The University of Texas at Dallas

School of Economic, Political and Policy Sciences

PSCI 7381: Social Networks

Spring 2021

Dr. Lauren Santoro

Final Paper

Social Network Analysis and the #AlevelResults Case: Discussions around the Use of Algorithms to Evaluate Students

Student: Federico Ferrero

Social Network Analysis and the #AlevelResults Case:
Discussions around the Use of Algorithms to Evaluate Students

Federico Ferrero

Introduction

Since the deployment of Web 2.0 technologies, online communication has been strongly stimulated around the world. Especially via the use of social networks, virtual interaction and collective organization have increased taking advantage of its low cost and the possibility of participation beyond geographical barriers (Makarem and Jae, 2016; Rim, Lee, and Yoo, 2020). Consequently, political discussions have arisen, and even social movements have been consolidated from Twitter, Facebook, and YouTube. In certain cases, these movements have positive effects on civic engagement (Boulianne, 2009) but, at the same time, there is still skepticism about the quality of these activisms which are sometimes considered devalued forms of political participation (known as "slacktivism") (Choi and Park, 2014).

In this context, we count with varied evidence of social movements driven from online sites (Beguerisse-Diaz, Garduno-Hernandez, Vangelov, Yaliraki and Barahona, 2014; Feng, 2016; Gleason, 2013; Yang, 2016) and even specific student movements and collective actions deployed on the internet around educational issues (Ahmed, 2019; Chan, 2013; García, Bülow, Ledezma and Chauveau, 2014; Sandoval-Almazan and Gil-Garcia, 2013). However, there is still limited knowledge about online discussions that address the specific effects that Artificial Intelligence techniques have on educational assessments.

While efforts to develop educational predictive analytics are increasing with the benevolent aim of, for example, identifying "at-risk" students and make pedagogical interventions (Holmes, Bialik, and Fadel, 2019; Jayaprakash, Moody, Lauría, Regan and Baron, 2014; Siegel, 2013; Williamson, 2016); there is still no clear and systematic evidence about what students opine about these systems. Indeed, there are no conclusive results about how students themselves are affected by the application of these assessment technologies. In this regard, some isolated claims begin to emerge around the effective and precise possibility of predicting performances as well as ethical issues linked to online surveillance, among others. It is therefore of interest to analyze what particularities online reactions assume around algorithmic-driven decision-making systems applied to educational settings.

Considering a particular Twitter discussion that focuses on this issue, this study is specifically interested in link formation factors as well as central actors that affect the flow of information when the network is in its initial phase of development.

Previous research reports that actors who are influencers in social media possess high levels of innovativeness, connectivity, involvement, exploratory behaviors, among other features (Xu, Sang, Blasiola and Park, 2014). Considering these findings, our research questions pay special attention to brokers who are assumed to be responsible for configuring discourses as well as disseminating them throughout the network. This means that we address an influence hypothesis to analyze the network (Robins, 2015) in a specific case of online discussion on educational topics that took place on Twitter in 2020.

To be precise, the study is intended to work with a particular Twitter discussion: the case established around the hashtag #AlevelResult.

The case includes special features that make it interesting to analyze because it is one of the first time that the application of Artificial Intelligence techniques in student evaluation has had such a resounding public reaction.

As it is known, British high school seniors annually take “A-Level” exams which in practical terms, determine their university admissions. However, in 2020 such tests were suspended due to the COVID-19 pandemic and school lockdowns. Instead, the Office of Qualifications and Examinations Regulation (called “Ofqual”) used an algorithm that adjusted the grades predicted by teachers and standardized the results at the national level considering the historical performance of the schools and the classification of students within their own schools.

As a general result, almost 40 % of the estimated grades were lowered, especially affecting university plans and opportunities for students’ social mobility coming from the poorest social sectors. As soon as the results were known in August 2020, the demonstrations and protests did not wait. Mainly on Twitter with the hashtag #AlevelResults, there was a significant volume of comments about the validity and disconcerting nature of the results obtained by the students.

On the basis of the above-mentioned discussion and the selected case, the research questions for this study can be formulated as follows:

- **RQ1**: How are the influential intermediaries on #AlavelResults Twitter discussion around the uses of algorithms to evaluate students characterized?
- **RQ2**: What factors contribute to the formation of ties in the #AlevelResults network?

