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INTEGRATED RECOMMENDATION AND RANKING MODULE FOR INSTITUTIONS

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Abstract

In this era of data where choices are way more than the number of users associated with it, the role of recommendation and ranking dominates one's selection. As with every spare second spent over the network, data generated by the interaction increases so rapidly. Through this data it becomes a task of just applying advanced algorithms to generate propaganda oriented campaigns for the welfare of any particular organisation associated. These organisations use this to manipulate the selections. With this paper we aim to develop a minimal error recommendation and ranking system that provides unbiased and desired results with the help of integrated machine learning techniques and neural network interconnections. We are considering big-data sets that are cloud based and oriented to pre-filtration and generalise categorisation of fetched data from the user, which contributes in speeding up the learning process of the module.

Keywords: Big-data, Cloud Based Server, Data Pre-Filtration, Institutional Ranking, Integrated Machine Learning, Recommendation And Ranking System, Neural Network,

INTRODUCTION

From the very beginning of mankind education has been an undistinguished part of life, either considering it to be the very ability of sparking fire to the science behind lending to other planets. We humans are educating our generations with the blessing of knowledge, as we understand that education not just makes one to learn things but helps them to justify their existence by creating a better self and this world a better place. Now in the present time educational institutions are considered as the bridge that fills the gap between knowledge and an individual. Starting with the very age when a young one is sent to play-school for learning the basic habitats of life to getting into a university for higher studies, we find that there are numerous big and small educational institutions associated with one's life that plays a vital role into their self building as an educated human.

While we find that the relevance of education and educational institutions are so high in one's life, it becomes a hap tic task of immensely great importance when it comes to opting for one for yourself. Thanks to modernisation at this current situation there are a large number of options available while choosing, But as said, “Great options come with great confusion” because each institution out there claims itself to be the best in order to attract the crowd to itself. As this very problem is associated with almost everyone in this world, the role of ranking and recommendation comes into existence for institutions.

Initialised first in 1983 when US News and World Reports officially published their ranking of America's best college [1], It ignited a streak of rat race among the institutions to overcome and outshine each other. The rankings and recommendations not just improvised the educational system but also added a major parameter for students to classify the best fit institution for them. Continuing up the lane with the vast changing educational environment in year 2004 the Quacquarelli Symonds (QS) world university ranking have been launched to march with the new trend of learning where focus have been tuned over four majors: teaching quality, research quality, graduate employability, and international outlook [1].

Even considering the most appreciated and acceptable ranking of this era (i.e QS world university ranking), it seems not much accountable when it comes to integrity as it's not justified for all the institutions present around the globe. When understanding more about the educational network of developing countries like Africa [9], we find that there are various loop-holes as the situations are different and the parameters that QS ranking offers seems to be unfair as well as unjustified. As the situation varies country to country and impact of external & internal stakeholders is very high on the educational system [7], the rankings have become country oriented [21]. In the month of September of 2015 The National Institutional Ranking Framework (NIRF) was introduced in India [5], here the institutions have been ranked based upon the parameters in order to strengthen the quality education throughout the nation [21]. The major factors over which the ranking in the module is parameterised are: Teaching Learning and Resources, Research and

Professional Practice, Graduation Outcome, Outreach and inclusivity, and

perception [7]. The NIRF continues to be the most trusted and authenticated ranking module in India but still it seems to be not much versatile, as India itself is a land of diversity the conditions vary state to state and place to place which is not taken as a key attribute while parameter sing.

In this paper a better integrated module is proposed which will provide unbiased and comparatively less error generating as well as generalised model for ranking and recommendation working upon the key technologies like machine learning, big-data, neural network, cloud based processing and data pre-filtration.

2. RELATED WORK

Recommendation modules are now working upon almost every digital platform that we use in our day to day life. Even big tech giants like Google, Face book, Amazon etc are controlling the choices we made in our everyday life right from the very beginning, starting from a simple notification on our devices regarding a video we must watch or an article associated to our field of research to shopping recommendation of product we just searched couple of moments back. Their complex algorithms are continuously working upon the data they have collected from our interaction [22]. As being a matter of high relevance a lot of researchers have published numerous articles and research work for parameter sing the ranking module and improving the recommendation

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generated [3-8]. With our module we applied a different approach by subjecting the attributes entered to the system, here we prosper them as the key which can be different for different countries depending upon the situation and the distribution of the educational network of that particular place. For example while ranking a university in the United States, we define course offered as a key and a criteria of ranking, we can define a different key such as acceptance rate for Africa. Using this key-based method justifies the rigidity of the module and enables it to be used globally.

