Exploration for the evolutionary mechanism of opinions on live streaming platforms

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Abstract:
Focusing on the opinion dynamics under the background of new social media, this research explores the evolution of public opinion in the live streaming platforms such as TikTok and Douyu, and establishes an integrated agent-based model approximating the characteristics of the live streaming platforms in real life. Based on our assumptions and standard settings, we found that when the initial opinion distribution is not completely unipolar, then at the end of the evolution, there will be a main opinion group whose opinion value is close to the host's information source value, and some small opinion groups distributed around the extreme negative opinion values. We also explore how psychological and sociological factors like individuals' assimilation and repulsion thresholds, negativity bias and positivity offsets, conformity and entertainment motivation affect the results of opinion evolution. Our key conclusions include that larger assimilation or repulsion thresholds would make the audiences easier to be led by the host and fewer audiences distributed at the extreme opinion areas; the increase of either positivity perception coefficient or intercept would not only enhance the assimilation effect of the host's information by increasing the main opinion group, but also increase the repulsion effect from the extreme negative opinion holders, thereby increasing the proportion of this part of audiences, while the increase of the negative perception coefficient can help to transform some non-extreme negative viewpoint holders to the main opinion group; an lift in the audiences' overall conformity level would increase the ratio of the main opinion group, but at the same time, the assimilation from non-extreme negative opinion holders will be reduced; entertainment motivation level pose an opposite effect to that of conformity. Besides, the model is roughly verified by an estimation test using MLE and SMM.

Keywords: Opinion Dynamics, Multi-Agent Modeling, Negativity Bias & Positivity Offset, Simulated Method of Moments

1. Introduction

With the development of social network sites (SNS), people have more extensive and convenient ways to express and share their opinions. In traditional online social media such as Facebook, Twitter and Microblog, users interact with each other by leaving comments on these platforms. Large quantities of online user generated contents (UGC), especially those comments left by users, provide researchers with plentiful resources to study the opinions of users in online communities.

Recently, a new kind of online social networking platforms, live streaming platforms, has become popular in Asian countries such as China, South Korea and Japan. Users can watch live streaming content by entering a live streaming room in these platforms. The biggest difference between these platforms and traditional video websites is that in the process of watching live streaming, one or more hosts interact with users as if talking to them (i.e., the audiences can watch the hosts while the hosts cannot see the audiences), and the content of live streaming is usually determined and generated by the hosts. Taking China's online live streaming platforms as an example, the content of live streaming mainly includes e-sports commentaries, entertainment performances and outdoor activities. Moreover, the form of user comments on the platforms is also very special: users' comments will be in the form of Danmu (screen bullets) scrolling across the live streaming room (see Figure 1), that is to say, viewers will see all comments sent at the same time scrolling on the screen (without the problem of network delay and blocking of certain users). In this process, hosts can also see the screen bullets left by the audiences in the background and respond to them in the live streaming. Besides leaving comments, audiences can also interact with the hosts by sending virtual gifts to them. Virtual gift giving, viewed as a sort of consumption behavior, requires users to pay a certain fee to buy gifts, and is usually not displayed in the bullet screens unless the gift is expensive enough.

Figure 1. Snapshot for Online Live streaming

Since the mode of online live streaming is relatively fresh, there are only few researches conducted on it among the literature we have consulted. In these limited resources, the core issues focus on the impact of bullet screens on people's feelings when watching live streaming (e.g., Djamasbi et al, 2016, Jia et al, 2018), and a few studied the natural language processing (NLP) of bullet screens.

In this study, we will focus on exploring the evolutionary mechanism of opinions on live streaming platforms based on opinion dynamics model SJBO, and upgrade the model by combining sociological and psychological factors like positivity offset and negativity bias, conformity effect and entertainment motivation. (Section 3) We also identified how variances in these factors affect the outcome of the opinion evolution by checking three metrics at the end of evolution: audiences' average opinion value, opinion value distribution, and the conversion rate of positive and negative opinions compared to the original state (Section 4). In the current literature, opinion dynamic models are rarely tested by real data. Therefore, in this research, we try to make an estimate of our model based on real data to make some difference. Two steps are processed sequentially in the estimation where we first use MLE to estimate part of the parameters and then turn to simulated method of moments for the rest (Section 5). Finally, we present the core conclusions of the study and some potential improvements for the model and its estimation (Section 6).

2. Related Theories

2.1 Continuous Opinion Dynamic Models

The study of the evolution of opinions in communities has always been an important and interesting topic in the field of dynamics. Researchers built different models of opinion evolution based on different backgrounds and theoretical bases. The model we used in this research falls into the category of continuous opinion dynamic models, in which the opinion of every agent at each moment can be any real value within a pre-defined range. The early continuous models characterized the changes of opinions of agents as linear formats, such as the classic model (De Groot, 1974). The updated opinion of an agent is formed by a weighted average of all the opinions in the community. In early continuous models, the opinion transition mode of the whole group can be expressed as a transition matrix. When the matrix is fixed or irrelevant to the opinions themselves, which keeps the model linear, the evolution results are able to be directly obtained through mathematical analysis (Hegselmann and Krause, 2002).

The Bounded Confidence (BC) model (Deffuant, 2002) breaks the convention of the linear form by associating the opinion transition function with the opinion values themselves. In this model, agents' opinions influence each other only when the difference of their views is below a certain threshold. This threshold, that is, bounded confidence, can be interpreted as the uncertainty of the agent's opinion. When the difference from another opinion exceeds the scope of such uncertainty, the agent will not consider incorporating such view. The general form of the BC model can be expressed as (2-1)-(2-2):

$$x_i^{t+1} = x_i^t + f(x_i^t, x_j^t)(x_j^t - x_i^t) \tag{2-1}$$

$$f(x_i^t, x_j^t) = \begin{cases} \mu, |x_j^t - x_i^t| \le u \\ 0, |x_j^t - x_i^t| > u \end{cases} \tag{2-2}$$

Where x_i^t represents the opinion value of agent i at time t, u represents the threshold (uncertainty) for adopting the opinion from others and μ denotes the degree of adoption. Noting that function of $f(x_i^t, x_j^t)$ plays a decisive role in the opinion update, we regard it as the kernel function of the BC model.

After the BC model was proposed, due to its flexibility and comprehensibility, it was widely used in the study of opinion dynamics. Researchers adjusted the basic model according to different backgrounds and problems, mostly in the point of the kernel function. The Social Judgment Based Opinion (SJBO) dynamics model (@Jager and Amblard, 2005) differs from the basic BC model by taking in the idea of social judgement theory (Sherif et al, 1961), which states that when the opinions of two agents are close enough, their opinions tend to assimilate with each other; when the gap between two opinions is large enough, they tend to repulse to each other; otherwise, the two agents will not influence the opinions of each other. The introduction of repulsion effect, or Boomerang effect (Hovland et al.1953), makes this model more comprehensive than the original BC model and more consistent with people's behaviors in reality. Therefore, we choose the SJBO model as the framework in this study for our modeling (2-3)-(2-4):

$$x_i^{t+1} = x_i^t + f(x_i^t, x_j^t)(x_j^t - x_i^t) \tag{2-3}$$

$$f(x_i^t, x_j^t) = \begin{cases} \alpha, & |x_j^t - x_i^t| < d_1 \\ 0, & d_1 \le |x_j^t - x_i^t| \le d_2 \\ -\beta, & |x_j^t - x_i^t| > d_2 \end{cases} \tag{2-4}$$

Where x_i^t represents the opinion value of agent i at time t, and d_1 represents the threshold for assimilation while d_2 is that for repulsion. α and β refer to the degree of assimilation and repulsion, respectively.

2.2 Negativity Bias and Positivity Offset

The concept of "Negativity Bias and Positivity Offset", which we integrate into the opinion dynamic model, reveals that people tend to respond differently according to whether the stimulus elicits a positive or a negative cognitive reaction. The idea of negative bias has been elaborated in the review of @Rozin and Royzman (2001). They suggested that Negativity Bias is manifested in four aspects:

- Negativity Potency: Negative entities are stronger than the equivalent positive entities

- Steeper Negative Gradients: The negativity of negative events grows more rapidly with approach to them in space or time than does the positivity of positive events
- Negativity Dominance: Combinations of negative and positive entities yield evaluations that are more negative than the algebraic sum of individual subjective valences would predict
- Negative Differentiation: Negative entities are more varied, yield more complex conceptual representations, and engage a wider response repertoire.

