Uncovering the Dynamic Interplay of YouTube Co-commenter Connections through Contextual Focal Structure Analysis

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Abstract- Contextual Focal Structure Analysis (CFSA) model aims to improve the discovery and interpretability of focal structure spreaders on social networks. This method can present influential sets of commenters and contexts in terms of specific interaction patterns or narrative structures on YouTube. The CFSA model utilizes multiplex networks, where the data is structured into multiple layers to consider the different activities of the users on social networks. The first layer is the co-commenter network based on two commenters commenting on the same video; then, the second layer is the network between videos and channels that shows to which channel the video belongs. The two layers have interconnections based on the commenters' activities and the participation relations on different YouTube channels. The model's performance was evaluated through the Cheng Ho disinformation narrative within the Indo-Pacific region on YouTube. The dataset includes more than 36,495 commenters and 145,923 videos on YouTube. The model results showed commenters activities with supplementary contexts in the form of co-commenter-Channels activities. Likewise, this study provides the best answer to "How to explain the dynamic interplay between commenters, videos, and YouTube channels in the Indo-Pacific region?" The research model discovered the most impactful contextual focal structure sets for the YouTube co-commenters network. The results involve popular channels such as "Asumsi," "Erwan Tuinesia," "KOMPASTV," and "metrotvnews," which primarily serve the Indonesian community in the Indo-Pacific region. Nevertheless, it is noteworthy that several of these channels are known for spreading misinformation.

Keywords- Indo-Pacific region; Cheng Ho; Multiplex Networks; Complex Network; Entropy; Contextual Focal Structures.

I. INTRODUCTION

The Indo-Pacific region is the world's speediest rising economic region, and its importance to the world's power countries like the United States of America, the Union Europe, and China will continue to expand over time [1]. The Indo-Pacific region is a vast area that encompasses numerous countries with diverse cultural, economic, and geopolitical backgrounds. Some of the countries that fall under the ambit of the Indo-Pacific region include Australia, Bangladesh, China, India, Indonesia, Japan, Malaysia, Pakistan, Philippines, Singapore, Taiwan, Thailand, and Vietnam. The Indo-Pacific region makes up more than one-third of all global economic activity and will account for more than half of the global economy by 2040 [1], 65% of the world's oceans, and 25% of its land [2]. In addition, the Indo-Pacific region's population growth in the next 20 years is driving massive demands for health education, health services, food agriculture and fisheries, natural resources, energy, and advanced manufacturing and green infrastructure [1]. Furthermore, like all great power countries, the European Union, the United States of America, China, Canada, and Japan seek to influence the region to set ways for their own interests [3]. Likewise, the United States is considered an Indo-Pacific power, "the future of each of our nations- and indeed the world- depends on a free and open Indo-Pacific enduring and flourishing in the decades ahead" President Joe Biden underlined this point on September 24, 2021[2]. However, China, the largest trading and economy in the world [3], has chosen the path of challenge and confrontation, where China is taking over and rising power that is viewed with suspicion and challenges for nations in the Indo-Pacific region and beyond [4].

Moreover, Indo-Pacific nations like China, India, Japan, Philippines, and Indonesia are leading the way in terms of active users and growth in the social media consumption [5]. For example, YouTube is a video-sharing site and is considered an integral part of the social media platforms [6] and is one of the famous platforms for sharing news and social activities that cover over 95% of the internet population in 80 different languages [7]. For instance, users within the Indo-Pacific region were split between India (467 million), Indonesia (139 million), and Japan (102 million), respectively [8]. Furthermore, YouTube's channels show a strong presence for the Indo-Pacific people to share content and recommendations on the posted videos, where the top four channels' distribution categorized to people and blogs (24.89%), entertainment (18.63%), gaming (12.66%), and music (11.13%) [9]. In fact, The recommendation system on YouTube is a critical driver and plays a significant role in driving video views on the platform. Its primary function is to provide users with video recommendations based on their viewing history and the content they are currently engaged with [10]. In this research paper, we analyzed the recommendations made by commenters on YouTube regarding a disinformation narrative known as "Cheng Ho" or "Zheng He" within the Indo-Pacific region.

