The Popularity-Homophily Index: A new way to measure Homophily in Directed Graphs

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Abstract
In networks, the well-documented tendency for people with similar characteristics to form connections is known as the principle of homophily. Being able to quantify homophily into a number has a significant real-world impact, ranging from government fund-allocation to finetuning the parameters in a sociological model. This paper introduces the “Popularity-Homophily Index” (PH Index) as a new metric to measure homophily in directed graphs. The PH Index takes into account the “popularity” of each actor in the interaction network, with popularity precalculated with an importance algorithm like Google PageRank. The PH Index improves upon other existing measures by weighting a homophilic edge leading to an important actor over a homophilic edge leading to a less important actor. The PH Index can be calculated not only for a single node in a directed graph but also for the entire graph. This paper calculates the PH Index of two sample graphs, and concludes with an overview of the strengths and weaknesses of the PH Index, and its potential applications in the real world.

Keywords: measuring homophily; popularity-homophily index; social interaction networks; directed graphs

1 Introduction
Homophilic, meaning “love of the same,” captures the tendency of agents, most commonly people, to connect with other agents that share sociodemographic, behavioral, or intrapersonal characteristics (McPherson et al, 2001). In the language of social interaction networks, homophily is the “tendency for friendships and many other interpersonal relationships to occur between similar people” (Thelwall, 2009). The social, economic, and political outcomes of homophily are significant. In urban settings for instance, homophilic tendencies in people tend to create exclaves of a highly concentrated race or ethnicity (Xu et al, 2021). Chinatown in San Francisco and Little Italy in New York, are prime examples of homophily in action. Race, socioeconomic factors, and religion all play a prime role in determining the likelihood of two people communicating with one another, or living nearby each other (Xu et al, 2021).

Identifying and measuring homophily can have significant real-world consequences. Identifying homophily in housing can help authorities deal with dogged pockets of segregation, while identifying homophily in social media can reveal the importance of
certain attributes and users, aiding social media companies, advertisers, and others (Weng et al, 2010). Measuring homophily provides numeric detail to the above situations, which in turn can influence the amount of funding allocated, and resources spent in response. For these reasons, an effective measure of homophily is needed. The most nuanced models need to take the structure of the graph into consideration.

This paper presents a new way of measuring the homophily of an attribute in a directed graph — the "Popularity-Homophily Index" or PH Index for short. The paper then looks at two example datasets, calculates the PH Index in both cases, and then compares their results.

The first dataset is a social network of Github developers. The second dataset is an internet network of links between political blogs in the lead-up to the 2004 US presidential election. These two graphs are radically different in their contents, but this paper finds that the PH Index has relevance in both. For sufficiently complex directed graphs, the PH Index is significantly more powerful than other related measures of homophily in common use, such as the classic External/Internal Index (EI Index).

2 Related Work

The idea and motivation to measure homophily in directed graphs is not new. For example, Twitter’s social network can be modelled as a directed graph, with users as nodes, and follower relations as directed edges. Measuring homophily was an important part of the development of TwitterRank, which measured the influence of prominent Twitterers in a sample dataset (Weng et al, 2010). Other papers have sought to determine the extent of the political “echo chamber” on social media such as Twitter. After classifying users as either Democratic or Republican based on the content of their tweets, one paper then sought to measure the political homophily present in the resulting graph (Colleoni et al, 2014). This measurement allowed them to quantify the scale and impact of the political echo chamber on social media. Additionally, “Degree Weighted Homophily” (DWH) takes the structure of the graph into account, and provably gives a lower-bound for the convergence time of certain simulations, where nodes represent “agents” that are either attracted to or repelled by their neighbors (Golub and Jackson, 2012). These simulations are often excellent models for the behavior of real-world people, such as the tendency of people of the same race to cluster in the same neighborhoods. However, DWH is nearly impossible to compute efficiently for real-world graphs, since its basic formulation takes exponential time to compute.

