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Social Network Extraction Based on Web. A Comparison of Superficial Methods

Mahyuddin K. M. Nasutiona,* , Shahrul Azman Noahb
b Knowledge

a Information Technology Department, Universitas Sumatera Utara, Medan 20155, Sumatera Utara, Indonesia
Technology Research Group, Faculty of Information Science & Technology, Universiti Kebangsaan Malaysia, Bangi 43600 UKM
Selangor, Malaysia

Abstract
The Web as a source of information has many potentials which allow to use the different treatments on social network extraction methods. The approaches generally we identified as superficial methods in unsupervised stream. However, the same resources of social networks, i.e. based on a community of social actors, reveal many of different approaches to produce social networks. Therefore, based on a treatment to another treatments, from the given treatments until the different social networks generated and it has been declared different methods. It requires comparison to reveal the properties of social networks and their methods in this paper. It is revealed that there is a core social network has similarity with other social networks is more than 1% as general property of the extracted social networks, whereby there is a social network for different methods has the common edges in graph.

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Keywords: Superficial method, occurrence, co-occurrence, hit count, snippet, URL address, Web, vertices, social actors, edges, strength relations

1. Introduction

The Web as an information source has a lot of potential to be extracted into consideration for decision making [1].
Extracting social network from Web not only considers the available potential only

but systematically is also the way
to gain structural social behavior [2]. Therefore, the methods applied for
extraction also vary, and each involves the
different potentialities of information source, although it involves the same
social actors. However, since the method
externally is outside the search engine system [3], although the methods in
unsupervised stream heavily depends on
the search engine [4], consequently the method can't fully utilize the information
resources optimally [5], moreover
the methods in supervised stream [6] such as the use of: Latent Dirichlet
Allocation (LDA) [7] or Hidden Markov
Model (HMM) [8], for example.

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Corresponding author. Tel.: +62-061-821-1633 ; fax: +62-061-821-9411.
E-mail address: mahyuddin@usu.ac.id

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The different information involvement of the Web in disclosing social networks has
resulted in the different approaches for extracting social network from Web [9,
10]. However, in the same potential, it has not been revealed that
there is a difference between these approaches. Therefore, this paper will reveal
the performance of each approach in
the superficial methods involving the experiment of social network extraction.

2. A Review

In the formal definition of social networks, expressed in graph theory G(E, V), it
has been disclosed that there
is a set of vertices V and a set of edges E, with which $v_i \in V$ $i = 1, \ldots, n$
denotes entities in social networks and
$v_i v_j \in E$ denotes relationship between entities v_i , $v_j \in V$ in a social network
[11, 12]. This definition reveals that
in the extraction of social networks using the basic superficial method (BSM)
occurs the process (a) determines the
social actors and (b) builds relationships between them [13, 14]. Next we consider
some basic characters related to
the superficial methods.

In the first process, the use of the social name ai (without quotes) in the query q
is to represent a social actor or

$$ai = q \leftarrow ai \ , \quad (1)$$

then generally search engines generate ambiguous information about the actor social

[15]. However, with the addition
of the keyword kw, in general it can reduce naturally the default property of used
social name [13, 16], i.e. consequent
of
awi = q ← ai , kw

(2)

happen reduction ambiguity, with which |awi | ≤ |ai |, |ai | ∈ ai is a cardinality
of ai and |awi | ∈ awi is a cardinality of
ai , kw [17]. While using the well-defined name of social actor (in quotes) in the
query q will raises the entire social
actors related information or
a”i” = q ← ”ai ”.

(3)

In last case, |a”i” | ≤ |ai |, and |a”i” |∈ a”i” is a cardinalty of ”ai ” [18]. As
well as with
aw”i” = q ← ”ai ”, ”kw”.

(4)

is about one of information concentrations of a social actor, |aw”i” | ≤ |a”i” |,
and |aw”i” | ∈ aw”i” is a cardinalty of
”ai ”, ”kw” [19, 20, 17].
In the second process, the relationship between two social actors is based on the
concept of co-occurrence [21, 22,
23]. Thus,
ai a j = q ← ai , a j ,

(5)

is a process to elevate the clue of relation be relationship between two actors,
with which |ai ∩ a j | ≤ |ai | and |ai ∩ a j | ≤
|a j |, and |ai ∩ a j |∈ ai a j is a cardinality of ai , a j . The addition of a
keyword towards the co-occurrence will usually
reduce the number of information presented, that is
awi aw j = q ← ai , ai , kw,

(6)

but it should meet that |awi ∩ aw j | ≤ |ai ∩ a j |, |awi ∩ aw j | ∈ awi aw j is a
cardinality of ai , ai , kw [10, 23]. Likewise,
the use of the well-defined name of social actor in the query will reveal the
relationoship between two social actors
appropriately, that is
a”i” a” j” = q ← ”ai ”, ”a j ”.

