Chapter

Significant Role of Trust and Distrust in Social Simulation

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Abstract

This paper introduces the Trust-Distrust Model and its applications, extending the Bounded Confidence Model, a theory of opinion dynamics, to include the relationship between trust and mistrust. In recent years, there has been an increase in the number of cases in which the prerequisites for conventional communication (e.g., the other person's gender, appearance, tone of voice, etc.) cannot be established without the exchange of personal information. However, in recent years, there has been an increase in the use of personal information, such as letters and pictograms "as cryptographic asset data" for two-way communication. However, there are advantages and disadvantages to using information assets in the form of personalized data, which are excerpts of personal information as described above. In the future, the discussion of trust value in the above data will accelerate in indicators such as personal credit scoring. In this paper, the Trust-Distrust Model will be discussed with respect to theories that also address charismatic people, the effects of advertising, and social divisions. Furthermore, simulations of the Trust-Distrust Model show that 55% agreement is sufficient to build social consensus. By addressing this theory, we hope to use it to discuss and predict social risk in future credit scoring discussions.

Keywords: opinion dynamics, trust, distrust, social simulation, consensus building, social division

1. Introduction

In society, people have different opinions and are influenced by the opinions of others. It is opinion dynamics that simulate what kind of opinion distribution it will form. Ideally, people in a society should be bound together by trust. However, in reality, people often distrust each other and rebel against each other. In this chapter, we will apply opinion dynamics to take into account the distrust between such people and describe how trust and distrust affect the composition of society.

Opinion dynamics is a field that has been studied for a long time with applications to consensus building and elections in society [1, 2]. The transition of social discussions leading to consensus building is an old problem, but it is also an important theme in the analysis of various communications on the Internet in modern society. The opinion dynamics of binary opinions (agree and disagree or agree and ignore) have long been studied in analogy with magnetic physics [3–9]. In addition, since 2000, the Bounded Confidence Model, which analyzes opinions not as binary values but as continuously varying quantities, has been presented, and more precise studies have been conducted [10–14].

However, the conventional Bounded Confidence Model implicitly assumes social consensus. In Gérard Weisbuch et al. [10] and Hegselmann-Krause [11], which are representative theories of the Bounded Confidence Model, the opinions of individual people are expressed as $I_i(t)$ in the following equation. Here, the coefficient D_{ij}, which indicates the degree of influence by other people's opinions, is limited to positive values.

$$I_i(t) = \sum_j D_{ij} I_j \tag{1}$$

In the Bounded Confidence Model, the coefficient is considered to be a factor that represents the speed of convergence of opinions. If the coefficient is limited to a positive value, the opinions of everyone converge without fail, and the larger the positive value, the faster the convergence. In other words, it is not the results of individual simulations that cause the convergence of social opinions, but rather the Bounded Confidence Model [10–14] itself, in which the convergence of social opinions is inherent from the beginning.

The reality of opinions in society is that not all opinions can be agreed upon. In social issues, it is rather rare to reach a consensus. In reality, we all experience cases where we feel opposition to someone's opinion. Therefore, Ishii and Kawahata extended the Bounded Confidence Model by introducing repulsion and distrust of opinions [15–20]. Simply put, the extension is that the coefficients are not limited to positive values, but negative values are introduced, and positive values indicate a trust relationship, while negative values indicate a distrust relationship. If the coefficient is negative, the opinions will be separated from each other every moment. In other words, they will never reach a consensus. This new theory of opinion dynamics is called the Trust-Distrust Model.

Using this theory of opinion dynamics, calculations have been made for the case of a person who is charismatically popular in society [20] and for the case of a person who is disliked by society as a whole [18], and calculations can also be made for the case of a society splitting, so this theory of opinion dynamics has the potential to enable social simulation calculations for many social movements.

In addition, the theory of opinion dynamics with multiple axes of opinion has been proposed by Ishii and Okano, and analysis has been conducted with two axes of opinion, so-called "official stance" and "real opinion" [21].

2. Trust and distrust in societies

Even between individuals with limited time and space, active exchange of opinions has become possible [22]. In recent years, there are more and more cases in which the prerequisite information for conventional communication (e.g., the other person's gender, appearance, tone of voice) cannot be established without exchanging personal information. In recent years, however, immediate two-way communication with excerpts of personal information such as letters and pictograms has become the norm. However, there are advantages and disadvantages to using information assets in the form of personalized data, which are excerpts of personal information as described above. The above discussion has already started in the 1950s when the use of the Internet was limited in the U.S. and the former Soviet Union; in the early 1990s, the Internet became available to the general public and the discussion was accelerated based on the concept of the information highway. Today, the status of information asset management and personalized data management differs from country to country. This has led to various problems in terms of economic loss and education related to the development of human resources involved in the proper management of information assets using data (e.g., data scientist training, legal development, moral and ethical education in handling data). In Japan, on the other hand, with the spread of mobile communications, the flat-rate system for telecommunications was applied early and actively operated at a rapid pace from the late 1990s to the early 2000s. In particular, the flat-rate system was introduced at a lower cost than in neighboring Asian countries, and advanced efforts were made in terms of information transmission. However, against the backdrop of this rapid progress, it is difficult to say that awareness-raising and legislation regarding the use of the Internet among the compulsory education generation and the generation that is not familiar with Internet literacy and cyber security (assumed to be socially vulnerable groups such as children and the elderly) has progressed. It is possible that communication is repeatedly evolving. In recent years, there have been cases of fake news being disseminated on a large scale. As a result, there have been cases where misconceptions about personal information have spread. In some cases, this may even occur in the community, resulting in a "big wave of information" on an individual basis. While we cannot be certain that there are adequate warnings and laws regarding how to use the Internet, communication may continue to evolve. Therefore, social networking services are always at risk of becoming hotbeds of conflicts and criminal activities that sometimes spill over into society as a whole, and risk management for them has been actively discussed in recent years. In particular, the COVID-19 disaster has increased the need for risk management due to the increased use of online communication. This issue raises concerns not only about the parties involved, but also about the responsibility of those who accidentally spread fake news that pose a great risk to the lives of both parties. How to deal with such cases will need to be discussed in the future. On the other hand, there are concerns about the emergence of a new "digital divide". In the past, the divide over the superiority of handling computer technology itself was a hot topic in Japan from 2004 to 2005. However, the new "digital divide" assumes that computer technology is available to some extent regardless of gender or age. The differences are differences in literacy due to differences in the ability to transmit information (such as loudness of voice) and extract information. It can be assumed that there will be cases of false understanding, such as being evaluated by the number of people on the web. In this regard, since the beginning of this year, social networking sites have taken measures such as speech control and account restrictions to ensure fairness in elections (e.g. in the US and English-speaking countries). However, in order to ensure fairness, there is a limit to large-scale policing through mechanical processes in the Japanese sphere, which has a complex linguistic context including English, katakana, hiragana, and kanji. Therefore, it can be said that education also requires reading comprehension in all kinds of texts and a perspective on preserving the information resources of individuals. In this regard, those who are vulnerable in the information environment, such as the generation that has not been adequately educated on cyber security, may be at risk of various fragmentation. As a result of this information gap, a threshold of distrust and trust in communication occurs, and sometimes there are scattered cases of major mistakes such as major social fragmentation, deadly attacks, and slander against completely disinterested entities. In the case of socially vulnerable people, there is a limit to the legal measures that can be taken without financial benefits such as hiring a lawyer, and there is a risk that socially vulnerable people who should be protected will be left defenseless or denounced. To remedy them, social protection and remedy mechanisms in online communities, such as digital citizenship, are also urgently needed, and even within those communities, consensus building, trust building, and to some extent, thresholds occur. In addition, slander and defamation may be committed without the person being aware of it and he or she may be held responsible for it.

