Enhanced Recommendation System in Community–Question-Answering Websites using Splay-Tree Methodology

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Abstract*: In community-driven ranking systems participants with superior scores acquire strong reputation than low scored participants. The community-question-aswering websites, like stackexchange network, participants with unreciprocated or unnoticed questions for a long time get a badge called tumbleweed without taking into account of their earlier period performance. The user-driven question and answering website considers this reward as a consolation prize and discourages them instead of encouraging. Mostly, the users who ask unnoticed questions are either a new or less scored participants. The center of attention of this research work is to propose a recommendation system that prevents unnoticed questions from the participants who are about to receive a tumbleweed badge. A splay-tree is a tree with a self-balancing ability which brings the newly accessed node to the apex of the tree. In this paper, the splay-tree correspond to participants' ranks and the highlight of the work is to raise average or beneath average scorer to apex without disturbing existing toppers.

***Keywords*: Community Question Answering, Ranking System, Splay and Semi-Splay-tree, Long Tail Problem, Collaborative Learning.**

I. INTRODUCTION

In Community Question Answering (CQA) platform, participants mostly target to win more reputation points in order to obtain special privileges provided by the CQA environment. Identifying and enhancing a potential user may further improve their contribution and reputation in the CQA. The CQA contributors fail to take the risk to answer the difficult question of a less interest topic because of their ignorance of the subject area. Contributor's reputation calculation is based on the quality and quantity of their contribution to the website. The changes of the subsequent revisions in reputation are preserved with the better quality contribution [1]-[4]. An expert is a person who is very knowledgeable about or skillful in a particular area. Accordingly, a user who poses reputation more than 2400 points in Stack overflow is considered as an expert [4]. It is hard to earn votes in CQA website like Stack Overflow (SO) because of the topic popularity among the people. Ranking the participants in CQA is similar to ranking web pages using the Page Rank algorithm. Lai et al (2017) proposed that the importance of a webpage can be recursively computed from the relative importance of all the web pages linking to it. Liu (2015) described a Zhihu Rank algorithm based on the topic similarities between participants and their questions to obtain an exclusive user authority ranking for each question [6].

II. MOTIVATION AND BACKGROUND

Author Community-driven question answering systems is an accumulation of reusable valuable knowledge which is crowd-sourcing information of questions and answers. The potential expert participants are identified based on their initial activities when joining the site since it is an indication of their long-term contribution [7]. Adler and Alfaro, (2007) and Alfaro et al (2011) explained in their work how user reputation has been evaluated to forecast the future participation of user quality. Increasing or decreasing the large-degree user's influences produces precise reputation ranking lists [9]. The sum of scores given by the peer contributors of the website is known as the reputation, later on, it is ranked among participants. Mean points are mostly gained by the registered participants over anonymous participants and also registered participants are considered as reliable participants [10].

Adamic et al (2008) proposed a method to identify concern experts as a help for specific participants and improves communication among different CQA's participants efficiently through promoting highly talented participants. Malicious participants, junk files and spam's (spam detector) had been demoted for each specific user. Information retrieval techniques are used in some of the work to identify the experts and to map the questions to answers for recommending answer providers. In [11]-[13] the authors choose the best answer to the question and direct a new question to the potential user. In [18] - [23] author proposed various authentication techniques for effective security; these techniques can be adopted for information and network security of community-question-answering websites preventing from various attacks. In this paper, potential participants are identified rather than high reputed experts to get preferences in attracting questions and peer participants votes.

III. ZHIHU RANK ALGORITHM

Zhihu is a Community-driven question and answering websites (CQA) [14].

Revised Manuscript Received on October 15, 2019

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Liu et al (2015) proved from Zhihu dataset that Zhihu Rank algorithm outperforms the Page Rank algorithm in the user authority ranking system by applying Latent Dirichlet Allocation. Zhihu Rank Algorithm is based on the iterative method of Page Rank. The model considers two aspects:

1. The relationship between participants - use Page Rank to get user ranking in topic z (*QZ*)
2. Topical similarity – extract topic of user and questions applying LDA (*UR*)

