Information Retrieval on social network: An Adaptive Proof

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Abstract. Information Retrieval has become one of the areas for studying to get the trustworthy information, with which the recall and precision become the measurement form that represents it. Nevertheless, development in certain scientific fields make it possible to improve the performance of the Information Retrieval. In this case, through social networks whereby the role of social actor degrees plays a role. This is an implication of the query in which co-occurrence becomes an indication of social networks. An adaptive approach we use by involving this query in sequence to a stand-alone query, it has proven the relationship among them.

1. Introduction
Information Retrieval (IR) is a part of computer science that systematically examines the relevance of information required with information sources, which mathematically derives and proves the measurement formulation of the relevance of information resources and information required. It is from models to methods [1]. In information era with such a large and change information source dynamically [2], also continue to grow, the role of IR is crucial for generating trustworthy information [3]. This is based on the work of the search engine, which logically means that the document \( \omega \) is relevant to the query \( q \) if it means query or \( \omega \Rightarrow q, \omega \in \Omega \), where \( \Omega \) is a space information [4].

One way of obtaining information is through the extraction of information or data mining, such as the extraction of social networks from the Web, or the mining of social structure from information sources by involving social network analysis (SNA) [5]. On the other hand, social networks obtained either by extracted (semi)-automatically or manually [6], or social networks either by document or in real terms are present in everyday life [7]. It technologically presents IR methods based on social networks [8]. Because after all the source of information such as the Web has always been a shadow of the actual state of the events [20]. However, little interest has been made to prove the existence of social network links with IR [10]. Therefore, this paper aims to reveal an IR formula adaptively based on social networks.

2. Basic Concept and Problem Definition
To be a conceptual bridge toward the problem definition, we disclose the basic concepts and related works of various literature as follows [11, 12].
Definition 1. A document $d$ consists of the words $w_k$, $k = 1, \ldots, K$ or contains some vocabularies (sometimes it expressed as tokens) i.e. $w_l$, $l = 1, \ldots, L$ where $L \leq K$ if every word has a weight $|w_l| = \sum_{i=1}^{K} p(w_k) = k_i/L$ where $|w_k| = p(w_k) = 1/K$ and $k_i$ the number of the same words for the word $w_k$ or $k_i$ is the word frequency of $w_k$.

Definition 2. A set of documents $D$ is a collection of documents $d_i, i = 1, \ldots, I$ arranged in such a way that each document has a weight $|d|$ and every vocabulary or word has a weight $|w|$.

2.1. Information Retrieval
To model IR approach required the standard data as the comparison for results returned by the access method toward information source. Therefore, based on Definition 2, a document-set $D_e$ serves as the comparative standard data for document generated by an access tool (search engine) whereby it depends on the query $q$ (we call it as the evaluation document or $D_e$). The document comparison result will be stated in the mutual document $D_r \cap D_e$ [4, 13].

Definition 3. Document set $D_r$ is set of documents $D = \{d_i|i = 1, \ldots, I\}$ such that each document has a unique identity $id_i = f(d_i)$ where $f$ is a mapping that collects different addresses of the same documents, or $D_r = \langle id_i, d_i \rangle$.

Definition 4. Evaluation document $D_e$ is a collection of documents that is accessed whereby each document has $id$ uniquely based on the information source.

In general, to estimate the trusty information we use the measurement referred to as recall and precision as follows [14].

Definition 5. Recall ($rec$) is a measurement to the relevant documents is retrieved by the tool, i.e.

$$rec = \frac{|D_r \cap D_e|}{|D_r|}$$

(1)

where $D_r$ is a set of relevant documents and $D_e$ is a set of the retrieved documents, and $|D_r \cap D_e|$ is the size of $D_r \cap D_e$ and $|D_r|$ is the size of $D_r$.

Definition 6. Precision ($prec$) is a measurement to the retrieved documents that is relevant to real documents based on tool, i.e.

$$prec = \frac{|D_r \cap D_e|}{|D_e|}$$

(2)

where $D_r$ is a set of relevant documents and $D_e$ is a set of the retrieved documents, and $|D_r \cap D_e|$ is the size of $D_r \cap D_e$ and $|D_e|$ is the size of $D_e$.

