

Review of Intent Diversity in Information Retrieval : Approaches, Models and Trends

M. Mustakim¹, Retantyo Wardoyo², Khabib Mustofa³

¹ Department of Informatics, Sunan Kalijaga State Islamic University, Yogyakarta,
Indonesia

^{2,3} Department of Computer Science & Electronics, Universitas Gadjah Mada,
Yogyakarta, Indonesia

{¹ taqiem235@yahoo.com, ² rw@ugm.ac.id, ³ khabib@ugm.ac.id }

Received: 14 August 2018; accepted: 19 September 2018

Abstract. The fast increasing volume of information databases made some difficulties for a user to find the information that they need. Its important for researchers to find the best method for challenging this problem. User intention detection can be used to increase the relevancies of information delivered from the information retrieval system. The study of intent detection and intent diversity in information retrieval is evolving. There is many research areas, approaches, and models done for this study. It's necessary to know what happened in this study, what's the result, what's evolved and what is still be a problem in this study. This research used a systematic mapping process to identify what area, approaches, and models that mostly used to detect user intention in information retrieval in four years later. The research begun with defining the research question, done searching papers in the period of 2015-2018 publication year used IEEE (ieeexplore.ieee.org), ScienceDirect (www.sciencedirect.com) dan Scopus (www.scopus.com) as the research databases and obtained 387 papers for review. After filtering obtained papers using inclusion and exclusion criteria, we got the remained papers are 67 papers related for review. The result of this research identified that Web Search/Social Media was mostly field area researched and implemented. 39% paper researched and implemented in this field area. A non-personalized item-based approach was mostly approach proposed and developed by researchers. 39% paper used this approach. A topic model was mostly model used by researchers. 34% paper used topic model in their research. The used of a non-personalized item-based approach still increasing from 2015 until 2017. It means that a non-personalized item-based approach still the necessary approach explored by the researchers in this study.

Keywords: intent detection, intent diversity, information retrieval.

1 Introduction

The volume of information stored in the database is increasingly fast and made some difficulties for a user to find the information they needed. Retrieving

information that suitable for user need from a large volume of information is very difficult and annoyed. It's important for researchers to do research challenging this problem.

User intention is one part that affects the perception of the user's relevance to the information they receive. There is many research of Information Retrieval Systems discussed the user's intention that showed in the queries. Various challenges exist considered how to support and defined algorithms that consider users' intention during the selection [1][2]. Predicting the user needs is a difficult job since user interests are complex, dynamic, context-dependent or even contradictory [3]. Hence, so many researchers proposed diverse approaches and strategies to tackle it.

The study of intent detection and intent diversity in information retrieval is evolving. There is many research areas, approaches, and models done for this study. It's necessary to know what happened in this study, what's the result, what's evolved and what is still be a problem in this study.

This research paper tries to find and categorize the area, approaches, and models have been proposed by the researchers, which can be used to define the conclusion of that results. Another aim is that this paper tries to find trends of intent diversity in information retrieval studies.

In this paper, we conduct the present literature review on Intent diversity in information retrieval. We collected research papers from various conferences and journals available on the web. To process review method is conducted three phases: planning, conducting, and reporting the review. The aim of the first phase "planning the review" is to define the objective of the literature review. The second phase "conducting the review" describes study areas, approaches, and models in intent diversity. In the third phase, we report the obtained report.

The remaining of this article organized as follows: Section 2 presents the research method of Systematic Mapping Study, section 3 explains the result of the study and section 4 present the conclusion and future work.

2 Research Method

Systematic Mapping Study is applied in this research to give the description of the research area, backgrounds, models, methods, approaches and the results from what have done of intent diversity in Information Retrieval. Systematic Mapping Study can help to answer the research questions by classifying the report and the research result [4]. The advantages of Systematic Mapping Study is that doesn't need so much effort to get a rough description from the results from the previous researches [5]. The systematic mapping gives a description of the research area, identify quantity, research type, approach and model used, trend and the result of research [5]. Fig. 1 shows the process steps of Systematic Mapping Study.

The processes are begun by defining Research Question (RQ) to make a scope of the research. The RQ identifies what will be answered from this research. Conduct search is a searching proses from previous research paper has published in journals or conferences based on the RQ expressed in the search strings. This step obtained papers based on the search string query. Screening of papers process filtered All obtained papers by defined inclusion and exclusion criteria. Keywording using

abstract classified papers to a classification scheme and data extraction and mapping process was the end process resulting the systematic map.