We hereof highlight the second manifestation, which we choose to incorporate in this research. The measurement of the steeper negative gradients is originally proposed in Cacioppo's works in 1994 and 1997, where the researchers utilize a bivariate plane to quantitatively analyze the relationship between individuals' attitudes and their evaluation of positive and negative stimuli. The bivalent model of evaluative activation can be expressed as (2-5):

$$Attitude = \frac{W_p}{W_p+W_n} P_i - \frac{W_n}{W_p+W_n} N_j + I_{ij} \tag{2-5}$$

Where $P_i(N_j)$ represents the level of positivity (negativity) activated by an attitude object; $W_p(W_n)$ represents the relative attitudinal effect of variations in positivity (negativity); I_{ij} represents nonadditive effects. On the basis of the approach- avoidance experiment conducted by miller et al. (1959), it is found that the negative weight in the above model should be greater than the positive weight (Negativity bias), and proposed that when the stimulus intensity was low, the positive evaluation process would be stronger (Positivity Offset), which was expressed by adding a positive intercept for positive evaluation. The modified version of this computational model is presented (2-6) with a visualized example result (see Figure 2):

$$Attitude = \left(W_p P_i + c\right) - W_n N_j + I_{ij} \tag{2-6}$$

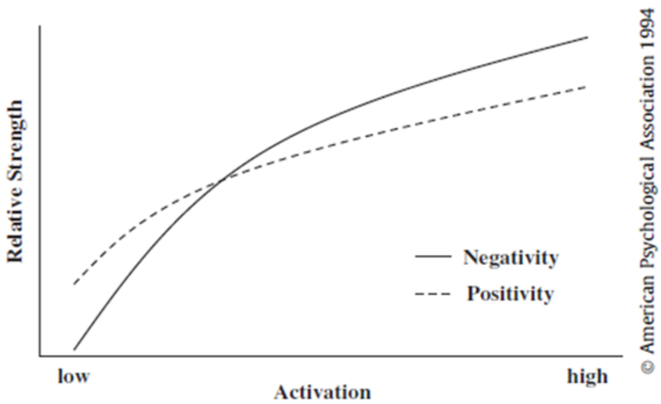


Figure 2. Activation function example result (1994)

2.3 Opinion Expression Theories

In the online live streaming platforms, the audiences will not express their opinions all the time, so in the construction of the dynamic model, we need to consider under what conditions audiences will send screen bullets on the platform. In this study, our consideration for the mechanism of people's opinion expression is related to two aspects: entertainment motivation theory and conformity effect (the spiral of silence).

In live streaming platforms, entertainment motivation is understood as audiences can gain pleasure from the act of sending bullet screens. This kind of motivation and pleasure-gain process is also revealed in other users' online behaviors like browsing the webpages and leaving comments (Ridings and Gefen, 2004), and some studies also suggested different individuals tend to have different level of entertainment motivations (Cotte et al. 2006). For example, active posters prefer online interactions to screen snoopers. We reflect this difference into the model with a random variable of beta-distribution, which we would discuss later in Section 3.

Conformity effect is also known by a well-known phenomenon: the spiral of silence (Noelle-Neumann, 1974). This theory generally stipulates that people are only willing to express their opinions when they are in line with the dominant opinion of the public. Otherwise, they will choose to remain silent due to the fear of being isolated or excluded. This inference about the spiral of silence rests on three core assumptions:

- People are in fear of isolation.
- People can assess the dominant opinions in their environment.
- The evaluation of the opinion climate can influence people's expression of their opinions.

In the online communities, however, the validity of these assumptions, especially the first assumption, has been questioned through later studies: Yun et al (2016) showed that people with minority perceptions will not keep silence in fear of isolation but will increase their willingness for speaking because of the feeling of hostility; Chun and Lee (2017) proposed that mediation factors such as the sense of social support and control also play important roles in whether or not people express opinions, not just the fear of being isolated. In general, expression of opinions in the online social networks do not strictly follow the traditional theory of the spiral of silence, and many factors that have been studied or not may play roles in it. In this study, we defined the hypothesis of fear of isolation in the traditional theory as a state of complete conformity, and individuals can be in a state between complete conformity and complete non-conformity. Individuals with different degrees of conformity have different disciplines of speaking after identifying the dominant opinion.

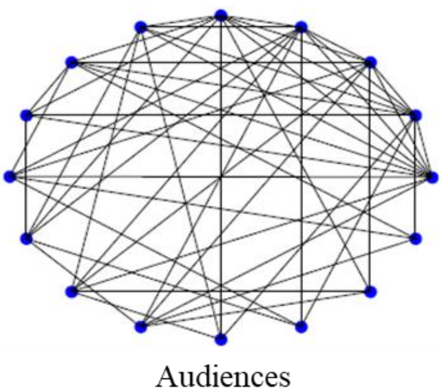
3. The Model

In this section, we are going to illustrate our SJBO model-based opinion evolutionary dynamics model of live streaming platform and its setup philosophy. We firstly notify the assumptions and notations for our model, and then elaborate on how we adapted the traditional SJBO model to the setting of live streaming platforms and also how we incorporated the psychological and sociological theories like negativity bias, positivity offset, conformity effect and entertainment motivation into our model.

3.1 Assumptions and Annotations

Assumptions:

- The structure of the live streaming platform is assumed to be static during our relatively short simulated evolution period, which means we also preclude the changes in the scale of the social network.
- The networks among the audiences (see in Figure 3) and between the host (see in Figure 4) and audiences are considered to be fully connected, which means that we do not consider the policy to shield the messages sent by certain agents.
- The host is a special node in the network. The information value generated by the host is actually an integration of factors like the hosts' opinions, live streaming content, and even the environment of the live streaming, so it is assumed to be a random variable. Although the host would sometimes also be affected by the audiences during the live streaming process, the impact is usually very small due to their high inner stability trained by the live streaming industry. Thus, the impact from the audiences' comments on the host is ignored.
- The impact from the gift sending messages is precluded in this study, since the messages of gift sending are displayed only if the gifts are expensive enough and sometimes the gift sending messages might come from other rooms, which are irrelevant to current live streaming. In addition, we believe that the analysis of consumption behavior like virtual gift sending requires different models from the analysis of pure opinion evolution.
- For most of the parameters, we assume they are presented as the average level of the audiences or the host, except for the entertainment parameter δ_i. This assumption neglects possible individual differences among the audiences to make the model more stable and reduce the difficulty for estimation.



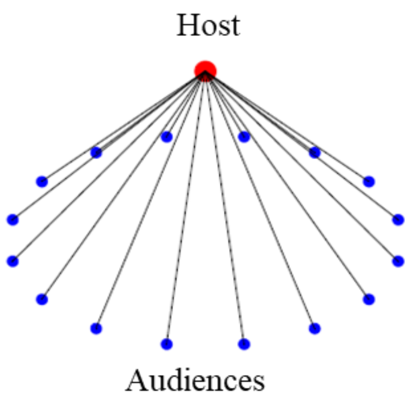


Figure 3. Audience-Audience Network   Figure 4. Host-Audience Network

Annotations for variables:

Variables	Definition	Range
$\boldsymbol{x_i^t}$	Opinion value of agent I at time t	$[-1,1]$
$\boldsymbol{\widetilde{x_i^t}}$	the value how others perceived agent i's opinion if expressed at time t	$[-1,1]$
$\boldsymbol{X_i^t}$	agent i's integrated opinion value perceived from all other agents who express opinions at time t (including the host)	$[-1,1]$
$\boldsymbol{f(x_i^t, X_i^t)}$	kernel function of opinion impact degree	
$\boldsymbol{\omega_{ij}^t}$	weight attached to agent j's opinion by agent i at time t	$(0,1]$
$\boldsymbol{S^t}$	the set of agents expressing opinions at time t (including the host)	
$\boldsymbol{\tau_i^t}$	opinion expression state for agent i at time t	0 or 1

Table 1. Variable Annotation Table

Annotations for parameters:

Parameters	Definition	Range
$\boldsymbol{m}$	mode of the opinion values of the host	$[-1,1]$
$\boldsymbol{l}$	Lower bound of the opinion values of the host	$[-1,1]$
$\boldsymbol{\alpha}$	assimilation coefficient	$[0,1]$
$\boldsymbol{\beta}$	repulsion coefficient	$[0,1]$
$\boldsymbol{d_1}$	assimilation threshold	$[0,1]$
$\boldsymbol{d_2}$	repulsion threshold	$[1,2]$
$\boldsymbol{\delta_i}$	entertainment parameter for agent i to express	$[0,1]$
$\boldsymbol{p}$	conformity parameter for agents to express when in majority	$[0,1]$
$\boldsymbol{b}$	Weight base of the opinion from the host in the integrated opinion of an agent	$(0,1]$
$\boldsymbol{k_P}$	the "slope" for perception of positive opinions	$(0,1]$
$\boldsymbol{c}$	the intercept for perception of positive opinions	$[0,1)$
$\boldsymbol{k_N}$	the "slope" for perception of negative opinions	$(0,1]$
$\boldsymbol{\theta}$	the exponent for marginal diminishing effect in opinion perception	$(0,1]$

Table 2. Parameter Annotation Table

3.2 Modeling Opinion Evolution

The original SJBO model was limited to the interaction between two agents, so we firstly extended the opinion dynamics model of SJBO from a dual scenario to a multiple-agent one by setting the variable X_i^t, suggesting each agent can be influenced by all revealed opinions as well as the information from the host. In addition, we modified the kernel function by binding a constraint factor (see Appendix 1) so that the opinion value will not exceed the predetermined range after each update. The multi-agent model is described as (3-1)-(3-2):

$$x_i^{t+1} = \begin{cases} x_i^t + f(x_i^t, X_i^t)(X_i^t - x_i^t) & i \neq H \\ Triang(l, m, 1) & i = H \end{cases} \tag{3-1}$$

Where

$$f(x_i^t, X_i^t) = \begin{cases} \frac{\alpha(1-|x_i^t|)}{2}, & |x_i^t - X_i^t| < d_1 \\ 0, & d_1 \leq |x_i^t - X_i^t| \leq d_2 \\ \frac{-\beta(1-|x_i^t|)}{2}, & |x_i^t - X_i^t| > d_2 \end{cases} \tag{3-2}$$

$$X_i^t = \sum_{j \in S^t \cap j \neq i} \omega_{ij}^t \widetilde{x_j^t} \tag{3-3}$$

