Ranking

by Bagus Rintarna

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Automatic Assessment of Technology Readiness Level Using LLDA-Helmholtz for Ranking University

First Author[a], Second Author[b,*], Third Author[b]

[a] *Department, University, Address, City, ZIP Code, Country*
[b]*Second Institution, Address, City, ZIP Code, Country*

[*]*Corresponding author: xxxxxxxx@xxx.ac.id*

Abstract—The assessment process of Technology Readiness Level (TRL) using quistionnaire-based tool for Indonesian universities academic paper is considered to be labour intensive. In this paper, a new insight of determining TRL of an academic paper based on a text mining technique is introduced. The content of research paper represented by their abstract published by university lecturers is justified to represents technology maturity of research. Abstracts of paper is collected from 9 most reputable universities in Indonesia. By utilizing Labeled Latent Dirichlet Allocation (LLDA), the abstracts are categorized into 1 of 9 level of TRL. For deterimining prior label of LLDA, we build a corpus of keyword representing each level of TRL based on Bloom Taxonomy. Beforehand, helmoltzs principle is utilized to select the text feature. Since Bloom Taxonomy has only 6 level, we split the keywords collection into 9 level of readiness by firstly sorting them. In the next step, university academic reputation is calculated based on the generated TRL by using our proposed formula. Lastly, the university ranking is generated according to the extracted academic reputation score. To evaluate the proposed method we compare our unversity rank with QS World University Rank. As the performance matrix, we calculate ranking gap and pearson correllation parameter. Helmholtz has successfully pruned 86% features and remain the rest of meaningfull features of text data. The utilization of Helmholtz feature selection significantly improve the pearson correllation score between our proposed method and the ground truth by 38%. In short, the new insight of university ranking introduced in this work is promising. For all indicator experiments, LLDA-Helmholtz perform even better results indicated by 0.95 pearson correllation coefficient between two ranking, while for LLDA without Helmhotz, the correllation is 0.78.

Keywords— **Technology Readiness Level; Labeled Latent Dirichlet Allocation; Helmholtz Principle; Bloom Taxonomy.**

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I. Introduction

Technology Readiness Assessment (TRA) was a tool to evaluate technology maturity for space technology by employing Technology Readiness Level (TRL) scale that ranges from 1 to 9. The assessment method was pioneered by NASA [1]. Trough regulation of minister of research and technology of higher education, Indonesian Government has adopted TRL to asses technology maturity of research and technology development in universities in Indonesia. The evaluation is aimed to assess the implementation of research program under the ministry of research and technology of higher education as well as to reduce the risk of failure in the technology implementation. TRL scoring is also used as a funding basis for the researcher by the ministry office. In the implementation, the TRL scoring process is conducted by using a spreadsheet-based questionnaire called Teknometer that contains several indicators. The assessment process is done by an expert. This questionnaire-based evaluation is accurate yet labour intensive in term of a large number of research paper that need to be evaluated.

With regard with the TRL hand assessment by an expert judgement, this research proposes a new technique based on several text mining approaches to evaluate TRL of Indonesian universities research paper. Text mining technique has many application in different field of research [2]. The evaluation of the proposed method is based on the research paper published by university staffs. A new insight that TRL can be represented by the content of research paper of university staffs is introduced. Therefore, research paper is then grabbed from 9 most reputable Indonesian universities, and then categorized by utilizing Labeled Latent Dirichlet Allocation [3]. Prior label for LLDA is determined by matching the content of the abstract with the corpus of keywords. We build the corpus of keywords based on Bloom Taxonomy. The building of keyword corpus involves sorting Bloom Taxonomy keyword using WordNet Similarity Algorithm.

TRL of research that is automatically generated by using the proposed method previously overviewed is then employed to assign academic reputation for university. TRL indicates the maturity of research being conducted. In term of university ranking assessment, this maturity measure is potential to evaluate university academic reputation by with the ranking is generated [4]. We propose a formula to calculate university academic reputation from TRL of university. In the last step, ranking is then generated based on the extracted university academic reputation. For the ground truth we use the university ranking from QS World University Rankings and compare the result with the ranking generated by our proposed method.

