International Journal of Multidisciplinary Education and Research
ISSN: 2455-4588; Impact Factor: RJIF 5.12
Received: 12-02-2019; Accepted: 15-02-2019
www.educationjournal.in
Volume 4; Issue 3; May 2019; Page No. 24-30

Research on teaching quality evaluation method in MOOC

Mingxi Zhang[1], Ruohan Qiu[2], Miao Tian[3], Xiaohong Wang[4]
[1-4] College of Communication and Art Design, University of Shanghai for Science and Technology, Shanghai, China

Abstract
MOOC allows students to study on-line through Internet at home or some other places, which transcends the barriers of geography and makes the study process easier. As the courses become massive, the problem of information overload plagues students, which makes the course taking difficult to students. Teaching evaluation aims to test the teaching quality of teachers for different courses, which is important to understand the course quality. However, the teaching evaluation of existing MOOC platform is too rough since only five levels are assigned to each course. Besides, there is also a lack of an effective evaluation for teachers. In this paper, we proposed a teaching evaluation model, namely TeachRank, which evaluate teaching quality based on the teaching network. The node in the teaching network represents students, teachers and courses, and the links include the links corresponding to course-taking relationship between students and courses, teaching relationship between teachers and courses. And then, we extend PageRank to teaching network for computing the node quality, in which the scores rated by the students and the link weights are considered. Not only the courses but also the teachers are evaluated by TeachRank. Experiments on real data demonstrate the effectiveness of our proposed TeachRank.

Keywords: online education platform, teaching evaluation, PageRank

1. Introduction

On-line education makes learning more convenient as kinds of course resources are available in the Internet. As one typical on-line education platform, MOOC (massive open online courses) allows students to study on-line through Internet at home or some other places. Through MOOC, students can get kinds of courses they want, which transcends the barriers of geography and makes the study process easier. Today, there are lots of MOOC platform, such as ICOURSE163 (https://www.icourse163.org/), IMOOC (https://www.imooc.com/) and MOOC-CHINA (http://www.mooc.cn/), which have attracted millions of students and helped provide them lots of valuable learning recourses. MOOC platforms provide a large amount of courses from different majors. For example, MOOC-CHINA collects the courses from Coursera, Udacity, and Edx, and the courses cover more than 25 fields, where more than 30,000 learners enroll courses. With the data of on-line courses becoming diverse and massive, the problem of information overload plagues us every day, which makes the course taking difficult to students. Teaching evaluation aims to test the teaching quality of teachers for different courses, which is important to understand the course quality.

Such a large amount of teaching resources provide kinds of choices for the learners, but at the same time, it has also disturbed learners to identify the course quality, which makes the selection of high-quality courses difficult. Since the teaching evaluation varies from person to person, sometimes the learners cannot be given an objective basis for class selection. Taking the MOOC-CHINA as an example, the evaluation of many courses is not comprehensive. Some courses will be recommended by more learners, while others will not. The learners can only rate the course. On the one hand, the scores are too rough for only five levels, so there will be many courses with the same scores. On the other hand, there is no evaluation for teachers. Therefore, it is necessary to develop a method that can exclude individual factors and provide an overall objective evaluation of the courses and the teachers effectively.

In this paper, we proposed a teaching evaluation model, namely TeachRank, which evaluates teaching quality based on the teaching network. The node in the teaching network represents students, teachers and courses, and the links include the links corresponding to course-taking relationship between students and courses, teaching relationship between teachers and courses. And then, we extend PageRank model [1-5] to teaching network for computing the node quality, in which the scores rated by the students and the link weights are considered. PageRank utilizes citation analysis for determining the level of a page through the hyperlink relationship of the network. Because PageRank considers the number of citations and reference quality of the page, it can effectively reflect the importance and authority of a page.

In this paper, we apply PageRank to teaching network for evaluates teaching quality. Based on PageRank, we evaluate the quality of courses depends on the number and quality of its learners, while the quality of the studied courses is evaluated by the quality of the learner. On this intuition, the quality of teachers is determined by the number and quality of the courses and learners they instruct. Not only the courses but also the teachers are evaluated by TeachRank. Experiments on real data demonstrate the effectiveness of our proposed TeachRank.

