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Institutional Collaboration and Competition in Artificial Intelligence

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ABSTRACT The institutional collaboration and competition in academia have benefited the development of science, with inter-institutional scientific work promoting the exchange of ideas and competing fields developing rapidly. However, understanding of how the institutions collaborate and compete in science is sorely lacking, especially in emerging fields. Artificial intelligence is such a booming field currently, changing the way we live and work daily. To illustrate the problem, we try to reveal the evolution of institutional collaboration and competition in artificial intelligence by applying *AI 2000* from the perspective of Science of Science. In this paper, we make multiple multidimensional statistical analyses by scrutinizing the collaboration network, research interests, talent flow, etc. We demonstrate the collaboration evolution in this field and find the advantage of inter-institutional collaboration is growing over time for papers that have been published more than 5 years. We discover the common cooperation modes of top institutions and visualize their closer cooperation. We highlight the critical resources competition among institutions in three dimensions and learn the recent trends in the field. In particular, we are concerned about the competition among institutions for cross-industry cooperation and notice the consistency of competitiveness and cross-industry collaboration. The research of this paper may support further research studies on institutional collaboration and competition as well as policy proposals for promoting scientific innovation, research management, and funding.

INDEX TERMS Artificial intelligence, Science of Science, cooperation and competition, data analytics, data science.

I. INTRODUCTION

With the advent of globalization in academic research, research institutions get closer and closer in collaboration, and they suffer increasingly fierce competition at the same time. As far as we know, the relationship of giants usually described as co-opetition (simultaneous pursuit of collaboration and competition), which results in technological innovation, common benefits enhance, and proportionately more significant share of the benefits gain [20]. It is the same as academic competition and collaboration. Study shows that both institutional competition and collaboration tend to lead to produce high-impact research [14], [16] and improve scientific performance [42]. However, increasing collaboration and competition both within and between research institutions brings all kinds of new questions for research evaluation and funding policy. Consequently, the academic collaboration network deserves a closer and more thorough look, which reflects both institutional collaboration and competition simultaneously. In reality, a significant number of domain scholars show a keen interest in exploring inter-institutional co-opetition, leading to many related

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studies, including international cooperation [1], [19], [44], collaboration for funding [49], university-industry collaboration [46], scientific innovation, and production in co-opetition [37], [39], etc.

For specific fields, there is an urgent need to explore the science behind institutional collaboration and competition, especially in emerging fields. In the past decades, artificial intelligence has dramatically changed the way we work and live [8], [38], and it is increasingly becoming a national strategy for broad application in industries. Moreover, it influences the larger trends in global sustainability [21]. However, the way artificial intelligence advances itself is much less well-understood [31]. On the one hand, collaboration and competition in the field of artificial intelligence progress its rapid development. On the other hand, its rapid development calls for closer collaboration among research institutions. What is worse, a large gap exists between promoting the development of artificial intelligence and understanding its co-opetition mechanism.

Due to lacking effective means in modeling and sufficient background knowledge, the question is far from solved until now. With the explosion and digitization of scholarly papers in the few decades, the Science of Science (SciSci) [15], [47] provides an unprecedented opportunity to study the development of artificial intelligence. Although scholars have done some significant work on SciSci in artificial intelligence, the science of co-opetition in academic research is sorely lacking.

In this work, we try to uncover the problem from the perspective of Science of Science, which will help us reveal the critical role of co-opetition in advancing the field. More specifically, we try to explore (1) **Q1.1:** the collaboration evolution of top scholars in this field; (2) **Q1.2**: collaboration patterns mining and analysis; (3) **Q2.1**: the competition among institutions for several vital resources: academic influence, scholars, technologies, etc.; (4) **Q2.2:** the competition among institutions for cross-industry cooperation. Our study is performed on a high-quality data set, which covers almost all the most influential scholars in artificial intelligence during the last decade. To sum up, our work presents detailed information on institutional collaboration and competition and an in-depth understanding of the evolution of co-opetition in this field, which may support further research studies and policy proposals.

II. THEORETICAL FRAMEWORK

Study shows that a relatively constrained number of ideas and scholars push the boundaries of science [33]. According to this theory, ideas and scientific activities of a few elite scholars impact on the field deeply. Exploring the research activities of top scholars will significantly help us understand the behind science in this field.