Only those who are in a superior position to apply the law are protected and enjoy many benefits, while those who are not in a position to denounce based on legal grounds may cry themselves to sleep or suffer losses without any social guarantee. In such cases, although there are problems such as surveillance society, digital citizenship, and other network communication in neighborly relations, the formation of communities that protect each other regardless of social class is more important. And there are expected to work as part of care work in online communities. In these elements, it can be said that mutual care communication based on mutual "trust" and very close relationships, neighborly relationships, is promoted. It can be hypothesized that these online pseudo-societies, which promote the building of invisible trust relationships formed between distant and nearby communities, have something in common with the wider society. Since the rapid spread of public networks, there have been growing expectations for elucidating the mechanisms of social phenomena that have become difficult to visualize and quantify [23]. However, in order to analyze the exchange of opinions left in the vast amount of log data in modern society, it goes without saying that a theory that corresponds to quantitative analysis, focusing on integration with analysis to large-scale data, is necessary. In addition, slander and defamation may be committed without the person being aware of it and he or she may be held responsible for it. Only those who are in a superior position to apply the law are protected and enjoy many benefits, while those who are in a position not to be denounced on legal grounds may cry themselves to sleep or suffer losses, without any social guarantee. Similar functions are ensured in functions such as suggestions in online search behavior and product recommendations in e-commerce, etc. In addition, opinions that infer our trust or distrust, which constitute the recommendation function, become "opinion aggregates" or "generalization models" that are automatically returned to us through public networks. These are the results of online consensus building; in COVID-19, generalized models and recommendations for various social crisis situations will be developed and analyzed based on large-scale data such as our behavior logs and opinions. However, the global spread of public networks has not been positive in all aspects, and while COVID-19 has increased excessively, problems such as online slander have also been highlighted. This chapter touches on those issues as well. In particular, a case can be envisioned where public opinion is formed from the aftermath of unconscious consensus building. This is the case today, when populism and propaganda are rampant. However, the use of online media was pioneered in the 2020 U.S. presidential election, and typical social networking sites such as Facebook and Twitter have been suppressed, and regulations and laws are being revised at a rapid pace. From this point of view, it can be inferred that the nature of online communication is entering a transitional period after COVID-19 and the 2020 U.S. presidential election. It is now possible to pseudo-analyze various opinions in society through online logs. Theories for analyzing the process of consensus building in society (or small groups) have long been proposed and studied from various perspectives [10–14]. However, in order to analyze the exchange of opinions left in the vast amount of log data of modern society, it goes without saying that a theory that corresponds to quantitative analysis, focusing on integration with analysis to large-scale data, is necessary. There are two main types of theories of opinion dynamics. One is the theory that treats contradictory conditions and discrete opinions as 1 (trust) and 0 (distrust), or 1 (trust) and -1 (distrust). In presidential elections in the U.S. and France, and in referendums such as those seen in Brexit, this dichotomous theory is more likely to be applied because voting takes place when there is one clear winner. The other method is the theory that regards opinions as a continuous value with one (or many) dimensions. For example, consensus building is often considered in this way [15–20]. As for the discussion of public health risk management in the COVID-19 disaster, which is imminent every day as described above, the number of articles being updated and recorrected is increasing every day. Changes in information on the web provide a bird's eye view of the situation, which is often different from the expected case. In addition, there is an urgent need to "democratize security" in order to appeal to, resolve, and protect vulnerable members of society who do not fully understand cyber security. Depending on future legal decisions, significant changes may occur. In addition, there is a need to share security awareness in cyberspace as well as offline crime arrest rates in society. In addition, in various online communities, organizations may be formed to protect each other's security in the form of blockchain, just like the "Ren" (ex. creation critics' community) formed in the Edo period in Japan. In the aforementioned communities, there is a communication and consensus that can only be established if there is a clear relationship of trust and distrust. In recent years, while consensus-based communication has increased, disparities and security issues have also been detected, and more and more fatal flaws and security errors in online communities have been uncovered that were not previously apparent. The mechanism by which these problems are discovered can occur when there is a sense of distrust among a certain number of people in a community. In the context of information and communication known as "technological warfare" or "quiet information warfare," the threshold values of parameters related to the sense of trust and distrust among communities are important information for communication to take place, but they are difficult to determine, quantify, and visualize clearly. Therefore, it is necessary to reason based on mathematical models, develop arguments and predictions, and confront possible risks and potential social problems. These issues, as well as election prediction, are themes that involve implicit understandings, such as floating and fixed votes, and consensus among regions, so we try to consider them together with social discussions in consensus building [15–21].

3. Opinion dynamics including both trust and distrust

In the opinion dynamics proposed by Ishii named Trust-Distrust Model, the time evolution of people's opinions in the society is expressed by the following Equation [16].

$$m\Delta I_i(t) = c_i A(t)\Delta t + \sum_{j=1}^{N} D_{ij} f\left(I_i, I_j\right)\left(I_j - I_i\right)\Delta t \tag{2}$$

The first term on the right-hand side is the influence of external media such as advertising, mass media reports, and government publicity, where A(t) is the influence from mass media from time to time, and the coefficient c_i is the coefficient of how much influence each person receives from that mass media. The coefficient D_{ij} can be negative [15, 16]. Here, the function $f(I_i,I_j)$ is a cutoff function that is ignored when the opinions are farther apart than a certain degree. Hegselmann-Krause [11] uses a simple step function, but here we use the Sigmoid function in the sense of a smooth cutoff.

$$f\left(I_i, I_j\right) = \frac{1}{1 + \exp\left(a\left(\left|I_i - I_j\right| - b\right)\right)} \tag{3}$$

Here, the coefficients of trust and distrust, D_{ij} and D_{ji}, are considered to be independent. Usually, D_{ij} is an asymmetric matrix with $D_{ij} \neq D_{ji}$. Moreover, D_{ij}

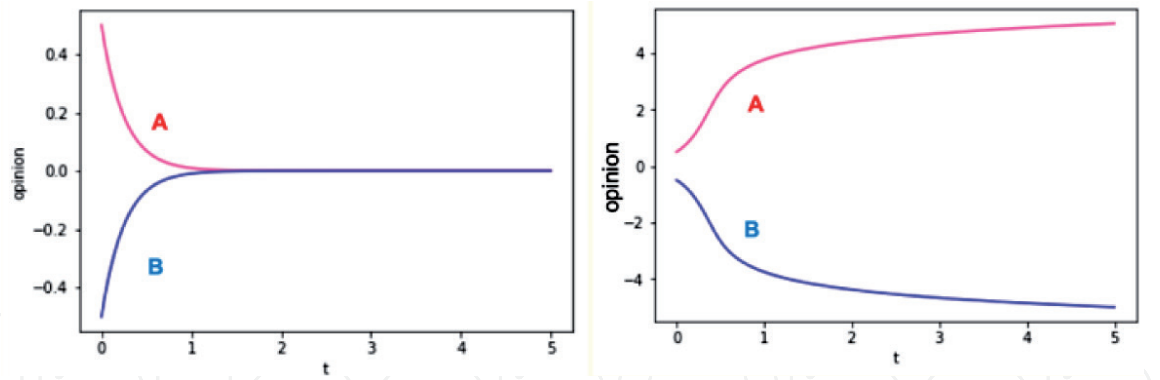

Figure 1.
Example of trust-distrust model calculation using Eq. (2). Two people. On the left is the case where two people are in a trust relationship with $D_{AB} > 0$ and $D_{BA} > 0$. On the right is the case where $D_{AB} < 0$ and $D_{BA} < 0$, and the two people are in a distrustful relationship.

and D_{ji} can take positive and negative values with different signs. A positive value means that i trusts j, while a negative value means that i does not trust j. Also, m is the strength of will of agent "i". For large values of m, the agent "i" is not so much influenced by mass media or other people's opinions.

The Trust-Distrust Model can be used to calculate the case of a person who is charismatically popular in society [22] and the case of a person who is disliked by society as a whole [18], and it can also be used to calculate the case of a society splitting up [23–25], so the Trust-Distrust Model has the potential to provide social simulation calculations for many social movements.

Here is a simple calculation using Trust-Distrust Model. **Figure 1** shows the opinion dynamics for the case of two people, where the left side of **Figure 1** shows the case where the two people trust each other ($D_{AB} > 0$, $D_{BA} > 0$). The right panel of **Figure 1** shows the case where two people in the calculation are shown as "A" and "B". distrust each other ($D_{AB} < 0$, $D_{BA} < 0$). The case of mutual trust can be found in Hegselmann-Krause [11], but the case of distrust cannot be calculated without this theory.

In this Trust-Distrust Model, the influence of the mass media is expressed by the first term on the right side of Eq. (2) called $c_iA(t)$. Here, $A(t)$ is the amount of mass media coverage of the focal topic. The quantity is simply the product of the number of seconds and the number of channels that handle the topic, and the coefficient c_i on this means that we can handle the fact that each person is affected differently by this mass media.

Based on Eq. (2), the individual opinions of the people, $I_i(t)$, are calculated over time. We assume that opinions can take values from $-\infty$ to $+\infty$; Hegselmann-Krause [11] has 0 to 1, but Trust-Distrust Model has no upper bound on extreme opinions (and no lower bound if negative). In this case, the initial opinions of people are distributed as uniform random numbers in the range of −20 to +20.

