A Training Report

On

Tweeting from Left to Right: Echo Chambers in Delhi Election

Submitted in partial fulfilment of requirements for the award of the

Degree of

Bachelor of Technology

In

Computer Science & Engineering

Submitted By

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June, 2021

CERTIFICATE

I hereby certify that the work which is being submitted in this report titled **"Tweeting from Left to Right: Echo Chambers in Delhi Election"**, in partial fulfilment of the requirement for the award of certification of "3rd Year Internship" in "Research Intern" submitted in Bharati Vidyapeeth's College of Engineering, New Delhi, is an authentic record of my own work carried out under the supervision of "Dr Vedika Gupta" and refers to other researchers work which are duly listed in the reference section.

The matter presented in this report has not been submitted for the award of any other certificate of this or any other institution.

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This is to certify that the statements made above by the candidates are correct and true to the best of our knowledge.

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Internal Examiner

External Examiner

CANDIDATES DECLARATION

I hereby declare that the work presented in this report entitled "**Tweeting from Left to Right: Echo Chambers in Delhi Election**", in partial fulfilment of the requirement for the award of the degree **Bachelor of Technology** and submitted in **Department of Computer Science & Engineering, Bharati Vidyapeeth's College of Engineering**, , **New Delhi** (**Affiliated to Guru Gobind Singh Indraprastha University**) is an authentic record of my own work carried out during the period from June **-** July 2021 under the guidance of **Dr. Vedika Gupta.**

The work reported in this has not been submitted by me for award of any other degree of this or any other institute.

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ORGANIZATION INTRODUCTION

The paper is organized in the following way:

Section 1 – Introduction of Project – "Tweeting from Left to Right: Echo Chambers in Delhi Election":

In this section we introduced the degree to which echo chambers exist in political discourse on Twitter, and how they are structured. We approach the study in terms of two components: the opinion that is shared by a user, and the "chamber", i.e., the social network around the user, which allows the opinion to "echo" back to the user as it is also shared by others. It also keeps complete attention towards removal of various inaccurate predictions which occurred in various other proposed models.

Section 2 – Literature Review:

This section discusses the similar work proposed and completed in the domain of natural language processing. It discusses various papers we have studied in order to know more about how echo chambers work and how they affect social media.

Section 3 – About Dataset:

In this section we described the dataset which consists of more than 1 million tweets related to two major political parties of Delhi Election 2020, Bharatiya Janata Party (BJP) and Aam Aadmi Party (AAP). The dataset originally consisted of four CSVs for the four classes, BJP Support, BJP Against, AAP Support, AAP Against.

Section 4 – Experimental Results:

In this section we have shown our experimental results along with a comparison table. We also discussed how the data shown in graphs denotes the changes in the echo chamber w.r.t to the political and cultural aspects and various implications that can be inferred from that.

Section 5 – Summary, Conclusion and Future Scope:

In this research we study echo chambers in political discussions in social media, in particular, we study the interplay between content and network, and the different roles of users.

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Preface

This report is prepared to fulfil the requirements of the B tech. Program of "Bharati Vidyapeeth's College of Engineering on “Tweeting from Left to Right: Echo Chambers in Indian Election”. We have chosen this topic because it is a very important way to detect echo chambers on any social media platform. an echo chamber can act as a mechanism to reinforce an existing opinion within a group and, as a result, move the entire group toward more extreme positions. We would like our model to be used by the researchers and analysts to explore the key differences between the main social media platforms and how they are likely to influence information spreading and echo chambers’ formation.

The prime focus in this study is to identify the two components in the phenomenon: the shared opinion and the "chamber" (i.e., the social network) that allows the opinion to "echo" (i.e., be re-shared in the network) – and look at how these two components interact. While social media makes it simple to interact with and receive information from anybody, it also makes fundamental influencing and unfriending techniques easier, which may lead to separated and polarised clusters known as "echo chambers." We investigate the conditions that lead to the creation of echo chambers in online social networks by proposing a basic model of information sharing in online social networks that includes the two elements of influence and unfriending.

Echo chambers have emerged as an issue of concern in the political discourse of democratic countries. There is growing concern that, as citizens become more polarized about political issues, they do not hear the arguments of the opposite side, but are rather surrounded by people and news sources who express only opinions they agree with. It is telling that Facebook and Narendra Modi have recently voiced such concerns. If echo chambers exist, then they might hamper the deliberative process in democracy.

