., clustering coefficient [12], while others explore more complex problems to analyze, such as the detection of community hubs [13] and the determination of the priority attachment mechanism [14], [15]. Some authors attempt to identify the structure of small world [16] or the property of scale-free [17]. Others propose new measures to assess the scientific collaboration [18]. Some articles have studied scientific collaborations, with a focus on network changes over time [19], [20]. In contrast, this article focuses on the collaborative network of the top authors in computer science rather than the general computer science collaboration network. Currently, there are many studies focused on computer science [21]–[24]. Recently, a specific group (top active) collaboration [23] is investigated in the field of computer science. However, there are few studies focusing on Turing Award laureates. Our results show the same conclusion in some respects and the details are introduced in Sections III and IV.

In this article, we characterize the network evolution in computer science. First, we regard all the Turing Award laureates as a group to establish the network called the Turing Award Collaboration Network. It is our aim to comprehend the structure of the entire computer science collaboration network. Then, we analyze the dynamics over a long-time period (42 years). Moreover, we intend to discover the correlation of the distance to Turing Award (TN) and other considered metrics. To achieve this goal, we adopt the data from the open source of the database systems and logic programming (DBLP) to incorporate the article information into the across-the-board collection of evolved network data. We also conduct many in-depth statistical analyses.

Based on the metrics of bibliometric levels, the development of computer science is abstracted into a collaborative evolutionary network centered on Turing Award laureates. The network evolution is described at both the bibliometric level and network level. In addition, we compare calculated metrics with the same-scale random network to eliminate the impact of network dimensions.

Contribution: To the best of our knowledge, this article is the early study of computer science network focused on the

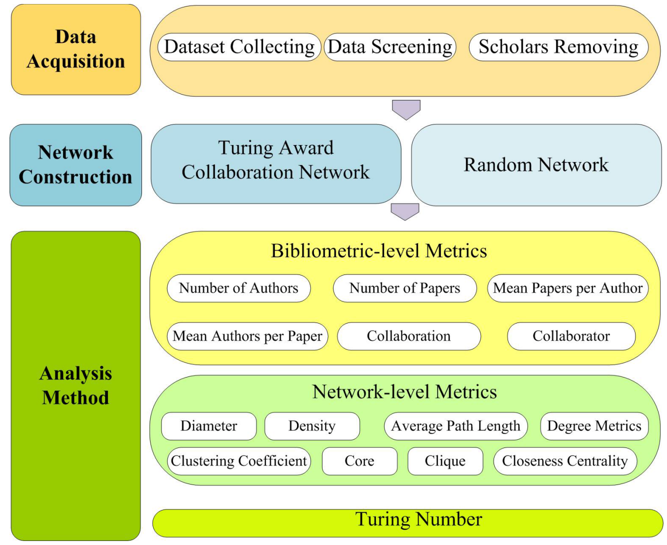

Fig. 1. Structure diagram of this article.

Turing Award. The main contributions of this article are as follows.

1) We present a new approach for establishing the collaboration network in the field of computer science centering on the Turing Award laureates.
2) We propose a metric called TN to measure the distance between scholars and the Turing Award.
3) We provide a comprehensive analysis of the network in conjunction with the bibliometric- and network-level metrics.
4) Finally, we analyze the correlation between the calculated metrics and TN to explore the scholars' properties related to the Turing Award.

II. Method

In this section, we will introduce the methods used in the research process including data acquisition, collaboration network construction, and some analysis metrics. The overall structure diagram of the study is shown in Fig. 1.

A. Data Acquirement

To study the evolution of the Turing Award Collaboration Network comprehensively, we collect available DBLP data set in public. DBLP is a literature data set of computer science that records information in regards to global computer science research. The personal bibliography records the scientific achievements of a researcher in one's career. The entire DBLP data set is stored in an XML form, and it can be downloaded from the website (http://dblp.uni-trier.de/xml/). The data set contains 3 297 544 bibliographies of 1 735 884 authors from 1971 to 2016. The data involve a variety of categories, but we only focus on journal and conference articles whose labels are "article," "inproceeding," and "proceeding." These three categories of articles have been verified to reflect the progress of computer science prominently [25].

To exclude those scholars who leave the academia in the early career, for instance, fresh graduates, we screened the

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data. We remove scholars with less than five, eight, and ten articles, respectively, and we find that they do not affect the final result. Finally, we select to remove scholars who published less than ten articles, gaining 2 796 297 articles and 192 650 authors. In addition, since this collaboration with so many authors shows weak social relationships, we have removed more than 100 coauthors' articles [26]. If these authors are not excluded, it would be very unreasonable for these authors to form a fully connected graph when building a collaboration network.

B. Turing Award Collaboration Network

When the data are obtained, we establish the collaboration network associated with the Turing Award laureates. We regard an author as a node and a copublished article as an edge. The number of common publications can be measured by the weights of links. It can cause changes in the network, mainly because their growth involves the dynamic interaction of links and weights, and some possible factors that can accelerate growth [27]. The network allows new links to appear among existing nodes. However, we focus more on the increasing scale of the collaboration network and the distances of authors to the Turing Award in this research, so we choose the unweighted network, i.e., if two authors publish an article together, there will be an edge between them.

We treat all the Turing Award laureates as a group and then we set its number to 0. The remaining scholars are assigned a sequence number starting from 1. If an author collaborates with any Turing Award laureate, he/she will be considered to be connected to the Turing Award. Intuitively, a Turing Award laureate is added to the Turing Award group in the year he/she won the Turing Award, while a scholar joins the network when the scholar began publishing articles. There are one or two laureates to join the Turing Award group each year. In addition, we explore the evolution of the network and investigate the rapid development of the computer science field.

