The influence of the turn taking on the diffusion of opinions

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Abstract. This master thesis focuses on influence graphs and opinion diffusion. Our goal is to investigate the effect of turn-taking functions on the opinion diffusion. To observe this we have made two multi agent simulations. One with binary opinions and where the communication between the agents takes the form of a conversation, and a second one with preferential opinions and a question-answer communication protocol. Our results highlight some differences between the turn-taking functions, but also shows the role of the influence graph. Furthermore, in the second simulation, we show that an important parameter, the existence of a Condorcet winner, is improved by the opinion diffusion process.

Keywords: Social choice; influence; turn taking ; multi-agent system; social network; influence graph, multi-agent simulation.

1 Introduction

Social choice theory is about studying collective decision making, this includes voting rules, judgement aggregation.

The point of this study is to find the best "way" to make collective decisions. For example, voting rule have different results relative to the context and which type of rules have been used, the point in this case of research is to find how have the best candidate elected at the end. Election field has been studied two centuries ago by mathematicians such as Borda, Condorcet. These researchers have created some election rules still used today [19]. In this work we will use both Borda rule and Condorcet winner. Social choice is also used in economics.

Many works exist about social choice as opinion propagation following a graph of influence. Adding a graph to represent the influence is interesting, this is representing the link between people. In real life we don't trust anyone but only some friend, an edge in the graph show us this link. It makes the opinion diffusion more realistic.

The quality of opinion propagation is assessed by various criteria, as how much time majority change or a consensus have been reached or how well the result of the election fit to the preference of our agent. All this experimentation allows us to find a better way to make collective decisions and also find weakness in our systems.

Study opinion diffusion through a social network is interesting, also in case of election result prediction or to understand what can affect elections. Prevent strategical manipulation of election is also a goal of social choice. Some work highlights problem with election rules as the separability problem [6] and try to bring efficient alternative. This field study is valuable to improve the way we make the election in our society.

In this master thesis, we will use multi-agent systems to experiment about social choice. Multi-agent systems are composed of many autonomous agents. These agents can communicate, collaborate, interact in multiple ways with each others. The point of multi-agent systems is the emergence of behavior, this behavior is created by all interaction from autonomous agents. This kind of simulation is efficient to create a simulation of our society more or less complex. In this work we will use multi-agent systems apply to social choice. Multi-agent systems has many application fields and it is not limited to Social choice.

Two types of agent exist reactive and cognitive. reactive agents that carry simple task, they act only in reaction to environmental stimuli. This first type of agent is used to recreated ants, who can sort some element in simulation. This experiment has been described in [10].

And cognitive ones are closer to human, they have the desire, knowledge and can think and make a decision in function of their environment. We use this type of agent, our agents will change their opinion in function of their neighbourhoods.

In this work we interest in decision making in a group of people. In this group we decide each person has an opinion on a subject and they are communicating their opinion to each of his friends. This type of behavior can be observed in real life, it is not uncommon to see friends talking before making a decision, or push some article about politics in a social network. But due to a lot of original personality, some people keep their opinion for them self for many reasons. In this experiment we choose to represent only person communicated his opinion. Friendships are determined by a graph randomly generated. We focus on the effect of different turn-taking function on the result of voting. A turn taking functions represent the organization in the conversation,it handle who are talking now and how we know who will talk after. The different function of turn-taking can be related to different situations in real life. Some are closer to friend conversation and others are near to professional meetings. To observe this effect, we will make two multi-agents simulations. In the first simulation binary opinion will be used and for the second it will be preference opinion.

The study of turn taking functions can be interesting how it affects the result of the decisions. In this work we use majority rules to find a winner in the binary case. This rule is used by agent to know if they need to change their opinion about an idea or about the rank of two alternatives. We try to assess if changing the turn taking function change the outcome of the election and how it modifies the evolution of a thought in a community of friends.

We think turn taking has an influence on opinion diffusion. We choose four different functions (synchronized, round robin , willingness to talk, next friend) and we hypothesised some function are more efficient than the other depending on the desired outcome. We will test our function in a different graph representing different kinds of communities. Graph influence the opinion diffusion too, so we can ask which is the best couple of graph and function. In fact, we are searching, which function to use in which context.

The paper is organized as follows. Section 2 discusses related work. The third section presents the model common on the two following experiments. Section 4 presents the first experiment, a multi agent simulation with binary opinion and four different turn taking functions. This simulation is like a discourse between agents. In this section we describe the part of the model specific of this simulation then we describe the two types of agents. After we present how the turn-taking function works and at the end we presents our results. Section 5 presents the second experiment about preferential opinion. This time the simulation is based on questions, each agent is asking his friends what is his opinion between two candidates, they still follow turn taking function. Section 6 concludes by discussing perspectives for future research.