In the successive fragments, the main ideas of the theoretical frameworks adopted by this research and the hypotheses it formulates will be briefly presented. Then, the methodological design aimed at producing both descriptive and inferential Social Network Analysis will be described. Subsequently, the results are presented via descriptive statistics, network visualizations, the ERGM model addressed to analyze the probability of tie formation according to specific nodes attributes, and the analysis of goodness-of-fit. Finally, conclusions are included as well as the discussions and limitations that arise from de results.

Theoretical Frameworks

The questions are addressed from two different theoretical frameworks: Social Network Theory and Two-Step Flow of Communication Theory.

First, it worth saying that this research adopts Social Network Theory (Kadushin, 2012; Luke, 2015) not just from a methodological application perspective but also because the questions themselves refer to a network phenomenon and encompass theoretical commitments that require its utilization. From the point of view of this theory, a network is a set of nodes representing social actors that relate to each other through edges: assumes the interdependence between entities and therefore understands these relationships as a key unit of analysis. Due to this reason, it differs from approaches that hold that observations are independent of each other and that the causal processes studied occur “within” individuals without being affected by other individuals or by contextual factors (Robins, 2015). At the same time, Social Network Theory offers the possibility of examining the general structure of networks as well as the role of particular social actors. In this latter case, the theory allows us to carry out centrality analysis and identify nodes who play roles of influential intermediaries in the diffusion of information among members and groups in the network (Burt, 1999).

Second, as the research questions focus on identifying who the key social mediators in a particular discussion on Twitter are, this study considers the Two-Step Flow of Communication Theory (Katz and Lazarsfeld, 1966). This theoretical framework understands that information is elaborated by opinion leaders, who interpret, construct, and disseminate information to the less active population. In this way, it is argued that most people shape their opinion based on the influence of opinion leaders who in turn are influenced by the media (that is why it is called "two-step communication flow"). Actually, this theoretical hypothesis discusses traditional models that assume that the media have a direct impact on audience positions. Now, if the Two-Step Flow Theory is used to analyze communication in virtual communities, opinion leaders can be considered information brokers in particular social networks. Specifically, it is understood that opinion leaders influence discussions on Twitter insofar as they occupy betweenness central positions in the network when they are followed, mentioned, or retweeted (Feng, 2016).

Hypotheses

This study is concerned with ties as outcomes because it aspires to know the factors that affect their establishment as well as characteristics and behaviors of certain users who act as brokers in the network. That is, factors that contribute to the creation of certain relationships among participants and specific attributes that make some people the more influential mediators. Therefore, the study postulates the tie formation and the brokers' influence relationships as the dependent variables.

Regarding the figure of brokers, the general conjecture is that in the beginning of the network development the positions of influential intermediaries are occupied mainly by student-movement related members, and not by other popular users linked to journalism and the government who ultimately represent interests other than those of students affected and their families. It is expected that the student voice has place in setting the agenda of the interactions.

But beyond this general approximation to the dynamic of links formation, other specific hypotheses will be tested in this study. These hypotheses are linked to exogenous attributes of our network: number of followers and followed accounts, number of tweets posted, and account profiles. Each one of these independent variables will be studied in its capability of affecting the formation of links in our network. Therefore, our dependent variable for the inferential model will be the establishment of ties in the #AlevelResults network.

First, there is evidence that when a user has a considerable number of followers, these ones are likely to retweet her/his messages or mention her/him to strengthen their connections (Feng, 2016).

Second, it has been shown that opinion leaders are more informed and seek information in a more active way than non-opinion leaders (Reddi, 2019). This finding, translated into the case of Twitter, implies that the more people a user follows, the more information she/he receives and consequently, the more likely it is that this user will create valuable tweets for others to reproduce and allude.

Third and regarding the number of published tweets, Castillo, Mendoza, and Poblete (2011) observe that high participation in terms of tweets issued (high values of out-degree centrality) increases the probability of establishing a connection on Twitter and obtaining visibility in the network.

Finally, and with respect to homophily phenomenon, there is important evidence of the tendency to interact with presumably similar others in many social networks (Himelboin, McCreery, and Smith, 2013; Schuster, Jörgens, and Kolleck, 2021). In many cases, the type of Twitter account profile can be a determining attribute of the connection when participants seek to reaffirm their positions via other similar peers. In the event that this characteristic is verified, the position of intermediaries could have a key importance to connect parts of networks that are internally homogeneous in terms of profile types.

On the basis of these findings and discussions, we raised the following hypotheses in the study of our particular network:

- **H1**: The number of followers increases the probability of establishing links in the #AlevelResults discussion.
- **H2**: The number of followed increases the probability of establishing links in the #AlevelResults discussion.
- **H3**: The number of tweets issued increases the likelihood of establishing connections in the #AlevelResults discussion.
- **H4**: The same type of Twitter account profiles are more likely to link to each other in the #AlevelResults discussion.

