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Artificial Intelligence in the 21st Century

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ABSTRACT The field of artificial intelligence (AI) has shown an upward trend of growth in the 21st century (from 2000 to 2015). The evolution in AI has advanced the development of human society in our own time, with dramatic revolutions shaped by both theories and techniques. However, the multidisciplinary and fast-growing features make AI a field in which it is difficult to be well understood. In this paper, we study the evolution of AI at the beginning of the 21st century using publication metadata extracted from 9 top-tier journals and 12 top-tier conferences of this discipline. We find that the area is in the sustainable development and its impact continues to grow. From the perspective of reference behavior, the decrease in self-references indicates that the AI is becoming more and more open-minded. The influential papers/researchers/institutions we identified outline landmarks in the development of this field. Last but not least, we explore the inner structure in terms of topics' evolution over time. We have quantified the temporal trends at the topic level and discovered the inner connection among these topics. These findings provide deep insights into the current scientific innovations, as well as shedding light on funding policies.

INDEX TERMS Artificial intelligence, data analytics, scientific impact, science of science, data science.

I. INTRODUCTION

Artificial Intelligence (AI) has grown dramatically and becomes more and more institutionalized in the 21^{st} Century. In this era of interdisciplinary science, of computer science, cybernetics, automation, mathematical logic, and linguistics [1], questions have been raised about the specific concept of AI [2]. Actually, as early as the 1940s and 1950s, scientists in the field of Mathematics, Engineering, and Computer Science had explored the possibilities of artificial brains and were trying to define the intelligence of the machine. In 1950, Turing [3] presented the famous ''Turing Test'' which defined of the concept of ''Machine Intelligence''. On this background, the origins of AI can be traced to the workshop held on the campus of Dartmouth College in 1965 [4], in which McCarthy persuaded participants to accept the concept of ''Artificial Intelligence''. It is likewise the beginning of the first ''Golden age'' of AI.

In simple terms, AI aims to extend and augment the capacity and efficiency of mankind in tasks of remaking nature and governing the society through intelligent machines, with the final goal of realizing a society where people and machines coexist harmoniously together [5]. Due to the historical development, AI has been utilized into several major subjects including computer vision, natural language processing, the science of cognition and reasoning, robotics, game theory, and machine learning since the 1980s [6], [7]. These subjects developed independently of each other. However, these disciplines basically had already abandoned the logical reasoning and heuristic search-based methods which were proposed 30 years ago. Instead, most of them were based on statistical methods which include modeling and learning.

Studies have already shown the ability of the quantitative analysis to reveal the nature of the specific field and its development over time [8], [9]. On the grounds of science of science [10], [11], many scientific online systems including AMiner [12], Google Scholar [13], and Microsoft Academic Services [14], have been developed for beer science. They also provide opportunities for providing direct access to scholarly big data. A significant body of work has concentrated on designing scientometric methods and tools to quantify the impact of publications [15], [16], researchers [17], venues, conferences [18], and others [19], [20]. On the basis of these results, researchers have already used these methods and tools to study scientific communities, to evaluate the impact of researchers, and to describe scientific collaboration [21], [22]. The statistical analyses based on the publication data of specific conferences and journals not only help researchers understand the evolvement of the research communities [23] but also can be the basis in a variety of situations for knowledge acquisition, consensus-building, and decision making [24].

Although more and more efforts based on the theory and technology of scholarly big data have been put forward [25]–[27], up to now, little attention has been paid to provide a statistical analysis [28], [29] with the widely accessible data source to portray the field of AI at the beginning of the 21^{st} Century. There is a need to understand the internal structure and its evolution over time through the quantitative analysis of this area by collecting bibliometric data [30].

To fill this gap, relying on the ability of the bibliometric analysis, we study the evolution of AI at the beginning of 21^{st} Century according to following four dimensions. First, we examine the evolving process of AI based on the growing volume of publications over time. Second, we emphasize on the impact and citation pattern to characterize the referencing behavior dynamics. Third, we try to identify the influential papers/researchers/institutions and explore their characteristics to quantify the milestone and landmark in this period. Finally, we explore the inner structure by investigating topics evolution and interaction. Our study is performed on a large-scale scholarly dataset which consists of 58,447 publications and 1,206,478 citations spanning from 2000 to 2015. The main findings are:

- In the context of AI's growth, we discover that the number of publications as well as the length of the author list has been increasing over the past 16 years. It suggests that the collaboration in the field of AI is becoming more and more common and the scope of research projects are becoming bigger. Instead of individual work, researchers are benefited from the collaboration efforts.
- From the perspective of reference behavior, the decrease in self-references including author self-references and journal/conference self-references indicates the science of AI is becoming more open-minded and more widely sharing. The development of techniques and tools (evidenced by the citing behavior of latest literature) in AI leads the area getting diverse.
- We use the average number of citations per paper of each author/institution as an indicator to evaluate their importance. Those influential entities are consistent with our intuitions.
- Finally, we explore the inner structure of AI in the 21^{st} Century. We identify hot keywords and topics from the perspective of how they change with time. Some topics have attained ''immortality'' in this period such as computer vision, pattern recognition, feature extraction, etc. Furthermore, based on the co-presence of different topics and the citation relationships among them, we find the inter-connection patterns and unveil the trend of development in this complex disciplinary.

Overall, our findings demonstrate that AI is becoming more and more collaborative, diverse, and challenging during the first 16 years of the 21^{st} Century. These results not only explain the development of AI overtime, but also identify the important changes. They also can give rise to important implications for institutions and governments to adjust research funding policies, for researchers to understand the potential development of AI, with the ultimate goal of advancing the evolution of AI.

II. METHODOLOGY

In this section, we first introduce publication dataset used in analyzing the corpus of AI. Next, we describe several measures quantifying the importance of authors and publications in this area. Finally, we emphasize on profiling the inner structure of the field based on the topic evolution.

A. DATASET

The issue is essential for our study: what exactly is an AI paper? Here we accept the most concise answer: an AI paper is a paper published in an AI journal/conference [31]. Though the definition is narrow, its obviousness enables us to profile the area easily. The publication metadata we used is obtained from Microsoft Academic Graph (MAG),[1] which contains six entity types of scholarly data, including authors, papers, institutions, journals, conferences, and the field of study. Our purpose is to construct and analyze the citation network of AI, so we select articles published in the list of top-tier journals and conferences of China Computer Federation (CCF) recommended international academic publications and Computing Research and Education Association of Australasia (CORE) under the category ''Artificial Intelligence''. Finally, we select articles from 9 journals and 12 conferences.

TABLE 1 and TABLE 2 list the journals/conferences and their basic statistics including the total number of papers, the total citations of these papers, the total number of unique authors, the average number of authors per paper, the average number of published papers per author, and the average number of citations per paper. In addition, we also list the frequency for the conference because some conferences will be held every two years which may result in the fluctuation of publications.

B. MEASURING RESEARCH OUTPUTS THROUGH ALTIMETRICS

We use following metrics to quantify the importance of authors and publications in this area.

1) MEASURING RESEARCH OUTPUTS THROUGH ALTIMETRICS

The average number of authors per paper is computed as $\frac{\sum_{p \in P} |au_p|}{|P|}$, where $|P|$ is the total number of papers in the

[1] http://research.microsoft.com/en-us/projects/mag/

TABLE 1. Statistics for each journal.

Journal name	Papers	Authors	Citations	Authors per paper	Authors per paper (max)	Papers per author	Citations per paper
Artificial Intelligence	2693	5127	31534	2.67	12	0.52	11.71
IEEE Transactions on Pattern Analysis and Machine Intelligence	3093	5600	187119	2.91	32	0.55	60.50
International Journal of Computer Vision	1612	3027	75522	2.93	19	0.53	46.85
Journal of Machine Learning Research	1598	3075	70717	2.85	23	0.52	44.25
Computational Linguistics	882	1231	13901	1.78	12	0.72	15.76
IEEE Transactions on Evolutionary Computation	891	1779	50468	2.79	11	0.505	56.64
IEEE Transactions on Fuzzy Systems	1740	2560	43373	2.62	9	0.68	24.93
Machine Learning	1216	2269	34729	2.41	14	0.54	28.56
Pattern Recognition	4998	9754	84674	2.92	19	0.51	16.94

TABLE 2. Statistics for each conference.

Conference name	Papers	Authors	Citations	Authors per paper	Authors per paper (max)	Papers per author	Citations per paper	Frequency
AAAI Conference on Artificial Intelligence	4938	9393	40383	3.00	23	0.53	8.18	every 2 years before 2004, every 1 year or 2 years since then
IEEE Conference on Computer Vision and Pattern Recognition	8384	12477	18604	3.16	24	0.67	21.78	once a year after 2003
International Conference on Computer Vision	4374	8775	71031	3.25	51	0.50	16.24	every 2 years
International Conference on Machine Learning	3199	5421	69292	2.90	21	0.59	21.66	once a year
International Joint Conference on Artificial Intelligence	3188	5871	35254	2.78	12	0.54	11.06	every two years
Annual Conference on Neural Information Processing Systems	4706	7072	90025	2.91	18	0.67	19.13	once a year
Annual Meeting of the Association for Computational Linguistics	4362	6617	64342	2.81	26	0.66	14.75	once a year
Annual Conference on Computational Learning Theory	613	761	6167	2.28	6	0.81	10.06	once a year
International Conference on Automated Planning and Scheduling	273	557	1248	2.97	9	0.49	4.57	once a year
International Conference on Principles of Knowledge Representation and Reasoning	569	849	5893	2.41	13	0.67	10.36	every 2 years
International Conference on Uncertainty in Artificial Intelligence	992	1379	12800	2.33	11	0.72	12.90	once a year
International Joint Conference on Autonomous Agents and Multi-agent Systems	4126	5928	35402	3.03	23	0.70	8.58	once a year

journals/conferences and $|au_p|$ is the number of authors in the paper. Similarly, the average number of papers per author and the citations per paper can be calculated as $\frac{|P|}{\sum_{p\in P}|au_p|}$ and $\frac{\sum_{p\in P}|ci_p|}{|P|}$ ($|ci_p|$ represents the total number of citations of the paper), respectively.

2) SELF-REFERENCE RATE

Author self-reference is the reference to an article from the same authors. The author self-reference rate in a paper is defined as the proportion of author self-references in the total number of references. It can be computed as $\frac{\sum_{r\in R}|ar_r|}{|R|}$, where $|R|$ is the total number of references of the journals/conferences and $|ar_r|$ is the number of author self-references.