II. RELATED WORK

Carmack [1] has provided a definition of TRL for nuclear fuel technology. The approach adopted Departement of Energy of USA TRA and applied it to nuclear fuels and material system. The paper adopted 9 level of maturity which is divided into three major functional categories namely Proof-of-Concept (level 1-3), Proof-of-Principle (level 4-6) and Proof-of-Performance (level7-9). Several criteria was established for each level. All the criteria must be met when Critical Technology Element (CTE) was considered achieving certain level. A development of quistionnaire based on Air Force Research Laboratory's was also discussed.

The application of TRL in supporting technology development project in National Energy Technology Laboratory (NETL) has been reported [5]. The objective of TRL assessment was to assist major decision on advanced fossil energy project under deployment. The paper described how SRL methodology of Departement of Defense was adopted and interpreted into a qualitative SRL value. As the result, a TRL-style metrics was introduced in evaluating the maturity of technology interfaces need to be disseminated. The metrics indicated the significant interfaces that was identified.

Another work reported the development of TRL tool to be implemented to verify the maturity of technology being deployed in Turkey's national laboratory and industry [6] especially in Turkey's defense industry. In the first phase a study was done to explore the awareness of its defense industry about TRL assessment. Only 47% of the firms that has idea about TRLs and more than half of them has no idea about TRLs. TRLs from US Departement of Defense (DoD) was adopted since it was aplicable in Turkish Industry. In the last phase, the work recommended an algorithm for TRL of Turkish defense industry along with Turkish TRL Calculator (TTRL) v 1.0.

Providing an accurate rate of commercialization was an important task of The Electric Power Research Institute (EPRI). Therefore, the performance of emerging post-combustion CO_2 capture (PCC) technology was reviewed to assign a TRL [7]. NASA TRL was adopted and tailored in order to meet EPRI's objective. A notable category modification was introduced i.e. Research for stages 1-3, Development for stages 4-6 and Demonstration for stages 7-9. For several process, EPRI succeeded to gather TRL development profile. Lastly, the paper concluded that TRL was a potential framework to characterize PCC technology.

In another work, a Pasuraman based Technology Readiness Index (TRI) was employed along with Davi's Technology Acceptance Model (TAM) to assess technology acceptance in Electronic Human Resource Management (e-HRM) in Turkey [8]. The instrument of survey was questionnaires that were sent to 500 participants from 500 largest private sector companies in Turkey. The major finding was that optimism and innovativeness dimension positively correllate to perceived usefulness and perceived ease of use.

Combining TRI and TAM, Walczuch quantified the relation between personality and technology acceptance [9]. Four personality category as proposed by Pasuraman was used i.e. optimism, innovativeness, discomfort and insecurity. TAM was used to represent apprehended usefullness and apprehended ease of technology being used. Data was collected from the employees of Belgian multi-site financial service provider. The result of research was surprising since innovativeness was negatively correlated to usefulness. Straub [10] has reviewed deeply the history and codification of NASA TRL system and how it was used by other agencies. The paper proposed the notion of TRL 10 advancing NASA TRL system that contains TRL 1-9 i.e. : technology concept, proof-of-concept, technology demonstration, conceptual design and prototype demonstration, preliminary design and prototype validation, detailed design and assembly level build, subsystem build and test, and system operational. The work defined TRL 10 as proven operation aiming to provide concept of more mature technology as a requirement of higher frequency space access.

In order to establish an elucidated source of information dealing with the maturity of the partitioning and transmutation (P-T) technology, The Global Nuclear Energy Partnership TRL definition was adopted [11]. Along with the maturity of P-T technology, the other system were also evaluated i.e: fast reactor (FR), accelerator driven subcritical transmutation system, aqueous reprocessing, molten salt electro-refining partitioning technology and oxide, metal and nitride fuels. For every system being reviewed, every specific definition of TRL was introduced. The use of IT has been strongly pushed for construction inductry by Malaysian government. Using a multiple scale of Technology Readiness Index form Pasuraman, the readiness of construction firm managers in embracing IT technology has been reviewed [12]. A TRI score for every respondent was calculated by counting the average of means of four components namely optimism, innovativeness, discomfort and insecurity.