Research Design and Methodology

This research is a network study basically focused on who communicates with whom on Twitter and therefore adopts Social Network Theory (Kadushin, 2012; Luke, 2015) to advance the analysis of the data.

Initially, all the actors (people, organizations, institutions, government offices, etcetera) who referred to the hashtag #AlevelResults in their tweets or those who were mentioned in the posting that included the hashtag were included in the database. So, the first network boundary was given by the use of the hashtag #AlevelResults. This yielded an initial base of 76,310 tweets downloaded from 8/14/2020 to 9/2/2020 when the hashtag was trending topic. Subsequently, a particular time-lapse filter was applied. As this cross-sectional study focuses on the first instances of the discussion development, it was decided to take the first 400 tweets (200 retweets and 200 replies/mentions). Following Kadushin (2012), network diffusion generally adopts an S-shaped curve in which a few people join early and through various interaction patterns "enlist" others before the discussion explodes and then disappears. These initial moments seem to set the agenda of the discussion and allow the visibility of actors who in more crowded moments would be overshadowed by public figures or media organization users.

As a result of this filtering process, in our final network there are 487 nodes that represent the first Twitter users that participated in the discussion with the hashtag #AlevelResults last August 14th, 2020 when the exam results were delivered to high school students. Therefore, the network is unipartite because only one mode or class of nodes is included.

The edges are in total 400 and as it was said before they represent two different types of links: either retweets or replies/mentions. Due to the nature of these links, the resultant network is directed because the direction of who is retweeting, replying, or mentioning other users matters. Concretely, in the Twitter environment, users can directly contact others by retweeting them (reposting the tweet of another participant), by replying to them (including other users' account names at the beginning of the tweet), or by mentioning other users in their post. This information exchange allows discussion participants to disseminate data publicly, engage others, attract the attention of particular users and sometimes organize public actions.

The study covers a large-scale social network system on Twitter that is not circumscribed to the United Kingdom because the discussion has had reverberations around the world. Based on this fact, this research uses a whole network type of design. This decision allows exploring and better assess full network connectivity and social influence processes. At the same time, it has been decided to focus on a specific area of the network around a particular user to analyze in more detail the connections of the main broker in the network. This could be considered an egonet although technically it is not because all the other connections of those who are linked to this node were also incorporated.

The gather of data had two instances. First, the electronic data coming from Twitter was collected via a Twitter Application Programming Interface (API). Second, other variable values that were not present in the original database were manually collected by exploring each user's Twitter bio.

Regarding the quality of measurements, simultaneous or excessively successive tweets have been crossed with usernames to detect bots. After this initial analysis, no false-positive nodes or edges were found in the sample of 400 tweets under analysis, although it could not be identified if there are falsely disaggregated nodes (which would be the case of the same user that utilizes two or more Twitter accounts simultaneously). At the same time, numbers of followers and of followed people showed some missing observations whose values were verified manually in the online site (but always recognizing that the number could have varied with respect to quantities in August 2020). In general terms, it is worth saying that the treatment carried out with missing values strengthened the quality of the base as a whole.

Overall, it is understood that the final electronic database is reliable because of the accuracy and detail with which the values were captured. Furthermore, validity threats were dismissed after verifying the inexistence of bots.

Finally, once the data was curated, the analysis took place. The analytical strategies encompassed two big moments. First, a descriptive Social Network Analysis with the objective of recording the behavior of the main centrality measures of the network as well as a summary of relevant exogenous variables. Along the same lines, visualizations of the network are included to describe its structure and most outstanding characteristics. The results are presented together with comments coming from an initial reading of the content of the tweets considered relevant. Second, an inferential Social Network Analysis was carried out using Exponential Random Graph Model (ERGM) to mainly analyze the casual effects related to the formation of links in our network.

Results

Descriptive SNA

According to Table 1, the density of the network is very low, almost zero (0.001686). As the network considers only the first 400 reactions around #AlevelResults, connectivity is minimal because actors involved are just establishing their first links with others. Likewise, a high number of components is observed (150), which is expectable in the initial moments of network formation.

If we focus on other descriptive statistics, the total degree average is 1.64. In the case of in-degree centrality measures the average is 2.05 with a maximum of 25 while out-degree mean is lower (1.2) with a maximum of only 8. This indicates that more contacts are initiated on the network compared to the received ones (almost double).