Topical similarity helps to calculate user ability ranking of every question (*QR*) using the formula, $QR=QZ+UR$. Limitation of the Zhihu Rank algorithm is; not including the action of a user, which is a significant factor, to the ranking algorithm [5]. This research work is an extension of the Zhihu Rank algorithm along with user activity. The dataset retrieved from a CQA website, Stack Overflow has been used for experimentation. The experimental results and the computation complexity show that the proposed method is more efficient compared to Zhihu Rank. Finding a good number of trustworthy users with deep knowledge in the related field [5] is the ultimate goal of the Zhihu Rank method. Participants and their relationships are represented as nodes and edges respectively in a digraph. Let user *A* has voted/answered the post of user *k*. The Zhihu Rank of user *k* is,

$$Zhihu\ Rank_k = \{(1-q)/m\} + pA_{k-1}\ ,$$

where *m* is the participant number and *q* is the probability of voting which is called as 'damping-factor' (Fu et al 2006). The Zhihu Rank algorithm continues to accomplish the iteration method until the ranking values become stabled within a threshold.

A. Stack Overflow

Stack Overflow is one of the websites of Stack Exchange networks of sites. The main features of Stack Overflow are:

- The site focuses on receiving answers on detailed and practical questions that are helpful for the computer programmers.
- A tag represents a specific topic. Each question has up to five tags.
- Rating system builds user reputation through voting. The Stack Overflow privileges are unlocked for participants with higher reputation score. Participants earn badges when posting a famous question, giving a valid answer or voting for others' comments.
- The quality of questions is maintained by admitting only questions that are focused on a specific problem.
- The programmers' reputation reveals their knowledge depth and their areas of interest.

The challenges of Stack Overflow:

- Expert participants are not interested in attending complicated questions on new topics, because such questions may take a longer time to answer and earn very few points.
- Since experts are not answering the complicated questions, the quality of the answers drops and many questions are unanswered, which affects the quality of the community and the learning.

B. Comparison between Zhihu and Stack Overflow websites

As Fig.1 shows, Stack Exchange websites has the high recognition than Zhihu by Amazon's recent statistics.

Fig.1. Statistics of Amazon - Zhihu's and Stack Exchange's popularity

As per the authorized data gathered till April 2017, Zhihu website had 18,500,000 visitors on average per day and more than 65,000,000 registered participants [5]. Zhihu is ranked in 183rd place globally whereas Stack Exchange is ranked 133rd globally as per Alexa (Amazon's statistics) rankings. StackOverflow is ranked 53rd globally which is higher than the parent Stack Exchange.

Stack Overflow is visited by about 50 million people every month out of them 21 million people are professional developers and university-level students who learn, share, and build their careers (https://insights.StackOverflow.com/survey/2018). Due to the high degree of popularity of the Stack Overflow community, in this research work, it is the representative sample of CQA website.

C. Stack Overflow dataset in Zhihu Rank

Inspired by data analysis of Stack Overflow, Zhihu dataset has been replaced with Stack Overflow dataset (www.stackexhange.com) in the Zhihu Rank method. Fig.2 depicts the architecture of Zhihu Rank algorithm in the Stack Overflow community.

The frequency distribution of Stack Overflow contributors' questions, answers, the number of answers for each question and the best answers' arrival time are displayed in diagrams, Fig.3 and Fig.4.