For journals and conferences, a self-reference is a reference to an article from the same journal/conference. The journal/conference self-reference rate is defined as the number of journal/conference self-references expressed as a percentage of the total references to the journal/conference. It can be computed as $\frac{\sum_{r\in R}|jr_r|}{|R|}$, where $|R|$ is the total number of references of the journals/conferences and $|jr_r|$ is the number of journal/conference self-reference.

C. THE INNER STRUCTURE OF AI

1) DISCOVERING TOPICS

AI is not an independent subject but belongs to the interdisciplinary science. In the MAG dataset, for each paper, it provides keywords which can represent the abstract

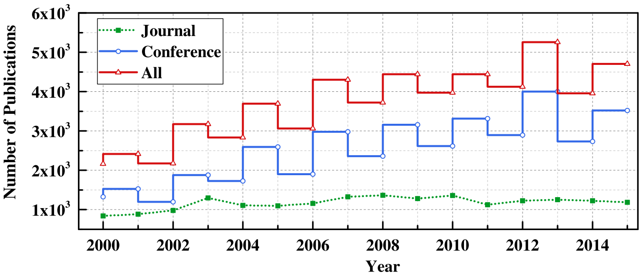


FIGURE 1. Changes in the number of papers in AI (every year) in the 21^{st} Century.

classification of the paper. It also provides the field of studyID of the paper mapped to its keywords. We first extract keywords for all papers published in the top journals/conferences during 2000 and 2015. According to these keywords, we map them to the studyID. Then, based on the hierarchical relationship for the study fields provided by MAG, we find the second-order parent field for the studyID to represent the topics in our work. Take keyword "KNN" as an example, it is one child of the field "machine learning" in hierarchies, at the same time, "machine learning" is the child of "data mining", which is the child node of the study field "Computer Science". So the second-order parent of "KNN" is "data mining".

2) THE RELEVANCE OF THE TOPICS

To further investigate the relevance of all topics, given two topic A and B, we compute the probability of B's occurrence on condition that A's occurrence as follows:

1) Calculate the probability of topic A and B's occurrence, $P_A = \frac{|N_A|}{|N|}$ and $P_B = \frac{|N_B|}{|N|}$, where $|N_A|$, $|N_B|$ represents the total number of papers containing the topic A and the topic B, respectively. $|N|$ is the total number of papers.
2) Compute $P_{AB} = \frac{|N_{AB}|}{|N|}$ where P_{AB} is the probability of A and B simultaneously appearing, and $|N_{AB}|$ is the number of publications simultaneously contains A and B.
3) $P(A|B) = \frac{P_{AB}}{P_B}$ is the probability that A appears under the condition that B appears.

3) PROPORTION OF THE TOPIC IN DIFFERENT YEARS

In order to observe the evolution of the topic over time, we use $\theta_k^{[t]}$ [32] to represent the proportion of topic k at year t. As can be seen, θ is the averaged topic distribution across all articles. This metric allows us to quantify the importance of the topic in the specific time period.

4) POPULAR TOPICS

To investigate popular topics, we compute the increase index between two time periods $r_k = \frac{\sum_{t=2008}^{2015} \theta_k^{[t]}}{\sum_{t=2000}^{2007} \theta_k^{[t]}}$ for each topic k. For the results, $r_k > 1$ demonstrates that the topic k becomes more popular in 2008-2015 than 2000-2007, while $r_k < 1$ indicates that the topic's popularity has a declining trend.

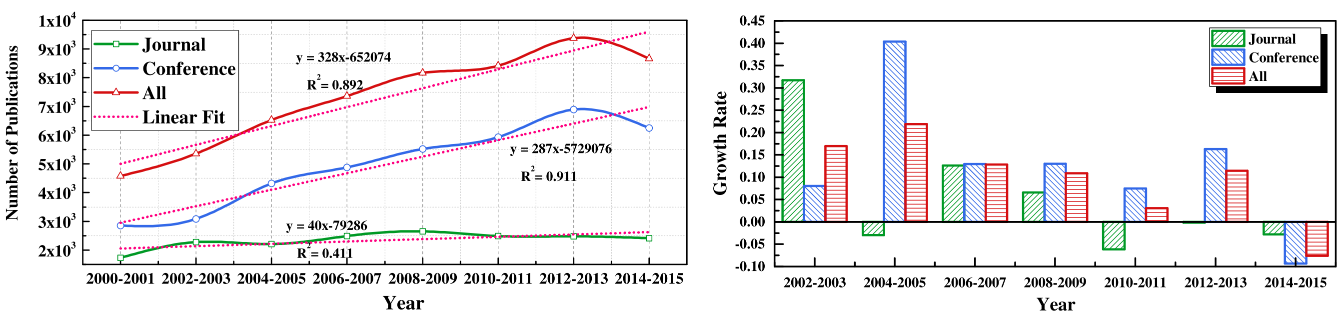
5) NETWORK OF TOPICS CO-PRESENCE

Meyer *et al.* [9] have performed experiments of co-citation analysis to unveil the evolution in the field of Social Simulation. Following by their steps, we employ the method to construct the network of topics co-presence to discover the interconnection patterns among them. Relying on the relevance of topics P_A, P_B, and P_{AB}, we compute a coefficient of co-presence $co(A, B) = \frac{{P_{AB}}^2}{min(P_A,P_B)*mean(P_A,P_B)}$. And thus, we choose the topics whose $co(A, B) > 0.1$ to construct the co-presence network.

III. RESULTS

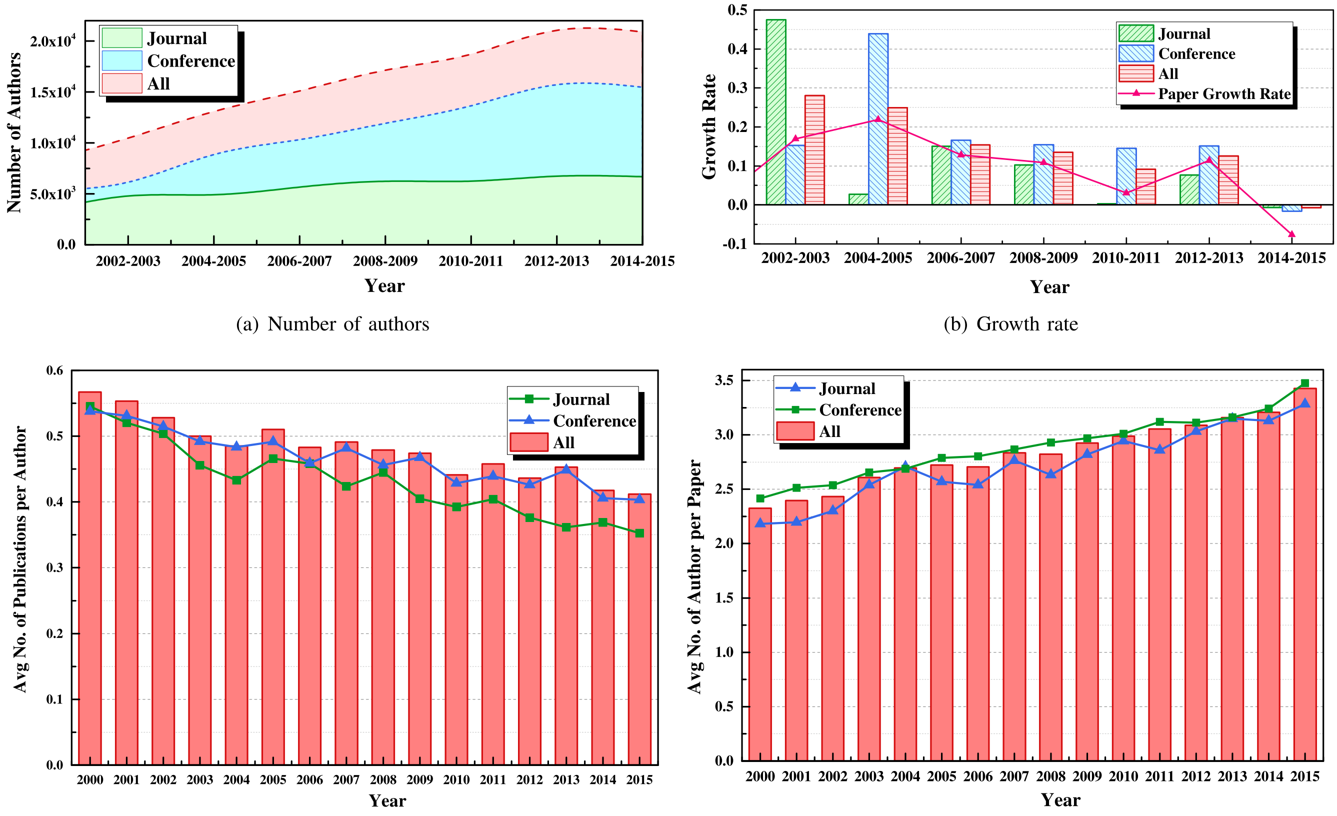
A. THE GROWTH OF AI

Throughout the development of AI, such as machine learning techniques shift, it has resulted in the explosion of publications and given birth to some sub-fields. The existence of this growth is supported by the number of papers published each year (see in Fig. 1). Some conferences occur every 2 years, which affects the number of publications and influences the overall results. In order to better demonstrate the development of this discipline, some statistics will be compiled every two years. In Fig. 2(a) we can see that the number of AI papers has been increasing roughly linearly in the 21^{st} Century. Note that, the growth rate of journal papers is distinguishable from the growth of conference papers. In general, the purpose of



(a) Number of publications (b) Growth rate

FIGURE 2. The evolution of the number of AI papers in the 21^{st} Century. (a) The number of publications every 2 years. (b) The growth rate of publications every two years.



(a) Number of authors

(b) Growth rate

(c) Authors per paper

(d) Papers per author

FIGURE 3. The evolution of the number of authors in the area of AI. (a) The number of authors every 2 years. (b) The growth rate of authors as well as total publications every two years. (c) The average number of authors per paper. (d) The average productivity of AI scientists.

conferences is mainly to provide the opportunity for scientists to communicate and see what others are doing. They can publish their findings as soon as possible, which is very important for subjects requiring timeliness. In contrast, journal papers have a longer review period which may result in the fluctuation of the growth rate.

Is the growth of papers driven by the growth in the number of scientists of AI? To answer this question, we analyze the number of authors in the dataset (Fig. 3(a)) and find that the growth rate has the same trend as the number of publications but it is a little higher (Fig. 3(b)). It leads to conclude that the increase of AI publications may be driven by the increasing number of authors. We do also observe that the average number of authors per paper is increasing over time (see in Fig. 3(c)) which declares the collaboration is becoming more and more common in this era.