When considering the capacity to act as an intermediary, the betweenness centrality of nodes is relevant. This centrality measure detects the amount of influence a node has over the flow of information in a network measuring to what extent a node is between pairs of other nodes. In a sense, it allows identifying the actors that serve as a “bridge” from one part of the network to another. In this regard, Table 1 shows that in the case of #AlavelResults the mean of betweenness centrality is low (0.03) with a maximum value of 13 that corresponds to our main broker in the network (mybluekite) to whom we will refer in depth later.

Regarding exogenous attributes, four are included in this study: (1) the number of each user's follower with a mean of 156,577; (2) the number of followed by each user with an average of 1805; (3) the number of tweets published by each user with mean of 0.82 and maximum of 8; and (4) an account profiles classification. This last variable reveals that the most six representative groups are ordinary users in the sense of not being public or popular figures (74 %), followed by politicians (6 %), professors and researchers (4 %), activists (3.5 %), media organizations (3.3 %), and journalists (3.1 %).

Table 1
Descriptive Statistics #AlevelResults Network and Specific Variables

	Total value	*Min*	*Median*	*Mean*	*Max*
Density of network	0.001686	-	-	-	-
Number of components	150	-	-	-	-
Total-degree	-	1	1	1.64	25
In-degree	-	0	0	2.05	25
Out-degree	-	0	1	1.20	8
Betweenness	-	0	0	0.03	13
Number of user's followers	-	0	784	156,577	14,793,668
Number of followed by user	-	0	694	1804.9	60,205
Number of tweets posted by user	-	0	1	0.82	8
Profile (top 6)					
Another Citizen	361 users				
Politician	29				
Professor/Researcher	20				
Activist	17				
Media Organization	16				
Journalist	15				

Figure 1 shows the structure of the network under analysis. The size of the nodes is proportional to their degree centrality and their color is determined by the account profiles that enter the discussion. At the same time, edges are classified according to whether the link corresponds to a reply/mention or if it represents a retweet.

When analyzing the graph, four observations can be referred to.

First, there is a group of central politicians who predominantly receive replies or mentions and who, for the most part, do not participate in the discussion with the hashtag. There are messages in which they are invited to intervene and express their opinions as well as other posts that are directly tweets of protest against them. In cases like Boris Johnson and Gavin Williamson, the Secretary of State for Education, their accounts are targeted for complaints after the release of exam results.

Second, there is another group of influential citizens that are not public figures and generally represent students affected and teachers. In their case, the main link type is the retweet. The retweet can be read as a strategy to reproduce messages considered valuable, just like authority quotes in other contexts of knowledge production. In a sense, the retweet implies an agreement with the content of the post and the intention of spreading it on the platform. In this group, are also included professors, researchers, and a union leader. In general terms and according to the content of these participants' tweets, we could locate here the figure of those who protest and emit complaints.

Third, we find media organizations that produce news related to the case and predominantly receive retweets of its content.

Finally, there is a sizable set of isolated participants (top right) who actually retweet their own posts (self-links are not depicted in the image) and a whole series of users that form isolated dyads. This group characterizes the majority of the participants who enter the discussion.

It should be noted that the visualization does not show proportionalities of the ties in relation to the number of tweets and it is not exhaustive with all the existing links (for example, the media organization LBC has a considerable in-degree centrality but the edges are not properly shown in the figure).