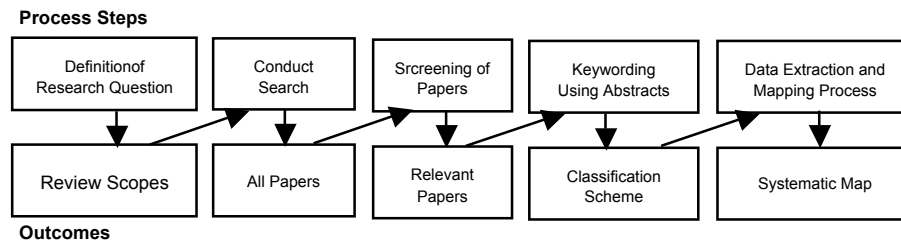


Fig. 1. Systematic Mapping Process [5]

3 Result

3.1 Research Question

The objective of this systematic mapping study is to give an overview of areas, approaches, models that researchers have done and to identify the trend of approaches and models that still necessary in field research of intent diversity in Information Retrieval. According to the objective, we formulate an RQ. The RQ inspired by the following PICO structures (Population, Intervention, Comparison, Outcome) [6]. Population (P) showed the target of the research, Intervention (I) told about the interesting issued for the research, Comparison (C) is aspects of the survey with which the intervention is being compared to and Outcome (O) is the setting of the Intervention. Based on PICO The research question that we aim at is :

In the field of information retrieval (P), intent diversity in information retrieval (I) mostly used what kind of approaches and models (C) and what kind of approaches and models that still necessary used in this field of tudy (O).

Since the main RQ is still general, we refined into three detail questions. Three detail RQs is as follows:

RQ1: Where is the intent diversity information retrieval system has been developed or used?

RQ2: What kind of approaches or models have been used to identify intent diversity in information retrieval?

RQ3: What kind of approaches or models that still necessary used on intent diversity study in information retrieval?

3.2 Searching of papers

The searching papers is a step of systematic mapping process that looks for the papers correlated with the Research Questions from the chosen sources. The search string keywords used in finding papers related to the RQ is (“intent” OR “intention”) AND (“information retrieval”), in the period of 2015-2018 publication year. This searching used IEEE (ieeexplore.ieee.org), ScienceDirect (www.sciencedirect.com) dan Scopus (www.scopus.com) as the research databases.

3.3 Screening of papers

From the previous process we obtained 387 papers, with the detail as showed in Table 1.

Those obtained papers would be selected based on the inclusion dan exclusion criteria and the redundant papers also need to be excluded. The inclusion and exclusion criteria could be seen in Table 2.

Table 1. Obtained papers

Searching database	Quantity
IEEE	27
ScienceDirect	170
Scopus	190
Total	387

Table 2. Inclusion and exclusion criteria

Inclusion criteria	Research that discussed intention information retrieval
	A study that addressed the issues of research question (RQ)
	International publication (Journal and Proceedings)
	Publication between 2015-2018
Exclusion criteria	Unrelated research of research question (RQ)
	Paper that is journal nor proceeding
	Publication not written in English

After filtering obtained papers using inclusion and exclusion criteria by reading the abstraction of each paper, we got the remained papers are 67 papers. Those papers then will be read in detail to get the data for answering the research questions defined.

3.4 Keywording using Abstract

Keywording is a way to reduce the time to develop the classification scheme. This process done in two steps. The step started by reading the abstracts dan seek the keywords and concepts that reflect the contribution of the paper. When the final set of keywords chosen, they clustered and categorized for the process mapping. The process of how the classification scheme in this study is defined follows a systematic process proposed by Peterson (2008) shown in Fig. 2.

After reading the keywords of abstracts, filtered papers categorized based on their research type, research areas, research approaches, models and research results. Types of research categorized into analysis research, experiment research, proposed model research, and review research.