In chapter 1 we discussed the introduction of the echo chamber and how it influences social media with respect to changes in different opinion of view and also based on their influence as well as tolerance level. In Chapter 2 we discussed the similar work proposed and completed in the domain of echo chambers in social media platforms. In Chapter 3 we discussed the methodology adopted and technology used by us to analyse these echo chambers. In the chapter 4 we discussed the results we obtained during this project.

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Abstract

Echo chambers, or circumstances in which one is only exposed to ideas that are similar to one's own, are becoming a growing problem for political debate in many democratic countries. The issue of political echo chambers on social media is examined in this study. We identify the two components in the phenomenon: the shared opinion and the "chamber" (i.e., the social network) that allows the opinion to "echo" (i.e., be re-shared in the network) – and look at how these two components interact. While social media makes it simple to interact with and receive information from anybody, it also makes fundamental influencing and unfriending techniques easier, which may lead to separated and polarised clusters known as "echo chambers." We investigate the conditions that lead to the creation of echo chambers in online social networks by proposing a basic model of information sharing in online social networks that includes the two elements of influence and unfriending. Users' attitudes and social relationships might be influenced by the content they are exposed to through sharing. For social-media users, we construct a production and consumption metric that reflects the political leaning of the material they post and receive. When we compare the two, we find that Twitter users are exposed to political ideas that are largely similar to their own. We also discovered that individuals who attempt to break down echo chambers by sharing material with opposing viewpoints must pay a proportional premium in terms of network centrality and content appreciation. Furthermore, we investigate the role of "opposition" party users in the development of echo chambers, who consume their information with a varied leaning but generate partisan content (with a single-sided leaning). Finally, we use our findings to forecast supporters and opponents based on social and content traits. While supporting users turn out relatively easy to identify, oppositions prove to be more challenging.

Chapter 1

Introduction

In this chapter we introduce about echo chambers in Indian politics using the concept of social analysis network on Twitter. An Information can come from many different sources and perspectives. But when you're only hearing the same perspectives and opinions over and over again, you may be in something called an echo chamber. An **echo chamber** is an environment where a person only encounters information or opinions that reflect and reinforce their own. Echo chambers can create misinformation and distort a person's perspective so they have difficulty considering opposing viewpoints and discussing complicated topics. They're fuelled in part by **confirmation bias**, which is the tendency to favour info that reinforces existing beliefs.

1.1 Online echo chambers

Echo chambers can happen **anywhere information is exchanged**, whether it's online or in real life. But on the Internet, almost anyone can quickly find like-minded people and perspectives via social media and countless news sources. This has made echo chambers far more numerous and easier to fall into.

The Internet also has a unique type of echo chamber called a filter bubble. Filter bubbles are created by algorithms that keep track of what you click on. Websites will then use those algorithms to primarily show you content that's similar to what you've already expressed interest in. This can prevent you from finding new ideas and perspectives online.