Figure 1
First Retweets, Replies, and Mentions in #AlevelResults discussion

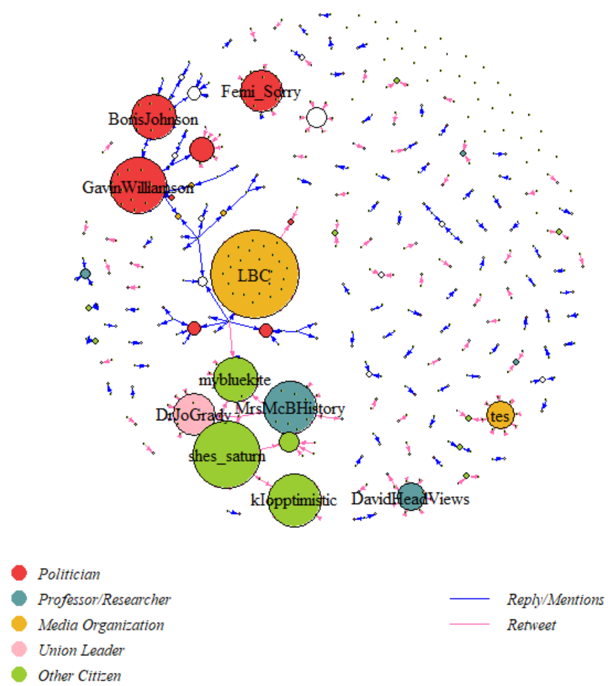


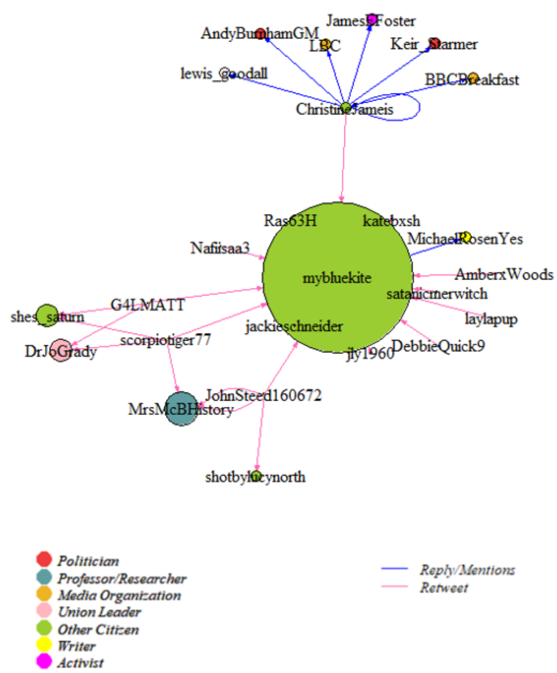
Figure 1 also does not say much in terms of users acting as mediators and interconnecting remote parts of the network. Consequently, the next question is who are the most influential actors in relation to betweenness centrality in our network? As can be seen in Table 2 only three accounts hold betweenness centrality in the entire network. None of these actors are public figures nor have a considerable number of followers and followed people. After exploring their Twitter biographies and the content of their tweets, they seem to be people not in favor of the use of the algorithm to evaluate students.

Table 2
Betweenness Centrality: Most Influential Actors in #AlevelResults Network

	Betweenness	*Followers*	*Followed*	*Tweet/s posted*	*Profile type*
mybluekite	13	59	354	1	Another citizen
Sumiyya_iqbal	1	268	374	1	Another citizen
Annie08240822	1	16	14	1	Another citizen

Clearly, mybluekite is the main broker in the network and due to her position, she acts as an intermediary between two of the groups previously identified. In Figure 3 it is shown in zoom all the links that mybluekite maintains and in turn all the links of all those with which she is connected. Clearly, she is an actor who is positioned on the network as a central figure from receiving retweets from other ordinary citizens like her. In particular, her connection with ChristineJameis is the pass that connects the politicians' top area with the bottom area of "other citizens" identified in Figure 1. Consequently, these two network fragments manage to establish a link through the intermediation that mybluekite exerts.

Figure 3
Main Broker in #AlevelResults discussion



It is interesting that our broker emits only one tweet that is highly reproduced. Mybluekite responds to a writer with a clearly antagonistic message. This confrontational message and addressed to a public figure (who is followed by 238,534 users), makes her get an important number of retweets that mostly come from students. An original tweet with an openly discussing tone that responds to a user with visibility on the network seems to be the combination that positions mybluekite as a recipient of retweets from users that share her same type of profile. Among these retweets, one of them is the one that makes her have access to a remote part of the network, establishing mybluekite as the main intermediary in the network.

Inferential SNA

An Exponential Random Graph Model (ERGM) is used given that it allows network modeling assuming the dependence of observations. Specifically, ERGM predicts the probability of a tie between actors, conditional on the rest of the network (all other ties). Following Robins, Pattison, Kalish and Lusher (2007) this approach models the characteristics of a theoretical network and estimates their weights with the purpose of identifying those characteristics of an empirically observed network that occur more often than the expected by chance. According to Luke (2015), ERGM is a generative statistical model that allows testing inferential hypotheses without the degeneracy problems that are frequently identified in other models. Additionally, ERGM is flexible and permits the user to introduce different types of covariates in the model.

Results from ERGM are shown in Table 3. Contrary to expectations, hypotheses 1 and 2 do not find support in our model: the number of followers and the number of followed people are not statistically significant predictors of the formation of a link in #AlevelResults network.