A recently developed and widely used measure of homophily is called the Assortativity Coefficient $r$, which satisfies the formula $r = \frac{\text{tr}(E) - \text{sum}(E^2)}{1 - \text{sum}(E^2)}$ (Newman, 2003). Easy and efficient to calculate, the assortativity coefficient has been widely used in research into homophily (Chang et al, 2007). In the case of a binary classification, $E$ is a 2x2 matrix containing the fraction of each possible type of edge in the graph. For example, if every node has a color attribute that is either “black” or “white”, the fraction of edges that start at a “black” node and end at “white” node is one of the 4 possible kinds of edges. Additionally, $\text{tr}$ is the trace of a matrix (the sum of its main diagonal), and $\text{sum}$ is the sum of the elements of the entire matrix.
A significant issue with the assortativity coefficient is that it does not take the overall structure of the graph into account since it reduces the entire graph into a matrix, losing much of the intricate complexity of the graph.

All of these measures of homophily have their advantages and drawbacks. The PH Index is influenced by many of these measures, and is designed to be versatile, easy, and efficient to calculate, while nuanced enough to take the entire structure of the graph into account.

3 Background

Define an edge to be a homophilic edge if it connects two nodes that share some attribute, and define it be a non-homophilic edge if otherwise. For the purposes of this paper, assume that every node attribute is binary, and can be represented as either 0 or 1. Many non-binary attributes can be converted into binary attributes with a bit of extra work. For example, if every node is a person with their own “height” attribute, we can create a binary attribute of ‘tallness’. Arbitrarily define a node to be ‘tall’ if its height attribute is more than 6 feet, and ‘not tall’ if otherwise.

Define a pair of similar nodes to be two nodes (not necessarily connected by an edge) that have the same value for a given attribute, either both 0 or both 1. For a given node $n$, one of the oldest, simplest, and most powerful measures of homophily is called the EI Index or alternatively the Coleman Homophily Index since it was introduced in his landmark book *Introduction to Mathematical Sociology* (Coleman, 1964).

In the set of all node $n$’s out edges (in the case of a directed graph), let $e_n$ represent the number of “external” non-homophilic edges, and $i_n$ represent the number of “internal” homophilic edges. Then the EI Index is defined by Equation 1.

$$EI = \frac{e_n - i_n}{e_n + i_n}$$ (1)

Note that the EI Index is -1 for a completely homophilic node (all of its edges are homophilic edges), and 1 for a completely heterophilic node (Coleman, 1964). The EI Index for the entire graph is simply the average of the EI Index for each individual node. Most random graphs that do not demonstrate homophily tend to have a value of the EI Index of approximately 0.

For the purposes of the PH Index, using the Weighted EI Index (WEI Index) is more appropriate. The necessity of the WEI Index stems from the fact that in a binary classification, the total number of nodes with one value of an attribute may differ significantly from the total number of nodes with the other value of that same attribute. For example, consider a social network of 200 individuals, with 180 men and 20 women. If Bob (a male) and Jennifer (a female) both are connected to a single man and a single woman, then their EI indices will both equal 0.0. However, common sense suggests that Jennifer exhibits a greater amount of homophily, since there are very few other women she could be connected to.

Influenced by the above observation, define the weight $w$ of node $n$ to be the ratio of the number of non-similar nodes in the entire graph, divided by the number of similar nodes. Therefore, Bob’s weight would equal 0.11, and Jennifer’s weight would
equal 9.0. For node \( n \), consider the same variables as in the definition of the EI Index. The equation for the WEI Index is stated in Equation 2.

\[
\text{WEI} = \frac{e_n w - i_n}{e_n w + i_n}
\]  

Equation 2

The Weighted EI Index essentially normalizes the EI Index, calculating it as if there were an equal number of nodes with each possible value of the attribute. In our example above, Bob’s WEI is 0.8 and Jennifer’s WEI is −0.8. As predicted, after weighting, Jennifer exhibits strong homophily.

### 4 Popularity

Define the *popularity* of a node to informally represent its importance or centrality in the graph. In the Twitter social network for example, both Barack Obama and Kim Kardashian would have a high ‘popularity’. There are multiple well-known methods to measure popularity in a directed graph. A few of the most common types are listed below.

#### 4.1 In-Degree Centrality

In-Degree Centrality is the simplest measure of popularity. It is also the fastest, with a runtime of \( O(V + E) \) (Zhang and Luo, 2017). Logically, it follows that a node with many incoming edges is important. Thus, a node’s popularity is simply its in-degree, normalized by the total number of nodes in the graph.