Fig. 3(d) plots how the average number of publications per author varies with time. There is a clear decline trend from 3.6 to 1.8 during 2000-2012, suggesting that the average productivity is becoming weaker in this period. After that time, the average number of papers per author has increased to 2.3 till 2015.

B. IMPACT AND CITATION PATTERN ANALYSIS

From Fig. 4 we can see that citations increase much more quickly than the number of publications (Fig. 2(a)).

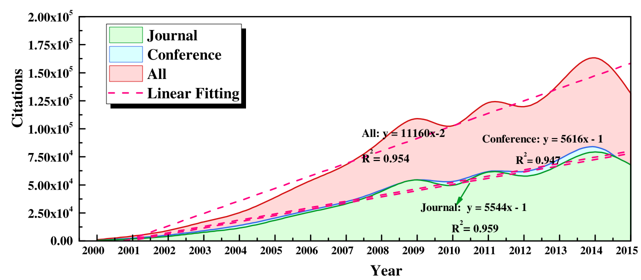
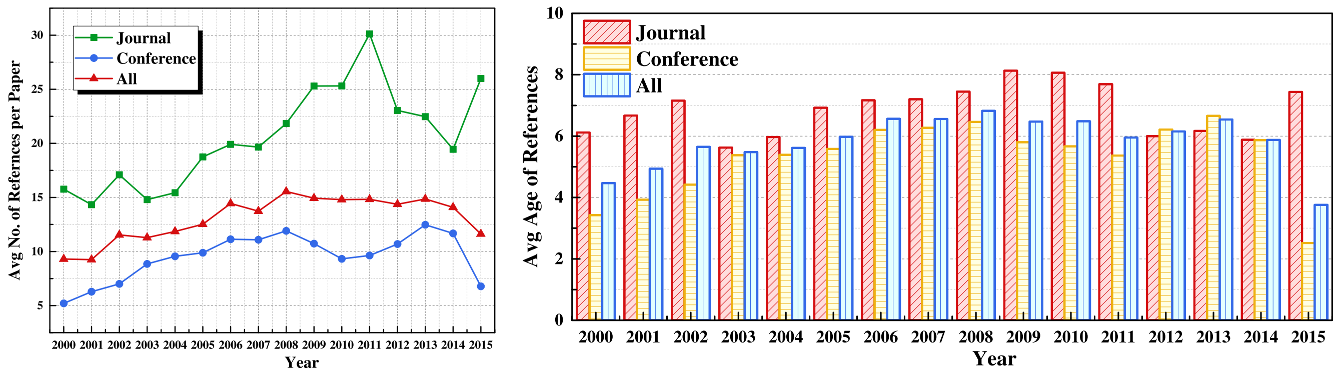


FIGURE 4. Changes in the citations.

It indicates that researchers pay more attention to others' work. The sharp growth of citations may be fuelled by two aspects: the increasing number of references per paper and the increasing number of publications.

Fig. 5(a) shows how the average length of a paper's reference list changes from 2000 to 2015. In general, journal papers have more references than conference papers. Conference papers concentrate more on the idea, so they can be accepted as long as they are reasonable and novel. Journal papers always require extensive experiments and results. So conference papers can be short but journal papers always have a requirement in pages which may cause the large difference in the number of references. The average number of references per paper has been growing steadily from



(a) Average number of references (b) Average age of references

FIGURE 5. The evolution of references. (a) The average number of references per paper. (b) The average age differences between the cited paper and the citing paper.

15 in 2000 to approximately 30 in 2011 (journal papers). Conference papers have the same trend (from 5 in 2000 to 10 in 2008).

The era evolved from deep referencing (i.e., referencing ''classical'' papers) to myopic referencing (i.e., referencing ''latest'' papers), which can be evidenced from the gradual decrease in the average reference age of the papers shown in Fig. 5(b). There is a clear discontinuity in the way scientists cite papers, occurring in 2011. Actually, in 2012, Krizhevsky *et al.* [33] first used deep learning to classify high-resolution images. The deep convolutional neural network much outperforms than the traditional machine learning technology. It makes people aware that deep learning may be much better and brings it back to the mainstream technology arena. Scientists have opened a new chapter in deep learning in 2012, more and more scholars try to keep abreast of the latest developments in deep learning. It may cause the average age differences decreasing between citing papers and cited papers.

The average number of citations per paper was unabated before 2009 (Fig. 6). However, we can find that both the

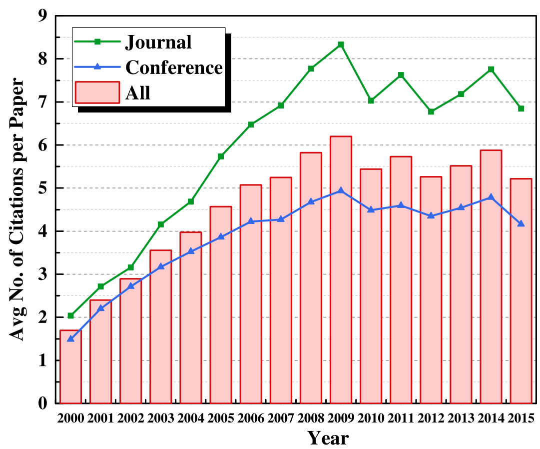


FIGURE 6. The average number of citations per paper.

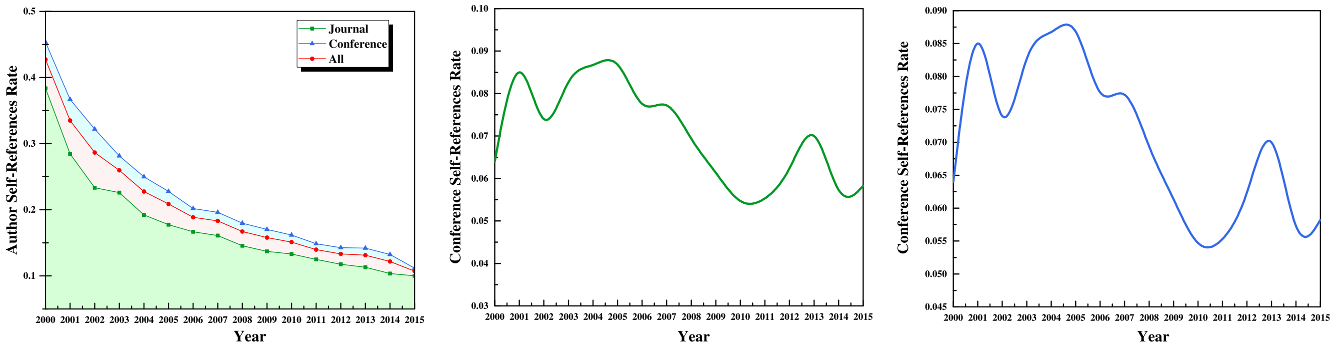
number of publications and citations show a fluctuation trend later. Especially, the rate of inflation within 18.7 percentage points of journal papers and 14.9 percentage of conference papers.

The boost of a paper's reference list size may be because scientists had increasingly cited their own papers over time. Fig. 7 provides the average self-references rate including author self-references, journal self-references, and conference self-references in a publication. The results turn out to be that researchers' tendency to cite their own papers has fallen over time. The average author self-reference rate is over 40% at the beginning of the 21^{st} Century and only 10-15% in the last part of the 2000s. In 2015, the rate of self-reference has actually dropped to only around 10%. Compared with journal self-reference rate, conference self-reference rate is much lower.

C. IDENTIFYING INFLUENTIAL PAPERS/ RESEARCHERS/INSTITUTIONS

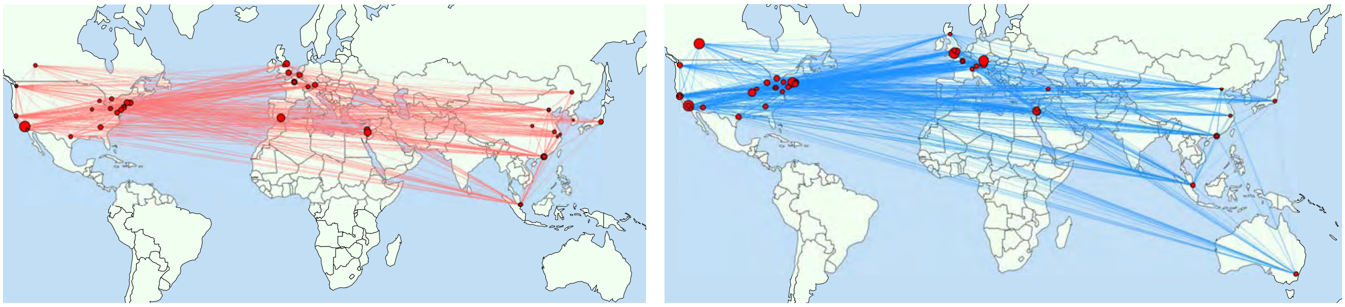
To quantify papers'/researchers'/institutions' importance in the development of this era, we use the total number of citations to quantify the important entities of AI in the 21^{st} Century. Here we consider the papers which have received the most citations during 2000-2015 as the influential papers. TABLE 3 shows the ranking of papers based on the total number of citations. These papers are all published during 2000-2015. We also divide the papers into journal papers and conference papers. From the ranking of these papers, we can identify crucial issues and the keyword in the different time periods. For example, at the beginning of the 21^{st} Century, researchers concentrated on the computer vision and then they invested significant time and efforts in data mining (feature extraction, deep learning).

In the same way, influential researchers are those who have the most citations per paper. TABLE 4 lists the top 30 researchers who have the highest average number of citations per paper as well as their total number of publications published in top-tier journals and conferences in our dataset.