2 Related Work

Graphs and influence Some topics in this master thesis have already been studied. Models of opinion diffusion have been described in [12,8]. This two paper describes to us two different diffusion models with graphs. The first was for binary opinion with Majority rule to update agent's opinion in function of their influences. And the second was for preferential opinion, agents are using pairs of candidate's and they are swapping their preferences if the candidates are adjacent and the majority of his neighbourhood disagrees with them.

Bredereck in this article [7] studies graph influence in the purpose of manipulation to reach a specific outcome of the election with binary opinion. Their agent is able to manipulate opinion diffusion with control of network links and update sequences.

Consensus in the case of opinion diffusion influenced by graph has also been studied in [3]. They are creating an algorithm to modify graph and always reach consensus even if the opinion targeted is a minority.

Sina et al [18], have created some model where voters can easily manipulate edges in a graph to adapt the network to his advantage.

Political context As is said in the introduction political science is a field of study in social choice. Wilczynski and Coro et al. [9,21] have produced some papers in political election context and show us how social influence like social media can change voter opinion. This paper focus on strategical agent. In Wilczynski [21] agents trust an opinion poll and update their preferences in function of him. In [4] they reuse previous paper to investigate on influence of opinion pool and manipulation of it. Coro article [9] is also about political election and influence using simulation.

Learning agents Subject of strategic voters has been studied by different papers. Learning agent is another way to create strategic voters, for instance, in [2], reinforcement learning is used to help our agents to make collective decisions. In this paper urn model have been used to have some correlation between agents.

The study of influence graph in opinion diffusion is quite recent compared to the first study in social choice.

Multiagents simulation in social choice Multi agents simulations are also used in studies of strategic voting, to see how influence can change the outcome of an Election, see for instance [20] they use different measures, for example, social welfare to see if the impact of influence are positive or not.

Turn taking Turn taking function have been studied by Sacks [16]more precisely conversation model between human. In [5] a framework of turn-taking is presented. This model is for agents which are more evolved than ours, with multiple senses as sight and hear.

Other Model of diffusion Many models of diffusion also exist, they have different types of opinion based on matrices, for example the Friedkin model [11]. Some other models are based on Sociophysics as the Izing model [14] but it is based on signed networks.

3 The Model

Let $V = \{1, \cdots, n\}$ be our set of voters. Each voter is positioned on an undirected graph $G = (V, E)$, this graph symbolizes the influence relation between agents. E represents a set of undirected edges (i, j) . That means i influences j and j influences i. An edge represents a friendship between two agents. Undirected edges have been chosen because they are used in more articles than directed edges.

All the 500ms a new election t append, every time all voters submit their ballot B_i. The first time the ballot represents their truthful opinion but the other times he represents their opinion influenced by their friends opinions. Let $inf(i)$ be the set of agents who influence i. He updates his opinion only if he knows at least half the opinion of his influencers and if their opinions are different from his opinion, let denote $inf_k(i)$ the set of agents whose opinion is known by agent i who's disagrees with him. Votes continue until stabilization or until a certain number of rounds.

During all simulation our voters diffuse their opinion following a specific function of turn taking. This function will determine which agent has to say his opinion to his neighbours, and which agent will talk after.

3.1 The Agents

We have many agents voters and only one agent legislator. The first type is a simple agent with an opinion and the ability to talk and listen to his neighbours, and they communicate their ballots to the legislator agent. This last agent is here to get all voters ballots and use F to know the result of votes and register it. In the next part agents will be described with a BDI (belief, desire, intent) perspective [1].

The BDI perspective can be compared with the game theoretical one [17]. The BDI model is more cognitive than game theories which are more strategical. But they are similar, for example, utility in game theory can be related to a desire, both evolve in function of different states of the world.

Agents have different in function of the type of opinion use, they will be described more precisely later.

3.2 The Graph

We choose to generate a random graph to simulate the influence in our simulation. We choose two types of graph: Erdős–Rényi and Barabási–Albert.

Erdős–Rényi This type of random graph has the property to be small-world. Another name of the small - world phenomenon is six degrees of separation, that is means one node can reach every other node in around 6 steps.

Let pd be the density probability and a set of N vertices. Then for each couple (i, j) of vertexes in N, an edge (i, j) is created with pd probability. In our experiments edges are undirected so when an edge (i, j) is created, his opposite (j, i) is also created.

Barabási–Albert The second type of graph used has the property to be scale free. This graph is closer to a social network, and he follows the rules of the preference attachment model. Preference attachment is the fact that a new node will be most probably be connected to another node with already high degree. In real life this phenomenon can be compared to a person had more chance to be connected with someone popular than someone unpopular.

