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Strengthening research partner collaboration in higher education for searching innovation through machine learning-based recommender system

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Abstract

Academic collaboration is tremendously important for higher education. Multidisciplinary academicians may be grouped as a better research collaboration than the previous one. Therefore, such a system is needed, even for a huge number of academicians in an institution. However, existing such recommendation tools are expensive. This paper suggests to develop a system by using machine learning approach in order to search a big academicians data effectively. Hence, with help of the standard of Naïve Bayes creates a flexible text search without depending on what select options including research location or case study instead of only research topic. Furthermore, the output of Naïve Bayes, then, is tranformed to percentage display in order to bring ease of understanding the gap of recommendation. It allows the user to choose a possible partner more than one. Therefore, this approach helps reduce time and effort.

Keywords: Higher Education, Naïve Bayes Algorithm, Recommendation System, Research Partner Collaboration, Sigmoid Activation Function.

1. Introduction

Higher education is the most important of creating cutting-edge technology for solving kinds of problems in a region in which the existence of higher education is impacted to the region itself. Therefore, academic research collaboration involved within higher education is the vanguard of the solution. Creating the best plausible collaboration is highly needed amongst faculties or in multidisciplinary (Samin & Azim, 2019). There is a strong positive relationship and a better collaboration providing a better outcome. Hence, it increases scientific publications (Amarante et al., 2021; Volkwein & Parmley, 2000). Co-authorship in the same university is important for improving research performance and better learning outcomes, academic writing, research publication skills, productivity, and time management (Abbas et al., 2020; Aldieri et al., 2019).

Private and public universities need to gain research atmospheric among academia with the merit of funding from the university itself or external funding (Abramo et al., 2010). But a large number of faculties may bring challenges in order to find a suitable research partner. The sheer volume of information of partner candidates also brings difficulty. In addition, in developing countries, the number of lecturers in a private university is relatively fluctuating that is because of factors like high living costs, low wages, etc. (Ramadhan & Putri, 2018). Therefore, it needs to manage such unstructured information datasets into a well-organized system. We propose a recommendation system for finding the most suitable research partner based on topic, object location, case study, or any else.

Researchers have recognized the existence of specialization of their research area (Khalid et al., 2011). This paper puts forward why enabling researchers to find partner collaboration by dynamic text search is important. In order to do so, we use the standard Naïve Bayes algorithm for classification task. Naïve Bayes has been widely used in solving text classification problems such as personality classification, complaint-level classification, spam classification, news categorization, etc. This algorithm shows the efficiency in practice. However, in higher education context, the output needed may be different.

In higher education environment, a researcher as user should find alternative partner candidates instead of only the best recommendation. With gauge information of how close the candidates to the criteria is, in the system, a user is able to set more than one criteria based on what research skills are needed. Then the output has to show a precise value compared to other candidates. According to the output, the user has the knowledge to see how strong the candidate is by looking at the value gap among candidates. Therefore, in higher education context, especially in developing universities, relying on Naïve Bayes classification is insufficient.

Recommendation System (RS) is typically used in lexical text from corpus data to cope amount of information just simply suggested for items based on user preferences. In higher education, there have been conducted applications of RS such as recommendation system on course selection and topic recommendation system, while text lexicon in higher education used for prediction of student placement and student retention (Cardona et al., 2020; Di Sipio et al., 2020; Guruge et al., 2021; Wadekar et al., 2018). In this paper, the algorithm is required to generate the amount of information to provide the best rank of suggestions (Saleh et al., 2015) [14]. For this reason, we are more interested in leveraging recommendation system along with its appropriate features using a standard Naïve Bayes. In addition, in some private universities, the problem of searching for research collaboration needs to be analyzed. It is because of the high circulation of lecturers entering or leaving private universities in Indonesia (Ramadhan & Putri, 2018).