What is important in Trust-Distrust Model is the coefficient D_{ij} represented in Eq. (2). In a complete network where all people are connected to all people, there are N^2 coefficients D_{ij} that express trust or distrust between individual people. Ishii and Kawahata have shown that if more than 55% of the N^2 D_{ij} are positive, that is, trustworthy, the system will form a consensus [17]. This result is also true for random networks [26].

4. Consensus building in societies

When people in a society are bound together by trust, they reach a consensus. This is the implicit assumption and conclusion of the bounded confidence model.

The time required to reach consensus and whether one or more opinions are reached can be analyzed from the calculations of the bounded confidence model.

However, if people in the society as a whole are not necessarily bound by trust, it becomes uncertain whether they will reach a consensus or not. If all the people in a society distrust each other, it is obvious that they will not reach a consensus. Then, there is an interesting question that can be confirmed by a mathematical model: what is the ratio of trust and distrust that will lead to consensus formation?

First, we use the Trust-Distrust Model to calculate whether the entire society, assuming 300 people, will form a consensus in a situation where people's connections are mixed with trust and mistrust. Assume that these 300 people are connected by a complete network. Suppose that the coefficient of trust D_{ij} connecting people occurs in a specified proportion of cases where the coefficient is a positive value determined by a random number between 0 and 1 and a negative value determined by a random number between −1 and 0. Let T be the proportion of positive or negative values of the trust coefficient D_{ij}. If T = 1, the every trust coefficient Dij is positive. For example, if T = 0.5, then the positive and negative values are 50–50.

The results of the calculations are shown in **Figure 2** and **Figure 3** [19]. **Figure 2** plots the highest value of the opinion distribution for calculations from T = 0.45 to T = 1. Since the calculations are for 300 people, the vertical axis of **Figure 2** is 300 if consensus is achieved. The highest value of the distribution is over 200, indicating that the situation is close to consensus formation. On the other hand, at T = 0.45, the highest value of the opinion distribution is less than 20, suggesting that the opinion distribution does not have a sharp peak. Therefore, at T = 0.45, the situation is far from consensus building.

The above results were calculated for a complete network of 300 people. Since a complete network cannot be realized in society, calculations for the case where people are connected in a different network structure are also presented. The calculations were done for random networks and scale-free networks.

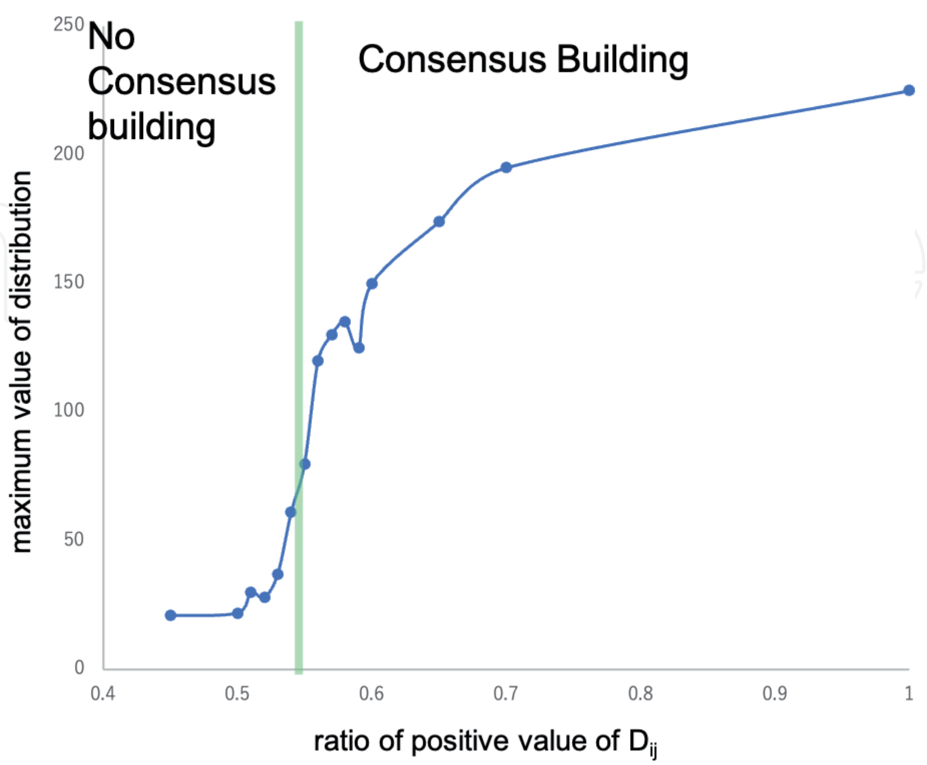

Figure 2.
Variation of the highest value of the opinion distribution with the proportion T of positive and negative values of the coefficient of confidence D_{ij}.

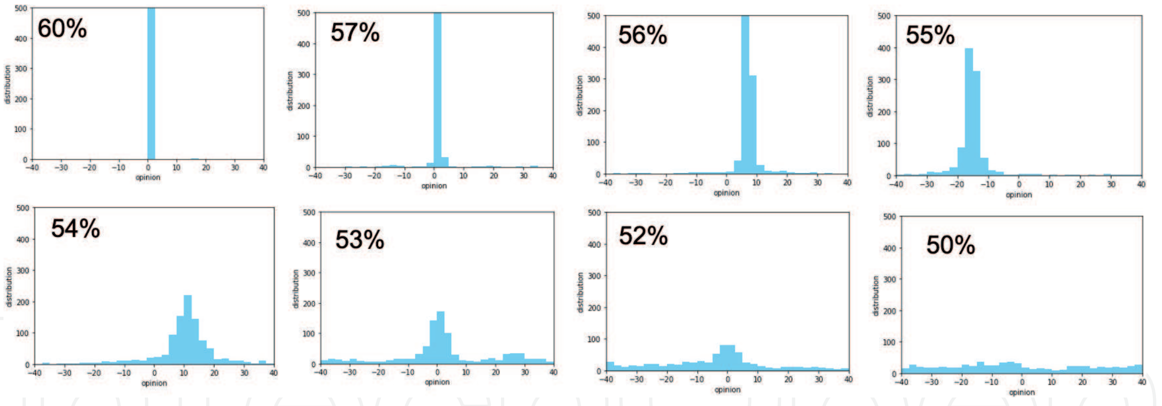

Figure 3.
The changes in the opinion distribution due to the ratio of positive and negative values of the coefficient of confidence D_{ij}, T, are calculated for T = 0.5, 0.52, 0.53, 0.54, 0.55, 0.56, 0.57, and 0.60. N = 1000 in this calculation. The probability of people connecting in a random network is set to 30%.

This can be seen in **Figure 3**, which shows the computation of the opinion distributions for T = 0.5, 0.52, 0.53, 0.54, 0.55, 0.56, 0.57, and 0.60. Let us assume that the entire society has 1000 people and is connected by a random network. The probability of people being connected is set to be 30%. As can be seen here, when T = 0.55 or higher, the opinion distribution has a sharp peak, indicating that a consensus has been formed. However, at T = 0.54, there is a peak, but it is not sharp, and at T = 0.53 or lower, the distribution of opinions is flattening out, clearly indicating that consensus has not been formed. The calculation for 300 people in the complete network is very similar to this calculation.

It is noteworthy that the highest value of the opinion distribution in **Figure 2** changes rapidly with the change of T. The peak of the opinion distribution appears after T = 0.5, and the height of the peak becomes higher after T = 0.55. In other words, the value of T determines whether a society is consensus-building or not. We can see that the borderline between the two is approximately T = 0.55.

The abrupt change in the highest value of the opinion distribution seen in **Figure 2** suggests that there is a borderline at around T = 0.55 where society may or may not reach a consensus. In other words, if more than 55% of the relationships in the entire social network are trust relationships, consensus building is achieved in the entire society. This means that it is not necessary for all relationships to be trusting in order for the entire society to reach consensus, but if more than 55% of the relationships are trusting, the society will reach consensus.

This conclusion suggests that in a democracy, for example, if more than 55% of the people support a certain policy in an election, it is possible for society to reach a consensus. It also suggests that it is difficult to reach a consensus when there is a strong opposition between those in favor and those against, such as when the number of those in favor is less than 55%. Thus, this conclusion is interesting as an application to political science.

The conclusion that 55% is the borderline of social consensus is very striking. However, I wonder if this conclusion is the same no matter what network structure people are connected to. **Figure 4** below shows a calculation for a random network of 1000 people, where the probability of joining the random network is assumed to be 1%.