The main contributions of this paper include: 1) Using PageRank algorithm and data mining to process the learners' feedback, and linking the quality of the course, the quality of the teacher and the quality of the learner, which provides a scientific and reasonable method for online education course recommendation; 2) Integrate multi-factors and output the PageRank value of the courses or teachers to facilitate the learners to obtain better teaching resources and enhance the learners' learning experience; 3) An effective assessment of the teacher is achieved without relying on the personal evaluation on the platform; 4) Calculate on a real data set and apply to the actual situation.

2. Related Work

Regarding the evaluation method of online education teaching quality, [6] determines the preliminary index system by using Delphi expert method to, and then improves the indicators through the questionnaire survey, and finally obtain fuzzy comprehensive evaluation scores of all levels of indicators by using the fuzzy comprehensive evaluation method. [7] uses the analytic hierarchy process (AHP) as an evaluation model to design an evaluation index system based on the hierarchical structure. Finally, the AHP-based evaluation model is used to evaluate the influence of online education and teaching. [8] uses the conversation model evaluation, which mainly evaluates the activities of teachers and students, students and students interacting with the environment through the media, and examine the advantages and disadvantages of a virtual learning environment from the interactivity of the various learning tools provided. Besides, [8-9] combined with big data, drawing on the RFM model [10] and other methods to evaluate the elements involved in the online education platform.

In recent years, researchers have applied the importance of PageRank to different fields. For examples, [11] applied it to the study of maximizing the influence of social network users; Su Cheng, Pan Yuntao, *et al.* [12] evaluate journals by PageRank. [13] applied PageRank to the book recommendation technology. [14] adopted the idea of PageRank in the research of news keyword extraction. [15] also applies this algorithm to the evaluation of institutional research influence.

3. Construct Education Network-Take the MOOC Platform as An Example.

The relationship between learners, courses, teachers, in the MOOC platform constitutes a Teaching Relationship Network notated with $G_1=(V_1,E_1)$, $G_2=(V_2,E_2)$. In which $V_1=V_S\cup V_C$ where V_S and V_C represent the entity collection of the student and course type, respectively; E_1 represents the elective relationship set, The ordered pair $(s,c)\in E_1$ represents the elective relationship between the student $s\in V_S$ and the course $c\in V_C$. In $V_2=V_C\cup V_T$, V_C and V_T represent the entity collection of the course and the teacher, respectively. E_2 represents the set of teaching relations, and the ordered pair $(c,t)\in E_2$ represents the teaching relationship between the course $c\in V_C$ and the teacher $t\in V_T$.

4. TeachRank Model

Constructing TeachRank Model by Using PageRank Model in Social Network Analysis, we can effectively evaluate the teaching quality in MOOC.

4.1 PageRank

When the PageRank algorithm calculates the order of a web page, it first calculates the number of times other web pages reference a web page. If it is cited more times, its quality may be higher, and if it is referenced by a high-quality web page, its quality may also be higher [2], and the quality of this page is averaged to the page it references. The design of the PageRank standard algorithm is as follows:

1. Take the World Wide Web link structure graph as G, the size of G is N.
2. For each node n of G, set its initial PR value $PR^{(0)}(n)=\frac{1}{N}$, Let temporary variable $I(n)=\frac{\alpha}{N}$, Calculate the number of outbound links of this node $Out(n)$. The parameter α is generally taken as 0.15.
3. For each node of G, if $Out(n)>0$, then:
   $I(P_i)=I(P_i)+(1-\alpha)\cdot\frac{PR^{(k-1)}(n)}{Out(n)}$
   Where $k=1,2,3\cdots,TN$ (TN represents the times of iterators)
   If $Out(n)=0$, then:
   $I(P_i)=I(P_i)+(1-\alpha)\cdot\frac{PR^{(k-1)}(n)}{N}$
4. For each node of G, $PR^{(k)}(n)=I(n)$, $I(n)=\frac{\alpha}{N}$.