Table 3
#AlevelResults ERGM Outputs

	Coefficient (standard error)
Edges	-6.204*** (0.096)
Number of followers	-0.000 (0.000)
Number of followed	-0.00002 (0.00001)
Number of tweets posted	0.200*** (0.035)
Twitter Profiles	-1.078*** (0.120)
Number of observations	237,169
Akaike Inf. Crit.	5585
Bayesian Inf. Crit.	5637

Note: *p<0.1: **p<0.05: ***p<0.01

However, hypotheses 3 and 4 cannot be rejected according to the outputs of our model. As we can see, the number of tweets published is a positive statistically significant predictor of the establishment of a link in #AlevelResults network at $p<0.01$. Holding all other effects constant, considering specifically the number of tweets posted by each user, the relative likelihood of observing a link in the network is 1.22.

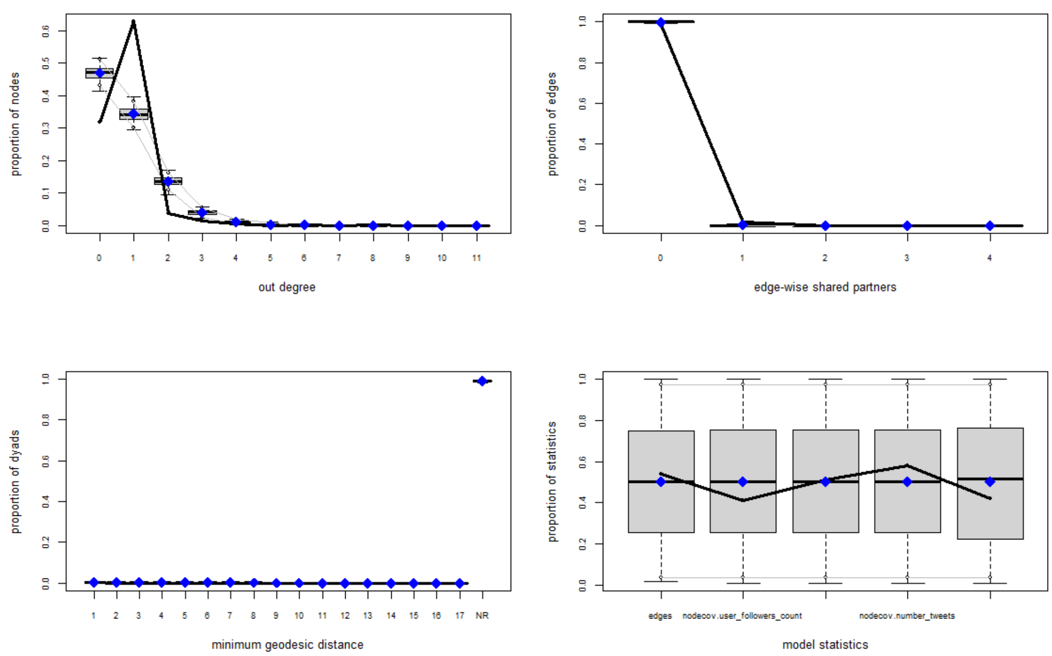
Just to give an example, the probability of our broker mybluekite of connecting with a more active user (for example someone who posted 8 tweets in the discussion, the maximum out-degree in the network) equals 0.012 while her likelihood of produce a link with a less-active user (someone who published only 1 tweet) is 0.003. In line with the evidence reported from other research, in our case, the probability of connecting in the network is also higher with a more participatory user.

With respect to the homophily hypothesis, we focus on if the same types of Twitter account profiles are more likely to link to each other in the #AlevelResults network. The model results indicate a negative coefficient of 1.078 statistically significant at $p<0.01$. Working with inverse logistic transformation, the probability of a link across different profiles is 0.002 while the probability of a tie between two nodes with the same profile type is equal to 0.0059. Therefore, the probability of forming a within-profile edge is 0.0038 higher than forming an across-profile edge.

This result, although it is not very considerable in terms of absolute values, indicates a trend in the formation of ties in the network and may be of interest to analyze the importance of actors who function as brokers intermediating among participants with different profiles.

In terms of model fit, errors standards are low and in comparison to the null model, AIC and BIC were getting smaller as the covariates were added to the model. Nevertheless, following the goodness-of-fit graphs in Figure 3, the final model does not achieve acceptable accuracy: the black lines -which indicate the value of particular statistics in our data (the observed network)- do not sit inside the 95% confidence-range bands (light grey lines). If p-values are analyzed in detail, this conclusion is endorsed. Initial p-values of out-degree and minimum geodesic distance show low values near 0, which indicate that there is a statistically significant difference between the observed value of the statistic and the simulated ones. At the same time, it should be noted that all model statistics reveal a good fit with p-values of 1 or near 1. Overall, it must be said that corrections are still necessary to make the simulated network in the model as close as possible to the observed network.

