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Social Network Analysis: Identification of Communication and Information Dissemination (Case Study of Holywings)

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ABSTRACT

Social media especially Twitter has been used by corporation or organization as an effective tool to interact and communicate with the consumers. Holywings is one of the popular restaurants in Indonesia that use social media as a tool to promote and disseminate information regarding their products and services. However, one of their promotional items has gone viral and invited public protests which turned into a trending topic on Twitter for a couple of weeks. Holywings allegedly improperly promoted their products by using the most honorable names, "Muhammad" and "Maria". Social network analysis of Twitter data is conducted to identify and examine information circulating among the users, which leads to wider public attention and law enforcement. In this study, we focused on the conversation about Holywings on Twitter from 24 June to 31 July 2022. The analysis was carried out using Python to retrieve data and Gephi software to visualize the interactions and the intensity of the network group in viewing the spread of information. The findings reveal the centrality account that caused the news to go viral are the CNN Indonesia (@CNNIndonesia) news media account and Haris Pertama (@knpiharis), with a centrality of 0.161 and 0.282, respectively. There are also 121 groups involved in the conversation with modularity of 0.821.

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1. INTRODUCTION

There are about 191.4 million social media users from the 273.4 million population in Indonesia are social media users. With the proliferation of data dissemination media on social media, social media users can quickly get data or information about everything [1]. The level of community response in the digital era has proven to be more responsive to events, phenomena, positive and negative sentiments in the development of social life in the real world or in the virtual world [2]

With so many active users of social media in Indonesia, it is not surprising that many brands are taking advantage of social media platform to disseminate information, such as notifying new products, conducting promotions to get benefits [3]. Twitter is one of the popular platforms widely used by Indonesians due to its features to provide information in a simple format, wide networks with segmented topics/conversations, and the ability to receive and forward information at the fingertips. Furthermore, Twitter provides benefits for the government, private sector, community, and business actors who are looking for free and simple tools to disseminate general and important information rapidly [4]. Businesses launch promotional activities to market their products in many ways by doing advertisements on tv, making banners, advertising on social media, including paying influencers or artists to disseminate information about their products [5].

One of the popular restaurants in Indonesia, namely Holywings, which has bar facilities with a variety of drinks and food, also uses Twitter social media for promotions. One of the promotions launched by this restaurant is free alcoholic drinks every for customers named "Muhammad" and/or "Maria". This advertisement went viral as many users of social media especially in Twitter, questioned about the motives and the marketing strategy initiated by the team. The advertisement was then taken down due to continuous criticism and protestation from various parties, accompanied by police reports [6]. Consequently, Holywings received notification from the authorities for the immediate closure of all their outlets. The rapid information circulated over Twitter has made this case viral and sufficient to draw public attention and authorities to take action.

Today, conversation in social media has been used as well by the authorities for various purposes, such as law enforcement, preserving public trust, including public awareness with regard to pandemic situation (Covid19) [7]. The public health information related to government recovery programs is somehow disrupted due to highly decentralized, fragmented, and loosely connected conversations around COVID-19 Eva et.al applied sentiment and social networks analysis on the dissemination of vaccination information on Twitter using the naive Bayes method as well as Sentiment Network Analysis resulted that 92% of Twitter user sentiment was positive for the Covid 19 vaccine and actors who the most important role in disseminating information was identified the President himself [8].

In this study, the researchers used measurement parameters in Social Network Analysis (SNA) to measure and map the scope that the researchers studied. Due to the flexibility and objectives to be achieved from the results of processing and analyzing the data in accordance with the characteristics of the human relationship itself, which is translated into words on Twitter social media [9]. Researchers used the Intact Group Comparison experimental method in determining centrality, implicity, and grouping with six stages, namely determining representative samples, instrumentation, conducting experiments, collecting and analyzing data, and for experiments using Gephi and Python to see the level of spread of Holywings data [10].

Therefore, this research was conducted to examine and analyze the pattern of delivery of information regarding the promotion of Holywings and to identify the dissemination of information through the network using Social Media Network Analysis [11]. So that this finding shows a visualization of the spread of Holywings promotional news that had resulted in harm to Holywings from June 22, when the news was uploaded to date, as well as identifying the values of centrality, influence, and clustering.

2. METHOD

This study is conducted through several stages, including data collection, Intact Group Method, Analyzing edges nodes, finding centrality influential, and grouping.

