SOCIAL MEDIA POLARISATION

Enrollment Number: 20803007 ,20803010 , 20803018

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Name of supervisor: Sakshi Gupta

Submitted in partial fulfilment of the degree of

5 year dual degree programme B.Tech

In

Computer Science Engineering

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CERTIFICATE

This is to certify that the work titled **"Social Media Polarisation"** submitted by **Ekta Goel, Rhea Jain and Chetna Sahay** in partial fulfilment for the award of degree of **Integrated M.Tech** of **Jaypee Institute of Information Technology, Noida** has been carried out under my supervision. This work has not been submitted partially or wholly to any other University or Institute for the award of this or any other degree or diploma.

Signature of Supervisor **……………………..**

Name of Supervisor **……………………..**

Designation **……………………..**

Date **……………………..**

ACKNOWLEDGEMENT

We would like to express our special thanks to Mrs. Sakshi Gupta who gave us the golden opportunity, guidance and supervision to do this wonderful project on the topic 'Social Media Polarisation', which also helped us in doing a lot of research and we came to know about so many new things we are really thankful to her.

Secondly, we would also like to appreciate the group effort that helped a lot in finalising this project within the limited time frame.

Signature of the Student ……………………..

Name of Student **Ekta Goel**

Enrollment Number **20803007**

Date **1 December 2022**

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Name of Student **Rhea Jain**

Enrollment Number **20803018**

Date **1 December 2022**

SUMMARY

In this research we have considered different models and their implementation to derive differences among all the opinions of the individual based on the algorithms.We have first studied the dynamics of opinion formation under random interactions with a fixed rate of communication between pairs of agents.We have studied voter model and its extensions to study the opinion based on neighbours with also considering opinion exchange processes inspired by the Sznajd model. We have described the structure of the social network statistically, assuming that the number of contacts of a given individual determines the probability that their opinion reaches and influences the opinion of another individual.

At the end, we have compared different graphs on the basis of the change in concentration of voters with positive opinion in each iteration. It further provided us with the judgement of identifying the most efficient algorithm among all.

Given the factual truth, we could guess which approach works best for the opinion shift dynamics of our network.

Signature of Student **Signature of Supervisor**

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS AND ACRONYMS

Symbols Used	**Meaning**
ε	Switching probability

Introduction

1.1 General Introduction

Social polarisation is the segregation within a society that emerges when factors such as income inequality, real-estate fluctuations and economic displacement result in the differentiation of social groups from high-income to low-income. It is a state and/or a tendency denoting the growth of groups at the extremities of the social hierarchy and the parallel shrinking of groups

The polarisation of society over controversial social issues has been the subject of study in social sciences for decades.The widespread usage of online social networks and social media, and the tendency of people to connect and interact with like-minded individuals has only intensified the phenomenon of polarization.Understanding and quantifying polarisation is a long-term challenge to researchers from several areas, also being a key information for tasks such as opinion analysis..

Also how users in a network update opinions based on their neighbour's opinions, as well as what global opinion structure is implied when users iteratively update opinions, is important in the context of viral marketing and information dissemination, as well as targeting messages to users in the network.

Our goal is to analyse the convergence properties of the opinion dynamics and explore the underlying characteristics that mark the phase transition from opinion polarisation to consensus.

1.2 Problem Statement

Our problem statement is 'The study of difference in opinion dynamics following different social media polarisation models'. How do the different factors on social media affect the opinions of a person in a connected network? Implementation of the above mentioned models to help in our understanding of the opinion dynamics.

Our research helped in working with binary opinion (can be either one or the other) and the understanding of different models.Also it helped in understanding the implementation of previous research already done on the topic. Our study also made us come across working with networks and thus creating our own data to iterate on and create results from.

1.3 Significance/Novelty of problem

Without knowing the working or the ground rules of opinion dynamics it would be nearly impossible to continue and make further improvements to previous studies done in the field of opinion dynamics.

The closer we get to understanding the differences between the models which are caused by certain types of factors, the closer we get to predicting the actual behaviour shift or opinion polarisation of members of a crowd in certain opinion dynamics. This problem is valid because it makes us study the past theories and models in order to go into the direction of future studies on the topic.

1.4 Brief Description of the Solution Approach

We have used a guided approach in studying and implementing the various models of opinion polarisation. Studies of multiple theories and models were followed by implementing what we understood into several codes of different models as presented. These codes were later followed by the representation of our results into diagrams and graphs to verify our results through thorough comparisons and gave us an even better understanding of the solutions given in the past to our problem statement.

Our approach involved a lot of research to fully understand the given model and then converting to code for the given model. On the completion of the code, the results were extracted by the means of graphs,bar chart and diagrams.

1.5 Comparison of existing approaches to the problem framed

We have used three models with different variations to study the behaviours exhibited in opinion shift dynamics. Namely Voter, Q Voter and Voter model with independent voter function. Voter model and Q Voter model differ in a single aspect of the number of people that affect the opinion of a defined voter, where voter model depends on one other person who is the neighbour of the defined voter, Q Voter model defines that the effect arises from more than one neighbours or Q number of people in the same network connected to our picked voter.

While both of these models deal with a single type of person changing their opinion, the independence model deals with two types of people, conformists and people who change their opinion based on the neighbourhood’s opinion,who exist with some probability. We also deal with the Sznajd model which deals with a pair's opinion and creates similar opinions accordingly.

Literature Survey

2.1 Summary of papers studied

We studied more than 30 different research papers related to the topic Social Media Polarisation. In our attempt to find a model that can be translated into code for evaluating the results, we went through 10 different research papers each to find different models for study. By our research, we decided to study and try to implement Voter, Q Voter, Voter Model with independence function and Sznajd Model.

We also studied more research papers to find similar models.

2.2 Integrated summary of the literature studied

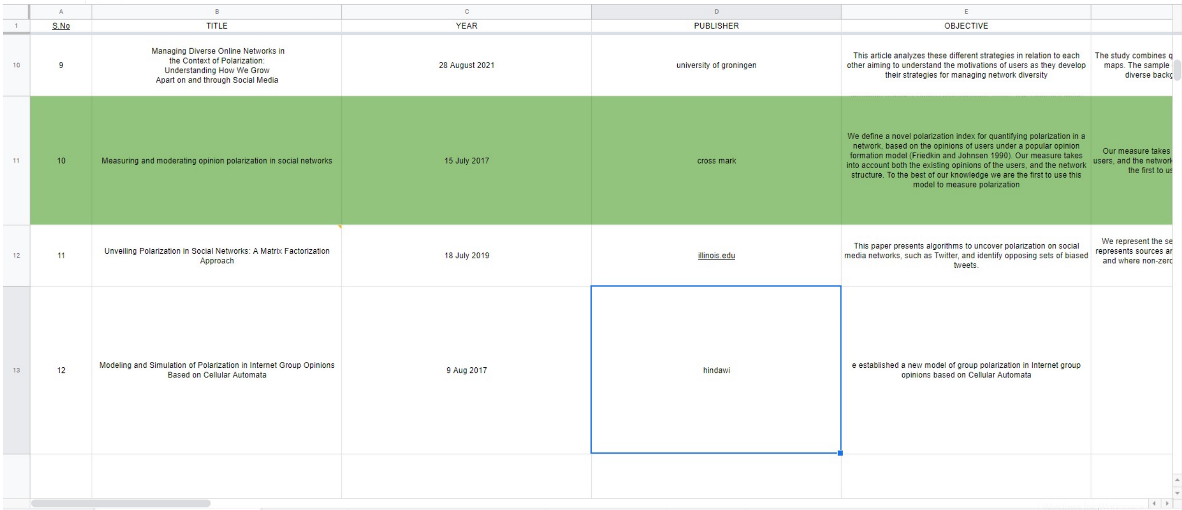
The excel sheet contains more than 3 different sheets with many opinion dynamics models. It consists of the data extracted and compiled for better viewing. We included aspects like models, dataset and publisher of the research paper for better reviewing and study approach.

	A	B	C	D	
1	S.No	TITLE	YEAR	PUBLISHER	
2	1	Opinion Polarization in Social Network	11 April 2022	The Royal Society	General C
3	2	Understanding Filter Bubbles and Polarization in Social Networks	20 Jun 2019	arXiv	Develo
4	3	Modeling Echo Chambers and Polarization Dynamics in Social Networks	27 January 2020	American Physical Society	the transi sta
5	4	A minimalistic model of bias, polarization and misinformation in social networks	26 March 2020	Springer Nature Limited	Develop a confirm drastic

Figure 1: First section of first excel sheet

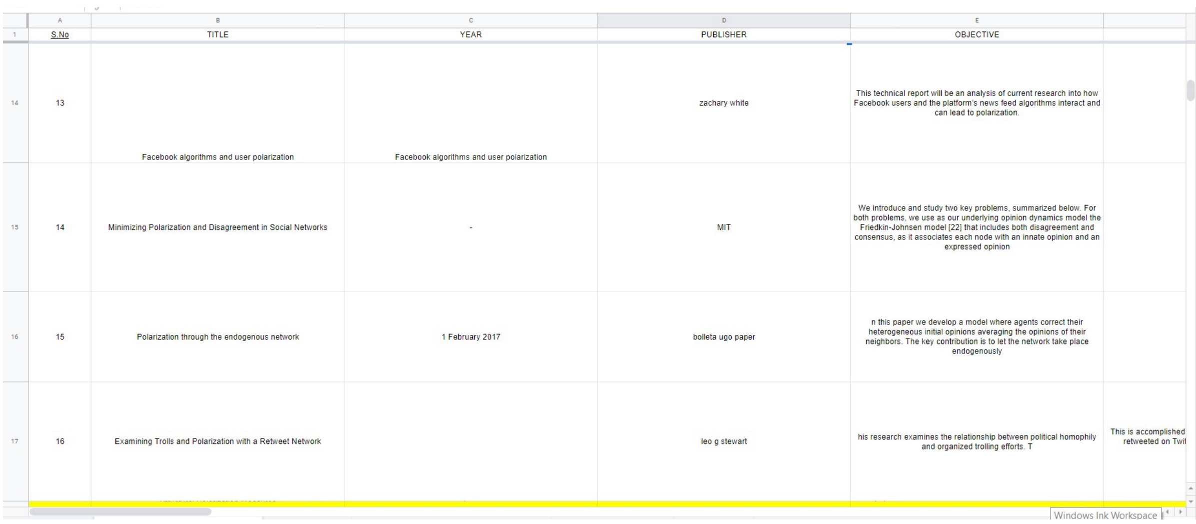
	A	B	C	D	E	
1	S.No	TITLE	YEAR	PUBLISHER	OBJECTIVE	
6	5	A model of opinion and propagation structure polarization in social media	9 January 2020	Springer Nature Switzerland AG. Part of Springer Nature.	opinion dynamics are affected by news propagation	the existence of echo slew of works that
7	6	Link recommendation algorithms and dynamics of polarization in online social networks	6 Dec 2021	National Academy of Science	*provide a complex adaptive–systems perspective on the effects of link recommendation algorithms* *the impacts of social-network algorithms and unveils avenues tosteer dynamics of radicalization and polarization in onlinesocial networks*	new connections ono recommendationalgor
8	7	Investigating political polarization in India through the lens of Twitter	31 July 2022	SPRINGER LINK	This study aims to examine the presence of polarization on Twitter social media platform with respect to different topics of political discussions among Indian politicians.	specific analysis of Indian government ev

Figure 2: Second section of first excel sheet



	A	B	C	D	E	
1	S.No	TITLE	YEAR	PUBLISHER	OBJECTIVE	
10	9	Managing Diverse Online Networks in the Context of Polarization: Understanding How We Grow Apart on and through Social Media	28 August 2021	university of groningen	This article analyzes these different strategies in relation to each other aiming to understand the motivations of users as they develop their strategies for managing network diversity	The study combines q maps. The sample diverse backg
11	10	Measuring and moderating opinion polarization in social networks	15 July 2017	cross mark	We define a novel polarization index for quantifying polarization in a network, based on the opinions of users under a popular opinion formation model (Friedkin and Johnsen 1990). Our measure takes into account both the existing opinions of the users, and the network structure. To the best of our knowledge we are the first to use this model to measure polarization	Our measure takes users, and the network the first to us
12	11	Unveiling Polarization in Social Networks: A Matrix Factorization Approach	18 July 2019	illinois.edu	This paper presents algorithms to uncover polarization on social media networks, such as Twitter, and identify opposing sets of biased tweets.	We represent the se represents sources ar and where non-zerc
13	12	Modeling and Simulation of Polarization in Internet Group Opinions Based on Cellular Automata	9 Aug 2017	hindawi	e established a new model of group polarization in Internet group opinions based on Cellular Automata	