Figure 3
Goodness-of-fit Diagnostics



Conclusions and Discussions

This study covers a case of online discussion on Twitter around the hashtag #AlevelResults with the purpose of identifying influential social actors and finding the contributor factors for the establishment of ties in the network.

The case constitutes one of the first examples in which there was considerable online repercussion around the results of student evaluations that apply Artificial Intelligence methods. Its study yields interesting insights in terms of how protest speeches are configured on pedagogical issues that affect students. Therefore, the analysis in this regard may be of interest to student movements that perceive their rights threatened and decide to participate in virtual debates deploying particular collective strategies.

The main results obtained indicate that in the case of #AlevelResults network: (1) there is little connectivity and multiple isolated dyads given the initial instance of network development; (2) the structure of the network shows that the two large groups of influential participants are the politicians (invited to participate or as targets of protests) and other non-popular citizens, mostly issuing complaints about the unfair nature of the exam results; (3) the users who act as intermediaries are few, they are not public figures and they participate by issuing criticisms against the application of the algorithm; (4) the main broker on the network emits only an original tweet with a confrontational tone and aimed at a user with visibility on the network, which makes her gain the reproduction of her message and, finally, her positioning as an influential actor.

According to these results, at least in the initial moments of the movement, the actors in charge of setting the agenda around the legitimate discourses that circulate on the network seem to be linked to the affected groups. Despite not being important users in terms of number of followers and levels of participation, they find strategies to make their voice heard and to replicate messages considered valuable. The question arises as to whether this configuration is maintained or altered with the entry of other more powerful users (profiles related to media and journalists that tend to monopolize the attention). The initial moments in online protests characterized by more horizontal relationships as well as the preservation of this form of democratic and non-hierarchical participation, clearly constitute topics of interest to be addressed in future investigations.

Other results of interest are those revealed by our inferential Social Network Analysis. ERGM outputs suggest that, unlike findings from other investigations, the number of followers and the number of followed people are not statistically significant predictors of the formation of a link in #AlevelResults network. Perhaps the period of time in which this study concentrates, allows making visible the formation of links between non-popular actors (different from media actors), which was definitely one of our objectives in the analysis considering the Two-Step Flow of Communication Theory. However, it is probable that even in #AlevelResults network, predictors such as the number of followers and followed are relevant at the moment of largest participation. In any case, it is suggestive that in the initial moments of participation, any user may have the chance to establish her/himself as an important actor in the discussion.

Additionally, it was found that the number of tweets published is a positive statistically significant predictor of the establishment of a link in our network. This data is interesting because, as has been stated before, the main intermediaries are exceptions to this rule since there are other factors that seem to be more important when it comes to winning connections (basically related to the tone of the content and the recipient of the message).

Likewise, our homophily hypothesis was confirmed: the probability of forming a within-profile edge is higher than forming an across-profile edge. Although the absolute values are not large, this trend suggests that in the initial moments of the protest, the approximation to other similar ones plays a role to be considered: something like an instance of self-confirmation among users via retweets. Whether this trend continues or not, is interesting as a question to answer since a debate would technically require confrontation with different and even antagonistic positions/profiles.

Without a doubt, there are limitations to overcome in this study, especially in terms of the goodness of fit of our ERGM. Adjustments to the model should be considered to achieve greater robustness and guarantee non-significant differences between the simulated and observed values. At the same time, more observations could be included in the analysis with the aim of representing other moments of development of the discussion such as the explosion and subsequent decline in users' participation. Finally, it must be said that the possibilities of generalization to other cases are not possible from a statistical point of view, although the findings presented here could be incorporated as hypotheses in future works that guarantee external validity.

References

Ahmed, A. K. (2020). # RhodesMustFall: How a Decolonial Student Movement in the Global South Inspired Epistemic Disobedience at the University of Oxford. *African Studies Review*, *63*(2), 281-303.

Beguerisse-Díaz, M., Garduno-Hernández, G., Vangelov, B., Yaliraki, S. N., & Barahona, M. (2014). Interest communities and flow roles in directed networks: the Twitter network of the UK riots. *Journal of The Royal Society Interface*, *11*(101), 20140940.