(7)

whereby |a”i” ∩ a” j” | ≤ |a”i” | and |a”i” ∩ a” j” | ≤ |a” j” |, |a”i” ∩ a” j” | ∈
a”i” a” j” is a cardinality of ”ai ”, ”a j ”. Thus, if
|a”i” ∩ a” j” | = 0, then it means exactly there is no relationship between two
social actors [14]. Whereas the addition of
a keyword towards the co-occurrence based on pattern as follows
wa”i” wa” j” = q ← ”ai ”, ”a j ”, ”kw”,

(8)

Fig. 1. A variety of social network extraction methods

produces the relationship of a pair of social actors, whereby |aw”i” ∩aw” j” | ≤ | a”i” ∩a” j” |, and |aw”i” ∩aw” j” | ∈ wa”i” wa” j”
is a cardinality of ”ai ”, ”a j ”, ”kw” [24].
In this case of occurrence, if each of ai , ”ai ”, ai , kw, and ”ai ”, ”kw” has a cardinality greater than 0, then each of them
contains one or more snippets and URL addresses [17], i.e. si , sa”i” , saw”i” , and saw”i” respectively is a snippet of them,
so uai , ua”i” , uawi , and uaw”i” respectively is a collection of URL addresses of them [4, 25]. Similar to co-occurrence,
each of ai , a j , ”ai ”, ”a j ”, ai , a j , kw, and ”ai ”, ”a j ”, ”kw” has a list of snippets or a list of URL addresses, if them has
a cardinality greater than 0. By involving Eq. (1) and uai ∈ ai , for a pair of social actors can be generated social
network S Nl. We call this approach as the underlying superficial method (USM) whereby the established relationship
can be validate the previous relationship by involving uai , ua j ∈ ai a j or using Eq. (5) in the joint underlying superficial
method (JUSM) for generating a social network S Nv as validation of S Nl. Similar to this concept, because sai ∈ ai
used in the descriptive superficial method (DSM) and generates descriptive social network S Nd, whereby sai , sa j ∈
ai a j that used in the joint descriptive superficial method (JDSM) generates the descriptive social network S Nvd as
validation of S Nd, see Fig. 1a. Likewise, if the concept of pattern is used in a query, various social networks will be
generated. But on the use of pattern, possibility of returning information be more appropriate so that it used as access
point to in more deep information, for example accessing the online database [26, 18]. We call the latter approach as
the seed based superficial method (SSM) that is sometimes it used as the basis for development of social network in
different than usually [27, 28], see Fig. 1b. In this case, it is a social network based on seed S N ps.

3. The Proposed Approach

Through the above reviews have been generated some treatments that may be used in methods for extracting social
network from Web. Each treatment comes from the same potential and with different approaches [29]. The potential
used in the extraction of a social network is the number of social actors as vertices in social network. The number of
social actors is the equal to number of the required occurrence, whereby occurrence as a treatment , but the realization
in the number of hit counts may be different or all hit counts must be greater than 0 [30, 31]. Thus, hit counts equal to
0 doesn't present snippet and URL addresses so no treatment may be applied there. Involvement of occurrence and/or co-occurrence in each method, results in the presence of different treatments
as different approaches. This different treatments, not only changes the complexity but also the presence of pseudo

similarity that helps in solving of resource constraints. The resource limitations associated with using search engines
to respond to the queries submitted. Therefore, BSM [15, 32, 33], USM [4] and DSM [18, 34] differ in resource
engagement iterations, but they still are same computationally. In addition, in certain method it can also be expanded

Table 1. List of methods and their complexity and realization

Method	Computation	occurrence	co-occurrence
BSM	106,491	462	106,491
BSMv1	106,491	462	106,491
BSMv2	106,491	462	106,491
PSM	106,491	462	106,491
PSMv1	106,491	462	106,491
PSMv2	106,491	462	106,491
USM	106,491	462	106,491
DSM	106,491	462	106,491
SSM	106,491	76	106,491
			0
			0
			0

vertices
462
373
389
462
369
382
462
434
462

realization
100.00%
80.74%
84.20%
100.00%
84.20%
82.68%
100.00%
93.94%
607.89%

edges
31,623
16,388
17,132
22,836
16,371
17,120
99,150
12,158
1,297

realization
29.70%
15.39%
16.09%
21.44%
15.38%
16.07%
93.11%
11.41%
1.22%

with different approaches, such as BSM converted into BSMv1 and / or BSMv2 by adding different or equal keywords,
so the possibility of extraction results will be different [19, 10].[33] Therefore, the comparison of the complexity of
performance on each method based on the reviews will show the feasibility and reliability of methods for the same
purpose in the extraction of social networks from the web [35].
The outcome of the method also shows the feasibility and reliability of the method. Output is about how much
relations in a social network, or number of edges as realization. The density of the social network as resultant of
method is determined by the many relationships of two social actors as outcomes. Therefore, if the relation between
two social actors is not limited to emotional closeness but also ideas and concepts