Numerous studies have been done about the evolution of collaboration networks in scholarly papers [2], [4]. The evolution of international research collaboration has been systematically studied [9], [10]. Inter-institutional collaboration modeling [18], [24], [27] and the impact of inter-institutional collaboration [3], [11], [30] has been explored by numerous scholars.

This study focuses on the collaboration and competition in artificial intelligence from the perspective of Science of Science. The impact of institutional collaboration and competition on the development of science is multi-faceted, such as productivity [29], influence [17], creativity [28], and so on. In particular, we mainly concern about the above mentioned four points in this work. An overview of our theoretical analysis and framework is as follows:

***Q1.1:** The collaboration evolution of top scholars in artificial intelligence*

With the development of scientific research, collaborative research is becoming increasingly international and diverse, especially in emerging fields. First of all, we try to explore the collaboration trend from two dimensions: international collaboration and inter-institutional collaboration. Although numerous studies proved that both of the outputs of international collaboration and domestic collaboration increased rapidly in the last decades, the influence of international collaboration on the impact of research results is different [43]. The yearly investigation will help us have a quantitative understanding of the trend of this field.

Both inter-institutional and intra-institutional collaboration is vital for academic innovation and effective cooperation, which have their own advantages. However, previous studies show that the diversity of participants in a paper will lead to greater impact [14], [16], [17]. To test and verify their theory in this field, we quantify the impact of a paper by its citation. And then, we try to uncover the detailed rules of research impact in this field.

In general, **Q1.1** aims at modeling the evolution of institutions' collaboration in this field.

***Q1.2:** Collaboration patterns mining and analysis*

With the geographical boundaries of cooperation are being broken, more and more new collaboration patterns are changing the efficiency and impact of scientific cooperation [2]. Study shows that patterns of collaboration vary between subjects and over time [6], [35]. A study shows that there are positive and significant benefits in scientific quality for inter-sector collaboration [11]. More specifically, publications with more number of institutions have received more citations [12], [16]. In this paper, we try to find some frequent patterns in inter-institutional collaborations, which will give us a better understanding of the collaborative model in this field. At last, we quantify the willingness of institutions to cooperate across institutions, which may help us throw light on inter-institutional efficiency.

Above all, **Q1.2** addresses the frequent collaboration patterns and the possible causes.

***Q2.1:** The competition among institutions for several vital resources*

The competition among research institutions is manifold, for example, competition in technologies, market, scholars, research resources, applications, etc. Meanwhile, it is fierce, especially in high-tech industries. In the field of artificial intelligence, the phenomenon of winner-takes-all is very common. Walker *et al.* find that some competition is good to drive quality but can be counterproductive when competing for limited resources [45]. What is more, Brankovic *et al.* explored the relationship between institutional ranking and competition, which shows that rankings produce or intensify competition [5]. The evolution of research fields varies over time [7]. In this paper, we leverage their competition in academic influence, top scholars, and research hotspots to explore the law behind it.

Primarily, **Q2.1** intends to explore the vital resources competition among top institutions.

Q2.2: *The competition among institutions for cross-industry cooperation*

For top institutions, they pursuit collaboration and competition simultaneously. Study shows that cross-industry cooperation leads to greater competitiveness and effectiveness [13], which combines expertise with the innovation of the tech industry [36].

In our opinion, cross-industry collaboration in academia brings innovations and applications. In this process, knowledge and technology transfer from academia to industry [22]. For companies, they may get more cutting-edge technology in the collaboration. Universities may turn their technology into products through long-term cooperation. Both of them may benefit from the process.

All in all, we try to check the relevance of cross-industry collaboration and academic influence of institutions.

III. MATERIALS AND METHODS

A. DATA

AMiner [1] is a big data mining service platform for science and technology information developed by Tsinghua University. And it is the second generation of ArnetMiner [41], including 133 million researchers, 272 million publications, 8.8 million concepts, and 754 million citations so far. Great efforts have been made in name disambiguation [40], [48] and organization alignment [25], [26] in AMiner, which achieves state-of-the-art performance. What is more, AMiner has become a strategic partner of Microsoft Academic Search and the official content provider of Sogou Scholar.