Due to the marginal number of nodes in the early years, we regard 1974 as the starting year for exploration. Since some authors never collaborate with other authors, we ignore the isolated nodes of the network. Due to the tiny number of isolated nodes, it hardly affects the experimental results by deleting isolated nodes. In other words, we only consider the largest connected subgraph of the network. Eventually, we obtain the maximum connected graph related to the Turing Award group, which is named as the Turing Award Collaboration Network. The network is shortened as the Turing Network in the following. Furthermore, we put each year as a unit to establish the time-series cumulative collaboration network separately. We also document the annual changes in the authors' properties and their collaborations in the Turing Award Collaboration Network.

C. Random Network

Intuitively, many of the calculated metrics for the Turing Award Collaboration Network are correlated with the size of the network of the year. Therefore, the annual change in metrics is not surprising. A more essential trend is to eliminate the correlation of metrics and network size so as to deepen our understanding of the internal changes of the Turing Network. The method we choose is to compare the Turing Network to the random network with the changes of the network's size. Therefore, in order to better reflect the network characteristics and to eliminate the scale effects concurrently, we construct a random network with the same number of nodes and edges as the Turing Network.

We select the most classic Erdős–Rényi (ER) random network [28], which is built via the number of nodes n and edges m, $G(n, m)$. The network is constructed by the following steps: 1) initialize a given number of nodes n and edges m; 2) select a pair of different nodes randomly without edges and add an edge; and 3) repeat step 2) until m edges in the network. Through the above-mentioned method, we construct a random network that retains the number of nodes and edges of the Turing Award Collaboration Network. We expect to exclude the correlation of the Turing network scale through its equivalent random network.

In the latter part of this article, ER Random Network is used as the experimental control group for our evaluation. The "Real Value" mentioned in all the result diagrams in this article is the analysis result of the Turing Award Collaboration Network constructed by us. Meanwhile, "Random Value" refers to the result obtained through the analysis of the ER Random Network.

D. Analysis Method

In this article, we analyze the Turing Award Collaboration Network by the bibliometric- and network-level methods.

1) Bibliometric-Level Metrics: To comprehensively understand the authors' outcomes and the evolution of the collaboration pattern, we have selected some typical metrics widely applied in related works [29], [30]. Common bibliometric-level metrics are as follows.

1) *Number of Authors:* The metric describes the numbers of authors who publish articles every year. We remove scholars who published less than ten articles, eventually obtaining 2 796 297 articles and 192 650 authors.
2) *Number of Articles:* This metric shows the number of articles published every year. We have utilized the articles from 1974 to 2016.
3) *Mean Articles per Author:* This metric explores the author's average productivity.
4) *Mean Authors per Article:* For this measure, we explore the average number of authors in each article.
5) *Collaboration:* Here, we consider the percentage of the different types of articles (one-, two-, three- and multiauthored articles).
6) *Collaborator:* This measure is related to the percentage of authors who tend to collaborate with others in publishing articles.

2) Network-Level Metrics: In the network-level analysis, the Turing Award Collaboration Network is investigated based on the macrometrics and micrometrics. The former is the overall profile of the social network's characteristics to display the network, while the latter emphasizes on the assessment of

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the nodes to capture the characteristics of each node [31]. In addition, to eliminate the impact of the network scale, we compare the metrics of the Turing Award Collaboration Network with metrics of the random network. The network-level metrics that are widely used to standardize or the metrics infer the structural aspects of the network are as follows.

1) *Diameter:* The given distance d_{ij} refers to the length of the shortest path connecting the two nodes i and j. The diameter D of the network is used to measure the maximum eccentricity, which is the maximum distance between any two nodes

$$D = \max_{i,j} d_{ij}. \tag{1}$$

2) *Density:* Density is used to measure connectivity across the network, and it is calculated by dividing the total number of edges by the total number of possible edges in the network with the same number of nodes. The formula for density p is

$$p = \frac{E}{\frac{1}{2}N(N-1)} \tag{2}$$

where N is the total number of nodes and E is the total number of edges in the network. We can adopt network density to characterize the extent of coherency and linkage between nodes in the network [32].

3) *Average Path Length:* The average shortest path length L is the average length of the shortest path between every two nodes in the network [33]

$$L = \frac{1}{N(N-1)} \sum_{i \neq j} d_{ij}. \tag{3}$$

In the collaboration network, the distance between coauthors of an article is 1, while the distance between authors who do not have direct cooperation but have the same coauthor is 2.

4) *Degree:* The adjacency matrix $A = (a_{ij})_{N \times N}$ of a given graph G is an Nth-order square matrix, and the element a_{ij} on the ith row and the jth column is defined as follows:

$$a_{ij} = \begin{cases} 1, & \text{if there is an edge between node } i \text{ and } j \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

The degree k_i of the node i refers to the number of nodes linked to the node i, which is expressed as

$$k_i = \sum_{j=1}^{N} a_{ij}. \tag{5}$$

5) *Average Neighbor Degree:* It measures the average degree of neighbors for each node. The average degree of the node i is

$$k_{nn,i} = \frac{1}{\mathrm{Num}(i)} \sum_{j \epsilon N(i)} k_j \tag{6}$$

where $N(i)$ is the set of neighbors of the node i, $\mathrm{Num}(i)$ is the number of nodes in $N(i)$, and k_j is the degree of the node j that belongs to $N(i)$.

6) *Degree Assortativity:* In order to identify the relevance of the centrality of a node to its neighbor nodes, we take a degree assortativity or a mean nearest neighbor connectivity as a metric of connection similarity [34]. It is a measure of the degree to either end of the edge by calculating the Pearson correlation coefficient r

$$r = \frac{\sum_i k_i j_i - M^{-1} \sum_i k_i \sum_i j_i}{\sqrt{[\sum_i k_i^2 - M^{-1}(\sum_i k_i)^2][\sum_i j_i^2 - M^{-1}(\sum_i j_i)^2]}} \tag{7}$$

where k_i and j_i are the degrees of the node for the ends of the ith edge in the network, along with $i = 1 \cdots M$. The range of the coefficient r is between -1 and 1.