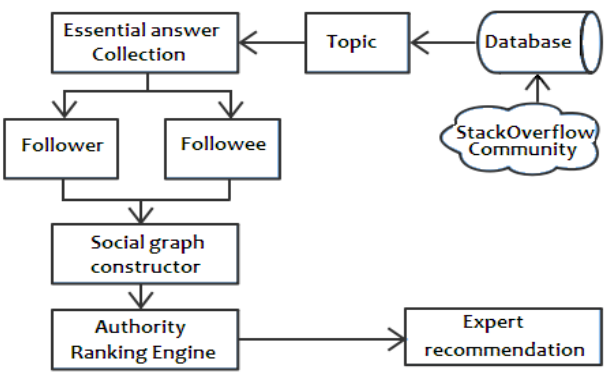
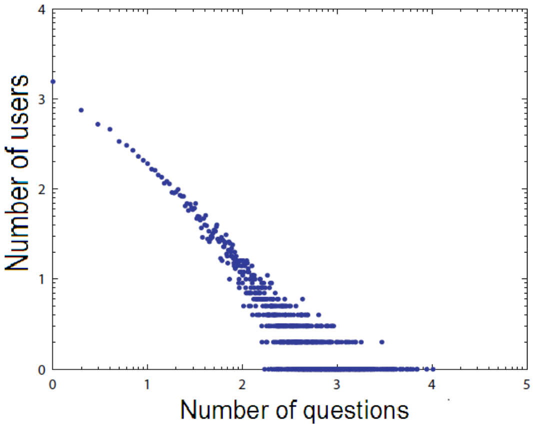
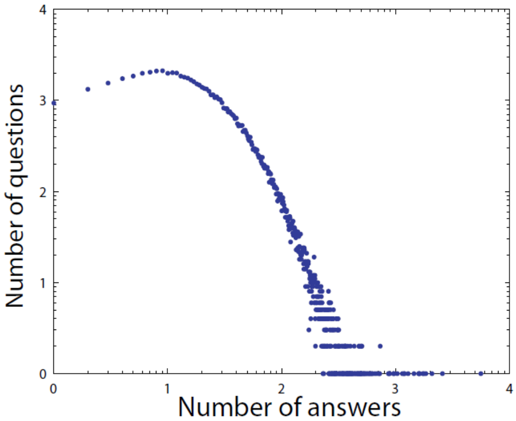


Fig.2. Architecture of Zhihu Rank on Stack Overflow data

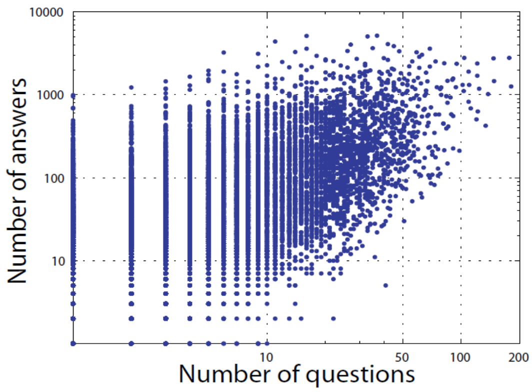


(a)

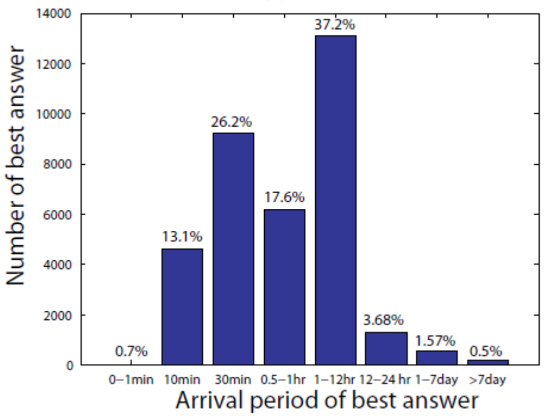


(b)

Fig.3. (a) Distribution of questions and participants (b) Distribution of questions and answers



(a)



(b)

Fig.4. (a) Number of questions and answers for each user (b) The distribution of arrival time of best answers'

Less number of participants posts a large number of questions and vice versa. Thus the frequency distributions of posted questions are high when the frequency distributions of participants are low, Fig.3(a). Very less number of questions obtains more number of answers, Fig.3(b). Many of the questions remain unanswered or receive only one answer from peer participants. For a user, Fig.4(a) shows the proportion of the number of questions (post) and the number of answers received for that post. The arrival period of the best answer after a week (greater than 7 days) is 0.5% which is less than the time of posting a question, 0.7%, Fig.4(b). The arrival period of best answer is highest after one hour of posting the question. The test data is collected from the Stack Overflow website.

Initially, for 8 weeks, participants' 'week' ranks are retrieved continuously. First, 50 top-ranked user details have been collected for analysis with 340 contributors. The studied 'week rank' data shows that highly ranked, 'rep-cap', participants retain their ranks, whereas participants ranked above 30 (i.e., {31,32,33,..}) have higher chances of getting low reputation and are in the decisive position of falling down in the ranking record as shown in Table-I. These participants are called 'less-active' participants. The studied statistical data of Stack Overflow from the weekly ranked participants' list based on the mathematical proposition concludes that almost 75% of participants' weekly-ranks go down to the lesser levels. The data inside each cell in the below Tables represents user detail – *Name, Member-for (in years), Week-Rank, Change-in-reputation, Total-Reputation, Week-Reputation* respectively.