#### 4.2 Betweenness Centrality

Betweenness Centrality defines a node’s popularity to be the fraction of shortest paths that pass through the node. Logically, it follows that the more central a node is in the graph, the higher the betweenness centrality, and the higher the importance of that node. The major drawback of this algorithm is its slowness: without optimization it runs in \( O(VE) \) (Zhang and Luo, 2017).

#### 4.3 PageRank

The PageRank algorithm is a direct upgrade on the In-Degree Centrality algorithm. It has a time complexity of \( O(k(V + E)) \), where \( k \) is the maximum number of iterations (the default in NetworkX is 100) to run the algorithm for. The intuition behind the algorithm is that since not all nodes are equally popular, they should not all be weighted the same. Therefore, not all incoming edges are equal, and they should not be counted equally. The PageRank algorithm was originally developed to order web pages for the search engine Google (Page et al, 1999). The full details of the PageRank algorithm are beyond the scope of this paper, although a short overview is provided. By treating page-rank as a “fluid”, at every iteration of the algorithm, each node equally distributes all of its “fluid” to its neighbors. Generally, a node with many incoming edges tends
to accumulate a lot of page-rank, although each incoming edge provides a different amount of “fluid” based on its node’s current amount of page-rank (Rogers, 2002). While the argument to justify PageRank may appear circular, the algorithm provably converges in most cases. Once convergence is reached, the amount of page-rank a node has is equal to its popularity.

5 Popularity-Homophily Index (PH Index)

The Popularity-Homophily Index, presented and developed in this paper, is a new method for measuring homophily in a directed graph. The PH Index for a node is closely related to the EI Index, and more specifically to the WEI Index. The major difference is that the PH index takes into account the popularity of a node’s set of neighbors.

The first step of the algorithm is to calculate the popularity of every node using one of the popularity algorithms above and store it in the array $P$. Additionally, normalize the array so that $\sum P = 1$.

The second step is to redefine the variables $e_n$ and $i_n$ that appeared in the formula for the WEI Index, as shown in Equation 3. Essentially, Equation 3 weights these variables by the popularity of the edges they accumulate over.

$$
e_n = \sum_{i \in \text{External Nodes}} P_i,$$

$$i_n = \sum_{i \in \text{Internal Nodes}} P_i$$  \hspace{1cm} (3)

Once $e_n$ and $i_n$ have been re-calculated, the formula for the PH Index is the same as the formula for the WEI Index.

Why does taking popularity into account create a more robust index of homophily? The reason is, in most real-world graphs, ties to influential nodes are a greater indication of homophilic tendencies than ties to less influential nodes. That is, not all out-edges are equally important. For example, research has shown that people’s daily lives are influenced by the YouTube vloggers that they follow (Ladhari et al, 2020). Additionally, the vlogger’s popularity tends to be proportional to the amount of influence that a vlogger has over a person, meaning that the most popular vloggers wield an enormous amount of influence over legions of devoted viewers (Ladhari et al, 2020). Naturally, this phenomenon extends beyond just vloggers, and it is not a stretch to say that an object or person’s “popularity” is fundamental to its role in society.

Finally, the PH Index can easily be extended to measure the homophily of an entire directed graph. First compute the PH Index for every node in $O(P + V + E)$ time. $O(P)$ represents the time needed to compute the popularity of every node, and it varies based on the algorithm used. $O(V + E)$ represents the time needed to actually compute the index for each node. Let $PH_n$ represent the value of the PH index for node $n$. The PH Index for the entire graph is simply a weighted average of the PH Index for every node. Once again, we need to weight by popularity, since highly popular nodes have a greater influence on the overall homophily of the graph than less popular.
nodes. Since we normalized the popularity array, the formula is simply the one stated in Equation 4.

\[
PH = \sum_{n \in \text{Nodes}} P_n \times PH_n
\]

Like the classic EI Index, a PH Index value of -1 implies complete homophily, while a value of 1 implies complete heterophily. Most non-homophilic graphs will have a PH index of approximately 0.

6 Experimental Data

This paper demonstrates the use of the PH Index on two sample directed graphs. The first graph is a network of software engineers on Github, a popular website for storing and sharing code (Rozemberczki et al., 2021). Two engineers are connected by a directed edge if one "follows" the other. Additionally, as part of the data, each engineer job has a binary classification and is either a web (0) or a machine learning (1) developer. This information was scraped from the developer profiles by a machine learning algorithm (Rozemberczki et al., 2021). The links in the graph themselves were scraped from the publicly available Github API. The data was collected by researchers at the University of Edinburgh led by Benedek Rozemberczki and accessed from the Stanford Network Analysis Project (Leskovec and Krevl, 2014).