As a widespread tool commonly used to judge maturity of technology application, TRL scale employ a nine level ordinal value. As the result, general mathematical operation cannot be carried out on [13]. The work proposed a methodology to conform the ordinal scale to be cardinal estimates for each TRL value by employing Analytic Hierarchy Process. The algorithm was used to calculate the cardinal coefficient value for each TRL scale corresponds by obtaining ratio scales of a set of elements from pair comparison. Finally a curve fit for the coefficient was also generated providing non integer TRL values that enable mathematical operation.

An evaluation of the maturity of composite recycling technology has been done by Rybicka [14]. The first allocation step of The TRL was adopted from Yang's framework [15] that has three categorization : lab scale (L), pilot scale (P) and commercial scale (C). To get the specific TRL level (1-9), following the first step, the process description of the project is then compared with Williamson's framework [16]. The assessment was implemented by designing a technology card containing detail of technology application characteristics and the process description of the project. Validation of the result of experiment was conducted by expert judgement.

Most work previously described rely on an expert judgement based on several TRL indicator. In term of the assessment of research program under the Indonesian ministry of research and technology of higher education, there is a lot of research paper need to be evaluated. In this context, the TRL evaluation is regarded to be ineffective if depend on the manual expert evaluation. This work provides an approach to solve this problem by determining TRL of research paper automatically based on several adopted text mining techniques.

III. PROPOSED METHOD

In this paper we introduce a new insight in determining TRL of research paper of Indonesian University by utilizing a topic modelling technique. Topic modelling technique is employed to classify the content of research paper into one out of nine TRL as presented in Figure 1. Therefore, the technique being introduced can be considered as a text classification task. The whole step of the proposed method is presented in Figure 2. There are seven steps in this works i.e.: 1) dataset and TRL corpus Development, 2) text pre-processing, 3) Helmholtz feature selection, 4) keyword corpus enrichment, 5) label assumption determination, 6) Gibs Sampling Inference for L-LDA, and 7) Adaboost-MH Optimization. The flow of the step is presented in Fig. 2.

System operate in real environment	9	Advanced Research
System Completed and validated	8	
Prototype demonstration in real environment	7	
Prototype demonstration	6	Applied Research
Subsystem validation in relevan environment	5	
Subsystem validation in laboratory	4	
Proving concept analytically	3	Basic Research
Concept formulation	2	
Basic principle of technology	1	

Fig. 1 TRL of Indonesian Research

A. Dataset and Corpus Preparation

Dataset used in this work is abstract of paper of academic staff from nine most reputable universities in Indonesia. The best university list used to choose the most reputable university refers to the ranking of QS World University Rankings for the region of Indonesia. We pick the abstract with the highest citation from metadata of Google Scholar to ensure that the abstract used for the experiment represents a qualified research since the assessment of the abstract is basically represent the evaluation of TRL of a research product.

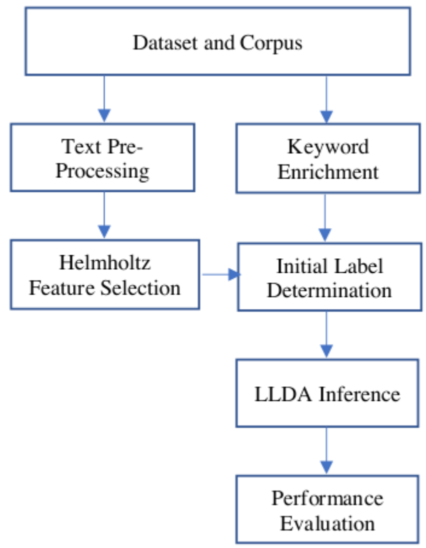

Fig. 2 Proposed Method

TRL Corpus contains keywords that represents the maturity of research of Indonesian Universities. Since Indonesian TRL has nine categories of maturity then we need to develop Corpus that consists of nine level of maturity. We develop the TRL corpus based on the keyword collection of Bloom's Taxonomy in assumption that taxonomy level of thinking in Bloom's Taxonomy represents the maturity of TRL. Since Bloom's Taxonomy has only six categories of keyword as presented in Table 1, we dispart the whole categories into 9 separate categories by firstly sort the keywords.