Note: (i) *Week-rank* is the rank of a user in that week; it is represented in the Table with a special # tag symbol.

(ii) *Change-in-reputation* is the difference between previous week-rank and the current week-rank

A system with user rating mechanism has been modified using the regression method to represent reputation. Zhihu and Stack Overflow are reputation-based CQA websites where Stack Overflow is popular than Zhihu. Stack Overflow user dataset is retrieved lively for 8 weeks continuously to identify the set of participants who need to be re-ranked and the data analysis reported that 'rep-cap' participants who are in top ranks retain their rank levels successfully. Top-ranked participants are preferred deliberately for answering the queries though they are unaware of new topics or not willing to answer the query. As a result, the long tail problem arises in the ranking system. Due to this problem, most of the questions in CQA remain unanswered or deleted before answering. Applying reputation based Zhihu Rank algorithm on Stack Overflow dataset concludes that the Zhihu Rank has the long tail problem.

IV. BAYESIAN INFERENCE METHOD IN COMMUNITY QUESTION ANSWERING SYSTEM

A user has been considered to perform remarkably until he gets a low reputation. If the user has a notable past or predicted future performance, his rank enhancement can encourage him to get a good reputation again. The Bayesian method is popularly used in the prediction based on prior and posterior probabilities.

Approximate the posterior distribution which is useful for identifying potential participants from the less-active category, i.e., who are predicted to perform (score) high in their future.

A. Bayesian Approximation in the user selection

This section derives trouble-free systematic rules for updating user reputation by introducing a Bayesian approximation method. Approximation technique for Bayesian inference is applicable in various areas of science and engineering. Probability is a relative frequency of an event. Bayesian probability is a degree of belief based on evidence. The primary motivation to use Bayesian methods is its consistency quality. Decision making under uncertainty considers all available information. The classical statistical approach estimates unknown constant using randomly taken sample data from the population of interest considering the parameters as fixed [15], [16]. The Bayesian approach constructs a prior distribution model for participants' rank using old information and/or subjective judgments, and then making use of current data for the population model parameters to form a posterior distribution model. The predicted value is the primary factor in the decision making in selecting a less-active user.

Obtain and analyze posterior and prior distribution for the parameters such as vote, comment, last response time, week reputation, change in reputation, etc. The choice of distribution for Bayesian analysis is essential and it is a conjugate of the geometric distribution. Bayesian online ranking systems model the reputation outcome by approximations of the posterior mean μ and variance σ^2. The observed data that is the overall reputation and the model parameters are random quantities [15], [16] according to the Bayesian approximation method.

Let θ is a probability density to estimate based on data x, L is the likelihood function, where $L= p(x|\theta)$. Then the conditional probability density functions,

$$P(\theta,x)=p(\theta)p(x|\theta)=p(x)p(\theta|x) \quad (1)$$

Therefore Bayes' rule state that,

$$p(\theta|x)= p(\theta)p(x|\theta)/p(x) \quad (2)$$

i.e., $p(\theta|x) \propto p(\theta)p(x|\theta) = p(\theta)L(x|\theta)$ (3)

Dividing by area under curve,

$$p(\theta|x) = p(\theta)L(x|\theta)/\int p(\theta)L(x|\theta)d\theta \quad (4)$$

Assume the initial participants' reputation follows a 'Gaussian distribution'. This is characterized by the following factors,

(i) The average reputation of the user
(ii) The degree of uncertainty in the participants' activity

V. THE SPLAY-TREE

Splay-trees are tree structures with rebalancing quality and data primarily accessed in recent times is close to the root. Extra storage and complexity are the problems with AVL trees [17]. The splay-tree provides the solution for the mentioned problem by binding the adjusting version of AVL trees with an amortized time of $O(\log n)$ for all operations. Any M successive processes initiated from an empty tree acquire at most $O(M \log(N))$. The CQA participants are represented as splay-tree nodes. In the splay-tree insert/find operations always rotates the recently accessed user to the root.

