Automatic Ranking System of University based on Technology Readiness Level Using LDA-Adaboost.MH

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***Abstract*—Regarding the intense competition among universities, a university ranking based on certain criteria is widely carried out. There are two core criteria for producing University Ranking, namely qualitative and quantitative criteria. Commonly, the ranking is yielded from an extensive survey involving related parties. Considering the labour intensive work of providing the ranking by the survey, this work proposes to measure the quality of university based on their technology readiness level by with the ranking of universities will be provided. Technology readiness level is the maturity level of research and technology implementation adopted by the university. To obtain an academic reputation score of universities based on the technology readiness level, we investigate the content of the academic paper of universities. We assume that the abstract of the paper represents the paper content. Accordingly, we collect the paper abstract of several reputable universities in Indonesia and mine the content by using LDA-Adaboost.MH. We also introduce formula to calculate university academic reputation. In the last step, a university ranking is generated. The results is comparable with the well-known QS University Rankings by 91.6% of similarity.**

Keywords— University Ranking, technology readiness level, LDA-Adaboost.MH

I. INTRODUCTION

The global trend of economic competition has put demand on research and higher education. This demand has led to intense competition among universities and in turn intensify the long-term development of universities worldwide [1]. One way of comparing so-called "*quality of university*" is by conducting a survey to develop a university ranking [2]. The ranking system indicates the globalization process of higher education [3]. Accordingly, it is important in informing related party about the quality indicator of the university [2] to improve their quality of decision regarding with the university.

Various types of institution have developed both national and global ranking system to meet the need of the related party, including policymaker, prospective students and research funder for benchmarking of universities [4]. Each institution has their own criteria of quality with their different weight of scoring system [5]. One of the most leading institution to develop the ranking system is Quacquarelli Symonds (QS) with their THES-QS Ranking List. The indicator used to measure the rank are the reputation of academic, the reputation of employer, the ratio of student and faculty, per faculty citation, the ratio of international faculty and the ratio of international student. Up to 50% of the indicator is developed based on internet survey involving academic staff and employer worldwide.

Regarding the labour intensive survey involved in developing university ranking system, this work proposes an automatic generation of university ranking based on Technology Readiness Level [6] issued by The Ministry of Research, Technology and Higher Education of The Republic of Indonesia called Tingkat Kesiapterapan Teknologi (TKT). TKT is a measure of the maturity level of the result of research and technology development. It is assessed in order to evaluate its readiness to be implemented in the public sector or industry. TKT level is evaluated based on a set of the indicator by an expert judgment pointed by the ministry office.

Since the application of text mining is promising [7][8], this work develops method to reveal university TKT level based on the content of their published academic paper by utilizing several text mining technique including LDA-Adaboost.MH without the need of an expert judgement. As an extension of LDA method that is useful to extract context of a text document or modelling a topic that has various fields of application [9], LDA-Adaboost.MH is a powerful topic model algorithm. The all technique will later be described in the rest of this paper. Lastly, we then calculate university academic reputation score by with the ranking will be generated using our proposed formula. Based on the experiment conducted on nine most reputable university in Indonesia, our ranking has 91.6% of similarity compared to QS University Ranking.

II. PREVIOUS WORK

A study [4] has compared global and national university ranking systems. Differences and similarities between national and global ranking system in term of the criteria used to provide scoring system was explored in the paper. The important finding presented in that study is that national ranking tends to use a large number of criteria while the global ranking system tend to employ a little indicator to generate scoring system.

Like was explained by [4], QS is one of the most leading global ranking system since 2004. It covers more than 800 universities in the world. Two of six indicators employed by QS is provided by an extensive survey. The two indicators are academic reputation with its weight of 40% and employer reputation with its weight of 10%. For the 2018 ranking edition, the survey involve over 70.000 academic staff and over 40.000 employers.

Another top university ranking system is published by Times Higher Education. Three most prominent indicator employed by Times Higher Education are teaching, research and citation. In providing the teaching score, it conducts an academic reputation survey annually to investigate the perceived prestige of university in teaching. The combined 2015 and 2016 survey resulted more than 20.000 responses. Regarding the extensive survey conducted to produce a university ranking, this work proposes to automatically generate ranking from paper abstracts of university's academic staff.