Defining over the recommendation perspective of the module we will consider the big institutional data generated [3] from the interaction of the user and the module, which will be classified according to the keywords of the searches and the search history of the associated user. After the classification of the data it will be transmitted over the cloud based environment that will hold the data in the form of chunks according to the defined attribute, later this data will be filtered depending upon the desired need and then sent as the test case for the machine learning algorithm which will generate a recommendation ultimately for the user.

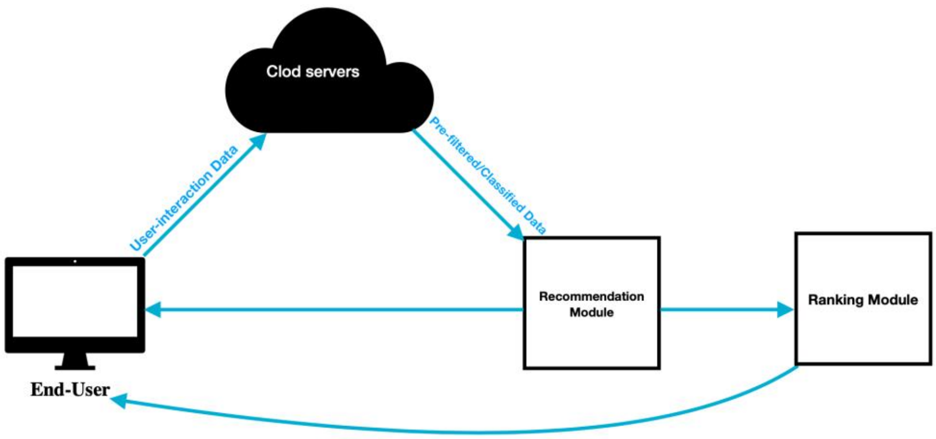

Fig. 1: The outer structure of the ranking and recommendation module

In Figure 1, the End-user and the module interaction is defined where the data after interaction is sent over the cloud based server where using the pre-filtration method that data is accumulated and classified on the basis of defined attributes and keys that are subjective to the particular implementation. Later on the classified data is sent over the recommendation module where the machine learning algorithms are applied in-order for better understanding of the user, then after the bidirectional flow of data takes place towards the End-user and the ranking module where the outcome of recommendation will again be treated as a parameter for ranking.

3. METHODOLOGY

While considering the complete structure to be divided into three major parts: Cloud based servers, recommendation module and ranking module. It provides a coping over to the problem of lagging as the flow of data is predefined and the tasks are divided over the parts associated with them. Here we target the big data produced by the

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educational institution and the data collected over the interface with the interaction of students or faculty members by classifying their search history and previous choices in terms of interests, course selection, duration of the course, preferred field of study etc. Now following we have discussed the various modules with their working fundamentals have been explained below.

3.1 Cloud-Based Servers

After the interaction of the users with the interface, data generated is sent over the cloud platform where the sets are created according to the keywords and predefined attributes. Later after the division of sets the process of extraction initialises so that the data is refined for transformation, the sets up- to now consist of the oriented data.

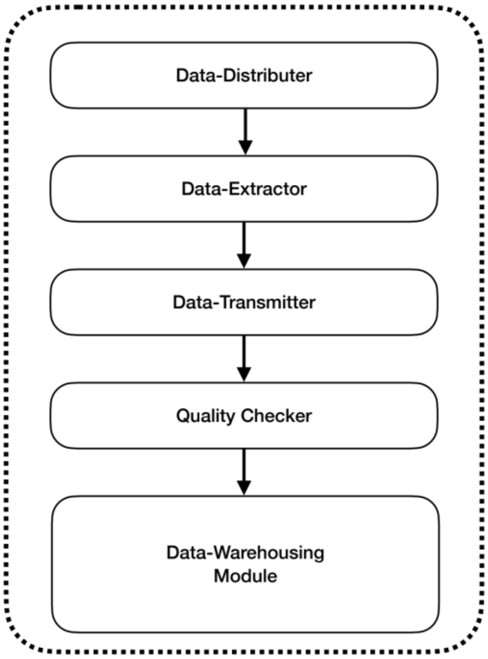

Fig. 2: Cloud-based Server architecture

At the end quality assurance is confined to ensure that none irrelevant data will be passed forward for warehousing in order to maintain the space-time complexity of the module. The modules associated within the cloud-based servers are as follows:-

(I) **Data-Distributor**: Responsible for dividing the data collected from the interaction into the form of sets according to the keywords associated and the test data present.

(II) **Data-Extractor**: The work of data is specified to pool out the data that shows any direct or indirect relationship with the attributes defined for users.