The second graph is a network of political blogs from the run up to the 2004 US Presidential election (Adamic and Glance, 2005). In this graph, a directed edge represents a hyperlink from one network to the other. Each blog has a binary classification as either left leaning (0) or right leaning (1), and the creators of the second graph used a combination of automated and manual labelling to create each label. The data was collected by Lada Adamic and Natalie Glance, and accessed from the KONECT Network Collection (Kunegis, 2013).

For purposes of comparison, two additional attributes were added. For the Github graph, each developer’s username was added. The "name length" attribute was engineered from this information based on whether or not the developer’s username was shorter than 7 characters in length, an arbitrary number. For the political blogs graph, the second attribute was purely random, set to either 0 or 1 with equal probability.

Basic information about the two graphs is listed in Table 1. For both graphs, both attributes are binary variables. Note that assortativity, the classic measure of homophily, ranges from 1 (complete homophily), down to 0 (no homophily), which is a different scale than the PH Index.

A visualization of both graphs is presented in Figures 1 and 2. Note how homophily is clearly visible in both graphs, although in the Github graph, the large number of nodes combined with the relatively small amount of machine learning developers, make it harder to see. The two-dimensional visualizations were made with Graphia (Freeman et al., 2020).

To store and manipulate the Github and Blog data, the python module NetworkX (Hagberg et al., 2008) was used. Both graphs were stored as NetworkX DiGraphs. All three popularity algorithms mentioned above are implemented into NetworkX,
Figure 1: Political Lean in the Blog Graph—Blue represents left leaning blogs, and Red represents right leaning blogs.

Figure 2: Job in the Github Graph—Blue represents web developers, and Red represents machine learning developers.
| Graph  | Nodes ($V$) | Edges ($E$) | Attribute 1 | Assortativity | Attribute 2 | Assortativity |
|--------|-------------|-------------|--------------|---------------|--------------|---------------|
| Github | 37,700      | 2,89,003    | Developer    | 0.378         | Name         | 0.012         |
| Blogs  | 1,224       | 19,025      | Political    | 0.823         | Pure Random  | 0.001         |

| Table 2: Github Graph PH Index |
|--------------------------------|
| Popularity Type | Attribute 1 (Web or ML Developer) | Attribute 2 (Short or Long Name) | Python Computation Time (seconds) |
|-----------------|----------------------------------|----------------------------------|----------------------------------|
| In-Degree Centrality | -0.554                           | -0.067                           | 0.14                             |
| Betweenness Centrality | -0.537                           | -0.003                           | 5077                             |
| PageRank        | -0.461                           | -0.113                           | 5.22                             |

| Table 3: Blog Graph PH Index |
|------------------------------|
| Popularity Type | Attribute 1 (Left or Right Lean) | Attribute 2 (Random Number Generator) | Python Computation Time (seconds) |
|-----------------|----------------------------------|--------------------------------------|----------------------------------|
| In-Degree Centrality | -0.738                           | -0.030                              | 0.14                             |
| Betweenness Centrality | -0.813                           | -0.001                              | 8.11                             |
| PageRank        | -0.709                           | -0.031                              | 0.84                             |

shortening the code required to compute the PH Index significantly. Figure 3 contains the basic python source-code for computing the weighted EI Index for a node. Figure 4 contains the basic python source-code for computing the overall PH Index for a directed graph.

7 Results

Using the code for the PH index, the homophily of each attribute in each graph could be measured. The results are organized in Tables 2 and 3.

While weighting by popularity has a huge impact on the final answer, this impact can be invisible if there are many popular nodes that are both highly homophilic and highly heterophilic.

As an example, the popularity, calculated with PageRank of every node in the Github dataset is plotted below in Figure 5, using the python package Matplotlib.
def WEI(graph, n, keyword, w):
    internal = 0
    external = 0
    if len(graph.edges(n)) == 0: return 0

    for u, v in graph.edges(n):
        if homophilic_edge(graph, u, v, keyword):
            internal += 1
            else:
                external += 1

    # Weight the EI Index
    root = graph.nodes[n][keyword]
    external /= w

    wei = (external - internal) / (external + internal)
    return wei

Figure 3: Find the weighted EI Index of node "n" in digraph "graph", based on attribute "keyword", with a precomputed weight "w"

def PHI(graph, keyword):
    # Compute normalized popularity of all nodes
    P = popularity(graph) # PageRank, In-Degree Centrality, etc.