Figure 3: Third section of first excel sheet



	A	B	C	D	E	
1	S.No	TITLE	YEAR	PUBLISHER	OBJECTIVE	
14	13	Facebook algorithms and user polarization	Facebook algorithms and user polarization	zachary white	This technical report will be an analysis of current research into how Facebook users and the platform's news feed algorithms interact and can lead to polarization.	
15	14	Minimizing Polarization and Disagreement in Social Networks	-	MIT	We introduce and study two key problems, summarized below. For both problems, we use as our underlying opinion dynamics model the Friedkin-Johnsen model [22] that includes both disagreement and consensus, as it associates each node with an innate opinion and an expressed opinion	
16	15	Polarization through the endogenous network	1 February 2017	bolleta ugo paper	n this paper we develop a model where agents correct their heterogeneous initial opinions averaging the opinions of their neighbors. The key contribution is to let the network take place endogenously	
17	16	Examining Trolls and Polarization with a Retweet Network		leo g stewart	his research examines the relationship between political homophily and organized trolling efforts. T	This is accomplished retweeted on Twi

Windows Ink Workspace

Figure 4: Fourth section of first excel sheet

	S.No	TITLE	YEAR	PUBLISHER	OBJECTIVE
18	17	How minimizing conflicts could lead to polarization	27 January 2022	Michelle Coscia,Luca Rossi	we create an agent based model to investigate how policing content and backlash on social media (i.e. conflict) can lead to an increase in polarization for both users and news sources.
19	18	Separating Polarization from Noise: Comparison and Normalization of Structural Polarization Measures	07 April 2022	Ali Salloum	We analyse eight of such methods and show that all of them yield high polarization scores even for random networks with similar density and degree distributions to typical real-world networks.
20	19		4 January 2022	HenriqueFerraz de Arruda, Felipe Maciel Cardosoa, GuilhermeFerraz de Arruda, AlexisR. Hernández, Luciano da Fontoura Costa, Yamir Moreno	
21	20	Social Network Interventions to Prevent Reciprocity-driven Polarization	May 3-7, 2021	Fernando P. Santos, Jorge M. Pacheco	Here we investigate the relationship between social networks and reputation-based cooperation (in a Prisoner's Dilemma setting) in large populations.
22	21	Social Networks, Political Discourse and Polarization during the 2017 Catalan elections	23 August 2018	Rafael Monroig,	This thesis investigates the political process in Spain and Catalonia during the Catalan election in December 2017.
23	22	Polarization in Dynamic Networks: A Hopfield Model of Emergent Structure	2003	Michael W. Macy, James A. Kitts, Andreas Flache, Stephen Benard	. Although we find that polarization into two antagonistic groups is a unique global attractor, we investigate the conditions under which uniform and pluralistic alignments may also be equilibria.
24	23	Searching for polarization in signed graphs: a local spectral approach	April 20, 2020	Han Xiao, Bruno Ordozgoiti, Aristides Gionis	in this paper we are interested in finding polarized communities that are related to a small set of seed nodes provided as input.
25	24	How to Quantify Polarization in Models of Opinion Dynamics	26 October 2021	Christopher Musco, Indu Ramesh, Johan Ugander, R. Teal Witter	Complementing recent work that seeks to resolve this apparent inconsistency by modifying opinion models, we instead resolve the inconsistency by proposing changes to how polarization is quantified.
26	25	Me, My Echo Chamber, and I: Introspection on Social Media Polarization	April 2018	Nabeel Gillani, Ann Yuan, Martin Saveski, Soroush Vosoughi, Deb Roy	In this paper, we introduce Social Mirror, a social network visualization tool that enables a sample of Twitter users to explore the

Figure 5:Fifth section of first excel sheet

	S.No	TITLE	YEAR	PUBLISHER	OBJECTIVE	
22	21	Social Networks, Political Discourse and Polarization during the 2017 Catalan elections	23 August 2018	Rafael Monroig,	This thesis investigates the political process in Spain and Catalonia during the Catalan election in December 2017.	
23	22	Polarization in Dynamic Networks: A Hopfield Model of Emergent Structure	2003	Michael W. Macy, James A. Kitts, Andreas Flache, Stephen Benard	. Although we find that polarization into two antagonistic groups is a unique global attractor, we investigate the conditions under which uniform and pluralistic alignments may also be equilibria.	
24	23	Searching for polarization in signed graphs: a local spectral approach	April 20, 2020	Han Xiao, Bruno Ordozgoiti, Aristides Gionis	in this paper we are interested in finding polarized communities that are related to a small set of seed nodes provided as input.	
25	24	How to Quantify Polarization in Models of Opinion Dynamics	26 October 2021	Christopher Musco, Indu Ramesh, Johan Ugander, R. Teal Witter	Complementing recent work that seeks to resolve this apparent inconsistency by modifying opinion models, we instead resolve the inconsistency by proposing changes to how polarization is quantified.	
26	25	Me, My Echo Chamber, and I: Introspection on Social Media Polarization	April 2018	Nabeel Gillani, Ann Yuan, Martin Saveski, Soroush Vosoughi, Deb Roy	In this paper, we introduce Social Mirror, a social network visualization tool that enables a sample of Twitter users to explore the politically-active parts of their social network.	
27	26	Disagreement and Polarization for Extended DeGroot Opinion Dynamics Model in Social Networks	2021	Shun Huang, Qingsong Liu, Li Chai	an extended DeGroot model is proposed to study the evolution of opinions in the social networks.	
28	27	On an Approach to Measure the Level of Polarization of Individuals' Opinions		IEEE	what are the causes leading to an increase in the le	From the perspecti formation [11]–[16 influence to explai
29	28	**Polarization and Fluctuations in Signed Social Networks**	8 Aug 2021	IEEE	analyze signed networks in which the opinions show persistent fluctuations	Much recent resea modeling and anal interpersonal relatio understand the implic
30	29	A Multi-Opinion Based Metric for Quantifying Polarization on Social Networks: A Case Study from India	19 April 2022	arXiv	a measure for quantifying polarization on social networks	Social media has bee communications and

Windows Ink Workspace

Figure 6:Sixth section of first excel sheet

The second excel sheet deals with specific models extracted from the published research papers in the first excel sheet. It contains the links and names of the models for easier retrieval and better communication of ideas.

	A	B	C	D	E	F	G	H	I	J
1	**Reference Model Name**	**Measurement Index**	**Paper no.**	**Link for the paper**						
2	Sznajd model-opinion exchange process Monte Carlo simulations of the stochastic opinion exchange processes	Boltzmann-type kinetic description of opinion formation on social networks	1	https://royalsocietypublishing.org/doi/10.1098/rsta.2021.0158						
3	Friedkin-Johnsen opinion dynamics model synthetic graphs generated from the stochastic block mode	Introduced network administrator who filters content for users by making small changes to the edge weights of a social network	2	https://arxiv.org/abs/1906.08772						
4	empirical findings on social interaction dynamics	propose a model that introduces the dynamics of radicalization as a reinforcing mechanism driving the evolution to extreme opinions from moderate initial conditions. reproduces the observed relation between users' engagement and opinions	3	https://journals.aps.org/prl/abstract/10.1103/PhysRevLett.124.048301						
5			4	https://www.nature.com/articles/s41598-020-62085-w						
6	extended work of Prasetya HA, Murata T. Modeling the co-evolving polarization of opinion and news propagation structure in social media. In: International conference on complex networks and their applications, Cambridge; 2018. Sznajd model Voter Model	opinion changes are invoked by news exposure	5	https://link.springer.com/article/10.1186/s40649-019-0076-z						
	F. Baumann, P. Lorenz-Spreen, I. M. Sokolov, M. Starnini, Modeling echo chambersand polarization dynamics in social networks.Phys. Rev. Lett.124, 048301 (2020) F. Baumann, P. Lorenz-Spreen, I. M. Sokolov, M. Starnini, Emergence of polarizedideological opinions in multidimensional topic spaces.Phys. Rev. X11, 011012 (2021)									

Figure 7:First section of second excel sheet

	A	B	C	D	E	F	G	H	I	J
7	F. Baumann, P. Lorenz-Spreen, I. M. Sokolov, M. Starnini, Modeling echo chambersand polarization dynamics in social networks.Phys. Rev. Lett.124, 048301 (2020) F. Baumann, P. Lorenz-Spreen, I. M. Sokolov, M. Starnini, Emergence of polarizedideological opinions in multidimensional topic spaces.Phys. Rev. X11, 011012 (2021) R. Gray, A. Franci, V. Srivastava, N. E. Leonard, Multiagent decision-making dynamicsinspired by honeybees.IEEE Trans. Control Netw. Syst.5, 793–806 (2018) A. Bizyaeva, A. Franci, N. E. Leonard, A general model of opinion dynamics withtunable sensitivity. arXiv [Preprint] (2020). https://arxiv.org/abs/2009.04332 (Accessed15 February 2021) N.E.Leonard,K.Lipsitz,A.Bizyaeva,A.Franci,Y.Lelkes,The nonlinearfeedbackdynamics of asymmetric political polarizationProc. Natl. Acad. Sci. U.S.A.118,e2102149118 (2021) A. Franci, V. Srivastava, N. E. Leonard, A realization theory for bio-inspired collectivedecision-making. arXiv [Preprint] (2015). https://arxiv.org/abs/1503.08526 (Accessed 15February 2021)	simulate a net-worked population ofNindividuals that adapt their opinionsthrough social influence. Each individualiis characterized by anopinionxi∈−∞,+∞(). The sign ofxirepresents individuals'stance toward a certain topic	6	https://www.pnas.org/doi/epdf/10.1073/pnas.2102141118						
8	1.twitter search api was used 2.xternal–internal index (E–I index), developed by Krackhardt and Stern (1988) 3.standard text mining approach	data analysis only	7	https://link.springer.com/article/10.1007/s13278-022-00939-z						
9	colleceted data from twitter	retweet-BERT	8	https://xmed.jmir.org/2021/3/e29570						
10	semi-structured interviews and ego-centered network maps	By mapping social media users' strategies for dealing with network diversity and the factors influencing these strategies through an in-depth and a cross-platform study, this article contributes to the body of	9	https://journals.sagepub.com/doi/10.1177/2056305120975713						

Figure 8: Second section of second excel sheet

	A	B	C	D	E	F	G	H	I	J
10	semi-structured interviews and ego-centered network maps	By mapping social media users' strategies for dealing with network diversity and the factors influencing these strategies through an in-depth and a cross-platform study, this article contributes to the body of research on social media and polarization.	9	https://journals.sagepub.com/doi/10.1177/2056305120975713						
11	opinion formation model (Friedkin and Johnsen 1990).	polarization index for quantifying polarization in a network	10	https://www.cs.uoi.gr/~tsap/publications/polarization.pdf						
12			11	https://www.ideals.illinois.edu/bitstream/handle/2142/94996/amin_polarization_techreport.pdf?sequence=2						
13	various simulation experiments	cellular automata model and network model of opinion spread	12	https://www.hindawi.com/journals/ddns/2015/140984/						
14	algorithms, used interchangeable in this paper with artificial intelligence, are used by the platform to achieve these goals. Th	onstrained algorithm" approach, which this demo represents on a website1 with percentage limits and a news search bar. This idea limits the effects of otherwise "greedy" algorithms, which attempt to maximize the shortterm reward rate at every individual step.	13	file:///C:/Users/rheaj/Downloads/White_Zachary_Technical_Report%20(1).pdf						
15	Friedkin-Johnsen Model	1.SPGREEDY: Simple Greedy Algorithm 2.FASTGREEDY: Fast Greedy Algorithm	14	file:///C:/Users/rheaj/Downloads/White_Zachary_Technical_Report%20(1).pdf						
16	paper by DeGroot (1974). Golub and Jackson (2010)	Network as given	15	https://www.amse-aixmarseille.fr/sites/default/files/events/bolletta-ugo-paper.pdf						