Cheng Ho is a disinformation narrative created to increase regional support for China and its geopolitical interest in the South China Sea, the Belt Road Initiative, and as a response to the accusations of China's oppression of Muslims [11]. The goal of pushing this narrative is to tackle the accusations of China's oppression of the Uyghur Muslims and increase support for China and its strategic pursuits including the aggression in the South China Sea.

Oftentimes, misinformation and disinformation are spread by commenters in a coordinated manner on social networks [12]. Highlighting focal groups of commenters on YouTube is the main contribution of this research, where these commenters could develop unique structures and act to influence individuals/communities to maximize information dissemination between Indo-Pacific region nations. Conventional community detection methods focus on larger communities and are oblivious to these influential groups. Şen et al. [13] proposed the Focal Structure Analysis (FSA) model to identify the smallest possible influential groups of users that can maximize information diffusion in social networks. Likewise, Alassad et al. [14] introduced the FSA 2.0 model to enhance the quality of the focal structure sets discovery and to overcome the limits in the activities of the influential users. The authors developed a bi-level decomposition optimization model to identify groups that could maximize the individual's influence in the first level and measure the network's stability in the second level. Both FSA and FSA 2.0 exclusively exhibit the activities of users in relation to other users. For instance, node i is linked to other nodes like j in the network, where neither model reveals any data on other activities taking place within the network. To improve the analysis of the state-of-the-art FSA model and FSA 2.0 model, this paper introduces the CFSA model to enhance the discovery and interpretability, reveals the context and highlights the interests of commenters in the form of contextual focal structure sets on YouTube.

The rest of the paper is organized as follows: Section II describes the research problem statement. Section III describes the YouTube dataset implemented to evaluate the model's performance and the overall structure of the methodology. The results in Section IV concluded that the CFSA results are interpretable and informative. Likewise, Section IV states the findings and presents the benefits of the proposed CFSA model enhanced the quality and the interpretability of the focal structure sets of commenters on YouTube. Finally, the conclusion, limitations, and future research path are given in Section V.

II. Research Problem Statement

The proposed research aims to highlight the CFSA model in YouTube's recommendation system. Given the raw datasets from the YouTube environment, the research problem statement is to implement a systematic model that utilizes the FSA 2.0 model [15] and the multiplex network approach to reveal the co-commenters' activities, interests and behavior in the form of context that may act in different cultural circumstances [12]. This approach involves different layers, including co-commenters, commenter-video, and video-channel in the form of participation layers.

Moreover, this research presents essential ideas and analysis to study questions like, can traditional community detection methods identify influential commenters and reveal the context on different YouTube channels? How the CFSA model utilizes the multiplex network to fill the gap in the information limitations? Finally, could the CFSA model structure the information to identify activities and explain the actions or interests of influential commenters? The next section discusses the methodology and the overall structure of the CFSA model.

III. Methodology

This section describes the technical intuition in our model; it consists of three main components. The data collection level is to collect all related context from Twitter including different trending hashtags related to events on Twitter network. The multiplex information matrix structure and CFS sets discovery level, where the layers of the multiplex network include co-commenters, commenter-video, and video-channel in the form of co-commenters' adjacency matrix layer and the participation layer network. Finally, the third level to validate and analyze the CFS set. For this level, we measure three Truth (GT) measures to calculate the amount of influence that any CFS set may generate in the entire structure of the network.

A. *Multiplex Matrix Structure*

In general, the adjacency matrix of an unweighted and undirected graph G with N nodes in an $N \times N$ symmetric matrix is $\mathbf{A} = \{a_{ij}\}$, with $a_{ij} = 1$, only if there is an edge between i and j in G, and $a_{ij} = 0$ otherwise. The adjacency matrix of layer graph G_α is $n_\alpha \times n_\alpha$ symmetric matrix $\mathbf{A}^\alpha = a^\alpha_{ij}$, with $a^\alpha_{ij} = 1$ only if there is an edge between (i, α), and (j, α) in G_α.