2.2. Social Network
To develop the social network, we have a set of social actors $A = \{a_i|i = 1, \ldots, I\}$ and we determine the relationship between social actors in pairs based on a set of relation clues $C = \{c_j|j = 1, \ldots, J\}$. Therefore, social network can be defined as follows [15, 16].

Definition 7. A social network (SN) is a graph $G(V, E)$, $V = \{v_i|i = 1, \ldots, I\}$ as a set of vertices in $G$ and $E = \{e_k|k = 1, \ldots, K\}$ as a set of edges in $G$ for representing the social relationships between social actors such that

(i) $\gamma_1 : A \xrightarrow{1:1} V$
(ii) \(\gamma_2 : R \rightarrow E\)

where \(R\) is a set of relation between social actors, i.e. \(r_j = c(a_k,a_l), r_j \in R, j = 1,\ldots,J, a_k,a_l \in A\). We notify a social network as \((< V, E, A, R, C, \gamma_1, \gamma_2>)\).

**Definition 8.** A graph \(G(V, E)\) is a star graph if one of vertex \(v_c \in V\) has degree \(d > 1\) is more than another vertices in \(V\) and other vertices have degree \(d(v_i) = 1, v_i \neq v_c,\) and \(v_c\) as center of star graph.

**Lemma 1.** If degree of social actors is \(d(a) > 1\), then \(a\) is a center of star graph.

*Proof.* For some of social actors we have degrees \(d(a_1) \geq d(a_2) \geq \ldots \geq d(a_m) > 1\). Based on it, there are \(m\) candidate vertices as center, there are \(m - 1\) candidate vertices as leafs, and then we build a star graph by a way we eliminate degrees until \(d() = 1\) of all vertices that are not center candidates. This method is done so that all \(d(a_i) > 1\) alternately will be the center of the star graph.

**Theorem 1.** The recall and precision as a presentation of IR can be enhanced on the basis of social network if and only if the social network is optimally shaped star graph.

### 3. An Approach

To be get information we use cognitive structures as an approach in some of implications as follows [4, 1].

**Lemma 2.** If \(D_r\) and \(D_e\) each contains uniquely document \(id\) that may be the same between two sets, then the same two \(id\) are based on the iteration of \(i: D_r \rightarrow D_e\) against \(i: D_e \rightarrow D_r\).

*Proof.* Suppose \(i: D_r \rightarrow D_e\) and \(i: D_e \rightarrow D_r\). \(i: D_e \rightarrow D_r\) is generated based on the \(\omega \Rightarrow \theta\) implication which is true value if the content \(q\) is in the \(\Omega\), in other case it is false. While \(D_r\) contains a set of documents with specified \(id\), and \(\omega \Rightarrow \theta\) is true if \(q \Rightarrow \theta\). Because \(D_r\) contains a set of \(id_j\), so \(q \Rightarrow \theta\) has to round every \(i: D_r \rightarrow D_e\), and looping \(i: D_e \rightarrow D_r\) done to \(id\) in \(D_e\).

**Lemma 3.** If \(D_r\) and \(D_e\) each contains a document \(id\) that might be the same so as to form \(D_r \cap D_e\), looping \(i: D_r \rightarrow D_e\) against \(i: D_e \rightarrow D_r\) generates a sequence number of \(D_e\).

*Proof.* Based on the assumptions and consequences of the Lemma 1 and Lemma 2. Suppose \(i: D_r \rightarrow D_e\) and \(i: D_e \rightarrow D_r\) with \(i: D_j, i: D_2, \ldots, i: D_m, j = 1,\ldots,m\), as a result sequence of \(\omega \Rightarrow \theta\). Therefore, by doing iteration \(i: D_r \rightarrow D_e\) against one by one against from \(i: D_j \rightarrow D_e\) from the sequence 1 to \(m\).

**Proposition 1.** If \(D_r \cap D_e\) contains a sequence of \(id\), then the value of \(D_r \cap D_e\) is \(j\) related to \(i: D_j\).

*Proof.* Based on the results of the Lemma 3, the size of \(|D_r \cap D_e|\) is smaller than or equal to \(m\), i.e. \(1 \leq |D_r \cap D_e| \leq m\).

**Proposition 2.** If \(D_r \cap D_e\) contains a sequence of \(id\), then the value of \(D_e\) is the last number of iteration towards \(i: D_j \rightarrow D_e\).