Let G_b be a fully connected undirected graph with N nodes. Let N_f be the number final of our graph. New nodes will be added to G_b to reach N. This new node will had a probability pi to be connected to another node i like:

$$pi = \frac{k_i}{\sum_j k_j}$$

With k_i degree of the node i and with the sum of all degrees of nodes in the graph.

4 Binary opinion case

Most papers, use a synchronized communication model between agents. Moreover, it appears that an asynchronous communication model is more realistic. Indeed, on social networks or even in meetings, only one person speaks at the same time. Each listener can update his belief during the speech or between two talks. Set up different function of turn taking is an interesting part of opinion diffusion, it could highlight differences in diffusion opinion. This simulation will have a communication protocol close to the speech, only one agent says his opinion at one time.

Let $S = \{s_1, \cdots, s_m\}$ be the different subjects our voter needs to have an opinion about. And F is the function to get all ballots and extract a winner. This function also determines which type of ballot is available for the vote.

Voters use a majority rule to know if his own opinion changes in function of their friends opinions like in [12].

$$\mathrm{B}_i^t = \begin{cases} B_i^{t-1}, & \text{if } |inf_k(i)| < |inf(i)|/2 \\ F(B_{inf_k(i)}^{t-1}), & \text{otherwise} \end{cases}$$

4.1 The Voters Agents

Knowledge A Voter agent knows at the beginning of the simulation, all agents he can influence and which agent can influence them. In our case with an undirected graph, all agents he influences can influence him. He also knows his own opinion at each stage.

Belief Our agent at the beginning of the simulation has no information about his neighbours opinions, but after one of his friends communicate with him he will know it. If his friends opinion change, he will still believe his opinion has not changed until his friend talks again.

Desire Our agents want to exchange their opinions with them friends. We can compare this desire to friends who in real life would seek to make a common decision that would satisfy the most of them.

Intent When he knows half or more of friends opinions he is able to use a majority rule to update his own opinion. And he is willing to propagate his opinion following a specific turn taking function and send his ballot to the legislator.

4.1.1 Legislator Agent

This agent is a passive agent. He is only here to do some tasks useful in the simulation. The legislator has access to information about the graph and number of voters in the simulation. Also, he is aware of which type of opinion is used in the simulation (binary or preferential) and he knows voters' ballots in each state and compile them to have a winner in the election, using a function F here corresponding to a majority rule. He will record all results and end simulation if it is stable or if it will never tend to stabilize. In our case the simulation stops if there are more than 100 rounds or if no agents change his opinion during 20 rounds. The maximal round number has been chosen arbitrarily with the purpose to let enough time for our simulation to reach stability. About the number of rounds with no agent changing his mind, we have chosen this number arbitrarily to be sure agents opinion are stable even if they still propagate opinion.

4.2 Turn taking function

Synchronized function The first function that was implemented, is the easiest. This function allows all agents at the same time to give his opinion to all of his friends. This function can be seen as a benchmark compared to this other function.

Round Robin Function is a representation of table round. This can be compared to how people give voice during a meeting. One person is designed to talk and when she finished, she gives the speaking turn to the next one. This model is also inspired by [16] in this article he analyses some conversation to find a simple pattern of turn taking. He highlights some mechanisms to change speaker, but a lot of them are based on gesture or overlap during the speech. These indicators are not represented in the simulations, agents are less complex than real humans. This paper also explains in some type of conversation the current speaker need to choose the next one. This fits to round robin model of speech. In this case our graph represents the influence between agents, in a meeting we can see and hear everybody but we only trust some of them.

$Fig.$1 represents a sample of communication with this turn taking function. The voter with id 1 have actually the floor and his neighbourhood of influence is composed by voter 6 and voter 32.

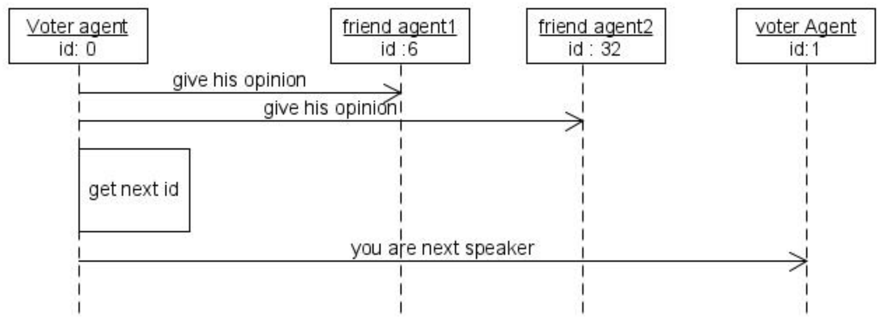

Fig. 1: UML sequence diagram representing communication between agent with round robin function.

Next friend function This function follows the same rule as the previous one. Except the agent who has the floor gives it randomly to one of his friends.