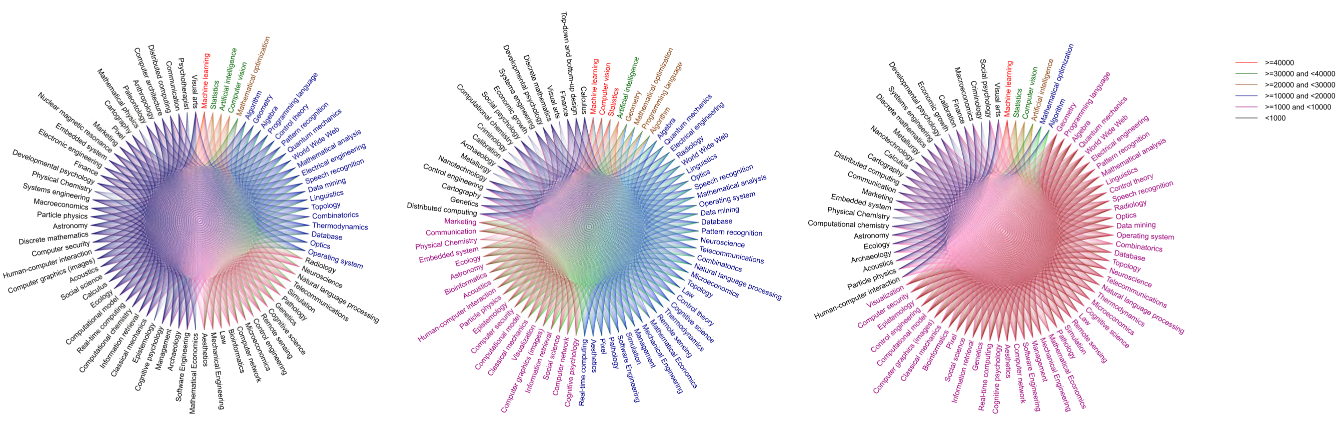
(a) Author self-references rate (b) Journal self-references rate (c) Conference self-references rate

FIGURE 7. **The evolution of referencing behavior. (a) The proportion of author self-references behavior in the top journals and conferences. (b) The average journal self-references rate of the top journals over time. (c) The average conference self-references rate of the top conferences over time.**



(a) Journal citations (b) Conference citations

FIGURE 8. **The overview of AI citation relationships between 2000 and 2015. The red circles represent: (a) the top 50 most-cited institutions on the basis of papers published in top-tier journals, and (b) the top 50 most-cited institutions on the basis of papers published in top-tier conferences. The lines represent the citation relationships among them.**



(a) (b) (c)

FIGURE 9. **The topics based on journals and conferences as well as their citation relationships. Different colors of topics represent the size of the topics measuring on the basis of the number of publications. (a) Journals. (b) Conferences. (c) All.**

Although some researchers have published few papers, they have received high citations. For example, Meyarivan and Pratap wrote the paper "A fast and elitist multi-objective genetic algorithm: NSGA-II" together. The paper has generated enormous interest and received numerous citations. So both of authors have a high average number of citations. Some researchers have published a large quantity of papers and some have relatively high citations but others don't. Andrew Y. Ng has published more than 80 papers in the top journals/conferences and the most famous one "Latent Dirichlet Allocation" has received more than 4,600 citations since published. By contrast, some are not as famous as this paper so the average citations may be a little lower.

Scientific institutions can be regarded as clusters of researchers with essential roles [34]. So it follows that influential institutions have the most citations per paper

TABLE 3. Ranking of papers based on the total number of citations received in 2000-2015.

	Journal papers			Conference papers		
No.	Title	Citations	Published year	Title	Citations	Published year
1	Distinctive Image Features from scale-Invariant Keypoints	9820	2004	Histograms of Oriented Gradients for Human Detection	4990	2005
2	A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II	6233	2002	Rapid Object Detection Using a Boosted Cascade of Simple Features	4512	2001
3	Latent Dirichlet Allocation	4618	2003	BLEU: A Method for Automatic Evaluation of Machine Translation	2475	2002
4	Normalized Cuts and Image Segmentation	3734	2000	Conditional Random Fields: Probabilistic Models for Segmenting and Labeling Sequence Data	2448	2001
5	Mean Shift: A Robust Approach toward Feature Space Analysis	3680	2002	Beyond Bags of Features: Spatial Pyramid Matching for Recognizing Natural Scene Categories	2291	2006
6	An Introduction to Variable and Feature Selection	3243	2003	Video Google: A Text Retrieval Approach to Object Matching in Videos	2090	2003
7	Content-based Image Retrieval at the End of the Early Years	2822	2000	On Spectral Clustering: Analysis and an Algorithm	2046	2002
8	A Flexible New Technique for Camera Calibration	2699	2000	Algorithms for Non-negative Matrix Factorization	1680	2001
9	Statistical Pattern Recognition: A Review	2545	2000	Thumbs up or Thumbs down?: Semantic Orientation Applied to Unsupervised Classification of Reviews	1309	2002
10	The Particle Swarm - Explosion, Stability, and Convergence in a Multidimensional Complex Space	2483	2002	Minimum Error Rate Training in Statistical Machine Translation	1201	2003
11	Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns	2460	2002	A Database of Human Segmented Natural Images and its Application to Evaluating Segmentation Algorithms and Measuring Ecological Statistics	1165	2001
12	Robust Real-Time Face Detection	2425	2004	Accurate Unlexicalized Parsing	1140	2003
13	Shape Matching and Object Recognition Using Shape Contexts	2058	2002	Scalable Recognition with a Vocabulary Tree	1140	2006
14	Robust Face Recognition via Sparse Representation	1977	2009	Object Class Recognition by Unsupervised Scale-Invariant Learning	1134	2003
15	Kernel-based object tracking	1964	2003	Locality Preserving Projections	1117	2003
16	Gene Selection for Cancer Classification using Support Vector Machines	1881	2002	Real-time tracking of non-Rigid Objects Using Mean Shift	1111	2000
17	Statistical Comparisons of Classifiers over Multiple Data Sets	1878	2006	Learning with Local and Global Consistency	1079	2004
18	Fast Approximate Energy Minimization via Graph Cuts	1818	2001	Laplacian Eigenmaps and Spectral Techniques for Embedding and Clustering	988	2002
19	Robust Real-time Object Detection	1744	2001	ImageNet Classification with Deep Convolutional Neural Networks	949	2012
20	A Taxonomy and Evaluation of Dense Two-Frame Stereo Correspondence Algorithms	1695	2002	PCA-SIFT: A More Distinctive Representation for Local Image Descriptors	925	2004
21	Detecting Faces in Images: A survey	1626	2002	Semi-Supervised Learning Using Gaussian Fields and Harmonic Functions	907	2003
22	A Performance Evaluation of Local Descriptors	1624	2005	Learning Realistic Human Actions from Movies	899	2008
23	Modeling the Shape of the Scene: A Holistic Representation of the Spatial Envelope	1610	2001	Distance Metric Learning with Application to Clustering with Side-Information	867	2003
24	Sparse Bayesian Learning and the Relevance Vector Machine	1587	2001	Interactive Graph Cuts for Optimal Boundary &Region Segmentation of Objects in N-D Images	861	2001
25	Learning Patterns of Activity Using Real-Time Tracking	1569	2000	Overview of the Face Recognition Grand Challenge	855	2005
26	From Few to Many: Illumination Cone Models for Face Recognition under Variable Lighting and Pose	1462	2001	ImageNet: A Large-Scale Hierarchical Image Database	829	2009
27	The FERET Evaluation Methodology for Face-Recognition Algorithms	1459	2000	A non-local Algorithm for Image Denoising	814	2005
28	Scale &Affine Invariant Interest Point Detectors	1398	2004	A Bayesian Hierarchical Model for Learning Natural Scene Categories	775	2005
29	Feature Selection Based on Mutual Information Criteria of Max-Dependency, Max-Relevance, and Min-Redundancy	1369	2005	Object Retrieval with Large Vocabularies and Fast Spatial Matching	725	2007
30	LIBLINEAR: A Library for Large Linear Classification	1328	2008	Computing Semantic Relatedness Using Wikipedia-Based Explicit Semantic Analysis	717	2007

TABLE 4. Ranking of authors based on the average number of citations per paper during 2000-2015.

No.	Author name	Total Citations	Number of Publications	Avg No. of Citations per Paper	Standard Deviation
1	T. Meyarivan	7517	2	3758.5	2474.5
2	Amrit Pratap	7517	2	3758.5	2474.5
3	Sameer Agarwal	6268	4	1567	2693.92
4	David Lowe	11157	14	796.93	2505.53
5	Michael J. Jones	5413	9	601.44	832.31
6	Paul Viola	10589	18	588.28	1144.60
7	Kalyanmoy Deb	8188	14	584.86	1598.56
8	Peter Meer	7266	19	382.42	914.89
9	Bill Triggs	6581	24	274.21	987.65
10	Partha Niyogi	5406	23	235.04	360.86
11	Matti Pietikainen	5986	32	187.06	465.07
12	Pedro F. Felzenszwalb	5045	27	186.85	313.94
13	Jitendra Malik	12159	67	181.48	520.14
14	Richard Szeliski	5404	31	174.32	315.88
15	Dorin Comaniciu	8129	50	162.58	590.30
16	Andrew Y. Ng	14723	92	160.03	524.62
17	Jianbo Shi	5665	37	153.11	604.66
18	David M. Blei	8718	57	152.95	610.13
19	Cordelia Schmid	13058	91	143.50	320.39
20	Andrew Mccallum	6659	56	118.91	355
21	Andrew Zisserman	8114	72	112.70	176.85
22	Anil K. Jain	9297	83	112.01	299.05
23	Michael I. Jordan	14949	145	103.10	431.47
24	Jean Ponce	5923	59	100.39	304.50
25	David J. Kriegman	5298	54	98.11	296.55
26	Antonio Torralba	6261	72	86.96	215.31
27	Pietro Perona	6648	78	85.23	182.35
28	William T. Freeman	6571	82	80.13	132.82
29	Sebastian Thrun	5835	84	69.46	149.53
30	Bernhard Scholkopf	6308	130	48.52	116.45

TABLE 5. Ranking of institutions based on the average number of citations per paper during 2000-2015.