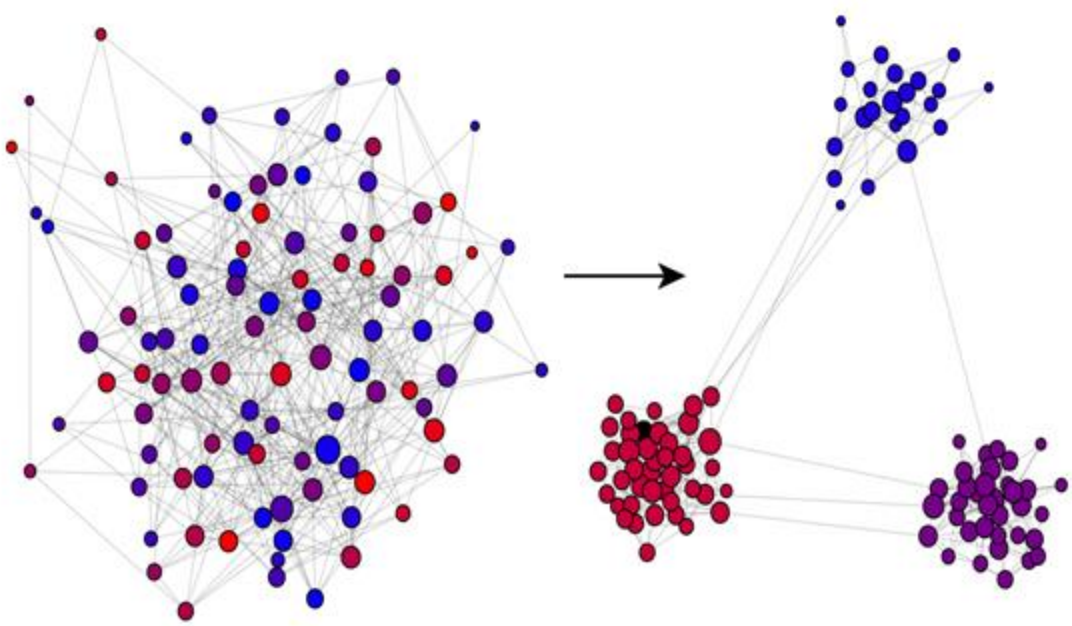


Figure 1 – Effect of Echo Chamber on social media

1.2 Recognizing echo chambers

Echo chambers can also be tricky to recognize, especially if you're in one. If you're ever wondering if a social group or website may be an echo chamber, stop and think about a few questions:

- Do they tend to only give one perspective on an issue?
- Is that viewpoint mainly supported by rumour or incomplete evidence?
- Are facts ignored whenever they go against that viewpoint?

If you answered yes to any of these questions, you may have found an echo chamber.

1.3 Avoiding echo chambers

There's no perfect way to avoid echo chambers, but here are a few tips that can help you stay on the right track.

- Make a habit of checking multiple news sources to ensure you're getting complete, objective info.
- Interact with people of different perspectives, and take care to discuss new ideas with facts, patience, and respect.
- Remember that just because you want something to be true, doesn't make it fact.

No matter where you go or who you meet, always take the time to stay informed, check your sources, and avoid echo chambers.

Echo chambers have emerged as an issue of concern in the political discourse of democratic countries. There is growing concern that, as citizens become more polarized about political issues, they do not hear the arguments of the opposite side, but are rather surrounded by people and news sources who express only opinions they agree with. It is telling that Facebook and Narendra Modi have recently voiced such concerns. If echo chambers exist, then they might hamper the deliberative process in democracy.

In this Research, we study the degree to which echo chambers exist in political discourse on Twitter, and how they are structured. We approach the study in terms of two components: the opinion that is shared by a user, and the "chamber", i.e., the social network around the user, which allows the opinion to "echo" back to the user as it is also shared by others. The opinion corresponds to content items shared by users, while the underlying social network is what allows their propagation. We say that an echo chamber exists if the political leaning of the content that users receive from the network agrees with that of the content they share.

As there is no consensus on a formal definition in the literature, we opt for this definition, which is general enough and reasonably captures the essence of the phenomenon. There are, however, a few previous works that have studied echo chambers under different perspectives. For instance, previous works have focused either on the differences between the content shared and read by partisans of different sides; the social network structure; or the structure of user interactions, such as blog linking and retweets. We adopt a definition which is broader in terms of content it is based on (it considers all content shared and produced, not only content pertaining to specific types of interactions, e.g., retweets), and which is defined jointly on content and network.

Specifically, we define production and consumption measures for social media users based on the political leaning of the content shared with and received from their network. We apply them to several datasets from Twitter, including a large one consisting of over 2.5 billion tweets, which captures 8 years' worth of exchanges between politically-savvy users. Our findings indicate there is large correlation between the leaning of content produced and consumed: echo chambers are prevalent on Twitter

Our study opens the road for further investigation of the echo chamber phenomenon. While establishing the existence of political echo chambers on Twitter, based on a broad definition and measurements over a large volume of data, it also invites a more nuanced analysis of such phenomenon – one that, instead of categorizing users in terms of partisanship, takes into account a variety of user attitudes (e.g., partisans, gatekeepers, and bipartisan). Such analysis might be crucial to understand how to nudge users towards consuming content that challenges their opinion and thus bridge echo chambers. Furthermore, our study shows the interdependence between content production & consumption and network properties in the context of echo chambers. This finding could help us in revisiting existing models for the dynamics of opinion formation and polarization on social networks that take into account not only the opinion (content) spread over the social network, but also its impact of structure of the network itself.

In next chapter we will discuss about the existing literature in the area of social network analysis on Twitter, specifically echo chambers.

Chapter 2

Literature Review

This chapter studies the existing literature in the area of social network analysis on Twitter, specifically echo chambers.