Likewise, the adjacency matrix of G_β is an $n \times m$ matrix $\rho = p_{i\alpha}$, with $p_{i\alpha} = 1$ only if there is an edge between the node i and the layer α in the participation graph, i.e., only if node i participates in layer α. We call it the participation matrix. The adjacency matrix of the coupling graph G_F is an $N \times N$ matrix $\mathcal{L} = \{c_{ij}\}$, with $c_{ij} = 1$ only if there is an edge between node-layer pair i and j in G_F, i.e., if they are representatives of the same node in different layers. We can arrange rows and columns of $\mathcal{L}$ such that node-layer pairs of the same layer are contiguous, and layers are ordered as shown in the next section. It results that $\mathcal{L}$ is a block matrix with zero diagonal blocks. Thus, $c_{ij} = 1$, with $i, j = 1, \ldots, N$ represents an edge between a node-layer pair in layer 1(co-commenter layer) and node layer pair in layer 2 (video-channel layer) if $i < n_1$ and $n_1 < j < n_2$ as shown in Figure 1. The supra-adjacency matrix is the adjacency matrix of the supra-graph $G_{\mathcal{M}}$. Just as $G_{\mathcal{M}}$, $\overline{A}$ is a synthetic representation of the whole multiplex $\mathcal{M}$. It can be obtained from the intra-layer adjacency matrices and the coupling matrix in the following way:

$$\overline{A} = \mathbf{A}^\alpha \oplus_\alpha \mathcal{L} \quad (1)$$

Where the same consideration as in $\mathcal{L}$ applies for the indices we also define. $\mathbf{A} = \oplus\, \mathbf{A}^\alpha$, which we call the intra-layer adjacency matrix.

Additionally, Figure 1 shows the Multiplex network, it is the union of the co-commenter layer and the video-channel layer. The participation layer is the interconnections between commenters, videos, and YouTube channels.

The CFSA model was built on a bi-level decomposition optimization problem to maximize the centrality values at the commenter level and maximize the network modularity values at the network level. Equation (2) shows the objective function used at the commenter level to maximize the centrality values in the multiplex network.

$$\max \sum_{i=1}^{n} \sum_{j=1}^{m} \left(\delta_i^{UU} \oplus \beta_{ij}^{UH} \hbar_j^{HH}\right) \quad (2)$$

Where n is the number of nodes in the co-commenter layer UU. m is the number of nodes in the video-channel layer HH. δ_i^{UU} is the sphere of influence for commenter i in UU. $\oplus$ is the direct sum. $\hbar_j^{HH}$ is the number of j channels in HH connected by an edge to commenter i in UU. Finally, β_{ij}^{UH} represents the interconnection in the participation layer and the links between commenters and channels, where

$\beta_{ij}^{UH} = 1$ if and only if commenter i in UU has a link with channel j in HH; otherwise 0.

The local clustering coefficient C_u was utilized to measure the level of transitivity and the density of a commenter's direct neighbors as shown in (3).

$$C_u = {}^{t_u}/_{d_u} \quad (3)$$

$$\beta_{ij}^{UH} c_{*,i} \qquad \forall i,j \quad (4)$$

Where t_u is the adjacency matrix of the network A, and d_u is the adjacency matrix of the complete graph G_F with no self-edges as shown in Figure 1. Equation (4) ensures the model considers the commenters to have edges to the participation network $\bar{A}$.

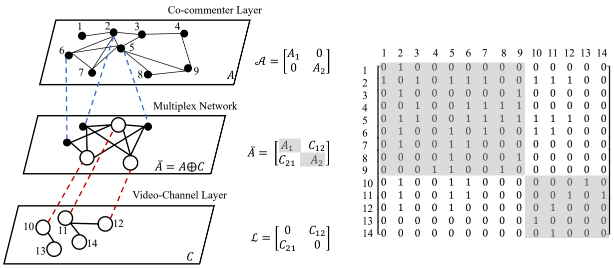

Figure 1. Multiplex network overall structure.