4.2 Quality of courses evaluation

There are a large number of learners in the online education platform. The relationship between these learners and the curriculum and teachers is similar to that of web pages on the Internet. Therefore, we can apply the PageRank algorithm to online education platforms for teaching quality assessment.

The quality of the course is influenced both by the number and quality of its learners. At the same time, the quality of the course will reflect the learning status of the learner to a certain extent. In this paper, the author treats the relationship between learners and courses in the teaching network as a two-way relationship, so there is no case where the number of links is zero. Use the above formula (1) to calculate the PR value of the course. Sort the values of the course. The higher the value, the higher the course ranking and apparently the higher the quality of the course.

4.3 Quality of Teachers evaluation

Teacher quality is a way to assess the level and popularity of a teacher. The quantity and quality of all the courses they taught determined the quality of each teacher. If the PageRank value of all the courses he taught is high, the quality of the teacher's teaching is higher. Based on this relationship between the teacher and the course, we do the following two treatments for the teacher's influence, calculating the total quality and average quality of each teacher.

4.3.1 The total quality of teachers

The total quality of the teachers, as the name implies, is to sum the PageRank values of all the courses taught by the teacher to obtain a total PageRank value. This value indicates the total quality of the teacher $SUM_{(t)}$, the higher the $SUM_{(t)}$, the higher the quality of the teacher. The total number of courses taught by the teacher is recorded as M, and the course collection is C. Calculated as follows:

$$SUM_{(t)}=\sum_{i=1}^{M}PR(C_i) \qquad (3)$$

After calculating the results, we sorted the total quality of the teachers.

4.3.2 The average quality of teacher

Because the number of courses taught by each teacher varies, this article continues to calculate

The averages based on the total quality of teachers. Measure the quality of the teacher by calculating the average value of the course taught by the teacher. The average teacher quality is recorded as $AVG_{(t)}$.The higher the average PR value of the course taught by the teacher, the higher the teacher's average quality $AVG_{(t)}$. Calculated as follows:

$$AVG_{(t)} = \frac{\sum_{i=1}^{M} PR_{(C_i)}}{M} \quad (4)$$

After calculating the results according to the formula, we also sorted the average quality of the teachers.

5. Experiments

5.1 Experimental configuration

In terms of machine configuration, the CPU is Intel(R) Core(TM) i7-8550U @1.80GHz and 8GB of memory. The Operating system is Windows 10, and the development environment is Visual Studio 2017. The total times of iterations when converging is 30, and the value of the parameter is 0.15. We conduct this experiment on the MOOC (http://mooc.guokr.com/) dataset. Using web crawlers to get data of courses and teachers, we finally get 2,981 learners, 2,951 courses, 2,219 teachers, and 30,391 elective relationships which are chosen lately to build the network of teaching relationships.

5.2 Evaluation method selection

This paper uses NDCG (Normalized Discounted Cumulative Gain) [16] as the evaluation index of PageRank ranking results. Calculated as follows:

$$\text{NDCG@K} = \frac{DCG}{iDCG}$$

Where K is the length of the sorted list, NDCG (Discounted cumulative gain) is the sum of the correlations of the sort results, which can also be used to measure the quality of sorted results. However, NDCG can only apply to the evaluation of the grade into two files. For the case where the sorting result is multi-level, it is necessary to manually sort the results to obtain the optimal sorting state. The DCG value in this arrangement state is recorded as $iDCG$, Use the relative ratio of the above two values to determine whether the ranking result is ideal. When the NDCG value is 1, the sorting result is consistent with the ideal result, and the quality of the sorting is high. If the NDCG value deviates from 1 farther, the sorting result is not ideal, and the sorting quality is poor, so the sorting algorithm should be optimized.