AI 2000 Most Influential Scholars [2] (*AI 2000* for short) named 2000 of the world's top-cited researchers from the artificial intelligence-related fields during the last decade (2009–2019) based on AMiner academic big data, which includes 2000 most influential artificial intelligence scholars in the past decades, 295760 papers, 3037 top-level research institutions, and 237984 collaborators. To ensure its impartiality and objectivity, *AI 2000* is automatically generated by a ranking algorithm, which ranks a scholar's academic influence through their citations in the top-level publications. The annual list is increasingly being officially recognized by the world's leading universities and research institutions for its authority, accuracy, and advancement.

B. METHODS

In this work, we delve into the institutional collaboration and competition in artificial intelligence by applying *AI 2000*.

Some critical methods have been used to clarify the above four points, which are listed as follows:

1) OUTPUTS AND ACADEMIC IMPACT

In this paper, we use the papers of scholars as their academic outputs. Paper citation is one of the important indexes to measure the influence of papers. To quantify the influence of each institution, we apply the sum of their papers' citations. For collaborative papers, we stipulate that each institution will receive the same amount of citations. To quantify the impact of the inter-institutional collaboration papers and intra-institutional collaboration papers, we calculate the average number of citations per year and get the average citation number ratio between inter-institution and intra-institution collaboration outputs in each year.

2) COLLABORATION NETWORK

The structure of scientific collaboration networks implies the social network of authors in a specific field [34]. The frequency of cooperation between scholars represents their cooperation tendencies. Its limitation lies in that it gives a cold shoulder for non-paper cooperations. However, it is still reasonable and accurate in reflecting the scientific collaboration of scholars.

To indicate the collaboration of institutions, we use the outputs (academic papers) of international collaboration instead, and a paper denotes a collaboration. We define most willing cooperative institutions as the number of their collaborators.

3) SCHOLAR TRAJECTORY

Mining the footprints of these scholars, we can count the academic experience of them in each institution. To address this question, we study the career trajectory of AI 2000 most influential scholars by applying Career Trajectory [3] in AMiner. Thus, we can list the number of scholars attracted by institutions from scholars' academic experiences. In this work, we use the number of scholars attracted by institutions to represent the attractiveness of institutions.

4) FREQUENT ITEMSETS MINING

The collaboration network implies these frequent collaboration patterns. We consider a collaboration between all the institutions involved in a paper. To throw light on frequent patterns in inter-institutional collaboration, we apply the FP-Growth algorithm [23] to find frequent itemsets. In this paper, we set the minimum support as 100 and emphasize the result of frequent 2-itemsets.

[1] http://aminer.org/
[2] https://www.aminer.cn/ai2000
[3] https://traj.aminer.cn/trajectory-index

5) RESEARCH HOTSPOTS

To find the research hotspots of an institution, we try to extract all the academic terminologies that appeared in their articles and count their frequency. In this way, we get competitive technologies in two decades by applying all kinds of natural language processing tools, such as NLTK [32].

IV. RESULTS AND DISCUSSION

Specially, the analysis in this paper is up to 2019. To facilitate viewing and visualizing, we show the latest year (2020) on the timeline.

A. COLLABORATION

In this section, we try to uncover the institutional collaboration from the collaboration network of scholars, which is extracted from the scholarly papers.

Q1.1: *The collaboration evolution of top scholars in artificial intelligence*

According to our methodology, Figure 1 provides a detailed and in-depth understanding of the evolution of international collaboration in artificial intelligence in recent years. As the red line shows, international collaboration contributes more than half of the outputs in this field in the past decade.

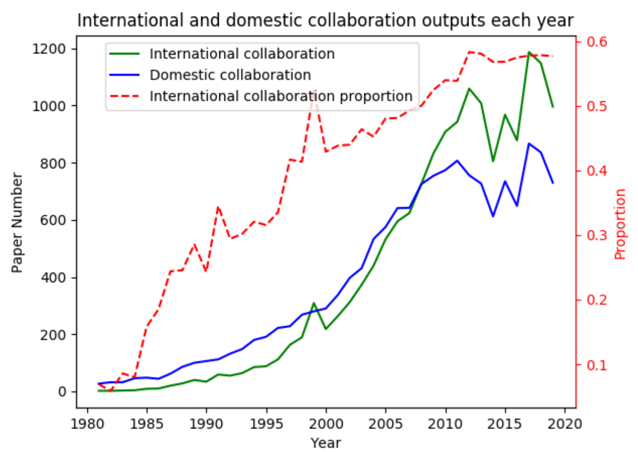

FIGURE 1. International and domestic collaboration outputs each year. The solid lines indicate the number of papers in each year (left y axis), and the dotted red line means the proportion (right y axis) of international cooperation papers in all papers.