Recommendation or suggestion from plenty of unstructured and raw text data is to provide a shortcut by giving the most related information. Hence, it is important in terms of saving time and energy. Our main focus is to analyze the problem in the context of higher education and to help academia to find research partners as preferences. As the aforementioned problem, in the spirit of increasing user intention to use, the RS should also pay attention to the ease of use and reliability of the system. Hence, feature selection of the algorithm preprocess is essential. Naïve Bayes is one of the widely used algorithms in developing the field of RS. The algorithm works on item features (Gaikwad et al., 2018). In recent years, content based RS has been applied for various uses such as recommendations on documents or news, while Syskill and Webert recommendation on web pages or personalized television programs (Cotter & Smyth, 2000; Pazzani et al., 1996). Based on the problem context, we propose a nonlinear approach to gain academic intention of use.

This paper concisely contributes: to leverage Sigmoid activation function to transform Naïve Bayes output into a range of 0-1 and multiplied by 100 to provide a percentage interpretation instead of just using Naïve Bayes classification in order to recommend the most suitable research partners; and to develop the proposed research partner recommendation system in web-based application with respect to user interface and user experience analysis, and to share the source code program. We organized the paper as follows. First, we review the system from the literature in section 2, while section 3 formulates the problem context. Section 4 evaluates the performance of the proposed system. Last, the conclusion of the paper in section 5.

2. Literature review

Naïve Bayes Classification is commonly used as statistical-based technique in content-based RS (Guruge et al., 2021). Content-based RS leverages statistical-based RS to improve valid recommendations. The other techniques are such as TF-IDF, decision trees, and artificial neural networks (Shah et al., 2016). This study uses content-based RS by Naïve Bayes algorithm in the context of classification at first. Then, the classifier is used to estimate the probability of researcher candidate that is the relevancy from text-based dataset. The generated output used keywords of the articles as inputs. For instance, Fab system uses 100 features of web pages to users for representing contents of the web pages (Pavlov & Pennock, 2002).

Neamah & El-Ameer (2018) generate content-based Naïve Bayes for course recommendations. The systems build with use case of course enrollment and ranking for user profile, while Ghani & Fano (2019) enable product recommendations by categorizing products from a department store. Miyahara & Pazzani (2000) implemented recommendations based on number of likes and dislikes, while Sipio et. al. based on GitHub repositories. To do so, Multinomial Naïve Bayesian network is conducted. Fan J., Zhou W., and Yang X (2019) introduce improving quality and quantity of recommendations by sharing content ratings on online social networks. And, content-based personalized recommendation using Bayesian hierarchical models is implemented by Zhang & Koren (2007) to recommend Netflix and MovieLens movies.

Activation function is commonly used in nonlinear optimization field, especially in machine learning. It plays an important role in machine learning as increasing the performance of classifier. Sigmoid activation function can transform a rough value into a range of 0 to 1 which is a useful approach for many applications (Eger et al., 2018). Various activation function such as sigmoid, relu, tanh, and step function show different behaviors whereas sigmoid used at most (Ramachandran et al., 2017). De Campos (2006) proposed a Bayesian approach in the representation of new assessments by applying Zadrozny's network to convert classifier into scoring (Zadrozny & Elkan, 2000). Tripathi et al. (2020) utilized Bayes as a classification in credit scoring.