TABLE I
KEYWORDS IN BLOOM'S TAXONOMY

Taxonomy Level	Number of Keywords
Knowledge	34
Comprehension	29
Application	35
Analysis	49
Synthesis	49
Evaluation	43
Total	239

To get a better result of the keyword matching, we enrich the collection of the corpus by using synonym word in WordNet Database. WordNet is a rich lexical Database that arranges its collection of words in the form of semantic network based on psycholinguistics theory [17]. WordNet is utilized in many application in the field of Natural Language Processing [18]. WordNet organizes its collection in the form of synonym set (henceforth *synset*) that shares the same sense rather than alphabetically. For example, the word *"car"* shares the same sense with *"auto", "automobile", "machine"* and *"motorcar"* i.e.: "a motor vehicle with four wheels". This set of words is called *synset* and associated with a certain part of speech (POS) namely noun, verb, adjective and adverb. The result of the enrichment process is presented in Table 2.

TABLE III
KEYWORDS IN THE CORPUS AFTER ENRICHMENT

TRL Level	Number of Keywords Before Enrichment	Number of Keywords After Enrichment
Level 1	27	132
Level 2	27	75
Level 3	27	70
Level 4	27	50
Level 5	28	120
Level 6	28	31
Level 7	28	122
Level 8	28	109
Level 9	28	100
Sum of Word	239	809

B. *Text Pre-Processing*

To provide a better classification results, text pre-processing plays fundamental role in text classification that utilize text mining technique. The role of text pre-processing is two folds : 1) clean up unimportant words and 2) eliminate non-alphabetic characters. In this work, text pre-processing involves tokenization, stop word removal, and stemming. Tokenization is the process of splitting document into elements usually called token. While stop word removal is the process that aims to remove punctuation, prepositions, connecting words and unimportant word. And the last stage of text pre-processing is stemming that aims to obtain the basic form of the word.

C. *Helmholtz Feature Selection*

Helmholtz principle is employed to seek the meaningful features of the abstract document and remove the rest. Accordingly, it is able to reduce the size of the feature being processed. It means reducing the working-time of the process. Helmholtz introduces a formula for filtering such features. The formula is called NFA or Number of False Alarms that can be seen in Equation (1).

$$NFA(w,P,D) = \binom{K}{m}\frac{1}{N^{m-1}} < 1 \qquad (1)$$

In Equation (1) *w* represents a word and *P* represents a part of document such as a sentence or paragraph, while *D* represents the whole document. The word *w* appears *m* times in *P* and *K* times in *D*. N = *L* / *B* where *L* is length of *D* and *B* is length of *P* in words. In this formula, N is the total number of documents. According to Alexander, Hellen, and Steven, if in some documents the word w appears m times and NFA < 1 then it is an unexpected event. And based on NFA, the meaning score of words are calculated using Equation (2).

$$Meaning(w,P,D) = -\frac{1}{m}\log NFA(w,P,D) \qquad (2)$$

In equation (2), log of NFA is utilized based on the observation that NFA values can be exponentially large or small [14]. If Meaning > $\boldsymbol{\varepsilon}$, then add word *w* to the set K_w and mark *w* as a meaningful word for P_i. We define a set of keywords as a set of all words with NFA < $\boldsymbol{\varepsilon}$, $\boldsymbol{\varepsilon}$ < 1. Smaller $\boldsymbol{\varepsilon}$ corresponds to more important words. It is easy to see that Meaning > $\boldsymbol{\varepsilon}$ is equivalent to NFA < $\boldsymbol{\varepsilon}$. The $\boldsymbol{\varepsilon}$ is a parameter that is used to vary the size of the set typically chosen strictly positive as we are only interested in meaningful words.

D. *LLDA Label Inference*

Labeled Latent Dirichlet Allocation (L-LDA) is one of the topic modeling technique that improve LDA by incorporating supervision. In this work, topic that is generated by L-LDA is considered as the label of TRL. LDA models a document as a mixture of topics. LDA only infers discrete probability distribution over topics per-document that often hard to interpret the generated topic to conform an end-use application [3]. As an extension of LDA, LLDA offer a solution for this limitation. Unlike LDA and another extension of LDA like Disc-LDA [19] and MMLDA [20], LLDA models directly each label of the document with one topic generated. LLDA can also be regarded as the improvement model of Multinomial Naïve Bayes in term of its mixture model [3]. In term of generating mixture of topics for each document, LDA and LLDA are similar.

