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# TOP BRAND ALTERNATIVE MEASUREMENT BASED ON CONSUMER NETWORK ACTIVITY

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In business intelligence effort, the legacy methodology to measure product brand awareness use techniques such as surveys, interviews, and questionnaires. This methodology requires expensive effort to collect data from respondent and takes considerably time to accomplish. The availability of Big Data in the form of social media interaction can benefit us. The conversation and user generated content from social media certainly can be used to measure brand awareness through consumer activity. We use Social Network Analysis methodology to measure the dynamic and evolution of brand conversations in social media. By comparing the network properties, we propose new alternative measurement methods of product brand awareness. Our proposed methodology is better adapted to large scale conversational data in social media. This measurement will also enhance the current methodology by viewing consumer opinions as a whole network and not as separated individual. This study is conducted via social networking conversations on Twitter using two industry case studies, they are the mobile operators and mobile phone brands in Indonesia.

Keywords: Brand Awareness, Social Network Analysis, Network Properties, User Generated Content, Social Media.

# 1. INTRODUCTION

Nowadays, There are many ways to measure the popularity of a brand by using brand awareness. Brand awareness is the ability of a prospective buyer or consumer to recognize or recall a brand that is part of a particular product category [1]. Brand awareness is not only a memory but also a learning process for consumers to a brand. One of reputable brand ranking in Indonesia market is called Top Brand awards.

Top Brand Award is an award given to the brands of consumer choice. This award can be seen as a representatives of product brand awareness from the consumer point of view. It is de facto standard of product brand awareness in Indonesia. In determining the ranking of those brands, they use legacy methodology through surveys and interviews in eleven major cities in Indonesia including Jakarta, Bandung, Semarang, Surabaya, Medan, Makassar, Pekanbaru, Balikpapan, Denpasar, Palembang,

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and Samarinda. The criteria seen in *Top Brand Award* are called *Top Brand Index*, in which the measurement consist of three sub measurement: *top of mind share, top of market share*, and *top of commitment share* [2]. The bigger number index means they considered as top brand award in their respective category. The ratings obtained in the category of mobile phones and mobile operators from Top Brand 2015 awards [2] are shown in Table.1 below:

Table-1. Top Brand Award

BRAND	Top Brand Index
Samsung	29.7%
Blackberry	24.7%
Nokia	16.7%
iPhone	4.5%
Smartfren	3.8%
Cross	3.0%
Advan	2.9%
Mito	2.5%

Lenovo	2.4%		
Oppo	2.3%		

(a) Mobile phone category

BRAND	Top Brand Index
Simpati	34.6%
XL Prabayar	14.1%
IM3	14.0%
Kartu AS	10.1%
Tri '3'	9.0%
Axis	6.9%

(b)Pre-paid simcard category

BRAND	Top Brand Index
Halo	54.8%
XL Pascabayar	15.4%
Matrix	10.8%
Telkom Flexi Pascabayar	7.3%
Smartfren Pascabayar	6.8%
Esia Pascabayar	3.1%

(c)Post-paid simcard category

The increasing number of user activity on online social network services such as *Twitter*, *Facebook*, *Instagram*, *etc.* produce large scale social conversation data about brands in the form of opinions, reviews, and sentiments. This behavior certainly an advantage for companies to extract consumers attitude toward their products. This is part of social network data analytics methodology [3]. Heuristically, we can construct metrics to measure this consumer voices to brand awareness related topics.

In extracting consumer voice, we have several choices. First we can implement sentiment analysis to all user posts, but this process is slow, expensive, and impossible to handle large scale conversation data such as in social media. Second choice, as an alternative of the first choice, we extract unstructured and incomplete information using graph formulation [4][5]. The graph formulation only need a user information and their relationship with other users. This methods is called *Social Network Analysis* (SNA) [6][7].

SNA is faster and cheaper to construct compare to legacy methodology. Based on Graph Theory, we also have advantage with the availability of many graph based metric which can help us to measure the dynamics and evolution of users around brand conversations. SNA basically measure the dynamics of market, information dissemination, word-of-mouth mechanism, communities formations, etc. SNA view that consumer voices are not isolated incident. They are influenced by neighborhood opinions, this is why representing consumer dynamics as social network is representative model to the real world problem. On the other hand, legacy methodology measures consumer voice by in depth and rigorous exploration. In some case, this methods is not desirable, since the management need fast, probably in real time feed information to support decisive decision making process [8][9].