7) *Clustering Coefficient:* The clustering coefficient represents the ratio of adjacent nodes to which the nodes are connected. By analyzing this metric, a highly aggregate coefficient means that the local network centering on this node is gathered together densely in a collaboration network. Suppose the degree of node i in the network is k_i, i.e., it has k_i neighbor nodes. If the k_i neighbor nodes are also neighbors, there are $(k_i(k_i-1)/2)$ edges between these neighbors, and this is the case with the largest number of edges. Clustering coefficient C_i of the node i can be expressed as

$$C_i = \frac{2E_i}{k_i(k_i-1)} \tag{8}$$

where E_i actually represents the number of edges that exist between node i and k_i neighbor nodes.

8) *Core:* The measure of the core can identify groups that are closely interconnected in the network [35]. Let $G = (V, E)$ be an undirected graph, and let $H = (W, R)$ be a subgraph of G, i.e., $H \subseteq G$. If subgraph H is a maximal connected subgraph in which all nodes have the degree at least K, it is defined to be a K-Core subgraph of G. It is calculated by the following equation, in the subgraph H for all $i \in W$:

$$k_{i \in W} \geq K. \tag{9}$$

Every node $i \in V$ has a core number of K, if it belongs to a K-core but not to a $(K+1) - Core$. If the nodes of the K-Core subgraph of G correspond to the maximum value of $K_{\max}$, we denote the main core as the maximum core number $K_{\max}$. In our network, connected nodes are independent of the other nodes connected to nodes existing outside the group.

9) *Clique:* The clique is defined as the largest set of nodes that all nodes are directly adjacent to each other. Under the node removal operation, a clique has an invariant attribute: if a node is deleted from a clique, the rest of the subgraph is still a clique. Each node contributes a q-clique (a completely connected subgraph Q consisting of q nodes) onto G. It indicates that each node in Q is no more than a distance q away from others. Thus, we can know that a clique is an interconnected component that ensures that each author of this clique writes at least one article with all other authors.

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10) *Degree Centrality:* The node v's degree centrality is to measure the number of other nodes that are directly connected to the node [36]. For normalization, it is divided by the maximum possible degree $n-1$ of the whole network. Thus, it is expressed as

$$C_D(i) = \frac{k_i}{N-1}. \tag{10}$$

11) *Closeness Centrality:* Throughout our established network, closeness centrality tends to give high values for nodes near the network center, and high-closeness centrality nodes are generally important influencers. In order to calculate this metric, we have [36]

$$C_C(i) = \frac{N-1}{\sum_{j\neq i}^{N} d_{ij}}. \tag{11}$$

3) TN: To find hierarchical relationships of the network, we explore relationships of the distance to the Turing Award and the related metrics (bibliometric level and network level). Enlightened by the previous study on the EN, we define the metric of the TN, first proposed, to measure the distance to the Turing Award. The explanation is as follows:

TN: The TN depicts the distance between the author and the Turing Award, which is similar to the concept of the shortest path distance. The TN of a Turing Award laureate is zero. For assigning TN, someone must be the coauthor of the research article, while another one needs to have a limited TN. Under the circumstance of treating the Turing Award laureates as a group, if one person's TN is $T+1$, the one's distance to the Turing Award is $T+1$, where T is the lowest TN of any coauthors. A TN refers to the minimum value of the shortest path of every author to all the Turing Award laureates. In other words, we calculate the shortest path length of each scholar to all the Turing Award laureates, and we take the minimum value as the TN. From the perspective of complex networks, the shorter the value of TN, the smaller the distance between scholars and the Turing Award laureates. Based on the definition of TN, we extend the concept of the EN and measure the shortest path length of a given author to any Turing Award laureate.

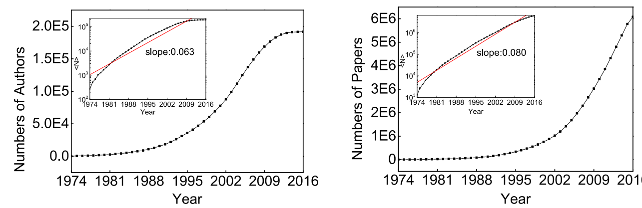
We anticipate discovering correlations of authors' productivity, position in the network, and distances to the Turing Award.

III. Results

The outstanding contribution of this article is the establishment of the Turing Award Collaboration Network and the exploration of relevant metrics for the analysis of the network. We explore the evolution of the network from 1974 to 2016. The results fall into two categories: bibliometric-level and network-level analyses.

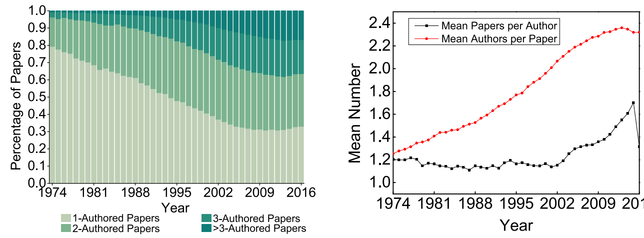
A. Bibliometric-Level Analysis

We first focus on the most intuitive metrics: the number of authors and articles. Fig. 2(a) shows the number of annual authors. The embedded graph displaces a log-linear distribution plotted with the same data that match the exponential fitting the formula $a * \exp(bx)$, where $b = 0.063$ and $R^2 = 0.94$. Fig. 2(b) shows the number of articles each year and the embedded graph displaces a log-linear distribution plotted with the same data that matches the exponential fitting $a * \exp(bx)$, where $b = 0.080$ and $R^2 = 0.97$. R^2 is used to describe the extent fitting of the linear function, where the higher the value (i.e., closer to 1), the better the fitting. We can observe that the two metrics increase exponentially every year.



(a) (b)

Fig. 2. The number of authors and articles each year. (a) Evolution of the number of authors versus year. (b) Evolution of the number of articles versus year. Each embedded graph displaces a log-linear distribution plotted with the same data. It indicates an exponential increase in the number of authors and articles produced each year.