However, LLDA introduced supervision to be able to infer topic that corresponds to document's label set.

In this work, we provide document's label set for LLDA by matching the abstract document with the corpus of keyword that previously built based on the Bloom's Taxonomy. In the application of LLDA, we make use of a python open source tool developed by Nakatani Shuyo. Every abstract document is represented into a tuple contained word index list and topic binary list.

E. *Academic Reputation Score Formula*

In this work, we propose a formula to calculate academic reputation score based on Technology Readiness Level of research. Firstly we introduce a level weight like presented in Table 4 that will be utilized for counting academic reputation score.

TABLE IIII
KEYWORDS IN THE CORPUS AFTER ENRICHMENT

No.	TRL Level	Level Weight
1.	TRL level 1	10
2.	TRL level 2	20
3.	TRL level 3	30
4.	TRL level 4	40
5.	TRL level 5	50

6.	TRL level 6	60
7.	TRL level 7	70
8.	TRL level 8	80
9.	TRL level 9	90

IV. EXPERIMENTS AND RESULTS

Experiment is conducted using 450 abstracts documents collected from nine most reputable universities in Indonesia i.e.: Institut Pertanian Bogor (IPB), Institut Teknologi Bandung (ITB), Institut Teknologi Sepuluh Nopember (ITS) Surabaya, Universitas Airlangga (UA), Universitas Brawijaya (UB), Universitas Diponegoro (Undip), Universitas Gajah Mada (UGM), Universitas Indonesia (UI) and Universitas Muhammadiyah Surakarta (UMS). The abstract is grabbed from the most cited paper in google scholar from those universities. For the ground truth of the experiment, we use QS World University Ranking 2017 for Indonesian University as can be seen in Table 4. We calculate ranking gap and pearson correllation for parameter performance of the ranking method.

TABLE IVV
WORLD UNIVERSITY RANKING 2017

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

The result of the pre-processing step of the text data is cleaned terms. Term in text classification task is feature by with the classification process will be carried out [4]. Feature selection is an important step in text classification task. Reducing the size of the feature means reducing time computation. Selecting meaningful features means providing better classification performance. In this work, we utilize Helmholtz principle [21] to select meaningful feature of the abstract document.

After the pre-processing, the step of the abstract documents, we perform feature selection by employing Helmoltz principle. The result of feature selection is presented in Table 5. The implementation of Helmholtz succesfully reduces 86% of the feature and left the 24% meaningfull features.

TABLE V
FEATURE SELECTION RESULT

University	Number of Feature after		Pruned Feature (%)
	Pre-Processing	Helmholtz	
IPB	6293	556	91
ITB	5643	612	89
ITS	6044	837	86
UA	5793	1695	71
UB	5469	536	90
Undip	5327	620	88
UGM	6308	652	90
UI	5645	689	88
UMS	6117	769	87
Average Pruned Feature (%)			86

In the next two tables, we present the result of the experiment comparing classification task using LLDA with and without Helmholtz feature selection. For the parameter of the performance, we use ranking gap between ground truth and our proposed method ranking. We present the ranking of LLDA without Helmholtz in Figure 3. The pearson correllation between the LLDA result without Helmholtz compared to ground truth is 0.3. We calculate pearson correllation between our ranking and the ground truth by using Equation (3). Pearson correlation coefficient measure the strength of association between two set of data. In our case (university ranking) when our ranking is fully equal with the ground truth ranking then the value of the coefficient will be 1. In the equation, r denotes pearson correlation coefficient, x is our ranking and y points the ground truth ranking while n is the number of universities experimented.