In the network level, the model measures every set of commenters' spheres of influence in the entire $\bar{A}$ network. This level is designed to measure the commenters' impact when they join $\bar{A}$ network. To measure the influence the commenters' identified from the commenter level, we utilize the spectral modularity method proposed in [6]. Furthermore, we utilized a vector parameter $\vec{c}\delta_{\substack{\imath m\times k\\ k\le m}}$ to transfer the commenters' information between the commenter level and the network level. The network level is designed based on the following set of equations.

$$\varrho_{jx} = \frac{1}{2m} Tr\left(\xi_{jx}\bar{A}\xi_{jx}^{T}\right) \qquad \forall j,x \quad (5)$$

$$\xi_{jx} = \{\, \overline{\vec{c}\delta}_{\substack{\imath m\times k\\ k\le m}} \cup\ \delta_{jx} |\ \overline{\vec{c}\delta}_{\substack{\imath m\times k,\\ k\le m}} \neq\ \delta_{jx}\} \qquad \forall j,x \quad (6)$$

$$\overline{\mu_{jx}^{Q}} = \max\{\varrho_{1x}, \varrho_{2x}, \dots, \varrho_{jx}\} \qquad \forall j,x \quad (7)$$

$$\mathbb{C}\varrho_{jx} = \delta_{jx}(\overline{\mu_{jx}^{Q}}) \qquad \forall j,x \quad (8)$$

The objective in the network-level is to identify sets of commenters that maximize the spectral modularity value ϱ_{jx} in each x iteration as shown in (5). Likewise, the model would search for the active set of commenters that will maximize the network's sparsity as indicated in (6). $\bar{A}$ is the modularity matrix. In constraint (6), $\xi_{jx} \in R^{m\times k}$ is the union between the commenters sets of users from the commenter level, $\overline{\vec{c}\delta}_{\substack{\imath m\times k\\ k\le m}}$, and the candidate sets of commenters δ_{jx} that presumably will maximize the network's sparsity. Constraint (7) is used to calculate the spectral modularity values $\overline{\mu_{jx}^{Q}}$. In constraint (8), $C\varrho_{jx}$ utilized to transfer back the results to the commenter level, where $\delta_{jx}(\overline{\mu_{jx}^{Q}})$ is the non-dominated solution that maximized the network's modularity. $C\varrho_{jx}^{M}$ is the set of commenters that maximized the modularity values when they joined the network and a vector parameter to interact with the commenter level and transfer the optimal solution from the network level to the commenter level. $C\varrho_{jx}^{M}$ selects the contextual focal structure sets that gather all the criteria from both levels at each iteration x.

B. *Data Collection*

YouTube's data API was used to collect an initial set of videos on key phrases relating to the Cheng Ho narrative at COSMOS research center, UA Little Rock, USA. The data collected was written to a MySQL database, where special queries were implemented against the database with a full-text search. To prevent personalized recommendations based on the user's history, we didn't log into the account used for collection and the browser instances and all cookies were cleared before a new crawl job. This data API run time was repeated in multiple iterations to get the most recent commenters' recommendations on videos, channels, and posted videos as shown in Table I.

TABLE I. YOUTUBE API DATA COLLECTION

Attempts	Number of Videos	Number of Unique Videos
Seed	50	50
Iterations 1-3	5985	3521
Iteration 4-5	145923	47101

Moreover, the retrieved data was in real-time, stored in different tables, and segmented into columns depending on the content as shown in Table .

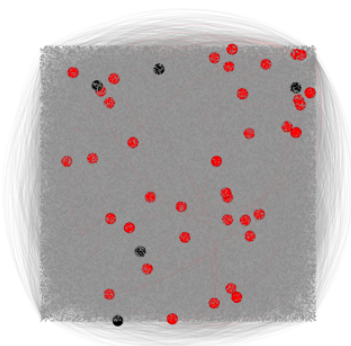

Figure 2. CO-COMMENTER YOUTUBE NETWORK. (COMPLEX NETWORK IN GRAY, CFS 3 (COMMENTERS IN RED, CHANNELS IS BLACK).