Willingness to talk function In this function, we give the floor to the agent who didn't speak for the longest time. In case of a tie, an agent is chosen randomly. With this function we expected to see every agent talk randomly at least once. In our society we encourage to give often our opinion, especially in social groups. Involvement in social group is important need to human, and to belong to a social group we need to give our opinion. The need for participation in social group are explained by Serge Moscovici in his book [15].

Fig.2 represents the willingness function. The voter with id 1 have actually the floor and his neighbourhood of influence is composed by voter 2 and voter 3.

4.3 Experimental design

The experiment of opinion diffusion on the multi-agent simulation described before has been initialized with a population of 31 voters and one legislator. Each voter has his own opinion, and only one subject to have a binary opinion. The simulation runs 50 times for each turn-taking function and each different graph with different average degrees. With Erdős–Rényi we use a probability of 0.4, 0.5 and 0.6 by creating an edge between two vertices. And for Barabási–Albert we use a base node at 12, 16 and 20. This value leads to degrees around 18, 23 and 26. This degree has been chosen to be equivalent to the ones chosen in the papers about Echo chamber [20] to facilitate the comparison of the results.

This multi agent simulation has been created with the jade framework in Java on a Windows machine.

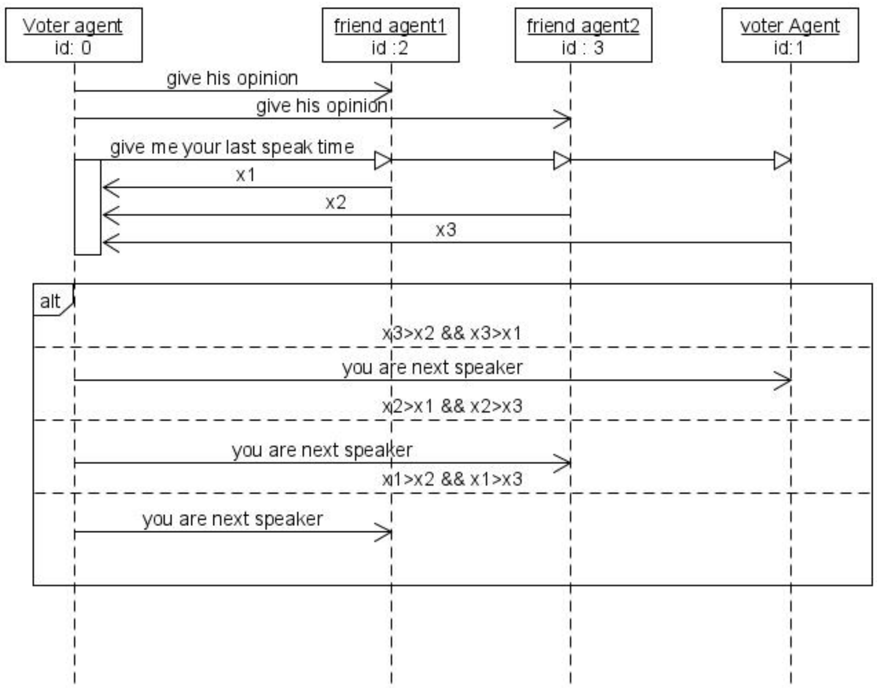

Fig. 2: UML sequence diagram representing communication between agent with Willingness to talk function.

4.4 Results and discussion

In Table 1 we have the percentage of simulations which lead to a consensus, that means all voters have the same opinion when the simulation is stable. We can observe the Erdős–Rényi graph rarely lead to consensus. Moreover, consensus can be reached with Barabási–Albert graph and synchronized function or round robin with almost the same probability.

For the next friend function, it is easy to see why we have more consensus with Barabási–Albert graph. Indeed, give the floor to a friend increased the probability of propagating the same opinion in each turn. Combined with preference attachment from Barabási–Albert graph we increase the probability all hubs in the a graph have the same opinion and propagate it.

For the Willingness function, we have a little less consensus than the other function. It appears the function of turn taking does not really influence on consensus, all functions have a similar rate of consensus. But the graph influence on consensus, acyclic graph strongly connected have more probability to ensure consensus [13].

Table 1: Percentage of consensus during a multi-agent simulation with 31 voters.

graph type	average degree	Synchronized	round robin	willingness	next friend
Erdős–Rényi	18,9	0%	0%	0%	0%
Erdős–Rényi	22,35	4%	0%	2%	0%
Erdős–Rényi	24,9	4%	2%	2%	6%
Barabási–Albert	18,5	6%	6%	2%	12%
Barabási–Albert	23	58%	48%	46%	46%
Barabási–Albert	26	58%	56%	40%	50%

Results from table 2 represent the percentage of switch majority. A switch majority is when the stabilized opinion is different from the first election. The simulation highlights some differences in turn taking function depending on the graph use. The number of switches in our population of agents is related to the graph, more switches appear in the Erdős – Rényi graph. But for both types of graphs switches increase when the probability of creating an edge reduce.