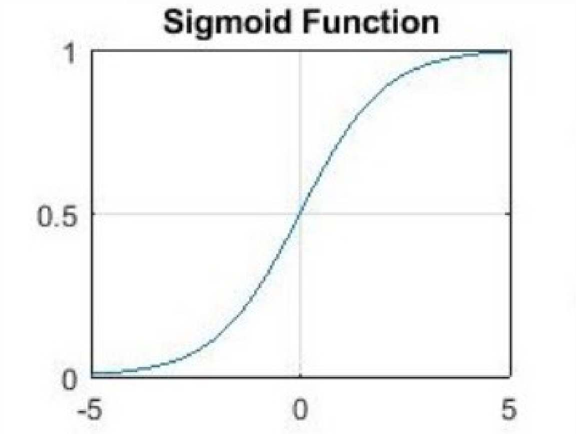

Fig. 1. Sigmoid activation function

Sigmoid activation function lies in the range of 0 to 1. When it reaches 0.5 then it converts to zero as shown in Fig. 1 (Nwankpa et al., 2018). It then defines real input values using derivatives with multiple degrees. Therefore, active research tends to apply to large-scale tasks. Ivaschenko & Milutkin (2019) applied the activation function based on NLP by providing a better accuracy. Hence, this system is also recommended in the context of human resources who looks for the best candidate based on their blogs and online presence. This approach is adopted with the preference of research topics, study objects, and case studies. Since the output is linear, a nonlinear function is required to convert it into a range of 0 to 1.

3. Method

This paper identifies a common problem in higher education when a university has a number of lecturers, there exists a difficulty in finding the best research collaboration. The proposed RS offers alternative research partners based on generated input data. The system consists of two phases. The first step is to use machine learning algorithm namely Naïve Bayes in order to classify research topics as input into which class of academicians. Second, to display the output score in percentage uses Sigmoid activation function as details in Figure. 3. This paper provides a specific case problem of higher education as shown in Table 1. As aforementioned problem, the proposed system conducts a trial for the lecturers at the Faculty of Information Technology and Business in Indonesia. Hence, we can observe what problem statements should be fulfilled by the system.

Table 1. Problem identification in higher education.

Problem statement	System requirement
Academicians in a private university is a high variety of research areas which not focuses in certain research areas.	System must able to synthesis from various research topics.
Articles are published in national journal which provided in Indonesian language.	System needs to process Indonesian corpus.
Input text field is in dropdown list or check list.	System displays input fields in text input.
Academicians are unhappy with the output in the shape of classes.	System displays output in percentage mode.

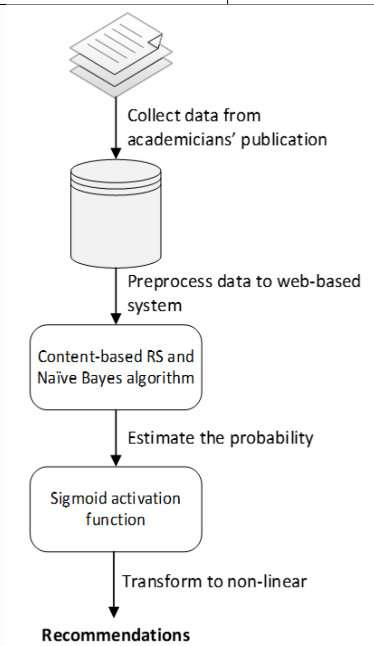

Fig. 2. Machine learning-based system for research recommendation.

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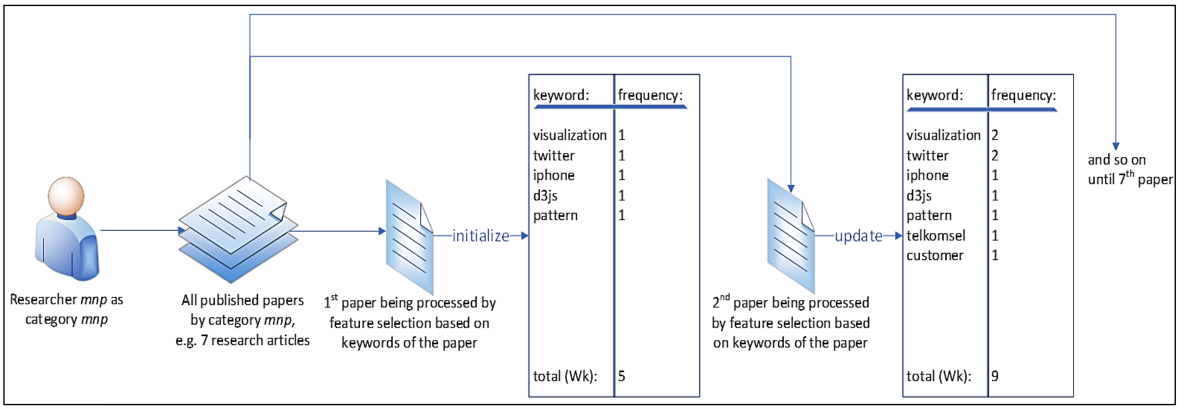

Fig. 3. Proposed algorithm workflow.