(a) (b)

Fig. 3. Percentage of articles in each year, and mean authors per article and articles per author in each year. (a) Distribution of authors per paper and the annual percentage of articles published by one, two, three, and more than three authors. (b) Mean articles per author versus year (black line) and the mean authors per article versus year (the red line).

As shown in Fig. 3(a), we can observe the changes in the collaboration pattern. In 1974, 79.3% of the authors published their own articles, and the synergy between scholars is still weak because only 0.8% of the articles has more than three authors. Since then, scholars have tended to collaborate with others to publish articles. We can observe that the average number of authors per article has increased from 1.25 to 2.28 during the whole period in Fig. 3(b). Subsequently, the number of articles written by individual authors continues to increase, but its percentage has dropped from 79.3% to less than 42.2%. In contrast, the number and the percentage of articles with multiple authors have increased significantly. The number of articles coauthored by the two authors is the highest among those articles. The reason is probably that with the rapid development of computer science, it is increasingly difficult to publish articles alone. We can realize that it is necessary to focus on team research.

The mean number of articles per author and authors per article is plotted in Fig. 3(b). From 1974 to 2002, the mean articles per author are hovering between 1.0 and 1.2 yearly. After 2002, it shows an upward trend, till 2015 to about 1.70, therewith following by some decline. Since the 1970s, articles'

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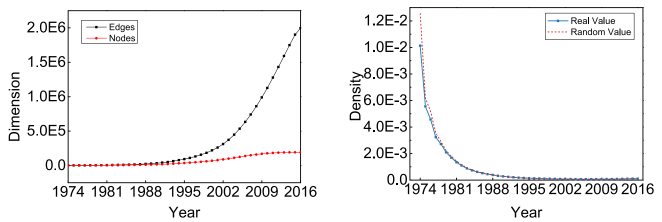
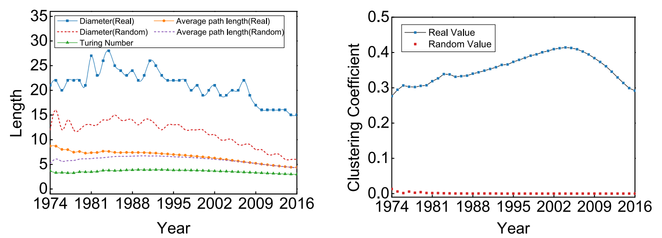


(a) (b)

Fig. 4. Evolution of dimension and density. (a) Growth of nodes and edges each year. The red line represents the trend of the node, and the black line represents the trend of edge. (b) Density of the Turing Award Collaboration Network compared to the random network. The blue and red lines represent trends in the Turing Network and the random network, respectively. (a) Dimension (nodes and edges). (b) Density.



(a) (b)

Fig. 5. Evolution of distance metrics and clustering coefficient. (a) Trends of network diameter, average shortest path, and TN. (b) Evolution of clustering coefficient. The solid line indicates the evolution of the Turing Network, and the dotted line is the evolution of the random network. (a) Different kinds of distance metrics. (b) Clustering coefficient.

average authors have increased quickly. At present, each article has an average of two authors.

B. Network-Level Analysis

The analysis of these network-level metrics provides insights into the evolution of the Turing Award Collaboration Network. Meanwhile, we compare some calculated metrics with those in the random network to better reflect the realities.

The evolution of nodes and edges in the entire collaboration network is shown in Fig. 4(a). It is demonstrated clearly that due to the growing number of authors and their collaborators, these metrics have increased notably each year.

In Fig. 4(b), we can observe the same phenomenon of random network trends, and the density is also declining. It is understandable that due to the increase in the number of new scholarships, the number of publications or collaborations with other authors is limited.

Fig. 5(a) shows the changes in diameter, which starts at 21, and then reaches the maximum 28 in 1984. Next, it drops to around 15 in 2016. The initial increasing of distance indicates that the network is gradually expanding, but the subsequent declining of the metric indicates that as the network continues to expand, the extent of collaboration is also increasing. It has the same tendency as the diameter of the random network, but the values are larger, and they indicate that relationships in this network are more complicated and dispersed than those in the random network.

The average shortest path length is plotted in Fig. 5(a). It can be seen that the initial network of the shortest path length

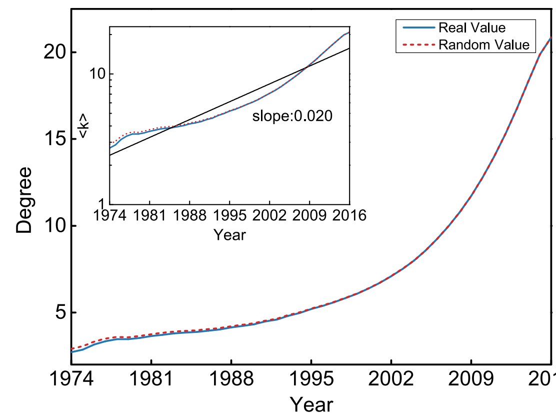


Fig. 6. Evolution of average degree. The embedded graph shows the log-linear graph. The blue line is the trend of the Turing Network, and the red line is the evolution of the random network.

is about 8.7 in 1974, and the path length steadily decreases from 1974 to 2016. Furthermore, the shortest path converges to about 4.3 at a later stage, and it indicates that a scholar in the network requires only four or five steps to achieve another scholar, which means that scientific information can be easily obtained by the need of the researcher [37]. Compared with the random network, the length is larger initially, but then it basically coincides with the random network. In accordance with the "Six Degree Separation" theory, the network is stabilized gradually. In addition, TN has the same trend as the average path length. However, the value of TN is smaller, which shows that the distance for authors to the Turing Award is shorter than the average distance in the network. We can notice that the value of TN differs greatly from the diameter. We deem that the definition of TN and network diameter is different. The former refers to the distance of any scholars to the group of the Turing Award laureates, and the latter measures the distance between any two scholars in the network. Due to the difference in definition, the average of the two metrics differs by about 20. Therefore, the diameter of the network fluctuates relatively large.