5.3 Experimental result

5.3.1 NDCG calculation results

Before evaluating the quality of sorting, this paper grades each sorting result, that is, each teacher and each course. For each course, the course is graded according to the official score of MOOC. When the score is >=9.5, the rating is 5; the score is between 9.0 and 9.5, the rating is 4, and so on. For teachers, examine all the courses taught by the teacher, and grade the teachers according to the grades of the courses as well as the number of students in each course. Using a weighted approach, We give the teachers different weights, and the weight is determined by the number of students in each course. For example, when the number of students is <=100, the weight is 1, and the numbers are between 100 and 300, the weight is 2, and so on.

This article analyzes with Top-20. The NDCG value of the course is 1, indicating that the PageRank sorting the result of the course is consistent with the optimal sorting state by course level. After that, there is a significant fluctuation of NDCG in K taking 6 to 14. However, as the value of K further increases, the NDCG value of the course gradually becomes 1. So overall, PageRank sorting quality is satisfactory. The following Chart 1 shows the NDCG of courses.

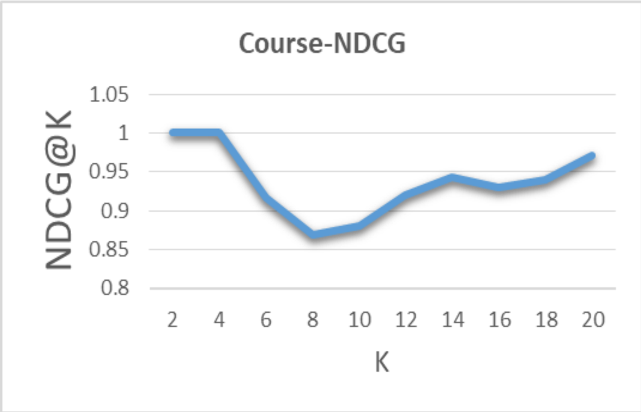

Fig 1: The NDCG diagram of the course

Comparing the sorting result with the ideal sorting obtained by the real analysis, the NDCG of the overall influence of the teacher is shown in Chart 2. We can find the change that as the K value increases, the NDCG value gradually approaches 1. This change indicates that the ranking result is becoming more reliable.

Calculate the average PageRank value of the course taught by the teacher, and sort the results to get the teacher's average quality ranking. Then calculate the NDCG value to evaluate the ranking quality. In Chart 3, We can find that the teacher's average influence NDCG value is between 0.96 and 0.99 when K takes different values, which shows that the PageRank ranking result is of higher quality.

.