In Fig. 3, the process starts from Google Scholar site by collecting all academic articles published by the faculty. Hence, the data collected includes national, international journals and proceeding articles. Due to dimensionality reduction issue, this paper determines three features; research topic, object or location, and case study. RS is an efficient approach in reducing the time while the traditional approach is time-consuming. Feature selection obtains appropriate keyword sets representing its article topics.

Then, designing the database is based on entity relational diagram and text classification. The essential of the proposed systems enforces researcher as output. Hence, all features must satisfy belong the article publication. For instance, if the system generates visualization as a topic, then it must be defined belongs to which researcher. An article can produce some topics that represent to a respected researcher. In order to gain user intention to use, this paper also considers to design UI/UX that copes above system requirements. Therefore, UI/UX literature adopts usability and responsive web quality principles.

The main flow of the proposed research partner recommendation system initializes selected P from database. The algorithm process uses researcher as a class or label. Then, formula (1) generates any relevant input data, oldScore, as in Fig. 3, by summing the probability of formula (1) with bias *b*. RS takes uses it to rank a list of recommendation. Recommendation system results high score for any profile which is mostly called from inputs.

$$P\left(W_k \mid S_j\right) = \frac{\mid f\left(w_k \middle| s_j\right) \mid}{\mid W_k \mid} \qquad (1)$$

Algorithm: Proposed RS

procedure rs on naïve bayes algorithm
initialize a set of keywords $P = \{x_1, \ldots, x_N\}$;
for each researcher S_j, $j = \{1, \ldots, J\}$:
  do declare bias $b = 1$;
  compute $P(W_k \mid S_j) = \frac{\mid f(w_k \mid s_j) \mid}{\mid W_k \mid}$, where
    k = number of papers of S_j,
    $f(W_k \mid S_j)$ = total keyword occurrences of W_k,
    W_k = total keywords of S_j in training data;
  compute oldScore(S_j) = $\sum_{k=1}^{K} P(Wk \mid Sj) + b$;
end

procedure sigmoid activation function //as nonlinear approach
for each researcher S_j, $j = \{1, \ldots, J\}$:
  do compute newScore(S_j) = $\frac{1}{1+e^{-oldScore(Sj)}}$;
  if newScore(S_j) ≤ 0.5:
    newScore(S_j) = 0;
  else:
    return newScore(S_j) * 100; //convert to percentage form
end

Fig. 4. Pseudocode for the proposed algorithm.

Moreover, because the output values shown are not satisfied by academia, the system may decrease potential user to create a new research collaboration. Therefore, a nonlinear approach is needed. If input data is in non-negative values, Sigmoid activation function will generate them below 0.5. Then, users are not interested in recommendation values that are below the 50% threshold, but rather they value values higher than 50%. Hence, we can set it to zero with the exception of the algorithm (see Fig. 4 for the pseudocode).

$$Sig(S_j) = \frac{1}{1 + e^{-oldScore(Sj)}} \qquad (2)$$

For example demonstration, the input data as shown in Fig. 5 processed by Naïve Bayes algorithm by matching the input words to Naïve Bayes features database. Suppose the database contains three researchers, then the input data will be compared to which researcher is. Based on Table 2, the total features of mnp researcher is 40 with the use of numerator f(Wk|Sj). Selected total feature means extracted keywords from the paper publication, for instance, researcher mnp being denominator

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Wk. The keyword is updated for the next processing paper. The process stops as all researcher publications have been processed.

Input text: *IoT, visualization, Surabaya, Application*

Fig. 5. Example of input text.