Searching operation in a splay-tree first finds the user similar to Binary Search Tree searching operation and then splays the user to the root. If a user n is on the access path in depth d before splaying, he is relocated at depth $d/2$ after splaying. The participants on the access path which are below the 'n' have been moved closer to the root while splaying 'n'. On the whole, the tree becomes more balanced by implementing most-recently used logic. The splay-tree structure is self-tuning with the top-down approach because no recursion or parent pointers are necessary. Splay-trees are *very* effective search trees because of the following reasons,

- Comparatively trouble-free – That is, no additional fields are required
- First-rate locality properties - That is, finding repeatedly accessed keys are inexpensive and easy (near the apex of the tree),
- Seldom accessed keys stay out of the way (near the bottom of the tree)

The Zig and Zag are rotations of a node performed during splaying operations. Let X is a non-root user with ≥ 2 ancestors, P is his parent and G is his grandparent node. When parent and grandparent nodes are in the same direction (left-left or right-right), Zig-Zig rotation is when parent and grandparent are in different directions (left-right, right-left), the Zig-Zag rotation. Splay-trees have a tendency to be balanced thus M processes acquires time $O(M \log N)$ for $M \geq N$ processes on N items. Freshly accessed items are close to the root of the tree and items near an accessed one are dragged toward the root thus the splay-tree has good "locality" properties. The semi-splaying operation is the rotation of a node either using zig or zag single rotation considering his parent as a root node.

A. Splaying Method with Two Trees

A self-balancing skill of the splay-tree brings the items that are recently accessed to the root node of the tree, thus the recently searched items to be accessible in $O(1)$ time if accessed again. Even if the depths of some nodes get huge, rebalancing quality guarantees that a long sequence of $O(N)$ searches does not occur. Two splay-trees are built in this work to replace a less-active user with his parent by using semi-splay (Zig or Zag) assuming his parent as a root node. A splay-tree t_1 is built according to reputation value and another tree t_2 is built as per the user activity (access frequency); thus, the lastly accessed user resides at the head of the tree. Searching time of a user 'x' is directly proportional to the number of links from the root node to 'x'. In some cases, participants are more active at the beginning with the highest reputation and later they may become less active. In other cases, though participants are active they score destitute status. In this paper, the former case has been discussed.

VI. EXPERIMENT AND DISCUSSIONS

The existing system, Zhihu Rank, finds the most authoritative user without considering user activity.

The proposed method encourages CQA's less-active contributors considering their past reputation score and the time of their latest post. The focus is to find the potential participants among less-active participants and to recommend them as answerer for the questions as per their subject of interest so that they can be get placed in 'Rep-Cap' category. The potential user is determined with subject knowledge and notable attribute values such as experience in CQA (Member for), Last accessed (hours Ago), Week rank, Week reputation, total reputation and Change in week reputation (compared to last week). The dataset of Stack Overflow, a famous community website, has been applied to the proposed system. Details of participants and their reputation/ranks are collected as test data. The 50 top-ranked user details have been collected for analysis with 340 contributors. Assuming Lower limit as 30 and Upper limit as 50, less-active participants range, the proposed Long-tail-free algorithm replaces selected potential less-active participants with their parent.

Naïve Bayes can also classify less-active and rep-cap participants. With Bayesian approximation method:

- Prior is 0.57;
- The probability of potential participants is 57.14%;
- The probability of non-potential participants is 42.86%.

Less-active participants with highest posterior and prior probability are the selected potential participants.

Display the splay-trees eliminating outliers (participants with beyond the range of reputation value). Bayesian approximation method predicts the potential less-active participants as described previously. In this sample data set (Table-I), 'M' (user Id) is predicted as a potential less-active user. Replace 'M' using the Long-tail-free algorithm and moves forward to ranking level 7 from 9. After replacement through the proposed method, M is at rank level 5. This concludes that a participant becomes more active after increasing the ranking status.

Table- I: User ranking position in a Splay-tree

User ID	Level in tree1	Level in tree2	Level in tree3	Level in tree4	Level in tree5
A	4	1	3	6	7
B	5	4	6	8	10
C	6	2	2	1	3
D	12	9	6	4	5
E	9	8	7	8	4
F	2	4	5	9	10
G	5	5	6	9	3
H	8	7	4	6	6
I	11	7	7	5	6
J	10	8	1	4	2
K	5	4	3	2	4
L	12	8	3	3	4
M	3	4	4	9	5
N	4	3	5	10	9
O	5	6	8	10	5
P	8	9	6	10	6
Q	6	6	5	7	5
R	7	9	9	11	6
S	4	5	3	7	4
T	11	9	4	3	1
U	10	8	5	2	2
V	2	2	4	7	8
W	5	3	5	8	9
X	4	5	2	5	6
Y	7	8	5	8	7

In the proposed method *maxtf, midtf, and mintf* are considered as 3, 2 and 1 respectively. In Table-I, level of the SO participants in the splay-tree is displayed. The participants are splayed using splay-tree algorithm and user M has been identified as a potential user in this sample data and implemented Long-tail-free algorithm to enhance his rank level in the ranking list of participants. The splay-tree level represents the ranking level of the participants since participants are arranged in the splay-tree based on their reputation and activity score.