III. METHODOLOGY

The primary goal of this work is to replace survey indicator of university ranking by using TKT level indicator to provide an academic reputation score to generate university ranking automatically. In this work, TKT level is determined without employing an expert judgement, but by utilizing a set of text mining technique to reveal the paper content. The description of how our proposed method work can be seen in Figure 1.

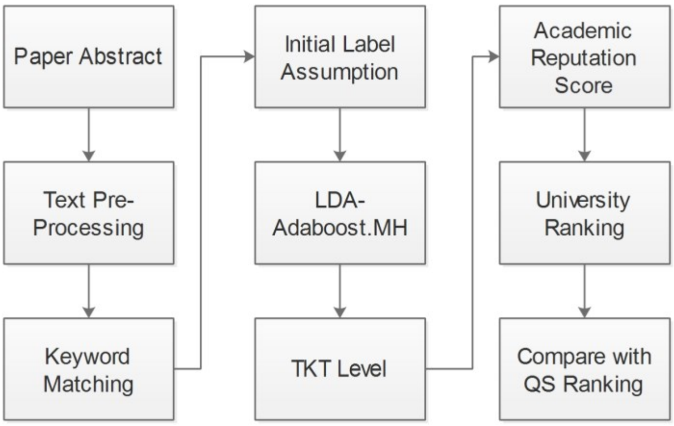

Figure 2. Proposed Method

A. *Text Pre-Processing*

The preprocessing stage is a process for cleaning up unnecessary words. In this research, the preprocessing stage consists of several sub-processes, including case-folding, tokenization, punctuation removal, stop words, and stemming. Case-folding is the process of converting uppercase letters into a lowercase in a document. While tokenization is the process of breaking up sentences into independent terms i.e.: single syllables. Punctuation removal aims to eliminate a non-letter character removal process. Stop words is a process of removing the term (term) that is not so important existence in the document. Stemming is prefix, suffix, infix removal process of a word (term) in a document [3].

B. *Keyword Matching*

This step aims to determine initial label assumption by matching abstract document with a set of keyword for every TKT Level. Since TKT has no set of keywords, we develop the keyword corpus by employing Bloom's Taxonomy of Learning Domain to describe the maturity of every TKT level. Bloom's Taxonomy is categorization system commonly employed to differentiate human perception level—i.e., thinking, learning, and understanding. There are six levels of cognitive domain, which are knowledge, comprehension, application, analysis, synthesis and evaluation, as can be seen in Table 1. Each of its levels has its own set of keywords.

Table 1. Bloom's Taxonomy

Level	Name	Description
1	Knowledge	Terms, ideas, procedure and theories identification
2	Comprehension	Define to other circumstances, similar to literal translation.
3	Application	Utilize general principles, or methods to certain concrete circumstances.
4	Analysis	Understand complex idea by segregating the organization into a small part and explore the relationship between parts.
5	Synthesis	Construct an idea and concept from considerable amount of source.
6	Evaluation	Perform assessment using external parameter or self-selected indicator

Since TKT has 9 levels of maturity as can be seen in Table 2, and Bloom's Taxonomy has only 6 level therefore we perform manual splitting after sorting the keywords to provide set of keywords for describing 9 maturity levels of TKT. To extend the coverage of the keyword, we enrich the keyword by employing synonyms in the WordNet library as the WordNet organizes its database in the form of synonym set i.e: synset [10]. Accordingly, we explore the WordNet database and extract the synonym of the prior keyword to provide better performance of the corpus of keywords.

C. *Determining TKT Level*

After keyword matching, LDA-Adaboost.MH plays an important role in calculating the top 3 levels of TKT with their respective weights. Adaboost.MH is a boosting algorithm for tackling multilable classification extended from Adaboost algorithm [11]. The weak hypothesis is built by individually verifying the whole features to specify their absence and presence in each class. However, since in text categorization, bag-of-words (BOW) produce a large number of features, the approach may lead to a costly time computation. In order to improve Adaboost.MH in term of learning and performance classification, a method called LDA-Adaboost.MH has been proposed [12]. The idea of LDA-Adaboost.MH is basically improving Adaboost.MH by using LDA algorithm. In this work, LDA-Adaboost.MH is utilized to determine the top 3 levels of TKT for every abstract document collected from nine most reputable universities in Indonesia.