Figure 9: Third section of second excel sheet

	A	B	C	D	E	F	G	H	I	J
15	Friedkin-Johnsen Model	1.SPGREEDY: Simple Greedy Algorithm 2.FASTGREEDY: Fast Greedy Algorithm	14	file:///C:/Users/rheaj/Downloads/White_Zachary_Technical_Report%20(1).pdf						
16	paper by DeGroot (1974). Golub and Jackson (2010)	Network as given	15	https://www.amse-aixmarseille.fr/sites/default/files/events/bolletta-ugo-paper.pdf						
17	Retweets of RU-IRA Troll Accounts ,To characterize the clusters, we examine the top ten hashtags used in account descriptions along with the most-retweeted and highest-followed accounts in each cluster. I	From this subset, we constructed a retweet graph where each node in the graph represents a Twitter account and directed edges between nodes represent retweets.	16	https://faculty.washington.edu/kstarbi/examining-trolls-polarization.pdf						
18	Lancichinetti–Fortunato–Radicchi (LFR) benchmark	model with two types of actors: users and media sources. Users receive news items shared by media sources and are able to re-share those within their social network or to flag them if they deem them unacceptable 2. We propose a general model accounting for user-user and user-source dynamics. While this is not modelled after any real-world online social network it has characteristics that can be founded on many online platforms and it can be used to simulate the underlying social dynamics that involve both users and news-sources. 3. 3 model-	17	https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0263184						

Figure 10: Fourth section of second excel sheet

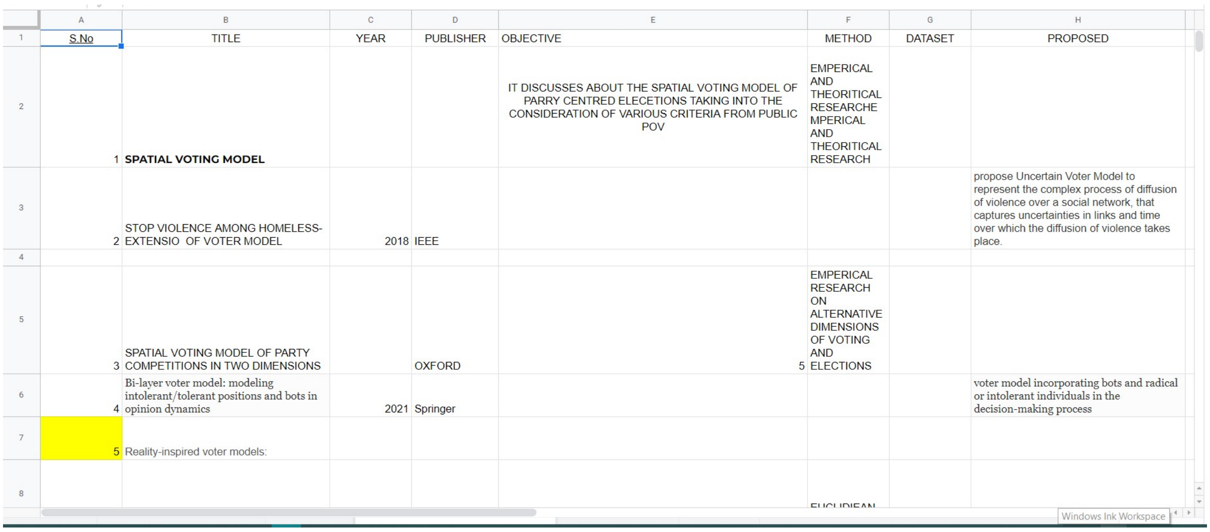
	A	B	C	D	E	F	G	H	I	J
22	This leads to the following four possible strategies: unconditional Defection (AllD), unconditional Cooperation (AllC), Discriminator strategy (Disc),	Here we investigate the relationship between social networks and reputation-based cooperation (in a Prisoner's Dilemma setting) in large populations.	20	https://www.ifaamas.org/Proceedings/aamas2021/pdfs/p1643.pdf						
23	This thesis investigates the political process in Spain and Catalonia during the Catalan election in December 2017.	It was explored from three perspectives: social networks, lexical and emotional discourse and ideological polarization.	21	https://ir.lib.uwo.ca/etd/5556/						
24	Our model is an extension of Hopfield's attractor network.	Consistent with earlier work on structural balance, we find that networks can selforganize into two antagonistic factions, without the knowledge or intent of the agents.	22	https://www.researchgate.net/publication/233821925_Polarization_in_Dynamic_Networks_A_Hopfield_Model_of_Emergent_Structure						
25	Our approach is inspired by the work of Mahoney et al. [24], and our paper extends their results to signed graphs	Second, we rely on recent results on signed graphs (i.e., Proposition 1 in Section 3), not present in the literature on unsigned graphs to the best of our knowledge.	23	https://arxiv.org/pdf/2001.09410.pdf						
26	Our results build on work by DeMarzo et al., who introduced a group-based polarization metric based on ideological alignment. We show that a central tool from that work, a limit analysis of individual opinions under the DeGroot model, can be extended to the dynamics of other group-based polarization measures, including established statistical measures like bimodality.	In conjunction with evidence from prior work that group-based measures better align with real-world perceptions of polarization,	24	https://arxiv.org/abs/2110.11981						
27	No model used. introduction of a social network visualizing tool.	The network is derived from a sample of 1.1M Twitter users who participated in the conversation about the US Presidential Election on the	25	https://dl.acm.org/doi/pdf/10.1145/3178876.3186130						

Figure 11:Fifth section of second excel sheet

	A	B	C	D	E	F	G	H	I	J
27	No model used. introduction of a social network visualizing tool.	The network is derived from a sample of 1.1M Twitter users who participated in the conversation about the US Presidential Election on the platform between June and mid-September 2016	25	https://dl.acm.org/doi/pdf/10.1145/3178876.3186130						
28	In this paper, an extended DeGroot model is proposed to study the evolution of opinions in the social networks	we apply the extended model to address the public opinion event heat problem. Finally, a case study that learning scenario is worked out to illustrate the effectiveness of the opinion dynamics model.	26	https://ieeexplore.ieee.org/document/9601817						
29	DeGroot model the Friedkin-Johnsen model the Krasnoshchekov model	opinions are presented by continuous scalar values that stand for individuals' attitudes towards a fixed topic of interest	27	https://ieeexplore.ieee.org/abstract/document/8911015						
30	C. Altafini, "Consensus problems on networks with antagonistic interactions", IEEE Trans. Autom. Control, vol. 58, no. 4, pp. 935-946, Apr. 2013.- a continuous time model over a signed graph where the opinions can take any real value J. M. Hendrickx, "A lifting approach to models of opinion dynamics with antagonisms", Proc. IEEE Conf. Decis. Control, pp. 2118-2123, Dec. 2014.-discrete-time signed opinion model Z. Meng, G. Shi, K. H. Johansson, M. Cao and Y. Hong, "Behaviors of networks with antagonistic interactions and switching topologies", Automatica, vol. 73, pp. 110-116, 2016.-discrete-time signed opinion model Voter Model	a novel opinion model over signed graphs that assume that the opinions are real numbers taking value in a closed interval and each edge of the graph indicates the friendly or antagonistic relationship between two individuals.-Inspired by the boomerang effect studied in social psychology	28	Polarization and Fluctuations in Signed Social Networks | IEEE Journals & Magazine | IEEE Xplore						
		The method proposed in our study provides a polarization score for a given network by								

Figure 12:Sixth section of second excel sheet

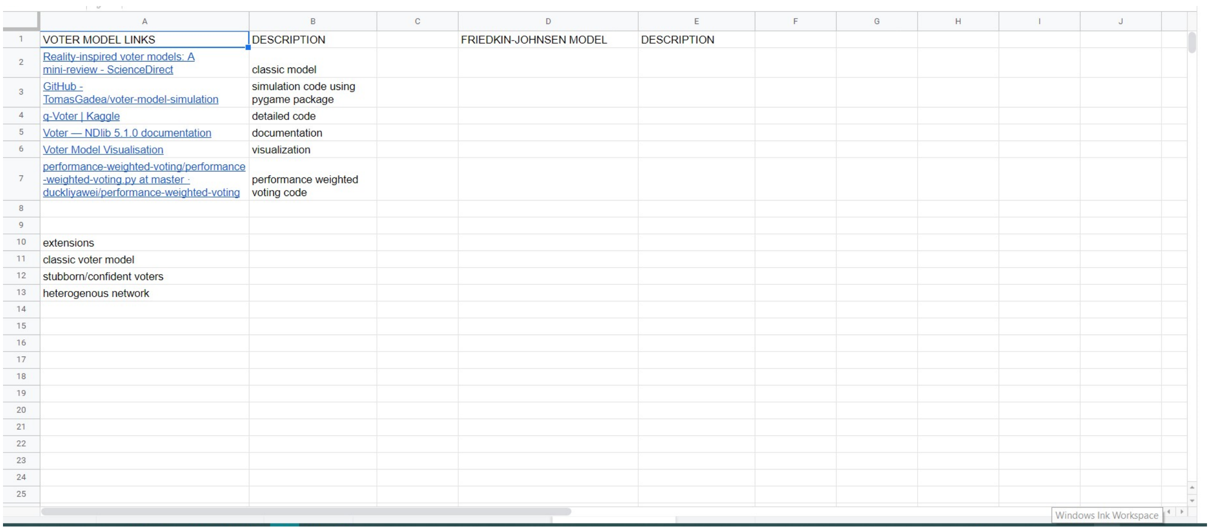
The third sheet deals with voter model extensions and further research work done on the classic voter model.



S.No	TITLE	YEAR	PUBLISHER	OBJECTIVE	METHOD	DATASET	PROPOSED
1	SPATIAL VOTING MODEL			IT DISCUSSES ABOUT THE SPATIAL VOTING MODEL OF PARRY CENTRED ELECETIONS TAKING INTO THE CONSIDERATION OF VARIOUS CRITERIA FROM PUBLIC POV	EMPERICAL AND THEORITICAL RESEARCHE MPERICAL AND THEORITICAL RESEARCH		
2	STOP VIOLENCE AMONG HOMELESS- EXTENSIO OF VOTER MODEL	2018	IEEE				propose Uncertain Voter Model to represent the complex process of diffusion of violence over a social network, that captures uncertainties in links and time over which the diffusion of violence takes place.
3	SPATIAL VOTING MODEL OF PARTY COMPETITIONS IN TWO DIMENSIONS		OXFORD	5	EMPERICAL RESEARCH ON ALTERNATIVE DIMENSIONS OF VOTING AND ELECTIONS		
4	Bi-layer voter model: modeling intolerant/tolerant positions and bots in opinion dynamics	2021	Springer				voter model incorporating bots and radical or intolerant individuals in the decision-making process
5	Reality-inspired voter models:						

Figure 13: Third excel sheet of types of voter model extensions

In total the literature summary dealt with more than 30 research papers that provide understanding of the topics and a better knowledge about our topic.



	A	B	C	D	E
1	VOTER MODEL LINKS	DESCRIPTION		FRIEDKIN-JOHNSEN MODEL	DESCRIPTION
2	Reality-inspired voter models: A mini-review - ScienceDirect	classic model			
3	GitHub - TomasGadea/voter-model-simulation	simulation code using pygame package			
4	q-Voter | Kaggle	detailed code			
5	Voter — NDlib 5.1.0 documentation	documentation			
6	Voter Model Visualisation	visualization			
7	performance-weighted-voting/performance-weighted-voting.py at master · duckliyawei/performance-weighted-voting	performance weighted voting code			
8					
9					
10	extensions				
11	classic voter model				
12	stubborn/confident voters				
13	heterogenous network				

Figure 14: Fourth excel sheet of extensions of Voter Model

Requirement analysis and solutions approach

3.1 Overall description of the project

Our project lies in the category of research cum development project. We have taken “social media polarisation” as our problem statement. Therefore, this project aims to predict the mechanism of polarisation i.e division on the basis of opinions formed on social media.

This project is based on various models with different types of algorithms to achieve the predictability of polarisation .Our project uses python as its programming language. First we have implemented a very basic voter model, and then by considering it as the fundamental base, we have implemented various other different models with improved algorithms and real life databases.

So as we kept progressing in this project, we discovered various other factors that affect the opinion of our object of study i.e voter. Networkx and matplotlib libraries have played a specific role by helping us to visualise these algorithms graphically and to draw conclusions from them.