Figure 4 shows that the sharp peak of the opinion distribution disappears completely at T = 0.6, and the sharp peak representing consensus emerges at about T = 0.75. In other words, if people's connections are sparse, such as the probability of joining in a random network is 1%, 55% is not the boundary of consensus formation.

For this quantitative check, we calculate the following quantity. This is the sum of the differences in the opinions of N people.

$$W = \frac{\sum_i \sum_j \left| I_i(t) - I_j(t) \right|}{\sum_i \sum_j \left| I_i(0) - I_j(0) \right|} \quad (4)$$

This W is W = 1 if the width of the opinion distribution remains the same over time, W < 1 if consensus is reached, and W > 1 if the opinion distribution is divergent without consensus.

Let us examine quantitatively the finding from previous researches [26, 27] that consensus is formed when positive trust between people in a society is at least 55% of all relationships. In **Figure 5**, we show the T dependence of W for various values of trustΔ. D_{ij} is between $-\Delta$ to Δ. The calculation of **Figure 5** is N = 1600, the connection rate of the random network is 30%. Since there are fluctuations due

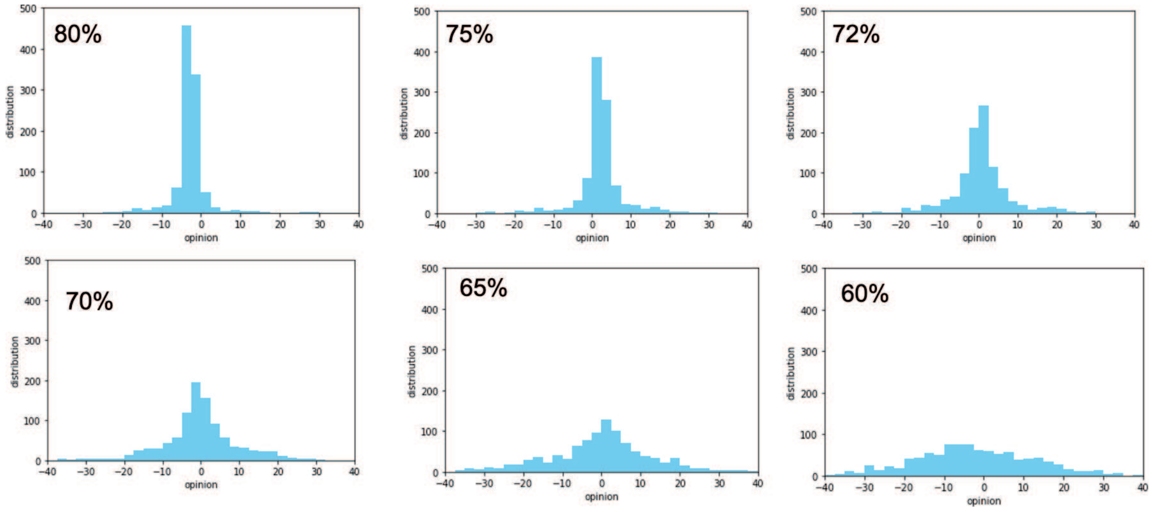

Figure 4.
The changes in the opinion distribution due to the ratio of positive and negative values of the coefficient of confidence D_{ij}, T, are calculated for T = 0.8, 0.75, 0.72, 0.70, 0.65, and 0.60. N = 1000 in this calculation. The probability of people connecting in a random network is set to 1%.

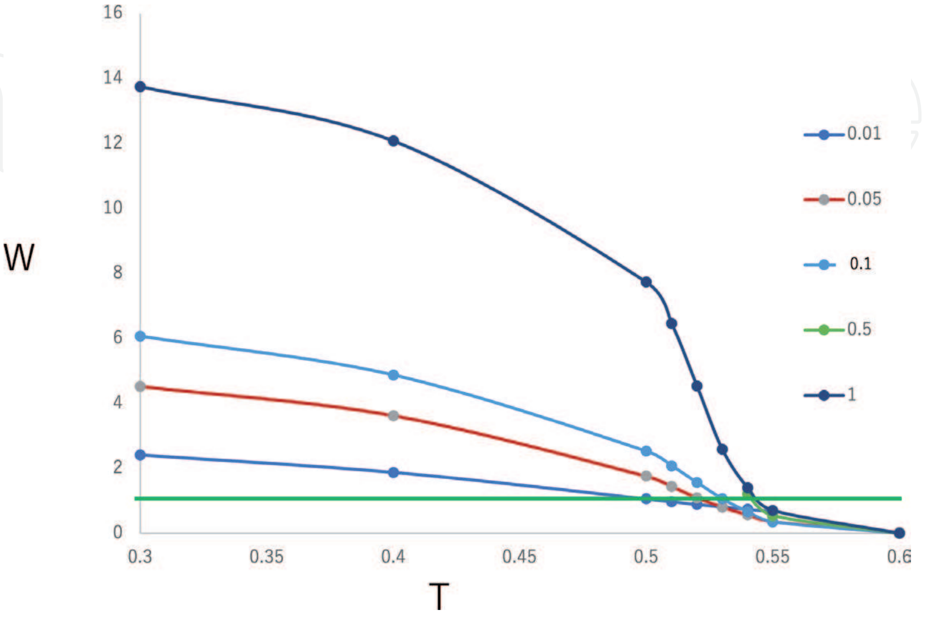

Figure 5.
The calculated W as a function of T, the proportion of positive values of the trust coefficient D_{ij}. N = 1600. Δ = 1.0. The average value of 10 calculations is used. The proportion 0.01, 0.05, 0.1, 0.5 and 1 is shown.

to random numbers, the calculated values are averaged over five times. The green horizontal line represents W = 1. In other words, if the calculation is below this green line, the society forms a consensus.

Figure 5 shows that the condition for consensus is satisfied at about T = 0.53–0.55, regardless of the size of D_{ij}. In particular, when $\Delta = 1.0$, we can see that when T is close to 0.55, there is a sharp inclination toward consensus. Therefore, the 55% consensus threshold from previous studies is supported. However, the threshold for consensus depends very much on the connection rate of the network: in the calculation for N = 1600, if Δ is 1.0, then W = 1 is T = 0.545 when the connection probability of the random network is 30%, but T = 0.69 when the connection probability is 1%. This means that if the network is sparsely connected, the threshold value of T will rapidly increase. In other words, if the network is sparsely connected, it will be difficult for society to reach a consensus.

In our previous work [27], we have performed the same type of calculations on scale-free networks, which are said to be closer to real human connections in society than random networks. However, in the case of scale-free networks, a clear consensus threshold such as 55% does not emerge.

5. Charismatic person

People in society are not uniform, but each individual is unique. A person who is especially popular among many people is called a charismatic person. In this section, we will use the Trust-Distrust Model to simulate the case of a charismatic person who is trusted by many people.

Here, a charismatic person is one who is popular with many people in society. Although being popular among others is not synonymous with being trusted by others, in this Trust-Distrust Model, a charismatic person is considered to be a positive value with a high coefficient of trust D_{ij} from others to the charismatic person. Thus, a charismatic person is defined as follows. The coefficient of trust, D_{ij}, is the strength with which person "i" is influenced by a person "j". Therefore, if the charismatic person is represented by "c" and D_{ic} is the trust from person "i" to