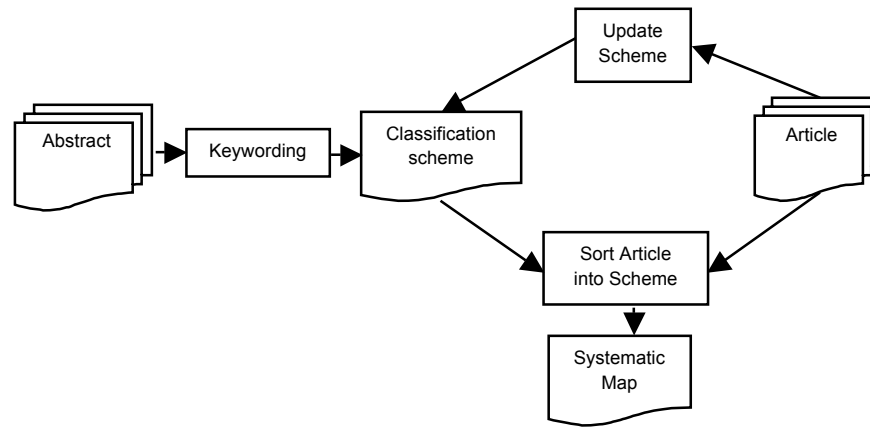


Fig. 2. Classification Scheme [5]

3.5 Data Extraction and Mapping Process

To answer the RQ1, we made Table 5. This table showed the field area of intent diversity information retrieval was researched and implemented. The categorization defined the cluster in which field area intent diversity in information retrieval implemented. intent diversity in Information retrieval, in particular, implemented in so many applications and fields like health, music, industry, and else. table 3 and fig. 3 presents the distribution of fields area and applications of intent diversity in information retrieval.

Table 3. Distribution of fields area of intent diversity information retrieval

Image	[7], [8], [9], [10], [11], [12], [13]
Health	[2], [1], [14], [15]
Music/ Movie	[3], [16], [17]
Web Search/Social Media	[18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43]
General	[44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66]
Others	[67], [68], [69], [70]

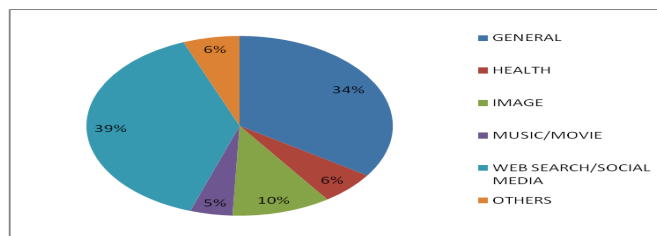


Fig. 3. Distribution of fields area of intent diversity information retrieval

To answer RQ2, filtered research papers, filtered once again. The paper which not in type experiment research or proposed model research removed from list papers. After the second filter, we obtained 31 papers that typically experimental research or proposed model research. From those papers, we found a lot of approaches adopted in implementation of intent diversity in information retrieval.

From the various approaches used in information retrieval, some researchers proposed intent information retrieval by considering terms in documents with regard to user's logs history and others doing so regardless of user history and profile during document search. Other researchers collaborate user logs with the other users, here called collaborative approaches. And the last group mines the intent of the user's query by enhancing the query based on previously existing queries. We grouped the papers based on the approach they used and the quantity of the papers year by year. Table 4 and Fig. 4 shows the distribution of approaches used in intent information retrieval.

Table 4. Statistically Approach Distribution of papers on Intent Diversity

Approach	Year			
	2015	2016	2017	2018
Personalized Item-Based	1	2	2	2
Non-Personalized Item-Based	2	4	6	-
Collaborative	1	-	2	1
Query Expansion	-	6	1	1

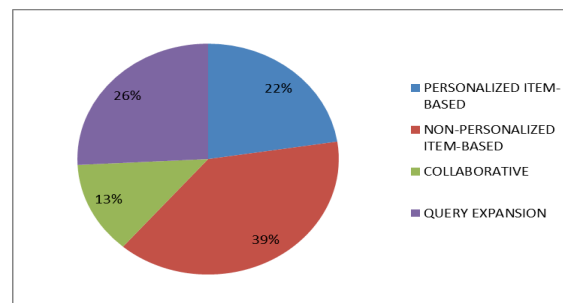


Fig. 4. Distribution of Intent Diversity Approach papers

Detail method/model of the aforementioned approaches seen in Table 5. It explains models of intent diversity approaches which used in the information retrieval field. The model distribution of intent diversity in information retrieval seen in Fig. 5. a Topic model which contain several models widely used in many research papers from 2015 until the beginning of 2018. There are 34% of research that uses several models, such as Latent Dirichlet Model, Intent Hierarchies, Lucene Model, Query Refinement Model, Restricted Boltzman Machine, Parametric Weighting, Deep

Learning, Illocution Model, Scientometric Model and UserLD Model. There is 22% research which used the ranking algorithm in general, and the other research used Vector Space Model and Statistic Language Model. Probabilistic Model used by only 6% researcher in an intent diversity information retrieval field.