At the end, we have compared different graphs on the basis of the change in concentration of voters with positive opinion in each iteration. It further provided us with the judgement of identifying the most efficient algorithm among all.

Given the factual truth, we could guess which approach works best for the opinion shift dynamics of our network.

3.2 Requirement analysis

For this project, we have a few requirements, listed down as below:

1. A working system with Python installed.
2. Libraries installed in the Python Version namely:
    - Networkx
    - Matplotlib
    - Numpy
    - Random
    - Matplotlib.pyplot

3. Dataset to implement for the algorithms

Our dataset needs to have two simple functionalities in it to work for our algorithms:

- Must be a connected node graph network to make sense of the change in opinion based on the neighbourhood of a node.
- Must be annotated with binary values_such as [0,1] or [-1,+1]. Since we are working only on binary opinion.

3.3 Solution Approach

We have created two type of code folders:

1) Random.py
2) Specific.py

We have implemented each library in both of these files.

Random.py

1. In random.py we have used a complete graph.
2. Then we randomly assigned binary opinion to all the nodes of the graph i.e [+1,-1].
3. After assigning the votes randomly, we have painted all the positive voters as blue and all the negative ones as red.
4. Then we have randomly chosen a voter whose opinion was to be studied based on the influence of its neighbours.
5. With each model, there are variations in the algorithm which determines the final opinion our voter will attain according to its neighbours.
6. At the end we have generated a bifurcation diagram which shows the variation of concentration of positive nodes with each iteration in each algorithm.
7. At every iteration, the bifurcation diagram was coming out to be different since we have considered the connection of edges randomly and also the voter was also being selected randomly.
8. So it became difficult for us to predict the model and compare it with others.
9. So now we decided to go ahead to make conditions uniform rather than random

Models of our project

Basic voter model

The voter model is a simple mathematical model of opinion formation in which voters are located at the nodes of a connected graph, each voter has an opinion (in the simplest case, 0 or 1), but in the general case, a randomly chosen voter assumes the opinion of one of its neighbours(the one it is connected to).

1. It is a classical model which is used as the base model or the beginning for the whole research.
2. In this model we have studied the influence of only one neighbour on the voter. The voter will change its opinion according to any one of all its neighbours.
3. We have first created a lobby of all the neighbours of the voter then selected a neighbour randomly from the lobby to check for and base opinion from.
4. Then the voter will change its opinion according to the value of its neighbour no matter what it is.
5. It does not matter what the community around the person believes as whole or in majority, but only the person selected that influences and thus changes the opinion of our selected voter.

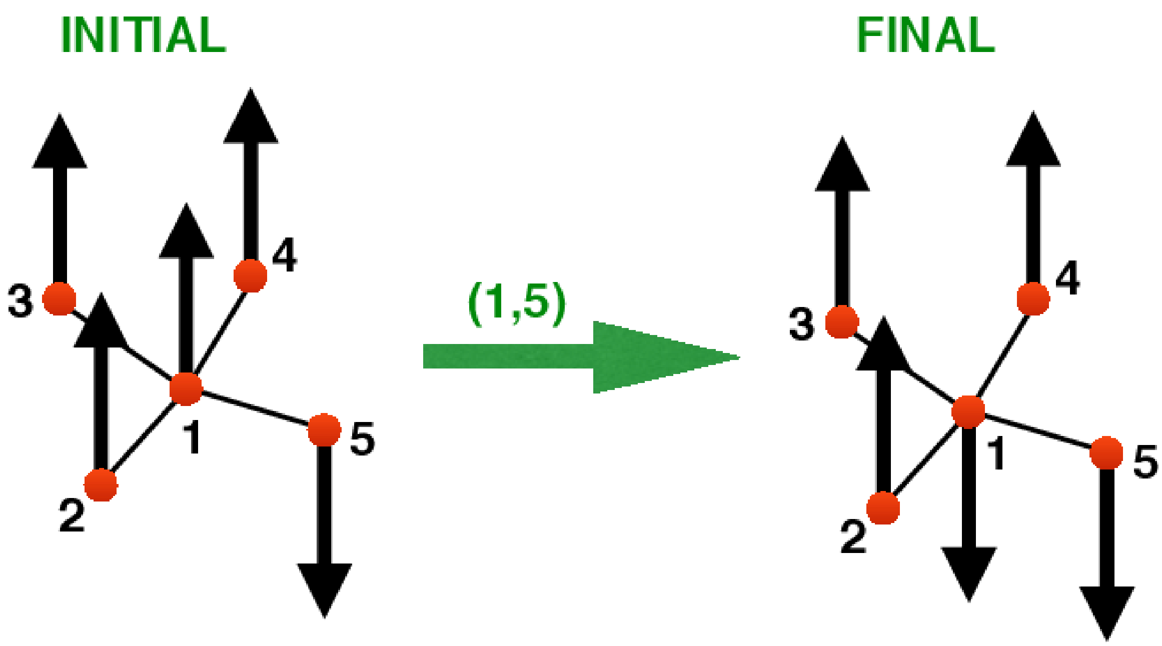


Figure 15: Voter Model

Q-voter model

Here, N individuals hold an opinion ±1. At each time step, a set of q neighbours are chosen and, if they agree, they influence one neighbour chosen at random, i.e. this agent copies the opinion of the group. If the group does not agree, the agent flips its opinion with probability ε.

1. It consists of more conditions than the basic voter model to assign the vote to the voter.
2. In this model we study the influence of a group of neighbours i.e lobby on the voter.
3. The group can be all of the neighbours or a number Q that can be taken by us. In case of a conflict between the two, the minimum value of [Q, no. of total neighbours] affects the resultant opinion of the chosen voter.
4. We have randomly connected the edges and have generated a random lobby of 7 nodes from the list of neighbours of the voter.
5. After that we checked that if all the members of the q lobby have the same opinion (i.e either they all are negative or all are positive), we have changed the opinion of the voter to the opinion of the qlobby.
6. Else we have taken a random value i.e epsilon (ε) which will determine if the voter will change its opinion or not (if all the members of the lobby do not have the same opinion).

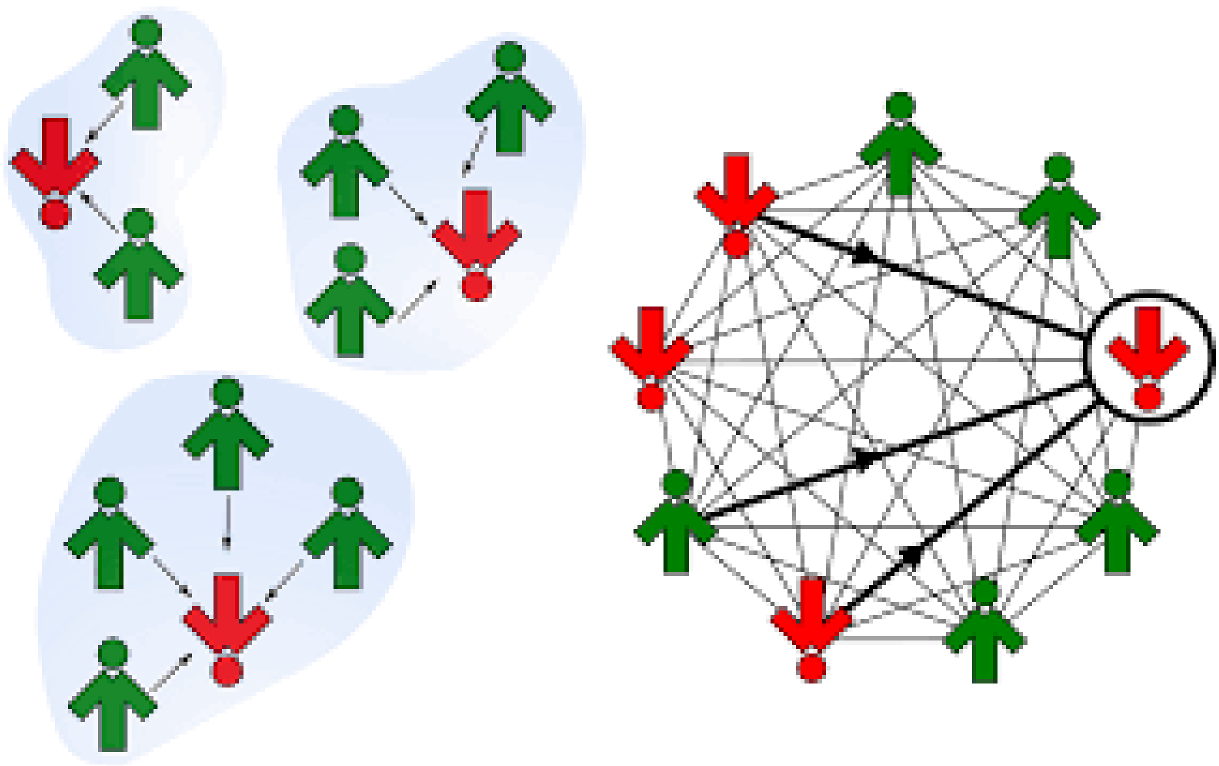


Figure 16: Q-Voter Model

Independence model

1) We have taken two types of voter here-
a) Conformists- who will change the opinion according to the lobby.
b) Independents- who will change opinion according to his/her personal opinion with probabilities 0.5(for each yes and no).

2) We have taken a graph with random connections and have made the q lobby out of the neighbours of voters.

3)The group can be all of the neighbours or a number Q that can be taken by us. In case of a conflict between the two, the minimum value of [Q, no. of total neighbours] affects the resultant opinion of the chosen voter.

4) If the voter is conformist, it will change it's opinion according to majority rule i.e if the sum of the positive votes is greater than the absolute sum of the negative votes then it will change it's opinion to positive and if it is less then it will change to negative vote.

5) If the voter is independent then it depends on him whether he wants to change opinion or not(we have taken 0.5 probability for change to either side).

6)To classify between independent and conformist we have undertaken a random probability p according to which we will apply the suitable conditions for each type of voter.

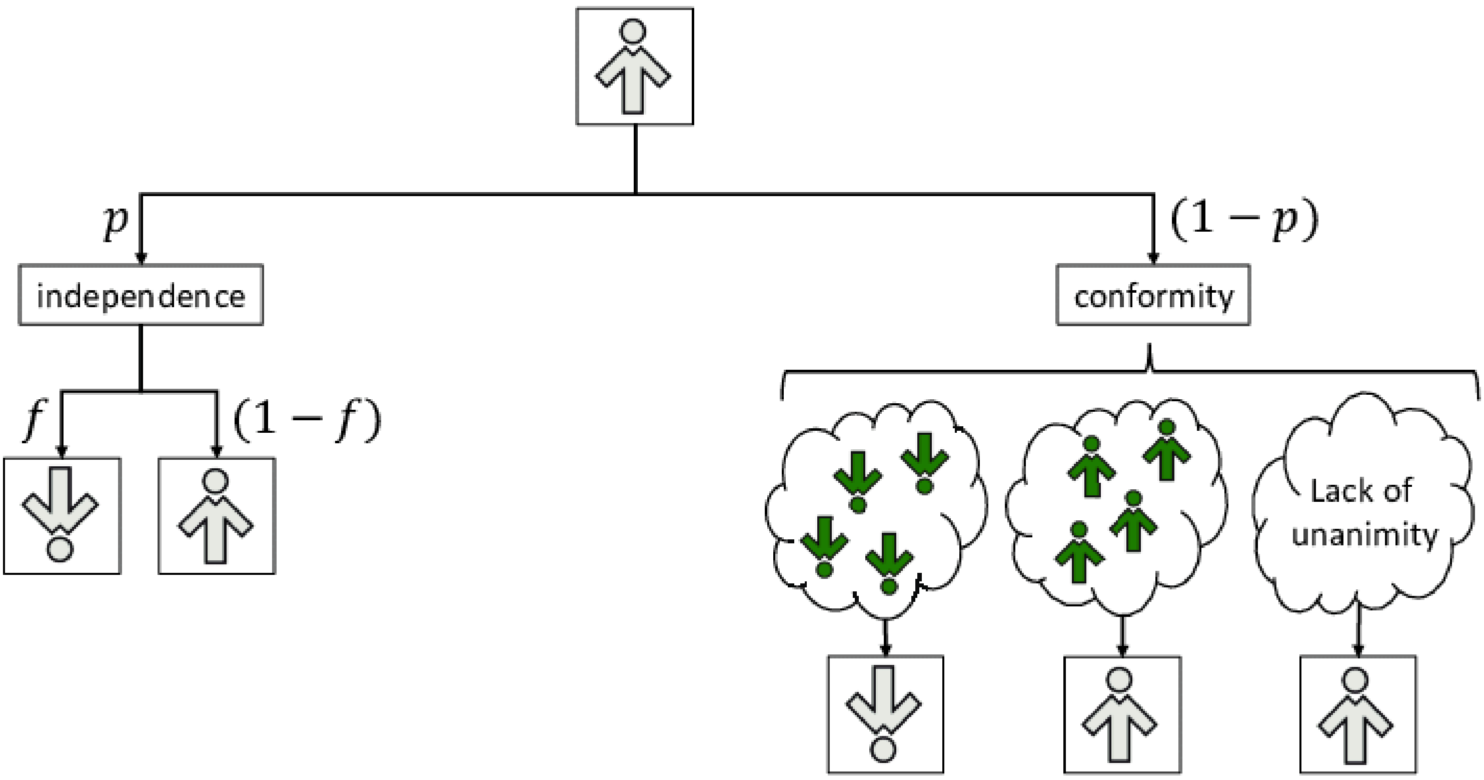


Figure 17:Independence Voter Model

Majority rule model

The Majority Rule model is a discrete model of opinion dynamics, proposed to describe public debates.