This result score satisfies system requirements as user may see the different score percentages. Researcher zul with score of 85.96% is the most relevant researcher for the example. Therefore, it does not classify the score but shows the percentage score of the relevancy. In this representation, users may desire to collaborate with more researchers regarding the percentage of relevancy. For example, a user is suggested to invite a researcher with a score 82.24% for the research collaboration. In terms of building the proposed program, this paper designs the relational database to see what are the features and labels in the system. The database consists of three tables with a primary key on lecturer profile table onto the department table. This purpose is to display the proposed algorithm result using UI/UX design.

Table 2. Numerical computation of the example.

Candi-dates	$P(W_k \mid S_j)$			
	IoT	*visu-alization*	*Su-rabaya*	*Appli-cation*
mnp	$^1/_{40}$	$^3/_{40}$	$^1/_{40}$	$^1/_{40}$
pur	$^5/_{45}$	$^3/_{45}$	$^{12}/_{45}$	$^7/_{45}$
zul	$^{10}/_{32}$	$^3/_{32}$	$^3/_{32}$	$^{10}/_{32}$

$$P(mnp|document) = {}^1/_{40} + {}^3/_{40} + {}^1/_{40} + {}^1/_{40} + 1 = 1.15$$

$$newScore(mnp) = \frac{1}{1+e^{-1.15}} \times 100\,\% = \mathbf{75.95\,\%}$$

$$P(pur|document) = {}^5/_{45} + {}^3/_{45} + {}^{12}/_{45} + {}^7/_{45} + 1 = 1.6$$

$$newScore(pur) = \frac{1}{1+e^{-1.6}} \times 100\,\% = \mathbf{82.24\,\%}$$

$$P(zul|document) = {}^{10}/_{32} + {}^3/_{32} + {}^3/_{32} + {}^{10}/_{32} + 1 = 1.8125$$

$$newScore(zul) = \frac{1}{1+e^{-1.8125}} \times 100\% = \mathbf{85.96\,\%}$$

The keywords table is purposely to be training data where it is computed by Naïve Bayes and Sigmoid Activation Function. It is not related to the other tables because of different needs. However, this approach still depends on the collected data from Google Scholar manually. Hence, it also contains a number of lecturer names which are to be labeled or class of the Naïve Bayes output.

4. Result and discussion

Experiments were conducted on a Core-i7 and RAM 8 GB. Datasets were validated using cross-validation method, as detailed in the testing scenarios with some interesting points from the experiment in the sub-section below. This paper emphasizes the use of nonlinear approaches in the field of RS. Some interesting results are highlighted. The system suggests not only the most recommended research partner but also alternative recommendations. This approach makes a possible new collaboration than one researcher. The interesting is as the case study at a private university with a majority of young researchers, denominator Wk in formula (1) inspires young researchers to create a specific research area rather than too many research topics. This is because the percentage can be decreased if the topic's relevancy is large. Hence, the generated features of the sample problem show high scores since it has only a few research topics. Another interesting point is the benefit of bias in the formula (1) can adjust the representation as time flies resulting huge number of researchers, which impacts to decrease in the score. It can be solved by simply change increase the bias value to be a better score representation.

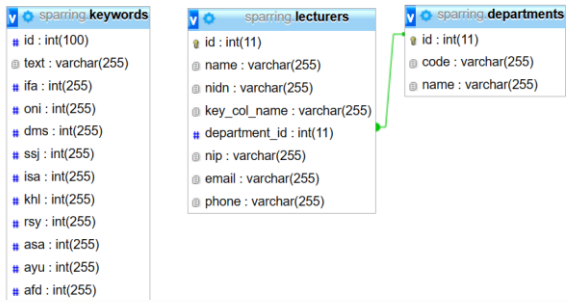

Fig. 6. Data flow diagram of the system.

This sub-section evaluates the performance of the proposed RS using k-cross validation. The designed experiment is conducted using binary classifications whose classes are determined by different researchers in a faculty. The dataset used from 26 publications for both researchers resulted in 94 features. As for performing exclusion cases, the threshold is important. If the input text does not belong to any class feature, then the data will not be used further or set as zero. Based on k-cross validation, the dataset was then folded into 80% for training data and 20% for testing data.