The synchronised function generates less switching in population opinion than the other for Barabási–Albert graph.

Next friend and Willingness function with Barabási–Albert graph produce more switching opinions than with Erdős–Rényi. And it is the opposite the round robin next id function.

The round robin function is the one which has the highest chance to switch. The willingness function is close to the round robin but any order is respected in willingness function compared to round robin. This difference may prevent the voters to switch as much as the round robin function. But this difference is thin. With this function we have more switches with Erdős – Rényi graphs.

Sometimes the switch occurs several times during simulations and finally the majority at the beginning of the simulation still win. When we have many switch in the simulation we have mostly one or two switches.This phenomena are mainly observed with round robin function and next friend function associate with Barabási–Albert graph. This phenomenon happens extremely rarely in the synchronized function .

Table 2: Percentage of minorities switch to majority during a multi-agent simulation with 31 voters. In parenthesis percentage of all switches including switch back.

graph type	average degree	Synchronized	round robin	willingness	next friend
Erdős–Rényi	18,9	50%	48%(54%)	20%(22%)	24%
Erdős–Rényi	22,35	32%	30%(32%)	20%(22%)	22%
Erdős–Rényi	24,9	28%	30%(32%)	18%	10%
Barabási–Albert	18,5	22%	8%(22%)	36%(40%)	32%(36%)
Barabási–Albert	23	8%(10%)	12%(20%)	14%	18%(22%)
Barabási–Albert	26	0%	6%(16%)	18%	22%(26%)

In table 3 we have the number of voters who have spoken before we reach stability.

Obviously it is the synchronized function who have the highest number of voters speaking, mode than 4000 speeches.

In Erdős–Rényi, average degrees do not change the number of voters needed to reach stability. But in Barabási–Albert, this number increases with the average degrees.

We can observe round robin is the function who need the least number of agents talking to be stable, and it is the next friend function who needs the more influence step to stabilize. With next friend function, we have some issue to propagate the opinion outside one group of neighbour. In conclusion, with a high rate of speech synchronous function is not realistic.

5 Preference Opinion Case

In this part we will use preferential opinions and a conversation between agents based on questions and answers. Previous turn-taking functions are still used,

Table 3: Number of voters speaking to reach stability during a multi-agent simulation with 31 voters.

graph type	average degree	Synchronized	round robin	willingness	next friend
Erdős–Rényi	18,9	4975,8	45,86	51,88	86,52
Erdős–Rényi	22,35	5619,72	45,44	53,8	93,74
Erdős–Rényi	24,9	6610,06	47,06	50,56	83,3
Barabási–Albert	18	5992,9	61,54	71,74	144,2
Barabási–Albert	23	6971,9	56,86	61,98	121,46
Barabási–Albert	26	7140,9	47,88	52,46	101,16

but updated to fit into the new model of conversation. The evolution of opinion diffusion will be studied with this new parameter.

Let $C = \{c_1, \cdots, c_m\}$ be the different candidates our voter needs to rank. P_i will be the preference of an agent i. Each preference P_i is a strict linear order representing the preferences of agent i. Let $c_1 \succ c_2$ signifies that c_1 is preferred to c_2. And F is the function to get all ballots and extract a winner. This function also determines which type of ballot is available for the vote. We will use in this work the plurality rule and the Borda rule.

As in binary case, election are run every 500ms. During the diffusion process, an agent i will ask to $inf(i)$ their opinion about one pair of candidates $(c_n c_m)$, these candidates are adjacent in P_i and the pair of candidate is chosen randomly. i updates his opinion only if he knows at least half the opinion of his influencers about this pair and if their opinion are different from his opinion. So if $|inf_k(i)|$ is superior at $|inf(i)|$ our agent will change his mind. Let denote $swap(P_i, c_n c_m)$ the function to reverse pair preference in P_i. In this model our agent will remember $inf_k(i)$ only until he asks a new question, then he will forget it to avoid contradictory knowledge about an influencers opinion. As previously votes continue until stabilization or until 1000 rounds, more rounds are allowed than in the binary case because of the greatest complexity of preferential opinion .

Voters use a majority rule to know if his own opinion changes in function of their friends' preferences about the pair like in the pairwise diffusion paper [8].

$$P_i^t = \begin{cases} P_i^{t-1}, & \text{if } |inf_k(i)| =< |inf(i)|/2 \\ swap(P_i^{t-1}, c_n c_m), & \text{otherwise} \end{cases}$$

For instance, if $|inf(i)| = 3$ he will swap his pair only if at least 2 agents are disagreeing with him.