TABLE II. DATASET RETRIEVED FROM YOUTUBE. MULTIPLEX NETWORK (UH), CO-COMMENTER LAYER (UU), VIDEO-CHANNEL (HH), NODE (N), EDGES (E)

Network	UH		UU		HH	
	E	N	E	N	E	N
Cheng Ho	68975	36559	68803	36495	87799	57686

C. CFS Sets Validation and Analysis

In this part of the solution procedure, we implemented various steps to validate the outputs of the CFSA model. These steps should quantitatively measure the impacts of the commenters' influence and illustrate their interest on YouTube networks. For this purpose, we implemented three measures to calculate the changes in the network; first, the modularity values [16], [17] we call it (Ground Truth Modularity (GTMOD)); second, the clustering coefficient method [18] (Ground Truth Clustering Coefficient (GTCC)); and lastly, the change in the number of communities (Ground Truth Network Stability (GTNS)).

Moreover, the solution procedure selects the top ten CFS sets from each Ground Truth (GT) measure (GTMOD, GTCC, and GTNS). In other words, the rate of changes in GTMOD, GTCC, and GTNS after suspending all CFS sets from the YouTube co-commenter-channel network is the identifier of the top ten CFS sets. The findings and theoretical and practical implications are presented in the next section.

IV. Results

This research aims to present the benefits of the proposed CFSA model that could enhance the quality and the discovery of the focal structure sets of commenters on YouTube.

The case study shown in Figure 2, implemented in the research was related to the Cheng Ho dataset. The CFSA model identified 30 CFS sets in the multiplex network (co-commenters-channels layer). These sets are different in size, number of commenters, channels, and network structures on YouTube.

Furthermore, Table shows the manual analysis and the activities of the co-commenter - channels identified in one of the CFS sets, witnessing "what is going on between online commenters on YouTube?" in the most straightforward and smallest possible sets. For example, CFS3 set, shown in Figure 3, includes 70 commenters who were active and shared comments on five YouTube channels. The CFS model identified this set as one of the most influential sets hosting live streams on YouTube in the Indo-Pacific reign and spreading information to the maximum number of YouTube accounts. Besides, to describe the structure of the CFS3 set in-depth, Figure 3 shows the spread of commenters (red dots) and the channels (gray dots) in the structure of the co-commenter-channel network. Equally, this set is considered one of the top influential sets, including commenters from different parts of the co-commenter network.

TABLE III. CFS3 SET IN COMPLEX SOCIAL NETWORKS

CFS Set Id	Number of commenters	Number of channels	Number of Edge
CFS3	**70**	**5**	**129**
Contexts	**@Asumsi @KOMPASTV, @metrotvnews, @Muhammad Hanif Hasballah, @TRANS7 OFFICIAL**		

Likewise, CFS3 includes commenters linked to different channels like "@Asumsi"; 1.27M subscribers; this YoutTube channel is a media-tech institution focusing on various affairs and pop culture that targets the younger Indonesian demographic as shown in Figure 3. This channel is interested in critical angle and telling stories from the unheard point of views, as we study the structure of CFS3 links other influential commenters active on different set of channels [19]. Likewise, CFS3 set shows "@KOMPASTV", 14.3M subscribers, it is another YouTube channel in the Indo-Pacific region, where this channel is the rapid advancement of information technology, has an impact on the behavior of the Indonesian people, especially for television and KompasTV lovers. This channel focuses on free streaming to be at the forefront of various social media [20]. Other channels like "@metrotvnews" [21], 6.31M subscribers, and "@TRANS7 OFFICIAL" [22], 24.3M subscribers.

The advantages of implementing the CFSA model would reveal different desires between commenters in the identified CFS sets. In other words, the results present that commenters have entirely different interests on different YouTube channels. These findings lead to commenters being active and interested increase engagement of the shared videos on different channels.