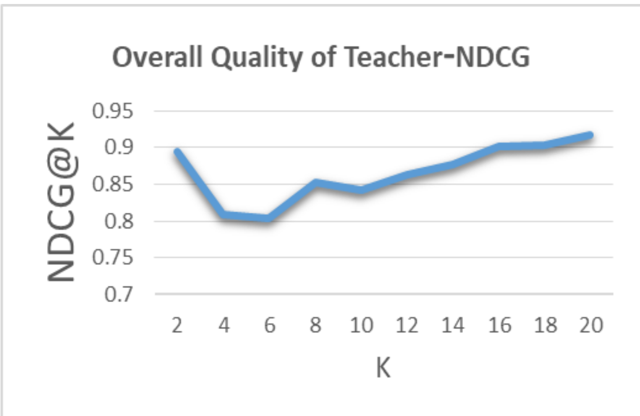

Fig 2: The NDCG diagram of overall quality of the teacher

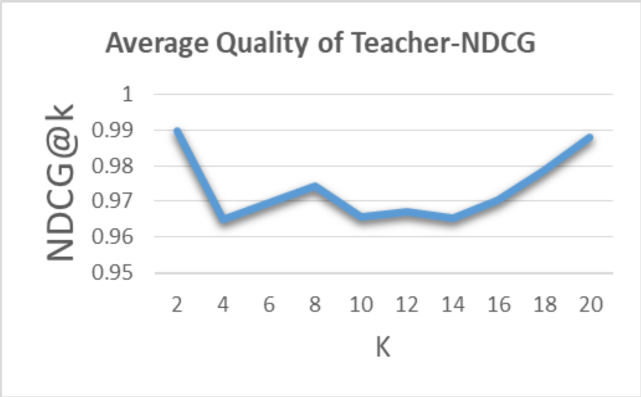

Fig 3: The NDCG diagram of average quality of the teacher

5.3.2 Case study

The top 20 courses are shown in Table 1. Collect the official evaluation information of each course in the MOOC, and compare it with the ranking results of this article to verify whether the ranking is reasonable and in line with the actual situation. The contents of the survey include the course score, the number of students, the number of evaluations, the degree of attention of the course, the interest level, and whether there are stars to recommend it. For example, the course Financial Analysis and Decision was officially rated as 9.7 in the MOOC, with 56,000 followers and 2,731 students who took the course, 870 of whom scored the course and 13 certified learners recommended the course. The official score of Shi-ji (1) is 9.7, the number of followers is 3,000, 1408 have been studied, 556 have scored for the course, and no one has recommended it. Factors can be seen that the course is less influential than the No.1 course. Continue to examine the third-ranked course "Ancient Chinese History and People - Qin Shi Huang". The course scored 9.6 points, with 2,1000 people paying attention, 785 people learned, 277 people rated it, and 4 certificates were recommended. The course is compared with the above two courses. The comprehensive quality of the course is lower than the first two courses, so the ranking results are consistent with the actual situation. We examined subsequent courses in the same way. Although there are some courses with adjacent ranking results, the actual quality ranking between them is slightly different from the ranking results in this paper, but overall, the ranking position is not biased.

Table 1: The course quality ranking

Rank	Course	Teacher	PageRank value
1	财务分析与决策(Financial analysis and decision making)	肖星 (Xiao Xing)	0.00607
2	史記 (一) (Shi-ji (1))	呂世浩 (Shih Hao-Lu)	0.005834
3	中國古代歷史與人物——秦始皇 (Ancient Chinese History and Characters - Qin Shi-huang)	呂世浩 (Shih Hao-Lu)	0.005041
4	Social Psychology	Scott Plous	0.004817
5	心理学概论 (Introduction to Psychology)	彭凯平 (Peng Kai-ping)	0.004643
6	Model Thinking	Scott Page	0.003338
7	Learning How to Learn: Powerful Mental Tools to Help You Master Tough Subjects	Terrence Sejnowski	0.003283
8	Crafting an Effective Writer: Tools of the Trade (Fundamental English Writing)	Lawrence (Larry) Barkley	0.003182
9	Microeconomics Principles	José Vázquez-Cognet	0.003097
10	Think Again: How to Reason and Argue	Walter Sinnott-Armstrong	0.002839
11	An Introduction to Interactive Programming in Python (Part 1)	Joe Warren	0.002807
12	Introduction to Forensic Science	Roderick Bates	0.002647
13	Programming for Everybody (Getting Started with Python)	Charles Severance	0.002571
14	Introduction to Marketing	David Bell	0.002559
15	Introduction to Guitar	Thaddeus Hogarth	0.002538
16	水果课：如何挑出最好吃的水果 (Fruit lesson: How to pick the best fruit)	桔子帮小帮主(Orange group)	0.002535
17	Machine Learning	Andrew Ng	0.002459
18	The Art of Photography	Shane Hulbert	0.002185
19	Introduction to Finance	Gautam Kaul	0.00218
20	Foundations of Psychology	Andrew Francis	0.002147

All the courses taught by the teachers are arranged, and the examination methods of each course are consistent with the above. The overall quality of each teacher is evaluated by considering the courses taught by the teachers, and the results are compared with the ranking results of this article. The first teacher in the total quality ranking in this article is Lu Shihao. His courses include Shi Ji (1) and The History and Characters of Ancient China - Qin Shi Huang. According to the quality analysis of the above courses, it can be seen that the two courses are quality courses, so the teacher is of high quality. Teacher Xiao Xing's courses include Financial Analysis and Decision Making and Financial Analysis and Valuation. Although the quality of Financial Analysis and Decision is high, the number of students in Financial Analysis and Valuation is only 48. Overall rated 8.1 points, so the overall quality of the teacher is lower than Lu Shihao teachers. Teacher Scott Plous's course is Social Psychology, which scores 9.5 points, 6,6,000 people follow, 967 people have learned, 170 people have scored it, no one recommended, so the overall quality of Scott Page is lower than the first two.