*Proof.* Based on the results of the Lemma 3, the size of \(|D_e|\) is smaller than or equal to \(m\), i.e. \(1 \leq |D_e| \leq m\), \(|D_e|\) is the last number of iteration towards \(D_e\).

By involving the above systematic: Lemma 1, Lemma 2, Lemma 3, Proposition 1 and Proposition 2, we disclose the following ordinances:
Algorithm 1:
INPUT : A set of $id_i$ from $D_r$
OUTPUT : $|D_r|$, $|D_e|$, $|D_r \cap D_e|$
STEPS : 
1. $id_j \leftarrow (\omega \Rightarrow q)$
2. Set $j = 1$ to $J$:
   Set $i = 1$ to $I$:
   if $id_j = id_i$ then:
      (a) $n = j$
      (b) Collect $id_j$ into $D_r \cap D_e$.
3. $|D_r| \leftarrow J$, $|D_e| \leftarrow I$, $|D_r \cap D_e| \leftarrow n$.

4. Adaptive Proof
Later in this paper, we reveal the interpretive outlines involving the above approach to prove adaptively Theorem 1.

Assuming that each query stands alone, based on Algorithm 1 the recall and precision calculations can be expressed as Fig. 1, although the query contains the co-occurrence of two names of the social actor [17]. However, since any query involving co-occurrence becomes a clue of the relationship between two social actors, so it is possible that one of the social actor names is the same actor on each query [18]. Thus, the queries produce social networks that are generally the form of star graph with one social actor as the center [19].

Suppose that there is a query sequence $q_1, \ldots, q_k$ whereby each query contains $q_1 \leftarrow a_1, a_2$; $q_2 \leftarrow a_1, a_3$; $\ldots$; $q_k \leftarrow a_1, a_k$. So we get a list of $D_{e_1}, D_{e_2}, \ldots, D_{e_k}$, or a sequence of $D_r \cap D_{e_1}, D_r \cap D_{e_2}, \ldots, D_r \cap D_{e_k}$, and a set of documents is a collection of evaluation documents as follows

$$D_{es} = \bigcup_{i=1}^{k} D_{e_i},$$

whereby $|D_{es}| \leq |D_{e_1}| + |E_{e_2}| + \ldots + |D_{e_k}|$. Whereas, a collection of documents comes from the comparison between $id$ of 2 sets of documents is $D_r \cap D_{es} = \bigcup_{i=1}^{k} D_r \cap D_{e_i}$, and based on Eq.
Figure 2. Adaptive approach to the recall and precision.

(3) it be

$$D_r \cap D_{cs} = D_r \cap \bigcup_{l=1}^{k} D_{el}$$  \hspace{1cm} (4)$$

whereby \( |D_r \cap D_{cs}| \leq |D_r \cap D_{e1}| + |D_r \cap D_{e2}| + \cdots + |D_r \cap D_{ek}| \). In general, in Eqs. (1) and (2), the value of \( |D_{e1}| + |D_{e2}| + \cdots + |D_{ek}| \) and the value of \( |D_r \cap D_{e1}| + |D_r \cap D_{e2}| + \cdots + |D_r \cap D_{ek}| \) each has been reduced to \( |\bigcup_{l=1}^{k} D_{el}| \) and \( |D_r \cup \bigcup_{l=1}^{k} D_{el}| \). This reduction as a result of merging the set of documents where the same documents to be listed once so that the value of \( |D_{cs}| \) close to the value of \( |D_r| \) or \( |D_r \cap D_{cs}| \leq |D_r| \), but the number of documents in \( D_{cs} \) has potential to exceed the number of documents in \( D_r \). This causes a low precision value even if recall value is high. Taking into account that the keyword can reduce unsuitable documents, each query with a form of co-occurrence (one of the social actor names being the keyword for the other) lifts the appropriate document up to the surface [20]. Randomly assigned queries such that every \( D_{el}, l \neq k, |D_{el}| \) has the highest value in accordance with \( |D_r \cap D_{el}| \) in sequence, where in the next sequence the value of \( |D_{el}| \) does not come from the same document in the previous query, while in the last query or for \( |D_{ek}| \) involves all possible documents, see Fig. 2. Thus by involving the same query as Fig. 1, taking into account the precise measurements consecutively. The query results, except the last query, are considered only to the extent that the last document is appropriate. In other words, if Eqs. (1) and (2) are restated based on Eqs. (3) and (4) as follows [1]

Recall = \( \frac{(m_1 + m_2 + \ldots + m_n)}{m} \)

Precision = \( \frac{(m_1 + m_2 + \ldots + m_n)(n_1 + n_2 + \ldots + n_k)}{m(\bigcup_{l=1}^{k} D_{el})} \)

As the implementation of the Eqs. (5) and (6) can be seen in Fig. 2. Theorem is proven.