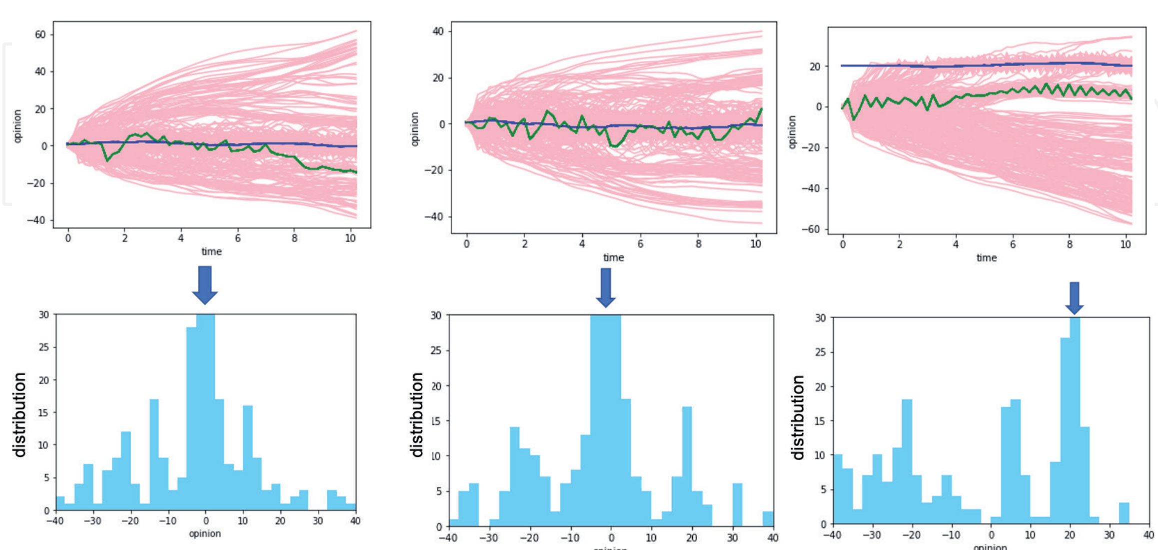

Figure 6.
Simulation of a single charismatic person. The charismatic person is trusted by the people in the society with a trust coefficient D_{ic} = 10, and the trust coefficients between other people in the society are determined by random numbers in the range of +1 to −1. The arrows show the opinion distribution of the charismatic person. The blue line in the opinion trajectory represents the opinion of a charismatic person, while the green line is a sample of the opinion trajectory of an ordinary person.

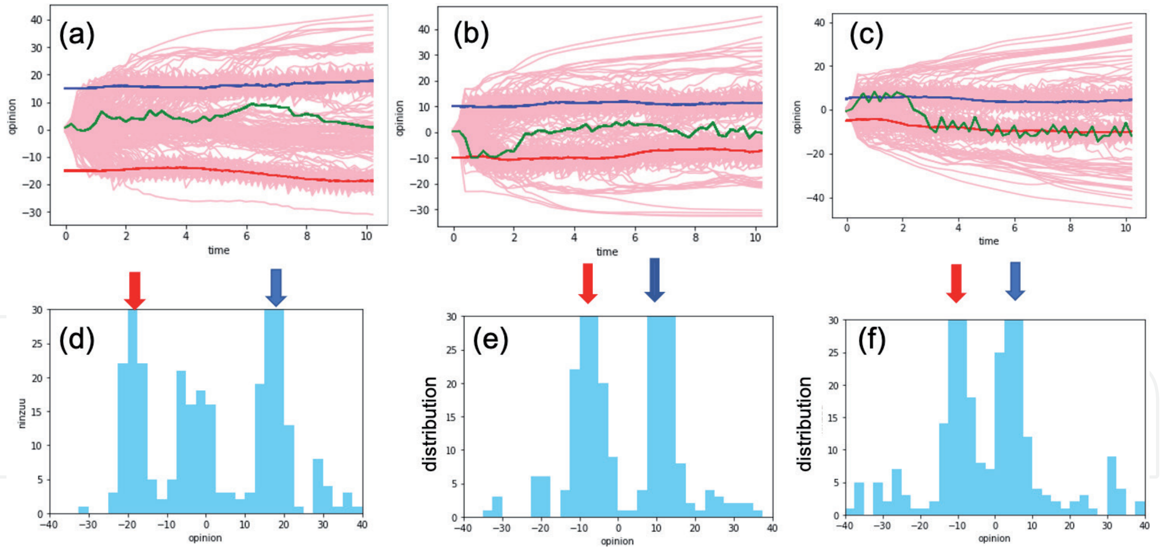

Figure 7.
Simulation of two charismatic persons. The charismatic persons are trusted by the people in the society with a trust coefficient D_{ic} = 10. The blue line and red line in the opinion trajectory represent the opinions of a charismatic person, while the green line is a sample of the opinion trajectory of an ordinary person.

the charismatic person. D_{ic} is larger than the influence from other people, then the charismatic person will have more influence.

Figure 6 shows the case where there is one charismatic person in a society of 300 people. It can be seen that many people have their opinions close to those of charismatic person. Thus, a charismatic person will be able to attract people with similar opinions. The more positive and larger the value of D_{ic}, the stronger the effect. This is called being popular in society.

Figure 7 shows the case where there are two charismatic people in the society. These two people are popular and have many people who agree with their opinions. If the two charismatic people are far apart in their opinions, a middle opinion group will be formed between their opinions, but if their opinions are close, there will be no middle ground and the society will be divided between them.

6. Mass media effect

Another feature that distinguishes the Trust-Distrust Model from the traditional bounded confidence model is that it can calculate the effect of advertising on the formation of social opinion. In this section, we will consider the impact of advertising on people's opinions of society. In general, advertising is the use of mass media to convey people's messages [28]. Here, we do not touch on the specific method of advertising or the content of advertising but set the impact of advertising per unit time on people as $A(t)$. $A(t)$ can be thought of as the amount of advertising per day, e.g., the amount of money spent on advertising.

The first term on the right-hand side of Eq. (2) is $A(t)$, where $A(t)$ represents the strength of advertising added to society from time to time. This term of the impact of advertising is adopted with reference to the term introduced in the mathematical model of hit phenomena [29, 30], which analyzes the impact of advertising on society.

In this section, the opinions people have are expressed as one-dimensional numerical values. Therefore, an opinion with a positive value simply means that it is expressed as a positive numerical value, not that it is an affirmative opinion. The situation is the same for opinions with a negative value. Therefore, whether an opinion is positive or negative only implies the direction of the opinion on a particular topic. Whether an opinion is positive or negative does not mean that it supports or does not support a particular topic. For example, on the topic of cola, it is possible to assign a positive value to an opinion that likes Coca-Cola and a negative value to an opinion that likes Pepsi-Cola. Conversely, it is also possible to make the opinion that you like Pepsi-Cola a positive opinion and the opinion that you like Coca-Cola a negative opinion.

Figure 8 shows the effect of advertising on the distribution of opinions. From left to right, the strength of advertising is A(t) = 0, 0.5, and 5.0. When A(t) = 5.0 on the right, social opinion distribution moves significantly in the positive direction. In other words, using Eq. (2), we can include the influence of advertising in our calculations.

If we define the advertising term A(t) as follows, we can concentrate the opinions of the people in the society into an arbitrary opinion.

$$A(t) = -A\tanh\left(aI_i(t) - b\right) \tag{5}$$

Here, a represents how narrowly the opinion distribution should be concentrated, and b specifies where the opinion distribution should be concentrated. By setting these a and b, we can decide which and how much of society's opinions should be concentrated. An example of this is shown in **Figure 9**. However, what kind of advertising can have this kind of effect is still another question.

An example of this extreme simulation is shown in **Figure 10**. Here, the opinion of the whole society is negative at first, but due to the influence of strong advertising, the opinion of all people in the society changes to a positive value. We do not know what kind of advertising can actually have this kind of effect on society, but we have shown that it is possible in principle as a mathematical model.

In the first term on the right-hand side of Eq. (2) of the Trust-Distrust Model, which represents the influence of advertising, the influence of advertising can be added separately to each person in society by setting the coefficient ci. This shows that it is possible to calculate micro-targeting, which is known in the field of marketing.

Eq. (2) also shows that people are influenced both by advertising from the mass media and by the people they are connected to in society. Today, with the development of social media, some people are not exposed to information from mass media such as television. Therefore, we will use the Trust-Distrust Model to investigate whether people who are not exposed to information from the mass media are indirectly influenced by the mass media through the influence of people who are connected to them in society [31].

In **Figure 11**, we set the number of people in society as a whole at 1000, of which 100 people, or 10%, are not affected by mass media. The connections between people are random networks, and the calculations for the percentage of connections are

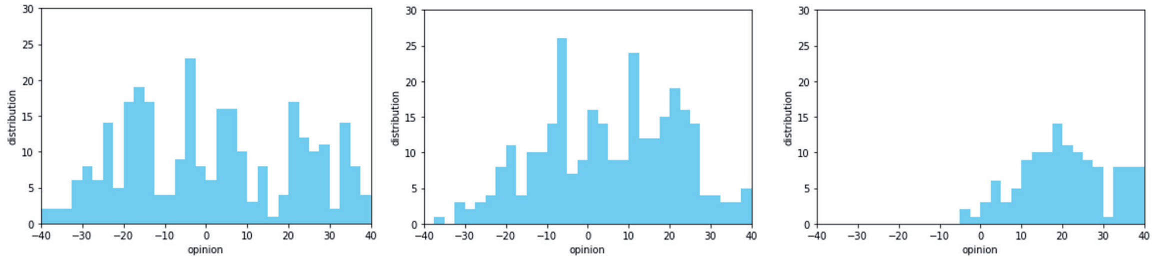

Figure 8.
It shows the effect of advertising on the distribution of opinions. From left to right, a(t) = 0, 0.5, 5.0. When a(t) = 5.0 on the right, social opinion moves significantly in the positive direction.