2.1. Data Collection

The data collection method using the library method is carried out by collecting journals, literature, papers, papers, books, and internet sites as library resources related to writing material, especially in sentiment analysis. Literature study also means data collection techniques by reviewing books, literature, notes, and various reports related to the problem to be solved [12]. The observation technique is one of the data collection techniques used by researchers to systematically observe and record the object under study, both in situations that actually occur.

2.2. Intact Group method

a. Determination of a representative sample
Researchers determine the technique of collecting samples in accordance with the research. Twitter data is realtime, therefore the researcher uses a non-probability sampling method, which is an accidental sampling technique where the researcher uses the data encountered during the data collection stage, and any interested data will be included in the data sample [13]. The researcher uses all data that is in

accordance with the characteristics of the research sourced from Twitter, then any tweet data that appears will match the keywords holywing, maria, and Muhammad [14].

b. Instrumentation

In the instrumentation stage, the researcher used multi nodes in the final result. The reason the researchers chose the multi-node method is to make the process easier and can also be arranged and divided equally among the nodes involved.

c. Collection

Data collection is used through social media Twitter in the form of tweets. Data collection is done by retrieving data on Twitter using Python with google collab tools, the data drawn there are 516 data obtained about Holywings, Muhammad, and Maria from the Indonesian language [15].

d. Data analysis

After getting the data that has been drawn, the data is analyzed by distinguishing the data that is considered as nodes or data edges, after that the analytical calculations are carried out using Python and tested using Gephi.

e. Experiment

Experiments were also carried out using the gephie tools to see the accuracy results of the two experiments using python and gephie tools.

2.3. Research Flow

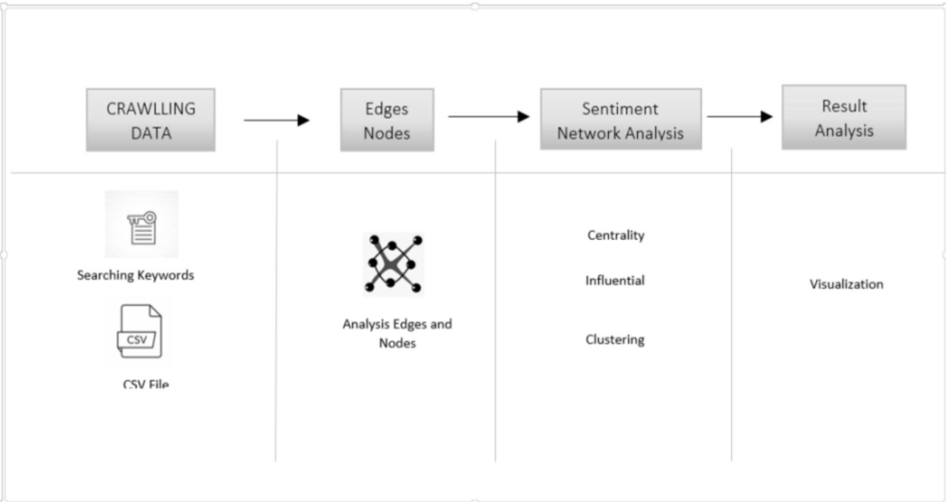

Figure 1. Social Network Analysis

a. SNA (Social Network Analysis)

Social network analysis is the process of mapping and analyzing human interactions. SNA can be used to obtain information such as interactions and friendships between users, which are described as graphs. SNA helps to understand social relationships that represent users with nodes (nodes), and relationships between users are represented by lines (edges) on the Online Social Network (OSN) [16].

b. Crawling the data

This study crawled on Twitter through the Twitter API using the tweepy module in the Python programming language [17]. The key data scrawled is "Holywings Muhammad Maria". After that, the raw tweet dataset is stored in the form of .xlsx, which will be further processed later. Data crawling took place on June 24, 2022. The data was collected from 516 tweets [18].

c. Analysis Edges and Nodes

SNA helps to understand the social relationships that symbolize the user with points (nodes) and the relationship between users is represented by lines (edges) in Online Social Network. The edges are username tweet. edges are Twitter account users, while nodes are tweets from Twitter account users. social network analysis using the retweet network connected using various nodes. Node shows the account associated with the conversation [19].

d. Implementation

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Implementation of data processing using python to obtain visualization results as well as centrality, influential, and clustering.

3. RESULT AND DISCUSSION

3.1. Crawling Data

When crawling data from twitter about Holywings with the keywords Holywings, Maria, Muhammad, 516 data related to this data were retrieved.