A. Evaluation Measures

The rank sum test, 'Mann Whitney U test' evaluate the metrics of the existing and proposed algorithm in this paper. A nonparametric rank sum test to compare outcomes between the Zhihu Rank and the Long-tail-free methods is the Mann Whitney U test. This test is sometimes called as 'Wilcoxon Rank Sum Test' which is used to test population of the Zhihu Rank and the Long-tail-free samples. In other words, to check samples are likely to derive from the same population with the same shape. Let *n* is the total number of samples. The sum of all ranks is n(n+1)/2. The test statistic is U, the smaller of $U_i = n_1 n_2 + [n_i(n_i+1)/2] - R_i$; $i =$ *and* 2, where R1 and R2 are the sums of the ranks in Long-tail-free and Zhihu Rank, respectively.

U_i= Mann-Whitney U test
n_1= Long-tail-free sample size
n_2= Zhihu Rank sample size
R_i = Rank of the sample size

Data comparison graph with test report for the Mann-Whitney test between Zhihu Rank and Long-tail-free shows the user rank improvement in the Long-tail-free algorithm. Mann-Whitney test report states that in the Long-tail-free ranking system, the participant ranks are near to zero that means the ranks are in high level with strong reputation compared to Zhihu Rank. The less-active and 'about to get tumbleweed' participants are prevented from the long tail problem in the proposed ranking system.

VII. CONCLUSION

Experimental results show that the proposed Long-tail-free algorithm outperforms existing algorithm Zhihu Rank which is based on the Page Rank algorithm in the recommendation of the long tail free re-ranking system. The highlight of the work is to bring up average or below average reputation scorer to the top without affecting the existing toppers**.** The average answer score represents the number of post and score of participants.

The Long-tail-free algorithm using Bayesian approximation method for user selection has a better ranking system than Zhihu Rank and this method is suitable to predict potential less-active participants depending on the user factors of the ranking system. The proposed system resolves efficiently the long tail problem in the existing Zhihu Rank method.

ACKNOWLEDGMENT

The author would like to thank Stack Overflow for providing the data used in this paper.