No.	Institutions	Number of Researchers	Total Number of Citations	Total Number of Publications	Avg No. of Citations per Paper	Standard Deviation
1	University of California Berkeley	355	52392	821	63.81	267.49
2	French Institute for Research in Computer Science and Automation	390	48630	879	55.32	262.56
3	Stanford University	617	61551	1279	48.12	159.36
4	Massachusetts Institute of Technology	686	59681	1447	41.24	115.80
5	University of Washington	381	31030	808	38.40	80.63
6	University of Illinois at Urbana Champaign	343	27433	732	37.48	159.05
7	Max Planck Society	377	40820	1110	36.78	136.71
8	Microsoft	792	73972	2156	34.31	114.49
9	Hebrew University of Jerusalem	183	18906	604	31.30	66.04
10	University of Pennsylvania	294	18761	647	29.00	62.37
11	IBM	490	24420	849	28.76	175.00
12	University of Toronto	306	23931	841	28.46	61.13
13	Carnegie Mellon University	943	62318	2297	27.13	74.90
14	University of Southern California	450	31631	1277	24.77	56.42
15	University of Texas at Austin	367	22432	923	24.30	67.12
16	Eth Zurich	259	14995	625	24.00	40.93
17	University of Massachusetts Amherst	216	14700	621	23.67	41.38
18	Nanyang Technological University	347	16890	714	23.66	82.77
19	University of Maryland College Park	365	21588	944	22.87	44.43
20	Chinese Academy of Sciences	546	22922	1139	20.12	50.61
21	Georgia Institute of Technology	337	13761	712	19.33	39.42
22	Technion Israel Institute of Technology	221	11407	596	19.14	50.70
23	University of California Los Angeles	226	11718	628	18.70	60.44
24	The Chinese University of Hong Kong	217	11540	654	17.65	25.97
25	University of Alberta	290	11986	780	15.367	28.74
26	National University of Singapore	421	14460	956	15.13	32.86
27	Tsinghua University	418	12615	839	15.04	44.46
28	Centre National De La Recherche Scientifique	486	10675	721	14.81	24.66
29	University of Michigan	218	7617	597	12.76	23.37
30	University of Tokyo	289	6233	644	9.68	17.62

published by the researcher who belongs to the institution. TABLE 5 lists the top 30 institutions as well as the number of researchers, the total number of citations, the total number of publications, and the average number of citations per paper. Note that the number of researchers represents the total number of authors who have published papers in

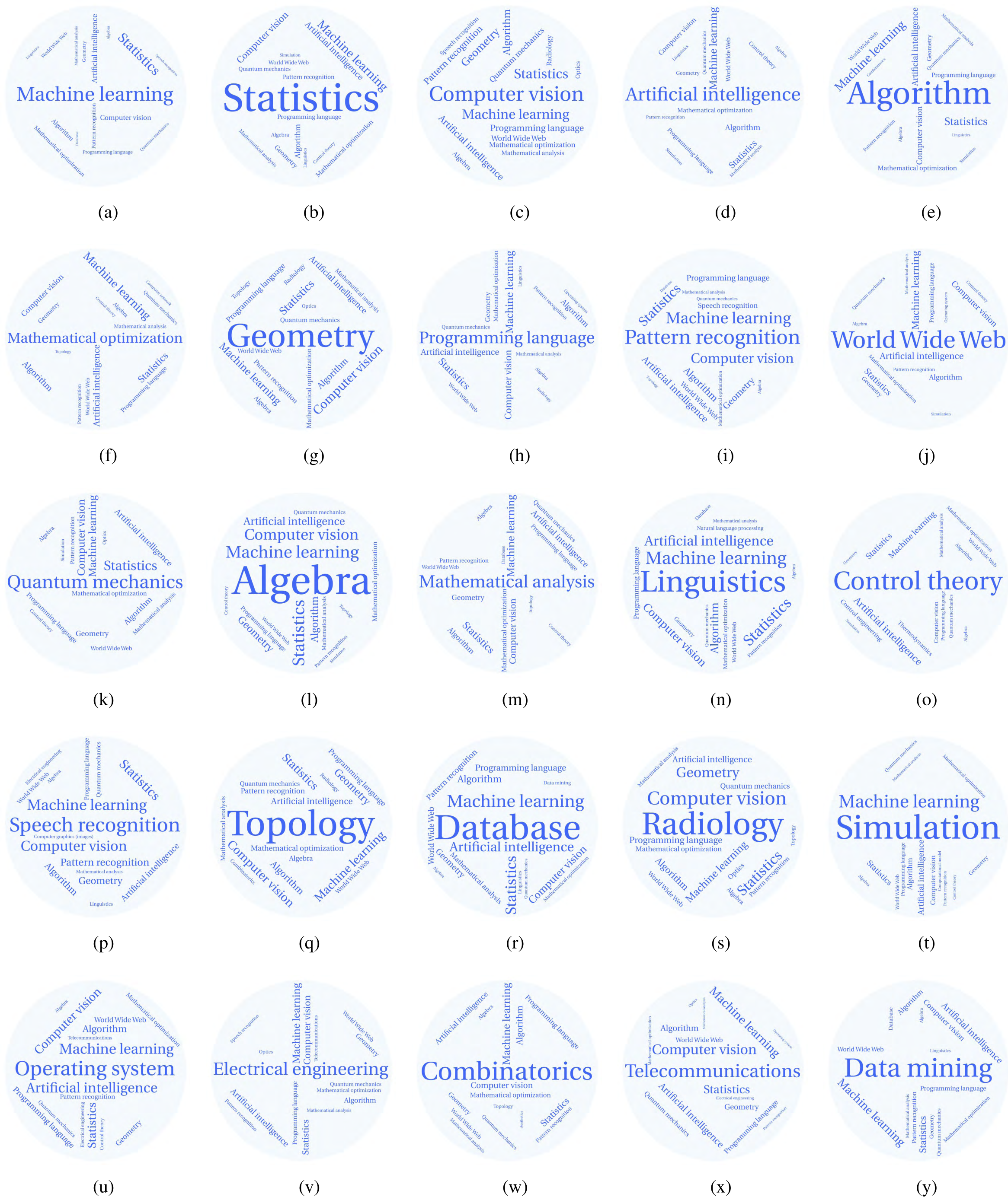


FIGURE 10. **Word-cloud of popular topics of journal papers. (a) 1. (b) 2. (c) 3. (d) 4. (e) 5. (f) 6. (g) 7. (h) 8. (i) 9. (j) 10. (k) 11. (l) 12. (m) 13. (n) 14. (o) 15. (p) 16. (q) 17. (r) 18. (s) 19. (t) 20. (u) 21. (v) 22. (w) 23. (x) 24. (y) 25.**

the top journals/conferences, and the total number of publications means the number of publications these researchers have published in the top journals/conferences. We can see that most of the institutions are located in North America (18 institutions) especially in America. Asia has the second most influential institutions (8 institutions) and the rest are distributed in Europe (4 institutions).

Furthermore, we also calculate the Standard Deviation (SD) of citations for each author and institution. A high value of SD means that points in the dataset are spread out over a wider range of values, while a low SD indicates that points are close to the mean. It aims to help readers better understand the importance of the target author/institution (e.g., some papers from the certain author/institution may attract a very high number of citations while others not).

Fig. 8 plots the world maps embedded with two types of influential institutions and the citation relationships among them during 2000 and 2015. Fig. 8(a) shows the

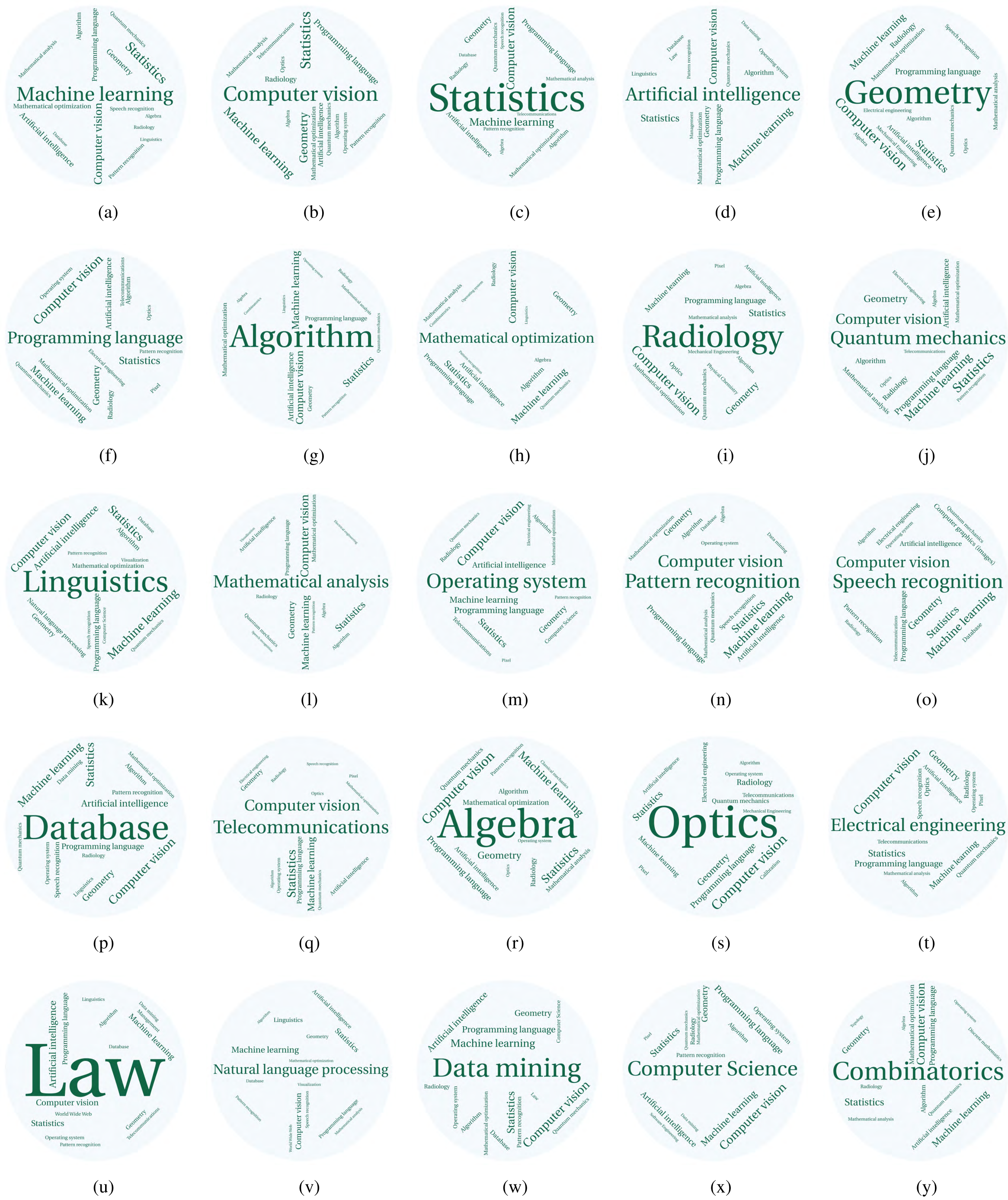
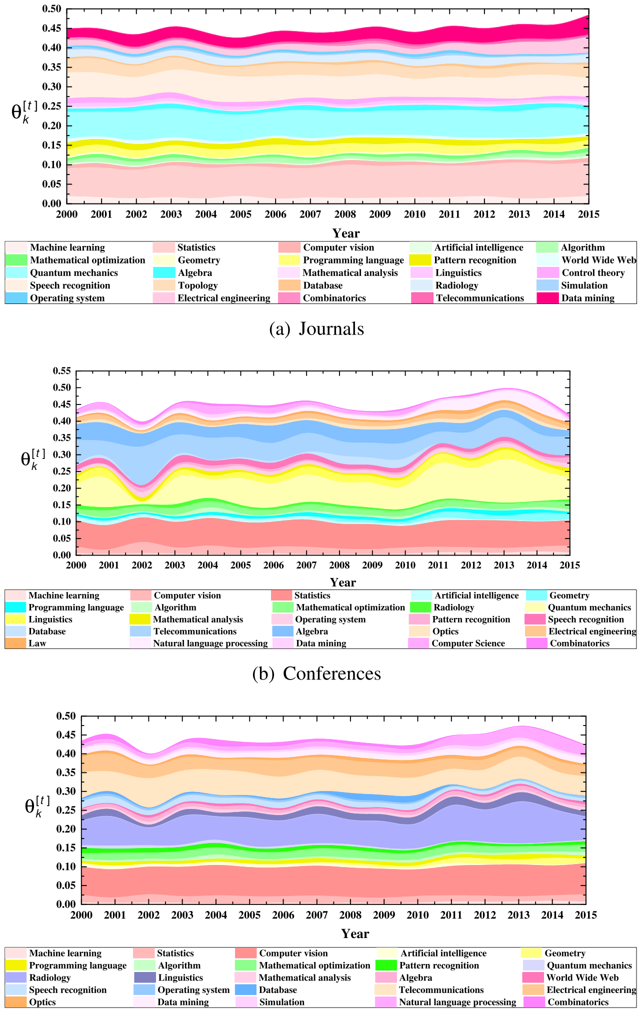