Table 1. Crawling Data Result

Algorithm 1. Crawling Data
Input
Input api_key
Api_secret
Acces_token
Acces_secret
Keywords Holywings Hana Muhammad
Output
CSV Files
Download

username	**tweet**
knpiharis	Holywings sudah mulai kembali bukaâ€¦. Kuat sekali Holywings ya padahal telah menghina 2 nama suci yaitu Muhammad dan Maria.
PDemokratjkt	Ketua Komisi A DPRD DKI Jakarta @RAMujiyono meminta Pemprov DKI Jakarta mengakomodir eks karyawan Holywings ditangkap
@moonareas	wkwk nama barunya Holywings

3.2. Implementation

Here are the results of preprocessing by taking one sample text. Starting from the raw data from the results of the crawling process, then preprocessing.

Table 2. Input Data

Algorithm 1. Input Data
Input
df = pd.read_csv('/content/drive/Mydrive/Colab Notebooks/Holywings.csv', sep = ";
Output
Edges Nodes

3.3. Nodes Edges

For automatic labeling is done using Python TextBlob. Here's a python script to do auto-labeling.

Table 3. Nodes Edges

Algorithm 1. Nodes Edges		
Input us_gaph.nodes()		
Output Graph with 588 nodes and 481 edges		
With the following result:		
0	Edges	Nodes
1	HK	CNNIndonesia
2	VANO OPEN fastrep wa di bio!	captain
3	VANO OPEN fastrep wa di bio!	Captain
4	ANTOINE VARANE. ???? ??JKT	CNNIndonesia

3.4. Visualization

Data visualization is the final stage of the public figure sentiment analysis process. This stage is the stage for visualizing the data that has been obtained in the form of diagrams, graphs, charts, and so on. The results of the visualization will display a graph [20].

Table 4. Visualization

Algorithm 1. Visualization
Input
nx.draw(us_graph,with_labels=True)
Output
visualization

With the following result:

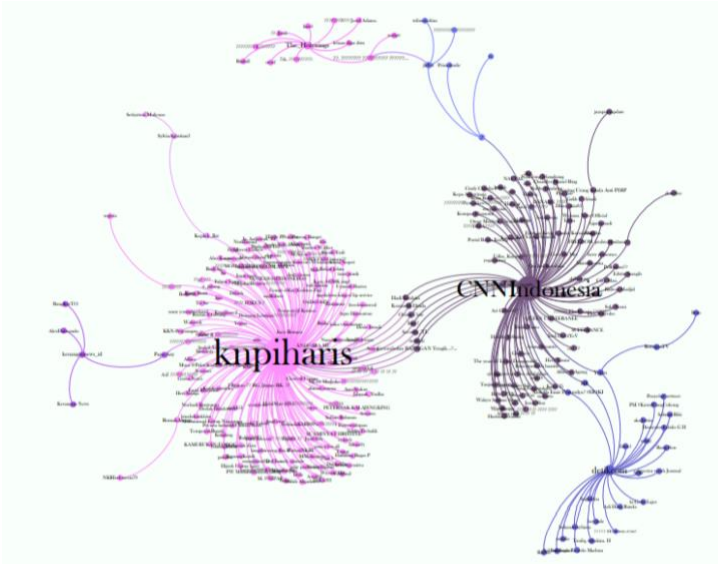

Figure 2.

The graph above describes a visualization in which the knpiharis account is the most influential account in the spread of holywings news, and the CNNIndonesia account is the first initial centrality account of the news of the holywings case rising. As can be seen there are several nodes such as detik.com, holywings website and others as the source of the news spread regarding the issue.