    # Compute Weighted EI Index for all nodes
    WEIs = []
    for n in graph.nodes:
        w = compute_weight(graph, n, keyword)
        WEIs.append((WEI(graph, n, keyword, w), n))

    # Final value of the index
    index = 0
    for x in WEIs:
        index += (P[x[1]] * x[0])
    return index

Figure 4: Find the Popularity Homophily Index for DiGraph "graph" and attribute "keyword"
(Hunter, 2007). Note that there are a handful of nodes with a huge influence. Consider the most popular 150 developers, 74 of them have a WEI Index below -0.461 (more homophilic than the PH Index), and 76 of them have a WEI Index above -0.461 (less homophilic than the PH Index). Naturally, since this split is so even, weighting by popularity does not have a huge impact on the final answer.

However, we notice a much larger impact of popularity weighting when we consider the second attribute of the Github graph. A developer is defined to have a “short” username if his username is under 7 letters long. Approximately 17% of all developers have a “short” username. However, for some unknown reason, the most popular developers seem to prefer short usernames, meaning that this “random” attribute can and may actually hold significance.

Out of the top 150 developers, who together account for merely 0.4% of the nodes but over 20% of the total popularity of the graph, an astounding 28% have a short username, a statistically significant difference. Due to the intrinsic nature of PageRank, popular nodes tend to have edges leading to other popular nodes, meaning that the most popular nodes tend to be slightly homophilic relative to name length. For this reason, the weighted PH Index relative to name length is -0.113 as opposed to roughly 0, which clearly indicates some amount of homophily.
8 Conclusion

The primary purpose of this paper is to introduce the Popularity-Homophily (PH) Index as a method to compute homophily in directed graphs. The index was tested on two real-world graphs, the Github developer dataset, and the Political Blogs dataset. In both cases, homophily was detected, and as expected from the assortativity coefficient, the magnitude of homophily in the former graph was smaller than the magnitude of homophily in the latter graph.

The major advantage of the PH Index occurs in graphs that are dominated by a limited number of main actors. These actors exert disproportional amounts of influence on the state of the graph, and in the real-world, a handful of homophilic connections to popular nodes can easily outweigh a multitude of heterophilic connections to less popular nodes. The PH Index has some versatility in that one of many possible algorithms can be employed in the first step, to calculate the popularity of each node. In order to decide which algorithm to use, the nature of the real-world data being analyzed must be considered. For most social networks like Twitter or Facebook, the PageRank algorithm is probably the most effective. However, for geographic data, Betweenness Centrality may be more preferable due to the literal connection between that algorithm and geography.

As a warning, the magnitude of the PH Index may be a red herring. The scale is not really linear, as a PH Index of -0.7 demonstrates much stronger homophily over -0.4 than what might be expected. Additionally, the magnitude of the PH Index may have a slightly different meaning in one graph when compared to another graph, since both graphs will have their own unique structure. For this reason, the main conclusions one should draw from the PH Index are in terms of relative magnitude.

9 Future Work

The full relevance and applications of the novel PH Index remain to be seen. Below are a few real-world areas of research where the PH Index may be applicable.

- On social media, are people with one political lean more homophilic than people with the opposite political lean?
- In a particular school, is gender, race, income level, age, etc. the main driver of homophilic relationships?
- In a citation network, professors in which disciplines are the most likely to cite papers written by professors in other disciplines?
References

Lada A. Adamic and Natalie Glance. The political blogosphere and the 2004 U.S. election: Divided they blog. In Proceedings of the 3rd International Workshop on Link Discovery, LinkKDD ’05, page 36–43, New York, NY, USA, 2005. Association for Computing Machinery. ISBN 1595932151. doi: 10.1145/1134271.1134277.

Hui Chang, Bei-Bei Su, Yue-Ping Zhou, and Da-Ren He. Assortativity and act degree distribution of some collaboration networks. Physica A: Statistical Mechanics and its Applications, 383(2):687–702, 2007. ISSN 0378-4371. doi: 10.1016/j.physa.2007.04.045.