(III) **Data-Transmitter**: After the categorisation and extraction of the data, the data-transmitter works as an interconnection and takes it forward for the quality analysis.

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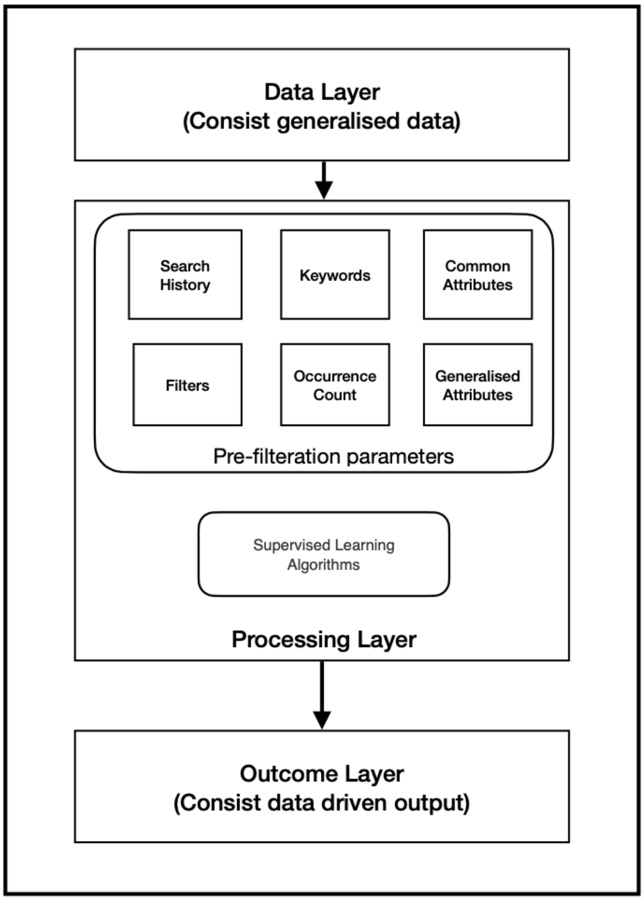

Fig. 3: Recommendation module architecture

(IV)**Quality Checker:** While the transmitter is ready to send over the database for getting stored, the quality checker ensures that there is no unwanted patch of data left in the packets.

(V) **Data-Warehousing Module:** When the desired data is finally obtained, it's been saved over the cloud servers and is ready for the further operations.

The data while being passed on to the recommendation module only contained sets of well defied orders and attributes.

3.2 Recommendation Module

The recommendation module consists of three layered linear unidirectional structure that comprise of data layer, processing layer and outcome layer. All three layers have various accountability that provides modules a versatility for being user centred. The module on one hand works over the user based integrity using [18] collaborative filtering while connecting the deep learning architecture which results as a non-linear relations oriented structure present in between predictions, and the accurate recommendations. E-commerce sites like Flip kart provide the user based recommendation in order to promote their architectural stability and to build up a user friendly module [19-21]. With applying distributive approach towards generating the output and setting up the structure as a result the produced recommendation is more user-oriented and rigid in

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terms of error prevention. The parts associated to the formation recommendation module are as follows:

(I) **Data Layer:** The data layer is the very initial part of the recommendation module which is defined to catch the data fetched from the cloud-based servers and post it forward to the processing layer. The data is not statically present in the data layer but only confined to the cloud layer which enables the best space-time complexity for the module.

(II) **Processing Layer:** The processing layer after receiving the data from the data layer categories the sets on the basis of pre-filtration parameters such as, search history, keywords, common attributes, filters(user dependent), occurrence count and generalised attributes. Afterwards the sets now obtained are information oriented and then finally sent to the supervised learning algorithm for confining the machine.

(III) **Outcome Layer**: The data collected is now stored over the outcome just for instance of time till a particular node is connected to the network. This outcome is now sent to the ranking module that considers this to be a key for creating the rank matrix.

3.3 Ranking Module

For ranking any of any particular institute/educational network there is parameterised analysis with the three major perspectives of faculty, students and institutional outreach. In figure 4 the flow diagram of the parameters are present that works over the big-data received from recommendation module and the data generated by the interaction with the interface, by using the data refined from the recommendation interface it provides a better edge when doing for unbiased and improved ranking as the data sets are way. Better in terms of space-time complexity as. Well as refined and none data is passed without proper analysis.