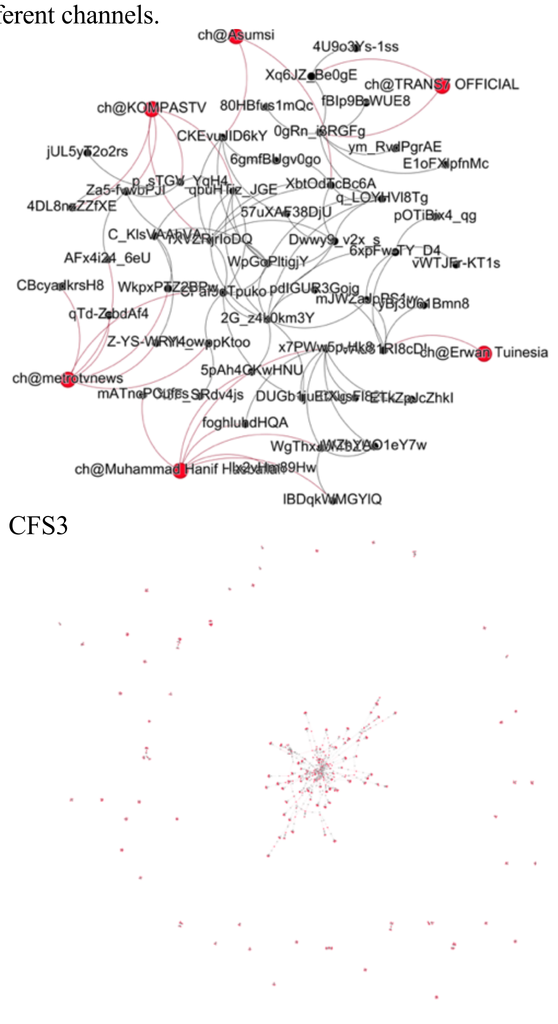

Figure 3. CFS sets in social networks. These three CFS sets changed the structure of the network as we can observe the changes before and after suspending these three sets from the network.

Moreover, to evaluate the influence of CFS sets, the ground truth measures were utilized to measure the impact of each CFS set of commenters on the entire co-commenter-channel network. For this purpose, the model suspended each CFS set from the network and then recalculated the GT measures to record the rate of the changes in the structure of the network. For example, when the model suspends CFS3 set shown in Figure 3 (top network), this set changed the structure of the network (**G**-CFS3) to a complete sparse co-commenter-channel network as shown in Figure 3 (bottom network). Furthermore, this set maximized the network's modularity values (GTMOD) from 0.7 to 0.957, and minimized the stability (GTNS) of the network (maximized number of communities) from 72 stable communities to 115 fragmented communities. Similarly, suspending CFS3 set from the network (G-CFS3) minimized the average clustering coefficient values (GTCC) from 0.029 to 0.0223.

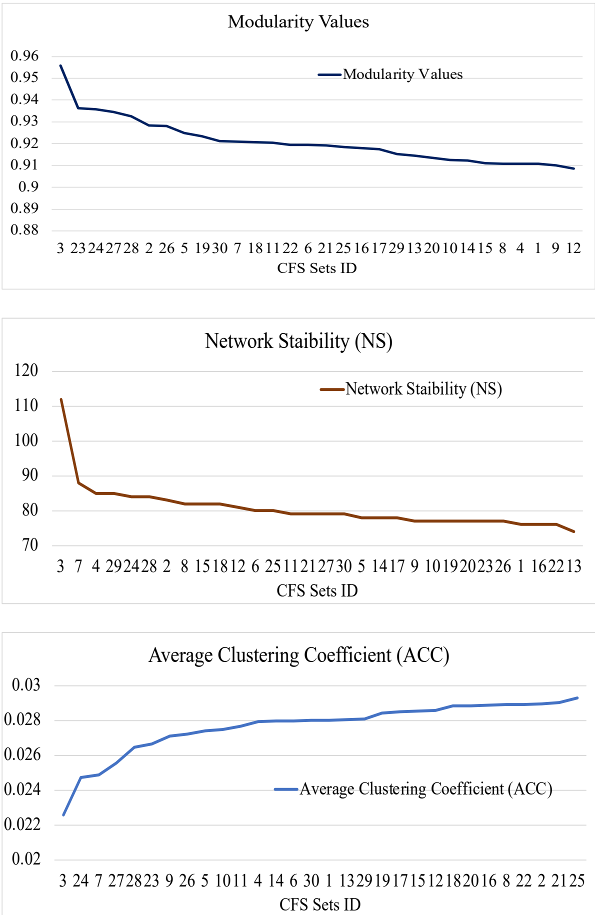

Figure 4. Changes in the network after suspending CFS sets.