In this way, we inspected the rest of the teachers. Considering that some teachers taught many courses, the overall quality of the teachers is higher. However, the actual quality of each course taught by the teacher is uneven. Based on this, we give the average quality ranking teacher. Take the teacher Jeff Leek as an example, this teacher has taught eight courses, and the teacher’s overall quality ranks high, ranking fourth. However, the actual official score for each course is between 6.5 and 7.5. To examine the average quality of teachers, the result of the teacher's ranking is 198, which is more in line with the actual situation. Xiao Xing, the second teacher in the overall quality of teachers, had a poor rating in the course “Financial Analysis and Valuation”, so the teacher fell in the fourth place in the average influence ranking.

Table 2: the teacher overall quality ranking

Rank	Teacher	Course	Sum
1	呂世浩(Shih Hao-Lu)	史記 (一) (Shi-ji(1)) 中國古代歷史與人物——秦始皇 (Ancient Chinese History and Characters - Qin Shi-huang)	0.00985844
2	肖星(Xiao Xing)	财务分析与决策 (Financial analysis and decision making) 财务分析与估值 (Financial analysis and valuation)	0.00621132
3	Scott-Plous	Social-Psychology	0.00583429
4	Jeff-Leek	The-Data-Scientist's-Toolbox R-Programming Getting-and-Cleaning-Data Exploratory-Data-Analysis Practical-Machine-Learning Statistical-Inference Regression-Models Reproducible-Research	0.00468592
5	彭凯平(Peng Kai-ping)	心理学概论 (Introduction to Psychology) 创新的积极心理学 (Innovative positive psychology)	0.00318211
6	Joe-Warren	An-Introduction-to-Interactive-Programming-in-Python-(Part-1) Principles-of-Computing-(Part-1) Algorithmic-Thinking-(Part-1) An-Introduction-to-Interactive-Programming-in-Python-(Part-2) Principles-of-Computing-(Part-2) The-Fundamentals-of-Computing-Capstone-Exam	0.00309747
7	Peter-K.-Bol	China-(Part-1):-Political-and-Intellectual-Foundations:-From-the-Sage-Kings-to-Confucius-and-the-Legalists China-(Part-3):-Cosmopolitan-Tang:-Aristocratic-Culture China-(Part-2):-The-Creation-and-End-of-a-Centralized-Empire China-(Part-6):-The-Manchus-and-the-Qing China-(Part-10):-Greater-China-Today:-The-People's-Republic-Taiwan-and-Hong-Kong China-(Part-4):-Literati-China:-Examinations-and-Neo-Confucianism China-(Part-7):-Invasions-Rebellions-and-the-End-of-Imperial-China China-(Part-9):-China-and-Communism	0.00283917
8	Maggie-Sokolik	College-Writing-2.2x:-English-Grammar-and-Essay-Writing Academic-and-Business-Writing How-to-Write-an-Essay 英语写作指导I (English writing guidance I) 英语写作指导II (English writing guidance II) \A-Christmas-Carol\-by-Dickens:-BerkeleyX-Book-Club Academic-and-Business-Writing 英语写作指导III (English writing guidance III)	0.00264663
9	Scott-Page	Model-Thinking Model-Thinking	0.00255906
10	Terrence-Sejnowski	Learning-How-to-Learn:-Powerful-Mental-Tools-to-Help-You-Master-Tough-Subjects Aprendiendo-a-aprender:-Poderosas-herramientas-mentales-con-las-que-podrás-dominar-temas-difíciles	0.00253828
11	Charles-Severance	Programming-for-Everybody-(Getting-Started-with-Python) Internet-History-Technology-and-Security Python-Data-Structures Using-Databases-with-Python Using-Python-to-Access-Web-Data Capstone:-Retrieving-Processing-and-Visualizing-Data-with-Python	0.0025347
12	Lawrence-(Larry)-Barkley	Crafting-an-Effective-Writer:-Tools-of-the-Trade-(Fundamental-English-Writing)	0.00245914