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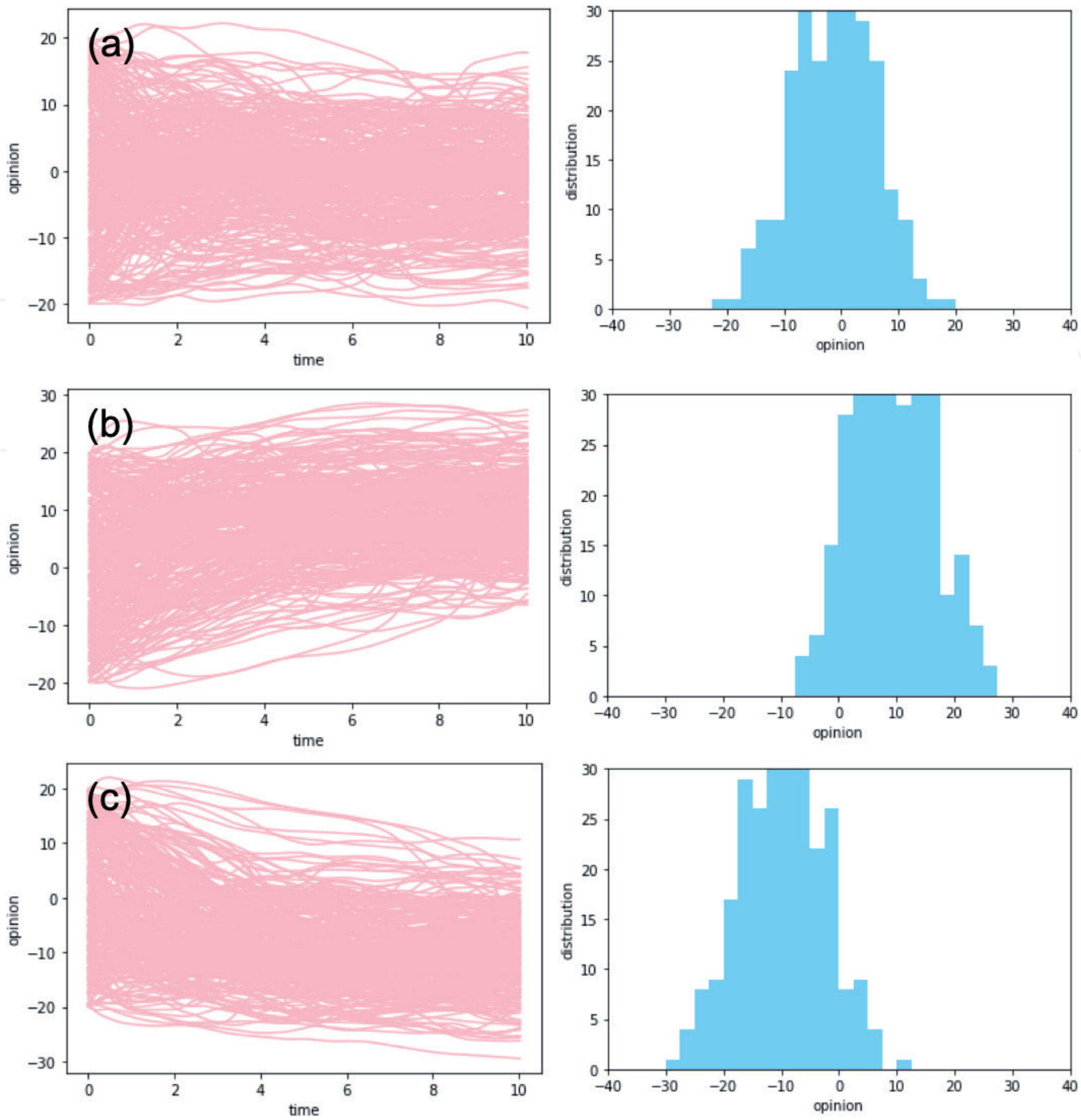

Figure 9.
Calculation of the concentration of the distribution of opinions in society under the influence of advertising, using Eq. (5). A = 5, a = 0.2. The values of b are (a) b = 0, (b) b = 10. (c) b = −10.

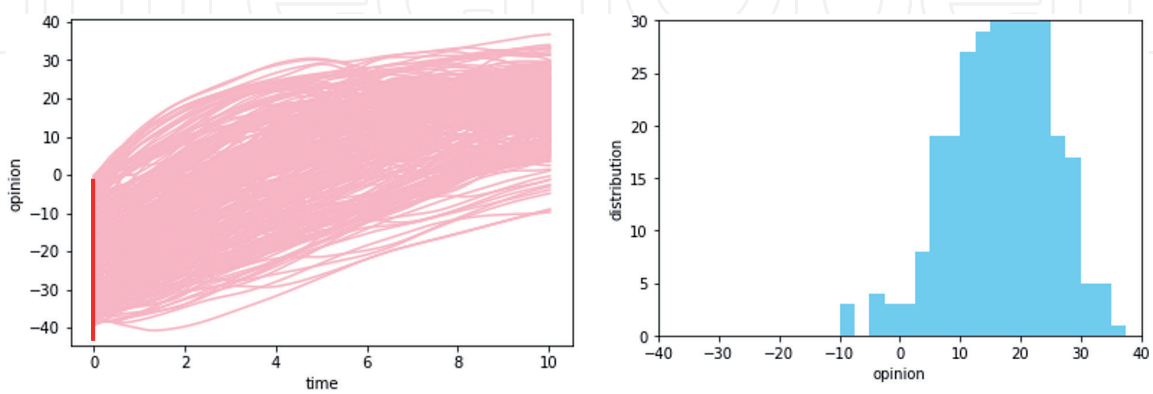

Figure 10.
Calculation of the concentration of the distribution of opinions in society under the influence of advertising, using Eq. (5). Parameters are a = 5, a = 0.2. Value of b is b = 20.

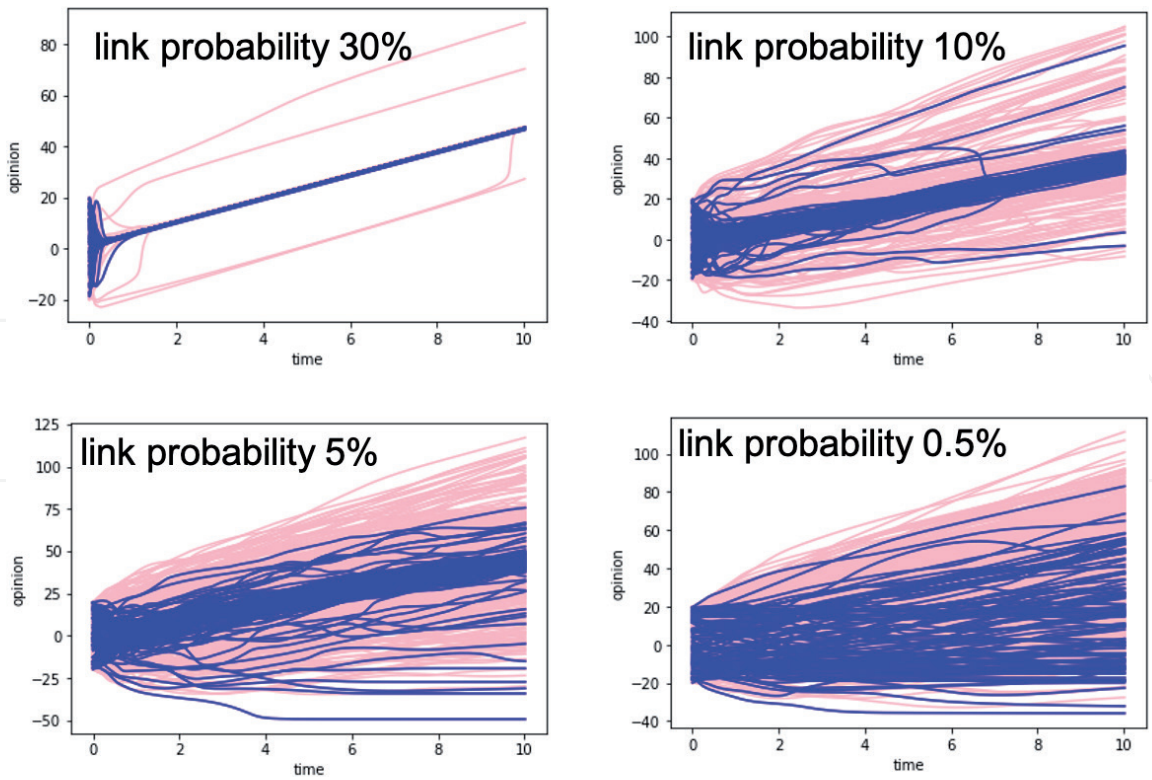

Figure 11.
Simulation of the movement of people who are not reached by the influence of mass media. Suppose the number of people in the society is 1000, and 100 people are not reached by the influence of mass media. Calculations are shown for random networks with connection probabilities of 30%, 10%, 5%, and 0.5%. The trajectory of the opinions of those who are influenced by the mass media is pink, and the trajectory of the opinions of those who are not reached by the mass media is blue. The coefficient of people's trust is set at a uniform random number in the range of 1 to −1, and the proportion of positive values is $T = 0.6$. The proportion of positive values is $T = 0.6$. The strength of advertising is $a = 5$.