Table 3. Confussion matrix.

		Ground Truth	
		Researcher x	*Researcher y*
Classifier Machine	*Researcher x*	• tp = 16	fp = 1
	Researcher y	fn = 2	tn = 7

• true positive (tp): correctly predicted collaborators
true negative (tn): correctly predicted negative values
false positive (fp): collaborator is predicted but actual data shows prediction to be false
false negative (fn): the proposed system fails to produce an accurate prediction

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn} \qquad (3)$$

Table 3 shows the system processes items based on confussion matrix for performance evaluation. The standard formula of accuracy (3) is used for the case study of private university in Indonesia. The accuracy of the proposed system is 88.4%. In order to fulfill the system requirements, UI/UX design takes part to build the web-based system. The usability principle is important in the process of designing a software including (1) focusing on content by simplifying content layout, (2) recognition rather than recall in terms of providing search text fields in the results, (3) aesthetic and minimalist design to embrace neatness, (4) user assistance to recognize, diagnose, and recover from errors, and (5) providing help and documentation to the system. The user interface result of implementing all the principles as shown in Fig. 7 in the web version.

Fig. 7. Proposed system on web view.

It follows with the interface in mobile devices which holds ease of use and the five usability principles (Fig 8)¬. In a mobile perspective, users are able to find alternative candidates for research partners without piled interface. The proposed design focuses on the proposed system using a responsive web approach which provides a high resolution for a better understanding of recommendations. Finally, performance evaluation using cross-validation is tested to the system and results accuracy of 88,4%.

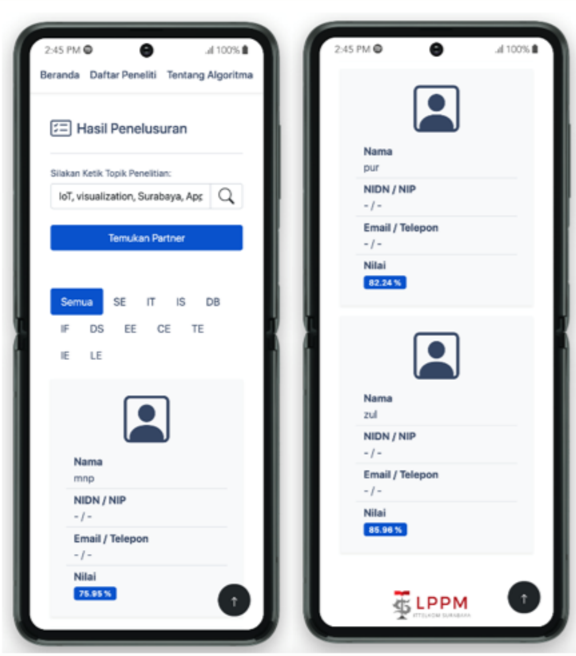

Fig. 8. Proposed system on mobile view.

The research partner recommendation system is a web-based application developed as a peer recommendation system by applying the Naive Bayes approach in calculating the score of each researcher from each research topic keyword given. The application is not only focused on being able to run the Naive Bayes algorithm but also provides the right UI / UX aspects so that the results of the algorithm can be translated into the right features and are easy to use (see Fig. 5). Therefore, this application is also built by going through the stages of SDLC such as planning, analysis, design, and implementation.

User flow, the form of features from the application of AI algorithms, and the development of database schemas are carried out in the planning and analysis stages. Then the UI/UX design is carried out at the design stage which applies usability principles such as minimalism design, error prevention, consistency, recognition rather than call, and so on. At the implementation stage, application design, and algorithms are translated into program code by interacting with data in the database. There are interesting findings in the development process, which is that at some point the database schema created becomes less efficient because it maintains a certain way to apply the AI algorithm used

Therefore, the experimental result does not satisfy minimum viable product (MVP) of the project due to inefficient data flow diagram. It can affect difficulty in updating the next version of the system development as we can see example of the data flow diagram in Fig. 6. In the depicted figure, as we might know, Naive Bayes algorithm has to label selected features in order to classify unknown data. However, in this example, the label will be formed as columns in the database which implies a number of columns occurred.