Main contributions in this research paper are the dataset created and the technology used. Some of the works done by researchers and analysts on echo chambers models have been mentioned in this section.

In the previous times various researchers and analysts mainly focused on [1] exploring the key differences between the main social media platforms and how they are likely to influence information spreading and echo chambers' formation whereas other researchers [2] revealed the existence and degree of an echo chamber effect from multiple dimensions, such as topic, interaction mechanism, and interaction level, and its impact on interaction content.

The goal of the [3] research was to look into the degree of polarisation and the structure of echo chambers in relation to COVID-19 discussions on Twitter in the United States. Then gave fresh insights into the categorization of partisan users by evaluating the user polarity predicted by retweet-BERT. Importantly, while both right- and left-leaning communities have echo chambers, the right-leaning community's echo chamber was considerably more densely linked and separated from the rest.

The goal of this study [4] was to see if being exposed to attitudinally congruent internet news feeds impacts people's false consensus effect, or how strongly they view public opinions as favourably biased and supportive of their own beliefs. The degree of agreement individuals encounter in online news feeds is anticipated to impact the amount of the false consensus effect, with high agreement leading to a larger estimate of public support for their own ideas than low agreement.

By examining blog consumption habits of audiences in the climate change blogosphere, this study [5] provides evidence for echo chamber effects. The goal of this study was to see if people who have low climate change danger perceptions read climate sceptic blogs more often than people who have high climate change risk perceptions read climate mainstream blogs. Audience members completed a self-administered survey that assessed are as follows:

a) Their climate change risk beliefs,

b) Whether they visit climate mainstream and/or sceptic blogs,

c) How many days per month they visit a blog, and

d) How much time they spend on a blog during a visit.

In this paper [6] researchers provide strategies and tools in this study to mine this data in order to extract social networks and the external variables that shape their structure. They show that some characteristics are stronger predictors of social connections than others, and that these indicators differ between user groups, in an examination of two data sets from Stanford University and the Massachusetts Institute of Technology (MIT). Their methods might be used to infer real-world relationships and to find, classify, and characterise groups.

Echo chambers and opinion [7] polarisation have lately been measured in a variety of geopolitical situations and across various social media platforms, raising worries about their potential influence on the dissemination of disinformation and discussion openness. They present a model that includes radicalization dynamics as a reinforcing process that drives the growth of moderate beginning circumstances to extremist beliefs. They analysed agents with diverse activities and homophily, based on empirical results on social interaction dynamics. Their findings offer insight on the mechanisms that may be at the root of social media polarisation and echo chambers.

In this study [8], there are concerns that in a high-choice media environment, people may choose media and material that reinforce their current ideas, leading to segregation based on interest or partisanship. Single media studies and studies that employ restricted definitions and measurements of being in an echo chamber, they believe, are problematic because they do not test the hypothesis in the realistic setting of a multiple media environments.

In [9] They investigate the development of these structures using evolutionary games as a lens. In their opinion an individual's reward is decided jointly by the scope of their viewpoint, the degree to which they adhere to their social neighbours and the advantages of doing so connections.

In [10] researchers discovered that social media and search engines are linked to an increase in the average ideological gap between people. Surprisingly, these same channels are linked to an increase in an individual's exposure to information from his or her opposing political party. Finally, the great majority of online news consumption is accounted for by people merely visiting the home sites of their favourite, usually mainstream, news providers, as a result of recent technical advances, both positive and bad. As a result, they found evidence for both sides of the argument while also discovering that the size of the impacts is rather small.

In this study [11] echo chambers, or settings in which one is only exposed to views that are similar to one's own, are becoming a growing problem for political debate in many democratic countries. Users that strive to break down echo chambers by sharing material with opposing viewpoints pay a 'price of bipartisanship' in terms of network centrality and content enjoyment, according to our findings.

The finding [12] shows that information that reinforces one's perspective increases news storey exposure whereas material that challenges one's opinion makes exposure just slightly less probable. Both factors have a little impact, but opinion-reinforcing information is the more important predictor. To answer the issue of how social media and recommender algorithms [13] contribute to the fragmentation of modern society into discrete echo chambers, they built an agent-based modelling (ABM) and analysed twelve alternative information filtering scenarios. Simulations demonstrate that under conditions of central information transmission over channels reaching a substantial portion of the population, echo chambers arise as a result of cognitive factors such as confirmation bias, even without any social or technical controls.