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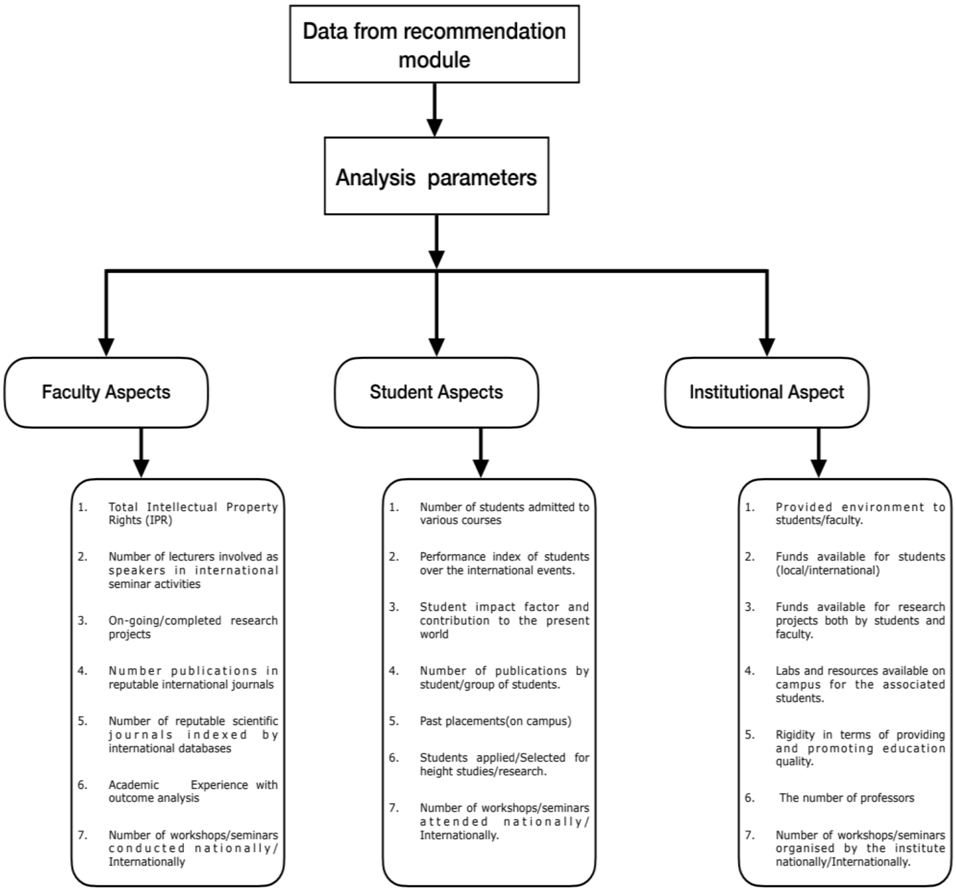

Fig. 4: Flow diagram of parameter analysis of ranking module

4. CONCLUSION

In this paper we have presented a better approach for ranking and recommendation system that can be implemented to multiple-levels of the present network and used to improvise the current system in terms of unbiased ranking of the institute as well as it promotes the cutting edge race among the institutes to outshine each other. With this it helps ultimately in the glorification and uplifting of the standards of educational networks. The cloud- server based approach provides a much advanced and improvised way to deal with the issue of space-time complexity, the data security and the transparency of the module is uni-structured and provides it the stability to be consistent over the educational networks of different countries which makes the module universal.

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References

[1] Huang, Mu-Hsuan. "Opening the black box of QS World University Rankings." *Research Evaluation* 21, no. 1 (2012): 71-78.

[2] Kanakarn Pupara, Wongpanya Nuankaew, Pratya Nuankaew, “An Institution Recommender System based on Student Context and Educational Institution in a Mobile Environment” 2019

[3] Surabhi Dwivedi, Dr Kumari Roshni VS, “Recommender System for Big Data”. 978-1-5386-1922-3/17

[4] S. JothiLakshmi, Dr. M. Thangaraj, “Design and Development of Recommender System for Target Marketing of Higher Education Institution Using EDM” International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 19 (2018) pp. 14431-14437

[5] Dr. P. S. Aithal, V. T. Shailashree, P. M. Suresh Kumar, “The Study of New National Institutional Ranking System Using ABCD Framework” International Journal of Current Research and Modern Education, ISSN 2455-5428, Volume I, 2016

[6] Amer-Al-Badarenah, Jamal Alsakran, “An Automated Recommendation System for Course Selection” International Journal of Advanced Computer Science and Applications, Vol. 7, No. 3, 2016

[7] Bhaskar Mukherjee “RANKING INDIAN UNIVERSITIES THROUGH RESEARCH AND PROFESSIONAL PRACTICES OF NATIONAL INSTITUTIONAL RANKING FRAMEWORK (NIRF): A CASE STUDY OF SELECT CENTRAL UNIVERSITIES IN INDIA” JOURNAL OF INDIAN LIBRARY ASSOCIATION, 52(4) OCT-DEC, 2016, 93-107

[8] Ankita Tabassum, Mahamudul Hasan, Shibbir Ahmed, Rahnuma Tasmin, Deen Md. Abdullah, Tasnim Musharrat, “University Ranking Prediction System by Analyzing Influential Global Performance Indicators”.