Agents take discrete opinions ±1, just like the Voter model. At each time step a group of r agents is selected randomly and they all take the majority opinion within the group.

1. In this case we have connected a graph randomly.
2. We have made a random q lobby out of the neighbours of the voter.
3. Then we have computed the sum i.e sum of positive nodes and sum of negative nodes.
4. Then we have compared the absolute values of both the sum.
5. If the positive sum is greater than the absolute sum of negative voters, then the voter will have a positive vote.
6. If the absolute sum of negative votes is greater than positive votes then voters will have the negative vote.
7. Hence the voter changes its opinion according to the majority instead of the earlier given probability of epsilon.
8. This model works on the common knowledge that the majority enjoys power.

Sznajd model

The Sznajd model is a variant of spin model employing the theory of social impact, which takes into account the fact that a group of individuals with the same opinion can influence their neighbours more than one single individual.

In the original model the social network is a 2-dimensional lattice, however we also implemented the variant on any complex networks.

Each agent has an opinion $\sigma i = \pm 1$. At each time step, a pair of neighbouring agents is selected and, if their opinion coincides, all their neighbours take that opinion.

1. In this model we have connected the graph randomly and chose the voter randomly.
2. Here, we have taken one neighbour to form the neighbouring pair (1 the voter itself and other one is the neighbour).
3. If the neighbouring pairs have the same opinion then all the neighbours of each voter of the pair will change their opinion to the opinion of the neighbouring pair.
4. If the neighbouring pair clashes, the neighbours of each voter will adopt the opinion of their other neighbour.

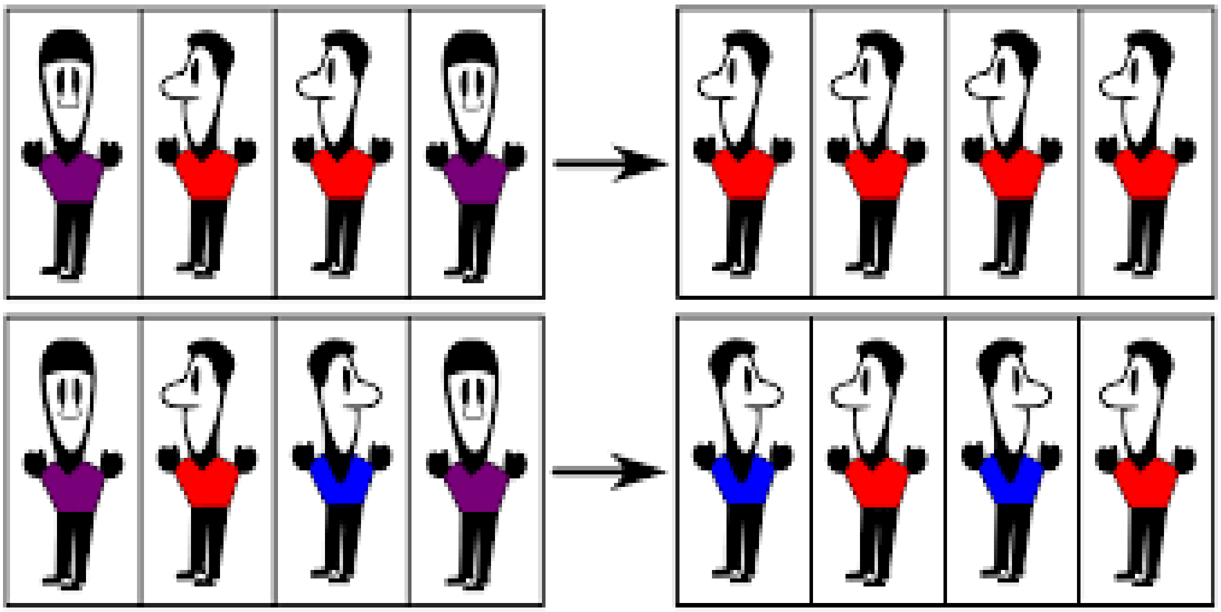


Figure 18: Sznajd Model(Social Representation)

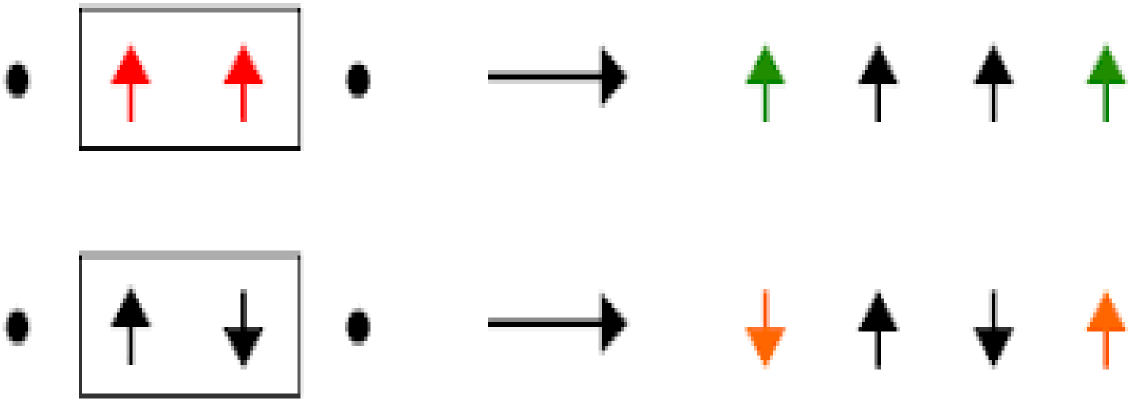


Figure 19: Sznajd Model(Graphical Representation)

Random.py (Randomly created Graphs)

In random.py we have kept everything random, from the choosing of nodes to the choice of lobby.

Random approach works at the mercy of the randomness of the random library thus the results are expected to be a little away from the factual truth. Reality is far from randomness when it comes to opinions.

The distribution of votes (annotation of data) is also random so the opinion in its initial state is also considered randomly thus giving a basis for random result.

Specific.py (Own Dataset)

In specific.py we have taken a specific dataset of facebook and generated a network of that dataset.

We have also kept our chosen voter fixed.

We have also applied conditions on assigning the votes to the nodes.

When all the above models were implemented in specific.py we were able to compare bifurcation diagrams of these models as now we kept all the conditions the same for every model.

Specific.py (Facebook Dataset)

We have imported a Facebook Connection dataset and introduced it into our algorithms.

The only issue for us was to annotate the data which we divided into two opinions with the probability of 0.5.

We kept our Algorithms in the same way as in the randomly generated graphs portion and recorded the results.

The bifurcation diagrams help us understand the results on an actual dataset.

Modelling and Implementation details

4.1 Design Diagram

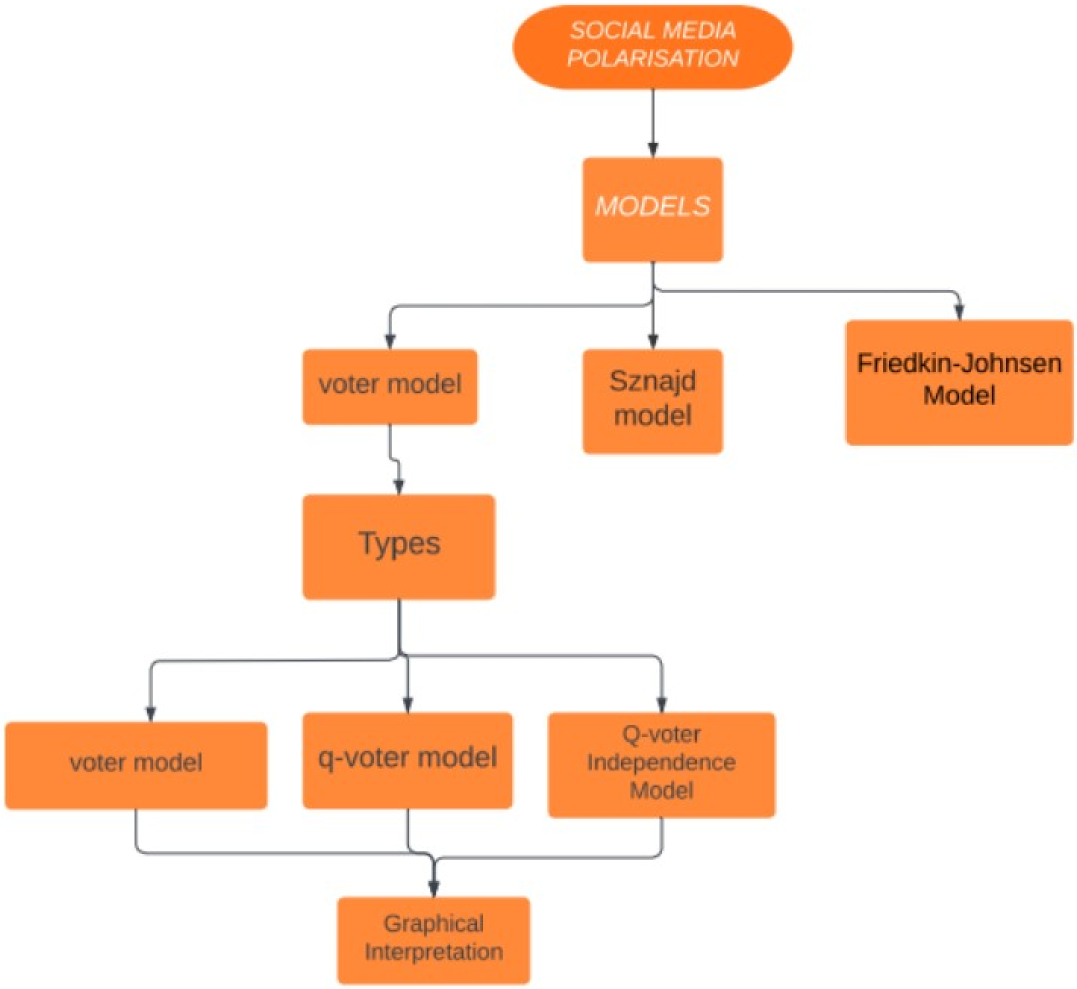


Figure 20: Basic Structure of Research

Random.py

Algorithms	Lobby (q)	epsilon	Nsteps	Viz step	Based on Majority Votes	Probability of Independence
Basic voter model	1	-	1000	100	-	-
Q-voter model	7	0.25	1000	100	-	-
Majority	7	-	1000	100	yes	-
Independence	7	-	1000	100	yes	Randomly generated(0.2)
Sznajd	-	-	1000	100	-	-

Table-1:Specifics of Randomly Created Graph

Specific.py

(Facebook Dataset)

Algorithms	lobby(q)	Nstep	Viz step	Sum of majority	p
Basic voter	1	1000	10	-	-
Q-voter model	7	1000	10	-	-
Majority	7	1000	10	yes	-
independence	7	1000	10	yes	-
Sznajd	7	1000	10	-	-

Table-2 Specifics of Imported Facebook Dataset

4.2 Implementation Details and Issues

We read the papers to find a basic understanding of the above described models. After gaining a basic understanding of the conditions and requirements, we proceeded towards the code implementation of the opinion dynamics models.