In this study [14] researchers pay special attention to how much consumers participate in selective exposure to media material that aligns with their political ideas, as well as how technology exacerbates this tendency.

In [15] echo chamber: rush Limbaugh and the conservative media establishment, the researchers study the Barak Obama election and formation of echo chambers. There are supporters and opposition with their opinions and differences which form an echo chamber.

The purpose of this study [16] is to give a more formal operationalization of the components of echo chambers based on these discoveries. They show that both information homogeneity (the echo) and multi-path information transmission (the chamber) play important roles in policy communication using exponential random graph (ERG) modelling. The confluence of these elements, produces echo chambers in the climate policy network. These findings lead to some significant implications regarding climate politics and, more broadly, the connection between science communication and elite policymaking. Whereas in study [17] their methods might be used to automatically infer real-world connections as well as to find, classify, and characterise groups.

In this research [18,19,20] k-core decomposition is used to create algorithms for analysing large-scale complicated networks. This decomposition, which is based on recurrent pruning of the least linked vertices, allows networks to be disentangled by increasingly focusing on their centre cores. Researchers created a generic visualisation technique based on this strategy that can be used to compare the structural features of different networks and emphasise their hierarchical structure.

In next chapter, we will discuss the dataset considered in this study.

Chapter 3

About Dataset

This chapter studies the dataset considered in this study.

3.1 Dataset Description:

The dataset we used in figure 2 dataset description consists of more than 1 million tweets related to two major political parties of Delhi Election 2020, Bharatiya Janata Party (BJP) and Aam Aadmi Party (AAP). The dataset originally consisted of four CSVs for the four classes, BJP Support, BJP Against, AAP Support, AAP Against. We combined all the four CSVs to generate a single CSV to work on, so that we can form echo-chambers out of them using different clustering algorithms. Our final dataset consisted of 3 major attributes: 'text', which contains the tweet text of any particular user, 'user_id', which consists of the id of the user tweeting any tweet and 'date', which consists of the date and time the tweet is generated.

	created_at	tweet	user_id	clean_text
0	2020-10-15 00:00:01	@smitabarooah @ModiOnceMore This video show ho...	3.60667e+08	smitabarooah ModiOnceMore This video show Modi...
1	2020-10-15 00:00:18	RT @NandiniOza: A day after his sister n fathe...	8.09904e+08	RT NandiniOza A day sister n father joined Con...
2	2020-10-15 00:00:20	RT @dpradhanbjp: Glimpses of the massive gathe...	3.49418e+09	RT dpradhanbjp Glimpses massive gathering supp...
3	2020-10-15 00:00:21	RT @JhaSanjay: Dear @ArvindKejriwal Ji: Let's ...	8.2426e+17	RT JhaSanjay Dear ArvindKejriwal Ji Let ' clea...
4	2020-10-15 00:00:22	@kavitavkhanna @VinodKhanna @BJP4India @PMOInd...	1.03281e+18	kavitavkhanna VinodKhanna BJP4India PMOIndia n...
5	2020-10-15 00:00:23	RT @drshamamohd: Why has EC not taken action a...	3.05728e+08	RT drshamamohd Why EC taken action PM Modi amp...
6	2020-10-15 00:00:25	RT @satishacharya: Vote for! Cartoon for @Amar...	1.99403e+07	RT satishacharya Vote Cartoon AmarUjalaNews 20...
7	2020-10-15 00:00:31	RT @sachinsingh1010: 75 year old Govindraj kil...	1.03083e+08	RT sachinsingh1010 75 year old Govindraj kille...
8	2020-10-15 00:00:36	#Modi got made 14000 houses for #SriLanka's Ta...	1.27257e+18	Modi got made 14000 houses SriLanka 's Tamil p...
9	2020-10-15 00:00:41	RT @Raksha_Kumar: Quick question: if #Demoneti...	1.27566e+18	RT Raksha_Kumar Quick question Demonetisation ...

Figure 2 – Dataset description

Snapshot of dataset consisting attributes: 'created at' that shows date and time of tweet creation, 'tweet' that stores the actual text data, 'user_id' that stores the id of user tweeting particular tweet and 'clean text' that stores the pre-processed tweets.

In next chapter we will analyse the experimental results obtained.

Chapter 4

Experimental Results

This chapter analyses the experimental results obtained and comparison between different clustering Algorithms. It also focuses on tolerance and influence parameters of various users existing in echo chamber.