Correspondingly, Figure 2 denotes the result of inter-institution collaboration.

By comparing the two proportions, we find that more than half of the inter-institutional collaboration comes from international collaboration since 1990. Whereas, the proportion of international inter-institutional collaboration grows dramatically since then.

What is more, we find a very interesting phenomenon in the academic impact evolution of inter-institution collaboration outputs in Figure 3.

In general, the papers of inter-institutional collaboration has a more significant impact in artificial intelligence as

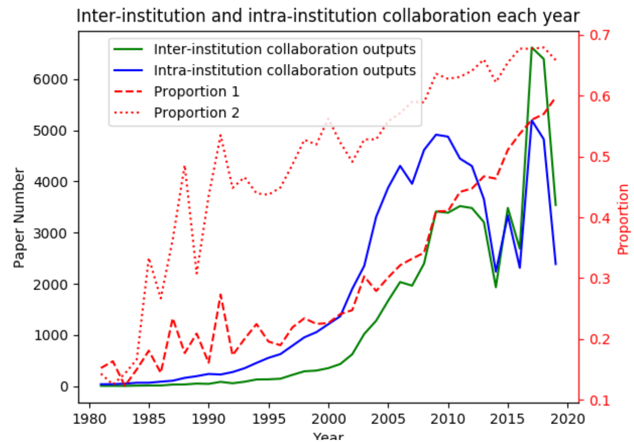

FIGURE 2. Inter-institution and intra-institution collaboration each year. The solid lines represent number of papers in each year (left y-axis); *Proportion 1* denotes the proportion of inter-institutional collaboration in all outputs, and *Proportion 2* means the proportion of international collaboration in inter-institutional collaboration.

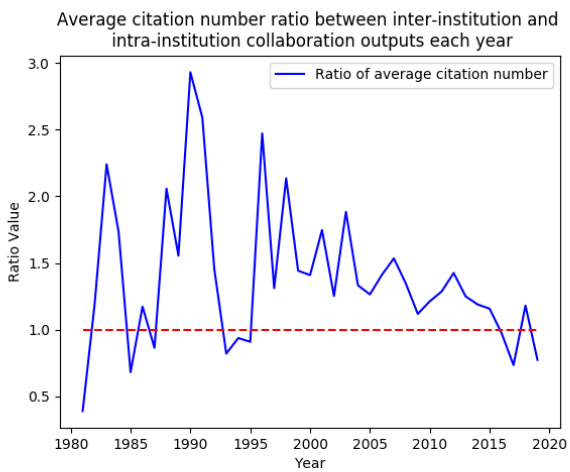

FIGURE 3. Average citation number ratio between inter-institution and intra-institution collaboration outputs each year. If the value is greater than 1, it means the outputs of inter-institution collaborations have a more significant impact. On the contrary, if it is less than 1, it denotes the outputs of intra-institution collaborations are more influential.

well. However, the advantage is not evident for papers published in recent 5 years. Nevertheless, the advantage of inter-institutional collaboration is growing over time for papers published more than 5 years.

Q1.2: *Collaboration patterns mining and analysis*

For the impact of research collaboration on scientific productivity and influence [29], institutions become long-term partners. We find the top 20 frequent 2-itemsets and their support values in this field, which is demonstrated in Table 1.

From the table, we find that Microsoft collaborates frequently with many world's top universities in artificial intelligence academic research, which is a microcosm of the growing popularity of cross-industry cooperation in academia. Meanwhile, there is very close cooperation between the world's top universities.

TABLE 1. Top 20 most frequent 2-itemsets of inter-institutional collaboration. *Collaboration Institutions* represents the frequent 2-itemsets in inter-institutional collaborations, and *Value* denotes their support values.