5. Conclusion

This paper presents a recommender system using Naïve Bayes algorithm and Sigmoid activation function based on a published article on Google Scholar. The proposed system helps to find the best research partner collaboration and also alternative researchers based on big data of researcher information in higher education. However, the output is in rough value because of statistical use of Naïve Bayes. Therefore, Sigmoid Activation Function transforms the display into a range of 0 to 1. Then the output can be shown in percentage mode. The implemented system shows that the proposed system has 88.4%. Of course, this approach has a limitation regarding data collection depends on collecting publication data from Google Scholar manually. In the future, we propose to leverage Google Scholar API to replace traditional data collection to be synchronized to Google Scholar.

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References

Abbas, A., Arrona-Palacios, A., Haruna, H., & Alvarez-Sosa, D. (2020). Elements of students' expectation towards teacher-student research collaboration in higher education. Proceedings - Frontiers in Education Conference, FIE, 2020-Octob. https://doi.org/10.1109/FIE44824.2020.9273902

Abramo, G., D'Angelo, C. A., & Solazzi, M. (2010). Assessing public-private research collaboration: Is it possible to compare university performance? Scientometrics, 84(1), 173–197. https://doi.org/10.1007/s11192-009-0104-0

Aldieri, L., Guida, G., Kotsemir, M., & Vinci, C. P. (2019). An investigation of impact of research collaboration on academic performance in Italy. In Quality and Quantity (Vol. 53, Issue 4). Springer Netherlands. https://doi.org/10.1007/s11135-019-00853-1

Amarante, V., Bucheli, M., & Vivas, R. (2021). Documentos de Trabajo Research networks and publications in Economics . Evidence from a small developing country. 11.

Cardona, T., Cudney, E. A., Hoerl, R., & Snyder, J. (2020). Data Mining and Machine Learning Retention Models in Higher Education. Journal of College Student Retention: Research, Theory and Practice. https://doi.org/10.1177/1521025120964920

Cotter, P., & Smyth, B. (2000). PTV: Intelligent Personalised TV Guides. Intelligent Applications of Artificial Intelligence.

De Campos, L. M. (2006). A scoring function for learning Bayesian networks based on mutual information and conditional independence tests. Journal of Machine Learning Research, 7, 2149–2187.

Di Sipio, C., Rubei, R., Di Ruscio, D., & Nguyen, P. T. (2020). A Multinomial Naïve Bayesian (MNB) Network to Automatically Recommend Topics for GitHub Repositories. ACM International Conference Proceeding Series, 71–80. https://doi.org/10.1145/3383219.3383227

Eger, S., Youssef, P., & Gurevych, I. (2018). Is it time to swish? Comparing Deep Learning Activation Functions across NLP tasks. Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, EMNLP 2018, 4415–4424. https://doi.org/10.18653/v1/d18-1472

Fan J., Zhou W., Yang X, L. B. & X. Y. (2019). Impact of social support and presence on swift guanxi and trust in social commerce. Industrial Management & Data Systems, 119(9), 2033–2054.

Gaikwad, R. S., Udmale, S. S., & Sambhe, V. K. (2018). E-commerce Recommendation System Using Improved Probabilistic Model. Lecture Notes in Networks and Systems, 10, 277–284. https://doi.org/10.1007/978-981-10-3920-1_28

Ghani, R., & Fano, A. (n.d.). Building Recommender Systems using a Knowledge Base of Product Semantics. Recommendation and Personalization in ECommerce.

Guruge, D. B., Kadel, R., & Halder, S. J. (2021). The state of the art in methodologies of course recommender systems—a review of recent research. Data, 6(2), 1–30. https://doi.org/10.3390/data6020018

Ivaschenko, A., & Milutkin, M. (2019). HR decision-making support based on natural language processing. Conference on Creativity in Intelligent Technologies and Data Science, 152–161.