4.1 Evaluation Metric of various Clustering Algorithms:

Table 1: Comparison between various clustering algorithms

Clustering Algorithms	Mean Shift	DBSCAN	K Means
silhouette_score	0.681993869	0.734424408	0.933227692
adjusted_rand_score	1	0.975376174	1
davies_bouldin_score	0.437564008	1.491471966	0.094045005
mutual_info_score	1.386294361	1.361653759	1.386294361
calinski_harabasz_score	1210.089914	2023.003291	141224.1733

1. **Silhouette_score:** The Silhouette Coefficient is defined for each sample and is composed of two scores:
a: The mean distance between a sample and all other points in the same cluster.
b: The mean distance between a sample and all other points in the next nearest cluster.
The Silhouette Coefficient for a set of samples is given as the mean of the Silhouette Coefficient for each sample. The score is bounded between -1 for incorrect clustering and +1 for highly dense clustering. Scores around zero indicate overlapping clusters. The score is higher when clusters are dense and well separated, which relates to a standard concept of a cluster.
2. **Adjusted_rand_score:** Another commonly used metric is the Rand Index. It computes a similarity measure between two clusters by considering all pairs of samples and counting pairs that are assigned in the same or different clusters in the predicted and true clustering.
The formula of the Rand Index is: The RI can range from zero to 1, a perfect match.

3. Davies_bouldin_score: The Davies-Bouldin Index is defined as the average similarity measure of each cluster with its most similar cluster. Similarity is the ratio of within-cluster distances to between-cluster distances. In this way, clusters which are farther apart and less dispersed will lead to a better score. The minimum score is zero, and differently from most performance metrics, the lower values the better clustering performance. Similarly, to the Silhouette Score, the D-B Index does not require the a-priori knowledge of the ground-truth labels, but has a simpler implementation in terms of formulation than Silhouette Score.

4. Mutual_info_score: The Mutual Information is another metric often used in evaluating the performance of Clustering algorithms. It is a measure of the similarity between two labels of the same data. Where |Ui| is the number of the samples in cluster Ui and |Vj| is the number of the samples in cluster Vj, the Mutual Information between clusters U and V is given as: Similarly, to Rand Index, one of the major drawbacks of this metric is requiring to know the ground truth labels a priori for the distribution. Something which is almost never true in real-life scenarios with Clustering.

5. **Calinski_harabasz_score:** Calinski-Harabasz Index is also known as the Variance Ratio Criterion. The score is defined as the ratio between the within-cluster dispersion and the between-cluster dispersion. The C-H Index is a great way to evaluate the performance of a Clustering algorithm as it does not require information on the ground truth labels. The higher the Index, the better the performance.

After Going through the comparison Table 1 we choose K-means clustering as our primary clustering algorithm for further evaluation of Echo chambers. We choose K-means clustering because we are getting higher silhouette score as higher the score clusters are denser, adjusted rand score as 1 which is a perfect match, lower davies boludin score as lower the value better is the clustering performance, mutual info score is almost similar to other clustering algorithms, high Calinski harabasz score as higher the index better the performance.