FIGURE 11. **Word-cloud of popular topics of conference papers. (a) 1. (b) 2. (c) 3. (d) 4. (e) 5. (f) 6. (g) 7. (h) 8. (i) 9. (j) 10. (k) 11. (l) 12. (m) 13. (n) 14. (o) 15. (p) 16. (q) 17. (r) 18. (s) 19. (t) 20. (u) 21. (v) 22. (w) 23. (x) 24. (y) 25.**

top 50 institutions who have received most citations based on the papers published in the top journals. Similarly, Fig. 8(b) shows the top 50 institutions who have received most citations based on the papers published in the top conferences. The size of circles on the map on behalf of the relative number of self-citations of the institution. It can be regarded as the overview of citation relationships among influential institutions. It illustrates the spread of knowledge is becoming more and more globalization. There is also a large difference in the way of reference behavior. Based on the citation ranking of journal papers, it seems that the influential institutions are located in Asia, Europe, and North America with evenly distributed citations. Top institutions based on the citations received by top conference papers are distributed in Asia, Europe, North America, and Oceania. The citation relationships occur widely between North America and Europe. Another interesting finding is that most institutions which have more self-citations are located in North America. It may



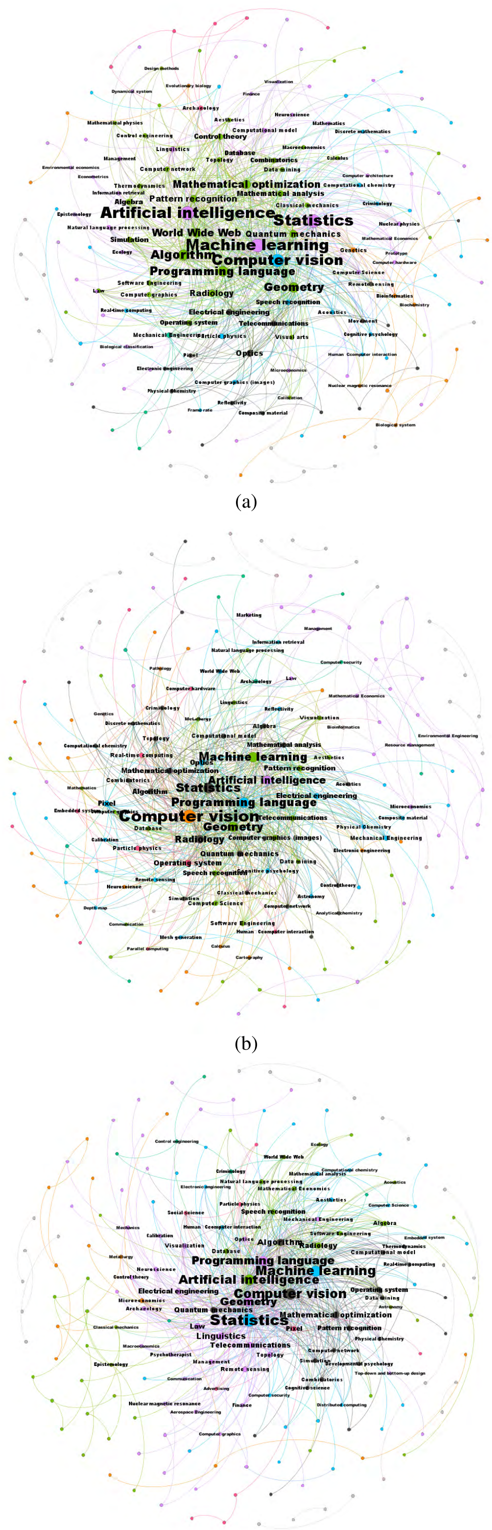
(a) Journals
(b) Conferences
(c) All

FIGURE 12. The evolution of topics over time. (a) Journals. (b) Conferences. (c) All.

be because that these institutions receive more citations than others.

D. THE INNER STRUCTURE OF AI

AI is not monolithic, but contains dozens of topics. These topics are individual and have their own intellectual challenges, methodologies and culture. To give a deeper insight into AI, we use keywords in the dataset to classify the entire literature into major topics. Keywords are usually used to abstractly classify the content of a paper. It also provides the basis for examining key topics and aspects in a particular field of research [35]. Hot keywords with a high frequency (top 1 percent) each year are provided in TABLE 6. Some topics have attained "immortality" in this period such as computer vision, pattern recognition, feature extraction, etc. Others are emerging topics in the recent years (for example, artificial intelligence and multi-agent system) which push AI to a new stage and also bring new opportunities to the development of AI.



(a)
(b)
(c)

FIGURE 13. Co-presence network of topics. (a) Journals. (b) Conferences. (c) All.

Further, we apply the method introduced in the Section II-C.1 to the dataset to divide AI into different topics. Fig. 9 plots these topics and the citation relationships among them. These topics are held together by AI. The size of the

TABLE 6. Ranking of hot keywords based on the frequency during 2000-2015.

Year	Rate of Hot Keywords	Hot Keywords
2000	0.382339344	computer vision, indexing terms, image segmentation, layout, pattern recognition, machine learning, shape, computational complexity, computer science, neural network, robustness, image reconstruction, feature extraction, satisfiability, motion estimation, image processing, neural networks, real-time, genetic algorithms, fuzzy systems, image analysis, reinforcement learning, object recognition, testing, multi-agent system
2001	0.408036454	computer vision, layout, image segmentation, shape, computer science, robustness, pattern recognition, image reconstruction, feature extraction, indexing terms, object recognition, motion estimation, image recognition, face recognition, real-time, lighting, image analysis, pixel, tracking, application software, face detection, machine learning, testing, probability, principal component analysis, genetic algorithms, data mining, computational geometry, geometry, genetic algorithm
2002	0.406982085	pattern recognition, indexing terms, multi-agent system, computational complexity, computer vision, Bayesian networks, machine learning, reinforcement learning, image segmentation, neural network, fuzzy systems, support vector machine, feature extraction, genetic algorithms, expert systems, real-time, fuzzy logic satisfiability, genetic algorithm, fuzzy control, object recognition, neural networks, fuzzy sets, testing fuzzy set theory, information retrieval
2003	0.426188228	computer vision, feature extraction, pattern recognition, image segmentation, machine vision, machine learning, indexing terms, object recognition, image reconstruction, support vector machine, layout, shape, computer science, motion estimation, robustness, image texture, multi-agent system, computational geometry, data mining edge detection, face recognition, principal component analysis, real-time, computational complexity, satisfiability, stereo vision, image recognition, image processing, image classification, pixel, feature selection, neural network, reinforcement learning, learning artificial intelligence
2004	0.460670194	computer vision, computer science, pattern recognition, image segmentation, indexing terms, artificial intelligence, multiagent systems, feature extraction, machine learning, multi-agent system, reinforcement learning, face recognition, algorithms support vector machine, object recognition, satisfiability, real-time, Markov processes, robustness, application software, computational complexity, principal component analysis, image reconstruction, tracking, protocols, image processing, data mining, layout, face detection, game theory shape
2005	0.427952329	computer vision, feature extraction, indexing terms, image segmentation, face recognition, pattern recognition, computer science, layout, machine learning, robustness, object recognition, learning artificial intelligence, image reconstruction, shape, image classification, artificial intelligence, support vector machine, algorithms, real-time, data mining, principal component analysis computational geometry, multi-agent system, satisfiability, image processing, image recognition, face detection, testing probability motion estimation, computational complexity, lighting, tracking, cluster analysis, geometry
2006	0.428291408	computer vision, pattern recognition, robustness, image segmentation, shape, layout, machine learning, computer science, artificial intelligence, indexing terms, feature extraction, face recognition, algorithms, support vector machine, image reconstruction, real-time, testing object, recognition image analysis, application softwares, data mining, computational complexity, multi-agent system, satisfiability, image recognition, lighting, face detection, principal component analysis, reinforcement learning, motion estimation, geometry, pixel, Bayesian methods, parameter estimation
2007	0.43633829	computer vision, image segmentation, feature extraction, machine learning, robustness, image reconstruction, face recognition, layout, pattern recognition, image classification, object recognition, learning artificial intelligence, shape, artificial intelligence, computer science, real-time, satisfiability, image recognition, indexing terms, algorithms, image processing, support vector machine, testing, principal component analysis, image resolution, data mining, multi-agent system, computational complexity, image registration, graph theory, image retrieval lighting, fuzzy set theory, statistical analysis, image analysis, pixel, motion estimation, face detection, image texture, probability
2008	0.421052632	computer vision, pixel, feature extraction, shape, image segmentation, robustness, layout, machine learning, computer science, image reconstruction, testing, pattern recognition, face recognition, computational modeling, object recognition, data mining, learning artificial intelligence, artificial intelligence, image processing, image classification, kernel, image recognition, algorithm design and analysis, optimization, tracking, algorithms, mathematical model, image analysis, computational complexity, visualization, histograms, image resolution, fuzzy set theory, estimation, classification algorithms, real-time, application software, principal component analysis, lighting, support vector machine
2009	0.467462283	computer vision, data mining feature extraction, pixel, image segmentation, shape, robustness, artificial intelligence, learning artificial intelligence, layout, machine learning, computational modeling, object recognition, image reconstruction, image classification, kernel, face recognition, computer science, testing histograms, pattern recognition, support vector machines, mathematical model, optimization, computational complexity, face, image recognition, lighting, algorithm design and analysis, geometry, image processing, estimation, databases, visualization, tracking, detectors, Markov processes, support vector machine, satisfiability, principal component analysis, graph theory, probability, image retrieval, solid modeling
2010	0.357232704	computer vision, feature extraction, pixel, image segmentation, layout, robustness, shape, machine learning, computer science, image reconstruction, face recognition, learning artificial intelligence, support vector machines, object recognition, image classification, optimization, kernel, pattern recognition, data mining, computational modeling, testing, histograms, image recognition, face, algorithm design and analysis, mathematical model, image analysis, databases, computational complexity, visualization, application software, support vector machine, principal component analysis, tracking, lighting, real-time, image processing, estimation, solid modeling
2011	0.383333333	feature extraction, computer vision, image segmentation, three dimensional, shape, learning artificial intelligence, computational modeling, image classification, image reconstruction, optimization, visualization, vectors estimation, face recognition, kernel, computer model, robustness, face, mathematical model, accuracy, object recognition, histograms, support vector machines, pose estimation, object tracking, databases, lighting, real-time, support vector machine, detectors, machine learning, graph theory, noise
2012	0.259340126	feature extraction, vectors, computer vision, learning artificial intelligence, image segmentation, image classification, optimization, visualization, shape, computational modeling, robustness, support vector machines, image reconstruction, kernel, estimation, face recognition, machine learning, object recognition, face, accuracy, detectors, mathematical model, algorithm design and analysis, object tracking, histograms, databases, measurement lighting
2013	0.291341579	feature extraction, learning artificial intelligence, computer vision, image segmentation, image classification, vectors, face recognition, image reconstruction, optimization, computational modeling, shape, object recognition, support vector machines, visualization, graph theory, object tracking, pose estimation, estimation, kernel, accuracy, detectors, probability, robustness, face, histograms, image recognition, computational complexity
2014	0.207227698	vectors, feature extraction, computer vision, optimization, visualization, learning artificial intelligence, image classification, image segmentation, computational modeling, estimation, shape, kernel, image reconstruction, robustness, accuracy, face recognition, object recognition, histograms, face, support vector machines, detectors, mathematical model
2015	0.127071823	feature extraction, optimization, vectors, computational modeling, mathematical model, uncertainty, image segmentation, computer vision, machine learning, visualization, data models, sociology, shape, indexes, crowdsourcing, face recognition, support vector machines, algorithm design and analysis