Khalid, S., Zohaib Irshad, M., & Mahmood, B. (2011). Job Satisfaction among Academic Staff: A Comparative Analysis between Public and Private Sector Universities of Punjab, Pakistan. International Journal of Business and Management, 7(1). https://doi.org/10.5539/ijbm.v7n1p126

Miyahara, K., & Pazzani, M. J. (2000). Collaborative filtering with the simple bayesian classifier. Pacific Rim International Conference on Artificial Intelligence, 679–689.

Neamah, A. A., & El-Ameer, A. S. (2018). Design and Evaluation of a Course Recommender System Using Content-Based Approach. 2018 International Conference on Advanced Science and Engineering (ICOASE), 1–6. https://doi.org/10.1109/ICOASE.2018.8548789

Nwankpa, C., Ijomah, W., Gachagan, A., & Marshall, S. (2018). Activation Functions: Comparison of trends in Practice and Research for Deep Learning. 1–20. http://arxiv.org/abs/1811.03378

Pavlov, D., & Pennock, D. (2002). A Maximum Entropy Approach to Collaborative Filtering in Dynamic, Sparse, High-Dimensional Domains. In S. Becker, S. Thrun, & K. Obermayer (Eds.), Advances in Neural Information Processing Systems (Vol. 15). MIT Press. https://proceedings.neurips.cc/paper/2002/file/cc7e2b878868cbae992d1fb743995d8f-Paper.pdf

Pazzani, M. J., Muramatsu, J., Billsus, D. S., & Webert. (1996). Identifying interesting web sites. Aaai, 54–59.

Ramachandran, P., Zoph, B., & Le, Q. V. (2017). Searching for activation functions. CoRR abs/1710.05941. ArXiv Preprint ArXiv:1710.05941.

Ramadhan, H. A., & Putri, D. A. (2018). Big Data, Kecerdasan Buatan, Blockchain, dan Teknologi Finansial di Indonesia. Direktorat Jenderal Aplikasi Informatika Kementerian Komunikasi Dan Informatika, 1–66. https://aptika.kominfo.go.id/wp-content/uploads/2018/12/Kajian-Kominfo-CIPG-compressed.pdf

Saleh, A. I., El Desouky, A. I., & Ali, S. H. (2015). Promoting the performance of vertical recommendation systems by applying new classification techniques. Knowledge-Based Systems, 75, 192–223. https://doi.org/10.1016/j.knosys.2014.12.002

Samin, H., & Azim, T. (2019). Knowledge Based Recommender System for Academia Using Machine Learning: A Case Study on Higher Education Landscape of Pakistan. IEEE Access, 7, 67081–67093. https://doi.org/10.1109/ACCESS.2019.2912012

Shah, L., Gaudani, H., & Balani, P. (2016). Survey on Recommendation System. International Journal of Computer Applications, 137(7), 43–49. https://doi.org/10.5120/ijca2016908821

Tripathi, D., Edla, D. R., Kuppili, V., & Bablani, A. (2020). Evolutionary Extreme Learning Machine with novel activation function for credit scoring. Engineering Applications of Artificial Intelligence, 96, 103980. https://doi.org/https://doi.org/10.1016/j.engappai.2020.103980

Volkwein, J. F., & Parmley, K. (2000). Comparing administrative satisfaction in public and private universities. Research in Higher Education, 41(1), 95–116. https://doi.org/10.1023/A:1007094429878

Wadekar, P. P., Pillai, Y. P., Roy, M. U., & Phadnis, P. N. (2018). Placement Predictor and Course Recommender System. Academia.Edu, 3960–3965. https://www.academia.edu/download/56794670/IRJET-V5I3929.pdf

Zadrozny, B., & Elkan, C. (n.d.). I ° : x, 694–699.

Zhang, Y., & Koren, J. (2007). SIGIR2007_Hierarchical_Bayesian_User_Modeling_in_RS.pdf. 47–54.

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