The weight ω_{ij}^t attached to opinions of different agents are assumed to be identical except for that of the host. Generally, when the number of scrolling comments is small, more attention is likely to be given to the host, while a single bullet screen will easily attract the attention of other audiences. As the number of scrolling opinions increases, the audiences will lose their attention to the host, but at the same time each comment also tends to gain less attention due to information overload (@Gu, 2007; @Jones, 2004), and these two attenuations has a tendency of marginal decreasing. In addition, we believe that the audience is not affected by the opinions expressed by themselves, so it is better to distinguish the expression state of the agent when calculating the weight. To approximate these properties, the calculation of weights is defined as (3-4):

$$\omega_{ij}^t = \begin{cases} b^{\sqrt{|S^t|-2}}, & \tau_i^t = 1, j = H \\ b^{\sqrt{|S^t|-1}}, & \tau_i^t = 0, j = H \\ \frac{1-b^{\sqrt{|S^t|-2}}}{|S^t|-2}, & \tau_i^t = 1, j \neq H \\ \frac{1-b^{\sqrt{|S^t|-1}}}{|S^t|-1}, & \tau_i^t = 0, j \neq H \end{cases} \tag{3-4}$$

$\widetilde{x_j^t}$ is the value of how agent *j*'s opinion is perceived by others, which is different from the actual value x_j^t because of the existence of positivity offset and negativity bias. In the setting of opinion evolution, this theory suggests that when the opinion absolute intensity is relatively low, positive stimulus would cause stronger positive perception than the negative response stimulated by negative stimulus while when the intensity becomes higher, negative perception tend to be stronger. Also, this relationship is also said to be marginal decreasing as the intensity rises. So, we formulate $\widetilde{x_j^t}$ as (3-5):

$$\widetilde{x_j^t} = \begin{cases} k_P\left(x_j^t\right)^\theta + c & x_j^t > 0 \\ -k_N\left(-x_j^t\right)^\theta & x_j^t \leq 0 \end{cases} \tag{3-5}$$

Where

$$0 \leq c \leq k_N - k_P < 1 - k_P, \qquad \theta \in (0,1)$$

Next, we would explain how τ_i^t and S^t evolve. These two variables relate to agents' expression state. τ_i^t is a Bernoulli variable denoting the expression state of agent i at time t, and S^t is the set to record all agents who express their opinions at time *t*. Entertainment motivation and conformity effect are considered in the determination of whether to send screen bullets. Agents would firstly identify whether they are in majority or minority, and make their expression decisions according to their levels of entertainment motivation and conformity.

When audience agents believe that their opinions are qualitatively consistent with the dominant opinion (i.e. same in positivity or negativity), they will judge themselves as belonging to the majority, otherwise they will consider themselves as belonging to the minority. In the real judgment of the dominant opinion, we assume that audiences will not actually calculate the number of positive and negative opinions to judge, but use the quasi-statistical sense: The dominant opinion is identified by the integration of all others' opinions, which is X_i^t in our model. Noticing that when agents have perceived the integrated opinion of others at time *t*, their opinions have already finished the opinion update to *t*+1. But since other audiences' expression states at time *t*+1 have not been formed, they can only rely on their integrated opinions at time *t*, not *t*+1, to make their judgements. This process can be expressed as:

$$x_i^{t+1}X_i^t \geq 0, i - \text{majority}$$
$$x_i^{t+1}X_i^t < 0, i - \text{minority}$$

After the judgements, the final decision of whether to send bullet screens is defined as (3-6), then the evolution of S^t is rendered by (3-7):

$$\tau_i^{t+1} \sim \begin{cases} 1 & i = H \\ B(1, \delta_i p) & i \neq H, i - \text{majority} \\ B(1, \delta_i(1-p)) & i \neq H, i - \text{minority} \end{cases} \tag{3-6}$$

$$S^t = \{i \mid \tau_i^t = 1\} \tag{3-7}$$

When $p = 1$, the agents are in completely conformity (see Table 3), which means they would only express when they are in majority as figure 5 suggested. When $p = 0.5$, there will be no difference for agents to make decision of expressing opinions between in majority or minority.

(p value)	***Conformity***	……	***Neutrality***	……	***Inconformity***
Majority	1	……	0.5	……	0
Minority	0	……	0.5	……	1

Table 3. Expression Probability Chart

4. Model Estimation

In this section, we are going to estimate the model we proposed with the opinion data collected from Douyu, an internet live streaming platform in China. We would firstly describe the opinion data and information obtained from the platform, then elaborate on the procedure of the model estimation.

4.1 Data Description

The data we collected come from *Douyu TV*, a leading live streaming enterprise in China. Each sample contains all messages generated in a certain duration of one live streaming. For each bullet screen data item in the sample, it includes information like the time when the bullet screen was sent, the nickname of the audience who sent it, and the bullet screen content (see Table 4).

Index	**Data-Type**	**Example/Range**
MessageID	Ordinal number	123
Time	Datetime	2018/10/12 19:48
Type	Category	Danmu or Gift
Nickname	Text	"小 v 爷 7788"
Content	Text and Emoji	"大气大气带起"
RoomID	Index	5706218

Table 4. Metadata of Bullet Screen

In order to turn opinion text into numerical values, we performed sentiment analysis on the content of each bullet screen via APIs of *BosonNLP*, an interface of Chinese text mining. The result of sentiment analysis is expressed as the probability of an opinion being positive, and the final sentiment score is calculated as the mean of the positivity (+1) and negativity (-1) of this comment, weighted by positivity and negativity possibilities.

Among the bullet screens, apart from text messages, there is a special kind of data – emojis (see Table 5) for us to deal with. For the sentiment analysis of emoticons, we referred to the method in the work of Novak et al (2015) to gain emoji's sentiment scores through empirical studies. Participants will be asked to fill out a questionnaire containing all the emojis in the Douyu platform, and they will make judgments between 1, 0, and -1 for each emoji, where 1 represents positive feelings, 0 stands for neutral and -1 means negative feelings. We obtained 525 effective samples for emoji labelling. Then, the final sentiment score for an emoji will be obtained by calculating the mean score of the labels. For text-emoji mixed contents, we would average the score of both parts.

index	**content**	**picture**
dy101	666	
dy102	发呆	
dy103	拜拜	
dy104	晕	

Table 5. Metadata of Emoji

4.2 Two-Step Estimation

To estimate the model, we select one sample from the data pool as the reference (more samples might be estimated later). The original model incorporates 14 parameters (2 from the shape parameters of the beta distribution of δ_i) to estimate, which is kind of difficult to implement for both accuracy and computation. We divide these parameters into two groups, one of which is more related to the expression state of the audiences, and the other is related to the interaction of opinions:

Parameter Group 1:

$$\alpha_{Beta}, \beta_{Beta}, p$$

Parameter Group 2:

$$\alpha, \beta, m, l, d_1, d_2, k_N, k_P, c, \theta, b$$

We first estimated the parameters in Group 1, here we assume that p = 0.5, which makes the audiences' expression probability irrelevant to whether they are in majority or minority for simplification. In this case, τ_i^t becomes a Bernoulli variable with the mean of $0.5\delta_i$. For every agent in the simulation, this Bernoulli process happens every time they make their decision to speak or not, so each δ_i could be approximated by the expression times of that agent multiply two. So, if we calculate the expression times for all the audiences in the sample, we are able to get a distribution of δ_i, which forms a beta distribution. We estimated α_{Beta}, β_{Beta} using MLE. Generalized Method of Moments is also tested with different bin numbers, but suggested an inferior result compared to that of MLE (see), regarding the log-likelihood metric (MLE = 3593.98, GMM=3539.31, see Figure 5). The values we gained from the first step estimation would be used in the second step of estimation.

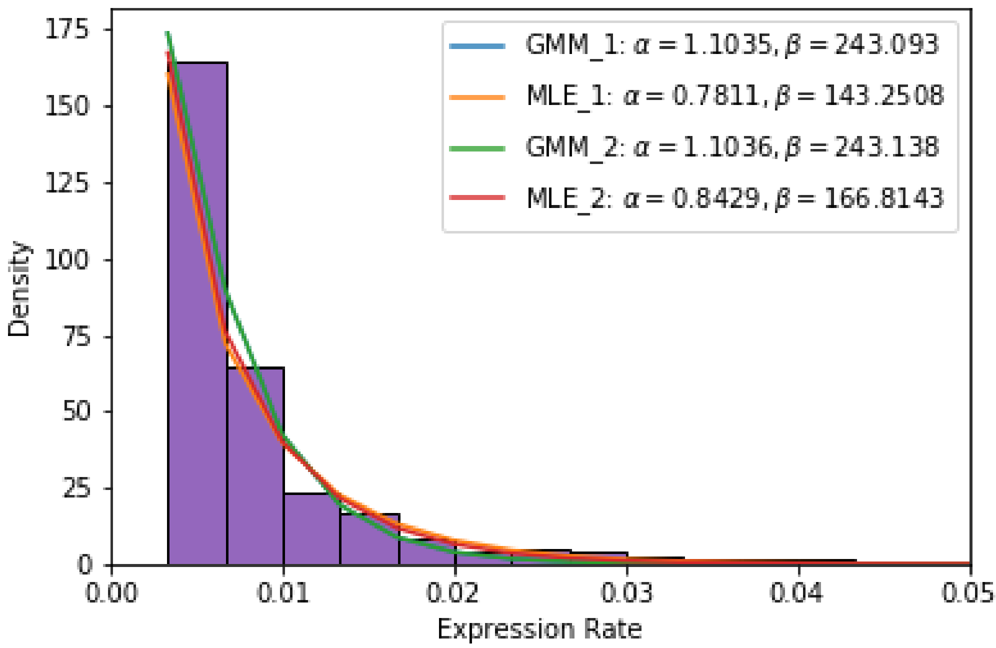


Figure 5. Beta Estimation Result

In the second step we would used simulated method of moments to estimate the remaining parameters. In this step, we also calibrate part of the parameters that are less impactful to the evolution results we are interested in. Previous study suggested that α, β are not quite impactful for the evolution results, which is also verified by our analysis in Section 5, so we set each of them to be 0.5. We also fixed the parameter $\theta = 0.5, k_N = 1$ to make the estimation for k_N and c more pinpointed.