TABLE 7. Increase index for popular topics.

Topic	r_k	Topic	r_k	Topic	r_k	Topic	r_k	Topic	r_k
World Wide Web	2.49	Artificial intelligence	1.25	Speech recognition	1.07	Aesthetics	0.94	Remote sensing	0.74
Control engineering	2.03	Programming language	1.21	Law	1.02	Data mining	0.92	Geometry	0.71
Computer Science	2.02	Topology	1.20	Natural language processing	1.02	Algebra	0.92	Mechanical Engineering	0.68
Real-time computing	1.88	Neuroscience	1.19	Quantum mechanics	1.00	Combinatorics	0.91	Cognitive psychology	0.63
Computer graphics (images)	1.82	Linguistics	1.16	Genetics	1.00	Computer network	0.89	Simulation	0.61
Software Engineering	1.67	Algorithm	1.15	Management	0.99	Telecommunications	0.87	Pixel	0.60
Pattern recognition	1.58	Social science	1.13	Electrical engineering	0.99	Computer vision	0.85	Classical mechanics	0.52
Control theory	1.42	Particle physics	1.10	Mathematical Economics	0.98	Mathematical optimization	0.79	Mathematical analysis	0.49
Operating system	1.40	Machine learning	1.09	Statistics	0.97	Radiology	0.77	Computational model	0.16
Thermodynamics	1.35	Optics	1.08	Microeconomics	0.96	Database	0.76	Visualization	0.11

topic measures based on the number of publications. Topics within AI cite each other in a statistically significant fashion, and tend not to be the same for the journals and conferences. Taken hot keywords (TABLE 6) and topics (Fig. 9) together, it drives to conclude that AI is heterogeneous. It contains various topics with widely different impact, lifetime, development but they all interact with each other.

Fig. 10 and Fig. 11 present the proportion of journals' topics during the study time period. With the frequency of these topics, we can prioritize them with great clarity. The most three popular topics are: "machine learning: statics, artificial intelligence, computer vision..."; "statics: artificial intelligence, computer vision, quantum mechanics...", and "computer vision: machine learning, programming language, pattern recognition...". For topics of conferences, the focuses are: "machine learning: computer vision, statics, programming language...", "computer vision: statics, programming language, machine learning...", and "statics: artificial intelligence, computer vision, geometry...". These topic clouds contain the popular topic and other topics related to it. The relevance can be represented by the size of the word. The definition of the relevance is purely based on the methods we have introduced in Section II-C.2.

For journal papers and conference papers, as defined previously in Section II-C.3, we use $\theta_k^{[t]}$ to analyze the temporal trend of the topic k. In this sense, we concentrate on the dynamics of the topic. Fig. 12 shows the proportion of the most popular topics from 2000 to 2015. These topics are shown in order of popularity from the bottom to the top. For topics in the journal level and the conference level, there are both commonalities and differences. For example, both of them concentrate on the topic "data mining", "combinatorics", and "telecommunications". Conferences focus on "natural language processing" but journals don't. This figure can also clearly reflect that the evolution of topics: some topics have been declining over time, however, some have received a great deal of attention.

To further investigate the popularity of topics, we use increase index defined in Section II-C.4 to evaluate these topics. TABLE 7 lists estimated r_k for all topics in a decreasing order. The hottest topics are "world wide web", "control engineering", and "computer science".

Fig. 13 is the structure of the topic co-presence network defined by Section II-C.5. The network clusters topics which are highly connected. For better visualization, we only choose the topics containing more than 100 papers and show the largest connected component of the network. Fig 13(a), Fig 13(b), and Fig 13(c) consist of 175 vertices and 751 edges, 180 vertices and 654 edges, and 185 vertices and 673 edges, respectively. As edges in these networks are selected based on the co-presence coefficient, they can reflect the topic structure in terms of the certain degree. Taking Fig 13(a) as an example, the topic "Machine Learning" appears heavily with "Algorithms" and "Statistics" (see in the clusters in green). It also can be used as a tool in measuring conception distance between topics in AI. In a word, topics in AI connect differently by their distribution and the co-presence coefficients are highly different.

IV. THREATS TO VALIDITY

In this section, we will identify and address the threats from the perspectives of construct validity, internal validity, external validity, and reliability.

A. CONSTRUCT VALIDITY

Construct validity refers to the appropriateness of inferences made on the basis of measurements. With the help of examining the content validity of the test, we divide the dataset according to the corresponding attributes of papers (e.g. publish years, number of citations), and randomly select the test set in proportion to compile the experiment. The results show that the experiments have a high content validity, which can also ensure the construct validity.

TABLE 8. **Ranking of papers based on the average number of citations per year received in 2000-2015.**

	Journal papers				Conference papers			
No.	Title	No. of Citations per Year	No. of Citations	Year	Title	No. of Citations per Year	No. of Citations	Year
1	Distinctive Image Features from Scale-Invariant Keypoints	818.33	9820	2004	Histograms of Oriented Gradients for Human Detection	453.64	4990	2005
2	A Fast and Elitist Multi-objective Genetic Algorithm: NSGA-II	445.21	6233	2002	Rapid Object Detection Using a Boosted Cascade of Simple Features	300.8	4512	2001
3	Latent Dirichlet allocation	355.23	4618	2003	ImageNet Classification with Deep Convolutional Neural Networks	237.25	949	2012
4	Robust Face Recognition via Sparse Representation	282.43	1977	2009	Beyond Bags of Features: Spatial Pyramid Matching for Recognizing Natural Scene Categories	229.1	2291	2006
5	Mean Shift: A Robust Approach toward Feature Space Analysis	262.86	3680	2002	BLEU: A Method for Automatic Evaluation of Machine Translation	176.79	2475	2002
6	An Introduction to Variable and Feature Selection	249.46	3243	2003	Conditional Random Fields: Probabilistic Models for Segmenting and Labeling Sequence Data	163.2	2448	2001
7	Normalized Cuts and Image Segmentation	233.38	3734	2000	Video Google: A Text Retrieval Approach to Object Matching in Videos	160.77	2090	2003
8	Robust Real-Time Face Detection	202.08	2425	2004	On Spectral Clustering: Analysis and an Algorithm	146.14	2046	2002
9	Statistical Comparisons of Classifiers over Multiple Data Sets	187.8	1878	2006	ImageNet: A Large-scale Hierarchical Image Database	118.43	829	2009
10	The Particle Swarm - Explosion, Stability, and Convergence in a Multidimensional Complex Space	177.36	2483	2002	Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation	115	230	2014
11	Content-based Image Retrieval at the end of the Early Years	176.38	2822	2000	Scalable Recognition with a Vocabulary Tree	114	1140	2006
12	Multi-resolution Gray-scale and Rotation Invariant Texture Classification with Local Binary Patterns	175.71	2460	2002	Learning Realistic Human Actions from Movies	112.38	899	2008
13	A Flexible New Technique for Camera Calibration	168.69	2699	2000	Algorithms for Non-negative Matrix Factorization	112	1680	2001
14	LIBLINEAR: A Library for Large Linear Classification	166	1328	2008	Thumbs up or Thumbs down?: Semantic Orientation Applied to Unsupervised Classification of Reviews	93.5	1309	2002
15	Scikit-learn: Machine Learning in Python	161.6	808	2011	Minimum Error Rate Training in Statistical Machine Translation	92.38	1201	2003
16	Object Detection with Discriminatively Trained Part-Based Models	159.5	957	2010	Learning with Local and Global Consistency	89.92	1079	2004
17	Statistical Pattern Recognition: A review	159.06	2545	2000	Accurate Unlexicalized Parsing	87.70	1140	2003
18	Kernel-based Object Tracking	151.08	1964	2003	Object Class Recognition by Unsupervised Scale-invariant Learning	87.23	1134	2003
19	A Performance Evaluation of Local Descriptors	147.64	1624	2005	Linear Spatial Pyramid Matching Using Sparse Coding for Image Classification	86	602	2009
20	Shape Matching and Object Recognition Using Shape Contexts	147	2058	2002	Locality Preserving Projections	85.92	1117	2003
21	Differential Evolution: A Survey of the State-of-the-Art	145.2	726	2011	Object Retrieval with Large Vocabularies and Fast Spatial Matching	80.56	725	2007
22	The Pascal Visual Object Classes (VOC) Challenge	137.67	826	2010	Locality-constrained Linear Coding for image classification	80.33	482	2010
23	Gene Selection for Cancer Classification using Support Vector Machines	134.36	1881	2002	Distributed Representations of Words and Phrases and their Compositionality	80	240	2013
24	Feature Selection based on Mutual Information Criteria of Max-dependency, Max-relevance, and Min-redundancy	124.45	1369	2005	Computing Semantic Relatedness using Wikipedia-based Explicit Semantic Analysis	79.67	717	2007
25	Fast Approximate Energy Minimization via Graph Cuts	121.2	1818	2001	Overview of the Face Recognition Grand Challenge	77.73	855	2005
26	A Taxonomy and Evaluation of Dense Two-Frame Stereo Correspondence Algorithms	121.07	1695	2002	A Database of Human Segmented Natural Images and its Application to Evaluating Segmentation Algorithms and Measuring Ecological Statistics	77.67	1165	2001
27	Scale & Affine Invariant Interest Point Detectors	116.5	1398	2004	Moses: Open Source Toolkit for Statistical Machine Translation	77.22	695	2007
28	Robust Real-time Object Detection	116.27	1744	2001	PCA-SIFT: A More Distinctive Representation for Local Image Descriptors	77.08	925	2004
29	Detecting Faces in Images: A Survey	116.14	1626	2002	ORB: An Efficient Alternative to SIFT or SURF	77	385	2011
30	Face Description with Local Binary Patterns: Application to Face Recognition	111.5	1115	2006	A Non-local Algorithm for Image Denoising	74	814	2005