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \quad (3)$$

TABLE VI
RANKING OF LLDA WITHOUT HELMHOLTZ

QS Rankings		LLDA Without Helholtz			Gap
Rank	University	Rank	University	Score	
1	ITB	6	ITB	6.700	5
2	UI	3	UI	6.741	1
3	UGM	5	UGM	6.732	2
4	UNAIR	4	UNAIR	6.735	0
5	IPB	7	IPB	6.673	2
6	UNDIP	1	UNDIP	8.876	5
7	ITS	2	ITS	7.663	5
8	UMS	8	UMS	6.668	0
9	UB	9	UB	5.059	0
	Total Gap				20

The utilization of Helmholtz feature selection in L-LDA classification is successful to increase the accuracy of the proposed method. The score of pearson correlation between L-LDA+Helmholtz is 0.68 significantly outperforms L-LDA without Helmholtz.

TABLE VII
RANKING OF LLDA WITH HELMHOLTZ

QS Rankings		LLDA with Helmholtz			Gap
Rank	University	Rank	University	Score	
1	ITB	2	ITB	6.503	1
2	UI	3	UI	6.335	1
3	UGM	6	UGM	5.528	3

4	UNAIR	4	UNAIR	6.180	0
5	IPB	1	IPB	7.461	4
6	UNDIP	7	UNDIP	5.501	1
7	ITS	8	ITS	5.490	1
8	UMS	5	UMS	6.007	3
9	UB	9	UB	5.086	0
		Total Gap			14

The results of experiment previously described in Table 6 and Table 7 is ranking generated based merely on academic reputation score using our proposed formula. We also experiment to generate ranking using all indicator employed by QS ranking system i.e.: academic reputation (40%), employer reputation (10%), faculty/student ratio (20%), citations per faculty (20%), number of professors (5%), and quality of citations (h-index & i10-index) (5%). We grabbed the information from each university. The result of the experiment indicating the gap with QS ranking is presented in Table 8 and Table 9. For LLDA without Helmholtz, the Pearson correlation coefficient is 0.78. While for LLDA with Helmholtz, the coefficient value is 0.95.

TABLE VIII
RANKING OF LLDA WITHOUT HELMHOLTZ WITH ALL QS INDICATOR

QS Rankings		LLDA without Helmholtz		Gap
Rank	University	Rank	University	
1.	UI	2.	UI	1
2.	ITB	1.	ITB	1
3.	UGM	4.	UGM	1
4.	UNAIR	7.	UNAIR	3
5.	IPB	6.	IPB	1
6.	UNDIP	3.	UNDIP	3
7.	ITS	5.	ITS	2
8.	UMS	8.	UMS	0
9.	UB	9.	UB	0
		Total Gap		12

TABLE IX
RANKING OF LLDA WITH HELMHOLTZ WITH ALL QS INDICATOR

QS Rankings		LLDA with Helmholtz		Gap
Rank	University	Rank	University	
1.	UI	1.	UI	1
2.	ITB	2.	ITB	1
3.	UGM	4.	UGM	1
4.	UNAIR	5.	UNAIR	1
5.	IPB	3.	IPB	2
6.	UNDIP	6.	UNDIP	0
7.	ITS	7.	ITS	0
8.	UMS	8.	UMS	0
9.	UB	9.	UB	0
		Total Gap		6

V. Conclusion

This work proposes an automatic ranking system of university based on LLDA-Helmholtz. LLDA is the improvement of a topic modelling method named Latent Dirichlet Allocation (LDA). For determining prior label of LLDA, we develop a keyword corpus based on a taxonomy level of thinking called Bloom's Taxonomy. We assume that keyword of Bloom's Taxonomy is able to represent the maturity level of TRL. We make use of Helmholtz principle for selecting meaning full feature of abstract document. In the evaluation step, we compare our ranking with QS ranking. The result of the experiment indicates that the proposed method is promising. Experiment emphasizes that Helmholtz has significant role in both reducing the feature and increasing the quality of the ranking. The best performance is achieved by using all indicator and employ LLDA with Helmholtz. Significant result is achieved by using all QS indicator and LLDA-Helmholtz for calculating university academic reputation validated using ranking gap and Pearson correlation coefficient.

Nomenclature

NFA	number of false alarm
w	word
P	part of document
D	document
L	length of document
B	length of P in words
N	total number of document
ϵ	variation parameter
r	Pearson correlation coefficient
x	system's ranking
y	ground truth ranking

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