Choosing moments is another core issue for the estimation in this step because the only variables (data) we have for this model is those opinion values, especially we do not have any information about the values produced by the host and those unexpressed opinions. Therefore, we need to estimate these 7 parameters based on the data of all expressed opinions. Currently, we calculated the average expressed opinion values, variances and positive opinion ratios at each time unit, and organize each of these statistics into 10 groups where each group contain values of 60 consecutive time units (different size of time frames could be tested later). The average value of the statistics in each time group would become the candidates of data moments. Correspondingly, we also set functions to calculate these statistics after each simulation as model moments. In this estimation, I used those moments of averaged average opinion values and averaged variance as the final moments, so there will be 20 moments to estimate these 7 parameters. Besides, the weighting matrix used here is the identity matrix and the error function are the distance between data and model moments.

The optimization process in the estimation was launched by Sequential Monte Carlo methods, which would filter parameter particles by assigning those of small values of the objective function with high probability to occur in the next generation, and finally yielded an optimized posterior distribution for each parameter. For the simulation of each parameter particle (a combination of all estimated parameters), we replicated them for 10 times. [1]

The estimation after 10 generation suggests that these remaining parameters have different sensitivity to the evolution process. (see Figure 6, Table 6) We found that for parameter d_1, d_2, k_P, c, the estimation results converge better with smaller standard deviation among the particles, but for the rest three, especially for m, l, we found the estimation is not so convincing since the standard deviation is still relatively high. Two factors are possibly responsible for this phenomenon: we do not incorporate any direct information related to the host in the estimation or the function of these two parameters are hard to be separated from others. We also calculated the value of criterion function, which is about 0.32, which is much smaller than the average criterion value of the first generation (over 1), verifying the model can be estimated from real data to some extent.

Parameter	m	l	d_1	d_2	b	k_P	c
Weighted Mean	0.239	-0.368	0.403	1.166	0.310	0.249	0.184
Weighted Std	0.464	0.430	0.094	0.076	0.322	0.189	0.140

Table 6. SMM Estimation Posterior Distribution

5. Experiment Analysis

In this section, we will analyze the sensitivity of the initial opinion distribution and those theory-related parameters to identify the specific effects of each parameter on the evolution of public opinion in the live streaming platform. Throughout the simulation process, we set the simulation time of the model to be 1000-time units to ensure that the model has reached a steady state at the end of the evolution. The platform is set to 500 viewers, and each group of parameters is subjected to 10 times of simulation (simulation of more times is also examined to ensure the robustness of the results). At the same time, when performing the impact analysis of a single parameter, we fix all other parameters. We set up a standard parameter group according to the estimation of some live streaming and intuition, the specific values are as follows:

$$x_i^0 = uniform(-1,1), \alpha = 0.5, \beta = 0.5, d_1 = 0.5, d_2 = 1.5, b = 0.75, l = 0.0$$
$$m = 0.75, k_P = 0.5, k_N = 1.0, c = 0.25, \theta = 0.5, p = 0.5, \delta_i = beta(1,150)$$

In the initial setting of τ_i^0, we set a certain number of viewers from 0 to 10 to speak according to the previous sample ($\tau_i^0 = 1$), and the rest of the audience do not speak ($\tau_i^0 = 0$). In the measurement of the results, we take three metrics at the end of the evolution into consideration: audiences' average opinion value, opinion value distribution, and the conversion rate of positive and negative opinions compared to the original state.

[1] We understand that 10 times is insufficient for presenting randomness in SMM, and would like to make the estimation with more replications on high-performance computing systems.

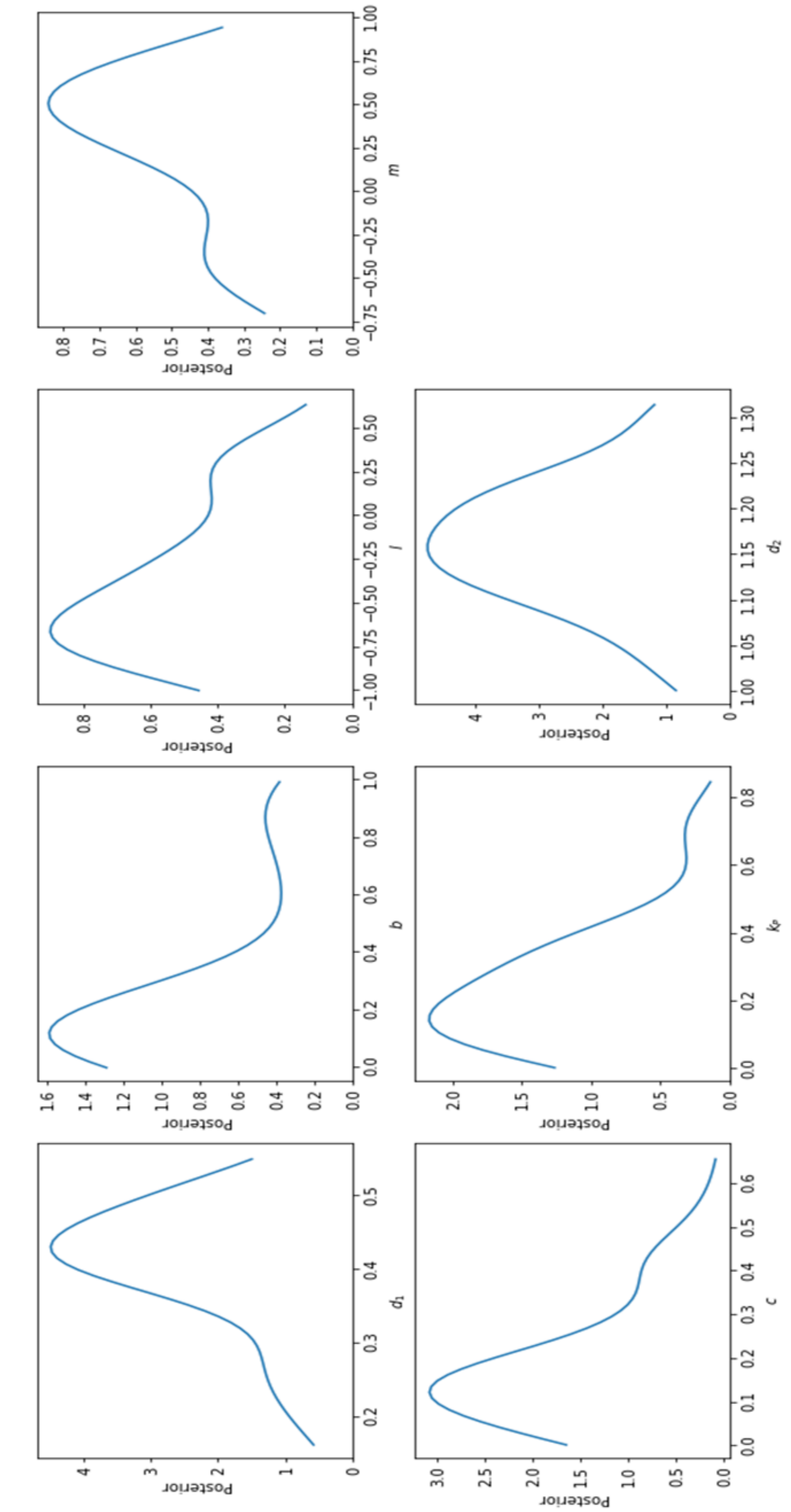


Figure 6. SMM Estimation Posterior Distribution

5.1 Effect of Initial Opinions

In a live broadcast platform, different viewers may have different attitudes when starting to watch a live streaming. For example, some viewers are fans of a certain host, and they may have a more positive point of view from the very beginning; some viewers tend to be verbally aggressive to the host at the beginning; some viewers watch the live broadcast just to kill time, and therefore may not have a very extreme initial opinion value. In this part of the analysis, we assume that the opinions of these audiences at the beginning are in a uniform distribution of a certain range, and explore the impact of different initial opinion value distributions on the evolution of the model. The simulation results are shown in Figure 7.

From the perspective of the final average opinion value, the distribution of the initial opinions has a great impact on the final average opinions. When people's initial attitude distribution is not biased (when the mean is zero), the milder their attitudes are, the closer they are to zero, the more susceptible they are to the influence of the host's information source. Since the host information source is set to a state that no negative information is disseminated, we can see that the average opinion level increases with the decrease of the initial distribution range, and gradually approaches the mode value of the host information source. When the initial distribution is biased, the polarity of the average opinion values at the end of evolution is consistent with the polarity of the initial opinion value distribution, that is, the stronger the polarity of the initial opinion distributions (positive and negative), the higher the average opinion value (positive and negative) polarity at the end of evolution.