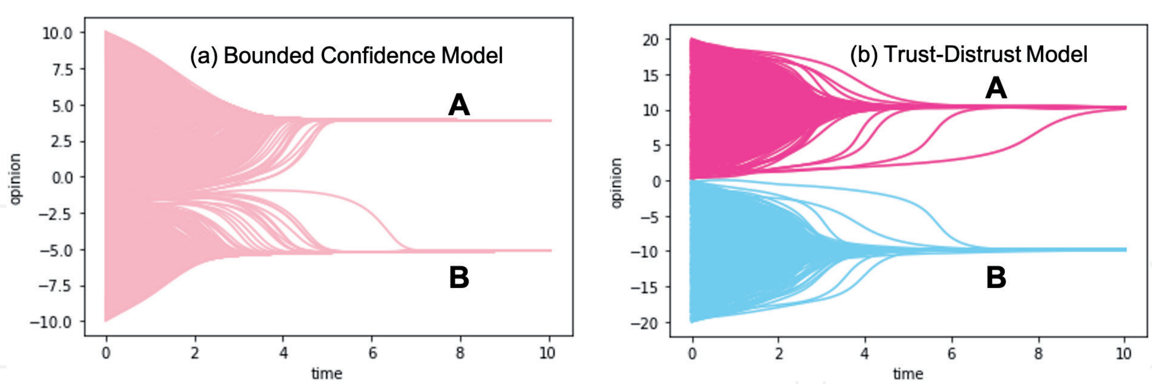

Figure 12.
Polarization of the distribution of opinions in society. (a) Polarization of opinions obtained by the bounded confidence model. The coefficient of trust $D_{ij} > 0$ for everyone in the pink locus of opinion. (b) Polarization of opinion obtained with the trust-distrust model. The red and blue groups in the locus of opinion are consensus with $D_{ij} > 0$ within the group and distrust with $D_{ij} < 0$ between the groups.

shown as 30%, 10%, 5%, and 0.5%. In **Figure 12**, the trajectory of the opinions of those who are influenced by the mass media is depicted in pink, and the trajectory of the opinions of those who are not influenced by the mass media is depicted in blue.

The calculation results show that when people's connections are sparse, some of the people who have not received the influence of mass media do not receive the influence of mass media even though they are connected to people in the society, and their opinions are about −40 and the trajectory of their opinions is horizontal. Even in that case, many people's opinions are moving in the direction influenced by the mass media, that is, in the positive direction, because of the connections between people in society, even if the influence of the mass media does not reach them.

On the other hand, when people are closely connected in random networks, as seen in the case of 30%, even those who are not reached by mass media influence reach consensus with those who are, indicating that opinions are moving in a positive direction influenced by mass media.

7. Division of society

The Trust-Distrust Model takes into account not only trust and consensus among people in a society but also distrust and opposition among people. Thus, phenomena such as social division can be reproduced in the simulation. Social divisions are often caused by serious conflicts in society, which is different from the phenomenon calculated by the Bounded Confidence Model, in which there are multiple consensus opinions because the opinions are far apart. In this sense, the Trust-Distrust Model seems to be a more suitable opinion dynamics theory for dealing with social fragmentation and division.

The most typical example of social division would be the American Civil War. The American society at that time was divided into two positions, and the war took the form of a war between two uncompromising and polarized groups. Another example would be the Reformation in Europe in the 16th century. Modern American society also seems to be divided into conservative and liberal, as seen in the 2020 presidential election. In Japan, during the Meiji Restoration in the mid-19th century, Japanese society was divided into conservative and reformist factions, and there was a civil war that lasted over a year. In addition to the past examples of wars, many countries are divided over whether to prioritize medical countermeasures or minimize economic damage in response to the spread of COVID-19 today, for example. Such divisions of opinion in society cannot be handled by the Bounded Confidence Model, since they clearly disagree with each other and with the opinions of others.

In the bounded confidence model, people in the society are basically in a trust relationship. In the bounded confidence model, people in the society are basically in a trusting relationship, and the cause of the polarization of opinions is therefore not affected by distant opinions. In the bounded confidence model, people are not influenced by opinions that are too far apart from their own, so the distribution of opinions in society becomes multipolar and coalesces into multiple opinions [10, 11].

However, in the case of the Trust-Distrust Model, it can be assumed that people in a society are divided into, say, two groups, and the groups are in conflict with each other and distrust each other. **Figure 12** shows the polarization of opinions in the bounded confidence model and in the trust-distrust model. **Figure 13** shows the polarization of opinions in the bounded confidence model and the trust-distrust model. Although they look the same, in the bounded confidence model, all people in society are bound by trust, while in the trust-distrust model, people in society are divided by distrust.

More generally, we think of a society as being divided into multiple endogroups. A distinction is made between the relations between people within an endogroup and the relations between an endogroup and people in another endogroup. Tajfel's idea [32] is to describe the relationship between an in-group and another in-group as an out-group.

This polarization of social opinion based on the Trust-Distrust Model is expressed in the concept of In-group and Out-group proposed by Tajfel [32], and **Figure 13** shows a schematic diagram of the opinions of people in society according to Tajfel's concept. In **Figure 14**, T_A and T_B are the proportions of positive values of the coefficient of trust Dij within groups A and B, and T_{AB} is the proportion of

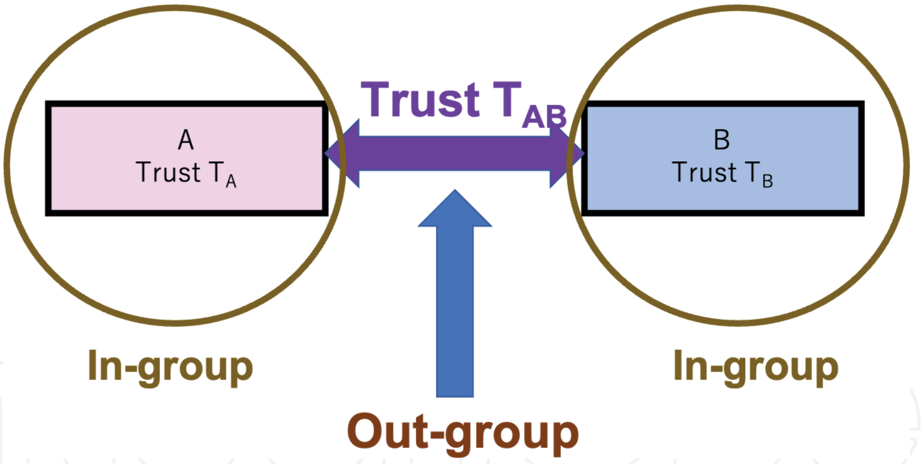

Figure 13.
In-group and out-group based on Tajfel's proposal. T_A and T_B are the proportions of positive values of the coefficient of trust Dij within groups a and B, and T_{AB} is the proportion of positive values of the coefficient of trust Dij between groups.