The first step to implement our models and run our code was to find a proper dataset to run our code on. The problem we faced first hand was to find a dataset. Minimum requirements for our dataset was to be 1) annotated and 2) connected which was difficult to find.

Thus the solution was to find a connected graph and annotate the data on the basis of some condition. To keep the data completely impartial we assigned half the nodes with one value and the other half with the other value.

We also generated a graph (synthetic dataset) that is completely connected and thus leaves no place for randomness in connecting the nodes to one another.

The second problem we went into was the visualisation of steps, our algorithms are set to work on for about 1000 times, which would be very difficult to show after every single step that takes place. Thus we divided the visualisation to some 100 steps which essentially means that the result is shown every 100 steps of the way.

To plot the continuous concentration of nodes for one ideology(opinion), we created a BIFURCATION DIAGRAM for each graph and dataset. This helped us in keeping a track of the change in trend for every step and how the overall opinion shifts and where it shifts to.

Testing

5.1 List of test cases

Blackbox Testing

Black Box Testing mainly focuses on input and output of software applications and it is entirely based on software requirements and specifications. It is also known as Behavioral Testing.

The Blackbox testing gives perfect outputs for our inputs and changes.

Figure 21: Output for Black-Box Testing

Unit Testing

Unit testing refers to the testing of proper working of our modules separately and together indicating no defect in the working as a module.

Unit testing shows that our two modules: compute_c(H) and repaint(H) are working well.

```python
def repaint(H):

    color_map = []
    for node, data in H.nodes(data=True):
        if data['vote'] == +1:
            color_map.append(0.25)  # blue color
        elif data['vote'] == -1:
            color_map.append(0.9)  # red color

    return color_map
def compute_c(H):

    Nplus = 0

    for node, data in H.nodes(data=True):
        if data['vote'] == +1:
            Nplus = Nplus + 1

    c = Nplus / H.number_of_nodes()

    return c
```

Figure 22:User Defined Functions

5.2 Limitations of the solution

- Binary Opinion

  Our project deals with binary opinion i.e only positive or negative opinion. In reality extremist opinions do not occur or occur in limitations. For making our model more realistic, we need to equip ourselves with a wider variety of opinions.

- Type of network use constricted

  Our code deals with node based lists and functions instead of edge based lists. What this means is that for our code, a list of edges would not yield the same output as a list with nodes.

  Our code functions more on node based functions instead of edge based functions and labels.

- Social Media contributes to consensus development which results in creating “echo chambers” that insulate people from opposing views about current events

Findings,Conclusions and Future Work

6.1 Findings

We have generated bifurcation diagrams of each model based on the variation of the concentration of positive nodes in each algorithm.

Dataset (Randomly Created Graphs)