In the Turing Award Collaboration Network, clustering coefficient increases from 0.28 in 1974 to 0.41, as shown in Fig. 5(b). However, it starts to decrease in 2004. Although the number of scholars has been increasing, they are gathered to a certain extent, not an unlimited association. This phenomenon shows specifically that in the 21st century, the collaboration pattern becomes increasingly unified over time. In addition, this metric is far greater than that in the random network, which indicates that the collaboration network tends to converge to form a high-density aggregation group.

The above-mentioned analysis shows that scholars are gradually involved in tight collaboration and a large number of scholars join the network through the collaboration. In the dynamics of degree (see Fig. 6), we can observe that the value is basically year-on-year rising with exactly the same trend in this metric of the random network. This metric shows a basic trend of linear growth and it distributes between 2 and 20. So far, the average node degree in the network has reached 20. The embedded graph shown in Fig. 6 displaces the logarithmic

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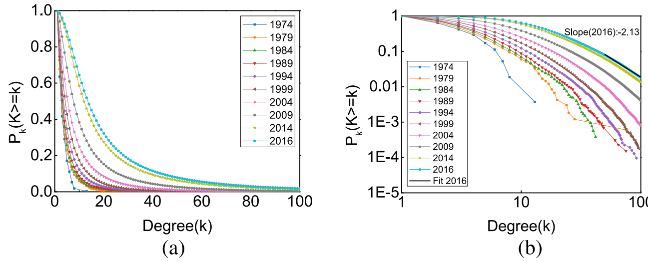

Fig. 7. Evolution of degree distribution. (a) Degree cumulative probability distribution each year. (b) Log–log degree cumulative probability distribution of the same network. Each line in both graphs represents the degree distribution of a certain year.

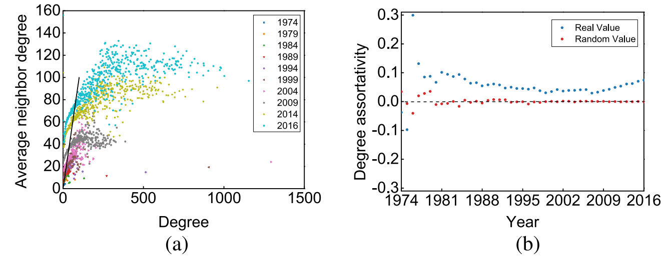

Fig. 8. Evolution of degree correlation. (a) Correlation of degree and average neighbor degree. Each color point refers to a certain year. The black line is the identity line $x = y$. (b) Degree assortativity of the Turing Award Collaboration Network (blue point) compared to the random network (red point).

linearity that matches the exponential fitting $a*\exp(bx)$, where $b = 0.020$ and $R^2 = 0.93$.

The Barabási–Albert model [38] of the scare-free network was first proposed in 1999. The significant feature of a scale-free network is that the degree distribution follows a power-law distribution $p(x) = cx^{-\alpha}$, where the scale-free coefficient $(-\alpha)$ is generally negative. Therefore, to explore whether the Turing Award Collaboration Network is a scale-free network, we need to analyze the degree distribution. We plot the degree distribution of the Turing Award Collaboration Network at several intervals of time points (i.e., 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, and 2016), as shown in Fig. 7. As a result of the degree distribution, several nodes have a high degree. However, a large number of nodes are low. From this point, degree distribution seems to follow the power-law distribution essentially, especially when the dimensions of the network (nodes and edges) are huge.

Subsequently, we plot the log–log distribution of degree distributions for different years shown in Fig. 7(b), which corresponds to the time points shown in Fig. 7(a). It can be concluded that these distributions are not purely power law; otherwise, these points roughly stay in a straight line. In contrast, the tail of the distribution conforms to exponential decay in 2016. In other words, the entire network cannot be used to fit the power-law distribution. From the analysis mentioned earlier, the Turing Award Collaboration Network cannot be considered as a scale-free network.

The relationship among scholars depends on the number of neighbors and their locations. In some networks, it has been noticed that the degree of their neighbors is related to their own degree. The degree for their neighbors is apt to be low when their degree is low. Conversely, the neighbor's degree is high when their own degree is high. In the collaboration pattern, the prevalent authors are highly associated with other popular authors, and the less popular authors are likely to be associated with the popular authors. We can quantify the correlation of these degrees by analyzing the correlation between the average neighbor degrees and their own degrees. The result is shown in Fig. 8(a).

The solid line represents the same degree as its average neighbor degree. From Fig. 8(a), we can discover that the average degree of the small-degree nodes' neighbors is significantly larger. However, with an increase of degree, the average neighbor degree of nodes is significantly higher than their degree. Another more accurate way is to calculate the assortativity coefficient, which needs to measure the preferences of nodes attached to other nodes in any way. The positive value of the degree assortativity indicates the correlation among similar-degree nodes (assortativity), while the negative value represents the relationships among different-degree nodes (disassortativity). In Fig. 8(b), the current degree assortativity of the Turing Award Collaboration Network is 0.074, positive; this condition indicates that the author tends to collaborate with other authors of a similar number of collaborators. Compared with the values in the random network, it can be seen that the degree assortativity has been increasing steadily, which is related to the increasing number of authors.

By analyzing the core and the clique, we can acknowledge the evolution of the network group. The sizes of the core and the clique are both rising each year, which also conforms to the rule of network evolution. The value of the clique is similar to the core's value at the early stages, while the clique's growth trend is significantly higher than the core's later. This phenomenon shows that extensive collaboration in the network is more prevalent than collaborating with the same person or group.