4.2 Detailed Analysis of Echo Chamber

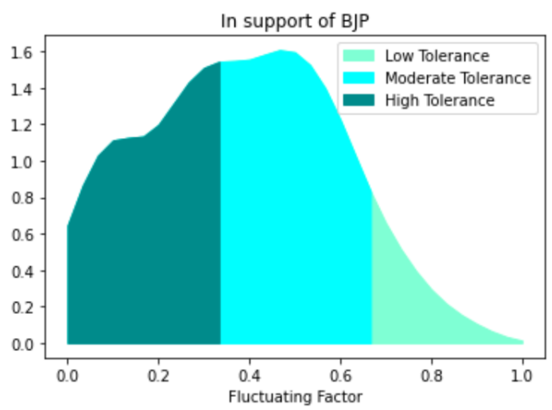


Figure 3.1

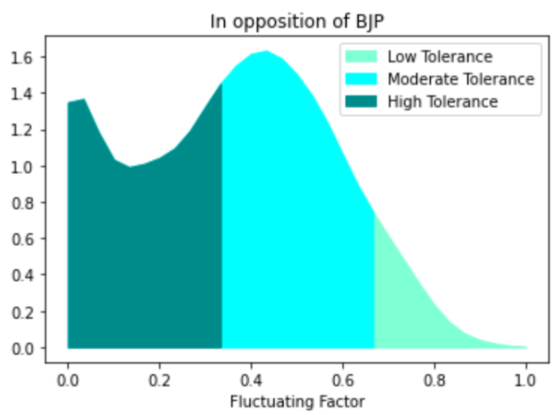
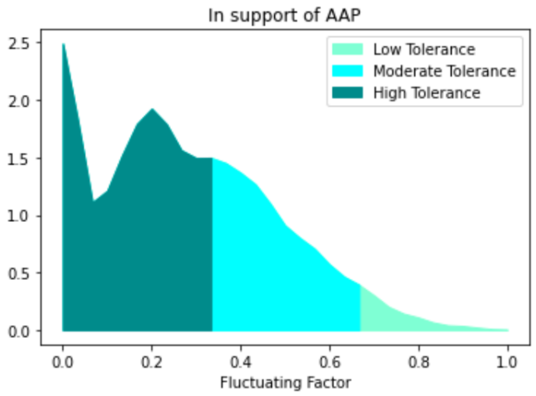


Figure 3.2



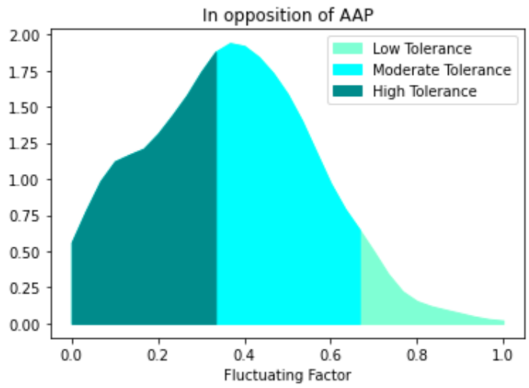
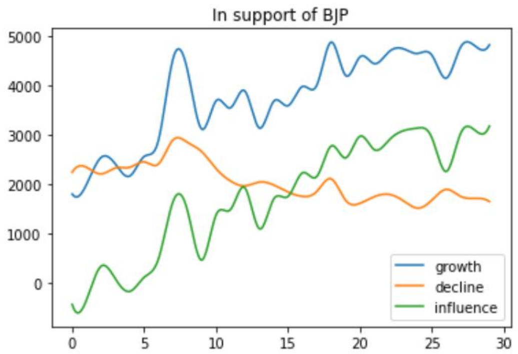


Figure 3.3 **Figure 3.4**

Figure 3: 3.1) Probability Density of people with each level of tolerance in support of BJP
3.2) Probability Density of people with each level of tolerance in opposition of BJP
3.3) Probability Density of people with each level of tolerance in support of AAP
3.4) Probability Density of people with each level of tolerance in opposition of AAP

Figure 3.1 shows the probability density of people with different levels of tolerance in support of BJP. It is clearly seen that the number of people with moderate level of tolerance are in majority while people with high level of tolerance are comparatively less. Hence it can be assumed that there are high chances that other eco-chambers can influence people with moderate level of tolerance in support of BJP. And it is clearly shown in figure 4.1 that over a period of 30 days, some people left this eco-chamber under the influence of other eco-chambers. Similar to Figure 3.1, Figure 3.2 also shows almost similar results. Number of people in opposition of BJP with moderate level of tolerance are comparatively higher than highly tolerant people. But their influence on other eco-chambers is quite high as clearly shown in Figure 4.2. It clearly shows that in a period of 30 days, this eco-chamber has influenced a huge number of people to tweet against BJP.