From the perspective of the distribution at the end of the evolution, in all cases where the initial opinion values are not completely positive, the final evolution results show one large opinion group and some small clusters of opinions with different polarities. The opinion values of the larger positive opinion group (also referred to as the main opinion group in the following analysis) are close to the mode of information values produced by the host, indicating that the information source of the host can pose an effective public opinion guidance, and the locations of these major opinion groups have the same change pattern as the average opinion. For the smaller negative opinion groups, once the initial distribution contains agents with negative opinions, regardless of whether the initial opinion distribution is biased or not, at the end of the evolution, those part always survive in a bigger or smaller size. The larger the negative polarity of the negative opinions held by these audiences, the lager these final negative groups would be.

From the perspective of the conversion rate, there is no situation in which initial positive opinion holders change to negative opinion holders in the end, indicating that the group of negative opinion holders left at the end of the evolution came from individuals who originally had negative opinions.

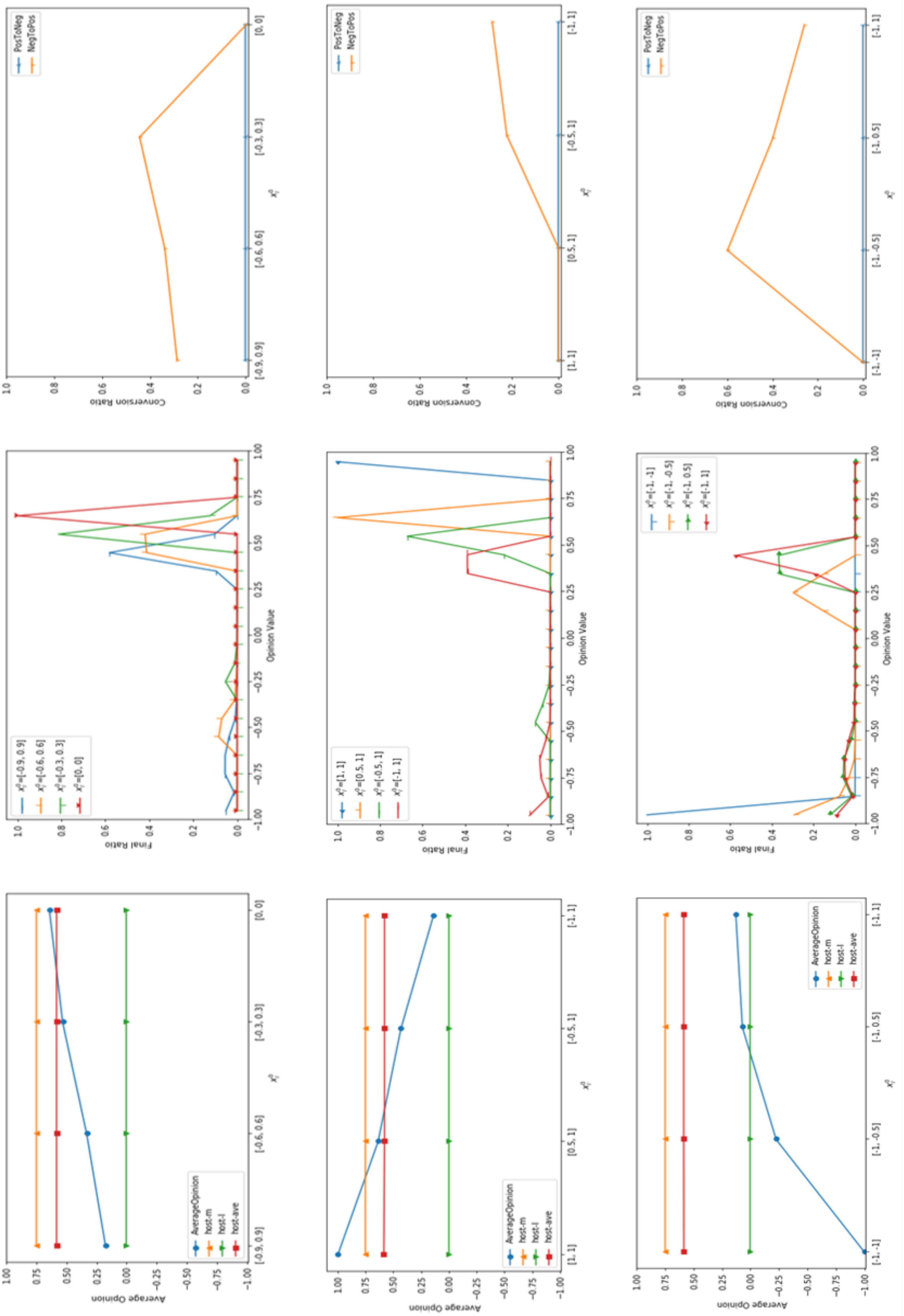


Figure 7. The effect of initial opinion distribution on final average opinion value, final opinion distribution and conversion rate

The above simulation results show that the host information source takes a dominant position in the evolution of the live streaming process, but the dominant position will be weakened by the negative opinions existing in the initial opinions, and the weakening effect will be increased by as the ratio of initial negative opinion values or polarity increases.

5.2 Effect of Assimilation and Repulsion

For this part, we would examine the effects of the assimilation and repulsion coefficients as well as thresholds. From the perspective of the final average opinion value, opinion distribution, and conversion rate, the influence of both assimilation and repulsion coefficients are not significant (see Figure 8). Only when the assimilation coefficient drops to zero, that is, when there is no assimilation, the above three indicators becomes quite different, but this special case is not really realistic.

From the analysis of the threshold of assimilation (see Figure 9), it can be found that it has a significant impact on the evolution of viewpoints. The increase of the assimilation threshold increases the average opinion level and the conversion rate of negative opinions at the end of the evolution. As for the final opinion distribution, the increase of the assimilation threshold will make the larger group of main opinion closer to the mode level of the host information source (m), enhancing the guiding role of the host, and reducing the proportion of the smaller negative opinion group. Increasing the threshold of repulsion has the same effect, but the effect is less significant.

To sum up, when the more moderate the audience (the larger their thresholds of assimilation and repulsion), the easier they are to be assimilated, but the more difficult they are to be repulsed. At this time, the host's public opinion guidance effect is enhanced, and the proportion of extreme negative opinion value groups at the end of evolution decreases.

5.3 Effect of Negativity Bias and Positivity Offset

In this part, we examine the effect of the parameters of positive perception coefficient, negative perception coefficient, positive perception intercept and the marginal diminishing coefficient.

According to Figure 10 and 11, it can be found that the influence of the change in the coefficient and intercept of the positive perception is consistent. As the intercept or coefficient of the positive perception increases, the average opinion values in the evolution result also shows an upward trend. At the same time, the major opinion values of the main opinion group are also increasing. This trend indicates that under the standard conditions we set, the increase in the intercept or coefficient of the positive perception would help the host to guide the main opinion group, so that their views are closer to the mode opinion value. Surprisingly, in the aspect of opinion polarization, the

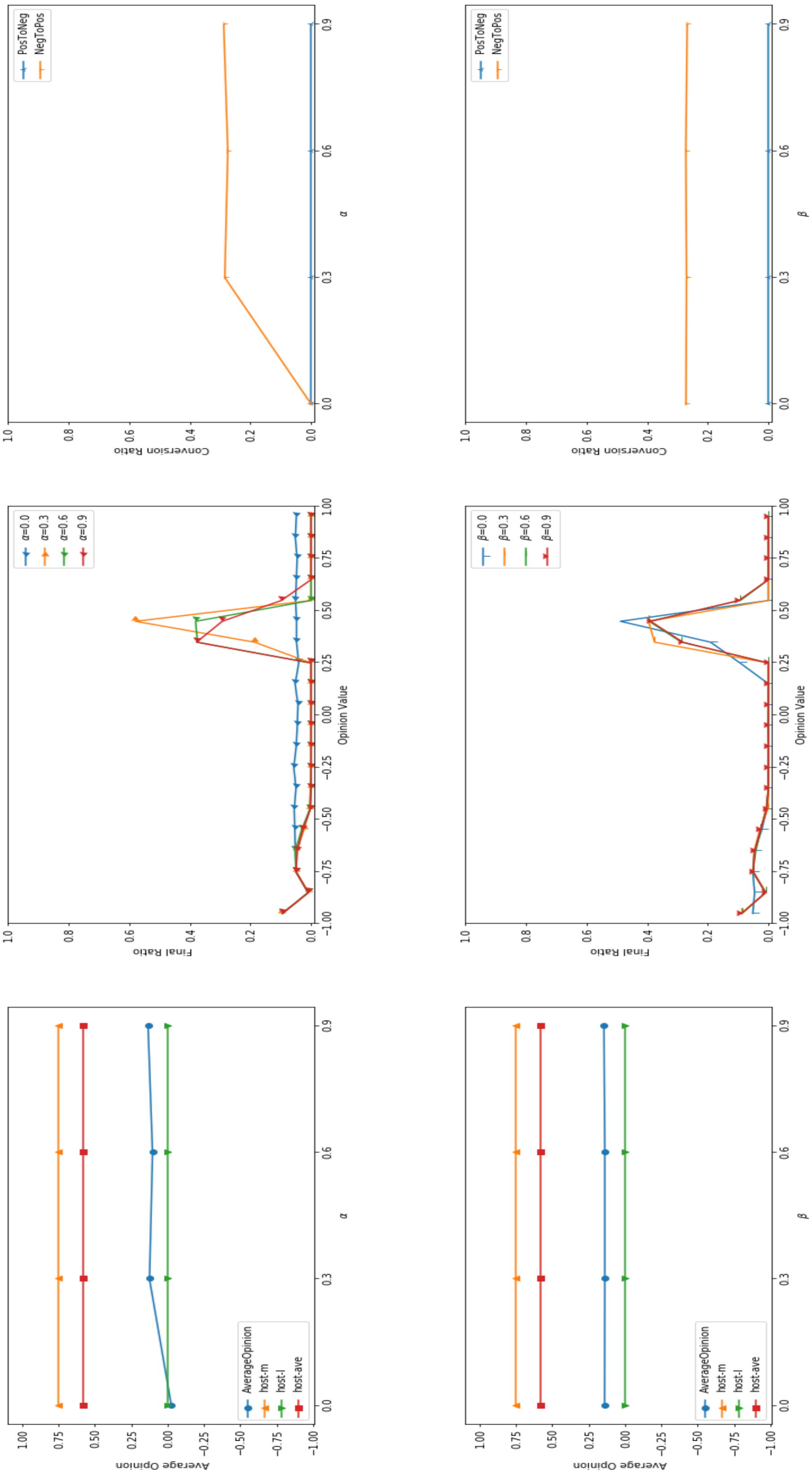


Figure 8. The effect of assimilation and repulsion coefficient on final average opinion value, final opinion distribution and conversion rate