Then, in order to inquire about the trend more clearly, we can observe the distribution in Fig. 9. The K-Core distribution of the Turing Award Collaboration Network is shown in Fig. 9(a). With the increase of K, the distribution of K-Core tends to be gentler. The majority of authors belong to small K-Cores (less than nine) and 20-Core contains most of the authors in 2016. The largest K-Core is 56 in 2016, which is not the group of the Turing Award laureates (K-Core is 51). The distribution of the clique is shown in Fig. 9(b), which is similar to the K-Core. However, the value of the clique is much greater than K-Core's value via the magnitude of the two pictures' abscissa (100 versus 10). This also verifies our thought: the Turing Award Collaboration Network tends to be of more team collaboration (also called "baotuan" in Chinese).

Degree centrality quantifies the number of nodes connected to other nodes. Closeness centrality evaluates whether nodes are connected to other prominent nodes or not.

From Fig. 10, we can observe that degree centrality of the Turing Award Collaboration Network has been decreasing over time, and it is smaller than the values in the random network. As the number of nodes in the network increases exponentially, it still leads to lower degree centrality. This means that the

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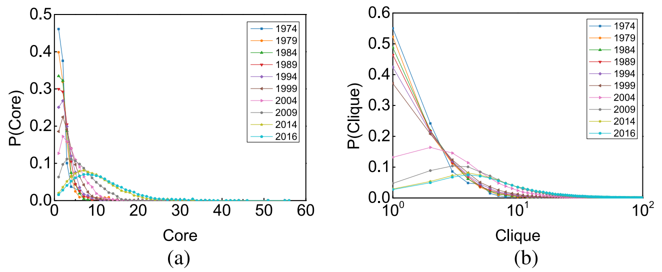


Fig. 9. Evolution of core and clique distribution. (a) K-core distribution of the Turing Network. (b) Clique distribution of the Turing Network. Each line refers to one specific year.

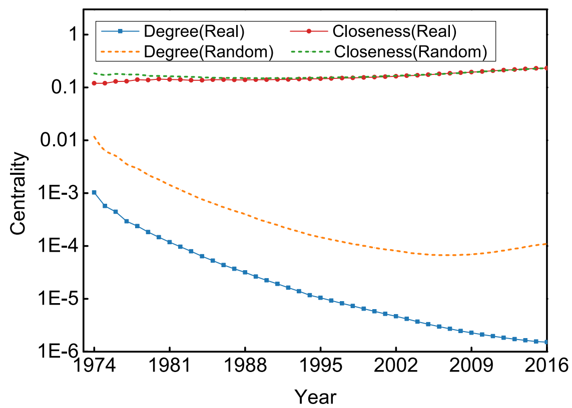


Fig. 10. Evolution of degree centrality and closeness centrality. The solid line refers to the evolution of the Turing Network, and the dotted line refers to the evolution of the random network.

links among scientists are almost similar across the network. It brings about the simultaneous development of opportunities for all scientists.

Closeness centrality shows a growth trend in Fig. 10. In contrast to degree centrality, the nodes have an increased pattern. The slope of the curve is larger at the later stages of the network dynamics, while the smaller slope of earlier stages can be attributed to the preferential attachment compared with the random network.

Because the number of nodes in the early network is small, the newly added nodes are more likely to be attached to the newly introduced nodes in each period. However, the added nodes are more likely to be attached to higher nodes, resulting in the increase of the slope of closeness centrality. This makes the newly added nodes hard to perform on the shortest path of the node pair during network evolution.

IV. Discussion

A. Evolution of the Turing Award Collaboration Network

After analyzing the structure of the Turing Award Collaboration Network over the years, we proceed to observe the evolution of the network intuitively. Therefore, we plot the evolution of the Turing Award Collaboration Network, as shown in Fig. 11. Because of the plentiful years involved, we take ten years as a span to show the changes from 1974 to 1984, 1994, and 2004. As there are overmuch nodes and edges, we only take the center of the network with the high K-Core. From Fig. 11, we can notice that with the development of the network, a growing number of nodes enter the network and the new relationships of the current nodes increase. As the number of nodes in the network increases, the connection among nodes becomes closer. In addition, the density of the network rises as the connections of nodes increase.

As the Turing Award laureates join the network gradually, they not only bring mounting nodes to join but also make the Turing Award for the network more central. Although we only take the high K-Core of the network, we can still observe the network's group aggregation and close contact of the network. Moreover, the central group is also gradually expanding. This result can be used to predict the person who is most likely to win the Turing Award and the new join should fit the variation trend of the network.

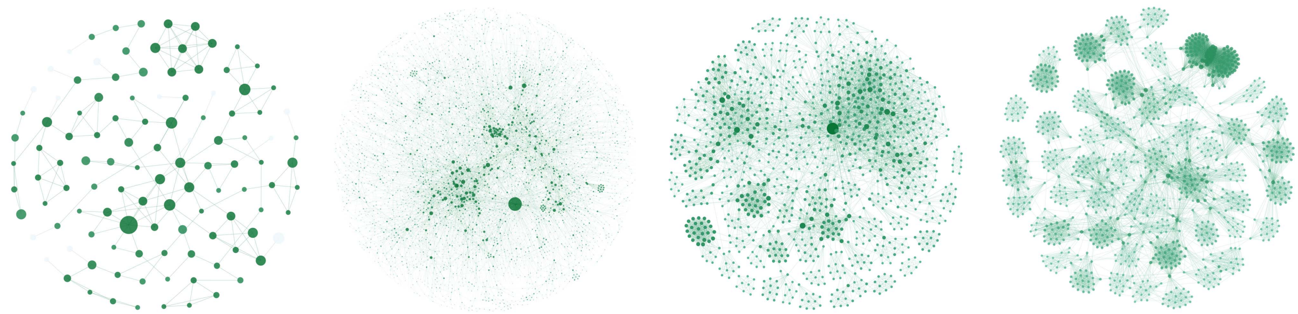
B. Correlation of TN and Distinct Metrics

In order to further explore the relationship of the various metrics and the Turing Award, we begin to analyze the impact of different TNs on the relevant metrics. Table I shows the evolution of TN. The time phase represents the change of the TN from 1974 to 1979, 1984, 1994, 2004, 2009, 2014, and 2016.