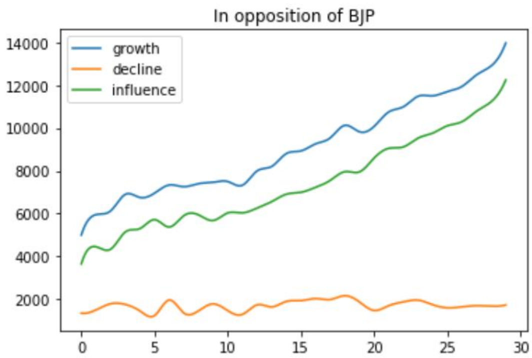


Figure 4.1 **Figure 4.2**

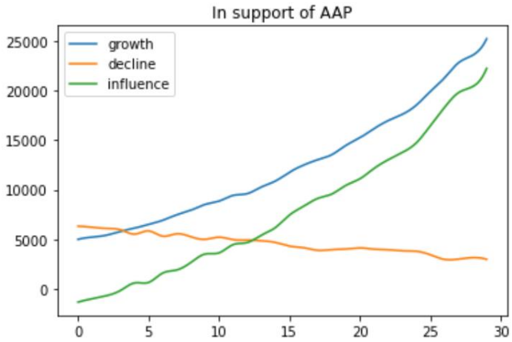


Figure 4.3

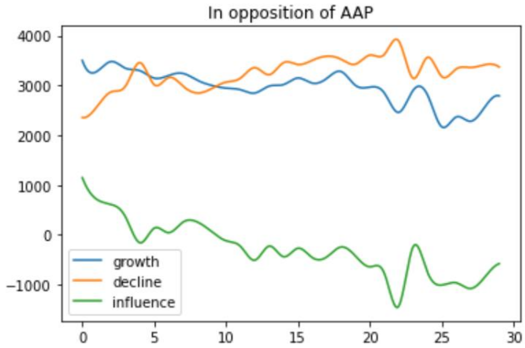


Figure 4.4

Figure 4: 4.1) Growth and Decline in number of people over a period of 30 days and corresponding Influence in support of BJP
4.2) Growth and Decline in number of people over a period of 30 days and corresponding Influence in opposition of BJP
4.3) Growth and Decline in number of people over a period of 30 days and corresponding Influence in support of AAP
4.4) Growth and Decline in number of people over a period of 30 days and corresponding Influence in opposition of AAP

Now talking about AAP, Figure 3.3 clearly shows that the number of people with high level of tolerance are comparatively very high compared to moderate and low level of tolerance in support of AAP. This indicates that influencing people of this eco-chamber is very difficult for other eco-chambers like BJP supporters or AAP oppositions. And it is also clearly visible in Figure 4.3, that over a period of 30 days, the number of people leaving this eco-chamber under the influence of other eco-chambers is very less. On the contrary, it can be seen that the influence of this eco-chamber over others is very high. It can be assumed that it was successful in influencing people with low and moderate level of tolerance from opposition of BJP and opposition of AAP eco-chambers. Lastly, Figure 3.4 shows that there are more people with moderate level of tolerance in opposition to the AAP Party and among the highly tolerant people, more are near the boundary of moderately tolerant people. This fact set this particular eco-chamber in risk of losing its users under the influence of highly influencing echo-chambers like AAP Supporters. And this was clearly shown in Figure 4.4 that over the period of 30 days, number of people leaving this eco-chamber are very high compared to people joining it, and this shows the poorest influencing power of any echo-chamber among the four.

In next chapter we will discuss about the limitation, conclusion and future scope of our research.

Table 2: Weekly progress Report

Weeks	**Work Done**
Week 1	Finalization of project idea
Week 2	Dataset Extraction and cleaning
Week 3	Write the code and compile the models
Week 4	Demonstration to your mentor
Week 5	Written the training report
Week 6	Prepared the presentation of our project
Week 7	Demonstration of the project idea

Chapter 5

Conclusion

In this chapter we will discuss conclusion, limitation and future scope of our research.

5.1 Conclusion

In this research we study echo chambers in political discussions in social media, in particular, we study the interplay between content and network, and the different roles of users. Germane to our approach is the definition of measures for the political leaning of content shared by users in social media. These measures, which are grounded in previous research, capture both the leaning of the content shared by a single user, as well as the leaning of the content to which such user is exposed, by virtue of its neighbourhood in the social network.

5.2 Limitation and Future Scope

The results shown in this study are just one step towards the understanding of echo chambers and the interplay between network and content, which open up several directions for future work. First, exploring more nuanced content and network features, which might lead to a better understanding of echo chambers in social media. For instance, n-gram features can turn out to be very informative for identifying good clusters, which indicates a distinctive writing style of the set of users. In this study we focused on content polarity clustering based techniques on a ground truth, but more powerful NLP techniques (e.g., topic modelling) might enable more powerful analysis. Second, designing probabilistic generative models to capture the observed echo-chamber structure in terms of content and network features – and the different user clusters like shown in this project. Our findings show the effect of tolerance and influence on each user in an echo chamber but this could be extended by adding a new parameter of unfriending between them. Most of the existing models for dynamics of opinion formation and polarization on social networks either use exclusively content features, or use a dynamic process on a fixed random network. However, in light of the current results, a comprehensive model for polarization should affect not only the opinion spread over the social network, but also the structure of the network itself.

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