James S. Coleman. Introduction to mathematical sociology. Free Press of Glencoe, New York, 1964.

Elanor Colleoni, Alessandro Rozza, and Adam Arvidsson. Echo chamber or public sphere? Predicting political orientation and measuring political homophily in Twitter using big data. Journal of Communication, 64(2):317–332, 03 2014. ISSN 0021-9916. doi: 10.1111/jcom.12084.

Tom C. Freeman, Sebastian Horsewell, Anirudh Patir, Josh Harling-Lee, Tim Regan, Barbara B. Shih, James Prendergast, David A. Hume, and Tim Angus. Graphia: A platform for the graph-based visualisation and analysis of complex data. bioRxiv, 2020. doi: 10.1101/2020.09.02.279349.

Benjamin Golub and Matthew O. Jackson. Network structure and the speed of learning measuring homophily based on its consequences. Annals of Economics and Statistics, 107/108:33–48, 2012. ISSN 21154430, 19683863. URL http://www.jstor.org/stable/23646571.

Aric Hagberg, Pieter Swart, and Daniel Chult. Exploring network structure, dynamics, and function using NetworkX. Technical report, Los Alamos National Laboratory, 2008.

John D. Hunter. Matplotlib: A 2D graphics environment. Computing in Science Engineering, 9(3):90–95, 2007. doi: 10.1109/MCSE.2007.55.

Jérôme Kunegis. KONECT: The Koblenz network collection. In Proceedings of the 22nd International Conference on World Wide Web, WWW ’13 Companion, page 1343–1350, New York, NY, USA, 2013. Association for Computing Machinery. ISBN 9781450320382. doi: 10.1145/2487788.2488173.

Riadh Ladhari, Elodie Massa, and Hamida Skandroni. YouTube vloggers’ popularity and influence: The roles of homophily, emotional attachment, and expertise. Journal of Retailing and Consumer Services, 54:102027, 2020. ISSN 0969-6989. doi: 10.1016/j.jretconser.2019.102027.

Jure Leskovec and Andrej Krevl. SNAP Datasets: Stanford large network dataset collection. http://snap.stanford.edu/data, June 2014.
Miller McPherson, Lynn Smith-Lovin, and James M Cook. Birds of a feather: Homophily in social networks. *Annual Review of Sociology, 27*(1):415–444, 2001. doi: 10.1146/annurev.soc.27.1.415.

M. E. J. Newman. The structure and function of complex networks. *SIAM Review, 45*(2):167–256, 2003. doi: 10.1137/S003614450342480.

Lawrence Page, Sergey Brin, Rajeev Motwani, and Terry Winograd. The PageRank citation ranking: Bringing order to the web. Technical Report 1999–66, Stanford InfoLab, November 1999. URL http://ilpubs.stanford.edu:8090/422/.

Ian Rogers. The Google Pagerank algorithm and how it works, 2002. URL http://www.iprcom.com/papers/pagerank.

Benedek Rozemberczki, Carl Allen, and Rik Sarkar. Multi-Scale attributed node embedding. *Journal of Complex Networks, 9*(2), 05 2021. ISSN 2051-1329. doi: 10.1093/comnet/cnab014.

Mike Thelwall. Homophily in MySpace. *Journal of the American Society for Information Science and Technology, 60*(2):219–231, 2009. doi: 10.1002/asi.20978.

Jianshu Weng, Ee-peng Lim, and Jing JIang. TwitterRank: Finding topic-sensitive influential twitterers. In *Proceedings of the third ACM international conference on Web search and data mining*, pages 261–270, 2010.

Yang Xu, Alexander Belyi, Paolo Santi, and Carlo Ratti. Quantifying segregation in an integrated urban physical-social space. *J. Roy. Soc. Interface, 16*:20190536, 2019. doi: 10.1098/rsif.2019.0536.

Junlong Zhang and Yu Luo. Degree centrality, betweenness centrality, and closeness centrality in social network. In *Proceedings of the 2017 2nd International Conference on Modelling, Simulation and Applied Mathematics (MSAM2017)*, pages 300–303. Atlantis Press, 2017/03. ISBN 978-94-6252-324-1. doi: 10.2991/msam-17.2017.68.