1) Bibliometric-Level Metrics Relationship: We first analyze the relationship between the bibliometric-level metrics and TN. The results are shown in Fig. 12. When TNs are 1, 2, and 3, the author's number of articles and collaborations are above the average. Then, both graphs demonstrate that the smaller the TN, the larger the bibliometric-level metric. The TN 0 in Fig. 12 is the average of all the Turing Award laureates. It can be seen that the number of articles and collaborations of the Turing Award laureates is no more than that of the general scholars. Besides, scholars with the TN 2 have a higher number of collaborations and articles than scholars' with the TN 1 in the later period. There is an upward trend in the growth of the network for all authors.

2) Network-Level Metrics Relationship: We analyze the impact of TN on the network-level metrics, and the results are shown in Fig. 13. The TN 0 in Fig. 13 is the total value of all the Turing Award laureates, while The TN 0 in Fig. 12 is the average. It is not appropriate for bibliometric-level metrics to use total value. For example, if we use total value, the amount of Turing Award laureates' articles is tiny compared to the rest of the authors' articles because the total Turing Award laureates number is tiny. Network-level metrics is based on the collaboration network structure. The influence of Turing Award laureates can be reflected through the network structure. Thus, it is better to consider the total value of TN 0. We can realize that the relationships between TN and the network-level metrics are not exactly the same as the bibliometric-level metrics.

The degree [see Fig. 13(a)], the core [see Fig. 13(c)], and the clique [see Fig. 13(d)] show that the smaller the TN, the greater the values. However, for the clustering coefficient depicted in Fig. 13(b), the correlation with TN cannot be seen, and there is no growth trend toward the year, which is similar to the annual clustering coefficient shown in Fig. 5(b).



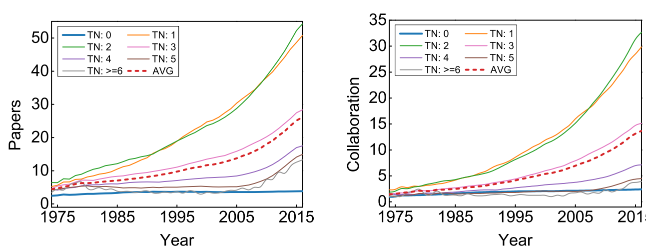
(a) 1974 (b) 1984 (c) 1994 (d) 2004

Fig. 11. Evolution of the Turing Award Collaboration Network. (a) Turing Network of all authors in 1974. (b) Due to the large number of nodes in Turing Network in 1984, it is not easy to observe network structure visually. Therefore, we select the five-core subnetwork of the Turing Network in 1984. (c) Eight-Core subnetwork of the Turing Network in 1994. (d) 15-Core subnetwork of the Turing Network in 2004. Network graphs were produced in Gephi, using the Fruchterman Reingold layout with scaling set to 5000 and gravity to 10. Node size is proportional to the authors' degree.

TABLE I

EVOLUTION OF TN FROM 1974 TO 1979, 1984, 1994, 2004, 2009, 2014, AND 2016

Metrics	Time phase								
	1979	1984	1989	1994	1999	2004	2009	2014	2016
Turing Number	3.469	3.767	3.899	3.866	3.760	3.571	3.305	3.039	2.964



(a) (b)

Fig. 12. Annual relationship of TN and specific bibliometric-level metrics. (a) Changes in the numbers of articles against the value of TN. (b) Changes in the numbers of collaborations with varying the value of TN. The dotted line indicates the average change of each metric.

In terms of centrality, closeness centrality is increasing yearly. The smaller TN is better for closeness centrality. However, degree centrality does not have such a strong correlation. It is noteworthy that, as time goes by, the correlations of TN and degree centrality are not large at later stages, despite some fluctuations exist. However, the changes in the closeness centrality are more obvious over time.

3) Correlation Coefficient: For the purpose of checking whether existing measures are associated with TN and changes in the subsequent years, we adopt the Spearman correlation coefficient to calculate the relationship of the relevant metrics and TN from 1974 to 2016 because many metrics do not conform to the normal distribution and the nonparametric correlations are more appropriate and more robust than the Pearson correlations. The Spearman correlation coefficient is defined as the Pearson correlation coefficient between rank variables. For the samples with size n, all original data are converted into rank data, and the correlation coefficient ρ is expressed as

$$\rho = \frac{\sum_i (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_i (x_i - \overline{x})^2 \sum_i (y_i - \overline{y})^2}} \tag{12}$$

where the raw data are assigned a corresponding rank based on their average descending position in the overall data. For example, given three values, 33, 21, and 44, their rank would be 2, 1, and 3. x_i is the TN rank of the ith sample. $\overline{x}$ is the average rank of all x. y_i is the metric rank of the ith sample. $\overline{y}$ is the average rank of all y. If y tends to increase as x increases, the Spearman correlation is positive. If y tends to decrease as x increases, the Spearman correlation is negative. If Spearman correlation is 0, it indicates that y has no tendency as x increases. As x and y get close to a complete monotonic correlation, the Spearman correlation increases in absolute value. When x and y are completely monotonic, the absolute value of the Spearman correlation coefficient is 1.

Fig. 14 shows that the relevant metrics are negatively correlated with TN except for the clustering coefficient. When the absolute value of the correlation coefficient is closer to 1, the metric is more correlated with TN. The trends of the vast majority of metrics are the same with some slight increases over years or some fluctuations. Of all the metrics, closeness centrality is of great relevant metric (the absolute value of the correlation coefficient is about 0.6 in 2016). There are some declines in the middle of the periods. The second is the core.