5. Conclusion

The involvement of social actors can be used to improve the performance of recall and precision through effective approaches. An effective approach is made to the use of queries in sequence via a stand-alone query. However, implementation needs to be done by involving data and search
engines, in addition to providing more definitive proof of the relation existence between the extracted social networks and IR.

References

[1] M K M Nasution, R Syah and M Elfida 2018 Information retrieval based on the extracted social network Applied Computational Intelligence and Mathematical Methods, Advances in Intelligent Systems and Computing 662.

[2] M K M Nasution, M Elveny, R Syah, and S A Noah 2015 Behaviour of the resources in the growth of social network Proceedings - 5th International Conference on Electrical Engineering and Informatics: Bridging the Knowledge between Academic, Industry, and Community, ICEEI 2015, 7525551.

[3] L Kirchhoff, K Stanoevska-Slabeva, T Nicolai, and M Fleck 2008 Using social network analysis to enhance information retrieval systems. Social Networks Applications Conference.

[4] M K M Nasution and S A Noah 2012 Information retrieval model: A social network extraction perspective Proceedings - 2012 International Conference on Information Retrieval and Knowledge Management, (CAMP’12), 6204999.

[5] M K M Nasution 2016 Social network mining: A definition of relation between the resources and SNA, International Journal on Advanced Science, Engineering and Information Technology 6(6).

[6] M Hamasaki, Y Matsuo, K Ishida, T Hope, T Nishimura, and H Takeda 2006 An integrated method for social network extraction Proceeding of the 15th International Conference on World Wide Web (WWW 2006).

[7] P Benhawi, N M Ali and H M Judi 2012 User engagement attributes and levels in Facebook Journal of Theoretical and Applied Information Technology 41(1).

[8] P Mika 2007 Social Networks and the Semantic Web Springer-Verlag: Berlin.

[9] M K M Nasution 2014 New method for extracting keyword for the social actor Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 8397 LNAI (PART 1).

[10] M K M Nasution, and O S Sitompul 2017 Enhancing extraction method for aggregating strength relation between social actors Advances in Intelligent Systems and Computing 573.

[11] M K M Nasution, and S A Noah 2011 Extraction of academic social network from online database 2011 International Conference on Semantic Technology and Information Retrieval (STAIR), 5995766.

[12] M K M Nasution, S A M Noah, and S Saad 2011 Social network extraction: Superficial method and information retrieval Proceeding of International Conference on Informatics for Development (ICID’11), (arXiv:1601.02904v1 [cs:IR] 12 Jan 2016).

[13] M K M Nasution 2015 Extracting keyword for disambiguating name based on the overlap principle International Conference on Information Technology and Engineering Application (4-th ICIBA), Book 1. (arXiv: 1602.00104v1 [cs:IR] 30 Jan 2016).

[14] W B Croft, D Metzler, T Strohman 2010 Search Engines Information Retrieval in Practice (New York: Addison Wesley).

[15] M K M Nasution 2016 Social network mining (SNM): A definition of relation between the resources and SNA International Journal on Advanced Science Engineering Information Technology 6(6).

[16] M K M Nasution, M Hardi, R Syah 2017 Mining of the social network extraction Journal of Physics: Conference Series 801 (1).

[17] M K M Nasution 2012 Simple search engine model: Adaptive properties for doubleton Cornell University Library (arXiv:1212.4702v1 [cs:IR] 19 Dec 2012).

[18] M K M Nasution 2013 Simple search engine model: Selective properties Cornell University Library (arXiv:1303.3964v1 [cs:IR] 16 Mar 2013).

[19] M K M Nasution, O S Sitompul, E P Simulingga, and S A Noah 2016 An extracted social network mining Proceedings of 2016 SAI Computing Conference (SAI).

[20] M K M Nasution 2014 New method for extracting keyword for the social actor Source of the Document Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 8397 LNAI (PART 1).