During all simulations our voters ask to their influencers, their opinion about a specific alternative following a specific function of turn taking. This function will determine which agent has to ask to his neighbourhood, and determine which agent will ask after. The alternative is randomly selected in C, the only constraint is the candidate must be adjacent in P_i.

5.1 The Agents

Agents works mostly in the same way in this case as in the binary case. but we can highlight some differences.

5.1.1 The Voters Agents

Knowledge In this case agents know the same things as in the binary case.

Belief Our agent at the beginning of the simulation have no information about his neighbourhood opinions, but after he asks a question about one pair to his friends he will gradually know all his friends preferences about this pair of candidates. If his friend opinion change, he will still believe his opinion has not changed until he asks a question again. The memory of our agent will be clean each time he asks a new question, to avoid contradictory knowledge.

Desire The purpose of a voter agent is mainly to know his neighbourhood preferences. Moreover, because of social convention, he wants to adapt his opinion to his neighbourhood.

Intent When he knows half or more of a friend's opinion, he is able to use a majority rule to update his own preferences about one pair of candidates. And he is willing to propagate his opinion when his friend asks his point of view and he asks for his influencers preferences about a specific pair following a specific turn taking function and sends his ballot to the legislator.

5.1.2 The Legislator Agent

In this case the only difference is he knows voters' ballots in each state and compile them to have a winner in the election, using a function F. We implement two functions corresponding to a plurality rule and Borda score.

Plurity rule Agents vote only for his favorite candidate. The candidate with the most points win.

Borda Score Each agent gives $|C|-1$ point to his favorite candidate, then $|C|-2$ to the second and so on until 0 points to the candidate he dislikes the most.

In case of a tie, we use a lexicographic tie-breaking following fixed order as $\{c_1 \succ c_2 \succ \cdots \succ c_m\}$. He will also find the Condorcet winner if he exists in the first election and in the last one.

5.2 Turn taking function

Synchronized function This function allows all agents at the same time to ask his friends about a single pair of candidates.

Round Robin Function and Next friend function are mostly the same with the exception we are not anymore in speech mode, but in the question answer mode. Our agent will ask to his friends their preference about one pair and gives the floor to the next agent (a random friend for next friends function or the next agent for round robin one) who also asks a question to his neighbour.

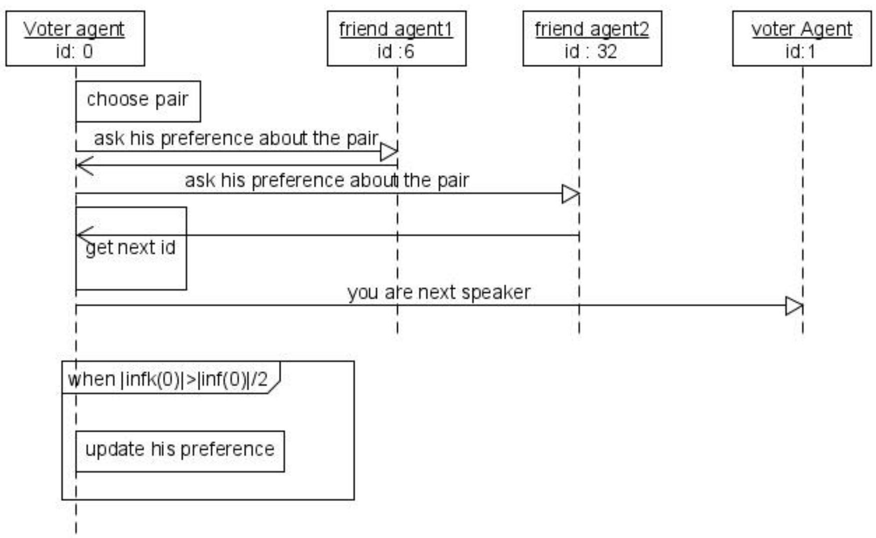

Fig. 3: UML sequence diagram representing communication between agent with round robin function.

$Fig.3$ represents a sample of communication with round robin turn taking function. The voter with id 1 have actually the floor and his neighbour of influence is composed by voter 6 and voter 32.

Willingness to talk function is the same as in the binary case with the exception we are not anymore in speech mode but in the question answer mode.