13	José-Vázquez-Cognet	Microeconomics-Principles	0.0021845
14	Eric-Grimson	Introduction-to-Computer-Science-and-Programming-Using-Python Introduction-to-Computational-Thinking-and-Data-Science 计算机科学和Python编程导论 (Introduction to Computer Science and Python Programming)	0.00214712
15	康仕仲(Shih-Chung-Jessy-Kang)	工程圖學2D (Engineering graphics 2D) 工程图学2D-CAD (Engineering graphics 2D-CAD) 工程圖學-3D-CAD (Engineering graphics 3D-CAD) 工程圖學-2D-CAD-專題 (Engineering graphics 2D-CAD special subject) 工程圖學-3D-CAD-專題 (Engineering graphics 3D-CAD special subject)	0.00209448
16	Walter--Sinnott-Armstrong	Think-Again:-How-to-Reason-and-Argue	0.00200941
17	Roderick--Bates	Introduction-to-Forensic-Science	0.00191116
18	David-Bell	Introduction-to-Marketing	0.00185092
19	Thaddeus-Hogarth	Introduction-to-Guitar	0.00181976
20	桔子帮小帮主(Orange group)	水果课：如何挑出最好吃的水果 (Fruit lesson: How to pick the best fruit)	0.00170857

Table 3: the teacher average quality ranking

Rank	Teacher	Course	Avg
1	Scott-Plous	Social-Psychology	0.00583429
2	吕世浩(Shih Hao-Lu)	史記 (一) (Shi-ji(1)) 中國古代歷史與人物——秦始皇 (Ancient Chinese History and Characters - Qin Shi-huang)	0.00492922
3	Lawrence-(Larry)-Barkley	Crafting-an-Effective-Writer:-Tools-of-the-Trade-(Fundamental-English-Writing)	0.00318211
4	肖星(Xiao Xing)	财务分析与决策 (Financial analysis and decision making) 财务分析与估值 (Financial analysis and valuation)	0.00310566
5	José-Vázquez-Cognet	Microeconomics-Principles	0.00309747
6	Walter--Sinnott-Armstrong	Think-Again:-How-to-Reason-and-Argue	0.00283917
7	Roderick--Bates	Introduction-to-Forensic-Science	0.00264663
8	David-Bell	Introduction-to-Marketing	0.00255906
9	Thaddeus-Hogarth	Introduction-to-Guitar	0.00253828
10	桔子帮小帮主(orange group)	水果课：如何挑出最好吃的水果 (Fruit lesson: How to pick the best fruit)	0.0025347
11	Andrew-Ng	Machine-Learning	0.00245914
12	彭凯平(Peng Kai-ping)	心理学概论 (Introduction to Psychology) 创新的积极心理学 (Innovative positive psychology)	0.00234296
13	Shane-Hulbert	The-Art-of-Photography	0.0021845
14	Andrew-Francis	Foundations-of-Psychology	0.00214712
15	歐麗娟(Li chuan-Ou)	紅樓夢 (The Red Chamber Dream)	0.00209448
16	Denise-Comer	English-Composition-I:-Achieving-Expertise	0.00200941
17	陳嫦芬(Chen Chang-fen)	職場素養(Professionalism)	0.00191116
18	李康化(Li Kang-hua)	Appreciation-of-Tang-and-Song-Poetry	0.00185092
19	彭天笑(Peng Tian-xiao)	大学英语 (口语) (College English (spoken))	0.00181976
20	Yuval-Harari	A-Brief-History-of-Humankind	0.00170857

6. Conclusion

This paper proposes a teaching quality assessment model (TeachRank), which applies the PageRank algorithm to the evaluation of teaching quality of online education platform. This model recommends quality courses and teachers from a large number of messy teaching resources to facilitate the choice of learners on the platform.