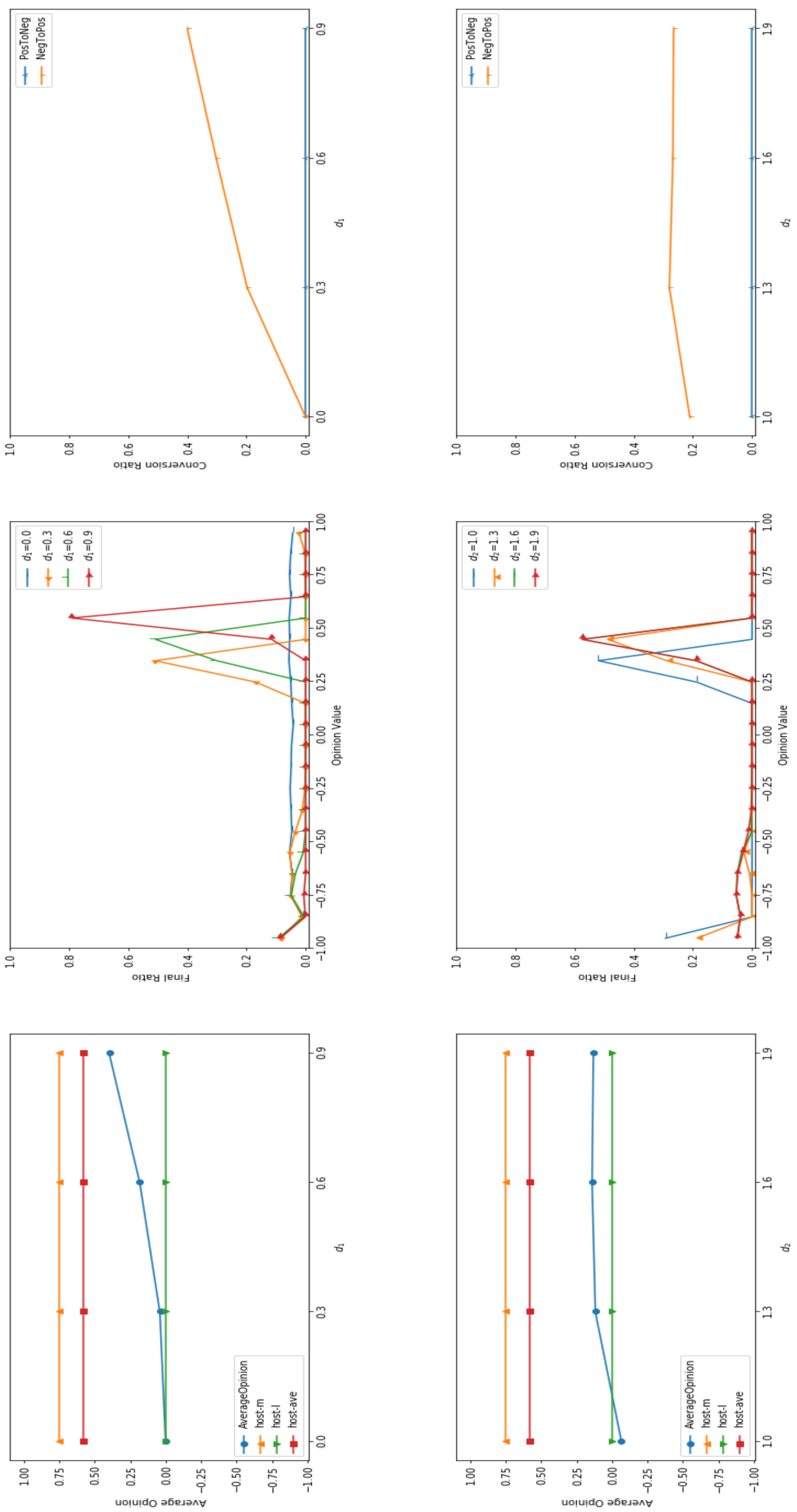


Figure 9. The effect of assimilation and repulsion threshold on final average opinion value, final opinion distribution and conversion rate

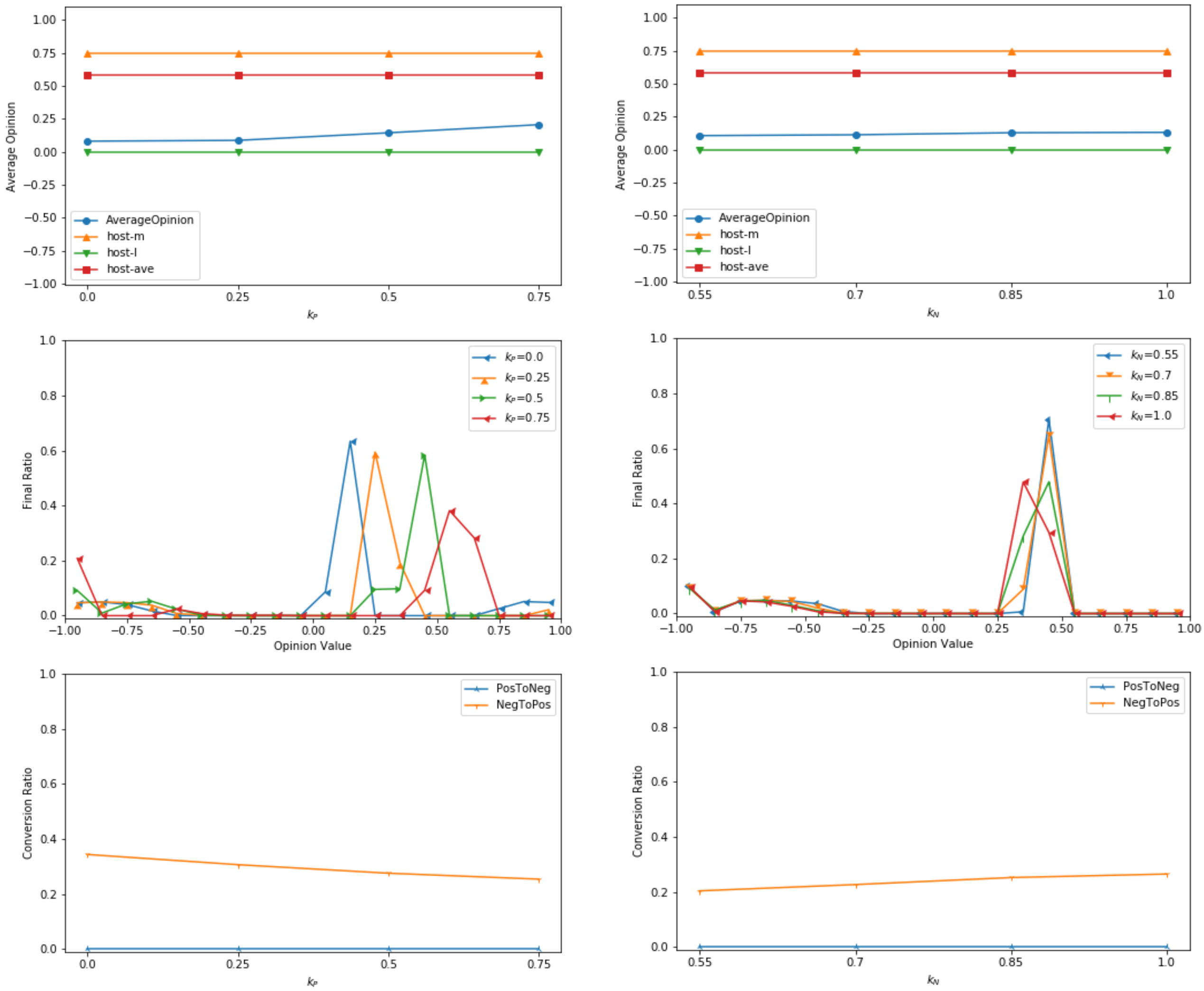


Figure 10. The effect of positive and negative perception coefficient on final average opinion value, final opinion distribution and conversion rate