Table 1. Nine level of Indonesian TKT of Research

Level	Description	Category
1	Basic principle of a technology	Basic Research
2	Concept formulation and application	
3	Proof of concept by analytical and experimental approach	
4	Subsystem validation in laboratory environment	Applied Research
5	Subsystem validation in relevant environment	
6	Model demonstration in relevant environment	
7	Model demonstration in real environment	Advance Research
8	Complete system has been validated in real environment	
9	System is succesfully operated in real environment	

The assignment of topic index containing the whole words in the training corpus is acquired after resampling iteration in certain number. The index will be utilized to compute the portion of document–topic θ_m and the distribution of topic-word $\alpha(z)$. As explained by [12], we employ Equation (1) and Equation (2) to assign the distribution of document–topic ϕ and the distribution of topic–word θ.

$$\phi_{k,w} = p(w|k) = \frac{n_{k,w} + \beta_w}{\sum w'(n_{k,w'} + \beta w')} \quad (1)$$

$$\theta_{w,k} = p(w|k) = \frac{n_{w,k} + \alpha k}{\sum k'(n_{w,k} + \beta k')} \quad (2)$$

In such equation, the count of topic k is assigned to the word token w is indicated by $n_{k,w}$. While $n_{w,k}$ denotes the count of topic k is assigned to some token of word in the document. Therefore, θ_{MxK} equals with $\theta_{w,k}$ with M denotes the total number of documents and K represents the total number of topics. And ϕ_{KxV} equals with $\phi_{k,w}$ with V points the vocabulary size.

D. Final Score Calculation

After determining TKT level using LDA-Adaboost.MH, we provide a formula to calculate academic reputation of a university based on the TKT level of their research like was presented in equation (3). The score is then employed to rank university in Indonesia and the result will be compared to QS University Rank.

$$final\ score = \frac{\sum(\varphi k,w\ x\ level\ weight)}{\sum level} \quad (3)$$

The result of TKT level determination is converted into academic reputation score indicated by the $final\ score$ by with the ranking will be generated as can be seen in equation (3). From the equation $\phi_{w,k}$ is probability score obtained from LDA-Adaboost.MH.

IV. RESULT AND DISCUSSION

In this section, we will present the result of the experiment using paper abstract of academic staff collected from nine most reputable universities in Indonesia i.e.: UI, ITB, UGM, ITS, UNAIR, UNDIP, IPB, UB, and UMS. For every university, we pick 50 paper abstracts. We compare LDA-Adaboost.MH with the baseline method of LDA in determining TKT level of paper abstracts. As the ground for the ranking, we use The 2017 QS World University Ranking. We present the results of LDA-Adaboost.MH with its respective academic reputation score in Table 1.

Table 1. Ranking result based on LDA-AdaBoost.MH

Rank	Name	Score
1	ITB	0.737132
2	IPB	0.734152
3	UI	0.662908
4	UNAIR	0.655131
5	UMS	0.6198
6	UGM	0.568995
7	ITS	0.568933
8	UNDIP	0.567653
9	UB	0.543208

While in Table 2, we present The 2017 QS World University Ranking as the ground truth of the experiment. Table 3 indicates the gap between LDA-AdaBoost.MH compare with the ground truth of QS World University Ranking. While in Table 4, we describe the gap between the baseline method of LDA compared with the ground truth ranking from The 2017 QS World University Ranking. The results seem to be promising.

Table 2. The 2017 QS University Ranking

Rank	Name
1	ITB
2	UI
3	UGM
4	UNAIR
5	IPB
6	UNDIP
7	ITS
8	UMS
9	UB

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Table 3. Final result of LDA-AdaBoost.MH

Rank	Name	Score	QS Rank	Gap
1	ITB	0.7371316	1	0
2	IPB	0.7341521	5	3
3	UI	0.6629078	2	1
4	UNAIR	0.6551306	4	0
5	UMS	0.6197999	8	3
6	UGM	0.5689949	3	3
7	ITS	0.5689327	7	0
8	UNDIP	0.5676525	6	2
9	UB	0.5432079	9	0
Total Gap				12

Table 4. Final result of LDA

Rank	Name	Score	QS rank	Gap
1	UNDIP	8.876	6	5
2	ITS	7.663	7	5
3	UI	6.741	2	1
4	UNAIR	6.735	4	0
5	UGM	6.732	3	2
6	ITB	6.7	1	5
7	IPB	6.673	5	2
8	UMS	6.668	8	0
9	UB	5.059	9	0
Total Gap				20

From Table 3 and 4 above, LDA's gap with qs ground truth ranking is 14 while LDA-AdaBoost.MH's gap with qs ground truth ranking is only 12 for the academic reputation. From Table 5 above, The LDA's all indicator similarity with QS Rankings is only 78.3% while LDA-AdaBoost.MH's similarity is increased to 91,6%.