Collaboration Institutions	Value
(Microsoft, University of Washington)	385
(Microsoft, Tsinghua University)	377
(Microsoft, University of Science & Technology of China)	348
(Microsoft, Carnegie Mellon University)	301
(Microsoft, University of Illinois Urbana Champaign)	218
(Microsoft, Massachusetts Institute of Technology)	212
(Chinese Academy of Sciences, University of Chinese Academy of Sciences)	210
(Microsoft, University of California Berkeley)	193
(Massachusetts Institute of Technology, Stanford University)	186
(Microsoft, Stanford University)	184
(Massachusetts Institute of Technology, University of California Berkeley)	180
(Microsoft, Peking University)	175
(Massachusetts Institute of Technology, Harvard University)	171
(Stanford University, University of California Berkeley)	169
(Carnegie Mellon University, University of Washington)	163
(Carnegie Mellon University, Massachusetts Institute of Technology)	157
(Carnegie Mellon University, Intel)	156
(Carnegie Mellon University, University of California Berkeley)	154
(IBM, University of Illinois Urbana Champaign)	153
(Microsoft, Hong Kong University of Science & Technology)	152

For further exploration of the collaboration patterns in top institutions, we try to visualize their collaboration networks. Before addressing this question, we consider that there is a difference between the different periods. Hence, we study the collaboration networks in the period of 2000 − 2009 and 2010 − 2019.

In 2000 − 2009, the institutions with the most collaborative institutions are Microsoft (376), MIT (347), UIUC (341), Carnegie Mellon University (336), Columbia University New York (324), etc. Whereas, in 2010 − 2019, they are MIT (710), Carnegie Mellon University (695), Chinese Academy of Sciences (666), Stanford University (631), Microsoft (602), etc. To facilitate visualization, we visualize the top 20 most willing cooperative institutions in 2000 − 2009 and 2010 − 2019, respectively. The cooperation network are demonstrated in Figure 4 and Figure 5.

In these two cooperation networks, the nodes denote institutions, the size of the node represents the number of collaborators of the institution, the edges imply the collaboration, and the values indicate the collaboration frequencies between institutions.

Comparing the two pictures, we find that the collaboration between top institutions has become closer, and their number of collaborators increased. It shows that academic cooperation has become more international, and the institutional boundaries for academic collaboration are being broken.

B. COMPETITION

In this section, we delve into the two dimensions to understand the institutional competition in this field.

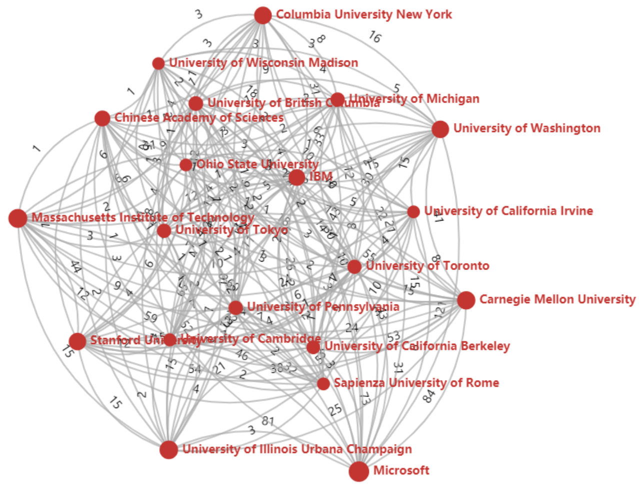

FIGURE 4. Cooperation network of top 20 most willing cooperative institutions in 2000 – 2009.

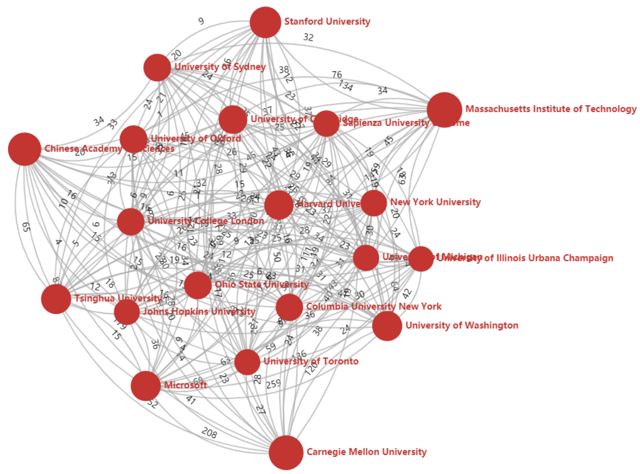

FIGURE 5. Cooperation network of top 20 most willing cooperative institutions in 2009 – 2019.