or other relationships, then the
outcome of the used method requires another consideration either from the point of density or description [12].
So, the way to see the performance of social network extraction methods is to compare some of the following,
1. Measurement of complexity: Computation (based on iteration), number of occurrences, and number of cooccurrences.
2. Percentage of output to number of relations potentially: realization of occurrences be vertices, and realization of
co-occurrences be edges.
3. Similarities between the social networks, i.e. by using Jaccard coefficient based on edges in social networks
[36, 11]:
[18]

$$Sime = \frac{|E1 \cap E2|}{|E1| + |E2| - |E1 \cap E2|} \quad (9)$$

|E1 ∩ E2 |, |E1 |, and |E2 | are number of edges in social networks: G1 (V1 , E1) and G2 (V2 , E2).
4. Experiment and Discussion
By using 76 social actors (professor) as seeds, as much as 385 other social actors is generated as potential for
building social network. The first approach as an initiation we use the SSM method by involving the source of information from the online database (such as DBLP) directly through a URL address based on each seed and extracting
the names of other social actors in co-occurrence formation. It is to get current information about relations between
social actors [18], and as contra against manual effort and not up-to-date information of DBpedia [38]. So, in this
experiment there are 462 social actors. We use this collection of social actors to form social networks both with other
superficial methods and different sources of information from the Web.
Each method produces different number of edges, although by using same number of vertices. In addition, methods
produce the different number of actors who have no relationship with others [37]. In order to produce the edges in the
network, each method produces unequal strength relations between the pairs of social actors, there are several strength
relations between social actors can be recognized by one method but cannot be disclosed by other methods, see Table
1. Therefore, each method uses different factors and concepts that serve as a basis for extracting relationships between
social actors from information sources [39].

[26]

Fig. 2. Similarity of edges in the social networks

Based on online database, such as DBLP, SSM generates new actors and their relations based on concept of coauthor relationship [18]. 76 professor (as academic actors) be seeds to get 385 other academic actors, but the social

network density based on relations only 1.22% of 106, 491 possible relations potentially [40].
For 462 social actors there are 106,491 potential relationships in symmetry. Through BSM, realized 462 occurrences and 106,491 co-occurrences into 31,623 strength relations. For the same case, but involving keywords:
1. Related to affiliation (in basic superficial method with keyword (BSMv1)), the approach produces 373 vertices
and 16,388 edges (as a realization).
2. While, by using keyword for developing a community (in basic superficial method with other keyword (BSMv2)),
the approach produces 389 vertices and 17,132 edges.
By using occurrences only, USM produces 462 vertices and 99,150 edges, USM produces 462 vertices and 99,150
edges, and DSM produces 434 vertices and 12,158 edges. In general, another approach developed from its basic
form in realization results in lower social network density than the original form. In this case, BSM, BSMv1, and
BSMv2 sequentially produce 29.70%, 15.39% and 16.09% strength relations of 106,491 relations potentially. As
well as with BSM, three methods: PSM, PSMv1, PSMv2 produce 21.44%, 15.38%, and 16.07% strength relations of
106,491 relations potentially, respectively. However, all approaches used as validation depend on the occurrences and
co-occurrences of the related method. For example, JUSM and JDSM depends on occurrences and co-occurrences
of BSM, or JUpSM and JDpSM depends on occurrences and co-occurrences of PSM. Thus the USM on its own is
different from the related approach, USM contains a pseudo-strength relations. It based on the domain similarity of
the website (the domains of URL addresses).
The similarity between social networks on the edges shows that there are methods that imply so close performance,
namely PSM, BSMv1 and BSMv2. While other methods show social networks as results that are different from the
others. In particular, that the similarity of social networks from SSM to other method shows the difference due to
the resulting actors having stronger relationships other than co-author relationship. Furthermore, the existence of
relationships within the online database is not necessarily detectable directly through queries in other methods, except
that it only reveals some of the content of the online database. So there is the core of all social networks of more than
1% as the same result of all methods.

5. Conclusion

Unequal treatments result in different approaches to information resources, although involving potential same social
actors, and this also results in several methods of extraction of social networks in the unsupervised stream. The
superficial methods that have similar treatment show the similarity of results. Different results show that the resulted
social networks have different characteristics. Nevertheless, the similarity between the edges of social networks shows
the existence of the core of social networks as the foundation for the development of a social network. Therefore,
different results from different methods suggest the needing next study for getting an integrity approach, while for
getting trusty information is by involving dataset as standard evaluation.

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