Table 5. All indicator ranking comparison between LDA-AdaBoost and QS Rankings(Ground Truth)

Lda-AdaBoost			QS 2016-2017 Rankings	
Rank	Name	Score	Rank	Name
1	ITB	0.6711	1	UI
2	UI	0.607	2	ITB
3	IPB	0.5417	3	UGM
4	UGM	0.5329	4	UNAIR
5	UNAIR	0.4529	5	IPB
6	UNDIP	0.44	6	UNDIP
7	ITS	0.437	7	ITS
8	UB	0.4178	8	UMS
9	UMS	0.4084	9	UB

V. CONCLUSION

This work presents a new insight of determining TKT level of research automatically without the need of expert judgement. The score of TKT level weight along with a probability score of LDA-Adaboost.MH is then employed to generate an academic reputation score by with a ranking is generate. From the experiment conducted useng paper abstract collected from nine most reputable universities in Indonesia indicates that the proposed method is promising by 91.6 of similarity compared to QS World University Ranking.

REFERENCES

[1] S. Marginson, "Global university rankings: Implications in general and for Australia," *Journal of Higher Education Policy and Management*, vol. 29, no. 2, pp. 131–142, 2007.

[2] S. Lindblad, "Navigating in the Field of University Positioning : on international ranking lists , quality indicators," *European Educational Research Journal*, vol. 7, no. 4, pp. 438–450, 2008.

[3] B. M. Kehm and B. Stensaker, *University Rankings, Diversity and The New Landscape of Higher Education*. Sense Publlisher, 2009.

[4] M. P. Çakır, C. Acartürk, and C. Çilingir, "A Comparative Analysis of Global and National University Ranking Systems," *Scientometrics*, vol. 103, pp. 813–848, 2015.

[5] S. Marginson and M. van der Wende, "To Rank or To Be Ranked: The Impact of Global Rankings in Higher Education," *Journal of Studies in International Education*, vol. 11, no. 3–4, pp. 306–329, 2007.

[6] B. Sauser, D. Verma, J. Ramirez-Marquez, and R. Gove, "From TRL to SRL: The concept of systems readiness levels," *Conference on Systems Engineering Research, Los Angeles, CA*, pp. 1–10, 2006.

[7] B. S. Rintyarna and R. Sarno, "Adapted Weighted

Graph for Word Sense Disambiguation," in *2016 4th International Conference on Information and Communication Technology (ICoICT)*, 2016, vol. 4, no. c, pp. 60–64.

[8] D. Aliyanto, R. Sarno, and B. S. Rintyarna, "Supervised Probabilistic Latent Semantic Analysis (sPLSA) for Estimating Technology Readiness Level," in *International Conference on Information & Communication Technology and System*, 2017, pp. 79–84.

[9] A. R. Baskara, R. Sarno, and A. Solichah, "Discovering Traceability between Business Process and Software Component using Latent Dirichlet Allocation," *2016 International Conference on Informatics and Computing (ICIC)*, no. Icic, pp. 3–8, 2016.

[10] R. Navigli and M. Lapata, "An Experimental Study of Graph Connectivity for Unsupervised Word Sense Disambiguation.pdf," *IEEE Transaction on Pattern Analysis and Machine Intelligence*, vol. 32, no. 4, pp. 678–692, 2010.

[11] R. E. Schapire and Y. Singer, "BoosTexter: A Boosting-based System for Text Categorization," *Machine Learning*, vol. 39, pp. 135–168, 2000.

[12] B. Al-Salemi, M. J. Ab Aziz, and S. A. Noah, "LDA-AdaBoost.MH: Accelerated AdaBoost.MH based on latent Dirichlet allocation for text categorization," *Journal of Information Science*, vol. 41, no. 1, pp. 27–40, 2015.