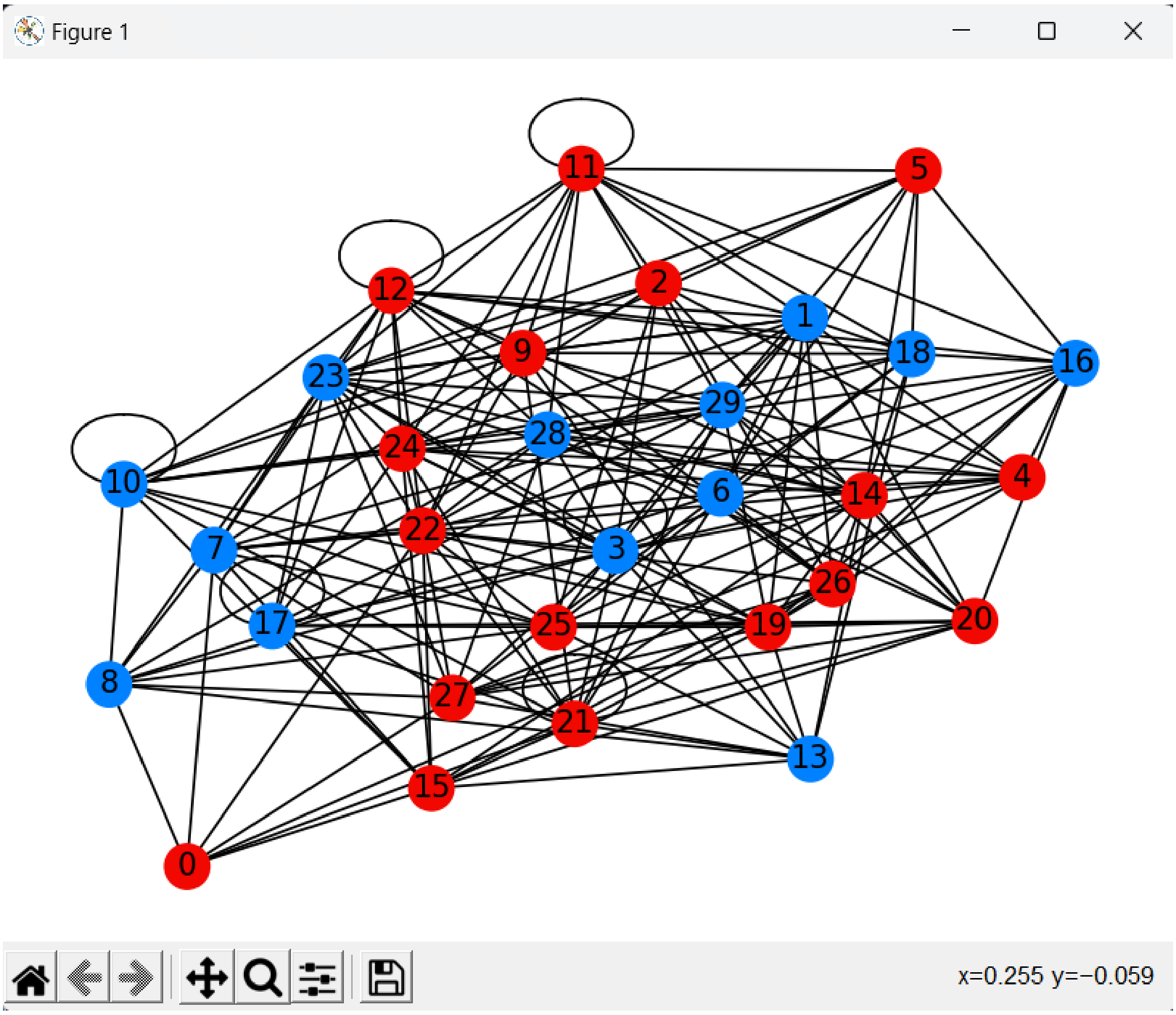


Figure 23: Initial Network Formed

Classical Voter Model

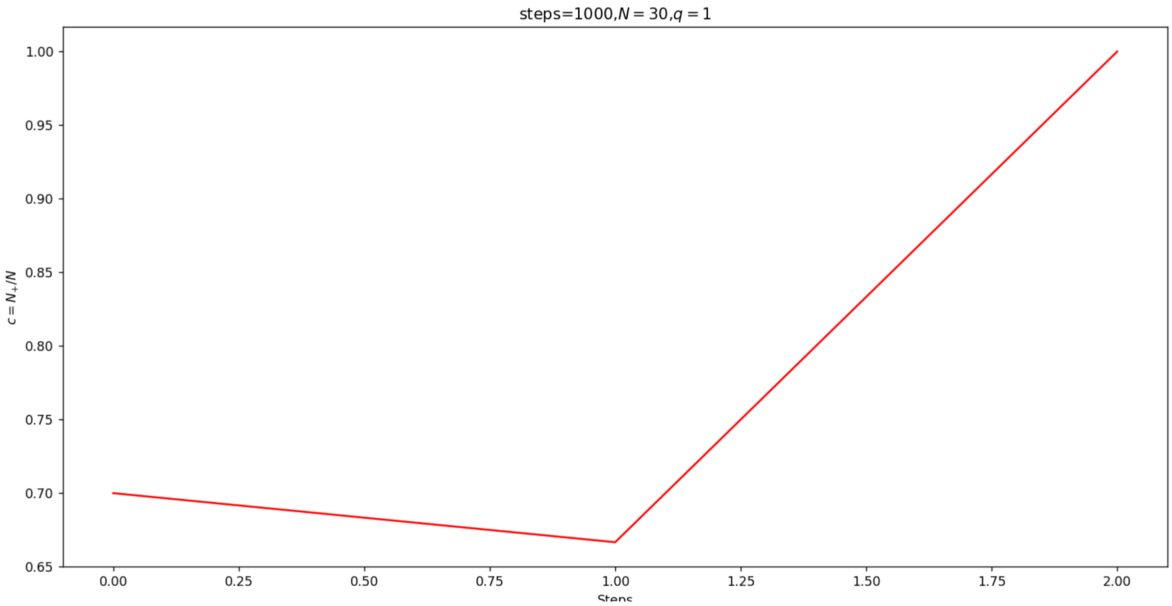


Figure 24: Bifurcation Diagram for Classical Voter Model

Independence Model

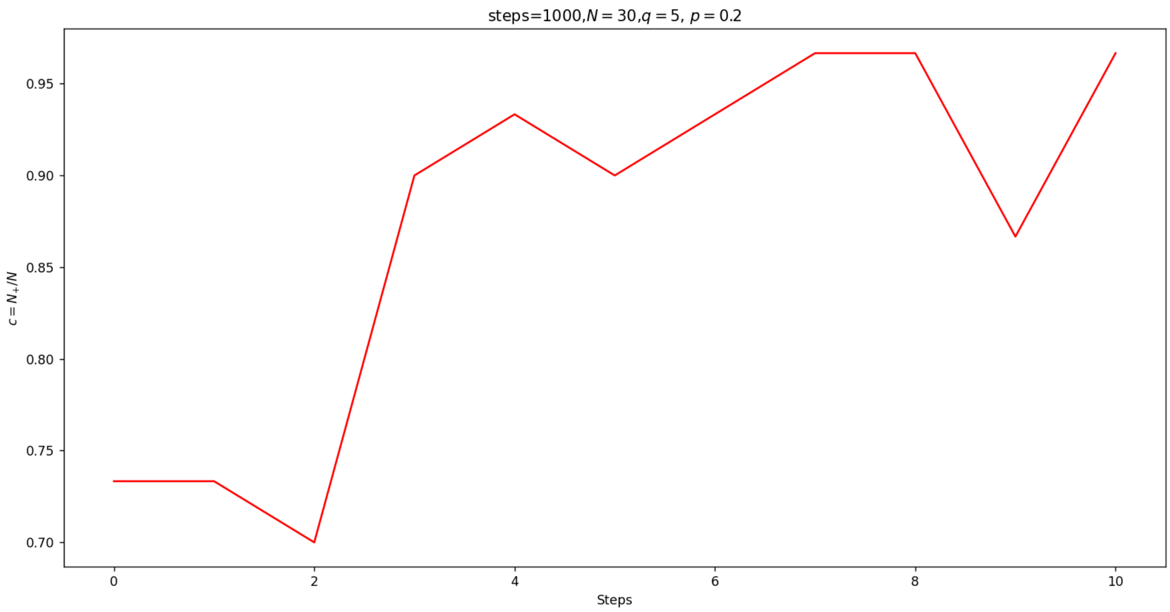


Figure 25: Bifurcation Diagram for Independence Voter Model

Majority Model

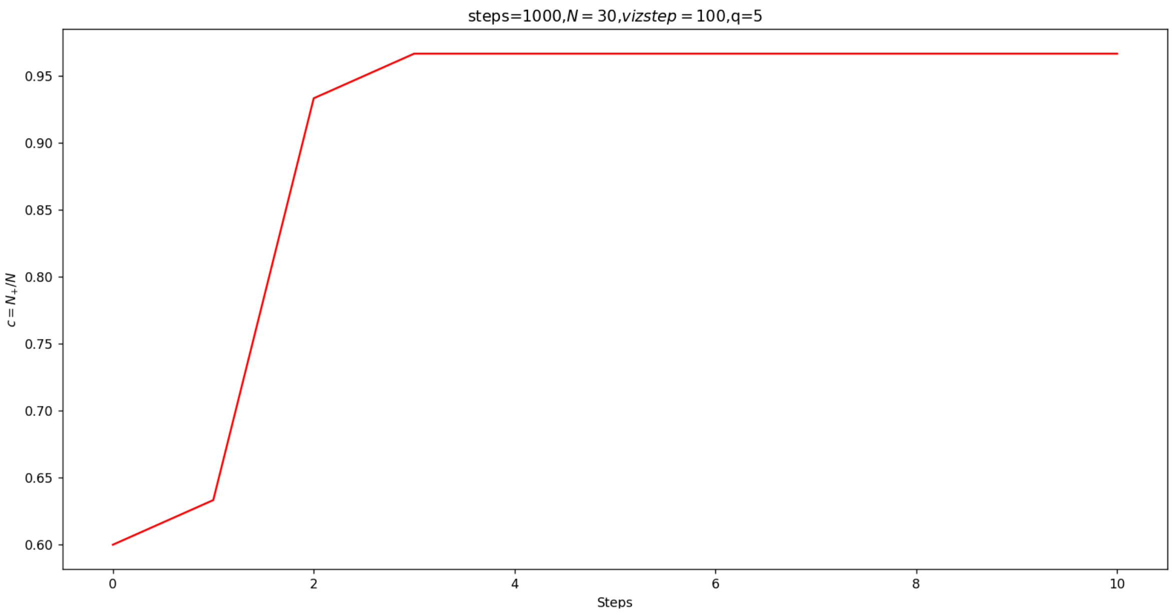


Figure 26: Bifurcation Diagram for Majority Voter Model

Majority Digraph

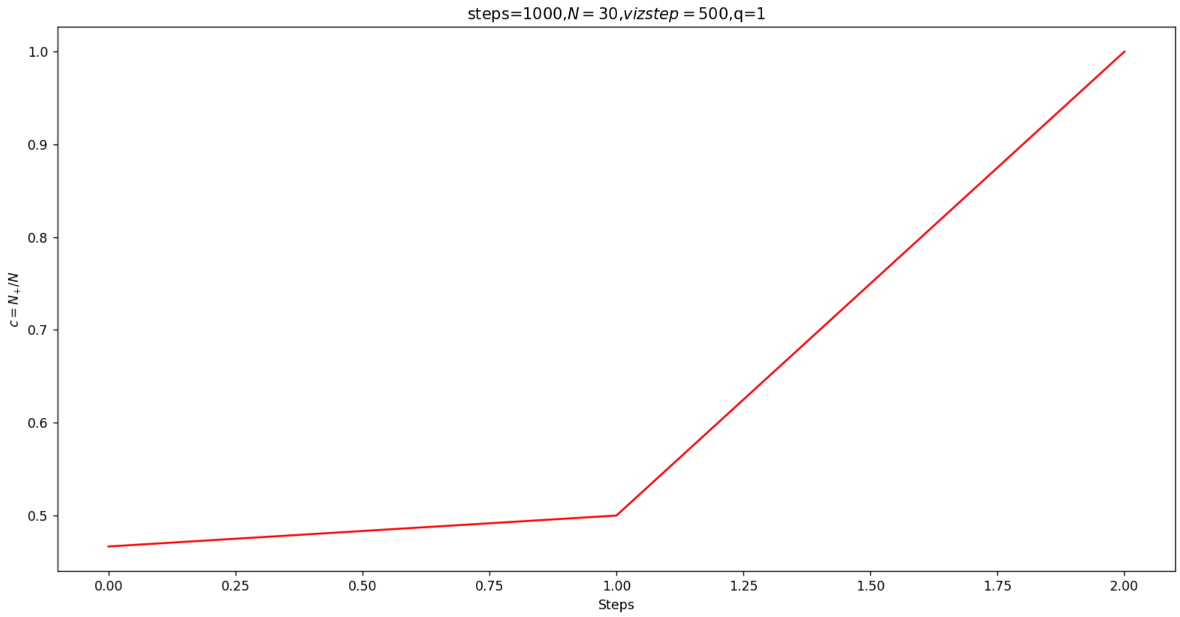


Figure 27: Bifurcation Diagram for Majority Digraph Voter Model

Sznajd Model

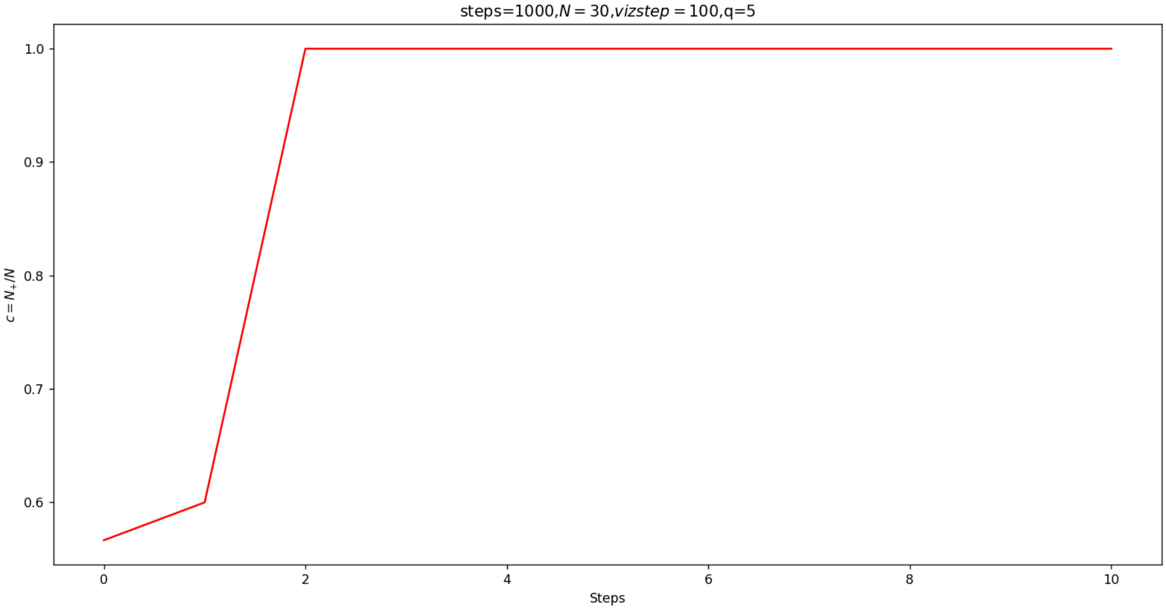


Figure 28: Bifurcation Diagram for Sznajd Model

Dataset (facebook dataset)