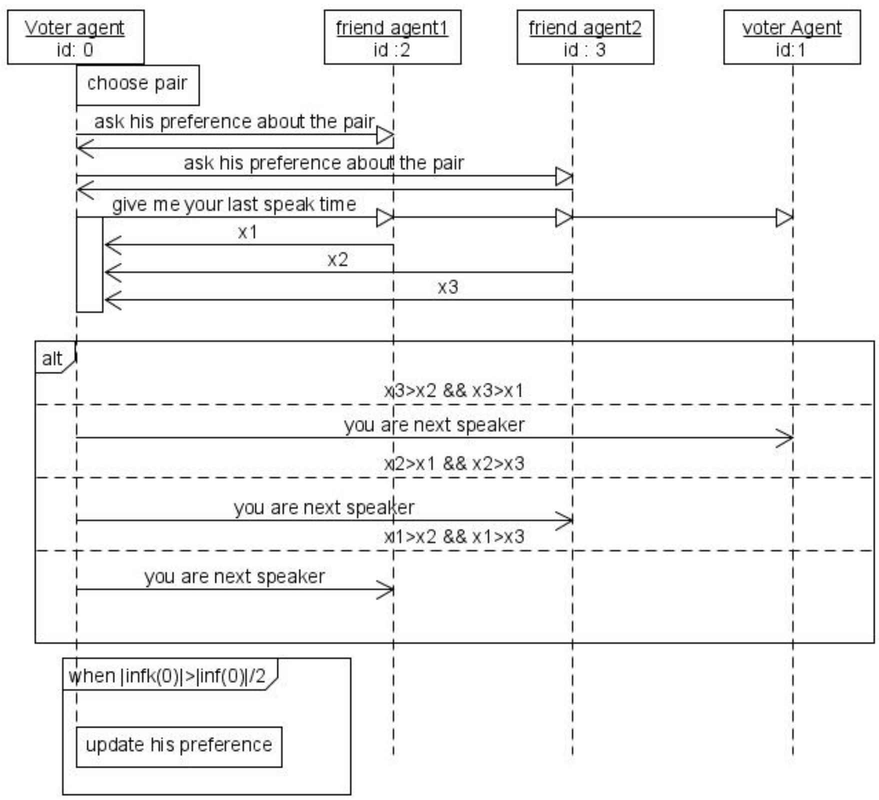

Fig. 4: UML sequence diagram representing communication between agent with Need to talk function.

$Fig.4$ represents the willingness to talk function. The voter with id 1 have actually the floor and his neighbour of influence is composed by voter 2 and voter 3.

5.3 Experimental Design

We will use the same graphs as the binary case, Erdős–Rényi with probability of 0.4,0.5 and 0.6 of creating an edge between two vertices, and Barabási–Albert with a base node at 12, 16 and 20. The simulation described before has been initialized with a population of 31 voters and 4 candidates to rank.

The simulation runs 100 times for each turn-taking function and each different graph with different average degrees.

5.4 Result and discussion

In this case all simulations stabilize. Moreover, in Table 4 we observe, we need more influence turn to reach a stable state than in the binary case. The increase of influence turn needed to stabilize can be explained by the number of possibilities in the binary case we have only one choice, yes or no, but in preference case we have one choice by pair of candidates.

The Synchronized function as in the binary case is not realistic, we always need more than 20000 turns before stabilization. For the other function, it is not round robin which is the faster in this case it is the willingness function follow by the next friend function.

Table 4: Number of voters speaking to reach stability during a multi-agent simulation with 31 voters.

graph type	average degree	Synchronized	round robin	willingness	next friend
Erdős–Rényi	18,9	81669	4366	2358,5	2066,5
Erdős–Rényi	22,35	79548,5	2088	915	1680
Erdős–Rényi	24,9	172492	2098,5	775	1543
Barabási–Albert	18	84388	7071	1041,5	1496
Barabási–Albert	23	59963	3043,75	1890,5	2217
Barabási–Albert	26	151660	3556,75	1550	1719

The second result, we observe is the Condorcet efficiency. The Condorcet efficiency is the measure of the quality of the election's results. It is the percentage of Condorcet winner existences. The Condorcet winner is the candidate who wins against all the other candidates, he does not always exist.

In our experiences we measure which percentage of Condorcet winner we have in the beginning of the simulation, at the end and how many times he is elected by the plurality rules and with Borda score.

In Figure 5 we observe this measure group by the turn taking function, we used the average percentage of each measure for each graph and degrees to create the histogram. In the beginning of the simulation, we can observe all turn taking functions have between 80% and 86% to have a Condorcet winner. When the opinion stabilizes all functions have more than 90% to have a Condorcet winner. Synchronized function reach 95% and next friend function is the lower. So the influence process has a good effect on the results of the decision making. That means let talking agents each other improve the chance to have candidate corresponding to the most profile in the simulation.

Yellow and green bars corresponding to the probability to elect the Condorcet at the end of the simulation with plurality rule and with Borda rule. With all function plurality rule elect more often the Condorcet winner than with Borda score. With a plurality rule agent vote for their most love candidate, it is not surprising if this rule elected the most time the Condorcet winner. But the fact that Borda rule does not elect the Condorcet winner as much as the plurality rules induce that the other candidates are close to the Condorcet winner in the profile of preferences.