Table 5. Detail of Intent Diversity Models

Vector Space Model	[1], [49], [37], [62], [39], [43].
Probabilistic Model	[26], [32].
Statistical Language Model	[15], [21], [55], [29], [35], [63].
Topics Model	[1], [47], [64], [70], [38], [68], [33], [30], [59], [24], [20].
Others	[2], [14], [53], [54], [34], [42], [50].

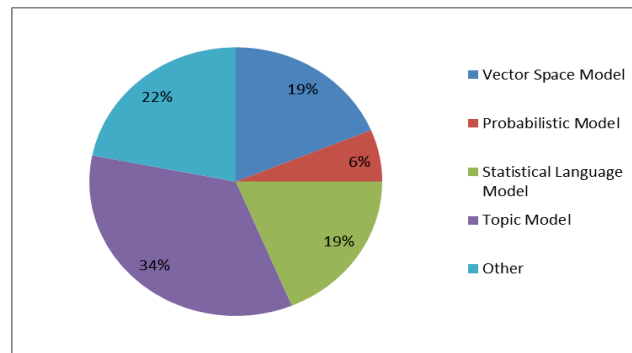


Fig. 5. Distribution of models of Intent diversity in information retrieval

To answer RQ3, we summarised the previous data into trends. The trends of intent diversity approach seen in Fig. 6, which showed that by 2015, the most widely proposed approach was the non-personalized item-based approach, followed by the personalized item-based approach, collaborative approach and there was no research used query expansion in this year. In 2016, the most widely used approach was query expansion, followed by the non-personalized item-based approach and personalized item-based approach, and there was no research used the collaborative approach in this year. Non-personalized item-based was the favorite approaches in 2017, followed by the personalized item-based approach, collaborative approach, and query expansion approach. at the beginning of 2018, the personalized item-based approach has been chosen to be proposed for tackle intent diversity issue, followed by the collaborative approach and query expansion approach, and still no research which proposed non-personalized item-based approach. According to fig. 6, the item-based approach still necessary for research due to increasing graphic, especially for the non-personalized item-based approach.

Based on the model used in the research of intent diversity in information retrieval, models grouped in the topic model seen as a favorite and necessary model that researchers still do research with. From all reviewed paper, 34% papers use these models. The model of this group such as Latent Dirichlet Model, Intent Hierarchies, Lucene Model, Query Refinement Model, Restricted Boltzman Machine, Parametric Weighting, Deep Learning, Illocution Model, Scientometric Model and UserLD Model.

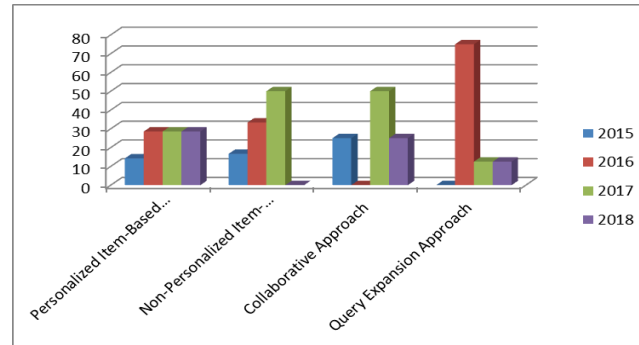


Fig. 6. Trend of Intent Diversity Approach

4 Conclusion and Future Work

This systematic mapping study of intent diversity in information retrieval started by finding papers which filter by defined search string related to RQ. in the searching phase, we got 387 papers related to the search string. After filtering using defined Inclusion and exclusion criteria we got 67 papers that related to RQ. The 67 paper then categorized based on their research type, research areas, research approaches, models and research results. All selected paper used to answer RQ1.

To answer RQ2 and RQ 3, the selected paper filtered once again. Papers that not experimental research nor proposed model research are excluded from the list. We got 31 paper that matches the criteria. There so many approaches have been proposed, developed and evaluated in different environments. Various approaches are grouped into four based on the process undertaken during the retrieval of information, that is personalized item-based (22%), non-personalized item-based (39%), collaboration (13%) and query expansion (26%). the item-based approach still the favorite approach for the researchers seen by the increase in a number of papers published from 2015 until 2017.

Based the 31 filtered publications classified, a majority model applied a Topic model (34%), followed by a general model which in this paper we call it Others model (22%), Vector Space model and Statistical Language model have the same position(19%), and the last is a Probabilistic model (6%). Those methods responded to different challenges according to the problems and environments. Thus, some approaches require further research.

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