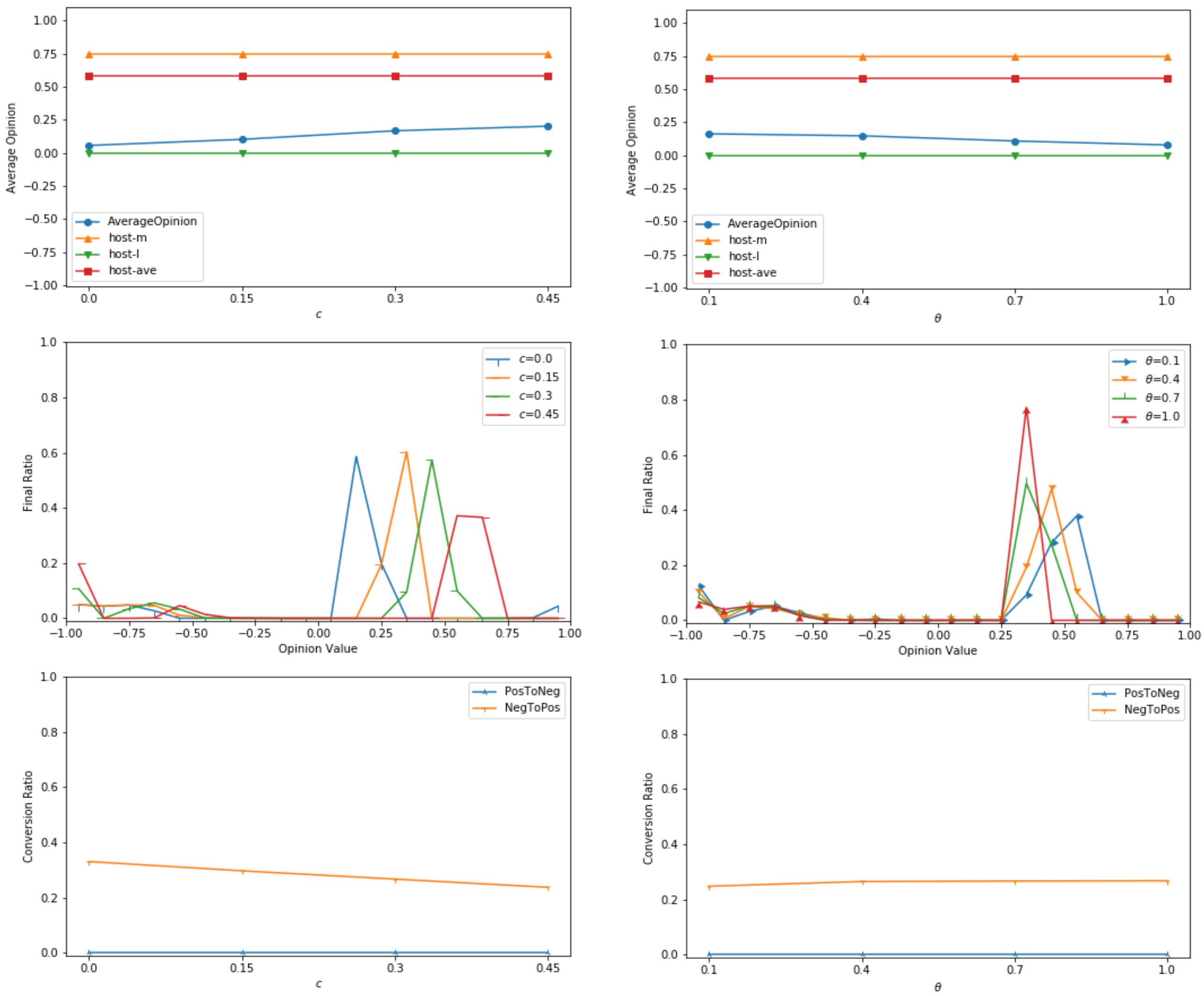


Figure 11. The effect of positive perception intercept and marginal effect coefficient on final average opinion value, final opinion distribution and conversion rate

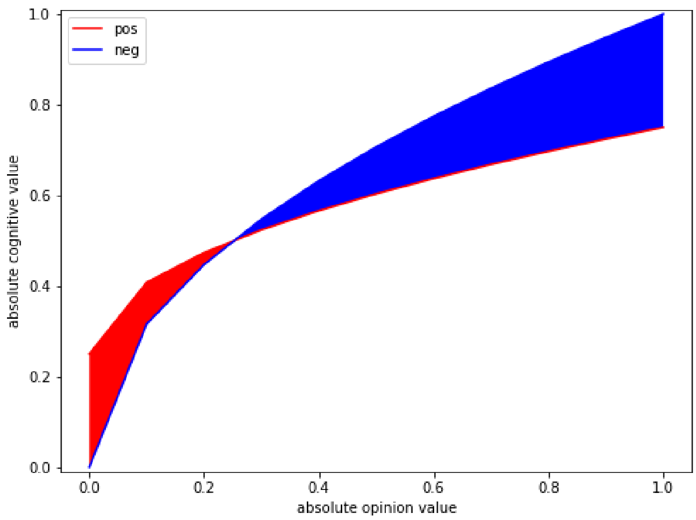


Figure 12. Positivity Offset (red) and Negativity Bias (blue)

change in the positive perception intercept shows that an increase in its value will increase the proportion of groups with extreme negative opinion values at the end of the evolution, while the groups of extreme positive value holders at the end of evolution decreases. We deduce that the increase in the coefficient or intercept of the positive perception makes more positive opinions have a larger perceived value, making it easier for some audiences who originally had slightly negative opinions to generate repulsion reactions or retain the original opinions, pushing them towards the negative pole, which can also be verified through the falling negative opinion conversion rate. The audience group which is originally located near the positive pole is more likely to be assimilated, so it is closer to the main opinion group.

The effect of the change in the coefficient of the negative perception curve is not as significant as that of the positive curve (see Figure 10). An important reason is that under our standard group, the host information source, which is the main source of the influence on the audience 's opinions, does not generate negative values. However, after many simulations, it is still found that with the increase of the negative curve coefficient, the conversion rate of negative opinions and the average opinion level have slightly increased. After inference, we think that after the coefficient of the negative curve increases, the perceived value of negative opinions becomes more negative. Some viewers who originally had strong negative opinions can assimilate more with viewers who have slighter negative opinions since the opinion distance could be smaller, and might even be transformed into positive opinion holders. This process is also coherent with the changes in average opinion values and conversion rates.

In addition, the marginal diminishing coefficient also have little impact on the evolution result of average opinion level and conversion rate, but make some differences on the final opinion distribution. When the marginal diminishing coefficient increases, the marginal diminishing effect decreases, the opinion value of the main opinion group slightly decreases, but at the same time the proportion of people increases, while the proportion of people near extreme negative opinions decreases accordingly. It can be found that this change pattern is different from the change pattern of the coefficient and intercept of the positive perception curve. Because when the marginal decreasing coefficient is larger, the perceived value of the opinion decreases, we might use the same inference ideas as when analyzing the coefficients and intercepts of the positive perception curve can be used to understand the effects of the diminishing marginal coefficients.

After observing the effects of individual parameters related to negative bias and positivity offset, we tried to further understand the overall impact of these two effects. We denote negative bias and positive shift as the dominant area of the two perception curves. The effect of positivity offset refers to the red area, while the effect of negative bias refers to the blue area, as shown in Figure 12. Based on this, we calculated the quantitative expressions of the two effects (5-1)-(5-3)

$$x^* = \left(\frac{c}{k_N - k_P}\right)^{\frac{1}{\theta}} \quad (5\text{-}1)$$

$$s_P = \int_0^{x^*}\left[(k_P - k_N)x^\theta + c\,\right] = \left(\frac{c*\theta}{\theta+1}\right)\left(\frac{c}{k_N - k_P}\right)^{\frac{1}{\theta}} \quad (5\text{-}2)$$

$$s_N = \int_{x^*}^{1}\left[(k_N - k_P)x^\theta - c\,\right] = \left(\frac{k_N - k_P}{\theta+1}\right) - c + \left(\frac{c*\theta}{\theta+1}\right)\left(\frac{c}{k_N - k_P}\right)^{\frac{1}{\theta}} \quad (5\text{-}3)$$

After analyzing the monotony of s_P and s_N, we found that the source of the increase in the positive offset (the decrease in the negative bias effect) can be the increase of the audience's perceived marginal diminishing coefficient, the increase of the positive perception coefficient and intercept, and the decrease of the negative perception coefficient. However, these four types of variances can result in different results in the final opinion distribution. Therefore, we cannot simply predict the change of evolution results of public opinion in live streaming by measuring the variance in the overall effect, but we need to trace back to the source of the differences, i.e., which parameters are changed.

5.4 Effect of Entertainment Motivation and Conformity

In this part, we examine the effect of the parameters of entertainment motivation and conformity, which are related to the expression state of agents (see Figure 13).

From the perspective of conformity, when the agents' speech state is completely conformed or completely non-conformed, the average opinion value at the end of the evolution is lower, and when it is in the middle state, the average opinion level is higher. In terms of the distribution of opinions, when we change from complete non-conformity to complete conformity, the opinion level of the main opinion group gradually approaches the mode value of the host information source, but the proportion of the opinion group holding a moderate negative opinion also continues to increase. In terms of conversion rate, as the conformity level of the audiences increases, the conversion rate of those initial negative opinions decreases, while the conversion rate of initial positive opinions remains at zero.