Q2.1: *The competition among institutions for several vital resources*

We try to reveal the competition among institutions from three dimensions: academic influence, scholars, and technologies.

1) ACADEMIC INFLUENCE

We quantified the annual academic impact of most influential institutions in the past two decades and visualized it in Figure 6.

Statistic shows that both universities and companies have made important contributions to research in this field. What is more, trends illustrate that Google is playing an increasingly important role in artificial intelligence research. However, advantages of IBM in this field are losing.

2) ATTRACTIVENESS TO SCHOLARS

According to the trajectory of a scholar's career, we quantify the attractiveness of institutions to scholars. Furthermore, we

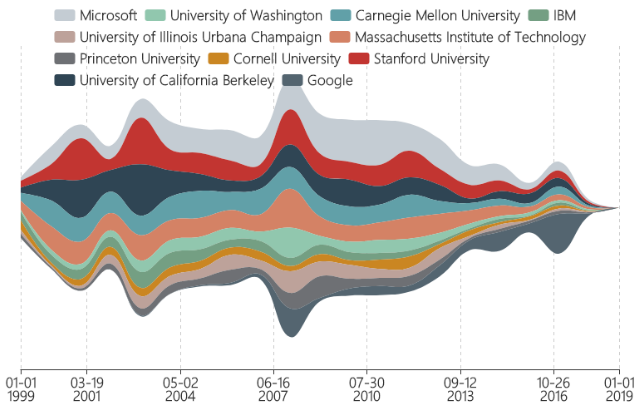

FIGURE 6. **The annual academic impact of top institutions. The width of each institution in each year represents its influence in this year.**

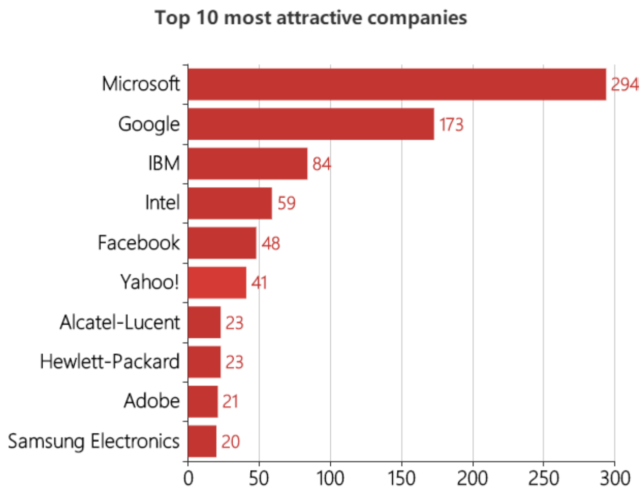

FIGURE 7. **Top 10 most attractive companies.The number means the number of scholars who have worked in this company.**

divide institutions into universities and companies, which will provide us two different perspectives.

AI giants are the most attractive to top scholars in the past few decades.

3) COMPETITIVE TECHNOLOGIES

We deem that the competitive technologies in different stage are different. So, we study the problem in the periods of 2000 – 2009 and 2010 – 2019 as well.

Figure 9 and Figure 10 illustrate the top 200 competitive technologies in 2000–2009 and 2010–2019, which contains only the stem of academic terminologies. The relative size of the word denotes its frequency in the papers. For example, the frequency of "data mine" (refers to "data mining") in Figure 9 is 1276, and the frequency of it in Figure 10 is 2951.

Comparing the two figures, we find that competitive technologies in two decades are quite different, which reflects the fierce competition in technology among institutions.