During this experiment we observe some case where we lost a Condorcet winner after opinion diffusion. The average percentage of lost Condorcet winners is 4.85% for every configuration of the simulations. Despite an increase in the number of Condorcet winner we still have a slight loss of those already present.

Except the synchronized function not realistic, it is the willingness function which has the best rate of Condorcet winner elected with plurality and Borda.

We can conclude with preferential opinion the willingness function seems to be a little better than round robin.

6 Conclusion

In this master thesis, we study opinion diffusion in influence graphs. We chose to perform two experiments, one about binary opinion and another one about preferential opinion. Both of them has been realized by multi agent simulation.

Keys points of this works are graphs of influence and turn taking function. At the beginning, we assume the way agents can propagate the opinion has an influence on final opinion. Our result shows us graph has an influence on consensus and majority switches, but each turn taking function has also influenced on switches, like round robin function which create rollback majority switches.

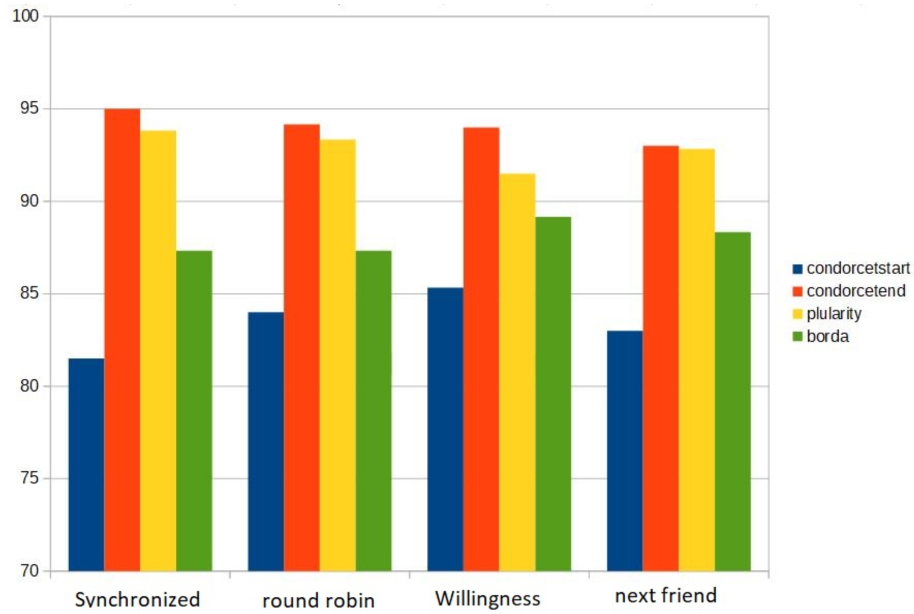

Fig. 5: Increase in the existence of a Concorcet winner. The blue column counts the number of initial profiles that admit a Condorcet winner, compared with the red one showing the same figure, but in the profile at the end of the opinion diffusion. The yellow and green column shows the percentage of profiles in which a Condorcet winner is elected by the plurality rule and the Borda rule respectively. The four groups of columns show the results for different turn functions, from left to right: synchronized, round robin, willingness to talk, and next friend function.

Another point sees in preferential opinion is the good effect of opinion diffusion, we have more chance to have a Condorcet winner after opinion diffusion. In both types of simulation, we see some function with a greater chance to lead us to quickly to stabilize. It is always the synchronized function who need the higher number of opinion diffusion turn to stabilize, but we have highlighted some efficiencies in round robin function to stabilize in binary opinion and Willingness function to stabilize in preferential opinion.

Some other experiment can be interesting to do in case of preferential opinion. We choose to have agent with limited memory to only one pair of alternative, because if they remember others opinion on many alternatives, they can have contradictory knowledge.

For example, we have three candidates, blue, red, orange and pink. Agent A know preference of agents B about the pair $\{pink \succ red\}$, $\{blue \succ red\}$,

$\{pink \succ orange\}$. If B change his mind and swap some candidates in his profile, A he will never know B change his opinion . Now A ask B about blue and orange , he will store in his memory $\{orange \succ blue\}$ and the opinion he store will not be transitive. If we want our agent to keep every answer in his memory we need to implement a system to check the consistency of an agent's opinion and corrects it if necessary.

During some mail exchange with Lilac members some ideas come to improve the simulations. We can imagine diversified our turn taking function. For example, the round robin function follows the order of the identifiers of the agents. We could implement a new order independent of the identifiers. Creating a new function of turn taking, which be halfway between the synchronous and asynchronous functions, for example splitting agents into groups using inside a synchronized function and between the group using an asynchronous function. We can also modify the simulation to add more realism and add more or less stubborn or credulous agents, changing her mind with more or less percentage of their friend who's disagrees with him.

Source can be find here for the binary case and here for the preferential case.

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