Boulianne, S. (2009). Does Internet use affect engagement? A meta-analysis of research. *Political communication*, *26*(2), 193-211.

Burt, R. S. (1999). The social capital of opinion leaders. *The Annals of the American Academy of Political and Social Science*, *566*(1), 37-54.

Castillo, C., Mendoza, M., & Poblete, B. (2011, March). Information credibility on twitter. In *Proceedings of the 20th international conference on World wide web* (pp. 675-684).

Chan, C. (2013). Young activists and the anti-patriotic education movement in post-colonial Hong Kong: Some insights from Twitter. *Citizenship, Social and Economics Education*, *12*(3), 148-162.

Choi, S., & Park, H. W. (2014). An exploratory approach to a Twitter-based community centered on a political goal in South Korea: Who organized it, what they shared, and how they acted. *New Media & Society*, *16*(1), 129-148.

Feng, Y. (2016). Are you connected? Evaluating information cascades in online discussion about the# RaceTogether campaign. *Computers in human behavior*, *54*, 43-53.

García, C., Bülow, M. V., Ledezma, J., & Chauveau, P. (2014). What can Twitter tell us about social movements' network topology and centrality? Analysing the case of the 2011–2013 Chilean student movement. *International Journal of Organisational Design and Engineering 4*, *3*(3-4), 317-337.

Gleason, B. (2013). # Occupy Wall Street: Exploring informal learning about a social movement on Twitter. *American Behavioral Scientist*, *57*(7), 966-982.

Himelboim, I., McCreery, S., & Smith, M. (2013). Birds of a feather tweet together: Integrating network and content analyses to examine cross-ideology exposure on Twitter. *Journal of computer-mediated communication*, *18*(2), 154-174.

Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial intelligence in education. *Boston: Center for Curriculum Redesign*.

Jayaprakash, S. M., Moody, E. W., Lauría, E. J., Regan, J. R., & Baron, J. D. (2014). Early alert of academically at-risk students: An open source analytics initiative. *Journal of Learning Analytics*, *1*(1), 6-47.

Kadushin, C. (2012). *Understanding social networks: Theories, concepts, and findings*. Oup Usa.

Katz, E., & Lazarsfeld, P. F. (1966). *Personal Influence, The part played by people in the flow of mass communications*. Transaction publishers.

Luke, D. A. (2015). *A user's guide to network analysis in R*. London: Springer.

Makarem, S. C., & Jae, H. (2016). Consumer boycott behavior: An exploratory analysis of twitter feeds. *Journal of consumer affairs*, *50*(1), 193-223.

Reddi, C. N. (2019). *Effective public relations and media strategy*. PHI Learning Pvt. Ltd..

Rim, H., Lee, Y., & Yoo, S. (2020). Polarized public opinion responding to corporate social advocacy: Social network analysis of boycotters and advocators. *Public Relations Review*, *46*(2), 101869.

Robins, G. (2015). *Doing social network research: Network-based research design for social scientists*. Sage.

Robins, G., Pattison, P., Kalish, Y., & Lusher, D. (2007). An introduction to exponential random graph (p*) models for social networks. *Social networks*, *29*(2), 173-191.

Sandoval-Almazan, R., & Gil-Garcia, J. R. (2013, January). Cyberactivism through Social Media: Twitter, YouTube, and the Mexican Political Movement" I'm Number 132". In *2013 46th Hawaii International Conference on System Sciences* (pp. 1704-1713). IEEE.

Schuster, J., Jörgens, H., & Kolleck, N. (2021). The rise of global policy networks in education: analyzing Twitter debates on inclusive education using social network analysis. *Journal of Education Policy*, *36*(2), 211-231.

Siegel, E. (2013). *Predictive analytics: The power to predict who will click, buy, lie, or die* (Vol. 10). Hoboken: Wiley.

Williamson, B. (2016). Digital education governance: data visualization, predictive analytics, and 'real-time'policy instruments. *Journal of Education Policy*, *31*(2), 123-141.

Xu, W. W., Sang, Y., Blasiola, S., & Park, H. W. (2014). Predicting opinion leaders in Twitter activism networks: The case of the Wisconsin recall election. *American Behavioral Scientist*, *58*(10), 1278-1293.

Yang, G. (2016). Narrative agency in hashtag activism: The case of #BlackLivesMatter. *Media and communication*, *4*(4), 13.

Appendix

R Code and Outputs:
https://federico-jf.github.io/Social-Network-Analysis-PSCI-7381/code_outputs.html