In this paper, we propose alternative measurement of brand awareness based on consumer network activity. Our research do not specifically doing

depth analytical effort on specific brands mentioned in Table 1. We use those brands as our case study to test our proposed methodology, because they are mentioned in *Top Brand Awards*.

The advantage of our methods is faster measurement process facing uncertainty in processing large-scale data from social media, incomplete data profile and complexity relationship of consumer activities in social media. This methods will certainly support large-scale data summarization and real time decision making process. Our experiment use *Twitter* conversations data for 7 days periods regarding two case studies of mobile operators: *Telkomsel*, *XL*, *Indosat* and mobile phones brands: *Samsung*, *Apple*, *Blackberry*, *Nokia* in Indonesia.

#### 2. SOCIAL NETWORK METHODOLOGY

Social Network Analysis (SNA) is a study of the relationship of individuals or other social units, such as an organization, to determine the dependence of the behavior associated with social relationships. In this relationship, described in a node and link. Node is an actor in a network and the link is a line connecting a node with other nodes [6].

We formulate the model as graph G(N.E) where  $N=\{n_1,n_2,...,n_i\}$  is a set of nodes and  $E=\{e_1,e_2,...,e_j\}$  is a set of edges. |N| is a number of nodes in the network and |E| is a number of edges in a network. The network has some attributes or certain properties that can be calculated and analyzed. The properties of this network are used to determine the model of a network and analyze it with other network model called network property [7]. We show several network properties formulation used in this measurement in Table-2.

The explanation of network properties used in this measurement (shown in Table-2) are as follows: Size shows the number of nodes and the number of edges exist in a network. Density means the ratio of the number of current edges to the number of possible edges in a network. Modularity is a measurement of how different group formed in network and how many group formed, bigger modularity value means there is a distinct border between each group, while smaller modularity value means fuzzy distinction between groups in a network. Diameter measures the longest distance between a pair of nodes, the smaller diameter is preferred in order to facilitate easier (faster) communication. Average Degree means average number node degree in the network, the greater average degree means network is easier to disseminate information and facilitate shortest path formation. Average Path Length shows the average number steps to take from a node to another node in the network, smaller average path length is preferred to facilitate faster transfer information. Clustering Coefficient illustrate how a node associated with other node in vicinity, the greater value means the relationship will be denser / clustered, which leads to formation of shortest path. Connected Component is a network component that is connected with at least one edge to other component, the smaller number component means

the network will clustered to only few big component.

Table-2. Network Properties and Formulation

Network	Formulation				
Property					
a.	E  = number of edges, $ N $ = number of				
Size	nodes				
Density	$Den = \frac{E}{(N)^*(N-1)}$				
	where $( N *( N)-1)$ ) is a maximum number				
	of edges				
	$M = \frac{1}{2m} {}_{ij} (A_{ij} \frac{k_i k_j}{2m}) (C_i, C_j)$				
	where A <sub>ij</sub> is number of edges inside the				
Modularity	community				
	k <sub>i</sub> kj/2m is expected number of connection				
	between node i and node j				
	$\delta(C_i, C_j)$ is the kronecker delta which equal				
	1 if $i = j$ , and otherwise is 0				
	$D = \max(d_{i,j})$				
Diameter	where $d_{i,j}$ is the shortest distance between				
	any pair node				
Avanaga	AvD =  E / N				
Average Degree	where $ E $ = number of edges, $ N $ =				
Degree	number of nodes				
Average Path	$APL = \frac{1}{n(n-1)} \int_{i}^{\infty} d(v_i, v_j)$				
Length	where n is number of nodes in G				
	$d(v_i,v_j)$ is the shortest distance between				
	node $v_i$ and node $v_j$				
Average Clustering Coefficient	$\overline{C} = \frac{1}{n} \sum_{i=1}^{n} C_i$				
	where $C_i$ is local clustering coefficient				
	value				
	n is the number of node in network				
Connected	Connected Component contains 's', set of				
Component	all nodes which can be reached from 's'.				