3.5. Centrality

Table 5. Centrality

Algorithm 1. Centrality
Input
Nx.degree_centrality(us_graph)
Output
'@Utun Rebon': 0.0017035775127768314, 'A-Z ????????????': 0.0017035775127768314, 'ANGGARA MU': 0.0017035775127768314, 'ANTOINE VARANE. ???? ??JKT': 0.0017035775127768314, 'Anisa?': 0.0017035775127768314, 'Abang rifqi ???? ??': 0.0017035775127768314, 'Abdul': 0.0017035775127768314, 'Abdulla Emir Pramudya? #HOKI': 0.0034071550255536627, 'Abi': 0.0017035775127768314, 'Abu Karan': 0.0017035775127768314, 'Adericky Yakub': 0.0017035775127768314, 'Adi Hans Randa': 0.0017035775127768314, 'AdiPPJ02': 0.0017035775127768314, 'Adi pati RANGGOLAWE': 0.0017035775127768314, 'Agus': 0.0017035775127768314, 'Agus Darmawan': 0.0017035775127768314, 'Agus Dimyati': 0.0017035775127768314, 'Ahmad Daud M': 0.0017035775127768314, 'Ahmad Yani': 0.0017035775127768314, 'Ajo Ali Bursi': 0.0017035775127768314, 'Alan Nugrohadi':[redacted]0.0017035775127768314, 'Albertus Agung': 0.0017035775127768314, 'AlexHaiwondo': 0.0017035775127768314, 'Alfian': 0.0017035775127768314, 'Alimugusi': 0.0017035775127768314, 'Allen Walker': 0.0017035775127768314, 'Amarasjd1': 0.0017035775127768314, 'Ami Syakur': 0.0017035775127768314, 'Anang': 0.0017035775127768314, 'Anang Susanto': 0.0017035775127768314, 'Andri.Rafly.Dzaki': 0.0017035775127768314, 'Andril Anwar??????????????????': 0.0017035775127768314, 'AngGreat': 0.0017035775127768314, 'AntiDungu2022': 0.0017035775127768314, 'Ari Gilbert07': 0.0017035775127768314, 'Arif M Iqbal': 0.0017035775127768314, 'Arya':

0.0017035775127768314, 'Athlafuzsc': 0.0017035775127768314, 'Awal02\x99': 0.0017035775127768314, 'Awi': 0.0017035775127768314, 'BASEGNOS': 0.0017035775127768314, 'BUNG-AJA': 0.0017035775127768314,

Table 6. Centrality Sorted

Algorithm 1. Centrality Values

Input

Sorted(nx.degree_centrality(us_graph).values())

Output

[0.0017035775127768314, 0.0017035775127768314, 0.0017035775127768314, 0.0017035775127768314,
0.0017035775127768314, 0.0017035775127768314, 0.0017035775127768314, 0.0017035775127768314,
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0.0017035775127768314, 0.0017035775127768314, 0.0017035775127768314, 0.0017035775127768314,
0.0017035775127768314,

After sorted the centrality and the highest result from degree centrality with number `0.161839863713799`

3.6. *Influential*

Table 7. Influential

Algorithm 1. Influential

Input

Most_influential = nx.degree_centrality(us_graph)

Output

```
knpiharis 0.282793867120954
CNNIndonesia 0.161839863713799
detikcom 0.040885860306643956
NyaiiBubu 0.027257240204429302
The_Holywings 0.017035775127768313
one_moslem1 0.01192504258943782
abu_waras 0.010221465076660989
convomf  0.008517887563884156
Coconuts_Bali 0.0068143100511073255
toplevel_view 0.0068143100511073255
? 0.0068143100511073255
keuangannews_id 0.0068143100511073255
jidtat 0.0068143100511073255
JAGALKADRUN1312 0.0051107325383304945
Yolan 0.0051107325383304945
??. ???????? ?????????? ?????????? ??????. 0.0051107325383304945
```

3.7 Clustering

Table 8. Clustering

Algorithm 1. Clustering

Input

nx.clustering(us_graph)

Output

Algorithm 1. Clustering


```
{'!': 0, '#ANIES2024INDONESIA#': 0, '#LogikaSederhana': 0, '#MujahidBetawie????????': ':
0, '??BINTANGtimur??': 0, '??gî? §?Þû\x86??': 0, "??w??'labus": 0, '': 0, 'ANGGARA MU':
0, 'ANTOINE VARANE. ???? ??JKT': 0, 'ANisa?': 0, 'Abang rifqi ???? ??': 0, 'Abdul': 0,
'Abdulla Emir Pramudya? #HOKI': 0, 'Abi': 0, 'Abu Karan': 0, 'Adericky Yakub': 0, 'Adi
Hans Randa': 0, 'AdiPPJ02': 0, 'Adipati RANGGOLAWE': 0, 'Agus': 0, 'Agus Darmawan': 0,
'Agus Dimyati': 0, 'Ahmad Daud M': 0, 'Ahmad Yani': 0, 'Ajo Ali Bursi': 0, 'Alan
Nugrohadi': 0, 'Albertus Agung': 0, 'AlexHaiwondo': 0, 'Alfian': 0, 'Alimugusi': 0, 'Allen
Walker': 0, 'Amarasjd1': 0, 'Ami Syakur': 0, 'Anang': 0, 'Anang Susanto': 0,
'Andri.Rafly.Dzaki': 0, 'Andril Anwar???????????????????': 0, 'AngGreat': 0,
'AntiDungu2022': 0, 'Ari Gilbert07': 0, 'Arif M Iqbal': 0, 'Arya': 0, 'Athlafuzsc': 0,
'Awal02\x99': 0, 'Awi': 0, 'BASEGNOS': 0, 'BUNG-AJA': 0, 'Ba9v5 PTY-': 0, 'Badir03': 0,
'Bang Ron': 0, 'BangKarTO': 0, 'Baru Lagi': 0, 'Bekti': 0, 'BeruangKutub': 0, 'Bobby
Ibrahim': 0, 'Boeng Moedji Hassan': 0, 'Budi Sp': 0, 'CNNIndonesia': 0, 'Cabey ???': 0,
'Cave Man': 0, 'Cemiti eMas {Golden Pin}': 0,
```