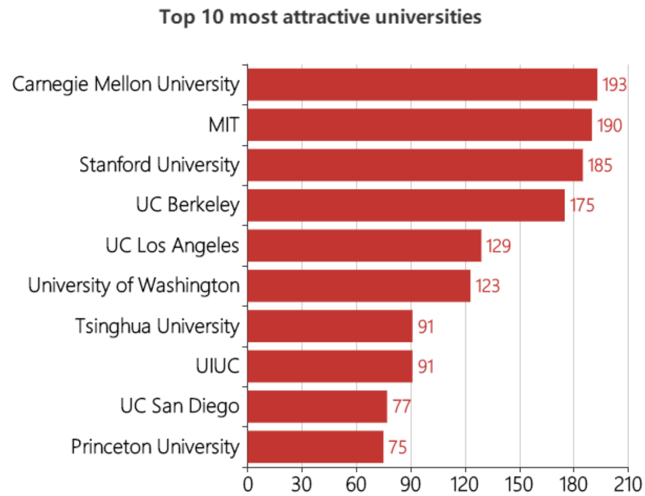

FIGURE 8. **Top 10 most attractive universities.The number means the number of scholars who have worked in this university.**

FIGURE 9. **Top 200 competitive technologies in 2000 – 2009.**

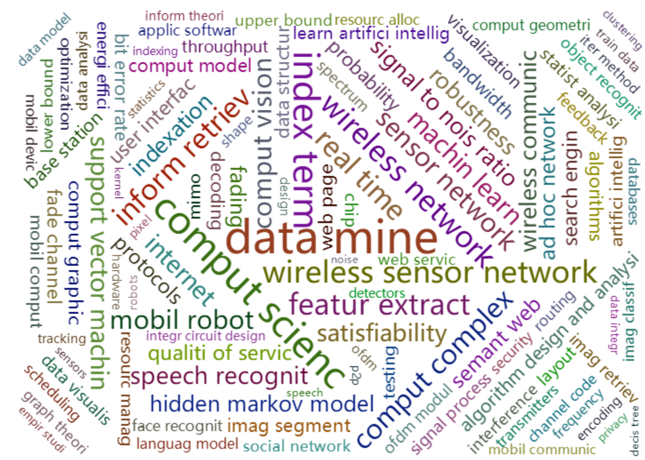

FIGURE 10. **Top 200 competitive technologies in 2010 – 2019.**

More specifically, 38.5% of research hotspots have been updated in 2000 – 2009. What is more, the research heat of these competitive technologies is changing over time.

TABLE 2. Top 10 universities in cross-industry cooperation.

Institution	Country	Num	Freq
Massachusetts Institute of Technology	USA	62	711
Carnegie Mellon University	USA	60	1024
University of California Berkeley	USA	53	674
University of Michigan	USA	52	388
University of Washington	USA	50	734
Stanford University	USA	50	694
University of Illinois Urbana Champaign	USA	49	718
Tsinghua University	CHN	47	668
Columbia University New York	USA	47	338
University of Texas Austin	USA	46	299

Q2.2: The competition among institutions for cross-industry cooperation

We list the top 10 universities in cross-industry cooperation in Table 2. In this table, *Num* denotes the number of collaborative companies, and *Freq* represents the number of times they collaborate.

At the same time, we find that Microsoft collaborates with 631 universities (8605 times), IBM collaborates with 523 universities (3240 times), and Google collaborates with 358 universities (2192 times).

In combination with the influence of the institution, the influence of the inter-institution cooperation outputs, and the cross-industry cooperation frequency, we find that they are positively correlated. There is no doubt that artificial intelligence benefits from cross-industry cooperation in the past decades.

V. CONCLUSION

In this paper, we explore how the institutions collaborate and compete in artificial intelligence by applying *AI 2000* from the perspective of Science of Science. We reveal the evolution of institutional collaboration and competition from multiple multidimensional statistical analyses by scrutinizing the collaboration network, research interests, talent flow, etc. Comparing with the studies mentioned above, our methods (1) focus on the impact of the most influential scholars on the field; (2) combine the collaboration and competition analysis to find the way science advance itself; (3) new discoveries from the perspective of SciSci. In the following study, we will focus on the collaboration and competition model of institutions. The research of this paper may support further research studies on institutional collaboration and competition as well as policy proposals in promoting scientific innovation and research effectiveness.

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