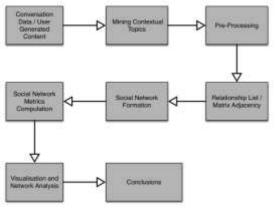


Figure-1. The research workflow

The workflow of our methodology are explained as follows: First, we decide which social media that we want to extract the information. The considerations are including which

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social media considered representatives to capture consumer voices. Second, we define and mine the topics that are representatives to the brand, this step including deciding which keyword, hashtag, or location to be captured. Third, the preprocessing step, where we remove / filter unrelated posts / tweets to our research topics. For example some tweets with keyword "XL" are tweets about size measurement, while we want to extract keyword "XL" contextual to cellular provider. In this case, in pre-processing step, we filter out unrelated tweets to our contextual research. Fourth, The interaction between actors are converted to an edge list or a matrix adjacency. The fifth and the sixth steps, we construct a social network and do metrics calculations. The two last step, we visualize the network topology, analyze the network, create the story and conclude the research.

## 3. CASE STUDY OF NETWORK MEASUREMENT

We collect conversation data from *Twitter* about mobile operators and mobile phones during last quarter in 2015. For mobile operator, we collect conversational data about *Telkomsel, XL* and *Indosat*. For mobile phones, we collect conversational data about *Samsung, Nokia, IPhone*, And *Blackberry*. All tweets are either location in Indonesia and in Bahasa. Ranks in each network property signify what is the preference of social network according to their definition in chapter 2, some properties prefer smaller number and other prefer higher number.

In mobile operator's industry, according to top brand award, both pre-paid and post-paid SIM Card is achieved by *Telkomsel*, the second is *XL* and the third is *Indosat*. Measurement from our social network methodology are shown in Table-3. Ranks are shown on each network property. The network visualization on each mobile operator are shown in Figure 2.

**Table-2.** Social network measurement for mobile operator's industry

Network	Telkomsel	XL	Indosat	Rank	
Property	<b>(T)</b>	(X)	(I)		
Size	8333 nodes	4164	3772	1. T	
	11084	nodes	nodes	2. X	
	edges	6375	4663	3. I	
		edges	edges		
Density	0.00055	0.00064	0.00056	1. X	
				2. I	
				3. T	
Modularity	0.491	0.864	0.751	1. T	
				2. I	
				3. X	
Diameter	15	17	18	1. T	
				2. X	
				3. I	
Average	2.615	3.063	2.474	1. X	
Degree				2. T	
				3. I	
Average	3.384	5.582	4.861	1. T	
Path				2. I	
Length				3. X	
Clustering	0.598	0.450	0.490	1. T	
Coefficient				2. I	
				3. X	
Connected	485	296	352	1. X	
Component				2. I	
				3. T	
6 6612/2011/4/400/008 doi:10.1166/asl.201					

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In mobile phone brands, according to top brand award, the first ranks is *Samsung*, followed by *Blackberry*, *Nokia*, and the last is *iPhone*. The social network visualization for mobile phone brands are shown in Figure 3. The network metric calculations and ranks are shown in Table 3.

To summarize overall brand measurement, we give higher weight score in each network property e.g. if a brand is in rank 1 then it gets 4 point in mobile phone brand and gets 3 point in mobile operators. We get overall brand ranks using social network measurement as sequential with sum value as follows: Mobile phone (Samsung(25), Nokia(22), IPhone(19), Blackberry(14)) and Mobile Operator (Telkomsel(17), Indosat(12), XL(11))