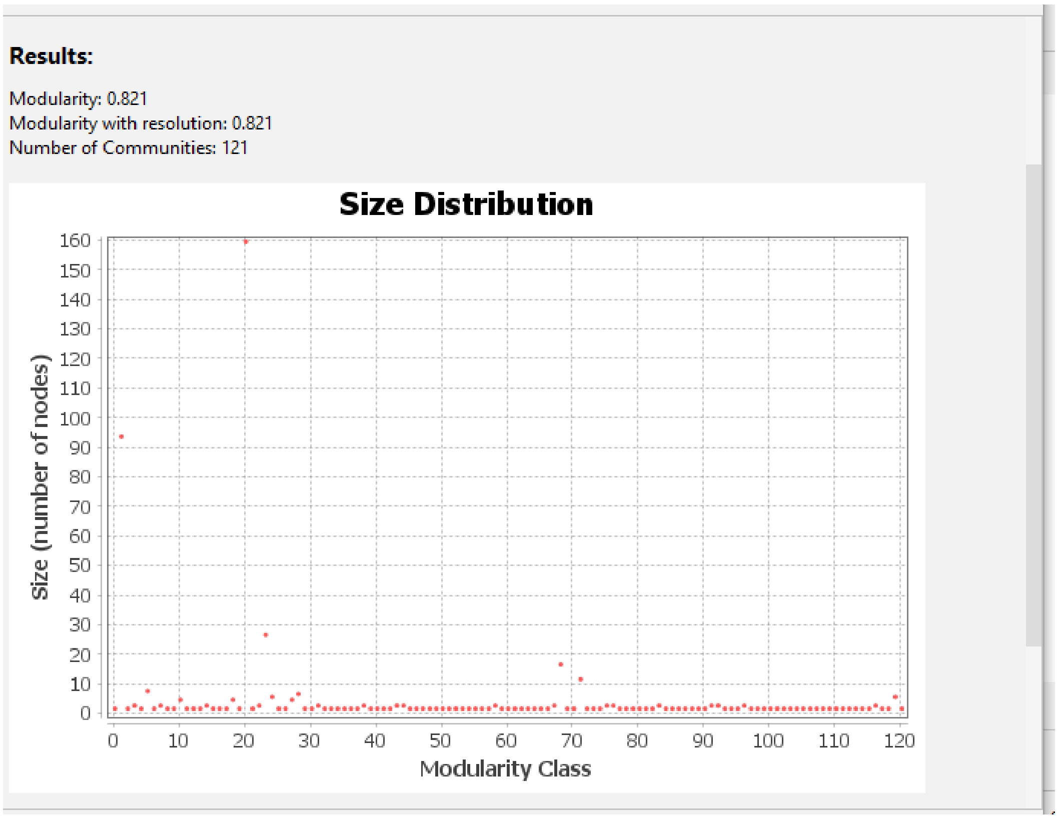

Figure 3. Clustering

As for the clustering, there are 121 groups with a modularity of 0.821 that affect the rise or fall of Holywings cases from Twitter tweets that are incorporated.

4. CONCLUSION

Sentiment Network Analysis can also be used in the future for new research in identifying the most influential, centrality accounts in news cases. SNA is very useful to identify the centrality of news spread and examine how the information is disseminated across the networks. This study has demonstrated how the identification of news viral is done using centrality, influential and clustering analysis. The centrality account or the first that caused this news to viral was the CNN Indonesia news media account then followed by the influential account by the name of knpiharis which caused many Twitter users to retweet the text. Consequently, the promotional campaign initiated by the Holywings hit Twitter trending topic for a couple of weeks and has drawn attention from the authorities due to police reports lodged by various parties. Consequently, the company suffered losses and needed to close 11 outlets permanently.

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