From the above-mentioned exploration, we can understand that the correlation of the relevant metrics and TN is always significant over time. From the perspective of the centrality, the correlation of the closeness centrality and TN is the highest. In other words, the author with a high closeness centrality is often closer to the Turing Award. In addition, the coefficient

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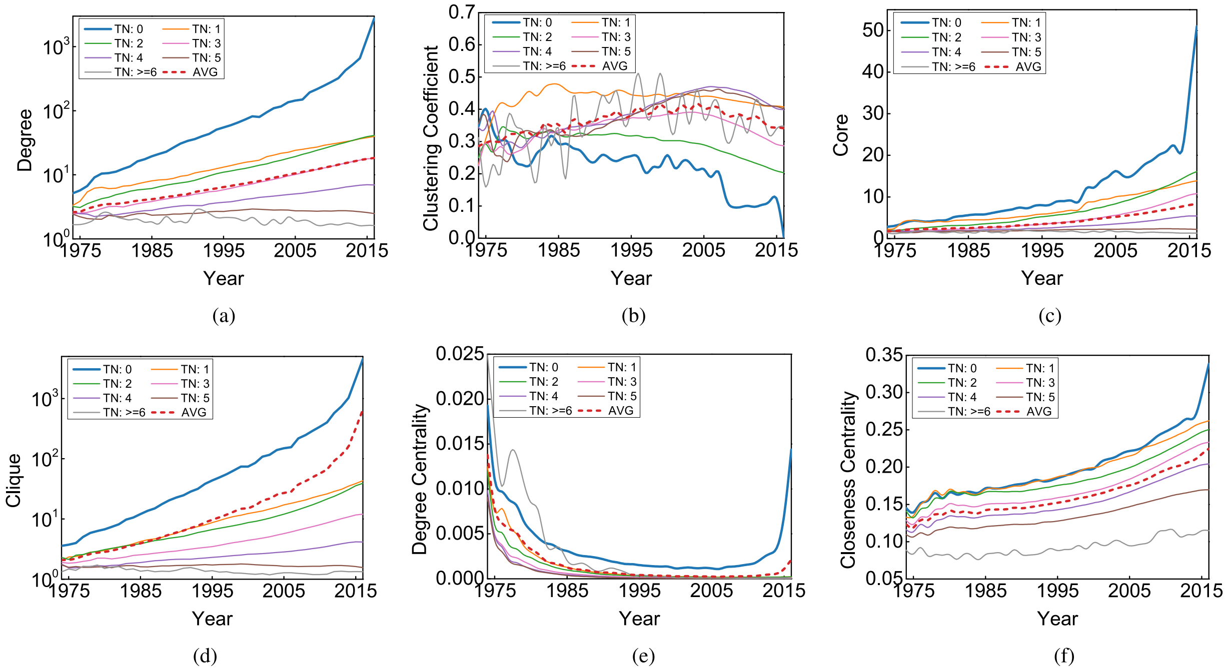

Fig. 13. Relationship between TN and specific network-level metrics. Each figure shows changes of a certain network-level metric against TN. The dotted line indicates average change of each metric. (a) Degree. (b) Clustering coefficient. (c) Core. (d) Clique. (e) Degree centrality. (f) Closeness centrality.

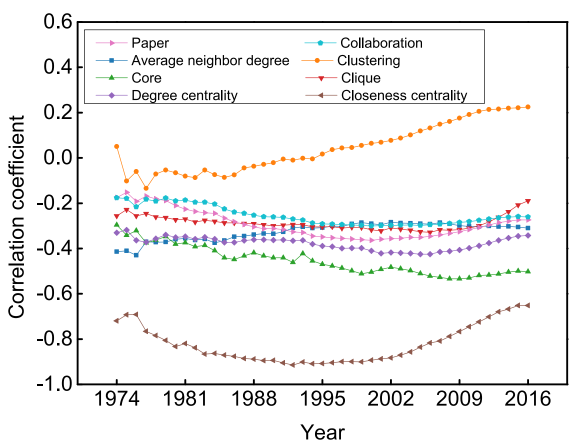

Fig. 14. Correlation coefficient of TN and specific metrics.

has an increasing trend yearly for degree centrality but has a stable trend for closeness centrality.

V. Conclusion

The ACM A.M. Turing Award is recognized as the highest honor prize in the realm of computer science. Half a century has passed since the first laureate was awarded. However, there are scarce researches to explore the potential mechanism of the Turing Award and collaboration pattern of its laureates. This article is the first research for the evolution of the Turing Award Collaboration Network. In this article, we analyze the evolution of the Turing Award Collaboration Network, which is extracted from the journal and conference articles recorded in DBLP from 1974 to 2016. We combine the metrics of the bibliometric-level method and the network-level approach to characterize the multiple attributes of the researchers.

The observations from the Turing Award Collaboration Network show that collaboration at different times has different types of strength and collaborative behavior. The number of articles and authors on the network has grown exponentially, indicating that the field of computer science has grown rapidly over the past 42 years. In the early stage, scholars did not pay attention to collaboration, so they were more inclined to publish articles alone. Gradually, they began to focus on collaboration so that multiple authors' articles account for a larger proportion than the single authors' articles. However, the average number of multiple authors' articles is limited to two authors. This consequence is consistent with other related disciplines [39], [40].

Scholars can connect to each other in four path lengths, characterizing the small-world properties. However, the Turing Award Collaboration Network is not the scale-free network, and then clustering coefficient began to decline in 2004. The reason may be that each author can collaborate with a limited number of scholars, so the scholars in the Turing Award Collaboration Network cannot be "preferential attachment" freely as the scale-free network. In addition, scholars tend to form a group to study the academic. Moreover, we further explore the relationship between the TN and the measured metrics. Consequently, we draw a conclusion that the closer the authors are to the Turing Award, the better the metrics. It shows that these authors are more superior. Compared with the random network, this network is more closely linked to the group but less connected because of the community.

As the possible future research direction, we believe that it would be necessary to expand the analysis of the performance metrics, including citations and h-index, [6], [41], to perceive whether the collaboration has an impact on them.

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