REFERENCES

1. B. Adler, L. de Alfaro, "A content-driven reputation system for the Wikipedia," in Proceedings of the 16th International World Wide Web Conference, (WWW 2007), ACM Press, 2007.
2. B. Adler, L. de Alfaro, I. Pye, and V. Raman, "Measuring author contributions to the Wikipedia," in Proc. of WikiSym: International Symposium on Wikis, ACM Press, 2008.
3. G. Druck, G. Miklau, and A. McCallum, "Learning to predict the quality of contributions to Wikipedia," in Proceedings of the Workshop on Wikipedia and Artificial Intelligence: An Evolving Synergy, AAAI Press, 2008, 7–12.
4. Y. Yang, C. Wang, J. Lai, "An efficient parallel topic-sensitive expert finding algorithm using spark," in IEEE International Conference on Big Data (Big Data), Date of Conference: 5-8 Dec. 2016 , Date Added to IEEE Xplore: 06 February 2017
5. M. Lai, C. Liu, C. Li, and Z. Yu, "Discovery of participants authority ranking in a community question answering website," in 4th International Conference on Information, Cybernetics and Computational Social Systems (ICCSS), 2017, doi:10.1109/iccss.2017.8091430
6. X. L. Liu, "Ranking online quality and reputation via the user activity," Research Center of Complex Systems Science, University of Shanghai for Science and Technology, 2015, Physica A 436, pp.629–636. http://dx.doi.org/10.1016/j.physa.2015.05.043
7. D. Movshovitz, "Analysis of the reputation system and user contribution on a question answering website: stack overflow," IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, ASONAM'13, Niagara, Ontario, 2013, ACM 978-1-4503-2240-9 /13/08
8. L. D. Alfaro, T. Adler, A. Kulshreshtha, and I. Pye, "Reputation system for open collaboration," Communications of the ACM, 54(8), 2011, pp.81–87, doi: 10.1145/1978542.1978560.
9. X. Liu, S. Ye, X. Li, Y. Luo, and Y. Rao, "ZhihuRank: A Topic-Sensitive Expert Finding Algorithm in Community Question Answering Websites," Advances in Web-Based Learning, ICWL 2015 Lecture Notes in Computer Science, 2015, pp.165-173. doi:10.1007/978-3-319-25515-6_15
10. M. F. Mohammed, C. P. Lim, and A. Quteishat, "A Novel Trust Measurement Method Based on Certified Belief in Strength for a Multi-Agent Classifier System," Neural Computing and Applications, 24(2), 2012, pp.421-429
11. L. A. Adamic, J. Zhang, E. Bakshy, and M. S. Ackerman, "Knowledge sharing and Yahoo Answers: everyone knows something," in Proceedings of the 17th International Conference World Wide Web, Beijing, China, 2008, pp.665–674
12. L. Song, C. Tekin, and M. V. Schaar, "Online Learning in Large-Scale Contextual Recommender Systems," IEEE Transactions on Services Computing, 9(3), 2016, pp.433-445. doi:10.1109/tsc.2014.2365795
13. Y. Yang, C. Wang, J. Lai, "An efficient parallel topic-sensitive expert finding algorithm using spark," in IEEE International Conference on Big Data (Big Data), Date of Conference: 5-8 Dec. 2016 , Date Added to IEEE Xplore: 06 February 2017 , ISBN Information: INSPEC Accession Number: 16652914.doi: 10.1109/BigData.2016.7841019
14. P. Nakov, D. Hoogeveen, L. Marquez, A. Moschitti, H. Mubarak, T. Baldwin, K. Verspoor, "SemEval-2017 Task 3: Community Question Answering," in Proceedings of the 11th International Workshop on Semantic Evaluations (SemEval-2017), Vancouver, Canada, August 3 - 4, 2017. c 2017 Association for Computational Linguistics, 2017, pp.27–48
15. H. Fu, D. K. Lin, and H. Tsai, "Damping factor in Google page ranking," Applied Stochastic Models in Business and Industry, 22(5-6), 2006, pp.431-444. doi:10.1002/asmb.656
16. R. Herbrich, T. Minka, and T. Graepel, "TrueSkill: A Bayesian skill rating system," Advances in Neural Information Processing Systems 19. MIT Press, Cambridge, MA, 2007.
17. A. B. Elmadani, "AVL Tree An Efficient Retrieval Engine In Classified Fingerprint Database," International Educational Applied Scientific Research Journal, 1(1), 2016, pp.30-35
18. S. Vaithyasubramanian, and A. Christy, "A scheme to create secured random password using Markov chain," In Artificial Intelligence and Evolutionary Algorithms in Engineering Systems, Springer, New Delhi, 2015, pp. 809-814.
19. S. Vaithyasubramanian, A. Christy, and D. Lalitha, "Generation of array passwords using Petri net for effective network and information security," In Intelligent Computing, Communication and Devices, Springer, New Delhi, 2015, pp. 189-200.
20. S. Vaithyasubramanian, A. Christy, and D. Lalitha, "Two factor authentications for secured login using array password engender by Petri net," Procedia Computer Science, 48, 2015, pp.313-318.
21. S. Vaithyasubramanian and A. Christy, "ATM PIN generation - A formal mathematical model to generate PIN using regular grammar, context free grammar and recognition through finite state machine, pushdown automata," Inderscience, International Journal of Internet Protocol Technology, Vol.12, No.1, 2019, pp.11-15, doi: 10.1504/IJIPT.2019.098485.
22. S. Vaithyasubramanian, A. Christy, and D. Saravanan, "Access to network login by three-factor authentication for effective information security," The Scientific World Journal, 2016.
23. S. Vaithyasubramanian, "Array CAPTCHAs (Completely Automated Public Turing test to tell Computer and Human Apart)," ASIA LIFE SCIENCES, 14(1), 2017, pp.247-254.

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