TABLE 9. Ranking of authors in 2000-2015.

No.	Ranking by Avg No. of Citations per Paper	Ranking by Total Citations	Ranking by total No. of Papers
1	T. Meyarivan	Michael I. Jordan	Nicholas R. Jennings
2	Amrit Pratap	Andrew Y. Ng	Xiaoou Tang
3	Sameer Agarwal	Cordelia Schmid	Michael I. Jordan
4	David Lowe	Jitendra Malik	Shuicheng Yan
5	Michael J. Jones	David Lowe	Bernhard Scholkopf
6	Paul Viola	Paul Viola	Pascal Fua
7	Kalyanmoy Deb	Anil K. Jain	Thomas S. Huang
8	Peter Meer	David M. Blei	Sarit Kraus
9	Bill Triggs	Kalyanmoy Deb	Zoubin Ghahramani
10	Partha Niyogi	Dorin Comaniciu	Rong Jin
11	Matti Pietikainen	Andrew Zisserman	Takeo Kanade
12	Pedro F. Felzenszwalb	Amrit Pratap	Lei Zhang
13	Jitendra Malik	T. Meyarivan	Rama Chellappa
14	Richard Szeliski	Peter Meer	Luc Van Gool
15	Dorin Comaniciu	Andrew Mccallum	Yoshua Bengio
16	Andrew Y. Ng	Pietro Perona	Michael Wooldridge
17	Jianbo Shi	Bill Triggs	Songchun Zhu
18	David M. Blei	William T. Freeman	Zhihua Zhou
19	Cordelia Schmid	Bernhard Scholkopf	Horst Bischof
20	Andrew Mccallum	Sameer Agarwal	Andrew Y. Ng
21	Andrew Zisserman	Antonio Torralba	Cordelia Schmid
22	Anil K. Jain	Matti Pietikainen	Alan Yuille
23	Michael I. Jordan	Jean Ponce	Edwin R. Hancock
24	Jean Ponce	Sebastian Thrun	Martial Hebert
25	David J. Kriegman	Jianbo Shi	Alexander J. Smola
26	Antonio Torralba	Michael J. Jones	David Zhang
27	Pietro Perona	Partha Niyogi	Jieping Ye
28	William T. Freeman	Richard Szeliski	Daphne Koller
29	Sebastian Thrun	David J. Kriegman	Sebastian Thrun
30	Bernhard Scholkopf	Pedro F. Felzenszwalb	Anil K. Jain

B. INTERNAL VALIDITY

Internal validity refers to the degree of correlation between the dependent variables and independent variables of the experiments. It is used to reflect how much of the change in the dependent variable is from the independent variable. There are many factors that affect the internal validity, such as experimental mortality, experimenter bias, and regression to the mean. In this paper, we combine the investigation with experiments in order to ensure the internal validity. We examined the development of AI in detail based on collecting the relative literature and making a summary before the experiments. The experimental results conform to the law of internal evolution of Science of Science itself to a certain extent and fairly accord with the development of the discipline based on the literature. Furthermore, we control our experiments to ensure the results are not obscured by the influence of other variables.

C. EXTERNAL VALIDITY

External validity refers to the degree of generalization of the experiential results. It indicates the level of generalization in the research. In our study, we aim to find out the changes in the field of AI from different perspectives. In the field of Science of Science, every field has its unique characteristics and development rules. Due to the development of related technologies, AI has developed rapidly in recent years. Our conclusions may not be applicable to other disciplines. Considerably more work will need to be done to discover changing patterns in each discipline.

D. RELIABILITY

In order to ensure the reliability of the results, we motivate the derivation of each metric in depth. For example, the metrics that we used to measure the growth of AI consider every entity of scholarly data. Furthermore, we have discussed alternate ways of measuring the same entity of interest. We rank the papers/authors/institutions based on different metrics (the results can be seen in APPENDICES A, B, and C).

V. CONCLUSION

In this work, we present an anatomy of AI spanning over the first 16 years of the 21^{st} Century. To better quantify the development, we have used scientific publications metadata covers 9 top-tier journals and 12 top-tier conferences from 2000 to 2015. In addition to the title, authors, and the authors' institutions, the metadata also provides us with the number of citations for each paper. According to the increasing number of publications, we have observed a growing trend in collaboration and a decreasing trend in the average productivity for each researcher. From the perspective of reference behavior, the development tendency of AI is becoming open-minded and popularized as reflected in reduced self-references rates over time. We also use the average number of citations per paper of each paper/author/institution as an indicator to evaluate their importance. Those influential entities are consistent with our intuitions. Finally, we explore the inner structure of this diverse area and conclude that the area consists of various topics. There are both differences and connections

TABLE 10. Ranking of institutions in 2000-2015.

No.	Ranking by Avg No. of Citations per Paper	Ranking by Total Citations	Ranking by total No. of Papers
1	University of California Berkeley	Microsoft	Carnegie Mellon University
2	French Institute for Research in Computer Science and Automation	Carnegie Mellon University	Microsoft
3	Stanford University	Sanford University	Massachusetts Institute of Technology
4	Massachusetts Institute of Technology	Massachusetts Institute of Technology	Stanford University
5	University of Washington	University of California Berkeley	University of Southern California
6	University of Illinois at Urbana Champaign	French Institute for Research in Computer Science and Automation	Chinese Academy of Sciences
7	Max Planck Society	Max Planck Society	Max Planck Society
8	Microsoft	University of Southern California	National University of Singapore
9	Hebrew University of Jerusalem	University of Washington	University of Maryland College Park
10	University of Pennsylvania	University of Illinois at Urbana Champaign	University of Texas at Austin
11	IBM	IBM	French Institute for Research in Computer Science and Automation
12	University of Toronto	Siemens	IBM
13	Carnegie Mellon University	University of Toronto	University of Toronto
14	University of Southern California	University of Oxford	Tsinghua University
15	University of Texas at Austin	Robotics Institute	University of California Berkeley
16	Eth Zurich	Chinese Academy of Sciences	University of Washington
17	University of Massachusetts Amherst	University of Texas at Austin	University of Alberta
18	Nanyang Technological University	University of Maryland College Park	University of Illinois at Urbana Champaign
19	University of Maryland College Park	University of California	Centre National De La Recherche Scientifique
20	Chinese Academy of Sciences	Cornell University	Nanyang Technological University
21	Georgia Institute of Technology	Hebrew University of Jerusalem	Georgia Institute of Technology
22	Technion Israel Institute of Technology	University of Pennsylvania	The Chinese University of Hong Kong
23	University of California Los Angeles	University of British Columbia	University of Pennsylvania
24	The Chinese University of Hong Kong	University of Oulu	University of Tokyo
25	University of Alberta	Nanyang Technological University	University of California Los Angeles
26	National University of Singapore	Columbia University	Eth Zurich
27	Tsinghua University	Katholieke Universiteit Leuven	University of Massachusetts Amherst
28	Centre National De La Recherche Scientifique	Eth Zurich	Hebrew University of Jerusalem
29	University of Michigan	Brown University	University of Michigan
30	University of Tokyo	University of Massachusetts Amherst	Technion Israel Institute of Technology

among them. These findings reveal the hidden patterns of AI in the 21^{st} Century. They also provide scientists with new opportunities to improve the comprehension of AI with the ultimate goal of forging a better world.

Despite the extensive analysis of this complex subjects, there are still a few limitations in this work. First, while this work focuses on the publications published in the top journals/conferences, it will be interesting to consider all publications in the field of AI. Second, its complexity has pushed us to respond to questions like: What is the inner structure of its collaboration network? What are the computational results based on the centrality measures for both vertices and edges? How will it change in the next ten years? Finally, it makes sense to explore the relationship between the future of AI and economic development.

APPENDIX A
RANKING OF PAPERS BASED ON THE AVERAGE NUMBER OF CITATIONS

TABLE 8 presents the ranking results of papers based on the average number of citations received per year in 2000-2015.

APPENDIX B
RANKING OF AUTHORS BASED ON DIFFERENT MEASUREMENTS

TABLE 9 provides the ranking results of authors based on different measurements including the average number of citations per paper, the total number of citations, and the total number of papers.

APPENDIX C
RANKING OF INSTITUTIONS BASED ON DIFFERENT MEASUREMENTS

TABLE 10 presents the ranking results of institutions based on different measurements including the average number of citations per paper, the total number of citations, and the total number of papers.

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