Furthermore, to evaluate the quality of the other identified CFS sets, the employed method designed to suspend each CFS set, recalculates the changes in the modularity values, the changes in the number of communities, and the average clustering coefficient values. The model procedure have to recalculate these changes after suspending all CFS set from the co-commenter-channel network. Likewise, the changes in the co-commenter-channels YouTube networks where considered as Figure 4 shows the changes after suspending each CFS sets. Due to the space limit, we will skip presenting other changes in the co-commenter-channels values.

Additionally, from the GT analysis, we identified the top ten influential sets based on each GT values. The top ten sets had a greater impact on the co-commenter network compared to other sets, as shown in the following results.

- Top ten CFS set based on GTMOD: (CFS3, CFS23, CFS24, CFS27, CFS28, CFS2, CFS26, CFS5, CFS19, CFS30).
- Top ten CFS sets based on GTCC: (CFS3, CFS24, CFS7, CFS27, CFS28, CFS23, CFS9, CFS26, CFS5, CFS10).
- Top ten CFS sets based on GTNS: (CFS3, CFS7, CFS4, CFS29, CFS24, CFS28, CFS2, CFS8, CFS15, CFS18).

In summary, the model identified the top ten influential CFS sets based on three different criteria for further research and investigation. For example, CFS3, CFS24, and CFS28 were in the top ten CFS sets based on three sets of measures. In addition, CFS3 showed an interesting structure as this set impacted the co-commenter-channels network the most.

Moreover, this effort explored the utilization of multiplex networks and the focal structure analysis characteristics to detect the contextual focal structure sets on YouTube co-commenter networks. In a methodological practice, this study extended the structure of the information matrix to relax the complexity of the added information and help to interpret the contextual actions of the co-commenters on YouTube channels.

V. Conclusion and Future Work

The CFSA model presented to reveal influential sets of YouTube commenters; where the co-commenter-channel multiplex network utilized to present their online contextual activities. Similarly, a participation layer representation is employed to capture the communication network among the commenters, posted videos, and the interconnection between the two layers (through co-commenter and YouTube channels). To measure the performance of the model, we utilized YouTube datasets related to the Indo-Pacific region, including Cheng Ho narrative videos. Additionally, we implemented a systematic procedure to measure each CFS set's impact on the co-commenter-channel network's stability. To accomplish this goal, the model temporarily removed each CFS set from the network and evaluated the alterations in modularity values, average clustering coefficient values, and network stability in the co-commenter-channels network. Finally, the model determined the top ten most influential CFS sets of co-commenters and their associated YouTube channels. Furthermore, the model revealed that the most influential set, CFS3, encompasses well-subscribed channels such as "Asumsi" [19], "Erwan Tuinesia"[23], "KOMPASTV" [20], and "metrotvnews" [21], primarily serving the Indonesian community in the Indo-Pacific region. Many of the channels are known to espouse misinformation.

Moreover, the characteristics of the CFSA model have practical implications and could be leveraged by social media platforms to develop and implement screening tools for users and communities' contextual activities on social networks. The CFSA model helps to distinguish contextual activities beyond the focal structures on social media. In addition, this study highlights the value of utilizing the multiplex network method and focal structure analysis models in revealing coordinating groups' contextual activities and information spread on social networks.

For future work, to improve the outcomes of the CFS model, we consider applying the model to small dynamic social networks. Next, implementing the CFSA model to analyze cross-platform scenarios, where this model could study contextual focal structure sets that simultaneously span across multiple social media platforms like Facebook, Twitter, Instagram, and YouTube.

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