From the perspective of entertainment motivation, with the increase of the second shape parameter, people's entertainment motivation will be closer to the preset minimal value of 0.002, that is, a smaller proportion of the audience will have greater entertainment motivation. Then, the overall expression rate of the audiences will also decline, so the host now shows a stronger leading role, and you can see that the average opinion value and the opinion value of the main opinion group show an upward trend. At the same time, due to the lack of assimilation from mild negative opinions, the proportion of groups with extreme negative opinions has also risen to a certain extent, and in terms of conversion rate, the entertainment motivation does not show a significant impact.

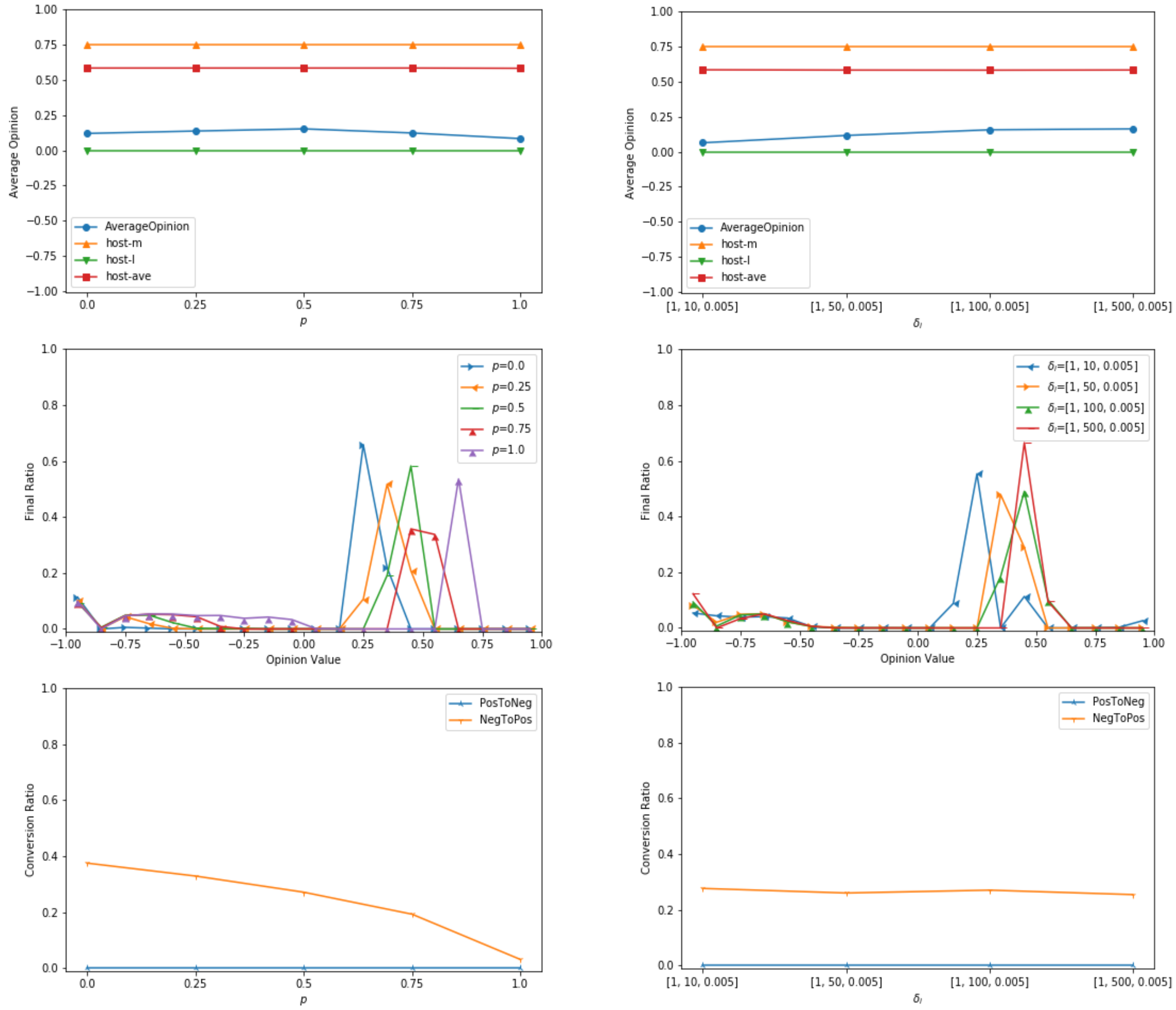


Figure 13. The effect of conformity effect and entertainment motivation on final average opinion value, final opinion distribution and conversion rate

6. Conclusions

In this study, we built an opinion dynamics model to simulate the opinion evolution on platforms based on the SJBO model, and extended the original dual interactive model to a multi-player interaction mode. The biggest contribution in modelling is that we introduced the theory of negative bias and positive bias into the model, and considered entertainment motivation and conformity in the process of making expression decisions, making the whole model closer to human perception and behavior patterns in reality.

We collected real opinion data samples from the Douyu live streaming platform, and tried to verify the usability of the model by using estimating the parameters from the data. The estimation of multi-agent model proves to be computationally expensive but still suggests the model is a rough approximation to the reality. Still, to fine-tune the model, we would try different formats of the opinion perception function and the host opinion functions in the future.

We tested the influence of initial state and relevant parameters in the model to see how they would influence the results of the opinion evolution in our standard settings. According to the simulation results, we have the following important conclusions:

1) When the initial opinion distribution is not completely unipolar, then at the end of the evolution, there will be a main opinion group whose opinion value is close to the host's information source value, and some small opinion groups distributed around the extreme negative opinion values. This suggests a leading role of the host in the evolution, but this role would be weakened by the increase of negative opinions in the initial state.

2) When the assimilation threshold and repulsion threshold of the audiences are bigger, the host's impact will increase, and the proportion of extreme opinions will decrease at the end of the evolution.

3) The impact of positive offset and negative bias on the evolution of opinions needs to be judged after tracing the source of the parameters. Among them, the increase of either positivity perception coefficient or intercept would not only enhance the assimilation effect of the host's information by increasing the main opinion group, but also increase the repulsion effect from the extreme negative opinion holders, thereby increasing the proportion of this part of audiences, while the increase of the negative perception coefficient can help to transform some non-extreme negative viewpoint holders to the main opinion group; and the increase in the marginal diminishing coefficient brings the opposite effect of the positive perception coefficient change.

4) When the audience's conformity is enhanced, the assimilation effect of the host information source to the main opinion group will be enhanced, but at the same time, the conversion from non-extreme negative opinion holders will be reduced.

5) When the audience's entertainment motivation increases, the frequency of expression of different opinions will increase, weakening the assimilation effect of the host information source to the main opinion group, but also reducing the proportion of extreme negative opinion holders.

Appendix

1. The mathematical proof for the factor $\frac{(1-|x_i^t|)}{2}$ in the kernel function:

The usage for this is to constrain the opinion value between -1 and 1. Given $x_i^t < 0$, the repulsion function will be used when X_i^t is positive and we need to ensure that $x_i^{t+1} > -1$.

$$\begin{aligned} x_i^{t+1} &= x_i^t + f(x_i^t, X_i^t)(X_i^t - x_i^t) \\ &= x_i^t - \frac{\beta(1-|x_i^t|)}{2}(X_i^t - x_i^t) \\ &= x_i^t - \frac{\beta(1+x_i^t)}{2}(X_i^t - x_i^t) \\ &\geq x_i^t - \frac{\beta}{2}[1-(x_i^t)^2] \end{aligned}$$

Given

$$\begin{aligned} & f(x) = x - \frac{\beta}{2}[1-x^2] \\ & If\ \beta \in [0,1],\ f(x)_{min} = f(-1) = -1 \\ & If\ \beta > 1, \quad f(x)_{min} = f\left(-\frac{1}{\beta}\right) = -\frac{1}{2}\left(\beta + \frac{1}{\beta}\right) \end{aligned}$$

To make $f\left(-\frac{1}{\beta}\right) \geq -1$, we obtain that $\beta = 1$, violating the assumption. Therefore, β has to be in $[0,1]$ with the constrain factor to make sure the opinion value will not cross the boundary.

2. Opinion Evolution Algorithm

Evolution Algorithm (pseudo code)

```
/*Given: the initial conditions: FirstExpressedValues,
A BroadcastPlatform (BP) object with members of TimeSpan, Population, Network G and other methods and parameters in the model
*/
Initialize the BroadcastPlatform with FirstExpressedValues

FOR t←1 to BP.TimeSpan
    Do temp←list()
    #update time stamp
    Set_node_attributes (BP.G, t, 'Time')
    #set the opinion value for the host
    BP.Host.SelfOpiniontriang←(BP.l,BP.m,1)
```

```
  FOR i←1 to BP.Population  /*host with index 0 is excluded*/
    #update the opinion of agent (audience) i
   Do BP.G.nodes[i].SelfOpinion←BP.AudienceOpinionTransition(i)
   #update the expression state of agent (audience) i
       BP.ExpressionMode(i)
 END

 #update the collection of agents who expressed their opinions
   BP.UpdateExpressionCollection()

   FOR i←1 to BP.Population
     #update the perceived opinion from others of agent (audience) i
   BP.G.nodes[i].OthersOpinion←BP.IntegratedOpinion(i)
        nodeinfo←{dictionary of nodes information including SelfOpinion, OthersOpinion,
        ExpressionState, Time…}
   temp.append(nodeinfo)
 END

 #add the information of all nodes at time t to the evolution record
   BP.record.append(temp)
END
```

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