Classical voter model bifurcation

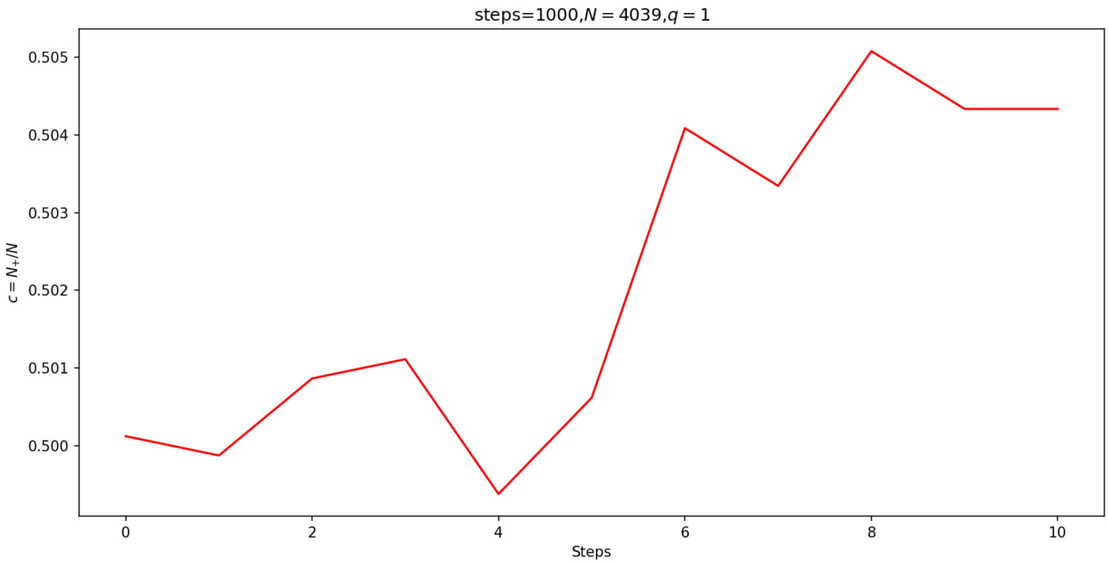


Figure 29: Bifurcation Diagram for Classical Voter Model

Q-voter Model

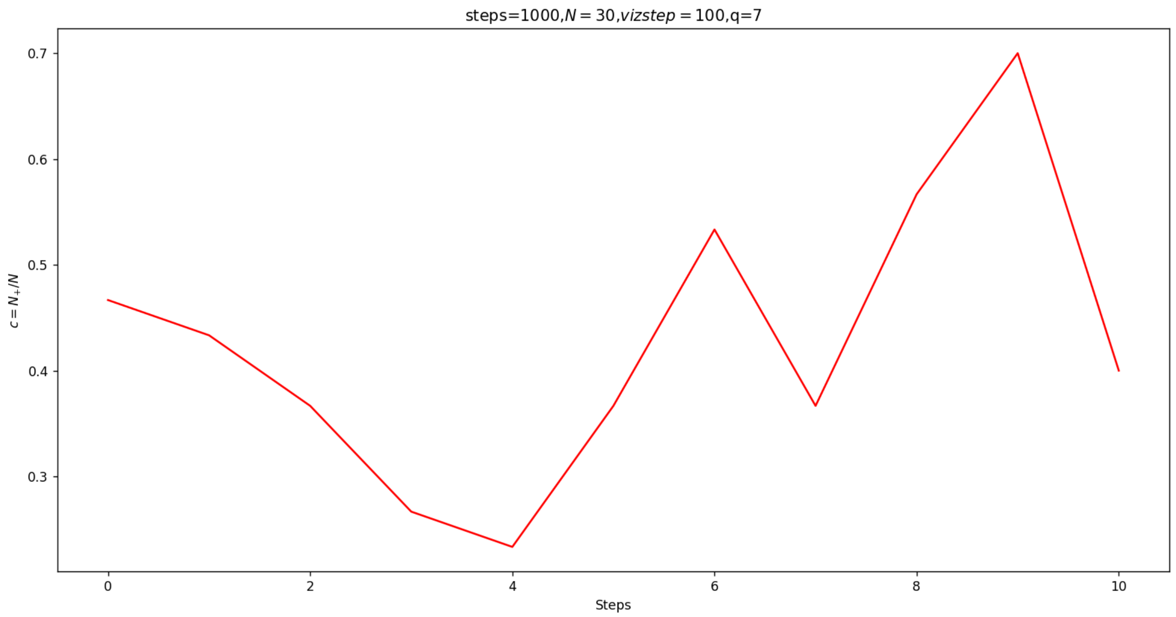


Figure 30: Bifurcation Diagram for Q Voter Model

Majority directed graph

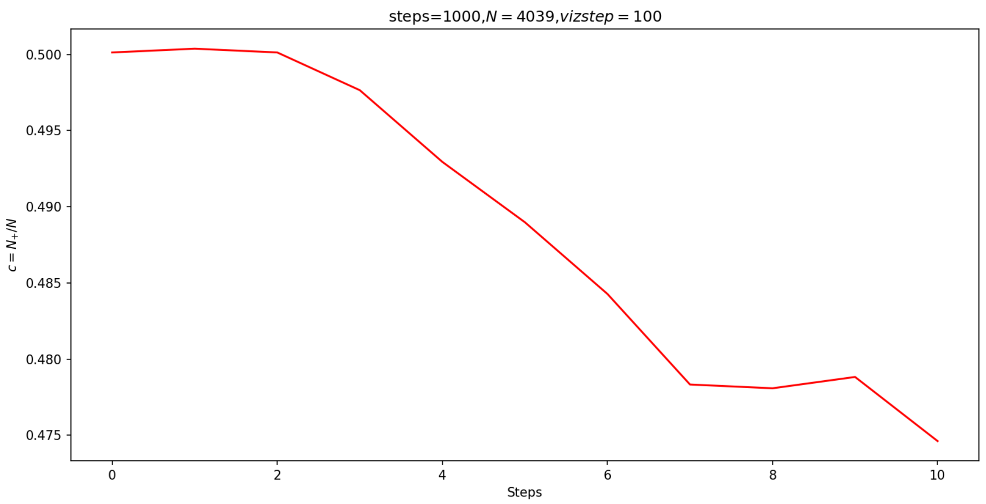


Figure 31: Bifurcation Diagram for Majority Digraph Model

Q-voter graph

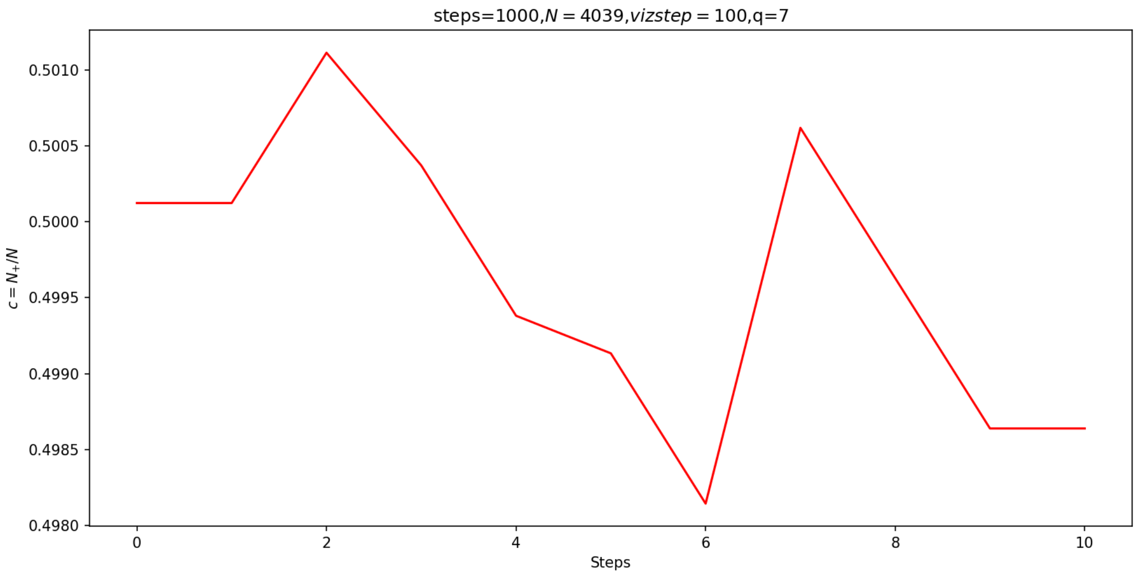


Figure 32: Bifurcation Diagram for Q Voter Model

Majority graph

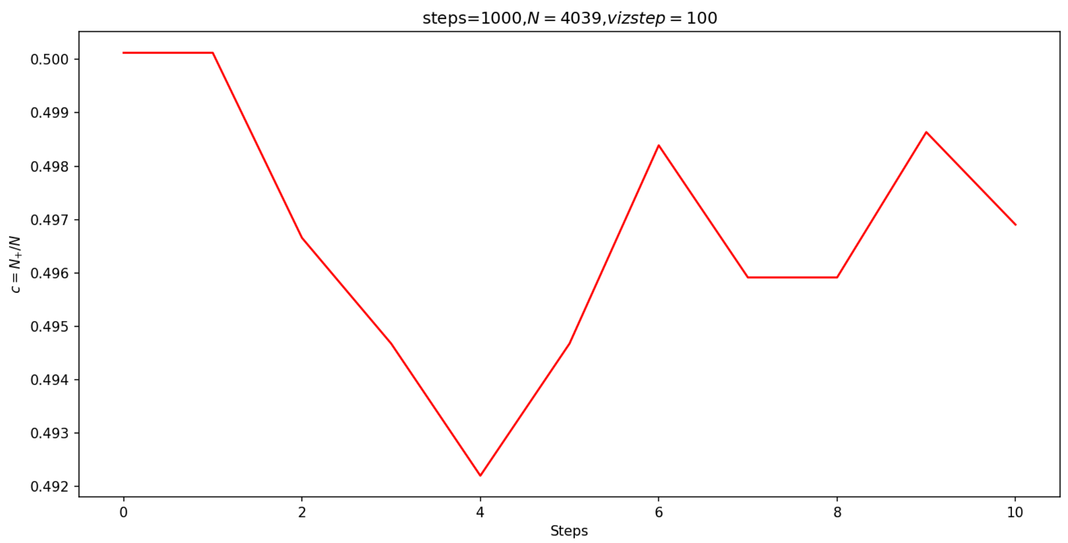


Figure 33: Bifurcation Diagram for Majority Model

Independence model

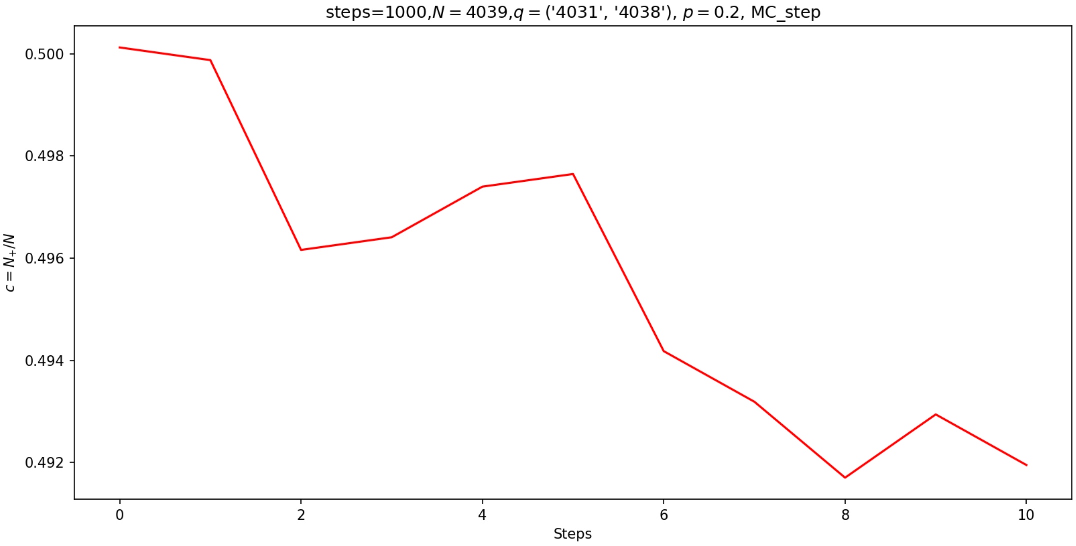


Figure 34: Bifurcation Diagram for Independence Model

Sznajd model

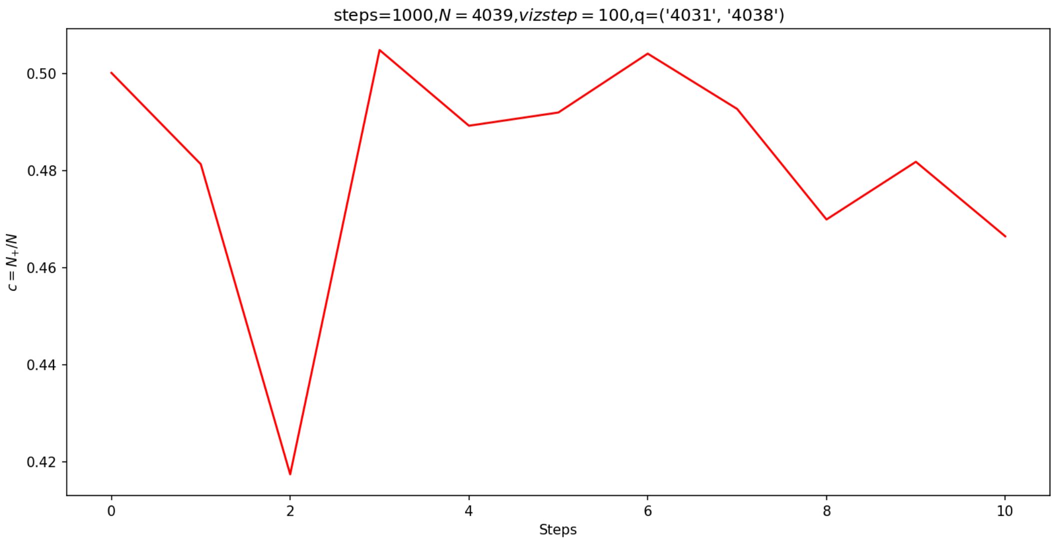


Figure 35: Bifurcation Diagram for Q Voter Model

6.2 Conclusions

Based on real dataset-facebook network

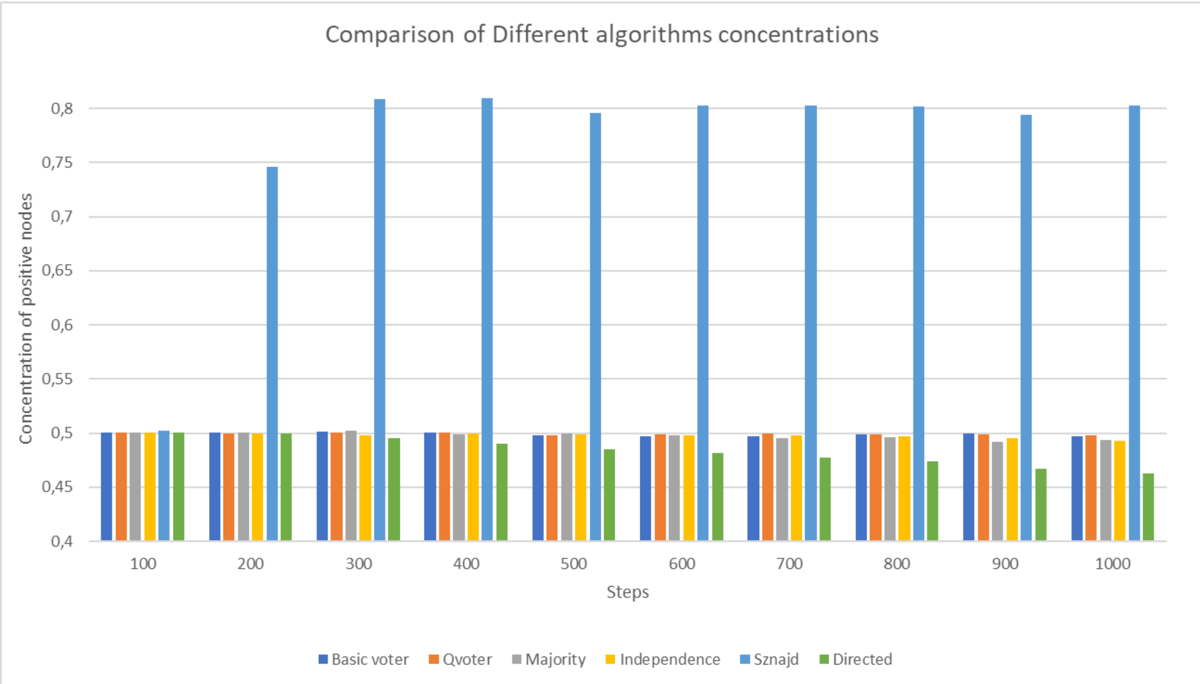


Figure 36: Bar graph for concentration of positive nodes in all models

We conclude that different algorithms would work for different types of social situations.

For example, for clashes and heated arguments or sides of opinions that completely deny each other, the sznajd model would work the best as it gives the best outcome of conflicting situations. In the same way when we talk about awareness for data security advice do not end up spreading that fast as hateful opinions or arguments thus some other model may apply.

6.3 Future work

1) We want to expand these algorithms for more variety of opinions than what we are currently dealing with which is binary opinion. We could add more values of opinions like neutral or a range of opinions like on the scale of 0 to 10 which happens for IMdb. Currently we have worked with directed and undirected graphs like Twitter and Facebook networks. The future research could focus less on the extremities and more on opinion types.

2) Branching out to several different types of networks. We have dealt with the datasets which were currently not annotated but connected. In the future we could aim for annotating the data and pre-process the data given in the form of tweets and retweets or simple text databases.

3) We could branch out into more models based on opinion dynamics which give us a closer understanding to different social opinions and make us more equipped to predict the polarisation for different types of social ideas.