By constructing a network graph of teaching relationships, learners, teachers, and courses are processed in the form of “web nodes”, and the quality ranking is obtained after multiple iterations of the PageRank algorithm. At present, there are few studies on the evaluation methods of online education platform teaching influence. However, personal factors have a significant influence on the results in traditional assessment methods. The PageRank algorithm based on massive data analysis is more objective, and the results are more reliable. Future research work will focus on the optimization of the application of the PageRank algorithm in this field. At the same time, through the integration of teachers' backgrounds, experiences, and other data, we can get a more comprehensive assessment of teacher quality.

7. Acknowledgment

This work was supported by Natural Science Foundation of Shanghai grant 16ZR14228; The 2018 Training Project for Outstanding Teaching Achievement Award of University of Shanghai for Science and Technology grant JXCGPY2018012; and The 2019 Teachers’ Teaching Development Project of University of Shanghai for Science and Technology grant CFTD193006.

8. References

1. The Pagerank Citation Ranking: Bringing Order to the

Web. Technical Report, Stanford Digital Library Technologies Project, 1998.
2. Brin S, Page L, the Anatomy of A Large-scale Hypertextual Web Search Engine", Computer Networks and ISDN Systems. 1998; 30(1-7):107-117.
3. LI Zhi-ying, YANG Wu, XIE Zhi-jun, Research on PageRank Algorithm, Computer Science. 2011; 38(10A):185-188.
4. YU Yi, GAN Ruo-xun, FAN Suo-hai, *et al*, Journal Evaluation Based on PageRank Algorithm and HITS Algorithm, Computer Science. 2014; 41(6A):110-113.
5. Cai Jianchao, Cai Ming, the Optimization of the PageRank Algorithm of Search Engine", Computer Applications and Software. 2008; 25(9):59-60.
6. Huang Wei, Liu Xuan, Shi Pei, *et al*, Online Education Evaluation Pattern in the Internet+ Era, Journal of Intelligence. 2016; 35(9):124-129.
7. Han Li-li, Research on MOOC Teaching Evaluation Model Based on Analytic Hierarchy Process, Electronic Technology. 2016; 45(11):17-18+16. (in Chinese)
8. Zhou Zhou, Online Education Course Quality Assessment Research, China Higher Education Evaluation. 2017; 28(2):19-23. (in Chinese)
9. Li Bao-ping, Zhou Ying, Research on Educational Evaluation based on Big Data, Modern Educational Technology. 2016; 26(6):5-12.
10. Zong Yang, Zhen Qin-hua, Chen Li, Research on the Value of Chinese MOOCs Learners——Analysis of Online Learning Behavior Based on RFM Model, Modern Distance Education, no. 2016; 2:21-28. (in Chinese)
11. GONG Xiu-wen, ZHANG Pei-yun, Research on Propagation Model and Algorithm for Influence Maximization in Social Network Based on PageRank, Computer Science. 2013; 40(6A):136-139.
12. Su Cheng, Pan Yun-tao, Yuan Jun-peng, *et al*, Journal Evaluation Research Based on PageRank, Chinese Journal of Scientific and Technical Periodicals. 2009; 20(4):614-617. (in Chinese)
13. Liu Hong, Research on PageRank Book Recommendation Technology, Bulletn of Science and Technology. 2013; 29(4):36-38.
14. GU Yi-ran, XU Meng-xin, Keyword Extraction from News Articles Based on PageRank Algorithm, Journal of University of Electronic Science and Technology of China. 2017: 46(5):777-783.
15. LI Yong, AN Xin-ying, ZHAO Ying-guang, *et al*, Evaluation on the Scientific and Research Influence of Institution Based on PageRan, Journal of Medical Informatics.2017; 38(6):54-58.
16. Järvelin K, kekäläinen J, Cumulated gain-based evaluation of ir techniques ACM Trans. Inf. Syst. 2002; 20(4):422-446.