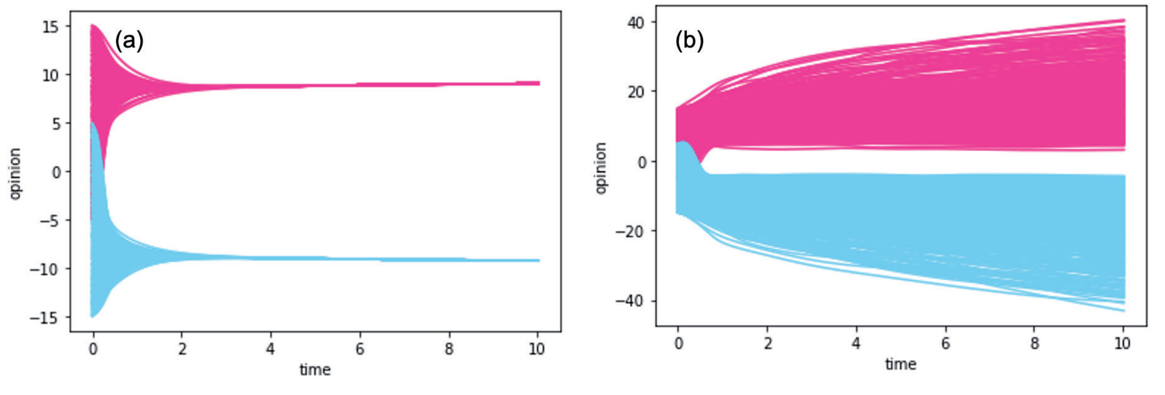

Figure 14.
Two typical examples of the distribution of opinions in a divided society. (a), $T_A = T_B = 0.8$. $T_{AB} = 0$. Group A and Group B form a consensus as In-group. However, with $T_{AB} = 0$. (b), $T_A = T_B = 0.5$. $T_{AB} = 0$.

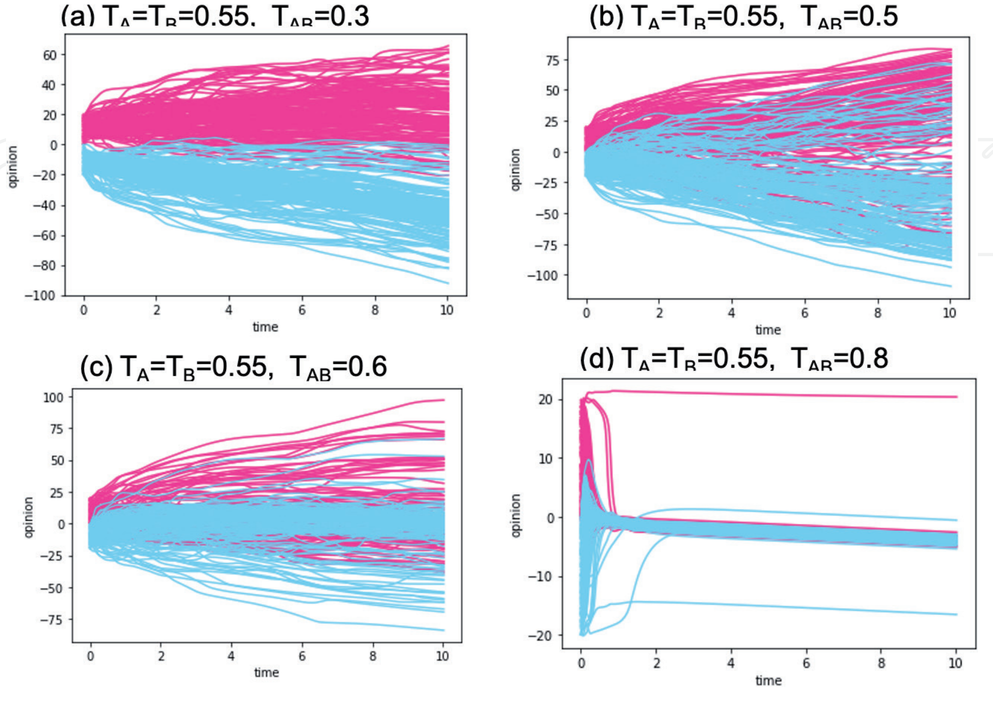

Figure 15.
Calculations using the trust-distrust model when society is divided into Group A and Group B. $T_A = T_B = 0.55$. $T_{AB} = 0.3, 0.5, 0.6, 0.8$. The opinion trajectories of people in Group A are in red and those of people in Group B are in blue.

positive values of the coefficient of trust Dij between groups. If $T_{AB} = 0$, then the two groups are completely split as in **Figure 13** (b).

Figure 14 shows two typical examples of the distribution of opinions in a divided society. In (a), $T_A = T_B = 0.8$. $T_{AB} = 0$. Group A and Group B form a consensus as In-group. However, with $T_{AB} = 0$, the trust between the groups is zero. On the other hand, in (b), $T_A = T_B = 0.5$. $T_{AB} = 0$, Group A and Group B do not form a consensus because of insufficient trust in the group, but the trajectories of the two groups are repulsive and do not mix because of distrust in the Out-group.

A typical example of (a) in **Figure 14** would be the American Civil War, where society was completely divided, and war broke out. However, as far as the votes for the 2020 presidential election in the United States are concerned, the two candidates are competing in each state, and there is no regional division.

Figure 15 shows the results when T_A and T_B are fixed at 0.55 and T_{AB} is varied. Here, T_{AB} is not zero, so even with $T_{AB} = 0.3$, Group A, and Group B mix a little. When $T_{AB} = 0.8$, the two groups are in an out-group trust relationship, and they form a single consensus. For these detailed calculations, please refer to References [33, 34].

8. Discussion and conclusion

In this paper, we introduced a new theory of opinion dynamics, the Trust-Distrust Model. Trust and mistrust play a very important role in this opinion dynamics theory. Trust brings people to a consensus, while distrust makes people repel. The Trust-Distrust Model is a theory that is suitable for simulating this situation.

The Bounded Confidence Model is a theory of opinion dynamics in which opinions take continuous values, and the Trust-Distrust Model is an extension of the Bounded Confidence Model. The Trust-Distrust Model is an extension of the Bounded Confidence Model in two respects: the coefficient D_{ij} is seen as the coefficient of trust between people, and when this value is negative, the relationship is distrustful. Also, the influence of mass media was incorporated as an external field to the differential equation that determines opinion. The extension of distrust as negative trust facilitates the simulation of social phenomena such as social divisions. It is possible to simulate consensus building as an In-group for each group in the society, and trust and distrust as Out-group among groups in detail. In this sense, the Trust-Distrust Model is a theory that facilitates the simulation of a real, complex society. The main theme of this paper is the consensus of information: "trust-distrust", the discussion of social impact through communication by various media formed by implicit understanding is represented by resistance to authority, populism, and risk. The focus tends to be on issues. Depending on the content and nature of the news, positive dissenting or agreeing opinions may have both similar and different tendencies depending on the source and content, and the ability of stakeholders to communicate in the discussion. The simulation results suggest that the network structure is significantly changed by the above. On SNS, we have already gradually introduced a mechanism to anticipate risks, such as (1) a mechanism to prohibit hackers from accessing the system with a system that is increasing in number mechanically, and (2) a mechanism to prohibit accounts due to posted content. Has been done. However, unpredictable behavior can occur. In addition, by accumulating information collectively, patterns for manipulating information will continue to grow. As mentioned above, in the 2020 US presidential election, strict regulations were imposed on large-scale web-based speech control and erroneous information transmission channels including bots. From this research, the network structure changes drastically due to the spread of erroneous information, the participation of untrustworthy information, the balance of the spread of reliable information, and the construction of the related party network, and the opinion is that phase transition occurs at a certain threshold. It was suggested. Significant changes may occur in the future due to future legislative decisions. Furthermore, we think that it is necessary to have a shared awareness not only of the crime clearance rate offline but also of security awareness in cyberspace as a social convention. In that respect as well, it is important to check facts in an online-offline environment and form a communication community in consideration of the reliability of information for a diverse risk society, or if it is distrustful for a risk society, it is wrong. It is necessary to consider various cases such as discussions when problems are overloaded, and it can be said that it is necessary to learn from past cases and prepare for them from hypothetical simulation results and case studies. In the future, there will be an increase in two-way communication across time and space by anonymizing personal information such as letters and pictograms, and extracting them "as cryptographic asset data" to represent social events. However, there are advantages and disadvantages to using information assets in the form of personalized data, which are excerpts of personal information as described above. In the future, the discussion of trust value in the above data will accelerate in indicators such as personal credit scoring. In this paper, the Trust-Distrust Model will be discussed with respect to theories that also address charismatic people, the effects of advertising, and social divisions. Furthermore, simulations of the Trust-Distrust Model show that 55% agreement is sufficient to build social consensus. By working on this theory, we hope to use it to discuss and predict social risk in future discussions in credit scoring.

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