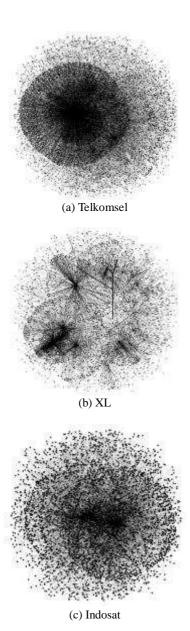


Figure-2. Mobile operators social network visualization

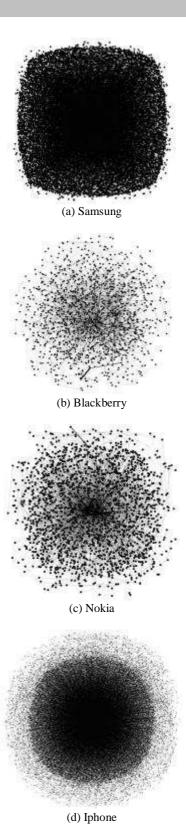


Figure-3. Mobile phone social network visualization

**Table-3**. Social network measurement for mobile phone industry

Network Property	Samsung (S)	Blackberry (B)	Nokia (N)	IPhone (I)	Rank
Size	11450 nodes 12805 edges	1381 nodes 1205 edges	1893 nodes 1604 edges	21014 nodes 21593 edges	1. I 2. S 3. N 4. B
Density	0.000017	0.000011	0.000054	0.000061	1. I

					2. N
					3. S
					4. B
Modularity	0.847	0.945	0.938	0.921	1. S
					2. I
					3. N
					4. B
Diameter	19	20	10	25	1. N
					2. S
					3. B
					4. I
Average	2.237	1.7455	1.661	2.055	1. S
Degree					2. I
					3. B
					4. N
Average	4.342	7.295	3.691	6.160	1.N
Path					2. S
Length					3. I
					4. B
Clustering	0.378	0.258	0.317	0.244	1. S
Coefficient					2. N
					3. B
					4. I
Connected	646	302	361	2329	1. B
Component					2. N
_					3. S
					4. I

## 4. NETWORK MARKET ANALYSIS

From mobile operator's industry, on each network properties measured, there are differentiation between SNA methodology on network property and legacy methodology, except size, diameter, modularity, and clustering coefficient network properties. In network Size and Diameter shows that Telkomsel has the larger size and shorter diameter, this signify that Telkomsel market in Twitter are more active and faster to deliver message to its member than other operators. XL is better in Density, Average Degree, and Connected Component. It shows that actors in XL market networks is more connected, has making larger number of conversations / connections, and fewer separate component / group than other operators. From the market size context *Telkomsel* is better, but from probability of information dissemination XL is better.

From mobile phone brands, there are also differentiation in SNA methodology on each network property and legacy methodology measurement. *iPhone* market network is larger and denser than any other brands, this shows that *iPhone* network has more conversations than any other brands and better possibilities to disseminate information to network member. *Samsung*, while it is the best brand in legacy methodology, their market network is only the best on *modularity*, *average degree*, and *clustering coefficient* network properties. These measurements show that Samsung does not have a distinct group, means that information can flow freely with almost the same probabilities to each member, in other words, information does not trap into a group of high connected actors.

Figure-2 and Figure-3 shows network visualization of both mobile operator's industry and mobile phone markets. The visualization help us to compare network characteristic, such as network size comparison, some network has larger and denser

comparing to others, some has distinct group such as *XL* or *Telkomsel* networks. But for deeper understanding of network characteristic, we need to calculate each network properties to see invisible network characteristics.

## 5. CONCLUSIONS

In the era where data is hard to get, market size are mostly measured by the number of potential buyers. This view is too simple to represent what happen in the market today. Market is really dynamic where people can acquire, transfer, influence their opinions, sentiments, recommendations to others very easy. Social media accelerate this market dynamic activity. Those dissemination of information can be captured by SNA methodology through respective metric based on network property. In classical brand awareness measurement, the approach are gathering individual perception about brand in question. This approach does not capture the dynamic market or how individual acquire their knowledge.

The result of brand ranking using legacy methods and SNA method are different. As expected, this is because SNA measures social network dynamics of the market, while legacy methods measure property of each sampled individual with complete and in-depth exploration. We argue that SNA methodology are better adapted to the future of Big Data era for the reason of processing speed.

If we need fast methods to measure brand awareness and given large scale data available, we can use SNA methodology. Otherwise, if we have time to explore or in need of high accuracy result, then legacy methodology still a good choice. However, in the era of high business competition like today, fast methods and probably close to real time are needed more than ever.

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