[9] John PA Ioannidis, Nikolaos A Patsopoulos, Fotini K Kavvoura, et al, “International ranking systems for universities and institutions: a critical appraisal”

[10] J. Moreno, D. Rodriguez, A. J. Nebro and J. A. Lozano, "Merge Nondominated Sorting Algorithm for Many-Objective Optimization," in IEEE Transactions on Cybernetics, doi: 10.1109/TCYB.2020.2968301

[11] Weihua Hu, Matthias Fey, Marinka Zitnik, Yuxiao Dong, Hongyu Ren, Bowen Liu, Michele Catasta, Jure Leskovec, “Machine Learning (cs.LG)”, arXiv:2004.07219v2

[12] H. Liu, Y. Ong, X. Shen and J. Cai, "When Gaussian Process Meets Big Data: A Review of Scalable GPs," in IEEE Transactions on Neural Networks and Learning Systems, doi: 10.1109/TNNLS.2019.2957109

[13] enthil Nathan, Chander Govindarajan, Adarsh Saraf, Manish Sethi, and Praveen Jayachandran, “Blockchain Meets Database: Design and Implementation of a Blockchain Relational Database”, arXiv:1903.01919

[14] Yanju Zhang, Sha Yu, Ruopeng Xie, Jiahui Li, André Leier, Tatiana T Marquez-Lago, Tatsuya Akutsu, A Ian Smith, Zongyuan Ge, Jiawei Wang, Trevor Lithgow, Jiangning Song, PeNGaRoo, a combined gradient boosting and ensemble learning framework for predicting non-classical secreted proteins, Bioinformatics, Volume 36, Issue 3, 1 February 2020, Pages 704–712

[15] Siddique, N., Alam, K. M. R., & Adeli, H. (2019). A Dynamic Ensemble Learning Algorithm for Neural Networks. Neural Computing and Applications. https://doi.org/10.1007/s00521-019-04359-7

[16] Windig, Willem, Andrey Bogomolov, and Sergey Kucheryavskiy. “Two-Way Data Analysis: Detection of Purest Variables.” Reference Module in Chemistry, Molecular Sciences and Chemical Engineering (2020): 275–307. Web.

[17] Leonelli, Sabina, "Scientific Research and Big Data", The Stanford Encyclopedia of Philosophy (Summer 2020 Edition), Edward N. Zalta (ed.),URL=<https://plato.stanford.edu/archives/sum2020/entries/ science-big-data/>

[18] Bobadilla, Jesus; Alonso, Santiago; Hernando, Antonio. 2020. "Deep Learning Architecture for Collaborative Filtering Recommender Systems." Appl. Sci. 10, no. 7: 2441.

[19] Varga, Ervin. "Recommender systems." In *Practical Data Science with Python 3*, pp. 317-339. Apress, Berkeley, CA, 2019.

[20] Pigi Kouki, James Schaffer, Jay Pujara, John O’Donovan, and Lise Getoor. 2019. Personalized explanations for hybrid recommender systems. In Proceedings of the 24th International Conference on Intelligent User Interfaces (IUI ’19). Association for Computing Machinery, New York, NY, USA, 379–390. DOI:https://doi.org/10.1145/3301275.3302306

[21] Kumar, Vishal, Akanksha Joshi, and Vinamra Sharma. "Institutional Recommendation and Ranking System Based on Integrated Datasets and Analysis." In *2020 International Conference on Advances in Computing and Communication Engineering (ICACCE)*, pp. 1-5. IEEE, 2020.

[22] James Davidson, Benjamin Liebald, Junning Liu, Palash Nandy, Taylor Van Vleet, Ullas Gargi, Sujoy Gupta, Yu He, Mike Lambert, Blake Livingston, and Dasarathi Sampath. 2010. The YouTube video recommendation system. In Proceedings of the fourth ACM conference on Recommender systems (RecSys '10). Association for Computing Machinery, New York, NY, USA, 293–296. DOI:https://doi.org/10.1145/1864708.1864770

[23] Jacobi, Jennifer A., Eric A. Benson, and Gregory D. Linden. "Recommendation system." U.S. Patent 7,908,183, issued March 15, 2011.